

# Data Table Lecture

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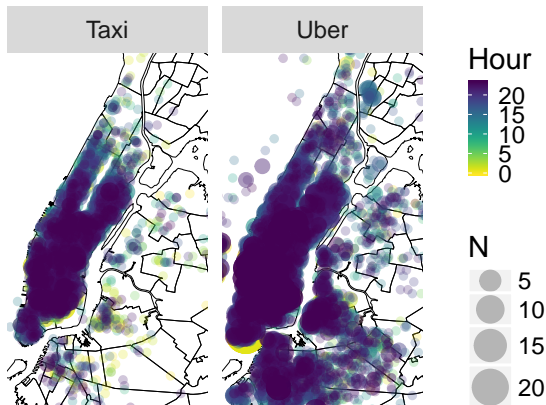
# How far does Uber driving get you?

- ▶ Uber advertised as great money-making solution, is that true
  - ▶ What days and times are most profitable to drive
- ▶ Use data.table to work with large data sets and create maps to investigate profitability of Uber

# Uber vs Taxi: Saturday

## Saturday ride pick-ups

April 12, 2014



Darker color indicates later rides  
Data from NYC TLC and BetaNYC

# Introduction: data.table Overview

- ▶ Allows for fast sub-setting, querying, and manipulating of data
  - ▶ Similar to dplyr
  - ▶ Simple and consistent syntax
- ▶ Fast and efficient at reading and processing data
- ▶ More info can be found here: <https://github.com/Rdatatable/data.table/wiki/Getting-started>

# Introduction: Simple Example

```
DT = data.table(x=letters[1:10], y=1:10, z=rep( c("odd", "e", "o", "v", "e", "n", "o", "d", "d", "e"), 10))
DF = as.data.frame(DT)
```

## *#1. Basic aggregation*

```
DT[, sum(y), by = z] # data
DF %>% group_by(z) %>% summarise(sum(y)) # dplyr
```

## *#2. Basic update operation*

```
DT[, y := cumsum(y), by = z]
DF %>% group_by(z) %>% mutate(y = cumsum(y))
```

# Reading in data

- ▶ `fread(input, ...)` quickly reads in large data sets
  - ▶ `input` may be quoted file path or URL
- ▶ Other helpful arguments include
  - ▶ `sep` — may specify character delimiter in file; generally not needed
  - ▶ `nrows` — limit number of rows read in
  - ▶ `na.strings` — specify character vector used to determine missing values
  - ▶ `colClasses` — tell whether column is character or numeric
  - ▶ `select/drop` — subset the data using vector of column names or column numbers

# Taxi data

- ▶ Data obtained from NYC Taxi and Limousine Commission under Freedom of Information Act
  - ▶ FiveThirtyEight provides data on their *github site*
- ▶ Include code cookbook for NYC Yellow cab data can be found *here*
- ▶ NAs are coded as blank characters
- ▶ Using a random sample of 200,000 rides in April, 2014

```
yellow.all <- fread(paste0(path, "yellow_ss_2014-04.csv"),  
head(yellow.all, n = 3)  
yellow.all[, V1 := NULL]
```

## Subsetting the data with i

- ▶ Basic structure of a data.table — `DT[i, ...]`
- ▶ `i` takes row sub-setting operations
  - ▶ Identical to basic row sub-setting with additional options
- ▶ Do not need to quote column names or use `$` notation
- ▶ For example:

```
# only want first 1000 observations
```

```
yellow.all[1:1000,]
```

```
# only want people who paid with a credit card
```

```
yellow.all[payment_type=="CRD",]
```

```
# only want people who tipped with a credit card
```

```
yellow.all[payment_type=="CRD" & tip_amount > 0,]
```

- ▶ What `dplyr` verb could we use to subset the data?



## Using Keys

- ▶ Filtering uses scan and sort method — can take long on unsorted data
- ▶ Setting key value sorts data.table by key
  - ▶ Sub-setting on key columns much faster
  - ▶ `setkey()` function
  - ▶ Numeric variables may require additional wrapper functions

```
setkey(yellow.all, payment_type)  
yellow.all[J("CRD")]
```

## Selecting Columns with j

- ▶ `DT[i, j, ...]`
- ▶ `j` works by taking a **list** of column names
  - ▶ Do not need to put names in quotes
  - ▶ Must use `J()`, `list()`, or `.( )`
  - ▶ `DT[, .(col1, col2, ...)]`
- ▶ May mix `i` and `j` to further subset

```
# only keep payment type and fare amount  
yellow.all[, .(payment_type, fare_amount)]
```

## In class Exercise 1:

- ▶ Create a data.frame of only payment type and fare amount for rides that cost more than \$10 in **both** data.table and dplyr

## With argument

- ▶ What if we want to pass a vector of column numbers instead of column names?
  - ▶ Can't do this in `data.table`
  - ▶ CAN do this in `data.frame`
- ▶ Setting `with = FALSE` regains `data.frame` functionality
  - ▶ `DT[i,j, with = , ...]`
  - ▶ Does not get rid of key functionality
  - ▶ May pass column names as quoted strings
  - ▶ `with = TRUE` is default

```
yellow.all[, 2:5, with = FALSE]
```

```
yellow.all[.("CRD"), 2:5, with = FALSE]
```

## Renaming and mutating variables with j

- ▶ Do not need to memorize any verbs in order to mutate

```
yellow.all[,  
  .(pickup_time = ymd_hms(pickup_datetime, tz = "EST"),  
    dist = trip_distance, fare = fare_amount)]
```

## Taxi Data at a Glance

- ▶ NYC is around 40 latitude and -80 longitude
- ▶ Notice anything strange?

Table 1: Summary of Unemployment Rate

Statistic	Mean	St. Dev.	Min	Max
passenger_count	1.696	1.360	0	6
trip_distance	2.899	3.421	0.000	76.500
pickup_longitude	-72.494	10.364	-82.334	0.000
pickup_latitude	39.935	5.709	0.000	51.721
dropoff_longitude	-72.434	10.562	-86.783	0.000
dropoff_latitude	39.903	5.819	0.000	50.381
fare_amount	12.470	10.209	2.500	310.300
tip_amount	1.473	2.241	0.000	113.330

# Final Sample Selection

- ▶ Only include taxi rides that are paid for by credit card
- ▶ Change lengthy variable names
- ▶ Drop:
  - ▶ `store_and_forward` entries
  - ▶ Trips with no distance traveled
  - ▶ Trips with 0 longitude or 0 latitude
  - ▶ Trips with 0 passengers
- ▶ **In-Class Exercise #2:** Translate dplyr code for final sample into `data.table` syntax

## Updating Data in Place

- ▶ Can either change values of existing column or add new column in place
- ▶ Columns are added directly to the new data set

```
# Create a rounded tip variable  
yellow.all[, tip_whole := round(tip_amount)]
```

- ▶ may also update multiple columns at once

```
yellow.all[, c("fare_whole", "total_whole") := .(  
  round(fare_amount), round(total_amount))]
```



## In-Class Exercise #3:

- ▶ Fill in the code below and create four new columns:
  - ▶ A dummy indicating the hour of the day
  - ▶ A dummy indicating the week of the year
  - ▶ A variable for the total time of the trip
  - ▶ A dummy indicating the day of the week
- ▶ Hint: Recall the properties of date objects and the lubridate package

```
day_names <- c("Monday", "Tuesday", "Wednesday",  
               "Thursday", "Friday", "Saturday", "  
               Sunday")  
  
yellow.ss <- as.data.table(yellow.ss)  
yellow.ss[, c( , , , ) := .( , ,  
  as.numeric( , unit = "secs")/60,  
  factor( , levels = day_names,  
         labels = day_names))]
```

## Summarizing the Data

- ▶ Can also use `j` option to summarize data
  - ▶ Use summary functions **without assigning** them to new variables

```
# what is the average distance (in miles) and time  
# (in minutes) of trips in april?  
yellow.ss[,.(mean(dist), mean(trip_time))]
```

- ▶ `by` = argument allows us to group variables and perform calculations
  - ▶ `DT[i,j, by =, ...]`

```
# what is the average distance (in miles) and time  
# (in minutes) of trips in april by weekday?  
setkey(yellow.ss, weekday, hour)  
yellow.ss[,.(avg_distance = mean(dist),  
             avg_time = mean(trip_time)),  
           by = .(weekday)]
```

## In-Class Exercise #4:

- ▶ Perhaps people tip better later in the evening?
- ▶ Translate the following code into dplyr:

```
yellow.ss[hour >= 22 | hour < 2,  
          .(mean(fare), mean(tip),  
            mean(tip/fare)),  
          by = .(weekday, hour)]
```

## The .N argument

- ▶ Special argument within the j argument
- ▶ Corresponds to total number of rows for group that is passed through
  - ▶ Similar to n() function in dplyr
  - ▶ Like j, can use i and by arguments

```
# number of rides on each weekday  
yellow.ss[,.(num_rides = .N), by=weekday]  
# number of rides that did not tip  
yellow.ss[tip == 0,.(.N), by=weekday]  
# recreate the average hourly fare, tips,  
yellow.ss[tip == 0,.(test = sum(fare)/.N), by=weekday]
```

## Chaining Argument

- ▶ So far only single data.table commands, DT[...]
- ▶ Can utilize sequences of commands in single call
  - ▶ DT[...] [....] [....]
  - ▶ Each call executes on the previous
  - ▶ Very similar to %>%

```
# calculate the the average amount of  
# gross earnings earnings per mile for  
# trips over 2 miles  
yellow.ss[,  
  gross_earnings := fare + tip][,  
  gepm := gross_earnings/dist][dist > 2,  
  .(max(gepm))]
```

## Are taxi rides profitable?

- ▶ In 2014 average maintenance were \$0.06/mile
- ▶ Using average weekly gas prices can calculate mpg
  - ▶ Suppose each taxi is a Ford Crown Victoria with 17 mpg
- ▶ can use `data.table` to merge data tables with `on = option`
  - ▶ Default is to merge by key
  - ▶ `DT1[DT2, on = c("merge_col1", "merge_col2", ...)]`
- ▶ columns used to merge do not have to have same name
  - ▶ `DT1[DT2, on = c("col1_DT1"="col1_DT2", "col2_DT1"="col2_DT2", ...)]`

```
gas_prices <- read.csv(paste0(path, "nyc_gas_prices.csv"))
gas_prices <- as.data.table(gas_prices)
```

```
yellow.mpg <- yellow.ss[gas_prices, on = "week"]
```

- ▶ **In-Class Exercise 5:** use the merged data and `data.table` chains to:
  - ▶ Create a new variable net earnings (Hint: How should we

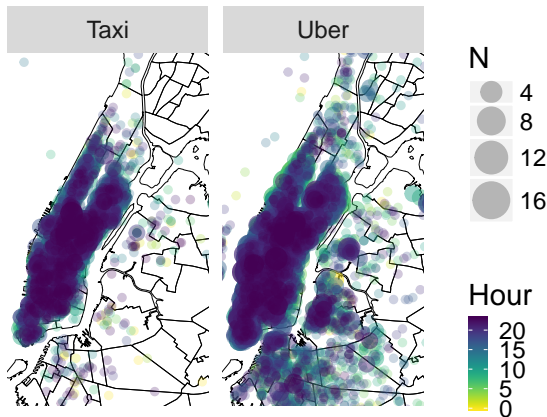
# Mapping the data

- ▶ GPS coordinates provided by NYC TLC
  - ▶ Pinpoint most frequented and profitable location
- ▶ Use downloaded shape file to create base of map
  - ▶ `ggmap` downloads maps directly from Google Maps API

# Uber vs Taxi: Tuesday

## Tuesday ride pick-ups

April 8, 2014



Darker color indicates later rides  
Data from NYC TLC and BetaNYC



## In-Class Exercise 6:

- ▶ Create a map that compares the number and time of Taxi cab rides on the average Tuesday to the number versus the number of Taxi cab rides on the average Saturday

## In-Class Exercise 7:

- ▶ Create a map that plots the most profitable locations for Taxi cab pick up
- ▶ *Hint:* you will use one less aes option