# FIT5202 2024 S2 Assignment 1 : Analysing Fraudulent Transaction Data

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# Part 1 : Working with RDDs (30%)

## 1.1 Working with RDD

In this section, you will need to create RDDs from the given datasets, perform partitioning in these RDDs and use various RDD operations to answer the queries.

1.1.1 Data Preparation and Loading Write the code to create a SparkContext object using SparkSession. To create a SparkSession you first need to build a SparkConf object that contains information about your application, use Melbourne time as the session timezone. Give an appropriate name for your application and run Spark locally with 4 cores on your machine.

In [2]:
```
from pyspark import SparkConf
from pyspark.sql import SparkSession

#Creating a SparkConf object
conf = SparkConf().setAppName("MySparkApp")\
                  .setMaster("local[4]")\
                  .set("spark.sql.session.timeZone", "Australia/Mel

#followed by a SparkSession using the SparkConf
spark = SparkSession.builder.config(conf=conf).getOrCreate()

# assigning a variable for SparkContext from the SparkSession
sc = spark.sparkContext
```

1.1.2 Load csv files into multiple RDDs.

In [3]:
```
# Loading CSV files into RDDs
transactions_rdd = sc.textFile("transactions.csv")
merchants_rdd = sc.textFile("merchant.csv")
customers_rdd = sc.textFile("customers.csv")
categories_rdd = sc.textFile("category.csv")
geolocations_rdd = sc.textFile("geolocation.csv")

# Transforming each line into a list of values
transactions_rdd = transactions_rdd.map(lambda line: line.split(","
merchant_rdd = merchants_rdd.map(lambda line: line.split(","))
customers_rdd = customers_rdd.map(lambda line: line.split(","))
category_rdd = categories_rdd.map(lambda line: line.split(","))
geolocation_rdd = geolocations_rdd.map(lambda line: line.split(",")
```

1.1.3 For each RDD, remove the header rows and display the total count and first 10 records. (Hint: You can use csv.reader to parse rows into RDDs.)

In [4]:
```
# Function to extract and filter the header row
def remove_header(rdd):
    header = rdd.first()
    return rdd.filter(lambda line: line != header)

# Function to display the total count and first 10 records of an RD
def display_rdd_info(rdd, rdd_name):
    print(f"\n{rdd_name} RDD:")
    print(f"Total count: {rdd.count()}")  # Count the number of rec
    print("First 10 records:")
    for record in rdd.take(10):
        print(record)

# Standard list of RDDs considered
rdd_list = [
    ("Transactions", transactions_rdd),
    ("Merchants", merchant_rdd),
    ("Customers", customers_rdd),
    ("Categories", category_rdd),
    ("Geolocations", geolocation_rdd)
]

# Excluding the header from each RDD to display the information
for rdd_name, rdd in rdd_list:
    rdd = remove_header(rdd)
    display_rdd_info(rdd, rdd_name)
```

```
Transactions RDD:
Total count: 22949835
First 10 records:
['"0c20530e90719213c442744161a1850b"', '1622367050', '87.18', '0',
'"794-45-4364"', '46', '2641132', '12']
['"984fc48fc946605deefc9d0967582811"', '1609183538', '276.97', '
0', '"436-80-2340"', '60', '2932280', '5']
```

```
['b13ff47c73689bc4c8320c0ce403b15d', '1655595319', '7.67', '0', '"
385-77-6544"', '87', '2708770', '2']
['"7cffae35cab67d9415f9f22d91ca7acc"', '1613234460', '198.96', '
0', '"450-56-1117"', '138', '1170872', '10']
['"22e01cb3403a4c7ce598ebe785e1e947"', '1605030979', '33.46', '0',
'"397-54-0253"', '218', '2470519', '5']
['"1d174d018228efcd1d5800f768628904"', '1608989049', '2.74', '0',
'"248-09-7729"', '222', '3436926', '9']
['"532536d65907e08d938cb31e3631ddd4"', '1650997797', '1.23', '0',
'"277-12-7638"', '337', '3750746', '2']
['"32d76f65b7512afbdc99331ee96bc6d7"', '1649986601', '7.78', '0',
'"615-63-3623"', '718', '3773961', '2']
['c3f29bca602c9e2e9a188567f06d632f', '1617032215', '218.8', '0',
'"877-16-8226"', '747', '2377216', '10']
['c56ef2e4a43d867128839b97bc1dbb66', '1609250028', '62.1', '0', '"
823-85-5801"', '950', '652447', '5']

Merchants RDD:
Total count: 3837031
First 10 records:
['Bins-Tillman', '6051', '1']
['"Hahn', ' Douglas and Schowalter"', '1276', '2']
['"Hayes', ' Marquardt and Dibbert"', '1383', '3']
['"Mueller', ' Gerhold and Mueller"', '1846', '4']
['Kerluke Inc', '1784', '5']
['Waelchi Inc', '4637', '6']
['Trantow PLC', '2176', '7']
['Runolfsson and Sons', '3968', '8']
['Bechtelar-Rippin', '1048', '9']
['"Schumm', ' Bauch and Ondricka"', '1553', '10']

Customers RDD:
Total count: 10000
First 10 records:
['"263-99-6044"', '"4241904966319315"', 'Melissa', 'Turner', 'F',
'"058 Stanley Cliff"', 'Risk manager', '"2005-05-30"', '3764433318
52', '6339']
['"292-61-7844"', '"30520471167198"', 'Mark', 'Brown', 'M', '"413
Angela Mall"', 'Trading standards officer', '"2003-04-19"', '87014
3739098', '6200']
['"491-28-3311"', '"180084219933088"', 'Courtney', 'Hall', 'F', '"
5712 Tamara Estate"', 'Optometrist', '"2002-04-17"', '96585502630
7', '3547']
['"826-23-1754"', '"2623398454615676"', 'Krystal', 'Branch', 'F',
'"1016 Bennett Mountains"', 'Banker', '"2001-07-15"', '1132474675
5', '6302']
['"172-11-9264"', '"639034043849"', 'Carol', 'Ellis', 'F', '"819 J
oseph Plains Suite 807"', 'Sports coach', '"2003-11-21"', '1134951
75185', '5227']
['"150-95-7922"', '"343731453038560"', 'Julie', 'Gibson', 'F', '"5
1844 Nicholas Lane"', 'Medical secretary', '"2006-03-06"', '719783
599768', '4047']
['"841-99-2980"', '"3525799136621031"', 'Joseph', 'Blankenship', '
M', '"91279 Natalie Place Apt. 172"', 'Toxicologist', '"2005-07-0
```

```
1"', '908554315130', '6271']
['"705-41-6699"', '"342694486959460"', 'Nicole', 'Gutierrez', 'F',
'"58874 Lane Trail Suite 213"', 'Product manager', '"2003-01-23"',
'772162574642', '6302']
['"016-22-4524"', '"3563009792513271"', 'Anna', 'Montgomery', 'F',
'"52812 Hall Point"', '"Loss adjuster', ' chartered"', '"2001-08-2
6"', '982712248618', '5614']
['"639-46-2126"', '"3587729343010715"', 'Nancy', 'Clark', 'F', '"0
558 Alex Flats Suite 414"', 'Hydrologist', '"2005-02-10"', '603471
636817', '6328']

Categories RDD:
Total count: 14
First 10 records:
['Entertainment', '1']
['Food_Dining', '2']
['Gas_Transport', '3']
['Grocery(Online)', '4']
['Grocery(In Store)', '5']
['Health_Fitness', '6']
['Home', '7']
['Pets', '8']
['Misc(Online)\\', '9']
['Misc(In Store)', '10']

Geolocations RDD:

Total count: 6342
First 10 records:
['Burkeville', 'TX', '75932', '31.0099', '-93.6585', '1', '1437']
['Fresno', 'TX', '77545', '29.5293', '-95.4626', '2', '19431']
['Osseo', 'MN', '55311', '45.1243', '-93.4996', '3', '65312']
['Pomona', 'CA', '91766', '34.0418', '-117.7569', '4', '154204']
['Vacaville', 'CA', '95688', '38.3847', '-121.9887', '5', '99475']
['South Lake Tahoe', 'CA', '96150', '38.917', '-119.9865', '6', '2
9800']
['Belvidere', 'TN', '37306', '35.1415', '-86.1728', '7', '2760']
['Columbia', 'SC', '29205', '33.9903', '-80.9997', '8', '333497']
['Chicago', 'IL', '60660', '41.9909', '-87.6629', '9', '2680484']
['Tunnelton', 'WV', '26444', '39.3625', '-79.7478', '10', '3639']
```

