Bootcamp outline

Day #1: Basic command line interface, reproducible research, and sequence alignment

Day #2: Intro to R and RStudio, data input, and cleaning

Day #3: R and data cleaning, manipulation, processing

Day #4: R and data plotting, presentations

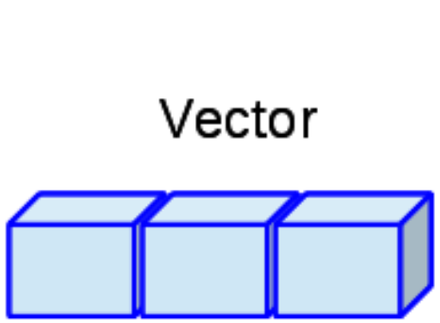
is a software environment for statistical computing

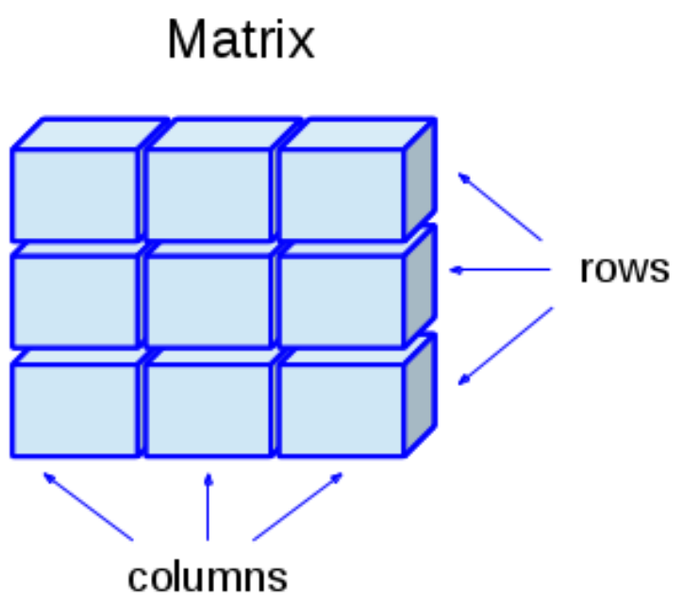
Data structures in R

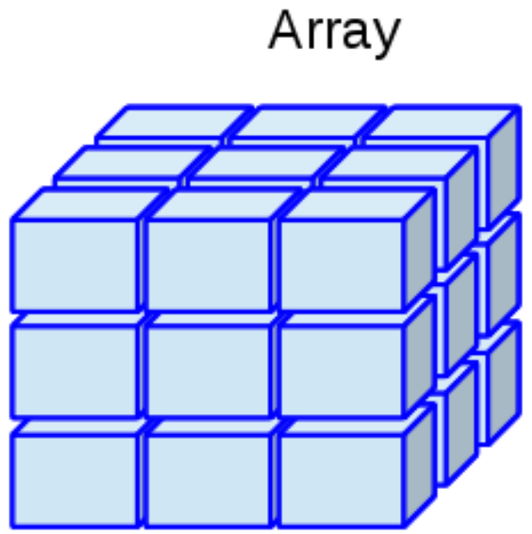
Vectors are one-dimensional data sets of any one data type

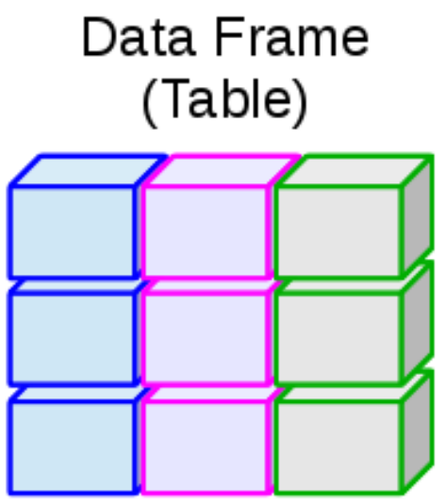
Data frames are two-dimensional data sets of any data type

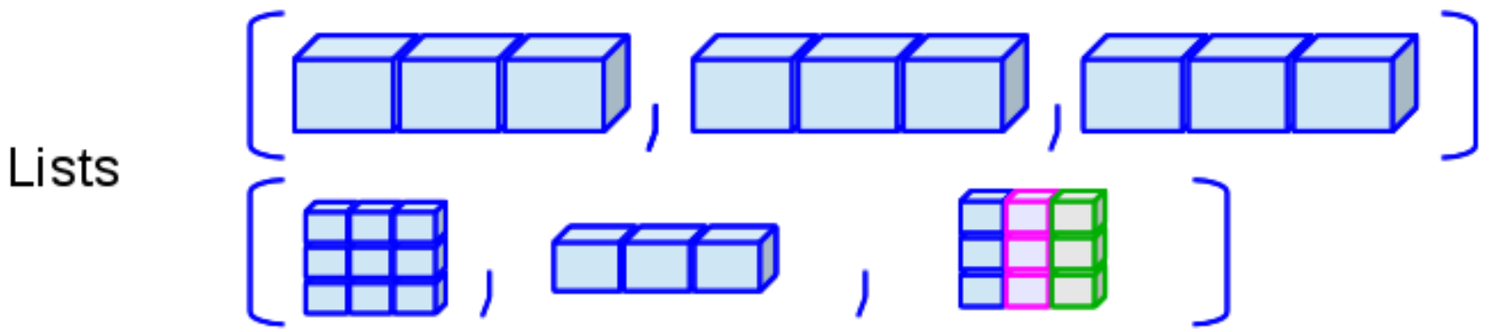
Lists are groups of vectors, data frames, or other lists.











How do we explore data objects?

`names(df)` = gives the names of columns of df

`rownames(df)` = gives the names of rows of df

`colnames(df)` = gives the names of columns of df

`dim(df)` = outputs the number of rows then columns of df

`length(df)` = outputs the length of df

`summary(df)` = outputs summary statistics of df

Other useful functions in R

`match, %in%` = match elements in object to another

`grep` = same as in CL, look for pattern in strings

`seq` = generate a sequence of numbers

`is.na` = gives TRUE or FALSE for NA data values

`unique` = same as in CL, look for unique data values

`merge, join` = merge two vectors or data frames

`c` = combine data

`rbind, cbind` = combine rows or columns, respectively

`rep` = replicate data

Flow of data analysis

1. Read — Yesterday

2. Tidy
3. Process — } Today

4. Plot
5. Present — } Tomorrow

What is the structure of your data?

1. Are there missing values?
2. What are the column names?
3. What are the dimensions?
4. What are the row values?
5. Are the data organized long or wide?

Introducing tidy data

Tidy data are easy to manipulate (dplyr), visualize (ggplot2) and model (many packages).

Each column is a variable (sample, replicate, phenotype, etc.).

Each row is an observation.

Let's make some messy data. Three people take two drugs and recored his/her heart rates:

```
messy <- data.frame(
            name = c("Kelly", "Bob", "Greg"),
            a = c(67, 80, 64),
            b = c(56, 90, 50))
```

Let’s go from messy to tidy

Each column is a variable (sample, replicate, phenotype, etc.)

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Let’s make some messy data. Three people take two drugs and recored his/her heart rates:

```
messy <- data.frame(
            name = c(“Kelly”, “Bob”, “Greg”),
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```

These data are wide. Also, columns a and b are not variables.

Let's go from messy to tidy

Each column is a variable (sample, replicate, phenotype, etc.)

Each row is an observation.

```
> messy
   name  a  b
1 Kelly 67 56
2   Bob 80 90
3  Greg 64 50
```

These data are wide. Also, columns a and b are not variables.

Use **`gather()`** to bring together a and b columns into key-value pairs (or variable-observation pairs)

```
> messy %>% gather(drug, heartrate, a:b)
```

Let's go from messy to tidy

```
> messy
   name  a  b
1 Kelly 67 56
2   Bob 80 90
3  Greg 64 50
```

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```
> messy %>% gather(drug, heartrate, a:b)
```

```
> messy %>% gather(drug, heartrate, a:b)
   name drug heartrate
1 Kelly    a        67
2   Bob    a        80
3  Greg    a        64
4 Kelly    b        56
5   Bob    b        90
6  Greg    b        50
```

Most of your data are already tidy.

Let's go from messy to tidy

Use **`gather()`** to bring together a and b columns into key-value pairs (or variable-observation pairs)

Use **`spread()`** to do the opposite to make long data wide again

```
> messy %>% gather(drug, heartrate, a:b) %>%
spread(key = drug, value = heartrate)
```

name	a	b
1 Kelly	67	56
2 Bob	80	90
3 Greg	64	50

Let's go from messy to tidy

Use `gather()` to bring together a and b columns into key-value pairs (or variable-observation pairs)

Use `spread()` to do the opposite to make long data wide again

Use `separate()` to split column data into different columns

Use `unite()` to combine column data into one column

Data Formats: Long *vs* Wide

Variables | Identifiers

Ozone	Solar.R	Wind	Temp	Month	Day
41	190	7.4	67	5	1
36	118	8.0	72	5	2
12	149	12.6	74	5	3
18	313	11.5	62	5	4
NA	NA	14.3	56	5	5
28	NA	14.9	66	5	6
23	299	8.6	65	5	7
19	99	13.8	59	5	8
8	19	20.1	61	5	9
NA	194	8.6	69	5	10
7	NA	6.9	74	5	11
16	256	9.7	69	5	12
11	290	9.2	66	5	13
14	274	10.9	68	5	14
18	65	13.2	58	5	15
14	334	11.5	64	5	16
34	307	12.0	66	5	17
6	78	18.4	57	5	18
30	322	11.5	68	5	19
11	44	9.7	62	5	20
1	8	9.7	59	5	21

Wide

Identifiers

Month	Day	variable	value
5	1	Ozone	41.0
5	2	Ozone	36.0
5	3	Ozone	12.0
5	4	Ozone	18.0
5	5	Ozone	NA
5	6	Ozone	28.0
5	7	Ozone	23.0
5	8	Ozone	19.0
5	9	Ozone	8.0
5	10	Ozone	NA
5	11	Ozone	7.0
5	12	Ozone	16.0
5	13	Ozone	11.0
5	14	Ozone	14.0
5	15	Ozone	18.0
5	16	Ozone	14.0
5	17	Ozone	34.0
5	18	Ozone	6.0
5	19	Ozone	30.0
5	20	Ozone	11.0
5	21	Ozone	1.0

Long

Data Formats: Long *vs* Wide

How to convert between long and wide data?

tidyr - “Easily tidy data with spread and gather functions.”

An example:

```
library(tidyr)
library(dplyr)

# make df object be 'airquality' dataset
df <- airquality

View(df)
```

Data Formats: Long *vs* Wide

An example:

```
library(tidyr)
library(dplyr)

# make df object be 'airquality' dataset
df <- airquality

View(df)
```

Variables | Identifiers

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7	NA	6.9	74	5	11
16	256	9.7	69	5	12
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34	307	12.0	66	5	17
6	78	18.4	57	5	18
30	322	11.5	68	5	19
11	44	9.7	62	5	20
1	8	9.7	59	5	21

Data Formats: Long *vs* Wide

Convert to long format

```
df1 <- df %>%
  gather(variable, value, -Month, -Day)
```

tidyr integrates with dplyr

Identifiers

Month	Day	variable	value
5	1	Ozone	41.0
5	2	Ozone	36.0
5	3	Ozone	12.0
5	4	Ozone	18.0
5	5	Ozone	NA
5	6	Ozone	28.0
5	7	Ozone	23.0
5	8	Ozone	19.0
5	9	Ozone	8.0
5	10	Ozone	NA
5	11	Ozone	7.0
5	12	Ozone	16.0
5	13	Ozone	11.0
5	14	Ozone	14.0
5	15	Ozone	18.0
5	16	Ozone	14.0
5	17	Ozone	34.0
5	18	Ozone	6.0
5	19	Ozone	30.0
5	20	Ozone	11.0
5	21	Ozone	1.0

Long

Data Formats: Long *vs* Wide

Convert back to wide format

```
df2 <- df1 %>%
  spread(variable,value)
```

Identifiers | Variables

Month	Day	Ozone	Solar.R	Wind	Temp
5	1	41	190	7.4	67
5	2	36	118	8.0	72
5	3	12	149	12.6	74
5	4	18	313	11.5	62
5	5	NA	NA	14.3	56
5	6	28	NA	14.9	66
5	7	23	299	8.6	65
5	8	19	99	13.8	59
5	9	8	19	20.1	61
5	10	NA	194	8.6	69
5	11	7	NA	6.9	74
5	12	16	256	9.7	69
5	13	11	290	9.2	66
5	14	14	274	10.9	68
5	15	18	65	13.2	58
5	16	14	334	11.5	64
5	17	34	307	12.0	66
5	18	6	78	18.4	57
5	19	30	322	11.5	68
5	20	11	44	9.7	62
5	21	1	8	9.7	59

Why do we care about long vs. wide data?

```
> messy %>% gather(drug, heartrate, a:b)
   name drug heartrate
1 Kelly    a        67
2   Bob    a        80
3  Greg    a        64
4 Kelly    b        56
5   Bob    b        90
6  Greg    b        50
```

Easy grouping leads to easy analysis

Easy summarization and plotting

Don’t forget **`unique()`**

Data tidying time

Flow of data analysis

1. Read

2. Tidy

3. Process

4. Plot

5. Present

Why do we care about processing data?

Measurement data can be overwhelming.

