> **Algoritmos para Big Data**
>
> **2023/24**

Data Stream Processing

This lecture is about processing a stream of data. We will rely on the structure streaming library of Apache Spark.

Structured streaming

A key aspect of structured streaming is to acquire/send data from a streaming data producer/consumer. That is, from a streaming source/sink.

Apache Spark provides methods to read/write from/to a stream, accordingly to some formats we may select from. Of course, some kind of configuration is required.

Firstly, there are the usual file-based formats like json, parquet, csv, text, and so on. Also, we can use socket connections to get/send text data from/to TCP servers, and more importantly, we can rely on functionalities of advanced message systems like Apache Kafka, which will play a sort of buffering role.

Secondly, we have to set an output mode, which defines how the results will be delivered. For instance, to see all data every time, only updates, or just the new records.

Further details can be found in https://spark.apache.org/docs/latest/structured-streaming-programming-guide.html

Problem formulation

This exercise is about detecting credit card frauds in near real-time. This case-study is based on a Kaggle dataset that it is available in https://www.kaggle.com/datasets/ealtman2019/credit-card-transactions. The dataset is expected to be a realistic example of synthetic data regarding credit card transactions.

We assume that a ML classification model has already been created and made available. Therefore, now we have to deal with a stream of transactions that are expected to be processed, like it would be in in a real-time scenario. Hence, we will simulate such scenario, mostly relying on Spark's Structured Streaming.

The functional requirements for the Spark program we are going to create are as follows:

1. To load a ML model previously built.
2. To process credit card transactions held in a simulated data stream, by applying the ML model.
3. To explore the results obtained.

Also, in order to speed up some processing, we will use some files that were computed in advance.

Data available

- The dataset about the stream of credit card transactions can be downloaded from the location

  > https://bigdata.iscte.me/abd/credit-card-transactions-stream.zip

- The ML classification model already built can be downloaded from the location

  > https://bigdata.iscte.me/abd/model-LinearSVM-credit-cards.zip

All the files are in parquet format.

Initial settings

Additional packages and imports

In [1]:
```python
import findspark, pyspark

from pyspark.sql import SparkSession
from pyspark.sql.types import *
import pyspark.sql.functions as F
```

In [2]:
```python
import os, sys
import time

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings("ignore")
```

In [3]:
```python
# Create the Spark session

findspark.init()
findspark.find()

spark = SparkSession\
        .builder\
        .appName("StreamingCreditCards")\
        .config("spark.sql.shuffle.partitions",6)\
        .config("spark.sql.repl.eagereval.enabled",True)\
        .getOrCreate()
```

```
Setting default log level to "WARN".
To adjust logging level use sc.setLogLevel(newLevel). For SparkR, use setLogLevel(newLevel).
24/04/09 14:01:56 WARN NativeCodeLoader: Unable to load native-hadoop library for your platform... using builtin-j
```

In [4]:
```python
spark
```

Out[4]: **SparkSession - in-memory**

SparkContext

Spark UI

Version	`v3.5.0`
Master	`local[*]`
AppName	`StreamingCreditCards`

In [5]:
```
# Some Spark related imports we will use hereafter

from pyspark.ml import PipelineModel
```

In [6]:
```
from IPython.core.display import HTML
display(HTML("<style>pre { white-space: pre !important; }</style>"))
```

Useful functions

In [7]:
```
def plotBarColoured(df, xcol, ycol, colour):
    return sns.barplot(data=df, x=xcol, y=ycol, color=colour)
```

Collect and label data

In [8]:
```
# ! pwd & ls -la
```

Checking working directory and data files

In [ ]:
```
pwd
```

In [10]:
```
data_dir =
```

In [ ]:
```
ls -la $data_dir
```

Reading the dataset

In [12]:
```
# Reading data

file_path =
df_transactions = spark.read.parquet(file_path)
```

Checking data

Schema, show and count.