In [5]:
```
# Function to understand the indices of the header
def print_header_with_indices(rdd, rdd_name):
    header = rdd.first()  # The first row is already split into a l
    print(f"\n{rdd_name} RDD Header (split into list with indices):
    for index, column_name in enumerate(header):
        print(f"{index}: \"{column_name}\"")

# printing the headers with indices which will help to drop the req
for rdd_name, rdd in rdd_list:
    print_header_with_indices(rdd, rdd_name)
```

```
Transactions RDD Header (split into list with indices):
0: ""id_transaction""
1: ""trans_timestamp""
2: ""amt""
3: ""is_fraud""
4: ""id_customer""
5: ""id_geolocation""
6: ""id_merchant""
7: ""id_category""

Merchants RDD Header (split into list with indices):
0: ""merchant""
1: ""id_geolocation""
2: ""id_merchant""

Customers RDD Header (split into list with indices):
0: ""id_customer""
1: ""cc_num""
2: ""firstname""
3: ""lastname""
4: ""gender""
5: ""address""
6: ""job""
7: ""dob""
8: ""acct_num""
9: ""id_geolocation""

Categories RDD Header (split into list with indices):
0: ""category""
1: ""id_category""

Geolocations RDD Header (split into list with indices):
0: ""city""
1: ""state""
2: ""zip""
3: ""lat""
4: ""long""
5: ""id_geolocation""
6: ""population""
```

1.1.4 Drop personal information columns from RDDs: cc_num, firstname, lastname, address.

In [6]:
```
# implementing inbuilt map function to retain only the necessary co
customers_rdd = customers_rdd.map(lambda field: (field[0], field[4]

# Verify the result by printing the first few records
print("\nCustomers RDD after removing personal information:")
for record in customers_rdd.take(10):
    print(record)
```

```
Customers RDD after removing personal information:
('"id_customer"', '"gender"', '"job"', '"dob"', '"acct_num"', '"id
_geolocation"')
('"263-99-6044"', 'F', 'Risk manager', '"2005-05-30"', '3764433318
52', '6339')
('"292-61-7844"', 'M', 'Trading standards officer', '"2003-04-1
9"', '870143739098', '6200')
('"491-28-3311"', 'F', 'Optometrist', '"2002-04-17"', '96585502630
7', '3547')
('"826-23-1754"', 'F', 'Banker', '"2001-07-15"', '11324746755', '6
302')
('"172-11-9264"', 'F', 'Sports coach', '"2003-11-21"', '1134951751
85', '5227')
('"150-95-7922"', 'F', 'Medical secretary', '"2006-03-06"', '71978
3599768', '4047')
('"841-99-2980"', 'M', 'Toxicologist', '"2005-07-01"', '9085543151
30', '6271')
('"705-41-6699"', 'F', 'Product manager', '"2003-01-23"', '7721625
74642', '6302')
('"016-22-4524"', 'F', '"Loss adjuster', ' chartered"', '"2001-08-
26"', '982712248618')
```

## 1.2 Data Partitioning in RDD

1.2.1 For each RDD, print out the total number of partitions and the number of records in each partition.

In [7]:
```
# Function to uunderstand data partition for each created RDD
def analyze_partitions(rdd, rdd_name):
    print(f"\nAnalyzing {rdd_name} RDD:")
    partition_sizes = rdd.glom().map(len).collect()
    for i, size in enumerate(partition_sizes):
        print(f"Partition {i} has {size} records.")
    return partition_sizes

# Calling the function to print the  partitions and it's records.
for rdd_name, rdd in rdd_list:
    analyze_partitions(rdd, rdd_name)
```

```
Analyzing Transactions RDD:
Partition 0 has 409655 records.
Partition 1 has 409552 records.
Partition 2 has 409551 records.
Partition 3 has 409568 records.
Partition 4 has 409556 records.
Partition 5 has 409615 records.
Partition 6 has 409623 records.
Partition 7 has 409562 records.
Partition 8 has 409556 records.

Partition 9 has 409568 records.
Partition 10 has 409558 records.
Partition 11 has 409590 records.
Partition 12 has 409620 records.
Partition 13 has 409626 records.
Partition 14 has 409575 records.
Partition 15 has 409576 records.
Partition 16 has 409570 records.
Partition 17 has 409576 records.
Partition 18 has 409544 records.
Partition 19 has 409653 records.
Partition 20 has 409581 records.
Partition 21 has 409577 records.
Partition 22 has 409557 records.
Partition 23 has 409565 records.
Partition 24 has 409576 records.
Partition 25 has 409604 records.
Partition 26 has 409617 records.
Partition 27 has 409570 records.
Partition 28 has 409541 records.
Partition 29 has 409582 records.
Partition 30 has 409562 records.
Partition 31 has 409584 records.
Partition 32 has 409654 records.
Partition 33 has 409598 records.
Partition 34 has 409547 records.
Partition 35 has 409578 records.
Partition 36 has 409581 records.
Partition 37 has 409574 records.
Partition 38 has 409564 records.
Partition 39 has 409657 records.
Partition 40 has 409580 records.
Partition 41 has 409565 records.
Partition 42 has 409561 records.
Partition 43 has 409583 records.
Partition 44 has 409557 records.
Partition 45 has 409596 records.
Partition 46 has 409630 records.
Partition 47 has 409566 records.
Partition 48 has 409568 records.
Partition 49 has 409558 records.
Partition 50 has 409582 records.
```

```
Partition 51 has 409555 records.
Partition 52 has 409599 records.
Partition 53 has 409657 records.
Partition 54 has 409563 records.
Partition 55 has 422753 records.

Analyzing Merchants RDD:
Partition 0 has 1094931 records.
Partition 1 has 1059961 records.
Partition 2 has 1059729 records.
Partition 3 has 622411 records.


Analyzing Customers RDD:
Partition 0 has 5003 records.
Partition 1 has 4998 records.

Analyzing Categories RDD:
Partition 0 has 7 records.
Partition 1 has 8 records.

Analyzing Geolocations RDD:
Partition 0 has 3179 records.
```

1.2.2 Answer the following questions:
a) How many partitions do the above RDDs have?
b) How is the data in these RDDs partitioned by default, when we do not explicitly specify any partitioning strategy? Can you explain why it is partitioned in this number?
c) Assuming we are querying the dataset based on transaction date, can you think of a better strategy to partition the data based on your available hardware resources?

# a) The transactions rdd has 56 partitions, followed by merchant rdd with 4 partitions and customers, categories and gelocations rdd's have 2 partitions each.

# b) Spark splits data based on its size and available resources. If no strategy is specifically stated, the division is random and equal. Since there is data skewness, considering the volume of data the spark has decided to give more partitions for the transaction CSV since it has more data when compared to the other data files.

# c) We can implement the range data partitioning where the partition takes place based on transaction date

1.2.3 Create a user defined function (UDF) to transform trans_timestamp to ISO format(YYYY-MM-DD hh:mm:ss), then call the UDF and add a new column trans_datetime.

