Supervised Learning Algorithm Comparison and Analysis

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Introduction

This is the supervised learning analysis report for home work 1. I obtained two data sets online. Use Decision Tree, Neutral Network, Boosting SVM and KNN algorithms to build a machine learning model to solve two classification problems.

The process is first analyze the input data and some easy feature engineering. Then use cross validation and grid search to find the best hyper parameters. Third steps is to draw a learning curve with the best hyper parameters. Last step is to train the model with all the training data and get a score on the validation model.

The report is divided by the data set. Some future work is also brought up to make the model more accurate or generalized for all the data.

DataSet 1: Income level classifier

1. Data Description

The data is obtained from UCI Adult Income Dataset. The data is extracted from 1994 Census database. The task is to predict whether a person will make more than 50K a year.

The features include many geographic information, like age, race, education, origin country etc.

What I like about the data set is there are decent amount of data points, about 30k data points. For feature wise, it has a mix of categorical data and numerical data. The data is clean, most of the data points have valid data points, except a few question marks, which I will explain how to impute later.

The problem itself is a non-linear problem, makes it suitable for decision tree, boosting, neutral network and KNN models. SVM can use a non-linear kernel for better result.

1.1 data details

Data shape is 32561,15. There are 6 numerical data and 9 categorical data.

One feature called fnlwgt represents the weight of the row data. According to the document, it could be used for data selection. To make data simple, I decided to exclude this feature.

One education feature is duplicate to the education.num, which is a very good encoding for categorical data education level, since larger number means the person has a higher education.

1.2 impute method

There are no null values in the data set. But there are columns with question marks.

A screenshot of a cell phone

Description automatically generated

For the first two columns, the I created another class as others for them. It might worth some analysis on whether they are highly correlated if we need to avoid multilinearity, like PCA method.

It turns out most of them are missing at the same time. There are seven rows left, where workclass is ‘neverworked’, I used same encoding for the occupation feature.

For the native.country feature, I checked distribution of the label to decide whether it’s a good idea to combine the small portion countries and other class.

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Description automatically generated

From the data, most of the data points are from states. i draw the below plot to check overall distribution of the labels.

A close up of a fence

Description automatically generated

The result shows that other class has about the same proportions of the positive labels and negative labels. So I decided to combine them as one large group of the other.

This will at the same time reduce the feature dimensions to avoid the curse of dimensionality.

1.3 historical plot

For the numerical data, I plot the histogram to check the overall distribution of the features.

A close up of text on a white background

Description automatically generated

The distribution looks good in general. There are not much of outliers to work with.

One thing to notice is the scale of the variables, the capital numbers are in thousands level where ages and hours are tens.

I need to scale down the feature for the neutral network to get good results. I will cover this in the later chapters.

1.4 one hot encoding and train test split

The last step of data preparation is to change categorical data to numerical data for model training. Here I used one hot encoding method.

I also leave 20% of data as testing data and 80% for training.

2. Model Training details

For the model training session, I used scikit-learn library for all the algorithms, data preprocessing, data validation and plotting parts.

2.1 data pipeline

As mentioned earlier, I divide training data with 8:2 for training and testing. Testing data is set aside but never touched during training session. This is done by scikit-learn’s train-test split method.

A close up of a screen

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I also created normalized data for future use. I tried min-max and standardized scaler and decided to go with standardized scaler for better training result.

A screen shot of a smart phone

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Besides the algorithm part, I also use GridSearch, cross-validation, learning curve to compare results to find the best hyper-parameters and find the best model to predict the results.

2.2 Decision Tree

For decision tree, I used DecisionTreeClassifier from scikit-learn library

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I started to use a model with default parameters to get a sense of the data.

I used 10 folds validation for the measurement. All default parameters, which means the score is accuracy.

A picture containing bird

Description automatically generated

As we learnt from the previous knowledge, decision tree is prone to be overfitting with high variance.

I plot a learning curve to check it out.

A close up of text on a white background

Description automatically generated

The two curves are not converging at the end and validation error is higher than the training error.

Next, I am using pre-tuning to tune the decision tree. The hyper-parameters are tree depth, max feature proportion and min samples leaf size. I used grid search to determine the best parameters.

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The learning curve with the best param is as below.

A close up of a map

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Description automatically generated

We can see from the plot that it’s improving from the initial default parameters. But still training and testing are not converging to the end, meaning either we need more training data or the model has high variance issue.

Another finding is that the fitting time is very fast and all below 1 second.

Final score of the model is as below.

A screenshot of a cell phone

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Another important information provided by decision tree is feature importance.

A screenshot of a social media post

Description automatically generated

An important finding here is that numerical features rank very high here, we will bring this back when I talk about KNN model later.

2.3 neural networks

For neural networks, I used scikit-learn’s MLPClassifier. For neural networks, they usually work great with lot’s of data. Here we have about 30k data points. It’s not as many in terms of deep learning. So we might want to limit the parameter size.

I also used default parameters and cross validation for the check.

A screenshot of a cell phone

Description automatically generated

As we can see the default parameters perform pretty good off the bat.

I also used grid search for the best parameters. Another thing to notice is that when I normalize the data, the learning curve is smoother than original data.

A screenshot of a cell phone

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Final result is as below.

A screenshot of a social media post

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2.4 Boosting

For boosting models, I tried both Gradient Boosting and Ada-Boosting algorithms. They both achieve similar results. I’ll focus on the Ada-Boosting.

For hyper-parameter here, I tried different base estimators (trees with different max depth) and number of estimators. As suggested by the question, I went aggressive with pruning by keeping the depth up to 3.

Here’s my grid search result.

A screenshot of a cell phone

Description automatically generated

Learning curve also shows better convergence than decision tree and neural networks.

The final test result also by far the best one.

A close up of a mans face

Description automatically generated

2.5 SVM

For SVM, my machine has a very slow training time, so instead of using grid search method, I use cross validation to compare linear and rbf kernels, parameter C and gamma (‘auto’ and fix number).

Details could be found in the notebook.

My finial decision is as below.

sv = svm.SVC(gamma='auto',C=10,kernel = ‘rbf’)

my learning curve is as below. The training time goes up to 400 seconds.

A close up of a map

Description automatically generated A close up of a map

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2.6 KNN

KNN is an instance-based learning. There are no parameters needed to be trained to predict the result. There are hyper-parameters like K and weight method to choose from. It also usually requires a lot of training data for better result.

I also used grid search to find my best hyper-parameters. The learning curve is shown as above. It’s not converging well as other and the final validation result is also not as good as other algorithms.

A screenshot of a cell phone

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3. Result and reasoning

For test scores, Ada-Boosting has the best score with 0.87. It also converges really well between training and testing error. Decision tree has the lowest training result due to overfitting.

For the training time, decision tree has the best training time while svm is the slowest. Other algorithms range between 5-20 seconds.

I think it makes sense to me for Ada-Boosting to perform well, since it’s an ensemble method that could take advantage of decision trees and also avoid overfitting.

Neural network is also very promising. It might perform better if proving more data.

4. Future work

Unbalanced label

Reference

1. UCI adult income data set http://archive.ics.uci.edu/ml/datasets/Adult