Problem Set 5: Trees, Forests, and Networks

Part 1: Exploring The Titanic

Your mission for this problem set is to use your knowledge of supervised machine learning to try to predict which passengers aboard the Titanic were most likely to survive. The prompts for this part of the problem set are deliberately vague - the goal is to leave it up to you how to structure (most of) your analysis. We **highly recommend** you closely go over the entire problem set once before starting; this is important, so that you understand the sequence of steps and not perform redundant work.

To get started, read about the prediction problem on Kaggle. Then, download the data here - you'll need the `train.csv` data. Treat this as your entire dataset, and further build train and test splits from this dataset whenever required.

1.1 Exploratory data analysis

Create 2-3 figures and tables that help give you a feel for the data. Make sure to at least check the data type of each variable, to understand which variables have missing observations, and to understand the distribution of each variable (and determine whether the variables should be standardized or not). Are any of the potential predictor variables (i.e., anything execpt for survival) collinear or highly correlated? Remember that this is the EDA phase, and we want to save pre-processing steps like imputations, transformations etc. and feature engineering for later.

In [1]:
```
import pandas as pd
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import seaborn as sns
import sklearn
from sklearn.linear_model import LinearRegression
from sklearn.model_selection import train_test_split, KFold, GridSearchCV
from sklearn.metrics import accuracy_score, precision_score, recall_score, roc_a
```

In [260…
```
# loading data
df = pd.read_csv ('train.csv')
# inspecting columns
df.columns
```

Out[260…
```
Index(['PassengerId', 'Survived', 'Pclass', 'Name', 'Sex', 'Age', 'SibSp',
       'Parch', 'Ticket', 'Fare', 'Cabin', 'Embarked'],
      dtype='object')
```

In [261…
```
# inspecting dataset
df.head()
```

Out[261…

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cab
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	Na
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C8
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	Na
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C1
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	Na

In [262…

```
# checking null values
df.isnull().sum()
```

Out[262…

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

In [263…

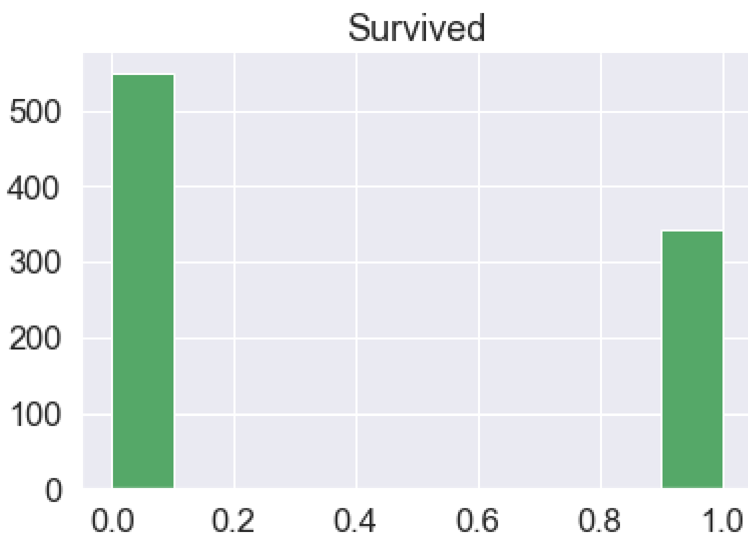
```
# inspecting data types
df.dtypes
```

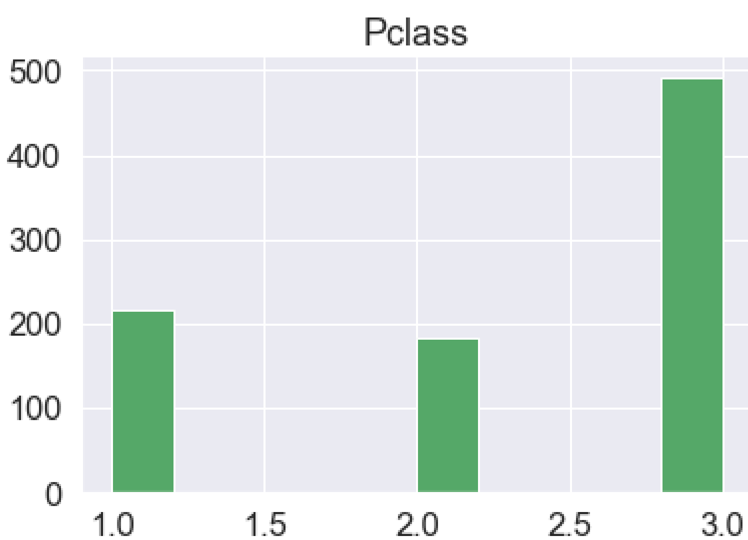
Out[263…

```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

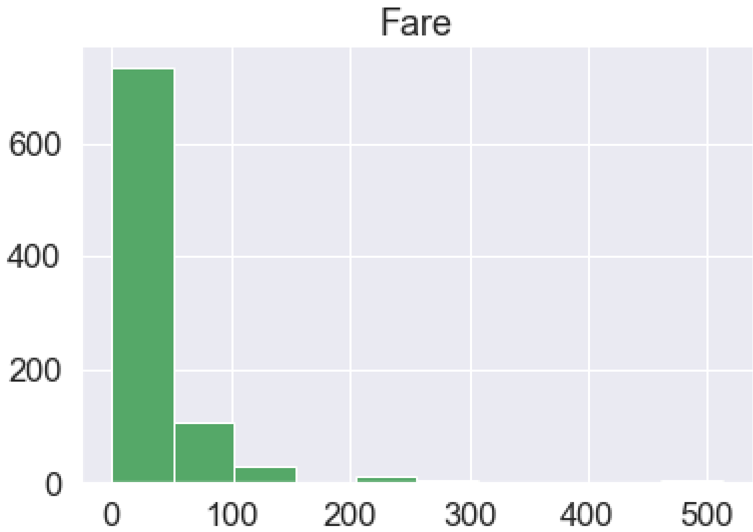
In [264…

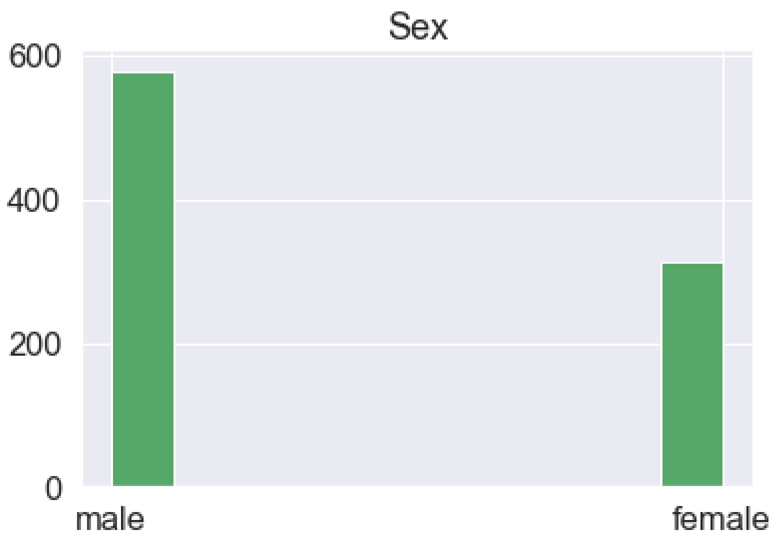
```
#inspecting distributions of variables
col = ['Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'Sex']

for i in col:
    plt.hist(df[i], facecolor='g', edgecolor='white')
    plt.title(i)


    #polishing
    ax = plt.gca()
    ax.spines['right'].set_color('none')
    ax.spines['top'].set_color('none')
    ax.yaxis.set_ticks_position('none')
    ax.xaxis.set_ticks_position('none')

    plt.gca().yaxis.grid(True) # Add horizontal grid lines
    plt.show()
```





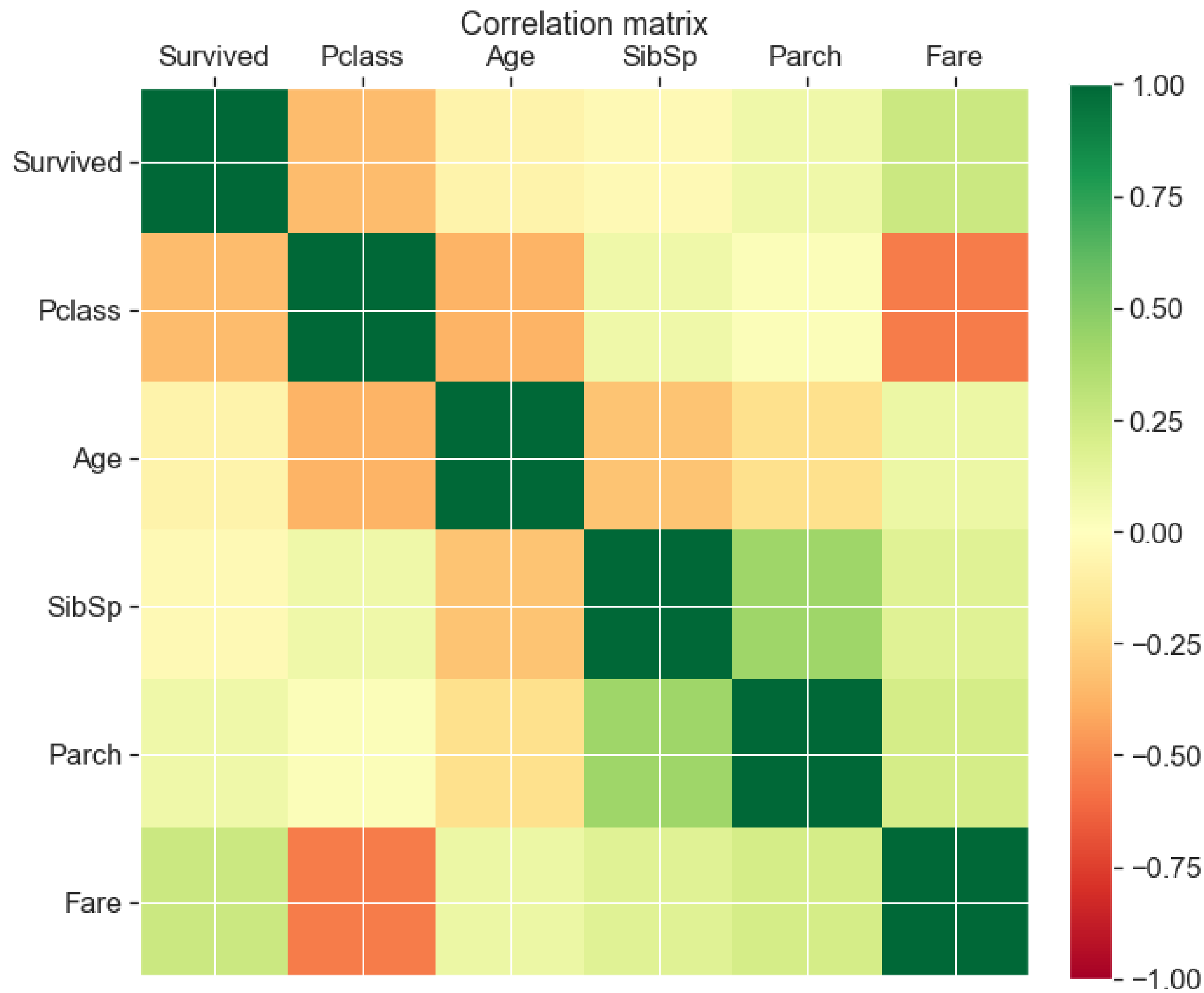

Age
0
50
100
150
0
20
40
60
80
SibSp
0
200
400
600
0
2
4
6
8
Parch
0
200
400
600
0
2
4
6





In [265…

```
#inspecting correlation matrix
df2 = df[['Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare']]

fig = plt.figure(figsize=(10, 10))
axes = fig.add_subplot(111)

mat = axes.matshow(df2.corr(method='pearson'), vmin=-1, vmax=1, cmap=plt.cm.RdYl

fig.colorbar(mat,fraction=0.046, pad=0.04)
axes.set_title('Correlation matrix')
axes.set_xticks(range(len(df2.columns)))
axes.set_xticklabels(df2.columns)
axes.set_yticks(range(len(df2.columns)))
axes.set_yticklabels(df2.columns)
axes.xaxis.set_ticks_position('top')
axes.yaxis.set_ticks_position('left')

plt.show()
```



It appears that Fare is the most highly correlated with Survived and Pclass is strongly negatively correlated. There are many null values.

1.2 Correlates of survival

Use whatever methods you can think of to try and figure out what factors seem to determine whether or not a person would survive the sinking of the Titanic. You can start with simple correlations, but will likely also want to use multiple regression and/or other methods in your toolkit. What do you conclude?

In [266…

```
#correlation
df.corr(method='pearson')
```

Out[266…

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
PassengerId	1.000000	-0.005007	-0.035144	0.036847	-0.057527	-0.001652	0.012658
Survived	-0.005007	1.000000	-0.338481	-0.077221	-0.035322	0.081629	0.257307
Pclass	-0.035144	-0.338481	1.000000	-0.369226	0.083081	0.018443	-0.549500
Age	0.036847	-0.077221	-0.369226	1.000000	-0.308247	-0.189119	0.096067
SibSp	-0.057527	-0.035322	0.083081	-0.308247	1.000000	0.414838	0.159651

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
Parch	-0.001652	0.081629	0.018443	-0.189119	0.414838	1.000000	0.216225
Fare	0.012658	0.257307	-0.549500	0.096067	0.159651	0.216225	1.000000

In [267…

```
from sklearn.linear_model import LogisticRegression
```

In [268…

```
def standardize(raw_data):
    return ((raw_data - np.mean(raw_data, axis = 0)) / np.std(raw_data, axis = 0
```

In [269…

```
# since we are regressing on a binary variable, we will use logisitc regression
X1 = standardize(np.array(df[['Fare']]))
y1 = np.array(df['Survived'])
model1 = LogisticRegression(solver='liblinear', random_state=0)
model1.fit(X1, y1)
print("Coef_: ",model1.coef_)
print("Intercept_: ",model1.intercept_)


X2 = standardize(np.array(df[['Pclass']]))
model2 = LogisticRegression(solver='liblinear', random_state=0)
model2.fit(X2, y1)
print("Coef_: ",model2.coef_)
print("Intercept_: ",model2.intercept_)
```

```
Coef_:  [[0.7460968]]
Intercept_:  [-0.45033943]
Coef_:  [[-0.70634223]]
Intercept_:  [-0.51265842]
```

I chose to use logisitc regression, as we are predicting a binary variable. Our first regression tells us that increasing the Fare by 1 unit multiplies the odds of surviving by e^.746. Our second regression tells us that increasing Class by 1 unit multiplies the odds of surviving by e^-.706.

1.3 Preprocessing steps

Take whatever pre-processing steps you believe are necessary for each variable in the dataset (for example, these might include normalization, standardization, log transforms, dummy-encoding, or dropping a variable altogether). For now, you can ignore null values in the dataset --- we'll come back to those later. Create a table describing the preprocessing step for each variable. Make sure the variables are alphabetized and your table is well-organized.

In [270…

```
#Refactor Sex into a binary variable where male=1 female=0
sex_dict = {"female":0 ,"male":1}
df['Sex'] = df['Sex'].replace(sex_dict)
df['Sex'] = pd.to_numeric(df['Sex'])
#One-hot encoding for port of embark
df.loc[df['Embarked'] == 'S', 'Embarked_S'] = 1
df.loc[df['Embarked'] != 'S', 'Embarked_S'] = 0
df.loc[df['Embarked'] == 'C', 'Embarked_C'] = 1
df.loc[df['Embarked'] != 'C', 'Embarked_C'] = 0
df.loc[df['Embarked'] == 'Q', 'Embarked_Q'] = 1
```

```
df.loc[df['Embarked'] != 'Q', 'Embarked_Q'] = 0

df_ = df.drop(['Embarked','Sex','PassengerId','Name','Ticket','Cabin'], axis=1)
df_ = df_.dropna()
```

Part 2: Decision Trees

2.1 Decision Tree

Using the basic Decision Tree Classifier in sklearn, fit a model to predict titanic survival, using 10-fold cross-validation. For this and the following problems, you should set aside some (20%) of your training data as held-out test data, prior to cross-validation.

Begin by using the default hyperparameters, and report the average training and cross-validated accuracy across the 10 folds. Then, fit a single decision tree model on all of the training data (i.e., no cross-validation in this particular step), and report the performance of this fitted model on the held-out test data -- how does it compare to the cross-validated accuracy? Finally, show a diagram of this tree (at least the first three levels of splits), and provide a couple sentences interpreting the tree diagram.

NOTE - You may drop columns with null values for now; we'll come back to those columns later in the problem set.

In [271…

```
print(df_.columns)
```

```
Index(['Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'Embarked_S',
       'Embarked_C', 'Embarked_Q'],
      dtype='object')
```

In [272…

```
from sklearn.model_selection import train_test_split
from sklearn import tree

# splitting data into train/test sets
training_data, testing_data = train_test_split(df_, test_size=0.2, random_state=
X_train = training_data[['Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'Embarked_S'
       'Embarked_C', 'Embarked_Q']]
Y_train = training_data['Survived']
X_test = testing_data[['Pclass', 'Age', 'SibSp', 'Parch', 'Fare', 'Embarked_S',
       'Embarked_C', 'Embarked_Q']]
Y_test = testing_data['Survived']
```

In [273…

```
from sklearn.model_selection import KFold

#default model cross-val
kf = KFold(n_splits=10, random_state=0, shuffle=True)
clf = sklearn.tree.DecisionTreeClassifier(random_state=0)

train_scores = []
test_scores = []

for train_index, test_index in kf.split(X_train):
```

```
    x_train , x_test = np.array(X_train)[train_index],np.array(X_train)[test_ind
    y_train , y_test = np.array(Y_train)[train_index] , np.array(Y_train)[test_i
    model = clf.fit(x_train,y_train)
    yhat_train = model.predict(x_train)
    yhat_test = model.predict(x_test)


    train_scores.append(accuracy_score(y_train, yhat_train))
    test_scores.append(accuracy_score(y_test, yhat_test))

print(np.mean(train_scores))
print(np.mean(test_scores))
```

```
0.9803460228608702
0.6410768300060496
```

In [274…

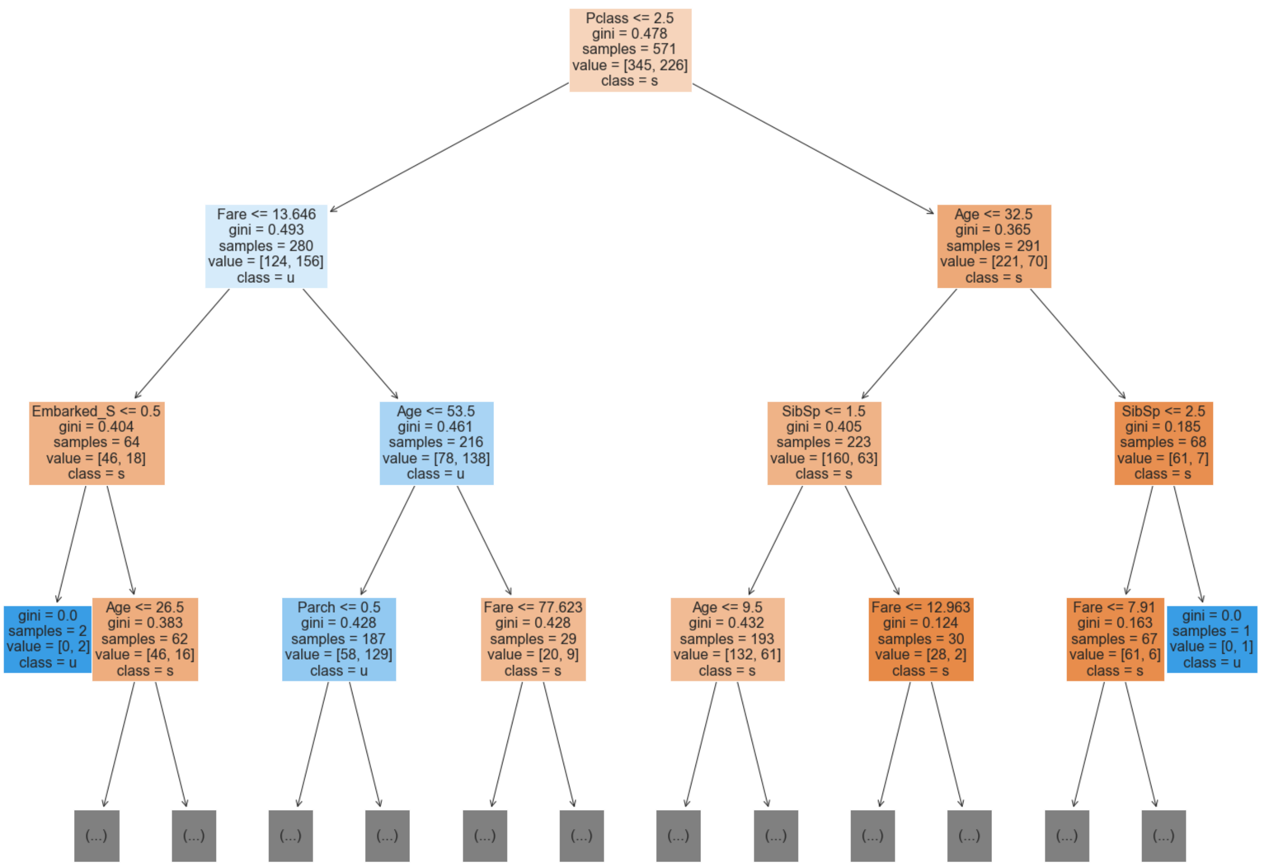
```
# fitting a single decision tree model on all of the training data
model2 = clf.fit(X_train,Y_train)
pred_train = model2.predict(X_train)
pred_test = model2.predict(X_test)
# report the performance of this fitted model on the held-out test data
score_train = accuracy_score(Y_train,pred_train)
score_test = accuracy_score(Y_test, pred_test)
print(score_train)
print(score_test)

# plotting
fig = plt.figure(figsize=(25,20))
tree.plot_tree(model2,
                   feature_names = ['Pclass', 'Age', 'SibSp', 'Parch', 'Fare', '
       'Embarked_C', 'Embarked_Q'],
                   class_names= 'survived',
                   max_depth = 3,
                   filled=True,
                   fontsize=16)
```

```
0.978984238178634
0.6363636363636364
```

Out[274…

```
[Text(0.5, 0.9, 'Pclass <= 2.5\ngini = 0.478\nsamples = 571\nvalue = [345, 226]
\nclass = s'),
 Text(0.21153846153846154, 0.7, 'Fare <= 13.646\ngini = 0.493\nsamples = 280\nva
lue = [124, 156]\nclass = u'),
 Text(0.07692307692307693, 0.5, 'Embarked_S <= 0.5\ngini = 0.404\nsamples = 64\n
value = [46, 18]\nclass = s'),
 Text(0.038461538461538464, 0.3, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]\nclass
= u'),
 Text(0.11538461538461539, 0.3, 'Age <= 26.5\ngini = 0.383\nsamples = 62\nvalue
= [46, 16]\nclass = s'),
 Text(0.07692307692307693, 0.1, '\n  (...)  \n'),
 Text(0.15384615384615385, 0.1, '\n  (...)  \n'),
 Text(0.34615384615384615, 0.5, 'Age <= 53.5\ngini = 0.461\nsamples = 216\nvalue
= [78, 138]\nclass = u'),
 Text(0.2692307692307692, 0.3, 'Parch <= 0.5\ngini = 0.428\nsamples = 187\nvalue
= [58, 129]\nclass = u'),
 Text(0.23076923076923078, 0.1, '\n  (...)  \n'),
 Text(0.3076923076923077, 0.1, '\n  (...)  \n'),
 Text(0.4230769230769231, 0.3, 'Fare <= 77.623\ngini = 0.428\nsamples = 29\nvalu
e = [20, 9]\nclass = s'),
 Text(0.38461538461538464, 0.1, '\n  (...)  \n'),
 Text(0.46153846153846156, 0.1, '\n  (...)  \n'),
 Text(0.7884615384615384, 0.7, 'Age <= 32.5\ngini = 0.365\nsamples = 291\nvalue
```

```
= [221, 70]\nclass = s'),
 Text(0.6538461538461539, 0.5, 'SibSp <= 1.5\ngini = 0.405\nsamples = 223\nvalue
= [160, 63]\nclass = s'),
 Text(0.5769230769230769, 0.3, 'Age <= 9.5\ngini = 0.432\nsamples = 193\nvalue =
[132, 61]\nclass = s'),
 Text(0.5384615384615384, 0.1, '\n  (...)  \n'),
 Text(0.6153846153846154, 0.1, '\n  (...)  \n'),
 Text(0.7307692307692307, 0.3, 'Fare <= 12.963\ngini = 0.124\nsamples = 30\nvalu
e = [28, 2]\nclass = s'),
 Text(0.6923076923076923, 0.1, '\n  (...)  \n'),
 Text(0.7692307692307693, 0.1, '\n  (...)  \n'),
 Text(0.9230769230769231, 0.5, 'SibSp <= 2.5\ngini = 0.185\nsamples = 68\nvalue
= [61, 7]\nclass = s'),
 Text(0.8846153846153846, 0.3, 'Fare <= 7.91\ngini = 0.163\nsamples = 67\nvalue
= [61, 6]\nclass = s'),
 Text(0.8461538461538461, 0.1, '\n  (...)  \n'),
 Text(0.9230769230769231, 0.1, '\n  (...)  \n'),
 Text(0.9615384615384616, 0.3, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]\nclass =
u')]
```



Average Training Accuracy: 0.9803460228608702 Average Test Acccuracy (cross-validated accuracy): 0.6410768300060496 Fitted Tree Test Accuracy: 0.6363636363636364

We can see that the fitted tree run on all the data performs slighly worse than the cross validated test accuracy.

Based on our tree diagram, we can see that this model first splits our data by class, which was the most negatively correlated value we found above. For the group where class is <= 2.5, our data is then split by Fare, the next highest correlation. For our data where class is greater than 2.5, our data is split by age, then by the amount of siblings/spouses.

2.2 Hyperparameter: Maximum Depth

Use all of the data (minus the held-out data) to re-fit a single decision tree with `max_depth = 4` (i.e., no cross-validation). Show the tree diagram and also plot the feature importance. What do you observe? How does the performance of this tree compare to the tree from 2.1?

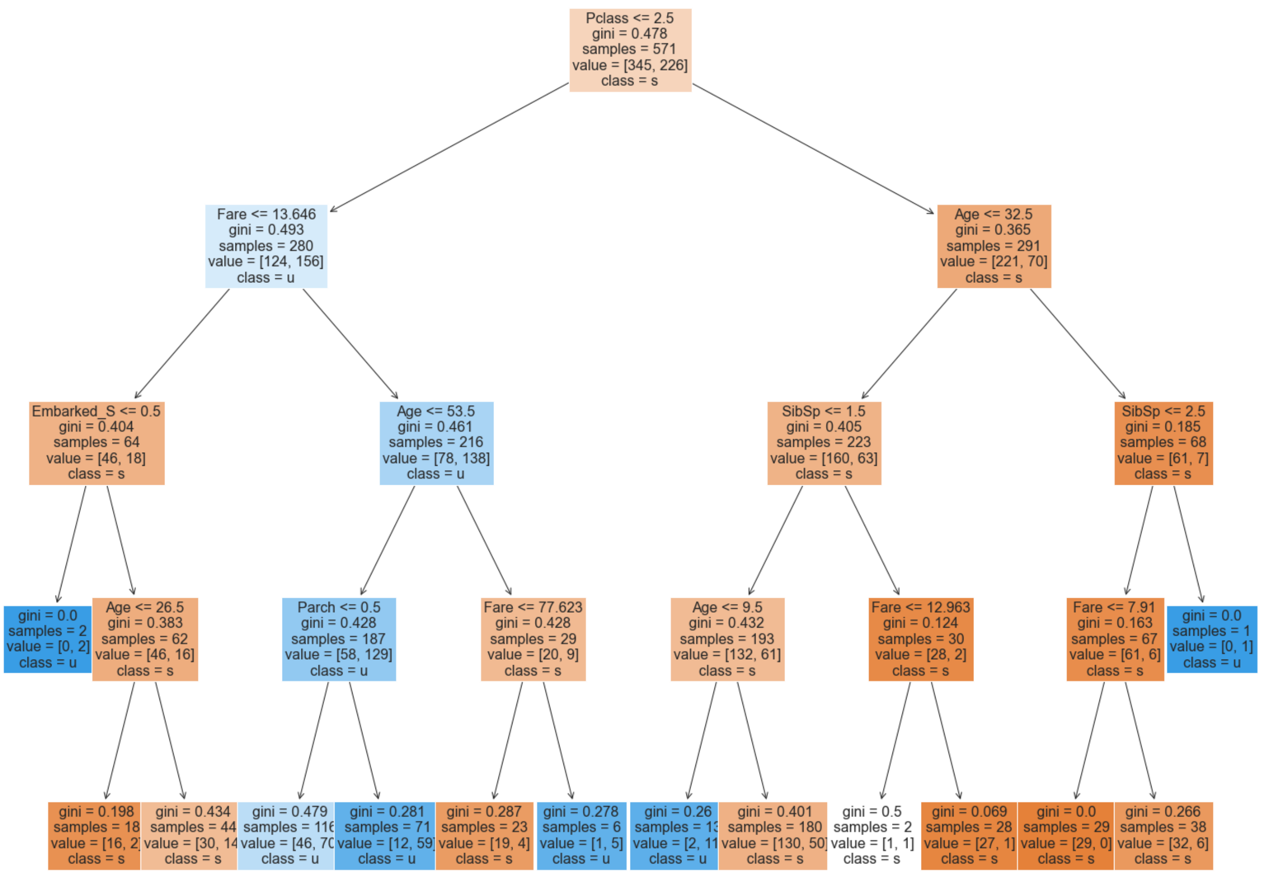
In [275…

```
# refit a single decision tree with max_depth = 4 with all data (minus held-out
clf2 = sklearn.tree.DecisionTreeClassifier(random_state=0, max_depth=4)

model3 = clf2.fit(X_train,Y_train)
pred2 = model3.predict(X_train)

# tree diagram
fig = plt.figure(figsize=(25,20))
tree.plot_tree(model3,
                    feature_names = X_train.columns,
                    class_names= 'survived',
                    max_depth = 4,
                    filled=True,
                    fontsize=16)
```

Out[275…

```
[Text(0.5, 0.9, 'Pclass <= 2.5\ngini = 0.478\nsamples = 571\nvalue = [345, 226]
\nclass = s'),
 Text(0.21153846153846154, 0.7, 'Fare <= 13.646\ngini = 0.493\nsamples = 280\nva
lue = [124, 156]\nclass = u'),
 Text(0.07692307692307693, 0.5, 'Embarked_S <= 0.5\ngini = 0.404\nsamples = 64\n
value = [46, 18]\nclass = s'),
 Text(0.038461538461538464, 0.3, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]\nclass
= u'),
 Text(0.11538461538461539, 0.3, 'Age <= 26.5\ngini = 0.383\nsamples = 62\nvalue
= [46, 16]\nclass = s'),
 Text(0.07692307692307693, 0.1, 'gini = 0.198\nsamples = 18\nvalue = [16, 2]\ncl
ass = s'),
 Text(0.15384615384615385, 0.1, 'gini = 0.434\nsamples = 44\nvalue = [30, 14]\nc
lass = s'),
 Text(0.34615384615384615, 0.5, 'Age <= 53.5\ngini = 0.461\nsamples = 216\nvalue
= [78, 138]\nclass = u'),
 Text(0.2692307692307692, 0.3, 'Parch <= 0.5\ngini = 0.428\nsamples = 187\nvalue
= [58, 129]\nclass = u'),
 Text(0.23076923076923078, 0.1, 'gini = 0.479\nsamples = 116\nvalue = [46, 70]\n
class = u'),
 Text(0.3076923076923077, 0.1, 'gini = 0.281\nsamples = 71\nvalue = [12, 59]\ncl
ass = u'),
 Text(0.4230769230769231, 0.3, 'Fare <= 77.623\ngini = 0.428\nsamples = 29\nvalu
e = [20, 9]\nclass = s'),
 Text(0.38461538461538464, 0.1, 'gini = 0.287\nsamples = 23\nvalue = [19, 4]\ncl
ass = s'),
 Text(0.46153846153846156, 0.1, 'gini = 0.278\nsamples = 6\nvalue = [1, 5]\nclas
s = u'),
 Text(0.7884615384615384, 0.7, 'Age <= 32.5\ngini = 0.365\nsamples = 291\nvalue
= [221, 70]\nclass = s'),
 Text(0.6538461538461539, 0.5, 'SibSp <= 1.5\ngini = 0.405\nsamples = 223\nvalue
= [160, 63]\nclass = s'),
 Text(0.5769230769230769, 0.3, 'Age <= 9.5\ngini = 0.432\nsamples = 193\nvalue =
[132, 61]\nclass = s'),
 Text(0.5384615384615384, 0.1, 'gini = 0.26\nsamples = 13\nvalue = [2, 11]\nclas
```

```
s = u'),
 Text(0.6153846153846154, 0.1, 'gini = 0.401\nsamples = 180\nvalue = [130, 50]\n
class = s'),
 Text(0.7307692307692307, 0.3, 'Fare <= 12.963\ngini = 0.124\nsamples = 30\nvalu
e = [28, 2]\nclass = s'),
 Text(0.6923076923076923, 0.1, 'gini = 0.5\nsamples = 2\nvalue = [1, 1]\nclass =
s'),
 Text(0.7692307692307693, 0.1, 'gini = 0.069\nsamples = 28\nvalue = [27, 1]\ncla
ss = s'),
 Text(0.9230769230769231, 0.5, 'SibSp <= 2.5\ngini = 0.185\nsamples = 68\nvalue
= [61, 7]\nclass = s'),
 Text(0.8846153846153846, 0.3, 'Fare <= 7.91\ngini = 0.163\nsamples = 67\nvalue
= [61, 6]\nclass = s'),
 Text(0.8461538461538461, 0.1, 'gini = 0.0\nsamples = 29\nvalue = [29, 0]\nclass
= s'),
 Text(0.9230769230769231, 0.1, 'gini = 0.266\nsamples = 38\nvalue = [32, 6]\ncla
ss = s'),
 Text(0.9615384615384616, 0.3, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]\nclass =
u')]
```



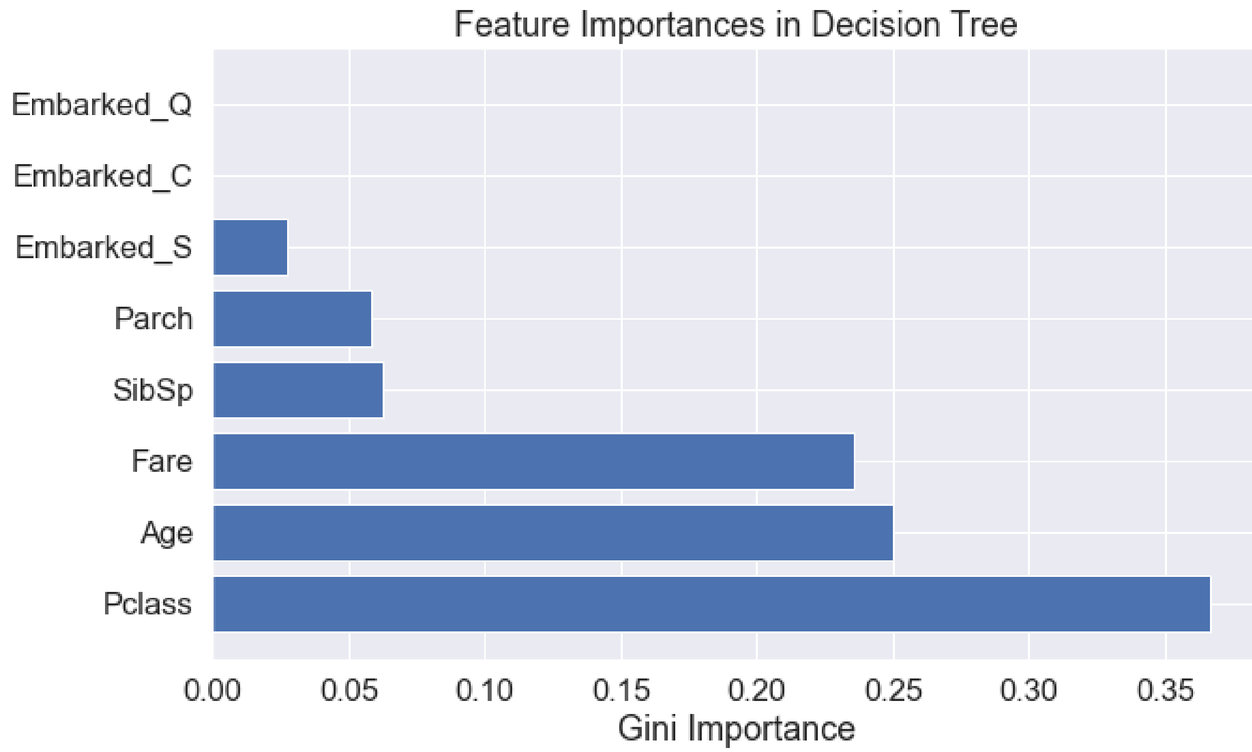
We can see that in this tree, our features are split in the same pattern as the previous tree, in line with our correlation analysis.

In [116…

```
# feature importance
importances = model3.feature_importances_
importances = pd.DataFrame([X_train.columns, importances]).T
importances.columns = ['Feature', 'Importance']
importances = importances.sort_values('Importance', ascending=False)[:10]
```

In [117…

```
# Bar chart
fig, ax = plt.subplots(1, figsize=(10, 6))
plt.barh(importances['Feature'], importances['Importance'])
ax.set_xlabel('Gini Importance')
ax.set_title('Feature Importances in Decision Tree')
plt.show()
```



It appears that the most important feature for our tree is Pclass, followed by Age, and then Fare.

2.3 Tuning Hyperparameters

The built-in algorithm you are using has several parameters which you can tune. Using cross-validation, show how the choice of these parameters affects performance.

First, show how `max_depth` affects train and cross-validated accuracy. On a single axis, plot train and cross-validated accuracy as a function of `max_depth` . Use a red line to show cross-validated accuracy and a blue line to show train accuracy. Do not use your held-out test data yet.

Second, show how cross-validated accuracy relates to both `max_depth` and `min_samples_leaf` . Specifically, create a 3-D plot where the x-axis is `max_depth` , the y-axis is `min_samples_leaf` , and the z-axis shows cross-validated accuracy. What combination of `max_depth` and `min-samples_leaf` achieves the highest accuracy? How sensitive are the results to these two parameters?

Finally, select the the best hyperparameters that you got through cross-validation, and fit a single decision tree on all of the training data using those hyperparameters. Display this tree and report the accuracy of this tree on the held-out data.

In [281…

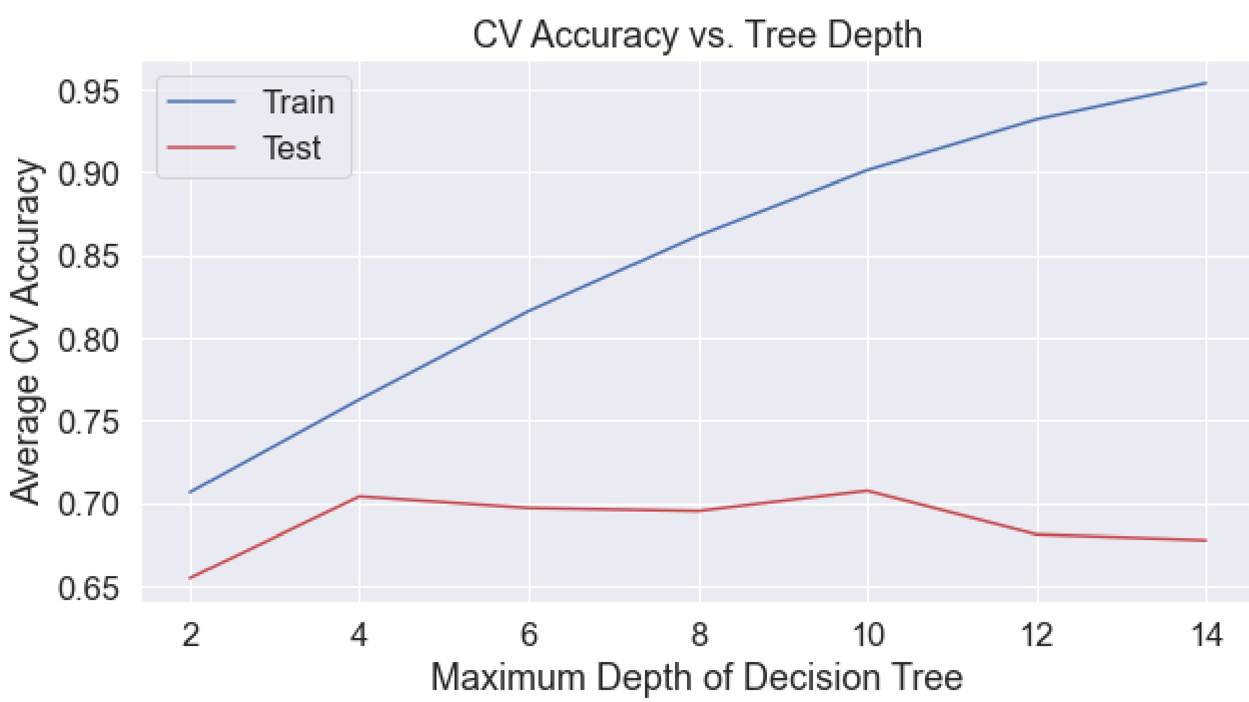
```
# tuning max depth with cross-val
cv = KFold(n_splits=3, shuffle=True, random_state=1)
params = {'max_depth':[2, 4, 6, 8, 10, 12, 14]}
cv_model = GridSearchCV(model, param_grid=params, scoring='accuracy', refit=True
cv_model.fit(X_train, Y_train)
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.head()
```

Out[281…

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param
0	0.003489	0.001566	0.001542	0.000591	2	{'max_depth
1	0.002125	0.000089	0.001145	0.000128	4	{'max_depth
2	0.001693	0.000078	0.000858	0.000032	6	{'max_depth
3	0.001830	0.000023	0.000928	0.000037	8	{'max_depth
4	0.001860	0.000034	0.000899	0.000032	10	{'max_depth 1(

In [282…

```
# Plot CV accuracy as a function of maximum depth
sns.set(font_scale=1.5)
fig, ax = plt.subplots(1, figsize=(10, 5))
ax.plot(cv_results['param_max_depth'], cv_results['mean_train_score'], label='Tr
ax.plot(cv_results['param_max_depth'], cv_results['mean_test_score'], label='Tes
ax.set_xlabel('Maximum Depth of Decision Tree')
ax.set_ylabel('Average CV Accuracy')
ax.set_title('CV Accuracy vs. Tree Depth')
ax.legend(loc='best')
plt.show()
```



Second, show how cross-validated accuracy relates to both `max_depth` and `min_samples_leaf` . Specifically, create a 3-D plot where the x-axis is `max_depth` , the y-axis is `min_samples_leaf` , and the z-axis shows cross-validated accuracy. What combination of `max_depth` and `min−samples_leaf` achieves the highest accuracy? How sensitive are the results to these two parameters?

Finally, select the the best hyperparameters that you got through cross-validation, and fit a single decision tree on all of the training data using those hyperparameters. Display this tree and report the accuracy of this tree on the held-out data.

In [283…

```
# tuning max depth and min samples leaf with cross-val
cv = KFold(n_splits=10, shuffle=True, random_state=1)
params = {'max_depth':[2, 4, 6, 8, 10, 12, 14], 'min_samples_leaf':[1,2,3,4,5]}
cv_model = GridSearchCV(model, param_grid=params, scoring='accuracy', refit=True
cv_model.fit(X_train, Y_train)
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.head()
```

Out[283…

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_min_
0	0.002659	0.001312	0.001320	0.000519	2	
1	0.001382	0.000160	0.000780	0.000097	2	
2	0.001142	0.000018	0.000670	0.000038	2	
3	0.001123	0.000004	0.000648	0.000009	2	
4	0.001120	0.000007	0.000648	0.000006	2	

5 rows × 32 columns

In [284…

```
print(cv_model.best_params_)
```

```
{'max_depth': 8, 'min_samples_leaf': 1}
```

In [285…

```
print(cv_results[(cv_results.param_min_samples_leaf == 1) & (cv_results.param_ma
```

```
    mean_test_score
15         0.700484
```

In [291…

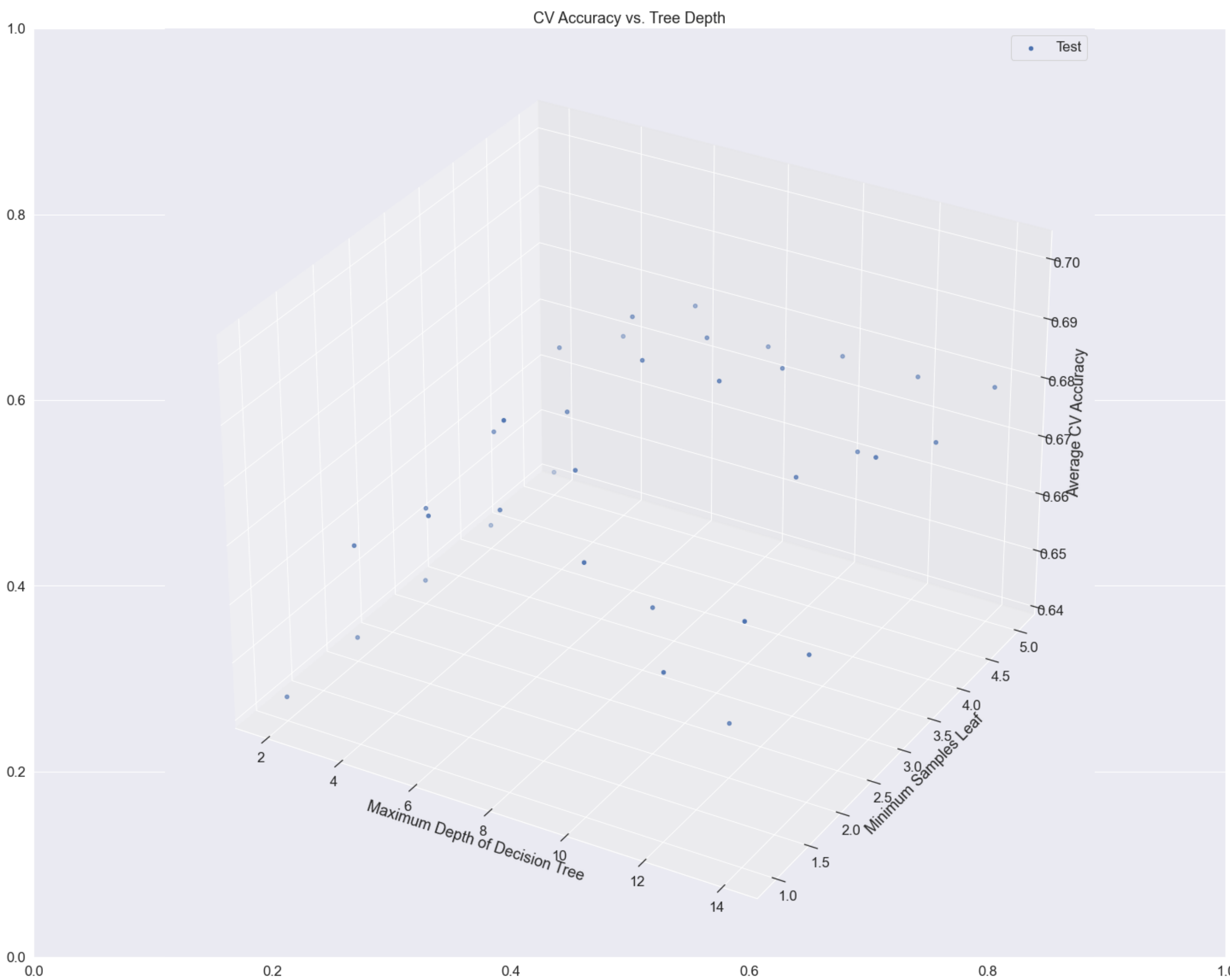
```
print('Min accuracy: ' + str(min(cv_results['mean_test_score'])))
print('Max accuracy: ' + str(max(cv_results['mean_test_score'])))
```

```
Min accuracy: 0.6428614640048397
Max accuracy: 0.7004839685420448
```

The best parameters we found through cross validation for this model are max_depth: 8 and min_samples_leaf: 1. Looking at the range of accuracies, we can see that our range is large enough to determine that our accuracy is sensitive to our parameters.

In [92]:

```
# 3D plot
sns.set(font_scale=1.5)
fig, ax = plt.subplots(1, figsize=(25, 20))
ax = plt.axes(projection='3d')
ax.scatter3D(cv_results['param_max_depth'], cv_results['param_min_samples_leaf']
ax.set_xlabel('Maximum Depth of Decision Tree')
ax.set_ylabel('Minimum Samples Leaf')
ax.set_zlabel('Average CV Accuracy')
ax.set_title('CV Accuracy vs. Tree Depth')
ax.legend(loc='best')
plt.show()
```



In [124…

```
# fitting model with best paramaters
model = cv_model.best_estimator_
model.fit(X_train, Y_train)
yhat = model.predict(X_test)
yhat_train = model.predict(X_train)

print('Best maximum depth: %i' % cv_model.best_params_['max_depth'])
print('Best min samples leaf: %i' % cv_model.best_params_['min_samples_leaf'])
```

```
print('Accuracy (train): %.2f' % accuracy_score(Y_train, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test, yhat))

print('Precision: %.2f' % recall_score(Y_test, yhat))


print('Recall: %.2f' % precision_score(Y_test, yhat))
```

```
Best maximum depth: 8
Best min samples leaf: 1
Accuracy (train): 0.85
Accuracy (test): 0.65
Precision: 0.58
Recall: 0.62
```

In [125…

```
# plotting
fig = plt.figure(figsize=(25,20))
tree.plot_tree(model,
                   feature_names = X_train.columns,
                   class_names= 'survived',
                   filled=True,
                   fontsize=16)
```

Out[125…

```
[Text(0.55859375, 0.9444444444444444, 'Pclass <= 2.5\ngini = 0.478\nsamples = 57
1\nvalue = [345, 226]\nclass = s'),
 Text(0.25390625, 0.8333333333333334, 'Fare <= 13.646\ngini = 0.493\nsamples = 2
80\nvalue = [124, 156]\nclass = u'),
 Text(0.0625, 0.7222222222222222, 'Embarked_S <= 0.5\ngini = 0.404\nsamples = 64
\nvalue = [46, 18]\nclass = s'),
 Text(0.05113636363636364, 0.6111111111111112, 'gini = 0.0\nsamples = 2\nvalue =
[0, 2]\nclass = u'),
 Text(0.07386363636363637, 0.6111111111111112, 'Age <= 26.5\ngini = 0.383\nsampl
es = 62\nvalue = [46, 16]\nclass = s'),
 Text(0.045454545454545456, 0.5, 'Fare <= 11.0\ngini = 0.198\nsamples = 18\nvalu
e = [16, 2]\nclass = s'),
 Text(0.03409090909090909, 0.3888888888888889, 'Age <= 22.0\ngini = 0.408\nsampl
es = 7\nvalue = [5, 2]\nclass = s'),
 Text(0.022727272727272728, 0.2777777777777778, 'Age <= 17.5\ngini = 0.5\nsample
s = 4\nvalue = [2, 2]\nclass = s'),
 Text(0.011363636363636364, 0.16666666666666666, 'gini = 0.0\nsamples = 1\nvalue
= [1, 0]\nclass = s'),
 Text(0.03409090909090909, 0.16666666666666666, 'Age <= 20.0\ngini = 0.444\nsamp
les = 3\nvalue = [1, 2]\nclass = u'),
 Text(0.022727272727272728, 0.05555555555555555, 'gini = 0.5\nsamples = 2\nvalue
= [1, 1]\nclass = s'),
 Text(0.045454545454545456, 0.05555555555555555, 'gini = 0.0\nsamples = 1\nvalue
= [0, 1]\nclass = u'),
 Text(0.045454545454545456, 0.2777777777777778, 'gini = 0.0\nsamples = 3\nvalue
= [3, 0]\nclass = s'),
 Text(0.056818181818181816, 0.3888888888888889, 'gini = 0.0\nsamples = 11\nvalue
= [11, 0]\nclass = s'),
 Text(0.10227272727272728, 0.5, 'Age <= 50.5\ngini = 0.434\nsamples = 44\nvalue
= [30, 14]\nclass = s'),
 Text(0.09090909090909091, 0.3888888888888889, 'Fare <= 7.75\ngini = 0.465\nsamp
les = 38\nvalue = [24, 14]\nclass = s'),
 Text(0.07954545454545454, 0.2777777777777778, 'gini = 0.0\nsamples = 3\nvalue =
[3, 0]\nclass = s'),
 Text(0.10227272727272728, 0.2777777777777778, 'Age <= 40.5\ngini = 0.48\nsample
s = 35\nvalue = [21, 14]\nclass = s'),
 Text(0.07954545454545454, 0.16666666666666666, 'Age <= 37.0\ngini = 0.459\nsamp
les = 28\nvalue = [18, 10]\nclass = s'),
 Text(0.06818181818181818, 0.05555555555555555, 'gini = 0.473\nsamples = 26\nval
```

```
ue = [16, 10]\nclass = s'),
 Text(0.09090909090909091, 0.05555555555555555, 'gini = 0.0\nsamples = 2\nvalue
= [2, 0]\nclass = s'),
 Text(0.125, 0.16666666666666666, 'Fare <= 11.75\ngini = 0.49\nsamples = 7\nvalu
e = [3, 4]\nclass = u'),
 Text(0.11363636363636363, 0.05555555555555555, 'gini = 0.0\nsamples = 2\nvalue
= [0, 2]\nclass = u'),
 Text(0.13636363636363635, 0.05555555555555555, 'gini = 0.48\nsamples = 5\nvalue
= [3, 2]\nclass = s'),
 Text(0.11363636363636363, 0.3888888888888889, 'gini = 0.0\nsamples = 6\nvalue =
[6, 0]\nclass = s'),
 Text(0.4453125, 0.7222222222222222, 'Age <= 53.5\ngini = 0.461\nsamples = 216\n
value = [78, 138]\nclass = u'),
 Text(0.34517045454545453, 0.6111111111111112, 'Parch <= 0.5\ngini = 0.428\nsamp
les = 187\nvalue = [58, 129]\nclass = u'),
 Text(0.2869318181818182, 0.5, 'Pclass <= 1.5\ngini = 0.479\nsamples = 116\nvalu
e = [46, 70]\nclass = u'),
 Text(0.23295454545454544, 0.3888888888888889, 'Fare <= 84.987\ngini = 0.417\nsa
mples = 81\nvalue = [24, 57]\nclass = u'),
 Text(0.19318181818181818, 0.2777777777777778, 'Age <= 47.5\ngini = 0.462\nsampl
es = 58\nvalue = [21, 37]\nclass = u'),
 Text(0.17045454545454544, 0.16666666666666666, 'Age <= 44.5\ngini = 0.491\nsamp
les = 46\nvalue = [20, 26]\nclass = u'),
 Text(0.1590909090909091, 0.05555555555555555, 'gini = 0.438\nsamples = 37\nvalu
e = [12, 25]\nclass = u'),
 Text(0.18181818181818182, 0.05555555555555555, 'gini = 0.198\nsamples = 9\nvalu
e = [8, 1]\nclass = s'),
 Text(0.2159090909090909, 0.16666666666666666, 'Fare <= 53.95\ngini = 0.153\nsam
ples = 12\nvalue = [1, 11]\nclass = u'),
 Text(0.20454545454545456, 0.05555555555555555, 'gini = 0.0\nsamples = 8\nvalue
= [0, 8]\nclass = u'),
 Text(0.22727272727272727, 0.05555555555555555, 'gini = 0.375\nsamples = 4\nvalu
e = [1, 3]\nclass = u'),
 Text(0.2727272727272727, 0.2777777777777778, 'Embarked_Q <= 0.5\ngini = 0.227\n
samples = 23\nvalue = [3, 20]\nclass = u'),
 Text(0.26136363636363635, 0.16666666666666666, 'Age <= 22.5\ngini = 0.165\nsamp
les = 22\nvalue = [2, 20]\nclass = u'),
 Text(0.25, 0.05555555555555555, 'gini = 0.48\nsamples = 5\nvalue = [2, 3]\nclas
s = u'),
 Text(0.2727272727272727, 0.05555555555555555, 'gini = 0.0\nsamples = 17\nvalue
= [0, 17]\nclass = u'),
 Text(0.2840909090909091, 0.16666666666666666, 'gini = 0.0\nsamples = 1\nvalue =
[1, 0]\nclass = s'),
 Text(0.3409090909090909, 0.3888888888888889, 'Fare <= 26.5\ngini = 0.467\nsampl
es = 35\nvalue = [22, 13]\nclass = s'),
 Text(0.32954545454545453, 0.2777777777777778, 'Age <= 33.0\ngini = 0.495\nsampl
es = 29\nvalue = [16, 13]\nclass = s'),
 Text(0.3068181818181818, 0.16666666666666666, 'Age <= 17.5\ngini = 0.469\nsampl
es = 16\nvalue = [6, 10]\nclass = u'),
 Text(0.29545454545454547, 0.05555555555555555, 'gini = 0.0\nsamples = 1\nvalue
= [1, 0]\nclass = s'),
 Text(0.3181818181818182, 0.05555555555555555, 'gini = 0.444\nsamples = 15\nvalu
e = [5, 10]\nclass = u'),
 Text(0.3522727272727273, 0.16666666666666666, 'Age <= 43.0\ngini = 0.355\nsampl
es = 13\nvalue = [10, 3]\nclass = s'),
 Text(0.3409090909090909, 0.05555555555555555, 'gini = 0.444\nsamples = 9\nvalue
= [6, 3]\nclass = s'),
 Text(0.36363636363636365, 0.05555555555555555, 'gini = 0.0\nsamples = 4\nvalue
= [4, 0]\nclass = s'),
 Text(0.3522727272727273, 0.2777777777777778, 'gini = 0.0\nsamples = 6\nvalue =
[6, 0]\nclass = s'),
 Text(0.4034090909090909, 0.5, 'Age <= 18.5\ngini = 0.281\nsamples = 71\nvalue =
[12, 59]\nclass = u'),
 Text(0.39204545454545453, 0.3888888888888889, 'gini = 0.0\nsamples = 26\nvalue
= [0, 26]\nclass = u'),
```

```
 Text(0.4147727272727273, 0.3888888888888889, 'Age <= 20.0\ngini = 0.391\nsample
s = 45\nvalue = [12, 33]\nclass = u'),
 Text(0.38636363636363635, 0.2777777777777778, 'Fare <= 31.517\ngini = 0.444\nsa
mples = 3\nvalue = [2, 1]\nclass = s'),
 Text(0.375, 0.16666666666666666, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]\nclas
s = u'),
 Text(0.3977272727272727, 0.16666666666666666, 'gini = 0.0\nsamples = 2\nvalue =
[2, 0]\nclass = s'),
 Text(0.4431818181818182, 0.2777777777777778, 'Embarked_C <= 0.5\ngini = 0.363\n
samples = 42\nvalue = [10, 32]\nclass = u'),
 Text(0.42045454545454547, 0.16666666666666666, 'Age <= 24.5\ngini = 0.252\nsamp
les = 27\nvalue = [4, 23]\nclass = u'),
 Text(0.4090909090909091, 0.05555555555555555, 'gini = 0.0\nsamples = 7\nvalue =
[0, 7]\nclass = u'),
 Text(0.4318181818181818, 0.05555555555555555, 'gini = 0.32\nsamples = 20\nvalue
= [4, 16]\nclass = u'),
 Text(0.4659090909090909, 0.16666666666666666, 'Fare <= 39.292\ngini = 0.48\nsam
ples = 15\nvalue = [6, 9]\nclass = u'),
 Text(0.45454545454545453, 0.05555555555555555, 'gini = 0.0\nsamples = 2\nvalue
= [2, 0]\nclass = s'),
 Text(0.4772727272727273, 0.05555555555555555, 'gini = 0.426\nsamples = 13\nvalu
e = [4, 9]\nclass = u'),
 Text(0.5454545454545454, 0.6111111111111112, 'Fare <= 77.623\ngini = 0.428\nsam
ples = 29\nvalue = [20, 9]\nclass = s'),
 Text(0.5227272727272727, 0.5, 'Age <= 75.5\ngini = 0.287\nsamples = 23\nvalue =
[19, 4]\nclass = s'),
 Text(0.5113636363636364, 0.3888888888888889, 'Parch <= 2.0\ngini = 0.236\nsampl
es = 22\nvalue = [19, 3]\nclass = s'),
 Text(0.5, 0.2777777777777778, 'Embarked_C <= 0.5\ngini = 0.172\nsamples = 21\nv
alue = [19, 2]\nclass = s'),
 Text(0.48863636363636365, 0.16666666666666666, 'gini = 0.0\nsamples = 15\nvalue
= [15, 0]\nclass = s'),
 Text(0.5113636363636364, 0.16666666666666666, 'Fare <= 35.077\ngini = 0.444\nsa
mples = 6\nvalue = [4, 2]\nclass = s'),
 Text(0.5, 0.05555555555555555, 'gini = 0.0\nsamples = 3\nvalue = [3, 0]\nclass
= s'),
 Text(0.5227272727272727, 0.05555555555555555, 'gini = 0.444\nsamples = 3\nvalue
= [1, 2]\nclass = u'),
 Text(0.5227272727272727, 0.2777777777777778, 'gini = 0.0\nsamples = 1\nvalue =
[0, 1]\nclass = u'),
 Text(0.5340909090909091, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue =
[0, 1]\nclass = u'),
 Text(0.5681818181818182, 0.5, 'Parch <= 1.5\ngini = 0.278\nsamples = 6\nvalue =
[1, 5]\nclass = u'),
 Text(0.5568181818181818, 0.3888888888888889, 'gini = 0.0\nsamples = 5\nvalue =
[0, 5]\nclass = u'),
 Text(0.5795454545454546, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue =
[1, 0]\nclass = s'),
 Text(0.86328125, 0.8333333333333334, 'Age <= 32.5\ngini = 0.365\nsamples = 291
\nvalue = [221, 70]\nclass = s'),
 Text(0.7720170454545454, 0.7222222222222222, 'SibSp <= 1.5\ngini = 0.405\nsampl
es = 223\nvalue = [160, 63]\nclass = s'),
 Text(0.6803977272727273, 0.6111111111111112, 'Age <= 9.5\ngini = 0.432\nsamples
= 193\nvalue = [132, 61]\nclass = s'),
 Text(0.6136363636363636, 0.5, 'Fare <= 10.798\ngini = 0.26\nsamples = 13\nvalue
= [2, 11]\nclass = u'),
 Text(0.6022727272727273, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue =
[1, 0]\nclass = s'),
 Text(0.625, 0.3888888888888889, 'Embarked_C <= 0.5\ngini = 0.153\nsamples = 12
\nvalue = [1, 11]\nclass = u'),
 Text(0.6136363636363636, 0.2777777777777778, 'gini = 0.0\nsamples = 10\nvalue =
[0, 10]\nclass = u'),
 Text(0.6363636363636364, 0.2777777777777778, 'Fare <= 15.494\ngini = 0.5\nsampl
es = 2\nvalue = [1, 1]\nclass = s'),
 Text(0.625, 0.16666666666666666, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]\nclas
```

```
s = s'),
 Text(0.6477272727272727, 0.16666666666666666, 'gini = 0.0\nsamples = 1\nvalue =
[0, 1]\nclass = u'),
 Text(0.7471590909090909, 0.5, 'Embarked_S <= 0.5\ngini = 0.401\nsamples = 180\n
value = [130, 50]\nclass = s'),
 Text(0.6931818181818182, 0.3888888888888889, 'Age <= 29.5\ngini = 0.498\nsample
s = 36\nvalue = [19, 17]\nclass = s'),
 Text(0.6818181818181818, 0.2777777777777778, 'Fare <= 6.987\ngini = 0.495\nsamp
les = 31\nvalue = [14, 17]\nclass = u'),
 Text(0.6704545454545454, 0.16666666666666666, 'gini = 0.0\nsamples = 3\nvalue =
[3, 0]\nclass = s'),
 Text(0.6931818181818182, 0.16666666666666666, 'Age <= 28.75\ngini = 0.477\nsamp
les = 28\nvalue = [11, 17]\nclass = u'),
 Text(0.6818181818181818, 0.05555555555555555, 'gini = 0.493\nsamples = 25\nvalu
e = [11, 14]\nclass = u'),
 Text(0.7045454545454546, 0.05555555555555555, 'gini = 0.0\nsamples = 3\nvalue =
[0, 3]\nclass = u'),
 Text(0.7045454545454546, 0.2777777777777778, 'gini = 0.0\nsamples = 5\nvalue =
[5, 0]\nclass = s'),
 Text(0.8011363636363636, 0.3888888888888889, 'Age <= 30.75\ngini = 0.353\nsampl
es = 144\nvalue = [111, 33]\nclass = s'),
 Text(0.7613636363636364, 0.2777777777777778, 'Age <= 24.75\ngini = 0.311\nsampl
es = 130\nvalue = [105, 25]\nclass = s'),
 Text(0.7386363636363636, 0.16666666666666666, 'Fare <= 8.175\ngini = 0.247\nsam
ples = 83\nvalue = [71, 12]\nclass = s'),
 Text(0.7272727272727273, 0.05555555555555555, 'gini = 0.324\nsamples = 54\nvalu
e = [43, 11]\nclass = s'),
 Text(0.75, 0.05555555555555555, 'gini = 0.067\nsamples = 29\nvalue = [28, 1]\nc
lass = s'),
 Text(0.7840909090909091, 0.16666666666666666, 'Fare <= 7.013\ngini = 0.4\nsampl
es = 47\nvalue = [34, 13]\nclass = s'),
 Text(0.7727272727272727, 0.05555555555555555, 'gini = 0.0\nsamples = 2\nvalue =
[0, 2]\nclass = u'),
 Text(0.7954545454545454, 0.05555555555555555, 'gini = 0.369\nsamples = 45\nvalu
e = [34, 11]\nclass = s'),
 Text(0.8409090909090909, 0.2777777777777778, 'Fare <= 19.262\ngini = 0.49\nsamp
les = 14\nvalue = [6, 8]\nclass = u'),
 Text(0.8295454545454546, 0.16666666666666666, 'SibSp <= 0.5\ngini = 0.496\nsamp
les = 11\nvalue = [6, 5]\nclass = s'),
 Text(0.8181818181818182, 0.05555555555555555, 'gini = 0.494\nsamples = 9\nvalue
= [4, 5]\nclass = u'),
 Text(0.8409090909090909, 0.05555555555555555, 'gini = 0.0\nsamples = 2\nvalue =
[2, 0]\nclass = s'),
 Text(0.8522727272727273, 0.16666666666666666, 'gini = 0.0\nsamples = 3\nvalue =
[0, 3]\nclass = u'),
 Text(0.8636363636363636, 0.6111111111111112, 'Fare <= 12.963\ngini = 0.124\nsam
ples = 30\nvalue = [28, 2]\nclass = s'),
 Text(0.8409090909090909, 0.5, 'Parch <= 1.0\ngini = 0.5\nsamples = 2\nvalue =
[1, 1]\nclass = s'),
 Text(0.8295454545454546, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue =
[1, 0]\nclass = s'),
 Text(0.8522727272727273, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue =
[0, 1]\nclass = u'),
 Text(0.8863636363636364, 0.5, 'Age <= 5.5\ngini = 0.069\nsamples = 28\nvalue =
[27, 1]\nclass = s'),
 Text(0.875, 0.3888888888888889, 'Age <= 4.5\ngini = 0.198\nsamples = 9\nvalue =
[8, 1]\nclass = s'),
 Text(0.8636363636363636, 0.2777777777777778, 'gini = 0.0\nsamples = 8\nvalue =
[8, 0]\nclass = s'),
 Text(0.8863636363636364, 0.2777777777777778, 'gini = 0.0\nsamples = 1\nvalue =
[0, 1]\nclass = u'),
 Text(0.8977272727272727, 0.3888888888888889, 'gini = 0.0\nsamples = 19\nvalue =
[19, 0]\nclass = s'),
 Text(0.9545454545454546, 0.7222222222222222, 'SibSp <= 2.5\ngini = 0.185\nsampl
es = 68\nvalue = [61, 7]\nclass = s'),
```

```
 Text(0.9431818181818182, 0.6111111111111112, 'Fare <= 7.91\ngini = 0.163\nsampl
es = 67\nvalue = [61, 6]\nclass = s'),
 Text(0.9318181818181818, 0.5, 'gini = 0.0\nsamples = 29\nvalue = [29, 0]\nclass
= s'),
 Text(0.9545454545454546, 0.5, 'Age <= 59.25\ngini = 0.266\nsamples = 38\nvalue
= [32, 6]\nclass = s'),
 Text(0.9431818181818182, 0.3888888888888889, 'Fare <= 7.988\ngini = 0.234\nsamp
les = 37\nvalue = [32, 5]\nclass = s'),
 Text(0.9090909090909091, 0.2777777777777778, 'Age <= 38.0\ngini = 0.5\nsamples
= 4\nvalue = [2, 2]\nclass = s'),
 Text(0.8977272727272727, 0.16666666666666666, 'gini = 0.0\nsamples = 1\nvalue =
[1, 0]\nclass = s'),
 Text(0.9204545454545454, 0.16666666666666666, 'Age <= 41.5\ngini = 0.444\nsampl
es = 3\nvalue = [1, 2]\nclass = u'),
 Text(0.9090909090909091, 0.05555555555555555, 'gini = 0.5\nsamples = 2\nvalue =
[1, 1]\nclass = s'),
 Text(0.9318181818181818, 0.05555555555555555, 'gini = 0.0\nsamples = 1\nvalue =
[0, 1]\nclass = u'),
 Text(0.9772727272727273, 0.2777777777777778, 'Age <= 38.5\ngini = 0.165\nsample
s = 33\nvalue = [30, 3]\nclass = s'),
 Text(0.9659090909090909, 0.16666666666666666, 'Fare <= 16.475\ngini = 0.375\nsa
mples = 12\nvalue = [9, 3]\nclass = s'),
 Text(0.9545454545454546, 0.05555555555555555, 'gini = 0.0\nsamples = 8\nvalue =
[8, 0]\nclass = s'),
 Text(0.9772727272727273, 0.05555555555555555, 'gini = 0.375\nsamples = 4\nvalue
= [1, 3]\nclass = u'),
 Text(0.9886363636363636, 0.16666666666666666, 'gini = 0.0\nsamples = 21\nvalue
= [21, 0]\nclass = s'),
 Text(0.9659090909090909, 0.3888888888888889, 'gini = 0.0\nsamples = 1\nvalue =
[0, 1]\nclass = u'),
 Text(0.9659090909090909, 0.6111111111111112, 'gini = 0.0\nsamples = 1\nvalue =
[0, 1]\nclass = u')]
```

Your observations here

2.4 Support Vector Machines, for comparison

As a starting point, use the basic sklearn SVM model, with the default constant penalization (C=1), to predict survival using the same set of features as above. Report your accuracy on the test and train sets.

Next, use cross-validation to determine a possibly better choice for C. Note that regularization is inversely proportional to the value of C in sklearn, i.e. the higher value you choose for C the less you regularize. Plot a graph with C on the x-axis and cross-validated accuracy on the y-axis.

How does the test performance with SVM for your best choice of C compare to the decision tree from 2.3?

In [140…

```
from sklearn import svm

# SVM model with default params
clf = svm.SVC(C=1)
clf.fit(X_train, Y_train)
yhat_train = clf.predict(X_train)
yhat_test = clf.predict(X_test)
print('Accuracy (train): %.2f' % accuracy_score(Y_train, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test, yhat_test))
```

```
Accuracy (train): 0.68
Accuracy (test): 0.65
```

In [141…

```
# SVM model using cross-val to tune C param
cv = KFold(n_splits=3, shuffle=True, random_state=1)
params = {'C':[0.0001,.001,.01,.1,.2,.3,.4,.5,.6,.7,.8,.9,1]}
cv_model = GridSearchCV(clf, param_grid=params, scoring='accuracy', refit=True,
cv_model.fit(X_train, Y_train)
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.head()
```

Out[141…

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_C	params	split0_test_
0	0.011632	0.003849	0.008546	0.001867	0.0001	{'C': 0.0001}	0.6
1	0.007252	0.000101	0.006330	0.000062	0.001	{'C': 0.001}	0.6
2	0.007447	0.000051	0.006361	0.000085	0.01	{'C': 0.01}	0.6
3	0.007307	0.000017	0.006141	0.000051	0.1	{'C': 0.1}	0.6
4	0.007156	0.000059	0.005902	0.000071	0.2	{'C': 0.2}	0.6

In [146…

```
# best model
```

```
print(cv_model.best_estimator_)
```

```
SVC(C=0.4)
```

In [154…

```
# cross validated performance
print(cv_results[(cv_results.param_C == .4)][['mean_test_score']])
```

```
   mean_test_score
6         0.681326
```

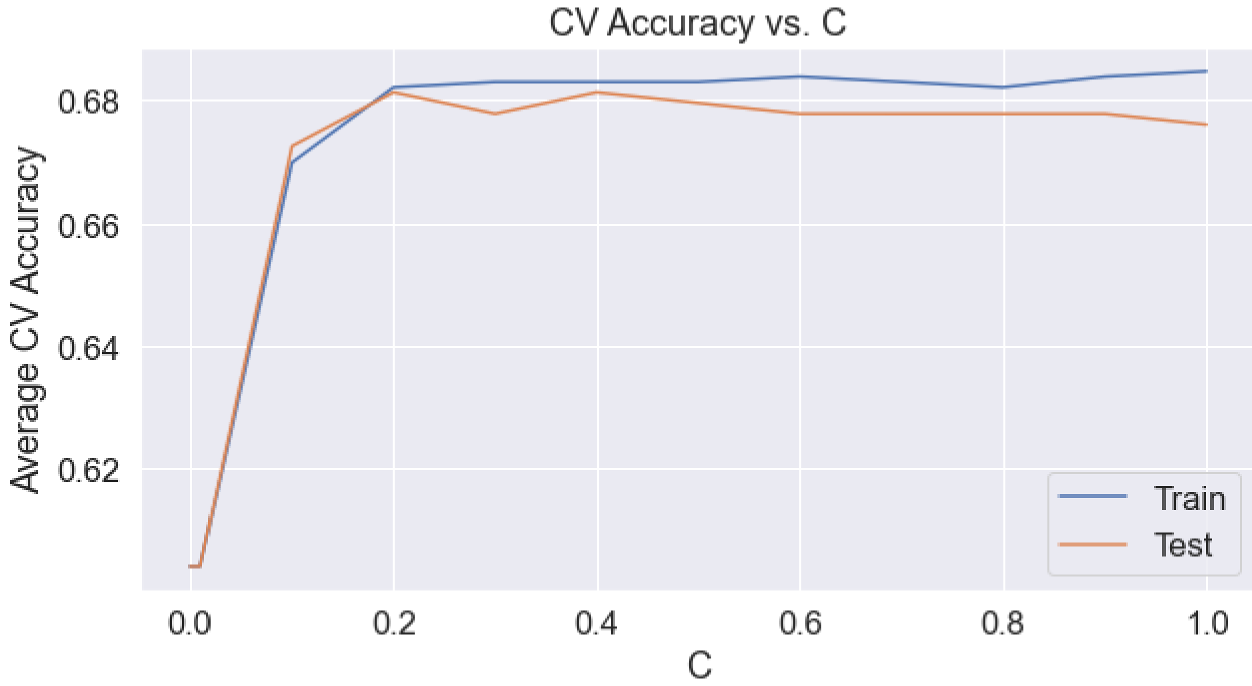
In [161…

```
# fitting model with best paramaters
svm_best = cv_model.best_estimator_
svm_best.fit(X_train, Y_train)
yhat = model.predict(X_test)
yhat_train = model.predict(X_train)

print('Best C: %.2f' % cv_model.best_params_['C'])

print('Accuracy (train): %.2f' % accuracy_score(Y_train, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test, yhat))

print('Precision: %.2f' % recall_score(Y_test, yhat))


print('Recall: %.2f' % precision_score(Y_test, yhat))
```

```
Best C: 0.40
Accuracy (train): 0.68
Accuracy (test): 0.65
Precision: 0.38
Recall: 0.71
```

In [162…

```
# Plot CV accuracy as a function of C
sns.set(font_scale=1.5)
fig, ax = plt.subplots(1, figsize=(10, 5))
ax.plot(cv_results['param_C'], cv_results['mean_train_score'], label='Train')
ax.plot(cv_results['param_C'], cv_results['mean_test_score'], label='Test')
ax.set_xlabel('C')
ax.set_ylabel('Average CV Accuracy')
ax.set_title('CV Accuracy vs. C')
ax.legend(loc='best')
plt.show()
```



SVM Accuracy (test): 0.65 Decision Tree Accuracy (test): 0.65

Our two models have the same test accuracy.

2.5 Missing Data, Imputation and Feature Engineering

Have you been paying close attention to your features? If not, now is a good time to start. Perform analysis that allows you to answer the following questions:

- Recall from part 1 that some features have missing data. Which features have missingness?
- Try running the decision tree and SVM models from part 1 using all columns, including those with missing data. What happens?
- Use one of the methods we discussed in class to impute missing values for each feature. For each feature with missingness, describe the method used and why it is appropriate to the feature.
- Find a way to engineer meaningful features from the "Name" and/or "Cabin" fields in the data.
- Rerun your decision tree and SVM on the new dataset with imputed missing values and the new features, including re-selecting hyperparameters via cross validation. What do you notice?

In [276…

```
# inspecting null values
df.isnull().sum()
```

Out[276…

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
```

```
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
Embarked_S       0
Embarked_C       0
Embarked_Q       0
dtype: int64
```

Our variables Age, Cabin, and Embarked have missing values

In [280…

```
#trying to run models with untouched variables
X_new = df.drop(['Survived', 'Name', 'Ticket', 'Cabin', 'Embarked'],axis=1)
model.fit(X_new,df['Survived'])
best_svm.fit(X_new,df['Survived'])
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-280-e679d4fab9c4> in <module>
      1 #trying to run models with untouched variables
      2 X_new = df.drop(['Survived', 'Name', 'Ticket', 'Cabin', 'Embarked'],axis
=1)
----> 3 model.fit(X_new,df['Survived'])
      4 best_svm.fit(X_new,df['Survived'])

~/opt/anaconda3/envs/aml2/lib/python3.7/site-packages/sklearn/tree/_classes.py i
n fit(self, X, y, sample_weight, check_input, X_idx_sorted)
    940             sample_weight=sample_weight,
    941             check_input=check_input,
--> 942             X_idx_sorted=X_idx_sorted,
    943         )
    944         return self

~/opt/anaconda3/envs/aml2/lib/python3.7/site-packages/sklearn/tree/_classes.py i
n fit(self, X, y, sample_weight, check_input, X_idx_sorted)
    164             check_y_params = dict(ensure_2d=False, dtype=None)
    165             X, y = self._validate_data(
--> 166                 X, y, validate_separately=(check_X_params, check_y_param
s)
    167             )
    168             if issparse(X):

~/opt/anaconda3/envs/aml2/lib/python3.7/site-packages/sklearn/base.py in _valida
te_data(self, X, y, reset, validate_separately, **check_params)
    576                 # :(
    577                 check_X_params, check_y_params = validate_separately
--> 578                 X = check_array(X, **check_X_params)
    579                 y = check_array(y, **check_y_params)
    580             else:

~/opt/anaconda3/envs/aml2/lib/python3.7/site-packages/sklearn/utils/validation.p
y in check_array(array, accept_sparse, accept_large_sparse, dtype, order, copy,
 force_all_finite, ensure_2d, allow_nd, ensure_min_samples, ensure_min_features,
estimator)
    798
    799         if force_all_finite:
--> 800             _assert_all_finite(array, allow_nan=force_all_finite == "all
ow-nan")
    801
    802     if ensure_min_samples > 0:

~/opt/anaconda3/envs/aml2/lib/python3.7/site-packages/sklearn/utils/validation.p
```

```
y in _assert_all_finite(X, allow_nan, msg_dtype)
    114             raise ValueError(
    115                 msg_err.format(
--> 116                     type_err, msg_dtype if msg_dtype is not None else X.
dtype
    117                 )
    118             )

ValueError: Input contains NaN, infinity or a value too large for dtype('float3
2').
```

Our models will not run because of NaN values

In [191…

```
df_new = df.copy()
```

In [192…

```
# For Age, I will impute mean value
df_new['Age'].fillna(df_new['Age'].mean(), inplace=True)
print(df_new['Age'].values)
```

```
[22.         38.         26.         35.         35.         29.69911765
 54.          2.         27.         14.          4.         58.
 20.         39.         14.         55.          2.         29.69911765
 31.         29.69911765 35.         34.         15.         28.
  8.         38.         29.69911765 19.         29.69911765 29.69911765
 40.         29.69911765 29.69911765 66.         28.         42.
 29.69911765 21.         18.         14.         40.         27.
 29.69911765  3.         19.         29.69911765 29.69911765 29.69911765
 29.69911765 18.          7.         21.         49.         29.
 65.         29.69911765 21.         28.5         5.         11.
 22.         38.         45.          4.         29.69911765 29.69911765
 29.         19.         17.         26.         32.         16.
 21.         26.         32.         25.         29.69911765 29.69911765
  0.83       30.         22.         29.         29.69911765 28.
 17.         33.         16.         29.69911765 23.         24.
 29.         20.         46.         26.         59.         29.69911765
 71.         23.         34.         34.         28.         29.69911765
 21.         33.         37.         28.         21.         29.69911765
 38.         29.69911765 47.         14.5        22.         20.
 17.         21.         70.5        29.         24.          2.
 21.         29.69911765 32.5        32.5        54.         12.
 29.69911765 24.         29.69911765 45.         33.         20.
 47.         29.         25.         23.         19.         37.
 16.         24.         29.69911765 22.         24.         19.
 18.         19.         27.          9.         36.5        42.
 51.         22.         55.5        40.5        29.69911765 51.
 16.         30.         29.69911765 29.69911765 44.         40.
 26.         17.          1.          9.         29.69911765 45.
 29.69911765 28.         61.          4.          1.         21.
 56.         18.         29.69911765 50.         30.         36.
 29.69911765 29.69911765  9.          1.          4.         29.69911765
 29.69911765 45.         40.         36.         32.         19.
 19.          3.         44.         58.         29.69911765 42.
 29.69911765 24.         28.         29.69911765 34.         45.5
 18.          2.         32.         26.         16.         40.
 24.         35.         22.         30.         29.69911765 31.
 27.         42.         32.         30.         16.         27.
 51.         29.69911765 38.         22.         19.         20.5
 18.         29.69911765 35.         29.         59.          5.
 24.         29.69911765 44.          8.         19.         33.
 29.69911765 29.69911765 29.         22.         30.         44.
 25.         24.         37.         54.         29.69911765 29.
 62.         30.         41.         29.         29.69911765 30.
```

```
35.          50.          29.69911765  3.          52.          40.
29.69911765 36.          16.          25.          58.          35.
29.69911765 25.          41.          37.          29.69911765 63.
45.          29.69911765  7.          35.          65.          28.
16.          19.          29.69911765 33.          30.          22.
42.          22.          26.          19.          36.          24.
24.          29.69911765 23.5          2.          29.69911765 50.
29.69911765 29.69911765 19.          29.69911765 29.69911765  0.92
29.69911765 17.          30.          30.          24.          18.
26.          28.          43.          26.          24.          54.
31.          40.          22.          27.          30.          22.
29.69911765 36.          61.          36.          31.          16.
29.69911765 45.5         38.          16.          29.69911765 29.69911765
29.          41.          45.          45.           2.          24.
28.          25.          36.          24.          40.          29.69911765
 3.          42.          23.          29.69911765 15.          25.
29.69911765 28.          22.          38.          29.69911765 29.69911765
40.          29.          45.          35.          29.69911765 30.
60.          29.69911765 29.69911765 24.          25.          18.
19.          22.           3.          29.69911765 22.          27.
20.          19.          42.           1.          32.          35.
29.69911765 18.           1.          36.          29.69911765 17.
36.          21.          28.          23.          24.          22.
31.          46.          23.          28.          39.          26.
21.          28.          20.          34.          51.           3.
21.          29.69911765 29.69911765 29.69911765 33.          29.69911765
44.          29.69911765 34.          18.          30.          10.
29.69911765 21.          29.          28.          18.          29.69911765
28.          19.          29.69911765 32.          28.          29.69911765
42.          17.          50.          14.          21.          24.
64.          31.          45.          20.          25.          28.
29.69911765  4.          13.          34.           5.          52.
36.          29.69911765 30.          49.          29.69911765 29.
65.          29.69911765 50.          29.69911765 48.          34.
47.          48.          29.69911765 38.          29.69911765 56.
29.69911765  0.75        29.69911765 38.          33.          23.
22.          29.69911765 34.          29.          22.           2.
 9.          29.69911765 50.          63.          25.          29.69911765
35.          58.          30.           9.          29.69911765 21.
55.          71.          21.          29.69911765 54.          29.69911765
25.          24.          17.          21.          29.69911765 37.
16.          18.          33.          29.69911765 28.          26.
29.          29.69911765 36.          54.          24.          47.
34.          29.69911765 36.          32.          30.          22.
29.69911765 44.          29.69911765 40.5         50.          29.69911765
39.          23.           2.          29.69911765 17.          29.69911765
30.           7.          45.          30.          29.69911765 22.
36.           9.          11.          32.          50.          64.
19.          29.69911765 33.           8.          17.          27.
29.69911765 22.          22.          62.          48.          29.69911765
39.          36.          29.69911765 40.          28.          29.69911765
29.69911765 24.          19.          29.          29.69911765 32.
62.          53.          36.          29.69911765 16.          19.
34.          39.          29.69911765 32.          25.          39.
54.          36.          29.69911765 18.          47.          60.
22.          29.69911765 35.          52.          47.          29.69911765
37.          36.          29.69911765 49.          29.69911765 49.
24.          29.69911765 29.69911765 44.          35.          36.
30.          27.          22.          40.          39.          29.69911765
29.69911765 29.69911765 35.          24.          34.          26.
 4.          26.          27.          42.          20.          21.
21.          61.          57.          21.          26.          29.69911765
80.          51.          32.          29.69911765  9.          28.
32.          31.          41.          29.69911765 20.          24.
 2.          29.69911765  0.75        48.          19.          56.
```

```
 29.69911765 23.          29.69911765 18.          21.          29.69911765
 18.          24.          29.69911765 32.          23.          58.
 50.          40.          47.          36.          20.          32.
 25.          29.69911765 43.          29.69911765 40.          31.
 70.          31.          29.69911765 18.          24.5         18.
 43.          36.          29.69911765 27.          20.          14.
 60.          25.          14.          19.          18.          15.
 31.           4.          29.69911765 25.          60.          52.
 44.          29.69911765 49.          42.          18.          35.
 18.          25.          26.          39.          45.          42.
 22.          29.69911765 24.          29.69911765 48.          29.
 52.          19.          38.          27.          29.69911765 33.
  6.          17.          34.          50.          27.          20.
 30.          29.69911765 25.          25.          29.          11.
 29.69911765 23.          23.          28.5         48.          35.
 29.69911765 29.69911765 29.69911765 36.          21.          24.
 31.          70.          16.          30.          19.          31.
  4.           6.          33.          23.          48.           0.67
 28.          18.          34.          33.          29.69911765 41.
 20.          36.          16.          51.          29.69911765 30.5
 29.69911765 32.          24.          48.          57.          29.69911765
 54.          18.          29.69911765  5.          29.69911765 43.
 13.          17.          29.          29.69911765 25.          25.
 18.           8.           1.          46.          29.69911765 16.
 29.69911765 29.69911765 25.          39.          49.          31.
 30.          30.          34.          31.          11.           0.42
 27.          31.          39.          18.          39.          33.
 26.          39.          35.           6.          30.5         29.69911765
 23.          31.          43.          10.          52.          27.
 38.          27.           2.          29.69911765 29.69911765  1.
 29.69911765 62.          15.           0.83        29.69911765 23.
 18.          39.          21.          29.69911765 32.          29.69911765
 20.          16.          30.          34.5         17.          42.
 29.69911765 35.          28.          29.69911765  4.          74.
  9.          16.          44.          18.          45.          51.
 24.          29.69911765 41.          21.          48.          29.69911765
 24.          42.          27.          31.          29.69911765  4.
 26.          47.          33.          47.          28.          15.
 20.          19.          29.69911765 56.          25.          33.
 22.          28.          25.          39.          27.          19.
 29.69911765 26.          32.        ]
```

In [193…

```
# For Embarked, I will impute most common value
df_new['Embarked'].fillna(df_new['Embarked'].mode())
```

Out[193…

```
0      S
1      C
2      S
3      S
4      S
      ..
886    S
887    S
888    S
889    C
890    Q
Name: Embarked, Length: 891, dtype: object
```

In [194…

```
# For Cabin, I will assign values 1-7 based on the first letter of their cabin a
# and I will code 0 for those without a cabin assignment (NA values) and T will
df_new['Cabin'] = df_new.Cabin.str[:1]
df_new.loc[df_new['Cabin'] == 'A', 'Cabin'] = 1
df_new.loc[df_new['Cabin'] == 'B', 'Cabin'] = 2
```

```
df_new.loc[df_new['Cabin'] == 'C', 'Cabin'] = 3
df_new.loc[df_new['Cabin'] == 'D', 'Cabin'] = 4
df_new.loc[df_new['Cabin'] == 'E', 'Cabin'] = 5
df_new.loc[df_new['Cabin'] == 'F', 'Cabin'] = 6
df_new.loc[df_new['Cabin'] == 'G', 'Cabin'] = 7
df_new.loc[df_new['Cabin'] == 'T', 'Cabin'] = 7
df_new['Cabin'].fillna(0, inplace=True)
```

In [195…

```
# For Names, I will take the first portion as an identifier
df_new['Title'] = df_new.Name.str.extract(' ([A-Za-z]+)\.', expand=False)
df_new.Title.value_counts()
```

Out[195…

```
Mr          517
Miss        182
Mrs         125
Master       40
Dr            7
Rev           6
Mlle          2
Major         2
Col           2
Countess      1
Capt          1
Ms            1
Sir           1
Lady          1
Mme           1
Don           1
Jonkheer      1
Name: Title, dtype: int64
```

In [196…

```
# reassigning titles with dummy variables
df_new.loc[df_new['Title'] == 'Mr', 'Title_Mr'] = 1
df_new.loc[df_new['Title'] != 'Mr', 'Title_Mr'] = 0
df_new.loc[df_new['Title'] == 'Miss', 'Title_Miss'] = 1
df_new.loc[df_new['Title'] != 'Miss', 'Title_Miss'] = 0
df_new.loc[df_new['Title'] == 'Mrs', 'Title_Mrs'] = 1
df_new.loc[df_new['Title'] != 'Mrs', 'Title_Mrs'] = 0
df_new.loc[df_new['Title'] == 'Master', 'Title_Master'] = 1
df_new.loc[df_new['Title'] != 'Master', 'Title_Master'] = 0
df_new.loc[~df_new['Title'].isin(['Mr','Miss','Mrs','Master']), 'Title_Other'] =
df_new.loc[df_new['Title'].isin(['Mr','Miss','Mrs','Master']), 'Title_Other'] =
```

In [197…

```
# dropping unecessary columns
df_new = df_new.drop(['Name', 'Sex', 'Embarked', 'Title', 'Ticket'], axis=1)
print(df_new.head())
print(df_new.columns)
```

```
   PassengerId  Survived  Pclass   Age  SibSp  Parch     Fare  Cabin  \
0            1         0       3  22.0      1      0   7.2500      0
1            2         1       1  38.0      1      0  71.2833      3
2            3         1       3  26.0      0      0   7.9250      0
3            4         1       1  35.0      1      0  53.1000      3
4            5         0       3  35.0      0      0   8.0500      0

   Embarked_S  Embarked_C  Embarked_Q  Title_Mr  Title_Miss  Title_Mrs  \
0         1.0         0.0         0.0       1.0         0.0        0.0
1         0.0         1.0         0.0       0.0         0.0        1.0
```

```
2          1.0         0.0         0.0        0.0         1.0        0.0
3          1.0         0.0         0.0        0.0         0.0        1.0
4          1.0         0.0         0.0        1.0         0.0        0.0

   Title_Master  Title_Other
0           0.0          0.0
1           0.0          0.0
2           0.0          0.0
3           0.0          0.0
4           0.0          0.0
Index(['PassengerId', 'Survived', 'Pclass', 'Age', 'SibSp', 'Parch', 'Fare',
       'Cabin', 'Embarked_S', 'Embarked_C', 'Embarked_Q', 'Title_Mr',
       'Title_Miss', 'Title_Mrs', 'Title_Master', 'Title_Other'],
      dtype='object')
```

In [198…

```
# ensuring there are no more null values
df_new.isnull().sum()
```

Out[198…

```
PassengerId     0
Survived        0
Pclass          0
Age             0
SibSp           0
Parch           0
Fare            0
Cabin           0
Embarked_S      0
Embarked_C      0
Embarked_Q      0
Title_Mr        0
Title_Miss      0
Title_Mrs       0
Title_Master    0
Title_Other     0
dtype: int64
```

In [199…

```
#splitting set into training and testing data
training_data, testing_data = train_test_split(df_new, test_size=0.2, random_sta
X_train_new = training_data[['Pclass', 'Age', 'SibSp', 'Parch',
       'Fare', 'Cabin', 'Embarked_S', 'Embarked_C', 'Embarked_Q',
       'Title_Mr', 'Title_Miss', 'Title_Mrs', 'Title_Master', 'Title_Other']]
Y_train_new = training_data['Survived']
X_test_new = testing_data[['Pclass', 'Age', 'SibSp', 'Parch',
       'Fare', 'Cabin', 'Embarked_S', 'Embarked_C', 'Embarked_Q',
       'Title_Mr', 'Title_Miss', 'Title_Mrs', 'Title_Master', 'Title_Other']]
Y_test_new = testing_data['Survived']
```

In [200…

```
# standardizing
X_train_new = standardize(X_train_new)
X_test_new = standardize(X_test_new)
```

In [201…

```
# rerunning Decision Tree
tree_model = sklearn.tree.DecisionTreeClassifier(random_state=0)

cv = KFold(n_splits=3, shuffle=True, random_state=1)
params = {'max_depth':[2, 4, 6, 8, 10, 12, 14], 'min_samples_leaf':[1,2,3,4,5]}
cv_model = GridSearchCV(tree_model, param_grid=params, scoring='accuracy', refit
cv_model.fit(X_train_new, Y_train_new)
```

```
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.head()
```

Out[201…

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_min_
0	0.003680	0.001912	0.001567	0.000408	2	
1	0.001981	0.000285	0.001211	0.000261	2	
2	0.001597	0.000025	0.000941	0.000010	2	
3	0.001611	0.000036	0.000953	0.000043	2	
4	0.001512	0.000057	0.000856	0.000015	2	

In [202…

```
print(cv_model.best_estimator_)
```

```
DecisionTreeClassifier(max_depth=4, min_samples_leaf=3, random_state=0)
```

In [203…

```
print(cv_results[(cv_results.param_min_samples_leaf == 3) & (cv_results.param_ma
```

```
   mean_test_score
7         0.820167
```

In [204…

```
# fitting model with best paramaters
model = cv_model.best_estimator_
model.fit(X_train_new, Y_train_new)
yhat = model.predict(X_test_new)
yhat_train = model.predict(X_train_new)

print('Best maximum depth: %i' % cv_model.best_params_['max_depth'])
print('Best min samples leaf: %i' % cv_model.best_params_['min_samples_leaf'])

print('Accuracy (train): %.2f' % accuracy_score(Y_train_new, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test_new, yhat))

print('Precision: %.2f' % recall_score(Y_test_new, yhat))


print('Recall: %.2f' % precision_score(Y_test_new, yhat))
```

```
Best maximum depth: 4
Best min samples leaf: 3
Accuracy (train): 0.85
Accuracy (test): 0.80
Precision: 0.67
Recall: 0.79
```

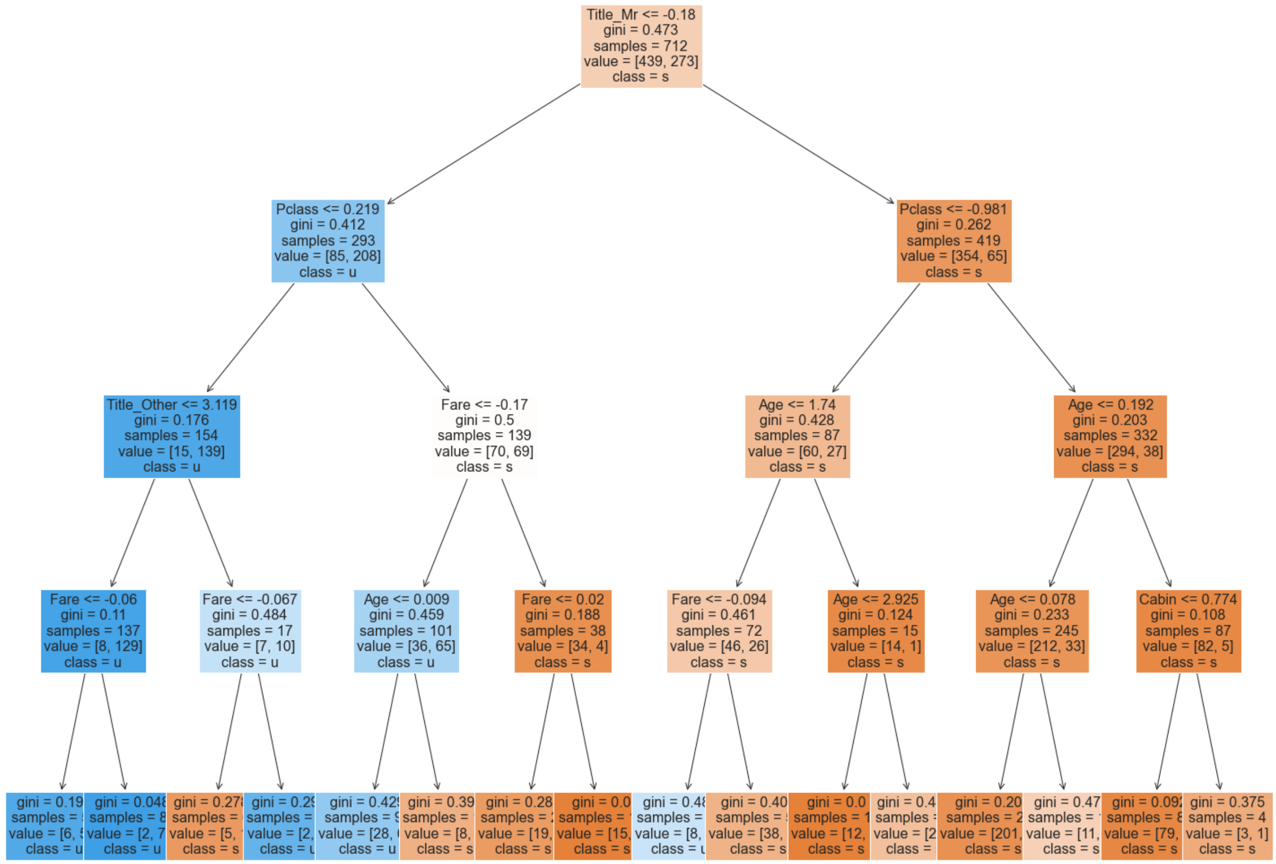
In [206…

```
best_tree = sklearn.tree.DecisionTreeClassifier(max_depth=4, min_samples_leaf=3,
```

```
best_tree.fit(X_train_new,Y_train_new)
fig = plt.figure(figsize=(25,20))
tree.plot_tree(best_tree,
                   feature_names = X_train_new.columns,
                   class_names= 'survived',
                   filled=True,
                   fontsize=16)
```

Out[206…

```
[Text(0.5, 0.9, 'Title_Mr <= -0.18\ngini = 0.473\nsamples = 712\nvalue = [439, 2
73]\nclass = s'),
 Text(0.25, 0.7, 'Pclass <= 0.219\ngini = 0.412\nsamples = 293\nvalue = [85, 20
8]\nclass = u'),
 Text(0.125, 0.5, 'Title_Other <= 3.119\ngini = 0.176\nsamples = 154\nvalue = [1
5, 139]\nclass = u'),
 Text(0.0625, 0.3, 'Fare <= -0.06\ngini = 0.11\nsamples = 137\nvalue = [8, 129]
\nclass = u'),
 Text(0.03125, 0.1, 'gini = 0.191\nsamples = 56\nvalue = [6, 50]\nclass = u'),
 Text(0.09375, 0.1, 'gini = 0.048\nsamples = 81\nvalue = [2, 79]\nclass = u'),
 Text(0.1875, 0.3, 'Fare <= -0.067\ngini = 0.484\nsamples = 17\nvalue = [7, 10]
\nclass = u'),
 Text(0.15625, 0.1, 'gini = 0.278\nsamples = 6\nvalue = [5, 1]\nclass = s'),
 Text(0.21875, 0.1, 'gini = 0.298\nsamples = 11\nvalue = [2, 9]\nclass = u'),
 Text(0.375, 0.5, 'Fare <= -0.17\ngini = 0.5\nsamples = 139\nvalue = [70, 69]\nc
lass = s'),
 Text(0.3125, 0.3, 'Age <= 0.009\ngini = 0.459\nsamples = 101\nvalue = [36, 65]
\nclass = u'),
 Text(0.28125, 0.1, 'gini = 0.429\nsamples = 90\nvalue = [28, 62]\nclass = u'),
 Text(0.34375, 0.1, 'gini = 0.397\nsamples = 11\nvalue = [8, 3]\nclass = s'),
 Text(0.4375, 0.3, 'Fare <= 0.02\ngini = 0.188\nsamples = 38\nvalue = [34, 4]\nc
lass = s'),
 Text(0.40625, 0.1, 'gini = 0.287\nsamples = 23\nvalue = [19, 4]\nclass = s'),
 Text(0.46875, 0.1, 'gini = 0.0\nsamples = 15\nvalue = [15, 0]\nclass = s'),
 Text(0.75, 0.7, 'Pclass <= -0.981\ngini = 0.262\nsamples = 419\nvalue = [354, 6
5]\nclass = s'),
 Text(0.625, 0.5, 'Age <= 1.74\ngini = 0.428\nsamples = 87\nvalue = [60, 27]\ncl
ass = s'),
 Text(0.5625, 0.3, 'Fare <= -0.094\ngini = 0.461\nsamples = 72\nvalue = [46, 26]
\nclass = s'),
 Text(0.53125, 0.1, 'gini = 0.488\nsamples = 19\nvalue = [8, 11]\nclass = u'),
 Text(0.59375, 0.1, 'gini = 0.406\nsamples = 53\nvalue = [38, 15]\nclass = s'),
 Text(0.6875, 0.3, 'Age <= 2.925\ngini = 0.124\nsamples = 15\nvalue = [14, 1]\nc
lass = s'),
 Text(0.65625, 0.1, 'gini = 0.0\nsamples = 12\nvalue = [12, 0]\nclass = s'),
 Text(0.71875, 0.1, 'gini = 0.444\nsamples = 3\nvalue = [2, 1]\nclass = s'),
 Text(0.875, 0.5, 'Age <= 0.192\ngini = 0.203\nsamples = 332\nvalue = [294, 38]
\nclass = s'),
 Text(0.8125, 0.3, 'Age <= 0.078\ngini = 0.233\nsamples = 245\nvalue = [212, 33]
\nclass = s'),
 Text(0.78125, 0.1, 'gini = 0.203\nsamples = 227\nvalue = [201, 26]\nclass =
s'),
 Text(0.84375, 0.1, 'gini = 0.475\nsamples = 18\nvalue = [11, 7]\nclass = s'),
 Text(0.9375, 0.3, 'Cabin <= 0.774\ngini = 0.108\nsamples = 87\nvalue = [82, 5]
\nclass = s'),
 Text(0.90625, 0.1, 'gini = 0.092\nsamples = 83\nvalue = [79, 4]\nclass = s'),
 Text(0.96875, 0.1, 'gini = 0.375\nsamples = 4\nvalue = [3, 1]\nclass = s')]
```



After imputing the data and feature engineering, we find that our mdoel improves and that our most significant featurues change.

In [207…

```
# rerunning SVM
svm_model = svm.SVC()
cv = KFold(n_splits=3, shuffle=True, random_state=1)
params = {'C':[0.0001,.001,.01,.1,.2,.3,.4,.5,.6,.7,.8,.9,1]}
cv_model = GridSearchCV(svm_model, param_grid=params, scoring='accuracy', refit=
cv_model.fit(X_train_new, Y_train_new)
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.head()
```

Out[207…

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_C	params	split0_test_
0	0.015462	0.005075	0.010964	0.001914	0.0001	{'C': 0.0001}	0.6
1	0.011104	0.000256	0.009359	0.000273	0.001	{'C': 0.001}	0.6
2	0.010913	0.000153	0.009310	0.000139	0.01	{'C': 0.01}	0.6
3	0.010132	0.000271	0.008519	0.000198	0.1	{'C': 0.1}	0.8
4	0.009397	0.000295	0.007628	0.000163	0.2	{'C': 0.2}	0.8

In [208…

```
print(cv_model.best_estimator_)
```

```
SVC(C=0.5)
```

In [210…

```
# cross validated performance
print(cv_results[(cv_results.param_C == .5)][['mean_test_score']])
```

```
   mean_test_score
7         0.832837
```

In [212…

```
# fitting model with best paramaters
svm_best = cv_model.best_estimator_
svm_best.fit(X_train_new, Y_train_new)
yhat = model.predict(X_test_new)
yhat_train = model.predict(X_train_new)

print('Best C: %.2f' % cv_model.best_params_['C'])

print('Accuracy (train): %.2f' % accuracy_score(Y_train_new, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test_new, yhat))

print('Precision: %.2f' % recall_score(Y_test_new, yhat))


print('Recall: %.2f' % precision_score(Y_test_new, yhat))
```

```
Best C: 0.50
Accuracy (train): 0.85
Accuracy (test): 0.80
Precision: 0.67
Recall: 0.79
```

After imputing the data and feature engineering, we find that our SVM model also improves.

2.6 ROC Curve

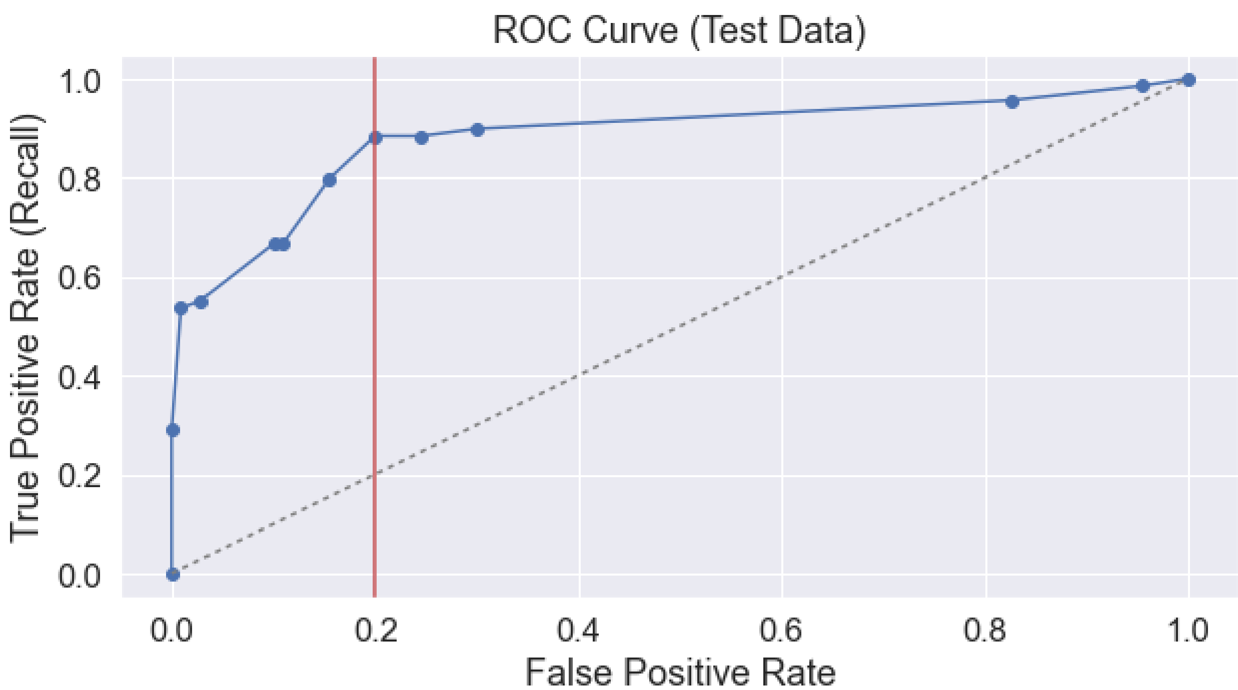
For your best decision tree from 2.5, plot the reciever operating characteristic (ROC) curve on the test set data. Report the area under the curve (AUC) score. *Hint*: scikit-learn's built-in predict_proba function may be helpful for this problem. For each model, identify the point on the ROC curve that is closest to the top-left corner, and identify the associated probability threshold for classification. Place a vertical line on your plot indicating the FPR value at the threshold. Finally, report accuracy on the test set using the threshold you identified. Comparing to the accuracy from 2.5, what do you observe?

In [224…

```
# ROC Curve
yhat_test_proba = best_tree.predict_proba(X_test_new)[:, 1]
fprs, tprs, thresholds = roc_curve(Y_test_new, yhat_test_proba)


# Get "optimal" threshold: the one closest to the top-left corner of the ROC gra
#distances_from_top_left = [np.sqrt(tprs[i]**2 + (1-fprs[i])**2) for i in range(
best_cutoff = np.argmax(tprs - fprs)
optimal_threshold = thresholds[best_cutoff]
#best_cutoff = np.argmin(distances_from_top_left)
print('Threshold closest to top-left corner of graph: %.2f (%.2f TPR, %.2f FPR)'
```

```
      (thresholds[best_cutoff], tprs[best_cutoff], fprs[best_cutoff]))

print('AUC score: %.2f' % roc_auc_score(Y_test_new, yhat_test_proba))

fig, ax = plt.subplots(1, figsize=(10, 5))
ax.scatter(fprs, tprs)
ax.plot(fprs, tprs)
ax.plot([0, 1], [0, 1], color='grey', dashes=[2, 2])
plt.axvline(x=fprs[best_cutoff], c='r')
ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate (Recall)')
ax.set_title('ROC Curve (Test Data)')
plt.show()
```

```
Threshold closest to top-left corner of graph: 0.27 (0.88 TPR, 0.20 FPR)
AUC score: 0.88
```



In [219…

```
from sklearn.metrics import accuracy_score, precision_score, recall_score, roc_a
```

In [227…

```
tp = best_tree.predict_proba(X_test_new)[:,1]
tp[tp >= thresholds[best_cutoff]] = 1
tp[threshold_tree_predictions < thresholds[best_cutoff]] = 0
print("Decision Tree accuracy for optimal threshold (", thresholds[best_cutoff],
```

```
Decision Tree accuracy for optimal threshold ( 0.2727272727272727 ) is:  0.83240
22346368715
```

We see that the accuracy improves from .80 to .83

Part 3: Many Trees

3.1: Random Forest

Use the random forest classifier to predict survival on the titanic. Use cross-validation on the training data to choose the best hyper-parameters --- including the maximum depth, number of trees in the forest, and the minimum samples per leaf.

- What hyperparameters did you select with cross-validation? You should use cross-validation to select all of the hyperparameters (i.e. search a grid of hyperparameters), and report the combination that maximizes cross-validated accuracy). You can use fewer cross validation folds than the 10 folds from previous problems, to keep your code from taking too long to run.
- How does the cross-validated performance (average across validation folds) compare to the test performance (using the top-performing, fitted model selected through cross-validation)?
- How does the RF performance compare to the decision tree and SVM from part 2.5?
- Create 3 subplots that show how cross-validated performance (y-axis) relates to the number of trees in the forest (x-axis), maximum depth (x-axis), and minimum samples per leaf (x-axis). What do you observe?

In [52]:

```
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor
from sklearn.metrics import accuracy_score, precision_score, recall_score, roc_a
```

In [229…

```
# default RF with no cross val using imputed data
rf = RandomForestClassifier(n_estimators=100, random_state=0)
rf.fit(X_train_new, Y_train_new)
yhat_train = rf.predict(X_train_new)
yhat_test = rf.predict(X_test_new)

print('Accuracy (train): %.2f' % accuracy_score(Y_train_new, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test_new, yhat_test))

print('Precision (train): %.2f' % recall_score(Y_train_new, yhat_train))
print('Precision (test): %.2f' % recall_score(Y_test_new, yhat_test))

print('Recall (train): %.2f' % precision_score(Y_train_new, yhat_train))
print('Recall (test): %.2f' % precision_score(Y_test_new, yhat_test))
```

```
Accuracy (train): 0.99
Accuracy (test): 0.80
Precision (train): 0.98
Precision (test): 0.72
Recall (train): 0.99
Recall (test): 0.76
```

In [230…

```
# Tune hyperparameters: max_depth, n_estimators, min_samples_split, min_samples_
model = RandomForestClassifier(random_state=0)
cv = KFold(n_splits=3, shuffle=True, random_state=0)
params = {'max_depth':[int(x) for x in np.linspace(3, 30, num = 5)], 'n_estimato
cv_model = GridSearchCV(model, param_grid=params, scoring='accuracy', refit=True
cv_model.fit(X_train, Y_train)
model = cv_model.best_estimator_
model.fit(X_train, Y_train)
yhat_train = model.predict(X_train)
yhat_test = model.predict(X_test)
```

```
print('Best maximum depth: %i' % cv_model.best_params_['max_depth'])
print('Best number of estimators: %i' % cv_model.best_params_['n_estimators'])
print('Best min samples split: %i' % cv_model.best_params_['min_samples_split'])
print('Best min samples leaf: %i' % cv_model.best_params_['min_samples_leaf'])

print('Accuracy (train): %.2f' % accuracy_score(Y_train, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test, yhat_test))

print('Precision (train): %.2f' % recall_score(Y_train, yhat_train))
print('Precision (test): %.2f' % recall_score(Y_test, yhat_test))

print('Recall (train): %.2f' % precision_score(Y_train, yhat_train))
print('Recall (test): %.2f' % precision_score(Y_test, yhat_test))
```

```
Best maximum depth: 9
Best number of estimators: 250
Best min samples split: 10
Best min samples leaf: 2
Accuracy (train): 0.82
Accuracy (test): 0.76
Precision (train): 0.70
Precision (test): 0.66
Recall (train): 0.82
Recall (test): 0.78
```

In [232…

```
rf_result_grid = pd.DataFrame(cv_model.cv_results_)
rf_result_grid
```

Out[232…

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_n
0	0.021814	0.005415	0.002688	0.000650	3	
1	0.034139	0.000038	0.003595	0.000027	3	
2	0.054840	0.000136	0.005291	0.000041	3	
3	0.075469	0.000036	0.006962	0.000026	3	
4	0.096328	0.000106	0.008754	0.000165	3	
...	...	...	...	...	...	
355	0.082043	0.000245	0.007792	0.000077	30	
356	0.104843	0.000256	0.009706	0.000053	30	

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_n
357	0.126819	0.000023	0.011587	0.000068	30	
358	0.149377	0.000080	0.013631	0.000119	30	
359	0.171774	0.000255	0.015468	0.000112	30	

360 rows × 20 columns

In [233…

```
optimal_idx = np.argmin(rf_result_grid.rank_test_score)
print("Accuracy best performing model (cross-validated): ",rf_result_grid.mean_t
print("Params best performing model: ",rf_result_grid.params[optimal_idx])
```

```
Accuracy best performing model (cross-validated):  0.7390833103701663
Params best performing model:  {'max_depth': 9, 'min_samples_leaf': 2, 'min_samp
les_split': 10, 'n_estimators': 250}
```

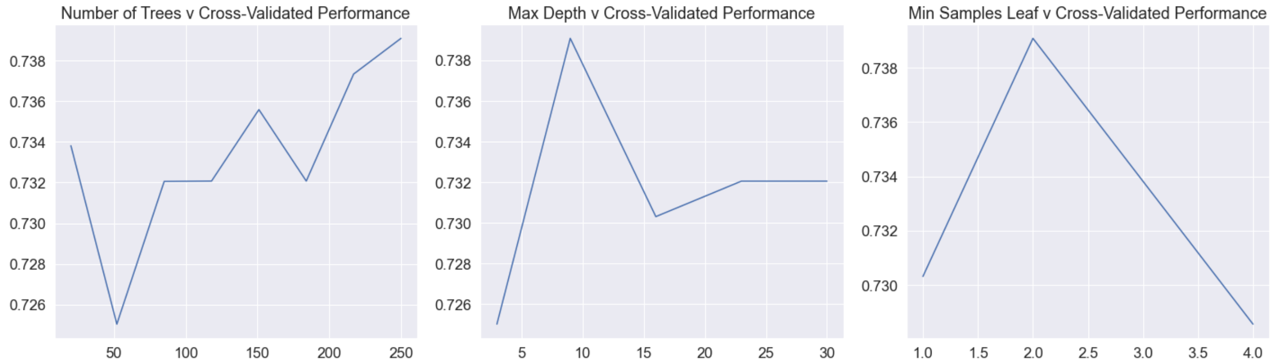
cross-validated performance: 0.76 Test Performance: 0.7390833103701663

We can see that the average cross-validated performance performs better than the test performance.

Create 3 subplots that show how cross-validated performance (y-axis) relates to the number of trees in the forest (x-axis), maximum depth (x-axis), and minimum samples per leaf (x-axis). What do you observe?

In [234…

```
fig, ax = plt.subplots(1, 3, figsize=(20, 6))
ax = ax.flatten()

numtrees = rf_result_grid[(rf_result_grid.param_min_samples_leaf == 2) & (rf_res
depth = rf_result_grid[(rf_result_grid.param_min_samples_leaf == 2) & (rf_result
minsamplesleaf = rf_result_grid[(rf_result_grid.param_n_estimators == 250) & (rf


ax[0].plot(numtrees.param_n_estimators,numtrees.mean_test_score)
ax[1].plot(depth.param_max_depth,depth.mean_test_score)
ax[2].plot(minsamplesleaf.param_min_samples_leaf,minsamplesleaf.mean_test_score)

ax[0].set_title('Number of Trees v Cross-Validated Performance')
ax[1].set_title('Max Depth v Cross-Validated Performance')
ax[2].set_title('Min Samples Leaf v Cross-Validated Performance')
plt.tight_layout()
plt.show()
```



We can see that each value chosen appears to be the peak of cross-val performance, as it should be. We can see in the first graph, the performance appears to increase as the number of trees increases. We may see a different optimal value if we were to expand our range, since we limited our value at 250 here.

In [235…

```
# Tune hyperparameters: max_depth, n_estimators, min_samples_split, min_samples_
model = RandomForestClassifier(random_state=0)
cv = KFold(n_splits=3, shuffle=True, random_state=0)
params = {'max_depth':[int(x) for x in np.linspace(3, 30, num = 5)], 'n_estimato
cv_model = GridSearchCV(model, param_grid=params, scoring='accuracy', refit=True
cv_model.fit(X_train_new, Y_train_new)
model = cv_model.best_estimator_
model.fit(X_train_new, Y_train_new)
yhat_train = model.predict(X_train_new)
yhat_test = model.predict(X_test_new)

print('Best maximum depth: %i' % cv_model.best_params_['max_depth'])
print('Best number of estimators: %i' % cv_model.best_params_['n_estimators'])
print('Best min samples split: %i' % cv_model.best_params_['min_samples_split'])
print('Best min samples leaf: %i' % cv_model.best_params_['min_samples_leaf'])

print('Accuracy (train): %.2f' % accuracy_score(Y_train_new, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test_new, yhat_test))

print('Precision (train): %.2f' % recall_score(Y_train_new, yhat_train))
print('Precision (test): %.2f' % recall_score(Y_test_new, yhat_test))

print('Recall (train): %.2f' % precision_score(Y_train_new, yhat_train))
print('Recall (test): %.2f' % precision_score(Y_test_new, yhat_test))
```

```
Best maximum depth: 9
Best number of estimators: 52
Best min samples split: 5
Best min samples leaf: 2
Accuracy (train): 0.88
Accuracy (test): 0.82
Precision (train): 0.78
Precision (test): 0.72
Recall (train): 0.90
Recall (test): 0.78
```

In [236…

```
rf_result_grid = pd.DataFrame(cv_model.cv_results_)
rf_result_grid
```

Out[236…

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_n

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_n
0	0.022148	0.005703	0.002795	0.000888	3	
1	0.034924	0.000022	0.003681	0.000017	3	
2	0.055930	0.000038	0.005442	0.000010	3	
3	0.077289	0.000119	0.007246	0.000015	3	
4	0.099351	0.000380	0.009113	0.000143	3	
...	...	...	...	...	...	
355	0.084515	0.000219	0.008131	0.000015	30	
356	0.107804	0.000394	0.010118	0.000004	30	
357	0.131632	0.000329	0.012254	0.000065	30	
358	0.154423	0.000497	0.014213	0.000004	30	
359	0.178039	0.000602	0.016499	0.000247	30	

360 rows × 20 columns

In [237…

```
optimal_idx = np.argmin(rf_result_grid.rank_test_score)
print("Accuracy best performing model (cross-validated): ",rf_result_grid.mean_t
print("Params best performing model: ",rf_result_grid.params[optimal_idx])
```

```
Accuracy best performing model (cross-validated):  0.8259109550993394
Params best performing model:  {'max_depth': 9, 'min_samples_leaf': 2, 'min_samp
les_split': 5, 'n_estimators': 52}
```

cross-validated performance: 0.88 Test Performance: 0.8259109550993394

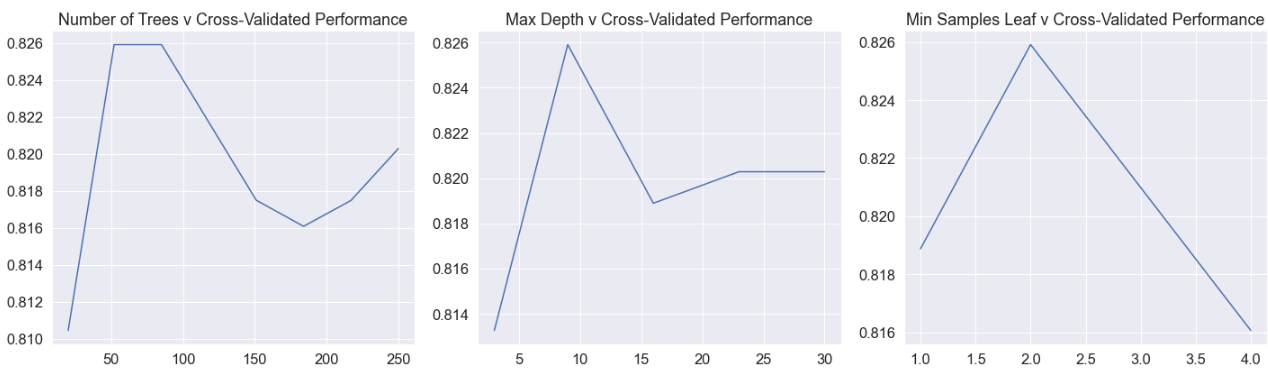
We can see that the average cross-validated performance performs better than the test performance.

Decision Tree accuracy: .8 SVM accuracy: .8 RF accuracy: .826

We can see that random forest performs better than our Decision Tree model and our SVM model.

In [239…

```
fig, ax = plt.subplots(1, 3, figsize=(20, 6))
ax = ax.flatten()

numtrees = rf_result_grid[(rf_result_grid.param_min_samples_leaf == 2) & (rf_res
depth = rf_result_grid[(rf_result_grid.param_min_samples_leaf == 2) & (rf_result
minsamplesleaf = rf_result_grid[(rf_result_grid.param_n_estimators == 52) & (rf_


ax[0].plot(numtrees.param_n_estimators,numtrees.mean_test_score)
ax[1].plot(depth.param_max_depth,depth.mean_test_score)
ax[2].plot(minsamplesleaf.param_min_samples_leaf,minsamplesleaf.mean_test_score)

ax[0].set_title('Number of Trees v Cross-Validated Performance')
ax[1].set_title('Max Depth v Cross-Validated Performance')
ax[2].set_title('Min Samples Leaf v Cross-Validated Performance')
plt.tight_layout()
plt.show()
```



We can see that each value chosen appears to be the peak of cross-val performance, as it should be.

Your observations here

3.2: Gradient Boosting

Use the Gradient Boosting classifier to predict survival on the Titanic. Tune your hyperparameters with cross validation. Again, you should tune more parameteres than just `max_depth`.

- How does the GBM performance compare to the other models?
- Create a figure showing the feature importances in your final model (with properly tuned hyperparameters)

In [240…

```
from sklearn.ensemble import GradientBoostingClassifier
```

In [241…

```
# default params gradient boosting on non-imputed data
gbc = GradientBoostingClassifier(random_state=0)
gbc.fit(X_train, Y_train)
```

```
yhat_train = gbc.predict(X_train)
yhat_test = gbc.predict(X_test)

print('Accuracy (train): %.2f' % accuracy_score(Y_train, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test, yhat_test))

print('Precision (train): %.2f' % recall_score(Y_train, yhat_train))
print('Precision (test): %.2f' % recall_score(Y_test, yhat_test))

print('Recall (train): %.2f' % precision_score(Y_train, yhat_train))
print('Recall (test): %.2f' % precision_score(Y_test, yhat_test))
```

```
Accuracy (train): 0.83
Accuracy (test): 0.73
Precision (train): 0.69
Precision (test): 0.66
Recall (train): 0.84
Recall (test): 0.71
```

In [242…

```
# Tune hyperparameters: max_depth, n_estimators, min_samples_split, min_samples_
gbc = GradientBoostingClassifier(random_state=0)
cv = KFold(n_splits=3, shuffle=True, random_state=0)
params = {'max_depth':[int(x) for x in np.linspace(3, 30, num = 5)], 'n_estimato
cv_model = GridSearchCV(gbc, param_grid=params, scoring='accuracy', refit=True,
cv_model.fit(X_train, Y_train)
gbc = cv_model.best_estimator_
gbc.fit(X_train, Y_train)
yhat_train = gbc.predict(X_train)
yhat_test = gbc.predict(X_test)

print('Best maximum depth: %i' % cv_model.best_params_['max_depth'])
print('Best number of estimators: %i' % cv_model.best_params_['n_estimators'])
print('Best min samples split: %i' % cv_model.best_params_['min_samples_split'])
print('Best min samples leaf: %i' % cv_model.best_params_['min_samples_leaf'])

print('Accuracy (train): %.2f' % accuracy_score(Y_train, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test, yhat_test))

print('Precision (train): %.2f' % recall_score(Y_train, yhat_train))
print('Precision (test): %.2f' % recall_score(Y_test, yhat_test))

print('Recall (train): %.2f' % precision_score(Y_train, yhat_train))
print('Recall (test): %.2f' % precision_score(Y_test, yhat_test))
```

```
Best maximum depth: 3
Best number of estimators: 52
Best min samples split: 2
Best min samples leaf: 2
Accuracy (train): 0.80
Accuracy (test): 0.74
Precision (train): 0.63
Precision (test): 0.66
Recall (train): 0.81
Recall (test): 0.74
```

In [243…

```
rf_result_grid = pd.DataFrame(cv_model.cv_results_)
rf_result_grid
```

Out[243…

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_n

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_m
0	0.009462	0.000567	0.000937	0.000114	3	
1	0.020878	0.000135	0.000959	0.000028	3	
2	0.032855	0.000299	0.001005	0.000009	3	
3	0.045009	0.000458	0.001069	0.000013	3	
4	0.057144	0.000377	0.001161	0.000051	3	
...	...	...	...	...	...	
355	0.191056	0.005571	0.002279	0.000106	30	
356	0.245331	0.006708	0.002694	0.000156	30	
357	0.303009	0.009756	0.003230	0.000211	30	
358	0.357710	0.011409	0.003826	0.000071	30	
359	0.412503	0.010933	0.004098	0.000118	30	

360 rows × 20 columns

In [244…

```
optimal_idx = np.argmin(rf_result_grid.rank_test_score)
print("Accuracy best performing model (cross-validated): ",rf_result_grid.mean_t
print("Params best performing model: ",rf_result_grid.params[optimal_idx])
```

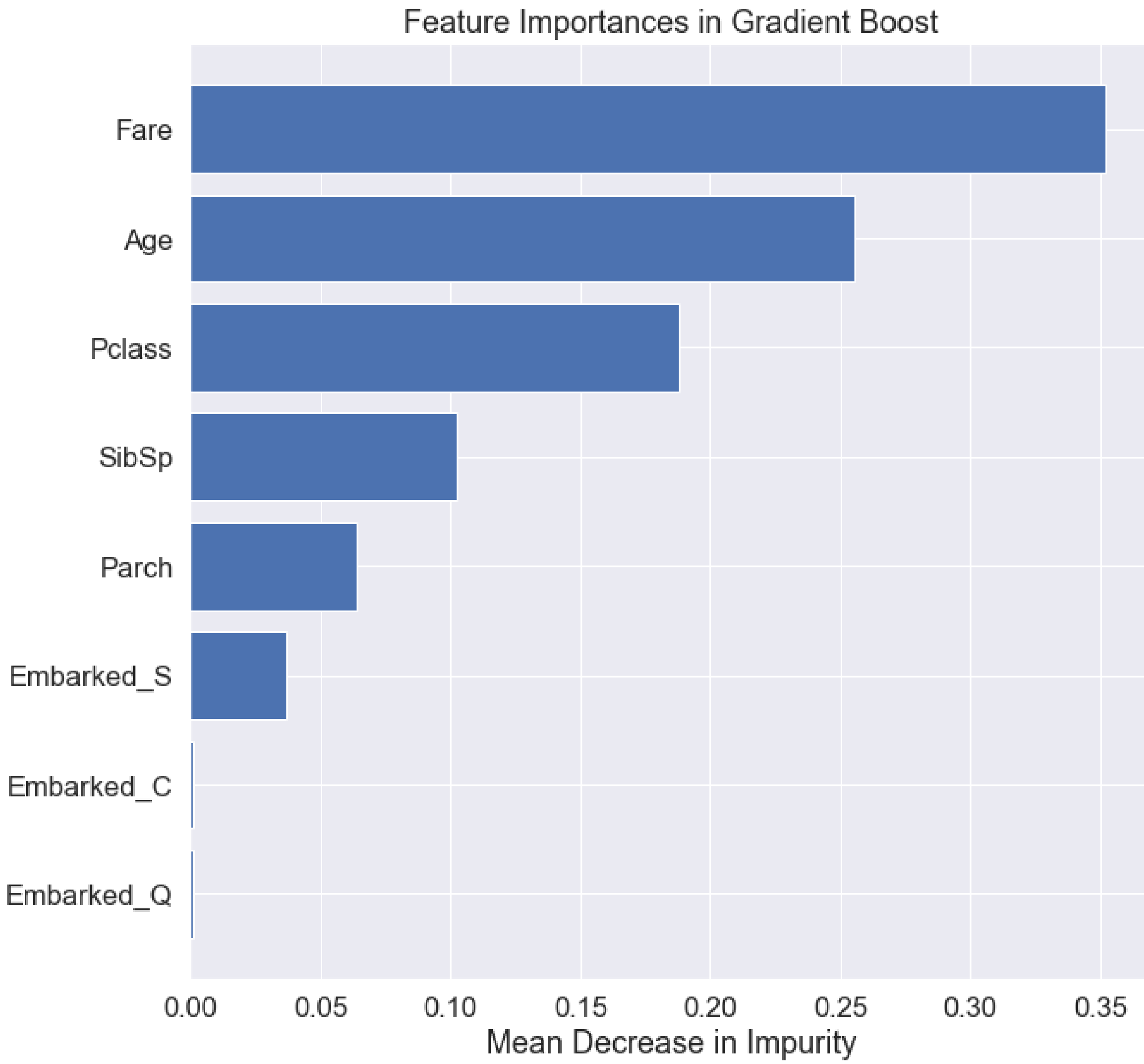
```
Accuracy best performing model (cross-validated):  0.7337742261412693
Params best performing model:  {'max_depth': 3, 'min_samples_leaf': 2, 'min_samp
les_split': 2, 'n_estimators': 52}
```

In [245…

```
# Get feature importances
importances = gbc.feature_importances_
#std = np.std([abc.feature_importances_ for abc in gbc.estimators_], axis=0)
importances = pd.DataFrame([X_train.columns, importances]).T
importances.columns = ['Feature', 'Importance']
importances = importances.sort_values('Importance', ascending=True)
```

In [246…

```
fig, ax = plt.subplots(1, figsize=(10, 10))
plt.barh(importances['Feature'], importances['Importance'])#, yerr=std)
ax.set_xlabel('Mean Decrease in Impurity')
ax.set_title('Feature Importances in Gradient Boost')
plt.show()
```



In [247…

```
# Tune hyperparameters: max_depth, n_estimators, min_samples_split, min_samples_
gbc = GradientBoostingClassifier(random_state=0)
cv = KFold(n_splits=3, shuffle=True, random_state=0)
params = {'max_depth':[int(x) for x in np.linspace(3, 30, num = 5)], 'n_estimato
cv_model = GridSearchCV(gbc, param_grid=params, scoring='accuracy', refit=True,
cv_model.fit(X_train_new, Y_train_new)
gbc = cv_model.best_estimator_
gbc.fit(X_train_new, Y_train_new)
yhat_train = gbc.predict(X_train_new)
yhat_test = gbc.predict(X_test_new)

print('Best maximum depth: %i' % cv_model.best_params_['max_depth'])
print('Best number of estimators: %i' % cv_model.best_params_['n_estimators'])
print('Best min samples split: %i' % cv_model.best_params_['min_samples_split'])
print('Best min samples leaf: %i' % cv_model.best_params_['min_samples_leaf'])
```

```
print('Accuracy (train): %.2f' % accuracy_score(Y_train_new, yhat_train))
print('Accuracy (test): %.2f' % accuracy_score(Y_test_new, yhat_test))

print('Precision (train): %.2f' % recall_score(Y_train_new, yhat_train))
print('Precision (test): %.2f' % recall_score(Y_test_new, yhat_test))

print('Recall (train): %.2f' % precision_score(Y_train_new, yhat_train))
print('Recall (test): %.2f' % precision_score(Y_test_new, yhat_test))
```

```
Best maximum depth: 3
Best number of estimators: 20
Best min samples split: 2
Best min samples leaf: 4
Accuracy (train): 0.85
Accuracy (test): 0.79
Precision (train): 0.77
Precision (test): 0.74
Recall (train): 0.82
Recall (test): 0.72
```

In [248…

```
rf_result_grid = pd.DataFrame(cv_model.cv_results_)
rf_result_grid
```

Out[248…

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_n
0	0.018186	0.003203	0.001413	0.000267	3	
1	0.025362	0.000600	0.000953	0.000027	3	
2	0.039822	0.000364	0.001022	0.000008	3	
3	0.054597	0.000394	0.001109	0.000002	3	
4	0.069522	0.000409	0.001198	0.000008	3	
...	...	...	...	...	...	
355	0.248503	0.006269	0.002819	0.000051	30	
356	0.317667	0.008626	0.003206	0.000081	30	
357	0.388222	0.013452	0.003728	0.000065	30	
358	0.459615	0.014289	0.004206	0.000095	30	

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_m
359	0.528168	0.016108	0.004729	0.000124	30	

360 rows × 20 columns

In [249…

```
optimal_idx = np.argmin(rf_result_grid.rank_test_score)
print("Accuracy best performing model (cross-validated): ",rf_result_grid.mean_t
print("Params best performing model: ",rf_result_grid.params[optimal_idx])
```

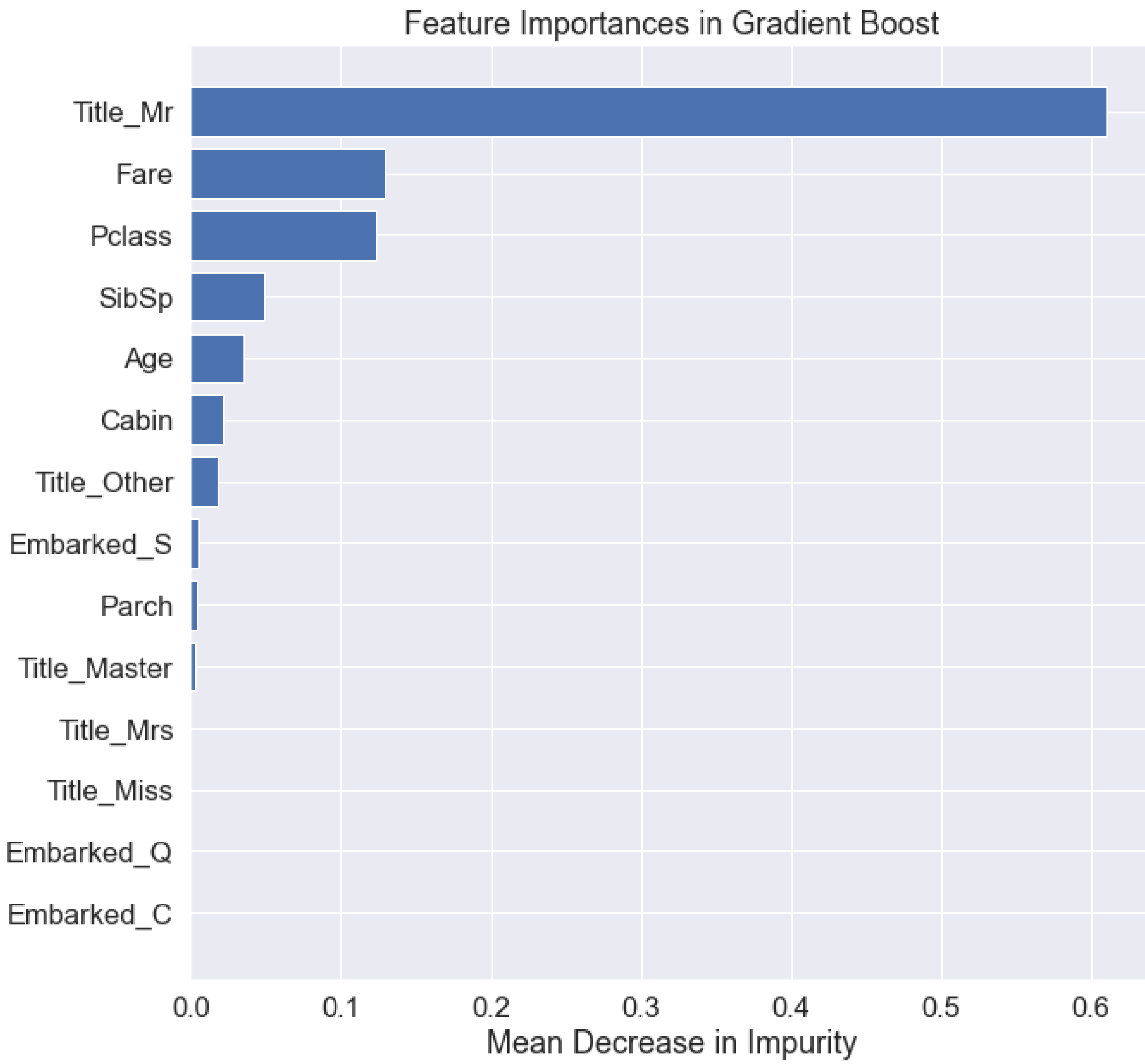
```
Accuracy best performing model (cross-validated):  0.8315191055325083
Params best performing model:  {'max_depth': 3, 'min_samples_leaf': 4, 'min_samp
les_split': 2, 'n_estimators': 20}
```

In [252…

```
# Get feature importances
importances = gbc.feature_importances_
#std = np.std([abc.feature_importances_ for abc in gbc.estimators_], axis=0)
importances = pd.DataFrame([X_train_new.columns, importances]).T
importances.columns = ['Feature', 'Importance']
importances = importances.sort_values('Importance', ascending=True)
```

In [253…

```
fig, ax = plt.subplots(1, figsize=(10, 10))
plt.barh(importances['Feature'], importances['Importance'])#, yerr=std)
ax.set_xlabel('Mean Decrease in Impurity')
ax.set_title('Feature Importances in Gradient Boost')
plt.show()
```



We can see a comparison of values in part 5, but overall, it appears that gradient boosting performs worse than random forest models and is on par with our other models.

Part 4: Neural Networks

Carry on the classification by using feed forward neural networks, using functionality imported from keras. You are responsible for choosing the number of layers, their corresponding size, the activation functions and the choice of gradient descent algorithm (and its parameters e.g. learning rate). Pick those parameters by hand. For some of them you can also perform cross-validation if you wish, but cross validation is not required. Your goal is to tune those parameters so that your test accuracy is at least above 75%.

Report your accuracy on the test set along with your choice of parameters. More specifically, report the number of layers, their size, the activation functions and your choice of optimization algorithm.

It is a good exercise to experiment with different optimizers (gradient descent, stochastic gradient descent, AdaGrad etc), learning rates, batch sizes etc. to get a feeling of how they affect neural network training. Experiment with some of these options. What do you observe?

In [ ]:

```
!pip install tensorflow==2.7
!pip install keras==2.3.1
```

In [32]:

```
import warnings
warnings.filterwarnings("ignore")

from sklearn.neural_network import MLPRegressor
from sklearn.metrics import r2_score, roc_auc_score, accuracy_score

from keras.models import Sequential
from keras.layers import Dense
import tensorflow as tf
```

```
Using TensorFlow backend.
```

In [256…

```
#non-imputed data (did not tune this to be higher than .75 accuracy, as I believ
np.random.seed(0)
tf.random.set_seed(0)

# Define NN
model = Sequential()
model.add(Dense(20, input_dim=len(X_train.columns), activation='sigmoid')) # Fir
model.add(Dense(10, activation='sigmoid'))
model.add(Dense(1, activation='sigmoid')) # For regression/classification, last
model.compile(loss='mse', optimizer='adam', metrics=['mse']) # No r2 metric avai

# Fit and predict with NN
model.fit(X_train, Y_train, epochs=50, batch_size=10, verbose=1)
yhat_train = model.predict(X_train)
yhat_test = model.predict(X_test)

# Get metrics
print('AUC on training set: %.2f' % roc_auc_score(Y_train, yhat_train))
print('AUC on test set: %.2f' % roc_auc_score(Y_test, yhat_test))
```

```
Epoch 1/50
571/571 [==============================] - 0s 722us/step - loss: 0.2351 - mse:
0.2351
Epoch 2/50
571/571 [==============================] - 0s 109us/step - loss: 0.2295 - mse:
0.2295
Epoch 3/50
571/571 [==============================] - 0s 109us/step - loss: 0.2227 - mse:
0.2227
Epoch 4/50
571/571 [==============================] - 0s 107us/step - loss: 0.2177 - mse:
0.2177
Epoch 5/50
571/571 [==============================] - 0s 112us/step - loss: 0.2138 - mse:
0.2138
Epoch 6/50
571/571 [==============================] - 0s 107us/step - loss: 0.2116 - mse:
0.2116
Epoch 7/50
571/571 [==============================] - 0s 111us/step - loss: 0.2099 - mse:
0.2099
```

```
Epoch 8/50
571/571 [==============================] - 0s 112us/step - loss: 0.2079 - mse:
0.2079
Epoch 9/50
571/571 [==============================] - 0s 106us/step - loss: 0.2064 - mse:
0.2064
Epoch 10/50
571/571 [==============================] - 0s 110us/step - loss: 0.2055 - mse:
0.2055
Epoch 11/50
571/571 [==============================] - 0s 115us/step - loss: 0.2043 - mse:
0.2043
Epoch 12/50
571/571 [==============================] - 0s 111us/step - loss: 0.2038 - mse:
0.2038
Epoch 13/50
571/571 [==============================] - 0s 114us/step - loss: 0.2027 - mse:
0.2027
Epoch 14/50
571/571 [==============================] - 0s 113us/step - loss: 0.2018 - mse:
0.2018
Epoch 15/50
571/571 [==============================] - 0s 112us/step - loss: 0.2010 - mse:
0.2010
Epoch 16/50
571/571 [==============================] - 0s 115us/step - loss: 0.2005 - mse:
0.2005
Epoch 17/50
571/571 [==============================] - 0s 114us/step - loss: 0.1997 - mse:
0.1997
Epoch 18/50
571/571 [==============================] - 0s 111us/step - loss: 0.1995 - mse:
0.1995
Epoch 19/50
571/571 [==============================] - 0s 108us/step - loss: 0.1987 - mse:
0.1987
Epoch 20/50
571/571 [==============================] - 0s 111us/step - loss: 0.1981 - mse:
0.1981
Epoch 21/50
571/571 [==============================] - 0s 108us/step - loss: 0.1980 - mse:
0.1980
Epoch 22/50
571/571 [==============================] - 0s 113us/step - loss: 0.1969 - mse:
0.1969
Epoch 23/50
571/571 [==============================] - 0s 115us/step - loss: 0.1964 - mse:
0.1964
Epoch 24/50
571/571 [==============================] - 0s 116us/step - loss: 0.1959 - mse:
0.1959
Epoch 25/50
571/571 [==============================] - 0s 115us/step - loss: 0.1955 - mse:
0.1955
Epoch 26/50
571/571 [==============================] - 0s 115us/step - loss: 0.1954 - mse:
0.1954
Epoch 27/50
571/571 [==============================] - 0s 114us/step - loss: 0.1951 - mse:
0.1951
Epoch 28/50
571/571 [==============================] - 0s 114us/step - loss: 0.1955 - mse:
0.1955
Epoch 29/50
571/571 [==============================] - 0s 113us/step - loss: 0.1942 - mse:
```

```
0.1942
Epoch 30/50
571/571 [==============================] - 0s 113us/step - loss: 0.1930 - mse:
0.1930
Epoch 31/50
571/571 [==============================] - 0s 110us/step - loss: 0.1927 - mse:
0.1927
Epoch 32/50
571/571 [==============================] - 0s 113us/step - loss: 0.1923 - mse:
0.1923
Epoch 33/50
571/571 [==============================] - 0s 113us/step - loss: 0.1915 - mse:
0.1915
Epoch 34/50
571/571 [==============================] - 0s 111us/step - loss: 0.1913 - mse:
0.1913
Epoch 35/50
571/571 [==============================] - 0s 112us/step - loss: 0.1911 - mse:
0.1911
Epoch 36/50
571/571 [==============================] - 0s 113us/step - loss: 0.1906 - mse:
0.1906
Epoch 37/50
571/571 [==============================] - 0s 115us/step - loss: 0.1906 - mse:
0.1906
Epoch 38/50
571/571 [==============================] - 0s 115us/step - loss: 0.1897 - mse:
0.1897
Epoch 39/50
571/571 [==============================] - 0s 113us/step - loss: 0.1894 - mse:
0.1894
Epoch 40/50
571/571 [==============================] - 0s 114us/step - loss: 0.1895 - mse:
0.1895
Epoch 41/50
571/571 [==============================] - 0s 114us/step - loss: 0.1895 - mse:
0.1895
Epoch 42/50
571/571 [==============================] - 0s 116us/step - loss: 0.1895 - mse:
0.1895
Epoch 43/50
571/571 [==============================] - 0s 113us/step - loss: 0.1885 - mse:
0.1885
Epoch 44/50
571/571 [==============================] - 0s 112us/step - loss: 0.1883 - mse:
0.1883
Epoch 45/50
571/571 [==============================] - 0s 114us/step - loss: 0.1885 - mse:
0.1885
Epoch 46/50
571/571 [==============================] - 0s 113us/step - loss: 0.1875 - mse:
0.1875
Epoch 47/50
571/571 [==============================] - 0s 115us/step - loss: 0.1876 - mse:
0.1876
Epoch 48/50
571/571 [==============================] - 0s 114us/step - loss: 0.1872 - mse:
0.1872
Epoch 49/50
571/571 [==============================] - 0s 114us/step - loss: 0.1883 - mse:
0.1883
Epoch 50/50
571/571 [==============================] - 0s 115us/step - loss: 0.1877 - mse:
0.1877
```

```
AUC on training set: 0.76
AUC on test set: 0.75
```

In [257…

```
pred_train = model.predict(X_train)
pred = model.predict(X_test)
pred_train[pred_train >= .5] = 1
pred_train[pred_train < .5] = 0
print(accuracy_score(Y_train,pred_train))

pred[pred >= .5] = 1
pred[pred < .5] = 0
print(accuracy_score(Y_test,pred))
```

```
0.7215411558669002
0.6993006993006993
```

In [258…

```
#imputed data
np.random.seed(0)
tf.random.set_seed(0)

# Define NN
model = Sequential()
model.add(Dense(20, input_dim=len(X_train_new.columns), activation='sigmoid')) #
model.add(Dense(10, activation='sigmoid'))
model.add(Dense(1, activation='sigmoid')) # For regression/classification, last
model.compile(loss='mse', optimizer='adam', metrics=['mse']) # No r2 metric avai

# Fit and predict with NN
model.fit(X_train_new, Y_train_new, epochs=50, batch_size=10, verbose=1)
yhat_train = model.predict(X_train_new)
yhat_test = model.predict(X_test_new)

# Get metrics
print('AUC on training set: %.2f' % roc_auc_score(Y_train_new, yhat_train))
print('AUC on test set: %.2f' % roc_auc_score(Y_test_new, yhat_test))
```

```
Epoch 1/50
712/712 [==============================] - 0s 600us/step - loss: 0.2294 - mse:
0.2294
Epoch 2/50
712/712 [==============================] - 0s 103us/step - loss: 0.2169 - mse:
0.2169
Epoch 3/50
712/712 [==============================] - 0s 103us/step - loss: 0.2030 - mse:
0.2030
Epoch 4/50
712/712 [==============================] - 0s 113us/step - loss: 0.1872 - mse:
0.1872
Epoch 5/50
712/712 [==============================] - 0s 112us/step - loss: 0.1722 - mse:
0.1722
Epoch 6/50
712/712 [==============================] - 0s 111us/step - loss: 0.1599 - mse:
0.1599
Epoch 7/50
712/712 [==============================] - 0s 112us/step - loss: 0.1506 - mse:
0.1506
Epoch 8/50
712/712 [==============================] - 0s 113us/step - loss: 0.1440 - mse:
0.1440
Epoch 9/50
```

```
712/712 [==============================] - 0s 114us/step - loss: 0.1395 - mse:
0.1395
Epoch 10/50
712/712 [==============================] - 0s 112us/step - loss: 0.1363 - mse:
0.1363
Epoch 11/50
712/712 [==============================] - 0s 112us/step - loss: 0.1339 - mse:
0.1339
Epoch 12/50
712/712 [==============================] - 0s 112us/step - loss: 0.1321 - mse:
0.1321
Epoch 13/50
712/712 [==============================] - 0s 109us/step - loss: 0.1309 - mse:
0.1309
Epoch 14/50
712/712 [==============================] - 0s 113us/step - loss: 0.1297 - mse:
0.1297
Epoch 15/50
712/712 [==============================] - 0s 113us/step - loss: 0.1287 - mse:
0.1287
Epoch 16/50
712/712 [==============================] - 0s 113us/step - loss: 0.1279 - mse:
0.1279
Epoch 17/50
712/712 [==============================] - 0s 114us/step - loss: 0.1272 - mse:
0.1272
Epoch 18/50
712/712 [==============================] - 0s 112us/step - loss: 0.1266 - mse:
0.1266
Epoch 19/50
712/712 [==============================] - 0s 110us/step - loss: 0.1261 - mse:
0.1261
Epoch 20/50
712/712 [==============================] - 0s 115us/step - loss: 0.1258 - mse:
0.1258
Epoch 21/50
712/712 [==============================] - 0s 113us/step - loss: 0.1255 - mse:
0.1255
Epoch 22/50
712/712 [==============================] - 0s 112us/step - loss: 0.1249 - mse:
0.1249
Epoch 23/50
712/712 [==============================] - 0s 113us/step - loss: 0.1251 - mse:
0.1251
Epoch 24/50
712/712 [==============================] - 0s 116us/step - loss: 0.1245 - mse:
0.1245
Epoch 25/50
712/712 [==============================] - 0s 111us/step - loss: 0.1241 - mse:
0.1241
Epoch 26/50
712/712 [==============================] - 0s 113us/step - loss: 0.1238 - mse:
0.1238
Epoch 27/50
712/712 [==============================] - 0s 111us/step - loss: 0.1239 - mse:
0.1239
Epoch 28/50
712/712 [==============================] - 0s 114us/step - loss: 0.1236 - mse:
0.1236
Epoch 29/50
712/712 [==============================] - 0s 111us/step - loss: 0.1232 - mse:
0.1232
Epoch 30/50
712/712 [==============================] - 0s 113us/step - loss: 0.1230 - mse:
0.1230
```

```
Epoch 31/50
712/712 [==============================] - 0s 113us/step - loss: 0.1229 - mse:
0.1229
Epoch 32/50
712/712 [==============================] - 0s 109us/step - loss: 0.1229 - mse:
0.1229
Epoch 33/50
712/712 [==============================] - 0s 111us/step - loss: 0.1223 - mse:
0.1223
Epoch 34/50
712/712 [==============================] - 0s 117us/step - loss: 0.1226 - mse:
0.1226
Epoch 35/50
712/712 [==============================] - 0s 113us/step - loss: 0.1217 - mse:
0.1217
Epoch 36/50
712/712 [==============================] - 0s 111us/step - loss: 0.1216 - mse:
0.1216
Epoch 37/50
712/712 [==============================] - 0s 113us/step - loss: 0.1217 - mse:
0.1217
Epoch 38/50
712/712 [==============================] - 0s 114us/step - loss: 0.1216 - mse:
0.1216
Epoch 39/50
712/712 [==============================] - 0s 112us/step - loss: 0.1215 - mse:
0.1215
Epoch 40/50
712/712 [==============================] - 0s 111us/step - loss: 0.1212 - mse:
0.1212
Epoch 41/50
712/712 [==============================] - 0s 114us/step - loss: 0.1212 - mse:
0.1212
Epoch 42/50
712/712 [==============================] - 0s 113us/step - loss: 0.1208 - mse:
0.1208
Epoch 43/50
712/712 [==============================] - 0s 114us/step - loss: 0.1210 - mse:
0.1210
Epoch 44/50
712/712 [==============================] - 0s 113us/step - loss: 0.1210 - mse:
0.1210
Epoch 45/50
712/712 [==============================] - 0s 114us/step - loss: 0.1208 - mse:
0.1208
Epoch 46/50
712/712 [==============================] - 0s 118us/step - loss: 0.1206 - mse:
0.1206
Epoch 47/50
712/712 [==============================] - 0s 117us/step - loss: 0.1205 - mse:
0.1205
Epoch 48/50
712/712 [==============================] - 0s 114us/step - loss: 0.1203 - mse:
0.1203
Epoch 49/50
712/712 [==============================] - 0s 115us/step - loss: 0.1201 - mse:
0.1201
Epoch 50/50
712/712 [==============================] - 0s 115us/step - loss: 0.1200 - mse:
0.1200
AUC on training set: 0.88
AUC on test set: 0.88
```

In [259…

```
pred_train = model.predict(X_train_new)
```

```
pred = model.predict(X_test_new)
pred_train[pred_train >= .5] = 1
pred_train[pred_train < .5] = 0
print(accuracy_score(Y_train_new,pred_train))

pred[pred >= .5] = 1
pred[pred < .5] = 0
print(accuracy_score(Y_test_new,pred))
```

```
0.8525280898876404
0.8212290502793296
```

After messing around with parameters, I found that after a while, changes to optimizer, activation, and amount of layers and sizes all have minimal changes. Feature engineering is very important to get good results here.

Part 5: Putting it all together!

Create a final table that summarizes the performance of your models as follows. What do you observe? Are there trends in which models and hyperparameters work best?

Model	Cross-validated Performance	Train Performance	Test Performance	Chosen Hyperparameters
Decision Tree	0.700484	0.85	0.65	max_depth = 8, min_samples_leaf = 1
Decision Tree (with imputed missing values and new features)	0.820167	.85	.80	max_depth = 4, min_samples_leaf = 3
SVM	0.681326	.68	.65	C = .4
SVM (with imputed missing values and new features)	0.832837	.85	.8	C = .5
Random Forest	0.7390833103701663	.82	.76	maximum depth: 9, number of estimators: 250, min samples split: 10, min samples leaf: 2
Random Forest (with imputed missing values and new features)	0.8259109550993394	.88	.82	maximum depth: 9, number of estimators: 52, min samples split: 5, min samples leaf: 2

Model	Cross-validated Performance	Train Performance	Test Performance	Chosen Hyperparameters
Gradient Boosting	0.7337742261412693	.80	.74	max_depth = 3, min_samples_leaf = 2, min_samples_split = 2, n_estimators = 52
Gradient Boosting (with imputed missing values and new features)	0.8315191055325083	.85	.79	max_depth = 3, min_samples_leaf = 4, min_samples_split = 2, n_estimators = 20
Neural Network	N/A	0.7215411558669002	0.6993006993006993	layers = 3, sizes= (20,10,1), activation = sigmoid, loss = mse, optimizer = adam, metrics = mse
Neural Network (with imputed missing values and new features)	N/A	0.8525280898876404	0.8212290502793296	layers = 3, sizes= (20,10,1), activation = sigmoid, loss = mse, optimizer = adam, metrics = mse

It appears that decision trees an SVMs perform about the same on our test data. Random Forest performs slighly better and gradient boosting performs slightly worse. Our neural network with imputed data and feature engineering performs as well as the random forest model with imputed values and new features. Overall, it appears that random forest perfoms the best for this set of data overall. We can see that our models using imputed data and new features perform better in every case.

Part 6: (Extra credit) Flex your ML chops

Add additional rows to the table from Part 5 based on other models you've learned in class.

- Which models perform the best, using the default parameters (i.e., no hyperparameter tuning)?
- How do models perform in terms of performance metrics beyond accuracy? (e.g. AUC score, precision, recall)
- For which models does careful hyperparameter tuning make the biggest different? Why do you think that is the case?
- Which tuned model has the largest gap between cross-validated performance and test performance? Why might that be?

In [ ]:
```
# Your code here
```

Your observations here