# Section 4: Predictive Modles

# Multiple and Logistic Regression, Trees

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Suggested Reading

OpenIntro Statistics, Chapter 8

# Previous Section

- Linear Patterns in Data (Leavitt, House Price)
- Simple Linear Regression
- Predictions (Confidence and Prediction Intervals)
- Least Squares Principle
- Hypothesis Testing (Google vs SP500)
- Model Diagnostics (Cancer and Smoking Data)
- Data transformations (World's Smartest Mammal

# This Section

- Multiple Regression (Newfood study, Golf Analysis)
- Interactions (how advertisement change price elasticity?)
- Predictive analytics cases(Target, Walmart, Airbnb, Stitch Fix)
- Logistic regression (NBA predictions, Horse predictions, LinkedIn)

# Multiple Regression

Many problems involve more than one independent (explanatory) variable or factor which affects the dependent or response variable.

- Multi-factor asset pricing models (APT). Stock returns, book-to-market ratios, Interest rates
- Demand for a product given prices of competing brands, advertising, household attributes (to formulate pricing strategies)
- Internet Analytics What do I like? Suggestions instead of Search! Alexa "book my Xmas vacation," "buy my best friend a birthday present"

# R Regression Commands

Given input-output vectors $x$ and $y$ `cor( ... )` computes correlation table

`model = lm(y ~ x)` for linear model (a.k.a regression)

`model = glm(y ~ x)` for logistic regression

`model = lm(y ~ x1+ ... + xp)` for linear multiple regression model

`plot(model)` diagnostics

`plot(cooks.distance(model))` influential points

`rstudent(model)` outliers

`summary(model)` provides a summary analysis of our model

`newdata = data.frame( ... )` constructs a new input variable

`predict.lm(model,newdata)` provides a prediction at a new input Regression

in Excel

`linest(yrange,xrange)` and `slope(yrange,xrange)`

# Regression Model

$Y$ = response or outcome variable

$X_1, \ldots, X_p$ = explanatory or input variable

The general relationship is given by

$$Y = f(X_1, \ldots, X_p) + \epsilon$$

And a linear relationship is written

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \epsilon$$

# MLR Assumptions

The Multiple Linear Regression (MLR) model

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \epsilon$$

assumptions follow those of simple linear regression:

1. The conditional mean of $Y$ is linear in the $X_j$ variables
2. The errors are normal $N(0, \sigma^2)$.

   We write

$$Y \mid X_1, \ldots, X_p \sim N\left(\beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p, \sigma^2\right)$$

# Statistical versus Economic Significance

When looking at the $\beta$ coefficients there are two issues

1. Statistical Significance: The $t$-ratios of the $\beta$'s
2. Economic Significance: The magnitudes of the $\beta$'s

   If $X_i$ increases by one unit holding the other $X$'s *constant*

   Then $Y$ will react by $\beta_i$ units.

   They are called marginal effects

At the end of the day use your judgment!

# Model Diagnostics

plot(model) provides diagnostics before model building!

There are many possible caveats

1. Running simple regressions gives you the wrong answer!
2. Multiple regression takes into account the correlation between the factors and the independent variable. It does all the work for you.
3. A variable might be insignificant once we have incorporated a more important predictor variable.

A common sense approach usually works well. If a variable never seems to be significant it typically isn't.

Model Prediction is the great equalizer!!

# Example: Newfood Data

Goal of Experiment

- A six month market test has been performed on the Newfood product.

  A breakfast cereal.
- Build a multiple regression model that gives us good sales forecasts.
- This dataset is the outcome of a *controlled experiment* in which the values of the independent variables which affect sales are *chosen* by the analyst.

# Example: Newfood Data

Analyses the factors which contribute to sales of a new breakfast cereal. Quantify the effects of business decisions such as choice of advertising level, location in store and pricing.

| variable | description |
|---|---|
| `sales` | new cereal sales |
| `price` | price |
| `adv` | low or high advertising (0 or 1) |
| `locat` | bread or breakfast section (0 or 1) |
| `inc` | neighborhood income |
| `svol` | size of store |

# Example: Newfood

1. What happens when you regress `sales` on `price, adv, locat`?
2. Run the "kitchen-sink" regression. Perform Diagnostic checks.
3. Which variables should we transform?
4. Run the new model. Perform diagnostics and variable selection.
5. What's the largest cooks distance?
6. Provide a summary of coefficients and statistical significance
7. Predict `sales` when $\texttt{price} = 30, \texttt{adv} = 1, \texttt{income} = 8$ and $\texttt{svol} = 34$.

   What happens when you predict at the median values of the characteristics?

# Example: Newfood

First we examine the correlation matrix:

| | sales | price | adv | locat | income |
|---|---|---|---|---|---|
| price | -0.658 | | | | |
| adv | 0.001 | 0.000 | | | |
| locat | -0.001 | 0.000 | 0.000 | | |
| income | 0.163 | -0.131 | -0.746 | 0.000 | |
| svol | 0.375 | -0.179 | -0.742 | -0.040 | 0.809 |

Remember: correlations are not $\beta$'s!!

# Newfood

Total sales volume is negatively correlated to advertising.

Income is negatively correlated with advertising as well.

How is the negative correlation apt to affect the advertising effects?

| | sales | price | adv |
|---|---|---|---|
| price | -0.658 | | |
| adv | 0.001 | 0.000 | |
| locat | -0.001 | 0.000 | 0.000 |

There's no correlation in the $X$'s by design!

# Newfood

Let's start by only including price, adv, locat

```
 sales = 562 - 12.8 price + 0.2 adv - 0.2 locat
Coefficients:
            Estimate Std. Error t value P(>|t|)
 (intercept)  562.31   53.14     10.58    0.000
 price       -12.812   1.780     -7.20    0.000
 adv            0.22   14.54      0.02    0.988
 locat         -0.22   14.54     -0.02    0.988
```

- Why is the marketer likely to be upset by this regression?!
- Why is the economist happy?

Let's add `income` and `svol` to the regression!

# Transformation

Power model: transform with log-log

```
log(sales) = 8.41 - 1.74 logprice + 0.150 adv + 0.0010 locat -
0.524 loginc  + 1.03 logsvol
Coefficients:
             Estimate Std. Error t value  P(>|t|)
 (intercept)    8.407    1.387    6.06    0.000
 logprice     -1.7430   0.2207   -7.90    0.000
 adv           0.1496   0.1005    1.49    0.141
 locat        0.00100 0.06088    0.02    0.987
 loginc       -0.5241   0.4958   -1.06    0.294
 logsvol       1.0308   0.2553    4.04    0.000
```

Why no logs for `adv` and `locat` variables?

The log(`svol`) coefficient is close to one!

$R^2 = 60\%$

# Transformation

On the transformed scale,

$$\log \textit{sales} = 8.41 - 1.74 \log \textit{price} + 0.150\text{adv} + 0.001\text{locat} - 0.524 \log \textit{inc} + 1.03 \log \textit{svol}$$

On the un-transformed scale,

$$\text{sales} = e^{8.41} (\text{price})^{-1.74} e^{0.15\text{adv}} e^{0.001\text{locat}} (\text{inc})^{-0.524} (\text{svol})^{1.03}$$

`sales/price,income and svol` are a power `sales/adv, locat` are exponential

# Interpretation

Interpret your regression model as follows

- Price elasticity is $\hat{\beta}_{\text{price}} = -1.74$. A 1% increase in price will drop sales 1.74%
- $\texttt{adv} = 1$ increases $\texttt{sales}$ by a factor of $e^{0.15} = 1.16$. That's a 16% improvement

Variable Selection: delete `locat` as its *statistically insignificant*.

# Prediction

predict.lm provides a $\hat{Y}$-prediction given a new $X_f$

```
# predict.lm at newdata
> predict.lm(modelnew,newdata,se.fit=T,interval="prediction")
$fit
       fit      lwr     upr
1 5.259691 4.739762 5.77962
$se.fit
[1] 0.05560662
```

Exponentiate-back to find $\text{sales} = e^{5.2596} = 192.40$.

newdata=data.frame(price=30,adv=1,income=8,svol=34)

# Interactions

- Does gender change the effect of education on wages?
- Do patients recover faster when taking drug A?
- How does advertisement affect price sensitivity?
- Interactions are useful. Particularly with dummy variables.
- We build a kitchen-sink model with all possible dummies (day of the week, gender,...)

# Models with Interactions

In many situations, $X_1$ and $X_2$ interact when predicting $Y$

Interaction Model: run the regression

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_1 X_2 + \epsilon$$

In R: `model = lm(y ~ x1 * x2)` gives $X_1 + X_2 + X_1 X_2$

In R: `model = lm(y ~ x1 : x2)` gives only $X_1 X_2$

The coefficients $\beta_1$ and $\beta_2$ are marginal effects.

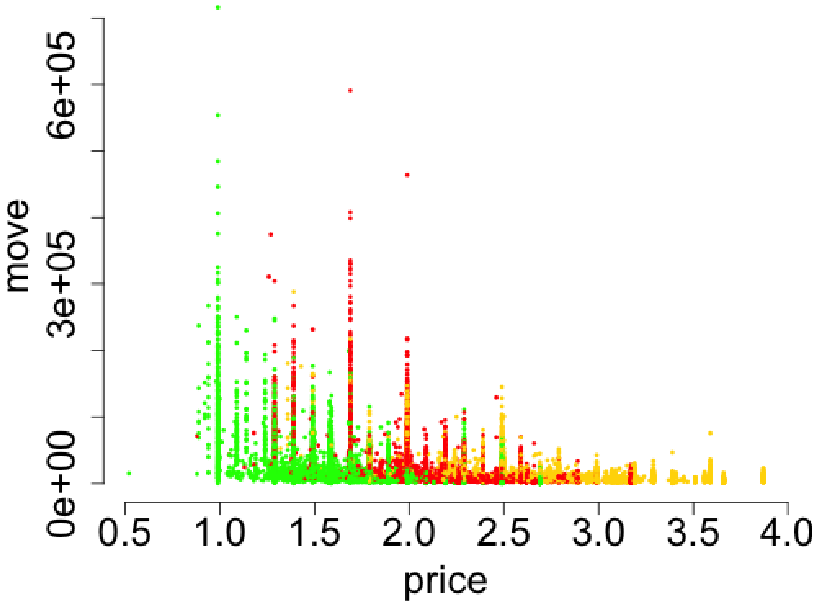
If $\beta_3$ is significant there's an interaction effect.

We leave $\beta_1$ and $\beta_2$ in the model whether they are significant or not.

