

```
In [134...]: import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
```

```
In [135...]: customer = pd.read_csv("Customer_Master.csv")
transaction = pd.read_csv("transactions.csv")
```

```
In [136...]: customer.head(2)
```

```
Out[136...]:
```

	customer_id	age_group	home_location	credit_score	account_age_years	account_type
0	1	26-35	Palpa	714	13	Savings
1	2	26-35	Kathmandu	607	7	Savings


```
In [137...]: transaction.head(2)
```

```
Out[137...]:
```

	transaction_id	customer_id	transaction_date	transaction_type	amount	location
0	TXN20241124104326	727	11/24/2024 15:29	Inward Remittance	13925.72	Nawalparasi
1	TXN20241204130277	539	12/4/2024 5:26	ATM Withdrawal	25037.35	Kathmandu

2 rows × 28 columns

Find intersecting columns

```
In [138...]: duplicate_cols = set(customer.columns).intersection(set(transaction.columns))
duplicate_cols
```

```
Out[138...]: {'account_age_years',
 'account_type',
 'age_group',
 'avg_monthly_income',
 'credit_score',
 'customer_id',
 'employment_status',
 'home_location',
 'international_activity',
 'mobile_banking_user',
 'risk_score',
 'transaction_frequency'}
```

```
In [139...]: duplicate_cols = duplicate_cols - {'customer_id'}
duplicate_cols
```

```
Out[139... {'account_age_years',
'account_type',
'age_group',
'avg_monthly_income',
'credit_score',
'employment_status',
'home_location',
'international_activity',
'mobile_banking_user',
'risk_score',
'transaction_frequency'}
```

```
In [140... transaction = transaction.drop(columns= duplicate_cols)
```

```
In [141... #check duplicate again
duplicate_cols = set(customer.columns).intersection(set(transaction.columns))
duplicate_cols
```

```
Out[141... {'customer_id'}
```

merge these datasets

```
In [142... dataset = customer.merge(transaction, on="customer_id", how="inner")
```

```
In [143... dataset.head(5)
```

```
Out[143...   customer_id  age_group  home_location  credit_score  account_age_years  account_type
0             1      26-35        Palpa          714                13       Savings
1             1      26-35        Palpa          714                13       Savings
2             1      26-35        Palpa          714                13       Savings
3             1      26-35        Palpa          714                13       Savings
4             1      26-35        Palpa          714                13       Savings
```

5 rows × 33 columns

```
In [144... #check for null
dataset.isna().sum()
```

```
Out[144...]:
```

customer_id	0
age_group	0
home_location	0
credit_score	0
account_age_years	0
account_type	0
avg_monthly_income	0
mobile_banking_user	0
primary_device	14202
primary_os	14202
primary_browser	14202
avg_transaction_amount	0
transaction_frequency	0
employment_status	0
preferred_transaction_types	0
international_activity	0
risk_score	0
transaction_id	0
transaction_date	0
transaction_type	0
amount	0
location	0
ip_address	0
device	79991
os	79963
browser	79967
attempt_sequence	0
time_of_day	0
transaction_velocity	0
status	0
auth_method	0
amount_deviation	0
is_suspicious	0

dtype: int64

```
In [145...]: dataset.shape
```

```
Out[145...]: (103500, 33)
```

```
In [146...]: #device, os and browser have about 77% of null data so we drop those columns  
dataset.drop(columns=["device", "os", "browser", "attempt_sequence"], inplace=True)
```

```
In [147...]: dataset.duplicated().sum()
```

```
Out[147...]: np.int64(0)
```

```
In [148...]: dataset.isna().sum()
```

```
Out[148...]:
```

customer_id	0
age_group	0
home_location	0
credit_score	0
account_age_years	0
account_type	0
avg_monthly_income	0
mobile_banking_user	0
primary_device	14202
primary_os	14202
primary_browser	14202
avg_transaction_amount	0
transaction_frequency	0
employment_status	0
preferred_transaction_types	0
international_activity	0
risk_score	0
transaction_id	0
transaction_date	0
transaction_type	0
amount	0
location	0
ip_address	0
time_of_day	0
transaction_velocity	0
status	0
auth_method	0
amount_deviation	0
is_suspicious	0

dtype: int64

```
In [149...]:
```

```
#now filling values with mode for 3 remaining columns
dataset["primary_device"].fillna(dataset["primary_device"].mode()[0], inplace= True)
dataset["primary_os"].fillna(dataset["primary_os"].mode()[0], inplace= True)
dataset["primary_browser"].fillna(dataset["primary_browser"].mode()[0], inplace= Tr
```

```
C:\Users\Sandesh Khatiwada\AppData\Local\Temp\ipykernel_11972\1276973883.py:2: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
```

The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
dataset["primary_device"].fillna(dataset["primary_device"].mode()[0], inplace= True)
```

```
C:\Users\Sandesh Khatiwada\AppData\Local\Temp\ipykernel_11972\1276973883.py:3: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
```

The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
dataset["primary_os"].fillna(dataset["primary_os"].mode()[0], inplace= True)
```

```
C:\Users\Sandesh Khatiwada\AppData\Local\Temp\ipykernel_11972\1276973883.py:4: FutureWarning: A value is trying to be set on a copy of a DataFrame or Series through chained assignment using an inplace method.
```

The behavior will change in pandas 3.0. This inplace method will never work because the intermediate object on which we are setting values always behaves as a copy.

