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

1.1 Background

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 [61] and Michie [54]), and although there has since been a significant body of work in the area [2, 3, 6, 7, 10, 15, 22, 28, 40, 49–51, 58, 62, 66, 71, 78, 79], it is evident that 'accuracy' or model 'confidence' is still used as a primary criterion for AI evaluation [34, 36, 72]. 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" [24], a problem commonly referred to as the *datashift* problem [74]. Analogously, Freitas [24] 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.*** *[24]*

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 [50]), what is known is (i) there exists a critical trade-off between accuracy and interpretability [18, 23, 30, 39, 42, 85], and (ii) a single quantifiable value cannot satisfy the subjective needs of end-users [24]. 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 [11, 35, 43]), 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" [56] to end-users. **Therefore, when human-decision makers must be interpretable themselves [64], 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. [20] discuss when explanations are not provided from a legal stance—for instance, those affected by algorithmic-based decisions have a 'right to explanation' [29, 80] 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 [20], however, in terms of explanations, what form they take and how they are proven correct are still open questions [50].

1.1.1 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

[1] In areas such as medicine [5, 10, 21, 37, 40, 47, 59, 63, 78, 84, 87], bioinformatics [17, 25, 38, 41, 76], finance [3, 16, 35] and customer analytics [49, 79].

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

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

person using it. The ability to encode ‘common sense reasoning’ [52] 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 [70] applies, just as others have done with similar issues in the SE realm [55, 82] (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 [20] 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 1.1.

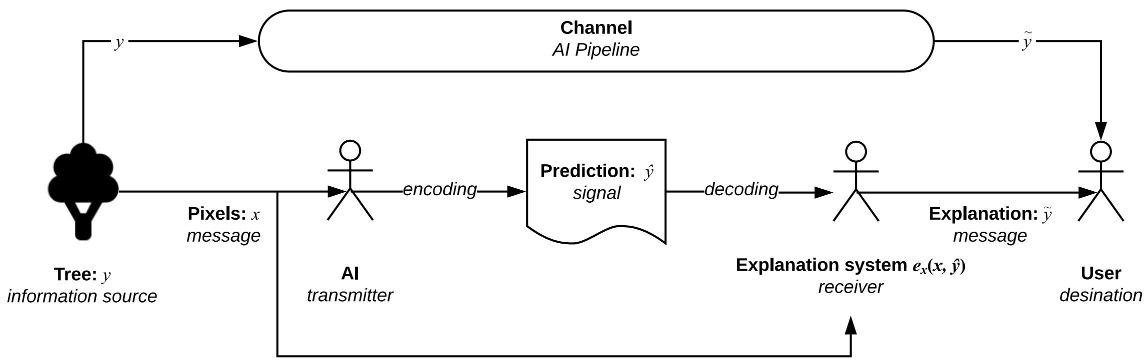

Figure 1.1: Theory of AI communication from information source, y, to intended user as explanations $\tilde{y}$.

1.1.2 Mechanics of Model Interpretation

How do we interpret models? Methods for developing interpretation models include: decision trees [9, 14, 31, 60, 65], decision tables [4, 49] and decision sets [46, 56]; input gradients, gradient vectors or sensitivity analysis [3, 48, 62, 66, 68]; exemplars [26, 44]; generalised additive models [11]; classification (*if-then*) rules [8, 13, 57, 77, 83] and falling rule lists [71]; nearest neighbours [51, 69, 75, 81, 86] and Naïve Bayes analysis [5, 12, 27, 33, 45, 47, 53, 87]. Several cross-domain studies have assessed the interpretability of these techniques against end-users, measuring response time, accuracy in model response and user confidence [1, 25, 32, 35, 51, 67, 73, 79], although it is generally agreed that decision rules and decision tables provide the most interpretation in non-linear models such as SVM's or NN's [25, 51, 79]. For an extensive survey of the benefits and fallbacks of these techniques, we refer to Freitas [24] and Doshi-Velez and Kim [19].

As it stands, AI presents an issue with. (For a detailed discussion, see Doshi-Velez et al. [20].

1.2 Motivation

1.3 Research Goals

1.4 Strategy and Roadmap

1.5 Contributions

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.** ⟩

2.3 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

Chapter 4

Project Status

4.1 Completed Work

4.2 Impact

4.3 Timeline

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