

Work in Classification

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Abstract goes here.

I. INTRODUCTION

In our introduction we want to start from big picture (LIGO, ML, pipelines) and narrow down to what work we are presenting here and why it is important. We also describe in which ways it is novel and how it compares to previous works like in [?]. We may also want to cite [?].

II. IMPROVING BINARY CLASSIFICATION THROUGH ML

In this section we may want to expand on the idea of using classification itself. We should mention which algorithms we attempted to use and why they did not work. Then we can talk more in detail about the ones that did work in the following subsections.

A. K-Nearest Neighbors (KNN)

One of the non-parametric algorithms we have used for classification is the `KNeighborsClassifier` (KNN). This algorithm assumes that similar things are near to each other. It captures the idea of similarity by computing the distance between points in a graph. It is also a lazy learning algorithm, because it doesn't have a training phase, it uses all the data for training while classification -the dataset is stored and at the time of classification, it acts on the dataset.

The workflow of the KNN algorithm is the following: first, after splitting the data into training and testing sets, we need to select the number of neighbors, K , which can

be any integer. Then, for each point of the testing dataset we compute the distance between the point and each row of the training data with a chosen metric (Euclidean, Manhattan, Chebysev, Mahalanobis), and we sort the points in ascending order based on the distance value. By choosing the top K neighbors from the sorted array, we assign a class to the test point, which is the most frequent class of the chosen neighbors.

B. Random Forest (RF)

III. DATA CONDITIONING

We should in principle condition the data in the same way but any differences can also be described here. [Talk here about the injection campaign and how the data is splitted into training and testing datasets \(?\)](#).

IV. RESULTS

Here we talk about overall results and specifically from each algorithm in the subsections below. [\[MMT: Below I described how to check the performance of the algorithms. Maybe a table with all the scores/sensitivities/precisions from both KNN and RF would be useful \(already got it in a google doc\)\]](#)

To measure the performance of the classifiers we use some common statistical quantities. The score is the number of correctly predicted events over the number of total events (a perfect classifier has a score of 1). It works best when there is an equal number of events for each label in the training set. It does not consider the importance of misclassification, or that the training data can be biased towards one specific label.

The mean score is computed by training the algorithm on the 90% of the dataset and testing it on the remaining 10%, cycling the train/test combination over the full dataset. To do that, we are going to use the training dataset, since it's the larger one. In order to train and test the model and create the different plots, we are going to use the training and testing files.

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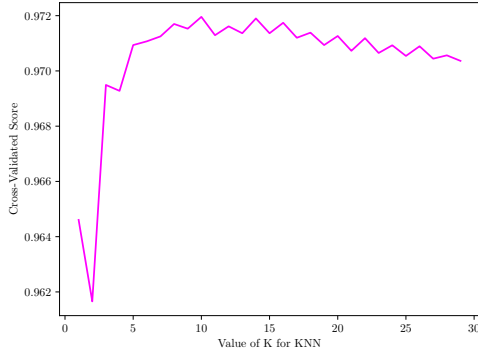


FIG. 1. Score of our KNN model as a function of the number of neighbors. We are considering *HasNS*.

Another useful quantity is the sensitivity. It is the ratio between the true positives and the sum of the true positives and false negatives. It measures how much the algorithm predicts *true* (in our case it would be that the event has NS or has REM), when it is actually *true*. Having a sensitivity equal to 1 would mean that our method predicts *true* for every event. Therefore, a method with high sensitivity will barely miss true alarms.

A quantity that measures how much you can trust a method when it predicts *true* is the precision. It is the ratio between the true positives and the sum of the true and the false positives. A precision equal to 1 means that the method never predicts *true* when it is actually *false*. This means that the method will never give false alarms.

A. KNN Results

1. *Has NS*

The metric we use to compute the distance between neighbors is the *Manhattan* metric (or the Minkowski's $L1$ distance), which is the distance between two points measured along axes at right angles. Having $p_1(x_1, y_1)$ and $p_2(x_2, y_2)$ the distance will be

$$d = |x_1 - x_2| + |y_1 - y_2|. \quad (1)$$

Moreover, the points are weighted uniformly. After applying cross-validation, we get that the optimal number of neighbors is $K_{NS} = 10$, with a mean score $s_m = 0 : 9718355224352762$ and a testing score $s_t = 0.9723828730478842$.

In Fig. 1 you can find how the mean score changes with the number of neighbors of the algorithm. The confusion matrix appears in Fig. 2, the probability as a function of m_1 and m_2 is shown in Figs. 3, and the true and false positive rates in terms of the threshold probability appear in Fig. 4.

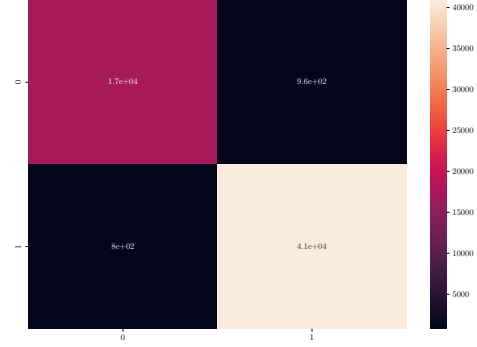


FIG. 2. Confusion matrix for our model for *HasNS*, using the independent recovered values.

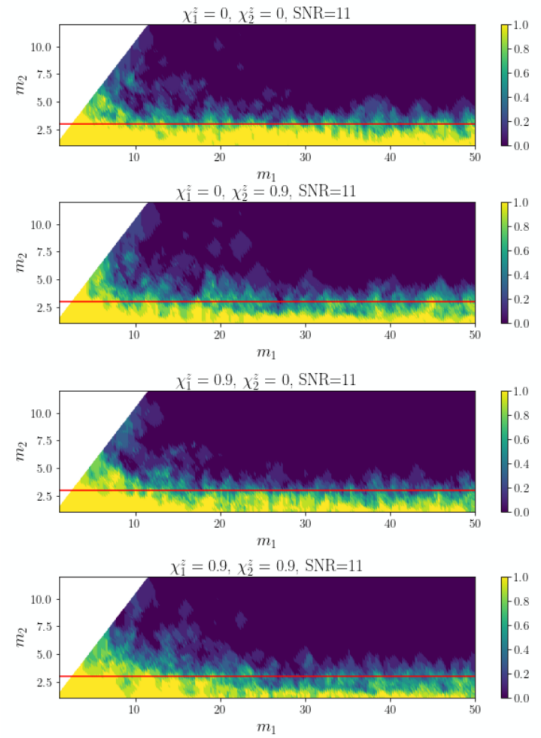


FIG. 3. Probability of having a remnant as a function of the values of the masses. The different panels show the results for different spins. The solid red line depicts the threshold mass for m_2 .

B. RF Results

V. CONCLUSIONS

Reiterate why what we did is important and how it improves current knowledge.

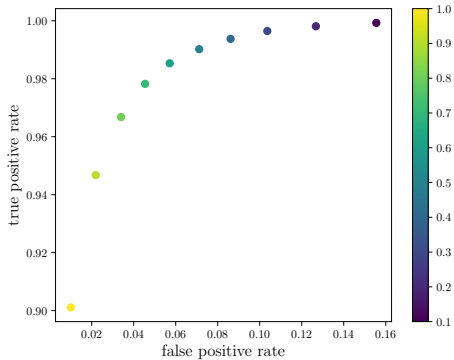


FIG. 4. Relation of the true and false positive rates as a function of the threshold applied to make the decision between having or not having a remnant.

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All plots were made using the python package `matplotlib` [?].

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