Customer Propensity Modeling

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DSC 680

Final Project 1

Data Imports

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
```

In [2]:
```
training = pd.read_csv('data/training_sample.csv')
testing = pd.read_csv('data/testing_sample.csv')
```

Cleaning and Exploring Data

In [3]:
```
print('Size of training dataset:', training.shape)
print('Size of testing dataset:', testing.shape)
```

```
Size of training dataset: (455401, 25)
Size of testing dataset: (151655, 25)
```

In [4]:
```
print('Null count of training dataset:', sum(training.isna().sum()))
print('Null count of testing dataset:', sum(testing.isna().sum()))
```

```
Null count of training dataset: 0
Null count of testing dataset: 0
```

In [5]:
```
training.columns
```

Out[5]:
```
Index(['UserID', 'basket_icon_click', 'basket_add_list', 'basket_add_detail',
       'sort_by', 'image_picker', 'account_page_click', 'promo_banner_click',
       'detail_wishlist_add', 'list_size_dropdown', 'closed_minibasket_click',
       'checked_delivery_detail', 'checked_returns_detail', 'sign_in',
       'saw_checkout', 'saw_sizecharts', 'saw_delivery', 'saw_account_upgrade',
       'saw_homepage', 'device_mobile', 'device_computer', 'device_tablet',
       'returning_user', 'loc_uk', 'ordered'],
      dtype='object')
```

In [6]:
```
testing.columns
```

Out[6]:
```
Index(['UserID', 'basket_icon_click', 'basket_add_list', 'basket_add_detail',
       'sort_by', 'image_picker', 'account_page_click', 'promo_banner_click',
```

```
       'detail_wishlist_add', 'list_size_dropdown', 'closed_minibasket_click',
       'checked_delivery_detail', 'checked_returns_detail', 'sign_in',
       'saw_checkout', 'saw_sizecharts', 'saw_delivery', 'saw_account_upgrade',
       'saw_homepage', 'device_mobile', 'device_computer', 'device_tablet',
       'returning_user', 'loc_uk', 'ordered'],
      dtype='object')
```

In [7]:

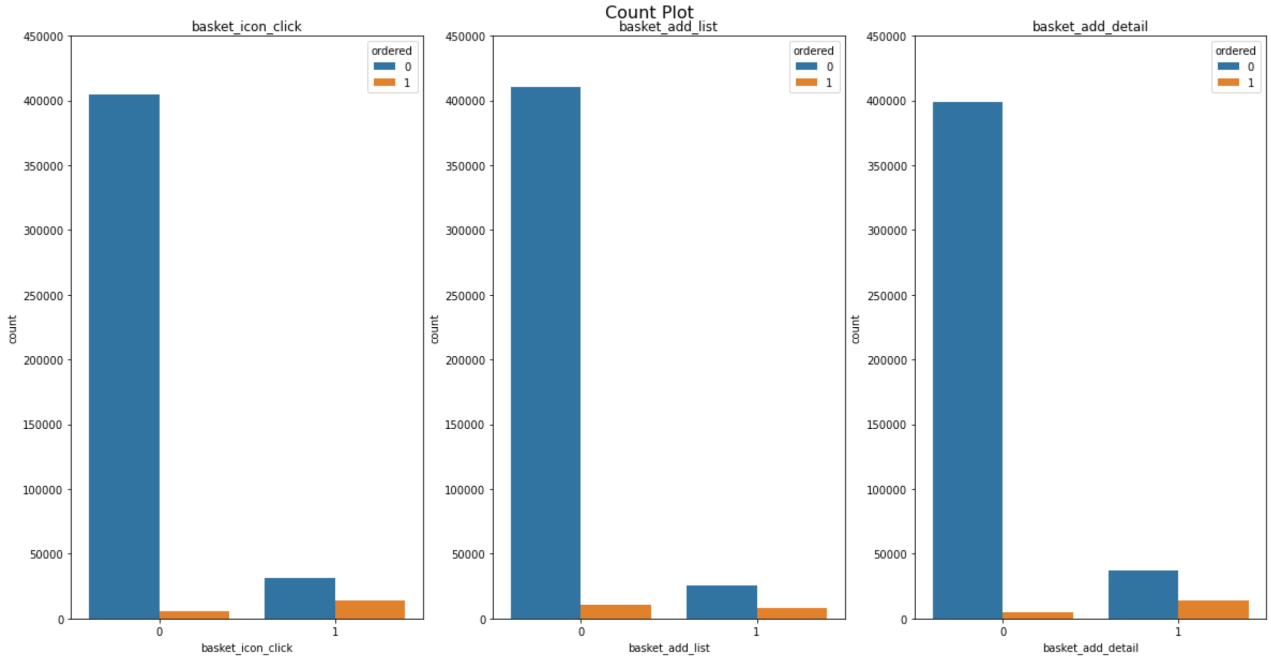
```
training.dtypes
```

Out[7]:

```
UserID                      object
basket_icon_click            int64
basket_add_list              int64
basket_add_detail            int64
sort_by                      int64
image_picker                 int64
account_page_click           int64
promo_banner_click           int64
detail_wishlist_add          int64
list_size_dropdown           int64
closed_minibasket_click      int64
checked_delivery_detail      int64
checked_returns_detail       int64
sign_in                      int64
saw_checkout                 int64
saw_sizecharts               int64
saw_delivery                 int64
saw_account_upgrade          int64
saw_homepage                 int64
device_mobile                int64
device_computer              int64
device_tablet                int64
returning_user               int64
loc_uk                       int64
ordered                      int64
dtype: object
```

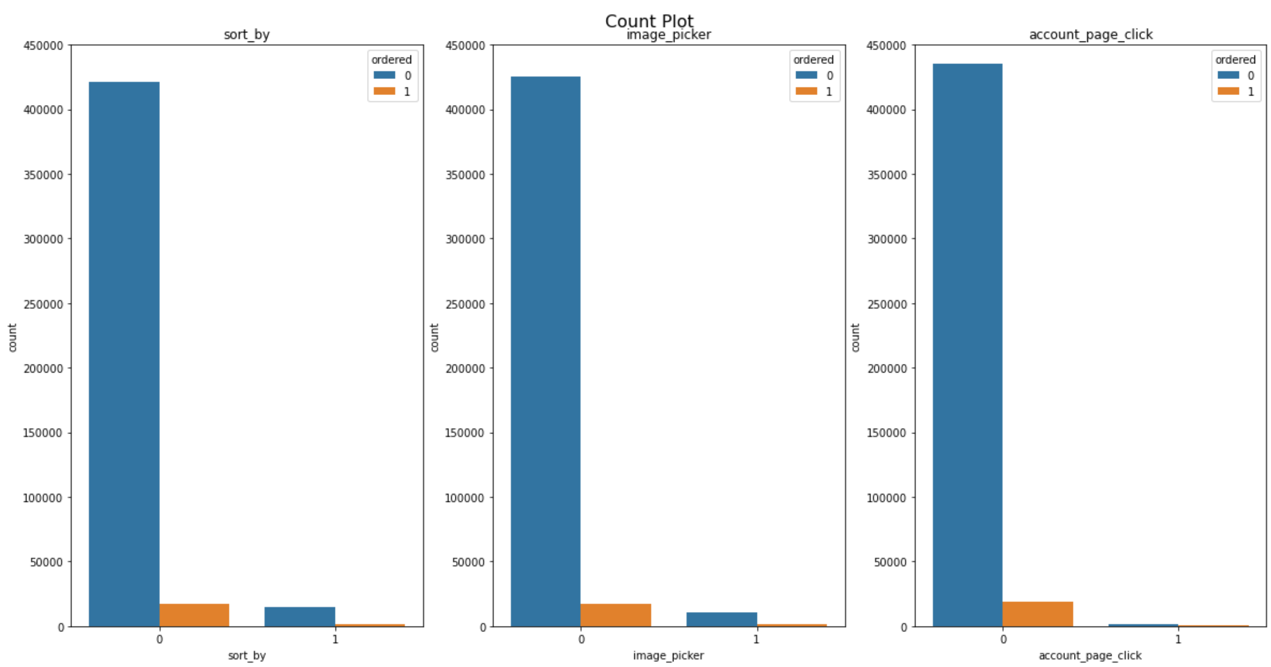
In [8]:

