Mirai Solutions
smarter analytics - better decisions

Big Data Analytics in R using `sparklyr`

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Apache Spark - Large-scale data processing

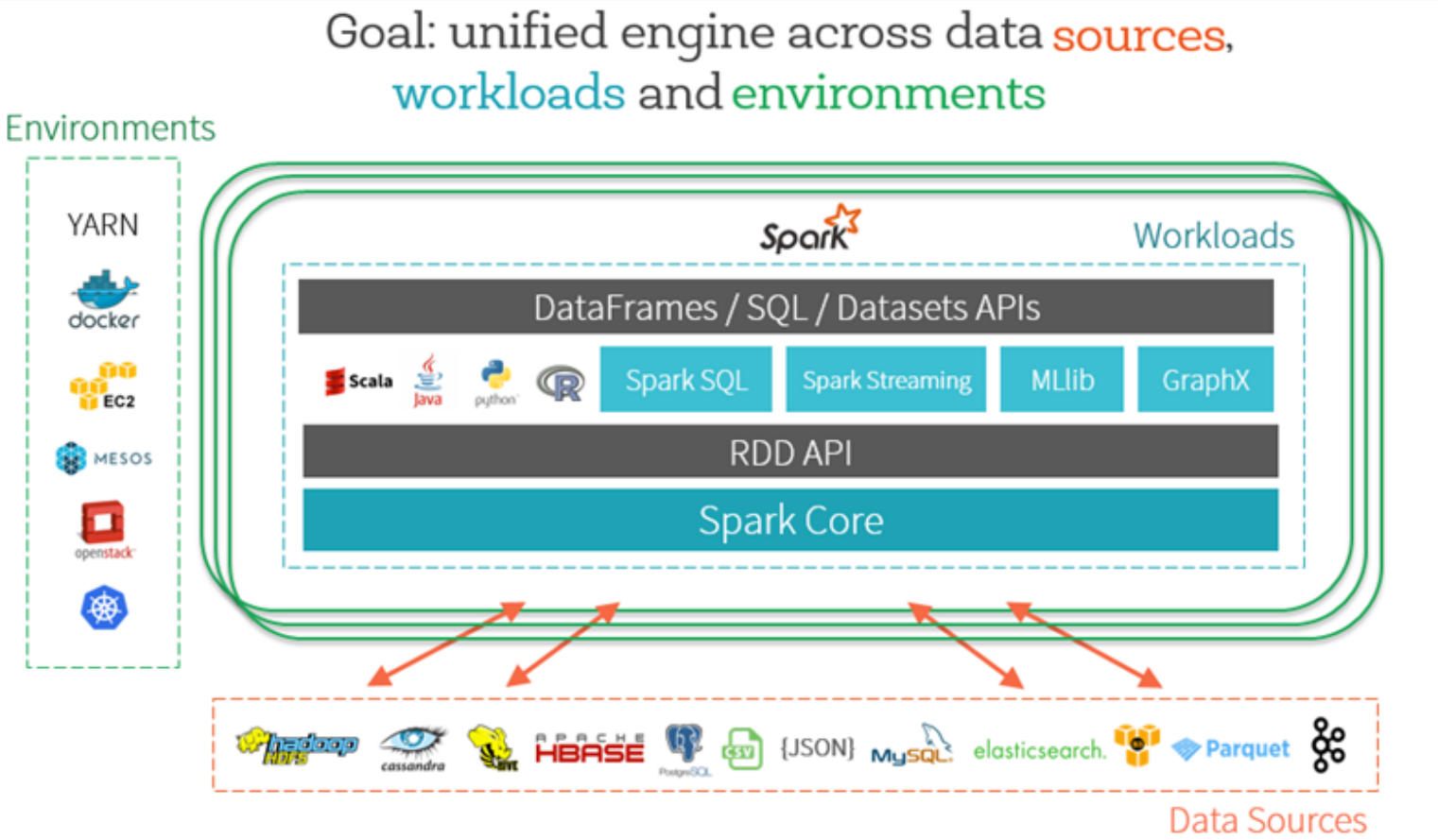
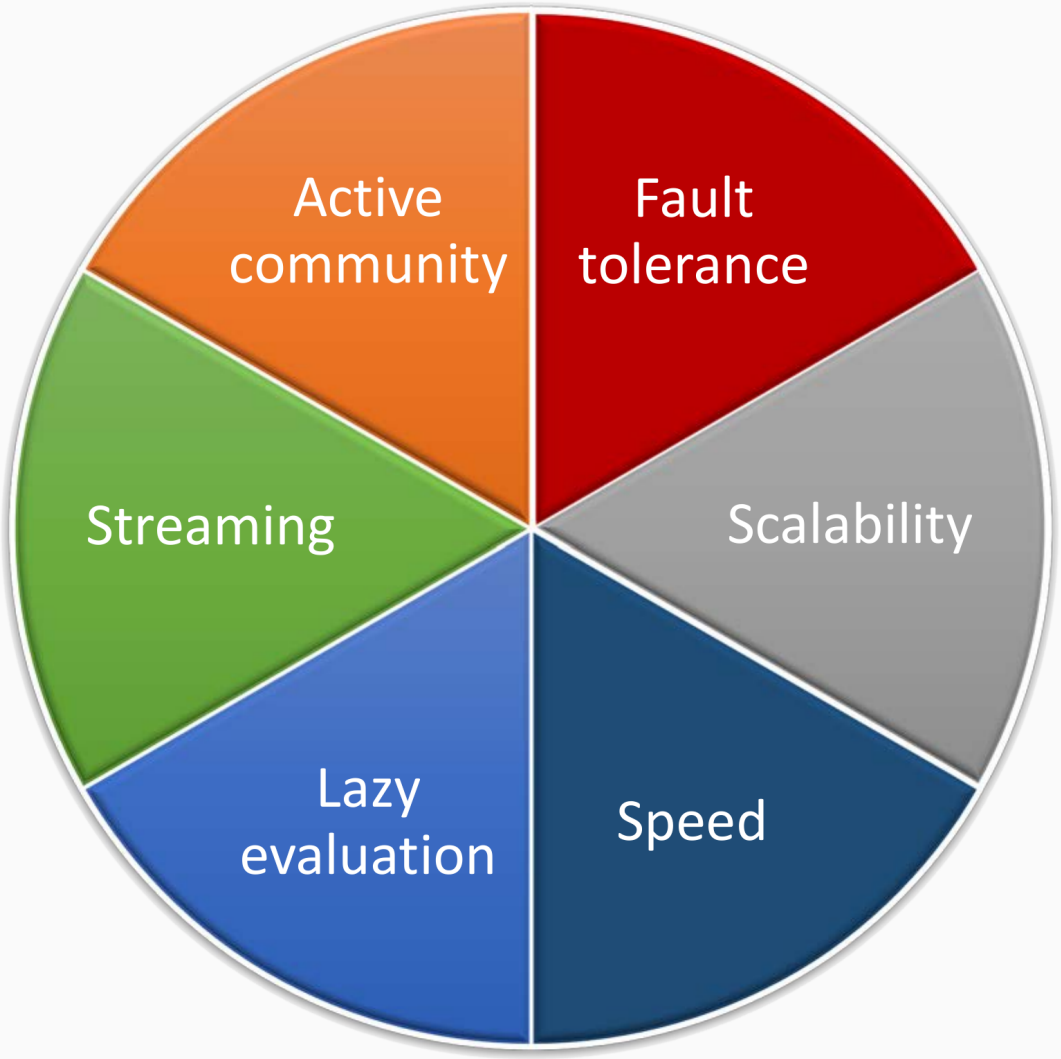


