Titanic data dictionary

survival: Survival

PassengerId: Unique Id of a passenger.

pclass: Ticket class

sex: Sex

Age: Age in years

sibsp: # of siblings / spouses aboard the Titanic

parch: # of parents / children aboard the Titanic

ticket: Ticket number

fare: Passenger fare

cabin: Cabin number

embarked: Port of Embarkation

In [1]:
```
# linear algebra
import numpy as np

# data processing
import pandas as pd

# data visualization
import seaborn as sns
%matplotlib inline
from matplotlib import pyplot as plt
from matplotlib import style

# Algorithms
from sklearn import linear_model
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier
from sklearn.linear_model import Perceptron
from sklearn.linear_model import SGDClassifier
from sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.svm import SVC, LinearSVC
from sklearn.naive_bayes import GaussianNB
train_df = pd.read_csv('data/Titanic.csv',index_col=0)

train_df.describe()
```

Out[1]:

	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

Let’s take a more detailed look at what data is actually missing:

In [2]:
```
total = train_df.isnull().sum().sort_values(ascending=False)
percent_1 = train_df.isnull().sum()/train_df.isnull().count()*100
percent_2 = (round(percent_1, 1)).sort_values(ascending=False)
missing_data = pd.concat([total, percent_2], axis=1, keys=['Total', '%'])
missing_data.head(5)
```

Out[2]:

	Total	%
Cabin	687	77.1
Age	177	19.9
Embarked	2	0.2
Fare	0	0.0
Ticket	0	0.0

The Embarked feature has only 2 missing values, which can easily be filled. The ‘Age’ feature, which has 177 missing values. The ‘Cabin’ feature needs further investigation, since 77 % of it are missing.

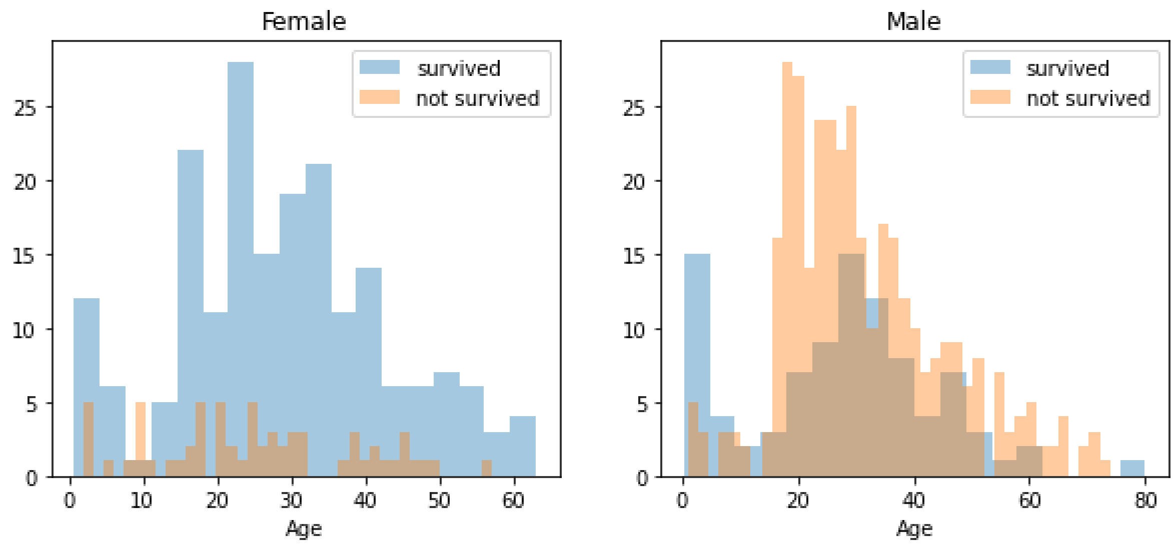
In [3]:
```
train_df.columns.values
```

Out[3]:
```
array(['Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp', 'Parch',
       'Ticket', 'Fare', 'Cabin', 'Embarked'], dtype=object)
```

Above you can see the 11 features + the target variable (survived). What features could contribute to a high survival rate ? To me it would make sense if everything except ‘PassengerId’, ‘Ticket’ and ‘Name’ would be correlated with a high survival rate.

Checking Age and Sex

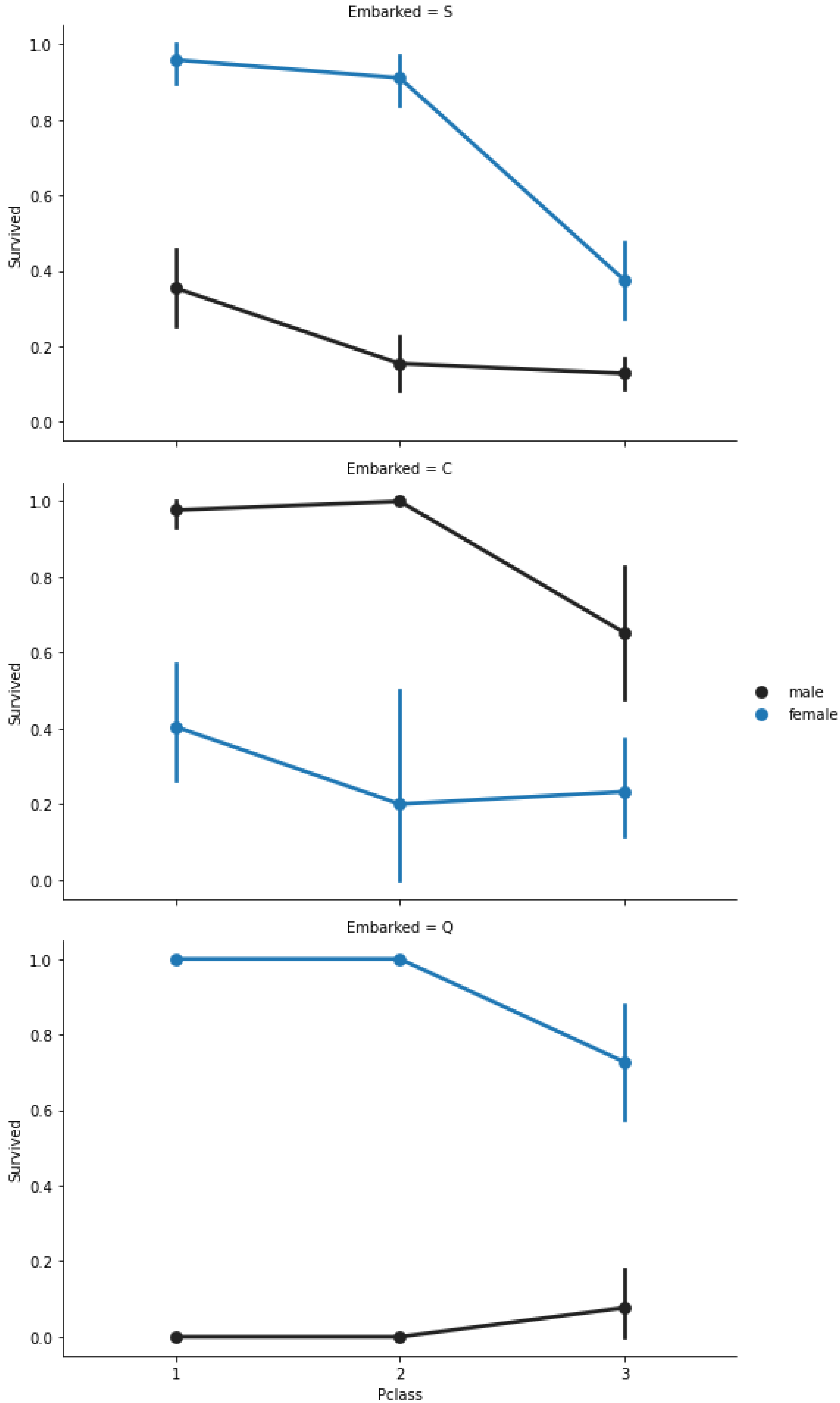
In [4]:
```
survived = 'survived'
not_survived = 'not survived'
fig, axes = plt.subplots(nrows=1, ncols=2,figsize=(10, 4))
women = train_df[train_df['Sex']=='female']
men = train_df[train_df['Sex']=='male']
ax = sns.distplot(women[women['Survived']==1].Age.dropna(), bins=18, label = s
urvived, ax = axes[0], kde =False)
ax = sns.distplot(women[women['Survived']==0].Age.dropna(), bins=40, label = n
ot_survived, ax = axes[0], kde =False)
ax.legend()
ax.set_title('Female')
ax = sns.distplot(men[men['Survived']==1].Age.dropna(), bins=18, label = survi
ved, ax = axes[1], kde = False)
ax = sns.distplot(men[men['Survived']==0].Age.dropna(), bins=40, label = not_s
urvived, ax = axes[1], kde = False)
ax.legend()
_ = ax.set_title('Male')
```



In [5]:
```
FacetGrid = sns.FacetGrid(train_df, row='Embarked', size=4.5, aspect=1.6)
FacetGrid.map(sns.pointplot, 'Pclass', 'Survived', 'Sex', palette=None,  order
=None, hue_order=None )
FacetGrid.add_legend()
```