Summarize with means, medians, dispersion of data

Summaries help us think about replication and error

Sometimes we don’t care about processing data

dplyr: the grammar of data analysis

Hadley Wickham: R guru

```
> rnorm(1000)
   [1]  0.7414303363 -0.9383127854 -0.5898356239 -1.4879381203 -0.1659582252  0.4690914210 -0.3598660699
  [11]  2.6412618078  0.2321025525 -0.1327265269  1.5190948454  0.9066730669  0.8596798670  1.4650258834
  [21]  0.3458054361 -0.4886197680  1.3973476592 -1.5638681539  1.2853007445  0.4101364885  0.2294735247
  [31]  0.4139866417 -0.6954449569  0.8041125473  0.5535330655 -0.4694144802  1.7690122917  0.4707698513
  [41] -0.4594998205  0.4043386537 -1.6870132729 -0.1942175306  1.1583540288 -0.0002630832 -0.1468545234
  [51] -0.4410132764  0.7364134275  2.0252124219 -1.4500256740  1.9125350969 -0.2343692491  1.3286159719
  [61]  1.1314206797 -0.9113800142  0.1240687944 -0.3060999484 -0.4709176421 -0.1122752856 -0.5401285711
  [71] -0.0686987744 -0.1373026497  0.6094719385 -1.4732265606  0.7573958380 -0.7515556914 -1.2857906361
  [81] -0.8857107791 -0.4069381352 -2.1758080948 -0.3569778668 -0.0397559943 -0.0961785023  0.6472138988
  [91] -0.8830039848 -2.0658918174  2.2363978861 -0.9000721943  1.1227886790  2.1469963330 -1.0971182540
 [101]  0.8612006384 -1.0684987091  1.5397207327 -0.0174112748  0.6287091546 -0.9850152543  1.4317789228
 [111] -0.9610323091 -0.8214297129  0.0698531890 -0.2544790671  0.9626996188  1.4312750227  1.1144196341
 [121]  0.8893473243 -1.2105287954 -1.2804874114 -1.5417165424 -0.5225043177 -0.2443883469  1.0395231050
 [131] -0.0216148381  1.0670464559 -1.0937062759 -0.3949936928  0.6399457290  0.3473726551 -0.5487464459
 [141]  2.1042373099 -0.8215960512  1.1647203780 -0.5018804363 -0.6276899976 -0.8121978140 -1.9868618662
 [151] -2.5904304497  0.5526988025 -0.3580881297 -0.3931144287 -0.6494195785 -0.1096485904  0.0678612489
 [161]  1.6343875443 -0.0683924766  1.2130360802 -0.6313426788  0.9838639622 -0.4797304977  0.1817758260
 [171]  0.0695651300  1.0314607326 -2.0653772732 -0.0865188406 -1.1631547204  0.5729574962 -1.2640545629
 [181] -0.9050088656  0.2930384939 -0.2051316675  0.9764933512 -0.2243143242 -0.9517134217 -0.3218631511
 [191] -0.1991329532 -0.0923899862 -1.9904200615 -1.3877169486 -0.7618046746  0.2040072200  1.9060898324
```

Data

arrange select
mutate filter
summarise

Simple operations

Simple, efficient storage, fast algorithms, database integration

dplyr: simple verbs

arrange	arrange the order of rows
select	select columns to keep
filter	filter rows to keep
mutate	mutate columns into new columns
group_by	group data by specific column(s)
summarise	summarize data by group

arrange arrange the order of rows

```
> head(df)

> df <- arrange(df, Row, TOF)

> head(df)
```

select select columns to keep

```
> head(df)

> reduced.df <- select(df, Row, Column, TOF, EXT, Red, Yellow)

> head(reduced.df)
```

mutate mutate columns into new columns

```
> head(reduced.df)

> reduced.df <- mutate(reduced.df, norm.yellow = Yellow/TOF)

> head(reduced.df)
```

filter filter rows to keep

```
> head(processed.df)

> processed.df <- filter(processed.df, Column %in% c(1:5, 7:11))

> head(processed.df)
```

group_by group data by specific column(s)

summarise summarize data by group

```
> head(reduced.df)
```

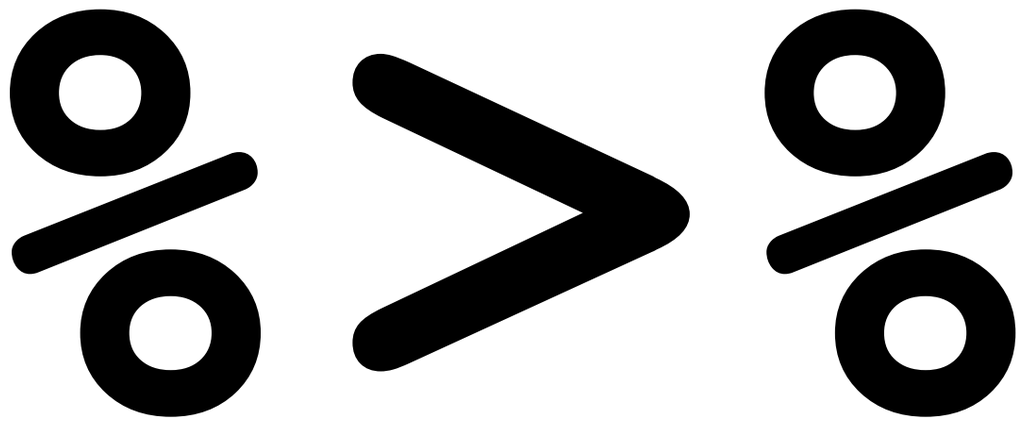
```
> reduced.df <- group_by(reduced.df, Row, Column)
```

```
> processed.df <- summarise(reduced.df, mean.TOF = mean(TOF, na.rm=TRUE))
```

```
> head(processed.df)
```

Divide and conquer

Let's put it all together



```
> processed.df <- df %>%
      select(Row, Column, TOF, EXT, Red, Yellow) %>%
      mutate(norm.yellow = Yellow/TOF) %>%
      group_by(Row, Column) %>%
      summarise(mean.TOF = mean(TOF, na.rm=TRUE)) %>%
      filter(Column %in% c(1:5, 7:11))
```

