Step 1 Data mining

In [1]:
```
%matplotlib inline
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
df=pd.read_csv('train.csv')
```

In [3]:
```
df.head()
```

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  891 non-null    int64  
 1   Survived     891 non-null    int64  
 2   Pclass       891 non-null    int64  
 3   Name         891 non-null    object 
 4   Sex          891 non-null    object 
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64  
 7   Parch        891 non-null    int64  
 8   Ticket       891 non-null    object 
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object 
 11  Embarked     889 non-null    object 
```

```
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

In [5]:
```
df.shape
```

Out[5]:
```
(891, 12)
```

In [6]:
```
# drop useless column and the column missing many data
df=df.drop(columns=['PassengerId','Name','Cabin','Ticket'])
```

In [7]:
```
#combine sibling number with parents number to famiy number
df['family']=df['SibSp']+df['Parch']
```

In [8]:
```
df=df.drop(columns=['SibSp','Parch'])
```

In [9]:
```
df['is_alone']=df['family'].apply(lambda x:1 if x==0 else 0)
```

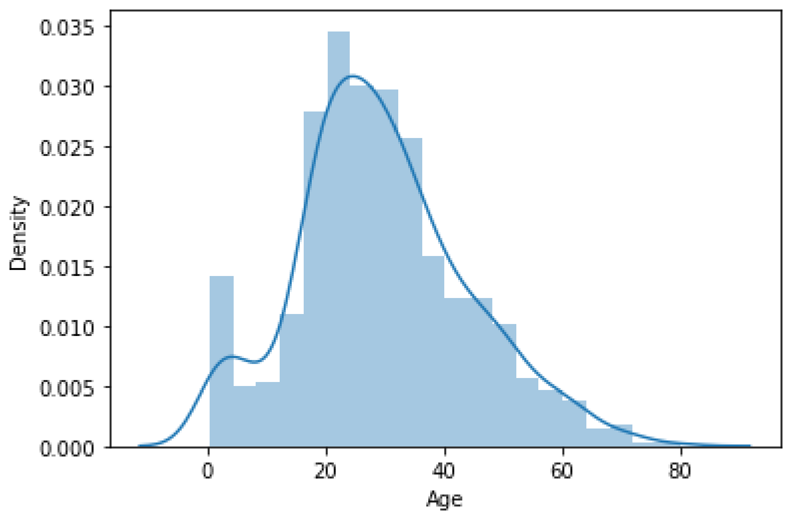
In [10]:
```
# trun sex to dummy variable
df['is_female']= df['Sex'].apply(lambda x:1 if x =='female' else 0 )
```

In [11]:
```
df=df.drop(columns=['Sex'])
```

In [12]:
```
# check the distribute of age
sns.distplot(df[df['Age'].notnull()]['Age'])
```

```
/Users/jameswang/opt/anaconda3/lib/python3.8/site-packages/seaborn/distributio
ns.py:2557: FutureWarning: `distplot` is a deprecated function and will be rem
oved in a future version. Please adapt your code to use either `displot` (a fi
gure-level function with similar flexibility) or `histplot` (an axes-level fun
ction for histograms).
  warnings.warn(msg, FutureWarning)
```

Out[12]:
```
<AxesSubplot:xlabel='Age', ylabel='Density'>
```



In [13]:
```
df['Age']=df['Age'].interpolate()
```

In [14]:

```
df['is_child']=df['Age'].apply(lambda x:1 if x<18 else 0)
```

In [15]:
```
#fill the Embarked
df['Embarked'].value_counts()
```

Out[15]:
```
S    644
C    168
Q     77
Name: Embarked, dtype: int64
```

In [16]:
```
df['Embarked']=df['Embarked'].fillna('S')
```

In [17]:
```
df=pd.get_dummies(df,prefix='is')
```

In [18]:
```
df.head()
```

Out[18]:

	Survived	Pclass	Age	Fare	family	is_alone	is_female	is_child	is_C	is_Q	is_S
0	0	3	22.0	7.2500	1	0	0	0	0	0	1
1	1	1	38.0	71.2833	1	0	1	0	1	0	0
2	1	3	26.0	7.9250	0	1	1	0	0	0	1
3	1	1	35.0	53.1000	1	0	1	0	0	0	1
4	0	3	35.0	8.0500	0	1	0	0	0	0	1

In [19]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 11 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Survived   891 non-null    int64  
 1   Pclass     891 non-null    int64  
 2   Age        891 non-null    float64
 3   Fare       891 non-null    float64
 4   family     891 non-null    int64  
 5   is_alone   891 non-null    int64  
 6   is_female  891 non-null    int64  
 7   is_child   891 non-null    int64  
 8   is_C       891 non-null    uint8  
 9   is_Q       891 non-null    uint8  
 10  is_S       891 non-null    uint8  
dtypes: float64(2), int64(6), uint8(3)
memory usage: 58.4 KB
```

In [20]:
```
x , y = df.drop(columns=['Survived']), df['Survived']
```

Step 2 Build model

In [29]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.svm import SVC, LinearSVC
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.model_selection import train_test_split
from sklearn.metrics import confusion_matrix
```

In [23]:

```
train_x, test_x, train_y, test_y = train_test_split(x,y,train_size=0.8,
                                                     test_size=0.2,random_stat
```

Logistic Regression

In [82]:

```
model_LR = LogisticRegression()
model_LR.fit(train_x,train_y)
pred_y=model_LR.predict(test_x)
acc_log_reg=round(model_LR.score(test_x,test_y)*100,2)
print(str(acc_log_reg)+'percent')
```

```
83.24percent
```

```
/Users/jameswang/opt/anaconda3/lib/python3.8/site-packages/sklearn/linear_mode
l/_logistic.py:763: ConvergenceWarning: lbfgs failed to converge (status=1):
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-regress
ion
  n_iter_i = _check_optimize_result(
```

In [53]:

```
confusion_matrix(test_y, pred_y, labels=[1, 0])
```

Out[53]:

```
array([[ 47,  20],
       [ 10, 102]])
```

In [41]:

```
a=str((102+47)/(102+10+20+47))
print('Correct rate is '+ a +'percent')
```

```
Correct rate is 0.8324022346368715percent
```

Decision Tree

In [75]:

```
model_tree =DecisionTreeClassifier(max_depth=3, random_state=20)
model_tree.fit(train_x,train_y)
pred_y=model_tree.predict(test_x)
acc_log_reg=round(model_tree.score(test_x,test_y)*100,2)
print(str(acc_log_reg)+'percent')
```

```
81.56percent
```

In [76]:

```
confusion_matrix(test_y, pred_y, labels=[1, 0])
```

Out[76]:

```
array([[ 38,  29],
       [  4, 108]])
```

In [77]:

```
a=str((38+108)/(38+29+4+108))
print('Correct rate is '+ a +'percent')
```

```
Correct rate is 0.8156424581005587percent
```

SVC

In [58]:
```
model_svc = SVC()
model_svc.fit(train_x,train_y)
pred_y=model_svc.predict(test_x)
acc_log_reg=round(model_svc.score(test_x,test_y)*100,2)
print(str(acc_log_reg)+'percent')
```

```
68.16percent
```

In [59]:
```
confusion_matrix(test_y, pred_y, labels=[1, 0])
```

Out[59]:
```
array([[ 22,  45],
       [ 12, 100]])
```

In [60]:
```
a=str((22+100)/(22+45+12+100))
print('Correct rate is '+ a +'percent')
```

```
Correct rate is 0.6815642458100558percent
```

Random Forest

In [83]:
```
model_RF = RandomForestClassifier(max_depth=3, random_state=20)
model_RF.fit( train_x, train_y)
pred_y=model_RF.predict(test_x)
acc_log_reg=round(model_RF.score(test_x,test_y)*100,2)
print(str(acc_log_reg)+'percent')
```

```
83.24percent
```

In [80]:
```
confusion_matrix(test_y, pred_y, labels=[1, 0])
```

Out[80]:
```
array([[ 40,  27],
       [  3, 109]])
```

In [81]:
```
a=str((40+109)/(40+27+3+109))
print('Correct rate is '+ a +'percent')
```

```
Correct rate is 0.8324022346368715percent
```

In [ ]:
```
# I have trained 4 model to make the classification. There are Logistic Regre
# Descision tree, SVC, and Random Forest. At first, I think the Random Forest
# best correct rate. However, Logistic Regression has the same correct rate a
# forest model. As a result, I will use both model to run the Hold_out testin
# which model is the best.
```

Step 3 Run the hand_out testing

In [114…
```
df1=pd.read_csv('holdout_test.csv')
```

In [115…
```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
```

```
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   Survived     0 non-null      float64
 1   PassengerId  418 non-null    int64  
 2   Pclass       418 non-null    int64  
 3   Name         418 non-null    object 
 4   Sex          418 non-null    object 
 5   Age          332 non-null    float64
 6   SibSp        418 non-null    int64  
 7   Parch        418 non-null    int64  
 8   Ticket       418 non-null    object 
 9   Fare         417 non-null    float64
 10  Cabin        91 non-null     object 
 11  Embarked     418 non-null    object 
dtypes: float64(3), int64(4), object(5)
memory usage: 39.3+ KB
```

In [120…

```
df1=df1.drop(columns=['PassengerId','Name','Cabin','Ticket'])
df1['family']=df1['SibSp']+df1['Parch']
df1=df1.drop(columns=['SibSp','Parch'])
df1['is_alone']=df1['family'].apply(lambda x:1 if x==0 else 0)
df1['is_female']= df1['Sex'].apply(lambda x:1 if x =='female' else 0 )
df1=df1.drop(columns=['Sex'])
df1['Age']=df1['Age'].interpolate()
df1['is_child']=df1['Age'].apply(lambda x:1 if x<18 else 0)
df1['Fare']=df1['Fare'].fillna(mean(df1[df1['Fare'].notnull()]['Fare']))
df1=df1.drop(columns=['Survived'])
df1=pd.get_dummies(df1,prefix='is')
```

In [121…

```
df1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 418 entries, 0 to 417
Data columns (total 10 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Pclass     418 non-null    int64  
 1   Age        418 non-null    float64
 2   Fare       418 non-null    float64
 3   family     418 non-null    int64  
 4   is_alone   418 non-null    int64  
 5   is_female  418 non-null    int64  
 6   is_child   418 non-null    int64  
 7   is_C       418 non-null    uint8  
 8   is_Q       418 non-null    uint8  
 9   is_S       418 non-null    uint8  
dtypes: float64(2), int64(5), uint8(3)
memory usage: 24.2 KB
```

In [122…

```
model_tree =DecisionTreeClassifier(max_depth=3, random_state=20)
model_tree.fit(train_x,train_y)
pred_df=model_tree.predict(df1)
```

In [125…

```
df_help=pd.read_csv('holdout_test.csv')
pred_result=pd.DataFrame({
    'PassengerId':df_help['PassengerId'],
    'Survived':pred_df
})
```

In [128…

```
pred_result.to_csv('Titanic_result_ccwang4.csv',index=False)
```

```
In [ ]:
```