Do developers understand the magic within?
A documentation framework for intelligent cloud services

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Abstract

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Contents

List of Abbreviations

A^{2}I^2 Applied Artificial Intelligence Institute. 40, 45, 48, 49

AI Artificial Intelligence. 1, 3, 26–28

API Application Programming Interface. 1, 3–15, 17, 20, 21, 29–36, 38, 40, 41, 43–46, 49, 51

BYOML Build Your Own Machine Learning. 3, 4

CDSS Clinical Decision Support System. 7, 10, 11

CIS Cloud Intelligence Service. 4–9, 11–14, 17–21, 23, 24, 26, 29, 34–41, 43–46, 49, 51

CNN Convolutional Neural Network. 10, 11, 24

CRUD Create, read, update, and delete. 31

cvCIS Computer Vision Cloud Intelligence Service. 5–10, 12, 13, 15, 17, 19, 20, 24, 33, 41, 46, 47

DCE Distributed Computing Environment. 30

HITL Human-in-the-loop. 11

HTTP Hypertext Transfer Protocol. 4, 30–33

IDL Interface Definition Language. 30, 32

JSON JavaScript Object Notation. 5

ML Machine Learning. 1, 3, 4, 10, 21, 27

NN Neural Network. 1, 25–27, 29

QoS Quality of Service. 30

RAML RESTful API Modeling Language. 32

REST REpresentational State Transfer. 5, 31–33

ROI Region of Interest. 10, 11

RPC Remote Procedure Call. 30

SE Software Engineer. 28

SOA Service-Level Agreement. 30

SOA Service-Oriented Architecture. 30

SOAP Simple Object Access Protocol. 5, 30–32

SQuaRE Systems and software Quality Requirements and Evaluation. 23

SVM Support Vector Machine. 26, 29

URI Uniform Resource Identifier. 31

V&V Verification & Validation. 17–22

WADL Web Application Description Language. 32

WS Web Service. 30

WSDL Web Services Description Language. 30

XML eXtendable Markup Language. 5, 30, 31

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Chapter 1

Introduction

Within the last half-decade, we have seen an explosion of cloud-based services typically marketed under an Artificial Intelligence (AI) banner. Vendors are rapidly pushing out AI-based solutions, technologies and products that encapsulate half a century worth of machine-learning research: a 2016 report by market research company Forrester captured such growth into four key areas [145] as replicated in Figure 1.1. Moreover, developers eager to develop a next generation of software are shifting away from mobile-first to 'AI-first' apps, that will reason, sense, think, act, listen, speak and execute our whims right within the palms of our hands. A wave of AI-first thinking embedded in companies' product lines is spearheaded through work achieved at Google, Microsoft and Facebook; for instance, Google's 2018 rebranding of *Google Research* to *Google AI* [105] or how AI is leveraged *at scale* within Facebook's infrastructure and platforms to serve its users with an AI-first attitude [171].

These services aim to lower the entry barrier to develop, test and deploy AI-first software in both skill and time. Software engineers needn't require a formal training in machine-learning nor a strong understanding of mathematics: thus, *skill required* is reduced. The training of such classifiers involves the laborious process of sourcing, curating and labelling large datasets: using such services does not, and thus *time* is reduced. To this end, they needn't require much machine-learning expertise or experience at all; instead, the process is abstracted behind an Application Programming Interface (API) call, only requiring knowledge on how to use a RESTful architecture [84] to access the cloud service.

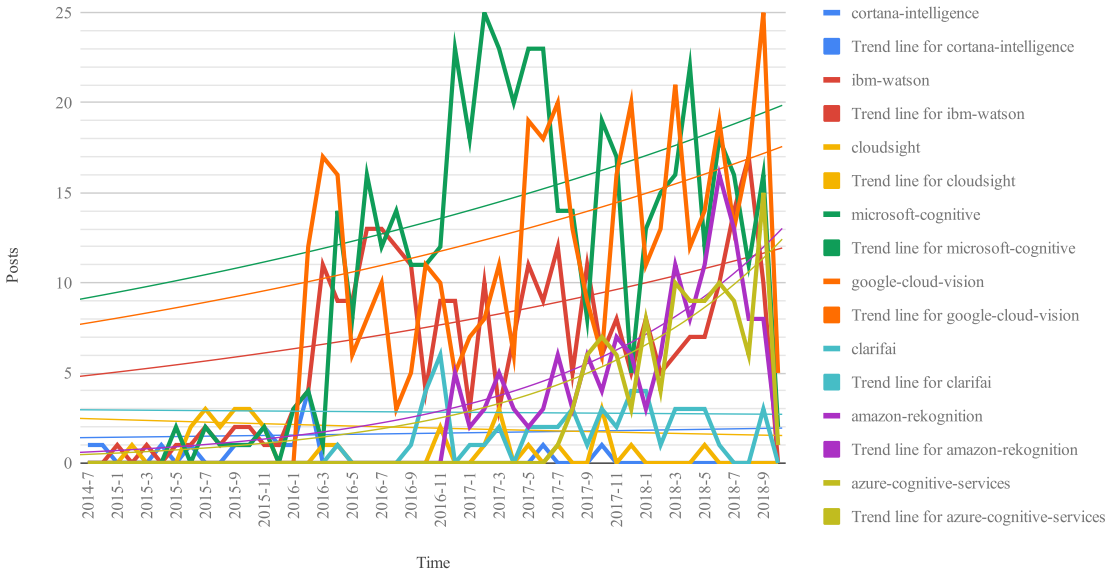
To contrast this with more traditional means, a developer may choose to write up a deep-learning Neural Network (NN) (for example) and train it using their own dataset. While this is laborious in time and demands significant knowledge in machine learning, the developer has full control over the models she creates. Alternatively, she may choose to download a pre-trained model and Machine Learning (ML) framework, such as Tensorflow [25]; less demanding in time but still requiring the knowledge to wire-up models with frameworks.

Figure 1.1: A Broad Range of AI-Based Products And Services Is Already Visible. (From [145].)

Category	Sample vendors and 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 (and more) • Microsoft: Cortana • Salesforce: MetaMind (acquisition)	• 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 • Voice, image recognition, various levels of NLP sophistication • Bots, agents
AI point solutions Point solutions provide specialized capabilities for NLP, 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, Explorer, Advisor • Narrative Science: Quill • Nuance: Dragon • Salesforce: MetaMind (acquisition) • Wise.io: Wise Support	• Semantic text, facial/visual recognition, voice intonation, intelligent narratives • Various levels of NLP from brief text messaging, chat/conversational messaging, full complex text understanding • Machine learning, predictive analytics, text analytics/mining • Knowledge management and search • Expert advisors, reasoning tools • Customer service, support • APIs
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 Machine Learning • IBM: Watson Developers, 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 • Rule-based reasoning • Vertical domain advisors (e.g., fraud detection in banking, financial advisors, healthcare) • Cognitive services and bots
Deep learning Platforms, advanced projects, and algorithms for deep learning.	• Amazon: FireFly • Google: TensorFlow/DeepMind • LoopAI Labs: LoopAI • Numenta: Grok • Vicarious: Vicarious	• Deep learning neural networks for categorization, clustering, search, image recognition, NLP, and more • Location pattern recognition • Brain neocortex simulation

This concept was coined by Google AI over various presentations as *The Machine Learning Spectrum* [167, 134, 21], which encompasses the variety of skill, effort, target audiences and outputs of various ML products. On one extreme is the research of developing algorithms (e.g., neural networks) to achieve intelligence, produced chiefly in academia—coined as Build Your Own Machine Learning (BYOML) [167, 21, 18]. On the other, such intelligence becomes heavily abstracted as easy-to-use APIs, targeted mainly towards developers as 'friendly' ML. In the middle lies a broad mix of combining both cloud and locally-hosted solutions (with varying levels of automation to assist in development) that turn custom datasets into some form of predictive intelligence. We illustrate this further within Table 1.1.

Figure 1.2: Number of posts categorised on Stack Overflow under popular computer vision cloud intelligence services.



With less time and skill required to build AI-first apps using these 'friendly' ML services, these services have begun to gain traction within developer circles: Figure 1.2 shows the increasing trend of posts since 2014 on Stack Overflow that categorise popular computer vision cloud APIs.[1] A growing popularity into such 'off-the-shelf', pre-packaged ML APIs sparked varied nomenclature in academia: *Cognitive Applications* and *Machine Learning Services* [108] or *Machine Learning as a Service* [186] are some coined phrases in which the intelligence is provided or created as a service via the cloud. Some of these services provide the infrastructure to rapidly begin training from custom datasets (Google's AutoML[2] is one such example) while others provide pre-trained datasets 'ready-for-use' in production

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

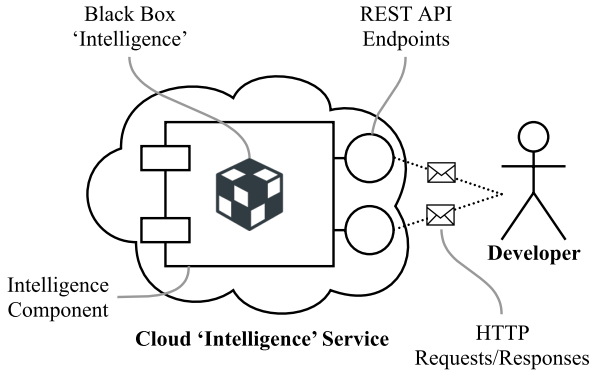
[2]`https://cloud.google.com/automl/` last accessed 7 December 2018.

Table 1.1: Comparison of the machine learning spectrum.

Comparator	**BYOML**	**ML F'work**	**Cloud ML**	**Auto-Cloud ML**	**CIS 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				✓	✓

without the need to train data. We refer to these latter services under the broader term Cloud Intelligence Service (CIS), and diagrammatically express their usage within Figure 1.3.

Figure 1.3: Overview of Cloud Intelligence Services.



The general workflow of a CIS is relatively simple: a developer accesses a CIS component via REST/SOAP API(s). For their given input, they receive an intelligent-like response typically serialised as JSON/XML. We note the intelligence component masks its 'intelligence' through a black-box: in recent years, there is a rise in providing human-level intelligence via crowdsourcing Internet marketplaces such as Amazon Mechanical Turk [20] or ScaleAPI [23]. Thus, a CIS may be powered by varying degrees of intelligence: human intelligence, machine learning, data mining or even intelligence by brute-force.

While there are many types of CISs evident (such as OCR transcription, text-to-speech and speech-to-text, object categorisation, object comparison, natural language processing etc.), we scope the work investigated in this study to Computer Vision Cloud Intelligence Services (cvCISs) [15, 8, 3, 22, 16, 10, 9, 12, 17, 24, 19, 11, 4]. The ubiquity of cvCISs is exemplified through evermore growing applications that use these APIs: aiding the vision-impaired [184, 66], accounting [147], data analytics [114], and student education [71]. Moreover, we refer to its growing adoption in developer circles within Figure 1.2.

1.1 Motivation: Current Developer Mindsets'

Figure 1.2 shows an increasing trend to the adoption and discussion of CISs with developers. As aforementioned, these services are accessible through APIs and consist of an 'intelligence' black box (Figure 1.3). When a term 'black box' is used, the input (or stimulus) is transformed to its to outputs (or response) without any understanding of the internal architecture by which this transformation occurs; indeed, this well-understood theory arose from the electronic sciences and since adapted to wider applications since the 1950s–60s [30, 50] to describe

"systems whose internal mechanisms are not fully open to inspection" [30].

In the world of machine learning and data mining, where we develop algorithms to make predictions in our datasets or discover patterns within them, these black boxes are inherently probabilistic and stochastic; there is little room for certainty in these results as such insight is purely statistical and associational [175] against its training dataset. As an example, a cvCIS returns the *probability* that a particular object (the response) exists in the raw pixels (the stimulus), and 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. Developers (at present) do not need to treat their programs in any such stochastic way as traditionally their mindset is that computers will always make certain outcomes. But in the day and age of stochastic and probabilistic systems, this mindset needs to shift.

There are thus therefore three key factors to consider when implementing, testing and developing with a CIS: (i) the API usability, (ii) the nature of stochastic and probabilistic systems, and (iii) how both impact on software quality.

1.1.1 The Impact on Software Quality

Do traditional techniques for documenting deterministic APIs also apply to non-deterministic systems? As APIs reflect a set of design choices made by their providers intended for use by the developer, does the mindset between the machine learning architect and the novice programmer match? Evaluations of API usability advocate for the accuracy, consistency and completeness of APIs and their documentation [178, 190] written by providers, while providers should consider mismatches between the developer's conceptual knowledge of the API its implementation [129]. However, consistency cannot be guaranteed in probabilistic systems, and the conceptual knowledge of such systems are still treated like black boxes. It is therefore imperative that CIS providers consider the impact of their API usability; if not, poor API usability hinders on the internal quality of development practices, slowing developers down to produce the software they need to create.

Moreover, CIS APIs are inherently non-deterministic in nature, but developers are still taught with the deterministic mindset that all API calls are the same. Simple arithmetic representations (e.g., $2 + 2 = 4$) will *always* result in 4; but a multi-layer perceptron neural network performing similar arithmetic representation [42] gives the probability where the target output (*exactly* 4) and the output inferred (*possibly* 4) matches as a percentage (or as an error where it does not match). That is, instead of an exact output, there is instead a *probabilistic* result: $2 + 2$ *may* equal 4 with a confidence of n. External quality must therefore

be considered in the outcome of these systems, such as in the case of thresholding values, to consider whether or not the inference has a high enough confidence to justify its result to end-users.

In order to fully understand this problem, there are multiple dimensions one must consider: the impact of software quality; the fact that these systems underneath are probabilistic and are stochastic; the cognitive biases of determinism in developers; the issue of consistency in API usage. While existing literature does extensively explore software quality and API usability, these studies have only had emphasis on deterministic systems and thus little work to date has investigated such factors on probabilistic systems that make up the core of cvCISs. We explore more of these facets in the motivating scenarios below.

1.1.2 Motivating Scenarios

The market for intelligent services is increasing (Figure 1.1) and as is developer uptake and enthusiasm in the software engineering community (Figure 1.2). We investigate the impact of the mismatch between the developer's mindset and the service provider's mindset as little work has been presented in in literature. How do developers work with a CIS, how usable are these cloud APIs, and how well do developers understand the non-deterministic and stochastic nature of a services backed by machine-learnt models?

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 low-risk photo detection application for his friends and family; and (ii) a high-risk cancer Clinical Decision Support System (CDSS) that uses patient scans to recommend to surgeons if the patient should be sent to surgery.

Motivating Scenario I: Tom's *PhotoSharer* App

Tom wants to develop a social media photo-sharing app on iOS and Android, *PhotoSharer*, that analyses photos taken on smartphones as they are taken. 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 as well as common objects (e.g., all photos with his Border Collie dog, all photos taken on a beach on a sunny day). His app will then share all of this analysed intelligence of his photos with his friends on a social-media-like platform, where his friends can search and view the photos.

Rather than building a computer vision engine from scratch, which would take far too much time and effort, Tom thinks he can achieve this using one of the common cvCISs. 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 cvCIS 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 rightfully expects it to be consistent with the Android Java equivalent `"doggy".substring(0, 2)`. Consistent, here, means two things: (i) that `'dog'` will *always* be returned every time he invokes the method in either language (i.e., a static response); and (ii) that `'dog'` will *always* be returned regardless of what programming language or string library is used, given the deterministic nature of the 'substring' construct (i.e., results for substring are API-agnostic).

Table 1.2: First six responses of image analysis for a Border Collie sent to three computer vision CIS APIs 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

More concretely, in Table 1.2, we illustrate how three cvCIS providers (anonymised) fail to provide similar consistency to that of the substring example above. If Tom uploads a photo of a border collie[3] to three different in August 2018 and January 2019, he would find that each provider is different in both the vocabulary used between them and the confidence values and research-methodology within the *same* provider vary within a matter of five months. But what

[3]The image used for these results can be found at `https://www.akc.org/dog-breeds/border-collie/`.

does a change in confidence mean? The tautological nature of the definition of these changing confidence values (as presented in the API documentation) provides no insight for Tom to understand why there a change in confidence, which we show in Table 1.3, unless he *knows* that the underlying models change with them. Thus, the deterministic problem of a substring compared to the nondeterministic nature of the CIS is not so simple to comprehend unless he is explicity told.

Table 1.3: Tautological definitions of 'confidence' found in the API documentation of three common cvCIS 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)."* [13]
	"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]." [14]
	"The overall score of the result. Range [0, 1]" [14]
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."* [6]
	"The level of confidence the service has in the caption." [7]
Provider C	*"The response shows that the operation detected five research-methodology (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."* [1]
	"[Provider C] also provide[s] a percentage score for how much confidence [Provider C] has in the accuracy of each detected label." [2]

To make an assessment of these APIs, he tries his best to read through the documentation of some cvCIS APIs, but he has no guiding framework to help his choose the right one. Some of the questions that come to mind include:

- What does confidence mean?
- Are these APIs consistent in how they respond?

- Will he need a combination of many cvCIS APIs to solve this task?
- How does he know when there is a defect in the response? How can he report it?
- How does he know what research-methodology the API can pick up, and what research-methodology it can't?
- How does it describe his photos and detect the faces?
- How can he interpret the results if he disagrees with it to help improve his app?
- Does he understand that the API uses a machine learnt model? Does he know what a ML model even is?
- If so, does he know when the models update? What is the release cycle?

Dazzled by this, he does some brief reading on Wikipedia but is confused by the immense technical detail to take in. He would like some form of guiding framework to assist his and in software engineering terms aligned to his background.

Although Tom generally anticipates some imperfections, he has no prior benchmark to guide him on what to expect. He understands that the app is not always going to be perfect: perhaps a few photos of his dog may be missed because the dog is in the background and not the foreground, or his friends can't find the photos of their recent trip to the beach because it wasn't sunny enough for the beach to be recognised. These imperfections appear to be low-risk, but may become socially awkward when in use; for instance, if some of Tom's friends have low self-esteem and use the app, they may be sensitive to being misidentified or even mislabelled. Privacy issues also come into play especially if certain friends have only 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, then Tom's partner's privacy is at risk.

Motivating Scenario II: Cancer Detection CDSS

Recent works 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., [144, 98, 79]), 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. Some studies have suggested that practitioner over-reliance may erode independent decision-making [116, 58]; therefore the risks in developing CDSSs powered by intelligent services become paramount.

In Figure 1.4 we present a context diagram for a fictional CDSS named *CancerAssist*. CancerAssist is used by a team of busy pathologists who review patient lymph node scans and discuss and recommend, on consensus, if the patient should or should not be sent to surgery. When consensus is made, the lead pathologist enters the verdict into CancerAssist—running passively in the background—to ensure no oversight has been made in the team's discussions. When a conflict exists between the team's verdict and CancerAssist's verdict, the system produces the scan with regions of interest it thinks the team should review. Where the team override the output of CancerAssist, this helps to reinforce CancerAssist's internal model as a Human-in-the-loop (HITL) learning process.

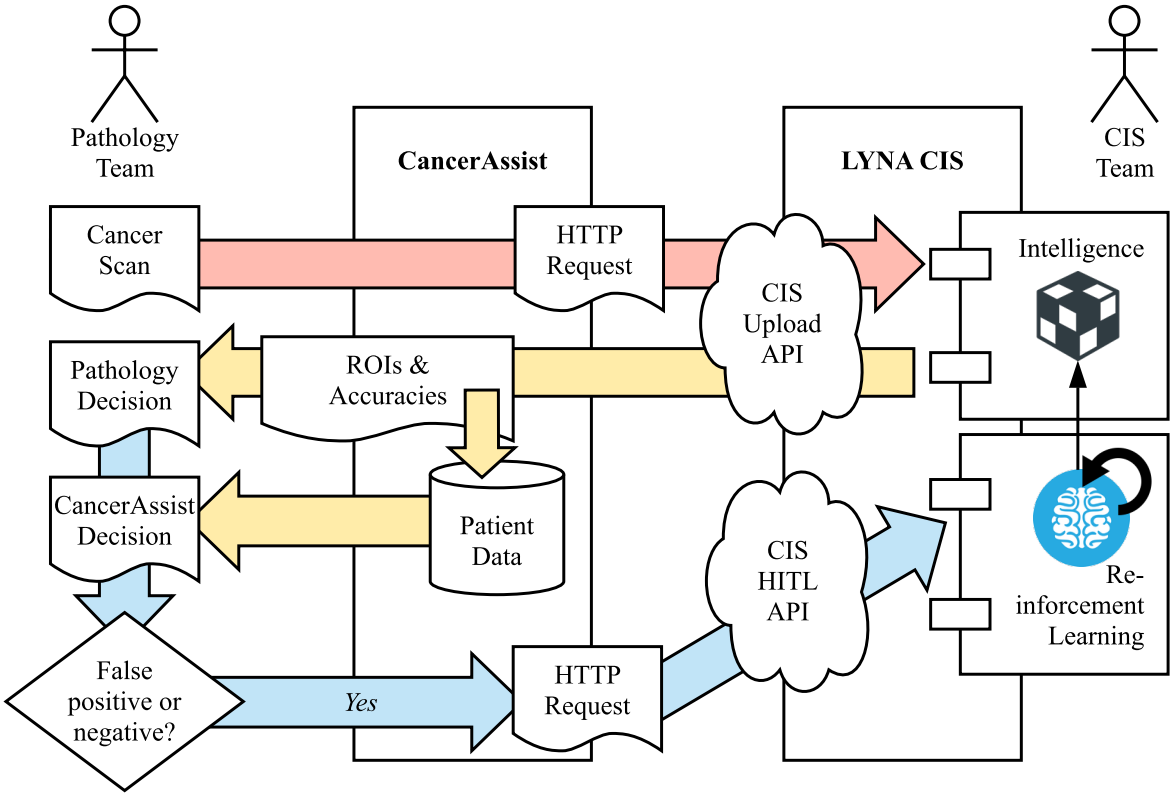


Figure 1.4: CancerAssist Context Diagram. ***Key:*** *Red Arrows = Scan Input; Yellow Arrows = Decision Output; Blue Arrows = HITL Feedback Input.*

Powering CancerAssist is Google AI's Lymph Node Assistant (LYNA) [144], a CNN based on the Inception-v3 model [221, 132]. To provide intelligence to CancerAssist, LYNA is hosted on a CIS, and thus the developers of CancerAssist call the relevant CIS API endpoints, in conjunction with extra information such as patient data and medical history, to produce the verdict. In the case of a positive verdict, the relevant ROIs CancerAssist has found are highlighted 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 CIS. As a result, they are unaware when updates to the model occur, nor do they know what training data they could provide to test their own 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 all the ontology tests that need to be assessed 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 CIS. The ramifications of not being able to test such a system and putting it out into production may prove fatal to patients.

Several questions in the production of CancerAssist and its use of a CIS may come into mind:

- When is the model updated and how do the CIS team communicate that the model is updated?
- What benchmark test set of data do I use to ensure that the changed model doesn't affect other results?
- How do we know that the assumptions made by the CIS team in training the model are correct?

Thus, it may be the case the improved documentation to communicate with the CIS and additional metadata is needed in the response object may prove useful. Such claims are further expanded upon in the following section.

1.2 Research Outcomes

In this work, we present a framework to improve the documentation quality of Computer Vision Cloud Intelligence Services (cvCISs) and their APIs. We demonstrate that developers currently lack the understanding of how these services function and our framework mitigates this by presenting a solution to improve the documentation quality of the APIs and improve the existing techniques used to integrate these services into developer's end-applications.

The goals of this study aim to provide a snapshot of current developer best practices towards the usage of CISs to provide a guiding framework and recommendations for software developers and CISs providers alike. Our anchoring perspective is software quality—specifically, validation and verification—within such systems and what best practices within the field of software engineering can be applied to assist in consumption of CISs. Based on the motivating case studies in Section 1.1, we articulate three Research Hypotheses (RH1–3) below and seven Research Questions (RQs) based on both empirical and non-empirical software engineering

methodology [207, 208].

RH1: ***Existing CISs present insufficient API documentation for general use.***

Research Hypothesis API documentation of intelligent services are inadequate and insufficient given the disparity of mindsets between the application developers and CIS providers. Chiefly, application developers have limited general understanding of the 'magic' that occurs behind these probabilistic 'intelligent' APIs. We do not know what key aspects of the documentation matter to them, nor what they do or do not understand of the existing documentation.

Research Goal To improve the effectiveness of the documentation in existing CIS providers, specifically of cvCIS APIs.

Research Questions

RQ1.1. What practices are in use for intelligent services' API documentation?

RQ1.2. How do developers currently understand and interpret the documentation given a lack of formal training in artificial intelligence? That is, what do they understand and not understand, and what key aspects of the API documentation matter do developers as they see it?

RQ1.3. What additional information or attributes would developers prefer to be included in the API documentation?

Research Contribution An intelligent service API documentation quality assessment framework to evaluate how well the service has been documented for software engineers to use.

RH2: ***Existing CISs present insufficient metadata for context-specificity.***

Research Hypothesis Intelligent service APIs respond with insufficient information for developers to operationalise the service into a business-driven application and, thus, additional metadata is needed to assist developers. Such metadata is likely to be needed as part of the response objects of the API.

Research Goal To improve the quality of *context-specific response data* from the API endpoints of intelligent services.

RH2: ***Existing CISs present insufficient metadata for context-specificity.*** **(cont)**

Research Questions

RQ2.1. What are current problems due to lack of return metadata?

RQ2.2. What additional metadata do developers desire to achieve implementing context-specific applications?

Research Contributions A list of metadata key-value-pairs that assist developers in using these APIs during the development of software that consume these services. In essence, improvements to the framework of Research Outcome 1: "*An intelligent service API documentation* and metadata *quality assessment framework*".

RH3: ***RH1 and RH2 improve quality, productivity or developer informativeness.***

Research Hypothesis The implication of hypotheses 1 and 2 suggest that improving both the documentation and providing further metadata will improve product quality (internal or external), and/or developer productivity and/or developer education in developing software with intelligent components.

Research Goal To confirm if improvements to API documentation and response metadata are reflected as improvements to product quality, developer productivity and/or developer education.

Research Questions

RQ3.1. Does an improvement of documentation or metadata correlate to an improvement in software quality, developer productivity and/or developer informativeness?

RQ3.2. With respect to RQ3.1, the three aspects are explored:

(a) Does the improvement cause increased product quality, as measured through improved external quality metrics?

(b) Does the improvement cause increased developer productivity, as measured through improved internal quality metrics?

(c) Does the improvement cause increased developer informativeness or increased confidence in developing CIS-powered applications?

►

RH3: ***RH1 and RH2 improve quality, productivity or developer informativeness.*** **(cont)**

Research Contribution A concrete sample solution or framework that improves such metrics, thereby confirming that our documentation and metadata quality assessment framework improves these facets.

Ultimately, we seek to understand the conceptual understanding of software engineers who operationalise stochastic and probabilistic systems, and furthermore understand knowledge representation with these systems' API documentation. Our motivation is to provide insight into current practices and compare the best practices with actual practise. We strive for this to provide developers with a guiding framework on how to best operationalise these systems via the form of some checklist or tool they can use to ensure optimal software quality.

It is anticipated that the findings from this study in the cvCISs space will be generalisable to other areas, such as time-series information, natural language processing and others.

Chapter 2

Background

In Chapter 1, we defined a common set of (artificial) intelligence-based cloud services that we label Cloud Intelligence Services (CISs). Specifically, we scope the primary body of this study's work on Computer Vision Cloud Intelligence Services (cvCISs) (e.g., Google Cloud Vision [15], AWS Rekognition [3], Azure Computer Vision [8], Watson Visual Recognition [16] etc.). We claim developers have a distinctly deterministic mindset (2 + 2 *always* equals 4) whereas a CIS's 'intelligence' component (a black box) may return 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 mindset mismatch have on the developer's approach towards building probabilistic software? What can we learn from common software engineering practices (e.g., [180, 213]) that apply to resolve this mismatch and thereby improve quality, such as Verification & Validation (V&V)? Chiefly, we anchor this question around three lenses of software engineering: creating a CIS, using a CIS, and the nature of CISs themselves.

Our chief concern lies with interaction and integration between CIS providers and consumers, the nature of applications built using a CIS, 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 CIS.** We investigate the internal quality attributes of creating a CIS from the CIS *provider's* perspective. That is, we ask if existing verification techniques are sufficient enough to ensure that the CIS being developed actually satisfies the CIS consumer's needs and if the internal perspective of creating the system with a non-deterministic mindset clashes with the outside perspective (i.e., pillar 2).
2. **The usage of the CIS.** We investigate the external quality attributes of using a CIS from the CIS *consumer's* perspective. That is, we ask if existing validation techniques are sufficient enough to ensure that the end-users can actually use a CIS to build their

software in the ways they expect the CIS to work.

3. **The nature of a CIS.** We investigate what standard software engineering practices apply when developing non-deterministic 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.

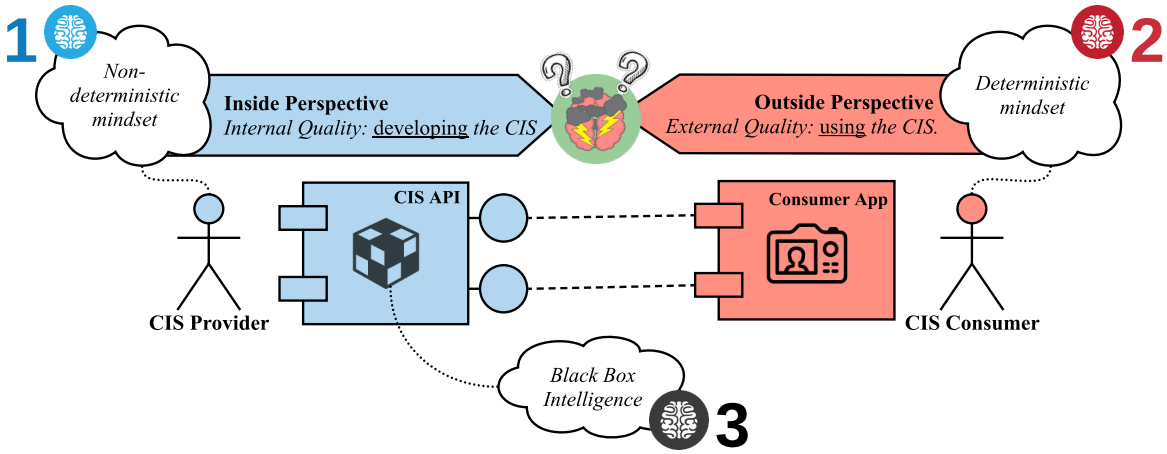


Figure 2.1: The three pillars by which we anchor the background: (1) developing a CIS with a non-deterministic mindset by the CIS provider; (2) the use of a CIS with a deterministic mindset by the CIS consumer; (3) the nature of a CIS itself.

Does a clash of deterministic consumer mindsets who use a CIS and the non-deterministic 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 core principles due to such mindset mismatch from the anchoring perspective of software quality, particularly around V&V.

2.1 Software Quality

> *Quality... you know what it is, yet you don't know what it is.*
>
> Robert Pirsig, 1974 [179]

The philosophical viewpoint of 'quality' remains highly debated and there are multiple facets to perceive this complex concept [93]. 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 [112]. 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" [111].

Using this sentence, what characteristics exist for non-deterministic CISs like that of a cvCIS? 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' [94, 65], 'meeting or exceeding customer expectation' [170], or 'fitness for use' [121]—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 [180] adapted the manufacturing-oriented view of quality from [41] 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 CIS, however, are any of the above actually guaranteed? Given that the core of a system built using on top of a CIS 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 [177] on his works on reliability. A high-school student sat a standardised test that was sent to 350,0000 students [222]. 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 an poor question and failing to ensure quality standards, in the phrases Boehm [44] coined.

This story describes the issues with the cost of quality [43] and the importance of V&V: just as the poorly written exam question had such a high toll the 45,000 unlucky students, so does poorly written software in production. As summarised by Pressman [180], data sourced from Cigital Inc. [61] 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 [224].

Formally, we refer to the IEEE Standard Glossary of Software Engineering Terminology [109] 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 a CIS, 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 CIS. Poor verification in the *internal quality* of the CIS will entail poor process standards, such as poor definitions and terminology used, support tooling and description of documentations [213]. Though it is commonplace for providers to have a 'ship-first-fix-later' mentality of 'good-enough' software [228], 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. Various studies have considered V&V in the context of web services on the cloud [159, 161, 86, 101, 54, 53, 241, 200], though few have recently considered how adding 'intelligence' to these services affects existing proposed frameworks and solutions. For a cvCIS, 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 CIS 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?

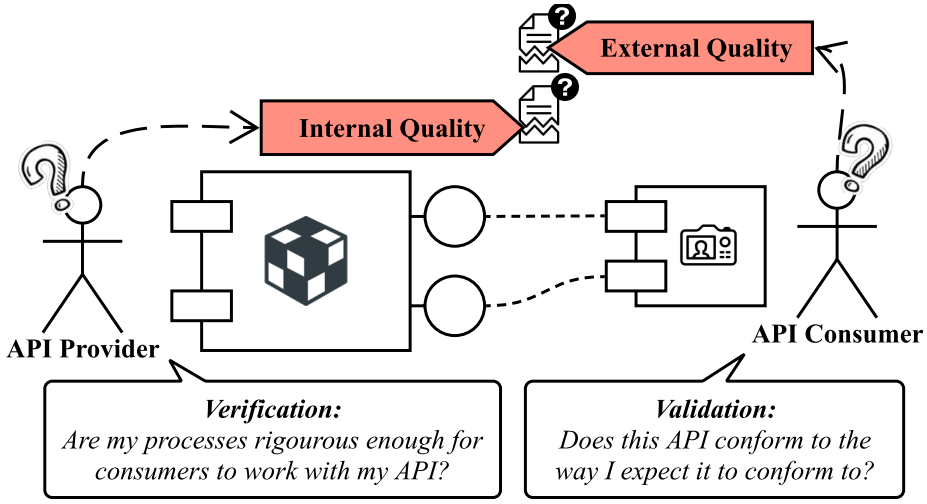


Figure 2.2: The 'leakage' of internal quality into the API consumer's product and external quality imposing on the API provider.

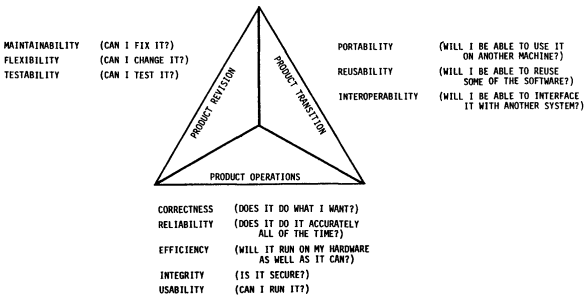
Therefore, just as the test answers with were both correct and incorrect at the same time, so is the same with CISs returning a probabilistic result: no result is certain. While V&V has been investigated in the area of mathematical and earth sciences for numerical probabilistic models and natural systems [166, 199], 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 the current verification approaches and tools do 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 clearly 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

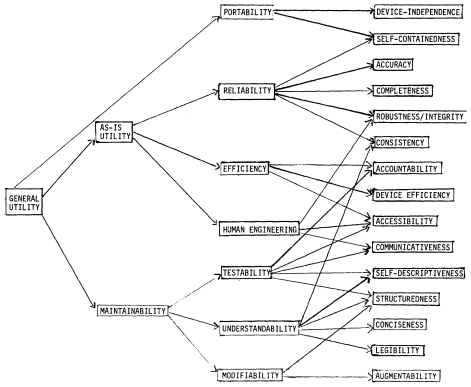
data was X), how can we achieve similar outputs when the system is not non-deterministic? A key problem with the probabilistic mindset is that once a model is 'fixed' by retraining it, while one data-point may be fixed, others may now have been effected, thereby not ensuring 100% validation. Thus, due to the unpredictable and blurry nature of probabilistic systems, V&V must be re-thought out extensively.

2.1.2 Quality Attributes and Models

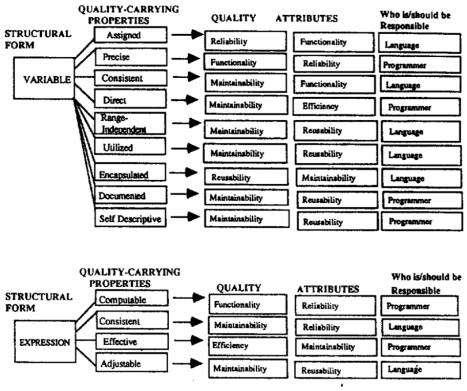
Similarly, quality models are used to capture internal and external quality attributes via measurable metrics. Is a similar issue reflected from that of V&V due to nondeterministic systems? As there is no 'one' definition of quality, there have been differing perspectives with literature placing varying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



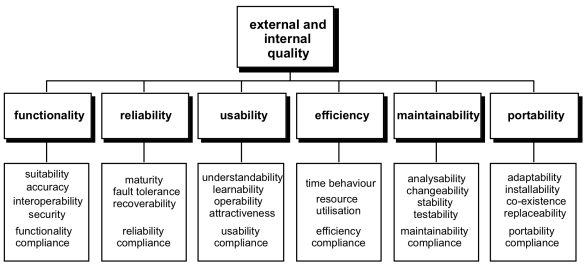
(a) McCall's quality software factors (1977) [149].



(b) Bohem's software quality characteristics tree (1978) [45].



(c) Dromey's quality-carrying properties and programming languages (1995) [77].



(d) ISO/IEC software product evaluation characteristics (1999) [113].

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

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 [198]. Rubey and Hartwick's 1968 study introduced the phrase 'attributes' as a "prose expres-

sion of the particular quality of desired software" (as worded by Boehm et al. [45]) and 'metrics' as mathematical parameters on a scale of 0 to 100. Early attempts to categorise wider factors under a framework was proposed by McCall, Richards, and Walters in the late 1970s [149, 57]. This model described quality from the three perspectives of product revision (*how can we keep the system operational?*), transition (*how can we migrate the system as needed?*) and operation (*how effective is the system at achieving its tasks?*) (Figure 2.3a). The model also introduced 11 attributes alongside numerous direct and indirect measures to help quantify quality. This model was further developed by Boehm et al. [45] who independently developed a model resembling McCall's, starting from an initial set of 11 software characteristics similar to that of McCall's but then diving deeper by defining 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 [77] defined a set of quality-carrying properties with structural forms associated to specific programming languages and conventions (Figure 2.3c). The model also supported quality defect identification and proposed an improved auditing method to automate defect detection for code editors in IDEs. As the need for quality models became prevalent, the International Organization for Standardization standardised software quality under ISO/IEC-9126 [113] (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 [110], 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 [26].

Of all the models described, there is one quality attribute that relates most with our narrative of CIS quality: reliability. The definition of reliability is largely the same among all quality models:

McCall et al. Extent to which a program can be expected to perform its intended function with required precision [150].

Boehm et al. Code possesses the characteristic *reliability* to the extent that it can be expected to perform its intended functions satisfactorily [45].

Dromey Functionality implies reliability. The reliability of software is therefore largely dependent on the same properties as functionality, that is, the correctness properties of a program [77].

ISO/IEC-9126 The capability of the software product to maintain a specified level of per-

formance when used under specified conditions [113].

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 a CIS 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 CIS reliability; a cvCIS 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.

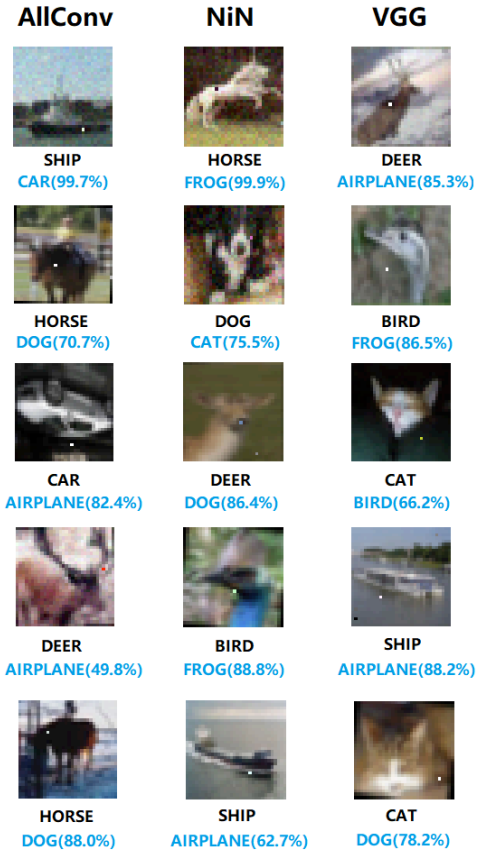
2.1.3 Reliability in Computer Vision

Testing computer vision deep-learning reliability is an area explored typically through the use of adversarial examples [220]. These input examples are where 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 [104]. Rosenfeld et al. [196] illustrated that inserting synthetic foreign objects to input images (e.g., a cartoon elephant) can completely alter classification output. Wang et al. [231] 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. [214] 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. [82] recently showed similar results that made a CNN interpret a stop road-sign (with mimiccid 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 [133, 81], "the real world may be adversarial enough" [157] to fool such software.

(a) Adding 10% impulse noise to an image of a teapot changes Google Cloud Vision's label from *teapot* (above) to *biology* (below) [104].



(b) One-pixel attacks applied to three NN: AllConv, NiN and VGG [214].

(c) Adversarial examples to trick face recognition from the source to target images [231].

Figure 2.4: Sample adversarial examples.

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 a CIS are treated as though they are nondeterministic; Chapter 2 introduces CISs as essentially black-box behaviour that can change over time. As such, we adopt the nondeterministic behaviour that they present.

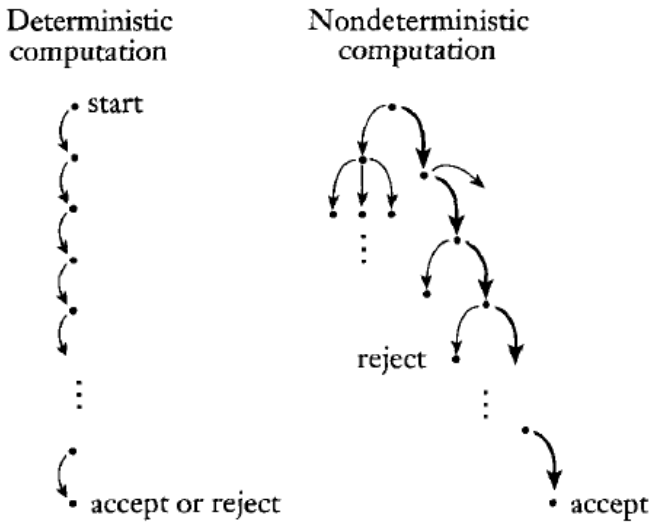


Figure 2.5: A deterministic system (left) always returns the same result in the same amount of steps. A nondeterministic system does not guarantee the same outcome, even with the same input data. Source: [85].

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 [182] and Michie [154]), and although there has since been a significant body of work in the area [210, 32, 185, 51, 197, 142, 46, 120, 31, 92, 68, 227, 39, 83, 140, 148, 173, 229], it is evident that 'accuracy' or model 'confidence' is still used as a primary criterion for AI evaluation [106, 115, 212]. 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 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" [88], a problem commonly referred to as the *datashift* problem [217]. Analogously, Freitas [88] 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 very 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.*** [88]

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 [142]), what is known is (i) there exists a critical trade-off between accuracy and interpretability [87, 119, 124, 96, 73, 243], and (ii) a single quantifiable value cannot satisfy the subjective needs of end-users [88]. As ever-growing domains ML become widespread[1], 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 [55, 125, 107]), there is often a mismatch between the formal objectives of the model (e.g., to minimise error) and complex real-world goals, where many other considerations (such as the human factors and cognitive science behind explanations[2]) are not realised: model optimisation is only worthwhile if they "actually solve the original [human-centred] task of providing explanation" [160] to end-users. **Therefore, when human-decision makers must be interpretable themselves [188], 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. [76] discuss when explanations are not provided from a legal stance—for instance, those affected by algorithmic-based decisions have a 'right to explanation'

[1] In areas such as medicine [38, 137, 174, 187, 245, 227, 120, 80, 240, 116, 51], bioinformatics [89, 219, 123, 72, 117], finance [32, 107, 70] and customer analytics [229, 140].

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

[95, 230] under the European Union's GDPR[3]. But, explanations are not the only way to ensure AI accountability: theoretical guarantees (mathematical proofs) or statistical evidence can also serve as guarantees [76], however, in terms of explanations, what form they take and how they are proven correct are still open questions [142].

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' [151] 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 [205] applies, just as others have done with similar issues in the Software Engineer (SE) realm [156, 235] (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 [76] and thusly 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.

2.2.3 Mechanics of Model Interpretation

How do we interpret models? Methods for developing interpretation models include: decision trees [49, 99, 63, 181, 193], decision tables [140, 33] and decision sets [135, 160]; input gradients, gradient vectors or sensitivity analysis [203, 185, 138, 197, 32]; exemplars [126, 90];

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

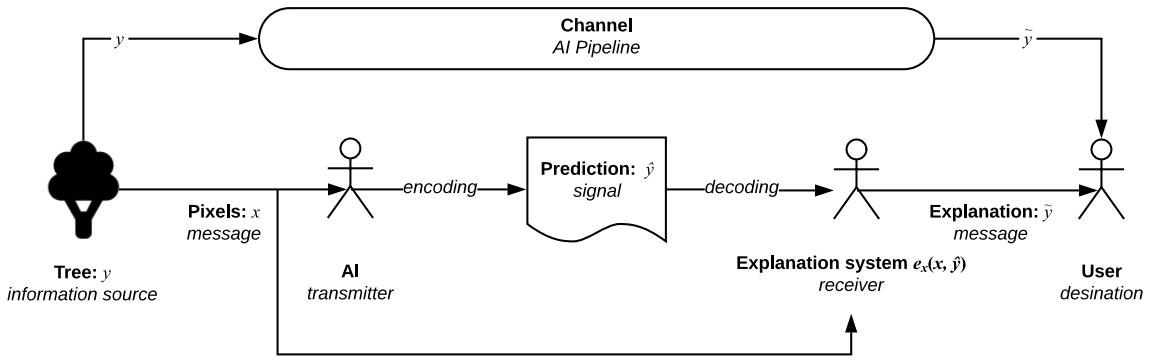


Figure 2.6: Theory of AI communication from information source, y, to intended user as explanations $\tilde{y}$.

generalised additive models [55]; classification (*if-then*) rules [226, 47, 62, 168, 237] and falling rule lists [210]; nearest neighbours [148, 204, 218, 234, 244] and Naïve Bayes analysis [38, 137, 131, 245, 153, 91, 59, 102].

Several cross-domain studies have assessed the interpretability of these techniques against end-users, measuring response time, accuracy in model response and user confidence [107, 100, 27, 215, 201, 89, 148, 229], although it is generally agreed that decision rules and decision tables provide the most interpretation in non-linear models such as SVMs or NNs [89, 148, 229]. For an extensive survey of the benefits and fallbacks of these techniques, we refer to Freitas [88], Doshi-Velez et al. [76] and Doshi-Velez and Kim [75].

2.3 Application Programming Interfaces

Application Programming Interfaces (APIs) are the interface between a developer needs and the software components at their disposal [29] by abstracting the underlying component behind a subroutine, protocol or specific tool. Therefore, is 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 a CIS) is therefore directly related to the quality the API offers [130].

Good APIs are known to be intuitive and require less documentation browsing [178], 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 [103]) 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 various 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).

2.3.1 The Development, Documentation and Usage of Web APIs

The development of web APIs (commonly referred to as a *web service*) and web APIs 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 [195]. This framework used the synchronous communication paradigm Remote Procedure Calls (RPCs) first introduced by Nelson [162] that allows procedures to be called in an remote address space as if it were local. Its communication paradigm, DCE/RPC [165], 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, a 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 over HTTP (and thus the Web) encoded using XML (instead of octet streams [165]). 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 (WS) applications, a realisation of the Service-Oriented Architecture (SOA) [56] 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 (SOA) whereby the consumer and provider agree upon a set level of service, which in some cases are legally binding [37]. 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 [108, 233]) and these are included within SOAP headers; thus, QoS aspects are independent from the transport layer and instead exist at the application layer [172]. 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

Figure 2.7: Worldwide search interest for SOAP (blue) and REST (red) since 2004. Source: [5]

drawback came about the mid-2000s [246, 172] 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 2.1 and 2.2).

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 [172]. That is, the HTTP is considered as a transport protocol solely. In 2000, Fielding [84] 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 [40].
- **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 2.1 and 2.2 but in a RESTful architecture (Listings 2.3 and 2.4) and it is clear why this style has grown more popular with developers (as we highlight in Figure 2.7). 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) [146]). Therefore, no RESTful service uses a standardised response document or invocation syntax. While there are proposals, such as WADL [97], RAML[4], API Blueprint[5], and the OpenAPI[6] specification (initially based on Swagger[7]), there is still no consensus as there was for SOAP and convergence of these IDLs is still underway.

Listing 2.1: A SOAP HTTP POST consumer request to retrieve customer record #43456 from a web service provider. Source: [35].

```
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 2.2: The SOAP HTTP service provider response for Listing 2.1. Source: [35].

```
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>
```

[4] https://raml.org last accessed 25 January 2019.
[5] https://apiblueprint.org last accessed 25 January 2019.
[6] https://www.openapis.org last accessed 25 January 2019.
[7] https://swagger.io last accessed 25 January 2019.

```
    </m:GetCustomerResponse>
  </env:Body>
</env:Envelope>
```

Listing 2.3: An equivalent HTTP consumer request to that of Listing 2.1, but using REST. Source: [35].

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

Listing 2.4: The REST HTTP service provider response for Listing 2.3. Source: [35].

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

{"Customer": "Foobar Quux, inc"}
```

2.3.2 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 machine learning techniques in computer vision cannot effectively formulate queries to help bridge those gaps in their understanding to figure out more about the cvCIS 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 [225]. 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 [158, 191, 74, 48] though these studies have not effectively communicated *why* these artefacts are important. What makes the developer *conceptually understand* these artefacts?

Robillard and Deline [191] 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 [190]. 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.* [191]

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*" [164]. This thereby reiterates the conceptual understanding of an API as paramount.

A later study by Ko and Riche [129] 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 CIS 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 CIS 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. Our proposal is to perform similar survey research (see Chapter 3) in the search for further insight into the developer's approach toward existing CIS APIs.

Chapter 3

Research Methodology

Investigating software engineering practices is oft 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 [78]. 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 1.2) anchored under the context of an existing 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. [78], Wohlin and Aurum [238], Wohlin et al. [239] and Shaw [206].

3.1 Research Questions Revisited

In Section 1.2, we introduce three hypothesis of this study (RH1–RH3), namely: (i) existing CIS APIs are poorly documented for general use (RH1); (ii) existing CIS APIs do not provide sufficient metadata when used in context-specific use cases (RH2); and (iii) the combination of improving documentation and metadata will ultimately improve one of software quality, developer productivity and/or developer understanding (RH3).

To discuss our research strategy, we revisit our research questions through the classification technique discussed by Easterbrook et al. [78], a technique originally proposed in the field of psychology by Meltzoff [152] but adapted to software engineering. Our research study

involves a mix of five *knowledge questions*, that focus on existing practices and the ways in which they work, and two *design questions*, that that focuses on designing better ways to approach software engineering tasks [208]. Both classes of questions are respectively concerned with empirical and non-empirical software engineering that, in practice, are best combined in long-term software engineering research studies (such as this one) as they assist in tackling the investigation of a specific problem, approaches to solve that problem and finding what solutions work best [236].

3.1.1 Knowledge Questions

In total, five knowledge questions are posed in this study to help us understand the way developers currently interact and work with a CIS API; two exploratory, one base-rate, and two relationship and causality questions.

We begin by formulating two *exploratory questions* to attempt to better understand the phenomena of poor API documentation and metadata; both RQ1.1 and RQ2.1 respectively describe and classify what practices are in use for existing CIS API documentation and what problems currently exist when no metadata is returned. Answering these two 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 an additional *base-rate question* that helps provide a basis to confirm that the phenomena occurring is normal (or unusual) behaviour by investigating the patterns of phenomena's occurrence. RQ1.2 is a descriptive-process question to help us understand how the developer currently understands existing CIS API documentation, given their 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.

Lastly, we investigate the relationship between the improved documentation and improvements to other aspects of the software development process. Chiefly, RQ3.1 is concerned with whether any improvements to metadata or documentation correlate to improvements in software quality, developer productivity, or developer education (and is a *relationship establishment question*). If we establish such a relationship, we refine the question and investigate the specific causes using three *causality questions* defined under RQ3.2, namely by associating three classes of measurable metrics (internal quality metrics, external quality metrics, developer education insight metrics) to the improved documentation.

3.1.2 Design Questions

RQ1.3 and RQ2.2 are both *design questions*; they are concerned with ways in which we can improve a CIS by investigating what additional attributes are needed in both the documentation and metadata that assist developers to achieve their goals. They are not classified as knowledge questions as we investigate what *will be* and not *what is*. By understanding the process by which developers desire additional attributes of metadata and documentation, we can help shape improvements to the existing design of a CIS.

3.2 Philosophical Stances

Philosophical stances guide the researcher's action by fortifying what constitutes 'valid truth' against a fundamental set of core beliefs [189]. In software engineering, four dominant philosophical stances are commonly characterised [64, 176]: 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 quite 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 [128]. 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 [52]. 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" [78], and this study utilises such an approach to shift the mindset of CIS 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 Design

Research methods are "a set of organising principles around which empirical data is collection and analysed" [78]. Creswell and Creswell [64] suggest 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 [209]. The mixed-methods approach combines five classes of field study methods (or empirical strategies/studies) most relevant in empirical software engineering research [78, 239, 122]: 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 [118] as it best compensates for weaknesses that exist in all research methods, and employs the best strengths of others.

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. [78].

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 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 several clearly defined hypotheses (RH1–RH3), 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 few 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.

Case Studies Case studies investigate phenomena in their real-life context and are well-suited when the boundary between context and phenomena is unknown [242]. 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, which we specifically relate back to RH2 (RQ2.1 and RQ2.2) in exploring whether the context of an application using a CIS requires the CIS context-specific or of context-agnostic. They also lend themselves to purposive sampling rather than random sampling, and thus we can selective choose cases that benefit the research goal of RH2 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 most problematic.

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 CIS APIs, we can use survey research to assist in answering our exploratory and base-rate research questions under RH1 and RH2 (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. However, with direct survey research techniques, low response rates may prove challenging, especially if no inducements can be offered for participation.

Ethnographies Ethnographies investigates the understanding of social interaction within community through field observation [192]. 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 few 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.

Action Research Action researchers simultaneously solve real-world problems while studying the experience of solving the problem [67] 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 cvCISs; thus, engaging action research as a primary method throughout the mixed-methods approach used in this research.

3.3.2 Review of Data Collection Techniques for Field Studies

Singer et al. developed a taxonomy [209, 139] 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 Figure 3.1.

3.4 Proposed Experiments

This section discusses two proposed experiments that we conduct in this study. For each experiment, we describe an overview of the experiment grounded known methods and techniques (Sections 3.3.1 and 3.3.2), our approach to analysing the data, as well as linking the experiment back to a research hypothesis and question (Section 1.2). A high-level overview of the proposed experiments and the major bodies of work they encompass is presented in Figure 3.2.

3.4.1 Experiment I: Develop Initial Framework

Experiment I shapes a context-agnostic approach to understand current usage patterns of CIS APIs and the ways by which developers interpret them. Briefly, this experiment is comprised under two phases of field survey research: (i) repository mining developer discussion forums (i.e., analysis of databases and documentation analysis) to understand what developers currently complain about on these forums and where their mismatch in understanding lies; (ii) conducting unstructured interviews and distributing a questionnaire to gather personal opinion based on individual developer's anecdotal remarks.

Relevance and Motivation

Experiment I aims to better understand the existing mindsets that developers have when approaching to use Computer Vision Cloud Intelligence Services (cvCISs). This work therefore ties in to RH1; by understanding the developer mindset in how they interpret cvCIS APIs, we are better informed to produce a framework that increases the effectiveness of the documentation of those existing cvCIS providers.

Figure 3.1: Questions asked by software engineering researchers (column 2) that can be answered by field study techniques. (From [209].)

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 modeling	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.

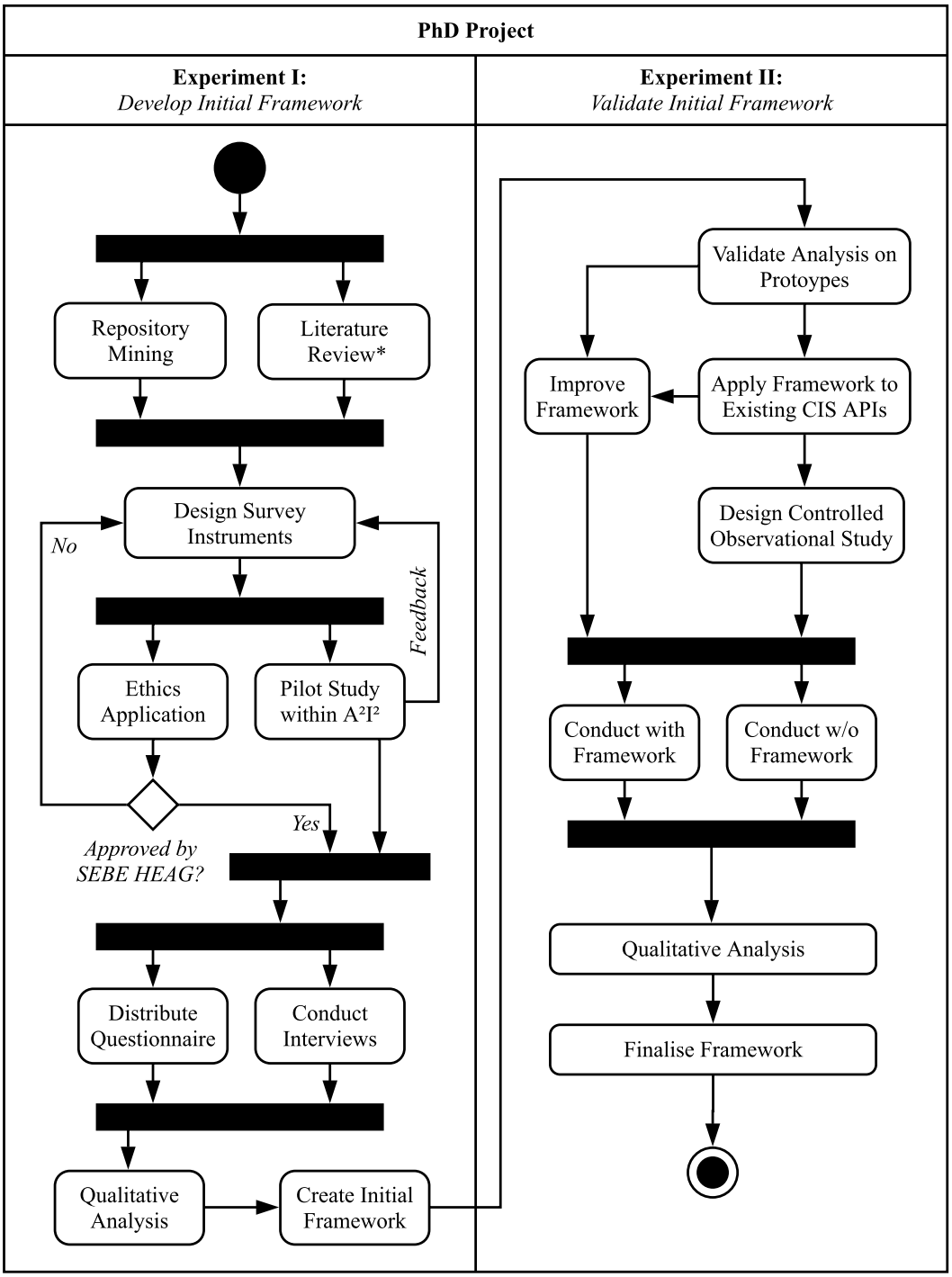


Figure 3.2: High-level activity diagram of the proposed experiments in this study.

RH1 postulates that the software engineering community do not fully understand the 'magic' behind CIS APIs. As described in Section 1.2, they face a gap in their understanding around the underlying architecture of pre-built, machine learnt APIs (RQ1.2). Software developers are therefore not well supported by the CIS providers, and therefore do not have a consistent set of common best practices when approaching to use these APIs (RQ1.1). It is therefore necessary that CIS providers provide additional information to gap this mismatched

understanding (RQ1.3).

Data Collection & Analysis

Phase 1: Repository Mining Developers typically congregate in search of discourses on issues they face in online forums, such as Stack Overflow and Quora, as well as writing their experiences in personal blogs such as Medium. The simplest of these platforms is Stack Overflow (a sub-community of the Stack Exchange family of targeted communities) that specifically targets developer issues on various using a simple Q&A interface, where developers can discuss technical aspects and general software development topics. Moreover, Stack Overflow is often acknowledged as *the* 'go-to' place for developers to find high-quality code snippets that assist in their problems [216].

Thus, to begin validating CIS API usage and misunderstanding in a generalised context (i.e., context-agnostic to the project at hand), we propose using repository mining on Stack Overflow to help answer our research questions. Specifically, we select Stack Overflow due to its targeted community of developers[1] and the availability of its publicly available dataset released as 'data dumps' on the Stack Exchange Data Explorer[2] and Google BigQuery[3]. Various studies conducted have also used Stack Overflow to mine developer discourse [60, 211, 163, 194, 169, 34, 141, 232, 36, 183, 28, 223].

Due to the enormity of the data produced, we will use qualitative analysis on the questions mined using assistive tools such as NVivo. For this, we will conduct a thematic analysis on the themes of each question mined, the relevance of the question to our research topic, and ensuring strict coding schemes (that reflect our research goals) are adhered to. We refer to Singer et al. [209] and Miles et al. [155] on coding and analysing this qualitative data gathered.

Phase 2: Personal Opinion Surveys We follow the triangulation approach proposed by Jick [118] to corroborate the qualitative data of developers' discussion of Stack Overflow with secondary survey research, thereby validating what people say on Stack Overflow with what is said and done in real life. Kitchenham and Pfleeger [127] provide an introduction on methods used to conduct personal opinion surveys which we adopt as an initial reference in (i) shaping our survey objectives around our research goals, (ii) designing a cross-sectional survey, (iii)

[1] We also acknowledge that there are other targeted software engineering Stack Exchange 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 Stack Overflow's 17 million.

[2] `https://data.stackexchange.com/stackoverflow` last accessed 17 January 2017.

[3] `https://console.cloud.google.com/marketplace/details/stack-exchange/stack-overflow` last accessed 17 January 2017.

developing and evaluating our two survey instruments (consisting of a structured questionnaire and semi-structured interview), (iv) evaluating our instruments, (v) obtaining the data and (vi) analysing the data.

As is good practice in developing questionnaire instruments to evaluate their reliability and validity [143], we evaluate our instrument design by asking several colleagues to critique it via pilot studies within A^2I^2. This assists in identifying any problems with the questionnaire itself and with any issues that may occur with the response rate and follow-up procedures. We follow a similar approach by practicing the interview instrument on several colleagues within A^2I^2.

Findings from the pilot study helps inform us for a widely distributed questionnaire and conducting interviews out in the field, where we recruit external software engineers in industry through the industry contacts of A^2I^2. Ethics approval from the Faculty of Science, Engineering and Built Environment Human Ethics Advisory Group (SEBE HEAG) will be required prior to externally conducting this survey research (see Appendix B). The quantitative (survey) and qualitative (interview) analysis allows us to to shape the research outcome of RH1—an API documentation quality assessment framework—and assists in stabilising our general understanding of how developers use these existing APIs.

3.4.2 Experiment II: Validate Initial Framework

Experiment II extends the *generalised* context of Experiment I by evaluating how the findings of Experiment I translates to context-specific applications. We confirm that the generalised findings are (indeed) genuine by conducting action research in combination with an observational study on software engineers. This experiment is also compromised of: (i) development of several prototypes using CIS APIs of differing contexts; (ii) presenting a solution framework to developers to interpret the improvement of their understanding when using a CIS.

Relevance and Motivation

Experiment II aims to contextualise the findings from Experiment I; that is, if we add *varying contexts* to the applications we write using CIS APIs, what is needed to extend the *context-agnostic* framework developed in Experiment I? This work relates back to RH2; adding context-specific metadata to the endpoints of these APIs, we can highlight what issues exist when such metadata is not present (RQ2.1) and what types of metadata developers seek (RQ2.2).

Moreover, the implication of the first two hypotheses suggest that applying an API documentation and metadata quality assessment framework may have an effect on other aspects

within the software engineering process (RH3). Thus, this experiment also confirms if our framework makes an improvement the areas if software quality, developer productivity and/or developer informativeness (RQ3.1 and RQ3.2).

Data Collection & Analysis

To confirm findings of the method within RH1 is genuine, we shift from reviewing the documentation from a general stance to a specialised (context-specific) stance in the use of these APIs.

This is firstly achieved by using existing CIS APIs to develop several basic 'prototypes', each having differing contexts. The number of prototypes to develop and the use cases they have will be informed by the results of Experiment I, and therefore cannot yet be described at this stage. Our action research in developing the prototypes will help inform any potential gaps that exist in the findings of RH1, especially with regards to context-specifity, and therefore improves the metadata component of our framework (as per the outcome of RH2).

This outcome will also help us design the next stage of the experiment, consisting of a comparative controlled study [202] to capture firsthand behaviours and interactions toward how software engineers approach using a CIS with and without our framework applied. We will provide improved documentation and metadata responses of a set of popular cvCISs that is documented with the additional metadata and whose information is organised using our framework.

We then recruit 20 developers of varying experience (from beginner programmer to principal engineer) to complete five tasks under an observational, comparative controlled study, 10 of which will (a) develop with the *new* framework, and the other 10 will (b) develop with the *as-is/existing* documentation. From this, we compare if the framework makes improvements by capturing metrics and recording the observational sessions for qualitative analysis. We use visual modelling to analyse the qualitative data using matrices [69], maps and networks [155] 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.

3.4.3 Primary Contributions arising from Experiments I and II

Ultimately, we seek to understand the conceptual understanding of software engineers who operationalise stochastic and probabilistic systems, and furthermore understand knowledge representation with these systems' API documentation. Our motivation is to provide insight into current practices and compare the best practices with actual practise. We strive for this to

provide developers with a guiding framework on how to best operationalise these systems via the form of some checklist or tool they can use to ensure optimal software quality.

It is anticipated that the findings from this study in the cvCISs space will be generalisable to other areas, such as time-series information, natural language processing and others.

3.5 Empirical Validity

In Section 3.2, we state that this study primarily adopts a critical theorist stance. Critical theorists assess research quality by the utility of the knowledge gained [78]. Lau [136] established criteria on validating information systems research specifically for action research unifying four dimensions of the research (conceptual foundation, study design, research process, and role expectations) against 22 varying criteria. We also partially adopt constructivism as we attempt to model the developer mindset rich in qualitative data, to which eight strategies identified by Creswell and Creswell [64] cover.

We identify possible threats to internal- (study design), external- (generality of results), and construct-validity (theoretical understanding) in the following sections, and describe how we mitigate these threats.

3.5.1 Threats to Internal Validity

Hawthorne Effect

Observational field techniques involving participants often run a risk producing misaligned results from laboratory versus environmental (practical) conditions. This is commonly known as the Hawthorne effect **[cite:Draper:2004,Robbins:1994]** and careful consideration of this effect must be reflected when designing our controlled observation (Section 3.4.2). We aim to carefully explain the purpose and protocol to research participants, encouraging them to act as much as possible as in their practical conditions. We also encourage the 'think-aloud' to participants protocol to reinforce this. By highlighting the Hawthorne effect to them, we anticipate that participants will be aware of the condition, and therefore avoid doing things that do not reflect real-world action.

Misleading Statements in Interviews

Similarly, threats to the interview survey instrument exist where participants do not often report differences in behaviour from what they actually do in practice [209]. We anticipate that conducting several interviews in a semi-structured manner may assist in following up

with unexpected statements (as opposed to structured interviews) and additionally corroborate findings using Jick's concurrent triangulation method [118] to verify potentially misleading statements from participants with questionnaire results and observation findings.

Participant Observation Accuracy

Conducting participant observations is a skill that requires training. While every effort will be instilled to ensure all relevant observations are noted, it is impossible for a single observer to note every possible interaction that occurs in all observations made. Therefore, it may required to validate the consistency of data collected using rater agreement exercises **[cite:Judd:1991]** and we will likely use a form of recording device (with participant consent) to ensure all information is transcribed correctly in the interview.

Unintended Interviewee Bias

Interviewers should introduce the research by which participants are involved in by describing an expiation of the research being conducted. However, the amount of information described may impact the bias instilled on the interviewee. For example, if the participant does not understand the goals of the study or feel that they are of the 'right target', then it is likely that they may choose not to be involved in the study or give misleading answers. On the other hand, if interviewees are told too much information, then they may filter responses and leave out vital data that the interviewer may be interested in. To mitigate this, varying levels of information will be 'tested' against colleagues to determine the right level of how much information is divulged at the beginning of the interview.

Poor Questionnaire Responses

Unless significant inducements are offered, Singer et al. [209] 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% **[cite:Baruch 1999]**. We observe that low response rates may adversely effect the findings of our survey, typically as software engineers find little time to do them. Tackling this issue can be resolved by carefully designing succinct, unambiguous and well-worded questions that we will verify against our colleagues and within the pilot study in A^2I^2, wherein any adjustments made due to the pilot study due to unexpected poor quality of the questionnaire will be reported and explained. We also adopt research conducted in the field of questionnaire design, such as ensuring all scales are worded with labels **[cite:Krosnick:1990]** or using a summating rating scale **[cite:Spector:1992]** to address a specific topic of interest if people are to make mistakes in their response or answer in different

ways at different times. Similar effects exist to that above where what occurs in reality is not what is reflected in our results; we refer to our concurrent triangulation approach to gap this risk.

3.5.2 Threats to External Validity

Representative Sample Size

Our results must generalise by ensuring a representative subset of the target population is found. If results do not generalise, then all that is found is potentially of little more value than personal anecdote [127]. Therefore, designing a well-defined sample frame to determine which developers we wish to target is empirical. For this, we refer to Kitchenham and Pfleeger [127].

Student Cohorts

External validity is typically undermined when students are recruited in software engineering research, which is common practice [78]. Analytical argument is required to describe why results on students are reflective of results found of developers in industry. Therefore, we anticipate that—through industry contacts at A^2I^2—we will be able to contact developers in industry, thereby minimising our reliance to use students as participants.

Concurrent Triangulation Strategy

A drawback with the concurrent triangulation strategy is that multiple sources of data are concurrently collected within the same time. Collecting and analysing data *sequentially*, instead of concurrently, allows for time to analyse data between studies, thus allowing each analysis to adapt as more emerging results are explored. Easterbrook et al. [78] states that the challenge in this approach is that it may be difficult for researchers to compare results of multiple analyses or resolve contradictions that begin to arise when this performed concurrently. A mitigation strategy, should this occur, would be to seek out further sources of evidence, or even reconduuct a follow-up study if time permits.

3.5.3 Threats to Construct Validity

Developer Informativeness

RH3 describes that if we improve the documentation of CIS APIs, then developers are more informed/educated in what they do. This therefore increases their productivity and the quality of the applications they build. However, the construct of ‘informativeness’ is difficult to

capture with standalone metrics, and using simple quantitative metrics such as time taken to complete a task or lines of code to implement it may not reflect that a developer is more ‘informed’. Therefore, we propose further investigation into understanding how to measure informativeness of software engineers to ensure that this construct validity does not impact our results too greatly.

Chapter 4

Project Status

A project timeline is given in Figure 4.1. The project timeline consists of four phases (one preliminary) and seven milestones:

Phase 0. Early problem investigation. Early investigation into the problem area, exploring potential aspects for research hypotheses to develop more substantially. The outcome is the first two chapters of this report (Milestone 1) and the early stages of a technical report attached in Appendix A.

Phase 1. Develop initial framework. Process of developing initial framework by mining developer forums (Stack Overflow) and designing and conduct our surveys. This maps to Experiment I (see Section 3.4.2). The outcome is an initial context-agnostic CIS API documentation quality assessment framework (Milestone 3) and confirmation of candidature complete (Milestone 2). As ethics approval is required, the current draft Ethics Application is attached in Appendix B.

Phase 2. Validate initial framework. Validating that the framework we develop in Phase 1 correctly reflects the needs of developers by trialing it in controlled observational studies. This maps to Experiment II (Section 3.4.2). The outcome is a framework that has been validated against developers (Milestone 4).

Phase 3. Finalise framework and thesis. Implement any additional findings from the validation of Phase 2 into the framework, thereby finalising the framework (Milestone 5). Original contribution is the framework and therefore the thesis can be submitted (Milestone 6) and reviewed before the study is complete (Milestone 7).

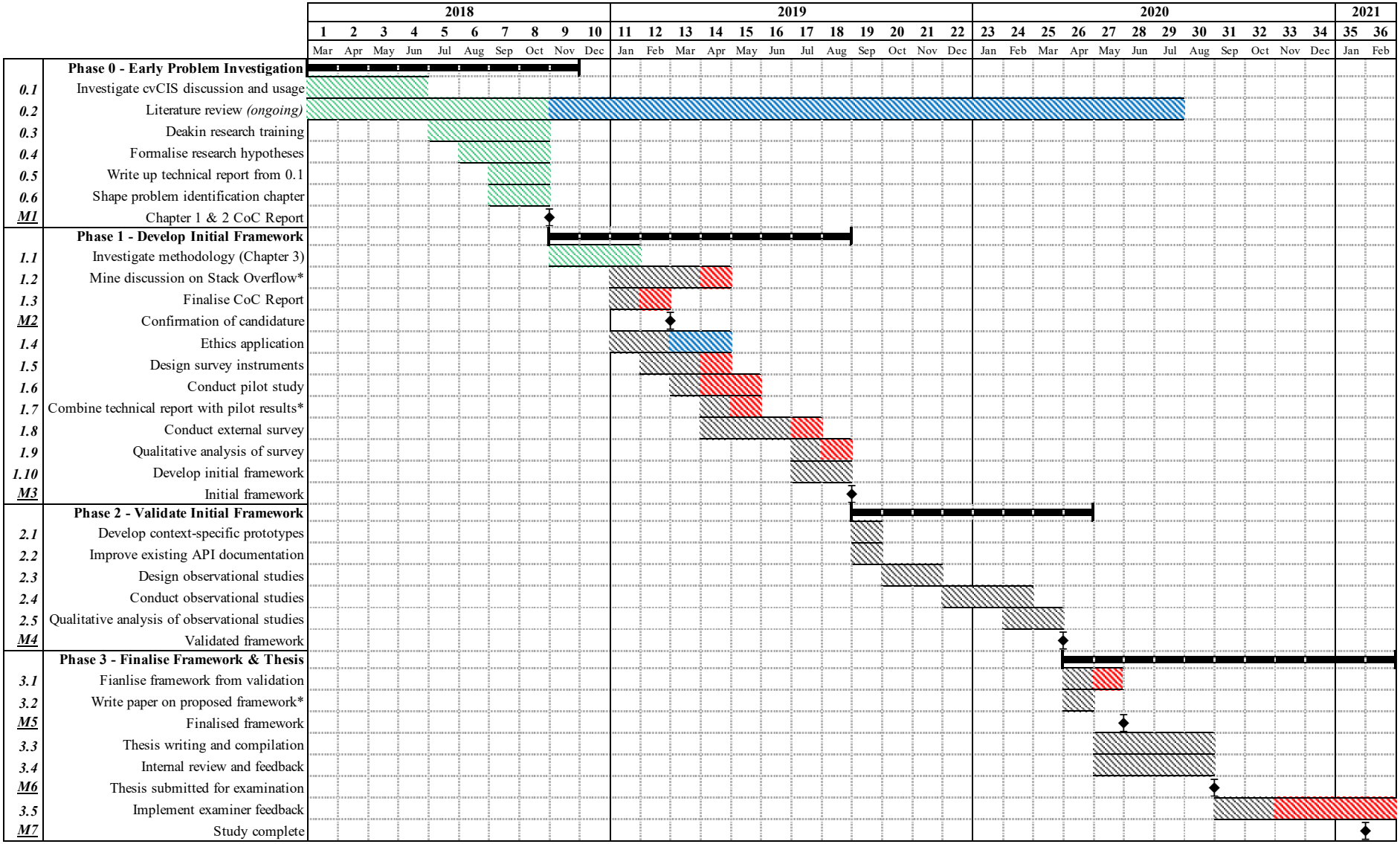


Figure 4.1: Project timeline.

Key: *Green Bar = Completed Task; Grey Bar = Planned Task; Red Bar = Slack Time; Blue Bar = Ongoing Task; Thick Black Line = Phase Duration; Diamond = Milestone; Asterisk = Potential publications.*

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Appendix A

Technical Report Manuscript

Losing trust: Are computer vision APIs are insufficient for developers?

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***Abstract*—Recent advances in computer vision are available as cloud APIs and their accessibility and simplicity is compelling. Multiple vendors now offer such software as a service and developers want to leverage these advances to provide value to end-users. However different services provide different performance and hence there is a need to make an evaluation of disparate services before selection. There currently exists no evaluation framework in assisting developers to make this choice, and the services' existing documentation and usage patterns hide information needed to make informed decisions. We evaluated the responses of three different computer vision cloud APIs over time using a static input dataset, verifying responses against the respective documentation. We found that there are: (1) inconsistencies in the vocabulary labels of these responses; (2) little ontology to describe the relationships between such labels; (3) a lack of definitions in terminologies used to document the APIs; (4) a lack of communication protocols to identify changes in responses over time. We propose several recommendations to both developers and API providers to improve the evaluation guidelines of such APIs.**

I. Introduction

The availability of Machine Learning as a Service (MLaaS) [1] has made AI tooling accessible to software developers and the entry barrier is lowered in both time and skill. Training AI-based computer vision analysers requires manually curating a dataset and writing a deep-learning classifier from scratch; laborious in time and requires machine-learning expertise. Contrast this to an MLaaS-powered computer vision analyser (e.g., [2–11]); the process is abstracted behind an API call, only requiring knowledge on how to use a RESTful architecture **[cite:Restful thesis]**. The ubiquity of MLaaS is exemplified through evermore growing applications that use these APIs: aiding the vision-impaired [12, 13], accounting [14], data analytics [15], and student education [16].

APIs reflect a set of design choices made by their providers. Evaluations of API usability show that developers must be wary of the accuracy and completeness of API documentation [17] written by provders, while providers should consider mismatches between the developer's conceptual knowledge of the API its implementation [18]. It is therefore imperative that developers of MLaSS APIs consider the impact of API usability.

Moreover, developers need to be wary of unintended side effects. Computer vision techniques may involve geometric manipulation or image transformation, or encapsulate deep-learning strategies or stochastic methods.[1] Where the latter is used, these APIs become inherently non-deterministic in nature, but developers are still taught with a deterministic mindset. Simple arithmetic representations (e.g., $2+2=4$) will *always* result in 4; but a multi-layer perceptron neural network performing similar arithmetic representation [19] gives a probability[2] where the target output (exactly 4) and the output inferred (possibly 4) matches as a percentage (or as an error where it does not match). That is, instead of an exact output, there is instead a *stochastic* result: $2+2$ *may* equal 4 with a confidence of n.

Is such information sufficiently conveyed to developers? If MLaaS APIs are to be used in production services, do they follow rigours software engineering practices [20, 21] to communicate and test this? It is agreed that software developed with rigour undergoes quality assessment using a Software Quality Assurance (SQA) framework [22]. Developers, therefore, follow such frameworks to mitigate risk impacting internal and external quality; vital for safety-critical systems. Such quality frameworks advocate best practices for reviews and audits, defect detection and analysis, standardisation of usage-patterns, change logs and usage of consistent vocabulary. Do such practices apply to computer vision APIs?

To our knowledge, few studies have been conducted to evaluate this claim. This study assesses the understanding, documentation, and variability of these APIs by comparing three publicly available computer vision APIs provided by prominent vendors to identify recommendations for improvement. We aide this paper with a motivating example in section II, discussing related work and our methodology in sections III and IV. Our findings are discussed in section V, from which we draw several recommendations to both developers and API providers in section VI.

II. Motivating Example

Consider a software developer named Pam. Pam wants to develop a social media photo-sharing mobile app that analyses her and her friends photos. Pam wants the app to categorise photos into scenes (e.g., day vs. night, landscape vs. indoors),

[1] We observe that Google Cloud Vision, for example, markets itself as using "powerful machine learning models" to perform image analysis.

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

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 with on the beach).

Rather than building a computer vision engine from scratch, Pam thinks she can achieve this using one of APIs A, B or C. However, Pam comes from a typical software engineering background and has insufficient knowledge of key computer vision terminology and no understanding of the processes behind deep-learning. She ultimately believes all are APIs alike and internalises a deterministic mindset of them; when she decides on one of the three APIs, she expects a static result always, just as she expects $2+2$ to always be 4.

To make an assessment of these APIs, she tries her best to read through the documentation of some computer vision APIs, but she has no guiding framework to help her choose the right one. Many questions come to mind:

- What does confidence mean?
- Will she need a combination of many computer vision APIs to solve this task?
- How does she know when there is a defect in the response?
- How does she know what labels the API can pick up, and what labels it can't?
- How does it describe her photos and detect the faces?
- How can she interpret the results if she disagrees with it to help improve her app?

Dazzled by this, she does some brief reading on Wikipedia but is confused by the immense technical detail to take in. She would like some form of guiding framework to assist her.

III. Related Work

If we were to view computer vision software through the lenses of an SQA framework, robustness often features as a quality attribute in myriad software quality models (e.g., [23–28]). Such models attempt to standardise these quality attributes against measurable metrics [29]. (We refer to the well-documented literature evaluating these models [30–33].) It is well-known that software quality exists in the evaluation of the end-product (external quality) and/or the assurances in the development processes (internal quality) [20], and thus we summate AI quality literature from both these viewpoints in the following two subsections.

A. External Quality: Robustness

A majority of recent work investigates the robustness of the deep-learning within computer vision technique implementation, thereby assessing the quality of the end-product. This is typically achieved using adversarial examples [34], 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 [35]. Rosenfeld et al. [36] illustrated that inserting synthetic foreign objects to input images (e.g., a cartoon elephant) can completely alter classification output. Wang et al. [37] 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. [38] 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. [39] recently showed similar results that made a CNN interpret a stop road-sign (with mimiccid graffiti) as a 45mph speed limit sign.

Thus, the state-of-the-art computer vision techniques may not be robust 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 [40, 41], "the real world may be adversarial enough" [42] to fool AI software.

B. Internal Quality: API and Services

From the *developer's* perspective, little has been achieved to assess API quality or assure quality of these computer vision services. APIs are the interface between developers' needs and the software components [43]; therefore, assessing such computer vision services from the quality of their APIs is thereby directly related to the development quality [29]. Good APIs should be intuitive and require less documentation browsing [17], thereby increasing productivity. Conversely, poor APIs that are hard to understand and work with reduce developer productivity, reducing product quality. The consequences of this have shown a higher demand of technical support (as measured in [44]) that, ultimately, causes the maintenance to be far more expensive, a phenomenon widely known in software engineering economics [45–47].

Ko and Riche [18] assessed the importance of a programmer's conceptual understanding of the background behind the task before implementing the task itself. The study demonstrated how developers had little confidence in their own metacognitive judgements to understand and assess the feasibility of using a particular Bluetooth API to implement a task that requires Bluetooth. While code examples helped (as suggested by the early attempts of API usability [29]), they failed to understand the vocabulary and concepts of 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.

Lastly, computer vision services are based on cloud computing fundamentals under a subset of the Platform as a Service (PaaS) model [48]. There has been work in the evaluation of such services in terms of quality attributes [49–54]: these attributes are exposed using Service Level Agreements (SLA) between vendors and customers, and customers denote their demanded Quality of Service (QoS) to ensure the cloud ser-

vices adhere to measurable KPI metrics [55]. Again, however, such metrics are not avaliable in computer vision services.

IV. Method

This study organically evolved by observing phenomena surrounding computer vision API internal quality, chiefly 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 API documentation and structured observations to quantitatively analyse the results over time. This, ultimately, helped us shape four key research questions which this paper addresses:

- **RQ1**. How well do computer vision API providers *conceptually describe* their API documentation in the techniques and terminology?
- **RQ2**. Given RQ1, how are these techniques ant terminologies expressed in the application guidelines they provide?
- **RQ3**. How do responses differ between various API providers given a single source dataset?
- **RQ4**. Given RQ2, how do the responses differ over time?

We conducted two experiments to address these questions against three popular computer vision services: AWS Rekognition [4], Google Cloud Vision [2], Azure Computer Vision [3]. These particular cloud APIs were chosen given the ubiquity of the hosting cloud platforms (AWS, Google Cloud and Azure), although we acknowledge similar services [5–11] also exist. For the remainder of this paper, we (i) refer to the API creator as *providers* and API users (developers) as *consumers* and (ii) de-identify our selected APIs by labelling them as APIs A, B and C but do not reveal mapping to prevent any implicit bias. We describe both experiments below.

A. Experiment I: API Documentation Evaluation

We observed how providers *conceptually* communicate computer vision techniques to consumers by reviewing the documentation in each of the provider's websites. We categorised varying computer vision techniques offered by the three providers and made a union of all overlaps using a consistent vocabulary (Table III). We note that we only use providers' home websites [2–4] as our primary source in order to assess the 'official' API documentation, and not from third party sources such as StackOverflow. From this, we make a qualitative interpretation on (1) the terminologies by which these techniques are communicated (Section V-A1) and (2) the way these terms are used in the guidelines of the APIs (Section V-A2), reviewing disparity between the terms and the suggestions made on their guidelines.

The second aspect to this experiment was to focus on the disparity of the terminology on ML 'confidence' Section V-A3). Therefore, we evaluated how this term is used in SDK and API documentation. In addition to searching through offical provider documentation, we captured any empirical evidence of the developer community having any confusion on mixed terminology by searching StackOverflow and Github issues. Both StackOverflow and GitHub issues were chosen as they provide insight into the discussion within the software engineering community. We made a StackOverflow search using text and tag matching:

```
confidence score accuracy api
  [api] or [image] or [documentation] or
  [google-cloud-vision] or
  [google-cloud-platform] or
  [microsoft-cognitive] or
  [azure-cognitive-services] or
  [amazon-rekognition] or
  [amazon-web-services] or [vision-api]
```

Similarly, we performed a similar match using equivalent GitHub syntax. These searches were conducted on August 16, 2018.

B. Experiment II: API Response Evaluation

⟨ TODO: **JG: need to do more images / get a bigger set of outcomes to compare - is there some 'standard' benchmark for testing image APIs???** ⟩ ⟨ TODO: **AC: @JG yes there is but they are not for testing image APIs; they are typically used for testing the AI.** ⟩

This second experiment involved sending a test image (of a Border Collie[3]) to all three services to evaluate the consistency of the responses between providers. This is highlighted in table I.

To assess evolution risk, we ran a five month experiment (April to August 2018) where we sent 30 images[4] on nine occasions. In total, we made 840 requests with a matching number of responses. For each response, we recorded the timestamp, the description and URL of the source image, the labels the service identified in those images and the accuracy of those labels. A total of 9576 labels and accuracies were identified.

We then performed quantitative analysis on each response by calculating the maximum confidences of each label over the period (that is, to get the labels of each image that were of the highest confidence consistently over the period). We also made note of the confidence changes over time by calculating the delta between the highest confidence value and the lowest confidence value per label, image and service. We selected the top three labels for each image over each service. These are aggregated in table II.

⟨ TODO: **JG: User Evaluation - do experiment with users of the APIs to get feedback to triangulate with the other findings..** ⟩ ⟨ TODO: **AC: @JG; I agree, but would need to get ethics for this to do so.** ⟩

V. Findings

A. Experiment I: API Documentation Evaluation

[3]Image of the Border Collie sourced from: https://www.akc.org/dog-breeds/border-collie/.

[4]For reproducibility, the original photos are available at: https://github.com/alexcu/cognitive-api-confidence-logger/tree/master/images

1) Techniques Analysis: Of all the services provided, we note that API A offers the most computer vision techniques (as tabulated in table III).

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. However, table III shows that localisation technique only exists in API A (in beta); all services provide object 'recognition', whereby a single primary object in labelled in an image. 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.

Thus, the terms 'localisation', 'detection', 'recognition' and 'analysis' are largely disparate for objects versus faces. It can be quite easy for one to make a quick confusion on the terms, thereby miscommunicating conceptual understanding to technical understanding. For example, Pam may easily confuse object 'recognition' as a means to locate the bounding boxes of all different objects in an image, but this intended functionality from the developer only exists under object 'localisation'.

Similarly, we notice similar patterns with object 'tagging' versus versus 'labelling'. API C uses the term 'Detect Labels' for object categorisation, API A uses 'Entity Detection' and API B uses 'Image Tagging': 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. Pam 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 exists in other developer areas (such as Web Development).

2) Safety-Critical Guidelines: Of all three services, API C provides the most extensive advice on using their service for safety-critical applications. As their service is the only one of the three assessed that allows for facial recognition within a collection of faces (see section V-A1), they list several guidelines in how to use their software to ensure quality in the wider usage of the application. These guidelines can be categorised into three risk categories dependent on the type of application using the service:

- **high risk**: for high risk applications (e.g., crime detection), do not to use facial recognition software to make autonomous decisions,
- **medium risk**: for medium risk applications (e.g., building authentication), to ensure a facial similarity match threshold of at least 99%,
- **low risk**: for low risk applications (e.g., finding missing persons), a benefit of using a similarity match threshold lower than 99%.

API A obfuscates restrictions in its legal Terms of Service that developers "will not... use the Services for High Risk Activities[5]... [and] the services [are not guaranteed to be] error-free or interrupted. Neither the software nor the services are designed, manufactured, or intended for high risk activities." **[cite:Link to https://cloud.google.com/terms/]**. API B does not make mention of high risk applications in its documentation.

3) Inconsistency of the term 'confidence': Self-redundancy in the term 'confidence' is tautologic across all three providers. Below, we detail references from the primary sources in addition to secondary sources found in StackOverflow and GitHub issues.

a) API A: API A provides a tautologic definition of 'confidence', and instead uses the term 'score' instead for the same concept. Usage in the how-to documentation [56] describes this as:

> *"Score is the confidence score, which ranges from 0 (no confidence) to 1 (very high confidence)."*

Once again, inspecting the .NET SDK documentation [57] shows a similar definition for 'confidence':

> *"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]."*

Note that the definition of the new 'score' term is, put bluntly, defined as the *"overall score of the result. Range [0, 1]"* [57].

b) API B: API B defines confidence in its how-to guide [58] as:

> *"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."*

Similarly, the Java SDK documentation [59] provides a similar lack of definition:

> *"The level of confidence the service has in the caption."*

c) API C: In the documentation of the `DetectLabels` operation [60] (used to detect 'labels' in an image) the following description is provided for confidence via an example:

> *"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."*

However, a tautologic definition is provided within the "Detecting Objects and Scenes" guide [61] to define what is meant by 'confidence' by a-likening it to a 'percentage score':

[5]Where 'High Risk Activities' is defined as: "the use or failure of the Services could lead to death, personal injury, or environmental damage."

*"[API C] also provide[s] **a percentage score** for how much confidence [API C] has in the accuracy of each detected label."*

Thus, in both these examples, the term 'confidence' is still not well described; what is meant by 'confidence' and interchanging the term 'confidence' with 'percentage score' may be confusing to developers. Investigating this with respect to API C's JavaDoc [62] or SDK documentation [63], the definition of 'confidence' again shows no further insight of the term:

"Level of confidence. Type: Float Valid Range: Minimum value of 0. Maximum value of 100."

d) Other Sources: In addition to the above documentation lacking precise definitions of 'confidence', we found users on StackOverflow find this lack of definition confusing. Using our search described in section IV, five of a total of eight search results indicate issues from users. Two of these issues relate to similar AI-based services on API A, with the rest on API B-based AI services. We summarise these issues below:

- **[64]:** Confusion on API A that the 'score' and 'topicality' values are always the same. User was also confused by meaning of 'score'.
- **[65]:** Unsure what the default thresholds were for facial recognition in API B.
- **[66]:** User unsure how to interpret 'score' for a related API of API B.
- **[67]:** User unsure what web entity 'score' meant for API A web search.
- **[68]:** User confused on API B facial recognition if two confidences equal to 1 meant that faces were exact match.

Additionally, we found similar confusion within GitHub issues of API A and API B, where developers are still unsure of best practices and calculation of 'score':

- **[69]:** In an issue thread on GitHub for API A, developers were unsure what is meant from the 'score' property and how it was calculated.
- **[70]:** In an issue thread on GitHub for API B, developers are unsure what best practices give optimal results in an image.

B. Experiment II: API Response Evaluation

1) Vocabulary of Labels: Upon reading through all the documentation of each provider, we note that boundary sets of what labels the computer vision can categorise and what it cannot. The disparity of this is emphasised within table II, where a subset of our images (provided in fig. 2) have completely disparate results labelled for the one conceptual image. We reinforce this in table I: the same image of a Border Collie was provided to all three services. The only consistency in the services was 'Dog' for all three APIs, and 'Animal' and 'Mammal' for APIs B and C. 'Border Collie', 'Dog' and 'Collie' are the most conceptually-specific labels across all three services for APIs.

Thus, taxonomy of specificity is unknown; if 'Border Collie' is detected as a dog breed, does this imply the hypernym 'Dog' is detected, and then 'Mammal', then 'Animal', then 'Object'? Only API B provides 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" [71].

Figure 1 shows an illustration of the breakdown of this taxonomy.

2) Confidence Variability: We identified that the confidence of labels are variable without notification by negligible amounts in both API A and API C. API B's models did not

TABLE I: First six responses of image analysis for a Border Collie sent to each API's demonstration website. The specificity (to 3 s.f.) and vocabulary of each label in the response varies between all services.

Label	A	B	C
Dog	0.990	0.999	0.992
Dog Like Mammal	0.960		
Dog Breed	0.940		
Border Collie	0.850		
Dog Breed Group	0.810		
Carnivoran	0.810		
Black		0.992	
Indoor		0.965	
Standing		0.792	
Animal		0.932	0.992
Canine			0.992
Collie			0.992
Mammal		0.929	0.992
Pet			0.992

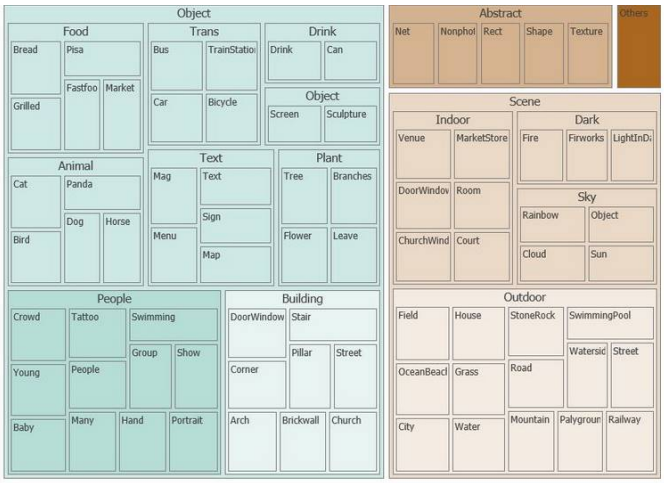

Fig. 1: Visualisation of Azure's 86-category [71]. The taxonomy provides a layer of specificity to objects. Users can search within a domain of a specific category if the object they are analysing is within a known domain.

TABLE II: First three responses comparing all labels against all APIs classified from the same source images identified in Figure 2. Note that API B's response for Image 5 only returned two responses, hence the missing third response.

Image #	API A			API B			API C		
	Resp. 1	Resp. 2	Resp. 3	Resp. 1	Resp. 2	Resp. 3	Resp. 1	Resp. 2	Resp. 3
1	*motor vehicle*	*car*	*vehicle*	*car*	*tree*	*outdoor*	*parking*	*parking lot*	*windshield*
2	*black*	*pink*	*mammal*	*indoor*	*bed*	*person*	*slide*	*toy*	*adorable*
3	*plant*	*walkway*	*flowerpot*	*outdoor*	*plant*	*stone*	*flora*	*jar*	*plant*
4	*countertop*	*kitchen*	*room*	*indoor*	*wall*	*floor*	*indoors*	*interior design*	*kitchen*
5	*vehicle*	*asphalt*	*automotive exterior*	*outdoor*	*ground*	N/A	*sunlight*	*flora*	*forest*
6	*wall*	*metal*	*public utility*	*building*	*ground*	*outdoor*	*rust*	*brick*	*face*
7	*road*	*lane*	*asphalt*	*tree*	*road*	*sky*	*freeway*	*road*	*building*
8	*rock*	*grass*	*walkway*	*ground*	*outdoor*	*sidewalk*	*rock*	*asphalt*	*tarmac*
9	*car*	*transport*	*town*	*outdoor*	*road*	*street*	*canopy*	*umbrella*	*automobile*


(a) Image #1.


(b) Image #2.


(c) Image #3.


(d) Image #4.


(e) Image #5.


(f) Image #6.


(g) Image #7.


(h) Image #8.


(i) Image #9.

Fig. 2: Images used for vocabulary of labels, as identified in Table 1.

change during our assessment period. This, in turn, causes some variability in the label thresholds that are returned. It should be noted that some labels drop entirely.

Upon investigation of any change log to communicate for these confidence changes, the only 'versioning' found was schema differences in the response provided.

⟨ TODO: **JG: The above would really benefit from more examples tried out...** ⟩ ⟨ TODO: **AC: @JG yes I agree.** ⟩

VI. Discussion

A. Recommendations for API Providers

1) Standardise Techniques Vocabulary: There lacks a standardised vocabulary of both describing these APIs and the labels in their responses. As found in previous studies [72], associating API features to their correct names when the naming is inconsistent can be difficult when the API is unfamiliar. Pam has no idea what 'tagging' versus 'labelling' means and thus may be confused by these unfamiliar APIs terms to describe what is conceptually the same technique. We suggest providers to shift away from using disparate terms for the same concept (e.g., 'image tagging' versus 'image categorisation' versus 'image labelling') and a taxonomy of these terms should be developed. Information may also be better communicated through meta-models to developers, and would be conceptually easier to digest when the terminology remains consistent.

2) Make labels more transparent: Pam does not know that API B can only provide back *'Dog'* for the same image that API A provides back with *'Border Collie'*; how can she toggle the level of specificity in her results? She also is frustrated that API C does detect the Border Collie, but labels this as just *'Collie'*: how is she meant to implement such pattern matching in a generic sense? Thus, we recommend vendors to improve the documentation of APIs by making known publicly available the boundary set of the training data used for the algorithms. This way, developers would be able to review the API's specificity for their intended use case (e.g., maybe Pam is satisfied her app can catalogue 'dogs' together, and in fact does not want specific dogs breeds catalogued). We also recommend that vendors publish usage guidelines should that include details of priors and how to evaluate the specific API results. This could also be included as metadata in the response object.

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 provided back to developers that encompass such detail. Furthermore, inconsistencies in the vocabulary used in the documentation around the AI makes using them even more conceptually challenging to developers. Providing as much metadata in the response object may resolve this.

4) Improve Versioning: Lastly, we recommend introducing a versioning system so that a model can be used from a specific date in production systems: when Pam tests her app today, she would like the API to remain the same for when her app is deployed in production tomorrow. Thus, in a request made to the vendor, Pam 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.

B. Recommendations for Developers

1) Be wary of API inconsistency: There is inherent inconsistency between these APIs: if evaluating these APIs, be aware that there is no standardised vocabulary in the labels they return. Therefore, developers need to stick with a specific vendor they feel that is right for them and not stray away. Issues such as the 'Border Collie' vs. 'Collie' terms can therefore be avoided.

2) Use case should inform API choice: Developers must also be decisive in which API is right for their use case. There is no 'one-size-fits-all' approach to these visualisation services, and therefore inherit risks are apparent. For example, API C is able to recognise faces unlike the other services, but they do advise humans to be the final decision-makers in making decisions from this data.

3) Avoid use in safety-critical systems: Lastly, these computer vision services are in a nascent stage; we recommend developers to avoid their use in safety critical systems due to their lack of stability and visibility of changes. To ensure results are correct over time, we recommend developers to create a representative dataset of the intended dataset and evaluate these changes against the API frequently. This will help identify when changes, if any, have occurred when vendors do not provide a line of communication when this occurs.

VII. Conclusions

We analysed three popular computer vision APIs for internal quality in a software engineering perspective. We identify that the definition of the term 'confidence' is an issue by the tautologic nature of its definition by the API providers, and by evidence supplied from developer community. We also identify that these services use inconsistent vocabulary both in describing their APIs and in the responses they give. Moreover, no training set provided to users to see what the algorithms were trained on, and thus developers remain unaware of what labels are and are not recognisable. We also found that APIs A and C change their models over time without any notification to developers: thus, we have compiled several recommendations for both developers consuming these APIs and the vendors who provide them.

While we have investigated this area in the area of computer vision APIs, we suspect similar patterns may occur in the documentation of other MLaaS-based services, such natural language processing or audio transcription. We remain this open for future work.

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TABLE III: Techniques of the three assessed cognitive vision APIs.

Technique	A	B	C
Object Recognition	•	•	•
Object Localisation	*(beta)*		
Scene Recognition	•	•	•
Unsafe Content Recognition	•	•	•
Text Extraction (OCR)	•	•	•
Handwriting Extraction	*(beta)*	•	
Face Detection	•	•	•
Face Analysis	•	•	•
Face Recognition		*(partial)*	•
News-Related Events	•		
Product/Logo Recognition	•		
Landmark Detection	•	•	
Image Analysis	•	•	•
Domain-Specific Analysis		•	
Image Description		•	
Image Type Identification		•	

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Appendix B

Ethics Application Draft