Data processing time

https://www.rstudio.com/wp-content/uploads/2015/02/data-wrangling-cheatsheet.pdf

Flow of data analysis

1. Read

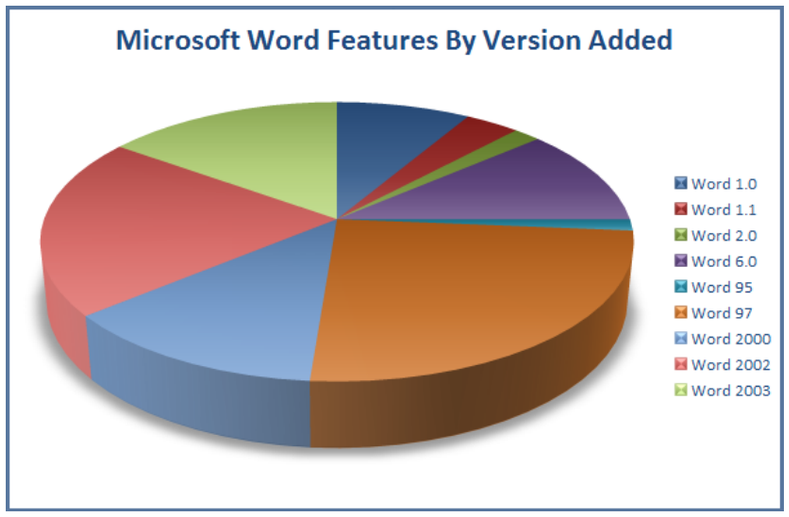
2. Tidy

3. Process

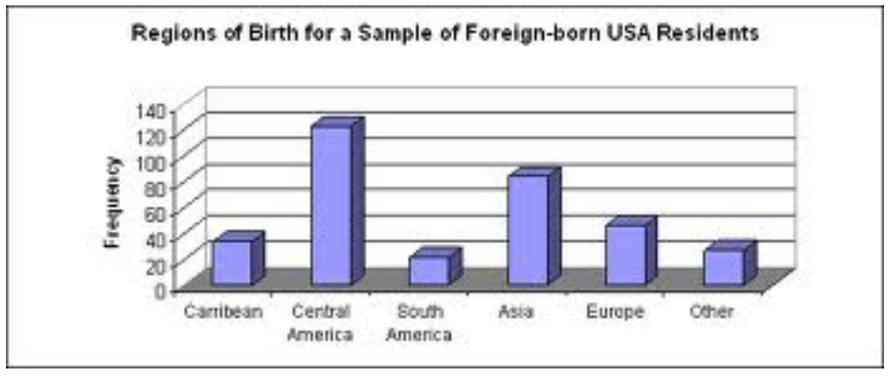
4. Plot

5. Present

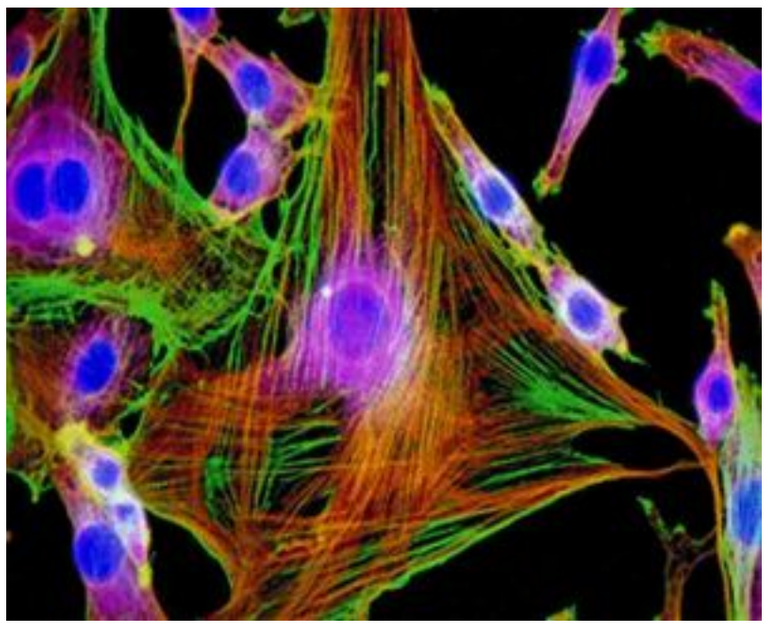
Plots should make data obvious and beautiful



Pie charts are impossible to interpret



Bar charts hide data



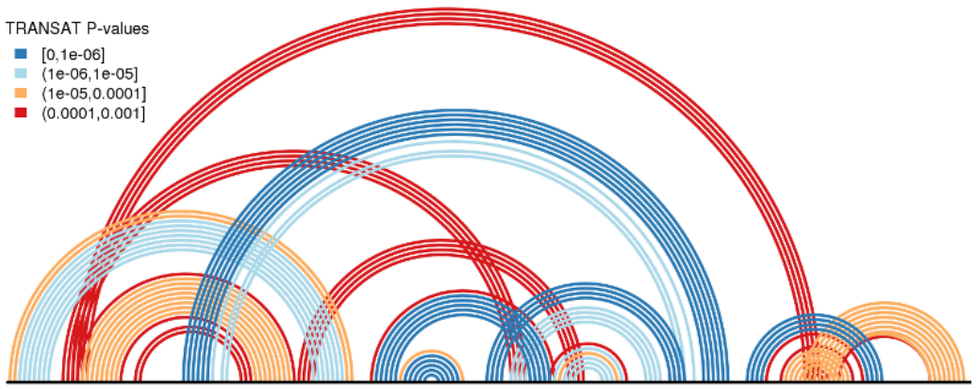
Beautiful, but…have to believe investigator on numbers, not quantitative, and hard to project

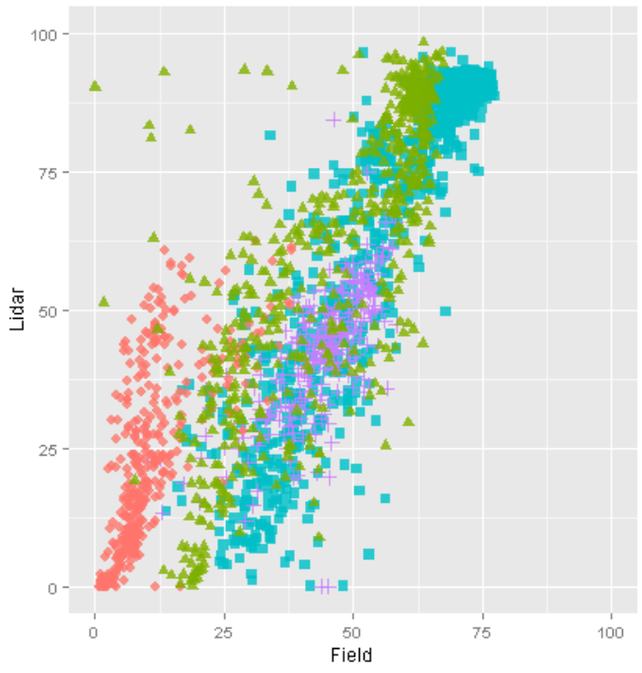
http://www.badfigure.org/

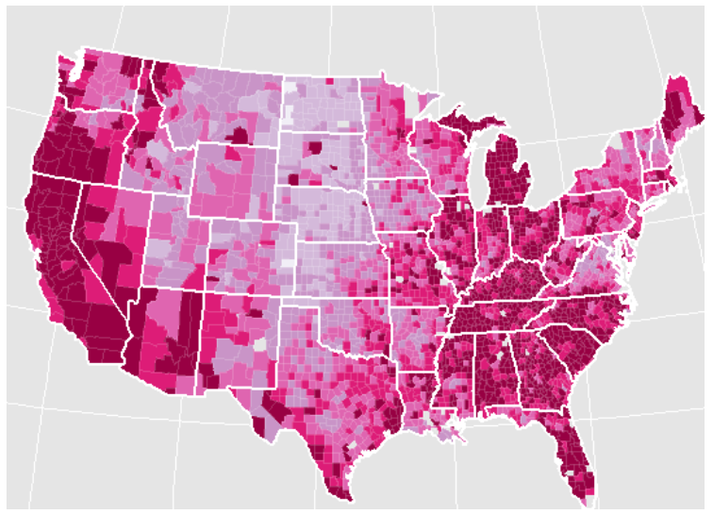
ggplot2: the grammar of graphics

Hadley Wickham: R guru

Edward Tufte: graphics guru







What is a grammar?

```
> rnorm(1000)
   [1]  0.7414303363 -0.9383127854 -0.5898356239 -1.4879381203 -0.1659582252  0.4690914210 -0.3598660699
  [11]  2.6412618078  0.2321025525 -0.1327265269  1.5190948454  0.9066730669  0.8596798670  1.4650258834
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  [91] -0.8830039848 -2.0658918174  2.2363978861 -0.9000721943  1.1227886790  2.1469963330 -1.0971182540
 [101]  0.8612006384 -1.0684987091  1.5397207327 -0.0174112748  0.6287091546 -0.9850152543  1.4317789228
 [111] -0.9610323091 -0.8214297129  0.0698531890 -0.2544790671  0.9626996188  1.4312750227  1.1144196341
 [121]  0.8893473243 -1.2105287954 -1.2804874114 -1.5417165424 -0.5225043177 -0.2443883469  1.0395231050
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 [191] -0.1991329532 -0.0923899862 -1.9904200615 -1.3877169486 -0.7618046746  0.2040072200  1.9060898324
```

Data

x y z

color

Aesthetics

points boxplot

line

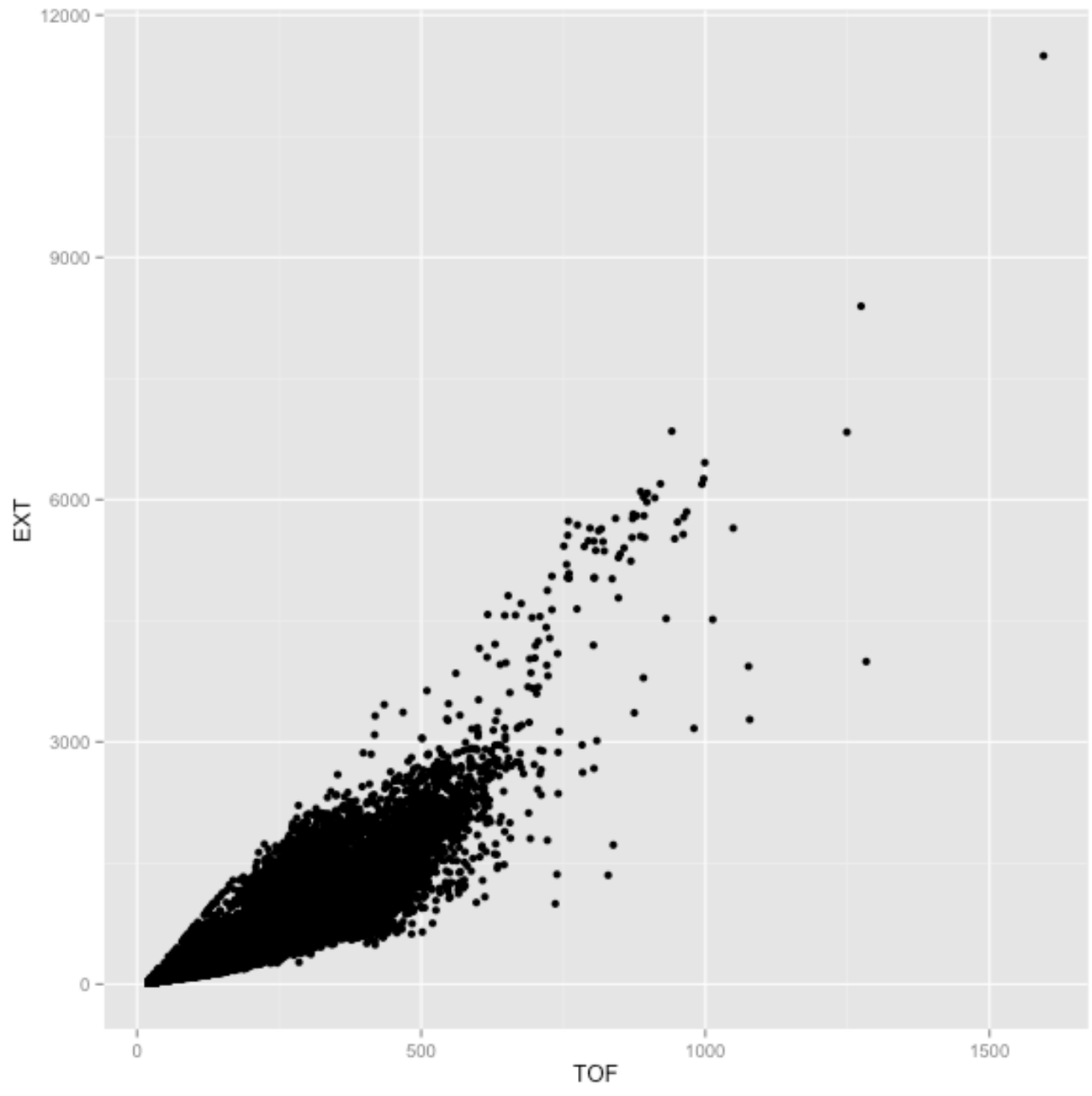
Geometric objects

http://ggplot2.org

Simple ggplot2 example

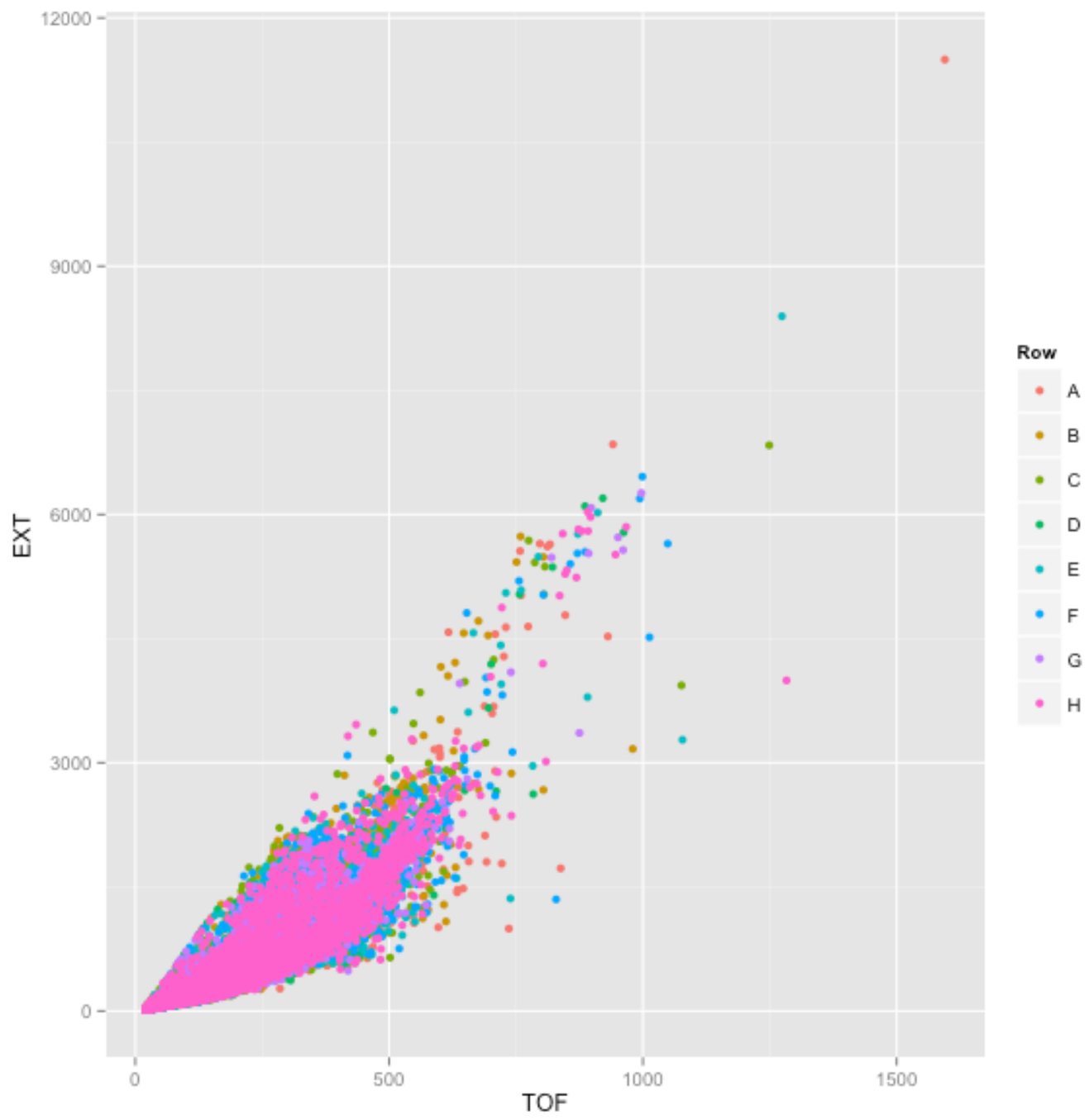
```
ggplot(data=df) + aes(x=TOF, y=EXT) + geom_point()
```

