The George Washington University

# Titanic Indi-Report

The Columbian College of Art and Science

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## Directory

# Introduction

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.

One of the reasons that the shipwreck led to such loss of life was that there were not enough lifeboats for the passengers and crew. Although there was some element of luck involved in surviving the sinking, some groups of people were more likely to survive than others, such as women, children, and the upper-class.

In our project, we found out the connection between passengers' features and the probability of death. We used decision tree for finding out the most important features that affect a passenger's death in a shipwreck. Secondly, SVM algorism were used to find a specific decision boundary to classify and finally, we compare the performances of prediction by using these three algorisms.

And our group shared works are shown in the following table:

| ITEM | Zhengting Zhu | Yueyan Tan | Jinyu Hu |
|---|---|---|---|
| Coding | SVM & Naïve Bayes | DATA & Decision Tree | |
| Report | Part 4 | Part 5 Result | Part 1,2,3 |
| PPT | Part 4 | Part 5 Result | Part 1,2,3 |

# Description of individual work

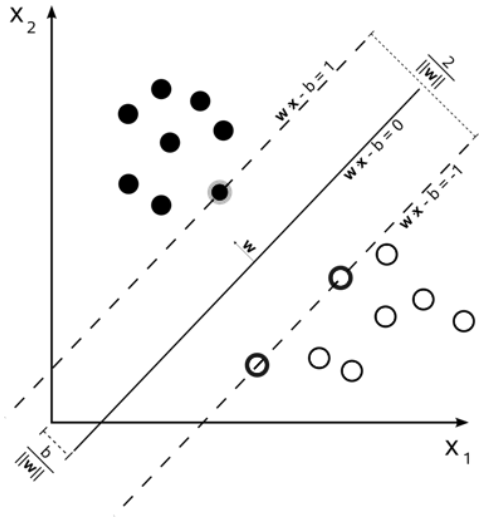
## background information

In this project, we use three models listing below:

**Support Vector Machines (SVM):**

In machine learning field, support vector machines (SVM) are supervised learning models that analyzing data for classification and regression.

A Support Vector Machine is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data, the algorithm outputs an optimal hyperplane which categorizes new

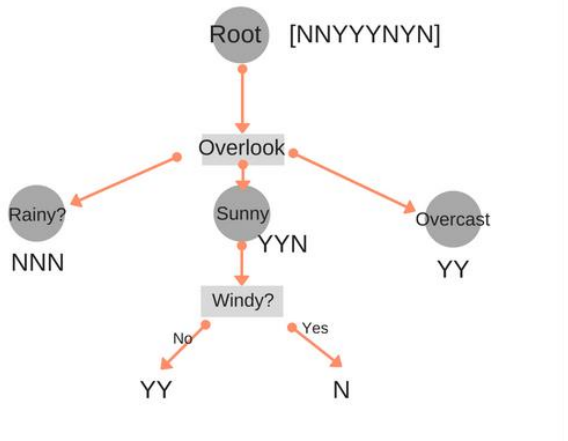



examples. The easiest model picture looks like this:

**Decision Tree:**

In Data Science field, a decision tree is support tool that uses a tree-like graph to show the decisions. A decision tree specially starts with a single node, and then branches into possible outcomes. Each of those outcomes leads to additional nodes, which branch into other possibilities. It is one approach to display an algorithm that only contains conditional control statements in classification analysis.

One possible model looks like this:




Some important factors of Decisions Tree are:

$$\text{Entropy} = \sum -pilog2pi$$

$$\text{Gini} = 1 - \sum (p_i^2)$$

Information Gain (IG) = Entropy (parent) – Average Entropy (children)

## Naïve Bayes

In machine learning field, naive Bayes classifiers are a group of simple probabilistic classifiers based on Bayes' theorem with independence assumptions between the features. It is a powerful algorithm used for real time prediction, text classification, recommendation system, etc.

Key mathematic equation list below:

$$P(C(Class)|X(Features)) = \frac{P(X|C) \times P(C)}{P(X)}$$

P(C(Class)|X(Features)): Posterior Probability of class (C) given predictor (X)

P(X|C): Likelihood - the conditional probability of the predictor

P(C): Prior Probability of the Class

P(X): Total probability

# My portion of the work

## My work in Coding

```
import numpy as np
import pandas as pd
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import confusion_matrix
from sklearn import tree
from sklearn.model_selection import train_test_split
from sklearn.svm import SVC
from sklearn.metrics import accuracy_score, roc_curve, roc_auc_score
from sklearn.metrics import classification_report
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
from pydotplus import graph_from_dot_data
import webbrowser
from sklearn.naive_bayes import GaussianNB
warnings.filterwarnings("ignore")
import os
os.environ["PATH"] += os.pathsep + r'C:\Users\yueya\Anaconda3\Library\bin\graphviz/'

#importing data
tt = pd.read_csv(r'data.csv', sep=',',header=0)
#%%------------------------------------------------------------------------
#%%------------------------------------------------------------------------

#data preprocessing
# look at first few rows
tt.head()

# replace missing characters as NaN
tt.replace('?', np.NaN, inplace=True)

# check the structure of mushroom_data
tt.info()

# check the null values in each column
print(tt.isnull().sum())

# check the summary of the mushroom_data
tt.describe(include='all')

# replace categorical mushroom_data with the most frequent value in that column
tt = tt.apply(lambda x: x.fillna(x.value_counts().index[0]))

# drop Cabin, ticket and name of passenger
tt.drop(['Cabin','Name', 'Ticket','Embarked'], axis=1, inplace=True)

# again check the null values in each column
print(tt.isnull().sum())

#Encoder features
X_data = pd.get_dummies(tt.iloc[:, 1:])
X = X_data.values
Y = tt.values[:, 0]
Y = Y.astype('int')
#%%------------------------------------------------------------------------
```

```
#%%-------------------------------------------------------------------------

# split the dataset into train and test
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=100)

# data visualization
ntrain=tt.shape[0]
import seaborn as sns
train=tt[:ntrain]
sns.pairplot(train,vars=['Age','Sex','Pclass',],hue='Survived',)
plt.title("data visualization")
plt.show()

# data standardize
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
sc.fit(X_train)
X_train = sc.transform(X_train)
X_test = sc.transform(X_test)

#%%-------------------------------------------------------------------------
# Decision Tree

# perform training with giniIndex.
# creating the classifier object
clf_gini = DecisionTreeClassifier(criterion="gini", random_state=100, max_depth=3, min_samples_leaf=5)

# performing training
clf_gini.fit(X_train, y_train)

# perform training with entropy.
# Decision tree with entropy
clf_entropy = DecisionTreeClassifier(criterion="entropy", random_state=100, max_depth=3, min_samples_leaf=5)
clf_entropy.fit(X_train, y_train)
#prediction
y_pred_gini = clf_gini.predict(X_test)

y_pred_entropy = clf_entropy.predict(X_test)

# calculate metrics gini model
print("\n")
print("Results Using Gini Index: \n")
print("Classification Report: ")
print(classification_report(y_test,y_pred_gini))
print("\n")
print("Accuracy : ", accuracy_score(y_test, y_pred_gini) * 100)
print("\n")
print ('-'*80 + '\n')

# calculate metrics entropy model
print("\n")
print("Results Using Entropy: \n")
print("Classification Report: ")
print(classification_report(y_test,y_pred_entropy))
print("\n")
print("Accuracy : ", accuracy_score(y_test, y_pred_entropy) * 100)
print ('-'*80 + '\n')
```

```
# confusion matrix for gini model
conf_matrix = confusion_matrix(y_test, y_pred_gini)
class_names = tt.Survived.unique()
df_cm = pd.DataFrame(conf_matrix, index=class_names, columns=class_names)

plt.figure(figsize=(5,5))
hm = sns.heatmap(df_cm, cbar=False, annot=True, square=True, fmt='d', annot_kws={'size': 20}, yticklabels=df_cm.columns, xticklabels=df_cm.columns)
hm.yaxis.set_ticklabels(hm.yaxis.get_ticklabels(), rotation=0, ha='right', fontsize=20)
hm.xaxis.set_ticklabels(hm.xaxis.get_ticklabels(), rotation=0, ha='right', fontsize=20)
plt.ylabel('True label',fontsize=20)
plt.xlabel('Predicted label',fontsize=20)
plt.title("Decision Tree - Gini")
plt.tight_layout()
plt.show()

# confusion matrix for entropy model
conf_matrix = confusion_matrix(y_test, y_pred_entropy)
class_names = tt.Survived.unique()
df_cm = pd.DataFrame(conf_matrix, index=class_names, columns=class_names)

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hm.xaxis.set_ticklabels(hm.xaxis.get_ticklabels(), rotation=0, ha='right', fontsize=20)
plt.ylabel('True label',fontsize=20)
plt.xlabel('Predicted label',fontsize=20)
plt.title("Decision Tree - Entropy")
plt.tight_layout()
plt.show()
# display decision tree
dot_data = tree.export_graphviz(clf_gini, filled=True, rounded=True, class_names='survived', feature_names=tt.iloc[:, 0:].columns, out_file=None)

graph = graph_from_dot_data(dot_data)
graph.write_pdf("decision_tree_gini.pdf")
webbrowser.open_new(r'decision_tree_gini.pdf')

dot_data = tree.export_graphviz(clf_entropy, filled=True, rounded=True, class_names='survived', feature_names=tt.iloc[:, 0:].columns, out_file=None)

graph = graph_from_dot_data(dot_data)
graph.write_pdf("decision_tree_entropy.pdf")
webbrowser.open_new(r'decision_tree_entropy.pdf')

#%%-----------------------------------------------------------------------
```