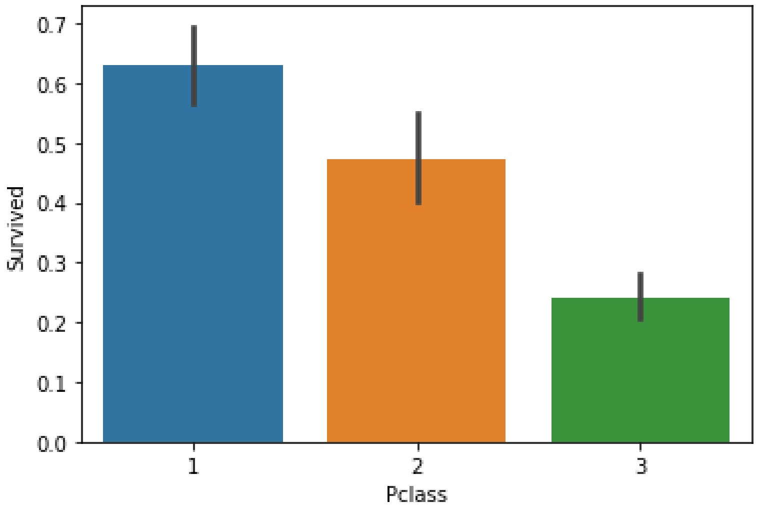
```
D:\Anaconda3\lib\site-packages\seaborn\axisgrid.py:243: UserWarning: The `siz
e` parameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```

Out[5]:
```
<seaborn.axisgrid.FacetGrid at 0x2293086fd30>
```


Embarked = S
Embarked = C
Embarked = Q
Survived
1.0
0.8
0.6
0.4
0.2
0.0
1
2
3
Pclass
male
female

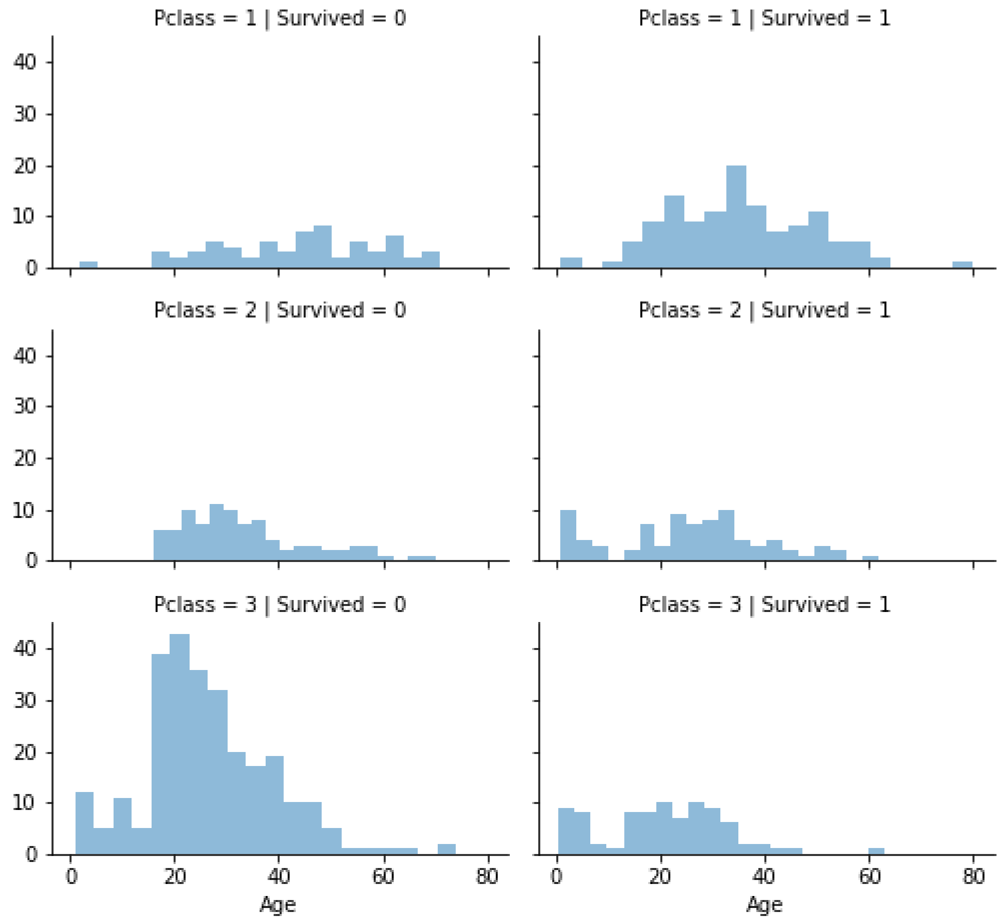
In [6]:
```
sns.barplot(x='Pclass', y='Survived', data=train_df)
```

Out[6]: <matplotlib.axes._subplots.AxesSubplot at 0x22930c61a00>



In [7]:
```
grid = sns.FacetGrid(train_df, col='Survived', row='Pclass', size=2.2, aspect=
1.6)
grid.map(plt.hist, 'Age', alpha=.5, bins=20)
grid.add_legend();
```

```
D:\Anaconda3\lib\site-packages\seaborn\axisgrid.py:243: UserWarning: The `siz
e` parameter has been renamed to `height`; please update your code.
  warnings.warn(msg, UserWarning)
```



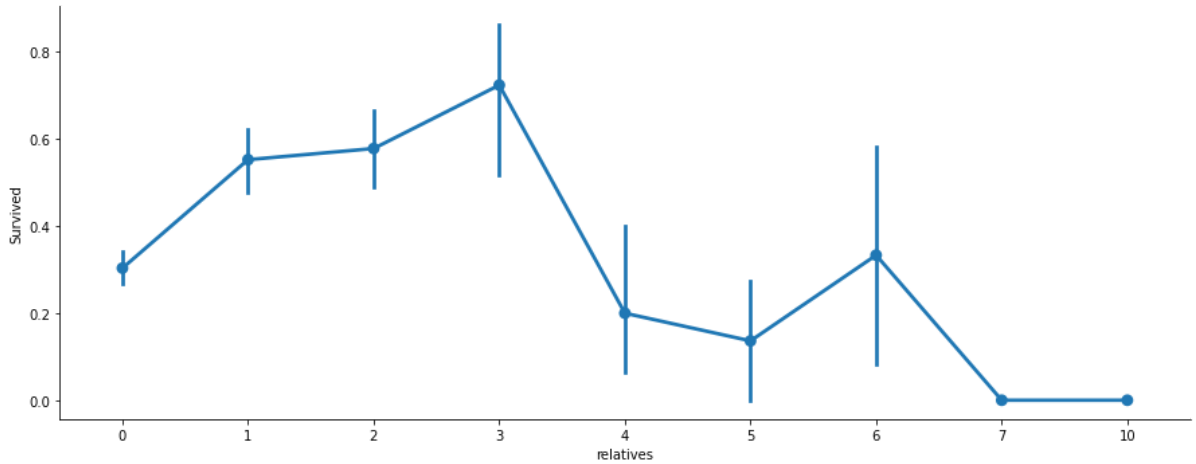
Create new feature, alone and not alone

In [8]:
```
data = [train_df]
for dataset in data:
    dataset['relatives'] = dataset['SibSp'] + dataset['Parch']
    dataset.loc[dataset['relatives'] > 0, 'not_alone'] = 0
    dataset.loc[dataset['relatives'] == 0, 'not_alone'] = 1
    dataset['not_alone'] = dataset['not_alone'].astype(int)
train_df['not_alone'].value_counts()
```

Out[8]:
```
1    537
0    354
Name: not_alone, dtype: int64
```

In [9]:
```
axes = sns.factorplot('relatives','Survived',
                      data=train_df, aspect = 2.5, )
```

```
D:\Anaconda3\lib\site-packages\seaborn\categorical.py:3666: UserWarning: The
`factorplot` function has been renamed to `catplot`. The original name will b
e removed in a future release. Please update your code. Note that the default
`kind` in `factorplot` (`'point'`) has changed `'strip'` in `catplot`.
  warnings.warn(msg)
```



Survived increase when relative between 0 and 3, but decrease at 4 or more

In [10]:
```
train_df.head()
```

Out[10]:

PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabi
1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	Na
2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C8
3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	Na
4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C12
5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	Na

New feature Deck from Cabin

In [11]:
```
import re
deck = {"A": 1, "B": 2, "C": 3, "D": 4, "E": 5, "F": 6, "G": 7, "U": 8}
data = [train_df]

train_df.head()

for dataset in data:
    dataset['Cabin'] = dataset['Cabin'].fillna("U0")
    dataset['Deck'] = dataset['Cabin'].map(lambda x: re.compile("([a-zA-Z]+)")
.search(x).group())
    dataset['Deck'] = dataset['Deck'].map(deck)
    dataset['Deck'] = dataset['Deck'].fillna(0)
    dataset['Deck'] = dataset['Deck'].astype(int)
# we can now drop the cabin feature
train_df = train_df.drop(['Cabin'], axis=1)
```

In [12]:
```
train_df.head()
```

Out[12]:

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

In [13]:
```
train_df["Age"].isnull().sum()
```

Out[13]: 177

In [14]:
```
#fill the null age with random data
```

In [15]:
```
data = [train_df]

for dataset in data:
    mean = train_df["Age"].mean()
    std = train_df["Age"].std()
    is_null = dataset["Age"].isnull().sum()
    # compute random numbers between the mean, std and is_null
    rand_age = np.random.randint(mean - std, mean + std, size = is_null)
    # fill NaN values in Age column with random values generated
    age_slice = dataset["Age"].copy()
    age_slice[np.isnan(age_slice)] = rand_age
    dataset["Age"] = age_slice
    dataset["Age"] = train_df["Age"].astype(int)
train_df["Age"].isnull().sum()
```

Out[15]: 0

In [16]:
```
train_df['Embarked'].describe()
```

Out[16]:
```
count     889
unique      3
top         S
freq      644
Name: Embarked, dtype: object
```

In [17]:
```
#Replace NaN in embarked feature
common_value = 'S'
data = [train_df]

for dataset in data:
    dataset['Embarked'] = dataset['Embarked'].fillna(common_value)
```

In [18]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 891 entries, 1 to 891
Data columns (total 13 columns):
 #   Column     Non-Null Count  Dtype  
---  ------     --------------  -----  
 0   Survived   891 non-null    int64  
 1   Pclass     891 non-null    int64  
 2   Name       891 non-null    object 
 3   Sex        891 non-null    object 
 4   Age        891 non-null    int32  
 5   SibSp      891 non-null    int64  
 6   Parch      891 non-null    int64  
 7   Ticket     891 non-null    object 
 8   Fare       891 non-null    float64
 9   Embarked   891 non-null    object 
 10  relatives  891 non-null    int64  
 11  not_alone  891 non-null    int32  
 12  Deck       891 non-null    int32  
dtypes: float64(1), int32(3), int64(5), object(4)
memory usage: 127.0+ KB
```

In [19]:
```
#Replace NaN in Fare feature

data = [train_df]

for dataset in data:
    dataset['Fare'] = dataset['Fare'].fillna(0)
    dataset['Fare'] = dataset['Fare'].astype(int)
```

In [20]:
```
#Categorize the title feature into numeric
titles = {"Mr": 1, "Miss": 2, "Mrs": 3, "Master": 4, "Rare": 5}
data = [train_df]

for dataset in data:
    # extract titles
    dataset['Title'] = dataset.Name.str.extract(' ([A-Za-z]+)\.', expand=False
)
    # replace titles with a more common title or as Rare
    dataset['Title'] = dataset['Title'].replace(['Lady', 'Countess','Capt', 'C
ol','Don', 'Dr',\
                                            'Major', 'Rev', 'Sir', 'Jonkheer',
'Dona'], 'Rare')
    dataset['Title'] = dataset['Title'].replace('Mlle', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Ms', 'Miss')
    dataset['Title'] = dataset['Title'].replace('Mme', 'Mrs')
    # convert titles into numbers
    dataset['Title'] = dataset['Title'].map(titles)
    # filling NaN with 0, to get safe
    dataset['Title'] = dataset['Title'].fillna(0)
train_df = train_df.drop(['Name'], axis=1)
```

In [21]:
```
#Categorize ‘Sex’ feature into numeric.
genders = {"male": 0, "female": 1}
data = [train_df]

for dataset in data:
    dataset['Sex'] = dataset['Sex'].map(genders)
```

In [22]:
```
train_df['Ticket'].describe()
```

Out[22]:
```
count      891
unique     681
top       1601
freq         7
Name: Ticket, dtype: object
```

In [23]:
```
train_df = train_df.drop(['Ticket'], axis=1)
```

In [24]:
```
#Categorize the Embarked feature into numeric

ports = {"S": 0, "C": 1, "Q": 2}
data = [train_df]

for dataset in data:
    dataset['Embarked'] = dataset['Embarked'].map(ports)
```

In [25]:
```
data[0].head()
```

Out[25]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	relatives	not_alone
PassengerId										
1	0	3	0	22	1	0	7	0	1	0
2	1	1	1	38	1	0	71	1	1	0
3	1	3	1	26	0	0	7	0	0	1
4	1	1	1	35	1	0	53	0	1	0
5	0	3	0	35	0	0	8	0	0	1

In [26]:
```
data[0].Age.unique()
```

Out[26]:
```
array([22, 38, 26, 35, 32, 54,  2, 27, 14,  4, 58, 20, 39, 55, 40, 31, 42,
       34, 15, 28,  8, 19, 21, 66, 24, 18,  3, 36, 43,  7, 49, 29, 65,  5,
       11, 45, 17, 16, 25,  0, 30, 33, 23, 46, 59, 71, 37, 41, 47, 70, 12,
        9, 51, 44,  1, 61, 56, 50, 62, 52, 63, 60, 10, 64, 13, 48, 53, 57,
       80,  6, 74])
```

In [27]:
```
#Convert age feature into new age range feature

data = [train_df]

for dataset in data:
    dataset['Age'] = dataset['Age'].astype(int)
    dataset.loc[ dataset['Age'] <= 11, 'Age'] = 0
    dataset.loc[(dataset['Age'] > 11) & (dataset['Age'] <= 18), 'Age'] = 1
    dataset.loc[(dataset['Age'] > 18) & (dataset['Age'] <= 22), 'Age'] = 2
    dataset.loc[(dataset['Age'] > 22) & (dataset['Age'] <= 27), 'Age'] = 3
    dataset.loc[(dataset['Age'] > 27) & (dataset['Age'] <= 33), 'Age'] = 4
    dataset.loc[(dataset['Age'] > 33) & (dataset['Age'] <= 40), 'Age'] = 5
    dataset.loc[(dataset['Age'] > 40) & (dataset['Age'] <= 66), 'Age'] = 6
    dataset.loc[ dataset['Age'] > 66, 'Age'] = 6

# let's see how it's distributed train_df['Age'].value_counts()
```

In [28]:
```
train_df['Age'].value_counts()
```

Out[28]:
```
6    169
4    159
5    139
3    136
2    127
1     93
0     68
Name: Age, dtype: int64
```

Fare: For the ‘Fare’ feature, we need to do the same as with the ‘Age’ feature.

In [29]:
```
train_df.head(10)
```

Out[29]:

PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	relatives	not_alone
1	0	3	0	2	1	0	7	0	1	0
2	1	1	1	5	1	0	71	1	1	0
3	1	3	1	3	0	0	7	0	0	1
4	1	1	1	5	1	0	53	0	1	0
5	0	3	0	5	0	0	8	0	0	1
6	0	3	0	4	0	0	8	2	0	1
7	0	1	0	6	0	0	51	0	0	1
8	0	3	0	0	3	1	21	0	4	0
9	1	3	1	3	0	2	11	0	2	0
10	1	2	1	1	1	0	30	1	1	0

In [30]:
```
data = [train_df]

for dataset in data:
    dataset.loc[ dataset['Fare'] <= 7.91, 'Fare'] = 0
    dataset.loc[(dataset['Fare'] > 7.91) & (dataset['Fare'] <= 14.454), 'Fare'
] = 1
    dataset.loc[(dataset['Fare'] > 14.454) & (dataset['Fare'] <= 31), 'Fare']
= 2
    dataset.loc[(dataset['Fare'] > 31) & (dataset['Fare'] <= 99), 'Fare']   =
3
    dataset.loc[(dataset['Fare'] > 99) & (dataset['Fare'] <= 250), 'Fare']   =
4
    dataset.loc[ dataset['Fare'] > 250, 'Fare'] = 5
    dataset['Fare'] = dataset['Fare'].astype(int)
```

Creating new Features I will add two new features to the dataset, that I compute out of other features.

1. Age times Class

In [31]:
```
data = [train_df]
for dataset in data:
    dataset['Age_Class']= dataset['Age']* dataset['Pclass']
```

1. Fare per Person

In [32]:
```
for dataset in data:
    dataset['Fare_Per_Person'] = dataset['Fare']/(dataset['relatives']+1)
    dataset['Fare_Per_Person'] = dataset['Fare_Per_Person'].astype(int)
# Let's take a last look at the training set, before we start training the mod
els.
train_df.head(10)
```

Out[32]:

PassengerId	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	relatives	not_alone
1	0	3	0	2	1	0	0	0	1	0
2	1	1	1	5	1	0	3	1	1	0
3	1	3	1	3	0	0	0	0	0	1
4	1	1	1	5	1	0	3	0	1	0
5	0	3	0	5	0	0	1	0	0	1
6	0	3	0	4	0	0	1	2	0	1
7	0	1	0	6	0	0	3	0	0	1
8	0	3	0	0	3	1	2	0	4	0
9	1	3	1	3	0	2	1	0	2	0
10	1	2	1	1	1	0	2	1	1	0

Now we will train several Machine Learning models and compare their results.

In [33]:
```
from sklearn.model_selection import train_test_split
#split train dataset to 80% for training and 20% for testing
train, test = train_test_split(train_df, test_size=0.2, random_state=42, shuff
le=True)

X_train = train.drop("Survived", axis=1)
Y_train = train["Survived"]
X_test  = test.drop("Survived", axis=1).copy()
```

Stochastic Gradient Descent (SGD):

In [34]:
```
sgd = linear_model.SGDClassifier(max_iter=5, tol=None)
sgd.fit(X_train, Y_train)
Y_pred = sgd.predict(X_test)

sgd.score(X_train, Y_train)

acc_sgd = round(sgd.score(X_train, Y_train) * 100, 2)
```

Random Forest:

In [35]:
```
random_forest = RandomForestClassifier(n_estimators=100)
random_forest.fit(X_train, Y_train)

Y_prediction = 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)
```

In [36]:
```
#Logistic Regression:
logreg = LogisticRegression()
logreg.fit(X_train, Y_train)

Y_pred = logreg.predict(X_test)

acc_log = round(logreg.score(X_train, Y_train) * 100, 2)
```

```
D:\Anaconda3\lib\site-packages\sklearn\linear_model\_logistic.py:762: Converg
enceWarning: 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-regres
sion
  n_iter_i = _check_optimize_result(
```

In [37]:
```
#K Nearest Neighbor:
# KNN
knn = KNeighborsClassifier(n_neighbors = 3)
knn.fit(X_train, Y_train)
Y_pred = knn.predict(X_test)
acc_knn = round(knn.score(X_train, Y_train) * 100, 2)
```

In [38]:
```
#Gaussian Naive Bayes:
gaussian = GaussianNB()
gaussian.fit(X_train, Y_train)
Y_pred = gaussian.predict(X_test)
acc_gaussian = round(gaussian.score(X_train, Y_train) * 100, 2)
```

In [39]:
```
#Perceptron:
perceptron = Perceptron(max_iter=5)
perceptron.fit(X_train, Y_train)

Y_pred = perceptron.predict(X_test)

acc_perceptron = round(perceptron.score(X_train, Y_train) * 100, 2)
```

```
D:\Anaconda3\lib\site-packages\sklearn\linear_model\_stochastic_gradient.py:5
70: ConvergenceWarning: Maximum number of iteration reached before convergenc
e. Consider increasing max_iter to improve the fit.
  warnings.warn("Maximum number of iteration reached before "
```

In [40]:
```
#Linear Support Vector Machine:
linear_svc = LinearSVC()
linear_svc.fit(X_train, Y_train)

Y_pred = linear_svc.predict(X_test)

acc_linear_svc = round(linear_svc.score(X_train, Y_train) * 100, 2)
```

```
D:\Anaconda3\lib\site-packages\sklearn\svm\_base.py:976: ConvergenceWarning: Liblinear failed to converge, increase the number of iterations.
  warnings.warn("Liblinear failed to converge, increase "
```

In [41]:
```
#Decision Tree
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)
```

In [42]:
```
#Which is the best Model ?
results = pd.DataFrame({
    'Model': ['Support Vector Machines', 'KNN', 'Logistic Regression',
              'Random Forest', 'Naive Bayes', 'Perceptron',
              'Stochastic Gradient Decent',
              'Decision Tree'],
    'Score': [acc_linear_svc, acc_knn, acc_log,
              acc_random_forest, acc_gaussian, acc_perceptron,
              acc_sgd, acc_decision_tree]})
result_df = results.sort_values(by='Score', ascending=False)
result_df = result_df.set_index('Score')
result_df.head(9)
```

Out[42]:

	Model
Score	
92.56	Random Forest
92.56	Decision Tree
84.97	KNN
81.60	Support Vector Machines
81.60	Logistic Regression
80.34	Stochastic Gradient Decent
77.95	Naive Bayes
40.87	Perceptron

As we can see, the Random Forest classifier goes on the first place. But first, let us check, how random-forest performs, when we use cross validation.

In [43]:
```
from sklearn.model_selection import cross_val_score
rf = RandomForestClassifier(n_estimators=100)
scores = cross_val_score(rf, X_train, Y_train, cv=10, scoring = "accuracy")
print("Scores:", scores)
print("Mean:", scores.mean())
print("Standard Deviation:", scores.std())
```

```
Scores: [0.83333333 0.80555556 0.73239437 0.85915493 0.8028169  0.77464789
 0.81690141 0.78873239 0.83098592 0.92957746]
Mean: 0.8174100156494524
Standard Deviation: 0.0499944434009704444
```

Our model has a average accuracy of 82% with a standard deviation of 4 %.

Feature Importance

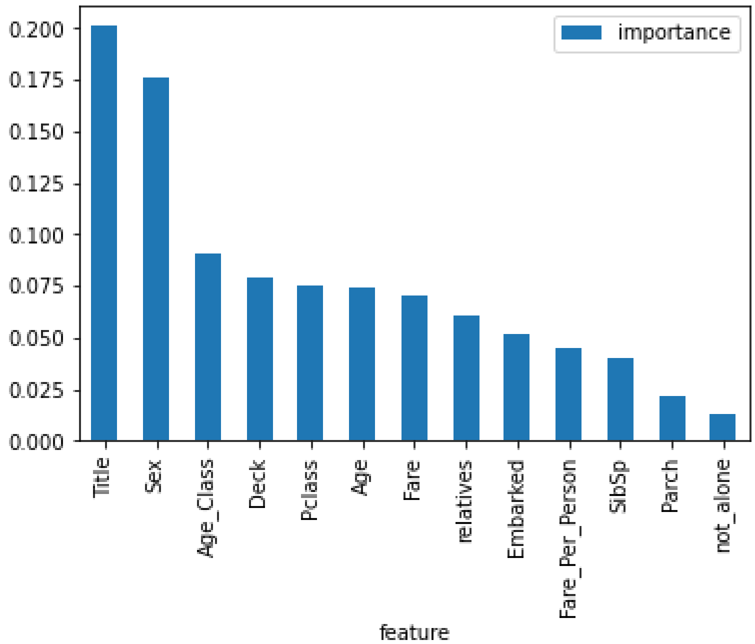
In [44]:
```
importances = pd.DataFrame({'feature':X_train.columns,'importance':np.round(random_forest.feature_importances_,3)})
importances = importances.sort_values('importance',ascending=False).set_index('feature')
importances.head(15)
```

Out[44]:

feature	importance
Title	0.201
Sex	0.176
Age_Class	0.091
Deck	0.079
Pclass	0.075
Age	0.074
Fare	0.070
relatives	0.061
Embarked	0.052
Fare_Per_Person	0.045
SibSp	0.040
Parch	0.022
not_alone	0.013

In [45]:
```
#plot the importance of the features
importances.plot.bar()
```

Out[45]: <matplotlib.axes._subplots.AxesSubplot at 0x22931614e80>



Conclusion: not_alone and Parch doesn’t play a significant role in our random forest classifiers prediction process.

Drop the features one by one

Drop not_alone

In [46]:
```
train  = train.drop("not_alone", axis=1)
test  = test.drop("not_alone", axis=1)

X_train = train.drop("Survived", axis=1)
Y_train = train["Survived"]
X_test  = test.drop("Survived", axis=1).copy()

#Training random forest again:
# Random Forest

random_forest = RandomForestClassifier(n_estimators=100, oob_score = True)
random_forest.fit(X_train, Y_train)
Y_prediction = 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)
print(round(acc_random_forest,2,), "%")
```

```
92.56 %
```

Drop Parch feature

In [47]:
```
train  = train.drop("Parch", axis=1)
test  = test.drop("Parch", axis=1)

X_train = train.drop("Survived", axis=1)
Y_train = train["Survived"]
X_test  = test.drop("Survived", axis=1).copy()

#Training random forest again:
# Random Forest

random_forest = RandomForestClassifier(n_estimators=100, oob_score = True)
random_forest.fit(X_train, Y_train)
Y_prediction = 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)
print(round(acc_random_forest,2,), "%")
```

```
92.56 %
```

drop Fare_Per_Person feature

In [48]:
```
train  = train.drop("Fare_Per_Person", axis=1)
test  = test.drop("Fare_Per_Person", axis=1)

X_train = train.drop("Survived", axis=1)
Y_train = train["Survived"]
X_test  = test.drop("Survived", axis=1).copy()

#Training random forest again:
# Random Forest

random_forest = RandomForestClassifier(n_estimators=100, oob_score = True)
random_forest.fit(X_train, Y_train)
Y_prediction = 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)
print(round(acc_random_forest,2,), "%")
```

```
92.56 %
```

drop Embarked feature

In [49]:
```
train  = train.drop("Embarked", axis=1)
test  = test.drop("Embarked", axis=1)

X_train = train.drop("Survived", axis=1)
Y_train = train["Survived"]
X_test  = test.drop("Survived", axis=1).copy()

#Training random forest again:
# Random Forest

random_forest = RandomForestClassifier(n_estimators=100, oob_score = True)
random_forest.fit(X_train, Y_train)
Y_prediction = 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)
print(round(acc_random_forest,2,), "%")
```

```
91.57 %
```

Drop SibSp feature

In [50]:
```
train  = train.drop("SibSp", axis=1)
test  = test.drop("SibSp", axis=1)

X_train = train.drop("Survived", axis=1)
Y_train = train["Survived"]
X_test  = test.drop("Survived", axis=1).copy()

#Training random forest again:
# Random Forest

random_forest = RandomForestClassifier(n_estimators=100, oob_score = True)
random_forest.fit(X_train, Y_train)
Y_prediction = 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)
print(round(acc_random_forest,2,), "%")
```

```
91.15 %
```

Drop AgeClass

In [51]:
```
train  = train.drop("Age_Class", axis=1)
test  = test.drop("Age_Class", axis=1)

X_train = train.drop("Survived", axis=1)
Y_train = train["Survived"]
X_test  = test.drop("Survived", axis=1).copy()

#Training random forest again:
# Random Forest

random_forest = RandomForestClassifier(n_estimators=100, oob_score = True)
random_forest.fit(X_train, Y_train)
Y_prediction = 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)
print(round(acc_random_forest,2,), "%")
```

```
91.15 %
```

Drop fare feature and let's see

In [52]:
```
train  = train.drop("Fare", axis=1)
test  = test.drop("Fare", axis=1)

X_train = train.drop("Survived", axis=1)
Y_train = train["Survived"]
X_test  = test.drop("Survived", axis=1).copy()

#Training random forest again:
# Random Forest

random_forest = RandomForestClassifier(n_estimators=100, oob_score = True)
random_forest.fit(X_train, Y_train)
Y_prediction = 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)
print(round(acc_random_forest,2,), "%")
```

```
88.62 %
```

Drop relatives feature

In [53]:
```
train  = train.drop("relatives", axis=1)
test  = test.drop("relatives", axis=1)

X_train = train.drop("Survived", axis=1)
Y_train = train["Survived"]
X_test  = test.drop("Survived", axis=1).copy()

#Training random forest again:
# Random Forest

random_forest = RandomForestClassifier(n_estimators=100, oob_score = True)
random_forest.fit(X_train, Y_train)
Y_prediction = 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)
print(round(acc_random_forest,2,), "%")
```

```
84.69 %
```

Our random forest model score start to decrease (but not big difference) when i remove the following features: Embarked,SibSp, relatives, and Fare

For All 4 bottom features (Age_Class, Parch, not_alone, and Fare_Per_Person features) there is no impact in the score when i drop this feature.

A general rule is that, the more features you have, the more likely your model will suffer from overfitting and vice versa. Since i'm a beginner in Machine Learning, i can't verify whether the model is overfitting or not.