Figure 1: A unified large-scale distributed data processing engine (Databricks 2017)

Why using Apache Spark?



Spark cluster components

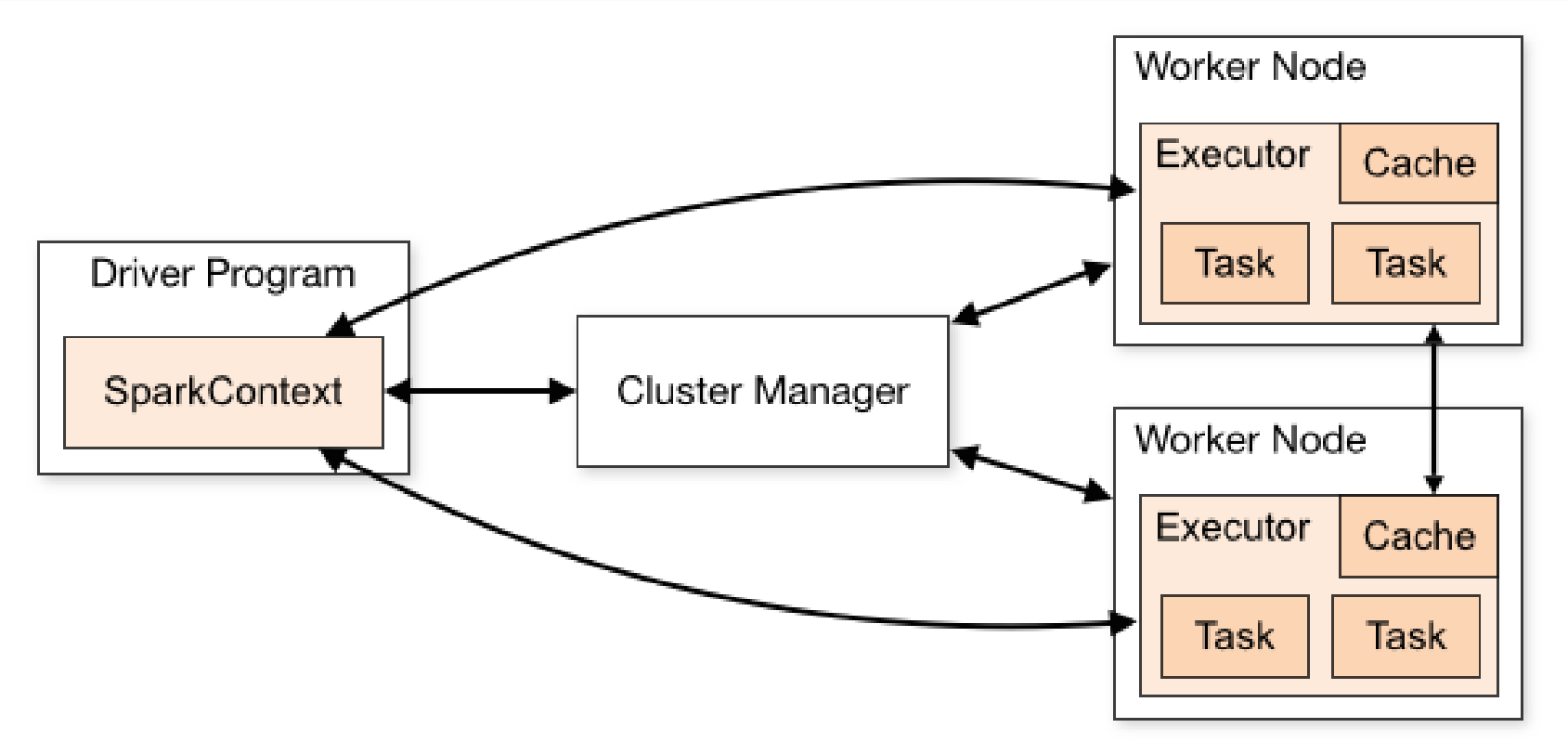


Figure 2: Overview of Spark cluster components (Apache Spark 2018)

`sparklyr` - An R interface to Spark

- Provides a `dplyr`-compatible backend to local and remote Apache Spark clusters
- Supports Spark's distributed machine learning library
- Provides a mechanism to build extension packages that can leverage the full Spark API
- Integrated into RStudio IDE

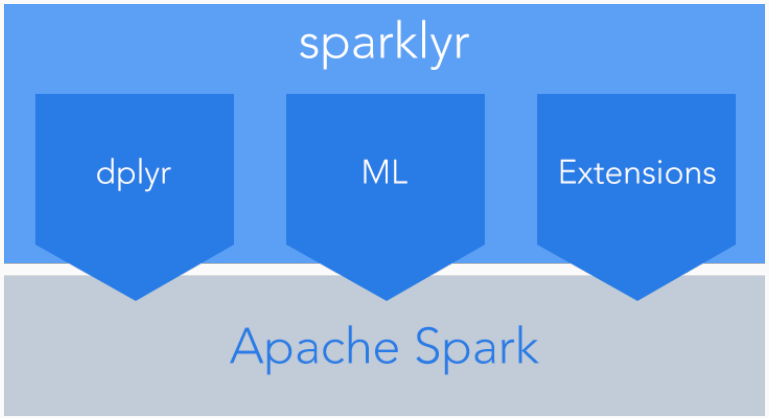


Figure 3: Different ways `sparklyr` can interact with Apache Spark (RStudio 2017b)

sparklyr - Connection to a Spark cluster

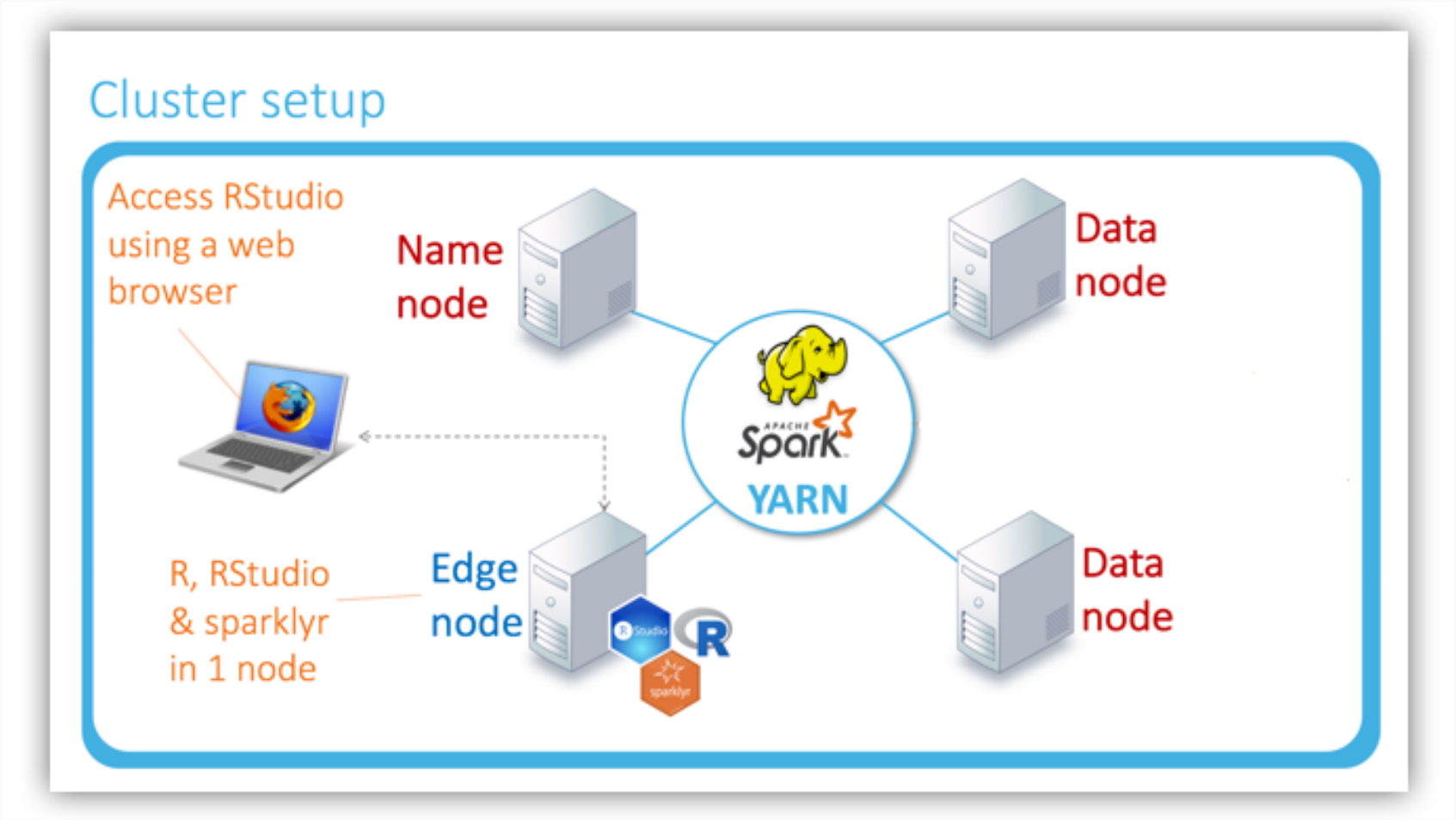


Figure 4: Using sparklyr to connect to a Spark cluster (RStudio 2017a)

sparklyr - How does it work?

- S3 class `tbl_spark` provides a `dplyr`-compatible reference to a (remote) Spark DataFrame
- `dplyr` verbs/commands are translated into Spark SQL statements which are then executed on Spark
- `dplyr` operations are lazy
  - data is never pulled into R unless you explicitly ask for it (e.g. `collect`, `count`, etc.)
  - it delays work until the last possible moment
- `sparklyr`'s `sdf_*` functions access the Spark DataFrame API directly
  - these functions will generally force any pending SQL operations in a dplyr pipeline
- `sparklyr`'s `spark_connection` implements a `DBI` interface for Spark

sparklyr - Connecting to Spark and loading data

```
library(sparklyr)
library(dplyr)
library(nycflights13)

sc <- spark_connect(master = "local")
flights <- copy_to(sc, flights, "flights")
src_tbls(sc)
```

```
[1] "flights"
```

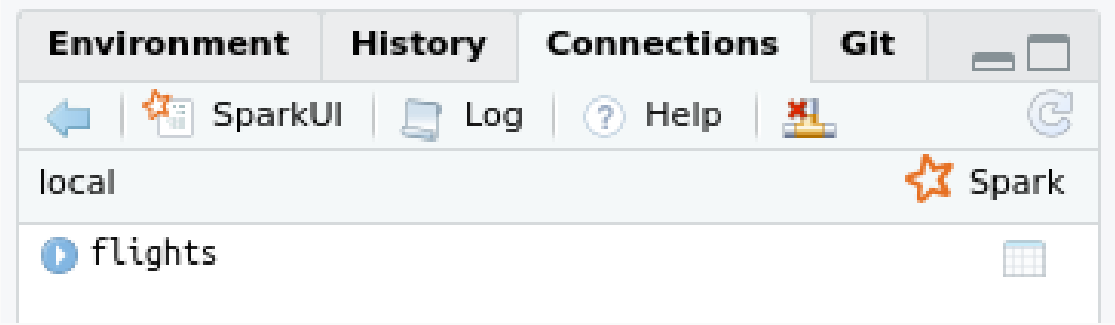


Figure 5: Spark integration in the RStudio IDE

sparklyr - Using dplyr verbs in a pipeline

```
# Find the most delayed connections
most_delayed <- flights %>%
  group_by(origin, dest) %>%
  summarize(avg_dep_delay = mean(dep_delay)) %>%
  arrange(desc(avg_dep_delay))
```

sparklyr - Spark SQL

```
> dbplyr::sql_render(most_delayed)

SELECT * FROM (SELECT `origin`, `dest`,
AVG(`dep_delay`) AS `avg_dep_delay` FROM
`flights` GROUP BY `origin`, `dest`) `drurrvydlq`
ORDER BY `avg_dep_delay` DESC
```

sparklyr - Retrieve data

```
# Collecting data into R's memory
most_delayed %>% head(10)
```

origin	dest	avg_dep_delay
EWR	TYS	41.81847
EWR	CAE	36.33684
EWR	TUL	34.90635
LGA	SBN	31.33333
EWR	OKC	30.56881
LGA	BHM	29.77860
LGA	CAE	29.50000
EWR	DSM	29.32824
EWR	JAC	28.70000
EWR	ROC	27.86122

sparklyr - Spark connection as DBI interface

```
library(DBI)
dbGetQuery(sc, "SELECT origin, dest, dep_delay
                FROM flights
                WHERE dep_delay < 0
                ORDER BY dep_delay
                LIMIT 5")
```

origin	dest	dep_delay
JFK	DEN	-43
LGA	MSY	-33
LGA	IAD	-32
LGA	TPA	-30
LGA	DEN	-27

Google BigQuery

A fast and highly scalable enterprise data warehouse for analytics

- Serverless and automatic high availability
- Petabyte scale
- High-speed streaming insertion API for real-time analytics
- Standard, ANSI:2011 compliant SQL dialect
- Free for up to 1TB of data analyzed each month and 10GB of data stored

sparkbq - Google BigQuery support for sparklyr

- sparklyr extension package for **Google BigQuery**
- Read/write BigQuery data directly into/from Spark (without having to go through R - cf. bigrquery)