In [8]:
```
import datetime
import logging

# Initialize logging
logging.basicConfig(level=logging.INFO)
logger = logging.getLogger(__name__)

# Transforming the time stamp to the ISO format
def transform_timestamp(record):
    try:
        # Considering the index of timestamp column in the RDD
        trans_timestamp = record[1]

        # Conversion of timestamp to ISO
        trans_datetime = datetime.datetime.fromtimestamp(int(trans_

        # trans_datetime appended to the original record and return
        return record + [trans_datetime]
    except Exception as e:
        logger.error(f"Error processing record {record}: {e}")
        # incase if the records has none
        return record + [None]

# applyting the transfromation using the inbuilt map function
transactions_rdd_with_datetime = transactions_rdd.map(transform_tim

# displaying the outputs to verify the transformation.
try:
    for record in transactions_rdd_with_datetime.take(10):
        print(record)
except Py4JJavaError as e:
    logger.error(f"Error occurred during take(): {e}")
```

```
['"id_transaction"', '"trans_timestamp"', '"amt"', '"is_fraud"',
'"id_customer"', '"id_geolocation"', '"id_merchant"', '"id_categor
y"', None]
['"0c20530e90719213c442744161a1850b"', '1622367050', '87.18', '0',
'"794-45-4364"', '46', '2641132', '12', '2021-05-30 09:30:50']
['"984fc48fc946605deefc9d0967582811"', '1609183538', '276.97', '
0', '"436-80-2340"', '60', '2932280', '5', '2020-12-28 19:25:38']
['b13ff47c73689bc4c8320c0ce403b15d', '1655595319', '7.67', '0', '"
385-77-6544"', '87', '2708770', '2', '2022-06-18 23:35:19']
['"7cffae35cab67d9415f9f22d91ca7acc"', '1613234460', '198.96', '
0', '"450-56-1117"', '138', '1170872', '10', '2021-02-13 16:41:0
0']
['"22e01cb3403a4c7ce598ebe785e1e947"', '1605030979', '33.46', '0',
'"397-54-0253"', '218', '2470519', '5', '2020-11-10 17:56:19']
```

```
['"1d174d018228efcd1d5800f768628904"', '1608989049', '2.74', '0',
'"248-09-7729"', '222', '3436926', '9', '2020-12-26 13:24:09']
['"532536d65907e08d938cb31e3631ddd4"', '1650997797', '1.23', '0',
'"277-12-7638"', '337', '3750746', '2', '2022-04-26 18:29:57']
['"32d76f65b7512afbdc99331ee96bc6d7"', '1649986601', '7.78', '0',
'"615-63-3623"', '718', '3773961', '2', '2022-04-15 01:36:41']
['c3f29bca602c9e2e9a188567f06d632f', '1617032215', '218.8', '0',
'"877-16-8226"', '747', '2377216', '10', '2021-03-29 15:36:55']
```

## 1.3 Query/Analysis

For this part, write relevant RDD operations to answer the following queries.

1.3.1 Calculate the summary of fraudulent transactions amount for each year, each month. Print the results in tabular format.

In [9]:
```python
#Will help in reducing and summing amounts based on the key
from operator import add

# First we filter out the fraud transactions before we proceed with
fraudulent_transactions = transactions_rdd_with_datetime.filter(lam

# Step 2: Map to ((year, month), amount)
def extract_year_month_amount(record):
    trans_datetime = record[-1]  # considering only the last elemen
    year, month, _ = trans_datetime.split('-') # negating day to co
    amount = float(record[2])
    return ((year, month), amount)

fraudulent_transactions_by_month = fraudulent_transactions.map(extr

# For each (year, month), sum all the corresponding amounts
summary_by_month = fraudulent_transactions_by_month.reduceByKey(add

# Collect the results from the RDD into a list
results = summary_by_month.collect()

# Print the results in tabular format
print(f"{'Year':<10}{'Month':<10}{'Total Fraudulent Amount':<20}")
print("="*40)
for (year, month), total_amount in sorted(results):
    print(f"{year:<10}{month:<10}{total_amount:<20.2f}")
```

```
Year      Month     Total Fraudulent Amount
========================================
2020      01        898993.87
2020      02        1055068.69
2020      03        864818.53
2020      04        797646.98
2020      05        925864.70
2020      06        983224.85
2020      07        904102.03
```

```
2020    08    1031171.33
2020    09    895572.70
2020    10    917590.31
2020    11    876092.53
2020    12    1047136.05
2021    01    925229.73
2021    02    789827.07
2021    03    892832.58
2021    04    907938.06
2021    05    967478.79
2021    06    883641.08
2021    07    997994.13
2021    08    935016.09
2021    09    868437.49
2021    10    1008533.07
2021    11    789345.70
2021    12    799928.90
2022    01    897735.25
2022    02    871017.78
2022    03    1001807.60
2022    04    882859.25
2022    05    929544.45
2022    06    995504.95
2022    07    962204.05
2022    08    965271.53
2022    09    931044.91
2022    10    946128.94
2022    11    996390.87
2022    12    976878.63
```

1.3.2 List 20 mechants that suffered the most from fraudulent activities(i.e. 20 highest amount of monetary loss).

In [16]:
```
from operator import add

# First we filter out the fraud transactions before we proceed with
#For each transaction T, if T.is_fraud == 1, keep the transaction.
fraudulent_transactions = transactions_rdd_with_datetime.filter(lam

# Get the merchant ID from the 6th field and remove any surrounding
def map_merchant_amount(record):
    id_merchant = record[6].strip()
    amount = float(record[2])
    return (id_merchant, amount)

#For each fraudulent transaction T, extract T.id_merchant and T.amo
merchant_amounts = fraudulent_transactions.map(map_merchant_amount)

# Aggregate the amounts by merchant ID
total_amounts_by_merchant_id = merchant_amounts.reduceByKey(add)

# Load the merchant.csv file into an RDD, loading to avoid error co
```

```
merchant_rdd = sc.textFile("merchant.csv")
header = merchant_rdd.first()  # Extract the header
merchant_rdd = merchant_rdd.filter(lambda line: line != header)

# Clean the merchant RDD to (id_merchant, merchant_name)
def clean_merchant(record):
    fields = record.split(",")
    if len(fields) >= 2:
        id_merchant = fields[1].strip()
        merchant_name = fields[0].strip().replace('"', '')
        return (id_merchant, merchant_name)
    else:
        return None
# Apply the clean_merchant function to each record in the merchant 
cleaned_merchant_rdd = merchant_rdd.map(clean_merchant).filter(lamb

# Joining total amounts with merchant names
total_amounts_by_merchant_name = total_amounts_by_merchant_id.join(
    .map(lambda x: (x[1][1], x[1][0]))  # (merchant_name, total_amo

# Aggregating by merchant to get total loss for each company
total_amounts_by_company = total_amounts_by_merchant_name.reduceByK

# total amount in descending order and take the top 20 merchants
top_20_merchants = total_amounts_by_company.takeOrdered(20, key=lam

# Printing the results
print(f"{'Company (Merchant Name)':<40}{'Total Fraudulent Loss (USD
print("="*60)
for merchant_name, total_loss in top_20_merchants:
    print(f"{merchant_name:<40}${total_loss:.2f}")
```

```
Company (Merchant Name)                 Total Fraudulent Loss (US
D)
============================================================
Kunze Inc                               $46912.29
Nader-Maggio                            $46902.51
Schumm PLC                              $46902.51
Kutch and Sons                          $46616.18
Connelly-Carter                         $46519.37
Kihn Inc                                $46513.77
Kiehn-Emmerich                          $46498.79
Rempel Inc                              $46464.95
Nolan-Williamson                        $46364.74
Botsford Ltd                            $46357.12
Koepp-Witting                           $46303.54
Lockman Ltd                             $46279.38
Cole PLC                                $46251.12
Deckow-O'Conner                         $46248.81
Champlin-Casper                         $46233.08
Conroy-Emard                            $46233.08

Sawayn PLC                              $46233.08
```

```
Fahey Inc                                   $46233.08
Kub PLC                                     $46233.08
Stoltenberg-Beatty                          $46233.08
```

# Part 2. Working with DataFrames (45%)

In this section, you need to load the given datasets into PySpark DataFrames and use DataFrame functions to answer the queries.

## 2.1 Data Preparation and Loading

2.1.1. Load the CSV files into separate dataframes. When you create your dataframes, please refer to the metadata file and think about the appropriate data type for each column.

In [17]:
```
from pyspark.sql import SparkSession

# Step 1: Initialize Spark Session
spark = SparkSession.builder \
    .appName("DataFrame Loading Task") \
    .getOrCreate()

# Step 2: Load CSV files into DataFrames without specifying schema
transactions_df = spark.read.csv("transactions.csv", header=True, i
customers_df = spark.read.csv("customers.csv", header=True, inferSc
merchants_df = spark.read.csv("merchant.csv", header=True, inferSch
categories_df = spark.read.csv("category.csv", header=True, inferSc
geolocations_df = spark.read.csv("geolocation.csv", header=True, in

# Step 3: Verify the DataFrames
transactions_df.show(5, truncate=False)
customers_df.show(5, truncate=False)
merchants_df.show(5, truncate=False)
categories_df.show(5, truncate=False)
geolocations_df.show(5, truncate=False)
```

```
+--------------------------------+---------------+------+--------+
-----------+--------------+-----------+-----------+
|id_transaction                  |trans_timestamp|amt   |is_fraud|
id_customer|id_geolocation|id_merchant|id_category|
+--------------------------------+---------------+------+--------+
-----------+--------------+-----------+-----------+
|0c20530e90719213c442744161a1850b|1622367050     |87.18 |0       |
794-45-4364|46            |2641132    |12         |
|984fc48fc946605deefc9d0967582811|1609183538     |276.97|0       |
436-80-2340|60            |2932280    |5          |
|b13ff47c73689bc4c8320c0ce403b15d|1655595319     |7.67  |0       |
385-77-6544|87            |2708770    |2          |
|7cffae35cab67d9415f9f22d91ca7acc|1613234460     |198.96|0       |
450-56-1117|138           |1170872    |10         |
|22e01cb3403a4c7ce598ebe785e1e947|1605030979     |33.46 |0       |
397-54-0253|218           |2470519    |5          |
```

```
          .              .           .           .
+---------------------------------+----------------+------+---------+
-----------+--------------+-----------+-----------+
only showing top 5 rows

+-----------+----------------+---------+--------+------+----------
----------------+--------------------------+-----------+----------
-+--------------+
|id_customer|cc_num          |firstname|lastname|gender|address
|job                       |dob       |acct_num    |id_geolocation|
+-----------+----------------+---------+--------+------+----------
----------------+--------------------------+-----------+----------
-+--------------+
|263-99-6044|4241904966319315|Melissa  |Turner  |F     |058 Stanle
y Cliff         |Risk manager              |2005-05-30|37644333185
2|6339          |
|292-61-7844|30520471167198  |Mark     |Brown   |M     |413 Angela
Mall            |Trading standards officer|2003-04-19|870143739098
|6200          |
|491-28-3311|180084219933088 |Courtney |Hall    |F     |5712 Tamar
a Estate        |Optometrist               |2002-04-17|96585502630

7|3547          |
|826-23-1754|2623398454615676|Krystal  |Branch  |F     |1016 Benne
tt Mountains    |Banker                    |2001-07-15|11324746755
|6302          |
|172-11-9264|639034043849    |Carol    |Ellis   |F     |819 Joseph
Plains Suite 807|Sports coach             |2003-11-21|113495175185
|5227          |
+-----------+----------------+---------+--------+------+----------
----------------+--------------------------+-----------+----------
-+--------------+
only showing top 5 rows

+-----------------------------+--------------+-----------+
|merchant                     |id_geolocation|id_merchant|
+-----------------------------+--------------+-----------+
|Bins-Tillman                 |6051          |1          |
|Hahn, Douglas and Schowalter|1276          |2          |
|Hayes, Marquardt and Dibbert|1383          |3          |
|Mueller, Gerhold and Mueller|1846          |4          |
|Kerluke Inc                  |1784          |5          |
+-----------------------------+--------------+-----------+
only showing top 5 rows

+------------------+-----------+
|category          |id_category|
+------------------+-----------+
|Entertainment     |1          |
|Food_Dining       |2          |
|Gas_Transport     |3          |
|Grocery(Online)   |4          |
|Grocery(In Store)|5          |
+------------------+-----------+
only showing top 5 rows
```

```
+----------+-----+-----+-------+---------+--------------+---------
-+
|city      |state|zip  |lat    |long     |id_geolocation|populatio
n|
+----------+-----+-----+-------+---------+--------------+---------
-+
|Burkeville|TX   |75932|31.0099|-93.6585 |1             |1437
|
|Fresno    |TX   |77545|29.5293|-95.4626 |2             |19431
|
|Osseo     |MN   |55311|45.1243|-93.4996 |3             |65312
|
|Pomona    |CA   |91766|34.0418|-117.7569|4             |154204
|
|Vacaville |CA   |95688|38.3847|-121.9887|5             |99475
|
+----------+-----+-----+-------+---------+--------------+---------
-+
only showing top 5 rows
```

2.1.2 Display the schema of the dataframes.

In [19]:
```
transactions_df.printSchema()
customers_df.printSchema()
merchants_df.printSchema()
categories_df.printSchema()
geolocations_df.printSchema()
```

```
root
 |-- id_transaction: string (nullable = true)
 |-- trans_timestamp: integer (nullable = true)
 |-- amt: double (nullable = true)
 |-- is_fraud: integer (nullable = true)
 |-- id_customer: string (nullable = true)
 |-- id_geolocation: integer (nullable = true)
 |-- id_merchant: integer (nullable = true)
 |-- id_category: integer (nullable = true)

root
 |-- id_customer: string (nullable = true)
 |-- cc_num: long (nullable = true)
 |-- firstname: string (nullable = true)
 |-- lastname: string (nullable = true)
 |-- gender: string (nullable = true)
 |-- address: string (nullable = true)
 |-- job: string (nullable = true)
 |-- dob: date (nullable = true)
 |-- acct_num: long (nullable = true)
 |-- id_geolocation: integer (nullable = true)

root
 |-- merchant: string (nullable = true)
 |-- id_geolocation: integer (nullable = true)
 |-- id_merchant: integer (nullable = true)

root
 |-- category: string (nullable = true)
 |-- id_category: integer (nullable = true)

root
 |-- city: string (nullable = true)
 |-- state: string (nullable = true)
 |-- zip: integer (nullable = true)
 |-- lat: double (nullable = true)
 |-- long: double (nullable = true)
 |-- id_geolocation: integer (nullable = true)
 |-- population: integer (nullable = true)
```

Think about: When the dataset is large, do you need all columns? How to optimize memory usage? Do you need a customized data partitioning strategy? (note: You don’t need to answer these questions.)

## 2.2 QueryAnalysis

Implement the following queries using dataframes. You need to be able to perform operations like filtering, sorting, joining and group by using the functions provided by the DataFrame API.

2.2.1. Transform the “trans_timestamp” to multiple columns: trans_year, trans_month, trans_day, trans_hour(24-hour format). (note: you can reuse your UDF from part 1 or create a new one.)

In [20]:
```
from pyspark.sql import functions as F
from pyspark.sql.types import IntegerType, StringType
from pyspark.sql.functions import udf
import datetime

# Defining the UDF to convert Unix timestamp to the desired date pa

def get_year(unix_timestamp):
    return datetime.datetime.fromtimestamp(unix_timestamp).year

def get_month(unix_timestamp):
    return datetime.datetime.fromtimestamp(unix_timestamp).month

def get_day(unix_timestamp):
    return datetime.datetime.fromtimestamp(unix_timestamp).day

def get_hour(unix_timestamp):
    return datetime.datetime.fromtimestamp(unix_timestamp).hour

# Writing UDF's to variables
udf_get_year = udf(get_year, IntegerType())
udf_get_month = udf(get_month, IntegerType())
udf_get_day = udf(get_day, IntegerType())
udf_get_hour = udf(get_hour, IntegerType())

# Applying the UDFs to create new columns
transactions_df = transactions_df \
    .withColumn("trans_year", udf_get_year(F.col("trans_timestamp"))
    .withColumn("trans_month", udf_get_month(F.col("trans_timestamp
    .withColumn("trans_day", udf_get_day(F.col("trans_timestamp")))
    .withColumn("trans_hour", udf_get_hour(F.col("trans_timestamp")

# displaying the transformation
transactions_df.select("trans_timestamp", "trans_year", "trans_mont
```

```
+---------------+----------+-----------+---------+----------+
|trans_timestamp|trans_year|trans_month|trans_day|trans_hour|
+---------------+----------+-----------+---------+----------+
|     1622367050|      2021|          5|       30|         9|
|     1609183538|      2020|         12|       28|        19|
|     1655595319|      2022|          6|       18|        23|
|     1613234460|      2021|          2|       13|        16|
|     1605030979|      2020|         11|       10|        17|
|     1608989049|      2020|         12|       26|        13|
|     1650997797|      2022|          4|       26|        18|
|     1649986601|      2022|          4|       15|         1|
|     1617032215|      2021|          3|       29|        15|
|     1609250028|      2020|         12|       29|        13|
+---------------+----------+-----------+---------+----------+
only showing top 10 rows
```