In [13]:
```
df_transactions.
```

```
root
 |-- User: integer (nullable = true)
 |-- Card: integer (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Month: integer (nullable = true)
 |-- Day: integer (nullable = true)
 |-- Time: timestamp (nullable = true)
 |-- Use Chip: string (nullable = true)
 |-- Merchant Name: long (nullable = true)
 |-- Merchant City: string (nullable = true)
 |-- Merchant State: string (nullable = true)
 |-- Zip: double (nullable = true)
 |-- MCC: integer (nullable = true)
 |-- Is Fraud?: string (nullable = true)
 |-- Correct Amount: float (nullable = true)
 |-- Hour: integer (nullable = true)
 |-- Min: integer (nullable = true)
 |-- Transaction_Id: long (nullable = true)

+-----+----+----+-----+---+-------------------+------------------+---------------------+-------------+-------------
```

```
|User|Card|Year|Month|Day|               Time|          Use Chip|       Merchant Name|Merchant City|Merchant State
+----+----+----+-----+---+-------------------+------------------+--------------------+-------------+--------------
|   0|   0|2002|    9|  1|2023-05-02 06:21:00| Swipe Transaction| 3527213246127876953|     La Verne|            CA
|   0|   0|2002|    9|  1|2023-05-02 06:42:00| Swipe Transaction| -727612092139916043|Monterey Park|            CA
|   0|   0|2002|    9|  2|2023-05-02 06:22:00| Swipe Transaction| -727612092139916043|Monterey Park|            CA
|   0|   0|2002|    9|  2|2023-05-02 17:45:00| Swipe Transaction| 3414527459579106770|Monterey Park|            CA
|   0|   0|2002|    9|  3|2023-05-02 06:23:00| Swipe Transaction| 5817218446178736267|     La Verne|            CA
|   0|   0|2002|    9|  3|2023-05-02 13:53:00| Swipe Transaction|-7146670748125200898|Monterey Park|            CA
|   0|   0|2002|    9|  4|2023-05-02 05:51:00| Swipe Transaction| -727612092139916043|Monterey Park|            CA
|   0|   0|2002|    9|  4|2023-05-02 06:09:00| Swipe Transaction| -727612092139916043|Monterey Park|            CA
|   0|   0|2002|    9|  5|2023-05-02 06:14:00| Swipe Transaction| -727612092139916043|Monterey Park|            CA
|   0|   0|2002|    9|  5|2023-05-02 09:35:00| Swipe Transaction| 4055257078481058705|     La Verne|            CA
|   0|   0|2002|    9|  5|2023-05-02 20:18:00| Swipe Transaction|-4500542936415012428|     La Verne|            CA
|   0|   0|2002|    9|  5|2023-05-02 20:41:00|Online Transaction|-9092677072201095172|       ONLINE|          NULL
|   0|   0|2002|    9|  6|2023-05-02 06:16:00| Swipe Transaction| 2027553650310142703|    Mira Loma|            CA
|   0|   0|2002|    9|  7|2023-05-02 06:16:00| Swipe Transaction| -727612092139916043|Monterey Park|            CA
|   0|   0|2002|    9|  7|2023-05-02 06:34:00| Swipe Transaction|-5475680618560174533|Monterey Park|            CA
|   0|   0|2002|    9|  7|2023-05-02 09:39:00| Swipe Transaction| 4055257078481058705|     La Verne|            CA
|   0|   0|2002|    9|  8|2023-05-02 06:10:00| Swipe Transaction|  -34551508091458520|     La Verne|            CA
|   0|   0|2002|    9|  8|2023-05-02 06:38:00| Swipe Transaction| 4060646732831064559|     La Verne|            CA
|   0|   0|2002|    9|  8|2023-05-02 13:48:00| Swipe Transaction| -727612092139916043|Monterey Park|            CA
|   0|   0|2002|    9|  8|2023-05-02 22:01:00| Swipe Transaction|-6733168469687845480|    Mira Loma|            CA
+----+----+----+-----+---+-------------------+------------------+--------------------+-------------+--------------
only showing top 20 rows
```

