

1. Tough to handle semi-structured and structured data





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D	NAME	SALARY
1	Alex	10000
2	Britney	15000
3	Christine	18000



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1	ID	NAME	SALARY	. 0
	1	Alex	10000	TICS
	2	Britney	15000	6160
	3	Christine	18000	

```
dataCSV = sc.textFile("data/Sample.csv")
dataCSV.collect()
```

['ID,NAME,SALARY', '1,Alex,10000', '2,Britney,15000', '3,Christine,18000']



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- Tough to handle semi-structured and structured data
- 2. No in-built optimization





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rdd.filter().join()





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Spark DataFrames



Distributed collection of semi-structured or structured data





Distributed collection of structured data

a. Similar to tables in relational databases and Python/R data frames

Id (Int)	First (String)	Last (String)	Url (String)	Published (Date)	Hits (Int)	Campaigns (List[Strings])
1	Jules	Damji	https:// tinyurl.1	1/4/2016	4535	[twitter, LinkedIn]
2	Brooke	Wenig	https:// tinyurl.2	5/5/2018	8908	[twitter, LinkedIn]
3	Denny	Lee	https:// tinyurl.3	6/7/2019	7659	<pre>[web, twitter, FB, LinkedIn]</pre>
4	Tathagata	Das	https:// tinyurl.4	5/12/2018	10568	[twitter, FB]



Distributed collection of structured data

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Jules	Damji	https:// tinyurl.1	1/4/2016	4535	[twitter, LinkedIn]		
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Tathagata	Das	https:// tinyurl.4	5/12/2018	10568	[twitter, FB]	-	
	(String) Jules Brooke Denny	(String) (String) Jules Damji Brooke Wenig Denny Lee	(String) (String) (String) Jules Damji https://tinyurl.1 Brooke Wenig https://tinyurl.2 Denny Lee https://tinyurl.3 Tathagata Das https://	(String) (String) (Date) Jules Damji https:// tinyurl.1 Brooke Wenig https:// 5/5/2018 tinyurl.2 Denny Lee https:// 6/7/2019 tinyurl.3 Tathagata Das https:// 5/12/2018	(String) (String) (Date) (Int) Jules Damji https:// tinyurl.1 1/4/2016 4535 Brooke Wenig https:// 5/5/2018 8908 tinyurl.2 Denny Lee https:// 6/7/2019 7659 tinyurl.3 Tathagata Das https:// 5/12/2018 10568	First Last Url Published Hits Campaigns (String) (String) (Date) (Int) (List[Strings]) Jules Damji https:// 1/4/2016 4535 [twitter, LinkedIn] tinyurl.1 Brooke Wenig https:// 5/5/2018 8908 [twitter, LinkedIn] tinyurl.2 Denny Lee https:// 6/7/2019 7659 [web, twitter, FB, LinkedIn] Tathagata Das https:// 5/12/2018 10568 [twitter, FB]	<pre>(String) (String) (Date) (Int) (List[Strings]) Jules Damji https:// 1/4/2016 4535 [twitter, LinkedIn] tinyurl.1 Brooke Wenig https:// 5/5/2018 8908 [twitter, LinkedIn] tinyurl.2 Denny Lee https:// 6/7/2019 7659 [web, twitter, FB, LinkedIn] Tathagata Das https:// 5/12/2018 10568 [twitter, FB]</pre>



- Distributed collection of structured data
- 2. High level operations





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- 2. High level operations
 - a. Aggregating, Filtering, Sorting, etc.





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- 2. High level operations
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 - b. Simpler queries





- Distributed collection of structured data
- 2. High level operations
 - a. Aggregating, Filtering, Sorting, etc.
 - b. Simpler queries
 - c. Optimised





Example

	Name	Score	
	Amanda	20	ticc
	Bella	31	ytics
	Charlie	30	/2
/ 4	David	35	ya
	Amanda	25	



```
from pyspark import SparkContext

# sc object
sc = SparkContext()

# sample rdd
rdd_orig = sc.parallelize([('Amanda', 20),('Bella', 31),('Charlie', 30),('David', 35),('Amanda', 25)])

# update pair rdd like ('Amanda', (20, 1))
rdd_pair = rdd_orig.mapValues(lambda x: (x,1))

# add scores and counts like ('Amanda', (45, 2))
rdd_count = rdd_pair.reduceByKey(lambda a,b: (a[0]+b[0], a[1]+b[1]))

# take average of score
rdd_avg = rdd_count.mapValues(lambda x: x[0]/x[1])

# collect result
rdd_avg.collect()

[('Amanda', 22.5), ('Charlie', 30.0), ('David', 35.0), ('Bella', 31.0)]
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from pyspark.sql import SparkSession
from pyspark.sql.functions import avg
# create sparksession object
spark = SparkSession.builder.getOrCreate()
# create dataframe
df = spark.createDataFrame([('Amanda',20),('Bella',31),('Charlie',30),("David",35),('Amanda',25)],
                        ["name", "score"])
# compute average
df_avg = df.groupBy("name").agg(avg("score"))
# display average
df_avg.show()
+----+
   name avg(score)
              22.5
 Amanda
Charlie
              30.0
  David
              35.0
  Bella
              31.0
+----+
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- Distributed collection of structured data
- 2. High level operations
- 3. Support for multiple formats and sources





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< XML /> { JSON }





more...





