

```

import pandas as pd
import numpy as np
import scipy.stats as stats
import matplotlib.pyplot as plt
import seaborn as sns

#1. Import claims_data.csv and cust_data.csv which is provided to you and combine the two datasets
#appropriately to create a 360-degree view of the data. Use the same for the subsequent questions.

# Load the dataset
claims_data = pd.read_csv("claims.csv")
cust_data = pd.read_csv("cust_demographics.csv")

df = claims_data.merge(cust_data, left_on="customer_id", right_on="CUST_ID",
how="inner")

df.head(5)

      claim_id  customer_id    incident_cause   claim_date claim_area \
0  54004764        21868593     Driver error  11/27/2017      Auto
1  33985796        75740424        Crime       10/03/2018     Home
2  53522022        30308357  Other driver error  02/02/2018      Auto
3  63017412        30308357     Driver error  04/04/2018      Auto
4  13015401        47830476  Natural causes  06/17/2018      Auto

police_report    claim_type claim_amount total_policy_claims fraudulent \
0            No  Material only        $2980                  1.0        No
1      Unknown  Material only        $2980                  3.0        No
2            No  Material only      $3369.5                  1.0       Yes
3            No  Material only        $1950                  6.0        No
4            No  Material only        $1680                  1.0        No

      CUST_ID  gender DateOfBirth State      Contact Segment
0  21868593  Female   12-Jan-79   VT  789-916-8172  Platinum
1  75740424  Female   13-Jan-70   ME  265-543-1264      Silver
2  30308357  Female   11-Mar-84   TN  798-631-4758      Silver
3  30308357  Female   11-Mar-84   TN  798-631-4758      Silver
4  47830476  Female   01-May-86   MA  413-187-7945      Silver

```

#2. Perform a data audit for the datatypes and find out if there are any mismatch within the current datatypes
#of the columns and their business significance.

```

# A2: Perform a data audit
print("\nData Types and Missing Values:")
print(df.info())
print("\nMissing Values Count:")
print(df.isnull().sum())

```

```

Data Types and Missing Values:
<class 'pandas.core.frame.DataFrame'>
Int64Index: 1085 entries, 0 to 1084
Data columns (total 16 columns):
 #   Column           Non-Null Count  Dtype  
---  -- 
 0   claim_id         1085 non-null   int64  
 1   customer_id     1085 non-null   int64  
 2   incident_cause  1085 non-null   object  
 3   claim_date       1085 non-null   object  
 4   claim_area       1085 non-null   object  
 5   police_report    1085 non-null   object  
 6   claim_type       1085 non-null   object  
 7   claim_amount     1085 non-null   float64
 8   total_policy_claims 1085 non-null   float64
 9   fraudulent       1085 non-null   object  
 10  CUST_ID          1085 non-null   int64  
 11  gender            1085 non-null   object  
 12  DateOfBirth      1085 non-null   object  
 13  State             1085 non-null   object  
 14  Contact           1085 non-null   object  
 15  Segment            1085 non-null   object  

```

```
0    claim_id            1085 non-null  int64
1    customer_id         1085 non-null  int64
2    incident_cause      1085 non-null  object
3    claim_date          1085 non-null  object
4    claim_area           1085 non-null  object
5    police_report        1085 non-null  object
6    claim_type           1085 non-null  object
7    claim_amount         1020 non-null  object
8    total_policy_claims 1075 non-null  float64
9    fraudulent           1085 non-null  object
10   CUST_ID             1085 non-null  int64
11   gender               1085 non-null  object
12   DateOfBirth          1085 non-null  object
13   State                1085 non-null  object
14   Contact              1085 non-null  object
15   Segment              1085 non-null  object
```

dtypes: float64(1), int64(3), object(12)

memory usage: 144.1+ KB

None

Missing Values Count:

```
claim_id            0
customer_id         0
incident_cause      0
claim_date          0
claim_area           0
police_report        0
claim_type           0
claim_amount         65
total_policy_claims 10
fraudulent           0
CUST_ID             0
gender               0
DateOfBirth          0
State                0
Contact              0
Segment              0
```

dtype: int64

#Another view

```
# A2: Perform a data audit
data_audit = pd.DataFrame({
    "Column Name": df.columns,
    "Data Type": df.dtypes.values,
    "Missing Values": df.isnull().sum().values,
    "Unique Values": df.nunique().values
})

print("\nData Audit Table:")
print(data_audit)
```

Data Audit Table:

	Column Name	Data Type	Missing Values	Unique Values
0	claim_id	int64	0	1085
1	customer_id	int64	0	1078
2	incident_cause	object	0	5

```

3      claim_date    object        0      100
4      claim_area    object        0       2
5      police_report object        0       3
6      claim_type    object        0       3
7      claim_amount   float64     65     676
8  total_policy_claims float64     10       8
9      fraudulent    object        0       2
10      CUST_ID      int64        0     1078
11      gender        object        0       2
12      DateOfBirth   object        0     1078
13      State         object        0      50
14      Contact       object        0     1078
15      Segment       object        0       3
16  injury_claim_unreported int64        0       2

```

#3. Convert the column `claim_amount` to numeric. Use the appropriate modules/attributes to remove the \$ sign.

A3: Convert `claim_amount` to numeric

```

if 'claim_amount' in df.columns:
    df['claim_amount'] = df['claim_amount'].replace('[$,]', '',
regex=True).astype(float)

```

#4. Of all the `injury` claims, some of them have gone unreported with the police. #Create an alert flag (1,0) for all such claims.

a4: Create alert flag for unreported injury claims

```
df['injury_claim_unreported'] = np.where(df['police_report'] == 'No', 0, 1)
```

```

selected_columns = ['claim_id', 'customer_id', 'claim_amount', 'incident_cause',
'police_report',
           'injury_claim_unreported']
df[selected_columns].head(5)

```

	claim_id	customer_id	claim_amount	incident_cause	police_report
0	54004764	21868593	2980.0	Driver error	No
1	33985796	75740424	2980.0	Crime	Unknown
2	53522022	30308357	3369.5	Other driver error	No
3	63017412	30308357	1950.0	Driver error	No
4	13015401	47830476	1680.0	Natural causes	No

`injury_claim_unreported`

```

0      0
1      1
2      0
3      0
4      0

```

#5. One customer can claim for insurance more than once and in each claim, multiple categories

#of claims can be involved. However, customer ID should remain unique.

#Retain the most recent observation and delete any duplicated records in the data based on the customer ID column.

A5: Retain most recent claim and remove duplicates

```
df['claim_date'] = pd.to_datetime(df['claim_date']) # Convert to datetime
df = df.sort_values(by='claim_date',
```

```
ascending=False).drop_duplicates(subset='customer_id', keep='first')  
df.head()
```

	claim_id	customer_id	incident_cause	claim_date	claim_area	\
226	49735712	17682060	Crime	2018-10-30	Home	
1055	43042986	58451506	Natural causes	2018-10-30	Auto	
1077	91386759	65208809	Natural causes	2018-10-30	Auto	
354	98795403	38011078	Crime	2018-10-30	Auto	
751	25213498	28932340	Driver error	2018-10-30	Auto	

	police_report	claim_type	claim_amount	total_policy_claims	\
226	Unknown	Material and injury	17020.0	1.0	
1055	No	Material only	2420.0	1.0	
1077	No	Material only	2290.0	1.0	
354	Unknown	Material only	1940.0	1.0	
751	Unknown	Material only	NaN	1.0	

	fraudulent	CUST_ID	gender	DateOfBirth	State	Contact	Segment	\
226	No	17682060	Female	21-Nov-74	NV	186-195-3465	Gold	
1055	No	58451506	Male	22-Apr-68	FL	673-574-7823	Gold	
1077	No	65208809	Male	22-Apr-64	VA	286-128-6132	Platinum	
354	No	38011078	Female	20-May-76	NE	271-123-1475	Gold	
751	No	28932340	Male	05-Jan-96	LA	652-265-8231	Gold	

	injury_claim_unreported							
226	1							
1055	0							
1077	0							
354	1							
751	1							

#6. Check for missing values and impute the missing values with an appropriate value.

#(mean for continuous and mode for categorical)

A6: Handle missing values

```
df.fillna({col: df[col].mean() if df[col].dtype in ['float64', 'int64']  
           else df[col].mode()[0] for col in df.columns}, inplace=True)
```

```
df.head()
```

	claim_id	customer_id	incident_cause	claim_date	claim_area	\
226	49735712	17682060	Crime	2018-10-30	Home	
1055	43042986	58451506	Natural causes	2018-10-30	Auto	
1077	91386759	65208809	Natural causes	2018-10-30	Auto	
354	98795403	38011078	Crime	2018-10-30	Auto	
751	25213498	28932340	Driver error	2018-10-30	Auto	

	police_report	claim_type	claim_amount	total_policy_claims	\
226	Unknown	Material and injury	17020.000000	1.0	
1055	No	Material only	2420.000000	1.0	
1077	No	Material only	2290.000000	1.0	
354	Unknown	Material only	1940.000000	1.0	
751	Unknown	Material only	12480.933366	1.0	

	fraudulent	CUST_ID	gender	DateOfBirth	State	Contact	Segment	\
226	No	17682060	Female	21-Nov-74	NV	186-195-3465	Gold	
1055	No	58451506	Male	22-Apr-68	FL	673-574-7823	Gold	

1077	No	65208809	Male	22-Apr-64	VA	286-128-6132	Platinum
354	No	38011078	Female	20-May-76	NE	271-123-1475	Gold
751	No	28932340	Male	05-Jan-96	LA	652-265-8231	Gold

injury_claim_unreported	
226	1
1055	0
1077	0
354	1
751	1

#7. Calculate the age of customers in years. Based on the age, categorize the customers according to the

#below criteria

#Children < 18

#Youth 18-30

#Adult 30-60

#Senior > 60

A7: Calculate age and categorize

from datetime import datetime

```
df['dob'] = pd.to_datetime(df['dob'], format='%d-%b-%y', errors='coerce')
df.loc[df['dob'].dt.year > datetime.now().year, 'dob'] -= pd.DateOffset(years=100)
df['age'] = (pd.to_datetime("today") - df['dob']).dt.days // 365
df.loc[df['age'] < 0, 'age'] = np.nan
df['age_category'] = pd.cut(df['age'], bins=[0, 18, 30, 60, 120],
labels=['Children', 'Youth', 'Adult', 'Senior'])
```

df.head()

	claim_id	customer_id	incident_cause	claim_date	claim_area	\
226	49735712	17682060	Crime	2018-10-30	Home	
1055	43042986	58451506	Natural causes	2018-10-30	Auto	
1077	91386759	65208809	Natural causes	2018-10-30	Auto	
354	98795403	38011078	Crime	2018-10-30	Auto	
751	25213498	28932340	Driver error	2018-10-30	Auto	

	police_report	claim_type	claim_amount	total_policy_claims	\
226	Unknown	Material and injury	17020.000000	1.0	
1055	No	Material only	2420.000000	1.0	
1077	No	Material only	2290.000000	1.0	
354	Unknown	Material only	1940.000000	1.0	
751	Unknown	Material only	12480.933366	1.0	

	fraudulent	CUST_ID	gender	DateOfBirth	State	Contact	Segment	\
226	No	17682060	Female	21-Nov-74	NV	186-195-3465	Gold	
1055	No	58451506	Male	22-Apr-68	FL	673-574-7823	Gold	
1077	No	65208809	Male	22-Apr-64	VA	286-128-6132	Platinum	
354	No	38011078	Female	20-May-76	NE	271-123-1475	Gold	
751	No	28932340	Male	05-Jan-96	LA	652-265-8231	Gold	

	injury_claim_unreported	age	age_category	dob
226	1	50.0	Adult	1974-11-21
1055	0	56.0	Adult	1968-04-22
1077	0	60.0	Adult	1964-04-22
354	1	48.0	Adult	1976-05-20
751	1	29.0	Youth	1996-01-05

```
# 8. What is the average amount claimed by the customers from various segments?
```

```
# A8: Average claim amount by segment
```

```
avg_claim_by_segment = df.groupby('Segment')['claim_amount'].mean()  
print("\nAverage Claim Amount by Segment:")  
print(avg_claim_by_segment)
```

```
Average Claim Amount by Segment:
```

```
Segment  
Gold      12788.392275  
Platinum 12370.790860  
Silver    12266.176689  
Name: claim_amount, dtype: float64
```

```
#9. What is the total claim amount based on incident cause for all the claims that  
have been done at least 20 days  
#prior to 1st of October, 2018.
```

```
# A9: Total claim amount for incidents before a given date
```

```
cutoff_date = pd.to_datetime('2018-09-10')  
total_claim_prior = df[df['claim_date'] < cutoff_date].groupby('incident_cause')[  
    'claim_amount'].sum()  
print("\nTotal Claim Amount by Incident Cause before October 2018:")  
print(total_claim_prior.apply(lambda x: f"{x:.2f}"))
```

```
Total Claim Amount by Incident Cause before October 2018:
```

```
incident_cause  
Crime          721,834.67  
Driver error   3,278,791.20  
Natural causes 1,312,799.90  
Other causes   3,725,236.73  
Other driver error 3,315,572.63  
Name: claim_amount, dtype: object
```

```
#10. How many adults from TX, DE and AK claimed insurance for driver  
#related issues and causes?
```

```
# A10: Adult claims from TX, DE, AK for driver-related issues
```

```
states_filter = df['State'].isin(['TX', 'DE', 'AK'])  
adult_driver_claims = df[(df['age_category'] == 'Adult') & states_filter &  
    (df['incident_cause'] == 'Driver error')].shape[0]  
print("\nNumber of Adults Claiming for Driver Issues in TX, DE, AK:",  
adult_driver_claims)
```

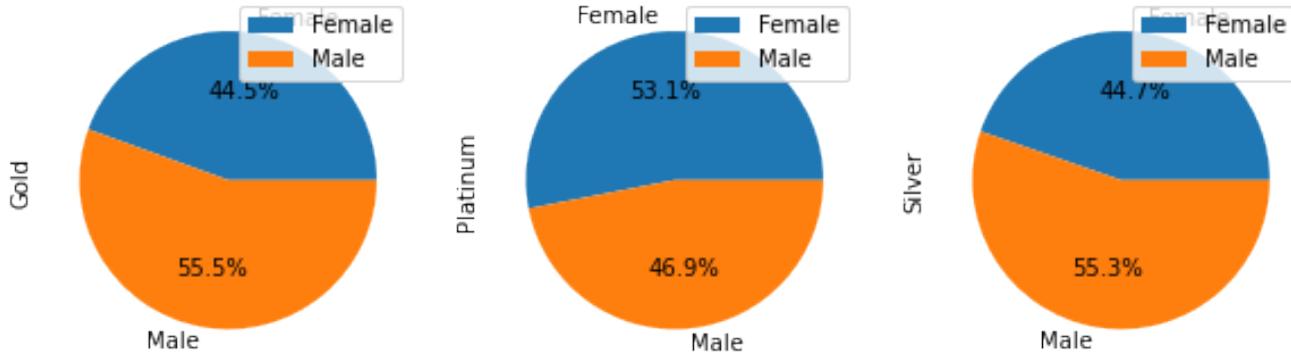
```
Number of Adults Claiming for Driver Issues in TX, DE, AK: 15
```

```
#11. Draw a pie chart between the aggregated value of claim amount based  
#on gender and segment. Represent the claim amount as a percentage on the pie chart.
```

```
# A11: Pie Chart for Claim Amount by Gender & Segment
```

```
claim_pivot = df.groupby(['gender', 'Segment'])['claim_amount'].sum().unstack()  
claim_pivot.plot(kind='pie', subplots=True, autopct='%.1f%%', figsize=(10, 5))  
plt.title("Claim Amount Distribution by Gender and Segment")  
plt.show()
```

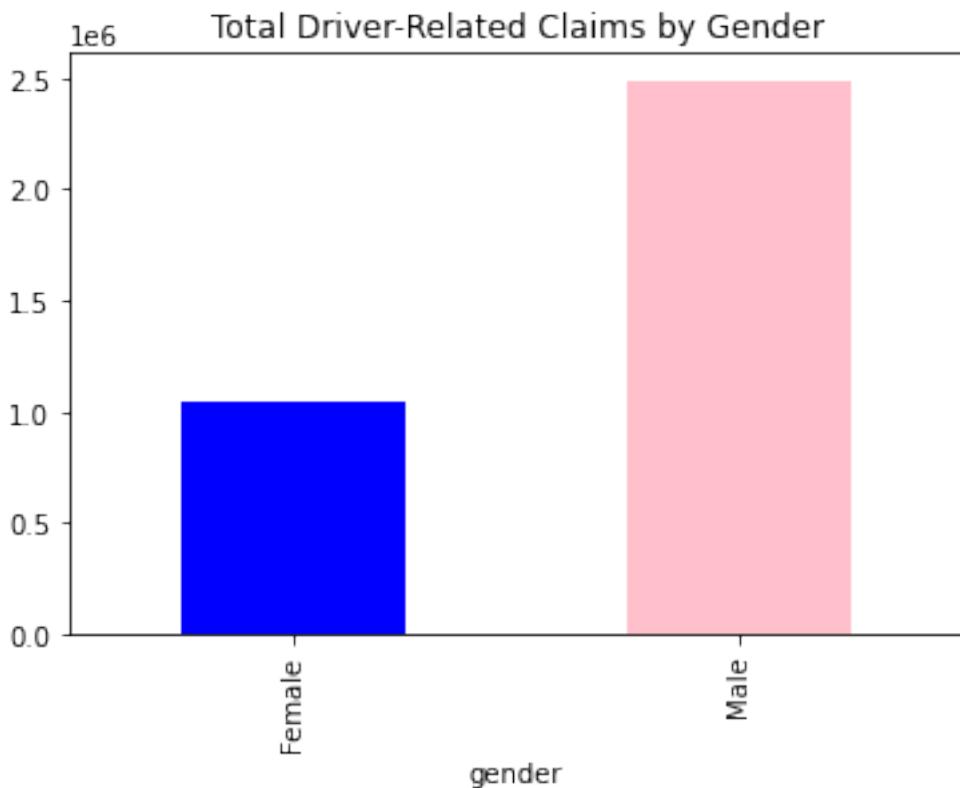
Claim Amount Distribution by Gender and Segment



#12. Among males and females, which gender had claimed the most for any type of driver related issues?

#E.g. This metric can be compared using a bar chart

```
# A12: Bar chart - Driver-related claims by gender
driver_claims_by_gender = df[df['incident_cause'] == 'Driver error'].groupby('gender')['claim_amount'].sum()
if driver_claims_by_gender.empty:
    print("No driver-related claims found for any gender.")
else:
    driver_claims_by_gender.plot(kind='bar', color=['blue', 'pink'])
    plt.title("Total Driver-Related Claims by Gender")
    plt.show()
```



#Q13 Which age group had the maximum fraudulent policy claims? Visualize it on a bar chart.

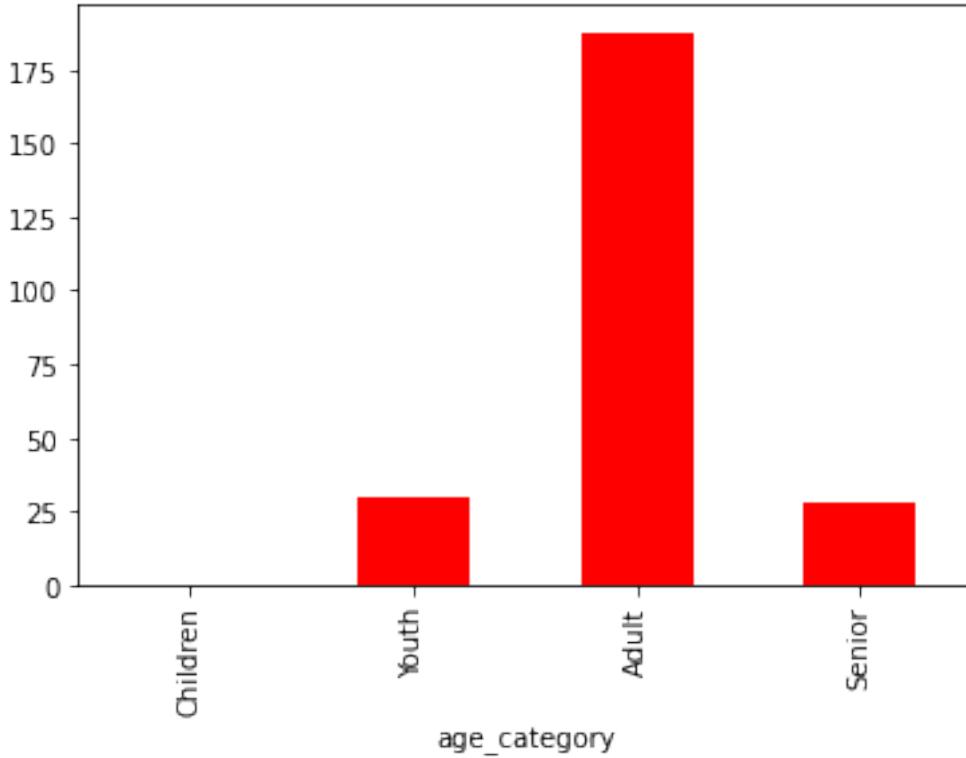
A13: Fraudulent claims by age group

```

fraud_by_age = df[df['fraudulent'] == 'Yes'].groupby('age_category').size()
fraud_by_age.plot(kind='bar', color='red')
plt.title("Fraudulent Policy Claims by Age Group")
plt.show()

```

Fraudulent Policy Claims by Age Group



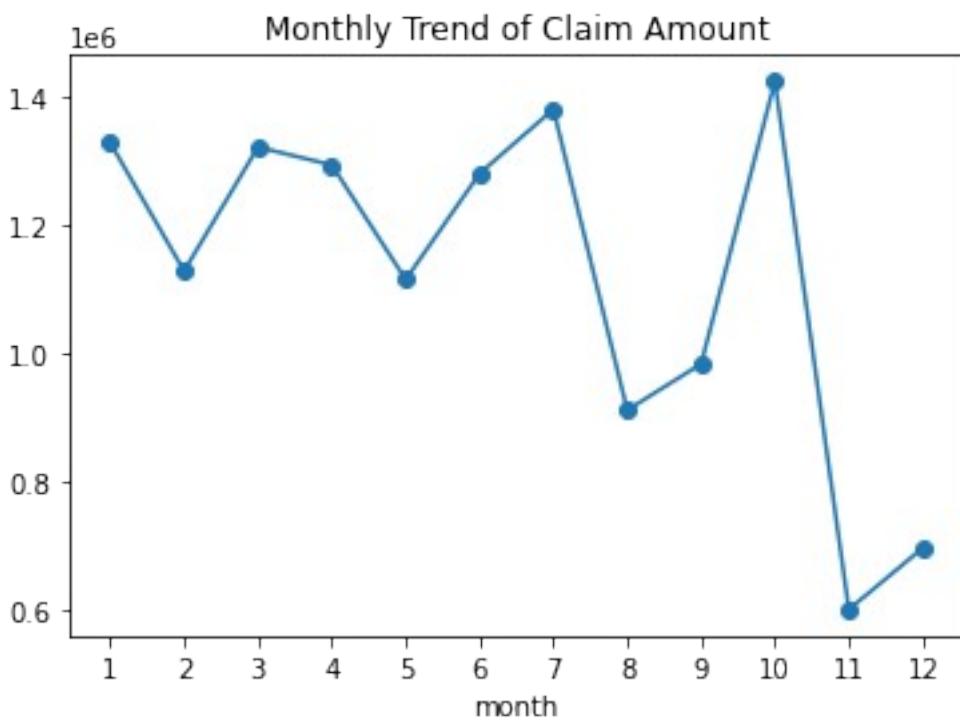
#Q14 Visualize the monthly trend of the total amount that has been claimed by the customers.

#Ensure that on the “month” axis, the month is in a chronological order not alphabetical order.

```

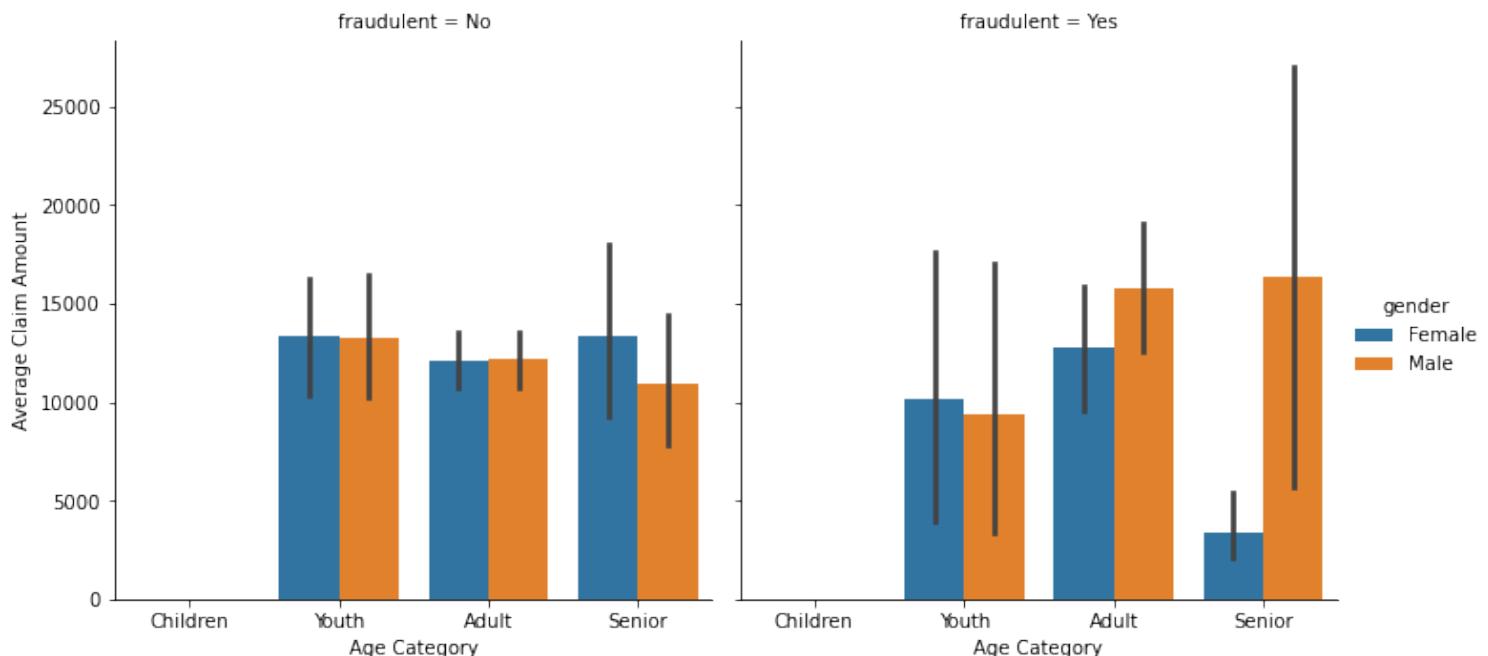
# A14: Monthly trend of claims
df['month'] = df['claim_date'].dt.month
df.groupby('month')['claim_amount'].sum().plot(kind='line', marker='o')
plt.xticks(range(1, 13))
plt.title("Monthly Trend of Claim Amount")
plt.show()

```



#Q15 What is the average claim amount for gender and age categories and suitably represent the above using
a faceted bar chart, one facet that represents fraudulent claims and the other for non-fraudulent claims.

```
# A15: Facet grid - Claim amount by gender, age category, fraud status
g = sns.catplot(data=df, x='age_category', y='claim_amount', hue='gender',
col='fraudulent', kind='bar')
g.set_axis_labels("Age Category", "Average Claim Amount")
plt.show()
```



#Based on the conclusions from exploratory analysis as well as suitable statistical tests, answer the

```
#below questions. Please include a detailed write-up on the parameters taken into  
consideration, the Hypothesis  
#testing steps, conclusion from the p-values and the business implications of the  
statements.
```

Hypothesis Testing

```
from scipy.stats import ttest_ind, chi2_contingency
```

```
#16 Is there any similarity in the amount claimed by males and females?
```

```
# a16: Test similarity in claim amounts between genders
```

```
male_claims = df[df['gender'] == 'Male']['claim_amount']
```

```
female_claims = df[df['gender'] == 'Female']['claim_amount']
```

```
t_stat, p_value = ttest_ind(male_claims, female_claims)
```

```
print("\nT-Test for Claim Amounts by Gender: p-value =", p_value)
```

```
T-Test for Claim Amounts by Gender: p-value = 0.3602836601081929
```

```
#17 Is there any relationship between age category and segment?
```

```
# A17: Relationship between age category and segment
```

```
age_seg_contingency = pd.crosstab(df['age_category'], df['Segment'])
```

```
chi2, p, dof, expected = chi2_contingency(age_seg_contingency)
```

```
print("\nChi-Square Test for Age Category and Segment: p-value =", p)
```

```
Chi-Square Test for Age Category and Segment: p-value = 0.9435195542868468
```

```
#18 The current year has shown a significant rise in claim amounts as
```

```
#compared to 2016-17 fiscal average which was $10,000.
```

```
# a18: Claim amounts in current year vs historical average
```

```
historical_avg = 10000
```

```
current_avg = df[df['claim_date'] >= '2018-01-01']['claim_amount'].mean()
```

```
t_stat, p_value = ttest_ind(df[df['claim_date'] >= '2018-01-01']['claim_amount'],  
[historical_avg]*len(df))
```

```
print("\nT-Test for Rise in Claim Amounts: p-value =", p_value)
```

```
T-Test for Rise in Claim Amounts: p-value = 1.046411231276106e-10
```

```
#Q19 Is there any difference between age groups and insurance claims?
```

```
# A19: Difference in insurance claims by age group
```

```
age_group_claims = df.groupby('age_category')['claim_amount'].mean()
```

```
print("\nAverage Claim Amount by Age Group:")
```

```
print(age_group_claims)
```

```
Average Claim Amount by Age Group:
```

```
age_category
```

```
Children           NaN
```

```
Youth        12642.977649
```

```
Adult         12632.656681
```

```
Senior        11087.681934
```

```
Name: claim_amount, dtype: float64
```

#Q20 Is there any relationship between total number of policy claims and the claimed amount?

```
# A20: Correlation between policy claims and claim amount
correlation = df[['total_policy_claims', 'claim_amount']].corr()
print("\nCorrelation Between Total Policy Claims and Claimed Amount:")
print(correlation)
```

Correlation Between Total Policy Claims and Claimed Amount:

	total_policy_claims	claim_amount
total_policy_claims	1.000000	-0.018001
claim_amount	-0.018001	1.000000