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 (https://www.kaggle.com/c/titanic)](https://www.kaggle.com/c/titanic). Then, download the data [here (https://www.kaggle.com/c/titanic/data)](https://www.kaggle.com/c/titanic/data) - 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 [2]:

```
import IPython
import numpy as np
import scipy as sp
import pandas as pd
import matplotlib
import sklearn
from sklearn.model_selection import KFold
import seaborn as sns
from sklearn.model_selection import train_test_split, KFold, GridSearchCV
from sklearn.ensemble import RandomForestClassifier, RandomForestRegressor, Gradient


%matplotlib inline
import matplotlib.pyplot as plt
```

In [3]:

```
# Your code here
df = pd.read_csv('train.csv')
df.head()
```

Out[3]:

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

In [4]:

```
df.isnull().sum()
```

Out[4]:

```
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 [5]:

```
summary = df.describe()
summary.T
```

Out[5]:

	count	mean	std	min	25%	50%	75%	max
PassengerId	891.0	446.000000	257.353842	1.00	223.5000	446.0000	668.5	891.0000
Survived	891.0	0.383838	0.486592	0.00	0.0000	0.0000	1.0	1.0000
Pclass	891.0	2.308642	0.836071	1.00	2.0000	3.0000	3.0	3.0000
Age	714.0	29.699118	14.526497	0.42	20.1250	28.0000	38.0	80.0000
SibSp	891.0	0.523008	1.102743	0.00	0.0000	0.0000	1.0	8.0000
Parch	891.0	0.381594	0.806057	0.00	0.0000	0.0000	0.0	6.0000
Fare	891.0	32.204208	49.693429	0.00	7.9104	14.4542	31.0	512.3292

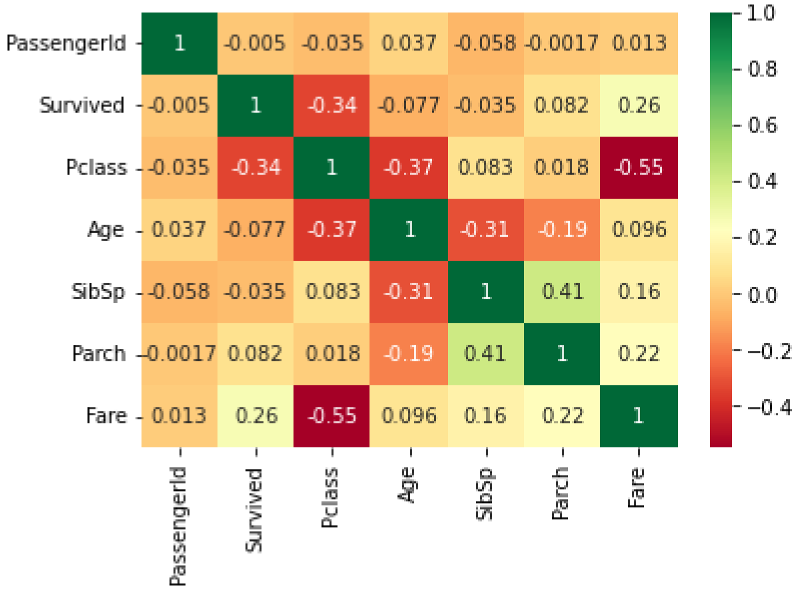
In [6]:

```
for columns in df.columns:
 print('%s: %s' %(columns,type(df[columns][0])))
```

```
PassengerId: <class 'numpy.int64'>
Survived: <class 'numpy.int64'>
Pclass: <class 'numpy.int64'>
Name: <class 'str'>
Sex: <class 'str'>
Age: <class 'numpy.float64'>
SibSp: <class 'numpy.int64'>
Parch: <class 'numpy.int64'>
Ticket: <class 'str'>
Fare: <class 'numpy.float64'>
Cabin: <class 'float'>
Embarked: <class 'str'>
```

In [7]:

```
import seaborn as sn

corrMatrix = df.corr()
#fig = plt.figure(figsize=(10,10))
sn.heatmap(corrMatrix, annot=True, cmap="RdYlGn")
plt.show()
```

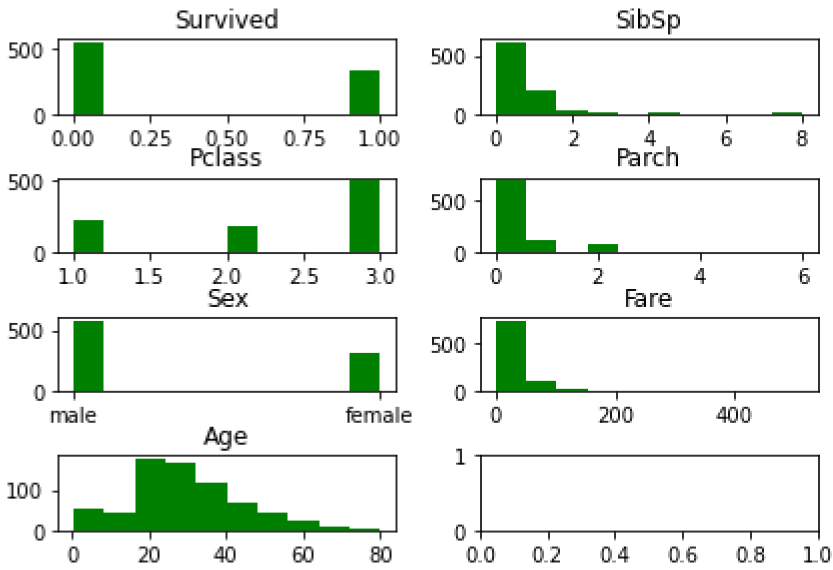


In [8]:

```
fig, axs = plt.subplots(4, 2)
fig.tight_layout()
#
axs[0][0].hist(df['Survived'], color='green')
axs[0][0].set_title('Survived')

axs[1][0].hist(df['Pclass'], color='green')
axs[1][0].set_title('Pclass')

axs[2][0].hist(df['Sex'], color='green')
axs[2][0].set_title('Sex')

axs[3][0].hist(df['Age'], color='green')
axs[3][0].set_title('Age')

axs[0][1].hist(df['SibSp'], color='green')
axs[0][1].set_title('SibSp')

axs[1][1].hist(df['Parch'], color='green')
axs[1][1].set_title('Parch')

axs[2][1].hist(df['Fare'], color='green')
axs[2][1].set_title('Fare')
```

Out[8]:

```
Text(0.5, 1.0, 'Fare')
```



1. `Age` , `Cabin` , and `Embarked` have missing value
2. `Age` is right skewed
3. `Pclass` and `Fare` are hightl correlated

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 [9]:

```
import statsmodels.api as sm
import statsmodels.formula.api as smf

# Your code here
print(smf.ols(formula='Survived ~ Age', data=df).fit().summary()) #family size

df['Age*Fare'] = df['Age']*df['Fare']
print(smf.ols(formula='Survived ~ Age + Fare + Age*Fare', data=df).fit().summary())
```

```
                            OLS Regression Results
==============================================================================
========
Dep. Variable:               Survived   R-squared:
0.006
Model:                            OLS   Adj. R-squared:
0.005
Method:                 Least Squares   F-statistic:
4.271
Date:                Mon, 04 Apr 2022   Prob (F-statistic):
0.0391
Time:                        23:28:15   Log-Likelihood:
-503.28
No. Observations:                 714   AIC:
1011.
Df Residuals:                     712   BIC:
1020.
Df Model:                           1
Covariance Type:            nonrobust
==============================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
------------------------------------------------------------------------------
--------
Intercept      0.4838      0.042     11.576      0.000       0.402
0.566
Age           -0.0026      0.001     -2.067      0.039      -0.005
-0.000
==============================================================================
========
Omnibus:                     3171.380   Durbin-Watson:
1.905
Prob(Omnibus):                  0.000   Jarque-Bera (JB):
116.965
Skew:                           0.380   Prob(JB):
3.99e-26
Kurtosis:                       1.168   Cond. No.
75.3
==============================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
                            OLS Regression Results
==============================================================================
========
```

```
Dep. Variable:                Survived   R-squared:
0.084
Model:                             OLS   Adj. R-squared:
0.080
Method:                  Least Squares   F-statistic:
21.76
Date:                 Mon, 04 Apr 2022   Prob (F-statistic):
1.73e-13
Time:                         23:28:15   Log-Likelihood:
-474.01
No. Observations:                  714   AIC:
956.0
Df Residuals:                      710   BIC:
974.3
Df Model:                            3
Covariance Type:             nonrobust
======================================================================
========
                 coef    std err          t      P>|t|      [0.025
0.975]
----------------------------------------------------------------------
--------
Intercept      0.4561      0.052      8.786      0.000       0.354
0.558
Age           -0.0047      0.002     -2.902      0.004      -0.008
-0.002
Fare           0.0016      0.001      1.595      0.111      -0.000
0.003
Age:Fare    3.136e-05   2.84e-05      1.102      0.271   -2.45e-05
8.72e-05
======================================================================
========
Omnibus:                      4251.826   Durbin-Watson:
1.913
Prob(Omnibus):                   0.000   Jarque-Bera (JB):
94.226
Skew:                            0.389   Prob(JB):
3.46e-21
Kurtosis:                        1.399   Cond. No.
6.60e+03
======================================================================
========

Notes:
[1] Standard Errors assume that the covariance matrix of the errors is
correctly specified.
[2] The condition number is large, 6.6e+03. This might indicate that t
here are
strong multicollinearity or other numerical problems.
```

1. `Age` is negatively correlated with `Survived`
2. `Fare` are positively correlated with `Survived`

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 [10]:

```
# Your code here

df['Sex'] = df['Sex'].apply(lambda x: 1 if x == 'male' else 0) #recode variable 'poo
#df['Embarked'] = df['Embarked'].apply(lambda x: 1 if x == 'male' else 0) #recode va

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

df['Age'] = standardize(df['Age'])
df['Fare'] = standardize(df['Fare'])
df['SibSp'] = standardize(df['SibSp'])
df['Parch'] = standardize(df['Parch'])

#dummy variables
df = pd.get_dummies(df, columns=['Embarked'])
df = pd.get_dummies(df, columns=['Pclass'])

df = df.drop(['PassengerId', 'Ticket'], axis=1)

df.head()
```

Out[10]:

	Survived	Name	Sex	Age	SibSp	Parch	Fare	Cabin	Age*Fare	Emb
0	0	Braund, Mr. Owen Harris	1	-0.530377	0.432793	-0.473674	-0.502445	NaN	159.5000	
1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	0	0.571831	0.432793	-0.473674	0.786845	C85	2708.7654	
2	1	Heikkinen, Miss. Laina	0	-0.254825	-0.474545	-0.473674	-0.488854	NaN	206.0500	
3	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	0	0.365167	0.432793	-0.473674	0.420730	C123	1858.5000	
4	0	Allen, Mr. William Henry	1	0.365167	-0.474545	-0.473674	-0.486337	NaN	281.7500	

Part 2: Decision Trees

2.1 Decision Tree

Using the basic [Decision Tree Classifier (http://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html#sklearn.tree.DecisionTreeClassifier)](http://scikit-learn.org/stable/modules/generated/sklearn.tree.DecisionTreeClassifier.html#sklearn.tree.DecisionTreeClassifier) 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 [11]:

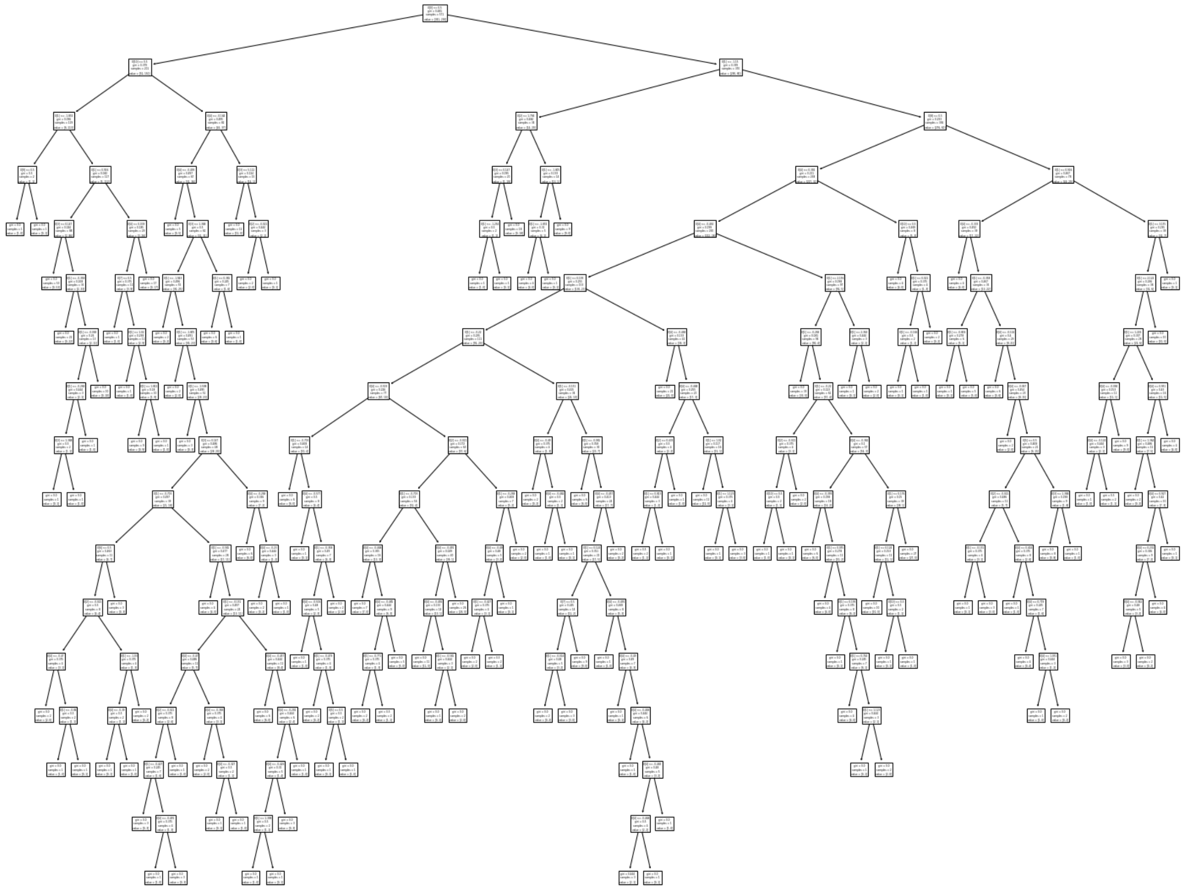
```
df_dropna = df.dropna(subset=['Age'])

np.random.seed(seed=13579)

# enter your code here
train_percent = .80
train_number = int(train_percent*len(df_dropna))
print('Total examples: %i' % len(df_dropna))
print('Number of training examples: %i' % train_number)
print('Number of testing examples: %i' % (len(df_dropna) - train_number))

ids = np.arange(0, len(df_dropna), 1)
ids = np.random.permutation(ids)
df_dropna_shuffled = df_dropna.iloc[ids]

df_train_dropna = df_dropna_shuffled[:train_number]
df_test_dropna = df_dropna_shuffled[train_number:]
```

```
Total examples: 714
Number of training examples: 571
Number of testing examples: 143
```

In [12]:

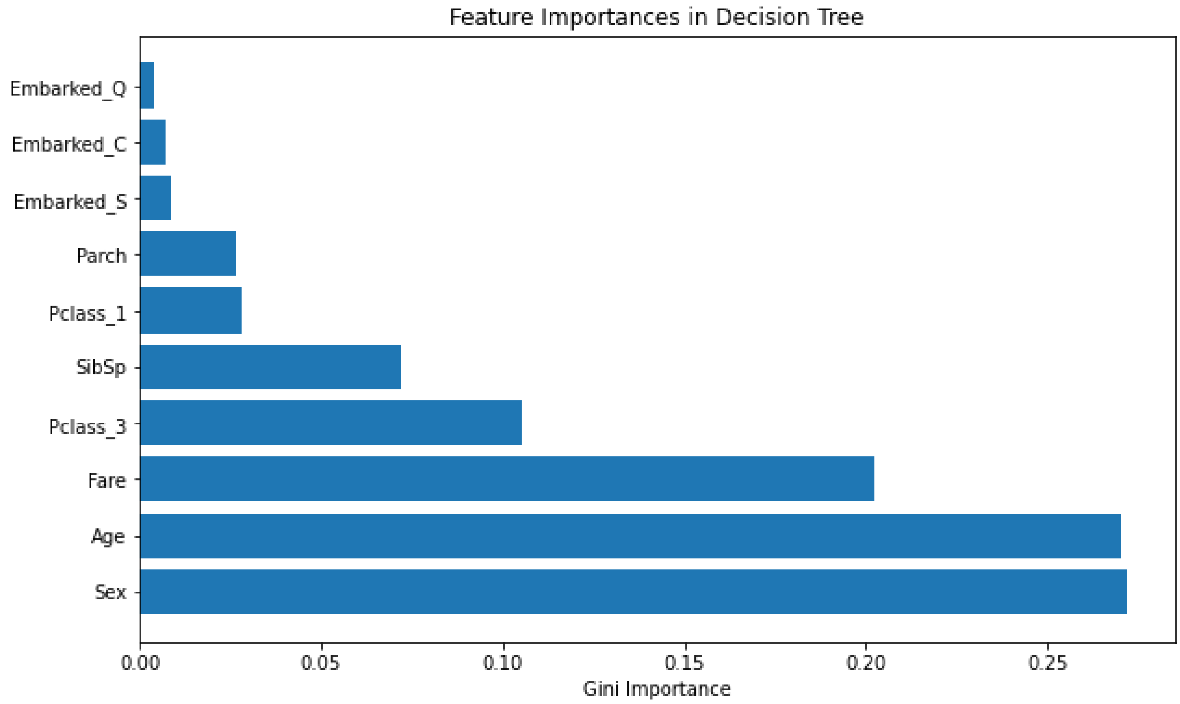
```
# Your code here
from sklearn.tree import DecisionTreeClassifier
from sklearn import metrics
from sklearn import tree

feature = ['Sex','Age','SibSp', 'Parch','Fare','Embarked_C','Embarked_Q', 'Embarked_
kf = KFold(n_splits=10)
acc_test = []
acc_train = []

for train, test in kf.split(df_train_dropna):
    X = df_train_dropna[feature]
    y = df_train_dropna['Survived']
    clf = DecisionTreeClassifier()
    clf = clf.fit(X.iloc[train],y.iloc[train])

    # calculate prediction
    y_pred_test = clf.predict(X.iloc[test])
    y_pred_train = clf.predict(X.iloc[train])

    # calculate accuracy
    acc_test.append(metrics.accuracy_score(y.iloc[test], y_pred_test))
    acc_train.append(metrics.accuracy_score(y.iloc[train], y_pred_train))

print('========== average training accuracy (CV) ==========')
print(np.mean(acc_train))

print('========== average cross-validation accuracy (CV) ==========')
print(np.mean(acc_test))

# fit a single decision tree model on all of the training data
clf = DecisionTreeClassifier().fit(df_train_dropna[feature], df_train_dropna['Surviv
y_pred = clf.predict(df_test_dropna[feature])
acc = metrics.accuracy_score(df_test_dropna['Survived'], y_pred)
print('========== accuracy (test data) ==========')
print(acc)

fig = plt.figure(figsize=(25,20))
tree.plot_tree(clf)
plt.show()
```

```
========== average training accuracy (CV) ==========
0.9920214500800206
========== average cross-validation accuracy (CV) ==========
0.7442226255293405
========== accuracy (test data) ==========
0.7342657342657343
```



In [13]:

```
importances = clf.feature_importances_
importances = pd.DataFrame([df_train_dropna[feature].columns, importances]).T
importances.columns = ['Feature', 'Importance']
importances = importances.sort_values('Importance', ascending=False)[:10]

# 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()
```



- the test data accuracy (0.734) is smaller than the average cross-validation accuracy (0.744)

2.2 Hyperparameter: Maximum Depth

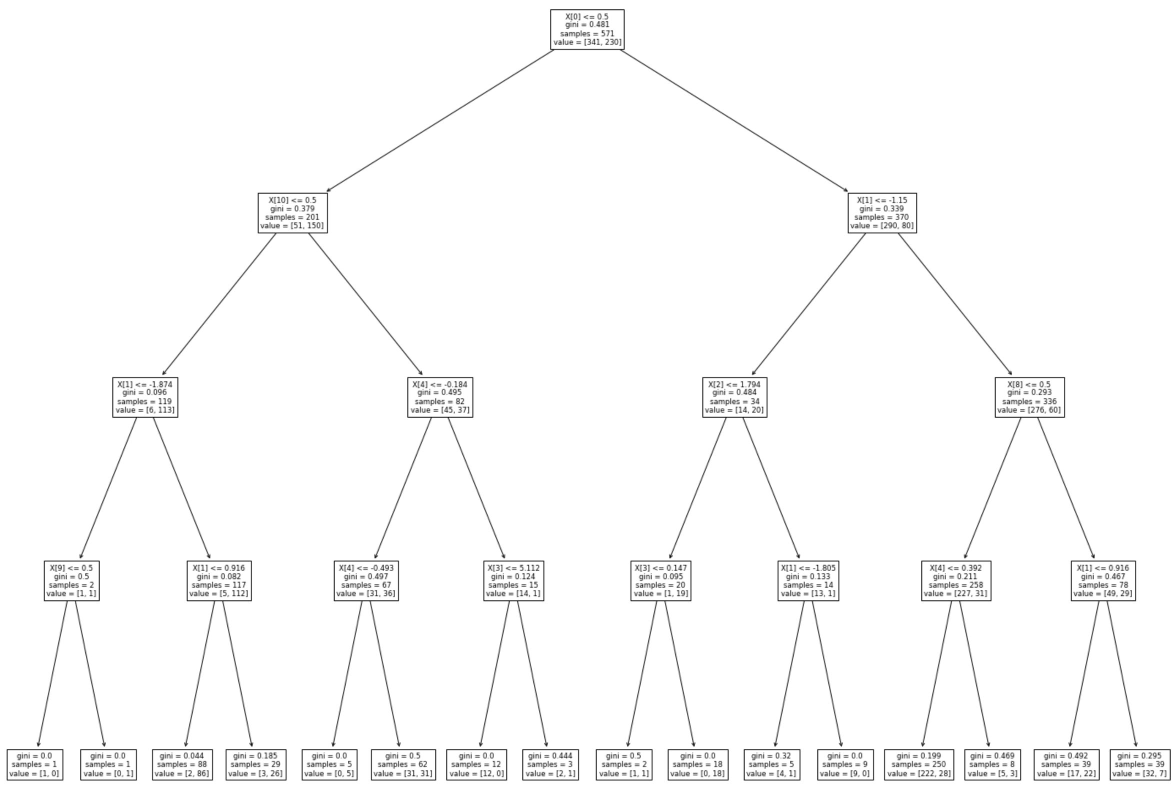
2.2 Hyperparameter: Maximum Depth

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 [14]:

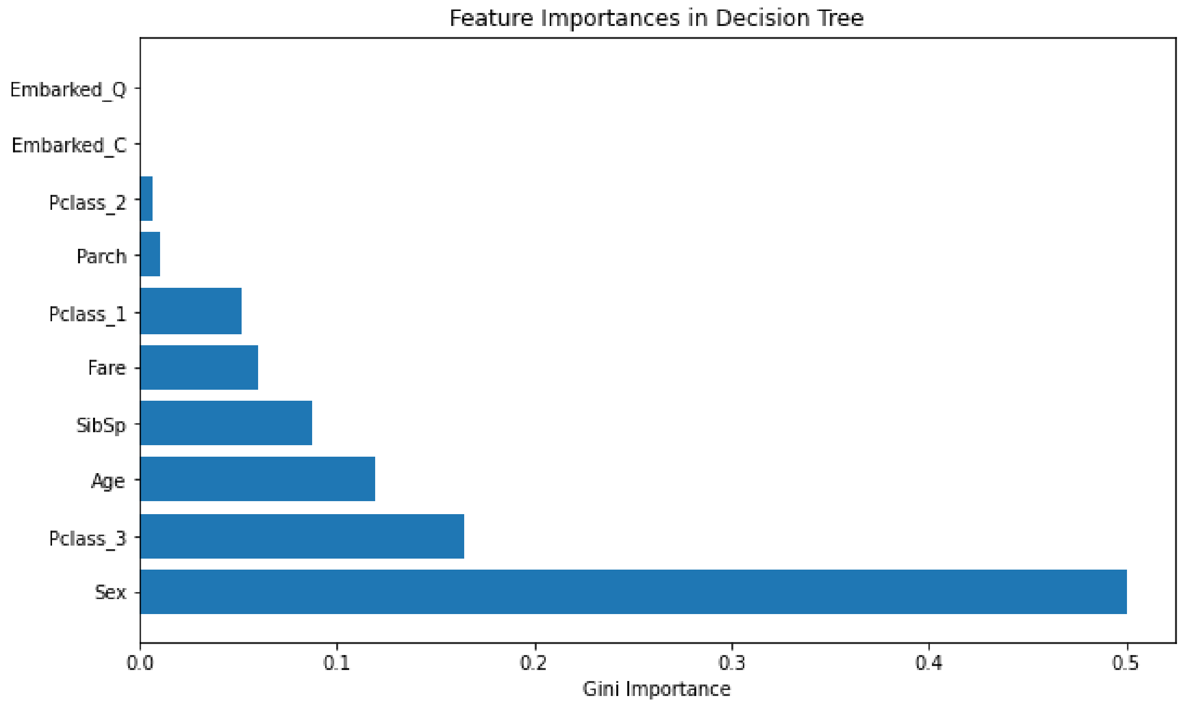
```
# Your code here
# fit a single decision tree model on all of the training data
clf = DecisionTreeClassifier(max_depth = 4).fit(df_train_dropna[feature], df_train_c
y_pred = clf.predict(df_test_dropna[feature])
acc = metrics.accuracy_score(df_test_dropna['Survived'], y_pred)
print('========== accuracy (test data) ==========')
print(acc)

#plot tree
fig = plt.figure(figsize=(25,20))
tree.plot_tree(clf)
plt.show()
```

```
========== accuracy (test data) ==========
0.7902097902097902
```



In [15]:

```
importances = clf.feature_importances_
importances = pd.DataFrame([df_train_dropna[feature].columns, importances]).T
importances.columns = ['Feature', 'Importance']
importances = importances.sort_values('Importance', ascending=False)[:10]

# 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()
```



- the performance of this tree (acc = 0.79) is better than the previous tree (acc = 0.73)
- the node of this tree is much fewer than the previous one
- both trees consider 'Sex' the most important feature. The first tree consider 'Age' as the second important feature, whereas the second three considers 'Pclass_3'

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.

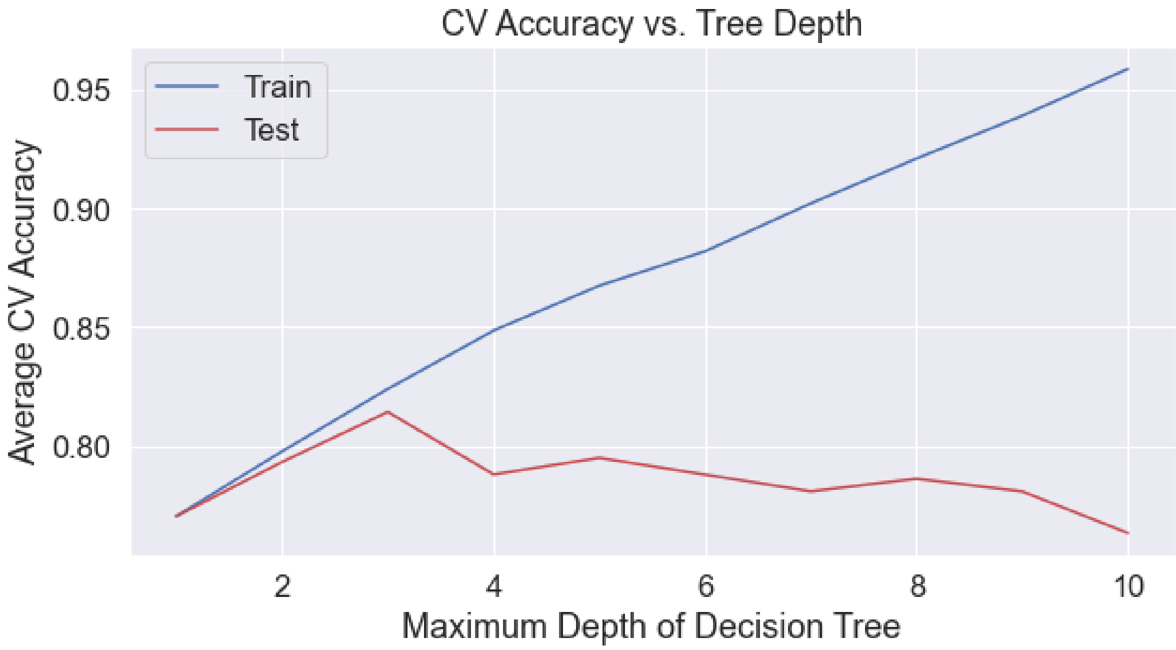
In [16]:

```
# Your code here
feature = ['Sex','Age','SibSp', 'Parch','Fare','Embarked_C','Embarked_Q', 'Embarked_
kf = KFold(n_splits=5)

maxdepth = np.linspace(1,10,10)
ACC_maxdepth = {}
ACC_maxdepth_train = []
ACC_maxdepth_test = []


for dep in maxdepth:
    acc_test = []
    acc_train = []
    for train, test in kf.split(df_train_dropna):
        X = df_train_dropna[feature]
        y = df_train_dropna['Survived']
        clf = DecisionTreeClassifier(max_depth = dep)
        clf = clf.fit(X.iloc[train],y.iloc[train])

        # calculate prediction
        y_pred_test = clf.predict(X.iloc[test])
        y_pred_train = clf.predict(X.iloc[train])

        # calculate accuracy
        acc_test.append(metrics.accuracy_score(y.iloc[test], y_pred_test))
        acc_train.append(metrics.accuracy_score(y.iloc[train], y_pred_train))

    ACC_maxdepth.update({dep: [np.mean(acc_train), np.mean(acc_test)]})
    ACC_maxdepth_train.append(np.mean(acc_train))
    ACC_maxdepth_test.append(np.mean(acc_test))
```

In [17]:

```
print(ACC_maxdepth)

sns.set(font_scale=1.5)
fig, ax = plt.subplots(1, figsize=(10, 5))

#scatter plot
plt.plot(maxdepth, ACC_maxdepth_train, label='Train', color = 'b')
plt.plot(maxdepth, ACC_maxdepth_test, label='Test', color = 'r')

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()
```

```
{1.0: [0.770574686168375, 0.7705263157894737], 2.0: [0.797719682137510
1, 0.7932723112128147], 3.0: [0.8239846059349688, 0.8142791762013731],
4.0: [0.8485009021459557, 0.7880396643783371], 5.0: [0.867328880187339
2, 0.7949809305873379], 6.0: [0.8817776114246229, 0.787948131197559],
7.0: [0.9019184997504703, 0.7809763539282991], 8.0: [0.920745518062113
7, 0.7862090007627766], 9.0: [0.9386991823102614, 0.7809458428680397],
10.0: [0.9584024338746209, 0.7634630053394356]}
```



In [18]:

```
# Your code here
# fit a single decision tree model on all of the training data
clf = DecisionTreeClassifier(max_depth = 3).fit(df_train_dropna[feature], df_train_d
y_pred = clf.predict(df_test_dropna[feature])
acc = metrics.accuracy_score(df_test_dropna['Survived'], y_pred)
print('========== accuracy (test data) ==========')
print(acc)
```

```
========== accuracy (test data) ==========
0.8391608391608392
```

In [19]:

```
feature = ['Sex','Age','SibSp', 'Parch','Fare','Embarked_C','Embarked_Q', 'Embarked_
X = df_train_dropna[feature]
y = df_train_dropna['Survived']

# Tune hyperparameter: max_depth, min_samples_leaf
model = DecisionTreeClassifier()
cv = KFold(n_splits=3, shuffle=True, random_state=1)
params = {'max_depth':[2, 4, 6, 8, 10], 'min_samples_leaf': [1,5,10]}
cv_model = GridSearchCV(model, param_grid=params, scoring='accuracy', refit=True, re
cv_model.fit(X, y)
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.sort_values('mean_test_score',ascending=False).head()
```

Out[19]:

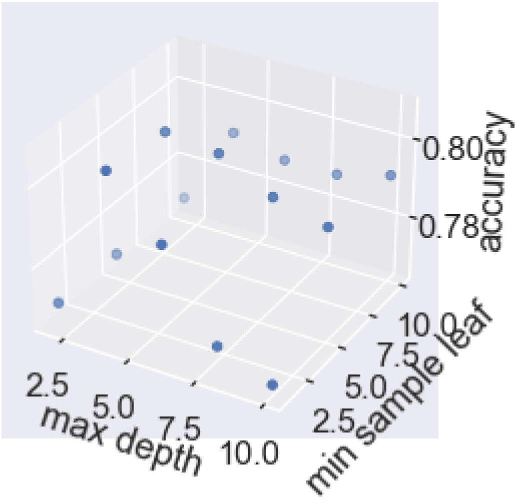
	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_min_
3	0.000962	0.000054	0.000494	0.000037	4	
4	0.000929	0.000090	0.000470	0.000029	4	
7	0.000875	0.000024	0.000445	0.000021	6	
10	0.000846	0.000014	0.000431	0.000016	8	
13	0.000909	0.000001	0.000444	0.000008	10	

In [20]:

```
# 3D scatter plot

fig = plt.figure()
ax = fig.add_subplot(projection='3d')

xs = cv_results['param_max_depth']
ys = cv_results['param_min_samples_leaf']
zs = cv_results['mean_test_score']
ax.scatter(xs, ys, zs)

ax.set_xlabel('max depth')
ax.set_ylabel('min sample leaf')
ax.set_zlabel('accuracy')
```

Out[20]:

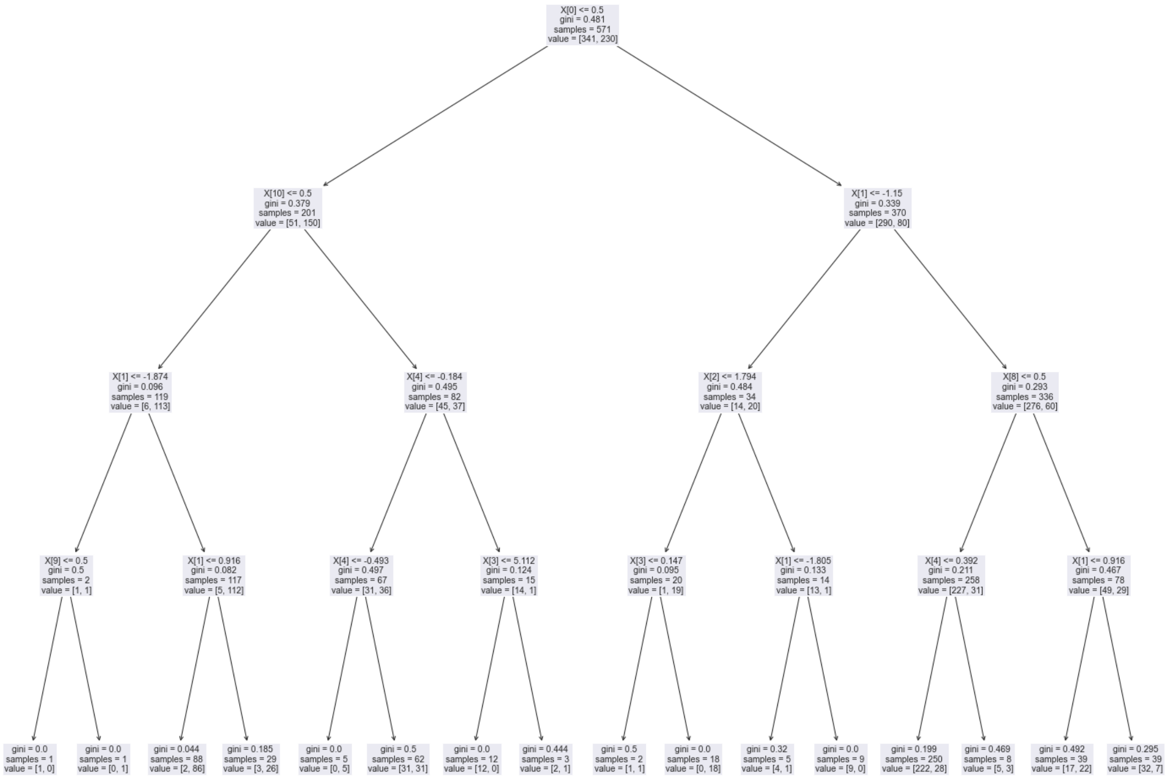
```
Text(0.5, 0, 'accuracy')
```



In [21]:

```
# model with the best hyperparameters got through cross-validation
model = DecisionTreeClassifier(max_depth = 4, min_samples_leaf = 1)
model.fit(X , y)
yhat_test = model.predict(df_test_dropna[feature])
acc = metrics.accuracy_score(df_test_dropna['Survived'], yhat_test)

print('========== accuracy (max_depth = 4, min_samples_leaf = 1) ==========')
print(acc)

# plot tree
fig = plt.figure(figsize=(25,20))
tree.plot_tree(model)
plt.show()
```

```
========== accuracy (max_depth = 4, min_samples_leaf = 1) ==========
0.7902097902097902
```



1. Within the scope of the hyperparameter I tuned, adding min_samples_leaf doe not provide a better

1. Within the scope of the hyperparameter I tuned, adding min_samples_leaf doe not provide a better performance.
2. combination of `max_depth` = 4 and `min-samples_leaf` =1 achieves the highest accuracy. Probably because the scope of the value I tuned is not large, the results to these two parameters does not seems to be very sensitive.

2.4 Support Vector Machines, for comparison

As a starting point, use the basic [sklearn SVM model (https://scikit-learn.org/stable/modules/svm.html)](https://scikit-learn.org/stable/modules/svm.html), 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 [22]:

```
# Your code here
from sklearn import svm

# Report your accuracy on the test and train sets.
feature = ['Sex','Age','SibSp', 'Parch','Fare','Embarked_C','Embarked_Q', 'Embarked_
X = df_train_dropna[feature]
y = df_train_dropna['Survived']

clf = svm.SVC()
clf.fit(X, y)

y_pred_test = clf.predict(df_test_dropna[feature])
y_pred_train = clf.predict(X)

y_test = df_test_dropna['Survived']

print("Accuracy(train set):",metrics.accuracy_score(y, y_pred_train))
print("Accuracy(test set):",metrics.accuracy_score(y_test, y_pred_test))
```

```
Accuracy(train set): 0.8353765323992994
Accuracy(test set): 0.8461538461538461
```

In [23]:

```
feature = ['Sex','Age','SibSp', 'Parch','Fare','Embarked_C','Embarked_Q', 'Embarked_
X = df_train_dropna[feature]
y = df_train_dropna['Survived']

model = svm.SVC()
cv = KFold(n_splits=5, shuffle=True, random_state=1)
params = {'C':np.linspace(1,10,10, dtype = int)}
cv_model = GridSearchCV(model, param_grid=params, scoring='accuracy', refit=True, re
cv_model.fit(X, y)
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.sort_values('mean_test_score',ascending=False).head()
```

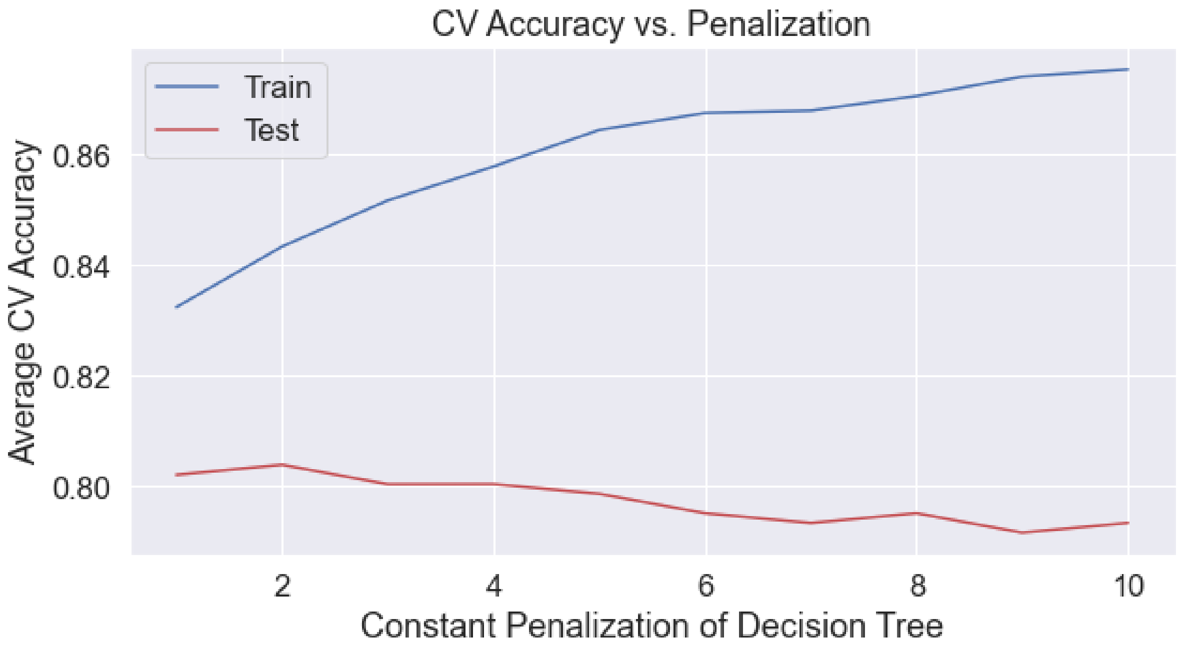
Out[23]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_C	params	split0_test_s
1	0.003120	0.000100	0.001530	0.000077	2	{'C': 2}	0.80
0	0.003480	0.000426	0.001820	0.000201	1	{'C': 1}	0.82
3	0.003056	0.000146	0.001386	0.000017	4	{'C': 4}	0.79
2	0.003062	0.000141	0.001455	0.000058	3	{'C': 3}	0.80
4	0.003152	0.000072	0.001405	0.000031	5	{'C': 5}	0.77

5 rows × 21 columns

In [24]:

```
#scatter plot
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', color
ax.plot(cv_results['param_C'], cv_results['mean_test_score'], label='Test', color =

ax.set_xlabel('Constant Penalization of Decision Tree')
ax.set_ylabel('Average CV Accuracy')
ax.set_title('CV Accuracy vs. Penalization')
ax.legend(loc='best')
plt.show()
```



In [25]:

```
feature = ['Sex','Age','SibSp', 'Parch','Fare','Embarked_C','Embarked_Q', 'Embarked_
X = df_train_dropna[feature]
y = df_train_dropna['Survived']

clf = svm.SVC(C =2)
clf.fit(X, y)

y_pred_test = clf.predict(df_test_dropna[feature])
y_pred_train = clf.predict(X)

y_test = df_test_dropna['Survived']

print("Accuracy(train set):",metrics.accuracy_score(y, y_pred_train))
print("Accuracy(test set):",metrics.accuracy_score(y_test, y_pred_test))
```

```
Accuracy(train set): 0.8423817863397548
Accuracy(test set): 0.8321678321678322
```

- the test performance with SVM for your best choice of C (acc = 0.83) is better compared with the decision tree from 2.3 (0.79)

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 [26]:

```
# Recall from part 1 that some features have missing data. Which features have missi
print(df.isnull().sum())
```

```
Survived        0
Name            0
Sex             0
Age           177
SibSp           0
Parch           0
Fare            0
Cabin         687
Age*Fare      177
Embarked_C      0
Embarked_Q      0
Embarked_S      0
Pclass_1        0
Pclass_2        0
Pclass_3        0
dtype: int64
```

In [27]:

```
## resplitting training and test data without dropping N/A
train_percent = .80
train_number = int(train_percent*len(df))

ids = np.arange(0, len(df), 1)
ids = np.random.permutation(ids)
df_shuffled = df.iloc[ids]

df_train = df_shuffled[:train_number]
df_test = df_shuffled[train_number:]
```

In [28]:

```python
# Try running the decision tree and SVM models from part 1 using all columns, incluc
np.random.seed(seed=13579)

feature_all = ['Sex','Age','SibSp', 'Parch','Fare','Embarked_C','Embarked_Q', 'Embar
X = df_train[feature_all]
y = df_train['Survived']
## SVM
clf = svm.SVC()
clf.fit(X, y)
y_pred = clf.predict(df_test[feature_all])

## DecisionTree
clf = DecisionTreeClassifier().fit(X, y)
y_pred = clf.predict(df_test[feature_all])

#print("Accuracy(train set):",metrics.accuracy_score(y, y_pred_train))
#print("Accuracy(test set):",metrics.accuracy_score(y_test, y_pred_test))
```

```
----------------------------------------------------------------------
-----
ValueError                                Traceback (most recent call
 last)
/Users/catherineyu/Desktop/MIMS/info 251/assignment/PS5/INFO251-PS5.ip
ynb Cell 42' in <cell line: 9>()
      <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/in
fo%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000042?line=6'>7</a> ## S
VM
      <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/in
fo%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000042?line=7'>8</a> clf
 = svm.SVC()
----> <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/in
fo%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000042?line=8'>9</a> clf.
fit(X, y)
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000042?line=9'>10</a> y_pr
ed = clf.predict(df_test[feature_all])
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000042?line=11'>12</a> ##
```

In [29]:

```
# Use one of the methods we discussed in class to impute missing values for each fea

# Age: replace NA in Age with the mean value of Age
mean = np.mean(df_train['Age'])
#df_train['Age_FE'] = df_train['Age']
df_train['Age'] = df_train['Age'].fillna(mean)

# Cabin: because the missing value percentage is almost 77 percent, I will choose to

# Find a way to engineer meaningful features from the "Name" and/or "Cabin" fields i
df_train['name_len'] = df_train.Name.str.split(" ").map(lambda x: len(x))

df_train.head()
```

```
/var/folders/2h/4fcst_952sn2rw58_smpkpzw0000gn/T/ipykernel_24252/29171
91451.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df_train['Age'] = df_train['Age'].fillna(mean)
/var/folders/2h/4fcst_952sn2rw58_smpkpzw0000gn/T/ipykernel_24252/29171
91451.py:14: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df_train['name_len'] = df_train.Name.str.split(" ").map(lambda x: le
n(x))
```

Out[29]:

	Survived	Name	Sex	Age	SibSp	Parch	Fare	Cabin	Age*Fare	Em
377	0	Widener, Mr. Harry Elkins	1	-0.185937	-0.474545	2.008933	3.610065	C82	5710.5000	
853	1	Lines, Miss. Mary Conover	0	-0.943705	-0.474545	0.767630	0.144885	D28	630.4000	
525	0	Farrell, Mr. James	1	0.744051	-0.474545	-0.473674	-0.492378	NaN	313.8750	
661	0	Badt, Mr. Mohamed	1	0.709607	-0.474545	-0.473674	-0.502949	NaN	289.0000	
514	0	Coleff, Mr. Satio	1	-0.392601	-0.474545	-0.473674	-0.497496	NaN	179.8992	

In [30]:

```
# feature engineering test set

mean = np.mean(df_test['Age'])
df_test['Age'] = df_test['Age'].fillna(mean)

df_test['name_len'] = df_test.Name.str.split(" ").map(lambda x: len(x))
df_test.head()
```

```
/var/folders/2h/4fcst_952sn2rw58_smpkpzw0000gn/T/ipykernel_24252/14016
73744.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df_test['Age'] = df_test['Age'].fillna(mean)
/var/folders/2h/4fcst_952sn2rw58_smpkpzw0000gn/T/ipykernel_24252/14016
73744.py:6: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas
-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
 (https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.htm
l#returning-a-view-versus-a-copy)
  df_test['name_len'] = df_test.Name.str.split(" ").map(lambda x: len
(x))
```

Out[30]:

	Survived	Name	Sex	Age	SibSp	Parch	Fare	Cabin	Age*Fare
404	0	Oreskovic, Miss. Marija	0	-0.668153	-0.474545	-0.473674	-0.474005	NaN	173.2500
431	1	Thorneycroft, Mrs. Percival (Florence Kate White)	0	0.022489	0.432793	-0.473674	-0.324253	NaN	NaN
740	1	Hawksford, Mr. Walter James	1	0.022489	-0.474545	-0.473674	-0.044381	D45	NaN
591	1	Stephenson, Mrs. Walter Bertram (Martha Eustis)	0	1.536263	0.432793	-0.473674	0.927454	D20	4069.8684
304	0	Williams, Mr. Howard Hugh "Harry"	1	0.022489	-0.474545	-0.473674	-0.486337	NaN	NaN

In [31]:

```
# CV SVM
feature_all = ['Sex','Age','SibSp', 'Parch','Fare','Embarked_C','Embarked_Q', 'Embar
X = df_train[feature_all]
y = df_train['Survived']

model = svm.SVC()
cv = KFold(n_splits=5, shuffle=True, random_state=1)
params = {'C':np.linspace(1,10,10, dtype = int)}
cv_model = GridSearchCV(model, param_grid=params, scoring='accuracy', refit=True, re
cv_model.fit(X, y)
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.sort_values('mean_test_score',ascending=False).head()
```

Out[31]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_C	params	split0_test_s
2	0.003961	0.000082	0.001886	0.000066	3	{'C': 3}	0.83
3	0.004101	0.000185	0.001970	0.000106	4	{'C': 4}	0.83
4	0.004071	0.000264	0.001812	0.000086	5	{'C': 5}	0.83
5	0.004201	0.000381	0.001781	0.000042	6	{'C': 6}	0.83
7	0.004453	0.000300	0.001791	0.000049	8	{'C': 8}	0.82

5 rows × 21 columns

In [32]:

```
model = cv_model.best_estimator_
model.fit(X, y)
yhat_test = model.predict(df_test[feature_all])

print('Best maximum depth: %i' % cv_model.best_params_['C'])

print('Accuracy (test): %.3f' % metrics.accuracy_score(df_test['Survived'], yhat_tes
```

```
Best maximum depth: 3
Accuracy (test): 0.838
```

In [33]:

```
# Rerun your decision tree and SVM on the new dataset with imputed missing values ar
# Tune hyperparameter: max_depth
feature_all = ['Sex','Age','SibSp', 'Parch','Fare','Embarked_C','Embarked_Q', 'Embar
X = df_train[feature_all]
y = df_train['Survived']

# CV DecisionTree
model = DecisionTreeClassifier()
cv = KFold(n_splits=5, shuffle=True, random_state=1)
params = {'max_depth':[2, 4, 6, 8, 10], 'min_samples_leaf': [1,5,10]}
cv_model = GridSearchCV(model, param_grid=params, scoring='accuracy', refit=True, re
cv_model.fit(X, y)
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.sort_values('mean_test_score',ascending=False).head()
```

Out[33]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_min_
11	0.001002	0.000007	0.000409	0.000008	8	
3	0.000930	0.000075	0.000423	0.000026	4	
14	0.001020	0.000010	0.000413	0.000009	10	
4	0.000888	0.000012	0.000415	0.000014	4	
7	0.001055	0.000072	0.000449	0.000055	6	

5 rows × 22 columns

In [34]:

```
model = cv_model.best_estimator_
model.fit(X, y)
yhat_test = model.predict(df_test[feature_all])

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 (test): %.3f' % metrics.accuracy_score(df_test['Survived'], yhat_tes
```

```
Best maximum depth: 8
Best min samples leaf: 10
Accuracy (test): 0.804
```

1. the variables with missing value are 'Age' and 'Cabin'
2. an error message occurs when there are missing values in the input data
3. For 'Age', I fill the missing values with the average value of 'Age'. For Cabin, because the missing value percentage is almost 77 percent, I choose to ignore this variable instead of feature engineering it.
4. I feature engineering 'Name' by making a new varible 'name_len' which equals to the number of words in a name.

5. After feature engineering, the accuracy of Decision Tree increase from 0.79 to 0.8. The accuracy of SVM drop from 0.85 to 0.83.

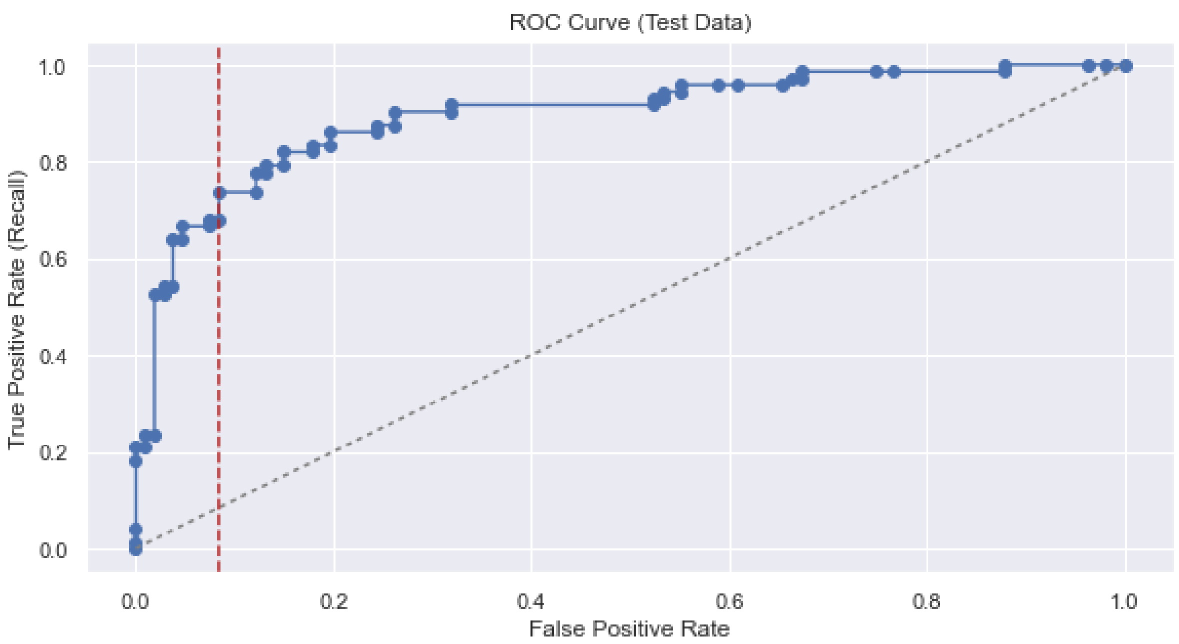
2.6 ROC Curve

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 [49]:

```
# Your code here
X_test = df_test[feature_all]
y_test = df_test['Survived']

yhat_test_proba = model.predict_proba(X_test)[:, 1]
fprs, tprs, thresholds = metrics.roc_curve(y_test, yhat_test_proba)

# Get area under the curve
print('AUC score: %.3f' % metrics.roc_auc_score(y_test, yhat_test_proba))

# roc curve
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(fprs[18], color='firebrick', linestyle='--', linewidth=1.5)

ax.set_xlabel('False Positive Rate')
ax.set_ylabel('True Positive Rate (Recall)')
ax.set_title('ROC Curve (Test Data)')
plt.show()
```

```
AUC score: 0.896
```



In [36]:

```
# Get "optimal" threshold: the one closest to the top-left corner of the ROC graph
distances_from_top_left = [np.sqrt(tprs[i]**2 + (1-fprs[i])**2) for i in range(len(t
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]))
```

```
Threshold closest to top-left corner of graph: 0.09 (0.92 TPR, 0.68 FP
R)
```

- Threshold closest to top-left corner of graph: 0.09 (0.92 TPR, 0.68 FPR)

Part 3: Many Trees

3.1: Random Forest

Use the random forest classifier (http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.RandomForestClassifier.html) 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 [37]:

```
# Your code here
# Tune hyperparameters: max_depth, n_estimators
model = RandomForestClassifier(random_state=1)
cv = KFold(n_splits=5, shuffle=True, random_state=1)
params = {'max_depth':[2, 4, 6, 8], 'n_estimators':[25, 50, 100], 'min_samples_leaf'
cv_model = GridSearchCV(model, param_grid=params, scoring='accuracy', refit=True, re
cv_model.fit(X, y)
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.sort_values('mean_test_score',ascending=False).head()
```

Out[37]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_max_depth	param_min_
38	0.054127	0.000670	0.004428	0.000149	8	
37	0.027720	0.000388	0.002416	0.000063	8	
29	0.049077	0.000237	0.003813	0.000068	6	
26	0.050381	0.000432	0.003923	0.000057	6	
36	0.014648	0.000756	0.001672	0.000075	8	

5 rows × 23 columns

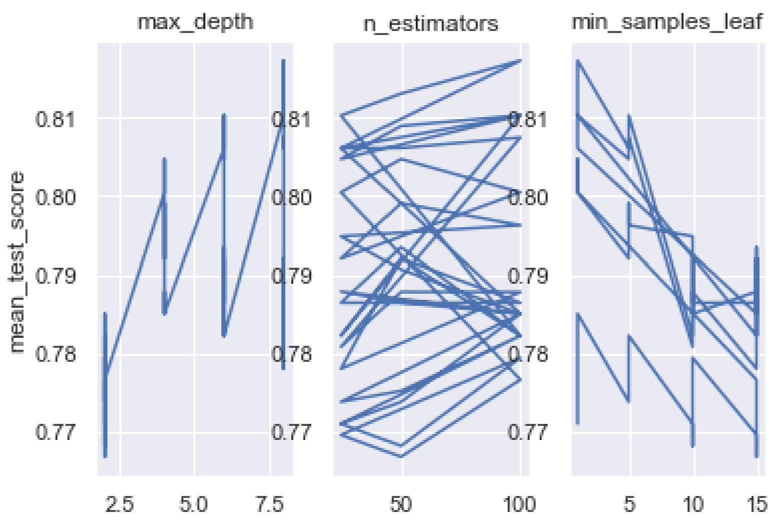
In [38]:

```
model = cv_model.best_estimator_
model.fit(X, y)
yhat_train = model.predict(X)
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_leaf: %i' % cv_model.best_params_['min_samples_leaf'])

print('Accuracy (train): %.2f' % metrics.accuracy_score(y, yhat_train))
print('Accuracy (test): %.2f' % metrics.accuracy_score(y_test, yhat_test))
```

```
Best maximum depth: 8
Best number of estimators: 100
Best min_samples_leaf: 1
Accuracy (train): 0.91
Accuracy (test): 0.84
```

In [39]:

```
# Create 3 subplots that show how cross-validated performance (y-axis) relates to th
sns.set(font_scale=1.0)

plt.subplot(1, 3, 1)
plt.plot(cv_results['param_max_depth'], cv_results['mean_test_score'])
plt.title('max_depth')
plt.ylabel('mean_test_score')


plt.subplot(1, 3, 2)
plt.plot(cv_results['param_n_estimators'], cv_results['mean_test_score'])
plt.title('n_estimators')

plt.subplot(1, 3, 3)
plt.plot(cv_results['param_min_samples_leaf'], cv_results['mean_test_score'])
plt.title('min_samples_leaf')

plt.show()
```



- Hthe cross-validated performance (0.82) is lower than the test performance (0.84)
- How does the RF performance (0.84) is better than both the decision tree (0.8) and SVM (0.83) from part 2.5

3.2: Gradient Boosting

Use the [Gradient Boosting classifier (http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.GradientBoostingClassifier.html)](http://scikit-learn.org/stable/modules/generated/sklearn.ensemble.GradientBoostingClassifier.html) 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 [40]:

```
# Your code here
model_GBC = GradientBoostingClassifier()
cv = KFold(n_splits=3, shuffle=True, random_state=1)
params = {'max_depth':[2, 4, 6, 8], 'learning_rate':[0.1, 0.01, 0.001],'n_estimators
cv_model = GridSearchCV(model_GBC, param_grid=params, scoring='accuracy', refit=True
cv_model.fit(X, y)
cv_results = pd.DataFrame(cv_model.cv_results_)
cv_results.sort_values('mean_test_score',ascending=False).head()
```

Out[40]:

	mean_fit_time	std_fit_time	mean_score_time	std_score_time	param_learning_rate	param_m
15	0.047793	0.000362	0.000952	0.000056	0.01	
29	0.482446	0.006650	0.003160	0.000079	0.001	
32	0.787110	0.043417	0.004047	0.000246	0.001	
0	0.026408	0.000912	0.001019	0.000135	0.1	
18	0.077888	0.004081	0.001167	0.000060	0.01	

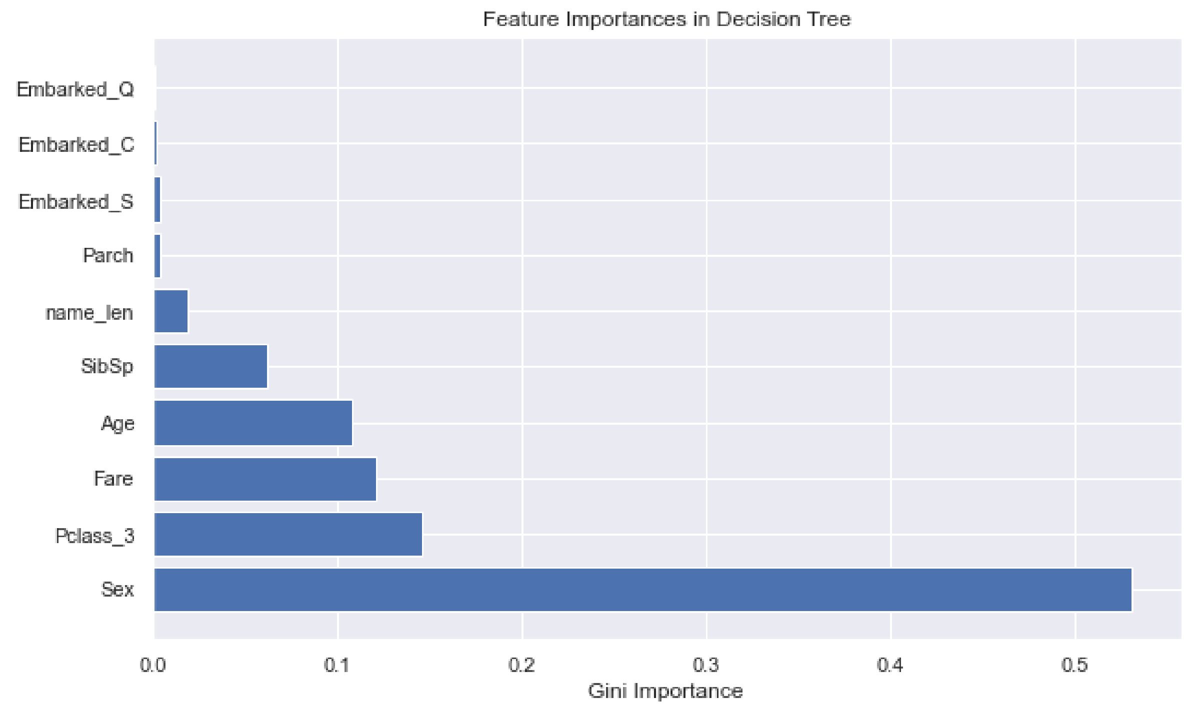
In [41]:

```
model_GBC = cv_model.best_estimator_
model_GBC.fit(X, y)
yhat_train = model_GBC.predict(X)
yhat_test = model_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 learning_rate: %f' % cv_model.best_params_['learning_rate'])

print('Accuracy (train): %.2f' % metrics.accuracy_score(y, yhat_train))
print('Accuracy (test): %.2f' % metrics.accuracy_score(y_test, yhat_test))
```

```
Best maximum depth: 4
Best number of estimators: 100
Best learning_rate: 0.010000
Accuracy (train): 0.86
Accuracy (test): 0.80
```

In [42]:

```
importances = model_GBC.feature_importances_
importances = pd.DataFrame([X.columns, importances]).T
importances.columns = ['Feature', 'Importance']
importances = importances.sort_values('Importance', ascending=False)[:10]

# 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()
```



- GBM performance (0.8)
- Random forest (0.83)
- Decision tree (0.80)
- SVM (0.83)

Part 4: Neural Networks

Carry on the classification by using feed forward neural networks, using functionality imported from [keras (https://keras.io/api/)](https://keras.io/api/). 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 [2]:

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

In [76]:

```
# Your code here
feature_all = ['Sex','Age','SibSp', 'Parch','Fare','Embarked_C','Embarked_Q', 'Embar
X = df_train[feature_all]
y = df_train['Survived']
X_test = df_test[feature_all]
y_test = df_test['Survived']

# Random seeds
np.random.seed(1)
tf.random.set_seed(1)

# Define NN
model = Sequential()
#model.add(Dense(5, input_dim=len(X.columns), activation='relu')) # First layer defi
#model.add(Dense(1, activation='relu'))

model.add(Dense(120, activation='relu', input_dim=20)) #input_dim = number of input
model.add(Dense(60, activation='relu'))
model.add(Dense(2, activation='softmax'))

model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'


# Fit and predict with NN
model.fit(X, y, epochs=50, batch_size=10, verbose=0)
yhat_train = model.predict(X)
yhat_test = model.predict(X_test)


# Get metrics
print(yhat_train)
#print('Accuracy on training set: %.2f' % model.evaluate(y, yhat_train, verbose=0))
#print('Accuracy on test set: %.2f' % model.evaluat(y_test, yhat_test,verbose=0))
```

```
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call
 last)
/Users/catherineyu/Desktop/MIMS/info 251/assignment/PS5/INFO251-PS5.ip
ynb Cell 67' in <cell line: 25>()
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000066?line=20'>21</a> mod
el.compile(loss='categorical_crossentropy', optimizer='adam', metrics=
['accuracy'])
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000066?line=23'>24</a> # F
it and predict with NN
---> <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000066?line=24'>25</a> mod
el.fit(X, y, epochs=50, batch_size=10, verbose=0)
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000066?line=25'>26</a> yha
t_train = model.predict(X)
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000066?line=26'>27</a> yha
t_test = model.predict(X_test)
```

```
File /opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.10/sit
e-packages/keras/utils/traceback_utils.py:67, in filter_traceback.<loc
als>.error_handler(*args, **kwargs)
     <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/li
b/python3.10/site-packages/keras/utils/traceback_utils.py?line=64'>65
</a> except Exception as e:  # pylint: disable=broad-except
     <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/li
b/python3.10/site-packages/keras/utils/traceback_utils.py?line=65'>66
</a>   filtered_tb = _process_traceback_frames(e.__traceback__)
---> <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/li
b/python3.10/site-packages/keras/utils/traceback_utils.py?line=66'>67
</a>   raise e.with_traceback(filtered_tb) from None
     <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/li
b/python3.10/site-packages/keras/utils/traceback_utils.py?line=67'>68
</a> finally:
     <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/li
b/python3.10/site-packages/keras/utils/traceback_utils.py?line=68'>69
</a>   del filtered_tb

File /opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.10/sit
e-packages/tensorflow/python/framework/func_graph.py:1129, in func_gra
ph_from_py_func.<locals>.autograph_handler(*args, **kwargs)
   <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/
python3.10/site-packages/tensorflow/python/framework/func_graph.py?lin
e=1126'>1127</a> except Exception as e:  # pylint:disable=broad-except
   <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/
python3.10/site-packages/tensorflow/python/framework/func_graph.py?lin
e=1127'>1128</a>   if hasattr(e, "ag_error_metadata"):
-> <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/
python3.10/site-packages/tensorflow/python/framework/func_graph.py?lin
e=1128'>1129</a>     raise e.ag_error_metadata.to_exception(e)
   <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/
python3.10/site-packages/tensorflow/python/framework/func_graph.py?lin
e=1129'>1130</a>   else:
   <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/
python3.10/site-packages/tensorflow/python/framework/func_graph.py?lin
e=1130'>1131</a>     raise

ValueError: in user code:

    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/engine/training.py", line 878, in train_function
*
        return step_function(self, iterator)
    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/engine/training.py", line 867, in step_function
**
        outputs = model.distribute_strategy.run(run_step, args=(dat
a,))
    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/engine/training.py", line 860, in run_step  **
        outputs = model.train_step(data)
    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/engine/training.py", line 808, in train_step
        y_pred = self(x, training=True)
    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/utils/traceback_utils.py", line 67, in error_han
dler
        raise e.with_traceback(filtered_tb) from None
    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/engine/input_spec.py", line 263, in assert_input
```

```
_compatibility
        raise ValueError(f'Input {input_index} of layer "{layer_name}"
is '

    ValueError: Input 0 of layer "sequential_19" is incompatible with
 the layer: expected shape=(None, 20), found shape=(None, 12)
```

In [74]:

```
X = df.drop(columns=['Name', 'Survived', 'Cabin'])

y = df.Survived
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_stat


# one hot encode outputs
y_train = tf.keras.utils.to_categorical(y_train)
y_test = tf.keras.utils.to_categorical(y_test)

# Define Sequential model
model = Sequential()
model.add(Dense(120, activation='relu', input_dim=20)) #input_dim = number of input
model.add(Dense(60, activation='relu'))
model.add(Dense(2, activation='softmax'))

optimizers = {"SGD_001": tf.keras.optimizers.SGD(learning_rate=0.001),
              "Adagrad_001": tf.keras.optimizers.Adagrad(learning_rate=0.001),
              "Adam_001": tf.keras.optimizers.Adam(learning_rate=0.001),
              "SGD_01": tf.keras.optimizers.SGD(learning_rate=0.01),
              "Adagrad_01": tf.keras.optimizers.Adagrad(learning_rate=0.01),
              "Adam_01": tf.keras.optimizers.Adam(learning_rate=0.01),
              "SGD_1": tf.keras.optimizers.SGD(learning_rate=0.1),
              "Adagrad_1": tf.keras.optimizers.Adagrad(learning_rate=0.1),
              "Adam_1": tf.keras.optimizers.Adam(learning_rate=0.1),
             }

perf = {}
for optim, opt in optimizers.items():
    # Compile the model
    model.compile(optimizer=opt,
                  loss='categorical_crossentropy',
                  metrics=['accuracy'])
    # training
    model.fit(X_train, y_train, epochs=30)

    # performance
    pred_train= model.predict(X_train)
    scores = model.evaluate(X_train, y_train, verbose=0)
    pred_test= model.predict(X_test)
    scores2 = model.evaluate(X_test, y_test, verbose=0)
    perf.update({optim: [scores[1], scores2[1]]})
```

```
Epoch 1/30

---------------------------------------------------------------------------
ValueError                                Traceback (most recent call
 last)
/Users/cathérineyu/Desktop/MIMS/info 251/assignment/PS5/INFO251-PS5.ip
ynb Cell 68' in <cell line: 28>()
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000074?line=29'>30</a> mod
el.compile(optimizer=opt,
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000074?line=30'>31</a>
loss='categorical_crossentropy',
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000074?line=31'>32</a>
```

```
metrics=['accuracy'])
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000074?line=32'>33</a> # t
raining
---> <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000074?line=33'>34</a> mod
el.fit(X_train, y_train, epochs=30)
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000074?line=35'>36</a> # p
erformance
     <a href='vscode-notebook-cell:/Users/catherineyu/Desktop/MIMS/inf
o%20251/assignment/PS5/INFO251-PS5.ipynb#ch0000074?line=36'>37</a> pre
d_train= model.predict(X_train)

File /opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.10/sit
e-packages/keras/utils/traceback_utils.py:67, in filter_traceback.<loc
als>.error_handler(*args, **kwargs)
     <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/li
b/python3.10/site-packages/keras/utils/traceback_utils.py?line=64'>65
</a> except Exception as e:  # pylint: disable=broad-except
     <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/li
b/python3.10/site-packages/keras/utils/traceback_utils.py?line=65'>66
</a>   filtered_tb = _process_traceback_frames(e.__traceback__)
---> <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/li
b/python3.10/site-packages/keras/utils/traceback_utils.py?line=66'>67
</a>   raise e.with_traceback(filtered_tb) from None
     <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/li
b/python3.10/site-packages/keras/utils/traceback_utils.py?line=67'>68
</a> finally:
     <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/li
b/python3.10/site-packages/keras/utils/traceback_utils.py?line=68'>69
</a>   del filtered_tb

File /opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.10/sit
e-packages/tensorflow/python/framework/func_graph.py:1129, in func_gra
ph_from_py_func.<locals>.autograph_handler(*args, **kwargs)
   <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/
python3.10/site-packages/tensorflow/python/framework/func_graph.py?lin
e=1126'>1127</a> except Exception as e:  # pylint:disable=broad-except
   <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/
python3.10/site-packages/tensorflow/python/framework/func_graph.py?lin
e=1127'>1128</a>   if hasattr(e, "ag_error_metadata"):
-> <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/
python3.10/site-packages/tensorflow/python/framework/func_graph.py?lin
e=1128'>1129</a>     raise e.ag_error_metadata.to_exception(e)
   <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/
python3.10/site-packages/tensorflow/python/framework/func_graph.py?lin
e=1129'>1130</a>   else:
   <a href='file:///opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/
python3.10/site-packages/tensorflow/python/framework/func_graph.py?lin
e=1130'>1131</a>     raise

ValueError: in user code:

    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/engine/training.py", line 878, in train_function
*
        return step_function(self, iterator)
    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/engine/training.py", line 867, in step_function
**
```

```
        outputs = model.distribute_strategy.run(run_step, args=(dat
a,))
    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/engine/training.py", line 860, in run_step  **
        outputs = model.train_step(data)
    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/engine/training.py", line 808, in train_step
        y_pred = self(x, training=True)
    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/utils/traceback_utils.py", line 67, in error_han
dler
        raise e.with_traceback(filtered_tb) from None
    File "/opt/homebrew/Caskroom/miniforge/base/envs/aml/lib/python3.1
0/site-packages/keras/engine/input_spec.py", line 263, in assert_input
_compatibility
        raise ValueError(f'Input {input_index} of layer "{layer_name}"
is '

    ValueError: Input 0 of layer "sequential_17" is incompatible with
 the layer: expected shape=(None, 20), found shape=(None, 11)
```

Your observations 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				
Decision Tree (with imputed missing values and new features)				
SVM				
SVM (with imputed missing values and new features)				
Random Forest				
Random Forest (with imputed missing values and new features)				
Gradient Boosting				
Gradient Boosting (with imputed missing values and new features)				
Neural Network				
Neural Network (with imputed missing values and new features)				

Your observations here

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 [13]:

```
# Your code here
```

Your observations here