For example, when doing 'df[col].method(value, inplace=True)', try using 'df.method({col: value}, inplace=True)' or df[col] = df[col].method(value) instead, to perform the operation inplace on the original object.

```
dataset["primary_browser"].fillna(dataset["primary_browser"].mode()[0], inplace= True)
```

In [150...]: dataset.isna().sum().sum()

Out[150...]: np.int64(0)

In [151...]: dataset.head(3)

Out[151...]

	customer_id	age_group	home_location	credit_score	account_age_years	account_type
0	1	26-35	Palpa	714	13	Savings
1	1	26-35	Palpa	714	13	Savings
2	1	26-35	Palpa	714	13	Savings

3 rows × 29 columns

Comparing different sorts of features

In [152...]

```
# visualizing which transaction type fraud is the most
count_and_rate = (
    dataset.groupby('transaction_type')['is_suspicious']
    .agg(['sum', 'count', 'mean'])
    .sort_values(by='mean', ascending=False)
)

print(count_and_rate)
```

transaction_type	sum	count	mean
Mobile Banking Transfer	1425	4775	0.298429
ATM Withdrawal	837	4947	0.169193
Wallet Load - eSewa	608	4514	0.134692
QR Payment	534	4382	0.121862
Mobile Banking Bill Payment	546	4652	0.117369
Branch Deposit	343	4161	0.082432
Electricity Bill Payment	154	3843	0.040073
Cheque Deposit	144	3626	0.039713
Water Bill Payment	146	3822	0.038200
POS Transaction	141	3836	0.036757
Internet Bill Payment	140	3877	0.036110
Outward Remittance	135	3849	0.035074
Hotel Booking Payment	139	4021	0.034569
Airline Ticket Payment	123	3840	0.032031
Interest Credit	119	3722	0.031972
Mobile Recharge	133	4245	0.031331
School Fee Payment	129	4159	0.031017
Inward Remittance	133	4404	0.030200
Wallet Load - IME Pay	111	3687	0.030106
Wallet Load - Khalti	124	4166	0.029765
Insurance Premium Payment	132	4437	0.029750
Loan Payment	128	4361	0.029351
Cheque Payment	118	4116	0.028669
Branch Withdrawal	111	4042	0.027462
Cable TV Payment	108	4016	0.026892

In [153...]

```
plt.figure(figsize=(70,20))
sns.barplot(
    data=count_and_rate,
```

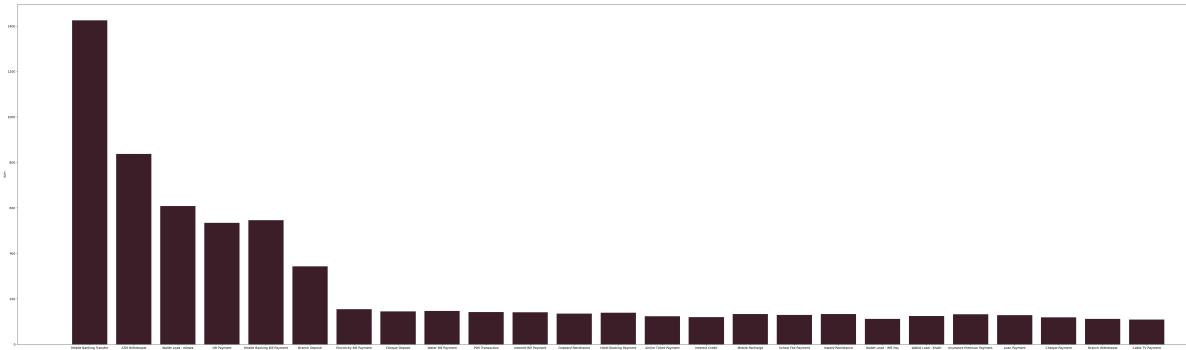
```

        x = 'transaction_type',
        y = 'sum',
        color = '#451828'
    )
plt.plot()

```

Out[153...]

[]



In [154...]

```

# time of day vs fraud
fraud_by_time = (
    dataset.groupby('time_of_day')['is_suspicious']
    .agg(['sum', 'mean'])
    .sort_values(by = 'sum', ascending=False)
    .reset_index()
)

print(fraud_by_time)

```

	time_of_day	sum	mean
0	Night	1907	0.137115
1	Business Hours	1434	0.042668
2	Late Night	1401	0.054545
3	Early Morning	1031	0.077864
4	Evening	988	0.057920

In [155...]

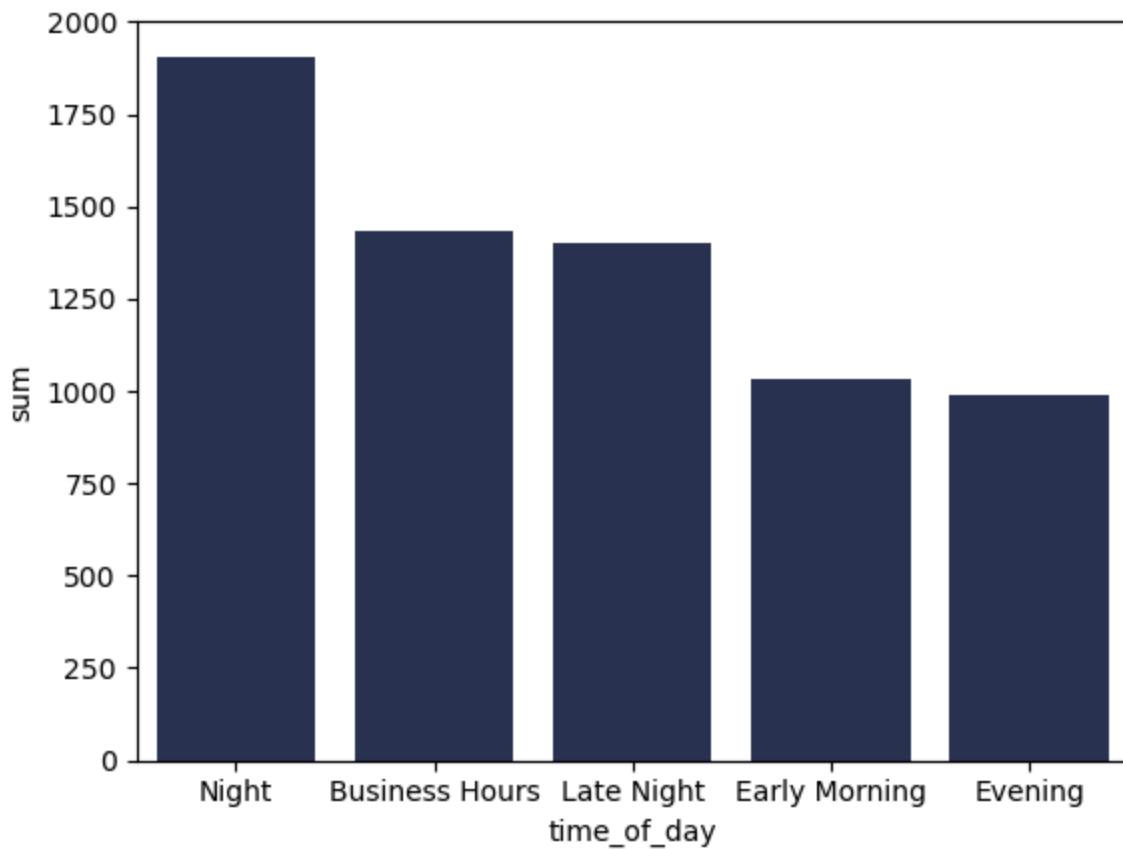
```

sns.barplot(
    data = fraud_by_time,
    x = 'time_of_day',
    y = 'sum',
    color= '#252d59'
)

```

Out[155...]

<Axes: xlabel='time_of_day', ylabel='sum'>



In [156]:

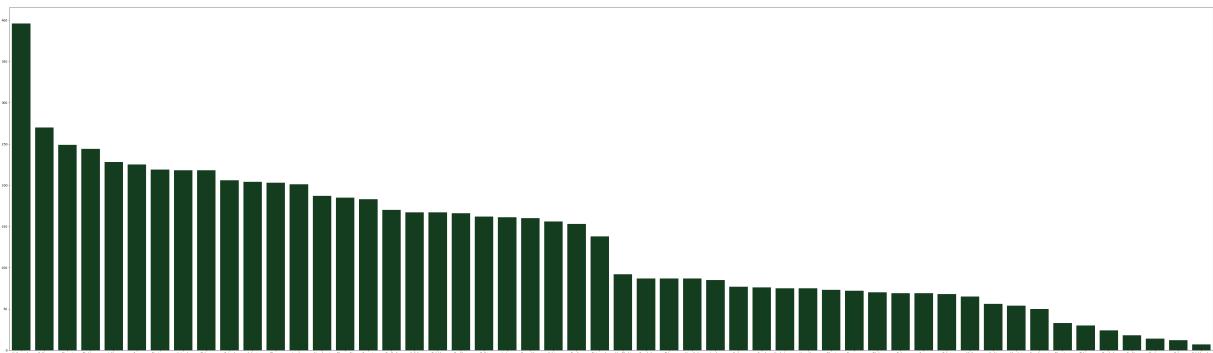
```
#Location vs fraud
fraud_by_location = (
    dataset.groupby('location')['is_suspicious']
    .agg(['sum', 'mean'])
    .sort_values(by = 'sum', ascending= False)
)

print(fraud_by_location)
```

	sum	mean
location		
Kathmandu	396	0.020643
Pokhara	270	0.032032
Birgunj	249	0.057546
Bhaktapur	244	0.051597
Lalitpur	228	0.051213
Ilam	225	0.069103
Biratnagar	219	0.045540
Hetauda	218	0.062662
Chitwan	218	0.069338
Butwal	206	0.076637
Itahari	204	0.080473
Dharan	203	0.058233
Janakpur	201	0.076021
Nepalgunj	187	0.074118
Dhangadhi	185	0.088900
Syangja	183	0.197198
Sindhuli	170	0.184783
Kailali	167	0.170234
Dolakha	167	0.178419
Bardibas	166	0.180043
Delhi	162	1.000000
Jeetpur	161	0.177508
Ramechhap	160	0.170576
Kalaiya	156	0.163522
Bardiya	153	0.160042
Birtamode	138	0.154190
Abu Dhabi	92	1.000000
Bangkok	87	1.000000
Tokyo	87	1.000000
New York	87	1.000000
London	85	1.000000
Sydney	77	1.000000
Seoul	76	1.000000
Kuala Lumpur	75	1.000000
Hong Kong	75	1.000000
Silguri	73	1.000000
Singapore	72	1.000000
Dhaka	70	1.000000
Doha	69	1.000000
Jhapa	69	0.015732
Dubai	68	1.000000
Mirik	65	1.000000
Kaski	56	0.014308
Mumbai	54	1.000000
Nawalparasi	50	0.016345
Bharatpur	33	0.016658
Tulsipur	30	0.012077
Darchula	24	0.016690
Gorkha	18	0.014458
Mustang	14	0.018767
Palpa	12	0.008708
Solukhumbu	7	0.017812

In [157...]

```
#figure for this
plt.figure(figsize=(70,20))
sns.barplot(data=fraud_by_location, x= 'location', y = 'sum', color='#0f451d')
plt.show()
```



In 「158...

```
#fraud by age
dataset['age_group'] = pd.Categorical(
    dataset['age_group'],
    ordered=True,
    categories=['18-25', '26-35', '36-45', '46-55', '56+']
)
dataset.groupby('age_group')['is_suspicious'].sum()
```

```
C:\Users\Sandesh Khatiwada\AppData\Local\Temp\ipykernel_11972\3527396111.py:8: 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.  
    dataset.groupby('age group')['is suspicious'].sum()
```

Out[158...]

```
age_group
18-25      1070
26-35      2032
36-45      1526
46-55      1104
56+         0
Name: is_suspicious, dtype: int64
```

In 「159...

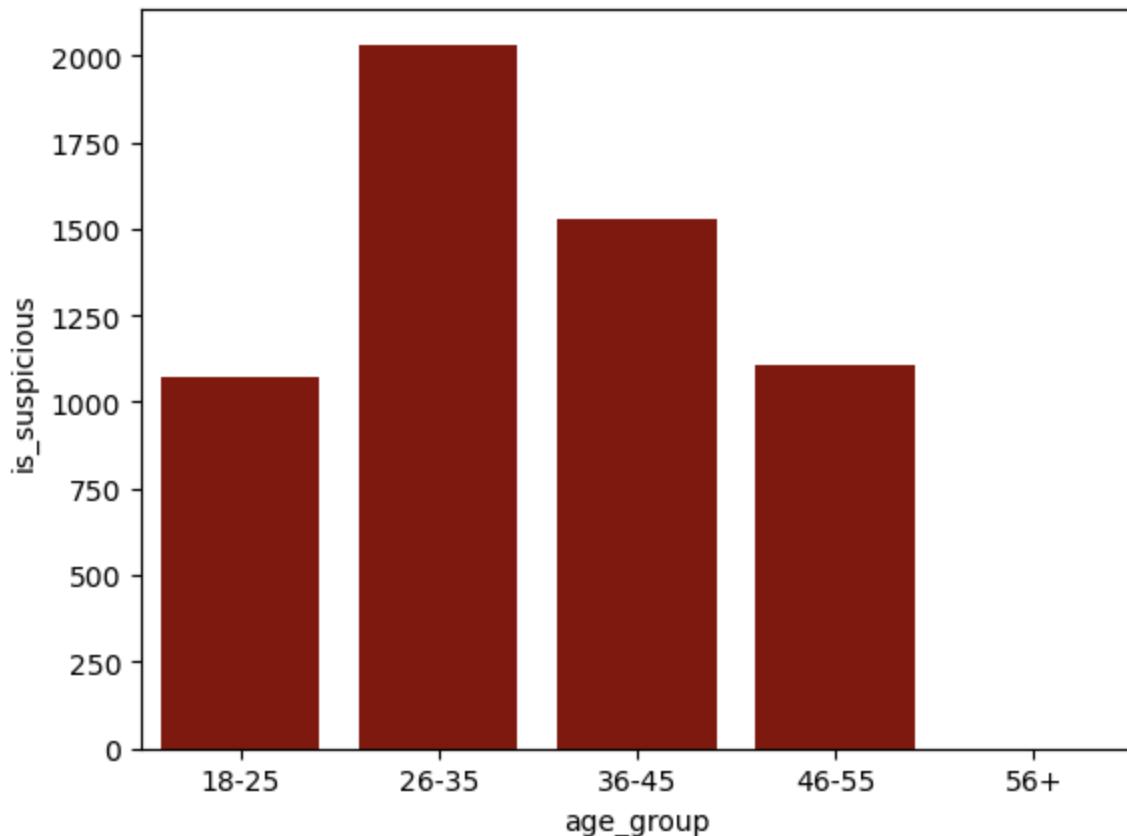
```
#make graph for this
# aggregate first
age_fraud = dataset.groupby('age_group', as_index=False)[['is_suspicious']].sum()

# plot
sns.barplot(data=age_fraud, x='age_group', y='is_suspicious', color='#8f0c00')
```

```
C:\Users\Sandesh Khatiwada\AppData\Local\Temp\ipykernel_11972\143820651.py:3: Future  
Warning: 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 observ  
ed=True to adopt the future default and silence this warning.  
    age_fraud = dataset.groupby('age group' as index=False)[['is suspicious']].sum()
```

Out[159]

```
<Axes: xlabel='age group', ylabel='is suspicious'>
```



In []:

```
#comparing fraud against various features
combined = (
    dataset.groupby(['transaction_type', 'time_of_day', 'location', 'age_group'])['
        .agg(['sum', 'count'])
        .sort_values(by='sum', ascending=False)
    )

print(combined)
```

C:\Users\Sandesh Khatiwada\AppData\Local\Temp\ipykernel_11972\318046994.py:3: Future Warning: 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.

```
dataset.groupby(['transaction_type', 'time_of_day', 'location', 'age_group'])['is_
suspicious']
```

					sum	count
transaction_type	time_of_day	location	age_group			
Mobile Banking Transfer	Night	Butwal	26-35	13	18	
		Syangja	26-35	13	14	
Wallet Load - eSewa	Night	Lalitpur	26-35	12	18	
ATM Withdrawal	Night	Birgunj	36-45	12	13	
Mobile Banking Transfer	Night	Dhangadhi	26-35	10	12	
...				
Airline Ticket Payment	Night	London	26-35	0	0	
			36-45	0	0	
ATM Withdrawal	Business Hours	Butwal	56+	0	0	
		Chitwan	18-25	0	6	
Water Bill Payment	Night	Sindhuli	36-45	0	0	

[32500 rows x 2 columns]

```
In [161...]: top5 = combined.sort_values(by='sum', ascending=False).head(5)
top5
```

```
Out[161...]:
```

					sum	count
transaction_type	time_of_day	location	age_group			
Mobile Banking Transfer	Night	Butwal	26-35	13	18	
		Syangja	26-35	13	14	
Wallet Load - eSewa	Night	Lalitpur	26-35	12	18	
ATM Withdrawal	Night	Birgunj	36-45	12	13	
Mobile Banking Transfer	Night	Dhangadhi	26-35	10	12	

```
In [162...]: top5 = combined.head(5).reset_index()
top5
```

```
Out[162...]:
```

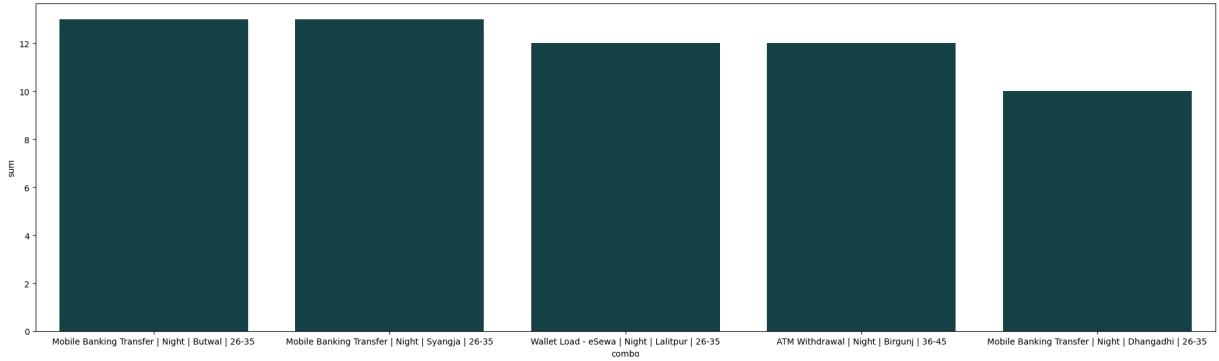
	transaction_type	time_of_day	location	age_group	sum	count
0	Mobile Banking Transfer	Night	Butwal	26-35	13	18
1	Mobile Banking Transfer	Night	Syangja	26-35	13	14
2	Wallet Load - eSewa	Night	Lalitpur	26-35	12	18
3	ATM Withdrawal	Night	Birgunj	36-45	12	13
4	Mobile Banking Transfer	Night	Dhangadhi	26-35	10	12

```
In [163...]: # convert everything to string before concatenation
top5 = top5.astype({
    "transaction_type": "string",
    "time_of_day": "string",
    "location": "string",
    "age_group": "string"
})
```

```
top5["combo"] = (
    top5["transaction_type"] + " | " +
    top5["time_of_day"] + " | " +
    top5["location"] + " | " +
    top5["age_group"]
)
```

```
In [164...]: plt.figure(figsize=(25,7))
sns.barplot(data=top5, x="combo", y="sum", color="#0f4a4f")
# plt.xticks(rotation=45)
```

```
Out[164...]: <Axes: xlabel='combo', ylabel='sum'>
```



```
In [ ]:
```

```
In [165...]: for col in dataset.columns:
    print("unique values of dataset[", col, "]: ", dataset[col].unique(), "\n")
```

```
'Manual Verification']

unique values of dataset[ amount_deviation ]: [1.49371800e+00 7.76204086e-01 1.2119
5564e+00 ... 7.58999995e+00
7.10757000e-04 8.92150926e+00]

unique values of dataset[ is_suspicious ]: [False True]
```

```
In [166... #normalizing avg_monthly_income , amount, credit_score , avg_transaction_amount
from sklearn.preprocessing import MinMaxScaler
ms_avg_monthly_income = MinMaxScaler(feature_range=(0, 1))
ms_amount = MinMaxScaler(feature_range=(0, 1))
ms_credit_score = MinMaxScaler(feature_range=(0, 1))
ms_avg_transaction_amount = MinMaxScaler(feature_range=(0, 1))
ms_amount_deviation = MinMaxScaler(feature_range=(0, 1))
```

```
In [167... dataset["avg_monthly_income"] = ms_avg_monthly_income.fit_transform(dataset[["avg_m
dataset["amount"] = ms_amount.fit_transform(dataset[["amount"]])
dataset["credit_score"] = ms_credit_score.fit_transform(dataset[["credit_score"]])
dataset["avg_transaction_amount"] = ms_avg_transaction_amount.fit_transform(dataset[["avg_t
dataset["amount_deviation"] = ms_amount_deviation.fit_transform(dataset[["amount_de
```

```
In [ ]:
```

```
In [168... #Label encoding age_group, home_location ,account_type , mobile_banking_user , pri
# preferred_transaction_types , location , time_of_day , status , auth_method , is_
```

```
In [169... from sklearn.preprocessing import LabelEncoder
le_age_group = LabelEncoder()
le_home_location = LabelEncoder()
le_account_type = LabelEncoder()
le_mobile_banking_user = LabelEncoder()
le_primary_device = LabelEncoder()
le_primary_os = LabelEncoder()
le_primary_browser = LabelEncoder()
le_employment_status = LabelEncoder()
le_preferred_transaction_types = LabelEncoder()
le_location = LabelEncoder()
le_time_of_day = LabelEncoder()
le_status = LabelEncoder()
le_auth_method = LabelEncoder()
le_is_suspicious = LabelEncoder()
le_transaction_type = LabelEncoder()
```

```
In [170... dataset["age_group"] = le_age_group.fit_transform(dataset["age_group"])
dataset["home_location"] = le_home_location.fit_transform(dataset["home_location"])
dataset["account_type"] = le_account_type.fit_transform(dataset["account_type"])
dataset["mobile_banking_user"] = le_mobile_banking_user.fit_transform(dataset["mobi
dataset["primary_device"] = le_primary_device.fit_transform(dataset["primary_device"])
dataset["primary_os"] = le_primary_os.fit_transform(dataset["primary_os"])
dataset["primary_browser"] = le_primary_browser.fit_transform(dataset["primary_brow
dataset["employment_status"] = le_employment_status.fit_transform(dataset["employm
dataset["preferred_transaction_types"] = le_preferred_transaction_types.fit_transfo
dataset["location"] = le_location.fit_transform(dataset["location"]))
```

```
dataset["time_of_day"] = le_time_of_day.fit_transform(dataset["time_of_day"])
dataset["status"] = le_status.fit_transform(dataset["status"])
dataset["auth_method"] = le_auth_method.fit_transform(dataset["auth_method"])
dataset["is_suspicious"] = le_is_suspicious.fit_transform(dataset["is_suspicious"])
dataset["transaction_type"] = le_transaction_type.fit_transform(dataset["transactio
```

In [171]:

```
label_maps = {
    "age_group": dict(zip(le_age_group.classes_, le_age_group.transform(le_age_group.classes_))),
    "home_location": dict(zip(le_home_location.classes_, le_home_location.transform(le_home_location.classes_))),
    "account_type": dict(zip(le_account_type.classes_, le_account_type.transform(le_account_type.classes_))),
    "mobile_banking_user": dict(zip(le_mobile_banking_user.classes_, le_mobile_banking_user.transform(le_mobile_banking_user.classes_))),
    "primary_device": dict(zip(le_primary_device.classes_, le_primary_device.transform(le_primary_device.classes_))),
    "primary_os": dict(zip(le_primary_os.classes_, le_primary_os.transform(le_primary_os.classes_))),
    "primary_browser": dict(zip(le_primary_browser.classes_, le_primary_browser.transform(le_primary_browser.classes_))),
    "employment_status": dict(zip(le_employment_status.classes_, le_employment_status.transform(le_employment_status.classes_))),
    "preferred_transaction_types": dict(zip(le_preferred_transaction_types.classes_, le_preferred_transaction_types.transform(le_preferred_transaction_types.classes_))),
    "location": dict(zip(le_location.classes_, le_location.transform(le_location.classes_))),
    "time_of_day": dict(zip(le_time_of_day.classes_, le_time_of_day.transform(le_time_of_day.classes_))),
    "status": dict(zip(le_status.classes_, le_status.transform(le_status.classes_))),
    "auth_method": dict(zip(le_auth_method.classes_, le_auth_method.transform(le_auth_method.classes_))),
    "is_suspicious": dict(zip(le_is_suspicious.classes_, le_is_suspicious.transform(le_is_suspicious.classes_))),
    "transaction_type": dict(zip(le_transaction_type.classes_, le_transaction_type.transform(le_transaction_type.classes_)))
}
label_maps
```

```
'School Fee Payment': np.int64(20),  
'Wallet Load - IME Pay': np.int64(21),  
'Wallet Load - Khalti': np.int64(22),  
'Wallet Load - eSewa': np.int64(23),  
'Water Bill Payment': np.int64(24)}}
```

In [172...]

```
dataset.head()
```

Out[172...]

	customer_id	age_group	home_location	credit_score	account_age_years	account_type
0	1	1	21	0.745794	13	3
1	1	1	21	0.745794	13	3
2	1	1	21	0.745794	13	3
3	1	1	21	0.745794	13	3
4	1	1	21	0.745794	13	3

5 rows × 29 columns

In [173...]

```
dataset.dtypes
```

Out[173...]

```
customer_id                int64  
age_group                 int64  
home_location              int64  
credit_score               float64  
account_age_years          int64  
account_type               int64  
avg_monthly_income         float64  
mobile_banking_user        int64  
primary_device             int64  
primary_os                 int64  
primary_browser            int64  
avg_transaction_amount    float64  
transaction_frequency      int64  
employment_status          int64  
preferred_transaction_types int64  
international_activity     bool  
risk_score                 int64  
transaction_id             object  
transaction_date           object  
transaction_type           int64  
amount                     float64  
location                   int64  
ip_address                 object  
time_of_day                 int64  
transaction_velocity        int64  
status                     int64  
auth_method                int64  
amount_deviation           float64  
is_suspicious              int64  
dtype: object
```

In [174...]

```
dataset['transaction_id'].nunique()
```

```
Out[174... 103492
```

```
In [175... dataset['transaction_date'].nunique()
```

```
Out[175... 98133
```

```
In [176... dataset.drop(columns=['ip_address', 'transaction_id', 'transaction_date'], inplace=True)
```

```
In [177... #now for algorithm seperate the data  
X = dataset.drop(columns=['is_suspicious'])  
y = dataset['is_suspicious']  
X.ndim
```

```
Out[177... 2
```

```
In [178... from sklearn.model_selection import train_test_split
```

```
In [179... # help(train_test_split)
```

```
In [180... X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.33, random_state=42)
```

```
In [181... from sklearn.ensemble import RandomForestClassifier  
from sklearn.linear_model import LogisticRegression
```

```
In [186... rf = LinearRegression()  
lg = LogisticRegression()
```

```
In [183... rf.fit(X_train, y_train)
```

```
Out[183... ▾ LinearRegression ⓘ ⓘ  
► Parameters
```

```
In [185... rf.score(X_test, y_test)
```

```
Out[185... 0.6133427224337857
```

```
In [ ]:
```

```
In [187... lg.fit(X_train, y_train)
```

```
D:\Installations\Miniconda\envs\dsml\Lib\site-packages\sklearn\linear_model\_logisti
c.py:473: ConvergenceWarning: lbfgs failed to converge after 100 iteration(s) (status=1):
STOP: TOTAL NO. OF ITERATIONS REACHED LIMIT

Increase the number of iterations to improve the convergence (max_iter=100).
You might also want to scale the data as shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-regression
n_iter_i = _check_optimize_result(
```

Out[187...]

```
▼ LogisticRegression ⓘ ⓘ
▶ Parameters
```

In [188...]

```
lg.score(X_test, y_test)
```

Out[188...]

```
0.9717171717171718
```

In []:

In [190...]

```
y_pred = lg.predict(X_test)
```

In [192...]

```
# finding confusion matrix for this
from sklearn.metrics import confusion_matrix, accuracy_score, classification_report
confusion_logistic = confusion_matrix(y_test, y_pred)
confusion_logistic
```

Out[192...]

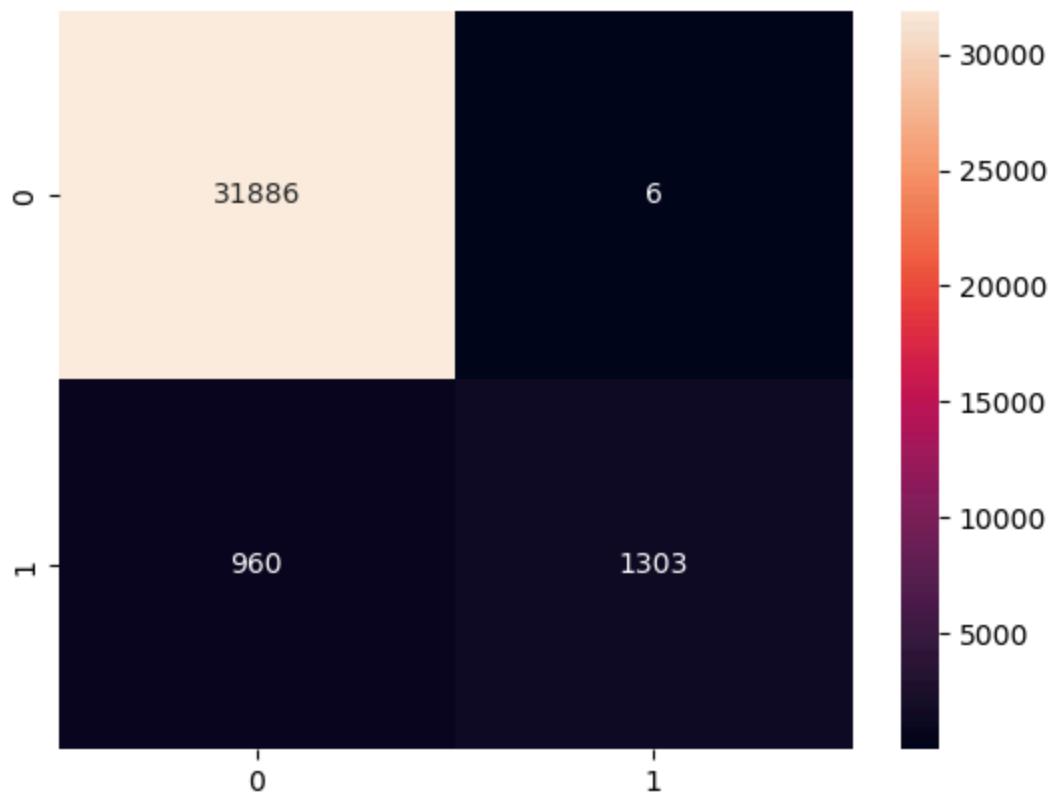
```
array([[31886,      6],
       [ 960, 1303]])
```

In [193...]

```
sns.heatmap(confusion_logistic, annot=True, fmt="d")
plt.plot()
```

Out[193...]

```
[]
```



In [196]:

```
# convert (run in a cell)
!jupyter nbconvert --to webpdf "D:/Github/Data-Science-And-Machine-Learning-Course/
```