Ravirajpurohit

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Titanic — Machine Learning from Disaster

Brief about the problem

I am trying hands-on basics of machine learning and found this Titanic problem as one of the best to practice on. This is one of the legendary problems on the Kaggle platform.

The challenge concerns one of the most infamous historical events — the Titanic shipwreck. During its first journey on April 15, 1912, the RMS Titanic, which was thought invincible, sank after hitting an iceberg. Regrettably, the insufficient number of lifeboats available on board resulted in the loss of 1502 out of 2224 passengers and crew.

Although luck played a role in determining survival, it appears that certain groups had a higher chance of surviving than others. The task at hand is to construct a forecasting model that answers the query, "Which groups of individuals had a greater likelihood of surviving?" by utilizing passenger data such as name, age, gender, socio-economic class, and other relevant factors.

> *About the dataset*

We have been provided with two datasets, train.csv, and test.csv, which contain comparable passenger information such as name, age, gender, socio-economic class, and more.

train.csv dataset contains information about a subset of passengers who were onboard (specifically, 891 individuals). It is crucial as it indicates whether or not they survived, which is commonly referred to as the "ground truth."

test.csv dataset contains similar information except for the “ground truth” for each passenger. Using the pattern found in the train.csv dataset, we need to predict whether the other 418 passengers on board found in the test.csv dataset survived or not.

> *Reference*

I have referred to the notebook provided by Alexis Cook in the official competition on Kaggle. Link — https://www.kaggle.com/code/alexisbcook/titanic-tutorial/notebook

Execution

```
## import required libraries
import numpy as np # linear algebra
import pandas as pd # data processing
```

> *load data*

Load the data into the workspace to process into a usable format and use for training machine learning model.

```
train_data = pd.read_csv("./data/train.csv")
train_data.tail()
```

```
test_data = pd.read_csv("./data/test.csv")
test_data.tail()
```

```
print("Shape Train data {}, Test data {}".format(train_data.shape, test_data.sha
```

```
Train data (891, 12), Test data (418, 11)
```

Data Processing

Process the data to get it in a usable format, clean it and replace/remove NaN values if required

```
## Drop the useless columns
train_data.drop(['Name','Cabin','Ticket'], axis=1, inplace=True)
test_data.drop(['Name','Cabin','Ticket'], axis=1, inplace=True)
```

```
## check if data contains nan values
train_data.isna().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Sex              0
Age            177
SibSp            0
Parch            0
Fare             0
Embarked         2
dtype: int64
```

```
test_data.isna().sum()
```

```
PassengerId     0
Pclass          0
Sex             0
Age            86
SibSp           0
Parch           0
Fare            1
Embarked        0
dtype: int64
```

```
## Fill na for Embarked column using most frequent value
train_data['Embarked'].fillna(train_data['Embarked'].mode()[0], inplace = True)
test_data['Embarked'].fillna(test_data['Embarked'].mode()[0], inplace = True)
```

```
## Fill na for Fare column using median value
test_data['Fare'].fillna(test_data['Fare'].median(), inplace = True)
```

```
## Fill na for Age column using mean-std, mean+std range
mean_train_data = train_data["Age"].mean()
std_train_data = train_data["Age"].std()

missing_count = train_data["Age"].isna().sum()

## generate random numbers in the range of mean-std , mean_std to fill NaNs
random_gen_age = np.random.randint(mean_train_data - std_train_data,
                                   mean_train_data + std_train_data,
                                   size = missing_count)

## fill nan
train_data_age = train_data["Age"].copy()
train_data_age[np.isnan(train_data_age)] = random_gen_age
train_data["Age"] = train_data_age

## convert data type to int
train_data["Age"] = train_data["Age"].astype(int)
```

```
## Fill na for Age column using mean-std, mean+std range
mean_test_data = test_data["Age"].mean()
std_test_data = test_data["Age"].std()

missing_count = test_data["Age"].isnull().sum()
## generate random numbers in the range of mean-std , mean_std to fill NaNs
random_gen_age = np.random.randint(mean_test_data - std_test_data,
                                   mean_test_data + std_test_data,
                                   size = missing_count)

## fill nan
test_data_age = test_data["Age"].copy() #creating a copy for further use test_da

## convert data type to int
test_data["Age"] = test_data["Age"].astype(int)
```

```
## Transform Pclass column into categories
train_data['Pclass'] = train_data.Pclass.astype('category')
test_data['Pclass'] = test_data.Pclass.astype('category')
```

```
## Transform age column into category
bins = [0,18,50,150]
labels=['Child','Adult','Senior']

## Categories - Child, Adult, Senior
train_data['Age_'] = pd.cut(train_data['Age'], bins=bins, labels=labels, right=F
train_data.drop('Age', axis = 1, inplace=True)
```

```
test_data['Age_'] = pd.cut(test_data['Age'], bins=bins, labels=labels, right=Fal
test_data.drop('Age', axis=1, inplace=True)
```

Data Preparation for Modelling

```
## prepare data for training and testing
train_data_X = pd.get_dummies(train_data.drop('Survived', axis=1))
test_data_X = pd.get_dummies(test_data)
train_data_X.head(5)
```

```
## final check for nan values
train_data_X.isna().sum()
```

```
PassengerId    0
SibSp          0
Parch          0
Fare           0
Pclass_1       0
Pclass_2       0
Pclass_3       0
Sex_female     0
Sex_male       0
Embarked_C     0
Embarked_Q     0
Embarked_S     0
Age__Child     0
Age__Adult     0
Age__Senior    0
dtype: int64
```

```
test_data_X.isnull().sum()
```

```
PassengerId    0
SibSp          0
Parch          0
Fare           0
Pclass_1       0
Pclass_2       0
Pclass_3       0
Sex_female     0
Sex_male       0
Embarked_C     0
Embarked_Q     0
Embarked_S     0
Age__Child     0
Age__Adult     0
```

```
Age__Senior    0
dtype: int64
```

Model Training

I will be training a Random Forest Classifier to fulfill the goal of this problem.

```
## import model library
from sklearn.ensemble import RandomForestClassifier ## label to provide to the m
```

```
y = train_data["Survived"]

## set the hyper parameters for the model
model = RandomForestClassifier(n_estimators=100, max_depth=8, random_state=1)
model.fit(train_data_X, y)
```

```
## predict output
predictions = model.predict(test_data_X)
```

```
## check the training accuracy
from sklearn.metrics import accuracy_score
accuracy_train = accuracy_score(y, model.predict(train_data_X))
print("Training accuracy is {} %".format(round(accuracy_train*100, 2)))
```

```
Training accuracy is 92.03 %
```

```
## format the output for submission
output = pd.DataFrame({'PassengerId': test_data.PassengerId,
                       'Survived': predictions})

## save the output as a csv file
output.to_csv('submission.csv', index=False)
```

Contribution

While Alexis Cook provided a great introduction to the problem, that is not the best possible solution. In this notebook, I have modified the data processing and code in a manner to produce better output than the reference; 3% better to be precise.

My contribution includes the following aspects mentioned in this notebook.

- I am using more features, namely SibSp, Parch, Pclass, Sex, Fare, Embarked, and Age.
- The additional features i.e. Embarked and Age are converted to categorical type as they are categorical features
- Age has been converted from a numerical to a categorical feature by defining brackets for age groups
- NaN values are also handled in Fare, Embarked, and Age features
- The Categorical features are filled with the most frequent value to fill NaN values
- The numerical feature Fare is filled with median value to fill NaN values
- Using the RandomForestClassifier in a better way i.e. tuning the hyperparameters like max_depth and n_estimators.
- I also tried the Support Vector Machine model to compare the accuracy. Random Forest Classifier turns out to be better, especially in the case of the testing dataset.

> *Output*

Finally, we can get the output generated from the machine learning model. This output is generated as a CSV file and can be submitted in the Kaggle competition to see the testing accuracy.

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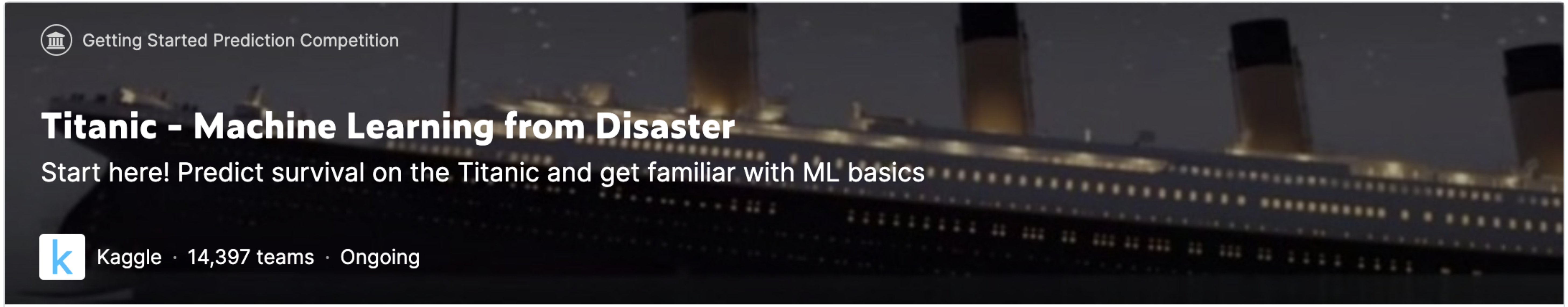

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