Spark & sparklyr part I

Programming for Statistical Science

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Supplementary materials

Full video lecture available in Zoom Cloud Recordings

Additional resources

- `sparklyr`: R interface for Apache Spark
- R Front End for Apache Spark
- Mastering Spark with R

Installing Spark

Install and load `sparklyr`.

```
install.packages("sparklyr")
```

```
library(sparklyr)
library(tidyverse)
packageVersion("sparklyr")
```

```
#> [1] '1.4.0'
```

Check the available versions of Spark to install.

```
spark_available_versions()
```

```
#>   spark
#> 1   1.6
#> 2   2.0
#> 3   2.1
#> 4   2.2
#> 5   2.3
#> 6   2.4
#> 7   3.0
```

Installing Spark

Install version 3.0 with

```
spark_install("3.0")
```

Do this on your home directory on the server or on your own machine. Once installed, you should see a directory `spark/` in your home directory.

Overview

Timeline

- The amount of digital information surpasses analog information around 2003. Managing this data at scale becomes a real and present problem.
- Google presents a research paper in 2003 on the Google File System - this system allowed them to split information into several files and store them across multiple machines.
- In 2004 Google publishes a paper describing how to processes on the Google File System, this approach came to be known as *MapReduce*.
- Shortly after Google's above publications, Yahoo begins work on an open source version of the Google File System and *MapReduce* algorithm.
- In 2006 Yahoo releases Hadoop and the Haddop Distributed File System (HDFS). Hadoop provides distributed storage (through the HDFS) and parallel processing of data (through a *MapReduce* algorithm) managed by a job scheduler and cluster manager (YARN).
- Facebook releases the Hive project in 2008 as way to bring SQL support to Hadoop. This alleviated the need of *MapReduce* operations to be written with JAVA code.

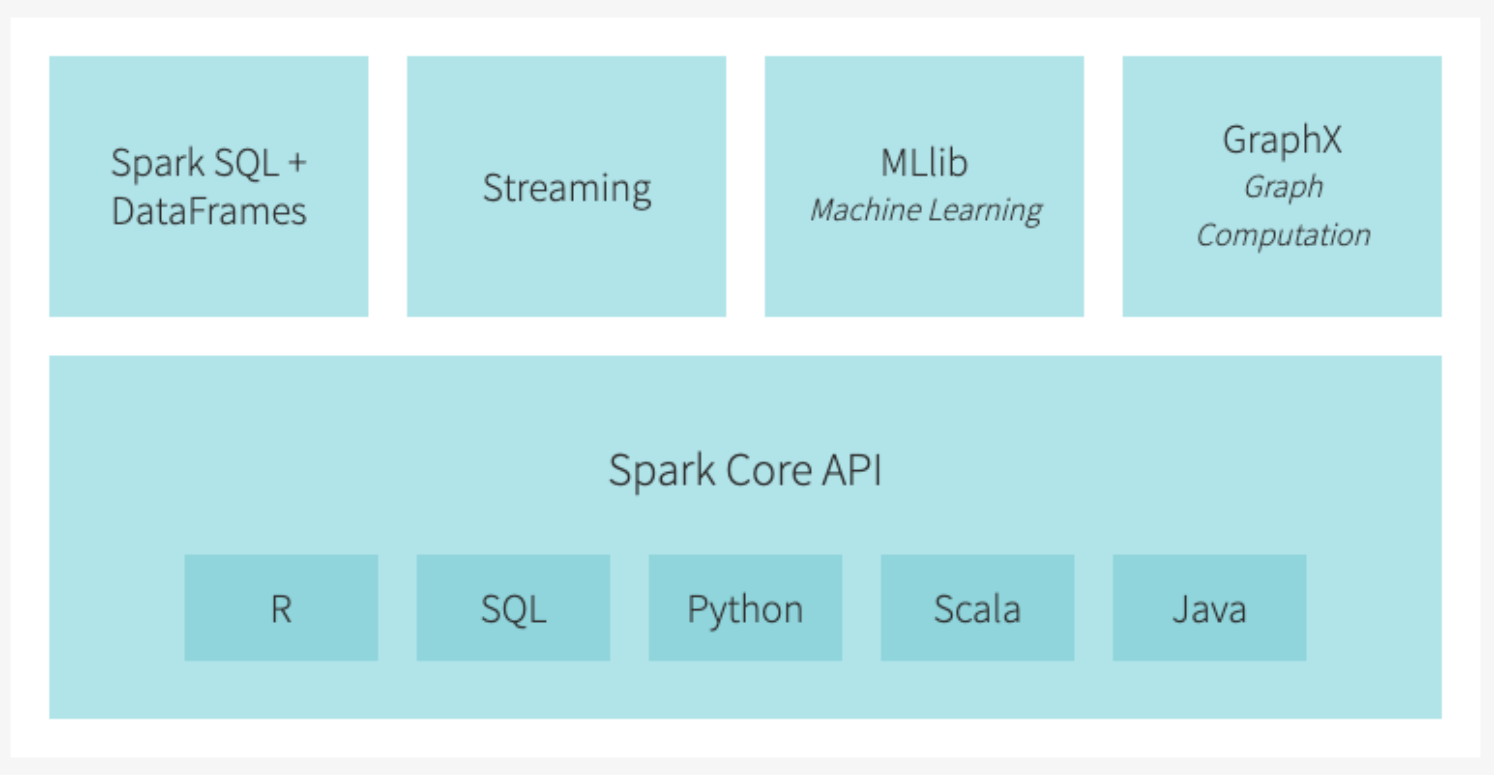
Timeline (continued)

- In 2009 Apache Spark begins as a research project at UC Berkeley. Its goal is to improve on *MapReduce*, and facilitate and optimize code to be run on multiple machines.
- Shortly after, Spark supports loading data in-memory, making it much faster than Hadoop's on-disk storage.
- In 2010, Spark was released as an open source project and then donated to the Apache Software Foundation in 2013. Spark is licensed under Apache 2.0, which allows you to freely use, modify, and distribute it.
- In 2013 and 2016 Spark sets records for sorting speeds. How much faster is Spark than Hadoop? **It takes 72 minutes and 2,100 computers to sort 100 terabytes of data using Hadoop, but only 23 minutes and 206 computers using Spark.**

What is Apache Spark?

- As described by Databricks, "Spark is a unified computing engine and a set of libraries for parallel data processing on computing clusters".
- Spark's goal is to support data analytics tasks within a single ecosystem: data loading, SQL queries, machine learning, and streaming computations.
- Spark is written in Scala and runs on Java. However, Spark can be used from R, Python, SQL, Scala, or Java.

The Spark ecosystem



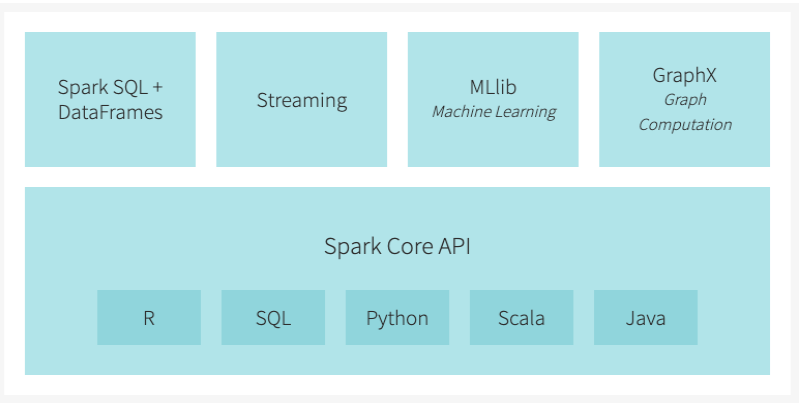
Spark's key features

- In-memory computation
- Fast and scalable
  - Efficiently scale up from one to many thousands of compute nodes
- Access data on a multitude of platforms
  - SQL and NoSQL databses
  - Cloud storage
  - Hadoop Distributed File System
- Real-time stream processing
- Libraries
  - Spark SQL
  - MLlib
  - Spark streaming
  - GraphX

What is `sparklyr`?

Package `sparklyr` provides an R interface for Spark. It works with any version of Spark.

- Use `dplyr` to translate R code into Spark SQL
- Work with Spark's MLlib
- Interact with a stream of data



The interface between R and Spark is young. If you know Scala, a great project would be to contribute to this R and Spark interaction by making Spark libraries available as an R package.

Connecting to Spark

Configure and connect

```
# add some custom configurations
conf <- list(
  sparklyr.cores.local = 4,
  `sparklyr.shell.driver-memory` = "16G",
  spark.memory.fraction = 0.5
)
```

