In [1]:
```
import pandas as pd
import numpy as np

import matplotlib as pyplot
import matplotlib.pyplot as plt; plt.rcdefaults()
import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns
```

In [2]:
```
df = pd.read_csv('train.csv')
```

# Review the data set

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

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 12 columns):
 #   Column                      Non-Null Count   Dtype  
---  ------                      --------------   -----  
 0   User_ID                     550068 non-null  int64  
 1   Product_ID                  550068 non-null  object 
 2   Gender                      550068 non-null  object 
 3   Age                         550068 non-null  object 
 4   Occupation                  550068 non-null  int64  
 5   City_Category               550068 non-null  object 
 6   Stay_In_Current_City_Years  550068 non-null  object 
 7   Marital_Status              550068 non-null  int64  
 8   Product_Category_1          550068 non-null  int64  
 9   Product_Category_2          376430 non-null  float64
 10  Product_Category_3          166821 non-null  float64
 11  Purchase                    550068 non-null  int64  
dtypes: float64(2), int64(5), object(5)
memory usage: 50.4+ MB
```

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

Out[4]:

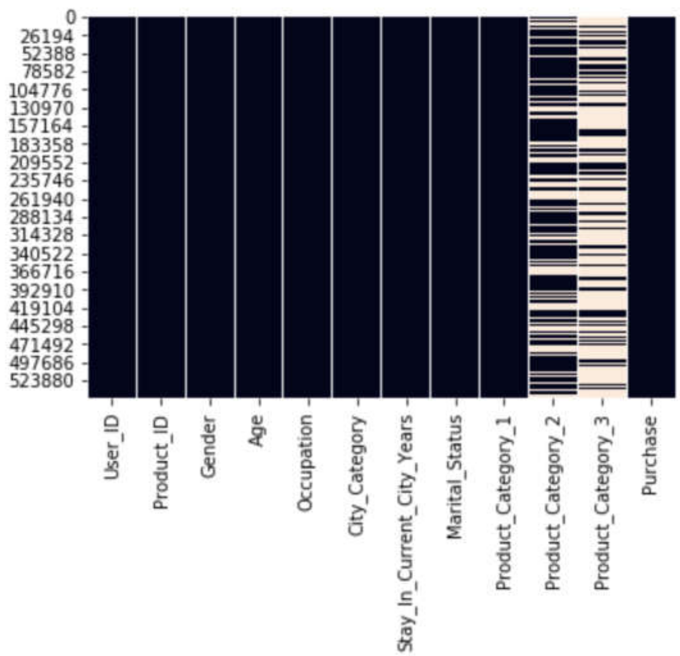
| | User_ID | Occupation | Marital_Status | Product_Category_1 | Product_Category_2 | Product_Categor |
|---|---|---|---|---|---|---|
| **count** | 5.500680e+05 | 550068.000000 | 550068.000000 | 550068.000000 | 376430.000000 | 166821.000 |
| **mean** | 1.003029e+06 | 8.076707 | 0.409653 | 5.404270 | 9.842329 | 12.668 |
| **std** | 1.727592e+03 | 6.522660 | 0.491770 | 3.936211 | 5.086590 | 4.125 |
| **min** | 1.000001e+06 | 0.000000 | 0.000000 | 1.000000 | 2.000000 | 3.000 |
| **25%** | 1.001516e+06 | 2.000000 | 0.000000 | 1.000000 | 5.000000 | 9.000 |
| **50%** | 1.003077e+06 | 7.000000 | 0.000000 | 5.000000 | 9.000000 | 14.000 |
| **75%** | 1.004478e+06 | 14.000000 | 1.000000 | 8.000000 | 15.000000 | 16.000 |
| **max** | 1.006040e+06 | 20.000000 | 1.000000 | 20.000000 | 18.000000 | 18.000 |

In [5]:
```
df.head()
```
Out[5]:

| | User_ID | Product_ID | Gender | Age | Occupation | City_Category | Stay_In_Current_City_Years | Marital_Status |
|---|---|---|---|---|---|---|---|---|
| **0** | 1000001 | P00069042 | F | 0-17 | 10 | A | 2 | 0 |
| **1** | 1000001 | P00248942 | F | 0-17 | 10 | A | 2 | 0 |
| **2** | 1000001 | P00087842 | F | 0-17 | 10 | A | 2 | 0 |
| **3** | 1000001 | P00085442 | F | 0-17 | 10 | A | 2 | 0 |
| **4** | 1000002 | P00285442 | M | 55+ | 16 | C | 4+ | 0 |

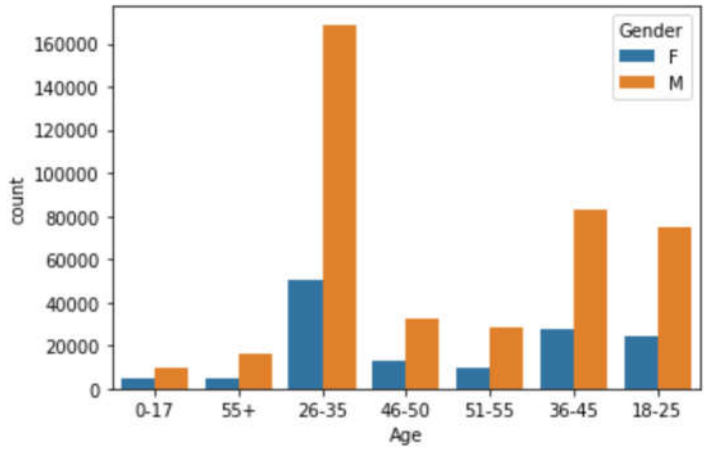
In [6]:
```
df['Product_Category_1'].unique()
```
Out[6]:
```
array([ 3,  1, 12,  8,  5,  4,  2,  6, 14, 11, 13, 15,  7, 16, 18, 10, 17,
        9, 20, 19], dtype=int64)
```

In [7]:
```
sns.heatmap(df.isnull(), cbar=False)
```
Out[7]: <matplotlib.axes._subplots.AxesSubplot at 0x1f9bebf3108>

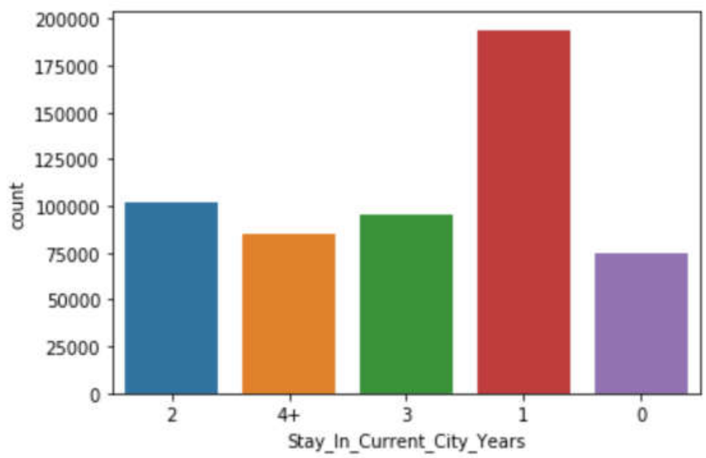



In [8]:
```
# Clear null values
df.isnull().sum()
```
Out[8]:
```
User_ID                            0
Product_ID                         0
Gender                             0
Age                                0
Occupation                         0
City_Category                      0
Stay_In_Current_City_Years         0
Marital_Status                     0
Product_Category_1                 0
Product_Category_2            173638
Product_Category_3            383247
Purchase                           0
dtype: int64
```

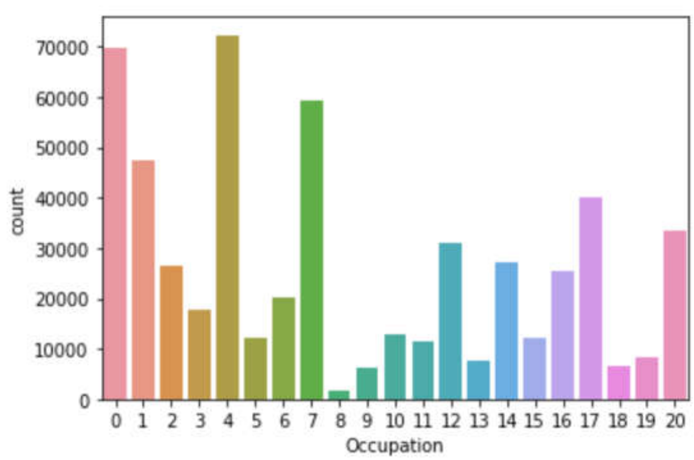
In [9]:
```
sns.countplot(df['Age'], hue=df['Gender'])
```
Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1f9c10e1c08>



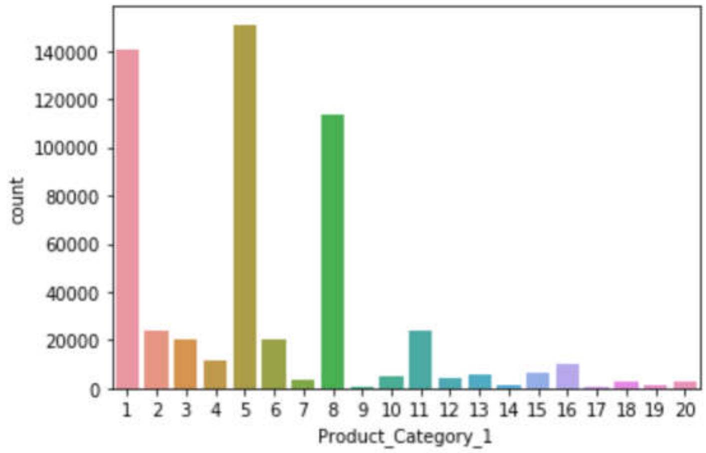

In [10]:
```
sns.countplot(df['Stay_In_Current_City_Years'])
```
Out[10]: <matplotlib.axes._subplots.AxesSubplot at 0x1f9c16b47c8>



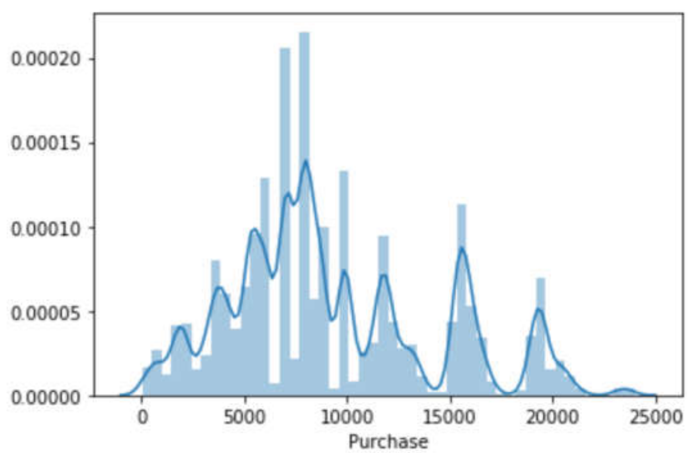

In [11]:
```
sns.countplot(df['Occupation'])
```
Out[11]: <matplotlib.axes._subplots.AxesSubplot at 0x1f9c1488ec8>



In [12]:
```
sns.countplot(df['Product_Category_1'])
```
Out[12]: <matplotlib.axes._subplots.AxesSubplot at 0x1f9c1d63288>




In [13]:
```
sns.distplot(df['Purchase'])
```
Out[13]: <matplotlib.axes._subplots.AxesSubplot at 0x1f9c13d6288>




We have labeled data - can use supervised learning We want to predict how much $$$ people spend - regression task

When we think about sales - consider demographic (age/gender/income/home), store (location/size/ads/product stock)

In [14]:
```
print(df['Product_ID'].unique())
print(len(df['Product_ID'].unique()))
```
```
['P00069042' 'P00248942' 'P00087842' ... 'P00370293' 'P00371644'
 'P00370853']
3631
```

# Prepare data

In [15]:
```
X = df.drop(['Purchase', 'Product_Category_2', 'Product_Category_3'], axis=1)
```

In [16]:
```
for cat in ['Age', 'City_Category', 'Stay_In_Current_City_Years']:
    tmp = pd.get_dummies(X[cat], prefix=cat, drop_first=True)
    X.drop(cat, axis=1, inplace=True)
    X = pd.concat([X, tmp], axis=1)
```

In [17]:
```
X['Gender'] = pd.get_dummies(X['Gender'], drop_first=True)
```

In [18]:
```
from sklearn.preprocessing import LabelEncoder

for c in ['Product_ID']:
    enc = LabelEncoder()
    X[c] = enc.fit_transform(X[c])
```

In [19]:
```
X["Occupation"] = X["Occupation"].astype('category')
```

In [20]:
```
X.head()
```

Out[20]:

| | User_ID | Product_ID | Gender | Occupation | Marital_Status | Product_Category_1 | Age_18-25 | Age_26-35 | Age_ |
|---|---|---|---|---|---|---|---|---|---|
| **0** | 1000001 | 672 | 0 | 10 | 0 | 3 | 0 | 0 | |
| **1** | 1000001 | 2376 | 0 | 10 | 0 | 1 | 0 | 0 | |
| **2** | 1000001 | 852 | 0 | 10 | 0 | 12 | 0 | 0 | |
| **3** | 1000001 | 828 | 0 | 10 | 0 | 12 | 0 | 0 | |
| **4** | 1000002 | 2734 | 1 | 16 | 0 | 8 | 0 | 0 | |

In [21]:
```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 550068 entries, 0 to 550067
Data columns (total 18 columns):
 #   Column                        Non-Null Count   Dtype
---  ------                        --------------   -----
 0   User_ID                       550068 non-null  int64
 1   Product_ID                    550068 non-null  int32
 2   Gender                        550068 non-null  uint8
 3   Occupation                    550068 non-null  category
 4   Marital_Status                550068 non-null  int64
 5   Product_Category_1            550068 non-null  int64
 6   Age_18-25                     550068 non-null  uint8
 7   Age_26-35                     550068 non-null  uint8
 8   Age_36-45                     550068 non-null  uint8
 9   Age_46-50                     550068 non-null  uint8
 10  Age_51-55                     550068 non-null  uint8
 11  Age_55+                       550068 non-null  uint8
 12  City_Category_B               550068 non-null  uint8
 13  City_Category_C               550068 non-null  uint8
 14  Stay_In_Current_City_Years_1  550068 non-null  uint8
 15  Stay_In_Current_City_Years_2  550068 non-null  uint8
 16  Stay_In_Current_City_Years_3  550068 non-null  uint8
 17  Stay_In_Current_City_Years_4+ 550068 non-null  uint8
dtypes: category(1), int32(1), int64(3), uint8(13)
memory usage: 22.0 MB
```

In [22]:
```
y = df["Purchase"]
```

In [23]:
```
X = X.drop(["User_ID"], axis=1)
```

In [24]:
```
from sklearn.preprocessing import StandardScaler
```

In [25]:
```
scaler = StandardScaler()
Xs = scaler.fit_transform(X)
```

## Regression Model Comparison

In [26]:
```
import sklearn
import xgboost as xgb

from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestRegressor
from sklearn.ensemble import GradientBoostingRegressor
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsRegressor
from sklearn.linear_model import Ridge
from sklearn.linear_model import Lasso
from sklearn.preprocessing import PolynomialFeatures
from sklearn import svm
```

In [27]:
```
from sklearn import metrics

def get_metrics(reg, y_test, y_pred):
    res = []

    res.append(str(reg.__class__.__name__))
    mae = metrics.mean_absolute_error(y_test, y_pred)
    res.append(mae)
    mse = metrics.mean_squared_error(y_test, y_pred)
    res.append(mse)
    rmse = np.sqrt(metrics.mean_squared_error(y_test, y_pred))
    res.append(rmse)
    r2 = metrics.r2_score(y_test, y_pred)
    res.append(r2)

    return res

def show_metrics(res):
    print(res[0])
    print(' MAE : ', res[1])
    print(' MSE : ', res[2])
    print(' RMSE: ', res[3])
    print(' R^2 : ', res[4])
```

In [28]:
```
X_train, X_test, y_train, y_test = train_test_split(Xs, y, test_size = 1/3, random_
state = 0)
```

In [29]:
```
# Start with plolynomial regression
pf = PolynomialFeatures(degree=2)
X_poly_train = pf.fit_transform(X_train)
X_poly_test = pf.fit_transform(X_test)
```

In [30]:
```
lr = LinearRegression()
lr.fit(X_poly_train, y_train)
```

Out[30]:
```
LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize=False)
```

In [31]:
```
y_pred = lr.predict(X_poly_test)
print(y_pred)
```

```
[13555.  5193.  8640. ...  7041.  7711. 12155.]
```

In [32]:
```
results = []
m = get_metrics(lr, y_test, y_pred)
m[0] = 'PolynomialRegression'
show_metrics(m)
results.append(m)
```

```
PolynomialRegression
 MAE :  3309.958206985318
 MSE :  19261757.748472918
 RMSE:  4388.821908949248
 R^2 :  0.23849121551232466
```

In [33]:
```
regressors = [
    Ridge(alpha=.5),
    Lasso(alpha=0.1),
    LinearRegression(),
    DecisionTreeRegressor(),
    RandomForestRegressor(),
    GradientBoostingRegressor(),
    xgb.XGBRegressor(objective ='reg:squarederror', colsample_bytree = 0.3, learnin
g_rate = 0.1,
                     max_depth = 5, alpha = 10, n_estimators = 10),
    # svm.SVC(kernel='rbf', gamma=0.7, C=1.0),
    KNeighborsRegressor(n_neighbors=3)
]

### Commented out regressors are processing over 100 minutes
```

```
In [34]: for r in regressors:
             print('========================================================================
==============')
             print('Running %s' % (r))
             r.fit(X_train, y_train)
             # print('Accuracy score for %s is %s' % (r, r.score(X_test, y_test) * 100))
             m = get_metrics(r, y_test, r.predict(X_test))
             show_metrics(m)
             results.append(m)
             print('========================================================================
==============')
             print('')
```

```
================================================================================
======
Running Ridge(alpha=0.5, copy_X=True, fit_intercept=True, max_iter=None,
      normalize=False, random_state=None, solver='auto', tol=0.001)
Ridge
 MAE :  3593.7867622984763
 MSE :  21952039.018481284
 RMSE:  4685.300312518002
 R^2 :  0.1321316170475142
================================================================================
======

================================================================================
======
Running Lasso(alpha=0.1, copy_X=True, fit_intercept=True, max_iter=1000,
      normalize=False, positive=False, precompute=False, random_state=None,
      selection='cyclic', tol=0.0001, warm_start=False)
Lasso
 MAE :  3593.7848869242807
 MSE :  21952043.356074445
 RMSE:  4685.300775411803
 R^2 :  0.1321314455618513
================================================================================
======

================================================================================
======
Running LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize
=False)
LinearRegression
 MAE :  3593.786431714285
 MSE :  21952039.006256834
 RMSE:  4685.300311213448
 R^2 :  0.13213161753080482
================================================================================
======

================================================================================
======
Running DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='deprecated',
                      random_state=None, splitter='best')
DecisionTreeRegressor
 MAE :  2630.8304546378868
 MSE :  13872403.005075026
 RMSE:  3724.5674923506253
 R^2 :  0.45155801000791973
================================================================================
======

================================================================================
======
Running RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
RandomForestRegressor
 MAE :  2104.1033457206127
```

## Try ANN

In [35]:
```
from sklearn.pipeline import Pipeline
from sklearn.preprocessing import MinMaxScaler
from keras.optimizers import Adam
from keras.models import Sequential
from keras.layers import Dense
from keras.wrappers.scikit_learn import KerasRegressor
```

```
Using TensorFlow backend.
```

In [36]:
```
model = Sequential()
model.add(Dense(17, input_dim=17, kernel_initializer='normal', activation='relu'))
model.add(Dense(27, activation='relu'))
model.add(Dense(11, activation='relu'))
model.add(Dense(3, activation='relu'))
model.add(Dense(1, activation='relu'))

optimizer = Adam(lr=0.35)
model.compile(loss='mse', optimizer=optimizer, metrics=['mse', 'mae'])
```

In [37]:

```
model.fit(X_train, y_train, epochs=300, batch_size=5000, verbose=1)
```

```
Epoch 1/300
366712/366712 [==============================] - 0s 1us/step - loss: 26250183.59
21 - mse: 26250192.0000 - mae: 3795.1655
Epoch 2/300
366712/366712 [==============================] - 0s 1us/step - loss: 18074555.00
54 - mse: 18074556.0000 - mae: 3146.5696
Epoch 3/300
366712/366712 [==============================] - 0s 1us/step - loss: 17228205.35
37 - mse: 17228208.0000 - mae: 3051.3696
Epoch 4/300
366712/366712 [==============================] - 0s 1us/step - loss: 16850510.21
17 - mse: 16850510.0000 - mae: 3011.1182
Epoch 5/300
366712/366712 [==============================] - 0s 1us/step - loss: 17581072.35
68 - mse: 17581074.0000 - mae: 3091.6904
Epoch 6/300
366712/366712 [==============================] - 0s 1us/step - loss: 16342514.04
16 - mse: 16342516.0000 - mae: 2964.5261
Epoch 7/300
366712/366712 [==============================] - 0s 1us/step - loss: 15924482.97
80 - mse: 15924482.0000 - mae: 2927.9519
Epoch 8/300
366712/366712 [==============================] - 0s 1us/step - loss: 15766800.70
47 - mse: 15766799.0000 - mae: 2912.5049
Epoch 9/300
366712/366712 [==============================] - 0s 1us/step - loss: 16444965.80
77 - mse: 16444965.0000 - mae: 2979.8274
Epoch 10/300
366712/366712 [==============================] - 0s 1us/step - loss: 16069738.93
82 - mse: 16069736.0000 - mae: 2937.9956
Epoch 11/300
366712/366712 [==============================] - 0s 1us/step - loss: 15010027.29
08 - mse: 15010027.0000 - mae: 2852.6082
Epoch 12/300
366712/366712 [==============================] - 0s 1us/step - loss: 12847770.65
33 - mse: 12847771.0000 - mae: 2656.2136
Epoch 13/300
366712/366712 [==============================] - 0s 1us/step - loss: 12201562.65
25 - mse: 12201563.0000 - mae: 2587.5259
Epoch 14/300
366712/366712 [==============================] - 0s 1us/step - loss: 11538222.25
72 - mse: 11538222.0000 - mae: 2544.5303
Epoch 15/300
366712/366712 [==============================] - 0s 1us/step - loss: 11169928.65
88 - mse: 11169929.0000 - mae: 2525.0774
Epoch 16/300
366712/366712 [==============================] - 0s 1us/step - loss: 10341835.55
42 - mse: 10341836.0000 - mae: 2428.5405
Epoch 17/300
366712/366712 [==============================] - 0s 1us/step - loss: 10086132.49
00 - mse: 10086132.0000 - mae: 2391.1746
Epoch 18/300
366712/366712 [==============================] - 0s 1us/step - loss: 10143938.56
89 - mse: 10143938.0000 - mae: 2388.6416
Epoch 19/300
366712/366712 [==============================] - 0s 1us/step - loss: 10246179.95
99 - mse: 10246182.0000 - mae: 2402.2083
Epoch 20/300
366712/366712 [==============================] - 0s 1us/step - loss: 9908738.943
6 - mse: 9908739.0000 - mae: 2369.1973
Epoch 21/300
366712/366712 [==============================] - 0s 1us/step - loss: 9922185.573
1 - mse: 9922186.0000 - mae: 2365.0410
Epoch 22/300
```

Out[37]: <keras.callbacks.callbacks.History at 0x1fa184128c8>

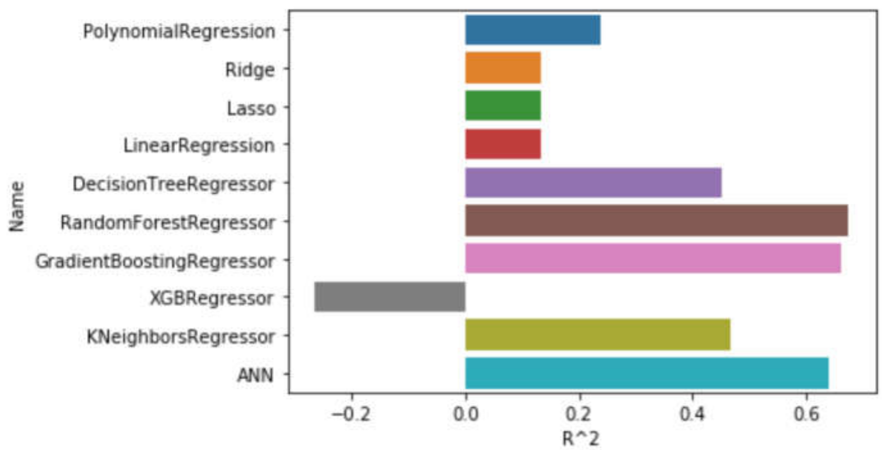
In [38]:
```
m = get_metrics(model, y_test, model.predict(X_test))
m[0] = 'ANN'
show_metrics(m)
results.append(m)
```

```
ANN
 MAE :   2280.8142783018657
 MSE :   9094922.777238183
 RMSE:   3015.778966906922
 R^2 :   0.640434498266234
```

In [39]:
```
res = pd.DataFrame(np.array(results))
res.columns = ['Name', 'MAE', 'MSE', 'RMSE', 'R^2']
```

In [40]:
```
sns.barplot(data=res, y='Name', x='R^2')
```

Out[40]: <matplotlib.axes._subplots.AxesSubplot at 0x1fa24883208>




In [41]:
```
df_r = pd.DataFrame(results)
df_r.head()
```

Out[41]:

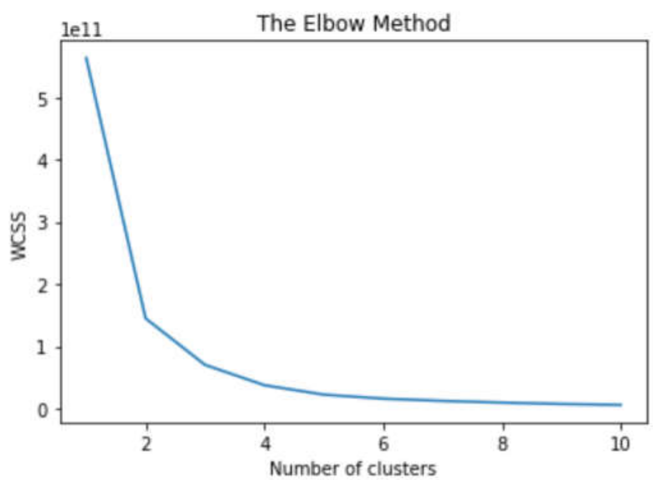
| | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| **0** | PolynomialRegression | 3309.958207 | 1.926176e+07 | 4388.821909 | 0.238491 |
| **1** | Ridge | 3593.786762 | 2.195204e+07 | 4685.300313 | 0.132132 |
| **2** | Lasso | 3593.784887 | 2.195204e+07 | 4685.300775 | 0.132131 |
| **3** | LinearRegression | 3593.786432 | 2.195204e+07 | 4685.300311 | 0.132132 |
| **4** | DecisionTreeRegressor | 2630.830455 | 1.387240e+07 | 3724.567492 | 0.451558 |

# Clustering Algorithm Comparison

### K-Means

In [42]:
```
from sklearn.cluster import KMeans
wcss = []
for i in range(1, 11):
    print("Running KMeans with %s clusters" % (i))
    kmeans = KMeans(n_clusters = i, init = 'k-means++', random_state = 42)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_)
plt.plot(range(1, 11), wcss)
plt.title('The Elbow Method')
plt.xlabel('Number of clusters')
plt.ylabel('WCSS') # sum of squares of the distances of each data point in all clus
ters to their centroids
plt.show()
```

```
Running KMeans with 1 clusters
Running KMeans with 2 clusters
Running KMeans with 3 clusters
Running KMeans with 4 clusters
Running KMeans with 5 clusters
Running KMeans with 6 clusters
Running KMeans with 7 clusters
Running KMeans with 8 clusters
Running KMeans with 9 clusters
Running KMeans with 10 clusters
```




## PCA

In [43]:
```
from sklearn.decomposition import PCA
pca = PCA(n_components = 3)
X_pca = pca.fit_transform(X)
explained_variance = pca.explained_variance_ratio_
```

In [44]:
```
print(explained_variance) # % of variance explained by each of the selected compone
nts
```

```
[9.99941231e-01 4.15276886e-05 1.50365374e-05]
```

In [45]:
```
print(pca.components_)
```

```
[[ 9.99999957e-01  6.78015193e-06  4.78419549e-05  5.64613034e-06
   2.90559777e-04 -5.80060188e-06 -7.43338167e-06  4.90866276e-06
   2.69169851e-06  2.62798511e-06  2.23825144e-06 -2.70419324e-06
   3.99272802e-06 -2.55125162e-07  1.24345339e-06  1.95922614e-07
  -1.46872062e-06]
 [-4.57358766e-05  7.79265580e-03  9.99906755e-01  1.83354708e-03
  -7.73317533e-03 -5.71348649e-03 -1.68022493e-03  3.58707265e-03
   8.55606948e-04  1.20291330e-03  1.30603065e-03 -8.90990100e-04
   2.46657997e-03 -1.58035596e-04 -7.60300602e-04  1.51493781e-03
   7.71763687e-04]
 [-2.90943163e-04 -5.05095526e-03  7.73703507e-03  2.48351949e-03
   9.99938267e-01 -3.49261764e-03 -2.25884654e-03  1.17554421e-03
   1.80871965e-03  1.67135689e-03  1.67204132e-03 -7.35715933e-04
  -1.03593996e-03  7.69793887e-04 -7.45522006e-04 -1.04656767e-03
   6.59269406e-04]]
```

# Feature Selection

In [46]:
```
from sklearn.feature_selection import VarianceThreshold
Xvt = X.copy(deep=True)
sel = VarianceThreshold(threshold=(.8 * (1 - .8)))
sel.fit_transform(Xvt)
```

Out[46]:
```
array([[672, 0, 10, ..., 0, 0, 0],
       [2376, 0, 10, ..., 0, 0, 0],
       [852, 0, 10, ..., 0, 0, 0],
       ...,
       [3568, 0, 15, ..., 1, 0, 0],
       [3568, 0, 1, ..., 0, 1, 0],
       [3566, 0, 0, ..., 1, 0, 0]], dtype=object)
```

In [47]:
```
regressors = [
    LinearRegression(),
    RandomForestRegressor(),
    KNeighborsRegressor(n_neighbors=3)
]

X_train, X_test, y_train, y_test = train_test_split(Xvt, y, test_size = 1/3, random
_state = 0)

for r in regressors:
    print('======================================================================
==============')
    print('Running %s' % (r))
    r.fit(X_train, y_train)

    m = get_metrics(r, y_test, r.predict(X_test))
    show_metrics(m)
    print('======================================================================
==============')
    print('')
```

```
================================================================================
======
Running LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize
=False)
LinearRegression
 MAE :  3593.7864317142844
 MSE :  21952039.006256834
 RMSE:  4685.300311213448
 R^2 :  0.13213161753080482
================================================================================
======

================================================================================
======
Running RandomForestRegressor(bootstrap=True, ccp_alpha=0.0, criterion='mse',
                      max_depth=None, max_features='auto', max_leaf_nodes=None,
                      max_samples=None, min_impurity_decrease=0.0,
                      min_impurity_split=None, min_samples_leaf=1,
                      min_samples_split=2, min_weight_fraction_leaf=0.0,
                      n_estimators=100, n_jobs=None, oob_score=False,
                      random_state=None, verbose=0, warm_start=False)
RandomForestRegressor
 MAE :  2103.764583410758
 MSE :  8209169.894973392
 RMSE:  2865.1648983912587
 R^2 :  0.6754525173659389
================================================================================
======

================================================================================
======
Running KNeighborsRegressor(algorithm='auto', leaf_size=30, metric='minkowski',
                    metric_params=None, n_jobs=None, n_neighbors=3, p=2,
                    weights='uniform')
KNeighborsRegressor
 MAE :  2253.43161572751
 MSE :  9501839.293711567
 RMSE:  3082.505359883672
 R^2 :  0.6243471553614997
================================================================================
======
```

**RFE**

In [48]:
```python
from sklearn.feature_selection import RFE

regressors = [
    LinearRegression(),
    # RandomForestRegressor(),
    DecisionTreeRegressor(),
    GradientBoostingRegressor()
]

X_train, X_test, y_train, y_test = train_test_split(Xvt, y, test_size = 1/3, random_state = 0)

for r in regressors:
    print('======================================================================================')
    print('Running %s' % (r))
    rfe = RFE(r, 3)
    ref = rfe.fit(X_train, y_train)
    print("Regressor: " + str(r.__class__.__name__))
    print("Support")
    print(rfe.support_)
    print("Ranking")
    print(rfe.ranking_)
    print('======================================================================================')
    print('')
```

```
================================================================================
======
Running LinearRegression(copy_X=True, fit_intercept=True, n_jobs=None, normalize
=False)
Regressor: LinearRegression
Support
[False  True False False  True False False False False False False False
  True False False False False]
Ranking
[15  1 14  9  1  7  6  4  5  2  3  8  1 13 10 12 11]
================================================================================
======

================================================================================
======
Running DecisionTreeRegressor(ccp_alpha=0.0, criterion='mse', max_depth=None,
                      max_features=None, max_leaf_nodes=None,
                      min_impurity_decrease=0.0, min_impurity_split=None,
                      min_samples_leaf=1, min_samples_split=2,
                      min_weight_fraction_leaf=0.0, presort='deprecated',
                      random_state=None, splitter='best')
Regressor: DecisionTreeRegressor
Support
[ True False  True False  True False False False False False False False
 False False False False False]
Ranking
[ 1  7  1  4  1 11  5  9 13 14 15  3 12  2  8  6 10]
================================================================================
======

================================================================================
======
Running GradientBoostingRegressor(alpha=0.9, ccp_alpha=0.0, criterion='friedman_
mse',
                          init=None, learning_rate=0.1, loss='ls', max_depth=3,
                          max_features=None, max_leaf_nodes=None,
                          min_impurity_decrease=0.0, min_impurity_split=None,
                          min_samples_leaf=1, min_samples_split=2,
                          min_weight_fraction_leaf=0.0, n_estimators=100,
                          n_iter_no_change=None, presort='deprecated',
                          random_state=None, subsample=1.0, tol=0.0001,
                          validation_fraction=0.1, verbose=0, warm_start=False)
Regressor: GradientBoostingRegressor
Support
[ True False False False  True False False False False False False False
  True False False False False]
Ranking
[ 1  7  2 14  1  8  9  6 13  3  5  4  1 10 11 12 15]
================================================================================
======
```