Predict Survival on The Titanic (Kaggle)

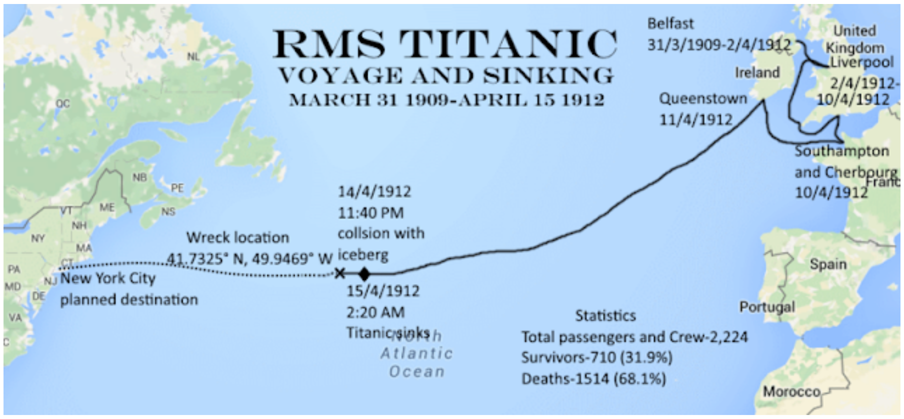
Two step prediction

1. Predict Ages for Nan Values using XGBoost Regressor
2. Predict Survival using XGBoost Classifier

Titanic Route

In [1]:
```
from IPython.core.display import Image
Image('./Titanic_Route.png')
```

Out[1]:



Import Libraries

In [2]:
```
import os
import seaborn as sns
import numpy as np
import pandas as pd
import IPython.display as display
from sklearn.preprocessing import LabelBinarizer,StandardScaler,LabelEncoder
from sklearn.metrics import classification_report,confusion_matrix,accuracy_score
from sklearn.metrics import mean_squared_error as mse, r2_score
from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
from xgboost import XGBRegressor,XGBClassifier
import xgboost as xgb
import matplotlib.pyplot as plt
from keras import layers,models,optimizers,regularizers
```

```
Using TensorFlow backend.
```

Data Loading

In [3]:
```
path_home = os.getcwd()
path_train = path_home + '/Dataset/train.csv'
path_test = path_home + '/Dataset/test.csv'
path_gensub = path_home + '/Dataset/gender_submission.csv'

train = pd.read_csv(path_train)
test = pd.read_csv(path_test)
sub_sample = pd.read_csv(path_gensub)
```

In [4]:
```
display.display(train.tail(5))
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.00	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.00	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.45	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.00	C148	C
890	891	0	3	Dooley, Mr. Patrick	male	32.0	0	0	370376	7.75	NaN	Q

Feature Engineering

In [5]:
```
func_scaler_util = lambda method, data: method(data.reshape(-1,1)).flatten()
```

In [6]:
```
def feature_engineering(dataset):
    ''' Feature Engineering '''
    dataset_prepro = dataset.copy()

    # Label Binarizer for gender class
    lb = LabelBinarizer()
    dataset_prepro['Sex'] = lb.fit_transform(dataset_prepro['Sex'].values)

    # Label Encoder for Categorical values for embarkation
    # S: Southampton in England, C: Cherbourg in France, Q: Queentown in Ireland
    le = LabelEncoder()
    le.fit(['S','C','Q','nan'])
    dataset_prepro['Embarked'] = le.transform(dataset_prepro['Embarked'].values)

    # Cabin Class
    le_cabin = LabelEncoder()
    le_cabin.fit(['N','A','B','C','D','E','F','G','T'])
    dataset_prepro['Cabin'] = le_cabin.transform(dataset_prepro['Cabin'].astype(str).str[0].values)

    # Titles
    dataset_prepro['Title'] = dataset_prepro.Name.str.extract(' ([A-Za-z]+)\.', expand=False)
    RareTitles = ['Lady','Countess','Capt','Col','Don','Dr','Major','Rev','Sir','Jonkheer','Dona']
    dataset_prepro['Title'] = dataset_prepro['Title'].replace(RareTitles,'Rare')
    dataset_prepro['Title'] = dataset_prepro['Title'].replace('Mlle', 'Miss')
    dataset_prepro['Title'] = dataset_prepro['Title'].replace('Ms', 'Miss')
    dataset_prepro['Title'] = dataset_prepro['Title'].replace('Mme', 'Mrs')
    title_mapping = {'Mr':1,'Miss':2,'Mrs':3,'Master':4,'Rare':5}
    dataset_prepro['Title'] = dataset_prepro['Title'].map(title_mapping)

    # Whether One is Alone
    dataset_prepro['FamilySize'] = dataset_prepro['SibSp'] + dataset_prepro['Parch'] + 1
    dataset_prepro['Family'] = 0
    dataset_prepro.loc[dataset_prepro['FamilySize'] > 1, 'Family'] = 1
    return dataset_prepro
```

Create Training Dataset to Predict Ages for Nan Values

In [7]:
```
# Feature Engineering for Categorical values
dataset_pred_age = pd.concat([train,test],sort=True)
dataset_pred_age.drop(['Survived','Ticket'],axis=1,inplace=True)
dataset_pred_age.dropna(how='any',axis=0,inplace=True)
dataset_pred_age = feature_engineering(dataset_pred_age)
col_list = ['Sex','Age','Fare','Family','Embarked','Pclass','Cabin','Title']
train_pred_age = dataset_pred_age[col_list].values

# Standardize fare after logarithmic conversion
fare_log = np.log1p(train_pred_age[:,2])*50 # Convert Fare values in logarithm
scaler_fare = StandardScaler()
scaler_fare.fit(fare_log.reshape(-1,1))
train_pred_age[:,2] = func_scaler_util(scaler_fare.transform,fare_log)

# Split whole dataset (test & training) into training & validation for age prediction
idx_age_pred = [0,2,3,4,5,6,7]
x, y = train_pred_age[:,idx_age_pred], train_pred_age[:,1]
x_train,x_val,y_train,y_val = train_test_split(x,y,test_size=0.15,random_state=42)
```

In [8]:
```
display.display(dataset_pred_age.describe())
```

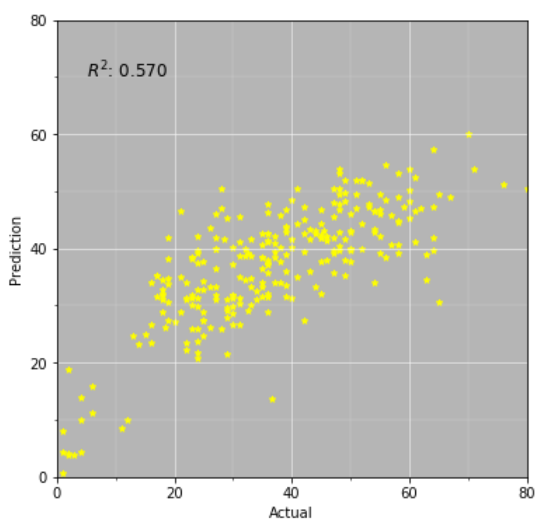
	Age	Cabin	Embarked	Fare	Parch	PassengerId	Pclass	Sex	SibSp	Title	FamilySize	
count	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.000000	270.0
mean	36.825630	2.366667	1.159259	84.942193	0.477778	663.955556	1.174074	0.511111	0.507407	2.044444	1.985185	0.5
std	15.569971	1.459108	0.983416	80.698651	0.788784	371.875891	0.490878	0.500805	0.643773	1.143052	1.137304	0.4
min	0.920000	0.000000	0.000000	0.000000	0.000000	2.000000	1.000000	0.000000	0.000000	1.000000	1.000000	0.0
25%	25.000000	1.000000	0.000000	30.000000	0.000000	337.250000	1.000000	0.000000	0.000000	1.000000	1.000000	0.0
50%	36.000000	2.000000	2.000000	60.587500	0.000000	661.500000	1.000000	1.000000	0.000000	2.000000	2.000000	1.0
75%	48.000000	3.000000	2.000000	103.193750	1.000000	968.500000	1.000000	1.000000	1.000000	3.000000	2.000000	1.0
max	80.000000	8.000000	2.000000	512.329200	4.000000	1306.000000	3.000000	1.000000	3.000000	5.000000	6.000000	1.0

Age Prediction for NaN values

In [9]:
```
def AxConfig(ax,prmax):
    ''' Configure Axis '''
    ax.set_xlim([prmax['xmin'],prmax['xmax']])
    ax.set_ylim([prmax['ymin'],prmax['ymax']])
    ax.set_xticks(np.arange(prmax['xmin'],prmax['xmax'] + 1e-6,prmax['xmajor']))
    ax.set_yticks(np.arange(prmax['ymin'],prmax['ymax'] + 1e-6,prmax['ymajor']))
    ax.set_xticks(np.arange(prmax['xmin'],prmax['xmax'] + 1e-6,prmax['xminor']),minor=True)
    ax.set_yticks(np.arange(prmax['ymin'],prmax['ymax'] + 1e-6,prmax['yminor']),minor=True)
    plt.grid(b=True,which='minor',color='w',linestyle='--',linewidth=0.2,zorder=-1)
    plt.grid(b=True,which='major',color='w',linestyle='-',linewidth=0.5,zorder=-1)
    ax.patch.set_facecolor('#B5B5B5')
```

In [10]:
```
def plot_age_pred(age_actual,age_pred):
    fig, ax = plt.subplots(figsize=(6,6))
    plt.scatter(age_actual,age_pred,c='yellow',s=20,marker='*')
    prmax = {'xmin':0,'xmax':80,'xmajor':20,'xminor':10,
             'ymin':0,'ymax':80,'ymajor':20,'yminor':10}
    AxConfig(ax,prmax)
    r2 = r2_score(age_actual,age_pred)
    ax.text(5, 70, '$R^{%d}$'%2 +': ' + '{:.3f}'.format(r2), fontsize=12)
    plt.ylabel('Prediction')
    plt.xlabel('Actual')
    plt.show()
```

In [11]:
```
xgb_reg_age = XGBRegressor(objective='reg:squarederror')
xgb_reg_age.fit(x_train,y_train)
age_actual = train_pred_age[:,1]
age_pred = xgb_reg_age.predict(train_pred_age[:,idx_age_pred])
plot_age_pred(age_actual,age_pred)
```



In [12]:
```python
def feature_importance(model,columns):
    ''' Feature Engineering '''
    importance = model.feature_importances_
    rankftr = np.argsort(importance)[::-1]
    importance = [importance[i] for i in rankftr]
    columns = [columns[i] for i in rankftr]
    for feature in zip(columns,importance):
        print(feature[0].ljust(9)+': '+'{:.2f}'.format(100*feature[1]).rjust(5)+'%')
    print('\n')
```

In [13]:
```python
columns = [col_list[i] for i in idx_age_pred]
print('\nFeatures importance for age prediction')
feature_importance(xgb_reg_age,columns)
```

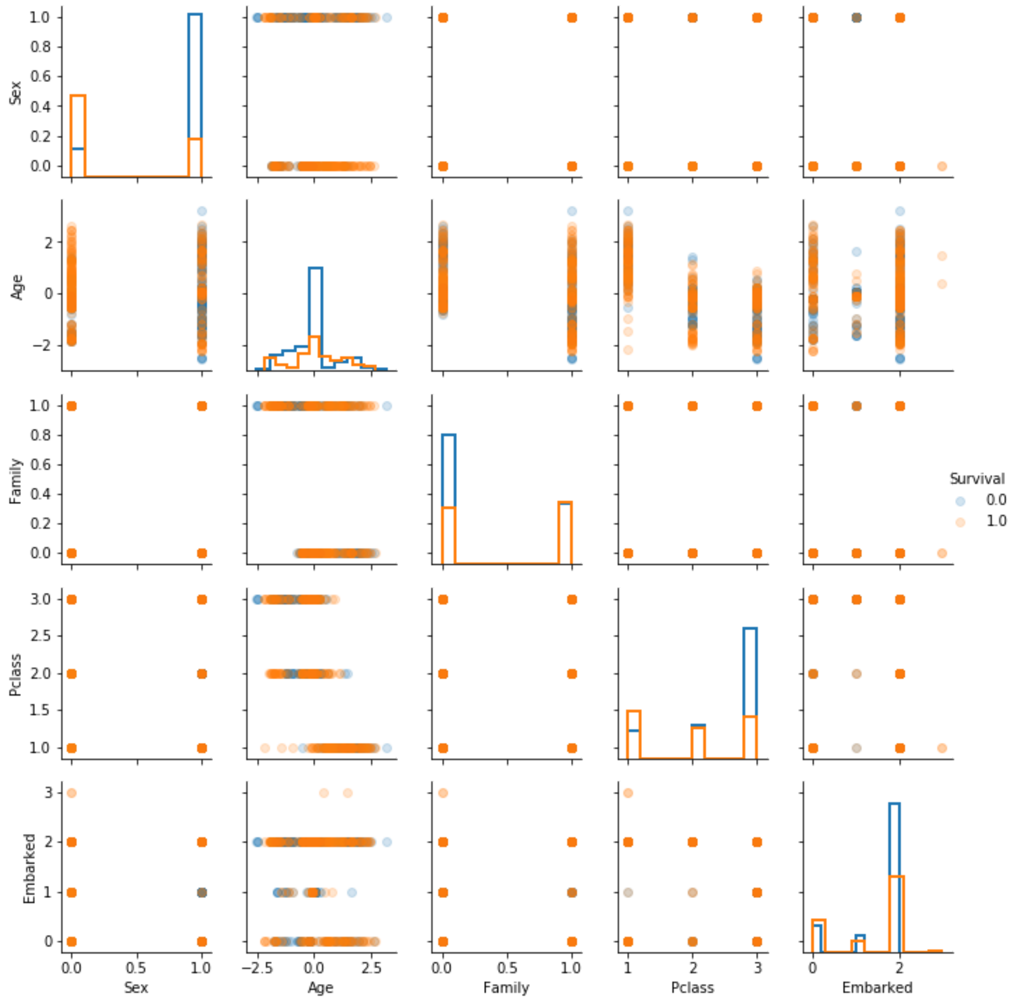
```
Features importance for age prediction
Pclass   : 44.32%
Title    : 16.40%
Family   : 12.50%
Cabin    : 10.36%
Fare     :  6.90%
Embarked :  5.48%
Sex      :  4.04%
```

Preprocessing and Overview

In [14]:
```python
def PreProcessing(dataset,col_list,xgb_reg_age,imp_median=None,training=True):
    dataset = dataset.copy()
    if training:
        target = np.array(dataset['Survived'])
        imp_median = SimpleImputer(missing_values=np.nan, strategy='median')
    else:
        target = None

    # Imputer for fare
    imp_median.fit(dataset[['Fare']])
    dataset['Fare'] = imp_median.transform(dataset[['Fare']])
    dataset['Fare'] = np.log1p(dataset['Fare'])*50
    dataset.loc[dataset['Embarked'].isnull(),'Embarked'] = 'nan'
    dataset.loc[dataset['Cabin'].isnull(),'Cabin'] = 'N'
    dataset['Fare'] = func_scaler_util(scaler_fare.transform,dataset['Fare'].values)

    feature = feature_engineering(dataset)[col_list].values

    # Predict age and scale it
    for i in range(len(feature)):
        feature_age = feature[i][idx_age_pred]
        feature[i,1] = xgb_reg_age.predict(np.reshape(feature_age,[1,7]))
    scaler_age = StandardScaler()
    scaler_age.fit(feature[:,1].reshape(-1,1))
    feature[:,1] = func_scaler_util(scaler_age.transform,feature[:,1])
    return feature,target,imp_median
```

In [15]:
```python
feature_train,target_train,imp_median = PreProcessing(train,col_list,xgb_reg_age)
```

In [16]:
```
df_pair_plot = pd.DataFrame(np.vstack((feature_train.T,target_train)).T,columns=col_list+['Survival'])
g = sns.PairGrid(df_pair_plot, vars=['Sex','Age','Family','Pclass','Embarked'], hue='Survival')
g.map_diag(plt.hist, histtype='step', linewidth=2)
g.map_offdiag(plt.scatter, alpha=0.2)
g = g.add_legend()
g.fig.set_size_inches(10,10)
plt.show()
```



Insights

Sex, Title: More female passengers survived than male.
Age: Thosed who didn't suvive aged at around the average.
Family: Passengers with family likely survived.
Pclass,Fare,Cabin: The higher the ticket class the more likely people survived.
Embarked: People who embarked at Cherbourg in France more likely survived.

In [17]:
```
df_pair_plot.describe()
```

Out[17]:

	Sex	Age	Fare	Family	Embarked	Pclass	Cabin	Title	Survival
count	891.000000	8.910000e+02	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000	891.000000
mean	0.647587	-1.847101e-16	-1.135509	0.397306	1.538721	2.308642	5.946128	1.728395	0.383838
std	0.477990	1.000562e+00	1.002317	0.489615	0.794231	0.836071	2.062347	1.030039	0.486592
min	0.000000	-2.532771e+00	-4.199453	0.000000	0.000000	1.000000	0.000000	1.000000	0.000000
25%	0.000000	-4.354854e-01	-1.937144	0.000000	1.000000	2.000000	7.000000	1.000000	0.000000
50%	1.000000	5.594664e-02	-1.367576	0.000000	2.000000	3.000000	7.000000	1.000000	0.000000
75%	1.000000	2.554337e-01	-0.614733	1.000000	2.000000	3.000000	7.000000	2.000000	1.000000
max	1.000000	3.203570e+00	2.255725	1.000000	3.000000	3.000000	8.000000	5.000000	1.000000

Survival prediction for each passenger using XGBoost Classifier

In [18]:
```
xgb_cls = XGBClassifier(objective='reg:squarederror')
xgb_cls.fit(feature_train,target_train)
```

Out[18]:
```
XGBClassifier(base_score=0.5, booster='gbtree', colsample_bylevel=1,
              colsample_bynode=1, colsample_bytree=1, gamma=0,
              learning_rate=0.1, max_delta_step=0, max_depth=3,
              min_child_weight=1, missing=None, n_estimators=100, n_jobs=1,
              nthread=None, objective='reg:squarederror', random_state=0,
              reg_alpha=0, reg_lambda=1, scale_pos_weight=1, seed=None,
              silent=None, subsample=1, verbosity=1)
```

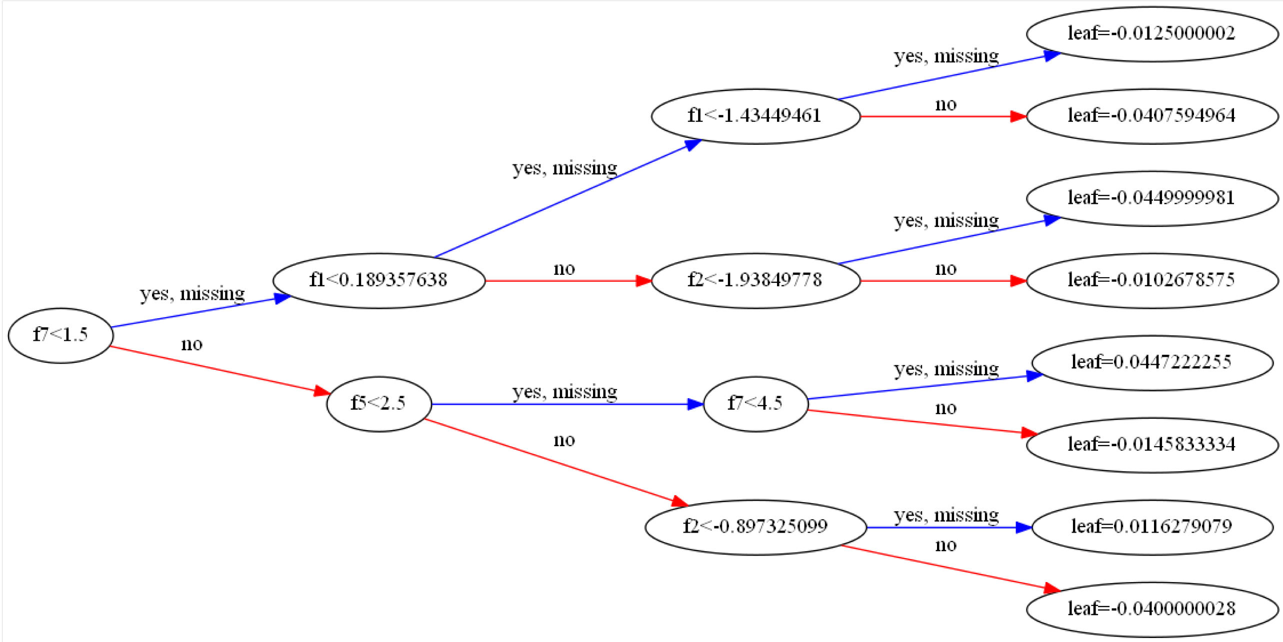
In [19]:
```
def result_summary(feature_train,target_train,model,columns):
    # Accuracy, Confusion Matrix, Classification Report
    pred_train = model.predict(feature_train)
    print('Accuracy: '+'{:.3f}'.format(accuracy_score(target_train,pred_train)))
    print('\nConfusion Matrix')
    print(confusion_matrix(target_train, pred_train))
    print('\nClassification Report')
    print(classification_report(target_train, pred_train))
    print('\nFeatures importance for survival prediction')
    feature_importance(model,columns)
```

In [20]:
```
result_summary(feature_train,target_train,xgb_cls,col_list)
```

```
Accuracy: 0.881

Confusion Matrix
[[519  30]
 [ 76 266]]

Classification Report
              precision    recall  f1-score   support

           0       0.87      0.95      0.91       549
           1       0.90      0.78      0.83       342

    accuracy                           0.88       891
   macro avg       0.89      0.86      0.87       891
weighted avg       0.88      0.88      0.88       891


Features importance for survival prediction
Title    : 62.17%
Pclass   : 17.54%
Embarked :  5.53%
Fare     :  4.63%
Cabin    :  4.59%
Age      :  3.69%
Sex      :  1.86%
Family   :  0.00%
```

In [21]:
```
def visualize_tree(xgb_cls,n_tree=0):
    ''' Visualize Gradient Boosting Decision Trees '''
    xgb.plot_tree(xgb_cls,num_trees=n_tree, rankdir='LR')
    fig = plt.gcf()
    fig.set_size_inches(200,100)
    plt.show()
```

```
In [22]: visualize_tree(xgb_cls,n_tree=0)
```



f1: Sex, f2: Age, f3: Fare, f4: Family, f5: Embarked, f6: Pclass, f7: Cabin, f8: Title

Output for submission

```
In [23]: feature_test,_,_ = PreProcessing(test,col_list,xgb_reg_age,imp_median,training=False)
         sub_sample['Survived'] = xgb_cls.predict(feature_test)
         sub_sample.to_csv(path_home + '/Dataset/submit_RFC_GS.csv',index=False)
```