Customer Segmentation

August 20, 2023

[52]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[179]:
```
data_size = 1000

data = {
    'customer_id': list(range(1000, 2000)),
    'age': np.random.randint(18, 100, data_size),
    'gender': np.random.choice(['Male', 'Female'], size=data_size),
    'marital_status': np.random.choice(['Married', 'Single', 'Divorced'],␣
 ↪size=data_size),
    'annual_income_in_usd': np.random.randint(25000, 150000, data_size),
    'total_purchases': np.random.randint(1, 50, data_size),
    'preferred_category': np.random.choice(['Electronics', 'Appliances',␣
 ↪'Clothing', 'Food', 'Health', 'Media'], size=data_size)
}
```

[180]:
```
df = pd.DataFrame(data)
```

[181]:
```
df.head()
```

[181]:
```
   customer_id  age  gender marital_status  annual_income_in_usd  \
0         1000   40  Female        Married                106098
1         1001   52    Male         Single                142620
2         1002   37  Female       Divorced                107244
3         1003   82    Male        Married                 65595
4         1004   60    Male       Divorced                 79122

   total_purchases preferred_category
0               11               Food
1               19               Food
2               41              Media
3               15           Clothing
4               28        Electronics
```

[182]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 7 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   customer_id           1000 non-null   int64
 1   age                   1000 non-null   int32
 2   gender                1000 non-null   object
 3   marital_status        1000 non-null   object
 4   annual_income_in_usd  1000 non-null   int32
 5   total_purchases       1000 non-null   int32
 6   preferred_category    1000 non-null   object
dtypes: int32(3), int64(1), object(3)
memory usage: 43.1+ KB
```

[183]:
```
df.describe()
```

[183]:

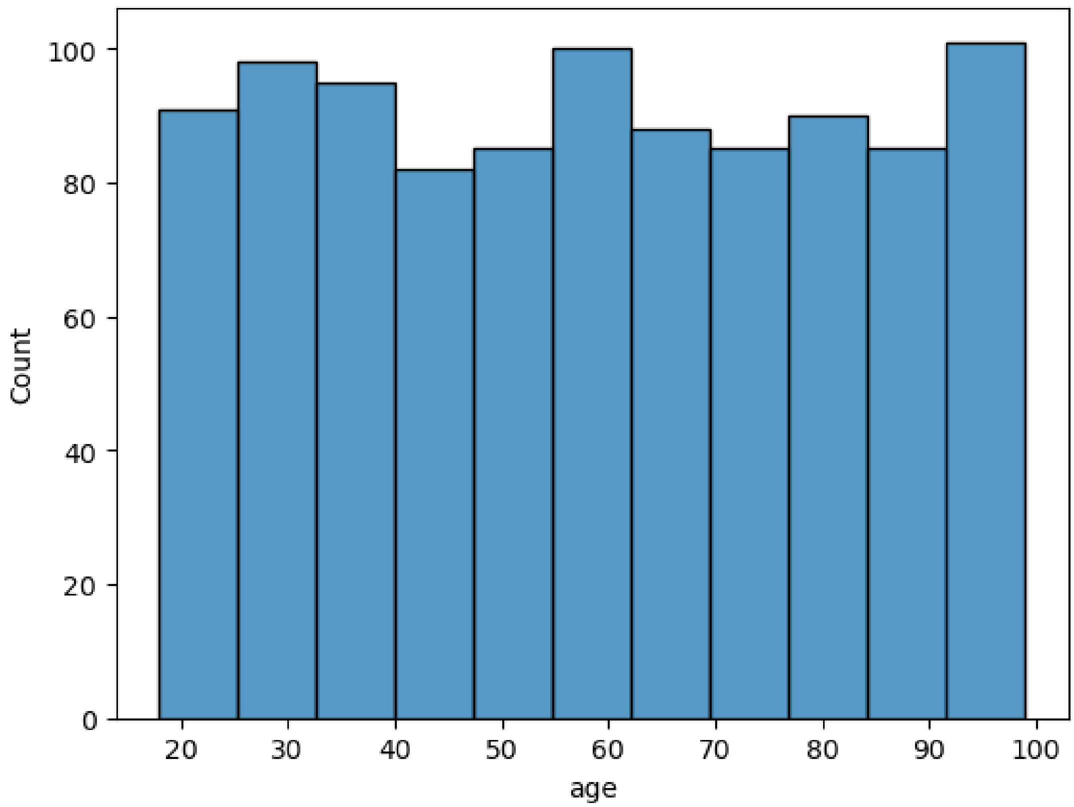
	customer_id	age	annual_income_in_usd	total_purchases
count	1000.000000	1000.000000	1000.000000	1000.000000
mean	1499.500000	58.324000	86599.276000	25.112000
