Towards Operationalising Cloud Intelligence Services using Software Engineering Practices

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October 16, 2018

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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 [73] 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* [53].

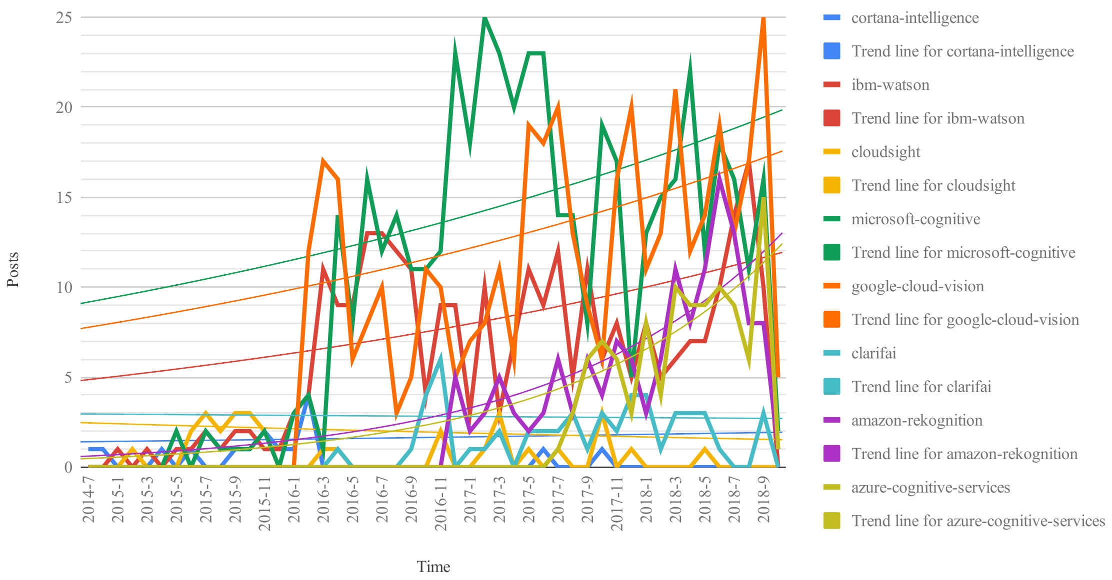
These services aim to lower the entry barrier to develop, test and deploy AI-first software in both skill and time. Software engineers needn't require a formal training in machine-learning nor a strong understanding of mathematics: thus, *skill required* is reduced. The training of such classifiers involves 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 [42] 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 [16]; 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 [73].)

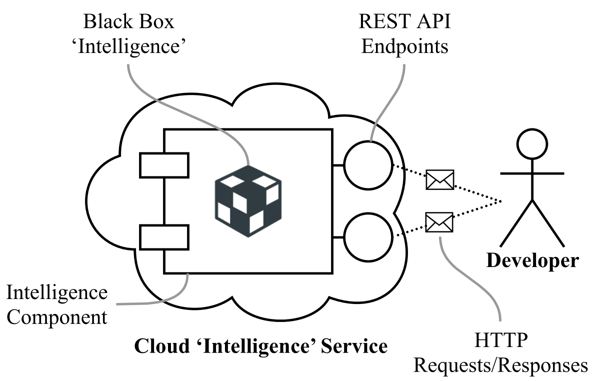
Category	Sample vendors and products	Typical use cases
Embedded AI Expert assistants leverage AI technology embedded in platforms and solutions.	• Amazon: Alexa • Apple: Siri • Facebook: Messenger • Google: Google Assistant (and more) • Microsoft: Cortana • Salesforce: MetaMind (acquisition)	• Personal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



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.[1] A growing popularity into such services sparked varied nomenclature: Cognitive or Intelligence Services, Artificial Intelligence or Machine Learning as a Service [89], Cloud Machine Learning and so on. We henceforth refer to such services under the term ‘Cloud Intelligence Services’ (CISs), and diagrammatically express their usage within Figure 1.3.

Figure 1.3: Overview of Cloud Intelligence Services.



A developer accesses a CIS component via a RESTful HTTP API endpoint(s). For their given input, they receive an intelligent-like response typically formatted in JSON. We note the

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

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 [12] or ScaleAPI [14]. Thus, a CIS may be powered by varying degrees of intelligence: human intelligence, computer manipulation or brute-force methods, or supervised or unsupervised learning.

While there are many types of CISs evident (such as OCR Transcription, Object Categorisation, Object Comparison, NLP etc.), we scope the work investigated to computer vision CIS analysers [8, 3, 1, 13, 9, 5, 4, 7, 10, 15, 11, 6, 2]. The ubiquity of computer vision CISs is exemplified through evermore growing applications that use these APIs: aiding the vision-impaired [87, 32], accounting [74], data analytics [56], and student education [35].

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 derives from electronic sciences since the 1950s–60s **[cite:Bunge, Mario 1963; Ashby, W. Ross, 1956, chapter 6]**. In many cases, these black boxes are inherently probabilistic and stochastic: for instance, a computer vision CIS usually returns the *probability* that a particular object (the response) exists in the raw pixels (the stimulus), and thus we must stochastically retrieve hundreds of these results to get an interpretation of the *distribution of overall confidence* returned from the service. There are thus therefore three factors to consider when implementing and using a CIS: (i) 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

APIs reflect a set of design choices made by their providers. Evaluations of API usability advocate for the accuracy, consistency and completeness of APIs and their documentation [84, 92] written by providers, while providers should consider mismatches between the developer’s conceptual knowledge of the API its implementation [66]. It is therefore imperative that CIS providers consider the impact of their API usability. Poor API usability, therefore, hinders on the internal quality of development practices, slowing developers down to produce the software they need to create.

Moreover, developers need to be wary of the probabilistic nature of probabilistic systems. These APIs become 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 [22] 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 computer vision CISs. We explore more of these facets in the motivating scenario below.

1.1.2 Motivating Scenario

How do developers work with a CIS? How usable are these APIs, and how well do developers understand the non-deterministic and stochastic nature of a deep-learning cloud-based API? To motivate such a scenario, let us introduce a fictional 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), generate brief descriptions of each photo, and catalogue photos of her friends as well as common objects (e.g., all photos with her Border Collie dog, all photos taken on a beach on a sunny day).

Rather than building a computer vision engine from scratch, which would take far too much time and effort, Pam thinks she can achieve this using one of the common computer vision CISs. 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. As she expects the same for whenever she calls, for example, any substring API with the call (or similar) of `substring("doggy", 0, 2)` and would expect the response `'dog'` as its output.

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. Some of the questions that may come to mind include:

- What does confidence mean? Aren't these APIs consistent?
- 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 can she report it?
- How does she know what labels the API can pick up, and what labels it can't?
- How does she know when the models update? What is the release cycle?
- 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 and in software engineering terms she can understand.

1.2 Research Goals

In this thesis, we explore the effect stochastic and probabilistic systems play on the usability of APIs with respect to computer vision CISs. Our 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 operationalisation such systems.

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. We propose two major bodies of work.

Goal 1: ***Understand the developer's mindset towards selecting a computer vision CIS.***

Goal 2: ***Determine what quality factors affect software built using computer vision CISs.***

Goal 3: ***Provide an evaluation framework developers wishing to use computer vision CISs.***

Chiefly, we can specify the following high-level research questions:

RQ1. How do software engineers understand and evaluate computer vision CISs for use in both generic and specific applications?

RQ2. Do software engineers follow best practices when evaluating computer vision CISs? How does this compare to actual practice?

RQ3. What is needed to improve the state-of-the-art of computer vision CISs in terms of API documentation?

RQ4. What aspects of validation and verification can be improved in the field of computer vision CISs?

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 computer vision CISs space will be generalisable to other areas, such as time-series information, natural language processing and others.

1.3 Methodology

For this study, we propose running several experiments involving developers and several computer vision CISs, using action-based mixed method approaches and involving documentary analysis. This study will organically evolve by observing phenomena surrounding computer vision API internal quality, chiefly their documentation and responses. We adopt 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 (RQs 3 and 4).

Our first proposal for usability studies will survey a number of developers from various levels of seniority and experience (gathering such demographical data to assess a wider sample size) to provide insight into how these developers perceive the non-deterministic nature of computer vision APIs, asking them specific questions about their conceptual understanding of computer vision to identify any outstanding gaps in their knowledge and factor this into known literature (RQs 1 and 2).

We will then conduct a structured interview with a 'mock' computer vision API to remove any developer bias toward any one particular computer vision API that already exists and by which the developer may have already used in the past. Here, we will investigate if developers have any patterns of practice and if they conform to software engineering best practices (RQs 1, 2 and 3).

From these insights, we can then develop a series of assistive recommendations that aide in improving the validation and verification of the existing computer vision API tooling. This may involve a third party tool that helps developers evaluate which particular API is right for their specific computer vision use case.

Chapter 2

Literature Review

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

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

2.1 Validation and Verification

⟨ TODO: **Unsure...** ⟩

2.2 Requirements Specification

⟨ TODO: **Unsure...** ⟩

2.3 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.** ⟩

2.4 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.** ⟩

2.4.1 The Importance of 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 [86] and Michie [78]), and although there has since been a significant body of work in the area [99, 19, 88, 26, 94, 72, 23, 61, 18, 48, 33, 106, 21, 41, 71, 75, 82, 107], it is evident that 'accuracy' or model 'confidence' is still used as a primary criterion for AI evaluation [54, 57, 100]. 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" [44], a problem commonly referred to as the *datashift* problem [102]. Analogously, Freitas [44] 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.*** *[44]*

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 [72]), what is known is (i) there exists a critical trade-off between accuracy and interpretability [43, 60, 63, 50, 37, 113], and (ii) a single quantifiable value cannot satisfy the subjective needs of end-users [44]. As ever-growing domains ML become widespread[1], these applications engage

[1] In areas such as medicine [20, 69, 83, 90, 114, 106, 61, 40, 112, 58, 26], bioinformatics [45, 104, 62, 36, 59],

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 [28, 64, 55]), 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" [80] to end-users. **Therefore, when human-decision makers must be interpretable themselves [91], 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. [39] discuss when explanations are not provided from a legal stance—for instance, those affected by algorithmic-based decisions have a 'right to explanation' [49, 108] 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 [39], however, in terms of explanations, what form they take and how they are proven correct are still open questions [72].

2.4.2 Explanation and Communication

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' [76] 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 [98] applies, just as others have done with similar issues in the SE realm [79, 110] (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 [39] 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*

finance [19, 55, 34] and customer analytics [107, 71].

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

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

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 2.1.

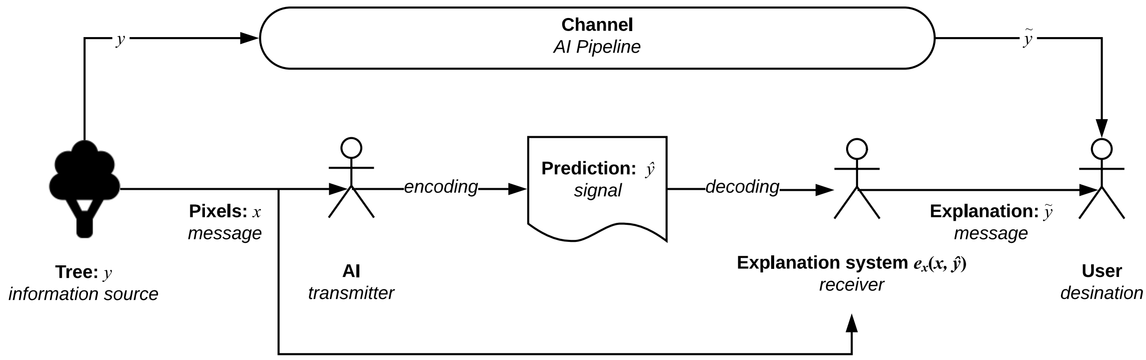


Figure 2.1: Theory of AI communication from information source, y, to intended user as explanations $\tilde{y}$.

2.4.3 Mechanics of Model Interpretation

How do we interpret models? Methods for developing interpretation models include: decision trees [25, 51, 31, 85, 93], decision tables [71**?**] and decision sets [68, 80]; input gradients, gradient vectors or sensitivity analysis [96, 88, 70, 94, 19]; exemplars [65, 46]; generalised additive models [28]; classification (*if-then*) rules [105, 24, 30, 81, 111] and falling rule lists [99]; nearest neighbours [75, 97, 103**?** , 109] and Naïve Bayes analysis [20, 69, 67, 114, 77, 47, 29, 52]. Several cross-domain studies have assessed the interpretability of these techniques against end-users, measuring response time, accuracy in model response and user confidence [55**?** , 17, 101, 95, 45, 75, 107], although it is generally agreed that decision rules and decision tables provide the most interpretation in non-linear models such as SVMs or NNs [45, 75, 107]. For an extensive survey of the benefits and fallbacks of these techniques, we refer to

Freitas [44] and Doshi-Velez and Kim [38].

As it stands, AI presents an issue with. (For a detailed discussion, see Doshi-Velez et al. [39].

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 Meta-modelling

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

To understand the methodology on how we captured our dataset, we must first introduce the three key notions behind MDE: technical spaces, models and systems. A system is a concrete "group or set of related or associated elements perceived or thought of as a unity or complex whole" [**?**]. Technical spaces were introduced by **?**] as a model management framework based on algebraic structures (e.g., trees, (hyper)graphs, and categories). Technical spaces are usually based on a three-tier conjecture: meta-meta-models, meta-models and models. Whereas a model is an abstract representation of a concrete system of specific purpose, a *meta*model, in contrast, describes the way to describe those models. A *meta-meta-*model can be used to describe the representation structure of our meta-models and defines a type system [27] that supports all underlying layers [**?**]. Figure 2.2 captures these concepts in further detail.

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

2.7 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.** ⟩

2.8 UX Consistency Principle

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

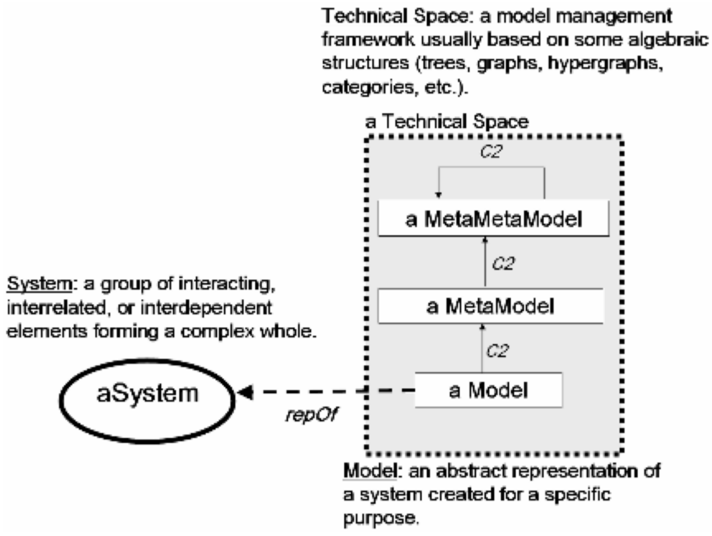


Figure 2.2: Systems, models and technical spaces. (From [**?**].)

⟨ 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?** ⟩

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

Chapter 5

Conclusion

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