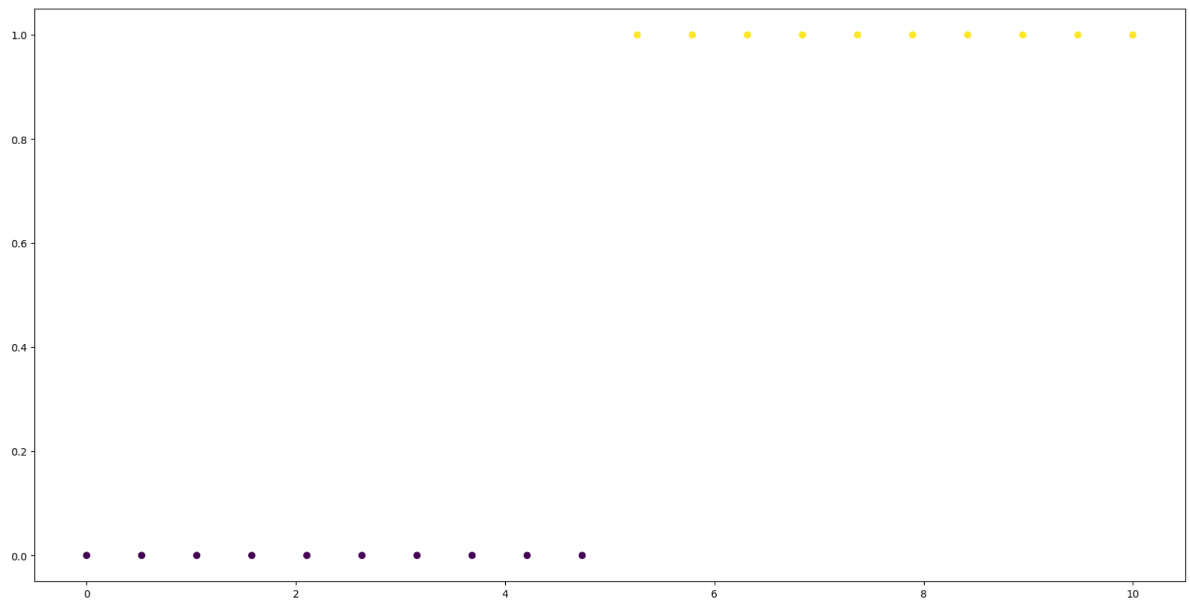
Assignment is at the bottom!

In [1]:
```
from sklearn.linear_model import LogisticRegression
import pandas as pd
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np

from pylab import rcParams
rcParams['figure.figsize'] = 20, 10


from sklearn.linear_model import LogisticRegression as Model
```

In [2]:
```
y = np.concatenate([np.zeros(10), np.ones(10)])
x = np.linspace(0, 10, len(y))
```

In [3]:
```
plt.scatter(x, y, c=y)
```

Out[3]:
```
<matplotlib.collections.PathCollection at 0x1b014e225e0>
```



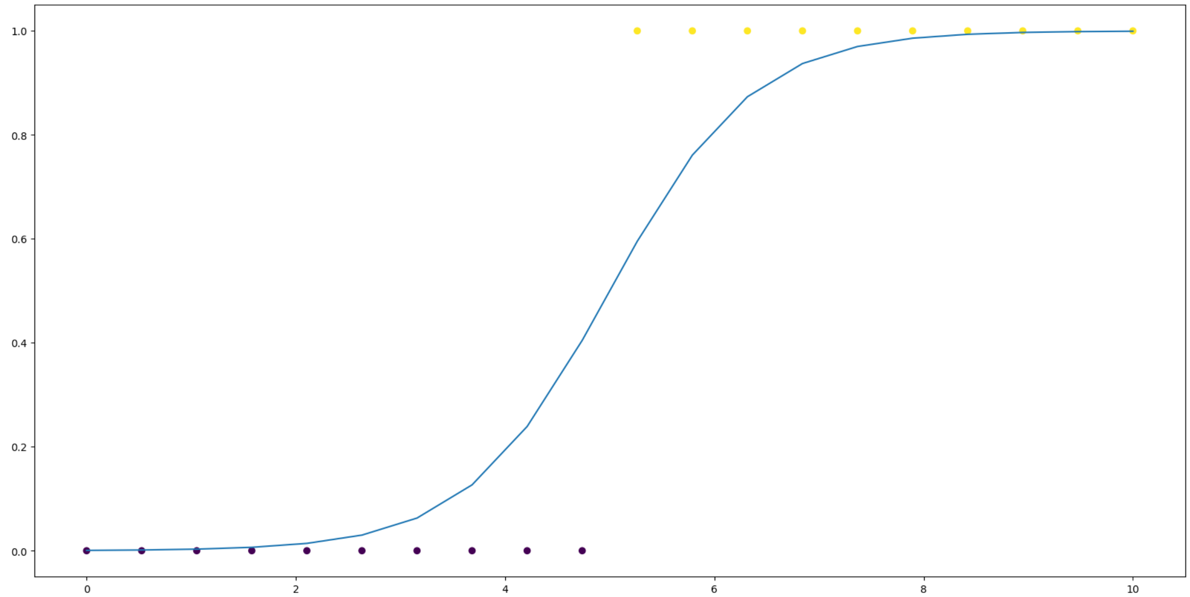
In [4]:
```
model = LogisticRegression()
```

In [5]:
```
model.fit(x.reshape(-1, 1),y)
```

Out[5]:
```
LogisticRegression()
```

In [6]:
```
plt.scatter(x,y, c=y)
plt.plot(x, model.predict_proba(x.reshape(-1, 1))[:,1])
```

Out[6]: [<matplotlib.lines.Line2D at 0x1b01552b6d0>]

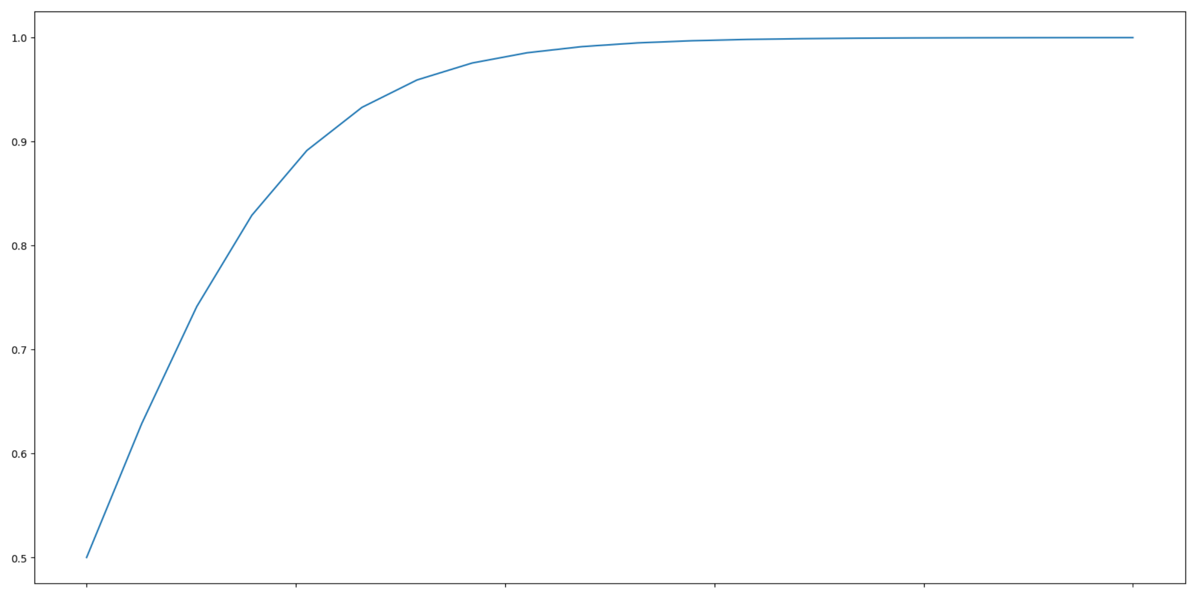


In [7]:
```
b, b0 = model.coef_, model.intercept_
model.coef_, model.intercept_
```

Out[7]: (array([[1.46709085]]), array([-7.33542562]))

In [8]:
```
plt.plot(x, 1/(1+np.exp(-x)))
```

Out[8]: [<matplotlib.lines.Line2D at 0x1b015aa5e50>]

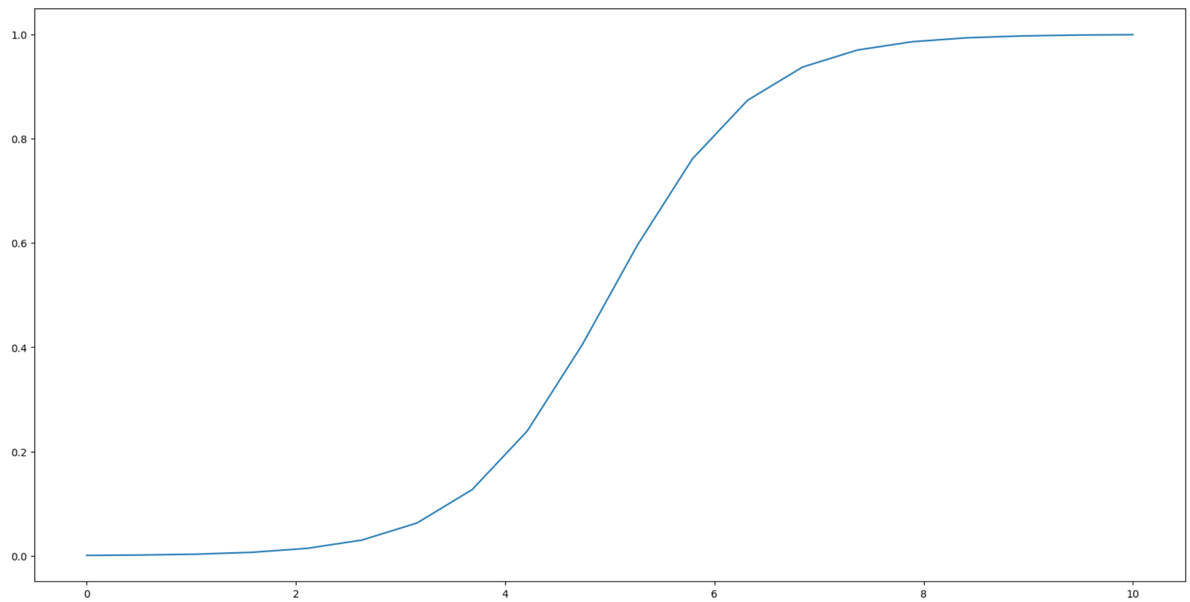


In [9]:
```
b
```

Out[9]: array([[1.46709085]])

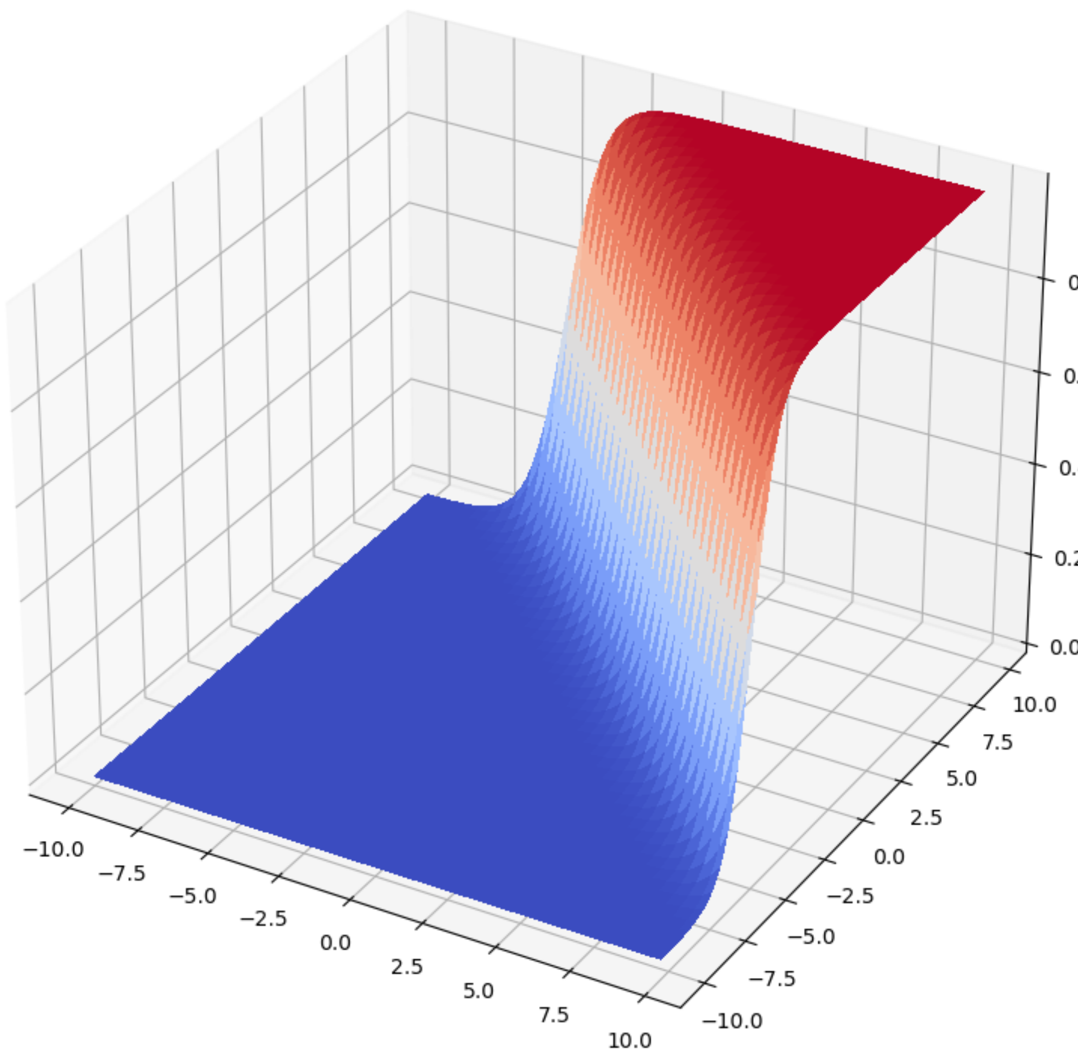
In [10]:
```
plt.plot(x, 1/(1+np.exp(-(b[0]*x +b0))))
```

Out[10]:
```
[<matplotlib.lines.Line2D at 0x1b015b0ae50>]
```



In [11]:
```
from mpl_toolkits.mplot3d import Axes3D  # noqa: F401 unused import

import matplotlib.pyplot as plt
from matplotlib import cm
from matplotlib.ticker import LinearLocator, FormatStrFormatter
import numpy as np


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

# Make data.
X = np.arange(-10, 10, 0.25)
Y = np.arange(-10, 10, 0.25)
X, Y = np.meshgrid(X, Y)
R = np.sqrt(X**2 + Y**2)
Z = 1/(1+np.exp(-(b[0]*X +b[0]*Y +b0)))
surf = ax.plot_surface(X, Y, Z, cmap=cm.coolwarm,
                       linewidth=0, antialiased=False)
```

```
C:\Users\Michael\AppData\Local\Temp\ipykernel_9076\290434025.py:10: Matplotli
bDeprecationWarning: Calling gca() with keyword arguments was deprecated in M
atplotlib 3.4. Starting two minor releases later, gca() will take no keyword
arguments. The gca() function should only be used to get the current axes, or
if no axes exist, create new axes with default keyword arguments. To create a
new axes with non-default arguments, use plt.axes() or plt.subplot().
  ax = fig.gca(projection='3d')
```



In [12]:
```
X
```

Out[12]:
```
array([[-10.  ,  -9.75,  -9.5 , ...,   9.25,   9.5 ,   9.75],
       [-10.  ,  -9.75,  -9.5 , ...,   9.25,   9.5 ,   9.75],
       [-10.  ,  -9.75,  -9.5 , ...,   9.25,   9.5 ,   9.75],
       ...,
       [-10.  ,  -9.75,  -9.5 , ...,   9.25,   9.5 ,   9.75],
       [-10.  ,  -9.75,  -9.5 , ...,   9.25,   9.5 ,   9.75],
       [-10.  ,  -9.75,  -9.5 , ...,   9.25,   9.5 ,   9.75]])
```

In [13]:
```
Y
```

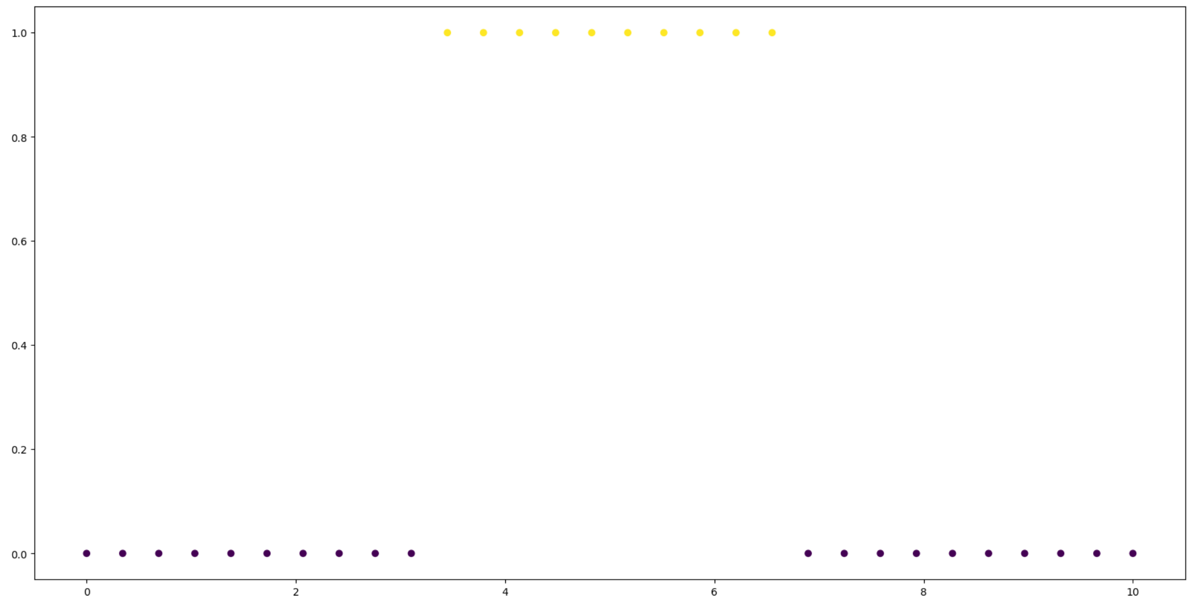
Out[13]:
```
array([[-10.  , -10.  , -10.  , ..., -10.  , -10.  , -10.  ],
       [ -9.75,  -9.75,  -9.75, ...,  -9.75,  -9.75,  -9.75],
       [ -9.5 ,  -9.5 ,  -9.5 , ...,  -9.5 ,  -9.5 ,  -9.5 ],
       ...,
       [  9.25,   9.25,   9.25, ...,   9.25,   9.25,   9.25],
       [  9.5 ,   9.5 ,   9.5 , ...,   9.5 ,   9.5 ,   9.5 ],
       [  9.75,   9.75,   9.75, ...,   9.75,   9.75,   9.75]])
```

What if the data doesn't really fit this pattern?

In [14]:
```
y = np.concatenate([np.zeros(10), np.ones(10), np.zeros(10)])
x = np.linspace(0, 10, len(y))
```

In [15]:
```
plt.scatter(x,y, c=y)
```

Out[15]: <matplotlib.collections.PathCollection at 0x1b015bb9b20>

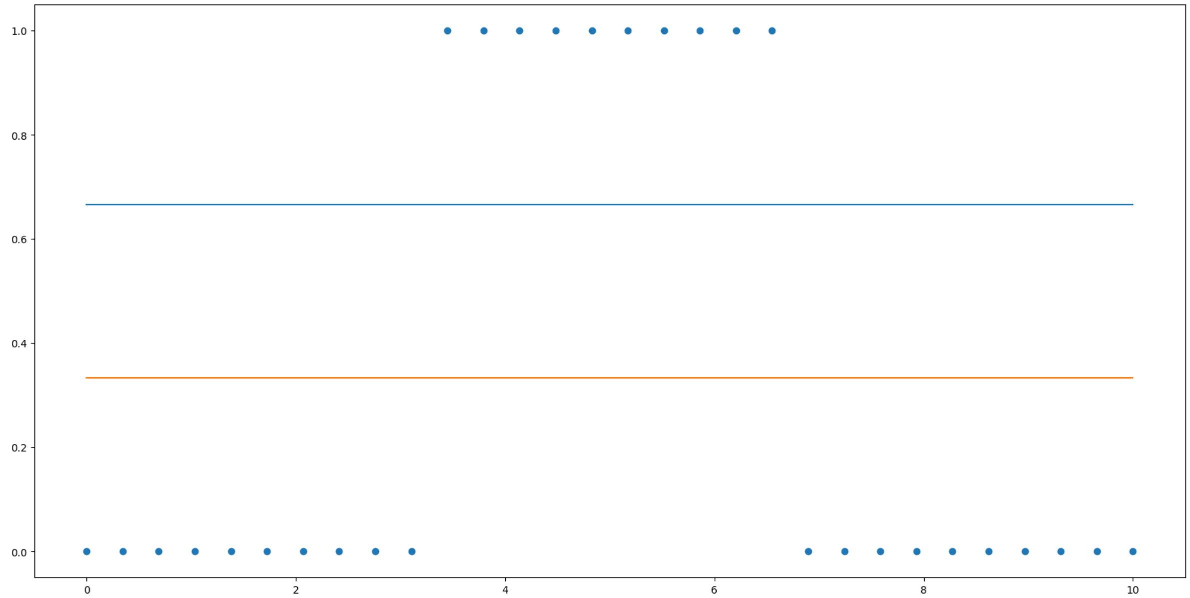


In [16]:
```
model.fit(x.reshape(-1, 1),y)
```

Out[16]: LogisticRegression()

In [17]:
```
plt.scatter(x,y)
plt.plot(x, model.predict_proba(x.reshape(-1, 1)))
```

Out[17]:
```
[<matplotlib.lines.Line2D at 0x1b0168e5310>,
 <matplotlib.lines.Line2D at 0x1b0168e5370>]
```



In [18]:
```
model1 = LogisticRegression()
model1.fit(x[:15].reshape(-1, 1),y[:15])
```

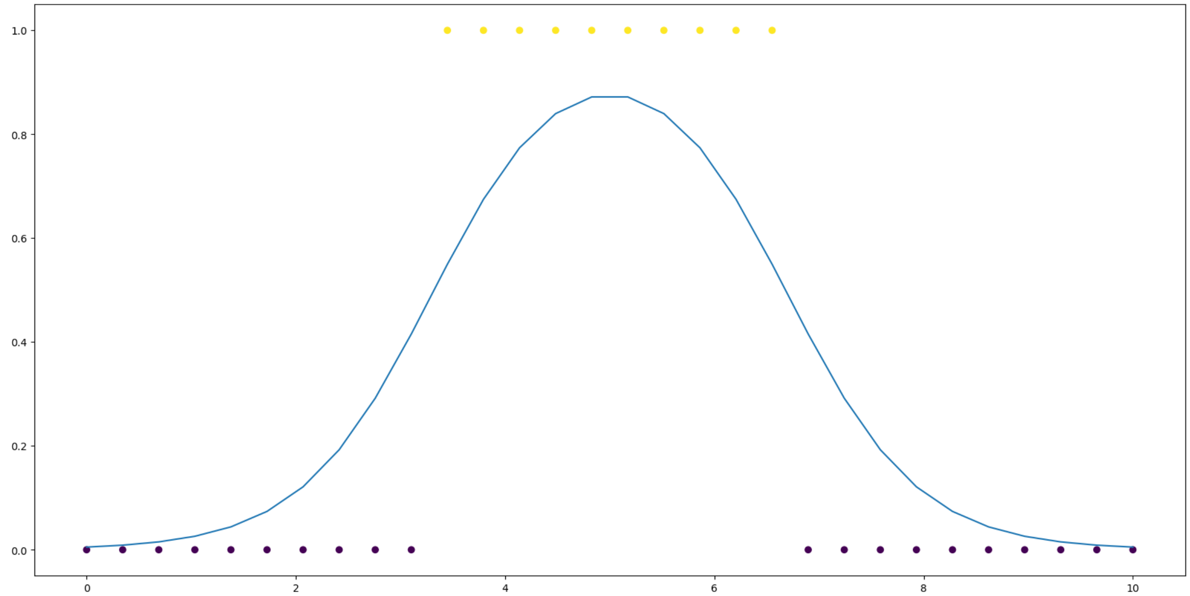
Out[18]:
```
LogisticRegression()
```

In [19]:
```
model2 = LogisticRegression()
model2.fit(x[15:].reshape(-1, 1),y[15:])
```

Out[19]:
```
LogisticRegression()
```

In [20]:
```
plt.scatter(x,y, c=y)
plt.plot(x, model1.predict_proba(x.reshape(-1, 1))[:,1] * model2.predict_proba
```

Out[20]: [<matplotlib.lines.Line2D at 0x1b016d72cd0>]



In [22]:
```
df = pd.read_csv('C:\\Users\\Michael\\Downloads\\adult.data', index_col=False)
golden = pd.read_csv('C:\\Users\\Michael\\Downloads\\adult.test', index_col=Fa
```

In [23]:
```
from sklearn import preprocessing

enc = preprocessing.OrdinalEncoder()
```

In [24]:
```
transform_columns = ['sex', 'workclass', 'education', 'marital-status',
                     'occupation', 'relationship', 'race', 'sex',
                     'native-country', 'salary']
```

In [25]:
```
x = df.copy()

x[transform_columns] = enc.fit_transform(df[transform_columns])

golden['salary'] = golden.salary.replace(' <=50K.', ' <=50K').replace(' >50K.'
xt = golden.copy()

xt[transform_columns] = enc.transform(golden[transform_columns])
```

In [26]:
```
df.salary.unique()
```

Out[26]: array([' <=50K', ' >50K'], dtype=object)

In [27]:
```
golden.salary.replace(' <=50K.', ' <=50K').replace(' >50K.', ' >50K').unique()
```

Out[27]: array([' <=50K', ' >50K'], dtype=object)

In [36]:
```
model.fit(preprocessing.scale(x.drop('salary', axis=1)), x.salary)
```

Out[36]:
```
LogisticRegression()
```

In [29]:
```
pred = model.predict(preprocessing.scale(x.drop('salary', axis=1)))
pred_test = model.predict(preprocessing.scale(xt.drop('salary', axis=1)))
```

In [30]:
```
x.head()
```

Out[30]:

	age	workclass	fnlwgt	education	education-num	marital-status	occupation	relationship	race	sex
0	39	7.0	77516	9.0	13	4.0	1.0	1.0	4.0	1.0
1	50	6.0	83311	9.0	13	2.0	4.0	0.0	4.0	1.0
2	38	4.0	215646	11.0	9	0.0	6.0	1.0	4.0	1.0
3	53	4.0	234721	1.0	7	2.0	6.0	0.0	2.0	1.0
4	28	4.0	338409	9.0	13	2.0	10.0	5.0	2.0	0.0

In [31]:
```
from sklearn.metrics import (
    accuracy_score,
    classification_report,
    confusion_matrix, auc, roc_curve
)
```

In [32]:
```
accuracy_score(x.salary, pred)
```

Out[32]:
```
0.8250360861152913
```

In [33]:
```
confusion_matrix(x.salary, pred)
```

Out[33]:
```
array([[23300,  1420],
       [ 4277,  3564]], dtype=int64)
```

In [34]:
```
print(classification_report(x.salary, pred))
```

```
              precision    recall  f1-score   support

         0.0       0.84      0.94      0.89     24720
         1.0       0.72      0.45      0.56      7841

    accuracy                           0.83     32561
   macro avg       0.78      0.70      0.72     32561
weighted avg       0.81      0.83      0.81     32561
```

In [35]:
```
print(classification_report(xt.salary, pred_test))
```

```
              precision    recall  f1-score   support

         0.0       0.85      0.94      0.89     12435
         1.0       0.70      0.45      0.55      3846

    accuracy                           0.82     16281
   macro avg       0.77      0.69      0.72     16281
weighted avg       0.81      0.82      0.81     16281
```

Assignment

1. Use your own dataset (`Heart.csv` is acceptable), create a train and a test set, and build 2 models: Logistic Regression and Decision Tree (shallow). Compare the test results using `classification_report` and `confusion_matrix`. Explain which algorithm is optimal

2. Repeat 1. but let the Decision Tree be much deeper to allow over-fitting. Compare the two models' test results again, and explain which is optimal

In [14]:
```
import pandas as pd
from sklearn import preprocessing
from sklearn.preprocessing import OneHotEncoder
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LogisticRegression
from sklearn.tree import DecisionTreeClassifier
from sklearn.metrics import classification_report, confusion_matrix, accuracy_

#Read the stars.csv and generate two dataframes, one as stars and one as golde
stars = pd.read_csv('C:\\Users\\Michael\\Desktop\\MLData\\stars.csv')
golden_stars = pd.read_csv('C:\\Users\\Michael\\Desktop\\MLData\\stars.csv')

#Identify/tag the categorical variables in the dataset to transform
cvariables = ['Color', 'Spectral_Class']

#Use OneHotEncoder to transform the categorical categories that are a part of
OH = OneHotEncoder(handle_unknown="ignore", sparse=False)
OHcategory = OH.fit_transform(stars[cvariables])
OHcategorygolden = OH.transform(golden_stars[cvariables])

# Create two dataframes that contain the transformed categorical values (we wi
Tcategories = OH.get_feature_names_out(cvariables)
StarsTcategories = pd.DataFrame(OHcategory, columns=Tcategories)
GstarsTcategories = pd.DataFrame(OHcategorygolden, columns=Tcategories)

#Concatenate transformed categorical dataframes with their respective datafram
Tstars = pd.concat([stars.drop(cvariables, axis=1), StarsTcategories], axis=1)
Tgstars = pd.concat([golden_stars.drop(cvariables, axis=1), GstarsTcategories]

#Identify dependent variable of interest that we would like to predict
Train_y = Tstars['Type']
Test_y = Tgstars['Type']

#Split the data into training and testing sets (train on Tstars dataframe)
Train_x, Test_x, Train_y, Test_y = train_test_split(Tstars.drop('Type', axis=1

#Logistic Regression model (define and fit to the training data + generate pre
STpred_log = Logistic.predict(preprocessing.scale(Test_x))
gSTpred_log = Logistic.predict(preprocessing.scale(Tgstars.drop('Type', axis=1
print("Logistic Regression - Test Set Performance")
print("Accuracy Score:", accuracy_score(Test_y, STpred_log))
print(classification_report(Test_y, STpred_log, zero_division=1))
print("Confusion Matrix:\n", confusion_matrix(Test_y, STpred_log))

#Shallow DecisionTree model (define it setting max_depth to 1 + fit to the tra
DecisionTreeShallow = DecisionTreeClassifier(max_depth=1)
DecisionTreeShallow.fit(preprocessing.scale(Train_x), Train_y)
STpred_decision = DecisionTreeShallow.predict(preprocessing.scale(Test_x))
gSTpred_decision = DecisionTreeShallow.predict(preprocessing.scale(Tgstars.dro
print("Decision Tree - Test Set Performance ")
print("Accuracy Score:", accuracy_score(Test_y, STpred_decision))
print(classification_report(Test_y, STpred_decision, zero_division=1))
print("Confusion Matrix:\n", confusion_matrix(Test_y, STpred_decision))
```

```
Logistic Regression - Test Set Performance
```

```
Accuracy Score: 0.9305555555555556
              precision    recall  f1-score   support

           0       0.74      1.00      0.85        14
           1       1.00      0.38      0.55         8
           2       1.00      1.00      1.00         8
           3       1.00      1.00      1.00        18
           4       1.00      1.00      1.00        12
           5       1.00      1.00      1.00        12

    accuracy                           0.93        72
   macro avg       0.96      0.90      0.90        72
weighted avg       0.95      0.93      0.92        72

Confusion Matrix:
 [[14  0  0  0  0  0]
 [ 5  3  0  0  0  0]
 [ 0  0  8  0  0  0]
 [ 0  0  0 18  0  0]
 [ 0  0  0  0 12  0]
 [ 0  0  0  0  0 12]]
Decision Tree - Test Set Performance
Accuracy Score: 0.20833333333333334
              precision    recall  f1-score   support

           0       1.00      0.00      0.00        14
           1       0.14      0.88      0.25         8
           2       0.35      1.00      0.52         8
           3       1.00      0.00      0.00        18
           4       1.00      0.00      0.00        12
           5       1.00      0.00      0.00        12

    accuracy                           0.21        72
   macro avg       0.75      0.31      0.13        72
weighted avg       0.83      0.21      0.08        72

Confusion Matrix:
 [[ 0  0 14  0  0  0]
 [ 0  7  1  0  0  0]
 [ 0  0  8  0  0  0]
 [ 0 18  0  0  0  0]
 [ 0 12  0  0  0  0]
 [ 0 12  0  0  0  0]]
```

In [15]:
```
print("With regards to being able to predict the classification of a star, I b
```

```
With regards to being able to predict the classification of a star, I believe
that the logistic regression model is the optimal choice. With regards to the
particular analysis, the logistic regression model yielded higher values asso
ciated with the precision, recall, and F1 score. Furthermore, it yielded a lo
wer frequency of Type 1 and Type 2 errors when compared to the shallow decisi
on tree model.
```

In [13]:
```
#Logistic Regression model (define and fit to the training data + generate pre
Logistic2 = LogisticRegression()
Logistic2.fit(preprocessing.scale(Train_x), Train_y)
STpred_log2 = Logistic2.predict(preprocessing.scale(Test_x))
gSTpred_log2 = Logistic2.predict(preprocessing.scale(Tgstars.drop('Type', axis
print("Logistic Regression - Test Set Performance")
print("Accuracy Score:", accuracy_score(Test_y, STpred_log2))
print(classification_report(Test_y, STpred_log2, zero_division=1))
print("Confusion Matrix:\n", confusion_matrix(Test_y, STpred_log2))

#Deep DecisionTree model (define it setting max_depth to 10 + fit to the train
DecisionTreeDeep = DecisionTreeClassifier(max_depth=10)
DecisionTreeDeep.fit(preprocessing.scale(Train_x), Train_y)
STpred_decision2 = DecisionTreeDeep.predict(preprocessing.scale(Test_x))
gSTpred_decision2 = DecisionTreeDeep.predict(preprocessing.scale(Tgstars.drop(
print("Decision Tree - Test Set Performance ")
print("Accuracy Score:", accuracy_score(Test_y, STpred_decision2))
print(classification_report(Test_y, STpred_decision2, zero_division=1))
print("Confusion Matrix:\n", confusion_matrix(Test_y, STpred_decision2))
```

```
Logistic Regression - Test Set Performance
Accuracy Score: 0.9583333333333334
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        14
           1       1.00      1.00      1.00        13
           2       1.00      1.00      1.00        11
           3       1.00      0.80      0.89        15
           4       0.77      1.00      0.87        10
           5       1.00      1.00      1.00         9

    accuracy                           0.96        72
   macro avg       0.96      0.97      0.96        72
weighted avg       0.97      0.96      0.96        72

Confusion Matrix:
 [[14  0  0  0  0  0]
 [ 0 13  0  0  0  0]
 [ 0  0 11  0  0  0]
 [ 0  0  0 12  3  0]
 [ 0  0  0  0 10  0]
 [ 0  0  0  0  0  9]]
Decision Tree - Test Set Performance
Accuracy Score: 0.5972222222222222
              precision    recall  f1-score   support

           0       1.00      0.71      0.83        14
           1       0.46      1.00      0.63        13
           2       1.00      0.00      0.00        11
           3       1.00      0.73      0.85        15
           4       0.00      0.00      0.00        10
           5       0.47      1.00      0.64         9

    accuracy                           0.60        72
   macro avg       0.66      0.57      0.49        72
```

```
weighted avg       0.70      0.60      0.53        72

Confusion Matrix:
 [[10  4  0  0  0  0]
 [ 0 13  0  0  0  0]
 [ 0 11  0  0  0  0]
 [ 0  0  0 11  4  0]
 [ 0  0  0  0  0 10]
 [ 0  0  0  0  0  9]]
```

In [16]:
```python
print("The second part of this assignment asked us to create a deeper decision
```

```
The second part of this assignment asked us to create a deeper decision tree
model, which I accomplished by setting the max_depth value to 10 (it was prev
iously set at 1 for the previous question, as that required a shallow decisio
n tree model). Once that modification was executed properly and I was able to
obtain the evaluation metrics, I was finally able to determine which is the o
ptimal algorithm with regards to being able to predict the classification of
a star. With that being said, the winning algorithm is once again the logisti
c regression model. I say this because the logistic regression model is super
ior when discussing the precision, recall, and F1 score. Once again, just lik
e the previous question, the logistic regression model yielded a lower freque
ncy of Type 1 and Type 2 errors when compared to the deeper decision tree mod
el.
```