Figure 6: https://github.com/miraisolutions/sparkbq

Example: Shakespeare public dataset (1)

```
library(sparklyr)
library(sparkbq)
library(dplyr)

config <- spark_config()
sc <- spark_connect(master = "local", config = config)

# Set Google BigQuery default settings
bigquery_defaults(
  billingProjectId = "<your_billing_project_id>",
  gcsBucket = "<your_gcs_bucket>",
  datasetLocation = "US"
)
```

Example: Shakespeare public dataset (2)

```
# Reading the public shakespeare data table
# https://cloud.google.com/bigquery/public-data/
# https://cloud.google.com/bigquery/sample-tables
hamlet <-
  spark_read_bigquery(
    sc,
    name = "shakespeare",
    projectId = "bigquery-public-data",
    datasetId = "samples",
    tableId = "shakespeare") %>%
  # NOTE: predicate pushdown to BigQuery!
  filter(corpus == "hamlet") %>%
  collect()
```

Example: NYC Taxi data (1)

- Dataset including records from all trips completed in Yellow taxis in NYC from 2009 to 2016.
- Records include:
  - pick-up and drop-off dates/times and locations
  - trip distances
  - fares, tips and payment types
  - driver-reported passenger counts
  - etc.
- R Markdown document: https://goo.gl/xM5NVC
- Knitted HTML document: https://goo.gl/SMrFXB

Example: NYC Taxi data (2)

Querying and (lazily) binding together all the NYC TLC yellow trips (2009-2016):

```
all_trips_spark_by_year <-
  lapply(2009:2016, function(year) {
    spark_read_bigquery(
      sc = sc,
      name = paste0("trips", year),
      projectId = "bigquery-public-data",
      datasetId = "new_york",
      tableId = paste0("tlc_yellow_trips_", year),
      repartition = 400
    )
  })

all_trips_spark <- Reduce(union_all, all_trips_spark_by_year)
```

Example: NYC Taxi data (3)

Calculate average tip (as percentage of the fare amount) per NYC neighborhood:

```
credit_trips_spark_1 <-
  all_trips_spark %>%
  filter(
    # Trips paid by credit card
    payment_type %in% c("CREDIT", "CRD", "1") &
    # Filter out bad data points
    fare_amount > 1 & tip_amount >= 0 &
    trip_distance > 0 & passenger_count > 0
  ) %>%
  select(
    vendor_id, pickup_datetime, dropoff_datetime,
    pickup_latitude, pickup_longitude, trip_distance,
    passenger_count, fare_amount, tip_amount
  )
```

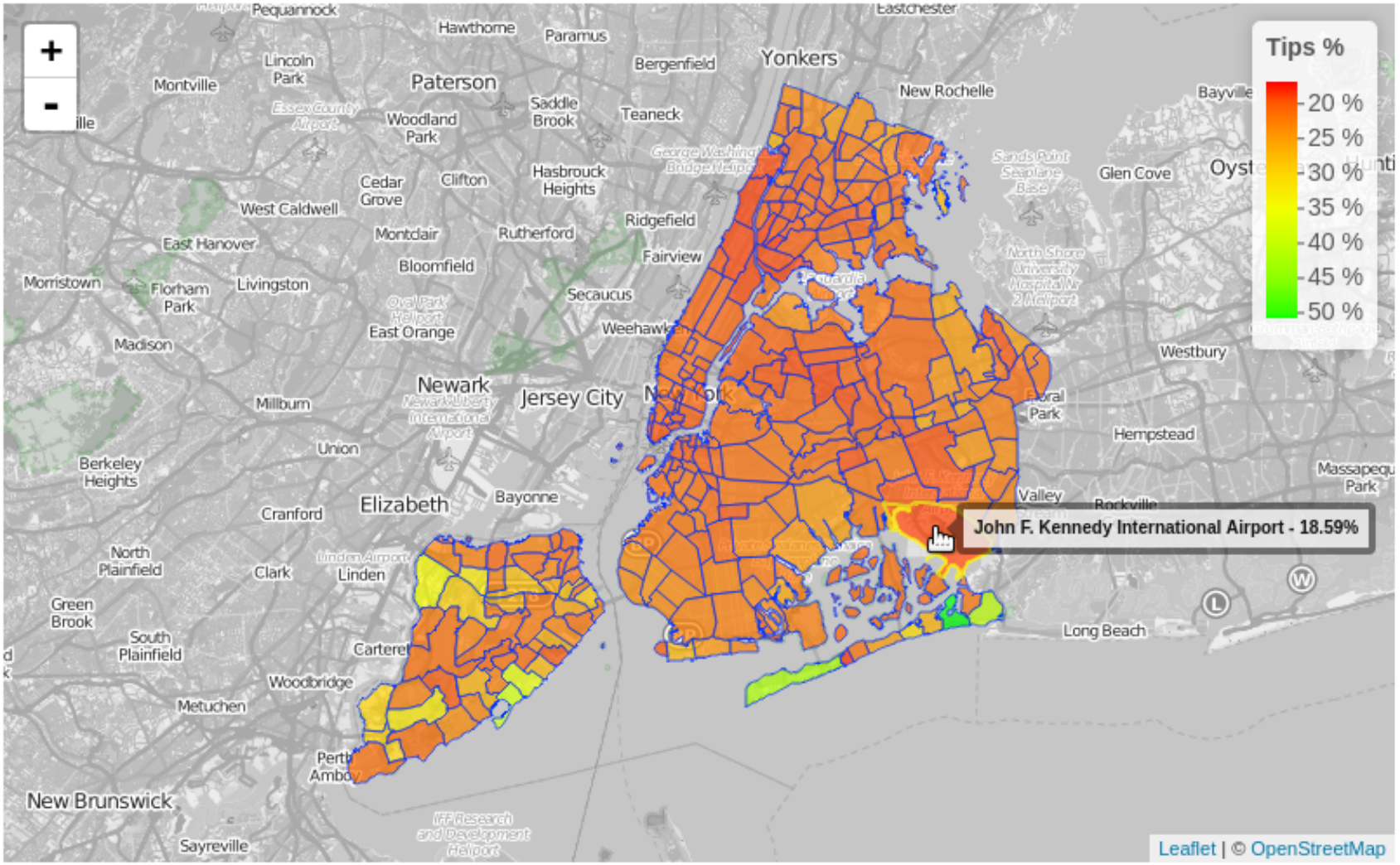
Example: NYC Taxi data (4)

```
credit_trips_spark_2 <- credit_trips_spark_1 %>%
  # Join with NYC neighborhoods
  sparkgeo::sdf_spatial_join(neighborhoods, pickup_latitude,
                             pickup_longitude) %>%
  # NOTE: timestamps are currently returned as microseconds
  # since the epoch
  mutate(
    trip_duration = (dropoff_datetime - pickup_datetime) / 1e6,
    pickup_datetime = from_unixtime(pickup_datetime / 1e6)
  ) %>%
  mutate(
    pickup_month = month(pickup_datetime),
    pickup_weekday = date_format(pickup_datetime, 'EEEE'),
    pickup_hour = hour(pickup_datetime),
    # Calculate tip percentage based on fare amount
    tip_pct = tip_amount / fare_amount * 100
  )
```

Example: NYC Taxi data (5)

```
credit_trips_spark <- credit_trips_spark_2 %>%
  select(
    vendor_id, pickup_month,
    pickup_weekday, pickup_hour,
    neighborhood, trip_duration,
    trip_distance, passenger_count,
    fare_amount, tip_pct
  ) %>%
  # Persist results to memory and/or disk
  sdf_persist()
```

Example: NYC Taxi data - Leaflet visualization



Final remarks

- `sparklyr` / Spark:
  - usually only relevant for **big data**
  - requires a good understanding of Spark and its configuration parameters and memory management
    - cluster sizing: number of executors, cores & memory per executor
    - know how your data is partitioned
    - cache/persist data to avoid recomputations

- `SparkR` offers functionality similar to `sparklyr`. However, `sparklyr` has the following advantages:
  - it offers native `dplyr` support
  - a local version of Spark (for development) can be easily installed via `spark_install` directly from R
  - it is extensible

Q & A

References

Apache Spark. 2018. "Cluster Mode Overview." https://spark.apache.org/docs/latest/cluster-overview.html.

Databricks. 2017. "Introduction to Apache Spark for Data Engineers." https://docs.databricks.com/spark/latest/gentle-introduction/for-data-engineers.html.

RStudio. 2017a. "Deploying Sparklyr." https://spark.rstudio.com/examples/.

———. 2017b. "Sparklyr." https://spark.rstudio.com/index.html.