**Propheticus: Generalizable Machine Learning Framework**

Internal Report

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**Abstract**—Due to recent technological developments, Machine Learning (ML), a subfield of Artificial Intelligence (AI), has been successfully used to process and extract knowledge from a variety of complex problems. However, a thorough ML approach is complex and highly dependent on the problem at hand. Additionally, implementing the logic required to execute the experiments is no small nor trivial deed, consequently increasing the probability of faulty code which can compromise the results. Propheticus is a data-driven framework which results of the need for a tool that abstracts some of the inherent complexity of ML, whilst being easy to understand and use, as well as to adapt and expand to assist the user’s specific needs. Propheticus systematizes and enforces various complex concepts of an ML experiment workflow, taking into account the nature of both the problem and the data. It contains functionalities to execute all the different tasks, from data preprocessing, to results analysis and comparison. Notwithstanding, it can be fairly easily adapted to different problems due to its flexible architecture, and customized as needed to address the user’s needs.

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**I. Introduction**

Today’s society generates and stores an exponentially increasing amount of data. With it comes the need to transform these data into different types of knowledge. Still, most of the gathering processes are loosely controlled, resulting in datasets which usually have irrelevant, noisy or unreliable, or even redundant and invalid data. At the same time, due to the recent technological developments, Machine Learning (ML) algorithms can now be applied to larger datasets and have shown their ability to adapt and extract knowledge in a variety of complex problems. This is because they are able to find (complex) patterns in the data and learn from them without relying on a predetermined model. Such models can then be used to make predictions on new unseen data based on what was learned.

Depending on the type of feedback available to the learning system, ML tasks can generally be classified into **Supervised**, **Unsupervised**, **Semi-supervised**, and **Reinforcement Learning**. Additionally, each of these high-level classes can be further divided (e.g. **Classification**, **Clustering**) each with its own characteristics and adequate techniques, which are also constrained by the nature of the problem (e.g. **timeseries**). As a result, even a “simplistic” approach can be rather complex in order to be relevant, otherwise, it may not represent the real problem.

To conduct an ML experiment it is then necessary to create the logic to study and execute the different configurations, considering various algorithms, techniques, and perspectives of the data. Finally, it is then required to conduct statistical comparison tests to identify which models are in fact better.

Consequentially, between mastering the theory and implementing the necessary logic to conduct the experiments, there are several possibilities for faults and mistakes. These can often be due to minor misinterpretations or faulty logic, yet they can ultimately undermine the complete set of experiments. This report gives a brief introduction to Propheticus, a generalizable ML framework which facilitates the use of ML algorithms and techniques, allowing the user to focus more on the problem itself.

**II. Related Work**

As Machine Learning (ML) became widely used various tools [1], [2], [3] were developed over time. Still, most are either limited to a specific approach or too complex to adapt and customize to the user’s needs. Moreover, although some tools already have a fair number of plugins, they are not actively developed or supported by the community, which results in a slower adoption of state-of-the-art algorithms and techniques. Finally, to the best of our knowledge, no single tool exists that is able to conduct all the tasks that Propheticus does, nor are they easily expandable or customizable.

**Scikit-learn** [4] is a well-known Python package which provides most of the “standard” ML algorithms and techniques. It is thoroughly documented, and its community is considerably large and active, which results in regular updates that keep it up to date with stable state-of-the-art techniques. Additionally, its structure is clear and simple, which allows the users to develop and seamlessly integrate with it. Due to all its strengths, Propheticus relies heavily on scikit-learn, although it could be easily changed to an equivalent functioning package.

Although in our perspective there was no “alternative” to Propheticus, it did not start with the purpose of replacing or overcoming existing software solutions. Its initial motivation was to develop a generalizable framework that could be easily used and integrated with different research fields, problems, and purposes. Moreover, one of the core goals of Propheticus is to be able to execute all the tasks usually associated with ML (e.g. data analysis/preprocessing, models’ execution, results log/analysis, models comparison) in a single product.
III. Propheticus Framework

Although Propheticus does not attempt to remove the complexity of the approach (nor should it, as simplifications usually result from relaxing or simplifying the problem), some of the process and “rules” of a Machine Learning (ML) experiment are fairly standard. As a result, one of the main goals of the framework is that it should clearly define the experiments workflow, validating and providing useful feedback to the users across the different steps. Although the framework aims at being configurable, allowing the users to adapt the experiments to fit their needs, there are various “mistakes” which can be easily detected when they are known (e.g. data leakage), yet they can be extremely complicated to identify when not attended to (some are in fact “silent errors” which, if not properly validated, may not even be detected, entirely compromising the validity of the experiments).

Propheticus is developed and maintained in the most recent version of Python, and extensively relies on the scikit-learn [4] and SciPy [5] (e.g. NumPy, Matplotlib, Pandas) packages. Tasks not available in these packages were included from other sources (e.g. imblearn [6], pycclustering [7]) and adapted to fit the generic structure of scikit-learn and SciPy.

One of the main objectives of Propheticus is that it should be able to execute the most common types of learning tasks (e.g. classification, clustering) and problems (e.g. timeseries). Still, as there are too many variations, its architecture was developed to be easily adaptable to the user’s needs.

Currently, the main use of Propheticus is based on a simple, yet comprehensive, Command Line Interface (CLI) that allows the user to intuitively explore and process the data. However, the analysis and combination of different techniques, algorithms, and even perspectives on the data can easily become impractical to handle individually. Hence, Propheticus contains a module that allows it to run autonomously based on the predefined configurations for each experiment.

Propheticus contains several functionalities for the various tasks. Concerning data analysis, different techniques can be used, from exploratory (e.g. boxplots, scatterplots) to descriptive analysis (e.g. averages, standard deviations). Regarding data preprocessing, multiple techniques are already included for feature selection and extraction (e.g. correlation, Principal Component Analysis (PCA)) and data balancing (e.g. undersampling, oversampling). Currently, Propheticus includes various algorithms (both binary and multiclass) for classification (including timeseries data) and clustering tasks. To assess the models’ performance, multiple runs are executed for each configuration and different methods can be used to have a better estimate (e.g. cross-validation). In the end, several metrics (e.g. precision, recall, f1-score) are stored for each fold/split and run, which are then used to generate various reports/graphs (e.g. confusion matrices, ROC-curves). Finally, Propheticus explores the notion of application scenarios (a scenario is a realistic situation of the problem at hand that depends on the criticality of the system) [8] which allows the user to compare/benchmark models based on a specific set of metrics. Nonetheless, statistical tests are required to assert which is better. Thus, Propheticus also includes a module that can statistically compare different models based on their results for the chosen metrics (assumptions testing, statistical test choices and post-hoc analyses are automatically made by analyzing the data/results).

IV. Conclusion

Data are nowadays one of the most important and valuable assets. Due to the recent technological developments Machine Learning (ML) algorithms and techniques have shown their ability to adapt and extract knowledge in a variety of complex problems. Although different tools already existed for exploring and making predictions based on the data, Propheticus attempts to go further and broader, providing a generalizable, flexible, and scalable framework for conducting ML experiments.

Although Propheticus is still in its early stages of development, it has already been used in different projects and problems: two masters dissertations [9, 10], an article [11], and is currently being used and developed in the context of a Ph.D. This will considerably broaden its scope to include techniques such as Deep Learning and Evolutionary Computation (EC) to assist in different steps of the process, from feature selection to the algorithms’ hyperparameters tuning.

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