Basic introduction to PySpark

BUILDING DATA ENGINEERING PIPELINES IN PYTHON



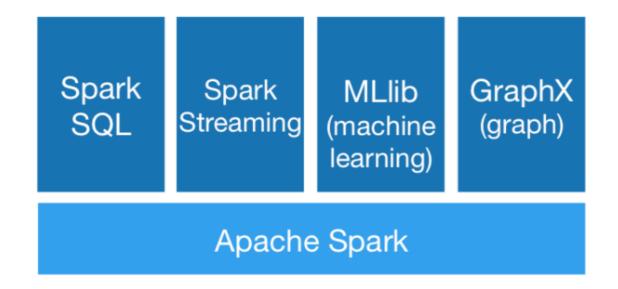
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What is Spark?

- A fast and general engine for large-scale data processing
- 4 libraries built on top of Spark core:



- API in several languages
 - Java, Scala, Python ("PySpark"), R

When to use Spark

Spark is used for:

- Data processing at scale
- Interactive analytics
- Machine learning

Spark is **not** used for:

- When you have only little data
- When you have only simple operations

Business case: finding the perfect diaper

Find the perfect diaper based on:

- qualitative attributes e.g. comfort
- quantitative attributes e.g. price

Scraped data available:

- prices.csv. pricing details per model per store
- ratings.csv. user ratings per model

Starting the Spark analytics engine

```
from pyspark.sql import SparkSession
```

```
spark = SparkSession.builder.getOrCreate()
```



Reading a CSV file

```
prices = spark.read.csv("mnt/data_lake/landing/prices.csv")
prices.show()
```

Reading a CSV file with headers

```
prices = spark.read.options(header="true").csv("mnt/data_lake/landing/prices.csv")
prices.show()
```

Automatically inferred data types

```
from pprint import pprint
pprint(prices.dtypes)
```

```
[('store', 'string'),
  ('countrycode', 'string'),
  ('brand', 'string'),
  ('price', 'string'),
  ('currency', 'string'),
  ('quantity', 'string'),
  ('date', 'string')]
```

Enforcing a schema

```
[('store', 'string'), ('countrycode', 'string'), ('brand', 'string'),
('price', 'float'), ('currency', 'string'), ('quantity', 'int'), ('date', 'date')]
```

Let's practice!

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Cleaning data

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Reasons to clean data

Most data sources are not ready for analytics. This could be due to:

- Incorrect data types
- Invalid rows
- Incomplete rows
- Badly chosen placeholders

Can we automate data cleaning?

Data cleaning depends on the context

- Can our system cope with data that is 95% clean and 95% complete?
- What are the implicit standards in the company?
 - regional datetimes vs. UTC
 - column naming conventions
 - 0 ...
- What are the low-level details of the systems?
 - representation of unknown / incomplete data
 - ranges for numerical values
 - meaning of fields



Selecting data types

Data type	Value type in Python
ByteType	Good for numbers that are within the range of -128 to 127.
ShortType	Good for numbers that are within the range of -32768 to 32767.
IntegerType	Good for numbers that are within the range of-2147483648 to 2147483647.
FloatType	float
StringType	string
BooleanType	bool
DateType	datetime.date



Badly formatted source data

cat bad_data.csv # prints the entire file on stdout

```
store, countrycode, brand, price, currency, quantity, date Aldi, BE, Diapers-R-Us, 6.8, EUR, 40, 2019-02-03
```

Kruidvat, NL, Nappy-k, 5.6, EUR, 40, 2019-02-15

DM, AT, Huggies, 7.2, EUR, 40, 2019-02-01



Spark's default handling of bad source data

```
prices = spark.read.options(header="true").csv('landing/prices.csv')
prices.show()
```

Handle invalid rows

```
+----+
| store|countrycode| brand|price|currency|quantity| date|
+----+
| Aldi| BE|Diapers-R-Us| 6.8| EUR| 40|2019-02-03|
|Kruidvat| NL| Nappy-k| 5.6| EUR| 40|2019-02-15|
| DM| AT| Huggies| 7.2| EUR| 40|2019-02-01|
+----+
```

The significance of null

```
+-----+
| store|countrycode| brand|price|currency|quantity| date|
+-----+
| Aldi| BE|Diapers-R-Us| 6.8| EUR| 40|2019-02-03|
|Kruidvat| null| Nappy-k| 5.6| EUR| null|2019-02-15|
+-----+
```

Supplying default values for missing data

```
prices.fillna(25, subset=['quantity']).show()
```

```
+----+
| store|countrycode| brand|price|currency|quantity| date|
+----+
| Aldi| BE|Diapers-R-Us| 6.8| EUR| 40|2019-02-03|
|Kruidvat| null| Nappy-k| 5.6| EUR| 25|2019-02-15|
+----+
```

Badly chosen placeholders

Example: contracts of employees

```
employees = spark.read.options(header="true").schema(schema).csv('employees.csv')
```

Conditionally replace values

```
from pyspark.sql.functions import col, when
from datetime import date, timedelta
one_year_from_now = date.today().replace(year=date.today().year + 1)
better_frame = employees.withColumn("end_date",
    when(col("end_date") > one_year_from_now, None).otherwise(col("end_date")))
better_frame.show()
```

Let's practice!

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Transforming data with Spark

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Why do we need to transform data?

Process:

- 1. Collect data
- 2. "Massage" data: involves cleaning and business logic
- 3. Derive insights

Example:

- 1. Collect data from booking.com and hotels.com.
- 2. Standardize hotel names, normalizing review scores.
- 3. Join datasets, filter on location and rank results.

1. Filtering rows

European purchases?

```
country | purchase_order
_____|____Ukraine | 32498562223
```

- 1. Filtering rows
- 2. Selecting and renaming columns

```
country | purchase_order | store_keep
_____|
Ukraine | 32498562223 | Oksana D.
Spain | 74398221190 | Pedro R.
```

->

```
country_of_purchase | purchase_order
______|
Ukraine | 32498562223
Spain | 74398221190
```

- 1. Filtering rows
- 2. Selecting and renaming columns
- 3. Grouping and aggregation

- 1. Filtering rows
- 2. Selecting and renaming columns
- 3. Grouping and aggregation
- 4. Joining multiple datasets

country purchase_order pr	ice	purchase_order	category
			food electronics
Spain 49876776100 \$20	6	74398221190	clothing

- 1. Filtering rows
- 2. Selecting and renaming columns
- 3. Grouping and aggregation
- 4. Joining multiple datasets
- 5. Ordering results

country purchase_orde	r price	country	purchase_order	price
			.	_
Spain 74398221190	\$26 =	=> Ukraine	32498562223	\$12
Ukraine 32498562223	\$12	Spain	74398221190	\$26
Spain 49876776100	\$54	Spain	49876776100	\$54

Recall the prices dataset

```
prices = spark.read.options(header="true").schema(schema).csv('landing/prices.csv')
```

Filtering and ordering rows

```
prices_in_belgium = prices.filter(col('countrycode') == 'BE').orderBy(col('date'))
```

```
| store|countrycode| brand|price|currency|quantity| date|
+-----+
|Kruidvat| BE| Nappy-k| 4.8| EUR| 30|2019-01-28|
| Aldi| BE|Diapers-R-Us| 6.8| EUR| 40|2019-02-03|
+-----+
```

- Function col creates Column objects
- Method orderBy sorts values by a certain column.

Selecting and renaming columns

```
prices.select(
)
```

Selecting and renaming columns

```
prices.select(
    col("store"),
    col("brand")
)
```

Selecting and renaming columns

```
prices.select(
    col("store"),
    col("brand").alias("brandname")
)
```

```
store brandname
    Aldi|Diapers-R-Us|
| Kruidvat|
              Nappy-k
|Carrefour|
              Nappy-k
| Kruidvat|
              Nappy-k
              Pampers |
    Tesco
       DM
              Huggies |
              Huggies |
       DM
```

Reducing duplicate values

```
prices.select(
    col("store"),
    col("brand").alias("brandname")
).distinct()
```

```
store brandname
      DM |
             Huggies
| Kruidvat|
             Nappy-k
|Carrefour|
             Nappy-k
    Aldi|Diapers-R-Us|
   Tesco
            Pampers
```

Grouping and aggregating with mean()

```
(prices
    .groupBy(col('brand'))
    .mean('price')
).show()
```

```
+-----+
| brand| avg(price)|
+-----+
|Diapers-R-Us| 6.800000190734863|
| Pampers| 6.300000190734863|
| Huggies| 7.0|
| Nappy-k|5.3666666348775225|
+-----+
```

Grouping and aggregating with agg()

```
(prices
    .groupBy(col('brand'))
    .agg(
        avg('price').alias('average_price'),
        count('brand').alias('number_of_items')
        )
).show()
```



Joining related data

```
store|countrycode| brand| model|price|currency|quantity|
                                            EUR| 40|2019-02-03|
    Aldil
               BE|Diapers-R-Us|6months| 6.8|
Kruidvat|
              BE
                      Nappy-k|2months| 4.8|
                                            EUR | 30 | 2019 - 01 - 28 |
|Carrefour| FR| Nappy-k|2months| 5.7|
                                            EUR| 30|2019-02-06|
                      Pampers | 3months | 6.3 |
                                            EUR| 35|2019-02-07|
   Tesco| IRL|
                      Huggies|newborn| 6.8|
                                            EUR | 40 | 2019 - 02 - 01 |
      brand| model|absorption_rate|comfort|
  ------
|Diapers-R-Us|6months|
    Nappy-k|2months|
    Pampers | 3months |
    Huggies|newborn|
```

Executing a join with 2 foreign keys

```
ratings_with_prices = ratings.join(prices, ["brand", "model"])
```

```
brand| model|absorption_rate|comfort| store|countrycode|price|currency|quantity|
   2| 3| Aldi|
|Diapers-R-Us|6months|
                                                           40 | 2019 - 02 -
                                           BEI 6.81
                                                     EUR
                       3| 4| Kruidvat|
   Nappy-k|2months|
                                           BE| 4.8|
                                                     EUR
                                                            30 | 2019 - 01 -
                       3 4 Carrefour FR 5.7
   Nappy-k|2months|
                                                     EUR |
                                                            30 | 2019 - 02 -
                       4| 4| Tesco| IRL| 6.3|
   Pampers | 3months |
                                                     EUR
                                                            35 | 2019 - 02 -
   Huggies|newborn|
                             5| DM| DE| 6.8|
                                                     EUR
                                                           40 | 2019 - 02 -
```

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Packaging your application

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Running your pipeline locally

Running a Python program:

```
python hello_world.py # script does something
```

Running a PySpark program *locally* is no different:

```
python my_pyspark_data_pipeline.py # script starts at least a SparkSession
```

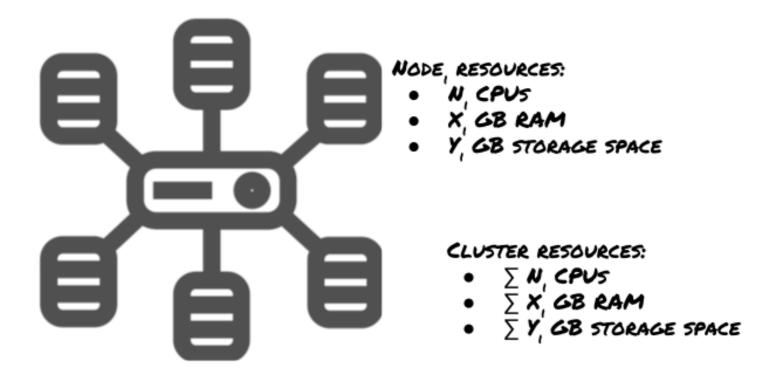
Conditions:

- local installation of Spark
- access to referenced resources
- classpath is properly configured

Using the "spark-submit" helper program

spark-submit comes with any Spark installation

- sets up launch environment for use with the cluster manager and the selected deploy mode
- 2. invokes main class/app/module/function



CLUSTER MANAGER:
"THESE ARE THE AVAILABLE RESOURCES.
WHO NEEDS SOMETHING?"

Basic arguments of "spark-submit"

```
spark-submit \
  --master "local[*]" \
  --py-files PY_FILES \
  MAIN_PYTHON_FILE \
  app_arguments
```

On your path, if Spark is installed URL of the cluster manager Comma-separated list of zip, egg or py Path to the module to be run Optional arguments parsed by main script

Collecting all dependencies in one archive

```
zip \
  --recurse-paths \
  dependencies.zip \
  pydiaper
```

```
spark-submit \
  --py-files dependencies.zip \
  pydiaper/cleaning/clean_prices.py
```

Let's practice!

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