Out[13]:
```
24386900
```

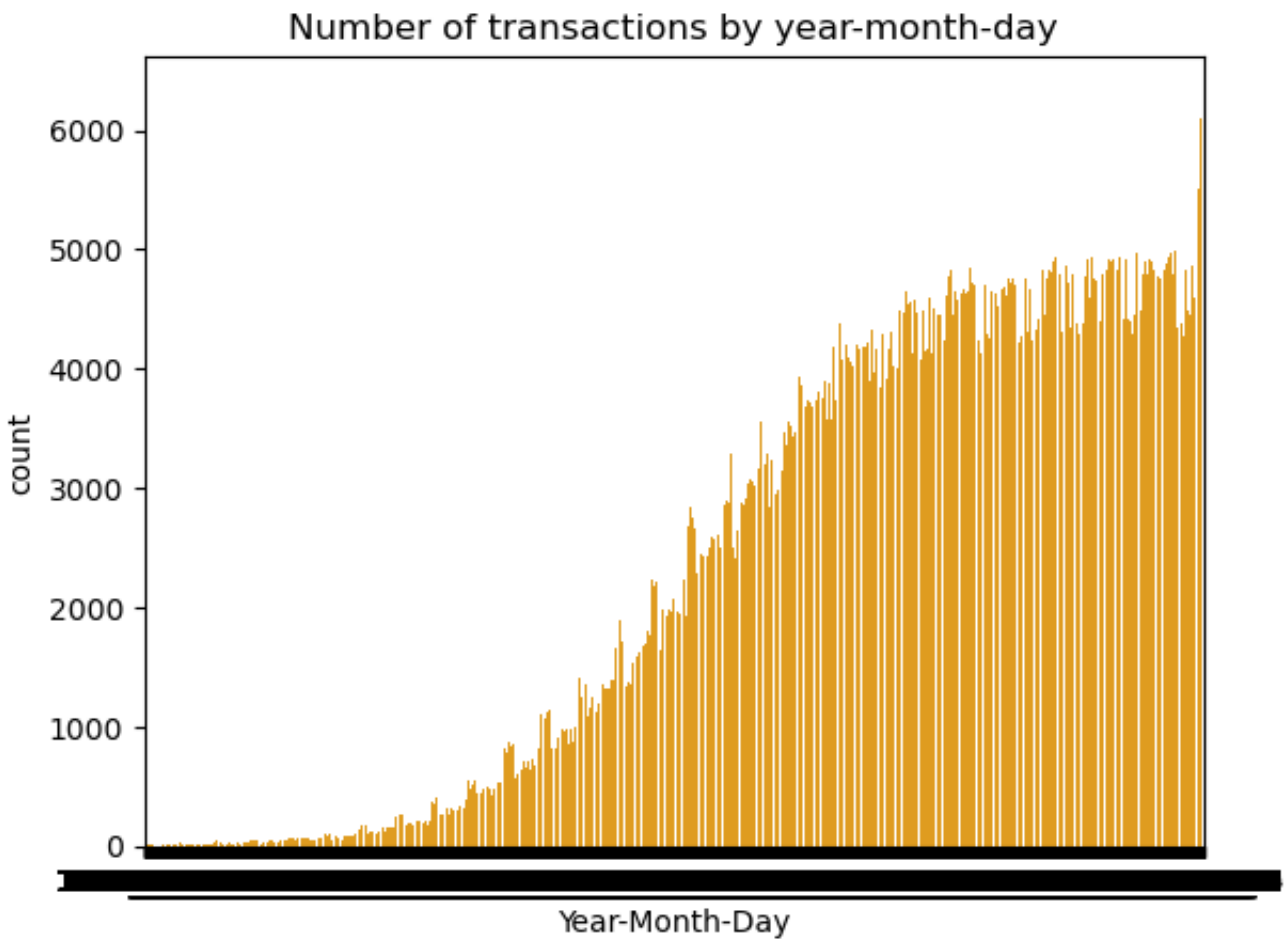
Explore and evaluate data

At this point, we assume that data has been properly checked while model was created.

We leave it now but proper checking is warranted. Just do a plot of transactions over time.