In [21]:

```
from pyspark.sql import functions as F

# Converting Unix timestamp to UTC timestamp
transactions_df = transactions_df.withColumn(
    "utc_time",
    F.from_unixtime(F.col("trans_timestamp")).cast("timestamp")
)

# Converting UTC timestamp to Melbourne time
transactions_df = transactions_df.withColumn(
    "melbourne_time",
    F.from_utc_timestamp(F.col("utc_time"), "Australia/Melbourne")
)

# Droping the intermediate 'utc_time' column since it is not requir
transactions_df = transactions_df.drop("utc_time")

# Extracting year, month, day, and hour from Melbourne time
transactions_df = transactions_df \
    .withColumn("trans_year", F.year("melbourne_time")) \
    .withColumn("trans_month", F.month("melbourne_time")) \
    .withColumn("trans_day", F.dayofmonth("melbourne_time")) \
    .withColumn("trans_hour", F.hour("melbourne_time"))

# displaying the tranformation.
transactions_df.select(
    "trans_timestamp",
    "melbourne_time",
    "trans_year",
    "trans_month",
    "trans_day",
    "trans_hour"
).show(10, truncate=False)
```

```
+---------------+-------------------+----------+-----------+------
---+----------+
|trans_timestamp|melbourne_time     |trans_year|trans_month|trans_
day|trans_hour|
+---------------+-------------------+----------+-----------+------
---+----------+
|1622367050     |2021-05-31 05:30:50|2021      |5          |31
|5         |
|1609183538     |2020-12-29 17:25:38|2020      |12         |29
|17        |
|1655595319     |2022-06-19 19:35:19|2022      |6          |19
|19        |
|1613234460     |2021-02-14 14:41:00|2021      |2          |14
|14        |
|1605030979     |2020-11-11 15:56:19|2020      |11         |11
|15        |
|1608989049     |2020-12-27 11:24:09|2020      |12         |27
|11        |
|1650997797     |2022-04-27 14:29:57|2022      |4          |27
|14        |
```

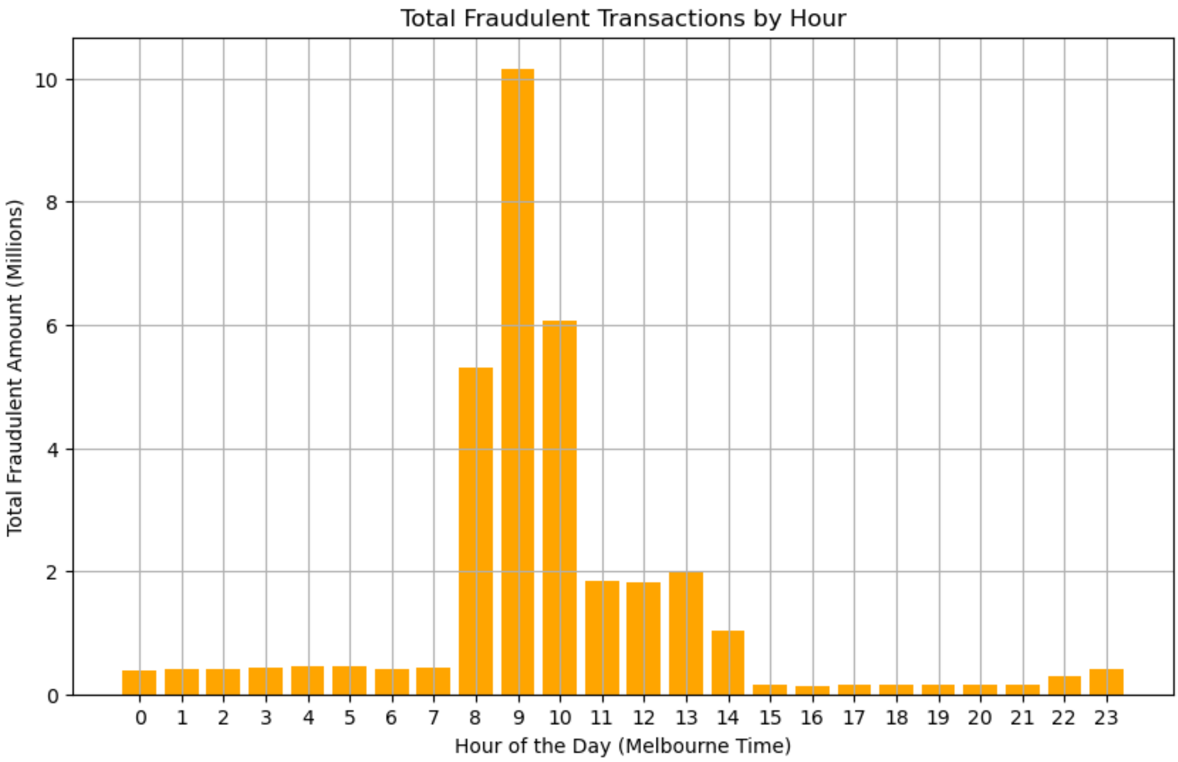
```
|14          |
|1649986601      |2022-04-15 21:36:41|2022      |4           |15
|21          |
|1617032215      |2021-03-30 13:36:55|2021      |3           |30
|13          |
|1609250028      |2020-12-30 11:53:48|2020      |12          |30
|11          |
+----------------+-------------------+----------+-----------+------
---+-----------+
only showing top 10 rows
```

2.2.2. Calculate the total amount of fraudulent transactions for each hour. Show the result in a table and plot a bar chart.

In [22]:
```
from pyspark.sql import functions as F
import matplotlib.pyplot as plt

# Filter for fraudulent transactions
fraud_transactions_df = transactions_df.filter(F.col("is_fraud") ==

# Group the transactions by the hour (trans_hour) and calculate the
fraud_by_hour_df = fraud_transactions_df.groupBy("trans_hour").agg(
    F.sum("amt").alias("total_fraud_amount")
)

# Sort the DataFrame by trans_hour
fraud_by_hour_df = fraud_by_hour_df.orderBy("trans_hour")

# displaying the results in a table
fraud_by_hour_df.show(truncate=False)

# Convert the Spark DataFrame into a Pandas DataFrame for visualiza
fraud_by_hour_pd = fraud_by_hour_df.toPandas()

# Converting y axis scale the total fraud amount to millions
fraud_by_hour_pd['total_fraud_amount_millions'] = fraud_by_hour_pd[

# bar chart with the y-axis in millions
plt.figure(figsize=(10, 6))
plt.bar(fraud_by_hour_pd['trans_hour'], fraud_by_hour_pd['total_fra
plt.xlabel('Hour of the Day (Melbourne Time)')
plt.ylabel('Total Fraudulent Amount (Millions)')
plt.title('Total Fraudulent Transactions by Hour')
plt.xticks(range(0, 24))
plt.grid(True)
plt.show()
```

```
+----------+------------------+
|trans_hour|total_fraud_amount|
+----------+------------------+
|0         |381445.31         |
```

```
|1         |417892.99000000005|
|2         |403231.68999999994|
|3         |430991.99         |
|4         |447647.10000000003|
|5         |450724.44         |
|6         |418971.51999999984|
|7         |421735.34         |
|8         |5294360.760000001 |
|9         |1.016169209E7     |
|10        |6074283.230000001 |
|11        |1843582.7500000002|
|12        |1827012.4099999997|
|13        |1989535.3699999996|
|14        |1027331.78        |
|15        |153623.16999999998|
|16        |135053.02         |
|17        |145336.47000000003|
|18        |144340.67         |
|19        |144448.36000000002|
+----------+------------------+
only showing top 20 rows

INFO:numexpr.utils:NumExpr defaulting to 4 threads.
```




2.2.3 Print number of small transactions(<=$100) from female who was born after 1990.

In [23]:
```
from pyspark.sql import functions as F

# Filtering customers born after 1990 and female
filtered_customers_df = customers_df.filter(
    (F.col("gender") == "F") &
    (F.year(F.col("dob")) > 1990)
)

# Joining transactions with filtered customers
joined_df = transactions_df.join(filtered_customers_df, on="id_cust

# Filter joined_df to keep only transactions where the transaction
small_transactions_df = joined_df.filter(F.col("amt") <= 100)

# Counting the number of transactions
small_transaction_count = small_transactions_df.count()

print(f"Number of small transactions (<= $100) from females born af
```

```
Number of small transactions (<= $100) from females born after 199
0: 1889691
```

2.2.4 We consider a fraud-to-sales(F2S) ratio of 3% as a benchmark. If a merchant has F2S >= 3%, it is considered operating at very high rick. How many companies are operating at very high risk? (note: The answer should be a single number.)

In [24]:
```
from pyspark.sql import functions as F
from pyspark.sql import SparkSession


# oin the transactions and merchants DataFrames on id_merchant to a
joined_df = transactions_df.join(merchants_df, on="id_merchant", ho

# Group the fraudulent transactions by merchant and compute the tot
fraud_amount_df = joined_df.filter(joined_df.is_fraud == 1) \
    .groupBy("merchant") \
    .agg(F.sum("amt").alias("total_fraud_amount"))

# Group all transactions by merchant and compute the total sales am
total_sales_df = joined_df.groupBy("merchant") \
    .agg(F.sum("amt").alias("total_sales_amount"))

# Performing an outer join on the merchant column to include mercha
f2s_df = fraud_amount_df.join(total_sales_df, "merchant", "outer")
    .fillna(0, subset=["total_fraud_amount", "total_sales_amount"])

# Calculating the the F2S ratio
f2s_df = f2s_df.withColumn("f2s_ratio", (f2s_df.total_fraud_amount

# Selecting merchants where the F2S ratio is greater than or equal
high_risk_merchants_df = f2s_df.filter(f2s_df.f2s_ratio >= 3)

# Counting the number of high-risk merchants
high_risk_company_count = high_risk_merchants_df.count()

print(f"Number of companies operating at very high risk: {high_risk
```

```
Number of companies operating at very high risk: 250
```

2.2.5 “Abbott and Adam Group” wants to know their total revenue(sum of non-fraud amt) in each state they operate, show the top 20 results by revenue in descending order. You output should include merchant name, state and total revenue. (note: Abbott and Adam group include all merchants who name start with “Abbott” or “Adam”.)

In [25]:
```
from pyspark.sql.functions import col, sum as spark_sum, desc

# Filtering Merchants Who Belong to "Abbott and Adam Group"
filtered_merchants_df = merchants_df.filter(
    (col("merchant").startswith("Abbott")) | (col("merchant").start
)

# Join transactions_df with filtered_merchants_df on id_merchant to
joined_df = transactions_df.join(filtered_merchants_df, "id_merchan

# Filtering out the  Non-Fraudulent Transactions
non_fraud_df = joined_df.filter(col("is_fraud") == 0)
```

```
# Joining with Geolocation to Get State Information
joined_with_state_df = non_fraud_df.join(geolocations_df, "id_geolo

# Aggregating the total Revenue by Merchant and State
revenue_df = joined_with_state_df.groupBy("merchant", "state").agg(
    spark_sum("amt").alias("total_revenue")
)

# Sorting by Total Revenue in Descending Order and Show Top 20
top_20_revenue_df = revenue_df.orderBy(desc("total_revenue")).limit

# Show the final result
top_20_revenue_df.show(truncate=False)
```

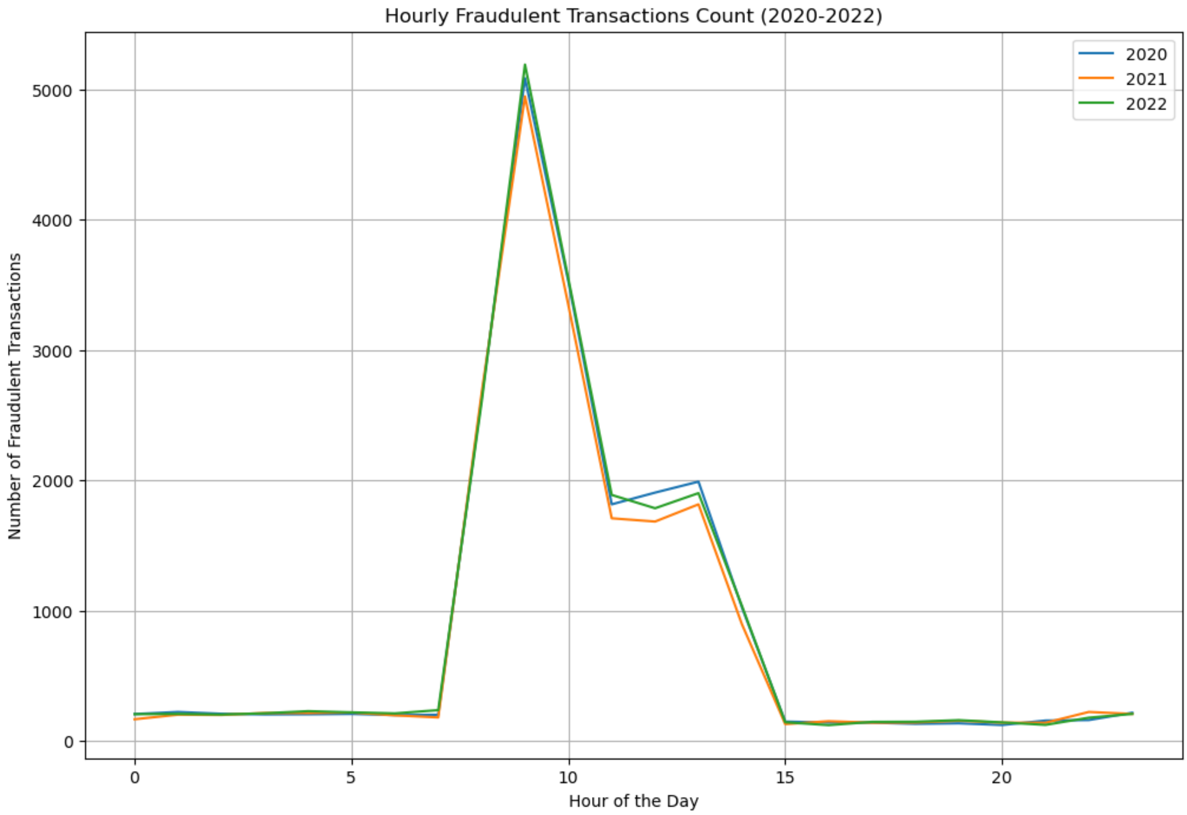
```
+--------------------------+-----+------------------+
|merchant                  |state|total_revenue     |
+--------------------------+-----+------------------+
|Abbott-Rogahn             |CA   |352865.9700000001 |
|Adams, Kovacek and Kuhlman|CA   |279898.79         |
|Adams-Barrows             |CA   |278485.78999999986|
|Abbott-Rogahn             |TX   |247959.91         |
|Adams-Barrows             |TX   |199538.5700000001 |
|Adams, Kovacek and Kuhlman|TX   |187685.3699999999 |
|Abbott-Rogahn             |NY   |182627.71         |
|Abbott-Rogahn             |FL   |178579.29000000004|
|Adams, Kovacek and Kuhlman|NY   |155427.12         |
|Adams-Barrows             |FL   |154059.63999999998|
|Adams, Kovacek and Kuhlman|FL   |150222.35000000003|
|Adams-Barrows             |NY   |145255.89999999997|
|Abbott-Rogahn             |IL   |119764.71999999996|
|Abbott-Rogahn             |PA   |118146.56000000001|
|Abbott-Rogahn             |OH   |105306.51999999999|
|Adams, Kovacek and Kuhlman|PA   |99076.17          |
|Adams, Kovacek and Kuhlman|OH   |98207.82          |
|Abbott-Rogahn             |GA   |97967.01999999999 |
|Adams, Kovacek and Kuhlman|NC   |97072.05000000003 |
|Abbott-Rogahn             |MI   |93076.11000000002 |
+--------------------------+-----+------------------+
```

2.2.6 For each year (2020-2022), aggregate the number(count) of fraudulent transactions every hour. Plot an appropriate figure and observe the trend. Write your observations from your plot (e.g. Is fraudulent activities increasing or decreasing? Are those frauds more active after midnight or during business hours?).

In [26]:

```
from pyspark.sql import functions as F
import matplotlib.pyplot as plt

#Filtering  for fraudulent transactions
fraud_transactions_df = transactions_df.filter(F.col("is_fraud") ==
```

```
# Add a new column trans_year by extracting the year from the melbo
fraud_transactions_df = fraud_transactions_df.withColumn("trans_yea

# Filtering for years 2020 to 2022 redudant
filtered_fraud_df = fraud_transactions_df.filter(
    (F.col("trans_year") >= 2020) & (F.col("trans_year") <= 2022)
)

# Group the transactions by trans_year and trans_hour and count how
hourly_fraud_count_df = filtered_fraud_df.groupBy("trans_year", "tr
    F.count("*").alias("fraud_count")
).orderBy("trans_year", "trans_hour")

# Converting the DataFrame to Pandas for plotting
hourly_fraud_count_pd = hourly_fraud_count_df.toPandas()

# plotting the data
plt.figure(figsize=(12, 8))

for year in range(2020, 2023):
    yearly_data = hourly_fraud_count_pd[hourly_fraud_count_pd['tran
    plt.plot(yearly_data['trans_hour'], yearly_data['fraud_count'],

plt.title("Hourly Fraudulent Transactions Count (2020-2022)")
plt.xlabel("Hour of the Day")
plt.ylabel("Number of Fraudulent Transactions")
plt.legend()
plt.grid(True)
plt.show()
```



**Most of the fraud transactions are taking place during the peak business hours with respect to melbourne timings, we can see spike of fraud transaction post 8AM and peaks at 9AM and gradually drops after 10AM, though the intensity is high until late afternoon the frequency of the fraud transaction gradually reduces post afternoon.**

## Part 3 RDDs vs DataFrame vs Spark SQL (25%)

Implement the following queries using RDDs, DataFrame in SparkSQL separately. Log the time taken for each query in each approach using the “%%time” built-in magic command in Jupyter Notebook and discuss the performance difference between these 3 approaches.

**Query: We consider city with population < 50K as small(denoted as S); 50K-200K as medium(M), >200K as large(L). For each city type, using customer age bucket of 10(e.g. 0-9, 10-19, 20-29...), show the percentage ratio of fraudulent transactions in each age bucket.**

In [30]:
```
from operator import add
from datetime import datetime
# Load the Transactions RDD
transactions_rdd = sc.textFile("transactions.csv")
transactions_header = transactions_rdd.first()  # Extract the heade
transactions_rdd = transactions_rdd.filter(lambda line: line != tra

# Load the Merchants RDD
merchants_rdd = sc.textFile("merchant.csv")
merchants_header = merchants_rdd.first()  # Extract the header
merchants_rdd = merchants_rdd.filter(lambda line: line != merchants_

# Load the Customers RDD
customers_rdd = sc.textFile("customers.csv")
customers_header = customers_rdd.first()  # Extract the header
customers_rdd = customers_rdd.filter(lambda line: line != customers_

# Load the Geolocations RDD
geolocations_rdd = sc.textFile("geolocation.csv")
geolocations_header = geolocations_rdd.first()  # Extract the heade
geolocations_rdd = geolocations_rdd.filter(lambda line: line != geo
```

### 3.1. RDD Implementation

In [56]:
```
%%time
# Defining a function that processes the date of birth to classify
def calculate_age_bucket(dob):
    try:
        dob_clean = dob.strip('"')
```

```
        current_year = datetime.now().year
        birth_year = int(dob_clean[:4])
        age = current_year - birth_year
        return f"{(age // 10) * 10}-{(age // 10) * 10 + 9}"
    except (ValueError, IndexError):
        return "Unknown"

# For each customer, map id_customer to their age bucket using the
customers_with_age_bucket = customers_rdd.map(lambda x: (x[0], calc

# Joining fraudulent transactions with customers' age data using id
transactions_with_customers = fraudulent_transactions_rdd.map(lambd
transactions_with_age = transactions_with_customers.join(customers_

# Classifying cities into small, medium, and large
def classify_city(population):
    try:
        pop_int = int(population.strip('"'))  # Handle quotes aroun
        if pop_int < 50000:
            return 'S'
        elif 50000 <= pop_int <= 200000:
            return 'M'
        else:
            return 'L'
    except ValueError:
        return 'Unknown'  # If population can't be converted, retur

geolocations_with_city_type = geolocations_rdd.map(lambda x: (x[5],

# Join transactions with city type
transactions_with_city = transactions_with_age.map(lambda x: (x[1][
transactions_with_city_type = transactions_with_city.join(geolocati

# For each transaction, map it to a (city_type, age_bucket) tuple,
fraud_count_by_city_age = transactions_with_city_type.map(lambda x:

# appending each transaction to its corresponding city type and cou
total_fraud_per_city = transactions_with_city_type.map(lambda x: (x

# Joining to calculate percentage of fraud per age bucket and city
fraud_count_by_city_age_modified = fraud_count_by_city_age.map(lamb
fraud_percentage_by_city_age = fraud_count_by_city_age_modified.joi
    .map(lambda x: ((x[0], x[1][0][0]), (x[1][0][1] / x[1][1]) * 10

# display results
fraud_percentage_result_rdd = fraud_percentage_by_city_age.collect(
print(f"{'City Type':<10}{'Age Bucket':<15}{'Fraud Percentage (%)':
print("="*45)
for ((city_type, age_bucket), percentage) in fraud_percentage_resul
    print(f"{city_type:<10}{age_bucket:<15}{percentage:<20.2f}")
```

```
City Type Age Bucket     Fraud Percentage (%)
=============================================
L         Unknown        25.00
```

```
L          20-29          12.50
L          80-89          4.17

L          60-69          8.33
L          70-79          4.17
L          40-49          25.00
L          30-39          12.50
L          50-59          8.33
M          20-29          4.17
M          60-69          4.17
M          Unknown        29.17
M          50-59          4.17
M          30-39          20.83
M          90-99          8.33
M          40-49          29.17
S          40-49          9.68
S          60-69          6.45
S          80-89          1.61
S          30-39          27.42
S          Unknown        33.87
S          20-29          6.45
S          50-59          14.52
CPU times: user 58 ms, sys: 17.5 ms, total: 75.5 ms
Wall time: 40.7 s
```

### 3.2. DataFrame Implementation

In [54]:

```
%%time
# Defining a UDF to calculate the age bucket
def calculate_age_bucket(dob):
    try:
        # Extract year from dob and calculate age (since dob is alr
        current_year = datetime.now().year
        birth_year = dob.year  # Extract year from the datetime.dat
        age = current_year - birth_year

        # Returning the age bucket
        return f"{(age // 10) * 10}-{(age // 10) * 10 + 9}"
    except (ValueError, AttributeError):
        # Incase of unknown format return Unknown
        return "Unknown"

# Convert the Python function into a Spark UDF for use in DataFrame
udf_calculate_age_bucket = F.udf(calculate_age_bucket)

# Applying the UDF to calculate the age_bucket for each customer an
customers_df = customers_df.withColumn("age_bucket", udf_calculate_

# Filtering the fraudulent transactions
fraudulent_transactions_df = transactions_df.filter(F.col("is_fraud

# Joining fraudulent transactions with customers on id_customer to
```

```
fraud_with_customers_df = fraudulent_transactions_df.join(customers

#  Defineing function to classify city type based on population
def classify_city(population):
    return when(F.col("population") < 50000, 'S').when((F.col("popu

# Adding city_type column based on the population in geolocations d
geolocations_df = geolocations_df.withColumn("city_type", classify_

# Join fraudulent transactions with customer data based on the id_c
fraud_with_city_df = fraud_with_customers_df.join(geolocations_df,

#  Group by city_type and age_bucket to get fraud counts
fraud_by_city_age_df = fraud_with_city_df.groupBy("city_type", "age

# Calculate total fraud transactions per city_type
total_fraud_by_city_df = fraud_with_city_df.groupBy("city_type").ag

# Join the fraud count and total fraud data based on city_type.
fraud_percentage_df = fraud_by_city_age_df.join(total_fraud_by_city
    .withColumn("fraud_percentage", (F.col("fraud_count") / F.col("

# displaying the final result
final_df = fraud_percentage_df.select("city_type", "age_bucket", "f

print(f"{'City Type':<10}{'Age Bucket':<15}{'Fraud Percentage (%)':
print("="*45)
for row in final_df.collect():
    print(f"{row['city_type']:<10}{row['age_bucket']:<15}{row['frau
```

```
City Type Age Bucket     Fraud Percentage (%)
=============================================
S         20-29          8.41
S         90-99          3.73
L         20-29          7.91
M         40-49          18.52
S         30-39          17.69
S         80-89          5.19
S         60-69          15.58
S         70-79          9.00
M         30-39          18.31
L         40-49          19.05
M         60-69          16.13
L         70-79          8.37
M         70-79          10.30
L         60-69          16.43
S         40-49          18.91
M         80-89          5.63
L         80-89          5.54
L         30-39          17.15
M         20-29          7.72
M         90-99          3.14
S         50-59          21.50
```

```
L         50-59          21.78
L         90-99          3.77
M         50-59          20.24

CPU times: user 16.2 ms, sys: 6.31 ms, total: 22.5 ms
Wall time: 10.4 s
```

#### 3.3. Spark SQL Implementation

In [51]:

```
%%time

# Adding city_type column to geolocations based on population
geolocations_df = geolocations_df.withColumn(
    "city_type",
    when(geolocations_df.population < 50000, 'S')
    .when((geolocations_df.population >= 50000) & (geolocations_df.
    .otherwise('L')
)

# Registering DataFrames as SQL tables to enable SQL queries.
transactions_df.createOrReplaceTempView("transactions")
customers_df.createOrReplaceTempView("customers")
geolocations_df.createOrReplaceTempView("geolocations")

# Create a query to calculate age buckets by extracting the year of
age_bucket_query = """
    SELECT
        id_customer,
        dob,
        CASE
            WHEN dob IS NULL THEN 'Unknown'
            ELSE CONCAT(FLOOR((YEAR(CURRENT_DATE()) - YEAR(dob)) /
        END AS age_bucket
    FROM customers
"""

# Execute the query and store the results in a new DataFrame
age_bucket_df = spark.sql(age_bucket_query)
age_bucket_df.createOrReplaceTempView("customers_with_age_bucket")

# Join transactions, customers (with age buckets), and geolocation
fraud_with_customers_query = """
    SELECT
        f.id_transaction,
        f.is_fraud,
        c.age_bucket,
        g.city_type
    FROM transactions f
    JOIN customers_with_age_bucket c ON f.id_customer = c.id_custom
    JOIN geolocations g ON f.id_geolocation = g.id_geolocation
    WHERE f.is_fraud = '1'
```

```
"""

# Run the fraud query and store it in a new SQL view for further pr
fraud_with_customers_df = spark.sql(fraud_with_customers_query)
fraud_with_customers_df.createOrReplaceTempView("fraud_with_custome

# Group the fraud data by city type and age bucket and count the tr
fraud_count_query = """
    SELECT
        city_type,
        age_bucket,
        COUNT(*) AS fraud_count
    FROM fraud_with_customers
    GROUP BY city_type, age_bucket
"""

# Execute the fraud count query and register it as a new SQL view.
fraud_count_df = spark.sql(fraud_count_query)
fraud_count_df.createOrReplaceTempView("fraud_count_by_city_age")

# Calculating totalfraud per city type
total_fraud_query = """
    SELECT
        city_type,
        COUNT(*) AS total_fraud
    FROM fraud_with_customers
    GROUP BY city_type
"""

# Execute the query
total_fraud_df = spark.sql(total_fraud_query)
total_fraud_df.createOrReplaceTempView("total_fraud_by_city")

# Calculating the fraud percentage by age bucket and city type
fraud_percentage_query = """
    SELECT
        f.city_type,
        f.age_bucket,
        (f.fraud_count / t.total_fraud) * 100 AS fraud_percentage
    FROM fraud_count_by_city_age f
    JOIN total_fraud_by_city t ON f.city_type = t.city_type
"""

# execute to display the final result
result_df = spark.sql(fraud_percentage_query)
result_df.show(truncate=False)
```

```
+---------+----------+------------------+
|city_type|age_bucket|fraud_percentage  |
+---------+----------+------------------+
|S        |20-29     |8.407914976926303 |
|S        |90-99     |3.726751503286254 |
|L        |20-29     |7.911556400069096 |
|M        |40-49     |18.521018717397975|
```

```
|S        |30-39     |17.686337575164313|
|S        |80-89     |5.191581596979444 |
|S        |60-69     |15.57824080548175 |
|S        |70-79     |8.995245420220948 |
|M        |30-39     |18.312365756366983|
|L        |40-49     |19.047619047619047|
|M        |60-69     |16.133783369131635|
|L        |70-79     |8.372200149709219 |
|M        |70-79     |10.303774163853943|
|L        |60-69     |16.427707721540855|
|S        |40-49     |18.909942665361488|
|M        |80-89     |5.627493096041731 |
|L        |80-89     |5.54499913629297  |
|L        |30-39     |17.147463580353545|
|M        |20-29     |7.720159558146671 |
|M        |90-99     |3.142068119054925 |
+---------+----------+------------------+
only showing top 20 rows

CPU times: user 10.4 ms, sys: 2.86 ms, total: 13.2 ms
Wall time: 12.5 s
```

### 3.4 Which one is the easiest to implement in your opinion? Log the time taken for each query, and observe the query execution time, among RDD, DataFrame, SparkSQL, which is the fastest and why? Please include proper reference. (Maximum 500 words.)

In my opinion, I find SparkSQL easiest since the operation on the data set can be easily implemented with concepts of SQL queries, join operations, and features which can be implemented easily, however implementing data frames is much faster and more convenient when compared to SparkSQL and RDD, and below are the reason,

With a wall time of 10.4 seconds, DataFrames are preferably the fastest approach that can be implemented. However, SparkSQL is a little close concerning wall time(12.5s), data frames are more likely to be considered due to less overhead. The wall time relating to SparkSQL is slightly higher than the data frame because SparkSql translates SQL queries into DataFrames operation before execution. Still, data frames provide direct access to the spark's query engine resulting in faster performance.

Why data frames are quick?

Catalyst Optimizer: DataFrames benefit from Sparks catalyst optimizer, which automatically optimizes the execution of queries by applying predicate pushdowns, join optimizations and query plan purning which leads to effiecient query exceution. [1]

Efficient Memory Usage: DataFrames avoids JAVA object serialization which requires RDDs, which minimizes overhead resulting in quick query execution. [2]

Tungsten Execution Engine: with use of TEE  in data frames memory and CPU usage is optimized, tungsten provides vectorized execution and cache-aware computation which significantly improves speed of operations over RDD. [2]

RDD's are the slowest as they do not benefit from the optmizations provided by the catalyst optimizer or the tungsten execution engine, they also give users low level control over the operations but at the cost of performance. [2]

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In [ ]: