Data Exploration and Analysis [Pyspark]

In [1]:
```
filename_path = "data/purchase_data.xltx"
# filename_path = "data/purchase_data_sample.xlsx"
topN=5
```

In [2]:
```
# %%capture
# !pip install -r requirements.txt
```

In [3]:
```
import sys
import pandas as pd
from pandas import DataFrame
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.ticker as mtick
import matplotlib
matplotlib.rcParams["figure.dpi"] = 100
%matplotlib inline
```

In [4]:
```
%cd /app
sys.path.append('src')
```

```
/app
```

0. Data loading

In [5]:
```
# Import PySpark related modules
from utils.data_exploration import init_spark, spark_load_data

# initialize the spark sessions
spark = init_spark( MAX_MEMORY='4G')

# Load the main dataset into pyspark data frame
spark_df = spark_load_data(spark, filename_path)
```

```
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
24/10/25 16:51:10 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using bu
iltin-java classes where applicable
24/10/25 16:52:51 WARN TaskSetManager: Stage 0 contains a task of very large size (2292 KiB). The maximum r
ecommended task size is 1000 KiB.

There are total 199999 rows
24/10/25 16:52:55 WARN TaskSetManager: Stage 3 contains a task of very large size (2292 KiB). The maximum r
ecommended task size is 1000 KiB.

Raw data :    Cust_ID            Name  Age                Date  Price  Quantity  \
0    48592   Tina Phillips   55 2020-01-01 00:11:40     60         4
1    30486     Lance Colon   41 2020-01-01 00:15:47    130         4
2     6380  Ashlee Johnson   60 2020-01-01 00:28:45    263         5
3    27554    William Bell   52 2020-01-01 00:33:57    136         3
4    14460   Anna Martinez   45 2020-01-01 01:32:30     23         3

   Purch_Amt  Category  Returns  Gender  Churn
0        240  Clothing      0.0    Male      0
1        520  Clothing      NaN    Male      1
2       1315      Home      0.0  Female      1
3        408     Books      0.0    Male      0
4         69      Home      1.0    Male      0
```

In [6]:
```python
spark_df.limit(5).toPandas()
```

```
24/10/25 16:52:56 WARN TaskSetManager: Stage 4 contains a task of very large size (2292 KiB). The maximum r
ecommended task size is 1000 KiB.
```

Out[6]:

	Cust_ID	Name	Age	Date	Price	Quantity	Purch_Amt	Category	Returns	Gender	Churn
0	48592	Tina Phillips	55	2020-01-01 00:11:40	60	4	240	Clothing	0.0	Male	0
1	30486	Lance Colon	41	2020-01-01 00:15:47	130	4	520	Clothing	NaN	Male	1
2	6380	Ashlee Johnson	60	2020-01-01 00:28:45	263	5	1315	Home	0.0	Female	1
3	27554	William Bell	52	2020-01-01 00:33:57	136	3	408	Books	0.0	Male	0
4	14460	Anna Martinez	45	2020-01-01 01:32:30	23	3	69	Home	1.0	Male	0

1. Data Preparation

In [7]:
```
from utils.data_exploration import data_preparation_pipeline

# run the data preparation pipeline
spark_df, missing_invalid_df = data_preparation_pipeline(spark, spark_df)
```

```
24/10/25 16:52:57 WARN TaskSetManager: Stage 5 contains a task of very large size (2292 KiB). The maximum r
ecommended task size is 1000 KiB.
24/10/25 16:52:58 WARN TaskSetManager: Stage 8 contains a task of very large size (2292 KiB). The maximum r
ecommended task size is 1000 KiB.
[Stage 8:=============================>                             (2 + 2) / 4]
- 36734/199999 invalid (negative) values found!!.
 18.367091835459178% samples were removed from the dataset
24/10/25 16:53:00 WARN TaskSetManager: Stage 11 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:01 WARN TaskSetManager: Stage 14 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.

- 0/163265 invalid computation(s) of Purch_Amt=Price*Quantity are found!!.
 0.0% samples were removed from the dataset
```

```
24/10/25 16:53:02 WARN TaskSetManager: Stage 17 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:03 WARN TaskSetManager: Stage 20 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:04 WARN TaskSetManager: Stage 23 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:05 WARN TaskSetManager: Stage 26 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:05 WARN TaskSetManager: Stage 29 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:06 WARN TaskSetManager: Stage 32 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:07 WARN TaskSetManager: Stage 35 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:08 WARN TaskSetManager: Stage 38 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:09 WARN TaskSetManager: Stage 41 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:10 WARN TaskSetManager: Stage 44 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:10 WARN TaskSetManager: Stage 47 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
24/10/25 16:53:11 WARN TaskSetManager: Stage 50 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
```

In [8]:
```
spark_df.limit(5).toPandas()
```

```
24/10/25 16:53:12 WARN TaskSetManager: Stage 53 contains a task of very large size (2292 KiB). The maximum recommended task size is 1000 KiB.
```

Out[8]:

	Cust_ID	Name	Age	Date	Price	Quantity	Purch_Amt	Category	Returns	Gender	Churn
0	48592	Tina Phillips	55	2020-01-01 00:11:40	60	4	240	Clothing	0.0	Male	0
1	30486	Lance Colon	41	2020-01-01 00:15:47	130	4	520	Clothing	0.0	Male	1
2	6380	Ashlee Johnson	60	2020-01-01 00:28:45	263	5	1315	Home	0.0	Female	1
3	27554	William Bell	52	2020-01-01 00:33:57	136	3	408	Books	0.0	Male	0
4	14460	Anna Martinez	45	2020-01-01 01:32:30	23	3	69	Home	1.0	Male	0

In [9]:
```
missing_invalid_df
```

Out[9]:

	Cust_ID	Name	Age	Date	Price	Quantity	Purch_Amt	Category	Returns	Gender	Churn
count	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
percentage	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

2.Data Analysis

In [10]:
```
from utils.data_exploration import data_analysis_pipeline

# run the data analysis pipeline
monthly_sales, past_sales_stats_df,current_sales_stats_df,growth_rate_dict,\
top_ranked_clients_df,worst_ranked_clients_df,\
    top_purchases_by_gender_df = data_analysis_pipeline(spark, spark_df, topN=topN, verbose=0)
```

```
24/10/25 16:53:14 WARN TaskSetManager: Stage 54 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:17 WARN TaskSetManager: Stage 62 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:19 WARN TaskSetManager: Stage 70 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:20 WARN TaskSetManager: Stage 78 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:21 WARN TaskSetManager: Stage 86 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:23 WARN TaskSetManager: Stage 94 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:24 WARN TaskSetManager: Stage 102 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:25 WARN TaskSetManager: Stage 103 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:28 WARN TaskSetManager: Stage 116 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:28 WARN TaskSetManager: Stage 117 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:30 WARN TaskSetManager: Stage 130 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:31 WARN TaskSetManager: Stage 131 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:33 WARN TaskSetManager: Stage 148 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:34 WARN TaskSetManager: Stage 149 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:36 WARN TaskSetManager: Stage 167 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:37 WARN TaskSetManager: Stage 168 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:38 WARN TaskSetManager: Stage 186 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:39 WARN TaskSetManager: Stage 187 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
24/10/25 16:53:45 WARN TaskSetManager: Stage 200 contains a task of very large size (2292 KiB). The maximum
recommended task size is 1000 KiB.
```

visualizations

In [11]:
```
monthly_sales
```

Out[11]:

	year	month	sum_Cust_ID	sum_Purch_Amt	avg_Purch_Amt	avg_Price	avg_Quantity	sum_Quantity	avg_Age	sum_Retu
0	2020	1	93337613	2224391	596.03	199.00	3.01	11251	49.99	157
1	2020	2	87439599	2132153	604.35	201.74	3.00	10585	50.10	145
2	2020	3	89405188	2272470	617.02	201.52	3.05	11251	49.26	151
3	2020	4	89597816	2181254	598.59	198.57	3.01	10962	49.78	148
4	2020	5	95521031	2277181	605.63	202.05	3.00	11276	49.82	151
5	2020	6	89719010	2198794	609.76	200.39	3.04	10977	49.78	145
6	2020	7	94187197	2294211	605.49	201.03	3.00	11377	49.70	150
7	2020	8	95895575	2329672	608.75	200.89	3.04	11642	50.09	156
8	2020	9	90657939	2170052	600.62	200.19	3.00	10829	49.58	150
9	2020	10	95462458	2306382	610.15	200.64	3.03	11451	50.12	155
10	2020	11	91899775	2139979	589.85	198.13	2.97	10791	49.68	147
11	2020	12	93392328	2209249	587.41	196.12	2.99	11254	49.69	151
12	2021	1	91394350	2176366	593.82	199.08	3.00	10978	49.30	150
13	2021	2	83722568	2069965	614.05	203.34	3.03	10211	50.20	135
14	2021	3	92048545	2203761	603.94	201.62	3.02	11028	49.85	153
15	2021	4	88151682	2176623	604.79	201.34	3.02	10879	50.17	142
16	2021	5	95001894	2320033	610.05	200.30	3.05	11590	49.63	154
17	2021	6	90064705	2181889	607.60	199.71	3.02	10858	49.70	145
18	2021	7	94737143	2258872	598.54	200.71	2.98	11255	49.64	154
19	2021	8	96993544	2299105	593.78	197.46	3.02	11676	49.60	153
20	2021	9	91712437	2160791	595.10	199.87	2.97	10779	50.30	144
21	2021	10	93080584	2193952	588.51	197.87	2.98	11101	49.25	153
22	2021	11	88503939	2129189	604.03	199.26	3.04	10707	49.72	141
23	2021	12	92342131	2297885	614.08	201.61	3.02	11303	49.37	152

	year	month	sum_Cust_ID	sum_Purch_Amt	avg_Purch_Amt	avg_Price	avg_Quantity	sum_Quantity	avg_Age	sum_Retu
24	2022	1	92339754	2223630	600.49	199.75	3.00	11095	49.45	15
25	2022	2	84556088	2007707	598.42	199.90	3.00	10054	49.13	13
26	2022	3	96714547	2288174	602.31	197.78	3.03	11497	50.04	15
27	2022	4	91555187	2268222	617.54	199.80	3.07	11262	49.57	14
28	2022	5	93563040	2206379	591.52	197.57	2.98	11113	50.34	15
29	2022	6	91322387	2160457	593.70	198.86	2.99	10874	50.08	14
30	2022	7	95063042	2298142	609.26	201.13	3.02	11407	49.62	15
31	2022	8	93777820	2214986	600.10	198.25	3.00	11059	49.31	15
32	2022	9	90280358	2140130	602.01	200.71	2.99	10637	49.80	14
33	2022	10	90959417	2201594	603.51	201.19	2.98	10887	49.91	15
34	2022	11	91178169	2177590	594.81	198.35	3.01	11007	49.93	15
35	2022	12	91822491	2244831	597.35	198.64	3.01	11327	49.81	15
36	2023	1	93764087	2244563	597.12	198.23	2.99	11221	50.28	15
37	2023	2	82892664	1989147	597.34	201.09	2.97	9894	49.98	13
38	2023	3	96325402	2306594	602.72	200.55	3.00	11477	49.63	15
39	2023	4	90731410	2131713	592.31	201.08	2.96	10670	49.63	14
40	2023	5	95109376	2367078	621.77	204.18	3.03	11544	49.76	15
41	2023	6	89071121	2157280	598.91	200.31	3.00	10801	49.78	14
42	2023	7	91854551	2182295	595.44	198.36	3.00	10998	49.76	14
43	2023	8	96005349	2280938	598.51	201.39	2.98	11345	49.67	15
44	2023	9	39287055	933647	590.92	197.34	2.99	4719	50.12	6

In [12]:
```python
past_sales_stats_df.round(1).to_dict(orient="records")
```

Out[12]:
```
[{'year': 2022,
  'sum_sum_Cust_ID': 829172223,
  'sum_sum_Purch_Amt': 19807827,
  'avg_avg_Price': 199.3,
  'sum_sum_Quantity': 98998,
  'avg_avg_Age': 49.7,
  'sum_sum_Returns': 13379.0,
  'sum_sum_Churn': 6631}]
```

In [13]:
```
current_sales_stats_df.round(1).to_dict(orient="records")
```

Out[13]:
```
[{'year': 2023,
  'sum_sum_Cust_ID': 775041015,
  'sum_sum_Purch_Amt': 18593255,
  'avg_avg_Price': 200.3,
  'sum_sum_Quantity': 92669,
  'avg_avg_Age': 49.8,
  'sum_sum_Returns': 12555.0,
  'sum_sum_Churn': 6240}]
```

In [14]:
```
growth_rate_dict
```

Out[14]:
```
{'year': 2023,
 'Cust_ID': -6.53,
 'Purch_Amt': -6.13,
 'Price': 0.49,
 'Quantity': -6.39,
 'Age': 0.28,
 'Returns': -6.16,
 'Churn': -5.9}
```

In [15]:
```
top_ranked_clients_df
```

Out[15]:

	Cust_ID	Name	Age	transactions count	latest transactions	sum_Purch_Amt	avg_Age	sum_Returns	sum_Churn	percentage
0	48382	Katelyn Clark	38	15	2023-04-01 13:02:11	8411	38.0	4.0	0	0.01
1	6347	Lori Taylor	63	14	2022-08-26 16:18:07	12648	63.0	8.0	0	0.01
2	35294	Roberto Rogers	64	14	2023-08-24 07:18:33	7653	64.0	5.0	14	0.01
3	28656	Rachel Ross	31	14	2023-07-11 17:38:40	8026	31.0	3.0	14	0.01
4	19960	Patrick Gamble	76	14	2023-05-21 02:40:09	8174	76.0	6.0	0	0.01

In [16]:

```
top_ranked_clients_df.astype(str).to_dict(orient="records")
```

Out[16]:
```
[{'Cust_ID': '48382',
  'Name': 'Katelyn Clark',
  'Age': '38',
  'transactions count': '15',
  'latest transactions': '2023-04-01 13:02:11',
  'sum_Purch_Amt': '8411',
  'avg_Age': '38.0',
  'sum_Returns': '4.0',
  'sum_Churn': '0',
  'percentage': '0.01'},
 {'Cust_ID': '6347',
  'Name': 'Lori Taylor',
  'Age': '63',
  'transactions count': '14',
  'latest transactions': '2022-08-26 16:18:07',
  'sum_Purch_Amt': '12648',
  'avg_Age': '63.0',
  'sum_Returns': '8.0',
  'sum_Churn': '0',
  'percentage': '0.01'},
 {'Cust_ID': '35294',
  'Name': 'Roberto Rogers',
  'Age': '64',
  'transactions count': '14',
  'latest transactions': '2023-08-24 07:18:33',
  'sum_Purch_Amt': '7653',
  'avg_Age': '64.0',
  'sum_Returns': '5.0',
  'sum_Churn': '14',
  'percentage': '0.01'},
 {'Cust_ID': '28656',
  'Name': 'Rachel Ross',
  'Age': '31',
  'transactions count': '14',
  'latest transactions': '2023-07-11 17:38:40',
  'sum_Purch_Amt': '8026',
  'avg_Age': '31.0',
  'sum_Returns': '3.0',
  'sum_Churn': '14',
  'percentage': '0.01'},
 {'Cust_ID': '19960',
  'Name': 'Patrick Gamble',
```

```
'Age': '76',
'transactions count': '14',
'latest transactions': '2023-05-21 02:40:09',
'sum_Purch_Amt': '8174',
'avg_Age': '76.0',
'sum_Returns': '6.0',
'sum_Churn': '0',
'percentage': '0.01'}]
```

In [17]:
```
worst_ranked_clients_df.astype(str).to_dict(orient="records")
```

Out[17]:

```
[{'Cust_ID': '32331',
  'Name': 'Sean Snyder',
  'Age': '47',
  'transactions count': '1',
  'latest transactions': '2023-02-22 10:09:00',
  'sum_Purch_Amt': '21',
  'avg_Age': '47.0',
  'sum_Returns': '0.0',
  'sum_Churn': '1',
  'percentage': '0.0'},
 {'Cust_ID': '6584',
  'Name': 'Cathy Benjamin',
  'Age': '55',
  'transactions count': '1',
  'latest transactions': '2023-05-15 19:21:16',
  'sum_Purch_Amt': '155',
  'avg_Age': '55.0',
  'sum_Returns': '0.0',
  'sum_Churn': '0',
  'percentage': '0.0'},
 {'Cust_ID': '37579',
  'Name': 'Sarah Henderson',
  'Age': '50',
  'transactions count': '1',
  'latest transactions': '2023-06-23 18:54:30',
  'sum_Purch_Amt': '868',
  'avg_Age': '50.0',
  'sum_Returns': '0.0',
  'sum_Churn': '0',
  'percentage': '0.0'},
 {'Cust_ID': '34634',
  'Name': 'Kelly Ortiz',
  'Age': '45',
  'transactions count': '1',
  'latest transactions': '2022-12-18 12:08:49',
  'sum_Purch_Amt': '918',
  'avg_Age': '45.0',
  'sum_Returns': '0.0',
  'sum_Churn': '0',
  'percentage': '0.0'},
 {'Cust_ID': '140',
  'Name': 'Richard Perez',
```

```
  'Age': '61',
  'transactions count': '1',
  'latest transactions': '2023-04-30 09:13:34',
  'sum_Purch_Amt': '692',
  'avg_Age': '61.0',
  'sum_Returns': '1.0',
  'sum_Churn': '0',
  'percentage': '0.0'}]
```

In [18]:
```
top_purchases_by_gender_df.astype(str).to_dict(orient="records")
```

Out[18]:
```
[{'Category': 'Books',
  'Female': '20143',
  'Male': '20516',
  'total': '40659',
  'percentage': '24.9',
  'MalePercentage': '50.46',
  'FemalePercentage': '49.54'},
 {'Category': 'Clothing',
  'Female': '20242',
  'Male': '20563',
  'total': '40805',
  'percentage': '24.99',
  'MalePercentage': '50.39',
  'FemalePercentage': '49.61'},
 {'Category': 'Electronics',
  'Female': '20479',
  'Male': '20473',
  'total': '40952',
  'percentage': '25.08',
  'MalePercentage': '49.99',
  'FemalePercentage': '50.01'},
 {'Category': 'Home',
  'Female': '20235',
  'Male': '20614',
  'total': '40849',
  'percentage': '25.02',
  'MalePercentage': '50.46',
  'FemalePercentage': '49.54'}]
```

3. Data Modeling

In [19]:
```
from utils.data_exploration import data_modeling_pipeline
data_modeling_pipeline()
```

Out[19]: {}

4. Model Deployment

In [20]:
```
from utils.data_exploration import model_deployment_pipeline
model_deployment_pipeline()
```

Out[20]: {}

DEV

In [ ]:

In [21]:
```
# Import other modules not related to PySpark
import os
import sys
import pandas as pd
from pandas import DataFrame
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.ticker as mtick
import matplotlib
from mpl_toolkits.mplot3d import Axes3D
import math
from IPython.core.interactiveshell import InteractiveShell
from datetime import *
import statistics as stats

matplotlib.rcParams["figure.dpi"] = 100
InteractiveShell.ast_node_interpurchase = "all"
```

```
%matplotlib inline

sys.path.append('src')
```

In [22]:
```
# Import PySpark related modules
from utils.data_exploration import init_spark

spark = init_spark( MAX_MEMORY='4G')
```

In [23]:
```
# filename_path = "data/purchase_data.xltx"
filename_path = "data/purchase_data_sample.xlsx"

# Load the main data set into pyspark data frame
df = pd.read_excel(filename_path)
spark_df = spark.createDataFrame(df)
print("Data frame type: " + str(type(spark_df)))
```

```
Data frame type: <class 'pyspark.sql.dataframe.DataFrame'>
```

In [24]:
```
# filename_path = "data/purchase_data_sample.xlsx"

# # save sample data
# save_sample_data(df, filename_path, nrows=100)
```

In [25]:
```
print("Data frame stats (string and numeric columns only):")
spark_df.describe().toPandas()
print(f"There are total {spark_df.count()} row, Lets show 5 rows:")
spark_df.limit(5).toPandas()
```

```
Data frame stats (string and numeric columns only):
```

```
24/10/25 16:53:50 WARN SparkStringUtils: Truncated the string representation of a plan since it was too lar
ge. This behavior can be adjusted by setting 'spark.sql.debug.maxToStringFields'.

There are total 100 row, Lets show 5 rows:
```

Out[25]:

	Cust_ID	Name	Age	Date	Price	Quantity	Purch_Amt	Category	Returns	Gender	Churn
0	17011	Zachary Roberts	29	2023-01-15 00:44:35	181	4	724	Clothing	0.0	Female	0
1	3176	Cathy Martinez	67	2021-06-27 22:22:58	135	2	270	Clothing	NaN	Female	1
2	17378	Brenda Harris	45	2022-02-11 07:08:28	322	3	966	Home	NaN	Male	0
3	16890	Amy Bailey	59	2022-01-19 04:57:55	-86	1	-86	Electronics	1.0	Female	0
4	8010	Justin Parks	65	2022-07-26 21:57:45	38	3	114	Home	0.0	Male	1

2.1 Schema & datatypes

The data columns format (bigint, timestamp, double, string) and columns made of signle values not arrays/list.

In [26]:

```
spark_df=spark_df.orderBy("Date")
```

In [27]:

```
print("Data Columns overview")
spark_df.printSchema()
pd.DataFrame(spark_df.dtypes, columns = ["Column Name","Data type"]).set_index(["Column Name"]).T
```

```
Data Columns overview
root
 |-- Cust_ID: long (nullable = true)
 |-- Name: string (nullable = true)
 |-- Age: long (nullable = true)
 |-- Date: timestamp (nullable = true)
 |-- Price: long (nullable = true)
 |-- Quantity: long (nullable = true)
 |-- Purch_Amt: long (nullable = true)
 |-- Category: string (nullable = true)
 |-- Returns: double (nullable = true)
 |-- Gender: string (nullable = true)
 |-- Churn: long (nullable = true)
```

Out[27]:

Column Name	Cust_ID	Name	Age	Date	Price	Quantity	Purch_Amt	Category	Returns	Gender	Churn
Data type	bigint	string	bigint	timestamp	bigint	bigint	bigint	string	double	string	bigint

In [28]:
```python
from utils.data_exploration import categorize_columns

# categorise the different columns
string_columns,numeric_columns,array_columns, timestamp_columns,unkown_columns =categorize_columns(spark_d
```

```
timestamp_columns [size= 1] = ['Date']
string_columns [size= 3] = ['Name', 'Category', 'Gender']
numeric_columns [size= 7] = ['Cust_ID', 'Age', 'Price', 'Quantity', 'Purch_Amt', 'Returns', 'Churn']
array_columns [size= 0] = []
unkown_columns [size= 0] = []
```

In [29]:
```python
from utils.data_exploration import count_missing_invalid_values

# count the missing values
count_missing_invalid_values(spark_df)
```

Out[29]:

	Cust_ID	Name	Age	Date	Price	Quantity	Purch_Amt	Category	Returns	Gender	Churn
count	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	18.0	0.0	0.0
percentage	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	18.0	0.0	0.0

3.1 replace missing values

- replace the 18% missingvalues of `Returns` by zero

In [30]:
```python
#Replace 0 for null on only population column
spark_df=spark_df.na.fill(value=0,subset=["Returns"])

# count the missing values
count_missing_values(spark_df)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
Cell In[30], line 5
      2 spark_df=spark_df.na.fill(value=0,subset=["Returns"])
      4 # count the missing values
----> 5 count_missing_values(spark_df)

NameError: name 'count_missing_values' is not defined
```

In [ ]:
```
from utils.data_exploration import plot_columns, generate_explode
```

In [ ]:
```
monthly_spark_df.columns
```

In [ ]:
```
#  plot the purchase amount history
plot_columns(monthly_spark_df,
             x_column="DateByMonth",
             y_columns=["sum_Purch_Amt", "sum_Quantity", "avg_Purch_Amt", "avg_Quantity","avg_Price"],
             subplot=True)
```

In [ ]:
```
x_column="DateByMonth"
y_columns=["avg_Price","avg_Quantity", "sum_Quantity"]
#  plot the purchase history
plot_columns(monthly_spark_df,
             x_column=x_column,
             y_columns=y_columns,
             subplot=True)
```

3.2 remove the unvalid value (negative price, quantity, others)

- remove the 18% negative quantities

In [ ]:
```
nb_unvalid_values = spark_df.select("*")\
        .where((col("Price")<0) | \
               (col("Quantity")<0) | \
               (col("Purch_Amt")<0) | \
               (col("Returns")<0) | \
               (col("Churn")<0)  ).count()
total_nb_samples = spark_df.count()

if nb_unvalid_values>=0:
    print(f"- {nb_unvalid_values}/{total_nb_samples} unvalid (negative) values are removed from the databas
    spark_df = spark_df.select("*")\
                        .where((col("Price")>=0) & \
                               (col("Quantity")>=0) & \
                               (col("Purch_Amt")>=0) & \
                               (col("Returns")>=0) & \
                               (col("Churn")>=0)  )
```

3.3 remove the unvalid unvalid computation(s) of Purch_Amt=Price*Quantity

- remove the 0% unvalid computation(s)

In [ ]:
```
nb_unvalid_Purch_Amt_values = spark_df.select("*")\
        .where((col("Price")*col("Quantity")!=col("Purch_Amt")) ).count()
if nb_unvalid_Purch_Amt_values>=0:
    print(f"- {nb_unvalid_values}/{total_nb_samples} unvalid computation(s) of Purch_Amt=Price*Quantity. Th
    spark_df = spark_df.select("*")\
                        .where((col("Price")*col("Quantity")==col("Purch_Amt")) )
```

In [ ]:
```
spark_df.limit(5).toPandas()
```

In [ ]:
```
ranked_product_clients_df = spark_df.select(spark_df.Category, spark_df.Cust_ID) \
    .distinct() \
    .groupBy(spark_df.Category) \
    .count() \
    .orderBy("count", ascending=False)

# Top 5 purchase types
highest_product_clients_df = ranked_product_clients_df.limit(5).toPandas()
# Rename column name : "count" --> Clients count
highest_product_clients_df.rename(columns = {"count":"Clients count"}, inplace = True)
# Caculate the total users, we will this result to compute percentage later
total_categories_clients = ranked_product_clients_df.groupBy().sum().collect()[0][0]
```

In [ ]:
```
ranked_product_clients_df.collect()[:5]
```

In [ ]:
```
highest_product_clients_df_renamed = highest_product_clients_df
# Compute the percentage of top 5 purchase type / total users
highest_product_clients_df_renamed["percentage"] = highest_product_clients_df["Clients count"] \
    / total_categories_clients * 100

# We assign the rest of users belong to another specific group that we call "others"
others = {"Category": "others",
          "Clients count": total_categories_clients - np.sum(highest_product_clients_df_renamed["Clients co
          "percentage": 100 - np.sum(highest_product_clients_df_renamed["percentage"])
}
```

```
highest_product_clients_df_renamed = pd.concat([highest_product_clients_df_renamed, pd.DataFrame(others, i
print("Top 5 categories that have the most users purchased:")
highest_product_clients_df_renamed
```

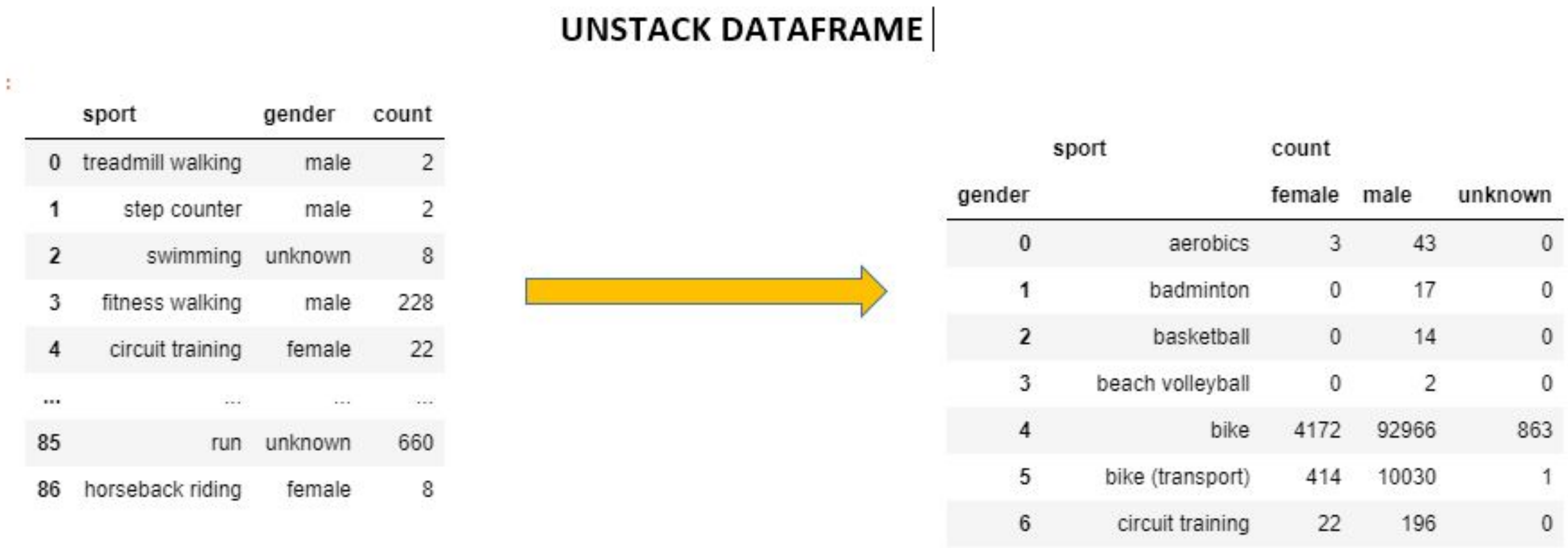
In [ ]:
```
highest_product_clients_df_renamed["Clients count"]
```

In [ ]:
```
# fig = plt.figure(figsize=(19.20,10.80))
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=plt.figaspect(0.35))

plot0 =   axs[0].bar(x=highest_product_clients_df_renamed["Category"]
                      , height=highest_product_clients_df_renamed["Clients count"])
title0 =  axs[0].set_title("Clients count", fontsize = "small")
xlabel0 = axs[0].set_xlabel("Category", fontsize = "small")
ylabel0 = axs[0].set_ylabel("Clients count", fontsize = "small")
xsticks_label = axs[0].set_xticklabels(highest_product_clients_df_renamed["Category"]
                                       ,rotation = "vertical", fontsize="small")
nb_categories=len(np.unique(highest_product_clients_df_renamed["Category"]))
explode = generate_explode(nb_categories)
# title1 = axs[1].set_title("User ratio", fontsize = "small")
plot1 = axs[1].pie(
      x=highest_product_clients_df_renamed["percentage"]
    , labels=highest_product_clients_df_renamed["Category"]
    , autopct="%1.1f%%", shadow=True, startangle=90 , explode=explode
    , radius=1.5
)

text = fig.text(0.5, 1.02,
                "Top 5 categories having the most users",
                ha="center",
                va="top",
                transform=fig.transFigure)
# fig.savefig('output', format='svg', dpi=1200)
plt.show()
```

The data shows that all categories have almost same number of client.

In [ ]:
```
# Let quick overview purchases by gender
# we have something like this
purchases_by_gender = spark_df.groupBy("Category", "Gender").count().toPandas()
purchases_by_gender[:5]
```

We want reshape the table above to flatten the gender column so that we can visualize on it. I draw a simple draft as follow



	sport	gender	count
0	treadmill walking	male	2
1	step counter	male	2
2	swimming	unknown	8
3	fitness walking	male	228
4	circuit training	female	22
...	...	...	...
85	run	unknown	660
86	horseback riding	female	8

	sport	count		
gender		female	male	unknown
0	aerobics	3	43	0
1	badminton	0	17	0
2	basketball	0	14	0
3	beach volleyball	0	2	0
4	bike	4172	92966	863
5	bike (transport)	414	10030	1
6	circuit training	22	196	0

To reshape the table like this in Pyspark, we use

```
spark_df.unstack()
```

In [ ]:
```
total_purchases = ranked_product_clients_df.count()
print(f"There are total: {total_purchases} purchases and here is the chart for purchases based on gender:")
# Add the infor of purchases based on gender
purchases_by_gender = spark_df.groupBy("Category", "Gender").count().toPandas()
nb_categories=len(np.unique(purchases_by_gender["Category"]))

# Visualize
fig = plt.figure(figsize=(25, nb_categories))
grid_size = (1,1);
ax = plt.subplot2grid(grid_size, (0,0), colspan=1, rowspan=1)
plot = purchases_by_gender.groupby(["Category", "Gender"]).agg(np.mean).groupby(level=0).apply(
    lambda x: 100 * x / x.sum()).unstack().plot(kind="barh", stacked=True, width=1  ## APPLY UNSTACK TO RES
                    , edgecolor="black", ax=ax, title="List of all purchases by gender")
ylabel = plt.ylabel("Category (Purchase)");
xlabel = plt.xlabel("Participation percentage by gender");
legend = plt.legend(
    sorted(purchases_by_gender["Gender"].unique()), loc="center left", bbox_to_anchor=(1.0, 0.5)
```

```
)
param_update = plt.rcParams.update({"font.size": 16});
ax = plt.gca()
formatter = ax.xaxis.set_major_formatter(mtick.PercentFormatter());
a = fig.tight_layout()
plt.show()
```

It seems that there **no domminent** gender across all shoing categories

In [ ]:
```
purchases_by_gender_df = purchases_by_gender.pivot_table(
    index="Category", columns="Gender", values="count", fill_value=0) \
    .reset_index().rename_axis(None, axis=1)

purchases_by_gender_df["total"] = purchases_by_gender_df["Male"] \
        + purchases_by_gender_df["Female"]
purchases_by_gender_df["percentage"] = purchases_by_gender_df["total"] \
    / np.sum(purchases_by_gender_df["total"]) * 100
top_purchases_by_gender_df = purchases_by_gender_df.sort_values(
    by="percentage", ascending=False
).head(5)

others = {"Category" : "others"}
for column in ["Female", "Male", "total", "percentage"]:
    value = np.sum(purchases_by_gender_df[column]) - np.sum(top_purchases_by_gender_df[column])
    others.update({column: value})
# top_purchases_by_gender_df = top_purchases_by_gender_df.append(others, ignore_index=True)
top_purchases_by_gender_df = pd.concat([top_purchases_by_gender_df, pd.DataFrame(others, index=[0])], igno

top_purchases_by_gender_df = top_purchases_by_gender_df.sort_values(
    by="percentage", ascending=False
)
top_purchases_by_gender_df
```

In [ ]:
```
fig, axs = plt.subplots(nrows=1, ncols=2, figsize=plt.figaspect(0.35))

plot0 = axs[0].bar(x=top_purchases_by_gender_df["Category"]
                   , height=top_purchases_by_gender_df["total"])
title0 = axs[0].set_title("Purchase count", fontsize="small")
xlabel0 = axs[0].set_xlabel("Category", fontsize="small")
ylabel0 = axs[0].set_ylabel("Purchase count (times)", fontsize="small")
xsticks_label = axs[0].set_xticklabels(top_purchases_by_gender_df["Category"]
```

```
                                        , rotation="vertical", fontsize="small")
explode =  generate_explode(nb_categories)
title1 = axs[1].set_title("Purchase ratio", fontsize = "small")
plot1 = axs[1].pie(
    x=top_purchases_by_gender_df["percentage"]
    , labels=top_purchases_by_gender_df["Category"]
    , autopct="%1.1f%%", shadow=True, radius=1#, explode=explode
)

text = fig.text(0.5, 1.02, "Top 5 product categories that were most purchased"
                , ha="center", va="top", transform=fig.transFigure)
```

Similarly, it seems all product categories are purchased equally

In [ ]:
```
spark_df.columns
```

In [ ]:
```
product_spdf = spark_df \
    .select(spark_df.Cust_ID, spark_df.Gender, spark_df.Category) \
    .groupBy(spark_df.Cust_ID, spark_df.Gender) \
    .count().orderBy("count", ascending = False)

# for nb_products in
min_number_of_categories = 1
count_nb_purchased_prouct={}
user_more_categories_df = product_spdf \
                    .filter(product_spdf["count"] == min_number_of_categories) \
                    .orderBy("count", ascending = False) \
                    .toPandas()
nb__purchased_prouct=user_more_categories_df["count"].sum()
count_nb_purchased_prouct.update({f"{min_number_of_categories}":nb__purchased_prouct})
user_more_categories_df.rename(columns = {"count":"shopping categories count"}, inplace = True)
user_more_categories_df.describe().astype(int).T
user_more_categories_df
```

In [ ]:
```
product_spdf.show()
```

In [ ]:
```
from pyspark.sql.window import Window
spark_df.withColumn("unique",
                    (f.count("Cust_ID")\
                     .over(Window.partitionBy("Cust_ID")) == 1)\
                    .cast('integer'))\
```

```
.orderBy("unique").show()
```

In [ ]:
```
product_spdf.show()
```

Based on the summary, there are 35200 clients purchased more than 1 product category. Among them in average a person bought about 2 product categories and there is some person playing up to 6 different product categories!

Now we look at the statistic by gender in box plot:

In [ ]:
```
plot = user_more_categories_df.boxplot(column="shopping categories count",
                                       by="Gender", fontsize="small", figsize=(6,7))
```

The boxplot showed the similar distribution by gender wwithout clear outliers

Distribution of records count per purchase

For a more detailed observation, we break down the record count per purchase into each individual sport.

Based on the distribution, the maximum records per purchase is 500, but not all purchases and sport types reach that number.

In [ ]:
```
print("\nPlot of purchased products category distribution by age:")
plot_size_x, plot_size_y = 5, 5
list_categories = spark_df.select("Category").distinct().toPandas()["Category"]
nb_rows = len(list_categories)//4 + (1 if len(list_categories)%4>0 else 0 )
figsize_x, figsize_y = plot_size_x * 4 + 3, plot_size_y * nb_rows + 1
figsize=(figsize_x, figsize_y)
fig = plt.figure(figsize=figsize) #
grid_size = (nb_rows,4)
ax = plt.subplot2grid(grid_size, (0,0), colspan=1, rowspan=1)
#fig, ax = plt.subplots()
Cust_Category_dist = spark_df.select("Age", "Category").toPandas().hist(
                                column="Age", by="Category",
                                bins=10, sharex = False, grid=True, ax = ax,
                                layout = grid_size, figsize=figsize
                                )
a = fig.tight_layout()
title = fig.text(0.5, 1, "Distribution of purchased products category per age", ha="center"
         , fontsize="large", transform=fig.transFigure);
ylabel = fig.text(0.01, 0.5, "Frequency (count)", va="center", rotation="vertical");
```

In [ ]:
```
nb_purchases_threshold = 5
# Filter spark_df with at least 10 records (as we are assumming if any user_id with less then 10 record wou
qualified_df = spark_df \
    .select(spark_df.Category, spark_df.Cust_ID, spark_df.Gender) \
    .groupBy(spark_df.Category, spark_df.Cust_ID, spark_df.Gender) \
    .count()
qualified_df = qualified_df.filter(qualified_df["count"] >= nb_purchases_threshold) \
    .orderBy("count", ascending = False)
```

In [ ]:
```
print(f"Number of users having more than {nb_purchases_threshold} purchases:")
qualified_pd_df = qualified_df.select("Cust_ID", "Gender").distinct() \
    .groupBy(qualified_df.Gender).count().toPandas()
qualified_pd_df.rename(columns={"count": "Clients count"}, inplace=True)
qualified_pd_df
qualified_clients_count = np.sum(qualified_pd_df["Clients count"])
total_clients_count = spark_df.select("Cust_ID").distinct().count()
qualified_percentage = round((qualified_clients_count / total_clients_count),2) * 100
print(f"\nSo there is {qualified_clients_count} / {total_clients_count} of users qualifying the {nb_purchas
     )
```

In [ ]:
```
spark_df0=spark_df
```

In [ ]:
```
spark_df=spark_df0
```

In [ ]:
```
#  Helper function to calculate statistic(s) of the column name from a tuple x of (sport, records list of t
#, the stats to calculate is also given as an input
def calculate_stats(x,column_name, stat_list):
    sport, records_list = x
    stat_dict = {"Category": sport}
    if "min" in stat_list:
        min_stat = min(records_list)
        stat_dict.update({"min " + column_name : min_stat})
    if "max" in stat_list:
        max_stat = max(records_list)
        stat_dict.update({"max " + column_name: max_stat})
    if "mean" in stat_list:
        average_stat = stats.mean(records_list)
        stat_dict.update({"mean " + column_name: average_stat})
    if "stdev" in stat_list:
        std_stat = stats.stdev(records_list)
        stat_dict.update({"stdev " + column_name: std_stat})
```

```
    if "50th percentile" in stat_list:
        median_stat = stats.median(records_list)
        stat_dict.update({"50th percentile " + column_name: median_stat})
    if "25th percentile" in stat_list:
        percentile_25th_stat = np.percentile(records_list, 25)
        stat_dict.update({"25th percentile " + column_name: percentile_25th_stat})
    if "75th percentile" in stat_list:
        percentile_75th_stat = np.percentile(records_list, 75)
        stat_dict.update({"75th percentile " + column_name: percentile_75th_stat})
    if "95th percentile" in stat_list:
        percentile_95th_stat = np.percentile(records_list, 95)
        stat_dict.update({"95th percentile " + column_name: percentile_95th_stat})
    return stat_dict

def to_list(a):
    return a

def extend(a, b):
    a.extend(b)
    return a

def retrieve_array_column_stat_df(spark_df, column_name, stat_list):
    # Convert sport & "column_name" to RDD to easily calculate the statistics of intervals by categories
    product_record_rdd = spark_df.select("Category", column_name).rdd \
    .map(tuple).combineByKey(to_list, extend, extend).persist()

    # Calculate statistics of the input column by calling calculate_stats function defined above
    record_statistic_df = pd.DataFrame(product_record_rdd.map(
        lambda x: calculate_stats(x, column_name,stat_list)).collect()
                                      )
    # Set proper dataframe column orders
    columns_order = ["Category"] + [stat + " " + column_name for stat in stat_list]
    # Re order columns
    return record_statistic_df[columns_order]

stat_list = ["min", "25th percentile", "mean", "50th percentile",
                     "75th percentile", "95th percentile", "max", "stdev"]
interval_statistic_df = retrieve_array_column_stat_df(spark_df, column_name="interval", stat_list=stat_list
print("\nLet\"s look at statistic for interval, in seconds (by sport):" )
interval_statistic_df
```

Now we plot those numbers in bar (for quantiles statistics) and line charts (for min/max/mean/stdev) for a more visualized feel.

Note: Due to the fact that the maximum interval and stdev have a much higher order of magnitude compared to the remaining columns, we need to put those 2 columns in a separate y axis on the right.

In [ ]:
```
print("\nSummarize statistics of interval sport:")
bar_columns = ["25th percentile interval", "50th percentile interval"
               , "75th percentile interval", "95th percentile interval"]
line_columns1 = ["min interval", "mean interval"]
line_columns2 = ["max interval", "stdev interval"]
interval_statistic_df = interval_statistic_df.sort_values(
    by="95th percentile interval", ascending=False
)
figsize=(13, 59)
fig, axs = plt.subplots(nrows=7, figsize=figsize)

d = axs[0].set_title("Interval statistics by sport", fontsize=18)
for i in range (7):
    interval_statistic_sub_df = interval_statistic_df.iloc[i*7:i*7+7,]
    #interval_statistic_sub_df
    plot1 = interval_statistic_sub_df[["Category"] + bar_columns] \
        .groupby(["Category"]).agg(np.mean).plot(
        kind="bar", stacked=True, grid=False, alpha=0.5, edgecolor="black", ax=axs[i],
    )
    plot2 = interval_statistic_sub_df[["Category"] + line_columns1].plot(x="Category", ax=axs[i], marker="o
    ax2 = axs[i].twinx()
    plot3 = interval_statistic_sub_df[["Category"] + line_columns2].plot( x="Category", ax=ax2, marker="o",
    a = axs[i].legend(loc="center left", fontsize=16, bbox_to_anchor=(1.2, 0.5), frameon=False)
    a = ax2.legend(  labels=["max interval (right)", "stdev interval (right)"]
                   , loc="center left", fontsize=16, bbox_to_anchor=(1.2, 0.11), frameon=False)
    b = axs[i].set_xticklabels(interval_statistic_sub_df["Category"],rotation = "horizontal", fontsize="sma
    c = axs[i].set_xlabel("Category (Purchase)", fontsize="small");
    d = axs[i].set_ylabel("Quantiles Statistics + min/mean\n(second)", fontsize=16);
    e = ax2.set_ylabel("Max/stdev Statistics\n(second)", fontsize=16)
    for tick in axs[i].yaxis.get_major_ticks():
        a = tick.label.set_fontsize(16)
    ax2.tick_params(axis="y", labelsize=16)
    b = plt.setp([a.get_xticklabels() for a in fig.axes[:-1]], visible=True)

plt.subplots_adjust(hspace=0.2)
plt.show();
```

Looking at the quantiles statistic, up to 95% of the interval data set does not have the interval larger than 400 seconds, while there are just a few outliers that made the maximum intervals reach up to 86400 seconds (a full days).

In [ ]:
```
# Retrive the table of gender, sport and purchase_start_time for plotting
start_time_df = spark_df.select("Gender", "Category","purchase_start_time").toPandas()
```

In [ ]:
```
purchases = start_time_df["Category"].unique()
plot_size_x, plot_size_y = 5, 5
figsize_x, figsize_y = (plot_size_x + 0.5) * 4 +3, (plot_size_y + 1) * 13 + 1


nrows, ncols = 13, 4
a = fig.subplots_adjust(hspace = 1, wspace = 1)
fig, axs = plt.subplots(nrows=nrows, ncols=ncols, figsize=(figsize_x, figsize_y))
print("\nPlotting distribution of purchase start time per sport type, break down by gender:")
a = plt.setp(axs, xticks=[0, 4, 8, 12, 16, 20])
for index, sport in enumerate(purchases):
    row_index, col_index = divmod(index, ncols)
    male_start_time_list = start_time_df[(start_time_df.sport == sport) &
                                        (start_time_df.Gender == "Male")]["purchase_start_time"]
    female_start_time_list = start_time_df[(start_time_df.sport == sport) &
                                        (start_time_df.Gender == "Female")]["purchase_start_time"]
    unknown_start_time_list = start_time_df[(start_time_df.sport == sport) &
                                        (start_time_df.Gender == "unknown")]["purchase_start_time"]
    if len(male_start_time_list) > 0:
        male_dist = axs[row_index, col_index].hist(male_start_time_list,
                                  bins = 12, alpha=0.5, label="Male", range=(0, 23))
    if len(female_start_time_list) > 0:
        female_dist = axs[row_index, col_index].hist(female_start_time_list,
                                  bins = 12, alpha=0.5, label="Female", range=(0, 23))
    if len(unknown_start_time_list) > 0:
        unknown_dist = axs[row_index, col_index].hist(unknown_start_time_list,
                                  bins = 12, alpha=0.5, label = "unknown", range=(0, 23))
    b= axs[row_index, col_index].set_title("Activitiy: " + sport, fontsize="small")
    a = axs[row_index, col_index].legend(loc="upper left", fontsize="small")
    a = plt.setp(axs[row_index, col_index].get_xticklabels(), fontsize="small")

for i in range(1,4):
    x = axs[12, i].set_visible(False)
a = fig.tight_layout()
z = fig.text(0.5, 1, "Distribution of purchase started time (hour) by sport"
             , ha="center", va="top", transform=fig.transFigure)
```

```
y = fig.text(0.5, 0.01, "Purchase started hour in a day (hour)"
             , ha="center", va="bottom", transform=fig.transFigure)
z = fig.text(0.02, 0.5, "Frequency (count)", va="center", rotation="vertical");
```

In [ ]:
```
stat_list = ["min", "25th percentile", "mean", "95th percentile", "max", "stdev"]
heart_rate_statistic_df = retrieve_array_column_stat_df(spark_df, column_name="heart_rate", stat_list=stat_
```

Due to the huge amount of users and purchase numbers, we just picked randomly up to a x number of users per gender (ex, 5), and up to y purchases per purchase type (ex, 10).

In [ ]:
```
# Support function helping to sample data
def sampling_data(max_clients_per_gender, max_purchases_per_sport):
    """
        max_clients_per_gender: maximum number of user to be selected randomly per gender
        max_purchases_per_sport: maximum number of purchases to be selected per sport
        (the categories existing in selected users)
    """
    # Get unique list of Cust_ID and gender, for sampling purpose
    users_genders = spark_df.select("Cust_ID", "Gender").distinct().toPandas()
    # Use "sample" function to pick up to 3 Cust_ID per gender from the unique Cust_ID list
    random_x_clients_per_gender = users_genders.groupby("Gender")["Cust_ID"].apply(
                lambda s: s.sample(min(len(s), max_clients_per_gender))
    )

    # Apply filter on the main pyspark dataframe for sampling
    samples_by_gender = spark_df.where(spark_df.Cust_ID.isin(list(random_x_clients_per_gender)))

    # Next, generate the unique purchase ids and sport types list from the sampled data set
    purchase_categories = samples_by_gender.select("id", "Category").distinct().toPandas()
    # Use "sample" function to pick up to 10 purchase ids for each kind of sport
    random_y_purchases_per_sport = purchase_categories.groupby("Category")["id"].apply(
        lambda s: s.sample(min(len(s), max_purchases_per_sport))
    )

    # Apply filter to the sampled dataset to continue reduce the number of purchases per purchase type
    samples_by_gender_and_sport = samples_by_gender.where(spark_df.id.isin(list(random_y_purchases_per_spo
    return samples_by_gender_and_sport
```

In [ ]:
```
# Use 2 variable to determine the sampling criteria:
# maximum users per gender and maximum purchases per sport
```

```
max_clients_per_gender, max_purchases_per_sport = 20, 15

# Collect the sampled data set to Pandas to be used with plot features
pd_df = sampling_data(max_clients_per_gender, max_purchases_per_sport).toPandas()
print("\nSampled data overview (only string and numeric columns):")
pd_df.describe()
```

we will normalize the time for all purchases by calulating the duration (in seconds) of each timestamp record from the first record of a purchase (the first datetime element of the list in that purchase).
Then we plot the heart rate on this normalized time, grouping by sport.

In [ ]:
```
# Lambda function to flatten a list of lists into a big single list
flattern = lambda l: set([item for sublist in l for item in sublist])

normalized_datetime_list = []
for index,data_row in pd_df.iterrows():
    min_date_time = min(data_row["date_time"])
    normalized_datetime_list.append(
        [(date_time - min_date_time).seconds for date_time in data_row["date_time"]]
    )

pd_df["normalized_date_time"] = normalized_datetime_list

print("New normalized datetime (first 7 rows):")
pd_df.head(7)[["Cust_ID", "Category", "date_time","normalized_date_time"]]

print("\nPlot raw heart rate (sampled) by normalized time:")

product_list = pd_df["Category"].unique()
# Define the length of the figure dynamically depends on the length of the sport list
fig, axs = plt.subplots(len(product_list), figsize=(15, 6*len(product_list)))
subplot_adj = fig.subplots_adjust(hspace = 0.6)
plot_setp = plt.setp(axs, yticks=range(0,250,20))

for product_index, sport in enumerate(product_list):
    purchase = pd_df[pd_df.sport == sport]
    max_time = max(flattern(purchase.normalized_date_time))
    for purchase_index, data_row in purchase.iterrows():
        label = "user: " + str(data_row["Cust_ID"]) + " - gender: " + data_row["Gender"]
        plot_i = axs[product_index].plot(
            data_row["normalized_date_time"], data_row["heart_rate"], label=label
```

```
        )
    title_i = axs[product_index].set_title("Activitiy: " + sport, fontsize="small")
    xlabel_i = axs[product_index].set_xlabel("Time (sec)", fontsize="small")
    xsticklabels_i = axs[product_index].set_xticklabels(
        range(0, max_time, 500),rotation = "vertical", fontsize=9
    )
    ysticklabels_i = axs[product_index].set_yticklabels(range(0,250,20),fontsize="small")
    legend_i = axs[product_index].legend(
        loc="center left", bbox_to_anchor=(1.0, 0.5), prop={"size": 9}
    )

x_label = fig.text(0.04, 0.5, "Heart rate (bpm)", va="center", rotation="vertical")
chart_title = fig.text(0.5, 1.3, "Raw heart rate (sample) by normalized time",
            ha="center", va="center", fontsize="small", transform=axs[0].transAxes)
```

In [ ]:

```
pd_df_small = sampling_data(max_clients_per_gender=2, max_purchases_per_sport=2).toPandas()
print("Sampled data (2 user, 2 purchases per sport):")
pd_df_small[["Cust_ID", "Gender","Category","id", "purchase_start_time"
             ,"PerWorkoutRecordCount", "duration", "longitude", "latitude", "altitude"]].describe()
```

In [ ]:

```
def get_fixed_mins_maxs(mins, maxs):
    deltas = (maxs - mins) / 12.
    mins = mins + deltas / 4.
    maxs = maxs - deltas / 4.

    return [mins, maxs]

purchase_count = pd_df_small.shape[0]
ncols = 3
nrows = math.ceil(purchase_count/ncols)
#purchase_count
fig = plt.figure(figsize=(8 * (ncols + 0.5), 8*nrows))

a = fig.subplots_adjust(hspace = 0.2, wspace=0.5)
#c = plt.setp(axs, yticks=range(0,250,20))

print("Plot purchase path in 3D graphs per each purchase:")
for row_index, row in pd_df_small.iterrows():
    if row_index==2:
        text = ax.text2D(
            0.01, 1, "Purchase path (longitude/latitude/altitude)"
```

```
            , fontsize=18, transform=ax.transAxes
        )
    min_long = min(row["longitude"]) - stats.stdev(row["longitude"])
    max_long = max(row["longitude"]) + stats.stdev(row["longitude"])
    minmax_long = get_fixed_mins_maxs(min_long, max_long)
    #minmax_long
    min_lat = min(row["latitude"]) - stats.stdev(row["latitude"])
    max_lat = max(row["latitude"]) + stats.stdev(row["latitude"])
    minmax_lat = get_fixed_mins_maxs(min_lat, max_lat)
    #minmax_lat
    min_alt = min(row["altitude"]) - stats.stdev(row["altitude"])
    max_alt = max(row["altitude"]) + stats.stdev(row["altitude"])
    minmax_alt = get_fixed_mins_maxs(min_alt, max_alt)
    #minmax_alt
    ax = fig.add_subplot(nrows, ncols, row_index + 1, projection="3d")
    title = "Activitiy: " + row["Category"] + " - Gender: " + row["Gender"] \
        + "\nRecords: " + str(int(row["PerWorkoutRecordCount"])) \
        + " - Duration: " + str(int(row["duration"])) + " minutes"
    title = ax.set_title(title, fontsize=16)
    scatter = ax.scatter(row["longitude"], row["latitude"], row["altitude"], c="r", marker="o")
    plot = ax.plot3D(
        row["longitude"], row["latitude"], row["altitude"], c="gray", label="Purchase path"
    )

    x_label = ax.set_xlabel("Longitude (Degree)", fontsize=16)
    y_label = ax.set_ylabel("Latitude (Degree)", fontsize=16)
    z_label = ax.set_zlabel("Altitude (m)", fontsize=16, rotation = 0)
    for t in ax.xaxis.get_major_ticks():
        font_size = t.label.set_fontsize(16)
    for t in ax.yaxis.get_major_ticks():
        font_size = t.label.set_fontsize(16)
    for t in ax.zaxis.get_major_ticks():
        font_size = t.label.set_fontsize(16)
    legend = ax.legend(loc="center left", bbox_to_anchor=(1.0, 0.5))
    ax.zaxis.set_rotate_label(False)
    #b = plt.setp(ax.get_xticklabels(), rotation=41)
    #b = plt.setp(ax.get_yticklabels(), rotation=-30)
    plt.gca().xaxis.set_major_formatter(mtick.FormatStrFormatter("%.3f"))
    plt.gca().yaxis.set_major_formatter(mtick.FormatStrFormatter("%.3f"))
    ax.pbaspect = [4, 2, 0.5]
    xlims = ax.set_xlim(minmax_long)
    ylims = ax.set_ylim(minmax_lat)
```

```
    # Some categories will not have altitude change so check it before set z limit
    if minmax_alt[0] != minmax_alt[1]: zlims = ax.set_zlim(minmax_alt)
    # Do this trick to enable tight_layout for 3D plot:
    for spine in ax.spines.values():
        b = spine.set_visible(False)
plt.rcParams["legend.fontsize"] = 16
a = plt.tight_layout()
plt.show()
```

Thank you for reading my work, wish you strong and stay safe