`pyspark`: pandas-on-Spark

Justin Post

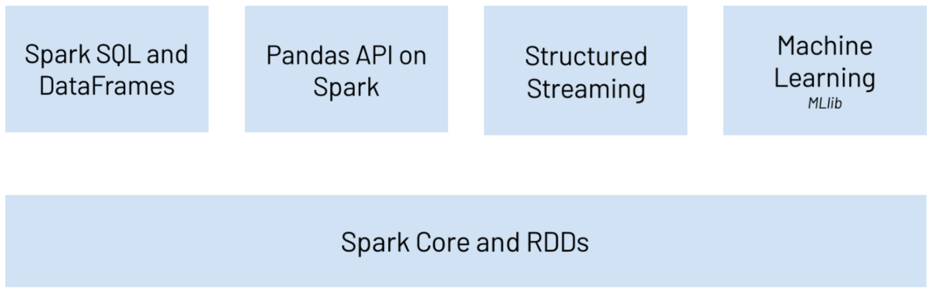
Spark Recap

Spark - Distributed processing software for big data workloads

- Generally faster than Hadoop's MapReduce (and much more flexible)
- DAGs make it fault tolerant and improve computational speed

Five major parts to (py)Spark

- Spark Core and RDDs as its foundation
- Spark SQL and DataFrames
- Pandas on Spark
- Spark Structured Streaming
- Spark Machine Learning (MLlib)



Data Object Used by pyspark

DataFrame APIs are commonly used in `pyspark`

- DataFrames (think usual relational database table) are created and implemented on top of RDDs
- DataFrames are stored across the cluster
    - When transformations are done, lazy evaluation is used
    - When actions are done, computation starts and results returned

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Two major DataFrame APIs in `pyspark`

- `pandas`-on-Spark DataFrames through the `pyspark.pandas` module
- Spark SQL DataFrames through `pyspark.sql` module

pandas-on-Spark

- `pandas` API on spark is super easy to use since we know `pandas`!
- First we can import our modules

```
import pandas as pd
import numpy as np
import pyspark.pandas as ps
```

pandas-on-Spark

- Now you can create a `pandas-on-Spark` series or a `pandas-on-Spark` DataFrame
- Note the `ps` not `pd`!

```
ps.Series([1, 3, 5, np.nan, 6, 8])
```

```
0    1.0
1    3.0
2    5.0
3    NaN
4    6.0
5    8.0
dtype: float64
```

pandas-on-Spark

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- Note the `ps` not `pd`!

```
ps.DataFrame(
    {'a': [1, 2, 3, 4, 5, 6],
     'b': [100, 200, 300, 400, 500, 600],
     'c': ["one", "two", "three", "four", "five", "six"]},
    index=[10, 20, 30, 40, 50, 60])
```

	a	b	c
10	1	100	one
20	2	200	two
30	3	300	three
40	4	400	four
50	5	500	five
60	6	600	six

pandas-on-Spark

- We can also convert from pandas to pandas-on-Spark

```
pdf = pd.read_csv("https://www4.stat.ncsu.edu/~online/datasets/red-wine.csv", delimiter = ";")
psdf = ps.from_pandas(pdf)
psdf.head()
```

	fixed acidity	volatile acidity	citric acid	residual sugar	chlorides	free sulfur dioxide	total sulfur dioxide	density	pH	sulphates	alcohol	quality
0	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5
1	7.8	0.88	0.00	2.6	0.098	25.0	67.0	0.9968	3.20	0.68	9.8	5
2	7.8	0.76	0.04	2.3	0.092	15.0	54.0	0.9970	3.26	0.65	9.8	5
3	11.2	0.28	0.56	1.9	0.075	17.0	60.0	0.9980	3.16	0.58	9.8	6
4	7.4	0.70	0.00	1.9	0.076	11.0	34.0	0.9978	3.51	0.56	9.4	5

pandas-on-Spark

- We now have a much of the same functionality from `pandas` available through `pandas-on-Spark` (API reference guide)
    - `.index`, `.columns`, `.shape`, `.info`
    - `.head()`, `tail()`
    - `[["column1", "column2"]]`, `.loc[]`
    - `.mean()`, `.sum()`, `.groupby()`, `.describe()`, `.value_counts()`

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```
psdf.loc[psdf.quality > 5, ["alcohol", "quality"]].head()
```

	alcohol	quality
3	9.8	6
7	10.0	7
8	9.5	7
16	10.5	7
19	9.2	6

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```
titanic_ps = ps.read_csv("titanic.csv") #data uploaded to jhub in data folder
titanic_ps["survived"].value_counts()
```

```
0.0    809
1.0    500
Name: survived, dtype: int64
```

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```
titanic_ps.groupby("survived").mean()
```

survived	pclass	age	sibsp	parch	fare	body
1	1.962000	28.918228	0.462000	0.476000	49.361184	NaN
0	2.500618	30.545369	0.521632	0.328801	23.353831	160.809917

pandas-on-Spark

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```
titanic_ps.describe()
```

	pclass	survived	age	sibsp	parch	fare	body
count	1309.000000	1309.000000	1046.000000	1309.000000	1309.000000	1308.000000	121.000000
mean	2.294882	0.381971	29.881135	0.498854	0.385027	33.295479	160.809917
std	0.837836	0.486055	14.413500	1.041658	0.865560	51.758668	97.696922
min	1.000000	0.000000	0.166700	0.000000	0.000000	0.000000	1.000000
25%	2.000000	0.000000	21.000000	0.000000	0.000000	7.895800	72.000000
50%	3.000000	0.000000	28.000000	0.000000	0.000000	14.454200	155.000000
75%	3.000000	1.000000	39.000000	1.000000	0.000000	31.275000	256.000000
max	3.000000	1.000000	80.000000	8.000000	9.000000	512.329200	328.000000

]

pandas-on-Spark

- `.transform()` and `.apply()` methods allow you to perform operations on columns or rows

```
def standardize(pser) -> ps.Series[np.float64]:
    return (pser + pser.mean())/pser.std()  # should always return the same length as input.
```

pandas-on-Spark

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```
def standardize(pser) -> ps.Series[np.float64]:
     return (pser + pser.mean())/pser.std()  # should always return the same length as input.

std_res = titanic_ps[["age", "fare"]] \
    .rename(columns = {"age": "o_age", "fare": "o_fare"}) \
    .join(titanic_ps[["age", "fare"]]
              .transform(standardize))
```

	o_age	o_fare	age	fare
0	29.0000	211.3375	4.085138	4.726416
1	0.9167	151.5500	2.136735	3.571295
2	2.0000	151.5500	2.211894	3.571295
3	30.0000	151.5500	4.154517	3.571295
4	25.0000	151.5500	3.807620	3.571295

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    .rename(columns = {"age": "o_age", "fare": "o_fare"}) \
    .join(titanic_ps[["age", "fare"]]
              .transform(standardize))
std_res.shape
```

```
(1310, 4)
```

pandas-on-Spark

- `.transform()` and `.apply()` methods allow you to perform operations on columns or rows

```
def standardize_positives(pser) -> ps.Series[np.float64]:
     return (pser[pser>30] + pser[pser>30].mean())/pser[pser>30].std()
# can return something short than input length
```

pandas-on-Spark

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    return (pser[pser>30] + pser[pser>30].mean())/pser[pser>30].std()
# can return something short than input length

std_pos = titanic_ps[["age"]].apply(standardize_positives)
std_pos.head()
```

	age
0	9.135889
1	10.636052
2	8.235791
3	9.635943
4	11.436139

pandas-on-Spark

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```
def standardize_positives(pser) -> ps.Series[np.float64]:
     return (pser[pser>30] + pser[pser>30].mean())/pser[pser>30].std()
# can return something short than input length

std_pos = titanic_ps[["age"]].apply(standardize_positives)
std_pos.shape
```

```
(437, 1)
```

To Jupyterlab

- Let's more easily handle the counting of words in our Oliver Twist example!

Recap

- **DataFrames** are the type of object (and name of the API) commonly used in `pyspark`
    - DataFrames built on RDDs
- pandas-on-Spark DataFrames through the `pyspark.pandas` module
    - Most of the usual pandas functionality!
- Lazy eval allows you to build up your transformations and then execute only when an action is performed

Important to know **limitations on** pandas **functionality**