Titanic Ensemble Stacking - Code + Research Paper

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1 Please Note: The Research paper is at the end of the code and DA

2 Titanic Survival Prediction Using Ensemble Stacking

Name: Sidhantha Poddar Registration number: 17BCE2044

Abstract: We have several machine learning models available today which work in a very different way and produce a different result. Considering a given data set some models might work for one case while other work and might not work for all the cases. If we can stack different models with their trained parameters, then we might be able to achieve a model with better validation accuracy. This paper presents an approach that uses multiple classification algorithms and combines them, in order to impart the final model with better accuracy and efficiency, avoiding overfitting. Here, we will be using the Titanic dataset for our project which consists of 12 columns; 11 attributes and 1 result column. We will further use the concept of feature engineering in which we will try to derive new attributes out of the available ones. After using multiple models for making the predictions we will make use a different approach to the ensemble to tune our final predictive model.

COMPARATIVE STUDY /RESULTS AND DISCUSSION We yielded a good score in terms of accuracy, 84% which clears us off the over-fitting trap. Upon using the Max Voting Ensemble Technique, we got a very high accuracy of 98.89% which was highly inclined to becoming a case of overfitting which is why we did not follow that path. Also, Precision itself cannot be one true metric to look at the performance of a model since accuracy takes in the assumption that the attributes are fairly distributed over the dataset which is hardly ever the case. Precision and Reminiscence should also be considered. Upon dropping the XGBoost in the Average Voting case, the accuracy also fell to a mere 40% which is also clearly an instance of under-fitting; a poor performing model. Hence our model worked better in comparison with Simple Ensemble Techniques.

3 Coding

3.1 Importing Libraries

[9]:
```
import pandas as pd
import numpy as np
import statistics
from sklearn import preprocessing
```

```
from sklearn.ensemble import RandomForestClassifier, AdaBoostClassifier,␣
 ↪GradientBoostingClassifier, ExtraTreesClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression

import matplotlib.pyplot as plt
import seaborn as sns
plt.style.use('bmh')
%matplotlib inline
```

[42]:
```
train = pd.read_csv('input/train.csv')
test = pd.read_csv('input/test.csv')
test_id = test['PassengerId']
combine = [train, test] # combine train and test data, easy to do data␣
 ↪manipulation
```

[43]:
```
train.head()
```

[43]:
```
   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
```

[44]:
```
titanic_df=train
titanic_df.info()
```

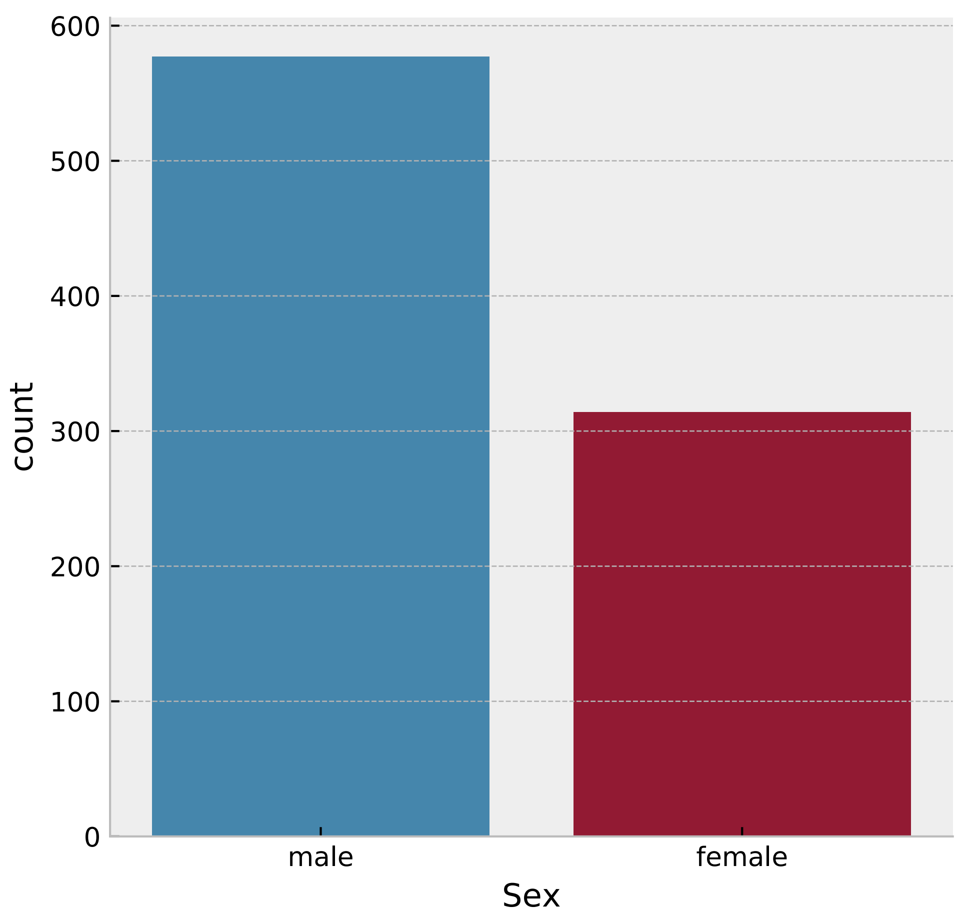
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
```

```
---  ------        --------------  -----
 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
```

3.2 Dataset vizualizations and analysis

[45]:
```
sns.factorplot('Sex',data=titanic_df,kind='count')
```

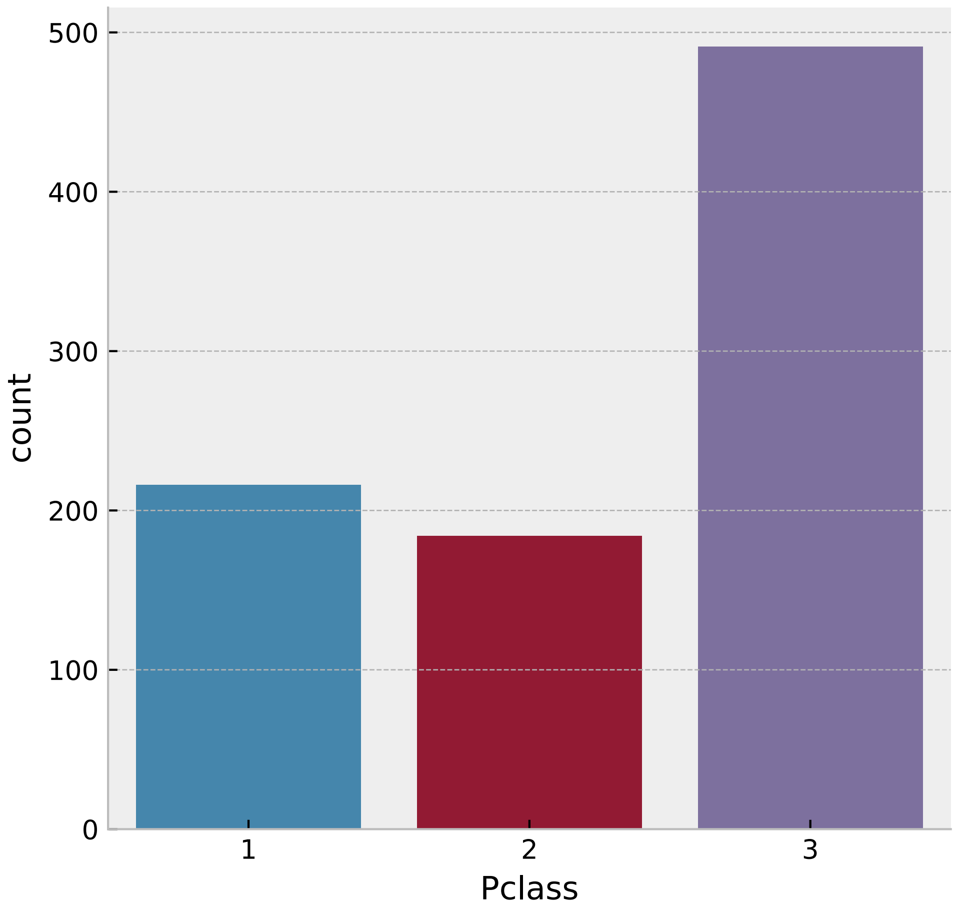
[45]:
```
<seaborn.axisgrid.FacetGrid at 0x7f56757d6210>
```



[46]:

```
sns.factorplot('Pclass',data=titanic_df,kind='count')
```

[46]: <seaborn.axisgrid.FacetGrid at 0x7f567577ef90>



[47]:

```
as_fig = sns.FacetGrid(titanic_df,hue='Sex',aspect=5)

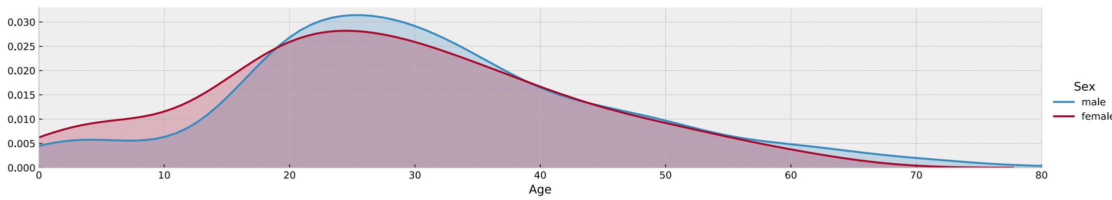
as_fig.map(sns.kdeplot,'Age',shade=True)

oldest = titanic_df['Age'].max()

as_fig.set(xlim=(0,oldest))

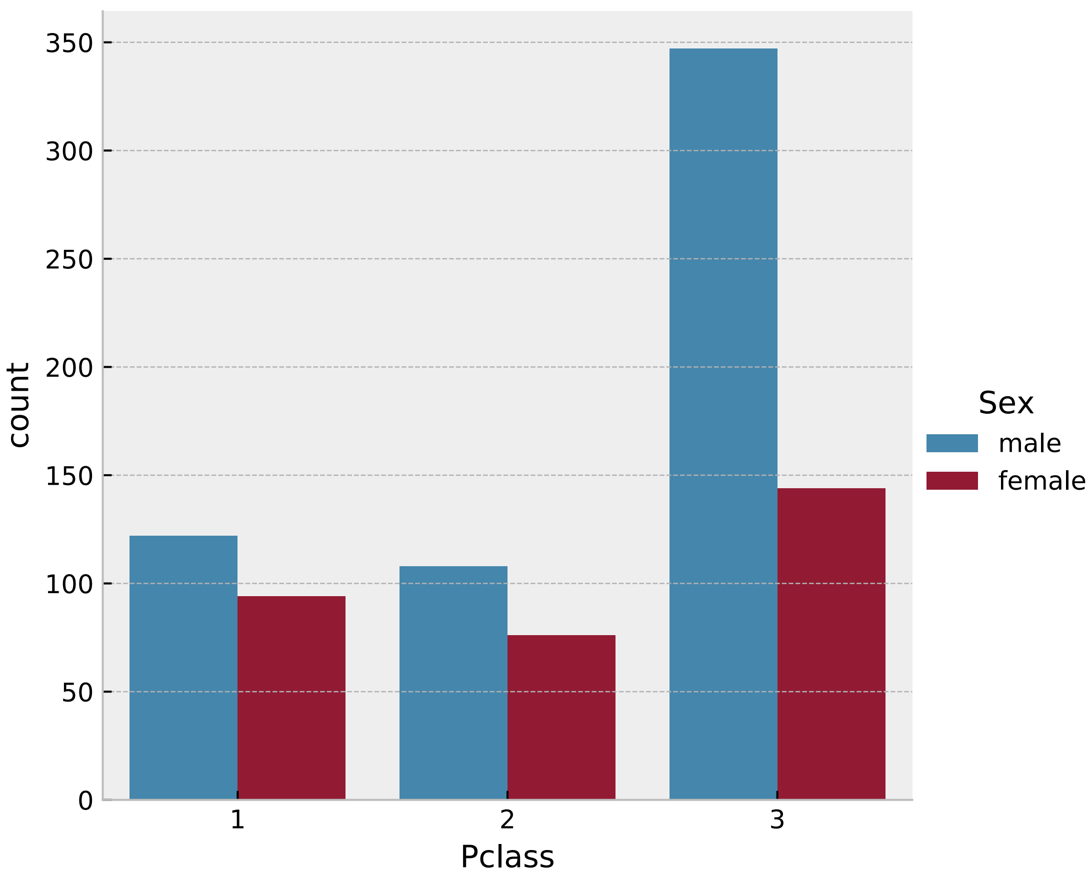
as_fig.add_legend()
```

[47]: <seaborn.axisgrid.FacetGrid at 0x7f566be28750>




```
[48]: sns.factorplot('Pclass',data=titanic_df,hue='Sex',kind='count')
```

```
[48]: <seaborn.axisgrid.FacetGrid at 0x7f566c34b610>
```



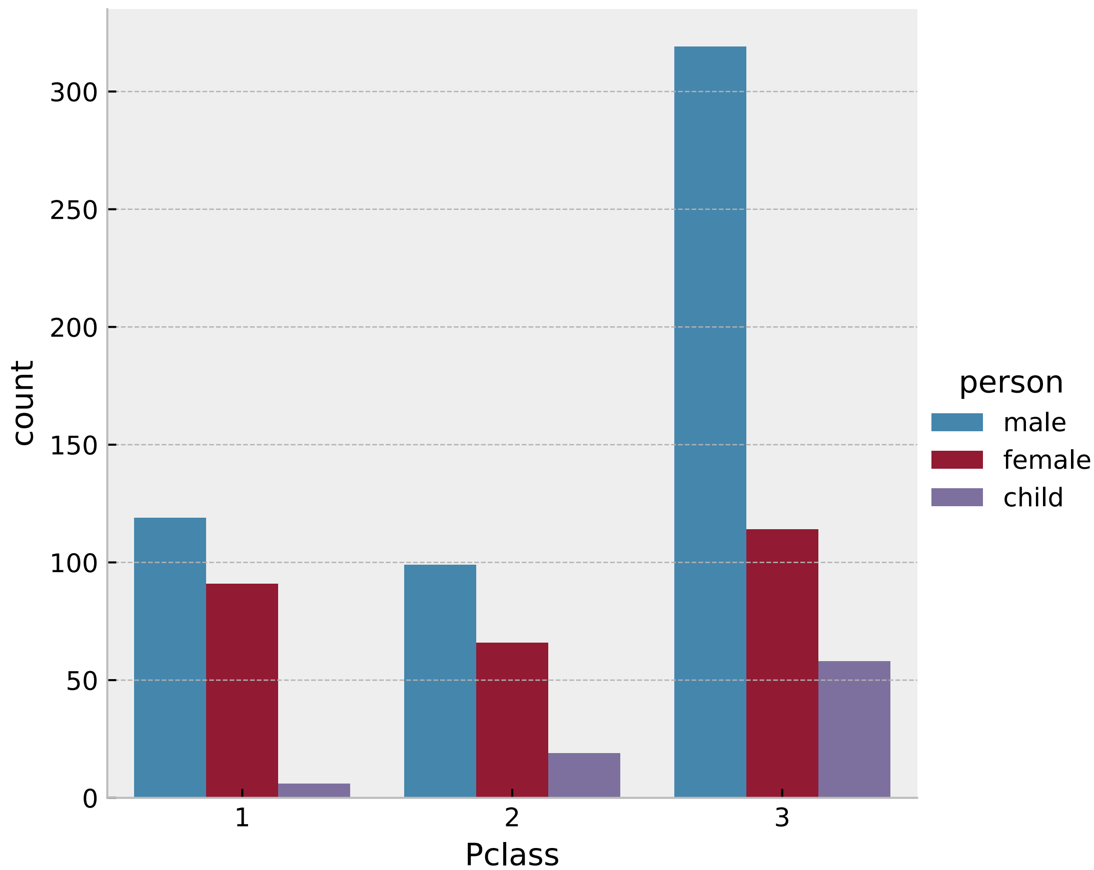

```
[49]: def titanic_children(passenger):

          age , sex = passenger
          if age <16:
              return 'child'
          else:
```

```
        return sex

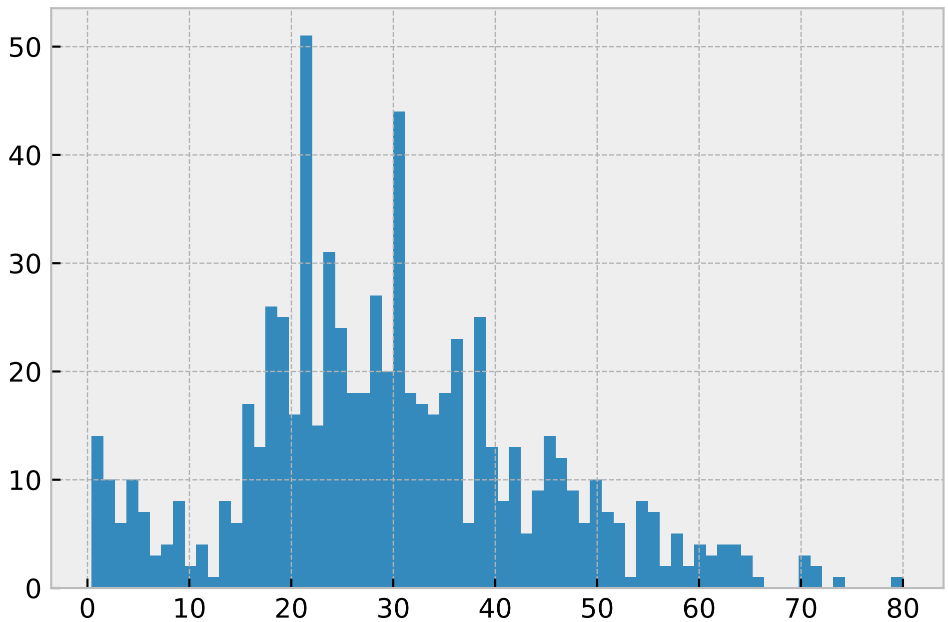
titanic_df['person'] = titanic_df[['Age','Sex']].apply(titanic_children,axis=1)
sns.factorplot('Pclass',data=titanic_df,hue='person',kind='count')
```

[49]: <seaborn.axisgrid.FacetGrid at 0x7f566c34be10>



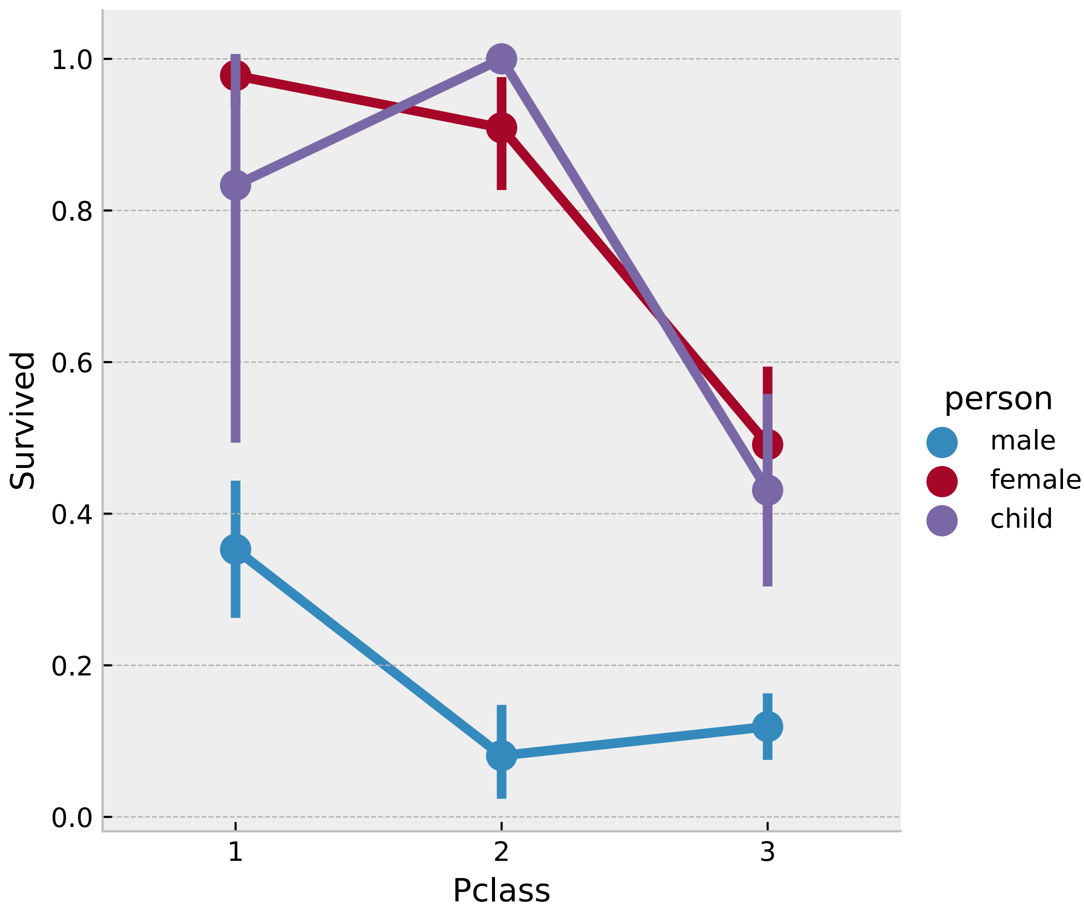
[50]:
```
titanic_df['Age'].hist(bins=70)
```

[50]: <matplotlib.axes._subplots.AxesSubplot at 0x7f566c190090>



[51]:
```
sns.factorplot('Pclass','Survived',data=titanic_df,hue='person')
```

[51]: <seaborn.axisgrid.FacetGrid at 0x7f566c50dc10>



The above graph shows that the survival rate for male is very low nevertheless of the class. And, the survival rate is less for the 3rd class passengers.

[52]:
```
as_fig = sns.FacetGrid(titanic_df,hue='Pclass',aspect=5)

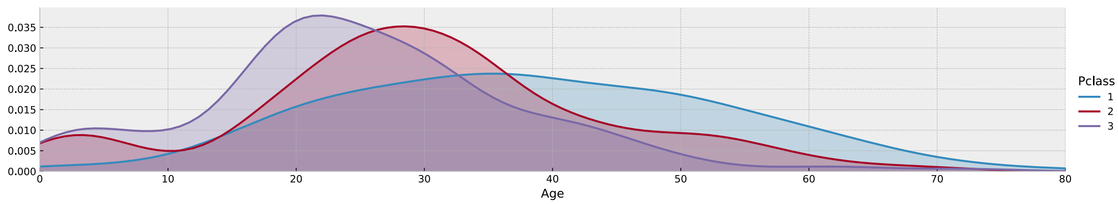
as_fig.map(sns.kdeplot,'Age',shade=True)

oldest = titanic_df['Age'].max()

as_fig.set(xlim=(0,oldest))

as_fig.add_legend()
```

[52]: <seaborn.axisgrid.FacetGrid at 0x7f566bda2c50>



From the above graphs, we can say that there are more number of passengers with a age group of 20 to 40 in all of the three classes which we are predicting.

3.3 Data Augumentation and preprocessing

Combining sibsp and parch to familysize to get better estimate

[53]:
```
for df in combine: # add feature 'FamilySize'
    df['FamilySize'] = df['SibSp'] + df['Parch'] + 1
trans1=combine[0]
trans1.head()
```

[53]:
```
   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  person  FamilySize
0      0         A/5 21171   7.2500   NaN        S    male           2
1      0          PC 17599  71.2833   C85        C  female           2
2      0  STON/O2. 3101282   7.9250   NaN        S  female           1
3      0            113803  53.1000  C123        S  female           2
4      0            373450   8.0500   NaN        S    male           1
```

adding new feature alone which tells us that if he travalled alone or not

[54]:
```
for df in combine: # add feature 'Alone'
    df['Alone'] = 0
    df.loc[df['FamilySize'] == 1, 'Alone'] = 1
trans2=combine[0]
```

```
trans2.head()
```

[54]:
```
   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  person  FamilySize  Alone
0      0         A/5 21171   7.2500   NaN        S    male           2      0
1      0          PC 17599  71.2833   C85        C  female           2      0
2      0  STON/O2. 3101282   7.9250   NaN        S  female           1      1
3      0            113803  53.1000  C123        S  female           2      0
4      0            373450   8.0500   NaN        S    male           1      1
```

[55]:
```
for df in combine: # fill missing values for 'Embarked'
    df['Embarked'].fillna(df['Embarked'].mode()[0], inplace=True)
trans3=combine[0]
print(trans3.info())
trans3.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 15 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     891 non-null    object
 12  person       891 non-null    object
```

 13 FamilySize   891 non-null   int64
 14 Alone   891 non-null   int64
dtypes: float64(2), int64(7), object(6)
memory usage: 104.5+ KB
None
```

[55]:
```
   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 person FamilySize Alone
0   0   A/5 21171   7.2500   NaN   S   male   2   0
1   0   PC 17599 71.2833   C85   C female   2   0
2   0 STON/O2. 3101282   7.9250   NaN   S female   1   1
3   0   113803 53.1000 C123   S female   2   0
4   0   373450   8.0500   NaN   S   male   1   1
```

[56]:
```python
for df in combine: # fill missing values for 'Fare' and transform into␣
 ↪categorical feature
    df['Fare'].fillna(df['Fare'].median(), inplace=True)
    df['farecat'] = 0
    df.loc[df['Fare'] <= 10.5, 'farecat'] = 0
    df.loc[(df['Fare'] > 10.5) & (df['Fare'] <= 21.679), 'farecat'] = 1
    df.loc[(df['Fare'] > 21.679) & (df['Fare'] <= 39.688), 'farecat'] = 2
    df.loc[(df['Fare'] > 39.688) & (df['Fare'] <= 512.329), 'farecat'] = 3
    df.loc[df['Fare'] > 512.329, 'farecat'] = 4

trans4=combine[0]
trans4.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 16 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     891 non-null    object
 12  person       891 non-null    object
 13  FamilySize   891 non-null    int64
 14  Alone        891 non-null    int64
 15  farecat      891 non-null    int64
dtypes: float64(2), int64(8), object(6)
memory usage: 111.5+ KB
```

[57]:
```
for df in combine: # fill missing values for 'Age' and transform into␣
↪categorical feature
    avg = df['Age'].mean()
    std = df['Age'].std()
    NaN_count = df['Age'].isnull().sum()

    age_fill = np.random.randint(avg-std, avg+std, NaN_count)
    df.loc[df['Age'].isnull(), 'Age'] = age_fill
    df['Age'] = df['Age'].astype(int)

    df['agecat']=0
    df.loc[df['Age'] <= 16, 'agecat'] = 0
    df.loc[(df['Age'] > 16) & (df['Age'] <= 32), 'agecat'] = 1
    df.loc[(df['Age'] > 32) & (df['Age'] <= 48), 'agecat'] = 2
    df.loc[(df['Age'] > 48) & (df['Age'] <= 64), 'agecat'] = 3
    df.loc[df['Age'] > 64, 'agecat'] = 4
trans5=combine[0]
trans5.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 17 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          891 non-null    int64
 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     891 non-null    object
 12  person       891 non-null    object
 13  FamilySize   891 non-null    int64
 14  Alone        891 non-null    int64
 15  farecat      891 non-null    int64
 16  agecat       891 non-null    int64
dtypes: float64(1), int64(10), object(6)
memory usage: 118.5+ KB
```

[58]:
```
import re
def only_title(name): # manipulation 'Name', extracting titles from names
    title = re.findall(' ([A-Za-z]+)\.', name)
    if title:
        return title[0]

for df in combine:
    df['Title'] = df['Name'].apply(only_title)

for df in combine:
    df['Title'] = df['Title'].replace(['Lady', 'Countess','Capt', 'Col', 'Don',␣
↪'Dr', 'Major',
                                       'Rev', 'Sir', 'Jonkheer', 'Dona'], 'Rare')
    df['Title'] = df['Title'].replace('Mlle', 'Miss')
    df['Title'] = df['Title'].replace('Ms', 'Miss')
    df['Title'] = df['Title'].replace('Mme', 'Mrs')

############ Encoding features, make them ready for classifiers
# feature_drop = ['PassengerId', 'Name', 'SibSp', 'Parch', 'Ticket', 'Cabin',␣
↪'FamilySize']
# for df in combine:
#     df.drop(feature_drop, axis=1, inplace=True)

trans6=combine[0]
trans6.head()
```

[58]:
```
   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      1
```

```
1  Cumings, Mrs. John Bradley (Florence Briggs Th…  female   38      1
2                             Heikkinen, Miss. Laina  female   26      0
3       Futrelle, Mrs. Jacques Heath (Lily May Peel)  female   35      1
4                           Allen, Mr. William Henry    male   35      0

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

   farecat  agecat Title
0        0       1    Mr
1        3       2   Mrs
2        0       1  Miss
3        3       2   Mrs
4        0       2    Mr
```

[59]:

```
for df in combine: # add feature 'Alone'
    df['gender'] = 0
    df.loc[df['Sex'] == "male", 'gender'] = 1
trans6=combine[0]
```

[60]:

```
trans6.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 19 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          891 non-null    int64
 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     891 non-null    object
 12  person       891 non-null    object
 13  FamilySize   891 non-null    int64
 14  Alone        891 non-null    int64
 15  farecat      891 non-null    int64
```

```
 16   agecat        891 non-null    int64
 17   Title         891 non-null    object
 18   gender        891 non-null    int64
dtypes: float64(1), int64(11), object(7)
memory usage: 132.4+ KB
```

3.4 Ensemble stacking method

[61]:
```python
def accuracy(k,prediction):
    match=0
    i=0
    for x in prediction:
        if x==k[i]:
            match+=1
        i+=1
    return(match/k.size)
```

Creating multiple models for stacking

[62]:
```python
from sklearn import tree
from sklearn.ensemble import RandomForestClassifier
X  = train[['gender','Pclass','agecat']]
X1 = test[['gender','Pclass','agecat']]
Y = train[['Survived']]
clf1 = tree.DecisionTreeClassifier()
clf1 = clf1.fit(X,Y)
pred1 = clf1.predict(X)
tpred1 = clf1.predict(X1)
k=np.array(Y)
print(accuracy(k,pred1))
```

```
0.8013468013468014
```

[63]:
```python
X  = train[['gender','Pclass','farecat',]]
X2 = test[['gender','Pclass','farecat',]]
Y = train[['Survived']]
X.insert(1, 'pred1', pd.DataFrame({"pread1":pred1}))
X2.insert(1, 'pred1', pd.DataFrame({"pread1":tpred1}))
clf2 = tree.DecisionTreeClassifier()
clf2 = clf2.fit(X,Y)
pred2 = clf2.predict(X)
tpred2 = clf2.predict(X2)
print(accuracy(k,pred2))
```

```
0.8215488215488216
```

[64]:
```python
X  = train[['gender','Pclass','farecat','FamilySize']]
X3 = test[['gender','Pclass','farecat','FamilySize']]
```

```
Y = train[['Survived']]
clf3=RandomForestClassifier(n_estimators=100)
clf3.fit(X,Y)
pred3=clf3.predict(X)
tpred3 = clf3.predict(X3)
print(accuracy(k,pred3))
```

0.8305274971941639

[65]:
```
X  = train[['gender','FamilySize','agecat','Pclass']]
Y = train[['Survived']]
X4 = test[['gender','FamilySize','agecat','Pclass']]
clf4=RandomForestClassifier(n_estimators=1000)
clf4.fit(X,Y)
pred4=clf4.predict(X)
tpred4=clf4.predict(X4)
print(accuracy(k,pred4))
```

0.8361391694725028

[66]:
```
from sklearn import linear_model
X  = train[['gender','FamilySize','agecat','Pclass','Parch','SibSp','Fare']]
Y = train[['Survived']]
X5=test[['gender','FamilySize','agecat','Pclass','Parch','SibSp','Fare']]
reg = linear_model.LinearRegression()
reg.fit(X,Y)
pred5=reg.predict(X)
tpred5=reg.predict(X5)
print(accuracy(k,pred5))
```

0.0

[67]:
```
from sklearn.linear_model import LogisticRegression
X  = train[['gender','FamilySize','agecat','Pclass','Parch','SibSp','Fare']]
Y = train[['Survived']]
X6=test[['gender','FamilySize','agecat','Pclass','Parch','SibSp','Fare']]
lreg = LogisticRegression(random_state=0,␣
 ↪solver='lbfgs',multi_class='multinomial')
lreg.fit(X,Y)
pred6=lreg.predict(X)
tpred6=lreg.predict(X5)
print(accuracy(k,pred6))
```

0.7890011223344556

[68]:
```
arr=[]
for i in pred5:
    arr=arr+ [i]
```

```
print(accuracy(pred1,pred2))
print(accuracy(pred1,pred3))
print(accuracy(pred1,pred4))
print(accuracy(pred1,pred6))
print(accuracy(pred2,pred3))
print(accuracy(pred2,pred4))
print(accuracy(pred2,pred6))
print(accuracy(pred3,pred4))
print(accuracy(pred3,pred6))
print(accuracy(pred4,pred6))
```

```
0.9169472502805837
0.867564534231201
0.8888888888888888
0.8462401795735129
0.9281705948372615
0.9494949494949495
0.9113355780022446
0.9405162738496072
0.920314253647587
0.8900112233445566
```

[69]:
```
totalcalc=[]
for i in range(0,len(pred1)):
    a1=pred1[i]
    a1+=pred2[i]*2**1
    a1+=pred3[i]*2**2
    a1+=pred4[i]*2**3
    a1+=pred6[i]*2**4
    totalcalc+=[a1]
```

[71]:
```
np.array(set(totalcalc))
```

[71]:
```
array({0, 1, 3, 4, 8, 10, 11, 12, 14, 15, 16, 17, 18, 19, 20, 22, 23, 24, 26,
27, 28, 29, 30, 31},
      dtype=object)
```

[73]:
```
arrx0=[0 for i in range(0,32)]
arrx1=[0 for i in range(0,32)]
for i in range(0,len(totalcalc)):
    if k[i]==1:
        arrx1[totalcalc[i]]+=1
    else:
        arrx0[totalcalc[i]]+=1

arrxf=[0 for i in range(0,32)]
for i in range(0,32):
```

```
    if arrx1[i]>arrx0[i]:
        arrxf[i]=1
    else:
        arrxf[i]=0
```

[74]:
```
for i in range(0,32):
    print(i,"\t",arrx1[i],"\t",arrx0[i])
```

```
0        71      450
1        1       8
2        0       0
3        0       1
4        5       2
5        0       0
6        0       0
7        0       0
8        8       3
9        0       0
10       0       1
11       6       0
12       9       1
13       0       0
14       1       0
15       4       0
16       10      21
17       0       4
18       2       4
19       0       2
20       9       10
21       0       0
22       2       0
23       0       1
24       1       2
25       0       0
26       0       1
27       1       1
28       2       5
29       1       1
30       28      20
31       181     11
```

[75]:
```
trtotalcalc=[]
for i in range(0,len(pred1)):
    a1=pred1[i]
    a1+=pred2[i]*2**1
    a1+=pred3[i]*2**2
    a1+=pred4[i]*2**3
```

```
    a1+=pred6[i]*2**4
    trtotalcalc+=[arrxf[a1]]
accuracy(k,trtotalcalc)
```

[75]: 0.8484848484848485

[76]:
```
ttotalcalc=[]
for i in range(0,len(tpred1)):
    a1=tpred1[i]
    a1+=tpred2[i]*2**1
    a1+=tpred3[i]*2**2
    a1+=tpred4[i]*2**3
    a1+=tpred6[i]*2**4
    ttotalcalc+=[arrxf[a1]]
```

3.4.1 Results after Stacking

[77]:
```
print(accuracy(pred1,trtotalcalc))
print(accuracy(pred2,trtotalcalc))
print(accuracy(pred3,trtotalcalc))
print(accuracy(pred4,trtotalcalc))
print(accuracy(pred6,trtotalcalc))
```

```
0.8877665544332211
0.9528619528619529
0.9483726150392817
0.9719416386083053
0.8686868686868687
```

[78]:
```
dummy_data1 = {
        'pred1': pred1,
        'pred2': pred2,
        'pred3':pred3,
        'pred4':pred4,
        #'pred5':arr
        }

df1 = pd.DataFrame(dummy_data1)
clf = tree.DecisionTreeClassifier()
clf = clf.fit(df1,Y)
```

predicting on test data

[79]:
```
predt=clf.predict(df1)
print(accuracy(k,predt))
```

```
0.8428731762065096
```

3.4.2 Results

the accuraccy increased from 78% to 84% after stacking models

[ ]:
```

```