In [14]:
```
# Just to remember ... number of transactions by year-month-day
```

```python
df_plot = ( df_transactions
            .groupby(['Year', 'Month', 'Day'])
            .count()
            .withColumn('Year-Month-Day', F.concat('Year',F.lit('_'),'Month',F.lit('_'),'Day'))
            .sort('Year-Month-Day', ascending=True)
            .toPandas()
          )
plotBarColoured(df_plot, 'Year-Month-Day', 'count', 'orange')
plt.title('Number of transactions by year-month-day')
plt.show()
```



In [15]:
```
df_plot.head()
```

Out[15]:

	Year	Month	Day	count	Year-Month-Day
0	1991	10	1	6	1991_10_1
1	1991	10	10	4	1991_10_10
2	1991	10	11	1	1991_10_11
3	1991	10	12	3	1991_10_12
4	1991	10	13	8	1991_10_13

Data Stream

As we have no real time scenario in place, we will simulate a data stream by creating a built-in `rate` source to generate events at 1-second intervals, and join those 'ticks' with data from our downloaded dataset. This creates a regular stream of sample values. Alternatively, for pratical applications, we could have used an Apache Kafka source or even a file source. Apache Kafka was the best solution for that matter.

In [16]:
```
rate_source = spark.readStream.format("rate").load()
```

In [17]:
```
rate_source.printSchema()
```

```
root
 |-- timestamp: timestamp (nullable = true)
 |-- value: long (nullable = true)
```

In [18]:
```
# We should guarantee that we are using data sorted by transaction id (aka time)

df_transactions = df_transactions.
```

In [19]:
```
df_transactions.select('Year', 'Month', 'Day', 'Time', 'Hour', 'Min', 'Transaction_ID').show(20,truncate=False)
```

```
[Stage 13:==================================================>      (8 + 1) / 9]
```

```
+----+-----+---+-------------------+----+---+--------------+
|Year|Month|Day|Time               |Hour|Min|Transaction_ID|
+----+-----+---+-------------------+----+---+--------------+
|2002|9    |1  |2023-05-02 06:21:00|6   |21 |0             |
|2002|9    |1  |2023-05-02 06:42:00|6   |42 |1             |
|2002|9    |2  |2023-05-02 06:22:00|6   |22 |2             |
|2002|9    |2  |2023-05-02 17:45:00|17  |45 |3             |
|2002|9    |3  |2023-05-02 06:23:00|6   |23 |4             |
|2002|9    |3  |2023-05-02 13:53:00|13  |53 |5             |
|2002|9    |4  |2023-05-02 05:51:00|5   |51 |6             |
|2002|9    |4  |2023-05-02 06:09:00|6   |9  |7             |
|2002|9    |5  |2023-05-02 06:14:00|6   |14 |8             |
|2002|9    |5  |2023-05-02 09:35:00|9   |35 |9             |
|2002|9    |5  |2023-05-02 20:18:00|20  |18 |10            |
|2002|9    |5  |2023-05-02 20:41:00|20  |41 |11            |
|2002|9    |6  |2023-05-02 06:16:00|6   |16 |12            |
|2002|9    |7  |2023-05-02 06:16:00|6   |16 |13            |
|2002|9    |7  |2023-05-02 06:34:00|6   |34 |14            |
|2002|9    |7  |2023-05-02 09:39:00|9   |39 |15            |
|2002|9    |8  |2023-05-02 06:10:00|6   |10 |16            |
|2002|9    |8  |2023-05-02 06:38:00|6   |38 |17            |
|2002|9    |8  |2023-05-02 13:48:00|13  |48 |18            |
|2002|9    |8  |2023-05-02 22:01:00|22  |1  |19            |
+----+-----+---+-------------------+----+---+--------------+
only showing top 20 rows
```

Creating a continuous data stream

Circularly replaying the data as long as the process is running. It will be a simulated streaming version of the data.

In [20]:
```
# Circularly replay the data

data_stream = ( rate_source
                    .select(F.expr(f'value % {num_transactions}').alias('Transaction_Id'), 'timestamp')
                    .join(df_transactions, 'Transaction_Id')
```

```
)
```

In [21]:
```
data_stream.printSchema()
```

```
root
 |-- Transaction_Id: long (nullable = true)
 |-- timestamp: timestamp (nullable = true)
 |-- User: integer (nullable = true)
 |-- Card: integer (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Month: integer (nullable = true)
 |-- Day: integer (nullable = true)
 |-- Time: timestamp (nullable = true)
 |-- Use Chip: string (nullable = true)
 |-- Merchant Name: long (nullable = true)
 |-- Merchant City: string (nullable = true)
 |-- Merchant State: string (nullable = true)
 |-- Zip: double (nullable = true)
 |-- MCC: integer (nullable = true)
 |-- Is Fraud?: string (nullable = true)
 |-- Correct Amount: float (nullable = true)
 |-- Hour: integer (nullable = true)
 |-- Min: integer (nullable = true)
```

