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► **To cite this version:**

Gabriel Ferrettini, Julien Aligon, Chantal Soulé-Dupuy, William Raynaut. A framework for user assistance on predictive models. Joint Conference of the Information Retrieval Communities in Europe (CIRCLE 2020), Jul 2020, Samatan, Gers, France. pp.32. hal-03138319

HAL Id: hal-03138319

<https://hal.science/hal-03138319>

Submitted on 11 Feb 2021

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A framework for user assistance on predictive models

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ABSTRACT

Data analysis generally requires very specialized skills, especially when applying machine learning tasks. The ambition of the paper is to propose a framework assisting a domain expert user to analyse his data, in a context of predictive analysis. In particular, the framework includes a recommender system for the workflow of analysis tasks. Because the lack of explanation in recommendations can lead to loss of confidence, a complementary system is proposed to better understand the predictive models recommended. This complementary system aims to help the user to understand and exploit the results of the data analysis, by relying on his data expertise. The framework is validated through a pool of questions and a mock-up showing the interest of the approach.

KEYWORDS

Recommendation system, Machine Learning, Predictive model, Prediction explanation

1 INTRODUCTION

In many cases, data analysis requires very specialized skills in the implementation and use of models. For instance, designing something as common and popular as a predictive model requires expert knowledge in the machine learning field. Thus, these analysis tasks are especially difficult to perform for a domain expert user, i.e. having a deep knowledge of the data to analyze, but without any background in machine learning. Several past works have been proposed to help these types of users, notably thanks to workflow recommender systems and model building assistance (as proposed in [20]). In general, these recommender systems offer very accurate analysis workflows and predictive models (drawing strength from workflows performed by past users). But the interaction with these systems is often limited to execute the predictive model proposed, without an easy way to validate and personalize it. This is a major drawback by which a user can lose confidence, due to a lack of explanations in the recommender system results. Indeed, neophyte users tend to struggle giving credence to a system they do not understand and are not familiar with. Given the fact that important decisions can be made using such a system, giving the user an opportunity to have confidence in the system is important. For example, the importance of transparency has been recognized for a long time in expert systems, as in [4], and studied more widely in the recommendation context in [28].

In this direction, the ambition of this paper is to propose a framework assisting domain expert users in performing sensible data analysis by himself (more precisely our work is focused on the task of multi-label classification). This framework includes a recommender system of workflows for predictive models and a complementary system explaining these results. The aim of this explanation system is to make the model transparent and effective, while giving confidence to the user. His involvement in all the stages of this framework should increase his confidence, while relying as little as possible on any other knowledge than his domain of expertise. Thus, the framework should allow a user to better select, personalize and understand the recommended predictive models. In order to achieve this, we explore novel ways of exploiting single prediction explanation. These new uses aim to help a non expert user to appropriate complex data analysis processes.

The paper is organized as follows. Section 2 details the limits of the current systems helping a user to analyze and classify his data. A review of existing solutions to better explain predictive models is also presented. Section 3 proposes a recommender system to be part of our framework and taking into account the drawbacks identified in the literature. Section 4 describes the explanation system for predictive models. Based on these two systems, Section 5 presents the organisation of the framework and how a user can easily select and fit the desired predictive model through the use of the explanation system. The framework is validated in Section 6 thanks to a use case and illustrated by a mock-up. In particular, this validation shows the framework is able to answer the following three questions:

- How a non expert user can appropriate the results of the recommendation by himself?
- How users can be confident in the produced results?
- How a model can be personalised without requiring machine learning knowledge?

2 RELATED WORKS

2.1 From the need of model recommendation...

Recommender systems based on collaborative filtering are known to be effective in various applications. For example, [3] suggests queries based on previous issues queries, applied in the general context of databases, while [14] recommends items based on user data obtained from a social network, and [2] provides sequences of queries based on similarities between *OLAP* user sessions.

Traditional collaborative filtering approaches however base their recommendations on similarities between users, identifying intrinsic traits they have in common. Such systems rarely consider the context in which the user evolves.

