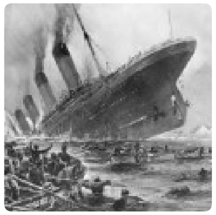
kaggle Search kaggle Competitions Datasets Kernels Discussion Learn



Henrique Yamahata

Titanic Problem, Begginer

3 voters

last run 5 hours ago · IPython Notebook HTML · 58 views
using data from Titanic: Machine Learning from Disaster · Public

Notebook Code Data (1) Output Comments (1) Log Versions (2) Forks (2) Fork Notebook

Notebook

Titanic Problem:

We want to discover which passengers survived through the data.

This notebook is divide by:

- Data analysis
- Feature Engineer at:
  - Gender, Embarked type, Name, Age and Fare
- Modeling with:
  - KNeighborsClassifier, LogisticRegression, DecisionTreeClassifier, RandomForestClassifier
  - Score and Cross-Validation

In [1]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

In [2]:

```
titanic = pd.read_csv("../input/train.csv")
titanic_test = pd.read_csv("../input/test.csv")
# Creating a list with two files, more accuracy for to the math to fill NaN values
combined = [titanic, titanic_test]
```

In [3]:

```
titanic.head()
```

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S

In [4]:

```
titanic_test.head()
```

Out[4]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	892	3	Kelly, Mr. James	male	34.5	0	0	330911	7.8292	NaN	Q
1	893	3	Wilkes, Mrs. James (Ellen Needs)	female	47.0	1	0	363272	7.0000	NaN	S
2	894	2	Myles, Mr. Thomas Francis	male	62.0	0	0	240276	9.6875	NaN	Q
3	895	3	Wirz, Mr. Albert	male	27.0	0	0	315154	8.6625	NaN	S
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	female	22.0	1	1	3101298	12.2875	NaN	S

Working with Gender

In [5]:

```
#Checking if exist some NaN value
len(titanic[titanic['Sex'].isnull()])
```

Out[5]:

```
0
```

In [6]:

```
#How many unique enters this array have.
titanic["Sex"].unique()
```

Out[6]:

```
array(['male', 'female'], dtype=object)
```

In [7]:

```
#Checking which gender have more survivers
titanic[['Survived', 'Sex']].groupby('Sex').mean()
```

Out[7]:

	Survived
Sex	
female	0.742038
male	0.188908

In [8]:

```
# Replacing Categorical variables by continuous, with this for and this list(combined),
# we can replace Sex in titanic and test_ticanic

dicsex = {"male": 0, "female": 1}
for dfsex in combined:
    dfsex['Sex'] = dfsex['Sex'].map(dicsex)

#other method
#titanic.loc[titanic["Sex"] == "male", "Sex"] = 0
#titanic.loc[titanic["Sex"] == "female", "Sex"] = 1
```

In [9]:

```
titanic.head()
```

Out[9]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	0	35.0	0	0	373450	8.0500	NaN	S

Working with Embarked type

In [10]:

```
#Checking if exist some NaN value
len(titanic[titanic['Embarked'].isnull()])
```

Out[10]:

2

In [11]:

```
titanic[titanic['Embarked'].isnull()]
```

Out[11]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
61	62	1	1	Icard, Miss. Amelie	1	38.0	0	0	113572	80.0	B28	NaN
829	830	1	1	Stone, Mrs. George Nelson (Martha Evelyn)	1	62.0	0	0	113572	80.0	B28	NaN

In [12]:

```
# Trying to found an insight, connecting all common variables of these people to predict where t
hey embarked, without success
titanic[(titanic['Pclass'] == 1) & (titanic['Survived'] == 1) & (titanic['Sex'] == 1)].groupby(
'Embarked').sum()
```

Out[12]:

	PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
Embarked								

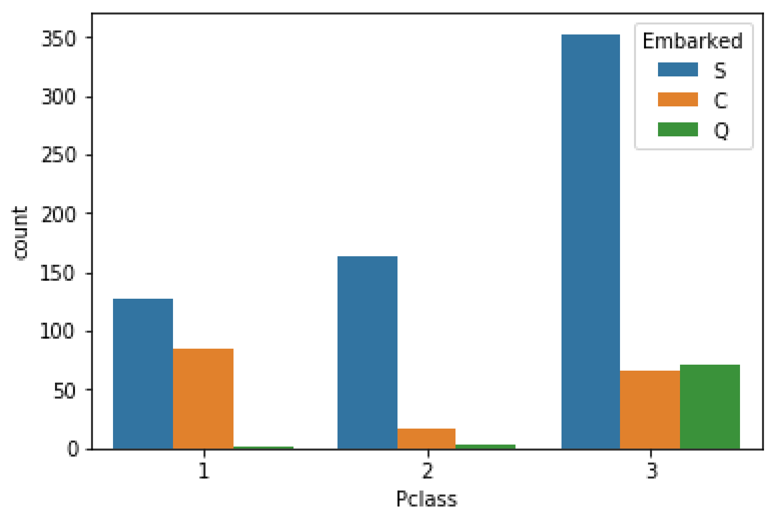
C	18038	42	42	42	1320.0	22	13	4943.8208
Q	413	1	1	1	33.0	1	0	90.0000
S	23788	46	46	46	1412.0	27	26	4450.1917

In [13]:

```
# Here we can see, at all classes most of people embarked on "S", so to fill this data with less
 variation we put "S".
sns.countplot(x = 'Pclass', data = titanic, hue = 'Embarked')
```

Out[13]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f71d1600cc0>
```



In [14]:

```
titanic["Embarked"] = titanic["Embarked"].fillna("S")
```

In [15]:

```
# Same concept to replace used at Sex column
dic_embarked = {"S": 0, "C": 1, "Q": 2}
for df_embarked in combined:
    df_embarked['Embarked'] = df_embarked['Embarked'].map(dic_embarked)
```

Working with Name

Combining both Dataset, BECAUSE EXIST THE POSSIBILITY THAT IN ONE DF DOESN'T EXIST THE SAME PRONOUNS TREATMENT in the other

In [16]:

```
# getting all Title from Name column in both DataFrames through the list and creating a new colu
mn with those titles
for df in combined:
    df['Title'] = df['Name'].str.extract(' ([A-Za-z]+)\.', expand=True)
```

In [17]:

```
# concat both updated dataframes to see the distribution of titles at titanic
combined_df = pd.concat([titanic, titanic_test], axis = 0)
combined_df['Title'].value_counts()
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:2: FutureWarning: Sorting because n
on-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=True'.
```

```
To retain the current behavior and silence the warning, pass sort=False
```

Out[17]:

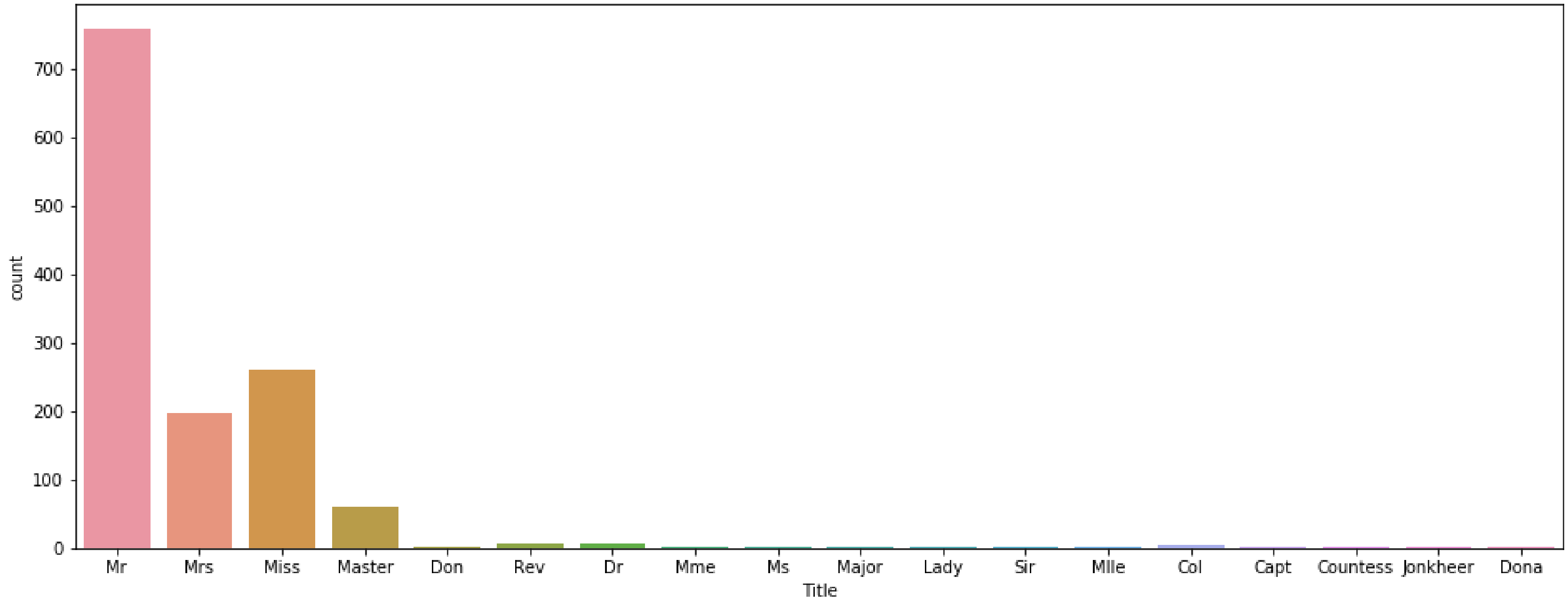
```
Mr          757
Miss        260
Mrs         197
Master       61
Dr            8
Rev           8
Col           4
Mlle          2
Major         2
Ms            2
Mme           1
Countess      1
Lady          1
Don           1
Capt          1
Dona          1
Jonkheer      1
Sir           1
Name: Title, dtype: int64
```

In [18]:

```
plt.subplots(figsize = (16,6))
sns.countplot(x = 'Title', data = combined_df)
```

Out[18]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f71d149e940>
```



In [19]:

```
# Same concept to replace used at Sex column, considering the 4 largest groups of people and the
 rest of them in 1 group
# Mr: 0
# Miss: 1
# Mrs: 2
# Master: 3
# Others: 4
titlemap = {"Mr": 0,
            "Miss": 1,
            "Mrs": 2,
            "Master": 3,
            "Dr": 4, "Rev": 4, "Col": 4, "Major": 4, "Mlle": 4,"Countess": 4, "Ms": 4,
            "Lady": 4, "Jonkheer": 4,"Don": 4, "Dona" : 4, "Mme": 4,"Capt": 4,"Sir": 4 }
for df in combined:
    df['Title'] = df['Title'].map(titlemap)
```

In [20]:

```
titanic.head()
```

Out[20]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Title
0	1	0	3	Braund, Mr. Owen Harris	0	22.0	1	0	A/5 21171	7.2500	NaN	0	0
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	1	38.0	1	0	PC 17599	71.2833	C85	1	2
2	3	1	3	Heikkinen, Miss. Laina	1	26.0	0	0	STON/O2. 3101282	7.9250	NaN	0	1
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	1	35.0	1	0	113803	53.1000	C123	0	2
4	5	0	3	Allen, Mr. William Henry	0	35.0	0	0	373450	8.0500	NaN	0	0

Working with Age

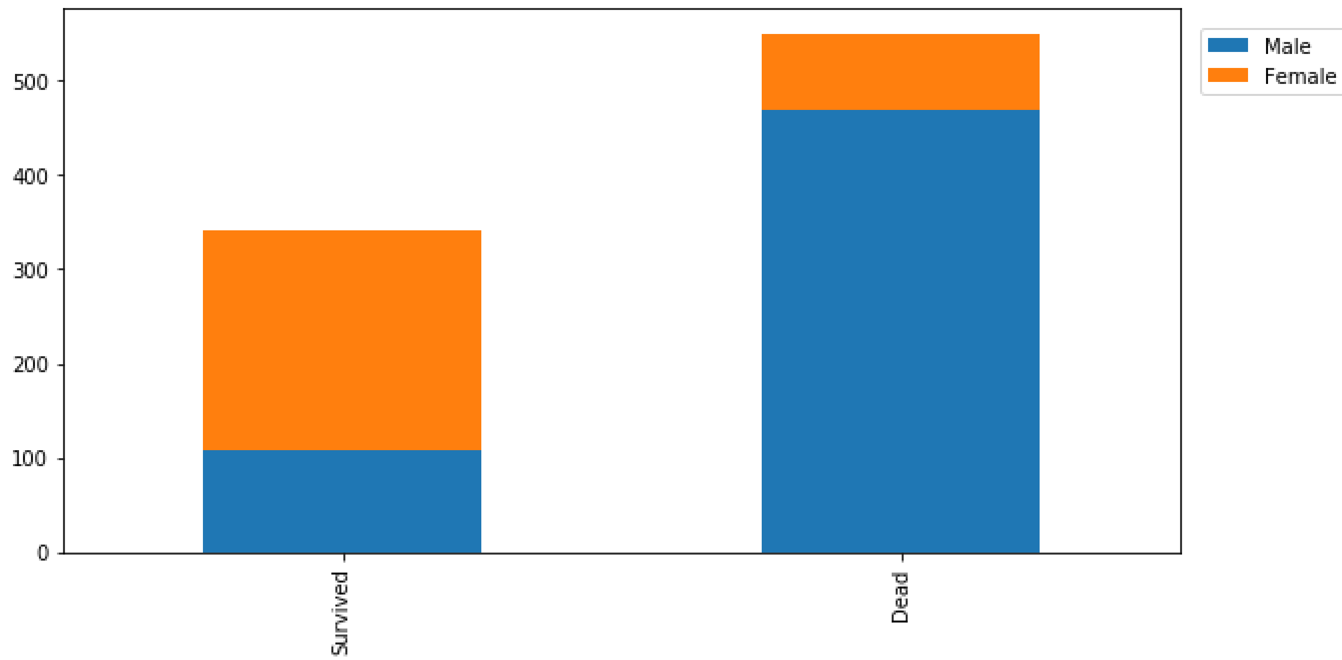
In [21]:

```
# Lets see how is the distribuition by gender for people who survived and whos dont.
survived = titanic[titanic['Survived']==1]['Sex'].value_counts()
# Extract how many peoples for each sex survived
dead = titanic[titanic['Survived']==0]['Sex'].value_counts()
```

```
# Extract how many peoples for each sex not survived
df = pd.DataFrame([survived,dead])
df.columns= ['Male', 'Female']
df.index = ['Survived','Dead']
df.plot(kind='bar',stacked=True, figsize=(10,5))
plt.legend(bbox_to_anchor=(1, 1), loc=2, borderaxespad=1)
```

Out[21]:

```
<matplotlib.legend.Legend at 0x7f71d1464208>
```



In [22]:

```
#looking for null values ate Age.
len(titanic[titanic['Age'].isnull()])
```

Out[22]:

```
177
```

In [23]:

```
# Here we need to make a decision, which  variable we'll relate with Age to fill the empty value
s
titanic[titanic['Age'].isnull()].head()
```

Out[23]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Title
5	6	0	3	Moran, Mr. James	0	NaN	0	0	330877	8.4583	NaN	2	0
17	18	1	2	Williams, Mr. Charles Eugene	0	NaN	0	0	244373	13.0000	NaN	0	0
19	20	1	3	Masselmani, Mrs. Fatima	1	NaN	0	0	2649	7.2250	NaN	1	2
26	27	0	3	Emir, Mr. Farred Chehab	0	NaN	0	0	2631	7.2250	NaN	1	0
28	29	1	3	O'Dwyer, Miss. Ellen "Nellie"	1	NaN	0	0	330959	7.8792	NaN	2	1

In [24]:

```
# looking to the first possibility, calculate new ages through Pclass
combined_df[['Age','Pclass']].groupby('Pclass').mean()
```

Out[24]:

	Age
Pclass	
1	39.159930
2	29.506705
3	24.816367

In [25]:

```
#Here we have more accuracy, title it is very related to age
combined_df = pd.concat([titanic, titanic_test], axis = 0)
combined_df[['Age','Title']].groupby('Title').mean()
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:2: FutureWarning: Sorting because n
on-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=True'.

To retain the current behavior and silence the warning, pass sort=False
```

