Data Exploration, Visualization, and Feature Engineering

Data Science Dojo

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Agenda

- Why data exploration and visualization
- Exploration and visualization using R
  - Core R functionality – iris dataset
  - Lattice package – mtcars dataset
  - ggplot2 package – diamonds data set
- Story-telling with data
  - Titanic data set

WHY DATA EXPLORATION AND VISUALIZATION

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Data beats algorithm but…

- More data usually yields good generalization performance, even with a simple algorithm
- But there are caveats
  - Amount of data may have diminishing returns
  - Data quality and variety matters
  - A decent performing learning algorithm is still needed
  - Most importantly, extracting useful features out of data is important

Dispelling common myths

- There is *NO* single ML algorithm that will take raw data and give you the best model

- You do *NOT* need to know a lot of machine learning algorithms to build robust predictive models

Janitorial work is important

- Not spending time on understanding your data is a source of many problems!
- Remember the 80/20 rule
  - 80% : Data cleaning, data exploration, feature engineering, pre-processing etc…
  - 20% : Model building

EXPLORATION AND VISUALIZATION USING R

Objectives

- Develop an understanding of the high-level thinking process of data exploration
- Making sense of data using visualization techniques
- Learning to perform feature engineering
- Becoming a good story teller.

I am new to R

- Focus on ideas/concepts rather than exact syntax. R help is your friend. ☺

  ?mean, ?sd

  help( )
  example( )

- All slides have code samples
- Sample code + slides: ‘Data Exploration and Visualization’ folder

Common Graphical Parameters

- Title of graph using the **main** function, main = "title"
- Label x- axis by using the **xlab** function, xlab = "label x axis"
- Label x- axis by using the **ylab** function, ylab = "label y axis"
- Colors controlled by **col**
- Customize features of the graph using the **par** function.
- Text and symbol size controlled by **cex**
- Plotting symbols controlled by **pch**
- Line width controlled by **lwd**

R to start exploring data commands

Commands	Description
read.csv() , read.table()	Load data/file into a dataframe
data()	Load a dataset
names()	List names of variables in a dataframe
head()	First 6 rows of data
tail()	Last 6 rows of data
str()	Display internal structure if R object
View()	View dataset in spreadsheet format
dim()	Dimensions(rows and columns) of dataframe
summary()	Display 5-number summary and mean
colnames()	Provide column names

CORE R GRAPHICS

The “iris” data set

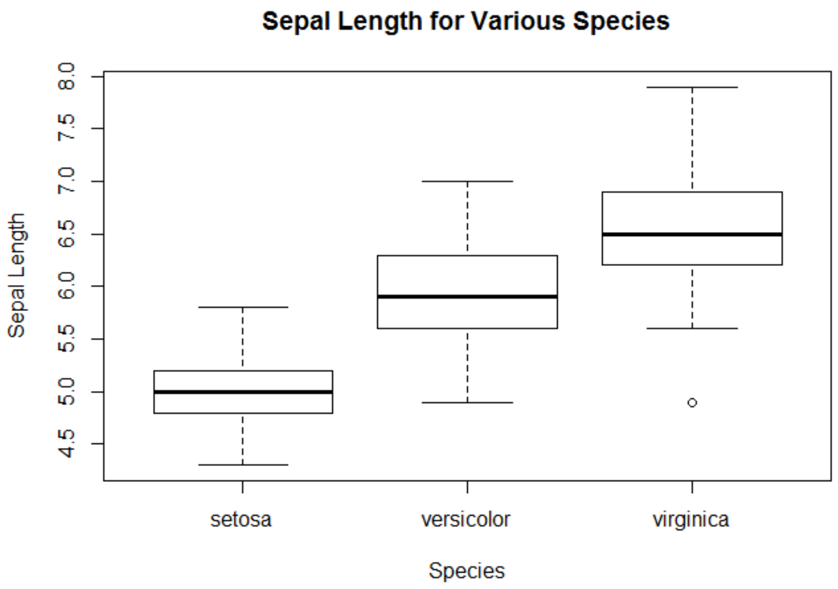
```
data(iris)
head(iris)
```

```
> head(iris)
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
1          5.1         3.5          1.4         0.2  setosa
2          4.9         3.0          1.4         0.2  setosa
3          4.7         3.2          1.3         0.2  setosa
4          4.6         3.1          1.5         0.2  setosa
5          5.0         3.6          1.4         0.2  setosa
6          5.4         3.9          1.7         0.4  setosa
```

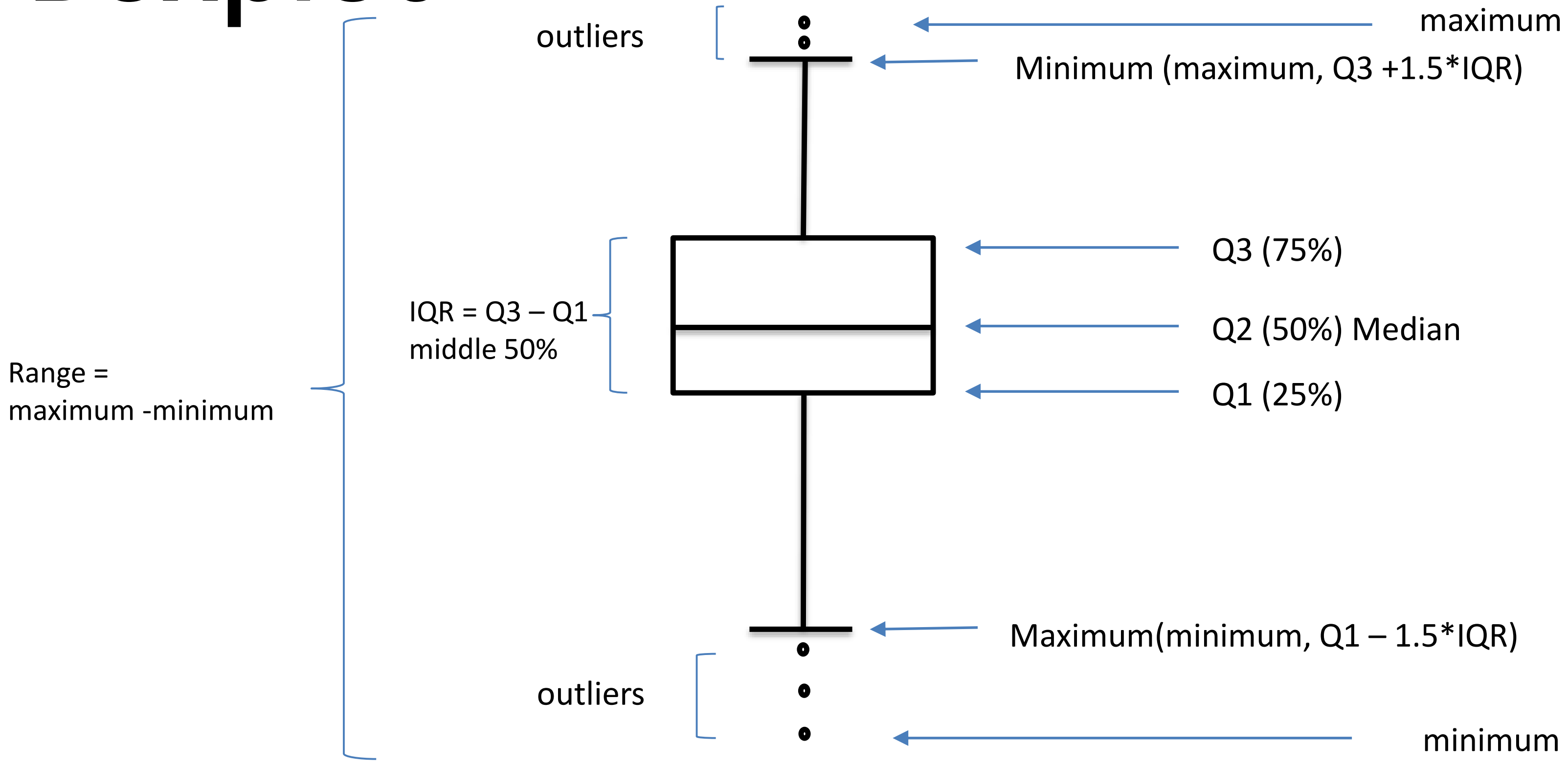
Boxplots

- Summarizes *quantitative/numeric* data

```
# Core Graphics
boxplot(Sepal.Length ~
Species,
data=iris, main="Sepal
Length for Various
Species", xlab="Species",
ylab="Sepal Length"
)
```



Boxplot



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Saving plots

- Save various formats

```
pdf("myplot.pdf")
boxplot(Sepal.Length ~ Species,
data=iris)
dev.off() # Returns plot to the
IDE
```

Function	Output to
pdf("mygraph.pdf")	pdf file
win.metafile("mygraph.wmf")	windows metafile
png("mygraph.png")	png file
jpeg("mygraph.jpg")	jpeg file
bmp("mygraph.bmp")	bmp file
postscript("mygraph.ps")	postscript file

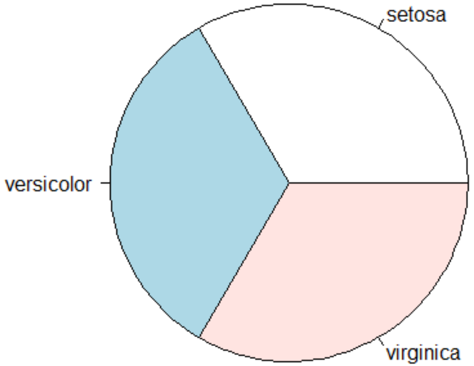
Windows Saves to default: Libraries\Documents

R Studio makes it easier

Pie Chart

- Summarizes *qualitative/categorical* variables

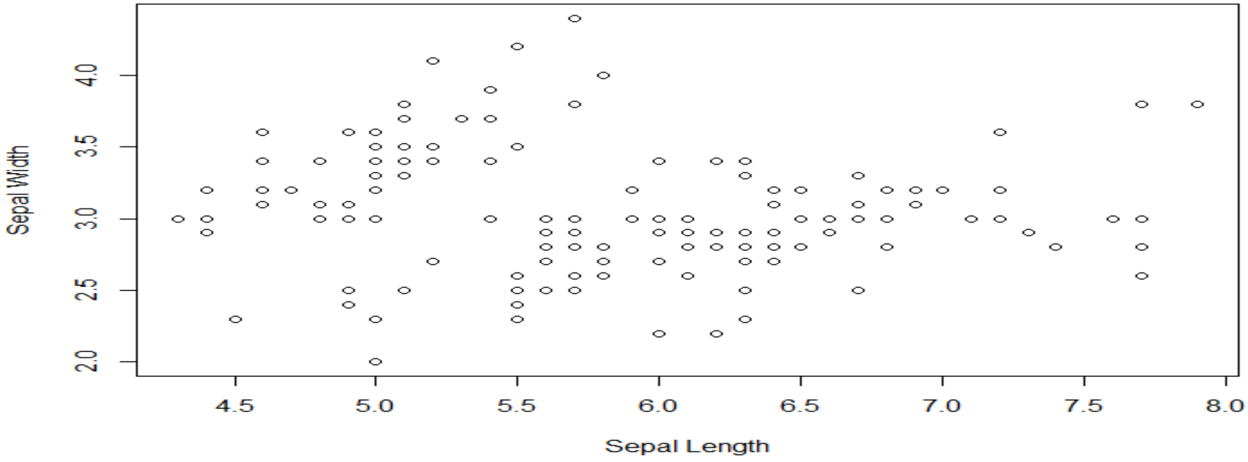
```
# Core Graphics
pie(table(iris$Species))
```



Plot

- Visual depiction of correlation between numeric quantities

```
# Core Graphics
plot(Sepal.Length ~ Sepal.Width,
data=iris,xlab= "Sepal Length", ylab=
"Sepal Width")
```



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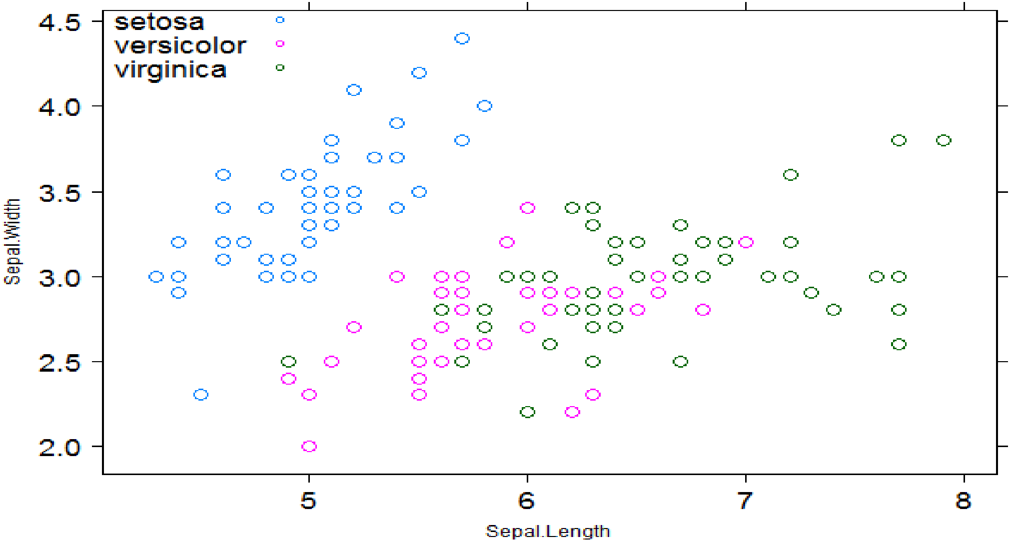
LATTICE GRAPHICS

xyplot

- Plot counterpart in Lattice package.

```
# Lattice Graphics
library(lattice)
xyplot(Sepal.Width ~
Sepal.Length, data=iris,
groups=Species)
```



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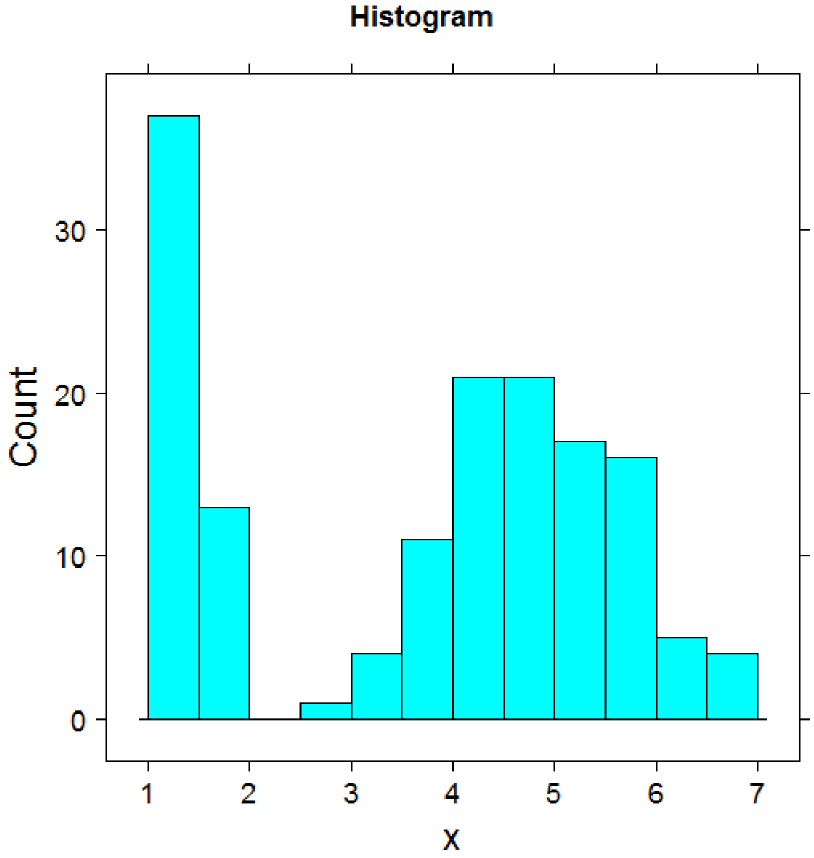
In-class Exercise 1

Contrast 2-D scatterplots for iris dataset(Petal.Length and Petal.Width) Summarize your findings.

