# Project Report 1

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In this project, we implement two basic machine learning models: logistic regression and naive bayes. These models are tested upon four classification datasets: Ionosphere Dataset, Iris Dataset, Car Evaluation Dataset and Adult Dataset. These datasets contains various type of features: both continuous and discrete. In the preprocessing phase, we first discretize all the continuous features, handling the missing values and values out of range. In the experiment phase, apart from reporting evaluation metrics upon various models with different datasets, we further investigate the influence of hyper-parameter tuning, feature selection and dataset selection.

## 1 Introduction

Classification tasks is one of the most common and important task in machine learning community. Given certain features, classification task is to categorize which class is most likely to be. In this project, we implement two basic machine learning models: logistic regression and naive bayes, and test their performance upone four dataset: Ionosphere Dataset<sup>1</sup>, Adult Dataset<sup>2</sup>, Iris Dataset<sup>3</sup> and Car Evaluation Dataset<sup>4</sup>. All the features are discretized during the pre-processing phase. We further investigate the influence of different training techniques, such as hyper-parameter tuning and feature selections, upon the performance of the models.

## 2 Datasets

We use four datasets including Ionosphere Dataset<sup>5</sup>, Adult Dataset<sup>6</sup>, Iris Dataset<sup>7</sup> and Car Evaluation Dataset<sup>8</sup>. The targets of all these four datasets are categorical classification (including binary classification). We exam four datasets to find that no missing values exist. We use replace function in pandas module to process all the target values into categorical count value. We will briefly describe the specific features and then introduce how to extract/process the features.

<sup>1</sup>https://archive.ics.uci.edu/ml/datasets/ionosphere

<sup>&</sup>lt;sup>2</sup>https://archive.ics.uci.edu/ml/datasets/Adult

 $<sup>^3</sup>$ https://archive.ics.uci.edu/ml/datasets/Iris

 $<sup>^4 {\</sup>tt https://archive.ics.uci.edu/ml/datasets/Car+Evaluation}$ 

 $<sup>^5 {</sup>m https://archive.ics.uci.edu/ml/datasets/ionosphere}$ 

 $<sup>^6 \</sup>mathtt{https://archive.ics.uci.edu/ml/datasets/Adult}$ 

<sup>&</sup>lt;sup>7</sup>https://archive.ics.uci.edu/ml/datasets/Iris

 $<sup>^8</sup>$ https://archive.ics.uci.edu/ml/datasets/Car+Evaluation

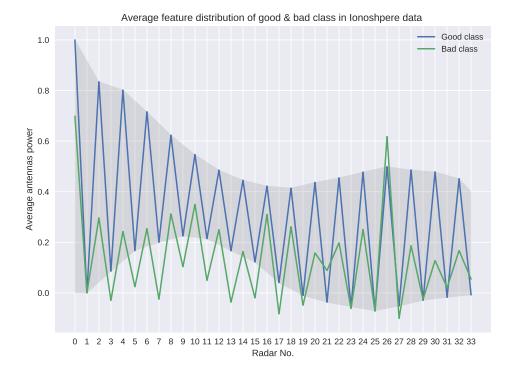


Figure 1: Distribution of average numerical features given "good" or "bad" class in ionosphere dataset

#### Ionosphere Dataset

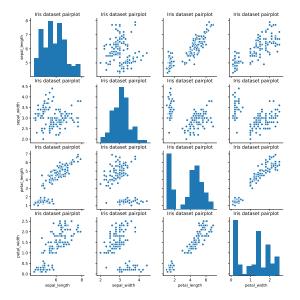
Ionosphere dataset contains 34 radar data (real values between -1 and 1)[1]. We find their distribution with respect to the "good" or "bad" target, which is reflected in Figure 1. We then remove radar 1 feature which is always 0. We can see that good class and bad class have quite distinct patterns in the antennas power value, which is essential in the following classification. We also fill between the intervals of good-class feature distribution to find that such surface is quite similar to the auto-correlated signals. Therefore, we use Principal Component Analysis to reduce the dimensions from 34 into 10 to learn the low-rank representation for more efficient and powerful training.

### **Adult Dataset**

Adult dataset aims to predict whether income exceeds 50 K/yr based on census data[2]. There are 14 features included with datatypes of continuous count values, continuous real values and categorical/binary values. We min-max normalize the continuous values (both count and real), discretize normalized real values into 10 categories and leave everything else untouched.

#### Iris Dataset

There are continuous real value attributes with 1 decimal precision, whose basic statistic information is listed in Figure 2 and Table 1, where sl,sw,pw,pw stand for  $sepal\ length$ ,  $sepal\ width$ ,  $petal\ width$ ,  $petal\ length\ [3]$ . Linear correlation between features can be found, e.g. petal length & petal width and petal length & sepal length. We also min-max normalize and discretize the normed real values.



	sl	sw	$\operatorname{pl}$	pw
count	150	150	150	150
mean	5.84	3.05	3.75	1.19
$\operatorname{std}$	0.82	0.43	1.76	0.76
$\min$	4.3	2.0	1.0	0.1
25%	5.1	2.8	1.6	0.3
50%	5.8	3.0	4.3	1.3
75%	6.4	3.3	5.1	1.8
max	7.9	4.4	6.9	2.5

Figure 2: Pairplot of iris data features

Table 1: Iris data description

#### Car Evaluation Dataset

In Car Evaluation Dataset, we use some categorical features of cars, e.g. price, door number and capacity, to predict the safety level of the cars [4]. This dataset is quite straightforward, we only transform the raw data into categorical features to predict the categorical safety level.

## 3 Results

## 4 Discussion and Conclusion

## 5 Statement of Contributions

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## References

- [1] Vincent G Sigillito, Simon P Wing, Larrie V Hutton, and Kile B Baker. Classification of radar returns from the ionosphere using neural networks. *Johns Hopkins APL Technical Digest*, 10(3):262–266, 1989.
- [2] Ron Kohavi. Scaling up the accuracy of naive-bayes classifiers: A decision-tree hybrid. In *Kdd*, volume 96, pages 202–207, 1996.
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[4]	Marko Bohanec and Vladislav Rajkovic. Knowledge acquisition and explanation for mattribute decision making. In 8th Intl Workshop on Expert Systems and their Application pages 59–78, 1988.				