Using sparklyr with an Apache Spark cluster

This document demonstrates how to use `sparklyr` with an Apache Spark cluster. Data are downloaded from the web and stored in Hive tables on HDFS across multiple worker nodes. RStudio Server is installed on the master node and orchestrates the analysis in spark. Here is the basic workflow.

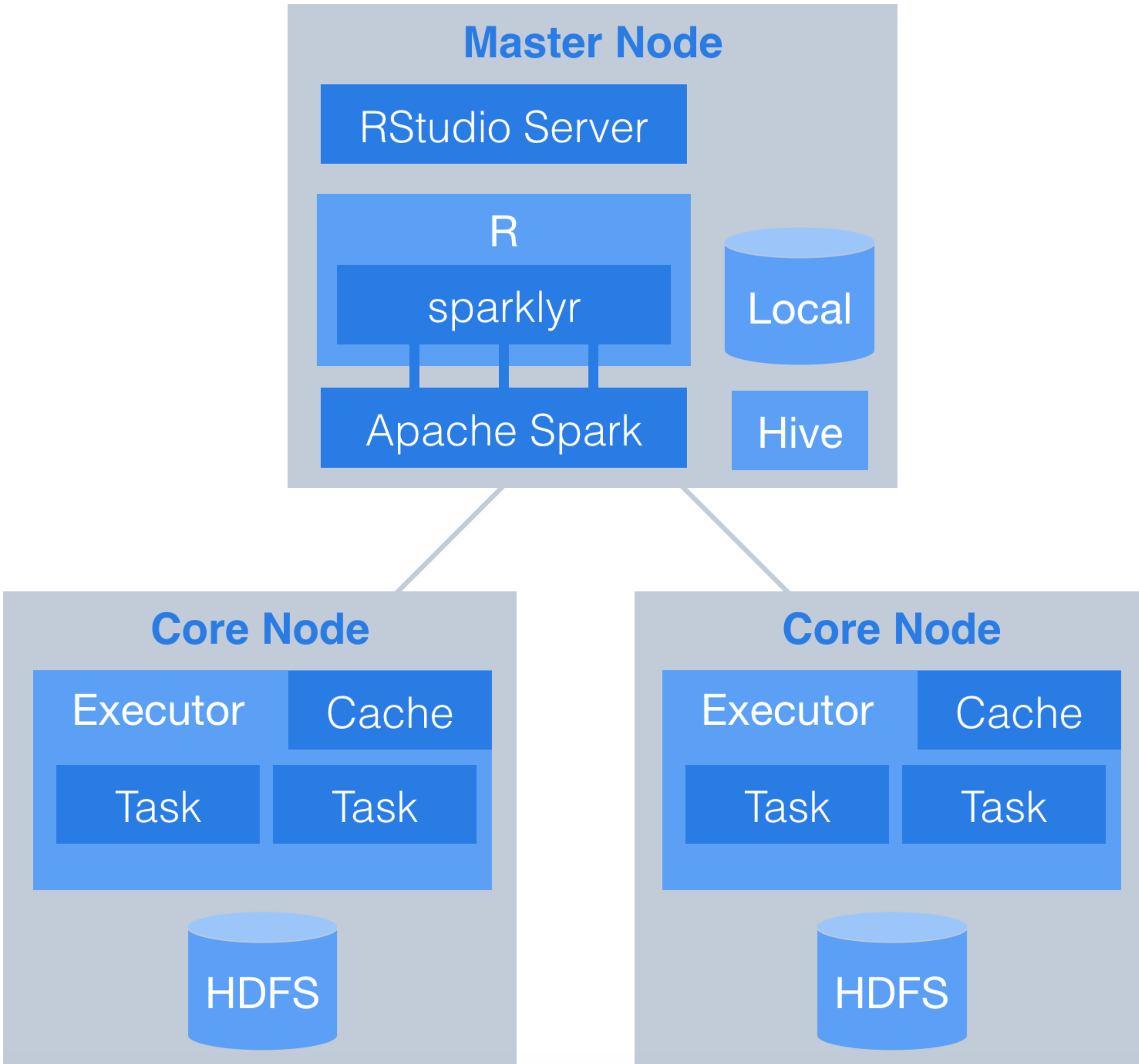
Data preparation

Set up the cluster

This demonstration uses Amazon Web Services (AWS), but it could just as easily use Microsot, Google, or any other provider. We will use Elastic Map Reduce (EMR) to easily set up a cluster with two core nodes and one master node. Nodes use virtual servers from the Elastic Compute Cloud (EC2). *Note: There is no free tier for EMR, charges will apply.*

Before beginning this setup we assume you have:

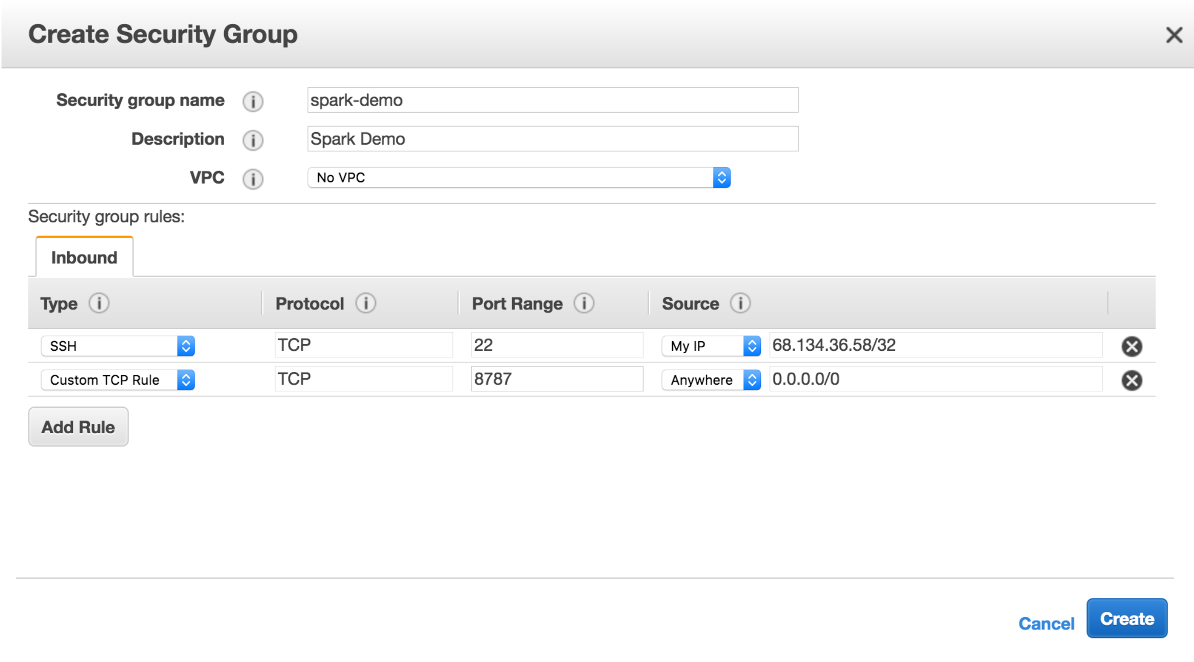
- Familiarity with and access to an AWS account
- Familiarity with basic linux commands
- Sudo privileges in order to install software from the command line



Build an EMR cluster

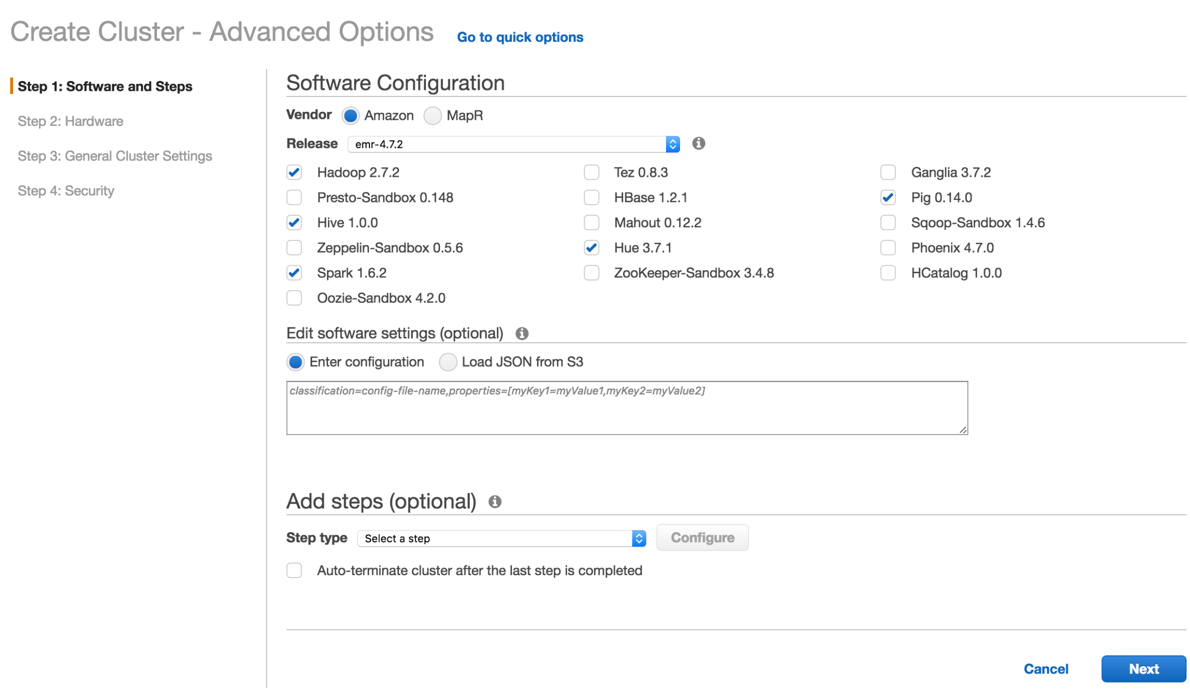
Before beginning the EMR wizard setup, make sure you create the following in AWS:

- An AWS key pair (.pem key) so you can SSH into the EC2 master node
- A security group that gives you access to port 22 on your IP and port 8787 from anywhere



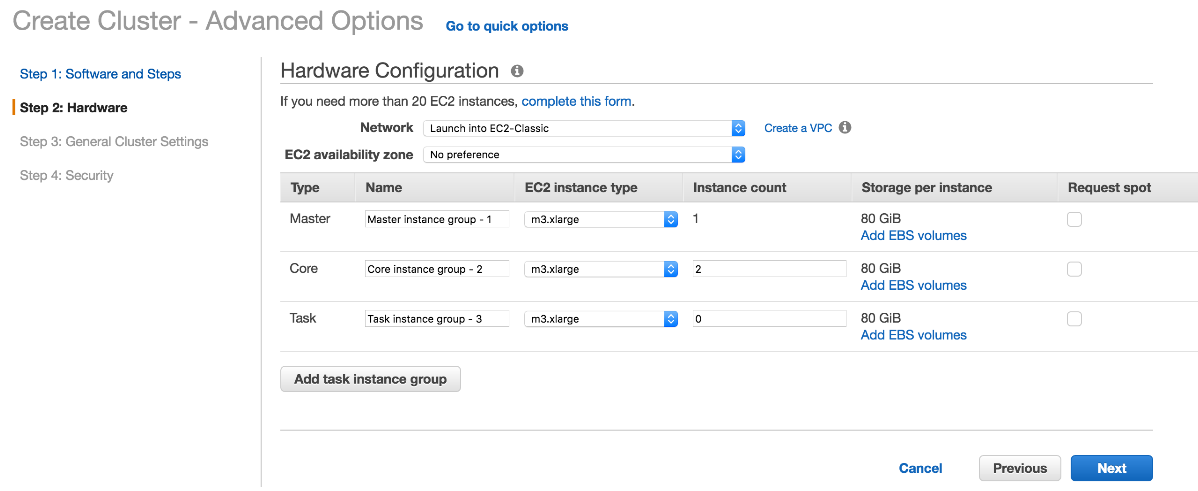
Step 1: Select software

Make sure to select Hive and Spark as part of the install. Note that by choosing Spark, R will also be installed on the master node as part of the distribution.



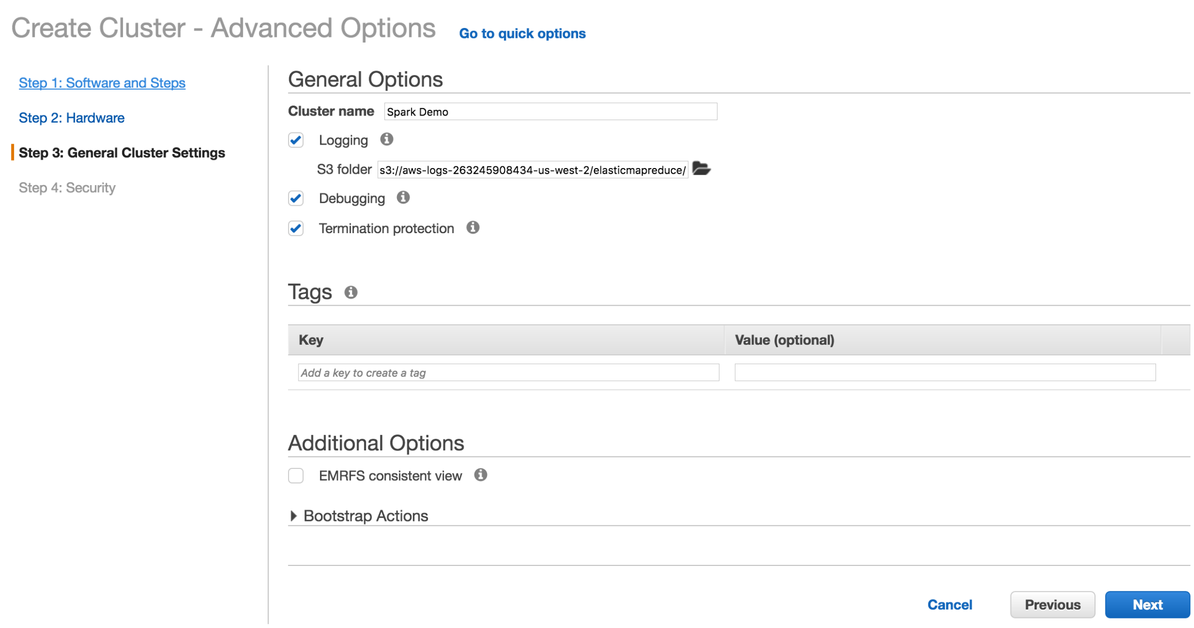
Step 2: Select hardware

Install 2 core nodes and one master node with m3.xlarge 80 GiB storage per node. You can easily increase the number of nodes later.



