ANZ VIRTUAL INTERNSHIP PROJECT

The task is based on a synthesised transaction dataset containing 3 months worth of transactions for 100 hypothetical customers. It contains purchases, recurring transactions, and salary transactions.

TASK 1 : Exploratory Data Analysis

1. Data :

The data is provided by the Data ANZ itself when we enroll ourselves in their program.

2. Features :

status : denotes the status of the transaction posted or authorized for transaction.

card_present_flag : Did the customer have a card during the transaction (1.1 = Yes or 0.0 = No).

bpay_biller_code : unique code of the BPay Transaction done by the customer.

account : account number of the customers who made transaction.

currency : currency type in which the transaction has been done (AUD dollars).

long_lat : Longitude and Latitude location of the customer.

txn_description : the mode of transaction the customer has done.

merchant_id : the merchant id where the customers have done their transaction.

merChant_code : unique merchant code for each customer.

first_name : first name of the customer.

balance : balance the customer had during the transaction of period 3 months.

date : date when the transaction took place.

gender : gender of the customer(Male or Female).

age : age of the customer.

merchant_suburb : the district or city where the merchant is located.

merchant_state : the state where the merchant is located.

extraction : extraction of the transaction data.

amount : the amount transacted by the customer.

transaction_id : unique transaction id given by the merchant when the customer makes an transaction.

country : country where the customer's are located (Australia).

customer_id = id for the customer's to differentiate them as unique.

merchant_long_lat : the latitude and longitude location of the merchant.

movement : mode of transaction (credit or debit).

The dataset is designed to simulate realistic transaction behaviours that are observed in ANZ's real transaction data, so many of the insights we can gather from the tasks below will be genuine

In [1]:

```
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import cartopy
from pandas_profiling import ProfileReport

sns.set_context("paper", rc={"font.size": 20, "axes.titlesize": 20, "axes.labelsize": 10})
```

Loading Data

In [2]:

```
data = pd.read_excel('E:\Forage Internship\ANZ\ANZ synthesised transaction dataset.xlsx')
data.head(30)
```

Out[2]:

	status	card_present_flag	bpay_biller_code	account	currency	long_lat	txn_description	mercha
0	authorized	1.0	NaN	ACC-1598451071	AUD	153.41 -27.95	POS	81c4 73be- d053f48
1	authorized	0.0	NaN	ACC-1598451071	AUD	153.41 -27.95	SALES-POS	830a 316e- e37caed
2	authorized	1.0	NaN	ACC-1222300524	AUD	151.23 -33.94	POS	835c 8cdf- e9d5717
3	authorized	1.0	NaN	ACC-1037050564	AUD	153.10 -27.66	SALES-POS	4851 c78a-

In [3]:

```
# Summarizing dataset
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12043 entries, 0 to 12042
Data columns (total 23 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   status             12043 non-null  object
 1   card_present_flag  7717 non-null   float64
 2   bpay_biller_code   885 non-null    object
 3   account            12043 non-null  object
 4   currency           12043 non-null  object
 5   long_lat           12043 non-null  object
 6   txn_description    12043 non-null  object
 7   merchant_id        7717 non-null   object
 8   merchant_code      883 non-null    float64
 9   first_name         12043 non-null  object
 10  balance            12043 non-null  float64
 11  date               12043 non-null  datetime64[ns]
 12  gender             12043 non-null  object
 13  age                12043 non-null  int64
 14  merchant_suburb    7717 non-null   object
 15  merchant_state     7717 non-null   object
 16  extraction         12043 non-null  object
 17  amount             12043 non-null  float64
 18  transaction_id     12043 non-null  object
 19  country            12043 non-null  object
 20  customer_id        12043 non-null  object
 21  merchant_long_lat  7717 non-null   object
 22  movement           12043 non-null  object
dtypes: datetime64[ns](1), float64(4), int64(1), object(17)
memory usage: 2.1+ MB
```

In [4]:

```
ProfileReport(data)
```

Summarize dataset: 100% 47/47 [00:15<00:00, 1.90it/s, Completed]

Generate report structure: 100% 1/1 [00:09<00:00, 9.24s/it]

Render HTML: 100% 1/1 [00:01<00:00, 1.95s/it]

Overview

Dataset statistics

Number of variables	23
Number of observations	12043
Missing cells	43948
Missing cells (%)	15.9%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	2.1 MiB
Average record size in memory	184.0 B

Variable types

Categorical	18
Unsupported	1
Numeric	3
DateTime	1

Alerts

`currency` has constant value "AUD"	**Constant**

Out[4]:

Dropping columns with redundant or missing data

In [5]:

```
data.drop(['bpay_biller_code', 'merchant_code', 'merchant_id', 'currency', 'country'], axis
data["date"] = pd.to_datetime(data["date"])
data.head(30)
```

