Dataset Information

This dataset comprises of sales transactions captured at a retail store. It's a classic dataset to explore and expand your feature engineering skills and day to day understanding from multiple shopping experiences. This is a regression problem. The dataset has 550,069 rows and 12 columns.

Attributes:

Column ID	Column Name	Data type	Description	Masked
0	User_ID	int64	Unique Id of customer	False
1	Product_ID	object	Unique Id of product	False
2	Gender	object	Sex of customer	False
3	Age	object	Age of customer	False
4	Occupation	int64	Occupation code of customer	True
5	City_Category	object	City of customer	True
6	Stay_In_Current_City_Years	object	Number of years of stay in city	False
7	Marital_Status	int64	Marital status of customer	False
8	Product_Category_1	int64	Category of product	True
9	Product_Category_2	float64	Category of product	True
10	Product_Category_3	float64	Category of product	True
11	Purchase	int64	Purchase amount	False

Import modules

In [40]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt
import warnings
%matplotlib inline
warnings.filterwarnings('ignore')
```

Loading the dataset

In [41]:
```
df = pd.read_csv('train.csv')
df.head()
```

Out[41]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
0	1000001	P00069042	F	0-17	10	A	2	0	3	NaN	NaN	8370
1	1000001	P00248942	F	0-17	10	A	2	0	1	6.0	14.0	15200
2	1000001	P00087842	F	0-17	10	A	2	0	12	NaN	NaN	1422
3	1000001	P00085442	F	0-17	10	A	2	0	12	14.0	NaN	1057
4	1000002	P00285442	M	55+	16	C	4+	0	8	NaN	NaN	7969

In [42]:
```
# statistical info
df.describe()
```

Out[42]:

	User_ID	Occupation	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
count	5.500680e+05	550068.000000	550068.000000	550068.000000	376430.000000	166821.000000	550068.000000
mean	1.003029e+06	8.076707	0.409653	5.404270	9.842329	12.668243	9263.968713
std	1.727592e+03	6.522660	0.491770	3.936211	5.086590	4.125338	5023.065394
min	1.000001e+06	0.000000	0.000000	1.000000	2.000000	3.000000	12.000000
25%	1.001516e+06	2.000000	0.000000	1.000000	5.000000	9.000000	5823.000000
50%	1.003077e+06	7.000000	0.000000	5.000000	9.000000	14.000000	8047.000000
75%	1.004478e+06	14.000000	1.000000	8.000000	15.000000	16.000000	12054.000000
max	1.006040e+06	20.000000	1.000000	20.000000	18.000000	18.000000	23961.000000

In [43]:
```
# datatype info
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
```

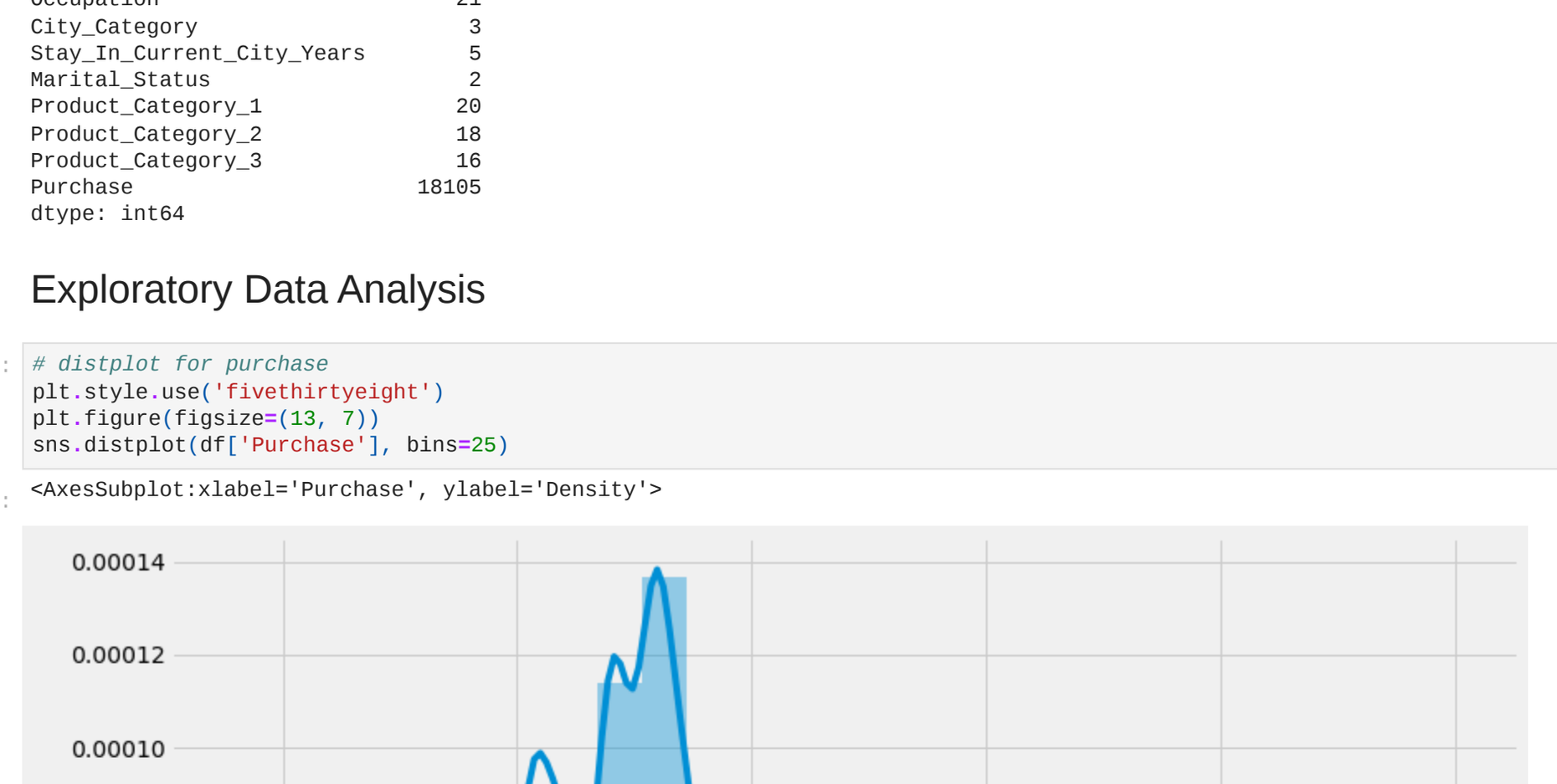
In [44]:
```
# find unique values
df.apply(lambda x: len(x.unique()))
```

Out[44]:
```
User_ID                        5891
Product_ID                     3631
Gender                            2
Age                               7
Occupation                       21
City_Category                     3
Stay_In_Current_City_Years        5
Marital_Status                    2
Product_Category_1               20
Product_Category_2               18
Product_Category_3               16
Purchase                      18105
dtype: int64
```

Exploratory Data Analysis

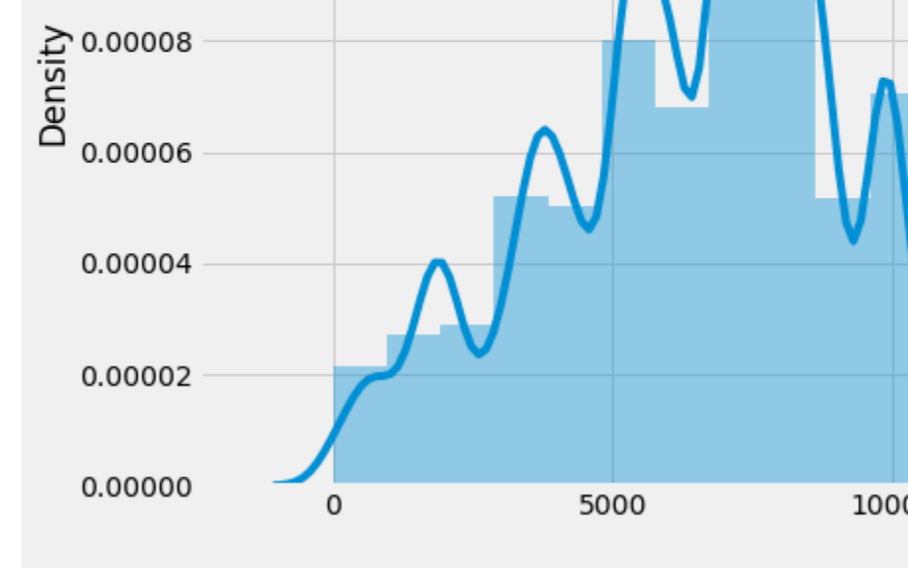
In [45]:
```
# distplot for purchase
plt.style.use('fivethirtyeight')
plt.figure(figsize=(13, 7))
sns.distplot(df['Purchase'], bins=25)
```

Out[45]: <AxesSubplot:xlabel='Purchase', ylabel='Density'>



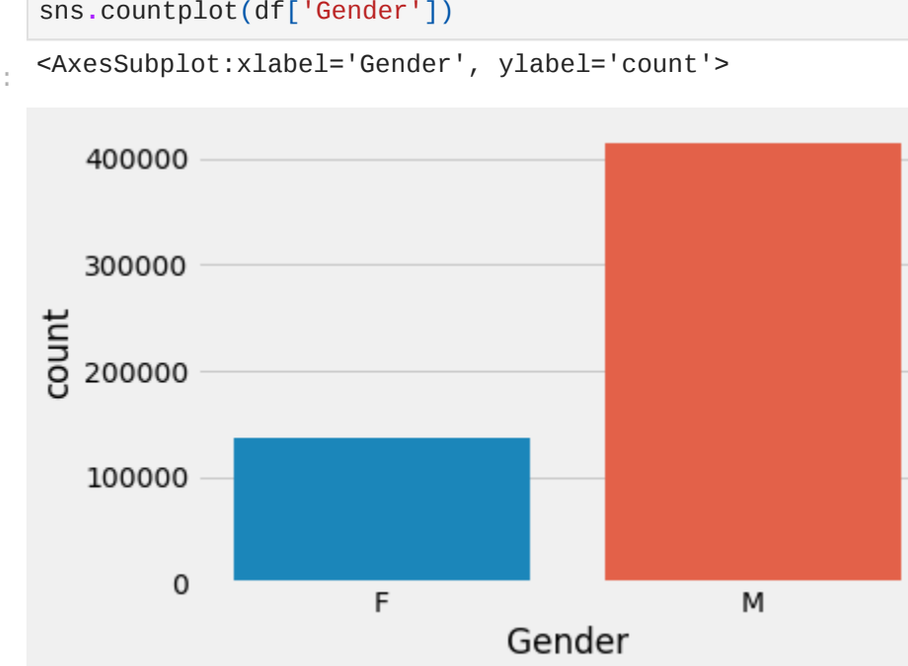
In [46]:
```
# distribution of numeric variables
sns.countplot(df['Gender'])
```

Out[46]: <AxesSubplot:xlabel='Gender', ylabel='count'>



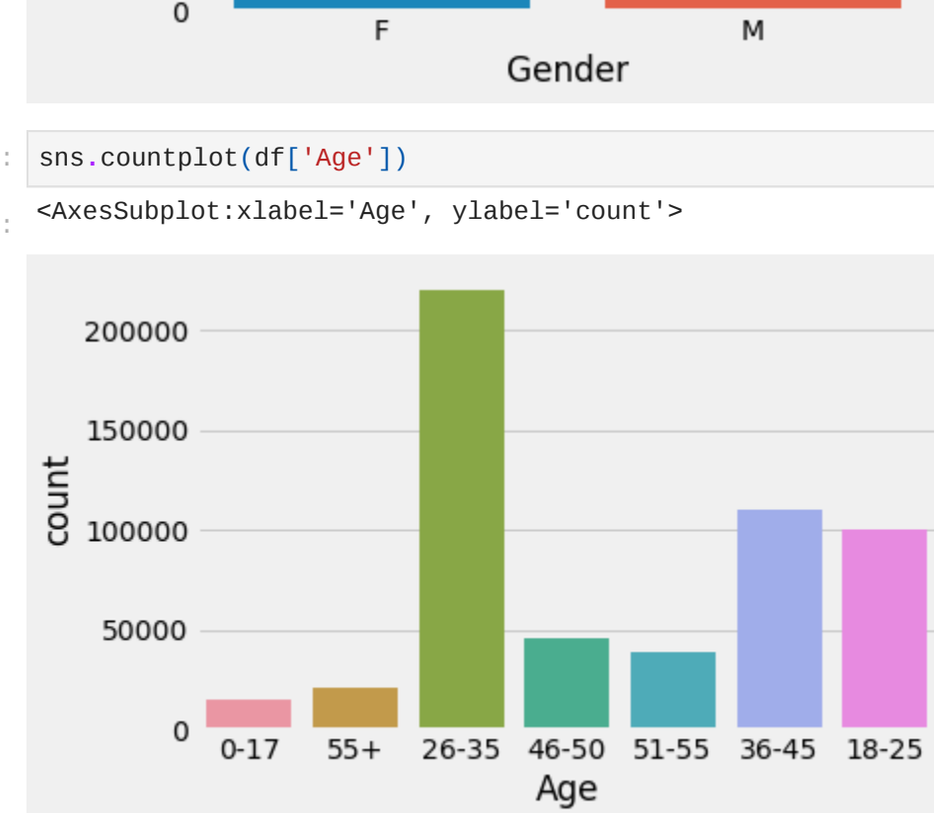
In [47]:
```
sns.countplot(df['Age'])
```

Out[47]: <AxesSubplot:xlabel='Age', ylabel='count'>



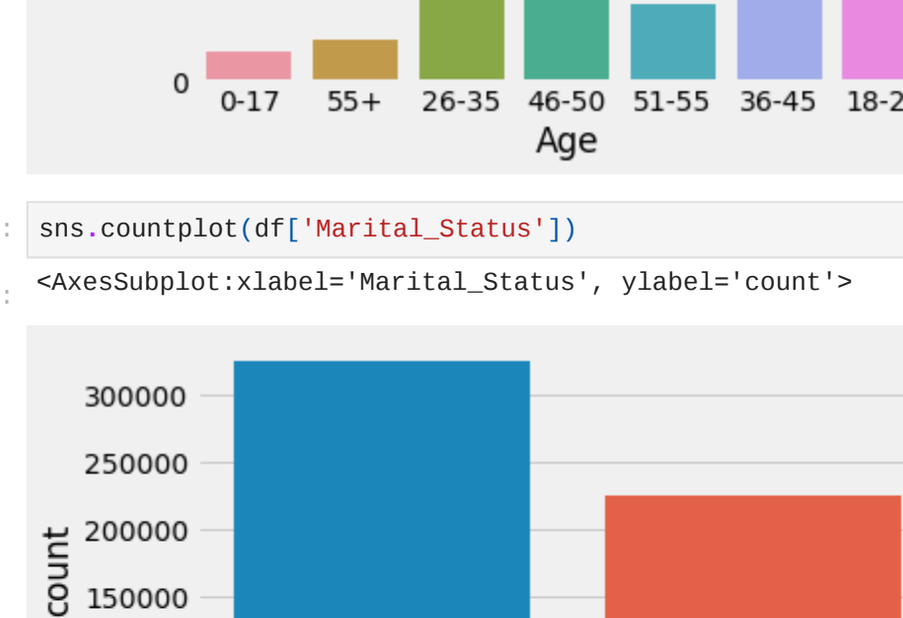
In [48]:
```
sns.countplot(df['Marital_Status'])
```

Out[48]: <AxesSubplot:xlabel='Marital_Status', ylabel='count'>



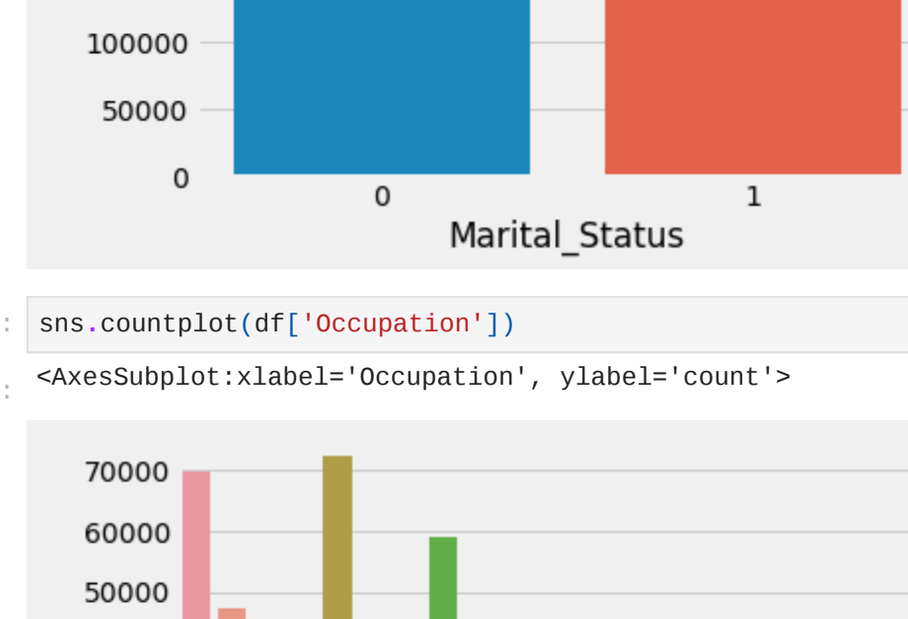
In [49]:
```
sns.countplot(df['Occupation'])
```

Out[49]: <AxesSubplot:xlabel='Occupation', ylabel='count'>



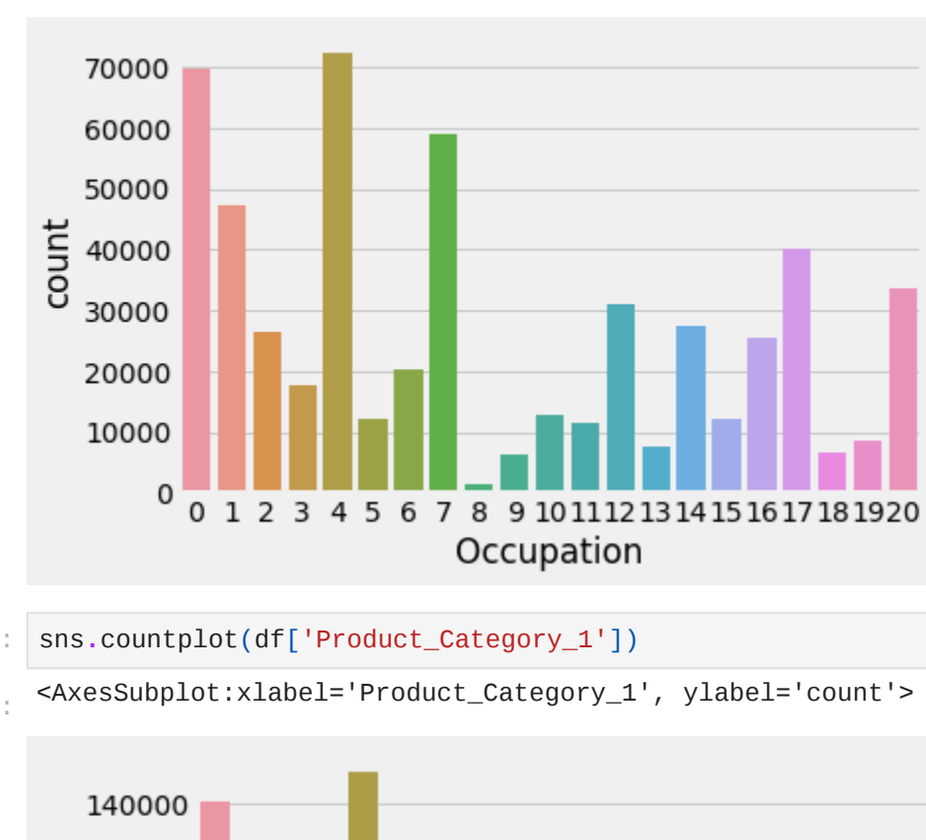
In [50]:
```
sns.countplot(df['Product_Category_1'])
```

Out[50]: <AxesSubplot:xlabel='Product_Category_1', ylabel='count'>



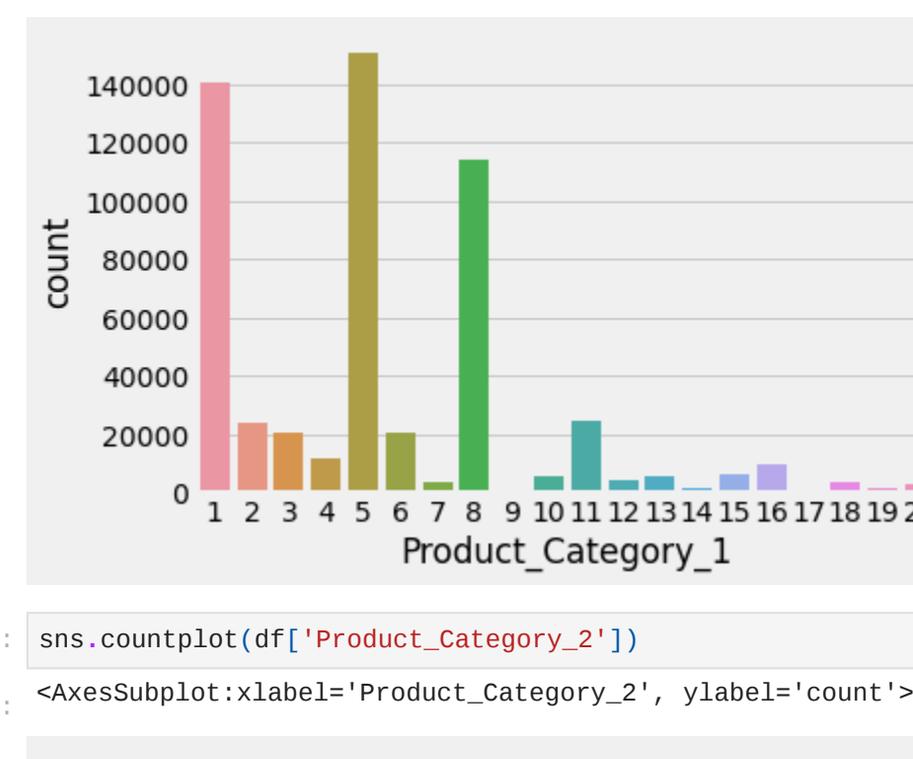
In [51]:
```
sns.countplot(df['Product_Category_2'])
```

Out[51]: <AxesSubplot:xlabel='Product_Category_2', ylabel='count'>



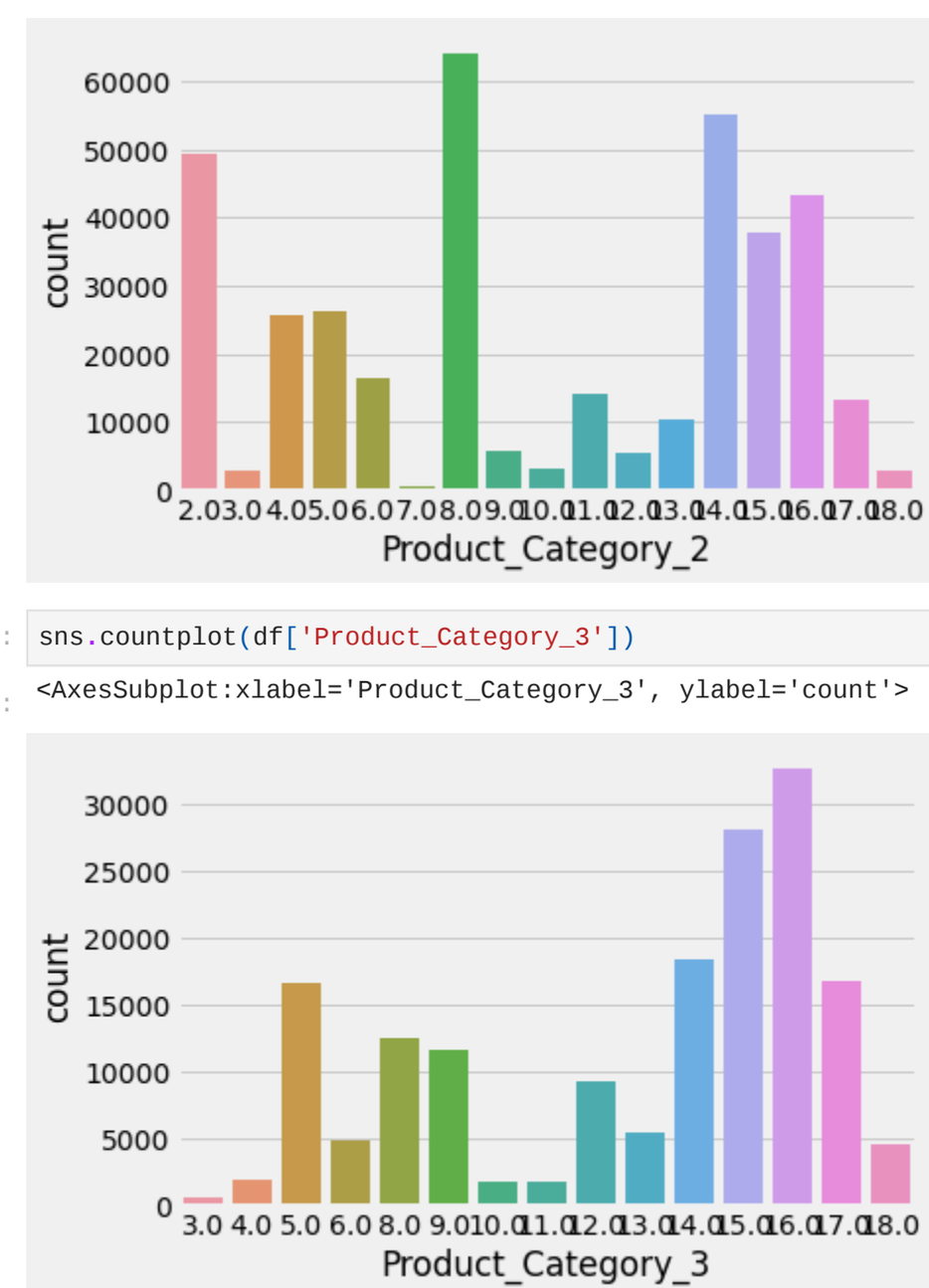
In [52]:
```
sns.countplot(df['Product_Category_3'])
```

Out[52]: <AxesSubplot:xlabel='Product_Category_3', ylabel='count'>



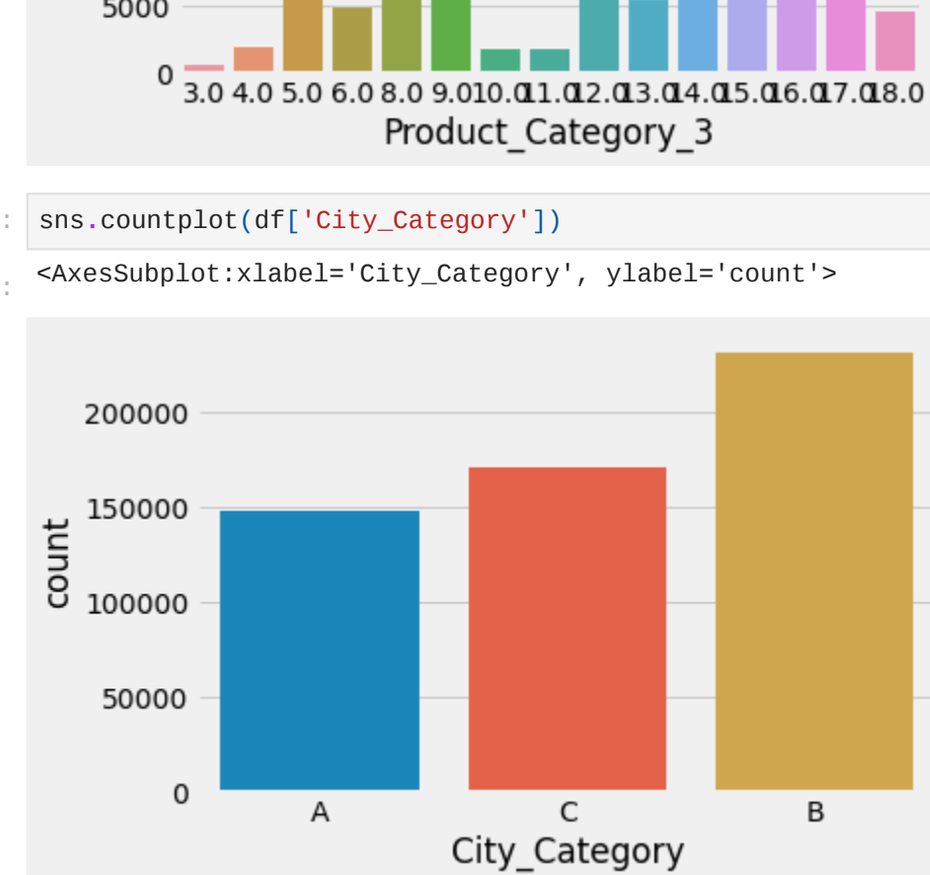
In [53]:
```
sns.countplot(df['City_Category'])
```

Out[53]: <AxesSubplot:xlabel='City_Category', ylabel='count'>

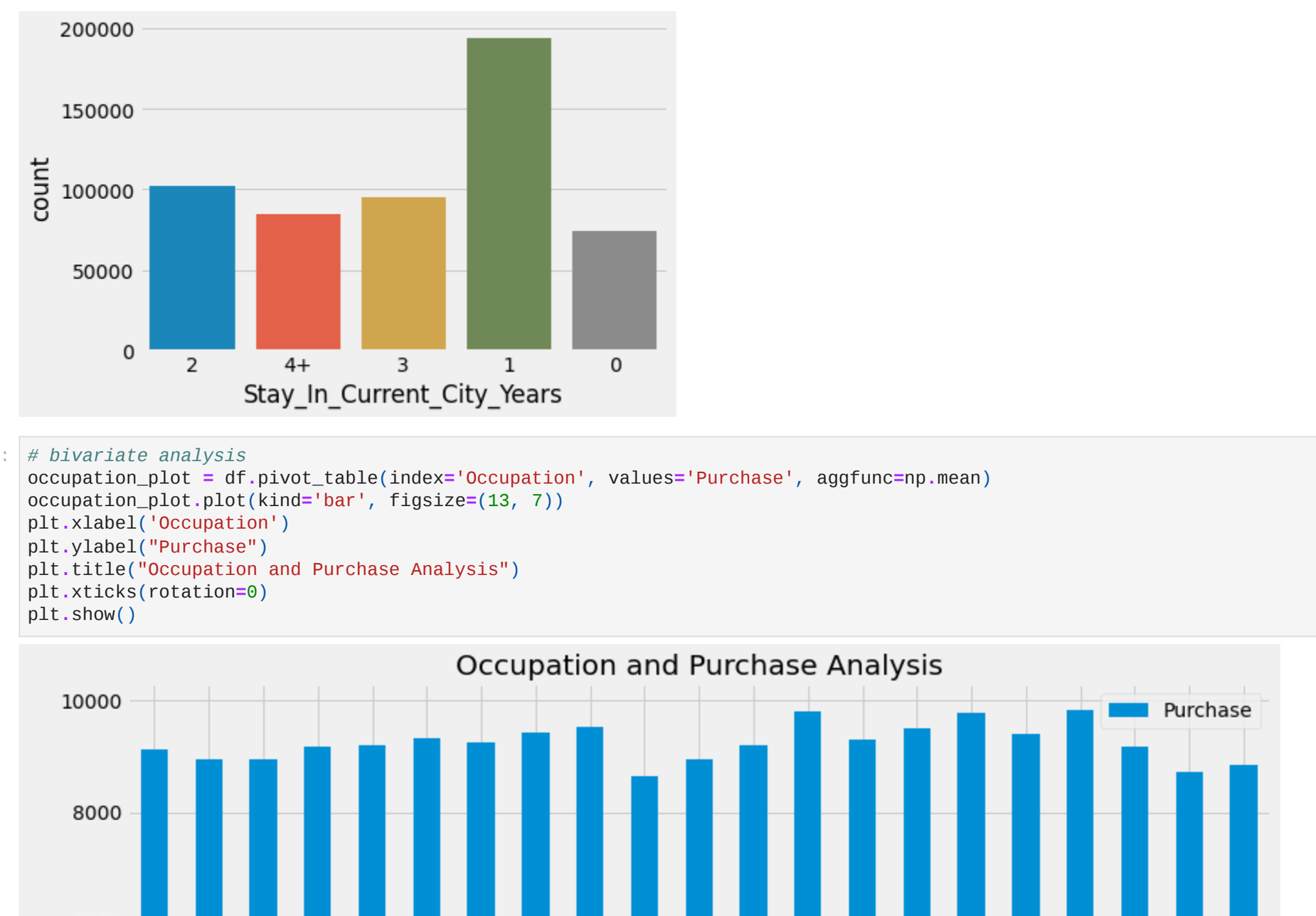


In [54]:
```
sns.countplot(df['Stay_In_Current_City_Years'])
```

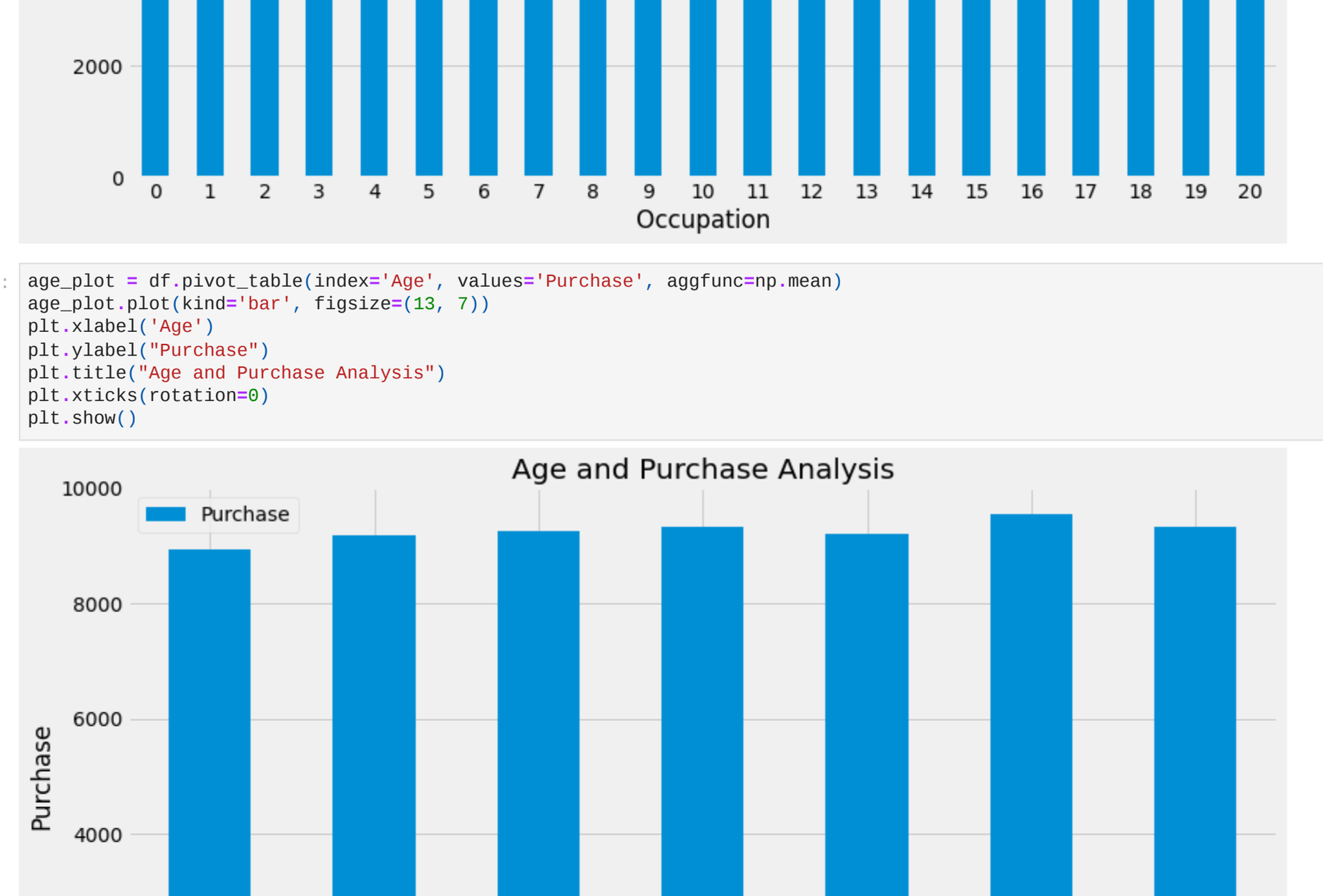
Out[54]: <AxesSubplot:xlabel='Stay_In_Current_City_Years', ylabel='count'>



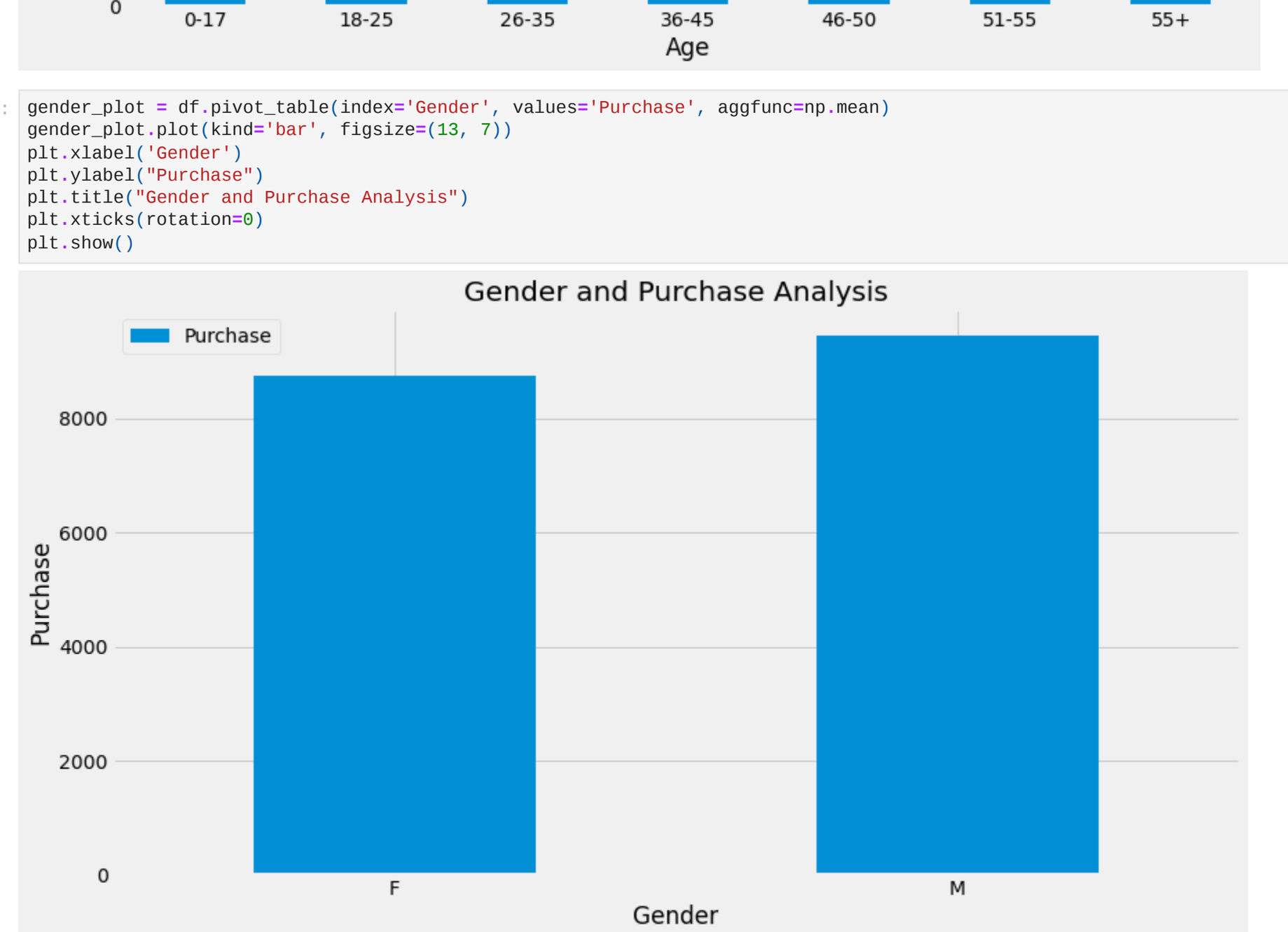
In [55]:
```
# bivariate analysis
occupation_plot = df.pivot_table(index='Occupation', values='Purchase', aggfunc=np.mean)
occupation_plot.plot(kind='bar', figsize=(13, 7))
plt.xlabel('Occupation')
plt.ylabel("Purchase")
plt.title("Occupation and Purchase Analysis")
plt.xticks(rotation=0)
plt.show()
```



In [56]:
```
age_plot = df.pivot_table(index='Age', values='Purchase', aggfunc=np.mean)
age_plot.plot(kind='bar', figsize=(13, 7))
plt.xlabel('Age')
plt.ylabel("Purchase")
plt.title("Age and Purchase Analysis")
plt.xticks(rotation=0)
plt.show()
```



In [57]:
```
gender_plot = df.pivot_table(index='Gender', values='Purchase', aggfunc=np.mean)
gender_plot.plot(kind='bar', figsize=(13, 7))
plt.xlabel('Gender')
plt.ylabel("Purchase")
plt.title("Gender and Purchase Analysis")
plt.xticks(rotation=0)
plt.show()
```



Preprocessing the dataset

In [58]:
```
# check for null values
df.isnull().sum()
```

Out[58]:
```
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 [59]:
```
df['Product_Category_2'] = df['Product_Category_2'].fillna(-2.0).astype("float32")
df['Product_Category_3'] = df['Product_Category_3'].fillna(-2.0).astype("float32")
```

In [60]:
```
df.isnull().sum()
```

Out[60]:
```
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            0
Product_Category_3            0
Purchase                      0
dtype: int64
```

In [61]:
```
# encoding values using dict
gender_dict = {'F':0, 'M':1}
df['Gender'] = df['Gender'].apply(lambda x: gender_dict[x])
df.head()
```

Out[61]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
0	1000001	P00069042	0	0-17	10	A	2	0	3	-2.0	-2.0	8370
1	1000001	P00248942	0	0-17	10	A	2	0	1	6.0	14.0	15200
2	1000001	P00087842	0	0-17	10	A	2	0	12	-2.0	-2.0	1422
3	1000001	P00085442	0	0-17	10	A	2	0	12	14.0	-2.0	1057
4	1000002	P00285442	1	55+	16	C	4+	0	8	-2.0	-2.0	7969

In [62]:
```
# to improve the metric use one hot encoding
# label encoding
cols = ['Age', 'City_Category', 'Stay_In_Current_City_Years']
from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for col in cols:
    df[col] = le.fit_transform(df[col])
df.head()
```

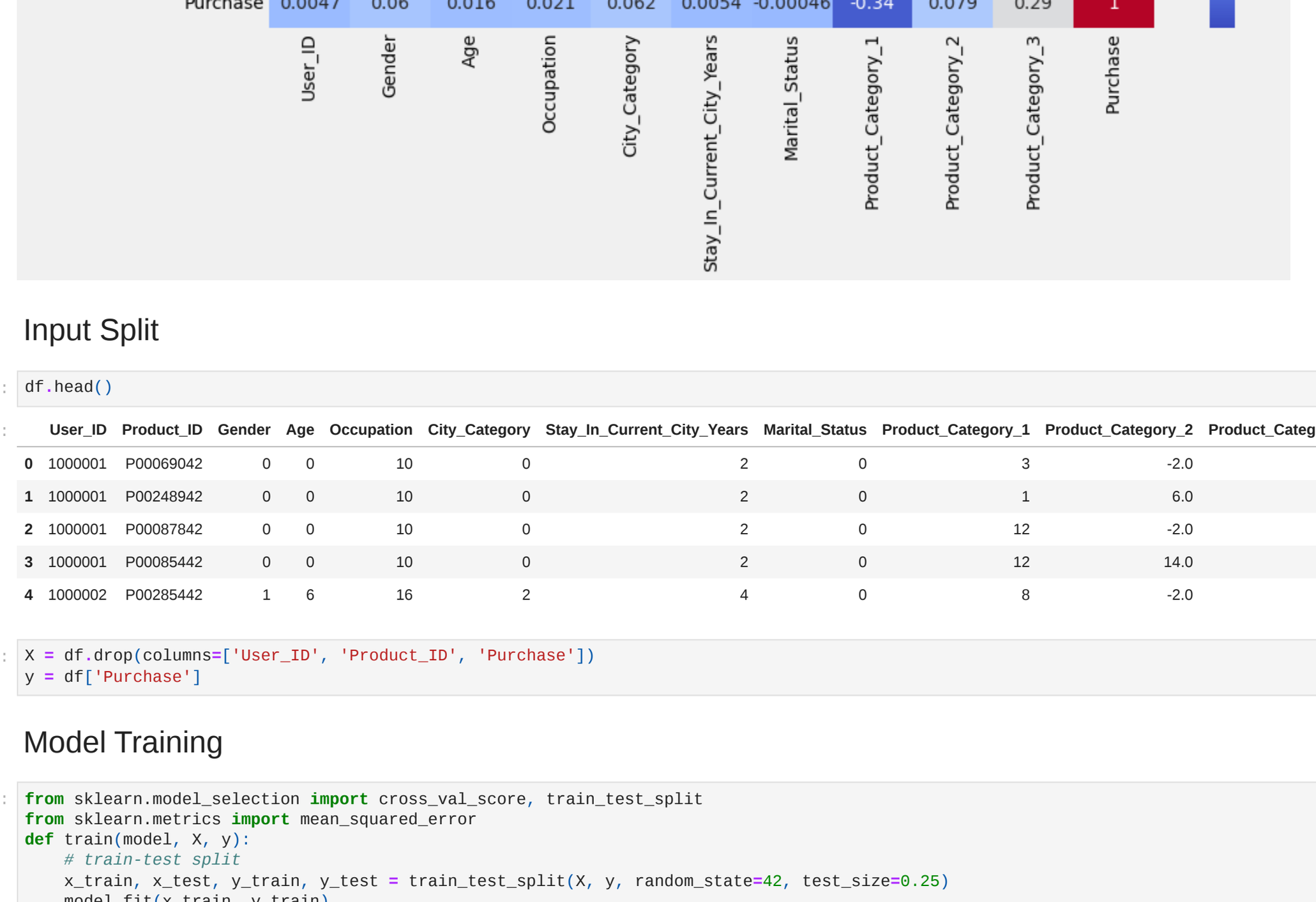
Out[62]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
0	1000001	P00069042	0	0	10	0	2	0	3	-2.0	-2.0	8370
1	1000001	P00248942	0	0	10	0	2	0	1	6.0	14.0	15200
2	1000001	P00087842	0	0	10	0	2	0	12	-2.0	-2.0	1422
3	1000001	P00085442	0	0	10	0	2	0	12	14.0	-2.0	1057
4	1000002	P00285442	1	6	16	2	4	0	8	-2.0	-2.0	7969

Coorelation Matrix

In [63]:
```
corr = df.corr()
plt.figure(figsize=(14,7))
sns.heatmap(corr, annot=True, cmap='coolwarm')
```

Out[63]: <AxesSubplot:>



Input Split

In [64]:
```
df.head()
```

Out[64]:

	User_ID	Product_ID	Gender	Age	Occupation	City_Category	Stay_In_Current_City_Years	Marital_Status	Product_Category_1	Product_Category_2	Product_Category_3	Purchase
0	1000001	P00069042	0	0	10	0	2	0	3	-2.0	-2.0	8370
1	1000001	P00248942	0	0	10	0	2	0	1	6.0	14.0	15200
2	1000001	P00087842	0	0	10	0	2	0	12	-2.0	-2.0	1422
3	1000001	P00085442	0	0	10	0	2	0	12	14.0	-2.0	1057
4	1000002	P00285442	1	6	16	2	4	0	8	-2.0	-2.0	7969

In [65]:
```
X = df.drop(columns=['User_ID', 'Product_ID', 'Purchase'])
y = df['Purchase']
```

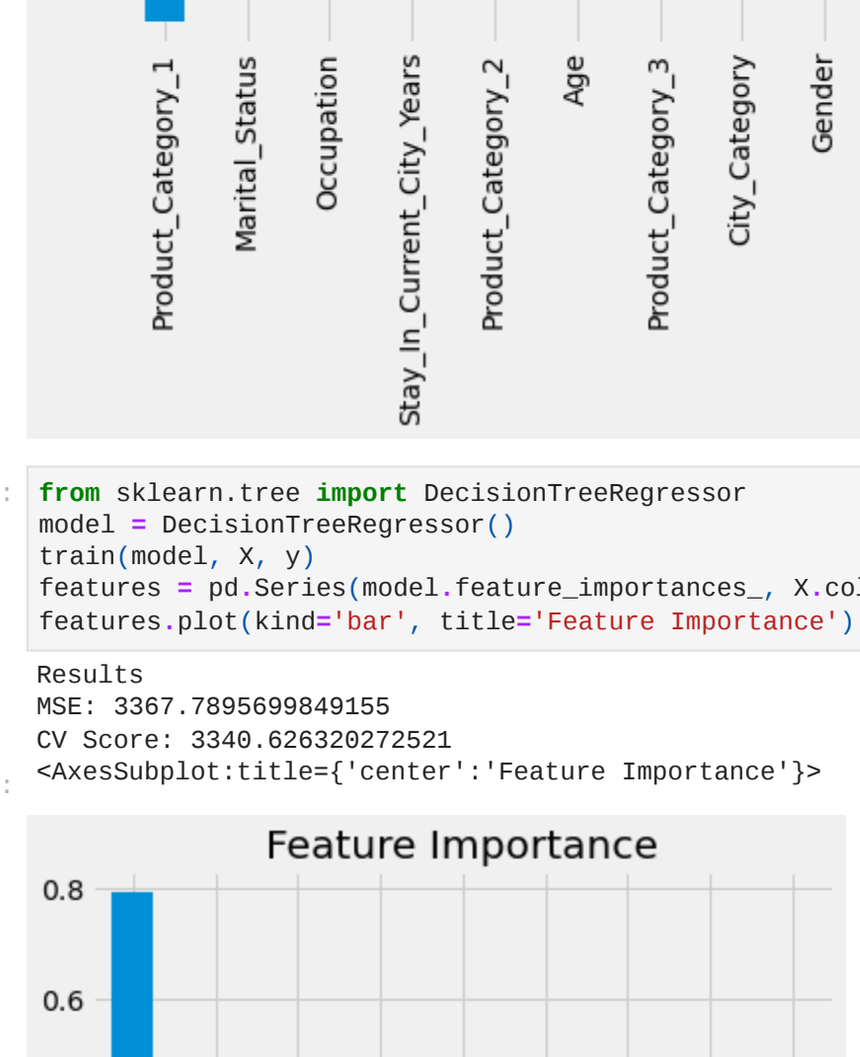
Model Training

In [66]:
```
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.metrics import mean_squared_error
def train(model, X, y):
    # train-test split
    x_train, x_test, y_train, y_test = train_test_split(X, y, random_state=42, test_size=0.25)
    model.fit(x_train, y_train)

    # predict the results
    pred = model.predict(x_test)

    # cross validation
    cv_score = cross_val_score(model, X, y, scoring='neg_mean_squared_error', cv=5)
    cv_score = np.abs(np.mean(cv_score))

    print("Results")
    print("MSE:", np.sqrt(mean_squared_error(y_test, pred)))
    print("CV Score:", np.sqrt(cv_score))
```

In [69]:
```
from sklearn.linear_model import LinearRegression
model = LinearRegression(normalize=True)
train(model, X, y)
coef = pd.Series(model.coef_, X.columns).sort_values()
coef.plot(kind='bar', title='Model Coefficients')
```

```
Results
MSE: 4617.994034201719
CV Score: 4625.252945835687
```

Out[69]: <AxesSubplot:title={'center':'Model Coefficients'}>



In [70]:
```
from sklearn.tree import DecisionTreeRegressor
model = DecisionTreeRegressor()
train(model, X, y)
features = pd.Series(model.feature_importances_, X.columns).sort_values(ascending=False)
features.plot(kind='bar', title='Feature Importance')
```

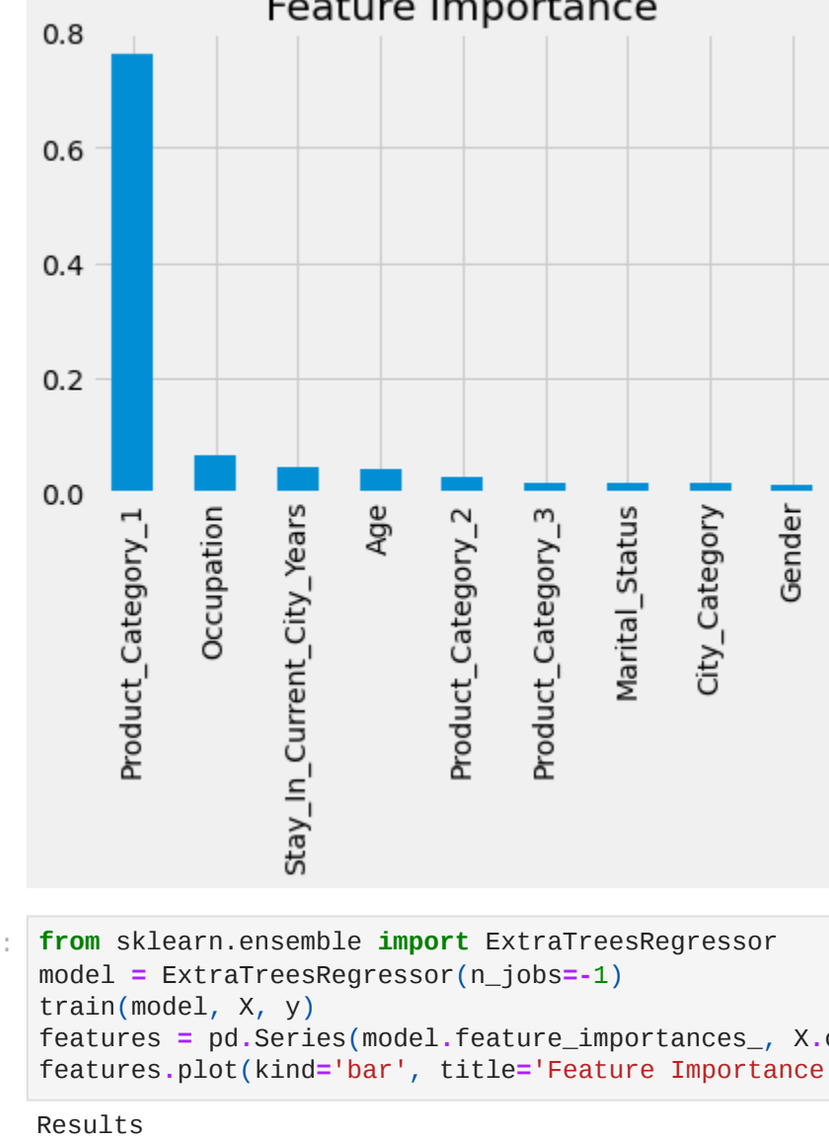
```
Results
MSE: 3367.7895699849155
CV Score: 3340.626320272521
```

Out[70]: <AxesSubplot:title={'center':'Feature Importance'}>

In [71]:
```
from sklearn.ensemble import RandomForestRegressor
model = RandomForestRegressor(n_jobs=-1)
train(model, X, y)
features = pd.Series(model.feature_importances_, X.columns).sort_values(ascending=False)
features.plot(kind='bar', title='Feature Importance')
```

```
Results
MSE: 3062.9668087689906
CV Score: 3051.7662103471885
```

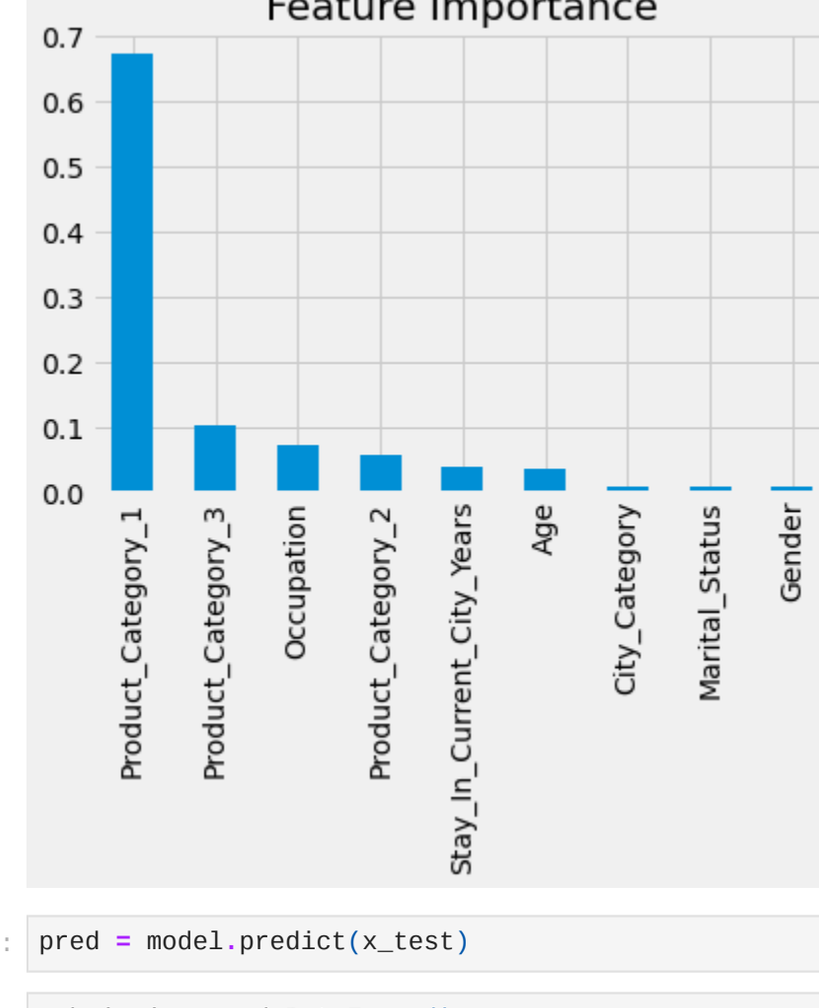
Out[71]: <AxesSubplot:title={'center':'Feature Importance'}>



In [72]:
```
from sklearn.ensemble import ExtraTreesRegressor
model = ExtraTreesRegressor(n_jobs=-1)
train(model, X, y)
features = pd.Series(model.feature_importances_, X.columns).sort_values(ascending=False)
features.plot(kind='bar', title='Feature Importance')
```

```
Results
MSE: 3196.038681243816
CV Score: 3180.373119232271
```

Out[72]: <AxesSubplot:title={'center':'Feature Importance'}>



In [73]:
```
pred = model.predict(x_test)
```

In [74]:
```
submission = pd.DataFrame()
submission['User_ID'] = x_test['User_ID']
submission['Purchase'] = pred
```

In [75]:
```
submission.to_csv('submission.csv', index=False)
```

In [ ]: