```python
#1. Import the Data
#1.1 Import the necessary libraries (pandas, matplotlib.pyplot,
seaborn, numpy, and scipy.stats)

import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np
from sklearn.preprocessing import OrdinalEncoder, OneHotEncoder
import scipy.stats as stats

#1.2 Read the CSV file (marketing_data.csv) using pd.read_csv() and
store it in a DataFrame (data)

data = pd.read_csv(r"C:\Users\User\OneDrive\Desktop\IIt K Analytics
course\Python\marketing_data.csv")

#1.3 Print a snapshot of the data (data.head()) and check the data
types and missing values (data.info())

data.head()
```

```
      ID  Year_Birth   Education Marital_Status      income   Kidhome
\
0   1826        1970  Graduation       Divorced  $84,835.00         0

1      1        1961  Graduation         Single  $57,091.00         0

2  10476        1958  Graduation        Married  $67,267.00         0

3   1386        1967  Graduation       Together  $32,474.00         1

4   5371        1989  Graduation         Single  $21,474.00         1


   Teenhome Dt_Customer  Recency  MntWines  ...  NumStorePurchases  \
0         0     6/16/14        0       189  ...                  6
1         0     6/15/14        0       464  ...                  7
2         1     5/13/14        0       134  ...                  5
3         1  05-11-2014        0        10  ...                  2
4         0  04-08-2014        0         6  ...                  2

   NumWebVisitsMonth  AcceptedCmp3  AcceptedCmp4  AcceptedCmp5
AcceptedCmp1  \
0                  1             0             0             0
0
1                  5             0             0             0
0
2                  2             0             0             0
0
3                  7             0             0             0
```

```
0
4                   7             1             0             0
0

   AcceptedCmp2  Response  Complain  Country
0             0         1         0       SP
1             1         1         0       CA
2             0         0         0       US
3             0         0         0      AUS
4             0         1         0       SP

[5 rows x 28 columns]
```

```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 28 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   2240 non-null   int64
 1   Year_Birth           2240 non-null   int64
 2   Education            2240 non-null   object
 3   Marital_Status       2240 non-null   object
 4   income               2216 non-null   object
 5   Kidhome              2240 non-null   int64
 6   Teenhome             2240 non-null   int64
 7   Dt_Customer          2240 non-null   object
 8   Recency              2240 non-null   int64
 9   MntWines             2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Response             2240 non-null   int64
 26  Complain             2240 non-null   int64
 27  Country              2240 non-null   object
dtypes: int64(23), object(5)
memory usage: 490.1+ KB
```

```
#2: Investigate the Variables
#2.1: Check variables like Dt_Customer and Income to ensure they are
imported correctly

data.columns = data.columns.str.replace(' ', '').str.lower()

#2.2: Convert the income column to a float by removing '$' and ',' and
using astype('float')

data['income'] = data['income'].str.replace('[\$,]', '',
regex=True).str.strip().astype('float')
```

```
<>:1: SyntaxWarning: invalid escape sequence '\$'
<>:1: SyntaxWarning: invalid escape sequence '\$'
C:\Users\User\AppData\Local\Temp\ipykernel_18292\2433560080.py:1:
SyntaxWarning: invalid escape sequence '\$'
  data['income'] = data['income'].str.replace('[\$,]', '',
regex=True).str.strip().astype('float')
```

```
#2.3:  Convert the Dt_Customer column to a datetime object using
pd.to_datetime()

data.dt_customer = pd.to_datetime(data.dt_customer)
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_18292\2431619090.py:1:
UserWarning: Could not infer format, so each element will be parsed
individually, falling back to `dateutil`. To ensure parsing is
consistent and as-expected, please specify a format.
  data.dt_customer = pd.to_datetime(data.dt_customer)
```

```
#3: Impute the Missing Value
#3.1: Check for missing values using data.isnull().sum()

data.isnull().sum()
```

```
id                     0
year_birth             0
education              0
marital_status         0
income                24
kidhome                0
teenhome               0
dt_customer            0
recency                0
mntwines               0
mntfruits              0
mntmeatproducts        0
mntfishproducts        0
mntsweetproducts       0
mntgoldprods           0
numdealspurchases      0
```

```
numwebpurchases          0
numcatalogpurchases      0
numstorepurchases        0
numwebvisitsmonth        0
acceptedcmp3             0
acceptedcmp4             0
acceptedcmp5             0
acceptedcmp1             0
acceptedcmp2             0
response                 0
complain                 0
country                  0
dtype: int64
```

```
#3.2:  Clean the marital_status and education categories (example combining similar categories)

data.marital_status.unique()
```

```
array(['Divorced', 'Single', 'Married', 'Together', 'Widow', 'YOLO',
       'Alone', 'Absurd'], dtype=object)
```

```
#3.3:  Impute missing income values based on similar education and marital_status categories' average incomes

def change(x):
  if x in ['Married', 'Together']:
    return 'couple'
  else :
    return 'alone'
data.marital_status = data.marital_status.apply(change)

agg_data = data.groupby(['education', 'marital_status'])
[['income']].mean().unstack()['income']
agg_data
```

```
marital_status         alone        couple
education
2n Cycle        51957.984375  45597.992647
Basic           17998.350000  21663.852941
Graduation      52615.569652  52779.380952
Master          53170.472000  52785.795833
PhD             54050.657143  57343.238562
```

```
for edu in data.education.unique():
  for status in data.marital_status.unique():
    val = agg_data.loc[edu, status]
    data.loc[(data.education == edu) & (data.marital_status == status)
& (data.income.isnull()),'income'] = val
```

```
#4: Create the Variables
#4.1: Calculate the age of customers based on year_birth

data['age'] = 2024 - data.year_birth

#4.2: Calculate spending as the sum of spending columns (mntwines,
mntfruits)

data['spending'] =
data.loc[:,data.columns.str.startswith('mnt')].sum(axis = 1)

#4.3: Calculate children_count as the sum of kidhome and teenhome

data['children_count'] = data.kidhome + data.teenhome

#4.4: Create a binary variable has_children indicating if a customer
has children

data['has_children'] = np.where((data.kidhome + data.teenhome) > 0,
1,0)

#4.5: Derive total_purchases from the sum of purchase columns

data['total_purchases'] = data.loc[:,
data.columns.str.endswith('purchases')].sum(axis = 1)

data['education_years'] = data.education.replace({'Basic':5,'2n
Cycle':8,'Graduation':12,'Master':18,'PhD':21})
```

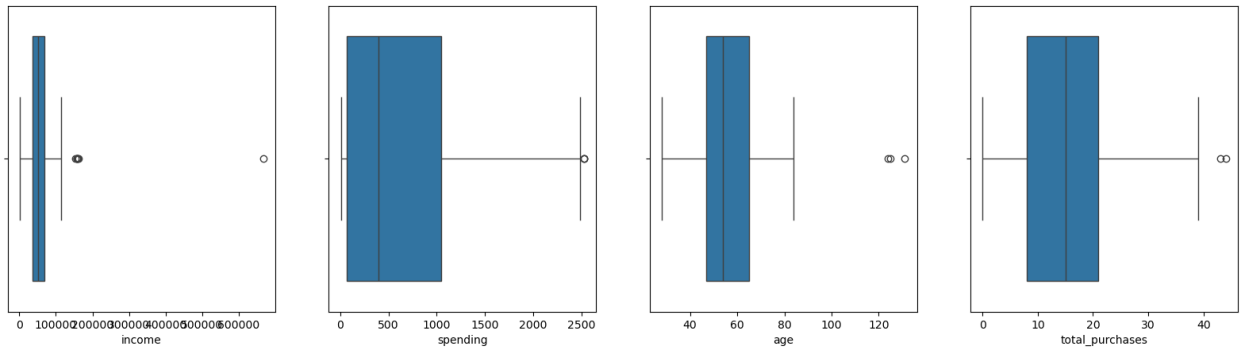
```
C:\Users\User\AppData\Local\Temp\ipykernel_18292\2722653900.py:1:
FutureWarning: Downcasting behavior in `replace` is deprecated and
will be removed in a future version. To retain the old behavior,
explicitly call `result.infer_objects(copy=False)`. To opt-in to the
future behavior, set `pd.set_option('future.no_silent_downcasting',
True)`
  data['education_years'] = data.education.replace({'Basic':5,'2n
Cycle':8,'Graduation':12,'Master':18,'PhD':21})
```

```
#5: Generate Box Plots and Histograms
#5.1: Plot box plots and histograms for numerical variables (income,
spending, age, and total_purchases) to understand their distributions
and identify outliers

data.columns
```

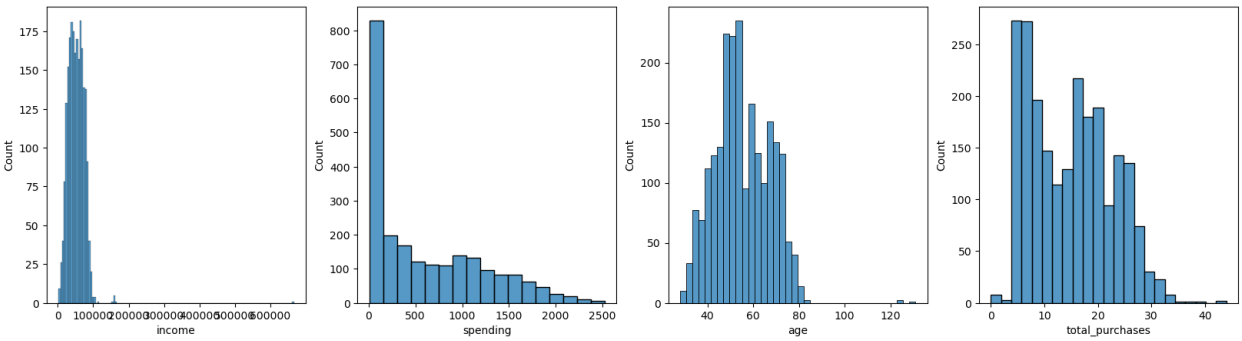
```
Index(['id', 'year_birth', 'education', 'marital_status', 'income',
'kidhome',
       'teenhome', 'dt_customer', 'recency', 'mntwines', 'mntfruits',
       'mntmeatproducts', 'mntfishproducts', 'mntsweetproducts',
       'mntgoldprods', 'numdealspurchases', 'numwebpurchases',
       'numcatalogpurchases', 'numstorepurchases',
'numwebvisitsmonth',
```

```
       'acceptedcmp3', 'acceptedcmp4', 'acceptedcmp5', 'acceptedcmp1',
       'acceptedcmp2', 'response', 'complain', 'country', 'age',
'spending',
       'children_count', 'has_children', 'total_purchases',
'education_years'],
      dtype='object')
```

```
num_vars = ['income', 'spending', 'age', 'total_purchases']

f,ax = plt.subplots(1, len(num_vars), figsize = (20,5))
i = 0
for v in num_vars:
  sns.boxplot(x = data[v], ax = ax[i])
  i += 1
plt.show()
```




```
f,ax = plt.subplots(1, len(num_vars), figsize = (20,5))
i = 0
for v in num_vars:
  sns.histplot(x = data[v], ax = ax[i])
  i += 1
plt.show()
```

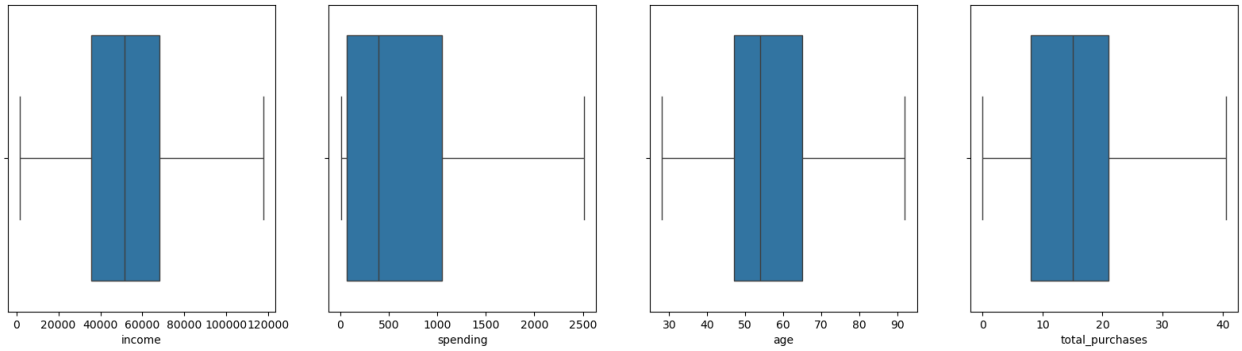



```
def outlier_detection(x):
  q1 = x.quantile(0.25)
  q3 = x.quantile(0.75)
  iqr = q3 - q1
```

```
  ll = q1 - (1.5 * iqr)
  ul = q3 + (1.5 * iqr)
  return ll, ul

#5.2: Perform outlier treatment by capping the outliers to the upper
and lower limits

for v in num_vars:
  print("Var = ", v)
  ll,ul = outlier_detection(data[v])
  print('ll = {} ul = {}'.format(ll,ul))
  data.loc[data[v]<ll, v] = ll
  data.loc[data[v]>ul, v] = ul
```

```
Var =  income
ll = -13587.75 ul = 117416.25
Var =  spending
ll = -1396.375 ul = 2510.625
Var =  age
ll = 20.0 ul = 92.0
Var =  total_purchases
ll = -11.5 ul = 40.5

C:\Users\User\AppData\Local\Temp\ipykernel_18292\1499794312.py:5:
FutureWarning: Setting an item of incompatible dtype is deprecated and
will raise an error in a future version of pandas. Value '-1396.375'
has dtype incompatible with int64, please explicitly cast to a
compatible dtype first.
  data.loc[data[v]<ll, v] = ll
C:\Users\User\AppData\Local\Temp\ipykernel_18292\1499794312.py:5:
FutureWarning: Setting an item of incompatible dtype is deprecated and
will raise an error in a future version of pandas. Value '-11.5' has
dtype incompatible with int64, please explicitly cast to a compatible
dtype first.
  data.loc[data[v]<ll, v] = ll
```

```
f,ax = plt.subplots(1, len(num_vars), figsize = (20,5))
i = 0
for v in num_vars:
  sns.boxplot(x = data[v], ax = ax[i])
  i += 1
plt.show()
```




```
#6: Encode the Data
#6.2: For education, we use an ordinal encoder

data.select_dtypes('object')
```

```
       education marital_status country
0     Graduation          alone      SP
1     Graduation          alone      CA
2     Graduation         couple      US
3     Graduation         couple     AUS
4     Graduation          alone      SP
...          ...            ...     ...
2235         PhD          alone      US
2236    2n Cycle         couple      SP
2237  Graduation          alone      SP
2238  Graduation         couple     IND
2239         PhD         couple      CA

[2240 rows x 3 columns]
```

```
data.education.unique()
```

```
array(['Graduation', 'PhD', '2n Cycle', 'Master', 'Basic'],
dtype=object)
```

```
ord = OrdinalEncoder(categories = [['Basic','2n Cycle','Graduation',
'Master','PhD']])
ord.fit(data[['education']])
data['education_encode'] =
ord.transform(data[['education']]).flatten()

#6.2: Use one-hot encoding for country and marital_status columns

ohe = OneHotEncoder()

country_encode =
pd.DataFrame(ohe.fit_transform(data[['country']]).toarray().astype(int
),
             columns = ohe.categories_[0])
country_encode
```

```
      AUS  CA  GER  IND  ME  SA  SP  US
0       0   0    0    0   0   0   1   0
1       0   1    0    0   0   0   0   0
2       0   0    0    0   0   0   0   1
3       1   0    0    0   0   0   0   0
4       0   0    0    0   0   0   1   0
...   ...  ..  ...  ...  ..  ..  ..  ..
2235    0   0    0    0   0   0   0   1
2236    0   0    0    0   0   0   1   0
2237    0   0    0    0   0   0   1   0
2238    0   0    0    1   0   0   0   0
2239    0   1    0    0   0   0   0   0

[2240 rows x 8 columns]
```

```
marital_status_encode =
pd.DataFrame(ohe.fit_transform(data[['marital_status']]).toarray().ast
ype(int),
             columns = ohe.categories_[0])
marital_status_encode
```

```
      alone  couple
0         1       0
1         1       0
2         0       1
3         0       1
4         1       0
...     ...     ...
2235      1       0
2236      0       1
2237      1       0
2238      0       1
2239      0       1

[2240 rows x 2 columns]
```

```
#Concat these new df to the old one

new_data = pd.concat([data,pd.get_dummies(data[['country',
'marital_status']])], axis = 1)

new_data.info()
```

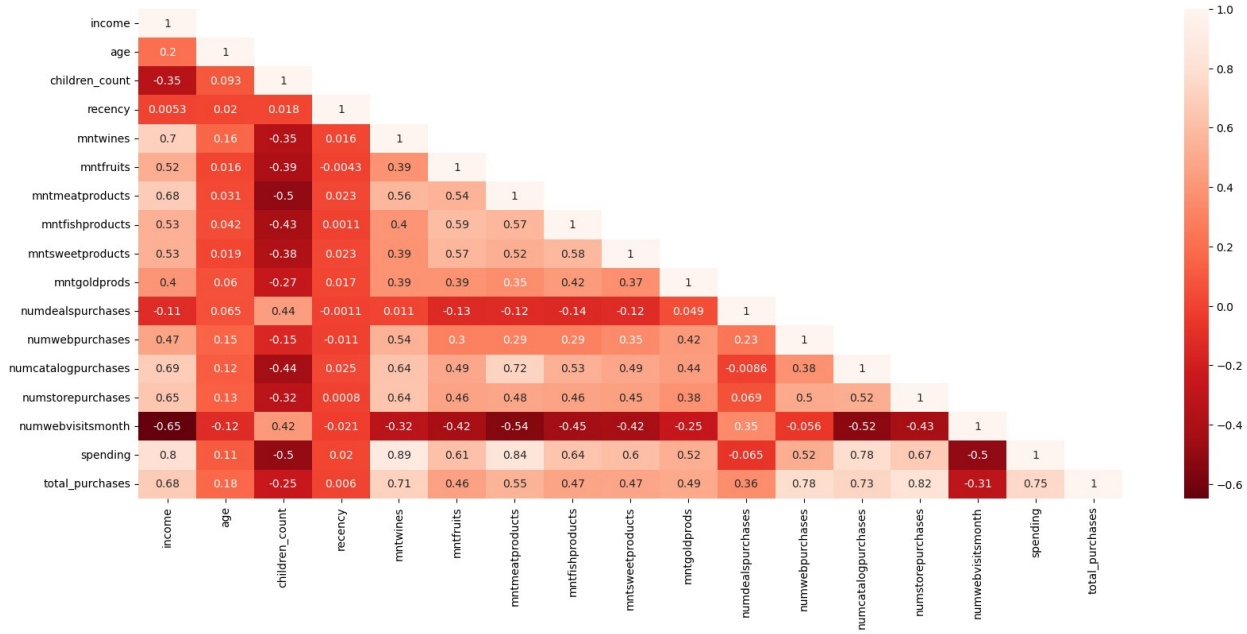
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 45 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    2240 non-null   int64
 1   year_birth            2240 non-null   int64
 2   education             2240 non-null   object
```

```
 3   marital_status          2240 non-null   object
 4   income                  2240 non-null   float64
 5   kidhome                 2240 non-null   int64
 6   teenhome                2240 non-null   int64
 7   dt_customer             2240 non-null   datetime64[ns]
 8   recency                 2240 non-null   int64
 9   mntwines                2240 non-null   int64
 10  mntfruits               2240 non-null   int64
 11  mntmeatproducts         2240 non-null   int64
 12  mntfishproducts         2240 non-null   int64
 13  mntsweetproducts        2240 non-null   int64
 14  mntgoldprods            2240 non-null   int64
 15  numdealspurchases       2240 non-null   int64
 16  numwebpurchases         2240 non-null   int64
 17  numcatalogpurchases     2240 non-null   int64
 18  numstorepurchases       2240 non-null   int64
 19  numwebvisitsmonth       2240 non-null   int64
 20  acceptedcmp3            2240 non-null   int64
 21  acceptedcmp4            2240 non-null   int64
 22  acceptedcmp5            2240 non-null   int64
 23  acceptedcmp1            2240 non-null   int64
 24  acceptedcmp2            2240 non-null   int64
 25  response                2240 non-null   int64
 26  complain                2240 non-null   int64
 27  country                 2240 non-null   object
 28  age                     2240 non-null   int64
 29  spending                2240 non-null   float64
 30  children_count          2240 non-null   int64
 31  has_children            2240 non-null   int32
 32  total_purchases         2240 non-null   float64
 33  education_years         2240 non-null   int64
 34  education_encode        2240 non-null   float64
 35  country_AUS             2240 non-null   bool
 36  country_CA              2240 non-null   bool
 37  country_GER             2240 non-null   bool
 38  country_IND             2240 non-null   bool
 39  country_ME              2240 non-null   bool
 40  country_SA              2240 non-null   bool
 41  country_SP              2240 non-null   bool
 42  country_US              2240 non-null   bool
 43  marital_status_alone    2240 non-null   bool
 44  marital_status_couple   2240 non-null   bool
dtypes: bool(10), datetime64[ns](1), float64(4), int32(1), int64(26),
object(3)
memory usage: 625.8+ KB
```

```
#7: Analyze the Correlation between the variables
#7.1: Select a subset of columns for correlation analysis

new_data.columns
```

```
Index(['id', 'year_birth', 'education', 'marital_status', 'income',
'kidhome',
       'teenhome', 'dt_customer', 'recency', 'mntwines', 'mntfruits',
       'mntmeatproducts', 'mntfishproducts', 'mntsweetproducts',
       'mntgoldprods', 'numdealspurchases', 'numwebpurchases',
       'numcatalogpurchases', 'numstorepurchases',
'numwebvisitsmonth',
       'acceptedcmp3', 'acceptedcmp4', 'acceptedcmp5', 'acceptedcmp1',
       'acceptedcmp2', 'response', 'complain', 'country', 'age',
'spending',
       'children_count', 'has_children', 'total_purchases',
'education_years',
       'education_encode', 'country_AUS', 'country_CA', 'country_GER',
       'country_IND', 'country_ME', 'country_SA', 'country_SP',
'country_US',
       'marital_status_alone', 'marital_status_couple'],
      dtype='object')
```

```
var_cor = ['income', 'age', 'children_count', 'recency', 'mntwines',
'mntfruits',
       'mntmeatproducts', 'mntfishproducts', 'mntsweetproducts',
       'mntgoldprods', 'numdealspurchases', 'numwebpurchases',
       'numcatalogpurchases', 'numstorepurchases',
'numwebvisitsmonth','spending', 'total_purchases'
       ]

#7.2: Compute the correlation matrix (new_data[var_cor].corr()) and
plot a heatmap (sns.heatmap())

cor_data = new_data[var_cor].corr()

plt.figure(figsize = (20,8))
m = np.ones_like(cor_data)
m[np.tril_indices_from(m)]= 0
sns.heatmap(cor_data, mask = m, annot = True, cmap = 'Reds_r')
plt.show()
```




```
# 8:Conduct a Hypothesis Testing
# 8.1:Define and test hypotheses related to customer behavior using statistical tests, such as (stats.ttest_ind())

#Test the following hypotheses:
#Older people are not as tech-savvy and probably prefer shopping in-store.
#H0: For older customers, the number of purchases in-store is less than or equal to the number of purchases online
#Ha: For older customers, the number of purchases in-store is greater than the number of purchases online.

store = new_data.loc[new_data.age >= 60, 'numstorepurchases']
web = new_data.loc[new_data.age >= 60, 'numwebpurchases']
stats.ttest_ind(store,web, alternative='greater' )

TtestResult(statistic=12.456766178670938, pvalue=2.4611358913448465e-34, df=1570.0)

#Since the p-value is much less than the alpha of 5%, we shall reject the null hypothesis and conclude that older customers prefer store purchases.
#Test the following hypotheses:
#Customers with kids probably have less time to visit a store and would prefer to shop online.
#H0: For customers who have children, the number of purchases online is less than or equal to the number of purchases in-store.
#Ha: For customers who have children, the number of purchases online is greater than the number of purchases in-store.
```

```
online = new_data.loc[new_data.has_children == 1,'numwebpurchases']
store_p = new_data.loc[new_data.has_children == 1,'numstorepurchases']
stats.ttest_ind(online, store_p, alternative = "greater")
```

```
TtestResult(statistic=-11.85534380488127, pvalue=1.0, df=3202.0)
```

```
#Since the p-value is 1 and much greater than the alpha of 5%, we fail
to reject the null hypothesis and conclude that people who have
children prefer store purchases over online purchases
#Other distribution channels may cannibalize sales at the store
#H0 : purchases through other channels <= no. of store purchases
#Ha : purchases through other channels > no. of store purchases
```

```
other = new_data.loc[:,['numwebpurchases',
'numcatalogpurchases']].sum(axis = 1)
store = new_data.loc[:, 'numstorepurchases']
stats.ttest_ind(other, store, alternative ="greater")
```

```
TtestResult(statistic=7.884334964023309, pvalue=1.971324447658957e-15,
df=4478.0)
```

```
#Since the p-value is much less than the alpha of 5%, we shall reject
the null hypothesis and conclude that other distribution channels,
such as web purchases or catalog purchases, are preferred over store
purchases.
#Identify wether the US fares significantly better than the rest of
the world in terms of total purchases
#H0 : total_purchases_us <= total_purchases_row
#Ha : total_purchases_us > total_purchases_row
```

```
total_purchases_us = new_data.loc[new_data.country ==
"US",'total_purchases']
total_purchases_row = new_data.loc[new_data.country !=
"US",'total_purchases']
stats.ttest_ind(total_purchases_us ,total_purchases_row, alternative =
'greater')
```

```
TtestResult(statistic=1.7339544907234352, pvalue=0.04153193317039351,
df=2238.0)
```

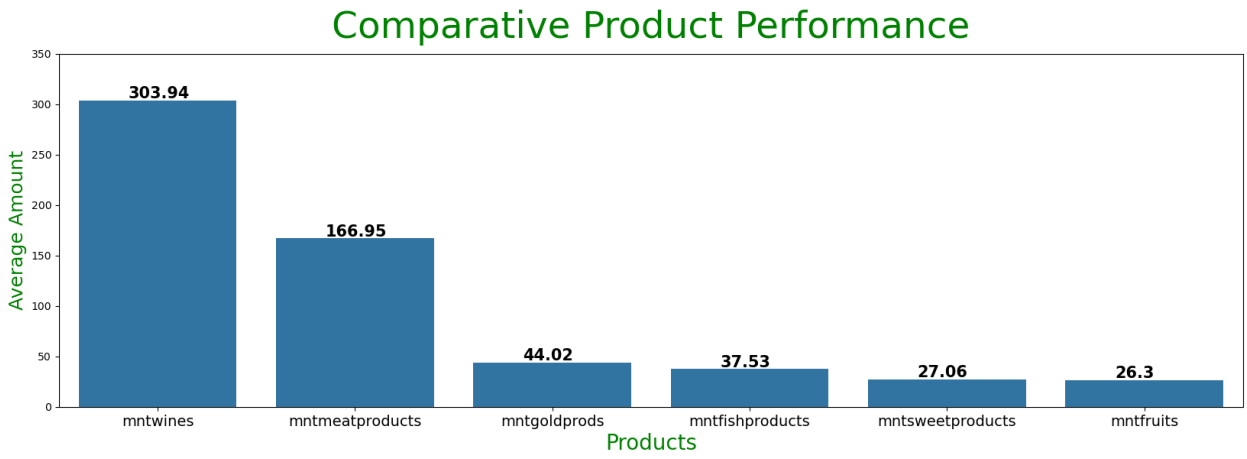
```
#At the 5% significance level, we reject the null hypothesis.
Therefore, we can conclude that the US performs better in terms of the
number of purchases compared to the rest of the world.
```