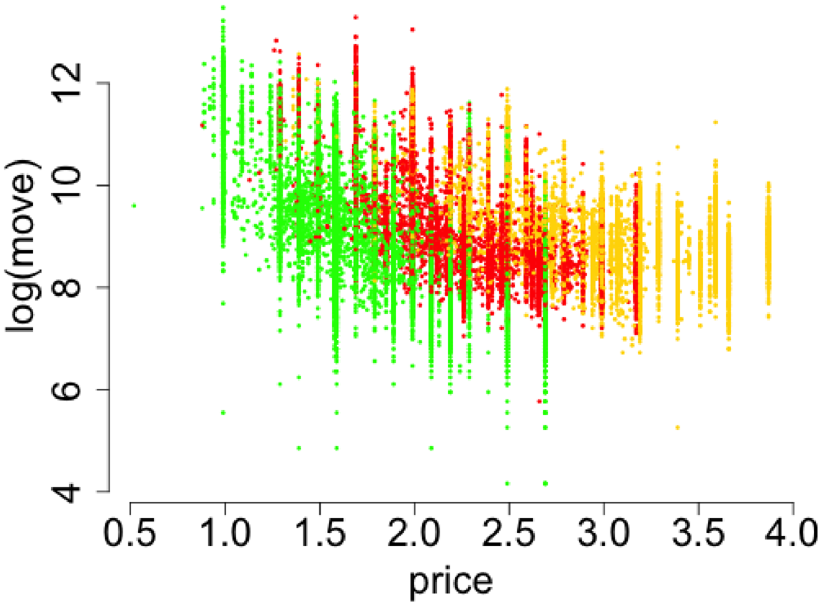
# Orange Juice

- 83 Chicagoland Stores (Demographic info for each)
- Price, sales (log units moved), and whether advertised (feat)

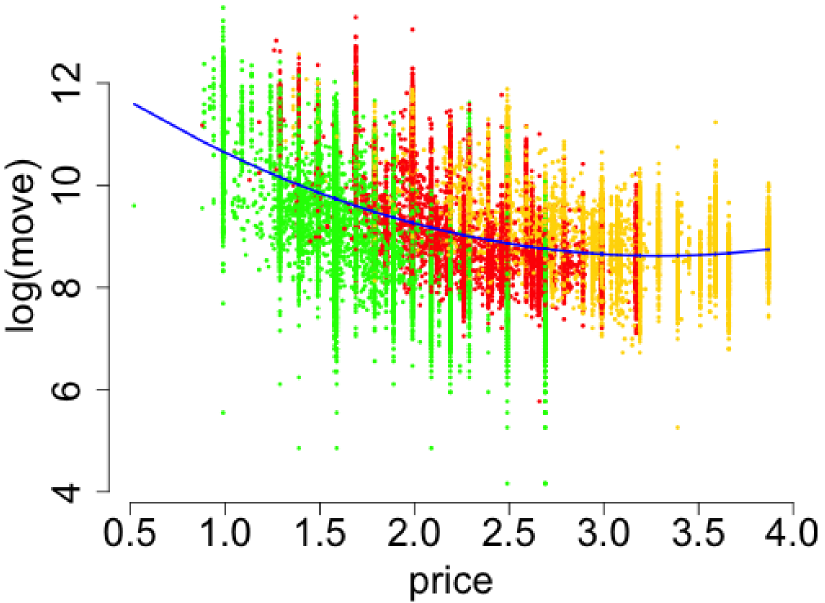
# Orange Juice: Price vs Sales



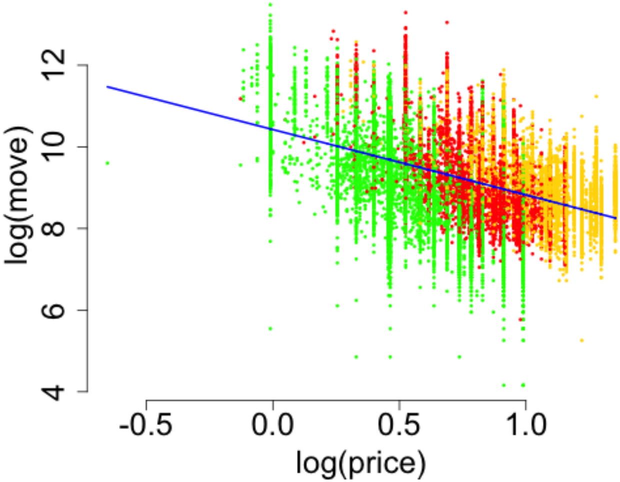
# Orange Juice: Price vs log(Sales)



# Orange Juice: Price vs log(Sales)



# Orange Juice: log(Price) vs log(Sales)




Why? Multiplicative (rather than additive) change.

# How does advertisement affect price sensitivity?

Original model

$$\log(\text{sales}) = \beta_0 + \beta_1 \log(\text{price}) + \beta_2 \text{feat}$$

If we feature the brand (in-store display promo or flyer ad), does it affect price sensitivity $\beta_1$? If we assume it does

$$\beta_1 = \beta_3 + \beta_4 \text{feat}$$

The new model is

$$\log(\text{sales}) = \beta_0 + (\beta_3 + \beta_4 \text{feat}) \log(\text{price}) + \beta_2 \text{feat}$$

After expanding

$$\log(\text{sales}) = \beta_0 + \beta_3 \log(\text{price}) + \beta_4 \text{feat} * \log(\text{price}) + \beta_2 \text{feat}$$

# How does advertisement affect price sensitivity?

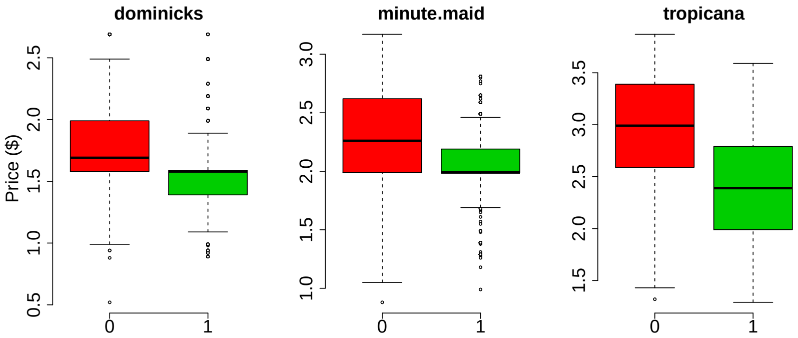
```
> print(lm(logmove ~ log(price)*feat, data=oj))

Call:
lm(formula = logmove ~ log(price) * feat, data = oj)

Coefficients:
    (Intercept)      log(price)     feat  log(price):feat
         9.6593          -0.9582       1.7144       -0.9773
```

Advertisement increases price sensitivity from -0.96 to -0.958 - 0.98 = -1.94!

Why?

# How does advertisement affect price sensitivity?

One of the reasons is that the price was lowered during the Ad campaign!




0 = not featured, 1 = featured

# Dummies

We want to understand effect of the brand on the sales

$$\log(\text{sales}) = \beta_0 + \beta_1 \log(\text{price}) + \cancel{\beta_2 \text{brand}}$$

But brand is not a number!

How can you use it in your regression equation?

We introduce dummy variables

| Brand | Intercept | brandminute.maid | brandtropicana |
|---|---|---|---|
| minute.maid | 1 | 1 | 0 |
| tropicana | 1 | 0 | 1 |
| dominicks | 1 | 0 | 0 |

$$\log(\text{sales}) = \beta_0 + \beta_1 \log(\text{price}) + \beta_{21}\text{brandminute.maid} + \beta_{22}\text{brandtropicana}$$

# Dummies

R will automatically do it it for you

```
> print(lm(logmove ~ log(price)+brand, data=oj))

Call:
lm(formula = logmove ~ log(price) + brand, data = oj)

Coefficients:
     (Intercept)        log(price)  brandminute.maid    brandtropicana
         10.8288           -3.1387            0.8702            1.5299
```

$$\log(\text{sales}) = \beta_0 + \beta_1 \log(\text{price}) + \beta_3 \text{brandminute.maid} + \beta_4 \text{brandtropicana}$$

$\beta_3$ and $\beta_4$ are “change relative to reference" (dominicks here).

## How does brand affect price sensitivity?

Interactions: `logmove ~ log(price) * brand`

No Interactions: `logmove ~ log(price) + brand`

| Parameter | Interactions | No Interactions |
|---|---|---|
| (Intercept) | 10.95 | 10.8288 |
| log(price) | -3.37 | -3.1387 |
| brandminute.maid | 0.89 | 0.8702 |
| brandtropicana | 0.96239 | 1.5299 |
| log(price):brandminute.maid | 0.057 | |
| log(price):brandtropicana | 0.67 | |

# Example: Golf Performance Data

Dave Pelz has written two best-selling books for golfers, *Dave Pelz's Short Game Bible*, and *Dave Pelz's Putting Bible*.

- Dave Pelz was formerly a “rocket scientist” (literally) Data analytics helped him refine his analysis It's the short-game that matters!
- The optimal speed for a putt

  Best chance to make the putt is one that will leave the ball 17 inches past the hole, if it misses.

# Golf Data

Year-end performance data on 195 players from the 2000 PGA Tour.

1. `nevents`, the number of official PGA events included in the statistics
2. `money`, the official dollar winnings of the player
3. `drivedist`, the average number of yards driven on par 4 and par 5 holes
4. `gir`, greens in regulation, measured as the percentage of time that the first (tee) shot on a par 3 hole ends up on the green, or the second shot on a par 4 hole ends up on the green, or the third shot on a par 5 hole ends up on the green
5. `avgputts`, which is the average number of putts per round.

Analyze these data to see which of nevents, rivedist, gir, avgputts is most

important for winning money.

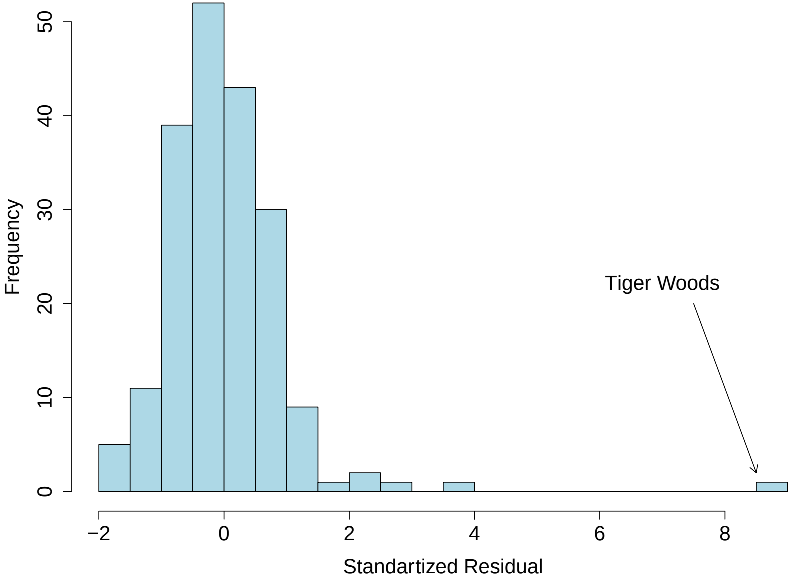
# Golf Data

Regression of Money on all explanatory variables:

```
lm(formula = money ~ nevents + drivedist + gir + avgputts)
Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)  14856638    4206466   3.532 0.000518 ***
nevents        -30066      11183  -2.689 0.007815 **
drivedist       21310       6913   3.083 0.002358 **
gir            120855      17429   6.934 6.22e-11 ***
avgputts    -15203045    2000905  -7.598 1.33e-12 ***
```