std	288.819436	23.744659	35019.782397	14.059414
min	1000.000000	18.000000	25022.000000	1.000000
25%	1249.750000	37.000000	56976.250000	13.000000
50%	1499.500000	57.500000	84772.000000	25.000000
75%	1749.250000	79.000000	115954.500000	37.000000
max	1999.000000	99.000000	149997.000000	49.000000

[184]:
```
df.isna().sum()
```

[184]:
```
customer_id             0
age                     0
gender                  0
marital_status          0
annual_income_in_usd    0
total_purchases         0
preferred_category      0
dtype: int64
```

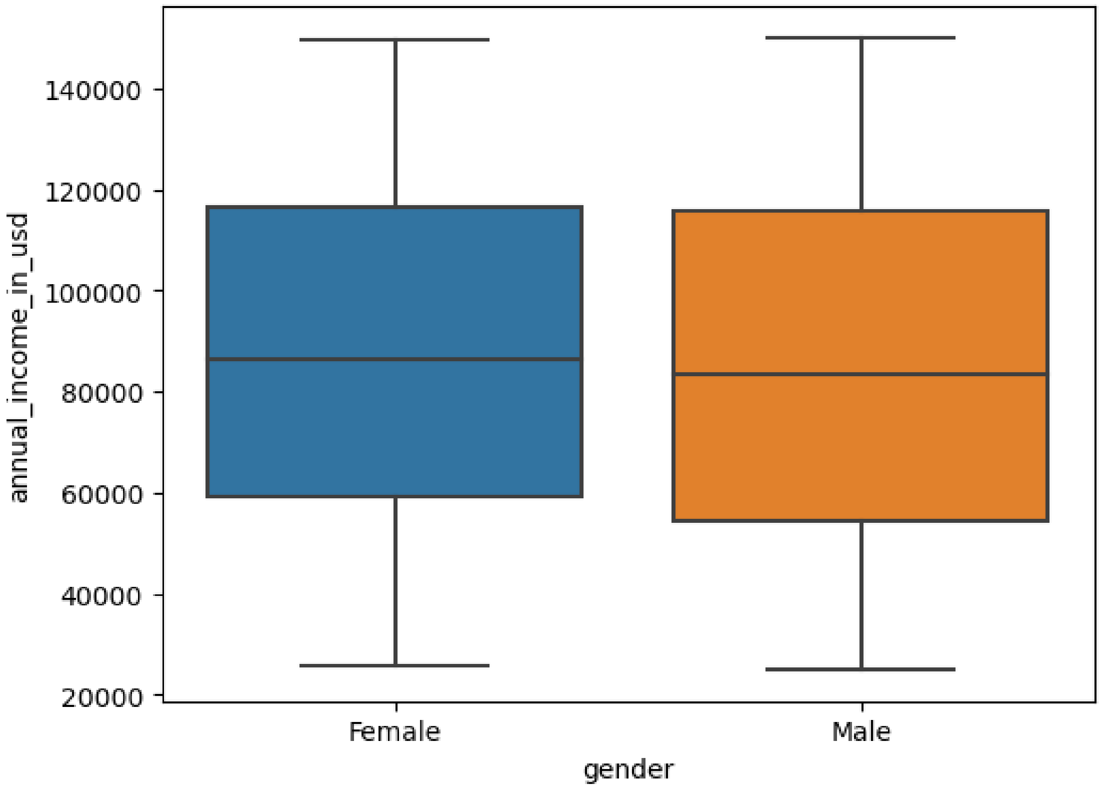
[185]:
```
sns.histplot(df.age)
```

[185]:
```
<Axes: xlabel='age', ylabel='Count'>
```



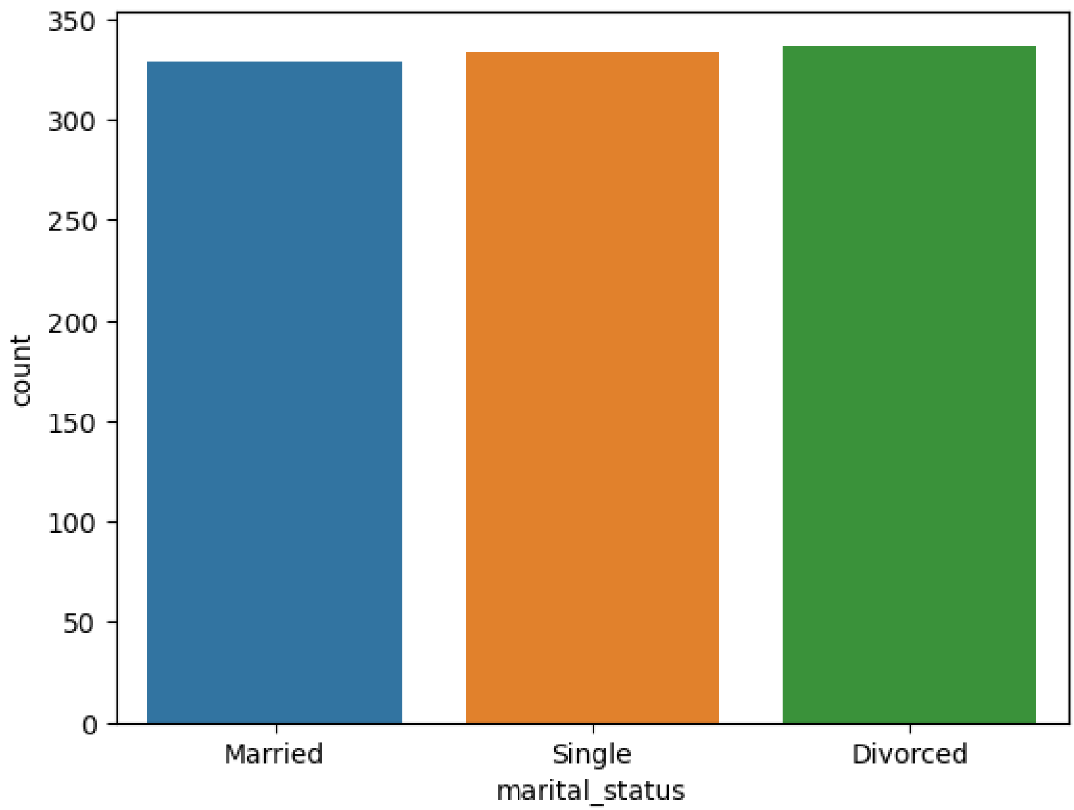
[186]:
```
