

Taming the Evolving Black Box:
**Improving Integration and Documentation of Pre-Trained
Machine Learning Components**

Alex Cummaudo
BSc Swinburne, BIT(Hons)
<ca@deakin.edu.au>

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Doctor of Philosophy*



Applied Artificial Intelligence Institute
Deakin University
Melbourne, Australia

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ABSTRACT

Software components hide implementation complexity by exposing a designed interface that permits easy integration and use. The explosive demand and interest in AI and deep learning has led to creation of software components that offer various ML functions. The promise is that these AI components improve productivity and application developers can use them without a deep understanding of their underlying mechanics. Application developers currently have access to multiple AI components with a prominent focus on visual object recognition, natural language processing, audio analysis, anomaly detection and forecasting from numerical data. Simplified variations of these components are offered via cloud computing as intelligent web services; these services are often marketed as ‘developer friendly’ ML with the claim of being just another component accessible on the cloud through a web-based RESTful API.

A developer’s conceptual understanding of components they use impacts the internal and external quality of software they produce. Hence, vendors of intelligent web services must give sufficient level of conceptual detail to enable integration and effective use of their pre-packaged capabilities, ultimately to help developers who integrate with their services produce high-quality software.

This thesis investigates these emerging intelligent web services. Based on an analysis of the observable behaviour of intelligent web services, we show that their probabilistic results and evolution is not effectively communicated in the documentation. Our work shows that developers interpret and use these services using anchors built upon their understanding of traditional (i.e., deterministic and non-probabilistic) software components. We show how this mismatch results in a weak conceptual understanding of highly-abstracted forms of ML, impacting software quality. To mitigate documentation issues, we propose a taxonomy of the key requirements of good API documentation, which we derive from existing literature and triangulated through a survey with developers. We use this information to assess the value placed by developers on each API documentation artefact and identify gaps in the services’ documentation, which can be improved to assist conceptual understanding. Additionally, we propose an architectural tactic designed to reduce and guard against common issues identified when ML becomes highly-abstracted. The proposed tactic is intended to better integrate conventional software components with probabilistic and non-deterministic intelligent web services, ultimately to improve overall solution robustness and, thus, software quality.

This thesis makes a substantial contribution to the software engineering discipline by showing the non-trivial implications to software quality resulting from improper usage of such services and offers a pathway to safer use of the exciting new advances from the field of AI and deep learning.

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To my family, friends, and teachers.

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This chapter is now over, the next chapter awaits...

— Alex Cummaudo
December 17, 2020

Statistics about this PhD

This PhD journey consisted of the following:

- 82,188 words;
- 38,281 lines of L^AT_EX;
- 7 accepted publications;
- 3 rejected publications;
- 4 conferences, 2 attended virtually;
- 827 days of candidature;
- 3.7 months of examination;
- 1 global pandemic; and,
- 21 years of since my first day of primary school.

“...Now what?”

— BLOAT, *FINDING NEMO* (2003)

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List of Publications

Below lists publications arising from work completed in this PhD.

1. A. Cummaudo, S. Barnett, R. Vasa, J. Grundy, and M. Abdelrazek, “Beware the evolving ‘intelligent’ web service! An integration architecture tactic to guard AI-first components,” in *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*. Virtual Event, USA: ACM, November 2020. DOI 10.1145/3368089.3409688, pp. 269–280
2. A. Cummaudo, S. Barnett, R. Vasa, and J. Grundy, “Threshy: Supporting Safe Usage of Intelligent Web Services,” in *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*. Virtual Event, USA: ACM, November 2020. DOI 10.1145/3368089.3417919, pp. 1645–1649
3. A. Cummaudo, R. Vasa, S. Barnett, J. Grundy, and M. Abdelrazek, “Interpreting Cloud Computer Vision Pain-Points: A Mining Study of Stack Overflow,” in *Proceedings of the 42nd International Conference on Software Engineering*. Seoul, Republic of Korea: ACM, June 2020. DOI 10.1145/3377811.3380404, pp. 1584–1596
4. A. Cummaudo, R. Vasa, J. Grundy, M. Abdelrazek, and A. Cain, “Losing Confidence in Quality: Unspoken Evolution of Computer Vision Services,” in *Proceedings of the 35th IEEE International Conference on Software Maintenance and Evolution*. Cleveland, OH, USA: IEEE, December 2019. DOI 10.1109/ICSME.2019.00051. ISBN 978-1-72-813094-1 pp. 333–342
5. A. Cummaudo, R. Vasa, and J. Grundy, “What should I document? A preliminary systematic mapping study into API documentation knowledge,” in *Proceedings of the 13th International Symposium on Empirical Software Engineering and Measurement*. Porto de Galinhas, Recife, Brazil: IEEE, October 2019. DOI 10.1109/ESEM.2019.8870148. ISBN 978-1-72-812968-6. ISSN 1949-3789 pp. 1–6
6. T. Ohtake, A. Cummaudo, M. Abdelrazek, R. Vasa, and J. Grundy, “Merging intelligent API responses using a proportional representation approach,” in *Proceedings of the 19th International Conference on Web Engineering*. Daejeon, Republic of Korea: Springer, June 2019. DOI 10.1007/978-3-030-19274-7_28. ISBN 978-3-03-019273-0. ISSN 1611-3349 pp. 391–406

List of Abbreviations

A²I² Applied Artificial Intelligence Institute. 51, 53

AI artificial intelligence. iii, 3–7, 10, 14, 16, 36, 38, 39, 57, 58, 61, 62, 72, 75, 78, 80–82, 92, 93, 95, 96, 99, 101, 113, 119–121, 153, 154, 177, 178, 181, 194, 201, 208, 210, 212

API application programming interface. iii, xxx, 3–18, 20, 22, 25, 26, 29, 30, 32, 33, 41–43, 46–48, 50, 53, 58, 59, 62, 64, 71–74, 77–84, 88–92, 94–99, 101, 102, 105, 106, 108–111, 113, 115, 117, 120, 123–128, 130–137, 140–149, 151–154, 156, 158, 159, 161, 162, 165, 168, 174, 177, 179, 181, 184–186, 192, 198, 201, 205, 207–209, 245, 248

AWS Amazon web services. 63, 66

BYOML Build Your Own Machine Learning. 7, 8

CC connected component. 156, 159–161, 165

CDSS clinical decision support system. 10, 12, 13

CNN convolutional neural network. 12, 13, 36, 60

CRUD create, read, update, and delete. 248

CVS computer vision service. 4, 9–12, 14, 16–20, 22–24, 26, 27, 29, 31, 32, 35, 41–43, 46–48, 50, 51, 53, 57–63, 66, 71, 73, 74, 77, 79, 84, 85, 89, 93, 98, 101, 103–105, 108, 111, 114, 115, 120, 123–125, 127, 134, 136, 138, 139, 142–149, 151, 153, 154, 156, 159, 161, 165, 168, 178, 179, 182, 184, 185, 192, 194, 199, 201, 205–210, 249

DCE distributed computing environment. 245

HITL human-in-the-loop. 13

HTTP Hypertext Transfer Protocol. 8, 189, 190, 193, 198, 245, 247, 248

IDL interface definition language. 245, 248

IRR inter-rater reliability. 97

IWS intelligent web service. 6, 7, 9, 11, 13, 14, 16, 17, 19, 20, 22, 23, 29–33, 35, 36, 41–43, 57–59, 61, 62, 70, 72, 74, 75, 77–85, 87–89, 91–99, 101, 102, 105, 106, 111, 113, 114, 121, 123, 124, 149, 151–153, 165, 167, 168, 170, 171, 173, 174, 177, 178, 180, 181, 184–187, 198–201, 205, 210–212, 249

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NN neural network. 15, 36–38, 40

PaaS Platform as a Service. 9, 13, 61

QoS quality of service. 61, 62, 245

RAML RESTful API Modeling Language. 248

REST REpresentational State Transfer. iii, 7, 58, 77, 78, 98, 152, 177, 201, 246, 248

ROI region of interest. 12, 13

RPC remote procedure call. 245

SDK software development kit. 59, 128, 143

SLA service-level agreement. 61, 245

SMS systematic mapping study. 22, 23, 26, 125–128, 133, 139, 148, 149

SO Stack Overflow. 7, 17, 20, 25, 26, 46, 47, 50, 53, 54, 62, 63, 77, 79–82, 84, 85, 87, 88, 91–98, 101–104, 106–109, 111–115, 118, 119, 121, 208

SOA service-oriented architecture. 245

SOAP Simple Object Access Protocol. 7, 245–248

SOLO Structure of the Observed Learning Outcome. 92–98

SQA service quality assurance. 59, 60

SQuaRE Systems and software Quality Requirements and Evaluation. 34

SUS System Usability Scale. 18, 124, 125, 127, 137, 138, 140, 148

SVM support vector machine. 36, 40

URI uniform resource identifier. 248

V&V verification & validation. 29–33, 42

WADL Web Application Description Language. 248

WSDL Web Services Description Language. 245

XML eXtendable markup language. 9, 245

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Part I

Preface

CHAPTER 1

3

4

5

Introduction

6

7 Abstraction layers are the application developer’s productivity powerhouse as de-
8 vellers need not continuously consider underlying mechanics. The ubiquitous ap-
9 plication programming interface (API) enables separation of concerns and reusable
10 component interaction; for example, complex graphics rendering and image manip-
11 ulation is all achievable via a half-dozen lines of code with appropriate libraries and
12 frameworks, for example OpenCV’s API.

13 ML, too, is being abstracted and offered behind APIs. The 2010s have shown
14 an explosion of cloud-based services providing *web* APIs typically marketed under
15 an AI banner. The ML algorithms, data processing pipelines, and infrastructure
16 bringing these techniques to life are also abstracted behind APIs calls, driven by
17 the motivation to make it easier for developers to blend AI into their software.
18 There is an explosion of interest from application developers (see Figure 1.1) that
19 are investigating and exploring how best to infuse recent advances in AI into their
20 software systems. Combined with an ever-increasing buffet of AI-based solutions,
21 technologies and products (see Table 1.1) for developers to choose from, it is evident
22 that we are at the cusp of a new generation of ‘AI-first’ software.

23 Application developers build procedural and functional applications, where code
24 typically evaluates deterministically to produce outcomes. Such software does not
25 rely on probabilistic behaviour, unlike AI-first software where, often, ML techniques
26 are employed. However, application developers, accustomed to such traditional
27 software engineering paradigms, may not be aware of potential side-effects of those
28 probabilistic techniques. Software that leverages recent advances in AI—more
29 specifically data-driven ML techniques—will often have a layer of rules that wrap
30 the ML components. AI-first software is, however, not *solely* procedural-driven
31 and combines large datasets with rules to produce outcomes. Therefore, they are
32 both *data-driven* and procedural-driven. The consequence is that large datasets—
33 that train ML models—combined with the algorithmic techniques behind these
34 models result in probabilistic behaviour. Further, since these models can continually

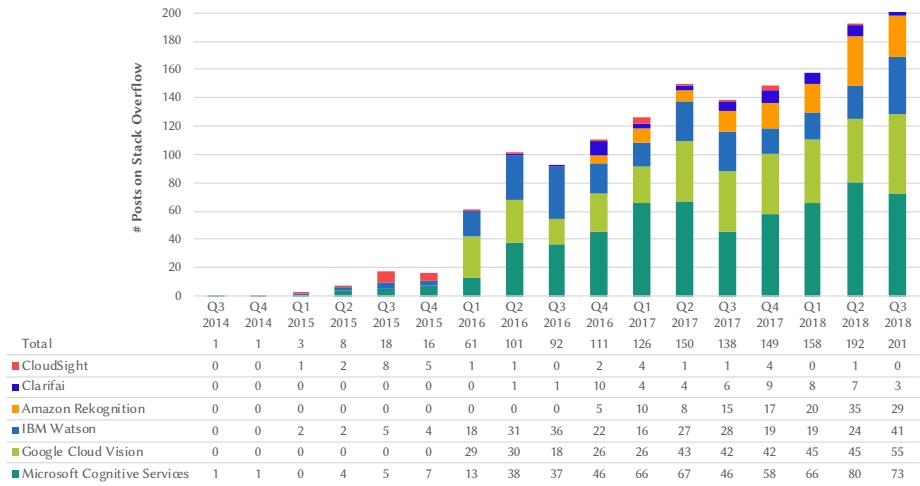


Figure 1.1: Increasing interest within the developer community for computer vision services (CVSs) is shown via Stack Overflow posts. These trends of CVS usage were measured as discussion of posts tagged with the relevant product name.¹ This graph is based on data from Chapter 5.

35 learn from *new* data with time, existing probabilistic behaviour can evolve and thus
36 regression testing techniques need to be adjusted as well for new data.

37 Developing AI-infused applications requires both code *and data*, and an applica-
38 tion developer can approach developing from three perspectives, further expanded
39 in Section 1.1:

- 40 1. The application developer defines an ML model from scratch and trains it from
41 a curated dataset. This approach is laborious in time and demands experience
42 and knowledge of ML methods, but the tradeoff is that they have full autonomy
43 in the models they create.
- 44 2. The application developer downloads a pre-trained model (e.g., YOLO [293]
45 for computer vision, or GPT-2 [289] for natural language processing) and
46 ‘plugs’ it into an existing ML framework, such as Tensorflow [1] or PyTorch
47 [272]. This approach removes the time taken to collect data, design and train
48 the ML model; the developers, still need to know where to find these models,
49 evaluate them, and then learn the frameworks² within which they operate to
50 use them effectively.
- 51 3. The application developer uses a cloud-based service. It is fast to integrate
52 into their applications, and the APIs offered abstract the technical know-how
53 behind a web call.

54 While much research has investigated these first two perspectives (see Chapter 2),
55 the third is yet to be deeply explored, despite the fact that vendors are promoting new
56 offerings encapsulated under this third perspective. As shown in Table 1.1, vendors

²Thus introducing a verbose list of ML terminology to her developer vocabulary. See a list of 328 terms provided by Google here: <https://developers.google.com/machine-learning/glossary/>. Last accessed 7 December 2018.

Table 1.1: A broad range of AI-based vendors, products, and services is emerging in recent years. (Adapted from [220].)

Category	Sample Vendors & Products	Typical Use Cases
Embedded AI: Expert assistants leverage AI technology embedded in platforms and solutions.	Amazon: <i>Alexa</i> Apple: <i>Siri</i> Facebook: <i>Messenger</i> Google: <i>Google Assistant</i> Microsoft: <i>Cortana</i> Salesforce: <i>MetaMind</i>	Personal assistants for search, simple inquiry, and growing as expert assistance (composed problems, not just search). Available on mobile platforms, devices, the internet of things, and as bots or agents. Used in voice, image recognition, and various levels of natural language processing sophistication.
AI point solutions: Point solutions provide specialised capabilities for natural language processing, vision, speech, and reasoning.	24[7]: <i>24/7</i> Admantx: <i>Admantx</i> Affectiva: <i>Affdex</i> Assist: <i>AssistDigital</i> Automated Insights: <i>Wordsmith</i> Beyond Verbal: <i>Beyond Verbal</i> Expert System: <i>Cogito</i> HPE: <i>Haven OnDemand</i> IBM: <i>Watson Analytics</i> Narrative Science: <i>Quill</i> Nuance: <i>Dragon</i> Salesforce: <i>MetaMind</i> Wise.io: <i>Wise Support</i>	Semantic text, facial/visual recognition, voice intonation, intelligent narratives. Various levels of natural language processing, from brief text messaging, chat/conversational messaging, full complex text understanding. Machine learning, predictive analytics, text analytics/mining, knowledge management and search. Used as expert advisors, reasoning tools, or in customer service.
AI platforms: Platforms that offer various AI tech, including (deep) machine learning, as tools, APIs, or services to build solutions.	CognitiveScale: <i>Engage, Amplify</i> Digital Reasoning: <i>Synthesys</i> Google: <i>Google Cloud ML</i> IBM: <i>Watson Knowledge Studio</i> Intel: <i>Saffron Natural Intelligence</i> IPsoft: <i>Amelia, Apollo, IP Center</i> Microsoft: <i>Cortana Intelligence Suite</i> Nuance: <i>360 platform</i> Salesforce: <i>Einstein</i> Wipro: <i>Holmes</i>	APIs, cloud services, on-premises for developers to build AI solutions. Insights/advice building and rule-based reasoning. Vertical domain advisors (e.g., fraud detection in banking, financial advisors, healthcare). Cognitive services and bots.

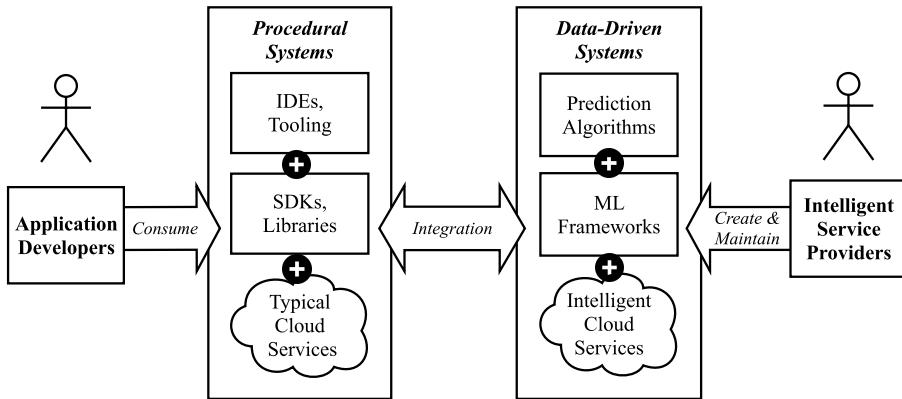


Figure 1.2: The application developer’s procedural-driven toolchain is distinct from data-driven toolchain. A developer must consume a typical, data-driven cloud service in a different way than an intelligent data-driven cloud service as they are not the same type of system.

57 are rapidly pushing out new ML-based offerings in the form of cloud-based APIs
58 end-points (AI platforms), where the API abstraction masks away the underlying me-
59 chanics of the models. Developers that use these cloud-based services are presented
60 with documentation providing a narrative (i.e., marketing and in the documentation)
61 that implies integration of these services are just like other cloud services. But does
62 this implication, coupled with abstractions that hide the assumptions made by the
63 AI-service providers, lead to developer pain-points and miscomprehension? If so,
64 how can the service providers improve their documentation to alleviate this? Do
65 these data-driven services share similarities to the runtime behaviour of traditional
66 cloud services? And if not, how best can the application developer integrate the
67 data-driven service into their a procedural-driven application to produce AI-first
68 software?

Table 1.2: Differing characteristics of intelligent and typical web services.

Intelligent web service	Typical web services
Probabilistic	Deterministic
Machine Learnt	Human Engineered
Data-Driven	Procedural-Driven
Black-Box	Black-Box

69 Figure 1.2 provides an illustrative overview between the context clashing of
70 procedural-driven applications and data-driven cloud services, and we contrast char-
71 acteristics of typical cloud systems and data-driven ones in Table 1.2.

72  In this thesis, we show that (i) developers do not properly understand the probabilistic data-driven machine-learnt behaviour abstracted behind the end-points, (ii) the ‘intelligent behaviour’ is not fully contained and leaks into the applications that make use of these end-points, and finally (iii) we present how these concerns can be addressed via better documentation and software architecture. that the integration and developer comprehension of cloud services differ from the procedural-driven nature of end-applications.

1.1 Research Context

73 There are a range of integration techniques available to developers, as reflected by
74 Google AI’s³ *machine learning spectrum* [205, 233, 265]. This range is grouped into
75 the three tiers aforementioned, encompassing skills, effort, users, and types of outputs
76 of integration techniques. At one extreme, this approach involves the academic
77 research of developing algorithms and self-sourcing data to achieve intelligence—
78 coined as Build Your Own Machine Learning (BYOML) [178, 233, 265]. The other
79 extreme involves off-the-shelf, ‘friendlier’ (abstracted) intelligence with easy-to-use
80 APIs targeted towards applications developers. The middle-ground involves a mix of
81 the two, with varying levels of automation to assist in development, that turns custom
82 datasets into machine intelligence. We illustrate the slightly varied characteristics
83 within this spectrum in Table 1.3 and Figure 1.3.

84 These cloud AI-services are gaining traction within developer circles: we show
85 an increasing trend of Stack Overflow posts mentioning intelligent computer vision
86 services in Figure 1.1.⁴ Academia provides varied nomenclature for these services,
87 such as *Cognitive Applications* and *Machine Learning Services* [364] or *Machine
88 Learning as a Service* [296]. For the context of this thesis, we will refer to such ser-
89 vices under broader term of **intelligent web services (IWSs)**,⁵ and diagrammatically
90 express their usage within Figure 1.4.

91 There are many types of IWSs available to software developers, offering a range
92 of functions, such as optical character recognition, text-to-speech and speech-to-
93 text transcription, object categorisation, facial analysis and recognition, and natural
94 language processing. The general workflow of using an IWS is more-or-less the
95 same: a developer accesses an IWS component via REST/SOAP API(s), which is

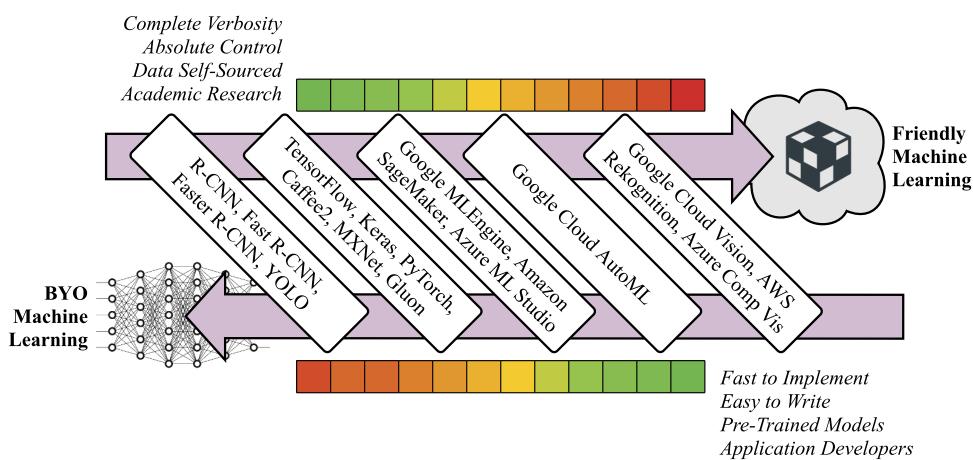
³Google AI was recently rebranded from Google Research, further highlighting how the ‘AI-first’ philosophy is increasingly becoming embedded in companies’ product lines and research and development teams. Spearheaded through work achieved at Google, Microsoft and Facebook, the emphasis on an AI-first attitude we see through Google’s 2018 rebranding of *Google Research* to *Google AI* [163] is evident. A further example includes how Facebook leverage AI *at scale* within their infrastructure and platforms [269].

⁴Query run on 12 October 2018 using StackExchange Data Explorer. Refer to <https://data.stackexchange.com/stackoverflow/query/910188> for full query.

⁵This term is an extension inspired by the term ‘web service’, as defined by the World Wide Web Consortium. See <https://bit.ly/2CQWJ2Z>, last accessed 19 July 2020.

Table 1.3: Comparison of the machine learning spectrum.

Comparator	BYOML	ML F'work	Cloud ML	Auto-Cloud ML	Cloud API
Hosting					
Locally	✓	✓			
Cloud			✓	✓	✓
Output					
Custom Model	✓	✓	✓	✓	
HTTP Response					✓
Autonomy					
Low					✓
Medium				✓	
High		✓	✓		
Highest	✓				
Time To Market					
Medium	✓	✓			
High			✓	✓	
Highest					✓
Data					
Self-Sourced	✓	✓	✓	✓	
Pre-Trained		✓			✓
Intended User					
Academics	✓	✓			
Data Scientist	✓	✓	✓	✓	
Developers				✓	✓

**Figure 1.3:** Examples within the ML spectrum of computer vision. Colour scales indicates the benefits (green) and drawbacks (red) of each end of the spectrum.

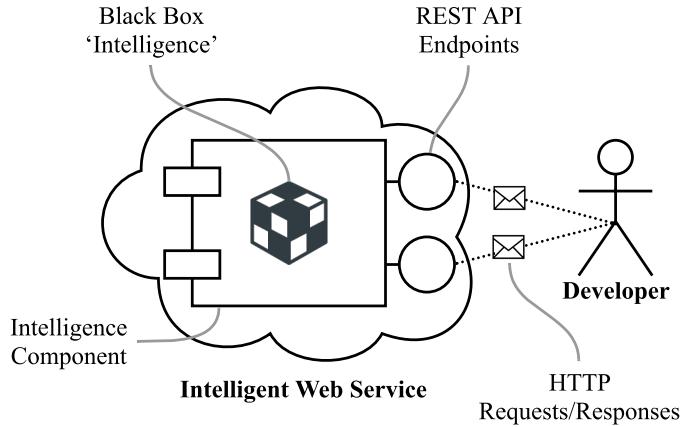


Figure 1.4: Overview of intelligent web services (IWSs).

⁹⁶ (typically) available as a cloud-based Platform as a Service (PaaS).^{6,7} Developers
⁹⁷ send a given request to analyse a specific piece of data (e.g., an image, body of text,
⁹⁸ audio file etc.) and receive some intelligence on the data (e.g., object detection, text
⁹⁹ sentiment, transcription of audio) in addition to an associated *confidence* value that
¹⁰⁰ represents the likelihood of that result. This is typically serialised as a JSON/XML
¹⁰¹ response object.

☞ Within this thesis, we scope our investigation to a mature subset of IWSs that provide computer vision intelligence [389, 392, 405, 406, 407, 413, 417, 426, 427, 429, 431, 478, 479]. For the context of this thesis, we will refer to such services as **CVSs**.

¹⁰² 1.2 Motivating Scenarios

¹⁰³ The market for computer vision services (CVSs) is expanding (Table 1.1) with a
¹⁰⁴ corresponding interest from developers (Figure 1.1). These services are inherently
¹⁰⁵ probabilistic in their behaviour, in that the end-points always return with a response
¹⁰⁶ with a probability. This is unlike a typical API that would return a response (*without*
¹⁰⁷ a probability) or an error. If developers do not fully understand the nature of these

⁶We note, however, that a development team may use a similar approach *internally* within a product line or service that may not necessarily reflect a PaaS model.

⁷A number of services provide the platform infrastructure to rapidly begin training from custom datasets, such as Google's AutoML (<https://cloud.google.com/automl/>, last accessed 7 December 2018). Others provide pre-trained datasets 'ready-for-use' in production without the need to train data.

¹⁰⁸ services when integrating with them, there is an impact on the quality of software
¹⁰⁹ they create.

¹¹⁰ To illustrate the context of use, we present the two scenarios of varying risk:
¹¹¹ (i) a fictional software developer, named Tom, who wishes to develop an inherently
¹¹² low-risk photo labelling application for his friends and family; and (ii) a high-risk
¹¹³ cancer clinical decision support system (CDSS) that uses patient scans to recom-
¹¹⁴ mend if surgeons should send their patients to surgery. Both describe scenarios
¹¹⁵ where AI-infused components has an impact to end-users when the software engi-
¹¹⁶ neers developing with them misunderstand the nuances of ML, ultimately affecting
¹¹⁷ external quality. Moreover, when developers lack a comprehension, this hinders
¹¹⁸ their productivity and understanding/appreciation of AI-based components.

¹¹⁹ 1.2.1 Low Risk Motivating Scenario

¹²⁰ Tom wants to develop a social media photo-sharing app on iOS and Android, *Photo-*
¹²¹ *Sharer*, that analyses photos taken on smartphones. Tom wants the app to categorise
¹²² photos into scenes (e.g., day vs. night, landscape vs. indoors), generate brief de-
¹²³ scriptions of each photo, and catalogue photos of his friends and common objects
¹²⁴ (e.g., photos with his Border Collie dog, photos taken on a beach on a sunny day with
¹²⁵ his partner). His app will shares this analysed photo intelligence with his friends on
¹²⁶ a social-media platform, where his friends can search and view the photos.

¹²⁷ Instead of building a computer vision engine from scratch, which takes too much
¹²⁸ time and effort, Tom thinks he can achieve this using one of the common CVSs. Tom
¹²⁹ comes from a typical software engineering background and has insufficient knowl-
¹³⁰ edge of key computer vision terminology and no understanding of its underlying
¹³¹ techniques. However, inspired by easily accessible cloud APIs that offer computer
¹³² vision analysis, he chooses to use these. Built upon his experience of using other
¹³³ similar cloud services, he decides on one of the CVS APIs, and expects a static result
¹³⁴ always and consistency between similar APIs. Analogously, when Tom invokes the
¹³⁵ iOS Swift substring method "doggy".prefix(3), he expects it to be consistent
¹³⁶ with the Android Java equivalent "doggy".substring(0, 2). Consistent, here,
¹³⁷ means two things: (i) that calling substring or prefix on 'dog' will *always*
¹³⁸ return in the same way every time he invokes the method; and (ii) that the result is
¹³⁹ *always* 'dog' regardless of the programming language or string library used, given
¹⁴⁰ the deterministic nature of the 'substring' construct (i.e., results for substring are
¹⁴¹ API-agnostic).

¹⁴² More concretely, in Table 1.4, we illustrate how three (anonymised) CVS
¹⁴³ providers fail to provide similar consistency to that of the substring example above.
¹⁴⁴ If Tom uploads a photo of a border collie⁸ to three different providers in August
¹⁴⁵ 2018 and January 2019, he would find that each provider is different in both the vo-
¹⁴⁶ cabulary used between. The confidence values and labels within the *same* provider
¹⁴⁷ varies within a matter of five months. The evolution of the confidence changes is not
¹⁴⁸ explicitly documented by the providers (i.e., when the models change) nor do they
¹⁴⁹ document what confidence means. Service providers use a tautological nature when

⁸The image used for these results is <https://www.akc.org/dog-breeds/border-collie/>.

Table 1.4: First six responses of image analysis for a Border Collie sent to three CVS providers five months apart. The specificity (to 3 s.f.) and vocabulary of each label in the response varies between all services, and—except for Provider B—changes over time. Any confidence changes greater than 1 per cent are highlighted in red.

Label	Provider A		Provider B		Provider C	
	Aug 2018	Jan 2019	Aug 2018	Jan 2019	Aug 2018	Jan 2019
Dog	0.990	0.986	0.999	0.999	0.992	0.970
Dog Like Mammal	0.960	0.962	-	-	-	-
Dog Breed	0.940	0.943	-	-	-	-
Border Collie	0.850	0.852	-	-	-	-
Dog Breed Group	0.810	0.811	-	-	-	-
Carnivoran	0.810	0.680	-	-	-	-
Black	-	-	0.992	0.992	-	-
Indoor	-	-	0.965	0.965	-	-
Standing	-	-	0.792	0.792	-	-
Mammal	-	-	0.929	0.929	0.992	0.970
Animal	-	-	0.932	0.932	0.992	0.970
Canine	-	-	-	-	0.992	0.970
Collie	-	-	-	-	0.992	0.970
Pet	-	-	-	-	0.992	0.970

150 defining what the confidence values are (as presented in the API documentation)
151 provides no insight for Tom to understand why there was a change in confidence,
152 which we show in Table 1.5, unless he *knows* that the underlying models change with
153 them. Furthermore, they do not provide detailed understanding on how to select a
154 threshold cut-off for a confidence value. Therefore, he's left with no understanding
155 on how best to tune for image classification in this instance. The deterministic prob-
156 lem of a substring compared to the nondeterministic nature of the IWS is, therefore,
157 non-trivial.

158 To make an assessment of these APIs, he tries his best to read through the
159 documentation of different CVS APIs, but he has no guiding framework to help him
160 choose the right one. A number of questions come to mind:

- 161 • What does ‘confidence’ mean?
- 162 • Which confidence is acceptable in this scenario?
- 163 • Are these APIs consistent in how they respond?
- 164 • Are the responses in APIs static and deterministic?
- 165 • Would a combination of multiple CVS APIs improve the response?
- 166 • How does he know when there is a defect in the response? How can he report
167 it?
- 168 • How does he know what labels the API knows, and what labels it doesn't?
- 169 • How does it describe his photos and detect the faces?
- 170 • Does he understand that the API uses a machine learnt model? Does he know
171 what a ML model is?
- 172 • Does he know when models update? What is the release cycle?

Table 1.5: Tautological definitions of ‘confidence’ found in the API documentation of three common CVS providers.

API Provider	Definition(s) of Confidence
Provider A	<p>“Score is the confidence score, which ranges from 0 (no confidence) to 1 (very high confidence).” [415]</p> <p>“Deprecated. Use score instead. The accuracy of the entity detection in an image. For example, for an image in which the ‘Eiffel Tower’ entity is detected, this field represents the confidence that there is a tower in the query image. Range [0, 1].” [416]</p> <p>“The overall score of the result. Range [0, 1]” [416]</p>
Provider B	<p>“Confidence score, between 0 and 1... if there insufficient confidence in the ability to produce a caption, the tags maybe [sic] the only information available to the caller.” [432]</p> <p>“The level of confidence the service has in the caption.” [430]</p>
Provider C	<p>“The response shows that the operation detected five labels (that is, beacon, building, lighthouse, rock, and sea). Each label has an associated level of confidence. For example, the detection algorithm is 98.4629% confident that the image contains a building.” [390]</p> <p>“[Provider C] also provide[s] a percentage score for how much confidence [Provider C] has in the accuracy of each detected label.” [391]</p>

173 Although Tom generally anticipates these CVSs to not be perfect, he has no
 174 prior benchmark to guide him on what to expect. The imperfections appear to be
 175 low-risk, but may become socially awkward when in use; for instance, if Tom’s
 176 friends have low self-esteem and use the app, they may be sensitive to the app not
 177 identifying them or mislabelling them. Privacy issues come into play especially
 178 if certain friends have access to certain photos that they are (supposedly) in; e.g.,
 179 photos from a holiday with Tom and his partner, however if the API identifies Tom’s
 180 partner as a work colleague, Tom’s partner’s privacy is at risk.

181 Therefore, the level of risk and the determination of what constitutes an ‘error’ is
 182 dependent on the situation. In the following example, an error caused by the service
 183 may be more dangerous.

184 1.2.2 High Risk Motivating Scenario

185 Recent studies in the oncology domain have used deep-learning convolutional neural
 186 networks (CNNs) to detect region of interests (ROIs) in image scans of tissue (e.g.,
 187 [32, 147, 219]), flagging these regions for doctors to review. Trials of such algorithms
 188 have been able to accurately detect cancer at higher rates than humans, and thus
 189 incorporating such capabilities into a CDSS is closer within reach. Studies have
 190 suggested these systems may erode a practitioner’s independent decision-making

[74, 175] due to over-reliance; therefore the risks in developing CDSSs powered by IWSs become paramount.

In Figure 1.5 we present a context diagram for a fictional CDSS named *CancerAssist*. A team of busy pathologists utilise CancerAssist to review patient lymph node scans and discuss and recommend, on consensus, if the patient requires an operation. When the team makes a consensus, the lead pathologist enters the verdict into CancerAssist—running passively in the background—to ensure there is no oversight in the team’s discussions. When a conflict exists between the team’s verdict and CancerAssist’s verdict, the system produces the scan with ROIs it thinks the team should review. Where the team overrides the output of CancerAssist, this reinforces CancerAssist’s internal model as a human-in-the-loop (HITL) learning process.

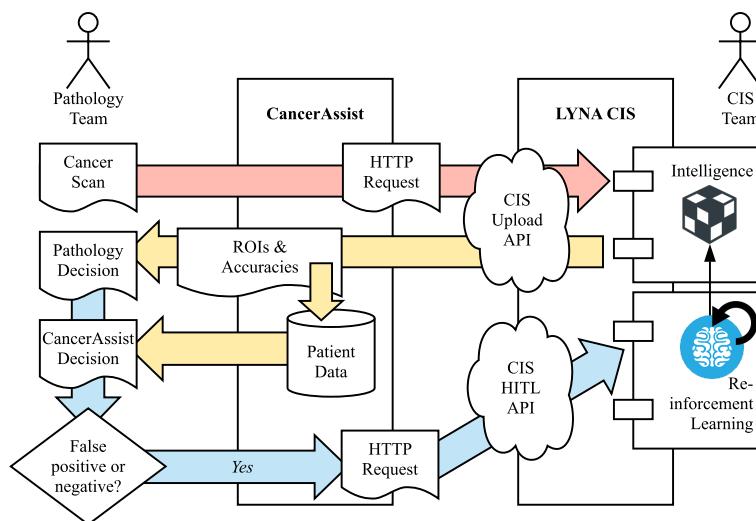


Figure 1.5: CancerAssist Context Diagram. **Key:** Red Arrows = Scan Input; Yellow Arrows = Decision Output; Blue Arrows = HITL Feedback Input.

Powering CancerAssist is Google AI’s Lymph Node Assistant (LYNA) [219], a CNN based on the Inception-v3 model [202, 343]. To provide intelligence to CancerAssist, the development team decide to host LYNA as an IWS using a cloud-based PaaS solution. Thus, CancerAssist provides API endpoints integrated with patient data and medical history, which produces the verdict. In the case of a positive verdict, CancerAssist highlights the relevant ROIs found with their respective bounding boxes and their respective cancer detection accuracies.

The developer of CancerAssist has no interaction with the Data Science team maintaining the LYNA IWS. As a result, they are unaware when updates to the model occur, nor do they know what training data they provide to test their system. The default assumptions are that the training data used to power the intelligence is near-perfect for universal situations; i.e., the algorithm chosen is the correct one for every assessable ontology tests in the given use case of CancerAssist. Thus, unlike deterministic systems—where the developer can manually test and validate the outcomes of the APIs—this is impossible for non-deterministic systems such

²¹⁸ as CancerAssist and its underlying IWS. The ramifications of not being able to test
²¹⁹ such a system and putting it out into production may prove fatal to patients.

²²⁰ Certain questions in the production of CancerAssist and its use of an IWS may
²²¹ come into mind:

- ²²² • When is the model updated and how do the IWS team communicate these
²²³ updates?
- ²²⁴ • What benchmark test set of data ensures that the changed model doesn't affect
²²⁵ other results?
- ²²⁶ • Are assumptions made by the IWS team who train the model correct?

²²⁷ Thus, to improve communication between developers and IWS providers, devel-
²²⁸ opers require enhanced documentation, additional metadata, and guidance tooling.

²²⁹ 1.3 Research Motivation

²³⁰ Evermore applications are considering IWSs as demonstrated by ubiquitous exam-
²³¹ ples: aiding the vision-impaired [94, 294], accounting [227], data analytics [173],
²³² and student education [100]. Our motivating examples illustrate impact on de-
²³³ velopers when CVSSs encapsulate assumptions and are poorly documented. Such
²³⁴ components are accessible through APIs consisting of ‘black box’ intelligence (Fig-
²³⁵ ure 1.4).⁹ ML models are inherently probabilistic and stochastic, contributing to
²³⁶ four critical issues for developers that motivate this research work: (i) communica-
²³⁷ tion of outputs (as probabilities), (ii) evolution of datasets, (iii) selecting appropriate
²³⁸ decision boundaries, and (iv) the clarity of documentation that address items i–iii.
²³⁹ We detail these four issues in the following subsections.

²⁴⁰ Ultimately, these four issues present major threats to software reliability if left
²⁴¹ unresolved. Given that such substantiative software engineering principles on re-
²⁴² liability, versioning and quality are under-investigated within the context of IWSs,
²⁴³ we aim to explore guidance from the software engineering literature to investigate
²⁴⁴ what aspects in the development lifecycle could aide in mitigating these issues when
²⁴⁵ developing using components that abstract ML, such as IWSs.

²⁴⁶ 1.3.1 Outputs are Probabilities

²⁴⁷ There is little room for certainty in these results as the insight is purely statistical
²⁴⁸ and associational [277] against its training dataset. **The interface between AI-**
²⁴⁹ **components and traditional software components is non-trivial when developers**
²⁵⁰ **do not appreciate the nuances, or use the anchors of libraries and components**
²⁵¹ **that have a more traditional behaviour [185, 245, 354, 359].** However, CVSSs
²⁵² return the *probability* that a particular object exists in an input images’ pixels via
²⁵³ confidence values. As an example, consider simple arithmetic representations (e.g.,

⁹The ‘black box’ refers to a system that transforms input (or stimulus) to outputs (or response) without any understanding of the internal architecture by which this transformation occurs. This arises from a theory in the electronic sciences and adapted to wider applications since the 1950s–60s [16, 64] to describe “systems whose internal mechanisms are not fully open to inspection” [16].

254 $2 + 2 = 4$). The deterministic mindset suggests that the result will *always* be
255 4. However, the non-deterministic (data-driven) mindset suggests that results are
256 probable: target output (*exactly* 4) and the output inferred (*a likelihood of* 4) matches
257 as a probable percentage (or as an error where it does not match).¹⁰ Instead of an
258 exact output, there is a *probabilistic* result: $2 + 2$ *may* equal 4 to a confidence of n .
259 Thus, for a more certain (though not fully certain) distribution of overall confidence
260 returned from the service, a developer must treat the problem stochastically by
261 testing this case hundreds if not thousands of times to find a richer interpretation of
262 the inference made and ensure reliability in its outcome.

263 1.3.2 Evolution of Datasets

264 Traditional software engineering principles advocate for software systems to be ver-
265 sioned upon substantial change. Unfortunately, endpoints are not versioned [88]. In
266 the context of computer vision, new labels may be introduced or dropped, confidence
267 values may differ, entire ontologies or specific training parameters may change, but
268 we hypothesise that is not effectively communicated to developers. Broadly speak-
269 ing, this can be attributed to a dichotomy of release cycles from the data science and
270 software engineering communities: the data science iterations and work by which
271 new models are trained and released runs at a faster cycle than the maintenance
272 cycle of traditional software engineering. Thus we see cloud vendors integrating
273 model changes without the *need* to update the API version unless substantial code or
274 schema changes are also introduced—the nuance changes in the internal model does
275 not warrant a shift in the API itself, and therefore the version shift in a new model
276 does not always propagate to a version shift in the API endpoint. As demonstrated
277 in Table 1.4, whatever input is uploaded at one time may not necessarily be the same
278 when uploaded at a later time. This again contrasts the rule-driven mindset, where
279 $2 + 2$ *always* equals 4. Therefore, in addition to the certainty of a result in a single
280 instance, the certainty of a result in *multiple instances* may differ with time, which
281 again impacts on the developers notion of reliable software. Currently, it is impos-
282 sible to invoke requests specific to a particular model that was trained at a particular
283 date in time, and therefore developers need to consider how evolutionary changes of
284 the services may impact their solutions *in production*. Again, whether there is any
285 noticeable behavioural changes from these changes is dependent on the context of
286 the problem domain—unless developers benchmark these changes against their own
287 domain-specific dataset and frequently check their selected service against such a
288 dataset, there is no way of knowing if substantive errors have been introduced.

289 1.3.3 Selecting Appropriate Decision Boundaries

290 As the only response from these computer vision classifiers are a label and confidence
291 value; **the decision boundaries needs to always be appropriately considered by**
292 **client code for each use case and each model selected.** The external quality of

293¹⁰Blake et al. [43] produces a multi-layer perceptron neural network performing arithmetic repre-
294 sentation.

such software needs to consider reliability in the case of thresholding confidence values—that is whether the inference has an appropriate level of confidence to justify a predicted (and reliable) result to end-users. Selecting this confidence threshold is non-trivial; a ML course from Google suggests that “it is tempting to assume that [a] classification threshold should always be 0.5, but thresholds are problem-dependent, and are therefore values that you must tune.” [141]. Approaches to turning these values are considered for data scientists, but are not yet well-understood for application developers with little appreciation of the nuances of ML.

1.3.4 Documentation of the above concerns

Similarly, developers should consider the internal quality of building AI-first software. Reliable API usability and documentation advocate for the accuracy, consistency and completeness of APIs and their documentation [282, 301] and providers should consider mismatches between a developer’s conceptual knowledge of the API its implementation [196]. **Unreliable APIs ultimately hinder developer performance and thus reduces productivity**, in addition to producing potentially unreliable software where documentation is not well-understood (or clear to the developer).

1.4 Research Goals

This thesis aims to investigate and better understand the nature of cloud-based computer vision services (CVSs)¹¹ as a concrete exemplar of intelligent web services (IWSs). We identify the maturity, viability and risks of CVSs through the anchoring perspective of *reliability* that affects the internal and external quality of software. We adopt the McCall [231] and Boehm [45] interpretations of reliability via the sub-characteristics of a service’s *consistency* and *robustness* (or fault/error tolerance), and the *completeness*¹² of its documentation. (A detailed discussion is further provided in Section 2.1.) This thesis explores and contributes towards *four* key facets regarding reliability in CVS usage and the completeness of its associated documentation. We formulate four primary research questions (RQs), based on both empirical and non-empirical software engineering methodology [241], further discussed in Chapter 3.

Firstly, we investigate adverse implications that arise when using CVSs that affects consistency and robustness (**Chapter 4**). We show how CVSs have a non-deterministic runtime behaviour and evolve with unintended and non-trivial consequences to developers. We demonstrate that these services have inconsistent behaviour despite offering the same functionality and pose evolution risk that effects robustness of consuming applications when responses change given the same (consistent) inputs.

¹¹As these services are proprietary, we are unable to conduct source code or model analysis, and hence are not used in the investigation of this thesis.

¹²We treat the API documentation of a CVS as a first-class citizen.

³³⁰ Formally, we structure the following RQs:

?

RQ1. What is the nature of cloud-based CVSs?

RQ1.1. What is their runtime behaviour?

RQ1.2. What is their evolution profile?

³³¹ Secondly, we investigate the reliability of the documentation these services offer through the lenses of its completeness. We collate prior knowledge of good ³³² API documentation and assess the efficacy of such knowledge against practitioners ³³³ (**Chapter 8**). We show that these service's behaviour and evolution is not ³³⁴ reliably documented adequately against this knowledge. Formally, we develop the ³³⁵ following RQs: ³³⁶

?

RQ2. Are CVS APIs sufficiently documented?

RQ2.1. What API documentation artefacts compromise a ‘complete’ API document, according to both literature and practitioners?

RQ2.2. What additional information or attributes do application developers need in CVS API documentation to make it more complete?

³³⁷ Thirdly, we investigate how software developers approach using these services ³³⁸ and directly assess developer pain-points resulting from the nature of CVSs and ³³⁹ their documentation (**Chapter 5**). We show that there is a statistically significant ³⁴⁰ difference in these complaints when contrasted against more established software ³⁴¹ engineering domains (such as web or mobile development) as expressed as questions ³⁴² asked on Stack Overflow. We provide a number of exploratory avenues for ³⁴³ researchers, educators, software engineers and IWS providers to alleviate these ³⁴⁴ complaints based on this analysis. Further, using a data set consisting of 1,245 Stack ³⁴⁵ Overflow questions, we explore the emotional state of developers to understand ³⁴⁶ which aspects (i.e., pain-points) developers are most frustrated with (**Chapter 6**) ³⁴⁷ and the types of traps developers can fall into when substantial documentation is not ³⁴⁸ provided for specific ML models (**Chapter 7**). We formulate the following RQs:

?

RQ3. Are CVSs more misunderstood than conventional software engineering domains?

RQ3.1. What types of issues do application developers face most when using CVSs, as expressed as questions on Stack Overflow?

RQ3.2. Which of these issues are application developers most frustrated with?

RQ3.3. Is the distribution CVS pain-points different to established software engineering domains, such as mobile or web development?

349 Lastly, we explore several strategies to help improve CVSs reliability. Firstly,
350 we investigate whether merging the responses of *multiple* CVSs can improve their
351 reliability and propose a novel algorithm—based on the proportional representation
352 method used in electoral systems—to merge labels and associated confidence values
353 from three providers (**Chapter 9**). Secondly, we develop an integration architec-
354 ture style (or facade) to guard against CVS evolution, and synthesise an integration
355 workflow that addresses the concerns raised by developers in addition to embed-
356 ding ‘complete’ documentation artefacts into the workflow’s design (**Chapters 10**
357 and **11**). Our final RQ is:

358 **② RQ4. What strategies can developers employ to integrate their appli-
cations with CVSs while preserving robustness and reliability?**

1.5 Research Methodology

359 This thesis employs a mixed-methods approach using the concurrent triangulation
360 strategy [57, 230]. The research presented consists of both empirical and non-
361 empirical research design. This section provides a high-level overview of the re-
362 search methodology within this thesis. Further details are provided in Section 1.7
363 and Chapter 3.

364 Firstly, RQ1–RQ3 are all empirical, knowledge-based questions [109, 237] that
365 aim to provide the software engineering community with a greater understanding
366 of the phenomena surrounding CVSs from three perspectives: the nature of the ser-
367 vices themselves, how developers perceive these services and how service providers
368 can improve these services. We answer RQ1 using a longitudinal experiment that
369 assesses both the services’ responses and associated documentation (complement-
370 ing RQ2.2). We adopt qualitative and quantitative data collection; specifically (i)
371 structured observations to quantitatively analyse the results over time, and (ii) docu-
372 mentary research methods to inspect service documentation. Secondly, we perform
373 systematic mapping study following the guidelines of Kitchenham and Charters
374 [192] and Petersen et al. [279] to better understand how API documentation of these
375 services can be improved (i.e., more complete), which targets RQ2. Based on the
376 findings from this study, we use a systematic taxonomy development methodol-
377 ogy specifically targeted toward software engineering [357] that structures scattered
378 API documentation knowledge into a taxonomy. We then validate this taxonomy
379 against practitioners using survey research, using a survey instrument inspired by
380 Brooke’s well-established System Usability Scale [61] and contextualising it within
381 API documentation utility, which answers RQ3.3. To answer RQ2.2, we perform
382 an empirical application of the taxonomy to three CVSs, and therefore assess where
383 improvements can be made. Thirdly, we adopt field survey research using repository
384 mining of developer discussion forums (i.e., Stack Overflow) to answer RQ3, and
385 classify these using both manual and automated techniques.

386 The second aspect of our research design involves non-empirical research, which
387 explores a design-based question [241] to answer RQ4. As the answers to our

388 first three RQs establish a greater understanding of the nature behind CVSs from
389 various perspectives, the strategies we design in RQ4 aims at designing more reliable
390 integration methods so that developers can better use these cloud-based services in
391 their applications.

392 1.6 Thesis Organisation

393 We organise the thesis into four parts. **Part I (The Preface)** includes introductory,
394 background and methodology chapters. This is a *PhD by Publication*, and
395 **Part II (Publications)** comprises of eight publications resulting from this work over
396 Chapters 4 to 11; publications are included verbatim except for terminology and for-
397 matting changes to better fit the suitability of a coherent thesis. **Part III (The Post-**
398 **face)** includes the conclusion and future works chapter, as well as a list of academic
399 studies and online artefacts referenced within the thesis. **Part IV (Appendices)** in-
400 cludes all supplementary material, including mandatory authorship statements and
401 ethics approval. Details of each chapter following this introductory chapter are
402 provided in the following section.

403 1.6.1 Part I: Preface

404 1.6.1.1 Chapter 2: Background

405 This chapter provides an overview of prior studies broadly around three key pillars:
406 the development of an IWS, the usage of an IWS, and the nature of an IWS. We use
407 the three perspectives of software quality (particularly, reliability), probabilistic and
408 non-deterministic systems, and explanation and communication theory to describe
409 prior work.

410 1.6.1.2 Chapter 3: Research Methodology

411 This chapter provides a summative review of research methods and philosophical
412 stances relevant to software engineering. We illustrate that the methods used within
413 our publications are sound via an analysis of the methodologies used in seminal
414 works referenced in this thesis.

415 1.6.2 Part II: Publications

416 1.6.2.1 Chapter 4: Exploring the nature of CVSs

417 This chapter was presented at the 2019 **International Conference on Software**
418 **Maintenance and Evolution (ICSME)** [88]. We describe an 11-month longitudi-
419 nal experiment assessing the behavioural (run-time) issues of three popular CVSs:
420 Google Cloud Vision [417], Amazon Rekognition [392] and Azure Computer Vi-
421 sion [431]. By using three different data sets—two of which we curate as additional
422 contributions—we demonstrate how the services are inconsistent amongst each other

⁴²³ and within themselves. This study answers RQ1: Despite presenting conceptually-
⁴²⁴ similar functionality, each service behaves and produces slightly varied (inconsistent)
⁴²⁵ results and demonstrates non-deterministic runtime behaviour. We discuss potential
⁴²⁶ evolution risks to consumers of such services as the services provide non-static
⁴²⁷ outputs for the same inputs, thereby having significant impact to the robustness of
⁴²⁸ consuming applications. Further details in the study include a brief assessment into
⁴²⁹ the lack of sufficient detail of these concerns in their documentation.

⁴³⁰ 1.6.2.2 *Chapter 5: Understanding developer struggles when using CVSs*

⁴³¹ This chapter was presented at the **2020 International Conference on Software**
⁴³² **Engineering (ICSE)** [91]. We conduct a mining study of 1,425 Stack Overflow
⁴³³ questions that provide indications of the types frustrations that developers face when
⁴³⁴ integrating CVSs into their applications. To gather what their pain-points are, we use
⁴³⁵ two classification taxonomies that also use Stack Overflow to understand generalised
⁴³⁶ and documentation-specific pain-points in mature software engineering domains.
⁴³⁷ This study answers RQ3 in detail and provides a validation to our motivation of
⁴³⁸ RQ2: we validate that the *completeness* of current CVS API documentation is a
⁴³⁹ main concern for developers and there is insufficient explanation into the errors
⁴⁴⁰ and limitations of the service. We find that the documentation does not adequately
⁴⁴¹ cover all aspects of the technical domain. In terms of integrating with the service,
⁴⁴² developers struggle most with simple errors and ways in which to use the APIs; this
⁴⁴³ is in stark contrast to mature software domains. Our interpretation is that developers
⁴⁴⁴ fail to understand the IWS lifecycle and the ‘whole’ system that wraps such services.
⁴⁴⁵ We also interpret that developers have a shallower understanding of the core issues
⁴⁴⁶ within CVSs (likely due to the nuances of ML as suggested in a discussion in the
⁴⁴⁷ paper), which warrants an avenue for future work in software engineering education.

⁴⁴⁸ 1.6.2.3 *Chapter 6: Ranking CVS pain-points by frustration*

⁴⁴⁹ This chapter has been published as a technical report pre-print on arXiv and an
⁴⁵⁰ extended version is **in review** for submission to the **2021 International Workshop**
⁴⁵¹ **on Emotion Awareness in Software Engineering (SEmotion)** [86]. In this work,
⁴⁵² we use our dataset consisting of the 1,425 Stack Overflow questions from [91] to
⁴⁵³ interpret the breakdown of emotions developers express per classification of pain-
⁴⁵⁴ points conducted in Chapter 5. We find that the distribution of various emotions
⁴⁵⁵ differ per question type, and developers are most frustrated when the expectations
⁴⁵⁶ of a CVS does not match the reality of what these services actually provide, which
⁴⁵⁷ shapes our answer for RQ3.2 and thus RQ3.

⁴⁵⁸ 1.6.2.4 *Chapter 7: Lessons in applying pre-trained models to Stack Overflow*

⁴⁵⁹ This chapter is **in review** the **2021 International Conference on Advanced In-**
⁴⁶⁰ **formation Systems Engineering (CAiSE)** [142]. This work presents a deeper
⁴⁶¹ investigation into the classification model used within Chapter 6 to better interpret
⁴⁶² the automation effort we conducted, thereby highlighting valuable lessons we learnt

Table 1.6: List of publications resulting from this thesis, separated by phenomena exploration (above) and solution design (below).

Ref.	Venue	Acronym	Rank ¹³	Published ¹⁴	Chapter	RQs
[88]	35 th International Conference on Software Maintenance and Evolution	ICSME	A	05 Dec 2019	Chapter 4	RQ1
[87]	13 th International Symposium on Empirical Software Engineering and Measurement	ESEM	A	17 Oct 2019	Excluded ¹⁵	RQ2.1
[91]	42 nd International Conference on Software Engineering	ICSE	A*	<i>In Press</i>	Chapter 5	RQ3
[86]	6 th International Workshop on Emotion Awareness in Software Engineering ¹⁶	SEmotion	A*	<i>In Progress</i>	Chapter 6	RQ3.2
[142]	33 rd International Conference on Advanced Information Systems Engineering	CAiSE	A	<i>In Progress</i>	Chapter 7	RQ3.2
[92]	IEEE Transactions on Software Engineering	TSE	Q1	<i>In Review</i>	Chapter 8	RQ2
[262]	13 th International Conference on Web Engineering	ICWE	B	26 Apr 2019	Chapter 9	RQ4
[89]	28 th Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering	FSE(d) ¹⁷	A*	<i>In Press</i>	Chapter 10	RQ4
[90]	28 th Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering	FSE	A*	<i>In Press</i>	Chapter 11	RQ4

¹³Conference publications ranking measured using the CORE Conference Ranks (<http://www.core.edu.au/conference-portal>) and Journal publications rankings using the Scimago Ranking (<https://www.scimagojr.com/>). Rankings retrieved January 2020.

¹⁴Date of publication, if applicable.

¹⁵The extended version of this conference proceeding is provided in Chapter 8.

¹⁶An ICSE 2021 workshop.

¹⁷We abbreviate this with an added ‘d’ (for the demonstrations track) to distinguish this paper from our full FSE 2020 paper.

463 from performing this exercise. Specifically, we find that the classification model we
464 used in this exercise presented substantial data imbalance, which presented unex-
465 pected results (namely, a high level of posts that showed the emotion, ‘love’). We
466 identify how novel documentation tooling such as model cards [244] or datasheets
467 [132] could have identified risks to our study earlier, and make suggestions needed
468 into future documentation efforts. This work presents complementary results to
469 RQ2 to help propose which documentation elements ML models (and thus IWSs)
470 should provide before diving ‘straight in’.

471 *1.6.2.5 Chapter 8: Investigating improvements to CVS API documentation*

472 This chapter was accepted as a paper at the **2019 International Symposium on**
473 **Empirical Software Engineering and Measurement (ESEM)** [91]. To understand
474 where to improve CVS documentation, we first need to investigate *what* makes a good
475 API document. This short paper initially answered one aspect of RQ2.1: the extent
476 by which *academic literature* has studied various API documentation artefacts.
477 By conducting an systematic mapping study resulting in 21 primary studies, we
478 systematically develop a taxonomy that combines documentation artefacts studied
479 in scattered work into a structured framework of 5 dimensions and 34 weighted
480 categorisations. We then extend this work by triangulating the taxonomy with
481 opinions from developers using a survey to assess the efficacy of these artefacts
482 (thereby answering the second aspect of RQ2.1). From this, we assess the how well
483 CVS providers document their APIs via a heuristic validation of the taxonomy, using
484 the three services from the ICSME publication to make recommendations where
485 documentation should be more complete, thereby answering RQ2.2 (and thus RQ2).
486 The extended version of this chapter has been submitted to the **IEEE Transactions**
487 **on Software Engineering (TSE)** in [92] and we are in the process of finalising a
488 minor review.

489 *1.6.2.6 Chapter 9: Merging responses of multiple CVSs*

490 This chapter was presented at the **2019 International Conference on Web Engi-**
491 **neering (ICWE)** [262]. Early exploration of CVSs showed that multiple services
492 use vastly different ontologies for the same input. As an initial strategy to improve
493 the reliability of these services, we explored if merging multiple responses using
494 WordNet [243] and a novel label merging algorithm based on the proportional rep-
495 resentation approach used in political voting could make any improvements. While
496 this approach resulted in a modest improvement to reliability, it did not consider to
497 the evolution issues or developer pain-points we later identified.

498 *1.6.2.7 Chapter 10: Developing a confidence thresholding tool*

499 This chapter was presented at the demonstrations track of the **2020 Joint European**
500 **Software Engineering Conference and Symposium on the Foundations of Soft-**
501 **ware Engineering (ESEC/FSE)** [89]. When integrating with a CVS, developers

502 need to select an appropriate confidence threshold suited to their use case and deter-
503 mine whether a decision should be made. An issue, however, is that these CVSs are
504 not calibrated to the specific problem-domain datasets and it is difficult for software
505 developers to determine an appropriate confidence threshold on their problem do-
506 main. This tool presents a workflow and supporting tool for application developers
507 to select decision thresholds suited to their domain that—unlike existing tooling—is
508 designed to be used in pre-development, pre-release and production. This tooling
509 forms part of a solution to RQ4 for developers to maintain robustness and reliability
510 in their systems.

511 **1.6.2.8 Chapter 11: Developing a CVS integration architecture**

512 This chapter was presented at the **2020 Joint European Software Engineering**
513 **Conference and Symposium on the Foundations of Software Engineering (ES-**
514 **EC/FSE)** [90]. Based on the findings, we propose a set of new service error codes
515 for describing the empirically observed error conditions of IWS based on our find-
516 ings in Chapter 4. To achieve this, we propose a proxy server intermediary that lies
517 between a client application and a IWS; the proxy server tactic is designed to return
518 these error codes when substantial evolution occurs against a benchmark dataset that
519 represents the application domain context (similar to that proposed in Chapter 10).
520 A technical evaluation of our implementation of this architecture identifies 1,054
521 cases of substantial evolution in confidence values and 2,461 cases of evolution in
522 the response label sets when 331 images were sent to a CVS.

523 **1.6.3 Part III: Postface**

524 In Chapter 12, we review the contributions made in this thesis and the relevance
525 and significance to identifying and resolving key issues when application developers
526 integrate with CVS. We evaluate these outcomes with reference to the research goals,
527 and discuss threats to validity of the work. Lastly, we discuss the various avenues
528 of research arising from this work. References from literature and a list of online
529 artefacts are provided after this concluding chapter.

530 **1.6.4 Part IV: Appendices**

531 Chapter A thru Chapter E are appendices. Chapter A provides additional material
532 referenced within this thesis but not provided in the body. The source code for the
533 reference architecture described in Chapter 11 is reproduced in Chapter B. The sup-
534 plimentary materials published with Chapter 8 are reproduced in Chapter C, which
535 also describes the list of primary sources arising in the systematic mapping study
536 we conducted. We provide mandatory coauthor declaration forms describing the
537 contribution breakdown for each publication within Chapter D. Chapter E contains
538 copies of the ethics clearance for various experiments within this thesis.

539 1.7 Research Contributions

540 The outcomes of answering the four primary research questions elaborated in Section 1.4 shapes three primary contributions this thesis offers to software engineering
 541 knowledge:
 542

- 543 • An **improved understanding in the landscape of CVSs**, with respect to their
 544 runtime behaviour and evolutionary profiles.
- 545 • A novel **service integration architecture** that helps developers with integrating
 546 their applications with CVSs.
- 547 • A **key list of attributes that should be documented**, to assist CVS providers
 548 to better document their services.

549 In this section, we detail how each publication forms a coherent body of work
 550 and how each publication relates to the primary contributions made.

551 After our exploratory analysis on the nature of CVSs (Chapter 4), we proposed
 552 two sets of recommendations targeted towards two stakeholders: (i) the service
 553 *consumers* (i.e., application developers) and (ii) the service *providers*. Our sub-
 554 sequent publications arose as a two-fold investigation to develop two strategies in
 555 which developers and providers can, respectively, (i) better integrate these intelli-
 556 gent components into their applications, and (ii) how these services can be better
 557 documented. Table 1.6 provides a tabulated form of the publications and research
 558 questions addressed within this thesis; for ease of reference, we refer to the publica-
 559 tions in within this section in their abbreviated form as listed in Table 1.6. We also
 560 provide abbreviations for easier reference in this section. A high-level overview of
 561 the cohesiveness of our publications is provided in Figure 1.6.

562 1.7.1 Contribution 1: Landscape Analysis & Preliminary Solutions

563 The first two bodies of work in this paper are the ICSME and ICWE papers. These
 564 two works investigated a landscape analysis CVSs from two perspectives: firstly, we
 565 conducted a longitudinal study to better understand the attributes associated with
 566 these services (ICSME)—particularly their evolution and behavioural profiles, and
 567 their potential impacts to software reliability—and tackled a preliminary solution
 568 facade to ‘merge’ responses of the services together (ICWE).

569 The ICSME paper confirmed our hypotheses that the services have a non-
 570 deterministic behavioural profile, and that the evolution occurring within the ML
 571 models powering these services are not sufficiently communicated to software en-
 572 gineers. This therefore led to follow up investigation into how developers perceive
 573 these services, and thereby determine if they are frustrated due to this lack of com-
 574 munication.

575 Our ICWE paper explored one aspect identified from the ICSME paper that
 576 we identified early on: that different services use different vocabularies to describe
 577 semantically similar objects but in different ways (e.g., ‘border collie’ vs. ‘collie’),
 578 despite offering functionally similar capabilities. We attempted to merge the re-
 579 sponse labels from these services using a proportional representation approach, and

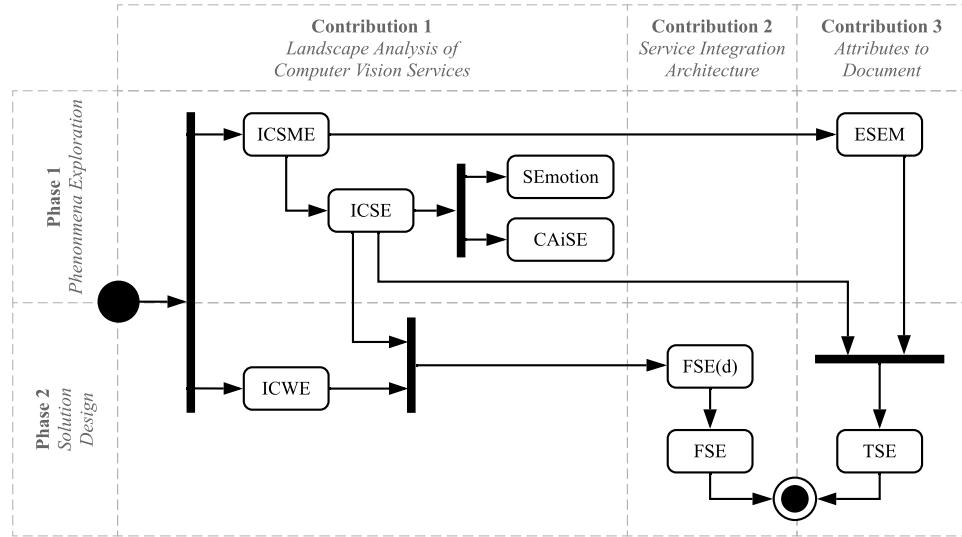


Figure 1.6: Activity diagram of the coherency of our publications, how our research was conducted, and relevant connections between publications. Our two-phase structure initial phenomena exploration and a proposed solutions to issues identified from the exploration. We map the contributions within each publication to the three primary contributions of the thesis. Acronyms of each publication are provided in Table 1.6.

upon comparison with more naive merge approaches, we improved label-merge performance by an F-measure of 0.015. However, while this was an interesting outcome for a preliminary solution design, investigation from our following work suggested that standardising ontologies between service providers becomes challenging and normalising the entire ontological hierarchy of response labels would need to fall under the responsibility of a certain body (that does not exist). Further, we did not find sufficient evidence that developers would frequently switch between service providers. Therefore, we opted for a shielded relay architecture in our later design work.

1.7.2 Contribution 2: Improving Documentation Attributes

As mentioned, our ICSME paper found that evolutionary and non-deterministic behavioural profile of are not adequately documented in pre-trained ML model APIs documentation, and further developers find this frustrating (Chapter 6) and potential issues can arise as a result (Chapter 7). A recommendation concluding from this work was that service providers should improve their documentation, however there lacked a strategy by which they could do this, and our hypotheses that developers were actually frustrated by this lack of communication was yet to be tested. This led to two follow-up further investigations as presented in our ICSE and ESEM papers.

One aspect of our ICSE paper was to confirm whether developers are actually frustrated with the service's limited API documentation. By mining Stack Overflow posts with reference to documentation issues, we adopted a 2019 documentation-related taxonomy by Aghajani et al. [3] to classify posts, and found that 47.87%

of posts classified fell under the ‘completeness’ dimension of Aghajani et al.’s taxonomy. This interpretation, therefore, warranted the recommendation proposed in the ICSME paper to improve service documentation.

However, though improvements to more complete documentation was justified from the ICSE paper, we needed to explore exactly *what* makes a ‘complete’ API document. By conducting a systematic mapping study resulting in 4,501 results, we curated 21 primary studies that outline the facets of API documentation knowledge. From these studies, we distilled a documentation framework describing a prioritised order of the documentation assets API’s should document that is described in our ESEM short paper. After receiving community feedback, we extended this short paper with a follow-up experiment submitted to TSE. By conducting a survey with developers, we assessed our API documentation taxonomy’s efficacy with practitioner opinions, thereby producing a weighted taxonomy against *both* literature and developer sources. Lastly, we triangulated both weightings against a heuristic evaluation against common CVS providers’ documentation. This allowed us to deduce which specific areas in existing CVS providers’ API documentation needed improvement, which was a primary contribution from our TSE article.

1.7.3 Contribution 3: Service Integration Architecture

Two recommendations from our ICSME study encouraged developers to test their applications with a representative ontology for their problem domain and to incorporate a specialised testing and monitoring techniques into their workflow. Strategies on *how* to achieve this were explored in later studies. Following a similar approach to our solution of improved API documentation, we validated the substantiveness of our recommendations using our mining study of Stack Overflow (our ICSE paper) to help inform us of generalised issues developers face whilst integrating CVSs into their applications. To achieve this, we used a Stack Overflow post classification taxonomy proposed by Beyer et al. [39] into seven categories, where 28.9% and 20.37% of posts asked issues regarding how to use the CVS API and conceptual issues behind CVSs, respectively. Developers presented an insufficient understanding of the non-deterministic runtime behaviour, functional capability, and limitations of these services and are not aware of key computer vision terminology. When contrasted to more conventional domains such as mobile-app development, the spread of these issues vary substantially.

We proposed two technical solutions in our two FSE papers to help alleviate this issue. Firstly, our FSE demonstrations paper—FSE(d) for short—provides a workflow for developers to better select an appropriate confidence threshold, and thus decision boundary, calibrated for their particular use case. In our ESEC/FSE paper, we provide a reference architecture for developers to guard against the non-deterministic issues that may ‘leak’ into their applications. This architecture tactic proposes a client-server intermediary proxy server, similar to the style proposed in our ICWE paper. However, unlike the ICWE paper that uses proportional representation approach to modify multiple sources, our FSE paper proposes a guarded relay, whereby a single service is used, and the proxy server maintains a lifecycle to

645 monitor evolution issues identified in ICSME and should be benchmarked against
646 the developer's dataset (i.e., against the particular application domain) as suggested
647 in FSE(d). For robust component composition, this architecture tactic handles four
648 key requirements: (i) it clearly defines erroneous conditions that occur when evo-
649 lution occurs in CVSs; (ii) it notifies of behavioural changes in the service; (iii) it
650 monitors the service for change and substantial impact this may have to the client
651 application; and (iv) is flexible enough to be implemented and adaptable to any client
652 application or specific intelligent service to facilitate reuse. Both FSE papers serve
653 as two primary contributions to RQ4.

CHAPTER 2

654

655

656

Background

657

658 In Chapter 1, we defined a common set of (artificial) intelligence-based cloud ser-
659 vices that we label intelligent web services (IWSs). Specifically, we scope the
660 primary body of this study’s work on computer vision services (CVSs) (e.g., Google
661 Cloud Vision [417], AWS Rekognition [392], Azure Computer Vision [431], Wat-
662 son Visual Recognition [427] etc.). We claim developers have not yet internalised
663 the nuances of working with components that have a probabilistic behaviour ($2 + 2$
664 *always equals 4*) whereas an IWS’s ‘intelligence’ component (a black box) returns
665 probabilistic results ($2 + 2$ *might equal 4 with a confidence of 95%*). Thus, there is a
666 mindset mismatch between probabilistic results (from the API provider) and results
667 interpreted with certainty (from the API consumer).

668 What affect does this anchor mismatch have on the developer’s approach towards
669 building probabilistic software? What can we learn from common software engi-
670 neering practices (e.g., [285, 332]) that apply to resolve this mismatch and thereby
671 improve quality, such as verification & validation (V&V)? Chiefly, we consider this
672 question around three lenses of software engineering: creating an IWS, using an
673 IWS, and the nature of IWSs themselves.

674 Our chief concern lies with interaction and integration between IWS providers
675 and consumers, the nature of applications built using an IWS, and the impact this
676 has on software quality. We triangulate this around three pillars, which we diagram-
677 matically represent in Figure 2.1.

678 **(1) The development of the IWS.** We investigate the internal quality attributes
679 of creating an IWS from the IWS *provider’s* perspective. That is, we ask if
680 existing verification techniques are sufficient enough to ensure that the IWS
681 being developed actually satisfies the IWS consumer’s needs and if the internal
682 perspective of creating the system with a procedural mindset clashes with the
683 outside perspective (i.e., pillar 2).

684 **(2) The usage of the IWS.** We investigate the external quality attributes of using
685 an IWS from the IWS *consumer’s* perspective. That is, we ask if existing

686 validation techniques are sufficient enough to ensure that the end-users can
 687 actually use an IWS to build their software in the ways they expect the IWS to
 688 work.

689 **(3) The nature of an IWS.** We investigate what standard software engineering
 690 practices apply when developing probabilistic systems. That is, we tackle what
 691 best practices exist when developing systems that are inherently stochastic and
 692 probabilistic, i.e., the ‘black box’ intelligence itself.

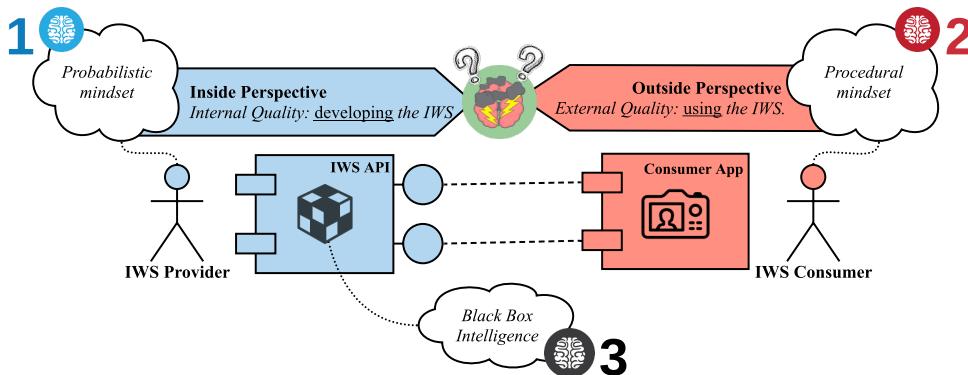


Figure 2.1: The three pillars by which we anchor the background: (1) developing an IWS with a probabilistic mindset by the IWS provider; (2) the use of a IWS with a procedural mindset by the IWS consumer; (3) the nature of a IWS itself.

693 Does a clash of procedural consumer mindsets who use a IWS and the proba-
 694 bilistic provider mindsets who develop them exist? And what impact does this have
 695 on the inside and outside perspective? Throughout this chapter, we will review these
 696 three core pillars due to such mindset mismatch from the anchoring perspective of
 697 software quality, particularly around verification & validation (V&V) and related
 698 quality attributes, probabilistic and non-deterministic software and the nature of
 699 APIs.

700 2.1 Software Quality

Quality... you know what it is, yet you don't know what it is.

ROBERT PIRSIG, 1974 [283]

701 The philosophical viewpoint of ‘quality’ remains highly debated and there are mul-
 702 tiple facets to perceive this complex concept [131]. Transcendentally, a viewpoint
 703 like that of Pirsig’s above shows that quality is not tangible but still recognisable; it’s
 704 hard to explicitly define but you know when it’s missing. The International Orga-
 705 nization for Standardization provides a breakdown of seven universally-applicable
 706 principles that defines quality for organisations, developers, customers and training
 707 providers [170]. More pertinently, the 1986 ISO standard for quality was simply
 708 “the totality of characteristics of an entity that bear on its ability to satisfy stated or

709 implied needs” [169].

710 Using this sentence, what characteristics exist for non-deterministic IWSs like
711 that of a CVS? How do we know when the system has satisfied its ‘stated or implied
712 needs’ when the system can only give us uncertain probabilities in its outputs? Such
713 answers can be derived from related definitions—such as ‘conformance to specifica-
714 tion or requirements’ [85, 137], ‘meeting or exceeding customer expectation’ [36],
715 or ‘fitness for use’ [182]—but these then still depend on the solution description or
716 requirements specification, and thus the same questions still apply.

717 *Software* quality is somewhat more concrete. Pressman [285] adapted the
718 manufacturing-oriented view of quality from [37] and phrased software quality
719 under three core pillars:

- 720 • **effective software processes**, where the infrastructure that supports the cre-
721 ation of quality software needs is effective, i.e., poor checks and balances,
722 poor change management and a lack of technical reviews (all that lie in the
723 *process* of building software, rather than the software itself) will inevitably
724 lead to a poor quality product and vice-versa;
- 725 • **building useful software**, where quality software has fully satisfied the end-
726 goals and requirements of all stakeholders in the software (be it explicit or
727 implicit requirements) *in addition to* delivering these requirements in reliable
728 and error-free ways; and lastly
- 729 • **adding value to both the producer and user**, where quality software provides
730 a tangible value to the community or organisation using it to expedite a
731 business process (increasing profitability or availability of information) *and*
732 provides value to the software producers creating it whereby customer support,
733 maintenance effort, and bug fixes are all reduced in production.

734 In the context of a non-deterministic IWS, however, are any of the above actually
735 guaranteed? Given that the core of a system built using an IWS is fully dependent
736 on the *probability* that an outcome is true, what assurances must be put in place to
737 provide developers with the checks and balances needed to ensure that their software
738 is built with quality? For this answer, we re-explore the concept of verification &
739 validation (V&V).

740 2.1.1 Validation and Verification

741 To explain V&V, we analogously recount a tale given by Pham [281] on his works
742 on reliability. A high-school student sat a standardised test that was sent to 350,0000
743 students [344]. A multiple-choice algebraic equation problem used a variable, *a*,
744 and intended that students *assume* that the variable was non-negative. Without
745 making this assumption explicit, there were two correct answers to the multiple
746 choice answer. Up to 45,000 students had their scores retrospectively boosted by up
747 to 30 points for those who ‘incorrectly’ answered, however, outcomes of a student’s
748 higher education were, thereby, affected by this one oversight in quality assessment.
749 The examiners wrote a poor question due to poor process standards to check if
750 their ‘correct’ answers were actually correct. The examiners “didn’t build the right

751 product” nor did they “build the product right” by writing a poor question and failing
752 to ensure quality standards, in the phrases Boehm [47] coined.

753 This story describes the issues with the cost of quality [46] and the importance
754 of V&V: just as the poorly written exam question had such a high toll on the 45,000
755 unlucky students, so does poorly written software in production. As summarised by
756 Pressman [285], data sourced from Digital [79] in a large-scale application showed
757 that the difference in cost to fix a bug in development versus system testing is
758 \$6,159 per error. In safety-critical systems, such as self-driving cars or clinical
759 decision support systems, this cost skyrockets due to the extreme discipline needed
760 to minimise error [347].

761 Formally, we refer to the IEEE Standard Glossary of Software Engineering
762 Terminology [166] for to define V&V:

763 **verification** The process of evaluating a system or component to determine
764 whether the products of a given development phase satisfy the
765 conditions imposed at the start of that phase.

766 **validation** The process of evaluating a system or component during or at the
767 end of the development process to determine whether it satisfies
768 specified requirements.

769 Thus, in the context of an IWS, we have two perspectives on V&V: that of the API
770 provider and consumer (Figure 2.2).

771 The verification process of API providers ‘leak’ out to the context of the de-
772 veloper’s project dependent on the IWS. Poor verification in the *internal quality*
773 of the IWS will entail poor process standards, such as poor definitions and termi-
774 nology used, support tooling and description of documentations [332]. Though
775 it is commonplace for providers to have a ‘ship-first-fix-later’ mentality of ‘good-
776 enough’ software [360], the consequence of doing so leads to consumers absorbing
777 the cost. Thus API providers must ensure that their verification strategies
778 are rigorous enough for the consumers in the myriad contexts they wish to use
779 it in. Studies have considered V&V in the context of web services on the cloud
780 [20, 69, 70, 119, 155, 252, 254, 382], though little have recently considered how
781 adding ‘intelligence’ to these services affects existing proposed frameworks and
782 solutions. For a CVS, what might this entail? Which assurances are given to the
783 consumers, and how is that information communicated? To verify if the service is
784 working correctly, does that mean that we need to deploy the system first to get a
785 wider range of data, given the stochastic nature of the black box?

786 Likewise, the validation perspective comes from that of the consumer. While the
787 former perspective is of creation, this perspective comes from end-user (developer)
788 expectation. As described in Chapter 1, a developer calls the IWS component using
789 an API endpoint. Again, the mindset problem arises; does the developer know what
790 to expect in the output? What are their expectations for their specific context? In
791 the area of non-deterministic systems of probabilistic output, can the developer be
792 assured that what they enter in a testing phase outcome the same result when in
793 production?

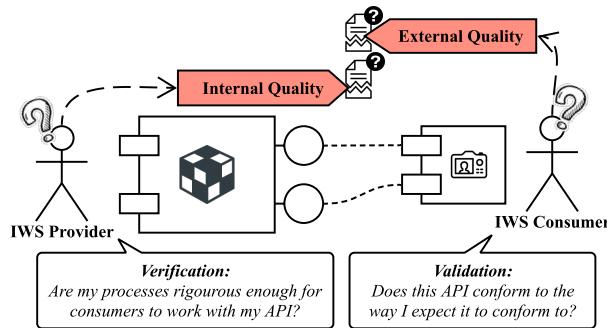


Figure 2.2: The ‘leakage’ of internal quality into the API consumer’s product and external quality imposing on the API provider.

794 Therefore, just as the test answers were both correct and incorrect at the
 795 same time, so is the same with IWSs returning a probabilistic result: no result is
 796 certain. While V&V has been investigated in the area of mathematical and earth
 797 sciences for numerical probabilistic models and natural systems [264, 310], from
 798 the software engineering literature, little work has been achieved to look at the
 799 surrounding area of probabilistic systems hidden behind API calls.

800 Now that a developer is using a probabilistic system behind a deterministic API
 801 call, what does it mean in the context of V&V? Do current verification approaches
 802 and tools suffice, and if not, how do we fix it? From a validation perspective of
 803 ML and end-users, after a model is trained and an inference is given and if the
 804 output data point is incorrect, how will end users report a defect in the system?
 805 Compared to deterministic systems where such tooling as defect reporting forms are
 806 filled out (i.e., given input data in a given situation and the output data was X), how
 807 can we achieve similar outputs when the system is not non-deterministic? A key
 808 problem with the probabilistic mindset is that once a model is ‘fixed’ by retraining
 809 it, while one data-point may be fixed, others may now have been effected, thereby
 810 not ensuring 100% validation. Thus, due to the unpredictable and blurry nature of
 811 probabilistic systems, V&V must be re-thought out extensively.

812 2.1.2 Quality Attributes and Models

813 Similarly, quality models are used to capture internal and external quality attributes
 814 via measurable metrics. Is a similar issue reflected from that of V&V due to
 815 nondeterministic systems? As there is no ‘one’ definition of quality, there have been
 816 differing perspectives with literature placing varying value on disparate attributes.

817 Quality attribute assessment models (like those shown in Figure 2.3) are an early
 818 concept in software engineering, and systematically evaluating software quality
 819 appears as early as 1968 [309]. Rubey and Hartwick’s 1968 study introduced the
 820 phrase ‘attributes’ as a “prose expression of the particular quality of desired software”
 821 (as worded by Boehm et al. [45]) and ‘metrics’ as mathematical parameters on a

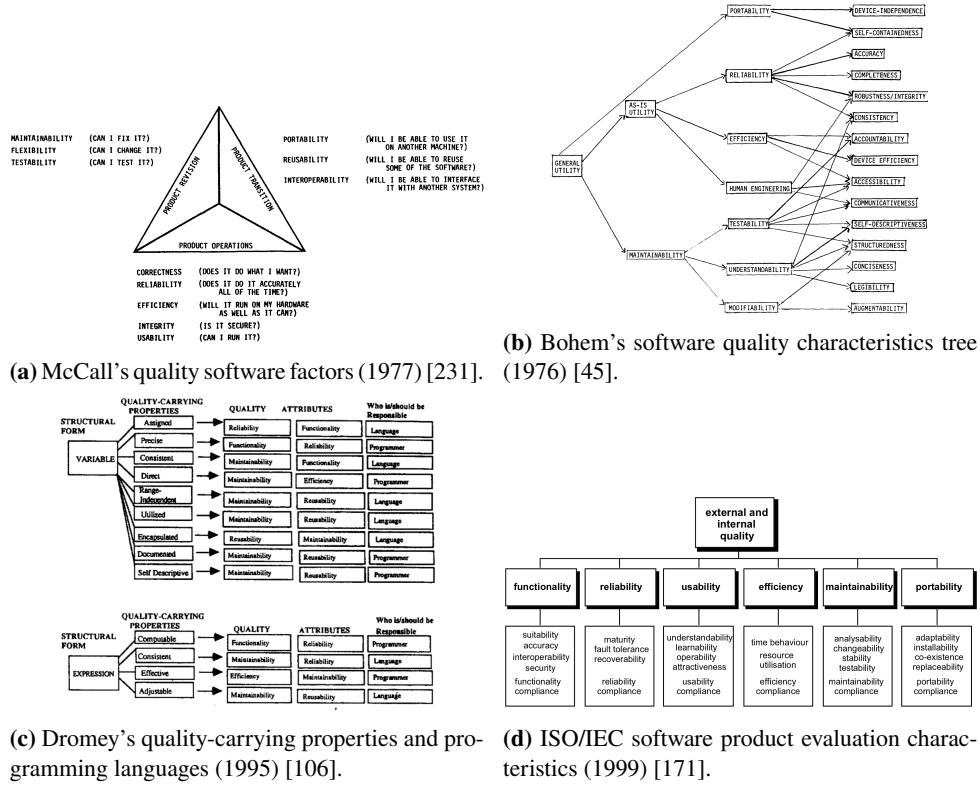


Figure 2.3: A brief overview of the development of software quality models since 1977.

scale of 0 to 100. Early attempts to categorise wider factors under a framework was proposed by McCall, Richards, and Walters in the late 1970s [73, 231]. This model described quality from the three perspectives of product revision (*how can we keep the system operational?*), transition (*how can we migrate the system as needed?*) and operation (*how effective is the system at achieving its tasks?*) (Figure 2.3a). The model also introduced 11 attributes alongside numerous direct and indirect measures to help quantify quality. This model was further developed by Boehm et al. [45] who independently developed a similar model, starting with an initial set of 11 software characteristics. It further defined candidate measurements of Fortran code to such characteristics, taking shape in a tree-like structure as in Figure 2.3b. In the mid-1990s, Dromey's interpretation [106] defined a set of quality-carrying properties with structural forms associated to specific programming languages and conventions (Figure 2.3c). The model also supported quality defect identification and proposed an improved auditing method to automate defect detection for code editors in IDEs. As the need for quality models became prevalent, the International Organization for Standardization standardised software quality under ISO/IEC-9126 [171] (the Software Product Evaluation Characteristics, Figure 2.3d), which has since recently been revised to ISO/IEC-25010 with the introduction of the Systems and software Quality Requirements and Evaluation (SQuaRE) model [168], separating quality into *Product Quality* (consisting of eight quality characteristics and 31 sub-

⁸⁴² characteristics) and *Quality In Use* (consisting of five quality characteristics and 9
⁸⁴³ sub-characteristics). An extensive review on the development of quality models in
⁸⁴⁴ software engineering is given in [6].

⁸⁴⁵ Of all the models described, there is one quality attribute that relates most
⁸⁴⁶ with our narrative of IWS quality: reliability. Reliability is the primary quality
⁸⁴⁷ factor investigated within this thesis (see Section 1.4). Both McCall and Boehm's
⁸⁴⁸ quality models have sub-characteristics of reliability relating to the primary research
⁸⁴⁹ questions that investigate the *robustness*, *consistency* and *completeness*¹ of CVSs
⁸⁵⁰ and its associated documentation. Moreover, the definition of reliability is similar
⁸⁵¹ among all quality models:

⁸⁵² **McCall et al.** Extent to which a program can be expected to perform its in-
⁸⁵³ tended function with required precision [231].

⁸⁵⁴ **Boehm et al.** Code possesses the characteristic *reliability* to the extent that
⁸⁵⁵ it can be expected to perform its intended functions satisfac-
⁸⁵⁶ torily [45].

⁸⁵⁷ **Dromey** Functionality implies reliability. The reliability of software is
⁸⁵⁸ therefore dependent on the same properties as functionality, that
⁸⁵⁹ is, the correctness properties of a program [106].

⁸⁶⁰ **ISO/IEC-9126** The capability of the software product to maintain a specified
⁸⁶¹ level of performance when used under specified conditions [171].

⁸⁶² These definitions strongly relate to the system's solution description in that
⁸⁶³ reliability is the ability to maintain its *functionality* under given conditions. But what
⁸⁶⁴ defines reliability when the nature of an IWS in itself is inherently unpredictable
⁸⁶⁵ due to its probabilistic implementation? Can a non-deterministic system ever be
⁸⁶⁶ considered reliable when the output of the system is uncertain? How do developers
⁸⁶⁷ perceive these quality aspects of reliability in the context of such systems? A system
⁸⁶⁸ cannot be perceived as 'reliable' if the system cannot reproduce the same results due
⁸⁶⁹ to a probabilistic nature. Therefore, we believe the literature of quality models does
⁸⁷⁰ not suffice in the context of IWS reliability; a CVS can interpret an image of a dog
⁸⁷¹ as a 'Dog' one day, but what if the next it interprets such image more specifically to
⁸⁷² the breed, such as 'Border Collie'? Does this now mean the system is unreliable?

⁸⁷³ Moreover, defining these systems in themselves is challenging when require-
⁸⁷⁴ ments specifications and solution descriptions are dependent on nondeterministic
⁸⁷⁵ and probabilistic algorithms. We discuss this further in Section 2.2.

⁸⁷⁶ 2.1.3 Reliability in Computer Vision

⁸⁷⁷ Testing computer vision deep-learning reliability is an area explored typically
⁸⁷⁸ through the use of adversarial examples [342]. These input examples are where

¹In McCall's model, completeness is a sub-characteristic of the 'correctness' quality factor; however in Boehm's model it is a sub-characteristic of reliability. For consistency in this thesis, *completeness* is referred in the Boehm interpretation.

879 images are slightly perturbed to maximise prediction error but are still interpretable
880 to humans. Refer to Figure 2.4.

881 Google Cloud Vision, for instance, fails to correctly classify adversarial examples
882 when noise is added to the original images [161]. Rosenfeld et al. [307] illustrated
883 that inserting synthetic foreign objects to input images (e.g., a cartoon elephant)
884 can alter classification output. Wang et al. [363] performed similar attacks on a
885 transfer-learning approach of facial recognition by modifying pixels of a celebrity’s
886 face to be recognised as a different celebrity, all while still retaining the same human-
887 interpretable original celebrity. Su et al. [337] used the ImageNet database to show
888 that 41.22% of images drop in confidence when just a *single pixel* is changed in the
889 input image; and similarly, Eykholt et al. [113] recently showed similar results that
890 made a CNN interpret a stop road-sign (with mimicked graffiti) as a 45mph speed
891 limit sign.

892 Thus, the state-of-the-art computer vision techniques may not be reliable enough
893 for safety critical applications (such as self-driving cars) as they do not handle inten-
894 tional or unintentional adversarial attacks. Moreover, as such adversarial examples
895 exist in the physical world [113, 204], “the real world may be adversarial enough”
896 [280] to fool such software.

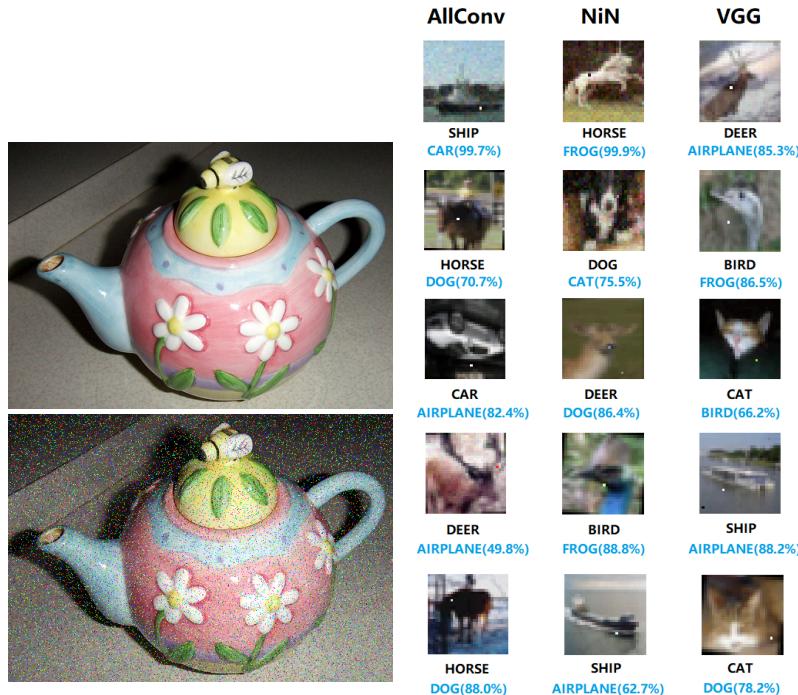
897 2.2 Probabilistic and Nondeterministic Systems

898 Probabilistic and nondeterministic systems are those by which, for the same given
899 input, different outcomes may result. The underlying models that power an IWS
900 are treated as though they are nondeterministic; Chapter 2 introduces IWSs as
901 essentially black-box behaviour that can change over time. As such, we adopt the
902 nondeterministic behaviour that they present.

903 2.2.1 Interpreting the Uninterpretable

904 As the rise of applied AI increases, the need for engineering interpretability around
905 models becomes paramount, chiefly from an external quality perspective that the
906 *reliability* of the system can be inspected by end-users. Model interpretability has
907 been stressed since early machine learning research in the late 1980s and 1990s (such
908 as Quinlan [287] and Michie [242]), and although there has since been a significant
909 body of work in the area [18, 34, 53, 66, 97, 115, 125, 135, 180, 213, 217, 228, 275,
910 295, 308, 329, 358, 361], it is evident that ‘accuracy’ or model ‘confidence’ is still
911 used as a primary criterion for AI evaluation [164, 174, 331]. Much research into
912 neural network (NN) or support vector machine (SVM) development stresses that
913 ‘good’ models are those with high accuracy. However, is accuracy enough to justify
914 a model’s quality?

915 To answer this, we revisit what it means for a model to be accurate. Accuracy
916 is an indicator for estimating how well a model’s algorithm will work with future
917 or unforeseen data. It is quantified in the AI testing stage, whereby the algorithm
918 is tested against cases known by humans to have ground truth but such cases are
919 unknown by the algorithm. In production, however, all cases are unknown by both



(a) Adding 10% impulse noise to an image of a teapot changes Google Cloud Vision's label from *teapot* (above) to *biology* (below) [161].

(b) One-pixel attacks applied to three neural network (NN): AllConv, NiN and VGG [337].



(c) Adversarial examples to trick face recognition from the source to target images [363].

Figure 2.4: Sample adversarial examples in state-of-the-art computer vision studies.

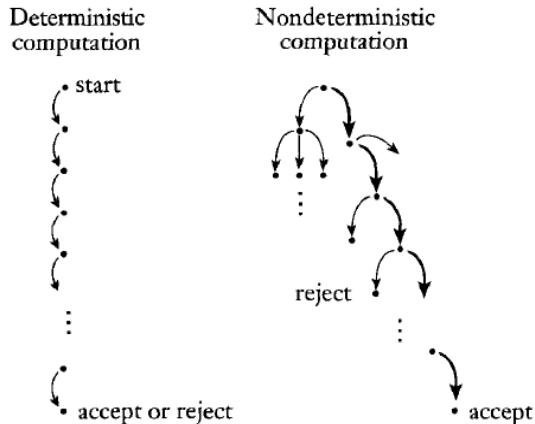


Figure 2.5: A deterministic system (left) always returns the same result in the same amount of steps. A nondeterministic system does not guarantee the same outcome, even with the same input data. Source: [117].

920 the algorithm *and* the humans behind it, and therefore a single value of quality is “not
 921 reliable if the future dataset has a probability distribution significantly different from
 922 past data” [121], a problem commonly referred to as the *datashift* problem [314].
 923 Analogously, Freitas [121] provides the following description of the problem:

924 *The military trained [a NN] to classify images of tanks into enemy
 925 and friendly tanks. However, when the [NN] was deployed in the field
 926 (corresponding to “future data”), it had a poor accuracy rate. Later,
 927 users noted that all photos of friendly (enemy) tanks were taken on a
 928 sunny (overcast) day. I.e., the [NN] learned to discriminate between
 929 the colors of the sky in sunny vs. overcast days! If the [NN] had
 930 output a comprehensible model (explaining that it was discriminating
 931 between colors at the top of the images), such a trivial mistake would
 932 immediately be noted.* [121]

933 So, why must we interpret models? While the formal definition of what it means
 934 to be *interpretable* is still somewhat disparate (though some suggestions have been
 935 proposed [217]), what is known is (i) there exists a critical trade-off between accuracy
 936 and interpretability [102, 120, 144, 179, 187, 384], and (ii) a single quantifiable value
 937 cannot satisfy the subjective needs of end-users [121]. As ever-growing domains
 938 ML become widespread², these applications engage end-users for real-world goals,
 939 unlike the aims in early ML research where the aim was to get AI working in the
 940 first place. In safety-critical systems where AI provide informativeness to humans
 941 to make the final call (see [71, 165, 190]), there is often a mismatch between the
 942 formal objectives of the model (e.g., to minimise error) and complex real-world
 943 goals, where other considerations (such as the human factors and cognitive science

²In areas such as medicine [33, 66, 111, 175, 180, 208, 276, 297, 358, 380, 387], bioinformatics [101, 122, 177, 186, 341], finance [18, 99, 165] and customer analytics [213, 361].

⁹⁴⁴ behind explanations³) are not realised: model optimisation is only worthwhile if they
⁹⁴⁵ “actually solve the original [human-centred] task of providing explanation” [253]
⁹⁴⁶ to end-users. **Therefore, when human-decision makers must be interpretable**
⁹⁴⁷ **themselves [298], any AI they depend on must also be interpretable.**

⁹⁴⁸ Recently, discussion behind such a notion to provide legal implications of in-
⁹⁴⁹ terpretability is topical. Doshi-Velez et al. [105] discuss when explanations are not
⁹⁵⁰ provided from a legal stance—for instance, those affected by algorithmic-based de-
⁹⁵¹ cisions have a ‘right to explanation’ [225, 362] under the European Union’s GDPR⁴.
⁹⁵² But, explanations are not the only way to ensure AI accountability: theoretical guar-
⁹⁵³ antees (mathematical proofs) or statistical evidence can also serve as guarantees
⁹⁵⁴ [105], however, in terms of explanations, what form they take and how they are
⁹⁵⁵ proven correct are still open questions [217].

⁹⁵⁶ 2.2.2 Explanation and Communication

⁹⁵⁷ From a software engineering perspective, explanations and interpretability are, by
⁹⁵⁸ definition, inherently communication issues: what lacks here is a consistent interface
⁹⁵⁹ between the AI system and the person using it. The ability to encode ‘common
⁹⁶⁰ sense reasoning’ [232] into programs today has been achieved, but *decoding* that
⁹⁶¹ information is what still remains problematic. At a high level, Shannon and Weaver’s
⁹⁶² theory of communication [322] applies, just as others have done with similar issues in
⁹⁶³ the software engineering realm [246, 374] (albeit to the domain of visual notations).
⁹⁶⁴ Humans map the world in higher-level concepts easily when compared to AI systems:
⁹⁶⁵ while we think of a tree first (not the photons of light or atoms that make up the
⁹⁶⁶ tree), an algorithm simply sees pixels, and not the concrete object [105] and the AI
⁹⁶⁷ interprets the tree inversely to humans. Therefore, the interpretation or explanation
⁹⁶⁸ is done inversely: humans do not explain the individual neurons fired to explain their
⁹⁶⁹ predictions, and therefore the algorithmic transparent explanations of AI algorithms
⁹⁷⁰ (“*which neurons were fired to make this AI think this tree is a tree?*”) do not work
⁹⁷¹ here.

⁹⁷² Therefore, to the user (as mapped using Shannon and Weaver’s theory), an AI
⁹⁷³ pipeline (the communication *channel*) begins with a real-world concept, y , that acts
⁹⁷⁴ as an *information source*. This information source is fed in as a *message*, x , (as pixels)
⁹⁷⁵ to an AI system (the *transmitter*). The transmitter encodes the pixels to a prediction,
⁹⁷⁶ \hat{y} , the *signal* of the message. This signal is decoded by the *receiver*, an explanation
⁹⁷⁷ system, $e_x(x, \hat{y})$, that tailors the prediction with the given input data to the intended
⁹⁷⁸ end user (the *destination*) as an explanation, \tilde{y} , another type of *message*. Therefore,
⁹⁷⁹ the user only sees the channel as an input/output pipeline of real-world objects, y ,
⁹⁸⁰ and explanations, \tilde{y} , tailored to *them*, without needing to see the inner-mechanics of
⁹⁸¹ a prediction \hat{y} . We present this diagrammatically in Figure 2.6.

³Interpretations and explanations are often used interchangeably.

⁴<https://www.eugdpr.org> last accessed 13 August 2018.

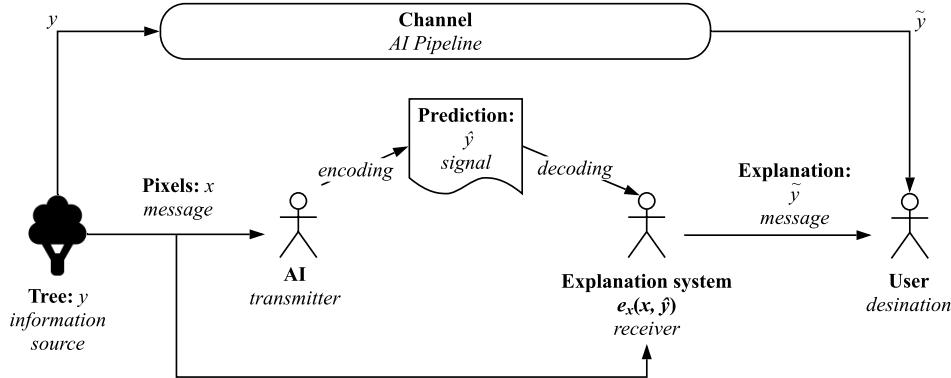


Figure 2.6: Theory of AI communication from information source, y , to intended user as explanations, \hat{y} .

982 2.2.3 Mechanics of Model Interpretation

983 How do we interpret models? Methods for developing interpretation models include:
 984 decision trees [59, 83, 152, 222, 288], decision tables [19, 213] and decision sets
 985 [206, 253]; input gradients, gradient vectors or sensitivity analysis [18, 210, 295,
 986 308, 319]; exemplars [123, 191]; generalised additive models [71]; classification
 987 (*if-then*) rules [55, 80, 267, 351, 377] and falling rule lists [329]; nearest neighbours
 988 [228, 290, 320, 372, 385] and Naïve Bayes analysis [33, 75, 114, 124, 156, 198, 208,
 989 387].

990 Cross-domain studies have assessed the interpretability of these techniques
 991 against end-users, measuring response time, accuracy in model response and user
 992 confidence [7, 122, 153, 165, 228, 313, 338, 361], although it is generally agreed
 993 that decision rules and decision tables provide the most interpretation in non-linear
 994 models such as SVMs or NNs [122, 228, 361]. For an extensive survey of the benefits
 995 and fallbacks of these techniques, we refer to Freitas [121], Doshi-Velez et al. [105]
 996 and Doshi-Velez and Kim [104].

997 An important factor in model interpretation is to avoid over-reliance, and thus,
 998 one mechanism of model interpretation is to reduce explanations altogether. For
 999 example, Bussone et al. [66] showed that, in clinical decision support systems,
 1000 confidence values alone only results in a slight effect on trust and reliance of a
 1001 system. However, having overly detailed explanations may also cause over-reliance
 1002 on systems if explanations are detailed but not necessarily true [66]. Hence, a
 1003 mechanism of model interpretation for the purpose of ensuring trust and reliance is
 1004 to deliberately show *fewer* explanations or *incorrect* explanations, thereby avoiding
 1005 over-reliance. A balance between under-explained and overly-explained models is
 1006 required. This is to encourage intuition in users of a system; similarly, in Ribeiro et al.
 1007 [295], it was shown that accuracy alone is not always the best way to ascertain trust.
 1008 Thus, intuitive factors are also mechanisms that can be encoded into explainable
 1009 models.

1010 2.3 Application Programming Interfaces

1011 Application programming interfaces (APIs) are the interface between a developer
1012 needs and the software components at their disposal [13] by abstracting the underlying
1013 component behind a subroutine, protocol or specific tool. Therefore, it is natural
1014 to assess internal quality (and external quality if the software is in itself a service to
1015 be used by other developers—in this case an IWS) is therefore directly related to the
1016 quality the API offers [197].

1017 Good APIs are known to be intuitive and require less documentation browsing
1018 [282], thereby increasing developer productivity. Conversely, poor APIs are those
1019 that are hard to interpret, thereby reducing developer productivity and product quality.
1020 The consequences of this have shown a higher demand of technical support (as
1021 measured in [157]) that, ultimately, causes the maintenance to be far more expensive,
1022 a phenomenon widely known in software engineering economics (see Section 2.1.1).

1023 While there are different types of APIs, such as software library/framework
1024 APIs for building desktop software, operating system APIs for interacting with the
1025 operating system, remote APIs for communication of varying technologies through
1026 common protocols, we focus on web APIs for communication of resources over
1027 the web (being the common architecture of cloud-based services). Further information
1028 on the development, usage and documentation of web APIs is provided in
1029 Section A.1.

1030 2.3.1 API Usability

1031 If a developer doesn't understand the overarching concepts of the context behind
1032 the API they wish to use, then they cannot formulate what gaps in their knowledge
1033 is missing. For example, a developer that knows nothing about ML techniques in
1034 computer vision cannot effectively formulate queries to help bridge those gaps in
1035 their understanding to figure out more about the CVS they wish to use.

1036 Balancing the understanding of the information need (both conscious and unconscious), how to phrase that need and how to query it in an information retrieval
1037 system is concept long studied in the information sciences [349]. In API design,
1038 the most common form to convey knowledge to developers is through annotated
1039 code examples and overviews to a platform's architectural and design decisions
1040 [56, 103, 250, 302] though these studies have not effectively communicated *why*
1041 these artefacts are important. What makes the developer *conceptually understand*
1042 these artefacts?

1044 Robillard and Deline [302] conducted a multi-phase, mixed-method approach to
1045 create knowledge grounded in the professional experience of 440 software engineers
1046 at Microsoft of varying experience to determine what makes APIs hard to learn,
1047 the results of which previously published in an earlier report [301]. Their results
1048 demonstrate that 'documentation-related obstacles' are the biggest hurdle in learning
1049 new APIs. One of these implications are the *intent documentation* of an API (i.e.,
1050 *what is the intent for using a particular API?*) and such documentation is required
1051 only where correct API usage is not self-evident, where advanced uses of the API are

1052 documented (but not the intent), and where performance aspects of the API impact
1053 the application developed using it. They conclude that professional developers do
1054 not struggle with learning the *mechanics* of the API, but in the *understanding* of how
1055 the API fits in upwards to its problem domain and downward to its implementation:

1056 *In the upwards direction, the study found that developers need help
1057 mapping desired scenarios in the problem domain to the content of the
1058 API, and in understanding what scenarios or usage patterns the API
1059 provider intends and does not intend to support. In the downwards
1060 direction, developers want to understand how the API's implementation
1061 consumes resources, reports errors and has side effects.* [302]

1062 These results particularly corroborate to that of previous studies where devel-
1063 opers quote that they feel that existing learning content currently focuses on “*how*
1064 to do things, not necessarily *why*” [261]. This thereby reiterates the conceptual
1065 understanding of an API as paramount.

1066 A later study by Ko and Riche [196] assessed the importance of a programmer’s
1067 conceptual understanding of the background behind the task before implementing the
1068 task itself, a notion that we find most relevant for users of IWS APIs. While the study
1069 did not focus on developing web APIs (rather implementing a Bluetooth application
1070 using platform-agnostic terminology), the study demonstrated how developers show
1071 little confidence in their own metacognitive judgements to understand and assess the
1072 feasibility of the intent of the API and understand the vocabulary and concepts within
1073 the domain (i.e., wireless connectivity). This indecision over what search results
1074 were relevant in their searches ultimately hindered their progress implementing the
1075 functionality, again decreasing productivity. Ko and Riche suggest to improve API
1076 usability by introducing the background of the API and its relevant concepts using
1077 glossaries linked to tutorials to each of the major concepts, and then relate it back to
1078 how to implement the particular functionality. Thus, an analysis of the conceptual
1079 understanding of IWS APIs by a range of developers (from beginner to professional)
1080 is critical to best understand any differences between existing studies and those that
1081 are nondeterministic.

1082 2.4 Summary

1083 This background chapter explored nuances of interacting and integrating with proba-
1084 bilistic components, namely IWSs, and the impacts this may have to software quality.
1085 Firstly, we explored both internal and external quality attributes of IWSs and how
1086 leakage of internal quality may affect the external quality of client applications.
1087 We discussed how V&V approaches can assist in improving quality assurance of
1088 probabilistic components, and reviewed how various software quality attributes and
1089 models emphasise reliability of systems and their associated documentation (namely,
1090 through the sub-characteristics of robustness, consistency and completeness). We
1091 applied this context to CVSs, giving examples where these cloud services may not
1092 be reliable. Lastly, we applied the narrative of reliability to the overarching nature

1093 of computer vision itself, exploring how the underlying ML models behind a CVS
1094 can potentially fail, and discussed how any such ML model should be explainable
1095 to ensure its reliability and trustworthiness. Lastly, we discussed the impact an API
1096 can have when it is of poor quality, again impacting the internal quality of a system.
1097 In the next chapter, we propose several research strategies in the search for further
1098 insight into the developer's approach toward existing IWS APIs.

CHAPTER 3

1099

1100

1101

Research Methodology

1102

1103 Investigating software engineering practices is often a complex task as it is imper-
1104 ative to understand the social and cognitive processes around software engineers
1105 and not just the tools and processes used [109]. This chapter explores our research
1106 methodology by exploring five key elements of empirical software engineering re-
1107 search: firstly, (i) we provide an extended focus to the study by reviewing our research
1108 questions (see Section 1.4) anchored under the context of an existing research ques-
1109 tion classification taxonomy, (ii) characterise our research goals through an explicit
1110 philosophical stance, (iii) explain how the stance selected impacts our selection of
1111 research methods and data collection techniques (by dissecting our choice of meth-
1112 ods used to reach these research goals), (iv) discuss a set of criteria for assessing the
1113 validity of our study design and the findings of our research, and lastly (v) discuss
1114 the practical considerations of our chosen methods.

1115 The foundations for developing this research methodology has been expanded
1116 from that proposed by Easterbrook et al. [109], Wohlin and Aurum [378], Wohlin
1117 et al. [379] and Shaw [324].

3.1 Research Questions Revisited

1118 To discuss our research strategy, we revisit our four primary and seven secondary
1119 research questions (RQs) through the classification technique discussed by Easter-
1120 brook et al. [109], a technique originally proposed in the field of psychology by
1121 Meltzoff and Cooper [237] but adapted to software engineering. A summary of the
1122 classifications made to our research questions are presented in Table 3.1.

1123 Our research study involves a mix of nine *empirical*¹ RQs, that focus on observ-
1124 ing and analysing existing phenomena, and two *non-empirical* RQs, that focuses
1125 on designing better approaches to solve software engineering tasks [241]. The use

¹Or ‘knowledge’ questions, that extend our *knowledge* on certain phenomena.

¹¹²⁷ of empirical *and* non-empirical RQs are best combined in long-term software engineering research studies where the phenomena are under-explored, as is the case ¹¹²⁸ with CVSs. Further, these approaches help propose solutions to issues found in the ¹¹²⁹ phenomena studied [375]. We discuss both our empirical and non-empirical RQs in ¹¹³⁰ Sections 3.1.1 and 3.1.2 below. ¹¹³¹

Table 3.1: A summary of our research questions classified using the strategies presented by Easterbrook et al. [109] and Meltzoff and Cooper [237].

#	RQ	Primary/ Secondary	RQ Classification
RQ1	What is the nature of cloud-based CVSs?	Primary	EMPIRICAL ↔ Exploratory ↔ Description/Classification
RQ1.1	What is their runtime behaviour?		EMPIRICAL ↔ Exploratory ↔ Description/Classification
RQ1.2	What is their evolution profile?		EMPIRICAL ↔ Exploratory ↔ Description/Classification
RQ2	Are CVS APIs sufficiently documented?	Primary	EMPIRICAL ↔ Exploratory ↔ Existence
RQ2.1	What API documentation artefacts compromise a ‘complete’ API document, according to both literature and practitioners?	Secondary	EMPIRICAL ↔ Exploratory ↔ Composition
RQ2.2	What additional information or attributes do application developers need in CVS API documentation to make it more complete?	Secondary	NON-EMPIRICAL ↔ Design
RQ3	Are CVSs more misunderstood than conventional software engineering domains?	Primary	EMPIRICAL ↔ Exploratory ↔ Descriptive-Comparative
RQ3.1	What types of issues do application developers face most when using CVSs, as expressed as questions on Stack Overflow?	Secondary	EMPIRICAL ↔ Base-Rate ↔ Frequency/Distribution
RQ3.2	Which of these issues are application developers most frustrated with?	Secondary	EMPIRICAL ↔ Exploratory ↔ Description/Classification
RQ3.3	Is the distribution CVS pain-points different to established software engineering domains, such as mobile or web development?	Secondary	EMPIRICAL ↔ Base-Rate ↔ Frequency/Distribution
RQ4	What strategies can developers employ to integrate their applications with CVSs while preserving robustness and reliability?	Primary	NON-EMPIRICAL ↔ Design

¹¹³² 3.1.1 Empirical Research Questions

¹¹³³ In total, we pose nine empirically-based RQs to help us understand the way developers ¹¹³⁴ currently interact and work with web services that provide computer vision. The ¹¹³⁵ majority of these questions are *exploratory* questions that contribute to a landscape ¹¹³⁶ analysis of these services (RQ1, RQ1.1 and RQ1.2), how well they are documented ¹¹³⁷ (RQ2), and the issues developers currently face when using them (RQ3). Our other

1138 exploratory questions complement the answers to these questions. For instance, to
1139 understand if CVSs are sufficiently documented (an *existence* exploratory question
1140 posed in RQ2), we need to understand the components of a ‘sufficient’ or ‘com-
1141 plete’ API document via RQ2.1 as proposed in both the literature and by software
1142 developers. While RQ2.1 does not directly relate to CVSs, answering it gives us
1143 an understanding the components of complete API documentation, and therefore,
1144 we can assess what aspects they are missing and where improvements can be made
1145 (RQ2.2). These questions are *descriptive and classification* questions that help de-
1146 scribe and classify what practices are in use for existing CVS API documentation
1147 and the nature behind these services. Answering these exploratory questions assists
1148 in refining preciser terms of the phenomena, ways in which we find evidence for
1149 them, and ensuring the data found is valid.

1150 By answering these questions, we have a clearer understanding of the phenom-
1151 ena; we then follow up by posing two additional *base-rate questions* that helps
1152 provide a basis to confirm that the phenomena occurring is normal (or unusual)
1153 behaviour by investigating the patterns of phenomena’s occurrence against other
1154 phenomena. RQ3.1 is a *frequency and distribution* question to help us understand
1155 what types of issues developers often encounter most, given a lack of formal extended
1156 training in artificial intelligence. This achieves us an insight into the developer’s
1157 mindset and regular thought patterns toward these APIs. We can then contrast
1158 this distribution using our second base-rate question (RQ3.3), that assesses the
1159 distributional differences between these intelligent components and non-intelligent
1160 (conventional) software components. Combined, these two questions can help us
1161 answer how the issues raised against CVSs are different to normal Stack Overflow
1162 issues—our *descriptive-comparative* question posed in RQ3—and, similarly, we can
1163 classify and rank which issues developers find most frustrating (RQ3.2).

1164 3.1.2 Non-Empirical Research Questions

1165 RQ2.2 and RQ4 are both non-empirically-based *design questions*; they are con-
1166 cerned with ways in which we can improve a CVS by investigating what additional
1167 attributes are needed in both the documentation of CVSs and in the integration
1168 architectures developers can employ to improve reliability and robustness in their
1169 applications. They are not classified as empirical questions as we investigate what
1170 *will be* and not *what is*. By understanding the process by which developers desire
1171 additional attributes of documentation and integration strategies, we can help shape
1172 improvements to the existing designs of using CVSs.

1173 3.2 Philosophical Stances

1174 Philosophical stances guide the researcher’s action by fortifying what constitutes
1175 ‘valid truth’ against a fundamental set of core beliefs [300]. In software engineer-
1176 ing, four dominant philosophical stances are commonly characterised [84, 278]:
1177 positivism (or post-positivism), constructivism (or interpretivism), pragmatism, and
1178 critical theory (or advocacy/participatory). To construct such a ‘validity of truth’,

¹¹⁷⁹ we will review these four philosophical stances in this section, and state the stance
¹¹⁸⁰ that we explicitly adopt and our reasoning for this.

¹¹⁸¹ *Positivism*

¹¹⁸² Positivists claim truth to be all observable facts, reduced piece-by-piece to smaller
¹¹⁸³ components which is incrementally verifiable to form truth. We do not base our
¹¹⁸⁴ work on the positivistic stance as the theories governing verifiable hypothesis must
¹¹⁸⁵ be precise from the start of the research. Moreover, due to its reductionist approach,
¹¹⁸⁶ it is difficult to isolate these hypotheses and study them in isolation from context.
¹¹⁸⁷ As our hypotheses are not context-agnostic, we steer clear from this stance.

¹¹⁸⁸ *Constructivism*

¹¹⁸⁹ Constructivists see knowledge embedded within the human context; truth is the
¹¹⁹⁰ *interpretive* observation by understanding the differences in human thought between
¹¹⁹¹ meaning and action [195]. That is, the interpretation of the theory is just as important
¹¹⁹² to the empirical observation itself. We partially adopt a constructivist stance as we
¹¹⁹³ attempt to model the developer's mindset, being an approach that is rich in qualitative
¹¹⁹⁴ data on human activity.

¹¹⁹⁵ *Pragmatism*

¹¹⁹⁶ Pragmatism is a less dogmatic approach that encourages the incomplete and approx-
¹¹⁹⁷ imate nature of knowledge and is dependent on the methods in which the knowledge
¹¹⁹⁸ was extracted. The utility of consensually agreed knowledge is the key outcome, and
¹¹⁹⁹ is therefore relative to those who seek utility in the knowledge—what is the useful
¹²⁰⁰ for one person is not so for the other. While we value the utility of knowledge, it is
¹²⁰¹ difficult to obtain consensus especially on an ill-researched topic such as ours, and
¹²⁰² therefore we do not adopt this stance.

¹²⁰³ *Critical Theory*

¹²⁰⁴ This study chiefly adopts the philosophy of critical theory [10]. A key outcome of
¹²⁰⁵ the study is to shift the developer's restrictive deterministic mindset and shed light
¹²⁰⁶ on developing a new framework actively with the developer community that seeks
¹²⁰⁷ to improve the process of using such APIs. In software engineering, critical theory
¹²⁰⁸ is used to “actively [seek] to challenge existing perceptions about software practice”
¹²⁰⁹ [109], and this study utilises such an approach to shift the mindset of CVS consumers
¹²¹⁰ and providers alike on how the documentation and metadata should not be written
¹²¹¹ with the ‘traditional’ deterministic mindset at heart. Thus, our key philosophical
¹²¹² approach is critical theory to seek out *what-can-be* using partial constructivism to
¹²¹³ model the current *what-is*.

3.3 Research Methods

1214 Research methods are “a set of organising principles around which empirical data is
1215 collection and analysed” [109]. Creswell [84] suggests that strong research design
1216 is reflected when the weaknesses of multiple methods complement each other. Us-
1217 ing a mixed-methods approach is therefore commonplace in software engineering
1218 research, typically due to the human-oriented nature investigating how software en-
1219 gineers work both individually (where methods from psychology may be employed)
1220 and together (where methods from sociology may be employed).

1222 Therefore, studies in software engineering are typically performed as field studies
1223 where researchers and developers (or the artefacts they produce) are analysed either
1224 directly or indirectly [328]. The mixed-methods approach combines five classes
1225 of field study methods (or empirical strategies/studies) most relevant in empirical
1226 software engineering research [109, 184, 379]: controlled experiments, case studies,
1227 survey research, ethnographies, and action research. We chiefly adopt a mixed-
1228 methods approach to our work using the *concurrent triangulation* mixed-methods
1229 strategy [230] as it best compensates for weaknesses that exist in all research methods,
1230 and employs the best strengths of others [84].

3.3.1 Review of Relevant Research Methods

1231 Below we review some of the research methods most relevant to our research ques-
1232 tions as refined in Section 3.1 as presented by Easterbrook et al. [109].

3.3.1.1 Controlled Experiments

1233 A controlled experiment is an investigation of a clear, testable hypothesis that guides
1234 the researcher to decide and precisely measure how at least one independent variable
1235 can be manipulated and effect at least one other dependent variable. They determine
1236 if the two variables are related and if a cause-effect relationship exists between
1237 them. The combination of independent variable values is a *treatment*. It is common
1238 to recruit human subjects to perform a task and measure the effect of a randomly
1239 assigned treatment on the subjects, though it is not always possible to achieve
1240 full randomisation in real-life software engineering contexts, in which case a *quasi-*
1241 *experiment* may be employed where subjects are not randomly assigned to treatments.

1242 While we have well-defined RQs, refining them into precise, *measurable* vari-
1243 ables is challenging due to the qualitative nature they present. A well-defined
1244 population is also critical and must be easily accessible; the varied range of beginner
1245 to expert software engineers with varied understanding of artificial intelligence
1246 concepts is required to perform controlled experiments, and thus recruitment may
1247 prove challenging. Lastly, the controlled experiment is essentially reductionist by
1248 affecting a small amount of variables of interest and controlling all others. This
1249 approach is too clinical for the practical outcomes by which our research goals aim
1250 for, and is therefore closely tied to the positivist stance.

1253 3.3.1.2 *Case Studies*

1254 Case studies investigate phenomena in their real-life context and are well-suited
1255 when the boundary between context and phenomena is unknown [383]. They offer
1256 understanding of how and why certain phenomena occur, thereby investigating ways
1257 cause-effect relationships can occur. They can be used to test existing theories
1258 (*confirmatory case studies*) by refuting theories in real-world contexts instead of
1259 under laboratory conditions or to generate new hypotheses and build theories during
1260 the initial investigation of some phenomena (*exploratory case studies*).

1261 Case studies are well-suited where the context of a situation plays a role in
1262 the phenomenon being studied. They also lend themselves to purposive sampling
1263 rather than random sampling, and thus it is possible to selectively choose cases that
1264 benefit our research goals and (using our critical theorist stance) select cases that
1265 will actively benefit our participant software engineering audience most to draw
1266 attention to situations regarded as problematic in CVS.

1267 3.3.1.3 *Survey Research*

1268 Survey research identifies characteristics of a broad population of individuals through
1269 direct data collection techniques such as interviews and questionnaires or indepen-
1270 dent techniques such as data logging. Defining that well-defined population is
1271 critical, and selecting a representative sample from it to generalise the data gathered
1272 usually assists in answering base-rate questions.

1273 By identifying representative sample of the population, from beginner to ex-
1274 perienced developers with varying understanding of CVS APIs, we can use survey
1275 research to assist in answering our exploratory and base-rate RQs (see Section 3.1.1)
1276 in determining the qualitative aspects of how individual developers perceive and
1277 work with the existing APIs, either by directly asking them, or by mining third-party
1278 discussion websites such as Stack Overflow (SO). Similarly, we can use this strategy
1279 to assess the developer’s understanding on what makes API documentation sufficient
1280 by assessing whether specific factors suggested from literature are useful according
1281 to developers. However, with direct survey research techniques, low response rates
1282 may prove challenging, especially if no inducements can be offered for participation.

1283 3.3.1.4 *Ethnographies*

1284 Ethnographies investigates the understanding of social interaction within community
1285 through field observation [304]. Resulting ethnographies help understand how soft-
1286 ware engineering technical communities build practices, communication strategies
1287 and perform technical work collaboratively.

1288 Ethnographies require the researcher to be highly trained in observational and
1289 qualitative data analysis, especially if the form of ethnography is participant observa-
1290 tion, whereby the researcher is embedded of the technical community for observation.
1291 This may require the longevity of the study to be far greater than a couple of weeks,
1292 and the researcher must remain part of the project for its duration to develop enough
1293 local theories about how the community functions. While it assists in revealing

1294 subtle but important aspects of work practices within software teams, this study
1295 does not focus on the study of teams, and is therefore not a research method relevant
1296 to this project.

1297 **3.3.1.5 Action Research**

1298 Action researchers simultaneously solve real-world problems while studying the
1299 experience of solving the problem [95] by actively seeking to intervene in the
1300 situation for the purpose of improving it. A precondition is to engage with a
1301 *problem owner* who is willing to collaborate in identifying and solving the problem
1302 faced. The problem must be authentic (a problem worth solving) and must have
1303 new knowledge outcomes for those involved. It is also characterised as an iterative
1304 approach to problem solving, where the knowledge gained from solving the problem
1305 has a desirable solution that empowers the problem owner and researcher.

1306 This research is most associated to our adopted philosophical stance of critical
1307 theory. As this project is being conducted under the Applied Artificial Intelligence
1308 Institute (A^2I^2) collaboratively with engaged industry clients, we have identified a
1309 need for solving an authentic problem that industry faces. The desired outcome
1310 of this project is to facilitate wider change in the usage and development of CVSs;
1311 thus, engaging action research as a potential method throughout the mixed-methods
1312 approach is used in this research.

1313 **3.3.2 Review of Data Collection Techniques for Field Studies**

1314 Singer et al. developed a taxonomy [211, 328] showcasing data collection techniques
1315 in field studies that are used in conjunction with a variety of methods based on the
1316 level of interaction between researcher and software engineer, if any. This taxonomy
1317 is reproduced in Table 3.2, where techniques used in this research study are starred.

1318 **3.4 Research Design**

1319 This section discusses an overview of the design of methods used within the experiments
1320 conducted under this thesis. For each experiment, we describe an overview of the
1321 experiment grounded known methods and techniques (Sections 3.3.1 and 3.3.2)
1322 and our approach to analysing the data, as well as relating the selecting method back
1323 to a specific RQ. Details of each experiment presented in this thesis, the coherency
1324 between them, and where they can be found are given in Sections 1.6 and 1.7.

1325 **3.4.1 Landscape Analysis of Computer Vision Services**

1326 To understand the behavioural and evolutionary profiles of CVSs (i.e., RQ1), we em-
1327 ployed a longitudinal study based around a dynamic system analysis [328]. Specif-
1328 ically, we used structured observations of three services using the same dataset to
1329 understand how the responses from these services change with time. Lastly, we

Table 3.2: Questions asked by software engineering researchers (column 2) that can be answered by field study techniques. (Adapted from [328].) Methods used within this research study are starred.

Technique	Used by researchers when their goal is to understand...	Volume of data	Also used by software engineers for...
DIRECT TECHNIQUES			
Brainstorming and focus groups	Ideas and general background about the process and product, general opinions (also useful to enhance participant rapport)	Small	Requirements gathering, project planning
Interviews and questionnaires	General information (including opinions) about process, product, personal knowledge etc.	Small to large	Requirements and evaluation
Conceptual modelling	Mental models of product or process.	Small	Requirements
Work diaries	Time spent or frequency of certain tasks (rough approximation, over days or weeks)	Medium	Time sheets
Think-aloud sessions	Mental models, goals, rationale and patterns of activities	Medium to large	UI evaluation
Shadowing and observation	Time spent or frequency of tasks (intermittent over relatively short periods), patterns of activities, some goals and rationale	Small	Advanced approaches to use case or task analysis
Participant observation (joining the team)	Deep understanding, goals and rationale for actions, time spent or frequency over a long period	Medium to large	–
INDIRECT TECHNIQUES			
Instrumenting systems	Software usage over a long period, for many participants	Large	Software usage analysis
Fly on the wall	Time spent intermittently in one location, patterns of activities (particularly collaboration)	Medium	–
INDEPENDENT TECHNIQUES			
Analysis of work databases	Long-term patterns relating to software evolution, faults etc.	Large	Metrics gathering
Analysis of tool use logs	Details of tool usage	Large	–
Documentation analysis	Design and documentation practices, general understanding	Medium	Reverse engineering
Static and dynamic analysis	Design and programming practices, general understanding	Large	Program comprehension, metrics, testing, etc.

1330 utilised documentation analysis to assess the overall ‘picture’ of how these services are documented. Further details on this experiment is given in **Chapter 4, Section 4.4.**

1333 3.4.2 Utility of API Documentation in Computer Vision Services

1334 To assess whether these services are sufficiently documented (i.e., RQ2), we conducted a systematic mapping study [192, 279] of the various academic sources detailing API documentation knowledge. We then consolidated this information into a structured taxonomy following a systematic taxonomy development method specific to software engineering studies [357].

1339 We then followed the triangulation approach proposed by Mayring [230] to validate the taxonomy by use of a personal opinion survey. Kitchenham and Pfleeger [193] provide an introduction on methods used to conduct personal opinion surveys which we adopted as an initial reference in (i) shaping our survey objectives around our research goals, (ii) designing a cross-sectional survey, (iii) developing and evaluating our survey instrument, (iv) evaluating our instruments, (v) obtaining the data and (vi) analysing the data. We adapted Brooke’s systematic usability scale [61] technique by basing our research questions against a known surveying instrument.

1347 As is good practice in developing questionnaire instruments to evaluate their reliability and validity [218], we evaluated our instrument design by asking colleagues to critique it via pilot studies within A²I². This assisted in identifying any problems with the questionnaire itself and with any issues that may have occurred with the response rate and follow-up procedures.

1352 Findings from the pilot study helped inform us for a widely distributed questionnaire using snow-balling sampling. Ethics approval from the Faculty of Science, Engineering and Built Environment Human Ethics Advisory Group (SEBE HEAG) was approved to externally conduct this survey research (see Chapter E). Further details on these methods are detailed within **Chapter 8, Section 8.3.**

1357 3.4.3 Developer Issues concerning Computer Vision Services

1358 Developers typically congregate in search of discourses on issues they face in online forums, such as Stack Overflow (SO) and Quora, as well as writing their experiences in personal blogs such as Medium. The simplest of these platforms is SO (a sub-community of the Stack Exchange family of targeted communities) that specifically targets developer issues on using a simple Q&A interface, where developers can discuss technical aspects and general software development topics. Moreover, SO is often acknowledged as *the ‘go-to’ place* for developers to find high-quality code snippets that assist in their problems [339].

1366 Thus, to begin understanding the issues developers face when using CVSs and whether there is a substantial difference to conventional domains (i.e., RQ3), we used repository mining on SO to help answer RQ3. Specifically, we selected SO due to its targeted community of developers² and the availability of its publicly

2We also acknowledge that there are other targeted software engineering Stack Exchange

¹³⁷⁰ available dataset released as ‘data dumps’ on the Stack Exchange Data Explorer³
¹³⁷¹ and Google BigQuery⁴. Studies conducted have also used SO to mine developer
¹³⁷² discourse [8, 21, 28, 77, 216, 258, 268, 292, 305, 330, 345, 365]. Further details on
¹³⁷³ how we approached the design for this study can be found in **Chapter 5, Section 5.4,**
¹³⁷⁴ **Chapter 6, Section 6.3, and Chapter 7, Section 7.2.2**

¹³⁷⁵ **3.4.4 Designing Improved Integration Strategies**

¹³⁷⁶ Our improved integration strategies (i.e., RQ4) evolved organically over the duration
¹³⁷⁷ of this research through the use of industry case studies and action research. We
¹³⁷⁸ developed several iterative prototypes to the integration strategies and used a mix
¹³⁷⁹ of statistical and technical evaluations to analyse whether our improved integration
¹³⁸⁰ strategies can prove useful. Further details about these approaches are detailed in
¹³⁸¹ **Chapter 9, Section 9.5.1 and Chapter 10, Section 10.3 and Chapter 11, Sec-**
¹³⁸² **tion 11.5.**

communities such as Stack Exchange Software Engineering (<https://softwareengineering.stackexchange.com>), though (as of January 2019) this much smaller community consists of only 52,000 questions versus SO’s 17 million.

³<https://data.stackexchange.com/stackoverflow> last accessed 17 January 2017.

⁴<https://console.cloud.google.com/marketplace/details/stack-exchange/stack-overflow> last accessed 17 January 2017.

1383

Part II

1384

Publications

CHAPTER 4

1385

1386

1387

Identifying Evolution in Computer Vision Services[†]

1388

1389 **Abstract** Recent advances in artificial intelligence (AI) and machine learning (ML), such
1390 as computer vision, are now available as intelligent web services (IWSs) and their acces-
1391 sibility and simplicity is compelling. Multiple vendors now offer this technology as cloud
1392 services and developers want to leverage these advances to provide value to end-users. How-
1393 ever, there is no firm investigation into the maintenance and evolution risks arising from use
1394 of these IWSs; in particular, their behavioural consistency and transparency of their function-
1395 ality. We evaluated the responses of three different IWSs (specifically computer vision) over
1396 11 months using 3 different data sets, verifying responses against the respective documenta-
1397 tion and assessing evolution risk. We found that there are: (1) inconsistencies in how these
1398 services behave; (2) evolution risk in the responses; and (3) a lack of clear communication
1399 that documents these risks and inconsistencies. We propose a set of recommendations to
1400 both developers and IWS providers to inform risk and assist maintainability.

1401

4.1 Introduction

1402

1403 The availability of intelligent web services (IWSs) has made artificial intelligence
1404 (AI) tooling accessible to software developers and promises a lower entry barrier for
1405 their utilisation. Consider state-of-the-art computer vision analysers, which require
1406 either manually training a deep-learning classifier, or selecting a pre-trained model
1407 and deploying these into an appropriate infrastructure. Either are laborious in time,
1408 and require non-trivial expertise along with a large data set when training or customi-
1409 sation is needed. In contrast, IWSs providing computer vision (i.e., computer vision
services or CVSs such as [392, 404, 405, 406, 413, 417, 425, 426, 427, 431, 444,

[†]This chapter is originally based on A. Cummaudo, R. Vasa, J. Grundy, M. Abdelrazek, and A. Cain, “Losing Confidence in Quality: Unspoken Evolution of Computer Vision Services,” in *Proceedings of the 35th IEEE International Conference on Software Maintenance and Evolution*. Cleveland, OH, USA: IEEE, December 2019. DOI 10.1109/ICSME.2019.00051. ISBN 978-1-72-813094-1 pp. 333–342. Terminology has been updated to fit this thesis.

¹⁴¹⁰ 445, 478, 479]) abstract these complexities behind a web application programming
¹⁴¹¹ interface (API) call. This removes the need to understand the complexities required
¹⁴¹² of machine learning (ML), and requires little more than the knowledge on how to
¹⁴¹³ use RESTful endpoints. The ubiquity of these services is exemplified through their
¹⁴¹⁴ rapid uptake in applications such as aiding the vision-impaired [94, 294].

¹⁴¹⁵ While IWSs have seen quick adoption in industry, there has been little work
¹⁴¹⁶ that has considered the software quality perspective of the risks and impacts posed
¹⁴¹⁷ by using such services. In relation to this, there are three main challenges: (1)
¹⁴¹⁸ incorporating stochastic algorithms into software that has traditionally been deter-
¹⁴¹⁹ ministic; (2) the general lack of transparency associated with the ML models; and
¹⁴²⁰ (3) communicating to application developers.

¹⁴²¹ ML typically involves use of statistical techniques that yield components with
¹⁴²² a non-deterministic external behaviour; that is, for the same given input, different
¹⁴²³ outcomes may result. However, developers, in general, are used to libraries and small
¹⁴²⁴ components behaving predictably, while systems that rely on ML techniques work
¹⁴²⁵ on confidence intervals¹ and probabilities. For example, the developer’s mindset
¹⁴²⁶ suggests that an image of a border collie—if sent to three intelligent computer vision
¹⁴²⁷ services (CVSs)—would return the label ‘dog’ consistently with time regardless
¹⁴²⁸ of which service is used. However, one service may yield the specific dog breed,
¹⁴²⁹ ‘border collie’, another service may yield a permutation of that breed, ‘collie’, and
¹⁴³⁰ another may yield broader results, such as ‘animal’; each with results of varying
¹⁴³¹ confidence values.² Furthermore, the third service may evolve with time, and
¹⁴³² thus learn that the ‘animal’ is actually a ‘dog’ or even a ‘collie’. The outcomes
¹⁴³³ are thus behaviourally inconsistent between services providing conceptually similar
¹⁴³⁴ functionality. As a thought exercise, consider if the sub-string function were created
¹⁴³⁵ using ML techniques—it would perform its operation with a confidence where the
¹⁴³⁶ expected outcome and the AI inferred output match as a *probability*, rather than a
¹⁴³⁷ deterministic (constant) outcome. How would this affect the developers’ approach
¹⁴³⁸ to using such a function? Would they actively take into consideration the non-
¹⁴³⁹ deterministic nature of the result?

¹⁴⁴⁰ Myriad software quality models and software engineering practices advocate
¹⁴⁴¹ maintainability and reliability as primary characteristics; stability, testability, fault
¹⁴⁴² tolerance, changeability and maturity are all concerns for quality in software com-
¹⁴⁴³ ponents [160, 285, 332] and one must factor these in with consideration to soft-
¹⁴⁴⁴ ware evolution challenges [139, 140, 239, 240, 350]. However, the effect this
¹⁴⁴⁵ non-deterministic behaviour has on quality when masked behind an IWS is still
¹⁴⁴⁶ under-explored to date in software engineering literature, to our knowledge. Where
¹⁴⁴⁷ software depends on IWSs to achieve functionality, these quality characteristics may
¹⁴⁴⁸ not be achieved, and developers need to be wary of the unintended side effects and
¹⁴⁴⁹ inconsistency that exists when using non-deterministic components. A CVS may
¹⁴⁵⁰ encapsulate deep-learning strategies or stochastic methods to perform image analy-

¹Varied terminology used here. Probability, confidence, accuracy and score may all be used interchangeably.

²Indeed, we have observed this phenomenon using a picture of a border collie sent to various CVSs.

1451 sis, but developers are more likely to approach IWSs with a mindset that anticipates
1452 consistency. Although the documentation does hint at this non-deterministic be-
1453 haviour (i.e., the descriptions of ‘confidence’ in various CVSs suggest they are
1454 not always confident, and thus not deterministic [390, 415, 432]), the integration
1455 mechanisms offered by popular vendors do not seem to fully expose the nuances,
1456 and developers are not yet familiar with the trade-offs.

1457 Do popular CVSs, as they currently stand, offer consistent behaviour, and if not,
1458 how is this conveyed to developers (if it is at all)? If CVSs are to be used in production
1459 services, do they ensure quality under rigorous service quality assurance (SQA)
1460 frameworks [160]? What evolution risk [139, 140, 239, 240] do they pose if these
1461 services change? To our knowledge, few studies have been conducted to investigate
1462 these claims. This paper assesses the consistency, evolution risk and consequent
1463 maintenance issues that may arise when developers use IWSs. We introduce a
1464 motivating example in Section 4.2, discussing related work and our methodology
1465 in Sections 4.3 and 4.4. We present and interpret our findings in Section 4.5. We
1466 argue with quantified evidence that these IWSs can only be considered with a mature
1467 appreciation of risks, and we make a set of recommendations in Section 4.6.

1468 4.2 Motivating Example

1469 Consider Rosa, a software developer, who wants to develop a social media photo-
1470 sharing mobile app that analyses her and her friends photos on Android and iOS.
1471 Rosa wants the app to categorise photos into scenes (e.g., day vs. night, outdoors
1472 vs. indoors), generate brief descriptions of each photo, and catalogue photos of her
1473 friends as well as common objects (e.g., all photos with a dog, all photos on the
1474 beach).

1475 Rather than building a computer vision engine from scratch, Rosa thinks she
1476 can achieve this using one of the popular CVSs (e.g., [392, 404, 405, 406, 413, 417,
1477 425, 426, 427, 431, 444, 445, 478, 479]). However, Rosa comes from a typical
1478 software engineering background with limited knowledge of the underlying deep-
1479 learning techniques and implementations as currently used in computer vision. Not
1480 unexpectedly, she internalises a mindset of how such services work and behave based
1481 on her experience of using software libraries offered by various SDKs. This mindset
1482 assumes that different cloud vendor image processing APIs more-or-less provide
1483 similar functionality, with only minor variations. For example, cloud object storage
1484 for Amazon S3 is both conceptually and behaviourally very similar to that of Google
1485 Cloud Storage or Azure Storage. Rosa assumes the CVSs of these platforms will,
1486 therefore, likely be very similar. Similarly, consider the string libraries Rosa will
1487 use for the app. The conceptual and behavioural similarities are consistent; a string
1488 library in Java (Android) is conceptually very similar to the string library she will
1489 use in Swift (iOS), and likewise both behave similarly by providing the same results
1490 for their respective sub-string functionality. However, **unlike the cloud storage and**
1491 **string libraries, different CVSs often present conceptually similar functionality**
1492 **but are behaviourally very different.** IWS vendors also hide the depth of knowledge
1493 needed to use these effectively—for instance, the training data set and ontologies

1494 used to create these services are hidden in the documentation. Thus, Rosa isn't even
1495 exposed to this knowledge as she reads through the documentation of the providers
1496 and, thus, Rosa makes the following assumptions:

- 1497 • **"I think the responses will be consistent amongst these CVSSs."** When Rosa
1498 uploads a photo of a dog, she would expect them all to respond with 'dog'. If
1499 Rosa decides to switch which service she is using, she expects the ontologies
1500 to be compatible (all CVSSs *surely* return dog for the same image) and therefore
1501 she can expect to plug-in a different service should she feel like it making only
1502 minor code modifications such as which endpoints she is relying on.
- 1503 • **"I think the responses will be constant with time."** When Rosa uploads the
1504 photo of a dog for testing, she expects the response to be the same in 10 weeks
1505 time once her app is in production. Hence, in 10 weeks, the same photo of the
1506 dog should return the same label.

1507 4.3 Related Work

1508 If we were to view CVSSs through the lenses of an SQA framework, robustness,
1509 consistency, and maintainability often feature as quality attributes in myriad soft-
1510 ware quality models (e.g., [171]). Software quality is determined from two key
1511 dimensions: (1) in the evaluation of the end-product (external quality) and (2) the
1512 assurances in the development processes (internal quality) [285]. We discuss both
1513 perspectives of quality within the context of our work in this section.

1514 4.3.1 External Quality

1515 4.3.1.1 Robustness for safety-critical applications

1516 A typical focus of recent work has been to investigate the robustness of deep-
1517 learning within computer vision technique implementation, thereby informing the
1518 effectiveness in the context of the end-product. The common method for this has
1519 been via the use of adversarial examples [342], where input images are slightly
1520 perturbed to maximise prediction error but are still interpretable to humans.

1521 Google Cloud Vision, for instance, fails to correctly classify adversarial examples
1522 when noise is added to the original images [161]. Rosenfeld et al. [307] illustrated
1523 that inserting synthetic foreign objects to input images (e.g., a cartoon elephant)
1524 can completely alter classification output. Wang et al. [363] performed similar
1525 attacks on a transfer-learning approach of facial recognition by modifying pixels of
1526 a celebrity's face to be recognised as a completely different celebrity, all while still
1527 retaining the same human-interpretable original celebrity. Su et al. [337] used the
1528 ImageNet database to show that 41.22% of images drop in confidence when just a
1529 *single pixel* is changed in the input image; and similarly, Eykholt et al. [113] recently
1530 showed similar results that made a convolutional neural network (CNN) interpret a
1531 stop road-sign (with mimicked graffiti) as a 45mph speed limit sign.

1532 The results suggest that current state-of-the-art computer vision techniques may
1533 not be robust enough for safety critical applications as they do not handle intentional

1534 or unintentional adversarial attacks. Moreover, as such adversarial examples exist in
1535 the physical world [113, 204], “the natural world may be adversarial enough” [280]
1536 to fool AI software. Though some limitations and guidelines have been explored
1537 in this area, the perspective of *Intelligent Web Services* is yet to be considered and
1538 specific guidelines do not yet exist when using CVSSs.

1539 4.3.1.2 *Testing strategies in ML applications*

1540 Although much work applies ML techniques to automate testing strategies, there is
1541 only a growing emphasis that considers this in the opposite sense; that is, testing
1542 to ensure the ML product works correctly. There are few reliable test oracles
1543 that ensure if an ML has been implemented to serve its algorithm and use case
1544 purposefully; indeed, “the non-deterministic nature of many training algorithms
1545 makes testing of models even more challenging” [15]. Murphy et al. [249] proposed
1546 a software engineering-based testing approach on ML ranking algorithms to evaluate
1547 the ‘correctness’ of the implementation on a real-world data set and problem domain,
1548 whereby discrepancies were found from the formal mathematical proofs of the ML
1549 algorithm and the implementation.

1550 Recently, Braiek and Khomh [54] conducted a comprehensive review of testing
1551 strategies in ML software, proposing several research directions and recommendations
1552 in how best to apply software engineering testing practices in ML programs.
1553 However, much of the area of this work specifically targets ML engineers, and not
1554 application developers. Little has been investigated on how application developers
1555 perceive and understand ML concepts, given a lack of formal training; we note that
1556 other testing strategies and frameworks proposed (e.g., [58, 248, 257]) are targeted
1557 chiefly to the ML engineer, and not the application developer.

1558 However, Arpteg et al. [15] recently demonstrated (using real-world ML projects)
1559 the developmental challenges posed to developers, particularly those that arise when
1560 there is a lack of transparency on the models used and how to troubleshoot ML
1561 frameworks using traditional software engineering debugging tools. This said, there
1562 is no further investigations into challenges when using the higher, ‘ML friendly’
1563 layers (e.g., IWSs) of the ‘machine learning spectrum’ [265], rather than the ‘lower
1564 layers’ consisting of existing ML frameworks and algorithms targeted toward the
1565 ML community.

1566 4.3.2 Internal Quality

1567 4.3.2.1 *Quality metrics for cloud services*

1568 CVSSs are based on cloud computing fundamentals under a subset of the Platform as
1569 a Service (PaaS) model. There has been work in the evaluation of PaaS in terms of
1570 quality attributes [128]: these attributes are exposed using service-level agreements
1571 (SLAs) between vendors and customers, and customers denote their demanded
1572 quality of service (QoS) to ensure the cloud services adhere to measurable KPI
1573 attributes.

1574 Although, popular services, such as cloud object storage, come with strong QoS
1575 agreement, to date IWSs do not come with deep assurances around their performance
1576 and responses, but do offer uptime guarantees. For example, how can Rosa demand
1577 a QoS that ensures all photos of dogs uploaded to her app guarantee the specific dog
1578 breeds are returned so that users can look up their other friend’s ‘border collie’s?
1579 If dog breeds are returned, what ontologies exist for breeds? Are they consistent
1580 with each other, or shortened? (‘Collie’ versus ‘border collie’; ‘staffy’ versus
1581 ‘staffordshire bull terrier’?) For some applications, these unstated QoS metrics
1582 specific to the ML service may have significant legal ramifications.

1583 4.3.2.2 *Web service documentation and documenting ML*

1584 From the *developer’s* perspective, little has been achieved to assess IWS quality
1585 or assure quality of these CVSs. Web services and their APIs are the bridge be-
1586 tween developers’ needs and the software components [13]; therefore, assessing
1587 such CVSs from the quality of their APIs is thereby directly related to the develop-
1588 ment quality [197]. Good APIs should be intuitive and require less documentation
1589 browsing [282], thereby increasing productivity. Conversely, poor APIs that are
1590 hard to understand and work with reduce developer productivity, thereby reducing
1591 product quality. This typically leads to developers congregating on forums such as
1592 Stack Overflow, leading to a repository of unstructured knowledge likely to concern
1593 API design [367]. The consequences of addressing these concerns in development
1594 leads to a higher demand in technical support (as measured in [157]) that, ultimately,
1595 causes the maintenance to be far more expensive, a phenomenon widely known in
1596 software engineering economics [47]. Rosa, for instance, isn’t aware of technical ML
1597 concepts; if she cannot reason about what search results are relevant when brows-
1598 ing the service and understanding functionality, her productivity is significantly
1599 decreased. Conceptual understanding is critical for using APIs, as demonstrated by
1600 Ko and Riche, and the effects of maintenance this may have in the future of her
1601 application is unknown.

1602 Recent attempts to document attributes and characteristics on ML models have
1603 been proposed. Model cards were introduced by Mitchell et al. [244] to describe how
1604 particular models were trained and benchmarked, thereby assisting users to reason
1605 if the model is right for their purposes and if it can achieve its stated outcomes.
1606 Gebru et al. [132] also proposed datasheets, a standardised documentation format to
1607 describe the need for a particular data set, the information contained within it and
1608 what scenarios it should be used for, including legal or ethical concerns.

1609 However, while target audiences for these documents may be of a more technical
1610 AI level (i.e., the ML engineer), there is still no standardised communication format
1611 for application developers to reason about using particular IWSs, and the ramifica-
1612 tions this may have on the applications they write is not fully conveyed. Hence, our
1613 work is focused on the application developer perspective.

4.4 Method

1615 This study organically evolved by observing phenomena surrounding CVSs by as-
1616 sessing both their documentation and responses. We adopted a mixed methods
1617 approach, performing both qualitative and quantitative data collection on these two
1618 key aspects by using documentary research methods for inspecting the documen-
1619 tation and structured observations to quantitatively analyse the results over time.
1620 This, ultimately, helped us shape the following research hypotheses which this paper
1621 addresses:

1622 [RH1] CVSs do not respond with consistent outputs between services, given the
1623 same input image.

1624 [RH2] The responses from CVSs are non-deterministic and evolving, and the same
1625 service can change its top-most response over time given the same input
1626 image.

1627 [RH3] CVSs do not effectively communicate this evolution and instability, intro-
1628 ducing risk into engineering these systems.

1629 We conducted two experiments to address these hypotheses against three popular
1630 CVSs: AWS Rekognition [392], Google Cloud Vision [417], Azure Computer
1631 Vision [431]. Specifically, we targeted the AWS DetectLabels endpoint [390],
1632 the Google Cloud Vision annotate:images endpoint [415] and Azure's analyze
1633 endpoint [432]. For the remainder of this paper, we de-identify our selected CVSs
1634 by labelling them as services A, B and C but do not reveal mapping to prevent
1635 any implicit bias. Our selection criteria for using these particular three services
1636 are based on the weight behind each service provider given their prominence in
1637 the industry (Amazon, Google and Microsoft), the ubiquity of their hosting cloud
1638 platforms as industry leaders of cloud computing (i.e., AWS, Google Cloud and
1639 Azure), being in the top three most adopted cloud vendors in enterprise applications
1640 in 2018 [299] and the consistent popularity of discussion amongst developers in
1641 developer communities such as Stack Overflow. While we choose these particular
1642 cloud CVSs, we acknowledge that similar services [405, 406, 413, 426, 427, 478, 479]
1643 also exist, including other popular services used in Asia [404, 425, 444, 445] (some
1644 offering 3D image analysis [403]). We reflect on the impacts this has to our study
1645 design in Section 4.7.

1646 Our study involved an 11-month longitudinal study which consisted of two 13
1647 week and 17 week experiments from April to August 2018 and November 2018 to
1648 March 2019, respectively. Our investigation into documentation occurred on August
1649 28 2018. In total, we assessed the services with three data sets; we first ran a pilot
1650 study using a smaller pool of 30 images to confirm the end-points remain stable,
1651 re-running the study with a larger pool of images of 1,650 and 5,000 images. Our
1652 selection criteria for these three data sets were that the images had to have varying
1653 objects, taken in various scenes and various times. Images also needed to contain
1654 disparate objects. Our small data set was sourced by the first author by taking photos
1655 of random scenes in an afternoon, whilst our second data set was sourced from
1656 various members of our research group from their personal photo libraries. We also

Table 4.1: Characteristics of our datasets and responses.

Data set	Small	Large	COCOVal17
# Images/data set	30	1,650	5000
# Unique labels found	307	3506	4507
Number of snapshots	9	22	22
Avg. days b/n requests	12 Days	8 Days	8 Days

wanted to include a data set that was publicly available prior to running our study, so for this data set we chose the COCO 2017 validation data set [215]. We have made our other two data sets available online ([408]). We collected results and their responses from each service’s API endpoint using a python script [412] that sent requests to each service periodically via cron jobs. Table 4.1 summarises various characteristics about the data sets used in these experiments.

We then performed quantitative analyses on each response’s labels, ensuring all labels were lowercased as case changed for services A and C over the evaluation period. To derive at the consistency of responses for each image, we considered only the ‘top’ labels per image for each service and data set. That is, for the same image i over all images in data set D where $i \in D$ and over the three services, the top labels per image (T_i) of all labels per image L_i (i.e., $T_i \subseteq L_i$) is that where the respective label’s confidences are consistently the highest of all labels returned. Typically, the top labels returned is a set containing only one element—that is, only one unique label consistently returned with the highest label ($|T_i| = 1$)—however there are cases where the top labels contains multiple elements as their respective confidences are *equal* ($|T_i| > 1$).

We measure response consistency under 6 aspects:

- (1) **Consistency of the top label between each service.** Where the same image of, for example, a dog is sent to the three services, the top label for service A may be ‘animal’, B ‘canine’ and C ‘animal’. Therefore, service B is inconsistent.
- (2) **Semantic consistency of the top labels.** Where a service has returned multiple top labels ($|T_i| > 1$), there may lie semantic differences in what the service thinks the image best represents. Therefore, there is conceptual inconsistency in the top labels for a service even when the confidences are equal.
- (3) **Consistency of the top label’s confidence per service.** The top label for an image does not guarantee a high confidence. Therefore, there may be inconsistencies in how confident the top labels for all images in a service is.
- (4) **Consistency of confidence in the intersecting top label between each service.** The spread of a top intersecting label, e.g., ‘cat’, may not have the same confidences per service even when all three services agree that ‘cat’ is the top label. Therefore, there is inconsistency in the confidences of a top label even where all three services agree.
- (5) **Consistency of the top label over time.** Given an image, the top label in one week may differ from the top label the following week. Therefore, there is inconsistency in the top label itself due to model evolution.



Figure 4.1: The only consistent label for the above image is ‘people’ for services C and B. The top label for A is ‘conversation’ and this label is not registered amongst the other two services.

Table 4.2: Ratio of the top labels (to images) that intersect in each data set for each permutation of service.

Service	Small	Large	COCOVal17	μ	σ
$A \cap B \cap C$	3.33%	2.73%	4.68%	2.75%	0.0100
$A \cap B$	6.67%	11.27%	12.26%	10.07%	0.0299
$A \cap C$	20.00%	13.94%	17.28%	17.07%	0.0304
$B \cap C$	6.67%	12.97%	20.90%	13.51%	0.0713

1693 **(6) Consistency of the top label’s confidence over time.** The top label of an
1694 image may remain static from one week to the next for the same service, but
1695 its confidence values may change with time. Therefore, there is inconsistency
1696 in the top label’s confidence due to model evolution.

1697 For the above aspects of consistency, we calculated the spread of variation for the
1698 top label’s confidences of each service for every 1 percent point; that is, the frequency
1699 of top label confidences within 100–99%, 99–98% etc. The consistency of top label’s
1700 and their confidences between each service was determined by intersecting the labels
1701 of each service per image and grouping the intersecting label’s confidences together.
1702 This allowed us to determine relevant probability distributions. For reproducibility,
1703 all quantitative analysis is available online [409].

1704 4.5 Findings

1705 4.5.1 Consistency of top labels

1706 4.5.1.1 Consistency across services

1707 Table 4.2 presents the consistency of the top labels between data sets, as measured
1708 by the cardinality of the intersection of all three services’ set of top labels divided
1709 by the number of images per data set. A combination of services present varied
1710 overlaps in their top labels; services A and C provide the best overlap for all three

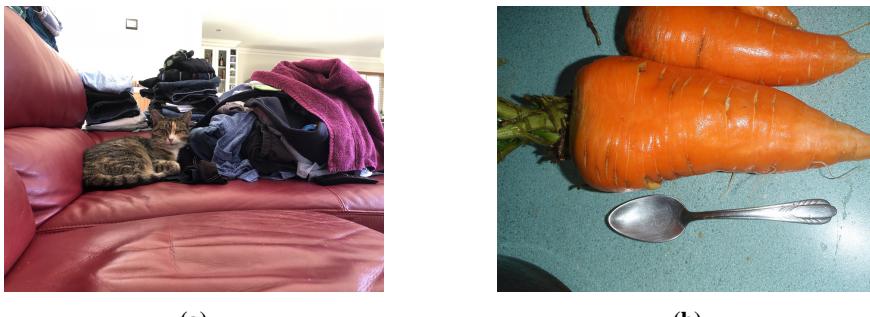


Figure 4.2: *Left:* The top labels for each service do not intersect, with each having a varied ontology: $T_1 = \{ A = \{ \text{'black'} \}, B = \{ \text{'indoor'} \}, C = \{ \text{'slide'}, \text{'toy'} \} \}$. (Service C returns both ‘slide’ and ‘toy’ with equal confidence.) *Right:* The top labels for each service focus on disparate subjects in the image: $T_1 = \{ A = \{ \text{'carrot'} \}, B = \{ \text{'indoor'} \}, C = \{ \text{'spoon'} \} \}$.

1711 data sets, however the intersection of all three irrespective of data sets is low.

The implication here is that, without semantic comparison (see Section 4.7), service vendors are not ‘plug-and-play’. If Rosa uploaded the sample images in this paper to her application to all services, she would find that only Figure 4.1 responds with ‘person’ for services B and C in their respective set of top labels. However, if she decides to then adopt service A, then Figure 4.1’s top label becomes ‘conversation’; the ‘person’ label does not appear within the top 15 labels for service A and, conversely, the ‘conversation’ label does not appear in the other services top 15.

Should she decide if the performance of a particular service isn't to her needs, then the vocabulary used for these labels becomes inconsistent for all other images; that is, the top label sets per service for Figure 4.2a shows no intersection at all. Furthermore, the part of the image each service focuses on may not be consistent for their top labels; in Figure 4.2b, service A's top label focuses on the vegetable ('carrot'), service C focuses on the 'spoon', while service B's focus is that the image is 'indoor's. It is interesting to note that service B focuses on the scene matter (indoors) rather than the subject matter. (Furthermore, we do not actually know if the image in Figure 4.2b was taken indoors.)

Hence, developers should ensure that the vocabulary used by a particular service is right for them before implementation. As each service does not work to the same standardised model, trained with disparate training data, and tuned differently, results will differ despite the same input. This is unlike deterministic systems: for example, switching from AWS Object Storage to Google Cloud Object storage will conceptually provide the same output (storing files) for the same input (uploading files). However, CVSSs do not agree on the top label for images, and therefore developers are likely to be vendor locked, making changes between services non-trivial.



Figure 4.3: *Left:* Service C is 98.49% confident of the following labels: { ‘beverage’, ‘chocolate’, ‘cup’, ‘dessert’, ‘drink’, ‘food’, ‘hot chocolate’ }. However, it is up to the developer to decide which label to persist with as all are returned. *Right:* Service B persistently returns a top label set of { ‘book’, ‘several’ }. Both are semantically correct for the image, but disparate in what the label is to describe.

1738 4.5.1.2 Semantic consistency where $|T_i| > 1$

1739 Service C returns two top labels for Figure 4.2a; ‘slide’ and ‘toy’. More than one
1740 top label is typically returned in service C (80.00%, 56.97%, and 81.66% of all
1741 images for all three data sets, respectively) though this also occurs in B in the large
1742 (4.97% of all images) and COCOVal17 data sets (2.38%). Semantic inconsistencies
1743 of what this label conceptually represents becomes a concern as these labels have
1744 confidences of *equal highest* consistency. Thus, some services are inconsistent in
1745 themselves and cannot give a guaranteed answer of what exists in an image; services
1746 C and B have multiple top labels, but the respective services cannot ‘agree’ on
1747 what the top label actually is. In Figure 4.3a, service C presents a reasonably high
1748 confidence for the set of 7 top labels it returns, however there is too much diversity
1749 ranging from a ‘hot chocolate’ to the hypernym ‘food’. Both are technically correct,
1750 but it is up to the developer to decide the level of hypernymy to label the image as.
1751 We also observe a similar effect in Figure 4.3b, where the image is labelled with
1752 both the subject matter and the number of subjects per image.

1753 Thus, a taxonomy of ontologies is unknown; if a ‘border collie’ is detected in
1754 an image, does this imply the hypernym ‘dog’ is detected, and then ‘mammal’, then
1755 ‘animal’, then ‘object’? Only service B documents a taxonomy for capturing what
1756 level of scope is desired, providing what it calls the ‘86-category’ concept as found
1757 in its how-to guide:

1758 “Identify and categorize an entire image, using a category taxonomy with parent/child hereditary hierarchies. Categories can be used alone, or with our new tagging models.” [433]

1761 Thus, even if Rosa implemented conceptual similarity analysis for the image, the
1762 top label set may not provide sufficient information to derive at a conclusive answer,
1763 and if simply relying on only one label in this set, information such as the duplicity
1764 of objects (e.g., ‘several’ in Figure 4.3b) may be missed.

Table 4.3: Ratio of the top labels (to images) that remained the top label but changed confidence values between intervals.

Service	Small	Large	COCOVal17	$\mu(\delta_c)$	$\sigma(\delta_c)$	Median(δ_c)	Range(δ_c)
A	53.33%	59.19%	44.92%	9.62e-8	6.84e-8	5.96e-8	[5.96e-8, 6.56e-7]
B	0.00%	0.00%	0.02%	-	-	-	-
C	33.33%	41.36%	15.60%	5.35e-7	8.76e-7	3.05e-7	[1.27e-7, 1.13e-5]

4.5.2 Consistency of confidence

4.5.2.1 Consistency of top label's confidence

In Figure 4.4, we see that there is high probability that top labels have high confidences for all services. In summary, one in nine images uploaded to any service will return a top label confident to at least 97%. However, there is higher probability for service A returning a lower confidence, followed by B. The best performing service is C, with 90% of requests having a top label confident to $\gtrapprox 95\%$, when compared to $\gtrapprox 87\%$ and $\gtrapprox 93\%$ for services A and B, respectively.

Therefore, Rosa could generally expect that the top labels she receives in her images do have high confidence. That is, each service will return a top label that they are confident about. This result is expected, considering that the ‘top’ label is measured by the highest confidence, though it is interesting to note that some services are generally more confident than others in what they present back to users.

4.5.2.2 Consistency of intersecting top label's confidence

Even where all three services do agree on a set of top labels, the disparity of how much they agree by is still of importance. Just because three services agree that an image contains consistent top labels, they do not always have a small spread of confidence. In Figure 4.6, the three services agree with $\sigma = 0.277$, significantly larger than that of all images in general $\sigma = 0.0831$. Figure 4.5 displays the cumulative distribution of all intersecting top labels’ confidence values, presenting slightly similar results to that of Figure 4.4.

4.5.3 Evolution risk

4.5.3.1 Label Stability

Generally, the top label(s) did not evolve in the evaluation period. 16.19% and 5.85% of images did change their top label(s) in the Large and COCOVal17 data sets in service A. Thus, top labels are stable but not guaranteed to be constant.

4.5.3.2 Confidence Stability

Similarly, where the top label(s) remained the same from one interval to the next, the confidence values were stable. Table 4.3 displays the proportion of images that changed their top label’s confidence values with various statistics on the confidence

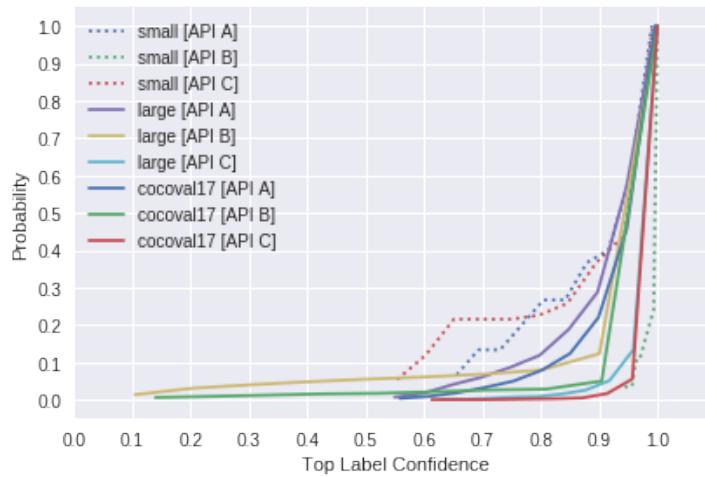


Figure 4.4: Cumulative distribution of the top labels' confidences. One in nine images return a top label(s) confident to $\gtrsim 97\%$, though there is a wider distribution for service A.

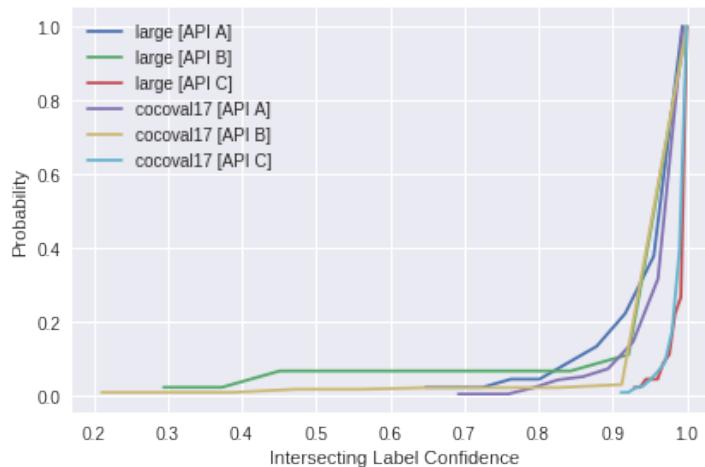


Figure 4.5: Cumulative distribution of intersecting top labels' confidences. The small data set is intentionally removed due to low intersections of labels (see Table 4.2).



Figure 4.6: All three services agree the top label for the above image is ‘food’, but the confidences to which they agree by vary significantly. Service C is most confident to 94.93% (in addition with the label ‘bread’); service A is the second most confident to 84.32%; service B is the least confident with 41.39%.

¹⁷⁹⁵ deltas between snapshots (δ_c). However, this delta is so minuscule that we attribute
¹⁷⁹⁶ such changes to statistical noise.

¹⁷⁹⁷ 4.6 Recommendations

¹⁷⁹⁸ 4.6.1 Recommendations for IWS users

¹⁷⁹⁹ 4.6.1.1 *Test with a representative ontology for the particular use case*

¹⁸⁰⁰ Rosa should ensure that in her testing strategies for the app she develops, there is an
¹⁸⁰¹ ontology focus for the types of vocabulary that are returned. Additionally, we noted
¹⁸⁰² that there was a sudden change in case for services A and C; for all comparative
¹⁸⁰³ purposes of labels, each label should be lower-cased.

¹⁸⁰⁴ 4.6.1.2 *Incorporate a specialised IWS testing methodology into the development 1805 lifecycle*

¹⁸⁰⁶ Rosa can utilise the different aspects of consistency as outlined in this paper as
¹⁸⁰⁷ part of her quality strategy. To ensure results are correct over time, we recommend
¹⁸⁰⁸ developers create a representative data set of the intended application’s data set
¹⁸⁰⁹ and evaluate these changes against their chosen service frequently. This will help
¹⁸¹⁰ identify when changes, if any, have occurred if vendors do not provide a line of
¹⁸¹¹ communication when this occurs.

¹⁸¹² 4.6.1.3 *IWSs are not ‘plug-and-play’*

¹⁸¹³ Rosa will be locked into whichever vendor she chooses as there is inherent incon-
¹⁸¹⁴ sistency between these services in both the vocabulary and ontologies that they use.
¹⁸¹⁵ We have demonstrated that very few services overlap in their vocabularies, chiefly
¹⁸¹⁶ because they are still in early development and there is yet to be an established,
¹⁸¹⁷ standardised vocabulary that can be shared amongst the different vendors. Issues
¹⁸¹⁸ such as those shown in Section 4.5.1 can therefore be avoided.

Throughout this work, we observed that the terminologies used by the various vendors are different. Documentation was studied, and we note that there is inconsistency between the ways techniques are described to users. We note the disparity between the terms ‘detection’, ‘recognition’, ‘localisation’ and ‘analysis’. This applies chiefly to object- and facial-related techniques. Detection applies to facial detection, which gives bounding box coordinates around all faces in an image. Similarly, localisation applies the same methodology to disparate objects in an image and labels them. In the context of facial ‘recognition’, this term implies that a face is *recognised* against a known set of faces. Lastly, ‘analysis’ applies in the context of facial analysis (gender, eye colour, expression etc.); there does not exist a similar analysis technique on objects.

We notice similar patterns with object ‘tagging’, ‘detection’ and ‘labelling’. Service A uses ‘Entity Detection’ for object categorisation, service B uses ‘Image Tagging’, and service C uses the term ‘Detect Labels’ : conceptually, these provide the same functionality but the lack of consistency used between all three providers is concerning and leaves room for confusion with developers during any comparative analyses. Rosa may find that she wants to label her images into day/night scenes, but this in turn means the ‘labelling’ of varying objects. There is therefore no consistent standards to use the same terminology for the same concepts, as there are in other developer areas (such as Web Development).

4.6.1.4 *Avoid use in safety-critical systems*

We have demonstrated in this paper that both labels and confidences are stable but not constant; there is still an evolution risk posed to developers that may cause unknown consequences in applications dependent on these CVSs. Developers should avoid their use in safety critical systems due to the lack of visible changes.

4.6.2 **Recommendations for IWS providers**

4.6.2.1 *Improve the documentation*

Rosa does not know that service A returns back ‘carrot’ for its top response, with service C returning ‘spoon’ (Figure 4.2b). She is unable to tell the service’s API where to focus on the image. Moreover, how can she toggle the level of specificity in her results? She is frustrated that service C can detect ‘chocolate’, ‘food’ and also ‘beverage’ all as the same top label in Figure 4.3a: what label is she to choose when the service is meant to do so for her, and how does she get around this? Thus, we recommend vendors to improve the documentation of services by making known the boundary set of the training data used for the algorithms. By making such information publicly available, developers would be able to review the service’s specificity for their intended use case (e.g., maybe Rosa is satisfied her app can catalogue ‘food’ together, and in fact does not want specific types of foods (‘hot chocolate’) catalogued). We also recommend that vendors publish usage guidelines that include details of priors and how to evaluate the specific service results.

Furthermore, we did not observe that the vendors documented how some images may respond with multiple labels of the exact same confidence value. It is not clear from the documentation that response objects can have duplicate top values, and tutorials and examples provided by the vendors do not consider this possibility. It is therefore left to the developer to decide which label from this top set of labels best suits for their particular use case; the documentation should describe that a rule engine may need to be added in the developer's application to verify responses. The implications this would have on maintenance would be significant.

4.6.2.2 Improve versioning

We recommend introducing a versioning system so that a model can be used from a specific date in production systems: when Rosa tests her app today, she would like the service to remain *static* the same for when her app is deployed in production tomorrow. Thus, in a request made to the vendor, Rosa could specify what date she ran her app's QA testing on so that she knows that henceforth these model changes will not affect her app.

4.6.2.3 Improve Metadata in Response

Much of the information in these services is reduced to a single confidence value within the response object, and the details about training data and the internal AI architecture remains unknown; little metadata is provided back to developers that encompass such detail. Early work into model cards and datasheets [132, 244] suggests more can be done to document attributes about ML systems, however at a minimum from our work, we recommend including a reference point via the form of an additional identifier. This identifier must also permit the developers to submit the identifier to another API endpoint should the developer wish to find further characteristics about the AI empowering the IWS, reinforcing the need for those presented in model cards and datasheets. For example, if Rosa sends this identifier she receives in the response object to the IWS descriptor API, she could find out additional information such as the version number or date when the model was trained, thereby resolving potential evolution risk, and/or the ontology of labels.

4.6.2.4 Apply constraints for predictions on all inputs

In this study, we used some images with intentionally disparate, and noisy objects. If services are not fully confident in the responses they give back, a form of customised error message should be returned. For example, if Rosa uploads an image of 10 various objects on a table, rather than returning a list of top labels with varying confidences, it may be best to return a 'too many objects' exception. Similarly, if Rosa uploads a photo that the model has had no priors on, it might be useful to return an 'unknown object' exception than to return a label it has no confidence of. We do however acknowledge that current state of the art computer vision techniques may have limits in what they can and cannot detect, but this limitation can be exposed in the documentation to the developers.

1899 A further example is sending a one pixel image to the service, analogous to
1900 sending an empty file. When we uploaded a single pixel white image to service A,
1901 we received responses such as ‘microwave oven’, ‘text’, ‘sky’, ‘white’ and ‘black’
1902 with confidences ranging from 51–95%. Prior checks should be performed on all
1903 input data, returning an ‘insufficient information’ error where any input data is below
1904 the information of its training data.

1905 **4.7 Threats to Validity**

1906 **4.7.1 Internal Validity**

1907 Not all CVSs were assessed. As suggested in Section 4.4, we note that there are
1908 other CVSs such as IBM Watson. Many services from Asia were also not considered
1909 due to language barriers (of the authors) in assessing these services. We limited our
1910 study to the most popular three providers (outside of Asia) to maintain focus in this
1911 body of work.

1912 A custom confidence threshold was not set. All responses returned from each of
1913 the services were included for analysis; where confidences were low, they were still
1914 included for analysis. This is because we used the default thresholds of each API to
1915 hint at what real-world applications may be like when testing and evaluating these
1916 services.

1917 The label string returned from each service was only considered. It is common
1918 for some labels to respond back that are conceptually similar (e.g., ‘car’ vs. ‘automobile’)
1919 or grammatically different (e.g., ‘clothes’ vs. ‘clothing’). While we could have
1920 employed more conceptual comparison or grammatical fixes in this study, we chose
1921 only to compare lowercased labels and as returned. We leave semantic comparison
1922 open to future work.

1923 Only introductory analysis has been applied in assessing the documentation of
1924 these services. Further detailed analysis of documentation quality against a rigorous
1925 documentation quality framework would be needed to fortify our analysis of the
1926 evolution of these services’ documentation.

1927 **4.7.2 External Validity**

1928 The documentation and services do change over time and evolve, with many allowing
1929 for contributions from the developer community via GitHub. We note that our
1930 evaluation of the documentation was conducted on a single date (see Section 4.4)
1931 and acknowledge that the documentation may have changed from the evaluation date
1932 to the time of this publication. We also acknowledge that the responses and labelling
1933 may have evolved too since the evaluation period described and the date of this
1934 publication. Thus, this may have an impact on the results we have produced in this
1935 paper compared to current, real-world results. To mitigate this, we have supplied the
1936 raw responses available online [410].

1937 Moreover, in this paper we have investigated *computer vision* services. Thus,
1938 the significance of our results to other domains such as natural language processing

¹⁹³⁹ or audio transcription is, therefore, unknown. Future studies may wish to repeat our
¹⁹⁴⁰ methodology on other domains to validate if similar patterns occur; we remain this
¹⁹⁴¹ open for future work.

¹⁹⁴² 4.7.3 Construct Validity

¹⁹⁴³ It is not clear if all the recommendations proposed in Section 4.6 are feasible
¹⁹⁴⁴ or implementable in practice. Construct validity defines how well an experiment
¹⁹⁴⁵ measures up to its claims; the experiments proposed in this paper support our three
¹⁹⁴⁶ hypotheses but these have been conducted in a clinical condition. Real-world case
¹⁹⁴⁷ studies and feedback from developers and providers in industry would remove the
¹⁹⁴⁸ controlled nature of our work.

¹⁹⁴⁹ 4.8 Conclusions & Future Work

¹⁹⁵⁰ This study explored three popular CVSs over an 11 month longitudinal experiment
¹⁹⁵¹ to determine if these services pose any evolution risk or inconsistency. We find that
¹⁹⁵² these services are generally stable but behave inconsistently; responses from these
¹⁹⁵³ services do change with time and this is not visible to the developers who use them.
¹⁹⁵⁴ Furthermore, the limitations of these systems are not properly conveyed by vendors.
¹⁹⁵⁵ From our analysis, we present a set of recommendations for both IWS vendors and
¹⁹⁵⁶ developers.

¹⁹⁵⁷ Standardised software quality models (e.g., [171]) target maintainability and
¹⁹⁵⁸ reliability as primary characteristics. Quality software is stable, testable, fault
¹⁹⁵⁹ tolerant, easy to change and mature. These CVSs are, however, in a nascent stage,
¹⁹⁶⁰ difficult to evaluate, and currently are not easily interchangeable. Effectively, the
¹⁹⁶¹ IWS response objects are shifting in material ways to developers, albeit slowly, and
¹⁹⁶² vendors do not communicate this evolution or modify API endpoints; the endpoint
¹⁹⁶³ remains static but the content returned does not despite the same input.

¹⁹⁶⁴ There are many potential directions stemming from this work. To start, we plan
¹⁹⁶⁵ to focus on preparing a more comprehensive datasheet specifically targeted at what
¹⁹⁶⁶ should be documented to application developers, and not data scientists. Reapplying
¹⁹⁶⁷ this work in real-world contexts, that is, to get real developer opinions and study
¹⁹⁶⁸ production grade systems, would also be beneficial to understand these phenomena
¹⁹⁶⁹ in-context. This will help us clarify if such changes are a real concern for developers
¹⁹⁷⁰ (i.e., if they really need to change between services, or the service evolution has real
¹⁹⁷¹ impact on their applications). We also wish to refine and systematise the method
¹⁹⁷² used in this study and develop change detectors that can be used to identify evolution
¹⁹⁷³ in these services that can be applied to specific ML domains (i.e., not just computer
¹⁹⁷⁴ vision), data sets, and API endpoints, thereby assisting application developers in their
¹⁹⁷⁵ testing strategies. Moreover, future studies may wish to expand the methodology
¹⁹⁷⁶ applied by refining how the responses are compared. As there does not yet exist a
¹⁹⁷⁷ standardised list of terms available between services, labels could be *semantically*
¹⁹⁷⁸ compared instead of using exact matches (e.g., by using stem words and synonyms
¹⁹⁷⁹ to compare similar meanings of these labels), similar to previous studies [262].

1980 This paper has highlighted only some high-level issues that may be involved
1981 in using these evolving services. The laws of software evolution suggest that for
1982 software to be useful, it must evolve [240, 350]. There is, therefore, a trade-off, as
1983 we have shown, between consistency and evolution in this space. For a component
1984 to be stable, any changes to dependencies it relies on must be communicated. We
1985 are yet to see this maturity of communication from IWS providers. Thus, developers
1986 must be cautious between integrating intelligent components into their applications
1987 at the expense of stability; as the field of AI is moving quickly, we are more likely to
1988 see further instability and evolution in IWSs as a consequence.

CHAPTER 5

1989

1990

1991

Interpreting Pain-Points in Computer Vision Services[†]

1992

1993 **Abstract** Intelligent web services (IWSs) are becoming increasingly more pervasive; ap-
1994 plication developers want to leverage the latest advances in areas such as computer vision
1995 to provide new services and products to users, and large technology firms enable this via
1996 RESTful APIs. While such APIs promise an easy-to-integrate on-demand machine in-
1997 tellIGENCE, their current design, documentation and developer interface hides much of the
1998 underlying machine learning techniques that power them. Such APIs look and feel like
1999 conventional APIs but abstract away data-driven probabilistic behaviour—the implications
2000 of a developer treating these APIs in the same way as other, traditional cloud services, such
2001 as cloud storage, is of concern. The objective of this study is to determine the various
2002 pain-points developers face when implementing systems that rely on the most mature of
2003 these intelligent web services, specifically those that provide computer vision. We use Stack
2004 Overflow to mine indications of the frustrations that developers appear to face when using
2005 computer vision services, classifying their questions against two recent classification tax-
2006 onomies (documentation-related and general questions). We find that, unlike mature fields
2007 like mobile development, there is a contrast in the types of questions asked by developers.
2008 These indicate a shallow understanding of the underlying technology that empower such
2009 systems. We discuss several implications of these findings via the lens of learning tax-
2010 onomies to suggest how the software engineering community can improve these services
2011 and comment on the nature by which developers use them.

[†]This chapter is originally based on A. Cummaudo, R. Vasa, S. Barnett, J. Grundy, and M. Abdellazek, “Interpreting Cloud Computer Vision Pain-Points: A Mining Study of Stack Overflow,” in *Proceedings of the 42nd International Conference on Software Engineering*. Seoul, Republic of Korea: ACM, June 2020. DOI 10.1145/3377811.3380404, pp. 1584–1596. Terminology has been updated to fit this thesis.

2012 5.1 Introduction

2013 The availability of recent advances in artificial intelligence (AI) over simple RESTful
2014 end-points offers application developers new opportunities. These new intelligent
2015 web services (IWSs) are AI components that abstract complex machine learning
2016 (ML) and AI techniques behind simpler API calls. In particular, they hide (either
2017 explicitly or implicitly) any data-driven and non-deterministic properties inherent
2018 to the process of their construction. The promise is that software engineers can
2019 incorporate complex machine learnt capabilities, such as computer vision, by simply
2020 calling an API end-point.

2021 The expectation is that application developers can use these AI-powered services
2022 like they use other conventional software components and cloud services (e.g., object
2023 storage like AWS S3). Furthermore, the documentation of these AI components is
2024 still anchored to the traditional approach of briefly explaining the end-points with
2025 some information about the expected inputs and responses. The presupposition
2026 is that developers can reason and work with this high level information. These
2027 services are also marketed to suggest that application developers do not need to fully
2028 understand how these components were created (i.e., assumptions in training data
2029 and training algorithms), the ways in which the components can fail, and when such
2030 components should and should not be used.

2031 The nuances of ML and AI powering IWSs have to be appreciated, as there are
2032 real-world consequences to software quality for applications that depend on them if
2033 they are ignored [88]. This is especially true when ML and AI are abstracted and
2034 masked behind a conventional-looking API call, yet the mechanisms behind the API
2035 are data-dependent, probabilistic and potentially non-deterministic [262]. We are
2036 yet to discover what long-term impacts exist during development and production due
2037 to poor documentation that do not capture these traits, nor do we know the depth of
2038 understanding application developers have for these components. Given the way AI-
2039 powered services are currently presented, developers are also likely to reason about
2040 these new services much like a string library or a cloud data storage service. That
2041 is, they may not fully consider the implications of the underlying statistical nature
2042 of these new abstractions or the consequent impacts on productivity and quality.

2043 Typically, when developers are unable to correctly align to the mindset of the
2044 API designer, they attempt to resolve issues by (re-)reading the API documentation.
2045 If they are still unable to resolve these issues on their own after some internet
2046 searching, they consider online discussion platforms (e.g., Stack Overflow, GitHub
2047 Issues, Mailing Lists) where they seek technological advice from their peers [4].
2048 Capturing what developers discuss on these platforms offers an insight into the
2049 frustrations developers face when using different software components as shown
2050 by recent works [38, 188, 305, 334, 366]. However, to our knowledge, no studies
2051 have yet analysed what developers struggle with when using the new generation of
2052 *intelligent* services. Given the re-emergent interest in AI and the anticipated value
2053 from this technology [220], a better understanding of issues faced by developers
2054 will help us improve the quality of services. Our hypothesis is that application
2055 developers do not fully appreciate the probabilistic nature of these services, nor do

2056 they have sufficient appreciation of necessary background knowledge—however, we
2057 do not know the specific areas of concern. The motivation for our study is to inform
2058 API designers on which aspects to focus in their documentation, education, and
2059 potentially refine the design of the end-points.

2060 This study involves an investigation of 1,825 Stack Overflow (SO) posts regarding
2061 one of the most mature types of IWSs—computer vision services (CVSs)—dating
2062 from November 2012 to June 2019. We adapt existing methodologies of prior SO
2063 analyses [38, 345] to extract posts related to CVSs. We then apply two existing SO
2064 question classification schemes presented at ICPC and ICSE in 2018 and 2019 [4, 39].
2065 These previous studies focused on mobile apps and web applications. Although not
2066 a direct motivation, our work also serves as a validation of the applicability of these
2067 two issue classification taxonomies [4, 39] in the context of IWSs (hence potential
2068 for generalisation). Additionally our work is the first—to our knowledge—to *test*
2069 the applicability of these taxonomies in a new study.

2070 The taxonomies in previous works focus on the specific aspects from the domain
2071 (e.g. API usage, specificity within the documentation etc.) and as such do not
2072 deeply consider the learning gap of an application developer. To explore the API
2073 learning implications raised by our SO analysis, we applied an additional lens of
2074 two taxonomies from the field of pedagogy. This was motivated by the need to offer
2075 an insight into the work needed to help developers learn how to use these relatively
2076 new services.

2077 The key findings of our study are:

- 2078 • The primary areas that developers raise as issues reflect a relatively primitive
2079 understanding of the underlying concepts of data-driven ML approaches used.
2080 We note this via the issues raised due to conceptual misunderstanding and
2081 confusion in interpreting errors,
- 2082 • Developers predominantly encounter a different distribution of issue types than
2083 were reported in previous studies, indicating the complexity of the technical
2084 domain has a non-trivial influence on intelligent API usage; and
- 2085 • Most of these issues can be resolved with better documentation, based on our
2086 analysis.

2087 The paper also offers a data-set as an additional contribution to the research
2088 community and to permit replication [411]. The paper structure is as follows:
2089 Section 5.2 provides motivational examples to highlight the core focus of our study;
2090 Section 5.3 provides a background on prior studies that have mined SO to gather
2091 insight into the software engineering community; Section 5.4 describes our study
2092 design in detail; Section 5.5 presents the findings from the SO extraction; Section 5.6
2093 offers an interpretation of the results in addition to potential implications that arise
2094 from our work; Section 5.7 outlines the limitations of our study; concluding remarks
2095 are given in Section 5.8.

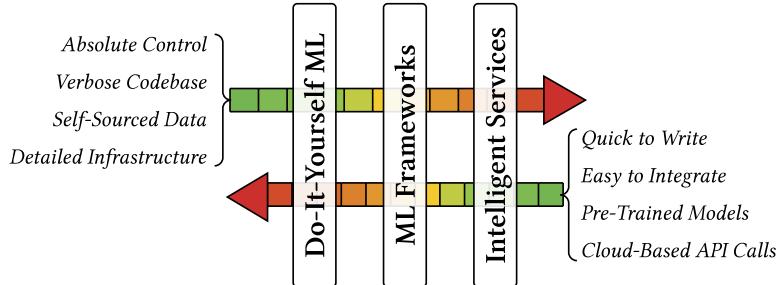


Figure 5.1: Some traits of Intelligent Services vs. ‘Do-It-Yourself’ ML. Green-to-red arrows indicate the presence of these traits. *Adapted from Ortiz [265].*

2096 5.2 Motivation

2097 “Intelligent” services are often available as a cloud end-point and provide de-
 2098 velopers a friendly approach to access recent AI/ML advances without being experts
 2099 in the underlying processes. Figure 5.1 highlights how these services abstract
 2100 away much of the technical know-how needed to create and operationalise these
 2101 IWSs [265]. In particular, they hide information about the training algorithm and
 2102 data-sets used in training, the evaluation procedures, the optimisations undertaken,
 2103 and—surprisingly—they often do not offer a properly versioned end-point [88, 262].
 2104 That is, the cloud vendors may change the behaviour of the services without sufficient
 2105 transparency.

2106 The trade-off towards ease of use for application developers, coupled with the
 2107 current state of documentation (and assumed developer background) has a cost as
 2108 reflected in the increasing discussions on developer communities such as SO (see
 2109 Figure 5.2). To illustrate the key concerns, we list below a few up-voted questions:

- 2110 • **unsure of ML specific vocabulary:** “*Though it’s now not SO clear to me
 2111 what ‘score’ actually means.*” [455]; “*I’m trying out the [IWS], and there’s a
 2112 score field that returns that I’m not sure how to interpret [it].*” [469]
- 2113 • **frustrated about non-deterministic results:** “*Often the API has troubles
 2114 in recognizing single digits... At other times Vision confuses digits with
 2115 letters.*” [468]; “*Is there a way to help the program recognize numbers better,
 2116 for example limit the results to a specific format, or to numbers only?*” [465]
- 2117 • **unaware of the limitations behind the services:** “*Is there any API available
 2118 where we can recognize human other body parts (Chest, hand, legs and other
 2119 parts of the body), because as per the Google vision API it’s only able to detect
 2120 face of the human not other parts.*” [449]
- 2121 • **seeking further documentation:** “*Does anybody know if Google has pub-
 2122 lished their full list of labels ([‘produce’, ‘meal’, ...]) and where I
 2123 could find that? Are those labels structured in any way? - e.g. is it known
 2124 that ‘food’ is a superset of ‘produce’, for example.*” [452]

2125 The objective of our study is to better understand the nature of the questions
 2126 that developers raise when using IWSs, in order to inform the service designers

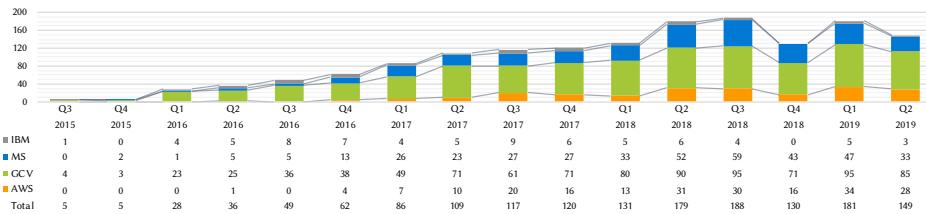


Figure 5.2: Trend of posts, where IBM = IBM Watson Visual Recognition, MS = Azure Computer Vision, AWS = AWS Rekognition and GCV = Google Cloud Vision. Three MS posts from Q4 2012, Q3 2013 and Q4 2013 have been removed for graph clarity.

and documenters. In particular, the knowledge we identify can be used to improve the documentation, educational material and (potentially) the information contained in the services’ response objects—these are the main avenues developers have to learn and reason about when using these services. There is previous work that has investigated issues raised by developers [4, 39, 345]. We build on top of this work by adapting the study methodology and apply the taxonomies offered to identify the nature of the issues and this results in the following research questions in this paper:

RQ1. How do developers mis-comprehend IWSs as presented within SO pain-points? While the AI community is well aware in the nuances that empower IWSs, such services are being released for application developers who may not be aware of their limitations or how they work. This is especially the case when machine intelligence is accessed via web-based APIs where such details are not fully exposed.

RQ2. Are the distribution of issues similar to prior studies? We compare how the distributions of previous studies’ of posts about conventional, deterministic API services differ from those of IWSs. By assessing the distribution of IWSs’ issues against similar studies that focus on mobile and web development, we identify whether a new taxonomy is needed specific to AI-based services, and if gaps specific to AI knowledge exist that need to be captured in these taxonomies.

5.3 Background

The primary goal of analysing issues is to better understand the root causes. Hence, a good issue classification taxonomy should ideally capture the underlying causal aspects (instead of pure functional groupings) [76]. Although this idea (of cause related classification) is not new (Chillarege advocated for it in this TSE paper in 1992), this is not a universally followed approach when studying online discussions and some recent works have largely classified issues into the “*what is*” and not “*how to fix it*” [28, 38, 355]. They typically (manually) classify discussion into either *functional areas* (e.g., Website Design/CSS, Mobile App Development, .NET Framework, Java [28]) or *descriptive areas* (e.g., Coding Style/Practice, Problem-/Solution, Design, QA [28, 355]). As a result, many of these studies do not give

us a prioritised means of targeted attack on how to *resolve* these issues with, for example, improved documentation. Interestingly, recent taxonomies that studied SO data (Aghajani et al. [4] and Beyer et al. [39]) were causal in nature and developed to understand discussions related to mobile and web applications. However, issues that arise when developers use IWSs have not been studied, nor do we know if existing issue classification taxonomies are sufficient in this domain.

Researchers studying APIs have also attempted to understand developer's opinions towards APIs [355], categorise the questions they ask about these APIs [28, 30, 39, 305], and understand API related documentation and usage issues [4, 5, 8, 28, 162, 345]. These studies often employ automation to assist in the data analysis stages of their research. Latent Dirichlet Allocation [8, 28, 305, 355] is applied for topic modelling and other ML techniques such as Random Forests [39], Conditional Random Fields [5] or Support Vector Machines [39, 162] are also used.

However, automatic techniques are tuned to classify into *descriptive* categories, that is, they help paint a landscape of *what is*, but generally do not address the causal factors to address the issues in great detail. For example, functional areas such as 'Website Design' [28], 'User Interface' [38] or 'Design' [356] result from such analyses. These automatic approaches are generally non-causal, making it hard to address reasons for *why* developers are asking such questions. However, not all studies in the space use automatic techniques; other studies employ manual thematic analysis [4, 30, 345] (e.g., card sorting) or a combination of both [38, 39, 305, 352]. Our work uses a manual approach for classification, and we use taxonomies that are more causally aligned allowing our findings to be directly useful in terms of addressing the issues.

Evidence-based software engineering [194] has helped shape the last 15 years worth of research, but the reliability of such evidence has been questioned [181, 183, 325]. Replication studies, especially in empirical works, can give us the confidence that existing results are adaptable to new domains; in this context, we extend (to IWSs) and work with study methods developed in previous works.

5.4 Method

5.4.1 Data Extraction

This study initially attempted to capture SO posts on a broad range of many IWSs by identifying issues related to four popular IWS cloud providers: Google Cloud [417], AWS [392], Azure [431] and IBM Cloud [427]. We based our selection criteria on the prominence of the providers in industry (Google, Amazon, Microsoft, IBM) and their ubiquity in cloud platform services. Additionally, in 2018, these services were considered the most adopted cloud vendors for enterprise applications [299].

However, during the filtering stage (see Section 5.4.2), we decided to focus on a subset of these services, computer vision, as these are one of the more mature and stable ML/AI-based services with widespread and increasing adoption in the developer community (see Figure 5.2). We acknowledge other services beyond the four analysed provide similar capabilities [405, 406, 413, 426, 478, 479] and only

2200 English-speaking services have been selected, excluding popular services from Asia
2201 (e.g., [403, 404, 425, 444, 445])—see Section 5.7. For comprehensiveness, we
2202 explain below our initial attempts to extract *all* IWSs.

2203 5.4.1.1 *Defining a list of IWSs*

2204 As there exists no global ‘list’ of IWSs to search on, we needed to derive a *corpus*
2205 of *initial terms* to allow us to know *what* to search for on the Stack Exchange Data
2206 Explorer¹ (SEDE). We began by looking at different brand names of cloud services
2207 and their permutations (e.g., Google Cloud Services and GCS) as well as various
2208 ML-related products (e.g., Google Cloud ML). To do this, we performed extensive
2209 Google searches² in addition to manually reviewing six ‘overview’ pages of the
2210 relevant cloud platforms. We identified 91 initial IWSs to incorporate into our
2211 search terms³.

2212 5.4.1.2 *Manual search for relevant, related terms*

2213 We then ran a manual search² on each term to determine if these terms were relevant.
2214 We did this by querying each term within SO’s search feature, reviewing the titles
2215 and body post previews of the first three pages of results (we did not review the
2216 answers, only the questions). We also noted down the user-defined *Tags* of each post
2217 (up to five per question); by clicking into each tag, we could review similar tags (e.g.,
2218 ‘project-oxford’ for ‘azure-cognitive-services’) and check if the tag had synonyms
2219 (e.g., ‘aws-lex’ and ‘amazon-lex’). We then compiled a *corpus of tags* consisting of
2220 31 terms.

2221 5.4.1.3 *Developing a search query*

2222 We recognise that searching SEDE via *Tags* exclusively can be ineffective (see [28,
2223 345]). To mitigate this, we produced a *corpus of title and body terms*. Such terms
2224 are those that exist within the title and body of the posts to reflect the ways in
2225 which individual developers commonly use to refer to different IWSs. To derive
2226 at such a list, we performed a search^{2,3} of the 31 tags above in SEDE, filtering
2227 out posts that were not answers (i.e., questions only) as we wanted to see how
2228 developers *phrase* their questions. For each search, we extracted a random sample
2229 of 100 questions (400 total for each service) and reviewed each question. We noted
2230 many patterns in the permutations of how developers refer to these services, such
2231 as: common misspellings ('bind' vs. 'bing'); brand misunderstanding ('Microsoft
2232 computer vision' vs. 'Azure computer vision'); hyphenation ('Auto-ML' vs. 'Auto
2233 ML'); UK and US English ('Watson Analyser' vs. 'Watson Analyzer'); and, the
2234 use of apostrophes, plurals, and abbreviations ('Microsoft's Computer Vision API',
2235 'Microsoft Computer Vision Services', 'GCV' vs. 'Google Cloud Vision'). We

¹<http://data.stackexchange.com/stackoverflow>

²This search was conducted on 17 January 2019

³For reproducibility, this is available at <http://bit.ly/2ZcwNJO>.

²²³⁶ arrived at a final list of 229 terms compromising all of the IWSs provided by
²²³⁷ Google, Amazon, Microsoft and IBM as of January 2019³.

²²³⁸ **5.4.1.4 Executing our search query**

²²³⁹ Our next step was to perform a case-insensitive search of all 229 terms within the
²²⁴⁰ body or title of posts. We used Google BigQuery's public data-set of SO posts⁴ to
²²⁴¹ overcome SEDE's 50,000 row limit and to conduct a case-insensitive search. This
²²⁴² search was conducted on 10 May 2019, where we extracted 21,226 results. We then
²²⁴³ performed several filtering steps to cleanse our extracted data, as explained below.

²²⁴⁴ **5.4.2 Data Filtering**

²²⁴⁵ **5.4.2.1 Refining our inclusion/exclusion criteria**

²²⁴⁶ We performed an initial manual filtering of the 50 most recent posts (sorted by
²²⁴⁷ descending *CreationDate* values) of the 21,226 posts above, assessing the suitability
²²⁴⁸ of the results and to help further refine our inclusion and exclusion criteria. We
²²⁴⁹ did note that some abbreviations used in the search terms (e.g., 'GCV', 'WCS'⁵),
²²⁵⁰ resulting in irrelevant questions in our result set. We therefore removed abbreviations
²²⁵¹ from our search query and consolidated all overlapping terms (e.g., 'Google Vision
²²⁵² API' was collapsed into 'Google Vision').

²²⁵³ We also recognised that 21,226 results would be non-trivial to analyse without
²²⁵⁴ automated techniques. As we wanted to do manual qualitative analysis, we reduced
²²⁵⁵ our search space to 27 search terms of just the *CVSs* within the original corpus of
²²⁵⁶ 229 terms. These were Google Cloud Vision [417], AWS Rekognition [392], Azure
²²⁵⁷ Computer Vision [431], and IBM Watson Visual Recognition [427]. This resulted
²²⁵⁸ in 1,425 results that were extracted on 21 June 2019. The query used and raw results
²²⁵⁹ are available online in our supplementary materials [411].

²²⁶⁰ **5.4.2.2 Duplicates**

²²⁶¹ Within 1,425 results, no duplicate questions were noted, as determined by unique
²²⁶² post ID, title or timestamp.

²²⁶³ **5.4.2.3 Automated and manual filtering**

²²⁶⁴ To assess the suitability and nature of the 1,425 questions extracted, the first author
²²⁶⁵ began with a manual check on a randomised sample of 50 questions. As the questions
²²⁶⁶ were exported in a raw CSV format (with HTML tags included in the post's body), we
²²⁶⁷ parsed the questions through an ERB templating engine script⁶ in which the ID, title,
²²⁶⁸ body, tags, created date, and view, answer and comment counts were rendered for
²²⁶⁹ each post in an easily-readable format. Additionally, SQL matches in the extraction
²²⁷⁰ process were also highlighted in yellow (i.e., in the body of the post) and listed at

⁴<http://bit.ly/2LrN7OA>

⁵Watson Cognitive Services

⁶We make this available for future use at: <http://bit.ly/2NqBB70>

the top of each post. These visual cues helped to identify 3 false positive matches where library imports or stack traces included terms within our corpus of 26 CVS terms. For example, aws-java-sdk-rekognition:jar is falsely matched as a dependency within an unrelated question. As such exact matches would be hard to remove without the use of regular expressions, and due to the low likelihood (6%) of their appearance, we did not perform any followup automatic filtering.

5.4.2.4 Classification

Our 1,425 posts were then split into 4 additional random samples (in addition to the random sample of 50 above). 475 posts were classified by the first author and three other research assistants, software engineers with at least 2 years industry experience, assisted to classify the remaining 900. This left a total of 1,375 classifications made by four people plus an additional 450 classifications made from reliability analysis, in which the remaining 50 posts were classified nine times (as detailed in Section 5.4.3.1). Thus, a total of 1,825 classifications were made from the original 1,425 posts extracted.

Whilst we could have chosen to employ topic modelling, these are too descriptive in nature (as discussed in Section 5.3). Moreover, we wanted to see if prior taxonomies can be applied to IWSs (as opposed to creating a new one) and compare if their distributions are similar. Therefore, we applied the two existing taxonomies described in Section 5.3 to each post; (i) a documentation-specific taxonomy that addresses issues directly resulting from documentation, and (ii) a generalised taxonomy that covers a broad range of SO issues in a well-defined software engineering area (specifically mobile app development). Aghajani et al.’s documentation-specific taxonomy (Taxonomy A) is multi-layered consisting of four dimensions and 16 sub-categories [4]. Similarly, Beyer’s SO generalised post classification taxonomy (Taxonomy B) consists of seven dimensions [39]. We code each dimension with a number, X , and each sub-category with a letter y : (Xy). We describe both taxonomies in detail within Table 5.1. Where a post was included in our results but not applicable to IWSs (see Section 5.4.2.3) or not applicable to a taxonomy dimension/category, then the post was flagged for removal in further analysis. Table 5.1 presents *our understanding* of the respective taxonomies; our intent is not to methodologically replicate Aghajani et al. or Beyer et al.’s studies in the IWS domain, rather to acknowledge related work in the area of SO classification and reduce the need to synthesise a new taxonomy. We baseline all coding against *our interpretation only*. Our classifications are therefore independent of the previous authors’ findings.

5.4.3 Data Analysis

5.4.3.1 Reliability of Classification

To measure consistency of the categories assigned by each rater to each post, we utilised both intra- and inter-rater reliability [234]. As verbatim descriptions from dimensions and sub-categories were considered quite lengthy from their original sources, all raters met to agree on a shared interpretation of the descriptions, which

Table 5.1: Descriptions of dimensions (■) and sub-categories (→) from both taxonomies used.

A Documentation-specific classification (Aghajani et al. [4])		
A-1	■ Information Content (What)	Issues related to what is written in the documentation
A-1a	→ <i>Correctness</i>	What exists in the documentation actually matches what is implemented in code
A-1b	→ <i>Completeness</i>	The documentation fully covers all aspects of the API's components
A-1c	→ <i>Up-to-dateness</i>	What is documented is accurate to the current version of the API
A-2	■ Information Content (How)	Issues related to how the document is written and organised
A-2a	→ <i>Maintainability</i>	The upkeep effort to ensure the documentation remains up to date
A-2b	→ <i>Readability</i>	The extent to which the documentation is interpretable
A-2c	→ <i>Usability</i>	How useable the organisation, look and feel of the documentation is
A-2d	→ <i>Usefulness</i>	The usefulness of the documentation, avoiding misinformation.
A-3	■ Process-Related	Issues related to the documentation process
A-3a	→ <i>Internationalisation</i>	Translating the documentation into other languages
A-3b	→ <i>Contribution-Related</i>	Contribution issues encountered when people contribute to the documentation
A-3c	→ <i>Configuration-Related</i>	Configuration issues of the documentation tool
A-3d	→ <i>Implementation-Related</i>	Unwanted development issues caused by (poor) documentation
A-3e	→ <i>Traceability</i>	Tracing documentation changes (when, when, who and why)
A-4	■ Tool-Related	Issues related to documentation tools (e.g., Javadoc)
A-4a	→ <i>Tooling Bugs</i>	Bugs that exist within the documentation tooling
A-3b	→ <i>Tooling Discrepancy</i>	Support as expectations not being fulfilled by these documentation tools
A-3c	→ <i>Tooling Help Required</i>	Help required due to improper usage of the tools
A-3d	→ <i>Tooling Migration</i>	Issues migrating the tool to a new version or another tool
B Generalised classification (Beyer et al. [39])		
B-1	■ API usage	Issue on how to implement something using a specific component provided by the API
B-2	■ Discrepancy	The questioner's <i>expected behaviour</i> of the API does not reflect the API's <i>actual behaviour</i>
B-3	■ Errors	Issue regarding some form of error when using the API, and provides an exception and/or stack trace to help understand why it is occurring
B-4	■ Review	The questioner is seeking insight from the developer community on what the best practices are using a specific API or decisions they should make given their specific situation
B-5	■ Conceptual	The questioner is trying to ascertain limitations of the API and its behaviour and rectify issues in their conceptual understanding on the background of the API's functionality
B-6	■ API change	Issue regarding changes in the API from a previous version
B-7	■ Learning	The questioner is seeking for learning resources to self-learn further functionality in the API, and unlike discrepancy, there is no specific problem they are seeking a solution for

2312 were then paraphrased as discussed in the previous subsection and tabulated in
2313 Table 5.1. To perform statistical calculations of reliability, each category was as-
2314 signed a nominal value and a random sample of 50 posts were extracted. Two-phase
2315 reliability analysis followed.

2316 Firstly, intra-rater agreement by the first author was conducted twice on 28 June
2317 2019 and 9 August 2019. Secondly, inter-rater agreement was conducted with the
2318 remaining four co-authors in addition to three research assistants within our research
2319 group in mid-August 2019. Thus, the 50 posts were classified an additional nine
2320 times, resulting in 450 classifications for reliability analysis. We include these
2321 classifications in our overall analysis.

2322 At first, we followed methods of reliability analysis similar to previous SO
2323 studies (e.g., [345]) using the percentage agreement metric that divides the number
2324 of agreed categories assigned per post by the total number of raters [234]. However,
2325 percentage agreement is generally rejected as an inadequate measure of reliability
2326 analysis [81, 148, 201] in statistical communities. As we used more than 2 coders
2327 and our reliability analysis was conducted under the same random sample of 50
2328 posts, we applied *Light's Kappa* [212] to our ratings, which indicates an overall
2329 index of agreement. This was done using the `irr` computational R package [127]
2330 as suggested in [148].

2331 **5.4.3.2 Distribution Analysis**

2332 In order to compare the distribution of categories from our study with previous studies
2333 we carried out a χ^2 test. We selected a χ^2 test as the following assumptions [326]
2334 are satisfied: (i) the data is categorical, (ii) all counts are greater than 5, and (iii)
2335 we can assume simple random sampling. The null hypothesis describes the case
2336 where each population has the same proportion of observations and the alternative
2337 hypothesis is where at least one of the null hypothesis statements is false. We chose
2338 a significance value, α , of 0.05 following a standard rule of thumb. As to the best
2339 of our knowledge this is the first statistical comparison using Taxonomy A and B on
2340 SO posts. To report the effect size we selected Cramer's Phi, ϕ_c which is well suited
2341 for use on nominal data [326].

2342 **5.5 Findings**

2343 We present our findings from classifying a total of 1,825 SO posts aimed at answering
2344 RQs 1 and 2. 450 posts were classified using Taxonomies A and B for reliability
2345 analysis as described in Section 5.4.3.1 and the remaining 1,375 posts were classified
2346 as per Section 5.4.2.4. A summary of our classification using Taxonomies A and B
2347 is shown in Figure 5.3.

2348 **5.5.1 Post classification and reliability analysis**

2349 When undertaking the classification, we found that 238 issues (13.04%) did not
2350 relate to IWSs directly. For example, library dependencies were still included in

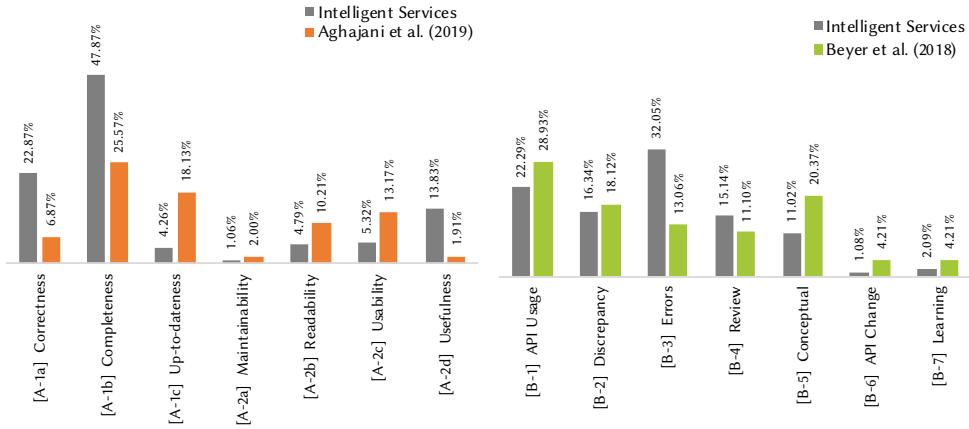


Figure 5.3: *Left:* Documentation-specific classification taxonomy results highlights a mostly similar distribution to that of Aghajani et al.’s findings [4]. *Right:* Generalised classification taxonomy results highlight differences from more mature fields (i.e., Android APIs in Beyer et al. [39]) to less mature fields (i.e., IWSs).

a number of results (see Section 5.4.2.3), and we found there to be many posts discussing Android’s Mobile Vision API as Google (Cloud) Vision. These issues were flagged and ignored for further analysis (see Section 5.4.2.4).

For our reliability analysis, we classified a total of 450 posts of which 70 posts were flagged as irrelevant. Landis and Koch [207] provide guidelines to interpret kappa reliability statistics, where $0.00 \leq \kappa \leq 0.20$ indicates *slight* agreement and $0.21 \leq \kappa \leq 0.40$ indicates *fair* agreement. Despite all raters meeting to agree on a shared interpretation of the taxonomies (see Section 5.4.3.1) our inter-rater measures aligned *slightly* (0.148) for Taxonomy A and *fairly* (0.295) for Taxonomy B. We report further in Section 5.7.

5.5.2 Developer Frustrations

We found Beyer et al.’s high-level abstraction taxonomy (Taxonomy B) was able to classify 86.52% of posts. 10.30% posts were assigned exclusively under Aghajani et al.’s documentation-specific taxonomy (Taxonomy A). We found that developers do not generally ask questions exclusive to documentation, and typically either pair documentation-related issues to their own code or context. The following two subsections further explain results from both Taxonomy A and B’s perspective.

5.5.2.1 Results from Aghajani et al.’s taxonomy

Results for Aghajani et al.’s low-level documentation taxonomy (Taxonomy A), indicates that most discussion on SO does not directly relate to documentation about an IWS. We did not find any process-related (A-3) or tool-related (A-4) questions as, understandably, the developers who write the documentation of the IWSs would not be posting questions of such nature on SO. One can *infer* documentation-related issues from posts (i.e., parts of the documentation *lacking* that may cause the issue

2375 posted). However, there are few questions that *directly* relate to documentation of
2376 IWSs.

2377 Few developers question or ask questions directly about the API documentation
2378 but some (47.87%) posts ask for additional information to understand the
2379 API (**completeness (A-1b)**), for example: “*Is there a full list of potential labels*
2380 *that Google’s Vision API will return?*” [452]; “*There seems to be very little to no*
2381 *documentation for AWS iOS text recognition inside an image?*” [450].

2382 22.87% of posts question the **accuracy (A-1a)** of certain parts of the cloud docu-
2383 mentation, especially in relation to incorrect quotas and limitations: “*Are the Cloud*
2384 *Vision API limits in documentation correct?*” [463], “*According to the Google Vision*
2385 *documentation, the maximum number of image files per request is 16. Elsewhere,*
2386 *however, I’m finding that the maximum number of requests per minute is as high as*
2387 *1800.*” [448].

2388 There are also many references (23.94%) addressing the confusing nature of
2389 some documentation, indicating that the **readability, usability and usefulness of**
2390 **the documentation (A-2b, A-2c and A-2d)** could be improved. For example, “*Am*
2391 *I encoding it correctly? The docs are quite vague.*” [446], “*The aws docs for this*
2392 *are really confusing.*” [475].

2393 5.5.2.2 Results from Beyer et al.’s taxonomy

2394 We found that a majority (32.05%) of posts are primarily **error-related questions**
2395 (**B-3**), including a dump of the stack trace or exception message from the service’s
2396 programming-language SDK (usually Java, Python or C#) that relates to a specific
2397 error. For example: “*I can’t fix an error that’s causing us to fall behind.*” [472]; “*I’m*
2398 *using the Java Google Vision API to run through a batch of images... I’m now getting*
2399 *a channel closed and ClosedChannelException error on the request.*” [466].

2400 **API usage questions (B-1)** were the second highest category at 22.29% of
2401 posts. Reading the questions revealed that many developers present an insufficient
2402 understanding of the behaviour, functional capability and limitation of these services
2403 and the need for further data processing. For example, while Azure provides an
2404 image captioning service, this is not universal to all CVSS: “*In Amazon Rekognition*
2405 *for image processing how do I get the caption for an image?*” [457]. Similarly,
2406 OCR-related and label-related questions often indicate interest in cross-language
2407 translation, where a separate translation service would be required: “*Can Google*
2408 *Cloud Vision generate labels in Spanish via its API?*” [471]; “[*How can I] specify*
2409 *language for response in Google Cloud Vision API*” [458]; “*When I request a text*
2410 *detection of an image, it gives only English Alphabet characters (characters without*
2411 *accents) which is not enough for me. How can I get the UTF-32 characters?*” [453].

2412 It was commonplace to see questions that demonstrate a lack of depth in under-
2413 standing and appreciating how these services work, instead posting simple debugging
2414 questions. For instance, in the 11.02% of **conceptual-related questions (B-5)** that
2415 we categorised, we noticed causal links to a misunderstanding (or lack of aware-
2416 ness) of the vocabulary used within computer vision. For example: “*The problem*
2417 *is that I need to know not only what is on the image but also the position of that*

²⁴¹⁸ object. Some of those APIs have such feature but only for face detection.” [464];
²⁴¹⁹ “I want to know if the new image has a face similar to the original image.... [the
²⁴²⁰ service] can identify faces, but can I use it to get similar faces to the identified face
²⁴²¹ in other images?” [456]. It is evident that some application developers are not aware
²⁴²² of conceptual differences in computer vision such as object/face *detection* versus
²⁴²³ *localisation* versus *recognition*.

²⁴²⁴ In the 16.34% of **discrepancy-related questions (B-2)**, we see further unawareness
²⁴²⁵ from developers in how the underlying systems work. In OCR-related questions,
²⁴²⁶ developers do not understand the pre-processing steps required before an OCR is
²⁴²⁷ performed. In instances where text is separated into multiple columns, for example,
²⁴²⁸ text is read top-down rather than left-to-right and segmentation would be required
²⁴²⁹ to achieve the expected results. For example, “*it appears that the API is using some*
²⁴³⁰ *kind of logic that makes it scan top to bottom on the left side and moving to right*
²⁴³¹ *side and doing a top to bottom scan.*” [470]; “*this method returns scanned text in*
²⁴³² *wrong sequence... please tell me how to get text in proper sequence.*” [476].

²⁴³³ A number of **review-related questions (B-4)** (15.14%) seem to provide some
²⁴³⁴ further depth in understanding the context to which these systems work, where training
²⁴³⁵ data (or training stages) are needed to understand how inferences are made: “*How*
²⁴³⁶ *can we find an exhaustive list (or graph) of all logos which are effectively recognized*
²⁴³⁷ *using Google Vision logo detection feature?*” [474]; “*when object banana is detected*
²⁴³⁸ *with accuracy greater than certain value, then next action will be dispatched... how*
²⁴³⁹ *can I confidently define and validate the threshold value for each item?*” [460].

²⁴⁴⁰ **API change (B-6)** was shown in 1.08% of posts, with evolution of the services
²⁴⁴¹ occurring (e.g., due to new training data) but not necessarily documented “*Recently*
²⁴⁴² *something about the Google Vision API changed... Suddenly, the API started to*
²⁴⁴³ *respond differently to my requests. I sent the same picture to the API today, and I*
²⁴⁴⁴ *got a different response (from the past).*” [473].

²⁴⁴⁵ 5.5.3 Statistical Distribution Analysis

²⁴⁴⁶ We obtained the following results $\chi^2 = 131.86$, $\alpha = 0.05$, $p \text{ value} = 2.2 \times 10^{-16}$ and
²⁴⁴⁷ $\phi_c = 0.362$ from our distribution analysis with Taxonomy A to compare our study
²⁴⁴⁸ with that of Aghajani et al. [4]. Comparing our study to Beyer et al. [39] produced the
²⁴⁴⁹ following results $\chi^2 = 145.58$, $\alpha = 0.05$, $p \text{ value} = 2.2 \times 10^{-16}$ and $\phi_c = 0.252$.
²⁴⁵⁰ These results show that we are able to reject the null hypothesis that the distribution
²⁴⁵¹ of posts using each taxonomy was the same as the comparison study. While there are
²⁴⁵² limited guidelines for interpreting ϕ_c when there is no prior information for effect
²⁴⁵³ size [340], Sun et al. suggests the following: $0.07 \leq \phi_c \leq 0.20$ indicates a *small*
²⁴⁵⁴ effect, $0.21 \leq \phi_c \leq 0.35$ indicates a *medium* effect, and $0.35 > \phi_c$ indicates a *large*
²⁴⁵⁵ effect. Based on this criteria we obtained a *large* effect size for the documentation-
²⁴⁵⁶ specific classification (Taxonomy A) and a *medium* effect size for the generalised
²⁴⁵⁷ classification (Taxonomy B).

2458 5.6 Discussion

2459 5.6.1 Answers to Research Questions

2460 5.6.1.1 How do developers mis-comprehend IWSs as presented within SO pain- 2461 points? (RQ1)

2462 Upon meeting to discuss the discrepancies between our categorisation of IWS usage
2463 SO posts, we found that our interpretations of the *posts themselves* were largely sub-
2464 jective. For example, many posts presented multi-faceted dimensions for Taxonomy
2465 B; Beyer et al. [39] argue that a post can have more than one question category and
2466 therefore multi-label classification is appropriate at times. We highlight this further
2467 in the threats to validity (Section 5.7).

2468 We have to define the context of IWSs to address RQ1. We use the concept
2469 of a “technical domain” [25] to define this context. A technical domain captures
2470 the domain-specific concerns that influence the non-functional requirements of a
2471 system [25]. In the context of IWSs, the technical domain includes exploration, data
2472 engineering, distributed infrastructure, training data, and model characteristics as
2473 first class citizens [25]. We would then expect to see posts on SO related to these
2474 core concerns.

2475 In Figure 5.3, for the documentation-specific classification, the majority of posts
2476 were classified as **Completeness (A1-b)** related (47.87%). An interpretation for this
2477 is that the documentation does not adequately cover the technical domain concerns.
2478 Comments by developers such as “*I'm searching for a list of all the possible image*
2479 *labels that the Google Cloud Vision API can return?*” [451] indicates the documen-
2480 tation does not adequately describe the training data for the API—developers do
2481 not know the required usage assumptions. Another quote from a developer, “*Can*
2482 *Google Cloud Vision generate labels in Spanish via its API? ... [Does the API]*
2483 *allow to select which language to return the labels in?*” [471] points to a lack of
2484 details relating to the characteristics of the models used by the API. It would seem
2485 that developers are unaware of aspects of the technical domain concerns.

2486 The next most frequent category is **Correctness (A-1a)** with 22.87% of posts. In
2487 the context of the technical domain there are many limits that developers need to be
2488 aware of: range and increments of a model score [88]; required data pre-processing
2489 steps for optimal performance; and features provided by the models (as explained in
2490 Section 5.5.2.2). Considering the relation between technical concerns and software
2491 quality, developers are right to question providers on correctness; “*Are the Cloud*
2492 *Vision API limits in documentation correct?*” [463].

2493 5.6.1.2 Are the distribution of issues similar to prior studies? (RQ2)

2494 Visual inspection of Figure 5.3 shows that the distributions for the documentation-
2495 specific classification and the generalised classification are different (compared to
2496 prior studies). As a sanity check we conducted a χ^2 test and calculated the effect
2497 size ϕ_c . We were able to reject the null hypothesis for both classification schemes,
2498 that the distribution of issues were the same as the previous studies (see Section 5.5).

²⁴⁹⁹ We now discuss the most prominent differences between our study and the previous
²⁵⁰⁰ studies.

²⁵⁰¹ In the context of IWS SO posts, Taxonomy B suggests that Errors (B-3) are
²⁵⁰² discussed most amongst developers. These results are in contrast to similar studies
²⁵⁰³ made in more *mature* API domains, such as Mobile Development [26, 27, 38, 39, 305]
²⁵⁰⁴ and Web Development [352]. Here, API Usage (B-1) is much more frequently
²⁵⁰⁵ discussed, followed by Conceptual (B-5), Discrepancy (B-2) and Errors (B-3). We
²⁵⁰⁶ argue in the following section that an improved developer understanding can be
²⁵⁰⁷ achieved by educating them about the IWS lifecycle and the ‘whole’ system that
²⁵⁰⁸ wraps such services.

²⁵⁰⁹ In the Android study API usage questions (B-1) were the highest category
²⁵¹⁰ (28.93% compared to 22.29% in our study). As stated in the analysis of the Error
²⁵¹¹ questions this discrepancy could be due to the maturity of the domain. However,
²⁵¹² another explanation could be the scope of the two individual studies. Beyer et al. [39]
²⁵¹³ used a broad search strategy consisting of posts tagged Android. This search term
²⁵¹⁴ fetches issues related to the entire Android platform which is significantly larger
²⁵¹⁵ than searching for computer vision APIs using 229 search terms. As a consequence
²⁵¹⁶ of more posts and more APIs there would be use cases resulting in additional posts
²⁵¹⁷ related to API Usage (B-1).

²⁵¹⁸ Applying existing SO taxonomies allowed us to better understand the distribution
²⁵¹⁹ of the issues across different domains. In particular, the issues raised around IWSs
²⁵²⁰ appear to be primarily due to poor documentation, or insufficient explanation around
²⁵²¹ errors and limitations. Hence, many of the concerns could be addressed by adding
²⁵²² more details to the end-point descriptions, and by providing additional information
²⁵²³ around how these services are designed to work.

²⁵²⁴ 5.6.2 The Developer’s Learning Approach

²⁵²⁵ In this subsection, we offer an explanation as to why developers are complaining
²⁵²⁶ about certain things when trying to use IWSs on SO (RQ1), as characterised through
²⁵²⁷ the use of prior SO classification frameworks (RQ2). This is described through
²⁵²⁸ the theoretical lenses of two learning taxonomies: Bloom’s context complexity and
²⁵²⁹ intellectual ability taxonomy, and the Structure of the Observed Learning Outcome
²⁵³⁰ (SOLO) taxonomy (i.e., the nature by which developer’s learn). We argue that the
²⁵³¹ issues with using IWSs relating to the lower-levels of these learning taxonomies
²⁵³² are easily solvable by slight fixes and improvements to the documentation of these
²⁵³³ services. However, the higher dimensions of these taxonomies demand far more
²⁵³⁴ rigorous mitigation strategies than documentation alone (potentially more structured
²⁵³⁵ education). Thus, many of the questions posted are from developers who are *learning*
²⁵³⁶ to *understand* the domain of IWSs and AI, and (hence) both SOLO and Bloom’s
²⁵³⁷ taxonomies are applicable for this discussion—as described below within the context
²⁵³⁸ of our domain—as pedagogical aides.

2539 **5.6.2.1 Bloom's Taxonomy**

2540 The cognitive domain under Bloom's taxonomy [44] consists of six objectives.
2541 Within the context of IWSs, developers are likely to ask questions due to causal links
2542 that exist in the following layers of Bloom's taxonomy: (i) *knowledge*, where the
2543 developer does not remember or know of the basic concepts of computer vision and
2544 AI (in essence, they may think that AI is as smart as a human); (ii) *comprehension*,
2545 where the developer does not understand how to interpret basic concepts, or they
2546 are mis-understanding how they are used in context; (iii) *application*, where the
2547 developer is struggling to apply existing concepts within the context of their own
2548 situation; (iv) *analysis*, where the developer is unable to analyse the results from IWSs
2549 (i.e., understand response objects); (v) *evaluation*, where the developer is unable to
2550 evaluate issues and make use of best-practices when using IWSs; and (vi) *synthesise*,
2551 where the developer is posing creative questions to ask if new concepts are possible
2552 with CVSs.

2553 **5.6.2.2 SOLO Taxonomy**

2554 The SOLO taxonomy [40] consists of five levels of understanding. The causal
2555 links behind the SO questions we have found relate to the following layers of the
2556 SOLO taxonomy: (i) *pre-structural*, where the developer has a question indicating
2557 incompetence or has little understanding of computer vision; (ii) *uni-structural*,
2558 where the developer is struggling with one key aspect (i.e., a simple question about
2559 computer vision); (iii) *multi-structural*, where the developer is questioning multiple
2560 concepts (independently) to understand how to build their system (e.g., system
2561 integration with the IWS); (iv) *relational*, where the developer is comparing and
2562 contrasting the best ways to achieve something with IWSs; and (v) *extended abstract*,
2563 where the developer poses a question theorising, formulating or postulating a new
2564 concept within IWSs.

2565 **5.6.2.3 Aligning SO taxonomies to Bloom's and SOLO taxonomies**

2566 To understand our findings with the lenses of pedagogical aids, we aligned Tax-
2567 onomies A and B to Bloom's and the SOLO taxonomies for a random sample of 50
2568 issues described in Section 5.4.3.1. To do this, we reviewed all 50 of these SO posted
2569 questions and applied both the Bloom and SOLO taxonomies. The primary author
2570 assigned each of the 50 questions a level within the Bloom and SOLO taxonomies,
2571 removed out noise (i.e., false positive posts of no relevance to IWSs) and unassigned
2572 dimensions from reliability agreement, and then compared the relevant dimensions
2573 of Taxonomy A and B dimensions (not sub-categories). The comparison of align-
2574 ments of posts to the five SOLO dimensions and six Bloom dimensions are shown
2575 in Figure 5.4. We acknowledge that this is only an approximation of the current
2576 state of the developer's understanding of IWSs. This early model will require further
2577 studies to perform a more thorough analysis, but we offer this interpretation for early
2578 discussion.

2579 As shown in Figure 5.4, the bulk of the posts fall in the lower constructs of

Table 5.2: Example Alignments of SO posts to Bloom's and the SOLO taxonomy.

Issue Quote	Bloom	SOLO
“I’m using Microsoft Face API for a small project and I was trying to detect a face inside a jpg file in the local system (say, stored in a directory D:\Image\abc.jpg)... but it does not work.” [467]	Knowledge	Pre-Structural
“The problem is that the response JSON is rather big and confusing. It says a lot about the picture but doesn’t say what the whole picture is of (food or something like that).” [447]	Comprehension	Uni-Structural
“The bounding box around individual characters is sometimes accurate and sometimes not, often within the same image. Is this a normal side-effect of a probabilistic nature of the vision algorithm, a bug in the Vision API, or of course an issue with how I’m interpreting the response?” [454]	Comprehension	Multi-Structural
“I’m working on image processing. SO far Google Cloud Vision and Clarifai are the best API’s to detect objects from images and videos, but both API’s doesn’t support object detection from 360 degree images and videos. Is there any solution for this problem?” [461]	Application	Uni-Structural
“Before I train Watson, I can delete pictures that may throw things off. Should I delete pictures of: Multiple dogs, A dog with another animal, A dog with a person, A partially obscured dog, A dog wearing glasses, Also, would dogs on a white background make for better training samples? Watson also takes negative examples. Would cats and other small animals be good negative examples?” [459]	Analysis	Relational

2580 Bloom’s and the SOLO taxonomy. This indicates that modification to certain doc-
 2581 umentation aspects can address many of these issues. For example, many issues
 2582 can be ratified with better descriptions of response data and error messages: “I was
 2583 exploring google vision and in the specific function ‘detectCrops’, gives me the crop
 2584 hints. what does this means exactly?” [462]; “I am a making a very simple API call
 2585 to the Google Vision API, but all the time it’s giving me error that ‘google.oauth2’
 2586 module not found.” [477]

2587 However, and more importantly, the higher-construct questions ranging from
 2588 the middle of the third dimensions on are not as easily solvable through improved
 2589 documentation (i.e., apply and multi-structural) which leaves 34.74% (Bloom’s)
 2590 and 11.84% (SOLO) unaccounted for, resolvable only through improved education
 2591 practices.

2592 5.6.3 Implications

2593 5.6.3.1 For Researchers

2594 **Investigate the evolution of post classification** Analysing how the distribution of
 2595 the reported issues changes over time would be an important study. This study could
 2596 answer questions such as ‘Does the evolution of IWSs follow the same pattern as
 2597 previous software engineering trends such as mobile app or web development?’ As
 2598 with any new emerging field, it is key to analyse how developers perceive such issues
 2599 over time. For instance, early issues with web or mobile app development matured

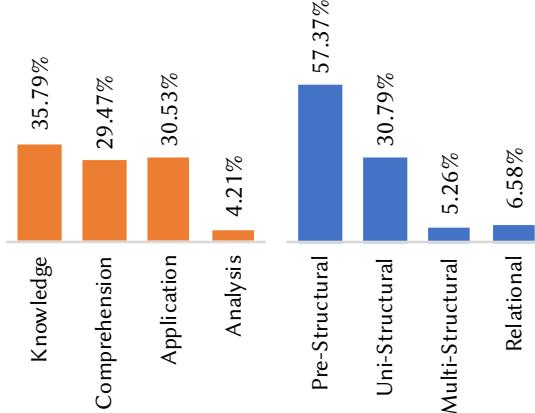


Figure 5.4: Alignment of Bloom (Orange) and SOLO (Blue) taxonomies against Taxonomy A and B dimensions against all 213 classifications made in the random sample of 50 posts.

as their respective domain matured, and we would expect similar results to occur in the IWSs space. Future researchers could plan for a longitudinal study, such as a long-term survey with developers to gather their insights in this evolving domain, reviewing case studies of projects that use intelligent web services from now into the future, or re-mining SO at a later date and comparing the results to this study. This will help assess evolving trends and characteristics, and determine how and if the nature of the developer's experience with IWSs (and AI in general) changes with time.

Investigate the impact of technical challenges on API usage As discussed above, IWSs have characteristics that may influence API usage patterns and should be investigated as a further avenue of research. Further mining of open source software repositories that make use of IWSs could be assessed, thereby investigating if API patterns evolve with the rise of AI-based applications.

5.6.3.2 For Educators

Education on high-level aspects of IWSs As demonstrated in our analysis of their SO posts, many developers appear to be unaware of the higher-level concepts that exist within the AI and ML realm. This includes the need to pre- and post-process data, the data dependency and instability that exists in these services, and the specific algorithms that empower the underlying intelligence and hence their limitations and characteristics. However, most developers don't seem to complain about these factors due to the lack of documentation (i.e., via Taxonomy A). Rather, they are unaware that such information should be documentation and instead ask generalised and open questions (i.e., via Taxonomy B). Thus, documentation improvements alone may not be enough to solve these issues. This results in uncertainty during the preparation and operation (usage) of such services. Such high-level conceptual information is currently largely missing in developer documentation for IWSs. Furthermore, many

of the background ML and AI algorithm information needed to understand and use intelligent systems in context are built within data science (not software engineering) communities. A possible road-map to mitigate this issue would be the development of a software engineer’s ‘crash-course’ in ML and AI. The aim of such a course would encourage software engineers to develop an appreciation of the nuances and the inherent risks and implications that comes with using IWSs. This could be taught at an undergraduate level to prepare the next generation of developers of a ‘programming 2.0’ era. However, the key aspects and implications that are presented with AI would need to be well-understood before such a course is developed, and determining the best strategy to curate the content to developers would be best left to the software engineering education domain. Further investigation in applying educational taxonomies in the area (such as our attempts to interpret our findings using Bloom’s and the SOLO taxonomies) would need to be thoroughly explored beforehand.

5.6.3.3 *For Software Engineers*

Better understanding of intelligent API contextual usage Our results show that developers are still learning to use these APIs. We applied two learning perspectives to interpret our results. In applying the two pedagogical taxonomies to our findings, we see that most issues seem to fall into the pre-structural and knowledge-based categories; little is asked of higher level concepts and a majority of issues do not offer complex analysis from developers. This suggests that developers are struggling as they are unaware of the vocabulary needed to actually use such APIs, further reinforcing the need for API providers to write overview documentation (as noted in prior work [87]) and not just simple endpoint documentation. This said, improved documentation isn’t always enough—as suggested by our discussion in Section 5.6.2, software engineers should explore further education to attain a greater appreciation of the nuances of ML when attempting to use these services.

5.6.3.4 *For Intelligent Service Providers*

Clarify use cases for IWSs Inspecting SO posts revealed that there is a level of confusion around the capabilities of different IWSs. This needs to be clarified in associated API documentation. The complication with this comes with targeting the documentation such that software developers (who are untrained in the nuances of AI and ML as per Section 5.6.3.2) can to digest it and apply it in-context to application development.

Technical domain matters More needs to be provided than a simple endpoint description as conventional APIs offer by describing the whole framework by which the endpoint sits, giving further context. This said, compared to traditional APIs, we find that developers complain less about the documentation and more about shallower issues. All expected pre-processing and post-processing needs to be clearly explained. A possible mitigation to this could be an interactive tutorial that helps developers fully understand the technical domain using a hands-on approach.

2667 For example, websites offer interactive Git tutorials⁷ to help developers understand
2668 and explore the technical domain matters under version control in their own pace.

2669 **Clarify limitations** API developers need to add clear limitations of the existing
2670 APIs. Limitations include list of objects that can be returned from an endpoint. We
2671 found that the cognitive anchors of how existing, conventional API documentation
2672 is written has become ‘ported’ to the computer vision realm, however a lot more
2673 overview documentation than what is given at present (i.e., better descriptions of
2674 errors, improved context of how these systems work in etc.) needs to be given. Such
2675 documentation could be provided using interactive tutorials.

2676 5.7 Threats to Validity

2677 5.7.1 Internal Validity

2678 As detailed in Section 5.4.3.1, Taxonomies A and B present slight and fair agreement,
2679 respectively, when inter-rater reliability was applied. The nature of our disagree-
2680 ments largely fell due to the subjectivity in applying either taxonomies to posts.
2681 Despite all coders agreeing to the shared interpretation of both taxonomies, both
2682 taxonomies are subjective in their application, which was not reported by either
2683 Aghajani et al. or Beyer et al.. In many cases, multi-label classification seemed ap-
2684 propriate, however both taxonomies use single-label mapping which we find results
2685 in too much subjectivity. This subjectivity, therefore, ultimately adversely affects
2686 inter-rater reliability (IRR) analysis. Thus, a future mitigation strategy for similar
2687 work should explore multi-label classification to avoid this issue; Beyer et al., for
2688 example, plan for multi-label classification as future work. However, these studies
2689 would need to consider the statistical challenges in calculating multi-rater, multi-
2690 label IRR for thorough reliability analysis in addressing subjectivity. The selection
2691 of SO posts used for our labelling, chiefly in the subjectivity of our classifications, is
2692 of concern. We mitigate this by an extensive review process assessing the reliability
2693 of our results as per Section 5.4.3.1. The classification of our posts into the SOLO
2694 and Bloom’s taxonomies was performed by the primary author only, and therefore
2695 no inter-rater reliability statistics were performed. However, we used these peda-
2696 gogy related taxonomies as a lens to gain an additional perspective to interpret our
2697 results. Future studies should attempt a more rigorous analysis of SO posts using
2698 Bloom’s and SOLO taxonomies. We only aligned posts to one category for each
2699 taxonomy and did not align these using multi-label classification. This brings more
2700 complexity to the analysis, and our attempts to repeat prior studies’ methodologies
2701 (see Section 5.3). Multi-label classification for IWSs SO posts is an avenue for future
2702 research.

⁷For example, <https://learngitbranching.js.org>.

2703 **5.7.2 External Validity**

2704 While every effort was made to select posts from SO relevant to CVSSs, there are
2705 some cases where we may have missed some posts. This is especially due to the
2706 case where some developers mis-reference certain IWSs under different names (see
2707 Section 5.4.2.1).

2708 Our SOLO and Bloom's taxonomy analysis has only been investigated through
2709 the lenses of IWSs, and not in terms of conventional APIs (e.g., Andriod APIs).
2710 Therefore, we are not fully certain how these results found would compare to other
2711 types of APIs. Two *existing* SO classification taxonomies were used rather than
2712 developing our own. We wanted to see if previous SO taxonomies could be applied
2713 to IWSs before developing a new, specific taxonomy, and these taxonomies were
2714 applied based on our interpretation (see Section 5.4.2.4) and may not necessarily
2715 reflect the interpretation of the original authors. Moreover, automated techniques
2716 such as topic modelling were not utilised as we found these produce descriptive
2717 classifications only (see Section 5.3). Hence, manual analysis was performed by
2718 humans to ensure categories could be aligned back to causal factors. Only English-
2719 speaking IWSs were selected; the applicability of our analysis to other, non-English
2720 speaking services may affect results. Use of computer vision in this study is an
2721 illustrative example to focus on one area of the IWSs spectrum. While our narrow
2722 scope helps us obtain more concrete findings, we suggest that wider issues exist in
2723 other IWS domains may affect the generalisability of this study, and suggest future
2724 work be explored in this space.

2725 **5.7.3 Construct Validity**

2726 Some questions extracted from SO produced false positives, as mentioned in Sec-
2727 tions 5.4.2.1, 5.4.2.3 and 5.5. However, all non-relevant posts were marked as noise
2728 for our study, and thus did not affect our findings. Moreover, SO is known to have
2729 issues where developers simply ask basic questions without looking at the actual
2730 documentation where the answer exists. Such questions, although down-voted, were
2731 still included in our data-set analysis, but as these were SO few, it does not have a
2732 substantial impact on categorised posts.

2733 **5.8 Conclusions**

2734 CVSSs offer powerful capabilities that can be added into the developer's toolkit via
2735 simple RESTful APIs. However, certain technical nuances of computer vision
2736 become abstracted away. We note that this abstraction comes at the expense of a full
2737 appreciation of the technical domain, context and proper usage of these systems. We
2738 applied two recent existing SO classification taxonomies (from 2018 and 2019) to see
2739 if existing taxonomies are able to fully categorise the types of complaints developers
2740 have. IWSs have a diverging distribution of the types of issues developers ask
2741 when compared to more mature domains (i.e., mobile app development and web
2742 development). Developers are more likely to complain about shallower, simple

2743 debugging issues without a distinct understanding of the AI algorithms that actually
2744 empower the APIs they use. Moreover, developers are more likely to complain about
2745 the completeness and correctness of existing IWS documentation, thereby suggesting
2746 that the documentation approach for these services should be reconsidered. Greater
2747 attention to education in the use of AI-powered APIs and their limitations is needed,
2748 and our discussion offered in Section 5.6.2 motivates future work in resolving these
2749 issues in the software engineering education space.

CHAPTER 6

2750

2751

2752

2753

Ranking Computer Vision Service Issues using Emotion[†]

2754 **Abstract** Software developers are increasingly using intelligent web services to implement
2755 ‘intelligent’ features. Studies show that incorporating AI into an application increases tech-
2756 nical debt, creates data dependencies, and introduces uncertainty due to non-deterministic
2757 behaviour. However, we know very little about the emotional state of software developers
2758 who deal with such issues. In this paper, we do a landscape analysis of emotion found in
2759 1,425 Stack Overflow posts about computer vision services. We investigate the application
2760 of an existing emotion classifier EmoTxt and manually verify our results. We found that the
2761 emotion profile varies for different question categories.

2762 6.1 Introduction

2763 Recent advances in artificial intelligence have provided software engineers with
2764 new opportunities to incorporate complex machine learning capabilities, such as
2765 computer vision, through cloud-based intelligent web services (IWSs). These new
2766 set of services, typically offered as API calls are marketed as a way to reduce the
2767 complexity involved in integrating AI-components. However, recent work shows that
2768 software engineers struggle to use these IWSs [91]. Furthermore, the accompanying
2769 documentation fails to address common issues experienced by software engineers
2770 and, often, engineers resort to online communication channels, such as, JIRA and
2771 Stack Overflow (SO) to seek advice from their peers [91].

2772 While seeking advice on the issues, software engineers tend to express their emo-
2773 tions (such as frustration or confusion) within the questions. Recognising the value
2774 of considering emotions, other researchers have investigated emotions expressed by

[†]This chapter is originally based on A. Cummaudo, U. Graetsch, M. Curumsing, S. Barnett, R. Vasa, and J. Grundy, “Manual and Automatic Emotion Analysis of Computer Vision Service Pain-Points,” in *Proceedings of the Sixth International Workshop on Emotion Awareness in Software Engineering*. Virtual Event, USA: IEEE, 2021, In Review. Terminology has been updated to fit this thesis.

2775 software developers within communication channels [266] including SO [68, 259];
2776 the broad motivation of these works is to generally understand the emotional land-
2777 scape and improve developer productivity [126, 247, 266]. However, previous works
2778 have not directly focused on the nature of emotions expressed in questions related to
2779 IWSs. We also do not know if certain types of questions express stronger emotions.

2780 The machine-learnt behaviour of these IWSs is typically non-deterministic and,
2781 given the dimensions of data used, their internal inference process is hard to reason
2782 about [88]. Compounding the issue, documentation of these cloud systems does not
2783 explain the limits, nor how they were created (esp. data sets used to train them).
2784 This lack of transparency makes it difficult for even senior developers to properly
2785 reason about these systems, so their prior experience and anchors do not offer
2786 sufficient support [91]. In addition, adding machine learned behaviour to a system
2787 incurs ongoing maintenance concerns [317]. There is a need to better understand
2788 emotions expressed by developers to inform cloud vendors and help them improve
2789 their documentation and error messages provided by their services.

2790 This work builds on top of recent work that explored *what* pain-points developers
2791 face when using IWSs through a general analysis of 1,425 SO posts (questions) [91]
2792 using an existing SO issue classification taxonomy [39]. In this work, we consider
2793 the emotional state expressed within these pain-points, using the same data set of
2794 1,425 SO posts. We identify the emotions in each SO question, and investigate if
2795 the distribution of these emotions is similar across the various types of questions.

2796 In order to classify emotions from SO posts, we use EmoTxt, a recently proposed
2797 toolkit for emotion recognition from text [67, 68, 259]. EmoTxt has been trained
2798 and built on SO posts using the emotion classification model proposed by Shaver
2799 et al. [323]. The category of issue was manually determined in our prior work.

2800 The key findings of our study are:

- 2801 • The distribution of emotions is different across the taxonomy of issues.
- 2802 • A deeper analysis of the results, obtained from the EmoTxt classifier, suggests
2803 that the classification model needs further refinement. Love and joy, the
2804 least expected emotions when discussing API issues, are visible across all
2805 categories.
- 2806 • A different emotion classification scheme is required to better reflect the
2807 emotions within the questions.

2808 In order to promote future research and permit replication, we make our data
2809 set publicly available.¹ The paper structure is as follows: Section 6.2 provides
2810 an overview on prior work surrounding the classification of emotions from text;
2811 Section 6.3 describes our research methodology; Section 6.4 presents the results
2812 from the EmoTxt classifier; Section 6.5 provides a discussion of the results obtained;
2813 Section 6.6 outlines the threats to validity; Section 6.7 presents the concluding
2814 remarks.

¹See <http://bit.ly/2RiULgW>.

2815 6.2 Emotion Mining from Text

2816 Several studies have investigated the role of emotions generally in software development [126, 266, 324, 381]. Work in the area of behavioural software engineering
2817 established the link between software developer's happiness and productivity [143].
2818 Wrobel [381] investigated the impact that software developers' emotion has on the
2819 development process and found that frustration and anger were amongst the emotions
2820 that posed the highest risk to developer's productivity.
2821

2822 Recent studies focused on emotion mining from text within communication chan-
2823 nels used by software engineers to communicate with their peers [126, 247, 259,
2824 266]. Murgia et al. [247] and Ortú et al. [266] investigated the emotions expressed
2825 by developers within an issue tracking system, such as JIRA, by labelling issue com-
2826 ments and sentences written by developers using Parrott's framework. Gachechiladze
2827 et al. [126] applied the Shaver framework to detect anger expressed in comments
2828 written by developers in JIRA. The Collab team [67, 259] extended the work done
2829 by Ortú et al. [266] and developed a gold standard data set collected from SO
2830 posts consisting of questions, comments and feedback. This data set was manually
2831 annotated using the Shaver's emotion model. The Shaver's model consists of a tree-
2832 structured, three level, hierarchical classification of emotions. The top level consists
2833 of six basic emotions namely, love, joy, anger, sadness, fear and surprise [323]. The
2834 subsequent levels further refines the granularity of the previous level. One of their
2835 recent work [259] involved 12 raters to manually annotate 4,800 posts (where each
2836 post included the question, answer and comments) from SO. The same question
2837 was assigned to three raters to reduce bias and subjectivity. Each coder was re-
2838 quested to indicate the presence/absence of each of the six basic emotions from the
2839 Shaver framework. As part of their work they developed an emotion mining toolkit,
2840 EmoTxt [67]. The work conducted by the Collab team is most relevant to our study
2841 since their focus is on identifying emotion from SO posts and their toolkit is trained
2842 on a large data set of SO posts.

2843 6.3 Methodology

2844 As mentioned in our introduction, this paper uses the data set reported in Cummaudo
2845 et al.'s ICSE 2020 paper [91]. As this paper is in press, we reproduce a summary
2846 of the methodology used in constructing this data set methodology below. For full
2847 details, we refer to the original paper. Supplementary materials used for this work
2848 are provided for replication.¹

2849 Our research methodology consisted of the following steps: (i) data extraction
2850 from SO resulting in 1,425 questions about intelligent computer vision services
2851 (CVSs); (ii) question classification using the taxonomy presented by Beyer et al. [39];
2852 (iii) automatic emotion classification using EmoTxt based on Shaver et al.'s emotion
2853 taxonomy [323]; and (iv) manual classification of 25 posts to better understand
2854 developers emotion. We calculated the inter-rater reliability between EmoTxt and
2855 our manually classified questions in two ways: (i) to see the overall agreement
2856 between the three raters in applying the Shaver et al. emotions taxonomy, and (ii) to

²⁸⁵⁷ see the overall agreement with EmoTxt’s classifications. Further details are provided
²⁸⁵⁸ below.

²⁸⁵⁹ 6.3.1 Data Set Extraction from Stack Overflow

²⁸⁶⁰ 6.3.1.1 Intelligent Service Selection

²⁸⁶¹ We contextualise this work within popular CVS providers: Google Cloud [417],
²⁸⁶² AWS [392], Azure [431] and IBM Cloud [427]. We chose these four providers given
²⁸⁶³ their prominence and ubiquity as cloud service vendors, especially in enterprise
²⁸⁶⁴ applications [299]. We acknowledge other services beyond the four analysed which
²⁸⁶⁵ provide similar capabilities [405, 406, 413, 426, 478, 479]. Additionally, only
²⁸⁶⁶ English-speaking services have been selected, excluding popular CVSs from Asia
²⁸⁶⁷ (e.g., [403, 404, 425, 444, 445]).

²⁸⁶⁸ 6.3.1.2 Developing a search query

²⁸⁶⁹ To understand the various ways developers refer to these services, we needed to find
²⁸⁷⁰ search terms that are commonplace in question titles and bodies that discuss the
²⁸⁷¹ service names. One approach is to use the *Tags* feature in SO. To discover which
²⁸⁷² tags may be relevant, we ran a search² within SO against the various brand names of
²⁸⁷³ these CVSs, reviewed the first three result pages, and recorded each tag assigned per
²⁸⁷⁴ question.³ However, searching using tags alone on SO is ineffective (see [28, 345]).
²⁸⁷⁵ To overcome this limitation, we ran a second query within the Stack Exchange Data
²⁸⁷⁶ Explorer⁴ (SEDE) using these tags, we sampled 100 questions (per service), and
²⁸⁷⁷ noted the permutations in how developers refer to each service⁵. We noted 229
²⁸⁷⁸ permutations.

²⁸⁷⁹ 6.3.1.3 Executing our search query

²⁸⁸⁰ Next, we needed to extract questions that make reference to any of these 229 per-
²⁸⁸¹ mutations. SEDE has a 50,000 row limit and does not support case-insensitivity,
²⁸⁸² however Google’s BigQuery does not. Therefore, we queried Google’s SO dataset
²⁸⁸³ on each of the 229 terms that may occur within the title or body of question posts,⁶
²⁸⁸⁴ which resulted in 21,226 questions.

²⁸⁸⁵ 6.3.1.4 Refining our inclusion/exclusion criteria

²⁸⁸⁶ To assess the suitability of these questions, we filtered the 50 most recent posts
²⁸⁸⁷ as sorted by their *CreationDate* values. This helped further refine the inclusion
²⁸⁸⁸ and exclusion criteria: for example, certain abbreviations in our search terms (e.g.,

²The query was run on January 2019.

³Up to five tags can be assigned per question.

⁴<http://data.stackexchange.com/stackoverflow>

⁵E.g., misspellings, misunderstanding of brand names, hyphenation, UK vs. US English, and varied uses of apostrophes, plurals, and abbreviations.

⁶See <http://bit.ly/2LrN70A>.

Table 6.1: Descriptions of dimensions from our interpretation of Beyer et al.’s SO question type taxonomy.

Dimension	Our Interpretation
API usage	Issue on how to implement something using a specific component provided by the API
Discrepancy	The questioner’s <i>expected behaviour</i> of the API does not reflect the API’s <i>actual behaviour</i>
Errors.....	Issue regarding an error when using the API, and provides an exception and/or stack trace to help understand why it is occurring
Review	The questioner is seeking insight from the developer community on what the best practices are using a specific API or decisions they should make given their specific situation
Conceptual.....	The questioner is trying to ascertain limitations of the API and its behaviour and rectify issues in their conceptual understanding on the background of the API’s functionality
API change.....	Issue regarding changes in the API from a previous version
Learning	The questioner is seeking for learning resources to self-learn further functionality in the API, and unlike discrepancy, there is no specific problem they are seeking a solution for

²⁸⁸⁹ ‘GCV’, ‘WCS’⁷) allowed for false positive questions to be included, which were
²⁸⁹⁰ removed. Furthermore, we consolidated all overlapping terms (e.g., ‘Google Vision
²⁸⁹¹ API’ was collapsed into ‘Google Vision’) to enhance the query. Additionally, we
²⁸⁹² reduced our 221 search terms to just 27 search terms by focusing on CVSs *only*⁸
²⁸⁹³ which resulted in 1,425 questions. No duplicates were recorded as determined by
²⁸⁹⁴ the unique ID, title and timestamp of each question.

²⁸⁹⁵ 6.3.1.5 *Manual filtering*

²⁸⁹⁶ The next step was to assess the suitability and nature of the 1,425 questions extracted.
²⁸⁹⁷ The second author ran a manual check on a random sample of 50 posts, which were
²⁸⁹⁸ parsed through a templating engine script⁹ in which the ID, title, body, tags, created
²⁸⁹⁹ date, and view, answer and comment counts were rendered for each post. Any match
²⁹⁰⁰ against the 27 search terms in the title or body of the post were highlighted, in which
²⁹⁰¹ three false positives were identified as either library imports or stack traces, such
²⁹⁰² as `aws-java-sdk-rekognition.jar`. In addition, we noted that there were false
²⁹⁰³ positive hits related to non-CVSs. We flagged posts of such nature as ‘noise’ and
²⁹⁰⁴ removed them from further classification.

⁷Watson Cognitive Services

⁸Our original data set aimed at extracting posts relevant to *all* IWSs, and not just CVSs. However, 21,226 questions were too many to assess without automated analysis, which was beyond the scope of our work.

⁹We make this available for future use at: <http://bit.ly/2NqBB70>.

2905 6.3.2 Question Type & Emotion Classification

2906 6.3.2.1 Manual classification of question category

2907 We classify our 1,425 posts using Beyer et al.'s taxonomy [39] as it was comprehensive and validated [91]. We split the posts into 4 additional random samples, in
 2908 addition to the random sample of 50 above. 475 posts were classified by the second
 2909 author and three other research assistants¹⁰ classified the remaining 900 (i.e., a total
 2910 of 1,375 classifications). An additional 450 classifications were assigned due to
 2911 reliability analysis, in which the remaining 50 posts were classified nine times by
 2912 various researchers in our group.¹¹

2913 Due to the nature of reliability analysis, multiple classifications (450) existed
 2914 for these 50 posts. Therefore, we applied a 'majority rule' technique to each post
 2915 allowing for a single classification assignment and therefore analysis within our re-
 2916 sults. When there was a majority then we used the majority classification; when
 2917 there was a tie, then we used the classification that was assigned the most out of the
 2918 entire 450 classifications. As an example, 3 raters classified a post as *API Usage*,
 2919 1 rater classified the same post as a *Review* question and 5 raters classified the post
 2920 as *Conceptual*, resulting in the post being classified as a *Conceptual* question. For
 2921 another post, three raters assigned *API Usage*, *Discrepancy* and *Learning* (respec-
 2922 tively), while 3 raters assigned *Review* and 3 raters assigned *Conceptual*. In this
 2923 case, *Review* and *Conceptual* were tied, but was resolved down to *Conceptual* as this
 2924 classification received 147 more votes than *Review* across all classifications made in
 2925 the sample of 50 posts.

2926 However, where a post was extracted from our original 1,425 posts but was either
 2927 a false positive, not applicable to IWSs (see Section 6.3.1.5), or not applicable to
 2928 a taxonomy dimension/category, then the post was flagged for removal in further
 2929 analysis. This was done 180 times, leaving a total of 1,245 posts.

2930 Our interpretation Beyer et al.'s taxonomy is provided in Table 6.1, which
 2931 presents a transcription of *our understanding* of the respective taxonomy. We
 2932 baselined all coding against *our interpretation only*, and thus our classifications
 2933 are therefore independent of Beyer et al.'s findings, since we baseline results via
 2934 Table 6.1's interpretation.

2936 6.3.2.2 Emotion classification using AI techniques

2937 After extracting and classifying all posts, we then piped in the body of each question
 2938 into a script developed to remove all HTML tags, code snippets, blockquotes and
 2939 hyperlinks, as suggested by Novielli et al. [259]. We replicated and extended the
 2940 study conducted by Novielli et al. [259] on our data set derived from 1,425 SO posts,
 2941 consisting of questions only. Our study consisted of three main steps, namely, (1)
 2942 automatic emotion classification using EmoTxt, (2) manual annotation process and,
 2943 (3) comparison of the automatic classification result with the manually annotated
 2944 data set.

¹⁰Software engineers in our research group with at least 2 years industry experience

¹¹Due to space limitations, reliability analysis is omitted and is reported in [91].

2945 6.3.2.3 Emotion classification using EmoTxt

2946 We started with a file containing 1,245 non-noise SO questions, each with an as-
2947 sociated question type as classified using the strategy discussed in Section 6.3.2.1.
2948 We pre-processed this file by extracting the question ID and body text to meet the
2949 format requirements of the EmoTxt classifier [67]. This classifier was used as it
2950 was trained on SO posts as discussed in Section 6.2. We ran the classifier for each
2951 emotion as this was required by EmoTxt model. This resulted in 6 output prediction
2952 files (one file for each emotion: *Love, Joy, Surprise, Sadness, Fear, Anger*). Each
2953 question within these files referenced the question ID and a predicted classification
2954 (YES or NO) of the emotion. We then merged the emotion prediction files into an
2955 aggregate file with question text and Beyer et al.’s taxonomy classifications. This
2956 resulted in 796 emotion classifications. We further analysed the classifications and
2957 generated an additional classification of *No Emotion* for the 622 questions where
2958 EmoTxt predicted NO for all the emotion classification runs.

2959 Of the 796 questions with emotion detected, 143 questions had 2 or more
2960 emotions predicted: 1 question¹² had up to 4 emotions detected (*Surprise, Sadness,*
2961 *Joy and Fear*), 28 questions had up to 3 emotions detected, and the remaining 114
2962 had up to two emotions detected.

2963 6.3.2.4 Manual Annotation Process

2964 In order to evaluate and also better understand the process used by EmoTxt to
2965 classify emotions, we manually annotated a small sample of 25 SO posts, randomly
2966 selected from our data set. Each of these 25 posts were assigned to three raters who
2967 carried out the following three steps: (i) identify the presence of an emotion; (ii)
2968 if an emotion(s) exists, classify the emotion(s) under one of the six basic emotions
2969 proposed by the Shaver framework [323]; (iii) if no emotion is identified, annotate as
2970 neutral. We then collated all rater’s results and calculated Light’s Kappa (L_K) [212]
2971 to measure the overall agreement *between* raters to measure the similarity in which
2972 independent raters classify emotions to SO posts. As L_K does not support multi-
2973 class classification (i.e., multiple emotions) per subjects (i.e., per SO post), we
2974 binarised the results each emotion and rater as TRUE or FALSE to indicate presence,
2975 calculated the L_K per emotion against the three raters, and averaged the result across
2976 all emotions to get an overall strength of agreement.

2977 6.3.2.5 Comparing EmoTxt results with the results from Manual Classification

2978 The next step involved comparing the ratings of the 25 SO posts that were manually
2979 annotated by the three raters with the results obtained for the same set of 25 SO
2980 posts from the EmoTxt classifier. Similar to Section 6.3.2.4, we used Cohen’s Kappa
2981 (C_K) [81] to measure the consistency of classifications of EmoTxt’s classifications
2982 versus the manual classifications of each rater. We separated the classifications
2983 per emotion and calculated C_K for each rater against EmoTxt and averaged these
2984 values for all emotions. After noticing poor results, the three raters involved in

¹²See <http://stackoverflow.com/q/55464541>.

²⁹⁸⁵ Section 6.3.2.4 were asked to compare and discuss the ratings from the EmoTxt
²⁹⁸⁶ classifier against the manual ratings.

²⁹⁸⁷ The findings from this process are presented and discussed in the next two
²⁹⁸⁸ sections.

²⁹⁸⁹ 6.4 Findings

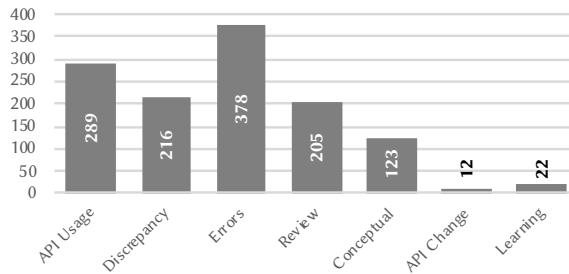


Figure 6.1: Distribution of SO question types.

²⁹⁹⁰ Figure 6.1 displays the overall distribution of question types from the 1,245
²⁹⁹¹ posts classified in [91], when adjusted for majority ruling as per Section 6.3.2.1. It
²⁹⁹² is evident that developers ask issues predominantly related to API errors when using
²⁹⁹³ CVSs and, additionally, how they can use the API to implement specific functionality.
²⁹⁹⁴ There are few questions related to version issues or self-learning.

Table 6.2: Frequency of emotions per question type.

Question Type	Fear	Joy	Love	Sadness	Surprise	Anger	No Emotion	Total
API Usage	50	22	34	18	59	13	135	331
Discrepancy	38	12	18	7	48	20	108	251
Errors	69	34	22	21	48	23	206	423
Review	34	16	15	16	42	14	98	235
Conceptual	26	10	10	7	21	5	59	138
API Change	4	2	2	1	1	1	5	16
Learning	3	4	2	0	4	0	11	24
Total	224	100	103	70	223	76	622	1418

²⁹⁹⁵ Table 6.2 displays the frequency of questions that were classified by EmoTxt
²⁹⁹⁶ when compared to our assignment of question types, while Figure 6.2 presents the
²⁹⁹⁷ emotion data proportionally across each type of question. *No Emotion* was the
²⁹⁹⁸ most prevalent across all question types, which is consistent with the findings of the
²⁹⁹⁹ Collab group during the training of the EmoTxt classifier. Interestingly, *API Change*
³⁰⁰⁰ questions had a distinct distribution of emotions, where 31.25% of questions had *No*
³⁰⁰¹ *Emotion* compared to the average of 42.01%. This is likely due to the low sample
³⁰⁰² size of *API Change* questions, with only 12 assignments, however the next highest
³⁰⁰³ set of emotive questions are found in the second largest sample (*API Usage*, at
³⁰⁰⁴ 59.21%) and so greater emotion detected is not necessarily proportional to sample

size. Unsurprisingly, *Discrepancy* questions had the highest proportion of the *Anger* emotion, at 7.97%, compared to the mean of 4.74%, which is indicative of the frustrations developers face when the API does something unexpected. *Love*, an emotion which we expected least by software developers when encountering issues, was present across the different question types. The two highest emotions, by average, were *Fear* (16.67%) and *Surprise* (14.90%), while the two lowest emotions were *Sadness* (4.47%) and *Anger* (4.74%). *Joy* and *Love* were roughly the same and fell in between the two proportion ends, with means of 8.96% and 8.16%, respectively.

Results from our reliability analysis showed largely poor results. Guidelines of indicative strengths of agreement are provided by Landis and Koch [207], where $\kappa \leq 0.000$ is *poor agreement*, $0.000 < \kappa \leq 0.200$ is *slight agreement* and $0.200 < \kappa \leq 0.400$ is *fair agreement*. Our readings were indicative of poor agreement between raters ($C_\kappa = -0.003$) and slight agreement with EmoTxt ($L_\kappa = 0.155$). The strongest agreements found were for *No Emotion* both between each of our three raters ($L_\kappa = 0.292$) and each rater and EmoTxt ($C_\kappa = 0.086$), with fair and slight agreement respectively.

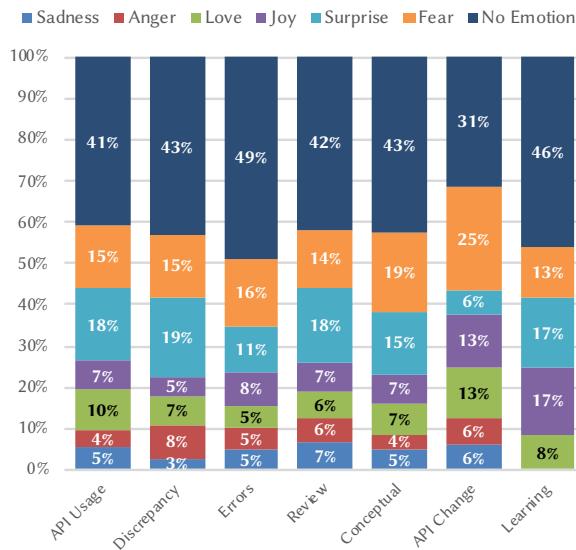


Figure 6.2: Proportion of emotions per question type.

6.5 Discussion

Our findings from the comparison between the manually annotated SO posts and the automatic classification revealed substantial discrepancies. Table 6.3 provide some sample questions from our data set and the emotion identified by EmoTxt within the text. A subset of questions analysed by our three raters do not indicate the automatic (EmoTxt) emotion, and upon manual inspection of the text after poor

Table 6.3: Sample questions comparing question type to emotion. Questions located at [https://stackoverflow.com/q/\[ID\]](https://stackoverflow.com/q/[ID]).

ID	Quote	Classification	Emotion
53249139	<i>"I'm trying to integrate my project with Google Vision API... I'm wondering if there is a way to set the credentials explicitly in code as that is more convenient than setting environment variables in each and every environment we are running our project on... I know for a former client version 1.22 that was possible... but for the new client API I was not able to find the way and documentation doesn't say anything in that regards."</i>	API Usage	Fear
40013910	<i>"I want to say something more about Google Vision API Text Detection, maybe any Google Expert here and can read this. As Google announced, their TEXT_DETECTION was fantastic... But for some of my pics, what happened was really funny... There must be something wrong with the text detection algorithm."</i>	Discrepancy	Anger
50500341	<i>"I just started using PYTHON and now i want to run a google vision cloud app on the server but I'm not sure how to start. Any help would be greatly appreciated."</i>	API Usage	Sadness
49466041	<i>"I am getting the following error when trying to access my s3 bucket... my hunch is it has something to do with the region...I have given almost all the permissions to the user I can think of.... Also the region for the s3 bucket appears to be in a place that can work with rekognition. What can I do?"</i>	Errors	Surprise
55113529	<i>"Following a tutorial, doing everything exactly as in the video... Hoping to figure this out as it is a very interesting concept...Thanks for the help... I'm getting this error:..."</i>	Errors	Joy
39797164	<i>"Seems that the Google Vision API has moved on and the open Sourced version has not....In my experiments this 'finds' barcodes much faster than using the processor that the examples show. Am I missing something somewhere?"</i>	API Change	Love

3028 results from our reliability analysis, an introspection of the data set sheds some light
3029 to the discrepancy. For example, question 55113529 shows no indication of *Joy*,
3030 rather the developer is expressing a state of confusion. The phrase “*Thanks for your*
3031 *help*” could be the reason why the miss-classification occurred if words like “thanks”
3032 were associated with joy. However, in this case, it seems unlikely that the developer
3033 is expressing joy as the developer has followed a tutorial but is still encountering
3034 an error. Similarly, question 39797164, classified as *Love* and question 50500341,
3035 classified as *Sadness* express a state of confusion and the urge to know more about the
3036 product; upon inspecting the entire question in context, it is difficult to consistently
3037 agree with the emotions as determined by EmoTxt, and further exploration into the
3038 behaviour and limitations of the model is necessary.

3039 Our results indicate further work is needed to refine the machine learning (ML)
3040 classifiers that mine emotions in the SO context. The question that arises is whether
3041 the classification model is truly reflective of real-world emotions expressed by soft-
3042 ware developers. As highlighted by Curumsing [93], the divergence of opinions with
3043 regards to the emotion classification model proposed by theorists raises doubts to the
3044 foundations of basic emotions. Most of the studies conducted in the area of emotion
3045 mining from text is based on an existing general purpose emotion framework from
3046 psychology [63, 259, 266]—none of which are tuned for software engineering do-
3047 main. In our study, we note the emotions expressed by software developers within
3048 SO posts are quite narrow and specific. In particular, emotions such as frustration
3049 and confusion would be more appropriate over love and joy.

3050 **6.6 Threats to Validity**

3051 **6.6.1 Internal Validity**

3052 The *API Change* and *Learning* question types were few in sample size (only 12 and
3053 22 questions, respectively). The emotion proportion distribution of these question
3054 types are quite different to the others. Given the low number of questions, the sample
3055 is too small to make confident assessments. Furthermore, our assignment of Beyer
3056 et al.’s question type taxonomy was single-label; a multi-labelled approach may work
3057 better, however analysis of results would become more complex. A multi-labelled
3058 approach would be indicative for future work.

3059 **6.6.2 External Validity**

3060 EmoTxt was trained on questions, answers and comments, however our data set
3061 contained questions only. It is likely that our results may differ if we included other
3062 discussion items, however we wished to understand the emotion within developers’
3063 *questions* and classify the question based on the question classification framework
3064 by Beyer et al. [39]. Moreover, this study has only assessed frustrations within the
3065 context of a concrete domain of CVSs. The generalisability of this study to other
3066 IWSs, such as natural language processing services, or conventional web services,
3067 may be different. Furthermore, we only assessed four popular CVSs; expanding the

3068 data set to include more services, including non-English ones, would be insightful.
3069 We leave this to future work.

3070 **6.6.3 Construct Validity**

3071 Some posts extracted from SO were false positives. Whilst flagged for removal
3072 (Section 6.3.1.5), we cannot guarantee that all false positives were removed. Fur-
3073 thermore, SO is known to have questions that are either poorly worded or poorly
3074 detailed, and developers sometimes ask questions without doing any preliminary
3075 investigation. This often results in down-voted questions. We did not remove such
3076 questions from our data set, which may influence the measurement of our results.

3077 **6.7 Conclusions**

3078 In this paper we analysed SO posts for emotions using an automated tool and cross-
3079 checked it manually. We found that the distribution of emotion differs across the
3080 taxonomy of issues, and that the current emotion model typically used in recent
3081 works is not appropriate for emotions expressed within SO questions. Consistent
3082 with prior work [214], our results demonstrate that machine learning classifiers for
3083 emotion are insufficient; human assessment is required.

CHAPTER 7

3084

3085

3086 Using Emotion Classification Models against Stack Overflow[†]

3087

3088 **Abstract** Pre-trained AI models are increasingly available as APIs and tool-kits to soft-
3089 ware engineers, making complex AI-enabled functionality available via standard and well-
3090 understood methods. However, reusing such models comes with risks relating to the lack of
3091 transparency of the model and training data bias, making it difficult to confidently employ
3092 the toolkit in a new situation. Vendors are responding and proposing artefacts such as
3093 model cards and datasheets to make models and their training more transparent. But is this
3094 enough? As part of an investigation into determining if a cloud-based intelligent web service
3095 was ready for production use, we processed developer questions on Stack Overflow using
3096 a published pre-trained classifier that was specifically tuned for the software engineering
3097 domain. In this paper, we present lessons learnt in this automation effort. We find the results
3098 were unexpected and led us to delve into model and training data—an option available to
3099 us because the information was available for research. We found that had a model card and
3100 datasheet been prepared, we could have identified risks to our study earlier on. However,
3101 model cards and datasheets specifications are not yet mature enough and additional tools
3102 and processes are still required to confirm a decision whether a model can be reused with
3103 confidence.

3104 7.1 Introduction

3105 Pre-trained AI models are increasingly available to software engineers either directly
3106 or wrapped into web-based components and toolkits.¹ The grand promise is the
3107 rapid creation of AI-infused functionality into end-applications as developers can
3108 simply reuse models instead of training them from scratch, as training is laborious

[†]This chapter is originally based on U. M. Graetsch, A. Cummaudo, M. K. Curumsing, R. Vasa, and J. Grundy, “Using Pre-Trained Emotion Classification Models against Stack Overflow Questions,” in *Proceedings of the 33rd International Conference on Advanced Information Systems Engineering*. Melbourne, VIC, Australia: Springer, 2021, In Review. Terminology has been updated to fit this thesis.

¹For example, Google’s Cloud AI or Microsoft Azure’s Cognitive Services.

3109 and resource-intensive [291]. Vendors do provide usage guidelines, component
3110 documentation, code examples and a compelling marketing narrative, although the
3111 limitations and risks are not as well-presented in official documentation [88, 91]. In
3112 practice, developers and technical architects study issue trackers and online forums
3113 such as Stack Overflow (SO) to assess and inform their decisions. This is also
3114 complemented by multiple studies that highlight the value and insights to be gained
3115 from these online forums [2, 335].

3116 This paper is the result of an investigation into determining if cloud-based
3117 intelligent web services (IWSs) are ready for a specific industry use case. Inspired
3118 by the possibility of finding insight from content in the online forums, we wanted to
3119 analyse the questions posed and issues raised—in particular on SO—that relate to
3120 that relate to IWSs that provide computer vision (i.e., computer vision services or
3121 CVSSs). Although a manual analysis is possible, we wanted to automate this process
3122 using natural language processing techniques, which was motivated by (i) the gain
3123 from automation—specifically having a repeatable process that can be tuned to focus
3124 on different aspects—and, more importantly, (ii) to learn about potential issues with
3125 these pre-trained models as we use one of these services to turn on themselves.

3126 In our analysis, beyond the direct summative aspects, we focused on emotions
3127 within the content posed on the online forums. This was motivated by work done
3128 by Wrobel [381], who suggested that frustration and anger were amongst the emotions
3129 that posed the highest risk to developer productivity. Our goal was to determine
3130 if negative emotions such as anger or frustration are the predominant theme within
3131 questions on these forums: the natural expectation is that developers would not pose
3132 questions unless they needed support and help. Similarly, we would expect the tone
3133 of responses to be neutral and hopefully supportive. Our focus, however, remains
3134 on the questions posed.

3135 Our findings, elaborated further in Section 7.2.3, were surprising. While the
3136 pre-trained model we selected was trained specifically on SO and tuned for emotions
3137 [67, 259], our results show that 14% issues can be considered in the category
3138 of *Love* or *Joy*, and a surprising small amount (5%) are in the category of *Anger* (or
3139 frustration). A closer examination using multiple human reviewers showed an even
3140 more interesting insight: the reviewers did not agree with the automated machine
3141 classification, and worse, the reviewers did not agree with each other, suggesting that
3142 training machines with a consistent set of labels is a non-trivial exercise. Finally,
3143 we reflected whether the pre-trained classifier could be better documented. We
3144 found vendors are recognising these challenges and are offering solutions to better
3145 document their models [132, 244]. However, when we looked into the information
3146 captured by these solutions, we found their specification to be very broad and addi-
3147 tional guidance for completion is required to help evaluate risks faced in an industry
3148 context (discussed in Section 7.3.3).

3149 7.2 Case Study

3150 In this section, we discuss the case study which inspired the initial objective of
3151 investigating if cloud-based IWSs were ready for use in an industrial context. To

3152 permit replication, the raw results produced from this case study are made available
3153 online at <https://bit.ly/36DIARI>.

3154 7.2.1 Scope

3155 To align with our use case, we narrowed our focus to cloud-based computer vision
3156 services (CVSs). Recent research has identified growth in questions on SO relating
3157 to such services, giving us confidence that we would have a rich data set [91]. We
3158 decided to explore emotions expressed by developers through the questions they
3159 pose on SO to identify whether developers are surprised, angry, frustrated, or overall
3160 positive? Previous works into developer questions show that despite the technical
3161 nature, their communications on SO do exhibit emotions [67, 258]. Although we
3162 could have read these posts manually, for consistency, repeatability, and efficiency,
3163 we chose to automate this process by utilising an emotion aware text classification
3164 system trained specifically on SO [259]. Our expectation was that we would gain
3165 some insight into the questions through the emotions, and we hypothesised that we
3166 would see a high proportion of surprise (i.e., the API does not work as expected)
3167 and anger (frustration due to mismatched expectations).

3168 7.2.2 Method

3169 We selected a published peer-reviewed emotion model as the text classifier. This
3170 classifier is included in the EMTk toolkit and has been specifically trained for emotional
3171 text classification in the software engineering domain [67]. The EMTk toolkit is
3172 available with a fully labelled training dataset [259], permitting reuse and analysis of
3173 internals. The classifier is based on Shaver et al.'s emotional hierarchy model [323]
3174 and performs binary classifications against text data provided in input files and an
3175 input parameter designating the emotion to be classified—one of *Love, Joy, Surprise,*
3176 *Fear, Sadness or Anger*. As input for the classifier, we used a dataset of the 1,425
3177 SO questions restricted to intelligent CVSs available in [91] and we ran the classifier
3178 with the same input dataset for each of the six emotions. To cross-check classified
3179 output, we manually annotated a random sample of 25 questions. Each of these 25
3180 posts were assigned to three raters who carried out the following three steps: (i)
3181 identify the presence of emotion(s); (ii) if emotion(s) exists, classify the emotion(s)
3182 under one of the six basic emotions as per the Shaver framework. After collating
3183 each rater's results, we calculated a Fleiss' Kappa [118] as a measure of inter-rater
3184 agreement per emotion for each of the three human raters (manual rating). We
3185 then used the results from the classifier as a 'fourth' *automated* rater, comparing
3186 the results with the manual rating by calculating the agreement for each emotion
3187 and calculated the observed percentage of agreement and Fleiss' Kappa for further
3188 inter-rater agreement analysis.

3189 7.2.3 Results

3190 Of the 1,425 SO questions, the classifier did not classify any emotion to 622 posts
3191 (labelled *No Emotion*). The remaining posts were classified: 224 posts as *Fear*, 223

Table 7.1: Results from Inter-Rater Agreements.

Emotion	Three Raters	Three Raters + Classifier
Anger	0.256	0.145
Fear	-0.014	-0.075
Joy	0.306	0.132
Love	1.000	-0.031
Sadness	-0.071	-0.053
Surprise	-0.056	-0.091
No Emotion	0.265	0.139

as *Surprise*, 70 as *Sadness*, 103 as *Love*, 100 as *Joy*, and 76 as *Anger*. Some posts classified against two or more emotions, and as a result, the total proportions do not add up to exactly 100%. Results from our inter-rater analysis are reported in Table 7.1.

Guidelines of indicative strengths of agreement are provided by Landis and Koch [207], where: $\kappa \leq 0$ indicates *poor* agreement; $0 < \kappa \leq 0.2$ indicates *slight* agreement; $0.2 < \kappa \leq 0.4$ indicates *fair* agreement; $0.4 < \kappa \leq 0.6$ indicates *moderate* agreement; $0.6 < \kappa \leq 0.8$ indicates *substantial* agreement. When using the classifier’s output as a fourth ‘rater’, there was slight agreement on *Anger*, *Joy*, and *No Emotion*. Between the three human raters, those same emotions were rated with fair agreement. Agreement for *Love* was unanimous amongst the three human raters, finding zero instances of *Love* across the sample (thus resulting in a kappa value of 1.00). Inter-rater agreement was poor for the *Fear*, *Sadness*, and *Surprise*.

7.3 Findings and Discussion

In this section, we reflect on our results with respect to limitations in the classifier and investigation of the peer-reviewed and published dataset used to train the classifier. Given the weak results, we also investigate whether model cards [244] and/or datasheets [132] could have provided a more effective approach to informing the viability and limits of the pre-trained model.

7.3.1 Limitations of the Text Classifier

The classifier did not assign any emotion to 43% posts. This result corroborates the findings by Murgia et al., who identified via a manual process *No Emotion* as the most prevalent classification [247]. For illustration, we provide a set of examples in ???. (The numbers in the raters column indicate the count of raters who assigned this label.) In the first example, each human rater assigned a different emotion to the same question, despite the classifier classifying it with *No Emotion*. The second example also highlights discrepancy between raters (two raters agree on *Joy*) but the classifier classified it as *Love*. Lastly, the third example highlights one example of consistency between all three raters and the classifier.

Table 7.2: Sample questions comparing EmoTxt to manual classification. Questions located at: [https://stackoverflow.com/q/\[ID\]](https://stackoverflow.com/q/[ID]).

Question ID	Quote	EmoTxt	Raters
54521080	<p><i>"I am aware that it is better to use AWS Rekognition for this. However, it does not seem to work well when I tried it out with the images I have (which are sort of like small containers with labels on them). The text comes out misspelled and fragmented. I am new to ML and Sagemaker ... Is it possible to do it with Sagemaker? I would appreciate it if someone pointed me in the right direction."</i></p>	No Emotion	Fear (1) Sadness (1) Surprise (1)
52446033	<p><i>"I am using the Google Cloud Vision API to search similar images (web detection) and it works pretty well. Google detects full matching images and partial matching images (cropped versions). I am looking for a way to detect more different versions. For example, when I look for a logo, I would like to detect large, small, square, rectangular versions of this logo. For now, I detect images that match exactly the one I upload and cropped versions. Do you know if this is possible and how can I do that?"</i></p>	Love	Joy (2) No Emotion (1)
54677464	<p><i>"I have implemented a QR scanner(QRScanner class) using Google Vision API. Once a value is detected it is passed to another activity(Info class) using Intents. The problem is that once a QR code is scanned the Info class gets opened several times.I want to limit the QRScanner class to get only one QR value and Info classed to be opened only once. Currently once a QR is detected the Info class gets called several times. I want the QRScanner to get only one value and Info class to get called only once."</i></p>	No Emotion	No Emotion (3)

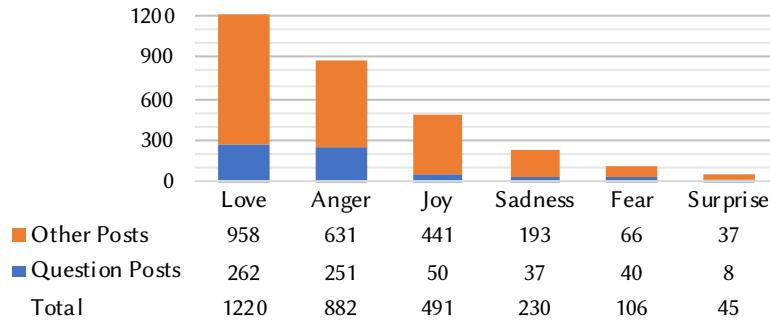


Figure 7.1: The emotion classifier training dataset distribution is largely skewed toward *Love*, resulting in data imbalance. (*No Emotion* labels were removed from this graph.)

7.3.2 Peering into the Training Dataset

We investigated the training dataset and related research documentation to see if that would give us further insights. We found two areas warranting further exploration—training data balance and training data annotation.

7.3.2.1 Data imbalance

We found that the purpose of the training dataset was actually to train two classifiers—a sentiment classifier and an emotional classifier. Each post in the training dataset was labelled with zero, one or more emotions. In addition, emotions were grouped, i.e., the positive emotions of *Joy* and *Love* were grouped into positive sentiment while *Sadness*, *Anger* and *Fear* were grouped into negative sentiment. *Surprise* was assigned either positive or negative sentiment, depending on context [68, 259]. Figure 7.1 shows the distribution of emotion labels across 4,800 posts in the training dataset; *No Emotion* is removed to emphasise emotion-only results. (Total count: 1959.)

Class imbalance and its impact on classifier models is a known problem in machine learning [221, 371], where one class (known as the majority, positive class) significantly outnumbers the other class (known as the minority, negative class). The impact of class imbalance on classification models results in minority classes with lower precision and lower recall than the majority class, since the classifier does not generate rules for the minority class. One set of relevant techniques for addressing class imbalance is data sampling; including undersampling or subsampling, oversampling and hybrid approaches [221]. Whilst the training dataset seems balanced for the purpose of sentiment analysis, there is a lack of balance across individual emotions. The predominant emotion in the training dataset was *No Emotion* at 40.8% of total posts. The most dominant emotions were *Love* and *Anger* at 25% and 18% respectively. Less than 1% of posts were labelled with *Surprise*. This means that the number of posts falling into some of the categories, for example, *Surprise* and *Fear* (i.e., 45 and 106 posts, respectively) is very low for training purposes.

Further, the training dataset was spread across different types of SO posts (i.e., questions posts, answer posts, question comments, answer comments) to capture the

3251 different emotional language, however our study was interested in classifying SO
3252 question posts only. Of the training dataset's 4,800 posts, only 1,044 were question
3253 posts and within that subset of posts, the distribution of emotions was more polarised
3254 than in the overall 4,800 posts. *Love* and *Anger* are the most predominant emotions
3255 in the training dataset, however *Anger* has a higher proportion (24%) in question
3256 posts, as opposed to only 18.4% in the overall dataset.

3257 In summary, the training dataset was not balanced within each emotion category
3258 and some emotions had very low sample numbers, as emphasised in the skew in
3259 Figure 7.1. Proportions of training data examples per question per emotion was very
3260 low for *Joy*, *Surprise*, *Sadness* and *Fear*. To address this imbalance and achieve
3261 better performance, training data could be enhanced to include additional samples
3262 or to use an oversampling approach. A recent study into class-balancing approaches
3263 in the context of defect prediction models found that class rebalancing does lead to
3264 a shift in the learned concepts [353].

3265 *7.3.2.2 Emotion labeling bias*

3266 In software engineering, hierarchical categorical emotional frameworks including
3267 those featured in Parrott [271], Ekman et al. [110] and Shaver et al. [323] have
3268 been assessed by researchers and pragmatically selected as the basis for training
3269 emotional classifiers. The chosen emotion framework is then used as the taxonomy
3270 truth labels for classifier training datasets. Data for labeling is sourced from systems
3271 such as SO and JIRA [126, 247, 259, 266]. In the software engineering domain,
3272 truth labeling of emotions has to date been done manually [126, 247, 259]. Emotion
3273 annotation involves at least a pair of annotators [11, 136]. For the EMTk training
3274 dataset, annotation was performed manually by a team of 12 coders, divided into four
3275 groups of three with a computer science background [67, 259]. Manual annotation
3276 challenges when coding emotions can be encountered due to different levels of
3277 semantic ambiguity within emotions and how humans express emotions in text [150].
3278 In the absence of an objective emotional truth, researchers' consistency is taken as
3279 a measure of correctness—i.e., multiple annotators that agree [247]. A measure of
3280 inter-rater agreement is Cohen's Kappa [81] (for two raters) or Fleiss' Kappa [118]
3281 for more raters. For the training data set, inter-rater agreement ranged from $\kappa = 0.30$
3282 (fair) for *Joy* to $\kappa = 0.66$ (substantial) for *Love*. The researchers specifically trained
3283 dataset coders for consistency. The challenge of this approach with a subject such
3284 as emotions is the opportunity for bias. In contrast, in other studies, researchers
3285 specifically attempted to reduce the opportunity for biases by including raters with
3286 different nationalities, skills, cultural backgrounds, by increasing the number of
3287 raters [266] and opting against consistency training [9]. As such, the approach
3288 taken to achieve consistency and makeup of label coders is important information
3289 for downstream consumers of an AI model.

3290 *7.3.2.3 Emotion labeling and classification granularity*

3291 Training data annotation was performed on SO posts—which included questions,
3292 answers, and comments to questions and answers. Emotion annotation can be

performed at different levels of granularity—word level [336], spans of words in a sentence [11], sentence level or larger. While a word level or keyword approach is considered too granular (as it does not capture the emotional context sufficiently), there is a risk of emotion progression during narratives and also within sentences [11, 247]. Our CVS dataset consisted of questions only as we were seeking to assess developer emotion expressed at the time of raising the question. Question posts are typically longer than comments and may contain multiple emotions expressed at different levels of intensity that are interpreted differently by different readers. For example, in the first question in ?? the first sentence does not carry any emotion while in the second part the reader expressed *Surprise* that the API does not work in all cases (*Surprise/Sadness*) and their lack of experience (*Fear*), and appreciation (possibly *Love*).

7.3.3 New tools: Model Cards and Datasheets

Model cards are emerging tools proposed by Google to communicate performance characteristics of pre-trained models [244]. Google have recently published sample model cards relating to their Cloud Vision API.² Microsoft have focused on a standardised process of dataset documentation through datasheets to encourage transparency and accountability by documenting the motivation, composition, collection process and intended uses of data [132]. IBM have proposed a FactSheet concept combining model and data information [14]. These tools are being adopted by organisations and researchers; for example, Open AI have published a basic model card of their generative language model and Google provided a sample model card for their Toxicity analyser [244]. Model cards are also being considered for high stakes environments such as clinical decision making [321], where they facilitate overarching governance regimes on how and when models can be used. For our case study, a combination of Model Card for the classifier and datasheet for training data could have provided a valuable, easy to digest first step to support an evaluation of the classifier for our context. However, the current specification of datasheet contents is very broad and lacks detailed directions for those completing the information. Had all the required information been provided to sufficient detail, including a highlight of the importance of consistency training, we could have better assessed whether an emotion assessment was appropriate. However, we would still have had to complete the study—but with rater consistency training and a better appreciation of the limits of the classifier.

7.3.4 Threats to validity

We sampled only 25 posts for inter-rater reliability and it remains a limitation of our analysis. Although, only 25 posts were sampled for inter-rater reliability, the first author reviewed an additional 500 posts and the inconsistency observed from the 25 posts maps to the broader analysis.

²<https://modelcards.withgoogle.com/model-reports> last accessed 25 May 2020.

7.4 Conclusion

3332 We started the journey presented in this work with an idea to use existing AI techniques to *automatically* investigate what other developers think of cloud intelligent 3334 services. This translated into our attempt to use a pre-trained model that learnt from 3335 posts provided by software engineers on SO. 3336

3337 Developers learn, improve and deepen their skills from documentation, formal or 3338 self-paced education, experience, and sharing their knowledge. Good documentation 3339 often forms the foundation that enables learning and also to create educational 3340 aids. In this work, we presented an observation case study that highlights a set of 3341 gaps in how a peer-reviewed model, published in the field of software engineering, 3342 lacks information about the limitations both within the documentation, as well as 3343 the articles published. To resolve these gaps, we investigated if new solutions 3344 that are being proposed such as model cards would have helped us. Model cards 3345 and datasheets will be a necessary and helpful first step, but as such we found 3346 their specification to be insufficient and additional guidance is required for those 3347 completing the cards and datasheets. Although we study only one pre-trained model 3348 in depth, our analysis shows that there are gaps in proposed solutions that can be 3349 addressed and our future work will focus on investigating other models and IWSs to 3350 develop a more detailed documentation approach, specifically those that are being 3351 aimed for software engineering.

CHAPTER 8

3352

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3354

Better Documenting Computer Vision Services[†]

3355

3356 **Abstract** Using cloud-based computer vision services (CVSs) is gaining traction with
3357 developers for many applications for many reasons: developers can simply access these
3358 AI-components through familiar RESTful APIs, and need not orchestrate large training and
3359 inference infrastructures or curate and label large training datasets. However, while their
3360 APIs *seem* familiar to use, their non-deterministic run-time behaviour and evolution profile
3361 are not adequately communicated to developers, and this results in developers struggling
3362 to use such APIs in-practice. Therefore, improving these services' API documentation is
3363 paramount, as a more complete document facilities the development process of intelligent
3364 software. This study presents an analysis of what facets a 'complete' API document should
3365 have, as synthesised into a taxonomy from 21 academic studies via a systematic mapping
3366 study. We triangulate these findings from literature against 83 developers to assess the
3367 efficacy and utility in-practice of such knowledge. We produce two weighted 'scores'
3368 for each dimension in our taxonomy based on (i) the number of papers producing these
3369 outcomes and their citation count and (ii) the extent to which developers *agree* with the
3370 recommendations arising from these studies (based on our survey). Furthermore, we apply
3371 the taxonomy to three popular CVSs and assess their compliance, producing a third 'score'
3372 using the taxonomy to identify 12 suggested improvements to the API documentation of
3373 these intelligent web services.

3374 8.1 Introduction

3375 Improving API documentation quality is a valuable task for any API—an extensive
3376 API document facilitates productivity, and therefore improved quality is better en-
3377 gineered into a system [236]. Where application developers integrate new services
3378 (such as computer vision services (CVSs) [88]) into their systems via APIs, their

[†]This chapter is originally based on A. Cummaudo, R. Vasa, and J. Grundy, "Requirements of API Documentation: A Case Study into Computer Vision Services," *IEEE Transactions on Software Engineering*, 2020, Unpublished. Terminology has been updated to fit this thesis.

productivity is affected either by inadequate skills (“*I’ve never used an API like this, so must learn from scratch*”) or, where their skills are adequate, an imbalanced cognitive load that causes excessive context switching (“*I have the skills for this, but am confused or misunderstand*”). This is commonly seen in the emerging computer vision web services space, where the documentation does not yet completely or correctly describe the APIs in full [91].

What causes a developer to be confused and how to mitigate it via an improved API document has been largely explored for conventional APIs. Various studies have provided a myriad of recommendations based on both qualitative and quantitative analysis of developer opinion. Such recommendations propose ways by which developers, managers and solution architects can construct systems better with improved documentation. However, while previous works have covered certain aspects of API usage, many have lacked a systematic review of literature and do not offer a taxonomy to consolidate these guidelines together. For example, some studies have considered the technical implementation improving API usability or tools to generate (or validate) API documentation from its source code (e.g., [224, 260, 368]); still lacks a consolidated effort to capture recommendations on how to *manually write* complete, correct, and effective API documentation. The works that *do* produce these recommendations from literature are largely scattered across multiple sources, and systematically capturing the information into a readily accessible, consolidated framework (designed to assist writing API documentation) must be validated in real-world circumstances to assess its efficacy with practitioners and existing documentation [87].

As a real-world use case, consider an intelligent web service (IWS)—such as CVSs—in which an AI-based component produces a non-deterministic result based on a machine-learnt data-driven algorithm, rather than a predictable, rule-driven one [88]. These services use machine intelligence to make predictions on images such as object labelling or facial recognition [392, 403, 404, 405, 406, 413, 417, 425, 426, 427, 431, 444, 445, 478, 479]. The impacts of poor and incomplete documentation results in developer complaints on online discussion forums such as Stack Overflow [91]. Many comments show that developers do not think in the non-deterministic mental model of the designers who created the CVSs. They ask many varied questions from their peers to try and clarify their understanding.

This paper significantly extends our previous work [87] by evaluating our API documentation taxonomy in two additional contexts. In our previous work, we developed a weighted metric for each dimension and category based on how many literary sources agree that the aspects of our taxonomy should be implemented. We refer to this as an ‘in-literature’ agreement score. We build upon this facet but *in-practice* by assessing the efficacy of our taxonomy against developers using a survey built upon an interpretation of the System Usability Scale (SUS) [61]. We produce a second weighting for the dimensions and categories of the taxonomy, referred to as a ‘in-practice’ agreement score. We then compare both the in-literature and in-practice scores directly, thereby contrasting the statistical agreement the two have. Lastly, we assess the taxonomy against three popular CVSs, namely Google Cloud Vision [417], Amazon Rekognition [392] and Azure Computer Vision [431].

3424 For each category in our taxonomy, we assess whether the respective service's
3425 documentation contains, partially-contains or does not contain the recommendation.
3426 From this, we triangulate each category's in-literature and in-practice score against
3427 the service's level of inclusion of the recommendation, thereby making a judgement
3428 as to where the services can improve their documentation to make them more
3429 complete.

3430 The primary contributions in this work are:

- 3431 • a systematic mapping study (SMS) consisting of 21 studies that capture what
3432 knowledge or artefacts should be contained within API documentation;
- 3433 • a five dimensional taxonomy consisting of 34 recommendations based on those
3434 consolidated from the 21 studies;
- 3435 • a score metric for each recommendation based on the number of papers that
3436 agree with the recommendation;
- 3437 • a score metric assessing the efficacy of the 34 recommendations that empirically
3438 reflects what is important to document from a *practitioner* point of view;
3439 and,
- 3440 • a heuristic validation of each recommendation against CVSs, assessing where
3441 existing CVS API documentation needs improvement.

3442 After performing our SMS on what API knowledge should be captured in doc-
3443 umentation to assist API designers, we propose our taxonomy consisting of the
3444 following dimensions: (1) Descriptions of API Usage; (2) Descriptions of Design
3445 Rationale; (3) Descriptions of Domain Concepts; (4) Existence of Support Artefacts;
3446 and (5) Overall Presentation of Documentation. Following this, we adopted the SUS
3447 surveying technique to assess the overall utility of each of these recommendations,
3448 producing a survey consisting of 43 questions. This survey was then tested three
3449 times within our research group: firstly against three researchers for feedback on the
3450 survey's design, secondly against three software engineers in our research group with
3451 varying levels of experience for developers for test-retest reliability [193], thirdly
3452 against 22 software engineers in our research group for wider feedback on the survey.
3453 Given these feedback improvements, we surveyed 83 external developers between
3454 May 2019 to October 2019, and then analysed the relevance of each recommendation
3455 from the practitioner's viewpoint. We also assessed the three CVSs for inclusion of
3456 each recommendation, and once our surveys were complete, determined a weighted
3457 'score' of each service to see where improvements to their documentation was made.

3458 This paper is structured as thus: Section 8.2 presents related work in the areas
3459 of API usability, intelligent CVSs, and the SUS; Section 8.3 is divided into two
3460 subsections, the first describing how primary sources were selected in a SMS with the
3461 second describing the development of our taxonomy from these sources; Section 8.4
3462 presents the taxonomy; Section 8.5 describes how we developed a survey instrument
3463 of 43 questions to validate the taxonomy against developers, and assess its efficacy
3464 against the three popular CVSs selected to make 12 suggested improvements to
3465 the existing service API documentation; Section 8.6 presents the findings from our
3466 validation analysis and the weightings for the taxonomy; Section 8.7 describes the

³⁴⁶⁷ threats to validity of this work and Section 8.8 provides concluding remarks and the
³⁴⁶⁸ future directions of this study. Additional materials are provided in Chapter C.

³⁴⁶⁹ 8.2 Related Work

³⁴⁷⁰ 8.2.1 API Usability and Documentation Knowledge

³⁴⁷¹ Use of the SMS approach has explored developer experience and API usability.
³⁴⁷² A 2018 study reviewed 36 API documentation generation tools and approaches, and
³⁴⁷³ analysed the tools developed and their inputs and documentation outputs [260]. The
³⁴⁷⁴ findings from this study emphasise that the largest effort in API documentation tool-
³⁴⁷⁵ ling is to assist developers to generate either example code snippets and/or templates
³⁴⁷⁶ or natural language descriptions of the API directly from the program’s source code.
³⁴⁷⁷ These snippets or descriptions can then be placed in the API documentation, thereby
³⁴⁷⁸ increasing the efficiency at which API documentation can be written. Additionally,
³⁴⁷⁹ tools from 12 studies target the maintainability of existing APIs of existing APIs,
³⁴⁸⁰ with tools from 11 studies target the correctness and accuracy of the documentation
³⁴⁸¹ by validating that what is written in the documentation is accurate to the technical
³⁴⁸² structure of the API. From the end-developer’s perspective, some tools (17 studies)
³⁴⁸³ help target improvements to the developer’s understandability and learnability of
³⁴⁸⁴ new APIs by linking in examples directly with questions such as on Stack Overflow.

³⁴⁸⁵ However, the results from this study regards the *tooling* used to either assist in
³⁴⁸⁶ producing, validating or learning from API documentation. While this is a systematic
³⁴⁸⁷ study with key insights into the types of tooling produced, there is still a gap for a
³⁴⁸⁸ SMS in what *guidelines* have been produced by the literature in developing natural-
³⁴⁸⁹ language documentation itself and how well developers *agree* to those guidelines,
³⁴⁹⁰ which our work has addressed.

³⁴⁹¹ Watson [368] performed a heuristic assessment from 35 popular APIs against 11
³⁴⁹² high-level universal design elements of API documentation. This study highlighted
³⁴⁹³ how many APIs, even popular ones, fail to grasp these basic design elements.
³⁴⁹⁴ For example, 25% of the documentation sets did not provide any basic overview
³⁴⁹⁵ documentation to the API. The heuristics used within Watson’s study is based on
³⁴⁹⁶ only three seminal works and only contains 11 design elements—our study extends
³⁴⁹⁷ these heuristics and structures them into a consolidated, hierarchical taxonomy which
³⁴⁹⁸ we then validate against practitioners.

³⁴⁹⁹ A taxonomy of distinct knowledge patterns within reference documentation
³⁵⁰⁰ by Maalej and Robillard [224] classified 12 distinct knowledge types. The tax-
³⁵⁰¹ onomy was then evaluated against the JDK 6 and .NET 4.0 frameworks, and showed
³⁵⁰² that the functionality and structure of these APIs are well-communicated, although
³⁵⁰³ core concepts and rationale about the API are quite rarer to see. The authors also
³⁵⁰⁴ identified low-value ‘non-information’—described as documentation that provides
³⁵⁰⁵ uninformative boilerplate text with no insight into the API at all—which was sub-
³⁵⁰⁶ stantially present in the documentation of methods and fields in the two frameworks.
³⁵⁰⁷ They recommend that developers factor their 12 distinct knowledge types into the
³⁵⁰⁸ process of code documentation, thereby preventing low-value non-information. The

3509 development of their taxonomy consisted of questions to model knowledge and information,
3510 thereby capturing the reason about disparate information units independent
3511 to context; a key difference to this paper is the systematic taxonomy approach utilised.

3512 8.2.2 Adapting the System Usability Scale

3513 The SUS was first introduced by Brooke as early as 1986 as a “quick and dirty”
3514 survey scale to easily assess the overall usability of a product or service in a timely
3515 manner. Its popularity in the usability community demonstrated the need for a
3516 tool that can collect a quantifiable rating of usability from a participant’s subjective
3517 opinion, and was later published in [61]. Since, its adoption as an industry standard is
3518 widely demonstrated [23, 62] and studies have adopted its ease of use for generalised
3519 purposes.

3520 While translation of the SUS into other languages [48, 229, 312] is generally
3521 the most adapted form of Brooke’s original survey, some studies have proposed
3522 alternative measurement models to the SUS, such as separating the usability and
3523 learnability components of the survey into a two-dimensional structure [48]. Other
3524 adaptations of the SUS include a 2014 study that proposed a usability scale based
3525 on the SUS for Handheld Augmented Reality applications [311] conceptualised
3526 against comprehensibility and manipulability. However, few studies have designed
3527 questionnaires patterned from the SUS in other contexts, and to our knowledge, this
3528 study presents an initial attempt at doing so in the API documentation knowledge
3529 domain.

3530 8.2.3 Computer Vision Services

3531 Recent studies into cloud-based CVs have demonstrated that poor reliability and
3532 robustness in computer vision can ‘leak’ into end-applications if such aspects are
3533 not sufficiently appreciated by developers. A study by Hosseini et al. [161] showed
3534 that Google Cloud Vision’s labelling fails when as little as 10% noise is added to the
3535 image. Facial recognition classifiers are easily confused by modifying pixels of a face
3536 and using transfer learning to adapt one person’s face into another [363]. Our own
3537 prior work found that the non-deterministic evolution of these types of services is not
3538 adequately communicated to developers [88], resulting in lost developer productivity
3539 whereby developers ask fundamental questions about the concepts behind these
3540 services, how they work, and where better documentation can be found [91]. This
3541 paper continues this line of research by providing a means for service providers to
3542 better document their services using a taxonomy and suggested improvements.

3543 8.3 Taxonomy Development

3544 We developed our taxonomy under two primary phases. First, we conducted a SMS
3545 identifying API documentation studies, following guidelines by Kitchenham and
3546 Charters [192] and Petersen et al. [279] (Section 8.3.1). A high level overview of
3547 this first phase is given in Figure 8.2. Second, we followed a software engineering

³⁵⁴⁸ taxonomy development method by Usman et al. [357] (Section 8.3.2) based on the
³⁵⁴⁹ findings of our SMS, which involved an extensive validation involving real-world
³⁵⁵⁰ developers and contextualised with computer vision APIs (Section 8.5).

³⁵⁵¹ 8.3.1 Systematic Mapping Study

³⁵⁵² 8.3.1.1 Research Questions (RQs)

³⁵⁵³ The first step in producing our SMS was to pose two RQs:

- ³⁵⁵⁴ • **RQ1:** What knowledge do API documentation studies contribute?
- ³⁵⁵⁵ • **RQ2:** How is API documentation studied?

³⁵⁵⁶ Our intent behind RQ1 was to collect as many studies provided by literature on how
³⁵⁵⁷ API documentation should be written using natural language (i.e., not using assistive
³⁵⁵⁸ tooling). This helped us shape and form the taxonomy provided in Section 8.4.
³⁵⁵⁹ Secondly, RQ2's intent was to understand how the studies derive at their conclusions,
³⁵⁶⁰ thereby helping us identify gaps in literature where future studies can potentially
³⁵⁶¹ focus.

³⁵⁶² 8.3.1.2 Automatic Filtering

³⁵⁶³ As done in similar software engineering studies [130, 138, 357], we explored au-
³⁵⁶⁴ tomatic filtering of online databases. We defined which SWEBOK knowledge
³⁵⁶⁵ areas [166] were relevant to devise a search query. Our search query was built using
³⁵⁶⁶ related knowledge areas, relevant synonyms, and the term 'software engineering'
³⁵⁶⁷ (for comprehensiveness) all joined with the OR operator. Due to the lack of a
³⁵⁶⁸ standard definition of an API, we include the terms: 'API' and its expanded term;
³⁵⁶⁹ software library, component and framework; and lastly software development kit
³⁵⁷⁰ (SDK). These too were joined with the OR operator, appended with an AND. Lastly,
³⁵⁷¹ the term 'documentation' was appended with an AND. Our final search string was:

```
( "software design" OR "software architecture" OR "software construction" OR "software development"
OR "software maintenance" OR "software engineering process" OR "software process" OR "software lifecycle"
OR "software methods" OR "software quality" OR "software engineering professional practice"
OR "software engineering" ) AND ( API OR "application programming interface" OR "software library"
OR "software component" OR "software framework" OR sdk OR "software development kit" ) AND (
documentation )
```

³⁵⁷² We executed the query on all available metadata (title, abstract and keywords) in
³⁵⁷³ May 2019 against Web of Science¹ (WoS), Compendex/Inspec² (C/I) and Scopus³.
³⁵⁷⁴ We selected three particular primary sources given their relevance in software en-
³⁵⁷⁵ gineering literature (containing the IEEE, ACM, Springer and Elsevier databases)
³⁵⁷⁶ and their ability to support advanced queries [60, 192]. A total 4,501 results⁴ were

¹<http://apps.webofknowledge.com> last accessed 23 May 2019.

²<http://www.engineeringvillage.com> last accessed 23 May 2019.

³<http://www.scopus.com> last accessed 23 May 2019.

⁴Raw results can be located at <http://bit.ly/2KxBLs4>.

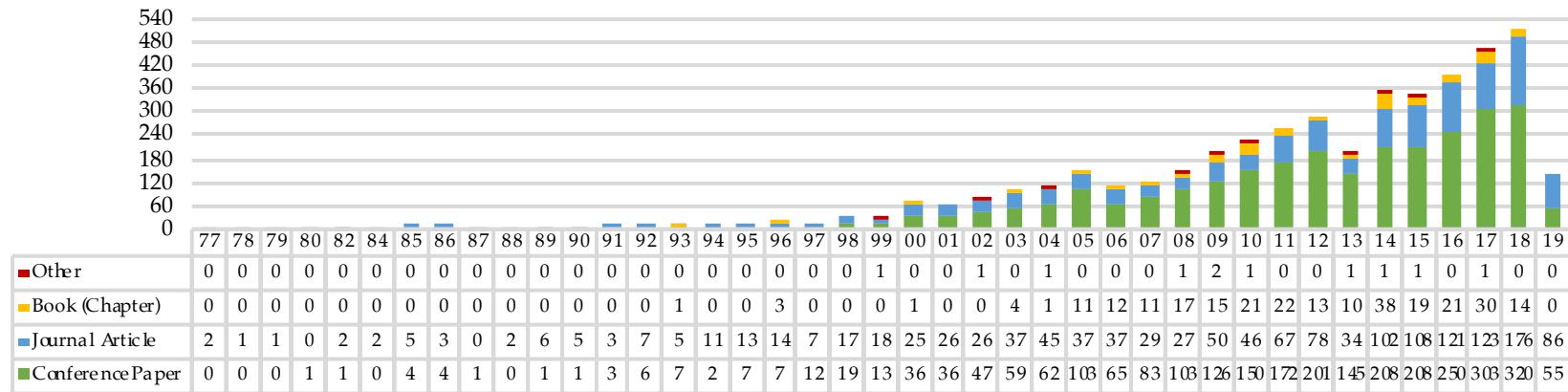


Figure 8.1: Search results by year and venue type.

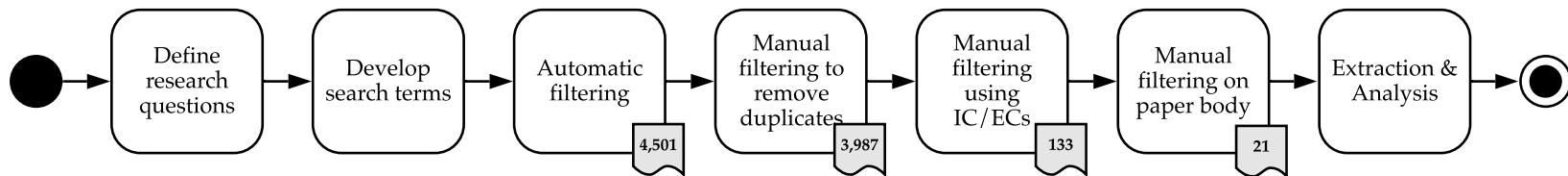


Figure 8.2: A high level overview of the filtering steps from defining and executing our search query to the data extraction of our primary studies. Number of accepted papers resulting from each filtering step is shown.

Table 8.1: Search results and publication types

Publication type	WoS	C/I	Scopus	Total
Conference Paper	27	442	2353	2822
Journal Article	41	127	1236	1404
Book	23	17	224	264
Other	0	5	6	11
Total	91	591	3819	4501

³⁵⁷⁷ found, with 549 being duplicates. Table 8.1 displays our results in further detail (duplicates not omitted); ³⁵⁷⁸ Figure 8.1 shows an exponential trend of API documentation publications produced within the last two decades. ³⁵⁷⁹ (As this search was conducted in May 2019, results taper in 2019.) ³⁵⁸⁰

³⁵⁸¹ 8.3.1.3 *Manual Filtering*

³⁵⁸² A follow-up manual filtering stage followed the 4,501 results obtained by automatic ³⁵⁸³ filtering. As described below, we applied the following inclusion criteria (IC) and ³⁵⁸⁴ exclusion criteria (EC) to each result:

- ³⁵⁸⁵ **IC1** Studies must be relevant to API documentation: specifically, we exclude
³⁵⁸⁶ studies that deal with improving the technical API usability (e.g., improved
³⁵⁸⁷ usage patterns);
- ³⁵⁸⁸ **IC2** Studies must propose new knowledge or recommendations to document
³⁵⁸⁹ APIs;
- ³⁵⁹⁰ **IC3** Studies must be relevant to software engineering as defined in SWEBOk;
- ³⁵⁹¹ **EC1** Studies where full-text is not accessible through standard institutional databases;
- ³⁵⁹² **EC2** Studies that do not propose or extend how to improve the official, natural
³⁵⁹³ language documentation of an API;
- ³⁵⁹⁴ **EC3** Studies proposing a third-party tool to enhance existing documentation or
³⁵⁹⁵ generate new documentation using data mining (i.e., not proposing strategies
³⁵⁹⁶ to improve official documentation);
- ³⁵⁹⁷ **EC4** Studies not written in English;
- ³⁵⁹⁸ **EC5** Studies not peer-reviewed.

³⁵⁹⁹ Each of these ICs and ECs were applied to every paper after exporting all ³⁶⁰⁰ metadata of our results to a spreadsheet. The first author then curated the publications ³⁶⁰¹ using the following revision process.

³⁶⁰² Firstly, we read the publication source—to rapidly omit non-software engineering ³⁶⁰³ papers—as well as the author keywords, title, and abstract of all 4,501 studies. ³⁶⁰⁴ As some studies were duplicated between our three primary sources, we needed to ³⁶⁰⁵ remove any repetitions. We sorted and reviewed any duplicate DOIs and fuzzy-³⁶⁰⁶ matched all very similar titles (i.e., changes due to punctuation between primary ³⁶⁰⁷ sources), thereby retaining only one copy of the paper from a single database. Sim-³⁶⁰⁸ilarly, as there was no limit to our date ranges, some studies were republished in

3609 various venues (i.e., same title but different DOIs). These were also removed using
3610 fuzzy-matching on the title, and the first instance of the paper's publication was
3611 retained. This second phase resulted in 3,987 papers.

3612 Secondly, we applied our inclusion and exclusion criteria to each of the 3,987
3613 papers by reading the abstract. Where there was any doubt in applying the criteria
3614 to the abstract alone, we automatically shortlisted the study. We rejected 427 studies
3615 that were unrelated to software engineering, 3,235 were not directly related to docu-
3616 menting APIs (e.g., to enhance coding techniques that improve the overall developer
3617 usability of the API), 182 proposed new tools to enhance API documentation or
3618 used machine learning to mine developer's discussion of APIs, and 10 were not in
3619 English. This resulted in 133 studies being shortlisted to the final phase.

3620 Thirdly, we re-evaluated each shortlisted paper by re-reading the abstract, the
3621 introduction and conclusion. We removed a further 64 studies that were on API
3622 usability or non API-related documentation (i.e., code commenting). At this stage,
3623 we decided to refine our exclusion criteria to better match the research goals of this
3624 study by including the word 'natural language' documentation in EC2. This removed
3625 studies where the focus was to improve technical documentation of APIs such as
3626 data types and communication schemas. Additionally, we removed 26 studies as
3627 they were related to introducing new tools (EC3), 3 were focused on tools to mine
3628 API documentation, 7 studies where no recommendations were provided, 2 further
3629 duplicate studies, and a further 10 studies where the full text was not available,
3630 not peer reviewed or in English. Books are commonly not peer-reviewed (EC5),
3631 however no books were shortlisted within these results. This final stage resulted in
3632 21 primary studies for further analysis, and the mapping of primary study identifiers
3633 to references S1–21 can be found in Section C.3.

3634 As a final phase, we conducted reliability analysis of our shortlisting method.
3635 We conducted intra-rater reliability of our 133 shortlisted papers using the test-
3636 retest approach suggested by Kitchenham and Charters [192]. We re-evaluated a
3637 random sample of 10% of the 133 shortlisted papers a week after initial studies were
3638 shortlisted. This resulted in *substantial agreement* [207], measured using Cohen's
3639 kappa ($\kappa = 0.7547$).

3640 8.3.1.4 Data Extraction & Systematic Mapping

3641 Of the 21 primary studies, we conducted abstract key-wording adhering to Petersen
3642 et al.'s guidelines [279] to develop a classification scheme. An initial set of keywords
3643 were applied for each paper in terms of their methodologies and research approaches
3644 (RQ2), based on an existing classification schema used in the requirements engi-
3645 neering field by Wieringa and Heerkens [375]. These are: *evaluation papers*, which
3646 evaluates existing techniques in-practice; *validation papers*, which investigates pro-
3647 posed techniques not yet implemented in-practice; *experience papers*, which do
3648 investigate or evaluate either proposed or existing techniques, but presents insight-
3649 ful experiences of authors that warrant communication to other practitioners; and
3650 *philosophical papers*, which presents new conceptual frameworks that describes a
3651 language by which we can describe our observations of existing or new techniques,

Table 8.2: Data extraction form

Data item(s)	Description
Citation metadata	Title, author(s), years, publication venue, publication type
Key recommendation(s)	As per IC2, the study must propose at least one recommendation on what should be captured in API documentation
Evaluation method	Did the authors evaluate their recommendations? If so, how?
Primary technique	The primary technique used to devise the recommendation(s)
Secondary technique	As above, if a second study was conducted
Tertiary technique	As above, if a third study was conducted
Research type	The research type employed in the study as defined by Wieringa and Heerkens's taxonomy

³⁶⁵² thereby implying a new viewpoint for understanding phenomena.

³⁶⁵³ After all primary studies had been assigned keywords, we noticed that all papers
³⁶⁵⁴ used field study techniques, and thus we consolidated these keywords using Singer
³⁶⁵⁵ et al.'s framework of software engineering field study techniques [328]. Singer et al.
³⁶⁵⁶ captures both study techniques *and* methods to collect data within the one framework,
³⁶⁵⁷ namely: *direct techniques*, including brainstorming and focus groups, interviews and
³⁶⁵⁸ questionnaires, conceptual modelling, work diaries, think-aloud sessions, shadowing
³⁶⁵⁹ and observation, participant observation; *indirect techniques*, including instrumenting
³⁶⁶⁰ systems, fly-on-the-wall; and *independent techniques*, including analysis of work
³⁶⁶¹ databases, tool use logs, documentation analysis, and static and dynamic analysis.

³⁶⁶² Table 8.2 describes our data extraction form, which was used to collect relevant
³⁶⁶³ data from each paper. Figure 8.3 presents our systematic mapping, where each study
³⁶⁶⁴ is mapped to one (or more, if applicable) of methodologies plotted against Wieringa
³⁶⁶⁵ and Heerkens's research approaches. We find that a majority of these studies survey
³⁶⁶⁶ developers using direct techniques (i.e., interviews and questionnaires) and some per-
³⁶⁶⁷ forming structured documentation analysis. Few studies report recent experiences,
³⁶⁶⁸ with the majority of API documentation knowledge being evaluation research, and
³⁶⁶⁹ some validation studies. There are few experience papers describing anecdotal ev-
³⁶⁷⁰ idence of API documentation knowledge, and almost no philosophical papers that
³⁶⁷¹ describe new conceptual ways at approaching API documentation as a large major-
³⁶⁷² ity of existing work either evaluates existing (in-practice) strategies or validates the
³⁶⁷³ effectiveness of new strategies.

³⁶⁷⁴ 8.3.2 Development of the Taxonomy

³⁶⁷⁵ A majority of taxonomies produced in software engineering studies are often made
³⁶⁷⁶ extemporaneously [357]. For this reason, we decided to proceed with a systematic
³⁶⁷⁷ approach to develop our taxonomy using the guidelines provided by Usman et al.
³⁶⁷⁸ [357], which are extended from lessons learned in more mature domains. In this

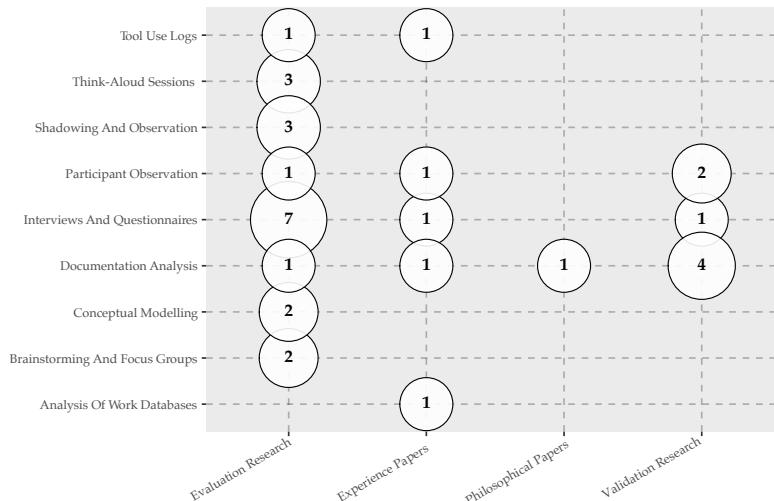


Figure 8.3: Systematic map: field study technique vs research type

3679 subsection, we outline the 4 phases and 13 steps taken to develop our taxonomy
 3680 based on Usman et al.'s technique. Usman et al.'s final *validation* phase is largely
 3681 detailed within Section 8.5 after we present our taxonomy in Section 8.4.

3682 8.3.2.1 Planning phase

3683 The preliminary phase involves answering the following:

- 3684 (1) *define the software engineering knowledge area*: The software engineering
 3685 knowledge area, as defined by the SWEBOK, is software construction;
- 3686 (2) *define the objective*: The main objective of the proposed taxonomy is to define
 3687 a set of categories that enables to classify different facets of natural-language
 3688 API documentation knowledge (not API *usability* knowledge) as reported in
 3689 existing literature;
- 3690 (3) *define the subject matter*: The subject matter of our proposed taxonomy is
 3691 documentation artefacts of APIs;
- 3692 (4) *define the classification structure*: The classification structure of our proposed
 3693 taxonomy is *hierarchical*;
- 3694 (5) *define the classification procedure*: The procedure used to classify the docu-
 3695 mentation artefacts is qualitative;
- 3696 (6) *define the data sources*: The basis of the taxonomy is derived from field study
 3697 techniques (see Section 8.3.1.4).

3698 8.3.2.2 Identification and extraction phase

3699 The second phase of the taxonomy development involves (7) *extracting all terms*
 3700 and *concepts* from relevant literature, which we have achieved from our SMS. These
 3701 terms are then consolidated by (8) *performing terminology control*, as some terms
 3702 may refer to different concepts and vice-versa.

3703 8.3.2.3 Design phase

3704 The design phase identified the core dimensions and categories within the extracted
3705 data items. The first step is to **(9) identify and define taxonomy dimensions**; for this
3706 study we utilised a bottom-up approach to identify each dimension, i.e., extracting the
3707 categories first and then nominating which dimensions these categories fit into using
3708 an iterative approach. As we used a bottom-up approach, step (9) also encompassed
3709 the second stage of the design phase, which is to **(10) identify and describe the**
3710 *categories* of each dimension. Thirdly, we **(11) identify and describe relationships**
3711 between dimensions and categories, which can be skipped if the relationships are
3712 too close together, as is the case of our grouping technique which allows for new
3713 dimensions and categories to be added. The last step in this phase is to **(12) define**
3714 *guidelines for using and updating the taxonomy*. The taxonomy is as simple as a
3715 checklist that can be heuristically applied to an API document, and each dimension
3716 is malleable and covers a broad spectrum of artefacts; while we do not anticipate
3717 any further dimensions to be added, new categories can easily be fitted into one of
3718 the dimensions (see Section 8.8). We provide guidelines for use in our application
3719 of the taxonomy against CVSSs within Sections 8.4 and 8.6.

3720 8.3.2.4 Validation phase

3721 In the final phase of taxonomy development, taxonomy designers must **(13) validate**
3722 *the taxonomy* to assess its usefulness. Usman et al. [357] describe three approaches to
3723 validate taxonomies: (i) orthogonal demonstration, in which the taxonomy's orthog-
3724 onality is demonstrated against the dimensions and categories, (ii) benchmarking
3725 the taxonomy against similar classification schemes, or (iii) utility demonstration by
3726 applying the taxonomy heuristically against subject-matter examples. In our study,
3727 we adopt utility demonstration by use of a survey and heuristic application of the
3728 taxonomy against real-world case-studies (i.e., within the domain of CVSSs). This is
3729 discussed in greater detail within Section 8.5.

3730 8.4 API Documentation Knowledge Taxonomy

3731 Our taxonomy consists of five dimensions (labelled A–E). We expand these five di-
3732 mensions into 34 categories (sub-dimensions). Each dimension respectively covers:

- 3733 • [A] Descriptions of API Usage** on *how* to use the API for the developer's
3734 intended use case;
- 3735 • [B] Descriptions of Design Rationale** on *when* the developer should choose
3736 this API for a particular use case;
- 3737 • [C] Descriptions of Domain Concepts** of the domain behind the API to
3738 understand *why* this API should be chosen for this domain;
- 3739 • [D] Existence of Support Artefacts** that describe *what* additional documen-
3740 tation the API provides; and
- 3741 • [E] Overall Presentation of Documentation** to help organise the *visualisa-*
3742 *tion* of the above information.

[A] Usage Description

- [A1] Quick-start guides #3
- [A2] Low-level reference manual #3 SH
- [A3] Explanation of high level architecture
- [A4] Introspection source code comments SH
- [A5] Code snippets of basic component function #2 #1 VH
- [A6] Step-by-step tutorials with multiple components #2 SH
- [A7] Downloadable production-ready source code
- [A8] Best-practices of implementation
- [A9] An exhaustive list of all components
- [A10] Minimum system requirements to use the API
- [A11] Instructions to install/update the API and its release cycle #4
- [A12] Error definitions describing how to address problems #5

[B] Design Rationale

- [B1] Entry-point purpose of the API #4
- [B2] What the API can develop
- [B3] Who should use the API
- [B4] Who will use the applications built using the API
- [B5] Success stories on the API
- [B6] Documentation comparing similar APIs to this API
- [B7] Limitations on what the API can/cannot provide #1

[C] Domain Concepts

- [C1] Relationship between API components and domain concepts
- [C2] Definitions of domain terminology
- [C3] Documentation for nontechnical audiences

[D] Support Artefacts

- [D1] FAQs
- [D2] Troubleshooting hints
- [D3] API diagrams
- [D4] Contact for technical support NH
- [D5] Printed guide
- [D6] Licensing information

[E] Documentation Presentation

- [E1] Searchable knowledge base
- [E2] Context-specific discussion forums
- [E3] Quick-links to other relevant components
- [E4] Structured navigation style
- [E5] Visualised map of navigational paths
- [E6] Consistent look and feel #5

Figure 8.4: Our proposed taxonomy on what artefacts should be documented in a complete API document.

3743 Further descriptions of the categories encompassing each dimension are given within
3744 Figure 8.4 and Section C.1, coded as $[Xi]$, where i is the category identifier within
3745 a dimension, $X \in \{A, B, C, D, E\}$.

3746 Section C.1 shows which of the primary sources (S1–21) provide the recommen-
3747 dation described as well as an ‘in-literature score’ (ILS). This score is a weighting
3748 calculated as a percentage of the number of primary studies that make the recom-
3749 mendation divided by the total of primary studies, and indicates the overall level
3750 of agreement that academic sources suggest these documentation artefacts. This
3751 score is contrasted to the ‘in-practice score’ (IPS) which indicates the overall level of
3752 agreement that *practitioners* think such documentation artefacts are needed. Further
3753 details about the ILS and IPS values, how they were calculated and analysed for
3754 each category, and a rigorous contrast between the two are provided Sections 8.5.1.2
3755 and 8.6.1 to 8.6.3. For comparative purposes, we illustrate a colour scale (from
3756 red to green) to indicate the relevancy weight between ILS and IPS values in Sec-
3757 tion C.1: for example, while quick-start guides [A1] are few referenced in academic
3758 sources at 14%, they are generally well-desired by practitioners 88% agreement.
3759 We then provide three columns that assesses the presence of these documentation
3760 artefacts against three popular CVSs: Google Cloud Vision, AWS’s Rekognition,
3761 and Azure Cloud Vision (abbreviated to GCV, AWS and ACV). A fully shaded
3762 circle (●) indicates that the documentation artefact was clearly found in the service,
3763 while a half-shaded circle (◐) indicates that the artefact was only partially present.
3764 An outlined circle (○) indicates that the service lacks the indicated documentation
3765 artefact within our taxonomy. This empirical assessment is further detailed in Sec-
3766 tion 8.6.5, which outlines concrete areas in the respective services’ documentation
3767 where improvements could be made, as well as hyperlinks to the documentation
3768 where relevant.

3769 Figure 8.4 illustrates these findings, with underlines indicating key artefacts and
3770 various iconography to indicate specific results. The computer icon (💻) includes a
3771 ranking from 1–5 of the top five most recommended artefacts according to devel-
3772 opers, as calculated from their relevant IPS scores. Conversely, the book icon (📖)
3773 indicates the rankings of the top five most recommended artefacts according to liter-
3774 ature. For example, while literature suggests the most useful documentation artefact
3775 are API usage description code snippets [A5], in-practice, we find that developers
3776 prefer design rationale on what the limitations of API are [B7] with code snippets
3777 coming in second place. Where there is strong agreement between developers and
3778 literature (within a standard deviation of 0.15) we use the handshake icon (🤝) and
3779 list whether both agree if the category is Very Helpful (VH), Slightly Helpful (SH) or
3780 Not Helpful (NH). Further details on this explanation are provided in Section 8.6.3.
3781 Lastly, we provide iconography for the presence (✓) or non-presence (✗) of these
3782 artefacts in *all three* CVSs assessed, per Section 8.6.2.

3783 8.5 Validating our Taxonomy

3784 8.5.1 Survey Study

3785 8.5.1.1 Designing the Survey

3786 We followed the guidelines by Kitchenham and Pfleeger [193] on conducting personal opinion surveys in software engineering to validate our survey. In developing
3787 our survey instrument, we shaped questions around each of our 5 dimensions and
3788 34 categories. To achieve this, we used Brooke's SUS [61] as inspiration and re-
3789 shaped the 34 categories around a question. Each dimension was marked a numeric
3790 question (3–7), and alphabetic sub-questions were marked for each sub-dimension
3791 or category.

3792 We used closed questioning where respondents could choose an answer on a
3793 5-point Likert-scale (1=*strongly disagree*, 2=*somewhat disagree*, 3=*neither agree*
3794 nor *disagree*, 4=*slightly agree* and 5=*strongly agree*). Like Brooke's study, each
3795 question alternated in positive and negative sentiment. Half of our questions were
3796 written where a likely common response would be in strong agreement and vice-
3797 versa for the other half, such that participants would have to “read each statement
3798 and make an effort to think whether they would agree or disagree with it” [61]. For
3799 example, the question regarding [B7] on API limitations was framed as: “*I believe it*
3800 *is important to know about what the limitations are on what the API can and cannot*
3801 *provide*” (Q4g), whereas the question regarding [C1] on domain concepts of the API
3802 was framed as: “*I wouldn't read through theory about the API's domain that relates*
3803 *theoretical concepts to API components and how both work together*” (Q5a).

3804 In addition, the remaining eight questions asked demographical information.
3805 An extra open question asked for further comments. The full survey is provided in
3806 Section C.5.

3808 8.5.1.2 Evaluating the Survey

3809 After the first pass at designing questions was completed, we evaluated our survey
3810 on three researchers within our research group for general feedback. This resulted
3811 in minor changes, such as slight re-wording of questions, clarifying the difference
3812 between web services and web APIs, and providing specific questions with examples
3813 (some with images). For example, the question regarding [A9] on an exhaustive list
3814 of all major components in the API was framed as “*I believe an exhaustive list*
3815 *of all major components in the API without excessive detail would be useful when*
3816 *learning an API*” (Q3i) with the example “e.g., a computer vision web API might
3817 *list object detection, object localisation, facial recognition, and facial comparison*
3818 *as its 4 components*”.

3819 After this, we conducted reliability analysis using a test-retest approach on three
3820 developers within our group seven weeks apart. This was calculated using the `irr`
3821 computational R package [127] (as suggested in [148]) and resulted in an average
3822 intra-class correlation of 0.63 which indicates a good overall index of agreement [78].

3823 8.5.1.3 Recruiting Participants

3824 Our target population for the study was application software developers with varying
3825 degrees of experience (including those who and who have not used CVSS or related
3826 tools before) and varying understanding of fundamental machine learning concepts.
3827 We began by recruiting software developers within our research group using a
3828 group-wide message sent on our internal messaging system. Of the 44 developers in
3829 our group's engineering cohort, 22 responses were returned, indicating an internal
3830 response rate of 50%.

3831 For external participant recruiting, we shared the survey on social media plat-
3832 forms and online-discussion forums relevant to software development. We adopted
3833 a non-probabilistic snowballing sampling where the participants, at the end of the
3834 survey, were encouraged to share the survey link to others using *AddThis*⁵. This
3835 resulted in 43 additional visits to the survey. Additionally, snowballing sampling was
3836 encouraged within members of our research group who shared the survey with an
3837 additional 21 participants. However, while there were a total of 86 respondents, only
3838 51 finished the survey, leaving 35 participants with partially completed responses.
3839 Our final response rate was therefore 59%, which is very close to median response
3840 rates of 60% [29] in information systems and 5% in software engineering [328].

3841 8.5.1.4 Analysing Response Data

3842 To analyse our response data, we used an adapted version of the SUS method to
3843 produce a score for each question's 5-point response. As per Brooke's methodology,
3844 we mapped the responses from their ordinal scale of 1–5 to 0–4, and subtracted that
3845 value by 1 for positive questions and subtracted the value from 5 for the negative
3846 questions [61]. Unlike Brooke's method, we averaged each response for every
3847 question and divided by four (i.e., now a 4-point scale) to obtain scores for each
3848 category. This is presented in Section C.1 under the 'in-practice score' (IPS) for
3849 each category.

3850 Demographics for our survey were consistent in terms of the experience levels of
3851 developers who responded. Most were professional programmers with 75% report-
3852 ing between 1–10 years of work experience. A majority of our respondents (33%)
3853 reported to be in mid-tier roles. Most worked in either consulting or information
3854 technology services, reported at 17% for both.

**3855 8.5.2 Empirical application of the taxonomy against Computer Vision
3856 Services**

3857 Once our taxonomy had been developed, we performed an empirical application
3858 against three CVSS: Google Cloud Vision [417], Amazon Rekognition [392] and
3859 Azure Computer Vision [431]. Our selection criteria in choosing these particular
3860 services to analyse is based on the prominence of the service providers in industry
3861 and the ubiquity of their cloud platforms (Google Cloud, Amazon Web Services,
3862 and Microsoft Azure) in addition to being the top three adopted vendors used for

⁵<https://www.addthis.com> last accessed 7 January 2020

3863 cloud-based enterprise applications [299]. In addition, we had conducted extensive
3864 investigation into the services' non-deterministic runtime behaviour and evolution
3865 profile in prior work [88] and have also identified developers' complaints about their
3866 incomplete documentation in a prior mining study on Stack Overflow [91].

3867 We began with an exploratory analysis of the presence of each dimension and
3868 its categories. Section C.2 displays all sources of documentation used; although we
3869 initially started on the respective services homepages [392, 417, 431], this search
3870 was expanded to other webpages hyperlinked. For each category, we listed the
3871 documentation's presence as either fully present, partially present or not present
3872 at all. This is shown in Section C.1 with the indication of (half-)filled circles or
3873 circle outlines for Google Cloud Vision (abbreviated to GCV), Amazon Rekognition
3874 (abbreviated to AWS), and Azure Computer Vision (abbreviated to ACV). Notes were
3875 taken for each webpage justifying the presence, and exact sources of documentation
3876 were listed when (partially) present. PDFs of each webpage were downloaded
3877 between 14–18 March 2019 for analysis.

3878 Once our analysis was completed and results from the survey finalised, we then
3879 calculated *weighted* ILS and IPS values for each dimension's category. This was done
3880 by multiplying the ILS and IPS values for each category (listed in Section C.1) by
3881 either 0, 0.5 or 1 for categories not present, partially present, or present (respectively)
3882 in each service. The 'maximum' ILS and IPS values indicate the highest possible
3883 score a service can be ranked as though *all* categories are present. Tables 8.3 and 8.4
3884 show the sum of weights for each category in its respective dimension, in addition to
3885 the maximum possible score. Again, we use the same abbreviations for each service
3886 as per Section C.1. The scores are normalised into percentages for comparative
3887 purposes as a ratio of the score over all dimensions for a particular service to
3888 the maximum possible score. For comparative purposes, these are illustrated in
3889 Figure 8.6.

3890 8.6 Taxonomy Analysis

3891 In this section, we analyse investigating the taxonomy from two perspectives. Firstly,
3892 we describe the ILS values, being an interpretation of the number of papers that
3893 conclude the recommendations in each category and dimension, and the weighted ILS
3894 scores, being an application of the taxonomy specifically to CVSs. Secondly, we look
3895 at the results from our survey and their respective IPS values, being an interpretation
3896 of how well developers agree with these recommendations, and the weighted IPS
3897 scores, being the application of how application developers would agree with the
3898 documentation of the CVSs. We then contrast the difference between what literature
3899 recommends and how well developers agree with these recommendations.

3900 8.6.1 In-Literature Scores for Taxonomy Categories

3901 ILS values indicate the proportion of papers that recommend categories within our
3902 taxonomy of all 21 studies. The most highly recommended categories from our
3903 SMS fall under the Descriptions of API Usage dimension. The majority (0.71) of

Table 8.3: Weighted ILS Scoring.

Dimension	GCV	AWS	ACV	Max
[A] Usage Description	2.64 (60%)	3.10 (71%)	3.02 (69%)	4.38
[B] Design Rationale	0.79 (55%)	0.95 (67%)	0.95 (67%)	1.43
[C] Domain Concepts	0.33 (54%)	0.14 (23%)	0.43 (69%)	0.62
[D] Support Artefacts	0.24 (31%)	0.52 (69%)	0.50 (66%)	0.76
[E] Documentation Presentation	1.05 (79%)	1.05 (79%)	0.98 (73%)	1.33
Total	5.05 (59%)	5.76 (68%)	5.88 (69%)	8.52

Table 8.4: Weighted IPS Scoring.

Dimension	GCV	AWS	ACV	Max
[A] Usage Description	4.84 (57%)	5.26 (62%)	5.62 (66%)	8.48
[B] Design Rationale	1.78 (43%)	2.51 (61%)	2.51 (61%)	4.13
[C] Domain Concepts	0.92 (51%)	0.55 (31%)	1.43 (80%)	1.80
[D] Support Artefacts	0.96 (28%)	1.80 (53%)	1.85 (55%)	3.36
[E] Documentation Presentation	2.66 (70%)	2.66 (70%)	2.38 (63%)	3.79
Total	11.17 (52%)	12.79 (59%)	13.79 (64%)	21.56

3904 studies advocate for code snippets as a necessary piece in the API documentation
 3905 puzzle [A5]. While code snippets generally only reflect small portions of API
 3906 functionality (limited to 15–30 LoC), this is complimented by step-by-step tutorials
 3907 (0.57) that tie in multiple (disparate) components of API functionality, generally
 3908 with some form of screenshots, demonstrating the development of a non-trivial
 3909 application using the API step-by-step [A6]. The third highest category scored was
 3910 also under the Descriptions of API Usage dimension, being low-level reference
 3911 documentation at 0.52 [A2]. These three categories were the only categories to be
 3912 scored as majority categories (i.e., their scores were above 0.50). The fourth and
 3913 fifth highest scores are an entry-level purpose/overview of the API (0.48) that gives
 3914 a brief motivation as to why a developer should choose a particular API over another
 3915 [B1] and consistency in the look and feel of the documentation throughout all of the
 3916 API’s official documentation (0.43) [E6].

3917 8.6.2 In-Practice Scores for Taxonomy Categories

3918 IPS values indicate the extent to which developers ‘agree’ with the statements made
 3919 in our survey, as calculated using the SUS technique [61]. These values are generally
 3920 greater than the ILS values, since they are ranked by all survey participants and are
 3921 not a ratio of the 21 primary studies. Unlike ILS scores, 28 categories scored
 3922 above 0.50. The highest dimension corroborates that of the ILS scores; within
 3923 the top five ranked ILS scores, Descriptions of API Usage categories feature four
 3924 times. However, developers generally find limitations on what the APIs can and
 3925 cannot provide the most useful, at 0.94, which falls under the Descriptions of Design

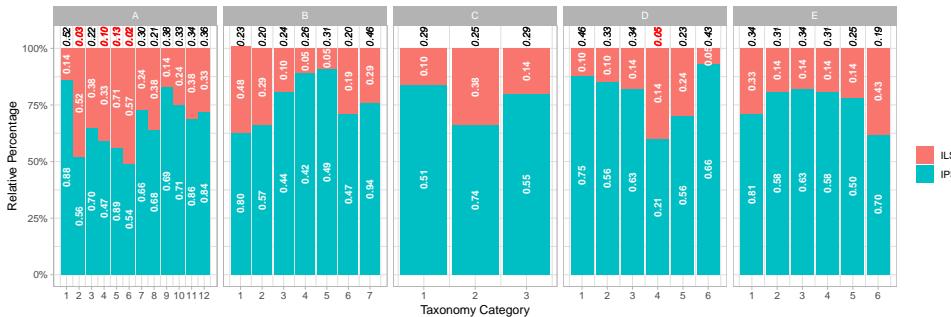


Figure 8.5: Comparison of ILS and IPS values for each category (grouped by dimensions) presented as a relative percentage.

Table 8.5: Labels assigned to ILS and IPS values.

Description	Lower Score Bound	Upper Score Bound
<i>Not Helpful</i>	0.00	0.24
<i>Slightly Unhelpful</i>	0.25	0.49
<i>Slightly Helpful</i>	0.50	0.74
<i>Very Helpful</i>	0.75	1.00

3926 Rationale dimension [B7]. Following this, the code-snippets [A5] is highly ranked (as
 3927 per the ILS values) with developers agreeing that code-snippets should be included in
 3928 most API documentation. Quick-start guides [A1] are the next most-useful category
 3929 that developers advocate for, reported at 0.88. Following this, the instructions on
 3930 how to install the API or begin using the API, its release cycle, and frequently it
 3931 is updated [A11] is also important, ranking fourth at 0.86. Lastly, error definitions
 3932 describing how developers can address problems [A12] were scored at 0.84.

3933 8.6.3 Contrasting In-Literature to In-Practice Scores

3934 Figure 8.5 highlights the relative percentage of each ILS and IPS value for all
 3935 subcategories, thereby indicating the relative agreement between the two. In this
 3936 graph, an ILS and/or IPS core approaching a relative percentage of 50% indicates
 3937 equal agreement whereby both developer's and literary references share a similar
 3938 distribution of recommendation agreement. Italicised labels above each column
 3939 indicates the standard deviation between the ILS and IPS values, where red labels
 3940 indicated a standard deviation less than 0.15 (i.e., developers and literature agree to
 3941 the values to a similar extent).

3942 Where the standard deviation between ILS and IPS values is less than 0.015
 3943 (as indicated by red labels above each column in Figure 8.5), then there is strong
 3944 alignment between both scores. However, of all 34 categories, only five cases of this
 3945 occur. Developers agree to the academic works that make the recommendations *to*
 3946 *the same relative proportion* as per the labels assigned in Table 8.5:

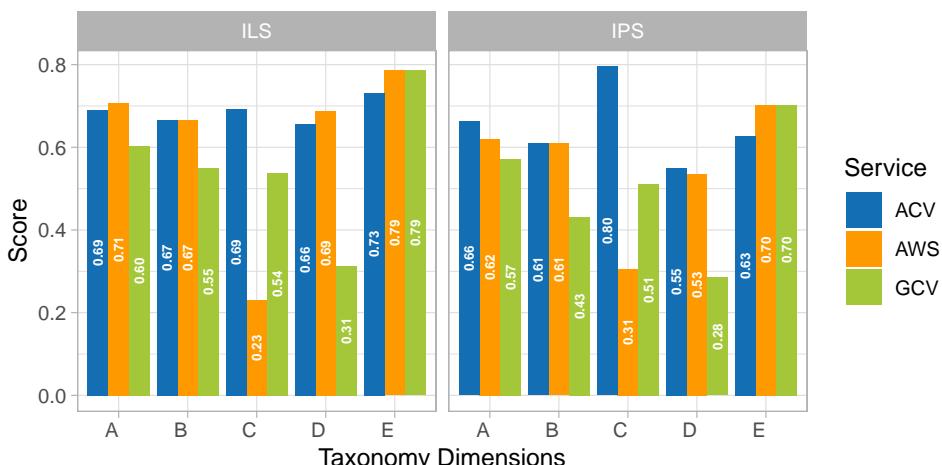
- 3947 • Having email addresses or phone numbers listed within an API is generally

3948 not helpful at all [D4],

- 3949 • Introspecting the source code comments of an API is only somewhat helpful
[A4],
- 3950 • Low-level reference documentation with all objects and methods (etc.) docu-
mented is slightly helpful [A2],
- 3951 • Following step-by-step tutorials are also slightly helpful [A6],
- 3952 • Code snippets are the most helpful [A5].

3953 The remaining categories in the dimension do not share strong association be-
3954 between both developer opinions and the number of papers producing recomme-
3955 dations. Due to the disparity between these ILS and IPS values, we do not report on
3956 their utility.

3957 8.6.4 Triangulating ILS and IPS with Computer Vision



3958 **Figure 8.6:** Comparison of the weighted ILS and IPS values for the three CVSs assessed.

3960 When applied in the context of CVSs, we see that Azure Computer Vision
3961 (ACV) and Amazon Rekognition (AWS) are better documented than Google Cloud
3962 Vision (GCV), particularly in Descriptions of Design Rationale and Descriptions
3963 of API Usage. Figure 8.6 highlights that Azure Computer Vision is especially well
3964 documented in Descriptions of Domain Concepts when measured using the weighted
3965 ILS and has the highest score of all services and dimensions. It is evident that Google
3966 Cloud Vision needs improved Descriptions of Design Rationale documentation and
3967 further Existence of Support Artefacts would be helpful. Generally speaking, Google
3968 Cloud Vision is less ‘complete’ than other services, except in Descriptions of Domain
3969 Concepts documentation and its Overall Presentation of Documentation.

3970 In the context of CVSs, IPS values share a similar distribution to ILS val-
3971 ues. Notably, in-practice, it seems developers prefer the documentation of Amazon
3972 Rekognition compared to the in-literature weighted scoring of Azure Computer
3973 Vision (Figure 8.6). Except in the case of documenting Descriptions of Domain

3974 Concepts, Amazon Rekognition scores slightly higher than Azure Computer Vision
3975 except for the Descriptions of Design Rationale documentation where it is equal.
3976 Similar to the ILS scoring, Google Computer Vision has low compliance to the
3977 recommendations proposed, except in its Overall Presentation of Documentation.

3978 8.6.5 Areas of Improvement for CVS Documentation

3979 Triangulating the taxonomy developed from literary sources, the developer survey
3980 on this taxonomy to understand its efficacy in-practice, and applying the taxonomy to
3981 the CVS domain, we are able to assess the key areas of improvement in this domain.

3982 For this assessment, we select the ILS or IPS values for categories that are
3983 considered either somewhat or very helpful (i.e., a score greater than 0.50). We then
3984 match these against categories that are found to be partially or not present within
3985 each service. In total, we found 12 categories where improvements can be made
3986 across all dimensions except Overall Presentation of Documentation, detailed below
3987 .

3988 8.6.5.1 Issues regarding Descriptions of API Usage

3989 **Quick-start guides [A1]:** Quick-start guides should provide a short tutorial that
3990 allows programmers to pick up the basics of an API in a programming language of
3991 their choice. For the services assessed, each offer various client SDKs (e.g., as Java
3992 or Python client libraries). Google Cloud Vision and Azure Computer Vision offer
3993 quick-start guides [420, 438] in which sets of articles target various SDKs or are
3994 client-agnostic with code snippets that can be changed to the client language/SDK
3995 of the developer's choice. Amazon Rekognition offers exercises in setting up the
3996 AWS SDK and using the command-line interface to interact with image analysis
3997 components [398], however this is client-agnostic nor does it provide details in how
3998 to get started with using the client SDKs.

 **Suggested improvement:** Ensure tutorials detail all client-libraries and how developers can produce a minimum working example using the service on their own computer using that client library. For each SDK offered, there should be details on how to install, authenticate and use a component using local data. For example, this may be as simple as using the service to determine if an image of a dog contains the label 'dog'.

3999 **Step-by-step tutorials [A6]:** Google Cloud Vision offers tutorials limited to one
4000 component. These do not sufficiently demonstrate how to combine *multiple compo-*
4001 *nents* of the API together and how developers should integrate it with a differ-
4002 ent platform, which a good step-by-step tutorial should detail. The official AWS
4003 Machine Learning blog [395] provides extensive tutorials (in some cases, with a
4004 suggested tutorial completion time of over an hour) that integrate multiple Amazon
4005 Rekognition components with other AWS components. Microsoft provide tutori-
4006 als [436, 441, 442] integrating multiple components within their service to mobile
4007 applications and the Azure platform.

 **Suggested improvement:** Ensure tutorials combine multiple components of the service together, are extensive, and require developers to spend a non-trivial amount of time to produce a basic application. For example, the tutorial may detail how to integrate the API into a smartphone application to achieve the following: (i) take a photo with the camera, (ii) detect if a person is within the image, (iii) analyse the visual features of the person.

4008 **Downloadable production-ready applications [A7]:** Microsoft provide a down-
4009 loadable application [440] that explores many components of the Azure Computer
4010 Vision API. The application is thoroughly documented with and also provides guid-
4011 ance on how to structure the architecture design of the program. While Rekognition
4012 and Google Cloud Vision also provide downloadable source code, they are largely
4013 under-documented, do not combine multiple components of the API together, and
4014 only use god-classes to handle all requests to the API [399, 422].

 **Suggested improvement:** Downloadable source code should be thoroughly docu-
mented, and should avoid the use of god-classes that demonstrate a single piece of the
service's functionality. Ideally, the architecture of a production-ready application should
be demonstrated to developers.

4015 **Understanding best-practices [A8]:** Google Cloud provides best-practices for its
4016 platform in both general and enterprise contexts [414, 423], but there is little advice
4017 provided to guide developers on how best to use Google Cloud Vision. Microsoft
4018 provides guidance on improving results of custom vision classifiers [437], but no
4019 further details on non-custom vision classifiers are found. We found the most detailed
4020 best-practices to be provided by Amazon Rekognition [397], which outlines more
4021 detailed strategies such as reducing data transfer by storing and referencing images
4022 on S3 Buckets or the attributes images should have in various scenarios (e.g., the
4023 angles of a person's face in facial recognition).

 **Suggested improvement:** Document best-practices for all major components of the
CVS. Guide developers on the types of input data that produce the best results, advisable
minimum image sizes and recommended file types, and suggest ways to overcome
limitations that improve usage and cost efficiency. Provide guidance in more than one
use case; give a range of scenarios that demonstrate different best practices for different
domains.

4024 **Exhaustive lists of all major API components [A9]:** Amazon provides a two-fold
4025 feature list that describes both the key features of Rekognition at a high-level [396]
4026 as well as a detailed, technical breakdown of each API operation provided within the
4027 service [394]. Microsoft also provide a list of high-level features that Azure Com-
4028 puter Vision can analyse [443] which provides hyperlinks to detailed descriptions of
4029 each feature. Google's Cloud Vision API provides a partial breakdown of the types
4030 of services provided, however this list is not fully complete, nor are there hyperlinks
4031 to more detailed descriptions of each of the features [424].

☞ **Suggested improvement:** Document key features that the computer vision classifier can perform at a high level. This should be easy to find from the service's landing page. Each feature should be described with reference to more detailed descriptions of the feature's exact API endpoint and required inputs, outputs and possible errors.

4032 **Minimum system requirements and dependencies [A10]:** Although there is no dedicated webpage for this on any of the services investigated, there are listed dependencies for the client libraries in Google's and Azure's quick-start guides [420, 434]. These may be embedded within the quick-start guide as developers are likely to encounter dependency issues when they first start using the API. We found it a challenge to discover similar documentation this in Amazon's documentation.

☞ **Suggested improvement:** Any system requirements and dependency issues should be well-highlighted within the documentation's quick-start guide; developers are likely to encounter these issues within the early stages of using an API, and it is highly relevant to provide solutions to these issues within the quick-starts.

4038 **Installation and release cycle notes [A11]:** It is imperative that developers know what has changed between releases and how frequently the releases are exported. 4039 We found release notes for Amazon Computer Vision, although they are only major 4040 releases and have not been updated since 2017 [393] which does not account for 4041 evolution in the service's responses [88]. Google's and Microsoft's release notes are 4042 generally more frequently updated, therefore developers can get a sense of its release 4043 frequency [421, 439]. However, there are evolution issues that are not addressed. 4044 Installation instructions are detailed within Rekognition's developer guide, outlining 4045 how to sign up for an account, and install the AWS command-line interface [401]. 4046

☞ **Suggested improvement:** Ensure release notes detail label evolution, including any new additional labels that may have been introduced within the service. Transparency around the changes made to the service should go beyond new features: document potential changes that may influence maintenance of a system using the CVS so that developers are aware of potential side-effects of upgrading to a newer release.

4047 8.6.5.2 Issues regarding Descriptions of Design Rationale

4048 **Limitations of the API [B7]:** The most detailed limitations documented were 4049 found on Rekognition's dedicated limitations page [400] that outlines functional 4050 limitations such as the maximum number of faces or words that can be detected 4051 in an image, the size requirements of images, and file type information. For the 4052 other services, functional limitations are generally found within each endpoint's API 4053 documentation, instead of within a dedicated page.

☞ **Suggested improvement:** Document all functional limitations in a dedicated page that outline the maximum and minimum input requirements the classifier can handle. Documentation of the types of labels the service can provide is also desired.

4054 8.6.5.3 Issues regarding Descriptions of Domain Concepts

4055 Conceptual understanding of the API [C1]: Azure Computer Vision provides
‘concept’ pages describing the high-level concepts behind computer vision and where
4056 these functions are implemented within the APIs (e.g., [435]). We were unable to
4057 find similar conceptual documentation for the other services assessed.
4058

💡 Suggested improvement: Document the concepts behind computer vision; differentiate
between foundational concepts such as object localisation, object recognition, facial
localisation and facial analysis such that developers are able to make the distinction
between them. Relate these concepts back to the API and provide references to where the
APIs implement these concepts.

4059 Definitions of domain-specific terminology [C2]: Terminologies relevant to ma-
4060 chine learning concepts powering these CVSs are well detailed within Google’s
4061 machine learning glossary [418], however few examples matching computer vision
4062 are immediately relevant. While this page is linked from the original Google Cloud
4063 Vision documentation, it may be too technical for application developers to grasp. A
4064 slightly better example of this is [443], where developers can understand computer
4065 vision terms in lay terms.

💡 Suggested improvement: Current CVSs use a myriad of terminologies to refer to the
same conceptual feature; for example, while Microsoft refers to object recognition as
‘image tagging’, Google refers to this as ‘label detection’. If a consolidation of terms
is not possible, then CVSs should provide a glossary that provides synonyms for these
terminologies so that developers can easily move between service providers without
needing to relink terms back to concepts.

4066 8.6.5.4 Issues regarding Existence of Support Artefacts

4067 Troubleshooting suggestions [D2]: The only troubleshooting tips found in our
4068 analysis were in Rekognition’s video service [402]. Further detailed instances of
4069 these troubleshooting tips could be expanded to non-video issues. For instance,
4070 if developers upload ‘noisy’ images, how can they inform the system of a specific
4071 ontology to use or to focus on parts of the foreground or background of the image?
4072 These are suggestions which we have proposed in prior work [88] that do not seem
4073 to be documented.

💡 Suggested improvement: Ensure troubleshooting tips provide advice for testing against
different types of valid input images.

4074 Diagrammatic overview of the API [D3]: None of the CVSs provide any overview
4075 of the API in terms of the features and processing steps on how they should be used.
4076 For instance, pre-processing and post-processing of input and response data should
4077 be considered and an understanding of how this fits into the ‘flow’ of an application
4078 highlighted. Moreover, no UML diagrams could be found.

☞ **Suggested improvement:** Provide diagrams illustrating the service within context of use, such as how it can be integrated with other service features or how a specific API endpoint may be used within a client application. Consider integrating interactive UML diagrams so that developers can easily explore various aspects of the documentation in a visual perspective.

4079 8.7 Threats to Validity

4080 8.7.1 Internal Validity

4081 Threats to *internal validity* represent internal factors of our study which affect
4082 concluded results. Kitchenham and Charters' guidelines on producing systematic
4083 reviews [192] suggest that researchers conducting reviews should discuss the review
4084 protocol, inclusion decisions, data extraction with a third party. Within this study,
4085 we discussed our protocols with other researchers within our research group and
4086 utilised test-retest reliability. Further assessments into reliability would involve an
4087 assessment of the review and extraction processes, which can be investigated using
4088 inter-rater reliability measures. Guidelines suggested by Garousi and Felderer [129]
4089 describe methods for independent analysis and conflict resolution could help resolve
4090 this.

4091 As stated in Section 8.3.2, we utilised a systematic software engineering tax-
4092 onomy development method by Usman et al. [357]. Two additional taxonomy
4093 validation approaches proposed by Usman et al. were not considered in our work:
4094 benchmarking and orthogonality demonstration. To our knowledge, there are no
4095 other studies that classify existing API knowledge studies into a structured taxon-
4096 omy, and therefore we are unable to benchmark our taxonomy against others. We
4097 would encourage the research community to conduct a replication of our work and
4098 investigate whether our taxonomy classification approaches are replicable to ensure
4099 that categories are reliable and the dimensions fit the objectives of the taxonomy.
4100 Moreover, we did not investigate orthogonality demonstration as our primary goals
4101 for this work were to investigate the efficacy of the taxonomy by practitioners and
4102 in-practice, with reference to our wider research area of intelligent CVSs. Therefore,
4103 we solely adopted the utility demonstration approach in two detailed experiments
4104 (Sections 8.5 and 8.6) to analyse the efficacy of our taxonomy and identify potential
4105 improvements for these services' API documentation.

4106 8.7.2 External Validity

4107 Threats to *external validity* concern the generalisation of our observations. Our
4108 systematic mapping study has used a broad range of sources however not all papers
4109 contributing to API documentation may have been found or captured within the
4110 taxonomy. While we attempted to include as many papers as we could find in our
4111 study, some papers may have been filtered out due to our exclusion criteria. For
4112 example, there are studies we found that were excluded as they were not written in
4113 English, and these excluding factors may alter our conclusions, introducing conflict-

4114 ing recommendations. However, given the consistency of these trends within the
4115 studies that were sourced, we consider this a low likelihood.

4116 Documentation of web APIs are non-static, and may evolve using contributions
4117 from both official sources and the developer community (e.g., via GitHub). We
4118 downloaded the three service’s API documentation in March of 2019—it is highly
4119 likely that new documentation may have been added since or modified since publi-
4120 cation. A recommendation to mitigate this would be to re-evaluate this study once
4121 intelligent CVSs have matured and become even more mainstream in developer
4122 communities.

4123 We also adopt research conducted in the field of questionnaire design, such as
4124 ensuring all scales are worded with labels [203] and have used a summatting rating
4125 scale [333] to address a specific topic of interest if people are to make mistakes in
4126 their response or answer in different ways at different times. This approach was
4127 also extended using the SUS methodology, in which positive and negative items
4128 were used—as multiple studies have shown [62, 312], this approach helps reduce
4129 poor-quality responses by minimising extreme responses and acquiescence biases.

4130 8.7.3 Construct Validity

4131 Threats to *construct validity* relates to the degree by which the data extrapolated
4132 in this study sufficiently measures its intended goals. Automatic searching was
4133 conducted in the SMS by choice of three popular databases (see Section 8.3.1).
4134 As a consequence of selecting multiple databases, duplicates were returned. This
4135 was mitigated by manually curating out all duplicate results from the set of studies
4136 returned. Additionally, we acknowledge that the lack manual searching of papers
4137 within particular venues may be an additional threat due to the misalignment of
4138 search query keywords to intended papers of inclusion. Thus, our conclusions are
4139 only applicable to the information we were able to extract and summarise, given the
4140 primary sources selected.

4141 While we have investigated the application of this taxonomy using a user study
4142 (Section 8.5.1), we would like to explore an observational study of developers
4143 to assess how improved and non-improved API documentation impacts developer
4144 productivity. The outcome of this work can help design a follow-up experiment,
4145 consisting of a comparative controlled study [318] that capture firsthand behaviours
4146 and interactions toward how software engineers approach using a CVS with and
4147 without our taxonomy applied. This can be achieved by providing ‘mock’ improved
4148 documentation with the suggested improvements included in this work. Such an ex-
4149 periment could recruit a sample of developers of varying experience (from beginner
4150 programmer to principal engineer) to complete a certain number of tasks under an
4151 observational, comparative controlled study, half of which will (a) develop using
4152 the improved ‘mock’ documentation, and the other half will (b) develop with the
4153 *as-is/existing* documentation. From this, we can compare if the framework makes
4154 improvements by capturing metrics and recording the observational sessions for
4155 qualitative analysis. Visual modelling can be adopted to analyse the qualitative data
4156 using matrices [98], maps and networks [315] as these help illustrate any causal, tem-

4157 poral or contextual relationships that may exist to map out the developer’s mindset
4158 and difference in approaching the two sets of designs of the same tasks.

4159 8.8 Conclusions & Future Work

4160 A good API document should facilitate a developer’s productivity, and is therefore
4161 associated to the quality of software produced; improving the quality of the docu-
4162 mentation of third-party APIs improves the quality of dependent software. However,
4163 there does not yet exist a consolidated taxonomy of key recommendations proposed
4164 by literature, and—more importantly—it is useful to know if what developers need
4165 *in-practice* differs to what documentation artefacts are anticipated by literature.
4166 Moreover, there has been little work on mapping the research produced in this space
4167 against the techniques used to arrive at the recommendations.

4168 This study prioritises which aspects of API documentation knowledge is both (i)
4169 suggested by literature, and (ii) is demanded *most* by developers. We conduct a
4170 SMS from a pool of 4,501 studies and identify 21 seminal studies. From this, we
4171 synthesise a taxonomy of the various documentation aspects that should improve
4172 API documentation quality. Furthermore, we also capture the most commonly used
4173 analysis techniques used in the academic literature. We then validate our taxonomy
4174 against developers to assess its efficacy with practitioners, and conduct a heuristic
4175 evaluation against three popular CVSs. We offer 12 detailed suggested improve-
4176 ments where these services currently have weaknesses, and where specifically they
4177 may be able to improve their documentation.

4178 Future extensions of our work may involve a restricted systematic literature
4179 review in API documentation artefacts, and many suggestions are further detailed
4180 in Section 8.7. Further, a review into the techniques of these primary studies may
4181 extend the mapping we conducted in this work, by evaluating the effectiveness of
4182 the various approaches used in each study and assessing these against the proposed
4183 conclusions of each study.

4184 The findings of our work provides a solid baseline for improving the documen-
4185 tation of non-deterministic software, such as CVSs. While our aim is to eventually
4186 improve the quality of API documentation, the ultimate goal is to improve the soft-
4187 ware engineer’s experience of non-deterministic IWSs. We hope the guidelines from
4188 this extensive study help both software developers and API providers alike by using
4189 our taxonomy as a go-to checklist for what should be considered in documenting any
4190 API.

CHAPTER 9

4191

4192

4193 Using a Facade Pattern to combine Computer Vision Services[†]

4194

4195 **Abstract** Intelligent computer vision services, such as Google Cloud Vision or Amazon
4196 Rekognition, are becoming evermore pervasive and easily accessible to developers to build
4197 applications. Because of the stochastic nature that ML entails and disparate datasets used in
4198 their training, the outputs from different computer vision services varies with time, resulting
4199 in low reliability—for some cases—when compared against each other. Merging multiple
4200 unreliable API responses from multiple vendors may increase the reliability of the overall
4201 response, and thus the reliability of the intelligent end-product. We introduce a novel
4202 methodology—inspired by the proportional representation used in electoral systems—to
4203 merge outputs of different intelligent computer vision API provided by multiple vendors.
4204 Experiments show that our method outperforms both naive merge methods and traditional
4205 proportional representation methods by 0.015 F-measure.

4206 9.1 Introduction

4207 With the introduction of intelligent web services (IWSs) that make machine learning
4208 (ML) more accessible to developers [296, 364], we have seen a large growth of
4209 intelligent applications dependent on such services [65, 134]. For example, consider
4210 the advances made in computer vision, where objects are localised within an image
4211 and labelled with associated categories. Cloud-based computer vision services
4212 (CVSs)—e.g., [392, 405, 413, 417, 426, 427, 431, 479]—are a subset of IWSs.
4213 They utilise ML techniques to achieve image recognition via a remote black-box
4214 approach, thereby reducing the overhead for application developers to understand
4215 how to implement intelligent systems from scratch. Furthermore, as the processing

[†]This chapter is originally based on T. Ohtake, A. Cummaudo, M. Abdelrazek, R. Vasa, and J. Grundy, “Merging intelligent API responses using a proportional representation approach,” in *Proceedings of the 19th International Conference on Web Engineering*. Daejeon, Republic of Korea: Springer, June 2019. DOI 10.1007/978-3-030-19274-7_28. ISBN 978-3-03-019273-0. ISSN 1611-3349 pp. 391–406. Terminology has been updated to fit this thesis.

4216 and training of the machine-learnt algorithms is offloaded to the cloud, developers
4217 simply send RESTful API requests to do the recognition. There are, however, inherit
4218 differences and drawbacks between traditional web services and IWSs, which we
4219 describe with the motivating scenario below.

4220 **9.1.1 Motivating Scenario: Intelligent vs Traditional Web Services**

4221 An application developer, Tom, wishes to develop a social media Android and iOS
4222 app that catalogues photos of him and his friends, common objects in the photo,
4223 and generates brief descriptions in the photo (e.g., all photos with his husky dog,
4224 all photos on a sunny day etc.). Tom comes from a typical software engineering
4225 background with little knowledge of computer vision and its underlying concepts.
4226 He knows that intelligent computer vision web APIs are far more accessible than
4227 building a computer vision engine from scratch, and opts for building his app using
4228 these cloud services instead.

4229 Based on his experiences using similar cloud services, Tom would expect consistency
4230 of the results from the same API and different APIs that provide the same (or
4231 similar) functionality. As an analogy, when Tom writes the Java substring method
4232 "doggy".substring(0, 2), he expects it to be the same result as the Swift equivalent
4233 "doggy".prefix(3). Each and every time he interacts with the substring
4234 method using either API, he gets "dog" as the response. This is because Tom is
4235 used to deterministic, rule-driven APIs that drive the implementation behind the
4236 substring method.

4237 Tom's deterministic mindset results in three key differentials between a traditional
4238 web services and an IWS:

4239 **(1) Given similar input, results differ between similar IWSs.** When Tom
4240 interacts with the API of an IWS, he is not aware that each API provider trains
4241 their own, unique ML model, both with disparate methods and datasets. These
4242 IWSs are, therefore, nondeterministic and data-driven; input images—even
4243 if they contain the same conceptual objects—often output different results.
4244 Contrast this to the substring method of traditional APIs; regardless of what
4245 programming language or string library is used, the same response is expected
4246 by developers.

4247 **(2) Intelligent responses are not certain.** When Tom interprets the response
4248 object of an IWS, he finds that there is a ‘confidence’ value or ‘score’. This
4249 is because the ML models that power IWSs are inherently probabilistic and
4250 stochastic; any insight they produce is purely statistical and associational [277].
4251 Unlike the substring example, where the rule-driven implementation provides
4252 certainty to the results, this is not guaranteed for IWSs. For example, a picture
4253 of a husky breed of dog is misclassified as a wolf. This could be due to
4254 adversarial examples [342] that ‘trick’ the model into misclassifying images
4255 when they are fully decipherable to humans. It is well-studied that such
4256 adversarial examples exist in the real world unintentionally [113, 204, 280].

4257 **(3) Intelligent APIs evolve over time.** Tom may find that responses to processing
4258 an image may change over time; the labels he processes in testing may evolve

4259 and therefore differ to when in production. In traditional web services, evo-
4260 lution in responses is slower, generally well-communicated, and usually rare
4261 (Tom would always expect "dog" to be returned in the substring example).
4262 This has many implications on software systems that depend on these APIs,
4263 such as confidence in the output and portability of the solution. Currently, if
4264 Tom switches from one API provider to another, or if he doesn't regularly test
4265 his app in production, he may begin to see a very different set of labels and
4266 confidence levels.

4267 9.1.2 Research Motivation

4268 These drawbacks bring difficulties to the intended API users like Tom. We identify a
4269 gap in the software engineering literature regarding such drawbacks, including: lack
4270 of best practices in using IWSs; assessing and improving the reliability of APIs for
4271 their use in end-products; evaluating which API is suitable for different developer
4272 and application needs; and how to mitigate risk associated with these APIs. We
4273 focus on improving reliability of CVSs for use in end-products. The key research
4274 questions in this paper are:

4275 **RQ1:** Is it possible to improve reliability by merging multiple CVS results?

4276 **RQ2:** Are there better algorithms for merging these results than currently in
4277 use?

4278 Previous attempts at overcoming low reliability include triple-modular redundancy
4279 [223]. This method uses three modules and decides output using majority
4280 rule. However, in CVSs, it is difficult to apply majority rule: these APIs respond with
4281 a list of labels and corresponding scores. Moreover, disparate APIs ordinarily output
4282 different results. These differences make it hard to apply majority rule because the
4283 type of outputs are complex and disparate APIs output different results for the same
4284 input. Merging search results is another technique to improve reliability [327]. It
4285 normalises scores of different databases using a centralised sample database. Nor-
4286 malising scores makes it possible to merge search results into a single ranked list.
4287 However, search responses are disjoint, whereas they are not in the context of most
4288 CVSs.

4289 In this paper, we introduce a novel method to merge responses of CVSs, using
4290 image recognition APIs endpoints as our motivating example. Section 9.2 describes
4291 naive merging methods and requirements. Section 9.3 gives insights into the struc-
4292 ture of labels. Section 9.4 introduces our method of merging computer vision labels.
4293 Section 9.5 compares precision and recall for each method. Section 9.6 presents
4294 conclusions and future work.

4295 9.2 Merging API Responses

4296 Image recognition APIs have similar interfaces: they receive a single input (image)
4297 and respond with a list of labels and associated confidence scores. Similarly, other
4298 supervised-AI-based APIs do the same (e.g., detecting emotions from text and

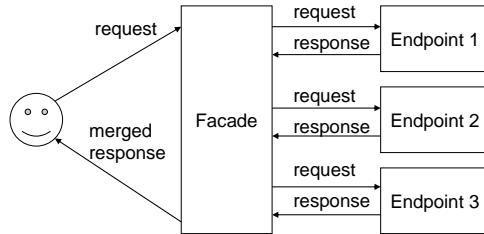


Figure 9.1: The user sends a request to the facade; this request is propagated to the relevant APIs. Responses are merged by the facade and returned back to the user.

4299 natural language processing [428, 480]). It is difficult to apply majority rule on such
 4300 disparate, complex outputs. While the outputs by *multiple* AI-based API endpoints
 4301 is different and complex, the general format of the output is the same: a list of labels
 4302 and associated scores.

4303 9.2.1 API Facade Pattern

4304 To merge responses from multiple APIs, we introduce the notion of an API facade.
 4305 It is similar to a metasearch engine, but differs in their external endpoints. The
 4306 facade accepts the input from one API endpoint (the facade endpoint), propagates
 4307 that input to all user-registered concrete (external) API endpoints simultaneously,
 4308 then ‘merges’ outputs from these concrete endpoints before sending this merged
 4309 response to the API user. We demonstrate this process in Figure 9.1.

4310 Although the model introduces more time and cost overhead, both can be miti-
 4311 gated by caching results. On the other hand, the facade pattern provides the following
 4312 benefits:

- 4313 • **Easy to modify:** It requires only small modifications to applications, e.g.,
 4314 changing each concrete endpoint URL.
- 4315 • **Easy to customise:** It merges results from disparate and concrete APIs ac-
 4316 cording to the user’s preference.
- 4317 • **Improves reliability:** It enhances reliability of the overall returned result by
 4318 merging results from different endpoints.

4319 9.2.2 Merge Operations

4320 The API facade is applicable to many use cases. However, this paper focuses on
 4321 APIs that output a list of labels and scores, as is the case for CVSs. Merge operations
 4322 involve the mapping of multiple lists and associated scores, produced by multiple
 4323 APIs, to just one list. For instance, a CVS receives a bowl of fruit as the input image
 4324 and outputs the following:

4325 `[[‘apple’, 0.9], [‘banana’, 0.8]]`

4326 where the first item is the label and the second item is the score. Similarly, another
 4327 computer vision API outputs the following for the same image:

4328 `[[‘apple’, 0.7], [‘cherry’, 0.8]].`

4329 Merge operations can, therefore, merge these two responses into just one response.
4330 Naive ways of merging results could make use of *max*, *min*, and *average* operations
4331 on the confidence scores. For example, *max* merges results to:

4332 `[[‘apple’, 0.9], [‘banana’, 0.8], [‘cherry’, 0.8]];`

4333 *min* merges results to:

4334 `[[‘apple’, 0.7]];`

4335 and *average* merges results to:

4336 `[[‘apple’, 0.8], [‘banana’, 0.4], [‘cherry’, 0.4]].`

4337 However, as the object’s labels in each result are natural language, the operations
4338 do not exploit the label’s semantics when conducting label merging. To improve
4339 the quality of the merged results, we consider the ontologies of these labels, as we
4340 describe below.

4341 9.2.3 Merging Operators for Labels

4342 Merge operations on labels are n -ary operations that map R^n to R , where $R_i =$
4343 $\{(l_{ij}, s_{ij})\}$ is a response from endpoint i and contains pairs of labels (l_{ij}) and scores
4344 (s_{ij}). Merge operations on labels have the following properties:

- 4345 • *identity* defines that merging a single response should output same response
4346 (i.e., $R = \text{merge}(R)$ is always true);
- 4347 • *commutativity* defines that the order of operands should not change the result
4348 (i.e., $\text{merge}(R_1, R_2) = \text{merge}(R_2, R_1)$ is always true);
- 4349 • *reflexivity* defines that merging multiple same responses should output same
4350 response (i.e., $R = \text{merge}(R, R)$ is always true); and,
- 4351 • *additivity* defines that, for a specific label, the merged response should have
4352 higher or equal score for the label if a concrete endpoint has a higher score.
4353 Let $R = \text{merge}(R_1, R_2)$ and $R' = \text{merge}(R'_1, R_2)$ be merged responses. R_1 and
4354 R'_1 are same, except R'_1 has a higher score for label l_x than R_1 . The additive
4355 score property requires that R' score for l_x should be greater than or equal to
4356 R score for l_x .

4357 The *max*, *min*, and *average* operations in Section 9.2.2 follow each of these rules
4358 as all operations calculate the score by applying these operations on each score.

Table 9.1: Statistics for the number of labels, on average, per service identified.

Endpoint	Average number of labels	Has synset	No synset
Amazon Rekognition	11.42 ± 7.52	10.74 ± 7.10 (94.0%)	0.66 ± 0.87
Google Cloud Vision	8.77 ± 2.15	6.36 ± 2.22 (72.5%)	2.41 ± 1.93
Azure Computer Vision	5.39 ± 3.29	5.26 ± 3.32 (97.6%)	0.14 ± 0.37

4359 9.3 Graph of Labels

4360 CVSs typically return lists of labels and their associated scores. In most cases, the
 4361 label can be a singular word (e.g., ‘husky’) or multiple words (e.g., ‘dog breed’).
 4362 Lexical databases, such as WordNet [243], can therefore be used to describe the
 4363 ontology behind these labels’ meanings. Figure 9.2 is an example of a graph of
 4364 labels and synsets. A synset is a grouped set of synonyms for a word. In this image,
 4365 we consider two fictional endpoints, endpoints 1–2. We label red nodes as labels
 4366 from endpoint 1, yellow nodes as labels from endpoint 2, and blue nodes as synsets
 4367 for the associated labels from both endpoints. As actual graphs are usually more
 4368 complex, Figure 9.2 is a simplified graph to illustrate the usage of associating labels
 4369 from two concrete sources to synsets.

4370 9.3.1 Labels and synsets

4371 The number of labels depends on input images and concrete API endpoints used.
 4372 Table 9.1 and Figure 9.3 show how many labels are returned, on average per image,
 4373 from Google Cloud Vision [417], Amazon Rekognition [392] and Azure Computer
 4374 Vision [431] image recognition APIs. These statistics were calculated using 1,000
 4375 images from Open Images Dataset V4 [419] Image-Level Labels set.

4376 Labels from Amazon and Microsoft tend to have corresponding synsets, and
 4377 therefore these endpoints return common words that are found in WordNet. On the
 4378 other hand, Google’s labels have less corresponding synsets: for example, labels
 4379 without corresponding synsets are car models and dog breeds.¹

4380 9.3.2 Connected Components

4381 A connected component (CC) is a subgraph in which there are paths between any
 4382 two nodes. In graphs of labels and synsets, CCs are clusters of labels and synsets
 4383 with similar semantic meaning. For instance, there are two CCs in Figure 9.2. CC 1
 4384 in Figure 9.2 has ‘beverage’, ‘dessert’, ‘chocolate’, ‘hot chocolate’,
 4385 ‘drink’, and ‘food’ labels from the red first endpoint and ‘coffee’, ‘hot
 4386 chocolate’, ‘drink’, ‘caffeine’, and ‘tea’ labels from the yellow second
 4387 endpoint. Therefore, these labels are related to ‘drink’. On the other hand, CC 2
 4388 in Figure 9.2 has ‘cup’ and ‘coffee cup’ labels from the first red endpoint and
 4389 ‘cup’, ‘coffee cup’, and ‘tableware’ labels from the yellow second endpoint.
 4390 These labels are, therefore, related to ‘cup’.

¹We noticed from our upload of 1,000 images that Google tries to identify objects in greater detail.

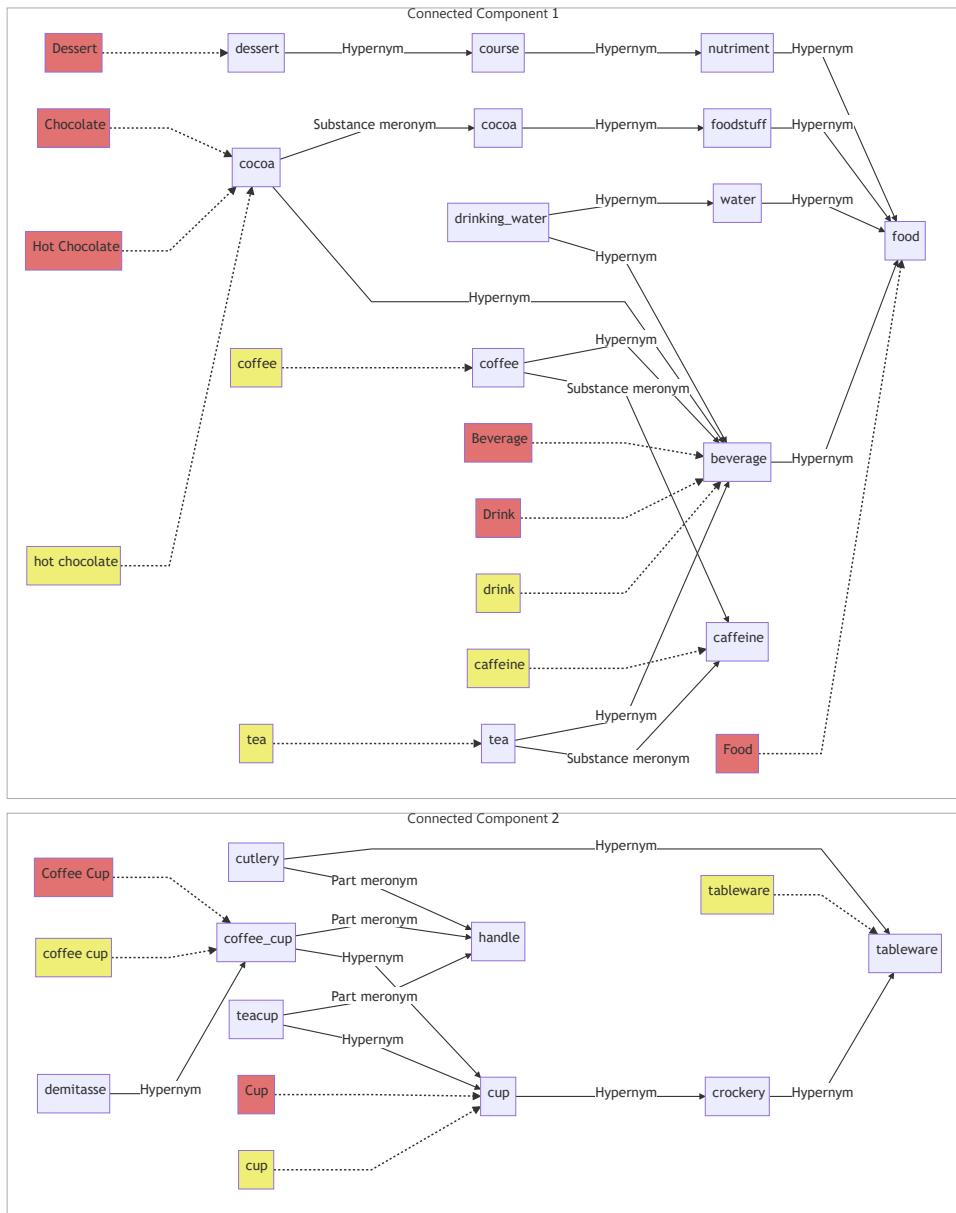


Figure 9.2: Graph of labels from two concrete endpoints (red and yellow) and their associated synsets related to both words (blue).

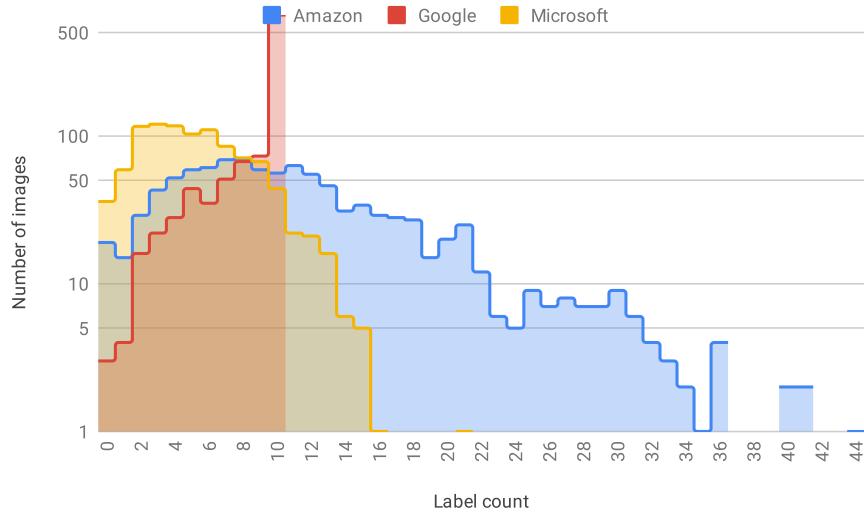


Figure 9.3: Number of labels responded from our input dataset to three concrete APIs assessed.

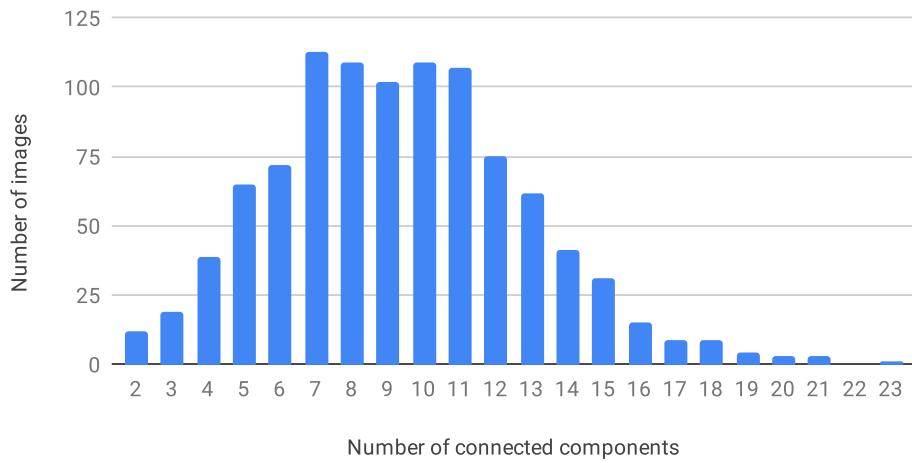


Figure 9.4: Number of connected components compared to the number of images.

4391 Figure 9.4 shows a distribution of number of CCs for the 1,000-image label
4392 detections on Amazon Rekognition, Google Cloud Vision, and Azure Computer
4393 Vision APIs. The average number of CCs is 9.36 ± 3.49 . The smaller number of
4394 CCs means that most of labels have similar meanings, while a larger value means
4395 that the labels are more disparate.

4396 9.4 API Results Merging Algorithm

4397 Our proposed algorithm to merge labels consists of four parts: (1) mapping labels to
4398 synsets, (2) deciding the total number of labels, (3) allocating the number of labels
4399 to CCs, and (4) selecting labels from CCs.

4400 9.4.1 Mapping Labels to Synsets

4401 Labels returned in CVS responses are words (in natural language) that do not always
4402 identify their intended meanings. For instance, a label *orange* may represent the
4403 fruit, the colour, or the name of the longest river in South Africa. To identify the
4404 actual meanings behind a label, our facade enumerates all synsets corresponding to
4405 labels. It then finds the most likely synsets for labels by traversing WordNet links.
4406 For instance, if an API endpoint outputs the ‘orange’ and ‘lemon’ labels, the
4407 facade regards ‘orange’ as a related synset word of ‘fruit’. If an API endpoint
4408 outputs ‘orange’ and ‘water’ labels, the facade regards ‘orange’ as a ‘river’.

4409 9.4.2 Deciding Total Number of Labels

4410 The number of labels in responses from endpoints vary as described in Section 9.3.1.
4411 The facade decides the number of merged labels using the numbers of labels from
4412 each endpoint. We formulate the following equation to calculate the number of
4413 labels:

$$\min_i(|R_i|) \leq \frac{\sum_i|R_i|}{n} \leq \max_i(|R_i|) \leq \sum_i|R_i|$$

4414 where $|R|$ is number of labels and scores in response, and n is number of endpoints.
4415 In case of naive operations in Section 9.2.2, the following is true:

$$\begin{aligned} |\text{merge}_{\max}(R_1, \dots, R_n)| &\leq \min_i(|R_i|) \\ \max_i(|R_i|) &\leq |\text{merge}_{\min}(R_1, \dots, R_n)| \leq \sum_i|R_i| \\ \max_i(|R_i|) &\leq |\text{merge}_{\text{average}}(R_1, \dots, R_n)| \leq \sum_i|R_i|. \end{aligned}$$

4416 The proposal uses $\lfloor \sum_i|R_i|/n \rfloor$ to conform to the necessary condition described in
4417 Section 9.4.3.

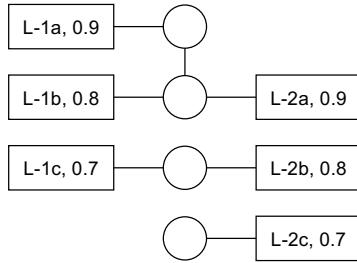


Figure 9.5: Allocation to connected components.

4418 9.4.3 Allocating Number of Labels to Connected Components

4419 The graph of labels and synsets is then divided into several CCs. The facade decides
 4420 how many labels are allocated for each CC. For example, in Figure 9.5, there are
 4421 three CCs, where square-shaped nodes are labels in responses from endpoints. Text
 4422 within these label nodes describe which endpoint outputs the label and score, for
 4423 instance, “L-1a, 0.9” is label *a* from endpoint *1* with a score 0.9. Circle-shaped nodes
 4424 represent synsets, where the edges between the label and synset nodes indicate the
 4425 relationships between them. Edges between synsets are links in WordNet.
 4426 Allegorically, allocating the number of labels to CCs is similar to proportional
 4427 representation in a political voting system, where CCs are the political parties and
 4428 labels are the votes to a party. Several allocation algorithms are introduced in
 4429 proportional representation, for instance, the D’Hondt and Hare-Niemeyer methods
 4430 [256]. However, there are differences from proportional representation in the polit-
 4431 ical context. For label merging, labels have scores and origin endpoints and such
 4432 information may improve the allocation algorithm. For instance, CCs supported
 4433 with more endpoints should have a higher allocation than CCs with fewer endpoints,
 4434 and CCs with higher scores should have a higher allocation than CCs with lower
 4435 scores. We introduce an algorithm to allocate the number of labels to CCs. This
 4436 allocates more to a CC with more supporting endpoints and higher scores. The steps
 4437 of the algorithm are:

- 4438 **Step I.** Sort scores separately for each endpoint.
- 4439 **Step II.** If all CCs have an empty score array or more, remove one, and go to Step
 4440 II.
- 4441 **Step III.** Select the highest score for each endpoint and calculate product of highest
 4442 scores.
- 4443 **Step IV.** A CC with the highest product score receives an allocation. This CC
 4444 removes every first element from the score array.
- 4445 **Step V.** If the requested number of allocations is complete, then stop allocation.
 4446 Otherwise, go to Step II.

4447 Tables 9.2 to 9.5 are examples of allocation iterations. In Table 9.2, the facade
 4448 sorts scores separately for each endpoint. For instance, the first CC in Figure 9.5
 4449 has scores of 0.9 and 0.8 from endpoint 1 and 0.9 from endpoint 2. All CCs have a

Table 9.2: Allocation iteration 1.

Scores	Highest	Product	Allocated
[0.9, 0.8], [0.9]	[0.9, 0.9]	0.81	0+1
[0.7], [0.8]	[0.7, 0.8]	0.56	0
[], [0.7]	[N/A, 0.7]	N/A	0

Table 9.4: Allocation iteration 3.

Scores	Highest	Product	Allocated
[0.8], []	—	—	1
[], []	—	—	1
[], [0.7]	—	—	0

Table 9.3: Allocation iteration 2.

Scores	Highest	Product	Allocated
[0.8], []	[0.8, N/A]	N/A	1
[0.7], [0.8]	[0.7, 0.8]	0.56	0+1
[], [0.7]	[N/A, 0.7]	N/A	0

Table 9.5: Allocation iteration 4.

Scores	Highest	Product	Allocated
[0.8]	[0.8]	0.8	1+1
[]	[N/A]	N/A	1
[0.7]	[0.7]	0.7	0

non-empty score array or more, so the facade skips Step II. The facade then picks the highest scores for each endpoint and CC. CC 1 has the largest product of highest scores and receives an allocation. In Table 9.3, the first CC removes every first score in its array as it received an allocation in Table 9.2. In this iteration, the second CC has largest product of scores and receives an allocation. In Table 9.4, the second CC removes every first score in its array. At Step II, all the three CCs have an empty array. The facade removes one empty array from each CC. In Table 9.5, the first CC receives an allocation. The algorithm is applicable if total number of allocation is less than or equal to $\max_i(|R_i|)$ as scores are removed in Step II. The condition is a necessary condition.

9.4.4 Selecting Labels from Connected Components

For each CC, the facade applies the *average* operator from Section 9.2.2 and takes labels with n -highest scores up to allocation, as per Section 9.4.3.

9.4.5 Conformance to properties

Section 9.2.3 defines four properties: identity, commutativity, reflexivity, and additivity. Our proposed method conforms to these properties:

- *identity*: the method outputs same result if there is one response;
- *commutativity*: the method does not care about ordering of operands;
- *reflexivity*: the allocations to CCs are same to number of labels in CCs; and
- *additivity*: increases in score increases or does not change the allocation to the corresponding CC.

9.5 Evaluation

9.5.1 Evaluation Method

To evaluate the merge methods, we merged CVS results from three representative image analysis API endpoints and compared these merged results against human-

4475 verified labels. Images and human-verified labels are sourced from 1,000 randomly-
4476 sampled images from the Open Images Dataset V4 [419] Image-Level Labels test
4477 set.

4478 The first three rows in Table 9.7 are the evaluation of original responses from
4479 each API endpoint. Precision, recall, and F-measure in Table 9.7 do not reflect
4480 actual values: for instance, it appears that Google performs best at first glance, but
4481 this is mainly because Google’s labels are similar to that of the Open Images label
4482 set.

4483 The Open Images Dataset uses 19,995 classes for labelling. The human-verified
4484 labels for the 1,000 images contain 8,878 of these classes. Table 9.6 shows the
4485 correspondence between each service’s labels and the Open Images Dataset classes.
4486 For instance, Amazon Rekognition outputs 11,416 labels in total for 1,000 images.
4487 There are 1,409 unique labels in 11,416 labels. 1,111 labels out of 1,409 can be
4488 found in Open Images Dataset classes. Rekognition’s labels matches to Open Images
4489 Dataset classes at 78.9% ratio, while Google has an outstanding matched percentage
4490 of 94.1%. This high match is likely due to Google providing both Google Cloud
4491 Vision and the Open Images Dataset—it is likely that they are trained on the same
4492 data and labels. An endpoint with higher matched percentage has a more similar
4493 label set to the Open Images Dataset classes. However, a higher matched percentage
4494 does not mean imply *better quality* of an API endpoint; it will increase apparent
4495 precision, recall, and F-measure only.

4496 The true and false positive (TP/FP) label averages and the TP/FP ratio is shown
4497 in Table 9.7. Where the TP/FP ratio is larger, the scores are more reliable, however
4498 it is possible to increase the TP/FP ratio by adding more false labels with low scores.
4499 On the other hand, it is impossible to increase F-measure intentionally, because
4500 increasing precision will decrease recall, and vice versa. Hence, the importance of
4501 the F-measure statistic is critical for our analysis.

4502 Let R_A , R_G , and R_M be responses from Amazon Rekognition, Google Cloud
4503 Vision, and Microsoft’s Azure Computer Vision, respectively. There are four sets
4504 of operands, i.e., (R_A, R_G) , (R_G, R_M) , (R_M, R_A) , and (R_A, R_G, R_M) . Table 9.7
4505 shows the evaluation of each operands set, Table 9.8 shows the averages of the four
4506 operands sets, and Figure 9.6 shows the comparison of F-measure for each methods.

4507 9.5.2 Naive Operators

4508 Results of *min*, *max*, and *average* operators are shown in Tables 9.7 and 9.8 and Fig-
4509 ure 9.6. The *min* operator is similar to *union* operator of set operation, and outputs
4510 all labels of operands. The precision of the *min* operator is always greater than any
4511 precision of operands, and the recall is always lesser than any precision of operands.
4512 *Max* and *average* operators are similar to *intersection* operator of set operations.
4513 Both operators output intersection of labels of operands and there is no clear relation
4514 to the precision and recall of operands. Since both operators have the same preci-
4515 sion, recall, and F-measure, Figure 9.6 groups them into one. The *average* operator
4516 performs well on the TP/FP ratio, where most of the same labels from multiple
4517 endpoints are TPs. In many cases of the four operand sets, all naive operators’

Table 9.6: Matching to human-verified labels.

Endpoint	Total	Unique	Matched	Matched %
Amazon Rekognition	11,416	1,409	1,111	78.9
Google Cloud Vision	8,766	2,644	2,487	94.1
Azure Computer Vision	5,392	746	470	63.0

Table 9.7: Evaluation results. A = Amazon Rekognition, G = Google Cloud Vision, M = Microsoft's Azure Computer Vision.

Operands	Operator	Precision	Recall	F-measure	TP average	FP average	TP/FP ratio
A		0.217	0.282	0.246	0.848 ± 0.165	0.695 ± 0.185	1.220
G		0.474	0.465	0.469	0.834 ± 0.121	0.741 ± 0.132	1.126
M		0.263	0.164	0.202	0.858 ± 0.217	0.716 ± 0.306	1.198
A, G	Min	0.771	0.194	0.310	0.805 ± 0.142	0.673 ± 0.141	1.197
A, G	Max	0.280	0.572	0.376	0.850 ± 0.136	0.712 ± 0.171	1.193
A, G	Average	0.280	0.572	0.376	0.546 ± 0.225	0.368 ± 0.114	1.485
A, G	D'Hondt	0.350	0.389	0.369	0.713 ± 0.249	0.518 ± 0.202	1.377
A, G	Hare-Niemeyer	0.344	0.384	0.363	0.723 ± 0.242	0.527 ± 0.199	1.371
A, G	Proposal	0.380	0.423	0.401	0.706 ± 0.239	0.559 ± 0.190	1.262
G, M	Min	0.789	0.142	0.240	0.794 ± 0.209	0.726 ± 0.210	1.093
G, M	Max	0.357	0.521	0.424	0.749 ± 0.135	0.729 ± 0.231	1.165
G, M	Average	0.357	0.521	0.424	0.504 ± 0.201	0.375 ± 0.141	1.342
G, M	D'Hondt	0.444	0.344	0.388	0.696 ± 0.250	0.551 ± 0.254	1.262
G, M	Hare-Niemeyer	0.477	0.375	0.420	0.696 ± 0.242	0.591 ± 0.226	1.179
G, M	Proposal	0.414	0.424	0.419	0.682 ± 0.238	0.597 ± 0.209	1.143
M, A	Min	0.693	0.143	0.237	0.822 ± 0.201	0.664 ± 0.242	1.239
M, A	Max	0.185	0.318	0.234	0.863 ± 0.178	0.703 ± 0.229	1.228
M, A	Average	0.185	0.318	0.234	0.589 ± 0.262	0.364 ± 0.144	1.616
M, A	D'Hondt	0.271	0.254	0.262	0.737 ± 0.261	0.527 ± 0.223	1.397
M, A	Hare-Niemeyer	0.260	0.245	0.253	0.755 ± 0.251	0.538 ± 0.218	1.402
M, A	Proposal	0.257	0.242	0.250	0.769 ± 0.244	0.571 ± 0.205	1.337
A, G, M	Min	0.866	0.126	0.220	0.774 ± 0.196	0.644 ± 0.219	1.202
A, G, M	Max	0.241	0.587	0.342	0.857 ± 0.142	0.714 ± 0.210	1.201
A, G, M	Average	0.241	0.587	0.342	0.432 ± 0.233	0.253 ± 0.106	1.712
A, G, M	D'Hondt	0.375	0.352	0.363	0.678 ± 0.266	0.455 ± 0.208	1.492
A, G, M	Hare-Niemeyer	0.362	0.340	0.351	0.693 ± 0.260	0.444 ± 0.216	1.559
A, G, M	Proposal	0.380	0.357	0.368	0.684 ± 0.259	0.484 ± 0.200	1.414

Table 9.8: Average of the evaluation result.

Operator	Precision	Recall	F-measure	TP/FP ratio
Min	0.780	0.151	0.252	1.183
Max	0.266	0.500	0.344	1.197
Average	0.266	0.500	0.344	1.539
D'Hondt	0.361	0.335	0.346	1.382
Hare-Niemeyer	0.361	0.336	0.347	1.378
Proposal	0.358	0.362	0.360	1.289

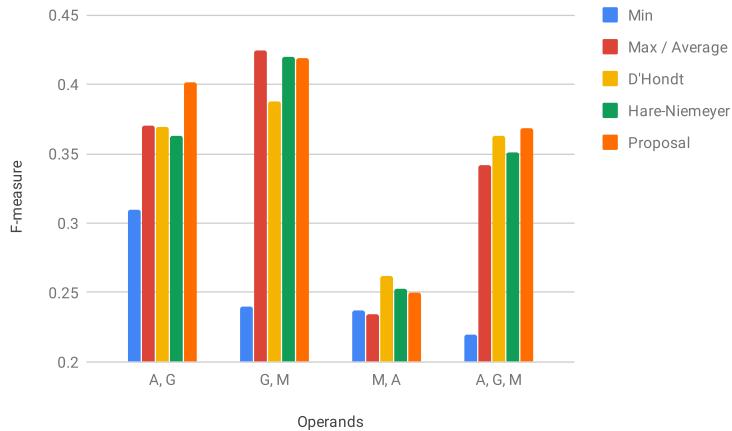


Figure 9.6: F-measure comparison.

4518 F-measures are between F-measures of operands. None of naive operators therefore
 4519 improve results by merging responses from multiple endpoints.

4520 **9.5.3 Traditional Proportional Representation Operators**

4521 There are many existing allocation algorithms in proportional representation, e.g.,
 4522 the Niemeyer and Niemeyer method [256]. These methods may be replacements of
 4523 those in Section 9.4.3. Other steps, i.e., Sections 9.4.1, 9.4.2 and 9.4.4, are the same
 4524 as for our proposed technique. Tables 9.7 and 9.8 and Figure 9.6 show the result of
 4525 these traditional proportional representation algorithms. Averages of F-measures by
 4526 traditional proportional representation operators are almost equal to that of the *max*
 4527 and *average* operators. It is worth noting that merging *M* and *A* responses results in
 4528 a better F-measure than each F-measure of *M* and *A* individually. As these are not
 4529 biased to human-verified labels, situations in the real-world usage should, therefore,
 4530 be similar to the case of *M* and *A*. Hence, RQ1 is true.

4531 **9.5.4 New Proposed Label Merge Technique**

4532 As shown in Table 9.8, our proposed new method performs best in F-measure.
 4533 Instead, the TP/FP ratio is less than *average*, the D'Hondt method, and Hare-
 4534 Niemeyer method. As described in Section 9.5.1, we argue that F-measure is a
 4535 more important measure than the TP/FP ratio (in this case). Therefore, RQ2 is
 4536 true. Shown in Table 9.7, our proposed new method improves the results when
 4537 merging *M* and *A* in non-biased endpoints. It is similar to traditional proportional
 4538 representation operators, but does not perform as well. However, it performs better
 4539 on other operand sets, and performs best overall as shown in Figure 9.6.

4540 **9.5.5 Performance**

4541 We used AWS EC2 m5.large instance (2 vCPUs, 2.5 GHz Intel Xeon, 8 GiB RAM);
 4542 Amazon Linux 2 AMI (HVM), SSD Volume Type; Node.js 8.12.0. It takes 0.370

4543 seconds to merge responses from three endpoints. Computational complexity of the
4544 algorithm in Section 9.4.3 is $O(n^2)$, where n is total number of labels in responses.
4545 (The estimation assumes that the number of endpoints is a constant.) Complexity of
4546 Step I in Section 9.4.3 is $O(n \log n)$, as the worst case is that all n labels are from
4547 one single endpoint and all n labels are in one CC. Complexity of Step II to Step V
4548 is $O(n^2)$, as the number of CCs is less than or equal to n and number of iterations
4549 are less than or equal to n . As Table 9.1 shows, the averaged total number of three
4550 endpoints is 25.58. Most of time for merging is consumed by looking up WordNet
4551 synsets (Section 9.4.1). The API facade calls each APIs on actual endpoints in
4552 parallel. It takes about 5 seconds, which is much longer than 0.370 seconds taken
4553 for the merging of responses.

4554 9.6 Conclusions and Future Work

4555 In this paper, we propose a method to merge responses from CVSs. Our method
4556 merges API responses better than naive operators and other proportional represen-
4557 tation methods (i.e., D'Hondt and Hare-Niemeyer). The average of F-measure of
4558 our method marks 0.360; the next best method, Hare-Niemeyer, marks 0.347. Our
4559 method and other proportional representation methods are able to improve the F-
4560 measure from original responses in some cases. Merging non-biased responses
4561 results in an F-measure of 0.250, while original responses have an F-measure be-
4562 tween 0.246 and 0.242. Therefore, users can improve their applications' precision
4563 with small modification, i.e., by switching from a singular URL endpoint to a facade-
4564 based architecture. The performance impact by applying facades is small, because
4565 overhead in facades is much smaller than API invocation. Our proposal method
4566 conforms identity, commutativity, reflexivity, and additivity properties and these
4567 properties are advisable for integrating multiple responses.

4568 Our idea of a proportional representation approach can be applied to other IWSs.
4569 If the response of such a service is list consisting of an entity and score, and if there is a
4570 way to group entities, a proposal algorithm can be applied. The opposite approach is
4571 to improve results by inferring labels. Our current approach picks some of the labels
4572 returned by endpoints. IWSs are not only based on supervised ML—thus to cover a
4573 wide range of IWSs, it is necessary to classify and analyse each APIs and establish
4574 a method to improve results by merging. Currently graph structures of labels and
4575 synsets (Figure 9.2) are not considered when merging results. Propagating scores
4576 from labels could be used, losing the additivity property but improving results for
4577 users. There are many ways to propagate scores. For instance, setting propagation
4578 factors for each link type would improve merging and could be customised for users'
4579 preferences. It would be possible to generate an API facade automatically. APIs
4580 with the same functionality have same or similar signatures. Machine-readable API
4581 documentation, for instance, OpenAPI Specification, could help a generator to build
4582 an API facade.

CHAPTER 10

4583

4584

4585

Threshy: Supporting Safe Usage of Intelligent Web Services[†]

4586

4587 **Abstract** Increased popularity of ‘intelligent’ web services provides end-users with machine-
4588 learnt functionality at little effort to developers. However, these services require a decision
4589 threshold to be set which is dependent on problem-specific data. Developers lack a systematic
4590 approach for evaluating intelligent services and existing evaluation tools are predominantly
4591 targeted at data scientists for pre-development evaluation. This paper presents a workflow
4592 and supporting tool, Threshy, to help *software developers* select a decision threshold suited to
4593 their problem domain. Unlike existing tools, Threshy is designed to operate in multiple work-
4594 flows including pre-development, pre-release, and support. Threshy is designed for tuning
4595 the confidence scores returned by intelligent web services and does not deal with hyper-
4596 parameter optimisation used in ML models. Additionally, it considers the financial impacts
4597 of false positives. Threshold configuration files exported by Threshy can be integrated into
4598 client applications and monitoring infrastructure. Demo: <https://bit.ly/2YKeYhE>.

4599 10.1 Introduction

4600 Machine learning algorithm adoption is increasing in modern software. End users
4601 routinely benefit from machine-learnt functionality through personalised recom-
4602 mendations [82], voice-user interfaces [251], and intelligent digital assistants [52]. The
4603 easy accessibility and availability of intelligent web services (IWSs)¹ is contributing
4604 to their adoption. These IWSs simplify the development of machine learning (ML)

[†]This chapter is originally based on A. Cummaudo, S. Barnett, R. Vasa, and J. Grundy, “Threshy: Supporting Safe Usage of Intelligent Web Services,” in *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*. Virtual Event, USA: ACM, November 2020. DOI 10.1145/3368089.3417919, pp. 1645–1649. Terminology has been updated to fit this thesis.

¹Such as Azure Computer Vision (<https://azure.microsoft.com/en-au/services/cognitive-services/computer-vision/>), Google Cloud Vision (<https://cloud.google.com/vision/>), or Amazon Rekognition (<https://aws.amazon.com/rekognition/>).

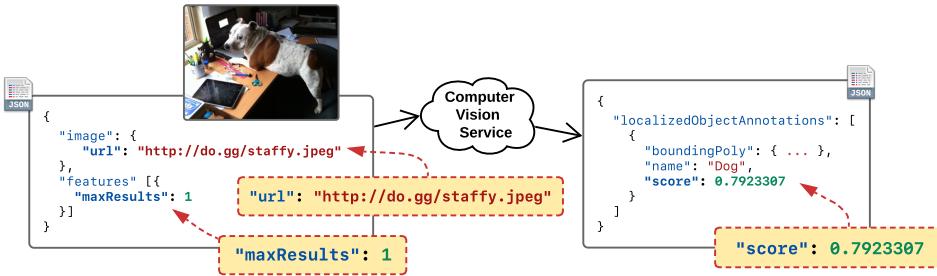


Figure 10.1: Request and response for an intelligent computer vision web service with only three configuration parameters: the image’s url, maxResults and score.

4605 solutions as they (i) do not require specialised ML expertise to build and maintain,
 4606 (ii) abstract away infrastructure related issues associated with ML [15, 317], and
 4607 (iii) provide web application programming interfaces (APIs) for ease of integration.

4608 However, unlike traditional web services, the functionality of these IWSs is
 4609 dependent on a set of assumptions unique to ML [88]. These assumptions are based
 4610 on the data used to train ML algorithms, the choice of algorithm, and the choice of
 4611 data processing steps—most of which are not documented. For developers, these
 4612 assumptions mean that the performance characteristics of an IWS in any particular
 4613 application problem domain is not fully knowable. IWSs represent this uncertainty
 4614 through a confidence value associated with their predictions.

4615 As an example, consider Figure 10.1, which illustrates an image of a dog up-
 4616 loaded to a real computer vision service (CVS). Developers have very few configura-
 4617 tion parameters in the upload payload (url of the image to analyse and maxResults
 4618 the number of objects to detect). The JSON output payload returns the confidence
 4619 value via a score field (0.792), the bounding box and a “dog” label. Developers
 4620 can only work with these parameters; unlike hyper-parameter optimisation available
 4621 to ML creators, who can configure the internal parameters of the algorithm while
 4622 training a model. Given the structure of the abstractions, developers have no insight
 4623 into which hyper-parameters are used or the algorithm selected and cannot tune the
 4624 underlying trained model when using an IWS. Thus an evaluation procedure must
 4625 be followed as a part of using an IWS for an application to work with and tune the
 4626 output confidence values for a given input set.

4627 A typical evaluation process would involve a test data set (curated by the devel-
 4628 opers using the IWS) that is used to determine an appropriate threshold. Choice of
 4629 a decision threshold is a critical element of the evaluation procedure [149]. This is
 4630 especially true for classification problems such as detecting if an image contains can-
 4631 cer. Simple approaches to selecting a threshold are often insufficient, as highlighted
 4632 in Google’s ML course: *“It is tempting to assume that [a] classification threshold
 4633 should always be 0.5, but thresholds are problem-dependent, and are therefore
 4634 values that you must tune.”*²

4635 As an example consider the predictions from two email spam classifiers shown

²See <https://bit.ly/36oMgWb>.

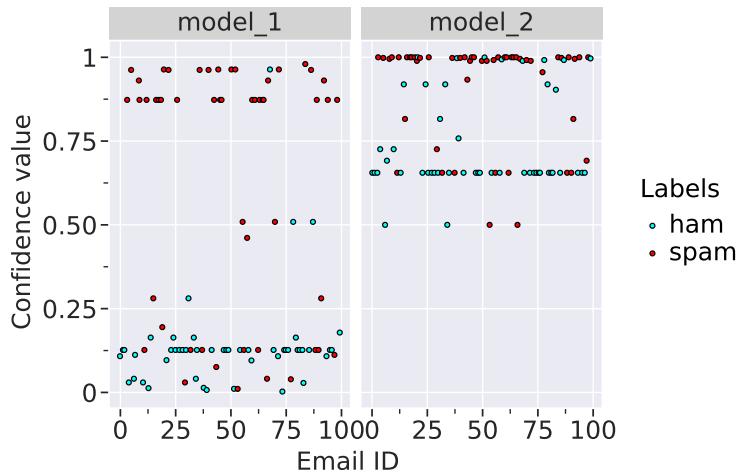


Figure 10.2: Predictions for 100 emails from two spam classifiers. Decision thresholds are classifier-dependent: a single threshold for both classifiers is *not* appropriate as ham emails are clustered at 0.12 (model_1) and at 0.65 (model_2). Developers must evaluate performance for *both* thresholds.

in Figure 10.2. The predicted safe emails, ‘ham’, are in two separate clusters (a simple threshold set to approx. 0.2 for model 1 and 0.65 for model 2, indicating that different decision thresholds may be required depending on the classifier. Also note that some emails have been misclassified; how many depends on the choice of decision threshold. An appropriate threshold considers factors outside algorithmic performance, such as financial cost and impact of wrong decisions. To select an appropriate decision threshold, developers using intelligent services need approaches to reason about and consider trade-offs between competing *cost factors*. These include impact, financial costs, and maintenance implications. Without considering these trade-offs, sub-optimal decision thresholds will be selected.

The standard approach for tuning thresholds in classification problems involve making trade-offs between the number of false positives and false negatives using the receiver operating characteristic (ROC) curve. However, developers (i) need to realise that this trade-off between false positives and false negatives is a data dependent optimisation process [316], (ii) often need to develop custom scripts and follow a trial-and-error based approach to determine a threshold, (iii) must have appropriate statistical training and expertise, and (iv) be aware that multi-label classification require more complex optimisation methods when setting label specific costs. However, current intelligent services do not sufficiently guide or support software engineers through the evaluation process, nor do they make this need clear in the documentation.

In this paper we present **Threshy**³, a tool to assist developers in selecting decision thresholds when using intelligent services. The motivation for developing Threshy arose from our work across a set of industry projects. Unlike existing tooling (see Section 10.4), **Threshy serves as a means to up-skill and educate**

³Threshy is available for use at <http://bit.ly/a2i2-threshy>

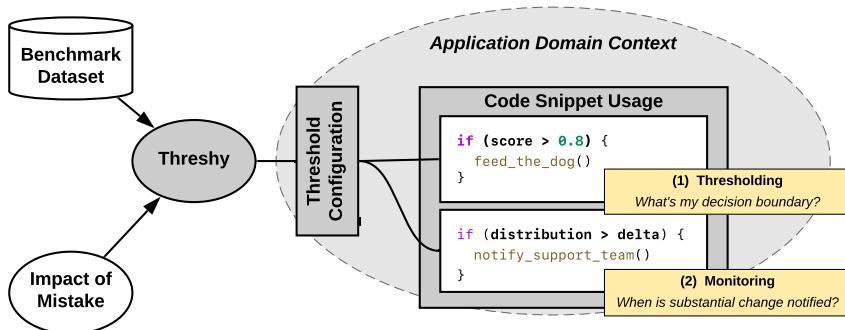


Figure 10.3: Threshy supports two key aspects for intelligent web services: threshold selection and monitoring.

software engineers in selecting machine-learnt decision thresholds, for example, on aspects such as confusion matrices. We re-iterate that the end-users of Threshy are software engineers and not data scientists—Threshy is not designed for hyper-parameter tuning of models, but for threshold tuning to use intelligent web services more robustly where internal models are not exposed. Threshy provides a visually interactive interface for developers to fine-tune thresholds and explore trade-offs of prediction hits/misses. This exposes the need for optimisation of thresholds, which is dependent on particular use cases.

Threshy improves developer productivity through automation of the threshold selection process by leveraging an optimisation algorithm to propose thresholds. Figure 10.3 illustrates the two key aspects by which Threshy supports developer's application domain context. Developers input a representative dataset of their application data (a benchmark dataset) in addition to cost factors to Threshy. Threshy's output helps developers select appropriate thresholds and can be used to monitor the evolution of an IWS. This algorithm considers different cost factors providing developers with summary information so they can make more informed trade-offs. Developers also benefit from the workflow implemented in Threshy by providing a reproducible procedure for testing and tuning thresholds for any category of classification problem (binary, multi-class, and multi-label). Threshy has also been designed to work for different input data types including images, text and categorical values. The output, is a configuration file that can be integrated into client applications ensuring that the thresholds can be updated without code changes, and continuously monitored in a production setting.

10.2 Motivating Example

As a motivating example consider Nina, a fictitious developer, who has been employed by Lucy's Tomato Farm to automate the picking of tomatoes from their vines (when ripe) using computer vision and a harvesting robot. Lucy's Farm grow five types of tomatoes (roma, cherry, plum, green, and yellow tomatoes). Nina's robot—using an attached camera—will crawl and take a photo of each vine to assess it for

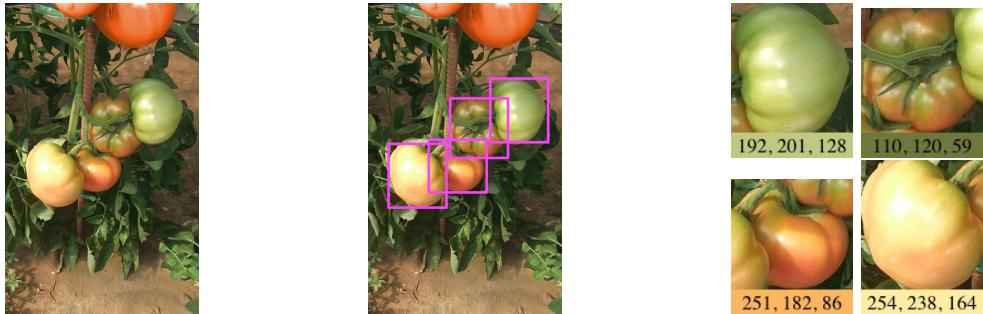


Figure 10.4: Pipeline of Nina’s harvesting robot. *Left:* Photo from harvesting robot’s webcam. *Centre:* Classification detecting different types of tomatoes. *Right:* Binary classification for ripeness (ripe/unripe) based on (R, G, B values).

4690 harvesting. Nina’s automated harvester needs to sort picked tomatoes into a respec-
 4691 tive container, and thus several business rules need to be encoded into the prediction
 4692 logic to sort each tomato detected based on its *ripeness* (ripe or not ripe) and *type of*
 4693 *tomato* (as above). Nina uses a two-stage pipeline consisting of a multi-class and a
 4694 binary classification model. She has decided to evaluate the viability of cloud based
 4695 intelligent services and use them if operationally effective.

4696 ?? illustrates an example of the pipeline as listed below:

- 4697 1. **Classify tomato ‘type’.** This stage uses an object localisation service to detect
 4698 all tomato-like objects in the frame and classifies each tomato into one of the
 4699 following labels: [‘roma’, ‘cherry’, ‘plum’, ‘green’, ‘yellow’, ‘unknown’].
- 4700 2. **Assess tomato ‘ripeness’.** This stage uses a crop of the localised tomatoes
 4701 from the original frame to assess the crop’s colour properties (i.e., average
 4702 colour must have $R > 200$ and $G < 240$). This produces a binary classification
 4703 to deduce whether the tomato is ripe or not.

4704 Nina only has a minimal appreciation of the evaluation method to use for off-
 4705 the-shelf computer vision (classification) services. She also needs to consider the
 4706 financial costs of misclassifying either the tomato type or the ripeness. Missing a
 4707 few ripe tomatoes isn’t a significant concern as the robot travels the field twice a
 4708 week during harvest season. However, picking an unripe tomato is expensive as
 4709 Lucy cannot sell them. Therefore, Nina needs a better (automated) way to assess
 4710 the performance of the service and set optimal thresholds for her picking robot, to
 4711 maximise profit.

4712 To assist in developing Nina’s pipeline, Lucy sampled a section of 1000 tomatoes
 4713 by taking a photo of each tomato, manually labelling its type, and assessing whether
 4714 the vine was ‘ripe’ or ‘not_ripe’. Nina ran the labelled images through an IWS,
 4715 with each image having a predicted type (multi-class) and ripeness (binary), with
 4716 respective confidence values.

4717 Nina combined the predictions, their respective confidence values, and Lucy’s
 4718 labelled ground truths into a CSV file which was then uploaded to Threshy. Nina
 4719 asked Lucy the farmer to assist in setting relevant costs (from a business perspective)
 4720 for correct predictions and false predictions. Threshy then recommended a choice

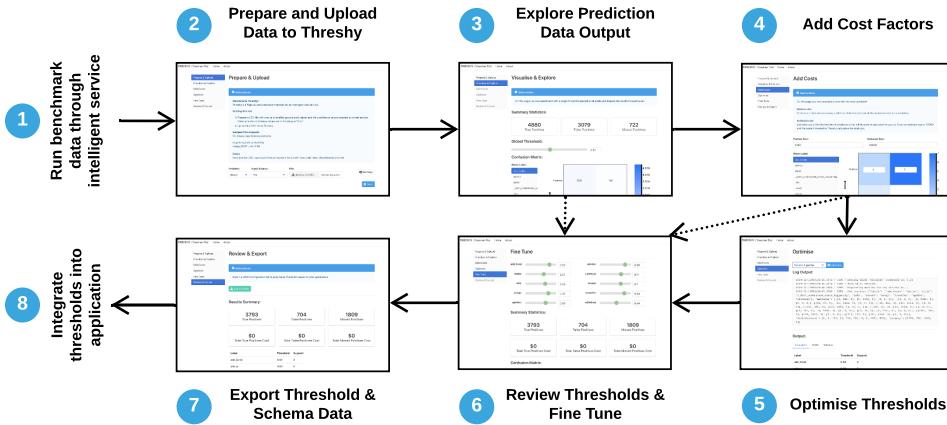


Figure 10.5: UI workflow for interacting with Threshy to optimise the thresholds for classification problem.

of decision threshold which Nina then fine tuned while considering the performance and cost implications.

10.3 Threshy

Threshy is a tool to assist software engineers with setting decision thresholds when integrating machine-learnt components in a system in collaboration with subject matter experts. Our tool also serves as a method to inform and educate engineers about the nuances to consider when using prepackaged ML services. Key novel features are:

- Automating threshold selection using an optimisation algorithm (NSGA-II [96]), optimising the results for each label.
- Support for user defined, domain-specific weights when optimising thresholds, such as financial costs and impact to society. This allows decision thresholds to be set within a business context as they differ between applications [107].
- Handles nuances of classification problems such as dealing with multi-objective optimisation, and metric selection—reducing errors of omission.
- Support key classification problems including binary (e.g. email is spam or ham), multi-class (e.g. predict the colour of a car), and multi-label (e.g. assign multiple topics to a document). Existing tools ignore multi-label classification.

Setting thresholds in Threshy is an eight step process as outlined in Figure 10.5. Software engineers ① run a benchmark dataset through the machine-learnt component to create a data file (CSV format) with true labels and predicted labels along with the predicted confidence values. The data file is then ② uploaded for initial exploration where engineers can ③ experiment with modifying a single global threshold for the dataset. Developers may choose to exit at this point (as indicated by dotted arrows in Figure 10.5). Optionally, the engineer ④ defines costs for missed predictions followed by selecting optimisation settings. The optional optimisation

4747 step of Threshy ⑤ considers the performance and costs when deriving the thresh-
4748 olds. Finally, the engineer can ⑥ review and fine tune the calculated thresholds,
4749 associated costs, and ⑦ download generated threshold meta-data to be ⑧ integrated
4750 into their application.

4751 Threshy runs a client/server architecture with a thin-client (see Figure 10.6).
4752 The web-based application consists of an interactive front-end where developers
4753 upload benchmark results—consisting of both human annotated labels and machine
4754 predictions from the IWS—and use threshold tuners (via sliders) to present a data
4755 summary of the uploaded information. Predicted model performances and costs are
4756 entered manually into the web interface by the developer. The Threshy back-end
4757 runs a data analyser, cost processor and metrics calculator when relevant changes
4758 are made to the front-end’s tuning sliders. Separating the two concerns allows for
4759 high intensity processing to be done on the server and not the front end.

4760 The data analyser provides a comprehensive overview of confusion matrices
4761 compatible for multi-label multi-class classification problems. When representing
4762 the confusion matrix, it is trivial to represent instances where multi-label multi-
4763 classification is not considered. For example, in the simplest case, a single row in
4764 the matrix represents a single label out of two classes, or each row has one label but it
4765 has multiple classes. However, a more challenging case to visualise arises when you
4766 have n labels and n classes; the true/false matches become too excessive to visualise
4767 as it is disproportionate to the true results. To deal with this issue, we condense the
4768 summary statistics down to three constructs: (i) number of true positives, (ii) false
4769 positives, (iii) missed positives. This allows us to optimise against the true positives
4770 and minimise the other two constructs. Threshy is a fully self-contained repository
4771 of the tool implementation, scripting and exploratory notebooks, which is available
4772 at <https://github.com/a2i2/threshy>.

4773 10.4 Related work

4774 Optimal machine-learnt decision boundaries depend on identifying the operating
4775 conditions of the problem domain. A systematic study by Drummond and Holte
4776 [107] classifies four operating conditions to determine a decision threshold: (i) the
4777 operating condition is known and the model trained matches perfectly; (ii) where
4778 the operating conditions are known but change with time, and thus the model must
4779 be adaptable to such changes; (iii) where there is uncertainty in the knowledge of
4780 the operating conditions certain changes in the operating condition are more likely
4781 than others; (iv) where there is no knowledge of the operating conditions and the
4782 conditions may change from the model in any possible way. Various approaches
4783 to determine appropriate thresholds exist for all four of these cases, such as cost-
4784 sensitive learning, ROC analysis, and Brier scores. However, an *automated* attempt
4785 to calibrate decision threshold boundaries is not considered, and is largely pitched
4786 at a non-software engineering audience. A recent study touches on this in model
4787 management for large-scale adversarial instances in Google’s advertising system
4788 [316], however this is only a single component within the entire architecture, and is
4789 not a tool that is useful for developer’s in varying contexts. Our Threshy provides a

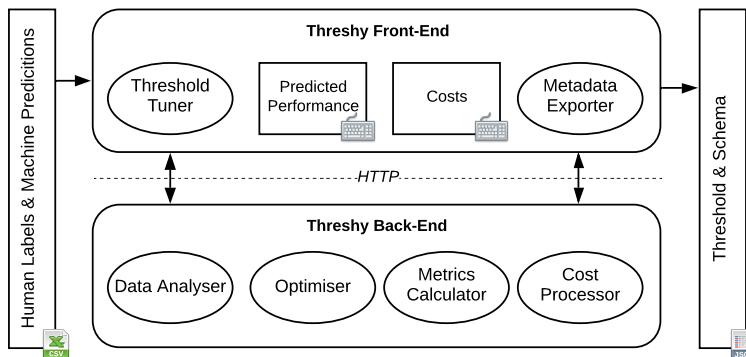


Figure 10.6: Architecture of Threshy.

‘plug-and-play’ style calibration method where any context/domain can have thresholds automatically calibrated *and* optimised for engineers. Threshy’s architecture supports a headless mode for use in monitoring workflows.

Support tools for ML frameworks generally fall into two categories. The first attempts to illuminate the ‘black box’ by offering ways in which developers can better understand the internals of the model to improve its performance. For extensive analyses and surveys into this area, see [159, 273]. However, a recent emphasis to probe only inputs and outputs of a model has been explored, exploring off-the-shelf models without knowledge of its unknowns (see Figure 10.2) to reflect the nature of real-world development. Google’s *What-If Tool* [373] for Tensorflow provides a means for data scientists to visualise, measure and assess model performance and fairness with various hypothetical scenarios and data features; similarly, Microsoft’s *Gamut* tool [158] provides an interface to test hypotheticals on Generalized Additive Models, and a *ModelTracker* tool [12] collates summary statistics on sample data to enable visualisation of model behaviour and access to key performance metrics.

However, these tools are focused toward pre-development model evaluation and not designed for software engineering workflows. Nor are they context-aware to the overall software system they are meant to target. They are also aimed at data scientists and model builders and do not consider consistent tooling that works across development, test, and production environments. Further, certain tools are tied to specific ML frameworks (e.g., What-If and Tensorflow). Our work, instead, attempts to bridge these gaps through a context-aware, structured workflow with an automated tool targeted to software developers; our tool is designed for software engineers to calibrate their thresholds and is used for IWS APIs in particular.

10.5 Conclusions & Future Work

Primary contributions of this work include Threshy, a tool for automating threshold selection, and the overall meta-workflow proposed in Threshy that developers can use as a point of reference for calibrating thresholds. In future work, we plan to evaluate Threshy with software engineers to identify additional insights required to

- 4819 make decision thresholds in practice and add code synthesis for monitoring concept drift and for implementing decision thresholds.
- 4820

CHAPTER 11

4821

4822

4823 An Integration Architecture Tactic to guard AI-first Components[†]

4824

4825 **Abstract** Intelligent web services provide the power of AI to developers via simple REST-
4826 ful API endpoints, abstracting away many complexities of machine learning. However,
4827 most of these intelligent web services (IWSs)—such as computer vision—continually learn
4828 with time. When the internals within the abstracted ‘black box’ become hidden and evolve,
4829 pitfalls emerge in the robustness of applications that depend on these evolving services.
4830 Without adapting the way developers plan and construct projects reliant on IWSs, signifi-
4831 cant gaps and risks result in both project planning and development. Therefore, how can
4832 software engineers best mitigate software evolution risk moving forward, thereby ensuring
4833 that their own applications maintain quality? Our proposal is an architectural tactic designed
4834 to improve intelligent service-dependent software robustness. The tactic involves creating
4835 an application-specific benchmark dataset baselined against an intelligent service, enabling
4836 evolutionary behaviour changes to be mitigated. A technical evaluation of our implemen-
4837 tation of this architecture demonstrates how the tactic can identify 1,054 cases of substantial
4838 confidence evolution and 2,461 cases of substantial changes to response label sets using a
4839 dataset consisting of 331 images that evolve when sent to a service.

4840 11.1 Introduction

4841 The introduction of intelligent web services (IWSs) into the software engineering
4842 ecosystem allows developers to leverage the power of artificial intelligence (AI)
4843 without implementing complex AI algorithms, source and label training data, or
4844 orchestrate powerful and large-scale hardware infrastructure. This is extremely

[†]This chapter is originally based on A. Cummaudo, S. Barnett, R. Vasa, J. Grundy, and M. Abd-elrazek, “Beware the evolving ‘intelligent’ web service! An integration architecture tactic to guard AI-first components,” in *Proceedings of the 28th ACM Joint Meeting on European Software Engineering Conference and Symposium on the Foundations of Software Engineering*. Virtual Event, USA: ACM, November 2020. DOI 10.1145/3368089.3409688, pp. 269–280. Terminology has been updated to fit this thesis.

4845 enticing for developers to embrace due to the effort, cost and non-trivial expertise
4846 required to implement AI in practice [284, 317].

4847 However, the vendors that offer these services also periodically update their
4848 behaviour (responses). The ideal practice for communicating the evolution of a
4849 web service involves updating the version number and writing release notes. The
4850 release notes typically describe new capabilities, known problems, and requirements
4851 for proper operation [50]. Developers anticipate changes in behaviour between ver-
4852 sioned releases although they expect the behaviour of a specific version to remain
4853 stable over time [359]. However, emerging evidence indicates that ‘intelligent’ ser-
4854 vices *do not* communicate changes explicitly [87]. Intelligent services evolve in
4855 unpredictable ways, provide no notification to developers and changes are undocu-
4856 mented [91]. To illustrate this, consider Figure 11.1, which shows the evolution of a
4857 popular computer vision service (CVS) with examples of labels and associated confi-
4858 dence scores changing are shown. This behaviour change severely negatively affects
4859 reliability. Applications may no longer function correctly if labels are removed or
4860 confidence scores change beyond predefined thresholds.

4861 Unlike traditional web services, the functionality of these IWSs is dependent
4862 on a set of assumptions unique to their machine learning principles and algorithms.
4863 These assumptions are based on the data used to train machine learning algorithms,
4864 the choice of algorithm, and the choice of data processing steps—most of which
4865 are not documented to service end users. The behaviour of these services evolve
4866 over time [88]—typically this implies the underlying model has been updated or
4867 re-trained.

4868 Vendors do not provide any guidance on how best to deal with this evolution in
4869 client applications. For developers to discover the impact on their applications they
4870 need to know the behavioural deviation and the associated impact on the robustness
4871 and reliability of their system. Currently, there is no guidance on how to deal with
4872 this evolution, nor do developers have an explicit checklist of the likely errors and
4873 changes that they must test for [91].

4874 In this paper, we present a reference architecture to detect the evolution of such
4875 IWSs, using a mature subset of these services that provide computer vision as an
4876 exemplar. This tactic can be used both by intelligent service consumers, to defend
4877 their applications against the evolutionary issues present in IWSs, and by service
4878 vendors to make their services more robust. We also present a set of error conditions
4879 that occur in existing CVSs.

4880 The key contributions of this paper are:

- 4881 • A set of new service error codes for describing the empirically observed error
4882 conditions in IWSs.
- 4883 • A new reference architecture for using IWSs with a Proxy Server that returns
4884 error codes based on an application specific benchmark dataset.
- 4885 • A labelled data set of evolutionary patterns in CVSs.
- 4886 • An evaluation of the new architecture and tactic showing its efficacy for
4887 supporting IWS evolution from both provider and consumer perspectives.

4888 The rest of this paper is organised thus: Section 11.2 presents a motivating



'natural foods' (.956) → 'granny smith' (.986)



'skiing' (.937) → 'snow' (.982)



'girl' (.660) → 'photography' (.738)



'water' (.972) → 'wave' (.932)



'tennis' (.982) → 'sports' (.989)



'neighbourhood' (.925) → 'blue' (.927)

Figure 11.1: Prominent CVSSs evolve with time which is not effectively communicated to developers. Each image was uploaded in November 2018 and March 2019 and the topmost label was captured. Specialisation in labels (*Left*), generalisation in labels (*Centre*) and emphasis change in labels (*Right*) are all demonstrated from the same service with no API change and limited release note documentation. Confidence values indicated in parentheses.

example that anchors our work; Section 11.3 presents a landscape analysis on IWSs; Section 11.4 presents an overview of our architecture; Section 11.5 describes the technical evaluation; Section 11.6 presents a discussion into the implications of our architecture, its limitations and potential future work; Section 11.7 discusses related work; Section 11.8 provides concluding remarks.

11.2 Motivating Example

We identify the key requirements for managing evolution of IWSs using a motivating example. Consider Michelina, a software engineer tasked with developing a fall detector system for helping aged care facilities respond to falls promptly. Michelina decides to build the fall detector with an intelligent service for detecting people as she has no prior experience with machine learning. The initial system built by Michelina consists of a person detector and custom logic to identify a fall based on rapid shape deformation (i.e., a vertical ‘person’ changing to a horizontal ‘person’ greater than specified probability threshold value). Due to the inherent uncertainty present in an intelligent service and the importance of correctly identifying falls, Michelina informs the aged care facility that they should manually verify falls before dispatching a nurse to the location. The aged care facility is happy with this approach but inform Michelina that only a certain percentage of falls can be manually verified based on the availability of staff. In order to reduce the manual work Michelina sets thresholds for a range of confidence scores where the system is uncertain. Michelina completes the fall detector using a well-known cloud-based intelligent image classification web service and her client deploys this new fall detection application.

Three months go by and then the aged care facility contact Michelina saying the percentage of manual inspections is far too high and could she fix it. Michelina is mystified why this is occurring as she thoroughly tested the application with a large dataset provided by the aged care facility. On further inspection Michelina notices that the problem is caused by some images classifying the person with a ‘child’ label rather than a ‘person’ label. Michelina is frustrated and annoyed at this behaviour as (i) the cloud vendor did not document or notify her of the change of the intelligent service behaviour, (ii) she does not know the best practice for dealing with such a service evolution, and (iii) she cannot predict how the service will change in the future. This experience also makes Michelina wonder what other types of evolution can occur and how can she minimise these behavioural changes on her critical care application. Michelina then begins building an ad-hoc solution hoping that what she designs will be sufficient.

For Michelina to build a robust solution she needs to support the following requirements:

- R1. Define a set of error conditions that specify the types of evolution that occur for an intelligent service.
- R2. Provide a notification mechanism for informing client applications of behavioural changes to ensure the robustness and reliability of the application.

- 4930 **R3.** Monitor the evolution of IWSs for changes that affect the application's behaviour.
- 4931
- 4932 **R4.** Implement a flexible architecture that is adaptable to different IWSs and application contexts to facilitate reuse.
- 4933

4934 11.3 Intelligent Services

4935 We present background information on IWSs describing how they differ from traditional web services, the dimensions of their evolution and the currently limited configuration options available to users.

4936

4937

4938 11.3.1 ‘Intelligent’ vs ‘Traditional’ Web Services

4939 Unlike conventional web services, IWSs are built using AI-based components. These 4940 components are unlike traditional software engineering paradigms as they are data-4941 dependent and do not result in deterministic outcomes. These services make future 4942 predictions on new data based solely against its training dataset; outcomes are 4943 expressed as probabilities that the inference made matches a label(s) within its 4944 training data. Further, these services are often marketed as forever evolving and 4945 ‘improving’. This means that their large training datasets may continuously update 4946 the prediction classifiers making the inferences, resulting both in probabilistic and 4947 non-deterministic outcomes [88, 161]. Critically for software engineers using the 4948 services, these non-deterministic aspects have not been sufficiently documented in 4949 the service’s API documented, which has been shown to confuse developers [91].

4950 A strategy to combat such service changes, which we often observe in traditional 4951 software engineering practices, are for such services to be versioned upon substantial 4952 change. Unfortunately emerging evidence indicates that prominent cloud vendors 4953 providing these IWSs do not release new versioned endpoints of the APIs when the 4954 *internal model* changes [88]. For IWSs, it is impossible to invoke requests specific 4955 to a particular version model that was trained at a particular date in time. This means 4956 that developers need to consider how evolutionary changes to the IWSs they make 4957 use of may impact their solutions *in production*.

4958 11.3.2 Dimensions of Evolution

4959 The various key dimensions of the evolution of IWSs is illustrated in Figure 11.2. 4960 There are two primary dimensions of evolution: *changes to the label sets* returned 4961 per image submitted and *changes to the confidences* per label in the set of labels 4962 returned per image. In the former, we identify two key aspects: cardinality changes 4963 and ontology changes. Cardinality changes occur when the service either introduces 4964 or drops a label for the same image at two different generations. Alternatively, the 4965 cardinality may remain stagnant, although this is not guaranteed. This results in 4966 an expectation mismatch by developers as to what labels can or will be returned by 4967 the service. For instance, the terms ‘black’ and ‘black and white’ may be found to 4968 be categorised as two separate labels. Secondly, the ontologies of these labels are 4969

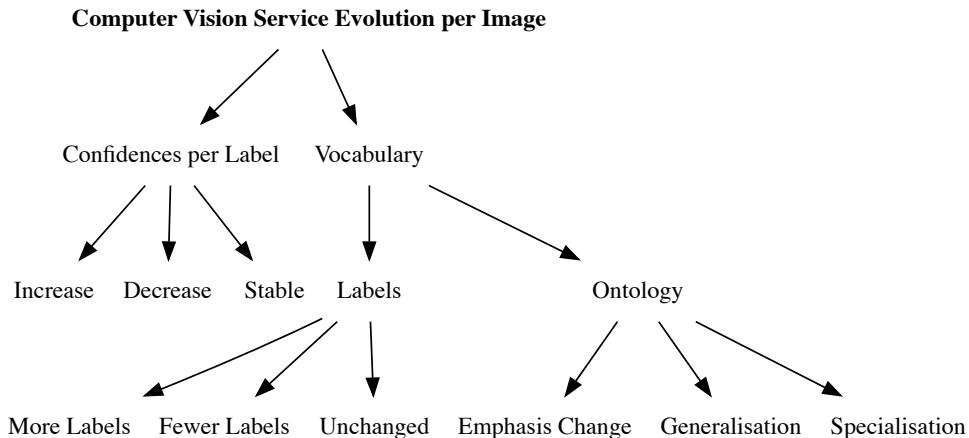


Figure 11.2: The dimensions of evolution identified within CVSSs.



Figure 11.3: A significant confidence increase ($\delta = +0.425$) from ‘window’ (0.559) to ‘water transportation’ (0.984) goes beyond simple decision boundaries.

4969 non-static, and a label may become more generalised into a hypernym, specialised
 4970 into a hyponym, or the emphasis of the label may change either to a co-hyponym or
 4971 another aspect in the image, such as the colour or scene, rather than the subject of
 4972 the image [88].

4973 Secondly, we have identified that the confidence values returned per label are also
 4974 non-static. While some services may present minor changes to labels’ confidences
 4975 resulting from statistical noise, other labels had significant changes that were beyond
 4976 basic decision boundaries. An example is shown in Figure 11.3. Developer code
 4977 written to assume certain ranges/confidence intervals will fail if the service evolves
 4978 in this way.

4979 **11.3.3 Limited Configurability**

4980 As an example, consider Figure 11.5, which illustrates an image of a dog uploaded to
 4981 a well-known cloud-based CVS. Developers have very few configuration parameters
 4982 in the upload payload (`url` for the image to analyse and `maxResults` for the number
 4983 of objects to detect). The JSON output payload provides the confidence value of its
 4984 estimated bounding box and label of the dog object via its `score` field (0.792). This
 4985 value indicates the level of confidence in the label returned, and is dependent on the
 4986 input to the underlying ML model used by that service. Developers set thresholds

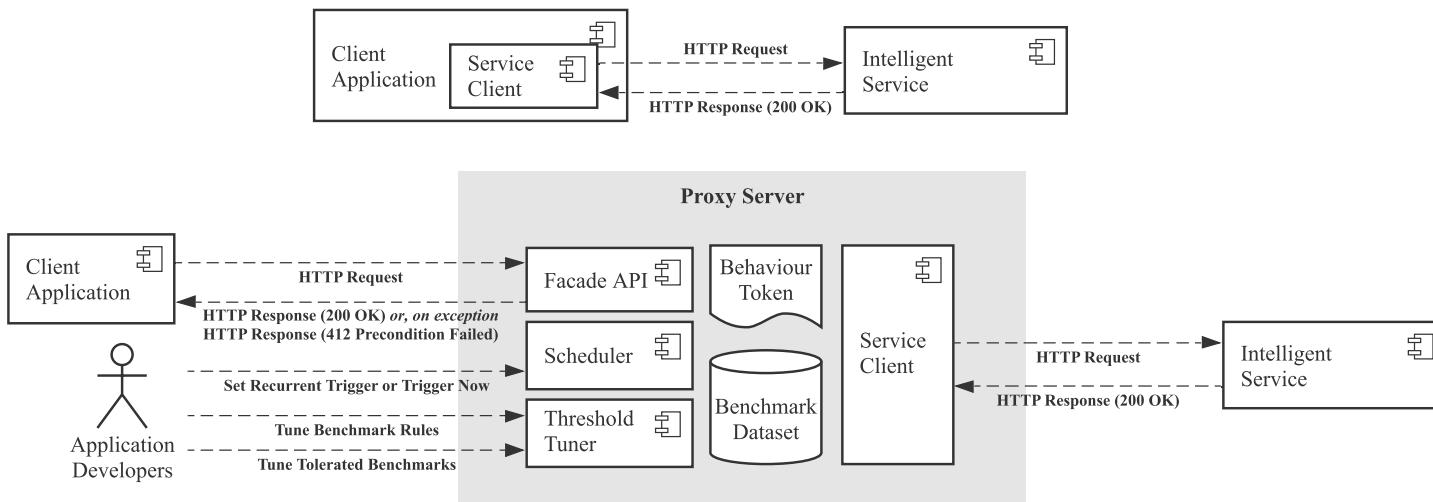


Figure 11.4: Top: Accessing an intelligent service directly. Bottom: Primary components of the Proxy Server approach.

as a decision boundary in this case, a threshold of “greater than 0.7” could indicate that the image contains a dog where as any other value the system is uncertain. These decision boundaries determine if the service’s output is accepted or rejected. However, these confidence scores change whenever a model is re-trained and these changes are not communicated or propagated to developers [88]. Developers can only modify these parameters to influence the score to improve the performance of the IWS. This is unlike many machine learning toolkit hyper-parameter optimisation facilities, which can be used to configure the internal parameters of the algorithm for training a model. In this case, developers using the IWS have no insight into which hyperparameters were used when training the model or the algorithm selected, and cannot tune the trained model. Thus an evaluation procedure must be followed as a part of using an intelligent service for an application to tune their output confidence values. and select appropriate threshold boundaries. While some service providers provide some guidance to thresholding,¹ they do not provide domain-specific tooling. This is because choice of appropriate thresholds is dependent on the data and must consider factors, such as algorithmic performance, financial cost, and impact of false-positives/negatives.

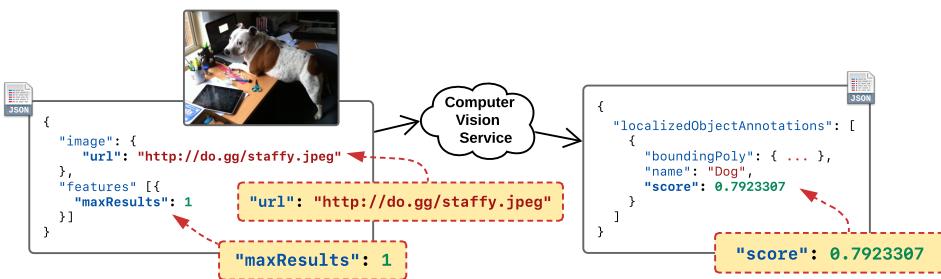


Figure 11.5: Request and response for an intelligent computer vision web service with only three configuration parameters: the image’s url, maxResults and score.

However, decision boundaries in service client code using simple If conditions around confidence scores is not a sufficient enough strategy, as evidence shows intelligent, non-deterministic web services change sporadically and unknowingly. Most traditional, deterministic code bases handle unexpected behaviour of called APIs via *error codes* and exception handling. Thus the non-deterministic components of the client code, such as those using CVSs, will also tend to conflict with their traditional deterministic components as the latter do not deal in terms of probabilities but in using error codes. This makes achieving robust component integration in client code bases hard. More sophisticated monitoring of IWSs in client code is therefore required to map the non-deterministic service behaviour changes to errors such that the surrounding infrastructure can support it and reduce interface boundary problems. While data science literature acknowledges the need for such an architecture [112] they do not offer any technical software engineering solutions to mitigate the issues such that software engineers have a pattern to work against it. To date, there do not

¹<https://bit.ly/36oMgWb> last accessed 20 May 2020.

Table 11.1: Potential reasons for a 412 Precondition Failed response.

Error Code	Error Description
No Key Yet	This indicates that the Proxy Server is still initialising its first behaviour token, i.e., k_0 does not yet exist.
Service Mismatch	The service encoded within the behaviour token provided to the Proxy Server does not match the service the Proxy Server is benchmarked against. This makes it possible for one Proxy Server to face multiple CVSSs.
Dataset Mismatch	The benchmark dataset B encoded within the behaviour token does not match the benchmark dataset encoded within the Proxy Server.
Success Mismatch	The success of each response within the benchmark dataset must be true for a behaviour token to be used within a request. This error indicates that k_r is, therefore, not successful.
Min Confidence Mismatch	The minimum confidence delta threshold set in k_t does not match that of k_r .
Max Labels Mismatch	The maximum label delta threshold set in k_t does not match that of k_r .
Response Length Mismatch	The number of responses within k_t does not match that within k_r .
Label Delta Mismatch	An image within B has either dropped or gained a number of labels that exceeds the maximum label delta. Thus, k_r exceeds the threshold encoded within k_t .
Confidence Delta Mismatch	One of the labels within an image encoded in k_r exceeds the confidence threshold encoded within k_t .
Expected Labels Mismatch	One of the expected labels for an image within k_t is now missing.

5018 yet exist IWS client code architectures, tactics or patterns that achieve this goal.

5019 11.4 Our Approach

5020 To address the requirements from Section 11.2 we have developed a new Proxy
5021 Service² that includes: (i) evaluation of an intelligent service using an application
5022 specific benchmark dataset, (ii) a Proxy Server to provide client applications with
5023 evolution aware errors, and (iii) a scheduled evolution detection mechanism. The
5024 current approach of using an intelligent API via direct access is shown in Figure 11.4
5025 (top). In contrast, an overview of our approach is shown in Figure 11.4 (bottom).
5026 The following sections describe our approach in detail.

5027 11.4.1 Core Components

5028 For the purposes of this paper we assume that the intelligent service of interest
5029 is an image recognition service, but our approach generalises to other intelligent,

²A reference architecture is provided at <http://bit.ly/2TlMmDh>.

5030 trained model-based services e.g., natural language processing, document recogni-
 5031 tion, voice, etc. Each image, when uploaded to the intelligent service returns a
 5032 response (R) which is a set describing a label (l) of what is in the image (i) along
 5033 with its associated confidence (c)—thus $R_i = \{(l_1, c_1), (l_2, c_2), \dots (l_n, c_n)\}$. Most
 5034 documentation of these services imply that these confidence values are all what is
 5035 needed to handle evolution in their systems. This means that if a label changes
 5036 beyond a certain threshold, then the developer can deal with the issue then (or ignore
 5037 it). While this approach may work in some simple application contexts, in many it
 5038 may not. Our Proxy Server offers a way to monitor if these changes go beyond a
 5039 threshold of tolerance, checking against a domain-specific dataset over time.

5040 11.4.1.1 Benchmark Dataset

5041 Monitoring an intelligent service for behaviour change requires a Benchmark Dataset,
 5042 a set of n images. For each image (i) in the Benchmark Dataset (B) there is an associ-
 5043 ated label (l) that represents the true value for that item; $B_i = \{(i_1, l_1), (i_2, l_2), \dots (i_n, l_n)\}$.
 5044 This dataset is used to check for evolution in IWSs by periodically sending each im-
 5045 age within the dataset to the service’s API, as per the rules encoded within the
 5046 Scheduler (see Section 11.4.1.6). By using a dataset specific to the application
 5047 domain, developers can detect when evolution affects their application rather than
 5048 triggering all non-impactful changes. This helps achieve our requirement *R3. Monitor*
5049 the evolution of IWSs for changes that affect the application’s behaviour. Using
 5050 application-specific datasets also ensures that the architectural style can be used for
 5051 different IWSs as only the data used needs to change. This design choice encourages
 5052 reuse satisfying requirement *R4. Implement a flexible architecture that is adapt-*
5053 able to different IWSs and application contexts to facilitate reuse. We propose an
 5054 initial set of guidelines on how to create and update the benchmark dataset within
 5055 Section 11.6.3.1.

5056 11.4.1.2 Facade API

5057 An architectural ‘facade’ is the central component to our mitigation strategy for
 5058 monitoring and detecting for changes in called IWSs. The facade acts as a guarded
 5059 gateway to the intelligent service that defends against two key issues: (i) potential
 5060 shifts in model variations that power the cloud vendor services, and (ii) ensures that
 5061 a context-specific dataset specific to the application being developed is validated
 5062 *over time*. By using a facade we can return evolution-aware error codes to the client
 5063 application satisfying requirement *R1. Define a set of error conditions that specify*
5064 the types of evolution that occur for an intelligent service and enabling requirement
5065 R3. Monitor the evolution of IWSs for changes that affect the application’s behaviour.
 5066 This works by ensuring every request made by the client application contains a valid
 5067 Behaviour Token (see Section 11.4.1.4) and will reject the request when evolution
 5068 has been identified by the Scheduler with an associated error code. The Facade API
 5069 essentially ‘blocks’ the client application out from accessing the intelligent service
 5070 when an invalid state has occurred.

Table 11.2: Rules encoded within a Behaviour Token.

Rule	Description
Max Labels	The value of n .
Min Confidence	The smallest acceptable value of c .
Max δ Labels	The minimum number of labels dropped or introduced from the current k_t and provided k_r to be considered a violation (i.e $ l(k_t) \Delta l(k_r) $).
Max δ Confidence	The minimum confidence change of <i>any</i> label from the current k_t and provided k_r to be considered a violation.
Expected Labels	A set of labels that every response must include.

5071 11.4.1.3 Threshold Tuner

5072 Selecting an appropriate threshold for detecting behavioural change depends on the
 5073 application context. Setting the threshold too low increases the likelihood of incor-
 5074 rect results, while setting the threshold too high means undesired changes are being
 5075 detected. Our approach enables developers to configure these parameters through a
 5076 Threshold Tuner, and consider competing factors such as algorithmic performance,
 5077 financial cost, and impact of false-positives/negatives. This component improves
 5078 robustness as now there is a systematic approach for monitoring and responding to
 5079 incorrect thresholds. Configurable thresholds meet our key requirements *R2* and *R3*.
 5080 An example of the component is detailed within our complement paper published in
 5081 the ESEC/FSE 2020 demonstrations track [89].

5082 11.4.1.4 Behaviour Token

5083 The Behaviour Token stores the current state of the Proxy Server by encoding specific
 5084 rules regarding the evolution of the intelligent service. The current token (at time t)
 5085 held by the Proxy Server is denoted by k_t . These rules are specified by the developer
 5086 upon initialisation of this Proxy Server, and are presented in Table 11.2. When the
 5087 Proxy Server is first initialised (i.e., at $t = 0$), the first Behaviour Token is created
 5088 based on the Benchmark Dataset and its configuration parameters (Table 11.2) and
 5089 is stored locally (thus k_0 is created). The Behaviour Token is passed to the client
 5090 application to be used in subsequent requests to the proxy server, where k_r represents
 5091 the Behaviour Token passed from the client application to the proxy server. Each
 5092 time the proxy server receives the Behaviour Token from the client the validity of the
 5093 token is validated with a comparison to the Proxy Server's current behaviour token
 5094 (i.e., $k_r \equiv k_t$). An invalid token (i.e., when $k_r \not\equiv k_t$) indicates that an error caused by
 5095 evolution has occurred and the application developer needs to appropriately handle
 5096 the exception. Behaviour Tokens are essential for meeting requirement *R3*. *Monitor*
 5097 *the evolution of IWSs for changes that affect the application's behaviour*.

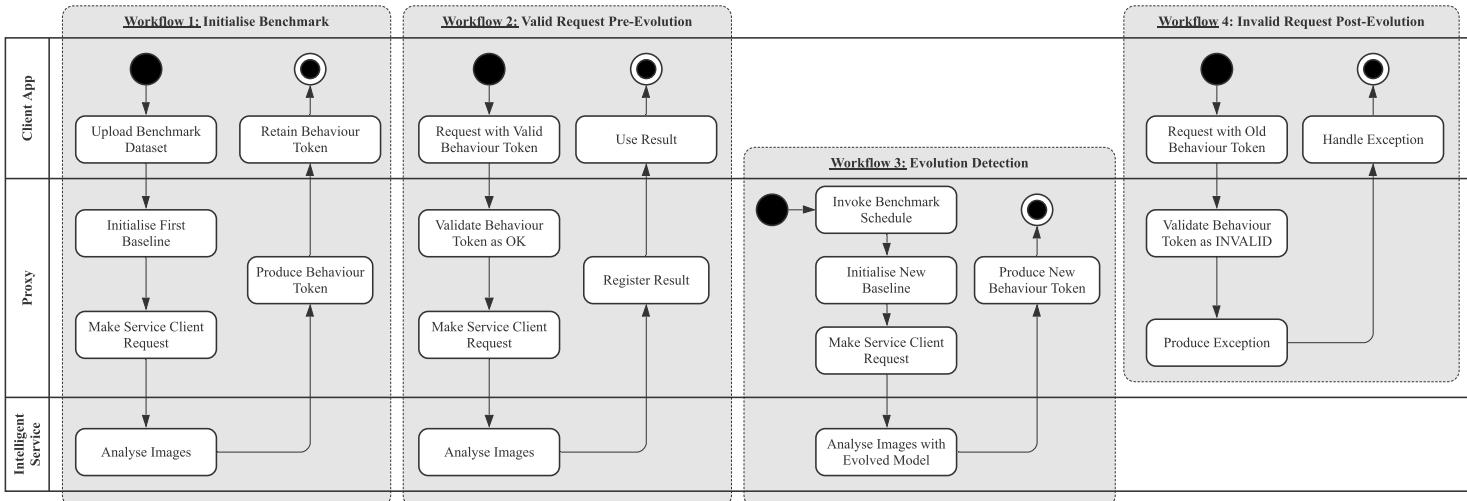


Figure 11.6: State diagram for the four workflows presented.

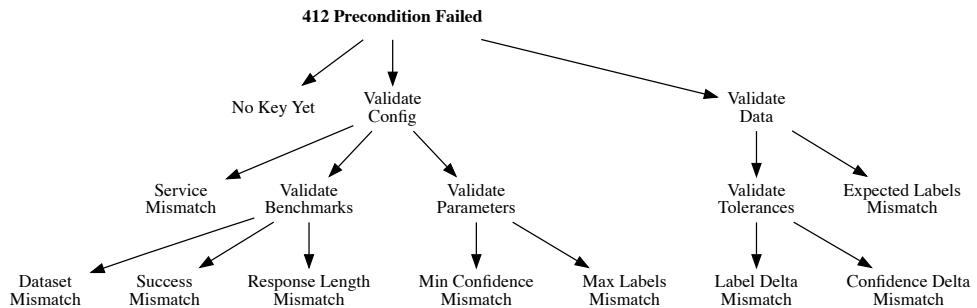


Figure 11.7: Precondition failure taxonomy; leaf nodes indicate error types returned to users.

5098 11.4.1.5 Service Client

5099 If any of the rules above are violated, then the response of the facade request varies
 5100 depending on the behaviour encoded within the behaviour token. This can be one
 5101 of:

- 5102 • **Error:** Where a HTTP non-200 code is returned by the facade to the client
 5103 application, indicating that the client application must deal with the issue
 5104 immediately;
- 5105 • **Warning:** Where a warning ‘callback’ endpoint is called with the violated
 5106 response to be dealt with, but the response is still returned to the client
 5107 application;
- 5108 • **Info:** Where the violated response is logged in the facade’s logger for the
 5109 developer to periodically read and inspect, and the response is returned to the
 5110 client application.

5111 We implement this Proxy Server pattern using HTTP conditional requests. As
 5112 we treat the Label as a first class citizen, we return the labels for a specific image
 5113 (r_i) only where the *Entity Tag* (ETag) or *Last Modified* validators pass. The k_r
 5114 is encoded within either the ETag (i.e., a unique identifier representing t) or as
 5115 the date labels (and thus models) were last modified (i.e., using the *If-Match*
 5116 or *If-Unmodified-Since* conditional headers). We note that the use of *weak*
 5117 ETags should be used, as byte-for-byte equivalence is not checked but only semantic
 5118 equivalence within the tolerances specified. Should t evolve to an invalid state (i.e.,
 5119 k_r is no longer valid against k_t) then the behaviour as described above will be
 5120 enacted.

5121 These HTTP header fields are used as the ‘backbone’ to help enforce robustness
 5122 of the services against evolutionary changes and context within the problem domain
 5123 dataset. Responses from the service are forwarded to the clients when such rules
 5124 are met, otherwise alternative behaviour occurs. For example, the most severe of
 5125 violated erroneous behaviour is the ‘Error’ behaviour. To enforce this rule, we
 5126 advocate for use of the 412 Precondition Failed HTTP error if a violation
 5127 occurs, as a *If-** conditional header was violated. An example of this architectural
 5128 pattern with the ‘Error’ behaviour is illustrated in Figure 11.6.

5129 We suggest the 412 Precondition Failed HTTP error be returned in the
5130 event that a behaviour token is violated against a new benchmark. Further details
5131 outlining the reasons why a precondition has failed are encoded within a JSON
5132 response sent back to the consuming application. The following describes the
5133 two broad categories of possible errors returned: *robustness precondition failure*
5134 or *benchmark precondition failure*. These are illustrated in a high level within
5135 Figure 11.7 where leaf nodes are the potential error types that can be returned. A
5136 list of the different error codes are given in Table 11.1, where errors above the rule
5137 are robustness expectations (which check for basic requirements such as whether the
5138 key provided encodes the same data as the dataset in the facade) while those below
5139 are benchmark expectations (which identifies evolution cases).

5140 11.4.1.6 Scheduler

5141 The Scheduler is responsible for triggering the Evolution Detection Workflow (de-
5142 scribed in detail below in Section 11.4.2). Developers set the schedule to run in
5143 the background at regular intervals or to trigger if violations occur z times. The
5144 Scheduler is the component that enables our architectural style to identify called
5145 intelligent service software evolution and to notify the client applications that such
5146 evolution has occurred. Client applications can then respond to this evolution in a
5147 timely manner rather than wait for the system to fail, as in our motivating example.
5148 The Scheduler is necessary to satisfy our requirements $R2$ and $R3$.

5149 11.4.2 Usage Example

5150 We explain how developer Michelina, from our motivating example, would use
5151 our proposed solution to satisfy the requirements described in Section 11.2. Each
5152 workflow is presented in Figure 11.6. Only *Workflow 1 - Initialise Benchmark* is
5153 executed once, while the rest are cycled. The description below assumes Michelina
5154 has implemented the Proxy.

5155 11.4.2.1 Workflow 1. Initialise Benchmark

5156 The first task that Michelina has to do is to prepare and initialise the benchmark
5157 dataset within the Proxy Server. To prepare a representative dataset, Michelina needs
5158 to follow well established guidelines such as those proposed by Pyle. Michelina also
5159 needs to manually assign labels to each image before uploading the dataset to the
5160 Proxy along with the thresholds to use for detecting behavioural change. The full set
5161 of parameters that Michelina has to set are based on the rules shown in Table 11.2.
5162 Michelina cannot use the Proxy to notify her of evolution until a Benchmark Dataset
5163 has been provided. The Proxy then sends each image in the Benchmark Dataset to
5164 the intelligent service and stores the results. From these results, a Behaviour Token
5165 is generated which is passed back to the Client Application. Michelina uses this
5166 token in all future requests to the Proxy as the token captures the current state of the
5167 intelligent service.

5168 *11.4.2.2 Workflow 2. Valid Request Pre-Evolution*

5169 Workflow 2 represents the steps followed when the intelligent service is behaving as
5170 expected. Michelina makes a request to label an image to the Proxy using the token
5171 that she received when registering the Benchmark Dataset. The token is validated
5172 with the Proxy’s current state token and then a request to label the image is made to
5173 the intelligent service if no errors have occurred. Results returned by the intelligent
5174 service are registered with the Proxy Server. Michelina can be confident that the
5175 result returned by our service is in line with her expectations.

5176 *11.4.2.3 Workflow 3. Evolution Detection*

5177 Workflow 3 describes how the Proxy functions when behavioural change is present
5178 in the called intelligent service. Michelina sets a schedule for once a day so that the
5179 Proxy’s Scheduler triggers Workflow 3. First, each image in the Benchmark Dataset
5180 is sent to the intelligent service. Unlike, Workflow 1, we already have a Behaviour
5181 Token that represents the previous state of the intelligent service. In this case, the
5182 model behind the intelligent service has been updated and provides different results
5183 for the Benchmark Dataset. Second, the Proxy updates the internal Behaviour Token
5184 ready for the next request. At this stage Michelina will be notified that the behaviour
5185 of the intelligent service has changed.

5186 *11.4.2.4 Workflow 4. Invalid Request Post-Evolution*

5187 Workflow 4 provides Michelina with an error message when evolution has been
5188 detected. Michelina’s client application makes a request to the Proxy Server with
5189 an old Behaviour Token. The Proxy Server then validates the client token which is
5190 invalid as the Behaviour Token has been updated. In this case, an exception is raised
5191 and an appropriate error message as discussed above is included in the response
5192 back to Michelina’s client application. Michelina can code her application to handle
5193 each error class in appropriate ways for her domain.

5194 **11.5 Evaluation**

5195 Our evaluation of our novel intelligent service Proxy Server approach uses a technical
5196 evaluation based on the results of an observational study. We used existing datasets
5197 from observational studies [88, 215] to identify problematic evolution in computer
5198 vision labelling services. This technical evaluation is designed to show: (i) what
5199 the responses are with and without our architecture present (highlighting errors); (ii)
5200 the overall increased robustness using enhanced responses; and (iii) the technical
5201 soundness of the approach. Thus, we propose the following research question which
5202 we answer in Section 11.5.2: “*Can the architecture identify evolutionary issues of*
5203 *computer vision services via error codes?*” Based on our findings we proposed and
5204 implemented the Proxy Server using a Ruby development framework which we have

5205 made available online for experimentation.³ Additional data was collected from the
5206 CVS and sent to the Proxy Server to evaluate how the service handles behavioural
5207 change.

5208 11.5.1 Data Collection and Preparation

5209 To minimise reviewer bias, we do not identify the name of the service used, however
5210 this service was one of the most adopted cloud vendors used in enterprise applications
5211 in 2018 [299]. The two existing datasets used [88, 215] consisted of 6,680 images.

5212 We initialised the benchmark (workflow 1) in November 2018, and sent each
5213 image to the service every eight days and captured the JSON responses through the
5214 facade API (workflow 2) until March 2019. This resulted in 146,960 JSON responses
5215 from the target CVS. We then selected the first and last set of JSON responses (i.e.,
5216 13,360 responses) and independently identified 331 cases of evolution of the original
5217 6,680 images. This was achieved by analysing the JSON responses for each image
5218 taken in using an evaluation script.⁴

5219 For each JSON response, evolution (as classified by Figure 11.2) was determined
5220 either by a vocabulary or confidence per label change in the first and last responses
5221 sent. For the 331 evolving responses, we calculated the delta of the label's confidence
5222 between the two timestamps and the delta in the number of labels recorded in the
5223 entire response. Further, for the highest-ranking label (by confidence), we manually
5224 classified whether its ontology became more specific, more generalised or whether
5225 there was substantial emphasis change. The distribution of confidence differences per
5226 these three groups are shown in Figure 11.8, with the mean confidence delta indicated
5227 with a vertical dotted line. This highlights that, on average, labels that change
5228 emphasis generally have a greater variation, such as the example in Figure 11.3.
5229 Further, we grouped each image into one of four broad categories—*food*, *animals*,
5230 *vehicles*, *humans*—and assessed the breakdown of ontology variance as provided
5231 in Table 11.3. We provide this dataset as an additional contribution and to permit
5232 replication.⁵ The parameters set for our initial benchmark were a delta label value of
5233 3 and delta confidence value of 0.01. Expected labels for relevant groups were also
5234 assigned as mandatory label sets (e.g., *animal* images used ‘animal’, ‘fauna’ and
5235 ‘organism’; *human* images used ‘human’ etc.).

5236 11.5.2 Results

5237 Examples of the March 2019 responses contrasting the proxy and direct service
5238 responses in our evaluation are shown in Figures 11.9 to 11.11. (Due to space limita-
5239 tions, the entire JSON response is partially redacted using ellipses.) These examples
5240 identify the label identified with the highest level of confidence in three examples
5241 against the ground truth label in the benchmark dataset. In total, the Proxy Server
5242 identified 1,334 labels added to the responses and 1,127 labels dropped, with, on
5243 average, a delta of 8 labels added. The topmost labels added were ‘architecture’

³<http://bit.ly/2TIMmDh> last accessed 5 March 2020.

⁴<http://bit.ly/2G7saFJ> last accessed 2 March 2020.

⁵<http://bit.ly/2VQrAUU> last accessed 5 March 2020.

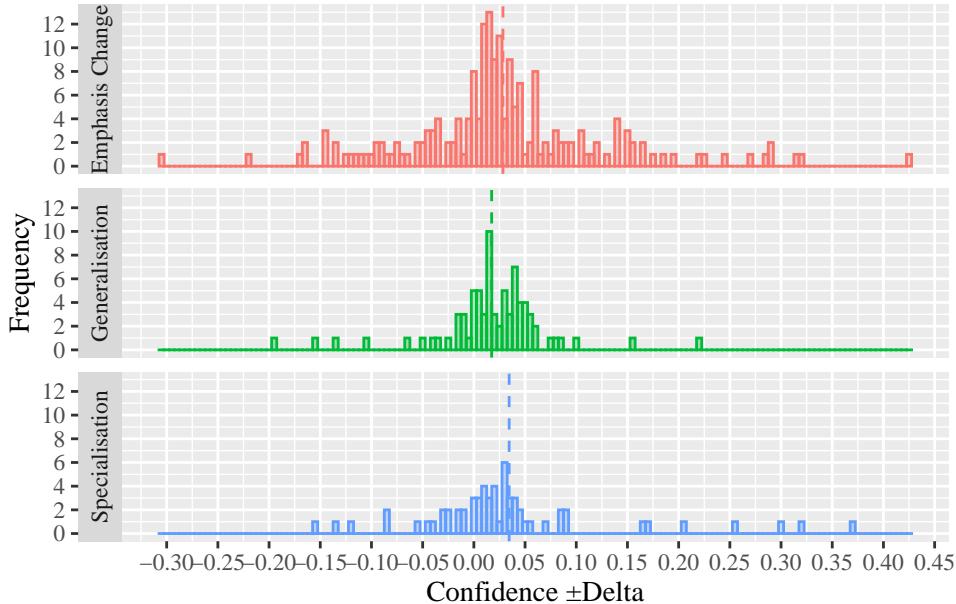


Figure 11.8: Histogram of confidence variation.

at 32 cases, ‘building’ at 20 cases and ‘ingredient’ at 20 cases; the topmost labels dropped were ‘tree’ at 21 cases, ‘sky’ at 19 cases and ‘fun’ at 17 cases. 1054 confidence changes were also observed by the Proxy Server, on average a delta increase of 0.0977.

In Figure 11.9, we highlight an image of a sheep that was identified as a ‘sheep’ (at 0.9622) in November 2018 and then a ‘mammal’ in March 2019. This evolution was classified by the Proxy Server as a confidence change error as the delta in the confidences between the two timestamps exceeds the parameter set of 0.01—in this case, ‘sheep’ was downgraded to the third-ranked label at 0.9816, thereby increasing by a value of 0.0194. As shown in the example, four other labels evolved for this image between the two time stamps (‘herd’, ‘livestock’, ‘terrestrial animal’ and ‘snout’) with an average increase of 0.1174 found. Such information is encoded as a 412 HTTP error returned back to the user by the Proxy Server, rejecting the request as substantial evolution has occurred, however the response *directly* from the service indicates no error at all (indicating by a 200 HTTP response).

Similarly, Figure 11.10 shows a violation of the number of acceptable changes in the number of labels a response should have between two timestamps. In November 2018, the response includes the labels ‘car’, ‘motor vehicle’, ‘city’ and ‘road’, however these labels are not present in the 2019 response. The response in 2019 introduces ‘transport’, ‘building’, ‘architecture’, and ‘house’. Therefore, the combined delta is 4 dropped and 4 introduced labels, exceeding our threshold set of 3.

Lastly, Figure 11.11 indicates an expected label failure. In this example, the label ‘fauna’ was dropped in the 2018 label set, which was an expected label of all animals we labelled in our dataset. Additionally, this particular response

Table 11.3: Variance in ontologies for the five broad categories.

Ontology Change	Food	Animal	Vehicles	Humans	Other	Total
Generalisation	8	13	11	8	38	78
Specialisation	5	12	1	1	43	62
Emphasis Change	18	4	10	21	138	191
Total	31	29	22	30	219	331

5269 introduced ‘green iguana’, ‘iguanidae’, and ‘marine iguana’ to its label
5270 set. Therefore, not only was this response in violation of the label delta mismatch, it
5271 was also in violation of the expected labels mismatch error, and thus is caught twice
5272 by the Proxy Server.

5273 11.5.3 Threats to Validity

5274 11.5.3.1 Internal Validity

5275 As mentioned, we selected a popular CVS provider to test our proxy server against.
5276 However, there exist many other CVSs, and due to language barriers of the authors,
5277 no non-English speaking service were selected despite a large number available from
5278 Asia. Further, no user evaluation has been performed on the architectural tactic so
5279 far, and therefore developers may suggest improvements to the approach we have
5280 taken in designing our tactic. We intend to follow this up with a future study.

5281 11.5.3.2 External Validity

5282 This paper only evaluates the object detection endpoint of a computer vision-based
5283 intelligent service. While this type of intelligent service is one of the more mature
5284 AI-based services available on the market—and is largely popular with develop-
5285 ers [91]—further evaluations of the our tactic may need to be explored against other
5286 endpoints (i.e., object localisation) or, indeed, other types of services, such as natural
5287 language processing, audio transcription, or on time-series data. Future studies may
5288 need to explore this avenue of research.

5289 11.5.3.3 Construct Validity

5290 The evaluation of our experiment was largely conducted under clinical conditions,
5291 and a real-world case study of the design and implementation of our proposed tactic
5292 would be beneficial to learn about possible side-effects from implementing such a
5293 design (e.g., implications to cost etc.). Therefore, our evaluation does not consider
5294 more practical considerations that a real-world, production-grade system may need
5295 to consider.



Label: Animal
Nov 2018: 'sheep' (0.9622)
Mar 2019: 'mammal' (0.9890)
Category: Confidence Change

Intelligent Service Response in March 2019

```

1 { "responses": [ { "label_annotations": [
2   { "mid": "/m/04rky",
3     "description": "mammal",
4     "score": 0.9890478253364563,
5     "topicality": 0.9890478253364563 },
6   { "mid": "/m/09686",
7     "description": "vertebrate",
8     "score": 0.9851104021072388,
9     "topicality": 0.9851104021072388 },
10  { "mid": "/m/07bgp",
11    "description": "sheep",
12    "score": 0.9815810322761536,
13    "topicality": 0.9815810322761536 },
14    ... ] } ]

```

Proxy Server Response in March 2019

```

1 { "error_code": 8,
2   "error_type": "CONFIDENCE_DELTA_MISMATCH",
3   "error_data": {
4     "source_key": { ... },
5     "source_response": { ... },
6     "violating_key": { ... },
7     "violating_response": { ... },
8     "delta_confidence_threshold": 0.01,
9     "delta_confidences_detected": {
10       "sheep": 0.01936030388219212,
11       "herd": 0.15035879611968994,
12       "livestock": 0.13112884759902954,
13       "terrestrial_animal": 0.1791478991508484,
14       "snout": 0.10682523250579834
15     },
16     "uri": "http://localhost:4567/demo/data/000000005992.jpeg"
17     ↵ ,
      "reason": "Exceeded confidence delta threshold ±0.01 in 5
      ↵ labels (delta mean=+0.1174)." } }

```

Figure 11.9: Example of substantial confidence change due to evolution.



Label: Vehicle
Nov 2018: 'vehicle' (0.9045)
Mar 2019: 'motorcycle' (0.9534)
Category: Label Set Change

Intelligent Service Response in March 2019

```

1 { "responses": [ { "label_annotations": [
2   { "mid": "/m/07yv9",
3     "description": "vehicle",
4     "score": 0.9045347571372986,
5     "topicality": 0.9045347571372986 },
6   { "mid": "/m/07bsy",
7     "description": "transport",
8     "score": 0.9012271165847778,
9     "topicality": 0.9012271165847778 },
10  { "mid": "/m/0dx1j",
11    "description": "town",
12    "score": 0.8946694135665894,
13    "topicality": 0.8946694135665894 },
14    ... ] } ] }
```

Proxy Server Response in March 2019

```

1 { "error_code": 7,
2   "error_type": "LABEL_DELTA_MISMATCH",
3   "error_data": {
4     "source_key": { ... },
5     "source_response": { ... },
6     "violating_key": { ... },
7     "violating_response": { ... },
8     "delta_labels_threshold": 5,
9     "delta_labels_detected": 8,
10    "uri": "http://localhost:4567/demo/data/000000019109",
11    "new_labels": [ "transport", "building", "architecture", "
12      ↪ house" ],
12    "dropped_labels": [ "car", "motor vehicle", "city", "road"
13      ↪ ],
13    "reason": "Exceeded label count delta threshold ±5 (4 new
13      ↪ labels + 4 dropped labels = 8)." } }
```

Figure 11.10: Example of substantial changes of a response's label set due to evolution.



Label: Fauna
Nov 2018: 'reptile' (0.9505)
Mar 2019: 'iguania' (0.9836)
Category: Ontology Specialisation

Intelligent Service Response in March 2019

```

1 | { "responses": [ { "label_annotations": [
2 |   { "mid": "/m/08_jw6",
3 |     "description": "iguania",
4 |     "score": 0.9835183024406433,
5 |     "topicality": 0.9835183024406433 },
6 |   { "mid": "/m/06bt6",
7 |     "description": "reptile",
8 |     "score": 0.9833670854568481,
9 |     "topicality": 0.9833670854568481 },
10 |   { "mid": "/m/01vq7_",
11 |     "description": "iguana",
12 |     "score": 0.9796721339225769,
13 |     "topicality": 0.9796721339225769 },
14 |   ... ] } ]

```

Proxy Server Response in March 2019

```

1 | { "error_code": 9,
2 |   "error_type": "EXPECTED_LABELS_MISMATCH",
3 |   "error_data": {
4 |     "source_key": { ... },
5 |     "violating_response": { ... },
6 |     "uri": "http://localhost:4567/demo/data/0052",
7 |     "expected_labels": [ "fauna" ],
8 |     "labels_detected": [ "iguana", "green iguana", "iguanidae"
9 |       ↪ , "lizard", "scaled reptile", "marine iguana", "
10 |       ↪ terrestrial animal", "organism" ],
      "labels_missing": [ "fauna" ],
      "reason": "The expected label(s) `fauna` are missing in
        ↪ the response." } }

```

Figure 11.11: Example of an expected label missing due to evolution.

5296 **11.6 Discussion**

5297 **11.6.1 Implications**

5298 *11.6.1.1 For cloud vendors*

5299 Cloud vendors that provide IWSs may wish to adopt the architectural tactic presented
5300 in this paper by providing a proxy, auxiliary service (or similar) to their existing ser-
5301 vices, thereby improving the current robustness of these services. Further, they
5302 should consider enabling developers of this technical domain knowledge by pre-
5303 venting client applications from using the service without providing a benchmark
5304 dataset, such that the service will return HTTP error codes. These procedures should
5305 be well-documented within the service’s API documentation, thereby indicating to
5306 developers how they can build more robust applications with their IWSs. Lastly,
5307 cloud vendors should consider updating the internal machine learning models less
5308 frequently unless substantial improvements are being made. Many different appli-
5309 cations from many different domains are using these IWSs so it is unlikely that
5310 the model changes are improving all applications. Versioned endpoints would help
5311 with this issue, although—as we have discussed—context using benchmark datasets
5312 should be provided.

5313 *11.6.1.2 For application developers*

5314 Developers need to monitor all IWSs for evolution using a benchmark dataset and
5315 application specific thresholds before diving straight into using them. It is clear that
5316 the evolutionary issues have significant impact in their client applications [88], and
5317 therefore they need to check the extent this evolution has between versions of an
5318 intelligent service (should versioned APIs be available). Lastly, application devel-
5319 opers should leverage the concept of a proxy server (or other form of intermediary)
5320 when using IWSs to make their applications more robust.

5321 *11.6.1.3 For project managers*

5322 Project managers need to consider the cost of evolution changes on their application
5323 when using IWSs, and therefore should schedule tasks for building maintenance
5324 infrastructure to detect evolution. Consider scheduling tasks that evaluates and
5325 identifies the frequency of evolution for the specific intelligent service being used.
5326 Our research we have found some IWSs that are not versioned but rarely show
5327 behavioural changes due to evolution.

5328 **11.6.2 Limitations**

5329 In the situation where a solo developer implements the Proxy Service the main
5330 limitation is the cost vs response time trade-off. Developers may want to be notified
5331 as soon as possible when a behavioural change occurs which requires frequent
5332 validation of the Benchmark Dataset. Each time the Benchmark Dataset is validated
5333 each item is sent as a request to the intelligent service. As cloud vendors charge

5334 per request to an intelligent service there are financial implications for operating
5335 the Proxy Service. If the developer optimises for cost then the application will take
5336 longer to respond to the behavioural change potentially impact end users. Developers
5337 need to consider the impact of cost vs response time when using the Proxy Service.

5338 Another limitation of our approach is the development effort required to imple-
5339 ment the Proxy Service. Developers need to build a scheduling component, batch
5340 processing pipeline for the Benchmark Dataset, and a web service. These com-
5341 ponents require developing and testing which impact project schedules and have
5342 maintenance implications. Thus, we advise developers to consider the overhead of
5343 a Proxy Service and way up the benefits with have incorrect behaviour caused by
5344 evolution of IWSs.

5345 11.6.3 Future Work

5346 11.6.3.1 Guidelines to construct and update the Benchmark Dataset

5347 Our approach assumes that each category of evolution is present in the Benchmark
5348 Dataset prepared by the developer. Further guidelines are required to ensure that the
5349 developer knows how to validate the data before using the Proxy Service. While the
5350 focus of this paper was to present and validate our architectural tactic, guidelines
5351 on how to construct and update benchmark datasets for this tactic will need to be
5352 considered in future work. Data science literature extensively covers dataset prepa-
5353 ration (e.g., [200, 286]), and many example benchmark datasets are readily available
5354 [24, 145, 376]. An initial set of guidelines are proposed as follows: data must be
5355 contextualised and appropriately sampled to be representative of the client applica-
5356 tion in particular the patterns present in the data, contain both positive and negative
5357 examples (this is/is not a cat); where to source data from (existing datasets, Google
5358 Images/Flickr, crowdsourced etc.); whether the dataset is synthetically generated to
5359 increase sample size; and how large a benchmark dataset size should be (i.e., larger
5360 the better but takes more effort and costs more). Benchmark datasets can also be
5361 used by software engineers provided the domain and context is appropriate for their
5362 specific application’s context. Software engineers also benefit from our approach
5363 even if these guidelines are not strictly adhered to provided they use an application-
5364 specific dataset (i.e., data collected from the input source for their application). The
5365 main reason for this is that without our proposed tactic there are limited ways to
5366 build robust software with intelligent services. Future testing and evaluation of these
5367 guidelines should be considered.

5368 11.6.3.2 Extend the evolution categories to support other IWSs

5369 This paper has used computer vision services to assess our proposed tactic, and
5370 therefore further investigation is needed into the evolution characteristics of other
5371 IWSs. The evolution challenges with services that provide optimisation algorithms
5372 such as route planning are likely to differ from CVSs. These characteristics of an
5373 application domain have shown to greatly influence software architecture [25] and
5374 further development of the Proxy Service will need to account for these differences.

5375 As an example, we have identified many similar issues that exist for natural language
 5376 processing, where topic modelling produces labels on large bodies of text with
 5377 associated confidences. Therefore, the *broader* concepts of our contribution (e.g.,
 5378 behaviour token parameters, error codes etc.) can be used to handle issues in natural
 5379 language processing to demonstrate the generalisability of the architecture to other
 5380 intelligent services. We plan to apply our tactic to natural language processing and
 5381 other intelligent services in our future work.

5382 11.6.3.3 *Provide tool support for optimising parameters for an application context*

5383 Appropriately using the Proxy Service requires careful selection of thresholds,
 5384 benchmark rules and schedule. Further work is required to support the developer in
 5385 making these decisions so an optimal application specific outcome is achieved. One
 5386 approach is to present the trade-offs to the developer and let them visualise the
 5387 impact of their decisions. We have developed an early prototype for such purpose
 5388 in [89].

5389 11.6.3.4 *Improvements for a more rigorous approach*

5390 Conducting a more formal evaluation of our proposed architecture would benefit
 5391 the robustness of the solution presented. This could be done in various ways,
 5392 for example, using a formal architecture evaluation method such as ATAM [189]
 5393 or a similar variant [51]; conducting user evaluation via brainstorming sessions or
 5394 interviews with practitioners who may provide suggestions to improve our approach;
 5395 determining better strategies to fully-automate the approach and reduce manual steps;
 5396 and using real-world industry case studies to identify other factors such as cost and
 5397 maintenance issues. All these are various avenues of research that would ultimately
 5398 benefit in a more well-rounded approach to the architectural tactic we have proposed.

5399 11.7 Related Work

5400 11.7.0.1 *Robustness of Intelligent Services*

5401 While usage of IWSs have been proven to have widespread benefits to the commu-
 5402 nity [94, 294], they are still largely understudied in software engineering literature,
 5403 particularly around their robustness in production-grade systems. As an example,
 5404 advancements in computer vision (largely due to the resurgence of convolutional
 5405 neural networks in the late 1990s [209]) have been made available through IWSs and
 5406 are given marketed promises from prominent cloud vendors, e.g., “with Amazon
 5407 Rekognition, you don’t have to build, maintain or upgrade deep learning pipelines”.⁶
 5408 However, while vendors claim this, the state of the art of *computer vision itself*
 5409 is still susceptible to many robustness flaws, as highlighted by many recent stud-
 5410 ies [113, 307, 363]. Further, each service has vastly different (and incompatible)
 5411 ontologies which are non-static and evolve [88, 262], certain services can mislabel

⁶<https://aws.amazon.com/rekognition/faqs/>, accessed 21 November 2019.

5412 images when as little as 10% noise is introduced [161], and developers have a shallow
5413 understanding of the fundamental AI concepts behind these issues, which presents a
5414 dichotomy of their understanding of the technical domain when contrasted to more
5415 conventional domains such as mobile application development [91].

5416 *11.7.0.2 Proxy Servers as Fault Detectors*

5417 Fault detection is an availability tactic that encompasses robustness of software [31].
5418 Our architecture implements the sanity check and condition monitoring techniques
5419 to detect faults [31, 167], by validating the reasonableness of the response from the
5420 intelligent service against the conditions set out in the rules encoded in the benchmark
5421 dataset and behaviour token. As we do in this study, the proxy server pattern can be
5422 used to both detect and action faults in another service as an intermediary between a
5423 client and a server. For example, addressing accessibility issues using proxy servers
5424 has been widely addressed [41, 42, 346, 386] and, more recently, they have been
5425 used to address in-browser JavaScript errors [108].

5426 **11.8 Conclusions**

5427 IWSs are gaining traction in the developer community, and this is shown with
5428 an evermore growing adoption of CVSs in applications. These services make
5429 integration of AI-based components far more accessible to developers via simple
5430 RESTful APIs that developers are familiar with, and offer forever-‘improving’ object
5431 localisation and detection models at little cost or effort to developers. However, these
5432 services are dependent on their training datasets and do not return consistent and
5433 deterministic results. To enable robust composition, developers must deal with the
5434 evolving training datasets behind these components and consider how these non-
5435 deterministic components impact their deterministic systems.

5436 This paper proposes an integration architectural tactic to deal with these issues
5437 by mapping the evolving and probabilistic nature of these services to deterministic
5438 error codes. We propose a new set of error codes that deal directly with the erroneous
5439 conditions that has been observed in IWSs, such as computer vision. We provide
5440 a reference architecture via a proxy server that returns these errors when they are
5441 identified, and evaluate our architecture, demonstrating its efficacy for supporting
5442 IWS evolution. Further, we provide a labelled dataset of the evolutionary patterns
5443 identified, which was used to evaluate our architecture.

5444

Part III

5445

Postface

CHAPTER 12

5446

5447

5448

Conclusions & Future Work

5449

5450 In this chapter, we provide a summary of the contributions within the body of
5451 this work. We evaluate the significance of the research outcomes to the software
5452 engineering research community and identify potential criticisms of these outcomes.
5453 Lastly, we indicate future avenues of research resulting from this thesis and provide
5454 concluding remarks.

5455 12.1 Contributions of this Work

5456 This thesis has presented three primary contributions to the body of software engi-
5457 neering knowledge. Namely, we have presented an improved understanding in the
5458 landscape of IWSs—concretely, those that provide computer vision—by examining
5459 their runtime behaviour and evolution profile over a longitudinal study (Chapter 4).
5460 The implications of this work emphasise the caution developers need to take be-
5461 fore diving deep into using these services, and highlight the substantial impacts to
5462 software quality if these considerations are ignored. We showed that developers
5463 find working with this software more frustrating when contrasted to conventional
5464 software engineering domains (Chapter 6), and that the distribution of the types of
5465 issues they face differs from that of the types of issues developers face in established
5466 areas such as mobile and web development (Chapter 5). Furthermore, developers
5467 find the completeness of the existing CVS API documentation poor (Chapter 5),
5468 and therefore an investigation into the attributes of what *constitutes* a complete API
5469 document according to literature and how developers respond to the efficacy of these
5470 attributes produced a taxonomy that, when applied to three CVS service providers,
5471 found 12 areas of improvement of the services’ documentation (Chapter 8). This
5472 taxonomy further serves as a go-to ‘checklist’ for any software engineer to review a
5473 prioritised list of documentation elements worth implementing into their own API
5474 documentation. Lastly our investigations into improved intelligent service integra-
5475 tion architectures proposes several strategies by which developers can guard against

5476 the non-deterministic evolutionary issues found in Chapter 4. Preliminary solutions
5477 such as that presented in Chapter 9 helped informed further investigations into how
5478 developers can use a novel workflow to better select appropriate confidence thresh-
5479 olds calibrated for their application’s domain (Chapter 10) and prevent evolution
5480 evident in CVSs via a client-server intermediary proxy server strategy (Chapter 11).
5481 A more extensive discussion into the contributions of this thesis is presented in
5482 Section 1.7.

5483 12.1.1 Answers to Research Questions

5484 In this subsection, we directly answer the four primary research questions that were
5485 posed in Section 1.4.

5486 12.1.1.1 *RQ1: “What is the nature of cloud-based CVSs?”*

☞ *These services are in nascent stage, are difficult to evaluate, and are not easily interchangeable. They present themselves as conceptually similar, but we find they functionally differ between vendors. Their labels are semantically disparate and work needs to be done on consolidating a standardised vocabulary for labels. Evolution within these services occurs and is not sufficiently versioned or documented to developers as results from services are non-static.*

5487 Irrespective of which service is used, the vocabulary used to label an image is
5488 disparate. We find that **there exists no common standard vocabulary** (e.g., ‘border
5489 collie’ vs. ‘collie’) and **semantic consistency for the same image between services**
5490 **is disparate**, for example as that shown in Figure 12.1 (left). The runtime behaviour
5491 of these services when contrasted against *each other* is, therefore, inconsistent, and
5492 thus (without semantic comparison of images, such as that suggested in Chapter 9)
5493 the vendors are not ‘plug-and-play’. In contrast to deterministic web services, the
5494 same result is functionally guaranteed despite which service is used. For instance,
5495 conceptually, a cloud storage service will provide the same output for the same
5496 input; that is, regardless of whether a developer uses AWS or Google Cloud object
5497 storage, when they upload a file, that file is (more or less) guaranteed to be stored.
5498 A deterministic input/output is, thereby, conceptually and functionally guaranteed.
5499 However, **we find that the nature of intelligent services are conceptually similar**
5500 **but functionally different between services**, and therefore developers are likely to
5501 become vendor locked. For instance, as we show in Section 4.5.1, one service may
5502 return the duplicity of objects in an image (e.g., ‘several’), while another service
5503 may return the subject of the image (e.g., ‘carrot’) or a hypernym of that subject
5504 (e.g., ‘food’), and another service may focus on the environment of the image (e.g.,
5505 ‘indoors’). Further, even when a label is consistent between services, we find the
5506 consistency of how *well* they agree to that result—as measured by their confidence
5507 score in the label—does not always strictly match in their level of agreement. As

5508 we show in Figure 12.1 (right), **distributions of agreement can be disparate even**
5509 **where services agree on a label for the same image.** Lastly, while intelligent
5510 services that provide computer vision are somewhat stable in the responses they
5511 return, **their responses are non-static.** There is no guarantee that a request with
5512 the same image sent in testing will return the same response, and we find that this
5513 potential evolution risk is not sufficiently communicated to developers.

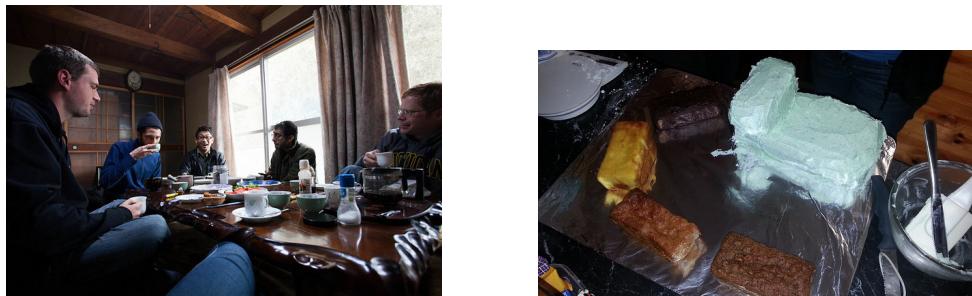


Figure 12.1: *Left:* Semantic consistency between services is not always guaranteed. Two services identified this image as ‘people’, while another identified ‘conversation’, which is not registered at all as a possible label from the other two services. *Right:* Even when services agree on a label, the distribution of their level of agreement is (at times) inconsistent—in the above image, ‘food’ is detected at confidence levels of three services ranging from 94.93% to 41.39%.

5514 12.1.1.2 *RQ2: “Are CVS APIs sufficiently documented?”*

☞ *These services are largely well-documented, but areas of improvement can be identified. By applying the five-dimensional taxonomy we propose in Chapter 8 to three services, we found there to be twelve ways vendors can better improve their services’ documentation. We found the ways in which developers can use these services for their purposes could be improved—such as improved tutorials that integrate multiple components of the service—and by providing better descriptions to improve developers’ conceptual understanding of computer vision.*

5515 To understand if these services are sufficiently documented, we first investigated
5516 what documentation artefacts constitute a complete API document, investigating
5517 literature and validating this against developers using a survey. These consist of five
5518 dimensions: usage description (or *how* developers can use the API); design rationale
5519 (or *when* the developers should use it); domain concepts (or *why* developers should
5520 use it in their application domain); support artefacts (or *what* additional documen-
5521 tation could be provided to support developers); and, documentation presentation
5522 (or *visualisation* of the prior four dimensions). This taxonomy is presented with
5523 further detail in Chapter C. **Developers argue that code snippets are the most**
5524 **important documentation artefact, followed closely by tutorials and low-level**

reference documentation. This is largely covered by existing research. When we apply this taxonomy to intelligent services such as CVSSs, we find that there can be improvements made to all dimensions except documentation presentation, which is sufficient. **The largest suggested improvements fall into the usage description dimension,** in which quick-start guides, step-by-step tutorials, reference applications, best-practices, listings of all API components, minimum system dependencies, and installation instructions require further detail. The second largest dimension falls into the domain concepts behind computer vision, where vendors should provide a greater emphasis behind computer vision concepts and definitions of relevant computer vision terminology (especially since many vendors refer to the same concept under different terms, such as ‘image tagging’ and ‘label detection’ for what is essentially object recognition). The lack of complete documentation in domain concepts was further reflected in developer discussions on Stack Overflow, as found in Chapter 5. Section 8.6.5 details these suggested improvements in greater detail.

12.1.1.3 RQ3: “Are CVSSs more misunderstood than conventional software engineering domains?”

 In conventional software engineering domains, where the technical domain is well-established and well-understood by developers, questions asked by developers are of greater depth. In contrast, their shallow understanding of the technical domain of computer vision is reflected by questions that highlight a poor understanding of the behaviour of these services and the contexts by which they work. Thus, simpler questions are asked, such as help with trying to understand basic error codes, or clarification of basic concepts and terminologies in computer vision. Therefore, we argue that they are more misunderstood seeing as the domain of intelligent services is still immature.

As expressed on Stack Overflow, we find developers struggle most with simple debugging issues, which reflects a shallow understanding of the AI concepts that empower these services. **The technical nuances become so abstracted away that developers begin to lack a full appreciation of the context and proper usage of these systems.** These questions reveal how developers do not have a strong grasp of the behaviour of these services and how further functional capability needs to be overcome by secondary phases of work, such as pre- and post-processing. **Their conceptual understanding of these services are poor,** with our findings suggesting that developers present a misunderstanding of the vocabulary used within computer vision, such as the differences between object and facial detection, localisation and recognition. The lack of strong conceptual understanding also reflects in discrepancy-based issues where developers cannot appreciate why services result in specific outcomes contrary to what they believe should happen. **We find these discrepancy-based issues to be the most frustrating for developers,** and argue that

5556 this is rooted in a need for developers to have some basic understanding of computer
 5557 vision before diving into services such as these. In terms of the documentation of
 5558 these services, **developers express frustration towards the completeness of the**
 5559 **documentation**, whereby they seek additional information from the official docu-
 5560 mentation sources but are unable to find anything to help resolve this gap. Further,
 5561 **they question the accuracy of the cloud documentation since it is in contrast**
 5562 **with the behaviour they observe**, as related to the discrepancy-based issues they
 5563 find. In contrast to more established domains, such as mobile and web-development,
 5564 the distribution of issues are different (see Figure 12.2). Rather than trying to in-
 5565 terpret simple errors (as is the case for CVSs), developers question API usage and
 5566 high-level conceptual questions. Developers have a greater appreciation for the
 5567 technical domain in these mature areas, resulting in fewer shallower questions asked.

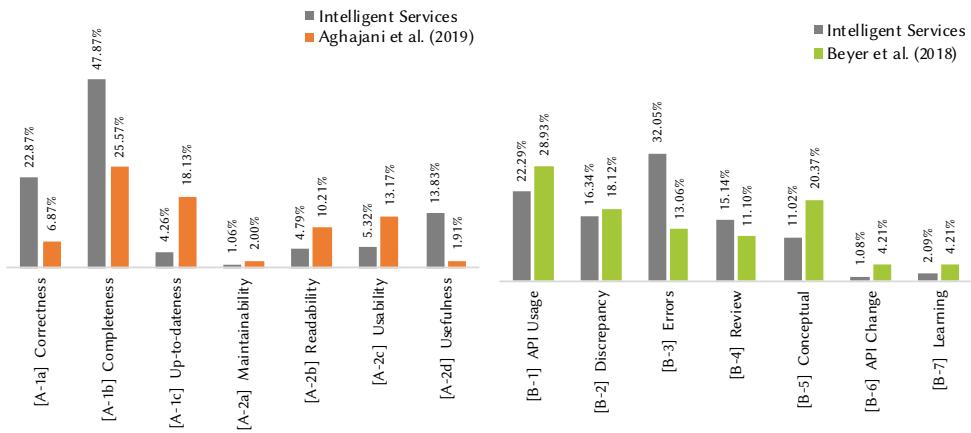


Figure 12.2: The distribution of documentation-specific questions (*left*) and generalised questions (*right*) differs between prior studies. Descriptions of each category for both question types are found in Table 5.1.

5568 **12.1.1.4 RQ4:** “What strategies can developers employ to integrate their applica-
 5569 tions with CVSs while preserving robustness and reliability?”

☞ Developers can employ the use of a facade-based architecture to merge the responses of multiple vendors using a novel, proportional-representation based approach using lexical databases to resolve ontological issues of labels. An integration strategy consisting of four workflows was presented in Chapter 11 to assist developers monitor and handle substantial evolution change in these services. Developers can deal with the probabilistic nature of these services by using a representative data set of their application’s data to fine-tune a confidence threshold and monitor threshold changes in a production setting.

5570 This thesis offers three strategies targeted at improved integration of developer
 5571 applications with CVSs. Chapter 9 successfully demonstrated that multiple services

can be combined using lexical databases to better improve the reliability of relying on a single service's label. Further, this strategy outperformed naive merge methods using a novel proportional representation method by 0.015 F-measure. This strategy uses the idea of a client-server intermediary facade to handle these operations and produce a consistent result regardless of which service is being used. This inspired further work presented in Chapter 11. To handle the evolutionary issues found in the services, we developed a novel integration architecture based on the proxy server strategy, integrating four key proposed workflows which can be used to guard against evolution and non-determinism in these services: (i) initialising a representative benchmark of domain-specific data used in the client application; (ii) validating that the service is behaving as expected against that benchmark; (iii) periodically detecting for evolution if behavioural change occurs, thereby notifying change; and lastly (iv) invalidating future requests if substantial evolution is detected in step (iii). This, in turn, resolves a non-deterministic response into a deterministic error when evolution is raised. Lastly, to deal with the uncertainty arising from probabilistic confidence values, we proposed Threshy (see Chapter 10), a tool to help developers select appropriate threshold boundaries resulting from their benchmark data sets and cost factors (due to missed predictions). Ultimately these strategies aim at improving the robustness of applications that are dependent on CVSs.

12.1.2 Limitations to Research Answers & Future Research

Throughout this thesis, we have used computer vision as a primary exemplar of intelligent AI components provided via the web. Limiting this research to such a narrow scope is an illustrative example that enables more concrete findings and potential solutions to a specific subset of intelligent web services (IWSs). As discussed in Section 1.2, these particular type of IWSs were selected due to both their increasing enthusiasm and uptake in developer communities (see Figure 1.1) and their maturity in the area. However, we acknowledge that there are myriad domains in the IWS space, such as audio and sentiment analysis, text-to-speech and speech-to-text, natural language processing, or time-series data analysis. Our analyses of CVSs chiefly targets content analysis (or object detection) endpoints of these services; other endpoints such as image description or object localisation exist, and were not considered as the main unit of analysis in this work. Further, this thesis selects only three prominent vendors of CVSs: Google, Microsoft and Amazon. While these vendors are considered to be the ubiquitous 'go-to' providers for cloud-based services (given their AWS, Google Cloud and Azure platforms) and were the most adopted for enterprise solutions [299], many other providers of computer vision intelligence exist [389, 405, 406, 407, 413, 426, 427, 429, 478, 479], including those from Asian market [403, 404, 425, 444, 445] where language barriers prevented analysis of these services.

Thus, the generalisability of our findings are a substantial threat to the external validity of our research answers and future research needs to investigate both other areas of IWSs to assess whether our findings and solutions are applicable to other intelligent domains and other types of services in the CVS market. Further, this

5615 thesis strongly emphasises investigations into identifying issues within web-based
5616 intelligent services. We establish a better understanding on their nature and run-
5617 time behaviour (RQ1), how they are documented (RQ2), and how well they are
5618 understood by developers (RQ3), but only offer limited solutions to these issues
5619 (e.g., RQ4). We encourage the software engineering community to use the issues
5620 identified in this work as a stepping-stone into future solutions, identifying other
5621 ways (beyond improved integration techniques) in which developers can handle
5622 these issues. For example, the broader concepts of our contributed architecture (e.g.,
5623 use of a behaviour token, its parameters, and the error codes proposed) can be shifted
5624 to handle issues in natural language processing to demonstrate the generalisability of
5625 the architecture to other intelligent services, since topic modelling produces labels
5626 with confidences and the approach can be largely transferred to this area.

5627 Other future work stemming from this thesis would be to explore the nature of
5628 other IWSs and understanding if similar evolution and behavioural runtime patterns
5629 exist with their computer vision equivalents (as identified in this thesis). Chiefly,
5630 future work on how to better support developers using different types of intelligent
5631 components would be an interesting area to explore, especially in applying our
5632 design strategies to combat the robustness issues we have identified to these other
5633 types of services and identify any potential pitfalls of our design. As our proposed
5634 architectural usage framework is a preliminary design, rigorous testing in real-
5635 world scenarios, such as a long-term industry case study implementing our design
5636 or conducting formal architecture evaluations such as ATAM [189], would be a
5637 possible avenue of research to verify the design. Further, our proposal makes use
5638 of the benchmark data set approach, but we are yet to explore and test potential
5639 guidelines in developing a benchmark data set. While we provide some potential
5640 guidelines in Section 11.6.3.1, these will need to be evaluated for practical use.

5641 Another key aspect would revolve around the documentation contributions of
5642 this study and investigating whether our suggested documentation improvements
5643 are applicable to these different services. Developing improved documentation and
5644 tooling that better support developers when using these IWSs (and how our proposed
5645 architecture fits in) should be explored.

5646 Moreover, since we find these services to be not yet as matured as traditional
5647 software development domains and—like similar emerging software engineering
5648 domains such as web development in the mid-1990s and early-2000s or mobile
5649 development from the mid-2000s to early-2010s—we suspect there to be substantial
5650 growth in the understanding of how we will use these services and maturity in the
5651 developer’s appreciation of its surrounding technical domain. Therefore, it would be
5652 beneficial to repeat some of the studies within this thesis and assess whether there is
5653 an improved understanding of the phenomena occurring within IWSs and whether
5654 developers have a developed mindset of these services and how they can be used.
5655 Thus, different tools, designs or suggestions may result from repetitional studies 5-10
5656 years in the future. This, therefore, identifies evolution in the *maturity* of intelligent
5657 services, and to highlight whether developers are showing a stronger understanding
5658 of the surrounding technical domain behind these services. We strongly encourage
5659 the software engineering community to explore these in such time to identify maturity

5660 in this emerging domain.

5661 12.2 Concluding Remarks

5662 To our knowledge, little prior investigation has been conducted to understand IWSs
5663 via the lenses of software quality—primarily the robustness, reliability of the services
5664 and completeness of its documentation. In this thesis, we have shown that the non-
5665 deterministic and probabilistic properties of computer vision IWSs present non-
5666 trivial impacts to the quality of software that they are integrated with, and it is
5667 pivotal that developers have a greater appreciation of the technical domain behind
5668 the AI techniques that empower such services.

5669 In identifying evolutionary and run-time issues of these services, the ways in
5670 which they are (currently) documented and these issues communicated (or not!), and
5671 analysing how developers perceive these services with a deterministic mindset, we
5672 have shown just how fragile the use of such services (as they stand) are. We strongly
5673 encourage vendors to use suggestions made within this research to improve both
5674 their documentation and their integration strategies so that developers can ensure
5675 more robust applications when using these services. Ultimately, intelligent AI
5676 components are still in a nascent stage, and therefore strongly suggest one message
5677 to eager developers: use with caution and be aware of the consequences!

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List of Online Artefacts

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6900 The online artefacts listed below have been downloaded and stored on the Deakin
6901 Research Data Store (RDS) for archival purposes at the following location:

6902 RDS29448-Alex-Cummaudo-PhD/datasets/webrefs

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Part IV

Appendices

APPENDIX A

Additional Materials

A.1 Development, Documentation and Usage of Web APIs

The development of web APIs (commonly referred to as a *web service*) traces its roots back to the early 1990s, where the Open Software Foundation’s distributed computing environment (DCE) introduced a collection of services and tools for developing and maintaining distributed systems using a client/server architecture [306]. This framework used the synchronous communication paradigm remote procedure calls (RPCs) first introduced by Nelson [255] that allows procedures to be called in a remote address space as if it were local. Its communication paradigm, DCE/RPC [263], enables developers to write distributed software with underlying network code abstracted away. To bridge remote DCE/RPCs over components of different operating systems and languages, an interface definition language (IDL) document served as the common service contract or *service interface* for software components.

This important leap toward language-agnostic distributed programming paved way for XML-RPC, enabling RPCs over HTTP (and thus the Web) encoded using XML (instead of octet streams [263]). As new functionality was introduced, this lead to the natural development of the Simple Object Access Protocol (SOAP), the backbone messaging connector for web service applications, a realisation of the service-oriented architecture (SOA) [72] pattern. The SOA pattern prescribes that services are offered by service providers and consumed by service consumers in a platform- and language-agnostic manner and are used in large-scale enterprise systems (e.g., banking, health). Key to the SOA pattern is that a service’s quality attributes (see Section 2.1) can be specified and guaranteed using a service-level agreement (SLA) whereby the consumer and provider agree upon a set level of service, which in some cases are legally binding [31]. This agreement can be measured using quality of service (QoS) parameters met by the service provider during the transportation layer (e.g., response time, cost of leasing resources, reliability guarantees, system availability and trust/security assurance [364, 370]). These attributes are included within SOAP headers; thus, QoS aspects are independent from the transport layer and instead exist at the application layer [274]. The IDL of SOAP is Web Services Description Language (WSDL), providing a description of how the web service is invoked, what parameters to expect, and what data structures are returned.

While it is rich in metadata and verbosity, discussions on whether this was a benefit or drawback came about the mid-2000s [274, 388] whether the amount of data transfer paid off (especially for mobile clients where data usage was scarce). Developer usability for debugging the SOAP ‘envelopes’ (messages POSTed over HTTP to the service provider component) was difficult, both due to the nature of XML’s wordiness and difficulty to test (by sending POST requests) in-browser. As a simple example, 25 lines (794 bytes) of HTTP communication is transferred to request a customer’s name from a record using SOAP (Listings A.1 and A.2).



Figure A.1: Worldwide search interest for SOAP (blue) and REST (red) since 2004. Source: Google Trends.

Listing A.1: A SOAP HTTP POST consumer request to retrieve customer record #43456 from a web service provider. Source: [22].

```
1 | POST /customers HTTP/1.1
2 | Host: www.example.org
3 | Content-Type: application/soap+xml; charset=utf-8
4 |
5 | <?xml version="1.0"?>
6 | <soap:Envelope
7 |   xmlns:soap="http://www.w3.org/2003/05/soap-envelope">
8 |   <soap:Body>
9 |     <m:GetCustomer
10 |       xmlns:m="http://www.example.org/customers">
11 |         <m:CustomerId>43456</m:CustomerId>
12 |       </m:GetCustomer>
13 |     </soap:Body>
14 |   </soap:Envelope>
```

Listing A.2: The SOAP HTTP service provider response for Listing A.1. Source: [22].

```
1 | HTTP/1.1 200 OK
2 | Content-Type: application/soap+xml; charset=utf-8
3 |
4 | <?xml version='1.0' ?>
5 | <env:Envelope
6 |   xmlns:env="http://www.w3.org/2003/05/soap-envelope" >
7 |   <env:Body>
8 |     <m:GetCustomerResponse
9 |       xmlns:m="http://www.example.org/customers">
10 |         <m:Customer>Foobar Quux, inc</m:Customer>
11 |       </m:GetCustomerResponse>
12 |     </env:Body>
13 |   </env:Envelope>
```

SOAP uses the architectural principle that web services (or the applications they provide) should remain *outside* the web, using HTTP only as a tunnelling protocol to enable remote communication [274]. That is, the HTTP is considered as a transport protocol solely. In 2000, Fielding [116] introduced REpresentational State Transfer (REST), which instead approaches the web as a medium to publish data (i.e., HTTP is part of the *application* layer instead). Hence, applications become amalgamated into of the Web. Fielding bases REST on four key principles:

- **URIs identify resources.** Resources and services have a consistent global address space that aides in their discovery via URIs [35].
- **HTTP verbs manipulate those resources.** Resources are manipulated using the four consistent CRUD verbs provided by HTTP: POST, GET, PUT, DELETE.
- **Self-descriptive messages.** Each request provides enough description and context for the server to process that message.
- **Resources are stateless.** Every interaction with a resource is stateless.

Consider the equivalent example of Listings A.1 and A.2 but in a RESTful architecture (Listings A.3 and A.4) and it is clear why this style has grown more popular with developers (as we highlight in Figure A.1). Developers have since embraced RESTful application programming interface (API) development, though the major drawback of RESTful services is its lack of a uniform IDL to facilitate development (though it is possible to achieve this using Web Application Description Language (WADL) [226]). Therefore, no RESTful service uses a standardised response document or invocation syntax. While there are proposals, such as WADL [146], RAML¹, API Blueprint², and the OpenAPI³ specification (initially based on Swagger⁴), there is still no consensus as there was for SOAP and convergence of these IDLs is still underway.

Listing A.3: An equivalent HTTP consumer request to that of Listing A.1, but using REST.
Source: [22].

```
1 | GET /customers/43456 HTTP/1.1
2 | Host: www.example.org
```

Listing A.4: The REST HTTP service provider response for Listing A.3.

```
1 | HTTP/1.1 200 OK
2 | Content-Type: application/json; charset=utf-8
3 |
4 | {"Customer": "Foobar Quux, inc"}
```

¹<https://raml.org> last accessed 25 January 2019.

²<https://apiblueprint.org> last accessed 25 January 2019.

³<https://www.openapis.org> last accessed 25 January 2019.

⁴<https://swagger.io> last accessed 25 January 2019.

A.2 Additional Figures

The following figures are listed in this section:

- **Figure A.2 (p251)** highlights potential causal factors that may influence a developer’s understanding of the documentation and response of IWSs. It was intended to be used as the basis of a survey study in Chapter 8, and can be used for future avenues of research.
- **Figure A.3 (p252)** was intended for the discussion in Chapter 5, where we propose that developers have a misaligned of the technical domain models within IWSs and more specifically CVSSs. We designed a draft technical domain model to describe the various aspects developers must consider when using these services, based on the work by Barnett [25].
- **Figure A.4 (p253)** describes potential questions that may arise to analyse and test the causal factors of the technical domain model proposed in Figure A.3. This lies an open avenue of future research.
- **Figure A.5 (p253)** emphasises dichotomy between an application using an IWS and the IWS’ training data (which is sourced from an unknown context) and the context of an application, which is known. This is to emphasise how the model produced from these services need to be calibrated to the application domain being used in order for the decision boundary of a single inference to be properly assessed by the developer. This image was originally included within the Threshy publication (Chapter 10) but was removed due to space limitations.
- **Figure A.6 (p254)** illustrates the domain model of Threshy (Chapter 10).
- **Figure A.7 (p254)** illustrates the dynamic model of using Threshy and its interactions between the application, front-end of Threshy and back-end of Threshy (Chapter 10).
- **Figure A.8 (p255)** was originally included within the publication Chapter 5 but was removed due to space limitations. It provides a high-level overview of the main steps we performed within this study.
- **Figure A.9 (p256)** is a class diagram of the reference architecture of the proposed architecture in Chapter 11. The implementation is provided in Chapter B. See Chapter 11 for more.
- **Figure A.10 (p257)** is a sequence diagram illustrating how the reference architecture can be used to create a new benchmark as per the implementation provided in Chapter B. See Chapter 11 for more.
- **Figure A.11 (p258)** is a sequence diagram illustrating how applications can make requests to the proxy server ‘facade’ as per the implementation provided in Chapter B. See Chapter 11 for more.
- **Figure A.12 (p259)** is a state diagram that illustrates the overall states that exist within the architecture tactic’s workflows. See Chapter 11 for more.
- **Figure A.13 (p260)** is a sequence diagram illustrating how the reference architecture handles evolution in an external service per the implementation provided in Chapter B. See Chapter 11 for more.

- **Figure A.14 (p261)** illustrates how the reference architecture is able to capture and handle three requests (two valid, one invalid) when sent to the proxy server. See Chapter 11 for more.

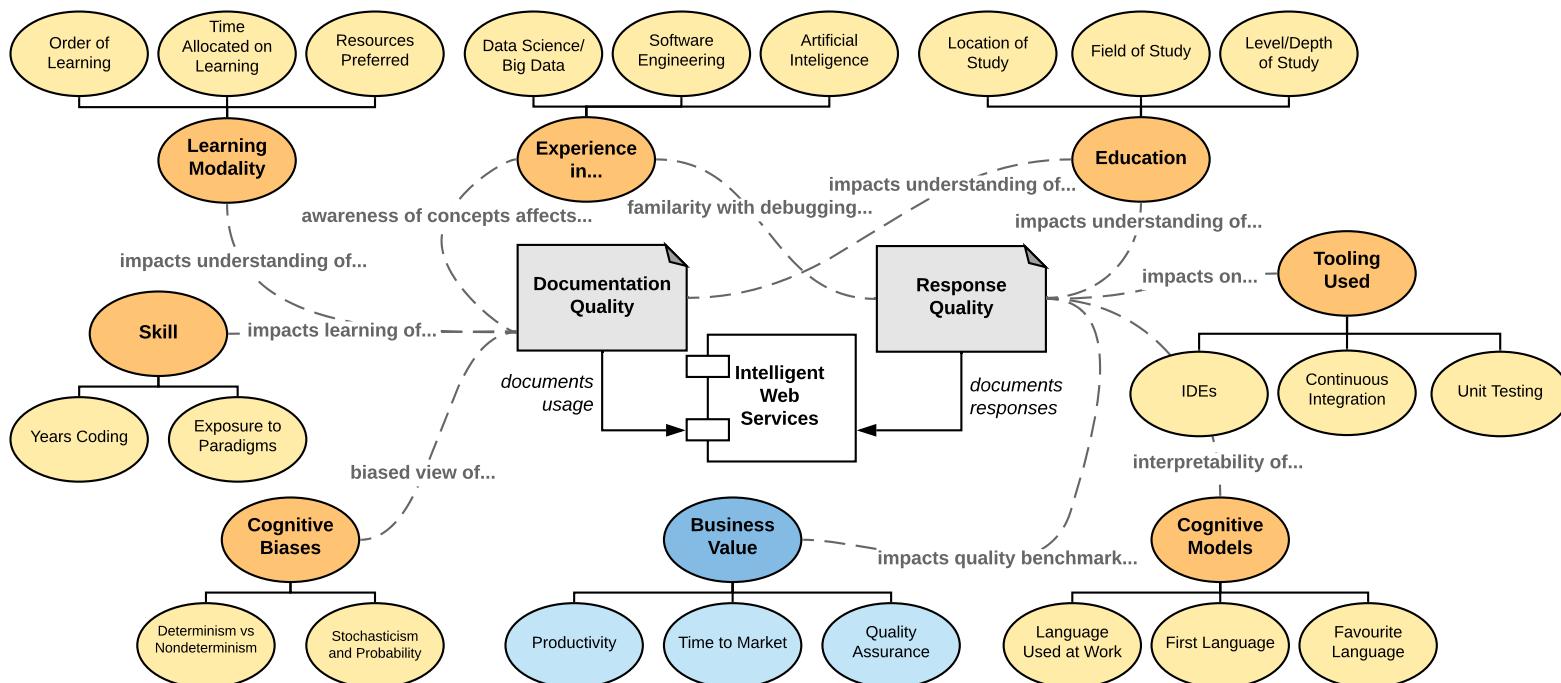
Figure A.2: Causal factors that may influence understanding of intelligent web services.

Figure A.3: A proposal technical domain model for intelligent services. (The ⓘ symbol indicates computer vision related services only.)

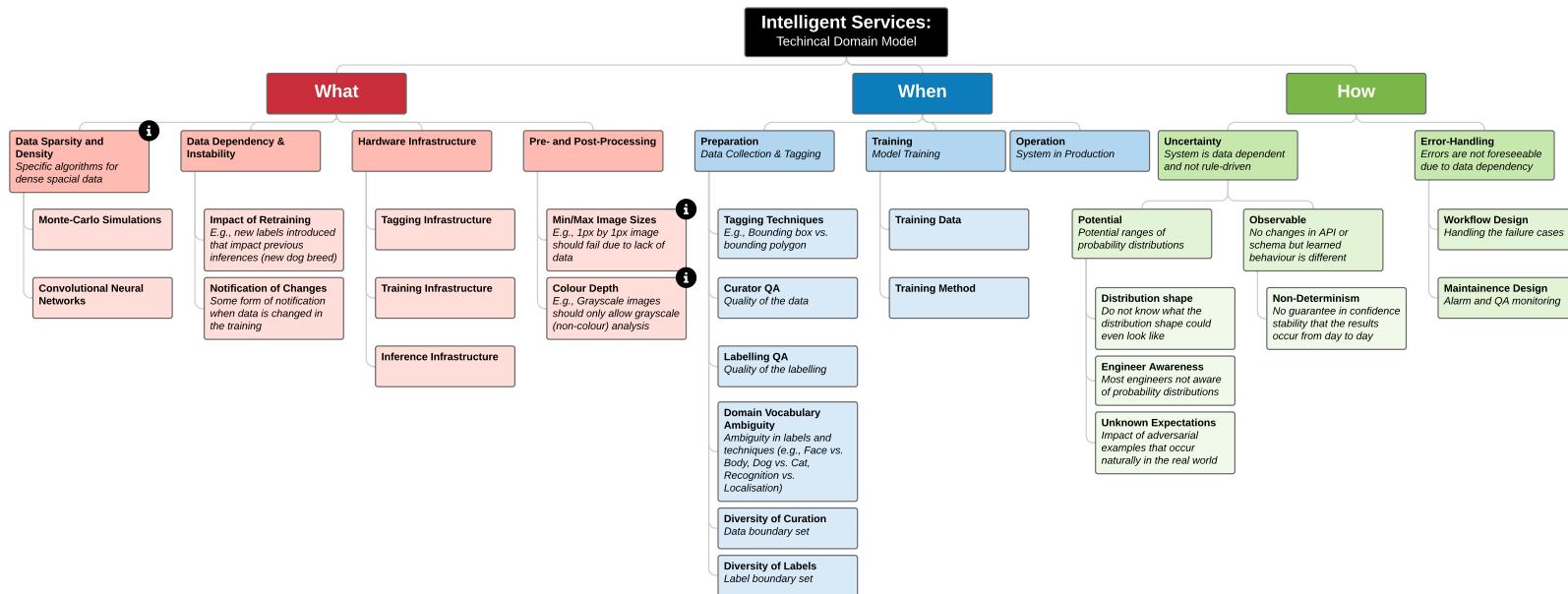


Figure A.4: Potential questions that can be asked around causal factors of a developer's understanding of an intelligent service.

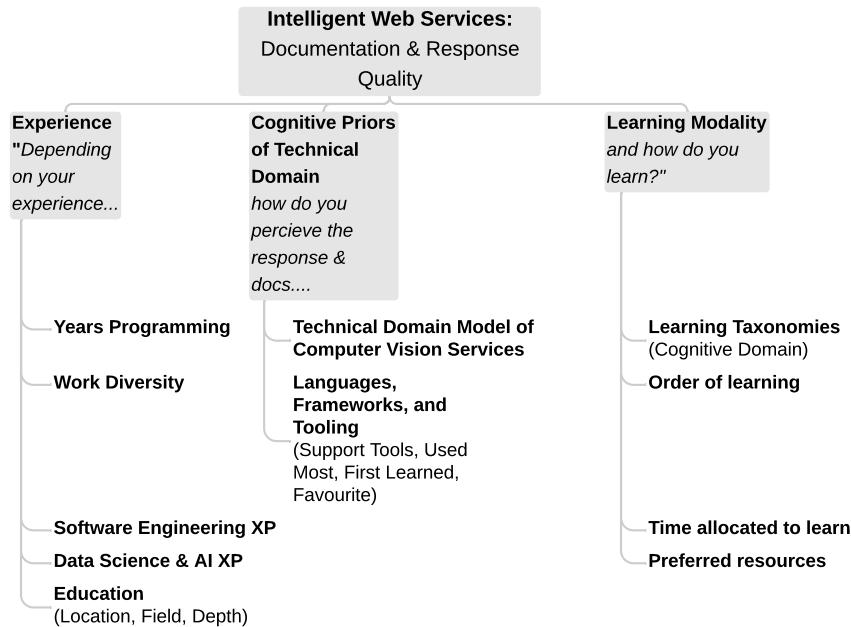


Figure A.5: Threshy assists with making appropriate decision boundaries in the application context by calibrating model (train on an unknown context) to your domain.

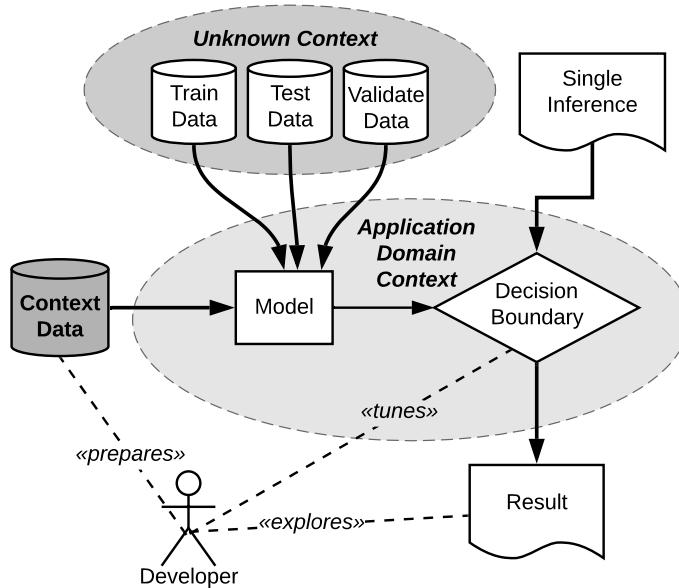


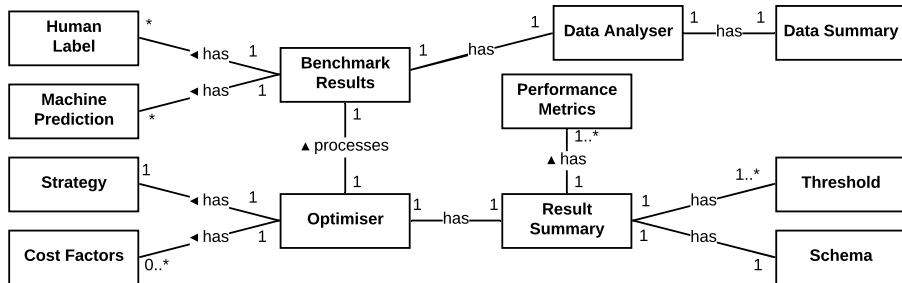
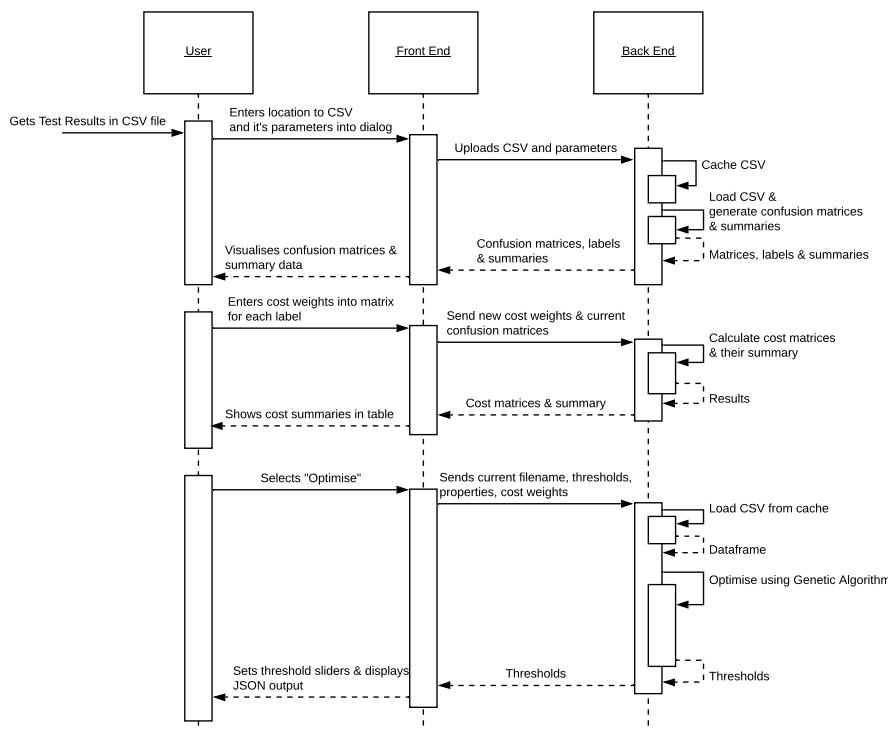
Figure A.6: Threshy domain model.**Figure A.7:** High level overview of Threshy's interaction between the front- and back-end.

Figure A.8: High-level overview of the methodology within Chapter 5.

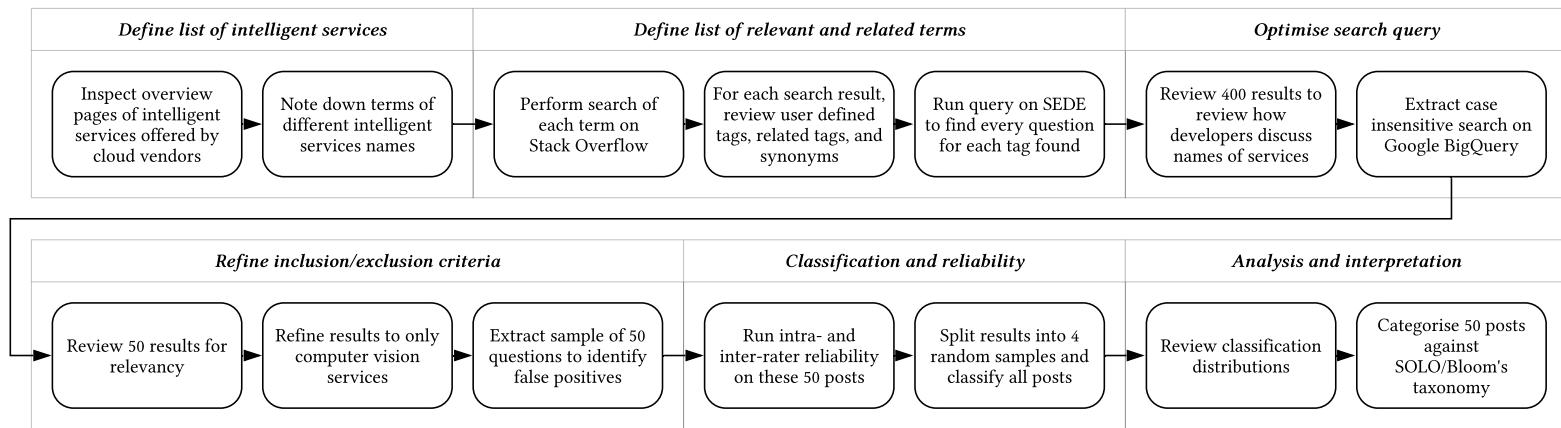


Figure A.9: Class diagram of the implementation of our architecture.

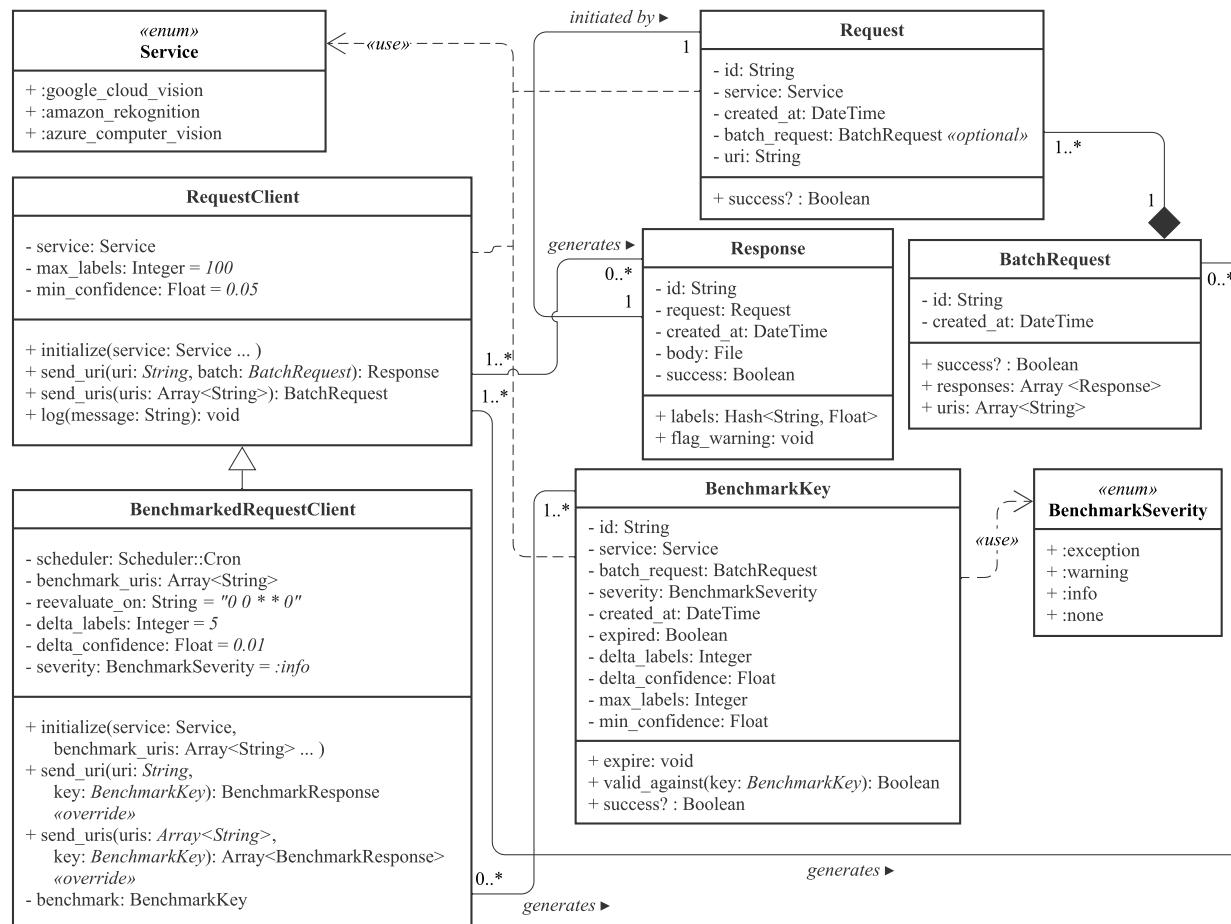


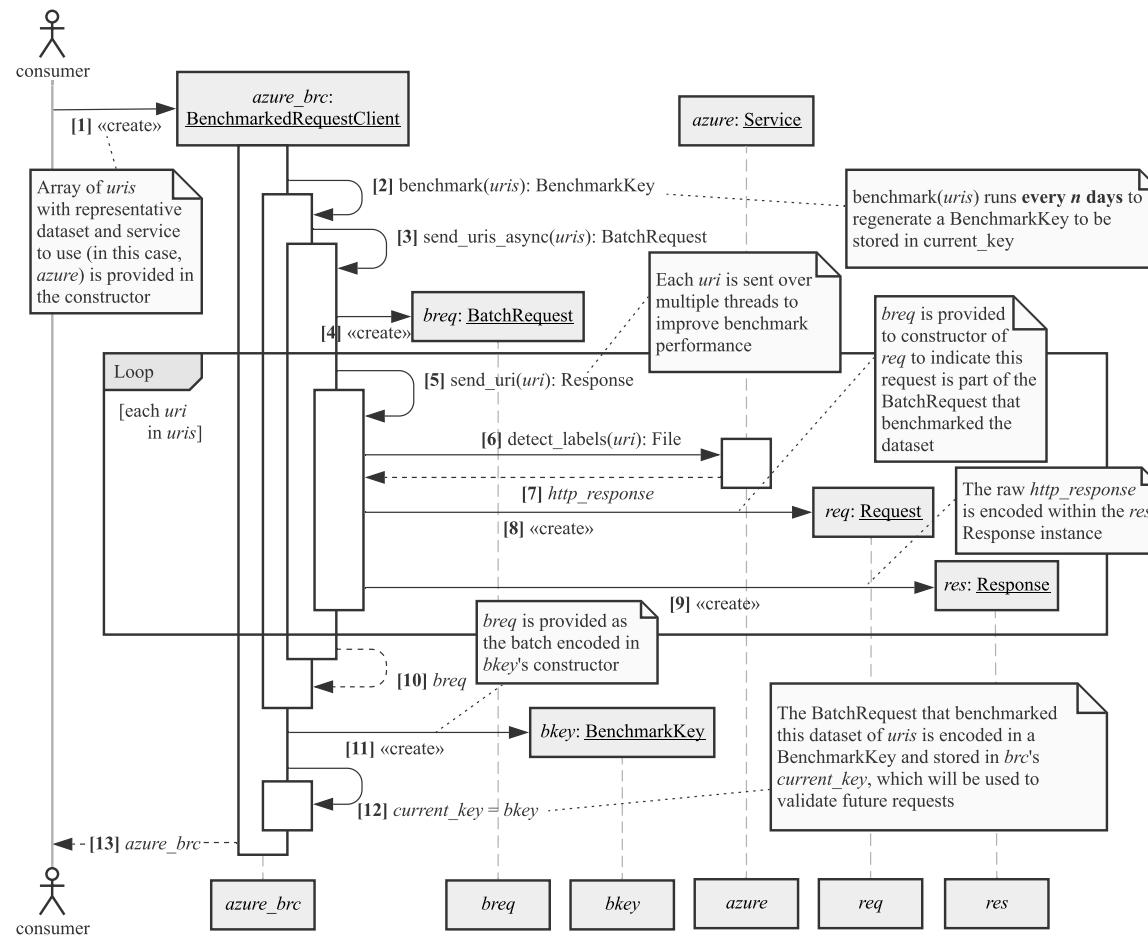
Figure A.10: Creation of a new benchmark proxy server using the architecture tactic.

Figure A.11: Making a request through the proxy server ‘facade’.

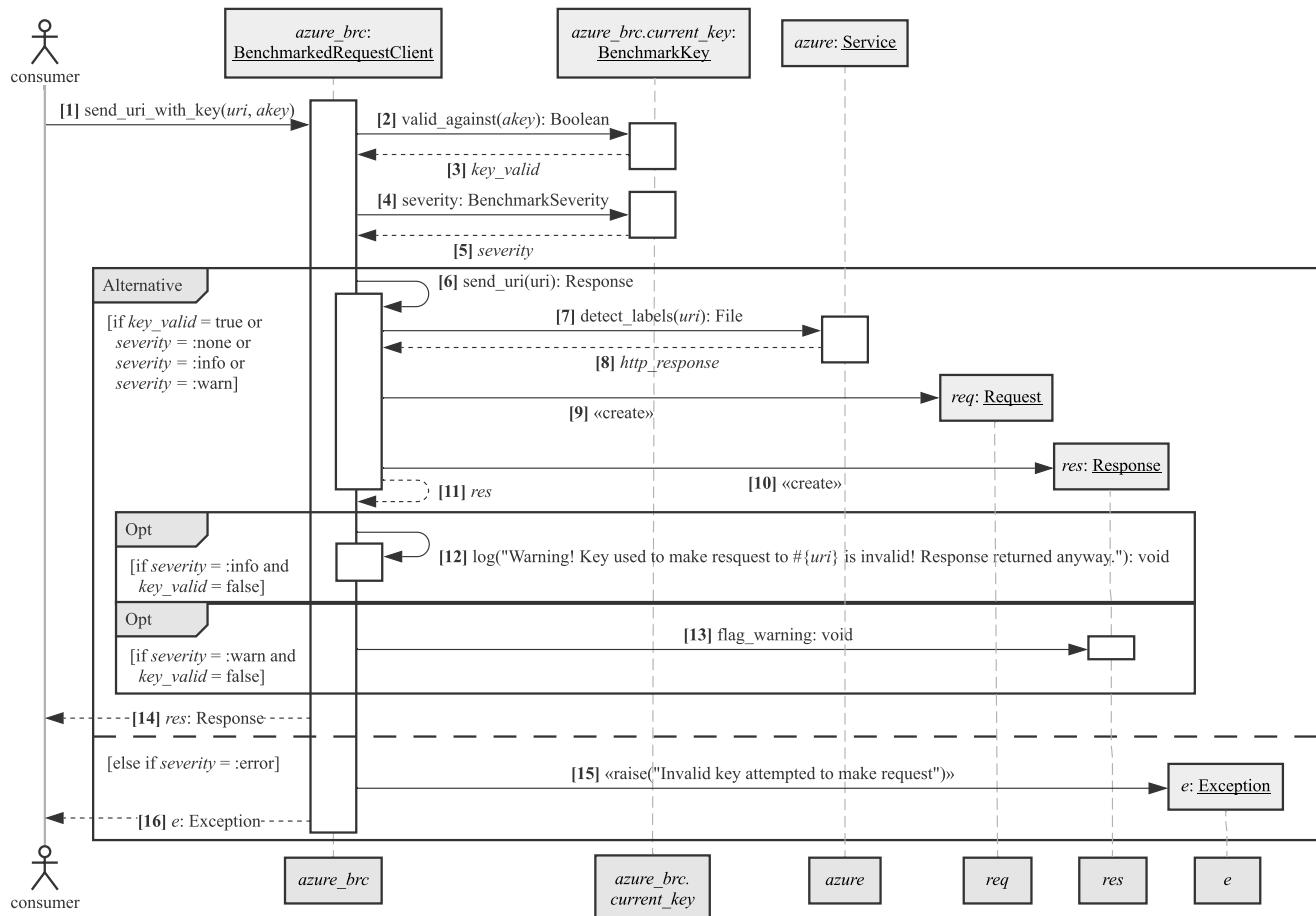


Figure A.12: State diagram of high-level workflows in the architectural tactic.

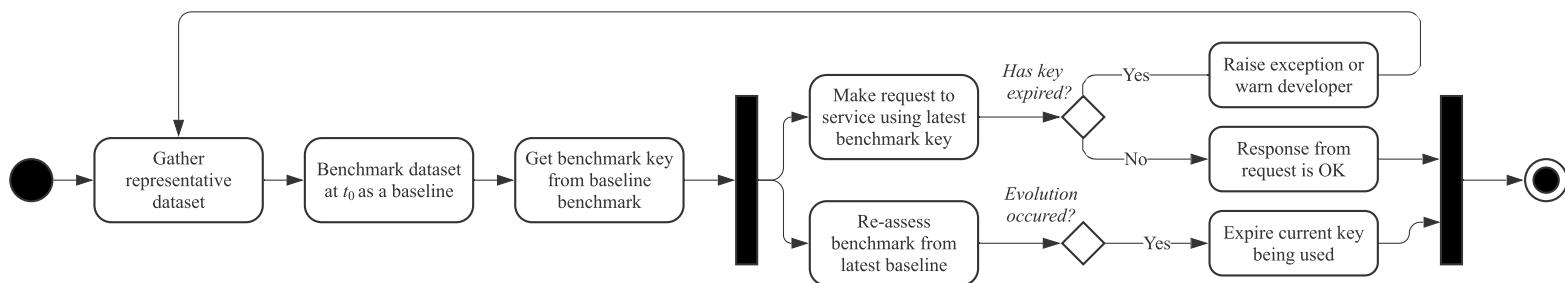
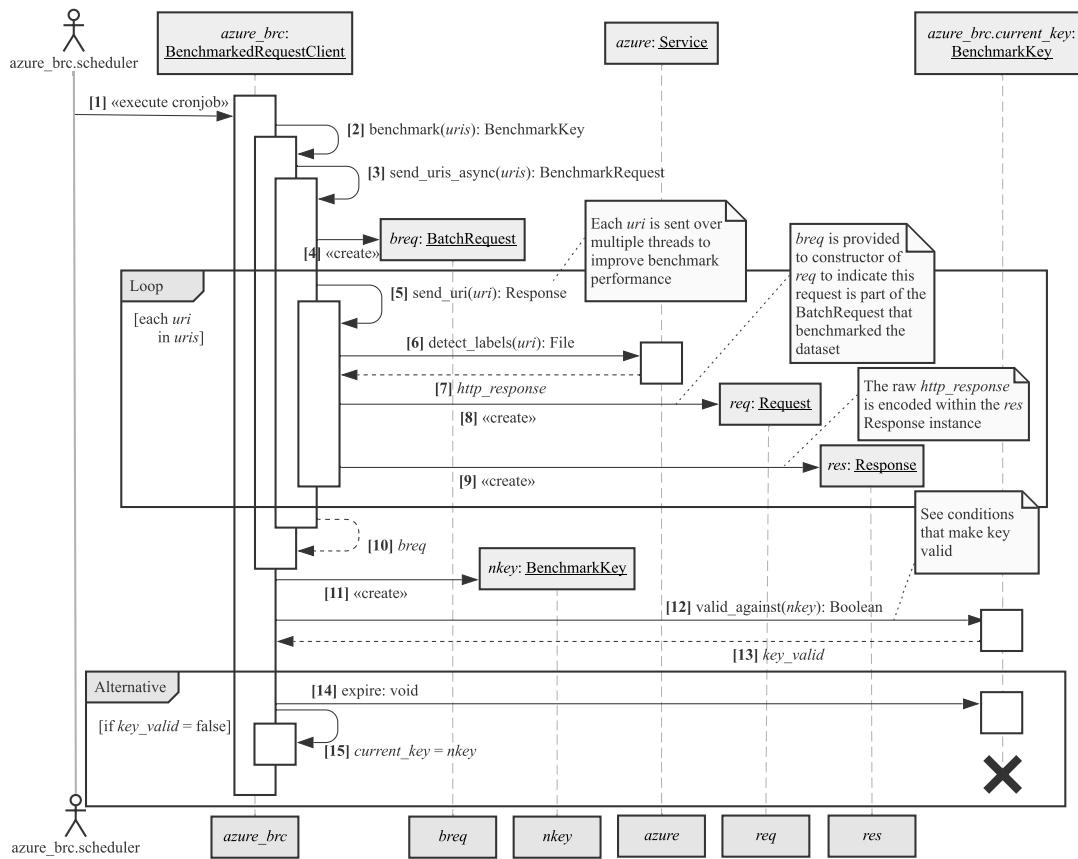


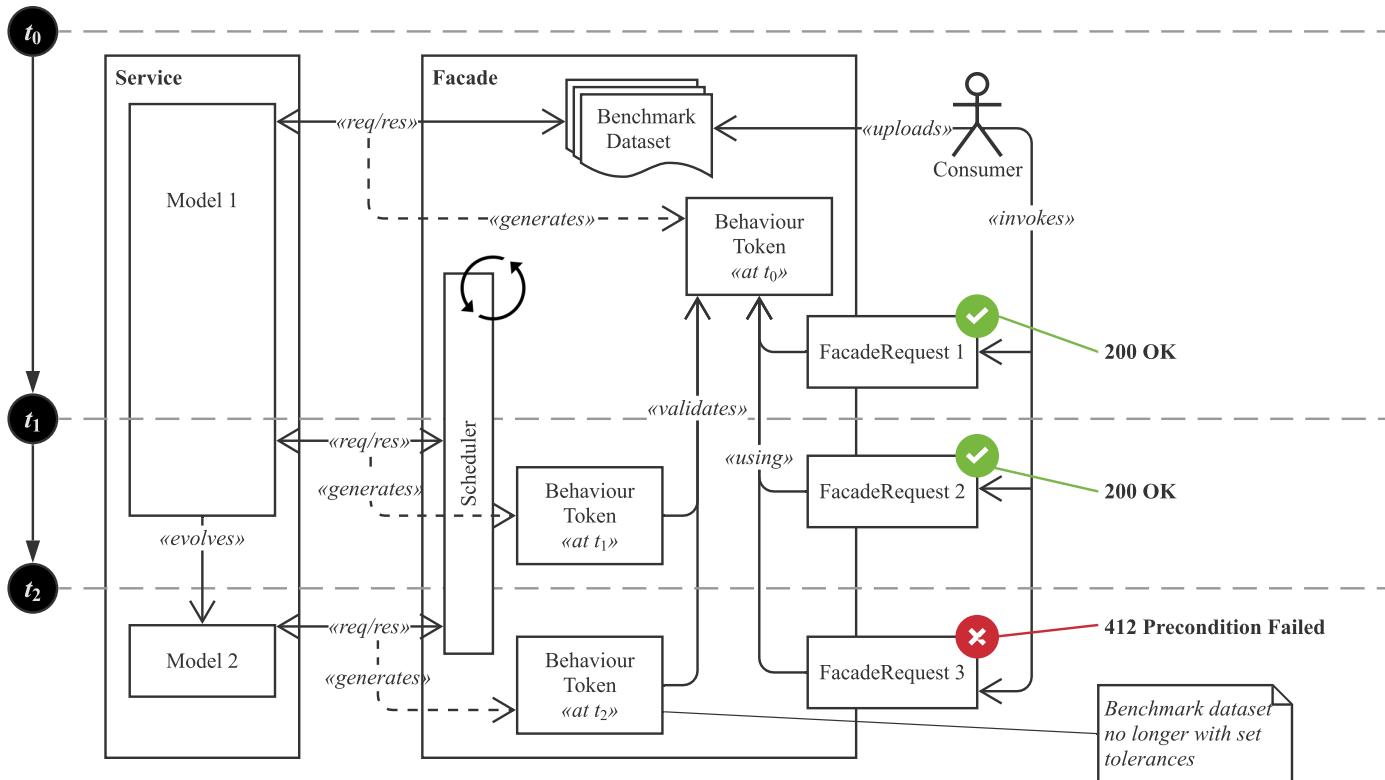
Figure A.13: Evolution occurring in the benchmark and how the architectural tactic notifies the consumer.



Conditions for a key to be valid

- both keys use the same services
- both keys encode the same URIs
- both keys have successful BatchRequests
- both keys must have BatchRequests with the same number of Response objects
- both keys must have the same cardinality of labels, within a margin of error of x delta labels
- for every label, each label must have a confidence value between both within a margin of error of y , i.e.: $\text{abs}(\text{conf}(\text{label}_i, \text{azure_brc.current_key}) - \text{conf}(\text{label}_i, \text{nkey})) \leq y$

Figure A.14: Evolution occurring in an intelligent service and how the architectural tactic handles it.



APPENDIX B

Reference Architecture Source Code

Listing B.1: Implementation of architecture module components.

```
1 # frozen_string_literal: true
2
3 # Author:: Alex Cummaudo (mailto:ca@deakin.edu.au)
4 # Copyright:: Copyright (c) 2019 Alex Cummaudo
5 # License:: MIT License
6
7 require 'sequel'
8 require 'logger'
9 require 'stringio'
10 require 'binding_of_caller'
11 require 'dotenv/load'
12 require 'google/cloud/vision'
13 require 'aws-sdk-rekognition'
14 require 'net/http/post/multipart'
15 require 'down'
16 require 'uri'
17 require 'json'
18 require 'tempfile'
19 require 'rufus-scheduler'
20
21 # Intelligent Computer Vision Service Benchmarker (ICVSB) module. This module
22 # implements an architectural pattern that helps overcome evolution issues
23 # within intelligent computer vision services.
24 module ICVSB
25   Thread.abort_on_exception = true
26   # The valid services this version of the ICVSB module supports. At present the
27   # only services supported are Google Cloud Vision, Amazon Rekognition, and
28   # Azure Computer Vision and their respective labelling/tagging endpoints. You
29   # can also request the demo.
30   # @see https://cloud.google.com/vision/docs/labels
31   # Google Cloud Vision labelling endpoint.
32   # @see https://docs.aws.amazon.com/rekognition/latest/dg/API_DetectLabels.html
33   # Amazon Rekognition's labelling endpoint.
34   # @see https://docs.microsoft.com/en-us/rest/api/cognitiveservices/
35   # computervision/tagimage/tagimage
```

```

35  # Azure Computer Vision's tagging endpoint.
36  VALID_SERVICES = %i[google_cloud_vision amazon_rekognition
37      ↪ azure_computer_vision demo].freeze
38
39  # A list of the valid severities that the ICVSB module supports. Exception
40  # prevents the response from being accessed; warning will still produce a
41  # response but the +error+ field will be filled in; info will only log
42  # errors to the ICVSB log file and keep +error+ empty and none ignores the
43  # errors entirely.
44  VALID_SEVERITIES = %i[exception warning info none].freeze
45
46  # Logs a message to the global ICVSB logger. If called from within the
47  # stack trace of a RequestClient, it will also add the message provided
48  # the RequestClient's log associated with the RequestClient's object id.
49  # @param [Logger::Severity] severity The type of severity to log.
50  # @param [String] message The message to log.
51  def self.lmessage(severity, message)
52      unless [Logger::DEBUG, Logger::INFO, Logger::WARN, Logger::ERROR, Logger::
53          ↪ FATAL, Logger::UNKNOWN].include?(severity)
54          raise ArgumentError, 'Severity must be a Logger::Severity type'
55      end
56      raise ArgumentError, 'Message must be a string' unless message.is_a?(String)
57
58      @log ||= Logger.new(ENV['ICVSB_LOGGER_FILE'] || STDOUT)
59
60      # Add message to global ICVSB logger
61      @log.add(severity, message)
62
63      # Find object_id within request_clients... when found add this message w/
64      # severity to that RC's log too
65      binding.frame_count.times do |n|
66          caller_obj_id = binding.of_caller(n).eval('object_id')
67          if @request_clients.keys.include?(caller_obj_id)
68              @request_clients[caller_obj_id].log(severity, "[RequestClient=#{
69                  ↪ caller_obj_id}] #{message}")
70          end
71      end
72
73      # Logs an error to the global ICVSB logger.
74      # @param [String] message The message to log.
75      def self.lerror(message)
76          lmessage(Logger::ERROR, message)
77
78      # Logs a warning to the global ICVSB logger.
79      # @param [String] message The message to log.
80      def self.lwarn(message)
81          lmessage(Logger::WARN, message)
82
83      # Logs an info message to the global ICVSB logger.
84      # @param [String] message The message to log.
85      def self.linfo(message)
86          lmessage(Logger::INFO, message)
87
88      # Logs a debug message to the global ICVSB logger.
89      # @param [String] message The message to log.
90      def self.ldebug(message)
91          lmessage(Logger::DEBUG, message)
92
93      # Register's a request client to the ICVSB's register of request clients.

```

```

96  # @param [RequestClient] request_client The request client to register.
97  def self.register_request_client(request_client)
98    raise ArgumentError, 'request_client must be a RequestClient' unless
99      ↪ request_client.is_a?(RequestClient)
100
101  @request_clients ||= {}
102  @request_clients[request_client.object_id] = request_client
103 end
104 #####
105 # Database schema creation seed #
106 #####
107 url = ENV['ICVSB_DATABASE_CONNECTION_URL'] || 'sqlite://icvsb.db'
108 log = ENV['ICVSB_DATABASE_LOG_FILE'] || 'icvsb.db.log'
109 dbc = Sequel.connect(url, logger: Logger.new(log))
110 # Create Services and Severity enums...
111 dbc.create_table?(:services) do
112   primary_key :id
113   column :name, String, null: false, unique: true
114 end
115 dbc.create_table?(:benchmark_severities) do
116   primary_key :id
117   column :name, String, null: false, unique: true
118 end
119 if dbc[:services].first.nil?
120   VALID_SERVICES.each { |s| dbc[:services].insert(name: s.to_s) }
121   VALID_SEVERITIES.each { |s| dbc[:benchmark_severities].insert(name: s.to_s) }
122 end
123 # Create Objects...
124 dbc.create_table?(:batch_requests) do
125   primary_key :id
126   column :created_at, DateTime, null: false
127 end
128 dbc.create_table?(:requests) do
129   primary_key :id
130   foreign_key :service_id, :services, null: false
131   foreign_key :batch_request_id, :batch_requests, null: true
132   foreign_key :benchmark_key_id, :benchmark_keys, null: true
133
134   column :created_at, DateTime, null: false
135   column :uri, String, null: false
136
137   index %i[service_id batch_request_id]
138 end
139 dbc.create_table?(:responses) do
140   primary_key :id
141   foreign_key :request_id, :requests, null: false
142
143   column :created_at, DateTime, null: false
144   column :body, File, null: true
145   column :success, TrueClass, null: false
146
147   index :request_id
148 end
149 dbc.create_table?(:benchmark_keys) do
150   primary_key :id
151   foreign_key :service_id, :services, null: false
152   foreign_key :batch_request_id, :batch_requests, null: false
153   foreign_key :benchmark_severity_id, :benchmark_severities, null: false
154
155   column :created_at, DateTime, null: false
156   column :expired, TrueClass, null: false
157   column :delta_labels, Integer, null: false
158   column :delta_confidence, Float, null: false

```

```

159   column :max_labels, Integer, null: false
160   column :min_confidence, Float, null: false
161   column :expected_labels, String, null: true
162
163   index %i[service_id batch_request_id]
164 end
165
166 # Service representing the list of VALID_SERVICES the ICVSB module supports.
167 class Service < Sequel::Model(dbc)
168   # The Service representing Google Cloud Vision's labelling endpoint.
169   # @see https://cloud.google.com/vision/docs/labels
170   # Google Cloud Vision labelling endpoint.
171   GOOGLE = Service[name: VALID_SERVICES[0].to_s]
172
173   # The Service representing Amazon Rekognition's labelling endpoint.
174   # @see https://docs.aws.amazon.com/rekognition/latest/dg/API_DetectLabels.html
175   # Amazon Rekognition's labelling endpoint.
176   AMAZON = Service[name: VALID_SERVICES[1].to_s]
177
178   # The Service representing Azure Computer Vision's tagging endpoint.
179   # @see https://docs.microsoft.com/en-us/rest/api/cognitiveservices/
180        ↪ computervision/tagimage/tagimage
181   # Azure Computer Vision's tagging endpoint.
182   AZURE = Service[name: VALID_SERVICES[2].to_s]
183
184   # The Service representing a demonstration of the facade.
185   DEMO = Service[name: VALID_SERVICES[3].to_s]
186 end
187
188 # Severity representing the list of VALID_SEVERITIES the ICVSB module
189 # supports. The severity is encoded within a BenchmarkKey.
190 class BenchmarkSeverity < Sequel::Model(dbc[:benchmark_severities])
191   # Exception severities will prevent responses from being accessed. This
192   # disallows access to the Response object encoded within a
193   # BenchmarkedRequestClient#send_uri_with_key or
194   # BenchmarkedRequestClient#send_uris_with_key result.
195   EXCEPTION = BenchmarkSeverity[name: VALID_SEVERITIES[0].to_s]
196
197   # Warning severities will allow the Response from being accessed but will
198   # additionally populate the +error+ value encoded within a
199   # BenchmarkedRequestClient#send_uri_with_key or
200   # BenchmarkedRequestClient#send_uris_with_key result.
201   WARNING = BenchmarkSeverity[name: VALID_SEVERITIES[1].to_s]
202
203   # Info severities will allow the Response from being accessed encoded within
204   # the result of a BenchmarkedRequestClient#send_uri_with_key or
205   # BenchmarkedRequestClient#send_uris_with_key call, however, information
206   # pertaining to issues with the request will be logged to the ICVSB log
207   # file.
208   INFO = BenchmarkSeverity[name: VALID_SEVERITIES[2].to_s]
209
210   # None severities will essentially ignore all benchmarking capabilities and
211   # 'switches off' the benchmarking.
212   NONE = BenchmarkSeverity[name: VALID_SEVERITIES[3].to_s]
213
214   # Overrides the to_s method to return the name.
215   # @return [String] The name of the severity type.
216   def to_s
217     name
218   end
219 end
220
221   # This class represents a single request made to a Service. It encodes the
222   # service, batch of requests (if applicable) and respective response.

```

```

222  class Request < Sequel::Modeldbc)
223    many_to_one :service
224    many_to_one :batch
225    many_to_one :benchmark_key
226    one_to_one :response
227
228    # @see Response#success.
229    def success?
230      response.success?
231    end
232  end
233
234  # This class represents a single response returned back from a Service. It
235  # encodes the request that was made to invoke the response.
236  class Response < Sequel::Modeldbc)
237    many_to_one :request
238
239    # Indicates if the response from the request was successful.
240    # @return [Boolean] True if the response was successful or false if the
241    # response contained some issue.
242    def success?
243      success
244    end
245
246    # Returns a hash of the entire response object, decoded from its
247    # Service-specific response Ruby type and into a simple hash object.
248    # @return [Hash] A hash representing the entire Service response object
249    # within a Hash type.
250    def hash
251      return nil if body.nil?
252
253      JSON.parse(body.lit.downcase.to_s, symbolize_names: true).to_h
254    end
255
256    # Returns hash of labels paired with their respective confidence values.
257    # Decodes each Service's individual response syntax into a simple
258    # key-value-pair that can be used for generalised use, regardless of which
259    # Service actually generated the response.
260    # @return [Hash] A hash with key-value-pairs representing the label (key)
261    # and value (confidence) of the response.
262    def labels
263      if success?
264        case request.service
265        when Service::GOOGLE
266          _google_cloud_vision_labels
267        when Service::AMAZON
268          _amazon_rekognition_labels
269        when Service::AZURE
270          _azure_computer_vision_labels
271        when Service::DEMO
272          _demo_service_labels
273        end
274      else
275        {}
276      end
277    end
278
279    # Returns the benchmark key ID of the request.
280    # @return [Integer] The benchmark key id of this response's request.
281    def benchmark_key_id
282      request.benchmark_key.id
283    end
284
285    # Returns the benchmark key of the request.

```

```
286  # @return [BenchmarkKey] The benchmark key of this response's request.
287  def benchmark_key
288    request.benchmark_key
289  end
290
291  # Sets the benchmark key of the request.
292  # @param [BenchmarkKey] value The new benchmark key to set.
293  # @return [void]
294  def benchmark_key=(value)
295    request.benchmark_key = value
296    request.save
297  end
298
299  # Sets the benchmark key id of the request.
300  # @param [Integer] value The new benchmark key id to set.
301  # @return [void]
302  def benchmark_key_id=(value)
303    request.benchmark_key_id = value
304    request.save
305  end
306
307  private
308
309  # Decodes a Google Cloud Vision label endpoint response into a simple hash.
310  # @return [Hash] A key-value-pair representing label => confidence.
311  def _google_cloud_vision_labels
312    hash[:responses][0][:label_annotations].map do |label|
313      [label[:description].downcase, label[:score]]
314    end.to_h
315  end
316
317  # Decodes an Amazon Rekognition label endpoint response into a simple hash.
318  # @return [Hash] See #{#_google_cloud_vision_labels}.
319  def _amazon_rekognition_labels
320    hash[:labels].map do |label|
321      [label[:name].downcase, label[:confidence] * 0.01]
322    end.to_h
323  end
324
325  # Decodes an Azure Computer Vision tagging endpoint into a simple hash.
326  # @return [Hash] See #{#_google_cloud_vision_labels}.
327  def _azure_computer_vision_labels
328    hash[:tags].map do |label|
329      [label[:name].downcase, label[:confidence]]
330    end.to_h
331  end
332
333  # Decodes the mock demo service response into a simple hash. This is simply
334  # a relay of Google's as the data is from Google Cloud Vision.
335  # @return [Hash] A key-value-pair representing label => confidence.
336  def _demo_service_labels
337    _google_cloud_vision_labels
338  end
339  end
340
341  # The batch request class collates multiple requests (URIs) invoked to a
342  # single Service's endpoint in a single request. It encodes all requests
343  # made to the service and can produce all responses back.
344  class BatchRequest < Sequel::Model(:dbc)
345    one_to_many :requests
346
347    # Indicates if every request in the batch of requests made were successful.
348    # @return [Boolean] True if every response was successful, false
349    # otherwise.
```

```
350  def success?
351    requests.map(&:success?).reduce(:&)
352  end
353
354  # Maps all Response objects that were returned back from this batch to an
355  # array.
356  # @return [Array<Response>] An array of Response objects from every Request
357  # made in this batch.
358  def responses
359    requests.map(&:response)
360  end
361
362  # Maps all URIs that were requested back within this batch.
363  # @return [Array<String>] An array of URI strings from every Request
364  # made in this batch.
365  def uris
366    requests.map(&:uri)
367  end
368
369
370  # The Benchmark Key encodes all information pertaining to the evolution of a
371  # specific service and is used to validate if a benchmark dataset has evolved
372  # with time. This key must be used in conjunction with the
373  # BenchmarkedRequestClient to ensure that responses made are still reasonable
374  # → to
375  # use or if the service should be re-benchmarked against a new dataset.
376  class BenchmarkKey < Sequel::Model(dbc)
377    many_to_one :service
378    many_to_one :benchmark_severity
379    many_to_one :batch_request
380
381  # Class that encapsulates reasons why a benchmark key can be invalidated.
382  class InvalidKeyError
383    module InvalidKeyErrorType
384      NO_KEY_YET = 'No key yet exists. It is likely key is still benchmarking
385      # → its first results.'
386      SERVICE_MISMATCH = 'Keys use different services'
387      DATASET_MISMATCH = 'Keys have different benchmark datasets'
388      SUCCESS_MISMATCH = 'One or both keys do not have successful service
389      # → responses'
390      MIN_CONFIDENCE_MISMATCH = 'Keys have different min confidence values'
391      MAX_LABELS_MISMATCH = 'Keys have different max label values'
392      RESPONSE_LENGTH_MISMATCH = 'Keys have different number of responses'
393      LABEL_DELTA_MISMATCH = 'Number of labels in one key exceeds the label
394      # → delta threshold'
395      CONFIDENCE_DELTA_MISMATCH = 'Confidence value for a label in one key
396      # → exceeds the confidence delta threshold'
397      EXPECTED_LABELS_MISMATCH = 'Expected labels missing from response'
398    end
399
400    include InvalidKeyErrorType
401    attr_reader :errorname, :errorcode, :data
402
403    def initialize(errorcode, data = '')
404      @errorname = InvalidKeyErrorType.constants.find { |c| InvalidKeyErrorType.
405        # → const_get(c) == errorcode }
406      @errorcode = InvalidKeyErrorType.constants.index(@errorname)
407      @data = data
408    end
409
410    def to_s
411      "[#{@errorcode}]:#{@errorname}] #{@data}"
412    end
413
```

```

408     def to_h
409     {
410       error_code: @errorcode,
411       error_type: @errorname,
412       error_data: @data
413     }
414   end
415 end
416
417 # @see BatchRequest#success?
418 def success?
419   batch_request.success?
420 end
421
422 # An alias for the +expired+ field on the key, adding a question mark at the
423 # end to make the field more 'Ruby-esque'.
424 # @return [Boolean] True if the key has expired and thus should not be used
425 # for future requests as it is no longer valid.
426 def expired?
427   expired
428 end
429
430 # Expires this key by writing over its +expired+ field and marking it
431 # true.
432 # @return [void]
433 def expire
434   self.expired = true
435   save
436 end
437
438 # Un-expires this key by writing over its +expired+ field and marking it
439 # true.
440 # @return [void]
441 def unexpire
442   self.expired = false
443   save
444 end
445
446 # Returns the comma-separated mandatory labels list as an set of values
447 # @return [Set<String>] The set of mandatory labels required by this key.
448 def expected_labels_set
449   Set[*expected_labels.split(',').map(&:downcase)]
450 end
451
452 # Validates another key against this key to ensure if the two keys are
453 # compatible or if evolution has occurred iff BenchmarkKey is provided to
454 # +key_or_response+. If a Response is provided instead, then validates that
455 # the response is okay against this key's encoded parameters.
456 # @param [BenchmarkKey,Response] key_or_response A key or response to
457 # validate against.
458 # @return [Array<Boolean,Array<BenchmarkKey::InvalidKeyError>>] Returns +true+
459 # if
460 # this key is valid against the other key OR a tuple with +false+ and
461 # BenchmarkKey::InvalidKeyError to explain why the key is invalid.
462 def valid_against?(key_or_response)
463   if key_or_response.is_a?(BenchmarkKey)
464     _validate_against_key(key_or_response)
465   elsif key_or_response.is_a?(Response)
466     _validate_against_response(key_or_response)
467   else
468     raise ArgumentError, 'key_or_response must be a BenchmarkKey or Response
469     ↪ type'
470   end
471 end

```

```

470
471     private
472
473     # Validates a key against this key as per rules encoded within this key.
474     # @param [BenchmarkKey] key The key to validate.
475     # @return See #valid_against?
476     def _validate_against_key(key)
477       ICSVSB.linfo("Validating key id=#{id} with other key id=#{key.id}")
478
479       # True if same key id...
480       return true if key == self
481
482       invalid_key_errors = []
483
484       # 1. Ensure same services!
485       if key.service == service
486         ICSVSB.ldebug('Services both match')
487       else
488         ICSVSB.lwarn("Service mismatch in validation: #{key.service.name} != #{service.name}")
489       invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
490         BenchmarkKey::InvalidKeyError::SERVICE_MISMATCH, {
491           source_key: {
492             id: id,
493             created_at: created_at,
494             service_name: service.name
495           },
496           violating_key: {
497             id: key.id,
498             created_at: key.created_at,
499             service_name: key.service.name
500           },
501           message: "Source key (id=#{id}) service=#{service.name} but \"\
502             \"validation key (id=#{key.id}) service=#{key.service.name}."
503         }
504       )
505     end
506
507     # 2. Ensure same benchmark dataset
508     symm_diff_uris = Set[*batch_request.uris] ^ Set[*key.batch_request.uris]
509     if symm_diff_uris.empty?
510       ICSVSB.ldebug('Same benchmark dataset has been used')
511     else
512       ICSVSB.lwarn('Benchmark dataset mismatch in key validation: ' \
513         "Symm difference contains #{symm_diff_uris.count} different URIs")
514       invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
515         BenchmarkKey::InvalidKeyError::DATASET_MISMATCH, {
516           source_key: {
517             id: id,
518             created_at: created_at,
519             dataset: batch_request.uris
520           },
521           violating_key: {
522             id: key.id,
523             created_at: key.created_at,
524             dataset: key.batch_request.uris
525           },
526           dataset_symmetric_difference: symm_diff_uris.to_a,
527           message: "Source key (id=#{id}) and validation key (id=#{key.id}) have \
528             \"different \"\
529             \"benchmark dataset URIS. The symmetric difference is: #{symm_diff_uris.\
530               to_a}.\"
531         }
532       )

```

```

531     end
532
533     # 3. Ensure successful request made in BOTH instances
534     our_key_success = success?
535     their_key_success = key.success?
536     if our_key_success && their_key_success
537         ICSVSB.ldebug('Both keys were successful')
538     else
539         ICSVSB.lwarn('Sucesss mismatch in key validation')
540         invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
541             BenchmarkKey::InvalidKeyError::SUCCESS_MISMATCH, {
542                 source_key: {
543                     id: id,
544                     created_at: created_at,
545                     successful_response: our_key_success
546                 },
547                 violating_key: {
548                     id: key.id,
549                     created_at: key.created_at,
550                     successful_response: their_key_success
551                 },
552                 message: "Source key (id=#{id}) success=#{our_key_success} but \"\
553                 \"validation key (id=#{key.id}) success=#{their_key_success}."
554             }
555         )
556     end
557
558     # 4. Ensure the same max labels
559     if key.max_labels == max_labels
560         ICSVSB.ldebug('Both keys have same max labels')
561     else
562         ICSVSB.lwarn('Max labels mismatch in key validation')
563         invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
564             BenchmarkKey::InvalidKeyError::MAX_LABELS_MISMATCH, {
565                 source_key: {
566                     id: id,
567                     created_at: created_at,
568                     max_labels: max_labels
569                 },
570                 violating_key: {
571                     id: key.id,
572                     created_at: key.created_at,
573                     max_labels: key.max_labels
574                 },
575                 message: "Source key (id=#{id}) max_labels=#{max_labels} but \"\
576                 \"validation key (id=#{key.id}) max_labels=#{key.max_labels}."
577             }
578         )
579     end
580
581     # 5. Ensure the same min confs
582     if key.min_confidence == min_confidence
583         ICSVSB.ldebug('Both keys have same min confidence')
584     else
585         ICSVSB.lwarn('Minimum confidence or max labels mismatch in key validation')
586         invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
587             BenchmarkKey::InvalidKeyError::MIN_CONFIDENCE_MISMATCH, {
588                 source_key: {
589                     id: id,
590                     created_at: created_at,
591                     min_confidence: min_confidence
592                 },
593                 violating_key: {
594                     id: key.id,

```

```

595         created_at: key.created_at,
596         min_confidence: key.min_confidence
597     },
598     message: "Source key (id=#{id}) min_confidence=#{min_confidence} but \"\
599     validation key (id=#{key.id}) min_confidence=#{key.min_confidence}."\
600   }
601 )
602 end
603
604 # 6. Ensure same number of results... (responses... not labels!)
605 our_response_length = batch_request.responses.length
606 their_response_length = key.batch_request.responses.length
607 if our_response_length == their_response_length
608   ICVSB.ldebug('Both keys have same number of encoded responses')
609 else
610   ICVSB.lwarn('Number of responses mismatch in key validation')
611   invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
612     BenchmarkKey::InvalidKeyError::RESPONSE_LENGTH_MISMATCH, {
613       source_key: {
614         id: id,
615         created_at: created_at,
616         num_responses: our_response_length
617       },
618       violating_key: {
619         id: key.id,
620         created_at: key.created_at,
621         num_responses: their_response_length
622       },
623       message: "Source key (id=#{id}) responses=#{our_response_length} but "\
624         ↪ \
625       "validation key (id=#{key.id}) responses=#{their_response_length}."\
626     }
627   )
628 end
629
630 # 7. Validate every label delta and confidence delta
631 our_requests = batch_request.requests
632 their_requests = key.batch_request.requests
633 our_requests.each do |our_request|
634   this_uri = our_request.uri
635   their_request = their_requests.find { |r| r.uri == this_uri }
636
637   our_labels = Set[*our_request.response.labels.keys]
638   their_labels = Set[*their_request.response.labels.keys]
639
640   # 7a. Label delta
641   symmm_diff_labels = our_labels ^ their_labels
642
643   msg_suffix = "URI = #{this_uri} from #{their_request.created_at} (req_id "\
644     ↪ =#{their_request.id})"\
645   " to #{our_request.created_at} (req_id=#{our_request.id})"
646
647   ICVSB.ldebug("Request id=#{our_request.id} #{our_labels.to_a} against "\
648     "id=#{their_request.id} #{their_labels.to_a} - symmm diff "\
649     "= #{symmm_diff_labels.to_a}")
650   if symmm_diff_labels.length > delta_labels
651     ICVSB.lwarn("Number of labels mismatch in key validation (margin of error "\
652       ↪ =#{delta_labels}): "\
653       "New/dropped labels = '#{(our_labels - their_labels).to_a.map { |l| "+#\
654         ↪ {l}" }.join(',')}'"\"
655       "#{(their_labels - our_labels).to_a.map { |l| "-#{l}" }.join(',')}'")
656   end
657   invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
658     BenchmarkKey::InvalidKeyError::LABEL_DELTA_MISMATCH, {
659       source_key: {

```

```

655         id: id,
656         created_at: created_at
657     },
658     source_response: {
659         id: our_request.id,
660         created_at: our_request.created_at,
661         body: our_request.response.hash
662     },
663     violating_key: {
664         id: key.id,
665         created_at: key.created_at
666     },
667     violating_response: {
668         id: their_request.id,
669         created_at: their_request.created_at,
670         body: their_request.response.hash
671     },
672     uri: this_uri,
673     delta_labels_threshold: delta_labels,
674     delta_labels_detected: symm_diff_labels.length,
675     new_labels: (our_labels - their_labels).to_a,
676     dropped_labels: (their_labels - our_labels).to_a,
677     message: "Source key (id=#{id}) and validation key (id=#{key.id})\n" +
678             "have #{symm_diff_labels.length} "\`  

679             "differing labels, which exceeds the delta label value of #{"\`  

680             "↳ delta_labels}. "\`  

681             "New/dropped labels = '#{(our_labels - their_labels).to_a.map { |l| "\`  

682             "↳ #[l]" }.join(',')}"\`  

683             "#{(their_labels - our_labels).to_a.map { |l| "-#{l}" }.join(',')}"\`  

684             ". #{msg_suffix}."  

685     }
686   )
687 else
688   ICSVSB.ldebug("Number of labels match both keys (within margin of error #{"\`  

689             "↳ delta_labels})")
690 end
691
692 # 7b. Confidence delta
693 delta_confs_exceeded = {}
694 our_request.response.labels.each do |label, conf|
695   our_conf = conf
696   their_conf = their_request.response.labels[label]
697
698   if their_conf.nil?
699     ICSVSB.ldebug("The label #{label} does not exist in the response id=#{\`  

700             "↳ their_request.response.id}. "\`  

701             'Skipping confidence comparison...')  

702   next  

703 end
704
705 delta = our_conf - their_conf
706 ICSVSB.ldebug("Request id=#{our_request.id} against id=#{their_request.id}\n" +
707             "for label '#{label}' confidence: #{our_conf}, #{their_conf} (delta=#{\`  

708             "↳ delta})")  

709 if delta > delta_confidence
710   ICSVSB.lwarn(
711     "Maximum confidence delta breached in key validation (margin of error\n" +
712     "↳ =#{delta_confidence}). "\`  

713     "#{msg_suffix}."  

714   )
715   delta_confs_exceeded[label] = delta
716 end
717
718 end
719
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711     if delta_confs_exceeded.empty?
712       ICSVB.ldebug("Both keys have confidence within margin of error #{
713         ↪ delta_confidence}")
714     else
715       invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
716         BenchmarkKey::InvalidKeyError::CONFIDENCE_DELTA_MISMATCH, {
717           source_key: {
718             id: id,
719             created_at: created_at
720           },
721           source_response: {
722             id: our_request.id,
723             created_at: our_request.created_at,
724             body: our_request.response.hash
725           },
726           violating_key: {
727             id: key.id,
728             created_at: key.created_at
729           },
730           violating_response: {
731             id: their_request.id,
732             created_at: their_request.created_at,
733             body: their_request.response.hash
734           },
735           uri: this_uri,
736           delta_confidence_threshold: delta_confidence,
737           delta_confidences_detected: delta_confs_exceeded,
738           message: "Source key (id=#{id}) has exceeded confidence delta of \"\n
739             validation key (id=#{key.id}): #{delta_confs_exceeded}. #{
740               ↪ msg_suffix}.\n
741           "
742         }
743       )
744     end
745   end
746
747   # Check if the responses are valid against this key
748   valid_response, invalid_reasons = valid_against?(our_request.response)
749   if valid_response
750     ICSVB.ldebug('Our response is valid against this key')
751   else
752     invalid_key_errors += invalid_reasons
753   end
754
755   [invalid_key_errors.empty?, invalid_key_errors.sort_by(&:errorcode)]
756 end
757
758 # Validates a response against this key as per rules encoded within this key.
759 # @param [Response] key The response to validate.
760 # @return See #valid_against?
761 def _validate_against_response(response)
762   invalid_key_errors = []
763
764   missing_expected_labels = expected_labels_set - Set[*response.labels.keys]
765   unless missing_expected_labels.empty?
766     invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
767       BenchmarkKey::InvalidKeyError::EXPECTED_LABELS_MISMATCH, {
768         source_key: {
769           id: id,
770           created_at: created_at
771         },
772         violating_response: {
773           id: response.id,
774           created_at: response.created_at,
775           body: response.hash
776         }
777       }
778     )
779   end
780
781   response
782 end

```

```

773     },
774     uri: response.request.uri,
775     expected_labels: expected_labels.split(','),
776     labels_detected: response.labels.keys,
777     labels_missing: missing_expected_labels.to_a,
778     message: "Expected key (id=#{id}) expects the following mandatory
779       ↪ labels: '#{expected_labels}'. \"\n
780     \"However, response (id=#{response.id}) has the following labels: '#{\n
781       ↪ response.labels.keys.join(',')}'. \"\n
782     \"The following labels are missing: '#{missing_expected_labels.to_a.join
783       ↪ (',')}'.\"\n
784   }
785   )
786 end
787 end
788
789 # The Request Client class is used to make non-benchmarked requests to the
790 # provided service's labelling endpoints. It handles creating respective
791 # +Request+ and +Response+ records to be committed to the benchmarker database.
792 # Requests made with the +RequestClient+ do *not* ensure that evolution risk
793 # has occurred (see BenchmarkedRequestClient).
794 class RequestClient
795   # Initialises a new instance of the requester to label endpoints.
796   # @param [Service] service The service to request from.
797   # @param [Fixnum] max_labels The maximum labels that the requester returns.
798   # Only supported if the service supports this parameter. Default is 100
799   # labels.
800   # @param [Float] min_confidence The confidence threshold by which labels
801   # are returned. Only supported if the service supports this parameter.
802   # Default is 0.50.
803   def initialize(service, max_labels: 100, min_confidence: 0.50)
804     unless service.is_a?(Service) && [Service::GOOGLE, Service::AMAZON, Service
805       ↪ ::AZURE, Service::DEMO].include?(service)
806       raise ArgumentError, "Service with name #{service.name} not supported."
807     end
808
809   # Registers logging for this client
810   ICVSB.register_request_client(self)
811   @logstrio = StringIO.new
812   @log = Logger.new(@logstrio)
813
814   @service = service
815   @service_client =
816     case @service
817     when Service::GOOGLE
818       Google::Cloud::Vision::ImageAnnotator.new
819     when Service::AMAZON
820       Aws::Rekognition::Client.new
821     when Service::AZURE
822       URI('https://australiaeast.api.cognitive.microsoft.com/vision/v2.0/tag')
823     when Service::DEMO
824       nil # Not client needed for mock...
825     end
826   @config = {
827     max_labels: max_labels,
828     min_confidence: min_confidence
829   }
830   @max_labels = max_labels
831   @min_confidence = min_confidence
832 end

```

```

833     attr_reader :max_labels, :min_confidence
834
835     # Sends a request to the client's respective service endpoint. Does *not*
836     # validate a response against a key (see BenchmarkedRequestClient).
837     # Params:
838     # @param [String] uri A URI to an image to detect labels.
839     # @param [BatchRequest] batch The batch that the request is being made
840     # under. Defaults to nil.
841     # @return [Response] The response record committed to the benchmark
842     # database.
843   def send_uri(uri, batch: nil)
844     raise ArgumentError, 'URI must be a string.' unless uri.is_a?(String)
845     raise ArgumentError, 'Batch must be a BatchRequest.' if !batch.nil? && !
846       ↪ batch.is_a?(BatchRequest)
847
848     batch_id = batch.nil? ? nil : batch.id
849     ICVSB.ldebug("Sending URI #{uri} to #{@service.name} - batch_id: #{batch_id}
850       ↪ ")
851
852     begin
853       request_start = DateTime.now
854       exception = nil
855       case @service
856       when Service::GOOGLE
857         response = _request_google_cloud_vision(uri)
858       when Service::AMAZON
859         response = _request_amazon_rekognition(uri)
860       when Service::AZURE
861         response = _request_azure_computer_vision(uri)
862       when Service::DEMO
863         response = _request_demo_service(uri)
864       end
865       ICVSB.ldebug("Successful response for URI #{uri} to #{@service.name} (
866         ↪ batch_id=#{batch_id})")
867     rescue StandardError => e
868       ICVSB.lwarn("Exception caught in send_uri: #{e.class} - #{e.message}")
869       exception = e
870     end
871     request = Request.create(
872       service_id: @service.id,
873       created_at: request_start,
874       uri: uri,
875       batch_request_id: batch_id
876     )
877     response = Response.create(
878       created_at: DateTime.now,
879       body: response[:body],
880       success: exception.nil? && response[:success],
881       request_id: request.id
882     )
883     ICVSB.ldebug("Request saved (id=#{request.id}) with response (id=#{response.
884       ↪ id})")
885   end
886
887   # Sends a batch request with multiple images to client's respective service
888   # endpoint. Does *not* validate a response against a key (see
889   # ICVSB::BenchmarkedRequestClient).
890   # @param [Array<String>] uris An array of URIs to an image to detect labels.
891   # @return [BatchRequest] The batch request that was created.
892   def send_uris(uris)
893     raise ArgumentError, 'URIs must be an array of strings.' unless uris.is_a?(
894       ↪ Array)
895

```

```

892     batch_request = BatchRequest.create(created_at: DateTime.now)
893     ICVSB.linfo("Initiated a batch request for #{uris.count} URIs")
894     uris.each do |uri|
895       send_uri(uri, batch: batch_request)
896     end
897     ICVSB.linfo("Batch is complete (id=#{batch_request.id})")
898     batch_request
899   end
900
901   # Performs the same operation as send_uris but performs sends each URI
902   # asynchronously. Saves a lot of time if you have lots of URIs. This method
903   # should not be used with an SQLite database.
904   # @see #send_uris
905   # @param [Array<String>] uri See #send_uris
906   # @return [Array<BatchRequest, Array<Thread>]] Returns both the array and an
907   # array of threads representing each request. Call +threads.join(&:each)+  

908   # to ensure all requests have finished.
909   def send_uris_async(uris)
910     raise ArgumentError, 'URIs must be an array of strings.' unless uris.is_a?(
911       → Array)
912     if ICVSB::Request.superclass.db.url.start_with?('sqlite')
913       raise StandardError, 'You are using SQLite and thus async operations are
914       → not supported.'
915     end
916
917     threads = []
918     batch_request = BatchRequest.create(created_at: DateTime.now)
919     ICVSB.linfo("Initiated an async batch request for #{uris.count} URIs")
920     uris.each do |uri|
921       threads << Thread.new do
922         send_uri(uri, batch: batch_request)
923       end
924     end
925     ICVSB.linfo("Async batch submitted (id=#{batch_request.id}). Wait for this
926       → batch to be complete!")
927     [batch_request, threads]
928   end
929
930   # Adds a message of a specific severity to this client's logger.
931   # @param [Logger::Severity] severity The type of severity to log.
932   # @param [String] message The message to log.
933   def log(severity, message)
934     unless [Logger::DEBUG, Logger::INFO, Logger::WARN, Logger::ERROR, Logger::
935       → FATAL, Logger::UNKNOWN].include?(severity)
936       raise ArgumentError, 'Severity must be a Logger::Severity type'
937     end
938     raise ArgumentError, 'Message must be a string' unless message.is_a?(String)
939
940     @log.add(severity, message)
941   end
942
943   # Gets the log of this client as a string.
944   # @return [String] The entire log.
945   def read_log
946     @logstrio.string
947   end
948
949   # Makes a request to Google Cloud Vision's +LABEL_DETECTION+ feature.
950   # @see https://cloud.google.com/vision/docs/labels
951   # @param [String] uri A URI to an image to detect labels. Google Cloud
952   # Vision supports JPEGs, PNGs, GIFs, BMPs, WEBPs, RAWs, ICOs, PDFs and

```

```

952      # TIFFs only.
953      # @return [Hash] A hash containing the response +body+ and whether the
954      # request was +successful+.
955      def _request_google_cloud_vision(uri)
956        begin
957          image = _download_image(
958            uri,
959            %w[
960              image/jpeg
961              image/png
962              image/gif
963              image/webp
964              image/x-dcraw
965              image/vnd.microsoft.icon
966              application/pdf
967              image/tiff
968            ]
969          )
970          exception = nil
971          res = @service_client.label_detection(
972            image: image.open,
973            max_results: @max_labels
974          ).to_h
975          rescue StandardError => e
976            exception = e
977            res = { service_error: "#{exception.class} - #{exception.message}" }
978          end
979        {
980          body: res.to_json,
981          success: exception.nil? && res.key?(:responses)
982        }
983      end
984
985      # Makes a request to Amazon Rekognition's +DetectLabels+ endpoint.
986      # @see https://docs.aws.amazon.com/rekognition/latest/dg/API_DetectLabels.html
987      # @param [String] uri A URI to an image to detect labels. Amazon Rekognition
988      # only supports JPEGs and PNGs.
989      # @return (see #_request_google_cloud_vision)
990      def _request_amazon_rekognition(uri)
991        begin
992          image = _download_image(uri, %w[image/jpeg image/png])
993          exception = nil
994          res = @service_client.detect_labels(
995            image: {
996              bytes: image.read
997            },
998            max_labels: @max_labels,
999            min_confidence: @min_confidence
1000          ).to_h
1001          rescue StandardError => e
1002            exception = e
1003            res = { service_error: "#{e.class} - #{e.message}" }
1004          end
1005        {
1006          body: res.to_json,
1007          success: exception.nil? && res.key?(:labels)
1008        }
1009      end
1010
1011      # Makes a request to Azure's +analyze+ endpoint with +visualFeatures+ of
1012      # +Tags+.
1013      # @see https://docs.microsoft.com/en-us/rest/api/cognitiveservices/
1014      # computervision/tagimage/tagimage
1015      # @param [String] uri A URI to an image to detect labels. Azure Computer

```

```

1015  # Vision only supports JPEGs, PNGs, GIFs, and BMPs.
1016  # @return (see #_request_google_cloud_vision)
1017  def _request_azure_computer_vision(uri)
1018      image = _download_image(uri, %w[image/jpeg image/png image/gif image/bmp])
1019
1020      http_req = Net::HTTP::Post::Multipart.new(
1021          @service_client,
1022          file: UploadIO.new(image.open, image.content_type, image.original_filename
1023                           ↩ )
1024          )
1025          http_req['Ocp-Apim-Subscription-Key'] = ENV['AZURE_SUBSCRIPTION_KEY']
1026
1027      http_res = Net::HTTP.start(@service_client.host, @service_client.port,
1028                                  ↩ use_ssl: true) do |h|
1029          h.request(http_req)
1030      end
1031
1032      tags_present = JSON.parse(http_res.body).key?('tags')
1033      {
1034          body: tags_present ? http_res.body : { service_error: http_res.body },
1035          success: tags_present
1036      }
1037
1038      # Makes a request to the mock demo server, returning JSON data at time 1
1039      # (t1) or time 2 (t2), depending on the timestamp flip (which can be
1040      # triggered by the PATCH /benchmark/:key endpoint).
1041      # @param [String] uri A URI to an image to detect labels.
1042      # @return (see #_request_google_cloud_vision)
1043  def _request_demo_service(uri)
1044      # Get the image id from the URI...
1045      regexp = %r{http://localhost:4567/demo/data/(\d{4,12}).jpe?g}
1046
1047      all_image_ids = JSON.parse(
1048          File.read(File.join('demo', 'categories.json'))
1049          )['all']
1050
1051      invalid_uri = (uri =~ regexp).nil?
1052      image_id = uri.match(regexp)[1] unless invalid_uri
1053      invalid_image_id = !all_image_ids.include?(image_id)
1054
1055      # Mock service can be switched to t1 or t2 at demo endpoint...
1056      body =
1057          if invalid_uri || invalid_image_id
1058              { service_error: 'The URI is not a valid demo URI.' }
1059          else
1060              body = JSON.parse(File.read(File.join('demo', "#{$image_id}.#{demotimestamp}.json")))
1061              { responses: [body] }#[{ label_annotations: body }]
1062          end
1063
1064          {
1065              body: body.to_json,
1066              success: !(invalid_uri || invalid_image_id)
1067          }
1068
1069      # Downloads the image at the specified URI.
1070      # @param [String] uri The URI to download.
1071      # @param [Array<String>] mimes Accepted mime types.
1072      # @return [File] if download was successful.
1073  def _download_image(uri, mimes)
1074      raise ArgumentError, 'URI must be a string.' unless uri.is_a?(String)
1075      raise ArgumentError, 'Mimes must be an array of strings.' unless mimes.is_a

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1076      ↢ ?(Array)
1077      raise ArgumentError, "Invalid URI specified: #{uri}." unless uri =~ URI::
1078      ↢ DEFAULT_PARSER.make_regexp
1079
1080      ICSVB.ldebug("Downloading image at URI: #{uri}")
1081      file = Down.download(uri)
1082      mime = file.content_type
1083
1084      unless mimes.include?(mime)
1085        raise ArgumentError, "Content type of URI #{uri} not accepted. Received #{
1086          ↢ mime}. Valid are: #{mimes}."
1087      end
1088
1089      file
1090    rescue Down::Error => e
1091      raise ArgumentError, "Could not access the URI #{uri} - #{e.class}"
1092    end
1093
1094    # The Benchmarked Request Client class is used to make requests to a service's
1095    # labelling endpoints, ensuring that the response from the endpoint has not
1096    # altered significantly as indicated by the expiration flags. It handles
1097    # creating respective +Request+ and +Response+ records to be committed to the
1098    # benchmarker database. Unlike the +RequestClient+, the
1099    # +BenchmarkedRequestClient+ ensures that, respective to a benchmark dataset,
1100    # evolution has not occurred and thus is safe to use the endpoint without
1101    # re-evaluation. Requires a BenchmarkKey to make any requests.
1102    class BenchmarkedRequestClient < RequestClient
1103      alias send_uri_no_key send_uri
1104      alias send_uris_no_key send_uris
1105      alias send_uris_no_key_async send_uris_async
1106
1107      # Initialises a new instance of the benchmarked requester to label
1108      # endpoints.
1109      # @param [Service] service (see RequestClient#initialize)
1110      # @param [Array<String>] dataset An array of URIs to benchmark
1111      # against.
1112      # @param [Fixnum] max_labels (see RequestClient#initialize)
1113      # @param [Float] min_confidence (see RequestClient#initialize)
1114      # @param [Hash] opts Additional benchmark-related parameters.
1115      # @option opts [String] :trigger_on_schedule A cron-tab string (see
1116      # +man 5 crontab+) that is used for the benchmarker to re-evaluate if the
1117      # current key should be expired. Default is every Sunday at midnight,
1118      # i.e., +0 0 * * 0+.
1119      # @option opts [String] :trigger_on_failcount Number of times the benchmark
1120      # request fails making requests for the benchmark to re-evaluate. Must
1121      # be a positive, non-zero number for the benchmark to trigger on failure,
1122      # else this field is ignored. Default is 0.
1123      # @option opts [BenchmarkSeverity] :severity The severity of warning for
1124      # the #BenchmarkKey to fail. Default is +BenchmarkSeverity::INFO+.
1125      # @option opts [String] :benchmark_callback_uri The URI to call with results
1126      # of a completed benchmark. Optional. If an invalid URI is specified this
1127      # will default to nil.
1128      # @option opts [String] :warning_callback_uri Required when the +:severity:+
1129      # is +BenchmarkSeverity::WARN+. If left blank, the effect of the benchmark
1130      # client is essentially a severity of +BenchmarkSeverity::NONE+, as no
1131      # warning endpoint can be called to notify of issues. If an invalid URI is
1132      # provided, this will default to nil.
1133      # @option opts [Boolean] :autobenchmark Automatically benchmark the client
1134      # as soon as it is initialised. If +false+, then you will need to call
1135      # the #benchmark method immediately (i.e., on your own thread). Defaults
1136      # to true, so will block the current thread before benchmarking is
1137      # complete.
1138      # @option opts [Fixnum] :delta_labels Number of labels that change for a

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1137 # #BenchmarkKey to expire. Default is 5.
1138 # @option opts [Float] :delta_confidences Minimum amount of difference for
1139 # the same label to have changed between the last benchmark for the
1140 # #BenchmarkKey to expire. Default is 0.01.
1141 # @option opts [Array<String>] :expected_labels Array of strings for the
1142 # various expected labels that should be expected in every result. Fails
1143 # otherwise. Encoded within the key.
1144 def initialize(service, dataset, max_labels: 100, min_confidence: 0.50, opts:
1145   ↪ {})
1146   super(service, max_labels: max_labels, min_confidence: min_confidence)
1147   @dataset = dataset
1148   @key_config = {
1149     delta_labels: opts[:delta_labels] || 5,
1150     delta_confidence: opts[:delta_confidence] || 0.01,
1151     severity: opts[:severity] || BenchmarkSeverity::INFO,
1152     expected_labels: opts[:expected_labels] || []
1153   }
1154   @benchmark_config = {
1155     trigger_on_schedule: opts[:trigger_on_schedule] || '0 0 * * 0',
1156     trigger_on_failcount: opts[:trigger_on_failcount] || 0,
1157     autobenchmark: opts[:autobenchmark].nil? ? true : opts[:autobenchmark]
1158   }
1159   # Validate URIs
1160   if !opts[:benchmark_callback_uri].nil? &&
1161     !(opts[:benchmark_callback_uri] =~ URI::DEFAULT_PARSER.make_regexp).nil?
1162     @benchmark_config[:benchmark_callback_uri] = URI(opts[:benchmark_callback_uri])
1163   end
1164   if !opts[:warning_callback_uri].nil? &&
1165     !(opts[:warning_callback_uri] =~ URI::DEFAULT_PARSER.make_regexp).nil?
1166     @benchmark_config[:warning_callback_uri] = URI(opts[:warning_callback_uri])
1167   end
1168   if !opts[:warning_callback_uri].nil? && opts[:severity] != BenchmarkSeverity
1169     ICVSB.lwarn("A warning callback URI #{opts[:warning_callback_uri]} was set
1170     ↪ but \"\n      'the severity is not WARNING. This callback will be ignored...'")
1171   end
1172
1173   @created_at = DateTime.now
1174   @demo_timestamp = 't1' if @service == Service::DEMO
1175   @is_benchmarking = false
1176   @last_benchmark_time = nil
1177   @benchmark_count = 0
1178   @invalid_state_count = 0
1179   trigger_benchmark if @benchmark_config[:autobenchmark]
1180   @scheduler = Rufus::Scheduler.new.schedule(@benchmark_config[:trigger_on_schedule]) do |cronjob|
1181     ICVSB.linfo("Cronjob starting for BenchmarkedRequestClient #{self} - \"\
1182       Scheduled at: #{cronjob.scheduled_at}; Last ran at: #{cronjob.last_time
1183       ↪ }.\")"
1184   trigger_benchmark
1185 end
1186
1187 # Exposes whether or not the client is currently benchmarking.
1188 # @return [Boolean] True if the client is benchmarking, false otherwise.
1189 def benchmarking?
1190   @is_benchmarking
1191 end
1192
1193 # Returns the next time a schedule to trigger a benchmark will run.

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```

1194  # @return [DateTime] The time the next trigger to benchmark will be run.
1195  def next_scheduled_benchmark_time
1196    DateTime.parse(@scheduler.next_time.to_t.to_s)
1197  end
1198
1199  # Returns the last time a schedule to trigger a benchmark was run.
1200  # @return [DateTime,nil] Time next DateTime the benchmark ran or nil if
1201  # the scheduler has never yet run.
1202  def last_scheduled_benchmark_time
1203    @scheduler.last_time.nil? ? nil : DateTime.parse(@scheduler.last_time.to_t.
1204      ↪ to_s)
1205  end
1206
1207  # Returns the average time taken to complete the last benchmark.
1208  # @return [Float] The time taken.
1209  def mean_scheduled_benchmark_duration
1210    @scheduler.mean_work_time
1211  end
1212
1213  # Returns the time taken to complete the last benchmark.
1214  # @return [Float] The time taken.
1215  def last_scheduled_benchmark_duration
1216    @scheduler.last_work_time
1217  end
1218
1219  attr_reader *%i[
1220    invalid_state_count
1221    current_key
1222    created_at
1223    dataset
1224    benchmark_count
1225    last_benchmark_time
1226    benchmark_config
1227    key_config
1228    service
1229  ]
1230
1231  attr_accessor :demo_timestamp
1232
1233  # Sends an image to this client's respective labelling endpoint, verifying
1234  # the key provided has not expired (and thus substantial evolution in the
1235  # labelling endpoint has not occurred for significant impact to the results).
1236  # Depending on the key's varied severity level, a response will be returned
1237  # with varied fields populated.
1238  # @param [URI] uri (see RequestClient#send_uri)
1239  # @param [BenchmarkKey] key The benchmark key required to make a request
1240  # to the service using this client. This key is verified against this
1241  # client's most recent benchmark, thereby ensuring no evolution has occurred
1242  # in the back-end service.
1243  # @return [Hash] A hash with the following keys: +:response+, the raw
1244  # #Response object returned from the #RequestClient.send_uri method (i.e.,
1245  # a non-benchmarked response) or +nil+ if the #key has expired or invalid
1246  # and the key's severity level is #BenchmarkSeverity::EXCEPTION;
1247  # +:labels+, a shortcut to the #Response.label method of the response or
1248  # +nil+ if the key has expired or was invalid and the key's severity level
1249  # is #BenchmarkSeverity::EXCEPTION; +:key_errors:+ a(n) error(s) response
1250  # indicating if the key has expired (a string value) which is only
1251  # populated if the key has a severity level of
1252  # #BenchmarkSeverity::EXCEPTION or #BenchmarkSeverity::WARNING;
1253  # +:response_errors:+ similar to :key_errors: but for the response;
1254  # +:cached:+ an optional DateTime indicating that there was no need to make
1255  # a request to the service as the benchmarker holds a cached response that
1256  # is still valid; this indicates the time at which the cached response was
# generated.

```

```

1257     def send_uri_with_key(uri, key)
1258       raise ArgumentError, 'URI must be a string.' unless uri.is_a?(String)
1259       raise ArgumentError, 'Key must be a BenchmarkKey.' unless key.is_a?(
1260         BenchmarkKey)
1261 
1262       if @current_key.nil?
1263         return {
1264           key_errors: [
1265             BenchmarkKey::InvalidKeyError.new(BenchmarkKey::InvalidKeyError::
1266               NO_KEY_YET)
1267           ]
1268         }
1269 
1270       result = {
1271         labels: nil,
1272         response: nil,
1273         key_errors: nil,
1274         response_errors: nil,
1275         service_error: nil,
1276         cached: nil
1277       }
1278 
1279       # Check for a cached result w/ this service given provided key...
1280       ICVSB.ldebug("Attempting to use a cached response for #{uri} + #{@service.
1281         name}...")
1282       Request.where(uri: uri, service_id: @service.id, benchmark_key_id: key.id)
1283         .order(Sequel.desc(:created_at)).each do |request|
1284         response = request.response
1285 
1286         # Ignore unsuccessful responses
1287         next if response.nil? || !response.success?
1288 
1289         # Check if the response's benchmark is still valid -- if so, just
1290         # reuse that result... (no need to actually ping service)
1291         key_is_valid, = @current_key.valid_against?(response.benchmark_key)
1292         ICVSB.ldebug("Cached key (id=#{response.benchmark_key.id}) is valid
1293           ↪ against current key \"\n
1294             "(id=#{@current_key.id})? #{key_is_valid}"")
1295         if !response.benchmark_key.nil? && key_is_valid
1296           return { labels: response.labels, response: response.hash, cached:
1297             ↪ DateTime.parse(response.created_at.to_s) }
1298         end
1299       end
1300       ICVSB.ldebug("Cached response failed! Will try to invoke a request to #{@
1301         service.name}")
1302 
1303       # Check for key validity
1304       ICVSB.ldebug("Checking if current key (id=#{@current_key.id}) is valid
1305           ↪ against key provided (id=#{key.id})...")
1306       key_valid, key_invalid_reasons = @current_key.valid_against?(key)
1307       # Invalid state count incrementemnt if key error exists...
1308       unless key_valid
1309         ICVSB.ldebug("Validation of current key (id=#{@current_key.id}) failed
1310           ↪ against key provided (id=#{key.id}). "
1311             "Reasons: #[key_invalid_reasons.join('; ')]")
1312         result[:key_errors] = key_invalid_reasons
1313         @invalid_state_count += 1
1314         ICVSB.linfo("Error has occured in key validation. Invalid state count
1315           ↪ count is now #{@invalid_state_count}.")
1316       end
1317 
1318       # If key is valid, raise request and check if response is valid
1319       ICVSB.ldebug("Key provided #[key.id] is valid against current key #{
1320

```

```

1312     ↪ @current_key.id}!")
1313   if key_valid
1314     ICVSB.ldebug("Invoking a request '#{uri}' to #{@service.name}...")
1315     response = send_uri_no_key(uri)
1316     ICVSB.ldebug("Response returned (id=#{response.id})! Labels: #{response.
1317       ↪ labels}")
1318     # Update the benchmark key id
1319     response.benchmark_key_id = @current_key.id
1320     ICVSB.ldebug("Updated response (id=#{response.id}) with benchmark key = #{
1321       ↪ response.benchmark_key_id}...")
1322     # Now check to see if it was valid given that the response was successful
1323     if response.success?
1324       ICVSB.ldebug("Checking if this response (id=#{response.id}) is valid
1325         ↪ against current key (id=#{key.id})")
1326       response_valid, response_invalid_reasons = @current_key.valid_against?(
1327         ↪ response)
1328     end
1329     result[:labels] = response.labels
1330     result[:response] = response.hash
1331     result[:service_error] = result[:response][:service_error].to_s unless
1332       ↪ result[:response][:service_error].nil?
1333     response_valid ||= !result[:response][:service_error].nil?
1334     # Increment invalid state count if response error ONLY (i.e., not service
1335       ↪ error)
1336     unless response_valid
1337       ICVSB.ldebug("Validation of current key (id=#{@current_key.id}) failed
1338         ↪ against response \"\
1339           "(id=#{response.id}). Reasons: #{response_invalid_reasons.join('; ')}")
1340       result[:response_errors] = response_invalid_reasons
1341       @invalid_state_count += 1
1342       ICVSB.linfo('Error has occurred in response validation. \
1343           "Invalid state count count is now #{@invalid_state_count}.')
1344     end
1345   end
1346
1347   # If benchmark trigger on num failures is set
1348   if @benchmark_config[:trigger_on_failcount].positive? &&
1349     @invalid_state_count > @benchmark_config[:trigger_on_failcount]
1350     ICVSB.linfo("Benchmark has failed #{@benchmark_config[:.
1351       ↪ trigger_on_failcount]} \"\
1352         'times... retriggering benchmark...'")
1353     @invalid_state_count = 0
1354     trigger_benchmark
1355   end
1356
1357   # Response behaviour is dependent on the severity encoded within the key
1358   case @current_key.benchmark_severity
1359   when BenchmarkSeverity::EXCEPTION
1360     # Only expose errors if they exist
1361     if (result[:key_errors].nil? || result[:key_errors].empty?) &&
1362       result[:response_errors].nil? &&
1363       result[:service_error].nil?
1364       result
1365     else
1366       {
1367         key_errors: result[:key_errors],
1368         response_errors: result[:response_errors],
1369         service_error: result[:service_error]
1370       }
1371     end
1372   when BenchmarkSeverity::WARNING
1373     # Flag a warning to the warning endpoint about this result if sev is WARN
1374     _flag_warning(result)
1375   end
1376 end

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```

1367   when BenchmarkSeverity::INFO
1368     # Log to info...
1369     unless key_valid
1370       ICVSB.lwarn("Benchmarked request made for #{uri} with invalid key \"\
1371         "(id=#{@current_key.id}) -- error reasons: #{key_invalid_reasons.join \
1372           '<-- ('; ')'}")
1373     end
1374     unless response_valid
1375       ICVSB.lwarn("Benchmarked request made for #{uri} and response violated \
1376         '<-- current key \"\
1377           "(id=#{@current_key.id}) -- error reasons: #{response_invalid_reasons. \
1378             '<-- join('; ')'}")
1379     end
1380   result
1381 when BenchmarkSeverity::NONE
1382   # Passthrough...
1383   result
1384 end
1385
# Makes a request to benchmark's the client's current key against the
# client's URIs to benchmark against. Expires the existing current key
# if a new benchmark key is no longer valid against the old benchmark key.
1386 # @return [void]
1387 def trigger_benchmark
1388   @is_benchmarking = true
1389   new_key = _benchmark
1390   old_key = @current_key
1391   expiry_occurred = false
1392   if @current_key.nil?
1393     @current_key = new_key
1394   else
1395     # Check if the key is valid
1396     valid_key, invalid_reasons = @current_key.valid_against?(new_key)
1397     unless valid_key
1398       ICVSB.lerror('BenchmarkedRequestClient no longer has a valid key! ' \
1399         "Reason(s) = '#{invalid_reasons.join('; ')}'" \
1400         "Expiring old key (id=#{@current_key.id}) with new key (id=#{new_key.id \
1401           '<-- })")
1402       @current_key.expire
1403       @current_key = new_key
1404       expiry_occurred = true
1405     end
1406   end
1407   # # Check if the responses are valid against the current key
1408   # new_key.batch_request.responses.each do |res|
1409   #   valid_response, invalid_reasons = @current_key.valid_against?(res)
1410   #   unless valid_response
1411   #     ICVSB.lerror('BenchmarkedRequestClient has a violated response! ' \
1412   #       "Reason(s) = '#{invalid_reasons.join('; ')}'. Falling back to old key (id \
1413   #         '<-- =#{old_key.nil? ? '<NONE>' : old_key.id})...")
1414   #     @current_key.expire
1415   #     @current_key = old_key
1416   #     @current_key.&.unexpire
1417   #     expiry_occurred = true
1418   #     break
1419   #   end
1420   #   @is_benchmarking = false
1421   #   _flag_benchmarking_complete(new_key, old_key, expiry_occurred)
1422 end
1423
# Locates the last behaviour token key from the given date
# @param [DateTime] Date at which the key should be searched from
1424
1425

```

```

1426      # @param [BenchmarkKey] The benchmark key found, or nil.
1427      def find_key_since(date)
1428        candidate_bks = BenchmarkKey.where(
1429          service_id: @service.id,
1430          benchmark_severity_id: @key_config[:severity].id,
1431          max_labels: @max_labels,
1432          min_confidence: @min_confidence,
1433          delta_labels: @key_config[:delta_labels],
1434          delta_confidence: @key_config[:delta_confidence],
1435          expected_labels: @key_config[:expected_labels].map(&:downcase).join(','),
1436        ).where(Sequel[:created_at] > date).reverse_order(:created_at)
1437        return nil if candidate_bks.nil?
1438
1439        candidate_bks.find do |bk|
1440          (Set[*bk.batch_request.uris] ^ Set[@dataset]).empty?
1441        end
1442      end
1443
1444    private
1445
1446    # Forwards a full result to the benchmarked request client's warning endpoint
1447    # @param [Hash] result See #send_uri_with_key
1448    # @return [void]
1449    def _flag_warning(result)
1450      return if @benchmark_config[:warning_callback_uri].nil? || @key_config[:  

1451        ↪ severity] != BenchmarkSeverity::WARNING
1452
1453      uri = @benchmark_config[:warning_callback_uri]
1454      data = result
1455      Thread.new do
1456        ICSVSB.linfo("POSTing to warning endpoint '#{uri}' data=#{data}")
1457        req = Net::HTTP::Post.new(uri)
1458        req.body = data.to_json
1459        req.content_type = 'application/json; charset=utf8'
1460        res = Net::HTTP.start(uri.hostname, uri.port) do |http|
1461          http.request(req)
1462        end
1463        ICSVSB.linfo("Response from warning endpoint: #{res.code} #{res.message}")
1464        ICSVSB.ldebug("Response body is: #{res.body}") if res.is_a?(Net::  

1465          ↪ HTTPSuccess)
1466      end
1467
1468    # Forwards a new key that has been generated due to benchmark trigger and
1469    # sends the current or old key (depending on expiry_occurred flag.)
1470    # @param [BenchmarkKey] new_key The new key that was generated from the
1471    # benchmark that was triggered.
1472    # @param [BenchmarkKey] old_or_current_key The current key, if expiry did
1473    # not occur, or the old key if expiry did occur.
1474    # @param [Boolean] expiry_occurred Indicates if the current_key was expired
1475    # and replaced with the new_key.
1476    # @return [void]
1477    def _flag_benchmarking_complete(new_key, old_or_current_key, expiry_occurred)
1478      return if @benchmark_config[:benchmark_callback_uri].nil?
1479
1480      uri = @benchmark_config[:benchmark_callback_uri]
1481      old_or_current_key_id = old_or_current_key.nil? ? nil : old_or_current_key.  

1482        ↪ id
1483      data = { new_key: new_key.id, old_key: old_or_current_key_id, expiry_occurred  

1484        ↪ : expiry_occurred }
1485      Thread.new do
1486        ICSVSB.linfo("POSTing to benchmark complete endpoint '#{uri}' data=#{data}"  

1487          ↪ )
1488        req = Net::HTTP::Post.new(uri)

```

```

1485     req.body = data.to_json
1486     req.content_type = 'application/json; charset=utf8'
1487     res = Net::HTTP.start(uri.hostname, uri.port) do |http|
1488       http.request(req)
1489     end
1490     ICVSB.linfo("Response from benchmark complete endpoint: #{res.code} #{res.
1491                   ↪ message}")
1491     ICVSB.ldebug("Response body is: #{res.body}") if res.is_a?(Net::
1492                   ↪ HTTPSuccess)
1493   end
1494
1495 # Benchmarks this client against a set of URIs, returning this client's
1496 # configurated key configuration. Internal method...
1497 # @return [BenchmarkKey] A key representing the result of this benchmark.
1498 def _benchmark
1499   @last_benchmark_time = DateTime.now
1500   @benchmark_count += 1
1501   ICVSB.linfo("Benchmarking dataset against dataset of #{@dataset.count} URIs.
1502               ↪ ")
1502   "Times benchmarked=#{benchmark_count}")
1503   br, thr = send_uris_no_key_async(@dataset)
1504   ICVSB.linfo("Benchmarking this dataset using batch request with id=#{br.id}.
1504               ↪ ")
1505   # Wait for all threads to finish...
1506   thr.each(&:join)
1507   ICVSB.linfo("Batch request with id=#{br.id} is now complete!")
1508   bk = BenchmarkKey.create(
1509     service_id: @service.id,
1510     benchmark_severity_id: @key_config[:severity].id,
1511     batch_request_id: br.id,
1512     created_at: DateTime.now,
1513     expired: false,
1514     delta_labels: @key_config[:delta_labels],
1515     delta_confidence: @key_config[:delta_confidence],
1516     expected_labels: @key_config[:expected_labels].map(&:downcase).join(','),
1517     max_labels: @max_labels,
1518     min_confidence: @min_confidence
1519   )
1520   # Ensure every response is updated with this key
1521   br.responses.each do |res|
1522     ICVSB.ldebug("Updating response id=#{res.id} to benchmark key id=#{bk.id}.
1522               ↪ ")
1523     res.benchmark_key_id = bk.id
1524   end
1525   ICVSB.linfo("Benchmarking dataset is complete (benchmark key id=#{bk.id}).")
1526   bk
1527 end
1528 end
1529 end

```

Listing B.2: Implementation of the architecture facade API.

```

1 # frozen_string_literal: true
2
3 # Author:: Alex Cummaudo (mailto:ca@deakin.edu.au)
4 # Copyright:: Copyright (c) 2019 Alex Cummaudo
5 # License:: MIT License
6
7 require 'sinatra'
8 require 'time'
9 require 'json'
10 require 'cgi'
11 require 'require_all'
12 require_all 'lib'
13
14
15 set :root, File.dirname(__FILE__)
16 set :public_folder, File.join(File.dirname(__FILE__), 'static')
17 set :show_exceptions, false
18 set :demo_folder, File.join(File.dirname(__FILE__), 'demo')
19
20 store = {}
21
22 before do
23   if request.body.size.positive?
24     request.body.rewind
25     @params = JSON.parse(request.body.read, symbolize_names: true)
26   end
27 end
28
29 def halt!(code, message)
30   content_type 'text/plain'
31   halt code, message
32 end
33
34 def check_brc_id(id, store)
35   halt! 400, 'Benchmark id must be a positive integer' unless id.integer? && id.
36   ↪ to_i.positive?
37   halt! 400, "No such benchmark request client exists with id=#{id}" unless store
38   ↪ .key?(id)
39 end
40
41 get '/' do
42   File.read(File.expand_path('index.html', settings.public_folder))
43 end
44
45 # Creates a new benchmark request client with given parameters
46 post '/benchmark' do
47   # Extract params
48   service = params[:service] || ''
49   benchmark_dataset = params[:benchmark_dataset] || ''
50   max_labels = params[:max_labels] || ''
51   min_confidence = params[:min_confidence] || ''
52   trigger_on_schedule = params[:trigger_on_schedule] || ''
53   trigger_on_failcount = params[:trigger_on_failcount] || ''
54   benchmark_callback_uri = params[:benchmark_callback_uri] || ''
55   warning_callback_uri = params[:warning_callback_uri] || ''
56   expected_labels = params[:expected_labels] || ''
57   delta_labels = params[:delta_labels] || ''
58   delta_confidence = params[:delta_confidence] || ''
59   severity = params[:severity] || ''
60
61   # Check param types
62   unless max_labels.integer? && max_labels.to_i.positive?

```

```

61     halt! 400, 'max_labels must be a positive integer'
62   end
63   unless min_confidence.float? && min_confidence.to_f.positive?
64     halt! 400, 'min_confidence must be a positive float'
65   end
66   unless delta_labels.integer? && delta_labels.to_i.positive?
67     halt! 400, 'delta_labels must be a positive integer'
68   end
69   unless delta_confidence.float? && delta_confidence.to_f.positive?
70     halt! 400, 'delta_confidence must be a positive float'
71   end
72   unless ICVSB::VALID_SERVICES.include?(service.to_sym)
73     halt! 400, "service must be one of #{ICVSB::VALID_SERVICES.join(', ', '')}"
74   end
75   unless trigger_on_schedule.cronline?
76     halt! 400, 'trigger_on_schedule must be a cron string in * * * * * (see man 5
77     ↪ crontab)'
78   end
79   unless trigger_on_failcount.integer? && trigger_on_failcount.to_i >= -1
80     halt! 400, 'trigger_on_failcount must be zero or positive integer'
81   end
82   if !benchmark_callback_uri.empty? && !benchmark_callback_uri.uri?
83     halt! 400, 'benchmark_callback_uri is not a valid URI'
84   end
85   unless ICVSB::VALID_SEVERITIES.include?(severity.to_sym)
86     halt! 400, "severity must be one of #{ICVSB::VALID_SEVERITIES.join(', ', '')}"
87   end
88   if ICVSB::BenchmarkSeverity[name: severity.to_s] == ICVSB::BenchmarkSeverity::
89     ↪ WARNING && !warning_callback_uri.uri?
90     halt! 400, 'Must provide a valid warning_callback_uri when severity is WARNING
91     ↪ '
92   end
93   halt! 400, 'benchmark_dataset has not been specified' if benchmark_dataset.
94     ↪ empty?
95   benchmark_dataset = benchmark_dataset.lines.map(&:strip)
96   expected_labels = expected_labels.empty? ? [] : expected_labels.split(',').map
97     ↪ (&:strip)
98   benchmark_dataset.each do |uri|
99     unless uri.uri?
100       halt! 400, "benchmark_dataset must be a list of uris separated by a newline
101         ↪ character; #{uri} is not a valid URI"
102     end
103   end
104
105   # Convert params
106   brc = ICVSB::BenchmarkedRequestClient.new(
107     ICVSB::Service[name: service.to_s],
108     benchmark_dataset,
109     max_labels: max_labels.to_i,
110     min_confidence: min_confidence.to_f,
111     opts: {
112       trigger_on_schedule: trigger_on_schedule,
113       trigger_on_failcount: trigger_on_failcount.to_i,
114       benchmark_callback_uri: benchmark_callback_uri,
115       warning_callback_uri: warning_callback_uri,
116       expected_labels: expected_labels,
117       delta_labels: delta_labels.to_i,
118       delta_confidence: delta_confidence.to_f,
119       severity: ICVSB::BenchmarkSeverity[name: severity.to_s],
120       autobenchmark: false
121     }
122   )

```

```

119  # Benchmark on new thread
120  Thread.new do
121    brc.trigger_benchmark
122    store[brc.object_id] = brc
123  end
124
125  store[brc.object_id] = brc
126
127  status 201
128  content_type 'application/json; charset=utf-8'
129  { id: brc.object_id }.to_json
130 end
131
132 # Gets all auxillary information about the benchmark
133 get '/benchmark/:id' do
134   id = params[:id].to_i
135   check_brc_id(id, store)
136   brc = store[id]
137
138   content_type 'application/json; charset=utf-8'
139   {
140     id: id,
141     service: brc.service.name,
142     created_at: brc.created_at,
143     current_key_id: brc.current_key ? brc.current_key.id : nil,
144     is_benchmarking: brc.benchmarking?,
145     last_scheduled_benchmark_time: brc.last_scheduled_benchmark_time,
146     next_scheduled_benchmark_time: brc.next_scheduled_benchmark_time,
147     mean_scheduled_benchmark_duration: brc.mean_scheduled_benchmark_duration,
148     last_scheduled_benchmark_duration: brc.last_scheduled_benchmark_duration,
149     invalid_state_count: brc.invalid_state_count,
150     last_benchmark_time: brc.last_benchmark_time,
151     benchmark_count: brc.benchmark_count,
152     config: {
153       max_labels: brc.max_labels,
154       min_confidence: brc.min_confidence,
155       key: brc.key_config,
156       benchmarking: brc.benchmark_config
157     },
158     benchmark_dataset: brc.dataset
159   }.to_json
160 end
161
162 patch '/benchmark/:id' do
163   # Set is_benchmarking to true to force the benchmark to reevaluate...
164   # Else, endpoint is ignored
165   id = params['id'].to_i
166   check_brc_id(id, store)
167   brc = store[id]
168
169   status 202
170   response = {
171     id: id,
172     service: brc.service.name,
173     current_key_id: brc.current_key ? brc.current_key.id : nil,
174     is_benchmarking: brc.benchmarking?
175   }
176   if brc.service == ICVSB::Service::DEMO && params[:demo_timestamp]
177     brc.demo_timestamp = params[:demo_timestamp] if ['t1', 't2'].include?(params[:  
      ↪ demo_timestamp])
178     response[:timestamp] = brc.demo_timestamp
179   end
180
181   brc.trigger_benchmark if params[:is_benchmarking] && !brc.benchmarking?

```

```

182
183   response.to_json
184 end
185
186 # Gets all auxillary information about this key's benchmark
187 get '/benchmark/:id/key' do
188   id = params[:id].to_i
189   check_brc_id(id, store)
190   brc = store[id]
191
192   halt! 422, 'The requested benchmark client is still benchmarking its first key'
193   ↪ if brc.current_key.nil?
194
195   current_key_id = brc.current_key.id
196   redirect "/key/#{current_key_id}"
197 end
198
199 get '/key/:id' do
200   id = params[:id].to_i
201   bk = BenchmarkKey[id: params[:id]]
202
203   halt! 400, 'id must be an integer' unless id.integer?
204   halt! 400, "No such benchmark key request client exists with id=#{id}" if bk.
205   ↪ nil?
206
207   content_type 'application/json; charset=utf-8'
208   {
209     id: bk.id,
210     service: bk.service.name,
211     created_at: bk.created_at,
212     benchmark_dataset: bk.batch_request.uris,
213     success: bk.success?,
214     expired: bk.expired?,
215     severity: bk.severity.name,
216     responses: bk.batch_request.responses.map(&:hash),
217     config: {
218       expected_labels: bk.expected_labels_set.to_a,
219       delta_labels: bk.delta_labels,
220       delta_confidence: bk.delta_confidence,
221       max_labels: bk.max_labels,
222       min_confidence: bk.min_confidence
223     }
224   }.to_json
225 end
226
227 # Gets the log of the benchmark with the given id
228 get '/benchmark/:id/log' do
229   id = params[:id].to_i
230
231   check_brc_id(id, store)
232
233   content_type 'text/plain'
234   store[id].read_log
235 end
236
237 post '/callbacks/benchmark' do
238   "Acknowledged benchmark completion with params: '#{params}'..."
239 end
240
241 post '/callbacks/warning' do
242   "Acknowledged benchmark warning params: '#{params}'..."
243 end
244
245 # Labels resources against the provided uri. This is a conditional HTTP request.

```

```

244 # Must provide "If-Match" request header field with at least one ETag. Note that
245 # the ETag must ALWAYS been provided in the following format:
246 #
247 # W/"<benchmark-id>[;<behaviour-token>]"
248 #
249 # Note that the ETag is a weak ETag; ``weak ETag values of two representations
250 # of the same resources might be semantically equivalent, but not byte-for-byte
251 # identical.'' (https://developer.mozilla.org/en-US/docs/Web/HTTP/Headers/ETag).
252 # That is, as the developer is not directly accessing the service, they are
253 # only getting a semantically equivalent representation of the labels, but not
254 # a byte-for-byte equivalent (the model may have changed slightly, given the
255 # latest benchmark used.)
256 #
257 # The first id, the benchmark-id, is mandatory as the request must know what
258 # benchmark dataset (and service) the requested URI is being made against.
259 #
260 # The following behaviour-token is optional, indicating the tolerances to which
261 # the response will be made, and the behaviour by which the response will change
262 # given if evolution has occurred since the last benchmark was made. (Not that
263 # internally to this project, we refer to the behaviour token as a BenchmarkKey
264 # -- see ICVSB::BenchmarkKey.)
265 #
266 # One may provide multiple ETags (separated by commas) in the format:
267 #
268 # W/"<benchmark-id1>[;<behaviour-token1>]",W/"<benchmark-id2>[;<behaviour-token2
269 # <-- >]" ...
270 #
271 # Where this is the case, the label requested will attempt to match ANY of the
272 # tags provided. If failure occurs for the first, it will default to the next
273 # ETag, and so on.
274 #
275 # If NO behaviour-token is specified, then then (additionally) one must provide
276 # an "If-Unmodified-Since" request header field, indicating that the resource
277 # (labels) must have been unmodified since the given date. This will attempt to
278 # automatically locate the nearest behaviour token that was generated after the
279 # given date and request the labels against that date.
280 #
281 # The endpoint will return one of the following HTTP responses:
282 #
283 # - 200 OK if this is the first request made to this URI;
284 # - 400 Bad Request if invalid parameters were provided by the client;
285 # - 412 Precondition Failed if the key/unmodified time provided is no longer
286 # valid, and thus the key provided (or time provided) is violating the
287 # valid tolerances embedded within the key (responding further details
288 # reasoning what tolerances were violated as metadata in the response body);
289 # - 428 Precondition Required if no If-Match field is provided in request;
290 # - 422 Unprocessable Entity if a service error has occurred, indicating the
291 # service cannot process the entity or a bad request was made.
292 # - 500 Internal Server Error if a facade error has occurred.
293 #
294 # The endpoint will return the following HTTP response headers:
295 #
296 # - ETag: The ETag that was used to successfully generate a response
297 # - Last-Modified: The last time the benchmark-id was benchmarked against
298 # its dataset
299 # - Expires: The next time the benchmark with the provided id will be
300 # benchmarked against its dataset
301 # - Age: Indicates that the response provided is cached (i.e., no changes
302 # to the service the last time it was benchmarked against the dataset
303 # to not be considered a violation); returns the time elapsed in seconds
304 # since then
305 get '/labels' do
306   image_uri = CGI.unescape(params[:image])

```

```

307 |     if_match = request.env['HTTP_IF_MATCH'] || ''
308 |     if_unmodified_since = request.env['HTTP_IF_UNMODIFIED_SINCE'] || ''
309 |
310 |     halt! 400, 'URI provided to analyse is not a valid URI' unless image_uri.uri?
311 |     halt! 428, 'Missing If-Match in request header' if if_match.nil?
312 |     if !if_unmodified_since.empty? && !if_unmodified_since.httpdate?
313 |       halt! 400, 'If Unmodified Since must be compliant with the RFC 2616 HTTP date
314 |         ↪ format'
315 |     end
316 |     if_unmodified_since_date = if_unmodified_since.empty? ? nil : Time.httpdate(
317 |       ↪ if_unmodified_since)
318 |
319 |     relay_body = nil
320 |     relay_etag = nil
321 |     relay_last_modified = nil
322 |     relay_expires = nil
323 |
324 |     # Scan through each comma-separated ETag
325 |     etags = if_match.scan(%r{W/"(\d+;?\d+)",?})
326 |     if etags.empty?
327 |       halt! 428, 'Malformed ETags provided. Ensure you are using the correct format.
328 |         ↪ '
329 |     end
330 |     etags.each do |etag|
331 |       etag = etag[0]
332 |       benchmark_id, benchmark_key_id = etag.split(';').map(&:to_i)
333 |
334 |       # Check if we have a valid benchmark id
335 |       check_brc_id(benchmark_id, store)
336 |       brc = store[benchmark_id]
337 |       bk = nil
338 |
339 |       # Check if we have a key; if no key we must have a If-Unmodified-Since.
340 |       if benchmark_key_id.nil? && if_unmodified_since.empty?
341 |         halt! 400, "You have provided a benchmark id (id=#{benchmark_id}) \"\
342 |           without a behaviour token. Please provide a behaviour token \
343 |           'or include the If-Unmodified-Since request header with a RFC \
344 |           '2616-compliant HTTP date string.'"
345 |       elsif !benchmark_key_id.nil?
346 |         # Check if valid key
347 |         if ICSVB::BenchmarkKey.where(id: benchmark_key_id).empty?
348 |           halt! 400, "No such key with id #{benchmark_key_id} exists!"
349 |         end
350 |         unless benchmark_key_id.integer? && benchmark_key_id.positive?
351 |           halt! 400, 'Behaviour token must be a positive integer.'
352 |         end
353 |
354 |         bk = ICSVB::BenchmarkKey[id: benchmark_key_id]
355 |       elsif !if_unmodified_since_date.nil?
356 |         bk = brc.find_key_since(if_unmodified_since_date)
357 |         halt! 412, "No compatible behaviour token found unmodified since #{
358 |           ↪ if_unmodified_since_date}." if bk.nil?
359 |
360 |       # Process...
361 |       result = brc.send_uri_with_key(image_uri, bk)
362 |
363 |       # Set HTTP status+body as appropriate if there is no more ETags or if
364 |       # this was a successful response (i.e., no errors so don't keep trying other
365 |       # ETags...)
366 |       error = result.key?(:key_errors) || result.key?(:response_errors) || result.
367 |         ↪ key?(:service_error)

```

```

366  if [etag] == etags.last || !error
367  if result[:key_errors] || result[:response_errors]
368    status 412
369    content_type 'application/json; charset=utf-8'
370
371    key_error_len = result[:key_errors].nil? ? 0 : result[:key_errors].length
372    res_error_len = result[:response_errors].nil? ? 0 : result[::
373      ↪ response_errors].length
374
375    key_error_data = result[:key_errors].nil? ? [] : result[:key_errors].map
376      ↪ (&:to_h)
377    res_error_data = result[:response_errors].nil? ? [] : result[::
378      ↪ response_errors].map(&:to_h)
379
380    relay_body = {
381      num_key_errors: key_error_len,
382      num_response_errors: res_error_len,
383      key_errors: key_error_data,
384      response_errors: res_error_data
385    }.to_json
386
387  elsif result[:service_error]
388    status 422
389    content_type 'text/plain'
390    relay_body = result[:service_error]
391
392  else
393    content_type 'application/json; charset=utf-8'
394    unless result[:cached].nil?
395      age_sec = ((DateTime.now - result[:cached]) * 24 * 60 * 60).to_i.to_s
396      headers 'Age' => age_sec
397    end
398    status 200
399    relay_body = result[:response].to_json
400  end
401
402  relay_etag = etag
403  relay_last_modified = brc.current_key.nil? ? brc.created_at.httpdate : brc.
404    ↪ current_key.created_at.httpdate
405  relay_expires = brc.next_scheduled_benchmark_time.httpdate
406
407  end
408  headers \
409    'ETag' => "W/\"#{relay_etag}\\"", \
410    'Expires' => relay_expires, \
411    'Last-Modified' => relay_last_modified
412
413  body relay_body
414
415  error do |e|
416    halt! 500, e.message
417  end
418
419  #####
420  # DEMONSTRATION RELATED API
421  #####
422  get '/demo/categories.json' do
423    content_type 'application/json; charset=utf-8'
424    send_file(File.join(settings.demo_folder, 'categories.json'))
425
426  get '/demo/random/:type.jpg' do
427    category_data = JSON.parse(
428      File.read(File.join(settings.demo_folder, 'categories.json'))
429    )
430    ok_categories = category_data.keys
431
432  end

```

```
426 |   category = params[:type]
427 |
428 |   halt! 400, 'No category provided' if category.empty?
429 |   unless ok_categories.include?(category)
430 |     halt! 400, "Unknown category '#{category}'. Accepted category types are: '#{
431 |       ↪ ok_categories.join("", "")}'."
432 |
433 |   id = category_data[category].sample
434 |
435 |   redirect "/demo/data/#{id}.jpg"
436 |
437 |
438 | get '/demo/data/:id.*' do |_|
439 |   image_id = params[:id].split('.').first
440 |   time_id = params[:id].split('.').last
441 |
442 |   unless File.exist?(File.join(settings.demo_folder, image_id + '.jpg'))
443 |     halt! 400, "No such image with id '#{image_id}' exists in the demo database."
444 |   end
445 |   unless %w[jpg jpeg json].include?(ext)
446 |     halt! 400, 'Invalid file extension. Suffix with .jp[e]g or .t1.json or .t2.
447 |       ↪ json.'
448 |   end
449 |   ext = 'jpg' if ext == 'jpeg'
450 |
451 |   if ext == 'jpg'
452 |     content_type 'image/jpeg'
453 |   else
454 |     content_type 'application/json; charset=utf-8'
455 |     halt! 400, 'Missing time id (.t1 or .t2).' if time_id.empty? || !%w[t1 t2].
456 |       ↪ include?(time_id)
457 |     image_id += '.' + time_id
458 |   end
459 |   send_file(File.join(settings.demo_folder, image_id + '.' + ext))
```

APPENDIX C

Supplementary Materials to Chapter 8

C.1 Detailed Overview of Our Proposed Taxonomy

The following pages detail our proposed taxonomy. Detailed descriptions of the five requirements of good API documentation (dimensions) and 34 generalised API documentation artefacts (categories/sub-dimensions) that help satisfy these requirements within our proposed taxonomy. Descriptions of examples of these documentation artefacts are italicised and provided for illustrative purposes. ILS = In-Literature Score, calculated as a ratio of papers that investigated or reported various issues concerning each artefact. IPS = In-Practice Score, calculated as the average response from our survey instrument. Colour scales indicate relevancy weight within ILS or IPS values for comparative purposes, where red = *lowest* and green = *highest*. GCV, AWS, ACV = Presence of category in Google Cloud Vision, Amazon Rekognition, and Azure Cloud Vision documentation. Presence indicated as *fully present* (●), *partially present* (◐), and *not present* (○).

Key	Description	Primary Sources	ILS	IPS	GCV	AWS	ACV
A Requirement 1: API Documentation should include Descriptions of API Usage							
A1	Quick-start guides; <i>i.e., a guide to rapidly get started using the API in a specific programming language.</i>	S4, S9, S10	Low	V High	●	○	●
A2	Low-level reference manual; <i>i.e., a manual documenting all API components to review fine-grade detail.</i>	S1, S3, S4, S8, S9, S10, S11, S12, S15, S16, S17	High	High	●	●	●
A3	Explanation of high level architecture; <i>i.e., explanations of the API's high-level architecture to better understand intent and context.</i>	S1, S2, S4, S11, S14, S16, S19, S20	Med	V High	●	●	●
A4	Introspection source code comments; <i>i.e., code implementation and code comments (where applicable) to understand the API author's mindset.</i>	S1, S4, S7, S12, S13, S17, S20	Med	High	○	○	○
A5	Code snippets of basic component function; <i>i.e., code snippets (with comments) of no more than 30 LoC to understand a basic component functionality within the API.</i>	S1, S2, S4, S5, S6, S7, S9, S10, S11, S14, S15, S16, S18, S20, S21	V High	V High	●	●	●
A6	Step-by-step tutorials with multiple components; <i>i.e., step-by-step tutorials, with screenshots to understand how to build a non-trivial piece of functionality with multiple components of the API.</i>	S1, S2, S4, S5, S7, S9, S10, S15, S16, S18, S20, S21	V High	V High	○	●	●
A7	Downloadable production-ready source code; <i>i.e., downloadable source code of production-ready applications that use the API to understand implementation in a large-scale solution.</i>	S1, S2, S5, S9, S15	Low	V High	○	○	●
A8	Best-practices of implementation; <i>i.e., best-practices of implementation to assist with debugging and efficient use of the API.</i>	S1, S2, S4, S5, S7, S8, S9, S14	Med	V High	○	●	○
A9	An exhaustive list of all components; <i>i.e., a list of all the major components that exist within the API.</i>	S4, S16, S19	Low	V High	○	●	●
A10	Minimum system requirements to use the API; <i>i.e., requirements and the dependencies to use the API on a particular system.</i>	S4, S7, S13, S17, S19	Low	V High	●	○	○
A11	Instructions to install/update the API and its release cycle; <i>i.e., instructions to install or begin using the API and details on its release cycle and how to update it.</i>	S4, S7, S8, S9, S11, S13, S16, S19	Med	V High	●	●	○
A12	Error definitions describing how to address problems	S1, S2, S4, S5, S9, S11, S13	Med	V High	○	○	○

Continued on next page...

Key	Description	Primary Sources	ILS	IPS	GCV	AWS	ACV
B Requirement 2: API Documentation should include Descriptions of the API's Design Rationale							
B1	Entry-point purpose of the API; <i>i.e., a brief description of the purpose or overview of the API as a low barrier to entry.</i>	S1, S2, S4, S5, S6, S8, S10, S11, S15, S16	High	V High	●	●	●
B2	What the API can develop; <i>i.e., descriptions of concrete types of applications the API can develop.</i>	S2, S4, S9, S11, S15, S18	Med	V High	●	●	●
B3	Who should use the API; <i>i.e., descriptions of the types of users who should use the API.</i>	S4, S9	V Low	High	●	○	○
B4	Who will use the applications built using the API; <i>i.e., descriptions of the types of users who will use the product the API creates.</i>	S4	V Low	Med	○	○	○
B5	Success stories on the API; <i>i.e., example success stories of major users that describe how well the API was used in production.</i>	S4	V Low	V High	●	●	●
B6	Documentation comparing similar APIs to this API	S2, S6, S13, S18	Low	High	●	○	●
B7	Limitations on what the API can/cannot provide	S4, S5, S8, S9, S14, S16	Med	V High	○	●	●
C Requirement 3: API Documentation should include Descriptions of the Domain Concepts behind the API							
C1	Relationship between API components and domain concepts	S3, S10	V Low	High	○	○	●
C2	Definitions of domain terminology; <i>i.e., definitions of the domain-terminology and concepts, with synonyms if applicable.</i>	S2, S3, S4, S6, S7, S10, S14, S16	Med	V High	●	○	●
C3	Documentation for nontechnical audiences; <i>i.e., generalised documentation for non-technical audiences regarding the API and its domain.</i>	S4, S8, S16	Low	High	●	●	●
D Requirement 4: API Documentation should include Additional Support Artefacts to aide Developer Productivity							
D1	FAQs	S4, S7	V Low	V High	●	●	●
D2	Troubleshooting hints	S4, S8	V Low	High	○	●	○○
D3	API diagrams; <i>i.e., diagrammatically representing API components using visual architectural representations.</i>	S6, S13, S20	Low	V High	○	○	○○
D4	Contact for technical support	S4, S8, S19	Low	Med	●	●	●
D5	Printed guide	S4, S6, S7, S9, S16	Low	V High	○	●	●

Continued on next page...

Key	Description	Primary Sources	ILS	IPS	GCV	AWS	ACV
D6	Licensing information	S7	V Low	V High	○	○	●
E Requirement 5: API Documentation should be Presented in an Easily Digestible Format							
E1	Searchable knowledge base	S3, S4, S6, S10, S14, S17, S18	Med	V High	●	●	●
E2	Context-specific discussion forums	S4, S10, S11	Low	V High	●	●	●
E3	Quick-links to other relevant components	S6, S16, S20	Low	V High	○	○	○
E4	Structured navigation style; <i>i.e.</i> , <i>breadcrumbs</i>	S6, S10, S20	Low	High	●	●	●
E5	Visualised map of navigational paths; <i>i.e.</i> , <i>to certain API components in the website</i> .	S6, S14, S20	Low	V High	○	○	○
E6	Consistent look and feel	S1, S2, S3, S5, S6, S8, S10, S15, S20	High	V High	●	●	●

C.2 Sources of Documentation

Sources of documentation used for the validation of the taxonomy. For clarity, exact webpages are not referenced for each category, but can be found in supplementary materials which can be downloaded from the URL listed in the paper.

Service	Document Sources
Google Cloud Vision	https://cloud.google.com/vision/docs/quickstart-client-libraries https://googleapis.github.io/google-cloud-java/google-cloud-clients/apidocs/index.html https://cloud.google.com/vision/#cloud-vision-use-cases https://cloud.google.com/vision/docs/quickstart-client-libraries#using_the_client_library https://cloud.google.com/vision/docs/tutorials https://cloud.google.com/community/tutorials?q=vision https://cloud.google.com/vision/docs/samples#mobile_platform_examples https://cloud.google.com/docs/enterprise/best-practices-for-enterprise-organizations https://cloud.google.com/functions/docs/bestpractices/tips https://cloud.google.com/vision/#derive-insight-from-images-with-our-powerful-cloud-vision-api https://cloud.google.com/vision/docs/quickstart-client-libraries https://cloud.google.com/vision/docs/release-notes https://cloud.google.com/vision/docs/reference/rpc/google.rpc#google.rpc.Code https://cloud.google.com/vision/#insight-from-your-images https://developers.google.com/machine-learning/glossary/ https://cloud.google.com/vision/docs/resources https://cloud.google.com/vision/sla https://cloud.google.com/vision/docs/data-usage https://cloud.google.com/vision/docs/support#searchbox https://cloud.google.com/vision/docs/support

Continued on next page...

Service	Document Sources
Amazon Rekognition	<p>https://docs.aws.amazon.com/rekognition/latest/dg/getting-started.html</p> <p>https://docs.aws.amazon.com/AWSJavaSDK/latest/javadoc/index.html</p> <p>https://aws.amazon.com/blogs/machine-learning/using-amazon-rekognition-to-identify-persons-of-interest-for-law-enforcement/</p> <p>https://aws.amazon.com/rekognition/#Rekognition_Image_Use_Cases</p> <p>https://docs.aws.amazon.com/rekognition/latest/dg/labels-detect-labels-image.html</p> <p>https://aws.amazon.com/rekognition/getting-started/#Tutorials</p> <p>https://aws.amazon.com/blogs/machine-learning/category/artificial-intelligence/amazon-rekognition/</p> <p>https://docs.aws.amazon.com/code-samples/latest/catalog/code-catalog-javascript-example_code-rekognition.html</p> <p>https://docs.aws.amazon.com/rekognition/latest/dg/best-practices.html</p> <p>https://docs.aws.amazon.com/rekognition/latest/dg/API_Operations.html</p> <p>https://aws.amazon.com/rekognition/image-features/</p> <p>https://aws.amazon.com/releasenotes/?tag=releasenotes%23keywords%23amazon-rekognition</p> <p>https://docs.aws.amazon.com/rekognition/latest/dg/setting-up.html</p> <p>https://aws.amazon.com/rekognition/</p> <p>https://aws.amazon.com/rekognition/</p> <p>https://docs.aws.amazon.com/rekognition/latest/dg/limits.html</p> <p>https://aws.amazon.com/rekognition/pricing/</p> <p>https://aws.amazon.com/rekognition/sla/</p> <p>https://aws.amazon.com/rekognition/faqs/</p> <p>https://docs.aws.amazon.com/rekognition/latest/dg/video-troubleshooting.html</p> <p>https://docs.aws.amazon.com/rekognition/latest/dg/rekognition-dg.pdf</p> <p>https://github.com/awsdocs/amazon-rekognition-developer-guide/issues</p> <p>https://forums.aws.amazon.com/thread.jspa?threadID=285910</p>

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Service	Document Sources
Azure Computer Vision	https://docs.microsoft.com/en-au/azure/cognitive-services/computer-vision/quickstarts-sdk/csharp-analyze-sdk https://docs.microsoft.com/en-us/java/api/overview/azure/cognitiveservices/client/computervision?view=azure-java-stable https://docs.microsoft.com/en-us/azure/architecture/example-scenario/ai/intelligent-apps-image-processing https://docs.microsoft.com/en-us/azure/cognitive-services/computer-vision/tutorials/java-tutorial https://docs.microsoft.com/en-us/azure/cognitive-services/custom-vision-service/logo-detector-mobile https://docs.microsoft.com/en-au/azure/cognitive-services/computer-vision/tutorials/storage-lab-tutorial https://docs.microsoft.com/en-us/azure/cognitive-services/computer-vision/tutorials/csharptutorial https://docs.microsoft.com/en-us/azure/cognitive-services/custom-vision-service/getting-started-improving-your-classifier https://docs.microsoft.com/en-au/azure/cognitive-services/computer-vision/home#analyze-images-for-insight https://docs.microsoft.com/en-au/azure/cognitive-services/computer-vision/vision-api-how-to-topics/howtocallvisionapi https://docs.microsoft.com/en-us/azure/cognitive-services/custom-vision-service/release-notes https://docs.microsoft.com/en-au/azure/cognitive-services/computer-vision/ https://azure.microsoft.com/en-au/services/cognitive-services/computer-vision/ https://azure.microsoft.com/en-us/pricing/details/cognitive-services/computer-vision/ https://docs.microsoft.com/en-au/azure/cognitive-services/computer-vision/concept-tagging-images https://docs.microsoft.com/en-au/azure/cognitive-services/computer-vision/home https://azure.microsoft.com/en-us/support/legal/sla/cognitive-services/v1_1/ https://docs.microsoft.com/en-au/azure/cognitive-services/computer-vision/faq https://azure.microsoft.com/en-us/support/legal/

C.3 List of Primary Sources

The following pages list of the primary sources found from our systematic mapping study. Each citation is referenced by a prefixed ‘S’. We also list the respective citation count, as measured by the number of citations the publication has from Google Scholar as at July 2020. We also list the venue ranking (as at 2020), as measured by Scimago Rankings or Qualis Ranking for Journals and CORE Rankings for conference publications. If no rank can be found, a dash is used.

Ref	Citation	Cite#	Rank
[S1]	M. P. Robillard, "What makes APIs hard to learn? Answers from developers," <i>IEEE Software</i> , vol. 26, no. 6, pp. 27–34, 2009, DOI 10.1109/MS.2009.193. ISSN 0740-7459	305	Q1
[S2]	M. P. Robillard and R. Deline, "A field study of API learning obstacles," <i>Empirical Software Engineering</i> , vol. 16, no. 6, pp. 703–732, 2011, DOI 10.1007/s10664-010-9150-8. ISSN 1382-3256	254	Q1
[S3]	A. J. Ko and Y. Riche, "The role of conceptual knowledge in API usability," in <i>Proceedings of the 2011 IEEE Symposium on Visual Languages and Human Centric Computing</i> . Pittsburgh, PA, USA: IEEE, September 2011. DOI 10.1109/VL-HCC.2011.6070395. ISBN 978-1-45-771245-6 pp. 173–176	33	A
[S4]	J. Nykaza, R. Messinger, F. Boehme, C. L. Norman, M. Mace, and M. Gordon, "What programmers really want: Results of a needs assessment for SDK documentation," in <i>Proceedings of the 20th Annual International Conference on Computer Documentation</i> . Toronto, ON, Canada: ACM, October 2002. DOI 10.1145/584955.584976, pp. 133–141	56	–
[S5]	R. Watson, M. Mark Stammes, J. Jeannot-Schroeder, and J. H. Spyridakis, "API documentation and software community values: A survey of open-source API documentation," in <i>Proceedings of the 31st ACM International Conference on Design of Communication</i> . Greenville, SC, USA: ACM, September 2013. DOI 10.1145/2507065.2507076, pp. 165–174	14	B1
[S6]	S. Y. Jeong, Y. Xie, J. Beaton, B. A. Myers, J. Stylos, R. Ehret, J. Karstens, A. Efeoglu, and D. K. Busse, "Improving documentation for eSOA APIs through user studies," in <i>Proceedings of the First International Symposium on End User Development</i> , vol. 5435 LNCS. Siegen, Germany: Springer, March 2009. DOI 10.1007/978-3-642-00427-8_6. ISSN 0302-9743 pp. 86–105	34	–
[S7]	E. Aghajani, C. Nagy, O. L. Vega-Marquez, M. Linares-Vasquez, L. Moreno, G. Bavota, and M. Lanza, "Software Documentation Issues Unveiled," in <i>Proceedings of the 41st International Conference on Software Engineering</i> . Montreal, QC, Canada: IEEE, May 2019. DOI 10.1109/ICSE.2019.00122. ISBN 978-1-72-810869-8. ISSN 0270-5257 pp. 1199–1210	6	A*
[S8]	S. Haselbock, R. Weinreich, G. Buchgeher, and T. Kriechbaum, "Microservice Design Space Analysis and Decision Documentation: A Case Study on API Management," in <i>Proceedings of the 11th International Conference on Service-Oriented Computing and Applications</i> , Paris, France, November 2019, DOI 10.1109/SOCA.2018.00008, pp. 1–8	2	C
[S9]	S. Inzunza, R. Juárez-Ramírez, and S. Jiménez, "API Documentation," in <i>Proceedings of the 6th World Conference on Information Systems and Technologies</i> . Naples, Italy: Springer, March 2018. DOI 10.1007/978-3-319-77712-2_22, pp. 229–239	3	C

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Ref	Citation	Cite#	Rank
[S10]	M. Meng, S. Steinhardt, and A. Schubert, "Application programming interface documentation: What do software developers want?" <i>Journal of Technical Writing and Communication</i> , vol. 48, no. 3, pp. 295–330, August 2018, DOI 10.1177/0047281617721853. ISSN 1541-3780	12	Q1
[S11]	R. S. Geiger, N. Varoquaux, C. Mazel-Cabasse, and C. Holdgraf, "The Types, Roles, and Practices of Documentation in Data Analytics Open Source Software Libraries: A Collaborative Ethnography of Documentation Work," <i>Computer Supported Cooperative Work: CSCW: An International Journal</i> , vol. 27, no. 3-6, pp. 767–802, May 2018, DOI 10.1007/s10606-018-9333-1. ISSN 1573-7551	4	Q1
[S12]	A. Head, C. Sadowski, E. Murphy-Hill, and A. Knight, "When not to comment: Questions and tradeoffs with API documentation for C++ projects," in <i>Proceedings of the 40th International Conference on Software Engineering</i> , ser. questions and tradeoffs with API documentation for C++ projects. Gothenburg, Sweden: ACM, May 2018. DOI 10.1145/3180155.3180176. ISSN 0270-5257 pp. 643–653	4	A*
[S13]	L. Aversano, D. Guardabascio, and M. Tortorella, "Analysis of the Documentation of ERP Software Projects," <i>Procedia Computer Science</i> , vol. 121, pp. 423–430, January 2017, DOI 10.1016/j.procs.2017.11.057. ISSN 1877-0509	4	–
[S14]	M. P. Robillard, A. Marcus, C. Treude, G. Bavota, O. Chaparro, N. Ernst, M. A. Gerosall, M. Godfrey, M. Lanza, M. Linares-Vásquez, G. C. Murphy, L. Moreno, D. Shepherd, and E. Wong, "On-demand developer documentation," in <i>Proceedings of the 33rd IEEE International Conference on Software Maintenance and Evolution</i> . Shanghai, China: IEEE, September 2017. DOI 10.1109/ICSME.2017.17, pp. 479–483	55	A*
[S15]	R. Watson, "Development and application of a heuristic to assess trends in API documentation," in <i>Proceedings of the 30th ACM International Conference on Design of Communication</i> . Seattle, WA, USA: ACM, October 2012. DOI 10.1145/2379057.2379112. ISBN 978-1-45-031497-8 pp. 295–302	10	B1
[S16]	W. Maalej and M. P. Robillard, "Patterns of knowledge in API reference documentation," <i>IEEE Transactions on Software Engineering</i> , 2013, DOI 10.1109/TSE.2013.12. ISSN 0098-5589	110	Q1
[S17]	D. L. Parnas and S. A. Vilkomir, "Precise documentation of critical software," in <i>Proceedings of 10th IEEE International Symposium on High Assurance Systems Engineering</i> . Plano, TX, USA: IEEE, November 2007. DOI 10.1109/HASE.2007.63. ISSN 1530-2059 pp. 237–244	2	B
[S18]	C. Bottomley, "What part writer? What part programmer? A survey of practices and knowledge used in programmer writing," in <i>Proceedings of the 2005 IEEE International Professional Communication Conference</i> . Limerick, Ireland: IEEE, July 2005. DOI 10.1109/IPCC.2005.1494255, pp. 802–812	0	–

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Ref	Citation	Cite#	Rank
[S19]	A. Taulavuori, E. Niemelä, and P. Kallio, “Component documentation - A key issue in software product lines,” <i>Information and Software Technology</i> , vol. 46, no. 8, pp. 535–546, June 2004, DOI 10.1016/j.infsof.2003.10.004. ISSN 0950-5849	40	Q1
[S20]	J. Kotula, “Using patterns to create component documentation,” <i>IEEE Software</i> , vol. 15, no. 2, pp. 84–92, 1998, DOI 10.1109/52.663791. ISSN 0740-7459	27	Q1
[S21]	S. G. McLellan, A. W. Roesler, J. T. Tempest, and C. I. Spinuzzi, “Building more usable APIs,” <i>IEEE Software</i> , vol. 15, no. 3, pp. 78–86, 1998, DOI 10.1109/52.676963. ISSN 0740-7459	105	Q1

C.4 Detailed Suggested Improvements

For this assessment, we select the ILS or IPS values for categories that are considered either somewhat or very helpful (i.e., a score greater than 0.50). We then match these against categories that are found to be partially or not present within each service. In total, we found 12 categories where improvements can be made across all dimensions except Overall Presentation of Documentation, detailed below .

C.4.1 Issues regarding Descriptions of API Usage

Quick-start guides [A1]: Quick-start guides should provide a short tutorial that allows programmers to pick up the basics of an API in a programming language of their choice. For the services assessed, each offer various client SDKs (e.g., as Java or Python client libraries). Google Cloud Vision and Azure Computer Vision offer quick-start guides [420, 438] in which sets of articles target various SDKs or are client-agnostic with code snippets that can be changed to the client language/SDK of the developer’s choice. Amazon Rekognition offers exercises in setting up the AWS SDK and using the command-line interface to interact with image analysis components [398], however this is client-agnostic nor does it provide details in how to get started with using the client SDKs.

 **Suggested improvement:** Ensure tutorials detail *all* client-libraries and how developers can produce a minimum working example using the service on their own computer using that client library. For each SDK offered, there should be details on how to install, authenticate and use a component using local data. For example, this may be as simple as using the service to determine if an image of a dog contains the label ‘dog’.

Step-by-step tutorials [A6]: Google Cloud Vision offers tutorials limited to one component. These do not sufficiently demonstrate how to combine *multiple components* of the API together and how developers should integrate it with a different platform, which a good step-by-step tutorial should detail. The official AWS Machine Learning blog [395] provides extensive tutorials (in some cases, with a suggested tutorial completion time of over an hour) that integrate multiple Amazon Rekognition components with other AWS components. Microsoft provide tutorials [436, 441, 442] integrating multiple components within their service to mobile applications and the Azure platform.

 **Suggested improvement:** Ensure tutorials combine *multiple* components of the service together, are extensive, and require developers to spend a non-trivial amount of time to produce a basic application. For example, the tutorial may detail how to integrate the API into a smartphone application to achieve the following: (i) take a photo with the camera, (ii) detect if a person is within the image, (iii) analyse the visual features of the person.

Downloadable production-ready applications [A7]: Microsoft provide a downloadable application [440] that explores many components of the Azure Computer Vision API. The application is thoroughly documented with and also provides guidance on how to structure the architecture design of the program. While Rekognition

and Google Cloud Vision also provide downloadable source code, they are largely under-documented, do not combine multiple components of the API together, and only use god-classes to handle all requests to the API [399, 422].

 **Suggested improvement:** Downloadable source code should be thoroughly documented, and should avoid the use of god-classes that demonstrate a single piece of the service's functionality. Ideally, the architecture of a production-ready application should be demonstrated to developers.

Understanding best-practices [A8]: Google Cloud provides best-practices for its platform in both general and enterprise contexts [414, 423], but there is little advice provided to guide developers on how best to use Google Cloud Vision. Microsoft provides guidance on improving results of custom vision classifiers [437], but no further details on non-custom vision classifiers are found. We found the most detailed best-practices to be provided by Amazon Rekognition [397], which outlines more detailed strategies such as reducing data transfer by storing and referencing images on S3 Buckets or the attributes images should have in various scenarios (e.g., the angles of a person's face in facial recognition).

 **Suggested improvement:** Document best-practices for all major components of the computer vision service. Guide developers on the types of input data that produce the best results, advisable minimum image sizes and recommended file types, and suggest ways to overcome limitations that improve usage and cost efficiency. Provide guidance in more than one use case; give a range of scenarios that demonstrate different best practices for different domains.

Exhaustive lists of all major API components [A9]: Amazon provides a two-fold feature list that describes both the key features of Rekognition at a high-level [396] as well as a detailed, technical breakdown of each API operation provided within the service [394]. Microsoft also provide a list of high-level features that Azure Computer Vision can analyse [443] which provides hyperlinks to detailed descriptions of each feature. Google's Cloud Vision API provides a partial breakdown of the types of services provided, however this list is not fully complete, nor are there hyperlinks to more detailed descriptions of each of the features [424].

 **Suggested improvement:** Document key features that the computer vision classifier can perform at a high level. This should be easy to find from the service's landing page. Each feature should be described with reference to more detailed descriptions of the feature's exact API endpoint and required inputs, outputs and possible errors.

Minimum system requirements and dependencies [A10]: Although there is no dedicated webpage for this on any of the services investigated, there are listed dependencies for the client libraries in Google's and Azure's quick-start guides [420, 434]. These may be embedded within the quick-start guide as developers are likely to encounter dependency issues when they first start using the API. We found it a challenge to discover similar documentation this in Amazon's documentation.

☞ **Suggested improvement:** Any system requirements and dependency issues should be well-highlighted within the documentation's quick-start guide; developers are likely to encounter these issues within the early stages of using an API, and it is highly relevant to provide solutions to these issues within the quick-starts.

Installation and release cycle notes [A11]: It is imperative that developers know what has changed between releases and how frequently the releases are exported. We found release notes for Amazon Computer Vision, although they are only major releases and have not been updated since 2017 [393] which does not account for evolution in the service's responses [88]. Google's and Microsoft's release notes are generally more frequently updated, therefore developers can get a sense of its release frequency [421, 439]. However, there are evolution issues that are not addressed. Installation instructions are detailed within Rekognition's developer guide, outlining how to sign up for an account, and install the AWS command-line interface [401].

☞ **Suggested improvement:** Ensure release notes detail label evolution, including any new additional labels that may have been introduced within the service. Transparency around the changes made to the service should go beyond new features: document potential changes that may influence maintenance of a system using the computer vision service so that developers are aware of potential side-effects of upgrading to a newer release.

C.4.2 Issues regarding Descriptions of Design Rationale

Limitations of the API [B7]: The most detailed limitations documented were found on Rekognition's dedicated limitations page [400] that outlines functional limitations such as the maximum number of faces or words that can be detected in an image, the size requirements of images, and file type information. For the other services, functional limitations are generally found within each endpoint's API documentation, instead of within a dedicated page.

☞ **Suggested improvement:** Document all functional limitations in a dedicated page that outline the maximum and minimum input requirements the classifier can handle. Documentation of the types of labels the service can provide is also desired.

C.4.3 Issues regarding Descriptions of Domain Concepts

Conceptual understanding of the API [C1]: Azure Computer Vision provides 'concept' pages describing the high-level concepts behind computer vision and where these functions are implemented within the APIs (e.g., [435]). We were unable to find similar conceptual documentation for the other services assessed.

☞ **Suggested improvement:** Document the concepts behind computer vision; differentiate between foundational concepts such as object localisation, object recognition, facial localisation and facial analysis such that developers are able to make the distinction between them. Relate these concepts back to the API and provide references to where the APIs implement these concepts.

Definitions of domain-specific terminology [C2]: Terminologies relevant to machine learning concepts powering these computer vision services are well detailed within Google’s machine learning glossary [418], however few examples matching computer vision are immediately relevant. While this page is linked from the original Google Cloud Vision documentation, it may be too technical for application developers to grasp. A slightly better example of this is [443], where developers can understand computer vision terms in lay terms.

↳ Suggested improvement: *Current computer vision services use a myriad of terminologies to refer to the same conceptual feature; for example, while Microsoft refers to object recognition as ‘image tagging’, Google refers to this as ‘label detection’. If a consolidation of terms is not possible, then computer vision services should provide a glossary that provides synonyms for these terminologies so that developers can easily move between service providers without needing to relink terms back to concepts.*

C.4.4 Issues regarding Existence of Support Artefacts

Troubleshooting suggestions [D2]: The only troubleshooting tips found in our analysis were in Rekognition’s video service [402]. Further detailed instances of these troubleshooting tips could be expanded to non-video issues. For instance, if developers upload ‘noisy’ images, how can they inform the system of a specific ontology to use or to focus on parts of the foreground or background of the image? These are suggestions which we have proposed in prior work [88] that do not seem to be documented.

↳ Suggested improvement: *Ensure troubleshooting tips provide advice for testing against different types of valid input images.*

Diagrammatic overview of the API [D3]: None of the computer vision services provide any overview of the API in terms of the features and processing steps on how they should be used. For instance, pre-processing and post-processing of input and response data should be considered and an understanding of how this fits into the ‘flow’ of an application highlighted. Moreover, no UML diagrams could be found.

↳ Suggested improvement: *Provide diagrams illustrating the service within context of use, such as how it can be integrated with other service features or how a specific API endpoint may be used within a client application. Consider integrating interactive UML diagrams so that developers can easily explore various aspects of the documentation in a visual perspective.*

C.5 Survey Questions

This section contains the exact text of the survey described in Section 8.5.1. Our instrument also included questions where answers were not included in the research reported in this article, e.g. questions 1 and 2 regarding consent and ensuring participants have had development experience. Images used within the survey have been removed.

Developer opinions towards the importance of web API documentation recommendations

In this study, we are finding out how important recommendations of web API documentation are to developers. From this, we will improve AI-powered APIs. While there are screenshots of example APIs in the questions, think of an API that you have used based on **your own prior experience** when answering these questions. Thanks for taking the time to answer these questions; it should only take you about **10–20 minutes** to complete.

Attribution Notice

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Implementation-specific documentation of web APIs

When answering these questions please answer with respect to **your own experience** in learning web APIs (if applicable). Any examples provided exist solely to help illustrate the statement. For each question, please nominate how much you agree with the following statements: *[Strongly agree, Somewhat agree, Neither agree nor disagree, Somewhat disagree, Strongly disagree]*

- Q3a. I think quick-start guides with code that help me get started with an API's client library are important. e.g., quick-start guides that show how to get started and interact with the API and its responses.
- Q3b. I don't find low-level documentation of all classes and methods particularly helpful. e.g., a generated online reference manual from Javadoc comments.
- Q3c. I would imagine that explanations of the API's high-level architecture, context and rationale would be important to better understand how to consume the API. e.g., a graphic showing how the API could fit into the wider context of an application.
- Q3d. If I want to understand why an API did something that I didn't expect, the source code comments generally don't help me. e.g., an example from the Lodash API that describes why `set.add` isn't directly returned.
- Q3e. I find small code snippets with comments to demonstrate a single component's basic functionality within the API a useful way to learn. e.g., 10-30 lines of code to demonstrating various how-tos of a computer vision API.
- Q3f. I think it's cumbersome to read through step-by-step tutorials that show how to build something non-trivial with multiple components using the API. e.g., a ten-step tutorial documenting how to combine face recognition, face analysis, scene description, and landmark detection API components to generate descriptions of photos.

- Q3g. I think it's useful to download source code of production-ready applications that demonstrate the use of multiple facets of the API. e.g., a downloadable iOS app that demonstrates how to perform image analysis on an iPhone/iPad.
- Q3h. I think official documentation describing the 'best-practices' of how to use the API to assist with debugging and efficiency is not helpful. e.g., an article describing the correct ways of doing things, the best tools to use, and how to write well-performing code.
- Q3i. I believe an exhaustive list of all major components in the API without excessive detail would be useful when learning an API. e.g., a computer vision web API might list object detection, object localisation, facial recognition, and facial comparison as its 4 components.
- Q3j. I believe minimum system requirements and/or dependencies to use the API do not always need to be part of official documentation. e.g., I can find descriptions of how to get started with a Python environment for a cloud platform on community forums instead of the API's website.
- Q3k. I think instructions on how to install or access the API, update it, and the frequency of its release cycle is all useful information to know about. e.g., a list showing the latest releases, what was added and how to update your application to make use of it.
- Q3l. Error codes describing specific problems with an API are not helpful. e.g., a list of canonical HTTP error codes and how to interpret them.

Rationale-specific documentation of web APIs

When answering these questions please answer with respect to **your own experience** in learning web APIs (if applicable). Any examples provided exist solely to help illustrate the statement. For each question, please nominate how much you agree with the following statements: [*Strongly agree, Somewhat agree, Neither agree nor disagree, Somewhat disagree, Strongly disagree*]

- Q4a. I think that, as a starting point when beginning to learn about an API, I would like to read about descriptions of the API's purpose and overview.
- Q4b. I don't find descriptions of the types of applications the API can develop helpful.
- Q4c. I believe that descriptions of the types of developers who should and shouldn't use the API is important to know.
- Q4d. I don't think that descriptions of the types of end-users who will use the product built using the API is important to know in advance.
- Q4e. I think that if I read success stories about when the API was previously used in production, I would have a better indicator of how I could use that API.
- Q4f. I think that documentation that compares an API to other, similar APIs confusing and not important.
- Q4g. I believe it is important to know about what the limitations are on what the API can and cannot provide.

Conceptual-specific documentation of web APIs

When answering these questions please answer with respect to **your own experience** in learning web APIs (if applicable). Any examples provided exist solely to help illustrate the

statement. For each question, please nominate how much you agree with the following statements: [*Strongly agree, Somewhat agree, Neither agree nor disagree, Somewhat disagree, Strongly disagree*]

- Q5a. I wouldn't read through theory about the API's domain that relates theoretical concepts to API components and how both work together.
 - Q5b. I think it is important to know the definitions of the API's domain-specific terminology and concepts (with synonyms where needed). e.g., a computer vision API that uses machine learning should list machine learning concepts.
 - Q5c. It's not really important to document information about the API to non-technical audiences, such as managers and other stakeholders. e.g., pricing information, uptime information, QoS metrics/SLAs etc.
-

General-support documentation of web APIs

When answering these questions please answer with respect to **your own experience** in learning web APIs (if applicable). Any examples provided exist solely to help illustrate the statement. For each question, please nominate how much you agree with the following statements: [*Strongly agree, Somewhat agree, Neither agree nor disagree, Somewhat disagree, Strongly disagree*]

- Q6a. I find lists of Frequently Asked Questions (FAQs) helpful.
 - Q6b. When something goes wrong, I don't read through troubleshooting suggestions for specific problems straight away as I like to solve it myself.
 - Q6c. I like to see diagrammatic representations of an API's components using visual architectural visualisations. e.g., UML class diagram, sequence diagram.
 - Q6d. I wouldn't look for email addresses and/or phone number for technical support in an API's documentation.
 - Q6e. I generally refer to a programmer's reference guide or textbook about the API when I need to.
 - Q6f. I don't think it's important to read about the licensing information about the API.
-

The effect of structure and tooling on web API documentation

When answering these questions please answer with respect to **your own experience** in learning web APIs (if applicable). Any examples provided exist solely to help illustrate the statement. For each question, please nominate how much you agree with the following statements: [*Strongly agree, Somewhat agree, Neither agree nor disagree, Somewhat disagree, Strongly disagree*]

- Q7a. I would like to use a searchable knowledge base to find information.
- Q7b. I think a context-specific discussion forum between developers isn't very helpful as it just introduces noise. e.g., issue trackers, Slack group.
- Q7c. I think links to other similar documentation frequently viewed by other developers would be useful. e.g., 'people who viewed this also viewed...'
- Q7d. If I get lost within the API's documentation, a 'breadcrumbs'-style of navigation isn't very useful to me.

- Q7e. A visualised map of navigational paths to common API components in the website would be useful to have. e.g., a large and complex API for Enterprise Service-Oriented Architecture where I could click into various boxes to read about components and arrows to read about how they are related.
- Q7f. I believe ensuring consistent look and feel of all documentation isn't necessary to a good API documentation.
-

Demographics

- Q8a. Are you, or do you aspire to be, a professional programmer? Or would you consider programming a hobby?
[Professional, Hobbyist]
- Q8b. How many years have you been programming?
[1–5 years, 6–10 years, 11–15 years, 16–20 years, 21–30 years, 31–40 years, 41+ years]
- Q8c. In what type of role would you say your current job falls into?
[Back-end developer, Data or business analyst, Data scientist or machine learning specialist, Database administrator, Designer, Desktop or enterprise applications developer, DevOps specialist, Educator or academic researcher, Embedded applications or devices developer, Engineering manager, Front-end developer, Full-stack developer, Game or graphics developer, Marketing or sales professional, Mobile developer, Product manager, QA or test developer, Student, System administration]
- Q8d. What level of seniority would you say this role falls into?
[Intern Role, Graduate Role, Junior Role, Mid-Tier Role, Senior Role, Lead Role, Principal Role, Management, N/A (e.g., I am a student), Other]
- Q8e. What industry would you say you work in?
[Cloud-based solutions or services, Consulting, Data and analytics, Financial technology or services, Healthcare technology or services, Information technology, Media, advertising, publishing, or entertainment, Other software development, Retail or eCommerce, Software as a service (SaaS) development, Web development or design, N/A (e.g., I am a student), Other industry not listed here]
-

*** End of Survey ***

APPENDIX D

Authorship Statements

Deakin University Authorship Procedure

Schedule A: Authorship Statement

1. Details of the publication and executive author

Title of publication	Losing Confidence in Quality: Unspoken Evolution of Computer Vision Services
Publication details	Presented at the 35th IEEE International Conference on Software Maintenance and Evolution, Cleveland, USA, 2019
Name of executive author	Alex Cummaudo
School/Institute/Division if at Deakin Organisation and address if non-Deakin	Applied Artificial Intelligence Institute
Email or phone	ca@deakin.edu.au

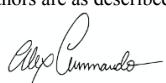
2. Inclusion of publication in a thesis

Is it intended to include this publication in a higher degree by research (HDR) thesis?
*If Yes, please complete Section 3
 If No, go straight to Section 4.*

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. <i>(If the same, write "as above")</i>	As above
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Thesis title	Taming the Evolving Black Box: Improving Integration and Documentation of Pre-Trained Machine Learning Components
If there are multiple authors, give a full description of HDR thesis author's contribution to the publication.	See page 2

I declare that the above is an accurate description of my contribution to this paper, and the contributions of other authors are as described below.

Signed: 

Dated: 22 July 2019

4. Description of all author contributions

Name and affiliation of author 1

Alex Cummaudo
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 1

Alex Cummaudo initiated the conception of the project. Additionally, he designed a detailed methodology, conducted all data collection via a data-collection instrument he designed and implemented and performed a majority of data analysis. He drafted the full manuscript and made further revisions, modifications and prepared the camera ready version for publication in the conference proceedings.

Name and affiliation of author 2

Rajesh Vasa
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 2

Rajesh Vasa contributed to the initial conception of this project by providing high-level guidance over overview of what the project and its experiments should comprise of. Rajesh also contributed to detailed revisions of the initial manuscripts, and assisted in advising Alex Cummaudo on improved analytical insight into the collected results. Rajesh Vasa also assisted in shaping the paper to specifically target the conference audience. Rajesh Vasa is the primary supervisor of Alex Cummaudo.

Name and affiliation of author 3

John Grundy
Faculty of Information Technology
Monash University

Contribution of author 3

John Grundy provided high-level oversight of the project. He contributed to detailed reviews of the methodology and manuscript. John Grundy is the external supervisor of Alex Cummaudo.

Name and affiliation of author 4

Mohamed Abdelrazek
School of Information Technology
Deakin University

Contribution of author 4

Mohamed Abdelrazek made final edits and suggestions to the final draft of the manuscript before submitting for peer review. Mohamed Abdelrazek is an associate supervisor of Alex Cummaudo.

Name and affiliation of author 5

Andrew Cain
School of Information Technology
Deakin University

Contribution of author 5

Andrew Cain made edits and suggestions to the abstract and introduction paragraphs of the manuscript. Andrew Cain is an associate supervisor of Alex Cummaudo.

5. Author declarations

I agree to be named as one of the authors of this work, and confirm:

- i. that I have met the authorship criteria set out in the Deakin University Research Conduct Policy,
- ii. that there are no other authors according to these criteria,
- iii. that the description in Section 4 of my contribution(s) to this publication is accurate,
- iv. that the data on which these findings are based are stored as set out in Section 7 below.

If this work is to form part of an HDR thesis as described in Sections 2 and 3, I further

- v. consent to the incorporation of the publication into the candidate's HDR thesis submitted to Deakin University and, if the higher degree is awarded, the subsequent publication of the thesis by the university (subject to relevant Copyright provisions).

Author 1

Alex Cummaudo


Signed: _____
Dated: 22 July 2019

Author 2

Rajesh Vasa


Signed: _____
Dated: 22 July 2019

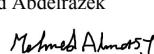
Author 3

John Grundy


Signed: _____
Dated: 22 July 2019

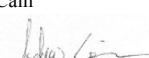
Author 4

Mohamed Abdelrazek


Signed: _____
Dated: 22 July 2019

Author 5

Andrew Cain


Signed: _____
Dated: 22 July 2019

6. Other contributor declarations

There are no other contributors for this publication to declare.

7. Data storage

The original data for this project are stored in the following locations. (The locations must be within an appropriate institutional setting. If the executive author is a Deakin staff member and data are stored outside Deakin University, permission for this must be given by the Head of Academic Unit within which the executive author is based.)

Data format	Comma separated values (CSV), iPython Notebook
Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/icsme19

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If the publication is to be included as part of an HDR thesis, a copy of this form must be included in the thesis with the publication.

Deakin University Authorship Procedure

Schedule A: Authorship Statement

1. Details of the publication and executive author

Title of publication	What should I document? A preliminary systematic mapping study into API documentation knowledge
Publication details	Presented at the 13th ACM/IEEE International Symposium on Empirical Software Engineering and Measurement (ESEM), Porto de Galinhas, Brazil, 2019
Name of executive author	Alex Cummaudo
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Organisation and address if non-Deakin	
Email or phone	ca@deakin.edu.au

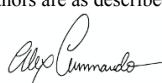
2. Inclusion of publication in a thesis

Is it intended to include this publication in a higher degree by research (HDR) thesis? Yes
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3. HDR thesis author's declaration

Name of HDR thesis author if different from above. <i>(If the same, write "as above")</i>	As above
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Thesis title	Taming the Evolving Black Box: Improving Integration and Documentation of Pre-Trained Machine Learning Components
If there are multiple authors, give a full description of HDR thesis author's contribution to the publication.	See page 2

I declare that the above is an accurate description of my contribution to this paper, and the contributions of other authors are as described below.

Signed: 
 Signed: *Alex Cummaudo*

Dated: 22 July 2019

4. Description of all author contributions

Name and affiliation of author 1	Alex Cummaudo Applied Artificial Intelligence Institute Deakin University
Contribution of author 1	Alex Cummaudo devised the conception of this project and the intended objectives and hypotheses. Additionally, he designed a detailed methodology, conducted data collection with a custom tool he wrote himself and performed analysis. He drafted the manuscript and made further revisions, modifications and prepared the camera ready version for publication in the conference proceedings.
Name and affiliation of author 2	Rajesh Vasa Applied Artificial Intelligence Institute Deakin University
Contribution of author 2	Rajesh Vasa contributed to the initial conception of this project by providing high-level guidance over overview of what the project and its experiments should comprise of. Rajesh also contributed to detailed revisions of the initial manuscripts, and assisted in advising Alex Cummaudo on improved analytical insight into the collected results. Rajesh Vasa also assisted in shaping the paper to specifically target the conference audience. Rajesh Vasa is the primary supervisor of Alex Cummaudo.
Name and affiliation of author 3	John Grundy Faculty of Information Technology Monash University
Contribution of author 3	John Grundy provided high-level oversight of the project. He contributed to detailed reviews of the methodology and manuscript. John Grundy is the external supervisor of Alex Cummaudo.

5. Author declarations

I agree to be named as one of the authors of this work, and confirm:

- i. that I have met the authorship criteria set out in the Deakin University Research Conduct Policy,
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Author 1

Alex Cummaudo


Signed:
Dated: 22 July 2019

Author 2

Rajesh Vasa


Signed:
Dated: 22 July 2019

Author 3

John Grundy


Signed:
Dated: 22 July 2019

6. Other contributor declarations

There are no other contributors for this publication to declare.

7. Data storage

The original data for this project are stored in the following locations. (The locations must be within an appropriate institutional setting. If the executive author is a Deakin staff member and data are stored outside Deakin University, permission for this must be given by the Head of Academic Unit within which the executive author is based.)

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Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/esem19

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Deakin University Authorship Procedure

Schedule A: Authorship Statement

1. Details of the publication and executive author

Title of publication	Interpreting Cloud Computer Vision Pain-Points: A Mining Study of Stack Overflow
Publication details	Presented at the 42nd International Conference on Software Engineering, Seoul, South Korea, 2020
Name of executive author	Alex Cummaudo
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Organisation and address if non-Deakin	
Email or phone	ca@deakin.edu.au

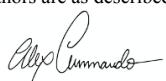
2. Inclusion of publication in a thesis

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If No, go straight to Section 4.*

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. <i>(If the same, write "as above")</i>	As above
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Thesis title	Taming the Evolving Black Box: Improving Integration and Documentation of Pre-Trained Machine Learning Components
If there are multiple authors, give a full description of HDR thesis author's contribution to the publication.	See page 2

I declare that the above is an accurate description of my contribution to this paper, and the contributions of other authors are as described below.

Signed: 

Dated: 27 August 2019

4. Description of all author contributions

Name and affiliation of author 1

Alex Cummaudo
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 1

Alex Cummaudo initiated the conception of the project. Additionally, he designed a detailed methodology, conducted the experiment and mined data against the methodology devised, performed a majority of data analysis and categorised 525 Stack Overflow posts. He drafted the full manuscript and made further revisions, modifications and prepared the camera ready version for publication in the conference proceedings.

Name and affiliation of author 2

Rajesh Vasa
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 2

Rajesh Vasa contributed to the initial conception of this project by providing high-level guidance over overview of what the project and its experiments should comprise of. Rajesh also contributed to detailed revisions of the initial manuscripts, and assisted in advising Alex Cummaudo on improved analytical insight into the collected results. Rajesh Vasa is the primary supervisor of Alex Cummaudo.

Name and affiliation of author 3

Scott Barnett
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 3

Scott Barnett conducted a statistical distribution analysis for this experiment. He contributed to detailed reviews of the methodology and manuscript. He also contributed a major section of the work regarding Technical Domain Models.

Name and affiliation of author 4

John Grundy
Faculty of Information Technology
Monash University

Contribution of author 4

John Grundy provided high-level oversight of the project. He contributed to detailed reviews of the methodology and manuscript. John Grundy is the external supervisor of Alex Cummaudo.

Name and affiliation of author 5

Mohamed Abdelrazek
School of Information Technology
Deakin University

Contribution of author 5

Mohamed Abdelrazek made final edits and suggestions to the final draft of the manuscript before submitting for peer review. Mohamed Abdelrazek is an associate supervisor of Alex Cummaudo.

5. Author declarations

I agree to be named as one of the authors of this work, and confirm:

- i. that I have met the authorship criteria set out in the Deakin University Research Conduct Policy,
- ii. that there are no other authors according to these criteria,
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- iv. that the data on which these findings are based are stored as set out in Section 7 below.

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- v. consent to the incorporation of the publication into the candidate's HDR thesis submitted to Deakin University and, if the higher degree is awarded, the subsequent publication of the thesis by the university (subject to relevant Copyright provisions).

Author 1

Alex Cummaudo


Signed: _____
Dated: 27 August 2019

Author 2

Rajesh Vasa


Signed: _____
Dated: 27 August 2019

Author 3

Scott Barnett


Signed: _____
Dated: 27 August 2019

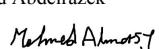
Author 4

John Grundy


Signed: _____
Dated: 27 August 2019

Author 5

Mohamed Abdelrazek


Signed: _____
Dated: 27 August 2019

6. Other contributor declarations

There are no other contributors for this publication to declare.

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Data format	Comma separated values (CSV), Excel Spreadsheet
Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/icse20

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If the publication is to be included as part of an HDR thesis, a copy of this form must be included in the thesis with the publication.

Deakin University Authorship Procedure

Schedule A: Authorship Statement

1. Details of the publication and executive author

Title of publication	Beware the evolving ‘intelligent’ web service! An integration architecture tactic to guard AI-first components
Publication details	Presented at the 28th Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering
Name of executive author	Alex Cummaudo
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Organisation and address if non-Deakin	
Email or phone	ca@deakin.edu.au

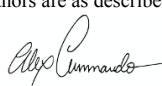
2. Inclusion of publication in a thesis

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*If Yes, please complete Section 3
 If No, go straight to Section 4.*

3. HDR thesis author’s declaration

Name of HDR thesis author if different from above. <i>(If the same, write “as above”)</i>	As above
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Thesis title	Taming the Evolving Black Box: Improving Integration and Documentation of Pre-Trained Machine Learning Components
If there are multiple authors, give a full description of HDR thesis author’s contribution to the publication.	See page 2

I declare that the above is an accurate description of my contribution to this paper, and the contributions of other authors are as described below.

Signed: 
 Alex Cummaudo

Dated: 10 March 2020

4. Description of all author contributions

Name and affiliation of author 1

Alex Cummaudo
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 1

Alex Cummaudo initiated the conception of the project, designed the architecture that is described in this paper and implemented its codebase. He designed the architectural designs appearing in the paper and many drafts of this design. Additionally, he designed a detailed methodology, conducted the experiment, performed data collection, and performed a majority of data analysis. He drafted the full manuscript and made further revisions, modifications and (will) prepare the camera ready version for publication in the conference proceedings.

Name and affiliation of author 2

Scott Barnett
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 2

Scott Barnett contributed to the initial concept of this project by providing feedback of the architecture designed. Scott also provided feedback to the architectural designs and figures/graphs appearing in this paper. Scott provided detailed reviews and edits of the introduction, approach and evaluation sections of the manuscript, and contributed to the limitations section.

Name and affiliation of author 3

Rajesh Vasa
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 3

Rajesh Vasa contributed to the initial conception of this project by providing high-level guidance over overview of what the project and its experiments should comprise of. Rajesh also contributed to detailed revisions of the initial manuscripts, and assisted in advising Alex Cummaudo on improved analytical insight into the collected results. Rajesh Vasa is the primary supervisor of Alex Cummaudo.

Name and affiliation of author 4

John Grundy
Faculty of Information Technology
Monash University

Contribution of author 4

John Grundy provided high-level oversight of the project. He contributed to detailed reviews of the methodology and manuscript. John Grundy is the external supervisor of Alex Cummaudo.

Name and affiliation of author 5

Mohamed Abdelrazek
School of Information Technology
Deakin University

Contribution of author 5

Mohamed Abdelrazek made final edits and suggestions to the final draft of the manuscript before submitting for peer review. Mohamed Abdelrazek is an associate supervisor of Alex Cummaudo.

5. Author declarations

I agree to be named as one of the authors of this work, and confirm:

- i. that I have met the authorship criteria set out in the Deakin University Research Conduct Policy,
- ii. that there are no other authors according to these criteria,
- iii. that the description in Section 4 of my contribution(s) to this publication is accurate,
- iv. that the data on which these findings are based are stored as set out in Section 7 below.

If this work is to form part of an HDR thesis as described in Sections 2 and 3, I further

- v. consent to the incorporation of the publication into the candidate's HDR thesis submitted to Deakin University and, if the higher degree is awarded, the subsequent publication of the thesis by the university (subject to relevant Copyright provisions).

Author 1

Alex Cummaudo


Signed: _____
Dated: 10 March 2020

Author 2

Scott Barnett


Signed: _____
Dated: 10 March 2020

Author 3

Rajesh Vasa


Signed: _____
Dated: 10 March 2020

Author 4

John Grundy


Signed: _____
Dated: 10 March 2020

Author 5

Mohamed Abdelrazek


Signed: _____
Dated: 10 March 2020

6. Other contributor declarations

There are no other contributors for this publication to declare.

7. Data storage

The original data for this project are stored in the following locations. (The locations must be within an appropriate institutional setting. If the executive author is a Deakin staff member and data are stored outside Deakin University, permission for this must be given by the Head of Academic Unit within which the executive author is based.)

Data format	Comma separated values (CSV), Excel Spreadsheet, Ruby Code
Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/fse2020

8. Additional notices

This form must be retained by the executive author, within the school or institute in which they are based.

If the publication is to be included as part of an HDR thesis, a copy of this form must be included in the thesis with the publication.

Deakin University Authorship Procedure

Schedule A: Authorship Statement

1. Details of the publication and executive author

Title of publication	Threshy: Supporting Safe Usage of Intelligent Web Services
Publication details	Presented at the 28th Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering (Demonstrations Track)
Name of executive author	Alex Cummaudo
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Organisation and address if non-Deakin	
Email or phone	ca@deakin.edu.au

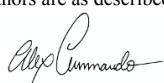
2. Inclusion of publication in a thesis

Is it intended to include this publication in a higher degree by research (HDR) thesis? Yes
*If Yes, please complete Section 3
If No, go straight to Section 4.*

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. <i>(If the same, write "as above")</i>	As above
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Thesis title	Taming the Evolving Black Box: Improving Integration and Documentation of Pre-Trained Machine Learning Components
If there are multiple authors, give a full description of HDR thesis author's contribution to the publication.	See page 2

I declare that the above is an accurate description of my contribution to this paper, and the contributions of other authors are as described below.

Signed: 

Dated: 14 January 2020

4. Description of all author contributions

Name and affiliation of author 1	Alex Cummaudo Applied Artificial Intelligence Institute Deakin University
Contribution of author 1	Alex Cummaudo drafted the manuscript for this work, prepared visualisations within the paper, made further revisions and changes per reviewer feedback and (will) prepare the camera ready version for publication in the conference proceedings. Alex also created the required demonstration video required for this publication (https://bit.ly/2YKeYhE), drafting the voiceover script, recording the voiceover itself, producing animations within the video, and recording a video of the tool in use.
Name and affiliation of author 2	Scott Barnett Applied Artificial Intelligence Institute Deakin University
Contribution of author 2	Scott Barnett contributed to the initial conception of this project by providing high-level guidance on the conceptual workflow and associated tooling. He also assisted in implementing the tool. Scott contributed to detailed reviews of the methodology and manuscript and provided feedback for the required video demonstration. Scott also provided a detailed revision of the manuscript and provided contribution to specific portions of the paper.
Name and affiliation of author 3	Rajesh Vasa Applied Artificial Intelligence Institute Deakin University
Contribution of author 3	Rajesh Vasa contributed guidance to the conceptual workflow and associated tooling presented in this paper. Rajesh also contributed to detailed revisions of the initial manuscripts and provided feedback on the tool and its associated demonstration video. Rajesh Vasa is the primary supervisor of Alex Cummaudo.
Name and affiliation of author 4	John Grundy Faculty of Information Technology Monash University
Contribution of author 4	John Grundy provided high-level oversight of the project. He contributed to detailed reviews of the manuscript and associated demonstration video. John Grundy is the external supervisor of Alex Cummaudo.

5. Author declarations

I agree to be named as one of the authors of this work, and confirm:

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- ii. that there are no other authors according to these criteria,
- iii. that the description in Section 4 of my contribution(s) to this publication is accurate,
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- v. consent to the incorporation of the publication into the candidate's HDR thesis submitted to Deakin University and, if the higher degree is awarded, the subsequent publication of the thesis by the university (subject to relevant Copyright provisions).

Author 1

Alex Cummaudo


Signed: _____
Dated: 14 January 2020

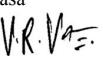
Author 2

Scott Barnett


Signed: _____
Dated: 14 January 2020

Author 3

Rajesh Vasa


Signed: _____
Dated: 14 January 2020

Author 4

John Grundy


Signed: _____
Dated: 14 January 2020

6. Other contributor declarations

There are no other contributors for this publication to declare.

7. Data storage

The original data for this project are stored in the following locations. (The locations must be within an appropriate institutional setting. If the executive author is a Deakin staff member and data are stored outside Deakin University, permission for this must be given by the Head of Academic Unit within which the executive author is based.)

Data format	JavaScript, Python, HTML, Keynote File, iMovie File
Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/icse(d)20

8. Additional notices

This form must be retained by the executive author, within the school or institute in which they are based.

If the publication is to be included as part of an HDR thesis, a copy of this form must be included in the thesis with the publication.

Deakin University Authorship Procedure

Schedule A: Authorship Statement

1. Details of the publication and executive author

Title of publication	Requirements of API Documentation: A Case Study into Computer Vision Services
Publication details	Submitted to the IEEE Transactions on Software Engineering
Name of executive author	Alex Cummaudo
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Organisation and address if non-Deakin	
Email or phone	ca@deakin.edu.au

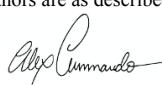
2. Inclusion of publication in a thesis

Is it intended to include this publication in a higher degree by research (HDR) thesis? Yes
*If Yes, please complete Section 3
If No, go straight to Section 4.*

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. <i>(If the same, write "as above")</i>	As above
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Thesis title	Taming the Evolving Black Box: Improving Integration and Documentation of Pre-Trained Machine Learning Components
If there are multiple authors, give a full description of HDR thesis author's contribution to the publication.	See page 2

I declare that the above is an accurate description of my contribution to this paper, and the contributions of other authors are as described below.

Signed: 
 Alex Cummaudo

Dated: 10 March 2020

4. Description of all author contributions

Name and affiliation of author 1	Alex Cummaudo Applied Artificial Intelligence Institute Deakin University
Contribution of author 1	Alex Cummaudo devised the conception of this project and the intended objectives and hypotheses. Additionally, he designed a detailed methodology, conducted data collection with a custom tool he wrote himself and performed analysis. He also designed and conducted the survey instrument listed within this publication. He drafted the full manuscript and made further revisions, modifications. He made detailed revisions to all graphs and figures within this paper.
Name and affiliation of author 2	Rajesh Vasa Applied Artificial Intelligence Institute Deakin University
Contribution of author 2	Rajesh Vasa contributed to the initial conception of this project by providing high-level guidance over overview of what the project and its experiments should comprise of. Rajesh also contributed to detailed revisions of the initial manuscript, and assisted in advising Alex Cummaudo on improved analytical insight into the collected results. Rajesh Vasa is the primary supervisor of Alex Cummaudo.
Name and affiliation of author 3	John Grundy Faculty of Information Technology Monash University
Contribution of author 3	John Grundy provided high-level oversight of the project. He contributed to detailed reviews of the methodology and manuscript. John Grundy is the external supervisor of Alex Cummaudo.
Name and affiliation of author 4	Mohamed Abdelrazek School of Information Technology Deakin University
Contribution of author 4	Mohamed Abdelrazek made final edits and suggestions to the final draft of the manuscript before submitting for peer review. Mohamed Abdelrazek is an associate supervisor of Alex Cummaudo.

5. Author declarations

I agree to be named as one of the authors of this work, and confirm:

- i. that I have met the authorship criteria set out in the Deakin University Research Conduct Policy,
- ii. that there are no other authors according to these criteria,
- iii. that the description in Section 4 of my contribution(s) to this publication is accurate,
- iv. that the data on which these findings are based are stored as set out in Section 7 below.

If this work is to form part of an HDR thesis as described in Sections 2 and 3, I further

- v. consent to the incorporation of the publication into the candidate's HDR thesis submitted to Deakin University and, if the higher degree is awarded, the subsequent publication of the thesis by the university (subject to relevant Copyright provisions).

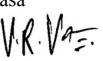
Author 1

Alex Cummaudo


Signed:
Dated: 10 March 2020

Author 2

Rajesh Vasa


Signed:
Dated: 10 March 2020

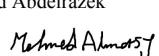
Author 3

John Grundy


Signed:
Dated: 10 March 2020

Author 4

Mohamed Abdelrazek


Signed:
Dated: 10 March 2020

6. Other contributor declarations

There are no other contributors for this publication to declare.

7. Data storage

The original data for this project are stored in the following locations. (The locations must be within an appropriate institutional setting. If the executive author is a Deakin staff member and data are stored outside Deakin University, permission for this must be given by the Head of Academic Unit within which the executive author is based.)

Data format	Comma separated values (CSV), Portable Document Format (PDF)
Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/tse2020

8. Additional notices

This form must be retained by the executive author, within the school or institute in which they are based.

If the publication is to be included as part of an HDR thesis, a copy of this form must be included in the thesis with the publication.

Deakin University Authorship Procedure

Schedule A: Authorship Statement

1. Details of the publication and executive author

Title of publication	Manual and Automatic Emotion Analysis of Computer Vision Service Pain-Points
Publication details	Submitted to the 6th International Workshop on Emotion Awareness in Software Engineering
Name of executive author	Alex Cummaudo
School/Institute/Division if at Deakin Organisation and address if non-Deakin	Applied Artificial Intelligence Institute
Email or phone	ca@deakin.edu.au

2. Inclusion of publication in a thesis

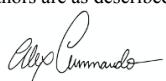
Is it intended to include this publication in a higher degree by research (HDR) thesis?

*If Yes, please complete Section 3
If No, go straight to Section 4.*

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. <i>(If the same, write "as above")</i>	As Above
School/Institute/Division if at Deakin	
Thesis title	Taming the Evolving Black Box: Improving Integration and Documentation of Pre-Trained Machine Learning Components
If there are multiple authors, give a full description of HDR thesis author's contribution to the publication.	See page 2

I declare that the above is an accurate description of my contribution to this paper, and the contributions of other authors are as described below.

Signed: 

Dated: 18 September 2020

4. Description of all author contributions

Name and affiliation of author 1	Alex Cummaudo Applied Artificial Intelligence Institute Deakin University
Contribution of author 1	Alex Cummaudo produced the data set of Stack Overflow posts used for analysis within this paper and contributed to the initial conception of this project. He drafted the methodology section that details how this data set was produced. Additionally, he drafted the threats to validity section, results and discussion sections. He reviewed the entire paper and made contributions to the findings and discussion sections. He assisted in conducting inter-rater reliability with two additional raters (Rajesh and Ulrike Maria). He prepared the graphs and tables, prepared the paper for submission, and ensured the paper was formatted to the guidelines and page limit. Alex made most of the contribution to the paper (in terms of content).
Name and affiliation of author 2	Ulrike Maria Graetsch Applied Artificial Intelligence Institute Deakin University
Contribution of author 2	Ulrike Maria's contributed to the initial conception of the project and performed the automatic EmoTxt classifier classifications on our Stack Overflow data set, which involved downloading and installing EmoTxt and adapting our data set to be compatible with EmoTxt. She drafted the findings and discussion sections based on the output from the EmoTxt classifier, including constructing the graphs and tables in the paper. Ulrike Maria also conducted a literature review into automatic emotion classifiers into Stack Overflow posts. She extracted the quotes from posts as presented in Table 3.
Name and affiliation of author 3	Maheswaree K Curumsing Applied Artificial Intelligence Institute Deakin University
Contribution of author 3	Maheswaree Curumsing contributed to the fleshing out of the project concept and coordinating the work. Maheswaree's expertise in emotion classification was leveraged in the paper, particularly around the background sections and in deciding the correct frameworks to classify posts. She conducted extensive literature reviews for this paper. Maheswaree drafted the introduction, background, part of the methodology and discussion. She was involved in classifying emotions within Stack Overflow posts for inter-rater reliability. She made further revisions to the manuscript and provided modifications where needed.
Name and affiliation of author 4	Scott Barnett Applied Artificial Intelligence Institute Deakin University
Contribution of author 4	Scott Barnett's contribution involved drafting the abstract,

conclusion and reviewing the entire manuscript for proofreading. Scott also contributed in the initial conception of the project by outlining techniques used to run the experiment.

Name and affiliation of author 5

Rajesh Vasa
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 5

Rajesh Vasa contributed to the initial conception of this project by providing high-level guidance over overview of what the project and its experiments should comprise of. Rajesh also contributed to detailed revisions of the initial manuscripts, and assisted in advising Alex Cummaudo on improved analytical insight into the collected results. Rajesh Vasa is the primary supervisor of Alex Cummaudo.

Name and affiliation of author 6

John Grundy
Faculty of Information Technology
Monash University

Contribution of author 6

John Grundy contributed to revisions of the manuscript and guidance for the publication venue. John Grundy is the external supervisor of Alex Cummaudo.

5. Author declarations

I agree to be named as one of the authors of this work, and confirm:

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- ii. that there are no other authors according to these criteria,
- iii. that the description in Section 4 of my contribution(s) to this publication is accurate,
- iv. that the data on which these findings are based are stored as set out in Section 7 below.

If this work is to form part of an HDR thesis as described in Sections 2 and 3, I further

- v. consent to the incorporation of the publication into the candidate's HDR thesis submitted to Deakin University and, if the higher degree is awarded, the subsequent publication of the thesis by the university (subject to relevant Copyright provisions).

Author 1

Alex Cummaudo



Signed: 
Dated: 18 September 2020

Author 2

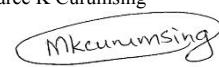
Ulrike Maria Graetsch

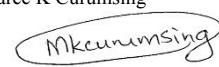


Signed: 
Dated: 18 September 2020

Author 3

Maheswaree K Curumsing



Signed: 
Dated: 18 September 2020

Author 4

Scott Barnett



Signed: 
Dated: 18 September 2020

Author 5

Rajesh Vasa



Signed: 
Dated: 18 September 2020

Author 6

John Grundy



Signed: 
Dated: 18 September 2020

6. Other contributor declarations

There are no other contributors for this publication to declare.

7. Data storage

The original data for this project are stored in the following locations. (The locations must be within an appropriate institutional setting. If the executive author is a Deakin staff member and data are stored outside Deakin University, permission for this must be given by the Head of Academic Unit within which the executive author is based.)

Data format	Comma separated values (CSV), Excel Spreadsheet
Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/semotion21

8. Additional notices

This form must be retained by the executive author, within the school or institute in which they are based.

If the publication is to be included as part of an HDR thesis, a copy of this form must be included in the thesis with the publication.

Deakin University Authorship Procedure

Schedule A: Authorship Statement

1. Details of the publication and executive author

Title of publication	Merging Intelligent API Responses Using a Proportional Representation Approach
Publication details	Presented at the 19th International Conference on Web Engineering (ICWE), Daejeon, South Korea, 2019
Name of executive author	Tomohiro Otake
School/Institute/Division if at Deakin Organisation and address if non-Deakin	Faculty of Science, Engineering and Built Environment
Email or phone	tomohiro.otake@deakin.edu.au

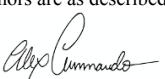
2. Inclusion of publication in a thesis

Is it intended to include this publication in a higher degree by research (HDR) thesis? Yes
*If Yes, please complete Section 3
If No, go straight to Section 4.*

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. <i>(If the same, write "as above")</i>	Alex Cummaudo
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Thesis title	Taming the Evolving Black Box: Improving Integration and Documentation of Pre-Trained Machine Learning Components
If there are multiple authors, give a full description of HDR thesis author's contribution to the publication.	See page 2

I declare that the above is an accurate description of my contribution to this paper, and the contributions of other authors are as described below.

Signed:  Dated: 2 August 2019

4. Description of all author contributions

Name and affiliation of author 1	Tomohiro Ohtake Faculty of Science, Engineering and Built Environment Deakin University
Contribution of author 1	Tomohiro Ohtake designed a detailed methodology for data collection in the primary experiment of this work. He conducted all data collection via a data-collection instrument he designed and implemented and performed a majority of data analysis. He drafted the full manuscript and made further revisions, modifications and prepared the camera ready version for publication in the conference proceedings.
Name and affiliation of author 2	Alex Cummaudo Applied Artificial Intelligence Institute Deakin University
Contribution of author 2	Alex Cummaudo's primary contribution to this work was the conception and writing up of the motivating sections in the manuscript. He additionally contributed to detailed editing of the manuscripting to make further revisions and modifications and implemented reviewer feedback.
Name and affiliation of author 3	Mohamed Abdelrazek Faculty of Science, Engineering and Built Environment Deakin University
Contribution of author 3	Mohamed Abdelrazek contributed to the initial conception of this project by providing high-level guidance over overview of what the project and its experiments should comprise of. Mohamed also contributed to detailed revisions of the initial manuscripts, and assisted in advising Tomohiro Ohtake on improved analytical insight into the collected results, and implementing reviewer feedback.
Name and affiliation of author 4	Rajesh Vasa Faculty of Science, Engineering and Built Environment Deakin University
Contribution of author 4	Rajesh Vasa provided high-level oversight of the project. He contributed to detailed reviews of the methodology and manuscript.
Name and affiliation of author 5	John Grundy Faculty of Information Technology Monash University
Contribution of author 5	John Grundy provided high-level oversight of the project. He contributed to detailed reviews of the methodology and manuscript.

5. Author declarations

I agree to be named as one of the authors of this work, and confirm:

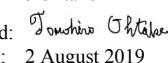
- i. that I have met the authorship criteria set out in the Deakin University Research Conduct Policy,
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- iii. that the description in Section 4 of my contribution(s) to this publication is accurate,
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Author 1

Tomohiro Otake

Signed: 
Dated: 2 August 2019

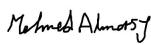
Author 2

Alex Cummaudo


Signed: 
Dated: 2 August 2019

Author 3

Mohamed Abdelrazek


Signed: 
Dated: 2 August 2019

Author 4

Rajesh Vasa


Signed: 
Dated: 2 August 2019

Author 5

John Grundy


Signed: 
Dated: 2 August 2019

6. Other contributor declarations

There are no other contributors for this publication to declare.

7. Data storage

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Data format	Comma separated values (CSV)
Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/icwe19

8. Additional notices

This form must be retained by the executive author, within the school or institute in which they are based.

If the publication is to be included as part of an HDR thesis, a copy of this form must be included in the thesis with the publication.

Deakin University Authorship Procedure

Schedule A: Authorship Statement

1. Details of the publication and executive author

Title of publication	Using Pre-Trained Emotion Classification Models on Stack Overflow Questions: Lessons Learned
Publication details	Submitted for the 33rd International Conference on Advanced Information Systems Engineering
Name of executive author	Ulrike Maria Graetsch
School/Institute/Division if at Deakin Organisation and address if non-Deakin	Applied Artificial Intelligence Institute
Email or phone	maria.graetsch@deakin.edu.au

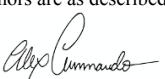
2. Inclusion of publication in a thesis

Is it intended to include this publication in a higher degree by research (HDR) thesis? Yes
*If Yes, please complete Section 3
If No, go straight to Section 4.*

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. <i>(If the same, write "as above")</i>	Alex Cummaudo
School/Institute/Division if at Deakin	Applied Artificial Intelligence Institute
Thesis title	Taming the Evolving Black Box: Improving Integration and Documentation of Pre-Trained Machine Learning Components
If there are multiple authors, give a full description of HDR thesis author's contribution to the publication.	See page 2

I declare that the above is an accurate description of my contribution to this paper, and the contributions of other authors are as described below.

Signed:  Dated: 2 June 2020

4. Description of all author contributions

Name and affiliation of author 1

Ulrike Maria Graestch
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 1

Ulrike Maria's contributed to the initial conception of the project and performed the automatic classifier classifications (EmoTxt) on our Stack Overflow data set, which involved downloading and installing EmoTxt and adapting our data set to be compatible with EmoTxt. Ulrike Maria drafted the initial manuscript, conducted the literature review presented in the work, and performed calculations on the inter-rater agreement statistics. She explored the training dataset of EmoTxt and investigated the data imbalance and emotion labelling bias discussed within the work, and proposal for future tooling to alleviate issues identified.

Name and affiliation of author 2

Alex Cummaudo
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 2

Alex Cummaudo produced the data set of Stack Overflow posts used for analysis within this paper. He performed a detailed review of the manuscript and made substantial changes to the paper's content, producing figures and tables within the paper. He revised the Fleiss' Kappa statistic and proposed changes to observed percentage agreement. He set up and conducted inter-rater reliability with two additional raters (Maheswaree and Ulrike Maria). He reviewed the entire paper and made contributions to the findings and discussion sections. He validated inter-rater reliability statistics against the three raters and against the automatic classifications made from EmoTxt. He prepared the paper for submission, and ensured the paper was formatted to the guidelines and page limit by reducing whitespace.

Name and affiliation of author 3

Rajesh Vasa
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 3

Rajesh Vasa contributed to the initial conception of this project by providing high-level guidance over overview of what the project and its experiments should comprise of. Rajesh also contributed to detailed revisions of the initial manuscripts, and assisted in advising Alex Cummaudo on improved analytical insight into the collected results. Rajesh Vasa is the primary supervisor of Alex Cummaudo.

Name and affiliation of author 4

Maheswaree K Curumsing
Applied Artificial Intelligence Institute
Deakin University

Contribution of author 4

Maheswaree K Curumsing's contribution involved structuring the approach used around the EmoTxt classifier to label emotions within Stack Overflow posts. Further, she contributed to the manual classification for inter-rater reliability. She made further revisions and proofreading to the manuscript and provided modifications

where needed. Maheswaree also contributed in the initial conception of the project by outlining techniques used to run the experiment and her expertise in emotion classification was leveraged in the paper.

5. Author declarations

I agree to be named as one of the authors of this work, and confirm:

- i. that I have met the authorship criteria set out in the Deakin University Research Conduct Policy,
- ii. that there are no other authors according to these criteria,
- iii. that the description in Section 4 of my contribution(s) to this publication is accurate,
- iv. that the data on which these findings are based are stored as set out in Section 7 below.

If this work is to form part of an HDR thesis as described in Sections 2 and 3, I further

- v. consent to the incorporation of the publication into the candidate's HDR thesis submitted to Deakin University and, if the higher degree is awarded, the subsequent publication of the thesis by the university (subject to relevant Copyright provisions).

Author 1

Ulrike Maria Graetsch



Signed:
Dated: 2 June 2020

Author 2

Alex Cummaudo



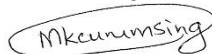
Signed:
Dated: 2 June 2020

Author 3

Rajesh Vasa


Signed:
Dated: 2 June 2020**Author 4**

Maheswaree K Curumsing


Signed:
Dated: 2 June 2020

6. Other contributor declarations

There are no other contributors for this publication to declare.

7. Data storage

The original data for this project are stored in the following locations. (The locations must be within an appropriate institutional setting. If the executive author is a Deakin staff member and data are stored outside Deakin University, permission for this must be given by the Head of Academic Unit within which the executive author is based.)

Data format	Comma separated values (CSV), Excel Spreadsheet
Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/caise21

8. Additional notices

This form must be retained by the executive author, within the school or institute in which they are based.

If the publication is to be included as part of an HDR thesis, a copy of this form must be included in the thesis with the publication.

APPENDIX E

Ethics Clearance



Rajesh Vasa and Alex Cummaudo
Applied Artificial Intelligence Institute (A²I²)
C.c Mohamed Abdelrazek, Andrew Cain

2 May 2019

Dear Rajesh and Alex

STEC-11-2019-CUMMAUDO titled "*Developer opinions towards the importance of web API documentation recommendations*"

Thank you for submitting the above project for consideration by the Faculty Human Ethics Advisory Group (HEAG). The HEAG recognised that the project complies with the National Statement on Ethical Conduct in Human Research (2007) and has approved it. You may commence the project upon receipt of this communication.

The approval period is for three years until **02/05/22**. It is your responsibility to contact the Faculty HEAG immediately should any of the following occur:

- Serious or unexpected adverse effects on the participants
- Any proposed changes in the protocol, including extensions of time
- Any changes to the research team or changes to contact details
- Any events which might affect the continuing ethical acceptability of the project
- The project is discontinued before the expected date of completion.

You will be required to submit an annual report giving details of the progress of your research. Please forward your first annual report on **02/05/20**. Failure to do so may result in the termination of the project. Once the project is completed, you will be required to submit a final report informing the HEAG of its completion.

Please ensure that the Deakin logo is on the Plain Language Statement and Consent Forms. You should also ensure that the project ID is inserted in the complaints clause on the Plain Language Statement, and be reminded that the project number must always be quoted in any communication with the HEAG to avoid delays. All communication should be directed to sciethic@deakin.edu.au

The Faculty HEAG and/or Deakin University Human Research Ethics Committee (HREC) may need to audit this project as part of the requirements for monitoring set out in the National Statement on Ethical Conduct in Human Research (2007).

If you have any queries in the future, please do not hesitate to contact me.

We wish you well with your research.

Kind regards

A handwritten signature in blue ink that reads "Teresa Treffry".

Teresa Treffry
Secretary, Human Ethics Advisory Group (HEAG)
Faculty of Science Engineering & Built Environment



Rajesh Vasa, Mohamed Abdelrazeq, Andrew Cain, Scott Barnett, Alex Cummaudo
Applied Artificial Intelligence Institute (A²I²) (G)

23rd July 2019

Dear Rajesh and research team

STEC-39-2019-CUMMAUDO titled "*Factors that impact the learnability, interpretability and adoption of intelligent services*".

Thank you for submitting the above project for consideration by the Faculty Human Ethics Advisory Group (HEAG). The HEAG recognised that the project complies with the National Statement on Ethical Conduct in Human Research (2007) and has approved it. You may commence the project upon receipt of this communication.

The approval period is for three years until 23/07/22. It is your responsibility to contact the Faculty HEAG immediately should any of the following occur:

- Serious or unexpected adverse effects on the participants
- Any proposed changes in the protocol, including extensions of time
- Any changes to the research team or changes to contact details
- Any events which might affect the continuing ethical acceptability of the project
- The project is discontinued before the expected date of completion.

You will be required to submit an annual report giving details of the progress of your research. Please forward your first annual report on 23/07/20. Failure to do so may result in the termination of the project. Once the project is completed, you will be required to submit a final report informing the HEAG of its completion.

Please ensure that the project number must always be quoted in any communication with the HEAG to avoid delays. All communication should be directed to sciethic@deakin.edu.au.

The Faculty HEAG and/or Deakin University Human Research Ethics Committee (HREC) may need to audit this project as part of the requirements for monitoring set out in the National Statement on Ethical Conduct in Human Research (2007).

If you have any queries in the future, please do not hesitate to contact me.

We wish you well with your research.

Kind regards

Rickie Morey

Rickie Morey
Senior Research Administration Officer
Representing the Human Ethics Advisory Group (HEAG)
Faculty of Science Engineering & Built Environment