Context-aware recommender systems should then be preferred when the context of the user is complex and more prominent [1]. In this case, the information obtained from multiple contexts can be very useful to improve the relevance and effectiveness of the recommender systems. Such approaches have attracted a particular attention over the last few years. For example, [16] shows that detecting user emotion (context) and factoring it into a collaborative filtering approach increased user satisfaction. [31] proposes a system suggesting collaborations between universities and industries based on the identification of similar contexts of researchers (defined on a multitude of aspects). [33] develops a similarity-based context-aware approach under the assumption that recommendations should be similar if the contextual situations of the users are similar. They demonstrated that integrating a similarity measure between multidimensional contexts could improve precision scores.

The problem of *data analysis workflow recommendation* has recently received an increased interest, advertising several promising methods [19, 23, 27, 32]. Their purpose is to assist user in solving a range of different data analysis problems by the recommendation of adequate workflows (defined as sequences of operators producing knowledge from data). However, none of these works arise from a perspective of *context-aware recommendation*, taking into account the particular context in which a data-analyst evolves. They only take into consideration the information related to their purpose, such as the *objective* of the analysis for planification methods [19].

We plan to consider more of the relevant information constituting the user's context. Indeed, a dataset to analyse has multiple features and is defined by particular characteristics, while the actual needs of a data-analyst can be complex and largely implicit. Experiments performed in the past can also be considered part of this context, as they carry information toward what was and can be done. Yet, even with a finer approach to the recommendation, the user is still not able to understand and use fully what is being recommended.

As discussed in the introduction, the need for better explanations and confidences in the recommendation results is essential for a user, furthermore for a domain expert. To overcome this *black box* problem in the recommendations, several solutions exist in the literature, whose a review can be found in [28]. In particular, a number of goals characterizing the different types of explanations in recommender systems is proposed, and how to evaluate them. In particular, the notions of *Transparency* (i.e. how the system works as in [9]), *Trust* (i.e. perceived confidence with the recommendations as in [7]), *Persuasiveness* (i.e. user acceptance with the recommendations as in [9]) and *Effectiveness* (i.e. make better decisions as in [24]) seem to fit at the best the objectives of recommendation explanations proposed in our framework.

2.2 ...to the need of model explanation

The existing systems and toolkits for machine learning (ML) and data analysis in general mostly focus on providing and explaining the *methods* and *algorithms*. This approach has proven particularly helpful for expert users, but still requires advanced knowledge of data analysis. Indeed, some of the most well-known data analysis platforms such as Weka [13] or Knime [5] provide detailed descriptions of the methods and algorithms they include, often giving

usage examples. Unfortunately, detailed descriptions are a poor substitute to an actual training in data analysis.

Some data analysis platforms, such as RapidMiner [15], Orange [11], for instance, have dedicated a great attention to the problem of presenting and explaining the analysis *results* to the user. By providing well-designed visualization interfaces, these platforms assist the user in understanding the results produced, which is a first step toward actually using them and acting on them. However, they cannot explain *how* these specific results have been achieved, which remains a significant disincentive for users in areas where wrong decisions can have grave consequences. Helping those users to grasp *why* a particular prediction is being made (in a way that would allow them to check this reasoning against their own expert knowledge) could greatly enhance their *trust* in a reasonable prediction, or on the contrary give them a meaningful reason to discard a biased one. This is the original intuition behind the need for prediction explanations.

More recently Google with its "what if" tool, mainly based on [30], proposes many exploratory machine learning tools. Those help a user to understand and exploit machine learning models in an intuitive way. This is mainly done by allowing the user to explore new data points with a trained model, and displaying different metrics in an easily interpretable way.

Our approach is to make machine learning more interpretable by relying on explanation of the predictions provided by predictive models. The possible applications of prediction explanations have been investigated by [22]. According to their paper, the interest for explaining a predictive model is threefold:

- First, it can be seen as a mean to understand how a model works in general, by peering at how it behaves in diverse points of the instance space.
- Second, it can help a non expert user to judge of the quality of a prediction and even pinpoint the cause of flaws in its classification. Correcting them would then lead the user to perform some intuitive feature engineering operations.
- Third, it can allow the user to decide the type of model preferable to another one, even if he has no knowledge of the principles underlying each of them.

A great number of works pertaining to prediction explanation led to [18], which theorized a category of explanation methods, named *additive* methods, and produced an interesting review of the different methods developed in this category. Some of these methods are described in detail in [10] and [26]. They are summarized in [18] as methods attributing for a given prediction, a weight to each attribute of the dataset. This creates a very simple "predictive model", mimicking the original model behavior locally. Thus, we have a simple interpretable linear model which gives information on the original model inner working in a small vicinity of the predicted instance. The methods from which these weights are attributed to each attribute varies between the different *additive* methods, but the end result is always this vector of weights.

Other lines of reasoning have been explored, such as in [6], which investigated prediction explanation from the point of view of model performance. Meaning that their metric shows which feature improves the performance of the model, rather than which

feature the model consider as important for its prediction. If this line of reasoning is really interesting for the model explanation field, it does not correspond to our scope as well as other methods, as we are aiming to help users understand how a model works, and not how to improve it. In this paper, we aim to facilitate the understanding of any machine learning model for users with no special knowledge of data analysis or machine learning. Thus, it is more relevant to focus on *additive* methods, as they generate a simple set of importance weights for each attribute. This set of weights is easy to interpret, even for someone without expertise on machine learning.

3 WORKFLOW RECOMMENDATION SYSTEM

In this section is described the basic principles of our workflow recommender system, as depicted in Figure 1. This section takes part of a previous work, described in more details in [21] and [20]. This recommender system has been showed to be an effective assistant for relevant workflow selection, through the experiments in [20]. This system is the base of the framework presented in Section 5.

3.1 Process overview and definitions

3.1.1 Dataset. Datasets are defined as a collection of instances described along attributes. Given $A = a_1, \dots, a_n$, the attributes of a dataset, an instance x is a vector of n attributes values: the description of x along the attribute set A .

3.1.2 Workflow. Workflows in their most general form usually consist in directed graphs of data analysis operators [23]. These can include the many possible steps of data analysis, such as various preprocessing (data cleaning, normalization, etc.), construction of models, search for patterns, or even parameter optimization for other operators. Note that, as explanation methods (see Section 4) are applied to supervised classification, for now we only consider workflows arising from such models.

3.1.3 System overview. The recommendation system is based on a meta-database of past machine-learning experiments. For each of them, one can access the base dataset of the experiment, the workflow used to create a machine learning model (from the dataset) and its performance.

In section 3.2 (step 1 of Figure 1), the method to determine how datasets are *similar* is presented. Then, in section 3.3 (step 2 of Figure 1), we present how the performance of a workflow is modeled according to the current user's needs. These user preferences filter the set of recommendations to propose relevant workflows described in the last section 3.4 (step 3 of Figure 1).

3.2 Dissimilarity between datasets

The measure of dissimilarity is based on the characteristics of the datasets to be compared. This dissimilarity is computed through two levels of meta-attributes: the difference between each dataset meta-attribute and the difference between each attribute meta-attribute.

3.2.1 Dataset meta-attributes. In order to dispose of a large selection of meta-attributes from diverse categories, we use the OpenML

platform [29]. This platform contains more than a hundred meta-attributes, from different statistical, information-theoretic, and landmarking approaches (complete list available on <http://www.openml.org/>).

3.2.2 Attribute meta-attributes. Individual attributes of datasets can be characterized along a set of measures, mostly consisting in non-aggregated versions of the previously described *Dataset meta-attributes*. To build our set of *attribute meta-attributes*, we use the 72 measures proposed in [21], able to characterize individuals attributes. The key idea is to compare attributes of different datasets along their *attributes meta-attributes*. However, as the intuition is to make use of all available information, attributes are compared by most similar pairs: For two datasets A and B , each attribute of A is paired with an attribute of B such as the total dissimilarity of each pairs is as low as possible.

3.3 Workflow filtering by user preference

In order to make the recommendations more accurate, the performance of a workflow is filtered according to the current user's needs. For instance, if a current user has a very high cost of false negatives (like the early diagnosis of a dangerous disease), then we should consider relevant workflows that exhibited good *recall* on similar datasets. Our approach is then to consider criteria able to characterize different aspects of workflow performance to model user preferences. Even considering only problems of supervised classification, many different criteria have been proposed to characterize different aspects of performance, like Cohen's *Kappa* [8], measuring agreement while accounting for the chance of random good guesses, or the more complex *Information Score* from [17], measuring the amount of *non-trivial* information produced by the model.

Then, the preference model of a user is represented as a set of performance criteria he is interested in (each of them associated to a weight qualifying its relative importance). For instance, a user who wants to avoid false negatives has *recall* measure as its most important criterion. But it does not mean that *precision* has to be ignored. A higher weight associated to *recall* represents the user preference.

3.4 Workflow recommendation by pareto front

Considering a current user, analysing a dataset and having defined his preferences, the system recommends workflows from past analysis. This implies to access to a base of past data analysis experiments, where (hopefully expert) users upload the analysis they perform. One such past analysis then consists in a dataset, upon which was applied a workflow, yielding a result.

The suggested workflow for the current analysis should then be determined according to two criteria:

- (1) The past analysis must have been produced on a dataset *similar* to the one of the current user.
- (2) Its results, evaluated according to the preferences expressed by the current user, should be satisfactory.

We thus face a problem of multi-criteria optimisation, where both dataset similarity and past performance matter. To solve it, a pareto recommendation approach is proposed.

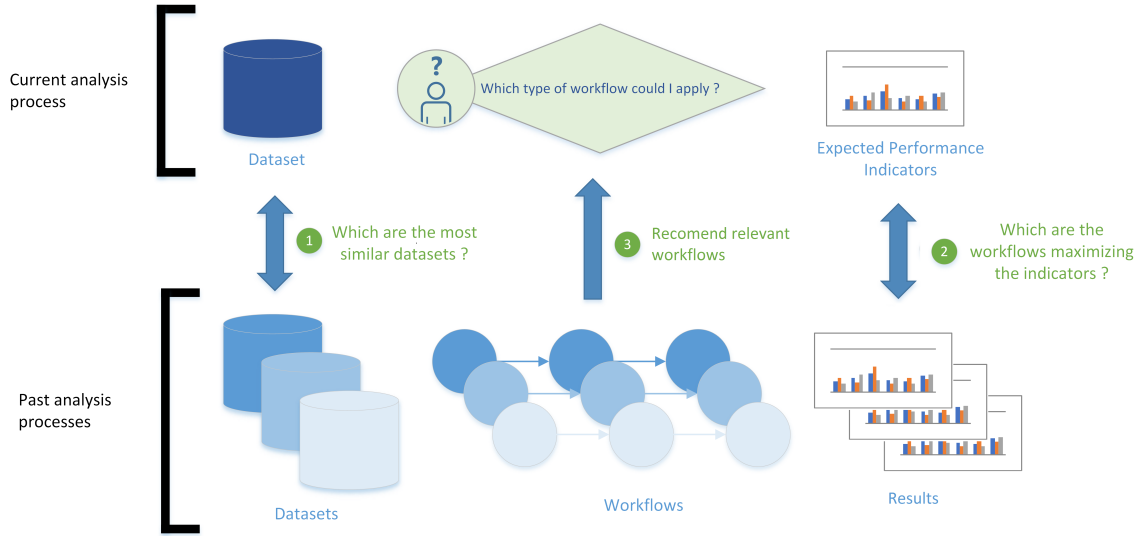


Figure 1: Global steps of the recommendation process

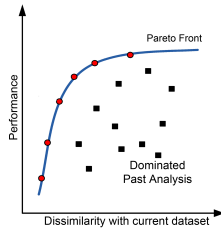


Figure 2: Pareto front of the best past analysis according to our two criteria

Consider the full Pareto front of past analysis as a set of recommendations. We can then consider our best possible candidates according to our two criteria (as shown in Figure 2), which increases the chances of finding one that suits the user, but requires an additional step to discriminate between candidates. Indeed, supplying the full set of recommendation would probably be useful to expert users, but is most likely to overwhelm a non-expert.

4 PREDICTIVE MODEL EXPLANATION SYSTEM

As introduced in Section 1 and developed in Section 2, the lack of understanding of prediction recommendations is a real problem encountered by most domain experts users. It leads to a lack of trusts in the models, and impairs its use. Moreover, even through a guidance, a lack of experience can lead to mistakes when analysing a dataset and considering not so well adapted predictions. In order to address those pitfalls, we aim to help the user understand the recommendation results. For this, we propose an explanation system mainly based on the domain user knowledge.

4.1 Explaining prediction results

Most of the methods of the literature are mainly devoted to explain a predictive model in a global way. These methods are not relevant when domain expert user (for instance a biologist) has to study the behavior of particular dataset instances over a predictive model (for instance in the context of cohort study). This is our main motivation to propose an explanation system able to understand the behavior of individual predictions. In particular, this method is detailed in [12] and the main principles are described below.

