Credit Card Spending Habits in India

This dataset contains insights into a collection of credit card transactions made in India, offering a comprehensive look at the spending habits of Indians across the nation. From the Gender and Card type used to carry out each transaction, to which city saw the highest amount of spending and even what kind of expenses were made, this dataset paints an overall picture about how money is being spent in India today.

Problem Statement

To analyze consumer trends and interests by looking at the type of purchases people make based on their gender and city.

Data Dictionary

- **City** The city in which the transaction took place. (String)
- **Date** The date of the transaction. (Date)
- **Card Type** The type of credit card used for the transaction. (String)
- **Exp Type** The type of expense associated with the transaction. (String)
- **Gender** The gender of the cardholder. (String)
- **Amount** The amount of the transaction. (Number)

Concepts Used

- **Exploratory Data Analysis**

In [1]:
```
# Importing libraries
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

import warnings
warnings.filterwarnings('ignore')
```

In [2]:
```
df = pd.read_csv("Credit card transactions - India - Simple.csv")
df.head()
```

Out[2]:

	index	City	Date	Card Type	Exp Type	Gender	Amount
0	0	Delhi, India	29-Oct-14	Gold	Bills	F	82475
1	1	Greater Mumbai, India	22-Aug-14	Platinum	Bills	F	32555
2	2	Bengaluru, India	27-Aug-14	Silver	Bills	F	101738
3	3	Greater Mumbai, India	12-Apr-14	Signature	Bills	F	123424
4	4	Bengaluru, India	5-May-15	Gold	Bills	F	171574

In [3]:
```
df.shape
```

Out[3]:
```
(26052, 7)
```

Our dataset has 26052 rows and 7 features.

In [4]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26052 entries, 0 to 26051
Data columns (total 7 columns):
 #   Column     Non-Null Count  Dtype 
---  ------     --------------  ----- 
 0   index      26052 non-null  int64 
 1   City       26052 non-null  object
 2   Date       26052 non-null  object
 3   Card Type  26052 non-null  object
 4   Exp Type   26052 non-null  object
 5   Gender     26052 non-null  object
 6   Amount     26052 non-null  int64 
dtypes: int64(2), object(5)
memory usage: 1.4+ MB
```

In [5]:
```
df.tail()
```

Out[5]:

	index	City	Date	Card Type	Exp Type	Gender	Amount
26047	26047	Kolkata, India	22-Jun-14	Silver	Travel	F	128191
26048	26048	Pune, India	3-Aug-14	Signature	Travel	M	246316
26049	26049	Hyderabad, India	16-Jan-15	Silver	Travel	M	265019
26050	26050	Kanpur, India	14-Sep-14	Silver	Travel	M	88174
26051	26051	Hyderabad, India	19-Oct-13	Signature	Bills	M	184410

In [6]:
```
df.drop(columns='index',inplace=True) # Removing the irrelevent Column
df=df.replace(', India','', regex=True) # India is common
```

In [7]:
```
df.isna().sum() # No missing values in dataset
```

Out[7]:
```
City         0
Date         0
Card Type    0
Exp Type     0
Gender       0
Amount       0
dtype: int64
```

In [8]:
```
# Descriptive analysis of categorical columns
df.describe(include = "object").T
```

Out[8]:

	count	unique	top	freq
City	26052	986	Bengaluru	3552
Date	26052	600	20-Sep-14	65
Card Type	26052	4	Silver	6840
Exp Type	26052	6	Food	5463
Gender	26052	2	F	13680

In [9]:
```
# Statistical summary for numerical variables.
df.describe().T
```

Out[9]:

	count	mean	std	min	25%	50%	75%	max
Amount	26052.0	156411.537425	103063.254287	1005.0	77120.25	153106.5	228050.0	998077.0

In [10]:
```
df.dtypes
```

Out[10]:
```
City         object
Date         object
Card Type    object
Exp Type     object
Gender       object
Amount        int64
dtype: object
```

Observations

From the categorical features, we observe that:

- Bengaluru is most frequent in transactions.
- Silver is the most used card Category type.
- Most of the transactions are done in food Category.
- Female does the most no of transactions.

From the numerical column (Amount), we observe that:

- The amount spent is ranging from 1k to 998k.

> - 25% of transactions amount lies between 1005 to 77k.
> - 50 % of transactions lies between 77k to 228k.
> - 25 % of transaction lies between 228k to 998k.

In [11]:
```
df.nunique()
```

Out[11]:
```
City           986
Date           600
Card Type        4
Exp Type         6
Gender           2
Amount       24972
dtype: int64
```

In [12]:
```
df.columns
```

Out[12]:
```
Index(['City', 'Date', 'Card Type', 'Exp Type', 'Gender', 'Amount'], dtype='object')
```

In [13]:
```
for x in ['City', 'Date', 'Card Type', 'Exp Type', 'Gender']:
    df[x] = df[x].astype("category")
```

In [14]:
```
# Examine the unique values in categorical column
col_names = ['City', 'Date', 'Card Type', 'Exp Type', 'Gender']
for x in col_names :
    print(x.upper()," : ",df[x].unique())
    print("_"*25)
    print('\033[1m'+"Value counts : "+ '\033[0m')

    print(df[x].value_counts())
    print("_"*30)
    print('\033[1m'+ "Normalised Value counts : "+ '\033[0m')
    print(df[x].value_counts(normalize=True).round(2))
    print("-"*80)
```

```
CITY  :  ['Delhi', 'Greater Mumbai', 'Bengaluru', 'Ahmedabad', 'Markapur', ..., 'Changanassery', 'Tirur', 'Srikalahasti', 'Wanaparthy', 'Fazilka']
Length: 986
Categories (986, object): ['Achalpur', 'Adilabad', 'Adityapur', 'Adoni', ..., 'Zamania', 'Zira',
                           'Zirakpur', 'Zunheboto']
_________________________
Value counts :
Bengaluru         3552
Greater Mumbai    3493
Ahmedabad         3491
Delhi             3482
Hyderabad          784
                  ...
Tirur                1
Mahbubnagar          1
Alirajpur            1
Varanasi             1
Vellore              1
Name: City, Length: 986, dtype: int64
______________________________
Normalised Value counts :
Bengaluru         0.14
Greater Mumbai    0.13
Ahmedabad         0.13
Delhi             0.13
Hyderabad         0.03
                  ...
Tirur             0.00
Mahbubnagar       0.00
Alirajpur         0.00
Varanasi          0.00
Vellore           0.00
Name: City, Length: 986, dtype: float64
--------------------------------------------------------------------------------
DATE  :  ['29-Oct-14', '22-Aug-14', '27-Aug-14', '12-Apr-14', '5-May-15', ..., '13-Dec-14', '22-Mar-15', '25-Jan-14', '9-May-14', '10-Jul-14']
Length: 600
Categories (600, object): ['1-Apr-14', '1-Apr-15', '1-Aug-14', '1-Dec-13', ..., '9-Nov-14',
                           '9-Oct-13', '9-Oct-14', '9-Sep-14']
_________________________
Value counts :
20-Sep-14    65
15-Nov-14    61
11-Aug-14    61
21-Dec-13    61
12-Jan-15    60
             ..
29-Aug-14    27
9-May-14     26
28-Feb-14    25
30-Jul-14    24
11-Apr-15    23
Name: Date, Length: 600, dtype: int64
______________________________
Normalised Value counts :
20-Sep-14    0.0
15-Nov-14    0.0
11-Aug-14    0.0
21-Dec-13    0.0
12-Jan-15    0.0
            ...
29-Aug-14    0.0
9-May-14     0.0
28-Feb-14    0.0
30-Jul-14    0.0
11-Apr-15    0.0
Name: Date, Length: 600, dtype: float64
--------------------------------------------------------------------------------
CARD TYPE  :  ['Gold', 'Platinum', 'Silver', 'Signature']
Categories (4, object): ['Gold', 'Platinum', 'Signature', 'Silver']
_________________________
Value counts :
Silver       6840
Signature    6447
Platinum     6398
Gold         6367
Name: Card Type, dtype: int64
______________________________
Normalised Value counts :
Silver       0.26
Signature    0.25
Platinum     0.25
Gold         0.24
Name: Card Type, dtype: float64
--------------------------------------------------------------------------------
EXP TYPE  :  ['Bills', 'Food', 'Entertainment', 'Grocery', 'Fuel', 'Travel']
Categories (6, object): ['Bills', 'Entertainment', 'Food', 'Fuel', 'Grocery', 'Travel']
_________________________
Value counts :
Food             5463
Fuel             5257
Bills            5078
Entertainment    4762
Grocery          4754
Travel            738
Name: Exp Type, dtype: int64
______________________________
Normalised Value counts :
Food             0.21
Fuel             0.20
Bills            0.19
Entertainment    0.18
```

```
Grocery          0.18
Travel           0.03
Name: Exp Type, dtype: float64
--------------------------------------------------------------------------------
GENDER  :  ['F', 'M']
Categories (2, object): ['F', 'M']
```

Value counts :

```
F    13680
M    12372
Name: Gender, dtype: int64
```

Normalised Value counts :

```
F    0.53
M    0.47
Name: Gender, dtype: float64
--------------------------------------------------------------------------------
```

In [15]:

```
df.groupby(['Exp Type','Card Type','Gender']).agg(['count', 'mean', 'median', 'max', 'min']).round(2)
```

Out[15]:

Exp Type	Card Type	Gender	Amount count	mean	median	max	min
Bills	Gold	F	695	206586.36	167044.0	996754	1056
		M	561	146089.88	145463.0	298960	1103
	Platinum	F	688	207965.25	176750.5	998077	2119
		M	541	145928.84	148125.0	299967	2333
	Signature	F	699	206795.96	173456.0	994537	1026
		M	560	145651.96	141371.5	299980	1274
	Silver	F	778	191294.95	167166.5	955468	1078
		M	556	152100.69	154846.0	299981	1169
Entertainment	Gold	F	576	146714.27	147689.5	299495	1061
		M	567	156897.78	164133.0	299610	1575
	Platinum	F	568	155525.51	154872.0	299017	1133
		M	619	157140.95	158829.0	299140	1388
	Signature	F	589	152166.29	153348.0	299936	1533
		M	581	153223.82	157616.0	299481	1240
	Silver	F	651	147759.57	142921.0	299794	1074
		M	611	151423.69	151449.0	299906	1610
Food	Gold	F	723	144768.96	144369.0	299641	1066
		M	599	148728.71	146464.0	299162	1171
	Platinum	F	738	153366.44	153875.5	298838	1243
		M	633	153450.83	153032.0	299751	1175
	Signature	F	706	155011.03	156681.5	299689	1265
		M	623	155393.30	160069.0	299641	1289
	Silver	F	845	148552.78	150995.0	299699	1028
		M	596	149117.17	148371.5	299837	1018
Fuel	Gold	F	657	146744.58	146550.0	299642	1038
		M	658	148833.94	146666.5	298784	1182
	Platinum	F	615	148317.62	149397.0	299568	2181
		M	687	149714.74	149480.0	299796	1332
	Signature	F	644	144849.31	142765.5	299664	1207
		M	642	147218.89	141871.5	299613	1678
	Silver	F	701	158877.23	166601.0	298637	1845
		M	653	155516.25	156947.0	299905	1161
Grocery	Gold	F	533	148773.87	150204.0	299920	1105
		M	586	148379.49	152467.0	299431	1099
	Platinum	F	550	150947.84	156921.0	298417	1005
		M	580	152309.50	151697.5	299353	1506
	Signature	F	632	151779.73	152048.0	299510	1024
		M	592	153391.09	151829.0	299550	1578
	Silver	F	713	150637.34	148447.0	298259	1104
		M	568	152224.49	154539.0	299052	1139
Travel	Gold	F	103	140501.17	145059.0	291788	1070
		M	109	153378.68	167896.0	293767	1200
	Platinum	F	93	140866.27	136851.0	299582	1496
		M	86	129687.56	114880.0	297137	3364
	Signature	F	98	154931.54	154779.0	296138	7743
		M	81	152046.23	147630.0	297354	6875
	Silver	F	85	154235.95	138545.0	299618	5769
		M	83	159071.45	167229.0	297660	4762

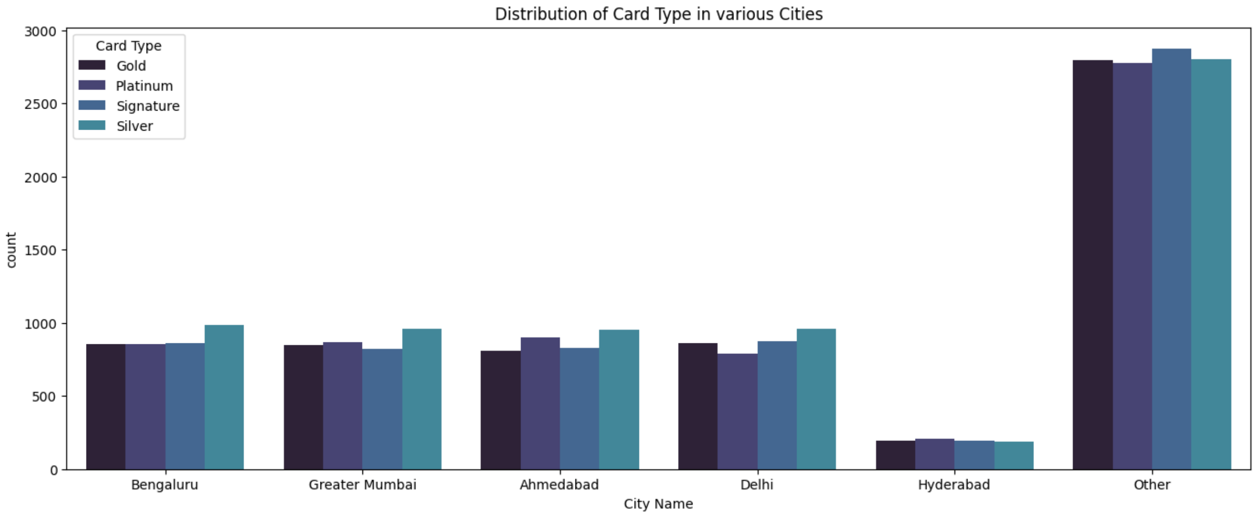
In [16]:
```
city=pd.DataFrame({'count' : df.groupby("City").size()}).reset_index()
df['City Name']=np.where(df.City.isin(city.nlargest(5,'count')['City'].tolist()), df.City, 'Other')
set_ord=city.nlargest(5,'count')['City'].tolist()
set_ord.append("Other")
```

In [17]:
```
df.groupby(["City Name",'Card Type']).size()
```

Out[17]:
```
City Name       Card Type
Ahmedabad       Gold          809
                Platinum      900
                Signature     828
                Silver        954
Bengaluru       Gold          857
                Platinum      853
                Signature     859
                Silver        983
Delhi           Gold          863
                Platinum      791
                Signature     872
                Silver        956
Greater Mumbai  Gold          848
                Platinum      868
                Signature     820
                Silver        957
Hyderabad       Gold          194
                Platinum      210
                Signature     192
                Silver        188
Other           Gold         2796
                Platinum     2776
                Signature    2876
                Silver       2802
dtype: int64
```

In [18]:
```
plt.figure(figsize = (16,6))
sns.countplot(x=df["City Name"],hue=df['Card Type'],order=set_ord,palette=sns.color_palette("mako"))
plt.title("Distribution of Card Type in various Cities")
```

Out[18]:
```
Text(0.5, 1.0, 'Distribution of Card Type in various Cities')
```



- Silver is the most used card type in top 4 city(with most trxns) ['Bengaluru', 'Greater Mumbai', 'Ahmedabad','Delhi']
- Platinum card user does the most no of transactions in hyderabad
- While in rest of the city "Other" signature is the most and platinum the least used card.

In [19]:
```
df.groupby(["City Name",'Exp Type']).size()
```

```
Out[19]: City Name       Exp Type
         Ahmedabad       Bills            680
                         Entertainment    622
                         Food             801
                         Fuel             760
                         Grocery          628
                         Travel             0
         Bengaluru       Bills            735
                         Entertainment    624
                         Food             805
                         Fuel             780
                         Grocery          608
                         Travel             0
         Delhi           Bills            701
                         Entertainment    594
                         Food             784
                         Fuel             782
                         Grocery          621
                         Travel             0
         Greater Mumbai  Bills            728
                         Entertainment    614
                         Food             742
                         Fuel             762
                         Grocery          647
                         Travel             0
         Hyderabad       Bills            142
                         Entertainment    134
                         Food             138
                         Fuel             129
                         Grocery          142
                         Travel            99
         Other           Bills           2092
                         Entertainment   2174
                         Food            2193
                         Fuel            2044
                         Grocery         2108
                         Travel           639
         dtype: int64
```

```
In [20]: plt.figure(figsize = (16,6))
         sns.countplot(x=df["City Name"],hue=df['Exp Type'],order=set_ord,palette=sns.color_palette("mako"))
         plt.title("Distribution of Expense Type in various Cities")
```

```
Out[20]: Text(0.5, 1.0, 'Distribution of Expense Type in various Cities')
```

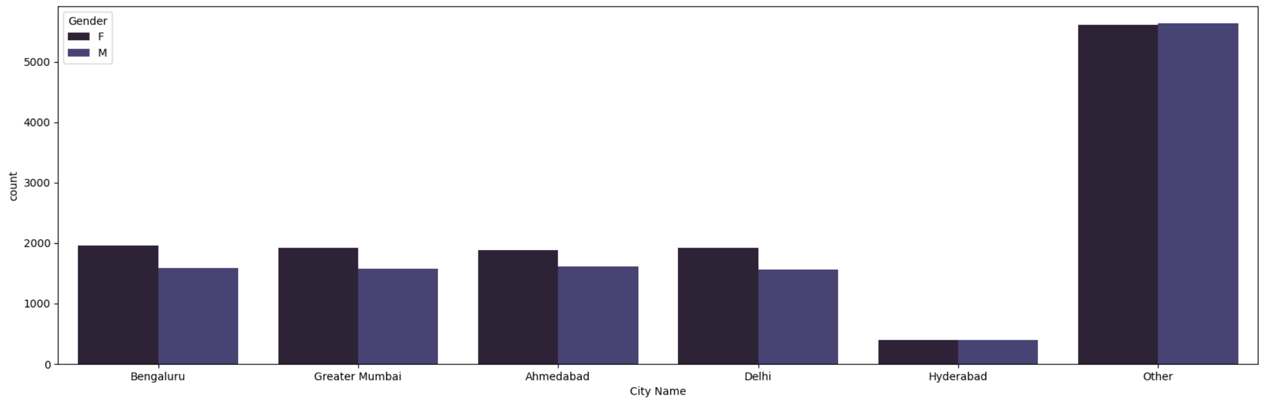
- Food is most frequent expense category in "OTHERS" and 3 out of top 4 city(with most trxns)
- In Hyderabad Bills and Grocery exceeds food category with minor difference of 4
- In Greater Mumbai fuel category has the most frequent transactions
- There is no transactions done in top 4 city for travel category.

```
In [21]: df.groupby(["City Name",'Gender']).size()
```

```
Out[21]: City Name       Gender
         Ahmedabad       F         1876
                         M         1615
         Bengaluru       F         1960
                         M         1592
         Delhi           F         1923
                         M         1559
         Greater Mumbai  F         1922
                         M         1571
         Hyderabad       F          389
                         M          395
         Other           F         5610
                         M         5640
         dtype: int64
```

```
In [22]: plt.figure(figsize = (20,6))
         sns.countplot(x=df["City Name"],hue=df['Gender'],order=set_ord,palette=sns.color_palette("mako"))
```

```
Out[22]: <Axes: xlabel='City Name', ylabel='count'>
```



- In top 4 city ['Bengaluru', 'Greater Mumbai', 'Ahmedabad','Delhi'] females dominates no of transactions
- The difference in no of transactions for female over man ranges from 200 to 400 in each of the city
- Male dominates over Hyderabad with minor difference of 6
- Male dominates over "Other" (rest of city combined) with few no's around to 30-40

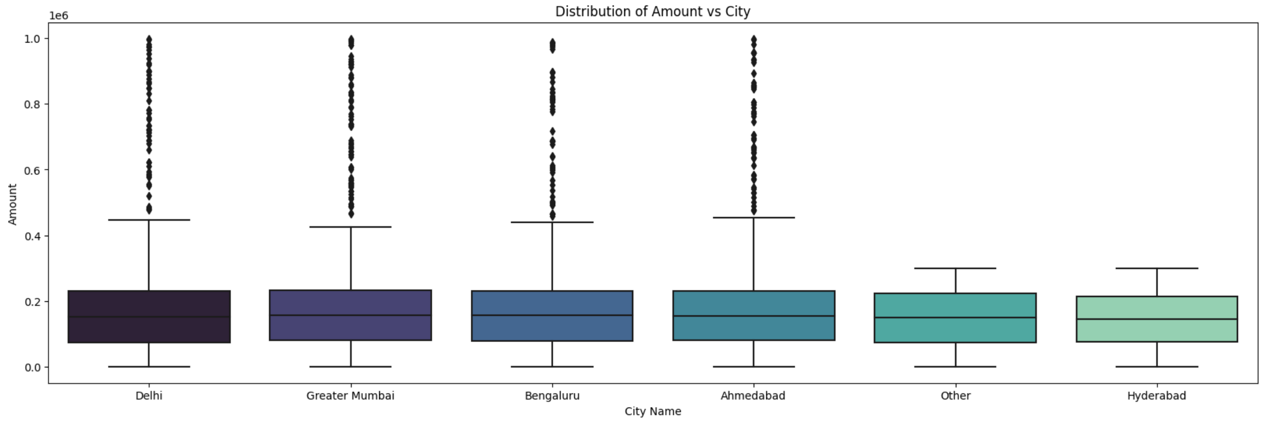
In [23]:
```
df.groupby('City Name').describe() # Top 5 cities
```

Out[23]:

	Amount							
	count	mean	std	min	25%	50%	75%	max
City Name								
Ahmedabad	3491.0	162645.176167	114120.339438	1024.0	80439.00	155813.0	231673.50	996291.0
Bengaluru	3552.0	161128.023367	110598.455781	1074.0	78969.75	158051.0	229747.00	987935.0
Delhi	3482.0	159945.207352	115475.932554	1005.0	73174.75	152373.5	231531.75	996754.0
Greater Mumbai	3493.0	165116.368737	120265.126185	1056.0	81374.00	158108.0	233161.00	998077.0
Hyderabad	784.0	146037.598214	84837.804389	1070.0	75278.00	144765.5	212849.25	299751.0
Other	11250.0	149914.503022	86508.250250	1018.0	74889.00	150772.5	224664.25	299980.0

In [24]:
```
plt.figure(figsize = (20,6))
sns.boxplot(data=df,x='City Name' ,y='Amount',palette=sns.color_palette("mako"))
plt.title("Distribution of Amount vs City")
```

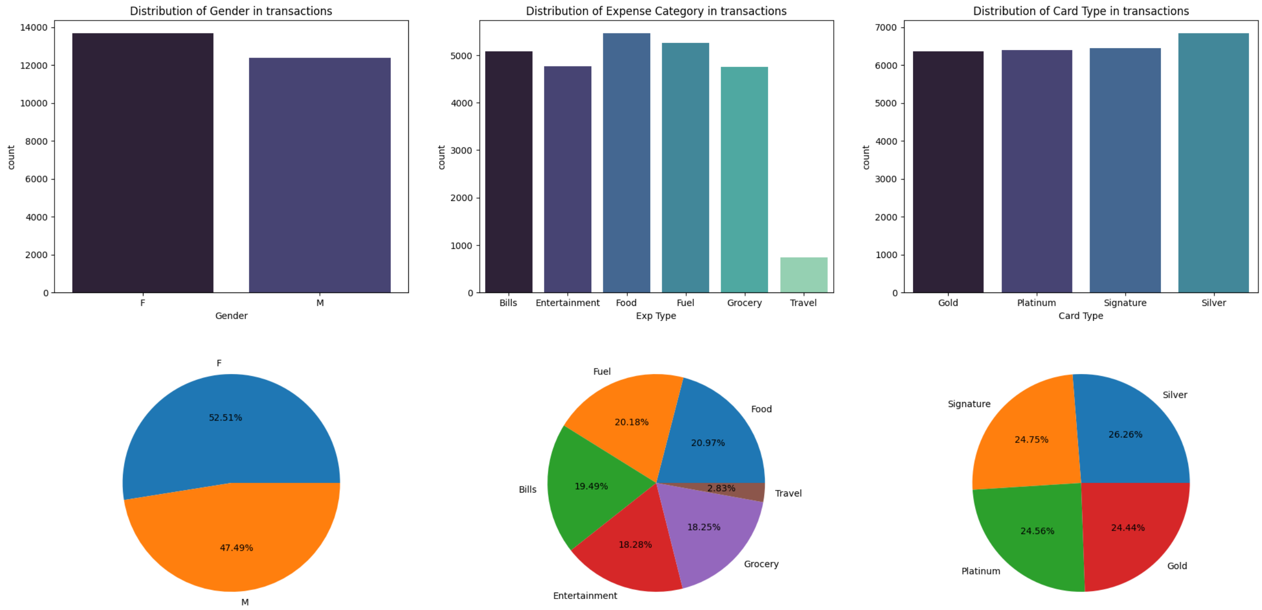
Out[24]: `Text(0.5, 1.0, 'Distribution of Amount vs City')`



- Mean amount for transaction lies around 150k (approx)
- Minimum amount spent and Median amount spent among all city category lies close to each other.

In [25]:
```
plt.subplots(2,3,figsize=(24,12))

plt.subplot(2,3,1)
sns.countplot(x=df["Gender"],palette=sns.color_palette("mako"))
plt.title("Distribution of Gender in transactions")

plt.subplot(2,3,2)
sns.countplot(x=df["Exp Type"],palette=sns.color_palette("mako"))
plt.title("Distribution of Expense Category in transactions")

plt.subplot(2,3,3)
sns.countplot(x=df["Card Type"],palette=sns.color_palette("mako"))
plt.title("Distribution of Card Type in transactions")

plt.subplot(2,3,4)
plt.pie(x=df["Gender"].value_counts(),labels=df["Gender"].value_counts().index,autopct="%0.2f%%")

plt.subplot(2,3,5)
plt.pie(x=df["Exp Type"].value_counts(),labels=df["Exp Type"].value_counts().index,autopct="%0.2f%%")
```

```
plt.subplot(2,3,6)
plt.pie(x=df["Card Type"].value_counts(),labels=df["Card Type"].value_counts().index,autopct="%0.2f%%")
plt.show()
```



- The no of transactions done by female is 5 % more then the male.
- We have 6 different expense categories in transactions.
- Food has the highest 20.97%.
- We can see most of Exp type categories (5 out of 6) has transaction share between 18.25 to 20.97
- We have (travel) 1 out of 6 category which has the least share with 2.83 %
- We have 4 different card type categories
- All 4 transaction share lie between 24.44 % to 26.26 %
- Silver is the most used card type in transactions

Non Graphical Analysis

In [26]:
```
df.groupby(['Card Type','Gender']).describe()
```

Out[26]:

		Amount							
		count	mean	std	min	25%	50%	75%	max
Card Type	**Gender**								
Gold	**F**	3287.0	159091.020079	121538.044533	1038.0	73667.50	149418.0	224995.00	996754.0
	M	3080.0	149872.517208	85645.824151	1099.0	74966.00	150944.0	223809.25	299610.0
Platinum	**F**	3252.0	163573.256150	115396.940061	1005.0	81216.75	157449.0	230606.00	998077.0
	M	3146.0	151207.498411	85676.176116	1175.0	78069.25	151100.5	224513.25	299967.0
Signature	**F**	3368.0	162709.367280	117954.072330	1024.0	77200.00	156323.0	232875.50	994537.0
	M	3079.0	151034.737252	86767.996243	1240.0	76314.00	150418.0	226617.50	299980.0
Silver	**F**	3773.0	159669.618076	109501.051441	1028.0	77400.00	155283.0	231830.00	955468.0
	M	3067.0	152324.826867	87071.732783	1018.0	79104.50	152958.0	227985.00	299981.0

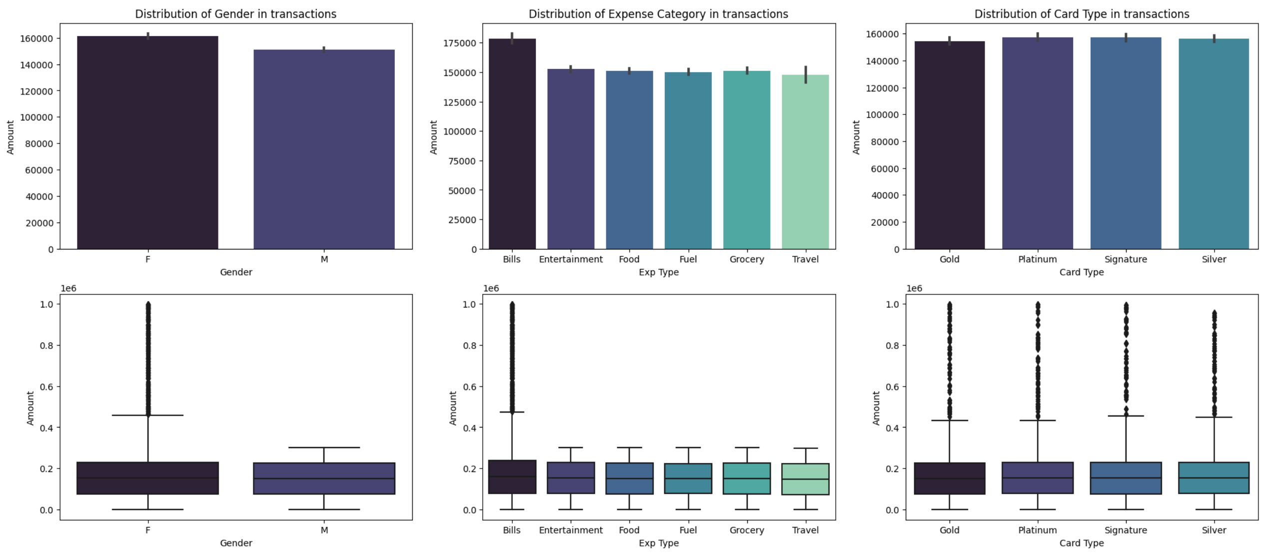
In [27]:
```
df.groupby(['Exp Type','Gender']).describe()
```

Out[27]:

		Amount							
		count	mean	std	min	25%	50%	75%	max
Exp Type	Gender								
Bills	F	2860.0	202809.604545	183838.739960	1026.0	84692.75	170763.0	251943.50	998077.0
	M	2218.0	147446.800721	86743.067538	1103.0	70693.50	148405.0	222329.25	299981.0
Entertainment	F	2384.0	150446.028943	87349.917747	1061.0	72821.75	150158.5	227840.25	299936.0
	M	2378.0	154656.939865	85866.032975	1240.0	81314.00	157918.5	228704.00	299906.0
Food	F	3012.0	150337.742032	86359.783304	1028.0	75275.25	151941.5	225124.50	299699.0
	M	2451.0	151736.731946	86666.914908	1018.0	76354.00	151201.0	225563.50	299837.0
Fuel	F	2617.0	149897.753535	86303.779979	1038.0	75897.00	151512.0	223706.00	299664.0
	M	2640.0	150323.257576	85572.373878	1161.0	79129.75	148679.0	225832.50	299905.0
Grocery	F	2428.0	150595.962932	86758.040202	1005.0	74531.00	151854.5	224839.75	299920.0
	M	2326.0	151573.914445	86123.306959	1099.0	77559.50	152680.5	226511.75	299550.0
Travel	F	379.0	147402.453826	84138.286902	1070.0	79449.00	142755.0	213139.50	299618.0
	M	359.0	148718.888579	89292.822418	1200.0	68352.50	149433.0	226564.00	297660.0

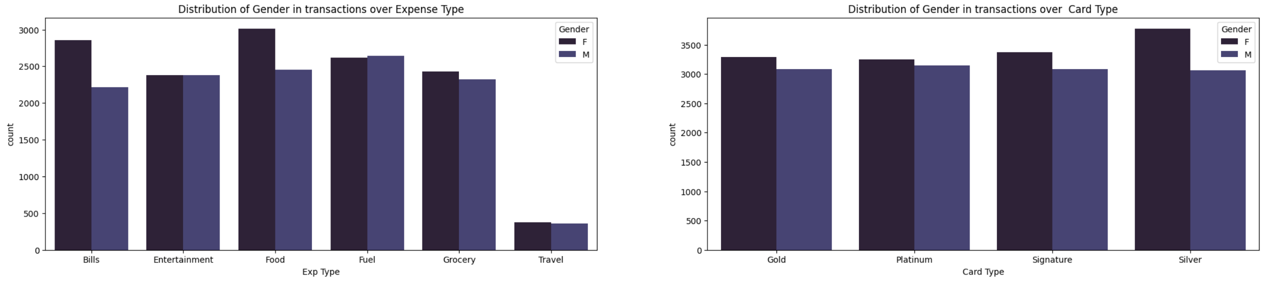
In [28]:

```
plt.subplots(2,3,figsize=(24,10))

plt.subplot(2,3,1)
sns.barplot(x=df["Gender"],y=df["Amount"],palette=sns.color_palette("mako"))
plt.title("Distribution of Gender in transactions")

plt.subplot(2,3,2)
sns.barplot(x=df["Exp Type"],y=df["Amount"],palette=sns.color_palette("mako"))
plt.title("Distribution of Expense Category in transactions")

plt.subplot(2,3,3)
sns.barplot(x=df["Card Type"],y=df["Amount"],palette=sns.color_palette("mako"))
plt.title("Distribution of Card Type in transactions")


plt.subplot(2,3,4)
sns.boxplot(data=df,x='Gender' ,y='Amount',palette=sns.color_palette("mako"))

plt.subplot(2,3,5)
sns.boxplot(data=df,x='Exp Type' ,y='Amount',palette=sns.color_palette("mako"))

plt.subplot(2,3,6)
sns.boxplot(data=df,x='Card Type' ,y='Amount',palette=sns.color_palette("mako"))

plt.show()
```



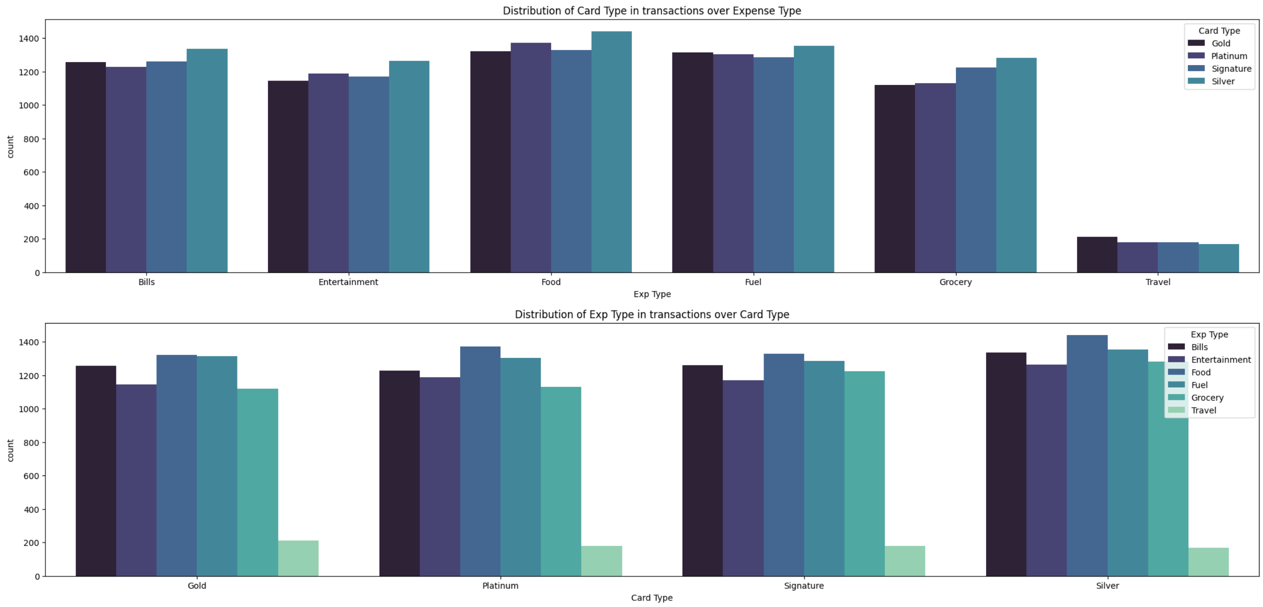
In [29]:

```
plt.subplots(1,2,figsize=(26,5))
plt.subplot(1,2,1)
sns.countplot(x=df["Exp Type"],hue=df["Gender"],palette=sns.color_palette("mako"))
plt.title("Distribution of Gender in transactions over Expense Type")

plt.subplot(1,2,2)
sns.countplot(x=df["Card Type"],hue=df["Gender"],palette=sns.color_palette("mako"))
plt.title("Distribution of Gender in transactions over  Card Type")
plt.show()
```



- Female has high no transactions in almost all exp category except fuel.
- Female has high no transactions in all Card type

In [30]:
```python
plt.subplots(2,1,figsize=(26,12))

plt.subplot(2,1,1)
sns.countplot(x=df["Exp Type"],hue=df["Card Type"],palette=sns.color_palette("mako"))
plt.title("Distribution of Card Type in transactions over Expense Type")

plt.subplot(2,1,2)
sns.countplot(x=df["Card Type"],hue=df["Exp Type"],palette=sns.color_palette("mako"))
plt.title("Distribution of Exp Type in transactions over Card Type")
plt.show()
```



Conclusions

- Top 3 City having highest no of transactions are Bengaluru, Greater Mumbai and Ahmedabad
- Last 3 City having lowest no of transactions are Alirajpur, Bagaha and Changanassery
- Silver is the highest used card & Gold is the least used card type.
- Food has the highest no of transactions whereas Travel has the lowest no of transactions.
- Females has the most no of transactions than Males.
- Silver has the highest overall amount while gold is least contribution to total amount.
- Bills has the highest overall amount while travel is least contribution to total amount.
- Female has the highest overall amount than men who contributes to total amount
- Only in Fuel expense subcategory no of transactions dominates for men.
- All subcategories in Card type dominated by womens
- Silver card holder dominates in all sub categories except Travel.
- Gold card holder has most transactions in travel sector
- Food is the most frequent category in all card types & travel being the least