Data **Aesthetics** **Geometric objects**



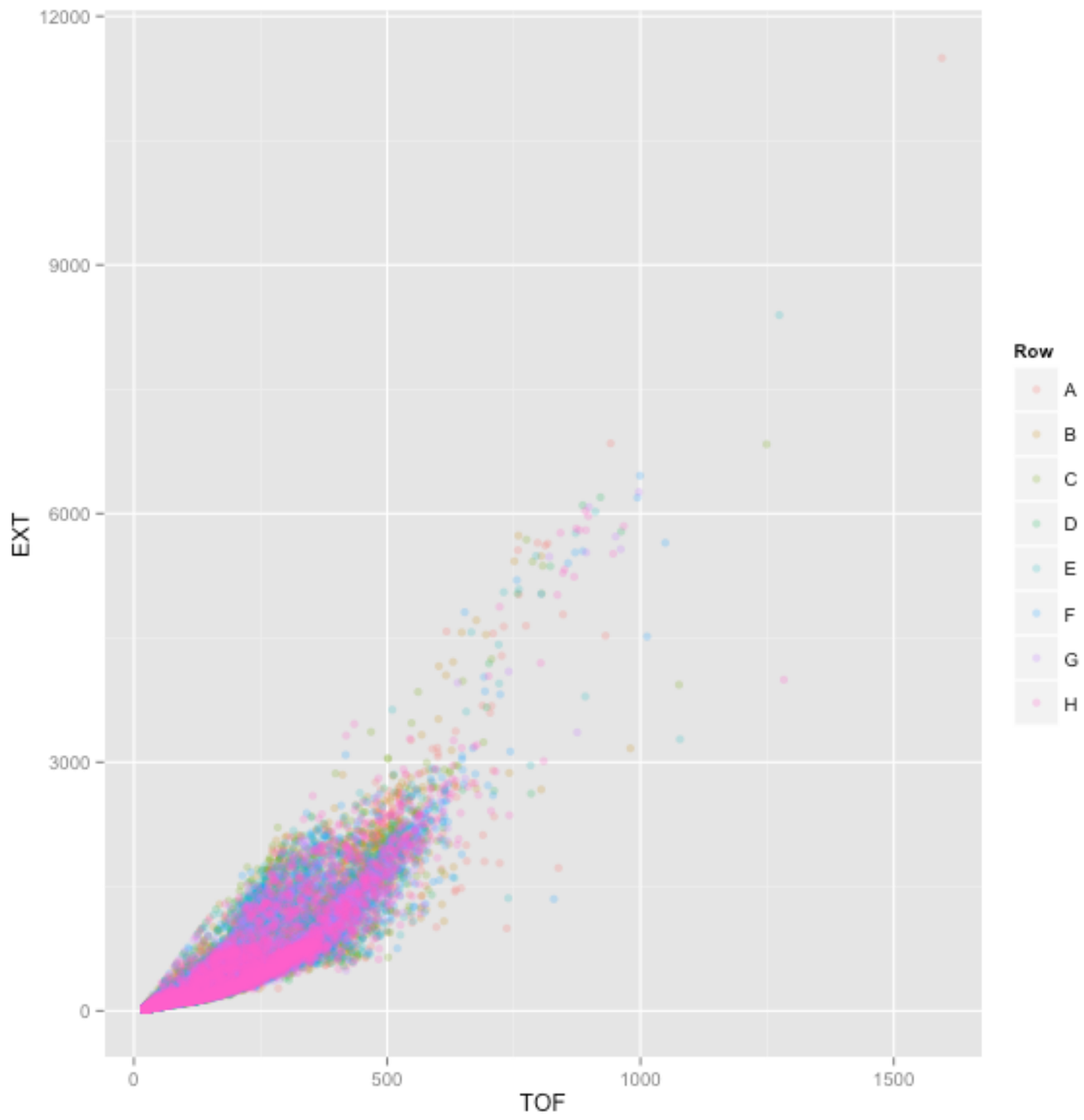
Let’s add some aesthetics

```
ggplot(data=df) + aes(x=TOF, y=EXT, color=Row) + geom_point()
```



Let’s add some aesthetics

```
ggplot(data=df) + aes(x=TOF, y=EXT, color=Row) + geom_point(alpha=0.25)
```



Aesthetics apply to data and geoms

```
ggplot(data=df) + aes(x=TOF, y=EXT, color=Row) + geom_point(alpha=0.25)
```

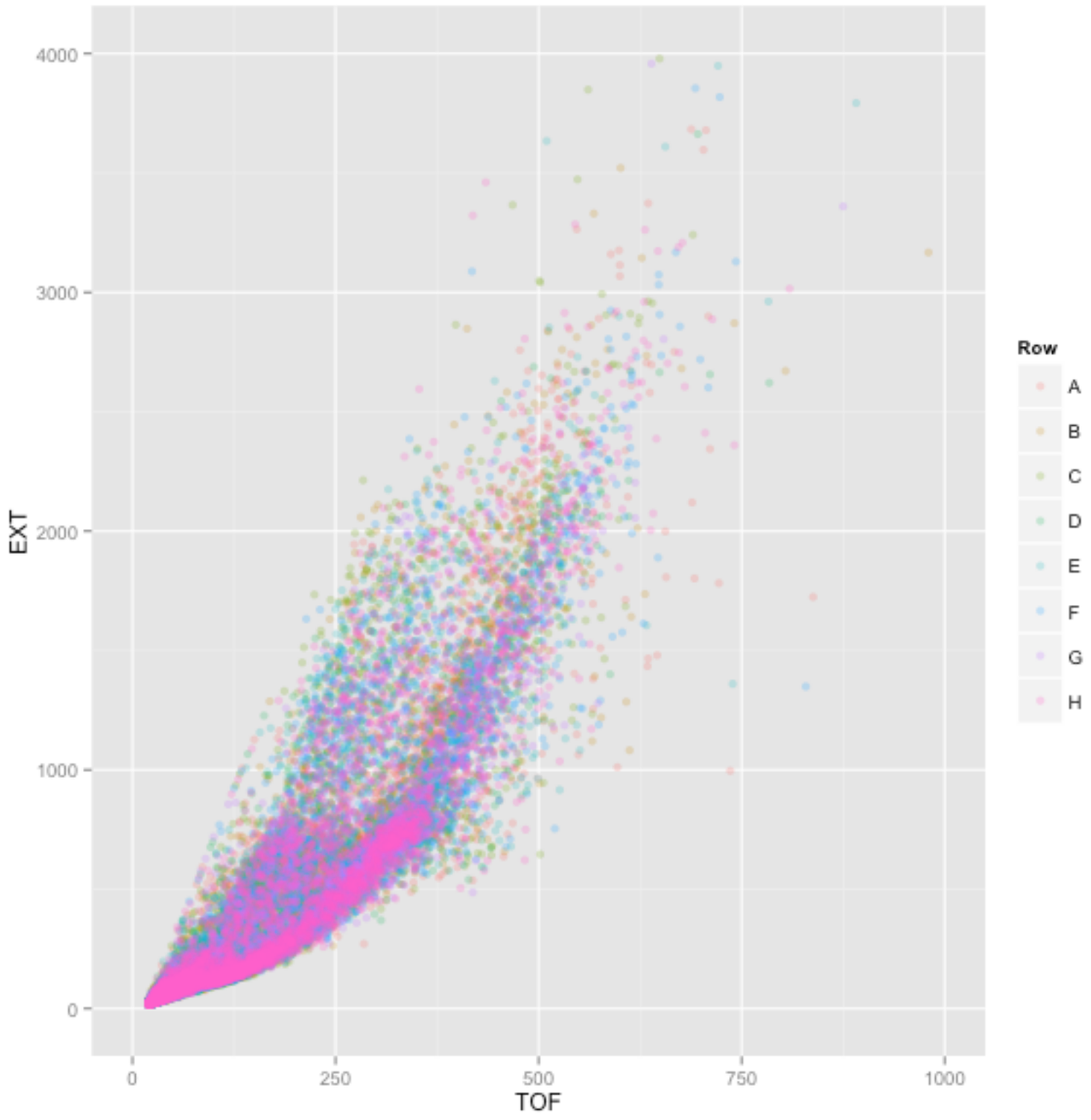
aesthetic from data **aesthetic constant**

Challenge:
Make a scatter plot with size from Column and shape = 2

Another aspect of grammar: coordinates

```
ggplot(data=df) + aes(x=TOF, y=EXT, color=Row) + geom_point(alpha=0.25) + xlim(0, 1000) + ylim(0,4000)
```

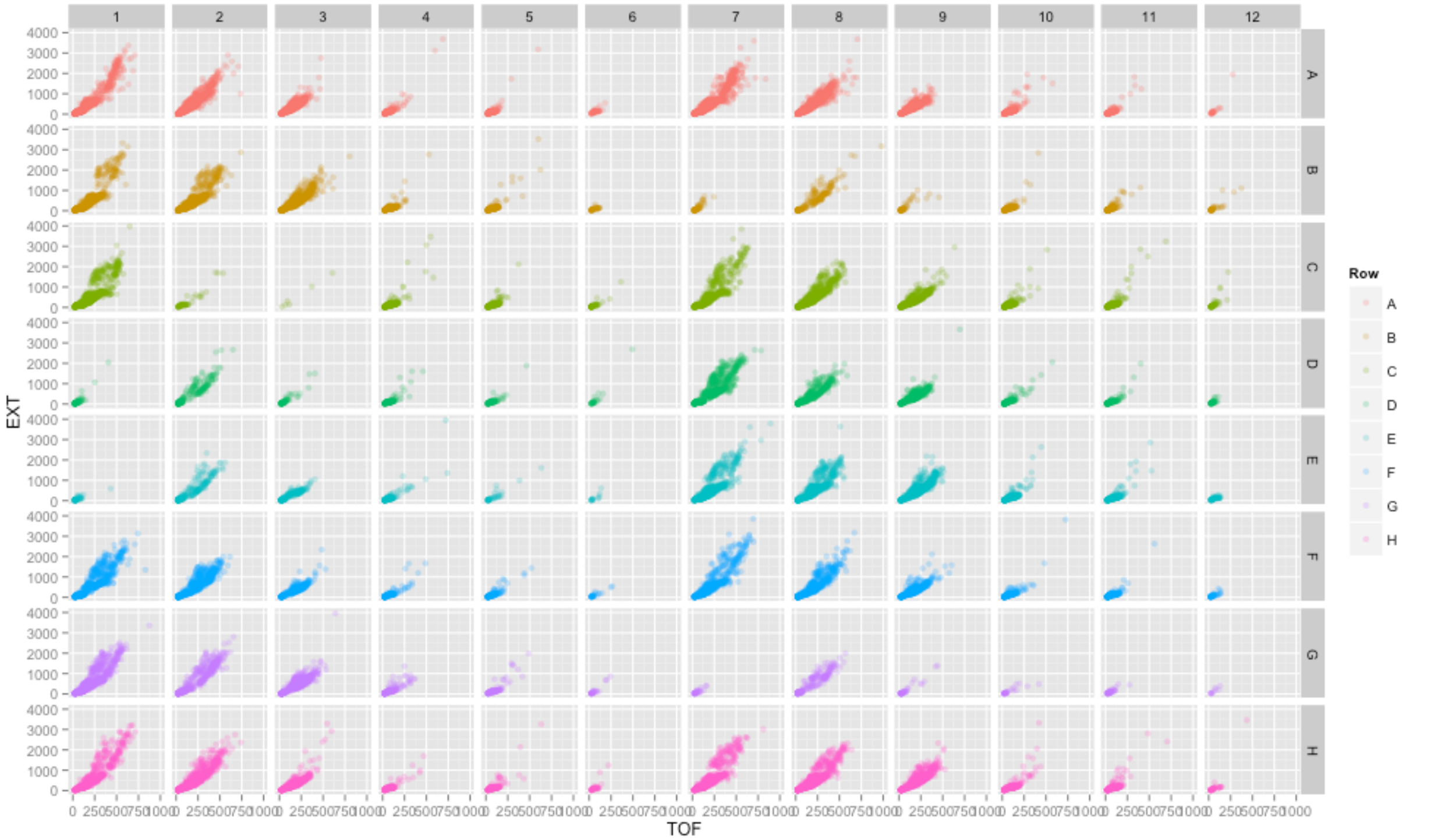
Data **Aesthetics** **Geometric objects** **Coordinates**



Another aspect of grammar: facets

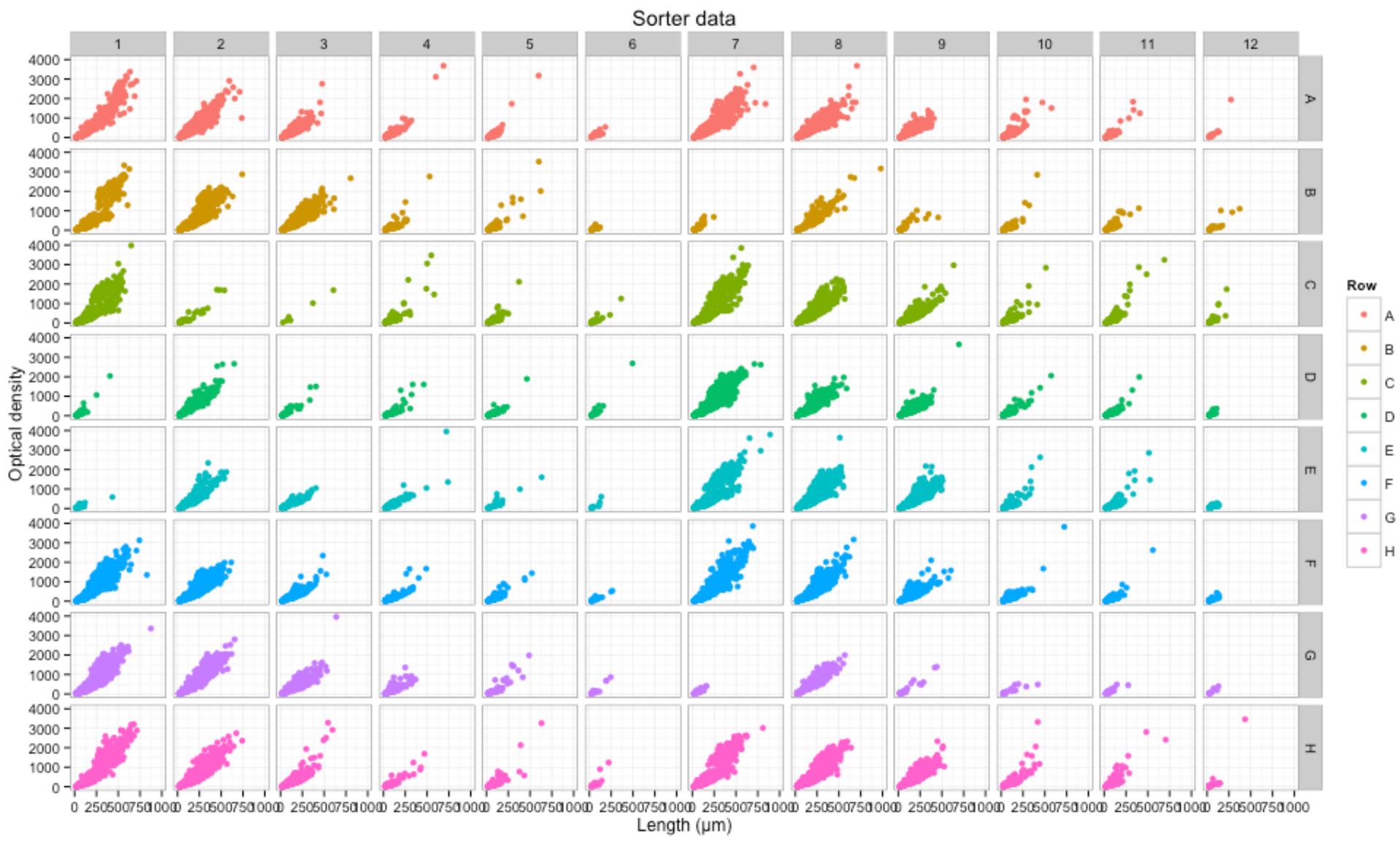
```
ggplot(data=df) + aes(x=TOF, y=EXT, color=Row) + geom_point(alpha=0.25) + xlim(0, 1000) + ylim(0,4000) + facet_grid(Row~Column)
```

Data **Aesthetics** **Geometric objects** **Coordinates** **Facets**



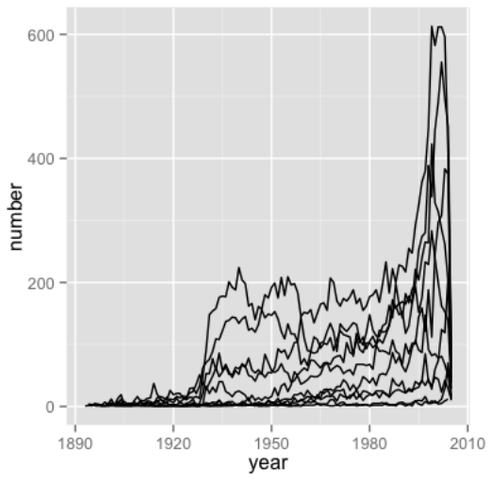
How to make the plot look prettier

```
ggplot(data=df) + aes(x=TOF, y=EXT, color=Row) +
     geom_point(alpha=0.25) +
     xlim(0, 1000) + ylim(0,4000) +
     labs(x="Length (μm)", y="Optical Density", title="Sorter Data") +
     facet_grid(Row~Column) +
     theme_bw()
```

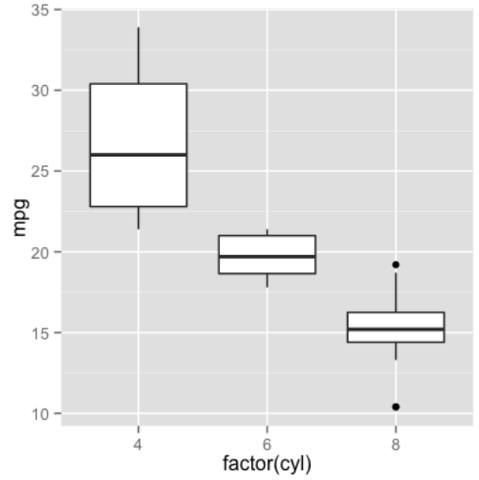


http://ggplot2.org

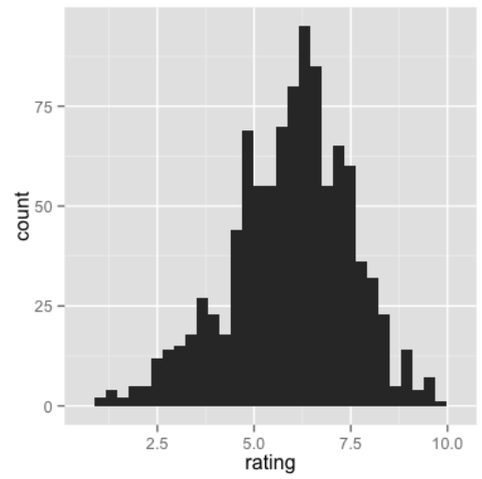
Other geometric objects



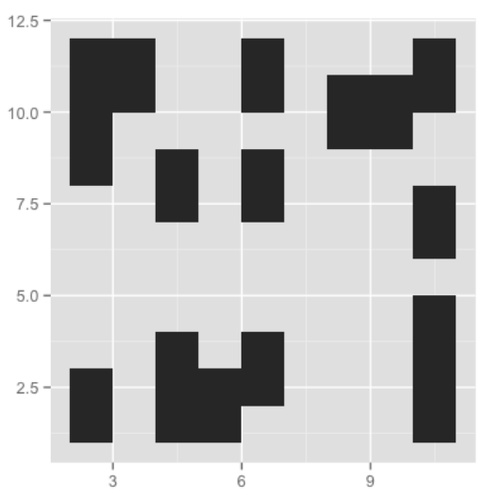
`geom_line`



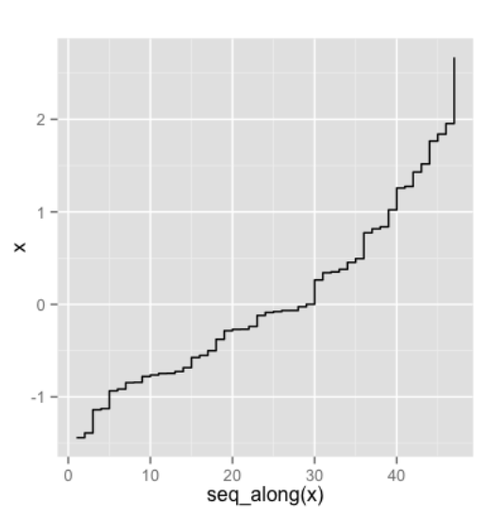
`geom_boxplot`



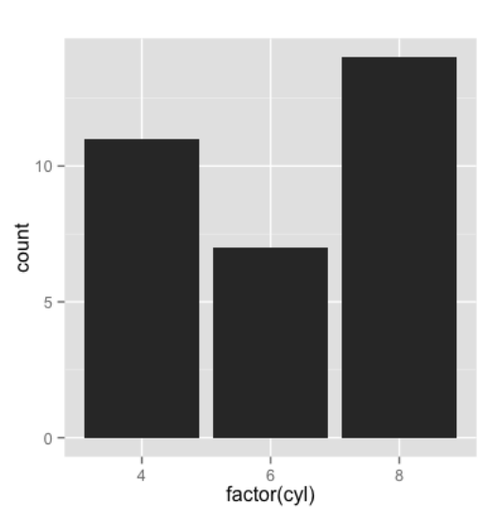
`geom_histogram`



`geom_rect`



`geom_step`



`geom_bar`

http://docs.ggplot2.org/current/

As always, ggplot2 is not the only way to plot data in R. Keep up with current trends.

http://flowingdata.com/

Data plotting time

https://www.rstudio.com/wp-content/uploads/2015/03/ggplot2-cheatsheet.pdf

Flow of data analysis

1. Read
2. Tidy
3. Process
4. Plot
5. Present

What to do when you are lost?

http://www.r-bloggers.com

http://gettinggeneticsdone.blogspot.com

http://rseek.org

Day #3 Homework

1. Think about your data analysis
2. Finish tidying, processing, and plotting your data