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Decision Support with Hybrid Intelligence

Adrian Calma[1] and Dominik Dellermann[2]

[1] Intelligent Embedded Systems Lab, University of Kassel, Germany
adrian.calma@uni-kassel.de
[2] vencortex
dominik.dellermann@vencortex.com

Abstract. Startups are the fresh blood of our economy and, besides universities, are thriving innovation. One of the first steps in this enriching journey to success, where they create jobs and new products, is getting funded. Decision makers, such as investors, incubators, and accelerators, receive a large amount of funding proposals. Currently, new ventures are evaluated "manually", often without any machine learning or any decision support at all. The implicit rules that every experienced decision maker has developed through years of failures and successes can not be codified, let alone be explained. It is *intuition*. We envision a learning system that is able to learn the intuition from multiple decision makers and guide them in their judgment. Our envisioned learning system relies on *hybrid intelligence*, which we define as *the ability to accomplish complex goals by combining human and artificial intelligence to collectively achieve superior results and continuously improve by learning from each other.*

Keywords: collective intelligence, hybrid intelligence, collaborative interactive learning

1 Introduction

Consider the following example: An investor evaluates funding proposals from hundreds of startups. Based on an intensive analysis of the submitted documents a decision is made. This is time consuming and biased towards ones believes. Thus, the decision is not 100% objective, as the investors rely on their intuition and "gut feeling". Such decisions are highly complex, as they are made under extreme uncertainty. Despite its limitations (i.e., bound rationality), human intuition is the best that we have to make predictions under extreme uncertainty. For such decisions traditional statistical methods fail, as they can not deal with the dynamic context and the need to annotate soft data such as the creativity of a new venture idea.

In case of a fund, there is more than one investor that analyzes the funding requests, whereas the set of analyzed funding proposals may be disjoint. That is, what investor A analyzes is not necessary analyzed by another investor B. Therefore, following questions arise:

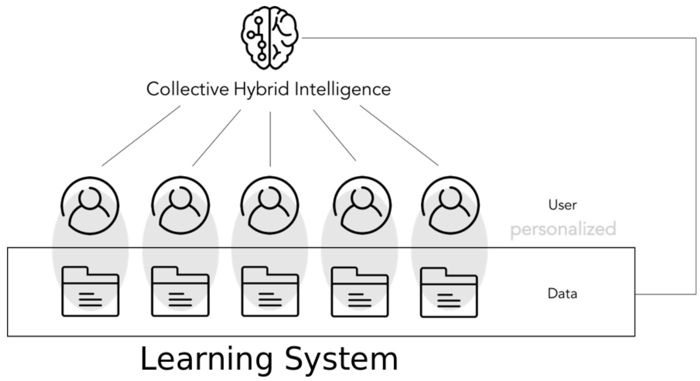

Fig. 1. Investors provide data on startup proposals and their judgment as well as profile information on their experience and investment history. The data is analyzed, and a personalized forecasting is returned. The investor has also access to the collective intelligence, which is a forecasting based on data from all investors.

1. How can individual decisions be *debiased*?
2. How can we make use of the *heterogeneous knowledge* of domain experts?
3. How can we *share* implicit *knowledge* without loosing competitive advantages?
4. How can we *efficiently* and *effectively* provide decisional guidance for entrepreneurial decision makers?
5. How can we interpret the decision of our learning model in such a way that it is *human readable*?

We envision a new way to learn from the collective intelligence (or intuition) of various domain experts to support decision makers and to provide high-quality decisional guidance, i.e., hybrid intelligence for artificial intuition. We, therefore, define hybrid intelligence as *"the ability to accomplish complex goals by combining human and artificial intelligence to collectively achieve superior results and continuously improve by learning from each other."* A learning system with hybrid intelligence capabilities offers decision makers

1. personalized guidance based on their previous decisions, which helps them be more consistent in their decisions and
2. guidance based on aggregated knowledge from multiples sources (e.g., investors, domain experts, etc.), which helps them to reduce bias

The decision support workflow is depicted in Figure 1: All startup data that the three investors received are submitted to the learning system. As we can see, the number of submitted requests is not the same over the three investors. The proportions can differ significantly between individual angel investors or large venture capital companies. Nevertheless, our proposed approach analyzes the submitted data and provides each investor with a personalized insight regarding its current data. This is done based on the history of previous decisions, as the more consistent the decisions are the better the outcome. In other words, we want to have consistent predictions of the future success of the ventures.

Moreover, the decision makers can benefit from the *collective intelligence*. They have access to forecasting values learned on data previously submitted by all system users (i.e., investors, domain experts, historical start-up data). Thus, the decision makers benefit from the experience and intuition of their peers and domain experts. Aggregating heterogeneous knowledge is required to make better predictions under such extreme uncertainty [1]. The basic rational of aggregating the judgment of multiple experts is that it reduces potential errors of individuals (e.g., biases or limited cognitive capabilities) [2].

2 Problem

We look at the problem from two perspectives: From the perspective of investment decision makers and from the perspective of entrepreneurs seeking for funding.

Investment Decision Makers The decision makers have to evaluate a large number of funding requests[3]. Ideally, they have access to a system that performs an automatic screening to provide efficient decisional guidance. The startups are scored based on the funding proposal, team data, news, current market situation, etc. To evaluate startups in this vein, decision makers require highly specialized and heterogeneous knowledge that they might not possess for each specific startup. Also, there is a need for visualizing these very heterogeneous startup data. Furthermore, the learning system should provide decision support: On the one hand, personalized decision support for a specific decision maker. That is, the decision indication is individually tailored based on the previous decisions, preferences, and risk profile of an investment decision maker. On the other, a second decision indication considers all the available information (i.e., data from all decision makers), thus providing a decision support based on hybrid intelligence. Moreover, the decision provided by the learning system has to be presented to the human decision makers in an interpretable. In this way the prediction is trusted by and justifiable to potential stakeholders.

Entrepreneurs The startups also benefit from using the learning system. Entrepreneurs get feedback regarding their team constellation, the value proposition, marketing strategy, or their business model. Receiving such feedback provides them with informative guidance which is an indicator for the current status of the venture and allows entrepreneurs to draw conclusions on what to do next. Moreover, in the long run, the learning system based on hybrid intelligence is capable to offer suggestive guidance, i.e., suggesting an entrepreneur a concrete sequence of actions based on the current state of a startup. Decisional guidance for entrepreneurs proved to be highly valuable to increase decision quality, effectiveness, and learning [4].

[3] For example, UnternehmerTUM [3] receives over 100 (pre-)incubation startup and tech projects per year and has a dealflow of over 1000 startups per year

3 Machine Learning Perspective

At first, we focus on the **personalized guidance**: learning the intuition behind how the decision makers evaluate the most important characteristics that define the concept "startup", such as team, value proposition, idea, etc.

In the preprocessing phase, we have to reduce the feature space to the most informative features, while keeping in mind that they have to be interpretable for humans. Moreover, we have to deal with heterogeneous input data. For example, in case of scoring the teams on a scale from 1 to 10, we have to statistically summarize different aspects of the team constellation, such as average, coverage, heterogeneity, etc. Another possible solution is to create an ensemble of different models [5]. That is, one model for each team size.

The cases mentioned above, we are neither dealing with a typical regression problem nor with a typical classification problem. As the score of a team takes values on a scale from 1 to 10, where the order is significant, we are dealing with an ranking learning problem [6] (also known as ordinal regression [7]).

Obviously, we have to quantify the costs, as we have to deal with an imbalanced learning problem (e.g., 70% of tech startups fail [8]). Thus, we have to adapt methods from cost-sensitive learning [9] in order to quantify the possible losses and wins of an investment portfolio.

Secondly, our learning system provides **hybrid collective guidance**: integration of multiple knowledge sources. That is, we have apply and adapt labeling fusion techniques [10] for our purpose of deriving collective knowledge from different types of sources, such as multiple investors and domain experts, news, or social media.

Certainly, in order to support entrepreneurs in building a successful venture (which might also help in ranking the startups), we have to develop a similarity measure, specially tailored for startups.

Startups as input data are hard to reduce to numbers (which we humans can easily understand and compare), whereas no reduction reduces the understanding and a fast comparison. Therefore, we envision the *startup blueprint*: Each core feature score is allocated a fixed pixel in the blueprint. The score value associated with that specific feature determines the color: The values is transformed to a color value (i.e., 0 to 255). In this way, humans can develop of sense of how a successful startup looks like and assess the different aspects of the core features in a visual way.

Nevertheless, we have to continuously improve the performance of our leaning system. Our models have to self adapt to new markets, new development fields, and investor requirements. Thus, we are in a highly dynamic context, where we have to exploit various knowledge [11] and automatically adapt the machine learning models [12].

We envision a future system that is able to effectively and efficiently manage a fund: it evaluates teams, makes requests, makes suggestions for startups, evaluates the progress, and autonomously invests. Obviously, we can not totally exclude humans, but we can reduce their workload, while training the human expert to make better decisions. By providing the human expert with feedback we aim at developing a socio-technical system that can provides better prediction that a single human or machine could offer in separation [13] By applying active learning techniques [14], we can acquire precise knowledge for the most informative aspects of the current market, new values and trends, and other relevant information.

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