sns.boxplot(data=df, x='gender', y='annual_income_in_usd')
```

[186]: <Axes: xlabel='gender', ylabel='annual_income_in_usd'>



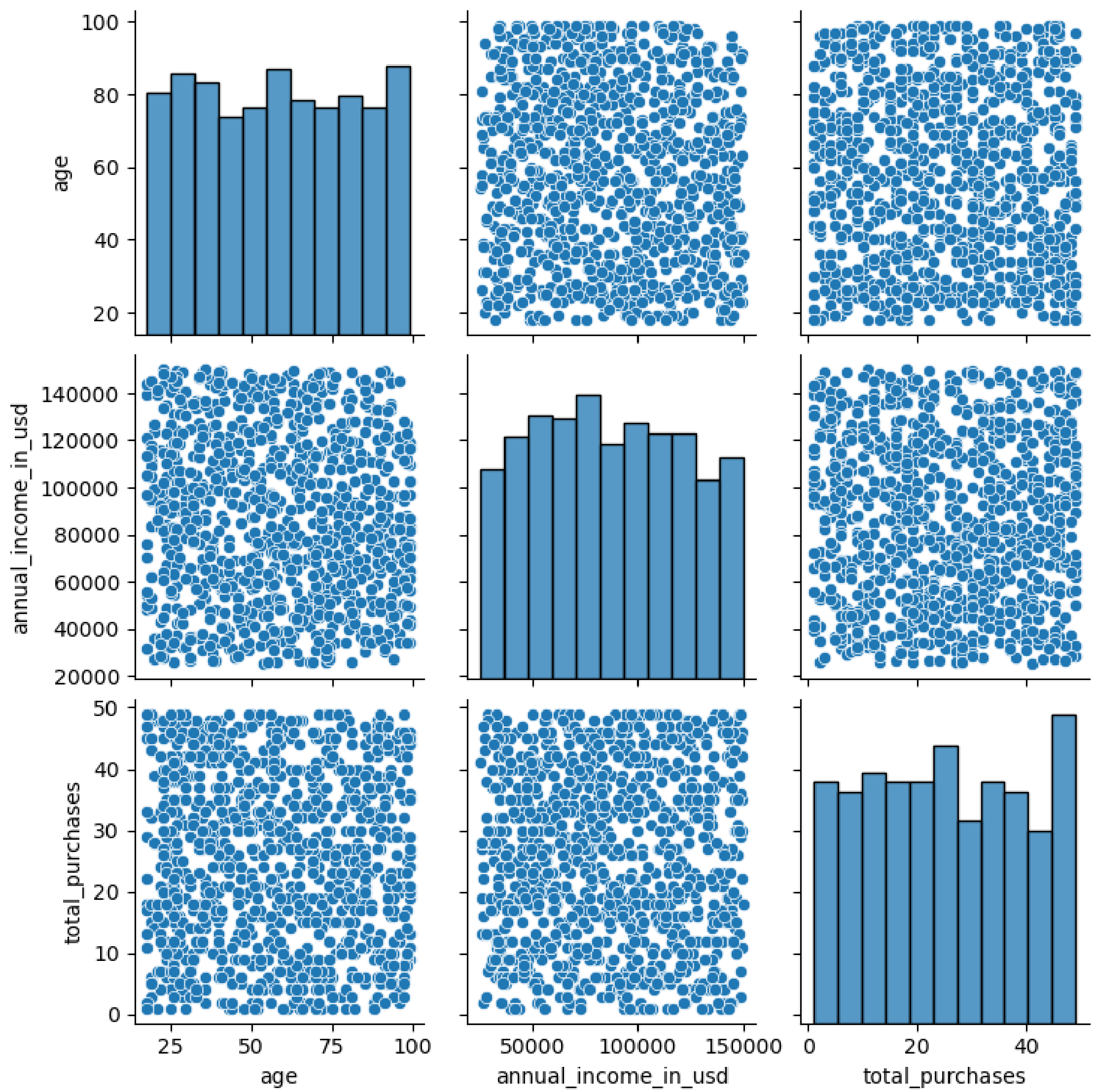
[187]:
```
sns.countplot(data=df, x='marital_status')
```

[187]: <Axes: xlabel='marital_status', ylabel='count'>



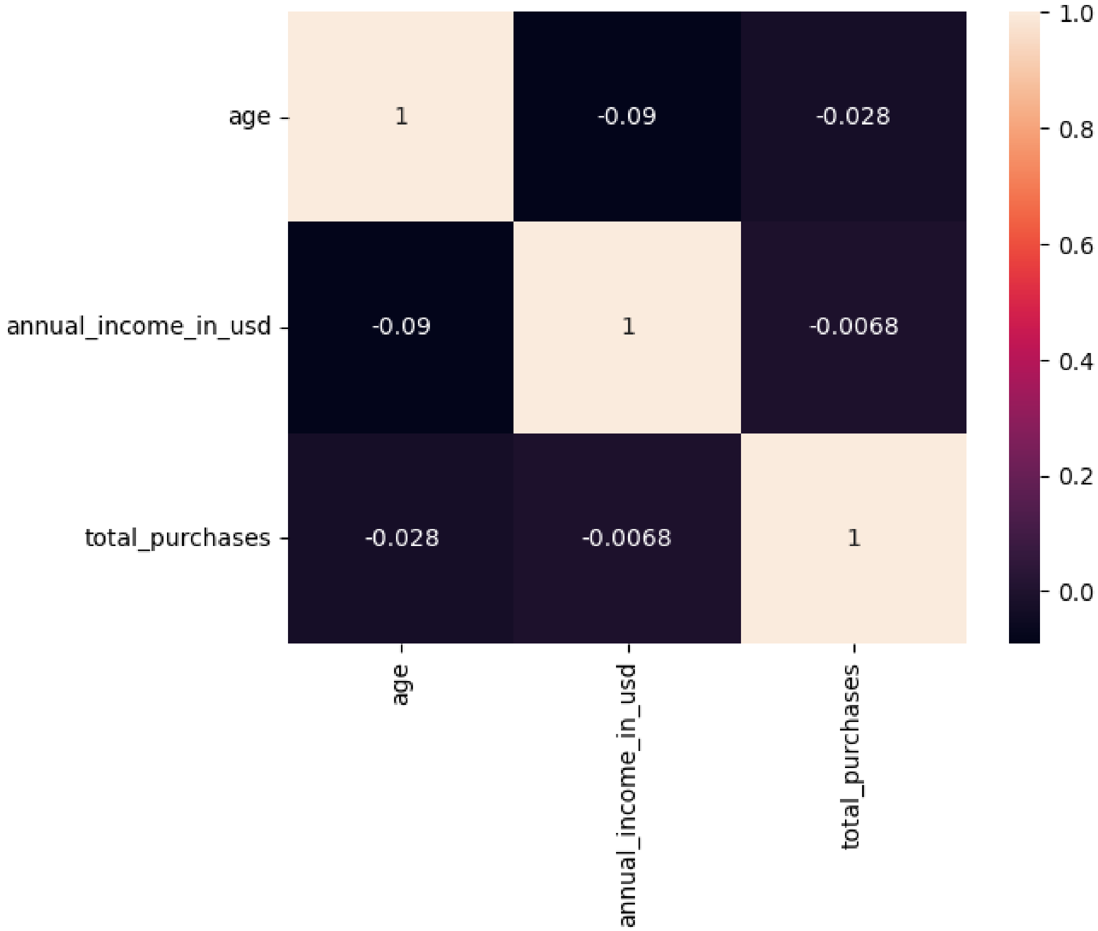
[188]:
```
sns.pairplot(df[['age', 'annual_income_in_usd', 'total_purchases']])
```

[188]: <seaborn.axisgrid.PairGrid at 0x2b0d1dfcb80>



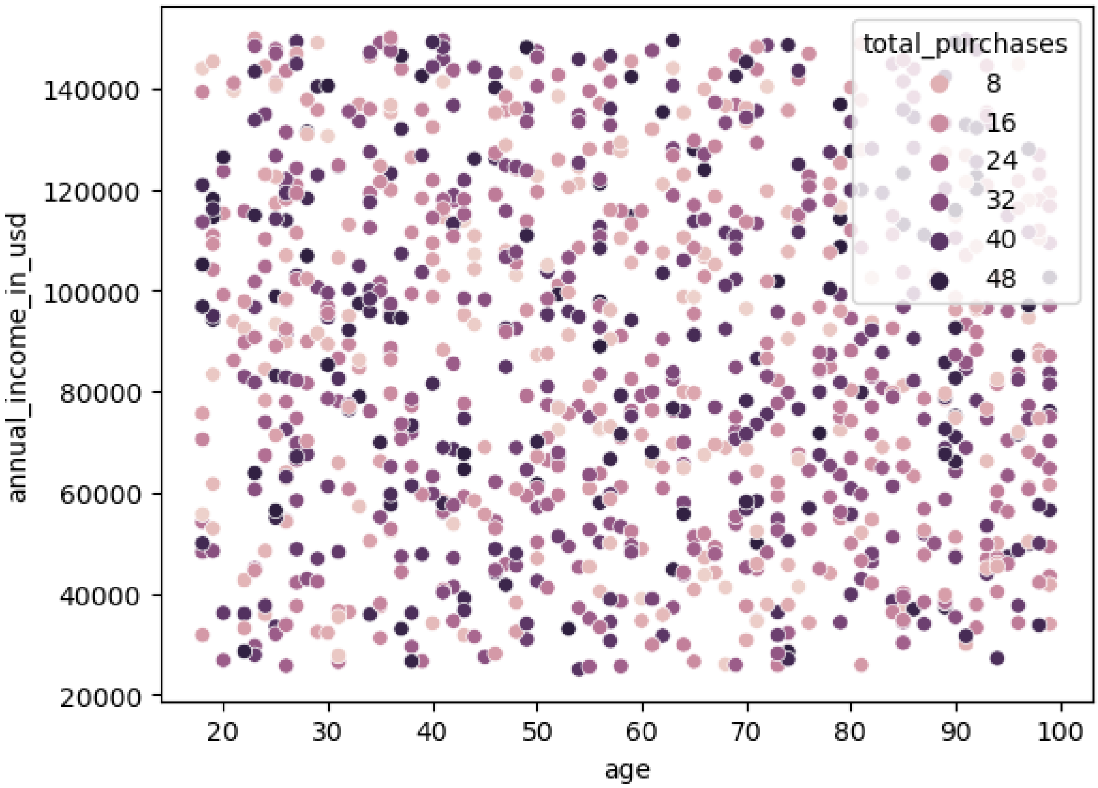
[189]:
```
sns.heatmap(df[['age', 'annual_income_in_usd', 'total_purchases']].corr(),␣
↪annot=True)
```

[189]: <Axes: >

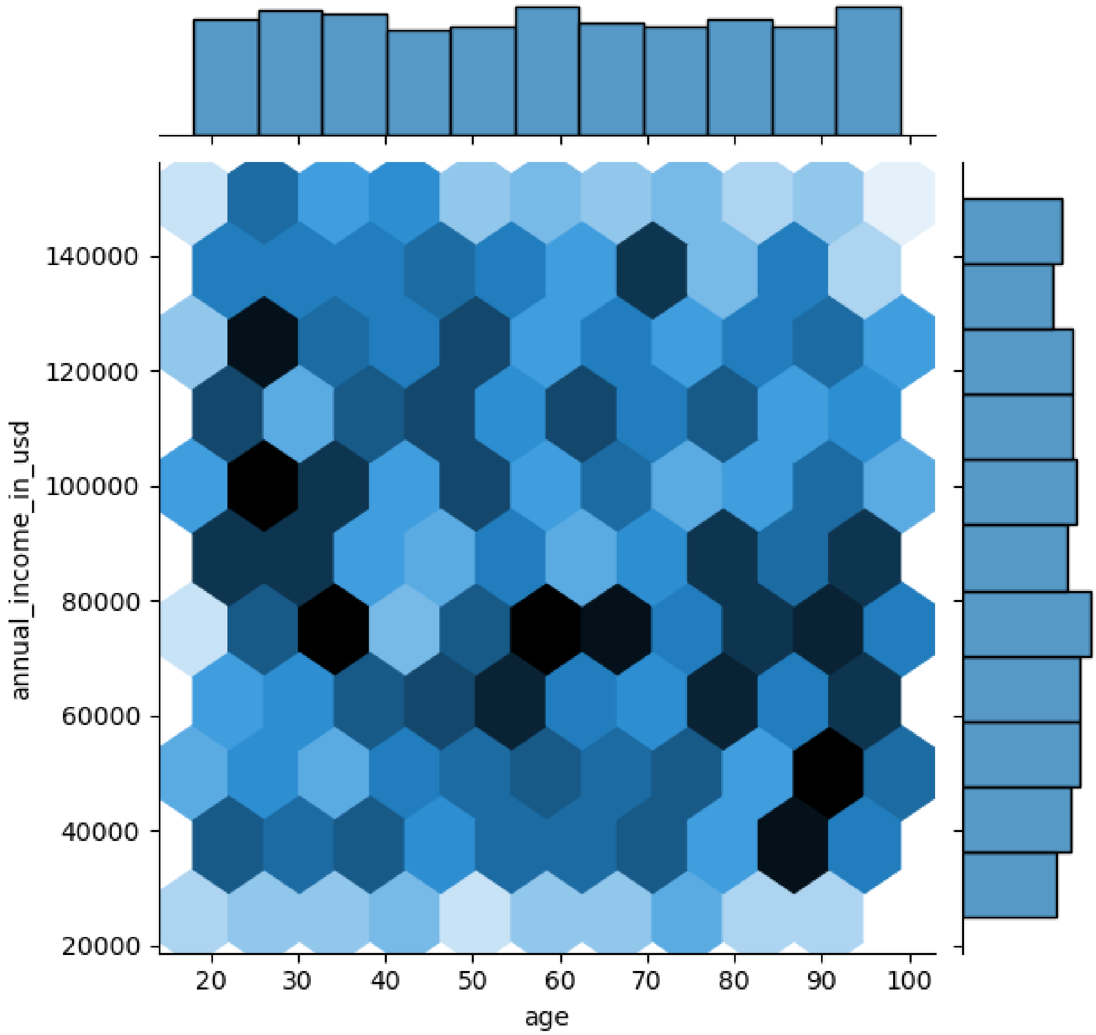


[190]:
```
sns.scatterplot(data=df[['age', 'annual_income_in_usd', 'total_purchases']],
    x='age', y='annual_income_in_usd', hue='total_purchases')
```

[190]:
```
<Axes: xlabel='age', ylabel='annual_income_in_usd'>
```



[191]:
```
sns.jointplot(data=df, x='age', y='annual_income_in_usd', kind='hex')
plt.show()
```



1 K Means

[192]:
```python
# features
X = df[['annual_income_in_usd', 'total_purchases']].values
X
```

[192]:
```
array([[106098,     11],
       [142620,     19],
       [107244,     41],
       …,
       [ 99362,     33],
       [ 66496,      3],
       [121458,     16]])
```

[193]:
```python
from sklearn.cluster import KMeans
```

[194]:
```python
# finding the right amount of clusters for kmeans using elbow method
wcss_list = []

for i in range(1, 11):
    kmeans = KMeans(n_clusters=i, init='k-means++', random_state=42)
    kmeans.fit(X)
    wcss_list.append(kmeans.inertia_)

plt.plot(range(1, 11), wcss_list)
plt.show()
```

```
D:\apps\anaconda\files\lib\site-packages\sklearn\cluster\_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
D:\apps\anaconda\files\lib\site-packages\sklearn\cluster\_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
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```
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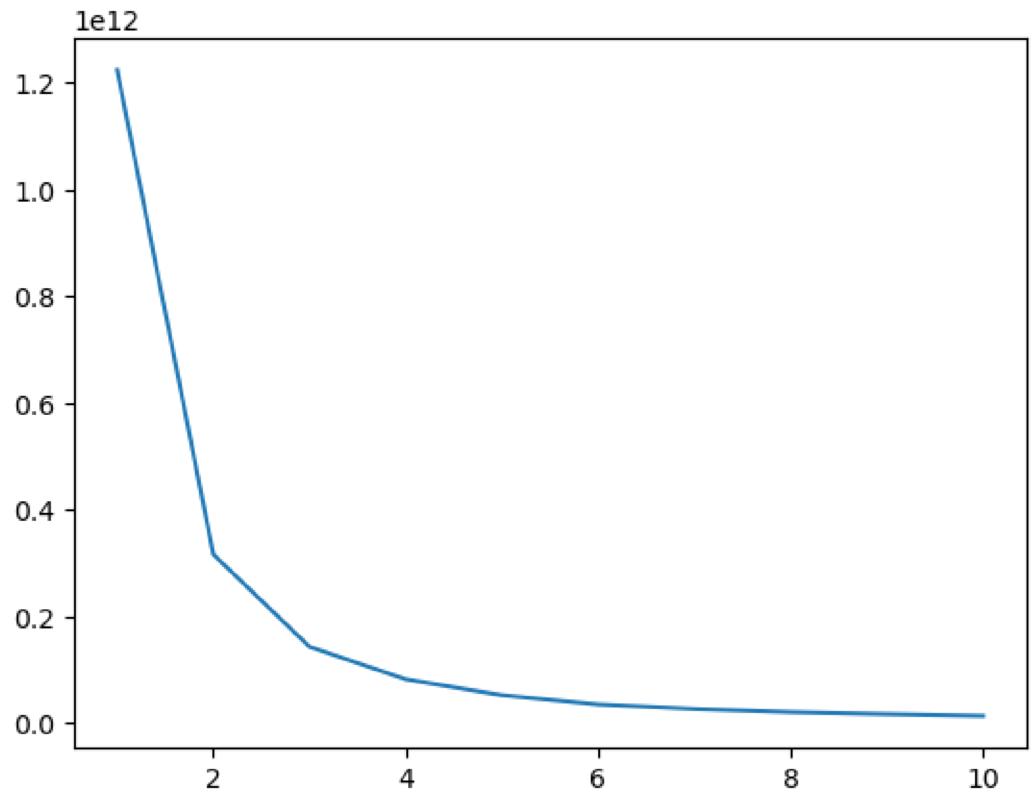
  warnings.warn(
```



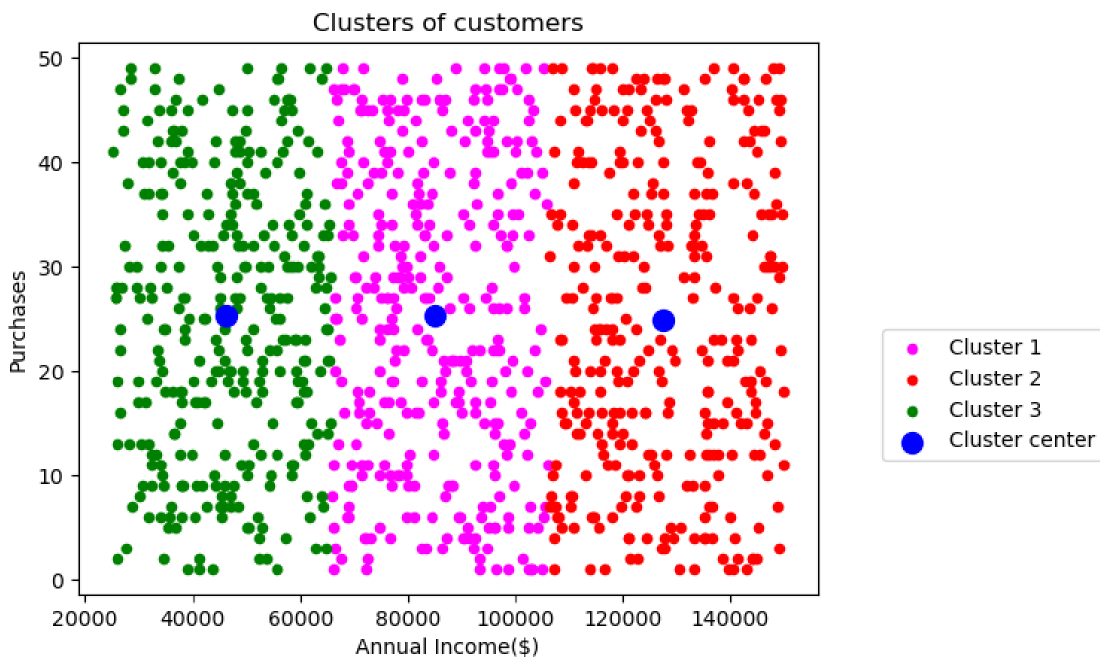
[195]:
```python
# K means clustering and its training
kmeans = KMeans(n_clusters=3, init='k-means++', random_state=42)
y_predict = kmeans.fit_predict(X)
```