Out[5]:

	status	card_present_flag	account	long_lat	txn_description	first_name	balance
0	authorized	1.0	ACC-1598451071	153.41 -27.95	POS	Diana	35.39
1	authorized	0.0	ACC-1598451071	153.41 -27.95	SALES-POS	Diana	21.20
2	authorized	1.0	ACC-1222300524	151.23 -33.94	POS	Michael	5.71
3	authorized	1.0	ACC-1037050564	153.10 -27.66	SALES-POS	Rhonda	2117.22
4	authorized	1.0	ACC-1598451071	153.41 -27.95	SALES-POS	Diana	17.95
5	posted	NaN	ACC-1608363396	151.22 -33.87	PAYMENT	Robert	1705.43
6	authorized	1.0	ACC-2776252858	144.95 -37.76	SALES-POS	Kristin	1248.36
7	authorized	1.0	ACC-2776252858	144.95 -37.76	POS	Kristin	1232.75
8	authorized	1.0	ACC-182446574	116.06 -32.00	POS	Tonya	213.16
9	posted	NaN	ACC-602667573	151.23 -33.96	INTER BANK	Michael	466.58
10	posted	NaN	ACC-2171593283	146.94 -36.04	PAYMENT	Fernando	4348.50
11	posted	NaN	ACC-2776252858	144.95 -37.76	PAYMENT	Kristin	1203.75
12	authorized	1.0	ACC-182446574	116.06 -32.00	SALES-POS	Tonya	207.08
13	posted	NaN	ACC-588564840	151.27 -33.76	INTER BANK	Isaiah	4438.16
14	posted	NaN	ACC-1496451953	145.16 -37.84	INTER BANK	Ricky	173.66
15	authorized	1.0	ACC-1903037542	153.05 -27.61	POS	Jeffrey	2.85
16	posted	NaN	ACC-2014856841	144.99 -37.90	INTER BANK	Patrick	260514.83
17	posted	NaN	ACC-4163822186	149.03 -34.97	PAYMENT	Karen	3117.94
18	posted	NaN	ACC-3954677887	115.72 -32.28	PAYMENT	Ruth	38.31
19	authorized	1.0	ACC-4258502723	145.45 -37.74	POS	Kimberly	708.28
20	authorized	1.0	ACC-1598451071	153.41 -27.95	POS	Diana	3.85

	status	card_present_flag	account	long_lat	txn_description	first_name	balance
21	authorized	0.0	ACC-2890243754	153.32 -27.93	POS	Joseph	275.93
22	authorized	1.0	ACC-3481401842	115.74 -31.72	SALES-POS	Tiffany	259.37
23	authorized	0.0	ACC-2615038700	145.35 -38.03	POS	Emily	30583.15
24	authorized	1.0	ACC-966140392	147.08 -37.97	POS	Joseph	793.64
25	posted	NaN	ACC-354106658	151.04 -33.80	INTER BANK	Christine	4474.38
26	posted	NaN	ACC-1443681913	150.92 -33.77	PAYMENT	Ryan	586.20
27	authorized	1.0	ACC-1710017148	150.82 -34.01	SALES-POS	Michelle	1636.91
28	authorized	1.0	ACC-2673069055	152.99 -27.49	SALES-POS	Richard	11525.54
29	authorized	0.0	ACC-1710017148	150.82 -34.01	SALES-POS	Michelle	1625.34

In [6]:

```
# Descriptive Statistics of Data
data.describe()
```

Out[6]:

	card_present_flag	balance	age	amount
count	7717.000000	12043.000000	12043.000000	12043.000000
mean	0.802644	14704.195553	30.582330	187.933588
std	0.398029	31503.722652	10.046343	592.599934
min	0.000000	0.240000	18.000000	0.100000
25%	1.000000	3158.585000	22.000000	16.000000
50%	1.000000	6432.010000	28.000000	29.000000
75%	1.000000	12465.945000	38.000000	53.655000
max	1.000000	267128.520000	78.000000	8835.980000

Average Transaction Amount: 187.93 AUD

Univariate Analysis

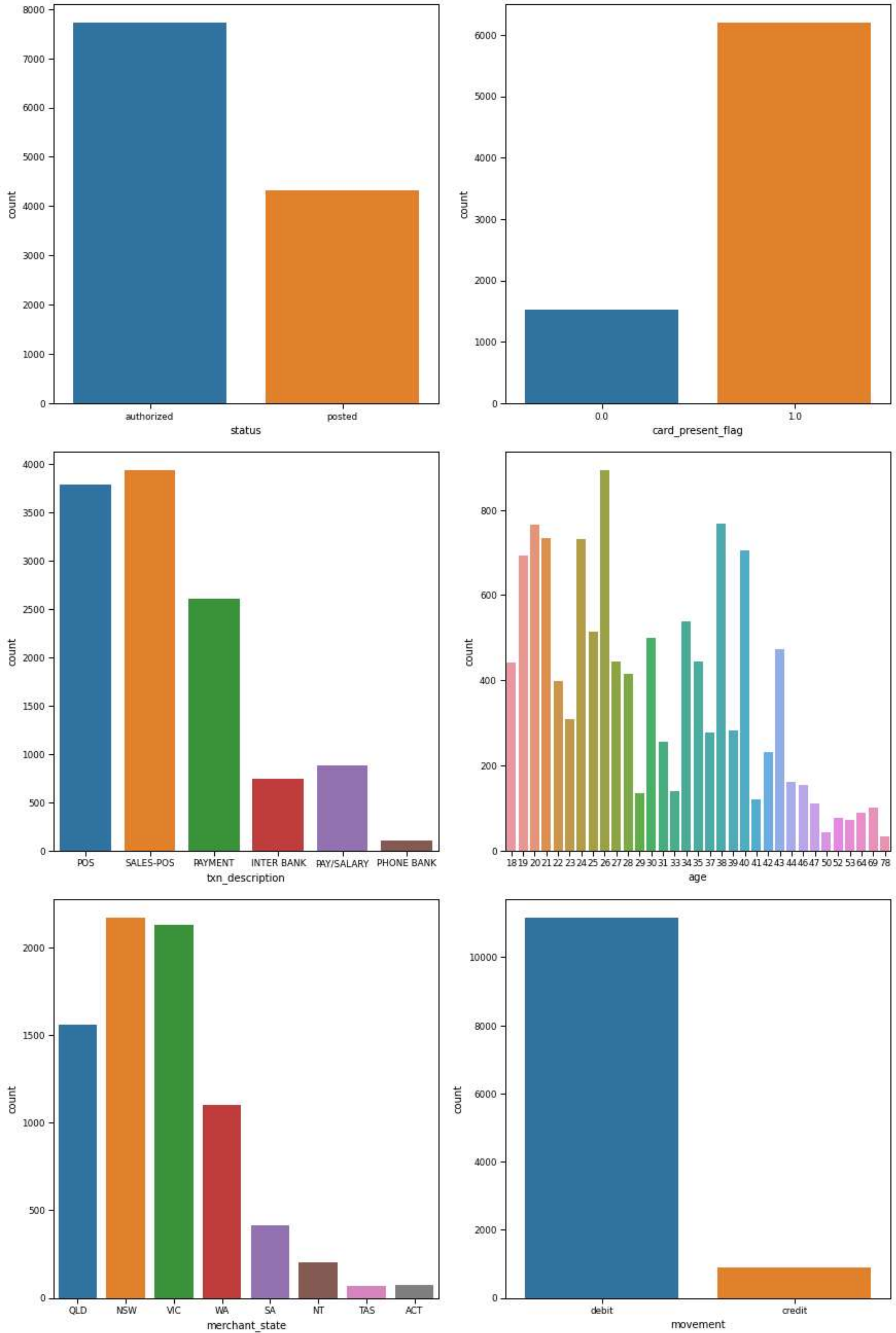
In [7]:

```
num_features = ['balance', 'amount']
cat_features = ['status', 'card_present_flag', 'txn_description', 'age', 'merchant_state',
```

Categorical Features

In [8]:

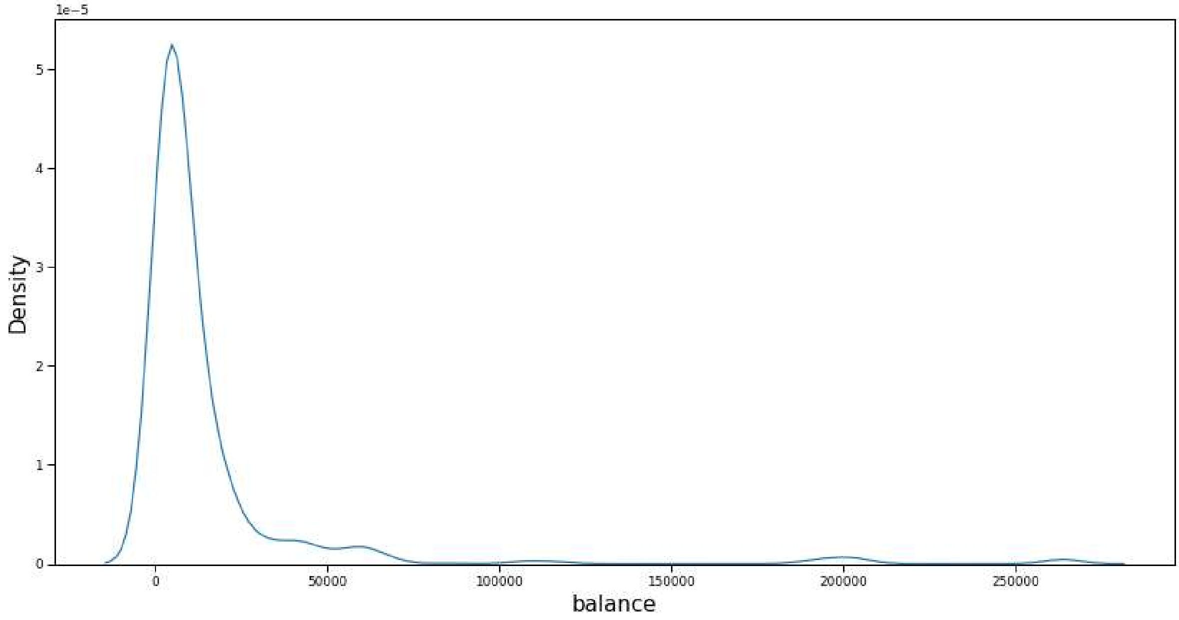
```
num_plots = len(cat_features)
total_cols = 2
total_rows = num_plots//total_cols
fig, axs = plt.subplots(nrows=total_rows, ncols=total_cols,
                        figsize=(6*total_cols, 6*total_rows), facecolor='w', constrained_la
for i, var in enumerate(cat_features):
    row = i//total_cols
    pos = i % total_cols
    plot = sns.countplot(x=var, data=data, ax=axs[row][pos])
```

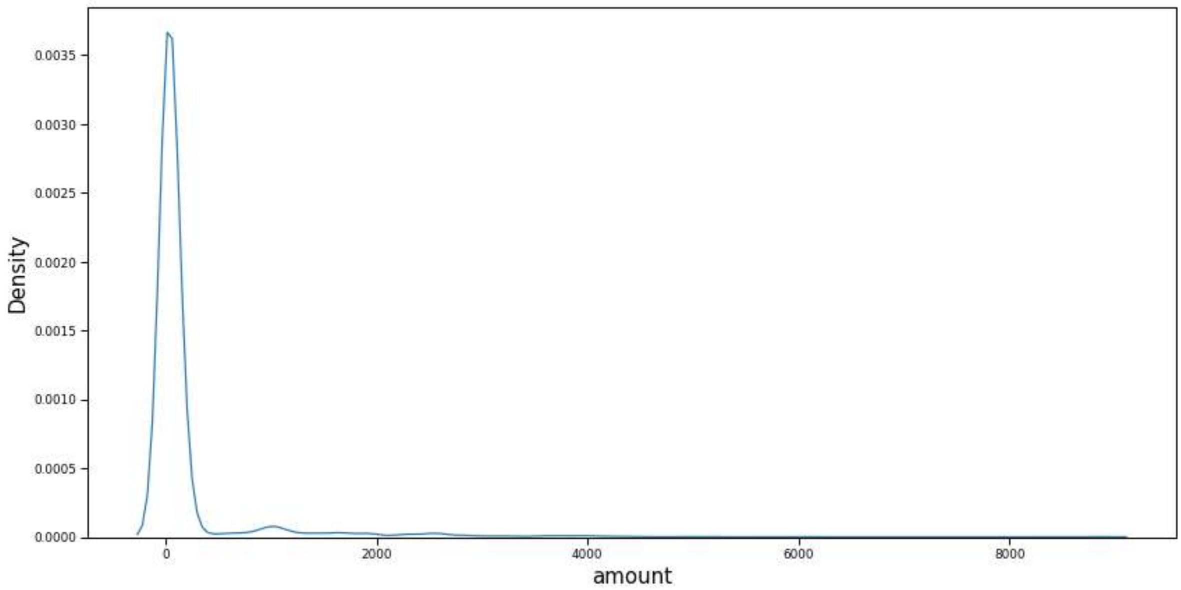


Numerical Features

In [9]:

```
for var in num_features:
    plt.figure(figsize=(7 * 2, 7 * 1), facecolor='w')
    sns.kdeplot(data[var])
    plt.xlabel(var, fontsize=15)
    plt.ylabel('Density', fontsize=15)
    plt.show()
```





Amount Outlier detection

In [10]:

```
plt.figure(figsize=(15, 8))
sns.boxplot(data[data['amount'] < 4000]['amount'])
plt.title("Outlier detection of Transaction Amount")
```

```
C:\Users\Kushal Gupta\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other a
rguments without an explicit keyword will result in an error or misinterpret
ation.
  warnings.warn(
```

Out[10]:

```
Text(0.5, 1.0, 'Outlier detection of Transaction Amount')
```

Balance Outlier detection

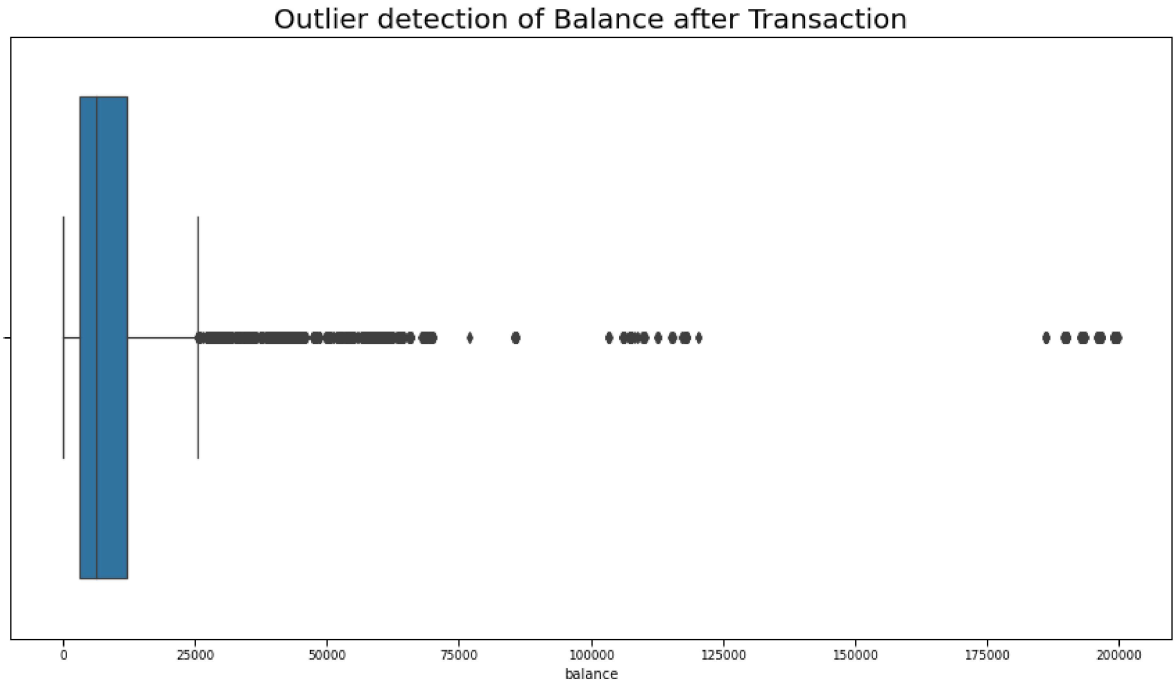
In [11]:

```
plt.figure(figsize=(15, 8))
sns.boxplot(data[data['balance'] < 200000]['balance'])
plt.title("Outlier detection of Balance after Transaction")
```

```
C:\Users\Kushal Gupta\anaconda3\lib\site-packages\seaborn\_decorators.py:36:
FutureWarning: Pass the following variable as a keyword arg: x. From version
0.12, the only valid positional argument will be `data`, and passing other a
rguments without an explicit keyword will result in an error or misinterpret
ation.
  warnings.warn(
```

Out[11]:

```
Text(0.5, 1.0, 'Outlier detection of Balance after Transaction')
```



In [12]:

```
ProfileReport(data)
```

Summarize dataset: 100% 42/42 [00:09<00:00, 2.67it/s, Completed]

Generate report structure: 100% 1/1 [00:09<00:00, 9.16s/it]

Render HTML: 100% 1/1 [00:01<00:00, 1.65s/it]

Overview

Dataset statistics

Number of variables	18
Number of observations	12043
Missing cells	17304
Missing cells (%)	8.0%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	1.7 MiB
Average record size in memory	144.0 B

Variable types

Categorical	14
Numeric	3
DateTime	1

Alerts

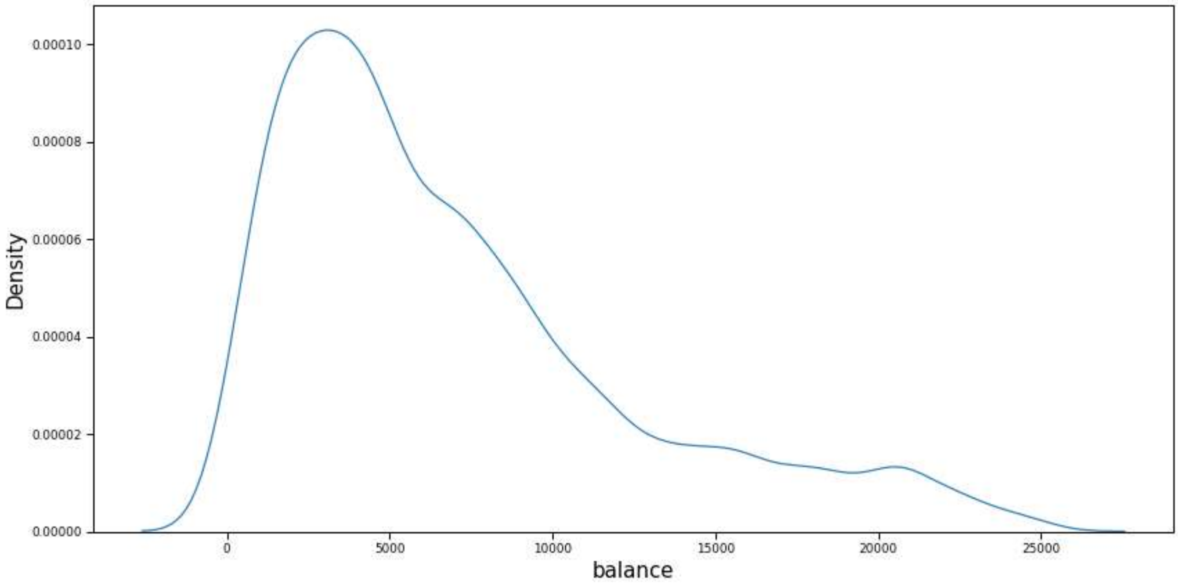
`account` has a high cardinality: 100 distinct values	High cardinality
`long_lat` has a high cardinality: 100 distinct values	High cardinality

Out[12]:

Plotting features again after removing outliers

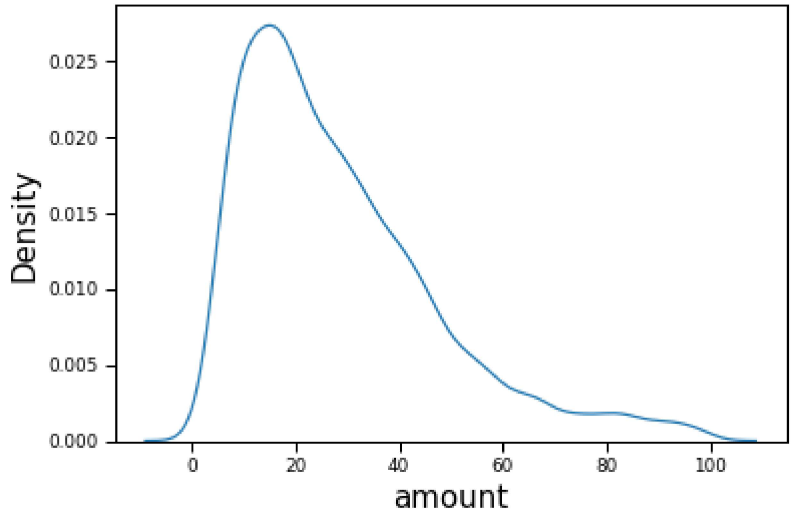
In [13]:

```
plt.figure(figsize=(14, 7), facecolor='w')
sns.kdeplot(data[data['balance'] < 25000]['balance'])
plt.xlabel("balance", fontsize=15)
plt.ylabel('Density', fontsize=15)
plt.show()
```



In [14]:

```
# plt.figure(figsize=(14, 7), facecolor='w')
sns.kdeplot(data[data['amount'] < 100]['amount'])
plt.xlabel("amount", fontsize=15)
plt.ylabel('Density', fontsize=15)
plt.show()
```



We observe that both the numerical features - balance and

amount are both right skewed

Total transactions made each day

In [15]:

```
data['date'].value_counts()
```

Out[15]:

```
2018-09-28    174
2018-08-17    172
2018-10-05    168
2018-10-17    162
2018-09-14    161
             ...
2018-08-06     99
2018-08-20     97
2018-10-23     96
2018-10-08     95
2018-10-30     89
Name: date, Length: 91, dtype: int64
```

Total transactions made by each customer

In [16]:

```
data['account'].value_counts()
```

Out[16]:

```
ACC-1598451071    578
ACC-1222300524    303
ACC-182446574     292
ACC-4258502723    260
ACC-1037050564    259
                 ...
ACC-1998563091     40
ACC-3881031190     37
ACC-721712940      34
ACC-4059612845     31
ACC-1217063613     25
Name: account, Length: 100, dtype: int64
```

In [17]:

```
data['month'] = data['date'].dt.month
```

In [18]:

```
data[data['month']==8]['account'].nunique()
```

Out[18]:

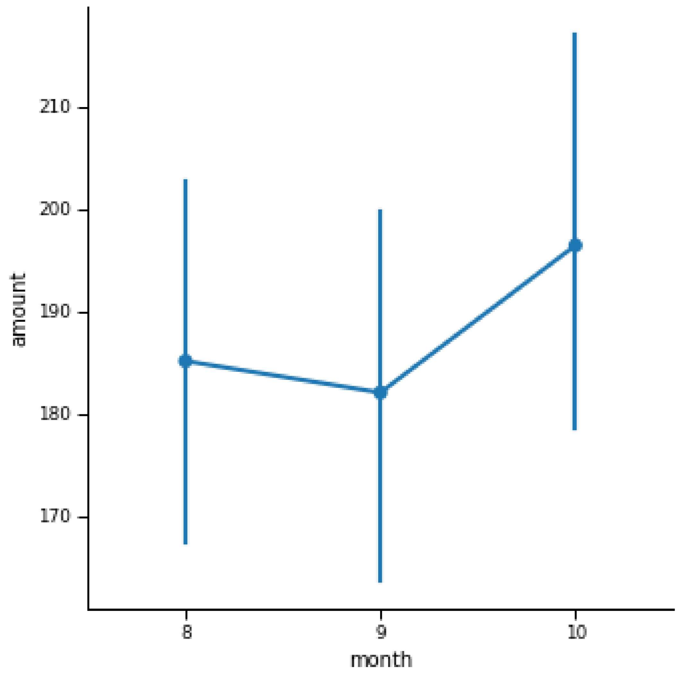
```
100
```

Average number of transactions made by customers each month

In [19]:

```
print(data['month'].value_counts() / 100)
sns.catplot(x="month", y="amount", kind="point", data=data);
```

```
10    40.87
9     40.13
8     39.43
Name: month, dtype: float64
```



Segmenting dataset by date

In [20]:

```
data_date_count = data.groupby('date').count()
data_date_sum = data.groupby('date').sum()
```

In [21]:

```
data_date_count
```

Out[21]:

	status	card_present_flag	account	long_lat	txn_description	first_name	balance	gende
date								
2018-08-01	137	84	137	137	137	137	137	13
2018-08-02	152	99	152	152	152	152	152	15
2018-08-03	157	99	157	157	157	157	157	15
2018-08-04	118	94	118	118	118	118	118	11
2018-08-05	100	73	100	100	100	100	100	10
...	...	...	...	...	...	...	...	.
2018-10-27	139	101	139	139	139	139	139	13
2018-10-28	143	101	143	143	143	143	143	14
2018-10-29	102	63	102	102	102	102	102	10
2018-10-30	89	50	89	89	89	89	89	8
2018-10-31	141	93	141	141	141	141	141	14

91 rows × 18 columns

In [22]:

```
data_date_sum
```

Out[22]:

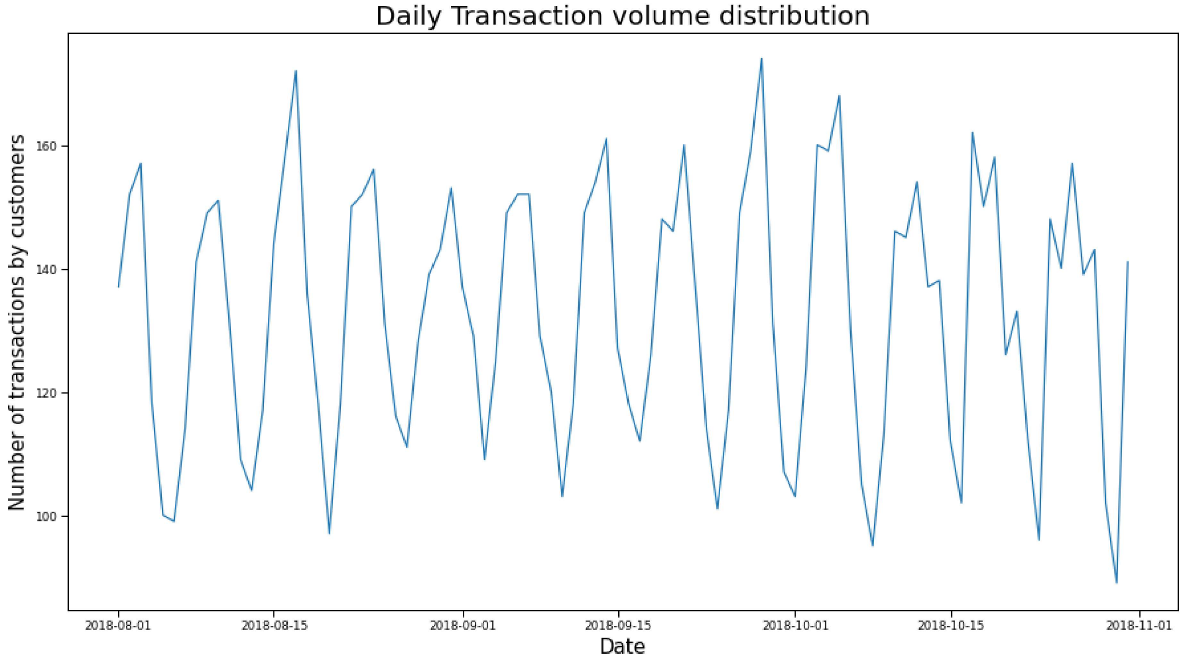
	card_present_flag	balance	age	amount	month
date					
2018-08-01	63.0	1360954.62	4142	29867.94	1096
2018-08-02	85.0	2122469.92	4787	21786.32	1216
2018-08-03	79.0	1599482.51	4985	38096.58	1256
2018-08-04	74.0	968403.51	3662	6296.05	944
2018-08-05	54.0	1329752.54	2991	4426.50	800
...	...	...	...	...	...
2018-10-27	81.0	2366504.71	4336	6971.58	1390
2018-10-28	78.0	2187733.76	4327	8438.11	1430
2018-10-29	47.0	2128124.72	3005	38549.14	1020
2018-10-30	43.0	1691619.62	2790	22062.34	890
2018-10-31	71.0	2367605.45	4323	21967.13	1410

91 rows × 5 columns

Daily Transaction volume distribution

In [23]:

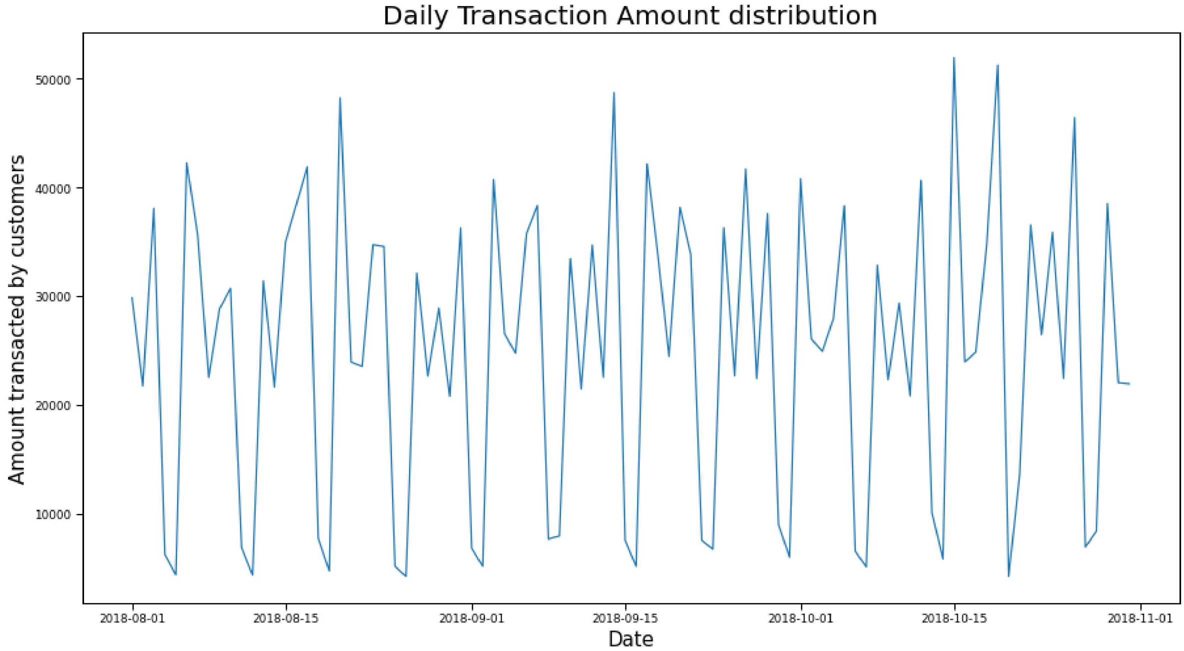
```
plt.figure(figsize=(15,8))
sns.lineplot(x=data_date_count.index, y=data_date_count['customer_id'])
plt.title("Daily Transaction volume distribution")
plt.xlabel("Date", fontsize=15)
plt.ylabel("Number of transactions by customers", fontsize=15)
plt.show()
```



Daily Transaction Amount distribution

In [24]:

```
plt.figure(figsize=(15,8))
sns.lineplot(x=data_date_sum.index, y=data_date_sum['amount'])
plt.title("Daily Transaction Amount distribution")
plt.xlabel("Date", fontsize=15)
plt.ylabel("Amount transacted by customers", fontsize=15)
plt.show()
```



From the above two line plots, we can infer that the number of transactions as well as the amount transacted are remarkably low on weekends especially on sunday.

Geospatial Plotting using the location data

In [25]:

```
import cartopy.crs as ccrs
import cartopy.feature as cfeature
```

In [26]:

```
data['long'] = data['long_lat'].apply(lambda x: x.split(' ')[0]).astype(float)
data['lat'] = data['long_lat'].apply(lambda x: x.split(' ')[1]).astype(float)
```

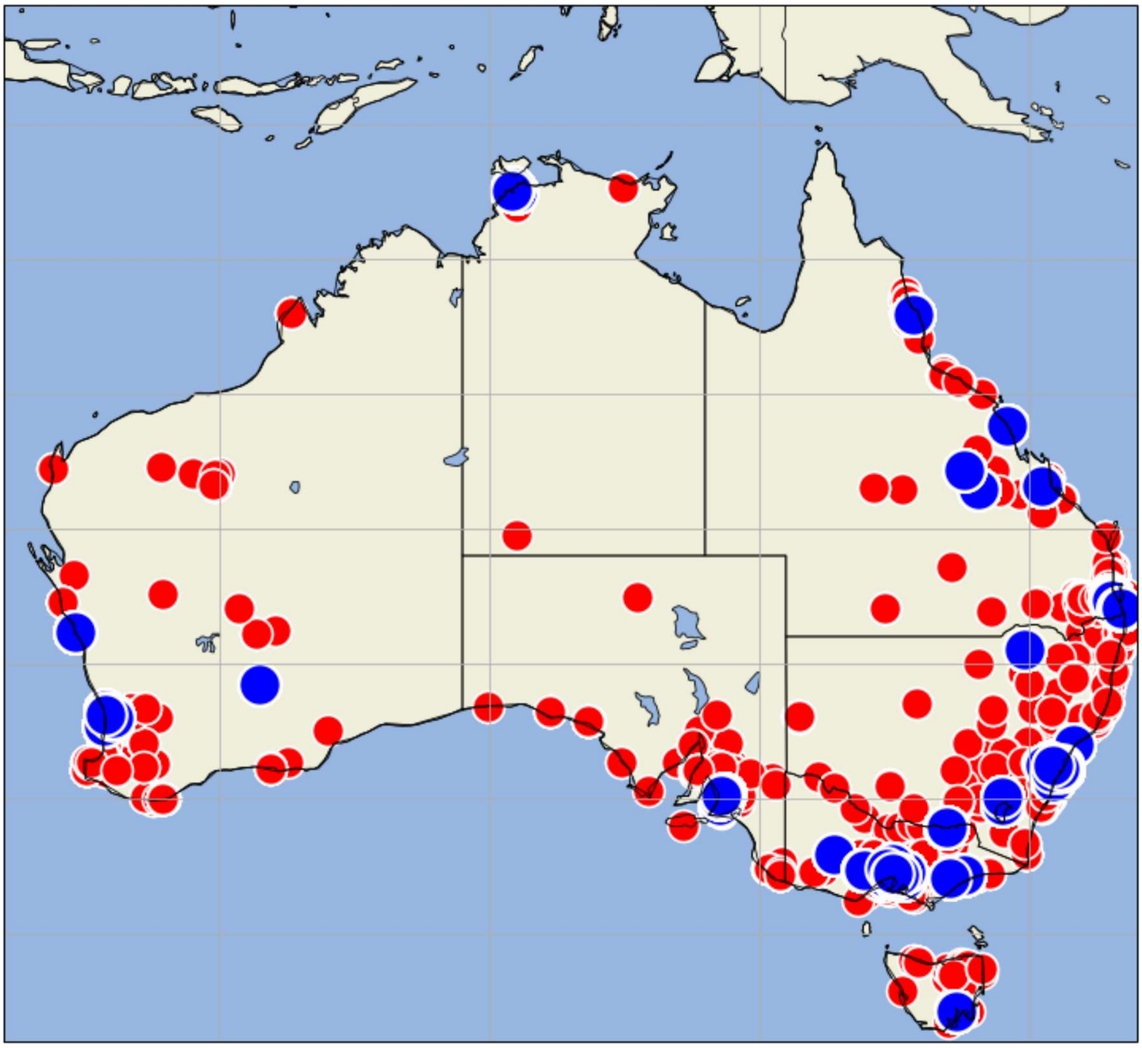
In [27]:

```
data['merchant_long'] = data['merchant_long_lat'].dropna(axis=0).apply(lambda x: str(x).spl
data['merchant_lat'] = data['merchant_long_lat'].dropna(axis=0).apply(lambda x: str(x).spli
```

In [28]:

```
plt.figure(figsize=(15,12))
ax = plt.axes(projection=ccrs.PlateCarree())
plt.title('Location of Customers')
ax.set_extent([112, 154, -44, -5.6], ccrs.PlateCarree())
ax.coastlines(resolution='110m')
ax.gridlines()
ax.add_feature(cfeature.STATES)
ax.add_feature(cartopy.feature.OCEAN)
ax.add_feature(cartopy.feature.LAND, edgecolor='black')
ax.add_feature(cartopy.feature.LAKES, edgecolor='black')
sns.scatterplot(
    x=data['merchant_long'],
    y=data['merchant_lat'],
    color="red",
    s=400,
    alpha=1,
    transform=ccrs.PlateCarree()
)
sns.scatterplot(
    x=data['long'],
    y=data['lat'],
    color="blue",
    s=700,
    alpha=1,
    transform=ccrs.PlateCarree()
)
# plt.savefig('map.png')
plt.show()
```

Location of Customers



- As we can see most of the merchants are based in and around Melbourne, Sydney, Brisbane, Perth, Adelaide.

In [ ]:

```

```