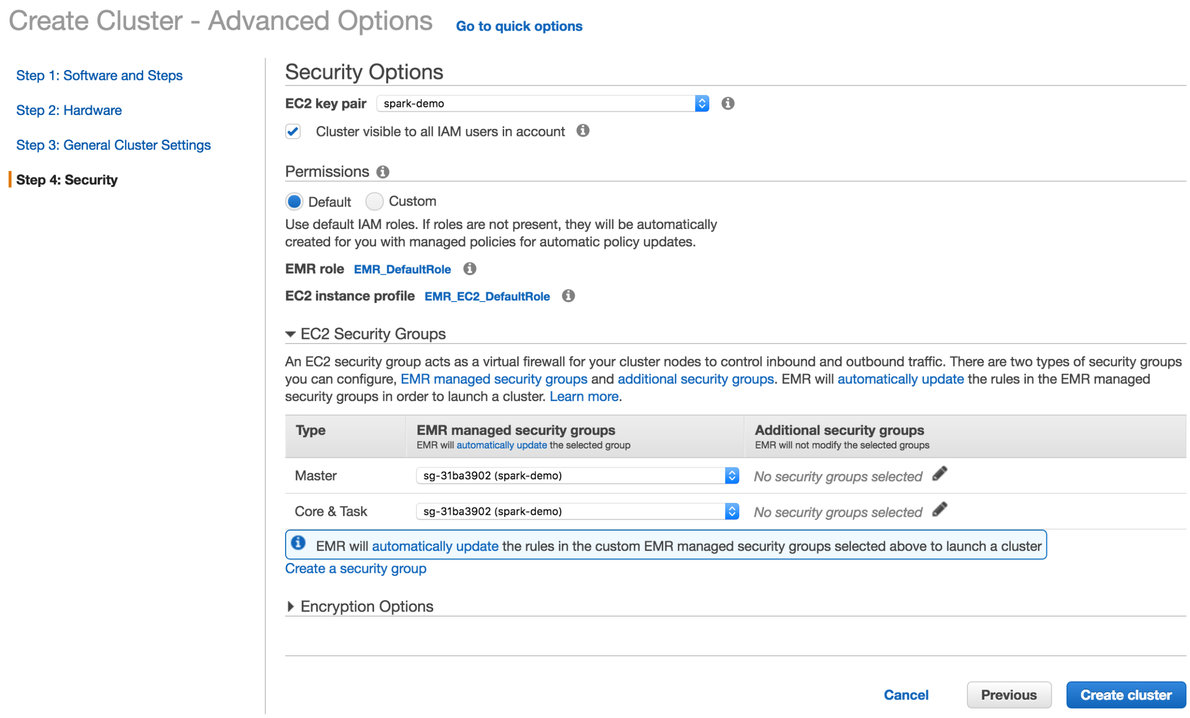
Step 3: Select general cluster settings

Click next on the general cluster settings.



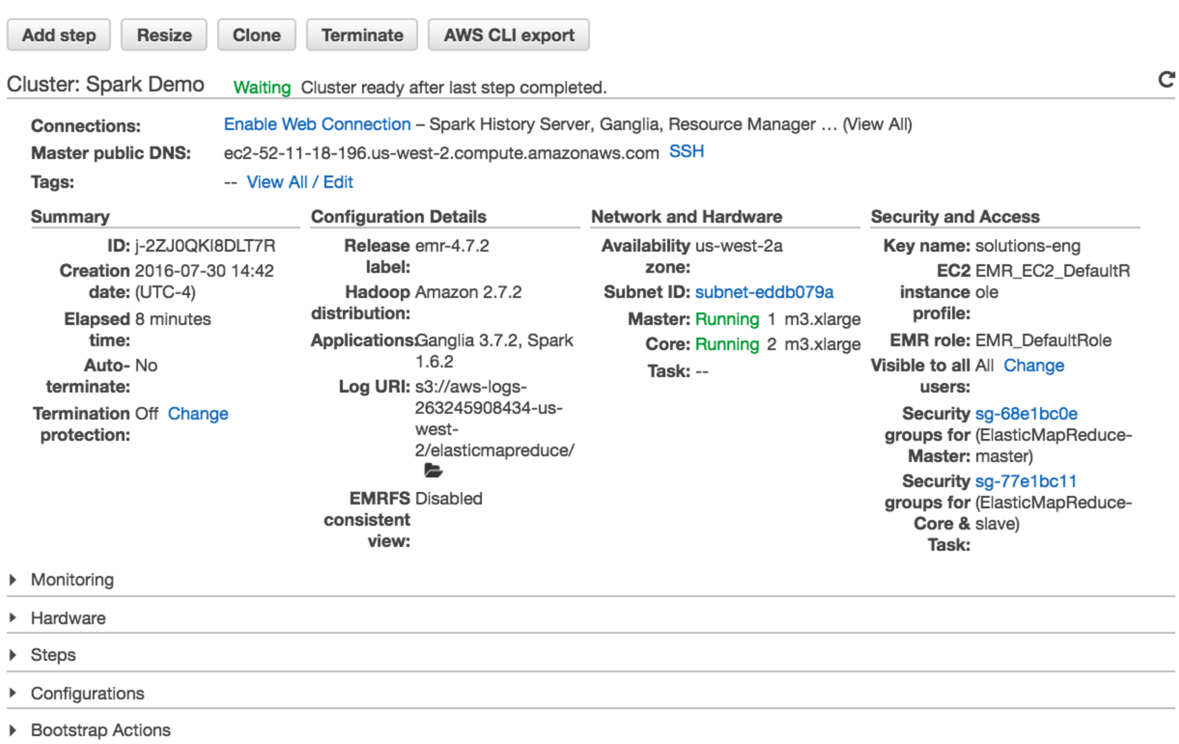
Step 4: Select security

Enter your EC2 key pair and security group. Make sure the security group has ports 22 and 8787 open.



Connect to EMR

The cluster page will give you details about your EMR cluster and instructions on connecting.



Connect to the master node via SSH using your key pair. Once you connect you will see the EMR welcome.

```
# Log in to master node
ssh -i ~/spark-demo.pem hadoop@ec2-52-10-102-11.us-west-2.compute.amazona
ws.com
```

```
Nathans-MBP-2:~ nwstephens$ ssh -i ~/spark-demo.pem hadoop@ec2-52-10-102-11.us-west-2.compute.amazonaws.com
Last login: Sat Jul 30 19:01:37 2016 from pool-68-134-36-58.bltmmd.fios.verizon.net

       __|  __|_  )
       _|  (     /   Amazon Linux AMI
      ___|\___|___|

https://aws.amazon.com/amazon-linux-ami/2016.03-release-notes/
16 package(s) needed for security, out of 26 available
Run "sudo yum update" to apply all updates.

EEEEEEEEEEEEEEEEEEEE MMMMMMMM           MMMMMMMM RRRRRRRRRRRRRRR
E::::::::::::::::::E M:::::::M         M:::::::M R::::::::::::::R
EE:::::EEEEEEEEE:::E M::::::::M       M::::::::M R:::::RRRRRR:::::R
  E::::E       EEEEE M:::::::::M     M:::::::::M RR::::R      R::::R
  E::::E             M::::::M:::M   M:::M::::::M   R:::R      R::::R
  E:::::EEEEEEEEEE   M:::::M M:::M M:::M M:::::M   R:::RRRRRR:::::R
  E::::::::::::::E   M:::::M  M:::M:::M  M:::::M   R:::::::::::RR
  E:::::EEEEEEEEEE   M:::::M   M:::::M   M:::::M   R:::RRRRRR::::R
  E::::E             M:::::M    M:::M    M:::::M   R:::R      R::::R
  E::::E       EEEEE M:::::M     MMM     M:::::M   R:::R      R::::R
EE:::::EEEEEEEE::::E M:::::M             M:::::M   R:::R      R::::R
E::::::::::::::::::E M:::::M             M:::::M RR::::R      R::::R
EEEEEEEEEEEEEEEEEEEE MMMMMMM             MMMMMMM RRRRRRR      RRRRRR

[hadoop@ip-172-30-0-221 ~]$
```

Install RStudio Server

EMR uses Amazon Linux which is based on Centos. Update your master node and install dependencies that will be used by R packages.

```
# Update
sudo yum update
sudo yum install libcurl-devel openssl-devel # used for devtools
```

The installation of RStudio Server is easy. Download the preview version (https://www.rstudio.com/products/rstudio/download/preview/) of RStudio and install on the master node.

```
# Install RStudio Server
wget -P /tmp https://s3.amazonaws.com/rstudio-dailybuilds/rstudio-server-
rhel-0.99-x86_64.rpm
sudo yum install --nogpgcheck /tmp/rstudio-server-rhel-0.99-x86_64.rpm
```

Create a User

Create a user called `rstudio-user` that will perform the data analysis. Create a user directory for `rstudio-user` on HDFS with the `hadoop fs` command.

```
# Make User
sudo useradd -m rstudio-user
sudo passwd rstudio-user

# Create new directory in hdfs
hadoop fs -mkdir /user/rstudio-user
hadoop fs -chmod 777 /user/rstudio-user
```

Download flights data

The flights (http://stat-computing.org/dataexpo/2009/the-data.html) data is a well known data source representing 123 million flights over 22 years. It consumes roughly 12 GiB of storage in uncompressed CSV format in yearly files.

Switch User

For data loading and analysis, make sure you are logged in as regular user.

```
# create directories on hdfs for new user
hadoop fs -mkdir /user/rstudio-user
hadoop fs -chmod 777 /user/rstudio-user

# switch user
su rstudio-user
```

Download data

Run the following script to download data from the web onto your master node. Download the yearly flight data and the airlines lookup table.

```
# Make download directory
mkdir /tmp/flights

# Download flight data by year
for i in {1987..2008}
  do
    echo "$(date) $i Download"
    fnam=$i.csv.bz2
    wget -O /tmp/flights/$fnam http://stat-computing.org/dataexpo/2009/$f
nam
    echo "$(date) $i Unzip"
    bunzip2 /tmp/flights/$fnam
  done

# Download airline carrier data
wget -O /tmp/airlines.csv http://www.transtats.bts.gov/Download_Lookup.as
p?Lookup=L_UNIQUE_CARRIERS

# Download airports data
wget -O /tmp/airports.csv https://raw.githubusercontent.com/jpatokal/open
flights/master/data/airports.dat
```

Distribute into HDFS

Copy data into HDFS using the `hadoop fs` command.

```
# Copy flight data to HDFS
hadoop fs -mkdir /user/rstudio-user/flights/
hadoop fs -put /tmp/flights /user/rstudio-user/

# Copy airline data to HDFS
hadoop fs -mkdir /user/rstudio-user/airlines/
hadoop fs -put /tmp/airlines.csv /user/rstudio-user/airlines

# Copy airport data to HDFS
hadoop fs -mkdir /user/rstudio-user/airports/
hadoop fs -put /tmp/airports.csv /user/rstudio-user/airports
```

Create Hive tables

Launch Hive from the command line.

```
# Open Hive prompt
hive
```

Create the metadata that will structure the flights table. Load data into the Hive table.

```
# Create metadata for flights
CREATE EXTERNAL TABLE IF NOT EXISTS flights
(
year int,
month int,
dayofmonth int,
dayofweek int,
deptime int,
crsdeptime int,
arrtime int,
crsarrtime int,
uniquecarrier string,
flightnum int,
tailnum string,
actualelapsedtime int,
crselapsedtime int,
airtime string,
arrdelay int,
depdelay int,
origin string,
dest string,
distance int,
taxiin string,
taxiout string,
cancelled int,
cancellationcode string,
diverted int,
carrierdelay string,
weatherdelay string,
nasdelay string,
securitydelay string,
lateaircraftdelay string
)
ROW FORMAT DELIMITED
FIELDS TERMINATED BY ','
LINES TERMINATED BY '\n'
TBLPROPERTIES("skip.header.line.count"="1");

# Load data into table
LOAD DATA INPATH '/user/rstudio-user/flights' INTO TABLE flights;
```

Create the metadata that will structure the airlines table. Load data into the Hive table.

```
# Create metadata for airlines
CREATE EXTERNAL TABLE IF NOT EXISTS airlines
(
Code string,
Description string
)
ROW FORMAT SERDE 'org.apache.hadoop.hive.serde2.OpenCSVSerde'
WITH SERDEPROPERTIES
(
"separatorChar" = '\,',
"quoteChar"     = '\"'
)
STORED AS TEXTFILE
tblproperties("skip.header.line.count"="1");

# Load data into table
LOAD DATA INPATH '/user/rstudio-user/airlines' INTO TABLE airlines;
```

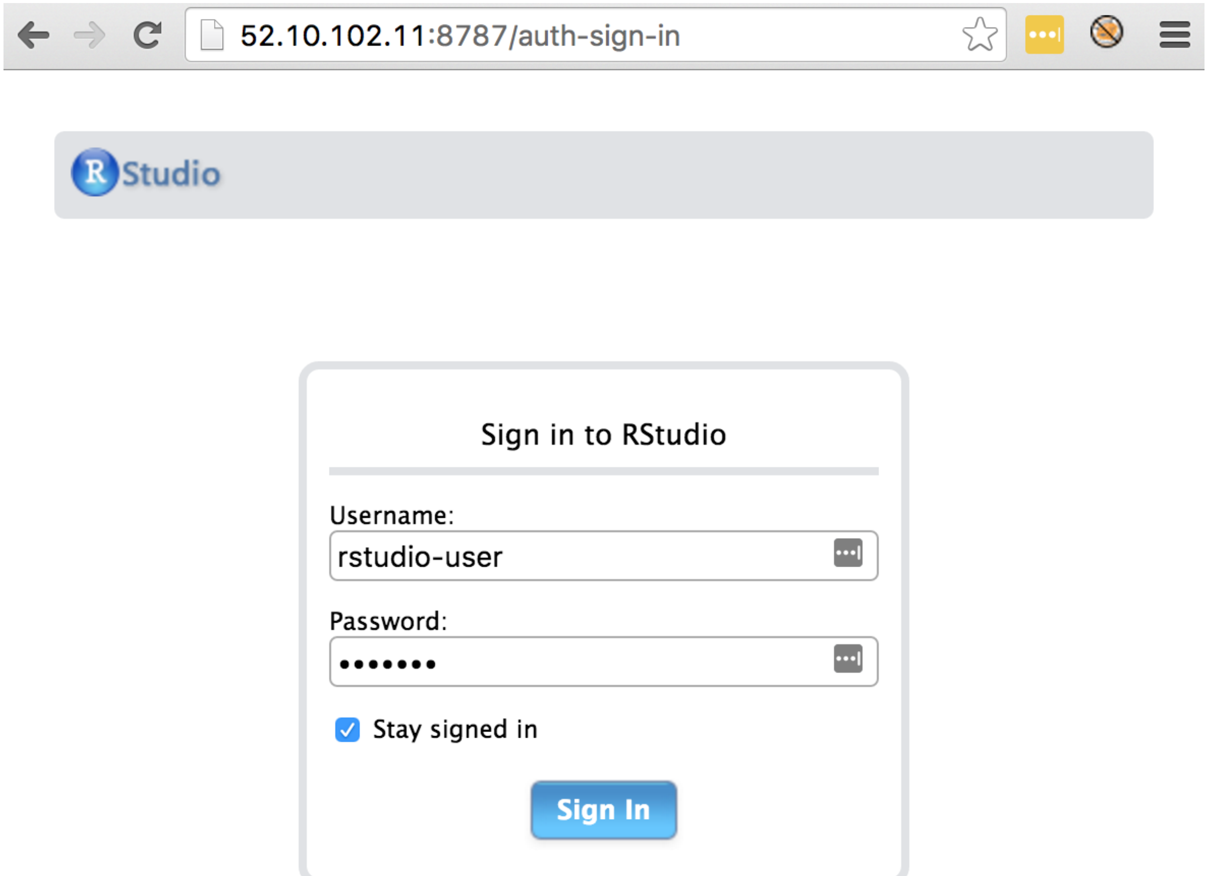
Create the metadata that will structure the airports table. Load data into the Hive table.

```
# Create metadata for airports
CREATE EXTERNAL TABLE IF NOT EXISTS airports
(
id string,
name string,
city string,
country string,
faa string,
icao string,
lat double,
lon double,
alt int,
tz_offset double,
dst string,
tz_name string
)
ROW FORMAT SERDE 'org.apache.hadoop.hive.serde2.OpenCSVSerde'
WITH SERDEPROPERTIES
(
"separatorChar" = '\,',
"quoteChar"     = '\"'
)
STORED AS TEXTFILE;

# Load data into table
LOAD DATA INPATH '/user/rstudio-user/airports' INTO TABLE airports;
```

Connect to Spark

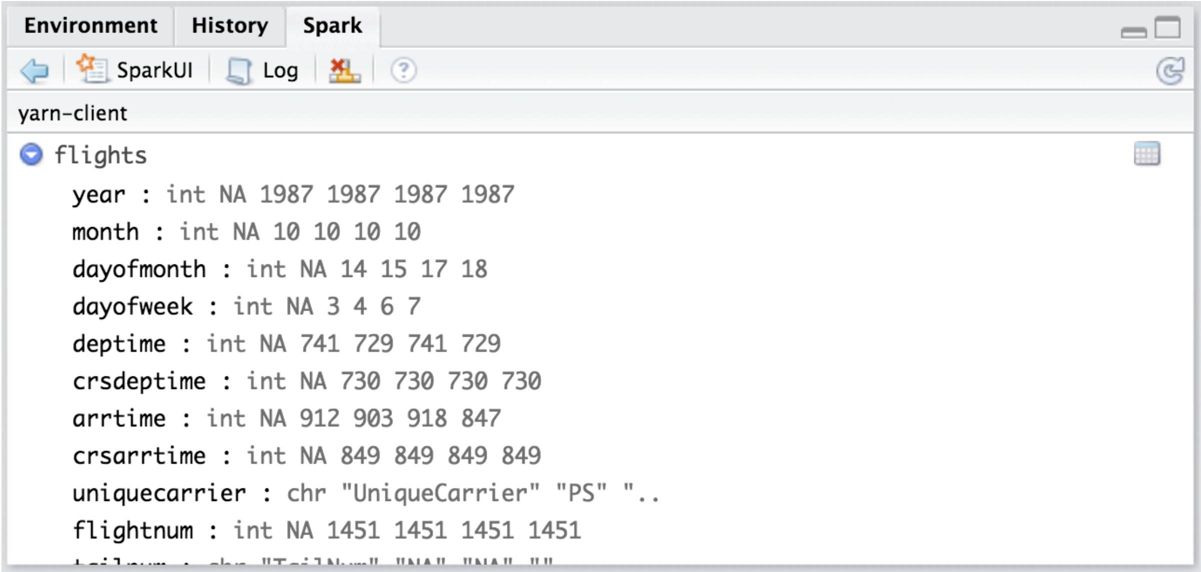
Log in to RStudio Server by pointing a browser at your master node IP:8787.



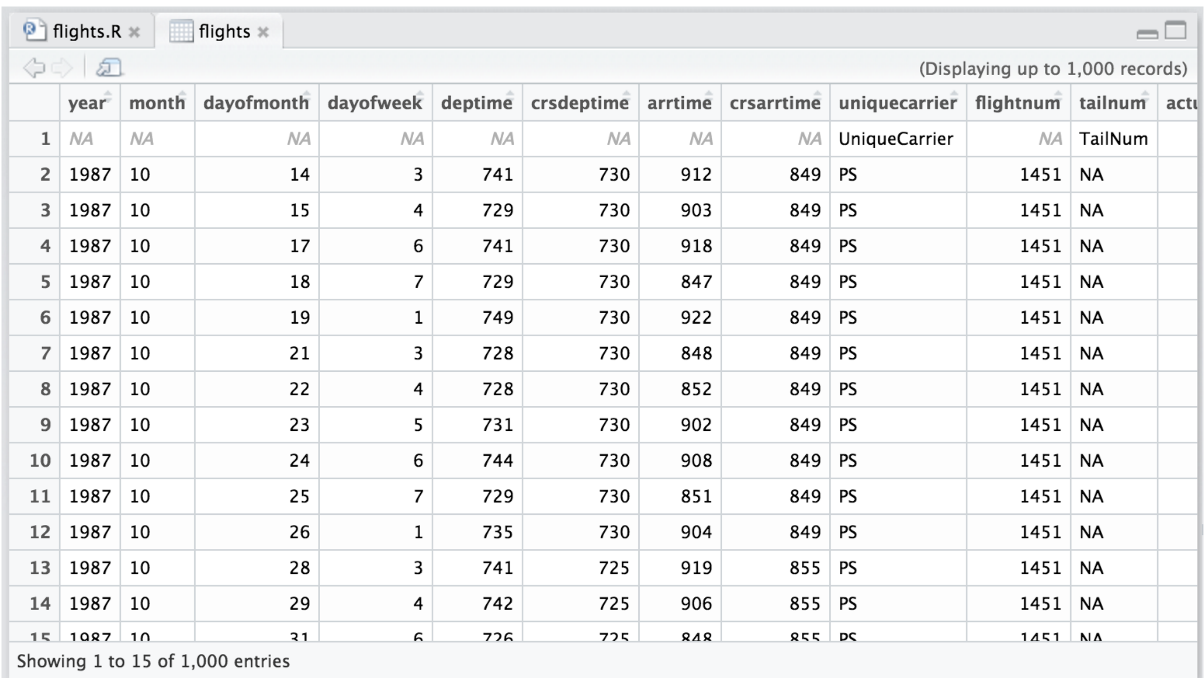
Set the environment variable `SPARK_HOME` and then run `spark_connect` . After connecting you will be able to browse the Hive metadata in the RStudio Server Spark pane.

```
# Connect to Spark
library(sparklyr)
library(dplyr)
library(ggplot2)
Sys.setenv(SPARK_HOME="/usr/lib/spark")
config <- spark_config()
sc <- spark_connect(master = "yarn-client", config = config, version =
'1.6.2')
```

Once you are connected, you will see the Spark pane appear along with your hive tables.



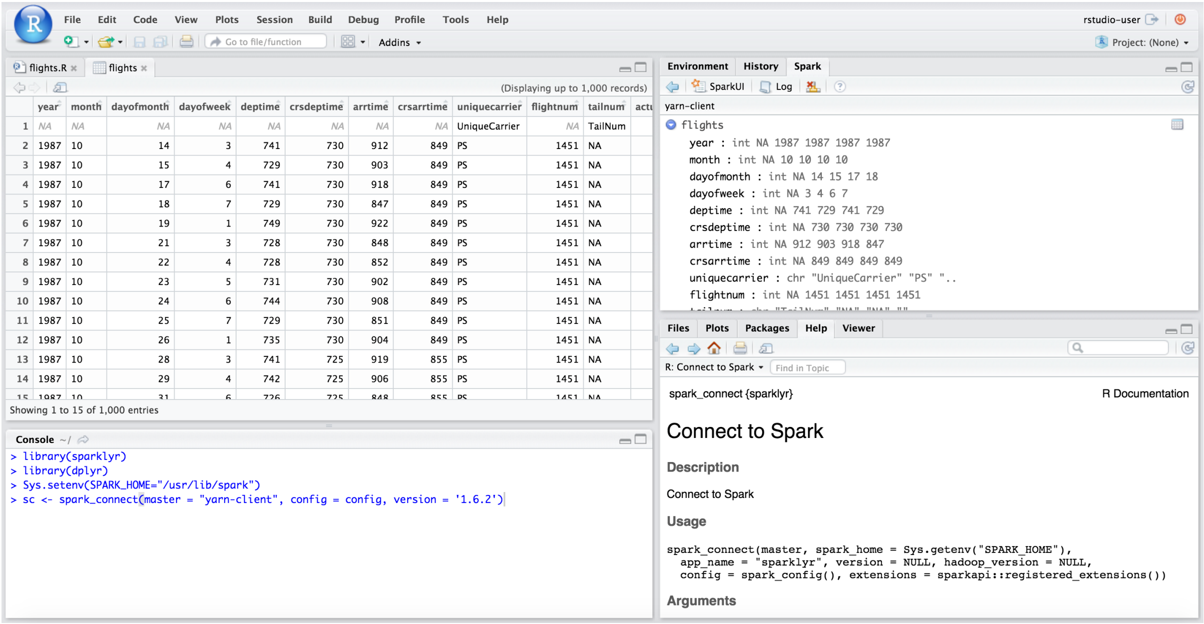
You can inspect your tables by clicking on the data icon.



	year	month	dayofmonth	dayofweek	deptime	crsdeptime	arrtime	crsarrtime	uniquecarrier	flightnum	tailnum	actu
1	NA	NA	NA	NA	NA	NA	NA	NA	UniqueCarrier	NA	TailNum	
2	1987	10	14	3	741	730	912	849	PS	1451	NA	
3	1987	10	15	4	729	730	903	849	PS	1451	NA	
4	1987	10	17	6	741	730	918	849	PS	1451	NA	
5	1987	10	18	7	729	730	847	849	PS	1451	NA	
6	1987	10	19	1	749	730	922	849	PS	1451	NA	
7	1987	10	21	3	728	730	848	849	PS	1451	NA	
8	1987	10	22	4	728	730	852	849	PS	1451	NA	
9	1987	10	23	5	731	730	902	849	PS	1451	NA	
10	1987	10	24	6	744	730	908	849	PS	1451	NA	
11	1987	10	25	7	729	730	851	849	PS	1451	NA	
12	1987	10	26	1	735	730	904	849	PS	1451	NA	
13	1987	10	28	3	741	725	919	855	PS	1451	NA	
14	1987	10	29	4	742	725	906	855	PS	1451	NA	
15	1987	10	31	6	726	725	848	855	PS	1451	NA	

Data analysis

Is there evidence to suggest that some airline carriers make up time in flight? This analysis predicts time gained in flight by airline carrier.



Cache the tables into memory

Use `tbl_cache` to load the flights table into memory. Caching tables will make analysis much faster. Create a dplyr reference to the Spark DataFrame.

```
# Cache flights Hive table into Spark
tbl_cache(sc, 'flights')
flights_tbl <- tbl(sc, 'flights')

# Cache airlines Hive table into Spark
tbl_cache(sc, 'airlines')
airlines_tbl <- tbl(sc, 'airlines')

# Cache airports Hive table into Spark
tbl_cache(sc, 'airports')
airports_tbl <- tbl(sc, 'airports')
```

Create a model data set

Filter the data to contain only the records to be used in the fitted model. Join carrier descriptions for reference. Create a new variable called `gain` which represents the amount of time gained (or lost) in flight.

```
# Filter records and create target variable 'gain'
model_data <- flights_tbl %>%
  filter(!is.na(arrdelay) & !is.na(depdelay) & !is.na(distance)) %>%
  filter(depdelay > 15 & depdelay < 240) %>%
  filter(arrdelay > -60 & arrdelay < 360) %>%
  filter(year >= 2003 & year <= 2007) %>%
  left_join(airlines_tbl, by = c("uniquecarrier" = "code")) %>%
  mutate(gain = depdelay - arrdelay) %>%
  select(year, month, arrdelay, depdelay, distance, uniquecarrier, descri
ption, gain)

# Summarize data by carrier
model_data %>%
  group_by(uniquecarrier) %>%
  summarize(description = min(description), gain=mean(gain),
            distance=mean(distance), depdelay=mean(depdelay)) %>%
  select(description, gain, distance, depdelay) %>%
  arrange(gain)
```

```
Source:   query [?? x 4]
Database: spark connection master=yarn-client app=sparklyr local=FALSE

                    description       gain  distance depdelay
                          <chr>      <dbl>     <dbl>    <dbl>
1        ATA Airlines d/b/a ATA -3.3480120 1134.7084 56.06583
2  ExpressJet Airlines Inc. (1) -3.0326180  519.7125 59.41659
3                     Envoy Air -2.5434415  416.3716 53.12529
4       Northwest Airlines Inc. -2.2030586  779.2342 48.52828
5          Delta Air Lines Inc. -1.8248026  868.3997 50.77174
6   AirTran Airways Corporation -1.4331555  641.8318 54.96702
7    Continental Air Lines Inc. -0.9617003 1116.6668 57.00553
8        American Airlines Inc. -0.8860262 1074.4388 55.45045
9             Endeavor Air Inc. -0.6392733  467.1951 58.47395
10              JetBlue Airways -0.3262134 1139.0443 54.06156
# ... with more rows
```

Train a linear model

Predict time gained or lost in flight as a function of distance, departure delay, and airline carrier.

```
# Partition the data into training and validation sets
model_partition <- model_data %>%
  sdf_partition(train = 0.8, valid = 0.2, seed = 5555)

# Fit a linear model
ml1 <- model_partition$train %>%
  ml_linear_regression(gain ~ distance + depdelay + uniquecarrier)

# Summarize the linear model
summary(ml1)
```

```
Deviance Residuals: (approximate):
     Min       1Q   Median       3Q      Max
-305.422   -5.593    2.699    9.750  147.871

Coefficients:
                    Estimate  Std. Error  t value  Pr(>|t|)
(Intercept)      -1.24342576  0.10248281 -12.1330 < 2.2e-16 ***
distance          0.00326600  0.00001670 195.5709 < 2.2e-16 ***
depdelay         -0.01466233  0.00020337 -72.0977 < 2.2e-16 ***
uniquecarrier_AA -2.32650517  0.10522524 -22.1098 < 2.2e-16 ***
uniquecarrier_AQ  2.98773637  0.28798507  10.3746 < 2.2e-16 ***
uniquecarrier_AS  0.92054894  0.11298561   8.1475 4.441e-16 ***
uniquecarrier_B6 -1.95784698  0.11728289 -16.6934 < 2.2e-16 ***
uniquecarrier_CO -2.52618081  0.11006631 -22.9514 < 2.2e-16 ***
uniquecarrier_DH  2.23287189  0.11608798  19.2343 < 2.2e-16 ***
uniquecarrier_DL -2.68848119  0.10621977 -25.3106 < 2.2e-16 ***
uniquecarrier_EV  1.93484736  0.10724290  18.0417 < 2.2e-16 ***
uniquecarrier_F9 -0.89788137  0.14422281  -6.2257 4.796e-10 ***
uniquecarrier_FL -1.46706706  0.11085354 -13.2343 < 2.2e-16 ***
uniquecarrier_HA -0.14506644  0.25031456  -0.5795    0.5622
uniquecarrier_HP  2.09354855  0.12337515  16.9690 < 2.2e-16 ***
uniquecarrier_MQ -1.88297535  0.10550507 -17.8473 < 2.2e-16 ***
uniquecarrier_NW -2.79538927  0.10752182 -25.9983 < 2.2e-16 ***
uniquecarrier_OH  0.83520117  0.11032997   7.5700 3.730e-14 ***
uniquecarrier_OO  0.61993842  0.10679884   5.8047 6.447e-09 ***
uniquecarrier_TZ -4.99830389  0.15912629 -31.4109 < 2.2e-16 ***
uniquecarrier_UA -0.68294396  0.10638099  -6.4198 1.365e-10 ***
uniquecarrier_US -0.61589284  0.10669583  -5.7724 7.815e-09 ***
uniquecarrier_WN  3.86386059  0.10362275  37.2878 < 2.2e-16 ***
uniquecarrier_XE -2.59658123  0.10775736 -24.0966 < 2.2e-16 ***
uniquecarrier_YV  3.11113140  0.11659679  26.6828 < 2.2e-16 ***
---
NA

R-Squared: 0.02385
Root Mean Squared Error: 17.74
```

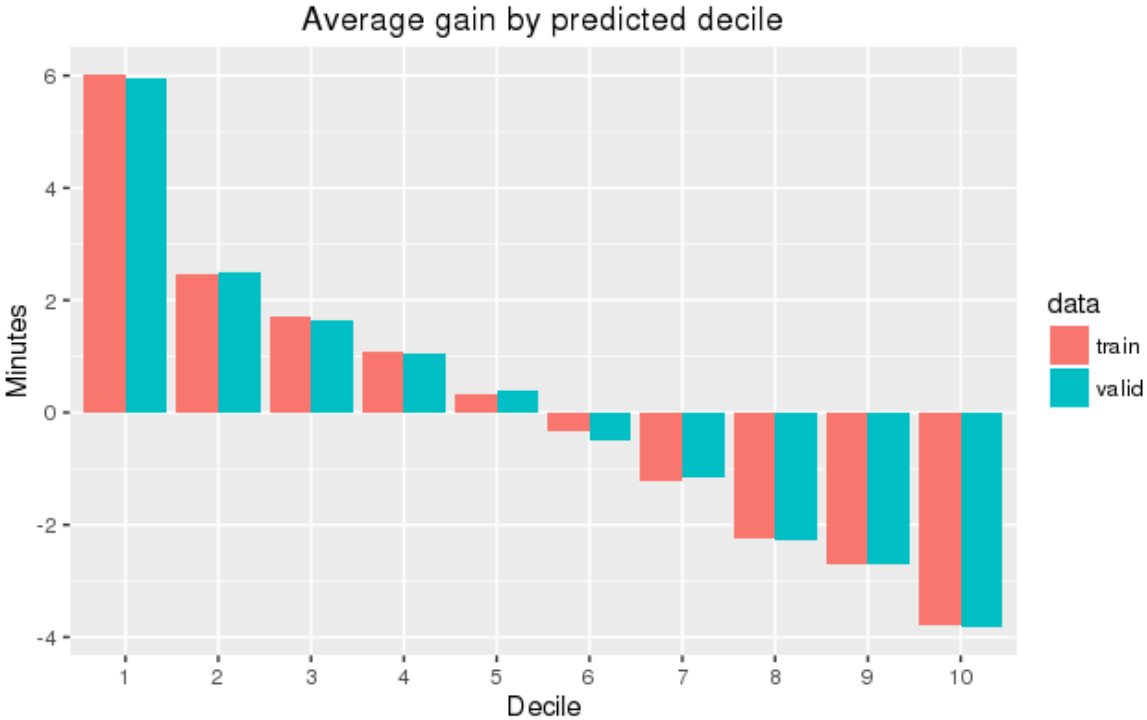
Assess model performance

Compare the model performance using the validation data.

```
# Calculate average gains by predicted decile
model_deciles <- lapply(model_partition, function(x) {
  sdf_predict(ml1, x) %>%
    mutate(decile = ntile(desc(prediction), 10)) %>%
    group_by(decile) %>%
    summarize(gain = mean(gain)) %>%
    select(decile, gain) %>%
    collect()
})

# Create a summary dataset for plotting
deciles <- rbind(
  data.frame(data = 'train', model_deciles$train),
  data.frame(data = 'valid', model_deciles$valid),
  make.row.names = FALSE
)

# Plot average gains by predicted decile
deciles %>%
  ggplot(aes(factor(decile), gain, fill = data)) +
  geom_bar(stat = 'identity', position = 'dodge') +
  labs(title = 'Average gain by predicted decile', x = 'Decile', y = 'Min
utes')
```



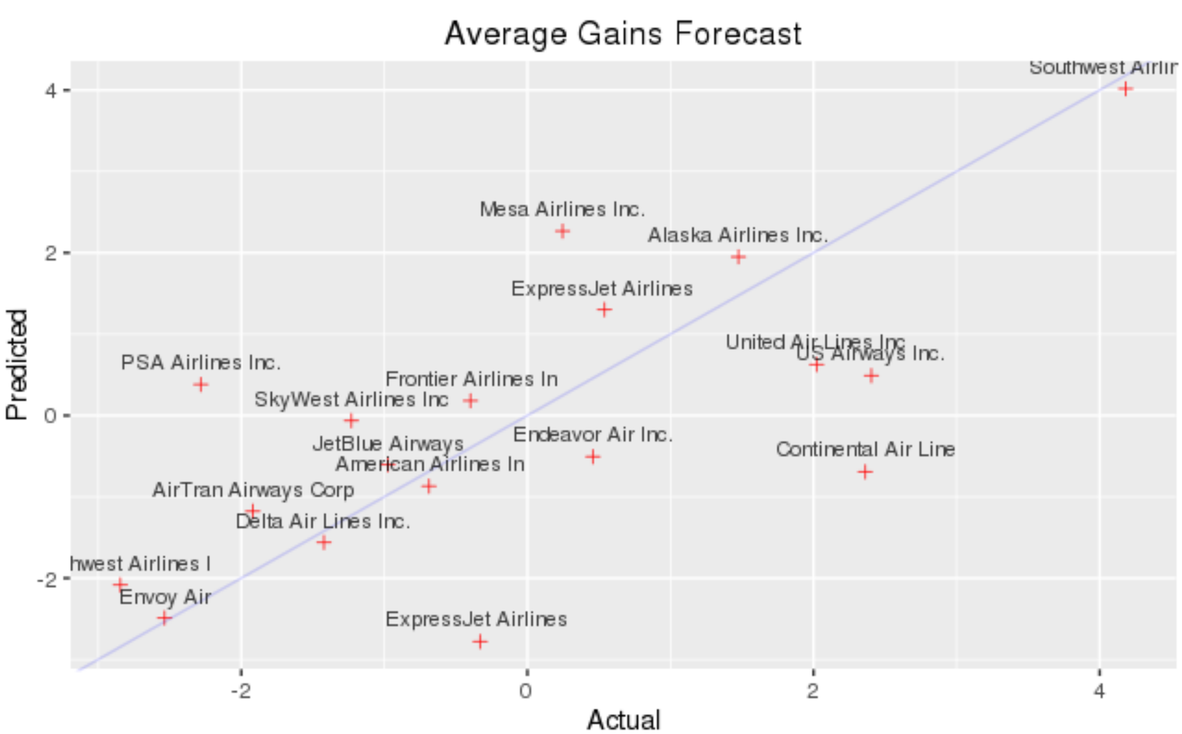
Visualize predictions

Compare actual gains to predicted gains for an out of time sample.

```
# Select data from an out of time sample
data_2008 <- flights_tbl %>%
  filter(!is.na(arrdelay) & !is.na(depdelay) & !is.na(distance)) %>%
  filter(depdelay > 15 & depdelay < 240) %>%
  filter(arrdelay > -60 & arrdelay < 360) %>%
  filter(year == 2008) %>%
  left_join(airlines_tbl, by = c("uniquecarrier" = "code")) %>%
  mutate(gain = depdelay - arrdelay) %>%
  select(year, month, arrdelay, depdelay, distance, uniquecarrier, descri
ption, gain, origin,dest)

# Summarize data by carrier
carrier <- sdf_predict(ml1, data_2008) %>%
  group_by(description) %>%
  summarize(gain = mean(gain), prediction = mean(prediction), freq = n())
 %>%
  filter(freq > 10000) %>%
  collect

# Plot actual gains and predicted gains by airline carrier
ggplot(carrier, aes(gain, prediction)) +
  geom_point(alpha = 0.75, color = 'red', shape = 3) +
  geom_abline(intercept = 0, slope = 1, alpha = 0.15, color = 'blue') +
  geom_text(aes(label = substr(description, 1, 20)), size = 3, alpha = 0.
75, vjust = -1) +
  labs(title='Average Gains Forecast', x = 'Actual', y = 'Predicted')
```



Some carriers make up more time than others in flight, but the differences are relatively small. The average time gains between the best and worst airlines is only six minutes. The best predictor of time gained is not carrier but flight distance. The biggest gains were associated with the longest flights.

Share Insights

This simple linear model contains a wealth of detailed information about carriers, distances traveled, and flight delays. These detailed insights can be conveyed to a non-technical audiance via an interactive flexdashboard (http://rmarkdown.rstudio.com/flexdashboard/index.html).

Build dashboard

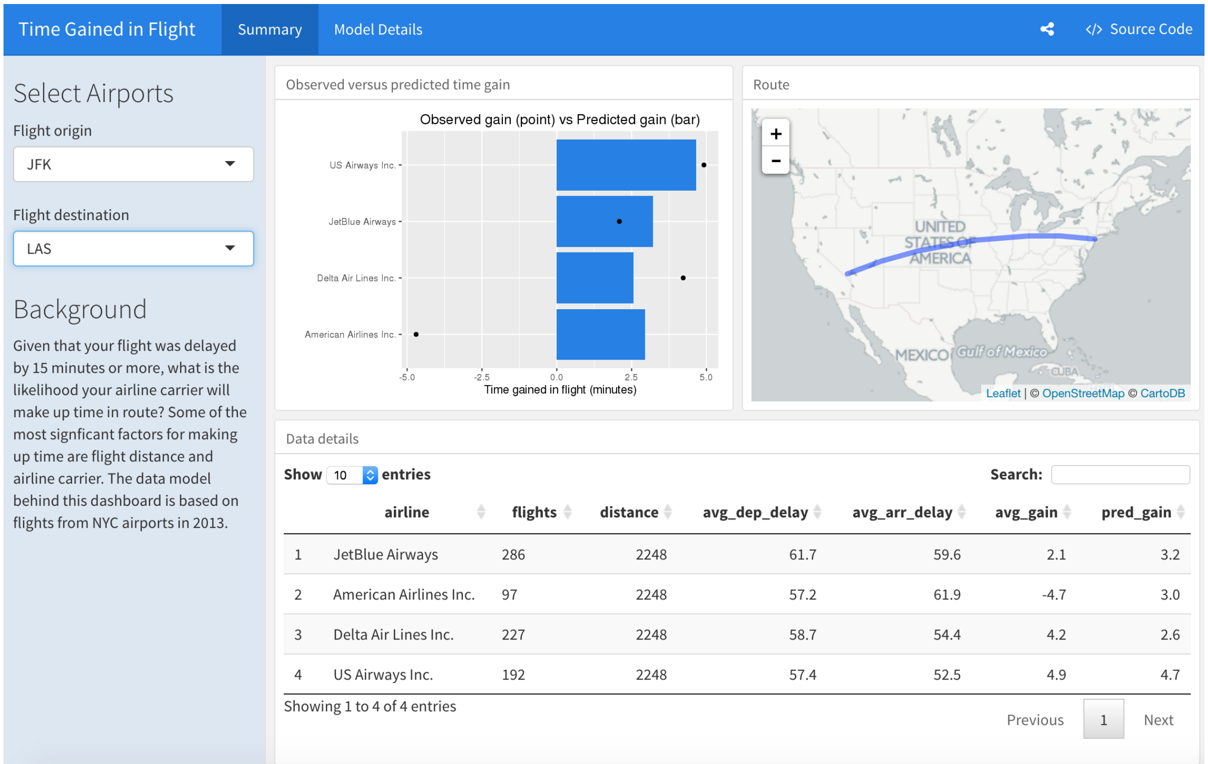
Aggregate the scored data by origin, destination, and airline. Save the aggregated data.

```
# Summarize by origin, destination, and carrier
summary_2008 <- sdf_predict(ml1, data_2008) %>%
  rename(carrier = uniquecarrier, airline = description) %>%
  group_by(origin, dest, carrier, airline) %>%
  summarize(
    flights = n(),
    distance = mean(distance),
    avg_dep_delay = mean(depdelay),
    avg_arr_delay = mean(arrdelay),
    avg_gain = mean(gain),
    pred_gain = mean(prediction)
    )

# Collect and save objects
pred_data <- collect(summary_2008)
airports <- collect(select(airports_tbl, name, faa, lat, lon))
ml1_summary <- capture.output(summary(ml1))
save(pred_data, airports, ml1_summary, file = 'flights_pred_2008.RData')
```

Publish dashboard

Use the saved data to build an R Markdown flexdashboard (http://rmarkdown.rstudio.com/flexdashboard/index.html). Publish the flexdashboard to Shiny Server (https://www.rstudio.com/products/shiny-server-pro/), Shinyapps.io (https://www.rstudio.com/products/shinyapps/) or RStudio Connect (https://www.rstudio.com/products/connect/).



(https://beta.rstudioconnect.com/content/1439/)