```
D:\apps\anaconda\files\lib\site-packages\sklearn\cluster\_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

[196]:
```python
# visualizing each cluster and their respective centers
plt.scatter(X[y_predict==0, 0], X[y_predict==0, 1], s=20, c='magenta',␣
 ↪label='Cluster 1')
plt.scatter(X[y_predict==1, 0], X[y_predict==1, 1], s=20, c='red',␣
 ↪label='Cluster 2')
plt.scatter(X[y_predict==2, 0], X[y_predict==2, 1], s=20, c='green',␣
 ↪label='Cluster 3')
```

```
plt.scatter(kmeans.cluster_centers_[:, 0], kmeans.cluster_centers_[:, 1], s =
    100, c = 'blue', label = 'Cluster center')

plt.title('Clusters of customers')
plt.xlabel('Annual Income($)')
plt.ylabel('Purchases')
plt.legend(bbox_to_anchor=(0.9, 0., 0.5, 0.5))
plt.show()
```



2 Summary

In our analysis using K-means clustering, we aimed to uncover underlying patterns and groupings within our dataset based on the features we selected. The goal was to identify distinct clusters of customers that exhibit similar behavior in terms of annual income and purchases.

Upon running the K-means clustering algorithm and examining the resulting visualization, we observed that the three clusters we defined seem to exhibit nearly identical patterns. This outcome raises several interesting insights and considerations.

The output image is clearly showing the three different clusters with different colors. The clusters are formed between two parameters of the dataset; Annual income of customer and Purchases. We can change the colors and labels as per the requirement or choice. We can also observe some points from the above patterns, which are given below:

Similar Patterns Across Clusters: The fact that all three clusters display comparable graphs suggests that the algorithm faced challenges in distinguishing clear and separate patterns within the data using the chosen features. While we had hoped to find distinct customer segments based on annual income and purchases, the data does not appear to exhibit these expected separations.

Potential Explanations: There could be several reasons behind this outcome. One possibility is that the features we selected are not sufficient to effectively differentiate between the clusters. This might indicate that additional factors or features need to be considered to accurately capture the nuances in customer behavior.

In conclusion, the current K-means clustering analysis has given us a starting point for understanding customer behavior based on annual income and purchases. While the initial results did not yield distinct clusters, they have provided us with directions for further exploration and refinement of our analysis methodology.

[ ]:

```

```

[ ]:

```

```