1. Research Background and Objective

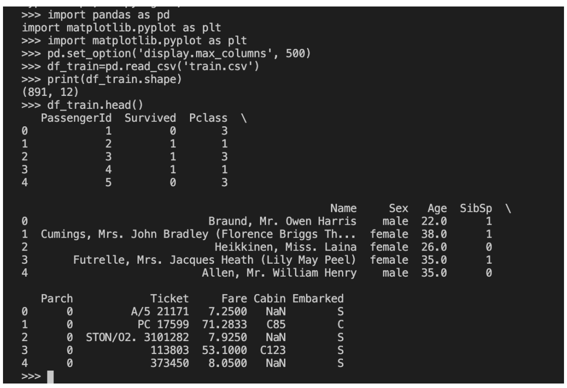
The sinking of the Titanic is one of the most infamous shipwrecks in history. On April 15, 1912, during her maiden voyage, the widely considered “unsinkable” RMS Titanic sank after colliding with an iceberg. Unfortunately, there weren’t enough lifeboats for everyone onboard, resulting in the death of 1502 out of 2224 passengers and crew. While there was some element of luck involved in surviving, it seems some groups of people were more likely to survive than others.

This research project is aimed to use machine learning to establish a model that predicts which passengers survived the Titanic shipwreck based on the passengers’ information, ie. name, age, gender, socio-economic class, etc. Several stages are applied in the studying process: define the research goal, data cleaning, data analysis and feature selection, modelling, model estimation and final results.

2. Data Enquiring and Data Cleaning

There are 3 datasets can be downloaded from Kaggle, train.csv, test.csv and gender_submission.csv, which are referred to the training dataset, testing dataset and a sample final submission file.

Training dataset can be loaded for further use using Pandas library. There are 891 sample observations and 12 features and Survived is the target variable and all other variables are the information of passengers.



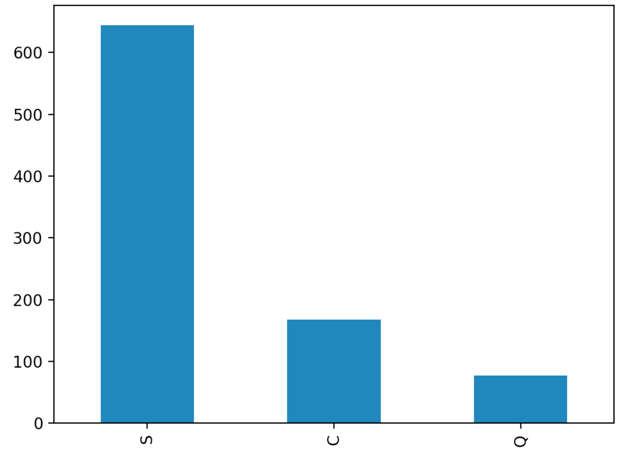
```
>>> import pandas as pd
import matplotlib.pyplot as plt
>>> import matplotlib.pyplot as plt
>>> pd.set_option('display.max_columns', 500)
>>> df_train=pd.read_csv('train.csv')
>>> print(df_train.shape)
(891, 12)
>>> df_train.head()
   PassengerId  Survived  Pclass  \
0            1         0       3
1            2         1       1
2            3         1       3
3            4         1       1
4            5         0       3

                                                Name     Sex   Age  SibSp  \
0                            Braund, Mr. Owen Harris    male  22.0      1
1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0      1
2                             Heikkinen, Miss. Laina  female  26.0      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                           Allen, Mr. William Henry    male  35.0      0

   Parch            Ticket     Fare Cabin Embarked
0      0         A/5 21171   7.2500   NaN        S
1      0          PC 17599  71.2833   C85        C
2      0  STON/O2. 3101282   7.9250   NaN        S
3      0            113803  53.1000  C123        S
4      0            373450   8.0500   NaN        S
>>>
```

Missing data processing:

The total number of missing values for each column can be calculated, there are 177 missing values for Age, 687 missing values for Cabin and 2 missing values for Embarked. The number of median age can be used to fill in the missing ages.

```
>>> df_train.isnull().sum()
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
>>>
```

Since there are only 2 missing values for Embarked, one way is that this two observation can be simply removed from the dataset, another way is that using the most frequent Embarked value to replace the NA values. Since ’S’ has the most frequent value, ’S’ is used to replace the original NA values in ‘Embarked’ column.



Categorical variables are converted into dummy/indicator variables to make it more applicable during the final modelling process. After converting, the original Embarked variable is transferring into Embarked_Q, Embarked_C and Embarked_S as showing.

```
>>> embarked_dummies = pd.get_dummies(df_train['Embarked'], prefix='Embarked')
>>> df_train = pd.concat([df_train, embarked_dummies], axis=1)
>>> df_train.drop('Embarked', axis=1, inplace=True)
>>> print(df_train.columns)
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked_C', 'Embarked_Q',
       'Embarked_S'],
      dtype='object')
>>>
```

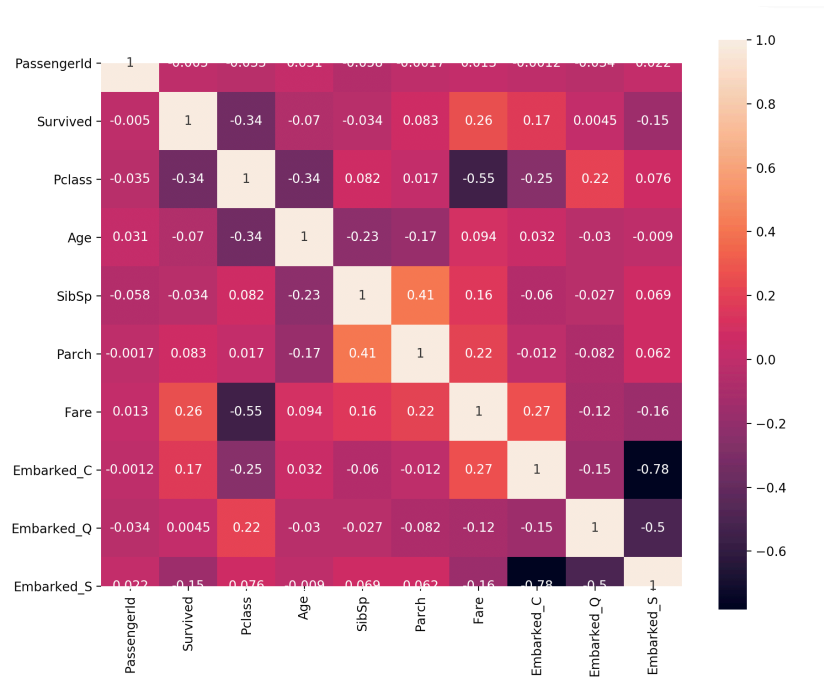
There are lots of missing values for Cabin, ‘Missing’ label is used to mark it as missing values during the process:

```
>>> df_train['Cabin'].fillna('Missing', inplace=True)
>>> df_train['Cabin'].unique()
array(['Missing', 'C85', 'C123', 'E46', 'G6', 'C103', 'D56', 'A6',
       'C23 C25 C27', 'B78', 'D33', 'B30', 'C52', 'C83', 'F33', 'F G73',
       'E31', 'A5', 'D10 D12', 'D26', 'C110', 'B58 B60', 'E101', 'F E69',
       'D47', 'B86', 'F2', 'C2', 'E33', 'B19', 'A7', 'C49', 'F4', 'A32',
       'B4', 'B80', 'A31', 'D36', 'D15', 'C93', 'C78', 'D35', 'C87',
       'B77', 'E67', 'B94', 'C125', 'C99', 'C118', 'D7', 'A19', 'B49',
       'D', 'C22 C26', 'C106', 'C65', 'E36', 'C54', 'B57 B59 B63 B66',
       'C7', 'E34', 'C32', 'B18', 'C124', 'C91', 'E40', 'T', 'C128',
       'D37', 'B35', 'E50', 'C82', 'B96 B98', 'E10', 'E44', 'A34', 'C104',
       'C111', 'C92', 'E38', 'D21', 'E12', 'E63', 'A14', 'B37', 'C30',
       'D20', 'B79', 'E25', 'D46', 'B73', 'C95', 'B38', 'B39', 'B22',
       'C86', 'C70', 'A16', 'C101', 'C68', 'A10', 'E68', 'B41', 'A20',
       'D19', 'D50', 'D9', 'A23', 'B50', 'A26', 'D48', 'E58', 'C126',
       'B71', 'B51 B53 B55', 'D49', 'B5', 'B20', 'F G63', 'C62 C64',
       'E24', 'C90', 'C45', 'E8', 'B101', 'D45', 'C46', 'D30', 'E121',
       'D11', 'E77', 'F38', 'B3', 'D6', 'B82 B84', 'D17', 'A36', 'B102',
       'B69', 'E49', 'C47', 'D28', 'E17', 'A24', 'C50', 'B42', 'C148'],
      dtype=object)
>>>
```

Similarly, the values of Cabin will be kept with leading categorical letter and removing the following numbers since categorical values are more applicable for logistic regression modelling. Here ‘M’ stands for missing value, if there is an M category existing before, then other letter should be used to avoid mixing.

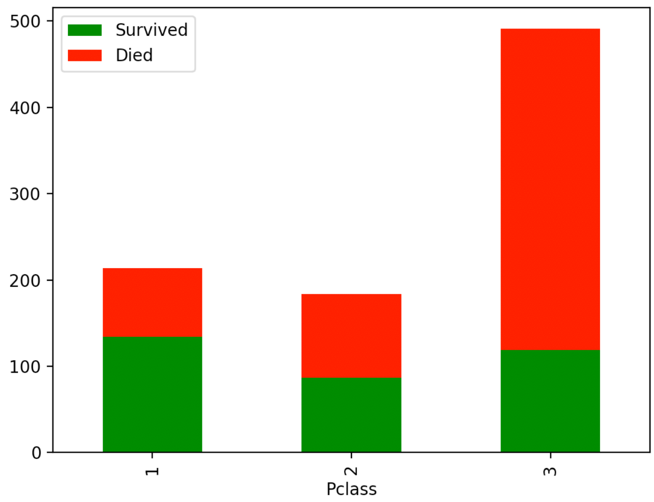
```
>>> df_train['Cabin'].unique()
array(['M', 'C', 'E', 'G', 'D', 'A', 'B', 'F', 'T'], dtype=object)
>>> 
```

3. Feature Selection and Engineering

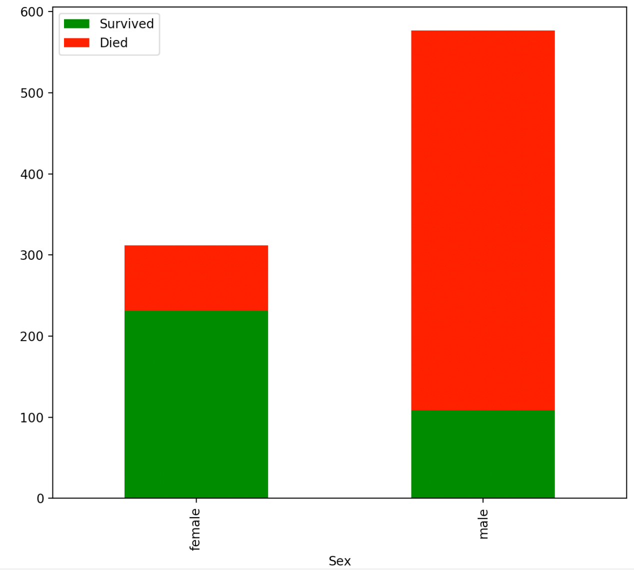


A quick review of correlations between each two variables are as snapshot showing. But the correlations between Survived with other variables seem very small and useless, the reason is that the correlation between variables are calculated based on the mean value and there is no mean value for categorical variable. Therefore, it is not a wise option by only observing the correlation matrix to select the model features, and more exploration is needed to apply to the train dataset.

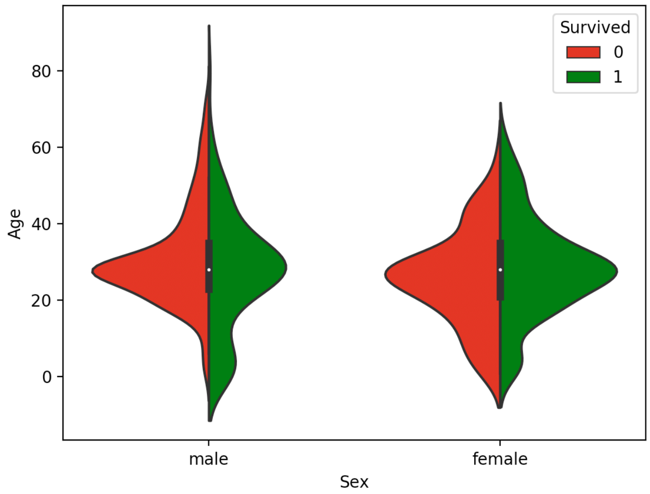
The proportion of survived and died of each Pclass category is different. The survival probability of Pclass1 > Pclass2 > Pclass3.



Similarly, Sex variable is closely related to Survived. Based on the plot female passengers have a higher probability to be survived during the sinking of Titanic event.

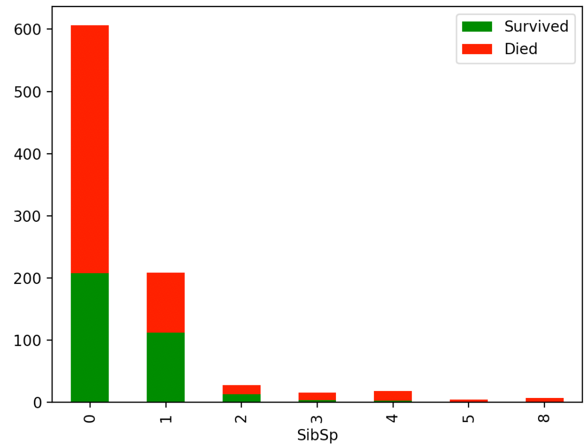


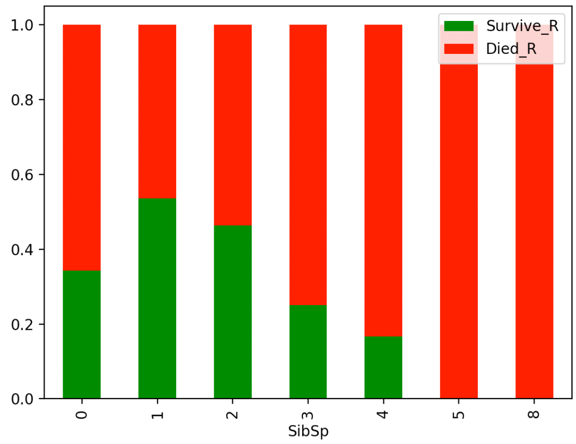
Based on Age and Sex in a violinplot, male passengers under 10 are more likely to survive and male between 20 to 40 have a much higher death rate. Age seems not very relevant to the female survival rate.



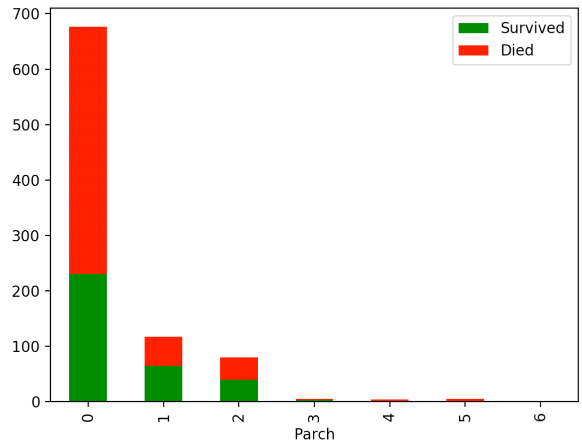
It’s hard to say SibSp closely relevant to survived when the SibSp number greater than 3 due to the volume is too small.Therefore, survival and died rate is transferred from the number of SibSp in the right plot.

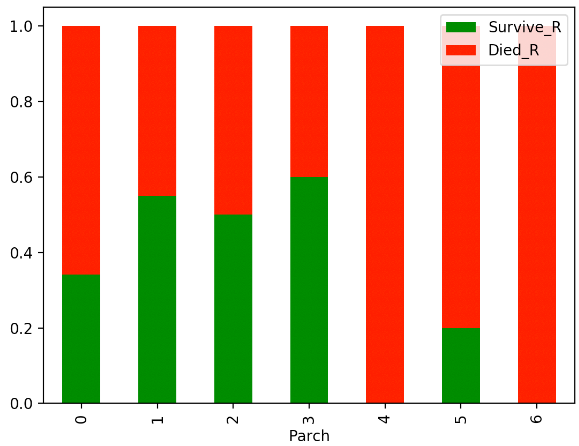
The survival rate is higher for those who have 1 or 2 sibling or spouse aboard Titanic. Those who have no SibSp have a higher survival rate than those who have 3 or 4 SibSp. The survival rate is almost 0 for those who have 5 or 8 SibSp aboard.



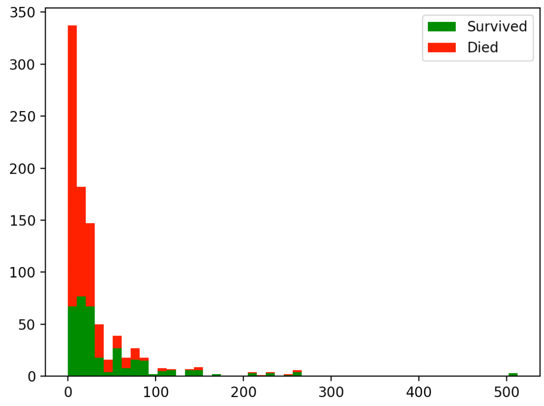


The similar process is applied when studying the feature Parch, which refers to parent and children aboard Titanic. The survival rate is higher for those who have 1, 2 or 3 Parch aboard. Those who have no Parch have higher survival rate than those who have 5 Parch. For those who have 4 or 6 Parch the survival rate is almost zero.

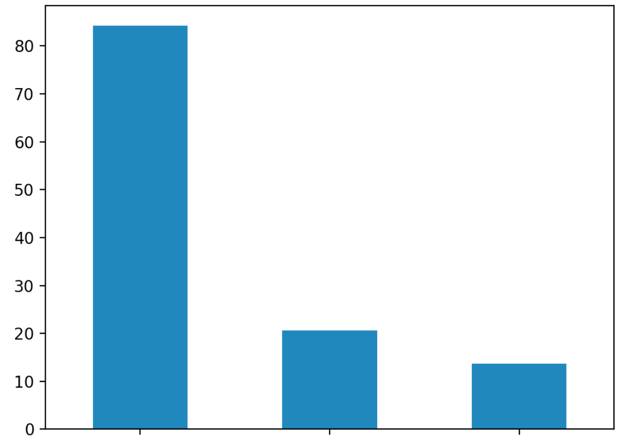




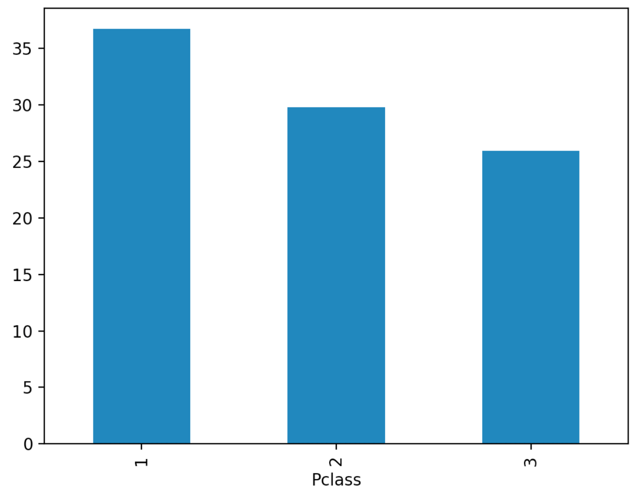
Regarding the ticket fare, it seems that the lower the ticket fare is, the higher death rate for the passengers.



The mean value of ticket fare regarding different kinds of Pclass is plotted as showing snapshot, and Pclass 1 has the highest ticket fare.



The mean value of age regarding different types of Pclass is plotted as right snapshot, and Pclass 1 have the highest mean age value.



Load the test dataset and remove the survived column since it's the final target.

```
>>> df_test = pd.read_csv('test.csv')
>>>
>>> targets = df_train['Survived']
>>> df_train.drop(['Survived'], 1, inplace=True)
>>>
>>> print(df_train.columns)
Index(['PassengerId', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parch',
       'Ticket', 'Fare', 'Cabin', 'Embarked_C', 'Embarked_Q', 'Embarked_S',
       'Died'],
      dtype='object')
>>> 
```

The test dataset can be merged with train dataset first and then do the data processing together.

```
>>> combined = df_train.append(df_test)
>>> combined.reset_index(inplace=True)
>>> combined.drop(['index', 'PassengerId'], inplace=True, axis=1)
>>> print(combined.columns)
Index(['Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parch', 'Ticket', 'Fare',
       'Cabin', 'Embarked_C', 'Embarked_Q', 'Embarked_S', 'Died', 'Embarked'],
      dtype='object')
>>>
```

```
>>> print(combined.shape)
(1307, 12)
>>> combined.head()
   Pclass                                               Name     Sex   Age  \
0       3                            Braund, Mr. Owen Harris    male  22.0
1       1  Cumings, Mrs. John Bradley (Florence Briggs Th...  female  38.0
2       3                             Heikkinen, Miss. Laina  female  26.0
3       1       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0
4       3                           Allen, Mr. William Henry    male  35.0

   SibSp  Parch            Ticket     Fare Cabin  Embarked_C  Embarked_Q  \
0      1      0         A/5 21171   7.2500     M           0           0
1      1      0          PC 17599  71.2833     C           1           0
2      0      0  STON/O2. 3101282   7.9250     M           0           0
3      1      0            113803  53.1000     C           0           0
4      0      0            373450   8.0500     M           0           0

   Embarked_S
0           1
1           0
2           1
3           1
4           1
```

Different passengers have different titles which can be observed in the name column from the dataset. Title info can be abstracted by splitting name column.

```
>>> titles = set()
>>> for name in combined['Name']:
...     titles.add(name.split(',')[1].split('.')[0].strip())
...
>>> print(titles)
{'Jonkheer', 'Dona', 'Ms', 'Don', 'Miss', 'Col', 'Mme', 'Sir', 'the Countess', 'Major', 'Capt', 'Dr', 'Mrs', 'Lady', 'Mlle', 'Mr', 'Master', 'Rev'}
>>>
```

Then a title dictionary can be defined and bin passengers with different titles into different categories.

```
>>> Title_Dictionary = {
...     "Capt": "Officer",
...     "Col": "Officer",
...     "Major": "Officer",
...     "Jonkheer": "Royalty",
...     "Don": "Royalty",
...     "Dona": "Royalty",
...     "Sir" : "Royalty",
...     "Dr": "Officer",
...     "Rev": "Officer",
...     "the Countess":"Royalty",
...     "Mme": "Mrs",
...     "Mlle": "Miss",
...     "Ms": "Mrs",
...     "Mr" : "Mr",
...     "Mrs" : "Mrs",
...     "Miss" : "Miss",
...     "Master" : "Master",
...     "Lady" : "Royalty"
... }
```

```
>>> combined['Title'] = combined['Name'].map(lambda name:name.split(',')[1].split('.')[0].strip())
>>>
>>> combined['Title'].unique()
array(['Mr', 'Mrs', 'Miss', 'Master', 'Don', 'Rev', 'Dr', 'Mme', 'Ms',
       'Major', 'Lady', 'Sir', 'Mlle', 'Col', 'Capt', 'the Countess',
       'Jonkheer', 'Dona'], dtype=object)
>>> combined['Title'] = combined['Title'].map(Title_Dictionary)
>>>
>>> combined['Title'].unique()
array(['Mr', 'Mrs', 'Miss', 'Master', 'Royalty', 'Officer'], dtype=object)
>>>
```

Now there is no missing value in Title column by checking isnull() function.

```
>>> combined[combined['Title'].isnull()]
Empty DataFrame
Columns: [Pclass, Name, Sex, Age, SibSp, Parch, Ticket, Fare, Cabin, Embarked_C, Embarked_Q, Embarked_S, Died, Embarked, Title]
Index: []
>>>
```

There are 86 missing age in test dataset by checking missing values in train dataset and test dataset separately.

```
>>> print(combined.iloc[:891]['Age'].isnull().sum())
0
>>> print(combined.iloc[891:]['Age'].isnull().sum())
86
>>>
```

Extract the first 891 rows which are from train dataset and group then by Sex, Pclass and Title, then get the median value for each group.

```
>>> grouped_train = combined.iloc[:891].groupby(['Sex','Pclass','Title'])
>>> grouped_median_train = grouped_train.median()
>>> grouped_median_train = grouped_median_train.reset_index()[['Sex', 'Pclass', 'Title', 'Age']]
>>>
>>> print(grouped_median_train)
       Sex  Pclass    Title   Age
0   female       1     Miss  29.0
1   female       1      Mrs  37.0
2   female       1  Officer  49.0
3   female       1  Royalty  40.5
4   female       2     Miss  24.0
5   female       2      Mrs  31.5
6   female       3     Miss  22.0
7   female       3      Mrs  29.0
8     male       1   Master   4.0
9     male       1       Mr  36.0
10    male       1  Officer  50.0
11    male       1  Royalty  40.0
12    male       2   Master   1.0
13    male       2       Mr  30.0
14    male       2  Officer  46.5
15    male       3   Master   6.5
16    male       3       Mr  28.0
>>>
```

Define a function through which return the median function for each Sex, Pclass and Title group category. Then using lambda function to fill in number returned by function when the values is not a number.

```
>>> def fill_age(row):
...     condition = (
...         (grouped_median_train['Sex'] == row['Sex']) &
...         (grouped_median_train['Title'] == row['Title']) &
...         (grouped_median_train['Pclass'] == row['Pclass'])
...     )
...     return grouped_median_train[condition]['Age'].values[0]
...
>>> combined['Age'] = combined.apply(lambda row: fill_age(row) if np.isnan(row['Age']) else row['Age'], axis=1)
>>>
>>> combined['Age'].unique()
array([22.  , 38.  , 26.  , 35.  , 28.  , 54.  ,  2.  , 27.  , 14.  ,
        4.  , 58.  , 20.  , 39.  , 55.  , 31.  , 34.  , 15.  ,  8.  ,
       19.  , 40.  , 66.  , 42.  , 21.  , 18.  ,  3.  ,  7.  , 49.  ,
       29.  , 65.  , 28.5 ,  5.  , 11.  , 45.  , 17.  , 32.  , 16.  ,
       25.  ,  0.83, 30.  , 33.  , 23.  , 24.  , 46.  , 59.  , 71.  ,
       37.  , 47.  , 14.5 , 70.5 , 32.5 , 12.  ,  9.  , 36.5 , 51.  ,
       55.5 , 40.5 , 44.  ,  1.  , 61.  , 56.  , 50.  , 36.  , 45.5 ,
       20.5 , 62.  , 41.  , 52.  , 63.  , 23.5 ,  0.92, 43.  , 60.  ,
       10.  , 64.  , 13.  , 48.  ,  0.75, 53.  , 57.  , 80.  , 70.  ,
       24.5 ,  6.  ,  0.67, 30.5 ,  0.42, 34.5 , 74.  , 22.5 , 18.5 ,
       31.5 , 67.  , 76.  , 26.5 , 60.5 , 11.5 ,  0.33,  6.5 ,  0.17,
       38.5 ])
>>> print(combined['Age'].isnull().sum())
0
>>>
```

Then the name column can be dropped since the effective information have been extracted.

```
combined.drop('Name', axis=1, inplace=True)
```

Convert the categorical variable title into dummy variables and then drop the original Title column.

```
>>> titles_dummies = pd.get_dummies(combined['Title'], prefix='Title')
>>> combined = pd.concat([combined, titles_dummies], axis=1)
>>> print(combined.columns)
Index(['Pclass', 'Sex', 'Age', 'SibSp', 'Parch', 'Ticket', 'Fare', 'Cabin',
       'Embarked_C', 'Embarked_Q', 'Embarked_S', 'Died', 'Embarked', 'Title',
       'Title_Master', 'Title_Miss', 'Title_Mr', 'Title_Mrs', 'Title_Officer',
       'Title_Royalty'],
      dtype='object')
>>> combined.drop('Title', axis=1, inplace=True)
```

Using mean value of ticket fare to fill in the missing fares.

Filling Embarked missing values with the most frequent value ’S’ as observed.

Similarly, categorical column embarked needs to be converted into dummy variables and drop the original Embarked column.

```
>>> train_cabin, test_cabin = set(), set()
>>> for c in combined.iloc[:891]['Cabin']:
...     try:
...         train_cabin.add(c[0])
...     except:
...         train_cabin.add('M')
...
>>> for c in combined.iloc[891:]['Cabin']:
...     try:
...         test_cabin.add(c[0])
...     except:
...         test_cabin.add('M')
...
>>> print(train_cabin)
{'D', 'T', 'C', 'M', 'E', 'G', 'A', 'F', 'B'}
>>> print(test_cabin)
{'D', 'C', 'M', 'E', 'G', 'A', 'F', 'B'}
>>>
```

Cabin missing values need to be filled in with ‘M’, which stands for missing value for both train and test dataset.

Convert the Cabin variable into dummy variables as well and drop the original Cabin column. Similarly, Pclass is applied the same process.

Mapping the male as 1 and female as 0 for Sex column.

Combine SibSp and Parch together into a new column as FamilySize. And categorise them into Single category if FamilySize is 1, small family if FamilySize is between 2 to 4, otherwise large family.

```
>>> print(combined.columns)
Index(['Sex', 'Age', 'SibSp', 'Parch', 'Ticket', 'Fare', 'Embarked_C',
       'Embarked_Q', 'Embarked_S', 'Died', 'Title_Master', 'Title_Miss',
       'Title_Mr', 'Title_Mrs', 'Title_Officer', 'Title_Royalty', 'Embarked_C',
       'Embarked_Q', 'Embarked_S', 'Cabin_A', 'Cabin_B', 'Cabin_C', 'Cabin_D',
       'Cabin_E', 'Cabin_F', 'Cabin_G', 'Cabin_M', 'Cabin_T', 'Pclass_1',
       'Pclass_2', 'Pclass_3', 'FamilySize', 'Single', 'SmallFamily',
       'LargeFamily'],
      dtype='object')
>>>
```

Different formats of values of ticket column can be observed, and some of them have non-digital prefix and some only have digital numbers. Therefore, the non-digital letters will be kept for ticket value and set it as NONE if it's all digital number for ticket value, through this way, the ticket column can be more categorical and converted into dummy variables.

```
>>> combined
      Sex   Age  SibSp  Parch              Ticket      Fare  Embarked_C  \
0       1  22.0      1      0           A/5 21171    7.2500         0.0
1       0  38.0      1      0            PC 17599   71.2833         1.0
2       0  26.0      0      0    STON/O2. 3101282    7.9250         0.0
3       0  35.0      1      0              113803   53.1000         0.0
4       1  35.0      0      0              373450    8.0500         0.0
...   ...   ...    ...    ...                 ...       ...         ...
1302    1  28.0      0      0           A.5. 3236    8.0500         NaN
1303    0  39.0      0      0            PC 17758  108.9000         NaN
1304    1  38.5      0      0  SOTON/O.Q. 3101262    7.2500         NaN
1305    1  28.0      0      0              359309    8.0500         NaN
1306    1   6.5      1      1                2668   22.3583         NaN
```

```
>>> def cleanTicket(ticket):
...     ticket = ticket.replace('.','')
...     ticket = ticket.replace('/','')
...     ticket = ticket.split()
...     ticket = map(lambda t : t.strip(), ticket)
...     ticket = [x for x in ticket if not x.isdigit()]
...     if len(ticket) > 0:
...         return ticket[0]
...     else:
...         return 'NONE'
...
>>> combined['Ticket'] = combined['Ticket'].map(cleanTicket)
>>>
>>> combined['Ticket'].unique()
array(['A5', 'PC', 'STONO2', 'NONE', 'PP', 'CA', 'SCParis', 'SCA4', 'A4',
       'SP', 'SOC', 'WC', 'SOTONOQ', 'WEP', 'STONO', 'C', 'SCPARIS',
       'SOP', 'Fa', 'LINE', 'FCC', 'SWPP', 'SCOW', 'PPP', 'SC', 'SCAH',
       'AS', 'SOPP', 'FC', 'SOTONO2', 'CASOTON', 'SCA3', 'STONOQ', 'AQ4',
       'A', 'LP', 'AQ3'], dtype=object)
>>>
```

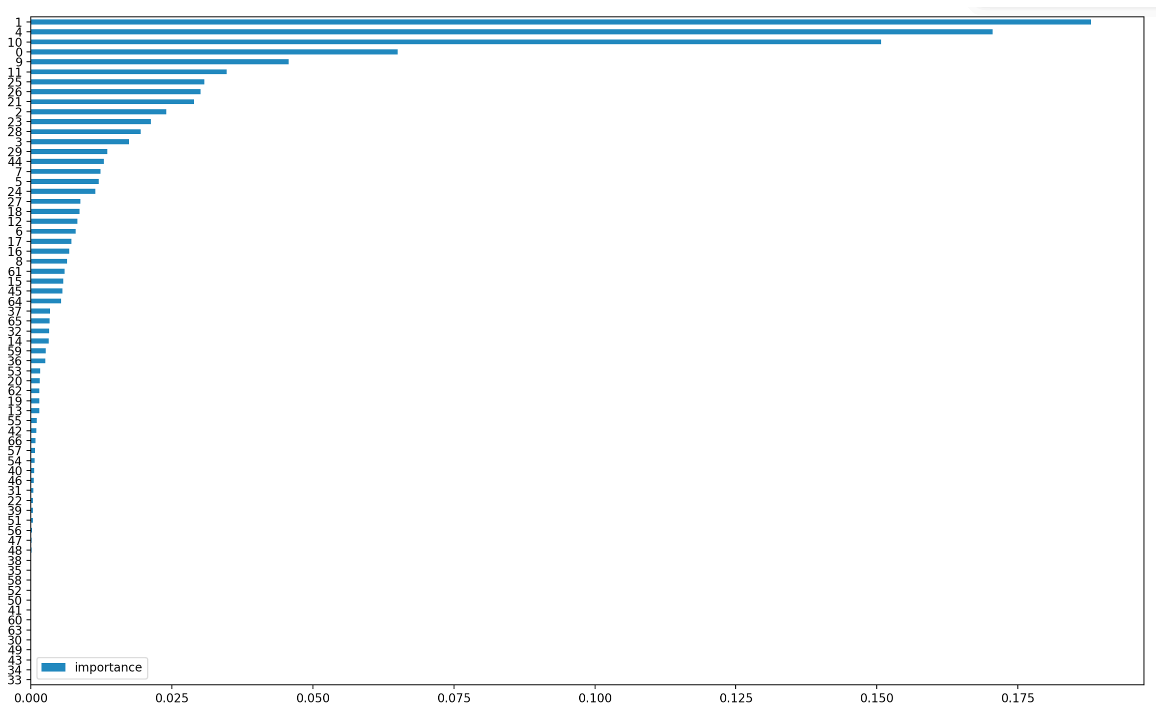
After all these data processing, there is no null values in each column and the shape of the combined dataset is 1307 * 67.

```
>>> combined.isnull().sum()
Sex               0
Age               0
SibSp             0
Parch             0
Fare              0
                 ..
Ticket_STONO2     0
Ticket_STONOQ     0
Ticket_SWPP       0
Ticket_WC         0
Ticket_WEP        0
Length: 67, dtype: int64
>>> print(combined.shape)
(1307, 67)
>>>
```

Extract the first 889 rows as train input and targets as output:

```
>>> print(targets)
0      0
1      1
2      1
3      1
4      0
      ..
886    0
887    1
888    0
889    1
890    0
Name: Survived, Length: 889, dtype: int64
>>> df_im_input=combined.iloc[:889]
>>> df_im_output=targets
```

Then random forest classifier is applied to check which features are important, and then the top 10 important features related to survived feature is chose to be the selected features.




```
>>> top_10_feature=features.nlargest(10, 'importance')
>>> top_10_feature
       feature  importance
1          Age    0.187940
4         Fare    0.170537
10    Title_Mr    0.150696
0          Sex    0.064985
9   Title_Miss    0.045723
11   Title_Mrs    0.034738
25    Pclass_3    0.030733
26  FamilySize    0.030060
21     Cabin_M    0.028923
2        SibSp    0.024047
>>> 
```

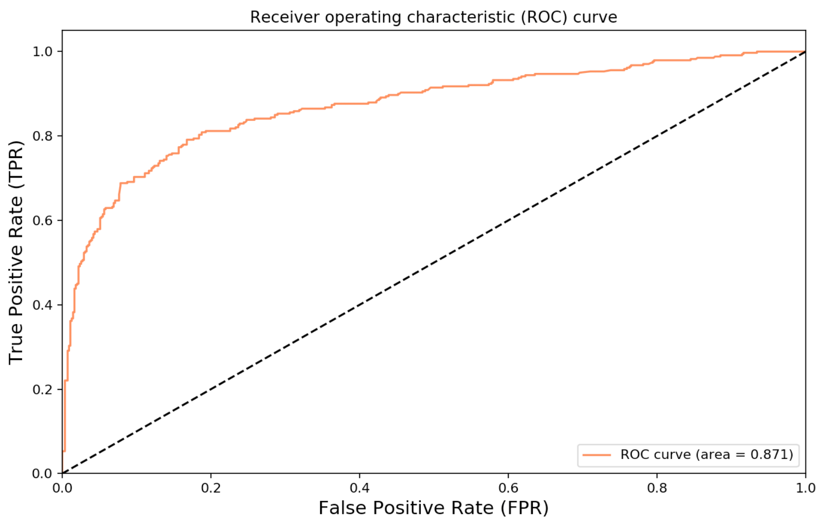
4. Modelling processing

Logistic regression model is applied since the final result of the prediction is survived or not. Using the train data with the selected top 10 important features and targets to train the model firstly, then do prediction to get the predicted results.

```
>>> from sklearn.linear_model import LogisticRegression
>>> logreg = LogisticRegression()
>>> logreg.fit(df_input_final,targets)
/Library/Frameworks/Python.framework/Versions/3.7/lib/python3.7/site-packages/sklearn/
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)
LogisticRegression()
>>> preds=logreg.predict(df_input_final)
>>> preds_probabilities = logreg.predict_proba(df_input_final)
>>> preds_probabilities.shape
(889, 2)
>>> pred_probs = preds_probabilities[:, 1]
>>>
```

Based on the prediction probability and the actual target, the ROC curve can be plotted as below, which is a good tool to check the binary classier model accuracy.

The ROC curve(area) is between 0 and 1, the higher the better. When the ROC curve(area = 0.5) which means this model has no prediction ability since the probability of a true guess is 0.5, when the ROC curve(area) is close to 1, it means the model accuracy is good.



The model accuracy on training data is 0.819 and the AUC is 0.871.

```
>>> from sklearn.metrics import confusion_matrix, accuracy_score
>>> print("accuracy: %2.3f" % accuracy_score(targets, preds))
accuracy: 0.819
>>> print("AUC: %2.3f" % auc(fpr, tpr))
AUC: 0.871
>>>
```

The related confusion matrix is as below: the true positive number is 481, false positive number is 68, the false negative number is 93 and the true negative number is 247.

```
>>> conf_m=confusion_matrix(targets, preds)
>>> conf_m
array([[481,  68],
       [ 93, 247]])
>>>
```

Applying the model with test datasets and get the final predictions:

```
>>> df_test_input_final=combined.iloc[889:][top_10_feature['feature']]
>>> df_test_preds=logreg.predict(df_test_input_final)
>>> submit = pd.DataFrame()
>>> test = pd.read_csv('test.csv')
>>> submit['PassengerId'] = test['PassengerId']
>>> submit['Survived'] = df_test_preds
>>> submit.to_csv('Titanic_LR_20200624.csv', index=False)
>>> submit.to_csv('Titanic_LR_1.csv', index=False)
>>>
```

The final accuracy of the submission is about 0.77751, which is a good practice.

6628 LJing 0.77751 1 2m

Your First Entry ↑

Welcome to the leaderboard!

Your score represents your submission's accuracy. For example, a score of 0.7 in this competition indicates you predicted Titanic survival correctly for 70% of people.

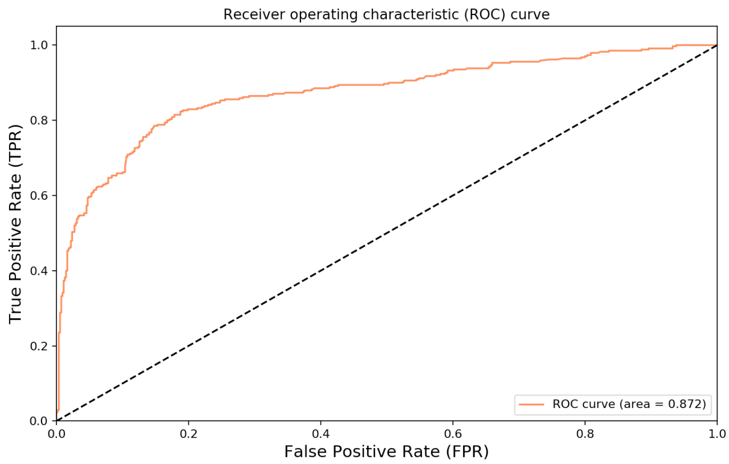
What next? You've got a few options:

- 💪 Learn skills that can improve your score in our Intro to Machine Learning course by Dan Becker.
- 🔍 Check out the discussion forum to find lots of tutorials and insights from other competitors.
- 🏆 Find a new challenge by entering one of our open, active competitions or searching our public datasets.

5. Model tuning

During the previous model processing, top 10 important features are selected to apply to the logistic regression model. More features can be selected to check if a better model performance can be reached or not. Therefore, top 15 important features is applied in the following model tuning process:

```
>>> top_15_feature
        feature  importance
1           Age    0.187940
4          Fare    0.170537
10     Title_Mr    0.150696
0           Sex    0.064985
9    Title_Miss    0.045723
11    Title_Mrs    0.034738
25     Pclass_3    0.030733
26   FamilySize    0.030060
21      Cabin_M    0.028923
2         SibSp    0.024047
23     Pclass_1    0.021314
28  SmallFamily    0.019479
3         Parch    0.017432
29  LargeFamily    0.013549
44  Ticket_NONE    0.012979
>>>
```



The ROC curve(area=0.872) is slightly higher than the previous one 0.871. The accuracy of train data is about 0.826.

```
>>> from sklearn.metrics import confusion_matrix, accuracy_score
>>> print("accuracy: %2.3f" % accuracy_score(targets, preds))
accuracy: 0.826
>>> print("AUC: %2.3f" % auc(fpr, tpr))
AUC: 0.872
>>>
>>> conf_m=confusion_matrix(targets, preds)
>>>
>>> conf_m
array([[477,  72],
       [ 83, 257]])
>>>
```

The final result is slightly better than choosing top 10 features to do the prediction:

5383	LJing	0.77990	2	~10s

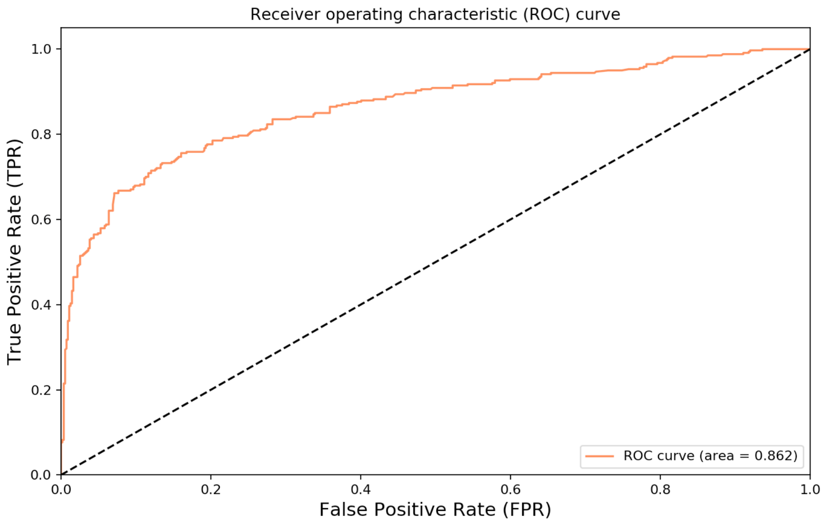
Your Best Entry ↑

Your submission scored 0.77990, which is an improvement of your previous score of 0.77751. Great job!

Tweet this!

Now fewer features selected to do the prediction, like top 8 features is used:

```
>>> top_8_feature
       feature  importance
1          Age    0.187940
4         Fare    0.170537
10    Title_Mr    0.150696
0          Sex    0.064985
9   Title_Miss    0.045723
11   Title_Mrs    0.034738
25    Pclass_3    0.030733
26  FamilySize    0.030060
>>> 
```




```
>>> print("accuracy: %2.3f" % accuracy_score(targets, preds))
accuracy: 0.811
>>> print("AUC: %2.3f" % auc(fpr, tpr))
AUC: 0.862
>>>
>>> conf_m=confusion_matrix(targets, preds)
>>> conf_m
array([[476,  73],
       [ 95, 245]])
>>> 
```

Though the accuracy on train dataset is 0.811 which is lower than the previous model performance, the final prediction on test dataset submitted on Kaggle is higher than previous ones, and 0.78229 is the highest out of this three times try.

4417 LJing 0.78229 3 ~10s

Your Best Entry

Your submission scored 0.78229, which is an improvement of your previous score of 0.77990. Great job!

Tweet this!

6. Conclusion and Findings

The model tuning part is only tried 3 times by selecting different top important features without other processing done. Some interesting conclusion can be observed:

- Though the model performance is not that good on training dataset, the test prediction may be good beyond expected.
- The model features section is not fixed, how many features selected depends the model performance and it takes time and effort to try and explore.
- Sometimes, less features selected may be have better model performance. In another word, keep the model as simple as possible to improve the model generalisation.
- Too many features selected may lead to model overfitting.