```
## for multiple columns
fig, ax = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle('Count Plot', fontsize=16, y=0.92)

columns = ['basket_icon_click', 'basket_add_list', 'basket_add_detail']
for i, col in enumerate(columns):
    graph = sns.countplot(x=training[col], hue=training["ordered"], ax=ax[i])
    graph.set_ylim(0,450000)
    ax[i].set_title(*[col])
```



In [9]:

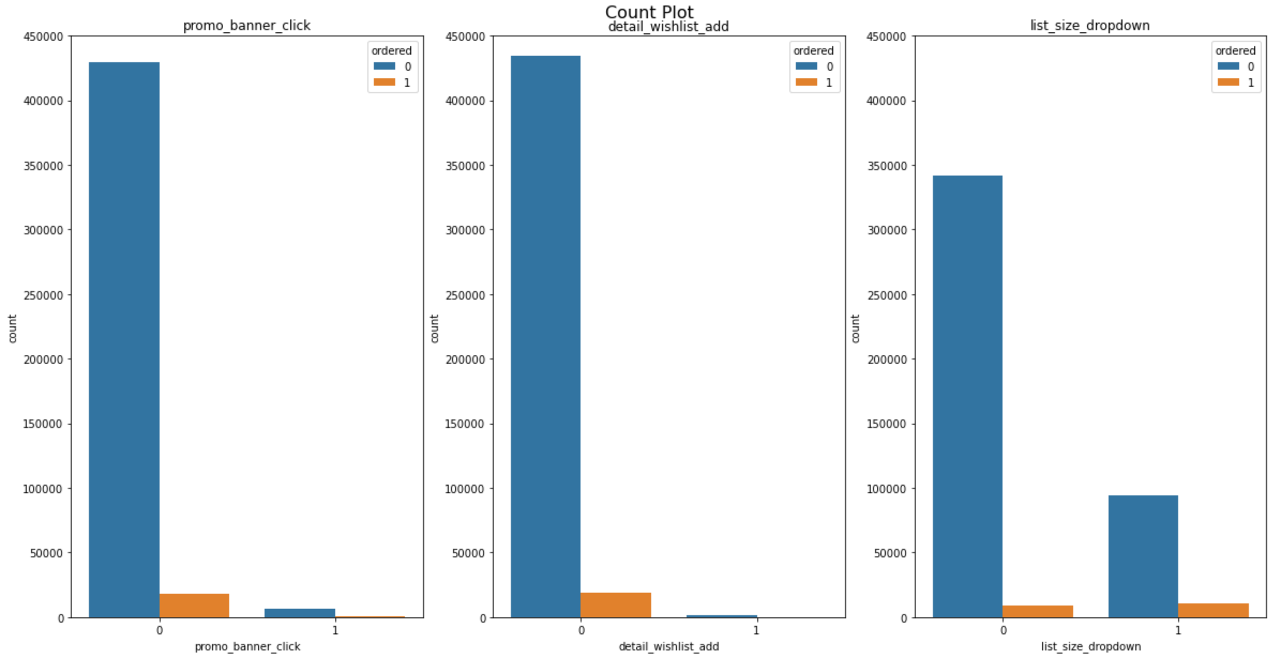
```
## for multiple columns
fig, ax = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle('Count Plot', fontsize=16, y=0.92)

columns = ['sort_by', 'image_picker', 'account_page_click']
for i, col in enumerate(columns):
    graph = sns.countplot(x=training[col], hue=training["ordered"], ax=ax[i])
    graph.set_ylim(0,450000)
    ax[i].set_title(*[col])
```



In [10]:

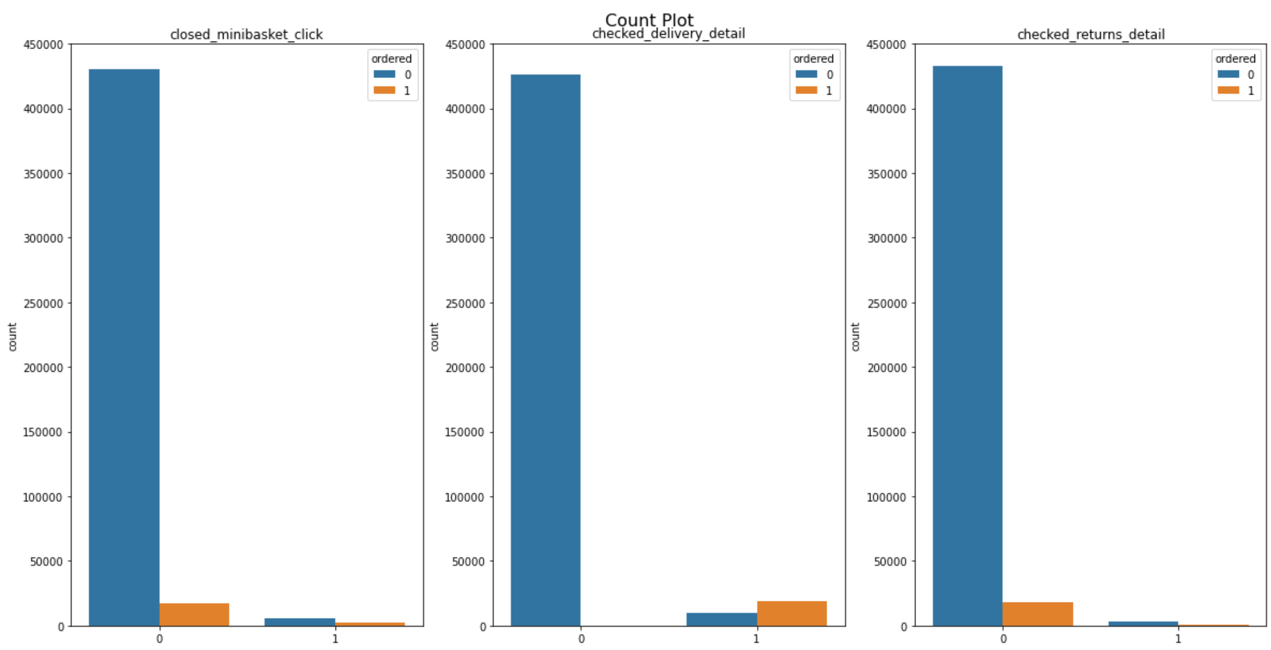
```
## for multiple columns
fig, ax = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle('Count Plot', fontsize=16, y=0.92)

columns = ['promo_banner_click', 'detail_wishlist_add', 'list_size_dropdown']
for i, col in enumerate(columns):
```

```
    graph = sns.countplot(x=training[col], hue=training["ordered"], ax=ax[i])
    graph.set_ylim(0,450000)
    ax[i].set_title(*[col])
```



In [11]:

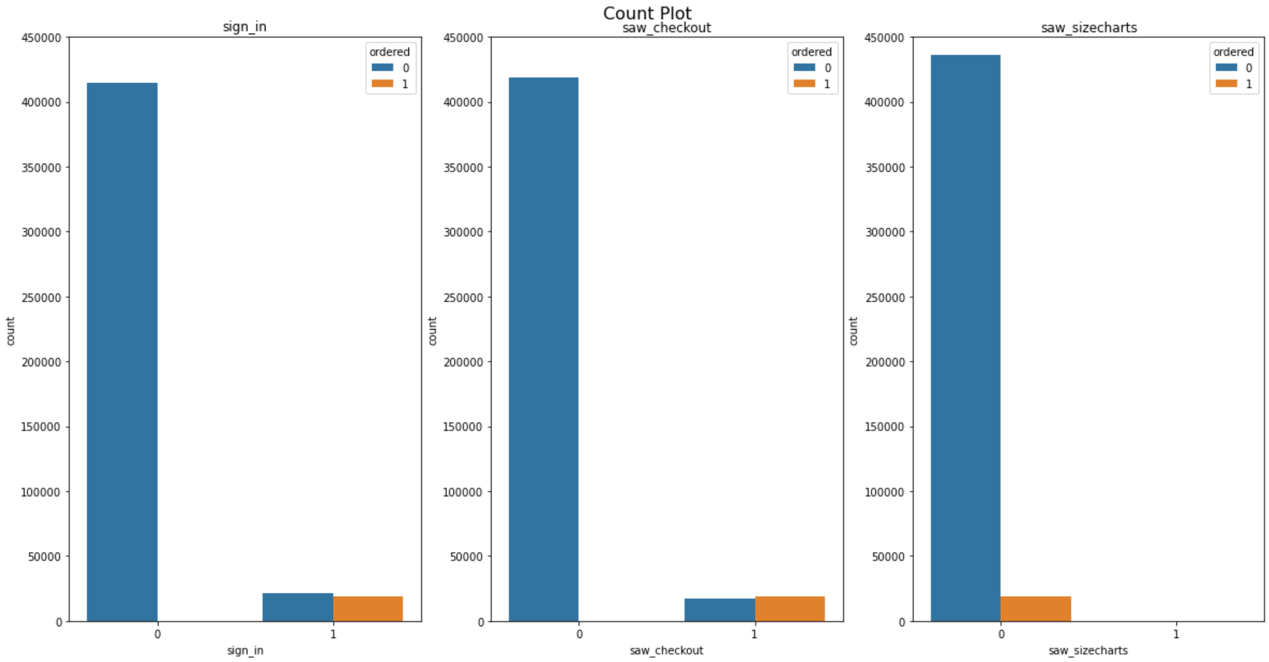
```
## for multiple columns
fig, ax = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle('Count Plot', fontsize=16, y=0.92)

columns = ['closed_minibasket_click', 'checked_delivery_detail', 'checked_return
for i, col in enumerate(columns):
    graph = sns.countplot(x=training[col], hue=training["ordered"], ax=ax[i])
    graph.set_ylim(0,450000)
    ax[i].set_title(*[col])
```



In [12]:

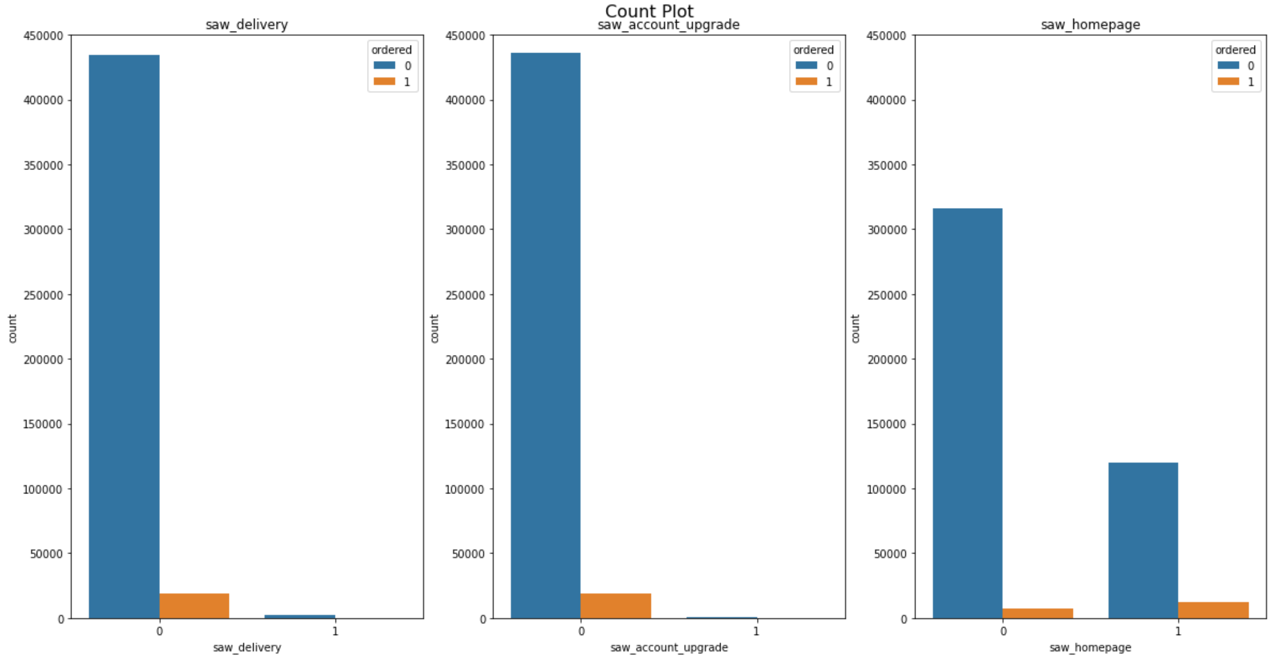
```
## for multiple columns
```

```
fig, ax = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle('Count Plot', fontsize=16, y=0.92)

columns = ['sign_in', 'saw_checkout', 'saw_sizecharts']
for i, col in enumerate(columns):
    graph = sns.countplot(x=training[col], hue=training["ordered"], ax=ax[i])
    graph.set_ylim(0,450000)
    ax[i].set_title(*[col])
```



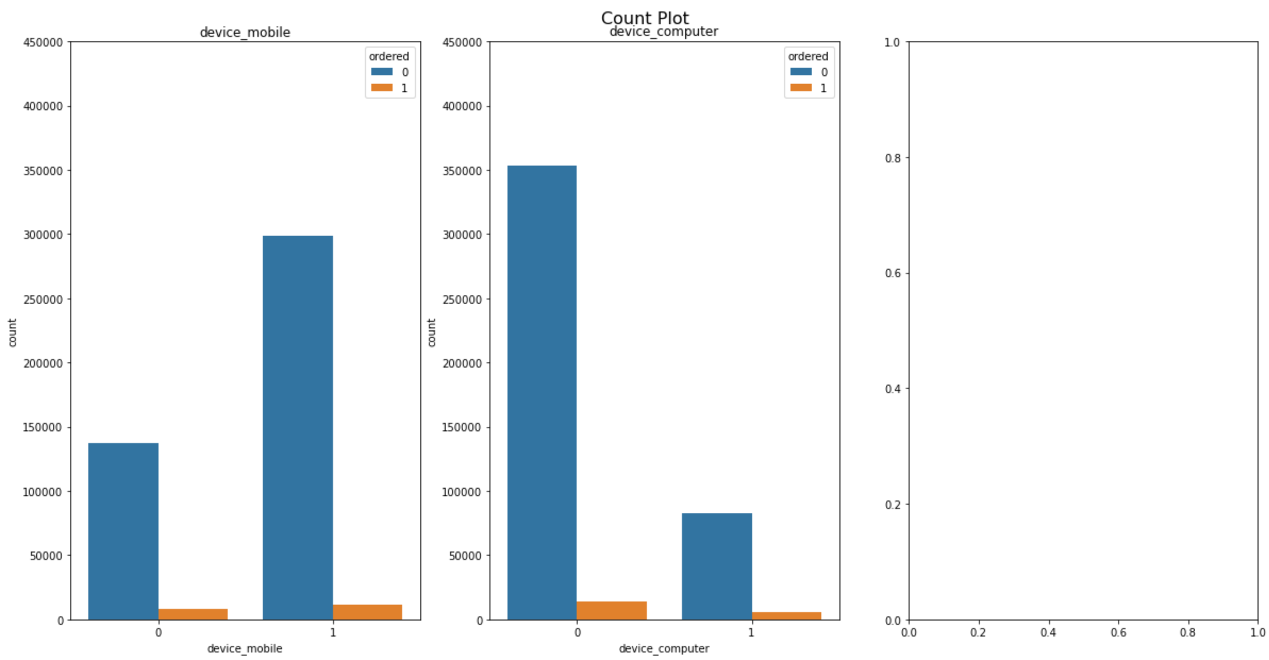
In [13]:

```
## for multiple columns
fig, ax = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle('Count Plot', fontsize=16, y=0.92)

columns = ['saw_delivery', 'saw_account_upgrade', 'saw_homepage']
for i, col in enumerate(columns):
    graph = sns.countplot(x=training[col], hue=training["ordered"], ax=ax[i])
    graph.set_ylim(0,450000)
    ax[i].set_title(*[col])
```



In [14]:

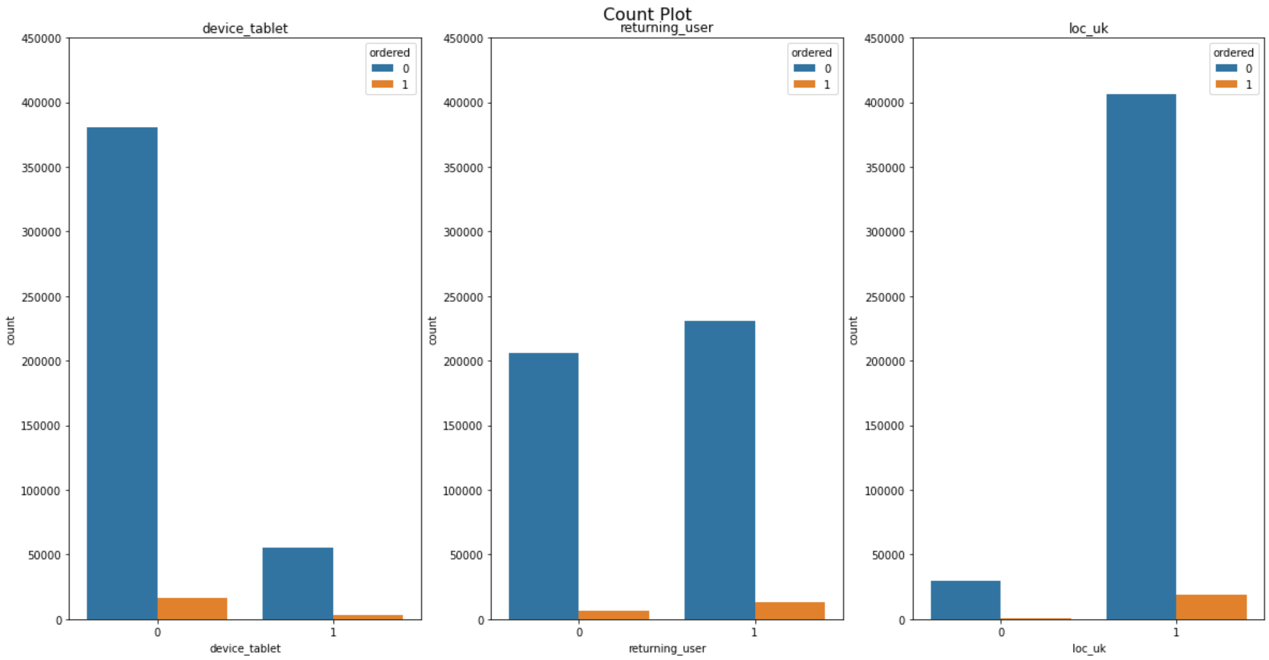
```
## for multiple columns
fig, ax = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle('Count Plot', fontsize=16, y=0.92)

columns = ['device_mobile', 'device_computer']
for i, col in enumerate(columns):
    graph = sns.countplot(x=training[col], hue=training["ordered"], ax=ax[i])
    graph.set_ylim(0,450000)
    ax[i].set_title(*[col])
```



In [15]:

```
## for multiple columns
fig, ax = plt.subplots(1, 3, figsize=(20, 10))
fig.suptitle('Count Plot', fontsize=16, y=0.92)

columns = ['device_tablet', 'returning_user', 'loc_uk']
for i, col in enumerate(columns):
```

```
    graph = sns.countplot(x=training[col], hue=training["ordered"], ax=ax[i])
    graph.set_ylim(0,450000)
    ax[i].set_title(*[col])
```



In [16]:

```
corr = training.corr()

corr.style.background_gradient(cmap='coolwarm')
```

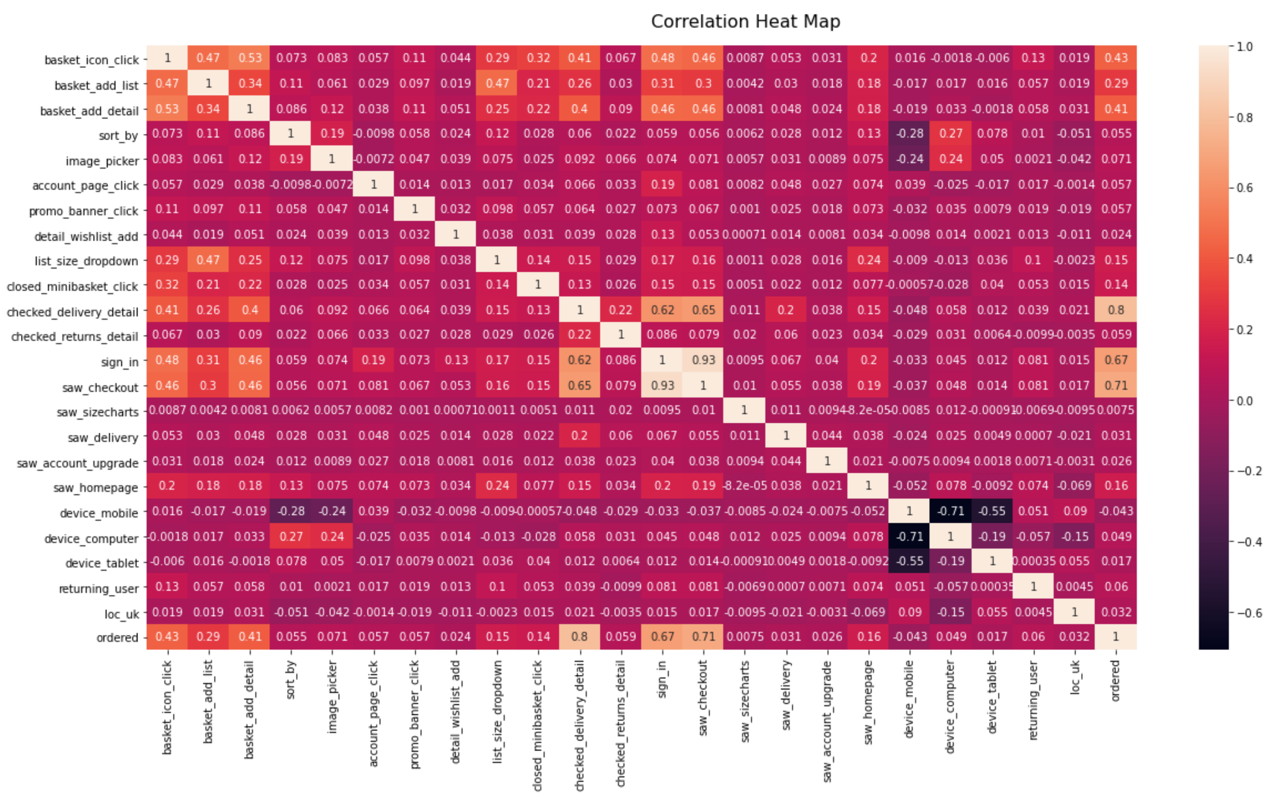
Out[16]:

	basket_icon_click	basket_add_list	basket_add_detail	sort_by	image_
basket_icon_click	1.000000	0.466671	0.529947	0.073016	0.(
basket_add_list	0.466671	1.000000	0.340968	0.106852	0.
basket_add_detail	0.529947	0.340968	1.000000	0.085854	0.
sort_by	0.073016	0.106852	0.085854	1.000000	0
image_picker	0.082893	0.061462	0.124230	0.185661	1.(
account_page_click	0.057253	0.028994	0.037502	-0.009754	-0.
promo_banner_click	0.109342	0.096608	0.109043	0.058155	0.(
detail_wishlist_add	0.044153	0.019061	0.050724	0.024056	0.
list_size_dropdown	0.291608	0.469625	0.247205	0.124273	0.
closed_minibasket_click	0.323940	0.208082	0.222444	0.028453	0.
checked_delivery_detail	0.405787	0.264766	0.404134	0.059635	0
checked_returns_detail	0.067149	0.030469	0.090434	0.022364	0.(
sign_in	0.478834	0.312276	0.461659	0.058662	0.
saw_checkout	0.458774	0.297681	0.456713	0.055959	(
saw_sizecharts	0.008741	0.004161	0.008101	0.006196	0.
saw_delivery	0.052922	0.030286	0.048410	0.028102	0.

	basket_icon_click	basket_add_list	basket_add_detail	sort_by	image_
saw_account_upgrade	0.030764	0.018150	0.024255	0.012194	0.
saw_homepage	0.203087	0.180221	0.175138	0.128205	0.
device_mobile	0.016203	-0.017202	-0.018800	-0.278043	-0.
device_computer	-0.001757	0.016629	0.032794	0.269589	0
device_tablet	-0.006019	0.015516	-0.001799	0.078088	0.
returning_user	0.126640	0.057443	0.057680	0.010366	0.
loc_uk	0.018518	0.018797	0.030956	-0.051148	-0.
ordered	0.428334	0.287666	0.414420	0.054636	0.

In [17]:

```
fig, ax = plt.subplots(1, 1, figsize=(20, 10))
fig.suptitle('Correlation Heat Map', fontsize=16, y=0.92)

sns.heatmap(training.corr(), annot = True)
plt.show()
```



In [18]:

```
training.corr()['ordered']
```

Out[18]:

```
basket_icon_click          0.428334
basket_add_list            0.287666
basket_add_detail          0.414420
sort_by                    0.054636
image_picker               0.071492
account_page_click         0.057279
promo_banner_click         0.056533
detail_wishlist_add        0.023516
list_size_dropdown         0.154867
```

```
closed_minibasket_click    0.140011
checked_delivery_detail    0.798720
checked_returns_detail     0.059484
sign_in                    0.665556
saw_checkout               0.708986
saw_sizecharts             0.007548
saw_delivery               0.031461
saw_account_upgrade        0.025857
saw_homepage               0.157778
device_mobile             -0.042907
device_computer            0.049208
device_tablet              0.016939
returning_user             0.060295
loc_uk                     0.031643
ordered                    1.000000
Name: ordered, dtype: float64
```

In [19]:

```python
training.corr()['ordered'] > 0.15
```

Out[19]:

```
basket_icon_click           True
basket_add_list             True
basket_add_detail           True
sort_by                    False
image_picker               False
account_page_click         False
promo_banner_click         False
detail_wishlist_add        False
list_size_dropdown          True
closed_minibasket_click    False
checked_delivery_detail     True
checked_returns_detail     False
sign_in                     True
saw_checkout                True
saw_sizecharts             False
saw_delivery               False
saw_account_upgrade        False
saw_homepage                True
device_mobile              False
device_computer            False
device_tablet              False
returning_user             False
loc_uk                     False
ordered                     True
Name: ordered, dtype: bool
```

In [20]:

```python
training.corr()['ordered'] > 0.02
```

Out[20]:

```
basket_icon_click           True
basket_add_list             True
basket_add_detail           True
sort_by                     True
image_picker                True
account_page_click          True
promo_banner_click          True
detail_wishlist_add         True
list_size_dropdown          True
closed_minibasket_click     True
checked_delivery_detail     True
checked_returns_detail      True
sign_in                     True
saw_checkout                True
saw_sizecharts             False
```

```
saw_delivery                 True
saw_account_upgrade          True
saw_homepage                 True
device_mobile               False
device_computer              True
device_tablet               False
returning_user               True
loc_uk                       True
ordered                      True
Name: ordered, dtype: bool
```

Feature Selection and Separating Predictors from Target Variable

Methods

For the feature selection I would like to try 2 different methods. 1st I would like to take the variables over 0.15 correlation with ordered which would be 8 features. 2nd I would like to take the variables that are over 0.02, which would be 20 features. This will change and influence the number of features that are being used in the model building portion. This could help us limit the total number of features used or it could prove that the more features the better the result.

In [21]:
```
predictors15 = training[['basket_icon_click', 'basket_add_list', 'basket_add_det
                        'checked_delivery_detail', 'sign_in', 'saw_checkout', 's
```

In [22]:
```
predictors02 = training.drop(['saw_sizecharts', 'device_mobile', 'device_tablet'
```

In [23]:
```
predictors15.head()
```

Out[23]:

	basket_icon_click	basket_add_list	basket_add_detail	list_size_dropdown	checked_delivery_d
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	0	0	
4	0	1	0	1	

In [24]:
```
predictors02.head()
```

Out[24]:

	basket_icon_click	basket_add_list	basket_add_detail	sort_by	image_picker	account_page_c
0	0	0	0	0	0	
1	0	0	0	0	0	
2	0	0	0	0	0	
3	0	0	0	0	0	
4	0	1	0	1	0	

In [25]:
```
target = training['ordered']
```

In [26]:
```
X_train15, X_test15, y_train15, y_test15 = train_test_split(predictors15, target

print( "Predictor - Training : ", X_train15.shape, "Predictor - Testing : ", X_t
```

```
Predictor - Training :  (341550, 8) Predictor - Testing :  (113851, 8)
```

In [27]:
```
X_train02, X_test02, y_train02, y_test02 = train_test_split(predictors02, target

print( "Predictor - Training : ", X_train02.shape, "Predictor - Testing : ", X_t
```

```
Predictor - Training :  (341550, 20) Predictor - Testing :  (113851, 20)
```

Building a Predictions Model

In [28]:
```
from sklearn.naive_bayes import GaussianNB
from sklearn.linear_model import LogisticRegression

from sklearn.metrics import confusion_matrix
from sklearn.metrics import accuracy_score
```

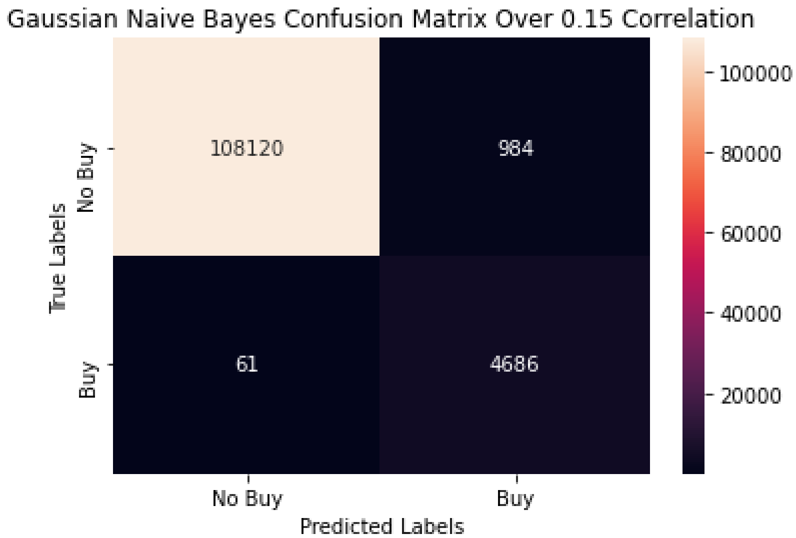
In [29]:
```
classifier = GaussianNB()
classifier = classifier.fit(X_train15, y_train15)
```

In [30]:
```
predictions15 = classifier.predict(X_test15)
```

In [31]:
```
confusion_matrix(y_test15, predictions15)
```

Out[31]:
```
array([[108120,    984],
       [    61,   4686]])
```

In [32]:
```
cm=confusion_matrix(y_test15, predictions15)

ax = plt.subplot()
sns.heatmap(cm, annot=True, fmt='g', ax=ax)

ax.set_xlabel('Predicted Labels');ax.set_ylabel('True Labels');
ax.set_title('Gaussian Naive Bayes Confusion Matrix Over 0.15 Correlation');
ax.xaxis.set_ticklabels(['No Buy', 'Buy']);ax.yaxis.set_ticklabels(['No Buy', 'B

plt.show()
```



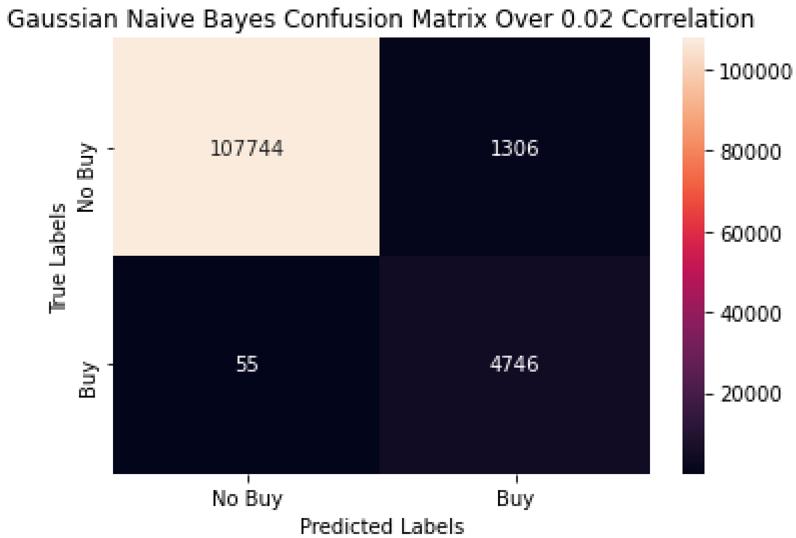
In [33]:
```
accuracy_score(y_test15, predictions15)
```
Out[33]: 0.9908213366593179

In [34]:
```
classifier = GaussianNB()
classifier = classifier.fit(X_train02, y_train02)
```

In [35]:
```
predictions02 = classifier.predict(X_test02)
```

In [36]:
```
confusion_matrix(y_test02, predictions02)
```
Out[36]:
```
array([[107744,   1306],
       [    55,   4746]])
```

In [37]:
```
cm=confusion_matrix(y_test02, predictions02)

ax = plt.subplot()
sns.heatmap(cm, annot=True, fmt='g', ax=ax)

ax.set_xlabel('Predicted Labels');ax.set_ylabel('True Labels');
ax.set_title('Gaussian Naive Bayes Confusion Matrix Over 0.02 Correlation');
ax.xaxis.set_ticklabels(['No Buy', 'Buy']);ax.yaxis.set_ticklabels(['No Buy', 'B

plt.show()
```



In [38]:
```
accuracy_score(y_test02, predictions02)
```

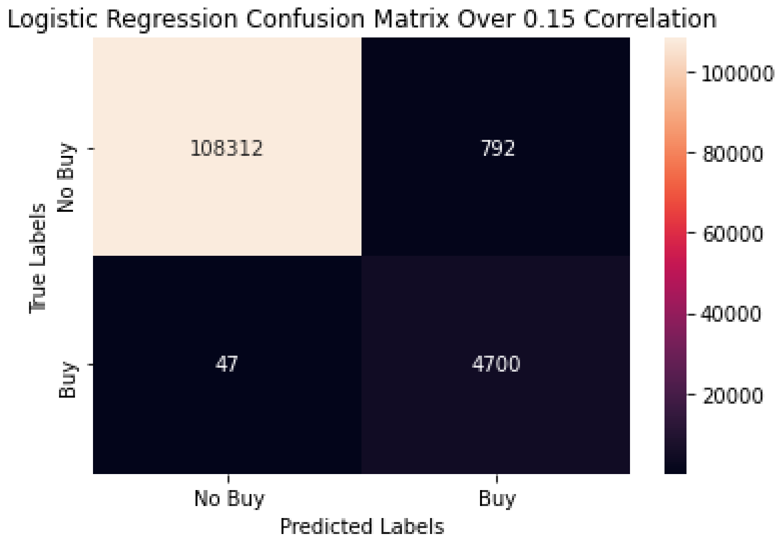
Out[38]: 0.9880457791323748

In [39]:
```
log = LogisticRegression()
```

In [40]:
```
log = log.fit(X_train15, y_train15)
```

In [41]:
```
logPredict15 = log.predict(X_test15)
```

In [42]:
```
cm=confusion_matrix(y_test15, logPredict15)

ax = plt.subplot()
sns.heatmap(cm, annot=True, fmt='g', ax=ax)

ax.set_xlabel('Predicted Labels');ax.set_ylabel('True Labels');
ax.set_title('Logistic Regression Confusion Matrix Over 0.15 Correlation');
ax.xaxis.set_ticklabels(['No Buy', 'Buy']);ax.yaxis.set_ticklabels(['No Buy', 'B

plt.show()
```



In [43]:
```
confusion_matrix(y_test15, logPredict15)
```

Out[43]:
```
array([[108312,    792],
       [    47,   4700]])
```

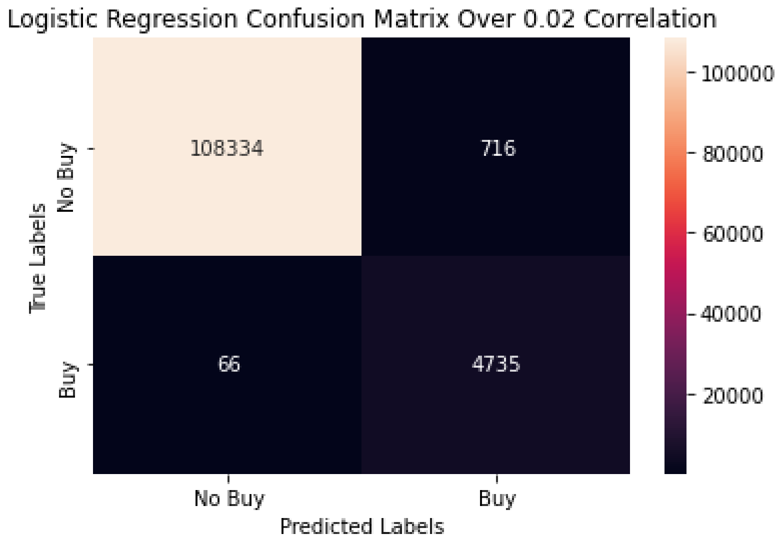
In [44]:
```
accuracy_score(y_test15, logPredict15)
```

Out[44]:
```
0.9926307190977681
```

In [45]:
```
log = LogisticRegression()
log = log.fit(X_test02, y_test02)
```

In [46]:
```
logPredict02 = log.predict(X_test02)
```

In [47]:
```
cm=confusion_matrix(y_test02, logPredict02)

ax = plt.subplot()
sns.heatmap(cm, annot=True, fmt='g', ax=ax)

ax.set_xlabel('Predicted Labels');ax.set_ylabel('True Labels');
ax.set_title('Logistic Regression Confusion Matrix Over 0.02 Correlation');
ax.xaxis.set_ticklabels(['No Buy', 'Buy']);ax.yaxis.set_ticklabels(['No Buy', 'B

plt.show()
```



In [48]:

```
confusion_matrix(y_test02, logPredict02)
```

Out[48]:

```
array([[108334,    716],
       [    66,   4735]])
```

In [49]:

```
accuracy_score(y_test02, logPredict02)
```

Out[49]:

```
0.9931313734618054
```

In [50]:

```
from sklearn.model_selection import GridSearchCV

LRparams = [{'penalty': ['none', 'l1', 'l2', 'elasticnet'], 'C': [0.001, 0.01, 0
```

In [51]:

```
LR_grid_search = GridSearchCV(estimator = LogisticRegression(),
                              param_grid = LRparams,
                              scoring = 'accuracy',
                              cv = 10,
                              n_jobs = -1)

LR_grid_search.fit(X_train15, y_train15)
bestLR = LR_grid_search.best_score_
bestParams = LR_grid_search.best_params_
print('Best Accuracy of Over 0.15 Correlation on Logistic Regression: ', bestLR)
print('Best Params of Over 0.15 Correlation on Logistic Regression: ', bestParam
```

```
/Users/wrasmussen/opt/anaconda3/lib/python3.7/site-packages/sklearn/model_select
ion/_search.py:925: UserWarning: One or more of the test scores are non-finite:
[0.99311667        nan 0.99195725        nan 0.99311667        nan
 0.99295564        nan 0.99311667        nan 0.99310789        nan
 0.99311667        nan 0.99311667        nan 0.99311667        nan
 0.99311667        nan 0.99311667        nan 0.99311667        nan]
  category=UserWarning
/Users/wrasmussen/opt/anaconda3/lib/python3.7/site-packages/sklearn/linear_mode
l/_logistic.py:1323: UserWarning: Setting penalty='none' will ignore the C and l
1_ratio parameters
  "Setting penalty='none' will ignore the C and l1_ratio "
Best Accuracy of Over 0.15 Correlation on Logistic Regression:  0.99311667398623
92
```

```
Best Params of Over 0.15 Correlation on Logistic Regression:  {'C': 0.001, 'pena
lty': 'none'}
```

In [52]:

```
LR_grid_search = GridSearchCV(estimator = LogisticRegression(),
                            param_grid = LRparams,
                            scoring = 'accuracy',
                            cv = 10,
                            n_jobs = -1)

LR_grid_search.fit(X_train02, y_train02)
bestLR = LR_grid_search.best_score_
bestParams = LR_grid_search.best_params_
print('Best Accuracy of Over 0.02 Correlation on Logistic Regression: ', bestLR)
print('Best Params of Over 0.02 Correlation on Logistic Regression: ', bestParam
```

```
/Users/wrasmussen/opt/anaconda3/lib/python3.7/site-packages/sklearn/model_select
ion/_search.py:925: UserWarning: One or more of the test scores are non-finite:
[0.99315766        nan 0.99197775        nan 0.99315766        nan
 0.99297321        nan 0.99315766        nan 0.99313717        nan
 0.99315766        nan 0.99316059        nan 0.99315766        nan
 0.99315766        nan 0.99315766        nan 0.99315766        nan]
  category=UserWarning
Best Accuracy of Over 0.02 Correlation on Logistic Regression:  0.99316059142146
1
Best Params of Over 0.02 Correlation on Logistic Regression:  {'C': 1, 'penalt
y': 'l2'}
```

In [53]:

```
GNB_params = {'var_smoothing': np.logspace(0,-9, num=100)}
```

In [54]:

```
GNB_grid_search = GridSearchCV(estimator = GaussianNB(),
                            param_grid = GNB_params,
                            scoring = 'accuracy',
                            cv = 10,
                            n_jobs = -1)

GNB_grid_search.fit(X_train15, y_train15)
bestGNB = GNB_grid_search.best_score_
bestParams = GNB_grid_search.best_params_
print('Best Accuracy of Over 0.15 Correlation on Logistic Regression: ', bestGNB
print('Best Params of Over 0.15 Correlation on Logistic Regression: ', bestParam
```

```
Best Accuracy of Over 0.15 Correlation on Logistic Regression:  0.99292636510027
81
Best Params of Over 0.15 Correlation on Logistic Regression:  {'var_smoothing':
0.008111308307896872}
```

In [55]:

```
GNB_grid_search.fit(X_train02, y_train02)
bestGNB = GNB_grid_search.best_score_
bestParams = GNB_grid_search.best_params_
print('Best Accuracy of Over 0.02 Correlation on Logistic Regression: ', bestGNB
print('Best Params of Over 0.02 Correlation on Logistic Regression: ', bestParam
```

```
Best Accuracy of Over 0.02 Correlation on Logistic Regression:  0.98857561118430
69
Best Params of Over 0.02 Correlation on Logistic Regression:  {'var_smoothing':
0.001}
```

Based on the results of the hyperparameter tuning used here we can conclude that the Logistic

Regression we used is the best model for that. We can also see that for the Gaussian Naive Bayes we can increase our scores by using a var_smoothing of 0.008111308307896872. Let's run that model for use in propensity modeling to compare to Logistic Regression.

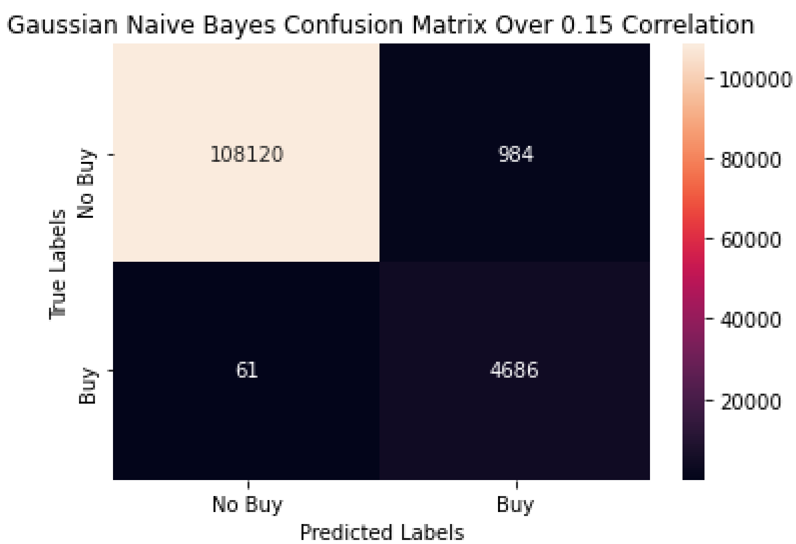
In [56]:
```
gnb = GaussianNB(var_smoothing = 0.008111308307896872)
gnb = classifier.fit(X_train15, y_train15)
```

In [57]:
```
predictions15 = gnb.predict(X_test15)
```

In [58]:
```
confusion_matrix(y_test15, predictions15)
```

Out[58]:
```
array([[108120,    984],
       [    61,   4686]])
```

In [59]:
```
cm=confusion_matrix(y_test15, predictions15)

ax = plt.subplot()
sns.heatmap(cm, annot=True, fmt='g', ax=ax)

ax.set_xlabel('Predicted Labels');ax.set_ylabel('True Labels');
ax.set_title('Gaussian Naive Bayes Confusion Matrix Over 0.15 Correlation');
ax.xaxis.set_ticklabels(['No Buy', 'Buy']);ax.yaxis.set_ticklabels(['No Buy', 'B

plt.show()
```



In [60]:
```
accuracy_score(y_test15, predictions15)
```

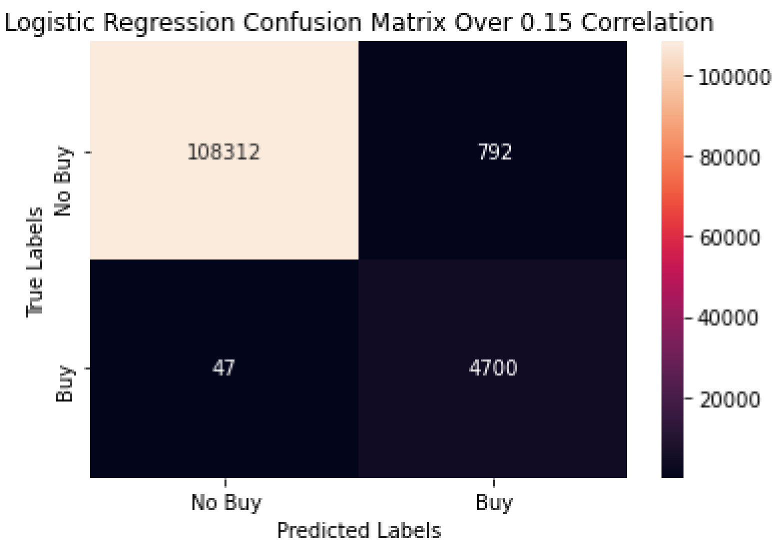
Out[60]: 0.9908213366593179

In [61]:
```
log15 = LogisticRegression()
```

In [62]:
```
log15 = log15.fit(X_train15, y_train15)
```

In [63]:
```
logPredict15 = log15.predict(X_test15)
```

In [64]:
```
cm=confusion_matrix(y_test15, logPredict15)

ax = plt.subplot()
sns.heatmap(cm, annot=True, fmt='g', ax=ax)

ax.set_xlabel('Predicted Labels');ax.set_ylabel('True Labels');
ax.set_title('Logistic Regression Confusion Matrix Over 0.15 Correlation');
ax.xaxis.set_ticklabels(['No Buy', 'Buy']);ax.yaxis.set_ticklabels(['No Buy', 'B

plt.show()
```



In [65]:
```
accuracy_score(y_test15, logPredict15)
```

Out[65]: 0.9926307190977681

Based on the results of these models we can deduct that the Logistic Regression or Gaussian Naive Bayes with Over 0.15 Correlation are the strongest models. These will be used going forward in the propensity modeling.

Propensity Modeling

In this step we will be validating across a different data set from yesterday's shoppers to see the probability they would purchase.

In [66]:
```
user_id = testing.UserID

yesterday = testing[['basket_icon_click', 'basket_add_list', 'basket_add_detail'
                        'checked_delivery_detail', 'sign_in', 'saw_checkout', 's
```

In [67]:
```
yesterday.shape
```

Out[67]: (151655, 8)

In [68]:
```
yesterday['propensity'] = log15.predict_proba(yesterday)[:,1]
```

```
/Users/wrasmussen/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.p
y:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

In [69]:
```
yesterday.head()
```

Out[69]:

	basket_icon_click	basket_add_list	basket_add_detail	list_size_dropdown	checked_delivery_de
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	1	0	
4	0	0	0	0	

In [70]:
```
yesterday.propensity.describe()
```

Out[70]:
```
count    1.516550e+05
mean     7.176702e-03
std      7.534979e-02
min      9.780716e-07
25%      3.342061e-06
50%      3.342061e-06
75%      4.299185e-06
max      9.598575e-01
Name: propensity, dtype: float64
```

In [106…
```
yesterday = pd.concat([user_id, yesterday], axis=1)
```

In [107…
```
yesterday.head()
```

Out[107…

	UserID	basket_icon_click	basket_add_list	basket_add_detail	list_size_dropdown	checke
0	9d24-25k4-47889d24-25k4-494b-398124	0	0	0	0	
1	7732-1k58-47887732-1k58-4475-679678	0	0	0	0	

	UserID	basket_icon_click	basket_add_list	basket_add_detail	list_size_dropdown	checke
2	94k2-632j-471394k2-632j-4b4j-228160	0	0	0	0	
3	jdd8-419d-4714jdd8-419d-4198-674376	0	0	1	0	
4	7473-7595-47147473-7595-4757-227547	0	0	0	0	

In [71]:

```
yesterdayGNB = testing[['basket_icon_click', 'basket_add_list', 'basket_add_deta
                        'checked_delivery_detail', 'sign_in', 'saw_checkout', 's
```

In [72]:

```
yesterdayGNB['propensity'] = gnb.predict_proba(yesterdayGNB)[:,1]
```

```
/Users/wrasmussen/opt/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.p
y:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stab
le/user_guide/indexing.html#returning-a-view-versus-a-copy
  """Entry point for launching an IPython kernel.
```

In [73]:

```
yesterdayGNB.head()
```

Out[73]:

	basket_icon_click	basket_add_list	basket_add_detail	list_size_dropdown	checked_delivery_d
0	0	0	0	0	
1	0	0	0	0	
2	0	0	0	0	
3	0	0	1	0	
4	0	0	0	0	

In [74]:

```
yesterdayGNB.propensity.describe()
```

Out[74]:

```
count    151655.000000
mean          0.009587
std           0.094510
min           0.000000
25%           0.000000
50%           0.000000
75%           0.000000
```

```
max             1.000000
Name: propensity, dtype: float64
```

In [108…

```python
yesterdayGNB = pd.concat([user_id, yesterdayGNB], axis=1)
```

In [109…

```python
target = yesterday[yesterday['propensity'] >= 0.5]
```

In [110…

```python
target.shape
```

Out[110…

```
(1182, 10)
```

In [113…

```python
target.head()
```

Out[113…

	UserID	basket_icon_click	basket_add_list	basket_add_detail	list_size_dropdown	chec
5	7j3d-j382-47157j3d-j382-4d3b-955343	1	0	1	1	
23	743b-08d2-4717743b-08d2-4634-230774	1	1	1	1	
58	b488-015d-472bb488-015d-4k88-211609	1	0	1	0	
162	7281-j047-47557281-j047-4425-872188	1	0	1	0	
287	0660-49k5-47890660-49k5-4070-438513	1	1	1	0	

In [111…

```python
target1 = yesterdayGNB[yesterdayGNB['propensity'] >= 0.5]
```

In [112…

```python
target1.shape
```

Out[112…

```
(1458, 10)
```

In [114…

```
target1.head()
```

Out[114…

	UserID	basket_icon_click	basket_add_list	basket_add_detail	list_size_dropdown	chec
5	7j3d-j382-47157j3d-j382-4d3b-955343	1	0	1	1	
23	743b-08d2-4717743b-08d2-4634-230774	1	1	1	1	
58	b488-015d-472bb488-015d-4k88-211609	1	0	1	0	
162	7281-j047-47557281-j047-4425-872188	1	0	1	0	
287	0660-49k5-47890660-49k5-4070-438513	1	1	1	0	

Results

Logistic Regression
Logistic Regression identified 1182 different users from yesterday with a propensity to purchase over 0.5 which means they are statistically more likely to purchase than not purchase.

Gaussian Naive Bayes
Using Gaussian Naive Bayes found 1458 different users from yesterday with a propensity to purchase over 0.5 which means they are statistically more likely to purhcase than not purchase.

Using These Results
From here now that we have the user_ids connected to the propensity to buy within the dataset we can start to target those users since they are most likely to purchase. We could export the dataframe in a csv format to pass onto sales to target or could export in another format as well.

In [ ]: