TITANIC

Machine Learning from Disaster

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1 Introduction

1.1 Project Overview

The sinking of the RMS Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the Titanic sank after colliding with an iceberg, killing 1502 out of 2224 passengers and crew.This sensational tragedy shocked the international community and led to better safety regulations for ships.
In my view,it is a classification problem.We should build a classification model,then we can predict the passenger survived or not by passenger features like Pclass,Sex and so on.The problem comes from kaggle.I download the related dataset from kaggle[1].

1.2 Problem Statement

In this project, i am going to complete the analysis of what sorts of people were likely to survive.In particular, i will apply the tools of machine learning to predict which passengers survived the tragedy.

1.3 Metrics

In this project,i will choose the F1 score[1] for the result.The F1 score can be interpreted as a weighted average of the precision and recall, where an F1 score reaches its best value at 1 and worst score at 0. The relative contribution of precision and recall to the F1 score are equal. The formula for the F1 score is:

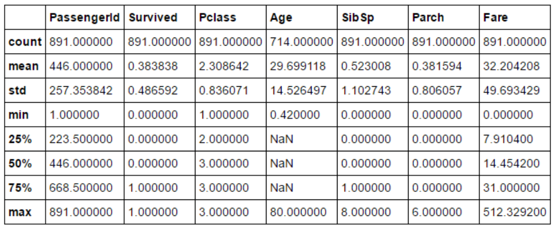
$$F1Score = 2 * (precision * recall)/(precision + recall)$$

2 Analysis

2.1 Data Exploration

In this part i will do data enigneering.Above all,i will show the features of the data sets.As you can see ,each passenger has eleven features.The statistical information can be seen in figure 1. The meaning of features can be seen below.

1. survival : Survival (0 = No; 1 = Yes)



	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	NaN	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	NaN	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	NaN	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Figure 1: Full_Data

2. pclass : Passenger Class (1 = 1st; 2 = 2nd; 3 = 3rd)
3. name : Name
4. sex : Sex
5. age : Age
6. sibsp : Number of Siblings/Spouses Aboard
7. parch : Number of Parents/Children Aboard
8. ticket : Ticket Number
9. fare : Passenger Fare
10. cabin : Cabin
11. embarked : Port of Embarkation (C = Cherbourg; Q = Queenstown; S = Southampton)

I select the null from the data,if the value if false it means that the values don't have nan,if it is true,it has nan.We can learn form the table that there are some missing values in Age,Cabin and Embarked.And we can know that the Age,Fare and Family have outliers i will process in next section.

PassengerId	Survived	Pclass	Name	Sex	Age
False	False	False	False	False	True
SibSp	Parch	Ticket	Fare	Cabin	Embarked
False	False	False	False	True	True

Table 1: Missing Values

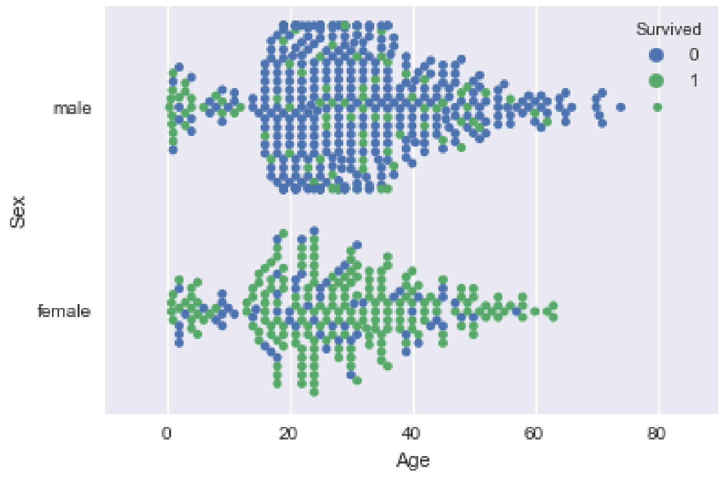


Figure 2: Age-Sex

2.2 Exploratory Visualization

This time i will use seaborn[2] to plot figures.
Figure 2 is about age and sex.We can obviously find that female survived more that male.Maybe male choose to let female go that time.That's truely gentleman.
Figure 3 is about the Embarked.From the picture we can learn that when Embarked is C it has the highest mean of survived.
Figure 4 is about Pclass and Fare,i want to explore if people cost more money have higher probablity survived.And i find that when class is 1 it have more probablity to survive cause it close to sky.
Figure 5 is about Family and Age,i want to find that if people have more sisters or parents in the ship have higher probablity to survive.And i find the truth is that people have many relatives do not survive may be it because people can't go themselves.

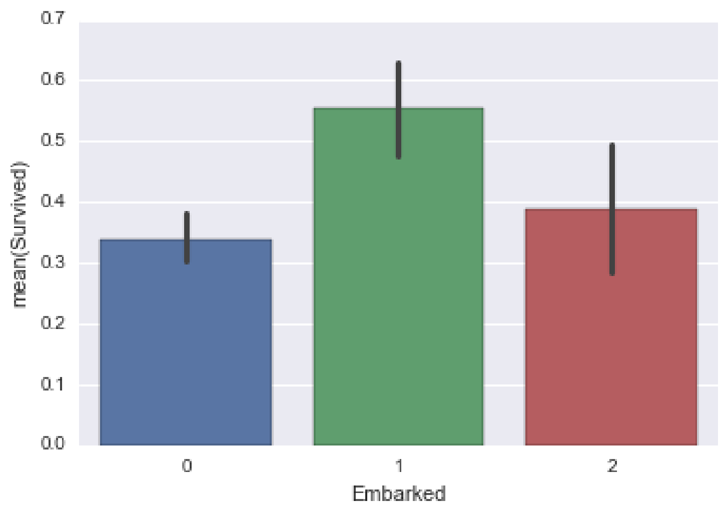


Figure 3: Embarked

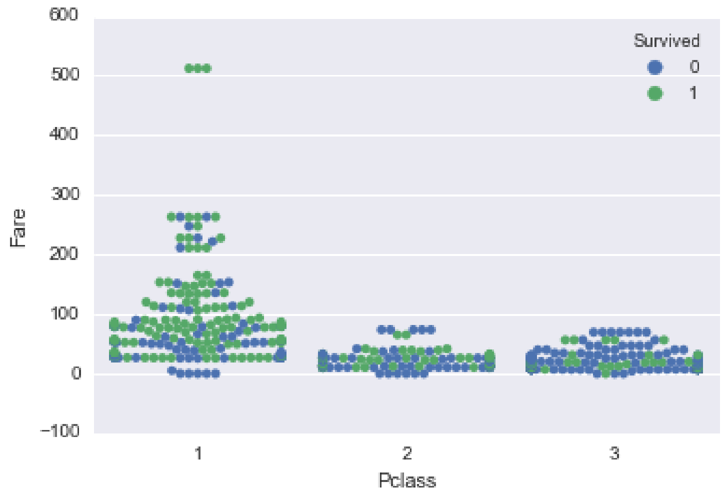


Figure 4: Pclass-Fare

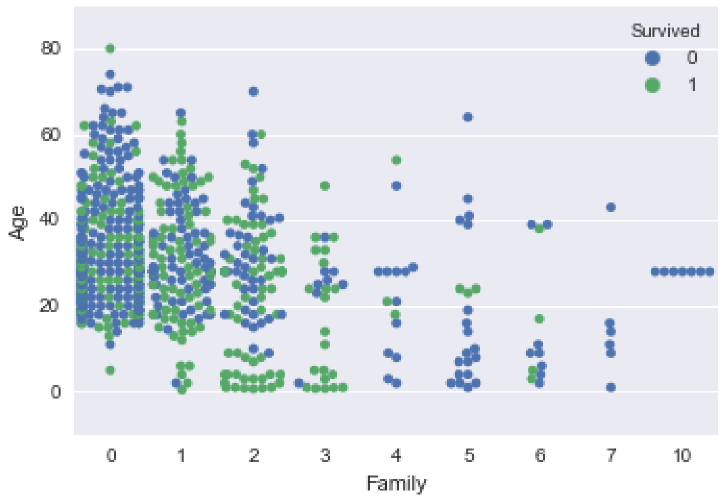


Figure 5: Family-Age

2.3 Algorithms and Techniques

In order to have a good prediction,i will choose a good model first.And now i will test three models to train.Then i will choose best of these to tune.
The models are SVM[3],KNN[4] and RandomForest[5] for my models.
And i will say something about these three algorithms.

SVM:

- In general application,we may consider use SVM to predict if students grade can pass the test,because students have many features like age,the education of parents,spend how much time studying and so on,SVM can be used for classification and regression.
- It is effective in high dimensional spaces,and have a good margin.So if we have many features it may perform well.
- When the number of features is much greater than the number of samples, it may give bad performances.

KNN:

- In general application,we can use it to predict the prices of house,knn can be used for regression.
- It has low cost if we need to re-practice.When the data have many overlapping features it may perform well.
- It's a lasy learner and if the data is not balanced it may give bad performances.

RandomForest:

- In general application,we can use RandomForest to predict if the passengers can survive in diaster using different features like sex,age and so on.
- It is very efficient to train and make a prediction.And it won't suffer from overfitting because it actually add the margin of each features.
- It is consisted of different weak learners which may be have a little more than 50% successful prediction ability and finally it become a strong learner.

2.4 Benchmark

I will test the f1 score of each model and find the best one.Besides,i will set the benchmark as the f1 score of each model and set the threshold as 0.6.Because i think that we should satisify at least 60% at least.And the f1 score in range from 0 to 1.

3 Methodology

3.1 Data Preprocessing

Above all, i will tell what i have done for data.
I change all string features into numerical features.

1. I let NaN in Age equals to the mean of Age.
2. I let Name equals to the length of Name.

3. I let Embarked equals to 0,1,2 when the value is S,C,Q.
4. I let Sex equals to 0,1 when it is male and female.
5. I Add new features Family equals to SibSp add Parch.
6. I delete PassengerId SibSp Parch,Cabin and Ticket.

It's easy to understand i change features into numerical,and i want to explain why i delete other features.To be honest,I think that the Cabin has a lot of null value which means little information.Besides,Name,Ticket is irregular.Therefore,i decide to delete these features.
As for outliers,in my opinion,i have two reasons not to delete.First,there are little data which is both outliers for two or more features.Second,i think each people has his value,i want to take them into considersation.

3.2 Implementation

This part i will tell the process for which metrics, algorithms, and techniques.
Firstly,i learn from sklearn and create three different models using their algorithm,then i also use the f1 score of sklearn to judge if this model can satisify the benchmark and my threshold value.More details can be seen in my Titanic.ipynb.
Besides in order to have a good train and test set.i use train_test_split[6] to split data.
And i use three times to test the models,and here are the table.

Models	Size	Time	Train Score	Test Score
SVM1	33%	0.010s	0.944	0.279
SVM2	66%	0.028s	0.931	0.247
SVM3	100%	0.033s	0.927	0.302
KNN1	33%	0.003s	0.678	0.641
KNN2	66%	0.002s	0.687	0.600
KNN3	100%	0.001s	0.708	0.627
Ran1	33%	0.021s	0.975	0.741
Ran2	66%	0.028s	0.978	0.778
Ran3	100%	0.040s	0.976	0.756

Table 2: Comparision Of Models

As we can see in the table,randomforest algorithm have the best test score,so i will choose it for my next model.

3.3 Refinement

Since i have choose the randomforest,now i will tune model for better results.
In order to get the best parameters,i will use grid search[7].
What i am going to change can be seen below:

- n_estimators:10,20,40,80,120,150,180
- criterion:gini,entropy
- max_features:log2,sqrt,None
- max_depth:5,6,7,8,9,10
- min_sample_ssplit:1,2,3
- warm_start:False,True

I will explain the meaning of each parameter.

- n_estimators means the number of trees in the forest.
- criterion means the function to measure the quality of a split. item max_features means the number of features to consider when looking for the best split.
- max_depth means the maximum depth of the tree.
- min_samples_split means the minimum number of samples required to split an internal node.
- warm_start means if reuse the solution of the previous call to fit and add more estimators to the ensemble.

I will tell what will happen if i change the parameters of the RandomForest model.I will give some examples, firstly if i increase the n_estimators it will add the number of trees,the more tree it have,the more weaker learner it will have.As for max_depth,if i increase it,it will ask more question to it self,however if it is to large,the model may suffer from underfitting.

4 Result

After 1269.8s searching,i finally get the optimal model parameters.The value can be seen below.

- 'warm_start': True
- 'oob_score': False
- 'n_jobs': 1,
- 'verbose': 0
- 'max_leaf_nodes': None
- 'bootstrap': True
- 'min_samples_leaf': 1
- 'n_estimators': 180
- 'min_samples_split': 3
- 'min_weight_fraction_leaf': 0.0
- 'criterion': 'entropy',
- 'random_state': None
- 'max_features': 'sqrt'
- 'max_depth': 10
- 'class_weight': None

4.1 Model Evaluation and Validation

During development,a validation set was used to evaluate the model.
The final parameters were chosen because they performed the best among the tried combinations.
You can see the figure 6 that when it is time to test the tuned model has the highest score.

5 Justification

I get the final f1 score is 0.7731 which is better than previous test.And comparing it to threshold it is higher than threshold.Therefore i think this model is significant enough to deal with the problem.To be more detailed,i use a random forest model having 180 trees and it ask 10 questions for each data.

6 Conclusion

You can see the figre 6 Model-Evaluation which shows that my tuned model really does better than previous.And it can be known from the higher f1 score. As for my process,i first explore the data,then do feature engineering adding or deleting some features.After that,i firstly choose three model to find the best one.Then i tune the best randomforest model to get best results.Obviously my model works better than ever.
The interesting thing i think is to find the best parameters,firstly i just tune the model by hand.For example,i change the init function to change parameters.And i find it is too hard and too boring.Fortunely,i think of Grid Search and use it to instead my hand.
In order to improve the result,i think we can add more parameters.For example,we can add more detailed parameters like n_estimators:10,20,30,40,50 an so on.Of course it will cost much more time.

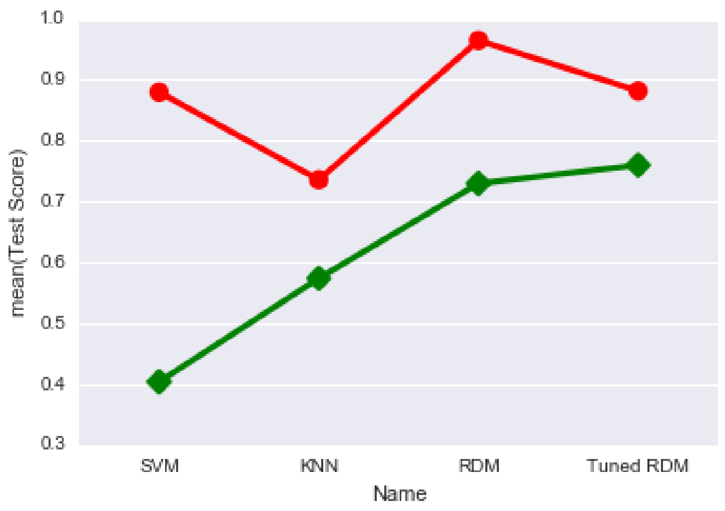


Figure 6: Model-Evaluation

7 Reference

1. https://www.kaggle.com/c/titanic
2. http://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html
3. http://web.stanford.edu/ mwaskom/software/seaborn/api.html
4. http://scikit-learn.org/stable/modules/svm.html#svm
5. http://scikit-learn.org/stable/modules/neighbors.html#neighbors
6. http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html
7. http://scikit-learn.org/stable/modules/cross_validation.html#cross-validation
8. http://scikit-learn.org/stable/modules/generated/sklearn.grid_search.GridSearchCV.html