`sparklyr.cores.local` - defaults to using all of the available cores

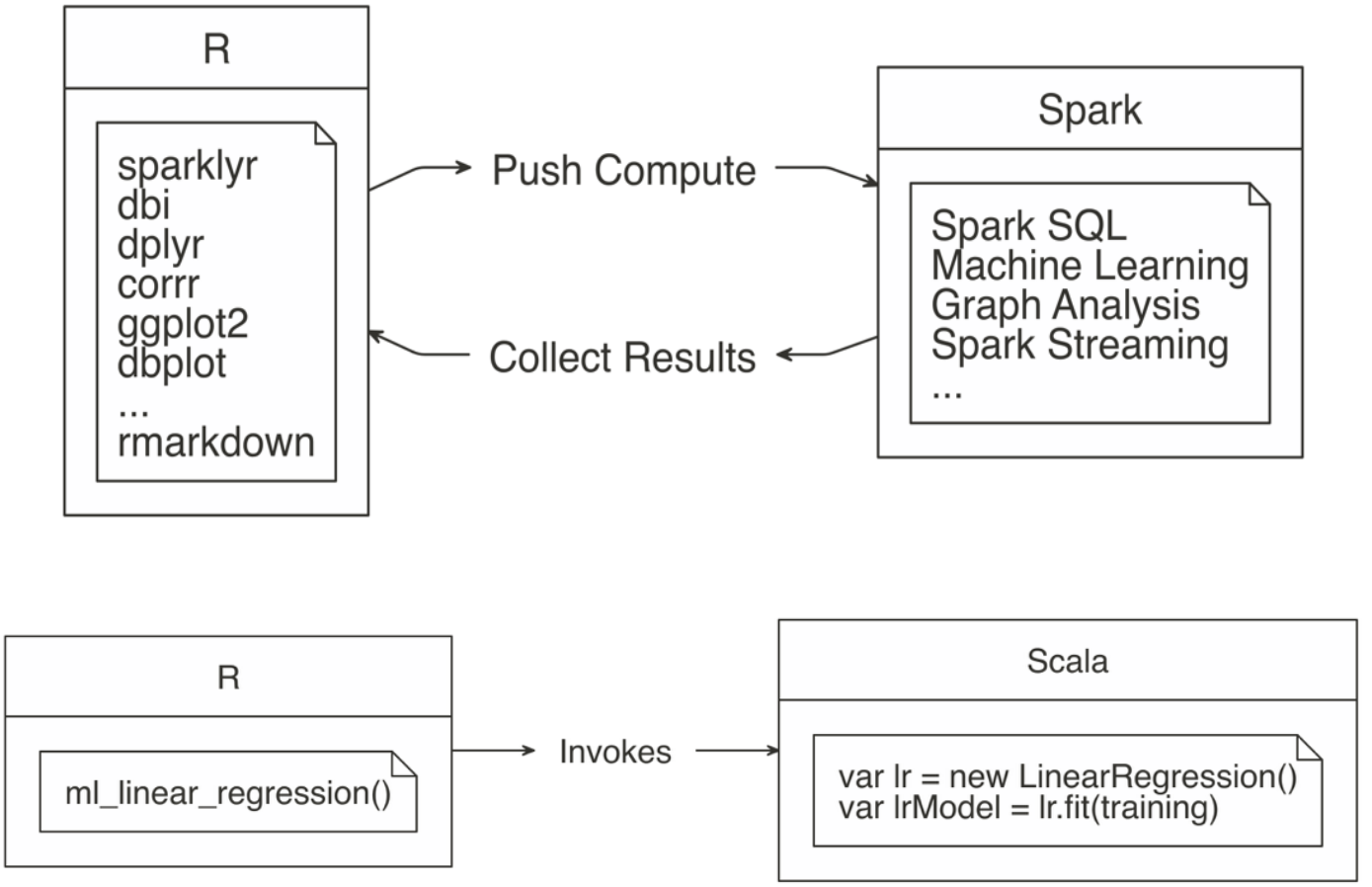
`sparklyr.shell.driver-memory` - limit is the amount of RAM available in the computer minus what would be needed for OS operations

`spark.memory.fraction` - default is set to 60% of the requested memory per executor

```
# create a spark connection
sc <- spark_connect(master = "local", version = "3.0", config = conf)
```

Analysis with `sparklyr`

Overview



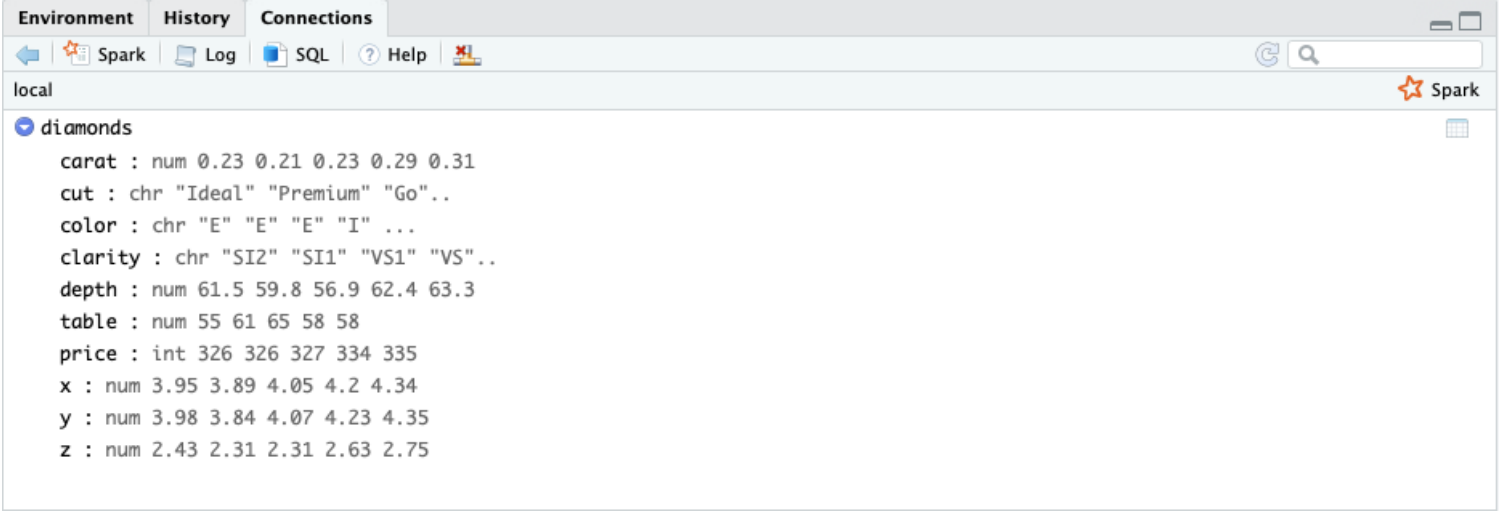
Source: https://therinspark.com/

Adding data that exists in R

Use `dplyr`'s `copy_to()` to add data from R into Spark.

```
diamonds_tbl <- copy_to(sc, diamonds)
```

You should see `diamonds` in your connections tab as a Spark DataFrame. In your environment you should see a list object named `diamonds_tbl`. This is our R reference to `diamonds` in Spark.



Data preview

```
diamonds_tbl
```

```
# Source: spark<diamonds> [?? x 10]
   carat cut       color clarity depth table price     x     y     z
   <dbl> <chr>     <chr> <chr>   <dbl> <dbl> <int> <dbl> <dbl> <dbl>
 1 0.23  Ideal     E     SI2      61.5    55   326  3.95  3.98  2.43
 2 0.21  Premium   E     SI1      59.8    61   326  3.89  3.84  2.31
 3 0.23  Good      E     VS1      56.9    65   327  4.05  4.07  2.31
 4 0.290 Premium   I     VS2      62.4    58   334  4.2   4.23  2.63
 5 0.31  Good      J     SI2      63.3    58   335  4.34  4.35  2.75
 6 0.24  Very Good J     VVS2     62.8    57   336  3.94  3.96  2.48
 7 0.24  Very Good I     VVS1     62.3    57   336  3.95  3.98  2.47
 8 0.26  Very Good H     SI1      61.9    55   337  4.07  4.11  2.53
 9 0.22  Fair      E     VS2      65.1    61   337  3.87  3.78  2.49
10 0.23  Very Good H     VS1      59.4    61   338  4     4.05  2.39
# … with more rows
```

Adding external data

https://www1.nyc.gov/site/tlc/about/tlc-trip-record-data.page

```
taxi_path <- str_c("/home/fac/sms185/.public_html/data/taxi/",
                   "yellow_tripdata_2009-01.csv")

taxi_tbl <- spark_read_csv(sc, name = "yellow_taxi_2009", path = taxi_pat
```

Data can also be read into Spark DataFrames with `spark_read_json()`, `spark_read_parquet()`, and a few other functions for various types of file formats.

Data preview

```
glimpse(taxi_tbl)
```

```
Rows: ??
Columns: 18
Database: spark_connection
$ vendor_name           <chr> "VTS", "VTS", "VTS", "DDS", "DDS", "DDS", "DDS", "V…
$ Trip_Pickup_DateTime  <dttm> 2009-01-04 02:52:00, 2009-01-04 03:31:00, 2009-01-…
$ Trip_Dropoff_DateTime <dttm> 2009-01-04 03:02:00, 2009-01-04 03:38:00, 2009-01-…
$ Passenger_Count       <int> 1, 3, 5, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2, 2, 1, 1, 1, …
$ Trip_Distance         <dbl> 2.63, 4.55, 10.35, 5.00, 0.40, 1.20, 0.40, 1.72, 1.…
$ Start_Lon             <dbl> -73.99196, -73.98210, -74.00259, -73.97427, -74.001…
$ Start_Lat             <dbl> 40.72157, 40.73629, 40.73975, 40.79095, 40.71938, 4…
$ Rate_Code             <chr> "NA", "NA", "NA", "NA", "NA", "NA", "NA", "NA", "NA…
$ store_and_forward     <chr> "NA", "NA", "NA", "NA", "NA", "NA", "NA", "NA", "NA…
$ End_Lon               <dbl> -73.99380, -73.95585, -73.86998, -73.99656, -74.008…
$ End_Lat               <dbl> 40.69592, 40.76803, 40.77023, 40.73185, 40.72035, 4…
$ Payment_Type          <chr> "CASH", "Credit", "Credit", "CREDIT", "CASH", "CASH…
$ Fare_Amt              <dbl> 8.9, 12.1, 23.7, 14.9, 3.7, 6.1, 5.7, 6.1, 8.7, 5.9…
$ surcharge             <dbl> 0.5, 0.5, 0.0, 0.5, 0.0, 0.5, 0.0, 0.5, 0.0, 0.0, 0…
$ mta_tax               <chr> "NA", "NA", "NA", "NA", "NA", "NA", "NA", "NA", "NA…
$ Tip_Amt               <dbl> 0.00, 2.00, 4.74, 3.05, 0.00, 0.00, 1.00, 0.00, 1.3…
$ Tolls_Amt             <dbl> 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, …
$ Total_Amt             <dbl> 9.40, 14.60, 28.44, 18.45, 3.70, 6.60, 6.70, 6.60, …
```

Basic wrangling

```
diamonds_tbl %>%
  group_by(cut) %>%
  summarise(mean_price = mean(price, na.rm = TRUE))
```

```
# Source: spark<?> [?? x 2]
  cut       mean_price
  <chr>          <dbl>
1 Premium        4584.
2 Ideal          3458.
3 Good           3929.
4 Fair           4359.
5 Very Good      3982.
```

The data is not being imported back into R. We can do that with `collect()`.

Basic wrangling

```
diamonds_tbl %>%
  group_by(cut) %>%
  summarise(mean_price = mean(price, na.rm = TRUE)) %>%
  collect()
```

```
# A tibble: 5 x 2
  cut       mean_price
  <chr>          <dbl>
1 Premium        4584.
2 Ideal          3458.
3 Good           3929.
4 Fair           4359.
5 Very Good      3982.
```

What's happening under the hood?

```
diamonds_tbl %>%
  group_by(cut) %>%
  summarise(mean_price = mean(price, na.rm = TRUE)) %>%
  show_query()
```

```
<SQL>
SELECT `cut`, AVG(`price`) AS `mean_price`
FROM `diamonds`
GROUP BY `cut`
```

This is the SQL statement that `sparklyr` and `dplyr` created and sent to Spark. We could write the SQL ourselves, but dplyr is easier.

R limitations

Rather than compute the mean, let's try to compute the 75th percentile.

```
diamonds_tbl %>%
  group_by(cut) %>%
  summarise(q_75 = quantile(price, probs = .75))
```

```
Error: org.apache.spark.sql.catalyst.parser.ParseException:
no viable alternative at input 'GROUP ('(line 1, pos 49)

== SQL ==
SELECT `cut`, PERCENTILE_CONT(0.75) WITHIN GROUP (ORDER BY `price`) AS `q
-------------------------------------------------^^^
FROM `diamonds`
GROUP BY `cut`
```

The problem is that there is no translation for function `quantile()`.

Hive SQL functions

Spark SQL is based on Hive SQL conventions and functions. If `sparklyr` and `dplyr` can't do the translation we need, we can use Hive functions directly in our R code that will ultimately get passed on to Spark SQL. A list of available Hive functions can be found here.

```
diamonds_tbl %>%
  group_by(cut) %>%
  summarise(q_75 = percentile(price, 0.75))
```

```
# Source: spark<?> [?? x 2]
  cut        q_75
  <chr>     <dbl>
1 Premium   6296
2 Ideal     4678.
3 Good      5028
4 Fair      5206.
5 Very Good 5373.
```

Function `percentile()` is not an R function. It's a Hive function!

Show query result

```
diamonds_tbl %>%
  group_by(cut) %>%
  summarise(q_75 = percentile(price, 0.75)) %>%
  show_query()
```

```
<SQL>
SELECT `cut`, percentile(`price`, 0.75) AS `q_75`
FROM `diamonds`
GROUP BY `cut`
```

January 2009 Yellow Cab Analysis

Data recall

```
taxi_tbl
```

```
taxi_tbl
# Source: spark<yellow_taxi_2009> [?? x 18]
   vendor_name Trip_Pickup_DateTi… Trip_Dropoff_DateT… Passenger_Count Tr
   <chr>       <dttm>              <dttm>                        <int>
 1 VTS         2009-01-04 02:52:00 2009-01-04 03:02:00               1
 2 VTS         2009-01-04 03:31:00 2009-01-04 03:38:00               3
 3 VTS         2009-01-03 15:43:00 2009-01-03 15:57:00               5
 4 DDS         2009-01-01 20:52:58 2009-01-01 21:14:00               1
 5 DDS         2009-01-24 16:18:23 2009-01-24 16:24:56               1
 6 DDS         2009-01-16 22:35:59 2009-01-16 22:43:35               2
 7 DDS         2009-01-21 08:55:57 2009-01-21 09:05:42               1
 8 VTS         2009-01-04 04:31:00 2009-01-04 04:36:00               1
 9 CMT         2009-01-05 16:29:02 2009-01-05 16:40:21               1
10 CMT         2009-01-05 18:53:13 2009-01-05 18:57:45               1
# … with more rows, and 12 more variables: Start_Lat <dbl>, Rate_Code <ch
#   store_and_forward <chr>, End_Lon <dbl>, End_Lat <dbl>, Payment_Type <
#   surcharge <dbl>, mta_tax <chr>, Tip_Amt <dbl>, Tolls_Amt <dbl>, Total
```

Clean up the variable names

Try to clean the names up with `janitor::clean_names()`.

```
janitor::clean_names(taxi_tbl)
```

```
Error in clean_names.default(taxi_tbl) :
  clean_names() must be called on a data.frame.
  Consider janitor::make_clean_names() for other
  cases of manipulating vectors of names.
```

What's happening?

```
names(taxi_tbl)
```

```
[1] "src" "ops"
```

Object `taxi_tbl` is a list specifying the connection. What can we do?

Fix names

Function `colnames()` seems to work.

```
colnames(taxi_tbl)
```

```
 [1] "vendor_name"           "Trip_Pickup_DateTime"  "Trip_Dropoff_DateTi
 [5] "Trip_Distance"         "Start_Lon"             "Start_Lat"
 [9] "store_and_forward"     "End_Lon"               "End_Lat"
[13] "Fare_Amt"              "surcharge"             "mta_tax"
[17] "Tolls_Amt"             "Total_Amt"
```

Create a function, `fix_names()`, that provides a more uniform structure given our `taxi_tbl` object

```
fix_names <- function(x) {
  colnames(x) %>%
    tolower() %>%
    stringr::str_remove(pattern = "trip_") %>%
    setNames(x, .)
}
```

Why does `colnames()` work here? See http://spark.apache.org/docs/latest/api/R/index.html.

```
taxi_tbl <- fix_names(taxi_tbl)
```

```
colnames(taxi_tbl)
```

```
 [1] "vendor_name"       "pickup_datetime"   "dropoff_datetime"
 [4] "passenger_count"   "distance"          "start_lon"
 [7] "start_lat"         "rate_code"         "store_and_forward"
[10] "end_lon"           "end_lat"           "payment_type"
[13] "fare_amt"          "surcharge"         "mta_tax"
[16] "tip_amt"           "tolls_amt"         "total_amt"
```

```
taxi_tbl
```

```
# Source: spark<yellow_taxi_2009> [?? x 18]
  vendor_name pickup_datetime     dropoff_datetime    passenger_count di
  <chr>       <dttm>              <dttm>                        <int>
1 VTS         2009-01-04 02:52:00 2009-01-04 03:02:00               1
2 VTS         2009-01-04 03:31:00 2009-01-04 03:38:00               3
3 VTS         2009-01-03 15:43:00 2009-01-03 15:57:00               5
# … with more rows, and 13 more variables: start_lon <dbl>, start_lat <db
#   rate_code <chr>, store_and_forward <chr>, end_lon <dbl>, end_lat <dbl
#   payment_type <chr>, fare_amt <dbl>, surcharge <dbl>, mta_tax <chr>,
#   tip_amt <dbl>, tolls_amt <dbl>, total_amt <dbl>
```

Fix payment_type

```
taxi_tbl %>%
  group_by(payment_type) %>%
  summarise(count = n())
```

```
# Source: spark<?> [?? x 2]
  payment_type   count
  <chr>          <dbl>
1 No Charge      40118
2 CASH         6024471
3 Credit       2865982
4 Cash         4995101
5 Dispute         8050
6 CREDIT        158691
```

```
taxi_tbl %>%
  mutate(payment_type = tolower(payment_type)) %>%
  show_query()
```

```
<SQL>
SELECT `vendor_name`, `pickup_datetime`, `dropoff_datetime`, `passenger_count`,
`distance`, `start_lon`, `start_lat`, `rate_code`, `store_and_forward`,
`end_lon`, `end_lat`, LOWER(`payment_type`) AS `payment_type`, `fare_amt`,
`surcharge`, `mta_tax`, `tip_amt`, `tolls_amt`, `total_amt`
FROM `yellow_taxi_2009`
```

Transform all payment types to lower case.

```
taxi_tbl <- taxi_tbl %>%
  mutate(payment_type = tolower(payment_type))
```

Bring everything back to R with `collect()` and check our result.

```
taxi_tbl %>%
  group_by(payment_type) %>%
  summarise(count = n()) %>%
  collect()
```

```
# A tibble: 4 x 2
  payment_type    count
  <chr>           <dbl>
1 cash         11019572
2 no charge       40118
3 dispute          8050
4 credit        3024673
```

Summary analysis

Let's compute some summary information about taxi trips.

```
taxi_tbl %>%
  select(passenger_count, distance, tip_amt, fare_amt, total_amt) %>%
  mutate(
    cost_per_passenger = passenger_count / total_amt,
    tip_pct            = tip_amt / fare_amt,
    cost_per_mile      = fare_amt / distance
  )
```

```
# Source: spark<?> [?? x 8]
   passenger_count distance tip_amt fare_amt total_amt
             <int>    <dbl>   <dbl>    <dbl>     <dbl>
 1               1     2.63    0         8.9       9.4
 2               3     4.55    2        12.1      14.6
 3               5    10.4     4.74     23.7      28.4
 4               1     5       3.05     14.9      18.4
 5               1     0.4     0         3.7       3.7
# … with more rows, and 3 more variables: cost_per_passenger <dbl>,
#   tip_pct <dbl>, cost_per_mile <dbl>
```

What query is being made with regards to Spark?

```
taxi_tbl %>%
  select(passenger_count, distance, tip_amt, fare_amt, total_amt) %>%
  mutate(
    cost_per_passenger = passenger_count / total_amt,
    tip_pct            = tip_amt / fare_amt,
    cost_per_mile      = fare_amt / distance
  ) %>%
  show_query()
```

```
<SQL>
SELECT `passenger_count`, `distance`, `tip_amt`, `fare_amt`,
`total_amt`,
`passenger_count` / `total_amt` AS `cost_per_passenger`,
`tip_amt` / `fare_amt` AS `tip_pct`,
`fare_amt` / `distance` AS `cost_per_mile`
FROM `yellow_taxi_2009`
```

Next, let's parse `pickup_datetime` to get the hour, day (as a name), month (as a name). We'll also include the tip percentage and fare cost per mile. Lastly we'll compute some summary measures.

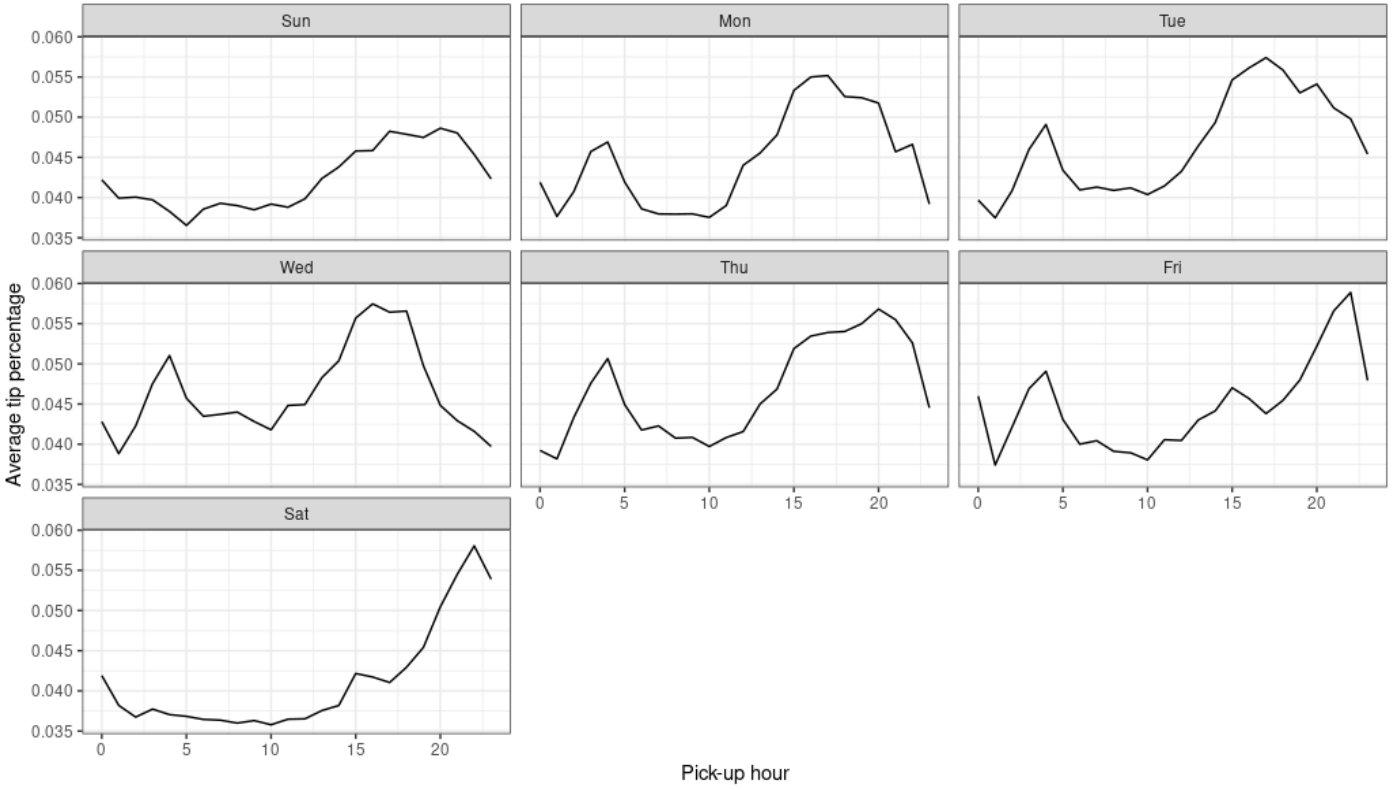
```
taxi_tbl_summary <- taxi_tbl %>%
  select(pickup_datetime, dropoff_datetime, distance,
         fare_amt, tip_amt, total_amt) %>%
  mutate(
    pickup_day    = date_format(pickup_datetime, "EEE"),
    pickup_hour   = hour(pickup_datetime)),
    tip_pct       = tip_amt / fare_amt,
    fare_per_mile = fare_amt / distance
  ) %>%
  group_by(pickup_hour, pickup_day) %>%
  summarise(
    avg_dist          = mean(distance),
    avg_fare          = mean(fare_amt),
    avg_tip_pct       = mean(tip_pct),
    avg_fare_per_mile = mean(fare_per_mile)
  ) %>%
  collect()
```

```
taxi_tbl_summary
```

```
# A tibble: 168 x 6
   pickup_hour pickup_day avg_dist avg_fare avg_tip_pct avg_fare_per_mile
         <int> <chr>          <dbl>    <dbl>       <dbl>              <dbl>
 1           1 Thu             3.08    10.5       0.0448               5.33
 2           7 Sun             3.68    11.6       0.0401               5.32
 3           8 Sat             2.82     9.37      0.0377               5.00
 4           6 Tue             2.85     9.33      0.0375               5.29
 5          11 Fri             2.33     9.23      0.0400               6.25
 6           0 Wed             3.16    10.4       0.0530               5.38
 7           6 Mon             3.12     9.95      0.0377               5.16
 8          17 Mon             2.41     9.36      0.0440               5.91
 9          16 Thu             2.34     9.85      0.0408              13.0
10          10 Wed             2.13     8.98      0.0457               6.49
# … with 158 more rows
```

We can now use `taxi_tbl_summary` just as we would any other object in R.

```
taxi_tbl_summary %>%
  ggplot(aes(x = pickup_hour, y = avg_tip_pct)) +
  geom_line() +
  facet_wrap(~factor(pickup_day, levels = c("Sun", "Mon", "Tue", "Wed",
                                            "Thu", "Fri", "Sat"))) +
  labs(x = "Pick-up hour", y = "Average tip percentage") +
  theme_bw()
```



Other useful functions

- Perform joins with the `*_join()` family of functions.
- Sampling can be done with `sample_n()` and `sample_frac()`.
- Write the results of your analysis into persistent storage with `spark_write_parquet()`, `spark_write_csv()`, or `spark_write_json()`.

Family of `sparklyr` functions

Sparklyr family of functions	Description
`spark_*()`	functions to manage and configure spark connections; functions to read and write data
`sdf_*()`	functions for manipulating SparkDataFrames
`ft_*()`	feature transformers for manipulating individual features
`ml_*()`	machine learning algorithms - K-Means, GLM, Survival Regression, PCA, Naive-Bayes, and more
`stream_*()`	functions for handling stream data

Exercise

Plot the pick-up locations for January 1, 2009 and January 2, 2009. Color code the points based on the price of the cab ride with buckets of [0, 10], (10, 20], and 20+. Do all your data wrangling in Spark and only collect the final tibble to plot using `ggplot2` in R.

References

1. A Gentle Introduction to Apache Spark. (2020). http://www.dcs.bbk.ac.uk/~dell/teaching/cc/book/databricks/spark-intro.pdf.

2. Javier Luraschi, E. (2020). Mastering Spark with R. https://therinspark.com/.

3. R Front End for Apache Spark. (2020). http://spark.apache.org/docs/latest/api/R/index.html.

4. sparklyr. (2020). https://spark.rstudio.com/.