In [22]:
```
cols_to_check = data_stream.columns
```

Model deployment

Loading the binary classification model

In [23]:
```
# Read the ML model via pipeline api (not the simple pipeline)

persisted_model = PipelineModel.
```

In [24]:
```
# Check the model, namely the stages that were used

persisted_model.stages
```

Out[24]:
```
[StringIndexerModel: uid=StringIndexer_e1064637f5a0, handleInvalid=skip, numInputCols=2, numOutputCols=2,
 OneHotEncoderModel: uid=OneHotEncoder_6a398697f374, dropLast=true, handleInvalid=error, numInputCols=2, numOutp
 VectorAssembler_f41b5139a541,
 LinearSVCModel: uid=LinearSVC_912312635f03, numClasses=2, numFeatures=11838]
```

Streaming data transformer

Let us set the operation to be applied to the stream.

In [25]:
```
# ML model directly applied to the streaming dataframe using `transform`

prediction_stream = persisted_model.transform(
```

In [26]:
```
prediction_stream.printSchema()
```

```
root
 |-- Transaction_Id: long (nullable = true)
 |-- timestamp: timestamp (nullable = true)
 |-- User: integer (nullable = true)
 |-- Card: integer (nullable = true)
 |-- Year: integer (nullable = true)
 |-- Month: integer (nullable = true)
 |-- Day: integer (nullable = true)
 |-- Time: timestamp (nullable = true)
 |-- Use Chip: string (nullable = true)
 |-- Merchant Name: long (nullable = true)
 |-- Merchant City: string (nullable = true)
 |-- Merchant State: string (nullable = true)
 |-- Zip: double (nullable = true)
 |-- MCC: integer (nullable = true)
 |-- Is Fraud?: string (nullable = true)
 |-- Correct Amount: float (nullable = true)
 |-- Hour: integer (nullable = true)
 |-- Min: integer (nullable = true)
 |-- Use Chip Index: double (nullable = false)
 |-- Merchant City Index: double (nullable = false)
 |-- Use Chip OHE: vector (nullable = true)
 |-- Merchant City OHE: vector (nullable = true)
 |-- features: vector (nullable = true)
 |-- rawPrediction: vector (nullable = true)
 |-- prediction: double (nullable = false)
```

Consuming predictions

The final step is to do something with the prediction data. For the time being, we are going to limit this step to just querying the data.

For real-world application, we can offer this kind of service to other applications.

Maybe in the form of an HTTP-based API or through pub/sub messaging interactions.

In [27]:

```
cols_to_check.append('prediction')
```

```
cols_to_check
```

Out[27]:
```
['Transaction_Id',
 'timestamp',
 'User',
 'Card',
 'Year',
 'Month',
 'Day',
 'Time',
 'Use Chip',
 'Merchant Name',
 'Merchant City',
 'Merchant State',
 'Zip',
 'MCC',
 'Is Fraud?',
 'Correct Amount',
 'Hour',
 'Min',
 'prediction']
```

In [28]:
```
# Just in case we want to start a table containing results but from scratch

spark.sql("drop table if exists cardtransactionstable")
```

Out[28]:
```
DataFrame[]
```

In [29]:
```
# In case we want to store in an in-memory table (the sink).
# The query name will be the table name

# After executing the code, the streaming computation will start in the background

query_1 = ( prediction_stream
                        .select(cols_to_check)
                        .writeStream
                        .queryName("cardtransactionstable")
                        .outputMode("append")  # append, update
                        .format("memory")
```

```
                        .start()
                   )
```

```
24/04/09 14:02:41 WARN ResolveWriteToStream: Temporary checkpoint location created which is deleted normally when
24/04/09 14:02:41 WARN ResolveWriteToStream: spark.sql.adaptive.enabled is not supported in streaming DataFrames/D
```

In [30]:
```
# Setup an aggregation by day concerning the number of frauds detected
#
# We leave this as exercise

# fraud_count = ...

# query_2 = ...
```

In [31]:
```
# Some extra checks

spark.streams.active[0].isActive
```

Out[31]:
```
True
```

In [32]:
```
query_1.status
```

Out[32]:
```
{'message': 'Initializing sources',
 'isDataAvailable': False,
 'isTriggerActive': False}
```

In [33]:
```
query_1.lastProgress
```

Exploring results

In [34]:
```
# Figure out the tables we hold

spark.sql("show tables").show(truncate=False)
```

```
+---------+---------------------+-----------+
|namespace|tableName            |isTemporary|
+---------+---------------------+-----------+
|         |cardtransactionstable|true       |
+---------+---------------------+-----------+
```

In [40]:
```python
# Interactively query in-memory table

spark.sql("select * from cardtransactionstable").show(truncate=False)
```

```
[Stage 37:>                 (0 + 8) / 9][Stage 39:>                 (0 + 0) / 1]
+--------------+-----------------------+----+----+----+-----+---+--------------------+------------------+-----------
|Transaction_Id|timestamp              |User|Card|Year|Month|Day|Time                |Use Chip          |Merchant Na
+--------------+-----------------------+----+----+----+-----+---+--------------------+------------------+-----------
|0             |2024-04-09 14:02:42.115|0   |0   |2002|9    |1  |2023-05-02 06:21:00|Swipe Transaction|35272132461
|2             |2024-04-09 14:02:44.115|0   |0   |2002|9    |2  |2023-05-02 06:22:00|Swipe Transaction|-7276120921
|4             |2024-04-09 14:02:46.115|0   |0   |2002|9    |3  |2023-05-02 06:23:00|Swipe Transaction|58172184461
|5             |2024-04-09 14:02:47.115|0   |0   |2002|9    |3  |2023-05-02 13:53:00|Swipe Transaction|-714667074£
|8             |2024-04-09 14:02:50.115|0   |0   |2002|9    |5  |2023-05-02 06:14:00|Swipe Transaction|-7276120921
|3             |2024-04-09 14:02:45.115|0   |0   |2002|9    |2  |2023-05-02 17:45:00|Swipe Transaction|34145274595
|6             |2024-04-09 14:02:48.115|0   |0   |2002|9    |4  |2023-05-02 05:51:00|Swipe Transaction|-7276120921
|7             |2024-04-09 14:02:49.115|0   |0   |2002|9    |4  |2023-05-02 06:09:00|Swipe Transaction|-7276120921
|1             |2024-04-09 14:02:43.115|0   |0   |2002|9    |1  |2023-05-02 06:42:00|Swipe Transaction|-7276120921
|9             |2024-04-09 14:02:51.115|0   |0   |2002|9    |5  |2023-05-02 09:35:00|Swipe Transaction|40552570784
|10            |2024-04-09 14:02:52.115|0   |0   |2002|9    |5  |2023-05-02 20:18:00|Swipe Transaction|-4500542936
+--------------+-----------------------+----+----+----+-----+---+--------------------+------------------+-----------
```

```
24/04/09 14:03:17 WARN DAGScheduler: Broadcasting large task binary with size 1498.6 KiB
[Stage 38:>                                                          (0 + 6) / 6]
```

In [41]:
```python
# Interactively another query in-memory table

spark.sql("select count(*) from cardtransactionstable").show()
```

```
+--------+
|count(1)|
+--------+
|      11|
+--------+
```

```
[Stage 45:>                 (0 + 8) / 9][Stage 46:>                 (0 + 0) / 8]
```

Visual analysis ... we leave it as an exercise!

Stopping the process

In [ ]:
```
# We can turn off the query now and eventually set up a different one

query_1.stop()
```

In [38]:
```
# Notice that in a production environment, we have to establish
# that the query is awaiting termination so to prevent the driver
# process from termination when the stream is ative

# query_1.awaitTermination()

# query_2.awaitTermination()
```

```
[Stage 30:====================================================>      (8 + 1) / 9]
```

Additional exercise

Once this exercise is completed, create a new notebook with similar implementation but using a different streaming setup. Specifically, relying also in the messaging system Apache Kafka.

References

- Learning Spark - Lightning-Fast Data Analytics, 2nd Ed. J. Damji, B. Wenig, T. Das, and D. Lee. O'Reilly, 2020
- Stream Processing with Apache Spark. G. Maas and F. Garillot. O'Reilly, 2019

In [ ]: