Report-01

December 5, 2024

1 Using Passenger Information to Predict their Survival on the Titanic

Titanic Dataset from: https://www.kaggle.com/competitions/titanic/data?select=train.csv
Arush Bodla

I'm trying to predict whether a passenger would survive on the Titanic. The dataset comes from kaggle, and has about 900 records. Each record has some information about the passenger, like their sex, age, ticket number, etc. Ultimately, Logistic Regression ends up being the best way to predict a passenger's survival, achieving an accuracy of 84% on a subset of the training data given by kaggle. The kaggle test set isn't labeled, so I can't use it to evaluate the accuracy of the model. This is also the second time I've used the Titanic set (the first time being with linear regression), so this is also a comparison between regression and classificatio on the data.

[1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
import seaborn as sns
from sklearn.metrics import confusion_matrix
from matplotlib.colors import LinearSegmentedColormap
from sklearn.preprocessing import OrdinalEncoder
from sklearn.neighbors import KNeighborsClassifier
from sklearn.linear_model import LogisticRegression
from sklearn import tree
from sklearn.tree import DecisionTreeClassifier
from sklearn.svm import SVC
```

1.1 EDA

I'll start by reading in the data, and examining how its structured. This includes looking at the datatypes, whether the features are balanced, and so on.

[2]:
```
data = pd.read_csv("../data/titanic_train.csv")
data
```

[2]:
```
     PassengerId  Survived  Pclass  \
0              1         0       3
```

```
1              2          1        1
2              3          1        3
3              4          1        1
4              5          0        3
..           …        …      …
886          887          0        2
887          888          1        1
888          889          0        3
889          890          1        1
890          891          0        3

                                                    Name     Sex   Age  SibSp  \
0                              Braund, Mr. Owen Harris    male  22.0      1
1    Cumings, Mrs. John Bradley (Florence Briggs Th…  female  38.0      1
2                               Heikkinen, Miss. Laina  female  26.0      0
3         Futrelle, Mrs. Jacques Heath (Lily May Peel)  female  35.0      1
4                             Allen, Mr. William Henry    male  35.0      0
..                                                 …     …    …    …
886                              Montvila, Rev. Juozas    male  27.0      0
887                       Graham, Miss. Margaret Edith  female  19.0      0
888           Johnston, Miss. Catherine Helen "Carrie"  female   NaN      1
889                              Behr, Mr. Karl Howell    male  26.0      0
890                                Dooley, Mr. Patrick    male  32.0      0

     Parch            Ticket     Fare Cabin Embarked
0        0         A/5 21171   7.2500   NaN        S
1        0          PC 17599  71.2833   C85        C
2        0  STON/O2. 3101282   7.9250   NaN        S
3        0            113803  53.1000  C123        S
4        0            373450   8.0500   NaN        S
..     …               …      …    …      …
886      0            211536  13.0000   NaN        S
887      0            112053  30.0000   B42        S
888      2        W./C. 6607  23.4500   NaN        S
889      0            111369  30.0000  C148        C
890      0            370376   7.7500   NaN        Q

[891 rows x 12 columns]
```

[3]:
```
data.dtypes
```

[3]:
```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
```

```
SibSp             int64
Parch             int64
Ticket           object
Fare            float64
Cabin            object
Embarked         object
dtype: object
```

Here's a basic description of each feature in the data: - Survived: Whether or not the passenger survived (target column) - PassengerId: An index for each passenger - Pclass: Socioeconomic class of the passenger (1 = lower, 2 = middle, 3 = upper) - SibSp: Number of siblings or spouses of the passenger - Parch: Number of parents or children of the passenger - Ticket: Ticket number/ID of the passenger - Fare: How much the passengers paid for the ticket - Cabin: Cabin number of the passenger - Embarked: The port the passenger got onboard (Cherbourg, Queenstown, Southampton)

[4]:
```
data.describe()
```

[4]:
```
       PassengerId    Survived      Pclass         Age       SibSp  \
count   891.000000  891.000000  891.000000  714.000000  891.000000
mean    446.000000    0.383838    2.308642   29.699118    0.523008
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

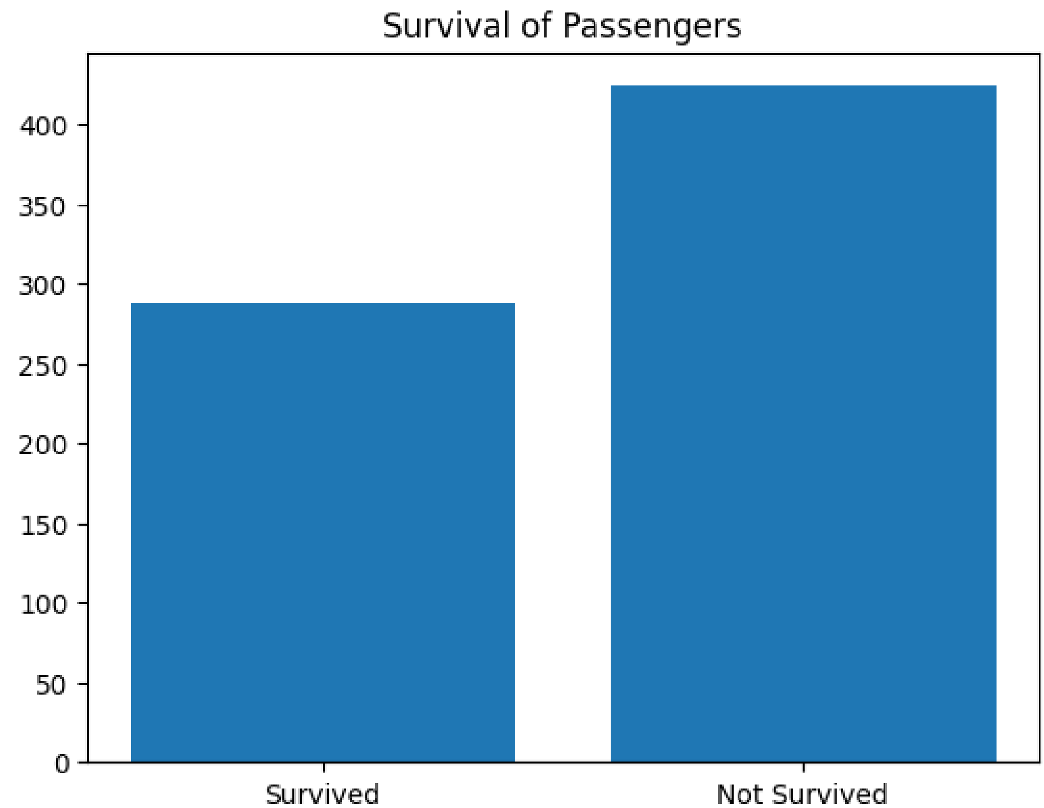
I'm going to remove all of the columns with fully unique values since they wouldn't be of much use. I'll also do some preprocessing.

[5]:
```
data.drop(columns=["PassengerId", "Name", "Ticket", "Cabin"], errors="ignore",␣
 ↪inplace=True)
data.dropna(inplace=True)
encoder = OrdinalEncoder()
for col in data.select_dtypes("object").columns:
    data[col] = encoder.fit_transform(data[[col]])
```

Here I'm going to plot the survivors and non-survivors to see if the data is balanced.

[6]:
```
survived = data[data["Survived"] == 1]
not_survived = data[data["Survived"] == 0]
plt.bar(["Survived", "Not Survived"], [survived.shape[0], not_survived.
  ↪shape[0]])
plt.title("Survival of Passengers")
print(f"Survival Rate: {np.mean(data.Survived)*100:.2f}%")
np.random.seed(102)
```

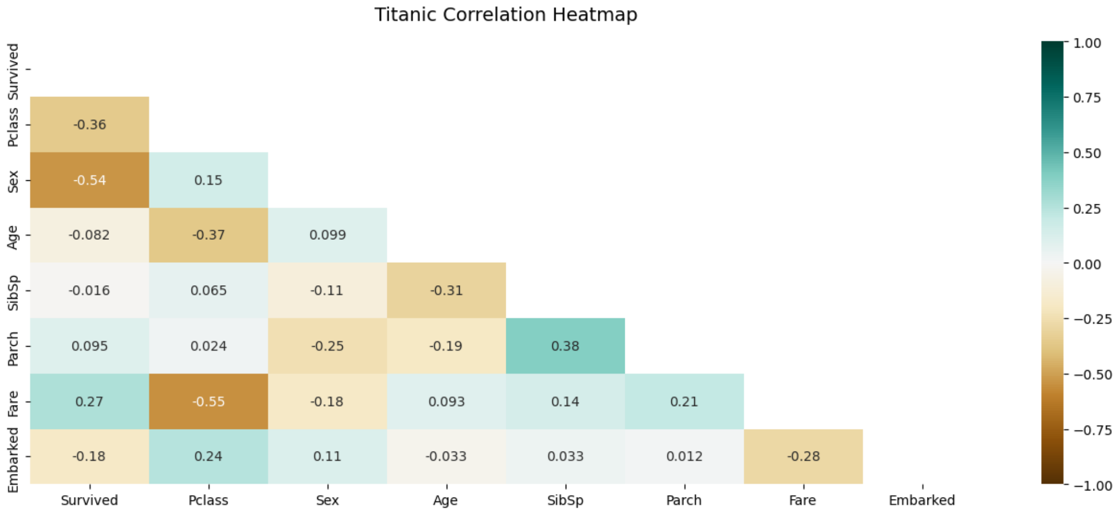
```
Survival Rate: 40.45%
```



About 40% of the people survived, which means the data is somewhat balanced. I'll see if there's any colinearity in the data.

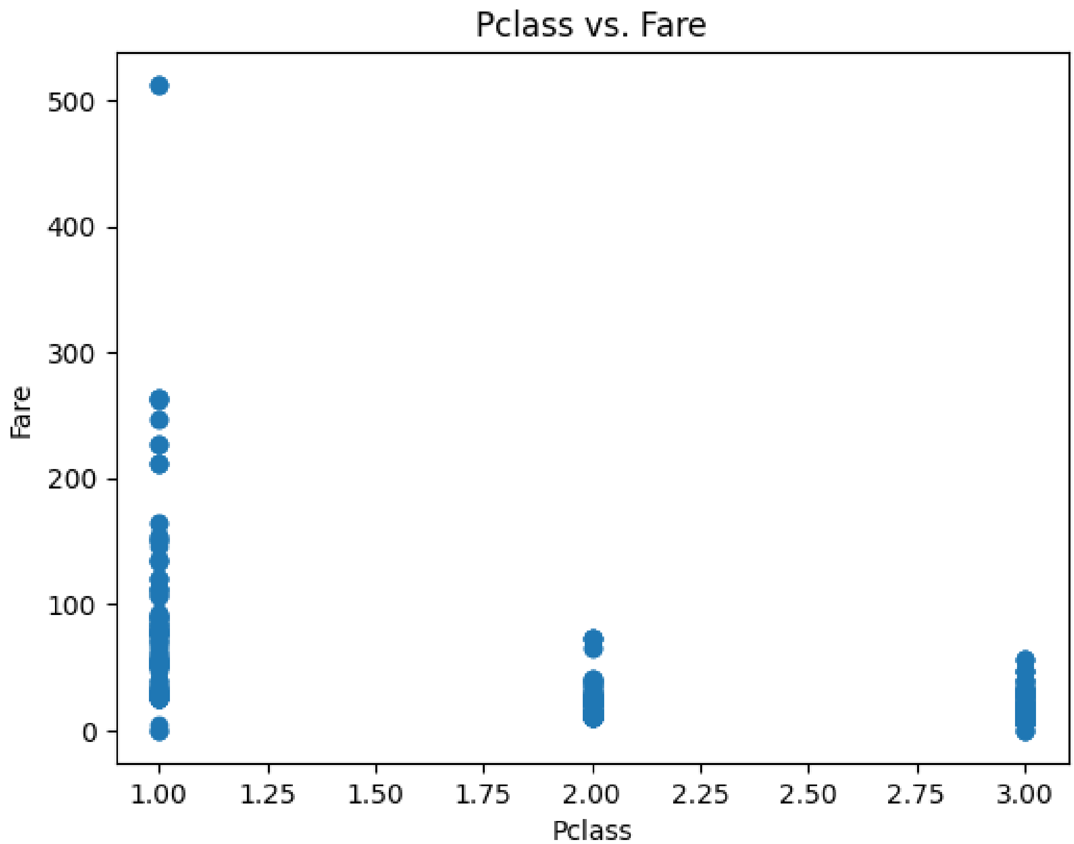
[7]:
```
corr_matrix = data.corr()
plt.figure(figsize=(16, 6))
mask = np.triu(np.ones_like(corr_matrix, dtype=np.bool))
heatmap = sns.heatmap(corr_matrix, mask=mask, vmin=-1, vmax=1, annot=True,␣
  ↪cmap='BrBG')
heatmap.set_title('Titanic Correlation Heatmap', fontdict={'fontsize':14},␣
  ↪pad=16);
```

```python
plt.show()
```

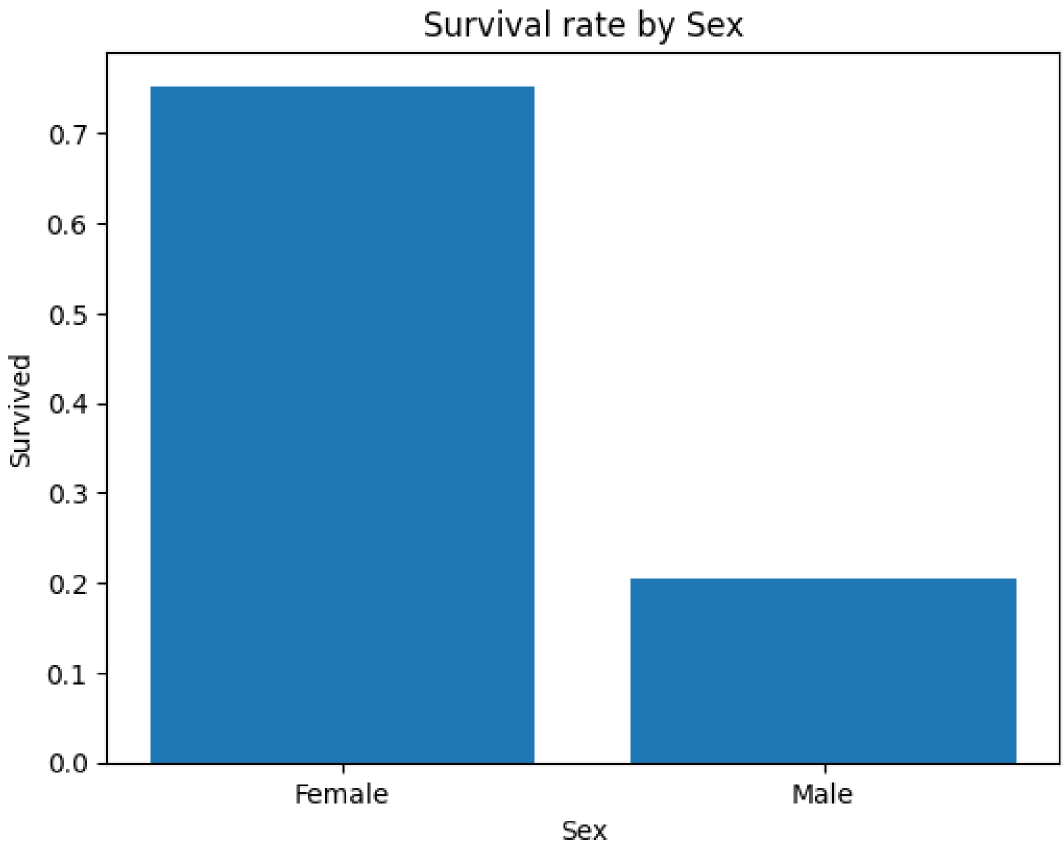


There's not much colinearity, so i'll leave the columns in. I'll plot Pclass vs Fare and Survived vs Sex, to see if the correlation is strong.

[8]:
```python
plt.scatter(data["Pclass"], data["Fare"])
plt.xlabel("Pclass")
plt.ylabel("Fare")
plt.title("Pclass vs. Fare")
plt.show()
```



[9]:
```
plt.bar(["Female", "Male"], [data[data["Sex"] == 0]["Survived"].mean(),␣
↪data[data["Sex"] == 1]["Survived"].mean()])
plt.xlabel("Sex")
plt.ylabel("Survived")
plt.title("Survival rate by Sex")
plt.show()
```



The correlation between Pclass and Fare is not really linear, so I'll leave it in. Also, it looks the survival rate for females on the ship is substantially higher than for males.

1.2 Helper Methods

I'll define some helper methods to calculate the acccuracy of a model, as well as create a comparison between two different models.

[10]:
```
def accuracy(model, X_test, y_test):
    cm = confusion_matrix(y_test, model.predict(X_test))
    return (cm[0][0] + cm[1][1]) / (cm[0][0] + cm[0][1] + cm[1][0] + cm[1][1])
```

[11]:
```
#colormaps so that higher values are good(green) for main diagonal and bad(red)␣
 ↪for the off diagonal
#red = (1, 0.4, 0.4)
#green = (0.4, 1, 0.4)
red = (0.6, 0, 0)
green = (0, 0.6, 0)
main_diag_cmap = LinearSegmentedColormap.from_list("main_diag", [red, (1, 1,␣
 ↪1), green])
```

```python
off_diag_cmap = LinearSegmentedColormap.from_list("off_diag", [green, (1, 1,␣
↪1), red])
def plot_confusion_comparison(cm1, cm2, ax, colorbar_message,␣
↪hide_bottom=False, hide_side=False, colorbar=True, extra_labels=True):
    diff = cm2 - cm1

    main_diag_mask = np.eye(2, dtype=bool)
    off_diag_mask = ~main_diag_mask

    max_abs_diff = np.abs(diff).max()
    vmin, vmax = -15, 15

    sns.heatmap(
        diff,
        mask=off_diag_mask, cmap=main_diag_cmap,
        annot=True, fmt="+d",
        cbar=colorbar,
        cbar_kws={"label": colorbar_message},
        linewidths=0.5,
        ax=ax,
        vmin=vmin, vmax=vmax,
        xticklabels=not hide_bottom, yticklabels=not hide_side
    )
    sns.heatmap(
        diff,
        mask=main_diag_mask, cmap=off_diag_cmap,
        annot=True, fmt="+d",
        cbar=False,
        linewidths=0.5,
        ax=ax,
        vmin=vmin, vmax=vmax,
        xticklabels=not hide_bottom, yticklabels=not hide_side
    )


    if(not hide_bottom):
        ax.set_xticklabels(["Died", "Survived"])

    if not hide_side:
        ax.set_yticklabels(["Died", "Survived"])

    if extra_labels:
        ax.set_xlabel("Predicted Labels")
        ax.set_ylabel("True Labels")
    else:
        ax.tick_params(length=0)
```

1.3 Testing and Optimizing Various Models

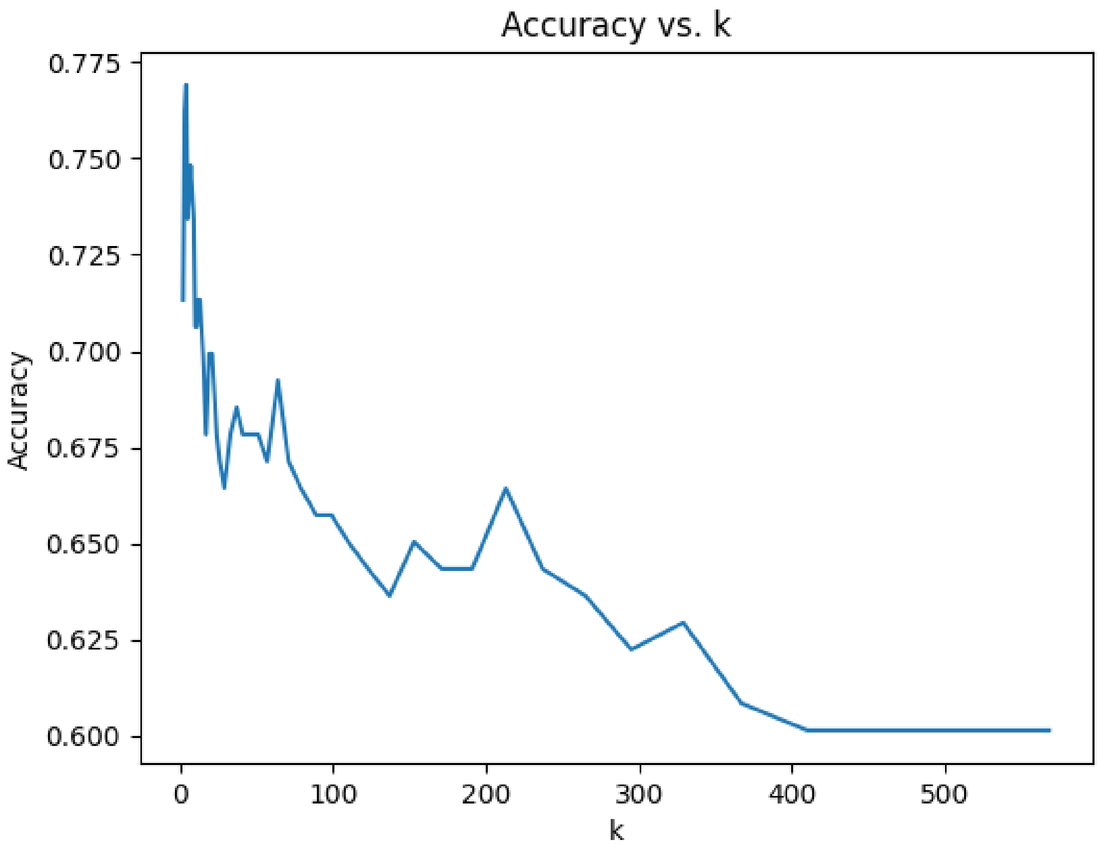
I'm going to try three models on this dataset: K nearest neighbors, logistic regression, and decison trees. My initial guess is that decision trees will be the best model, but I'll start with k nearest neighbors. I'm using a 80/20 train/test split, and the same split will be used to test each model to reduce the luck factor that may be present in the test set.

[12]:
```
X = data.drop(columns=["Survived"])
y = data["Survived"]
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
↪random_state=102)
```

1.3.1 K nearest neighbors

The first thing I'll optimize for the k nearest neighbors model is k.

[13]:
```
model = KNeighborsClassifier(n_neighbors=7)
model.fit(X_train, y_train)

k_values = np.unique(np.logspace(1, np.log(X_train.shape[0]), 50, base=np.e)).
↪astype(int)
scores = []
for k in k_values:
    model = KNeighborsClassifier(n_neighbors=k)
    model.fit(X_train, y_train)
    scores.append(accuracy(model, X_test, y_test))

plt.title("Accuracy vs. k")
plt.xlabel("k")
plt.ylabel("Accuracy")
plt.plot(k_values, scores)
plt.show()
print("Best k:", k_values[np.argmax(scores)], "\nAccuracy:", np.max(scores))
knnbestk = k_values[np.argmax(scores)]
```

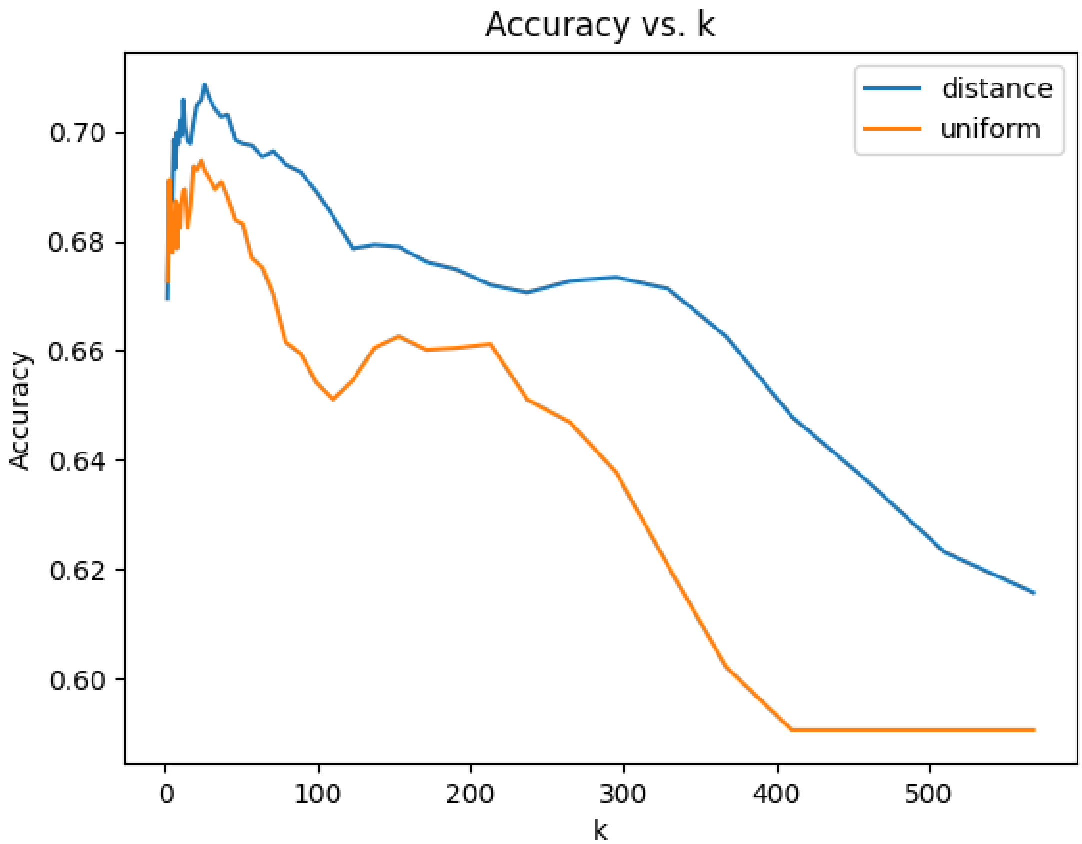



```
Best k: 4
Accuracy: 0.7692307692307693
```

It looks like k=4 is the best amount, but the model is not that great. Small k values look more accurate, and after about 30, the accuracy quickly drops down. I'll see if other parameters can make it better. The first thing I'm testing is the "weights" parameter, which determines how the K-nearest neighbors to the point influence the final result. With "distance", the closest few points matter more towards the output than further points do, while uniform has each of the k closest points equally important.

[14]:
```python
seednum = 102
def test_distance_uniform():
    global seednum
    scored = []
    scoreu = []
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,␣
 ↪random_state=seednum)
    seednum += 1
    for k in k_values:
        model = KNeighborsClassifier(n_neighbors=k, weights="distance")
```

```python
        model.fit(X_train, y_train)
        scored.append(accuracy(model, X_test, y_test))
        model = KNeighborsClassifier(n_neighbors=k, weights="uniform")
        model.fit(X_train, y_train)
        scoreu.append(accuracy(model,X_test, y_test))
    return np.array(scored), np.array(scoreu)

scoredtotal = np.zeros(len(k_values))
scoreutotal = np.zeros(len(k_values))
for i in range(20):
    scored, scoreu = test_distance_uniform()
    scoredtotal += scored
    scoreutotal += scoreu

scored = scoredtotal / (20)
scoreu = scoreutotal / (20)

plt.title("Accuracy vs. k")
plt.xlabel("k")
plt.ylabel("Accuracy")
plt.plot(k_values, scored, label="distance")
plt.plot(k_values, scoreu, label="uniform")
plt.legend()
plt.show()
```



[15]:
```
print("Best k (distance):", k_values[np.argmax(scored)], "\nAccuracy:", np.
    ↪max(scored))
print("Best k (uniform):", k_values[np.argmax(scoreu)], "\nAccuracy:", np.
    ↪max(scoreu))
```

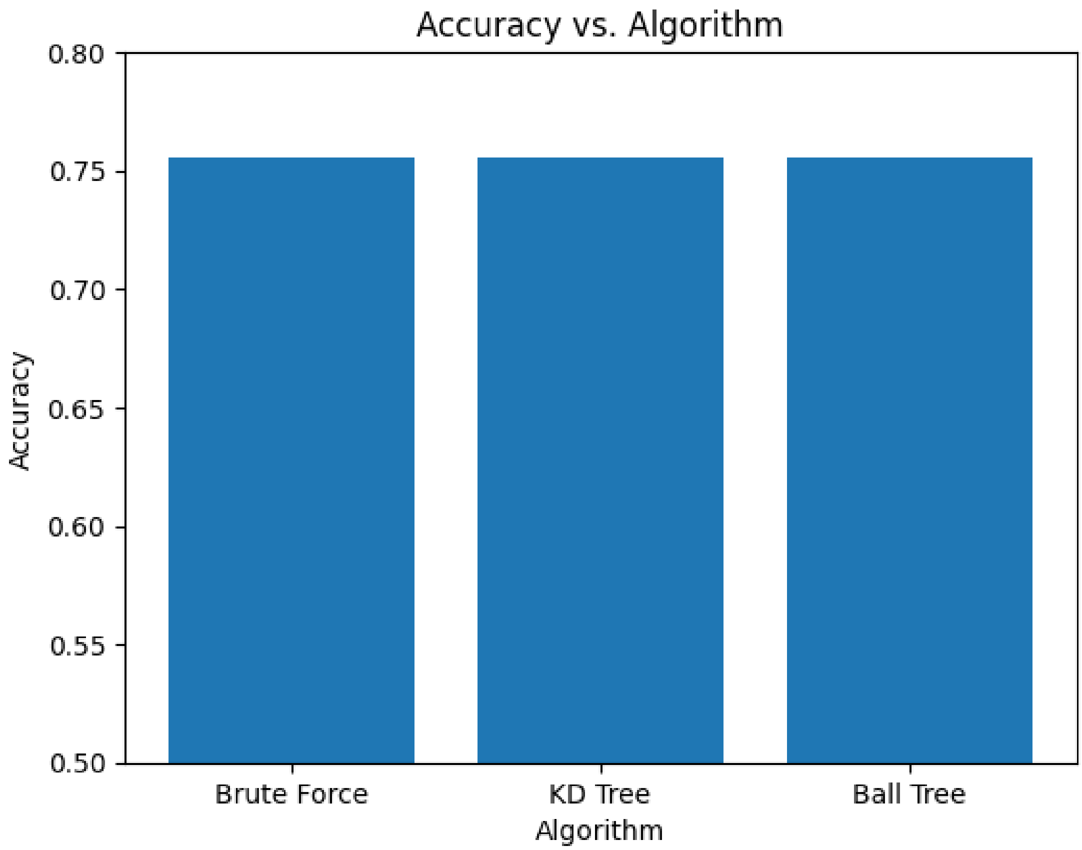
```
Best k (distance): 26
Accuracy: 0.7087412587412586
Best k (uniform): 24
Accuracy: 0.6947552447552447
```

Looks like distance is the better option. Also, the original test train split looks like it was very forgiving to the model, since the average of 20 splits tank the accuracy down a few percent. Next, I'll test the algorithm parameter, which determines how the k nearest neighbors are found.

[16]:
```
model = KNeighborsClassifier(n_neighbors=knnbestk, weights="distance",␣
    ↪algorithm="brute")
model.fit(X_train, y_train)
brute = accuracy(model, X_test, y_test)
```

```
model = KNeighborsClassifier(n_neighbors=knnbestk, weights="distance",␣
 ↪algorithm="kd_tree")
model.fit(X_train, y_train)
kd_tree = accuracy(model, X_test, y_test)

model = KNeighborsClassifier(n_neighbors=knnbestk, weights="distance",␣
 ↪algorithm="ball_tree")
model.fit(X_train, y_train)
ball_tree = accuracy(model, X_test, y_test)

print("Brute Force:", brute)
print("KD Tree:", kd_tree)
print("Ball Tree:", ball_tree)

plt.title("Accuracy vs. Algorithm")
plt.xlabel("Algorithm")
plt.ylabel("Accuracy")
plt.bar(["Brute Force", "KD Tree", "Ball Tree"], [brute, kd_tree, ball_tree])
plt.ylim(0.5, 0.8)
plt.show()
```

```
Brute Force: 0.7552447552447552
KD Tree: 0.7552447552447552
Ball Tree: 0.7552447552447552
```

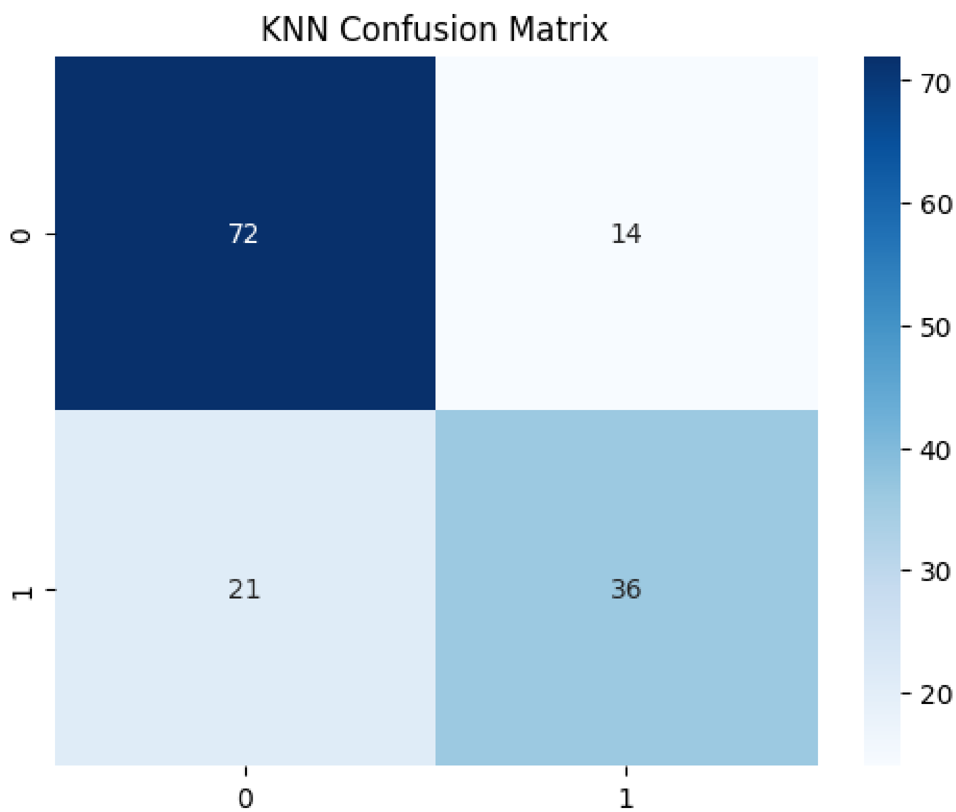


They're the exact same, so I'll leave the algorithm at auto. The final KNN classifier is below:

[17]:
```
model = KNeighborsClassifier(n_neighbors=knnbestk, weights="distance",␣
  ↪algorithm="auto")
model.fit(X_train, y_train)
print("Accuracy: ", accuracy(model, X_test, y_test))
```

```
Accuracy:  0.7552447552447552
```

[18]:
```
cm_knn = confusion_matrix(y_test, model.predict(X_test))

plt.title("KNN Confusion Matrix")
plt.xlabel("Actual")
plt.ylabel("Predicted")
sns.heatmap(cm_knn, annot=True, cmap="Blues")
plt.show()
```



That's a decent imrovement over linear regression, about 5-6% more. (For context, the linear regression model got 68% accuracy.) As for the correlation matrix, I don't have anything to go off yet, so I'm assuming the model is doing well.

1.3.2 Logistic Regression

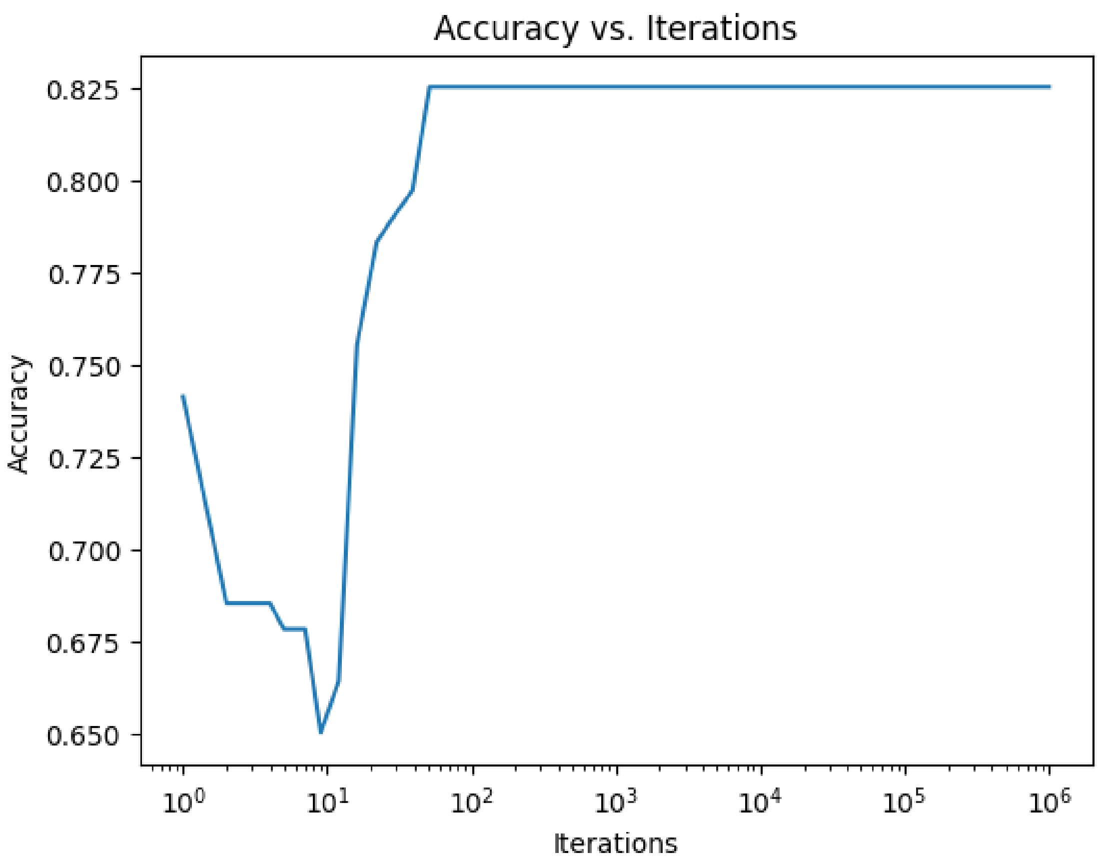
[19]:
```
model = LogisticRegression(max_iter=1000, random_state=102) #arbitrary for␣
↪convergence
model.fit(X_train, y_train)
print("Accuracy: ", accuracy(model, X_test, y_test))
```

```
Accuracy:  0.8251748251748252
```

This is much better than KNN, without even setting any parameters. I'll look at the max iterations first.

[20]:
```
import warnings
warnings.filterwarnings("ignore", category=UserWarning)
#suppress convergence warnings


iters = np.unique(np.logspace(0, 6, 50, base=10)).astype(int)
```

```python
acc = []


for i in iters:
    model = LogisticRegression(max_iter=i, random_state=102)
    model.fit(X_train, y_train)
    acc.append(accuracy(model, X_test, y_test))

plt.title("Accuracy vs. Iterations")
plt.xlabel("Iterations")
plt.ylabel("Accuracy")
plt.xscale("log")
plt.plot(iters, acc)
plt.show()
```



[21]:
```python
bestiter = iters[np.argmax(acc)]
print("Best iterations:", bestiter, "\nAccuracy:", np.max(acc))
```

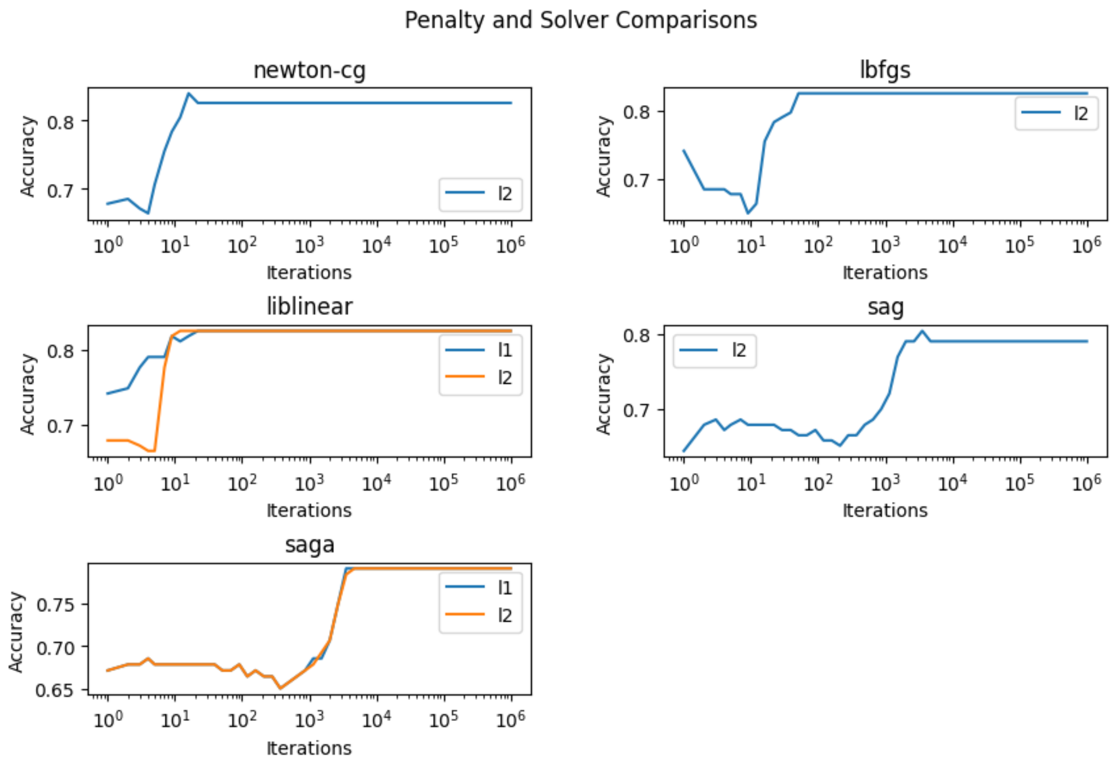
```
Best iterations: 51
Accuracy: 0.8251748251748252
```

The best number of iterations is around 50, and it flatlines towards the end. I'll try the different penalty parameter and solver combinations next.

[22]:
```
solvers = {'newton-cg': ['l2'], 'lbfgs' : ['l2'], 'liblinear': ['l1', 'l2'],␣
↪'sag':['l2'], 'saga': ['l1', 'l2']}

fig, axes = plt.subplots(3, 2, figsize=(10, 6))
axes = axes.ravel()
axes[-1].set_visible(False)

fig.subplots_adjust(hspace=0.8, wspace=0.3)
fig.suptitle("Penalty and Solver Comparisons")

max_acc = 0
best_solver = ""
best_penalty = ""
best_iter = 0


for i, (solver, penalties) in enumerate(solvers.items()):
    ax = axes[i]
    ax.set_title(solver)
    ax.set_xscale("log")
    for penalty in penalties:
        acc = []
        for iter in iters:
            model = LogisticRegression(penalty=penalty, solver=solver,␣
↪max_iter=iter, random_state=102)
            model.fit(X_train, y_train)
            a = accuracy(model, X_test, y_test)
            acc.append(a)
            if(a > max_acc) or (a == max_acc and iter < best_iter):
                max_acc = a
                best_solver = solver
                best_penalty = penalty
                best_iter = iter
        ax.plot(iters, acc, label=penalty)
    ax.legend()
    ax.set_ylabel("Accuracy")
    ax.set_xlabel("Iterations", fontsize=10)
print("Best Accuracy:", max_acc)
print("Best Solver:", best_solver)
print("Best Penalty:", best_penalty)
print("Best Iterations:", best_iter)
plt.show()
```

```
Best Accuracy: 0.8391608391608392
Best Solver: newton-cg
```

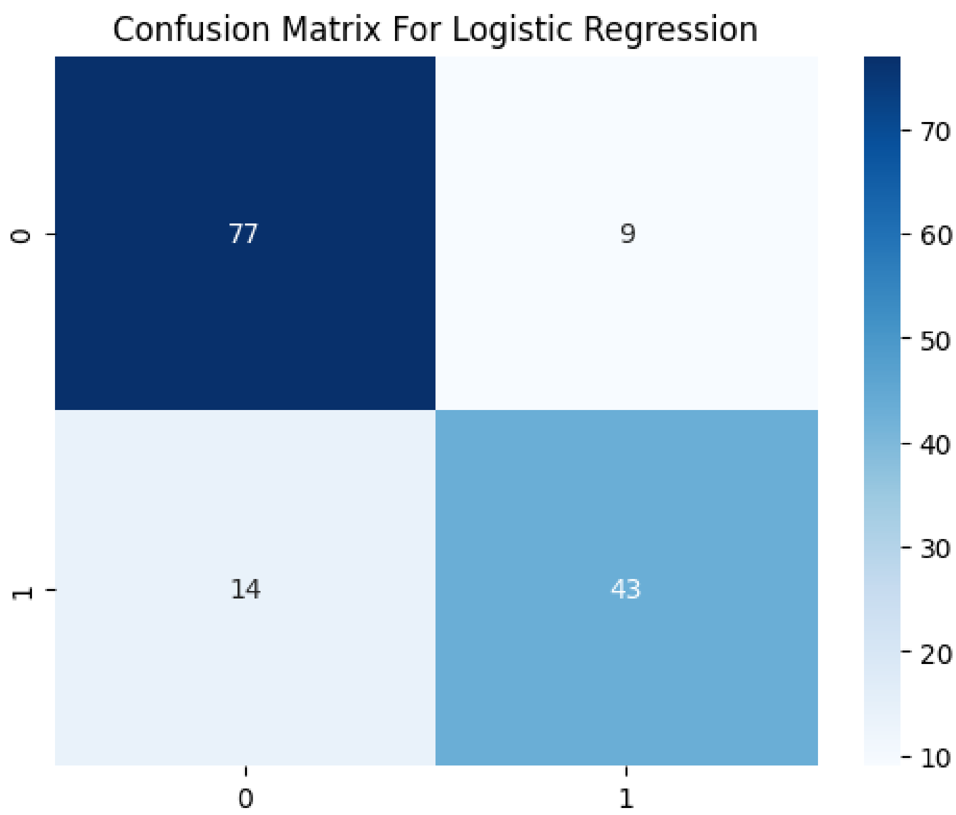
```
Best Penalty: l2
Best Iterations: 16
```



The best combination looks like it's newton-cg with l2 regression. The accuracy is 84% identified correctly, and it's much better than linear regression and KNN. The final model is below:

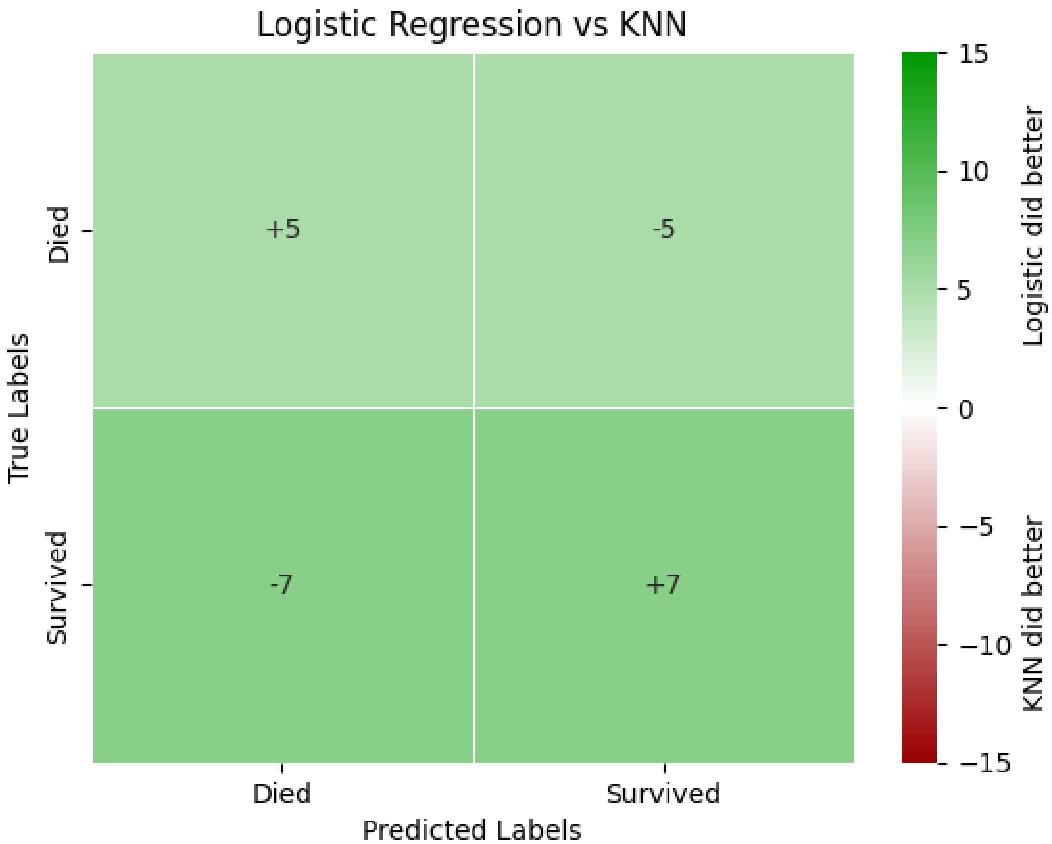
[23]:
```
model = LogisticRegression(penalty=best_penalty, solver=best_solver,␣
  ↪max_iter=best_iter, random_state=102)
model.fit(X_train, y_train)
print("Accuracy: ", accuracy(model, X_test, y_test))
cm_log = confusion_matrix(y_test, model.predict(X_test))

plt.title("Confusion Matrix For Logistic Regression")
sns.heatmap(cm_log, annot=True, cmap="Blues")
plt.show()
```

```
Accuracy:  0.8391608391608392
```



Comparisons between the two model as a difference heatmap is below:
green values mean the logistic regression model did better, red means the KNN model did better.
The numbers show how many cases the two models differed by.

[24]:
```
fig, ax = plt.subplots()
ax.set_title("Logistic Regression vs KNN")
plot_confusion_comparison(cm_knn, cm_log, ax, "KNN did better ␣
↪ Logistic did better")
plt.show()
```



It looks like the logistic regression outperformed KNN in all cases.

1.3.3 Decision Trees

[25]:
```
model = DecisionTreeClassifier(random_state=102)
model.fit(X_train, y_train)
print(accuracy(model, X_test, y_test))
```

```
0.7202797202797203
```

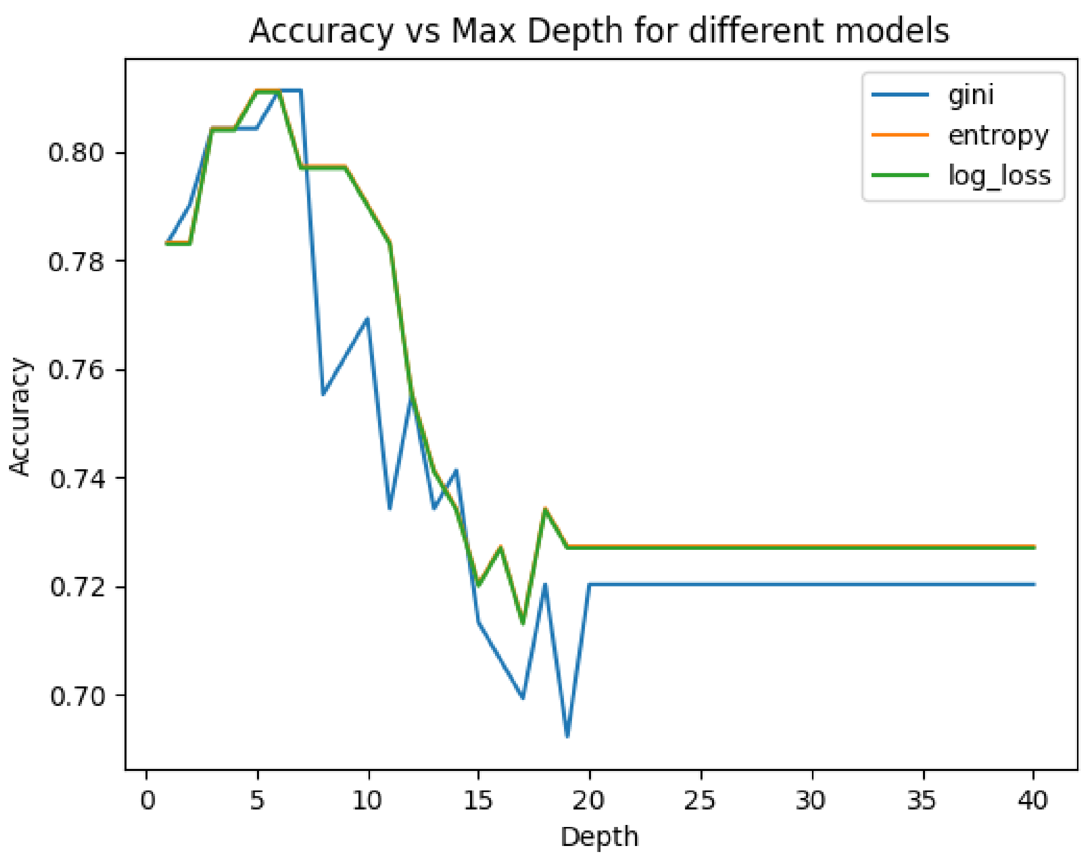
It starts out worse than logistic regression, but I think with parameter changes it can end up being better. First, I'll test the max depth and criterion parameters.

[26]:
```
layers = np.unique(np.linspace(1, 40, 50).astype(int))
acc = [[], [], []]

for layer in layers:
    model = DecisionTreeClassifier(random_state=102, criterion='gini',␣
 ↪max_depth=layer)
    model.fit(X_train, y_train)
    acc[0].append(accuracy(model, X_test, y_test))
```

```
    model = DecisionTreeClassifier(random_state=102, criterion='entropy',␣
↪max_depth=layer)
    model.fit(X_train, y_train)
    acc[1].append(accuracy(model, X_test, y_test))
    model = DecisionTreeClassifier(random_state=102, criterion='log_loss',␣
↪max_depth=layer)
    model.fit(X_train, y_train)
    acc[2].append(accuracy(model, X_test, y_test))
```

[27]:

```
plt.plot(layers, acc[0], label="gini")
plt.plot(layers, acc[1], label="entropy")
plt.plot(layers, np.array(acc[2]) - 0.0003, label="log_loss")
plt.legend()
plt.xlabel("Depth")
plt.ylabel("Accuracy")
plt.title("Accuracy vs Max Depth for different models")
plt.show()

bestlayers = layers[np.argmax(acc[2])]
print("Best layers:", bestlayers, "\nAccuracy:", np.max(acc[2]))
```



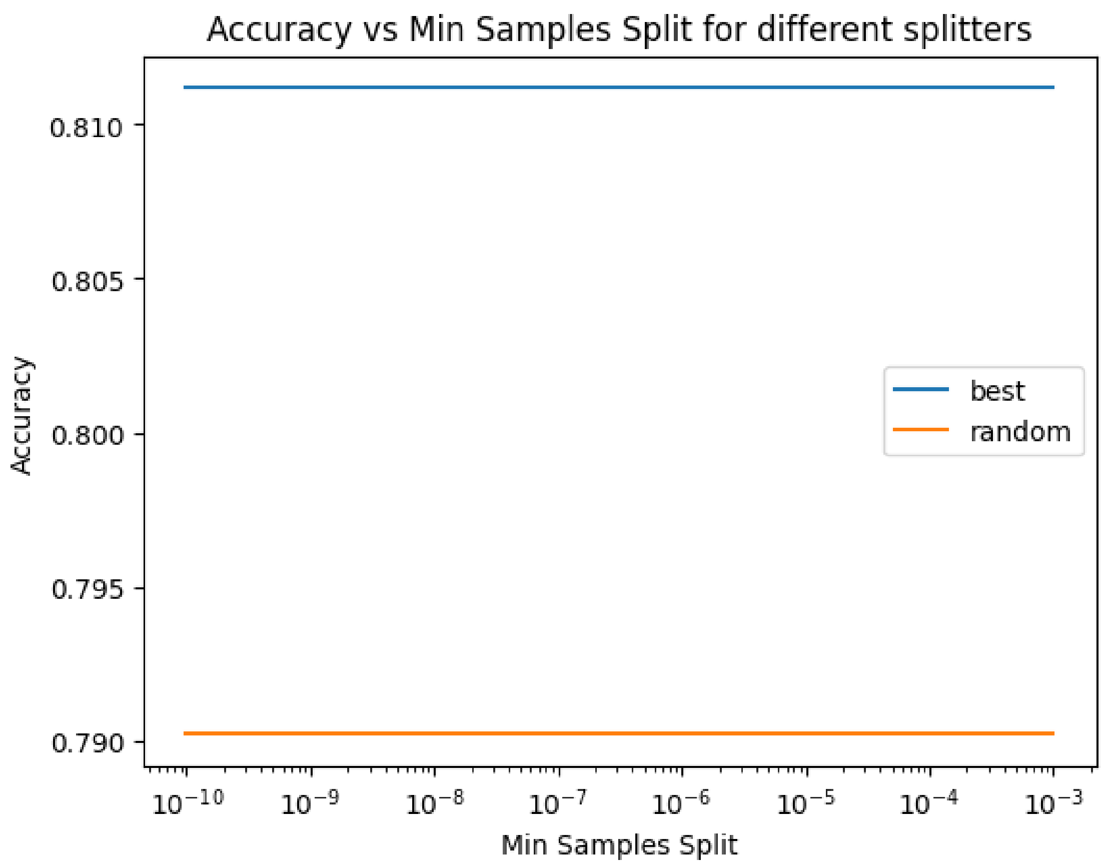
```
Best layers: 5
Accuracy: 0.8111888111888111
```

It looks like entropy and log_loss are identical, so I had to shift log_loss down by a bit so both are visible on the graph (You can just barely see the sliver of orange). After about 20 layers, it looks like the accuracy stayed the same. I'll go with log_loss because it has the same peak with less layers, so it'll probably run faster. Just these two parameters alone shoots up the accuracy, about 9%.

Next, I'll test the min_samples_split and splitter parameters.

[28]:
```python
acc = [[],[]]
alphas = np.logspace(-10, -3, 50, base=10)

for alpha in alphas:
    model = DecisionTreeClassifier(random_state=102, criterion='entropy',␣
 ↪max_depth=5, min_samples_split=alpha, splitter='best')
    model.fit(X_train, y_train)
    acc[0].append(accuracy(model, X_test, y_test))
    model = DecisionTreeClassifier(random_state=102, criterion='entropy',␣
 ↪max_depth=5, min_samples_split=alpha, splitter='random')
    model.fit(X_train, y_train)
    acc[1].append(accuracy(model, X_test, y_test))
```

[29]:
```python
plt.plot(alphas, acc[0], label="best")
plt.plot(alphas, acc[1], label="random")
plt.xscale("log")
plt.legend()
plt.xlabel("Min Samples Split")
plt.ylabel("Accuracy")
plt.title("Accuracy vs Min Samples Split for different splitters")
plt.show()
```



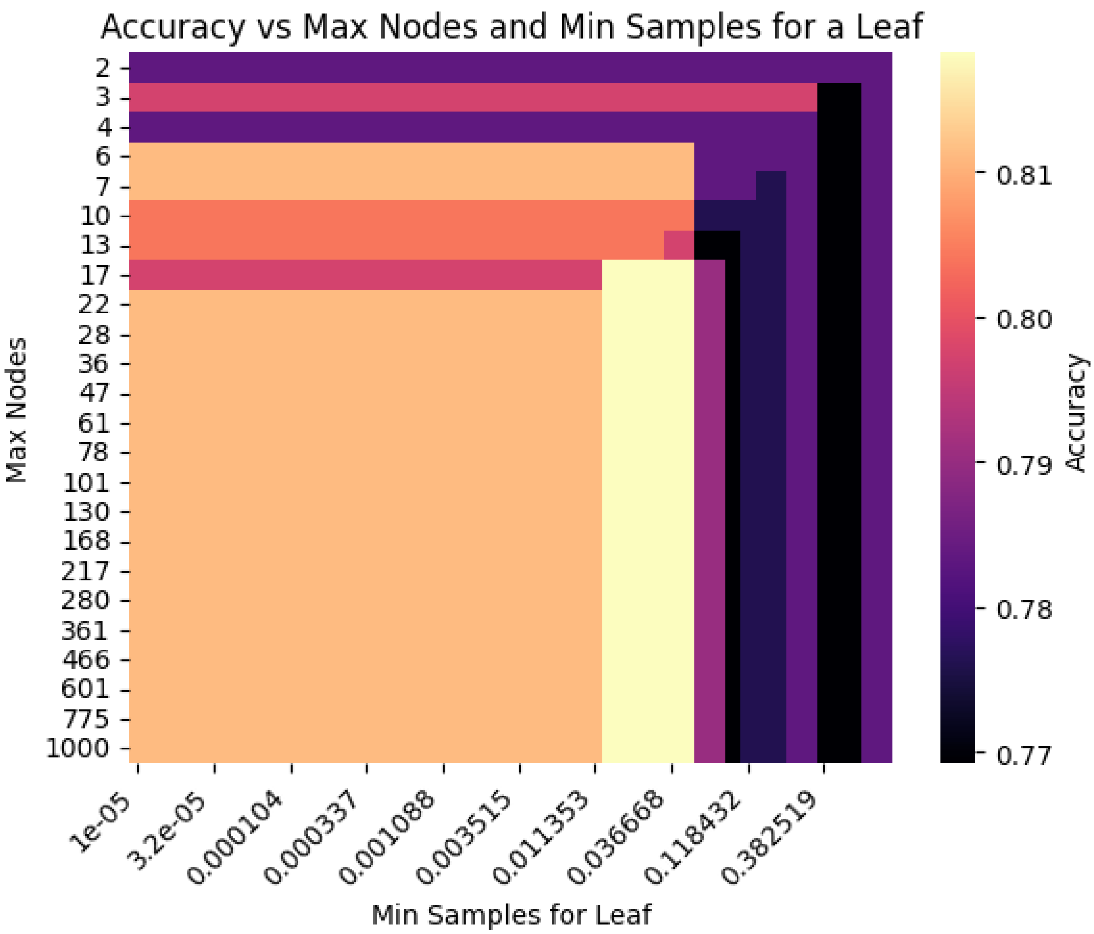
It looks like min_samples_split does nothing, and the best splitter is best. I'll test min_samples_leaf and max_leaf_nodes next.

[30]:
```
maxnodes = np.unique(np.logspace(0.35, 3, 25, base=10).astype(int))
minsamples = np.logspace(-5, -0.01, 50, base=10)
acc = np.zeros((len(maxnodes), len(minsamples)))

for i in range(len(maxnodes)):
    for j in range(len(minsamples)):
        model = DecisionTreeClassifier(random_state=102, criterion='entropy',␣
↪max_depth=5, min_samples_split=minsamples[j], max_leaf_nodes=maxnodes[i])
        model.fit(X_train, y_train)
        acc[i][j] = accuracy(model, X_test, y_test)
```

[31]:
```
bestacc = np.max(acc)
am = np.argmax(acc)
bestmaxnodes = maxnodes[int(am / len(minsamples))]
bestminsamples = minsamples[am % len(minsamples)]
print("Best Max Nodes:", bestmaxnodes, "\nBest Min Samples:", bestminsamples,␣
↪"\nAccuracy:", bestacc)
```

```
Best Max Nodes: 17
Best Min Samples: 0.014352870800722006
Accuracy: 0.8181818181818182
```

[32]:
```
sns.heatmap(acc, annot=False, cmap="magma", xticklabels=np.round(minsamples,␣
↪6), yticklabels=maxnodes, cbar_kws={'label': 'Accuracy'})
plt.gca().set_xticks(plt.gca().get_xticks()[::5])
plt.title("Accuracy vs Max Nodes and Min Samples for a Leaf")
plt.xlabel("Min Samples for Leaf")
plt.ylabel("Max Nodes")
plt.xticks(rotation=45, ha="right")
plt.show()
```

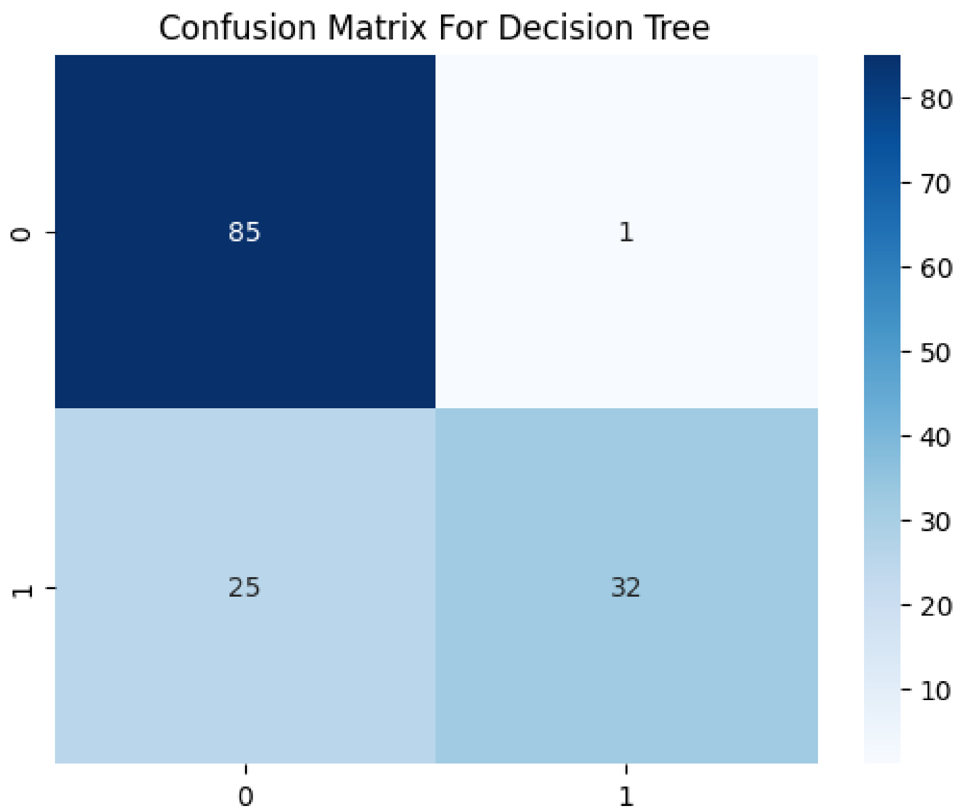


It looks like the peak accuracy for the decision tree is 82%, with 17 max nodes, and 0.14% of the database required to make a leaf node. Here's the final model:

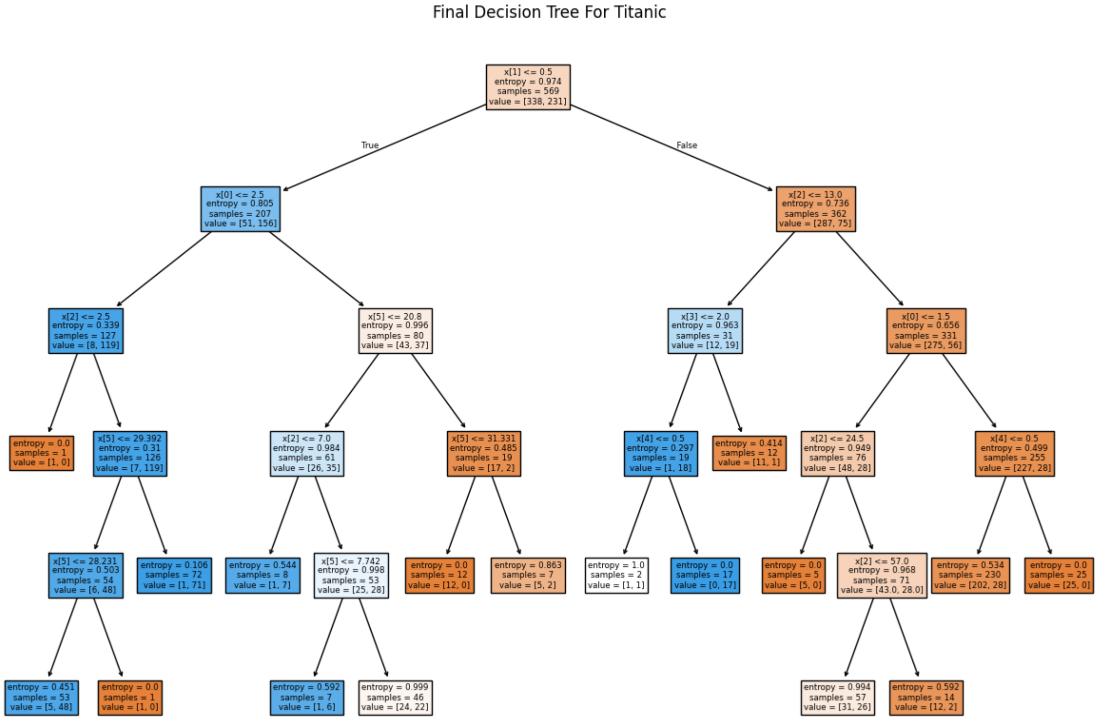
[33]:

```
model = DecisionTreeClassifier(criterion='entropy', max_depth=5,␣
 ↪min_samples_split=bestminsamples, max_leaf_nodes=bestmaxnodes,␣
 ↪random_state=102)
model.fit(X_train, y_train)
print("Accuracy: ", accuracy(model, X_test, y_test))
cm_tree = confusion_matrix(y_test, model.predict(X_test))

plt.title("Confusion Matrix For Decision Tree")
sns.heatmap(cm_tree, annot=True, cmap="Blues")
plt.show()
```

```
Accuracy:  0.8181818181818182
```

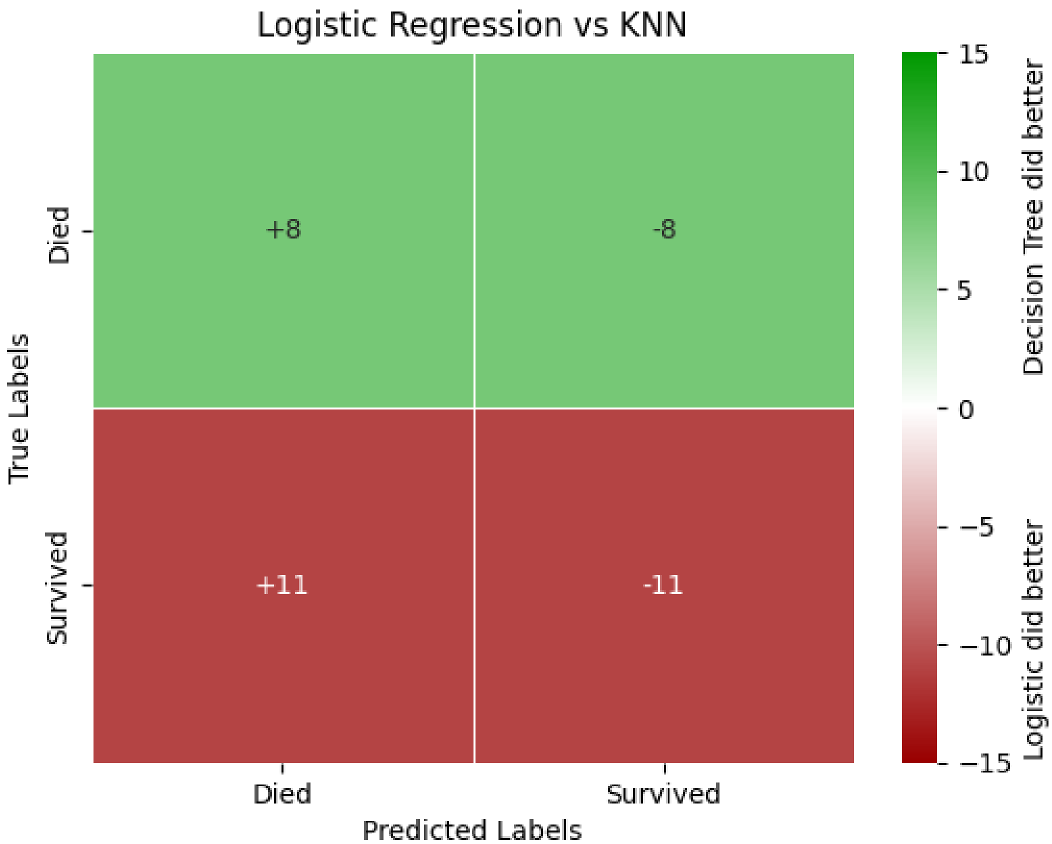


[34]:
```
fig, ax = plt.subplots(figsize=(15, 10))
tree.plot_tree(model, ax=ax, filled=True)
ax.set_title("Final Decision Tree For Titanic")
plt.show()
```



Here's a comparison between between decision tree and logistic regression:

[35]:
```
fig, ax = plt.subplots()
ax.set_title("Logistic Regression vs KNN")
plot_confusion_comparison(cm_log, cm_tree, ax, "Logistic did better     Decision Tree did better")
plt.show()
```



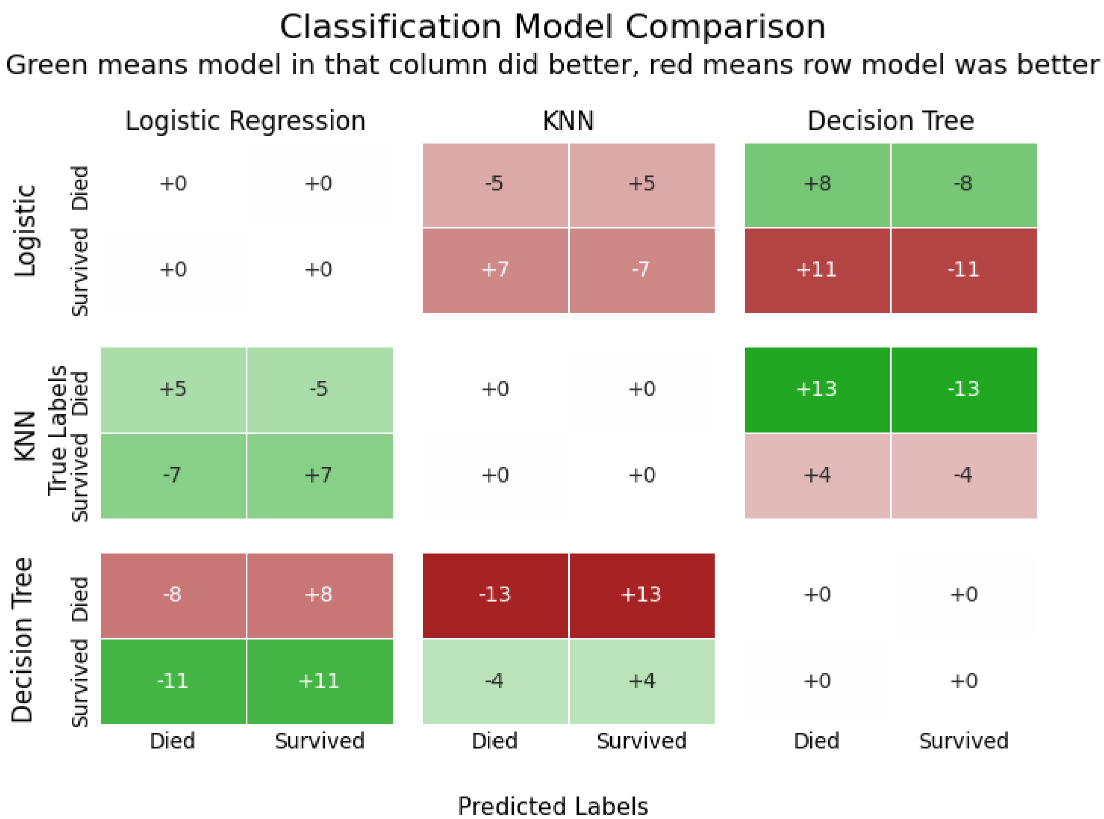
So far, it looks like the decision tree is worse than logistic regression. Overall, it looks like Logistic is the best model.

1.4 Model Comparison and Conclusion

I'm creating a heatmap display to compare the 3 different models to each other. The confusion matrices are subtracted, and the number of observations in the test set that each model got are displayed. Redder values in the heatmap means the model labeled in that row did better, and green means the model labeled in that column did better.

[36]:
```
fig, axes = plt.subplots(3, 3, figsize=(8, 5))
plt.subplots_adjust(wspace=0.1, hspace=0.2)

fig.suptitle("Classification Model Comparison", fontsize=16, y=1.05)
fig.text(0.5, .98, "Green means model in that column did better, red means row␣
 ↪model was better", ha="center", va="center", fontsize=13)
fig.text(0.093, 0.5, "True Labels", ha="center", va="center", fontsize=11,␣
 ↪rotation="vertical")
fig.text(0.5, 0, "Predicted Labels", ha="center", va="center", fontsize=11)
```

```python
cms = [cm_log, cm_knn, cm_tree]
models = ["Logistic Regression", "KNN", "Decision Tree"]

axes[0][0].set_title("Logistic Regression")
axes[0][1].set_title ("KNN")
axes[0][2].set_title("Decision Tree")

axes[0][0].text(-0.5, 1, "Logistic", fontsize=12, ha="center", va="center", rotation="vertical")
axes[1][0].text(-0.5, 1, "KNN", fontsize=12, ha="center", va="center", rotation="vertical")
axes[2][0].text(-0.5, 1, "Decision Tree", fontsize=12, ha="center", va="center", rotation="vertical")


for i in range(3):
    for j in range(3):
        ax = axes[i][j]
        plot_confusion_comparison(cms[i], cms[j], ax, "", hide_bottom=(i != 2), hide_side=j != 0, colorbar=False, extra_labels=False)
```

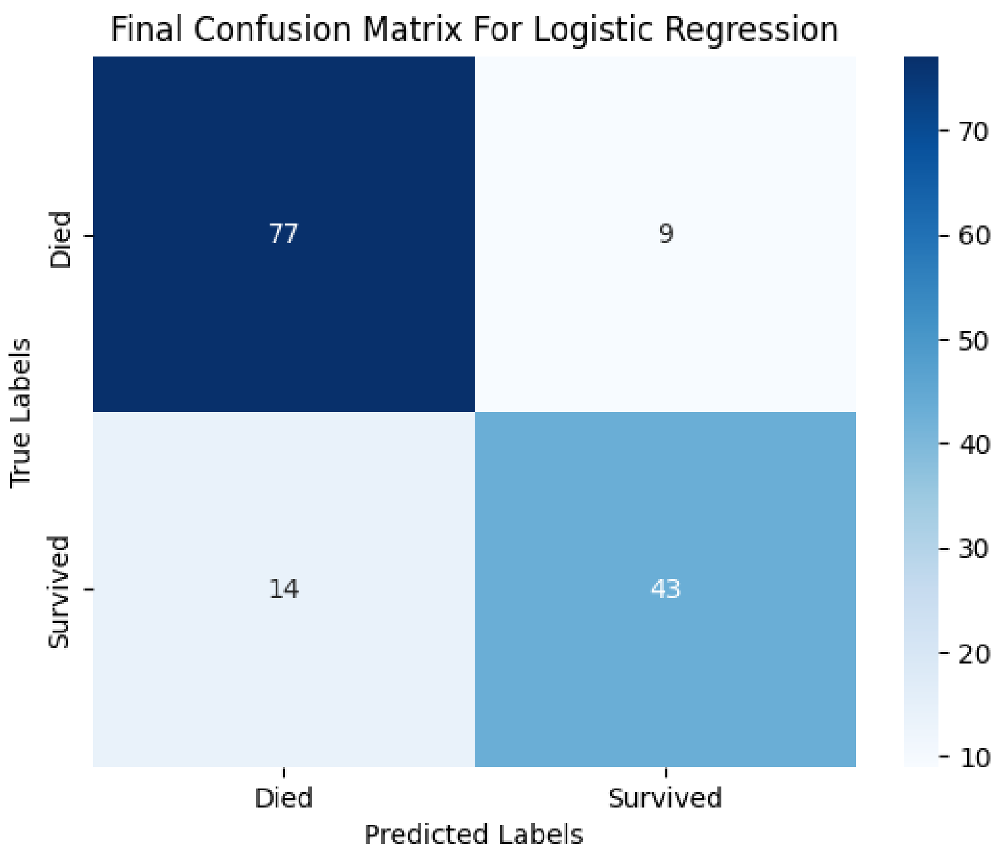


Logistic Regression had the greenest column and the reddest row, so it was the overall best model. All of them were relatively close however, only differing by a handful of cases. The best accuracy achieved by the models was 84% (Only 23 people were left to drown, yay!). Here is the best model:

Logistic Regression: - Max iterations: 16 - Solver: newton-cg - Penalty: l2

[37]:
```
model = LogisticRegression(penalty=best_penalty, solver=best_solver,␣
    ↪max_iter=best_iter, random_state=102)
model.fit(X_train, y_train)
print("Accuracy: ", accuracy(model, X_test, y_test))
cm_log = confusion_matrix(y_test, model.predict(X_test))

plt.title("Final Confusion Matrix For Logistic Regression")
ax = sns.heatmap(cm_log, annot=True, cmap="Blues")
plt.xlabel("Predicted Labels")
plt.ylabel("True Labels")
ax.set_xticklabels(["Died", "Survived"])
ax.set_yticklabels(["Died", "Survived"])
plt.show()
```

```
Accuracy:  0.8391608391608392
```



[ ]:

```

```