In [1]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

1 K-Means Clustering

Load Data

In [2]:
```python
df = pd.read_csv('/Users/chenjiqing/Public/2022_Spring_term/QBS108 Applied ML/2022 file/Homework 2/tcga_pancancer/pancancer.csv')
df = df.drop('Unnamed: 0',axis=1)
df
```

Out[2]:

	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14
0	-25.875320	56.783945	-58.522554	-23.657779	59.226184	32.978484	-55.835789	3.992981	-16.705564	-14.854115	-16.739289	-12.236637	0.631551	-0.895200	31.014503
1	-78.976524	-62.312761	33.852422	-2.165579	-5.288384	0.446068	24.361695	-44.745726	17.395310	-22.758601	13.726631	11.176496	-6.800069	9.362851	-7.950115
2	87.151357	-23.404469	-10.054268	63.831495	-8.287112	-42.402161	36.263516	-54.548902	33.558731	2.175367	-26.291564	-12.975848	24.410122	-28.263414	-17.609067
3	-43.224891	-24.016296	-4.744443	-66.180500	75.203354	-46.929467	37.587578	-20.590401	8.761443	-20.297368	4.353383	-2.354844	5.791677	1.503404	-1.664383
4	-63.589175	-66.331180	6.376695	25.804671	-35.920993	-20.097241	4.684812	-1.233395	-26.762385	18.346569	11.932363	0.081588	-3.752243	4.445100	-0.940169
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
660	-77.968110	-64.215899	53.033778	16.772297	7.374632	51.174647	-22.336068	-17.173816	-16.990365	9.496480	19.249984	-17.164237	9.619327	-10.789798	8.587151
661	1.411024	33.721905	-97.514669	-35.977829	-32.405695	54.035778	27.624459	1.633711	-30.978002	-22.327608	15.138285	-20.205383	-6.395287	5.546136	2.314934
662	-69.761387	-80.963905	40.077150	7.640976	-18.890106	18.978991	-2.254887	-34.397698	2.597095	-6.976562	-11.659815	-6.662376	9.278010	-4.117283	-30.055490
663	-24.481133	61.988138	-65.444488	34.473801	-6.558216	54.685834	42.522086	0.694724	43.626111	22.321826	-20.691297	44.923379	-14.805007	-20.591455	-25.827407
664	5.547498	47.154601	-49.546932	1.701638	-56.533622	-96.443116	34.725324	69.097112	65.273405	45.460026	32.333668	-22.421023	0.659979	27.597299	13.250129

665 rows × 15 columns

In [3]:
```python
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 665 entries, 0 to 664
Data columns (total 15 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       665 non-null    float64
 1   1       665 non-null    float64
 2   2       665 non-null    float64
 3   3       665 non-null    float64
 4   4       665 non-null    float64
 5   5       665 non-null    float64
 6   6       665 non-null    float64
 7   7       665 non-null    float64
 8   8       665 non-null    float64
 9   9       665 non-null    float64
 10  10      665 non-null    float64
 11  11      665 non-null    float64
 12  12      665 non-null    float64
 13  13      665 non-null    float64
 14  14      665 non-null    float64
dtypes: float64(15)
memory usage: 78.1 KB
```

- No missing Values

In [4]:
```python
df.describe()
```

Out[4]:

	0	1	2	3	4	5	6	7	8	9	10	11	12
count	6.650000e+02	6.650000e+02	6.650000e+02	6.650000e+02	6.650000e+02	6.650000e+02	6.650000e+02	6.650000e+02	6.650000e+02	6.650000e+02	6.650000e+02	6.650000e+02	6.650000e+02
mean	5.128730e-16	2.564365e-16	6.838306e-16	-7.265700e-16	-8.547883e-17	-5.128730e-16	2.564365e-16	-1.709577e-16	2.136971e-16	2.564365e-16	8.547883e-16	-8.547883e-17	3.846547e-16
std	8.126705e+01	6.536298e+01	5.221270e+01	3.631874e+01	3.486074e+01	3.342800e+01	2.608269e+01	2.340081e+01	2.243101e+01	1.965236e+01	1.914324e+01	1.779294e+01	1.708988e+01
min	-1.018639e+02	-9.465788e+01	-1.238769e+02	-1.209602e+02	-7.862494e+01	-9.644312e+01	-8.113492e+01	-7.474574e+01	-5.490130e+01	-5.870098e+01	-7.391167e+01	-5.091354e+01	-5.368153e+01
25%	-5.585776e+01	-5.007898e+01	-2.176080e+01	-2.296131e+01	-2.246344e+01	-2.361122e+01	-1.600493e+01	-1.637985e+01	-1.411962e+01	-1.336469e+01	-1.203067e+01	-1.022459e+01	-1.027628e+01
50%	-3.121861e+01	-1.626691e+01	9.400684e+00	-6.231582e+00	-3.753839e+00	1.149227e+00	-1.129484e+00	4.821054e-01	-6.971027e-01	-3.945739e-01	-1.057407e+00	-1.360354e-01	-1.799235e+00
75%	1.828140e+00	3.597135e+01	3.356166e+01	1.716525e+01	1.390316e+01	2.234912e+01	1.621502e+01	1.574662e+01	1.330756e+01	1.237379e+01	1.109708e+01	8.011535e+00	8.542092e+00
max	1.799845e+02	1.977116e+02	1.300737e+02	1.657368e+02	1.253445e+02	9.710720e+01	1.063313e+02	8.092908e+01	9.623726e+01	8.809292e+01	8.502497e+01	5.819931e+01	8.065588e+01

1-1 a. Choose a suitable type of plot and visualize the first two features of the data.

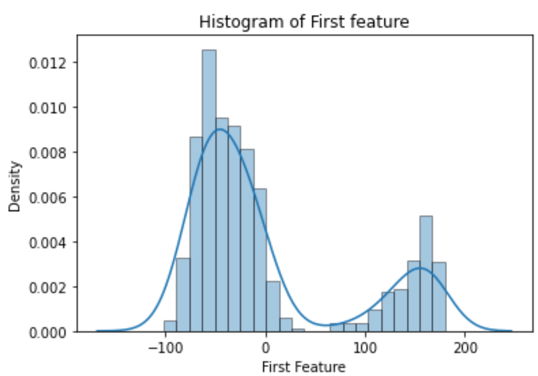
In [5]:
```
# load module
import seaborn as sns
```

First feature

In [6]:
```
sns.distplot(df['0'], hist = True, hist_kws = {"edgecolor":"black"})
plt.title("Histogram of First feature")
plt.xlabel("First Feature")
```

```
/Users/chenjiqing/anaconda3/envs/Class/lib/python3.7/site-packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed i
n a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histogram
s).
  warnings.warn(msg, FutureWarning)
```

Out[6]: Text(0.5, 0, 'First Feature')

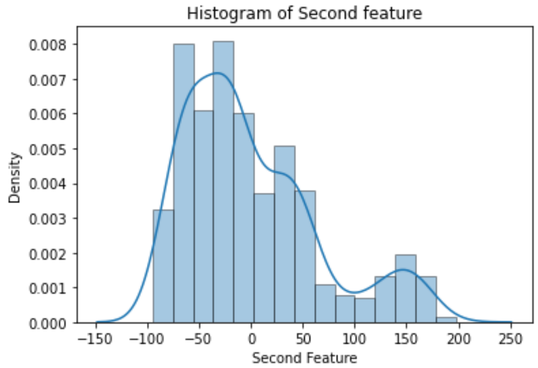


Second feature

In [7]:
```
sns.distplot(df['1'], hist = True, hist_kws = {"edgecolor":"black"})
plt.title("Histogram of Second feature")
plt.xlabel("Second Feature")
```

```
/Users/chenjiqing/anaconda3/envs/Class/lib/python3.7/site-packages/seaborn/distributions.py:2557: FutureWarning: `distplot` is a deprecated function and will be removed i
n a future version. Please adapt your code to use either `displot` (a figure-level function with similar flexibility) or `histplot` (an axes-level function for histogram
s).
  warnings.warn(msg, FutureWarning)
```

Out[7]: Text(0.5, 0, 'Second Feature')



1-1 b. From your plot, how many clusters, k, do you recognize in the dataset?

- According to Histogram plot, I think 2 clusters in the dataset.

1-2 a. Using the k-Means algorithm, implement a clustering model. Train the clustering model using all 15 features from the data.

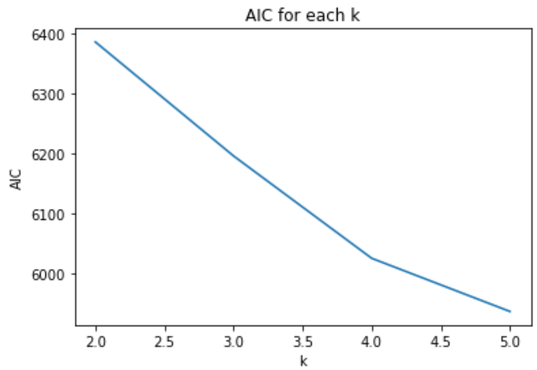
In [8]:
```
from sklearn.cluster import KMeans

k_cluster = []
AICs = []
BICs = []
for k in range(2,6):
    kmeans = KMeans(n_clusters=k, random_state=3).fit(df)
    AIC = df.shape[0]*np.log(kmeans.inertia_/df.shape[0]) + 2*k
    BIC = df.shape[0]*np.log(kmeans.inertia_/df.shape[0]) + k*np.log(df.shape[0])
    k_cluster.append(k)
    AICs.append(AIC)
    BICs.append(BIC)
```

Plot AIC for each value of k.

In [9]:
```
plt.plot(k_cluster, AICs)
plt.title("AIC for each k")
plt.xlabel("k")
plt.ylabel("AIC")
```

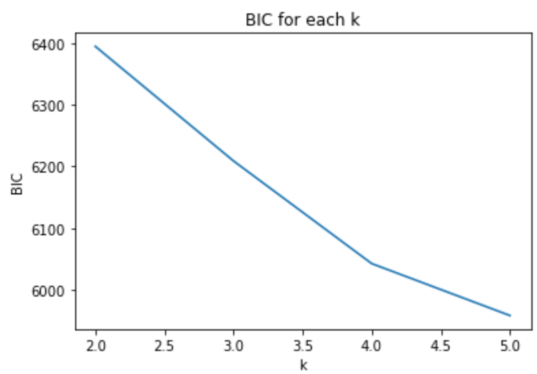
Out[9]:
```
Text(0, 0.5, 'AIC')
```



Plot BIC for each value of k.

In [10]:
```
plt.plot(k_cluster, BICs)
plt.title("BIC for each k")
plt.xlabel("k")
plt.ylabel("BIC")
```

Out[10]: Text(0, 0.5, 'BIC')



1-2 b. Which value of k is optimal?

- According to AIC and BIC plots, the optimal k is 5 (with lowest AIC and BIC values). The result doesn't meet my expectation in 1.1b

2 K-Nearest Neighbor Classification

Load Data

Training Set

In [11]:
```
df_train = pd.read_csv('/Users/chenjiqing/Public/2022_Spring_term/QBS108 Applied ML/2022 file/Homework 2/wine/train.csv')
df_train = df_train.assign(good_quality = np.where(df_train['good_quality']==False,0,1)) # Convert target into 1, 0
df_train
```

Out[11]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	good_quality
0	7.6	0.420	0.08	2.70	0.084	15.0	48.0	0.99680	3.21	0.59	10.0	0

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	good_quality
1	5.7	0.600	0.00	1.40	0.063	11.0	18.0	0.99191	3.45	0.56	12.2	1
2	7.5	0.610	0.26	1.90	0.073	24.0	88.0	0.99612	3.30	0.53	9.8	0
3	8.9	0.480	0.24	2.85	0.094	35.0	106.0	0.99820	3.10	0.53	9.2	0
4	7.0	0.620	0.18	1.50	0.062	7.0	50.0	0.99510	3.08	0.60	9.3	0
...	...	...	...	...	...	...	...	...	...	...	...	...
1018	7.4	0.635	0.10	2.40	0.080	16.0	33.0	0.99736	3.58	0.69	10.8	1
1019	10.3	0.440	0.50	4.50	0.107	5.0	13.0	0.99800	3.28	0.83	11.5	0
1020	6.6	0.520	0.08	2.40	0.070	13.0	26.0	0.99358	3.40	0.72	12.5	1
1021	5.1	0.510	0.18	2.10	0.042	16.0	101.0	0.99240	3.46	0.87	12.9	1
1022	11.6	0.410	0.54	1.50	0.095	22.0	41.0	0.99735	3.02	0.76	9.9	1

1023 rows × 12 columns

In [12]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1023 entries, 0 to 1022
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         1023 non-null   float64
 1   volatile acidity      1023 non-null   float64
 2   citric acid           1023 non-null   float64
 3   residual sugar        1023 non-null   float64
 4   chlorides             1023 non-null   float64
 5   free sulfur dioxide   1023 non-null   float64
 6   total sulfur dioxide  1023 non-null   float64
 7   density               1023 non-null   float64
 8   pH                    1023 non-null   float64
 9   sulphates             1023 non-null   float64
 10  alcohol               1023 non-null   float64
 11  good_quality          1023 non-null   int64  
dtypes: float64(11), int64(1)
memory usage: 96.0 KB
```

- No missing values in each feature

Validation Set

In [13]:
```
df_val = pd.read_csv('/Users/chenjiqing/Public/2022_Spring_term/QBS108 Applied ML/2022 file/Homework 2/wine/val.csv')
df_val = df_val.assign(good_quality = np.where(df_val['good_quality']==False,0,1)) # Convert target into 1, 0
df_val
```

Out[13]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	good_quality
0	7.0	0.655	0.16	2.1	0.074	8.0	25.0	0.99606	3.37	0.55	9.7	0
1	10.4	0.440	0.42	1.5	0.145	34.0	48.0	0.99832	3.38	0.86	9.9	0
2	5.2	0.480	0.04	1.6	0.054	19.0	106.0	0.99270	3.54	0.62	12.2	1
3	9.7	0.320	0.54	2.5	0.094	28.0	83.0	0.99840	3.28	0.82	9.6	0
4	8.1	0.870	0.00	2.2	0.084	10.0	31.0	0.99656	3.25	0.50	9.8	0
...	...	...	...	...	...	...	...	...	...	...	...	...
251	8.7	0.690	0.31	3.0	0.086	23.0	81.0	1.00020	3.48	0.74	11.6	1
252	5.0	1.020	0.04	1.4	0.045	41.0	85.0	0.99380	3.75	0.48	10.5	0

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	good_quality
253	9.9	0.590	0.07	3.4	0.102	32.0	71.0	1.00015	3.31	0.71	9.8	0
254	9.1	0.500	0.30	1.9	0.065	8.0	17.0	0.99774	3.32	0.71	10.5	1
255	7.8	0.590	0.33	2.0	0.074	24.0	120.0	0.99680	3.25	0.54	9.4	0

256 rows × 12 columns

In [14]:
```
df_val.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 256 entries, 0 to 255
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         256 non-null    float64
 1   volatile acidity      256 non-null    float64
 2   citric acid           256 non-null    float64
 3   residual sugar        256 non-null    float64
 4   chlorides             256 non-null    float64
 5   free sulfur dioxide   256 non-null    float64
 6   total sulfur dioxide  256 non-null    float64
 7   density               256 non-null    float64
 8   pH                    256 non-null    float64
 9   sulphates             256 non-null    float64
 10  alcohol               256 non-null    float64
 11  good_quality          256 non-null    int64  
dtypes: float64(11), int64(1)
memory usage: 24.1 KB
```

- No missing values in each feature

Testing Set

In [15]:
```
df_test = pd.read_csv('/Users/chenjiqing/Public/2022_Spring_term/QBS108 Applied ML/2022 file/Homework 2/wine/test.csv')
df_test = df_test.assign(good_quality = np.where(df_test['good_quality']==False,0,1)) # Convert target into 1, 0
df_test
```

Out[15]:

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	good_quality
0	10.8	0.470	0.43	2.10	0.171	27.0	66.0	0.99820	3.17	0.76	10.8	1
1	8.1	0.820	0.00	4.10	0.095	5.0	14.0	0.99854	3.36	0.53	9.6	0
2	9.1	0.290	0.33	2.05	0.063	13.0	27.0	0.99516	3.26	0.84	11.7	1
3	10.2	0.645	0.36	1.80	0.053	5.0	14.0	0.99820	3.17	0.42	10.0	1
4	12.2	0.450	0.49	1.40	0.075	3.0	6.0	0.99690	3.13	0.63	10.4	0
...	...	...	...	...	...	...	...	...	...	...	...	...
315	10.1	0.270	0.54	2.30	0.065	7.0	26.0	0.99531	3.17	0.53	12.5	1
316	6.9	0.390	0.24	2.10	0.102	4.0	7.0	0.99462	3.44	0.58	11.4	0
317	9.1	0.340	0.42	1.80	0.058	9.0	18.0	0.99392	3.18	0.55	11.4	0
318	9.1	0.765	0.04	1.60	0.078	4.0	14.0	0.99800	3.29	0.54	9.7	0
319	8.2	0.320	0.42	2.30	0.098	3.0	9.0	0.99506	3.27	0.55	12.3	1

320 rows × 12 columns

In [16]:
```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 320 entries, 0 to 319
```

```
Data columns (total 12 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   fixed acidity         320 non-null    float64
 1   volatile acidity      320 non-null    float64
 2   citric acid           320 non-null    float64
 3   residual sugar        320 non-null    float64
 4   chlorides             320 non-null    float64
 5   free sulfur dioxide   320 non-null    float64
 6   total sulfur dioxide  320 non-null    float64
 7   density               320 non-null    float64
 8   pH                    320 non-null    float64
 9   sulphates             320 non-null    float64
 10  alcohol               320 non-null    float64
 11  good_quality          320 non-null    int64  
dtypes: float64(11), int64(1)
memory usage: 30.1 KB
```

- No missing values in each feature

In [17]:
```
# Set Features and Target for each set.
df_train_y = df_train['good_quality'].copy()
df_val_y = df_val['good_quality'].copy()
df_test_y = df_test['good_quality'].copy()
df_train = df_train.drop(['good_quality'], axis=1).copy()
df_val = df_val.drop(['good_quality'], axis=1).copy()
df_test = df_test.drop(['good_quality'], axis=1).copy()

print(df_train.shape)
print(df_train_y.shape)
print(df_val.shape)
print(df_val_y.shape)
print(df_test.shape)
print(df_test_y.shape)
```

```
(1023, 11)
(1023,)
(256, 11)
(256,)
(320, 11)
(320,)
```

In [18]:
```
# Pre-processed data
from sklearn.preprocessing import StandardScaler
SS = StandardScaler()

df_train_SS = SS.fit_transform(df_train)
df_val_SS = SS.transform(df_val)
df_test_SS = SS.transform(df_test)
```

2-1. Train an k-Nearest Neighbors algorithm on the training dataset of your choice of k's

In [19]:
```
from sklearn.neighbors import KNeighborsClassifier
k_cluster =[]
accuracy = []
for k in range(2,11):
    knn = KNeighborsClassifier(n_neighbors=k)
    knn = knn.fit(df_train_SS, df_train_y)
    print("k: ", k)
    print("Train Accuracy: ", knn.score(df_train_SS, df_train_y))
    print("Validation Accuracy: ", knn.score(df_val_SS, df_val_y))
    print('-'*20)
    k_cluster.append(k)
    accuracy.append(knn.score(df_val_SS, df_val_y))
```

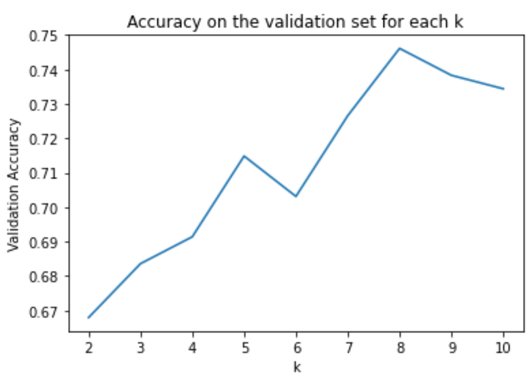
```
k:  2
Train Accuracy:  0.8787878787878788
```

```
Validation Accuracy:  0.66796875
--------------------
k:  3
Train Accuracy:  0.8699902248289345
Validation Accuracy:  0.68359375
--------------------
k:  4
Train Accuracy:  0.8250244379276638
Validation Accuracy:  0.69140625
--------------------
k:  5
Train Accuracy:  0.820136852394917
Validation Accuracy:  0.71484375
--------------------
k:  6
Train Accuracy:  0.8005865102639296
Validation Accuracy:  0.703125
--------------------
k:  7
Train Accuracy:  0.7947214076246334
Validation Accuracy:  0.7265625
--------------------
k:  8
Train Accuracy:  0.7839687194525904
Validation Accuracy:  0.74609375
--------------------
k:  9
Train Accuracy:  0.7859237536656891
Validation Accuracy:  0.73828125
--------------------
k:  10
Train Accuracy:  0.7771260997067448
Validation Accuracy:  0.734375
--------------------
```

2-2. Report the classification accuracy of this model on the validation set for different values for k. Plot these accuracies against k and report the optimal value for k.

In [20]:
```
plt.plot(k_cluster, accuracy)
plt.title("Accuracy on the validation set for each k")
plt.xlabel("k")
plt.ylabel("Validation Accuracy")
```

Out[20]:
```
Text(0, 0.5, 'Validation Accuracy')
```



- According to the plot, the optimal value for k is 8.

2-3. Report the classification accuracy of this model on the data in test.csv using the optimal value of k that you found in 2.2.

In [21]:
```
knn = KNeighborsClassifier(n_neighbors=8)
knn = knn.fit(df_train_SS, df_train_y)
print("k: ", 8)
print("Train Accuracy: ", knn.score(df_train_SS, df_train_y))
print("Testing Accuracy: ", knn.score(df_test_SS, df_test_y))
```

```
k:  8
Train Accuracy:  0.7839687194525904
Testing Accuracy:  0.71875
```

3 Decision Tree Classification

Load Data

Training Set

In [22]:
```
df_train = pd.read_csv('/Users/chenjiqing/Public/2022_Spring_term/QBS108 Applied ML/2022 file/Homework 2/titanic/train.csv')
df_train
```

Out[22]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Cabin	Embarked	Title
0	1	1	female	24	0	0	69.3000	B35	C	Mrs
1	0	3	female	3	3	1	21.0750	NaN	S	Miss
2	1	3	female	16	0	0	7.7333	NaN	Q	Miss
3	1	3	male	32	0	0	56.4958	NaN	S	Mr
4	0	3	male	22	0	0	7.1250	NaN	S	Mr
...	...	...	...	...	...	...	...	...	...	...
493	0	2	male	52	0	0	13.5000	NaN	S	Mr
494	0	3	male	33	1	1	20.5250	NaN	S	Mr
495	1	2	male	38	0	0	13.0000	NaN	S	Mr
496	0	3	male	38	8	2	69.5500	NaN	S	Mr
497	1	1	female	56	0	1	83.1583	C50	C	Mrs

498 rows × 10 columns

In [23]:
```
df_train.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 498 entries, 0 to 497
Data columns (total 10 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Survived  498 non-null    int64  
 1   Pclass    498 non-null    int64  
 2   Sex       498 non-null    object 
 3   Age       498 non-null    int64  
 4   SibSp     498 non-null    int64  
 5   Parch     498 non-null    int64  
 6   Fare      498 non-null    float64
 7   Cabin     113 non-null    object 
 8   Embarked  497 non-null    object 
 9   Title     498 non-null    object 
dtypes: float64(1), int64(5), object(4)
memory usage: 39.0+ KB
```

- Cabin and Embarked contain missing values

In [24]:
```
print("Sex:")
```

```
print(df_train.Sex.value_counts(),"\n")
print("Cabin:")
print(df_train.Cabin.value_counts(),"\n")
print("Embarked:")
print(df_train.Embarked.value_counts(),"\n")
print("Title:")
print(df_train.Title.value_counts(),"\n")
```

```
Sex:
male      333
female    165
Name: Sex, dtype: int64

Cabin:
C23 C25 C27    4
E101           3
G6             3
D35            2
C22 C26        2
              ..
B4             1
C78            1
D30            1
C87            1
B37            1
Name: Cabin, Length: 91, dtype: int64

Embarked:
S    373
C     85
Q     39
Name: Embarked, dtype: int64

Title:
Mr        295
Miss      102
Mrs        61
Master     27
Rare       13
Name: Title, dtype: int64
```

Validation Set

In [25]:
```
df_val = pd.read_csv('/Users/chenjiqing/Public/2022_Spring_term/QBS108 Applied ML/2022 file/Homework 2/titanic/val.csv')
df_val
```

Out[25]:

	Survived	Pclass	Sex	Age	SibSp	Parch	Fare	Cabin	Embarked	Title
0	1	3	female	24	1	0	15.8500	NaN	S	Mrs
1	1	2	female	24	0	0	13.0000	F33	S	Miss
2	0	3	male	40	1	1	15.5000	NaN	Q	Mr
3	1	3	male	22	2	0	23.2500	NaN	Q	Mr
4	1	2	female	3	1	2	41.5792	NaN	C	Miss
...	...	...	...	...	...	...	...	...	...	...
120	1	2	female	31	1	1	26.2500	NaN	S	Mrs
121	1	3	male	19	0	0	7.7500	NaN	Q	Mr
122	1	1	female	43	0	1	211.3375	B3	S	Mrs
123	0	2	male	52	0	0	13.0000	NaN	S	Mr
124	1	1	female	35	1	0	53.1000	C123	S	Mrs

125 rows × 10 columns

In [26]:
```
df_val.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 125 entries, 0 to 124
Data columns (total 10 columns):
 #   Column    Non-Null Count  Dtype
---  ------    --------------  -----
 0   Survived  125 non-null    int64
 1   Pclass    125 non-null    int64
 2   Sex       125 non-null    object
 3   Age       125 non-null    int64
 4   SibSp     125 non-null    int64
 5   Parch     125 non-null    int64
 6   Fare      125 non-null    float64
 7   Cabin     26 non-null     object
 8   Embarked  125 non-null    object
 9   Title     125 non-null    object
dtypes: float64(1), int64(5), object(4)
memory usage: 9.9+ KB
```

- Cabin contains missing values

In [27]:
```
print("Sex:")
print(df_val.Sex.value_counts(),"\n")
print("Cabin:")
print(df_val.Cabin.value_counts(),"\n")
print("Embarked:")
print(df_val.Embarked.value_counts(),"\n")
print("Title:")
print(df_val.Title.value_counts(),"\n")
```

```
Sex:
male      77
female    48
Name: Sex, dtype: int64

Cabin:
C65            2
C83            2
D46            1
D37            1
B101           1
B71            1
B51 B53 B55    1
E121           1
F33            1
C2             1
F38            1
E33            1
B3             1
B18            1
C124           1
D9             1
D26            1
C125           1
C123           1
C68            1
A19            1
E58            1
D49            1
A24            1
Name: Cabin, dtype: int64

Embarked:
S    84
C    25
Q    16
Name: Embarked, dtype: int64

Title:
```

```
Mr        73
Miss      26
Mrs       22
Master     4
Name: Title, dtype: int64
```

Testing Set

In [28]:

```
df_test = pd.read_csv('/Users/chenjiqing/Public/2022_Spring_term/QBS108 Applied ML/2022 file/Homework 2/titanic/test.csv')
df_test
```

Out[28]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Cabin	Embarked	Title
0	3	male	22	1	1	15.2458	NaN	C	Master
1	2	male	31	0	0	10.5000	NaN	S	Mr
2	3	male	20	0	0	7.9250	NaN	S	Mr
3	2	female	6	0	1	33.0000	NaN	S	Miss
4	3	female	14	1	0	11.2417	NaN	C	Miss
...	...	...	...	...	...	...	...	...	...
263	3	male	27	0	0	8.6625	NaN	S	Mr
264	1	male	27	0	0	0.0000	NaN	S	Mr
265	1	male	65	0	0	26.5500	E38	S	Mr
266	3	male	17	0	0	8.6625	NaN	S	Mr
267	1	male	28	0	0	26.5500	C52	S	Mr

268 rows × 9 columns

In [29]:

```
df_test.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 268 entries, 0 to 267
Data columns (total 9 columns):
 #   Column    Non-Null Count  Dtype  
---  ------    --------------  -----  
 0   Pclass    268 non-null    int64  
 1   Sex       268 non-null    object 
 2   Age       268 non-null    int64  
 3   SibSp     268 non-null    int64  
 4   Parch     268 non-null    int64  
 5   Fare      268 non-null    float64
 6   Cabin     65 non-null     object 
 7   Embarked  267 non-null    object 
 8   Title     268 non-null    object 
dtypes: float64(1), int64(4), object(4)
memory usage: 19.0+ KB
```

- Cabin and Embarked contain missing values

In [30]:

```
print("Sex:")
print(df_test.Sex.value_counts(),"\n")
print("Cabin:")
print(df_test.Cabin.value_counts(),"\n")
print("Embarked:")
print(df_test.Embarked.value_counts(),"\n")
print("Title:")
print(df_test.Title.value_counts(),"\n")
```

```
Sex:
male      167
female    101
```

```
Name: Sex, dtype: int64

Cabin:
E25                2
B58 B60            2
D                  2
B57 B59 B63 B66    2
C126               2
B96 B98            2
C52                2
C92                1
B49                1
E34                1
C82                1
C148               1
C110               1
D17                1
C104               1
C123               1
D11                1
C86                1
A31                1
A7                 1
E68                1
B69                1
D21                1
D19                1
D10 D12            1
B28                1
E77                1
A6                 1
E49                1
E36                1
D20                1
B39                1
C78                1
C45                1
B30                1
F33                1
E63                1
G6                 1
B86                1
C22 C26            1
F2                 1
E38                1
A20                1
B38                1
D7                 1
D28                1
D47                1
D36                1
D15                1
C106               1
C95                1
C124               1
A5                 1
D48                1
B20                1
D50                1
B78                1
C93                1
Name: Cabin, dtype: int64

Embarked:
S    187
C     58
Q     22
Name: Embarked, dtype: int64

Title:
Mr        149
Miss       57
```

```
Mrs         43
Rare        10
Master       9
Name: Title, dtype: int64
```

3-1. Preprocess the data

- Set Features and Target for training and validation set.

In [31]:
```
df_train_y = df_train['Survived'].copy()
df_val_y = df_val['Survived'].copy()
df_train = df_train.drop(['Survived'], axis=1).copy()
df_val = df_val.drop(['Survived'], axis=1).copy()

print(df_train.shape)
print(df_train_y.shape)
print(df_val.shape)
print(df_val_y.shape)
```

```
(498, 9)
(498,)
(125, 9)
(125,)
```

- For each set, more than 75% values in Cabin are missing values so I will remove this feature for the following analysis.

In [32]:
```
df_train2 = df_train.drop('Cabin',axis=1).copy()
df_val2 = df_val.drop('Cabin',axis=1).copy()
df_test2 = df_test.drop('Cabin',axis=1).copy()
```

- Because Decision Tree only can handle numbers so I need to convert the strings to numeric. However, in vlidation set, the 'Title' feature doesn't have 'Rare' label. As a result, I need to combine training, testing, and validation set together first, then, convert the strings to numeric.

In [33]:
```
# Combine 3 dataset
df_train2['set'] = "Train"
df_val2['set'] = "Val"
df_test2['set'] = "Test"

df = pd.concat([df_train2,df_val2,df_test2])
df
```

Out[33]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Title	set
0	1	female	24	0	0	69.3000	C	Mrs	Train
1	3	female	3	3	1	21.0750	S	Miss	Train
2	3	female	16	0	0	7.7333	Q	Miss	Train
3	3	male	32	0	0	56.4958	S	Mr	Train
4	3	male	22	0	0	7.1250	S	Mr	Train
...	...	...	...	...	...	...	...	...	...
263	3	male	27	0	0	8.6625	S	Mr	Test
264	1	male	27	0	0	0.0000	S	Mr	Test
265	1	male	65	0	0	26.5500	S	Mr	Test
266	3	male	17	0	0	8.6625	S	Mr	Test
267	1	male	28	0	0	26.5500	S	Mr	Test

891 rows × 9 columns

In [34]:
```
print("Sex:")
print(df.Sex.value_counts(),"\n")
print("Embarked:")
print(df.Embarked.value_counts(),"\n")
print("Title:")
print(df.Title.value_counts(),"\n")
```

```
Sex:
male      577
female    314
Name: Sex, dtype: int64

Embarked:
S    644
C    168
Q     77
Name: Embarked, dtype: int64

Title:
Mr        517
Miss      185
Mrs       126
Master     40
Rare       23
Name: Title, dtype: int64
```

In [35]:
```
# convert the strings to numeric
# Since Embarked has missing values, I will turn missing into new category.
df = df.assign(Sex = np.where(df['Sex']=='male',0,1),
               Embarked = np.where(df['Embarked']=='C',0,np.where(df['Embarked']=='S',1,
                                                   np.where(df['Embarked']=='Q',2,3))),
               Title = np.where(df['Title']=='Mr',0,np.where(df['Title']=='Miss',1,
                                                 np.where(df['Title']=='Mrs',2,
                                                          np.where(df['Title']=='Master',3,4))))).copy()

df
```

Out[35]:

	Pclass	Sex	Age	SibSp	Parch	Fare	Embarked	Title	set
0	1	1	24	0	0	69.3000	0	2	Train
1	3	1	3	3	1	21.0750	1	1	Train
2	3	1	16	0	0	7.7333	2	1	Train
3	3	0	32	0	0	56.4958	1	0	Train
4	3	0	22	0	0	7.1250	1	0	Train
...	...	...	...	...	...	...	...	...	...
263	3	0	27	0	0	8.6625	1	0	Test
264	1	0	27	0	0	0.0000	1	0	Test
265	1	0	65	0	0	26.5500	1	0	Test
266	3	0	17	0	0	8.6625	1	0	Test
267	1	0	28	0	0	26.5500	1	0	Test

891 rows × 9 columns

In [36]:
```
# Check
print("Sex:")
print(df.Sex.value_counts(),"\n")
print("Embarked:")
print(df.Embarked.value_counts(),"\n")
```

```
print("Title:")
print(df.Title.value_counts(),"\n")
```

```
Sex:
0    577
1    314
Name: Sex, dtype: int64

Embarked:
1    644
0    168
2     77
3      2
Name: Embarked, dtype: int64

Title:
0    517
1    185
2    126
3     40
4     23
Name: Title, dtype: int64
```

In [37]:

```
# Split it back to 3 dataset
df_train3 = df[df['set'] =='Train'].copy()
df_train3 = df_train3.drop('set',axis=1)
print(df_train3)

df_val3 = df[df['set'] =='Val'].copy()
df_val3 = df_val3.drop('set',axis=1)
print(df_val3)

df_test3 = df[df['set'] =='Test'].copy()
df_test3 = df_test3.drop('set',axis=1)
print(df_test3)
```

```
     Pclass  Sex  Age  SibSp  Parch     Fare  Embarked  Title
0         1    1   24      0      0  69.3000         0      2
1         3    1    3      3      1  21.0750         1      1
2         3    1   16      0      0   7.7333         2      1
3         3    0   32      0      0  56.4958         1      0
4         3    0   22      0      0   7.1250         1      0
..      ...  ...  ...    ...    ...      ...       ...    ...
493       2    0   52      0      0  13.5000         1      0
494       3    0   33      1      1  20.5250         1      0
495       2    0   38      0      0  13.0000         1      0
496       3    0   38      8      2  69.5500         1      0
497       1    1   56      0      1  83.1583         0      2

[498 rows x 8 columns]
     Pclass  Sex  Age  SibSp  Parch      Fare  Embarked  Title
0         3    1   24      1      0   15.8500         1      2
1         2    1   24      0      0   13.0000         1      1
2         3    0   40      1      1   15.5000         2      0
3         3    0   22      2      0   23.2500         2      0
4         2    1    3      1      2   41.5792         0      1
..      ...  ...  ...    ...    ...       ...       ...    ...
120       2    1   31      1      1   26.2500         1      2
121       3    0   19      0      0    7.7500         2      0
122       1    1   43      0      1  211.3375         1      2
123       2    0   52      0      0   13.0000         1      0
124       1    1   35      1      0   53.1000         1      2

[125 rows x 8 columns]
     Pclass  Sex  Age  SibSp  Parch     Fare  Embarked  Title
0         3    0   22      1      1  15.2458         0      3
1         2    0   31      0      0  10.5000         1      0
2         3    0   20      0      0   7.9250         1      0
3         2    1    6      0      1  33.0000         1      1
4         3    1   14      1      0  11.2417         0      1
..      ...  ...  ...    ...    ...      ...       ...    ...
```

```
263       3    0   27     0     0   8.6625        1     0
264       1    0   27     0     0   0.0000        1     0
265       1    0   65     0     0  26.5500        1     0
266       3    0   17     0     0   8.6625        1     0
267       1    0   28     0     0  26.5500        1     0

[268 rows x 8 columns]
```

3-2. Decision Trees Classification

3-2-a. Initialize a binary decision tree model for the training data.

In [38]:
```
from sklearn.tree import DecisionTreeClassifier
from sklearn import tree
dt = DecisionTreeClassifier(random_state=0)
```

In [39]:
```
dt2 = dt.fit(df_train3, df_train_y)
tree.plot_tree(dt2)
```

Out[39]:
```
[Text(173.75830792682927, 211.04470588235293, 'X[7] <= 0.5\ngini = 0.471\nsamples = 498\nvalue = [309, 189]'),
 Text(83.94100609756097, 198.25411764705882, 'X[0] <= 1.5\ngini = 0.277\nsamples = 295\nvalue = [246, 49]'),
 Text(19.053658536585367, 185.4635294117647, 'X[5] <= 15.644\ngini = 0.46\nsamples = 53\nvalue = [34, 19]'),
 Text(15.42439024390244, 172.6729411764706, 'gini = 0.0\nsamples = 4\nvalue = [4, 0]'),
 Text(22.682926829268293, 172.6729411764706, 'X[5] <= 27.135\ngini = 0.475\nsamples = 49\nvalue = [30, 19]'),
 Text(10.887804878048781, 159.88235294117646, 'X[2] <= 53.5\ngini = 0.408\nsamples = 7\nvalue = [2, 5]'),
 Text(7.258536585365854, 147.09176470588235, 'gini = 0.0\nsamples = 5\nvalue = [0, 5]'),
 Text(14.517073170731708, 147.09176470588235, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
 Text(34.4780487804878, 159.88235294117646, 'X[3] <= 0.5\ngini = 0.444\nsamples = 42\nvalue = [28, 14]'),
 Text(21.775609756097563, 147.09176470588235, 'X[4] <= 1.5\ngini = 0.34\nsamples = 23\nvalue = [18, 5]'),
 Text(18.146341463414636, 134.30117647058825, 'X[2] <= 32.0\ngini = 0.298\nsamples = 22\nvalue = [18, 4]'),
 Text(14.517073170731708, 121.51058823529411, 'X[5] <= 29.85\ngini = 0.48\nsamples = 10\nvalue = [6, 4]'),
 Text(7.258536585365854, 108.72, 'X[5] <= 28.725\ngini = 0.32\nsamples = 5\nvalue = [4, 1]'),
 Text(3.629268292682927, 95.92941176470588, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
 Text(10.887804878048781, 95.92941176470588, 'X[4] <= 0.5\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
 Text(7.258536585365854, 83.13882352941175, 'X[2] <= 48.0\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
 Text(3.629268292682927, 70.34823529411764, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(10.887804878048781, 70.34823529411764, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(14.517073170731708, 83.13882352941175, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(21.775609756097563, 108.72, 'X[2] <= 28.0\ngini = 0.48\nsamples = 5\nvalue = [2, 3]'),
 Text(18.146341463414636, 95.92941176470588, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(25.40487804878049, 95.92941176470588, 'X[5] <= 30.25\ngini = 0.5\nsamples = 4\nvalue = [2, 2]'),
 Text(21.775609756097563, 83.13882352941175, 'X[2] <= 33.0\ngini = 0.444\nsamples = 3\nvalue = [1, 2]'),
 Text(18.146341463414636, 70.34823529411764, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(25.40487804878049, 70.34823529411764, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
 Text(29.034146341463416, 83.13882352941175, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(21.775609756097563, 121.51058823529411, 'gini = 0.0\nsamples = 12\nvalue = [12, 0]'),
 Text(25.40487804878049, 134.30117647058825, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(47.18048780487805, 147.09176470588235, 'X[5] <= 100.981\ngini = 0.499\nsamples = 19\nvalue = [10, 9]'),
 Text(43.551219512195125, 134.30117647058825, 'X[5] <= 85.638\ngini = 0.492\nsamples = 16\nvalue = [7, 9]'),
 Text(39.921951219512195, 121.51058823529411, 'X[5] <= 79.425\ngini = 0.497\nsamples = 13\nvalue = [7, 6]'),
 Text(36.29268292682927, 108.72, 'X[6] <= 0.5\ngini = 0.496\nsamples = 11\nvalue = [5, 6]'),
 Text(32.66341463414634, 95.92941176470588, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
 Text(39.921951219512195, 95.92941176470588, 'X[2] <= 39.5\ngini = 0.469\nsamples = 8\nvalue = [5, 3]'),
 Text(36.29268292682927, 83.13882352941175, 'X[5] <= 67.925\ngini = 0.48\nsamples = 5\nvalue = [2, 3]'),
 Text(32.66341463414634, 70.34823529411764, 'X[2] <= 23.0\ngini = 0.375\nsamples = 4\nvalue = [1, 3]'),
 Text(29.034146341463416, 57.557647058823534, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(36.29268292682927, 57.557647058823534, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
 Text(39.921951219512195, 70.34823529411764, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(43.551219512195125, 83.13882352941175, 'gini = 0.0\nsamples = 3\nvalue = [3, 0]'),
 Text(43.551219512195125, 108.72, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
 Text(47.18048780487805, 121.51058823529411, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
 Text(50.80975609756098, 134.30117647058825, 'gini = 0.0\nsamples = 3\nvalue = [3, 0]'),
 Text(148.8283536585366, 185.4635294117647, 'X[5] <= 51.698\ngini = 0.217\nsamples = 242\nvalue = [212, 30]'),
 Text(106.21280487804879, 172.6729411764706, 'X[6] <= 0.5\ngini = 0.205\nsamples = 233\nvalue = [206, 27]'),
 Text(68.9560975609756, 159.88235294117646, 'X[2] <= 29.5\ngini = 0.337\nsamples = 28\nvalue = [22, 6]'),
 Text(65.32682926829268, 147.09176470588235, 'X[2] <= 28.5\ngini = 0.469\nsamples = 16\nvalue = [10, 6]'),
 Text(61.69756097560976, 134.30117647058825, 'X[5] <= 10.546\ngini = 0.408\nsamples = 14\nvalue = [10, 4]'),
 Text(54.4390243902439, 121.51058823529411, 'X[2] <= 22.5\ngini = 0.198\nsamples = 9\nvalue = [8, 1]'),
 Text(50.80975609756098, 108.72, 'X[2] <= 21.0\ngini = 0.375\nsamples = 4\nvalue = [3, 1]'),
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Text(47.18048780487805, 95.92941176470588, 'gini = 0.0\nsamples = 3\nvalue = [3, 0]'),
Text(54.4390243902439, 95.92941176470588, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(58.06829268292683, 108.72, 'gini = 0.0\nsamples = 5\nvalue = [5, 0]'),
Text(68.9560975609756, 121.51058823529411, 'X[2] <= 23.5\ngini = 0.48\nsamples = 5\nvalue = [2, 3]'),
Text(65.32682926829268, 108.72, 'X[4] <= 0.5\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
Text(61.69756097560976, 95.92941176470588, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(68.9560975609756, 95.92941176470588, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(72.58536585365854, 108.72, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
Text(68.9560975609756, 134.30117647058825, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
Text(72.58536585365854, 147.09176470588235, 'gini = 0.0\nsamples = 12\nvalue = [12, 0]'),
Text(143.46951219512195, 159.88235294117646, 'X[5] <= 13.25\ngini = 0.184\nsamples = 205\nvalue = [184, 21]'),
Text(117.27073170731708, 147.09176470588235, 'X[2] <= 30.5\ngini = 0.22\nsamples = 159\nvalue = [139, 20]'),
Text(96.62926829268292, 134.30117647058825, 'X[5] <= 8.206\ngini = 0.173\nsamples = 94\nvalue = [85, 9]'),
Text(93.0, 121.51058823529411, 'X[5] <= 8.081\ngini = 0.242\nsamples = 64\nvalue = [55, 9]'),
Text(89.37073170731708, 108.72, 'X[3] <= 0.5\ngini = 0.222\nsamples = 63\nvalue = [55, 8]'),
Text(76.21463414634147, 95.92941176470588, 'X[5] <= 7.825\ngini = 0.206\nsamples = 60\nvalue = [53, 7]'),
Text(60.79024390243902, 83.13882352941175, 'X[2] <= 23.0\ngini = 0.278\nsamples = 30\nvalue = [25, 5]'),
Text(51.71707317073171, 70.34823529411764, 'X[5] <= 7.785\ngini = 0.105\nsamples = 18\nvalue = [17, 1]'),
Text(48.08780487804878, 57.557647058823534, 'gini = 0.0\nsamples = 16\nvalue = [16, 0]'),
Text(55.34634146341464, 57.557647058823534, 'X[2] <= 21.5\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(51.71707317073171, 44.767058823529396, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(58.97560975609756, 44.767058823529396, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(69.86341463414634, 70.34823529411764, 'X[5] <= 3.525\ngini = 0.444\nsamples = 12\nvalue = [8, 4]'),
Text(66.23414634146341, 57.557647058823534, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(73.49268292682927, 57.557647058823534, 'X[2] <= 26.5\ngini = 0.397\nsamples = 11\nvalue = [8, 3]'),
Text(66.23414634146341, 44.767058823529396, 'X[5] <= 7.396\ngini = 0.278\nsamples = 6\nvalue = [5, 1]'),
Text(62.60487804878049, 31.976470588235287, 'X[2] <= 24.5\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(58.97560975609756, 19.185882352941178, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(66.23414634146341, 19.185882352941178, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(69.86341463414634, 31.976470588235287, 'gini = 0.0\nsamples = 4\nvalue = [4, 0]'),
Text(80.75121951219512, 44.767058823529396, 'X[2] <= 27.5\ngini = 0.48\nsamples = 5\nvalue = [3, 2]'),
Text(77.1219512195122, 31.976470588235287, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(84.38048780487806, 31.976470588235287, 'X[6] <= 1.5\ngini = 0.375\nsamples = 4\nvalue = [3, 1]'),
Text(80.75121951219512, 19.185882352941178, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(88.00975609756098, 19.185882352941178, 'X[2] <= 29.5\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(84.38048780487806, 6.39529411764704, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(91.6390243902439, 6.39529411764704, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(91.6390243902439, 83.13882352941175, 'X[2] <= 19.5\ngini = 0.124\nsamples = 30\nvalue = [28, 2]'),
Text(88.00975609756098, 70.34823529411764, 'X[5] <= 7.973\ngini = 0.444\nsamples = 6\nvalue = [4, 2]'),
Text(84.38048780487806, 57.557647058823534, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(91.6390243902439, 57.557647058823534, 'X[2] <= 16.5\ngini = 0.48\nsamples = 5\nvalue = [3, 2]'),
Text(88.00975609756098, 44.767058823529396, 'gini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(95.26829268292683, 44.767058823529396, 'X[2] <= 18.0\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
Text(91.6390243902439, 31.976470588235287, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(98.89756097560976, 31.976470588235287, 'gini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(95.26829268292683, 70.34823529411764, 'gini = 0.0\nsamples = 24\nvalue = [24, 0]'),
Text(102.52682926829269, 95.92941176470588, 'X[2] <= 21.0\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
Text(98.89756097560976, 83.13882352941175, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(106.15609756097561, 83.13882352941175, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(96.62926829268292, 108.72, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(100.25853658536586, 121.51058823529411, 'gini = 0.0\nsamples = 30\nvalue = [30, 0]'),
Text(137.9121951219512, 134.30117647058825, 'X[5] <= 7.763\ngini = 0.281\nsamples = 65\nvalue = [54, 11]'),
Text(134.2829268292683, 121.51058823529411, 'gini = 0.0\nsamples = 20\nvalue = [20, 0]'),
Text(141.54146341463414, 121.51058823529411, 'X[2] <= 32.5\ngini = 0.369\nsamples = 45\nvalue = [34, 11]'),
Text(124.30243902439025, 108.72, 'X[5] <= 7.91\ngini = 0.5\nsamples = 8\nvalue = [4, 4]'),
Text(117.0439024390244, 95.92941176470588, 'X[5] <= 7.875\ngini = 0.375\nsamples = 4\nvalue = [3, 1]'),
Text(113.41463414634147, 83.13882352941175, 'X[2] <= 31.5\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(109.78536585365855, 70.34823529411764, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(117.0439024390244, 70.34823529411764, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(120.67317073170732, 83.13882352941175, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(131.5609756097561, 95.92941176470588, 'X[5] <= 8.206\ngini = 0.375\nsamples = 4\nvalue = [1, 3]'),
Text(127.93170731707318, 83.13882352941175, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
Text(135.19024390243902, 83.13882352941175, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(158.78048780487805, 108.72, 'X[5] <= 10.0\ngini = 0.307\nsamples = 37\nvalue = [30, 7]'),
Text(146.07804878048782, 95.92941176470588, 'X[2] <= 38.5\ngini = 0.191\nsamples = 28\nvalue = [25, 3]'),
Text(142.4487804878049, 83.13882352941175, 'gini = 0.0\nsamples = 15\nvalue = [15, 0]'),
Text(149.70731707317074, 83.13882352941175, 'X[5] <= 7.988\ngini = 0.355\nsamples = 13\nvalue = [10, 3]'),
Text(146.07804878048782, 70.34823529411764, 'X[2] <= 46.0\ngini = 0.49\nsamples = 7\nvalue = [4, 3]'),
Text(142.4487804878049, 57.557647058823534, 'X[5] <= 7.835\ngini = 0.48\nsamples = 5\nvalue = [2, 3]'),
Text(138.81951219512194, 44.767058823529396, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(146.07804878048782, 44.767058823529396, 'X[5] <= 7.91\ngini = 0.5\nsamples = 4\nvalue = [2, 2]'),
Text(142.4487804878049, 31.976470588235287, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
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Text(149.70731707317074, 31.976470588235287, 'X[2] <= 41.5\ngini = 0.444\nsamples = 3\nvalue = [1, 2]'),
Text(146.07804878048782, 19.185882352941178, 'gini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(153.33658536585367, 19.185882352941178, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(149.70731707317074, 57.557647058823534, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(153.33658536585367, 70.34823529411764, 'gini = 0.0\nsamples = 6\nvalue = [6, 0]'),
Text(171.4829268292683, 95.92941176470588, 'X[2] <= 45.0\ngini = 0.494\nsamples = 9\nvalue = [5, 4]'),
Text(164.22439024390243, 83.13882352941175, 'X[2] <= 40.5\ngini = 0.48\nsamples = 5\nvalue = [2, 3]'),
Text(160.5951219512195, 70.34823529411764, 'X[2] <= 38.5\ngini = 0.5\nsamples = 4\nvalue = [2, 2]'),
Text(156.9658536585366, 57.557647058823534, 'X[2] <= 36.0\ngini = 0.444\nsamples = 3\nvalue = [1, 2]'),
Text(153.33658536585367, 44.767058823529396, 'gini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(160.5951219512195, 44.767058823529396, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(164.22439024390243, 57.557647058823534, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(167.85365853658539, 70.34823529411764, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(178.74146341463415, 83.13882352941175, 'X[5] <= 11.75\ngini = 0.375\nsamples = 4\nvalue = [3, 1]'),
Text(175.11219512195123, 70.34823529411764, 'X[2] <= 66.0\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(171.4829268292683, 57.557647058823534, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(178.74146341463415, 57.557647058823534, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(182.37073170731708, 70.34823529411764, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(169.66829268292685, 147.09176470588235, 'X[5] <= 25.075\ngini = 0.043\nsamples = 46\nvalue = [45, 1]'),
Text(166.0390243902439, 134.30117647058825, 'gini = 0.0\nsamples = 29\nvalue = [29, 0]'),
Text(173.29756097560977, 134.30117647058825, 'X[2] <= 33.0\ngini = 0.111\nsamples = 17\nvalue = [16, 1]'),
Text(169.66829268292685, 121.51058823529411, 'X[2] <= 31.5\ngini = 0.245\nsamples = 7\nvalue = [6, 1]'),
Text(166.0390243902439, 108.72, 'gini = 0.0\nsamples = 6\nvalue = [6, 0]'),
Text(173.29756097560977, 108.72, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(176.9268292682927, 121.51058823529411, 'gini = 0.0\nsamples = 10\nvalue = [10, 0]'),
Text(191.44390243902438, 172.6729411764706, 'X[5] <= 63.023\ngini = 0.444\nsamples = 9\nvalue = [6, 3]'),
Text(187.81463414634146, 159.88235294117646, 'X[2] <= 30.0\ngini = 0.375\nsamples = 4\nvalue = [1, 3]'),
Text(184.18536585365854, 147.09176470588235, 'X[2] <= 27.0\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(180.55609756097562, 134.30117647058825, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(187.81463414634146, 134.30117647058825, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(191.44390243902438, 147.09176470588235, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
Text(195.07317073170734, 159.88235294117646, 'gini = 0.0\nsamples = 5\nvalue = [5, 0]'),
Text(263.57560975609755, 198.25411764705882, 'X[0] <= 2.5\ngini = 0.428\nsamples = 203\nvalue = [63, 140]'),
Text(228.6439024390244, 185.4635294117647, 'X[7] <= 3.5\ngini = 0.215\nsamples = 106\nvalue = [13, 93]'),
Text(215.0341463414634, 172.6729411764706, 'X[5] <= 149.035\ngini = 0.082\nsamples = 93\nvalue = [4, 89]'),
Text(205.9609756097561, 159.88235294117646, 'X[2] <= 49.5\ngini = 0.048\nsamples = 82\nvalue = [2, 80]'),
Text(198.70243902439026, 147.09176470588235, 'X[5] <= 22.0\ngini = 0.026\nsamples = 75\nvalue = [1, 74]'),
Text(195.07317073170734, 134.30117647058825, 'X[5] <= 20.25\ngini = 0.087\nsamples = 22\nvalue = [1, 21]'),
Text(191.44390243902438, 121.51058823529411, 'gini = 0.0\nsamples = 20\nvalue = [0, 20]'),
Text(198.70243902439026, 121.51058823529411, 'X[2] <= 28.5\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(195.07317073170734, 108.72, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(202.33170731707318, 108.72, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(202.33170731707318, 134.30117647058825, 'gini = 0.0\nsamples = 53\nvalue = [0, 53]'),
Text(213.21951219512195, 147.09176470588235, 'X[2] <= 51.5\ngini = 0.245\nsamples = 7\nvalue = [1, 6]'),
Text(209.59024390243903, 134.30117647058825, 'X[5] <= 19.606\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(205.9609756097561, 121.51058823529411, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(213.21951219512195, 121.51058823529411, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(216.84878048780487, 134.30117647058825, 'gini = 0.0\nsamples = 5\nvalue = [0, 5]'),
Text(224.10731707317075, 159.88235294117646, 'X[5] <= 152.506\ngini = 0.298\nsamples = 11\nvalue = [2, 9]'),
Text(220.47804878048782, 147.09176470588235, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
Text(227.73658536585367, 147.09176470588235, 'gini = 0.0\nsamples = 9\nvalue = [0, 9]'),
Text(242.25365853658536, 172.6729411764706, 'X[1] <= 0.5\ngini = 0.426\nsamples = 13\nvalue = [9, 4]'),
Text(238.62439024390244, 159.88235294117646, 'X[6] <= 0.5\ngini = 0.298\nsamples = 11\nvalue = [9, 2]'),
Text(234.99512195121952, 147.09176470588235, 'X[5] <= 37.55\ngini = 0.444\nsamples = 3\nvalue = [1, 2]'),
Text(231.3658536585366, 134.30117647058825, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
Text(238.62439024390244, 134.30117647058825, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(242.25365853658536, 147.09176470588235, 'gini = 0.0\nsamples = 8\nvalue = [8, 0]'),
Text(245.8829268292683, 159.88235294117646, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
Text(298.5073170731707, 185.4635294117647, 'X[5] <= 22.904\ngini = 0.5\nsamples = 97\nvalue = [50, 47]'),
Text(269.47317073170734, 172.6729411764706, 'X[7] <= 2.5\ngini = 0.469\nsamples = 72\nvalue = [27, 45]'),
Text(265.8439024390244, 159.88235294117646, 'X[5] <= 7.744\ngini = 0.483\nsamples = 66\nvalue = [27, 39]'),
Text(249.51219512195124, 147.09176470588235, 'X[5] <= 6.987\ngini = 0.18\nsamples = 10\nvalue = [1, 9]'),
Text(245.8829268292683, 134.30117647058825, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
Text(253.14146341463416, 134.30117647058825, 'gini = 0.0\nsamples = 9\nvalue = [0, 9]'),
Text(282.1756097560976, 147.09176470588235, 'X[2] <= 26.5\ngini = 0.497\nsamples = 56\nvalue = [26, 30]'),
Text(260.40000000000003, 134.30117647058825, 'X[4] <= 0.5\ngini = 0.48\nsamples = 30\nvalue = [18, 12]'),
Text(247.69756097560978, 121.51058823529411, 'X[6] <= 1.5\ngini = 0.305\nsamples = 16\nvalue = [13, 3]'),
Text(240.4390243902439, 108.72, 'X[2] <= 25.5\ngini = 0.142\nsamples = 13\nvalue = [12, 1]'),
Text(236.80975609756098, 95.92941176470588, 'gini = 0.0\nsamples = 11\nvalue = [11, 0]'),
Text(244.06829268292682, 95.92941176470588, 'X[7] <= 1.5\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
Text(240.4390243902439, 83.13882352941175, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
Text(247.69756097560978, 83.13882352941175, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
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 Text(254.95609756097562, 108.72, 'X[5] <= 7.89\ngini = 0.444\nsamples = 3\nvalue = [1, 2]'),
 Text(251.3268292682927, 95.92941176470588, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(258.5853658536586, 95.92941176470588, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
 Text(273.10243902439026, 121.51058823529411, 'X[7] <= 1.5\ngini = 0.459\nsamples = 14\nvalue = [5, 9]'),
 Text(269.47317073170734, 108.72, 'X[2] <= 17.5\ngini = 0.496\nsamples = 11\nvalue = [5, 6]'),
 Text(265.8439024390244, 95.92941176470588, 'X[3] <= 2.5\ngini = 0.444\nsamples = 9\nvalue = [3, 6]'),
 Text(258.5853658536586, 83.13882352941175, 'X[5] <= 11.375\ngini = 0.278\nsamples = 6\nvalue = [1, 5]'),
 Text(254.95609756097562, 70.34823529411764, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(262.2146341463415, 70.34823529411764, 'gini = 0.0\nsamples = 5\nvalue = [0, 5]'),
 Text(273.10243902439026, 83.13882352941175, 'X[5] <= 14.5\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
 Text(269.47317073170734, 70.34823529411764, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(276.7317073170732, 70.34823529411764, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
 Text(273.10243902439026, 95.92941176470588, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
 Text(276.7317073170732, 108.72, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
 Text(303.9512195121951, 134.30117647058825, 'X[6] <= 1.5\ngini = 0.426\nsamples = 26\nvalue = [8, 18]'),
 Text(294.8780487804878, 121.51058823529411, 'X[2] <= 36.5\ngini = 0.484\nsamples = 17\nvalue = [7, 10]'),
 Text(287.61951219512196, 108.72, 'X[4] <= 3.0\ngini = 0.397\nsamples = 11\nvalue = [3, 8]'),
 Text(283.99024390243903, 95.92941176470588, 'X[3] <= 0.5\ngini = 0.32\nsamples = 10\nvalue = [2, 8]'),
 Text(280.3609756097561, 83.13882352941175, 'gini = 0.0\nsamples = 4\nvalue = [0, 4]'),
 Text(287.61951219512196, 83.13882352941175, 'X[2] <= 32.0\ngini = 0.444\nsamples = 6\nvalue = [2, 4]'),
 Text(283.99024390243903, 70.34823529411764, 'X[5] <= 19.262\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
 Text(280.3609756097561, 57.557647058823534, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
 Text(287.61951219512196, 57.557647058823534, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(291.2487804878049, 70.34823529411764, 'gini = 0.0\nsamples = 3\nvalue = [0, 3]'),
 Text(291.2487804878049, 95.92941176470588, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(302.13658536585365, 108.72, 'X[5] <= 15.673\ngini = 0.444\nsamples = 6\nvalue = [4, 2]'),
 Text(298.5073170731707, 95.92941176470588, 'gini = 0.0\nsamples = 4\nvalue = [4, 0]'),
 Text(305.76585365853657, 95.92941176470588, 'gini = 0.0\nsamples = 2\nvalue = [0, 2]'),
 Text(313.0243902439025, 121.51058823529411, 'X[2] <= 41.0\ngini = 0.198\nsamples = 9\nvalue = [1, 8]'),
 Text(309.3951219512195, 108.72, 'gini = 0.0\nsamples = 7\nvalue = [0, 7]'),
 Text(316.6536585365854, 108.72, 'X[3] <= 0.5\ngini = 0.5\nsamples = 2\nvalue = [1, 1]'),
 Text(313.0243902439025, 95.92941176470588, 'gini = 0.0\nsamples = 1\nvalue = [1, 0]'),
 Text(320.2829268292683, 95.92941176470588, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(273.10243902439026, 159.88235294117646, 'gini = 0.0\nsamples = 6\nvalue = [0, 6]'),
 Text(327.54146341463417, 172.6729411764706, 'X[2] <= 6.0\ngini = 0.147\nsamples = 25\nvalue = [23, 2]'),
 Text(323.91219512195124, 159.88235294117646, 'X[2] <= 4.5\ngini = 0.346\nsamples = 9\nvalue = [7, 2]'),
 Text(320.2829268292683, 147.09176470588235, 'X[2] <= 2.5\ngini = 0.219\nsamples = 8\nvalue = [7, 1]'),
 Text(316.6536585365854, 134.30117647058825, 'gini = 0.0\nsamples = 5\nvalue = [5, 0]'),
 Text(323.91219512195124, 134.30117647058825, 'X[2] <= 3.5\ngini = 0.444\nsamples = 3\nvalue = [2, 1]'),
 Text(320.2829268292683, 121.51058823529411, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(327.54146341463417, 121.51058823529411, 'gini = 0.0\nsamples = 2\nvalue = [2, 0]'),
 Text(327.54146341463417, 147.09176470588235, 'gini = 0.0\nsamples = 1\nvalue = [0, 1]'),
 Text(331.1707317073171, 159.88235294117646, 'gini = 0.0\nsamples = 16\nvalue = [16, 0]')]
```
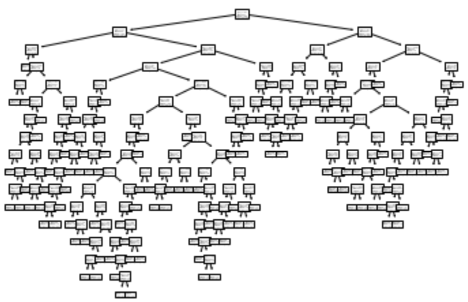



In [40]:
```
dt2.score(df_train3, df_train_y)
```

Out[40]: 0.9919678714859438

In [41]:
```
dt2.score(df_val3, df_val_y)
```

Out[41]: 0.768

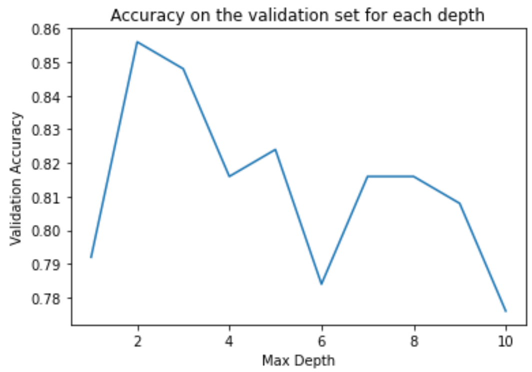
- The model is overfiting for default setting.

3-2-b. Improve a decision tree model by tuning some hyperparam- eters for terminating the splitting process. Tune the maximum depth of the tree

In [42]:
```
depth =[]
accuracy = []
for max_depth in range(1,11):
    dt = DecisionTreeClassifier(random_state=0, max_depth=max_depth)
    dt = dt.fit(df_train3, df_train_y)
    print("Max Depth: ", max_depth)
    print("Train Accuracy: ", dt.score(df_train3, df_train_y))
    print("Validation Accuracy: ", dt.score(df_val3, df_val_y))
    print('-'*20)
    depth.append(max_depth)
    accuracy.append(dt.score(df_val3, df_val_y))

plt.plot(depth, accuracy)
plt.title("Accuracy on the validation set for each depth")
plt.xlabel("Max Depth")
plt.ylabel("Validation Accuracy")
```

```
Max Depth:  1
Train Accuracy:  0.7751004016064257
Validation Accuracy:  0.792
--------------------
Max Depth:  2
Train Accuracy:  0.7811244979919679
Validation Accuracy:  0.856
--------------------
Max Depth:  3
Train Accuracy:  0.8273092369477911
Validation Accuracy:  0.848
--------------------
Max Depth:  4
Train Accuracy:  0.8413654618473896
Validation Accuracy:  0.816
--------------------
Max Depth:  5
Train Accuracy:  0.8534136546184738
Validation Accuracy:  0.824
--------------------
Max Depth:  6
Train Accuracy:  0.8815261044176707
Validation Accuracy:  0.784
--------------------
Max Depth:  7
Train Accuracy:  0.8975903614457831
Validation Accuracy:  0.816
--------------------
Max Depth:  8
Train Accuracy:  0.9156626506024096
Validation Accuracy:  0.816
--------------------
Max Depth:  9
Train Accuracy:  0.9397590361445783
Validation Accuracy:  0.808
--------------------
Max Depth:  10
Train Accuracy:  0.9558232931726908
Validation Accuracy:  0.776
--------------------
```

Out[42]:
```
Text(0, 0.5, 'Validation Accuracy')
```



- According to the plot, the optimum maximum depth is 2.

3-2-C. Train a decision tree classifier using the optimum setting of max- imum depth found in 3.2b on all data from the training and validation set.

In [43]:
```
# Combine training and validation set
df_train_val = pd.concat([df_train3, df_val3])
df_train_val_y = pd.concat([df_train_y, df_val_y])

# Set Decision tree classifier
dt = DecisionTreeClassifier(random_state=1, max_depth = 2)

# Train model
dt.fit(df_train_val, df_train_val_y)
```

Out[43]:
```
DecisionTreeClassifier(max_depth=2, random_state=1)
```

In [44]:
```
# Predict
y_pred = dt.predict(df_test3)
y_pred

# Create data frame for Prediction
df_pred = pd.DataFrame(y_pred)
df_pred

# save the predictions
df_pred.to_csv('F0034WQ_dt_prediction.csv', index=False, header = False)
```

4 Random Forest Classification

4-1. Initialize a random forest classifier.

In [45]:
```
from sklearn.ensemble import RandomForestClassifier

rf = RandomForestClassifier(max_depth=2, random_state=0)
rf.fit(df_train3, df_train_y)

# Accuracy on Validation set in default set
print("Validation Accuracy: ", rf.score(df_val3, df_val_y))
```

```
Validation Accuracy:  0.816
```

4-2. Optimize your classifier by tuning two hyperparameters to maximize the accuracy of your model:

In [46]:
```
from sklearn.model_selection import GridSearchCV
```

```
# Create the grid search hyperparameter
grid_hyper =  {'max_depth': [1, 2, 3, 4, 5, 6, 7, 8, 9, 10],
               'n_estimators': [50,100,150,200,250]}

# classifier
rf = RandomForestClassifier(random_state = 2)

# search different combinations.
rf_GRCV = GridSearchCV(estimator = rf, param_grid = grid_hyper, cv = 10)

# Fit the model
rf_GRCV.fit(df_train_val, df_train_val_y)

# best hyperparameters
print("Optimum parameters: ", rf_GRCV.best_params_)
```

```
Optimum parameters:  {'max_depth': 7, 'n_estimators': 150}
```

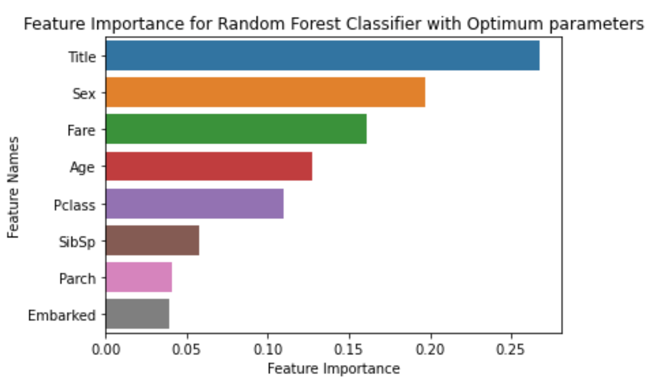
4-3. Report and interpret the feature importance of each feature by your random forest model.

In [47]:
```
# classifier with best hyperparameters
rf = RandomForestClassifier(random_state = 2, max_depth = 7, n_estimators = 150)
rf.fit(df_train_val, df_train_val_y)
```

Out[47]:
```
RandomForestClassifier(max_depth=7, n_estimators=150, random_state=2)
```

In [48]:
```
# Generate feature importance and feature names
feature_importance = np.array(rf.feature_importances_)
feature_names = np.array(df_train_val.columns)

# Generate a DataFrame for feature importance
data={'feature_names':feature_names,'feature_importance':feature_importance}
feature_importance_df = pd.DataFrame(data)

# Sort the DataFrame according to feature importance
feature_importance_df.sort_values(by=['feature_importance'], ascending=False, inplace=True)

# Plot
import seaborn as sns
sns.barplot(x = feature_importance_df['feature_importance'], y = feature_importance_df['feature_names'])
plt.title('Feature Importance for Random Forest Classifier with Optimum parameters')
plt.xlabel('Feature Importance')
plt.ylabel('Feature Names')
```

Out[48]:
```
Text(0, 0.5, 'Feature Names')
```



- According to the above plot, we can see the most important feature in my model is "Title".

4-4. Predict the survivals on testing data using the classifier with the opti- mum parameters from 4.2.

In [49]:
```
# Predict
y_pred = rf.predict(df_test3)
y_pred

# Create data frame for Prediction
df_pred = pd.DataFrame(y_pred)
df_pred

# save the predictions
df_pred.to_csv('F0034WQ_rf_prediction.csv', index=False, header = False)
```

5. SVM classification

In [50]:
```
# Pre-processed data
from sklearn.preprocessing import StandardScaler
SS = StandardScaler()

df_train3_SS = SS.fit_transform(df_train3)
df_val3_SS = SS.transform(df_val3)
df_test3_SS = SS.transform(df_test3)
```

5-1. Build SVM classifiers with the following three kernels: linear, polynomial with degree = 2, and radial basis function kernel. Train the classifiers and calculate the performance of each classifier on the validation set.

In [51]:
```
from sklearn.metrics import accuracy_score, log_loss
from sklearn.svm import SVC

svm_linear = SVC(kernel = 'linear')
svm_poly = SVC(kernel = 'poly', degree = 2, probability = True)
svm_rbf = SVC(kernel = 'rbf', probability = True)

# kernels: linear
svm_linear.fit(df_train3_SS, df_train_y)
print("kernels: linear")
print("Validation Accuracy: ", svm_linear.score(df_val3_SS, df_val_y))
print('-'*20)

# kernels: polynomial with degree = 2
svm_poly.fit(df_train3_SS, df_train_y)
print("kernels: polynomial with degree = 2")
print("Validation Accuracy: ", svm_poly.score(df_val3_SS, df_val_y))
print('Loss of Validation Set:', log_loss(df_val_y, svm_poly.predict_proba(df_val3_SS)) )
print('-'*20)

# kernels: radial basis function
svm_rbf.fit(df_train3_SS, df_train_y)
print("kernels: radial basis function")
print("Validation Accuracy: ", svm_rbf.score(df_val3_SS, df_val_y))
print('Loss of Validation Set:', log_loss(df_val_y, svm_rbf.predict_proba(df_val3_SS)) )
print('-'*20)
```

```
kernels: linear
Validation Accuracy:  0.84
--------------------
kernels: polynomial with degree = 2
Validation Accuracy:  0.856
Loss of Validation Set: 0.4049651318151844
--------------------
kernels: radial basis function
Validation Accuracy:  0.856
```

```
Loss of Validation Set: 0.3780804868895341
--------------------
```

5-2. Which kernel gives the best result? Use your classifier with the this kernel to predict the survival outcomes in the testing set.

- Although classifier with kernel = polynomial and classifier with kernel = radial basis function return same accuracy, classifier with kernel = radial basis function returns smaller Loss. As a result, classifier with kernel = radial basis function gives the best result.

In [52]:
```
# Predict
y_pred = svm_rbf.predict(df_test3_SS)
y_pred

# Create data frame for Prediction
df_pred = pd.DataFrame(y_pred)
df_pred

# save the predictions
df_pred.to_csv('F0034WQ_svm_prediction.csv', index=False, header = False)
```

In [ ]: