Titanic Classification Exercise

Setup and Load the data

In [1]:
```
# Setup

import os
import pandas as pd
import numpy as np
```

In [2]:
```
# Load the data

TITANIC_DATA_PATH = os.path.join("datasets", "titanic")

# This function returns a pandas DataFrame object containing all the data.
def load_titanic_data(filename, data_path=TITANIC_DATA_PATH):
    csv_path = os.path.join(data_path, filename)
    return pd.read_csv(csv_path)

training_data = load_titanic_data("train.csv")
test_data = load_titanic_data("test.csv")
```

Note that the test data does not contain the labels, our goal is to train the best model possible on the training data, then make predictions on the test data, and upload the results to Kaggle.com to see our final score.

Start to explore and understand the data

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

Out[3]:

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Ca
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	C
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	

The attributes have the following meaning:

- Survived: that's the target, 0 means the passenger did not survive, while 1 means he/she survived.
- Pclass: passenger class.
- Name, Sex, Age: self-explanatory
- SibSp: how many siblings & spouses of the passenger aboard the Titanic.
- Parch: how many children & parents of the passenger aboard the Titanic.
- Ticket: ticket id
- Fare: price paid (in pounds)
- Cabin: passenger's cabin number
- Embarked: where the passenger embarked the Titanic

In [4]:
```
training_data.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
```

Notice:

Name and Sex are both objects, probably strings. We will probably need to convert these to numerical attributes or drop them (We probably don't need to know the names)

We are missing some values and we will need to deal with those in somehow. We are missing some values for:

- Age (714/891)
- Cabin (204/891)
- Embarked (889)

I think we should be able to use the median age to fill in the blanks for age, and we can probably drop the 'Cabin' and 'Embarked' categories.

I think we can probably also add a class to combine SibSp and Parch into a Family class.

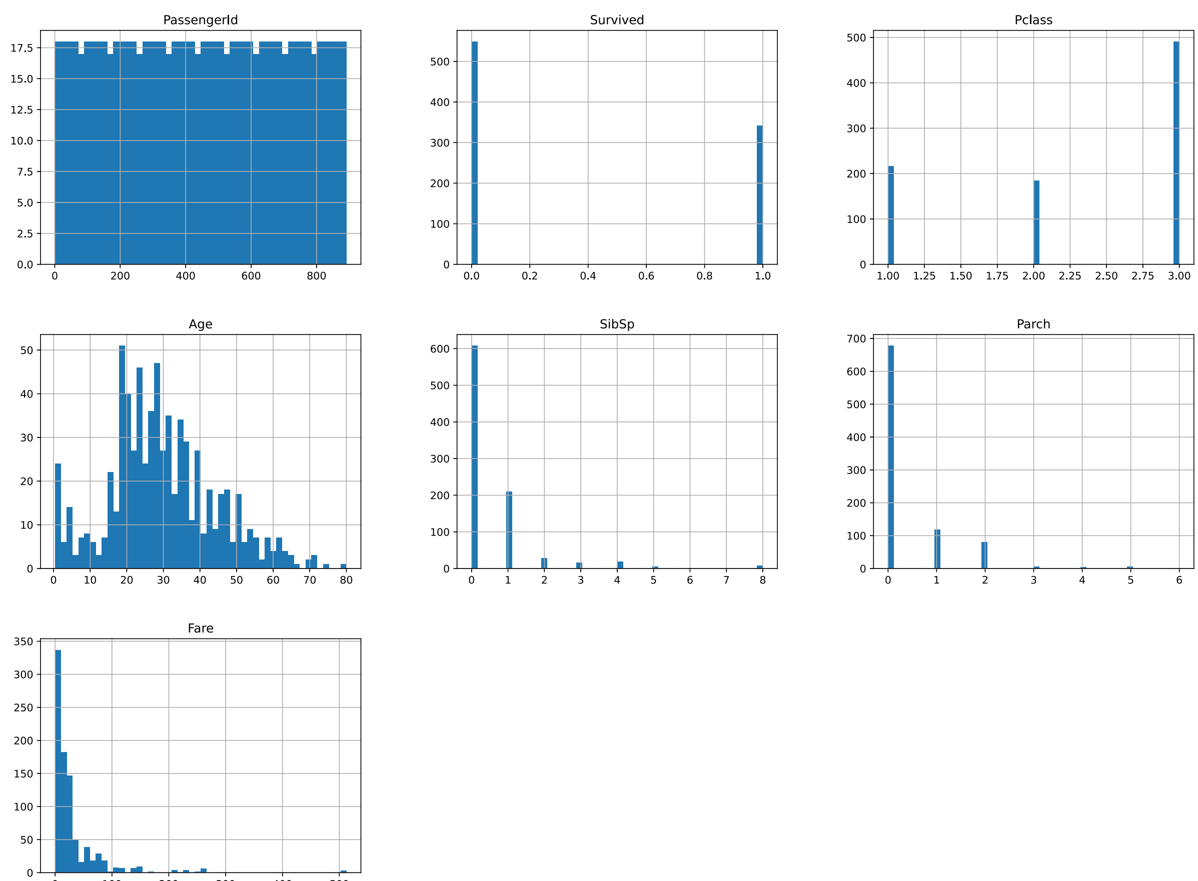
I think we can also drop the PassengerId class for the row index and just remember that it's offset by 1.

In [5]:
```
# Let's take a deeper look at the numerical attributes next.
training_data.describe()
```

Out[5]:

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

In [6]:
```
# We can also plot a histogram of each numerical attribute to get a feel for o
ur data
%matplotlib inline
# ^ Jupyter notebook command for inline matplotlib
import matplotlib.pyplot as plt
training_data.hist(bins=50, figsize=(20,15))
plt.show()
```



In [7]:
```
# Drop unnecessary attributes
training_data = training_data.drop("PassengerId", axis=1)
training_data = training_data.drop("Name", axis=1)
training_data = training_data.drop("Ticket", axis=1)
training_data = training_data.drop("Cabin", axis=1)
training_data = training_data.drop("Embarked", axis=1)
training_data.head()
```

Out[7]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare
0	0	3	male	22.0	1	0	7.2500
1	1	1	female	38.0	1	0	71.2833
2	1	3	female	26.0	0	0	7.9250
3	1	1	female	35.0	1	0	53.1000
4	0	3	male	35.0	0	0	8.0500

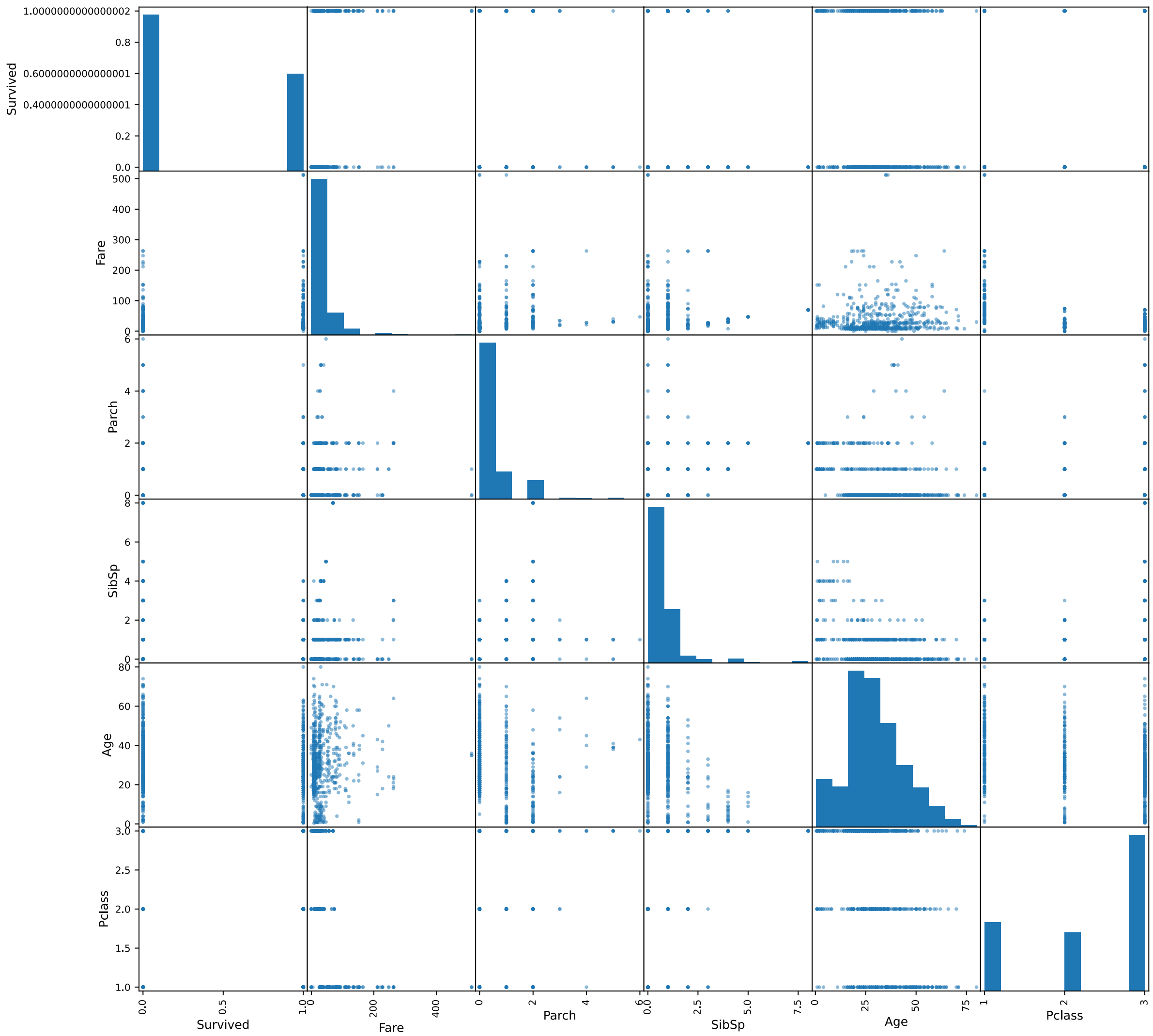
Discover and Visualize the Data to gain Insights

In [8]:
```
## Looking for Correlations
# Compute the standard correlation coefficient (Pearson's r) between every pai
r of attributes
correlation_matrix = training_data.corr()

# Look at how much each attribute correlates with the 'Survived' attribute.
correlation_matrix["Survived"].sort_values(ascending=False)
```

Out[8]:
```
Survived    1.000000
Fare        0.257307
Parch       0.081629
SibSp      -0.035322
Age        -0.077221
Pclass     -0.338481
Name: Survived, dtype: float64
```

In [9]:
```
# Scatter matrix plots are used to plot every numerical attribute against ever
y other
# numerical attribute, plus a histogram of each numberial attribute
from pandas.plotting import scatter_matrix

# Here are just a few since 11*11=121 plots
attributes=["Survived", "Fare", "Parch", "SibSp", "Age", "Pclass"]
scatter_matrix(training_data[attributes], figsize=(15,15))
```

Out[9]:
```
array([[<AxesSubplot:xlabel='Survived', ylabel='Survived'>,
        <AxesSubplot:xlabel='Fare', ylabel='Survived'>,
        <AxesSubplot:xlabel='Parch', ylabel='Survived'>,
        <AxesSubplot:xlabel='SibSp', ylabel='Survived'>,
        <AxesSubplot:xlabel='Age', ylabel='Survived'>,
        <AxesSubplot:xlabel='Pclass', ylabel='Survived'>],
       [<AxesSubplot:xlabel='Survived', ylabel='Fare'>,
        <AxesSubplot:xlabel='Fare', ylabel='Fare'>,
        <AxesSubplot:xlabel='Parch', ylabel='Fare'>,
        <AxesSubplot:xlabel='SibSp', ylabel='Fare'>,
        <AxesSubplot:xlabel='Age', ylabel='Fare'>,
        <AxesSubplot:xlabel='Pclass', ylabel='Fare'>],
       [<AxesSubplot:xlabel='Survived', ylabel='Parch'>,
        <AxesSubplot:xlabel='Fare', ylabel='Parch'>,
        <AxesSubplot:xlabel='Parch', ylabel='Parch'>,
        <AxesSubplot:xlabel='SibSp', ylabel='Parch'>,
        <AxesSubplot:xlabel='Age', ylabel='Parch'>,
        <AxesSubplot:xlabel='Pclass', ylabel='Parch'>],
       [<AxesSubplot:xlabel='Survived', ylabel='SibSp'>,
        <AxesSubplot:xlabel='Fare', ylabel='SibSp'>,
        <AxesSubplot:xlabel='Parch', ylabel='SibSp'>,
        <AxesSubplot:xlabel='SibSp', ylabel='SibSp'>,
        <AxesSubplot:xlabel='Age', ylabel='SibSp'>,
        <AxesSubplot:xlabel='Pclass', ylabel='SibSp'>],
       [<AxesSubplot:xlabel='Survived', ylabel='Age'>,
        <AxesSubplot:xlabel='Fare', ylabel='Age'>,
        <AxesSubplot:xlabel='Parch', ylabel='Age'>,
        <AxesSubplot:xlabel='SibSp', ylabel='Age'>,
        <AxesSubplot:xlabel='Age', ylabel='Age'>,
        <AxesSubplot:xlabel='Pclass', ylabel='Age'>],
       [<AxesSubplot:xlabel='Survived', ylabel='Pclass'>,
        <AxesSubplot:xlabel='Fare', ylabel='Pclass'>,
        <AxesSubplot:xlabel='Parch', ylabel='Pclass'>,
        <AxesSubplot:xlabel='SibSp', ylabel='Pclass'>,
        <AxesSubplot:xlabel='Age', ylabel='Pclass'>,
        <AxesSubplot:xlabel='Pclass', ylabel='Pclass'>]], dtype=object)
```



Create new attribute combinations

In [10]:
```
training_data["Fmembers"] = training_data["Parch"] + training_data["SibSp"]

# check out the new combinations
correlation_matrix = training_data.corr()
correlation_matrix["Survived"].sort_values(ascending=False)
```

Out[10]:
```
Survived     1.000000
Fare         0.257307
Parch        0.081629
Fmembers     0.016639
SibSp       -0.035322
Age         -0.077221
Pclass      -0.338481
Name: Survived, dtype: float64
```

Prepare the Data for Machine Learning Algorithms

We need to take care of the missing attributes and categorical attributes.

In [11]:
```
# Create the Labels
training_labels = training_data["Survived"].copy()
training_labels.head()
```

Out[11]:
```
0    0
1    1
2    1
3    1
4    0
Name: Survived, dtype: int64
```

In [12]:
```
# Drop the Target Value
training_data = training_data.drop("Survived", axis=1)
training_data.head()
```

Out[12]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Fmembers
0	3	male	22.0	1	0	7.2500	1
1	1	female	38.0	1	0	71.2833	1
2	3	female	26.0	0	0	7.9250	0
3	1	female	35.0	1	0	53.1000	1
4	3	male	35.0	0	0	8.0500	0

In [13]:
```
training_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 7 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Pclass    891 non-null    int64  
 1   Sex       891 non-null    object 
 2   Age       714 non-null    float64
 3   SibSp     891 non-null    int64  
 4   Parch     891 non-null    int64  
 5   Fare      891 non-null    float64
 6   Fmembers  891 non-null    int64  
dtypes: float64(2), int64(4), object(1)
memory usage: 48.9+ KB
```

In [14]:
```
# Let's start by fixing the missing 'Age' values by filling them in with the m
edian.
# Note that this method computes and fills the median of ALL missing attribute
values.

from sklearn.impute import SimpleImputer
imputer = SimpleImputer(strategy="median")

training_data_numerical_attributes = training_data.drop("Sex", axis=1)

imputer.fit(training_data_numerical_attributes)

# Compute median of each numerical attribute
imputer.statistics_
training_data_numerical_attributes.median().values

# Transform the training dataset by replacing missing values with the learned
 values
X = imputer.transform(training_data_numerical_attributes)

# Note that type(X) is numpy.ndarray
```

In [15]:
```
# Let's check that this worked by converting 'X' back into a pandas DataFrame
 object and looking
# info again.

training_data_transformed = pd.DataFrame(X, columns=training_data_numerical_at
tributes.columns, index=training_data_numerical_attributes.index)
# ^ Note this is just to demonstrate, we don't use 'training_data_transformed'
again.
training_data_transformed.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Pclass    891 non-null    float64
 1   Age       891 non-null    float64
 2   SibSp     891 non-null    float64
 3   Parch     891 non-null    float64
 4   Fare      891 non-null    float64
 5   Fmembers  891 non-null    float64
dtypes: float64(6)
memory usage: 41.9 KB
```

In [16]:
```
# Next we need to handle the categorical attributes
training_data_transformed.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 6 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Pclass    891 non-null    float64
 1   Age       891 non-null    float64
 2   SibSp     891 non-null    float64
 3   Parch     891 non-null    float64
 4   Fare      891 non-null    float64
 5   Fmembers  891 non-null    float64
dtypes: float64(6)
memory usage: 41.9 KB
```

In [17]:
```
# We only have the 'Sex' attribute we need to convert to a binary value.
training_data_categorical_attributes = training_data[["Sex"]]
training_data_categorical_attributes.head(10)
```

Out[17]:

	Sex
0	male
1	female
2	female
3	female
4	male
5	male
6	male
7	male
8	female
9	female

In [18]:
```
# Let's convert this using the OneHotEncoder
from sklearn.preprocessing import OneHotEncoder
category_encoder = OneHotEncoder()
training_data_categorical_attributes_1hot = category_encoder.fit_transform(tra
ining_data_categorical_attributes)
training_data_categorical_attributes_1hot
```

Out[18]:
```
<891x2 sparse matrix of type '<class 'numpy.float64'>'
	with 891 stored elements in Compressed Sparse Row format>
```

In [19]:
```
training_data_categorical_attributes_1hot.toarray()
```

Out[19]:
```
array([[0., 1.],
       [1., 0.],
       [1., 0.],
       ...,
       [1., 0.],
       [0., 1.],
       [0., 1.]])
```

In [20]:
```
category_encoder.categories_
```

Out[20]:
```
[array(['female', 'male'], dtype=object)]
```

In [21]:
```
# I don't think this is exactly what we wanted,
# I think it would be better to just have a 0 or 1 value, not a tuple.

# Different approach:
training_data_categorical_attributes["Sex"].replace('male', 0, inplace=True)
training_data_categorical_attributes["Sex"].replace('female', 1, inplace=True)
training_data_categorical_attributes.head(10)
```

Out[21]:

	Sex
0	0
1	1
2	1
3	1
4	0
5	0
6	0
7	0
8	1
9	1

In [22]:
```
# This seems a lot better.
```

Custom Transformers

Here is a small transformer class that adds the combined attributes we created above.

The 'add_fmembers' hyperparameter will allow us to easily find out if adding this attribute helps the ML algorithm or not.

In [23]:
```
# Should we reset the data here? I think I should come back to this.
```

In [24]:
```
from sklearn.base import BaseEstimator, TransformerMixin

SibSp_index, Parch_index = 3, 4 # The column in X

class NumericalAttributesTransformer(BaseEstimator, TransformerMixin):
    def __init__(self, add_fmembers = True): # no *args or **kargs
        self.add_fmembers = add_fmembers

    def fit(self, X, y=None):
        return self # nothing else to do

    def transform(self, X, y=None):
        if self.add_fmembers:
            fmembers = X[:, SibSp_index] + X[:, Parch_index]
            return np.c_[X, fmembers]
        else:
            return np.c_[X]

class CategoricalAttributesTransformer(BaseEstimator, TransformerMixin):
    def fit(self, X, y=None):
        return self # nothing else to do

    def transform(self, X, y=None):
        X["Sex"].replace('male', 0, inplace=True)
        X["Sex"].replace('female', 1, inplace=True)
        return np.c_[X]

# Demo only:
#numerical_Attributes_Transformer = NumericalAttributesTransformer(add_fmember
s=False)
#training_data_numerical_attributes = numerical_Attributes_Transformer.transfo
rm(training_data_numerical_attributes)
```

Transformation Pipelines

In [25]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import StandardScaler
```

In [26]:
```
# Here is a small pipeline for the numerical attributes

numerical_attributes_pipeline = Pipeline([
    ('imputer', SimpleImputer(strategy='most_frequent')), # Fill blank values
 with most frequent
    ('numerical_attributes_transformer', NumericalAttributesTransformer(add_fm
embers=True)),
    ('std_scaler', StandardScaler()), # Feature Scaling
])

#training_data_numerical_attributes_transformed = numerical_attributes_pipelin
e.fit_transform(training_data_numerical_attributes)
#training_data_numerical_attributes_transformed
# ^ Note that we don't use this result, we use the numerical pipeline below in
the full pipeline
```

In [27]:
```
# Here is a small pipeline for the categorical attributes

categorical_attributes_pipeline = Pipeline([
    ('categorical_attributes_transformer', CategoricalAttributesTransformer
()),
])

#training_data_categorical_attributes_transformed = categorical_attributes_pip
eline.fit_transform(training_data_categorical_attributes)
#training_data_categorical_attributes_transformed
# ^ Note that we don't use this result, we use the categorical pipeline below
 in the data transformation pipeline
```

In [28]:
```
# Data transformation pipeline to apply all the transformations to the titanic
data

from sklearn.compose import ColumnTransformer

numerical_attributes = list(training_data_numerical_attributes)
categorical_attributes = ["Sex"]

data_transformation_pipeline = ColumnTransformer([
    ('numerical_attributes_pipeline', numerical_attributes_pipeline, numerical
_attributes),
    ('categorical_attributes_pipeline', categorical_attributes_pipeline, categ
orical_attributes),
])

training_data_prepared = data_transformation_pipeline.fit_transform(training_d
ata)
```

In [29]:
```
# Let's turn this back into a Pandas DataFrame Object just to make sure everyt
hing worked.

training_data_prepared_data_frame = pd.DataFrame(training_data_prepared)

training_data_prepared_data_frame.head()
```

Out[29]:

	0	1	2	3	4	5	6	7
0	0.827377	-0.497793	0.432793	-0.473674	-0.502445	0.059160	-0.508282	0.0
1	-1.566107	0.715048	0.432793	-0.473674	0.786845	0.059160	0.776342	1.0
2	0.827377	-0.194583	-0.474545	-0.473674	-0.488854	-0.560975	-0.494741	1.0
3	-1.566107	0.487640	0.432793	-0.473674	0.420730	0.059160	0.411552	1.0
4	0.827377	0.487640	-0.474545	-0.473674	-0.486337	-0.560975	-0.492233	0.0

In [30]:
```
training_data_prepared_data_frame.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       891 non-null    float64
 1   1       891 non-null    float64
 2   2       891 non-null    float64
 3   3       891 non-null    float64
 4   4       891 non-null    float64
 5   5       891 non-null    float64
 6   6       891 non-null    float64
 7   7       891 non-null    float64
dtypes: float64(8)
memory usage: 55.8 KB
```

Select and Train a Model

SGD Classifier

Let's start with a SGD Classifier

In [31]:
```
from sklearn.linear_model import SGDClassifier

sgd_classifier = SGDClassifier(random_state=42)
sgd_classifier.fit(training_data_prepared, training_labels)
```

Out[31]:
```
SGDClassifier(random_state=42)
```

In [32]:
```
# Let's see if this worked
some_person = training_data_prepared[0]
sgd_classifier.predict([some_person])
```

Out[32]:
```
array([0], dtype=int64)
```

In [33]:
```
# This looks like it worked, the first passenger entry we had did not survive.
(Survived == 0)
```

In [34]:
```
# Now lets use cross_val_score() to evaluate our SGDClassifier model
from sklearn.model_selection import cross_val_score
cross_val_score(sgd_classifier, training_data_prepared, training_labels, cv=3,
scoring="accuracy")
```

Out[34]:
```
array([0.71717172, 0.75757576, 0.7979798 ])
```

In [35]:
```
# 74%-77% Accuracy isn't a bad start.
# But we need to use a confusion matrix to correctly evaluate the performance
 of our model (pg. 90)
```

In [36]:
```
# Get the training predictions
from sklearn.model_selection import cross_val_predict
# cross_val_predict works like cross_val_score but returns the predictions mad
e on each test fold.

training_predictions = cross_val_predict(sgd_classifier, training_data_prepare
d, training_labels, cv=3)
```

In [37]:
```
# Now we are ready to get the confusion matrix
from sklearn.metrics import confusion_matrix
confusion_matrix(training_labels, training_predictions)
```

Out[37]:
```
array([[437, 112],
       [104, 238]], dtype=int64)
```

Remember the confusion matrix:

TN | FP

FN | TP

In this context, TN == Died, TP == Survived

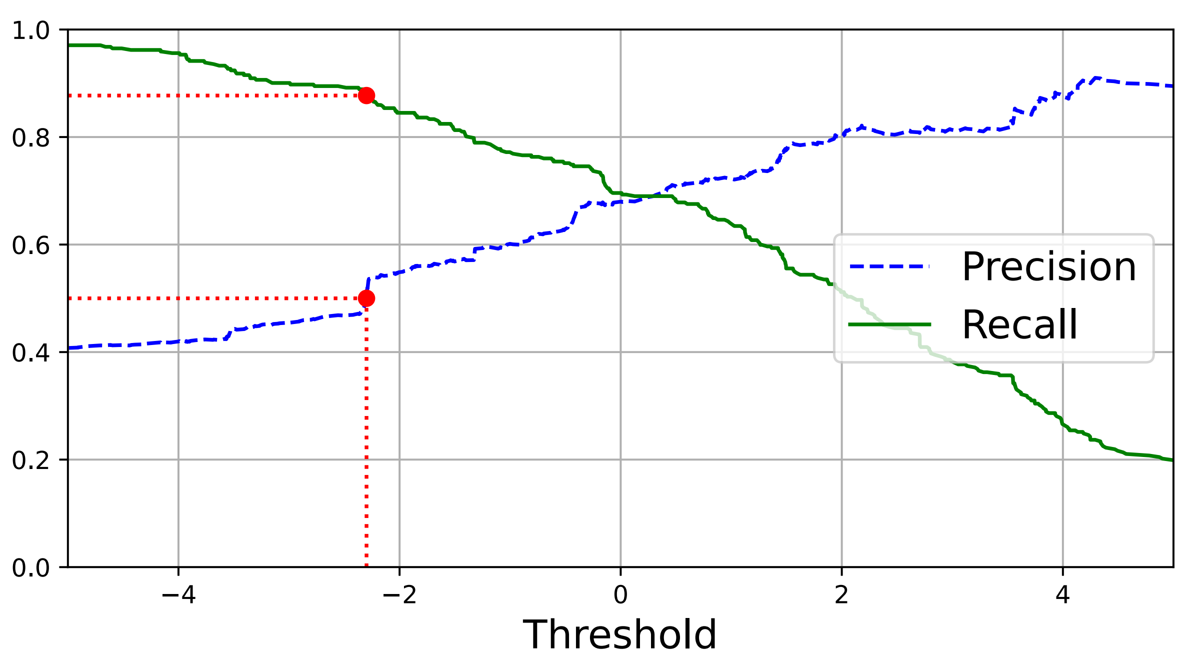
In [38]:
```
# Now let's calculate the precision and recall of the classifier
from sklearn.metrics import precision_score, recall_score

# Precision: The accuracy of the positve predictions is called the precision o
f the classifier.
# precision = TP / (TP + FP)

print(precision_score(training_labels, training_predictions))

# Recall: The senesitivity or the true positive rate (TPR) is the ratio of pos
itive instances that are # correctly detected by the classifier
# recall = TP / (TP + FN)

print(recall_score(training_labels, training_predictions))
```

```
0.68
0.695906432748538
```

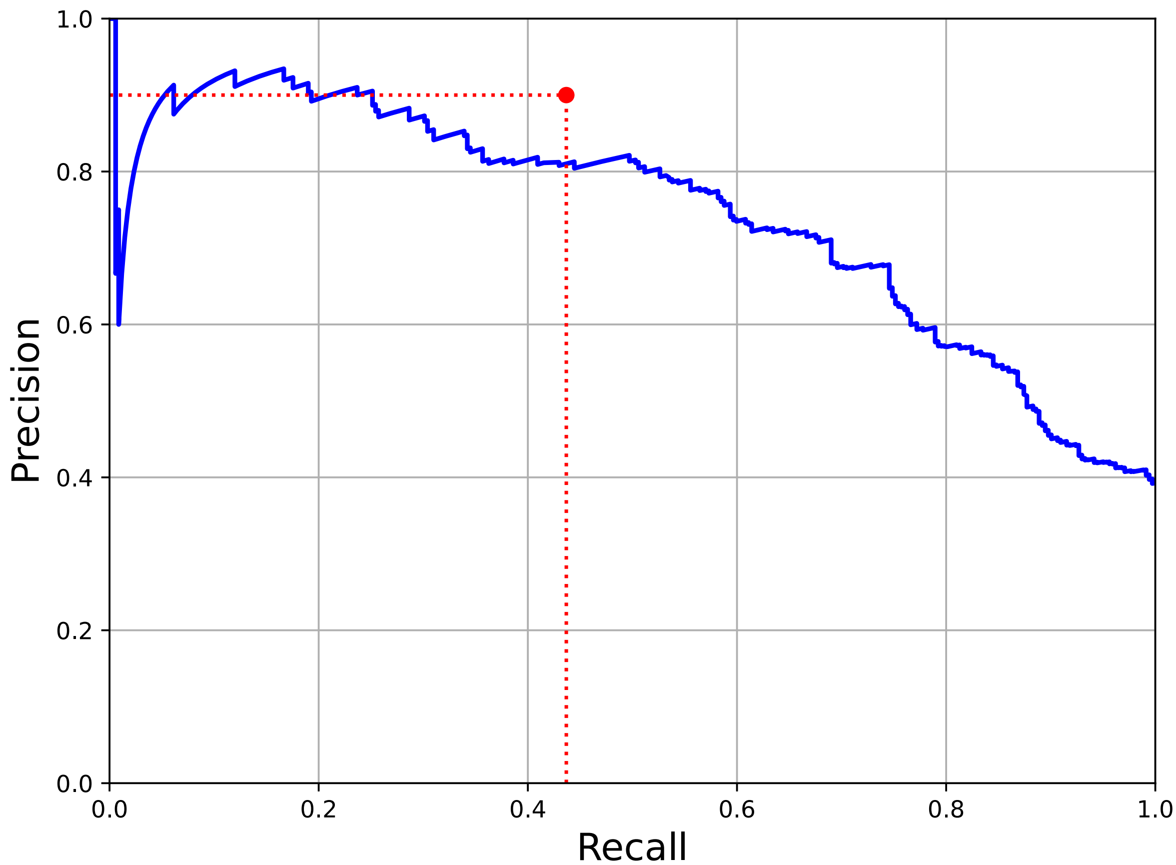
In [39]:
```
# Now let's calculate the F1 score
from sklearn.metrics import f1_score
f1_score(training_labels, training_predictions)
```

Out[39]: 0.6878612716763006

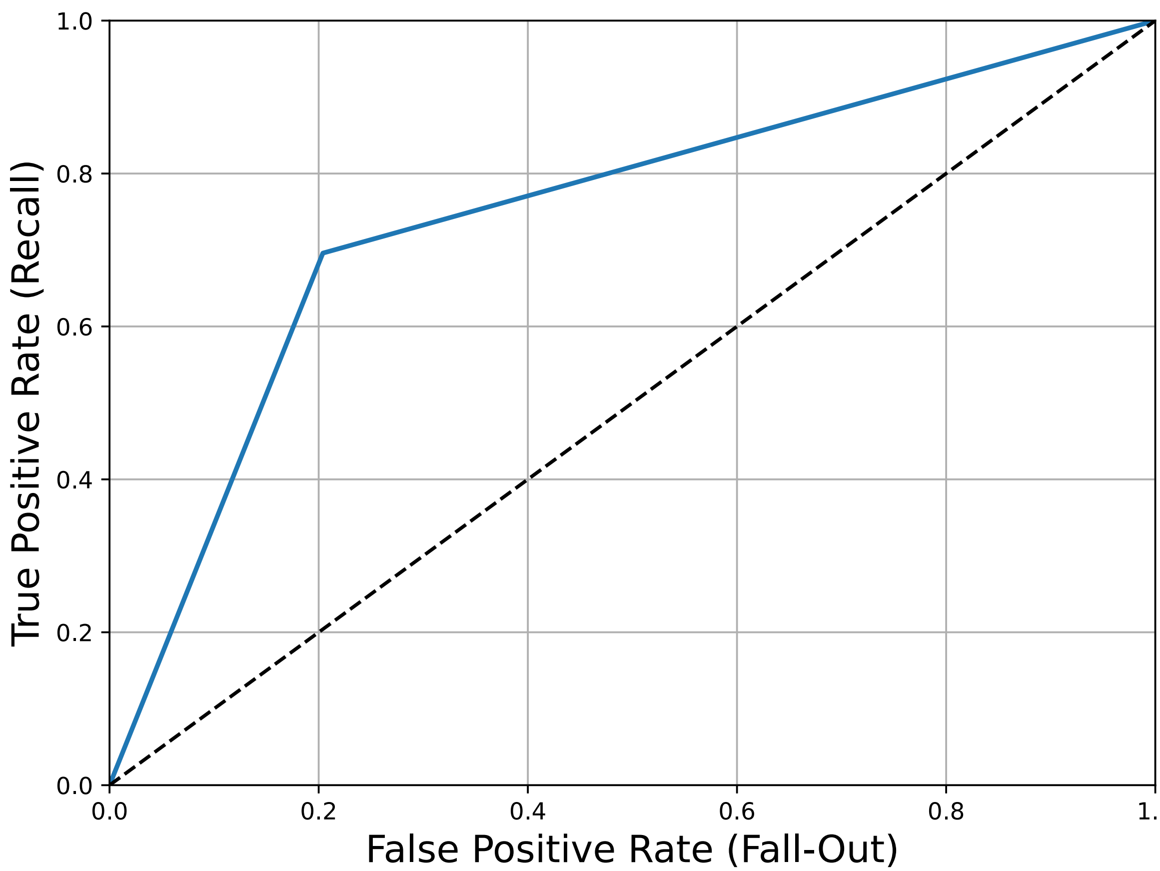
In [40]:
```
# Let's do the following cross-validation to decide on which threshold value t
o use
training_scores_sgd = cross_val_predict(sgd_classifier, training_data_prepared
, training_labels, cv=3, method="decision_function")

from sklearn.metrics import precision_recall_curve

precisions, recalls, thresholds = precision_recall_curve(training_labels, trai
ning_scores_sgd)

def plot_precision_recall_vs_threshold(precisions, recalls, thresholds):
    plt.plot(thresholds, precisions[:-1], "b--", label="Precision")
    plt.plot(thresholds, recalls[:-1], "g-", label="Recall")
    plt.legend(loc="center right", fontsize=16)
    plt.xlabel("Threshold", fontsize=16)
    plt.grid(True)
    plt.axis([-5, 5, 0, 1])

recall_50_precision = recalls[np.argmax(precisions >= 0.50)]
threshold_50_precision = thresholds[np.argmax(precisions >= 0.50)]

plt.figure(figsize=(8, 4))
plot_precision_recall_vs_threshold(precisions, recalls, thresholds)
plt.plot([threshold_50_precision, threshold_50_precision], [0., 0.5], "r:")
plt.plot([-5, threshold_50_precision], [0.5, 0.5], "r:")
plt.plot([-5, threshold_50_precision], [recall_50_precision, recall_50_precisi
on], "r:")
plt.plot([threshold_50_precision], [0.5], "ro")
plt.plot([threshold_50_precision], [recall_50_precision], "ro")
plt.show()
```



In [41]:
```
# We can also plot precision vs. recall
def plot_precision_vs_recall(precisions, recalls):
    plt.plot(recalls, precisions, "b-", linewidth=2)
    plt.xlabel("Recall", fontsize=16)
    plt.ylabel("Precision", fontsize=16)
    plt.axis([0, 1, 0, 1])
    plt.grid(True)

plt.figure(figsize=(8, 6))
plot_precision_vs_recall(precisions, recalls)
plt.plot([0.4368, 0.4368], [0., 0.9], "r:")
plt.plot([0.0, 0.4368], [0.9, 0.9], "r:")
plt.plot([0.4368], [0.9], "ro")
plt.show()
```



In [42]:
```
# Next let's plot the ROC Curve
from sklearn.metrics import roc_curve

fpr_sgd, tpr_sgd, thresholds_sgd = roc_curve(training_labels, training_predict
ions)

def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0,1], 'k--') # Dashed diagonal
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate (Fall-Out)', fontsize=16)
    plt.ylabel('True Positive Rate (Recall)', fontsize=16)
    plt.grid(True)

plt.figure(figsize=(8, 6))
plot_roc_curve(fpr_sgd, tpr_sgd)
plt.show()
```



In [43]:
```
# Next let's computer the ROC AUC (Area under the Curve)
from sklearn.metrics import roc_auc_score
roc_auc_score(training_labels, training_scores_sgd)
```

Out[43]: 0.80535050437265

RandomForestClassifier

https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html#sklearn.ensemble.RandomFo
(https://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html#sklearn.ensemble.RandomFo

Next we’ll try a RandomForestClassifier and compare its ROC curve and ROC AUC Score

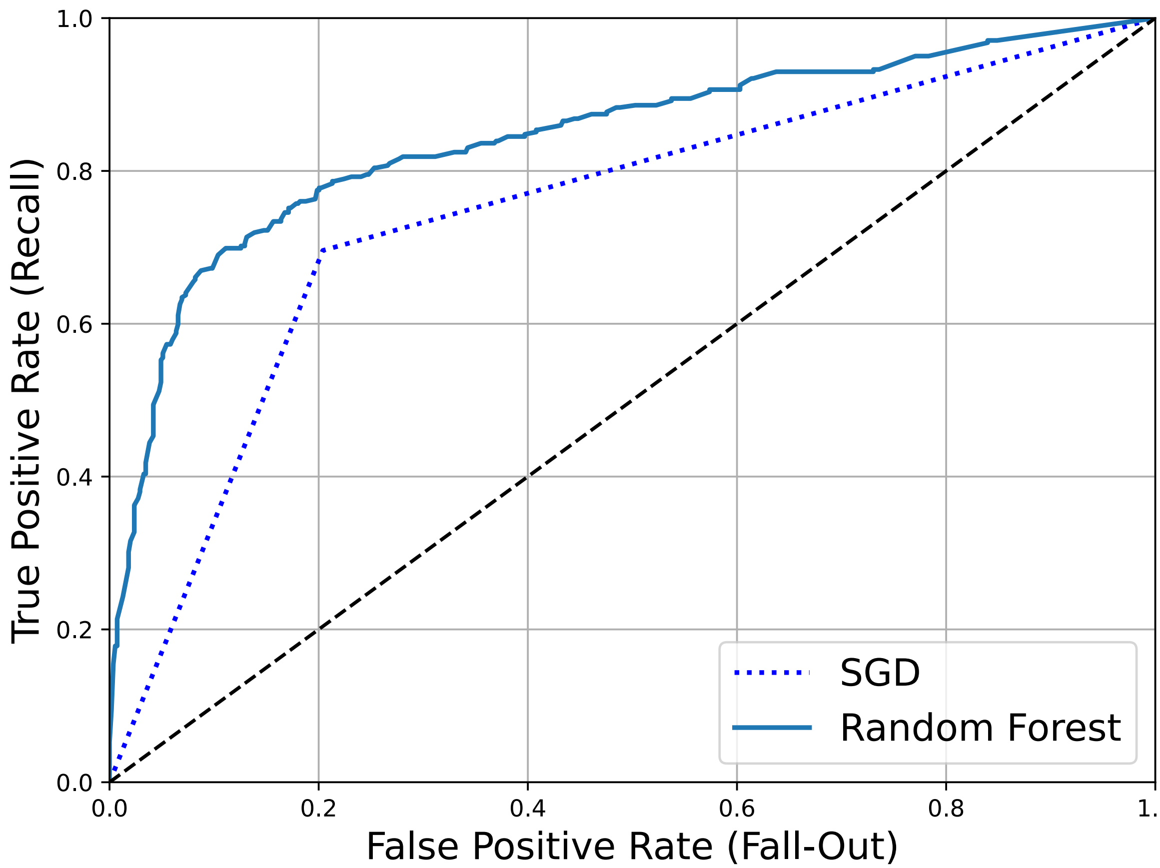
Note that the RandomForestClassifier doesn't have a decision_function() instead we need to use its predict_proba() function.

Generally SKLearn classifiers have one or the other or both.

In [44]:
```
from sklearn.ensemble import RandomForestClassifier

random_forest_classifier = RandomForestClassifier(random_state=42)
training_probabilities_rfc = cross_val_predict(random_forest_classifier, train
ing_data_prepared, training_labels, cv=3, method="predict_proba")
```

In [45]:
```
# The roc_curve() function expects labels and scores but instead of scores we
 can give it probabilities
training_scores_rfc = training_probabilities_rfc[:,1] # score = proba of posit
ive class
fpr_rfc, tpr_rfc, thresholds_rfc = roc_curve(training_labels, training_scores_
rfc)
```

In [46]:
```
# Now we can plot the ROC Curve for the RF Classifier and compare it to the SG
D Classifier
plt.figure(figsize=(8, 6))
plt.plot(fpr_sgd, tpr_sgd, "b:", linewidth=2, label="SGD")
plot_roc_curve(fpr_rfc, tpr_rfc, "Random Forest")
plt.grid(True)
plt.legend(loc="lower right", fontsize=16)
plt.show()
```



In [47]:
```
# From our graph we can see the RandomForestClassifier is superior to the SGDC
lassifier
# because the ROC Curve is closer to the top left corner and has a greater AUC
value.
roc_auc_score(training_labels, training_scores_rfc)
```

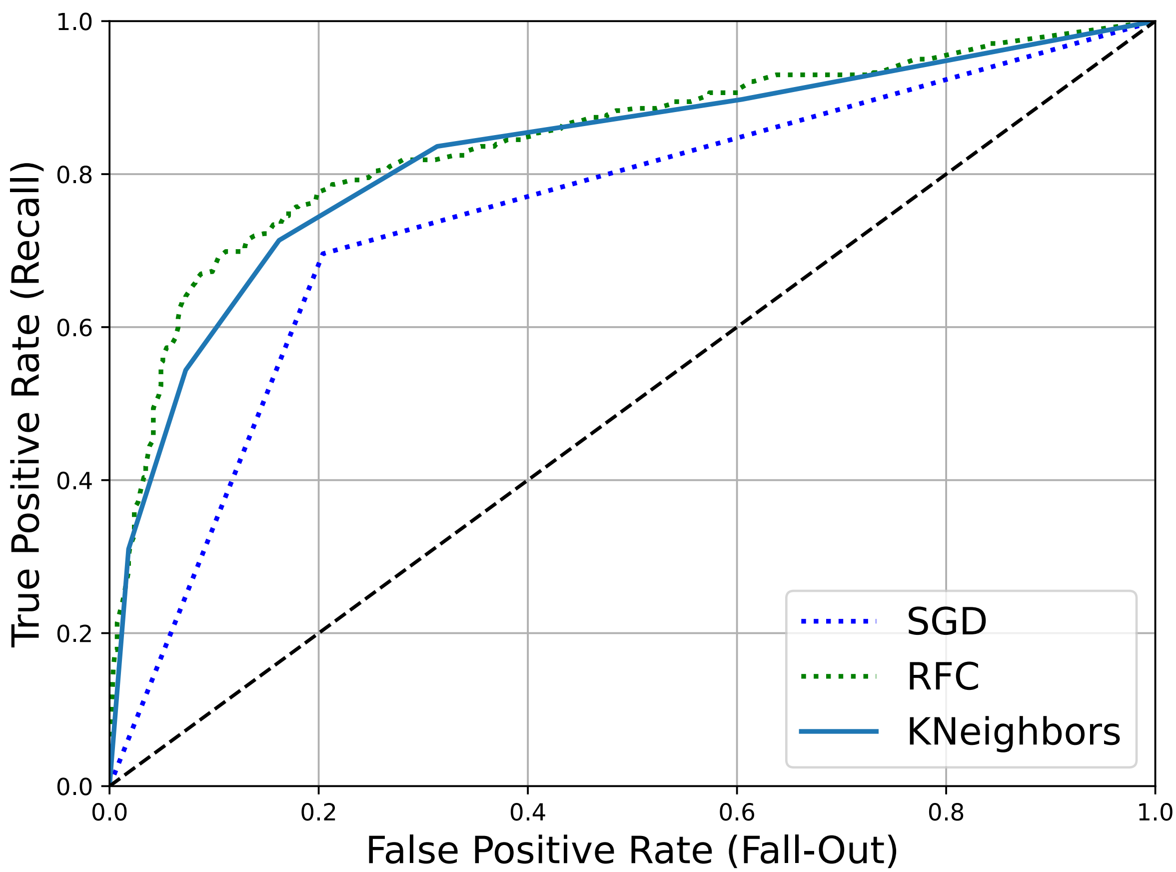
Out[47]: 0.8436285005166224

KNeighborsClassifier

https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html#sklearn.neighbors.KNeighborsCl
(https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.KNeighborsClassifier.html#sklearn.neighbors.KNeighborsCl

In [48]:
```
from sklearn.neighbors import KNeighborsClassifier

knn_classifier = KNeighborsClassifier()

training_probabilities_knn = cross_val_predict(knn_classifier, training_data_p
repared, training_labels, cv=3, method="predict_proba")

training_scores_knn = training_probabilities_knn[:,1] # score = proba of posit
ive class
fpr_knn, tpr_knn, thresholds_knn = roc_curve(training_labels, training_scores_
knn)
```

In [49]:
```
# Now we can plot the ROC Curve for the KNN Classifier and compare it to the S
GD and RF Classifiers
plt.figure(figsize=(8, 6))
plt.plot(fpr_sgd, tpr_sgd, "b:", linewidth=2, label="SGD")
plt.plot(fpr_rfc, tpr_rfc, "g:", linewidth=2, label="RFC")
plot_roc_curve(fpr_knn, tpr_knn, "KNeighbors")
plt.grid(True)
plt.legend(loc="lower right", fontsize=16)
plt.show()
```



In [50]:
```
roc_auc_score(training_labels, training_scores_knn)
```

Out[50]: 0.827109896782028

In [51]:
```
# KNN is slightly worse than RFC
```

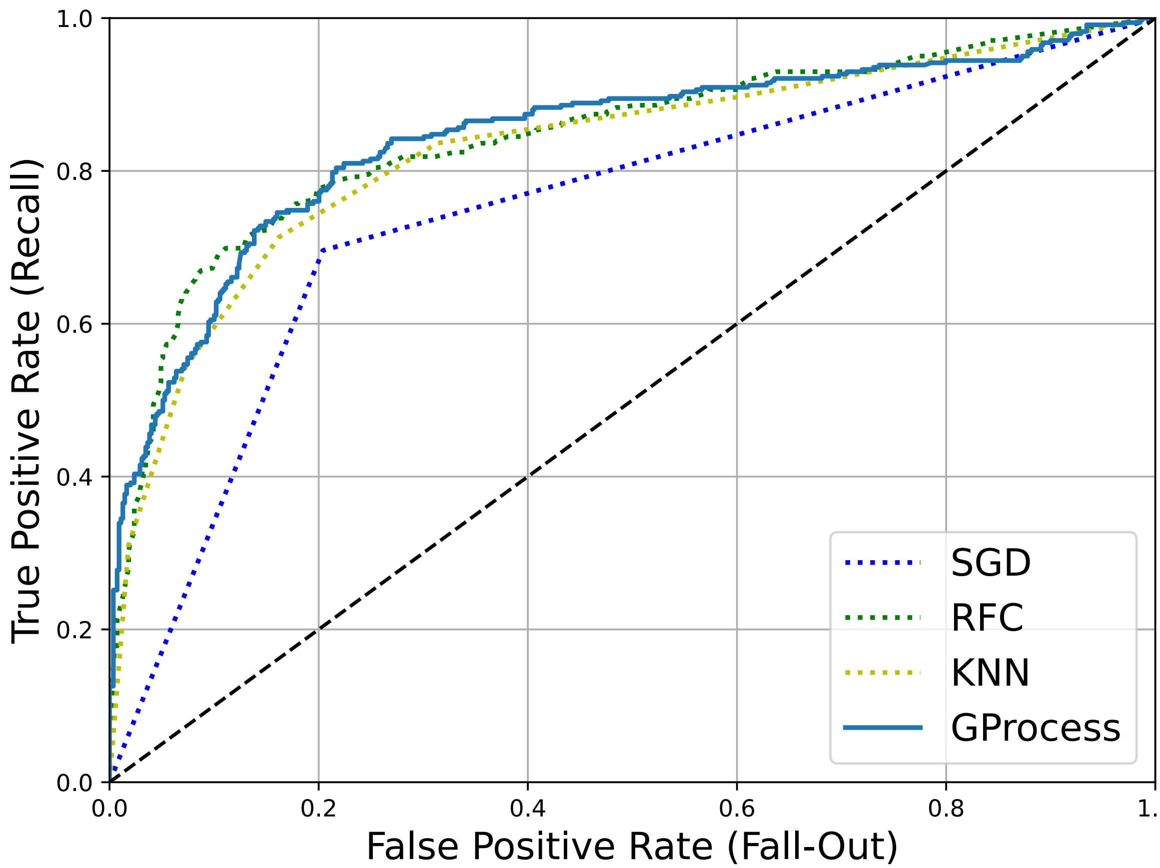
GaussianProcessClassifier

https://scikit-learn.org/stable/modules/generated/sklearn.gaussian_process.GaussianProcessClassifier.html#sklearn.gaussian_
(https://scikit-learn.org/stable/modules/generated/sklearn.gaussian_process.GaussianProcessClassifier.html#sklearn.gaussian_

In [52]:

```
from sklearn.gaussian_process import GaussianProcessClassifier

gp_classifier = GaussianProcessClassifier()

training_probabilities_gp = cross_val_predict(gp_classifier, training_data_prepared, training_labels, cv=3, method="predict_proba")

training_scores_gp = training_probabilities_gp[:,1] # score = proba of positive class
fpr_gp, tpr_gp, thresholds_gp = roc_curve(training_labels, training_scores_gp)
```

In [53]:
```
plt.figure(figsize=(8, 6))
plt.plot(fpr_sgd, tpr_sgd, "b:", linewidth=2, label="SGD")
plt.plot(fpr_rfc, tpr_rfc, "g:", linewidth=2, label="RFC")
plt.plot(fpr_knn, tpr_knn, "y:", linewidth=2, label="KNN")
plot_roc_curve(fpr_gp, tpr_gp, "GProcess")
plt.grid(True)
plt.legend(loc="lower right", fontsize=16)
plt.show()
```



In [54]:
```
roc_auc_score(training_labels, training_scores_gp)
```

Out[54]:
```
0.8438868117470361
```

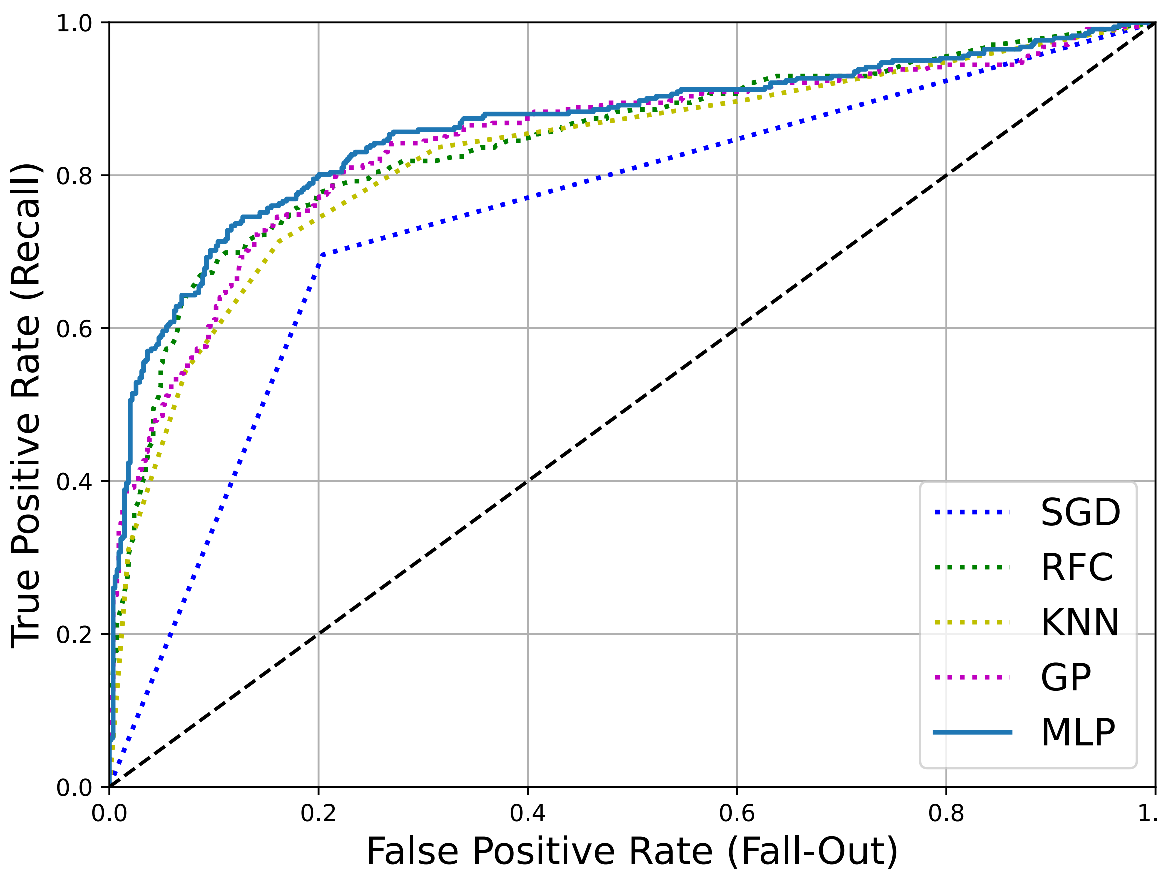
In [55]:
```
# The Guassian Process Classifier ROC AUC score is about the same as the RFC C
lassifier
```

MLPClassifier (Neural Network)

[https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html#sklearn.neural_network.MLPClass (https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html#sklearn.neural_network.MLPClass](https://scikit-learn.org/stable/modules/generated/sklearn.neural_network.MLPClassifier.html#sklearn.neural_network.MLPClass)

In [56]:
```
from sklearn.neural_network import MLPClassifier

mlp_classifier = MLPClassifier()

training_probabilities_mlp = cross_val_predict(mlp_classifier, training_data_p
repared, training_labels, cv=5, method="predict_proba")

training_scores_mlp = training_probabilities_mlp[:,1] # score = proba of posit
ive class
fpr_mlp, tpr_mlp, thresholds_mlp = roc_curve(training_labels, training_scores_
mlp)
```

In [57]:
```
plt.figure(figsize=(8, 6))
plt.plot(fpr_sgd, tpr_sgd, "b:", linewidth=2, label="SGD")
plt.plot(fpr_rfc, tpr_rfc, "g:", linewidth=2, label="RFC")
plt.plot(fpr_knn, tpr_knn, "y:", linewidth=2, label="KNN")
plt.plot(fpr_gp, tpr_gp, "m:", linewidth=2, label="GP")
plot_roc_curve(fpr_mlp, tpr_mlp, "MLP")
plt.grid(True)
plt.legend(loc="lower right", fontsize=16)
plt.show()
```



In [58]:
```
roc_auc_score(training_labels, training_scores_mlp)
```

Out[58]: 0.8614573014199128

Select a Model Conclusion

While the MLP Classifier had the highest AUC score, it wasn't much higher than the RFC or GP Classifiers.

As such, I don't think it is worth it to use a much more powerful model to justify a 1% improvement over a simpler model.

As such, I am going to move ahead with the RFC classifier and focus on tuning it's hyperparameters next.

Fine-Tune Your Model

GridSearchCV

https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html (https://scikit-learn.org/stable/modules/generated/sklearn.model_selection.GridSearchCV.html)

In [59]:
```
from sklearn.model_selection import GridSearchCV

parameter_grid = {
    'n_estimators': [10, 30, 100, 300],
    'max_depth': [1, 3, 10, 30, 100],
    'min_samples_split': [1, 3, 10, 30],
    'min_samples_leaf': [1, 3, 10, 30],
    'max_features': [1, 3, 10, 30, 100],
    'bootstrap': [True, False],
    'random_state': [42]
}

random_forest_classifier = RandomForestClassifier()

grid_search = GridSearchCV(
    estimator = random_forest_classifier,
    param_grid = parameter_grid,
    cv = 3,
    n_jobs = -1,
    verbose = 2
)

grid_search.fit(training_data_prepared, training_labels)
```

```
Fitting 3 folds for each of 3200 candidates, totalling 9600 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    1.3s
[Parallel(n_jobs=-1)]: Done 130 tasks      | elapsed:    2.5s
[Parallel(n_jobs=-1)]: Done 836 tasks      | elapsed:    6.9s
[Parallel(n_jobs=-1)]: Done 1968 tasks      | elapsed:   14.0s
[Parallel(n_jobs=-1)]: Done 3428 tasks      | elapsed:   26.0s
[Parallel(n_jobs=-1)]: Done 4528 tasks      | elapsed:   34.1s
[Parallel(n_jobs=-1)]: Done 6452 tasks      | elapsed:   46.5s
[Parallel(n_jobs=-1)]: Done 8880 tasks      | elapsed:  1.1min
[Parallel(n_jobs=-1)]: Done 9569 out of 9600 | elapsed:  1.1min remaining:
0.1s
[Parallel(n_jobs=-1)]: Done 9600 out of 9600 | elapsed:  1.1min finished
```

Out[59]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'bootstrap': [True, False],
                         'max_depth': [1, 3, 10, 30, 100],
                         'max_features': [1, 3, 10, 30, 100],
                         'min_samples_leaf': [1, 3, 10, 30],
                         'min_samples_split': [1, 3, 10, 30],
                         'n_estimators': [10, 30, 100, 300],
                         'random_state': [42]},
             verbose=2)
```

In [60]:
```
grid_search.best_params_
```

Out[60]:
```
{'bootstrap': True,
 'max_depth': 10,
 'max_features': 1,
 'min_samples_leaf': 3,
 'min_samples_split': 3,
 'n_estimators': 100,
 'random_state': 42}
```

In [61]:
```
grid_search.best_score_
```

Out[61]:
```
0.8338945005611672
```

In [62]:
```
# This doesn't look all that promising, maybe we should zero in on best parame
ters and create a distribution closer to those.
```

In [63]:
```
parameter_grid = {
    'n_estimators': [80, 90, 100, 110, 120],
    'max_depth': [24, 26, 28, 30, 32, 34, 36],
    'min_samples_split': [6, 8, 10, 12, 14],
    'min_samples_leaf': [1, 2, 3, 4],
    'max_features': [1, 2, 3, 4, 5],
    'bootstrap': [True, False],
    'random_state': [42]
}

random_forest_classifier = RandomForestClassifier()

grid_search = GridSearchCV(
    estimator = random_forest_classifier,
    param_grid = parameter_grid,
    cv = 3,
    n_jobs = -1,
    verbose = 2
)

grid_search.fit(training_data_prepared, training_labels)
```

```
Fitting 3 folds for each of 7000 candidates, totalling 21000 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    0.1s
[Parallel(n_jobs=-1)]: Done 228 tasks      | elapsed:    3.3s
[Parallel(n_jobs=-1)]: Done 634 tasks      | elapsed:    9.0s
[Parallel(n_jobs=-1)]: Done 1200 tasks      | elapsed:   17.5s
[Parallel(n_jobs=-1)]: Done 1930 tasks      | elapsed:   28.1s
[Parallel(n_jobs=-1)]: Done 2820 tasks      | elapsed:   41.3s
[Parallel(n_jobs=-1)]: Done 3874 tasks      | elapsed:   56.4s
[Parallel(n_jobs=-1)]: Done 5088 tasks      | elapsed:  1.2min
[Parallel(n_jobs=-1)]: Done 6466 tasks      | elapsed:  1.6min
[Parallel(n_jobs=-1)]: Done 8004 tasks      | elapsed:  1.9min
[Parallel(n_jobs=-1)]: Done 9706 tasks      | elapsed:  2.4min
[Parallel(n_jobs=-1)]: Done 11568 tasks      | elapsed:  2.8min
[Parallel(n_jobs=-1)]: Done 13594 tasks      | elapsed:  3.2min
[Parallel(n_jobs=-1)]: Done 15780 tasks      | elapsed:  3.7min
[Parallel(n_jobs=-1)]: Done 18130 tasks      | elapsed:  4.2min
[Parallel(n_jobs=-1)]: Done 20640 tasks      | elapsed:  4.7min
[Parallel(n_jobs=-1)]: Done 21000 out of 21000 | elapsed:  4.8min finished
```

Out[63]:
```
GridSearchCV(cv=3, estimator=RandomForestClassifier(), n_jobs=-1,
             param_grid={'bootstrap': [True, False],
                         'max_depth': [24, 26, 28, 30, 32, 34, 36],
                         'max_features': [1, 2, 3, 4, 5],
                         'min_samples_leaf': [1, 2, 3, 4],
                         'min_samples_split': [6, 8, 10, 12, 14],
                         'n_estimators': [80, 90, 100, 110, 120],
                         'random_state': [42]},
             verbose=2)
```

In [64]:
```
grid_search.best_params_
```

Out[64]:
```
{'bootstrap': True,
 'max_depth': 24,
 'max_features': 4,
 'min_samples_leaf': 1,
 'min_samples_split': 6,
 'n_estimators': 110,
 'random_state': 42}
```

In [65]:
```
grid_search.best_score_
```

Out[65]:
```
0.8395061728395062
```

In [66]:
```
# This isn't an improvement (0.2% improvement) over the initial best parameter
s we found.
```

Analyze the Best Models and Their Error

Feature Importance

In [67]:
```
# Let's look at the relative importance of each attribute for making accurate
 predictions
feature_importances = grid_search.best_estimator_.feature_importances_
extra_attributes = ["Fmembers"]
category_encoder = data_transformation_pipeline.named_transformers_["categoric
al_attributes_pipeline"]
category_attributes = ["Sex"]
attributes = numerical_attributes + extra_attributes + category_attributes
print(sorted(zip(feature_importances, attributes), reverse=True))
```

```
[(0.3171671644864373, 'Sex'), (0.1972279906589765, 'Age'), (0.162097954980763
2, 'Fmembers'), (0.15098528166892008, 'Fare'), (0.09128394834012139, 'Pclas
s'), (0.04667474749742113, 'Fmembers'), (0.021790991004203095, 'SibSp'), (0.0
12771921363157374, 'Parch')]
```

In [68]:
```
# Let's create a pipeline to select the most important 'k' features

def indices_of_top_k(array, k):
    return np.sort(np.argpartition(np.array(array), -k)[-k:])

class TopFeatureSelector(BaseEstimator, TransformerMixin):
    def __init__(self, feature_importances, k):
        self.feature_importances = feature_importances
        self.k = k
    def fit(self, X, y=None):
        self.feature_indices_ = indices_of_top_k(self.feature_importances, sel
f.k)
        return self
    def transform(self, X):
        return X[:, self.feature_indices_]

# Note that this feature selector assumes you have already computed the featur
e importances
```

In [69]:
```
k = 6
top_k_feature_indices = indices_of_top_k(feature_importances, k)
top_k_feature_indices
```

Out[69]:
```
array([0, 1, 4, 5, 6, 7], dtype=int64)
```

In [70]:
```
np.array(attributes)[top_k_feature_indices]
```

Out[70]:
```
array(['Pclass', 'Age', 'Fare', 'Fmembers', 'Fmembers', 'Sex'],
      dtype='<U8')
```

In [71]:
```
# Let's double check that these are indeed the top k features:
sorted(zip(feature_importances, attributes), reverse=True)[:k]
```

Out[71]:
```
[(0.3171671644864373, 'Sex'),
 (0.1972279906589765, 'Age'),
 (0.1620979549807632, 'Fmembers'),
 (0.15098528166892008, 'Fare'),
 (0.09128394834012139, 'Pclass'),
 (0.04667474749742113, 'Fmembers')]
```

Feature Importance Pipeline

In [72]:
```
# Now let's create a new pipeline that runs the previously defined preparation
pipeline, and adds top k feature selection:
preparation_and_feature_selection_pipeline = Pipeline([
    ('preparation', data_transformation_pipeline),
    ('feature_selection', TopFeatureSelector(feature_importances, k))
])
```

In [73]:
```
# Let's test that this is working.
# To check, let's look at the features of the first 3 instances and compare th
em to the top k features

training_data_prepared_top_k_features = preparation_and_feature_selection_pipe
line.fit_transform(training_data)
```

In [74]:
```
training_data_prepared_top_k_features[0:3]
```

Out[74]:
```
array([[ 0.82737724, -0.49779327, -0.50244517,  0.05915988, -0.50828223,
         0.        ],
       [-1.56610693,  0.71504807,  0.78684529,  0.05915988,  0.77634215,
         1.        ],
       [ 0.82737724, -0.19458293, -0.48885426, -0.56097483, -0.4947405 ,
         1.        ]])
```

In [75]:
```
training_data_prepared[0:3, top_k_feature_indices]
```

Out[75]:
```
array([[ 0.82737724, -0.49779327, -0.50244517,  0.05915988, -0.50828223,
         0.        ],
       [-1.56610693,  0.71504807,  0.78684529,  0.05915988,  0.77634215,
         1.        ],
       [ 0.82737724, -0.19458293, -0.48885426, -0.56097483, -0.4947405 ,
         1.        ]])
```

In [76]:
```
# They match, looks good.
```

Full Pipeline

A single pipeline that does the full data preparation plus the final prediction

In [77]:
```
prepare_and_select_and_predict_pipeline = Pipeline([
    ('preparation', data_transformation_pipeline),
    ('feature_selection', TopFeatureSelector(feature_importances, k)),
    ('random_forest', RandomForestClassifier(**grid_search.best_params_)) # Th
ese params are from above
])

prepare_and_select_and_predict_pipeline.fit(training_data, training_labels)
```

Out[77]:
```
Pipeline(steps=[('preparation',
                 ColumnTransformer(transformers=[('numerical_attributes_pipel
ine',
                                                  Pipeline(steps=[('imputer',
                                                                   SimpleImpu
ter(strategy='most_frequent')),
                                                                  ('numerical
_attributes_transformer',
                                                                   NumericalA
ttributesTransformer()),
                                                                  ('std_scale
r',
                                                                   StandardSc
aler())]),
                                                  ['Pclass', 'Age', 'SibSp',
                                                   'Parch', 'Fare',
                                                   'Fmembers']),
                                                 ('categorical_attributes_pip
el...
                                                  Pipeline(steps=[('categoric
al_attributes_transformer',
                                                                   Categorica
lAttributesTransformer())]),
                                                  ['Sex'])])),
                ('feature_selection',
                 TopFeatureSelector(feature_importances=array([0.09128395, 0.
19722799, 0.02179099, 0.01277192, 0.15098528,
       0.04667475, 0.16209795, 0.31716716]),
                                    k=6)),
                ('random_forest',
                 RandomForestClassifier(max_depth=24, max_features=4,
                                        min_samples_split=6, n_estimators=11
0,
                                        random_state=42))])
```

In [78]:
```
# Let's try the full pipeline on a few instances:

some_data = training_data.iloc[:4]
some_labels = training_labels.iloc[:4]

print("Predictions:\t", prepare_and_select_and_predict_pipeline.predict(some_d
ata))
print("Labels:\t\t", list(some_labels))
```

```
Predictions:     [0 1 1 1]
Labels:          [0, 1, 1, 1]
```

In [79]:
```
# We can see that the full pipeline is working.
```

Explore some data preparation automation

In [80]:
```
param_grid = [{
    'preparation__numerical_attributes_pipeline__imputer__strategy': ['mean',
'median', 'most_frequent'],
    'feature_selection__k': list(range(1, len(feature_importances) + 1))
}]

grid_search_prep = GridSearchCV(prepare_and_select_and_predict_pipeline, param
_grid, cv=5,
                                scoring='neg_mean_squared_error', verbose=2, n
_jobs = -1)
grid_search_prep.fit(training_data, training_labels)
```

```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    0.5s
[Parallel(n_jobs=-1)]: Done 120 out of 120 | elapsed:    2.2s finished
```

Out[80]:

```
GridSearchCV(cv=5,
             estimator=Pipeline(steps=[('preparation',
                                        ColumnTransformer(transformers=[('num
erical_attributes_pipeline',
                                                                         Pipe
line(steps=[('imputer',

SimpleImputer(strategy='most_frequent')),

('numerical_attributes_transformer',

NumericalAttributesTransformer()),

('std_scaler',

StandardScaler())]),
                                                                         ['Pc
lass',
                                                                          'Ag
e',
                                                                          'Si
bSp',
                                                                          'Pa
rch',
                                                                          'Fa
re',
                                                                          'Fm
embers']),
                                                                        ('...
       0.04667475, 0.16209795, 0.31716716]),
                                                            k=6)),
                                       ('random_forest',
                                        RandomForestClassifier(max_depth=24,
                                                               max_features=
4,
                                                               min_samples_sp
lit=6,
                                                               n_estimators=1
10,
                                                               random_state=4
2))]),
             n_jobs=-1,
             param_grid=[{'feature_selection__k': [1, 2, 3, 4, 5, 6, 7, 8],
                          'preparation__numerical_attributes_pipeline__impute
r__strategy': ['mean',

'median',

'most_frequent']}],
             scoring='neg_mean_squared_error', verbose=2)
```

In [81]:
```
grid_search_prep.best_params_
```

Out[81]:
```
{'feature_selection__k': 6,
 'preparation__numerical_attributes_pipeline__imputer__strategy': 'median'}
```

In [82]:
```
# Measure accuracy on the training set
from sklearn.metrics import accuracy_score

predictions = grid_search_prep.predict(training_data)
accuracy_score(training_labels, predictions)
```

Out[82]:
```
0.9371492704826038
```

In [83]:
```
# That's a lot better, but we could very likely just be overfitting the traini
ng data now.
```

In [84]:
```
# Let's look at the F1 score:
f1_score(training_labels, predictions, average="macro")
```

Out[84]:
```
0.932620320855615
```

In [85]:
```
# Let's look at the ROC AUC score:
probabilities = cross_val_predict(grid_search_prep, training_data, training_la
bels, cv=3, method="predict_proba")
scores = probabilities[:,1] # score = proba of positive class
fpr, tpr, thresholds = roc_curve(training_labels, scores)
```

```
Fitting 5 folds for each of 24 candidates, totalling 120 fits
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    0.1s
[Parallel(n_jobs=-1)]: Done 120 out of 120 | elapsed:    1.6s finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
Fitting 5 folds for each of 24 candidates, totalling 120 fits
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    0.1s
[Parallel(n_jobs=-1)]: Done  89 out of 120 | elapsed:    1.3s remaining:
0.4s
[Parallel(n_jobs=-1)]: Done 120 out of 120 | elapsed:    1.6s finished
[Parallel(n_jobs=-1)]: Using backend LokyBackend with 16 concurrent workers.
Fitting 5 folds for each of 24 candidates, totalling 120 fits
[Parallel(n_jobs=-1)]: Done   9 tasks      | elapsed:    0.0s
[Parallel(n_jobs=-1)]: Done 120 out of 120 | elapsed:    1.6s finished
```

In [86]:
```
roc_auc_score(training_labels, scores)
```

Out[86]:
```
0.8535029133245988
```

In [87]:
```
# This isn't any better than when we began hyperparameter tuning for this mode
l...
```