My work in Report

# Results

## Decision Tree

For the first part of our project, we used Decision-Tree algorism for figuring out the degree of importance of each feature. We began with Decision Tree for the following reasons:

1. It is an algorism with widely used and could be well-visualized, which would be much easier for the readers from different background to understand our project results.
2. Decision Tree is simple to understand and to interpret, which also benefit the readers.
3. Decision Tree requires little data preparation. Other techniques such as SVM often require data normalization, dummy variables need to be created and blank values to be removed.
4. It is able to handle both numerical and categorical data. Other techniques like logistic regression and other statistical algorisms are usually specialized in analyzing datasets that have only one type of variable and the data we used (The Titanic data set) includes both categorical as well as numerical data, which means decision tree would be a good tool for the project.
5. It is possible to validate a model using statistical tests. That makes it possible to account for the reliability of the model, such that we could fit the ROC for the prediction which would be much simple for readers to get our results.

Firstly, we got the decision tree by using entropy for calculating, as is shown in figure1:

Before getting the result, we may guess that the most important features for affecting the possibility of survival would be gender or age, while according to the result, we could find out that the most important feature for deciding whether the passenger could survival from the shipwreck is “parch” ( number of parents / children aboard the Titanic), which indicates that passengers with parents or children together would have much stronger desire of survival or higher rate or survival than others when facing the big disaster.

Moving down, we could see that “sibsp” (number of siblings / spouses aboard the Titanic) and “pclass” (Ticket class) are also important features that have effect on possibility of the survival. The reason of “sibsp” maybe the same with the feature “parch”. While “Pclass” also have such importance may because the rich or upper class always have priority over resources which is a harsh reality in our society.

Then, we got the decision tree by using Gini for calculating, as is shown in figure2:

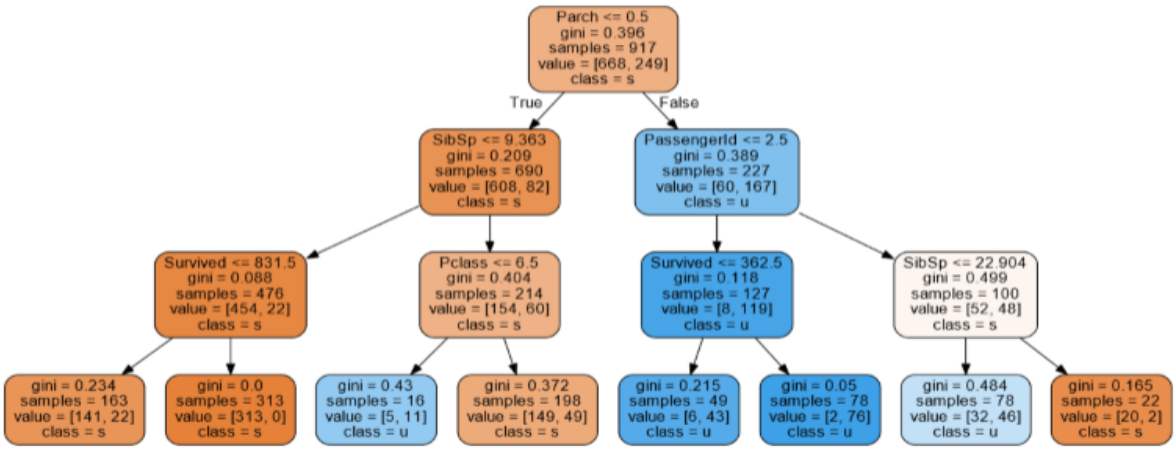


Figure 2 Decision Tree-GINI

Firstly, we got the decision tree by using entropy for calculating, as is shown in figure1:

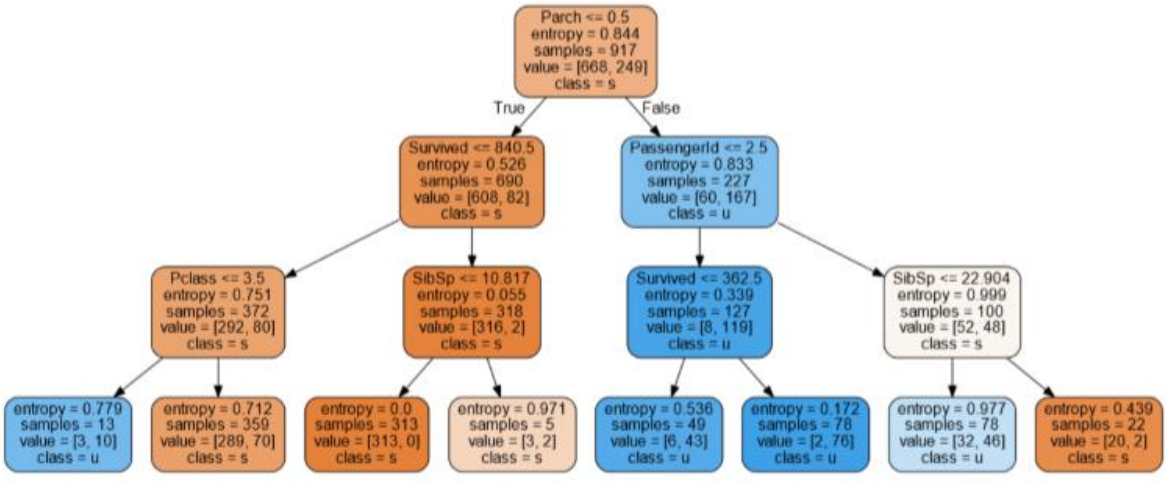


Figure 1 Decision Tree-Entropy

Additionally, we also predict in both methods as is shown in Figure 3 and Figure 4:

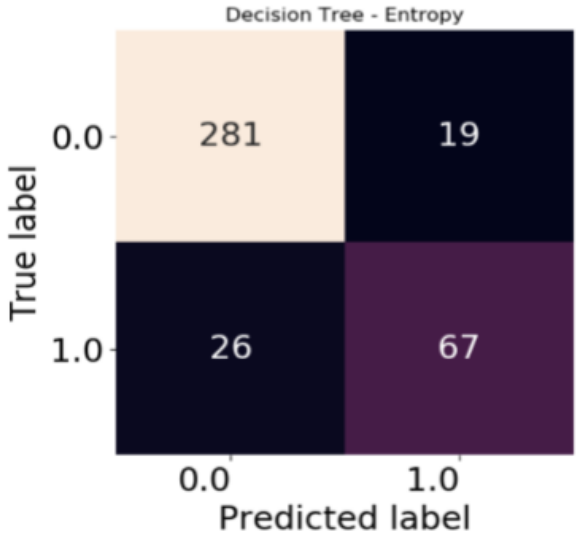


Figure 3 Entropy

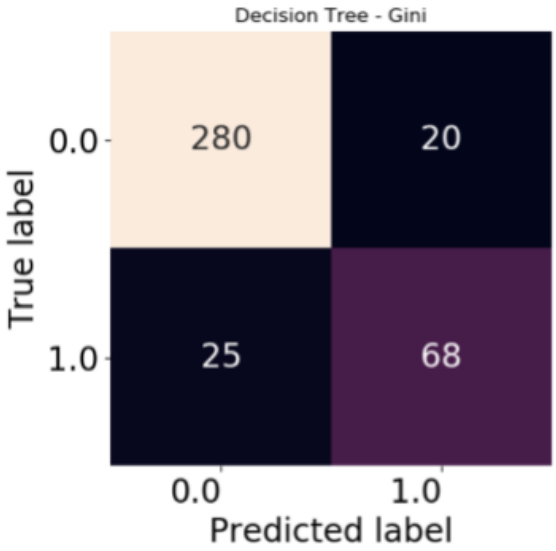


Figure 4 GINI

From the Figure 2, Figure 3 and Figure 4, it is easy to find out that Figure 2 is almost the same as figure 1 we got from entropy which means that both of these two calculations provide quite similar information and would not have much differences in the results. And for the performance of prediction with this two method, they were also the same (The prediction accuracy of both GINI and Entropy are 88.55% ). While in the real life's application, more researchers would like to use Gini for calculation, then what is the differences between these two calculations ? After summarizing, we find that they are different in the following ways:

1. Entropy mostly used on categorical data set (discrete data sets).
2. Gini mostly used on contagious data set.
3. Entropy is slower to compute, while Gini is faster.

**Support Vector Machine**

For the second part of our project, Support Vector Machine were used for getting the specific decision boundary between two classes (survived and died), which may be helpful for discovering the effective features for that possibility of survival in shipwreck.

A Support Vector Machine (SVM) is a discriminative classifier formally defined by a separating hyperplane. In other words, given labeled training data (supervised learning), the algorithm outputs an optimal hyperplane which categorizes new examples. The reason we used SVM in this part because of the following reasons:

1. It has a regularization parameter, which makes the user think about avoiding over-fitting. Secondly it uses the kernel trick, so you can build in expert knowledge about the problem via engineering the kernel.
2. An SVM is defined by a convex optimization problem (no local minima) for which there are efficient methods (e.g. SMO).
3. It is an approximation to a bound on the test error rate, and there is a substantial body of theory behind it which suggests it should be a good idea.

In this part of our project, the specific decision boundary would be helpful for classify correctly and we could get the equation of the decision boundary. Besides, SVM also used for predict the possibility of survival of a passenger in the shipwreck, therefore the results of SVM and Decision Tree could be used for compare the performance of different algorisms.

According to the results we got from SVM, as shown in Figure 5 and Figure 6:

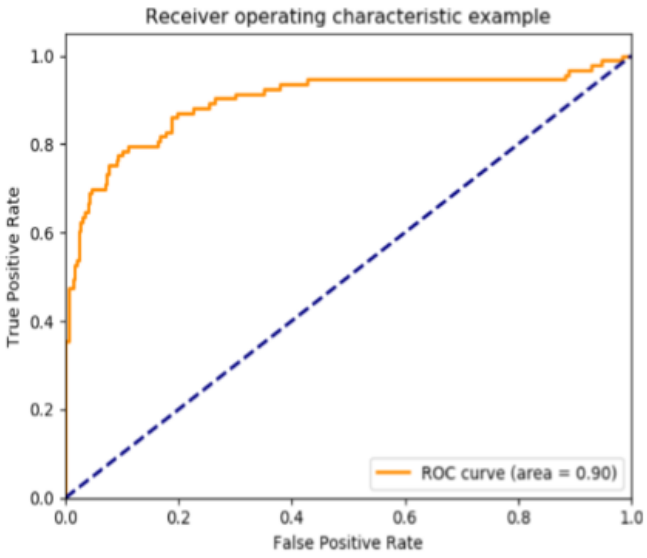


Figure 5 ROC Curve

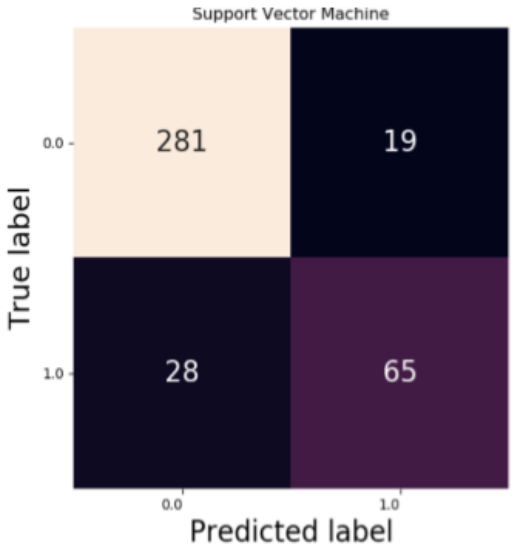


Figure 6 SVM

According to the Figure 5, the AUC=0.9 which means SVM is a good classifier in this case. The AUC value is equivalent to the probability that a randomly chosen positive example is ranked higher than a randomly chosen negative example. ROC Curve were used in this part is because when the distribution of positive and negative samples in the test set changes, the ROC curves can remain unchanged. Class imbalance is often found in the actual data set, that is, the negative sample is much more than the positive sample (or the opposite), and the distribution of the positive and negative samples in the test data may change over time.

From Figure 6, we could indicate that the prediction accuracy of SVM is the same as Decision Tree (Entropy), which is about 87.78%, therefore, we may draw the conclusion that there is no significant difference between the performances of Decision Tree and SVM algorism in predicting the possibility of survival in shipwreck (Titanic case).

**Naïve Bayes**

For the last part of research, we intended to find out that whether Naïve Bayes algorism would perform better in prediction than Decision Tree or SVM, Since Naïve Bayes has lots of advantages than other Machine Learning algorisms:

1. NB is a very simple algorism which is easy to implement and fast.
2. If the NB conditional independence assumption holds, then it will converge quicker than discriminative models like logistic regression.
3. Even if the NB assumption doesn't hold, it works great in practice.
4. NB only needs less training data.
5. NB is highly scalable. It scales linearly with the number of predictors and data points.
6. It can be used for both binary and multi-class classification problems.
7. It can make probabilistic predictions.
8. It can handle continuous and discrete data.
9. It is not sensitive to irrelevant features.

From the results we got from SVM, as shown in Figure 7:

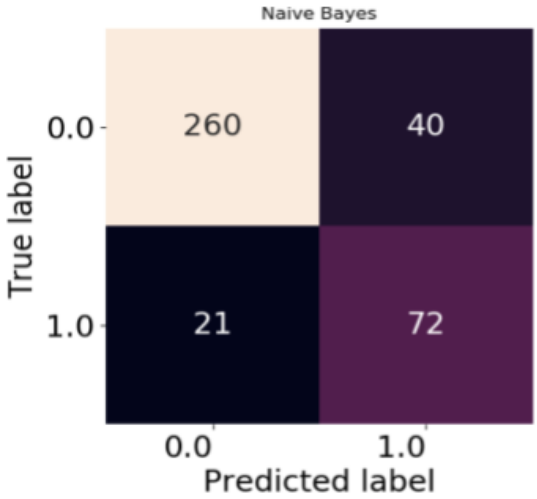


Figure 7 Naïve Bayes

According to the results we got from python in Figure 7, we could find out that the false positive rate is much higher than the other two algorisms (accuracy of prediction is only 84.47%), which means in real life of future, rescue workers would spend much time for recuing trapped person

who may has died in the shipwreck, and it would absolutely waste much rescuing time and money if researchers doing such prediction by using Naïve Bayes algorism. Taking all these above into consideration, we may draw the conclusion that although Naïve Bayes has lots of advantages, it is not a appropriate algorism for prediction in this case.

# Calculation

Calculation=(154-21)/(154+15)*100%=0.78

# References


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