Underlying principle. Our prediction explanation system relies on the principle of analysing the influence of each attribute on the model prediction. This way, we aim to emphasize the most important attributes according to the model. The explanation of the model is realized by comparing the impact of the absence and presence of the attributes to determine their influence. However, considering that each attribute is independent of the others presents a limit. Therefore, in order to take into account this dependency between attributes, it is necessary to consider the influence of attribute groups on prediction. These influences are then aggregated in a unique score by using Shapley’s individuals participation in group efforts, described in [25].

4.2 Explanation of a single attribut influence

Given a dataset of instances described along the attributes of A , the influence of the attribute a_i on the classification of an instance x by the classifier confidence function f on the class C can be represented as:

$$inf_{f,a_i}^C(x) = f(x_{a_i}) - f(\emptyset) \tag{1}$$

Where $f(x_{a_i})$ represents the probability that the instance x is included in the class C with only the knowledge of the attribute a_i (according to the predictive model). This formula can be used

with groups of attributes, which leads us to an influence inspired by Shapley's work:

$$I_{a_i}^C(x) = \sum_{A' \subseteq A \setminus a_i} p(A', A) * (inf_{f_i, (A' \cup a_i)}^C(x) - inf_{f_i, A'}^C(x)) \quad (2)$$

With $p(A', A)$ the Shapley's value, a penalty function accounting for the size of the subset A' .

$$p(A', A) = \frac{|A'|! * (|A| - |A'| - 1)!}{|A|!} \quad (3)$$

Due to the exponential complexity of the formula, an optimisation of the calculation of the influence of an attribute is proposed in [12]. It produces with a satisfactory approximation with a relatively small loss in accuracy).

5 ORGANISATION OF THE FRAMEWORK

We now present the framework including the two systems described in the two previous sections. Our framework is separated into two use cases. In Section 5.1, we show how a domain expert user can be guided through the complex process of selecting a predictive model among a set of possible ones, while Section 5.2 illustrates how explanations bring new insights during the feature refinement of a predictive model. These two processes are illustrated in Figure 3 and are based on the most common functionalities of the literature described in Section 2.

Remember that this framework is intended for users who have no prior knowledge of machine learning, but who have expertise in their own field (e.g. biologists, doctors, engineers...). These users produce data that they are required to analyze. It is therefore assumed that they have a solid knowledge of this data, but not of machine learning methods.

5.1 Model selection via prediction explanation

Workflows recommendation - First, a user produces data he wants to analyse. The data is given as input of the recommender system, along with their specifications for the analysis: the target feature and their preferences in term of results. The system then suggests a set of possible workflows which are the most able to analyse the user's data.

Execution - Among this selection of possible workflows, the user can select all or a set of them. He can access a description of each workflow and its inner working if desired, allowing him to perform a first selection of the possible workflows. The workflows selected are then executed and produce a set of predictive models.

Model explanation - Using these models, the system can generate the classification of a given instance of the dataset and provide its afferent explanation for each model. These explanations take the form of attribute influences. For instance, in Figure 4, a user is informed that a particular patient is predicted to have diabetes by both models A and B , but that A made this decision considering mostly the patient's diet, while B also considers his weight as important. In order to allow the user to explore the models in an intuitive way, a set of 10 instances are recommended for his review. This selection of instances aims to provide the user with a set of prediction explanations as diverse as possible, without overwhelming him with a space too large to be explored efficiently by humans.

5.2 Feature selection via prediction explanation

Feature engineering - Thanks to the prediction explanations, a user can access the reasoning behind each model, allowing him to detect possible flaws in the proposed models. As an example, prediction explanation allowed personnel of an hospital performing a medical study described in [22] to realise that some attributes should not have been included in their dataset. Moreover, based on his own domain of expertise, a user can assess the importance of each feature, comparatively to the importance given to them by the models. Thus, the user can select undesirable features and remove them from the dataset.

Model selection - Once the final desired features have been determined, the user exploits his domain knowledge to assess the reasoning behind each model. This assessment is based both on a global evaluation, such as Cohen kappa or the area under the ROC curve, and local information on the prediction. This allows the user to select the desired final model by choosing the best performing model, but also the one with the most relevant use of the dataset features.

6 VALIDATION OF THE FRAMEWORK

In order to validate the answers to our original questions indicated in Section 1, we propose a mock-up of our framework. This mock-up illustrates a use case, based on the well-known UCI pimas indians diabetes dataset (available on many platforms, as kaggle), since familiarity with the dataset is beneficial to the understanding of this validation.

In our use case, a biologist is aiming to study the dataset of pimas indians diabetes, and uses our recommendation system to provide possible analysis workflows. First, as described in 5, the user enters the diabetes dataset as input of the recommender system, and asks it to perform a recommendation.

6.1 Helping a non expert user appropriate the results of the recommendation by himself

Instead of recommending one of the workflows of the pareto front (see Section 3.4), the user is presented the four best recommendations from the pareto front. A description of each workflow is made available to the user, allowing him to perform a first selection among the different options. Although these descriptions are necessarily technical, they are essential for a user to understand what is happening when each workflow is executed. The workflows and their descriptions are depicted in Figure 5. As an example, we can see in the figure that a workflow is not only the production of a predictive model, but also successive operations of transformation applied in the dataset. These workflows are then executed and presented to the user through a set of selected instances. These instances are selected in a way that favours a large diversity in predictions explanations. The exact algorithm used here is the one presented in [22]. The user can thus explore each predictive model through this set of instances, by viewing a diverse set of keypoints, illustrating the models. This allows him to infer how the whole model works, with minimal information. The instances and their attached prediction explanations are depicted as in Figure 6. On the left, the user can select the instance he wants to study, and decide

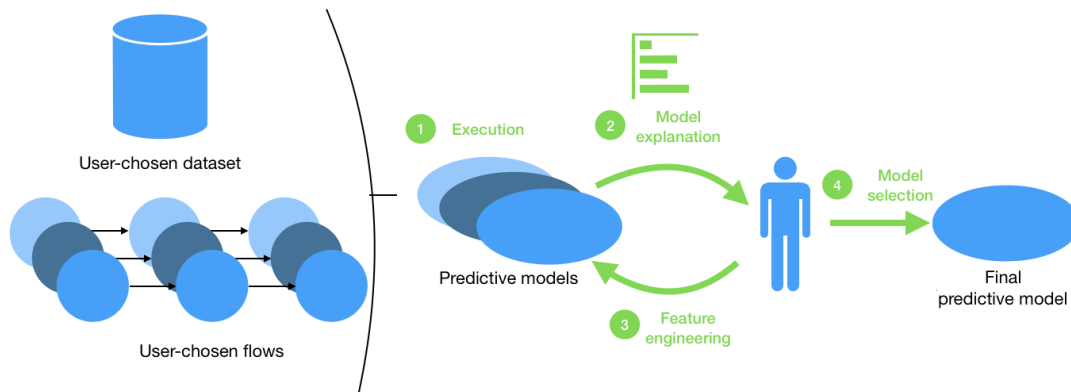


Figure 3: Building a predictive model

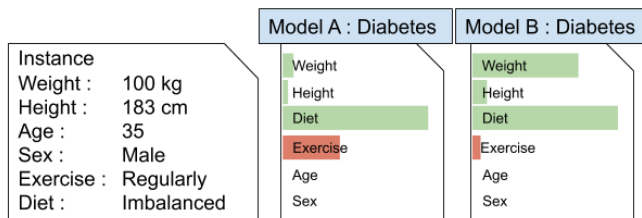


Figure 4: Explaining a prediction

to eventually remove attributes from the dataset. On the right is presented the prediction explanation of the selected instance for each of the models. In our use case, we can see the scientist selects the instance 49. Automatically, an explanation is proposed where random forest and bagging J48 (an optimized decision tree) models mainly base their prediction on their blood pressure and age, whereas the naive bayes is mostly influenced by the mass of the instance. This allows an immediate access to the inner workings of each presented workflow, which is solely based on the domain knowledge of the user. Thus, by presenting the results and how they were obtained, the user is informed of the conclusion of the prediction, without having to rely blindly on the model.

Therefore, through prediction explanation, the user can access to a new type of information that does not rely on expertise in data analysis to be understood. He can understand and appropriate the results of the recommendation system thanks to his own domain-based knowledge: without understanding the inner workings of each model. He can visualize how each model uses the data to make predictions.

6.2 Giving a user confidence in the produced results

Through this explanation method, the user can choose between models without having to rely solely on global measures of performance. He is able to use his own judgement rather than by the only proposal of a fully automated process. This also makes it possible to evaluate possible defects in the models, which is not always possible with only conventional metrics. As an example, the global

accuracy of a model or the kappa score does not warn a user of an inappropriate attribute which should be removed from the dataset.

In our mock-up example, the user can decide that the age of a patient is not that important in determining if he is likely to have diabetes. At the same time, if our user considers a patient’s mass as a valid indicator, it indicates him that the naive bayes model is more interesting in his case (supposing the instances he reviewed are consistent with this explanation). This understanding of a model, its strengths, and its flaws gives the user a stronger confidence in what is being accomplished during the data analysis process. By pinpointing eventual problems in the predictive model, he also becomes able to know when the model is reliable.

6.3 Personalising a model without requiring data analysis knowledge

Once the user have studied his models, he can assess which workflows fit best his requirements. In particular, the user can identify which features are mainly used by the workflows, and decide which are important for his study. In our mock-up example, the biologist might want to study the impact of less evident diabetes indicators, and decide to remove the insulin and plasma features from his dataset (like presented in Figure 7). This forces the workflows to use the other features, and maybe highlight new important indicators. We can see in Figure 7 that the J48 workflow has significantly changed its behavior, while Adaboost model has simply adjusted the importance of each attribute.

By this process, the user accomplishes feature selection without having data analysis knowledge or expertise. His domain knowledge allows him to assess the interest of a feature and decide if the workflows are using them well or not.

7 CONCLUSION AND PERSPECTIVES

We have presented a framework that proposes a new way to assist a user in analyzing their data in two steps. In the first step, a recommendation system provides possible analysis workflows and predictive models, similar to what other users would have done in the past for a similar dataset. In the second step, the proposal of a model explanation allows a domain expert user to study the predictive models by himself.

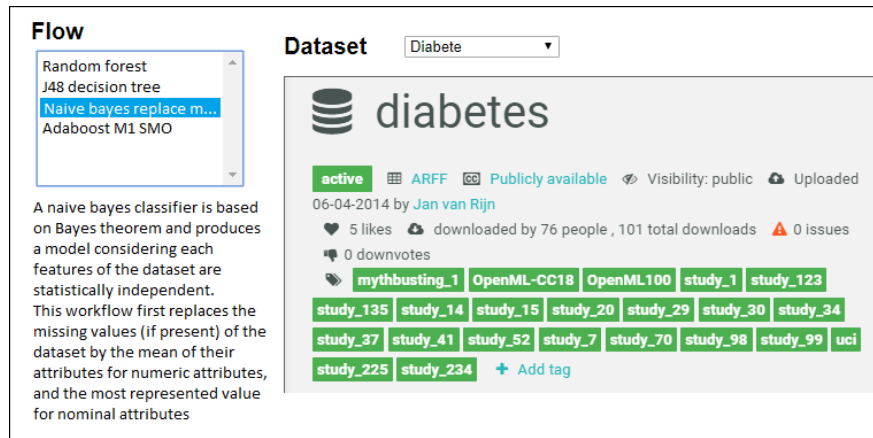


Figure 5: Workflow recommendation

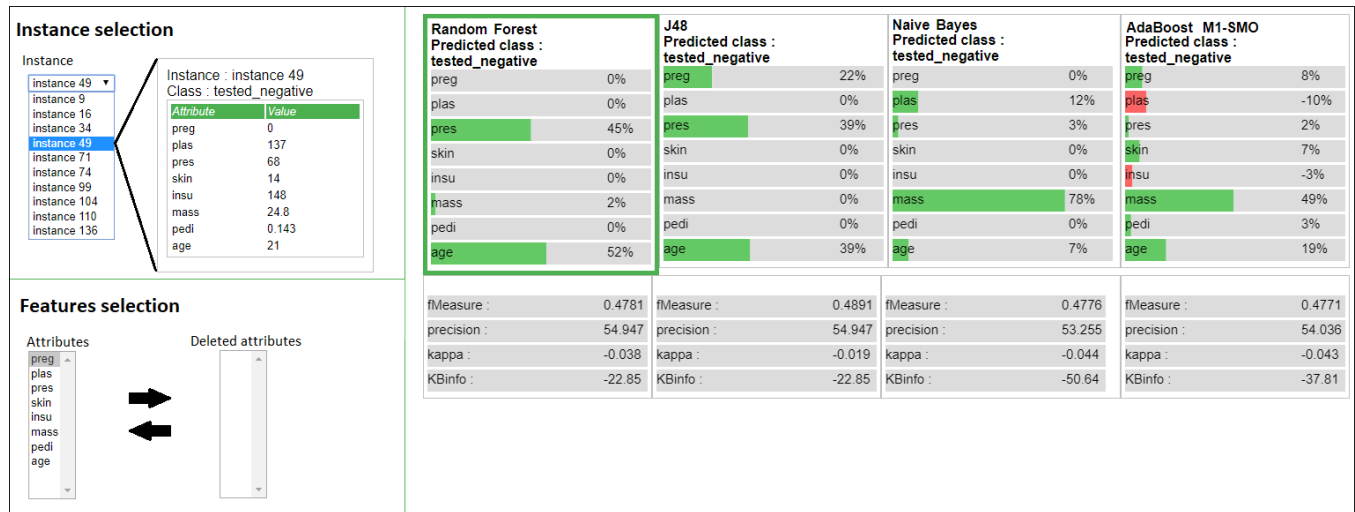


Figure 6: Visualization of prediction results through prediction explanations

We have shown this framework brings an answer to possible unresolved data analysis pitfalls, by a better understanding of data analysis models and building the user's confidence.

However, this method still has to be tested in real-world situations. A prototype is then being developed, in interaction with biologists of the institute of Cardiovascular and Metabolic Diseases (INSERM institute). A medium-term perspective is to form a cohort of actual domain expert users to assess the efficiency of our framework and its capacity to assist them with real-world problems.

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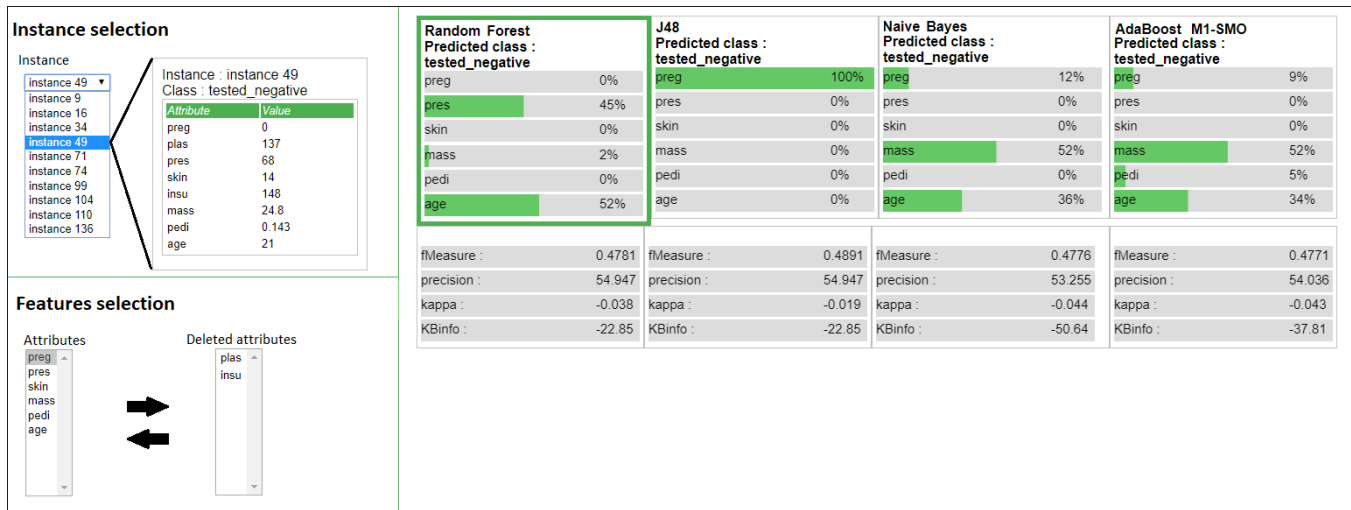


Figure 7: New prediction explanations once the attributes plasma and insulin have been removed

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