Improved Usage of Pre-Trained Machine Learning Models Abstracted through Software Components

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A thesis submitted in partial fulfilment of the requirements for the
Doctor of Philosophy

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January 12, 2021

ABSTRACT

Software components hide implementation complexity by exposing a designed interface that permits easy integration and use. The explosive demand and interest in artificial intelligence (AI) and deep learning has led to creation of software components that offer various machine learning (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.

Acknowledgements

A long journey of 20 years education has led me to this thesis, and there are so many people who've helped me get to this point that deserve thanking. To start, I must thank my family; you have always been there for me in times good and bad. I'm especially grateful to my mother, Rosa, my father, Paul, my siblings, Marc and Lisa, and my nonna, Michelina Bonacci, for your love and support. I also thank my nieces Nina and Lucy (though too young to read this now!) for bringing us all so much joy in these few years. I must thank all my teachers, particularly Natalie Heath from my time at Parade College, whose hard efforts certainly paid off in my tertiary education. And, of course, I thank all those who have helped shape this thesis. Firstly, to Professor Rajesh Vasa: thank you for your many revisions, patience, ideas, and efforts to shape this work. Your years of guidance—both as a supervisor and as a mentor—has reshaped my worldview I now approach thought and problem-solving in a remarkably new light. Secondly, I thank Professor John Grundy for being such an approachable and hard-working supervisor, always willing to provide structure, feedback, and guidance to help me get over the finish line. I also thank Dr Scott Barnett for the interest you have shown in my work and for the joint collaborations we achieved in the last two years. I thank Associate Professor Mohamed Abdelrazek for your many contributions within this thesis. Lastly, I thank Associate Professor Andrew Cain, who not only taught me the realm of programming back in undergraduate days, but who first suggested a PhD was within my reach which I'd never even fathomed. I must thank everyone at the Applied Artificial Intelligence Institute for creating such an enjoyable environment to work in, especially Jake Renzella, Reuben Wilson, Dean Biddau, Beth Bland, Mahdi Babaei, Rodney Pilgrim, and Simon Vajda and for their friendship over these years and for all the coffee runs, conversations, and ideas shared. And, lastly, to Tom Fellowes: thank you for being by my side throughout this journey as we have worked to complete our PhDs together.

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

— Alex Cummaudo
January 12, 2021

Statistics about this PhD

This PhD journey consisted of the following:

- 82,188 words;
- 38,281 lines of LaTeX;
- 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)

Contents

List of Publications

Below lists publications arising from work completed in this PhD.

1. A. Cummaudo, R. Vasa, J. Grundy, and M. Abdelrazek, “Requirements of API Documentation: A Case Study into Computer Vision Services,” *IEEE Transactions on Software Engineering*, pp. 1–1, 2020, DOI 10.1109/TSE.2020.3047088
2. 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
3. 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
4. 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
5. 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
6. 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
7. 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

A^2I^2 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, 113–115, 120–123, 125, 126, 156, 157, 161, 162, 176, 185, 186, 189, 202, 209, 216, 218, 220

API application programming interface. iii, 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, 104–107, 109, 110, 113, 115, 121, 125–131, 133–157, 159–162, 164, 166, 167, 169, 170, 173, 176, 182, 183, 185, 187, 189, 192–194, 200, 206, 209, 213, 215–217, 253, 256

BYOML Build Your Own Machine Learning. 7, 8

CC connected component. 164, 167–169, 173

CDSS clinical decision support system. 10, 12

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

CRUD create, read, update, and delete. 256

CVS computer vision service. 4, 9–12, 14, 16–20, 22–27, 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, 104, 106, 110, 111, 114, 115, 120, 125–129, 131, 138, 139, 141, 142, 144, 148–151, 153–157, 159, 161, 162, 164, 167, 169, 173, 176, 186, 187, 190, 192, 193, 200, 202, 207, 209, 213–218, 257

DCE distributed computing environment. 253

DSM Distributional Semantic Model. 115

HITL human-in-the-loop. 13

HTML Hypertext Markup Language. 84

HTTP Hypertext Transfer Protocol. 8, 197, 198, 201, 206, 253, 255, 256

IDE integrated development environment. 34

IDL interface definition language. 253, 256

ILS In-Literature Score. 127, 139, 144–148, 153, 155, 156

IPS In-Practice Score. 127, 139, 143–149, 156

IRR inter-rater reliability. 97

IWS intelligent web service. 6, 7, 9, 11–14, 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, 110, 113, 114, 123, 124, 157, 159–161, 173, 175, 176, 178, 180–182, 185, 186, 188, 189, 192–195, 206–209, 213, 218–220, 257

JSON JavaScript Object Notation. 9, 176, 190, 198, 200

ML machine learning. iii, xix, 3–8, 10, 11, 14, 16, 17, 20, 22, 25, 33, 38, 41, 43, 57, 58, 61, 62, 72, 74, 78–80, 82, 83, 95, 96, 101, 105, 110, 111, 119, 121, 159, 160, 173, 175, 176, 178, 180, 182

NN neural network. 15, 36–38, 40

PaaS Platform as a Service. 7, 13, 61

QoS quality of service. 61, 62, 253

RAML RESTful API Modeling Language. 256

REST REpresentational State Transfer. iii, 7, 58, 77, 78, 98, 125, 160, 185, 209, 254, 256

ROI region of interest. 12, 13

RPC remote procedure call. 253

SDK software development kit. 59, 89, 133, 150

SLA service-level agreement. 61, 253

SMS systematic mapping study. 22, 23, 26, 127–131, 137, 146, 147, 152, 154, 156, 157

SO Stack Overflow. 7, 17, 20, 25, 26, 46, 47, 50, 53, 54, 62, 63, 77, 79–85, 87, 88, 91–98, 101–106, 108, 110, 111, 113–117, 119, 120, 122–124, 216

SOA service-oriented architecture. 253

SOAP Simple Object Access Protocol. 7, 253–256

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, 127, 141, 143

SVM support vector machine. 36, 40, 115

SWEBOK Software Engineering Body of Knowledge. 133, 134, 137

URI uniform resource identifier. 256

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

WADL Web Application Description Language. 256

WSDL Web Services Description Language. 253

XML eXtendable markup language. 9, 253

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Part I

Preface

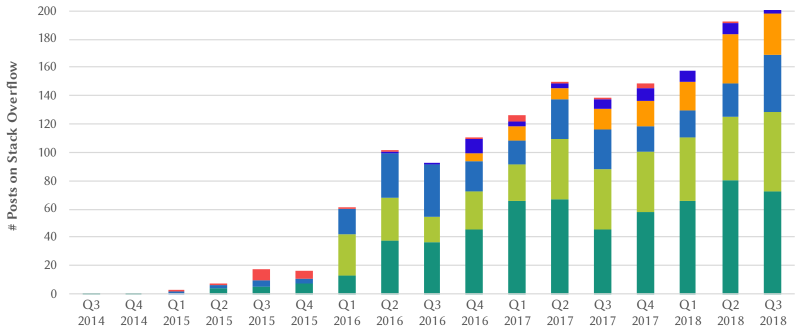
CHAPTER 1

Introduction

Abstraction layers are the application developer's productivity powerhouse as developers need not continuously consider underlying mechanics. The ubiquitous application programming interface (API) enables separation of concerns and reusable component interaction. For example, complex graphics rendering and image manipulation is all achievable via a half-dozen lines of code with appropriate libraries and frameworks, such as OpenCV's API [54].

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

Application developers build procedural and functional applications, where code typically evaluates deterministically to produce outcomes. Such software does not rely on probabilistic behaviour. This is unlike AI-first software where, often, ML techniques are employed. However, application developers, who are accustomed to such traditional software engineering paradigms, may not be aware of potential side-effects of those probabilistic techniques. Software that leverages recent advances in AI—and, more specifically, data-driven ML techniques—will often have a layer of rules that wrap the ML components. AI-first software is, however, not *solely* procedural-driven, and combines large datasets with rules to produce outcomes. Therefore, they are both *data-driven* and procedural-driven. The consequence is that large datasets (that train ML models) combined with the algorithmic techniques



	Q3 2014	Q4 2014	Q1 2015	Q2 2015	Q3 2015	Q4 2015	Q1 2016	Q2 2016	Q3 2016	Q4 2016	Q1 2017	Q2 2017	Q3 2017	Q4 2017	Q1 2018	Q2 2018	Q3 2018
Total	1	1	3	8	18	16	61	101	92	111	126	150	138	149	158	192	201
CloudSight	0	0	1	2	8	5	1	1	0	2	4	1	1	4	0	1	0
Clarifai	0	0	0	0	0	0	0	1	1	10	4	4	6	9	8	7	3
Amazon Rekognition	0	0	0	0	0	0	0	0	0	5	10	8	15	17	20	35	29
IBM Watson	0	0	2	2	5	4	18	31	36	22	16	27	28	19	19	24	41
Google Cloud Vision	0	0	0	0	0	0	29	30	18	26	26	43	42	42	45	45	55
Microsoft Cognitive Services	1	1	0	4	5	7	13	38	37	46	66	67	46	58	66	80	73

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.

behind these models result in probabilistic behaviour. Further, since these models can continually learn from *new* data with time, existing probabilistic behaviour can evolve and thus regression testing techniques need to be adjusted as well for new data.

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

1. The application developer defines an ML model from scratch and trains it from a curated dataset. This approach is laborious in time and demands experience and knowledge of ML methods, but the tradeoff is that they have full autonomy in the models they create.
2. The application developer downloads a pre-trained model (e.g., YOLO [298] for computer vision, or GPT-2 [294] for natural language processing) and 'plugs' it into an existing ML framework, such as Tensorflow [1] or PyTorch [276]. This approach removes the time taken to collect data, design and train the ML model; the developers, still need to know where to find these models, evaluate them, and then learn the frameworks[2] within which they operate to use them effectively.
3. The application developer uses a cloud-based service. It is fast to integrate into their applications, and the APIs offered abstract the technical know-how behind a web call.

While much research has investigated these first two perspectives (see Chapter 2),

[2]Thus 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 [223].)

Category	Sample Vendors & Products	Typical Use Cases
Embedded AI: Expert assistants leverage AI technology embedded in platforms and solutions.	Amazon: *Alexa* Apple: *Siri* Facebook: *Messenger* Google: *Google Assistant* Microsoft: *Cortana* Salesforce: *MetaMind*	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]: *24[7]* Admantx: *Admantx* Affectiva: *Affdex* Assist: *AssistDigital* Automated Insights: *Wordsmith* Beyond Verbal: *Beyond Verbal* Expert System: *Cogito* HPE: *Haven OnDemand* IBM: *Watson Analytics* Narrative Science: *Quill* Nuance: *Dragon* Salesforce: *MetaMind* Wise.io: *Wise Support*	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: *Engage, Amplify* Digital Reasoning: *Synthesys* Google: *Google Cloud ML* IBM: *Watson Knowledge Studio* Intel: *Saffron Natural Intelligence* IPsoft: *Amelia, Apollo, IP Center* Microsoft: *Cortana Intelligence Suite* Nuance: *360 platform* Salesforce: *Einstein* Wipro: *Holmes*	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.

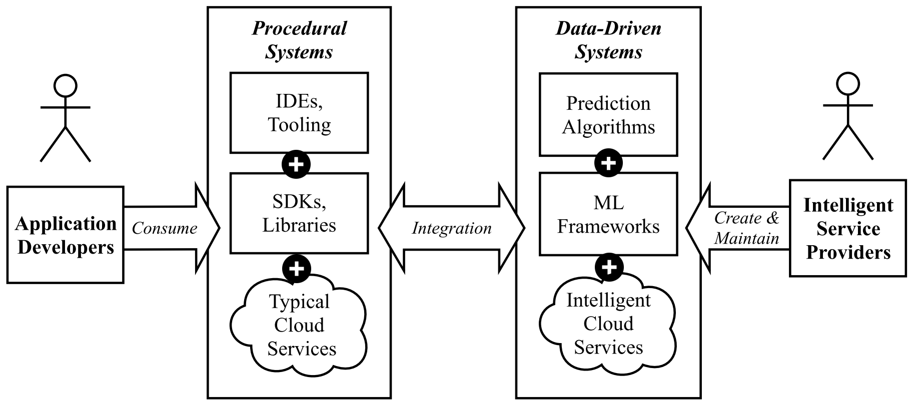


Figure 1.2: The application developer's procedural-driven toolchain is distinct from data-driven toolchain. A developer must consume a typical, data-driven cloud service in a different way than an intelligent data-driven cloud service as they are not the same type of system.

the third is yet to be deeply explored, despite the fact that vendors are promoting new offerings encapsulated under this third perspective. As shown in Table 1.1, vendors are rapidly pushing out new ML-based offerings in the form of cloud-based APIs end-points (AI platforms), where the API abstraction masks away the underlying mechanics of the models. Developers that use these cloud-based services are presented with documentation providing a narrative (i.e., marketing and in the documentation) that implies integration of these services are just like other cloud services. But does this implication, coupled with abstractions that hide the assumptions made by the AI-service providers, lead to developer pain-points and miscomprehension? If so, how can the service providers improve their documentation to alleviate this? Do these data-driven services share similarities to the runtime behaviour of traditional cloud services? And if not, how best can the application developer integrate the data-driven service into their a procedural-driven application to produce AI-first 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

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

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.

1.1 Research Context

There are a range of integration techniques available to developers, as reflected by Google AI's[3] *machine learning spectrum* [208, 235, 269]. This range is grouped into the three tiers aforementioned, encompassing skills, effort, users, and types of outputs of integration techniques. At one extreme, this approach involves the academic research of developing algorithms and self-sourcing data to achieve intelligence—coined as Build Your Own Machine Learning (BYOML) [181, 235, 269]. The other extreme involves off-the-shelf, 'friendlier' (abstracted) intelligence with easy-to-use APIs targeted towards applications developers. The middle-ground involves a mix of the two, with varying levels of automation to assist in development, that turns custom datasets into machine intelligence. We illustrate the slightly varied characteristics within this spectrum in Table 1.3 and Figure 1.3.

These cloud AI-services are gaining traction within developer circles: we show an increasing trend of Stack Overflow posts mentioning intelligent computer vision services in Figure 1.1.[4] Academia provides varied nomenclature for these services, such as *Cognitive Applications* and *Machine Learning Services* [368] or *Machine Learning as a Service* [301]. For the context of this thesis, we will refer to such services under broader term of **intelligent web services (IWSs)**,[5] and diagrammatically express their usage within Figure 1.4.

There are many types of IWSs available to software developers, offering a range of functions, such as optical character recognition, text-to-speech and speech-to-text transcription, object categorisation, facial analysis and recognition, and natural language processing. The general workflow of using an IWS is more-or-less the same: a developer accesses an IWS component via REST/SOAP API(s), which is (typically) available as a cloud-based Platform as a Service (PaaS).[6,7] Developers

[3]Google 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* [165] is evident. A further example includes how Facebook leverage AI *at scale* within their infrastructure and platforms [273].

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

[5]This 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.

[6]We 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.

[7]A number of services provide the platform infrastructure to rapidly begin training from custom

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				✓	✓

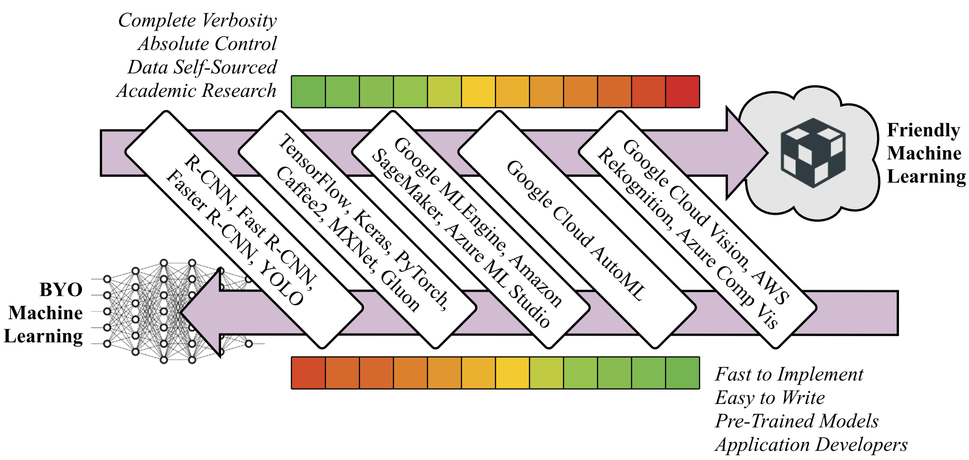


Figure 1.3: Examples within the ML spectrum of computer vision. Colour scales indicates the benefits (green) and drawbacks (red) of each end of the spectrum.

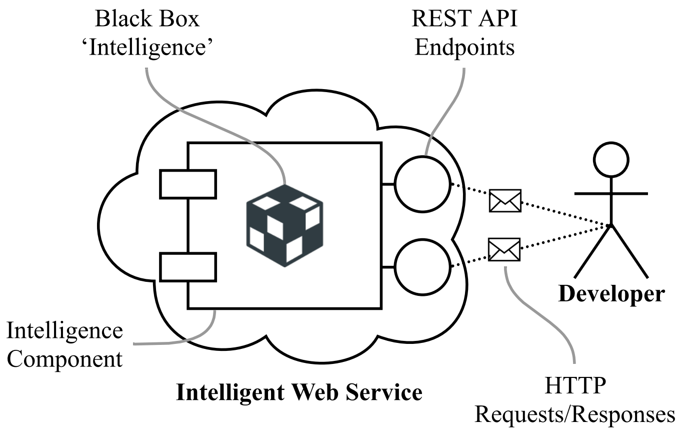


Figure 1.4: Overview of intelligent web services (IWSs).

send a given request to analyse a specific piece of data (e.g., an image, body of text, audio file etc.) and receive some intelligence on the data (e.g., object detection, text sentiment, transcription of audio) in addition to an associated *confidence* value that represents the likelihood of that result. This is typically serialised as a JSON/XML response object.

> ☞ *Within this thesis, we scope our investigation to a mature* subset *of IWSs that provide computer vision intelligence [395, 398, 411, 412, 413, 419, 423, 432, 433, 435, 437, 485, 486]. For the context of this thesis, we will refer to such services as* ***computer vision services or CVSs****.*

1.2 Motivating Scenarios

The market for computer vision services (CVSs) is expanding (Table 1.1) with a corresponding interest from developers (Figure 1.1). These services are inherently probabilistic in their behaviour, in that the end-points always return with a response with a probability. This is unlike a typical API that would return a response (*without* a probability) or an error. If developers do not fully understand the nature of these services when integrating with them, there is an impact on the quality of software they create.

To illustrate the context of use, we present the two scenarios of varying risk: (i) a fictional software developer, named Tom, who wishes to develop an inherently

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.

low-risk photo labelling application for his friends and family; and (ii) a high-risk cancer clinical decision support system (CDSS) that uses patient scans to recommend if surgeons should send their patients to surgery. Both describe scenarios where AI-infused components has an impact to end-users when the software engineers developing with them misunderstand the nuances of ML, ultimately affecting external quality. Moreover, when developers lack a comprehension, this hinders their productivity and understanding/appreciation of AI-based components.

1.2.1 Low Risk Motivating Scenario

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

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

More concretely, in Table 1.4, we illustrate how three (anonymised) CVS providers fail to provide similar consistency to that of the substring example above. If Tom uploads a photo of a border collie[8] to three different providers in August 2018 and January 2019, he would find that each provider is different in both the vocabulary used between. The confidence values and labels within the *same* provider varies within a matter of five months. The evolution of the confidence changes is not explicitly documented by the providers (i.e., when the models change) nor do they document what confidence means. Service providers use a tautological nature when defining what the confidence values are (as presented in the API documentation) provides no insight for Tom to understand why there was a change in confidence, which we show in Table 1.5, unless he *knows* that the underlying models change with them. Furthemore, they do not provide detailed understanding on how to select a

[8]The 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**

threshold cut-off for a confidence value. Therefore, he's left with no understanding on how best to tune for image classification in this instance. The deterministic problem of a substring compared to the nondeterministic nature of the IWS is, therefore, non-trivial.

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

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

Although Tom generally anticipates these CVSs to not be perfect, he has no prior benchmark to guide him on what to expect. The imperfections appear to be low-risk, but may become socially awkward when in use; for instance, if Tom's friends have low self-esteem and use the app, they may be sensitive to the app not

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	*"Score is the confidence score, which ranges from 0 (no confidence) to 1 (very high confidence)."* [421]
	"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]." [422]
	"The overall score of the result. Range [0, 1]" [422]
Provider B	*"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."* [438]
	"The level of confidence the service has in the caption." [436]
Provider C	*"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."* [396]
	"[Provider C] also provide[s] a percentage score for how much confidence [Provider C] has in the accuracy of each detected label." [397]

identifying them or mislabelling them. Privacy issues come into play especially if certain friends have access to certain photos that they are (supposedly) in; e.g., photos from a holiday with Tom and his partner, however if the API identifies Tom's partner as a work colleague, Tom's partner's privacy is at risk.

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

1.2.2 High Risk Motivating Scenario

Recent studies in the oncology domain have used deep-learning convolutional neural networks (CNNs) to detect region of interests (ROIs) in image scans of tissue (e.g., [33, 149, 222]), flagging these regions for doctors to review. Trials of such algorithms have been able to accurately detect cancer at higher rates than humans, and thus incorporating such capabilities into a CDSS is closer within reach. Studies have suggested these systems may erode a practitioner's independent decision-making [75, 177] 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.

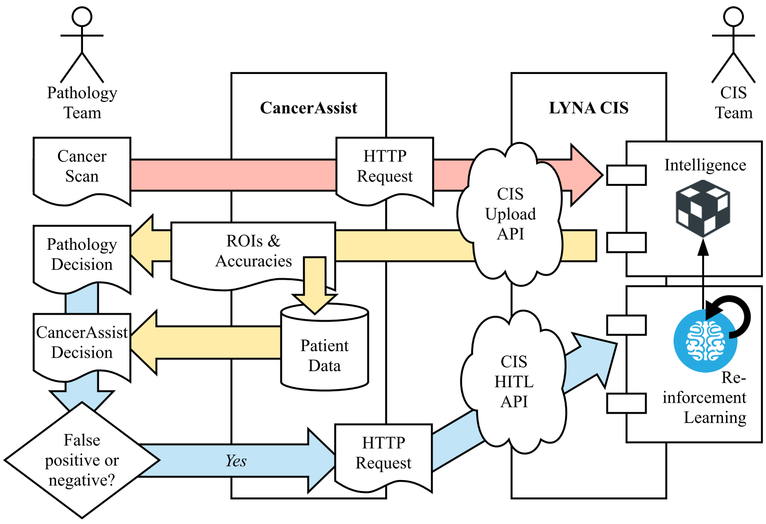


Figure 1.5: CancerAssist Context Diagram. ***Key:*** *Red Arrows = Scan Input; Yellow Arrows = Decision Output; Blue Arrows = HITL Feedback Input.*

Powering CancerAssist is Google AI's Lymph Node Assistant (LYNA) [222], a CNN based on the Inception-v3 model [205, 347]. 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 are 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 as CancerAssist and its underlying IWS. The ramifications of not being able to test such a system and putting it out into production may prove fatal to patients.

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

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

Thus, to improve communication between developers and IWS providers, developers require enhanced documentation, additional metadata, and guidance tooling.

1.3 Research Motivation

Evermore applications are considering IWSs as demonstrated by ubiquitous examples: aiding the vision-impaired [95, 299], accounting [230], data analytics [175], and student education [101]. Our motivating examples illustrate impact on developers when CVSs encapsulate assumptions and are poorly documented. Such components are accessible through APIs consisting of 'black box' intelligence (Figure 1.4).[9] ML models are inherently probabilistic and stochastic, contributing to four critical issues for developers that motivate this research work: (i) communication of outputs (as probabilities), (ii) evolution of datasets, (iii) selecting appropriate decision boundaries, and (iv) the clarity of documentation that address items i–iii. We detail these four issues in the following subsections.

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

1.3.1 Outputs are Probabilities

There is little room for certainty in these results as the insight is purely statistical and associational [281] against its training dataset. **The interface between AI-components and traditional software components is non-trivial when developers do not appreciate the nuances, or use the anchors of libraries and components that have a more traditional behaviour [188, 247, 358, 363].** However, CVSs return the *probability* that a particular object exists in an input images' pixels via confidence values. As an example, consider simple arithmetic representations (e.g., $2 + 2 = 4$). The deterministic mindset suggests that the result will *always* be 4. However, the non-deterministic (data-driven) mindset suggests that results are probable: target output (*exactly* 4) and the output inferred (*a likelihood of* 4) matches

[9] The '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 [17, 65] to describe "systems whose internal mechanisms are not fully open to inspection" [17].

as a probable percentage (or as an error where it does not match).[10] Instead of an exact output, there is a *probabilistic* result: $2 + 2$ *may* equal 4 to a confidence of n. Thus, for a more certain (though not fully certain) distribution of overall confidence returned from the service, a developer must treat the problem stochastically by testing this case hundreds if not thousands of times to find a richer interpretation of the inference made and ensure reliability in its outcome.

1.3.2 Evolution of Datasets

Traditional software engineering principles advocate for software systems to be versioned upon substantial change. Unfortunately, endpoints are not versioned [89]. In the context of computer vision, new labels may be introduced or dropped, confidence values may differ, entire ontologoies or specific training parameters may change, but we hypothesise that is not effectively communicated to developers. Broadly speaking, this can be attributed to a dichotomy of release cycles from the data science and software engineering communities: the data science iterations and work by which new models are trained and released runs at a faster cycle than the maintenance cycle of traditional software engineering. Thus we see cloud vendors integrating model changes without the *need* to update the API version unless substantial code or schema changes are also introduced—the nuance changes in the internal model does not warrant a shift in the API itself, and therefore the version shift in a new model does not always propagate to a version shift in the API endpoint. As demonstrated in Table 1.4, whatever input is uploaded at one time may not necessarily be the same when uploaded at a later time. This again contrasts the rule-driven mindset, where $2 + 2$ *always* equals 4. Therefore, in addition to the certainty of a result in a single instance, the certainty of a result in *multiple instances* may differ with time, which again impacts on the developers notion of reliable software. Currently, it is impossible to invoke requests specific to a particular model that was trained at a particular date in time, and therefore developers need to consider how evolutionary changes of the services may impact their solutions *in production*. Again, whether there is any noticeable behavioural changes from these changes is dependent on the context of the problem domain—unless developers benchmark these changes against their own domain-specific dataset and frequently check their selected service against such a dataset, there is no way of knowing if substantive errors have been introduced.

1.3.3 Selecting Appropriate Decision Boundaries

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

[10] Blake et al. [44] produces a multi-layer perceptron neural network performing arithmetic representation.

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." [144]. 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 [286, 305] and providers should consider mismatches between a developer's conceptual knowledge of the API its implementation [199]. **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 [233] and Boehm [46] 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 [243], 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.

[11]As 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.

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

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?

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

> **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?

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

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

> **RQ4. What strategies can developers employ to integrate their applications with CVSs while preserving robustness and reliability?**

1.5 Research Methodology

This thesis employs a mixed-methods approach using the concurrent triangulation strategy [58, 232]. The research presented consists of both empirical and non-empirical research design. This section provides a high-level overview of the research methodology within this thesis. Further details are provided in Section 1.7 and Chapter 3.

Firstly, RQ1–RQ3 are all empirical, knowledge-based questions [110, 239] that aim to provide the software engineering community with a greater understanding of the phenomena surrounding CVSs from three perspectives: the nature of the services themselves, how developers perceive these services and how service providers can improve these services. We answer RQ1 using a longitudinal experiment that assesses both the services' responses and associated documentation (complementing RQ2.2). We adopt qualitative and quantitative data collection; specifically (i) structured observations to quantitatively analyse the results over time, and (ii) documentary research methods to inspect service documentation. Secondly, we perform systematic mapping study following the guidelines of Kitchenham and Charters [195] and Petersen et al. [283] to better understand how API documentation of these services can be improved (i.e., more complete), which targets RQ2. Based on the findings from this study, we use a systematic taxonomy development methodology specifically targeted toward software engineering [361] that structures scattered API documentation knowledge into a taxonomy. We then validate this taxonomy against practitioners using survey research, using a survey instrument inspired by Brooke's well-established System Usability Scale [62] and contextualising it within API documentation utility, which answers RQ3.3. To answer RQ2.2, we perform an empirical application of the taxonomy to three CVSs, and therefore assess where improvements can be made. Thirdly, we adopt field survey research using repository mining of developer discussion forums (i.e., Stack Overflow) to answer RQ3, and classify these using both manual and automated techniques.

The second aspect of our research design involves non-empirical research, which explores a design-based question [243] to answer RQ4. As the answers to our first three RQs establish a greater understanding of the nature behind CVSs from various perspectives, the strategies we design in RQ4 aims at designing more reliable integration methods so that developers can better use these cloud-based services in their applications.

1.6 Thesis Organisation

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

1.6.1 Part I: Preface

1.6.1.1 Chapter 2: Background

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

1.6.1.2 Chapter 3: Research Methodology

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

1.6.2 Part II: Publications

1.6.2.1 Chapter 4: Exploring the nature of CVSs

This chapter was presented at the 2019 **International Conference on Software Maintenance and Evolution (ICSME)** [89]. We describe an 11-month longitudinal experiment assessing the behavioural (run-time) issues of three popular CVSs: Google Cloud Vision [423], Amazon Rekognition [398] and Azure Computer Vision [437]. By using three different data sets—two of which we curate as additional contributions—we demonstrate how the services are inconsistent amongst each other and within themselves. This study answers RQ1: Despite presenting conceptually-similar functionality, each service behaves and produces slightly varied (inconsistent) results and demonstrates non-deterministic runtime behaviour. We discuss potential evolution risks to consumers of such services as the services provide non-static outputs for the same inputs, thereby having significant impact to the robustness of consuming applications. Further details in the study include a brief assessment into the lack of sufficient detail of these concerns in their documentation.

1.6.2.2 Chapter 5: Understanding developer struggles when using CVSs

This chapter was presented at the **2020 International Conference on Software Engineering (ICSE)** [92]. We conduct a mining study of 1,425 Stack Overflow questions that provide indications of the types frustrations that developers face when integrating CVSs into their applications. To gather what their pain-points are, we use two classification taxonomies that also use Stack Overflow to understand generalised and documentation-specific pain-points in mature software engineering domains. This study answers RQ3 in detail and provides a validation to our motivation of RQ2: we validate that the *completeness* of current CVS API documentation is a main concern for developers and there is insufficient explanation into the errors and limitations of the service. We find that the documentation does not adequately cover all aspects of the technical domain. In terms of integrating with the service, developers struggle most with simple errors and ways in which to use the APIs; this is in stark contrast to mature software domains. Our interpretation is that developers fail to understand the IWS lifecycle and the 'whole' system that wraps such services. We also interpret that developers have a shallower understanding of the core issues within CVSs (likely due to the nuances of ML as suggested in a discussion in the paper), which warrants an avenue for future work in software engineering education.

1.6.2.3 Chapter 6: Ranking CVS pain-points by frustration

This chapter has been published as a technical report pre-print on arXiv and an extended version is **in review** for submission to the **2021 International Workshop on Emotion Awareness in Software Engineering (SEmotion)** [87]. In this work, we use our dataset consisting of the 1,425 Stack Overflow questions from [92] to interpret the breakdown of emotions developers express per classification of pain-points conducted in Chapter 5. We find that the distribution of various emotions differ per question type, and developers are most frustrated when the expectations of a CVS does not match the reality of what these services actually provide, which shapes our answer for RQ3.2 and thus RQ3.

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

This chapter is **in review** for the **2021 International Conference on Advanced Information Systems Engineering (CAiSE)** [145]. This work presents a deeper investigation into the classification model used within Chapter 6 to better interpret the automation effort we conducted, thereby highlighting valuable lessons we learnt from

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
[89]	35^{th} International Conference on Software Maintenance and Evolution	ICSME	A	Sep 2019	Chapter 4	RQ1
[88]	13^{th} International Symposium on Empirical Software Engineering and Measurement	ESEM	A	Sep 2019	Excluded[15]	RQ2.1
[92]	42^{nd} International Conference on Software Engineering	ICSE	A*	Jun 2020	Chapter 5	RQ3
[87]	6^{th} International Workshop on Emotion Awareness in Software Engineering[16]	SEmotion	A*	*In Review*	Chapter 6	RQ3.2
[145]	33^{rd} International Conference on Advanced Information Systems Engineering	CAiSE	A	*In Review*	Chapter 7	RQ3.2
[93]	IEEE Transactions on Software Engineering	TSE	Q1	Dec 2020	Chapter 8	RQ2
[266]	13^{th} International Conference on Web Engineering	ICWE	B	Apr 2019	Chapter 9	RQ4
[90]	28^{th} Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering	FSE(d)[17]	A*	Nov 2020	Chapter 10	RQ4
[91]	28^{th} Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering	FSE	A*	Nov 2020	Chapter 11	RQ4

[13] Measured as at Jan 2020 using CORE Conference (`http://www.core.edu.au/conference-portal`) and Scimago Rankings (`https://scimagojr.com/`).
[14] Date of publication, if applicable.
[15] The extended version of this conference proceeding is provided in [93], Chapter 8.
[16] An ICSE 2021 workshop.
[17] We abbreviate this with an added ‘d’ (for the demonstrations track) to distinguish this paper from our full FSE 2020 paper.

performing this exercise. Specifically, we find that the classification model we used in this exercise presented substantial data imbalance, which presented unexpected results (namely, a high level of posts that showed the emotion, 'love'). We identify how novel documentation tooling such as model cards [246] or datasheets [134] could have identified risks to our study earlier, and make suggestions needed into future documentation efforts. This work presents complementary results to RQ2 to help propose which documentation elements ML models (and thus IWSs) should provide before diving 'straight in'.

1.6.2.5 Chapter 8: Investigating improvements to CVS API documentation

This chapter was accepted as a paper at the **2019 International Symposium on Empirical Software Engineering and Measurement (ESEM)** [92]. The extended version of this chapter was published in the **IEEE Transactions on Software Engineering (TSE)** [93]. To understand where to improve CVS documentation, we first need to investigate *what* makes a good API document. This short paper initially answered one aspect of RQ2.1: the extent by which *academic literature* has studied various API documentation artefacts. By conducting an systematic mapping study resulting in 21 primary studies, we systematically develop a taxonomy that combines documentation artefacts studied in scattered work into a structured framework of 5 dimensions and 34 weighted categorisations. We then extend this work by triangulating the taxonomy with opinions from developers using a survey to assess the efficacy of these artefacts (thereby answering the second aspect of RQ2.1). From this, we assess the how well CVS providers document their APIs via a heuristic validation of the taxonomy, using the three services from the ICSME publication to make recommendations where documentation should be more complete, thereby answering RQ2.2 (and thus RQ2).

1.6.2.6 Chapter 9: Merging responses of multiple CVSs

This chapter was presented at the **2019 International Conference on Web Engineering (ICWE)** [266]. Early exploration of CVSs showed that multiple services use vastly different ontologies for the same input. As an initial strategy to improve the reliability of these services, we explored if merging multiple responses using WordNet [245] and a novel label merging algorithm based on the proportional representation approach used in political voting could make any improvements. While this approach resulted in a modest improvement to reliability, it did not consider to the evolution issues or developer pain-points we later identified.

1.6.2.7 Chapter 10: Developing a confidence thresholding tool

This chapter was presented at the demonstrations track of the **2020 Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)** [90]. When integrating with a CVS, developers need to select an appropriate confidence threshold suited to their use case and determine whether a decision should be made. An issue, however, is that these CVSs are not calibrated to the specific problem-domain datasets and it is difficult for software developers to determine an appropriate confidence threshold on their problem domain. This tool presents a workflow and supporting tool for application developers to select decision thresholds suited to their domain that—unlike existing tooling—is designed to be used in pre-development, pre-release and production. This tooling forms part of a solution to RQ4 for developers to maintain robustness and reliability in their systems.

1.6.2.8 Chapter 11: Developing a CVS integration architecture

This chapter was presented at the **2020 Joint European Software Engineering Conference and Symposium on the Foundations of Software Engineering (ESEC/FSE)** [91]. Based on the findings, we propose a set of new service error codes for describing the empirically observed error conditions of IWS based on our findings in Chapter 4. To achieve this, we propose a proxy server intermediary that lies between a client application and a IWS; the proxy server tactic is designed to return these error codes when substantial evolution occurs against a benchmark dataset that represents the application domain context (similar to that proposed in Chapter 10). A technical evaluation of our implementation of this architecture identifies 1,054 cases of substantial evolution in confidence values and 2,461 cases of evolution in the response label sets when 331 images were sent to a CVS.

1.6.3 Part III: Postface

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

1.6.4 Part IV: Appendices

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

1.7 Research Contributions

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

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

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

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

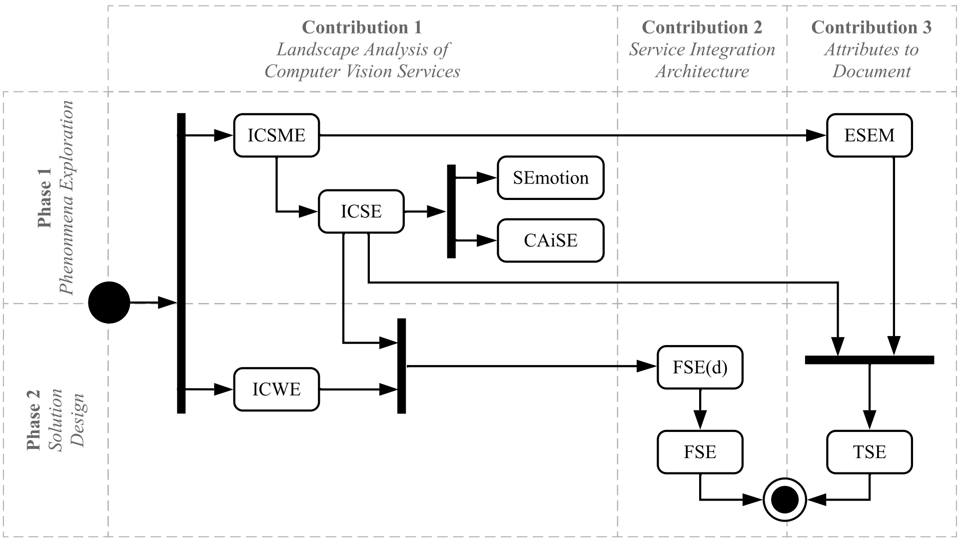


Figure 1.6: Activity diagram of the coherency of our publications, how our research was conducted, and relevant connections between publications. Our two-phase structure initial phenomena exploration and a proposed solutions to issues identified from the exploration. We map the contributions within each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

1.7.1 Contribution 1: Landscape Analysis & Preliminary Solutions

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

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

Our ICWE paper explored one aspect identified from the ICSME paper that we identified early on: that different services use different vocabularies to describe semantically similar objects but in different ways (e.g., ‘border collie’ vs. ‘collie’), despite offering functionally similar capabilities. We attempted to merge the response labels from these services using a proportional representation approach, and 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. [40] 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 monitor evolution issues identified in ICSME and should be benchmarked against the developer's dataset (i.e., against the particular application domain) as suggested in FSE(d). For robust component composition, this architecture tactic handles four key requirements: (i) it clearly defines erroneous conditions that occur when evolution occurs in CVSs; (ii) it notifies of behavioural changes in the service; (iii) it monitors the service for change and substantial impact this may have to the client application; and (iv) is flexible enough to be implemented and adaptable to any client application or specific intelligent service to facilitate reuse. Both FSE papers serve as two primary contributions to RQ4.

CHAPTER 2

Background

In Chapter 1, we defined a common set of (artificial) intelligence-based cloud services that we label intelligent web services (IWSs). Specifically, we scope the primary body of this study's work on computer vision services (CVSs) (e.g., Google Cloud Vision [423], AWS Rekognition [398], Azure Computer Vision [437], Watson Visual Recognition [433] etc.). We claim developers have not yet internalised the nuances of working with components that have a probabilistic behaviour ($2+2$ *always* equals 4) whereas an IWS's 'intelligence' component (a black box) returns probabilistic results ($2+2$ *might* equal 4 *with a confidence of* 95%). Thus, there is a mindset mismatch between probabilistic results (from the API provider) and results interpreted with certainty (from the API consumer).

What affect does this anchor mismatch have on the developer's approach towards building probabilistic software? What can we learn from common software engineering practices (e.g., [289, 336]) that apply to resolve this mismatch and thereby improve quality, such as verification & validation (V&V)? Chiefly, we consider this question around three lenses of software engineering: creating an IWS, using an IWS, and the nature of IWSs themselves.

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

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

(2) The usage of the IWS. We investigate the external quality attributes of using an IWS from the IWS *consumer's* perspective. That is, we ask if existing validation techniques are sufficient enough to ensure that the end-users can actually use an IWS to build their software in the ways they expect the IWS to work.

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

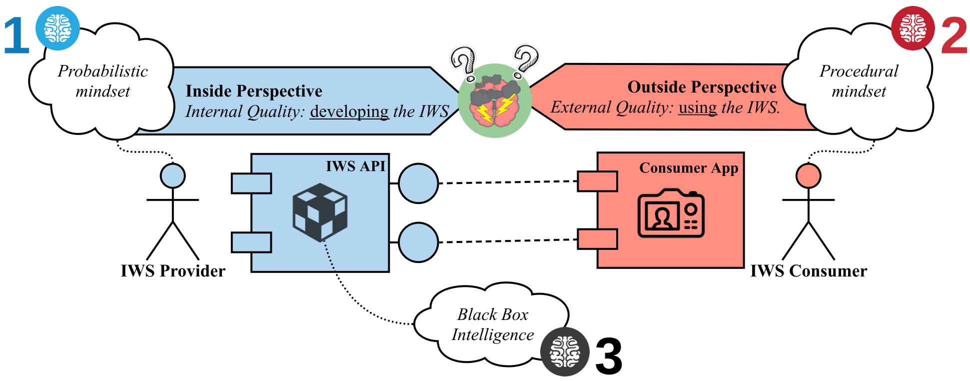


Figure 2.1: The three pillars by which we anchor the background: (1) developing an IWS with a probabilistic mindset by the IWS provider; (2) the use of a IWS with a procedural mindset by the IWS consumer; (3) the nature of a IWS itself.

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

2.1 Software Quality

> *Quality... you know what it is, yet you don't know what it is.*
>
> Robert Pirsig, 1974 [287]

The philosophical viewpoint of 'quality' remains highly debated and there are multiple facets to perceive this complex concept [133]. Transcendentally, a viewpoint like that of Pirsig's above shows that quality is not tangible but still recognisable; it's hard to explicitly define but you know when it's missing. The International Organization for Standardization provides a breakdown of seven universally-applicable principles that defines quality for organisations, developers, customers and training providers [172]. More pertinently, the 1986 ISO standard for quality was simply "the totality of characteristics of an entity that bear on its ability to satisfy stated or implied needs" [171].

Using this sentence, what characteristics exist for non-deterministic IWSs like that of a CVS? How do we know when the system has satisfied its 'stated or implied needs' when the system can only give us uncertain probabilities in its outputs? Such answers can be derived from related definitions—such as 'conformance to specification or requirements' [86, 139], 'meeting or exceeding customer expectation' [37], or 'fitness for use' [185]—but these then still depend on the solution description or requirements specification, and thus the same questions still apply.

Software quality is somewhat more concrete. Pressman [289] adapted the manufacturing-oriented view of quality from [38] and phrased software quality under three core pillars:

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

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

2.1.1 Validation and Verification

To explain V&V, we analogously recount a tale given by Pham [285] on his works on reliability. A high-school student sat a standardised test that was sent to 350,0000 students [348]. A multiple-choice algebraic equation problem used a variable, *a*, and intended that students *assume* that the variable was non-negative. Without making this assumption explicit, there were two correct answers to the multiple choice answer. Up to 45,000 students had their scores retrospectively boosted by up to 30 points for those who 'incorrectly' answered, however, outcomes of a student's higher education were, thereby, affected by this one oversight in quality assessment. The examiners wrote a poor question due to poor process standards to check if their 'correct' answers were actually correct. The examiners "didn't build the right product” nor did they “build the product right” by writing a poor question and failing to ensure quality standards, in the phrases Boehm [48] coined.

This story describes the issues with the cost of quality [47] and the importance of V&V: just as the poorly written exam question had such a high toll on the 45,000 unlucky students, so does poorly written software in production. As summarised by Pressman [289], data sourced from Cigital [80] in a large-scale application showed that the difference in cost to fix a bug in development versus system testing is $6,159 per error. In safety-critical systems, such as self-driving cars or clinical decision support systems, this cost skyrockets due to the extreme discipline needed to minimise error [351].

Formally, we refer to the IEEE Standard Glossary of Software Engineering Terminology [168] for to define V&V:

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

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

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

The verification process of API providers ‘leak’ out to the context of the developer’s project dependent on the IWS. Poor verification in the *internal quality* of the IWS will entail poor process standards, such as poor definitions and terminology used, support tooling and description of documentations [336]. Though it is commonplace for providers to have a ‘ship-first-fix-later’ mentality of ‘good-enough’ software [364], the consequence of doing so leads to consumers absorbing the cost. Thus API providers must ensure that their verification strategies are rigorous enough for the consumers in the myriad contexts they wish to use it in. Studies have considered V&V in the context of web services on the cloud [21, 70, 71, 121, 157, 256, 258, 387], though little have recently considered how adding ‘intelligence’ to these services affects existing proposed frameworks and solutions. For a CVS, what might this entail? Which assurances are given to the consumers, and how is that information communicated? To verify if the service is working correctly, does that mean that we need to deploy the system first to get a wider range of data, given the stochastic nature of the black box?

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

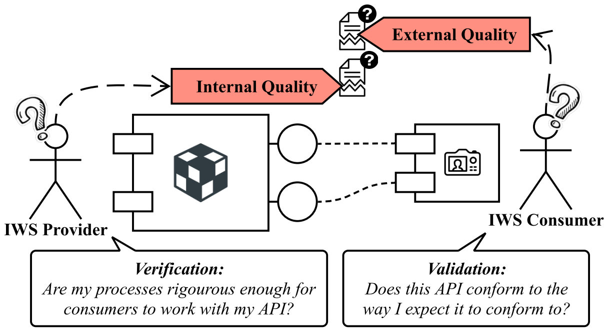


Figure 2.2: The 'leakage' of internal quality into the API consumer's product and external quality imposing on the API provider.

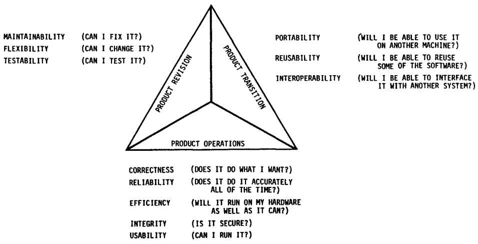
Therefore, just as the test answers with were both correct and incorrect at the same time, so is the same with IWSs returning a probabilistic result: no result is certain. While V&V has been investigated in the area of mathematical and earth sciences for numerical probabilistic models and natural systems [268, 314], from the software engineering literature, little work has been achieved to look at the surrounding area of probabilistic systems hidden behind API calls.

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

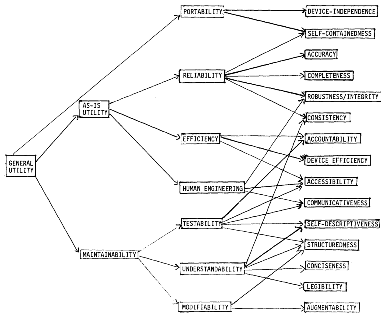
2.1.2 Quality Attributes and Models

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

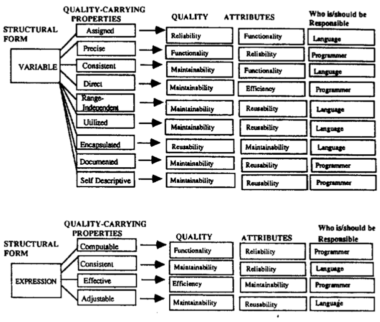
Quality attribute assessment models (like those shown in Figure 2.3) are an early concept in software engineering, and systematically evaluating software quality appears as early as 1968 [313]. Rubey and Hartwick's 1968 study introduced the phrase 'attributes' as a "prose expression of the particular quality of desired software" (as worded by Boehm et al. [46]) and 'metrics' as mathematical parameters on a scale of



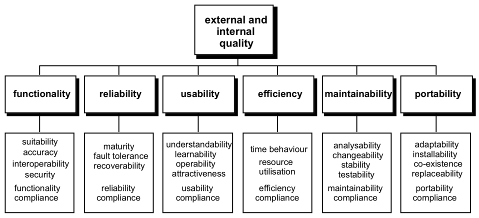
(a) McCall's quality software factors (1977) [233].



(b) Bohem's software quality characteristics tree (1976) [46].



(c) Dromey's quality-carrying properties and programming languages (1995) [107].



(d) ISO/IEC software product evaluation characteristics (1999) [173].

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

0 to 100. Early attempts to categorise wider factors under a framework was proposed by McCall, Richards, and Walters in the late 1970s [74, 233]. 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. [46] 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 [107] 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 integrated development environments (IDEs). As the need for quality models became prevalent, the International Organization for Standardization standardised software quality under ISO/IEC-9126 [173] (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 [170], separating quality into *Product Quality* (consisting of eight

quality characteristics and 31 sub-characteristics) and *Quality In Use* (consisting of five quality characteristics and 9 sub-characteristics). An extensive review on the development of quality models in software engineering is given in [6].

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

McCall et al. Extent to which a program can be expected to perform its intended function with required precision [233].

Boehm et al. Code possesses the characteristic *reliability* to the extent that it can be expected to perform its intended functions satisfactorily [46].

Dromey Functionality implies reliability. The reliability of software is therefore dependent on the same properties as functionality, that is, the correctness properties of a program [107].

ISO/IEC-9126 The capability of the software product to maintain a specified level of performance when used under specified conditions [173].

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

Moreover, defining these systems in themselves is challenging when requirements specifications and solution descriptions are dependent on nondeterministic and probabilistic algorithms. We discuss this further in Section 2.2.

2.1.3 Reliability in Computer Vision

Testing computer vision deep-learning reliability is an area explored typically through the use of adversarial examples [346]. These input examples are where

[1]In 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.

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

Google Cloud Vision, for instance, fails to correctly classify adversarial examples when noise is added to the original images [163]. Rosenfeld et al. [311] illustrated that inserting synthetic foreign objects to input images (e.g., a cartoon elephant) can alter classification output. Wang et al. [367] performed similar attacks on a transfer-learning approach of facial recognition by modifying pixels of a celebrity's face to be recognised as a different celebrity, all while still retaining the same human-interpretable original celebrity. Su et al. [341] used the ImageNet database to show that 41.22% of images drop in confidence when just a *single pixel* is changed in the input image; and similarly, Eykholt et al. [114] recently showed similar results that made a CNN interpret a stop road-sign (with mimicked graffiti) as a 45mph speed limit sign.

Thus, the state-of-the-art computer vision techniques may not be reliable enough for safety critical applications (such as self-driving cars) as they do not handle intentional or unintentional adversarial attacks. Moreover, as such adversarial examples exist in the physical world [114, 207], "the real world may be adversarial enough" [284] to fool such software.

2.2 Probabilistic and Nondeterministic Systems

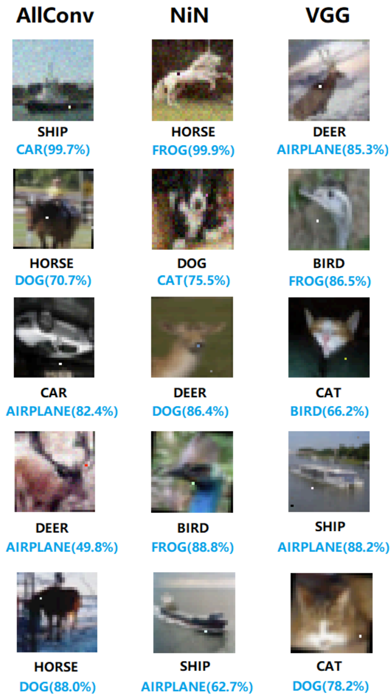
Probabilistic and nondeterministic systems are those by which, for the same given input, different outcomes may result. The underlying models that power an IWS are treated as though they are nondeterministic; Chapter 2 introduces IWSs as essentially black-box behaviour that can change over time. As such,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

2.2.1 Interpreting the Uninterpretable

As the rise of applied AI increases, the need for engineering interpretability around models becomes paramount, chiefly from an external quality perspective that the *reliability* of the system can be inspected by end-users. Model interpretability has been stressed since early machine learning research in the late 1980s and 1990s (such as Quinlan [291] and Michie [244]), and although there has since been a significant body of work in the area [19, 35, 53, 67, 98, 116, 127, 137, 183, 216, 220, 231, 279, 300, 312, 333, 362, 365], it is evident that 'accuracy' or model 'confidence' is still used as a primary criterion for AI evaluation [166, 176, 335]. Much research into neural network (NN) or support vector machine (SVM) development stresses that 'good' models are those with high accuracy. However, is accuracy enough to justify a model's quality?

To answer this, we revisit what it means for a model to be accurate. Accuracy is an indicator for estimating how well a model's algorithm will work with future or unforeseen data. It is quantified in the AI testing stage, whereby the algorithm is tested against cases known by humans to have ground truth but such cases are 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) [163].



(b) One-pixel attacks applied to three neural network (NN): AllConv, NiN and VGG [341].

(c) Adversarial examples to trick face recognition from the source to target images [367].

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

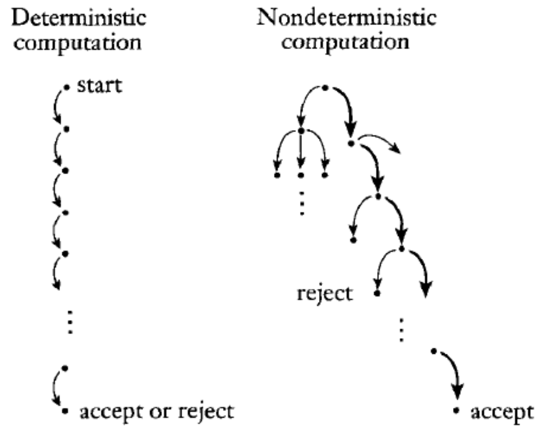


Figure 2.5: A deterministic system (left) always returns the same result in the same amount of steps. A nondeterministic system does not guarantee the same outcome, even with the same input data. Source: [118].

the algorithm *and* the humans behind it, and therefore a single value of quality is "not reliable if the future dataset has a probability distribution significantly different from past data" [123], a problem commonly referred to as the *datashift* problem [318]. Analogously, Freitas [123] provides the following description of the problem:

> *The military trained [a NN] to classify images of tanks into enemy and friendly tanks. However, when the [NN] was deployed in the field (corresponding to "future data"), it had a poor accuracy rate. Later, users noted that all photos of friendly (enemy) tanks were taken on a sunny (overcast) day. I.e., the [NN] learned to discriminate between the colors of the sky in sunny vs. overcast days!* ***If the [NN] had output a comprehensible model (explaining that it was discriminating between colors at the top of the images), such a trivial mistake would immediately be noted.*** [123]

So, why must we interpret models? While the formal definition of what it means to be *interpretable* is still somewhat disparate (though some suggestions have been proposed [220]), what is known is (i) there exists a critical trade-off between accuracy and interpretability [103, 122, 146, 182, 190, 389], and (ii) a single quantifiable value cannot satisfy the subjective needs of end-users [123]. As ever-growing domains ML become widespread[2], these applications engage end-users for real-world goals, unlike the aims in early ML research where the aim was to get AI working in the first place. In safety-critical systems where AI provide informativeness to humans to make the final call (see [72, 167, 193]), there is often a mismatch between the formal objectives of the model (e.g., to minimise error) and complex real-world goals, where other considerations (such as the human factors and cognitive science

[2]In areas such as medicine [34, 67, 112, 177, 183, 211, 280, 302, 362, 384, 393], bioinformatics [102, 124, 179, 189, 345], finance [19, 100, 167] and customer analytics [216, 365].

behind explanations[3]) are not realised: model optimisation is only worthwhile if they "actually solve the original [human-centred] task of providing explanation" [257] to end-users. **Therefore, when human-decision makers must be interpretable themselves [303], any AI they depend on must also be interpretable.**

Recently, discussion behind such a notion to provide legal implications of interpretability is topical. Doshi-Velez et al. [106] discuss when explanations are not provided from a legal stance—for instance, those affected by algorithmic-based decisions have a 'right to explanation' [228, 366] under the European Union's GDPR[4]. But, explanations are not the only way to ensure AI accountability: theoretical guarantees (mathematical proofs) or statistical evidence can also serve as guarantees [106], however, in terms of explanations, what form they take and how they are proven correct are still open questions [220].