Histogram

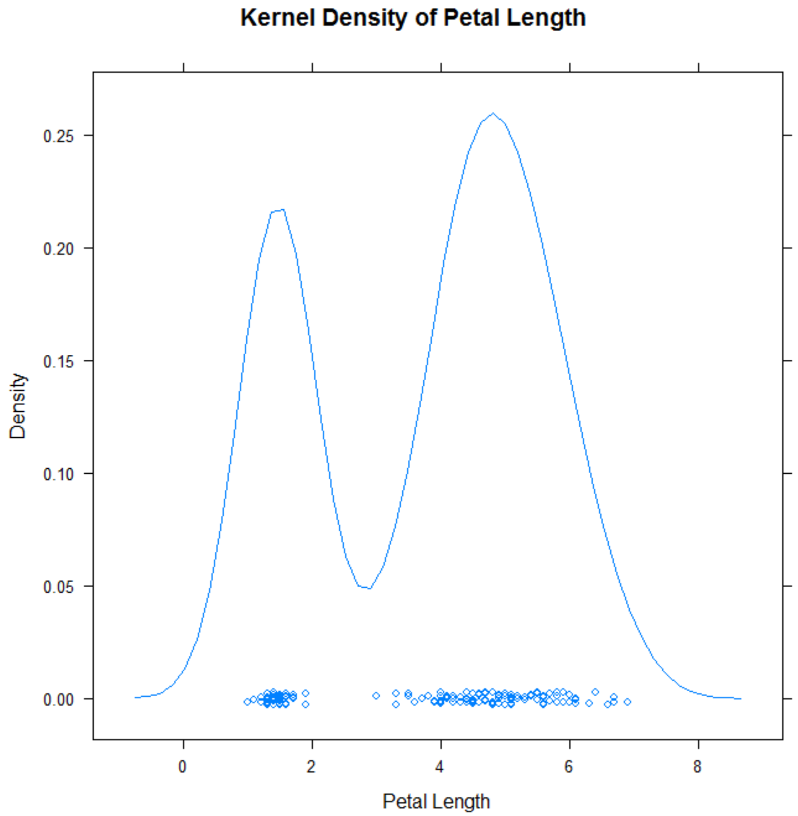


- Spread of a numeric feature
- Places values in "bins"

```
histogram(iris$Petal.Length,
breaks=10, type="count",
main="Histogram")
```

Vary ‘breaks’ parameter

Density plots



- Variation on histogram
- Estimates density function from counts
- Does not work with missing values

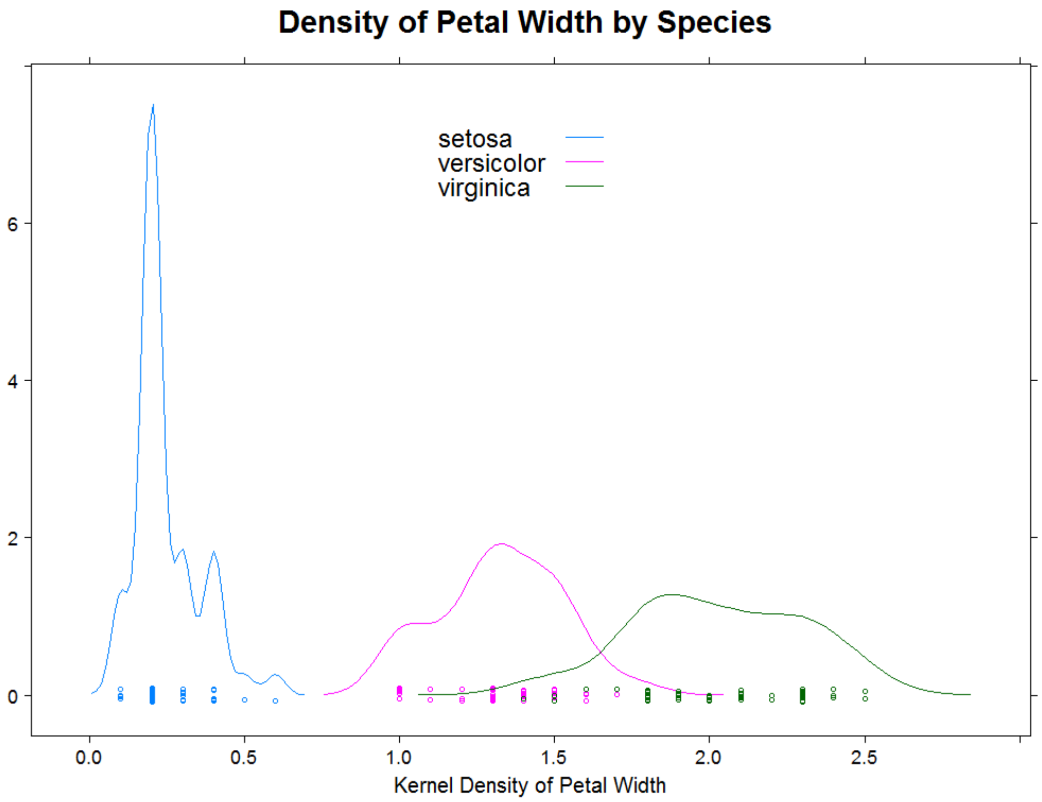
```
densityplot(iris$Petal.Length,
main="Kernel Density of Petal
Length", xlab="Petal Length",
type="percent", n=150)
```

Try adding plot.points=F

The devil is in the details

- The details are in segments
- Segmentation reveals hidden patterns
- Create as many segments as possible
  - Your domain understanding will help in creating segments

Multiple density plots




```
densityplot(~Petal.Width,
data=iris,
groups=Species,
plot.points=F,
xlab=list(label="Kernel
Density of Petal Width",
fontsize=20), ylab="",
main=list(label="Density
of Petal Width by
Species", fontsize=24))
```

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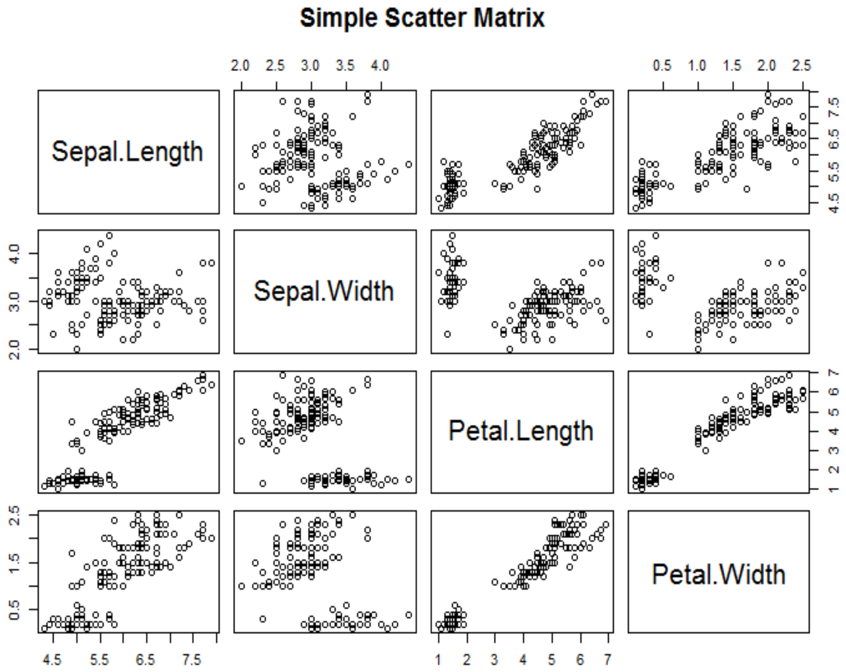
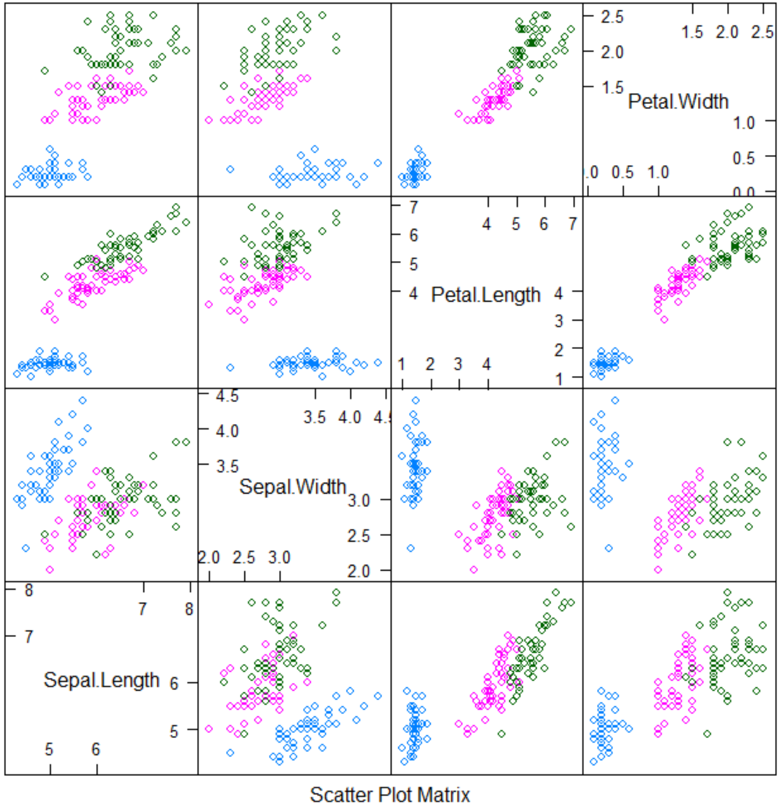
Scatterplot matrix

- Multiple relationships on one graph
- Good for initial explorations

```
# Core Graphics
pairs(~ Sepal.Length + Sepal.Width
+ Petal.Length + Petal.Width,
data=iris, main="Simple Scatter
Matrix")
```



Scatterplot matrix




```
# Lattice Graphics
splom(iris[1:4],
groups=iris$Species)
```

Enhanced Scatterplot matrix

- Very slow!
- Use carefully

```
library(GGally)

ggpairs(iris,
ggplot2::aes(color=
Species))
```

In-class Exercise 2

Using the "mtcars" dataset, predict mpg based on other columns.

Create at least 2 different plots illustrating useful relationships in data and summarize your findings.

The “mtcars” data set

```
data(mtcars)
head(mtcars)
```

```
> head(mtcars)
```

	mpg	cyl	disp	hp	drat	wt	qsec	vs	am	gear	carb
Mazda RX4	21.0	6	160	110	3.90	2.620	16.46	0	1	4	4
Mazda RX4 Wag	21.0	6	160	110	3.90	2.875	17.02	0	1	4	4
Datsun 710	22.8	4	108	93	3.85	2.320	18.61	1	1	4	1
Hornet 4 Drive	21.4	6	258	110	3.08	3.215	19.44	1	0	3	1
Hornet Sportabout	18.7	8	360	175	3.15	3.440	17.02	0	0	3	2
Valiant	18.1	6	225	105	2.76	3.460	20.22	1	0	3	1

GGPLOT2 GRAPHICS

The diamonds data set

```
library(ggplot2)
data(diamonds)
head(diamonds)
```

```
> head(diamonds)
  carat       cut color clarity depth table price    x    y    z
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  0.29   Premium     I     VS2  62.4    58   334 4.20 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
```

ggplot Fundamentals

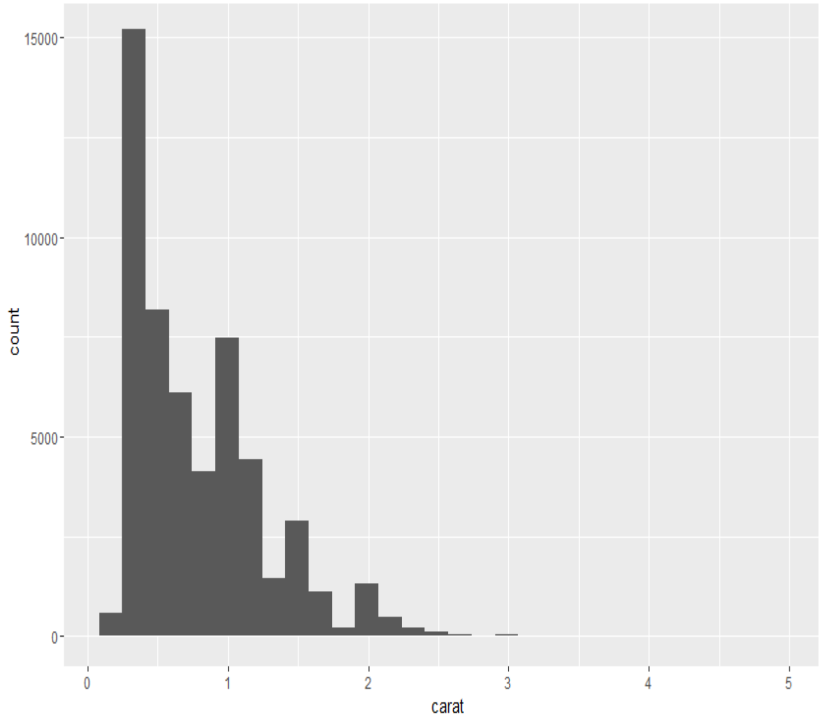
- ggplot() is the basic function
- geom_*() creates a graph layer
  - geom_histogram()
  - geom_boxplot()
- aes() defines an "aesthetic" either globally or by layer

Layering

```
ggplot(diamonds, aes())    +    geom_point()
```

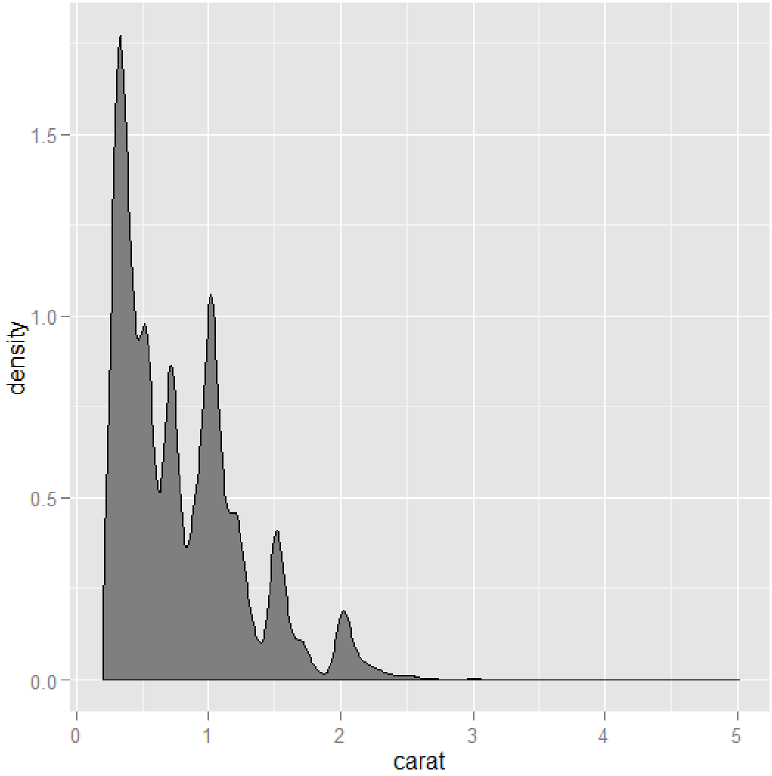
$\underbrace{\texttt{ggplot(diamonds, aes())}}_{\text{Layer 1}} + \underbrace{\texttt{geom\_point()}}_{\text{Layer 2}}$

Histogram




```
ggplot(diamonds, aes(x=carat))+
geom_histogram()
```

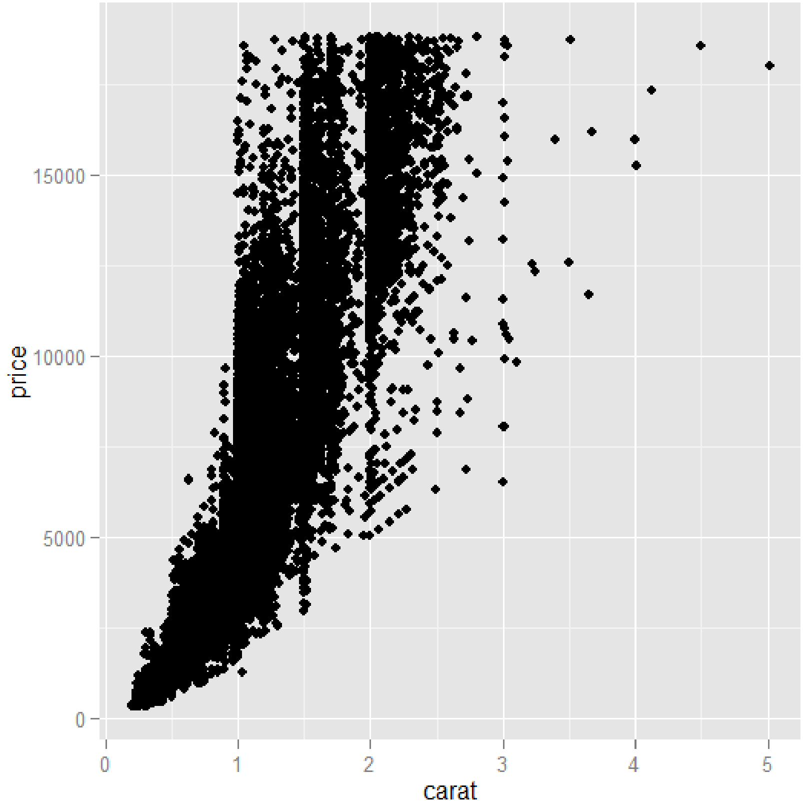
Density plot




```
ggplot(diamonds) +
geom_density(aes(x=carat),
fill="gray50")
```

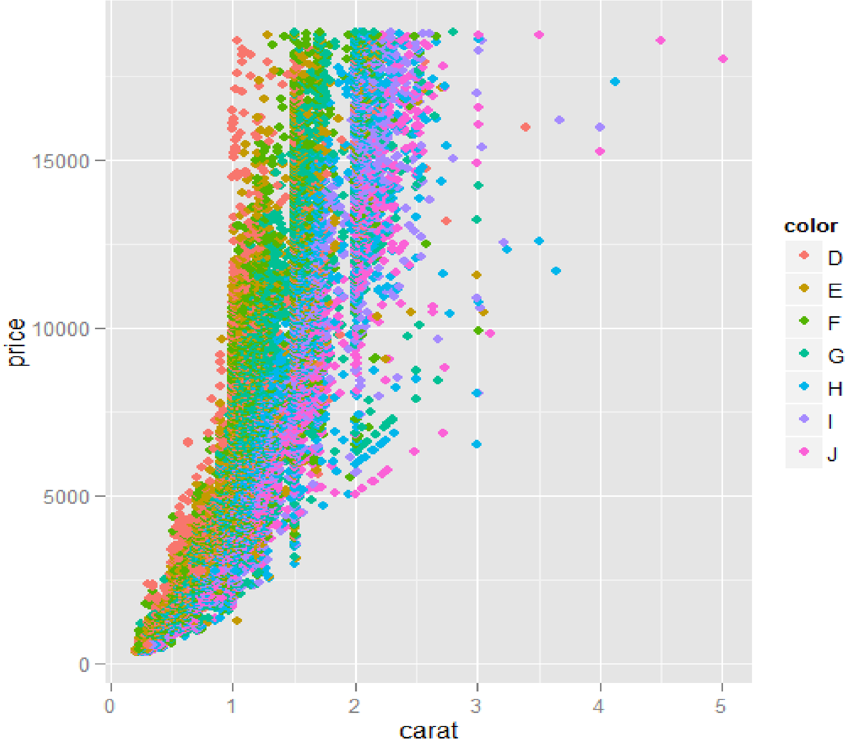
- Note the location of aes()

Scatter plots



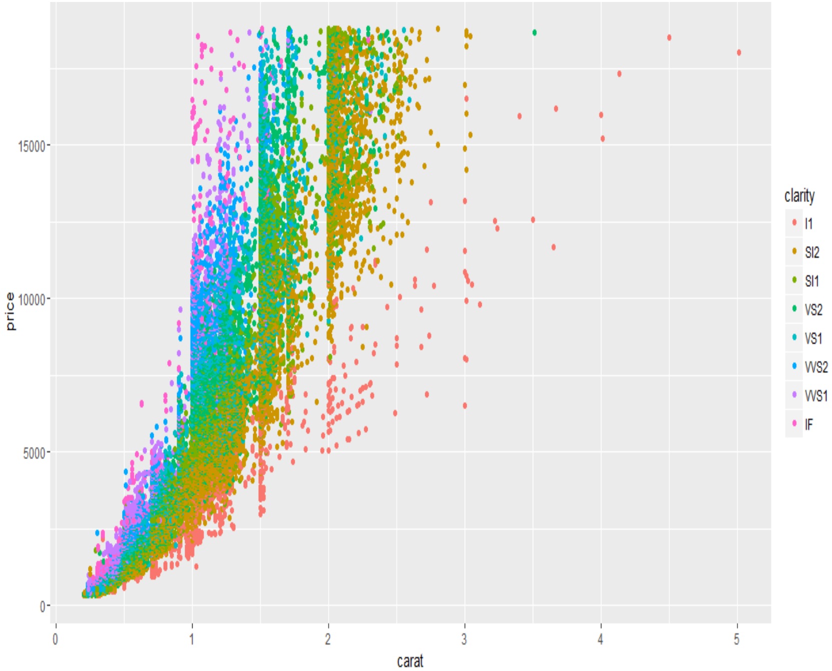

```
ggplot(diamonds,
aes(x=carat,y=price)) +
geom_point()
```

ggplot object



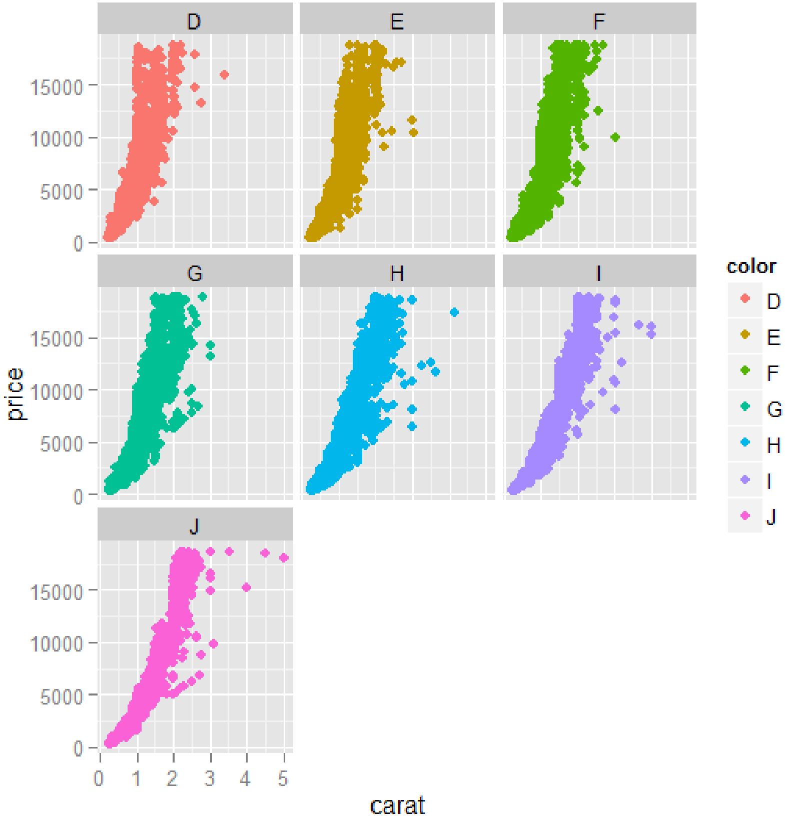

```
# Store the plot for future
modification
g <- ggplot(diamonds,
aes(x=carat, y=price))

# add settings specific to
geom_point layer
g + geom_point(aes(color=color))
```

ggplot object



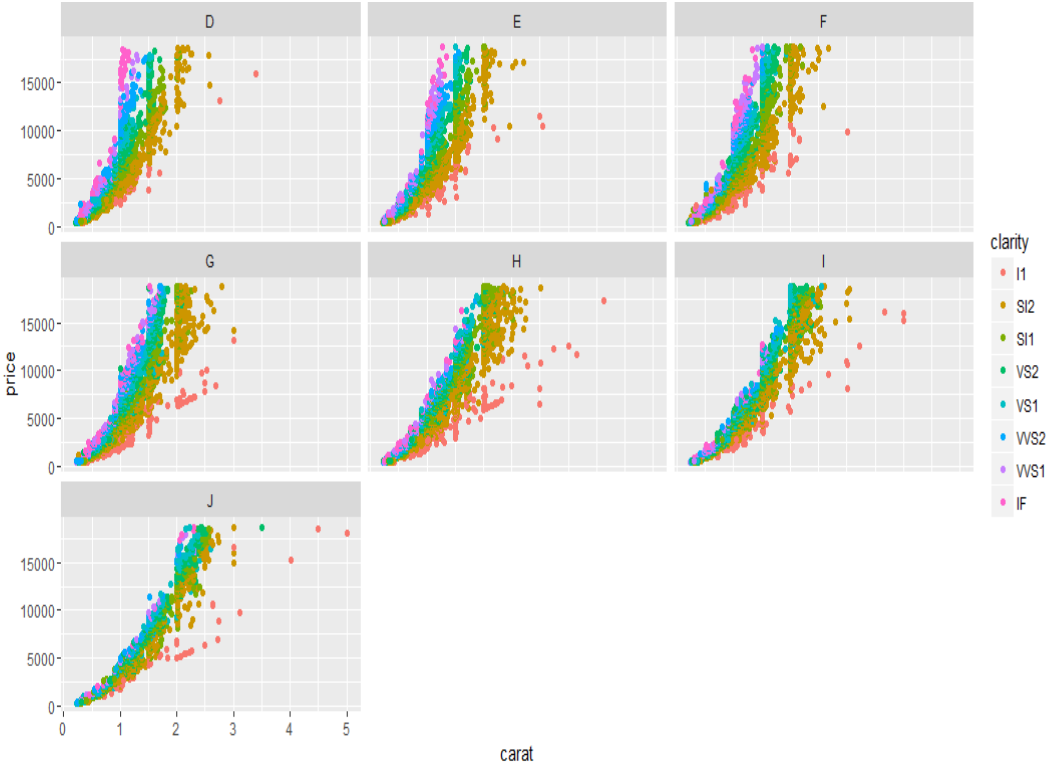

```r
# Store the plot for future modification
g <- ggplot(diamonds, aes(x=carat, y=price))

# add settings specific to geom_point layer
g +
geom_point(aes(color=clarity))
```

Separating the segments



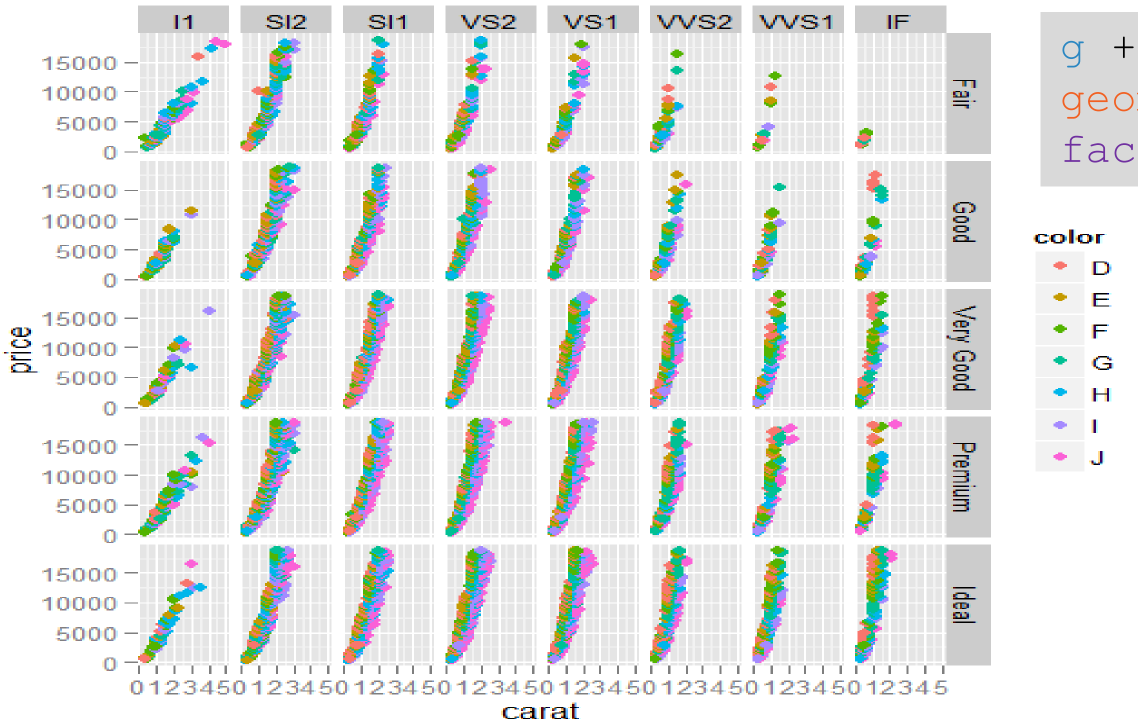

```
g +
geom_point(aes(color=color)) +
facet_wrap(~ color)
```

Separating the segments




```
g +
geom_point(aes(color
=clarity)) +
facet_wrap(~ color)
```

More segments!




```
g +
geom_point(aes(color=color))+
facet_grid(cut ~ clarity)
```

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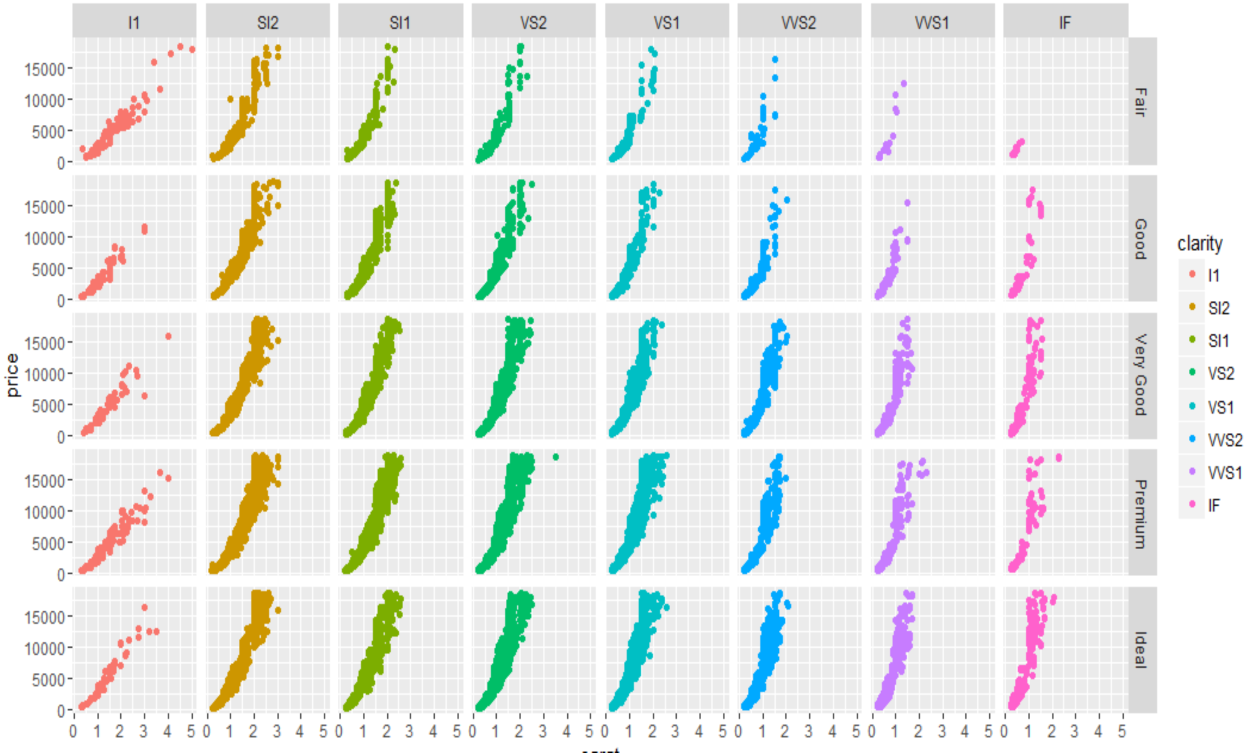
More segments!




```
g +
geom_point(aes
(color=clarity
)) +
facet_grid(cut
~ clarity)
```

Summary

- ✓ Basics of R
- ✓ Graphing in R – Core, Lattice and ggplot2 Look at multiple types of graphs.
- ✓ Visualize and segment dataset to gain insights about data.
- ✓ Identify key features
- ✓ Summarizing findings

STORYTELLING WITH TITANIC

Finding the data set

- Set your working directory to the bootcamp root
- Load data in from "Datasets/titanic.csv"

Looking at the first few rows

```
titanic <- read.csv("Datasets/titanic.csv")
head(titanic)
```

```
> head(titanic)
  PassengerId Survived Pclass                                                Name    Sex Age SibSp Parch           Ticket    Fare Cabin Embarked
1           1        0      3                             Braund, Mr. Owen Harris   male  22     1     0        A/5 21171  7.2500                S
2           2        1      1 Cumings, Mrs. John Bradley (Florence Briggs Thayer) female  38     1     0         PC 17599 71.2833   C85        C
3           3        1      3                              Heikkinen, Miss. Laina female  26     0     0 STON/O2. 3101282  7.9250                S
4           4        1      1        Futrelle, Mrs. Jacques Heath (Lily May Peel) female  35     1     0           113803 53.1000  C123        S
5           5        0      3                            Allen, Mr. William Henry   male  35     0     0           373450  8.0500                S
6           6        0      3                                    Moran, Mr. James   male  NA     0     0           330877  8.4583                Q
> 
```

What features should we consider?

What is the data type of each column?

```
str(titanic)
```

```
'data.frame':	891 obs. of  12 variables:
 $ PassengerId: int  1 2 3 4 5 6 7 8 9 10 ...
 $ Survived   : int  0 1 1 1 0 0 0 0 1 1 ...
 $ Pclass     : int  3 1 3 1 3 3 1 3 3 2 ...
 $ Name       : Factor w/ 891 levels "Abbing, Mr. Anthony",..: 109 191 358 277 16 559 520 629 417 581 ...
 $ Sex        : Factor w/ 2 levels "female","male": 2 1 1 1 2 2 2 2 1 1 ...
 $ Age        : num  22 38 26 35 35 NA 54 2 27 14 ...
 $ SibSp      : int  1 1 0 1 0 0 0 3 0 1 ...
 $ Parch      : int  0 0 0 0 0 0 0 1 2 0 ...
 $ Ticket     : Factor w/ 681 levels "110152","110413",..: 524 597 670 50 473 276 86 396 345 133 ...
 $ Fare       : num  7.25 71.28 7.92 53.1 8.05 ...
 $ Cabin      : Factor w/ 148 levels "","A10","A14",..: 1 83 1 57 1 1 131 1 1 1 ...
 $ Embarked   : Factor w/ 4 levels "","C","Q","S": 4 2 4 4 4 3 4 4 4 2 ...
```

Casting & Human Readability

Set target column as a factor

```
titanic$Survived <- as.factor(titanic$Survived)
```

Rename factors and columns

```
levels(titanic$Survived) <- c("Dead", "Survived")
levels(titanic$Embarked) <- c("Unknown", "Cherbourg",
                              "Queenstown", "Southampton")
str(titanic[,c("Embarked","Survived")])
```

```
'data.frame':  891 obs. of  2 variables:
 $ Embarked: Factor w/ 4 levels
"Unknown","Cherbourg",..: 4 2 4 4 4 3 4 ...
 $ Survived: Factor w/ 2 levels "0","1": 1 2 2 2
1 1 1 1 2 2 ...
```

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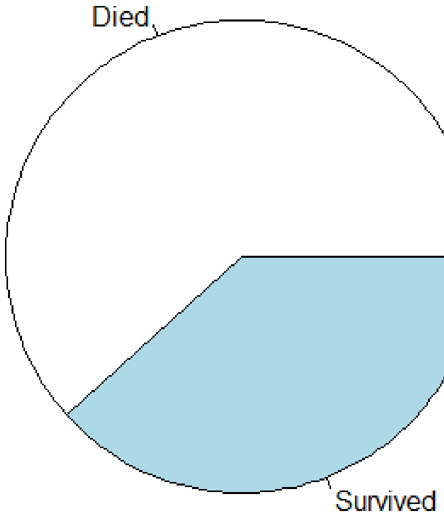
Class distribution: Pie Chart

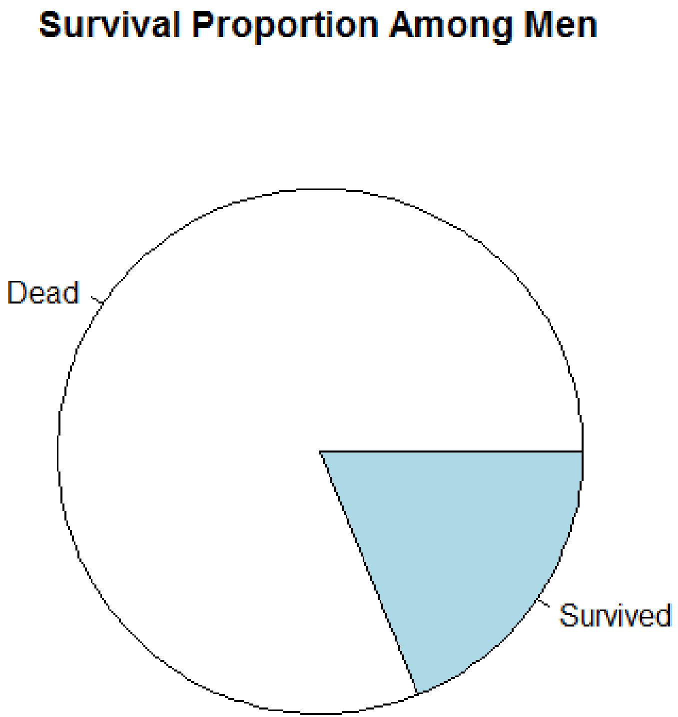
```
survivedTable <- table(titanic$Survived)
par(mar=c(0, 0, 0, 0))
pie(survivedTable, labels=c("Died", "Survived"))
```

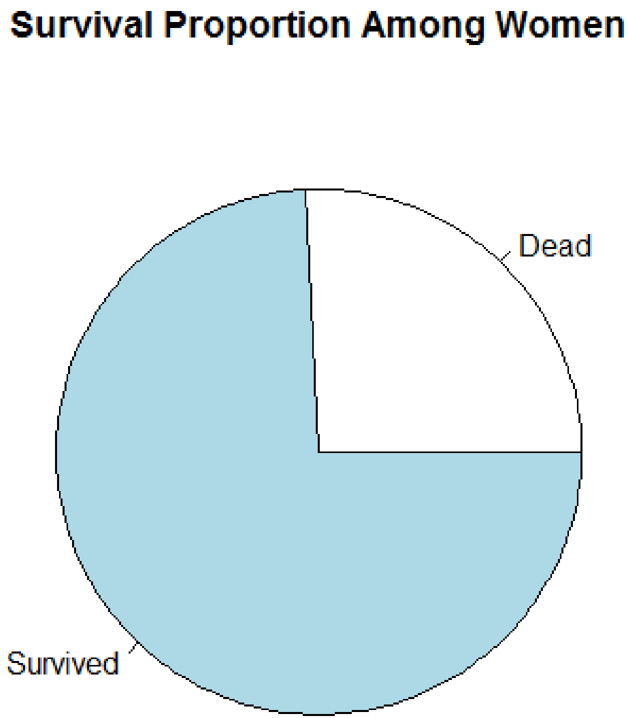


Is Sex a Good predictor?

```
#Identify where sex = male for all columns
male <- titanic[titanic$Sex == "male",]

#Identify where sex = female for all columns
female <- titanic[titanic$Sex == "female",]

par(mfrow=c(1,2)) #two figures arranged in 1 row and 2
columns
pie(table(male$Survived), labels=c("Dead","Survived"))

pie(table(female$Survive), labels=c("Dead","Survived"))
```

Is Sex a Good predictor?





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Is Age a Good Predictor?

```
summary(titanic$Age)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
0.42	20.12	28.00	29.70	38.00	80.00	177

- How about by survival?

```
summary(titanic[titanic$Survived
=="Dead",]$Age)
```

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
1.00	21.00	28.00	30.63	39.00	74.00	125

```
summary(titanic[titanic$Survived
=="Survived",]$Age)
```

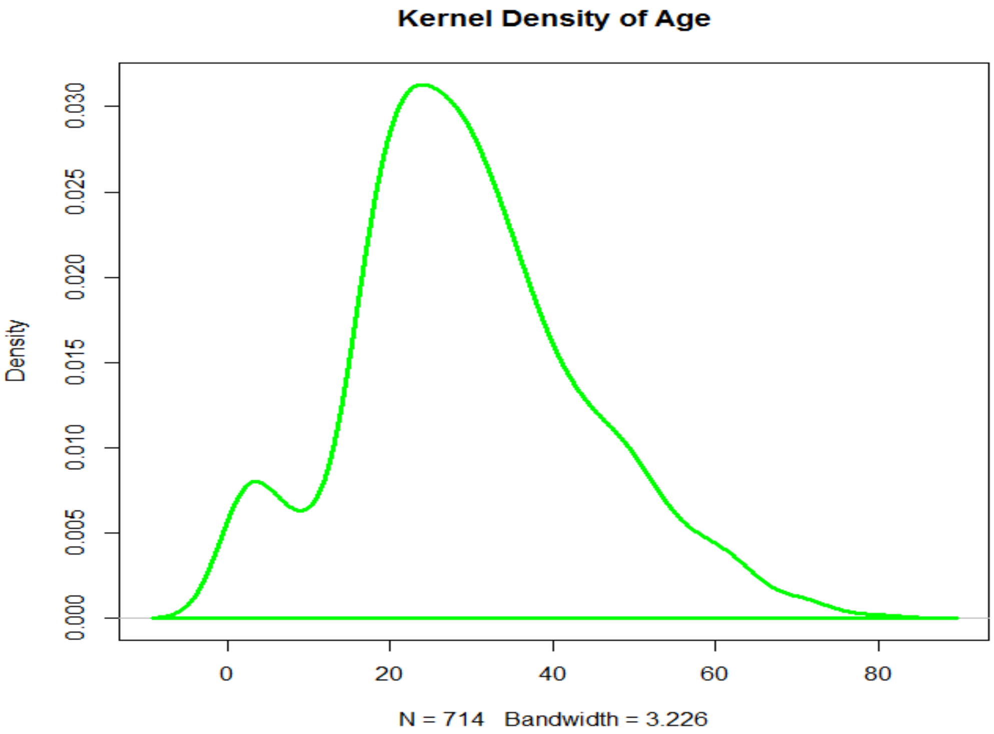
Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
0.42	19.00	28.00	28.34	36.00	80.00	52

In-class Exercise 3

- Create 2 boxplots of Age
  - Segmented by Gender
  - Segmented by Survived

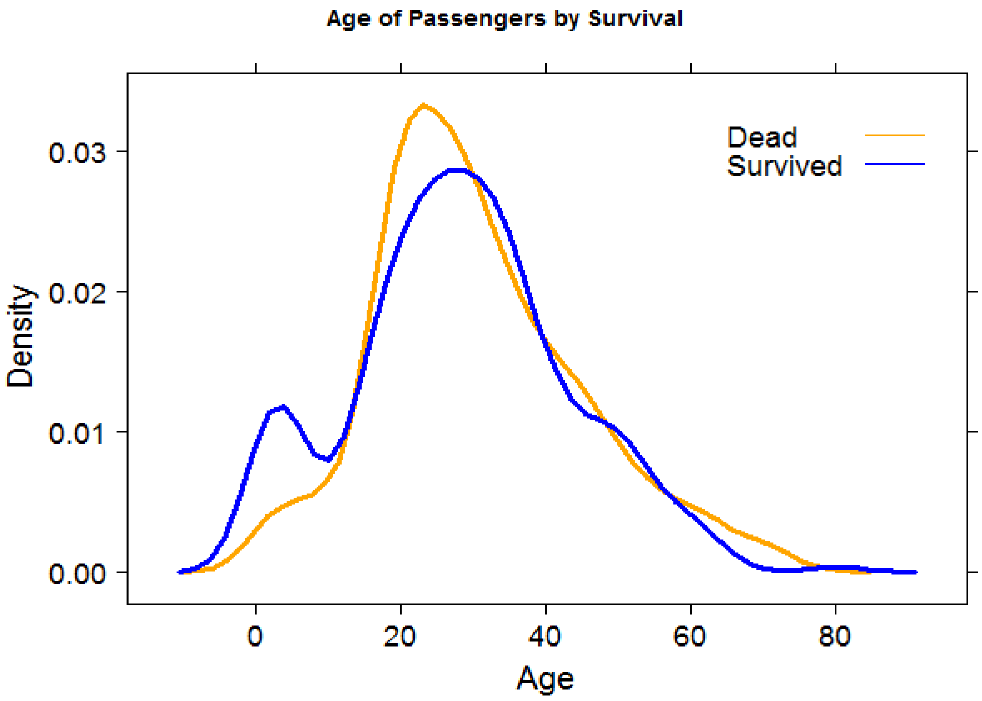
- Create a density plot of Age
  - na.omit() may be useful

Sample solution




```
density(titanic$Age)
#NAs prevent this
> d <-
density(na.omit(titanic$Ag
e))
> plot(d, main="Kernel
Density of Age")
>
polygon(d,border="green",l
wd=3)
```

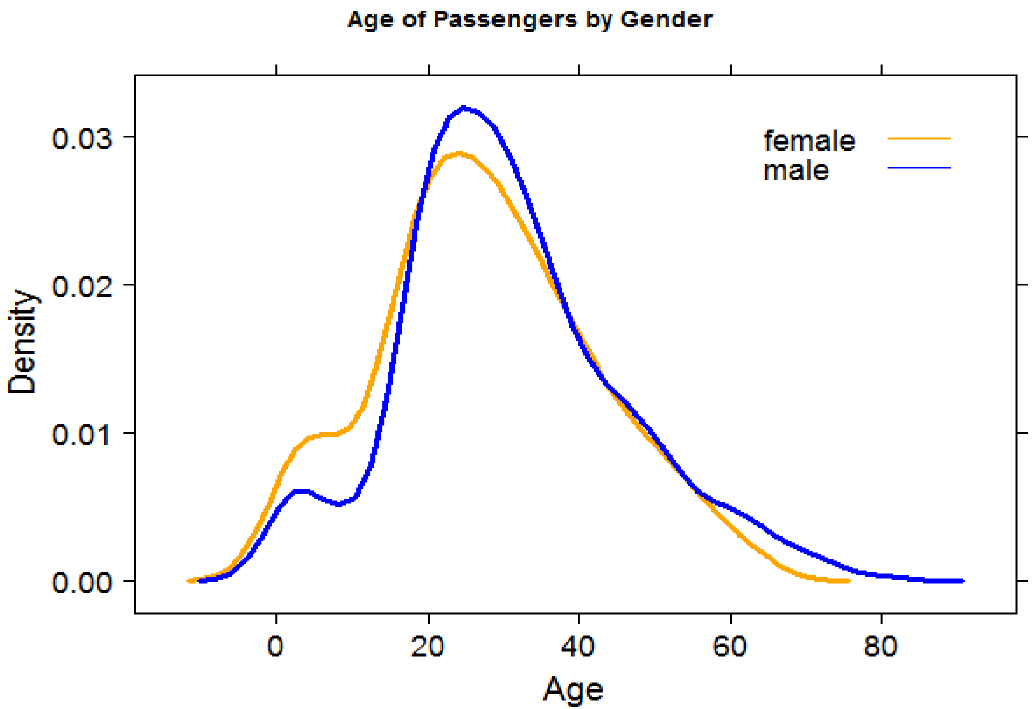
Is Age a good predictor for Survival?




```
densityplot(~ Age,
data=titanic,
groups=Survived,
plot.points=F, lwd=3)
```

Note: will break with missing values

Is Age a good predictor for Gender?




```
densityplot(~ Age,
data=titanic, groups=Sex,
plot.points=F, lwd=3)
```

Questions?