Out[25]:

	Age
Title	
0	32.252151
1	21.774238
2	36.994118
3	5.482642
4	42.656250

In [26]:

```
# this is one function to verify all null values at AGE, and substitute to this respective new v
alue considering Title
# using combined_df, we can be more accurate to get the new mean values, because we consider a b
igger data
def impute_age(cols):
    Age = cols[0]
    Title = cols[1]

    if pd.isnull(Age):
        if Title == 0:
            return combined_df['Age'][combined_df['Title'] == 0].mean()
        elif Title == 1:
            return combined_df['Age'][combined_df['Title'] == 1].mean()
        elif Title == 2:
            return combined_df['Age'][combined_df['Title'] == 2].mean()
        elif Title == 3:
            return combined_df['Age'][combined_df['Title'] == 3].mean()
        else:
            return combined_df['Age'][combined_df['Title'] == 4].mean()
    else:
        return Age
```

In [27]:

```
# aplly the function on DF's, titanic and titanic_test
titanic['Age'] = titanic[['Age','Title']].apply(impute_age,axis=1)
titanic_test['Age'] = titanic_test[['Age','Title']].apply(impute_age,axis=1)
```

In [28]:

```
# To improve our machine learning model, we need to smooth our data, so we'll divide our Age val
ues in 5 categories
for df_age in combined:
```

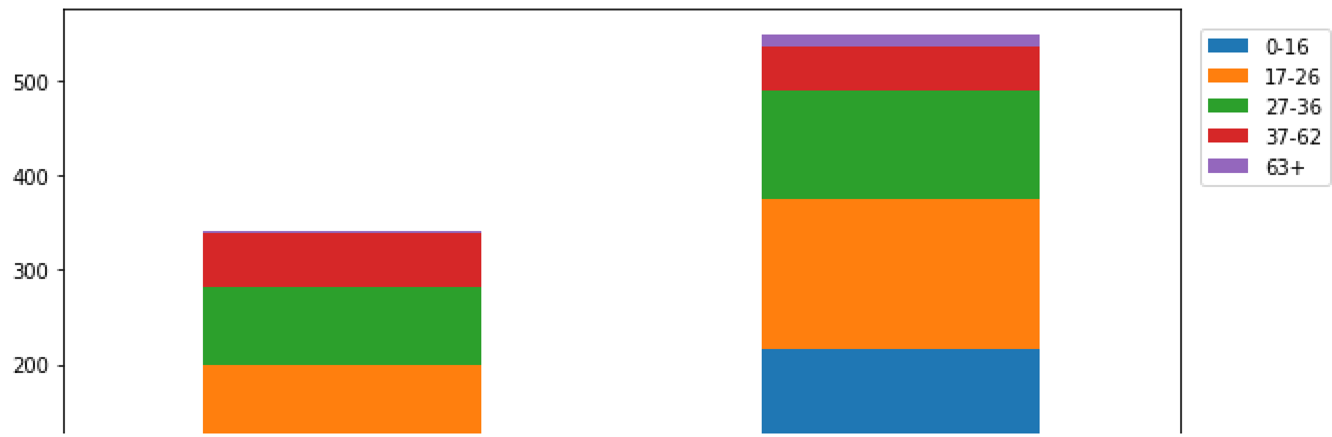
```
    df_age.loc[ df_age['Age'] <= 16, 'Age'] = 0,
    df_age.loc[(df_age['Age'] > 16) & (df_age['Age'] <= 26), 'Age'] = 1,
    df_age.loc[(df_age['Age'] > 26) & (df_age['Age'] <= 36), 'Age'] = 2,
    df_age.loc[(df_age['Age'] > 36) & (df_age['Age'] <= 62), 'Age'] = 3,
    df_age.loc[ df_age['Age'] > 62, 'Age'] = 4
    #using this for, we can substitute all values at titanic and also titanic_test
```

In [29]:

```
# Lets see how is the distribuition by Age for people who survived and whos dont.
survivedAge = titanic[titanic['Survived']==1]['Age'].value_counts()
# Extract how many peoples for each Age survived
deadAge = titanic[titanic['Survived']==0]['Age'].value_counts()
# Extract how many peoples for each Age not survived
df = pd.DataFrame([survivedAge,deadAge])
df.columns= ['0-16','17-26', '27-36', '37-62', '63+']
df.index = ['Survived','Dead']
df.plot(kind='bar',stacked=True, figsize=(10,5))
plt.legend(bbox_to_anchor=(1, 1), loc=2, borderaxespad=1)
```

Out[29]:

```
<matplotlib.legend.Legend at 0x7f71d15010f0>
```

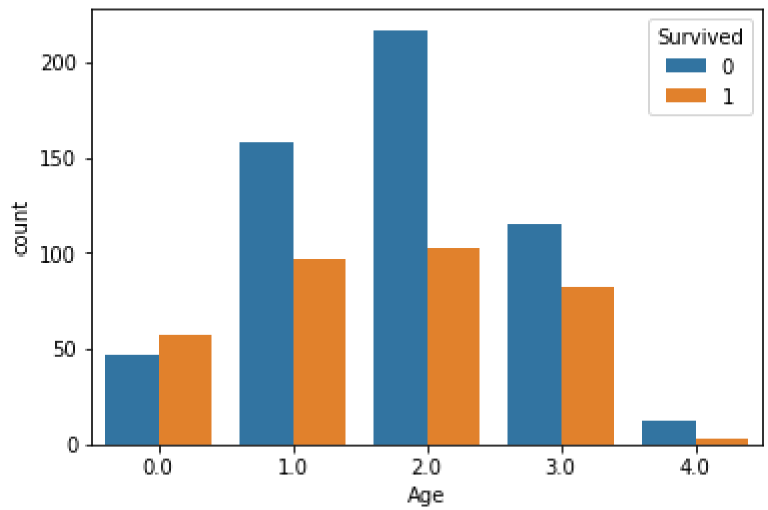


In [30]:

```
df_age2 = titanic[['Age', 'Survived']]
sns.countplot(x = 'Age', hue = 'Survived', data = df_age2)
```

Out[30]:

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f71d1399e80>
```



In [31]:

```
titanic_test.head()
```

Out[31]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Title

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Title
0	892	3	Kelly, Mr. James	0	2.0	0	0	330911	7.8292	NaN	2	0
1	893	3	Wilkes, Mrs. James (Ellen Needs)	1	3.0	1	0	363272	7.0000	NaN	0	2
2	894	2	Myles, Mr. Thomas Francis	0	3.0	0	0	240276	9.6875	NaN	2	0
3	895	3	Wirz, Mr. Albert	0	2.0	0	0	315154	8.6625	NaN	0	0
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	1	1.0	1	1	3101298	12.2875	NaN	0	2

Working with FARE

In [32]:

```
#looking for null values ate Fare, Test DF.
titanic_test[titanic_test['Fare'].isnull()]
```

Out[32]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Title
152	1044	3	Storey, Mr. Thomas	0	3.0	0	0	3701	NaN	NaN	0	0

In [33]:

```
#looking for null values ate Fare, Train DF.
titanic[titanic['Fare'].isnull()]
```

Out[33]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Title

In [34]:

```
# In general, the fare paid is directly relate to the class. the miss value was replaced by the
 mean value at third class
titanic_test['Fare'] = titanic_test['Fare'].fillna(combined_df['Fare'][combined_df['Pclass'] ==
3].mean())
```

In [35]:

```
combined_df = pd.concat([titanic, titanic_test], axis = 0)
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:1: FutureWarning: Sorting because n
on-concatenation axis is not aligned. A future version
of pandas will change to not sort by default.

To accept the future behavior, pass 'sort=True'.

To retain the current behavior and silence the warning, pass sort=False

  """Entry point for launching an IPython kernel.
```

In [36]:

```
combined_df['Fare'].describe()
# Isn't good to see the distribution in that way
```

Out[36]:

```
count    1309.000000
mean       33.280206
std        51.741830
min         0.000000
```

```
25%        7.895800
50%       14.454200
75%       31.275000
max      512.329200
Name: Fare, dtype: float64
```

In [37]:

```
# To improve our machine learning model, we need to smooth our data, so we'll divide our Fare va
lues in 4 categories
for dataset in combined:
    dataset.loc[ dataset['Fare'] <= 17, 'Fare'] = 0,
    dataset.loc[(dataset['Fare'] > 17) & (dataset['Fare'] <= 30), 'Fare'] = 1,
    dataset.loc[(dataset['Fare'] > 30) & (dataset['Fare'] <= 100), 'Fare'] = 2,
    dataset.loc[ dataset['Fare'] > 100, 'Fare'] = 3
```

In [38]:

```
titanic_test.head()
```

Out[38]:

	PassengerId	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked	Title
0	892	3	Kelly, Mr. James	0	2.0	0	0	330911	0.0	NaN	2	0
1	893	3	Wilkes, Mrs. James (Ellen Needs)	1	3.0	1	0	363272	0.0	NaN	0	2
2	894	2	Myles, Mr. Thomas Francis	0	3.0	0	0	240276	0.0	NaN	2	0
3	895	3	Wirz, Mr. Albert	0	2.0	0	0	315154	0.0	NaN	0	0
4	896	3	Hirvonen, Mrs. Alexander (Helga E Lindqvist)	1	1.0	1	1	3101298	0.0	NaN	0	2

Cabin

In [39]:

```
for dfcabin in combined:
    dfcabin['Cabin'] = dfcabin['Cabin'].str[:1]
```

In [40]:

```
# if we try to associate Cabin location to Fare, data are very confused
print(titanic[titanic['Fare'] == 0]['Cabin'].unique())
print(titanic[titanic['Fare'] == 1]['Cabin'].unique())
print(titanic[titanic['Fare'] == 2]['Cabin'].unique())
print(titanic[titanic['Fare'] == 3]['Cabin'].unique())
```

```
[nan 'G' 'D' 'F' 'E' 'B' 'A']
[nan 'C' 'F' 'D' 'B' 'A' 'E']
['C' 'E' nan 'A' 'D' 'B' 'F' 'T']
['C' 'B' 'D' nan 'E']
```

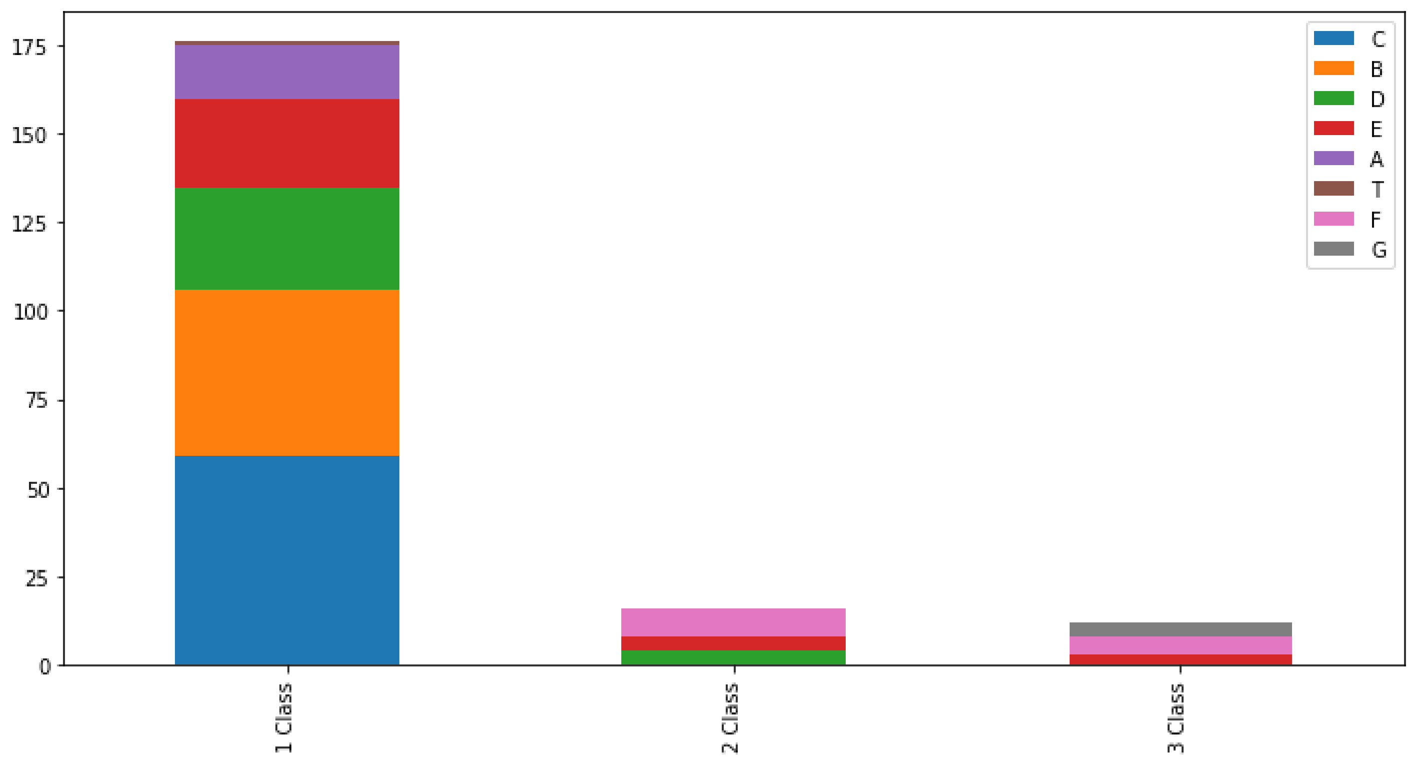
In [41]:

```
# if we try to associate Cabin location to Pclass, we can see a pattern
print(titanic[titanic['Pclass'] == 1]['Cabin'].unique())
print(titanic[titanic['Pclass'] == 2]['Cabin'].unique())
print(titanic[titanic['Pclass'] == 3]['Cabin'].unique())
```

```
['C' 'E' 'A' nan 'B' 'D' 'T']
[nan 'D' 'F' 'E']
[nan 'G' 'F' 'E']
```

In [42]:

```
PC1 = titanic[titanic['Pclass'] == 1]['Cabin'].value_counts()
PC2 = titanic[titanic['Pclass'] == 2]['Cabin'].value_counts()
PC3 = titanic[titanic['Pclass'] == 3]['Cabin'].value_counts()
dfCabin = pd.DataFrame([PC1, PC2, PC3])
dfCabin.index = ['1 Class', '2 Class', '3 Class']
dfCabin.plot(kind = 'bar', stacked = True, figsize = (12,6))
plt.style.use('bmh')
```



In [43]:

```
# Due Cabin A,B,T,C only exist at First class, they become only A
titanic['Cabin'].replace(['B', 'T', 'C'], ['A', 'A', 'A'], inplace = True);
titanic_test['Cabin'].replace(['B', 'T', 'C'], ['A', 'A', 'A'], inplace = True);
```

In [44]:

```
titanic['Cabin'].unique()
```

Out[44]:

```
array([nan, 'A', 'E', 'G', 'D', 'F'], dtype=object)
```

In [45]:

```
dicCabins = {"A": 0, "D": 0.5, "E": 1, "F": 1.5, "G": 2}
for dataset2 in combined:
    dataset2['Cabin'] = dataset2['Cabin'].map(dicCabins)
```

In [46]:

```
def impute_cabin(cols):
    Cabin  = cols[0]
    Pclass = cols[1]

    if pd.isnull(Cabin):
        if Pclass == 1:
            return 0
        elif Pclass == 2:
            return 1
        else:
            return 1.5
    else:
        return Cabin
titanic['Cabin'] = titanic[['Cabin','Pclass']].apply(impute_cabin,axis=1)
titanic_test['Cabin'] = titanic[['Cabin','Pclass']].apply(impute_cabin,axis=1)
```

MODELING

In [47]:
```
from sklearn.model_selection import KFold
from sklearn.model_selection import cross_val_score
k_fold = KFold(n_splits=100, shuffle=True, random_state=0)
```

from sklearn.model_selection import train_test_split

X_train, X_teste, Y_train, Y_teste = train_test_split(titanic.drop(["Survived",'PassengerId', 'Name', 'Ticket', 'Cabin'], axis=1) , titanic["Survived"], test_size = 0.3, random_state = 101)

In [48]:
```
X_train = titanic.drop(["Survived",'PassengerId', 'Name', 'Ticket'], axis=1)
Y_train = titanic["Survived"]
X_test  = titanic_test.drop(["PassengerId", 'Name', 'Ticket'], axis=1)
```

In [49]:
```
from sklearn.neighbors import KNeighborsClassifier
knn = KNeighborsClassifier(n_neighbors = 25)
knn.fit(X_train, Y_train)
Y_pred = knn.predict(X_test)
acc_knn = round(knn.score(X_train, Y_train) * 100, 2)
score_knn = cross_val_score(knn, X_train, Y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy')
print('KNN Cross: {}\nKNN:       {}'.format(round(np.mean(score_knn)*100,3), acc_knn))
```

```
KNN Cross: 82.167
KNN:       83.05
```

In [50]:

In [50]:

```
from sklearn.linear_model import LogisticRegression
logistic = LogisticRegression()
logistic.fit(X_train, Y_train)
Y_pred = logistic.predict(X_test)
acc_log = round(logistic.score(X_train, Y_train) * 100, 2)
score_lr = cross_val_score(logistic, X_train, Y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy'
)
print('Logistic Cross: {}\nLogistic:       {}'.format(round(np.mean(score_lr)*100,2), acc_log))
```

```
Logistic Cross: 81.17
Logistic:       81.71
```

In [51]:

```
from sklearn.tree import DecisionTreeClassifier

decision_tree = DecisionTreeClassifier()
decision_tree.fit(X_train, Y_train)
Y_pred = decision_tree.predict(X_test)
acc_decision_tree = round(decision_tree.score(X_train, Y_train) * 100, 2)
score_dt = cross_val_score(decision_tree, X_train, Y_train, cv=k_fold, n_jobs=1, scoring = 'accu
racy')
print('Decision Tree Cross: {}\nDecision Tree:       {}'.format(round(np.mean(score_dt)*100,2),
acc_decision_tree))
```

```
Decision Tree Cross: 79.72
Decision Tree:       89.79
```

In [52]:

```
from sklearn.ensemble import RandomForestClassifier
```

```
random_forest = RandomForestClassifier(n_estimators=200)
random_forest.fit(X_train, Y_train)
Y_pred = random_forest.predict(X_test)
random_forest.score(X_train, Y_train)
acc_random_forest = round(random_forest.score(X_train, Y_train) * 100, 2)
score_rf = cross_val_score(random_forest, X_train, Y_train, cv=k_fold, n_jobs=1, scoring = 'accu
racy')
print('Random Forest Cross: {}\nRandom Forest:       {}'.format(round(np.mean(score_rf)*100,2),
acc_random_forest))
```

```
Random Forest Cross: 80.26
Random Forest:       89.79
```

In [53]:

```
from sklearn.ensemble import GradientBoostingClassifier

gbk = GradientBoostingClassifier()
gbk.fit(X_train, Y_train)
Y_pred = gbk.predict(X_test)
acc_gbk = round(gbk.score(X_train, Y_train) * 100, 2)
score_gbk = cross_val_score(gbk, X_train, Y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy')
print('Gradient Boosting Classifier Cross: {}\nGradient Boosting Classifier:       {}'.format(ro
und(np.mean(score_gbk)*100,2), acc_gbk))
```

```
Gradient Boosting Classifier Cross: 82.46
Gradient Boosting Classifier:       86.08
```

In [54]:

```
from sklearn.svm import SVC
```

```
svc = SVC(gamma = 'scale')
svc.fit(X_train, Y_train)
Y_pred = svc.predict(X_test)
acc_svc = round(svc.score(X_train, Y_train) * 100, 2)
score_svc = cross_val_score(svc, X_train, Y_train, cv=k_fold, n_jobs=1, scoring = 'accuracy')
print('SVC Cross: {}\nSVC:       {}'.format(round(np.mean(score_svc)*100,2), acc_svc))
```

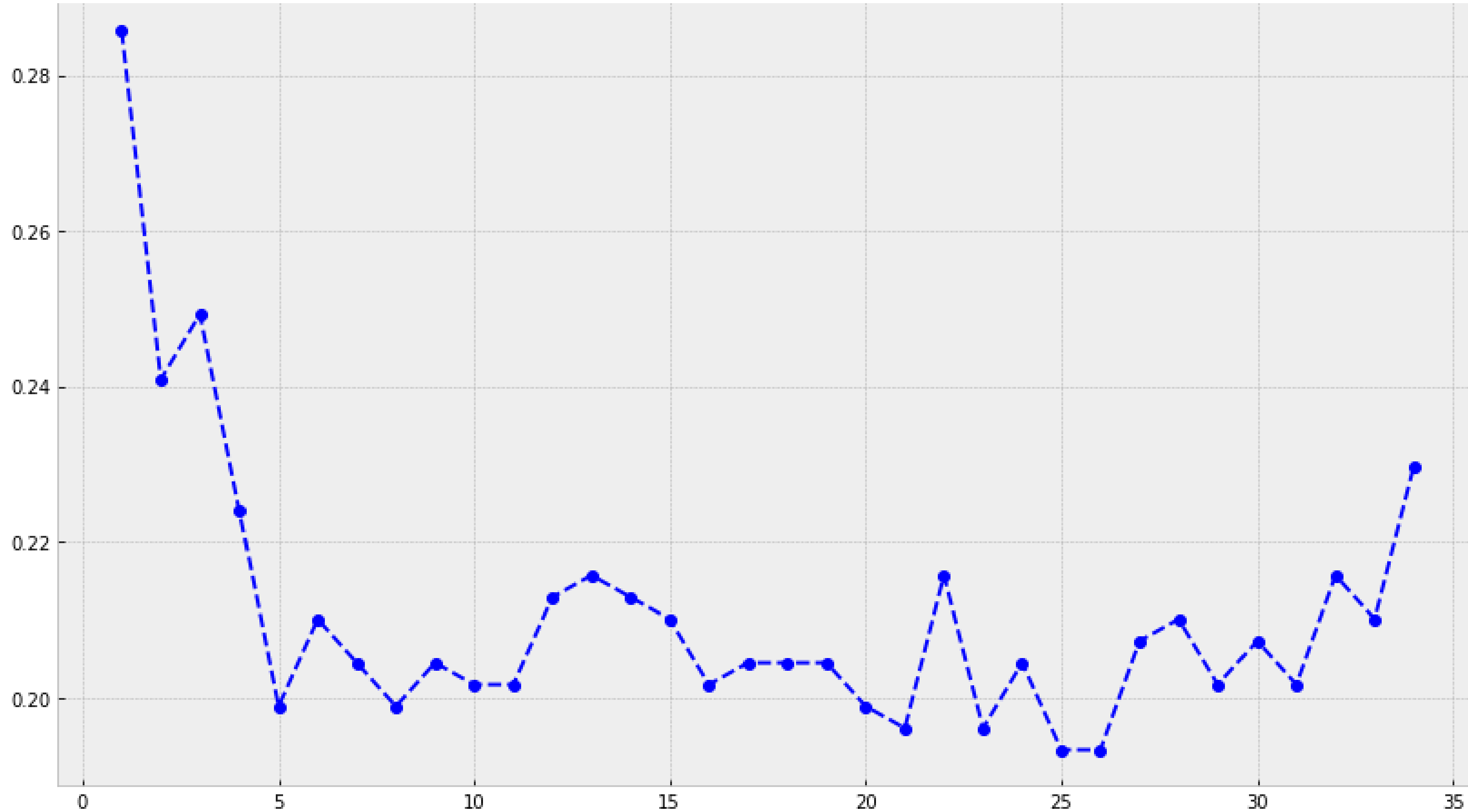
```
SVC Cross: 82.28
SVC:       83.95
```

In [55]:

```
from sklearn.model_selection import train_test_split
x_trainG, x_testeG, y_trainG, y_testeG = train_test_split(titanic.drop(["Survived",'PassengerId'
,
                                                                          'Name', 'Ticket', 'Cabin'],
                                                                           axis=1), titanic["Survived"
],
                                                                           test_size = 0.4, random_sta
te = 101)
error_rate = []
for i in range(1,35):
    knnG = KNeighborsClassifier(n_neighbors = i)
    knnG.fit(x_trainG, y_trainG)
    y_predG = knnG.predict(x_testeG)
    error_rate.append(np.mean(y_predG!=y_testeG))
plt.figure(figsize = (14, 8))
plt.plot(range(1, 35), error_rate, color = 'blue', ls = 'dashed', marker = 'o')
```

Out[55]:

```
[<matplotlib.lines.Line2D at 0x7f71d121cf98>]
```



In [56]:

```
models = pd.DataFrame({
    'Model': ['Logistic Regression', 'Decision Tree',
              'Random Forest', 'KNN', 'Gradient Boosting Classifier', 'SVC'],
    'Score': [np.mean(score_lr)*100, np.mean(score_dt)*100, np.mean(score_rf)*100,
             np.mean(score_knn)*100, np.mean(score_gbk)*100, np.mean(score_svc)*100]})
print('Cross Validation')
models.sort_values(by='Score', ascending=False)
```

```
Cross Validation
```

Out[56]:

	Model	Score
4	Gradient Boosting Classifier	82.458333
5	SVC	82.277778
3	KNN	82.166667
0	Logistic Regression	81.166667
2	Random Forest	80.263889
1	Decision Tree	79.722222

In [57]:

```
models = pd.DataFrame({
    'Model': ['Logistic Regression', 'Decision Tree',
              'Random Forest', 'KNN', 'Gradient Boosting Classifier', 'SVC'],
    'Score': [acc_log, acc_decision_tree, acc_random_forest,
             acc_knn, acc_gbk, acc_svc]})
print('Score')
models.sort_values(by='Score', ascending=False)
```

```
Score
```

Out[57]:

	Model	Score
1	Decision Tree	89.79
2	Random Forest	89.79
4	Gradient Boosting Classifier	86.08
5	SVC	83.95

3	KNN	83.05
0	Logistic Regression	81.71

In [58]:

```
# Run the Model First
submission = pd.DataFrame({
        "PassengerId": titanic_test["PassengerId"],
        "Survived": Y_pred
    })
submission.to_csv('submission.csv', index=False)
```

Did you find this Kernel useful?
Show your appreciation with an upvote

3

Comments (1)

All Comments

Sort by Hotness

Click here to enter a comment...

Henrique Yamahata Kernel Author • Posted on Latest Version • 37 minutes ago • Options • Reply

0

i'll work with the Tickets and family and improve the code soon !!