2.2.2 Explanation and Communication

From a software engineering perspective, explanations and interpretability are, by definition, inherently communication issues: what lacks here is a consistent interface between the AI system and the person using it. The ability to encode 'common sense reasoning' [234] into programs today has been achieved, but *decoding* that information is what still remains problematic. At a high level, Shannon and Weaver's theory of communication [326] applies, just as others have done with similar issues in the software engineering realm [248, 378] (albeit to the domain of visual notations). Humans map the world in higher-level concepts easily when compared to AI systems: while we think of a tree first (not the photons of light or atoms that make up the tree), an algorithm simply sees pixels, and not the concrete object [106] and the AI interprets the tree inversely to humans. Therefore, the interpretation or explanation is done inversely: humans do not explain the individual neurons fired to explain their predictions, and therefore the algorithmic transparent explanations of AI algorithms (*"which neurons were fired to make this AI think this tree is a tree?"*) do not work here.

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

[3] *Interpretations* and *explanations* are often used interchangeably.

[4] `https://www.eugdpr.org` last accessed 13 August 2018.

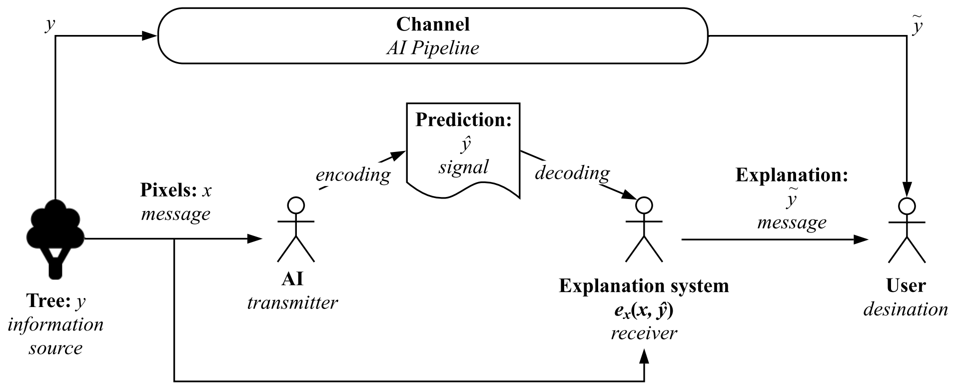


Figure 2.6: Theory of AI communication from information source, y, to intended user as explanations, $\tilde{y}$.

2.2.3 Mechanics of Model Interpretation

How do we interpret models? Methods for developing interpretation models include: decision trees [60, 84, 154, 225, 292], decision tables [20, 216] and decision sets [209, 257]; input gradients, gradient vectors or sensitivity analysis [19, 213, 300, 312, 323]; exemplars [125, 194]; generalised additive models [72]; classification (*if-then*) rules [56, 81, 271, 355, 381] and falling rule lists [333]; nearest neighbours [231, 295, 324, 376, 390] and Naïve Bayes analysis [34, 76, 115, 126, 158, 201, 211, 393].

Cross-domain studies have assessed the interpretability of these techniques against end-users, measuring response time, accuracy in model response and user confidence [7, 124, 155, 167, 231, 317, 342, 365], although it is generally agreed that decision rules and decision tables provide the most interpretation in non-linear models such as SVMs or NNs [124, 231, 365]. For an extensive survey of the benefits and fallbacks of these techniques, we refer to Freitas [123], Doshi-Velez et al. [106] and Doshi-Velez and Kim [105].

An important factor in model interpretation is to avoid over-reliance, and thus, one mechanism of model interpretation is to reduce explanations altogether. For example, Bussone et al. [67] showed that, in clinical decision support systems, confidence values alone only results in a slight effect on trust and reliance of a system. However, having overly detailed explanations may also cause over-reliance on systems if explanations are detailed but not necessarily true [67]. Hence, a mechanism of model interpretation for the purpose of ensuring trust and reliance is to deliberately show *fewer* explanations or *incorrect* explanations, thereby avoiding over-reliance. A balance between under-explained and overly-explained models is required. This is to encourage intuition in users of a system; similarly, in Ribeiro et al. [300], it was shown that accuracy alone is not always the best way to ascertain trust. Thus, intuitive factors are also mechanisms that can be encoded into explainable models.

2.3 Application Programming Interfaces

Application programming interfaces (APIs) are the interface between a developer needs and the software components at their disposal [14] by abstracting the underlying component behind a subroutine, protocol or specific tool. Therefore, it is natural to assess internal quality (and external quality if the software is in itself a service to be used by other developers—in this case an IWS) is therefore directly related to the quality the API offers [200].

Good APIs are known to be intuitive and require less documentation browsing [286], thereby increasing developer productivity. Conversely, poor APIs are those that are hard to interpret, thereby reducing developer productivity and product quality. The consequences of this have shown a higher demand of technical support (as measured in [159]) that, ultimately, causes the maintenance to be far more expensive, a phenomenon widely known in software engineering economics (see Section 2.1.1).

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

2.3.1 API Usability

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

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 system is concept long studied in the information sciences [353]. In API design, the most common form to convey knowledge to developers is through annotated code examples and overviews to a platform's architectural and design decisions [57, 104, 254, 306] though these studies have not effectively communicated *why* these artefacts are important. What makes the developer *conceptually understand* these artefacts?

Robillard and Deline [306] conducted a multi-phase, mixed-method approach to create knowledge grounded in the professional experience of 440 software engineers at Microsoft of varying experience to determine what makes APIs hard to learn, the results of which previously published in an earlier report [305]. Their results demonstrate that 'documentation-related obstacles' are the biggest hurdle in learning new APIs. One of these implications are the *intent documentation* of an API (i.e., *what is the intent for using a particular API?*) and such documentation is required only where correct API usage is not self-evident, where advanced uses of the API are documented (but not the intent), and where performance aspects of the API impact the application developed using it. They conclude that professional developers do not struggle with learning the *mechanics* of the API, but in the *understanding* of how the API fits in upwards to its problem domain and downward to its implementation:

> *In the* upwards *direction, the study found that developers need help mapping desired scenarios in the problem domain to the content of the API, and in understanding what scenarios or usage patterns the API provider intends and does not intend to support. In the* downwards *direction, developers want to understand how the API's implementation consumes resources, reports errors and has side effects.* [306]

These results particularly corroborate to that of previous studies where developers quote that they feel that existing learning content currently focuses on "*how* to do things, not necessarily *why*" [265]. This thereby reiterates the conceptual understanding of an API as paramount.

A later study by Ko and Riche [199] assessed the importance of a programmer's conceptual understanding of the background behind the task before implementing the task itself, a notion that we find most relevant for users of IWS APIs. While the study did not focus on developing web APIs (rather implementing a Bluetooth application using platform-agnostic terminology), the study demonstrated how developers show little confidence in their own metacognitive judgements to understand and assess the feasibility of the intent of the API and understand the vocabulary and concepts within the domain (i.e., wireless connectivity). This indecision over what search results were relevant in their searches ultimately hindered their progress implementing the functionality, again decreasing productivity. Ko and Riche suggest to improve API usability by introducing the background of the API and its relevant concepts using glossaries linked to tutorials to each of the major concepts, and then relate it back to how to implement the particular functionality. Thus, an analysis of the conceptual understanding of IWS APIs by a range of developers (from beginner to professional) is critical to best understand any differences between existing studies and those that are nondeterministic.

2.4 Summary

This background chapter explored nuances of interacting and integrating with probabilistic components, namely IWSs, and the impacts this may have to software quality. Firstly, we explored both internal and external quality attributes of IWSs and how leakage of internal quality may affect the external quality of client applications. We discussed how V&V approaches can assist in improving quality assurance of probabilistic components, and reviewed how various software quality attributes and models emphasise reliability of systems and their associated documentation (namely, through the sub-characteristics of robustness, consistency and completeness). We applied this context to CVSs, giving examples where these cloud services may not be reliable. Lastly, we applied the narrative of reliability to the overarching nature of computer vision itself, exploring how the underlying ML models behind a CVS can potentially fail, and discussed how any such ML model should be explainable to ensure its reliability and trustworthiness. Lastly, we discussed the impact an API can have when it is of poor quality, again impacting the internal quality of a system. In the next chapter, we propose several research strategies in the search for further insight into the developer's approach toward existing IWS APIs.

CHAPTER 3

Research Methodology

Investigating software engineering practices is often a complex task as it is imperative to understand the social and cognitive processes around software engineers and not just the tools and processes used [110]. This chapter explores our research methodology by exploring five key elements of empirical software engineering research: firstly, (i) we provide an extended focus to the study by reviewing our research questions (see Section 1.4) anchored under the context of an existing research question classification taxonomy, (ii) characterise our research goals through an explicit philosophical stance, (iii) explain how the stance selected impacts our selection of research methods and data collection techniques (by dissecting our choice of methods used to reach these research goals), (iv) discuss a set of criteria for assessing the validity of our study design and the findings of our research, and lastly (v) discuss the practical considerations of our chosen methods.

The foundations for developing this research methodology has been expanded from that proposed by Easterbrook et al. [110], Wohlin and Aurum [382], Wohlin et al. [383] and Shaw [328].

3.1 Research Questions Revisited

To discuss our research strategy, we revisit our four primary and seven secondary research questions (RQs) through the classification technique discussed by Easterbrook et al. [110], a technique originally proposed in the field of psychology by Meltzoff and Cooper [239] but adapted to software engineering. A summary of the classifications made to our research questions are presented in Table 3.1.

Our research study involves a mix of nine *empirical*[1] RQs, that focus on observing and analysing existing phenomena, and two *non-empirical* RQs, that focuses on designing better approaches to solve software engineering tasks [243]. The use

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

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 with CVSs. Further, these approaches help propose solutions to issues found in the phenomena studied [379]. We discuss both our empirical and non-empirical RQs in Sections 3.1.1 and 3.1.2 below.

Table 3.1: A summary of our research questions classified using the strategies presented by Easterbrook et al. [110] and Meltzoff and Cooper [239].

#	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?	Secondary	EMPIRICAL ↪ *Exploratory* ↪ *Description/Classification*
RQ1.2	What is their evolution profile?	Secondary	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*

3.1.1 Empirical Research Questions

In total, we pose nine empirically-based RQs to help us understand the way developers currently interact and work with web services that provide computer vision. The majority of these questions are *exploratory* questions that contribute to a landscape analysis of these services (RQ1, RQ1.1 and RQ1.2), how well they are documented (RQ2), and the issues developers currently face when using them (RQ3). Our other exploratory questions complement the answers to these questions. For instance, to understand if CVSs are sufficiently documented (an *existence* exploratory question posed in RQ2), we need to understand the components of a 'sufficient' or 'complete' API document via RQ2.1 as proposed in both the literature and by software developers. While RQ2.1 does not directly relate to CVSs, answering it gives us an understanding the components of complete API documentation, and therefore, we can assess what aspects they are missing and where improvements can be made (RQ2.2). These questions are *descriptive and classification* questions that help describe and classify what practices are in use for existing CVS API documentation and the nature behind these services. Answering these exploratory questions assists in refining preciser terms of the phenomena, ways in which we find evidence for them, and ensuring the data found is valid.

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

3.1.2 Non-Empirical Research Questions

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

3.2 Philosophical Stances

Philosophical stances guide the researcher's action by fortifying what constitutes 'valid truth' against a fundamental set of core beliefs [304]. In software engineering, four dominant philosophical stances are commonly characterised [85, 282]: positivism (or post-positivism), constructivism (or interpretivism), pragmatism, and critical theory (or advocacy/participatory). To construct such a 'validity of truth', we will review these four philosophical stances in this section, and state the stance that we explicitly adopt and our reasoning for this.

Positivism

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

Constructivism

Constructivists see knowledge embedded within the human context; truth is the *interpretive* observation by understanding the differences in human thought between meaning and action [198]. That is, the interpretation of the theory is just as important to the empirical observation itself. We partially adopt a constructivist stance as we attempt to model the developer's mindset, being an approach that is rich in qualitative data on human activity.

Pragmistism

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

Critical Theory

This study chiefly adopts the philosophy of critical theory [11]. A key outcome of the study is to shift the developer's restrictive deterministic mindset and shed light on developing a new framework actively with the developer community that seeks to improve the process of using such APIs. In software engineering, critical theory is used to "actively [seek] to challenge existing perceptions about software practice" [110], and this study utilises such an approach to shift the mindset of CVS consumers and providers alike on how the documentation and metadata should not be written with the 'traditional' deterministic mindset at heart. Thus, our key philosophical approach is critical theory to seek out *what-can-be* using partial constructivism to model the current *what-is*.

3.3 Research Methods

Research methods are “a set of organising principles around which empirical data is collection and analysed” [110]. Creswell [85] suggests that strong research design is reflected when the weaknesses of multiple methods complement each other. Using a mixed-methods approach is therefore commonplace in software engineering research, typically due to the human-oriented nature investigating how software engineers work both individually (where methods from psychology may be employed) and together (where methods from sociology may be employed).

Therefore, studies in software engineering are typically performed as field studies where researchers and developers (or the artefacts they produce) are analysed either directly or indirectly [332]. The mixed-methods approach combines five classes of field study methods (or empirical strategies/studies) most relevant in empirical software engineering research [110, 187, 383]: controlled experiments, case studies, survey research, ethnographies, and action research. We chiefly adopt a mixed-methods approach to our work using the *concurrent triangulation* mixed-methods strategy [232] as it best compensates for weaknesses that exist in all research methods, and employs the best strengths of others [85].

3.3.1 Review of Relevant Research Methods

Below we review some of the research methods most relevant to our research questions as refined in Section 3.1 as presented by Easterbrook et al. [110].

3.3.1.1 Controlled Experiments

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

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

3.3.1.2 Case Studies

Case studies investigate phenomena in their real-life context and are well-suited when the boundary between context and phenomena is unknown [388]. They offer understanding of how and why certain phenomena occur, thereby investigating ways cause-effect relationships can occur. They can be used to test existing theories (*confirmatory case studies*) by refuting theories in real-world contexts instead of under laboratory conditions or to generate new hypotheses and build theories during the initial investigation of some phenomena (*exploratory case studies*).

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

3.3.1.3 Survey Research

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

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

3.3.1.4 Ethnographies

Ethnographies investigates the understanding of social interaction within community through field observation [308]. Resulting ethnographies help understand how software engineering technical communities build practices, communication strategies and perform technical work collaboratively.

Ethnographies require the researcher to be highly trained in observational and qualitative data analysis, especially if the form of ethnography is participant observation, whereby the researcher is embedded of the technical community for observation. This may require the longevity of the study to be far greater than a couple of weeks, and the researcher must remain part of the project for its duration to develop enough local theories about how the community functions. While it assists in revealing subtle but important aspects of work practices within software teams, this study does not focus on the study of teams, and is therefore not a research method relevant to this project.

3.3.1.5 *Action Research*

Action researchers simultaneously solve real-world problems while studying the experience of solving the problem [96] by actively seeking to intervene in the situation for the purpose of improving it. A precondition is to engage with a *problem owner* who is willing to collaborate in identifying and solving the problem faced. The problem must be authentic (a problem worth solving) and must have new knowledge outcomes for those involved. It is also characterised as an iterative approach to problem solving, where the knowledge gained from solving the problem has a desirable solution that empowers the problem owner and researcher.

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

3.3.2 Review of Data Collection Techniques for Field Studies

Singer et al. developed a taxonomy [214, 332] showcasing data collection techniques in field studies that are used in conjunction with a variety of methods based on the level of interaction between researcher and software engineer, if any. This taxonomy is reproduced in Table 3.2, where techniques used in this research study are starred.

3.4 Research Design

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

3.4.1 Landscape Analysis of Computer Vision Services

To understand the behavioural and evolutionary profiles of CVSs (i.e., RQ1), we employed a longitudinal study based around a dynamic system analysis [332]. Specifically, we used structured observations of three services using the same dataset to 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 [332].) 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.

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**.

3.4.2 Utility of API Documentation in Computer Vision Services

To assess whether these services are sufficiently documented (i.e., RQ2), we conducted a systematic mapping study [195, 283] 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 [361].

We then followed the triangulation approach proposed by Mayring [232] to validate the taxonomy by use of a personal opinion survey. Kitchenham and Pfleeger [196] 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 [62] technique by basing our research questions against a known surveying instrument.

As is good practice in developing questionnaire instruments to evaluate their reliability and validity [221], we evaluated our instrument design by asking colleagues to critique it via pilot studies within A^2I^2. This assisted in identifying any problems with the questionnaire itself and with any issues that may have occured with the response rate and follow-up procedures.

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**.

3.4.3 Developer Issues concerning Computer Vision Services

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 [343].

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 developers[2] and the availability of its publicly

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

available dataset released as ‘data dumps’ on the Stack Exchange Data Explorer[3] and Google BigQuery[4]. Studies conducted have also used SO to mine developer discourse [8, 22, 28, 78, 219, 262, 272, 297, 309, 334, 349, 369]. Further details on how we approached the design for this study can be found in **Chapter 5, Section 5.4**, **Chapter 6, Section 6.3**, and **Chapter 7, Section 7.3**

3.4.4 Designing Improved Integration Strategies

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

Part II

Publications

CHAPTER 4

Identifying Evolution in Computer Vision Services[†]

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

4.1 Introduction

The availability of intelligent web services (IWSs) has made artificial intelligence (AI) tooling accessible to software developers and promises a lower entry barrier for their utilisation. Consider state-of-the-art computer vision analysers, which require either manually training a deep-learning classifier, or selecting a pre-trained model and deploying these into an appropriate infrastructure. Either are laborious in time, and require non-trivial expertise along with a large data set when training or customisation is needed. In contrast, IWSs providing computer vision (i.e., computer vision services or CVSs such as [398, 410, 411, 412, 419, 423, 431, 432, 433, 437, 451,

[†]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.

452, 485, 486]) abstract these complexities behind a web application programming interface (API) call. This removes the need to understand the complexities required of machine learning (ML), and requires little more than the knowledge on how to use RESTful endpoints. The ubiquity of these services is exemplified through their rapid uptake in applications such as aiding the vision-impaired [95, 299].

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

ML typically involves use of statistical techniques that yield components with a non-deterministic external behaviour; that is, for the same given input, different outcomes may result. However, developers, in general, are used to libraries and small components behaving predictably, while systems that rely on ML techniques work on confidence intervals[1] and probabilities. For example, the developer's mindset suggests that an image of a border collie—if sent to three intelligent computer vision services (CVSs)—would return the label 'dog' consistently with time regardless of which service is used. However, one service may yield the specific dog breed, 'border collie', another service may yield a permutation of that breed, 'collie', and another may yield broader results, such as 'animal'; each with results of varying confidence values.[2] Furthermore, the third service may evolve with time, and thus learn that the 'animal' is actually a 'dog' or even a 'collie'. The outcomes are thus behaviourally inconsistent between services providing conceptually similar functionality. As a thought exercise, consider if the sub-string function were created using ML techniques—it would perform its operation with a confidence where the expected outcome and the AI inferred output match as a *probability*, rather than a deterministic (constant) outcome. How would this affect the developers' approach to using such a function? Would they actively take into consideration the non-deterministic nature of the result?

Myriad software quality models and software engineering practices advocate maintainability and reliability as primary characteristics; stability, testability, fault tolerance, changeability and maturity are all concerns for quality in software components [162, 289, 336] and one must factor these in with consideration to software evolution challenges [142, 143, 241, 242, 354]. However, the effect this non-deterministic behaviour has on quality when masked behind an IWS is still under-explored to date in software engineering literature, to our knowledge. Where software depends on IWSs to achieve functionality, these quality characteristics may not be achieved, and developers need to be wary of the unintended side effects and inconsistency that exists when using non-deterministic components. A CVS may encapsulate deep-learning strategies or stochastic methods to perform image analy-

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

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

sis, but developers are more likely to approach IWSs with a mindset that anticipates consistency. Although the documentation does hint at this non-deterministic behaviour (i.e., the descriptions of 'confidence' in various CVSs suggest the they are not always confident, and thus not deterministic [396, 421, 438]), the integration mechanisms offered by popular vendors do not seem to fully expose the nuances, and developers are not yet familiar with the trade-offs.

Do popular CVSs, as they currently stand, offer consistent behaviour, and if not, how is this conveyed to developers (if it is at all)? If CVSs are to be used in production services, do they ensure quality under rigorous service quality assurance (SQA) frameworks [162]? What evolution risk [142, 143, 241, 242] do they pose if these services change? To our knowledge, few studies have been conducted to investigate these claims. This paper assesses the consistency, evolution risk and consequent maintenance issues that may arise when developers use IWSs. We introduce a motivating example in Section 4.2, discussing related work and our methodology in Sections 4.3 and 4.4. We present and interpret our findings in Section 4.5. We argue with quantified evidence that these IWSs can only be considered with a mature appreciation of risks, and we make a set of recommendations in Section 4.6.

4.2 Motivating Example

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

Rather than building a computer vision engine from scratch, Rosa thinks she can achieve this using one of the popular CVSs (e.g., [398, 410, 411, 412, 419, 423, 431, 432, 433, 437, 451, 452, 485, 486]). However, Rosa comes from a typical software engineering background with limited knowledge of the underlying deep-learning techniques and implementations as currently used in computer vision. Not unexpectedly, she internalises a mindset of how such services work and behave based on her experience of using software libraries offered by various SDKs. This mindset assumes that different cloud vendor image processing APIs more-or-less provide similar functionality, with only minor variations. For example, cloud object storage for Amazon S3 is both conceptually and behaviourally very similar to that of Google Cloud Storage or Azure Storage. Rosa assumes the CVSs of these platforms will, therefore, likely be very similar. Similarly, consider the string libraries Rosa will use for the app. The conceptual and behavioural similarities are consistent; a string library in Java (Android) is conceptually very similar to the string library she will use in Swift (iOS), and likewise both behave similarly by providing the same results for their respective sub-string functionality. However, **unlike the cloud storage and string libraries, different CVSs often present conceptually similar functionality but are behaviourally very different**. IWS vendors also hide the depth of knowledge needed to use these effectively—for instance, the training data set and ontologies used to create these services are hidden in the documentation. Thus, Rosa isn't even exposed to this knowledge as she reads through the documentation of the providers and, thus, Rosa makes the following assumptions:

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

4.3 Related Work

If we were to view CVSs through the lenses of an SQA framework, robustness, consistency, and maintainability often feature as quality attributes in myriad software quality models (e.g., [173]). Software quality is determined from two key dimensions: (1) in the evaluation of the end-product (external quality) and (2) the assurances in the development processes (internal quality) [289]. We discuss both perspectives of quality within the context of our work in this section.

4.3.1 External Quality

4.3.1.1 Robustness for safety-critical applications

A typical focus of recent work has been to investigate the robustness of deep-learning within computer vision technique implementation, thereby informing the effectiveness in the context of the end-product. The common method for this has been via the use of adversarial examples [346], where input images are slightly perturbed to maximise prediction error but are still interpretable to humans.

Google Cloud Vision, for instance, fails to correctly classify adversarial examples when noise is added to the original images [163]. Rosenfeld et al. [311] illustrated that inserting synthetic foreign objects to input images (e.g., a cartoon elephant) can completely alter classification output. Wang et al. [367] performed similar attacks on a transfer-learning approach of facial recognition by modifying pixels of a celebrity's face to be recognised as a completely different celebrity, all while still retaining the same human-interpretable original celebrity. Su et al. [341] used the ImageNet database to show that 41.22% of images drop in confidence when just a *single pixel* is changed in the input image; and similarly, Eykholt et al. [114] recently showed similar results that made a convolutional neural network (CNN) interpret a stop road-sign (with mimicked graffiti) as a 45mph speed limit sign.

The results suggest that current state-of-the-art computer vision techniques may not be robust enough for safety critical applications as they do not handle intentional or unintentional adversarial attacks. Moreover, as such adversarial examples exist in the physical world [114, 207], "the natural world may be adversarial enough" [284] to fool AI software. Though some limitations and guidelines have been explored in this area, the perspective of *Intelligent* Web Services is yet to be considered and specific guidelines do not yet exist when using CVSs.

4.3.1.2 Testing strategies in ML applications

Although much work applies ML techniques to automate testing strategies, there is only a growing emphasis that considers this in the opposite sense; that is, testing to ensure the ML product works correctly. There are few reliable test oracles that ensure if an ML has been implemented to serve its algorithm and use case purposefully; indeed, "the non-deterministic nature of many training algorithms makes testing of models even more challenging" [16]. Murphy et al. [251] proposed a software engineering-based testing approach on ML ranking algorithms to evaluate the 'correctness' of the implementation on a real-world data set and problem domain, whereby discrepancies were found from the formal mathematical proofs of the ML algorithm and the implementation.

Recently, Braiek and Khomh [55] conducted a comprehensive review of testing strategies in ML software, proposing several research directions and recommendations in how best to apply software engineering testing practices in ML programs. However, much of the area of this work specifically targets ML engineers, and not application developers. Little has been investigated on how application developers perceive and understand ML concepts, given a lack of formal training; we note that other testing strategies and frameworks proposed (e.g., [59, 250, 261]) are targeted chiefly to the ML engineer, and not the application developer.

However, Arpteg et al. [16] recently demonstrated (using real-world ML projects) the developmental challenges posed to developers, particularly those that arise when there is a lack of transparency on the models used and how to troubleshoot ML frameworks using traditional software engineering debugging tools. This said, there is no further investigations into challenges when using the higher, 'ML friendly' layers (e.g., IWSs) of the 'machine learning spectrum' [269], rather than the 'lower layers' consisting of existing ML frameworks and algorithms targeted toward the ML community.

4.3.2 Internal Quality

4.3.2.1 Quality metrics for cloud services

CVSs are based on cloud computing fundamentals under a subset of the Platform as a Service (PaaS) model. There has been work in the evaluation of PaaS in terms of quality attributes [130]: these attributes are exposed using service-level agreements (SLAs) between vendors and customers, and customers denote their demanded quality of service (QoS) to ensure the cloud services adhere to measurable KPI attributes.

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

4.3.2.2 Web service documentation and documenting ML

From the *developer's* perspective, little has been achieved to assess IWS quality or assure quality of these CVSs. Web services and their APIs are the bridge between developers' needs and the software components [14]; therefore, assessing such CVSs from the quality of their APIs is thereby directly related to the development quality [200]. Good APIs should be intuitive and require less documentation browsing [286], thereby increasing productivity. Conversely, poor APIs that are hard to understand and work with reduce developer productivity, thereby reducing product quality. This typically leads to developers congregating on forums such as Stack Overflow, leading to a repository of unstructured knowledge likely to concern API design [371]. The consequences of addressing these concerns in development leads to a higher demand in technical support (as measured in [159]) that, ultimately, causes the maintenance to be far more expensive, a phenomenon widely known in software engineering economics [48]. Rosa, for instance, isn't aware of technical ML concepts; if she cannot reason about what search results are relevant when browsing the service and understanding functionality, her productivity is significantly decreased. Conceptual understanding is critical for using APIs, as demonstrated by Ko and Riche, and the effects of maintenance this may have in the future of her application is unknown.

Recent attempts to document attributes and characteristics on ML models have been proposed. Model cards were introduced by Mitchell et al. [246] to describe how particular models were trained and benchmarked, thereby assisting users to reason if the model is right for their purposes and if it can achieve its stated outcomes. Gebru et al. [134] also proposed datasheets, a standardised documentation format to describe the need for a particular data set, the information contained within it and what scenarios it should be used for, including legal or ethical concerns.

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

4.4 Method

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

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

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

[RH3] CVSs do not effectively communicate this evolution and instability, introducing risk into engineering these systems.

We conducted two experiments to address these hypotheses against three popular CVSs: AWS Rekognition [398], Google Cloud Vision [423], Azure Computer Vision [437]. Specifically, we targeted the AWS `DetectLabels` endpoint [396], the Google Cloud Vision `annotate:images` endpoint [421] and Azure's `analyze` endpoint [438]. For the remainder of this paper, we de-identify our selected CVSs by labelling them as services A, B and C but do not reveal mapping to prevent any implicit bias. Our selection criteria for using these particular three services are based on the weight behind each service provider given their prominence in the industry (Amazon, Google and Microsoft), the ubiquity of their hosting cloud platforms as industry leaders of cloud computing (i.e., AWS, Google Cloud and Azure), being in the top three most adopted cloud vendors in enterprise applications in 2018 [120] and the consistent popularity of discussion amongst developers in developer communities such as Stack Overflow. While we choose these particular cloud CVSs, we acknowledge that similar services [411, 412, 419, 432, 433, 485, 486] also exist, including other popular services used in Asia [410, 431, 451, 452] (some offering 3D image analysis [409]). We reflect on the impacts this has to our study design in Section 4.7.

Our study involved an 11-month longitudinal study which consisted of two 13 week and 17 week experiments from April to August 2018 and November 2018 to March 2019, respectively. Our investigation into documentation occurred on August 28 2018. In total, we assessed the services with three data sets; we first ran a pilot study using a smaller pool of 30 images to confirm the end-points remain stable, re-running the study with a larger pool of images of 1,650 and 5,000 images. Our selection criteria for these three data sets were that the images had to have varying objects, taken in various scenes and various times. Images also needed to contain disparate objects. Our small data set was sourced by the first author by taking photos of random scenes in an afternoon, whilst our second data set was sourced from 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 [218]. We have made our other two data sets available online ([414]). We collected results and their responses from each service's API endpoint using a python script [418] 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 ∩ B ∩ C	3.33%	2.73%	4.68%	2.75%	0.0100
A ∩ B	6.67%	11.27%	12.26%	10.07%	0.0299
A ∩ C	20.00%	13.94%	17.28%	17.07%	0.0304
B ∩ C	6.67%	12.97%	20.90%	13.51%	0.0713

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

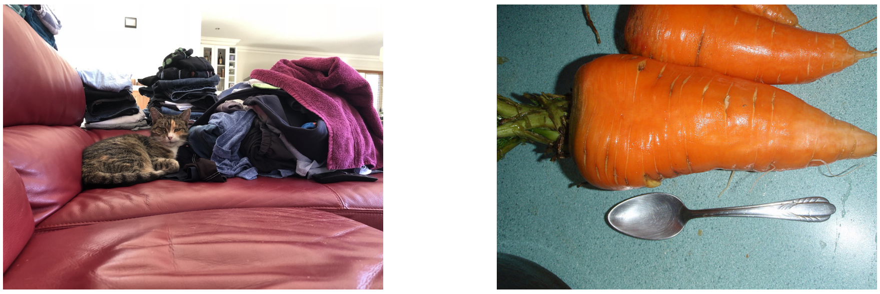
For the above aspects of consistency, we calculated the spread of variation for the top label's confidences of each service for every 1 percent point; that is, the frequency of top label confidences within 100–99%, 99–98% etc. The consistency of top label's and their confidences between each service was determined by intersecting the labels of each service per image and grouping the intersecting label's confidences together. This allowed us to determine relevant probability distributions. For reproducibility, all quantitative analysis is available online [415].

4.5 Findings

4.5.1 Consistency of top labels

4.5.1.1 Consistency across services

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



(a) (b)

Figure 4.2: *Left:* The top labels for each service do not intersect, with each having a varied ontology: T_i = { A = {'black'}, B = {'indoor'}, C = {'slide', '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_i = { A = { 'carrot' }, B = { 'indoor' }, C = { 'spoon' } }.

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, CVSs do not agree on the top label for images, and therefore developers are likely to be vendor locked, making changes between services non-trivial.

(a)

(b)

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.

4.5.1.2 Semantic consistency where $|T_i| > 1$

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

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

> *"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."* [439]

Thus, even if Rosa implemented conceptual similarity analysis for the image, the top label set may not provide sufficient information to derive at a conclusive answer, and if simply relying on only one label in this set, information such as the duplicity 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 $\gtrsim$ 95%, when compared to $\gtrsim$ 87% and $\gtrsim$ 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

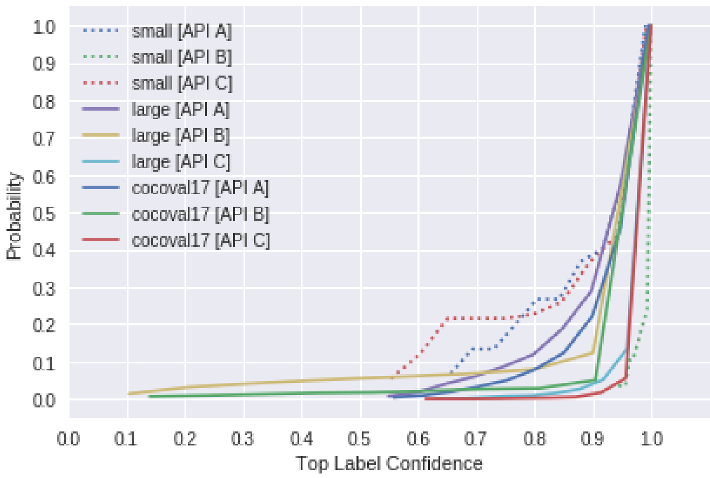


Figure 4.4: Cumulative distribution of the top labels' confidences. One in nine images return a top label(s) confident to $\gtrsim 97\%$, though there is a wider distribution for service A.

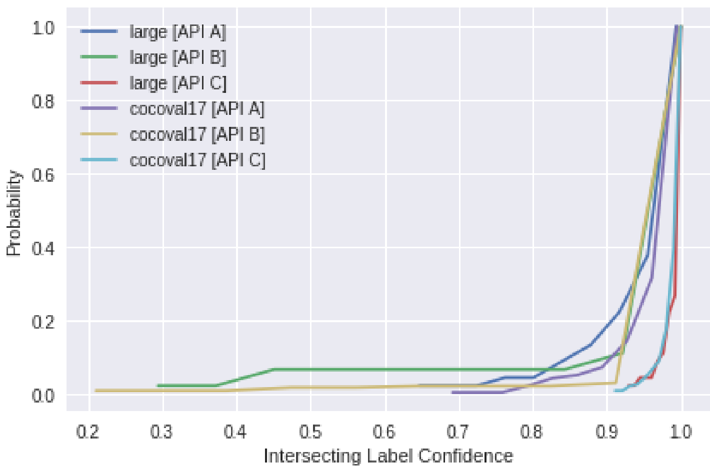


Figure 4.5: Cumulative distribution of intersecting top labels' confidences. The small data set is intentionally removed due to low intersections of labels (see Table 4.2).

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%.

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

4.6 Recommendations

4.6.1 Recommendations for IWS users

4.6.1.1 Test with a representative ontology for the particular use case

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

4.6.1.2 Incorporate a specialised IWS testing methodology into the development lifecycle

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

4.6.1.3 IWSs are not ‘plug-and-play’

Rosa will be locked into whichever vendor she chooses as there is inherent inconsistency between these services in both the vocabulary and ontologies that they use. We have demonstrated that very few services overlap in their vocabularies, chiefly because they are still in early development and there is yet to be an established, standardised vocabulary that can be shared amongst the different vendors. Issues 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 should 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 [134, 246] 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.

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

4.7 Threats to Validity

4.7.1 Internal Validity

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

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

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

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

4.7.2 External Validity

The documentation and services do change over time and evolve, with many allowing for contributions from the developer community via GitHub. We note that our evaluation of the documentation was conducted on a single date (see Section 4.4) and acknowledge that the documentation may have changed from the evaluation date to the time of this publication. We also acknowledge that the responses and labelling may have evolved too since the evaluation period described and the date of this publication. Thus, this may have an impact on the results we have produced in this paper compared to current, real-world results. To mitigate this, we have supplied the raw responses available online [416].

Moreover, in this paper we have investigated *computer vision* services. Thus, the significance of our results to other domains such as natural language processing or audio transcription is, therefore, unknown. Future studies may wish to repeat our methodology on other domains to validate if similar patterns occur; we remain this open for future work.

4.7.3 Construct Validity

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

4.8 Conclusions & Future Work

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

Standardised software quality models (e.g., [173]) target maintainability and reliability as primary characteristics. Quality software is stable, testable, fault tolerant, easy to change and mature. These CVSs are, however, in a nascent stage, difficult to evaluate, and currently are not easily interchangeable. Effectively, the IWS response objects are shifting in material ways to developers, albeit slowly, and vendors do not communicate this evolution or modify API endpoints; the endpoint remains static but the content returned does not despite the same input.

There are many potential directions stemming from this work. To start, we plan to focus on preparing a more comprehensive datasheet specifically targeted at what should be documented to application developers, and not data scientists. Reapplying this work in real-world contexts, that is, to get real developer opinions and study production grade systems, would also be beneficial to understand these phenomena in-context. This will help us clarify if such changes are a real concern for developers (i.e., if they really need to change between services, or the service evolution has real impact on their applications). We also wish to refine and systematise the method used in this study and develop change detectors that can be used to identify evolution in these services that can be applied to specific ML domains (i.e., not just computer vision), data sets, and API endpoints, thereby assisting application developers in their testing strategies. Moreover, future studies may wish to expand the methodology applied by refining how the responses are compared. As there does not yet exist a standardised list of terms available between services, labels could be *semantically* compared instead of using exact matches (e.g., by using stem words and synonyms to compare similar meanings of these labels), similar to previous studies [266].

This paper has highlighted only some high-level issues that may be involved in using these evolving services. The laws of software evolution suggest that for software to be useful, it must evolve [242, 354]. There is, therefore, a trade-off, as we have shown, between consistency and evolution in this space. For a component to be stable, any changes to dependencies it relies on must be communicated. We are yet to see this maturity of communication from IWS providers. Thus, developers must be cautious between integrating intelligent components into their applications at the expense of stability; as the field of AI is moving quickly, we are more likely to see further instability and evolution in IWSs as a consequence.

CHAPTER 5

Interpreting Pain-Points in Computer Vision Services[†]

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

5.1 Introduction

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

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

The nuances of ML and AI powering IWSs have to be appreciated, as there are real-world consequences to software quality for applications that depend on them if they are ignored [89]. This is especially true when ML and AI are abstracted and masked behind a conventional-looking API call, yet the mechanisms behind the API are data-dependent, probabilistic and potentially non-deterministic [266]. We are yet to discover what long-term impacts exist during development and production due to poor documentation that do not capture these traits, nor do we know the depth of understanding application developers have for these components. Given the way AI-powered services are currently presented, developers are also likely to reason about these new services much like a string library or a cloud data storage service. That is, they may not fully consider the implications of the underlying statistical nature of these new abstractions or the consequent impacts on productivity and quality.

Typically, when developers are unable to correctly align to the mindset of the API designer, they attempt to resolve issues by (re-)reading the API documentation. If they are still unable to resolve these issues on their own after some internet searching, they consider online discussion platforms (e.g., Stack Overflow, GitHub Issues, Mailing Lists) where they seek technological advice from their peers [4]. Capturing what developers discuss on these platforms offers an insight into the frustrations developers face when using different software components as shown by recent works [39, 191, 309, 338, 370]. However, to our knowledge, no studies have yet analysed what developers struggle with when using the new generation of *intelligent* services. Given the re-emergent interest in AI and the anticipated value from this technology [223], a better understanding of issues faced by developers will help us improve the quality of services. Our hypothesis is that application developers do not fully appreciate the probabilistic nature of these services, nor do they have sufficient appreciation of necessary background knowledge—however, we do not know the specific areas of concern. The motivation for our study is to inform API designers on which aspects to focus in their documentation, education, and potentially refine the design of the end-points.

This study involves an investigation of 1,825 Stack Overflow (SO) posts regarding one of the most mature types of IWSs—computer vision services (CVSs)—dating from November 2012 to June 2019. We adapt existing methodologies of prior SO analyses [39, 349] to extract posts related to CVSs. We then apply two existing SO question classification schemes presented at ICPC and ICSE in 2018 and 2019 [4, 40]. These previous studies focused on mobile apps and web applications. Although not a direct motivation, our work also serves as a validation of the applicability of these two issue classification taxonomies [4, 40] in the context of IWSs (hence potential for generalisation). Additionally our work is the first—to our knowledge—to *test* the applicability of these taxonomies in a new study.

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

The key findings of our study are:

- The primary areas that developers raise as issues reflect a relatively primitive understanding of the underlying concepts of data-driven ML approaches used. We note this via the issues raised due to conceptual misunderstanding and confusion in interpreting errors,

- Developers predominantly encounter a different distribution of issue types than were reported in previous studies, indicating the complexity of the technical domain has a non-trivial influence on intelligent API usage; and

- Most of these issues can be resolved with better documentation, based on our analysis.

The paper also offers a data-set as an additional contribution to the research community and to permit replication [417]. The paper structure is as follows: Section 5.2 provides motivational examples to highlight the core focus of our study; Section 5.3 provides a background on prior studies that have mined SO to gather insight into the software engineering community; Section 5.4 describes our study design in detail; Section 5.5 presents the findings from the SO extraction; Section 5.6 offers an interpretation of the results in addition to potential implications that arise from our work; Section 5.7 outlines the limitations of our study; concluding remarks are given in Section 5.8.

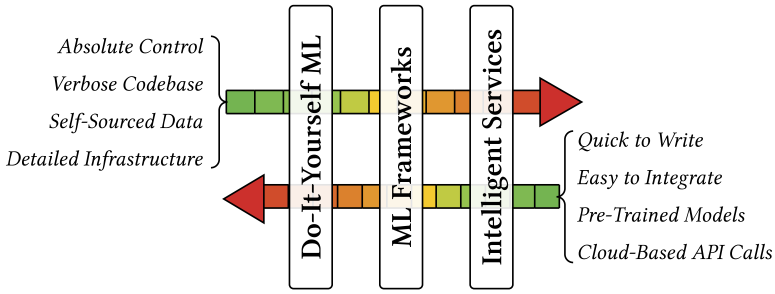


Figure 5.1: Some traits of Intelligent Services vs. 'Do-It-Yourself' ML. Green-to-red arrows indicate the presence of these traits. *Adapted from Ortiz [269].*

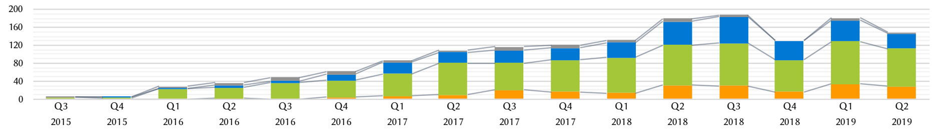
5.2 Motivation

"Intelligent" services are often available as a cloud end-point and provide developers a friendly approach to access recent AI/ML advances without being experts in the underlying processes. Figure 5.1 highlights how these services abstract away much of the technical know-how needed to create and operationalise these IWSs [269]. In particular, they hide information about the training algorithm and data-sets used in training, the evaluation procedures, the optimisations undertaken, and—surprisingly—they often do not offer a properly versioned end-point [89, 266]. That is, the cloud vendors may change the behaviour of the services without sufficient transparency.

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

- **unsure of ML specific vocabulary:** "*Though it's now not SO clear to me what 'score' actually means.*" [462]; "*I'm trying out the [IWS], and there's a score field that returns that I'm not sure how to interpret [it].*" [476]
- **frustrated about non-deterministic results:** "*Often the API has troubles in recognizing single digits... At other times Vision confuses digits with letters.*" [475]; "*Is there a way to help the program recognize numbers better, for example limit the results to a specific format, or to numbers only?*" [472]
- **unaware of the limitations behind the services:** "*Is there any API available where we can recognize human other body parts (Chest, hand, legs and other parts of the body), because as per the Google vision API it's only able to detect face of the human not other parts.*" [456]
- **seeking further documentation:** "*Does anybody know if Google has published their full list of labels (`['produce', 'meal', ...]`) and where I could find that? Are those labels structured in any way? - e.g. is it known that '`food`' is a superset of '`produce`', for example.*" [459]

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



	Q3 2015	Q4 2015	Q1 2016	Q2 2016	Q3 2016	Q4 2016	Q1 2017	Q2 2017	Q3 2017	Q4 2017	Q1 2018	Q2 2018	Q3 2018	Q4 2018	Q1 2019	Q2 2019
IBM	1	0	4	5	8	7	4	5	9	6	5	6	4	0	5	3
MS	0	2	1	5	5	13	26	23	27	27	33	52	59	43	47	33
GCV	4	3	23	25	36	38	49	71	61	71	80	90	95	71	95	85
AWS	0	0	0	1	0	4	7	10	20	16	13	31	30	16	34	28
Total	5	5	28	36	49	62	86	109	117	120	131	179	188	130	181	149

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, 40, 349]. 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) [77]. 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, 39, 359]. 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, 359]). 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. [40]) 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 [359], categorise the questions they ask about these APIs [28, 30, 40, 309], and understand API related documentation and usage issues [4, 5, 8, 28, 164, 349]. These studies often employ automation to assist in the data analysis stages of their research. Latent Dirichlet Allocation [8, 28, 309, 359] is applied for topic modelling and other ML techniques such as Random Forests [40], Conditional Random Fields [5] or Support Vector Machines [40, 164] 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' [39] or 'Design' [360] 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, 349] (e.g., card sorting) or a combination of both [39, 40, 309, 356]. 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 [197] has helped shape the last 15 years worth of research, but the reliability of such evidence has been questioned [184, 186, 329]. 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 [423], AWS [398], Azure [437] and IBM Cloud [433]. 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 [120].

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 [411, 412, 419, 432, 485, 486] and only

English-speaking services have been selected, excluding popular services from Asia (e.g., [409, 410, 431, 451, 452])—see Section 5.7. For comprehensiveness, we explain below our initial attempts to extract *all* IWSs.

5.4.1.1 Defining a list of IWSs

As there exists no global 'list' of IWSs to search on, we needed to derive a *corpus of initial terms* to allow us to know *what* to search for on the Stack Exchange Data Explorer[1] (SEDE). We began by looking at different brand names of cloud services and their permutations (e.g., Google Cloud Services and GCS) as well as various ML-related products (e.g., Google Cloud ML). To do this, we performed extensive Google searches[2] in addition to manually reviewing six 'overview' pages of the relevant cloud platforms. We identified 91 initial IWSs to incorporate into our search terms[3].

5.4.1.2 Manual search for relevant, related terms

We then ran a manual search[2] on each term to determine if these terms were relevant. We did this by querying each term within SO's search feature, reviewing the titles and body post previews of the first three pages of results (we did not review the answers, only the questions). We also noted down the user-defined *Tags* of each post (up to five per question); by clicking into each tag, we could review similar tags (e.g., 'project-oxford' for 'azure-cognitive-services') and check if the tag had synonyms (e.g., 'aws-lex' and 'amazon-lex'). We then compiled a *corpus of tags* consisting of 31 terms.

5.4.1.3 Developing a search query

We recognise that searching SEDE via *Tags* exclusively can be ineffective (see [28, 349]). To mitigate this, we produced a *corpus of title and body terms*. Such terms are those that exist within the title and body of the posts to reflect the ways in which individual developers commonly use to refer to different IWSs. To derive at such a list, we performed a search[2,3] of the 31 tags above in SEDE, filtering out posts that were not answers (i.e., questions only) as we wanted to see how developers *phrase* their questions. For each search, we extracted a random sample of 100 questions (400 total for each service) and reviewed each question. We noted many patterns in the permutations of how developers refer to these services, such as: common misspellings ('bind' vs. 'bing'); brand misunderstanding ('Microsoft computer vision' vs. 'Azure computer vision'); hyphenation ('Auto-ML' vs. 'Auto ML'); UK and US English ('Watson Analyser' vs. 'Watson Analyzer'); and, the use of apostrophes, plurals, and abbreviations ('Microsoft**'s** Computer Vision API', 'Microsoft Computer Vision Services', 'GCV' vs. 'Google Cloud Vision'). We

[1] `http://data.stackexchange.com/stackoverflow`

[2] This search was conducted on 17 January 2019

[3] For reproducibility, this is available at `http://bit.ly/2ZcwNJO`.

arrived at a final list of 229 terms compromising all of the IWSs provided by Google, Amazon, Microsoft and IBM as of January 2019[3].

5.4.1.4 *Executing our search query*

Our next step was to perform a case-insensitive search of all 229 terms within the body or title of posts. We used Google BigQuery's public data-set of SO posts[4] to overcome SEDE's 50,000 row limit and to conduct a case-insensitive search. This search was conducted on 10 May 2019, where we extracted 21,226 results. We then performed several filtering steps to cleanse our extracted data, as explained below.

5.4.2 Data Filtering

5.4.2.1 *Refining our inclusion/exclusion criteria*

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

We also recognised that 21,226 results would be non-trivial to analyse without automated techniques. As we wanted to do manual qualitative analysis, we reduced our search space to 27 search terms of just the *CVSs* within the original corpus of 229 terms. These were Google Cloud Vision [423], AWS Rekognition [398], Azure Computer Vision [437], and IBM Watson Visual Recognition [433]. This resulted in 1,425 results that were extracted on 21 June 2019. The query used and raw results are available online in our supplementary materials [417].

5.4.2.2 *Duplicates*

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

5.4.2.3 *Automated and manual filtering*

To assess the suitability and nature of the 1,425 questions extracted, the first author began with a manual check on a randomised sample of 50 questions. As the questions were exported in a raw CSV format (with HTML tags included in the post's body), we parsed the questions through an ERB templating engine script[6] in which the ID, title, body, tags, created date, and view, answer and comment counts were rendered for each post in an easily-readable format. Additionally, SQL matches in the extraction process were also highlighted in yellow (i.e., in the body of the post) and listed at

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[4]http://bit.ly/2LrN7OA

[5]Watson Cognitive Services

[6]We 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 [40]. 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 [236]. 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	↪ ***Correctness***	What exists in the documentation actually matches what is implemented in code
A-1b	↪ ***Completeness***	The documentation fully covers all aspects of the API's components
A-1c	↪ ***Up-to-dateness***	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	↪ ***Maintainability***	The upkeep effort to ensure the documentation remains up to date
A-2b	↪ ***Readability***	The extent to which the documentation is interpretable
A-2c	↪ ***Usability***	How useable the organisation, look and feel of the documentation is
A-2d	↪ ***Usefulness***	The usefulness of the documentation, avoiding misinformation.
A-3	■ **Process-Related**	Issues related to the documentation process
A-3a	↪ ***Internationalisation***	Translating the documentation into other languages
A-3b	↪ ***Contribution-Related***	Contribution issues encountered when people contribute to the documentation
A-3c	↪ ***Configuration-Related***	Configuration issues of the documentation tool
A-3d	↪ ***Implementation-Related***	Unwanted development issues caused by (poor) documentation
A-3e	↪ ***Traceability***	Tracing documentation changes (when, when, who and why)
A-4	■ **Tool-Related**	Issues related to documentation tools (e.g., Javadoc)
A-4a	↪ ***Tooling Bugs***	Bugs that exist within the documentation tooling
A-3b	↪ ***Tooling Discrepancy***	Support as expectations not being fulfilled by these documentation tools
A-3c	↪ ***Tooling Help Required***	Help required due to improper usage of the tools
A-3d	↪ ***Tooling Migration***	Issues migrating the tool to a new version or another tool
B	**Generalised classification (Beyer et al. [40])**	
B-1	■ **API usage**	Issue on how to implement something using a specific component provided by the API
B-2	■ **Discrepancy**	The questioner's *expected behaviour* of the API does not reflect the API's *actual behaviour*
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

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

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

At first, we followed methods of reliability analysis similar to previous SO studies (e.g., [349]) using the percentage agreement metric that divides the number of agreed categories assigned per post by the total number of raters [236]. However, percentage agreement is generally rejected as an inadequate measure of reliability analysis [82, 150, 204] in statistical communities. As we used more than 2 coders and our reliability analysis was conducted under the same random sample of 50 posts, we applied *Light's Kappa* [215] to our ratings, which indicates an overall index of agreement. This was done using the `irr` computational R package [129] as suggested in [150].

5.4.3.2 Distribution Analysis

In order to compare the distribution of categories from our study with previous studies we carried out a χ^2 test. We selected a χ^2 test as the following assumptions [330] are satisfied: (i) the data is categorical, (ii) all counts are greater than 5, and (iii) we can assume simple random sampling. The null hypothesis describes the case where each population has the same proportion of observations and the alternative hypothesis is where at least one of the null hypothesis statements is false. We chose a significance value, α, of 0.05 following a standard rule of thumb. As to the best of our knowledge this is the first statistical comparison using Taxonomy A and B on SO posts. To report the effect size we selected Cramer's Phi, ϕ_c which is well suited for use on nominal data [330].

5.5 Findings

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

5.5.1 Post classification and reliability analysis

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

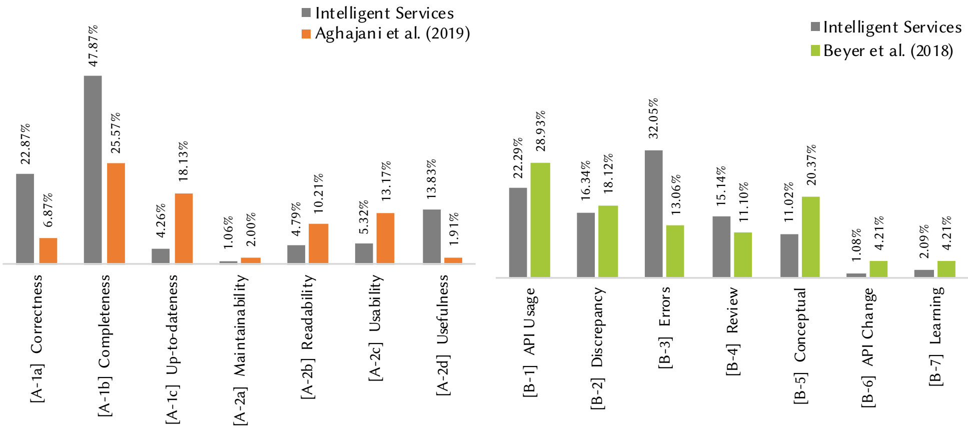


Figure 5.3: *Left:* Documentation-specific classification taxonomy results highlights a mostly similar distribution to that of Aghajani et al.'s findings [4]. *Right:* Generalised classification taxonomy results highlight differences from more mature fields (i.e., Android APIs in Beyer et al. [40]) to 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 [210] 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 posted). However, there are few questions that *directly* relate to documentation of IWSs.

Few developers question or ask questions directly about the API documentation, but some (47.87%) posts ask for additional information to understand the API (**completeness (A-1b)**), for example: "*Is there a full list of potential labels that Google's Vision API will return?*" [459]; "*There seems to be very little to no documentation for AWS iOS text recognition inside an image*" [457].

22.87% of posts question the **accuracy (A-1a)** of certain parts of the cloud documentation, especially in relation to incorrect quotas and limitations: "*Are the Cloud Vision API limits in documentation correct?*" [470], "*According to the Google Vision documentation, the maximum number of image files per request is 16. Elsewhere, however, I'm finding that the maximum number of requests per minute is as high as 1800.*" [455].

There are also many references (23.94%) addressing the confusing nature of some documentation, indicating that the **readability, usability and usefulness of the documentation (A-2b, A-2c and A-2d)** could be improved. For example, "*Am I encoding it correctly? The docs are quite vague.*" [453], "*The aws docs for this are really confusing.*" [482].

5.5.2.2 *Results from Beyer et al.'s taxonomy*

We found that a majority (32.05%) of posts are primarily **error-related questions (B-3)**, including a dump of the stack trace or exception message from the service's programming-language SDK (usually Java, Python or C#) that relates to a specific error. For example: "*I can't fix an error that's causing us to fall behind.*" [479]; "*I'm using the Java Google Vision API to run through a batch of images... I'm now getting a* `channel closed` *and* `ClosedChannelException` *error on the request.*" [473].

API usage questions (B-1) were the second highest category at 22.29% of posts. Reading the questions revealed that many developers present an insufficient understanding of the behaviour, functional capability and limitation of these services and the need for further data processing. For example, while Azure provides an image captioning service, this is not universal to all CVSs: "*In Amazon Rekognition for image processing how do I get the caption for an image?*" [464]. Similarly, OCR-related and label-related questions often indicate interest in cross-language translation, where a separate translation service would be required: "*Can Google Cloud Vision generate labels in Spanish via its API?*" [478]; "*[How can I] specify language for response in Google Cloud Vision API*" [465]; "*When I request a text detection of an image, it gives only English Alphabet characters (characters without accents) which is not enough for me. How can I get the UTF-32 characters?*" [460].

It was commonplace to see questions that demonstrate a lack of depth in understanding and appreciating how these services work, instead posting simple debugging questions. For instance, in the 11.02% of **conceptual-related questions (B-5)** that we categorised, we noticed causal links to a misunderstanding (or lack of awareness) of the vocabulary used within computer vision. For example: "*The problem is that I need to know not only <u>what</u> is on the image but also the <u>position</u> of that* *object. Some of those APIs have such feature but only for face detection.*" [471]; "*I want to know if the new image has a face similar to the original image.... [the service] can identify faces, but can I use it to get similar faces to the identified face in other images?*" [463]. It is evident that some application developers are not aware of conceptual differences in computer vision such as object/face *detection* versus *localisation* versus *recognition*.

In the 16.34% of **discrepancy-related questions (B-2)**, we see further unawareness from developers in how the underlying systems work. In OCR-related questions, developers do not understand the pre-processing steps required before an OCR is performed. In instances where text is separated into multiple columns, for example, text is read top-down rather than left-to-right and segmentation would be required to achieve the expected results. For example, "*it appears that the API is using some kind of logic that makes it scan top to bottom on the left side and moving to right side and doing a top to bottom scan.*" [477]; "*this method returns scanned text in wrong sequence... please tell me how to get text in proper sequence.*" [483].

A number of **review-related questions (B-4)** (15.14%) seem to provide some further depth in understanding the context to which these systems work, where training data (or training stages) are needed to understand how inferences are made: "*How can we find an exhaustive list (or graph) of all logos which are effectively recognized using Google Vision logo detection feature?*" [481]; "*when object* `banana` *is detected with accuracy greater than certain value, then next action will be dispatched... how can I confidently define and validate the threshold value for each item?*" [467].

API change (B-6) was shown in 1.08% of posts, with evolution of the services occurring (e.g., due to new training data) but not necessarily documented "*Recently something about the Google Vision API changed... Suddenly, the API started to respond differently to my requests. I sent the same picture to the API today, and I got a different response (from the past).*" [480].

5.5.3 Statistical Distribution Analysis

We obtained the following results $\chi^2 = 131.86$, $\alpha = 0.05$, $p\ value = 2.2\times10^{-16}$ and $\phi_c = 0.362$ from our distribution analysis with Taxonomy A to compare our study with that of Aghajani et al. [4]. Comparing our study to Beyer et al. [40] produced the following results $\chi^2 = 145.58$, $\alpha = 0.05$, $p\ value = 2.2\times10^{-16}$ and $\phi_c = 0.252$. These results show that we are able to reject the null hypothesis that the distribution of posts using each taxonomy was the same as the comparison study. While there are limited guidelines for interpreting ϕ_c when there is no prior information for effect size [344], Sun et al. suggests the following: $0.07 \leq \phi_c \leq 0.20$ indicates a *small* effect, $0.21 \leq \phi_c \leq 0.35$ indicates a *medium* effect, and $0.35 > \phi_c$ indicates a *large* effect. Based on this criteria we obtained a *large* effect size for the documentation-specific classification (Taxonomy A) and a *medium* effect size for the generalised classification (Taxonomy B).

5.6 Discussion

5.6.1 Answers to Research Questions

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

Upon meeting to discuss the discrepancies between our categorisation of IWS usage SO posts, we found that our interpretations of the *posts themselves* were largely subjective. For example, many posts presented multi-faceted dimensions for Taxonomy B; Beyer et al. [40] argue that a post can have more than one question category and therefore multi-label classification is appropriate at times. We highlight this further in the threats to validity (Section 5.7).

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

In Figure 5.3, for the documentation-specific classification, the majority of posts were classified as **Completeness (A1-b)** related (47.87%). An interpretation for this is that the documentation does not adequately cover the technical domain concerns. Comments by developers such as "*I'm searching for a list of all the possible image labels that the Google Cloud Vision API can return?*" [458] indicates the documentation does not adequately describe the training data for the API—developers do not know the required usage assumptions. Another quote from a developer, "*Can Google Cloud Vision generate labels in Spanish via its API? ... [Does the API] allow to select which language to return the labels in?*" [478] points to a lack of details relating to the characteristics of the models used by the API. It would seem that developers are unaware of aspects of the technical domain concerns.

The next most frequent category is **Correctness (A-1a)** with 22.87% of posts. In the context of the technical domain there are many limits that developers need to be aware of: range and increments of a model score [89]; required data pre-processing steps for optimal performance; and features provided by the models (as explained in Section 5.5.2.2). Considering the relation between technical concerns and software quality, developers are right to question providers on correctness; "*Are the Cloud Vision API limits in documentation correct?*" [470].

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

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

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

In the context of IWS SO posts, Taxonomy B suggests that Errors (B-3) are discussed most amongst developers. These results are in contrast to similar studies made in more *mature* API domains, such as Mobile Development [26, 27, 39, 40, 309] and Web Development [356]. Here, API Usage (B-1) is much more frequently discussed, followed by Conceptual (B-5), Discrepancy (B-2) and Errors (B-3). We argue in the following section that an improved developer understanding can be achieved by educating them about the IWS lifecycle and the 'whole' system that wraps such services.

In the Android study API usage questions (B-1) were the highest category (28.93% compared to 22.29% in our study). As stated in the analysis of the Error questions this discrepancy could be due to the maturity of the domain. However, another explanation could be the scope of the two individual studies. Beyer et al. [40] used a broad search strategy consisting of posts tagged Android. This search term fetches issues related to the entire Android platform which is significantly larger than searching for computer vision APIs using 229 search terms. As a consequence of more posts and more APIs there would be use cases resulting in additional posts related to API Usage (B-1).

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

5.6.2 The Developer's Learning Approach

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

5.6.2.1 *Bloom's Taxonomy*

The cognitive domain under Bloom's taxonomy [45] consists of six objectives. Within the context of IWSs, developers are likely to ask questions due to causal links that exist in the following layers of Bloom's taxonomy: (i) *knowledge*, where the developer does not remember or know of the basic concepts of computer vision and AI (in essence, they may think that AI is as smart as a human); (ii) *comprehension*, where the developer does not understand how to interpret basic concepts, or they are mis-understanding how they are used in context; (iii) *application*, where the developer is struggling to apply existing concepts within the context of their own situation; (iv) *analysis*, where the developer is unable to analyse the results from IWSs (i.e., understand response objects); (v) *evaluation*, where the developer is unable to evaluate issues and make use of best-practices when using IWSs; and (vi) *synthesise*, where the developer is posing creative questions to ask if new concepts are possible with CVSs.

5.6.2.2 *SOLO Taxonomy*

The SOLO taxonomy [41] consists of five levels of understanding. The causal links behind the SO questions we have found relate to the following layers of the SOLO taxonomy: (i) *pre-structural*, where the developer has a question indicating incompetence or has little understanding of computer vision; (ii) *uni-structural*, where the developer is struggling with one key aspect (i.e., a simple question about computer vision); (iii) *multi-structural*, where the developer is questioning multiple concepts (independently) to understand how to build their system (e.g., system integration with the IWS); (iv) *relational*, where the developer is comparing and contrasting the best ways to achieve something with IWSs; and (v) *extended abstract*, where the developer poses a question theorising, formulating or postulating a new concept within IWSs.

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

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

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.*" [474]	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).*" [454]	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?*" [461]	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?*" [468]	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?*" [466]	Analysis	Relational

Bloom's and the SOLO taxonomy. This indicates that modification to certain documentation aspects can address many of these issues. For example, many issues can be ratified with better descriptions of response data and error messages: "*I was exploring google vision and in the specific function 'detectCrops', gives me the crop hints. what does this means exactly?*" [469]; "*I am a making a very simple API call to the Google Vision API, but all the time it's giving me error that 'google.oauth2' module not found.*" [484]

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

5.6.3 Implications

5.6.3.1 For Researchers

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

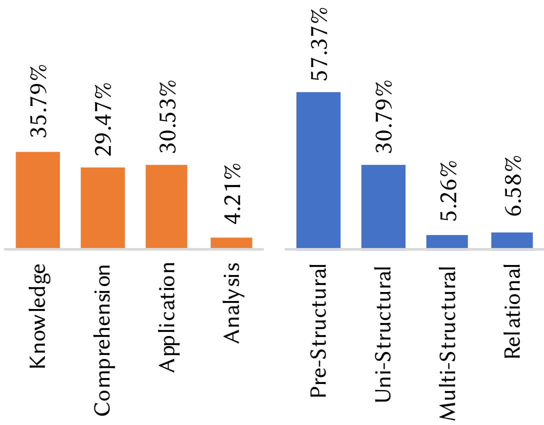


Figure 5.4: Alignment of Bloom (Orange) and SOLO (Blue) taxonomies against Taxonomy A and B dimensions against all 213 classifications made in the random sample of 50 posts.

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 [88]) 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.

For example, websites offer interactive Git tutorials[7] to help developers understand and explore the technical domain matters under version control in their own pace.

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

5.7 Threats to Validity

5.7.1 Internal Validity

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

[7] For example, `https://learngitbranching.js.org`.

5.7.2 External Validity

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

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

5.7.3 Construct Validity

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

5.8 Conclusions

CVSs offer powerful capabilities that can be added into the developer's toolkit via simple RESTful APIs. However, certain technical nuances of computer vision become abstracted away. We note that this abstraction comes at the expense of a full appreciation of the technical domain, context and proper usage of these systems. We applied two recent existing SO classification taxonomies (from 2018 and 2019) to see if existing taxonomies are able to fully categorise the types of complaints developers have. IWSs have a diverging distribution of the types of issues developers ask when compared to more mature domains (i.e., mobile app development and web development). Developers are more likely to complain about shallower, simple debugging issues without a distinct understanding of the AI algorithms that actually empower the APIs they use. Moreover, developers are more likely to complain about the completeness and correctness of existing IWS documentation, thereby suggesting that the documentation approach for these services should be reconsidered. Greater attention to education in the use of AI-powered APIs and their limitations is needed, and our discussion offered in Section 5.6.2 motivates future work in resolving these issues in the software engineering education space.

CHAPTER 6

Ranking Computer Vision Service Issues using Emotion[†]

Abstract Software developers are increasingly using intelligent web services to implement 'intelligent' features. However, studies show that incorporating machine learning into an application increases technical debt, creates data dependencies, and introduces uncertainty due to their non-deterministic behaviour. We know very little about the emotional state of software developers who have to deal with such issues; a reduced developer experience when using such services results in productivity loss. In this paper, we conduct a landscape analysis of emotion found in 1,425 Stack Overflow questions about computer vision services. We used an existing emotion classifier, EmoTxt, and manually verified its classification results. We found that the emotion profile varies for different types of questions, and a discrepancy exists between automatic and manual emotion analysis due to subjectivity.

6.1 Introduction

Recent advances in artificial intelligence (AI) have provided software engineers with new opportunities to incorporate complex machine learning (ML) capabilities, such as computer vision, through cloud based intelligent web services (IWSs). These new set of services, typically offered as API calls are marketed as a way to reduce the complexity involved in integrating AI-components. However, recent work shows that software engineers struggle to use these IWSs [92]. Furthermore, the accompanying documentation fails to address common issues experienced by software engineers and often, engineers resort to online communication channels, such as Stack Overflow (SO), to seek advice from their peers [92].

[†]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.

While seeking advice on the issues, software engineers tend to express their emotions (such as frustration or confusion) within the questions. Emotions with negative sentiment have been shown to have adverse effects to developer productivity, as shown in [385], and thus—recognising the value of considering emotions—other literature has investigated how emotions are expressed by software developers within communication channels [270] including SO [69, 263]. The broad motivation of these works is to generally understand the emotional landscape and improve developer productivity [128, 249, 270]. However, previous works have not directly focused on the nature of emotions expressed in questions related to IWSs. We also do not know if certain types of questions express stronger emotions. Thus, understanding the emotional state of developers facing issues with these services can help shed light into prioritised choices of these services, avoid common issues which are the most frustrating (and thus highest productivity loss), and ultimately improve the developer experience (DevX) whilst using these services.

The machine-learnt behaviour of these cloud IWSs is typically non-deterministic and, given the dimensions of data used, their internal inference process is hard to reason about [89]. Compounding the issue, documentation of these cloud systems does not explain the limits, nor how they were created (esp. information about the datasets used to train them). This lack of transparency makes it difficult for even senior developers to properly reason about these systems, so their prior experience and anchors do not offer sufficient support [92]. In addition, adding machine learned behaviour to a system incurs ongoing maintenance concerns [321]. There is a need to better understand emotions expressed by developers; as reduced negative emotions whilst writing software can improve productivity [385] and DevX, we can use such insight to help cloud vendors make improvement which would generate the most value, e.g., overall service/API design, documentation of the services or clarification in error messages.

In our recent work [92], we explored the types of pain-points developers face when using IWSs through a general analysis of 1,425 SO questions using an existing SO question type classification taxonomy [40] (presented in Table 6.1). This study extends this body of work by considering the *emotional state* expressed within those same pain-points. We identify the emotion(s) in each SO question (if any), and investigate if the distribution of these emotions is similar across the various types of questions. To automate classification of these emotions, we used EmoTxt, an emotion classifier included in the EMTk toolkit for emotion recognition from text [68, 69, 263]. EmoTxt has been trained and built on SO posts using the emotion classification model proposed by Shaver et al. [327]. Additionally, we manually classified a sample of 300 posts using the same guidelines used to train EmoTxt, provided in [263] (based on [327]). The key contributions of this study are:

- Identifying that the distribution of emotions is different across the taxonomy of issues.
- A deeper analysis of the results obtained from the EmoTxt classifier suggests that the classification model needs further refinement. *Love* and *joy*, the least expected emotions when discussing API issues, are visible across all categories.

- In order to promote future research and permit replication, we make our dataset publicly available.[1]

The paper is structured as follows: Section 6.2 provides an overview on prior work surrounding the classification of emotions from text; Section 6.3 describes our research methodology; Section 6.4 presents the results from the EmoTxt classifier; Section 6.5 provides a discussion of the results obtained; Section 6.6 outlines the threats to validity; Section 6.7 presents the concluding remarks.

6.2 Motivation

Developing software raises various emotions in developers at different times, including enjoyment, frustration, satisfaction, even fear and rage [68, 270, 385, 386]

Studies on the role of emotions within the workplace, including the software engineering domain, have established a correlation between emotion and productivity [385, 386]. Negative emotions impact productivity negatively, whilst positive emotions impact positively. The exception is *anger*, which was found to generate a motivating state to "try harder" in a subset of developers (i.e., 13% of respondents in Wrobel's study [385] responded that anger had a *positive* impact to make developers more motivated. However, overall, *anger* was still found to have an negative impact on productivity). In recent years, researchers have focused on identifying the emotions expressed by software engineers within communication channels such as JIRA to communicate with their peers [128, 249, 263, 270]. Most of these studies make use of one of the well established emotion classification framework during their emotion mining process. Murgia et al. [249] and Ortu et al. [270] investigated the emotions expressed by developers within an issue tracking system, such as JIRA, by labelling issue comments and sentences written by developers using Parrott's emotion framework. Gachechiladze et al. [128] applied the Shaver's emotion framework to detect anger expressed in comments written by developers in JIRA.

The Collab team [68, 263] extended the work done by Ortu et al. [270] and developed an emotion mining toolkit, EmoTxt [68] based on a gold standard dataset collected from 4,800 SO posts (of type questions, question comments, answers and answer comments). 12 graduate computer science students were recruited as raters to manually annotate these 4,800 SO posts using the Shaver's emotion model which consists of a tree-structured, three level, hierarchical classification of emotions. The top level consists of six basic emotions namely, love, joy, anger, sadness, fear and surprise [327]. The work conducted by the Collab team is most relevant to our study since their focus is on identifying emotion from SO posts and their classifier is trained on a large dataset of SO posts. Unlike their study, we focus on a single domain (computer vision services or CVSs) to analysing emotion, as opposed to a wide spectrum of domains. Further, we validate our work with a smaller group of people—diverse in age and cultural backgrounds—to gather a wider sense of emotion classification (i.e., due to the subjective nature of emotions). Lastly, in this

[1] See `https://bit.ly/2RIGQ2N`.

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 *expected behaviour* of the API does not reflect the API's *actual behaviour*
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

work, our intent is to analyse the questions only (not all types of posts) to understand the frustration faced at the time the developers face an issue with the service.

6.3 Methodology

6.3.1 Dataset

This paper extends our existing work by utilising our previously curated dataset of 1,425 SO questions on four popular computer vision service (CVS) providers: Google Cloud Vision, Amazon Rekognition, Azure Computer Vision, and IBM Watson. Each question is assigned a question type per the taxonomy prescribed in Beyer et al. [40] (for reference, we provide our interpretation of this taxonomy within Table 6.1). For further details on how this dataset was produced, we refer to the original paper [92].

After performing additional cleansing of this dataset (to remove noise), we performed *both* automatic and manual emotion classification based on Shaver et al.'s emotion taxonomy [327]. Automatic emotion detection was performed using using the EmoTxt classifer, and manual classification was performed by three co-authors on a sample of 300 posts. We calculated the inter-rater reliability between EmoTxt and our manually classified questions in two ways: (i) to see the overall agreement between the three raters in applying the Shaver et al. emotions taxonomy, and (ii) to see the overall agreement with EmoTxt's classifications. Additional dataset cleansing and results from manual and automatic emotion classification are available online at `https://bit.ly/2RIGQ2N`.

6.3.2 Additional Dataset Cleansing

As described in [92], the 1,425 questions extracted were split into 5 random samples. The first author classified the first sample of 475 questions, with three other research assistants[2] classifying the remaining 900 questions over samples of 300 posts. The remaining 50 posts were used for reliability analysis, whereby these 50 posts were classified nine times by various researchers in our group, resulting in a total of 450 classifications for the 50 posts.

Each question was classified a question issue type (as described by Table 6.1) or, where the question was a false-positive resulting from our original search query, we flagged the post as 'noise' and removed them from further classification. 186 posts were flagged as noise, with a total of 1,239 were successfully assigned a question type.

To remove duplicity resulting from the reliability analysis, we applied a 'majority rules' technique to each of these 50 posts, in which the issue type most consistent amongst the nine raters per question would win. As an example, three raters classified a post as *API Usage*, one rater classified the same post as a *Review* question and five raters classified the post as *Conceptual*. Therefore, the question was assigned as a *Conceptual* question. However, in four cases, there was a tie in the majority. To resolve this, we used the issue type that was most assigned within the 50 posts. For example, in another question, three raters each assigned the same post as *Discrepancy* and *Errors*, while the remaining three three raters flagged the post as noise. In this case, the tie was resolved down to *Errors* as this classification received 72 more votes than *Discrepancy* and 88 more votes than noisy posts across all classifications made in the sample of 50 posts.

6.3.3 Automatic Emotion Classification

After all questions had been classified an issue type, we then piped in the body of each question into a script developed to remove all HTML tags, code snippets, blockquotes and hyperlinks, as suggested by Novielli et al. [263]. We replicated and extended the study conducted by Novielli et al. [263] on our dataset consisting of questions only. We started with a file containing the 1,239 non-noise SO questions, each with its associated question type given in Table 6.1. We pre-processed this file by extracting the question ID and body text to meet the format requirements of the EmoTxt classifier [68]. This classifier was used as it was trained on SO posts as discussed in Section 6.2. We ran the classifier for each emotion as this was required by EmoTxt model. This resulted in six output prediction files (one file for each emotion: *Love*, *Joy*, *Surprise*, *Sadness*, *Fear*, *Anger*), which referenced a question ID and a binary value indicating emotion presence. We then merged these emotion prediction files into an aggregate file with question text and Beyer et al.'s question type classifications that was performed in [92].

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

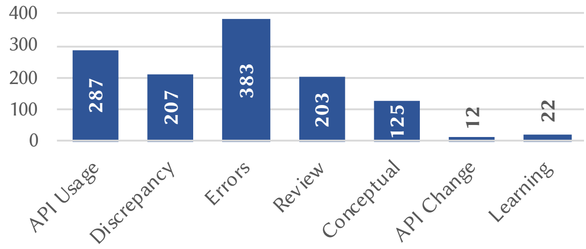


Figure 6.1: Distribution of the types of questions raised.

6.3.4 Manual Emotion Classification

In order to evaluate and also better understand the process used by EmoTxt to classify emotions, we randomly sampled 300 SO posts of various emotion annotations resulting from EmoTxt. Each of these 300 posts were assigned to three raters (co-authors of this paper) who individually reviewed the question text against each of the six basic emotions [327] and flag an emotion if deemed present, otherwise flagging *No Emotion* instead. Each rater reviewed each question against the guidelines provided in [263]. We then conducted reliability analysis of all three rater's results to measure the similarity in which independent raters classified each emotions against each SO post. This was done by calculating Cohen's Kappa (C_κ) [82] to measure the average inter-rater agreement *between* pairs of raters, and then Light's Kappa (L_κ) [215] to measure the *overall* agreement amongst the three raters. Results are reported in Table 6.3.

6.3.5 Comparing Manual and Automatic Classification Methods

The next step involved comparing the ratings of the 300 SO posts that were manually annotated by the three raters against the results obtained for the same set of 300 SO posts from the EmoTxt classifier. We separated the classifications per emotion and calculated C_κ for each rater against EmoTxt, and then L_κ to measure the overall agreement. The three raters then met together to compare and discuss the ratings from the EmoTxt classifier against the manual ratings. Results are reported in Table 6.3.

6.4 Findings

Figure 6.1 displays the overall distribution of question types from the 1,239 posts after applying noise-filtering and majority ruling to our original 1,425 questions extracted. It is evident that developers ask issues predominantly related to API errors when using CVSs and, additionally, how they can use the API to implement specific functionality. There are few questions related to version issues or self-learning. For further discussion into these results, we refer to [92].

Table 6.2 displays the frequency of questions that were classified by EmoTxt when compared to our assignment of question types. Figure 6.2 presents the emotion

Table 6.2: Frequency of emotions per question type.

Question Type	Fear	Joy	Love	Sadness	Surprise	Anger	No Emotion	Total
API Usage	47	22	34	17	59	13	136	328
Discrepancy	35	12	17	7	46	20	105	242
Errors	73	34	23	21	47	23	207	428
Review	35	16	15	16	42	14	95	233
Conceptual	27	9	10	8	21	5	61	141
API Change	4	2	2	1	1	1	5	16
Learning	3	4	2	0	4	0	11	24
Total	224	99	103	70	220	76	620	1412

data proportionally across each type of question. In total, 792 emotions were detected within the 1,239 non-noisy posts, and 620 questions where EmoTxt predicted *No Emotion* for all the emotion classification runs. Of the 792 questions with emotion detected, 114 questions had two emotions predicted, 28 questions had three emotions detected, and one question[3] had four emotions detected (*Surprise*, *Sadness*, *Joy* and *Fear*).

No Emotion was the most prevalent across all question types, which is consistent with the findings of the Collab group during the training of the EmoTxt classifier. Questions classified as *API Change* had the broadest distribution of emotions, with EmoTxt reporting 31.25% of these types of questions as *No Emotion*, compared to overall average of 42.10%. However, this is likely due to the low sample size of *API Change* questions (with only 12 questions assigned this issue type). The next highest set of emotive questions are found in the second and fourth largest samples (*Review* at 203 posts, and *API Usage* at 287 posts); therefore, higher proportions of emotion is not necessarily correlated to sample size.

Unsurprisingly, *Discrepancy*-based questions—indicative of the frustrations developers face when the API does something unexpected—had the highest proportion of *Anger* detected, at 8.26%, compared to *Anger*'s mean of 4.77%. To our surprise, *Love* (which we expected least by software developers when encountering issues) was present across all of the different question types. On average, this was reported at 8.15%. The two highest emotions, by average, were *Fear* (μ =16.77%)and *Surprise* (μ =14.82%). In contrast, to our surprise, the two least-detected emotions reported by EmoTxt were *Sadness* (μ =4.53%) and *Anger* (μ =4.77%%). *Joy* and *Love* were roughly the same, and fell in between the two proportion ends, with means of 8.85% and 8.15%, respectively.

As shown in Table 6.3, results from our reliability analysis between human raters indicated subjectivity in emotion interpretation. Guidelines of indicative strengths of agreement are provided by Landis and Koch [210], where $\kappa \leq 0.00$ is *poor* agreement, $0.00 < \kappa \leq 0.20$ is *slight* agreement and $0.20 < \kappa \leq 0.40$ is *fair* agreement. Our assessments across the 300 questions indicate slight agreement for *Love*, *Surprise*, *Sadness*, *Anger* and *No Emotion*, and fair agreement for *Joy* and *Fear*. When combining human raters and EmoTxt, the inter-rater agreement was

[3] See `http://stackoverflow.com/q/55464541`.

Table 6.3: Inter-rater agreement between humans ($R_{1..3}$) and EmoTxt (E) and indicative guidelines of strength.

Emotion	$C_\kappa(R_1,R_2)$	$C_\kappa(R_1,R_3)$	$C_\kappa(R_2,R_3)$	$L_\kappa(R_{1..3})$	$C_\kappa(R_1,E)$	$C_\kappa(R_2,E)$	$C_\kappa(R_3,E)$	$L_\kappa(R_{1..3},E)$
Love	0.30 *Fair*	0.17 *Slight*	0.04 *Slight*	**0.17 *Slight***	0.37 *Fair*	0.27 *Fair*	0.05 *Slight*	**0.20 *Slight***
Joy	0.21 *Fair*	0.16 *Slight*	0.57 *Fair*	**0.31 *Fair***	0.1 *Slight*	0.07 *Slight*	-0.01 *Poor*	**0.18 *Slight***
Surprise	0.21 *Fair*	0.13 *Slight*	0.15 *Slight*	**0.16 *Slight***	0.17 *Slight*	0.04 *Slight*	0.06 *Slight*	**0.13 *Slight***
Sadness	0.11 *Slight*	0.05 *Slight*	0.01 *Slight*	**0.05 *Slight***	0.09 *Slight*	0.04 *Slight*	0.02 *Slight*	**0.05 *Slight***
Fear	0.19 *Slight*	0.22 *Fair*	0.36 *Fair*	**0.26 *Fair***	-0.02 *Poor*	-0.06 *Poor*	0.01 *Slight*	**0.12 *Slight***
Anger	0.19 *Slight*	0.19 *Slight*	0.07 *Slight*	**0.15 *Slight***	0.13 *Slight*	0.16 *Slight*	0.03 *Slight*	**0.13 *Slight***
No Emotion	0.30 *Fair*	0.16 *Slight*	0.09 *Slight*	**0.18 *Slight***	0.25 *Fair*	0.06 *Slight*	0.04 *Slight*	**0.15 *Slight***

slight across all emotions.

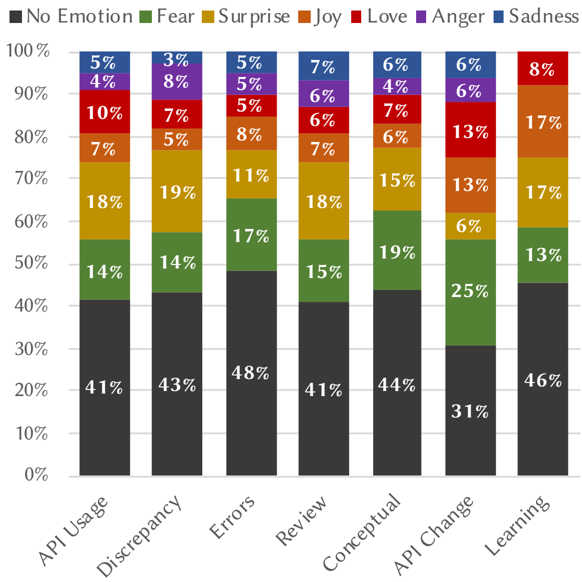


Figure 6.2: Proportion of emotions per question type.

6.5 Discussion

Our findings from the comparison between the manually annotated SO posts and the automatic classification revealed substantial discrepancies. Table 6.4 provides some sample questions[4] from our dataset, with the Beyer et al. question classification type noted with [Q], the emotion(s) identified by EmoTxt within the text noted with [E], and the emotion(s) classified by the three raters indicated with [$R_{1..3}$]. The subset of questions analysed by our three raters do not indicate the automatic (EmoTxt) emotion, and upon manual inspection of the text after poor results from our reliability analysis, an introspection of the dataset sheds some light to the discrepancy.

For example, the first question in Table 6.4 shows no indication of *Joy*, but EmoTxt classifies it to this emotion. Phrases like *"I'm **pretty** sure..."* could be the

[4]Questions located at https://stackoverflow.com/q/[ID].

Table 6.4: Sample of various question types ([Q]) against emotion(s) identified by EmoTxt ([E]) and the three raters ([$R_{1..3}$]).

Question ID and Quote	**Classifications**
51444352: *"I'm pretty sure I set up my IAM role appropriately (I literally attached the ComprehendFullAccess policy to the role) and the Cognito Pool was also setup appropriately (I know this because I'm also using Rekognition and it works with the IAM Role and Cognito ID Pool I created) and yet every time I try to send a request to AWS Comprehend I get the error... Any idea of what I can do in this situation?"*	[Q]: Errors [E]: Joy [R_1]: Surprise [R_2]: Surprise [R_3]: Anger
53117918: *"Ok so I have been stuck here for about more than a week now and I know its some dumb mistake. Just can't figure it out. I am working on a project that is available of two platforms, Android & iOS. Its sort of a facial recognition app... Is there anything I need to change? Is there any additional setup I need to do to make it work?Please let me know. Thanks."*	[Q]: Discrepancy [E]: Love, Surprise, Anger [R_1]: Sadness, Anger [R_2]: Sadness, Anger [R_3]: Anger
52829583: *"I was trying to make the google vision OCR regex searchable... it fails when there is the text of other languages.It's happening because I have only English characters in google vision word component as follows.As I can't include characters from all the languages, I am thinking to include the inverse of above... So where can I find ALL THE SPECIAL CHARACTERS WHICH ARE IDENTIFIED AS A SEPARATE WORD BY GOOGLE VISION? Trial and error, keep adding the special characters I find is one option. But that would be my last option."*	[Q]: Review [E]: Anger [R_1]: Joy, Anger [R_2]: Anger [R_3]: Surprise
50190527: *"I am trying to perform OCR on pdf documents using google cloud vision API, i uploaded a pdf document into a cloud bucket and downloaded the oauth key file and added it in the script as below. But when i run the file, i get the permission denined: 403 error, can anyone please give me instructions on how to fix it, i did extensive google search and did not yield any results, i am surely missing something here... I have checked the older stack overflow questions and the links provided in answers are not active anymore.Thanks in advance for your help."*	[Q]: API Usage [E]: No Emotion [R_1]: Sadness [R_2]: No Emotion [R_3]: Anger
52126752: *"I am trying to call google cloud vision api from xamarin C# android application code.I have set environment variable but still I was not able to call api.So I decided to call it by passing credential json file but now I am getting error deserializing JSON credential datahere is my code"*	[Q]: Errors [E]: Surprise [R_1]: No Emotion [R_2]: No Emotion [R_3]: Anger
48145425: *"I am Deploying Google cloud vision Ocr in My angular2 webapp. but i am getting many of the errors when i add this code in my webapp code. please help me to sort out this."*	[Q]: Errors [E]: Fear [R_1]: Fear [R_2]: No Emotion [R_3]: Sadness

reason why poor classification occurred, where words like "pretty" are associated with *Joy*, albeit in completely different context. It seems likely that the developer is experiencing a confusing situation when the API throws unexpected errors; thus [R_1] and [R_2] noting *Surprise*. Similarly, in the second question presented in Table 6.4, EmoTxt classifies *Love*, *Surprise*, and *Anger*. It is difficult to find an element of love or appreciation elsewhere in this context beyond the closing remarks: *"**Please** let me know. **Thanks**."*. Moreover, the disparity between EmoTxt and the agreed emotions between the first two reviewers shows that EmoTxt cannot detect the frustration (*Anger*) in the developer's tone, which is evident in their opening sentence, *"I have been **stuck here** for about more than a week and I know it is some **dumb mistake**."*.

These results indicate that introspection into the behaviour and limitations of the EmoTxt model is necessary. Our results indicate further work is needed to refine the ML classifiers that mine emotions in the SO context. The question that arises is whether the classification model is truly reflective of real-world emotions expressed by software developers. As highlighted by Curumsing [94], the divergence of opinions with regards to the emotion classification model proposed by theorists raises doubts to the foundations of basic emotions. Most of the studies conducted in the area of emotion mining from text is based on an existing general purpose emotion framework from psychology [64, 263, 270]—none of which are finely tuned for the software engineering domain.

6.6 Threats to Validity

6.6.1 Internal validity

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

6.6.2 External validity

EmoTxt was trained on questions, answers and comments, however our dataset contained questions only. It is likely that our results may differ if we included other discussion items, however we wished to understand the emotion within developers' *questions* and classify the question based on the question classification framework by Beyer et al. [40]. Moreover, this study has only assessed frustrations within the context of a concrete domain; intelligent CVSs. The generalisability of this study to other IWSs, such as natural language processing services, or conventional web services, may be different. Furthermore, we only assessed four popular CVSs; expanding the dataset to include more services, including non-English ones, would be insightful. We leave this to future work.

6.6.3 Construct validity

Some posts extracted from SO were false positives. Whilst flagged for removal, we cannot guarantee that all false positives were removed. Furthermore, SO is known to have questions that are either poorly worded or poorly detailed, and developers sometimes ask questions without doing any preliminary investigation. This often results in down-voted questions. We did not remove such questions from our dataset, which may influence the measurement of our results.

6.7 Conclusion

We wanted to see how developers emotions are indicated in Stack Overflow (SO) posts when using CVSs. We analysed 1,425 SO posts about CVSs for emotions using an automated tool and then cross-checked our results manually. We found that the distribution of emotion differs across the taxonomy of issues, and that the current emotion model typically used in recent works is not appropriate for emotions expressed within SO questions. Consistent with prior work [217], our results demonstrate that ML classifiers for emotion are insufficient; human assessment is required.

CHAPTER 7

Using Emotion Classification Models against Stack Overflow[†]

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

7.1 Introduction

Pre-trained artificial intelligence (AI) models are increasingly available to software developers either directly or wrapped into web-based components and toolkits; for example, Google's Cloud AI[1] or Microsoft Azure's Cognitive Services.[2] The grand

[†]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.

[1]`https://bit.ly/2VheoH2` last accessed 29 Nov 2020.

[2]`https://bit.ly/37jiwvU` last accessed 29 Nov 2020.

promise is the rapid creation of AI-infused functionality into end-applications as developers can simply reuse models instead of training them from scratch, as training is laborious and resource-intensive [296]. Vendors do provide usage guidelines, component documentation, code examples and a compelling marketing narrative, although the limitations and risks are not as well-presented in official documentation [89, 92]. In practice, developers and technical architects study issue trackers and online forums such as Stack Overflow (SO) to assess and inform their decisions. Multiple studies highlight the value and insights to be gained from these online forums [2, 92, 339].

This work began as an investigation determining whether these services are production-ready for certain industry use cases (e.g., computer vision). Inspired by the possibility of finding insight from content in the online forums, we wanted to analyse the issues raised on SO by developers that relate to computer vision-based intelligent web services (IWSs), i.e., computer vision services (CVSs). Although manual analysis is feasible for this task, we decided to use a pre-trained natural language processing technique for a more automated approach to understand developers' frustration. This was motivated by (i) the gain from automation—specifically having an efficient, repeatable process and, more importantly, (ii) to learn about potential issues when using pre-trained models in a related, but new, contexts. Section 7.2 explains this in further detail.

In our analysis, beyond the direct summative aspects, we focused on emotions within the content posed on the online forums. This was motivated by work done by Wrobel [385], who suggested that some negative emotions can pose risk to developer productivity. However, while anger is a negative emotion, it can (in some people) generate a motivating response [385]. Our goal was to determine whether negative emotions (and specifically, *which* negative emotions) are the predominant theme within questions on these forums regarding IWSs. The natural expectation is that developers would not pose questions unless they needed support and help, and we expected to find a high prevalence of anger-based emotion in the questions (frustration that the service is not working as they think should), and perhaps surprise at any unexpected behaviour. Similarly, we would expect the tone of responses to questions to be neutral, and hopefully supportive. Our focus, however, remains on the questions posed.

Our findings, elaborated further in Section 7.4, were surprising. While the pre-trained model we selected was trained specifically on SO and tuned for emotions [68, 263], our results show that 14% issues were considered by the model with the positive emotions of *Love* or *Joy*, and only a surprisingly small amount (5%) fell into *Anger* (or frustration). A closer examination using multiple human reviewers showed an even more interesting insight: human reviewers did not agree with the automated machine classification, and worse, the reviewers did not agree with each other, suggesting that training machines with a consistent set of labels is a non-trivial exercise. Finally, we reflected whether the pre-trained classifier could be better documented. We found vendors are recognising these challenges and are offering solutions to better document their models [134, 246]. However, when we looked into the information captured by these solutions, we found their specification to be very broad and additional guidance for completion is required to help evaluate risks faced in an industry context (discussed in Section 7.5).

7.2 Motivation

The initial context of our work was to explore reusable cloud-based CVSs,[3] arising for use in an industry context on a client project. Our prior research has identified growth in questions on SO relating to such services [92], thus enabling us to explore a rich dataset about developers' concerns about these pre-packaged and cloud-based AI-components.

Aware that productivity of software developers can be adversely impacted by negative emotion [385], we decided to explore the emotions within our dataset expressed by developers through the questions they pose on SO. Our intent was to identify whether developers are surprised, angry, frustrated, or overall positive about using these CVSs (as expressed as emotions in their SO questions). This was motivated by prior work, which shows that—despite their technical nature—SO questions do exhibit emotion [68, 262]. Although we could have read these posts manually, for consistency, repeatability, and efficiency, we chose to automate this process by utilising an emotion-aware text classification system trained specifically on SO data [263]. Our expectation was that we would gain some insight into the questions through the emotions, and we hypothesised that we would see a high proportion of surprise (i.e., the API does not work as expected) and anger (frustration due to mismatched expectations).

To permit replication, the raw results produced from this case study are made available online at `https://bit.ly/3eSp7ku`.

7.3 Method

We selected a classifier included in the EMTk toolkit that was specifically trained for emotional text classification in the software engineering domain [68]. The EMTk toolkit is available with a fully labelled training dataset [263], permitting reuse and analysis of internals. The classifier is based on Shaver et al.'s emotional hierarchy model [327] and performs binary classifications against text data provided in input files and an input parameter designating the emotion to be classified—one of *Love*, *Joy*, *Surprise*, *Fear*, *Sadness* or *Anger*. The classifier utilises support vector machine (SVM) classification and a Distributional Semantic Model (DSM) built using Word2Vec. This model is trained on 20 million SO posts. The DSM approach facilitates classification to take into consideration the surrounding context of the word, in addition to the polarity of individual words [69].

As input for the classifier, we used a dataset of 1,425 SO questions restricted to intelligent CVSs, available from Cummaudo et al. [92]. We ran the classifier with the same input dataset for each of the six emotions. To cross-check classified output, we manually annotated a random sample of 300 questions with zero or more of the

[3] Such as Google Cloud Vision, Azure Computer Vision, or Amazon Rekgonition

Table 7.1: Emotion classification frequencies.

Emotion	**Frequency**	**Proportion**
Love	103	7.2%
Joy	100	7.0%
Surprise	223	15.6%
Sadness	70	4.9%
Fear	224	15.7%
Anger	76	5.3%
No Emotion	622	43.6%

Table 7.2: Results from Inter-Rater Agreements.

Emotion	**Three Raters**	**Three Raters + Classifier**
Love	0.13 *(slight)*	0.19 *(slight)*
Joy	0.23 *(fair)*	0.13 *(slight)*
Surprise	0.15 *(slight)*	0.11 *(slight)*
Sadness	-0.01 *(poor)*	0.00 *(poor)*
Fear	0.25 *(fair)*	0.07 *(slight)*
Anger	0.05 *(slight)*	0.04 *(slight)*
No Emotion	0.09 *(slight)*	0.10 *(slight)*

six emotions. Each of these 300 posts were assigned to three raters who individually carried out the following three steps: (i) identify the presence of emotion(s); (ii) if emotion(s) exists, classify the emotion(s) under one or more of the six basic emotions as per the Shaver framework. The coding guidelines provided by Novielli et al. [263] were adhered to to assist with emotion classification per post. After collating each rater's results, we calculated a Fleiss' Kappa (κ) [119] as a measure of inter-rater agreement per emotion for each of the three human raters (manual rating), using the `irr` computational R package [129] per suggestions provided in [150]. Once completed, the three raters discussed discrepancies between posts classified with different emotion where agreement for that emotion was low, however we did not change any emotions that were initially assigned as this would impact reliability of our interpretation of Novielli et al. [263]'s guidelines. We then used the results from the classifier as a 'fourth' *automated* rater, comparing the results with the manual rating by calculating the agreement for each emotion and Fleiss' Kappa for further inter-rater agreement analysis.

Of the 1,425 SO questions, the classifier did not classify any emotion in 622 posts (labelled *No Emotion*). The remaining posts were classified as: 224 posts as *Fear*, 223 as *Surprise*, 70 as *Sadness*, 103 as *Love*, 100 as *Joy*, and 76 as *Anger*. Some posts were classified against two or more emotions, and as a result, the total proportions do not add up to exactly 100%. See Table 7.1. Results from our inter-rater analysis are reported in Table 7.2.

Guidelines of indicative strengths of agreement are provided by Landis and Koch [210], 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. These interpretations suggest that, when using the classifier's output as a fourth 'rater', there was slight agreement on all emotions except *Sadness*, where agreement was poor. Agreement amongst the three human raters was slight for *Love, Surprise, Anger and No Emotion*, fair for both *Joy and Fear*, and poor for *Sadness*.

7.4 Results

In this section, we present our findings with respect to limitations in the classifier and our investigation of the dataset that was used to train the classifier. Given the weak results, we then discuss whether model cards [246] and/or datasheets [134] could have provided a more effective approach to informing the viability and limits of the pre-trained model.

7.4.1 Limitations of the Text Classifier

The classifier did not assign any emotion to more than 43% of the SO posts. This result corroborates the findings by Murgia et al., who identified via a manual process *No Emotion* as the most prevalent classification [249]. For illustration, we provide a set of examples in Table 7.3. (The ratings column indicates the emotion labels assigned by each of the three human raters $R_{1..3}$ and the label assigned by the classifier C.) The first example given in Table 7.3 illustrates a neutral example, where none of the raters, including the classifier identified any emotion. In the second example, the classifier did not detect any emotion, however all three human raters agreed that the question indicated *Sadness*. In the third example, each rater identified different emotions, thereby indicating complete disagreement. In the fourth example, the classifier interpreted the question as *Joy*, whereas the human raters identified *Surprise* and *Anger*. Whilst that question had a word typically associated with *Joy* (i.e., "I'm <u>pretty</u> sure..."), the realistic context here is that the phrase 'pretty' indicates no emotion and the wider context of the question shows how the human raters identified a sense of frustration (anger) and surprise at the results the developer is finding. Lastly, two, additional examples are presented in the last and second-last rows of Table 7.3 to highlight different inconsistencies both between human raters and the classifier.

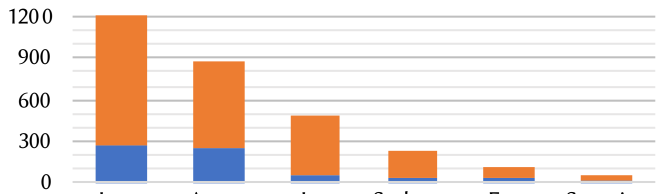
We investigated our training dataset and related research documentation to see if that would give us further insights. We found two areas warranting further exploration—training data balance and training data annotation.

7.4.2 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*

Table 7.3: Human Raters (*R1, R2, R3*) versus automated classifier (*C*). Questions located at: https://stackoverflow.com/q/[ID].

Question ID and Quote	Ratings
[42375271] *"Can we use Microsoft Emotion API in our Android Apps, considering the fact that it's still in its 'Preview' mode...can we create our own customized app using the code of EMOTION API to recognize the moods of users in our own app?"*	[C]: No Emotion [R_1]: No Emotion [R_2]: No Emotion [R_3]: No Emotion
[55599305] *"I have consumed the google cloud vision api to recognize a document with a table, but sometimes the image will be a little rotated, im triyng to get the value using theof the key i want, but how do i get it if it's not on the same.I was thinking of making a 'line' above and below the and finding if the point is between that, but i dont know how to do it."*	[C]: No Emotion [R_1]: Sadness [R_2]: Sadness [R_3]: Sadness
[43534783] *"Can someone try Google VisionAPI FaceTracker and see if it works? ...All I get when I try running it is a black screen (after fixing). I don't get any errors in the logs either."*	[C]: Fear [R_1]: Surprise [R_2]: No Emotion [R_3]: Anger
[51444352] *"I'm pretty sure I set up my IAM role appropriately (I literally attached the ComprehendFullAccess policy to the role) and the Cognito Pool was also setup appropriately (I know this because I'm also using Rekognition and it works with the IAM Role and Cognito ID Pool I created) and yet every time I try to send a request to AWS Comprehend I get the error... Any idea of what I can do in this situation?"*	[C]: Joy [R_1]: Surprise [R_2]: Surprise [R_3]: Anger
[50190527] *"I am trying to perform OCR on pdf documents using google cloud vision API, i uploaded a pdf document into a cloud bucket and downloaded the oauth key file and added it in the script as below. But when i run the file, i get the permission denined: 403 error, can anyone please give me instructions on how to fix it, i did extensive google search and did not yield any results, i am surely missing something here... I have checked the older stack overflow questions and the links provided in answers are not active anymore.Thanks in advance for your help."*	[C]: No Emotion [R_1]: Sadness [R_2]: No Emotion [R_3]: Anger
[48145425] *"I am Deploying Google cloud vision Ocr in My angular2 webapp. but i am getting many of the errors when i add this code in my webapp code. please help me to sort out this."*	[C]: Fear [R_1]: Fear [R_2]: No Emotion [R_3]: Sadness



	Love	Anger	Joy	Sadness	Fear	Surprise
Other Posts	958	631	441	193	66	37
Question Posts	262	251	50	37	40	8
Total	1220	882	491	230	106	45

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.)

was assigned either positive or negative sentiment, depending on context [69, 263]. Figure 7.1 shows the distribution of emotion labels across 4,800 posts in the training dataset; *No Emotion* ($n = 1959$) is removed to emphasise emotion-only results. Note: some posts in the training data set were classified as more than 1 emotion, hence the total counts add up to greater than 4800.

Class imbalance and its impact on classifier models is a known problem in machine learning (ML) [224, 375], 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 [224]. 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 different emotional language, however our study was interested in classifying SO question posts only. Of the training dataset's 4,800 posts, only 1,044 could be identified as question posts and within that subset of posts, the distribution of emotions was more polarised than in the overall 4,800 posts. *Love* and *Anger* are the most predominant emotions in the training dataset, however *Anger* has a higher proportion (24%) in question posts, as opposed to only 18.4% in the overall dataset.

In summary, the training dataset was not balanced within each emotion category and some emotions had very low sample numbers, as emphasised in the skew in Figure 7.1. Proportions of training data examples per question per emotion was very low for *Joy*, *Surprise*, *Sadness* and *Fear*. To address this imbalance and achieve better performance, training data could be enhanced to include additional samples or to use an oversampling approach. A recent study into class-balancing approaches in the context of defect prediction models found that class rebalancing does lead to a shift in the learned concepts [357].

7.4.3 Emotion Labeling Bias

In software engineering, hierarchical categorical emotional frameworks—including those featured in Parrott [275], Ekman et al. [111] and Shaver et al. [327]—have been assessed by researchers and pragmatically selected as the basis for training emotional classifiers. The chosen emotion framework is then used as the taxonomy of truth labels for classifier training datasets. Data for labeling is sourced from systems such as SO and JIRA [128, 249, 263, 270]. In the software engineering domain, truth labeling of emotions has, to date, been done manually [128, 249, 263]. Emotion annotation involves at least a pair of annotators [12, 138]. For the EMTk training dataset, annotation was performed manually by a team of 12 coders, divided into four groups of three with a computer science background [68, 263]. Manual annotation challenges when coding emotions can be encountered due to different levels of semantic ambiguity within emotions and how humans express emotions in text [152].

In the absence of an objective emotional truth, researchers' consistency is taken as a measure of correctness—i.e., multiple annotators that agree [249]. A measure of inter-rater agreement is Cohen's Kappa [82] (for two raters) or Fleiss' Kappa [119] for more raters. For the training dataset, inter-rater agreement ranged from $\kappa = 0.30$ (fair) for *Joy* to $\kappa = 0.66$ (substantial) for *Love*. The researchers specifically trained dataset coders for consistency. The challenge of this approach with a subject such as emotions is the opportunity for bias. In contrast, in other studies that used annotation, researchers specifically attempted to reduce the opportunity for biases by including raters with different nationalities, skills, cultural backgrounds, by increasing the number of raters [270] and opting against consistency training [9]. As such, the approach taken to achieve consistency and makeup of label coders is important information for downstream consumers of an AI model.

7.4.4 Emotion Labelling and Classification Granularity

Training data annotation was performed on SO posts—which included questions, answers, and comments to questions and answers. Emotion annotation can be performed at different levels of granularity—word level [340], spans of words in a sentence [12], 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 [12, 249]. 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, see the fifth question in Table 7.3. We see that the first sentence does not carry any emotion, as the author is stating the steps to reproduce their issue. However, in the second sentence—where the API generates a "403 error"—the author expresses a mix of both *Sadness* and *Anger* (i.e., frustration) since their "extensive google search" yielded no results, for which they begin to self-doubt ("i am surely missing something here"). Lastly, *Love* is demonstrated in the last sentence, via appreciation in advance for potential responses to their question.

7.5 Discussion

There is a growing trend emerging from key industry vendors to better document pre-trained models using various means. For example, Google has proposed model cards to communicate performance characteristics of pre-trained models [246]. Google has also published sample model cards relating to their Cloud Vision API for face and object detection[4] and, more recently, released a model card tookit[5] to encourage other ML practitioners to produce their own. Furthermore, this toolkit is now integrated into the Python library `scikit-learn` to help developers automatically generate model cards.[6] Microsoft has 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 [134]. This is a key building block of the 'Responsible ML' initiative led by the partnership on AI,[7] which aims to increase the transparency of AI and accountability of ML system documentation.[8] Lastly, IBM too has proposed a 'FactSheet' concept combining model and data information [15].

These tools are being adopted by organisations and researchers; for example, Open AI has published a basic model card of their generative language model[9] and Google provided a sample model card for its toxicity analyser in its model card proposal paper [246]. Model cards are also being considered for high stakes environments such as clinical decision making [325], where they facilitate overarching governance regimes on how and when models can be used.

In our case study, the combination of a model card for the classifier as well as a datasheet for training data would have provided valuable, easy to digest, and initial support to help evaluate whether the classifier is right for our context. However, the current specification of datasheet contents is very broad and lacks detailed directions for those completing required information. The model cards proposed by Google are focused on performance characteristics and do not sufficiently focus on the underlying data that was used to train and, hence, define the context of the classifier.

Had all the required information been provided to sufficient detail, including a highlight of the importance of rater consistency training, we could have better

[4] `https://bit.ly/2IXDLel` last accessed 28 November 2020.
[5] `https://bit.ly/3k7rLnk` last accessed 28 November 2020.
[6] `https://bit.ly/36bXnEK` last accessed 28 November 2020.
[7] `https://bit.ly/33kebYc` last accessed 28 November 2020.
[8] `https://bit.ly/3lf8WPD` last accessed 28 November 2020.
[9] `https://bit.ly/3o6ECsj` last accessed 30 November 2020.

assessed risks and clarified at the outset whether an automated emotion assessment was an appropriate exercise. Further, with this information, we would be able perform our study with an more extensive rater consistency training, as well as a better appreciation of the limits of the classifier.

Hence, model cards and datasheets present rich opportunities for improving confidence and understanding in pre-trained AI technology. Now that toolkits are becoming increasingly available to make it easier for developers to generate toolkits, we suggest further research to evaluate model cards and datasheets (and combinations of the two) before pre-trained models are selected for specific tasks. This would make a valuable case study which we leave open for future work. Further, development of guidelines for model cards and datasheet creation, use and maintenance based on empirical evidence is also largely missing in literature; another avenue for potential research especially for use in industry contexts. A key challenge identified by this case study was the difficulty of validating results of an emotional classifier. An additional research study could aim to capture developer emotion directly as they log questions and facilitate learning of developer emotion classification through this direct method (e.g., a think-aloud study). This proposed approach to capturing data may shed further light into the emotional state an individual developer is experiencing *as they write* their questions. However, it would be of interest to assess if it is possible to draw conclusions about emotions that developers feel *in general*, due to the subjective nature of emotion. That is, it is possible that different developers would report a range of emotions even when they write similar posts.

Once validation of the results can be improved, additional improvement could be considered for the EMTk classifier including training it on questions only and using some of the identified data balancing techniques to re-balance the dataset. Another area of potential research is whether providing feedback to developers about the emotional content in their posts would change what they communicate. For instance, would it assist developer productivity if they were made aware of the emotional content of their contributions/posts?

7.6 Threats to Validity

This case study represents only one detailed example of a classifier trained on the emotional model proposed by Shaver et al. [327], documented in academic articles aimed to support research [68, 69, 262, 263]. This impacts the external validity of our study as the results cannot be generalised to other domains or emotion classifiers. To mitigate this, it would be very useful and informative to compare and validate our findings across a number of classifiers, however this is challenging since there is generally a lack of detailed information (i.e., model cards and datasheets) for available classifiers to support the analysis. This said, even a simple comparative analysis of emotion classification outputs is difficult because emotional classifiers are typically trained on a specific emotional model. A mapping between emotional models would therefore be needed, which demands expertise beyond software engineering research.

Another key limitation is that our analysis focused on SO questions on a particular topic, whereas the EMTk had been trained on a mixture of different posts and topics. This again impacts the external validity of our results. It is not appropriate to draw a general conclusion from this analysis that emotions cannot be reliably classified by analysing text. In fact, there were higher inter rater scores achieved for EMTk's training dataset. Possibly additional rounds of clarification and moderation would yield a higher score and higher confidence.

It is common for questions on SO to be duplicates or downvoted, typically due to poor wording or a lack of detail in the body of the question. Duplicate and downvoted questions were not removed from our dataset used in the experiment, and, furthermore, any poorly worded questions may have impacted the automatic classifier's emotion labelling. This is likely to have impacted the measurement of our results.

7.7 Related Work

Emotion detection from text has been explored by researchers in depth. A recent survey of approaches, including the different emotion models and computational approaches, can be found in Sailunaz et al. [315] and Alswaidan and Menai [10]. Recently, researchers have also explored deep learning, specifically bidirectional BLSTM models, to improve emotion detection from text [32]. Most approaches are supervised learning based, and hence rely on a labelled dataset for training.

Some related work of special interest has been done in the area of sentiment analysis, where discussions touched on emotion recognition. Novielli et al. [262] investigated the suitability of using sentiment analysis tools to measure affect in SO questions and comments. In their analysis, they discussed that developers expressed negative emotions associated with their technical issues and that developers mainly express their frustrations for not being able to solve a problem. For questions with positive sentiment, they found that the positive lexicon did not express emotions, but rather positive opinions and use of positive speech acts associated with politeness and gratitude in advance of receiving a response. Also, of interest is the evaluation of sentiment analysis tools evaluated on SO, JIRA and App Review datasets by Lin et al. [217]. This study found that the prediction accuracy of the tools that were evaluated were biased against the majority class (neutral emotion).

The use of biometric sensors is also an area of active research for software developer emotion recognition. This includes conducting experiments with correlated sensor data analysing the emotions software developers present whilst working [140]. Further work could include using the biometric-based data as a data source for truth labels for emotion analysis as developers write their questions on SO, supporting the proposed studies mentioned in Section 7.5.

7.8 Conclusion

We started this work with an idea to use existing AI techniques to *automatically* investigate what other developers think of cloud IWSs. This translated into our attempt to use a pre-trained model that learnt from posts provided by software engineers on SO. Developers learn, improve and deepen their skills from documentation, formal or self-paced education, experience, and sharing their knowledge. Good documentation often forms the foundation that enables learning and also to create educational aids.

In this paper, we presented an observation case study that highlights a set of gaps in how a peer-reviewed model, published in the field of software engineering, lacks information about the limitations both within the documentation, as well as the articles published. To resolve these gaps, we investigated if new solutions that are being proposed (such as model cards) would have been of use to us before conducting our experiment. Model cards and datasheets will be a necessary and helpful first step, but as such we found their specification to be insufficient and additional guidance is required for those documenting the models cards and datasheets. Although we study only one pre-trained model in depth, our analysis shows that there are gaps in proposed solutions that can be addressed, and our future work will focus on investigating other models and IWSs to develop a more detailed documentation approach, specifically those that are being aimed for software engineering.

CHAPTER 8

Better Documenting Computer Vision Services†

Abstract Using cloud-based computer vision services (CVSs) is gaining traction, where developers access AI-powered components through familiar RESTful APIs, not needing to orchestrate large training and inference infrastructures or curate/label training datasets. However, while these APIs *seem* familiar to use, their non-deterministic run-time behaviour and evolution is not adequately communicated to developers. Therefore, improving these services' API documentation is paramount—more extensive documentation facilitates the development process of intelligent software. In a prior study, we extracted 34 API documentation artefacts from 21 seminal works, devising a taxonomy of five key requirements to produce quality API documentation. We extend this study in two ways. Firstly, by surveying 104 developers of varying experience to understand what API documentation artefacts are of *most value* to practitioners. Secondly, identifying which of these highly-valued artefacts are or are not well-documented through a case study in the emerging CVS domain. We identify: (i) several gaps in the software engineering literature, where aspects of API documentation understanding is/is not extensively investigated; and (ii) where industry vendors (in contrast) document artefacts to better serve their end-developers. We provide a set of recommendations to enhance intelligent software documentation for both vendors and the wider research community.

8.1 Introduction

Improving API documentation quality is a valuable task for any API. Succinct API documentation of good quality facilitates productivity [214, 252, 253], and therefore improved quality is better engineered into a system [238]. Where application developers integrate new services into their systems via APIs, their pro-

† This chapter is originally based on A. Cummaudo, R. Vasa, J. Grundy, and M. Abdelrazek, "Requirements of API Documentation: A Case Study into Computer Vision Services," *IEEE Transactions on Software Engineering*, pp. 1–1, 2020, DOI 10.1109/TSE.2020.3047088. Terminology has been updated to fit this thesis.

ductivity 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"*). As a real-world use case, consider intelligent computer vision services (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 [89]. These services use machine intelligence to make predictions on images such as object labelling or facial recognition [398, 409, 410, 411, 412, 419, 423, 431, 432, 433, 437, 451, 452, 485, 486]. The impacts of poor and incomplete documentation results in developer complaints on online discussion forums such as Stack Overflow [92]. 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.

It is therefore important to ensure developers have access to high-quality API documentation artefacts when consuming these services. Vendors should cover all documentation artefacts that the wider developer community find valuable, and the research community should aide in this process by investigating with types of information that comprise these artefacts, or the aspects of information design to best present this information. What causes a developer to be confused when using an API, and how to mitigate it via improved documentation, has been largely explored by researchers for *conventional* APIs (an overview is provided in Section 8.2). Various studies provide a myriad of recommendations into the value of API documentation artefacts based on both qualitative and quantitative analyses, involving developer opinions (from surveys), observation of developers, event logging or content analysis (see Figure 8.3). Such guidelines propose ways for developers, managers, and solution architects can construct systems better with improved documentation.

However, there does not yet exist a consolidated *systematic* review of this literature. Further, few studies offer a taxonomy to consolidate these guidelines together, and there still lacks a consolidated effort to capture guidelines on the requirements of good quality API documentation. Studies that produce these guidelines from literature are largely scattered across multiple sources. Investigating the ways by which these guidelines are produced can provide software engineering researchers with better insight into the research methods and data collection techniques used to produce these guidelines. Some studies, for example, use case studies, others use focus groups and brainstorming, or interviews and surveys. The extent to which researchers rely on developer opinion for API documentation guidelines is evident, and gaps in the methodological approaches that researchers use should be emphasised to shine light into new ways of conducting research in this important area. Furthermore, systematically capturing the information distilled from these guidelines into a readily accessible, consolidated taxonomy (designed to assist writing API documentation) must be validated in real-world circumstances to assess its efficacy with practitioners.

In our prior work, we proposed an API documentation taxonomy that was comprised of 21 key primary sources [88]. This paper significantly extends our previous work by addressing limitations in the existing taxonomy, thus refining it. Previously, we developed a metric for each dimension (topmost-layers) and category (leaf nodes) within the taxonomy [88]. This metric is an indication of the specific areas of API documentation software engineering researchers have focused their efforts, as measured by the ratio of papers that investigated or reported various issues concerning the documentation artefacts defined within our taxonomy. For the context of this paper, we refer to this metric as an 'in-literature' score, or ILS. Within this paper, we build upon this facet but *in-practice* by assessing the efficacy of our taxonomy against developers using a survey instrument inspired by the System Usability Scale (SUS) [62]. Each artefact within the taxonomy is measured against this instrument for its utility, and a metric is produced to indicate how well developers *value* each of these artefacts. We refer to this metric as an 'in-practice' score, or IPS. (Details for how the IPS is calculated are in given in Section 8.5.1.4.) We then identify the artefacts that are highly researched, the ones that developers demand the most, and where gaps in these artefacts remain for future research exploration.

Lastly, while our prior work focused on *generalised* API documentation, in this extension, we apply our taxonomy to a case study of interest: i.e., better documenting CVSs. We empirically assess the taxonomy against three popular CVSs, namely Google Cloud Vision [423], Amazon Rekognition [398] and Azure Computer Vision [437]. For each category in our taxonomy, we assess whether the respective service's documentation contains, partially-contains or does not contain the documentation artefact from our taxonomy, thus determining the extent to which the requirements of good API documentation are met within the vendors' own documentation. From this, we triangulate each ILS and IPS value against the service's level of inclusion of its respective documentation artefact, thereby making a judgement as to where the services can improve their documentation to make them more complete. Lastly, we present a ranking of each artefact for where research or vendors should be focus their documentation efforts that is of high value to both developers *and* to industry vendors.

Thus, through this triangulation of the taxonomy with existing literature, utility to practitioners, and application via a case study (CVSs), we summarise three aspects of API documentation by identifying:

(i) the documentation artefacts that been extensively studied by researchers, and those that warrant further attention by the software engineering research community (via high/low ILS values);

(ii) the documentation artefacts that are considered to be the most- and least-important from a practitioner's point of view (via high/low IPS values);

(iii) the documentation artefacts that have been well-established by vendors (via our case study on three prominent CVSs).

To demonstrate how our taxonomy was developed, we include an extended revision of the systematic mapping study (SMS) from our existing work. The taxonomy we proposed consists of five key requirements: (1) Descriptions of API Usage; (2) Descriptions of Design Rationale; (3) Descriptions of Domain Concepts; (4) Existence of Support Artefacts; and (5) Overall Presentation of Documentation.

Following this, we developed a survey instrument to assess the overall utility of each of the artefacts that contribute towards these five requirements, which consisted of 43 questions of alternating positive and negative sentiment. We then narrow our focus down to our case study by applying the prioritised documentation artefacts (as identified by the survey) to three CVSs. Once our surveys were complete, we provide some general guidelines as to where cloud CVSs can make improvements to their API documentation. Lastly, we compare and contrast the results from our SMS to the results of the survey and of our case study, thereby identifying where future research efforts into API documentation should focus to give the biggest value back to practitioners.

Our key contributions in this work are:

- a score metric for each category that indicates where the highest research priorities have been in the existing literature;
- a score metric assessing the efficacy of the 34 categories that empirically reflects what artefacts are of the highest value from a *practitioner* point of view;
- a heuristic validation of each artefact against CVSs, assessing where existing CVS API documentation needs improvement;
- a number of practical recommendations for CVS vendors to better improve the quality of their API documentation; and
- an identification of the gaps for future research into API documentation based on the highest need by developers but, so far, has captured the least attention by researchers.

This paper is structured as follows: Section 8.2 presents related work; Section 8.3 is divided into two subsections, the first describing how primary sources were selected in the SMS with the second describing the development of our taxonomy from these sources; Section 8.4 presents the taxonomy; Section 8.5 describes how we developed a survey instrument of 43 questions to validate the taxonomy against developers, and assess its efficacy against the three popular CVSs selected; Section 8.6 presents the findings from our validation analysis; Section 8.7 describes the threats to validity of this work; and Section 8.8 provides concluding remarks and the future directions of this study. Additional materials are provided in Chapter C.

8.2 Related Work

8.2.1 Systematic Reviews in Software Documentation

Systematic reviews into how developers produce and use software documentation gives researchers consolidated insights into the efforts of multiple, disparate API documentation studies. For example, a recent 2018 study explored 36 API documentation generation tools and approaches, and analysed the tools developed and their inputs and documentation outputs [264]. The findings from this study emphasise that the largest effort in API documentation tooling is to assist developers to generate either example code snippets and/or templates or natural language descriptions of the API directly from the program's source code. These snippets or descriptions can then be placed in the API documentation, thereby increasing the efficiency at which API documentation can be written. Additionally, tools from 12 studies target the maintainability of existing APIs of existing APIs, while tools from 11 studies target the correctness and accuracy of the documentation by validating that what is written in the documentation is accurate to the technical structure of the API. From the end-developer's perspective, some tools (17 studies) help target improvements to the developer's understandability and learnability of new APIs by linking in examples directly with questions such as on Stack Overflow. However, the results from this study regards the *tooling* used to either assist in producing, validating or learning from API documentation. While this is a systematic study with key insights into the types of tooling produced, there is still a gap for an SMS in what *guidelines* have been produced by the literature in developing natural language documentation itself—and how well developers *agree* to those guidelines—which our work has addressed.

An extensive SMS into studies presented in the *overall* software documentation domain was given in Zhi et al. [392]. This study reviewed a set of 69 papers from 1971 to 2011 to develop a systematic map on the various research aspects relating to documentation cost, benefit and quality, finding that 38% of papers propose novel techniques while 29% contribute empirical evidence (i.e., validation and evaluation papers—see Section 8.3.1.4). The authors find that a majority of papers discuss quality aspects of software documentation, namely the quality attributes of completeness, consistency and accessibility, and that the main usage of software documentation regards maintenance aid and program comprehension. Another key insight—relevant to our study—found that, on average, survey-based studies into documentation involved 106 participants and generally these participants were from the same (or only two) organisations. However, unlike our study, this study formalises the documentation efforts of *any* software document, and not exclusively into API documentation artefacts required to help developers produce software. Further, our study differs in that the results from our study are consolidated into a structured taxonomy, instead of a meta-model which Zhi et al. perform, which is then triangulated against a real-world use case (i.e., intelligent CVSs) and software developers via a survey.

8.2.2 API Usability and Documentation Knowledge

API usability and its impact on documentation knowledge is an imperative area of study, since it provides useful links between API documentation and more technical issues related to API design or tools. Extensive discussions from Myers and Stylos [253] and Myers et al. [252] encapsulate a 30-year effort to evaluate and improve API usability through lenses adapted human-computer interaction research. Essentially, by treating a developer as the 'end-user' of an API (i.e., interacting and programming with the API in their own systems), the authors discuss various case studies by which API usability was improved by various human-centred approaches, resulting in improved learnability of the API in addition to improved productivity and effectiveness in using the API. While the methods are primarily used for end-user usability testing, their observations highlight the importance of good aesthetic and interaction design of developer's tooling and the need for new tooling to augment what developers already do to reduce learning overhead. An extensive review of the usability methods used, and their benefits to API usability, demonstrates how various techniques—grounded through established usability guidelines and frameworks—can be used to assess how an API's usability impacts its key stakeholders (i.e., API designers, developers, and end-users). The role of API *documentation* in context to an API's overall usability is imperative; for instance, limited documentation on a particular API (and limited code snippets) is often a key complaint to poor API usability [253]. Exploring aspects on information design elements within API documentation is therefore critical to mitigate such complaints.

In Watson [372], the authors performed a heuristic assessment from 35 popular APIs against 11 high-level universal design elements of API documentation. Of these 35 APIs, 28 were open-source software repositories and seven came from commercial independent software vendors. Two coders manually inspected each API's respective documentation sets, starting from the documentation's entry page and using the navigation features of the documentation to further explore the documentation. Both coders evaluated each of the 11 heuristics, noting whether they could be found. This study highlighted how many APIs, even popular ones, fail to grasp these basic design elements. For example, 25% of the documentation sets did not provide any basic overview documentation to the API. Therefore, from a practitioner's perspective, the study describes a high-level overview of how certain documentation artefacts address their needs and whether they are typically found in documentation. However, while the methodological approach used in this study to assess the heuristics is similar to our approach, the heuristics themselves used within Watson's study is based on only three seminal works and only contains 11 design elements. Our study extends these heuristics and structures them into a consolidated, hierarchical taxonomy which we then validate against practitioners.

A taxonomy of distinct knowledge patterns within reference documentation by Maalej and Robillard [227] classified 12 distinct knowledge types. Unlike our work, which uses an SMS of existing studies as the source of our taxonomy development, this study uses a grounded method via theoretical sampling of the API documentation of two mature (extensively documented) open source systems. This was performed by each author to elicit a list of knowledge types over an iterative six month process. The taxonomy was then evaluated against the JDK 6 and .NET 4.0 frameworks using a sample of 5574 documentation units and 17 trained coders to assign each knowledge type to the documentation unit. Results showed that the functionality and structure of these APIs are well-communicated, although core concepts and rationale about the API are quite rarer to see. The authors also identified low-value 'non-information'—described as documentation that provides uninformative boilerplate text with no insight into the API at all—which was substantially present in the documentation of methods and fields in the two frameworks. They recommend that developers factor their 12 distinct knowledge types into the process of code documentation, thereby preventing low-value non-information, and thus developers can use the patterns of knowledge to evaluate the content, organisation, and utility of their own documentation. The development of their taxonomy consisted of questions to model knowledge and information, thereby capturing the reason about disparate information units independent to context; a key difference to this paper is the *systematic* taxonomy approach utilised and the source of information of our taxonomy (i.e., existing literature).

8.2.3 Computer Vision Services

Recent studies into cloud-based CVSs have demonstrated that poor reliability and robustness in computer vision can 'leak' into end-applications if such aspects are not sufficiently appreciated by developers. A study by Hosseini et al. [163] showed that Google Cloud Vision's labelling fails when as little as 10% noise is added to the image. Facial recognition classifiers are easily confused by modifying pixels of a face and using transfer learning to adapt one person's face into another [367]. Our own prior work found that the non-deterministic evolution of these types of services is not adequately communicated to developers [89], resulting in lost developer productivity whereby developers ask fundamental questions about the concepts behind these services, how they work, and where better documentation can be found [92]. This paper continues this line of research by providing a means for service providers to better document their services using a taxonomy and suggested improvements.

8.3 Taxonomy Development

We developed our taxonomy under two primary phases. First, we conducted an SMS identifying API documentation studies, following guidelines by Kitchenham and Charters [195] and Petersen et al. [283] (Section 8.3.1). A high level overview of this first phase is given in Figure 8.2. Second, we followed a software engineering taxonomy development method by Usman et al. [361] (Section 8.3.2) based on the findings of our SMS, which involved an extensive validation involving real-world developers and contextualised with computer vision APIs (Section 8.5).

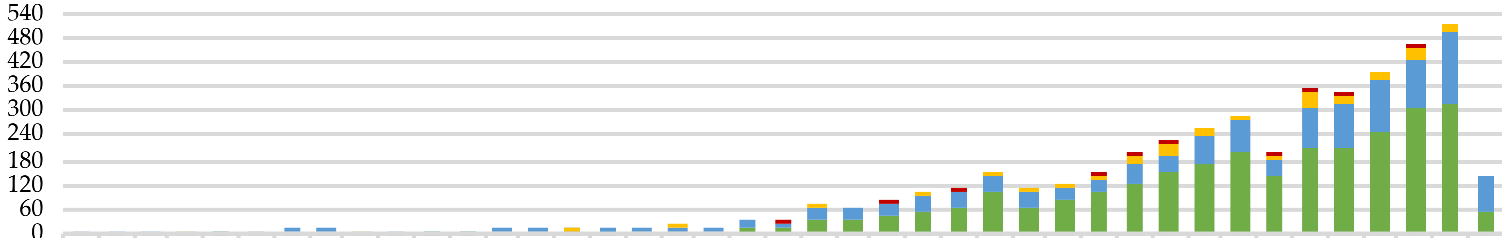
8.3.1 Systematic Mapping Study

8.3.1.1 Research Questions (RQs)

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

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

Our intent behind RQ1 was to collect as many studies provided by literature on how API documentation should be written using natural language, i.e., not using assistive tooling. In this regard, documentation 'knowledge' encompasses any natural language API documentation artefact associated with the implementation of an application using a third-party API. As the goals of this study are to arrive at a



	77	78	79	80	82	84	85	86	87	88	89	90	91	92	93	94	95	96	97
Other	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Book (Chapter)	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	3	0
Journal Article	2	1	1	0	2	2	5	3	0	2	6	5	3	7	5	11	13	14	7
Conference Paper	0	0	0	1	1	0	4	4	1	0	1	1	3	6	7	2	7	7	12

	98	99	00	01	02	03	04	05	06	07	08	09	10	11	12	13	14	15	16	17	18	19
Other	0	1	0	0	1	0	1	0	0	0	1	2	1	0	0	1	1	1	0	1	0	0
Book (Chapter)	0	0	1	0	0	4	1	11	12	11	17	15	21	22	13	10	38	19	21	30	14	0
Journal Article	17	18	25	26	26	37	45	37	37	29	27	50	46	67	78	34	102	108	121	123	176	86
Conference Paper	19	13	36	36	47	59	62	103	65	83	103	126	150	172	201	145	208	208	250	303	320	55

Figure 8.1: Search results by year and venue type.

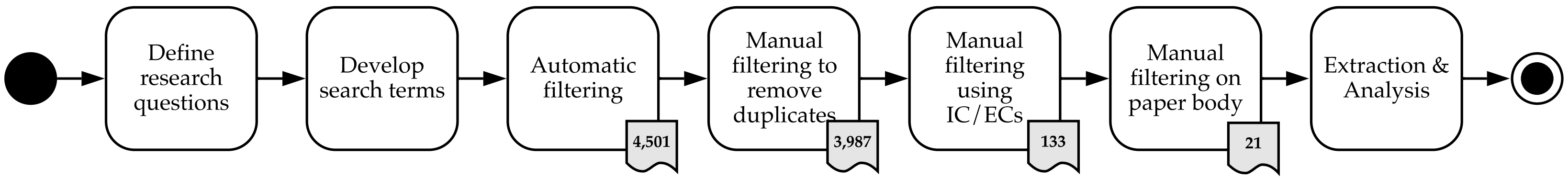


Figure 8.2: A high level overview of the filtering steps from defining and executing our search query to the data extraction of our primary studies. Number of accepted papers resulting from each filtering step is shown.

taxonomy encapsulating the requirements of good API documentation (Section 8.4), we sought to arrive at studies that provide useful information to developers that informs the relevance and value of which aspects of API documentation are more useful than others. This captures the knowledge that developers need to know about what aspects of their APIs should be documented and the artefacts by which they do this. This helped us shape and form the taxonomy provided in Section 8.4. Secondly, RQ2's intent was to understand how the studies derive at their conclusions, thereby helping us identify gaps in literature where future studies can potentially focus.

8.3.1.2 Automatic Filtering

As done in similar software engineering studies [132, 141, 361], we explored automatic filtering of online databases. We defined which SWEBOK knowledge areas [168] were relevant to devise a search query. Our search query was built using related knowledge areas, relevant synonyms, and the term 'software engineering' (for comprehensiveness) all joined with the OR operator. Due to the lack of a standard definition of an API, we include the terms: 'API' and its expanded term; software library, component and framework; and lastly SDK and its expanded term. These too were joined with the OR operator, appended with an AND. Lastly, 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)

We executed the query on all available metadata (title, abstract and keywords) in May 2019 against Web of Science[1] (WoS), Compendex/Inspec[2] (C/I) and Scopus[3]. We selected three particular primary sources given their relevance in software engineering literature (containing the IEEE, ACM, Springer and Elsevier databases) and their ability to support advanced queries [61, 195]. A total 4,501 results[4] were found, with 549 being duplicates. Table 8.1 displays our results in further detail (duplicates not omitted); Figure 8.1 shows an exponential trend of API documentation publications produced within the last two decades. (As this search was conducted in May 2019, results taper in 2019.)

8.3.1.3 Manual Filtering

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

[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.
[4] Raw results can be located at `http://bit.ly/2KxBLs4`.

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

IC1 Studies must be relevant to API documentation: specifically, we exclude studies that deal with improving the technical API usability (e.g., improved usage patterns);

IC2 Studies must discuss artefacts that document APIs;

IC3 Studies must be relevant to software engineering as defined in SWEBOK;

EC1 Studies where full-text is not accessible through standard institutional databases;

EC2 Studies that do not propose or extend how to improve the official, natural language documentation of an API;

EC3 Studies proposing a third-party tool to enhance existing documentation or generate new documentation using data mining (i.e., not proposing strategies to improve official documentation);

EC4 Studies not written in English;

EC5 Studies not peer-reviewed.

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

Firstly, we read the publication source—to rapidly omit non-software engineering papers—as well as the author keywords, title, and abstract of all 4,501 studies. As some studies were duplicated between our three primary sources, we needed to remove any repetitions. We sorted and reviewed any duplicate DOIs and fuzzy-matched all very similar titles (i.e., changes due to punctuation between primary sources), thereby retaining only one copy of the paper from a single database. Similarly, as there was no limit do our date ranges, some studies were republished in various venues (i.e., same title but different DOIs). These were also removed using fuzzy-matching on the title, and the first instance of the paper's publication was retained. This second phase resulted in 3,987 papers.

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

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

As a final phase, we conducted reliability analysis of our shortlisting method. We conducted intra-rater reliability of our 133 shortlisted papers using the test-retest approach suggested by Kitchenham and Charters [195]. We re-evaluated a random sample of 10% of the 133 shortlisted papers a week after initial studies were shortlisted. This resulted in *substantial agreement* [210], measured using Cohen’s kappa ($\kappa = 0.7547$).

8.3.1.4 Data Extraction & Systematic Mapping

Of the 21 primary studies, we conducted abstract key-wording adhering to Petersen et al.’s guidelines [283] to develop a classification scheme. An initial set of keywords were applied for each paper in terms of their methodologies and research approaches (RQ2), based on an existing classification schema used in the requirements engineering field by Wieringa and Heerkens [379]. These are: *evaluation papers*, which evaluates existing techniques currently used in-practice; *validation papers*, which investigates proposed techniques not yet implemented in-practice; *experience papers*, which are written by practitioners in the field and provide insight into their experiences of adopting existing techniques; and *philosophical papers*, which presents new conceptual frameworks that describes a language by which we can describes our observations of existing or new techniques, thereby implying a new viewpoint for understanding phenomena. For example, documenting APIs using code snippets is a commonly used practice by developers (see the primary sources listed in Appendix C.1), and conducting an experiment exploring how quickly practitioners achieve this would be an evaluation paper. In contrast, a validation paper explores novel techniques that are proposed but not yet implemented in practice; for example, a paper proposing that APIs should document success stories so that developers know where, why, and how the API was successfully implemented may test this novel technique via field study experiments (e.g., interviewing developers on the new technique) without reference to real-world examples. A paper written by a group of developers sharing their insights into the improvements of their documentation before and after providing extensive tutorials would be an experience

Table 8.2: Data extraction form

Data item(s)	Description
Citation metadata	Title, author(s), years, publication venue, publication type
Artefact(s) discussed	As per IC2, the study must identify at least one API documentation artefact
Evaluation method	Did the authors evaluate their proposed artefacts? If so, how?
Primary technique	The primary technique used to devise the artefact(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

paper. Philosophical papers may propose entirely new vocabulary to explore API documentation, devising new frameworks from which other researchers can explore the field from a new viewpoint.

After all primary studies had been assigned keywords, we noticed that all papers used field study techniques, and thus we consolidated these keywords using Singer et al.'s framework of software engineering field study techniques [332]. Singer et al. captures both study techniques *and* methods to collect data within the one framework, namely: *direct techniques*, including brainstorming and focus groups, interviews and questionnaires, conceptual modelling, work diaries, think-aloud sessions, shadowing and observation, participant observation; *indirect techniques*, including instrumenting systems, fly-on-the-wall; and *independent techniques*, including analysis of work databases, tool use logs, documentation analysis, and static and dynamic analysis.

Table 8.2 describes our data extraction form, which was used to collect relevant data from each paper. Figure 8.3 presents our systematic mapping, where each study is mapped to one (or more, if applicable) of methodologies plotted against Wieringa and Heerkens's research approaches. We find that a majority of these studies survey developers using direct techniques (i.e., interviews and questionnaires) and some performing structured documentation analysis. Few studies report recent experiences; literature reports the artefacts that document APIs from evaluation research, in addition to some validation studies. There are few experience papers describing anecdotal evidence, and almost no philosophical papers that describe new conceptual ways at approaching API documentation as a large majority of existing work either evaluates existing (in-practice) strategies or validates the effectiveness of new strategies.

8.3.2 Development of the Taxonomy

A majority of taxonomies produced in software engineering studies are often made extemporaneously [361]. For this reason, we decided to proceed with a systematic approach to develop our taxonomy using the guidelines provided by Usman et al. [361], which are extended from lessons learned in more mature domains. In this subsection, we outline the 4 phases and 13 steps taken to develop our taxonomy based on Usman et al.'s technique. Usman et al.'s final *validation* phase is largely detailed within Section 8.5 after we present our taxonomy in Section 8.4.

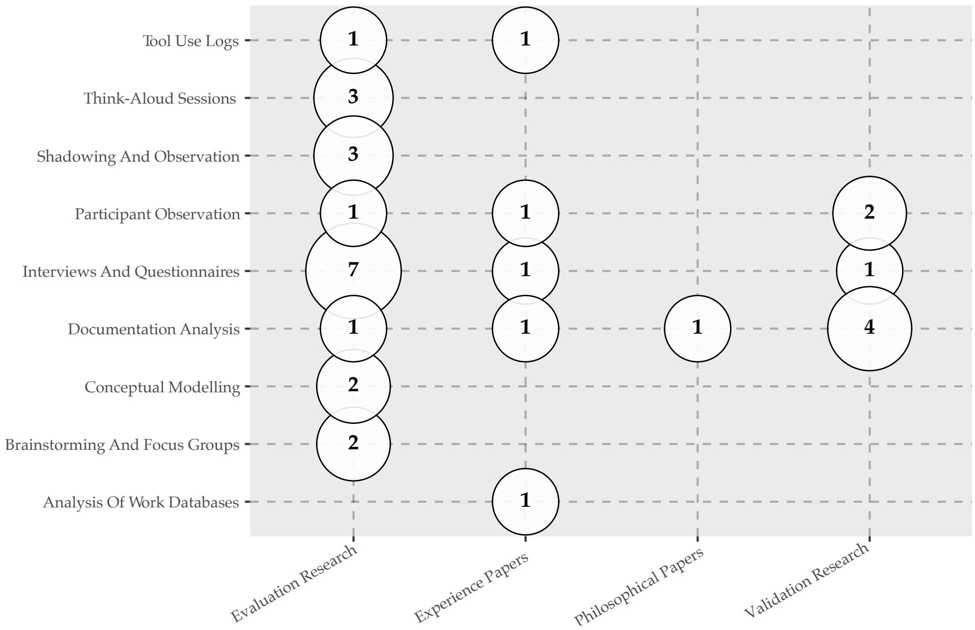


Figure 8.3: Systematic map: field study technique vs research type

Formally, Usman et al. provides guidelines to define these units under the first six stages under the planning phase. In our study, our preliminary phase involves answering the following:

(1) *define the software engineering knowledge area*: The software engineering knowledge area, as defined by the SWEBOK, is software construction;

(2) *define the objective*: The main objective of the proposed taxonomy is to define a set of categories that enables to classify different facets of natural language API *documentation* artefacts (not API *usability*) as reported in existing literature;

(3) *define the subject matter*: The subject matter of our proposed taxonomy is documentation artefacts of APIs;

(4) *define the classification structure*: The classification structure of our proposed taxonomy is *hierarchical*;

(5) *define the classification procedure*: The procedure used to classify the documentation artefacts is qualitative;

(6) *define the data sources*: The basis of the taxonomy is derived from field study techniques (see Section 8.3.1.4).

8.3.2.1 Identification and extraction phase

The second phase of the taxonomy development involves **(7)** *extracting all terms and concepts* from relevant literature, which we have achieved from our SMS. These terms are then consolidated by **(8)** *performing terminology control*, as some terms may refer to different concepts and vice-versa. For example, Watson defines one of the heuristics used in the study's experiment as "sample apps to understand how to use the elements of an API in context and as another source from which to copy program code... a sample app is a complete application that includes examples of the API as well as the other functions that comprise a complete program" [372]. In this case, the term 'sample app', 'program code', and 'complete application' were extracted as a term of interest and noted. Similarly, in Robillard [305], the phrase 'applications' is used to define a category of example code snippets which "consists of code segments from complete applications" and is generally some form of "demonstration samples sometimes distributed with an API... that developers can download from various source code repositories" [305]. Again, the phrase 'complete applications', 'demonstration samples', 'download', and 'source code' was identified as a terms of interest and noted. Once all papers were read, we consolidated a list of all of these noted highlights to help consolidate the terms and perform terminology control. In this example, the phrase 'Downloadable source code demonstrating complete sample applications' was consolidated from both Watson and Robillard's studies, which—in addition to the other primary studies that iteratively changed wording slightly due to steps (9–10)—formed the basis of the taxonomy dimension [**A7**].

8.3.2.2 Design phase

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

8.3.2.3 Validation phase

In the final phase of taxonomy development, taxonomy designers must **(13)** *validate the taxonomy* to assess its usefulness. Usman et al. [361] describe three approaches to validate taxonomies: (i) orthogonal demonstration, in which the taxonomy's orthogonality is demonstrated against the dimensions and categories, (ii) benchmarking the taxonomy against similar classification schemes, or (iii) utility demonstration by applying the taxonomy heuristically against subject-matter examples. In our study, we adopt utility demonstration by use of a survey and heuristic application of the taxonomy against real-world case-studies (i.e., within the domain of CVSs). This is is discussed in greater detail within Section 8.5.

8.4 A Taxonomy for API Documentation

Our taxonomy consists of five dimensions (labelled A–E). These five dimensions are made of 34 categories, which represent API documentation artefacts that contribute towards these dimensions. In the context of our taxonomy, a category can represent (i) discrete and self-contained documentation artefacts (e.g., quick start guides [**A1**]), (ii) additional information used to describe the API (e.g., licensing information about the API [**D6**]), or (iii) aspects regarding the information design of this documentation (e.g., consistent look and feel [**E6**]). Collectively, the categories form the *requirements* of good quality API documentation, as expressed through the five dimensions. When worded as questions, each dimension respectively covers the following:

- [**A**] **Descriptions of API Usage**: *how* does the developer use this API for their intended use case?
- [**B**] **Descriptions of Design Rationale**: *when* should the developer choose this particular API for their intended use case?
- [**C**] **Descriptions of Domain Concepts**: *why* does the developer select this particular API for their application's domain and does the API's domain align with the application's domain?
- [**D**] **Existence of Support Artefacts**: *what* additional API documentation can the developer find to aid their productivity?
- [**E**] **Overall Presentation of Documentation**: is the *visualisation* of the above information well organised and easy for the developer to digest?

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

Appendix C.1 shows which of the primary sources (S1–21) reports aspects of the artefacts described as an 'in-literature score' (ILS). This score is calculated as a percentage of the number of primary studies that investigated or reported various issues regarding the specific artefact divided by the total of primary studies (see Section 8.6.1.2). This score is contrasted to the 'in-practice score' (IPS) which indicates the overall level of agreement that *practitioners* think such documentation artefacts are needed (see Section 8.6.1.1). For comparative purposes, we illustrate a colour scale (from red to green) to indicate the relevancy weight between ILS and IPS values in Appendix C.1 as per their assigned, discretised intervals (see Table 8.3). We also show illustrative interpretations of these generalised artefacts through italicised examples within Appendix C.1. We then provide three columns that assesses the presence of these documentation artefacts against three popular CVSs: Google Cloud Vision, AWS's Rekognition, and Azure Cloud Vision (abbreviated to GCV, AWS and ACV). A fully shaded circle (●) indicates that the documentation artefact was

[A] Descriptions of API Usage

- [A1] Quick-start guides
- [A2] Low-level reference manual ✓
- [A3] Explanation of high level architecture ✓
- [A4] Introspection source code comments ✗
- [A5] Code snippets of basic component function ✓
- [A6] Step-by-step tutorials with multiple components
- [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
- [A12] Error definitions describing how to address problems

[B] Descriptions of the API's Design Rationale

- [B1] Entry-point purpose of the API ✓
- [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

[C] Descriptions of Domain Concepts behind the API

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

[D] Existence of Support Artefacts

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

[E] Overall Presentation of Documentation

- [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 ✓

Figure 8.4: Our proposed taxonomy: The requirements of good-quality API documentation (dimensions) represented through individual documentation artefacts (categories).

clearly found in the service, while a half-shaded circle (◐) indicates that the artefact was only partially present. An outlined circle (○) indicates that the service lacks the indicated documentation artefact within our taxonomy. This empirical assessment is further detailed in Section 8.6.3, which outlines concrete areas in the respective services' documentation where improvements could be made, as well as hyperlinks to the documentation where relevant.

Figure 8.4 illustrates a condensed version of taxonomy. We provide iconography for the presence (✔) or non-presence (✖) of these artefacts in *all three* CVSs assessed, per Section 8.6.1.1.

8.5 Validating the Taxonomy

8.5.1 Survey Study

8.5.1.1 Designing the Survey

We followed the guidelines by Kitchenham and Pfleeger [196] on conducting personal opinion surveys in software engineering to validate our survey. In developing our survey instrument, we shaped questions around each of our 5 dimensions and 34 categories. To achieve this, we used Brooke's SUS [62] as a loose inspiration and re-shaped the 34 categories around a question that imitates the style of wording of questions used in the SUS. Each dimension was marked a numeric question (Q#3–7), and alphabetic sub-questions were marked for each sub-dimension or category.

We used closed questioning where respondents could choose an answer on a 5-point Likert-scale (1=*strongly disagree*, 2=*somewhat disagree*, 3=*neither agree nor disagree*, 4=*slightly agree* and 5=*strongly agree*). Like Brooke's study, each question alternated in positive and negative sentiment. Half of our questions were written where a likely common response would be in strong agreement and vice-versa for the other half, such that participants would have to "read each statement and make an effort to think whether they would agree or disagree with it" [62]. For example, the question regarding [**B7**] on API limitations was framed as: "*I believe it is important to know about what the limitations are on what the API can and cannot provide*" (Q4g), whereas the question regarding [**C1**] on domain concepts of the API was framed as: "*I wouldn't read through theory about the API's domain that relates theoretical concepts to API components and how both work together*" (Q5a).

In addition, the remaining eight questions asked demographical information. An extra open question asked for further comments. The full survey is provided in Appendix C.5 and anonymised survey data is available at `https://bit.ly/33siqll`.

8.5.1.2 Evaluating the Survey

After the first pass at designing questions was completed, we evaluated our survey on three researchers within our research group for general feedback. This resulted in minor changes, such as slight re-wording of questions and providing specific questions with examples (some with images). For example, the question regarding [**A9**] on an exhaustive list of all major components in the API was framed as "*I believe*

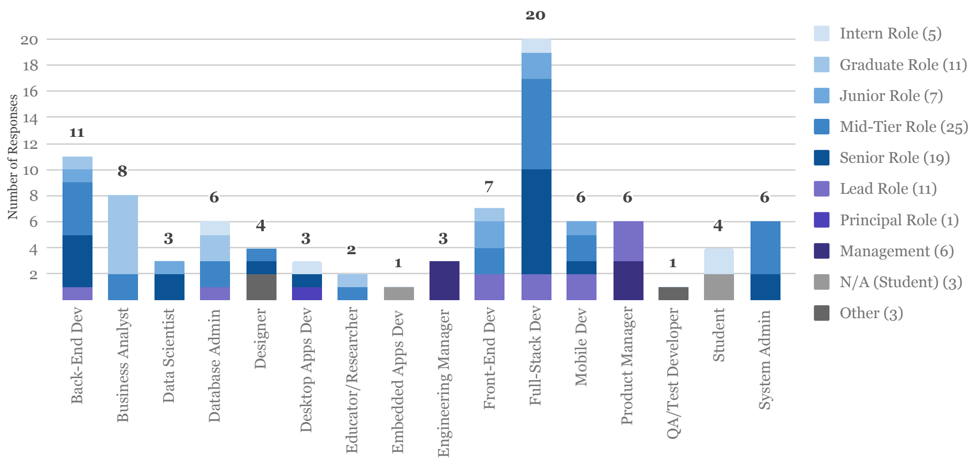


Figure 8.5: A wide variety of roles and seniority were observed in our respondents.

an exhaustive list of all major components in the API without excessive detail would be useful when learning an API" (Q3i) with the example "*e.g., a computer vision web API might list object detection, object localisation, facial recognition, and facial comparison as its 4 components*".

After this, we conducted reliability analysis using a test-retest approach on three developers within our group seven weeks apart. Using the R statistical computation environment [293], we conducted our analysis using the `irr` package [129] (as suggested in [150]) and resulted in an average intra-class correlation (ICC) of 0.63 which indicates a good overall index of agreement [79].

8.5.1.3 Recruiting Participants

Our target population for the study was application software developers with varying degrees of experience (including those who and who have not used CVSs or related tools before) and varying understanding of fundamental machine learning concepts. We began by recruiting software developers within our research group using a group-wide message sent on our internal messaging system. Of the 44 developers in our group's engineering cohort,[5] 22 responses were returned, indicating an internal response rate of 50.00%. Based on the 22 results from this internal trial, we calculated the median time to our complete survey was just over 20 minutes.

For external participant recruiting, we shared the survey on social media platforms and online-discussion forums relevant to software development. We adopted a non-probabilistic snowballing sampling where the participants, at the end of the survey, were encouraged to share the survey link to others using *AddThis*.[6] Additionally, snowballing sampling was encouraged within members of our research group who were asked to share the survey. This sampling approach resulted in 38 external responses. A further 44 participants were recruited via Amazon Mechanical

[5]Our research group's engineering cohort consists of fully-qualified software engineers, with on average 5+ years industry experience.

[6]`https://www.addthis.com/` last accessed 7 January 2020.

Turk[7]—often referred to as MTurk—which has been a successful approach adopted in previous software engineering surveys (e.g., [180]). To ensure our target demographic was selected, we applied the participant filter option 'Employment Industry - Software & IT Services'. An additional 13 responses were partially filled (on average at a completion rate of 43.23%). These partially completed responses were included in our analysis since they did yield some insight (see Section 8.7.2). As participants recruited via MTurk have a financial incentive to complete surveys,[8] we ensured strict quality control was applied to each survey response we received. For example, 37 participants opened the survey but did not answer any questions; for this reason, all survey responses by these participants were discarded. We identified that 12 MTurk responses were filled out too quickly (where the median response time was under five minutes; well below the internal average of 20 minutes), and further analysis of these 12 responses indicated poor reading of the question, and thus poor responses; this was identified via our use of alternating positively- and negatively-worded questions. Thus, 12 MTurk responses were removed from the final analysis. Therefore, our final response rate yielded 104 responses of the total 153 participants reached; an overall response rate of 67.97%.

8.5.1.4 Analysing Response Data

To analyse our response data, we produced a single score for each question's 5-point response. In line with with Brooke's SUS methodology [62], we subtracted one from the raw value of positive items, and subtracted the raw value from five for the negative items. This resulted in values on an ordinal scale of 0–4. We then averaged each response for every question and divide by four (i.e, now a 4-point scale) to obtain scores for each category. For example, two responses of *strongly agree*=5 and one of *neither agree nor disagree*=3 were given to [**A1**] (positively worded); these values are mapped to 4 and 2, respectively, and are averaged (to 3.33) which is then divided by a maximum possible score of four, giving 0.84. We then discretise these calculated values into five intervals (as per Table 8.3, see Section 8.6.1.1) to interpret the findings; this is presented in Appendix C.1 under the 'in-practice score' (IPS) for each category.

Demographics for our survey were consistent in terms of the experience levels of developers who responded. 78% of respondents indicated they were professional programmers. Years of programming experience were: <1 year (3.30%); 1–5 years (41.76%); 6–10 years (35.16%); 11–15 years (9.89%); 16–20 years (5.49%); 21–30 years (3.30%); 31–40 years (1.10%); 41+ years (0.00%). A wide range of roles and seniority were listed by developers as presented in Figure 8.5, thereby indicating that our results include the different expectations of API documentation from a variety of sources. The highest role was a full-stack developer at either a mid-tier or senior role, followed by mid-tier or senior back-end developers and graduate and junior business analysts. Various managerial roles were also listed.

[7] `https://www.mturk.com/` last accessed 9 July 2020.

[8] A total budget of AUD$600 was allocated for recruitment via MTurk, with each participant receiving between AUD$3.50–$10.00.

Only five students (5.00%) responded in our study, two listing themselves as interns with one as an embedded applications developer. Most respondents were Australian (40.00%), Indian (26.70%) or from the United States (20.00%). Besides information technology services (30.77%), consulting and other software development (both at 9.89%) were the most predominant industries listed by participants.

8.5.2 Empirical Application on Computer Vision Services

Once our taxonomy had been developed and assessed with developers, we performed an empirical application against three CVSs: Google Cloud Vision [423], Amazon Rekognition [398] and Azure Computer Vision [437]. Our selection criteria in choosing these particular services to analyse is based on the prominence of the service providers in industry and the ubiquity of their cloud platforms (Google Cloud, Amazon Web Services, and Microsoft Azure) in addition to being the top three adopted vendors used for cloud-based enterprise applications [120]. In addition, we had conducted extensive investigation into the services' non-deterministic runtime behaviour and evolution profile in prior work [89] and have also identified developers' complaints about their incomplete documentation in a prior mining study on Stack Overflow [92].

We began with an exploratory analysis of the presence of each dimension and its categories. Appendix C.2 displays all sources of documentation used; although we initially started on the respective services homepages [398, 423, 437], this search was expanded to other webpages hyperlinked. For each category, we listed the documentation's presence as either fully present, partially present or not present at all. This is shown in Appendix C.1 with the indication of (half-)filled circles or circle outlines for Google Cloud Vision (abbreviated to GCV), Amazon Rekognition (abbreviated to AWS), and Azure Computer Vision (abbreviated to ACV). Notes were taken for each webpage justifying the presence, and exact sources of documentation were listed when (partially) present. PDFs of each webpage were downloaded between 14–18 March 2019 for analysis. Analysis was performed manually by the lead author by manual inspection of the downloaded web pages (as PDFs) and presence of each item was noted by the lead author using an approach similar to Watson [372].

8.6 Taxonomy Analysis

In this section, we analyse investigating the taxonomy from two perspectives. Firstly, we contrast the ILS values, being an interpretation of the relevancy researchers have emphasised, against the IPS values found from the results of our survey (being an interpretation of what documentation artefacts developers value more). We are therefore able to identify the API documentation artefacts that are of high value to practitioners, but are yet to be deeply explored by researchers. Secondly, we contrast the IPS values against our assessment of CVSs, and whether important API documentation artefacts have been included in popular services. We are therefore able to identify whether vendors have or have not already included these highly-

Table 8.3: Intervals of ILS (top) and IPS (bottom) values and frequencies.

Research Attention	Range	Frequency	Categories
Very Low	$0.00 \leq \text{ILS}([Xi]) < 0.14$	7	B4, B5, D6, B3, C1, D1, D2
Low	$0.14 \leq \text{ILS}([Xi]) < 0.29$	13	A1, A9, C3, D3, D4, E2, E3, E4, E5, B6, A7, A10, D5
Medium	$0.29 \leq \text{ILS}([Xi]) < 0.43$	9	B2, B7, A4, A12, E1, A3, A8, A11, C2
High	$0.43 \leq \text{ILS}([Xi]) < 0.57$	3	E6, B1, A2
Very High	$0.57 \leq \text{ILS}([Xi]) \leq 0.71$	2	A6, A5
Value to Developers	**Range**	**Frequency**	**Categories**
Very Low	$0.00 \leq \text{IPS}([Xi]) < 0.18$	0	–
Low	$0.18 \leq \text{IPS}([Xi]) < 0.36$	0	–
Medium	$0.36 \leq \text{IPS}([Xi]) < 0.53$	6	D4, B4, C3, C1, E4, B3
High	$0.53 \leq \text{IPS}([Xi]) < 0.71$	16	A4, B6, A2, D2, A6, E2, B5, D6, A8, B2, E6, A10, E5, D5, A9, D3
Very High	$0.71 \leq \text{IPS}([Xi]) \leq 0.89$	12	E3, A7, A3, C2, A12, B1, D1, A11, A1, E1, A5, B7

valued documentation artefacts within their own APIs, and where existing areas of improvement lie.

8.6.1 Exploring IPS and ILS Values

8.6.1.1 IPS Results

IPS values indicate the extent to which developers agree with the statements made in our survey, as calculated by the method described in Section 8.5.1.4. The interpretation of these values are the documentation artefacts (categories) that developers *value* the most. Thus collectively, these artefacts indicate the overall level of importance towards specific API documentation requirements (dimensions).

To interpret these values, we group the data from each of our survey's 34 statements (for each category) into an ordinal scale of five intervals. These intervals indicate relative value to developers; a documentation artefact has *very low* value to developers, *low* value, *medium* value, *high* value, or *very high* value. Table 8.3 presents these intervals and frequencies of each, with the order of the categories shown in the last column indicating raw IPS values (least useful to most useful) before discretisation in ascending order.

Practitioners tend to agree that each documentation artefact is important to have, and thus IPS values likely fall into the *High* or *Very High* intervals. Only six categories fall into the *Medium* interval and none fall into lower intervals. Developers find technical support contact information [**D4**] to be of the lowest value (see Table 8.3), likely since developers tend to rely on crowd-sourced peer support through mediums such as Stack Overflow. They also see little value in: descriptions of the types of end-users the API is intended for [**B4**]; documentation for non-technical audiences [**C3**]; conceptual information relating the API back to its application domain [**C1**]; structured navigation of the presented API documentation [**E4**]; and descriptions of the intended developers who should be using the API [**B3**].

8.6.1.2 ILS Results

ILS values indicate overall research attention of categories of our taxonomy through the proportion of papers in our SMS that investigated or reported various issues regarding a specific API documentation artefact. Collectively, each of these categories combined form a dimension (labelled A–E) in a bottom-up approach (see Section 8.3.2.2). Each dimension (top-node) describes the requirements of good quality API documentation, while the category (leaf-node) is the specific API documentation artefact that, collectively, form the requirement. A category with a high ILS value indicates that existing studies that there is substantial attention by researchers on this specific documentation artefact (or, collectively, requirement of good quality API documentation). Conversely, a lower ILS value indicates less attention reported on these categories (artefact) or dimensions (requirement) by the software engineering research community.

To demonstrate the attention of these documentation artefacts within literature, we interpret the ILS values in a similar fashion to the IPS values. It is represented as a discretised value of intervals within a five-dimensional ordinal scale, where the attention on these artefacts in literature are one of: *very low* attention, *low* attention, *medium* attention, *high* attention, *very high* attention. Table 8.3 indicates the boundaries for each interval (as calculated by the highest ILS value of 0.71 divided by the five intervals) in addition to the frequency of categories appearing in each interval. The order of the categories shown in the last column indicate the ascending order (least research attention to most) of raw ILS values before discretisation. As shown, most of the artefacts (20) found in the taxonomy are discussed in literature disproportionately more than others (i.e., those that fall into the 'low' (13) or 'very low' (7) intervals), though the underlying reasons behind this should be considered on a case-by-case basis (see Section 8.7.3).

There are only five categories that fall into the 'high' or 'very high' intervals, three of which fall under dimension [**A**], Descriptions of API Usage. Research attention on a particular documentation artefact that is considered *Very High* gravitates towards code snippets [**A5**] and tutorials [**A6**]. Code snippets are the readiest form of API documentation for developers, representing exemplary nuggets of information for developers to rapidly digest singular components of the API's functionality. While code snippets generally only reflect small portions of API functionality (generally limited to 15–30 LoC), this is complimented by step-by-step tutorials. These may tie in multiple (disparate) components of API functionality to demonstrate development of more non-trivial applications. Therefore, unsurprisingly, research has substantially explored how best API developers can extract code snippets or write tutorials for these purposes in mind. This is followed by low-level reference documentation [**A2**]—under the 'high' interval—whereby developers should document all client-facing implementation or usage aspects of their API (e.g., class, method, parameter descriptions etc.). Lastly, the entry-level purpose/overview of an API

[**B1**] and consistency in the look and feel of the documentation throughout all of the API's official documentation [**E6**] are fall under the 'high' interval. API vendors must give motivation as to why a developer should choose a particular API over another, articulating the *need* of their API, presenting this and other documentation aspects in the easiest way for developers to consume.

8.6.1.3 Research Opportunities for High-Value Artefacts

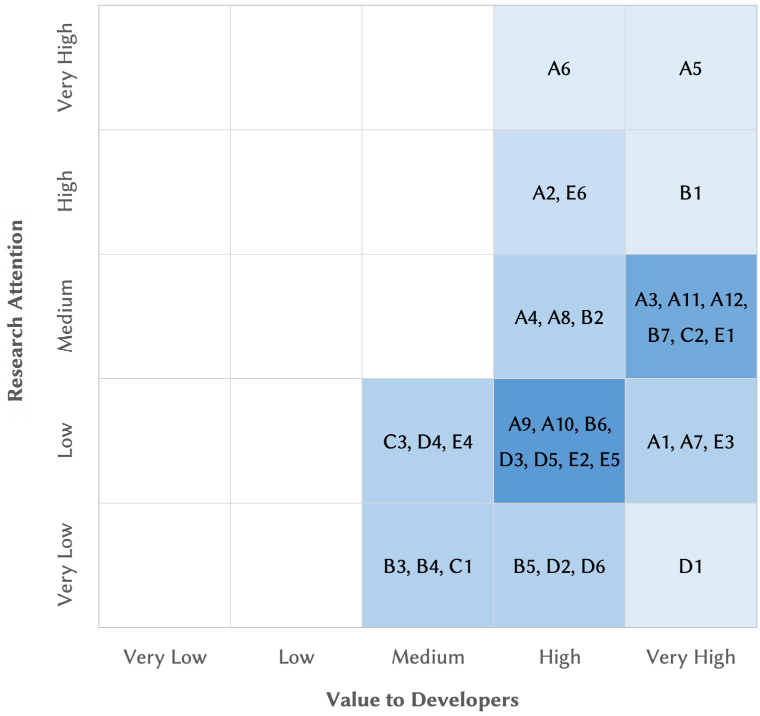


Figure 8.6: Value of API documentation artefacts to developers (IPS) vs their research attention (ILS). Colour intensity represents greater number of categories in each intersection

In this section, we explore the ILS and IPS values as two distinct indicators of research exploration that would provide the most value to practitioners. We then provide a qualitative discussion by inspecting the intersection of categories at each respective interval identified by our SMS and survey study. Thus, we are able to determine documentation artefacts (categories) and requirements (dimensions) that provide the *greatest value* to developers but have not gained proportional attention in the software engineering literature when compared to other artefacts, and vice-versa. Graphically, we represent these intersections within a five-by-five matrix with intervals of the IPS (x axis) plotted against intervals of the ILS (y axis). Intersections between the two are listed for each category within the taxonomy. This is presented in Figure 8.6.

There is a distinction between (very-)highly valued documentation artefacts whose research attention is (very-)low, as presented in the bottom-right of Figure 8.6. Most notably, we find that developers find Existence of Support Artefacts [**D**] a highly valued API documentation requirement, but there still exists a substantial gap in existing literature into this requirement. For example, besides category [**D4**] (which is of only *Medium* value to developers), less research has explored all other dimension [**D**] categories (though there may be understandable reasons as to why, as detailed in Section 8.7.3). Furthermore, developers highly value detailed Descriptions of API Usage [**A**] through many documentation artefacts, notably quick-start guides [**A1**], downloadable sample applications [**A7**], exhaustive list of major components [**A9**], and system requirements to use the API [**A10**]. Such artefacts emphasise the need for developers to rapidly pick-up a new API; however, the best ways to provide such information is still open to further investigation in literature.

Conversely, the top-right of Figure 8.6 emphasises (very)-highly researched artefacts that are of (very)-high value to developers. Here we see that Descriptions of API Usage [**A**] is the most-researched requirement, with code snippets [**A5**] being an API usage artefact that is both most-researched and of highest value. Hence, this demonstrates how many existing studies have an empirical basis on software developers (e.g., via surveys or interviews; see Figure 8.3)—code snippets is a well-researched artefact since most developers agree to its need in the documentation of APIs. Therefore, it is clear to see how the correlation between the respective ILS and IPS values for [**A5**] are high. However, if we look at other areas of our taxonomy, such as [**A12**], [**B7**], [**D3**], [**E3**] or [**E5**], we find that developers do indeed desire these aspects of API documentation, and, consequently, demand usage descriptions, design rationale descriptions, support artefacts, or good presentation of the documentation to be a necessary requirement of good quality API documentation. Thus, these aspects have not gained proportional attention in literature, thereby highlighting future research potential.

8.6.2 Triangulating IPS, ILS and Computer Vision

To interpret our comparison of IPS values with CVSs, we introduce a calculated ‘presence score’ for each category. As discussed in Section 8.5.2, we empirically evaluate each category of our taxonomy with three CVSs: Azure Computer Vision (ACV), Amazon Rekognition (AWS) and Google Cloud Vision (GCV). We indicate whether the respective API documentation artefact is present, partially present, or nor present (as listed in Appendix C.1). To interpret this data, we assign a full circle (●) for present, half-circle (◐) for partially present and an empty circle (○) for not present. Combinations of presence for each category per service are indicated with the three circles of varying shade. For example, [**A1**] has a presence score of ●●◐ because it was found to be present in both GCV and ACV but only partially present in AWS; [**B3**] has a presence score of ◐○○ because it was only found to be partially present in GCV, etc. For a list of full presence values, see Appendix C.1.

We illustrate which artefacts industry vendors provide developers with and the artefact’s respective developer value using this combination of three circles. Using a similar approach to the previous section, these results are presented in a ten-by-five matrix as illustrated in Figure 8.7. If only one service fully implements a documentation artefact of (very-)high value to developers (● ○ ○), if one or two

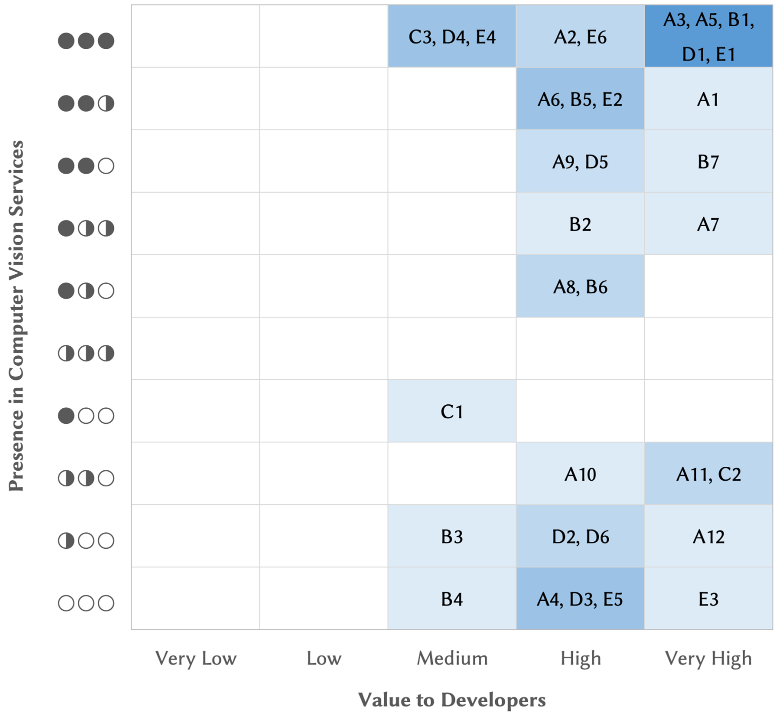


Figure 8.7: Value of API documentation artefacts to developers (IPS) vs their presence in CVSs. Colour intensity represents greater number of categories in each intersection.

services partially implement the artefact (◑○○ and ◑◑○) or if none do (○○○), then we believe there is room for improvement for service vendors to improve their documentation and include these artefacts.

In this instance, we can see 10 categories listed in Figure 8.7 that developers feel are important but are not fully implemented across all three CVS vendors. This is especially the case for dimensions [**A**] (Descriptions of API Usage) and [**D**] (Existence of Support Artefacts), corroborating our findings with existing gaps in literature under Section 8.6.1.3. In other words, while both the goals of existing studies and CVS vendors have emphasised the need for artefacts such as code-snippets [**A5**], tutorials [**A6**], and entry-points to the API [**B1**], less attention is given to by *both* literature and vendors on the same, (very-)highly valued aspects to developers (e.g., troubleshooting hints [**D2**], licensing information [**D6**] or links to related components [**E3**]).

Furthermore, from our analysis, we can see areas with which the research community has and has *not* paid extensive attention to. We still see that vendors have paid attention to artefacts even where there has been less research attention, namely [**D1**] (FAQs), [**B5**] (success stories), [**A7**] (downloadable sample applications), [**A1**] (quick-start guides), [**E2**] (forums), [**D5**] (printable guides), and [**A9**] (API component lists). These seven categories are of (very) high value to developers but research attention on these topics are (very) low; however, their presence score within CVSs are ●◑◑ or greater. Hence, we can see that vendors address developer's concerns despite the lack of attention by software engineering researchers in these areas, and thus future research potential to better serve developers and ensure vendors' implementation of these documentation artefacts is evident.

From the above, we can therefore conclude that the vendors' documentation largely covers a majority of API documentation requirements. However, there still remains opportunity for improvement to API documentation by either vendors and/or the research community: that is, low research attention on documentation artefacts that present high value to developers which are *also* generally missing from vendor documentation. To explore this aspect, we triangulate the documentation artefacts (categories) that have a low or very low research attention and that are only present in one service, partially present in one or two, or not present at all. This results in three documentation requirements that warrant further exploration by industry vendors or the research community (see Table 8.4).

8.6.3 Recommendations Resulting from Analysis

In this section, we triangulate the taxonomy developed from literary sources, the developer survey on this taxonomy to understand its efficacy in-practice, and the application of the taxonomy to CVSs to provide several recommendations for both service providers and researchers. Our recommendations are based both on extrapolations of our findings, our prior work, and existing experience with such work.

8.6.3.1 Recommendations for vendors

Table 8.4 emphasises how service vendors still lack key documentation requirements of critical importance to developers that are still widely under-researched in software engineering literature. The largest of these requirements are the need for vendors to provide additional support artefacts [**D**] and the need for vendors to present this in a way that's most digestible for developers to understand [**E**]. A list of detailed suggestions for vendors are provided in Appendix C.4; here we discuss generalised findings on a sample of key artefacts.

For example, no services assessed had any form of diagrammatic overview of their APIs at a high-level [**D3**], thereby indicating how various components of their APIs work together, such as how specific endpoints work or an overview of the lifecyle of the technical domain behind these endpoints (i.e., label/train/infer/re-train), thereby incorporating conceptual relationships behind the API [**C1**]. For instance, an interactive overview of the developer's need to pre-process their data, send it to the service, and post-process the response data would help developers understand how the service better fits into the 'flow' of their application. Moreover, we failed to find lower-level diagrammatic overviews of the client SDKs—such as a UML diagram—that developers find very useful. We strongly advise vendors to provide diagrams illustrating the service within context to help support existing written documentation.

Troubleshooting hints [**D2**] are also a valuable support artefact, but were only found for AWS's video processing endpoints. As our prior work shows, developers are likely to question what aspects of the service can and cannot do, such as the types

Table 8.4: Documentation artefacts of high value to developers that have less attention in software engineering literature and are under-documented in CVSs. Documentation requirements (i.e., dimensions) separated by rules.

Artefact	Value	Research Attention	Presence in Computer Vision Services
[**A10**] Documenting API's minimum system requirements and/or dependencies	High	**Low:** 5 studies (23%)	**Score=1.0:** No dedicated web pages found for this artefact in any service. Dependencies for client libraries embedded within GCV and ACV quick-start guides [426, 440]. Other system requirements not listed.
[**D2**] Troubleshooting hints	High	**Very Low:** 2 studies (10%)	**Score=0.5:** Only found in AWS's video recognition service [408], but no troubleshooting tips found for non-video image recognition.
[**D3**] Diagrammatic representation of API	Very High	**Low:** 3 studies (14%)	**Score=0.0:** Not found for any service.
[**D6**] Licensing Information	Very High	**Very Low:** 1 study (5%)	**Score=0.5:** Partially present only in ACV [444]; information is non-specific to the licensing terms of ACV exclusively.
[**E3**] Quick-links to other relevant components	Very High	**Low:** 3 studies (14%)	**Score=0:** Not found for any service.
[**E5**] Visualised map of navigational paths	Very High	**Low:** 3 studies (14%)	**Score=0:** Not found for any service.

of labels it can find, or how to make it focus on specific ontologies when an input image is provided; e.g., time of day (day vs night) location (indoors vs outdoors) or the subject of the image (dog vs cat) [92]. Troubleshooting in identifying service evolution [92] would also be important, since developers are likely to overlook subtle (but application-breaking) changes to response data, such as labels introduced/removed or confidence changes. Therefore, vendors must document detailed troubleshooting suggestions on their websites on how best to resolve discrepancies in the results found from these services. This could easily be tied in with [**A12**] to incorporate usage description requirements when errors are presented to users and how to deal with them; also largely missing from existing documentation.

Another important aspect is the need to make documentation of one component more easily relatable to other parts of the documentation [**E3**]. Again, no service provided quick-links to related documentation; an example here could be links to definitions of domain-specific terminology [**C2**] to help developers with the learning process of adopting these new generation of APIs (e.g., the 'score' field could be linked back to a video explaining the concept of probability within the services' guesses).

8.6.3.2 Recommendations for researchers

As shown in Table 8.4, we see that there are cases of (very) high-value documentation artefacts (to practitioners) in which literature has not paid great attention to. For example, for the requirement of API usage description [**A**], practitioners agree that both code snippets [**A5**] and documenting system requirements to use the API [**A10**] are of, at least, high value. However, while code snippets has had *consistent* attention within the software engineering research community (i.e., 15 papers spanning 1998–2019), we see that system requirements documentation only gained fluctuating interest by researchers (i.e., predominantly in the 2000s, with two further papers in the last three years). Thus, five papers investigating *some* aspects on this artefact may not cover *all* its aspects; for example, we may have identified a *need* to document these requirements and dependencies, but does this mean we know *all* aspects on how to produce them, the best way to *communicate* them, and the most efficient means for developers to *consume* that information? Contrasting this artefact against the 15 papers on code snippets, we see two documentation artefacts of at least high value to practitioners, yet, evidently, researchers have paid attention to one over the other.

As Figure 8.6 shows, the need for additional support [**D**] within documentation is the largest requirement that *may* be an indicator for further research in this domain (see Section 8.7.3). Notably, RQ2 of our SMS identified the methodologies and data collection techniques by which our existing understanding of API documentation requirements were gathered; as demonstrated through Figure 8.3, a majority of our understanding is grounded through the opinions of developers, namely evaluation research using direct techniques. Too many studies are shown to rely on a handful of data collection techniques (interviews and questionnaires, shadowing and observation, think-aloud sessions) and a stronger emphasis for indirect and independent techniques is needed moving forward; there is therefore a gap in literature on *other* types of data collection techniques that may provide different insights into satisfying the documentation requirements within our taxonomy.

For example, we see [**A9**] (exhaustive list of major API components) as a high-value documentation artefact that satisfies the requirement of the API usage description [**A**]. However research attention is lower. A validation research paper could propose a method to generate a baseline list of these components through an independent technique, such mining the API codebase for its major components through class usage (static analysis) or analysing an existing work database or tool use logs to see which components developers have accessed the most. This would satisfy the need for the documentation artefact, bolstering the API usage requirement and exploring new techniques to do so.

Few philosophical papers result in a lack of insight into completely new ways of exploring API documentation. Further exploration into this type of research may help us devise a whole new framework of producing API documentation. For example, as shown by developers and vendors, quick-start guides [**A1**] are highly valued, and well-documented in CVSs. But literature does not provide any vocabulary or frameworks into how best to develop such guides. Involving both software engineering researchers and developers through a brainstorming or focus group to conceptualise, devise, and refine such a framework may be a worthwhile study to better improve our understanding of quick-start guides whilst also exploring new approaches to research new guidelines.

Beyond requirement [**A**], another insight identified is the need for developers to have visualised maps of navigational paths [**E5**] which is not yet provided by any of the CVS providers investigated. With the low ILS value in this category (14% or 3 studies), we see a potential research topic for future exploration. For example, if research can demonstrate that such visualised maps are not just something developers desire, but can make them *more effective* in their day-to-day work, then this could be a strong case made to vendors to improve the presentation of their documentation.

Thus, as we have shown in these sample recommendations, many potential studies and research directions can stem by exploring the discrepancies of API documentation in literature, in practice, and their presence in CVSs (i.e., as a sample case study) when assessed on a case-by-case basis. The method researchers decide upon depends the research questions they wish to address; thus, observations we present in Figure 8.3 may trigger fruitful reasoning about approaches future research could take, however inferring methodological gaps will need to be compatible with research goals. Thus, mapping these discrepancies to gaps in the techniques used in studies to devise of novel ways to improve API documentation whilst also exploring new methodologies should be balanced carefully by researchers.

8.7 Threats to Validity

8.7.1 Internal Validity

Threats to *internal validity* represent internal factors of our study which affect concluded results. Kitchenham and Charters' guidelines on producing systematic reviews [195] suggest that researchers conducting reviews should discuss the review protocol, inclusion decisions, data extraction with a third party. Within this study, we discussed our protocols with other researchers within our research group and utilised test-retest reliability. Further assessments into reliability would involve an assessment of the review and extraction processes, which can be investigated using inter-rater reliability measures. Guidelines suggested by Garousi and Felderer [131] describe methods for independent analysis and conflict resolution could help resolve this.

As stated in Section 8.3.2, we utilised a systematic software engineering taxonomy development method by Usman et al. [361]. Two additional taxonomy validation approaches proposed by Usman et al. were not considered in our work: benchmarking and orthogonality demonstration. To our knowledge, there are no other studies that classify existing API documentation studies into a structured taxonomy, and therefore we are unable to benchmark our taxonomy against others. We would encourage the research community to conduct a replication of our work and investigate whether our taxonomy classification approaches are replicable to ensure that categories are reliable and the dimensions fit the objectives of the taxonomy. Moreover, we did not investigate orthogonality demonstration as our primary goals for this work were to investigate the efficacy of the taxonomy by practitioners and in-practice, with reference to our wider research area of intelligent CVSs. Therefore, we solely adopted the utility demonstration approach in two detailed experiments (Sections 8.5 and 8.6) to analyse the efficacy of our taxonomy and identify potential improvements for these services' API documentation.

8.7.2 External Validity

Threats to *external validity* concern the generalisation of our observations. Our SMS has used a broad range of sources however not all papers contributing to API documentation may have been found or captured within the taxonomy. While we attempted to include as many papers as we could find in our study, some papers may have been filtered out due to our exclusion criteria. For example, there are studies we found that were excluded as they were not written in English, and these excluding factors may alter our conclusions, introducing conflicting recommendations. However, given the consistency of these trends within the studies that were sourced, we consider this a low likelihood.

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

Unless significant inducements are offered, Singer et al. [332] report that a consistent response rate of 5% has been found in software engineering questionnaires distributed and in information systems the median response rates for surveys are 60% [29]. We observe that low response rates may adversely effect the findings of our survey, typically as software engineers find little time to do them [332]. When compared to typical software engineering studies, our response rate of 67.97% was likely successful due to designing and carefully testing succinct, unambiguous and well-worded questions with researchers within our research group. All adjustments made from the pilot study due to unexpected poor quality of the questionnaire have been reported and explained in Section 8.5.1.2. However, further improvements could be made to increase this response rate.

The survey reached 82 external and 22 internal participants. This yielded a total of 104 participants. However, only 91 participants fully completed the survey and, on average, those who only partially completed the survey completed 43.23% of all questions. Therefore, demographic data for these participants is largely missing. To verify the reliability of partially submitted responses, we calculated the average response of each item in our survey (i.e., question) for all fully completed results and all partially completed results. All partially completed questions, except [**B7**], were within 1 standard deviation from the mean, and therefore we believe the 13 partial results to be valid when excluding B7. Even if these partial results are excluded, our full-response participant count of 91 is still comparable to existing studies, such as Nykaza et al. [265] (57 participants), Robillard and Deline [306] (80 participants), or [305] (83 participants). Therefore, given these comparable numbers, we believe this does not compromise validity of our results.

We also adopt research conducted in the field of questionnaire design, such as ensuring all scales are worded with labels [206] and have used a summating rating scale [337] to address a specific topic of interest if people are to make mistakes in their response or answer in different ways at different times. This approach was also extended using alternating positive and negative sentiment for each question—as multiple studies have shown [63, 316], this approach helps reduce poor-quality responses by minimising extreme responses and acquiescence biases.

8.7.3 Construct Validity

Threats to *construct validity* relates to the degree by which the data extrapolated in this study sufficiently measures its intended goals. Our interpretation of the ILS (as given in Sections 8.4 and 8.6.1.2) is reported as the proportion of papers whose research investigates or explores issues regarding the aspects of specific API documentation artefacts (i.e., categories in the taxonomy) that, collectively, comprise the requirements of good API documentation (i.e., dimensions in the taxonomy). Every effort has been made in this work to provide a constructive analysis on the API documentation landscape, however, the studies that comprise the ILS may differ in their intent toward a specific documentation artefact. For example, some studies may have distinct goals to extensively study *how* code snippets [**A5**] specifically improve developer productivity (e.g., through interviews or by observational studies), while others may just reflect that code snippets are a commonly-used artefact self-reported by developers (e.g., through a survey). Thus, the interpretation of the ILS may range between deep exploration of an artefact or whether a study mentions the artefact without any attempts to thoroughly investigate it. For this reason, we suggest that a high ILS value for a category within the taxonomy suggests that the documentation artefact is within the attention of the research community, and that subsequent attention **may** be required for those artefacts with low ILS values as a *potential indicator* for future research (i.e., it also may *not*). However, each artefact with a low ILS (but high IPS) would need to be carefully examined in isolation to evaluate whether future research is indeed warranted, and how that research can be conducted with the ultimate goal to assist practitioners.

Automatic searching was conducted in the SMS by choice of three popular databases (see Section 8.3.1). As a consequence of selecting multiple databases, duplicates were returned. This was mitigated by manually curating out all duplicate results from the set of studies returned. Additionally, we acknowledge that the lack manual searching of papers within particular venues may be an additional threat due to the misalignment of search query keywords to intended papers of inclusion. Thus, our conclusions are only applicable to the information we were able to extract and summarise, given the primary sources selected.

While we have investigated the application of this taxonomy using a user study (Section 8.5.1), we would like to explore a controlled study of developers to assess how improved and non-improved API documentation impacts developer productivity. The outcome of this work can help design a follow-up experiment, consisting of a comparative controlled study [322] that capture firsthand behaviours and interactions toward how software engineers approach using a CVS with and without our taxonomy applied. This can be achieved by providing ‘mock’ improved documentation with the suggested improvements included in this work. Such an experiment could recruit a sample of developers of varying experience (from beginner programmer to principal engineer) to complete a certain number of tasks under a comparative controlled study, half of which will (a) develop using the improved ‘mock’ documentation, and the other half will (b) develop with the *as-is/existing* documentation. From this, we can compare if the taxonomy makes improvements by capturing metrics and recording the sessions for qualitative analysis. Visual modelling can be adopted to analyse the qualitative data using matrices [99], maps and networks [319] as these help illustrate any causal, temporal or contextual relationships that may exist to map out the developer’s mindset and difference in approaching the two sets of designs of the same tasks.

8.8 Conclusions & Future Work

The emergence of AI-based intelligent components present significant challenges to our existing understanding of traditional API documentation. The inherent probabilistic and non-deterministic nature of these components means that developers must shift their mindset of conventional APIs, and vendors of these services must similarly shift the mindset of documenting their APIs using traditional means. Without adapting to the new mental model (of the vendors designing these services) and by vendors presenting poor or incomplete (traditional) documentation that is not compatible with these next-generation components, developers face many struggles. They fail to grasp how to properly understand how these services work, seeking further documentation or support from their peers on forums on such as Stack Overflow [92]. This ultimately hinders developers' productivity and thus adversely affects the internal quality of the applications that they build.

This study has explored the artefacts and means by which traditional API documentation is studied through the use of an SMS of 4,501 studies, identifying 21 key works. From this, we synthesised a taxonomy of the various documentation artefacts that improves API documentation quality, and thus collectively synthesising the requirements of good API documentation. Furthermore, we also capture the most commonly used analysis techniques used in the academic literature to understand the means by which the goals of these studies resulted in their findings. We then validate our taxonomy against developers to assess its efficacy with practitioners, and conduct a heuristic evaluation against three popular CVSs. We determine that developers demand certain documentation artefacts more than others, since not all documentation artefacts are equally valued. We map the value (to developers) of these artefacts against their exposure within the software engineering literature, thereby highlighting the gaps by which future research could expand upon. Furthermore, we present a similar mapping against how well the coverage CVSs have incorporated such artefacts into their own API documentation, thus highlighting that while industry vendors cover most documentation artefacts that may not be in the interest to researchers, some artefacts with low research interest are still largely missing (see Table 8.4). We therefore provide several generalised recommendations to vendors and the wider research community to explore how best these artefacts can be better addressed and incorporated into further research, thus improving our understanding of the requirements of good API documentation.

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

The findings of our work provides a solid baseline for improving the documentation of non-deterministic software, such as CVSs. While our aim is to eventually improve the quality of API documentation, the ultimate goal is to improve the software engineer's experience of non-deterministic and abstracted AI-based components, such as intelligent web services (IWSs). We hope the guidelines from this extensive study help both software developers and API providers alike by using our taxonomy as a go-to checklist for what should be considered in documenting any API.

CHAPTER 9

Using a Facade Pattern to combine Computer Vision Services†

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

9.1 Introduction

With the introduction of intelligent web services (IWSs) that make machine learning (ML) more accessible to developers [301, 368], we have seen a large growth of intelligent applications dependent on such services [66, 136]. For example, consider the advances made in computer vision, where objects are localised within an image and labelled with associated categories. Cloud-based computer vision services (CVSs)—e.g., [398, 411, 419, 423, 432, 433, 437, 486]—are a subset of IWSs. They utilise ML techniques to achieve image recognition via a remote black-box approach, thereby reducing the overhead for application developers to understand 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.

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

9.1.1 Motivating Scenario: Intelligent vs Traditional Web Services

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

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

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

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

(2) Intelligent responses are not certain. When Tom interprets the response object of an IWS, he finds that there is a 'confidence' value or 'score'. This is because the ML models that power IWSs are inherently probabilistic and stochastic; any insight they produce is purely statistical and associational [281]. Unlike the substring example, where the rule-driven implementation provides certainty to the results, this is not guaranteed for IWSs. For example, a picture of a husky breed of dog is misclassified as a wolf. This could be due to adversarial examples [346] that 'trick' the model into misclassifying images when they are fully decipherable to humans. It is well-studied that such adversarial examples exist in the real world unintentionally [114, 207, 284].

(3) Intelligent APIs evolve over time. Tom may find that responses to processing an image may change over time; the labels he processes in testing may evolve and therefore differ to when in production. In traditional web services, evolution in responses is slower, generally well-communicated, and usually rare (Tom would always expect `"dog"` to be returned in the substring example). This has many implications on software systems that depend on these APIs, such as confidence in the output and portability of the solution. Currently, if Tom switches from one API provider to another, or if he doesn't regularly test his app in production, he may begin to see a very different set of labels and confidence levels.

9.1.2 Research Motivation

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

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

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

Previous attempts at overcoming low reliability include triple-modular redundancy [226]. This method uses three modules and decides output using majority rule. However, in CVSs, it is difficult to apply majority rule: these APIs respond with a list of labels and corresponding scores. Moreover, disparate APIs ordinarily output different results. These differences make it hard to apply majority rule because the type of outputs are complex and disparate APIs output different results for the same input. Merging search results is another technique to improve reliability [331]. It normalises scores of different databases using a centralised sample database. Normalising scores makes it possible to merge search results into a single ranked list. However, search responses are disjoint, whereas they are not in the context of most CVSs.

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

9.2 Merging API Responses

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

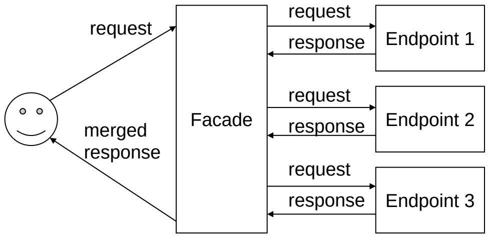


Figure 9.1: The user sends a request to the facade; this request is propagated to the relevant APIs. Responses are merged by the facade and returned back to the user.

natural language processing [434, 487]). It is difficult to apply majority rule on such disparate, complex outputs. While the outputs by *multiple* AI-based API endpoints is different and complex, the general format of the output is the same: a list of labels and associated scores.

9.2.1 API Facade Pattern

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

Although the model introduces more time and cost overhead, both can be mitigated by caching results. On the other hand, the facade pattern provides the following benefits:

- **Easy to modify:** It requires only small modifications to applications, e.g., changing each concrete endpoint URL.
- **Easy to customise:** It merges results from disparate and concrete APIs according to the user's preference.
- **Improves reliability:** It enhances reliability of the overall returned result by merging results from different endpoints.

9.2.2 Merge Operations

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

```
[['apple', 0.9], ['banana', 0.8]]
```

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

```
[['apple', 0.7], ['cherry', 0.8]].
```

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

```
[['apple', 0.9], ['banana', 0.8], ['cherry', 0.8]];
```

min merges results to:

```
[['apple', 0.7]];
```

and *average* merges results to:

```
[['apple', 0.8], ['banana', 0.4], ['cherry', 0.4]].
```

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

9.2.3 Merging Operators for Labels

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

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

The *max*, *min*, and *average* operations in Section 9.2.2 follow each of these rules 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

9.3 Graph of Labels

CVSs typically return lists of labels and their associated scores. In most cases, the label can be a singular word (e.g., ‘husky’) or multiple words (e.g., ‘dog breed’). Lexical databases, such as WordNet [245], can therefore be used to describe the ontology behind these labels’ meanings. Figure 9.2 is an example of a graph of labels and synsets. A synset is a grouped set of synonyms for a word. In this image, we consider two fictional endpoints, endpoints 1–2. We label red nodes as labels from endpoint 1, yellow nodes as labels from endpoint 2, and blue nodes as synsets for the associated labels from both endpoints. As actual graphs are usually more complex, Figure 9.2 is a simplified graph to illustrate the usage of associating labels from two concrete sources to synsets.

9.3.1 Labels and synsets

The number of labels depends on input images and concrete API endpoints used. Table 9.1 and Figure 9.3 show how many labels are returned, on average per image, from Google Cloud Vision [423], Amazon Rekognition [398] and Azure Computer Vision [437] image recognition APIs. These statistics were calculated using 1,000 images from Open Images Dataset V4 [425] Image-Level Labels set.

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

9.3.2 Connected Components

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

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

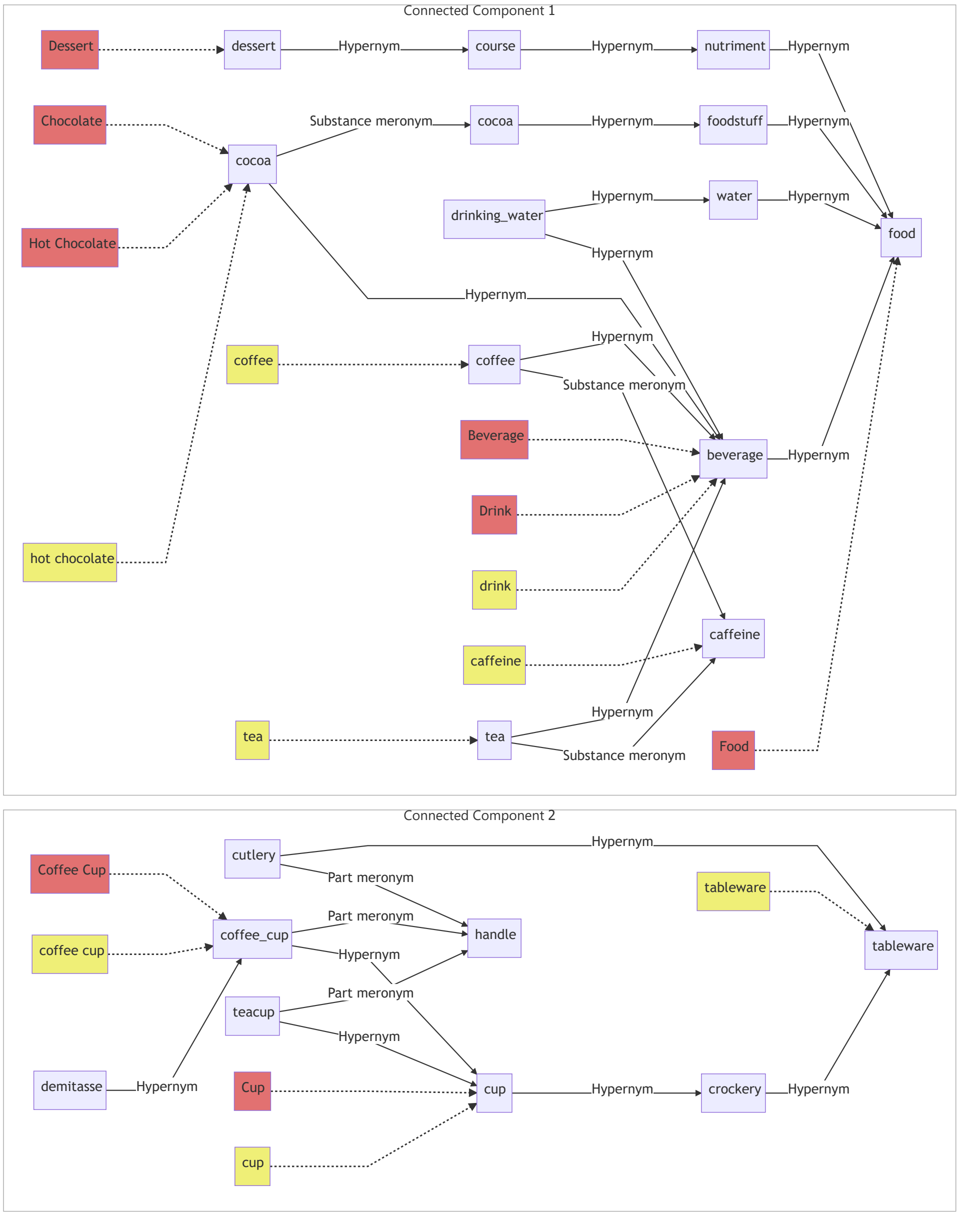


Figure 9.2: Graph of labels from two concrete endpoints (red and yellow) and their associated synsets related to both words (blue).

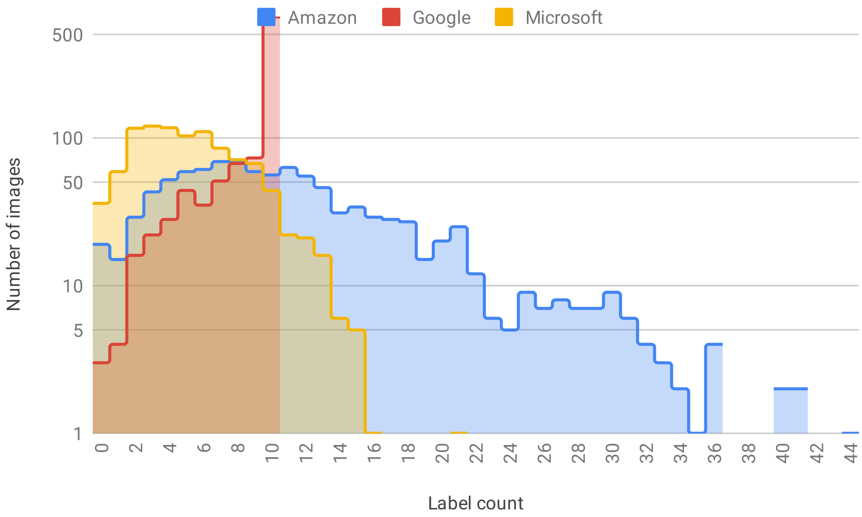


Figure 9.3: Number of labels responded from our input dataset to three concrete APIs assessed.

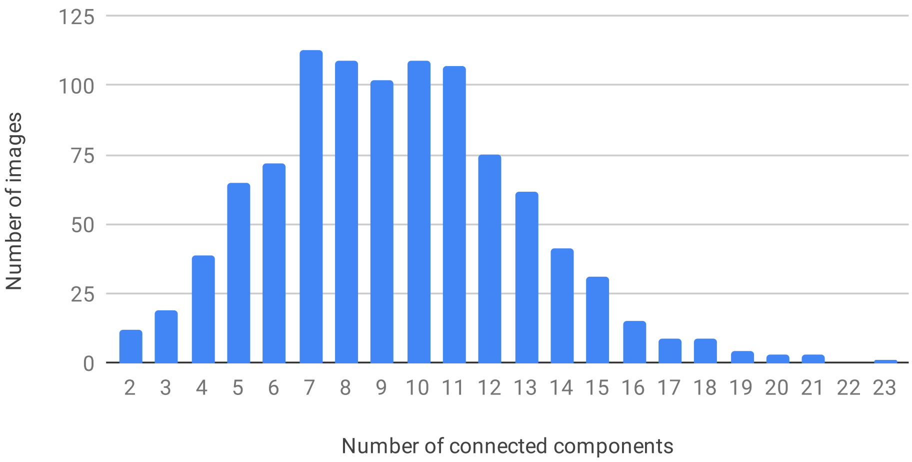


Figure 9.4: Number of connected components compared to the number of images.

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

9.4 API Results Merging Algorithm

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

9.4.1 Mapping Labels to Synsets

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

9.4.2 Deciding Total Number of Labels

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

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

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

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

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

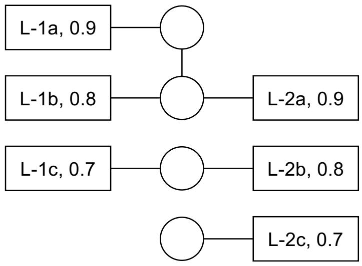


Figure 9.5: Allocation to connected components.

9.4.3 Allocating Number of Labels to Connected Components

The graph of labels and synsets is then divided into several CCs. The facade decides how many labels are allocated for each CC. For example, in Figure 9.5, there are three CCs, where square-shaped nodes are labels in responses from endpoints. Text within these label nodes describe which endpoint outputs the label and score, for instance, "L-1a, 0.9" is label *a* from endpoint *1* with a score *0.9*. Circle-shaped nodes represent synsets, where the edges between the label and synset nodes indicate the relationships between them. Edges between synsets are links in WordNet.

Allegorically, allocating the number of labels to CCs is similar to proportional representation in a political voting system, where CCs are the political parties and labels are the votes to a party. Several allocation algorithms are introduced in proportional representation, for instance, the D'Hondt and Hare-Niemeyer methods [260]. However, there are differences from proportional representation in the political context. For label merging, labels have scores and origin endpoints and such information may improve the allocation algorithm. For instance, CCs supported with more endpoints should have a higher allocation than CCs with fewer endpoints, and CCs with higher scores should have a higher allocation than CCs with lower scores. We introduce an algorithm to allocate the number of labels to CCs. This allocates more to a CC with more supporting endpoints and higher scores. The steps of the algorithm are:

Step I. Sort scores separately for each endpoint.

Step II. If all CCs have an empty score array or more, remove one, and go to Step II.

Step III. Select the highest score for each endpoint and calculate product of highest scores.

Step IV. A CC with the highest product score receives an allocation. This CC removes every first element from the score array.

Step V. If the requested number of allocations is complete, then stop allocation. Otherwise, go to Step II.

Tables 9.2 to 9.5 are examples of allocation iterations. In Table 9.2, the facade sorts scores separately for each endpoint. For instance, the first CC in Figure 9.5 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 9.3: 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 9.4: Allocation iteration 3.

Scores	Highest	Product	Allocated
[0.8], []	—	—	1
[], []	—	—	1
[], [0.7]	—	—	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-verified labels. Images and human-verified labels are sourced from 1,000 randomly-sampled images from the Open Images Dataset V4 [425] Image-Level Labels test set.

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

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

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

Let R_A, R_G, and R_M be responses from Amazon Rekognition, Google Cloud Vision, and Microsoft's Azure Computer Vision, respectively. There are four sets 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 shows the evaluation of each operands set, Table 9.8 shows the averages of the four operands sets, and Figure 9.6 shows the comparison of F-measure for each methods.

9.5.2 Naive Operators

Results of *min*, *max*, and *average* operators are shown in Tables 9.7 and 9.8 and Figure 9.6. The *min* operator is similar to *union* operator of set operation, and outputs all labels of operands. The precision of the *min* operator is always greater than any precision of operands, and the recall is always lesser than any precision of operands. *Max* and *average* operators are similar to *intersection* operator of set operations. Both operators output intersection of labels of operands and there is no clear relation to the precision and recall of operands. Since both operators have the same precision, recall, and F-measure, Figure 9.6 groups them into one. The *average* operator performs well on the TP/FP ratio, where most of the same labels from multiple 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

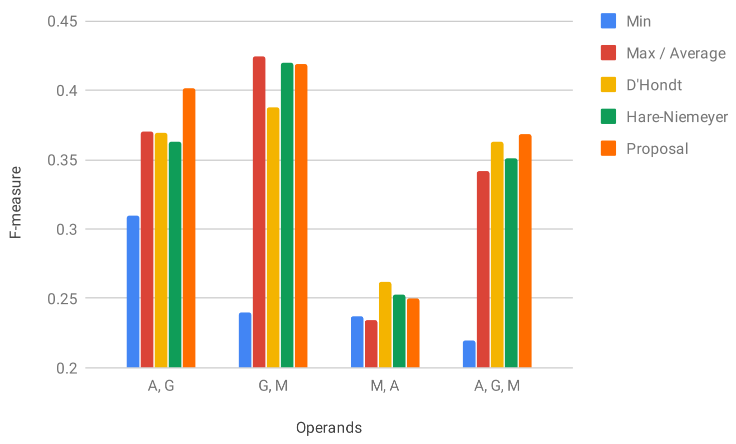


Figure 9.6: F-measure comparison.

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

9.5.3 Traditional Proportional Representation Operators

There are many existing allocation algorithms in proportional representation, e.g., the Niemeyer and Niemeyer method [260]. These methods may be replacements of those in Section 9.4.3. Other steps, i.e., Sections 9.4.1, 9.4.2 and 9.4.4, are the same as for our proposed technique. Tables 9.7 and 9.8 and Figure 9.6 show the result of these traditional proportional representation algorithms. Averages of F-measures by traditional proportional representation operators are almost equal to that of the *max* and *average* operators. It is worth noting that merging M and A responses results in a better F-measure than each F-measure of M and A individually. As these are not biased to human-verified labels, situations in the real-world usage should, therefore, be similar to the case of M and A. Hence, RQ1 is true.

9.5.4 New Proposed Label Merge Technique

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

9.5.5 Performance

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

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

9.6 Conclusions and Future Work

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

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

CHAPTER 10

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

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

10.1 Introduction

Machine learning algorithm adoption is increasing in modern software. End users routinely benefit from machine-learnt functionality through personalised recommendations [83], voice-user interfaces [255], and intelligent digital assistants [52]. The easy accessibility and availability of intelligent web services (IWSs)[1] is contributing 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.

[1]Such 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/`).

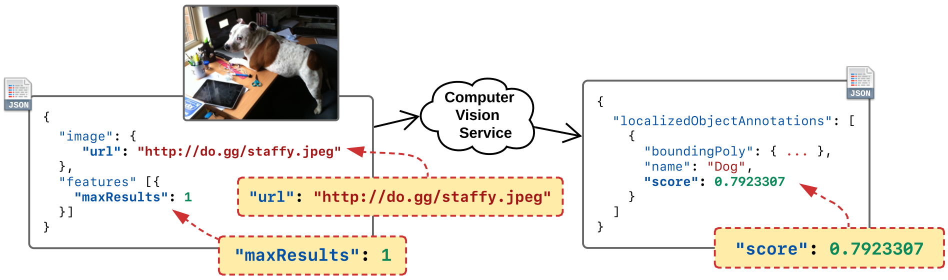


Figure 10.1: Request and response for an intelligent computer vision web service with only three configuration parameters: the image's `url`, `maxResults` and `score`.

solutions as they (i) do not require specialised ML expertise to build and maintain AI-based solutions, (ii) abstract away infrastructure related issues associated with ML [16, 321], and (iii) provide web application programming interfaces (APIs) for ease of integration.

However, unlike traditional web services, the functionality of these IWSs is dependent on a set of assumptions unique to ML [89]. These assumptions are based on the data used to train ML algorithms, the choice of algorithm, and the choice of data processing steps—most of which are not documented. For developers, these assumptions mean that the performance characteristics of an IWS in any particular application problem domain is not fully knowable. IWSs represent this uncertainty through a confidence value associated with their predictions.

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

A typical evaluation process involves a test data set (curated by the developers using the IWS) that is used to determine an appropriate threshold. Choice of a decision threshold is a critical element of the evaluation procedure [151]. This is especially true for classification problems such as detecting if an image contains cancer. Simple approaches to selecting a threshold are often insufficient, as highlighted in Google's ML course: *"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**."*[2]

[2] See `https://bit.ly/36oMgWb`.

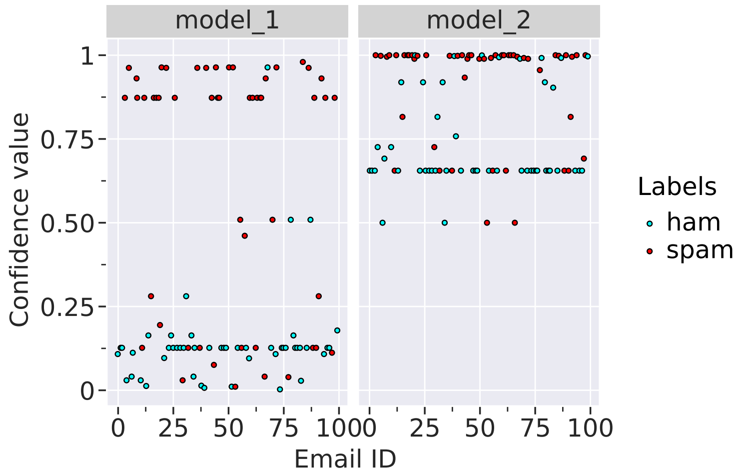


Figure 10.2: Predictions for 100 emails from two spam classifiers. Decision thresholds are classifier-dependent: a single threshold for both classifiers is *not* appropriate as ham emails are clustered at 0.12 (model_1) and at 0.65 (model_2). Developers must evaluate performance for *both* thresholds.

As an example consider the predictions from two email spam classifiers shown 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 [320], (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, and is an implemented example

[3]Threshy is available for use at `http://bit.ly/a2i2-threshy`

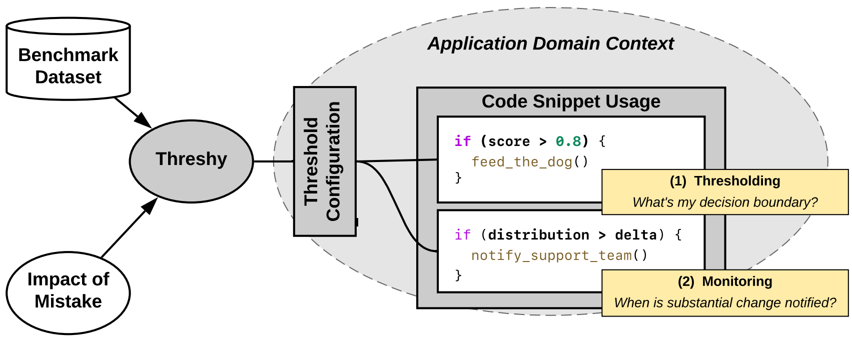


Figure 10.3: Threshy supports two key aspects for intelligent web services: threshold selection and monitoring.

of the threshold tuner component presented in our proposed architecture tactic [91] (see Chapter 11). While Threshy has been designed to specifically handle pre-trained classification ML models where the hyperparameters cannot be tuned, the overall conceptual design serves as inspiration for general model calibration. Unlike existing tooling (see Section 10.4), **Threshy serves as a means to up-skill and educate 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 while considering different cost factors 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.

This paper is structured as so: we provide a motivating example in Section 10.2; we present an overview of Threshy in Section 10.3, providing an overview of the architecture and implementation details and give a usage example; we offer a pre-

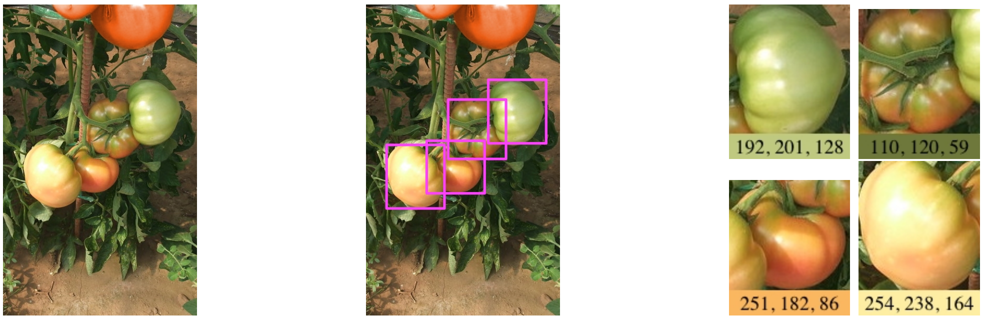


Figure 10.4: Pipeline of Nina's harvesting robot. *Left:* Photo from harvesting robot's webcam. *Centre:* Classification detecting different types of tomatoes. *Right:* Binary classification for ripeness (ripe/unripe) based on (R, G, B values).

liminary evaluation strategy of Threshy in **??**; we give a background of some related work in the area within Section 10.4; we present our conclusions, limitations and future avenues of this research in Section 10.5.

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 harvesting. Nina's automated harvester needs to sort picked tomatoes into a respective container, and thus several business rules need to be encoded into the prediction logic to sort each tomato detected based on its *ripeness* (ripe or not ripe) and *type of tomato* (as above). Nina uses a two-stage pipeline consisting of a multi-class and a binary classification model. She has decided to evaluate the viability of cloud based intelligent services and use them if operationally effective.

Figure 10.4 illustrates an example of the pipeline as listed below:

1. **Classify tomato 'type'.** This stage uses an object localisation service to detect all tomato-like objects in the frame and classifies each tomato into one of the following labels: `['roma','cherry','plum','green','yellow','unknown']`.
2. **Assess tomato 'ripeness'.** This stage uses a crop of the localised tomatoes from the original frame to assess the crop's colour properties (i.e., average colour must have R > 200 and G < 240). This produces a binary classification to deduce whether the tomato is ripe or not.

Nina only has a minimal appreciation of the evaluation method to use for off-the-shelf computer vision (classification) services. She also needs to consider the financial costs of misclassifying either the tomato type or the ripeness. Missing a few ripe tomatoes isn't a significant concern as the robot travels the field twice a week during harvest season. However, picking an unripe tomato is expensive as

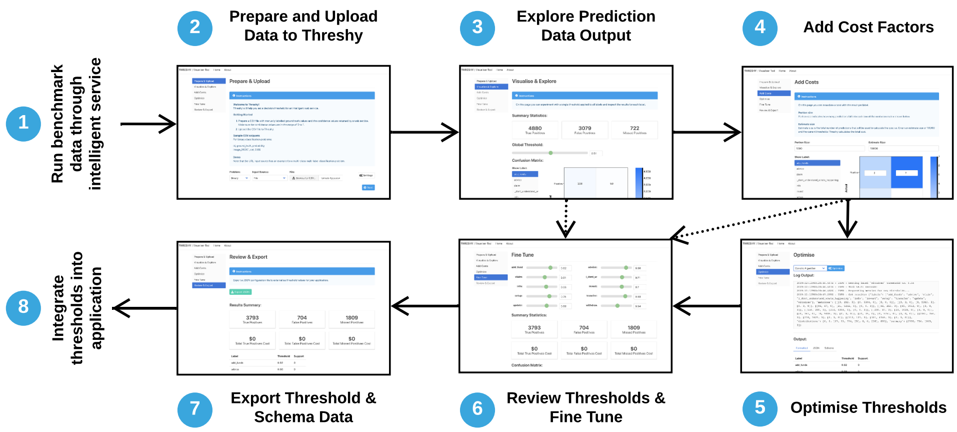


Figure 10.5: UI workflow for interacting with Threshy to optimise the thresholds for classification problem.

Lucy cannot sell them. Therefore, Nina needs a better (automated) way to assess the performance of the service and set optimal thresholds for her picking robot, to maximise profit.

To assist in developing Nina's pipeline, Lucy sampled a section of 1000 tomatoes by taking a photo of each tomato, manually labelling its type, and assessing whether the vine was `'ripe'` or `'not_ripe'`. Nina ran the labelled images through an IWS, with each image having a predicted type (multi-class) and ripeness (binary), with respective confidence values.

Nina combined the predictions, their respective confidence values, and Lucy's labelled ground truths into a CSV file which was then uploaded to Threshy. Nina asked Lucy the farmer to assist in setting relevant costs (from a business perspective) for correct predictions and false predictions. Threshy then recommended a choice 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 [97]), 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 [108].
- 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 step of Threshy (5) considers the performance and costs when deriving the thresholds. Finally, the engineer can (6) review and fine tune the calculated thresholds, associated costs, and (7) download generated threshold meta-data to be (8) integrated into their application.

Threshy runs a client/server architecture with a thin-client (see Figure 10.6). The web-based application consists of an interactive front-end where developers upload benchmark results—consisting of both human annotated labels and machine predictions from the IWS—and use threshold tuners (via sliders) to present a data summary of the uploaded information. Predicted model performances and costs are entered manually into the web interface by the developer. The Threshy back-end runs a data analyser, cost processor and metrics calculator when relevant changes are made to the front-end's tuning sliders. Separating the two concerns allows for high intensity processing to be done on the server and not the front end.

The data analyser provides a comprehensive overview of confusion matrices compatible for multi-label multi-class classification problems. When representing the confusion matrix, it is trivial to represent instances where multi-label multi-classification is not considered. For example, in the simplest case, a single row in the matrix represents a single label out of two classes, or each row has one label but it has multiple classes. However, a more challenging case to visualise arises when you have n labels and m classes as the true/false matches become too excessive to visualise; $n * m * 4$ fields need to be presented. We resolve this challenge by summarising the statistics down to three constructs: (i) number of true positives, (ii) false positives, and (iii) missed positives. This allows us to optimise against the true positives and minimise the other two constructs. Threshy is a fully self-contained repository of the tool implementation, scripting and exploratory notebooks, which is available at `https://github.com/a2i2/threshy`.

10.4 Related work

10.4.1 Decision Boundary Estimation

Optimal machine-learnt decision boundaries depend on identifying the operating conditions of the problem domain. A systematic study by Drummond and Holte

[108] classifies four operating conditions to determine a decision threshold: (i) the operating condition is known and the model trained matches perfectly; (ii) where the operating conditions are known but change with time, and thus the model must be adaptable to such changes; (iii) where there is uncertainty in the knowledge of the operating conditions certain changes in the operating condition are more likely than others; and (iv) where there is no knowledge of the operating conditions and the conditions may change from the model in any possible way. Various approaches to determine appropriate thresholds exist for all four of these cases, such as cost-sensitive learning, ROC analysis, and Brier scores. However, an *automated* attempt to calibrate decision threshold boundaries is not considered, and is largely pitched at a non-software engineering audience. A recent study touches on this in model management for large-scale adversarial instances in Google's advertising system [320], however this is only a single component within the entire architecture, and is not a tool that is useful for developers in varying contexts. Threshy provides a '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.

10.4.2 Tooling for ML Frameworks

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 [161, 277]. 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* [377] 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 [160] provides an interface to test hypotheticals on Generalized Additive Models, and a *ModelTracker* tool [13] 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. They also do not provide synthesised output for using intelligent web services with predetermined thresholds. 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.

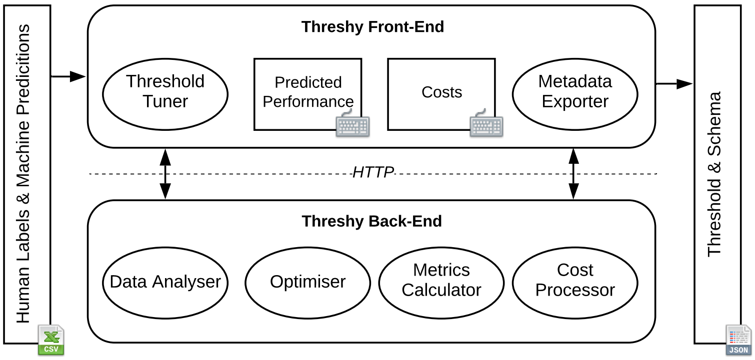


Figure 10.6: Architecture of Threshy.

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. Threshy only deals with classification problems and adapting our method to other problem domains is left as future work. Furthermore, we plan to evaluate Threshy with practitioners for user-acceptance and add support for code synthesis for calibrating the API responses.

CHAPTER 11

An Integration Architecture Tactic to guard AI-first Components†

Abstract Intelligent web services provide the power of AI to developers via simple RESTful API endpoints, abstracting away many complexities of machine learning. However, most of these intelligent web services (IWSs)—such as computer vision—continually learn with time. When the internals within the abstracted 'black box' become hidden and evolve, pitfalls emerge in the robustness of applications that depend on these evolving services. Without adapting the way developers plan and construct projects reliant on IWSs, significant gaps and risks result in both project planning and development. Therefore, how can software engineers best mitigate software evolution risk moving forward, thereby ensuring that their own applications maintain quality? Our proposal is an architectural tactic designed to improve intelligent service-dependent software robustness. The tactic involves creating an application-specific benchmark dataset baselined against an intelligent service, enabling evolutionary behaviour changes to be mitigated. A technical evaluation of our implementation of this architecture demonstrates how the tactic can identify 1,054 cases of substantial confidence evolution and 2,461 cases of substantial changes to response label sets using a dataset consisting of 331 images that evolve when sent to a service.

11.1 Introduction

The introduction of intelligent web services (IWSs) into the software engineering ecosystem allows developers to leverage the power of artificial intelligence (AI) without implementing complex AI algorithms, source and label training data, or 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. 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. Terminology has been updated to fit this thesis.

enticing for developers to embrace due to the effort, cost and non-trivial expertise required to implement AI in practice [288, 321].

However, the vendors that offer these services also periodically update their behaviour (responses). The ideal practice for communicating the evolution of a web service involves updating the version number and writing release notes. The release notes typically describe new capabilities, known problems, and requirements for proper operation [50]. Developers anticipate changes in behaviour between versioned releases although they expect the behaviour of a specific version to remain stable over time [363]. However, emerging evidence indicates that 'intelligent' services *do not* communicate changes explicitly [88]. Intelligent services evolve in unpredictable ways, provide no notification to developers and changes are undocumented [92]. To illustrate this, consider Figure 11.1, which shows the evolution of a popular computer vision service (CVS) with examples of labels and associated confidence scores with how they changed. This behaviour change severely negatively affects reliability. Applications may no longer function correctly if labels are removed or confidence scores change beyond predefined thresholds.

Unlike traditional web services, the functionality of these IWSs is dependent on a set of assumptions unique to their machine learning principles and algorithms. These assumptions are based on the data used to train machine learning algorithms, the choice of algorithm, and the choice of data processing steps—most of which are not documented to service end users. The behaviour of these services evolve over time [89]—typically this implies the underlying model has been updated or re-trained.

Vendors do not provide any guidance on how best to deal with this evolution in client applications. For developers to discover the impact on their applications they need to know the behavioural deviation and the associated impact on the robustness and reliability of their system. Currently, there is no guidance on how to deal with this evolution, nor do developers have an explicit checklist of the likely errors and changes that they must test for [92].

In this paper, we present a reference architecture to detect the evolution of such IWSs, using a mature subset of these services that provide computer vision as an exemplar. This tactic can be used both by intelligent service consumers, to defend their applications against the evolutionary issues present in IWSs, and by service vendors to make their services more robust. We also present a set of error conditions that occur in existing CVSs.

The key contributions of this paper are:

- A set of new service error codes for describing the empirically observed error conditions in IWSs.
- A new reference architecture for using IWSs with a Proxy Server that returns error codes based on an application specific benchmark dataset.
- A labelled data set of evolutionary patterns in CVSs.
- An evaluation of the new architecture and tactic showing its efficacy for supporting IWS evolution from both provider and consumer perspectives.

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 CVSs 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.

R3. Monitor the evolution of IWSs for changes that affect the application's behaviour.

R4. Implement a flexible architecture that is adaptable to different IWSs and application contexts to facilitate reuse.

11.3 Intelligent Services

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.

11.3.1 'Intelligent' vs 'Traditional' Web Services

Unlike conventional web services, IWSs are built using AI-based components. These components are unlike traditional software engineering paradigms as they are data-dependent and do not result in deterministic outcomes. These services make future predictions on new data based solely against its training dataset; outcomes are expressed as probabilities that the inference made matches a label(s) within its training data. Further, these services are often marketed as forever evolving and 'improving'. This means that their large training datasets may continuously update the prediction classifiers making the inferences, resulting both in probabilistic and non-deterministic outcomes [89, 163]. Critically for software engineers using the services, these non-deterministic aspects have not been sufficiently documented in the service's API documented, which has been shown to confuse developers [92].

A strategy to combat such service changes, which we often observe in traditional software engineering practices, are for such services to be versioned upon substantial change. Unfortunately emerging evidence indicates that prominent cloud vendors providing these IWSs do not release new versioned endpoints of the APIs when the *internal model* changes [89]. For IWSs, it is impossible to invoke requests specific to a particular version model that was trained at a particular date in time. This means that developers need to consider how evolutionary changes to the IWSs they make use of may impact their solutions *in production*.

11.3.2 Dimensions of Evolution

The various key dimensions of the evolution of IWSs is illustrated in Figure 11.2. There are two primary dimensions of evolution: *changes to the label sets* returned per image submitted and *changes to the confidences* per label in the set of labels returned per image. In the former, we identify two key aspects: cardinality changes and ontology changes. Cardinality changes occur when the service either introduces or drops a label for the same image at two different generations. Alternatively, the cardinality may remain stagnant, although this is not guaranteed. This results in an expectation mismatch by developers as to what labels can or will be returned by the service. For instance, the terms 'black' and 'black and white' may be found to be categorised as two separate labels. Secondly, the ontologies of these labels are

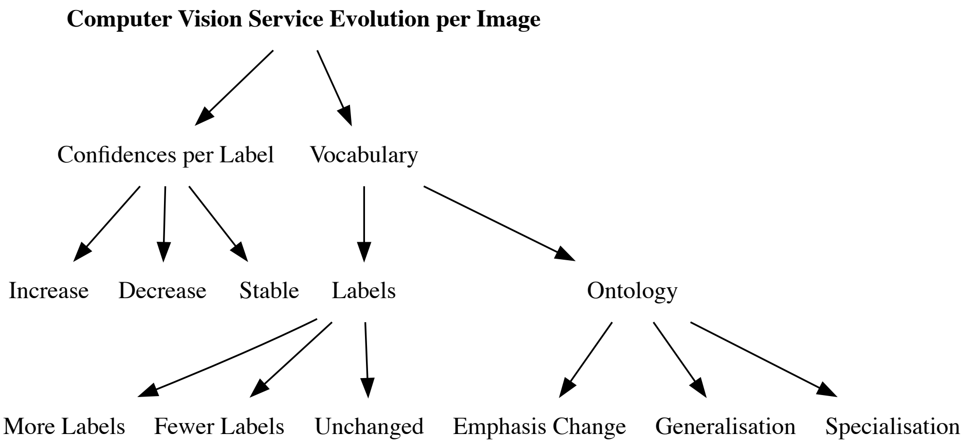


Figure 11.2: The dimensions of evolution identified within CVSs.

Figure 11.3: A significant confidence increase ($\delta = +0.425$) from `'window'` (0.559) to `'water transportation'` (0.984) goes beyond simple decision boundaries.

non-static, and a label may become more generalised into a hypernym, specialised into a hyponym, or the emphasis of the label may change either to a co-hyponym or another aspect in the image, such as the colour or scene, rather than the subject of the image [89].

Secondly, we have identified that the confidence values returned per label are also non-static. While some services may present minor changes to labels' confidences resulting from statistical noise, other labels had significant changes that were beyond basic decision boundaries. An example is shown in Figure 11.3. Developer code written to assume certain ranges/confidence intervals will fail if the service evolves in this way.

11.3.3 Limited Configurability

As an example, consider Figure 11.5, which illustrates an image of a dog uploaded to a well-known cloud-based CVS. Developers have very few configuration parameters in the upload payload (`url` for the image to analyse and `maxResults` for the number of objects to detect). The JSON output payload provides the confidence value of its estimated bounding box and label of the dog object via its `score` field (0.792). This value indicates the level of confidence in the label returned, and is dependent on the input to the underlying ML model used by that service. Developers set

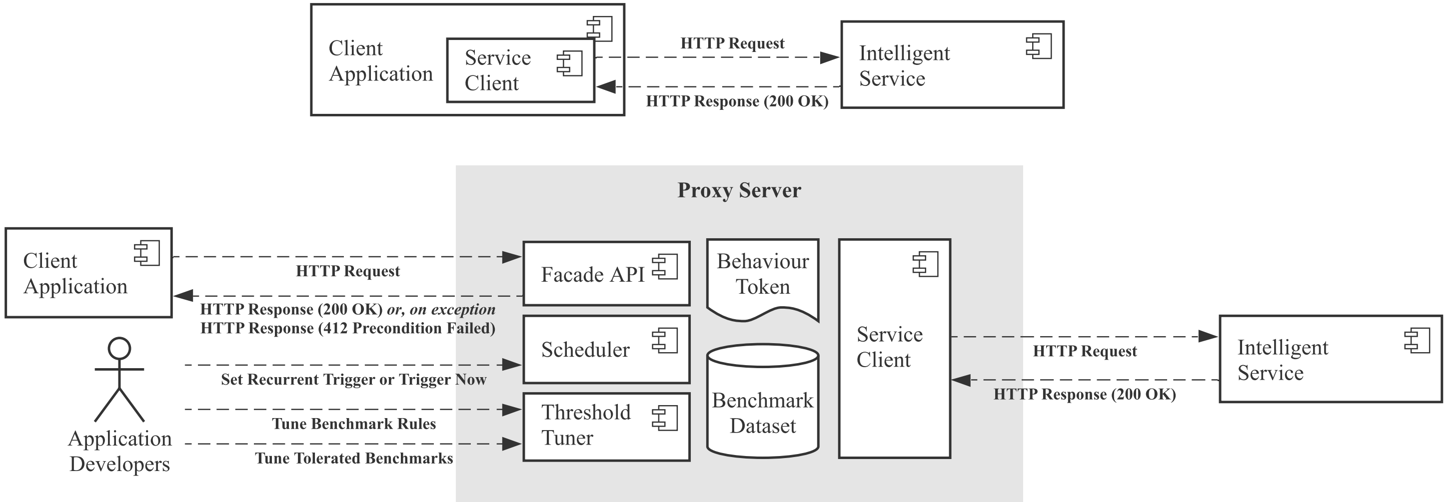


Figure 11.4: *Top:* Accessing an intelligent service directly. *Bottom:* Primary components of the Proxy Server approach.

thresholds 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 [89]. Developers can only modify these decision boundaries 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.

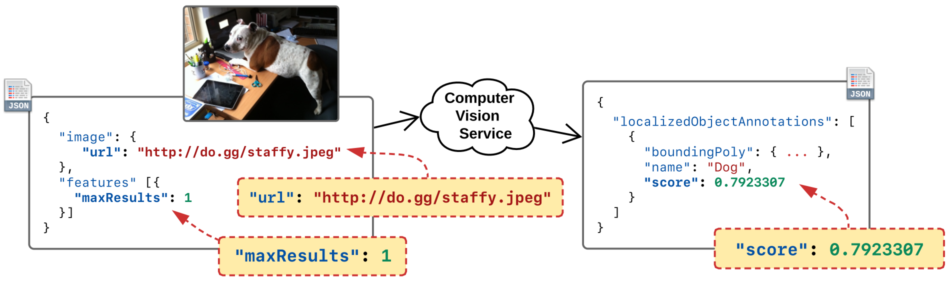


Figure 11.5: Request and response for an intelligent computer vision web service with only three configuration parameters: the image’s `url`, `maxResults` and `score`.

However, decision boundaries in service client code using simple `If` conditions around confidence scores is not a sufficient 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 [113] 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 CVSs.
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.

yet exist IWS client code architectures, tactics or patterns that achieve this goal.

11.4 Our Approach

To address the requirements from Section 11.2 we have developed a new Proxy Service[2] that includes: (i) evaluation of an intelligent service using an application specific benchmark dataset, (ii) a Proxy Server to provide client applications with evolution aware errors, and (iii) a scheduled evolution detection mechanism. The current approach of using an intelligent API via direct access is shown in Figure 11.4 (top). In contrast, an overview of our approach is shown in Figure 11.4 (bottom). The following sections describe our approach.

11.4.1 Core Components

For the purposes of this paper we assume that the intelligent service of interest is an image recognition service, but our approach generalises to other intelligent,

[2]A reference architecture is provided at `http://bit.ly/2TIMmDh`.

trained model-based services e.g., natural language processing, document recognition, voice, etc. Each image, when uploaded to the intelligent service returns a response (R) which is a set describing a label (l) of what is in the image (i) along with its associated confidence (c)—thus $R_i = \{(l_1, c_1), (l_2, c_2), \ldots (l_n, c_n)\}$. Most documentation of these services imply that these confidence values are all what is needed to handle evolution in their systems. This means that if a label changes beyond a certain threshold, then the developer can deal with the issue then (or ignore it). While this approach may work in some simple application contexts, in many it may not. Our Proxy Server offers a way to monitor if these changes go beyond a threshold of tolerance, checking against a domain-specific dataset over time.

11.4.1.1 Benchmark Dataset

Monitoring an intelligent service for behaviour change requires a Benchmark Dataset, a set of n images. For each image (i) in the Benchmark Dataset (B) there is an associated label (l) that represents the true value for that item; $B_i = \{(i_1, l_1), (i_2, l_2), \ldots (i_n, l_n)\}$. This dataset is used to check for evolution in IWSs by periodically sending each image within the dataset to the service's API, as per the rules encoded within the Scheduler (see Section 11.4.1.6). By using a dataset specific to the application domain, developers can detect when evolution affects their application rather than triggering all non-impactful changes. This helps achieve our requirement *R3. Monitor the evolution of IWSs for changes that affect the application's behaviour*. Using application-specific datasets also ensures that the architectural style can be used for different IWSs as only the data used needs to change. This design choice encourages reuse, satisfying requirement *R4. Implement a flexible architecture that is adaptable to different IWSs and application contexts to facilitate reuse*. We propose an initial set of guidelines on how to create and update the benchmark dataset within Section 11.6.3.1.

11.4.1.2 Facade API

An architectural 'facade' is the central component to our mitigation strategy for monitoring and detecting for changes in called IWSs. The facade acts as a guarded gateway to the intelligent service that defends against two key issues: (i) potential shifts in model variations that power the cloud vendor services, and (ii) ensures that a context-specific dataset specific to the application being developed is validated *over time*. By using a facade we can return evolution-aware error codes to the client application satisfying requirement *R1. Define a set of error conditions that specify the types of evolution that occur for an intelligent service* and enabling requirement *R3. Monitor the evolution of IWSs for changes that affect the application's behaviour.* This works by ensuring every request made by the client application contains a valid Behaviour Token (see Section 11.4.1.4) and will reject the request when evolution has been identified by the Scheduler with an associated error code. The Facade API essentially 'blocks' the client application out from accessing the intelligent service 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 $\lvert l(k_t) \triangle l(k_r) \rvert$).
Max δ Confidence	The minimum confidence change of *any* 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.

11.4.1.3 Threshold Tuner

Selecting an appropriate threshold for detecting behavioural change depends on the application context. Setting the threshold too low increases the likelihood of incorrect results, while setting the threshold too high means undesired changes are being detected. Our approach enables developers to configure these parameters through a Threshold Tuner, and consider competing factors such as algorithmic performance, financial cost, and impact of false-positives/negatives. This component improves robustness as now there is a systematic approach for monitoring and responding to incorrect thresholds. Configurable thresholds meet our key requirements *R2* and *R3*. An example of the component is detailed within our complement paper published in the ESEC/FSE 2020 demonstrations track [90] (see Chapter 10).

11.4.1.4 Behaviour Token

The Behaviour Token stores the current state of the Proxy Server by encoding specific rules regarding the evolution of the intelligent service. The current token (at time t) held by the Proxy Server is denoted by k_t. These rules are specified by the developer upon initialisation of this Proxy Server, and are presented in Table 11.2. When the Proxy Server is first initialised (i.e., at $t = 0$), the first Behaviour Token is created based on the Benchmark Dataset and its configuration parameters (Table 11.2) and is stored locally (thus k_0 is created). The Behaviour Token is passed to the client application to be used in subsequent requests to the proxy server, where k_r represents the Behaviour Token passed from the client application to the proxy server. Each time the proxy server receives the Behaviour Token from the client the validity of the token is validated with a comparison to the Proxy Server's current behaviour token (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 evolution has occurred and the application developer needs to appropriately handle the exception. Behaviour Tokens are essential for meeting requirement *R3. Monitor the evolution of IWSs for changes that affect the application's behaviour.*

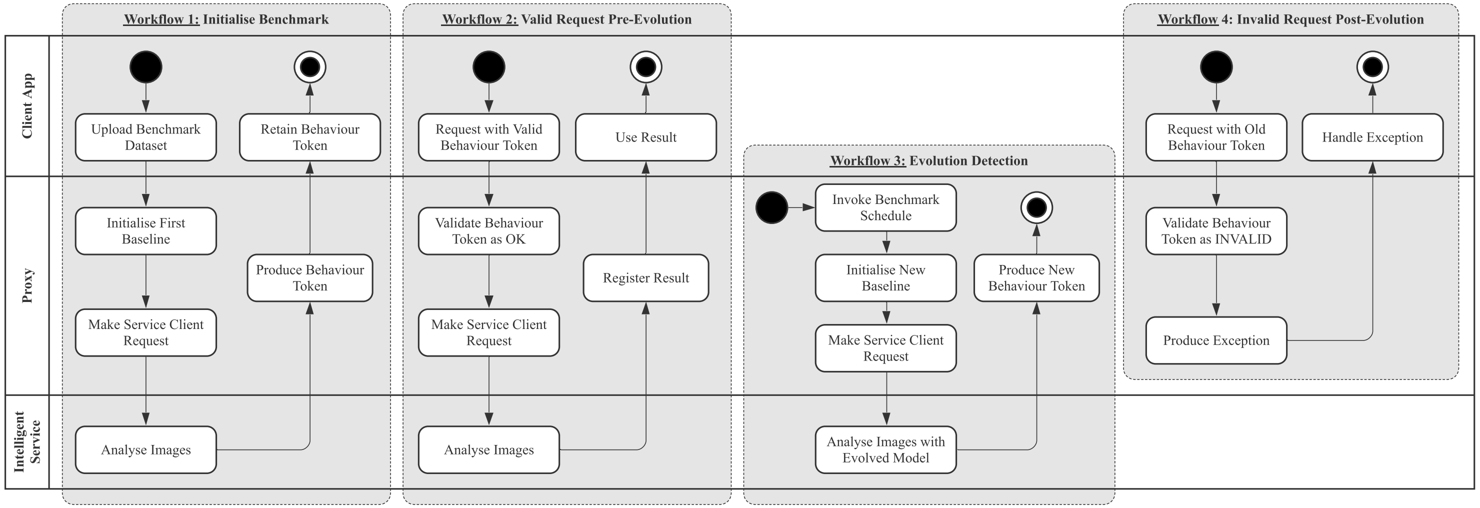


Figure 11.6: State diagram for the four workflows presented.

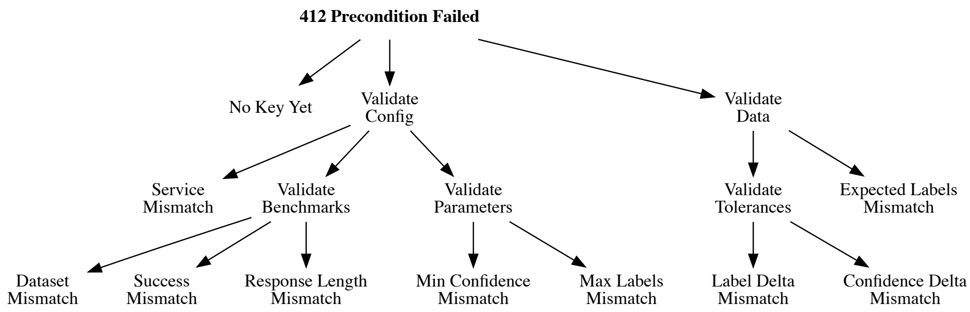


Figure 11.7: Precondition failure taxonomy; leaf nodes indicate error types returned to users.

11.4.1.5 Service Client

If any of the rules above are violated, then the response of the facade request varies depending on the behaviour encoded within the behaviour token. This can be one of:

- **Error:** Where a HTTP non-200 code is returned by the facade to the client application, indicating that the client application must deal with the issue immediately;
- **Warning:** Where a warning 'callback' endpoint is called with the violated response to be dealt with, but the response is still returned to the client application;
- **Info:** Where the violated response is logged in the facade's logger for the developer to periodically read and inspect, and the response is returned to the client application.

We implement this Proxy Server pattern using HTTP conditional requests. As we treat the Label as a first class citizen, we return the labels for a specific image (r_i) only where the *Entity Tag* (ETag) or *Last Modified* validators pass. The k_r is encoded within either the ETag (i.e., a unique identifier representing t) or as the date labels (and thus models) were last modified (i.e., using the `If-Match` or `If-Unmodified-Since` conditional headers). We note that the use of *weak* ETags should be used, as byte-for-byte equivalence is not checked but only semantic equivalence within the tolerances specified. Should t evolve to an invalid state (i.e., k_r is no longer valid against k_t) then the behaviour as described above will be enacted.

These HTTP header fields are used as the 'backbone' to help enforce robustness of the services against evolutionary changes and context within the problem domain dataset. Responses from the service are forwarded to the clients when such rules are met, otherwise alternative behaviour occurs. For example, the most severe of violated erroneous behaviour is the 'Error' behaviour. To enforce this rule, we advocate for use of the `412 Precondition Failed` HTTP error if a violation occurs, as a `If-*` conditional header was violated. An example of this architectural pattern with the 'Error' behaviour is illustrated in Figure 11.6.

We suggest the `412 Precondition Failed` HTTP error be returned in the event that a behaviour token is violated against a new benchmark. Further details outlining the reasons why a precondition has failed are encoded within a JSON response sent back to the consuming application. The following describes the two broad categories of possible errors returned: *robustness precondition failure* or *benchmark precondition failure*. These are illustrated in a high level within Figure 11.7 where leaf nodes are the potential error types that can be returned. A list of the different error codes are given in Table 11.1, where errors above the rule are robustness expectations (which check for basic requirements such as whether the key provided encodes the same data as the dataset in the facade) while those below are benchmark expectations (which identifies evolution cases).

11.4.1.6 Scheduler

The Scheduler is responsible for triggering the Evolution Detection Workflow (described in detail below in Section 11.4.2). Developers set the schedule to run in the background at regular intervals (e.g., via a cron-job) or to trigger if violations occur z times. The Scheduler is the component that enables our architectural style to identify called intelligent service software evolution and to notify the client applications that such evolution has occurred. Client applications can then respond to this evolution in a timely manner rather than wait for the system to fail, as in our motivating example. The Scheduler is necessary to satisfy our requirements *R2* and *R3*.

11.4.2 Usage Example

We explain how developer Michelina, from our motivating example, would use our proposed solution to satisfy the requirements described in Section 11.2. Each workflow is presented in Figure 11.6. Only *Workflow 1 - Initialise Benchmark* is executed once, while the rest are cycled. The description below assumes Michelina has implemented the Proxy.

11.4.2.1 Workflow 1. Initialise Benchmark

The first task that Michelina has to do is to prepare and initialise the benchmark dataset within the Proxy Server. To prepare a representative dataset, Michelina needs to follow well established guidelines such as those proposed by Pyle. Michelina also needs to manually assign labels to each image before uploading the dataset to the Proxy along with the thresholds to use for detecting behavioural change. The full set of parameters that Michelina has to set are based on the rules shown in Table 11.2. Michelina cannot use the Proxy to notify her of evolution until a Benchmark Dataset has been provided. The Proxy then sends each image in the Benchmark Dataset to the intelligent service and stores the results. From these results, a Behaviour Token is generated which is passed back to the Client Application. Michelina uses this token in all future requests to the Proxy as the token captures the current state of the intelligent service.

11.4.2.2 Workflow 2. Valid Request Pre-Evolution

Workflow 2 represents the steps followed when the intelligent service is behaving as expected. Michelina makes a request to label an image to the Proxy using the token that she received when registering the Benchmark Dataset. The token is validated with the Proxy's current state token and then a request to label the image is made to the intelligent service if no errors have occurred. Results returned by the intelligent service are registered with the Proxy Server. Michelina can be confident that the result returned by our service is in line with her expectations.

11.4.2.3 Workflow 3. Evolution Detection

Workflow 3 describes how the Proxy functions when behavioural change is present in the called intelligent service. Michelina sets a schedule for once a day so that the Proxy's Scheduler triggers Workflow 3. First, each image in the Benchmark Dataset is sent to the intelligent service. Unlike, Workflow 1, we already have a Behaviour Token that represents the previous state of the intelligent service. In this case, the model behind the intelligent service has been updated and provides different results for the Benchmark Dataset. Second, the Proxy updates the internal Behaviour Token ready for the next request. At this stage Michelina will be notified that the behaviour of the intelligent service has changed.

11.4.2.4 Workflow 4. Invalid Request Post-Evolution

Workflow 4 provides Michelina with an error message when evolution has been detected. Michelina's client application makes a request to the Proxy Server with an old Behaviour Token. The Proxy Server then validates the client token which is invalid as the Behaviour Token has been updated. In this case, an exception is raised and an appropriate error message as discussed above is included in the response back to Michelina's client application. Michelina can code her application to handle each error class in appropriate ways for her domain.

11.5 Evaluation

Our evaluation of our novel intelligent service Proxy Server approach uses a technical evaluation based on the results of an observational study. We used existing datasets from observational studies [89, 218] to identify problematic evolution in computer vision labelling services. This technical evaluation is designed to show: (i) what the responses are with and without our architecture present (highlighting errors); (ii) the overall increased robustness using enhanced responses; and (iii) the technical soundness of the approach. Thus, we propose the following research question which we answer in Section 11.5.2: *"Can the architecture identify evolutionary issues of computer vision services via error codes?"* Based on our findings we proposed and implemented the Proxy Server using a Ruby development framework which we have made available online for experimentation.[3] Additional data was collected from the CVS and sent to the Proxy Server to evaluate how the service handles behavioural change.

11.5.1 Data Collection and Preparation

To minimise reviewer bias, we do not identify the name of the service used, however this service was one of the most adopted cloud vendors used in enterprise applications in 2018 [120]. The two existing datasets used [89, 218] consisted of 6,680 images.

We initialised the benchmark (workflow 1) in November 2018, and sent each image to the service every eight days and captured the JSON responses through the facade API (workflow 2) until March 2019. This resulted in 146,960 JSON responses from the target CVS. We then selected the first and last set of JSON responses (i.e., 13,360 responses) and independently identified 331 cases of evolution of the original 6,680 images. This was achieved by analysing the JSON responses for each image taken in using an evaluation script.[4]

For each JSON response, evolution (as classified by Figure 11.2) was determined either by a vocabulary or confidence per label change in the first and last responses sent. For the 331 evolving responses, we calculated the delta of the label's confidence between the two timestamps and the delta in the number of labels recorded in the entire response. Further, for the highest-ranking label (by confidence), we manually classified whether its ontology became more specific, more generalised or whether there was substantial emphasis change. The distribution of confidence differences per these three groups are shown in Figure 11.8, with the mean confidence delta indicated with a vertical dotted line. This highlights that, on average, labels that change emphasis generally have a greater variation, such as the example in Figure 11.3. Further, we grouped each image into one of four broad categories—*food*, *animals*, *vehicles*, *humans*—and assessed the breakdown of ontology variance as provided in Table 11.3. We provide this dataset as an additional contribution and to permit replication.[5] The parameters set for our initial benchmark were a delta label value of 3 and delta confidence value of 0.01. Expected labels for relevant groups were also assigned as mandatory label sets (e.g., *animal* images used `'animal'`, `'fauna'` and `'organism'`; *human* images used `'human'` etc.).

11.5.2 Results

Examples of the March 2019 responses contrasting the proxy and direct service responses in our evaluation are shown in Figures 11.9 to 11.11. (Due to space limitations, the entire JSON response is partially redacted using ellipses.) These examples identify the label identified with the highest level of confidence in three examples against the ground truth label in the benchmark dataset. In total, the Proxy Server identified 1,334 labels added to the responses and 1,127 labels dropped, with, on 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.

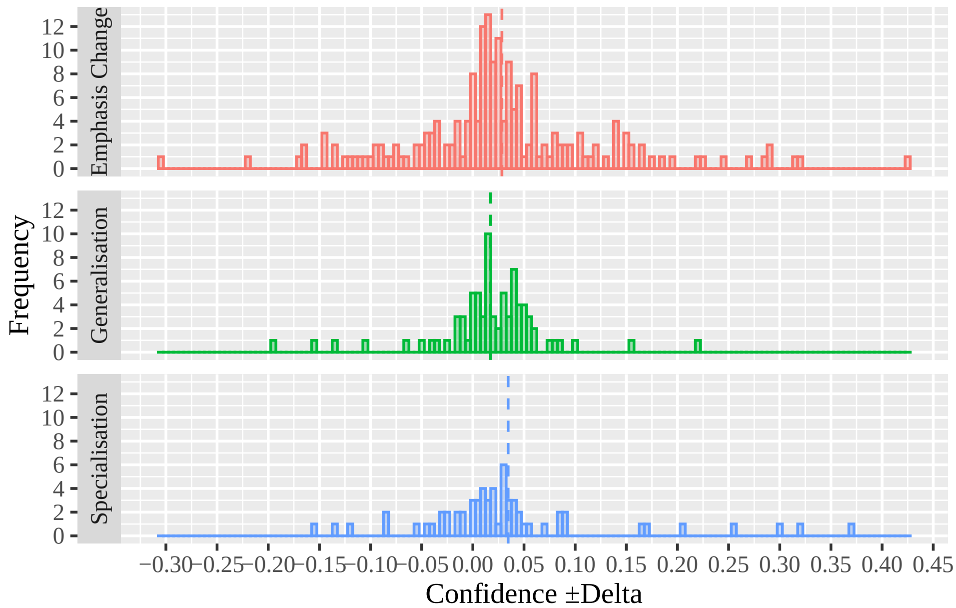


Figure 11.8: Histogram of confidence variation.

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

introduced `'green iguana'`, `'iguanidae'`, and `'marine iguana'` to its label set. Therefore, not only was this response in violation of the label delta mismatch, it was also in violation of the expected labels mismatch error, and thus is caught twice by the Proxy Server.

11.5.3 Threats to Validity

11.5.3.1 Internal Validity

As mentioned, we selected a popular CVS provider to test our proxy server against. However, there exist many other CVSs, and due to language barriers of the authors, no non-English speaking service were selected despite a large number available from Asia. Further, no user evaluation has been performed on the architectural tactic so far, and therefore developers may suggest improvements to the approach we have taken in designing our tactic. We intend to follow this up with a future study.

11.5.3.2 External Validity

This paper only evaluates the object detection endpoint of a computer vision-based intelligent service. While this type of intelligent service is one of the more mature AI-based services available on the market—and is largely popular with developers [92]—further evaluations of the our tactic may need to be explored against other endpoints (i.e., object localisation) or, indeed, other types of services, such as natural language processing, audio transcription, or on time-series data. Future studies may need to explore this avenue of research.

11.5.3.3 Construct Validity

The evaluation of our experiment was largely conducted under clinical conditions, and a real-world case study of the design and implementation of our proposed tactic would be beneficial to learn about possible side-effects from implementing such a design (e.g., implications to cost etc.). Therefore, our evaluation does not consider more practical considerations that a real-world, production-grade system may need to consider.

Label: Animal
Nov 2018: `sheep` (0.9622)
Mar 2019: `mammal` (0.9890)
Category: Confidence Change

Intelligent Service Response in March 2019

```
{ "responses": [ { "label_annotations": [
  { "mid": "/m/04rky",
    "description": "mammal",
    "score": 0.9890478253364563,
    "topicality": 0.9890478253364563 },
  { "mid": "/m/09686",
    "description": "vertebrate",
    "score": 0.9851104021072388,
    "topicality": 0.9851104021072388 },
  { "mid": "/m/07bgp",
    "description": "sheep",
    "score": 0.9815810322761536,
    "topicality": 0.9815810322761536 },
  ... ] } ] }
```

Proxy Server Response in March 2019

```
{ "error_code": 8,
  "error_type": "CONFIDENCE_DELTA_MISMATCH",
  "error_data": {
    "source_key": { ... },
    "source_response": { ... },
    "violating_key": { ... },
    "violating_response": { ... },
    "delta_confidence_threshold": 0.01,
    "delta_confidences_detected": {
      "sheep": 0.01936030388219212,
      "herd": 0.15035879611968994,
      "livestock": 0.13112884759902954,
      "terrestrial animal": 0.1791478991508484,
      "snout": 0.10682523250579834
    },
    "uri": "http://localhost:4567/demo/data/000000005992.jpeg",
    "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

```
{ "responses": [ { "label_annotations": [
  { "mid": "/m/07yv9",
    "description": "vehicle",
    "score": 0.9045347571372986,
    "topicality": 0.9045347571372986 },
  { "mid": "/m/07bsy",
    "description": "transport",
    "score": 0.9012271165847778,
    "topicality": 0.9012271165847778 },
  { "mid": "/m/0dx1j",
     "description": "town",
     "score": 0.8946694135665894,
     "topicality": 0.8946694135665894 },
  ... ] } ] }
```

Proxy Server Response in March 2019

```
{ "error_code": 7,
  "error_type": "LABEL_DELTA_MISMATCH",
  "error_data": {
    "source_key": { ... },
    "source_response": { ... },
    "violating_key": { ... },
    "violating_response": { ... },
    "delta_labels_threshold": 5,
    "delta_labels_detected": 8,
    "uri": "http://localhost:4567/demo/data/000000019109.jpeg"
        ↪ ,
    "new_labels": [ "transport", "building", "architecture", "
        ↪ house" ],
    "dropped_labels": [ "car", "motor vehicle", "city", "road"
        ↪  ],
    "reason": "Exceeded label count delta threshold ±5 (4 new
        ↪  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

```
{ "responses": [ { "label_annotations": [
  { "mid": "/m/08_jw6",
    "description": "iguania",
    "score": 0.9835183024406433,
    "topicality": 0.9835183024406433 },
  { "mid": "/m/06bt6",
    "description": "reptile",
    "score": 0.9833670854568481,
    "topicality": 0.9833670854568481 },
  { "mid": "/m/01vq7_",
    "description": "iguana",
    "score": 0.9796721339225769,
    "topicality": 0.9796721339225769 },
  ... ] } ] }
```

Proxy Server Response in March 2019

```
{ "error_code": 9,
  "error_type": "EXPECTED_LABELS_MISMATCH",
  "error_data": {
    "source_key": { ... },
    "violating_response": { ... },
    "uri": "http://localhost:4567/demo/data/0052.jpeg",
    "expected_labels": [ "fauna" ],
    "labels_detected": [ "iguana", "green iguana", "iguanidae"
        ↪ , "lizard", "scaled reptile", "marine iguana", "
        ↪ 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.

11.6 Discussion

11.6.1 Implications

11.6.1.1 For cloud vendors

Cloud vendors that provide IWSs may wish to adopt the architectural tactic presented in this paper by providing a proxy, auxiliary service (or similar) to their existing services, thereby improving the current robustness of these services. Further, they should consider enabling developers of this technical domain knowledge by preventing client applications from using the service without providing a benchmark dataset, such that the service will return HTTP error codes. These procedures should be well-documented within the service's API documentation, thereby indicating to developers how they can build more robust applications with their IWSs. Lastly, cloud vendors should consider updating the internal machine learning models less frequently unless substantial improvements are being made. Many different applications from many different domains are using these IWSs so it is unlikely that the model changes are improving all applications. Versioned endpoints would help with this issue, although—as we have discussed—context using benchmark datasets should be provided.

11.6.1.2 For application developers

Developers need to monitor all IWSs for evolution using a benchmark dataset and application specific thresholds before diving straight into using them. It is clear that the evolutionary issues have significant impact in their client applications [89], and therefore they need to check the extent this evolution has between versions of an intelligent service (should versioned APIs be available). Lastly, application developers should leverage the concept of a proxy server (or other form of intermediary) when using IWSs to make their applications more robust.

11.6.1.3 For project managers

Project managers need to consider the cost of evolution changes on their application when using IWSs, and therefore should schedule tasks for building maintenance infrastructure to detect evolution. Consider scheduling tasks that evaluates and identifies the frequency of evolution for the specific intelligent service being used. Our research we have found some IWSs that are not versioned but rarely show behavioural changes due to evolution.

11.6.2 Limitations

In the situation where a solo developer implements the Proxy Service the main limitation is the cost vs response time trade-off. Developers may want to be notified as soon as possible when a behavioural change occurs which requires frequent validation of the Benchmark Dataset. Each time the Benchmark Dataset is validated each item is sent as a request to the intelligent service. As cloud vendors charge per request to an intelligent service there are financial implications for operating the Proxy Service. If the developer optimises for cost then the application will take longer to respond to the behavioural change potentially impact end users. Developers need to consider the impact of cost vs response time when using the Proxy Service.

Another limitation of our approach is the development effort required to implement the Proxy Service. Developers need to build a scheduling component, batch processing pipeline for the Benchmark Dataset, and a web service. These components require developing and testing which impact project schedules and have maintenance implications. Thus, we advise developers to consider the overhead of a Proxy Service and way up the benefits with have incorrect behaviour caused by evolution of IWSs.

11.6.3 Future Work

11.6.3.1 Guidelines to construct and update the Benchmark Dataset

Our approach assumes that each category of evolution is present in the Benchmark Dataset prepared by the developer. Further guidelines are required to ensure that the developer knows how to validate the data before using the Proxy Service. While the focus of this paper was to present and validate our architectural tactic, guidelines on how to construct and update benchmark datasets for this tactic will need to be considered in future work. Data science literature extensively covers dataset preparation (e.g., [203, 290]), and many example benchmark datasets are readily available [24, 147, 380]. An initial set of guidelines are proposed as follows: data must be contextualised and appropriately sampled to be representative of the client application in particular the patterns present in the data, contain both positive and negative examples (this is/is not a cat); where to source data from (existing datasets, Google Images/Flickr, crowdsourced etc.); whether the dataset is synthetically generated to increase sample size; and how large a benchmark dataset size should be (i.e., larger the better but takes more effort and costs more). Benchmark datasets can also be used by software engineers provided the domain and context is appropriate for their specific application's context. Software engineers also benefit from our approach even if these guidelines are not strictly adhered to provided they use an application-specific dataset (i.e., data collected from the input source for their application). The main reason for this is that without our proposed tactic there are limited ways to build robust software with intelligent services. Future testing and evaluation of these guidelines should be considered.

11.6.3.2 Extend the evolution categories to support other IWSs

This paper has used computer vision services to assess our proposed tactic, and therefore further investigation is needed into the evolution characteristics of other IWSs. The evolution challenges with services that provide optimisation algorithms such as route planning are likely to differ from CVSs. These characteristics of an application domain have shown to greatly influence software architecture [25] and further development of the Proxy Service will need to account for these differences.

As an example, we have identified many similar issues that exist for natural language processing, where topic modelling produces labels on large bodies of text with associated confidences. Therefore, the *broader* concepts of our contribution (e.g., behaviour token parameters, error codes etc.) can be used to handle issues in natural language processing to demonstrate the generalisability of the architecture to other intelligent services. We plan to apply our tactic to natural language processing and other intelligent services in our future work.

11.6.3.3 Provide tool support for optimising parameters for an application context

Appropriately using the Proxy Service requires careful selection of thresholds, benchmark rules and schedule. Further work is required to support the developer in making these decisions so an optimal application specific outcome is achieved. One approach is a to present the trade-offs to the developer and let them visualise the impact of their decisions. We have developed an early prototype for such purpose in [90].

11.6.3.4 Improvements for a more rigorous approach

Conducting a more formal evaluation of our proposed architecture would benefit the robustness of the solution presented. This could be done in various ways, for example, using a formal architecture evaluation method such as ATAM [192] or a similar variant [51]; conducting user evaluation via brainstorming sessions or interviews with practitioners who may provide suggestions to improve our approach; determining better strategies to fully-automate the approach and reduce manual steps; and using real-world industry case studies to identify other factors such as cost and maintenance issues. All these are various avenues of research that would ultimately benefit in a more well-rounded approach to the architectural tactic we have proposed.

11.7 Related Work

11.7.0.1 Robustness of Intelligent Services

While usage of IWSs have been proven to have widespread benefits to the community [95, 299], they are still largely understudied in software engineering literature, particularly around their robustness in production-grade systems. As an example, advancements in computer vision (largely due to the resurgence of convolutional neural networks in the late 1990s [212]) have been made available through IWSs and are given marketed promises from prominent cloud vendors, e.g., "with Amazon Rekognition, you don't have to build, maintain or upgrade deep learning pipelines".[6] However, while vendors claim this, the state of the art of *computer vision itself* is still susceptible to many robustness flaws, as highlighted by many recent studies [114, 311, 367]. Further, each service has vastly different (and incompatible) ontologies which are non-static and evolve [89, 266], certain services can mislabel

[6] `https://aws.amazon.com/rekognition/faqs/`, accessed 21 November 2019.

images when as little as 10% noise is introduced [163], and developers have a shallow understanding of the fundamental AI concepts behind these issues, which presents a dichotomy of their understanding of the technical domain when contrasted to more conventional domains such as mobile application development [92].

11.7.0.2 Proxy Servers as Fault Detectors

Fault detection is an availability tactic that encompasses robustness of software [31]. Our architecture implements the sanity check and condition monitoring techniques to detect faults [31, 169], by validating the reasonableness of the response from the intelligent service against the conditions set out in the rules encoded in the benchmark dataset and behaviour token. As we do in this study, the proxy server pattern can be used to both detect and action faults in another service as an intermediary between a client and a server. For example, addressing accessibility issues using proxy servers has been widely addressed [42, 43, 350, 391] and, more recently, they have been used to address in-browser JavaScript errors [109].

11.8 Conclusions

IWSs are gaining traction in the developer community, and this is shown with an evermore growing adoption of CVSs in applications. These services make integration of AI-based components far more accessible to developers via simple RESTful APIs that developers are familiar with, and offer forever-'improving' object localisation and detection models at little cost or effort to developers. However, these services are dependent on their training datasets and do not return consistent and deterministic results. To enable robust composition, developers must deal with the evolving training datasets behind these components and consider how these non-deterministic components impact their deterministic systems.

This paper proposes an integration architectural tactic to deal with these issues by mapping the evolving and probabilistic nature of these services to deterministic error codes. We propose a new set of error codes that deal directly with the erroneous conditions that has been observed in IWSs, such as computer vision. We provide a reference architecture via a proxy server that returns these errors when they are identified, and evaluate our architecture, demonstrating its efficacy for supporting IWS evolution. Further, we provide a labelled dataset of the evolutionary patterns identified, which was used to evaluate our architecture.

Part III

Postface

CHAPTER 12

Conclusions & Future Work

In this chapter, we provide a summary of the contributions within the body of this work. We evaluate the significance of the research outcomes to the software engineering research community and identify potential criticisms of these outcomes. Lastly, we indicate future avenues of research resulting from this thesis and provide concluding remarks.

12.1 Contributions of this Work

This thesis has presented three primary contributions to the body of software engineering knowledge. Namely, we have presented an improved understanding in the landscape of IWSs—concretely, those that provide computer vision—by examining their runtime behaviour and evolution profile over a longitudinal study (Chapter 4). The implications of this work emphasise the caution developers need to take before diving deep into using these services, and highlight the substantial impacts to software quality if these considerations are ignored. We showed that developers find working with this software more frustrating when contrasted to conventional software engineering domains (Chapter 6), and that the distribution of the types of issues they face differs from that of the types of issues developers face in established areas such as mobile and web development (Chapter 5). Furthermore, developers find the completeness of the existing CVS API documentation poor (Chapter 5), and therefore an investigation into the attributes of what *constitutes* a complete application programming interface (API) document according to literature and how developers respond to the efficacy of these attributes produced a taxonomy that, when applied to three CVS service providers, found 12 areas of improvement of the services' documentation (Chapter 8). This taxonomy further serves as a go-to 'checklist' for any software engineer to review a prioritised list of documentation elements worth implementing into their own API documentation. Lastly our investigations into improved intelligent service integration architectures proposes several strategies by which developers can guard against the non-deterministic evolutionary issues found in Chapter 4. Preliminary solutions such as that presented in Chapter 9 helped informed further investigations into how developers can use a novel workflow to better select appropriate confidence thresholds calibrated for their application's domain (Chapter 10) and prevent evolution evident in CVSs via a client-server intermediary proxy server strategy (Chapter 11). A more extensive discussion into the contributions of this thesis is presented in Section 1.7.

12.1.1 Answers to Research Questions

In this subsection, we directly answer the four primary research questions that were posed in Section 1.4.

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.*

Irrespective of which service is used, the vocabulary used to label an image is disparate. We find that **there exists no common standard vocabulary** (e.g., 'border collie' vs. 'collie') and **semantic consistency for the same image between services is disparate**, for example as that shown in Figure 12.1 (left). The runtime behaviour of these services when contrasted against *each other* is, therefore, inconsistent, and thus (without semantic comparison of images, such as that suggested in Chapter 9) the vendors are not 'plug-and-play'. In contrast to deterministic web services, the same result is functionally guaranteed despite which service is used. For instance, conceptually, a cloud storage service will provide the same output for the same input; that is, regardless of whether a developer uses AWS or Google Cloud object storage, when they upload a file, that file is (more or less) guaranteed to be stored. A deterministic input/output is, thereby, conceptually and functionally guaranteed. However, **we find that the nature of intelligent services are conceptually similar but functionally different between services**, and therefore developers are likely to become vendor locked. For instance, as we show in Section 4.5.1, one service may return the duplicity of objects in an image (e.g., 'several'), while another service may return the subject of the image (e.g., 'carrot') or a hypernym of that subject (e.g., 'food'), and another service may focus on the environment of the image (e.g., 'indoors'). Further, even when a label is consistent between services, we find the consistency of how *well* they agree to that result—as measured by their confidence score in the label—does not always strictly match in their level of agreement. As we show in Figure 12.1 (right), **distributions of agreement can be disparate even where services agree on a label for the same image**. Lastly, while intelligent services that provide computer vision are somewhat stable in the responses they return, **their responses are non-static**. There is no guarantee that a request with the same image sent in testing will return the same response, and we find that this 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%.

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.*

To understand if these services are sufficiently documented, we first investigated what documentation artefacts constitute a complete API document, investigating literature and validating this against developers using a survey. These consist of five dimensions: usage description (or *how* developers can use the API); design rationale (or *when* the developers should use it); domain concepts (or *why* developers should use it in their application domain); support artefacts (or *what* additional documentation could be provided to support developers); and, documentation presentation (or *visualisation* of the prior four dimensions). This taxonomy is presented with further detail in Chapter C. **Developers argue that code snippets are the most 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 CVSs, 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 8.6.3 details these suggested improvements in greater detail.

12.1.1.3 RQ3: "Are CVSs 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 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 this is rooted in a need for developers to have some basic understanding of computer vision before diving into services such as these. In terms of the documentation of these services, **developers express frustration towards the completeness of the documentation**, whereby they seek additional information from the official documentation sources but are unable to find anything to help resolve this gap. Further, **they question the accuracy of the cloud documentation since it is in contrast with the behaviour they observe**, as related to the discrepancy-based issues they find. In contrast to more established domains, such as mobile and web-development, the distribution of issues are different (see Figure 12.2). Rather than trying to interpret simple errors (as is the case for CVSs), developers question API usage and high-level conceptual questions. Developers have a greater appreciation for the technical domain in these mature areas, resulting in fewer shallower questions asked.

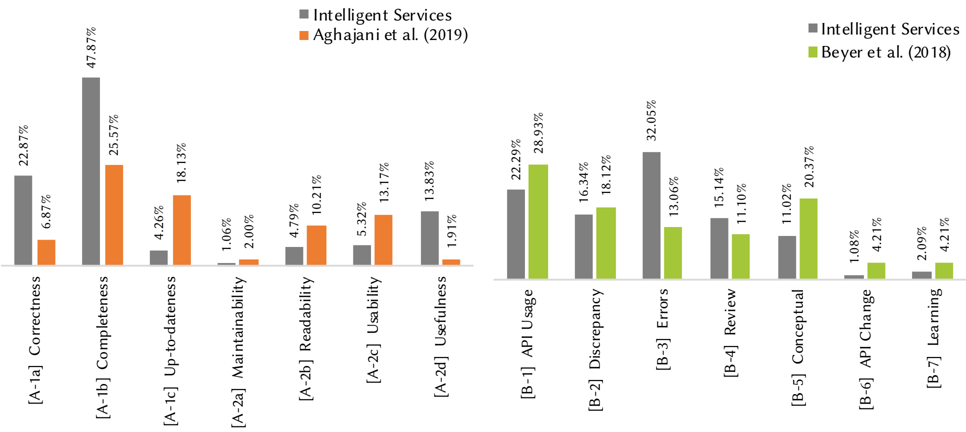


Figure 12.2: The distribution of documentation-specific questions (*left*) and generalised questions (*right*) differs between prior studies. Descriptions of each category for both question types are found in Table 5.1.

12.1.1.4 RQ4: *"What strategies can developers employ to integrate their applications 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.*

This thesis offers three strategies targeted at improved integration of developer 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 [120], many other providers of computer vision intelligence exist [395, 411, 412, 413, 419, 432, 433, 435, 485, 486], including those from Asian market [409, 410, 431, 451, 452] 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 thesis strongly emphasises investigations into identifying issues within web-based intelligent services. We establish a better understanding on their nature and runtime behaviour (RQ1), how they are documented (RQ2), and how well they are understood by developers (RQ3), but only offer limited solutions to these issues (e.g., RQ4). We encourage the software engineering community to use the issues identified in this work as a stepping-stone into future solutions, identifying other ways (beyond improved integration techniques) in which developers can handle these issues. For example, the broader concepts of our contributed architecture (e.g., use of a behaviour token, its parameters, and the error codes proposed) can be shifted to handle issues in natural language processing to demonstrate the generalisability of the architecture to other intelligent services, since topic modelling produces labels with confidences and the approach can be largely transferred to this area.

Other future work stemming from this thesis would be to explore the nature of other IWSs and understanding if similar evolution and behavioural runtime patterns exist with their computer vision equivalents (as identified in this thesis). Chiefly, future work on how to better support developers using different types of intelligent components would be an interesting area to explore, especially in applying our design strategies to combat the robustness issues we have identified to these other types of services and identify any potential pitfalls of our design. As our proposed architectural usage framework is a preliminary design, rigorous testing in real-world scenarios, such as a long-term industry case study implementing our design or conducting formal architecture evaluations such as ATAM [192], would be a possible avenue of research to verify the design. Further, our proposal makes use of the benchmark data set approach, but we are yet to explore and test potential guidelines in developing a benchmark data set. While we provide some potential guidelines in Section 11.6.3.1, these will need to be evaluated for practical use.

Another key aspect would revolve around the documentation contributions of this study and investigating whether our suggested documentation improvements are applicable to these different services. Developing improved documentation and tooling that better support developers when using these IWSs (and how our proposed architecture fits in) should be explored.

Moreover, since we find these services to be not yet as matured as traditional software development domains and—like similar emerging software engineering domains such as web development in the mid-1990s and early-2000s or mobile development from the mid-2000s to early-2010s—we suspect there to be substantial growth in the understanding of how we will use these services and maturity in the developer's appreciation of its surrounding technical domain. Therefore, it would be beneficial to repeat some of the studies within this thesis and assess whether there is an improved understanding of the phenomena occurring within IWSs and whether developers have a developed mindset of these services and how they can be used. Thus, different tools, designs or suggestions may result from repetitional studies 5-10 years in the future. This, therefore, identifies evolution in the *maturity* of intelligent services, and to highlight whether developers are showing a stronger understanding of the surrounding technical domain behind these services. We strongly encourage the software engineering community to explore these in such time to identify maturity in this emerging domain.

12.2 Concluding Remarks

To our knowledge, little prior investigation has been conducted to understand IWSs via the lenses of software quality—primarily the robustness, reliability of the services and completeness of its documentation. In this thesis, we have shown that the non-deterministic and probabilistic properties of computer vision IWSs present non-trivial impacts to the quality of software that they are integrated with, and it is pivotal that developers have a greater appreciation of the technical domain behind the AI techniques that empower such services.

In identifying evolutionary and run-time issues of these services, the ways in which they are (currently) documented and these issues communicated (or not!), and analysing how developers perceive these services with a deterministic mindset, we have shown just how fragile the use of such services (as they stand) are. We strongly encourage vendors to use suggestions made within this research to improve both their documentation and their integration strategies so that developers can ensure more robust applications when using these services. Ultimately, intelligent AI components are still in a nascent stage, and therefore strongly suggest one message to eager developers: use with caution and be aware of the consequences!

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List of Online Artefacts

The online artefacts listed below have been downloaded and stored on the Deakin Research Data Store (RDS) for archival purposes at the following location:

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[476] Stack Overflow User #738248 'lavuy', "Meaning of score in Microsoft Cognitive Service's Entity Linking API," http://bit.ly/2TD9vVw, 2019, accessed: 22 June 2019.

[477] Stack Overflow User #7604576 'Alagappan Narayanan', "Text extraction - line-by-line," http://bit.ly/31Yc21s, 2019, accessed: 22 June 2019.

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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 [310]. This framework used the synchronous communication paradigm remote procedure calls (RPCs) first introduced by Nelson [259] that allows procedures to be called in a remote address space as if it were local. Its communication paradigm, DCE/RPC [267], 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 [267]). 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) [73] 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 [368, 374]). These attributes are included within SOAP headers; thus, QoS aspects are independent from the transport layer and instead exist at the application layer [278]. 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 [278, 394] 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: [23].

```
POST /customers HTTP/1.1
Host: www.example.org
Content-Type: application/soap+xml; charset=utf-8

<?xml version="1.0"?>
<soap:Envelope
  xmlns:soap="http://www.w3.org/2003/05/soap-envelope">
  <soap:Body>
    <m:GetCustomer
      xmlns:m="http://www.example.org/customers">
      <m:CustomerId>43456</m:CustomerId>
    </m:GetCustomer>
  </soap:Body>
</soap:Envelope>
```

Listing A.2: The SOAP HTTP service provider response for Listing A.1. Source: [23].

```
HTTP/1.1 200 OK
Content-Type: application/soap+xml; charset=utf-8

<?xml version='1.0' ?>
<env:Envelope
  xmlns:env="http://www.w3.org/2003/05/soap-envelope" >
  <env:Body>
    <m:GetCustomerResponse
      xmlns:m="http://www.example.org/customers">
      <m:Customer>Foobar Quux, inc</m:Customer>
    </m:GetCustomerResponse>
  </env:Body>
</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 [278]. That is, the HTTP is considered as a transport protocol solely. In 2000, Fielding [117] 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 [36].
- **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 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) [229]). Therefore, no RESTful service uses a standardised response document or invocation syntax. While there are proposals, such as WADL [148], RAML[1], API Blueprint[2], and the OpenAPI[3] specification (initially based on Swagger[4]), 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: [23].

```
GET /customers/43456 HTTP/1.1
Host: www.example.org
```

Listing A.4: The REST HTTP service provider response for Listing A.3.

```
HTTP/1.1 200 OK
Content-Type: application/json; charset=utf-8

{"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 (p259)** 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 (p260)** 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 CVSs. 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 (p261)** 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 (p261)** 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 (p262)** illustrates the domain model of Threshy (Chapter 10).
- **Figure A.7 (p262)** 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 (p263)** 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 (p264)** 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 (p265)** 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 (p266)** 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 (p267)** 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 (p268)** 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 (p269)** 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.

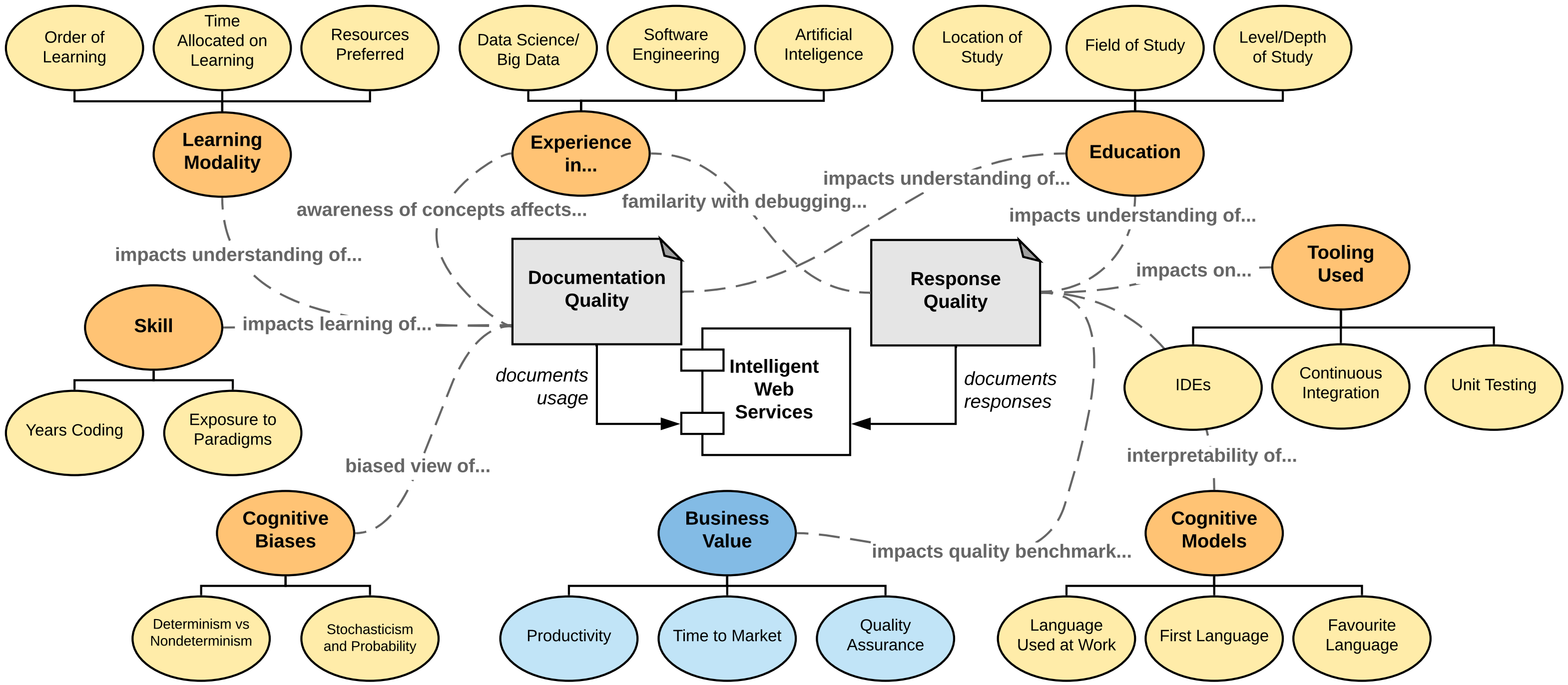


Figure A.3: A proposal technical domain model for intelligent services. (The ℹ symbol indicates computer vision related services only.)

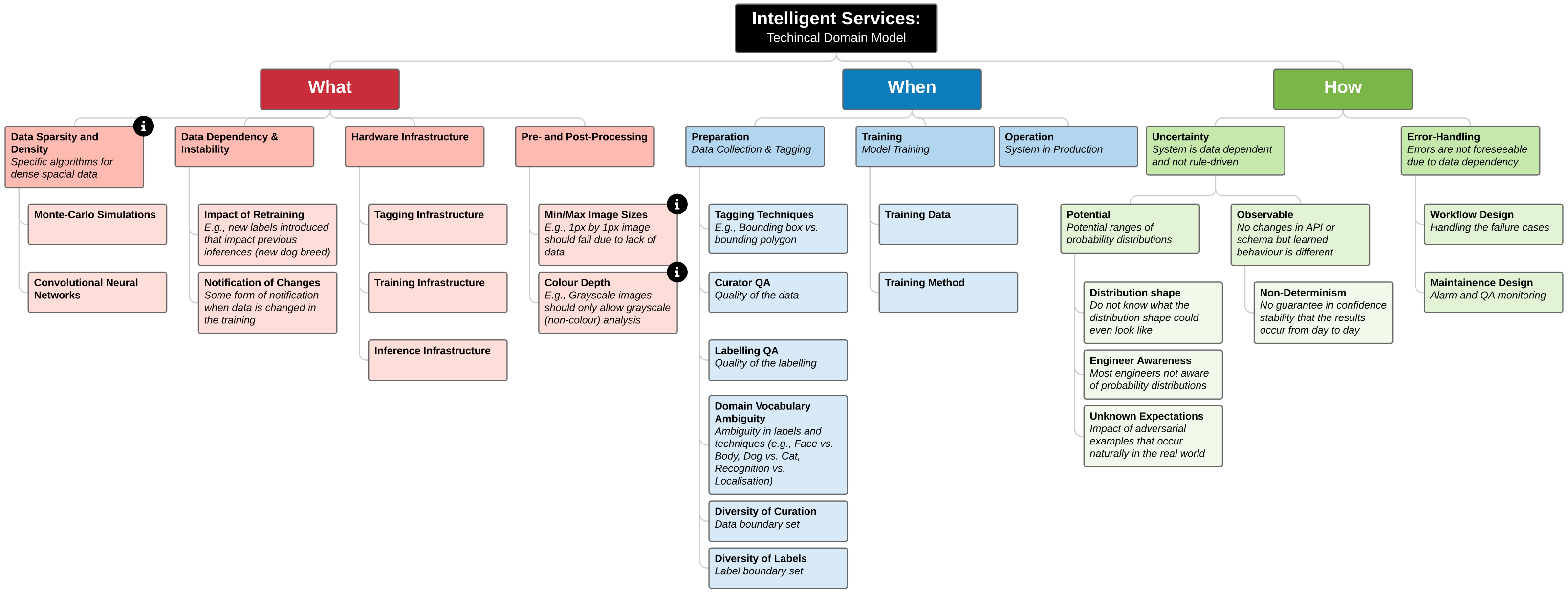


Figure A.4: Potential questions that can be asked around causal factors of a developer's understanding of an intelligent service.

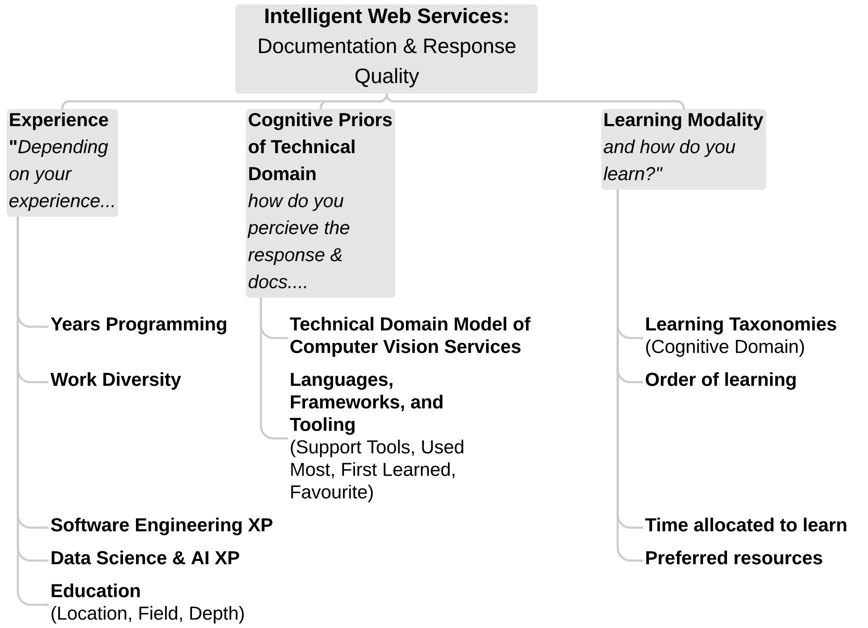


Figure A.5: Threshy assists with making appropriate decision boundaries in the application context by calibrating model (train on an unknown context) to your domain.

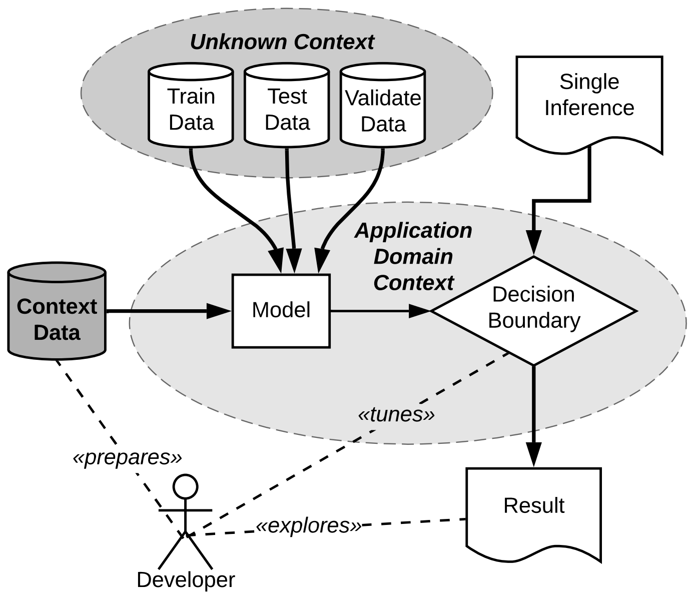


Figure A.6: Threshy domain model.

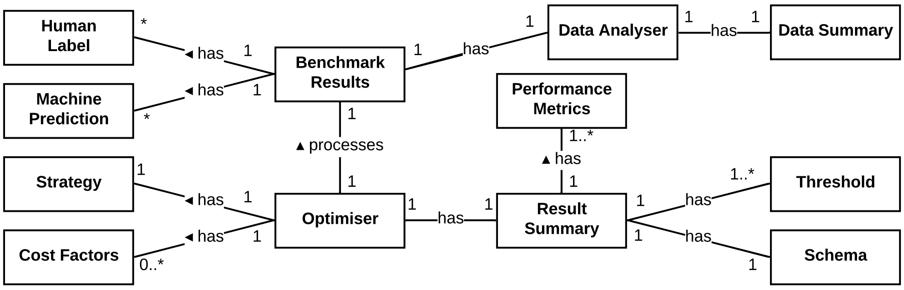


Figure A.7: High level overview of Threshy's interaction between the front- and back-end.

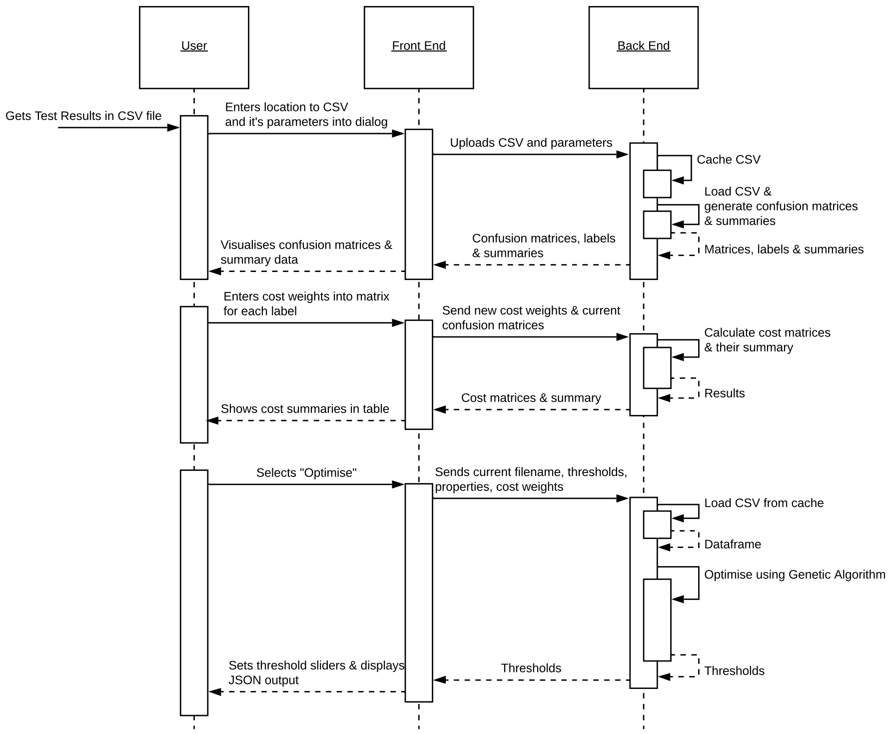


Figure A.8: High-level overview of the methodology within Chapter 5.

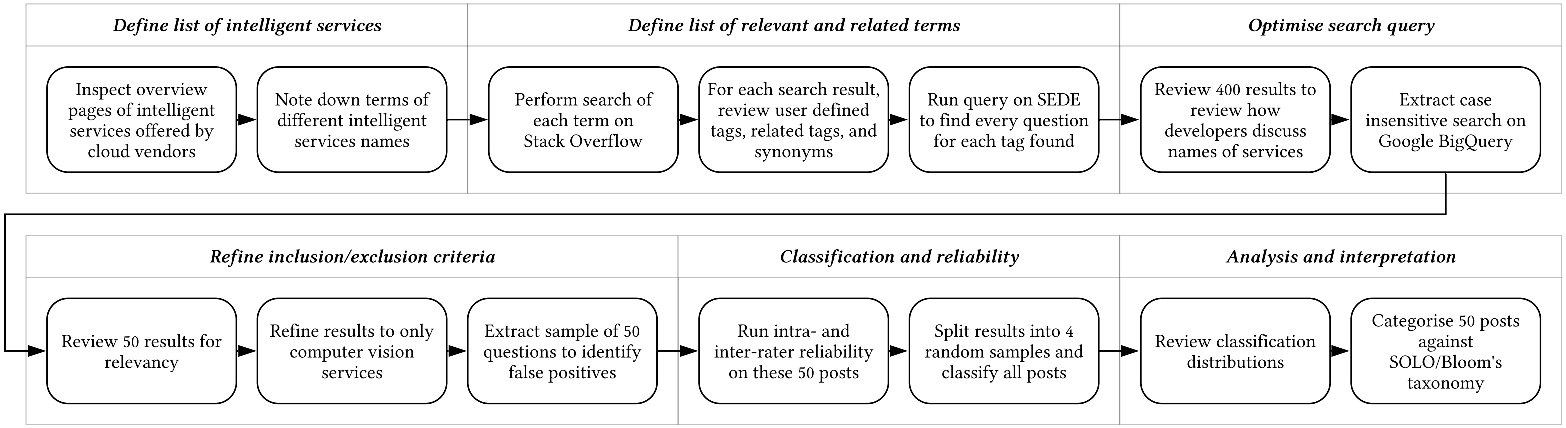


Figure A.9: Class diagram of the implementation of our architecture.

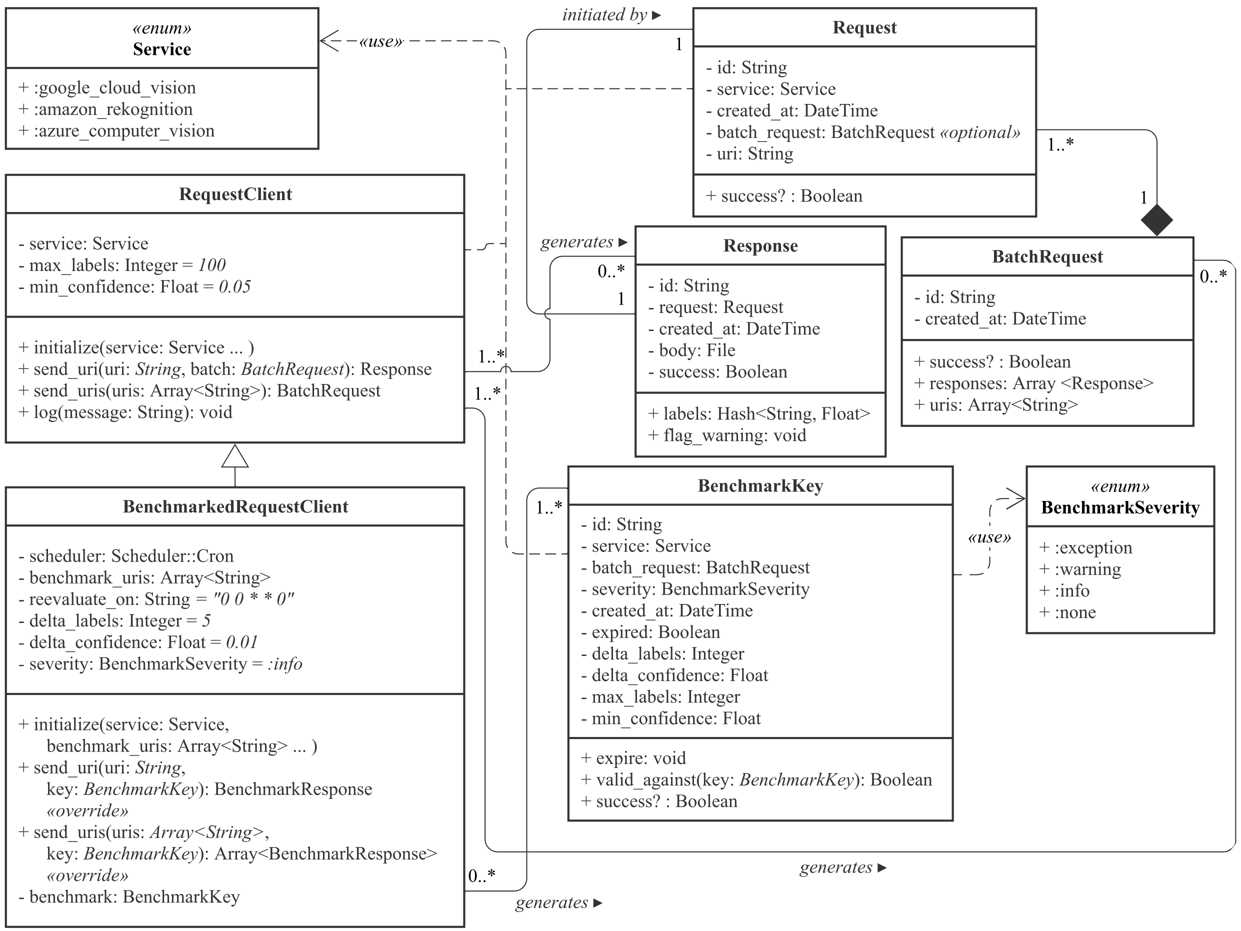


Figure A.10: Creation of a new benchmark proxy server using the architecture tactic.

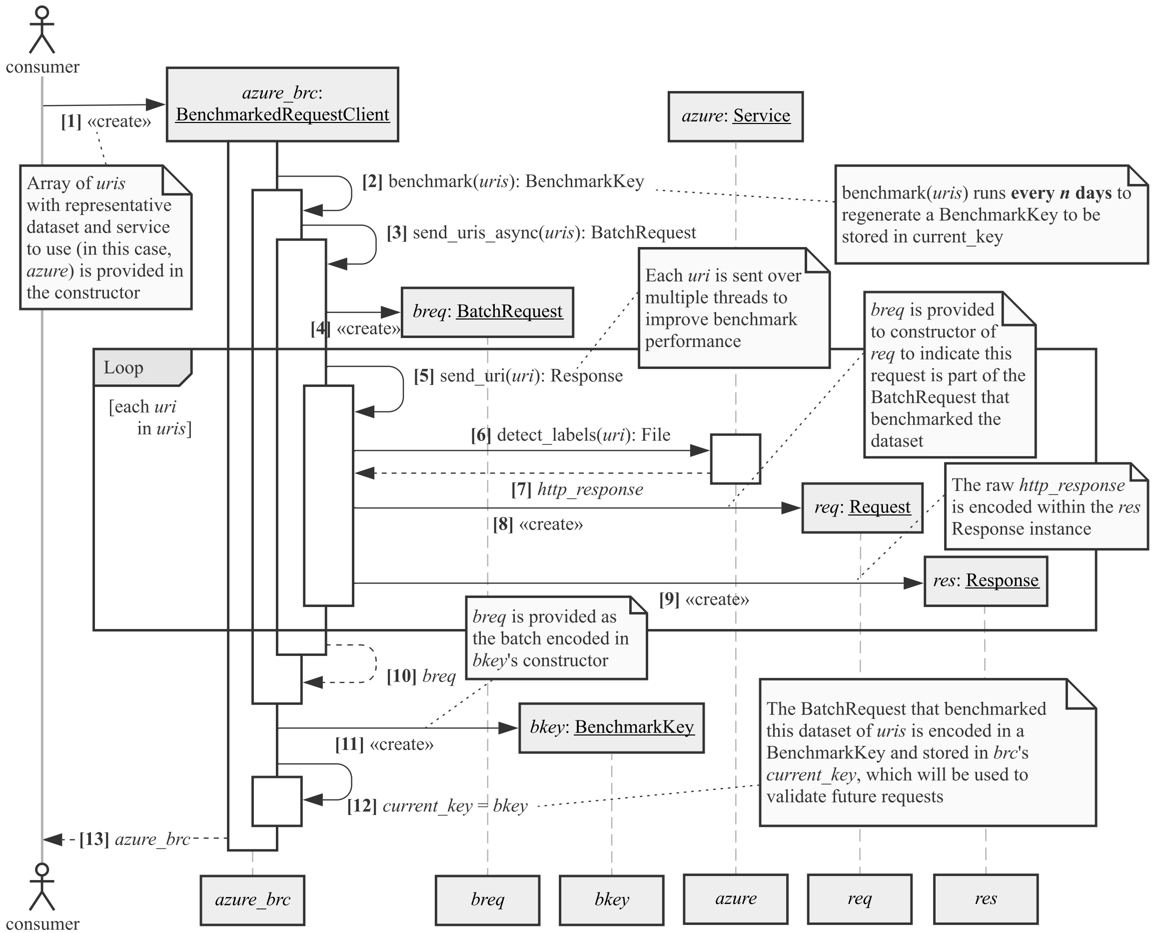


Figure A.11: Making a request through the proxy server ‘facade’.

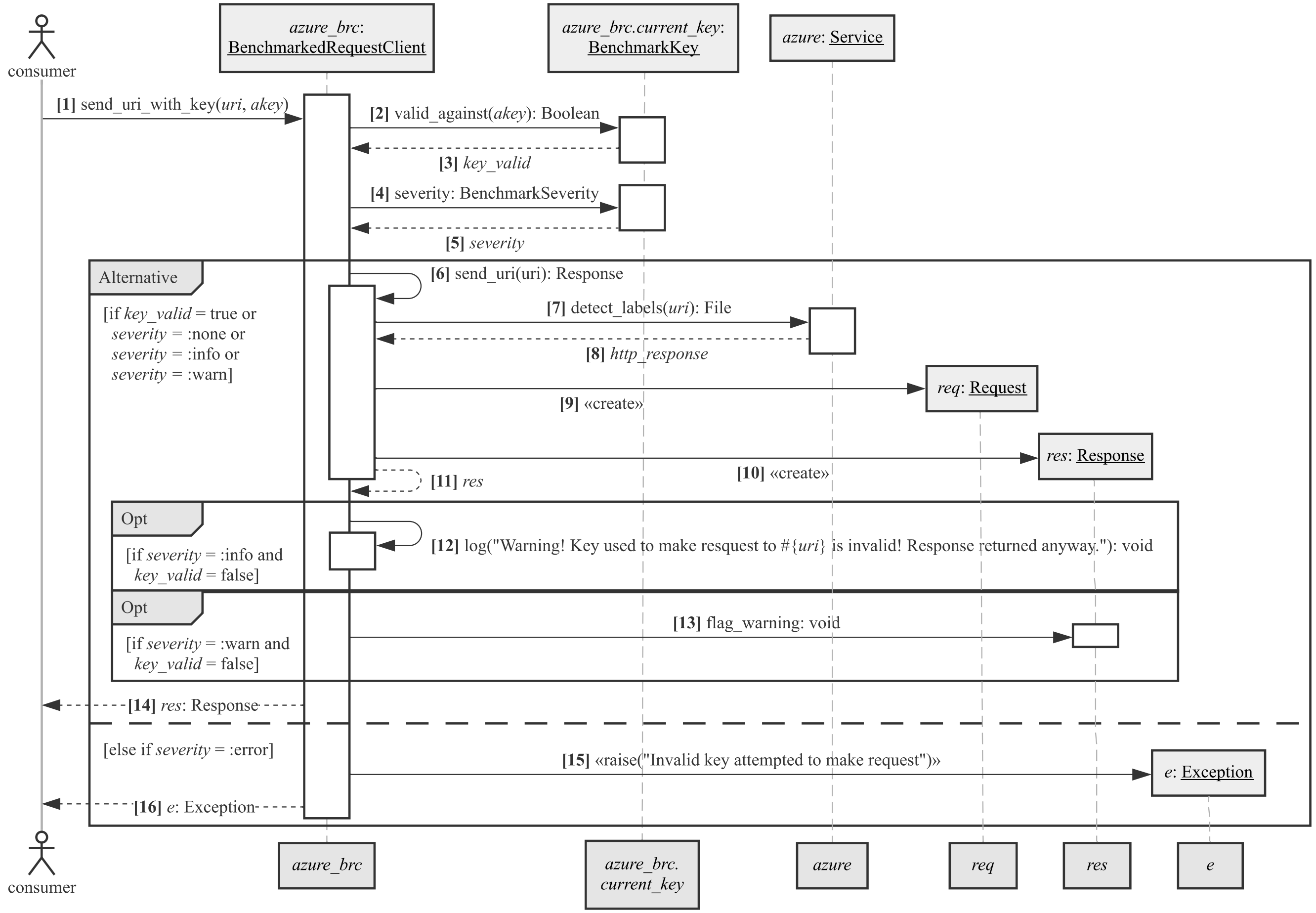


Figure A.12: State diagram of high-level workflows in the architectural tactic.

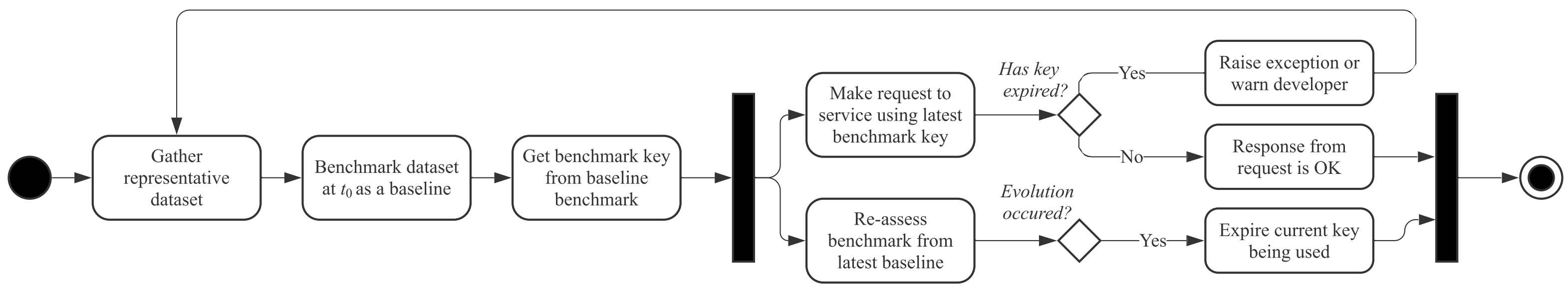
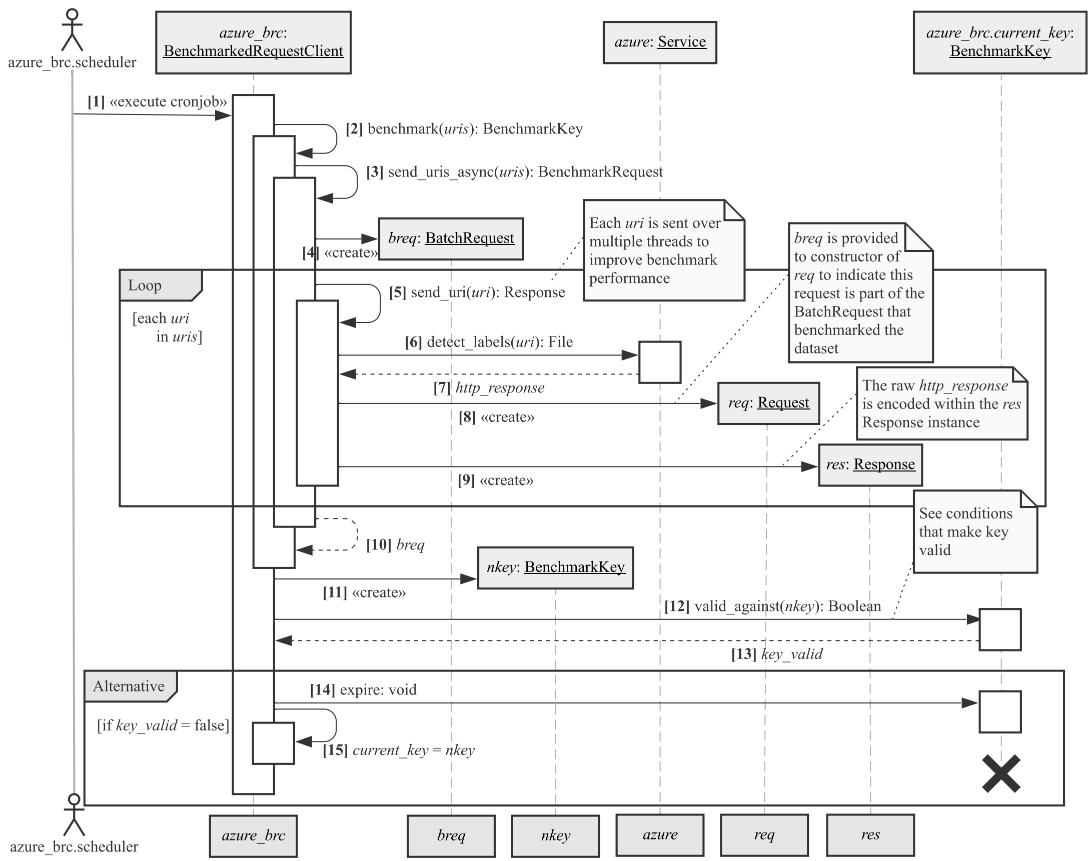


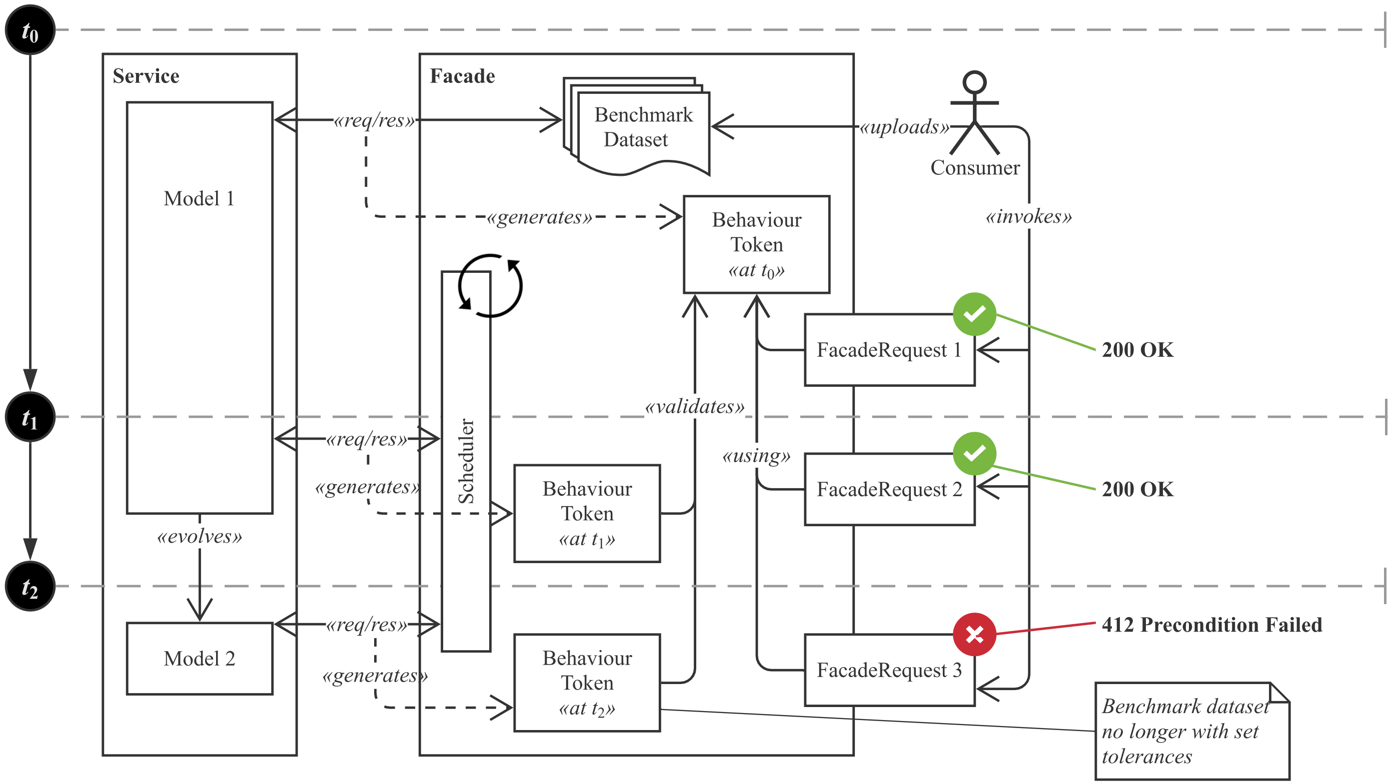
Figure A.13: Evolution occurring in the benchmark and how the architectural tactic notifies the consumer.



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 Resposne 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.: abs(conf(label$_n$, azure_brc.current_key) – conf(label$_n$, nkey)) <= 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.

```ruby
# frozen_string_literal: true

# Author:: Alex Cummaudo (mailto:ca@deakin.edu.au)
# Copyright:: Copyright (c) 2019 Alex Cummaudo
# License:: MIT License

require 'sequel'
require 'logger'
require 'stringio'
require 'binding_of_caller'
require 'dotenv/load'
require 'google/cloud/vision'
require 'aws-sdk-rekognition'
require 'net/http/post/multipart'
require 'down'
require 'uri'
require 'json'
require 'tempfile'
require 'rufus-scheduler'

# Intelligent Computer Vision Service Benchmarker (ICVSB) module. This module
# implements an architectural pattern that helps overcome evolution issues
# within intelligent computer vision services.
module ICVSB
  Thread.abort_on_exception = true
  # The valid services this version of the ICVSB module supports. At present the
  # only services supported are Google Cloud Vision, Amazon Rekognition, and
  # Azure Computer Vision and their respective labelling/tagging endpoints. You
  # can also request the demo.
  # @see https://cloud.google.com/vision/docs/labels
  # Google Cloud Vision labelling endpoint.
  # @see https://docs.aws.amazon.com/rekognition/latest/dg/API_DetectLabels.html
  # Amazon Rekognition's labelling endpoint.
  # @see https://docs.microsoft.com/en-us/rest/api/cognitiveservices/
      ↪ computervision/tagimage/tagimage
```

```ruby
# Azure Computer Visions's tagging endpoint.
VALID_SERVICES = %i[google_cloud_vision amazon_rekognition azure_computer_vision demo].freeze

# A list of the valid severities that the ICVSB module supports. Exception
# prevents the response from being accessed; warning will still produce a
# response but the +error+ field will be filled in; info will only log
# errors to the ICVSB log file and keep +error+ empty and none ignores the
# errors entirely.
VALID_SEVERITIES = %i[exception warning info none].freeze

# Logs a messaage to the global ICVSB logger. If called from within the
# stack trace of a RequestClient, it will also add the message provided
# the RequestClient's log associated with the RequestClient's object id.
# @param [Logger::Severity] severity The type of severity to log.
# @param [String] message The message to log.
def self.lmessage(severity, message)
  unless [Logger::DEBUG, Logger::INFO, Logger::WARN, Logger::ERROR, Logger::FATAL, Logger::UNKNOWN].include?(severity)
    raise ArgumentError, 'Severity must be a Logger::Severity type'
  end
  raise ArgumentError, 'Message must be a string' unless message.is_a?(String)

  @log ||= Logger.new(ENV['ICVSB_LOGGER_FILE'] || STDOUT)

  # Add message to global ICVSB logger
  @log.add(severity, message)
  # Find object_id within request_clients... when found add this message w/
  # severity to that RC's log too
  binding.frame_count.times do |n|
    caller_obj_id = binding.of_caller(n).eval('object_id')
    if @request_clients.keys.include?(caller_obj_id)
      @request_clients[caller_obj_id].log(severity, "[RequestClient=#{caller_obj_id}] #{message}")
      break
    end
  end
end

# Logs an error to the global ICVSB logger.
# @param [String] message The message to log.
def self.lerror(message)
  lmessage(Logger::ERROR, message)
end

# Logs a warning to the global ICVSB logger.
# @param [String] message The message to log.
def self.lwarn(message)
  lmessage(Logger::WARN, message)
end

# Logs an info message to the global ICVSB logger.
# @param [String] message The message to log.
def self.linfo(message)
  lmessage(Logger::INFO, message)
end

# Logs a debug message to the global ICVSB logger.
# @param [String] message The message to log.
def self.ldebug(message)
  lmessage(Logger::DEBUG, message)
end

# Register's a request client to the ICVSB's register of request clients.
```

```
# @param [RequestClient] request_client The request client to register.
def self.register_request_client(request_client)
  raise ArgumentError, 'request_client must be a RequestClient' unless request_client.is_a?(RequestClient)

  @request_clients ||= {}
  @request_clients[request_client.object_id] = request_client
end

##################################
# Database schema creation seed #
##################################
url = ENV['ICVSB_DATABASE_CONNTECTION_URL'] || 'sqlite://icvsb.db'
log = ENV['ICVSB_DATABASE_LOG_FILE'] || 'icvsb.db.log'
dbc = Sequel.connect(url, logger: Logger.new(log))
# Create Services and Severity enums...
dbc.create_table?(:services) do
  primary_key :id
  column :name, String, null: false, unique: true
end
dbc.create_table?(:benchmark_severities) do
  primary_key :id
  column :name, String, null: false, unique: true
end
if dbc[:services].first.nil?
  VALID_SERVICES.each { |s| dbc[:services].insert(name: s.to_s) }
  VALID_SEVERITIES.each { |s| dbc[:benchmark_severities].insert(name: s.to_s) }
end
# Create Objects...
dbc.create_table?(:batch_requests) do
  primary_key :id
  column :created_at, DateTime, null: false
end
dbc.create_table?(:requests) do
  primary_key :id
  foreign_key :service_id, :services, null: false
  foreign_key :batch_request_id, :batch_requests, null: true
  foreign_key :benchmark_key_id, :benchmark_keys, null: true

  column :created_at, DateTime, null: false
  column :uri, String, null: false

  index %i[service_id batch_request_id]
end
dbc.create_table?(:responses) do
  primary_key :id
  foreign_key :request_id, :requests, null: false

  column :created_at, DateTime, null: false
  column :body, File, null: true
  column :success, TrueClass, null: false

  index :request_id
end
dbc.create_table?(:benchmark_keys) do
  primary_key :id
  foreign_key :service_id, :services, null: false
  foreign_key :batch_request_id, :batch_requests, null: false
  foreign_key :benchmark_severity_id, :benchmark_severities, null: false

  column :created_at, DateTime, null: false
  column :expired, TrueClass, null: false
  column :delta_labels, Integer, null: false
  column :delta_confidence, Float, null: false
```

```ruby
    column :max_labels, Integer, null: false
    column :min_confidence, Float, null: false
    column :expected_labels, String, null: true

    index %i[service_id batch_request_id]
  end

  # Service representing the list of VALID_SERVICES the ICVSB module supports.
  class Service < Sequel::Model(dbc)
    # The Service representing Google Cloud Vision's labelling endpoint.
    # @see https://cloud.google.com/vision/docs/labels
    # Google Cloud Vision labelling endpoint.
    GOOGLE = Service[name: VALID_SERVICES[0].to_s]

    # The Service representing Amazon Rekognition's labelling endpoint.
    # @see https://docs.aws.amazon.com/rekognition/latest/dg/API_DetectLabels.html
    # Amazon Rekognition's labelling endpoint.
    AMAZON = Service[name: VALID_SERVICES[1].to_s]

    # The Service representing Azure Computer Vision's tagging endpoint.
    # @see https://docs.microsoft.com/en-us/rest/api/cognitiveservices/
        ↪ computervision/tagimage/tagimage
    # Azure Computer Visions's tagging endpoint.
    AZURE = Service[name: VALID_SERVICES[2].to_s]

    # The Service representing a demonstration of the facade.
    DEMO = Service[name: VALID_SERVICES[3].to_s]
  end

  # Severity representing the list of VALID_SEVERITIES the ICVSB module
  # supports. The severity is encoded within a BenchmarkKey.
  class BenchmarkSeverity < Sequel::Model(dbc[:benchmark_severities])
    # Exception severities will prevent responses from being accessed. This
    # disallows access to the Response object encoded within a
    # BenchmarkedRequestClient#send_uri_with_key or
    # BenchmarkedRequestClient#send_uris_with_key result.
    EXCEPTION = BenchmarkSeverity[name: VALID_SEVERITIES[0].to_s]

    # Warning severities will allow the Response from being accessed but will
    # additionally populate the +error+ value encoded within a
    # BenchmarkedRequestClient#send_uri_with_key or
    # BenchmarkedRequestClient#send_uris_with_key result.
    WARNING = BenchmarkSeverity[name: VALID_SEVERITIES[1].to_s]

    # Info severities will allow the Response from being accessed encoded within
    # the result of a BenchmarkedRequestClient#send_uri_with_key or
    # BenchmarkedRequestClient#send_uris_with_key call, however, information
    # pertaining to issues with the request will be logged to the ICVSB log
    # file.
    INFO = BenchmarkSeverity[name: VALID_SEVERITIES[2].to_s]

    # None severities will essentially ignore all benchmarking capabilities and
    # 'switches off' the benchmarking.
    NONE = BenchmarkSeverity[name: VALID_SEVERITIES[3].to_s]

    # Overrides the to_s method to return the name.
    # @return [String] The name of the severity type.
    def to_s
      name
    end
  end

  # This class represents a single request made to a Service. It encodes the
  # service, batch of requests (if applicable) and respective response.
```

```ruby
class Request < Sequel::Model(dbc)
  many_to_one :service
  many_to_one :batch
  many_to_one :benchmark_key
  one_to_one :response

  # @see Response#success.
  def success?
    response.success?
  end
end

# This class represents a single response returned back from a Service. It
# encodes the reqeust that was made to invoke the response.
class Response < Sequel::Model(dbc)
  many_to_one :request

  # Indicates if the response from the request was successful.
  # @return [Boolean] True if the response was successful or false if the
  # response contained some issue.
  def success?
    success
  end

  # Returns a hash of the entire response object, decoded form its
  # Service-specific response Ruby type and into a simple hash object.
  # @return [Hash] A hash representing the entire Service response object
  # within a Hash type.
  def hash
    return nil if body.nil?

    JSON.parse(body.lit.downcase.to_s, symbolize_names: true).to_h
  end

  # Returns hash of labels paired with their respective confidence values.
  # Decodes each Service's individual response syntax into a simple
  # key-value-pair that can be used for generalised use, regardless of which
  # Service actually generated the response.
  # @return [Hash] A hash with key-value-pairs representing the label (key)
  # and value (confidence) of the response.
  def labels
    if success?
      case request.service
      when Service::GOOGLE
        _google_cloud_vision_labels
      when Service::AMAZON
        _amazon_rekognition_labels
      when Service::AZURE
        _azure_computer_vision_labels
      when Service::DEMO
        _demo_service_labels
      end
    else
      {}
    end
  end

  # Returns the benchmark key ID of the request.
  # @return [Integer] The benchmark key id of this response's request.
  def benchmark_key_id
    request.benchmark_key.id
  end

  # Returns the benchmark key of the request.
```

```ruby
  # @return [BenchmarkKey] The benchmark key of this response's request.
  def benchmark_key
    request.benchmark_key
  end

  # Sets the benchmark key of the request.
  # @param [BenchmarkKey] value The new benchmark key to set.
  # @return [void]
  def benchmark_key=(value)
    request.benchmark_key = value
    request.save
  end

  # Sets the benchmark key id of the request.
  # @param [Integer] value The new benchmark key id to set.
  # @return [void]
  def benchmark_key_id=(value)
    request.benchmark_key_id = value
    request.save
  end

  private

  # Decodes a Google Cloud Vision label endpoint response into a simple hash.
  # @return [Hash] A key-value-pair representing label => confidence.
  def _google_cloud_vision_labels
    hash[:responses][0][:label_annotations].map do |label|
      [label[:description].downcase, label[:score]]
    end.to_h
  end

  # Decodes an Amazon Rekognition label endpoint response into a simple hash.
  # @return [Hash] See #{#_google_cloud_vision_labels}.
  def _amazon_rekognition_labels
    hash[:labels].map do |label|
      [label[:name].downcase, label[:confidence] * 0.01]
    end.to_h
  end

  # Decodes an Azure Computer Vision tagging endpoint into a simple hash.
  # @return [Hash] See #{#_google_cloud_vision_labels}.
  def _azure_computer_vision_labels
    hash[:tags].map do |label|
      [label[:name].downcase, label[:confidence]]
    end.to_h
  end

  # Decodes the mock demo service response into a simple hash. This is simply
  # a relay of Google's as the data is from Google Cloud Vision.
  # @return [Hash] A key-value-pair representing label => confidence.
  def _demo_service_labels
    _google_cloud_vision_labels
  end
end

# The batch request class collates multiple requests (URIs) invoked to a
# single Service's endpoint in a single request. It encodes all requests
# made to the service and can produce all responses back.
class BatchRequest < Sequel::Model(dbc)
  one_to_many :requests

  # Indicates if every request in the batch of requests made were successful.
  # @return [Boolean] True if every response was successful, false
  # otherwise.
```

```ruby
  def success?
    requests.map(&:success?).reduce(:&)
  end

  # Maps all Response objects that were returned back from this batch to an
  # array.
  # @return [Array<Response>] An array of Response objects from every Request
  # made in this batch.
  def responses
    requests.map(&:response)
  end

  # Maps all URIs that were requested back within this batch.
  # @return [Array<String>] An array of URI strings from every Request
  # made in this batch.
  def uris
    requests.map(&:uri)
  end
end

# The Benchmark Key encodes all information pertaining to the evolution of a
# specific service and is used to validate if a benchmark dataset has evolved
# with time. This key must be used in conjunction with the
# BenchmarkedRequestClient to ensure that responses made are still reasonable
      ↪ to
# use or if the service should be re-benchmarked against a new dataset.
class BenchmarkKey < Sequel::Model(dbc)
  many_to_one :service
  many_to_one :benchmark_severity
  many_to_one :batch_request

  # Class that encapsulates reasons why a benchmark key can be invalided.
  class InvalidKeyError
    module InvalidKeyErrorType
      NO_KEY_YET = 'No key yet exists. It is likely key is still benchmarking
            ↪ its first results.'
      SERVICE_MISMATCH = 'Keys use different services'
      DATASET_MISTMATCH = 'Keys have different benchmark datasets'
      SUCCESS_MISMATCH = 'One or both keys do not have successful service
            ↪ responses'
      MIN_CONFIDENCE_MISMATCH = 'Keys have different min confidence values'
      MAX_LABELS_MISMATCH = 'Keys have different max label values'
      RESPONSE_LENGTH_MISMATCH = 'Keys have different number of responses'
      LABEL_DELTA_MISMATCH = 'Number of labels in one key exceeds the label
            ↪ delta threshold'
      CONFIDENCE_DELTA_MISMATCH = 'Confidence value for a label in one key
            ↪ exceeds the confidence delta threshold'
      EXPECTED_LABELS_MISMATCH = 'Expected labels missing from response'
    end

    include InvalidKeyErrorType
    attr_reader :errorname, :errorcode, :data

    def initialize(errortype, data = '')
      @errorname = InvalidKeyErrorType.constants.find { |c| InvalidKeyErrorType.
            ↪ const_get(c) == errortype }
      @errorcode = InvalidKeyErrorType.constants.index(@errorname)
      @data = data
    end

    def to_s
      "[#{@errorcode}::#{@errorname}] #{@data}"
    end

```

```ruby
    def to_h
      {
        error_code: @errorcode,
        error_type: @errorname,
        error_data: @data
      }
    end
  end

  # @see BatchRequest#success?
  def success?
    batch_request.success?
  end

  # An alias for the +expired+ field on the key, adding a question mark at the
  # end to make the field more 'Ruby-esque'.
  # @return [Boolean] True if the key has expired and thus should not be used
  # for future requests as it is no longer valid.
  def expired?
    expired
  end

  # Expires this key by writing over its +expired+ field and marking it
  # true.
  # @return [void]
  def expire
    self.expired = true
    save
  end

  # Un-expires this key by writing over its +expired+ field and marking it
  # true.
  # @return [void]
  def unexpire
    self.expired = false
    save
  end

  # Returns the comma-separated mandatory labels list as an set of values
  # @return [Set<String>] The set of mandatory labels required by this key.
  def expected_labels_set
    Set[*expected_labels.split(',').map(&:downcase)]
  end

  # Validates another key against this key to ensure if the two keys are
  # compatible or if evolution has occured iff BenchmarkKey is provided to
  # +key_or_response+. If a Response is provided instead, then validates that
  # the response is okay against this key's encoded parameters.
  # @param [BenchmarkKey,Response] key_or_response A key or response to
  # validate against.
  # @return [Array<Boolean,Array<BenchmarkKey::InvalidKeyError>>] Returns +true+
    ↪ if
  # this key is valid against the other key OR a tuple with +false+ and
  # BenchmarkKey::InvalidKeyError to explain why the key is invalid.
  def valid_against?(key_or_response)
    if key_or_response.is_a?(BenchmarkKey)
      _validate_against_key(key_or_response)
    elsif key_or_response.is_a?(Response)
      _validate_against_response(key_or_response)
    else
      raise ArgumentError, 'key_or_response must be a BenchmarkKey or Response
        ↪ type'
    end
  end
```

```

  private

  # Validates a key against this key as per rules encoded within this key.
  # @param [BenchmarkKey] key The key to validate.
  # @return See #valid_against?
  def _validate_against_key(key)
    ICVSB.linfo("Validating key id=#{id} with other key id=#{key.id}")

    # True if same key id...
    return true if key == self

    invalid_key_errors = []

    # 1. Ensure same services!
    if key.service == service
      ICVSB.ldebug('Services both match')
    else
      ICVSB.lwarn("Service mismatch in validation: #{key.service.name} != #{service.name}")
      invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
        BenchmarkKey::InvalidKeyError::SERVICE_MISMATCH, {
          source_key: {
            id: id,
            created_at: created_at,
            service_name: service.name
          },
          violating_key: {
            id: key.id,
            created_at: key.created_at,
            service_name: key.service.name
          },
          message: "Source key (id=#{id}) service=#{service.name} but "\
            "validation key (id=#{key.id}) service=#{key.service.name}."
        }
      )
    end

    # 2. Ensure same benchmark dataset
    symm_diff_uris = Set[*batch_request.uris] ^ Set[*key.batch_request.uris]
    if symm_diff_uris.empty?
      ICVSB.ldebug('Same benchmark dataset has been used')
    else
      ICVSB.lwarn('Benchmark dataset mismatch in key validation: '\
        "Symm difference contains #{symm_diff_uris.count} different URIs")
      invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
        BenchmarkKey::InvalidKeyError::DATASET_MISTMATCH, {
          source_key: {
            id: id,
            created_at: created_at,
            dataset: batch_request.uris
          },
          violating_key: {
            id: key.id,
            created_at: key.created_at,
            dataset: key.batch_request.uris
          },
          dataset_symmetric_difference: symm_diff_uris.to_a,
          message: "Source key (id=#{id}) and valiation key (id=#{key.id}) have different "\
          "benchmark dataset URIS. The symmetric difference is: #{symm_diff_uris.to_a}."
        }
      )
```

```
    end

    # 3. Ensure successful request made in BOTH instances
    our_key_success = success?
    their_key_success = key.success?
    if our_key_success && their_key_success
      ICVSB.ldebug('Both keys were successful')
    else
      ICVSB.lwarn('Sucesss mismatch in key validation')
      invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
        BenchmarkKey::InvalidKeyError::SUCCESS_MISMATCH, {
          source_key: {
            id: id,
            created_at: created_at,
            successful_response: our_key_success
          },
          violating_key: {
            id: key.id,
            created_at: key.created_at,
            successful_response: their_key_success
          },
          message: "Source key (id=#{id}) success=#{our_key_success} but "\
          "validation key (id=#{key.id}) success=#{their_key_success}."
        }
      )
    end

    # 4. Ensure the same max labels
    if key.max_labels == max_labels
      ICVSB.ldebug('Both keys have same max labels')
    else
      ICVSB.lwarn('Max labels mismatch in key validation')
      invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
        BenchmarkKey::InvalidKeyError::MAX_LABELS_MISMATCH, {
          source_key: {
            id: id,
            created_at: created_at,
            max_labels: max_labels
          },
          violating_key: {
            id: key.id,
            created_at: key.created_at,
            max_labels: key.max_labels
          },
          message: "Source key (id=#{id}) max_labels=#{max_labels} but "\
            "validation key (id=#{key.id}) max_labels=#{key.max_labels}."
        }
      )
    end

    # 5. Ensure the same min confs
    if key.min_confidence == min_confidence
      ICVSB.ldebug('Both keys have same min confidence')
    else
      ICVSB.lwarn('Minimum confidence or max labels mismatch in key validation')
      invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
        BenchmarkKey::InvalidKeyError::MIN_CONFIDENCE_MISMATCH, {
          source_key: {
            id: id,
            created_at: created_at,
            min_confidence: min_confidence
          },
          violating_key: {
            id: key.id,
```

```
            created_at: key.created_at,
            min_confidence: key.min_confidence
          },
          message: "Source key (id=#{id}) min_confience=#{min_confidence} but "\
          "validation key (id=#{key.id}) min_confidence=#{key.min_confidence}."
        }
      )
    end

    # 6. Ensure same number of results... (responses... not labels!)
    our_response_length = batch_request.responses.length
    their_response_length = key.batch_request.responses.length
    if our_response_length == their_response_length
      ICVSB.ldebug('Both keys have same number of encoded responses')
    else
      ICVSB.lwarn('Number of responses mismatch in key validation')
      invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
        BenchmarkKey::InvalidKeyError::RESPONSE_LENGTH_MISMATCH, {
          source_key: {
            id: id,
            created_at: created_at,
            num_responses: our_response_length
          },
          violating_key: {
            id: key.id,
            created_at: key.created_at,
            num_responses: their_response_length
          },
          message: "Source key (id=#{id}) responses#=#{our_response_length} but " \
          "validation key (id=#{key.id}) responses#=#{their_response_length}."
        }
      )
    end

    # 7. Validate every label delta and confidence delta
    our_requests = batch_request.requests
    their_requests = key.batch_request.requests
    our_requests.each do |our_request|
      this_uri = our_request.uri
      their_request = their_requests.find { |r| r.uri == this_uri }

      our_labels = Set[*our_request.response.labels.keys]
      their_labels = Set[*their_request.response.labels.keys]

      # 7a. Label delta
      symm_diff_labels = our_labels ^ their_labels

      msg_suffix = "URI = #{this_uri} from #{their_request.created_at} (req_id=#{their_request.id})"\
        " to #{our_request.created_at} (req_id=#{our_request.id})"

      ICVSB.ldebug("Request id=#{our_request.id} {#{our_labels.to_a}} against "\
        "id=#{their_request.id} {#{their_labels.to_a}} - symm diff "\
        "= {#{symm_diff_labels.to_a}}")
      if symm_diff_labels.length > delta_labels
        ICVSB.lwarn("Number of labels mismatch in key validation (margin of error=#{delta_labels}): "\
          "New/dropped labels = '#{(our_labels - their_labels).to_a.map { |l| "+#{l}" }.join(',')}'"\
          "#{(their_labels - our_labels).to_a.map { |l| "-#{l}" }.join(',')}")
        invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
          BenchmarkKey::InvalidKeyError::LABEL_DELTA_MISMATCH, {
            source_key: {
```

```
        id: id,
        created_at: created_at
      },
      source_response: {
        id: our_request.id,
        created_at: our_request.created_at,
        body: our_request.response.hash
      },
      violating_key: {
        id: key.id,
        created_at: key.created_at
      },
      violating_response: {
        id: their_request.id,
        created_at: their_request.created_at,
        body: their_request.response.hash
      },
      uri: this_uri,
      delta_labels_threshold: delta_labels,
      delta_labels_detected: symm_diff_labels.length,
      new_labels: (our_labels - their_labels).to_a,
      dropped_labels: (their_labels - our_labels).to_a,
      message: "Source key (id=#{id}) and validation key (id=#{key.id}) have #{symm_diff_labels.length} "\
      "differing labels, which exceeds the delta label value of #{delta_labels}. "\
      "New/dropped labels = '#{(our_labels - their_labels).to_a.map { |l| "+#{l}" }.join(',')}"\
      "#{(their_labels - our_labels).to_a.map { |l| "-#{l}" }.join(',')}'"\
      ". #{msg_suffix}."
    }
  )
else
  ICVSB.ldebug("Number of labels match both keys (within margin of error #{delta_labels})")
end

# 7b. Confidence delta
delta_confs_exceeded = {}
our_request.response.labels.each do |label, conf|
  our_conf = conf
  their_conf = their_request.response.labels[label]

  if their_conf.nil?
    ICVSB.ldebug("The label #{label} does not exist in the response id=#{their_request.response.id}. "\
      'Skipping confidence comparison...')
    next
  end

  delta = our_conf - their_conf
  ICVSB.ldebug("Request id=#{our_request.id} against id=#{their_request.id} "\
    "for label '#{label}' confidence: #{our_conf}, #{their_conf} (delta=#{delta})")
  if delta > delta_confidence
    ICVSB.lwarn(
      "Maximum confidence delta breached in key validation (margin of error =#{delta_confidence}). "\
      "#{msg_suffix}."
    )
    delta_confs_exceeded[label] = delta
  end
end
```

```
      if delta_confs_exceeded.empty?
        ICVSB.ldebug("Both keys have confidence within margin of error #{delta_confidence}")
      else
        invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
          BenchmarkKey::InvalidKeyError::CONFIDENCE_DELTA_MISMATCH, {
            source_key: {
              id: id,
              created_at: created_at
            },
            source_response: {
              id: our_request.id,
              created_at: our_request.created_at,
              body: our_request.response.hash
            },
            violating_key: {
              id: key.id,
              created_at: key.created_at
            },
            violating_response: {
              id: their_request.id,
              created_at: their_request.created_at,
              body: their_request.response.hash
            },
            uri: this_uri,
            delta_confidence_threshold: delta_confidence,
            delta_confidences_detected: delta_confs_exceeded,
            message: "Source key (id=#{id}) has exceeded confidence delta of "\
              "validation key (id=#{key.id}): #{delta_confs_exceeded}. #{msg_suffix}."
          }
        )
      end

      # Check if the responses are valid against this key
      valid_response, invalid_reasons = valid_against?(our_request.response)
      if valid_response
        ICVSB.ldebug('Our response is valid against this key')
      else
        invalid_key_errors += invalid_reasons
      end
    end

    [invalid_key_errors.empty?, invalid_key_errors.sort_by(&:errorcode)]
  end

  # Validates a response against this key as per rules encoded within this key.
  # @param [Response] key The response to validate.
  # @return See #valid_against?
  def _validate_against_response(response)
    invalid_key_errors = []

    missing_expected_labels = expected_labels_set - Set[*response.labels.keys]
    unless missing_expected_labels.empty?
      invalid_key_errors << BenchmarkKey::InvalidKeyError.new(
        BenchmarkKey::InvalidKeyError::EXPECTED_LABELS_MISMATCH, {
          source_key: {
            id: id,
            created_at: created_at
          },
          violating_response: {
            id: response.id,
            created_at: response.created_at,
            body: response.hash
```

```
          },
          uri: response.request.uri,
          expected_labels: expected_labels.split(','),
          labels_detected: response.labels.keys,
          labels_missing: missing_expected_labels.to_a,
          message: "Expected key (id=#{id}) expects the following mandatory labels: '#{expected_labels}'. "\
          "However, response (id=#{response.id}) has the following labels: '#{response.labels.keys.join(',')}'. "\
          "The following labels are missing: '#{missing_expected_labels.to_a.join(',')}'."
        }
      )
    end

    [invalid_key_errors.empty?, invalid_key_errors]
  end
end

# The Request Client class is used to make non-benchmarked requests to the
# provided service's labelling endpoints. It handles creating respective
# +Request+ and +Response+ records to be commited to the benchmarker database.
# Requests made with the +RequestClient+ do *not* ensure that evolution risk
# has occured (see BenchmarkedRequestClient).
class RequestClient
  # Initialises a new instance of the requester to label endpoints.
  # @param [Service] service The service to request from.
  # @param [Fixnum] max_labels The maximum labels that the requester returns.
  # Only supported if the service supports this parameter. Default is 100
  # labels.
  # @param [Float] min_confidence The confidence threshold by which labels
  # are returned. Only supported if the service supports this parameter.
  # Default is 0.50.
  def initialize(service, max_labels: 100, min_confidence: 0.50)
    unless service.is_a?(Service) && [Service::GOOGLE, Service::AMAZON, Service::AZURE, Service::DEMO].include?(service)
      raise ArgumentError, "Service with name #{service.name} not supported."
    end

    # Registers logging for this client
    ICVSB.register_request_client(self)
    @logstrio = StringIO.new
    @log = Logger.new(@logstrio)

    @service = service
    @service_client =
      case @service
      when Service::GOOGLE
        Google::Cloud::Vision::ImageAnnotator.new
      when Service::AMAZON
        Aws::Rekognition::Client.new
      when Service::AZURE
        URI('https://australiaeast.api.cognitive.microsoft.com/vision/v2.0/tag')
      when Service::DEMO
        nil # Not client needed for mock...
      end
    @config = {
      max_labels: max_labels,
      min_confidence: min_confidence
    }
    @max_labels = max_labels
    @min_confidence = min_confidence
  end

```

```ruby
  attr_reader :max_labels, :min_confidence

  # Sends a request to the client's respective service endpoint. Does *not*
  # validate a response against a key (see BenchmarkedRequestClient).
  # Params:
  # @param [String] uri A URI to an image to detect labels.
  # @param [BatchRequest] batch The batch that the request is being made
  # under. Defaults to nil.
  # @return [Response] The response record commited to the benchmarker
  # database.
  def send_uri(uri, batch: nil)
    raise ArgumentError, 'URI must be a string.' unless uri.is_a?(String)
    raise ArgumentError, 'Batch must be a BatchRequest.' if !batch.nil? && !batch.is_a?(BatchRequest)

    batch_id = batch.nil? ? nil : batch.id
    ICVSB.ldebug("Sending URI #{uri} to #{@service.name} - batch_id: #{batch_id}")

    begin
      request_start = DateTime.now
      exception = nil
      case @service
      when Service::GOOGLE
        response = _request_google_cloud_vision(uri)
      when Service::AMAZON
        response = _request_amazon_rekognition(uri)
      when Service::AZURE
        response = _request_azure_computer_vision(uri)
      when Service::DEMO
        response = _request_demo_service(uri)
      end
      ICVSB.ldebug("Succesful response for URI #{uri} to #{@service.name} (batch_id=#{batch_id})")
    rescue StandardError => e
      ICVSB.lwarn("Exception caught in send_uri: #{e.class} - #{e.message}")
      exception = e
    end
    request = Request.create(
      service_id: @service.id,
      created_at: request_start,
      uri: uri,
      batch_request_id: batch_id
    )
    response = Response.create(
      created_at: DateTime.now,
      body: response[:body],
      success: exception.nil? && response[:success],
      request_id: request.id
    )
    ICVSB.ldebug("Request saved (id=#{request.id}) with response (id=#{response.id})")
    response
  end

  # Sends a batch request with multiple images to client's respective service
  # endpoint. Does *not* validate a response against a key (see
  # ICVSB::BenchmarkedRequestClient).
  # @param [Array<String>] uris An array of URIs to an image to detect labels.
  # @return [BatchRequest] The batch request that was created.
  def send_uris(uris)
    raise ArgumentError, 'URIs must be an array of strings.' unless uris.is_a?(Array)

```

```ruby
    batch_request = BatchRequest.create(created_at: DateTime.now)
    ICVSB.linfo("Initiated a batch request for #{uris.count} URIs")
    uris.each do |uri|
      send_uri(uri, batch: batch_request)
    end
    ICVSB.linfo("Batch is complete (id=#{batch_request.id})")
    batch_request
  end

  # Performs the same operation as send_uris but performs sends each URI
  # asynchronously. Saves a lot of time if you have lots of URIs. This method
  # should not be used with an SQLite database.
  # @see #send_uris
  # @param [Array<String>] uri See #send_uris
  # @return [Array<BatchRequest, Array<Thread>] Returns both the array and an
  # array of threads representing each request. Call +threads.join(&:each)+
  # to ensure all requests have finished.
  def send_uris_async(uris)
    raise ArgumentError, 'URIs must be an array of strings.' unless uris.is_a?(Array)
    if ICVSB::Request.superclass.db.url.start_with?('sqlite')
      raise StandardError, 'You are using SQLite and thus async operations are not supported.'
    end

    threads = []
    batch_request = BatchRequest.create(created_at: DateTime.now)
    ICVSB.linfo("Initiated an async batch request for #{uris.count} URIs")
    uris.each do |uri|
      threads << Thread.new do
        send_uri(uri, batch: batch_request)
      end
    end
    ICVSB.linfo("Async batch submitted (id=#{batch_request.id}). Wait for this batch to be complete!")
    [batch_request, threads]
  end

  # Adds a message of a specific severity to this client's logger.
  # @param [Logger::Severity] severity The type of severity to log.
  # @param [String] message The message to log.
  def log(severity, message)
    unless [Logger::DEBUG, Logger::INFO, Logger::WARN, Logger::ERROR, Logger::FATAL, Logger::UNKNOWN]
           .include?(severity)
      raise ArgumentError, 'Severity must be a Logger::Severity type'
    end
    raise ArgumentError, 'Message must be a string' unless message.is_a?(String)

    @log.add(severity, message)
  end

  # Gets the log of this client as a string.
  # @return [String] The entire log.
  def read_log
    @logstrio.string
  end

  private

  # Makes a request to Google Cloud Vision's +LABEL_DETECTION+ feature.
  # @see https://cloud.google.com/vision/docs/labels
  # @param [String] uri A URI to an image to detect labels. Google Cloud
  # Vision supports JPEGs, PNGs, GIFs, BMPs, WEBPs, RAWs, ICOs, PDFs and
```

```
# TIFFs only.
# @return [Hash] A hash containing the response +body+ and whether the
# request was +success+ful.
def _request_google_cloud_vision(uri)
  begin
    image = _download_image(
      uri,
      %w[
        image/jpeg
        image/png
        image/gif
        image/webp
        image/x-dcraw
        image/vnd.microsoft.icon
        application/pdf
        image/tiff
      ]
    )
    exception = nil
    res = @service_client.label_detection(
      image: image.open,
      max_results: @max_labels
    ).to_h
  rescue StandardError => e
    exception = e
    res = { service_error: "#{exception.class} - #{exception.message}" }
  end
  {
    body: res.to_json,
    success: exception.nil? && res.key?(:responses)
  }
end

# Makes a request to Amazon Rekogntiion's +DetectLabels+ endpoint.
# @see https://docs.aws.amazon.com/rekognition/latest/dg/API_DetectLabels.html
# @param [String] uri A URI to an image to detect labels. Amazon Rekognition
# only supports JPEGs and PNGs.
# @return (see #_request_google_cloud_vision)
def _request_amazon_rekognition(uri)
  begin
    image = _download_image(uri, %w[image/jpeg image/png])
    exception = nil
    res = @service_client.detect_labels(
      image: {
        bytes: image.read
      },
      max_labels: @max_labels,
      min_confidence: @min_confidence
    ).to_h
  rescue StandardError => e
    exception = e
    res = { service_error: "#{e.class} - #{e.message}" }
  end
  {
    body: res.to_json,
    success: exception.nil? && res.key?(:labels)
  }
end

# Makes a request to Azure's +analyze+ endpoint with +visualFeatures+ of
# +Tags+.
# @see https://docs.microsoft.com/en-us/rest/api/cognitiveservices/computervision/tagimage/tagimage
# @param [String] uri A URI to an image to detect labels. Azure Computer
```

```ruby
  # Vision only supports JPEGs, PNGs, GIFs, and BMPs.
  # @return (see #_request_google_cloud_vision)
  def _request_azure_computer_vision(uri)
    image = _download_image(uri, %w[image/jpeg image/png image/gif image/bmp])

    http_req = Net::HTTP::Post::Multipart.new(
      @service_client,
      file: UploadIO.new(image.open, image.content_type, image.original_filename )
    )
    http_req['Ocp-Apim-Subscription-Key'] = ENV['AZURE_SUBSCRIPTION_KEY']

    http_res = Net::HTTP.start(@service_client.host, @service_client.port, use_ssl: true) do |h|
      h.request(http_req)
    end

    tags_present = JSON.parse(http_res.body).key?('tags')
    {
      body: tags_present ? http_res.body : { service_error: http_res.body },
      success: tags_present
    }
  end

  # Makes a request to the mock demo server, returning JSON data at time 1
  # (t1) or time 2 (t2), depending on the timestamp flip (which can be
  # triggered by the PATCH /benchmark/:key endpoint).
  # @param [String] uri A URI to an image to detect labels.
  # @return (see #_request_google_cloud_vision)
  def _request_demo_service(uri)
    # Get the image id from the URI...
    rexp = %r{http:\/\/localhost:4567\/demo\/data\/(\d{4,12})\.jpe?g}

    all_image_ids = JSON.parse(
      File.read(File.join('demo', 'categories.json'))
    )['all']

    invalid_uri = (uri =~ rexp).nil?
    image_id = uri.match(rexp)[1] unless invalid_uri
    invalid_image_id = !all_image_ids.include?(image_id)

    # Mock service can be switched to t1 or t2 at demo endpoint...
    body =
      if invalid_uri || invalid_image_id
        { service_error: 'The URI is not a valid demo URI.' }
      else
        body = JSON.parse(File.read(File.join('demo', "#{image_id}.#{demo_timestamp}.json")))
        { responses: [body] }#[{ label_annotations: body }] }
      end

    {
      body: body.to_json,
      success: !(invalid_uri || invalid_image_id)
    }
  end

  # Downloads the image at the specified URI.
  # @param [String] uri The URI to download.
  # @param [Array<String>] mimes Accepted mime types.
  # @return [File] if download was successful.
  def _download_image(uri, mimes)
    raise ArgumentError, 'URI must be a string.' unless uri.is_a?(String)
    raise ArgumentError, 'Mimes must be an array of strings.' unless mimes.is_a
```

```ruby
?(Array)
    raise ArgumentError, "Invalid URI specified: #{uri}." unless uri =~ URI::DEFAULT_PARSER.make_regexp

    ICVSB.ldebug("Downloading image at URI: #{uri}")
    file = Down.download(uri)
    mime = file.content_type

    unless mimes.include?(mime)
      raise ArgumentError, "Content type of URI #{uri} not accepted. Recieved #{mime}. Valid are: #{mimes}."
    end

    file
  rescue Down::Error => e
    raise ArgumentError, "Could not access the URI #{uri} - #{e.class}"
  end
end

# The Benchmarked Request Client class is used to make requests to a service's
# labelling endpoints, ensuring that the response from the endpoint has not
# altered significantly as indicated by the expiration flags. It handles
# creating respective +Request+ and +Response+ records to be commited to the
# benchmarker database. Unlike the +RequestClient+, the
# +BenchmarkedRequestClient+ ensures that, respective to a benchmark dataset,
# evolution has not occured and thus is safe to use the endpoint without
# re-evaluation. Requires a BenchmarkKey to make any requests.
class BenchmarkedRequestClient < RequestClient
  alias send_uri_no_key send_uri
  alias send_uris_no_key send_uris
  alias send_uris_no_key_async send_uris_async

  # Initialises a new instance of the benchmarked requester to label
  # endpoints.
  # @param [Service] service (see RequestClient#initialize)
  # @param [Array<String>] dataset An array of URIs to benchmark
  # against.
  # @param [Fixnum] max_labels (see RequestClient#initialize)
  # @param [Float] min_confidence (see RequestClient#initialize)
  # @param [Hash] opts Additional benchmark-related parameters.
  # @option opts [String] :trigger_on_schedule A cron-tab string (see
  # +man 5 crontab+) that is used for the benchmarker to re-evaluate if the
  # current key should be expired. Default is every Sunday at midnight,
  # i.e., +0 0 * * 0+.
  # @option opts [String] :trigger_on_failcount Number of times the benchmark
  # request fails making requests for the benchmark to re-evalauate. Must
  # be a positive, non-zero number for the benchmark to trigger on failure,
  # else this field is ignored. Default is 0.
  # @option opts [BenchmarkSeverity] :severity The severity of warning for
  # the #BenchmarkKey to fail. Default is +BenchmarkSeverity::INFO+.
  # @option opts [String] :benchmark_callback_uri The URI to call with results
  # of a completed benchmark. Optional. If an invalid URI is specified this
  # will default to nil.
  # @option opts [String] :warning_callback_uri Required when the +:severity:+
  # is +BenchmarkSeverity::WARN+. If left blank, the effect of the benchmark
  # client is essentially a severity of +BenchmarkSeverity::NONE+, as no
  # warning endpoint can be called to notify of issues. If an invalid URI is
  # provided, this will default to nil.
  # @option opts [Boolean] :autobenchmark Automatically benchmark the client
  # as soon as it it initialised. If +false+, then you will need to call
  # the #benchmark method immediately (i.e., on your own thread). Defaults
  # to true, so will block the current thread before benchmarking is
  # complete.
  # @option opts [Fixnum] :delta_labels Number of labels that change for a
```

```ruby
  # #BenchmarkKey to expire. Default is 5.
  # @option opts [Float] :delta_confidences Minimum amount of difference for
  # the same label to have changed between the last benchmark for the
  # #BenchmarkKey to expire. Default is 0.01.
  # @option opts [Array<String>] :expected_labels Array of strings for the
  # various expected labels that should be expected in every result. Fails
  # otherwise. Encoded within the key.
  def initialize(service, dataset, max_labels: 100, min_confidence: 0.50, opts: {})
    super(service, max_labels: max_labels, min_confidence: min_confidence)
    @dataset = dataset
    @key_config = {
      delta_labels: opts[:delta_labels] || 5,
      delta_confidence: opts[:delta_confidence] || 0.01,
      severity: opts[:severity] || BenchmarkSeverity::INFO,
      expected_labels: opts[:expected_labels] || []
    }
    @benchmark_config = {
      trigger_on_schedule: opts[:trigger_on_schedule] || '0 0 * * 0',
      trigger_on_failcount: opts[:trigger_on_failcount] || 0,
      autobenchmark: opts[:autobenchmark].nil? ? true : opts[:autobenchmark]
    }
    # Validate URIs
    if !opts[:benchmark_callback_uri].nil? &&
       !(opts[:benchmark_callback_uri] =~ URI::DEFAULT_PARSER.make_regexp).nil?
      @benchmark_config[:benchmark_callback_uri] = URI(opts[:benchmark_callback_uri])
    end
    if !opts[:warning_callback_uri].nil? &&
       !(opts[:warning_callback_uri] =~ URI::DEFAULT_PARSER.make_regexp).nil?
      @benchmark_config[:warning_callback_uri] = URI(opts[:warning_callback_uri])
    end

    if !opts[:warning_callback_uri].nil? && opts[:severity] != BenchmarkSeverity::WARNING
      ICVSB.lwarn("A warning callback URI #{opts[:warning_callback_uri]} was set but "\
        'the severity is not WARNING. This callback will be ignored...')
    end

    @created_at = DateTime.now
    @demo_timestamp = 't1' if @service == Service::DEMO
    @is_benchmarking = false
    @last_benchmark_time = nil
    @benchmark_count = 0
    @invalid_state_count = 0
    trigger_benchmark if @benchmark_config[:autobenchmark]
    @scheduler = Rufus::Scheduler.new.schedule(@benchmark_config[:trigger_on_schedule]) do |cronjob|
      ICVSB.linfo("Cronjob starting for BenchmarkedRequestClient #{self} - "\
        "Scheduled at: #{cronjob.scheduled_at}; Last ran at: #{cronjob.last_time}.")
      trigger_benchmark
    end
  end

  # Exposes whether or not the client is currently benchmarking.
  # @return [Boolean] True if the client is benchmarking, false otherwise.
  def benchmarking?
    @is_benchmarking
  end

  # Returns the next time a schedule to trigger a benchmark will run.
```

```
  # @return [DateTime] The time the next trigger to benchmark will be run.
  def next_scheduled_benchmark_time
    DateTime.parse(@scheduler.next_time.to_t.to_s)
  end

  # Returns the last time a schedule to trigger a benchmark was run.
  # @return [DateTime,nil] Time next DateTime the benchmark ran or nil if
  # the scheduler has never yet run.
  def last_scheduled_benchmark_time
    @scheduler.last_time.nil? ? nil : DateTime.parse(@scheduler.last_time.to_t.to_s)
  end

  # Returns the average time taken to complete the last benchmark.
  # @return [Float] The time taken.
  def mean_scheduled_benchmark_duration
    @scheduler.mean_work_time
  end

  # Returns the time taken to complete the last benchmark.
  # @return [Float] The time taken.
  def last_scheduled_benchmark_duration
    @scheduler.last_work_time
  end

  attr_reader *%i[
    invalid_state_count
    current_key
    created_at
    dataset
    benchmark_count
    last_benchmark_time
    benchmark_config
    key_config
    service
  ]

  attr_accessor :demo_timestamp

  # Sends an image to this client's respective labelling endpoint, verifying
  # the key provided has not expired (and thus substantial evolution in the
  # labelling endpoint has not occured for significant impact to the results).
  # Depending on the key's varied severity level, a response will be returned
  # with varied fields populated.
  # @param [URI] uri (see RequestClient#send_uri)
  # @param [BenchmarkKey] key The benchmark key required to make a request
  # to the service using this client. This key is verified against this
  # client's most recent benchmark, thereby ensuring no evolution has occured
  # in the back-end service.
  # @return [Hash] A hash with the following keys: +:response+, the raw
  # #Response object returned from the #RequestClient.send_uri method (i.e.,
  # a non-benchmarked response) or +nil+ if the #key has expired or invalid
  # and the key's severity level is #BenchmarkSeverity::EXCEPTION;
  # +:labels:, a shortcut to the #Response.label method of the response or
  # +nil+ if the key has expired or was invalid and the key's severity level
  # is #BenchmarkSeverity::EXCEPTION; +:key_errors:+ a(n) error(s) response
  # indicating if the key has expired (a string value) which is only
  # populated if the key has a severity level of
  # #BenchmarkSeverity::EXCEPTION or #BenchmarkSeverity::WARNING;
  # +:response_errors:+ similar to :key_errors: but for the response;
  # +:cached:+ an optional DateTime inciating that there was no need to make
  # a request to the service as the benchmarker holds a cached response that
  # is still valid; this indicates the time at which the cached response was
  # generated.
```

```ruby
  def send_uri_with_key(uri, key)
    raise ArgumentError, 'URI must be a string.' unless uri.is_a?(String)
    raise ArgumentError, 'Key must be a BenchmarkKey.' unless key.is_a?(BenchmarkKey)

    if @current_key.nil?
      return {
        key_errors: [
          BenchmarkKey::InvalidKeyError.new(BenchmarkKey::InvalidKeyError::NO_KEY_YET)
        ]
      }
    end

    result = {
      labels: nil,
      response: nil,
      key_errors: nil,
      response_errors: nil,
      service_error: nil,
      cached: nil
    }

    # Check for a cached result w/ this service given provided key...
    ICVSB.ldebug("Attempting to use a cached response for #{uri} + #{@service.name}...")
    Request.where(uri: uri, service_id: @service.id, benchmark_key_id: key.id)
           .order(Sequel.desc(:created_at)).each do |request|
      response = request.response

      # Ignore unsuccessful responses
      next if response.nil? || !response.success?

      # Check if the response's benchmark is still valid -- if so, just
      # reuse that result... (no need to actually ping service)
      key_is_valid, = @current_key.valid_against?(response.benchmark_key)
      ICVSB.ldebug("Cached key (id=#{response.benchmark_key.id}) is valid against current key "\
        "(id=#{@current_key.id})? #{key_is_valid}")
      if !response.benchmark_key.nil? && key_is_valid
        return { labels: response.labels, response: response.hash, cached: DateTime.parse(response.created_at.to_s) }
      end
    end
    ICVSB.ldebug("Cached response failed! Will try to invoke a request to #{@service.name}")

    # Check for key validity
    ICVSB.ldebug("Checking if current key (id=#{@current_key.id}) is valid against key provided (id=#{key.id})...")
    key_valid, key_invalid_reasons = @current_key.valid_against?(key)
    # Invalid state count incremement if key error exists...
    unless key_valid
      ICVSB.ldebug("Validation of current key (id=#{@current_key.id}) failed against key provided (id=#{key.id}). "\
        "Reasons: #{key_invalid_reasons.join('; ')}")
      result[:key_errors] = key_invalid_reasons
      @invalid_state_count += 1
      ICVSB.linfo("Error has occured in key validation. Invalid state count count is now #{@invalid_state_count}.")
    end

    # If key is valid, raise request and check if response is valid
    ICVSB.ldebug("Key provided #{key.id} is valid against current key #{
```

```
        @current_key.id}!")
    if key_valid
      ICVSB.ldebug("Invoking a request '#{uri}' to #{@service.name}...")
      response = send_uri_no_key(uri)
      ICVSB.ldebug("Response returned (id=#{response.id})! Labels: #{response.labels}")
      # Update the benchmark key id
      response.benchmark_key_id = @current_key.id
      ICVSB.ldebug("Updated response (id=#{response.id}) with benchmark key = #{response.benchmark_key_id}...")
      # Now check to see if it was valid given that the response was successful
      if response.success?
        ICVSB.ldebug("Checking if this response (id=#{response.id}) is valid against current key (id=#{key.id})")
        response_valid, response_invalid_reasons = @current_key.valid_against?(response)
      end
      result[:labels] = response.labels
      result[:response] = response.hash
      result[:service_error] = result[:response][:service_error].to_s unless result[:response][:service_error].nil?
      response_valid ||= !result[:response][:service_error].nil?
      # Incremenet invalid state count if response error ONLY (i.e., not service error)
      unless response_valid
        ICVSB.ldebug("Validation of current key (id=#{@current_key.id}) failed against response "\
          "(id=#{response.id}). Reasons: #{response_invalid_reasons.join('; ')}")
        result[:response_errors] = response_invalid_reasons
        @invalid_state_count += 1
        ICVSB.linfo('Error has occured in response validation. '\
          "Invalid state count count is now #{@invalid_state_count}.")
      end
    end

    # If benchmark trigger on num failures is set
    if @benchmark_config[:trigger_on_failcount].positive? &&
       @invalid_state_count > @benchmark_config[:trigger_on_failcount]
      ICVSB.linfo("Benchmark has failed #{@benchmark_config[:trigger_on_failcount]} "\
        'times... retriggering benchmark...')
      @invalid_state_count = 0
      trigger_benchmark
    end

    # Response behaviour is dependent on the severity encoded within the key
    case @current_key.benchmark_severity
    when BenchmarkSeverity::EXCEPTION
      # Only expose errors if they exist
      if (result[:key_errors].nil? || result[:key_errors].empty?) &&
         result[:response_errors].nil? &&
         result[:service_error].nil?
        result
      else
        {
          key_errors: result[:key_errors],
          response_errors: result[:response_errors],
          service_error: result[:service_error]
        }
      end
    when BenchmarkSeverity::WARNING
      # Flag a warning to the warning endpoint about this result if sev is WARN
      _flag_warning(result)
      result
```

```ruby
    when BenchmarkSeverity::INFO
      # Log to info...
      unless key_valid
        ICVSB.lwarn("Benchmarked request made for #{uri} with invalid key "\
          "(id=#{@current_key.id}) -- error reasons: #{key_invalid_reasons.join('; ')}")
      end
      unless response_valid
        ICVSB.lwarn("Benchmarked request made for #{uri} and response violated current key "\
          "(id=#{@current_key.id}) -- error reasons: #{response_invalid_reasons.join('; ')}")
      end
      result
    when BenchmarkSeverity::NONE
      # Passthrough...
      result
    end
  end

  # 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.
  # @return [void]
  def trigger_benchmark
    @is_benchmarking = true
    new_key = _benchmark
    old_key = @current_key
    expiry_occured = false
    if @current_key.nil?
      @current_key = new_key
    else
      # Check if the key is valid
      valid_key, invalid_reasons = @current_key.valid_against?(new_key)
      unless valid_key
        ICVSB.lerror('BenchmarkedRequestClient no longer has a valid key! '\
          "Reason(s) ='#{invalid_reasons.join('; ')}'"\
          "Expiring old key (id=#{@current_key.id}) with new key (id=#{new_key.id})")
        @current_key.expire
        @current_key = new_key
        expiry_occured = true
      end
    end
    # # Check if the responses are valid against the current key
    # new_key.batch_request.responses.each do |res|
    # valid_response, invalid_reasons = @current_key.valid_against?(res)
    # unless valid_response
    # ICVSB.lerror('BenchmarkedRequestClient has a violated response! '\
    # "Reason(s) = '#{invalid_reasons.join(';')}'. Falling back to old key (id=#{old_key.nil? ? '<NONE>' : old_key.id})...")
    # @current_key.expire
    # @current_key = old_key
    # @current_key&.unexpire
    # expiry_occured = true
    # break
    # end
    # end
    @is_benchmarking = false
    _flag_benchmarking_complete(new_key, old_key, expiry_occured)
  end

  # Locates the last behaviour token key from the given date
  # @param [DateTime] Date at which the key should be searched from
```

```
  # @param [BenchmarkKey] The benchmark key found, or nil.
  def find_key_since(date)
    candidate_bks = BenchmarkKey.where(
      service_id: @service.id,
      benchmark_severity_id: @key_config[:severity].id,
      max_labels: @max_labels,
      min_confidence: @min_confidence,
      delta_labels: @key_config[:delta_labels],
      delta_confidence: @key_config[:delta_confidence],
      expected_labels: @key_config[:expected_labels].map(&:downcase).join(','),
    ).where(Sequel[:created_at] > date).reverse_order(:created_at)
    return nil if candidate_bks.nil?

    candidate_bks.find do |bk|
      (Set[*bk.batch_request.uris] ^ Set[*@dataset]).empty?
    end
  end

  private

  # Forwards a full result to the benchmarked request client's warning endpoint
  # @param [Hash] result See #send_uri_with_key
  # @return [void]
  def _flag_warning(result)
    return if @benchmark_config[:warning_callback_uri].nil? || @key_config[:severity] != BenchmarkSeverity::WARNING

    uri = @benchmark_config[:warning_callback_uri]
    data = result
    Thread.new do
      ICVSB.linfo("POSTing to warning endpoint '#{uri}' data=#{data}")
      req = Net::HTTP::Post.new(uri)
      req.body = data.to_json
      req.content_type = 'application/json;charset=utf8'
      res = Net::HTTP.start(uri.hostname, uri.port) do |http|
        http.request(req)
      end
      ICVSB.linfo("Response from warning endpoint: #{res.code} #{res.message}")
      ICVSB.ldebug("Response body is: #{res.body}") if res.is_a?(Net::HTTPSuccess)
    end
  end

  # Forwards a new key that has been generated due to benchmark trigger and
  # sends the current or old key (depending on expiry_occured flag.)
  # @param [BenchmarkKey] new_key The new key that was generated from the
  # benchmark that was triggered.
  # @param [BenchmarkKey] old_or_current_key The current key, if expiry did
  # not occur, or the old key if expiry did occur.
  # @param [Boolean] expiry_occured Indicates if the current_key was expired
  # and replaced with the new_key.
  # @return [void]
  def _flag_benchmarking_complete(new_key, old_or_current_key, expiry_occured)
    return if @benchmark_config[:benchmark_callback_uri].nil?

    uri = @benchmark_config[:benchmark_callback_uri]
    old_or_current_key_id = old_or_current_key.nil? ? nil : old_or_current_key.id
    data = { new_key: new_key.id, old_key: old_or_current_key_id, expiry_occured: expiry_occured }
    Thread.new do
      ICVSB.linfo("POSTing to benchmark complete endpoint '#{uri}' data=#{data}")
      req = Net::HTTP::Post.new(uri)
```

```ruby
        req.body = data.to_json
        req.content_type = 'application/json;charset=utf8'
        res = Net::HTTP.start(uri.hostname, uri.port) do |http|
          http.request(req)
        end
        ICVSB.linfo("Response from benchmark complete endpoint: #{res.code} #{res.message}")
        ICVSB.ldebug("Response body is: #{res.body}") if res.is_a?(Net::HTTPSuccess)
      end
    end

    # Benchmarks this client against a set of URIs, returning this client's
    # configurated key configuration. Internal method...
    # @return [BenchmarkKey] A key representing the result of this benchmark.
    def _benchmark
      @last_benchmark_time = DateTime.now
      @benchmark_count += 1
      ICVSB.linfo("Benchmarking dataset against dataset of #{@dataset.count} URIs. "\
        "Times benchmarked=#{benchmark_count}")
      br, thr = send_uris_no_key_async(@dataset)
      ICVSB.linfo("Benchmarking this dataset using batch request with id=#{br.id}.")
      # Wait for all threads to finish...
      thr.each(&:join)
      ICVSB.linfo("Batch request with id=#{br.id} is now complete!")
      bk = BenchmarkKey.create(
        service_id: @service.id,
        benchmark_severity_id: @key_config[:severity].id,
        batch_request_id: br.id,
        created_at: DateTime.now,
        expired: false,
        delta_labels: @key_config[:delta_labels],
        delta_confidence: @key_config[:delta_confidence],
        expected_labels: @key_config[:expected_labels].map(&:downcase).join(','),
        max_labels: @max_labels,
        min_confidence: @min_confidence
      )
      # Ensure every response is updated with this key
      br.responses.each do |res|
        ICVSB.ldebug("Updating response id=#{res.id} to benchmark key id=#{bk.id}.")
        res.benchmark_key_id = bk.id
      end
      ICVSB.linfo("Benchmarking dataset is complete (benchmark key id=#{bk.id}).")
      bk
    end
  end
end
```

Listing B.2: Implementation of the architecture facade API.

```ruby
# frozen_string_literal: true

# Author:: Alex Cummaudo (mailto:ca@deakin.edu.au)
# Copyright:: Copyright (c) 2019 Alex Cummaudo
# License:: MIT License

require 'sinatra'
require 'time'
require 'json'
require 'cgi'
require 'require_all'
require_all 'lib'


set :root, File.dirname(__FILE__)
set :public_folder, File.join(File.dirname(__FILE__), 'static')
set :show_exceptions, false
set :demo_folder, File.join(File.dirname(__FILE__), 'demo')

store = {}

before do
  if request.body.size.positive?
    request.body.rewind
    @params = JSON.parse(request.body.read, symbolize_names: true)
  end
end

def halt!(code, message)
  content_type 'text/plain'
  halt code, message
end

def check_brc_id(id, store)
  halt! 400, 'Benchmark id must be a positive integer' unless id.integer? && id.to_i.positive?
  halt! 400, "No such benchmark request client exists with id=#{id}" unless store.key?(id)
end

get '/' do
  File.read(File.expand_path('index.html', settings.public_folder))
end

# Creates a new benchmark request client with given parameters
post '/benchmark' do
  # Extract params
  service = params[:service] || ''
  benchmark_dataset = params[:benchmark_dataset] || ''
  max_labels = params[:max_labels] || ''
  min_confidence = params[:min_confidence] || ''
  trigger_on_schedule = params[:trigger_on_schedule] || ''
  trigger_on_failcount = params[:trigger_on_failcount] || ''
  benchmark_callback_uri = params[:benchmark_callback_uri] || ''
  warning_callback_uri = params[:warning_callback_uri] || ''
  expected_labels = params[:expected_labels] || ''
  delta_labels = params[:delta_labels] || ''
  delta_confidence = params[:delta_confidence] || ''
  severity = params[:severity] || ''

  # Check param types
  unless max_labels.integer? && max_labels.to_i.positive?
```

```ruby
  halt! 400, 'max_labels must be a positive integer'
end
unless min_confidence.float? && min_confidence.to_f.positive?
  halt! 400, 'min_confidence must be a positive float'
end
unless delta_labels.integer? && delta_labels.to_i.positive?
  halt! 400, 'delta_labels must be a positive integer'
end
unless delta_confidence.float? && delta_confidence.to_f.positive?
  halt! 400, 'delta_confidence must be a positive float'
end
unless ICVSB::VALID_SERVICES.include?(service.to_sym)
  halt! 400, "service must be one of #{ICVSB::VALID_SERVICES.join(', ')}"
end
unless trigger_on_schedule.cronline?
  halt! 400, 'trigger_on_schedule must be a cron string in * * * * * (see man 5 crontab)'
end
unless trigger_on_failcount.integer? && trigger_on_failcount.to_i >= -1
  halt! 400, 'trigger_on_failcount must be zero or positive integer'
end
if !benchmark_callback_uri.empty? && !benchmark_callback_uri.uri?
  halt! 400, 'benchmark_callback_uri is not a valid URI'
end

unless ICVSB::VALID_SEVERITIES.include?(severity.to_sym)
  halt! 400, "severity must be one of #{ICVSB::VALID_SEVERITIES.join(', ')}"
end
if ICVSB::BenchmarkSeverity[name: severity.to_s] == ICVSB::BenchmarkSeverity::WARNING && !warning_callback_uri.uri?
  halt! 400, 'Must provide a valid warning_callback_uri when severity is WARNING'
end

halt! 400, 'benchmark_dataset has not been specified' if benchmark_dataset.empty?
benchmark_dataset = benchmark_dataset.lines.map(&:strip)
expected_labels = expected_labels.empty? ? [] : expected_labels.split(',').map(&:strip)
benchmark_dataset.each do |uri|
  unless uri.uri?
    halt! 400, "benchmark_dataset must be a list of uris separated by a newline character; #{uri} is not a valid URI"
  end
end

# Convert params
brc = ICVSB::BenchmarkedRequestClient.new(
  ICVSB::Service[name: service.to_s],
  benchmark_dataset,
  max_labels: max_labels.to_i,
  min_confidence: min_confidence.to_f,
  opts: {
    trigger_on_schedule: trigger_on_schedule,
    trigger_on_failcount: trigger_on_failcount.to_i,
    benchmark_callback_uri: benchmark_callback_uri,
    warning_callback_uri: warning_callback_uri,
    expected_labels: expected_labels,
    delta_labels: delta_labels.to_i,
    delta_confidence: delta_confidence.to_f,
    severity: ICVSB::BenchmarkSeverity[name: severity.to_s],
    autobenchmark: false
  }
)
```

```
  # Benchmark on new thread
  Thread.new do
    brc.trigger_benchmark
    store[brc.object_id] = brc
  end

  store[brc.object_id] = brc

  status 201
  content_type 'application/json;charset=utf-8'
  { id: brc.object_id }.to_json
end

# Gets all auxillary information about the benchmark
get '/benchmark/:id' do
  id = params[:id].to_i
  check_brc_id(id, store)
  brc = store[id]

  content_type 'application/json;charset=utf-8'
  {
    id: id,
    service: brc.service.name,
    created_at: brc.created_at,
    current_key_id: brc.current_key ? brc.current_key.id : nil,
    is_benchmarking: brc.benchmarking?,
    last_scheduled_benchmark_time: brc.last_scheduled_benchmark_time,
    next_scheduled_benchmark_time: brc.next_scheduled_benchmark_time,
    mean_scheduled_benchmark_duration: brc.mean_scheduled_benchmark_duration,
    last_scheduled_benchmark_duration: brc.last_scheduled_benchmark_duration,
    invalid_state_count: brc.invalid_state_count,
    last_benchmark_time: brc.last_benchmark_time,
    benchmark_count: brc.benchmark_count,
    config: {
      max_labels: brc.max_labels,
      min_confidence: brc.min_confidence,
      key: brc.key_config,
      benchmarking: brc.benchmark_config
    },
    benchmark_dataset: brc.dataset
  }.to_json
end

patch '/benchmark/:id' do
  # Set is_benchmarking to true to force the benchmark to reevaluate...
  # Else, endpoint is ignored
  id = params['id'].to_i
  check_brc_id(id, store)
  brc = store[id]

  status 202
  response = {
    id: id,
    service: brc.service.name,
    current_key_id: brc.current_key ? brc.current_key.id : nil,
    is_benchmarking: brc.benchmarking?
  }
  if brc.service == ICVSB::Service::DEMO && params[:demo_timestamp]
    brc.demo_timestamp = params[:demo_timestamp] if ['t1','t2'].include?(params[:
        ↪ demo_timestamp])
    response[:timestamp] = brc.demo_timestamp
  end

  brc.trigger_benchmark if params[:is_benchmarking] && !brc.benchmarking?
```

```

  response.to_json
end

# Gets all auxillary information about this key's benchmark
get '/benchmark/:id/key' do
  id = params[:id].to_i
  check_brc_id(id, store)
  brc = store[id]

  halt! 422, 'The requested benchmark client is still benchmarking its first key' if brc.current_key.nil?

  current_key_id = brc.current_key.id
  redirect "/key/#{current_key_id}"
end

get '/key/:id' do
  id = params[:id].to_i
  bk = BenchmarkKey[id: params[:id]]

  halt! 400, 'id must be an integer' unless id.integer?
  halt! 400, "No such benchmark key request client exists with id=#{id}" if bk.nil?

  content_type 'application/json;charset=utf-8'
  {
    id: bk.id,
    service: bk.service.name,
    created_at: bk.created_at,
    benchmark_dataset: bk.batch_request.uris,
    success: bk.success?,
    expired: bk.expired?,
    severity: bk.severity.name,
    responses: bk.batch_request.responses.map(&:hash),
    config: {
      expected_labels: bk.expected_labels_set.to_a,
      delta_labels: bk.delta_labels,
      delta_confidence: bk.delta_confidence,
      max_labels: bk.max_labels,
      min_confidence: bk.min_confidence
    }
  }.to_json
end

# Gets the log of the benchmark with the given id
get '/benchmark/:id/log' do
  id = params[:id].to_i

  check_brc_id(id, store)

  content_type 'text/plain'
  store[id].read_log
end

post '/callbacks/benchmark' do
  "Acknowledged benchmark completion with params: '#{params}'..."
end

post '/callbacks/warning' do
  "Acknowledged benchmark warning params: '#{params}'..."
end

# Labels resources against the provided uri. This is a conditional HTTP request.
```

```
# Must provide "If-Match" request header field with at least one ETag. Note that
# the ETag must ALWAYS been provided in the following format:
#
# W/"<benchmark-id>[;<behaviour-token>]"
#
# Note that the ETag is a weak ETag; ``weak ETag values of two representations
# of the same resources might be semantically equivalent, but not byte-for-byte
# identical.'' (https://developer.mozilla.org/en-US/docs/Web/HTTP/Headers/ETag).
# That is, as the developer is not directly accessing the service, they are
# only getting a semantically equivalent representation of the labels, but not
# a byte-for-byte equivalent (the model may have changed slightly, given the
# latest benchmark used.)
#
# The first id, the benchmark-id, is mandatory as the request must know what
# benchmark dataset (and service) the requested URI is being made against.
#
# The following behaviour-token is optional, indicating the tolerances to which
# the response will be made, and the behaviour by which the response will change
# given if evolution has occured since the last benchmark was made. (Not that
# internally to this project, we refer to the behaviour token as a BenchmarkKey
# -- see ICVSB::BenchmarkKey.)
#
# One may provide multiple ETags (separated by commas) in the format:
#
# W/"<benchmark-id1>[;<behaviour-token1>]",W/"<benchmark-id2>[;<behaviour-token2>]" ...
#
# Where this is the case, the label requested will attempt to match ANY of the
# tags provided. If failure occurs for the first, it will default to the next
# ETag, and so on.
#
# If NO behaviour-token is specified, then then (additionally) one must provide
# an "If-Unmodified-Since" request header field, indicating that the resource
# (labels) must have been unmodified since the given date. This will attempt to
# automatically locate the nearest behaviour token that was generated after the
# given date and request the labels against that date.
#
# The endpoint will return one of the following HTTP responses:
#
# - 200 OK if this is the first request made to this URI;
# - 400 Bad Request if invalid parameters were provided by the client;
# - 412 Precondition Failed if the key/unmodified time provided is no longer
# valid, and thus the key provided (or time provided) is violating the
# valid tolerances embedded within the key (responding further details
# reasoning what tolerances were violated as metadata in the response body);
# - 428 Precondition Required if no If-Match field is provided in request;
# - 422 Unprocessable Entity if a service error has occured, indicating the
# service cannot process the entity or a bad request was made.
# - 500 Internal Server Error if a facade error has occured.
#
# The endpont will return the following HTTP response headers:
#
# - ETag: The ETag that was used to successfully generate a response
# - Last-Modified: The last time the benchmark-id was benchmarked against
# its dataset
# - Expires: The next time the benchmark with the provided id will be
# benchmarked against its dataset
# - Age: Indicates that the repsonse provided is cached (i.e., no changes
# to the service the last time it was benchmarked against the dataset
# to not be considered a violation); returns the time elapsed in seconds
# since then
get '/labels' do
  image_uri = CGI.unescape(params[:image])

```

```
if_match = request.env['HTTP_IF_MATCH'] || ''
if_unmodified_since = request.env['HTTP_IF_UNMODIFIED_SINCE'] || ''

halt! 400, 'URI provided to analyse is not a valid URI' unless image_uri.uri?
halt! 428, 'Missing If-Match in request header' if if_match.nil?
if !if_unmodified_since.empty? && !if_unmodified_since.httpdate?
  halt! 400, 'If Unmodified Since must be compliant with the RFC 2616 HTTP date format'
end

if_unmodified_since_date = if_unmodified_since.empty? ? nil : Time.httpdate(if_unmodified_since)

relay_body = nil
relay_etag = nil
relay_last_modified = nil
relay_expires = nil

# Scan through each comma-separated ETag
etags = if_match.scan(%r{W\/"(\d+;?\d+)",?})
if etags.empty?
  halt! 428, 'Malformed ETags provided. Ensure you are using the correct format.'
end
etags.each do |etag|
  etag = etag[0]
  benchmark_id, benchmark_key_id = etag.split(';').map(&:to_i)

  # Check if we have a valid benchmark id
  check_brc_id(benchmark_id, store)
  brc = store[benchmark_id]
  bk = nil


  # Check if we have a key; if no key we must have a If-Unmodified-Since.
  if benchmark_key_id.nil? && if_unmodified_since.empty?
    halt! 400, "You have provided a benchmark id (id=#{benchmark_id}) "\
             'without a behaviour token. Please provide a behaviour token '\
             'or include the If-Unmodified-Since request header with a RFC '\
             '2616-compliant HTTP date string.'
  elsif !benchmark_key_id.nil?
    # Check if valid key
    if ICVSB::BenchmarkKey.where(id: benchmark_key_id).empty?
      halt! 400, "No such key with id #{benchmark_key_id} exists!"
    end
    unless benchmark_key_id.integer? && benchmark_key_id.positive?
      halt! 400, 'Behaviour token must be a positive integer.'
    end

    bk = ICVSB::BenchmarkKey[id: benchmark_key_id]
  elsif !if_unmodified_since_date.nil?
    bk = brc.find_key_since(if_unmodified_since_date)
    halt! 412, "No compatible behaviour token found unmodified since #{if_unmodified_since_date}." if bk.nil?
  end

  # Process...
  result = brc.send_uri_with_key(image_uri, bk)

  # Set HTTP status+body as appropriate if there is no more ETags or if
  # this was a successful response (i.e., no errors so don't keep trying other
  # ETags...)
  error = result.key?(:key_errors) || result.key?(:response_errors) || result.key?(:service_error)
```

```
    if [etag] == etags.last || !error
      if result[:key_errors] || result[:response_errors]
        status 412
        content_type 'application/json;charset=utf-8'

        key_error_len = result[:key_errors].nil? ? 0 : result[:key_errors].length
        res_error_len = result[:response_errors].nil? ? 0 : result[:response_errors].length

        key_error_data = result[:key_errors].nil? ? [] : result[:key_errors].map(&:to_h)
        res_error_data = result[:response_errors].nil? ? [] : result[:response_errors].map(&:to_h)

        relay_body = {
          num_key_errors: key_error_len,
          num_response_errors: res_error_len,
          key_errors: key_error_data,
          response_errors: res_error_data
        }.to_json
      elsif result[:service_error]
        status 422
        content_type 'text/plain'
        relay_body = result[:service_error]
      else
        content_type 'application/json;charset=utf-8'
        unless result[:cached].nil?
          age_sec = ((DateTime.now - result[:cached]) * 24 * 60 * 60).to_i.to_s
          headers 'Age' => age_sec
        end
        status 200
        relay_body = result[:response].to_json
      end
      relay_etag = etag
      relay_last_modified = brc.current_key.nil? ? brc.created_at.httpdate : brc.current_key.created_at.httpdate
      relay_expires = brc.next_scheduled_benchmark_time.httpdate
    end
  end
  headers \
    'ETag' => "W/\"#{relay_etag}\"", \
    'Expires' => relay_expires, \
    'Last-Modified' => relay_last_modified
  body relay_body
end

error do |e|
  halt! 500, e.message
end

###
# DEMONSTRATION RELATED API
###
get '/demo/categories.json' do
  content_type 'application/json;charset=utf-8'
  send_file(File.join(settings.demo_folder, 'categories.json'))
end

get '/demo/random/:type.jpg' do
  category_data = JSON.parse(
    File.read(File.join(settings.demo_folder, 'categories.json'))
  )
  ok_categories = category_data.keys

```

```ruby
  category = params[:type]

  halt! 400, 'No category provided' if category.empty?
  unless ok_categories.include?(category)
    halt! 400, "Unknown category '#{category}'. Accepted category types are: '#{ok_categories.join("', '")}'."
  end

  id = category_data[category].sample

  redirect "/demo/data/#{id}.jpg"
end

get '/demo/data/:id.*' do |_, ext|
  image_id = params[:id].split('.').first
  time_id = params[:id].split('.').last

  unless File.exist?(File.join(settings.demo_folder, image_id + '.jpg'))
    halt! 400, "No such image with id '#{image_id}' exists in the demo database."
  end
  unless %w[jpg jpeg json].include?(ext)
    halt! 400, 'Invalid file extension. Suffix with .jp[e]g or .t1.json or .t2.json.'
  end
  ext = 'jpg' if ext == 'jpeg'

  if ext == 'jpg'
    content_type 'image/jpeg'
  else
    content_type 'application/json;charset=utf-8'
    halt! 400, 'Missing time id (.t1 or .t2).' if time_id.empty? || !%w[t1 t2].include?(time_id)
    image_id += '.' + time_id
  end

  send_file(File.join(settings.demo_folder, image_id + '.' + ext))
end
```

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.e., a guide to rapidly get started using the API in a specific programming language.*	S4, S9, S10	Low	V High	●	◑	●
A2	Low-level reference manual; *i.e., a manual documenting all API components to review fine-grade detail.*	S1, S3, S4, S8, S9, S10, S11, S12, S15, S16, S17	High	High	●	●	●
A3	Explanation of high level architecture; *i.e., explanations of the API's high-level architecture to better understand intent and context.*	S1, S2, S4, S11, S14, S16, S19, S20	Med	V High	●	●	●
A4	Introspection source code comments; *i.e., code implementation and code comments (where applicable) to understand the API author's mindset.*	S1, S4, S7, S12, S13, S17, S20	Med	High	○	○	○
A5	Code snippets of basic component function; *i.e., code snippets (with comments) of no more than 30 LoC to understand a basic component functionality within the API.*	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.e., step-by-step tutorials, with screenshots to understand how to build a non-trivial piece of functionality with multiple components of the API.*	S1, S2, S4, S5, S7, S9, S10, S15, S16, S18, S20, S21	V High	V High	◑	●	●
A7	Downloadable production-ready source code; *i.e., downloadable source code of production-ready applications that use the API to understand implementation in a large-scale solution.*	S1, S2, S5, S9, S15	Low	V High	◑	◑	●
A8	Best-practices of implementation; *i.e., best-practices of implementation to assist with debugging and efficient use of the API.*	S1, S2, S4, S5, S7, S8, S9, S14	Med	V High	○	●	◑
A9	An exhaustive list of all components; *i.e., a list of all the major components that exist within the API.*	S4, S16, S19	Low	V High	○	●	●
A10	Minimum system requirements to use the API; *i.e., requirements and the dependencies to use the API on a particular system.*	S4, S7, S13, S17, S19	Low	V High	◑	○	◑
A11	Instructions to install/update the API and its release cycle; *i.e., instructions to install or begin using the API and details on its release cycle and how to update it.*	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.e., a brief description of the purpose or overview of the API as a low barrier to entry.*	S1, S2, S4, S5, S6, S8, S10, S11, S15, S16	High	V High	●	●	●
B2	What the API can develop; *i.e., descriptions of concrete types of applications the API can develop.*	S2, S4, S9, S11, S15, S18	Med	V High	◑	◑	●
B3	Who should use the API; *i.e., descriptions of the types of users who should use the API.*	S4, S9	V Low	High	◑	○	○
B4	Who will use the applications built using the API; *i.e., descriptions of the types of users who will use the product the API creates.*	S4	V Low	Med	○	○	○
B5	Success stories on the API; *i.e., example success stories of major users that describe how well the API was used in production.*	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.e., definitions of the domain-terminology and concepts, with synonyms if applicable.*	S2, S3, S4, S6, S7, S10, S14, S16	Med	V High	◑	○	◑
C3	Documentation for nontechnical audiences; *i.e., generalised documentation for non-technical audiences regarding the API and its domain.*	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.e., diagrammatically representing API components using visual architectural representations.*	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	○	●	●

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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.e., breadcrumbs*	S6, S10, S20	Low	High	●	●	●
E5	Visualised map of navigational paths; *i.e., to certain API components in the website.*	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

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Service	Document Sources
Amazon Rekgonition	https://docs.aws.amazon.com/rekognition/latest/dg/getting-started.html https://docs.aws.amazon.com/AWSJavaSDK/latest/javadoc/index.html https://aws.amazon.com/blogs/machine-learning/using-amazon-rekognition-to-identify-persons-of-interest-for-law-enforcement/ https://aws.amazon.com/rekognition/#Rekognition_Image_Use_Cases https://docs.aws.amazon.com/rekognition/latest/dg/labels-detect-labels-image.html https://aws.amazon.com/rekognition/getting-started/#Tutorials https://aws.amazon.com/blogs/machine-learning/category/artificial-intelligence/amazon-rekognition/ https://docs.aws.amazon.com/code-samples/latest/catalog/code-catalog-java-example_code-rekognition.html https://docs.aws.amazon.com/rekognition/latest/dg/best-practices.html https://docs.aws.amazon.com/rekognition/latest/dg/API_Operations.html https://aws.amazon.com/rekognition/image-features/ https://aws.amazon.com/releasenotes/?tag=releasenotes%23keywords%23amazon-rekognition https://docs.aws.amazon.com/rekognition/latest/dg/setting-up.html https://aws.amazon.com/rekognition/ https://aws.amazon.com/rekognition/ https://docs.aws.amazon.com/rekognition/latest/dg/limits.html https://aws.amazon.com/rekognition/pricing/ https://aws.amazon.com/rekognition/sla/ https://aws.amazon.com/rekognition/faqs/ https://docs.aws.amazon.com/rekognition/latest/dg/video-troubleshooting.html https://docs.aws.amazon.com/rekognition/latest/dg/rekognition-dg.pdf https://github.com/awsdocs/amazon-rekognition-developer-guide/issues https://forums.aws.amazon.com/thread.jspa?threadID=285910

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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," *IEEE Software*, 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," *Empirical Software Engineering*, 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 *Proceedings of the 2011 IEEE Symposium on Visual Languages and Human Centric Computing*. 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 *Proceedings of the 20th Annual International Conference on Computer Documentation*. Toronto, ON, Canada: ACM, October 2002. DOI 10.1145/584955.584976, pp. 133–141	56	–
[S5]	R. Watson, M. Mark Stamnes, J. Jeannot-Schroeder, and J. H. Spyridakis, "API documentation and software community values: A survey of open-source API documentation," in *Proceedings of the 31st ACM International Conference on Design of Communication*. 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 *Proceedings of the First International Symposium on End User Development*, 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 *Proceedings of the 41st International Conference on Software Engineering*. 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 *Proceedings of the 11th International Conference on Service-Oriented Computing and Applications*, 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 *Proceedings of the 6th World Conference on Information Systems and Technologies*. 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?" *Journal of Technical Writing and Communication*, 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," *Computer Supported Cooperative Work: CSCW: An International Journal*, 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 *Proceedings of the 40th International Conference on Software Engineering*, 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," *Procedia Computer Science*, 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 *Proceedings of the 33rd IEEE International Conference on Software Maintenance and Evolution*. 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 *Proceedings of the 30th ACM International Conference on Design of Communication*. 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," *IEEE Transactions on Software Engineering*, 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 *Proceedings of 10th IEEE International Symposium on High Assurance Systems Engineering*. 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 *Proceedings of the 2005 IEEE International Professional Communication Conference*. Limerick, Ireland: IEEE, July 2005. DOI 10.1109/IPCC.2005.1494255, pp. 802–812	0	–

Continued on next page...

Ref	Citation	Cite#	Rank
[S19]	A. Taulavuori, E. Niemelä, and P. Kallio, "Component documentation - A key issue in software product lines," *Information and Software Technology*, 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," *IEEE Software*, 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," *IEEE Software*, 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 [426, 445] 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 [404], 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* <u>*all*</u> *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 [401] 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 [442, 448, 449] integrating multiple components within their service to mobile applications and the Azure platform.

> ☞ ***Suggested improvement:*** *Ensure tutorials combine* <u>*multiple*</u> *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 [447] 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 [405, 428].

> ☞ ***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 [420, 429], 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 [443], but no further details on non-custom vision classifiers are found. We found the most detailed best-practices to be provided by Amazon Rekognition [403], 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 [402] as well as a detailed, technical breakdown of each API operation provided within the service [400]. Microsoft also provide a list of high-level features that Azure Computer Vision can analyse [450] 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 [430].

> ☞ ***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 [426, 440]. 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 [399] which does not account for evolution in the service's responses [89]. Google's and Microsoft's release notes are generally more frequently updated, therefore developers can get a sense of its release frequency [427, 446]. 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 [407].

> ☞ ***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 [406] 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., [441]). 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 [424], 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 [450], 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 [408]. 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 of background of the image? These are suggestions which we have proposed in prior work [89] 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 use. 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.

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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.*	Yes

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. *(If the same, write "as above")*	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: 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

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	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 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.*	Yes

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. *(If the same, write "as above")*	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: 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

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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: Alex Cummaudo
Dated: 22 July 2019

Author 2 Rajesh Vasa

Signed: V.R. Vasa
Dated: 22 July 2019

Author 3 John Grundy

Signed: J Grundy
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), Portable Document Format (PDF)
Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/esem19

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	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 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.*	Yes

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. *(If the same, write "as above")*	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: 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 Barnet 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

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iii. that the description in Section 4 of my contribution(s) to this publication is accurate,

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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: 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.

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/icse20

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	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 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.*	Yes

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. *(If the same, write "as above")*	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: 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.

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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: 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 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.*	Yes

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. *(If the same, write "as above")*	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: 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 Barnet 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:

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: 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 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.*	Yes

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. *(If the same, write "as above")*	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.*	Yes

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. *(If the same, write "as above")*	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: Alex Cummaudo   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:

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: 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 Ohtake
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? *If Yes, please complete Section 3* *If No, go straight to Section 4.*	Yes

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. *(If the same, write "as above")*	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: Alex Cummaudo 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,

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	Tomohiro Ohtake 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

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)
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? *If Yes, please complete Section 3* *If No, go straight to Section 4.*	Yes

3. HDR thesis author's declaration

Name of HDR thesis author if different from above. *(If the same, write "as above")*	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: Alex Cummaudo 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 Fliess' 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: UMGraetsch
Dated: 2 June 2020

Author 2 Alex Cummaudo

Signed: Alex Cummaudo
Dated: 2 June 2020

Author 3 Rajesh Vasa

Signed: V.R. Vasa
Dated: 2 June 2020

Author 4 Maheswaree K Curumsing

Signed: Mkcurumsing
Dated: 2 June 2020

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), Excel Spreadsheet
Storage location	Deakin University Research Data Store (RDS) Location: RDS29448-Alex-Cummaudo-PhD/results/caise21

8. Additional notices

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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.

APPENDIX E

Ethics Clearance

DEAKIN
UNIVERSITY AUSTRALIA
Worldly

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

Teresa Treffry

Teresa Treffry
Secretary, Human Ethics Advisory Group (HEAG)
Faculty of Science Engineering & Built Environment

Faculty of Science Engineering & Built Environment Human Ethics Advisory Group
Geelong Waurn Ponds Campus, Geelong, VIC 3220
Tel 03 522 72270 Fax 03 522 72028 sciethic@deakin.edu.au www.deakin.edu.au

Rajesh Vasa, Mohamed Abdelrazek, Andrew Cain, Scott Barnett, Alex Cummaudo
Applied Artificial Intelligence Institute (A^2I^2) (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