$R^2 = 50\%$

# Residuals


Frequency
0
10
20
30
40
50
−2
0
2
4
6
8
Standartized Residual
Tiger Woods

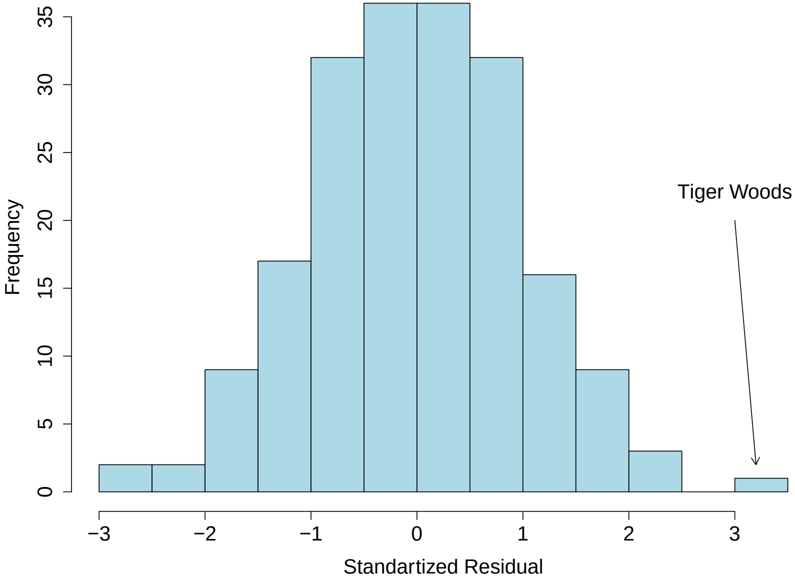
# Regression

Transform with `log(Money)` as it has much better residual diagnostic plots.

```
lm(formula = log(money) ~ nevents + drivedist + gir + avgputts, data = d

Coefficients:
              Estimate Std. Error t value Pr(>|t|)
(Intercept)  36.149228   3.577630  10.104   <2e-16 ***
nevents      -0.008987   0.009511  -0.945   0.3459
drivedist     0.014091   0.005880   2.397   0.0175 *
gir           0.165672   0.014824  11.176   <2e-16 ***
avgputts    -21.128752   1.701784 -12.416   <2e-16 ***
```

$R^2 = 67\%$. There's still 33% of variation to go

# Residuals for `log(Money)`



# Regression

Variable selection: $t$-stats for `nevents` is $< 1.5$.

```
lm(formula = log(money) ~ drivedist + gir + avgputts, data = d00)

Residuals:
Min        1Q   Median        3Q       Max
-1.48002 -0.37038  0.00079  0.40227  1.96546

Coefficients:
Estimate Std. Error t value Pr(>|t|)
(Intercept)  36.17370    3.57653  10.114   <2e-16 ***
drivedist     0.01463    0.00585   2.501   0.0132 *
gir           0.16577    0.01482  11.186   <2e-16 ***
avgputts    -21.36844    1.68230 -12.702   <2e-16 ***
```

The fewer the putts the better golfer you are. Duh!

`avgputts` per round is hard to decrease by one!

# Evaluating the Coefficients

1. Greens in Regulation (GIR) has a $\hat{\beta} = 0.17$. If I can increase my GIR by one, I'll earn $e^{0.17} = 1.18\%$ An extra 18%
2. DriveDis has a $\hat{\beta} = 0.014$. A 10 yard improvement, I'll earn $e^{0.014 \times 10} = e^{0.14} = 1.15\%$ An extra 15%

Caveat: Everyone has gotten better since 2000!

# Main Findings

Tiger was 9 standard deviations better than the model.

- Taking `logs` of `Money` helps the residuals!
- An exponential model seems to fit well. The residual diagnostics look good
- The $t$-ratios for `nevents` are under 1.5.

# Over-Performers

Outliers: biggest over and under-performers in terms of money winnings, compared with the performance statistics.

Woods, Mickelson, and Els won major championships by playing well when big money prizes were available.

Over-Performers

| Name | Money | Predicted | Error |
|---|---|---|---|
| Tiger Woods | 9,188,321 | 3,584,241 | 5,604,080 |
| Phil Mickelson | 4,746,457 | 2,302,171 | 2,444,286 |
| Ernie Els | 3,469,405 | 1,633,468 | 1,835,937 |
| Hal Sutton | 3,061,444 | 1,445,904 | 1,615,540 |

# Under-Performers

Underperformers are given by large negative residuals Glasson and Stankowski should win more money.

| Name | Money | Predicted | Error |
|---|---|---|---|
| Kenny Perry | $889,381$ | $1,965,740$ | $-1,076,359$ |
| Paul Stankowski | $669,709$ | $1,808,690$ | $-1,138,981$ |
| Bill Glasson | $552,795$ | $1,711,530$ | $-1,158,735$ |
| Jim McGovern | $266,647$ | $1,397,818$ | $-1,131,171$ |

# Lets look at 2018 data

Highest earners are

| name | nevents | money | drivedist | gir | avgputts |
|---|---|---|---|---|---|
| Justin Thomas | 23 | 8,694,821 | 311.800 | 68.770 | 1.714 |
| Dustin Johnson | 20 | 8,457,352 | 314 | 70.570 | 1.699 |
| Justin Rose | 18 | 8,130,678 | 303.500 | 69.950 | 1.732 |
| Bryson DeChambeau | 26 | 8,094,489 | 305.700 | 69.650 | 1.758 |
| Brooks Koepka | 17 | 7,094,047 | 313.400 | 68.280 | 1.747 |
| Bubba Watson | 24 | 5,793,748 | 313.100 | 68.210 | 1.773 |

# Overperformers

| name | money | Predicted | Error |
|---|---|---|---|
| Justin Thomas | 8,694,821 | 5,026,220 | 3,668,601 |
| Dustin Johnson | 8,457,352 | 6,126,775 | 2,330,577 |
| Justin Rose | 8,130,678 | 4,392,812 | 3,737,866 |
| Bryson DeChambeau | 8,094,489 | 3,250,898 | 4,843,591 |
| Brooks Koepka | 7,094,047 | 4,219,781 | 2,874,266 |
| Bubba Watson | 5,793,748 | 3,018,004 | 2,775,744 |
| Webb Simpson | 5,376,417 | 2,766,988 | 2,609,429 |
| Francesco Molinari | 5,065,842 | 2,634,466 | 2,431,376 |
| Patrick Reed | 5,006,267 | 2,038,455 | 2,967,812 |
| Satoshi Kodaira | 1,471,462 | -1,141,085 | 2,612,547 |

# Underperformers

| name | money | Predicted | Error |
|---|---|---|---|
| Trey Mullinax | 1,184,245 | 3,250,089 | -2,065,844 |
| J.T. Poston | 940,661 | 3,241,369 | -2,300,708 |
| Tom Lovelady | 700,783 | 2,755,854 | -2,055,071 |
| Michael Thompson | 563,972 | 2,512,330 | -1,948,358 |
| Matt Jones | 538,681 | 2,487,139 | -1,948,458 |
| Hunter Mahan | 457,337 | 2,855,898 | -2,398,561 |
| Cameron Percy | 387,612 | 3,021,278 | -2,633,666 |
| Ricky Barnes | 340,591 | 3,053,262 | -2,712,671 |
| Brett Stegmaier | 305,607 | 2,432,494 | -2,126,887 |

# Let's Look at 2020

| name | drivedist | gir | avgputts | residual |
|---|---|---|---|---|
| Bryson DeChambeau | 344.4 | 71.53 | 1.748 | 1,658,171 |
| Jason Kokrak | 309.7 | 68.65 | 1.676 | 1469110 |
| Matthew Wolff | 314.4 | 64.24 | 1.659 | 1407259 |
| Patrick Cantlay | 303.1 | 68.06 | 1.75 | 1406472 |
| Xander Schauffele | 304.9 | 68.52 | 1.669 | 1207284 |
| Martin Laird | 299.8 | 78.57 | 1.768 | 1006939 |
| Justin Thomas | 301.3 | 63.43 | 1.679 | 858123 |

Standard deviation of the residual is 334,595. DeChambeau is 5 sigmas away from the average PGA player!

# Findings

Here's three interesting effects:

- Tiger Woods is 8 standard deviations better!
- Increasing driving distance by 10 yards makes you 15% more money
- Increasing GIR by one makes you 18% more money.
- Detect Under- and Over-Performers

Go Play!!

# Regression

1. Input and Plot Data In `R`: `plot` and `summary` commands
2. "Kitchen-Sink" Regression `lm` command with all variables
3. Residual Diagnostics and `plot(model)` Fitted values and Standardised residuals. Outliers and Influence
4. Transformation?

   Correct the 4-in-1 plots and assumptions.

# Regression Strategy

1. Variable Selection *t*-state and *p*-values from `summary(model)`
2. Final Regression Re-run the model. Interpret the coefficients `summary(model)`. Economic and Statistical Significance
3. Prediction `predict.lm`. Out-of-sample forecasting A model is only as good as its predictions!!

# Machine Learning Tools

There's the list of methods we'll go through

1. Linear Regression
2. Multiple Regression
3. K-Nearest Neighbor
4. Simple Tree
5. Random Forests/Bagging
6. Boosting
7. Classification

   Logistic Regression

   Support Vector Machine (SVM)
8. Deep Learning

   Nonlinearity. Keras.

# Boston Housing Prices

Boston Housing Data (MASS package in R).

14 features (columns) and 506 observations (rows).

- CRIM - per capita crime rate by town
- ZN - proportion of residential land zoned for lots over 25,000 sq.ft.
- INDUS - proportion of non-retail business acres per town.
- CHAS - Charles River dummy variable (1 if tract bounds river; 0 otherwise)
- NOX - nitric oxides concentration (parts per 10 million)
- RM - average number of rooms per dwelling
- AGE - proportion of owner-occupied units built prior to 1940
- DIS - weighted distances to five Boston employment centres
- RAD - index of accessibility to radial highways
- TAX - full-value property-tax rate per $10,000
- PTRATIO - pupil-teacher ratio by town
- B - $1000(Bk - 0.63)^2$ where Bk is the proportion of blacks by town
- LSTAT - % lower status of the population
- MEDV - Median value of owner-occupied homes in $1000's

# Predicting Boston Housing Prices

Here we fit different model to the Boston Housing Data, which is available in the MASS package of R and it has 14 features (columns) and 506 observations (rows).

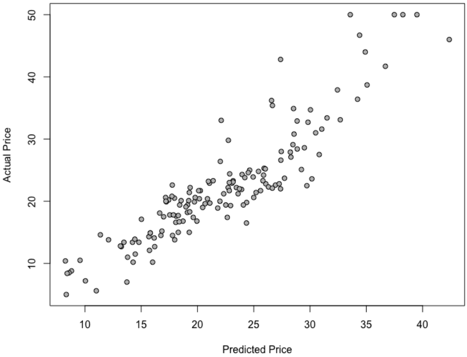
- Variable to predict: MEDV (median value of owner-occupied homes in 1000s).
- Features include CRIM (per capita crime rate), DIS (distance to Boston employment centers), RM (average number of rooms per dwelling), LSTAT (percent of population with lower socio-economic status), among others

# Multiple Regression

- Kitchen sink LM: $y =$MEDV, rest are independent variables. RMSE = 4.38
- Next we try

  log(MEDV) $\sim$ CRIM+CHAS+NOX+RM+DIS+PTRATIO+RAD+B+LSTAT

  The RMSE here is 4.18



# k-Nearest Neighbors

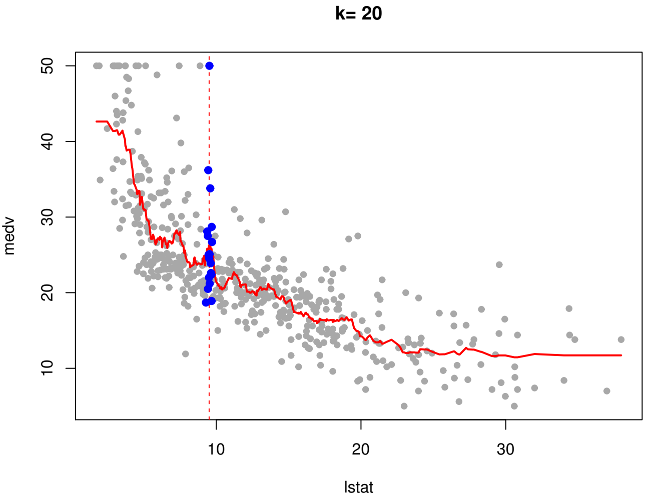
Points that are “closer" to the place I am trying to predict should be more relevant...

How about averaging the closest 20 neighbors?

What do I mean by closest? We will choose the 20 points that are closest to the X value we are trying to predict.

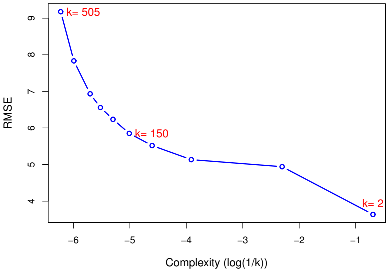
This is what is called the k-nearest neighbors algorithm

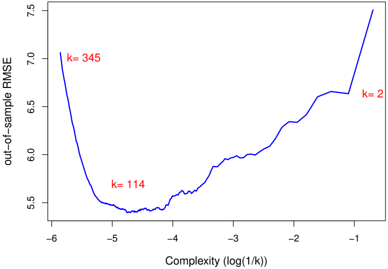
# k-Nearest Neighbors



# k-nearest neighbors

What is the accuracy of different models?




In-Sample RMSE

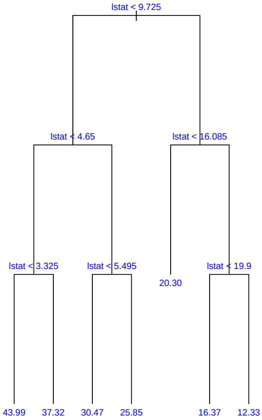
Out-of-sample RMSE

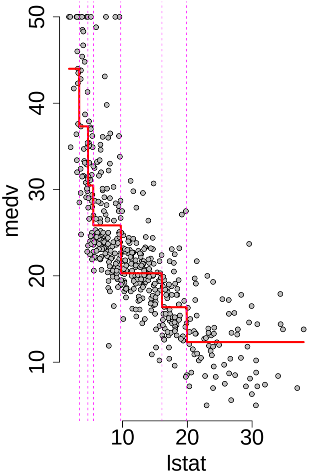
Now, the model where k = 46 looks like the most accurate choice!!

# Tree Models: Random Forests and XGBoost

Tree $=$ piecewise regression (a.k.a step function).

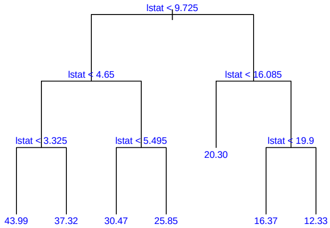
Categorical and numeric $y$ and $x$ very nicely and is fast The leaves of the tree have our best prediction ...

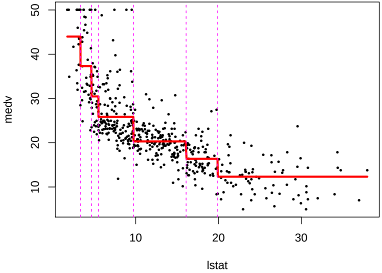


# Regression Trees

At left is the tree fit to the data. At each interior node there is a decision rule of the form $\{x < c\}$. If $x < c$ you go left, otherwise you go right. Each observation is sent down the tree until it hits a bottom node or leaf of the tree.

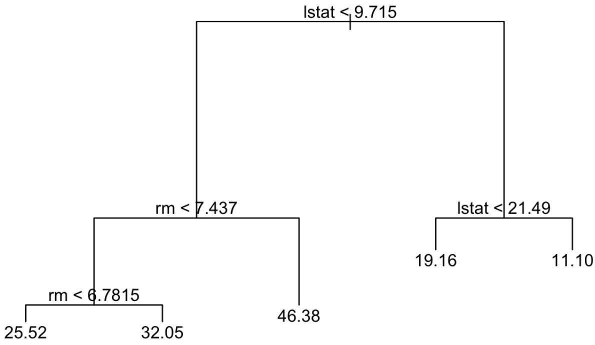



The set of bottom nodes gives us a partition of the predictor (x) space into disjoint regions. At right, the vertical lines display the partition. With just one $x$, this is just a set of intervals.

# Regression Trees

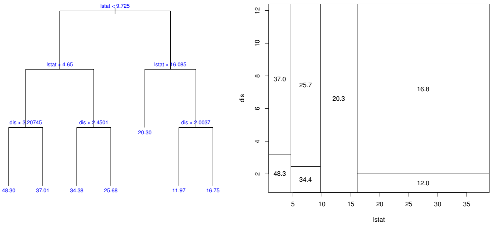
Use 10-fold cross-validation. Set number of leaves to be 5 in pruning. Build a tree in the shape of:




This tree model achieves an out-of-sample MSE of 5.01.

# Regression Trees

Here is a tree with x = (x1, x2) = (lstat,dis) and y=medv. Now the decision rules can use either of the two x?s.

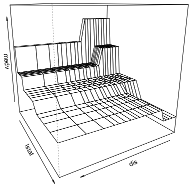



At right is the partition of the x space corresponding to the set of bottom nodes (leaves). The average y for training observations assigned to a region is printed in each region and at the bottom nodes.

# Regression Trees

This is the regression function given by the tree.

It is a step function which can seem dumb, but it delivers non- linearity and interactions in a simple way and works with a lot of variables.




Notice the interaction.

The effect of dis depends on lstat!!

# Bagging

Treat the sample as if it were the population and then take iid draws.

That is, you sample with replacement so that you can get the same original sample value more than once in a bootstrap sample.

To Bootsrap Aggregate (Bag) we:

- Take B bootstrap samples from the training data, each of the same size as the training data.
- Fit a large tree to each bootstrap sample (we know how to do this fast!). This will give us B trees.
- Combine the results from each of the B trees to get an overall prediction.

# Bagging and Random Forest

- For numeric $y$ we can combine the results easily by making our overall prediction the average of the predictions from each of the B trees.
- For categorical $y$, it is not quite so obvious how you want to combine the results from the different trees.
- Often people let the trees vote: given $x$ get a prediction from each tree and the category that gets the most votes (out of B ballots) is the prediction.
- Alternatively, you could average the $\hat{p}$ from each tree. Most software seems to follow the vote plan.

# Random Forest and Bagging

Include all 13 predictors for each split of the tree (a.k.a bagging)

Achieves an out-of-sample MSE of 3.66.

After we limit the number of predictors to be 6, we can achieve an even lower MSE of 3.35.

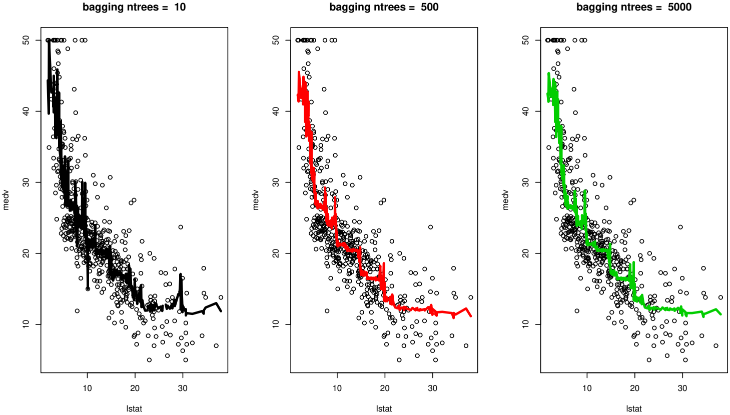
Random Forest beats Bagging.

# Bagging and Random Forest

With 10 trees our fit is too jumbly.

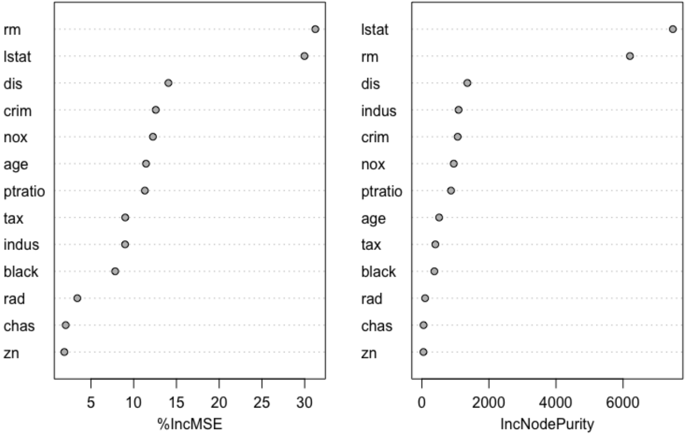
With 1,000 and 5,000 trees the fit is not bad and very similar.

Note that although our method is based multiple trees (average over) so we no longer have a simple step function!!



# Random Forest and Bagging

Use an importance function to check the effect of each variable:




Across all trees in random forest, lstat (the wealth level) and rm (house size) are by far the two most important variables.

## Boosting

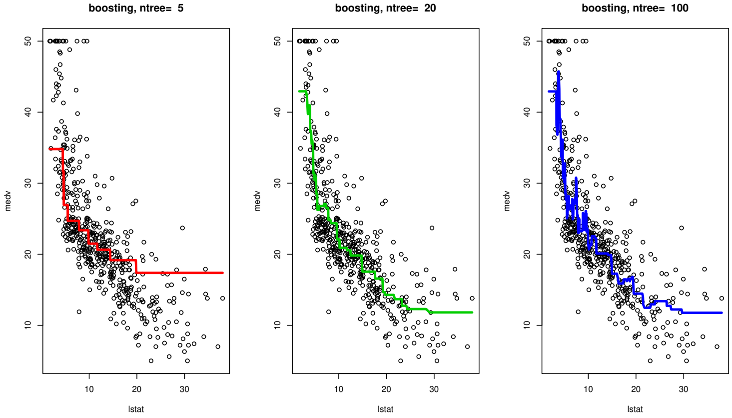
Like Random Forests, boosting is an ensemble method is that the overall fit it produced from many trees. The idea however, is totally different!!

In Boosting we:

- Fit the data with a single tree.
- Crush the fit so that it does not work very well.
- Look at the part of y not captured by the crushed tree and fit a new tree to what is “left over".
- Crush the new tree. Your new fit is the sum of the two trees.
- Repeat the above steps iteratively. At each iteration you fit “what is left over" with a tree, crush the tree, and then add the new crushed tree into the fit.
- Your final fit is the sum of many trees.

# Boosting

Here are some boosting fits where we vary the number of trees, but fix the depth at 2 (suitable with 1 x) and shrinkage = $\lambda$ at .2.

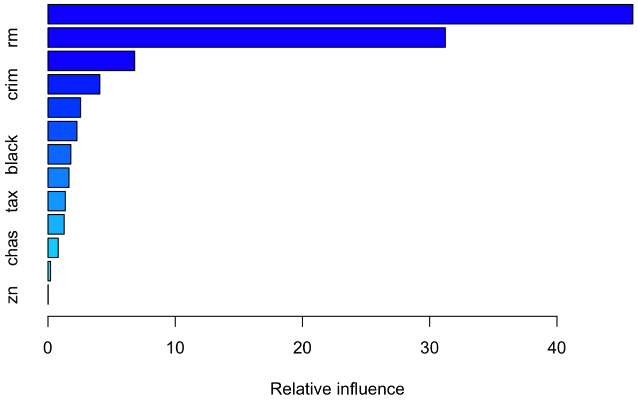


# Boosting

Train the Boosting model with 5000 trees and depth of 4,

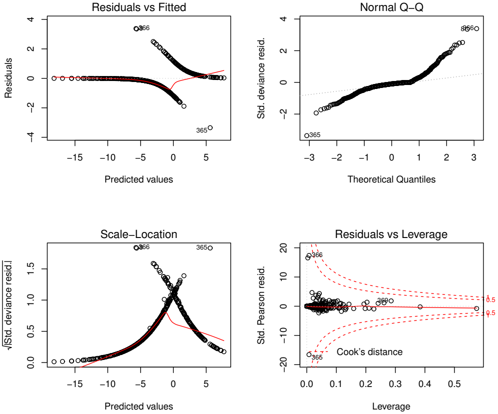
Out-of-sample MSE of 3.44, which is only slightly worse than Random Forest.

And we can still observe the significance of lstat and rm.



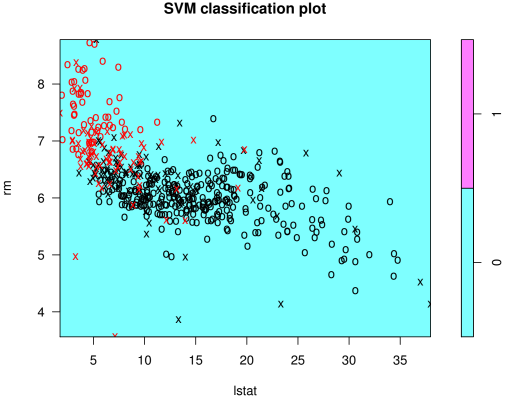
# Classification: Logistic Regression

We classified the response as 1 and 0, based on medv $>$25 and medv$\leq$ 25. We then tried the logistic regression and give the diagnostic plot:



# Classification: SVM

We include all the variables in the model, but the plot here only highlight the support vectors related to rm and lstat.



# Deep Learning: Keras

First layer is dense with 200 neurons. Includes input_shape which gives the dimensionality of the input data. Then add a dense layer with just a single neuron to serve as the output layer.

Out-of-sample MSE of 11.47.

A dense DL model doesn't do particularly well probably due to over-fitting on such as small set.

# Target

Target and other retailers use predictive analytics to study consumer purchasing behaviour to see what type of coupons or promotions you might like

Here's a famous story about a father and his daughter. Target predicted that his daugther was pregnant from her purchasing behaviour long before they were buying diapers

Here's the original link ...

Target and Pregnancy

## Getting a customer to a routine is the key

- M.I.T experiment: t-shaped maze with chocolate at the end and behind the barrier that opens after a loud click
- While each animal wandered through the maze, its brain was working furiously
- As the scientists repeated the experiment, again and again, the rats eventually stopped sniffing corners and making wrong turns and began to zip through the maze with more and more speed
- As each rat learned how to complete the maze more quickly, its mental activity decreased

## Learning routines from data is the basis for modern marketing

- Habits is a three-step loop: cue, a trigger (go into automatic mode), then the routine
- Febreze: original adds were targeting a wrong routine (kill the smell), no sails. They the ad said: use Febreze after cleaning each room. Now it is one of the most successful products.
- Target used the fact that customers who going through a major life event change their habits (routines). They can identify due dates from registry.

# Walmart

Walmart began using predictive analytics in 2004. Mining trillions of bytes' worth of sales data from recent hurricanes

Determine what customers most want to purchase leading up to a storm.

Strawberry Pop-Tarts are one of the most purchased food items, especially after storms, as they require no heating and can be eaten at any meal

Walmart and Hurricances

# Germany's Otto

Otto sells other brands, does not stock those goods itself, hard to avoid one of the two evils: shipping delays until all the orders are ready for fulfilment, or lots of boxes arriving at different times.

- Analyze around 3 billion past transactions and 200 variables–past sales, searches on Otto's site and weather information. They predict what customers will buy a week before they order. This system has proved so reliable, predicting with 90% accuracy what will be sold within 30 days, that Otto allows it automatically to purchase around $200,000$ items a month from third-party brands with no human intervention.

Economist

Germany's Otto

# Stitch Fix CEO Says AI Is 'So Real' and Incredibly Valuable

Stitch Fix asks customers for insights and feedback alongside their size and color preference for items, even the ones customers didn't like or buy, in exchange for a clear value proposition.

The breadth and depth of their data are valuable.

Their model relies on a combination of data science – machine learning, AI and natural language processing – and human stylists; on top of complex customer profiles built by data, stylists can layer the nuances of buying and wearing clothes.

# Uber Pool

Bayes predicts where you're going to be dropped off.

Uber constructs prior probabilities for riders, Uber cars, and popular places.

Combine to construct a joint probability table

Then calculate the posterior probability of destination for each person and pool travellers together

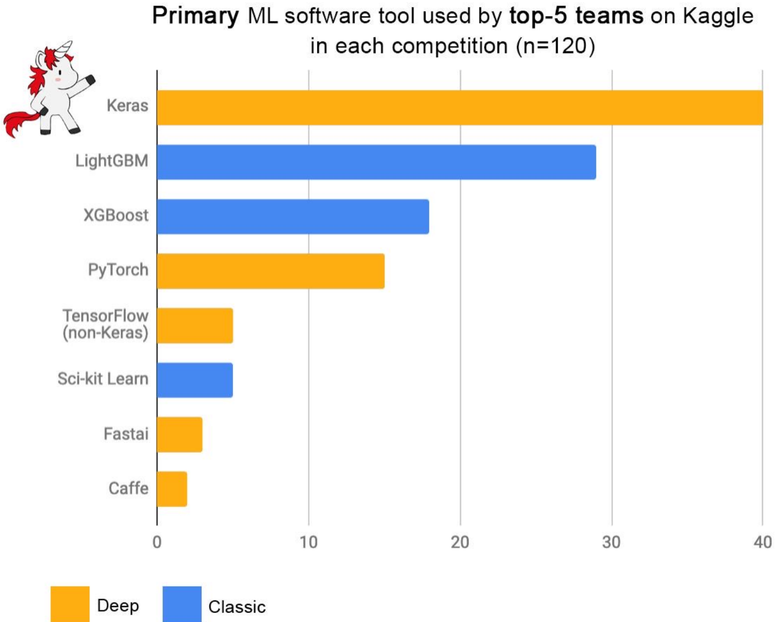
Uber Pool

# Kaggle: Predictive Culture

**353 Competitions**

| | |
| --- | --- |
| **Passenger Screening Algorithm Challenge**<br>Improve the accuracy of the Department of Homeland Security's threat recognition algorithms<br>Featured · 2 years ago · terrorism, image data, object detection | **$1,500,000**<br>518 teams |
| **Zillow Prize: Zillow's Home Value Prediction (Zestimate)**<br>Can you improve the algorithm that changed the world of real estate?<br>Featured · 2 years ago · real estate, housing | **$1,200,000**<br>3,775 teams |
| **Data Science Bowl 2017**<br>Can you improve lung cancer detection?<br>Featured · 2 years ago · healthcare, binary classification, image data | **$1,000,000**<br>1,972 teams |
| **Heritage Health Prize**<br>Identify patients who will be admitted to a hospital within the next year using historical claims data. (Ent...<br>Featured · 6 years ago | **$500,000**<br>1,351 teams |

# Most frequenlty used predictiv models



# Airbnb

Airbnb New User Bookings Prediction Competition New users on Airbnb can book a place to stay in 34,000+ cities across 190+ countries.

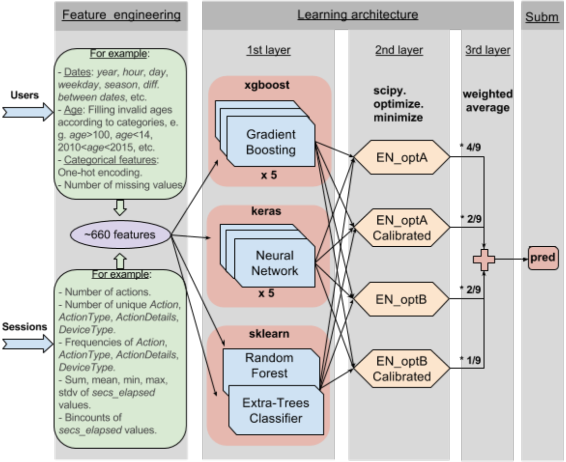
Accurately predict where a new user will book their first travel experience

Airbnb can then personalized content, decrease the average time to first booking, and better forecast demand.

12 classes–major destinations, and a did not book category

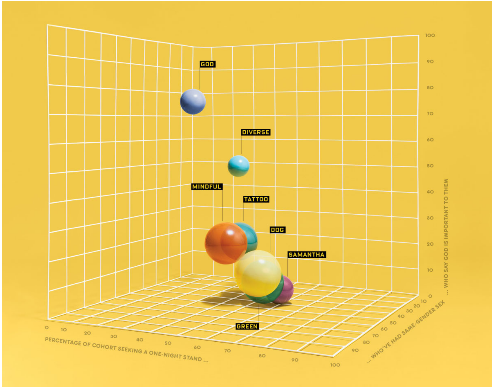
# Airbnb

List of users, demographics, web session records, and content data




Winner has the best out-of-sample prediction!!

# Hacking OkCupid



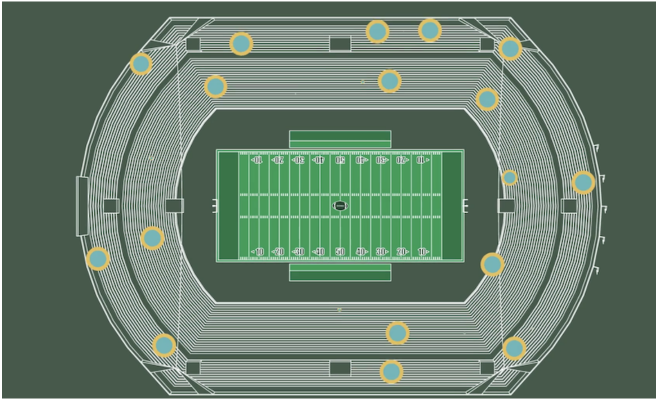

Sorted daters into seven clusters, like "Diverse" and "Mindful," each with distinct characteristics.

Wired article

NOVA Video

# NFL Dynamic Pricing

Predict price demand for any given Lions game for any given seat in the stadium



https://grahamschool.uchicago.edu/academic-programs/masters-degrees/analytics/nfl-capstone

# NFL Dynamic Pricing

We submitted our report on June 2016 suggesting that some areas of the stadium were priced efficiently and some were underpriced or overpriced.

On Fed 2017, Detroit Jock City wrote

"Detroit Lions tickets will cost a little more on average for 2017, but some areas of the stadium will decrease or hold steady."

## Detroit Lions: Ticket Prices Get Modest Increase for 2017 Season

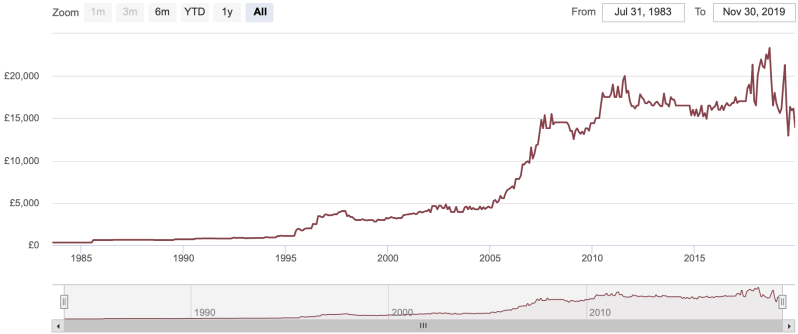
by Matt Snyder 2 years ago Follow @snyder_matthew

TWEET SHARE + COMMENT

***Detroit Lions tickets will cost a little more on average for 2017, but some areas of the stadium will decrease or hold steady.***

https://detroitjockcity.com/2017/02/10/detroit-lions-2017-ticket-prices/

# Wine: Latour 1982 Price History




wininvestment

# Château Latour: grand vin

## Bottle of Bordeaux wine sells for £135,000 at Christie's

28 May 2011

Share

**A single bottle of wine has sold for £135,000 in auction.**

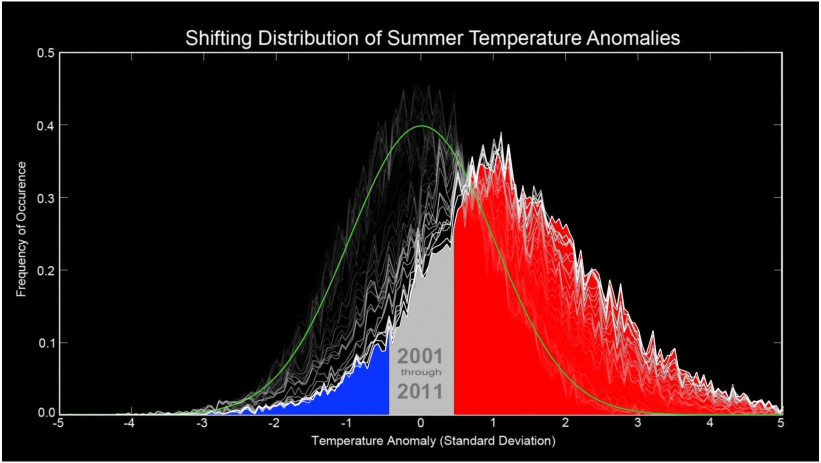
An expensive tipple - many houses cost less than the £135,000 bottle

The six-litre bottle of 1961 Chateau Latour was sold in Hong Kong by London-based Christie's auction house.

The sum was more than three times the expected price. Wine experts said the bottle was of "perfect provenance".

It would take someone earning the average UK wage more than five years to save up for the bottle. After tax, Prime Minister David Cameron could not afford it with his annual salary.

# Global Warming




Shifting Distribution of Northern Hemisphere Summer Temperature Anomalies, 1951-2011

NASA article with animation

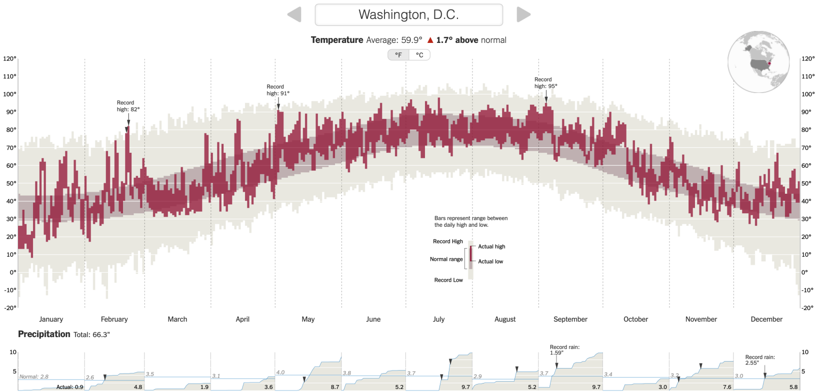
## Climate statistics and public policy

Change in global mean temperature is not one of the most sensitive indicator

- Sea surface temperature and Land surface temperature
- Sea level rise (thermal expansion and ice melt): Greenland and West Antarctic are melting + glacial melt
- Ocean acidification: $CO_2$ gets absorbed by water, it produces carbolic acid
- Seasonal changes; winter - summer temperature has been decreasing since 1954. Shift changes (earlier seasons) lead to ecological effects
- Hurricanes: increase in maximum wind velocity = sea surface temperature + the difference between sea surface temperature and the average air temperature in the outflow of the hurricane

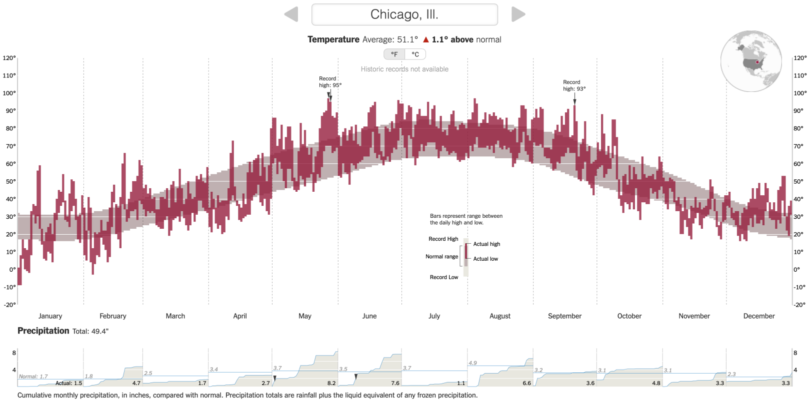
Guttorp paper

# 2018 was the fourth-warmest year on record.



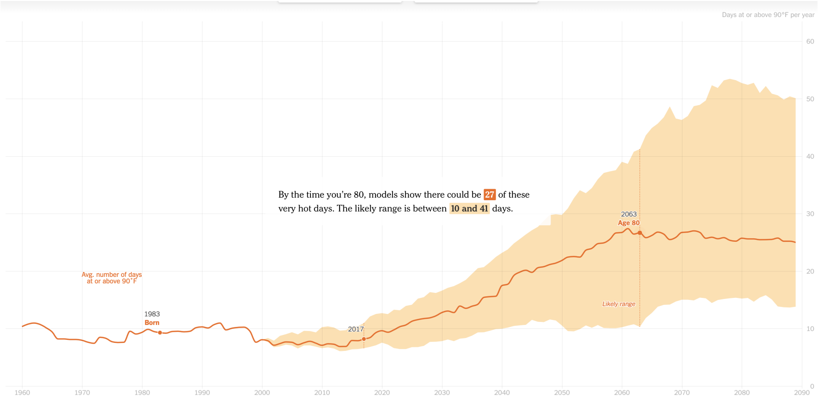

Cumulative monthly precipitation, in inches, compared with normal. Precipitation totals are rainfall plus the liquid equivalent of any frozen precipitation.

# 2018 was the fourth-warmest year on record.




NYT article

# How Much Hotter Is Your Hometown Than When You Were Born?



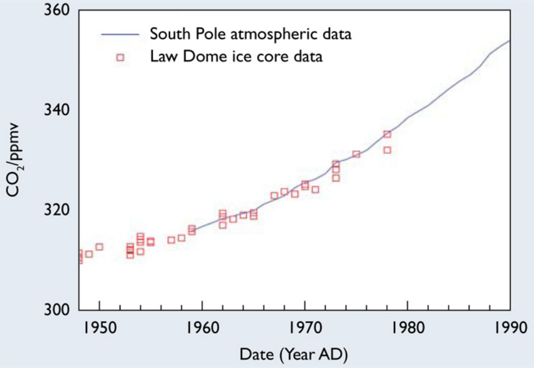

NYT article

# Ice cores is an important source of data

Ice core. Cylinder of ice drilled out of an ice sheet or glacier. Most ice core records come from Antarctica and Greenland.

The oldest continuous ice core records to date extend 123,000 years in Greenland and 800,000 years in Antarctica.

Fig 1: *Measurements of $CO_2$ from the Law Dome ice core[1] fall onto the line of annual average atmospheric measurements from South Pole[2]*



# Ice Core Datasets

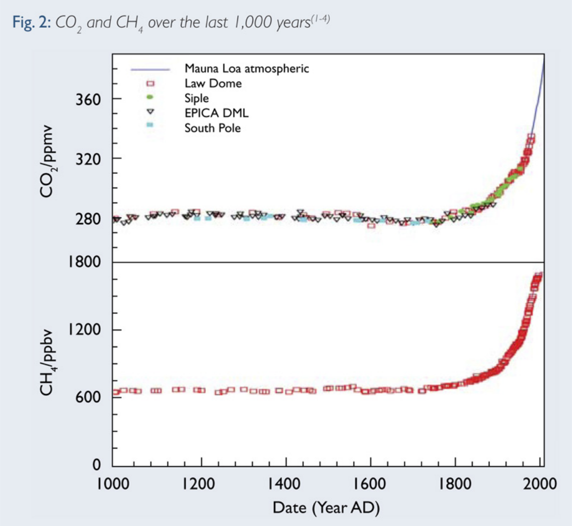
## Ice Core Basics

- has been around since the 1950s
- Mostly from Greenland and Antarctica
- bubbles in the ice core preserve actual samples of the world's ancient atmosphere

The World Data Center (WDC) for Paleoclimatology maintains archives of ice core data from polar and low-latitude mountain glaciers and ice caps throughout the world. Proxy climate indicators include oxygen isotopes, methane concentrations, dust content, as well as many other parameters.

https://www.ncdc.noaa.gov/data-access/paleoclimatology-data/datasets/ice-core

# CO2 was stable over the last millennium




In the early 19th century CO2 concentration started to rise, and its concentration is now nearly 40% higher than it was before the industrial revolution

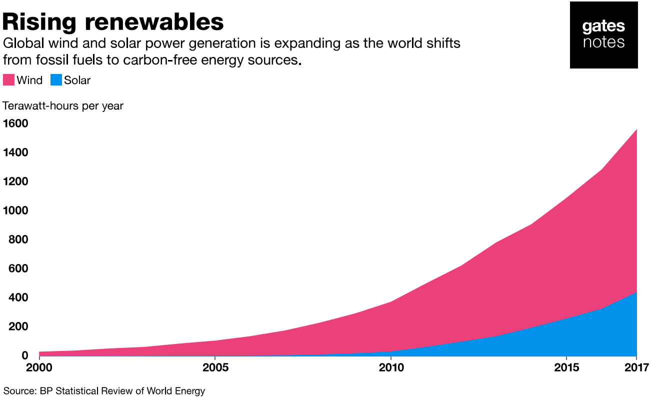
# Things we learned from ice core

Ice cores contain information about past temperature, and about many other aspects of the environment.

- Atmospheric carbon dioxide levels are now 40% higher than before the industrial revolution. This increase is due to fossil fuel usage and deforestation.
- The magnitude and rate of the recent increase are almost certainly unprecedented over the last 800,000 years.
- Methane also shows a huge and unprecedented increase in concentration over the last two centuries.

BAS article, The Verge Article

# Gates thinks we can use more renewables and nuclear




Need better storage + generation (wind/sun) technology

Source: https://www.gatesnotes.com/Energy/A-critical-step-to-reduce-climate-change

## Business Statistics: 41000

**Predictive Analytics**

**Logistic Regression**

Vadim Sokolov

The University of Chicago Booth School of Business

http://vsokolov.org/courses/41000/

# Predictive Analytics

## General Introduction

Predictive Analytics is the most widely used tool for high dimensional input-output analysis

$$Y = F(X) \text{ where } X = (X_1, \ldots, X_p)$$

- Consumer Demand (Amazon, Airbnb, ... )
- Maps (Bing, Uber)
- Pricing
- Healthcare

The applications are endless ....

# Logistic Regression: Classification

When the Y we are trying to predict is *categorical* (or *qualitative*) we say that we have a *classification* problem.

For a numeric (or *quantitative*) Y we predict it's value

For a binary output we predict the probability its going to happen

$$p(Y = 1 \mid X = x)$$

where X is our usual list of predictors, $X_1, \ldots, X_p$

# Logistic Regression

Suppose that we have a binary response, $Y$ taking the value 0 or 1

- Win or lose
- Sick or healthy
- Buy or not buy
- Pay or default

The goal is to predict the probability that $Y$ equals 1

You can then do classification and categorize a new data-point

# Example: Default Data

Here's a typical problem

Assessing credit risk and default data ...

- $Y$: whether or not a customer defaults on their credit card (No or Yes)
- $X$: The average balance that customer has remaining on their credit card after making their monthly payment.

  ... plus as many other features you think might predict $Y$ ...

# Logistic Regression

$Y$ is an indicator: $Y = 0$ or 1.

$X$ is our usual set of predictors/covariates

We need to model the probability that $Y = 1$ as

$$p(Y = 1 \mid X_1, \ldots, X_p) = f\left(\beta_1 X_1 + \ldots + \beta_p X_p\right)$$

where $f$ is increasing and $0 < f(X) < 1$ The logit-transform is given by $f(x) = e^x/(1 + e^x)$

# Logistic Regression

The logistic regression model is linear in log-odds

$$\log\left(\frac{p\,(Y=1 \mid X)}{1-p\,(Y=1 \mid X)}\right) = \beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p$$

When $x_i$ goes up by 1 unit log-odds go up by $\beta_i$

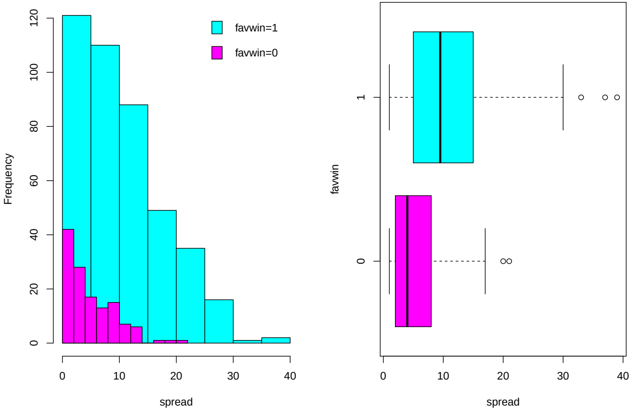
These model are easy to fit in R:

$$glm(Y \sim X1 + X2, family = binomial)$$

- "g" is for generalized; binomial indicates $Y = 0$ or 1
- "glm" has a bunch of other options.

# Example: NBA point spread

Does the Vegas point spread predict whether the favorite wins or not?




Turquoise = Favorites does win, Purple = Favorite does not win

# R: Logistic Regression

In R: the output gives us ...

```
nbareg = glm(favwin~spread-1, family=binomial)
summary(nbareg)
Call:
glm(formula = favwin ~ spread - 1, family = binomial)
Coefficients:
       Estimate  Std. Error  z value  P(>|z|)
spread  0.15600    0.01377   11.33   <2e-16 ***
# prediction
newweek=c(8,4)
```

The $\beta$ measures how our log-odds change! $\beta = 0.156$

# NBA Point Spread Prediction

"Plug-in" the values for the new game into our logistic regression

$$P\left(\text{favwin} \mid \text{spread}\right) = \frac{e^{\beta x}}{1 + e^{\beta x}}$$

Check that when $\beta = 0$ we have $p = \frac{1}{2}$.

- Given our new values spread$=8$ or spread$=4$,

  The win probabilities are 77% and 65%, respectively. Clearly, the bigger spread means a higher chance of winning.

# Credit Card Default

10,000 observations

```
> head(Default)
  default student   balance    income
1      No      No  729.5265 44361.625
2      No     Yes  817.1804 12106.135
3      No      No 1073.5492 31767.139
4      No      No  529.2506 35704.494
5      No      No  785.6559 38463.496
6      No     Yes  919.5885  7491.559
```

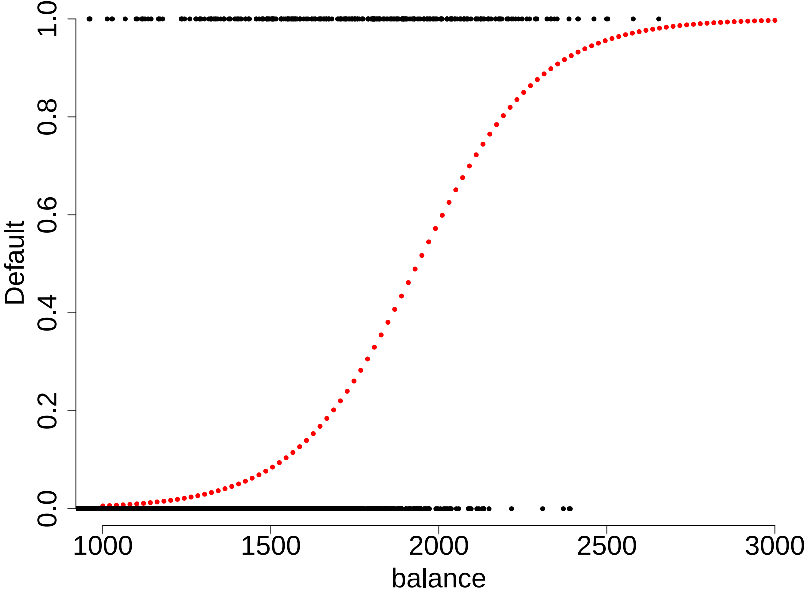
# Let's build a logisti regression model

```
Call:
glm(formula = default ~ balance, family = binomial, data = Default)

Coefficients:
              Estimate  Std. Error z value  Pr(>|z|)
(Intercept) -1.065e+01  3.612e-01  -29.49   <2e-16 ***
balance      5.499e-03  2.204e-04   24.95   <2e-16 ***
```

# Predicting default

```
> predict.glm(glm.fit,newdata = list(balance=1000))
        1
-5.152414
> -1.065e+01 + 5.499e-03*1000
[1] -5.151
> predict.glm(glm.fit,newdata = list(balance=1000), type="response")
          1
0.005752145
> exp(-1.065e+01 + 5.499e-03*1000)/(1+exp(-1.065e+01 + 5.499e-03*1000))
[1] 0.005760236
```

# Predicting default



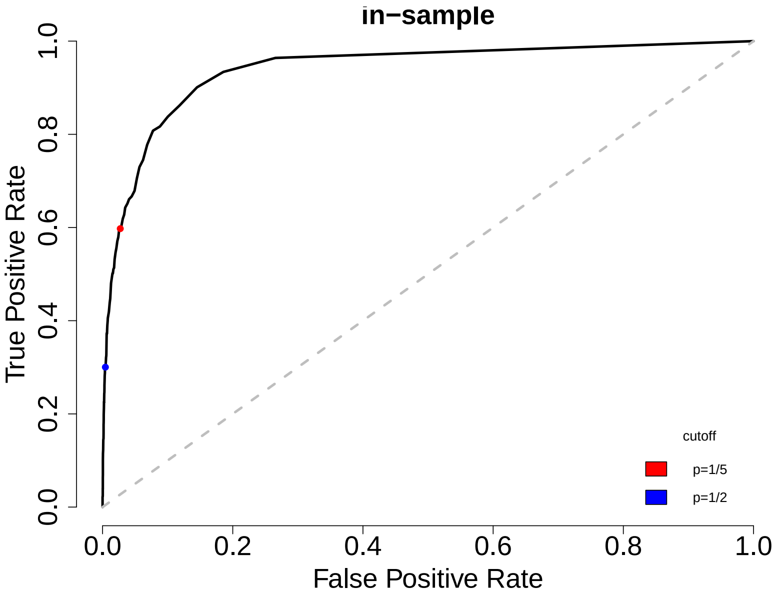
# Evalute the model

Accuracy = 0.96

| | Predicted: YES | Predicted: NO |
|---|---|---|
| Actual: YES | TPR=0.6 | FNR=0.4 |
| Actual: NO | FPR=0.03 | TNR=0.97 |

I used $p = 0.2$ as a cut-off. What if I use smaller or larger $p$, e.g. $p = 0$?

# ROC Curve Shows what happens for different cut-off values

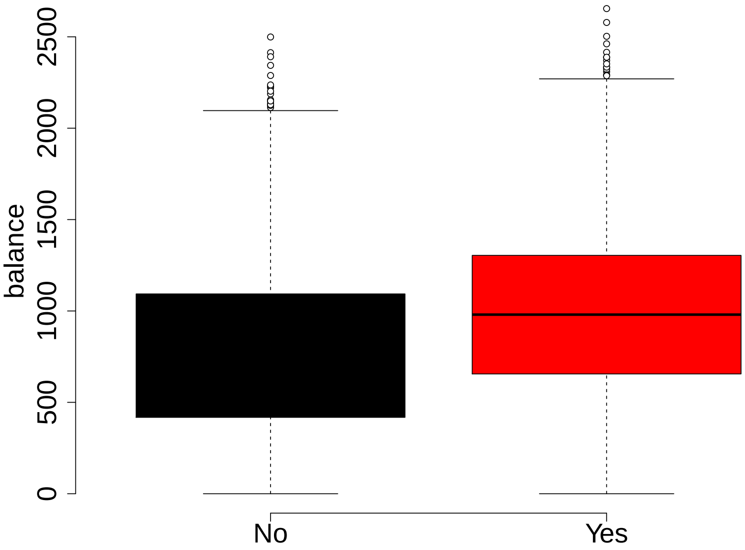


# Look at other predictors

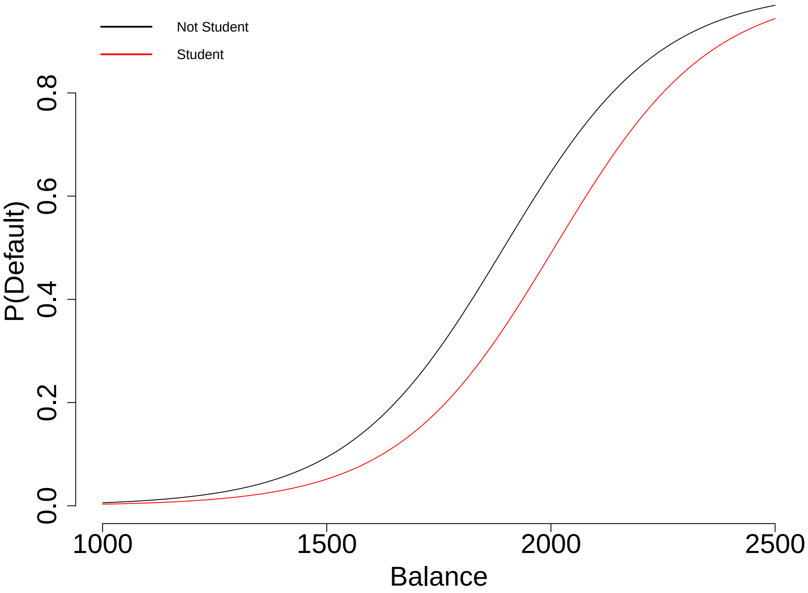
```
Call:
glm(formula = default ~ balance + income + student, family = binomial,
    data = Default)

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept) -1.087e+01  4.923e-01 -22.080  < 2e-16 ***
balance      5.737e-03  2.319e-04  24.738  < 2e-16 ***
income       3.033e-06  8.203e-06   0.370  0.71152
studentYes  -6.468e-01  2.363e-01  -2.738  0.00619 **
```

Student is significant!?

# Student vs Balance



# Let's adjust for balance



# Data Science in Tennis

Data science plays a major role in tennis

- IBM (major sponsor of grand slams) has developed an AI toolbox
- We will analyze the Tennis Major Tournament Match Statistics Data Set
- Each row is a game from four major Tennis tournaments in 2013 (Australia Open, French Open, US Open, and Wimbledon). Let's load the data and familiarize ourselves with it

# How important are the breakpoints in tennis?

```r
d = read.csv("~/book/bookmd/data/tennis.csv")
dim(d)
```

```
## [1] 943  44
```

```r
str(d[,1:5])
```

```
## 'data.frame':    943 obs. of  5 variables:
##  $ Player1: chr  "Lukas Lacko" "Leonardo Mayer" "Marcos Baghdatis" "Dmitry Tu"..
##  $ Player2: chr  "Novak Djokovic" "Albert Montanes" "Denis Istomin" "Michael "..
##  $ Round  : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ Result : int  0 1 0 1 0 0 0 1 0 1 ...
##  $ FNL1   : int  0 3 0 3 1 1 2 2 0 3 ...
```

We have data for 943 matches and for each match we have 44 columns, including names of the players, their gender, surface type and match statistics

# Peak at the data

Let's look at the few columns of the randomly selected five rows of the data

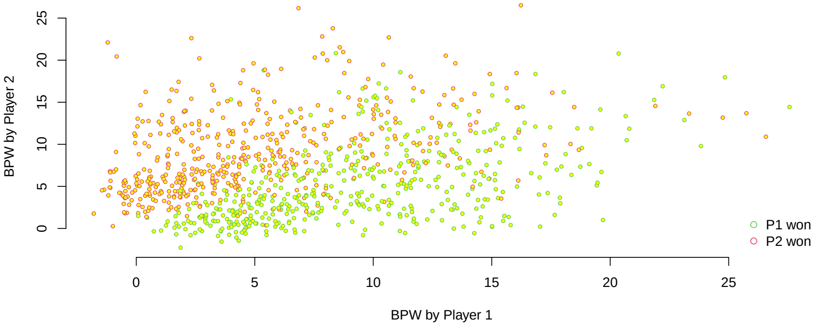
```
d[sample(1:943,size = 5),c("Player1","Player2","Round","Result",
                            "gender","surf")]
```

```
##              Player1            Player2 Round Result gender  surf
## 554     Jurgen Zopp Marcel Granollers     1      0      M  Hard
## 112   Fabio Fognini     Novak Djokovic     4      0      M  Hard
## 39  Thomaz Bellucci     Julian Reister     1      1      M  Hard
## 669        A Cornet      A Tomljanovic     2      1      W  Hard
## 744       D.Istomin            A.Seppi     1      0      M Grass
```

# Number of break points won by each player

We will plot BPW (break points won) by each player on the scatter plot and will colorize each dot according to the outcome

```
n = dim(d)[1]
plot(d$BPW.1+rnorm(n),d$BPW.2+rnorm(n), pch=21, bty="n",
    col=d$Result+2, cex=0.6, bg="yellow", lwd=0.8,
    xlab="BPW by Player 1", ylab="BPW by Player 2")
legend("bottomright", c("P1 won", "P2 won"), col=c(3,2), pch=21,
      bg="yellow", bty='n')
```




There is clearly a pattern! Let's quantify it using logistic regression.

# Logistic regression

```
which(is.na(d$BPW.1)) # there is one row with NA value for the BPW.1 value and we remove it
```

```
## [1] 171
```

```
d = d[-171,]; n = dim(d)[1]
m = glm(Result ~ BPW.1 + BPW.2-1, data=d, family = "binomial" )
summary(m)
```

```
##
## Call:
## glm(formula = Result ~ BPW.1 + BPW.2 - 1, family = "binomial",
##     data = d)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max
## -3.425  -0.668  -0.055   0.636   3.085
##
## Coefficients:
##       Estimate Std. Error z value Pr(>|z|)
## BPW.1   0.4019     0.0264    15.2   <2e-16 ***
## BPW.2  -0.4183     0.0277   -15.1   <2e-16 ***
```

# How well our model captures the pattern?

`R` output does not tell us how accurate our model is but we can quickly check it by using the `table` function. We will use 0.5 as a threshold for our classification.

```
table(d$Result, as.integer(m$fitted.values>0.5))
```

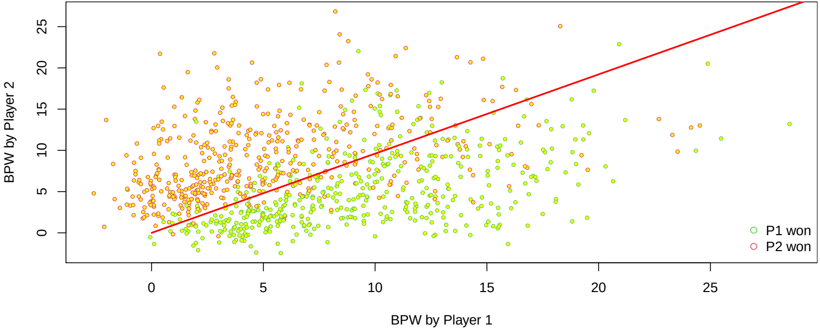
```
##
##       0   1
##   0 416  61
##   1  65 400
```

Thus, our model got (416+400)/942 = 87% of the predictions correctly!

# GLM Line

Let's see the line found by the `glm` function

```
plot(d$BPW.1+rnorm(n),d$BPW.2+rnorm(n), pch=21, col=d$Result+2, cex=0.6,
     bg="yellow", lwd=0.8,xlab="BPW by Player 1", ylab="BPW by Player 2")
legend("bottomright", c("P1 won", "P2 won"), col=c(3,2), pch=21,
       bg="yellow", bty='n')

x = seq(0,30,length.out = 200)
y  =  -m$coefficients[1]*x/m$coefficients[2]
lines(x,y, lwd=2, col="red")
```



# What did we find?

- Effect of a break point on the game outcome is significant
- It is symmetric, Dah! Effect of loosing break point is the same as the effect of winning one
- The chances of winning when P1 wins three more break points compared to the opponent:

```
predict.glm(m,newdata = data.frame(BPW.1 = c(0), BPW.2 = c(0)), type="response")
```

```
##   1
## 0.5
```

```
predict.glm(m,newdata = data.frame(BPW.1 = c(3), BPW.2 = c(0)), type="response")
```

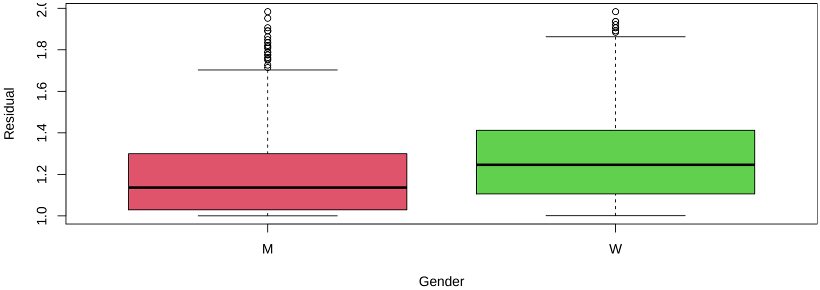
```
##    1
## 0.77
```

Chances go up by 27%.

# Are women's matches less predictable?

We can test thus statement by looking at the residuals. The larger the residual the less predictable the game.

```
d$res = abs(m$residuals)
outlind = which(d$res<2)
boxplot(d$res[outlind] ~ d$gender[outlind], col=c(2,3), xlab="Gender",
        bty='n', ylab="Residual")
```




Looks like the crowd wisdom that Women's matches are less predictable is correct.

## LinkedIn Study: How to Become an Executive

Analyze the career paths of about $459,000$ LinkedIn members who worked at a Top 10 consultancy between 1990 and 2010 and became a VP, CXO, or partner at a company with at least 200 employees.

About $64,000$ members reached this milestone. $\hat{p} = 0.1394$.

- Look at their profiles – educational background, gender, work experience, and career transitions.
- Build a model to predict the probability of becoming an executive.

Conditional on making it into the database ....

# Logistic Regression

Logistic regression with 8 key features (a.k.a. covariates):

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + ... + \beta_8 X_8$$

- $p$: Probability of “success” – reach VP/CXO/Partner at a company with at least 200 employees.
- $X_i (i = 1, 2, ..., 8)$: Features to predict the “success” probability.

# Features

Location Features: $X_1$ Metro region: whether a member has worked in one of the top 10 largest cities in the U.S. or globally.

Personal Features: $X_2$ Gender: Inferred from member names: 'male', or 'female'.

Education Features: $X_3$ Graduate education type: whether a member has an MBA from a top U.S. program / a non-top program / a top non-U.S. program / another advanced degree.

$X_4$ Undergraduate education type: whether a member has attended a school from the U.S. News national university rankings / a top 10 liberal arts college /a top 10 non-U.S. school.

# Features

Work Experience:

$X_5$ Company count: # different companies in which a member has worked.

$X_6$ Function count: # different job functions in which a member has worked.

$X_7$ Industry sector count: # different industries in which a member has worked.

$X_8$ Years of experience: # years of work experience, including years in consulting, for a member.

# $\hat{\beta}'s$ of Features[1]

1. Location: Metro region: 0.28
2. Personal: Gender(Male): 0.31
3. Education: Graduate education type: 1.16,

   Undergraduate education type: 0.22
4. Work Experience: Company count: 0.14,

   Function count: 0.26,

   Industry sector count: -0.22,

   Years of experience: 0.09

# Main Findings

1. Working across job functions, like marketing or finance, is good. Each additional job function provides a boost that, on average, is equal to three years of work experience. Switching industries has a slight negative impact. Learning curve? Lost network?
2. MBAs are worth the investment. But pedigree matters.
   *Top five program equivalent to* 13 *years of work experience!!!*
3. Location matters. NYC helps.

# Examples

Person A (p=6%): Male in Tulsa, Oklahoma, Undergraduate degree, 1 job function for 3 companies in 3 industries, 15-year experience.

Person B (p=15%): Male in London, Undergraduate degree from top international school, Non-MBA Master, 2 different job functions for 2 companies in 2 industries, 15-year experience.

Person C (p=63%): Female in New York City, Top undergraduate program, Top MBA program, 4 different job functions for 4 companies in 1 industry, 15-year experience.

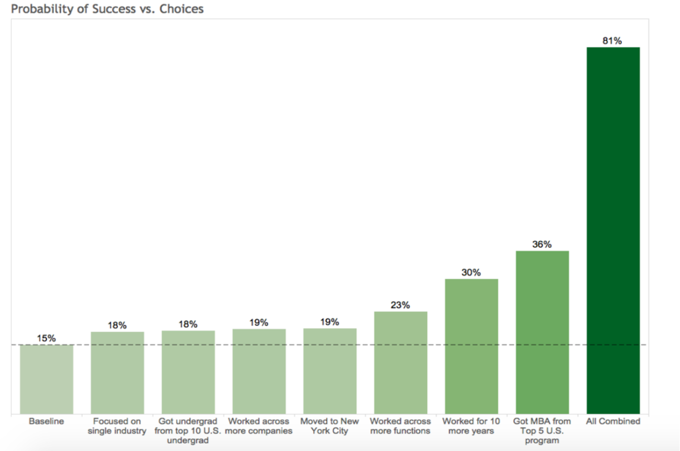
# Let's re-design Person B!!

Person B (p=15%): Male in London, Undergraduate degree from top international school, Non-MBA Master, 2 different job functions for 2 companies in 2 industries, 15-year experience.

1. Work in one industry rather than two. Increase 3%
2. Undergrad from top 10 US program rather than top international school. 3%
3. Worked for 4 companies rather than 2. Another 4%
4. Move from London to NYC. 4%
5. Four job functions rather than two. 8%. A 1.5X effect.
6. Worked for 10 more years. 15%. A 2X effect.

NYT article

# Choices and Impact (Person B)



## Summary

- Multiple Regression (Newfood study, Golf Analysis)
- Interactions (how advertisement change price elasticity?)
- Predictive analytics cases(Target, Walmart, Airbnb, Stitch Fix)
- Logistic regression (NBA predictions, Horse predictions, LinkedIn)