A Guiding Framework to Improve the Operationalisation of Artificial Intelligence using Enhanced Documentation Standards and Software Engineering Practices

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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 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 [53] 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. Most prominently spearheading this wave of AI-first thinking is Google, as evident through their 2018 rebranding of *Google Research* to *Google AI* [34].

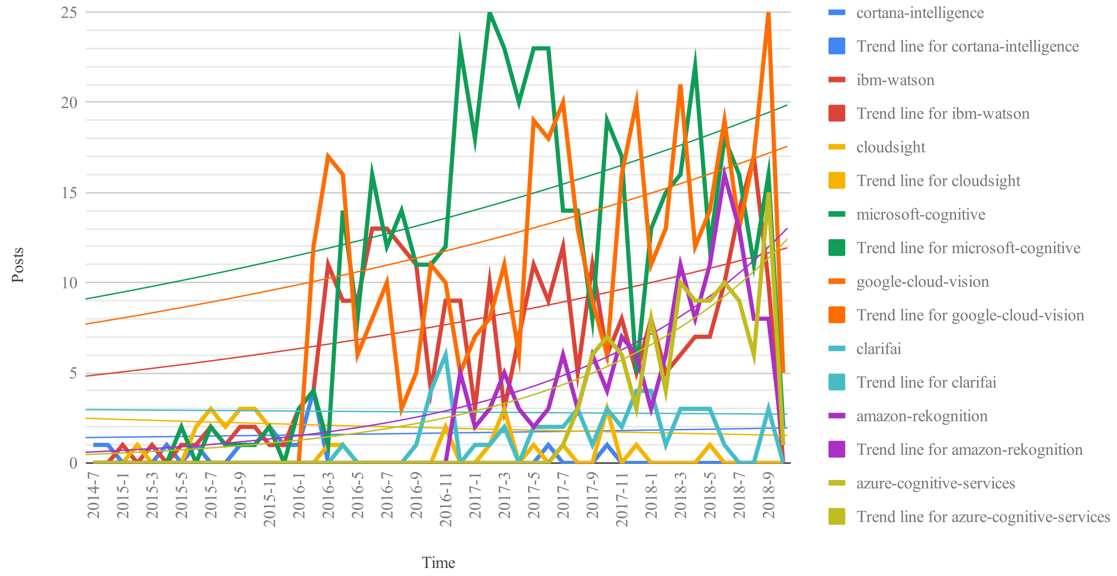
These services aim to lower the entry barrier to develop, test and deploy AI-first software in both skill and time. Software engineers needn't require a formal training in machine-learning nor a strong understanding of mathematics: thus, *skill required* is reduced. The training of such classifiers involves 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 API call, only requiring knowledge on how to use a RESTful architecture **[cite:Restful thesis]** to access the cloud service.

To contrast this with more traditional means, a developer may choose to write up a deep-learning 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 ML framework, such as Tensorflow [**?**]; 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 [53].)

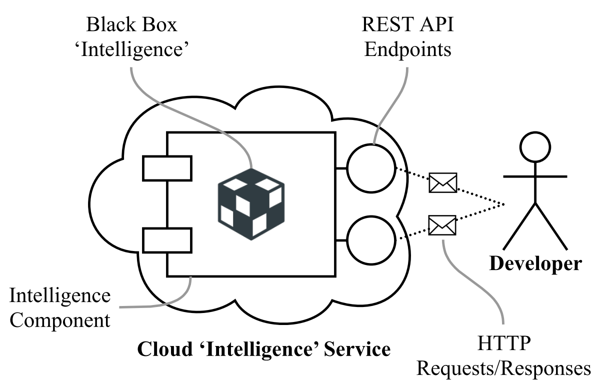
Category	Sample vendors and products	Typical use cases
Embedded AI Expert assistants leverage AI technology embedded in platforms and solutions.	• Amazon: Alexa • Apple: Siri • Facebook: Messenger • Google: Google Assistant (and more) • Microsoft: Cortana • Salesforce: MetaMind (acquisition)	• Personal 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

Figure 1.2: Number of posts categorised on StackOverflow under popular computer vision cloud intelligence services. Query run on 12 October 2018 using StackExchange Data Explorer. Refer to `https://data.stackexchange.com/stackoverflow/query/910188` for full query.



With less time and skill required to build AI-first apps using these cloud services, these services have begun to gain traction within developer circles: Figure 1.2 shows the increasing trend of posts since 2014 on StackOverflow that categorise popular computer vision cloud APIs. A growing popularity into such services sparked varied nomenclature: Cognitive Services, Machine Learning as a Service [68], Cloud ML and so on. We refer to such services as Cloud Intelligence Services (CISs), and diagramatically express their usage within Figure 1.3.

Figure 1.3: Overview of Cloud Intelligence Services.



A developer accesses a CIS component via a RESTful API endpoint(s). The input and response communicate through HTTP, typically as JSON content. The 'intelligence' component masks intelligence through a black-box. We do not refer to the 'intelligence' through the lenses of *artificial* intelligence as the nature of these services may mask human intelligence, as noted by previous work **[cite:Paper Scott told me about about humans tagging]**. Their response is hence used by the developer in whichever use case they would like.

While there are many types of CISs evident, we scope the work investigated to CV analysers (e.g., [**? ? ? ? ? ? ? ? ? ?**]). The ubiquity of CV CISs is exemplified through evermore growing applications that use these APIs: aiding the vision-impaired [66, 14], accounting [54], data analytics [37], and student education [17].

1.1 Motivation

1.2 Research Goals

1.3 Research Methodology

1.4 Intended Contributions

In this thesis we...

1.5 Thesis Structure

1.6 Strategy and Roadmap

Chapter 2

Literature Review

⟨ TODO: **Reiterate research claims from Chapter 1 - Introduction.** ⟩

⟨ TODO: **Review literature around this claim from theoretical lenses.** ⟩

2.1 Software Quality

⟨ TODO: **Background on the development of software quality models.** *McCall's model was one of the first software quality models introduced. It described quality from X perspectives... this was further developed by the ISO quality model, which enhanced by Y... In the late 1990s, Dromey's interperation expanded...*⟩

⟨ TODO: **Relate software quality to CV systems; internal & external quality.** ⟩

⟨ TODO: **Discuss gaps in the software quality literature relating directly to CV quality.** ⟩

2.2 Probabilistic and Stochastic Systems

⟨ TODO: **What are stochastic/probabilistic systems? E.g., model interpretation?** ⟩

⟨ TODO: **What understanding might be missing from model interpretation? Relate back to topic.** ⟩

2.2.1 Model Interpretability

As the rise of applied AI increases, the need for engineering interpretability around models becomes paramount. Model interpretability has been stressed since early machine learning research in the late 1980s and 1990s (such as Quinlan [65] and Michie [58]), and although there has since been a significant body of work in the area [77, 3, 67, 9, 72, 52, 6, 42, 2, 29, 15, 84, 5, 23, 51, 55, 62, 85], it is evident that 'accuracy' or model 'confidence' is still used as a primary criterion for AI evaluation [35, 38, 78]. Indeed, much research into NN or 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" [25], a problem commonly referred to as the *datashift* problem [80]. Analogously, Freitas [25] 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.*** *[25]*

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 [52]), what is known is (i) there exists a critical trade-off between accuracy and interpretability [24, 41, 44, 31, 19, 90], and (ii) a single quantifiable value cannot satisfy the subjective needs of end-users [25]. 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 [10, 45, 36]), 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])

[1] In areas such as medicine [4, 49, 63, 69, 91, 84, 42, 22, 89, 39, 9], bioinformatics [26, 82, 43, 18, 40], finance [3, 36, 16] and customer analytics [85, 51].

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

are not realised: model optimisation is only worthwhile if they "actually solve the original [human-centred] task of providing explanation" [60] to end-users. **Therefore, when human-decision makers must be interpretable themselves [70], 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. [21] discuss when explanations are not provided from a legal stance—for instance, those affected by algorithmic-based decisions have a 'right to explanation' [30, 86] 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 [21], however, in terms of explanations, what form they take and how they are proven correct are still open questions [52].

2.2.2 AI Communication Mismatch

From a SE 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' [56] 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 [76] applies, just as others have done with similar issues in the SE realm [59**?**] (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 [21] 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 predic-

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

tion 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 2.1.

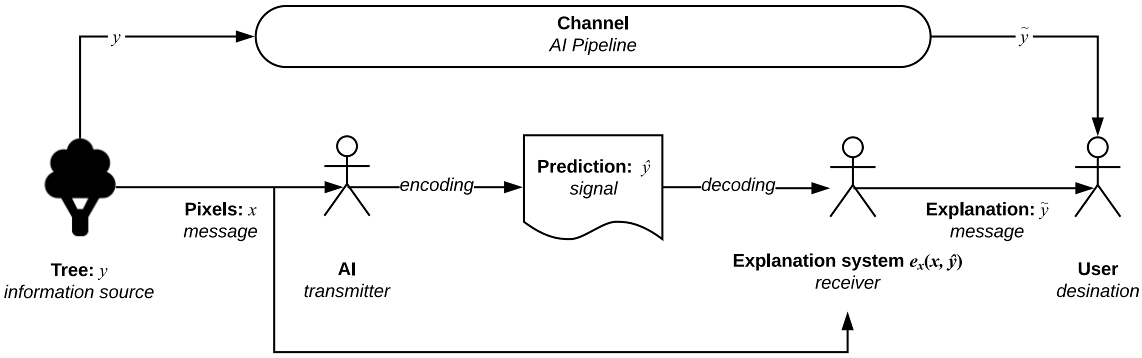


Figure 2.1: Theory of AI communication from information source, y, to intended user as explanations $\tilde{y}$.

2.2.3 Mechanics of Model Interpretation

How do we interpret models? Methods for developing interpretation models include: decision trees [8, 32, 13, 64, 71], decision tables [51**?**] and decision sets [48, 60]; input gradients, gradient vectors or sensitivity analysis [74, 67, 50, 72, 3]; exemplars [46, 27]; generalised additive models [10]; classification (*if-then*) rules [83, 7, 12, 61, 88] and falling rule lists [77]; nearest neighbours [55, 75, 81**?** , 87] and Naïve Bayes analysis [4, 49, 47, 91, 57, 28, 11, 33]. Several cross-domain studies have assessed the interpretability of these techniques against end-users, measuring response time, accuracy in model response and user confidence [36**?** , 1, 79, 73, 26, 55, 85], although it is generally agreed that decision rules and decision tables provide the most interpretation in non-linear models such as SVMs or NNs [26, 55, 85]. For an extensive survey of the benefits and fallbacks of these techniques, we refer to Freitas [25] and Doshi-Velez and Kim [20].

As it stands, AI presents an issue with. (For a detailed discussion, see Doshi-Velez et al. [21].

2.3 Cognitive Biases

⟨ TODO: **Background; what are cognitive biases and how does it relate to SE?** ⟩

⟨ TODO: **Literature of CB specifically in SE.** ⟩

⟨ TODO: **List potential CBs with relation to the AI-based systems.** ⟩

2.4 UX Consistency Principle

⟨ TODO: **Background; what is UX consistency? What does it advocate for and why?** ⟩

⟨ TODO: **What lessons can we learn from UX consistency, and how can we apply it to SE?** ⟩

⟨ TODO: **What are the gaps in SE that do not conform to practices of UX consistency w.r.t. AI systems development?** ⟩

2.5 API Documentation and Standards

⟨ TODO: **What are API documentation standards? What do they advocate for?** ⟩

⟨ TODO: **What is missing for AI documentation? What is the gap?** ⟩

2.6 Validation and Verification

⟨ TODO: **Unsure...** ⟩

2.7 Requirements Specification

⟨ TODO: **Unsure...** ⟩

2.8 Meta-modelling

⟨ TODO: **What is meta-modelling? Can get this from honours thesis...?** ⟩

⟨ TODO: **How does this differ in AI context?** ⟩

Chapter 3

Methodology

3.1 Data Collection and Ethics

3.2 Approach

3.3 Evaluation Methods

3.4 Threats to Validity

3.4.1 Internal Threats

3.4.2 External Threats

3.4.3 Construct

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Project Status

4.1 Completed Work

4.2 Impact

4.3 Timeline

Chapter 5

Conclusion

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