```
#9:Visualize the Data
#9.1: Visualize the performance of products (prod_data) using a bar
plot
```

```
prod_data =
new_data.loc[:,new_data.columns.str.startswith('mnt')].mean().round(2)
```

```
.sort_values(ascending = False)
plt.figure(figsize = (20,6))
sns.barplot(x = prod_data.index, y = prod_data.values,
order=prod_data.index)
for i in range(prod_data.size):
  plt.annotate(prod_data[i], xy = (i-0.15, prod_data[i]+2), size =15 ,
weight = 'heavy')
plt.ylim(0, 350)
plt.xlabel( 'Products', size = 20, color = 'green')
plt.ylabel( 'Average Amount', size = 18, color = 'green')
plt.title('Comparative Product Performance', size = 35, pad = 15,
color = 'green')
plt.xticks(size = 14)
plt.show()
```

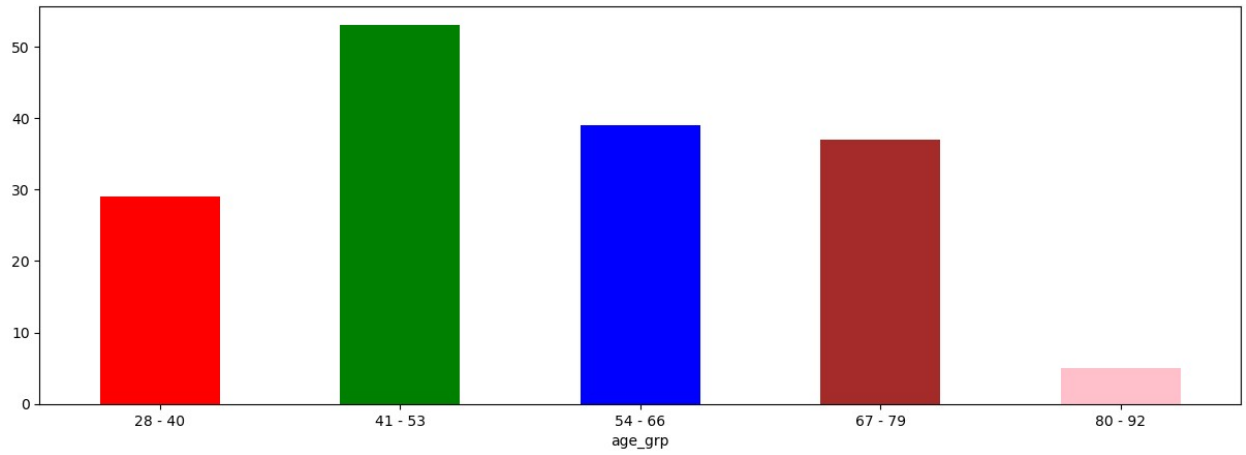
```
C:\Users\User\AppData\Local\Temp\ipykernel_18292\1272569968.py:5:
FutureWarning: Series.__getitem__ treating keys as positions is
deprecated. In a future version, integer keys will always be treated
as labels (consistent with DataFrame behavior). To access a value by
position, use `ser.iloc[pos]`
  plt.annotate(prod_data[i], xy = (i-0.15, prod_data[i]+2), size =15 ,
weight = 'heavy')
```




```
#9.2: Explore the relationship between age and campaign acceptance
rate (acceptedcmp5) using a bar plot

data['age_grp'] = pd.cut(data.age, bins = 5, labels = [1,2,3,4,5])

grpd_age = data.groupby('age_grp')['age'].agg(['min','max'])
grpd_age['group'] = grpd_age['min'].astype(str) + ' - '
+grpd_age['max'].astype(str)
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_18292\3866832219.py:1:
FutureWarning: The default of observed=False is deprecated and will be
changed to True in a future version of pandas. Pass observed=False to
```

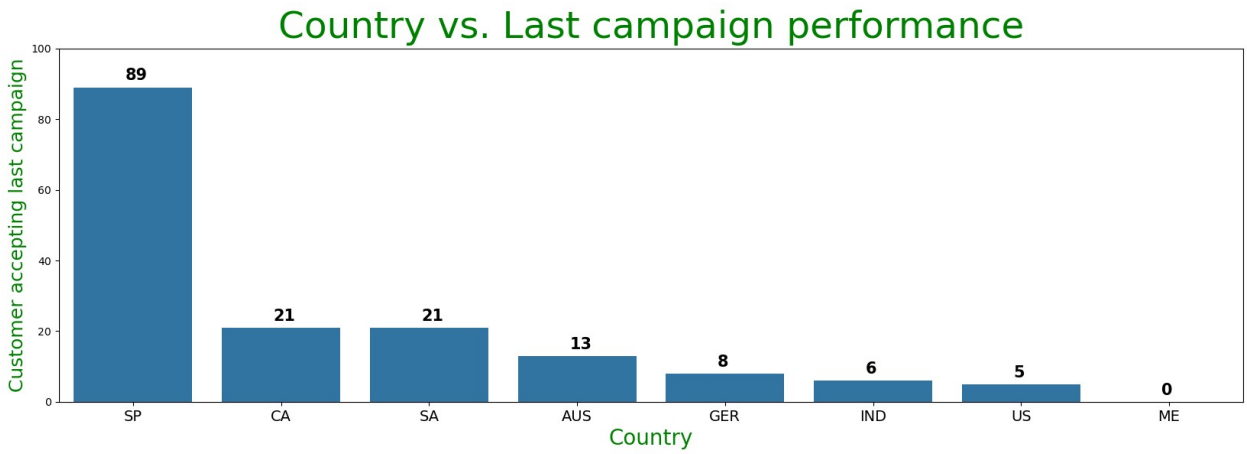
```
retain current behavior or observed=True to adopt the future default
and silence this warning.
  grpd_age = data.groupby('age_grp')['age'].agg(['min','max'])

#Renaming labels

data.age_grp = data.age_grp.replace([1,2,3,4,5], grpd_age.group)

C:\Users\User\AppData\Local\Temp\ipykernel_18292\1402206506.py:1:
FutureWarning: The behavior of Series.replace (and DataFrame.replace)
with CategoricalDtype is deprecated. In a future version, replace will
only be used for cases that preserve the categories. To change the
categories, use ser.cat.rename_categories instead.
  data.age_grp = data.age_grp.replace([1,2,3,4,5], grpd_age.group)

vc = data[data.acceptedcmp5 == 1].age_grp.value_counts().sort_index()
plt.figure(figsize = (15,5))
vc.plot.bar(color = ['red', 'green', 'blue', 'brown', 'pink'])
plt.xticks(rotation = 0)
plt.show()
```




```
#9.3: Determine the country with the most customers who accepted the
last campaign using a bar plot

accptd_data = new_data.groupby('country')
[['acceptedcmp5']].agg('sum').squeeze().sort_values(ascending = False)
plt.figure(figsize = (20,6))
sns.barplot(x = accptd_data.index, y = accptd_data.values,
order=accptd_data.index)
for i in range(accptd_data.size):
  plt.annotate(accptd_data[i], xy = (i-0.05, accptd_data[i]+2), size
=15 , weight = 'heavy')
plt.ylim(0,100)
plt.xlabel( 'Country', size = 20, color = 'green')
plt.ylabel( 'Customer accepting last campaign', size = 18, color =
'green')
```

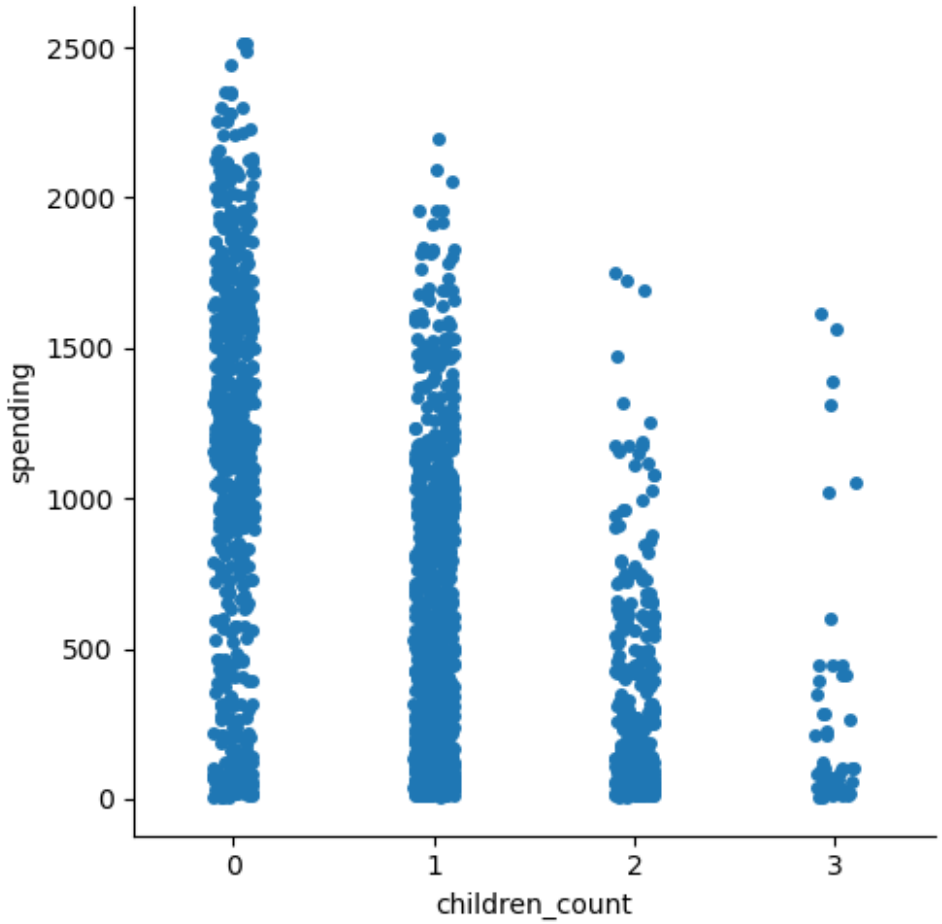
```
plt.title('Country vs. Last campaign performance', size = 35, pad =
10, color = 'green')
plt.xticks(size = 14)
plt.show()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_18292\3857655800.py:5:
FutureWarning: Series.__getitem__ treating keys as positions is
deprecated. In a future version, integer keys will always be treated
as labels (consistent with DataFrame behavior). To access a value by
position, use `ser.iloc[pos]`
  plt.annotate(accptd_data[i], xy = (i-0.05, accptd_data[i]+2), size
=15 , weight = 'heavy')
```



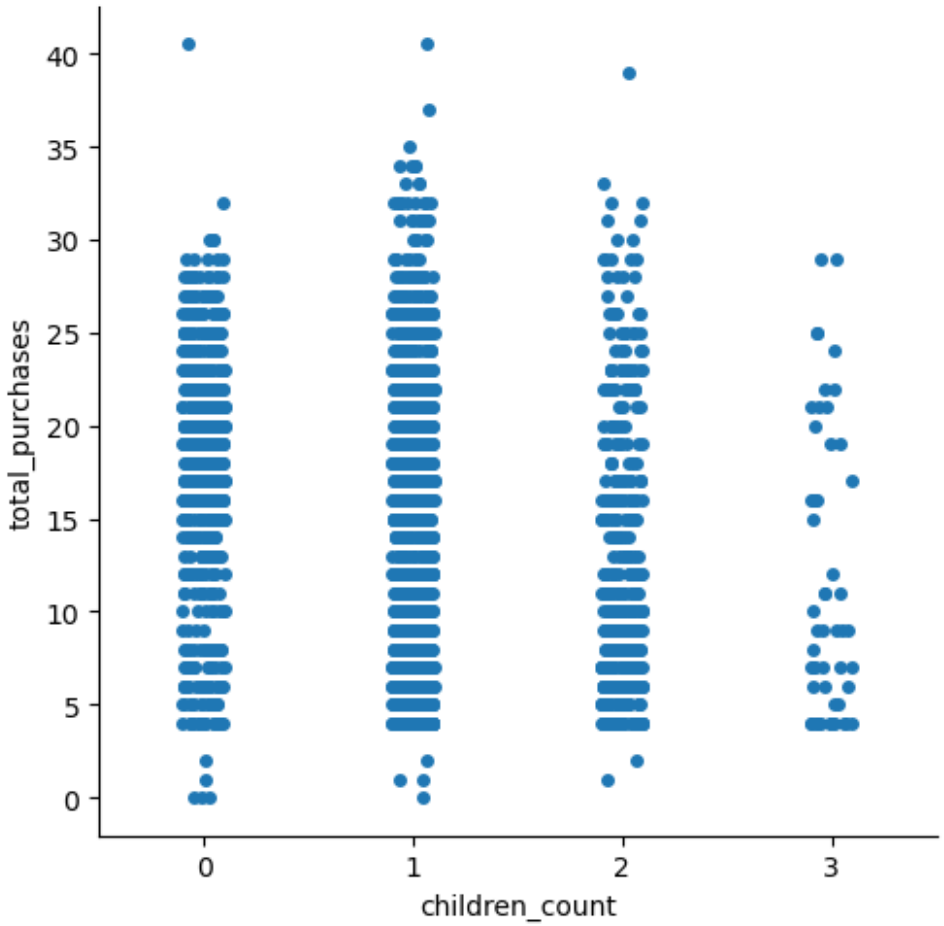

```
#9.4: Analyze the relationship between children_count and spending
using a strip plot

sns.catplot(x = 'children_count', y = 'spending',data = new_data, kind
= "strip")
```

```
<seaborn.axisgrid.FacetGrid at 0x245611d3950>
```




```
sns.catplot(x = 'children_count', y = 'total_purchases',data =
new_data, kind = "strip")
```

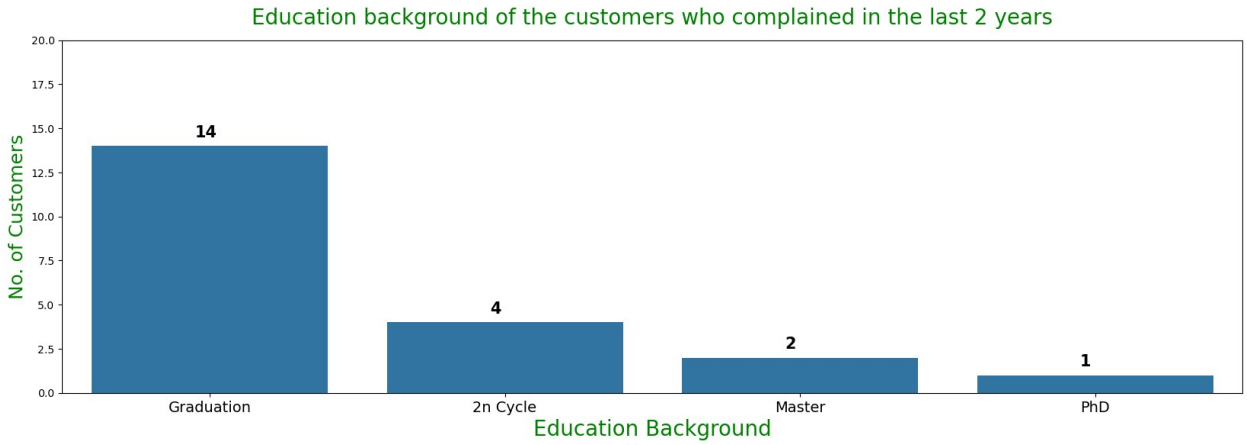
```
<seaborn.axisgrid.FacetGrid at 0x2456085d040>
```



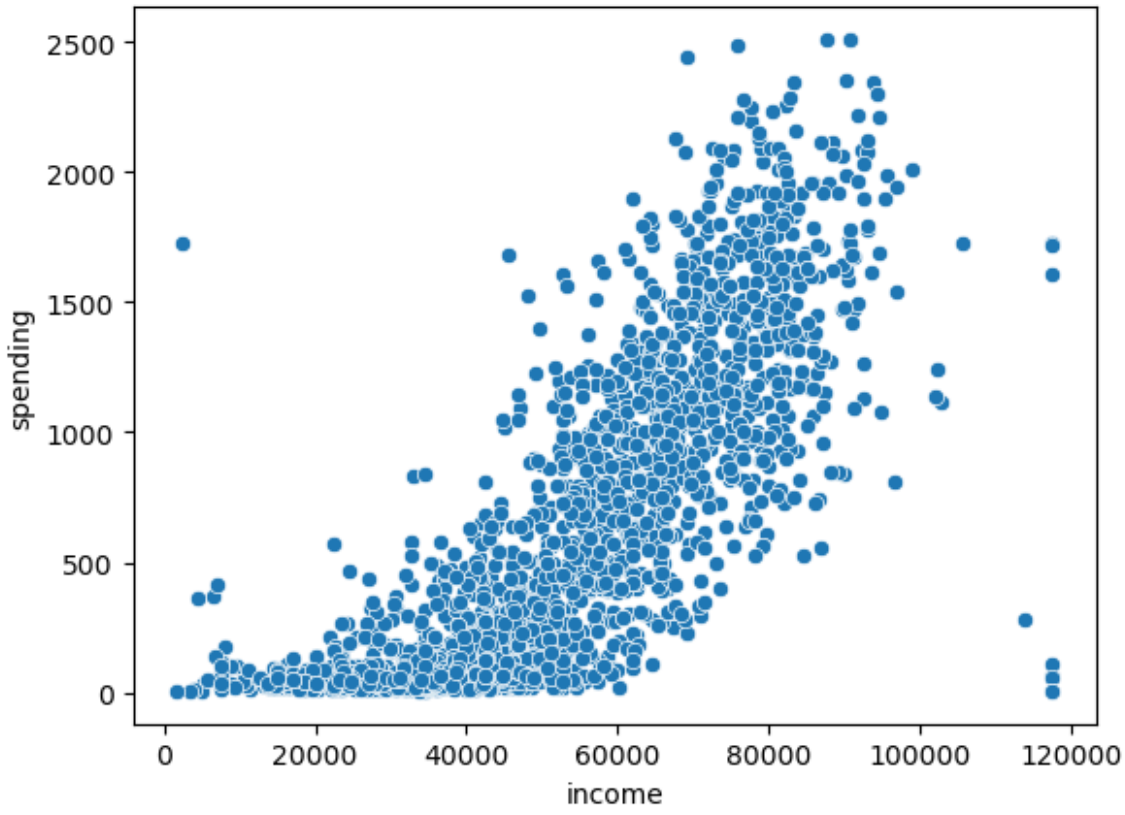

```
#9.5:  Visualize the education background of customers who complained
in the last two years using a bar plot

vc = new_data.loc[new_data.complain == 1, 'education'].value_counts()
plt.figure(figsize = (20,6))
sns.barplot(x = vc.index, y = vc.values, order=vc.index)
for i in range(vc.size):
  plt.annotate(vc[i], xy = (i-0.05, vc[i]+0.5), size =15 , weight =
'heavy')
plt.ylim(0, 20)
plt.xlabel( 'Education Background', size = 20, color = 'green')
plt.ylabel( 'No. of Customers', size = 18, color = 'green')
plt.title('Education background of the customers who complained in the
last 2 years', size = 20, pad = 15, color = 'green')
plt.xticks(size = 14)
plt.show()
```

```
C:\Users\User\AppData\Local\Temp\ipykernel_18292\3740582564.py:5:
FutureWarning: Series.__getitem__ treating keys as positions is
deprecated. In a future version, integer keys will always be treated
as labels (consistent with DataFrame behavior). To access a value by
```

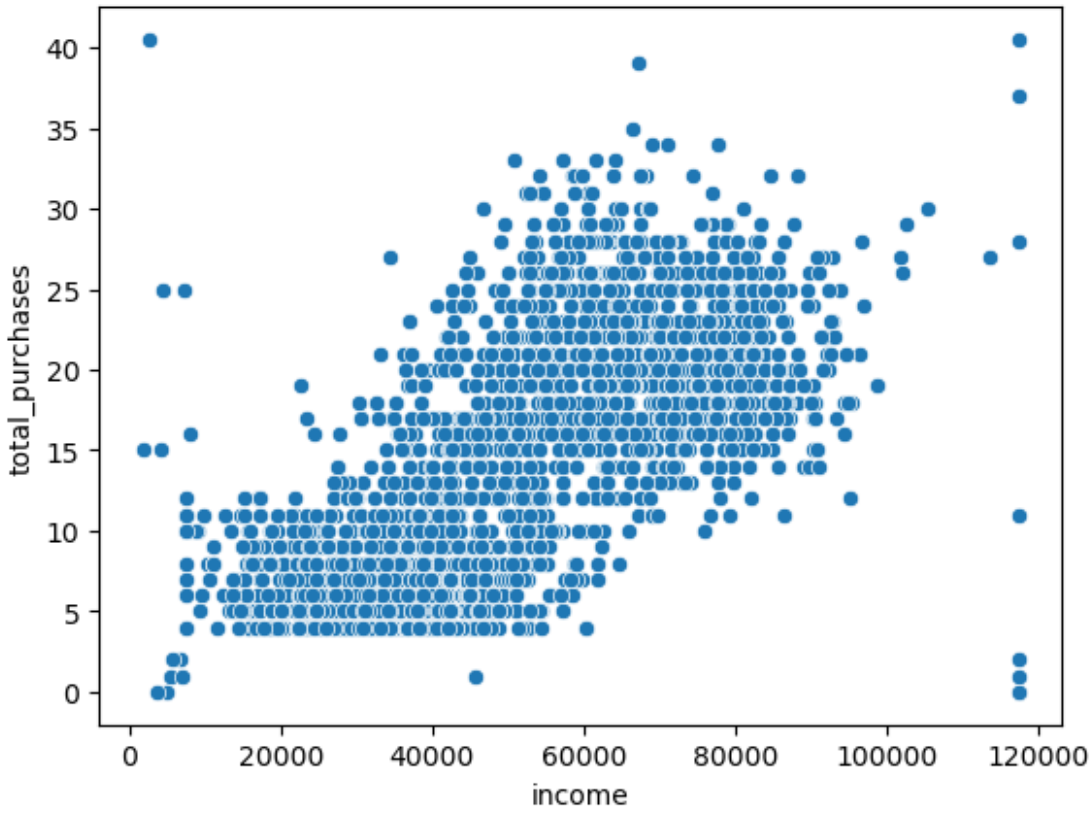
```
position, use `ser.iloc[pos]`
  plt.annotate(vc[i], xy = (i-0.05, vc[i]+0.5), size =15 , weight =
'heavy')
```




```
#9.6: Explore the relationship between income and spending using a
scatter plot

sns.scatterplot(x = 'income', y = 'spending', data = new_data)

<Axes: xlabel='income', ylabel='spending'>
```

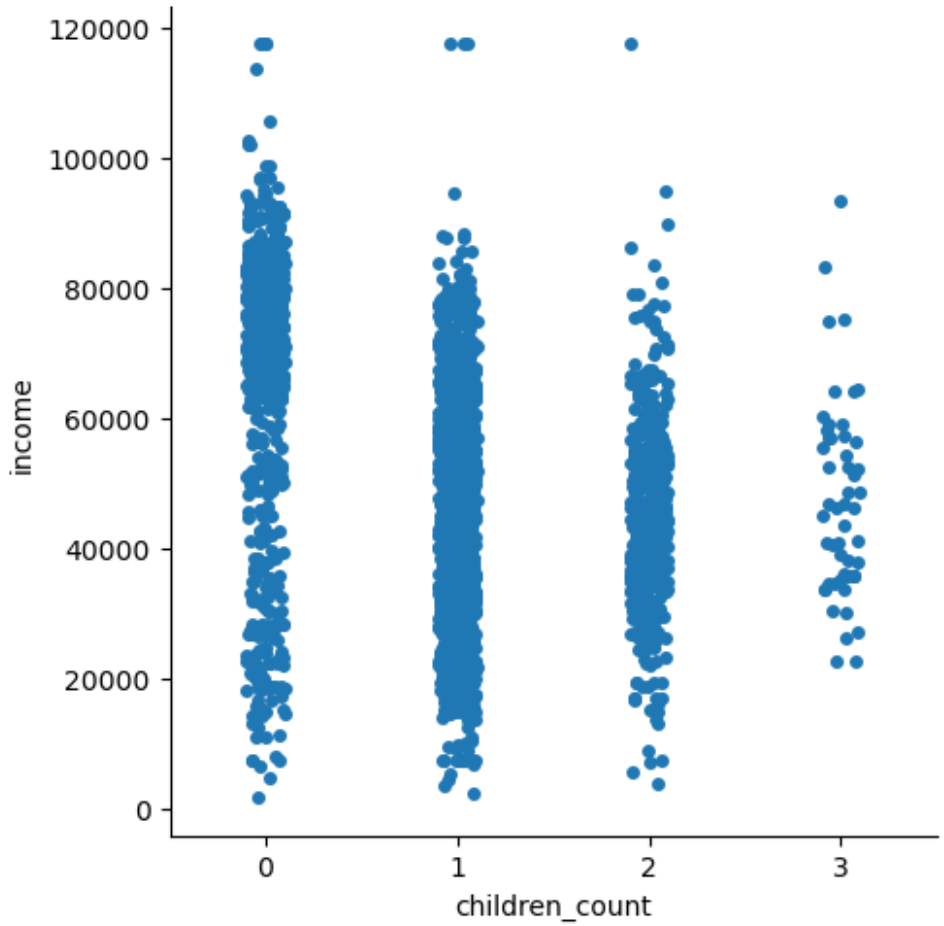


```
sns.scatterplot(x = 'income', y = 'total_purchases', data = new_data)
plt.show()
```




```
sns.catplot(y = 'income', x = 'children_count', data = new_data, kind
= 'strip', ax = ax)
plt.show()
```

```
D:\Python\Lib\site-packages\seaborn\categorical.py:2761: UserWarning:
catplot is a figure-level function and does not accept target axes.
You may wish to try stripplot
  warnings.warn(msg, UserWarning)
```


120000
100000
80000
60000
40000
20000
0
income
0
1
2
3
children_count