Logistic Regression .2

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Introduction: ¶

In this Tutorial, we will train a logistic regression model to predict if customer is more likely to make a purchase.

The model will be trained based on 3 key features : Age, Gender, Salary.

This is a binary (binomial) classification : puchase did happen: 1, not purchased : 0

At the end, we will take a look into the results and the metrics used to evaluate the model, and how to manage the threshold

or the classification boundary.

The data has been retrieved from kaggle.

I - Data Exploration & Preprocessing

In [1]:
```
#Importing necessary packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

In [2]:
```
#Reading dataset
dataset = pd.read_csv("purchase.csv")
```

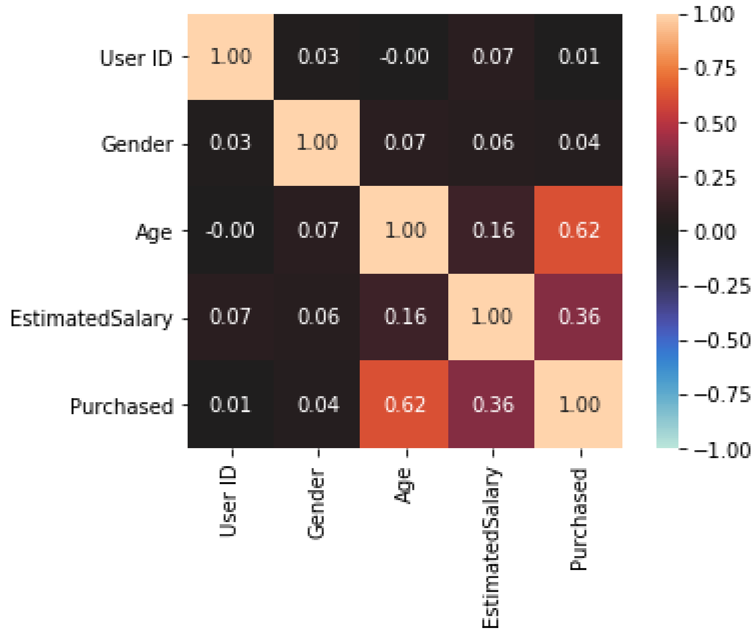
In [3]:
```
dataset
```

Out[3]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	Male	19	19000	0
1	15810944	Male	35	20000	0
2	15668575	Female	26	43000	0
3	15603246	Female	27	57000	0
4	15804002	Male	19	76000	0
...	...	...	...	...	...
395	15691863	Female	46	41000	1
396	15706071	Male	51	23000	1
397	15654296	Female	50	20000	1
398	15755018	Male	36	33000	0
399	15594041	Female	49	36000	1

400 rows × 5 columns

In [4]:
```
# You can use NOMINAL class to view the correlation (including the categorical va

from dython import nominal
nominal.associations(dataset, nominal_columns=['Gender'])
```



Out[4]:
```
{'corr':                     User ID    Gender       Age  EstimatedSalary  Purcha
sed
 User ID          1.000000  0.025249 -0.000721         0.071097   0.007120
 Gender           0.025249  1.000000  0.073741         0.060435   0.042469
 Age             -0.000721  0.073741  1.000000         0.155238   0.622454
 EstimatedSalary  0.071097  0.060435  0.155238         1.000000   0.362083
 Purchased        0.007120  0.042469  0.622454         0.362083   1.000000,
 'ax': <matplotlib.axes._subplots.AxesSubplot at 0xb3a5b88>}
```

In [ ]:

In [5]:
```
#Checking for missing data
dataset.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 400 entries, 0 to 399
Data columns (total 5 columns):
 #   Column           Non-Null Count  Dtype 
---  ------           --------------  ----- 
 0   User ID          400 non-null    int64 
 1   Gender           400 non-null    object
 2   Age              400 non-null    int64 
 3   EstimatedSalary  400 non-null    int64 
 4   Purchased        400 non-null    int64 
dtypes: int64(4), object(1)
memory usage: 15.8+ KB
```

In [6]:
```
dataset.isna().any().sum()
```

Out[6]: 0

In [7]:
```
#Properties of data
dataset.describe()
```

Out[7]:

	User ID	Age	EstimatedSalary	Purchased
count	4.000000e+02	400.000000	400.000000	400.000000
mean	1.569154e+07	37.655000	69742.500000	0.357500
std	7.165832e+04	10.482877	34096.960282	0.479864
min	1.556669e+07	18.000000	15000.000000	0.000000
25%	1.562676e+07	29.750000	43000.000000	0.000000
50%	1.569434e+07	37.000000	70000.000000	0.000000
75%	1.575036e+07	46.000000	88000.000000	1.000000
max	1.581524e+07	60.000000	150000.000000	1.000000

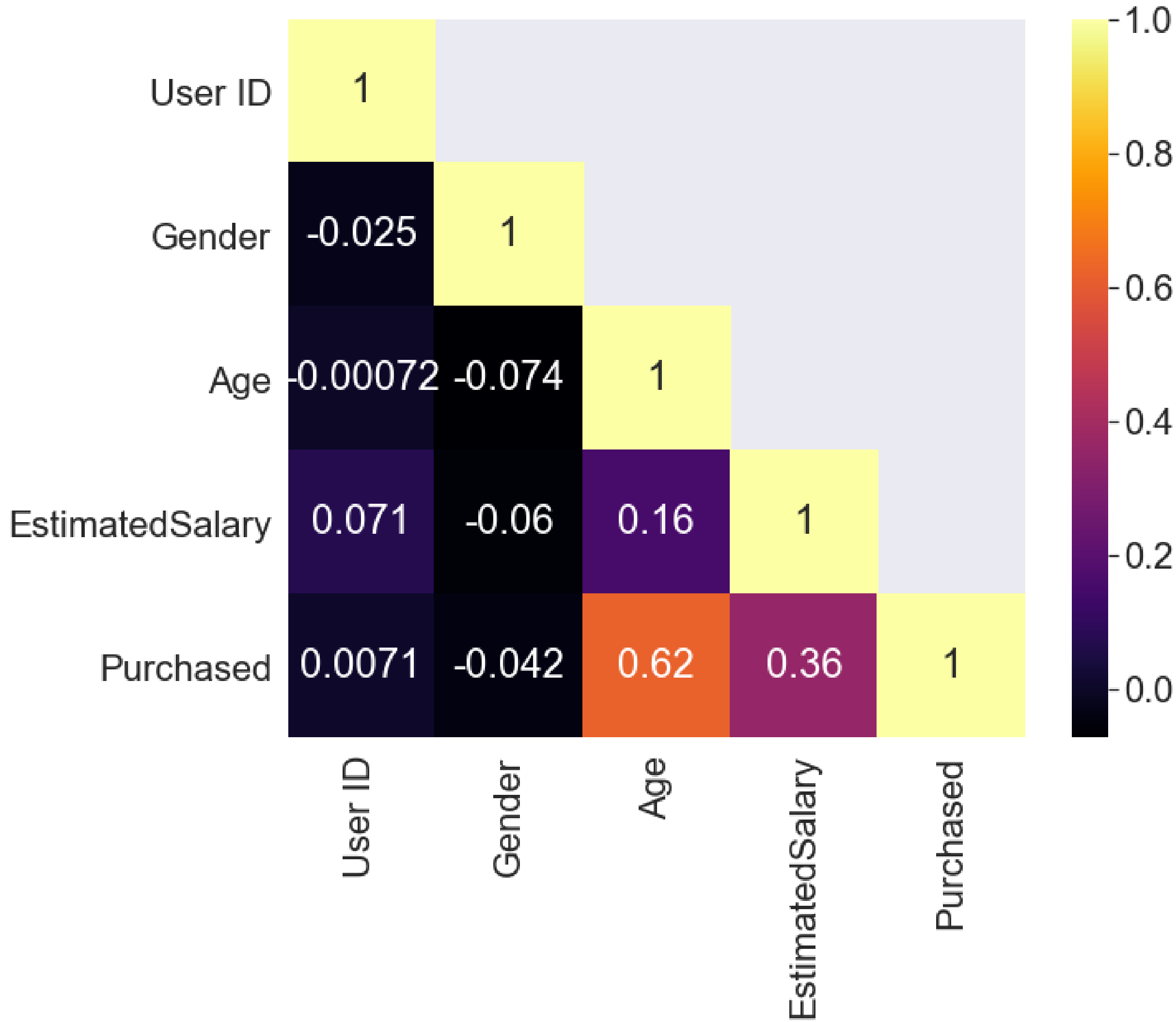
In [8]:
```
#Encode the categorical feature - Gender using LabelEncoder

from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

dataset['Gender'] = le.fit_transform(dataset['Gender'])

dataset.head()
```

Out[8]:

	User ID	Gender	Age	EstimatedSalary	Purchased
0	15624510	1	19	19000	0
1	15810944	1	35	20000	0
2	15668575	0	26	43000	0
3	15603246	0	27	57000	0
4	15804002	1	19	76000	0

In [9]:
```
#heatmap - correlation matrix of features
plt.figure(figsize=(10,8))
sns.set( font_scale= 2)
sns.heatmap(dataset.corr(),annot=True,cmap='inferno',mask=np.triu(dataset.corr(),
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0xb2b4b08>



In [10]:
```
dataset.drop("User ID", axis =1, inplace =True)
```

In [11]:
```
dataset
```

Out[11]:

	Gender	Age	EstimatedSalary	Purchased
0	1	19	19000	0
1	1	35	20000	0
2	0	26	43000	0
3	0	27	57000	0
4	1	19	76000	0
...	...	...	...	...
395	0	46	41000	1
396	1	51	23000	1
397	0	50	20000	1
398	1	36	33000	0
399	0	49	36000	1

400 rows × 4 columns

In [12]:
```
#checking for duplicate samples
dataset.duplicated().sum()
```

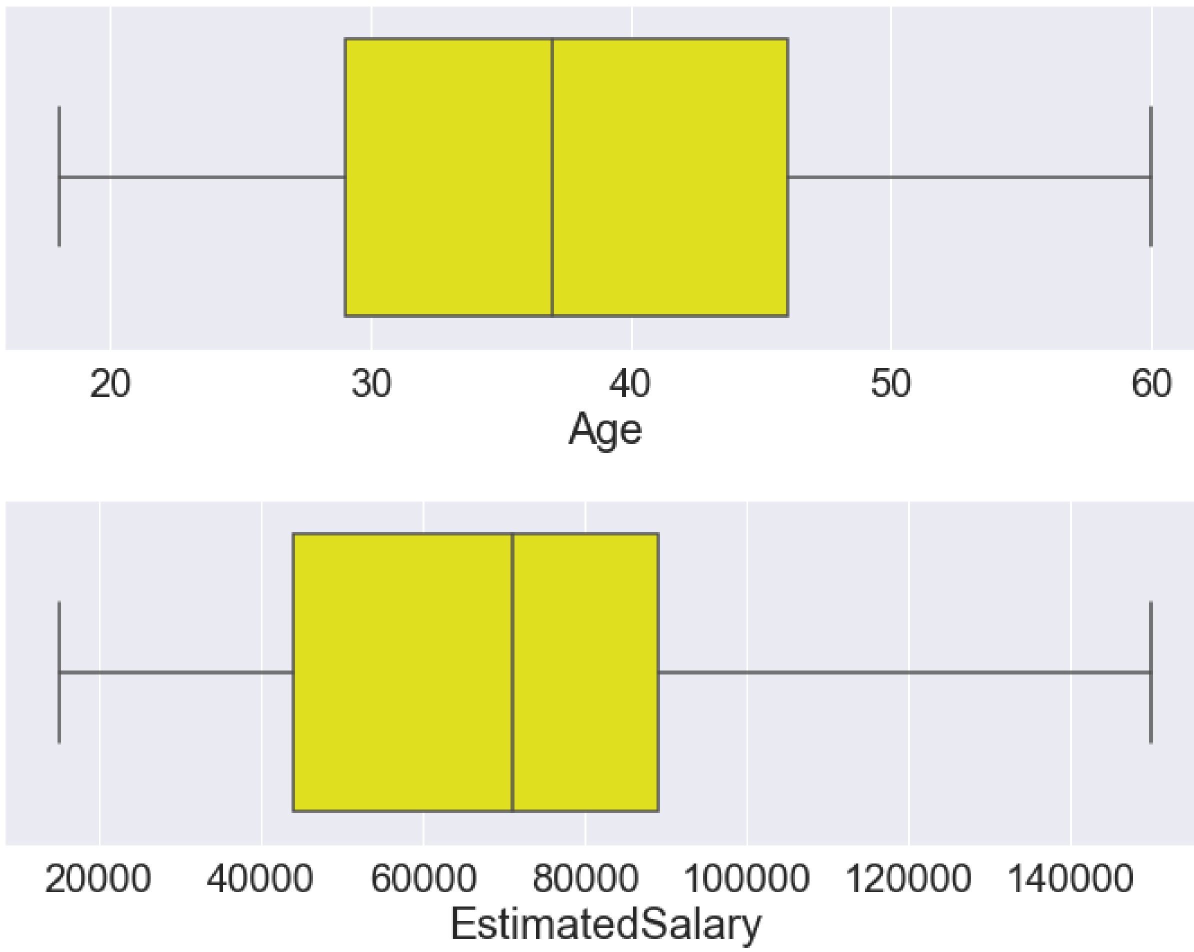
Out[12]:
```
20
```

In [13]:
```
#dropping ALL duplicate values
dataset.drop_duplicates(keep = False, inplace = True)
```

In [14]:
```
dataset.shape
```

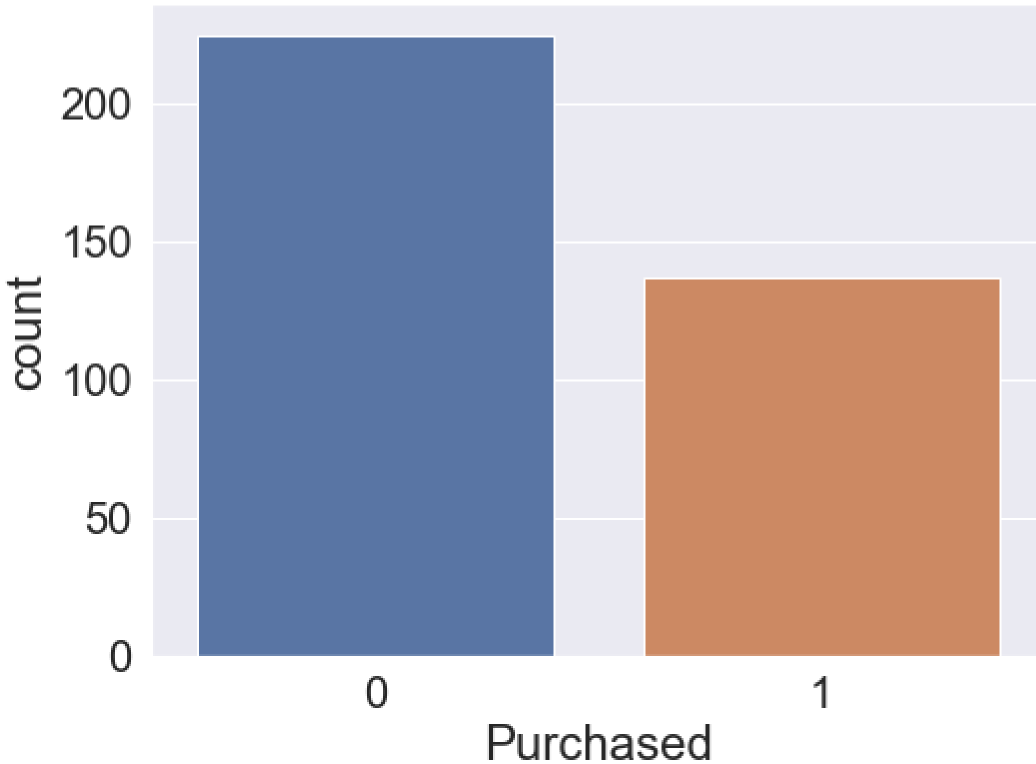
Out[14]:
```
(362, 4)
```

In [15]:
```
#Checking if any outliers
plt.figure(figsize=(10, 8))

plt.subplot(2,1,1)
sns.boxplot(dataset['Age'],color='yellow')

plt.subplot(2,1,2)
sns.boxplot(dataset['EstimatedSalary'], color='yellow')

plt.tight_layout()
```



In [16]:
```
#Output distribution
plt.figure(figsize=(8, 6))
sns.countplot('Purchased', data=dataset)
```

Out[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xc9ba048>
```



Define X and y, Convert them into arrays

In [17]:
```
X = dataset.drop("Purchased", axis = 1).values
y = dataset["Purchased"].values
```

In [ ]:

II - Train & Evaluate the model

Splitting the data

In [18]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, randor
```

Feature scaling

In [19]:
```
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

X_train = scaler.fit_transform(X_train)
X_test = scaler.transform(X_test)
```

In [20]:
```
print(X_train[:3, :])
```

```
[[-0.96263527 -1.37394385  0.3233538 ]
 [-0.96263527  0.12620169  0.1205811 ]
 [-0.96263527  1.81386542 -1.29882782]]
```

Create and fit the model

In [21]:
```
from sklearn.linear_model import LogisticRegression

log_reg = LogisticRegression()

log_reg.fit(X_train, y_train)
```

Out[21]:
```
LogisticRegression(C=1.0, class_weight=None, dual=False, fit_intercept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=100,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=0,
                   warm_start=False)
```

Predictions for X_test

In [22]:
```
y_pred = log_reg.predict(X_test)
y_pred_proba = log_reg.predict_proba(X_test)
```

In [23]:
```
pd.DataFrame(y_pred_proba)
```

Out[23]:

	0	1
0	0.934922	0.065078
1	0.131239	0.868761
2	0.565517	0.434483
3	0.988452	0.011548
4	0.240856	0.759144
...	...	...
68	0.352628	0.647372
69	0.652208	0.347792
70	0.982579	0.017421
71	0.994265	0.005735
72	0.388475	0.611525

73 rows × 2 columns

Changing the classification threshold

In [80]:
```
def my_filter(x):
    if x > 0.9:
        return 1
    else:
        return 0
```

In [81]:
```
y_pred_new = np.array([my_filter(x) for x in y_pred_proba[:,1]])
```

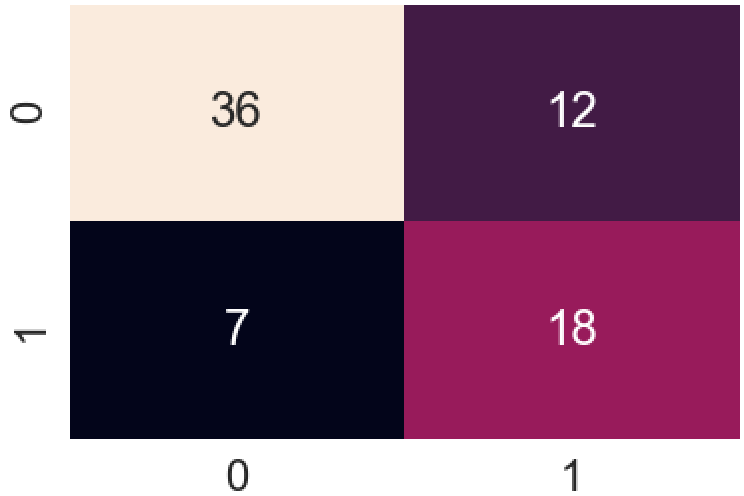
In [82]:
```
y_pred_new
```

Out[82]:
```
array([0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 1, 0, 1, 1,
       1, 0, 0, 1, 0, 1, 1, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0])
```

Confusion matrix for the default threshold:

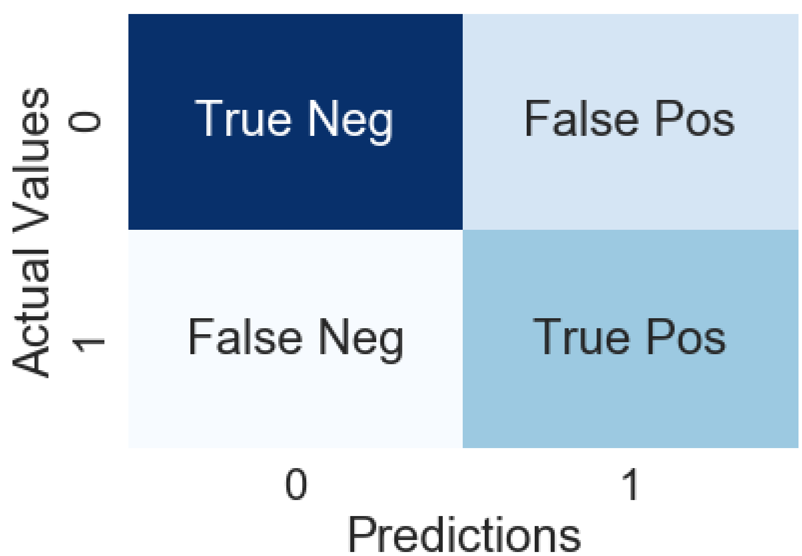
In [83]:
```
from sklearn.metrics import confusion_matrix
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cbar = False)
```

Out[83]: <matplotlib.axes._subplots.AxesSubplot at 0xfd86348>



In [84]:
```
sns.set( font_scale=2)
labels =np.array([['True Neg','False Pos'],['False Neg','True Pos']])
sns.heatmap(confusion_matrix(y_test, y_pred), annot=labels,fmt='', cmap='Blues',

plt.xlabel('Predictions')
plt.ylabel('Actual Values')
```

Out[84]: Text(20.5, 0.5, 'Actual Values')



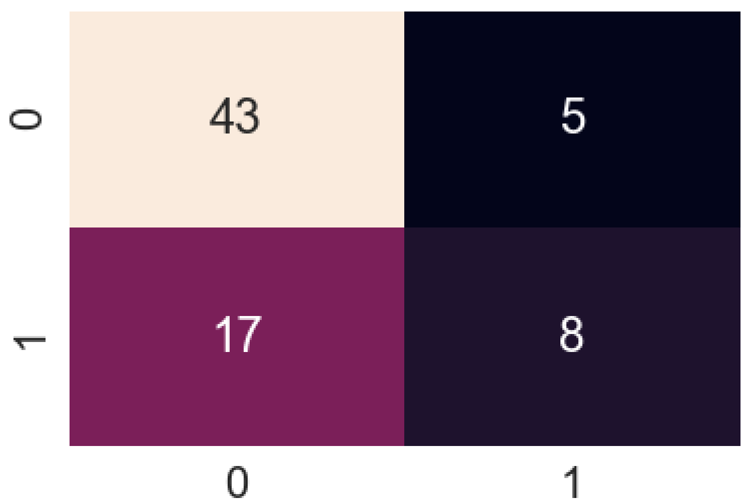
Definitions :

$$\begin{aligned} precision &= \frac{TP}{TP+FP} \\ recall &= \frac{TP}{TP+FN} \\ F1 &= \frac{2\times precision\times recall}{precision+recall} \\ accuracy &= \frac{TP+TN}{TP+FN+TN+FP} \\ specificity &= \frac{TN}{TN+FP} \end{aligned}$$

Confusion matrix for a new threshold:

In [85]:
```
sns.heatmap(confusion_matrix(y_test, y_pred_new), annot=True, cbar = False)
```

Out[85]:
```
<matplotlib.axes._subplots.AxesSubplot at 0xfb1e808>
```



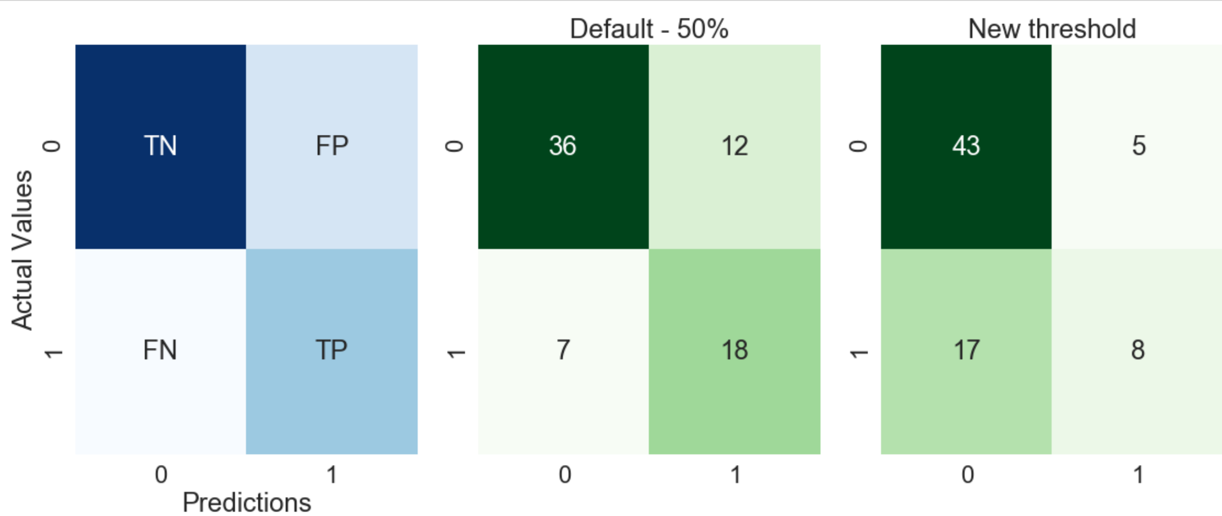
In [86]:
```
#Metrics based result
from sklearn.metrics import classification_report
print(classification_report(y_test, y_pred_new))
```

```
              precision    recall  f1-score   support

           0       0.72      0.90      0.80        48
           1       0.62      0.32      0.42        25

    accuracy                           0.70        73
   macro avg       0.67      0.61      0.61        73
weighted avg       0.68      0.70      0.67        73
```

In [87]:
```
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.84      0.75      0.79        48
           1       0.60      0.72      0.65        25

    accuracy                           0.74        73
   macro avg       0.72      0.73      0.72        73
weighted avg       0.76      0.74      0.74        73
```

In [88]:
```
plt.figure(figsize = (16,7))

#Confusion matrix with labels
plt.subplot(1,3,1)
labels =np.array([['TN','FP'],['FN','TP']])
sns.heatmap(confusion_matrix(y_test, y_pred), annot=labels,fmt='', cmap='Blues',
plt.xlabel('Predictions')
plt.ylabel('Actual Values')

#Confusion matrix (0.5)
plt.subplot(1,3,2)
sns.heatmap(confusion_matrix(y_test, y_pred), annot=True, cmap='Greens', cbar = F
plt.title("Default - 50%")

#Confusion matrix (new threshold)
plt.subplot(1,3,3)
sns.heatmap(confusion_matrix(y_test, y_pred_new), annot=True,cmap='Greens', cbar
plt.title("New threshold")


plt.tight_layout()
```



In [ ]:

In [92]:
```
dataset.head(3)
```

Out[92]:

	Gender	Age	EstimatedSalary	Purchased
0	1	19	19000	0
1	1	35	20000	0
2	0	26	43000	0

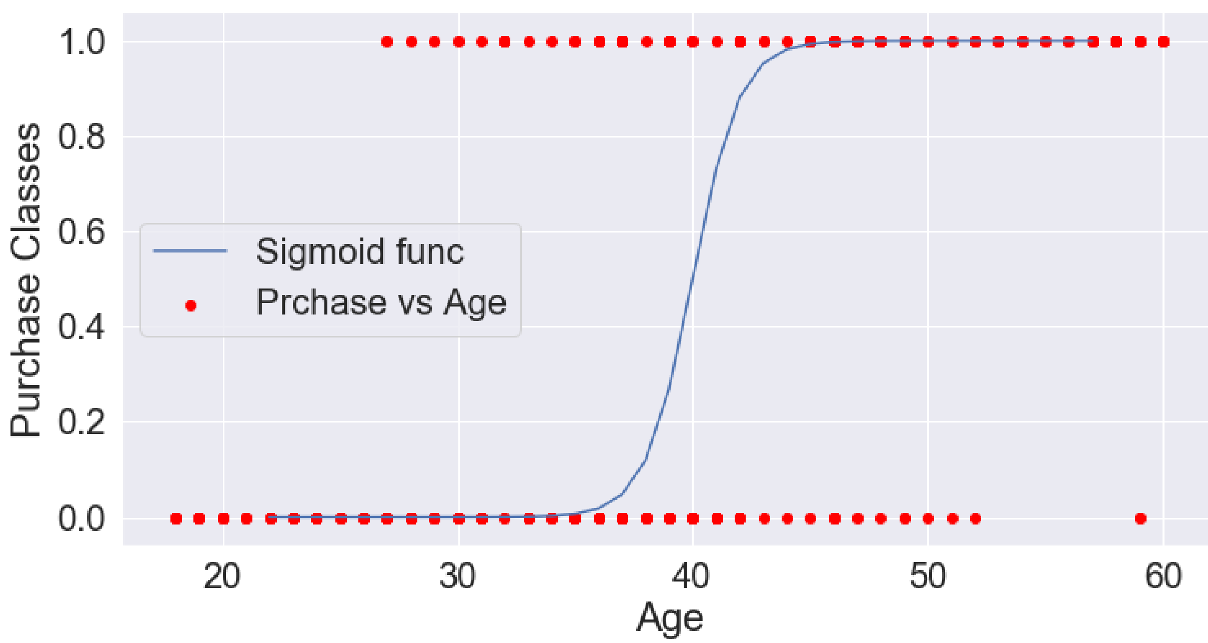
In [ ]:

In [ ]:

Plotting a sigmoid function and a scatter of data

In [119]:
```
plt.figure(figsize = (12,6))
x = np.arange(-18,18)
plt.plot(x + 40, 1/(1+np.exp(-x)) , label = "Sigmoid func")
plt.scatter(x = dataset["Age"], y = dataset["Purchased"], color = "red" , label =

plt.xlabel("Age")
plt.ylabel("Purchase Classes")
plt.legend(loc = 6)
#dataset.plot.scatter(x = "EstimatedSalary", y = "Purchased")
```

Out[119]: <matplotlib.legend.Legend at 0x10576a48>



In [ ]: