## i\* Meets AI: New Roles in Requirements Modelling

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## Abstract

The prospects for i\* modelling to meet the emerging challenges poses by RE for AI are reviewed.

## **Keywords**

Artificial intelligence, fairness, data requirements, social issues, values

In this talk I will outline some ideas about how i\* can be applied to the concerns of fairness in AI [1] and how this suggests new roles in data modelling requirements, extensions to softgoals and the concepts of dependency in i\*. The implications of RE for AI have been explored in the AIRE workshop series as well as modelling using i\* to explore roles with AI development to illuminate how data science, AI and software engineers are all necessary to contribute to the overall requirements picture [2]. System-level modelling with i\* has also been explored in software ecosystems [3]. Combinations of models ranging from goals to i\* and other system models have been used to explore different viewpoints in RE [4]. In multiple modelling languages, including i\*, study of chronic disease management systems has demonstrated how multiple layers of models could map influences from the socio, political and business levels to operational requirements [5]. I will take up the role viewpoints theme in AI and propose how i\* might be used to model the emerging problem space of AI applications.

First, the case study to anchor my arguments. A call centre in a service engineering domain (see Figure 1a) of telecommunications logs data on customer calls, customer satisfaction, call duration, repeat calls, etc. The company aims are to improve customer satisfaction and call-centre agents' performance. Metrics are calculated on mean call duration, satisfaction ratios, call load/agent, etc. Satisfaction is recorded as a simple 1-5 scale rating at the end of each call. A machine learning classifier has been trained on customer call data sets to identify profiles of dissatisfied customers and underperforming agents, with the objective of improving customer relationship management. The company is concerned with fairness in any treatment of underperforming agents and the completeness of identifying satisfied customers. The application poses two requirements problems: (i) how to identify 'fairness' and (ii) an accuracy/completeness of classification for satisfaction, as well as the AI problem of conformance with ethical standards for fairness to avoid legal challenges from unfair treatment of employees. The problem overview is summarised in Figure 1(a), showing the dependencies between agents for the service company with the softgoals of efficiency for the company and customer satisfaction as a shared goal.

The approach to this problem develops awareness requirements concepts [6]: how can monitors be developed to evaluate classified output for fairness? This begs the question of defining fairness and operationalising definitions as metrics and measures. Fairness can be evaluated against training set metadata, e.g. ethnicity, gender, age and other demographic variables for call-centre agents.

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**Figure 1**: (a) High level overview of the Call Centre system including the ML classifier agent, (b) Dependencies and awareness requirements linking input and output data with ML classifiers

Awareness requirements (Figure 1b) are implied to check the distribution of underperforming operators against their demographics to ensure there is no statistically significant bias by age, gender, ethnicity, etc., using standard tests such as analysis of variance and regression. Developing a monitoring process to detect digression in classifier output with respect to attributes distribution in the subject population becomes the responsibility of requirements and software engineers, while defining tolerance limits and selecting statistical tests necessitates the expertise of data analysts. Requirements are thus extended into the realm of data science; furthermore, any digressions which are detected trigger a further class of requirements for investigation and adaptation, e.g. call duration can be longer for female operators who tend to be more patient and thorough than males, while older operators have longer response times from normal ageing effects. i\* models were extended from strategic dependencies between agents, goals and softgoals implicit in the baseline system, to model dependencies between attributes of agents in input data models, fairness values elaborated from softgoals and the original system goals specified for the classifier's requirements. More detailed i\* dependency models describing the training data domain were compared with models describing the classifier output so interrelated (training-output) models dependencies could be investigated with the addition of softgoals representing fairness values (i.e. Equality, Social responsibility, Diversity) and other 'soft issues' [7,8] Several hidden dependencies were discovered during requirements and data analysis, for example temporal biases. Customer calls may show peak loads at certain times of year, such as winter, on the arrival of new more complex products, or even diurnal variations with call peaks in mid-morning. All these aspects could introduce bias in efficiency metrics associated with individual call-centre agents whose shift patterns happened to be exposed to these variations. Customer satisfaction was also susceptible to biases ranging from the type of industry, where some domains had more complex and hence error-prone products, to company size where lack of in-house expertise in small enterprises could lead to more calls and lower satisfaction.

While these problems may become apparent during system operation, it is desirable to discover them at design (or classifier training) time and then implement counter measures either through awareness requirements and monitors where management can be alerted to take appropriate action, such as improving classifier training with better selection of training data, use of supervised learning to mark up relevant bias examples, transfer learning from selected training

sets, and ultimately classifier self-correction by learning bias controls, etc. The implications of corrective requirements involve communication with another group of experts: ML classifier developers and operators [1]. The lessons for RE modelling were, first, the extension of system models into data analysis to express the dependencies between classifier input (training + operational data sets), and output as categories in agent sub-classes and distributions, with original system hard and softgoals while including hidden softgoals expressing fairness values and hidden biases. Dependencies indicated awareness requirements [6] and alerts when statistical tests or simple constraints were violated as transgressions of expected fairness norms. Awareness requirements needed prioritisation to distinguish between weaker advisory alerts and strong violations necessitating halting system operation. While i\* has been extended for data modelling and migrations towards implementation [9], I argue that further research is needed to guide the process of dependency checking between data models of ML classifier input and output, the operational context in the form of system models, and specification of awareness requirements to check violations of fairness, softgoals and integrity constraints.

While i\* model inspection helped to identify many potential biases and consequent awareness requirements, a more systematic, reusable process is desirable. Knowledge gathered during this application was gleaned from data scientists and ML experts, which indicated issues for developing a 'lingua franca' among the contributing communities from AI, data science and RE, developing insights from [2]. i\* models provided an important overview for each community which could be understood as dependencies between goals and system actors. Ideally this knowledge needs to be documented as patterns for awareness requirements and monitoring processes associated with fairness criteria. Patterns which have an extensive history in software engineering, have rarely been applied in RE, with some exceptions [10]. I will review the prospects for reusable i\* model patterns for AI classifier biases, which combined generalised models of classifier problems annotated with possible dependencies for analysis and notes of awareness requirements which may be associated with generalised problem domains.

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