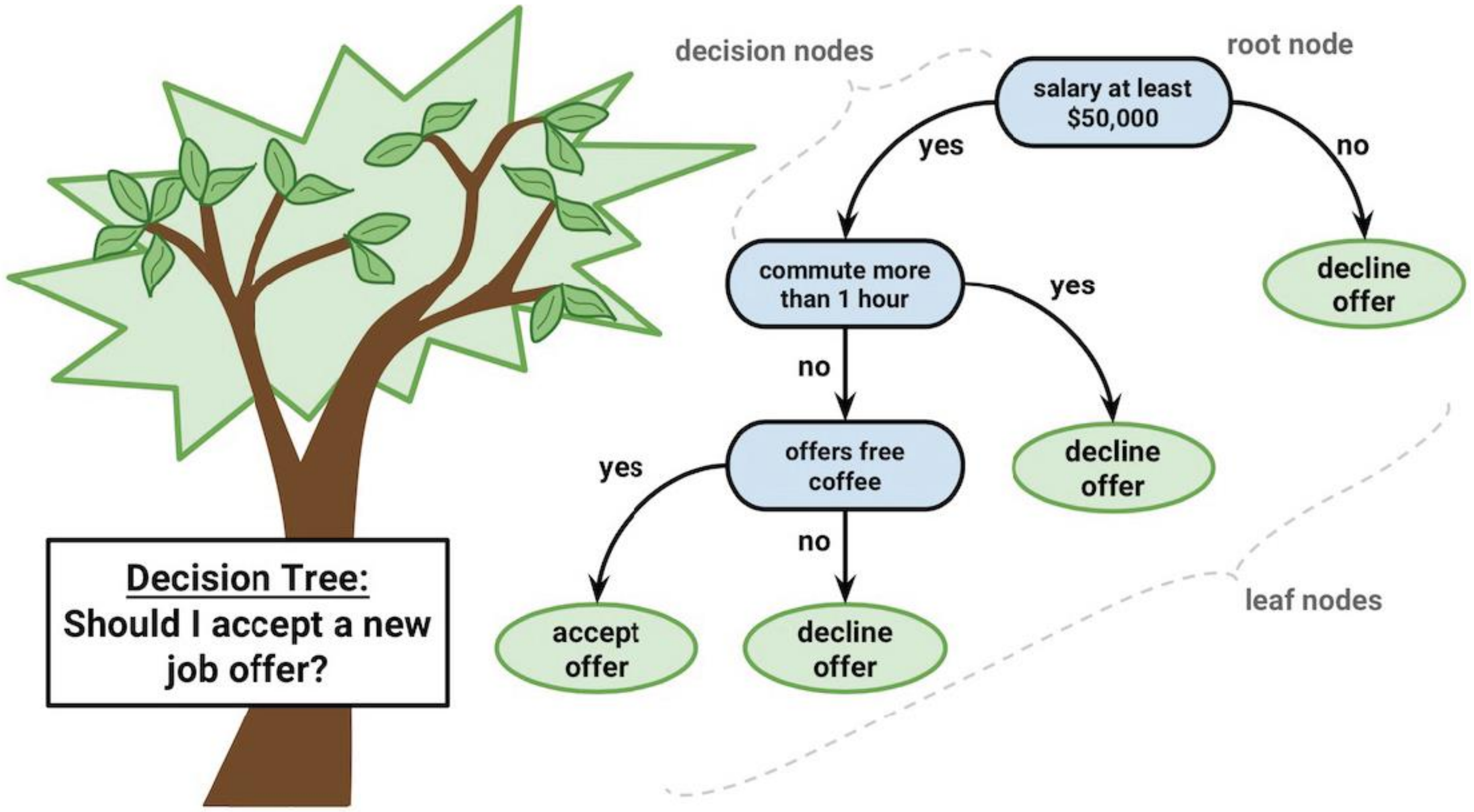
# Memorization Method - part 2

CCE20005: Introduction to Data Science
Presented by Hyebong Choi

## Contents

## Decision Tree

# Decision Tree Model

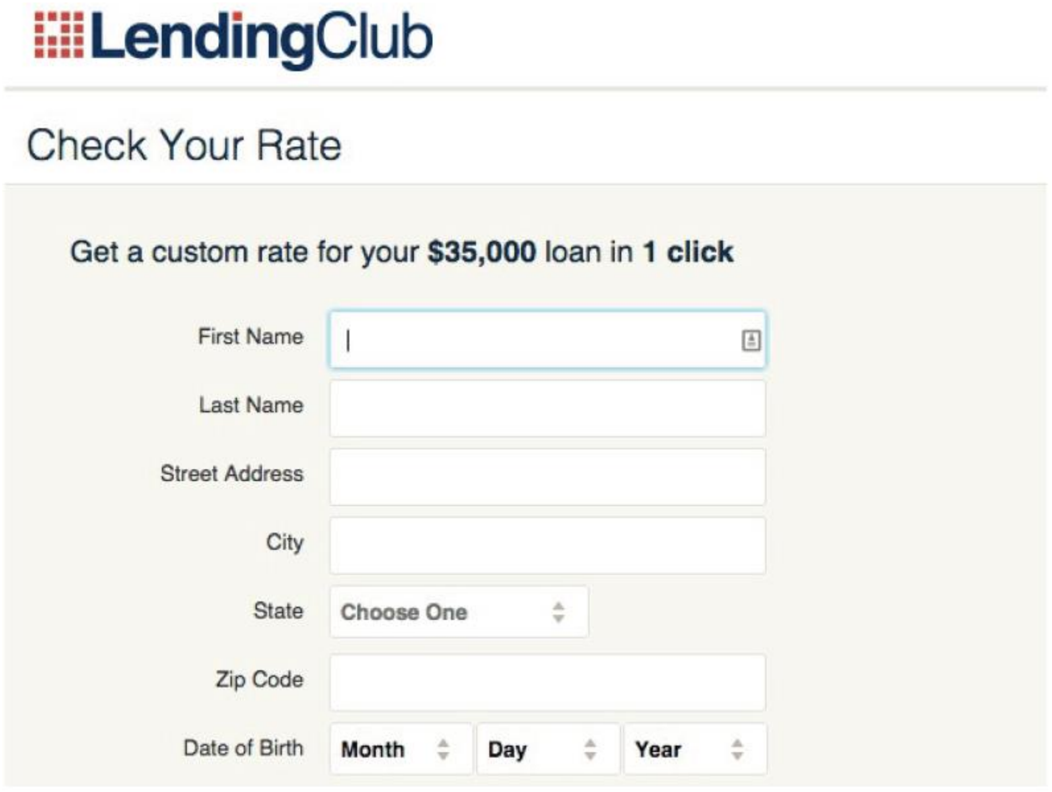


Before accepting a job offer, You may consider several conditions

Tree model organizes the conditions to make a decision

Conditions are organized from most significant condition to less significant ones

# Loan Applications


LendingClub

Check Your Rate

Get a custom rate for your **$35,000** loan in **1 click**

|  |  |
|---|---|
| First Name |  |
| Last Name |  |
| Street Address |  |
| City |  |
| State | Choose One |
| Zip Code |  |
| Date of Birth | Month / Day / Year |

considering:

amount of loan

purpose

credit history

income

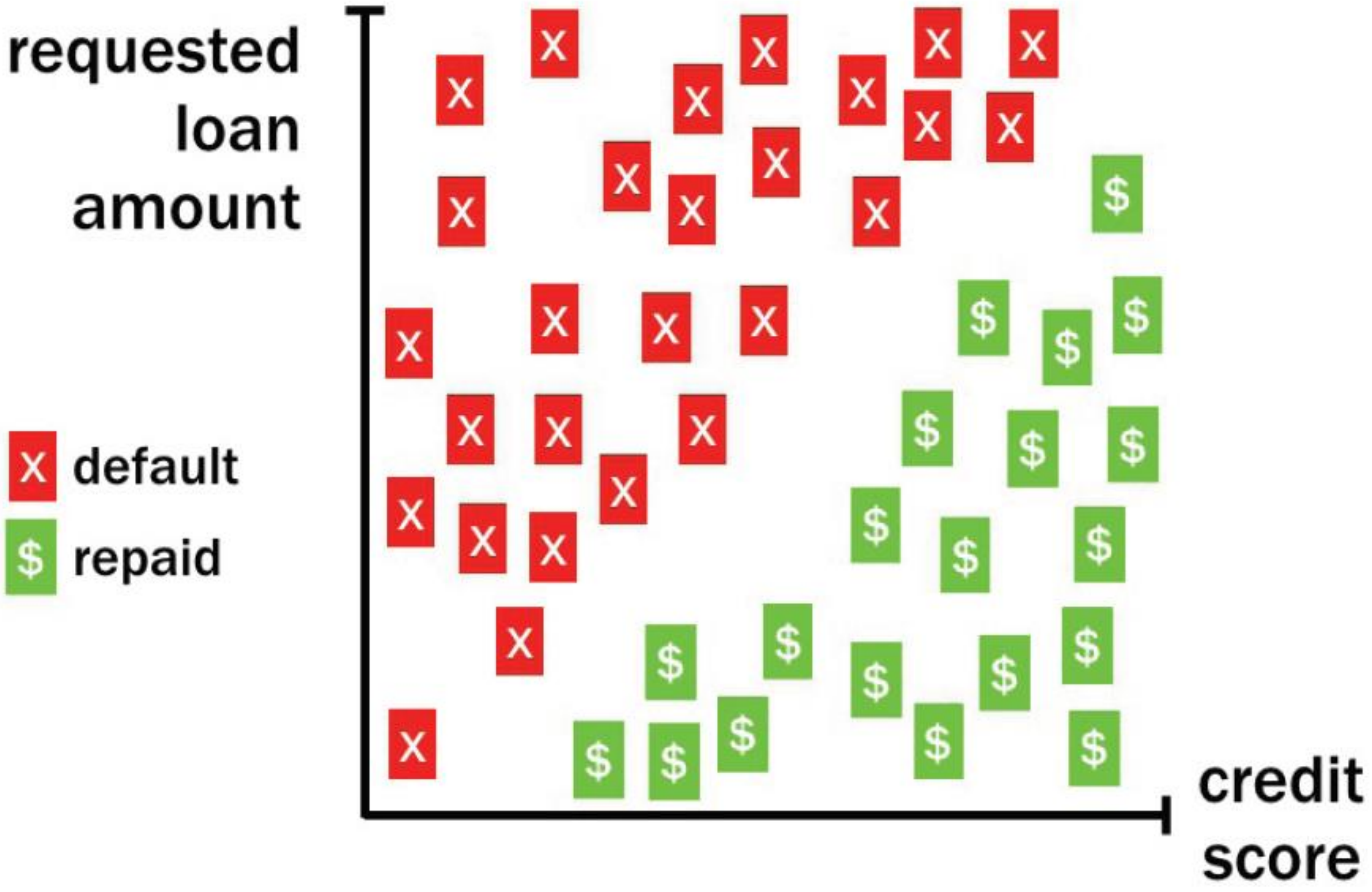
...

Decide:

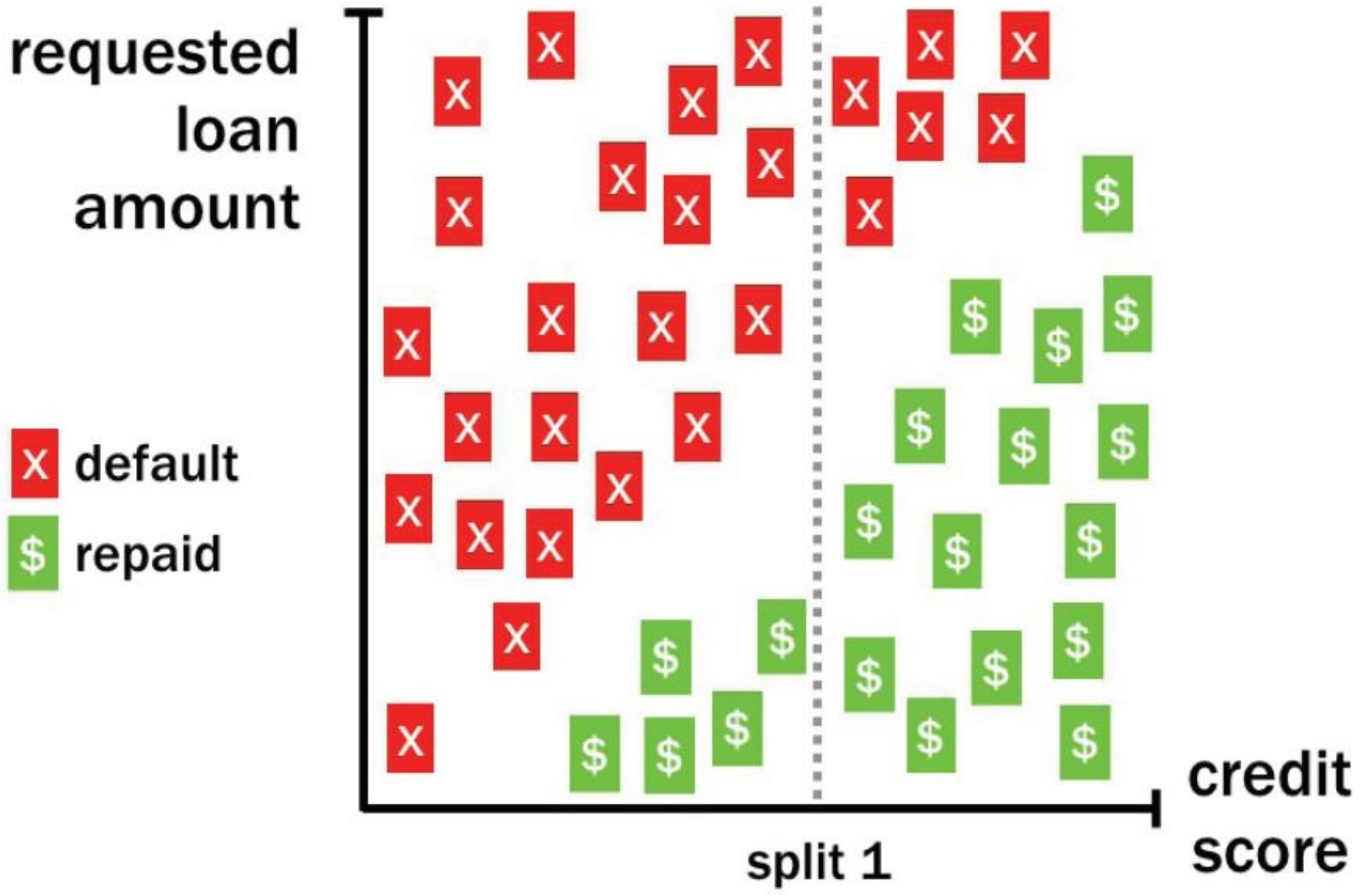
approve or decline

decision tree model is useful when deciding process is better to be **interpretable** and hence **transparent**

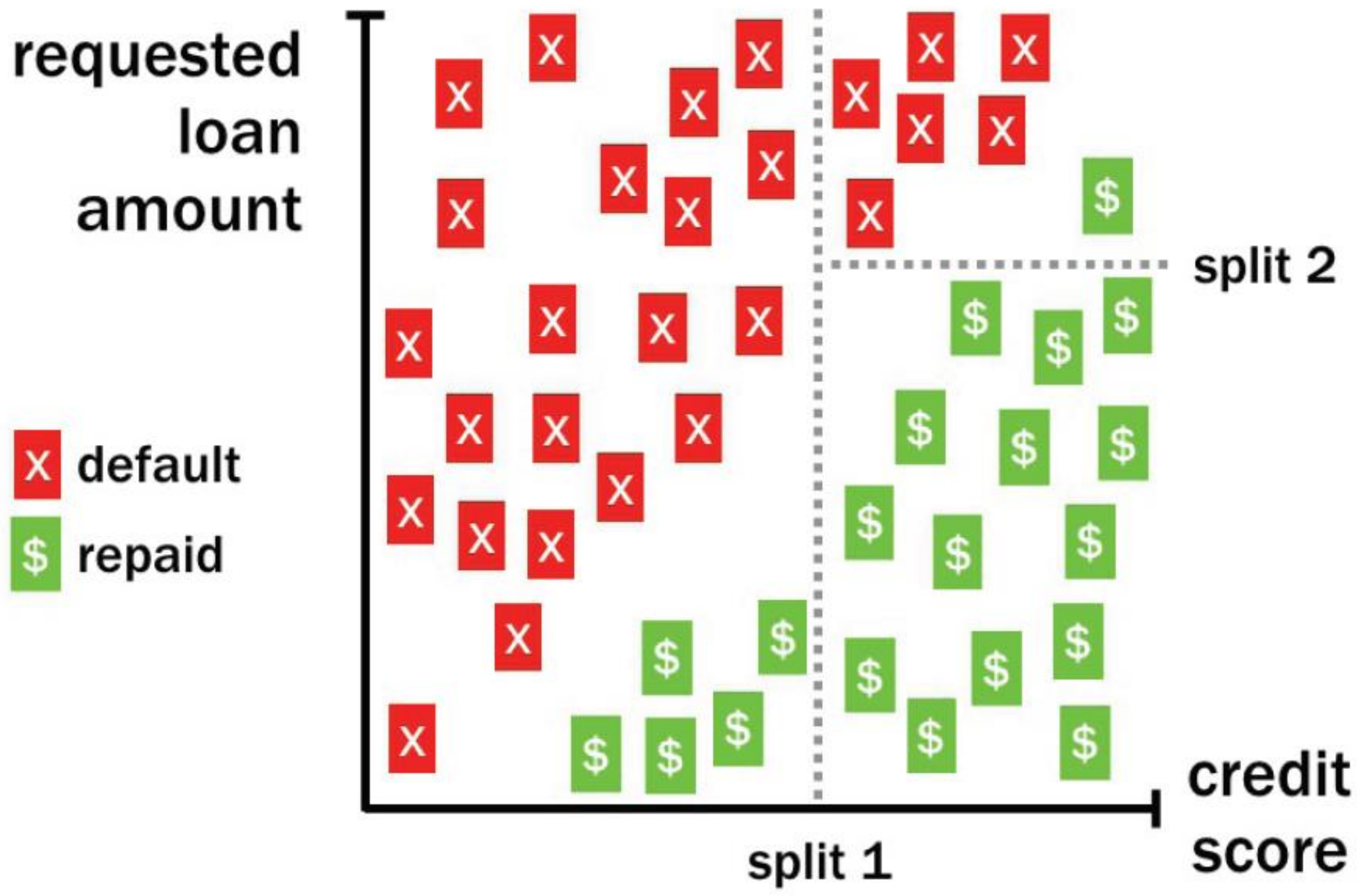
## Divide and Conquer



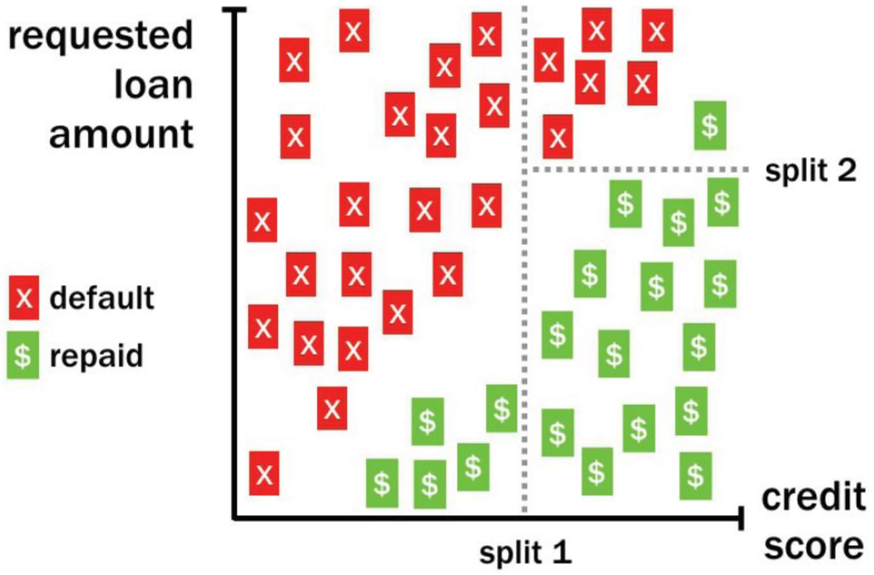
## Divide and Conquer

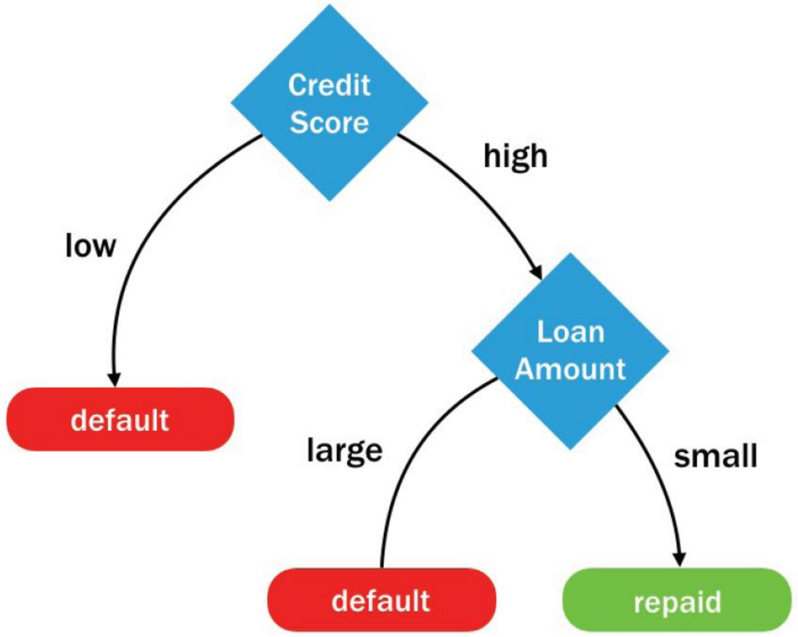


## Divide and Conquer



## The resulting tree





# Building a simple decision tree

```
load(url('https://github.com/hbchoi/SampleData/blob/master/dtree_data.RData?raw=true'))

str(loans)

## 'data.frame':    11312 obs. of  14 variables:
##  $ loan_amount       : Factor w/ 3 levels "HIGH","LOW","MEDIUM": 2 2 2 3 2 3 3 2 1 3 ...
##  $ emp_length        : Factor w/ 5 levels "< 2 years","10+ years",..: 2 1 4 3 1 1 3 2 2 1 ...
##  $ home_ownership    : Factor w/ 4 levels "MORTGAGE","OTHER",..: 4 4 4 3 4 4 4 1 4 4 ...
##  $ income            : Factor w/ 3 levels "HIGH","LOW","MEDIUM": 2 2 3 3 2 2 1 1 1 3 ...
##  $ loan_purpose      : Factor w/ 14 levels "car","credit_card",..: 2 1 1 12 10 3 10 7 3 7 ...
##  $ debt_to_income    : Factor w/ 3 levels "AVERAGE","HIGH",..: 2 3 3 3 1 1 3 1 1 3 ...
##  $ credit_score      : Factor w/ 3 levels "AVERAGE","HIGH",..: 1 1 3 1 1 1 1 2 1 1 ...
##  $ recent_inquiry    : Factor w/ 2 levels "NO","YES": 2 2 2 2 1 2 2 1 1 2 ...
##  $ delinquent        : Factor w/ 3 levels "IN PAST 2 YEARS",..: 3 3 3 3 3 3 3 3 3 3 ...
##  $ credit_accounts   : Factor w/ 3 levels "AVERAGE","FEW",..: 2 2 2 1 2 2 3 3 1 1 ...
##  $ bad_public_record : Factor w/ 2 levels "NO","YES": 1 1 1 1 1 1 1 1 1 1 ...
##  $ credit_utilization: Factor w/ 3 levels "HIGH","LOW","MEDIUM": 1 2 1 3 3 1 3 2 1 3 ...
##  $ past_bankrupt     : Factor w/ 2 levels "NO","YES": 1 1 1 1 1 1 1 1 1 1 ...
##  $ outcome           : Factor w/ 2 levels "default","rapid": 2 1 2 1 1 1 1 2 1 1 ...
```

The **loans** dataset contains 11,312 randomly-selected people who were applied for and later received loans from Lending Club, a US-based peer-to-peer lending company.

# Building a simple decision tree

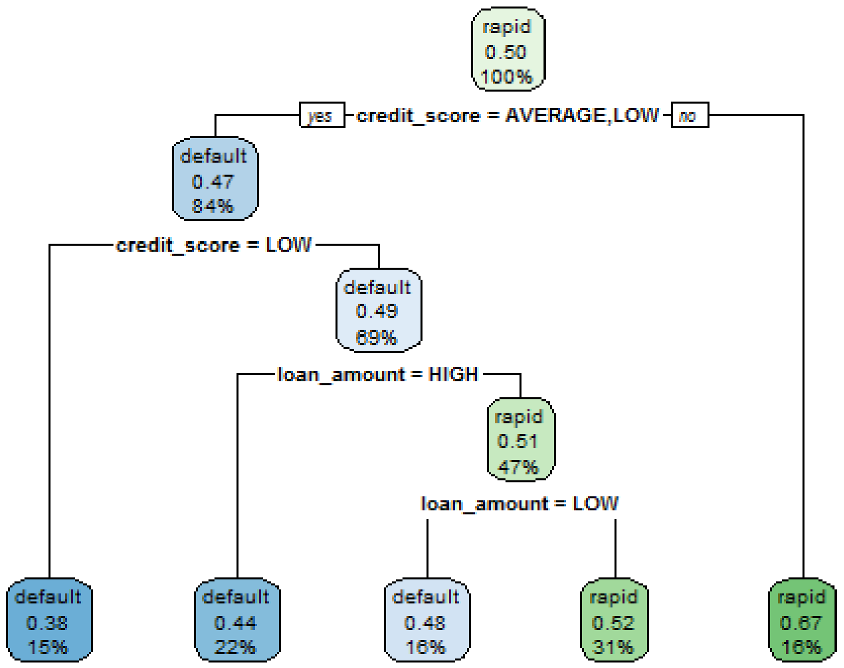
```
library(rpart)

loan_model <- rpart(outcome ~ loan_amount + credit_score, data = loans, method = "class",
control = rpart.control(cp = 0))

# Examine the loan_model object
loan_model
```

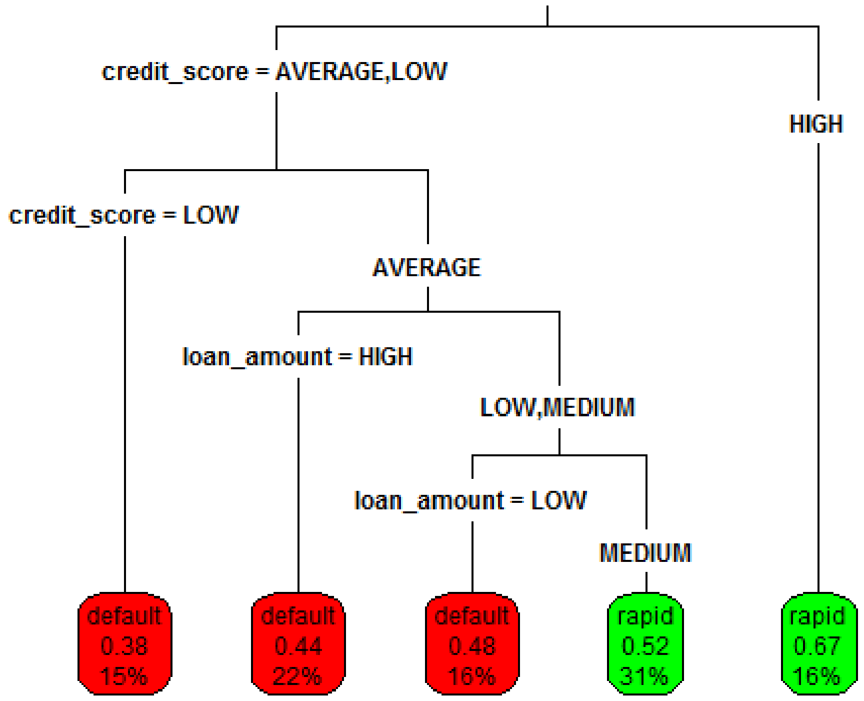
```
## n= 11312
##
## node), split, n, loss, yval, (yprob)
##       * denotes terminal node
##
##  1) root 11312 5654 rapid (0.4998232 0.5001768)
##    2) credit_score=AVERAGE,LOW 9490 4437 default (0.5324552 0.4675448)
##      4) credit_score=LOW 1667  631 default (0.6214757 0.3785243) *
##      5) credit_score=AVERAGE 7823 3806 default (0.5134859 0.4865141)
##       10) loan_amount=HIGH 2472 1079 default (0.5635113 0.4364887) *
##       11) loan_amount=LOW,MEDIUM 5351 2624 rapid (0.4903756 0.5096244)
##         22) loan_amount=LOW 1810  874 default (0.5171271 0.4828729) *
##         23) loan_amount=MEDIUM 3541 1688 rapid (0.4767015 0.5232985) *
##    3) credit_score=HIGH 1822  601 rapid (0.3298573 0.6701427) *
```

We will build a decision tree to try to learn patterns in the outcome of these loans (either repaid or default) based on the requested loan amount and credit score at the time of application.

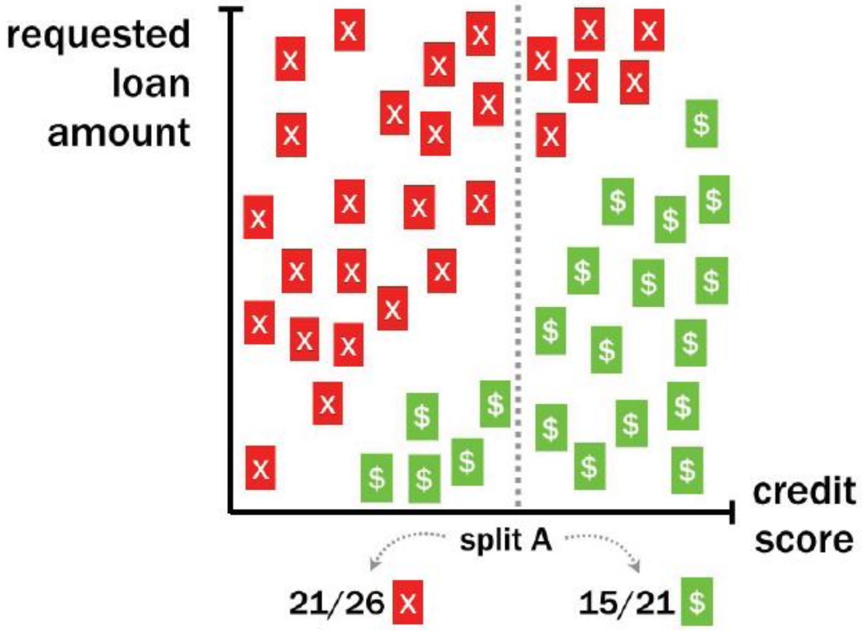
# Visualizing the Model

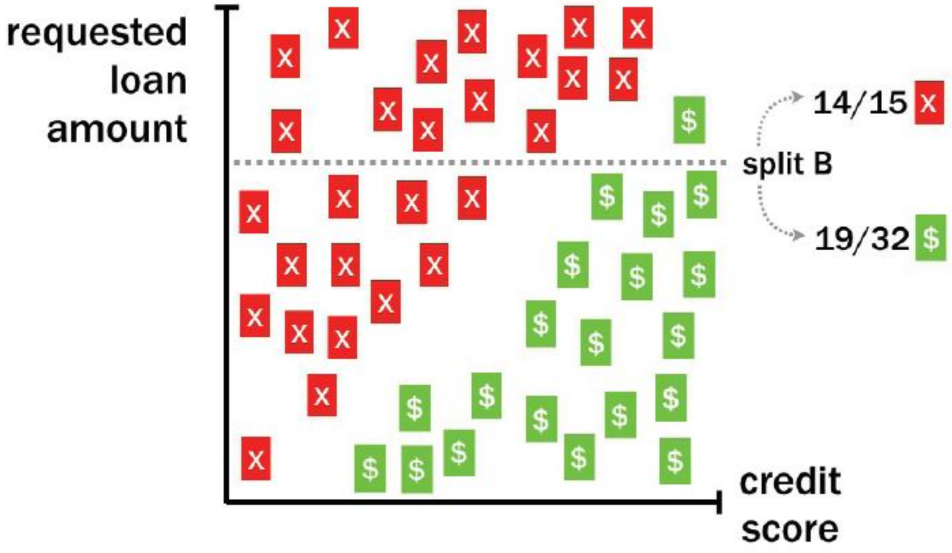
```r
# Load the rpart.plot package
library(rpart.plot)

# Plot the loan_model with default settings
rpart.plot(loan_model)

# Plot the loan_model with customized settings
rpart.plot(loan_model, type = 3, box.palette = c("red", "green"), fallen.leaves = TRUE)
```



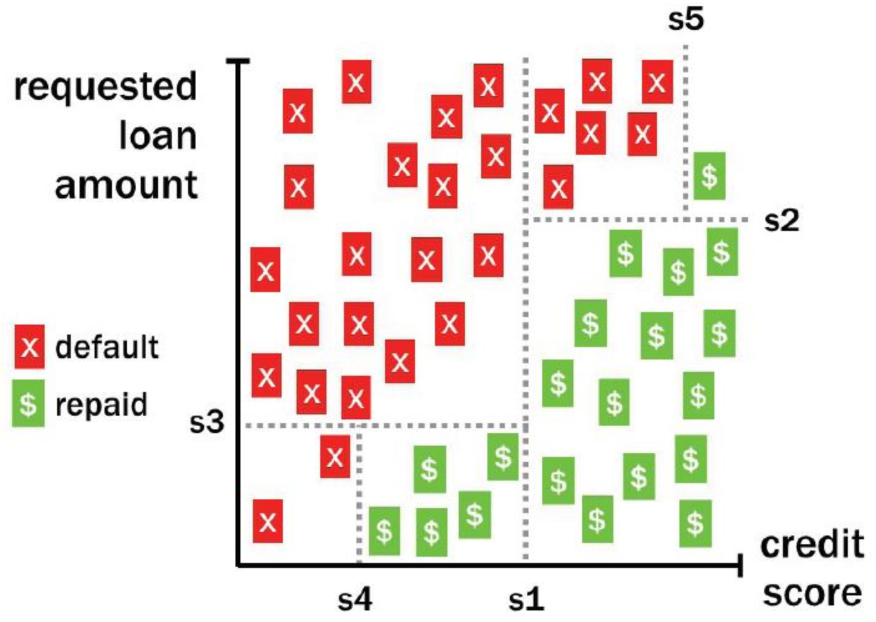


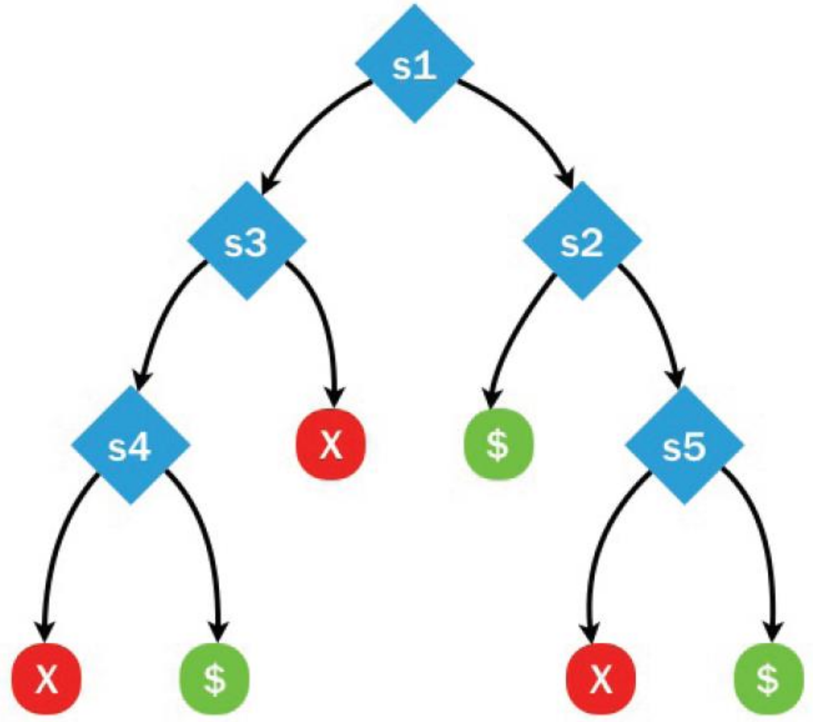
## Choosing where to split





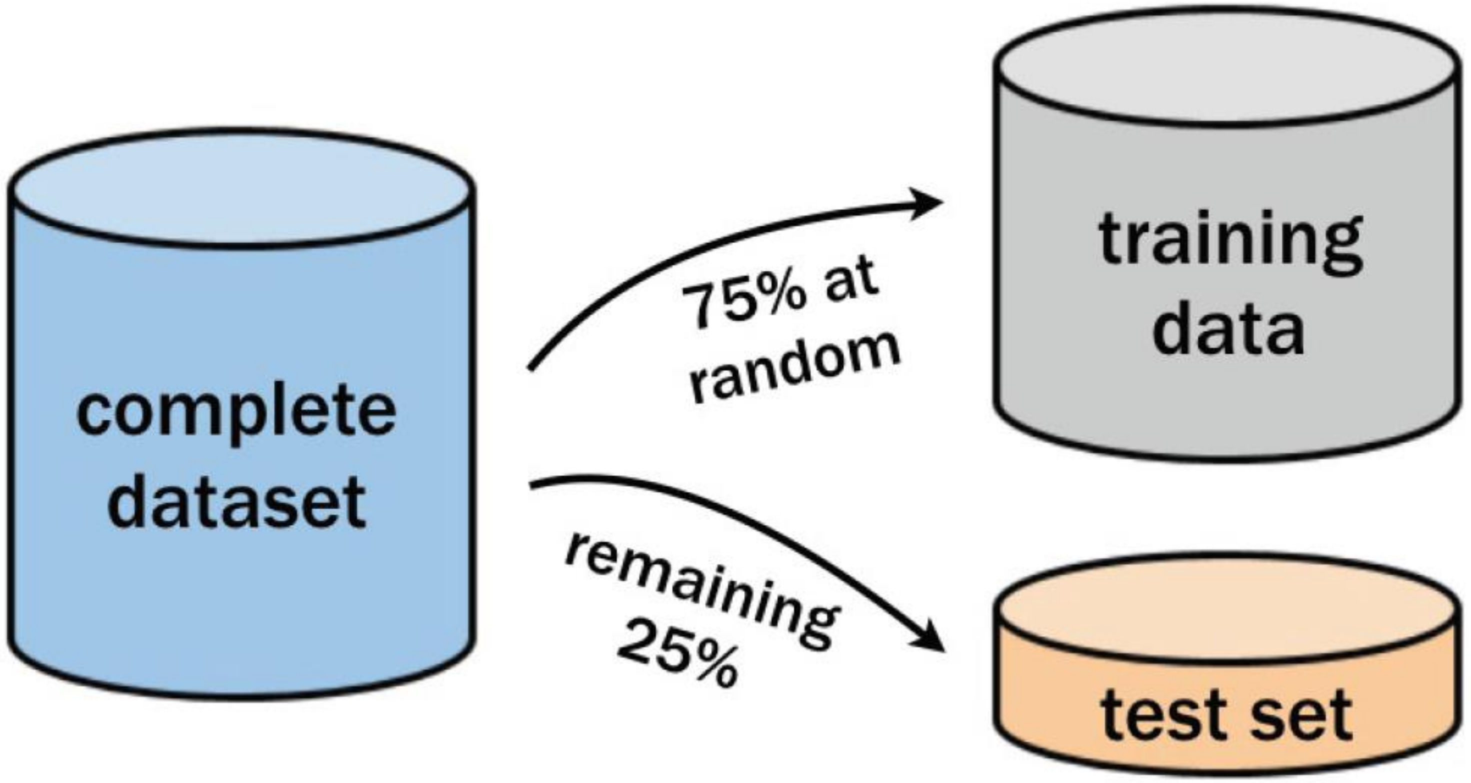
## The problem of overfitting





Some over-grown decision trees capture errors that is too specific to the training dataset, which cannot be observed in general cases
Predicting very well on training data does not always guarantee that work well in the real world problem.

## Evaluating model performance



performance on train data >> perf. on test data => high likely to be over-fitted
performance on train data ≈ perf. on test data => less likely to be over-fitted
We should limit the **complexity** somehow to avoid **overfitting problem**

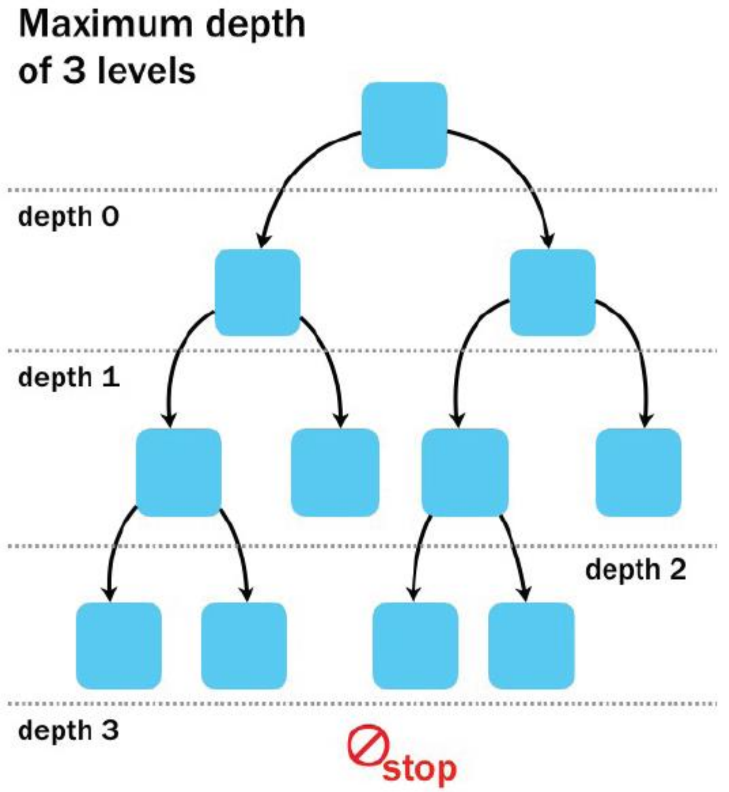
```
loan_model <- rpart(outcome ~ ., data = loans_train, method = "class", control = rpart.control(cp = 0))

# Make predictions on the training dataset
loans_train$pred <- predict(loan_model, loans_train, type = 'class')

# Examine the confusion matrix
table(loans_train$outcome, loans_train$pred)

##
##           default rapid
##   default    2932  1269
##   rapid      1084  3199

# Compute the accuracy on the training dataset
mean(loans_train$outcome == loans_train$pred)

## [1] 0.7226544

# Make predictions on the test dataset
loans_test$pred <- predict(loan_model, loans_test, type = 'class')

# Examine the confusion matrix
table(loans_test$outcome, loans_test$pred)

##
##           default rapid
##   default     821   632
##   rapid       546   829

# Compute the accuracy on the test dataset
mean(loans_test$outcome == loans_test$pred)

## [1] 0.5834512

loans_train <- loans_train[-15]
loans_test <- loans_test[-15]
```

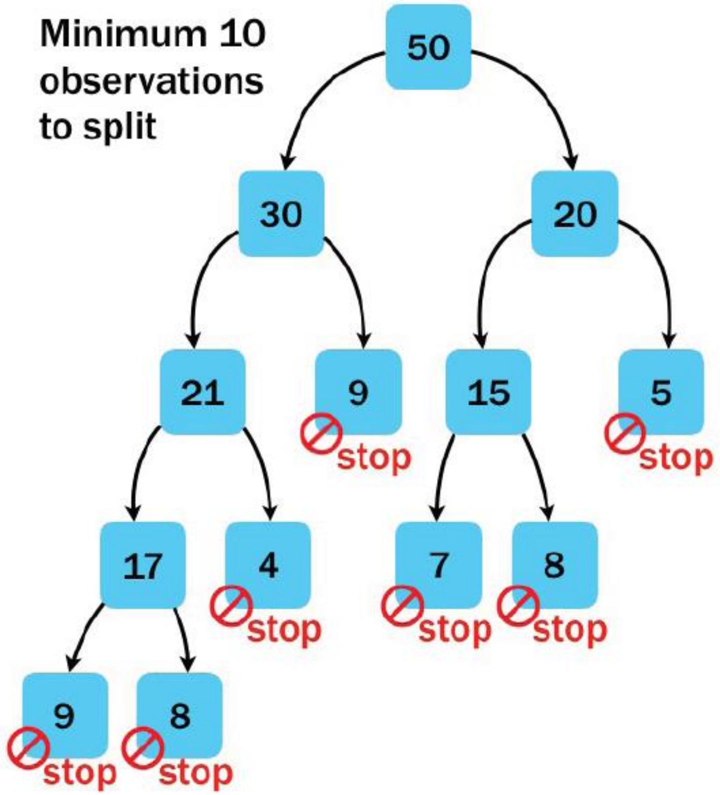
Lending Club has additional information about the applicants, such as home ownership status, length of employment, loan purpose, and past bankruptcies, that may be useful for making more accurate predictions.
Using all of the available applicant data, we build a more sophisticated lending model using the training dataset and test the model on training and test datasets.

## Limiting Tree Model's Complexity

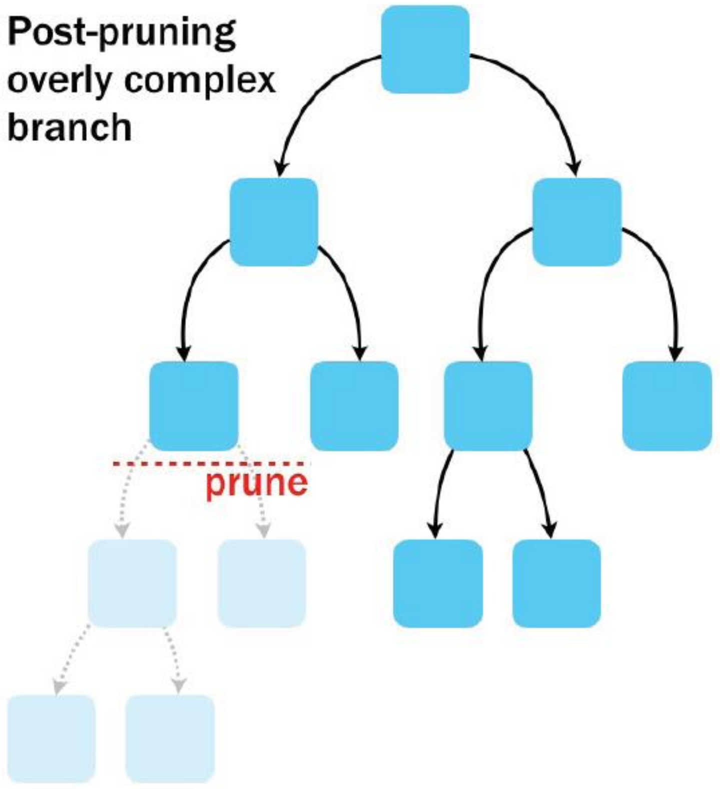
- Two Approaches
  - Pre-pruning
    - Restrict complexity before growing the model
  - Post-Pruning
    - Cut out two complex branches after having tree model

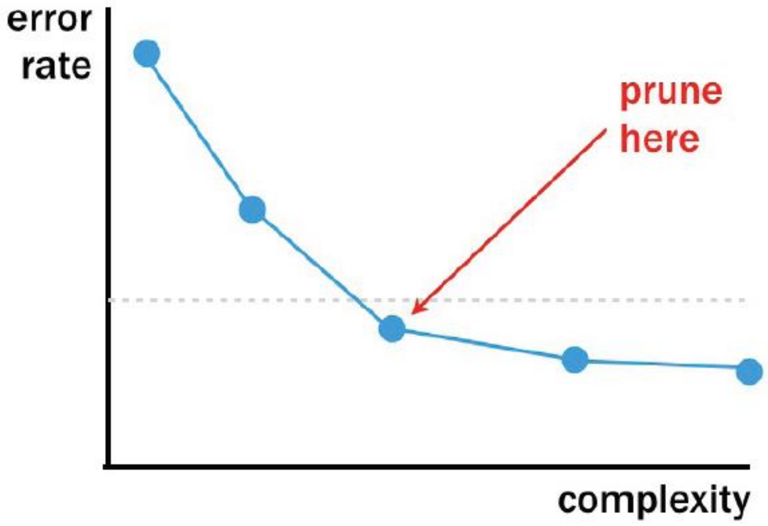
## Pre-pruning


Maximum depth of 3 levels
depth 0
depth 1
depth 2
depth 3
stop


Minimum 10 observations to split
50
30
20
21
9
15
5
17
4
7
8
9
8
stop

## Post-pruning



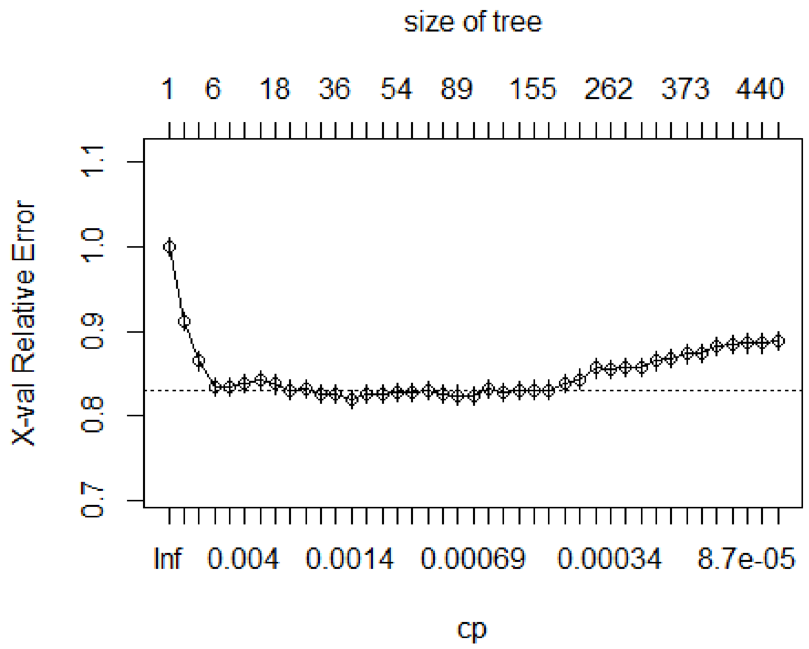


## Pre-pruning

```
# Grow a tree with maxdepth of 6
loan_model <- rpart(outcome ~ ., data = loans_train, method = "class",
control = rpart.control(cp = 0, maxdepth = 6))

# Compute the accuracy of the simpler tree
loans_test$pred <- predict(loan_model, loans_test, type = 'class')
mean(loans_test$outcome == loans_test$pred)

## [1] 0.5919378

# Grow a tree with minsplit of 500
loan_model2 <- rpart(outcome ~ ., data = loans_train, method =
"class", control = rpart.control(cp = 0, minsplit = 500))

# Compute the accuracy of the simpler tree
loans_test$pred2 <- predict(loan_model2, loans_test, type = 'class')
mean(loans_test$outcome == loans_test$pred2)

## [1] 0.5922914
```

# Post-pruning

```
# Grow an overly complex tree
loan_model <- rpart(outcome ~ ., data = loans_train, method = "class", control =
rpart.control(cp = 0))

# Examine the complexity plot
plotcp(loan_model)
```



```
# Prune the tree
loan_model_pruned <- prune(loan_model, cp = 0.0014)

# Compute the accuracy of the pruned tree
loans_test$pred <- predict(loan_model_pruned, loans_test, type = 'class')
mean(loans_test$outcome == loans_test$pred)

## [1] 0.6007779
```

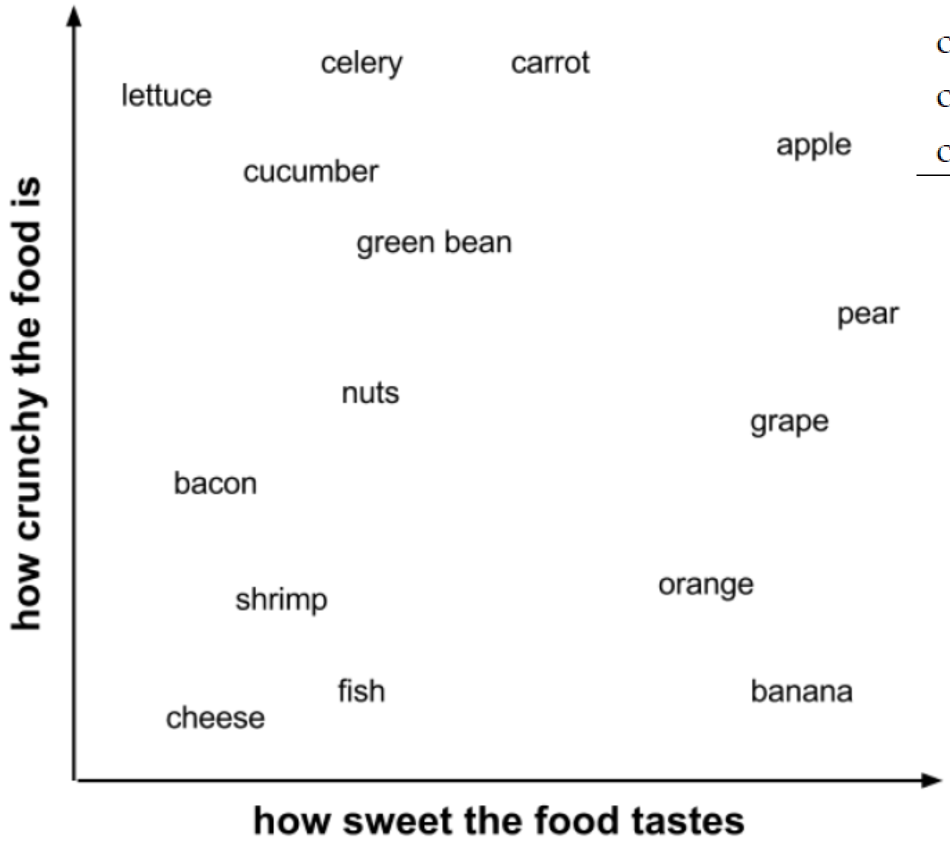
## Ref.

- rpart manual: https://cran.r-project.org/web/packages/rpart/rpart.pdf
- An Introduction to Recursive Partitioning Using the RPART Routines: https://cran.r-project.org/web/packages/rpart/vignettes/longintro.pdf
- Plotting rpart trees with the rpart.plot package: http://www.milbo.org/rpart-plot/prp.pdf

## k Nearest Neighbors

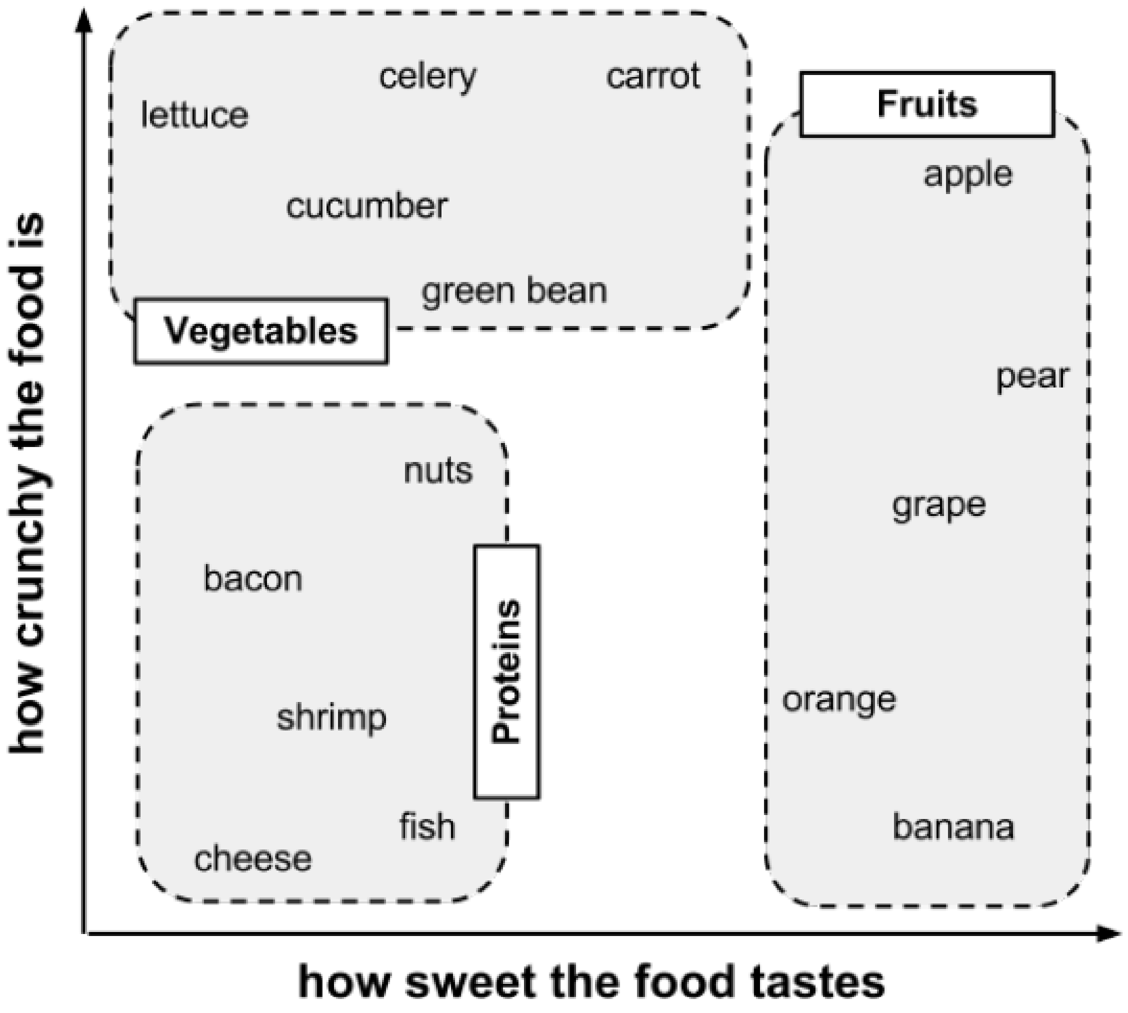
# k-Nearest Neighbors (kNN)

| ingredient | sweetness | crunchiness | food type |
|---|---|---|---|
| apple | 10 | 9 | fruit |
| bacon | 1 | 4 | protein |
| banana | 10 | 1 | fruit |
| carrot | 7 | 10 | vegetable |
| celery | 3 | 10 | vegetable |
| cheese | 1 | 1 | protein |



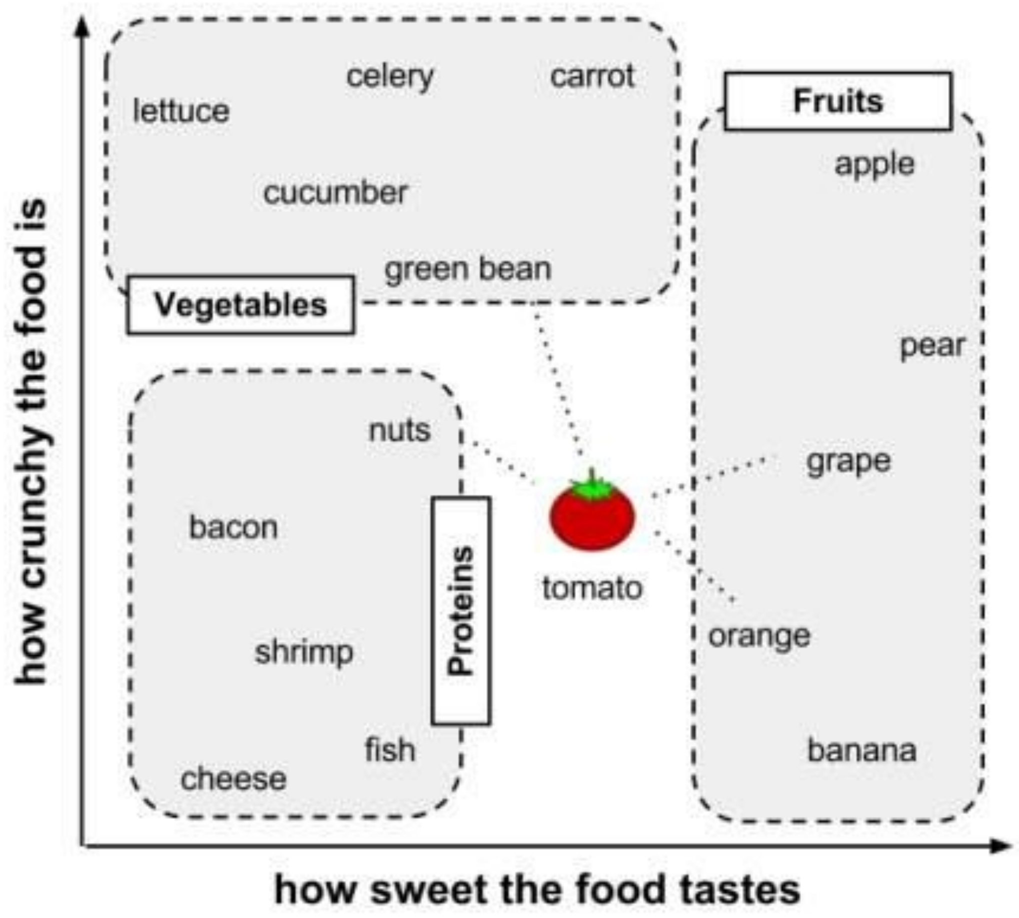
Similar Foods are located near to each other geographically

## k-Nearest Neighbors (kNN)



Similar Foods are located near to each other geographically

# k-Nearest Neighbors (kNN)



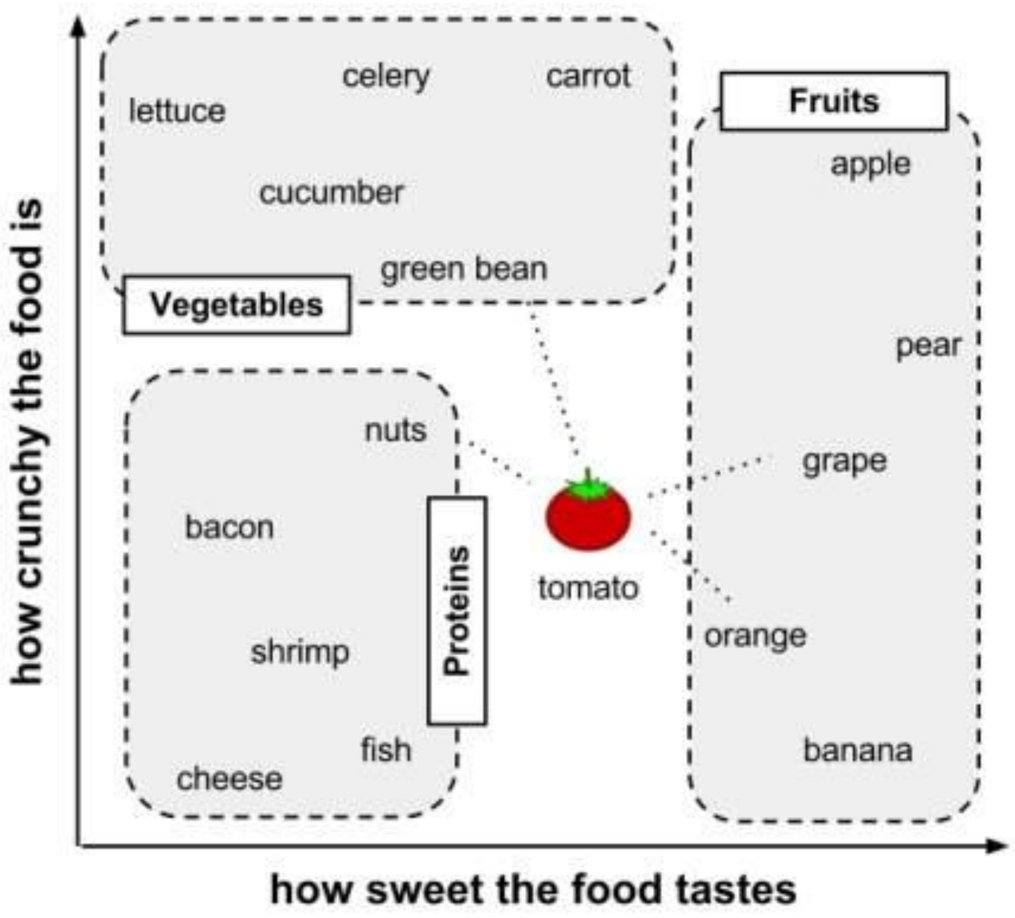
Then what is tomato?

Tomato is close to green bean, nuts, orange, and graph

1 Veg, 1 Protein, 2 Fruits

We may consider tomato belongs to Fruits class

## k-Nearest Neighbors (kNN)



In kNN method, we decide according to most similar examples = nearest neighbors

Majority class would be our answer

The portion could be estimated probability

How many neighbors do we need to consider?

**k** -> # of neighbor to be consider for classification ( or regression)

## Measuring similarity with distance

distance between object *p* and *q*

*Euclidean distance*

$$\sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2 + \cdots + (p_d - q_d)^2}$$

$p_1, p_2, \ldots, p_d$ and $q_1, q_2, \ldots, q_d$ are feature sets of *p* and *q*

Other distance measures:

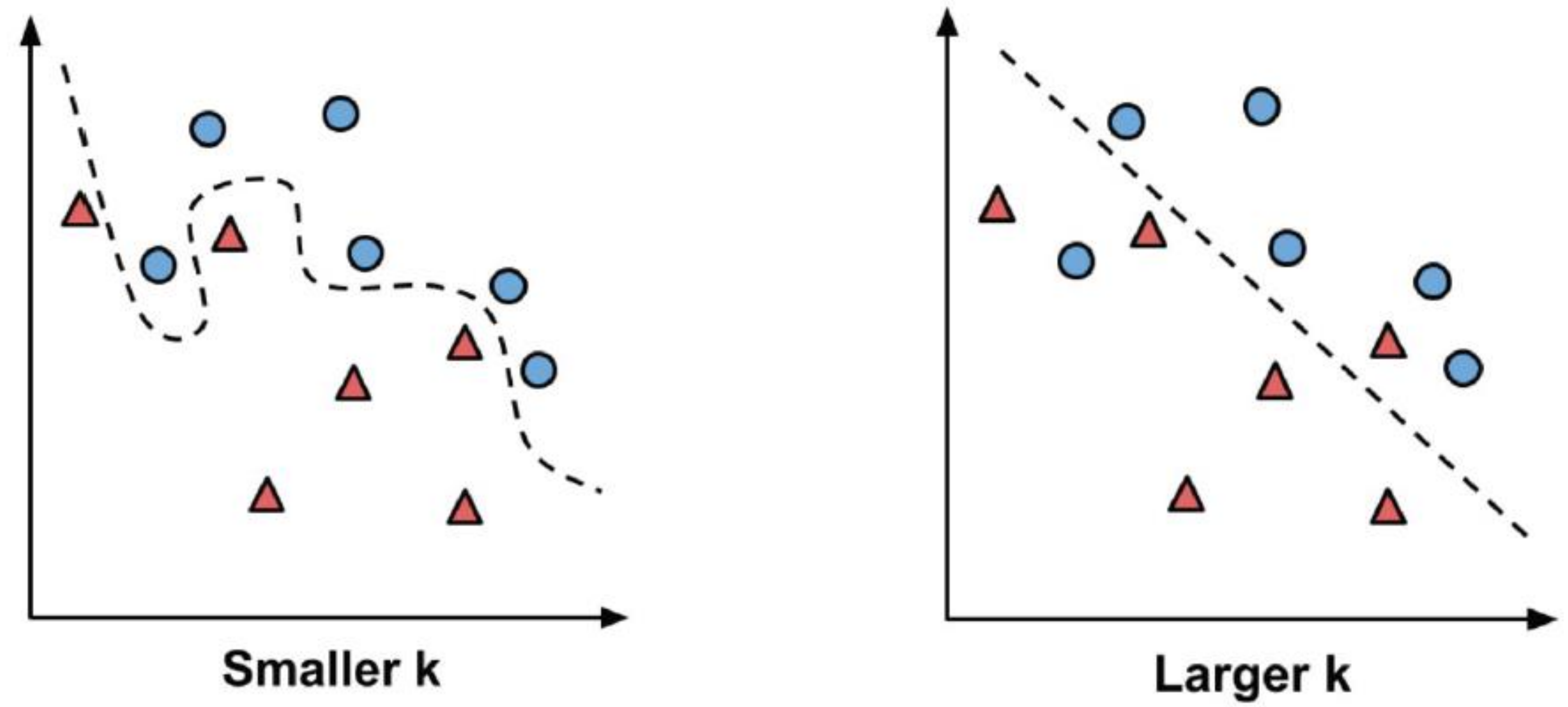
Manhattan distance, Cosign Similarity, Minkowski, ...

## Applying nearest neighbors in R

```
library(class)
pred <- knn(training_data, testing_data, training_labels)
```

## Choosing **k**

Bigger 'k' is not always better



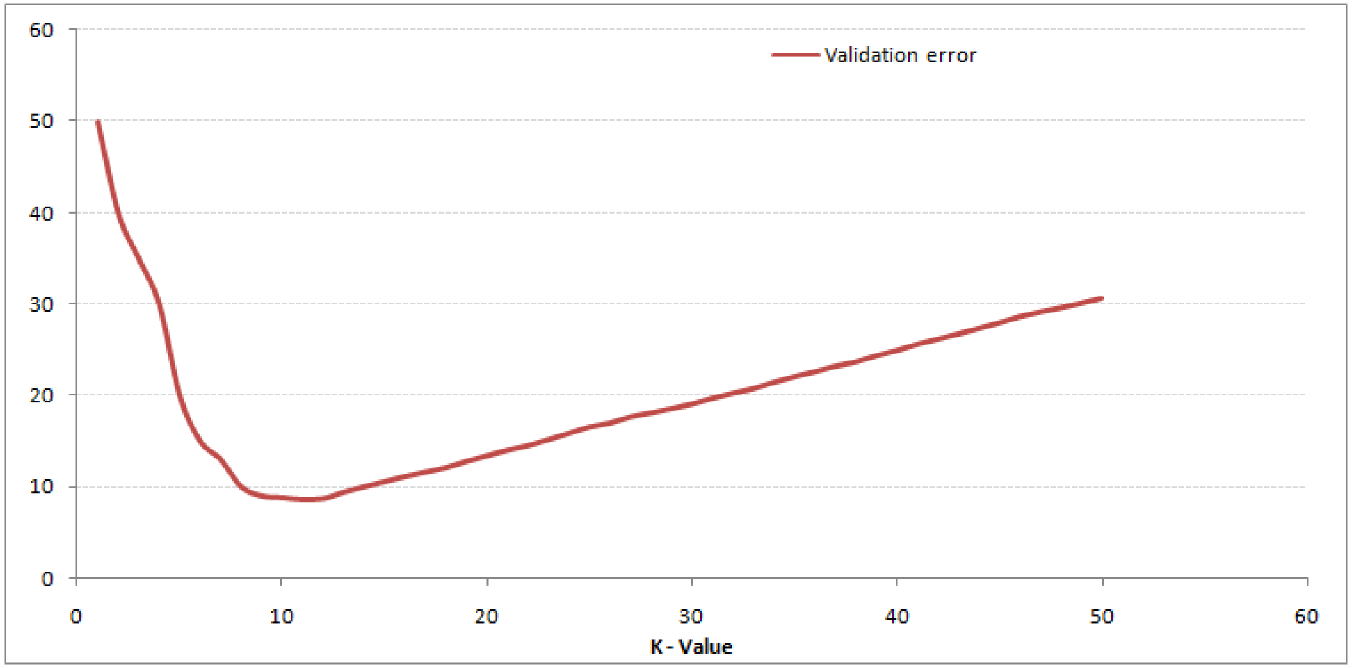
# Choosing k

There is no right k for all the problems

You may try different k to find the best

Suggesting square root of # of training examples, empirically

When a certain class is very rare, larger k would be better to see sufficient number of example (about 10?) in each class



## kNN – example

- Diagnosing Breast Cancer with KNN
- "Breast Cancer Wisconsin Diagnostic" dataset from the *UCI Machine Learning Repository*
  - 30 numeric measurements comprise the mean, standard error, and worst (that is, largest) value for 10 different characteristics of the digitized cell nuclei.

Radius

Texture

Perimeter

Area

Smoothness

Compactness

Concavity

Concave points

Symmetry

Fractal dimension

## Loading Data

```
wbcd <- read.csv("https://github.com/hbchoi/SampleData/raw/master/wisc_bc_data.csv",
stringsAsFactors = F)

str(wbcd)
```

```
## 'data.frame':    569 obs. of  32 variables:
##  $ id                : int  87139402 8910251 905520 868871 9012568 906539 925291
87880 862989 89827 ...
##  $ diagnosis         : chr  "B" "B" "B" "B" ...
##  $ radius_mean       : num  12.3 10.6 11 11.3 15.2 ...
##  $ texture_mean      : num  12.4 18.9 16.8 13.4 13.2 ...
##  $ perimeter_mean    : num  78.8 69.3 70.9 73 97.7 ...
##  $ area_mean         : num  464 346 373 385 712 ...
...
##  $ points_worst      : num  0.0939 0.0793 0.0743 0.0861 0.0818 ...
##  $ symmetry_worst    : num  0.283 0.294 0.3 0.21 0.249 ...
##  $ dimension_worst   : num  0.0677 0.0759 0.0788 0.0678 0.0677 ...
```

## Data Preparation

Var. ID is not helpful to determine the type of tumor, hence remove it

```
# removing ID variable
wbcd <- wbcd[,-1]

table(wbcd$diagnosis)

##
##   B   M
## 357 212

# changing value for clear interpretation
wbcd$diagnosis <- ifelse(wbcd$diagnosis == 'B', 'Benign', 'Malignant')
```

## Normalization

Var. in larger scale contributes more to the distance than Var. in smaller scale

*e.g.* area_mean has bigger effect on Euclidean distance than smoothness_mean

Having all variables in same scale is important preprocessing for kNN

- *normalization*

```
summary(wbcd[c("radius_mean", "area_mean", "smoothness_mean")])
```

```
##   radius_mean       area_mean      smoothness_mean
##  Min.   : 6.981   Min.   : 143.5   Min.   :0.05263
##  1st Qu.:11.700   1st Qu.: 420.3   1st Qu.:0.08637
##  Median :13.370   Median : 551.1   Median :0.09587
##  Mean   :14.127   Mean   : 654.9   Mean   :0.09636
##  3rd Qu.:15.780   3rd Qu.: 782.7   3rd Qu.:0.10530
##  Max.   :28.110   Max.   :2501.0   Max.   :0.16340
```

# min-max normalization

setting the scale of variables to 0~1

0 for minimum value, 1 for maximum value

```
minmax_norm <- function(x) {
  (x-min(x))/(max(x)-min(x))
}

wbcd_norm <- sapply(wbcd[,-1], minmax_norm)

summary(wbcd_norm[,c("radius_mean", "area_mean", "smoothness_mean")])
```

```
##   radius_mean        area_mean       smoothness_mean
##  Min.   :0.0000   Min.   :0.0000   Min.   :0.0000  
##  1st Qu.:0.2233   1st Qu.:0.1174   1st Qu.:0.3046  
##  Median :0.3024   Median :0.1729   Median :0.3904  
##  Mean   :0.3382   Mean   :0.2169   Mean   :0.3948  
##  3rd Qu.:0.4164   3rd Qu.:0.2711   3rd Qu.:0.4755  
##  Max.   :1.0000   Max.   :1.0000   Max.   :1.0000  
```

## kNN – split test and training data

```
# split data into train and test set
dim(wbcd_norm)

## [1] 569  30

wbcd_train <- wbcd_norm[1:469, ]
wbcd_test <- wbcd_norm[470:569, ]

wbcd_train_label <- wbcd[1:469, 1]
wbcd_test_label <- wbcd[470:569, 1]

# choosing proper k
sqrt(nrow(wbcd_train))

## [1] 21.65641
```

## kNN – Making Prediction

```
library(class)
wbcd_test_pred <- knn(train = wbcd_train, test = wbcd_test, cl = wbcd_train_label,
k = 21)


wbcd_test_pred
```

```
##   [1] Benign    Malignant Benign    Benign    Malignant Benign    Malignant
##   [8] Benign    Malignant Benign    Malignant Benign    Malignant Malignant
##  [15] Benign    Benign    Malignant Benign    Malignant Benign    Malignant
##  [22] Malignant Malignant Malignant Benign    Benign    Benign    Benign
##  [29] Malignant Malignant Malignant Malignant Malignant Malignant Benign
##  [36] Benign    Benign    Benign    Benign    Malignant Malignant Benign
##  [43] Malignant Malignant Benign    Malignant Malignant Malignant Malignant
##  [50] Malignant Malignant Benign    Benign    Benign    Benign    Benign
##  [57] Benign    Benign    Malignant Benign    Benign    Benign    Benign
##  [64] Benign    Malignant Malignant Benign    Benign    Benign    Benign
##  [71] Benign    Malignant Benign    Benign    Malignant Malignant Benign
##  [78] Benign    Benign    Malignant Benign    Benign    Benign    Malignant
##  [85] Benign    Benign    Malignant Benign    Benign    Benign    Benign
##  [92] Malignant Benign    Benign    Benign    Benign    Benign    Malignant
##  [99] Benign    Malignant
## Levels: Benign Malignant
```

## Performance

```
#accuracy
mean(wbcd_test_label == wbcd_test_pred)

## [1] 0.98

#confusion matrix
cmat <- table(wbcd_test_label, wbcd_test_pred)
cmat

##                  wbcd_test_pred
## wbcd_test_label Benign Malignant
##       Benign        61         0
##       Malignant      2        37

#precision
cmat[2,2] / sum(cmat[,2])

## [1] 1

#recall
cmat[2,2] / sum(cmat[2,])

## [1] 0.9487179
```

We hope to avoid false negative rather than false positive.

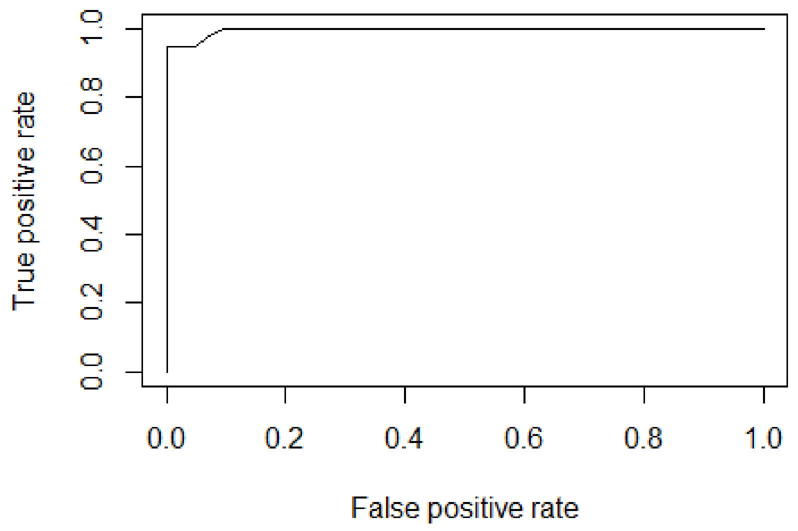
How can?

## kNN – Probabilistic Interpretation

```
wbcd_test_pred <- knn(train = wbcd_train, test = wbcd_test, cl = wbcd_train_label, k =
21, prob = TRUE)

head(wbcd_test_pred)

## [1] Benign    Benign    Benign    Benign    Malignant Benign
## Levels: Benign Malignant

head(attributes(wbcd_test_pred)$prob)

## [1] 1.000000 0.952381  0.952381  0.952381   1.000000     1.000000

      P(Benign) P(Benign) P(Benign) P(Benign) P(Malignant) P(Benign)

# converting all Prob to P(Malignant)
wbcd_test_pred_prob <- ifelse(wbcd_test_pred == 'Malignant',
                              attributes(wbcd_test_pred)$prob,
                              1-attributes(wbcd_test_pred)$prob)

head(wbcd_test_pred_prob)

## [1] 0.00000000 0.04761905 0.04761905 0.04761905 1.00000000 0.00000000
```

# ROC curve and AUC

```
library(ROCR)

plot(performance(prediction(wbcd_test_pred_prob, wbcd_test_label == 'Malignant'),
'tpr', 'fpr'))

calAUC <- function(predCol, targetCol){
  perf <- performance(prediction(predCol, targetCol), 'auc')
  as.numeric(perf@y.values)
}

# AUC for our kNN
calAUC(wbcd_test_pred_prob, wbcd_test_label == 'Malignant')

## [1] 0.9964271
```



## Adjusting Threshold

```
# set lower threshold
threshold <- 0.1
wbcd_test_pred_new <- ifelse(wbcd_test_pred_prob > threshold,
                             'Malignant', 'Benign')
cmat <- table(wbcd_test_label, wbcd_test_pred_new)
cmat

##                 wbcd_test_pred_new
## wbcd_test_label Benign Malignant
##       Benign        54         7
##       Malignant      0        39

#accuracy
mean(wbcd_test_label == wbcd_test_pred_new)

## [1] 0.93

#precision
cmat[2,2] / sum(cmat[,2])

## [1] 0.8478261

#recall
cmat[2,2] / sum(cmat[2,])

## [1] 1
```

Accuracy is lower,

but zero false negative !

## One more Thing

Euclidean distance makes sense only when input variables are **numeric**

-> Non-numeric Variables need to be converted to numeric, i.e. ***dummy coding***

```
# dummy coding

sample_df <- data.frame(blood_type = c('A', 'B', 'A','O', 'AB'),
                        skin_color = c('black', 'white', 'yellow', 'red',
'black'),
                        age = c(22, 35, 21, 26, 70))

library(caret)

predict(dummyVars(~ blood_type+skin_color, data = sample_df), sample_df)
```

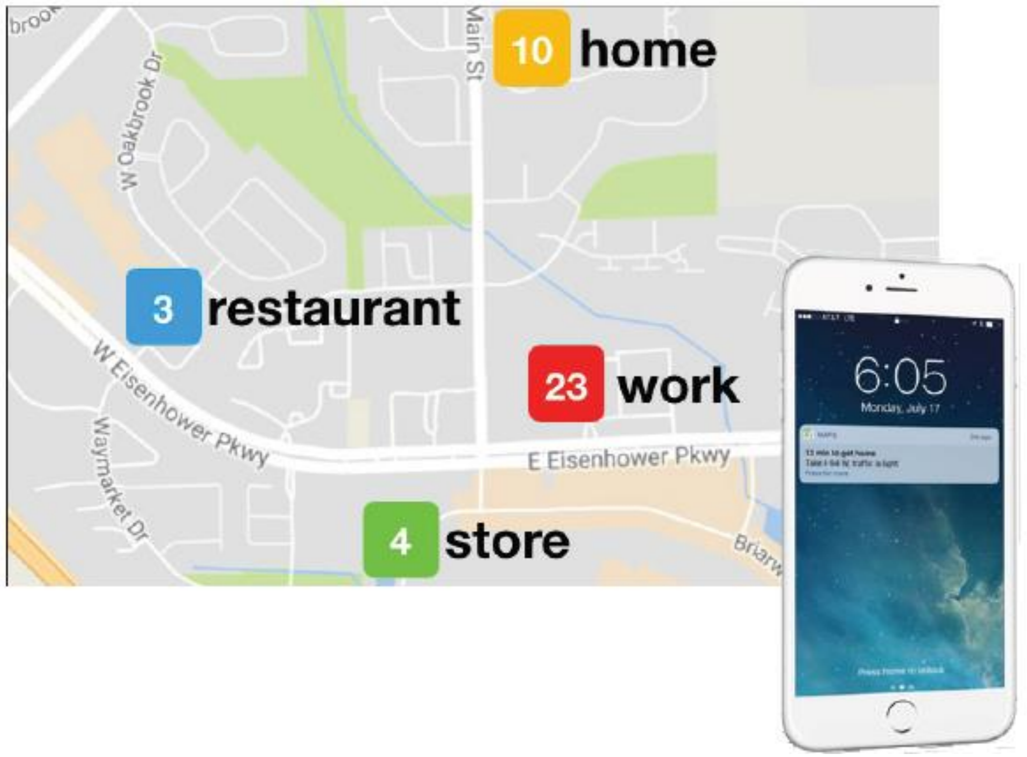
```
sample_df

##   blood_type skin_color age
## 1          A      black  22
## 2          B      white  35
## 3          A     yellow  21
## 4          O        red  26
## 5         AB      black  70
```

dummy encoding

```
##   blood_type.A blood_type.AB blood_type.B blood_type.O skin_color.black
## 1            1             0            0            0                1
## 2            0             0            1            0                0
## 3            1             0            0            0                0
## 4            0             0            0            1                0
## 5            0             1            0            0                1
##   skin_color.red skin_color.white skin_color.yellow
## 1              0                0                 0
## 2              0                1                 0
## 3              0                0                 1
## 4              1                0                 0
## 5              0                0                 0
```

## Naïve Bayes

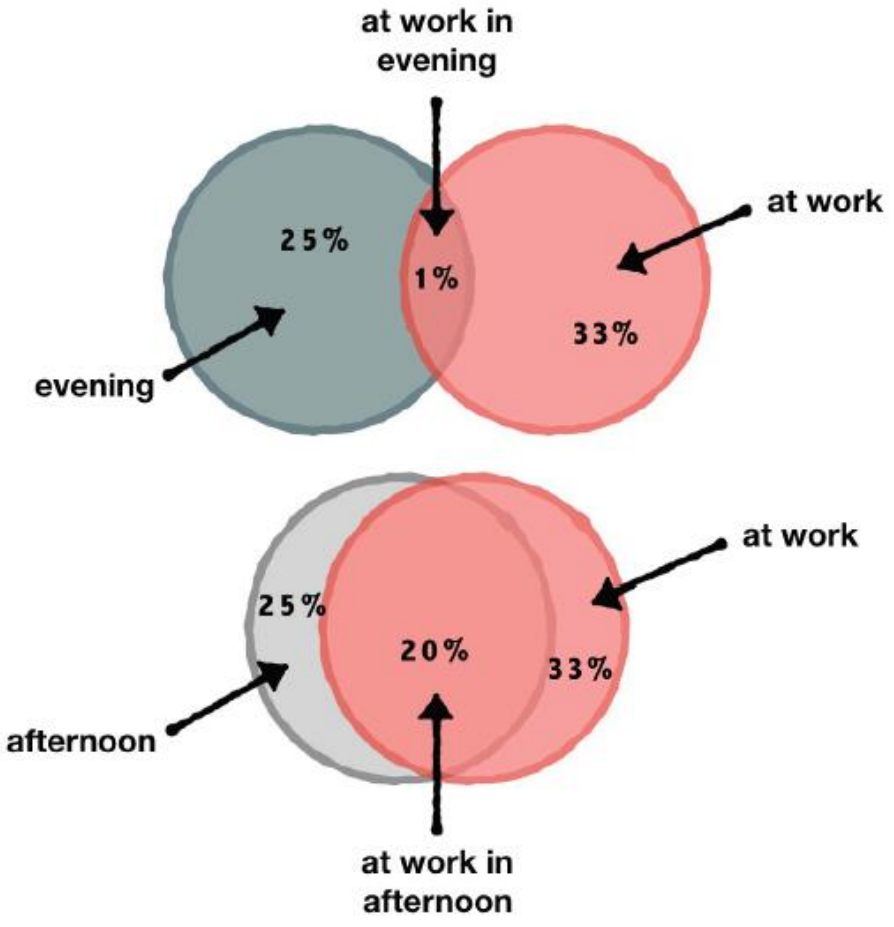
## Estimating probability



The **probability** of A is denoted P(A)

P(work) = 23 / 40 = 57.5%
P(store) = 4 / 40 = 10.0%

## Joint probability and independent events



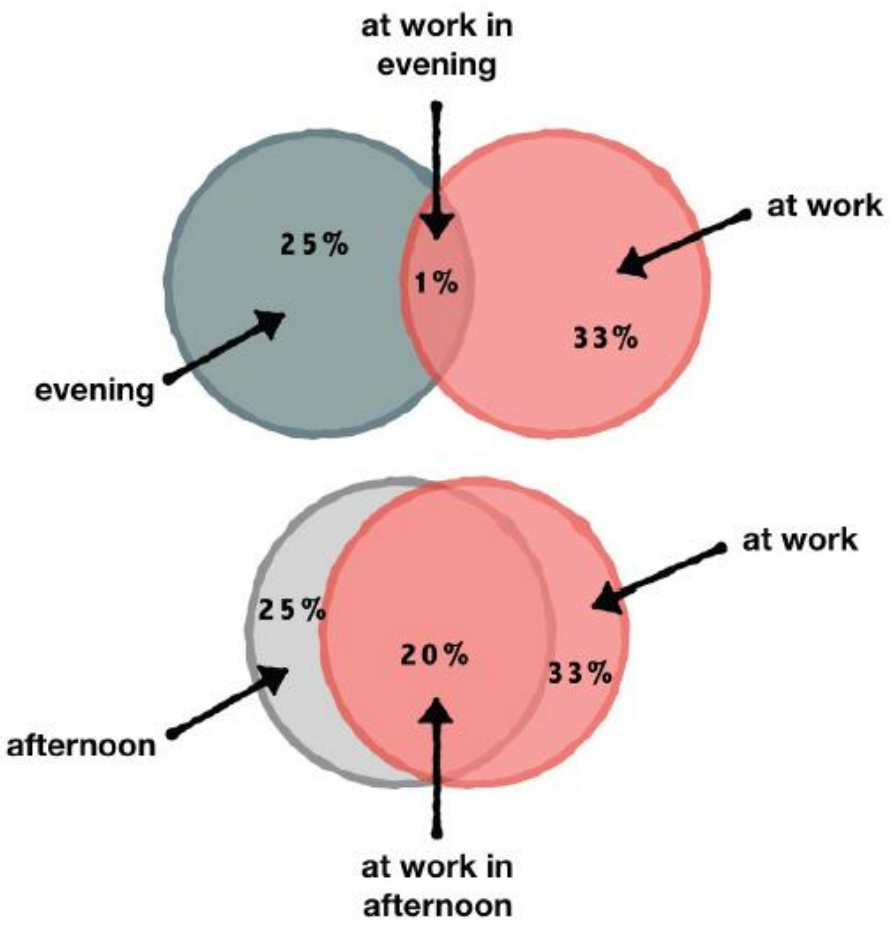
The **joint probability** of events A and B is denoted P(A and B)

- P(work and evening) = 1%
- P(work and afternoon) = 20%

Event A and B are **independent**
-> occurring A does not affect P(B) and vice versa
P(evening) = 25%
p(weekend) = 28.5%

then P(evening and weekend) = P(evening) x p(weekend) = 7.1%

## Conditional probability and dependent events



The conditional probability of events A and B is denoted **P(A | B)**
P(A | B) = P(A and B) / P(B)
P(work | evening) = 1 / 25 = 4%
P(work | afternoon) = 20 / 25 = 80%

Event A and B are **dependent**
P(A) over event B
hence P(A) ≠ P(A|B)

# Naïve Bayes

we want to know:

P(work | afternoon), P(home | afternoon), ...

$$\text{P(work | afternoon)} = \frac{\text{P( work and afternoon)}}{\text{P(afternoon)}}$$

$$= \frac{\text{P( work and afternoon)}}{\text{P(afternoon)}} \cdot \frac{\text{P( work)}}{\text{P(work)}} = \frac{\text{P( work and afternoon)}}{\text{P(work)}} \cdot \frac{\text{P( work)}}{\text{P(afternoon)}}$$

$$= \text{P(afternoon | work)} \cdot \frac{\text{P( work)}}{\text{P(afternoon)}}$$

Prior Probability

Likelihood

$$\mathrm{P}(\text{outcome} = \text{True} \mid a = A) = \frac{\mathrm{P}(\text{outcome} = \text{True}) \times \mathrm{P}(a = A \mid \text{outcome} = \text{True})}{\mathrm{P}(a = A)}$$

Posterior Probability

Marginal Likelihood

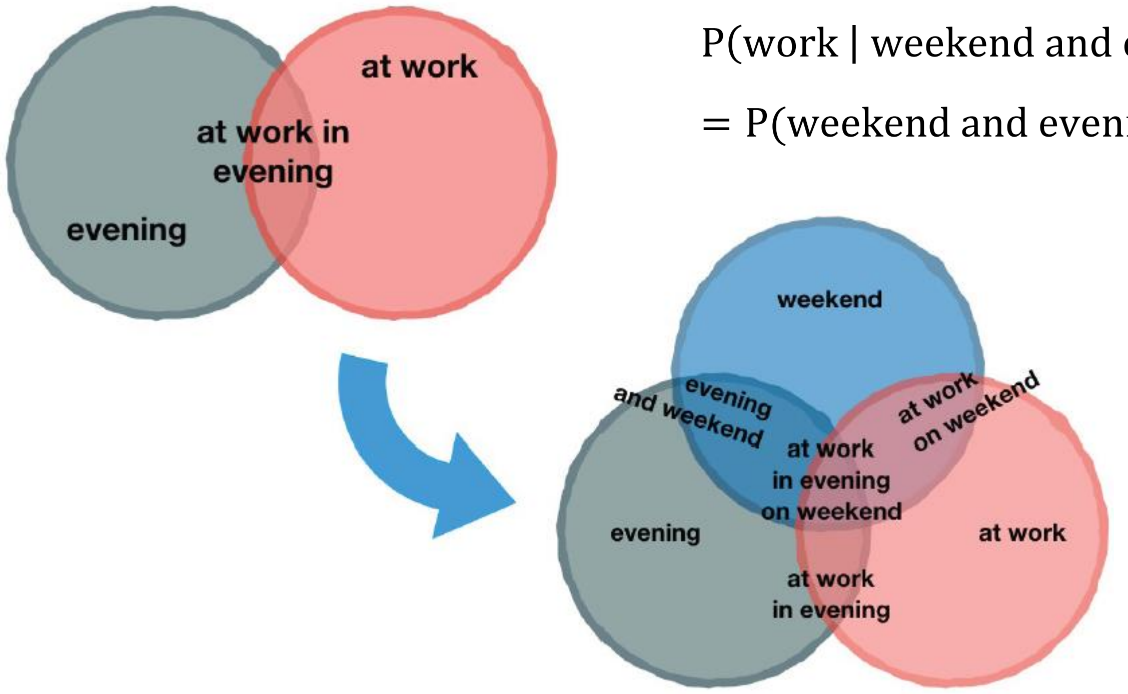
# Naïve Bayes

$$P(\text{work} \mid \text{afternoon}) = P(\text{afternoon} \mid \text{work}) \cdot \frac{P(\text{work})}{P(\text{afternoon})}$$

| frequency | morning | after noon | evening | total |
|---|---|---|---|---|
| work | 14 | 14 | 2 | 30 |
| home | 5 | 5 | 25 | 35 |
| church | 5 | 8 | 2 | 15 |
| downtown | 2 | 6 | 12 | 20 |
| total | 26 | 33 | 41 | 100 |

| likelihood | morning | after noon | evening | total |
|---|---|---|---|---|
| work | 14/30 | 14/30 | 2/30 | 30 |
| home | 5/35 | 5/35 | 25/35 | 35 |
| church | 5/15 | 8/15 | 2/15 | 15 |
| downtown | 2/20 | 6/20 | 12/20 | 20 |
| total | 26/100 | 33/100 | 41/100 | 100 |

## The challenge of multiple predictors



$$P(\text{work} \mid \text{weekend and evening})$$
$$= P(\text{weekend and evening} \mid \text{work}) \cdot \frac{P(\text{work})}{P(\text{weekend and evening})}$$

$P(\text{work} \mid \text{weekend and evening})$, $P(\text{work} \mid \text{weekend and morning})$,
$P(\text{work} \mid \text{weekend and afternoon})$, $P(\text{work} \mid \text{weekday and evening})$, $P(\text{work} \mid \text{weekday and morning})$,
...

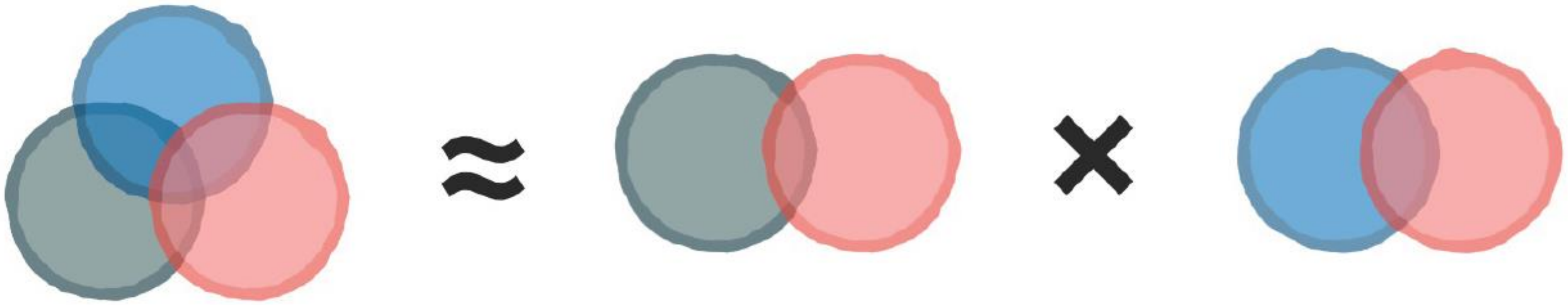
More input variables we have, more combination we need to consider...

**Computationally expensive!!**

## Naivety Assumption

Naïve Bayes assumes that all input variables are conditionally independent

**Which simplifies the problem**



$$P(ev_1 \& \cdots ev_N \mid y{=}{=}T) \approx P(ev_1 \mid y{=}{=}T) \times P(ev_2 \mid y{=}{=}T) \times \cdots P(ev_N \mid y{=}{=}T)$$

$$P(ev_1 \& \cdots ev_N \mid y{=}{=}F) \approx P(ev_1 \mid y{=}{=}F) \times P(ev_2 \mid y{=}{=}F) \times \cdots P(ev_N \mid y{=}{=}F)$$

$$P(y{=}{=}T \mid ev_1 \& \cdots ev_N) \approx \frac{P(y{=}{=}T) \times (P(ev_1 \mid y{=}{=}T) \times \cdots P(ev_N \mid y{=}{=}T))}{P(ev_1 \& \cdots ev_N)}$$

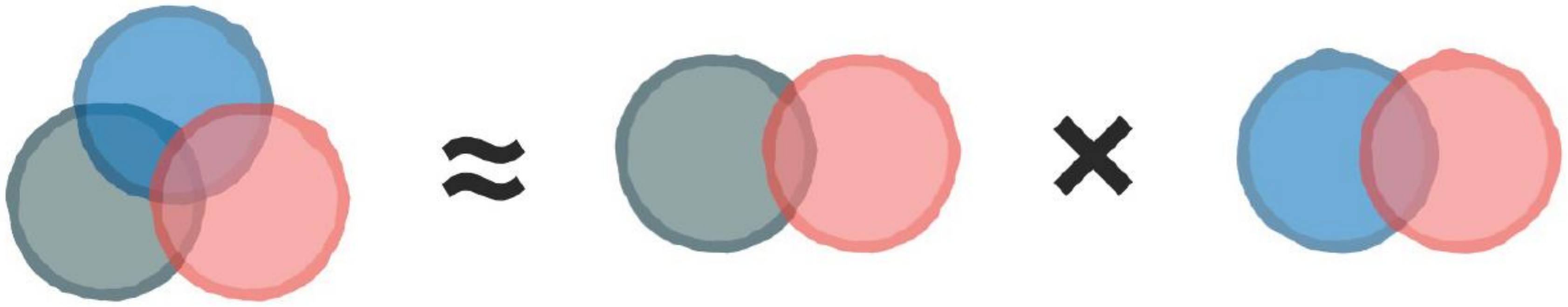
$$P(y{=}{=}F \mid ev_1 \& \cdots ev_N) \approx \frac{P(y{=}{=}F) \times (P(ev_1 \mid y{=}{=}F) \times \cdots P(ev_N \mid y{=}{=}F))}{P(ev_1 \& \cdots ev_N)}$$

## Naivety Assumption

The independence assumption is rarely true in practice

However it performs admirably on many real-world tasks

<u>Naïve Bayes is good approximation of complex probability model</u>



# sample dataset for trial

```
load(url('https://github.com/hbchoi/SampleData/raw/master/nb_data.RData'))
head(locations)
```

```
##   month day   weekday daytype hour hourtype location
## 1     1   4 wednesday weekday    0    night     home
## 2     1   4 wednesday weekday    1    night     home
## 3     1   4 wednesday weekday    2    night     home
## 4     1   4 wednesday weekday    3    night     home
```

```
str(locations)
```

```
## 'data.frame':    2184 obs. of  7 variables:
##  $ month   : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ day     : int  4 4 4 4 4 4 4 4 4 4 ...
##  $ weekday : Factor w/ 7 levels "friday","monday",..: 7 7 7 7 7 7 7 7 7 7 ...
##  $ daytype : Factor w/ 2 levels "weekday","weekend": 1 1 1 1 1 1 1 1 1 1 ...
##  $ hour    : int  0 1 2 3 4 5 6 7 8 9 ...
##  $ hourtype: Factor w/ 4 levels "afternoon","evening",..: 4 4 4 4 4 4 3 3 3 3 ...
##  $ location: Factor w/ 7 levels "appointment",..: 3 3 3 3 3 3 3 3 3 4 ...
```

```
head(where9am)
```

```
##   daytype location
## 1 weekday   office
## 2 weekday   office
## 3 weekday   office
## 4 weekend     home
## 5 weekend     home
## 6 weekday   campus
```

## simple Naïve Bayes model

```r
library(naivebayes)
```

```r
locmodel <- naive_bayes(location ~ daytype, data = where9am)
locmodel
```

```
## ===================== Naive Bayes =====================
## Call:
## naive_bayes.formula(formula = location ~ daytype, data = where9am)
##
## A priori probabilities:
##
## appointment      campus        home      office
##  0.01098901  0.10989011  0.45054945  0.42857143
##
## Tables:
##
## daytype   appointment    campus      home    office
##   weekday   1.0000000 1.0000000 0.3658537 1.0000000
##   weekend   0.0000000 0.0000000 0.6341463 0.0000000
```

## make prediction

```
test_simple
```

```
##   daytype
## 1 weekday
## 2 weekend
```

```
predict(locmodel, newdata = test_simple)
```

```
## [1] office home
## Levels: appointment campus home office
```

```
predict(locmodel, newdata = test_simple, type = 'prob')
```

```
##      appointment    campus      home office
## [1,]  0.01538462 0.1538462 0.2307692    0.6
## [2,]  0.00000000 0.0000000 1.0000000    0.0
```

## A more sophisticated location model

```
dim(locations_train)
```

```
## [1] 2088    7
```

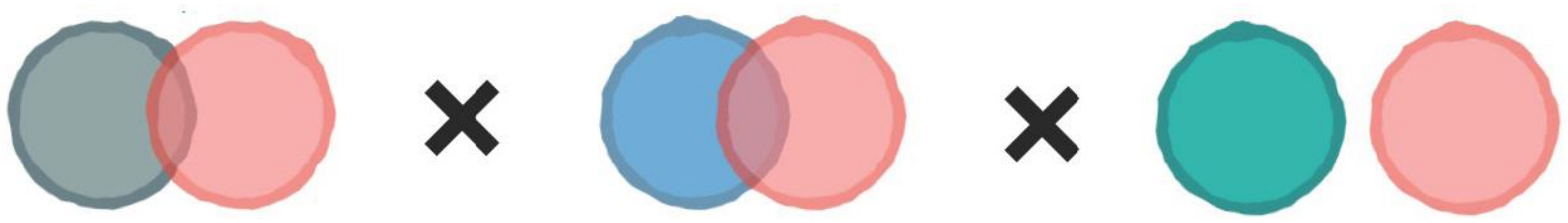
```
dim(locations_test)
```

```
## [1] 96  7
```

```
locmodel <- naive_bayes(location ~ daytype + hourtype, data = locations_train)
pred <- predict(locmodel, locations_test)

## accuracy of our model
mean(locations_test$location == pred)
```

```
## [1] 0.8854167
```

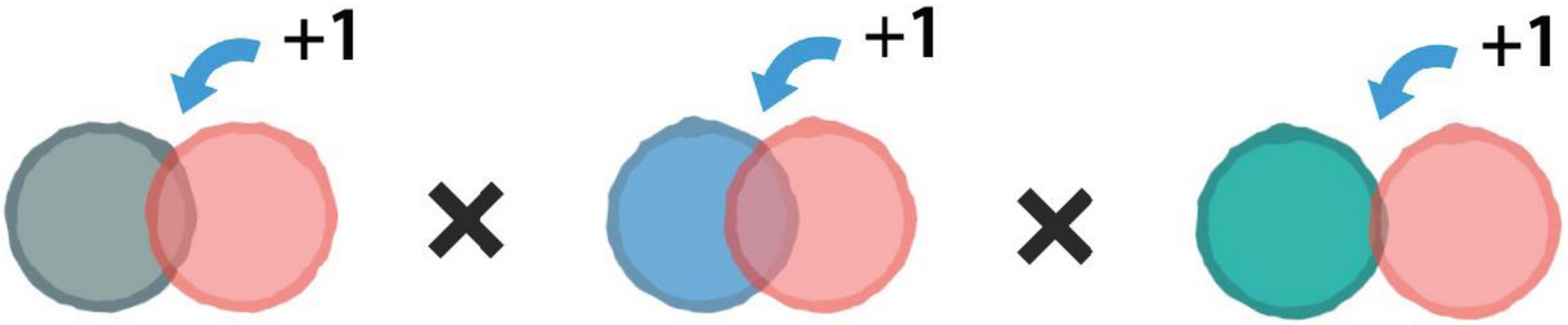
## An "infrequent" problem



P(afternoon|office) 0.3 × P(May|office) 0.2 × P(weekend|office) 0

Joint Event that never happened before, nullify effect of all other events

## The Laplace correction



P(afternoon|office)
0.31

P(May|office)
0.21

P(weekend|office)
0.01

```
locmodel <- naive_bayes(location ~ daytype + hourtype, data = locations_train)
pred <- predict(locmodel, locations_test, type = 'prob')
head(pred, n = 4)

##      appointment campus      home office    restaurant       store theater
## [1,]           0      0 0.9978926      0 0.0007773246 0.001330089       0
## [2,]           0      0 0.9978926      0 0.0007773246 0.001330089       0
## [3,]           0      0 0.9978926      0 0.0007773246 0.001330089       0
## [4,]           0      0 0.9978926      0 0.0007773246 0.001330089       0

locmodel

## ===================== Naive Bayes =====================
...
##
## daytype   appointment    campus      home    office restaurant     store
##   weekday   0.5000000 1.0000000 0.6396517 1.0000000  0.8051948 0.6666667
##   weekend   0.5000000 0.0000000 0.3603483 0.0000000  0.1948052 0.3333333
##
## daytype     theater
##   weekday 0.0000000
##   weekend 1.0000000
##
##
## hourtype    appointment     campus       home     office restaurant
##   afternoon  0.50000000 0.54166667 0.11587408 0.66666667 0.51948052
##   evening    0.25000000 0.01388889 0.18687207 0.03307888 0.16883117
##   morning    0.25000000 0.44444444 0.23241795 0.30025445 0.29870130
##   night      0.00000000 0.00000000 0.46483590 0.00000000 0.01298701
##
## hourtype         store    theater
##   afternoon 0.10256410 0.00000000
##   evening   0.87179487 1.00000000
##   morning   0.00000000 0.00000000
##   night     0.02564103 0.00000000
```

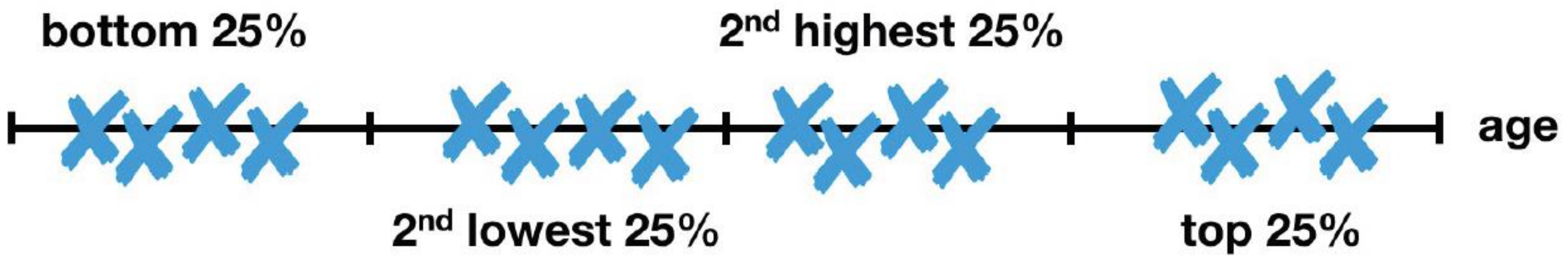
```r
# laplace corrected model
locmodel_lap <- naive_bayes(location ~ daytype + hourtype, data = locations_train, laplace = 1)
pred <- predict(locmodel_lap, locations_test, type = 'prob')
head(pred, n = 4)
```

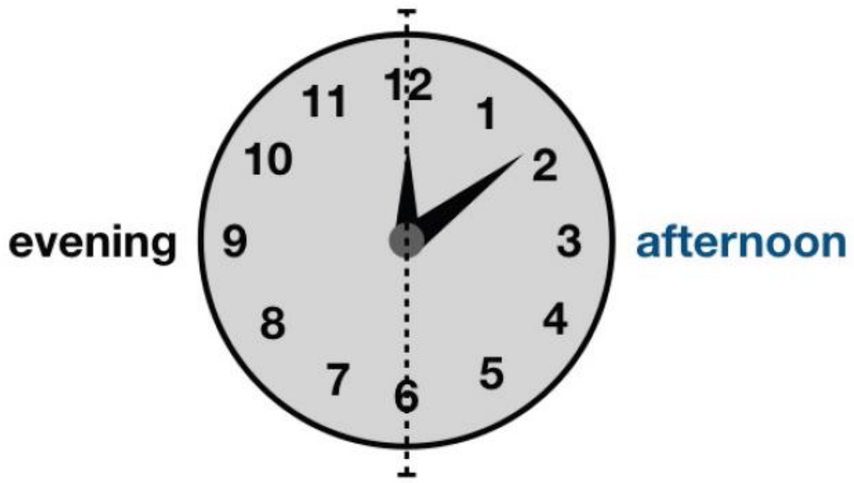
```
##       appointment      campus      home       office  restaurant
## [1,] 0.0007114617 4.61692e-05 0.9947752 9.829844e-06 0.001397514
## [2,] 0.0007114617 4.61692e-05 0.9947752 9.829844e-06 0.001397514
## [3,] 0.0007114617 4.61692e-05 0.9947752 9.829844e-06 0.001397514
## [4,] 0.0007114617 4.61692e-05 0.9947752 9.829844e-06 0.001397514
##           store     theater
## [1,] 0.00206529 0.000994573
## [2,] 0.00206529 0.000994573
## [3,] 0.00206529 0.000994573
## [4,] 0.00206529 0.000994573
```

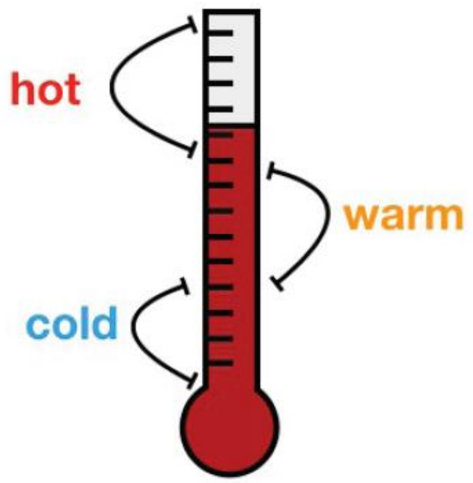
```r
locmodel_lap
```

```
##
## daytype   appointment     campus       home     office restaurant
##   weekday  0.33333333 0.92405063 0.63733333 0.98500000 0.75000000
##   weekend  0.33333333 0.01265823 0.35933333 0.00250000 0.19047619
##
## daytype        store    theater
##   weekday 0.58695652 0.07692308
##   weekend 0.30434783 0.53846154
##
## hourtype    appointment     campus       home     office restaurant
##   afternoon  0.33333333 0.50632911 0.11600000 0.65750000 0.48809524
##   evening    0.20000000 0.02531646 0.18666667 0.03500000 0.16666667
##   morning    0.20000000 0.41772152 0.23200000 0.29750000 0.28571429
##   night      0.06666667 0.01265823 0.46333333 0.00250000 0.02380952
##
## hourtype         store    theater
##   afternoon 0.10869565 0.07692308
##   evening   0.76086957 0.53846154
##   morning   0.02173913 0.07692308
##   night     0.04347826 0.07692308
```

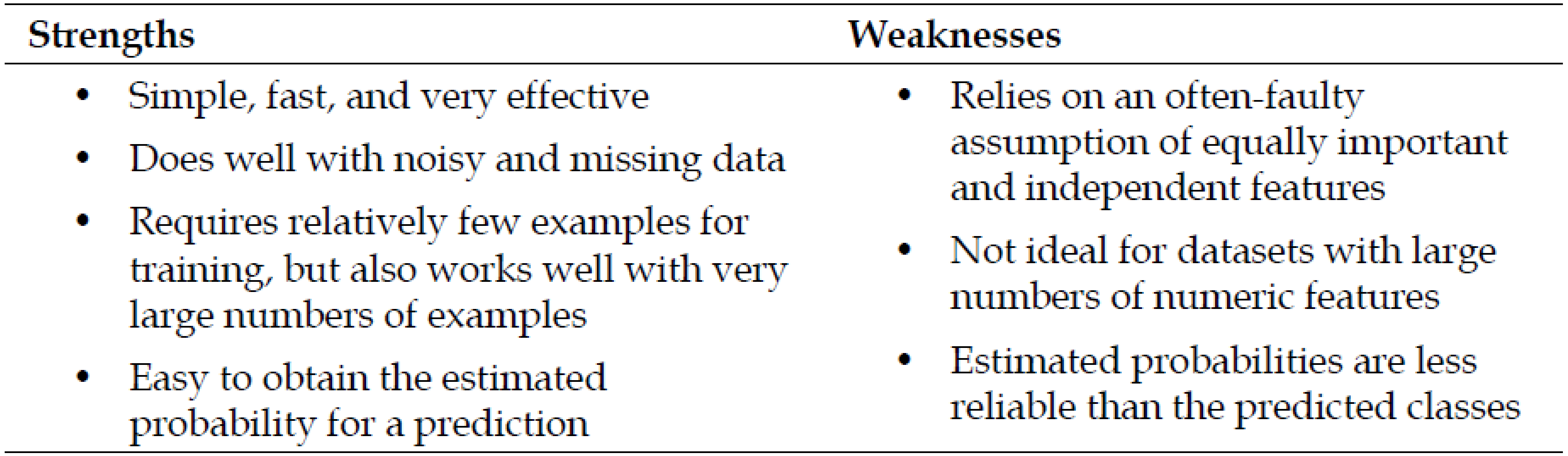
## Binning numeric data for Naive Bayes







## Naïve Bayes



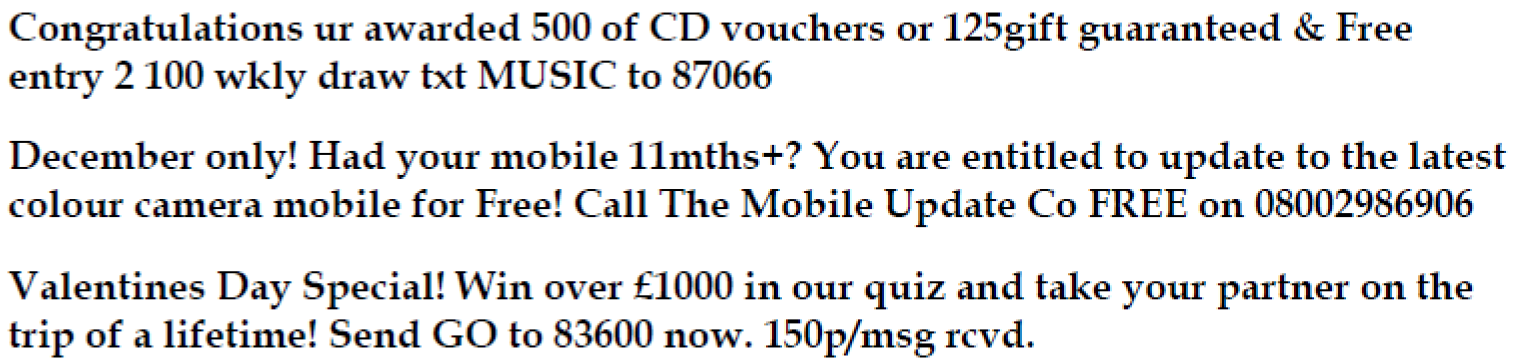
| Strengths | Weaknesses |
|---|---|
| • Simple, fast, and very effective<br>• Does well with noisy and missing data<br>• Requires relatively few examples for training, but also works well with very large numbers of examples<br>• Easy to obtain the estimated probability for a prediction | • Relies on an often-faulty assumption of equally important and independent features<br>• Not ideal for datasets with large numbers of numeric features<br>• Estimated probabilities are less reliable than the predicted classes |

## References

- Practical Data Science with R, by Nina Zumel and John Mount
- R을 이용한 데이터 분석 실무, 서민구, 길벗
- [DBGUIDE 연재] ggplot2를 이용한 R 시각화
  - http://freesearch.pe.kr/archives/3134

## Appendix - Example

- SMS (short message service) spam filtering
  - Spam – spam

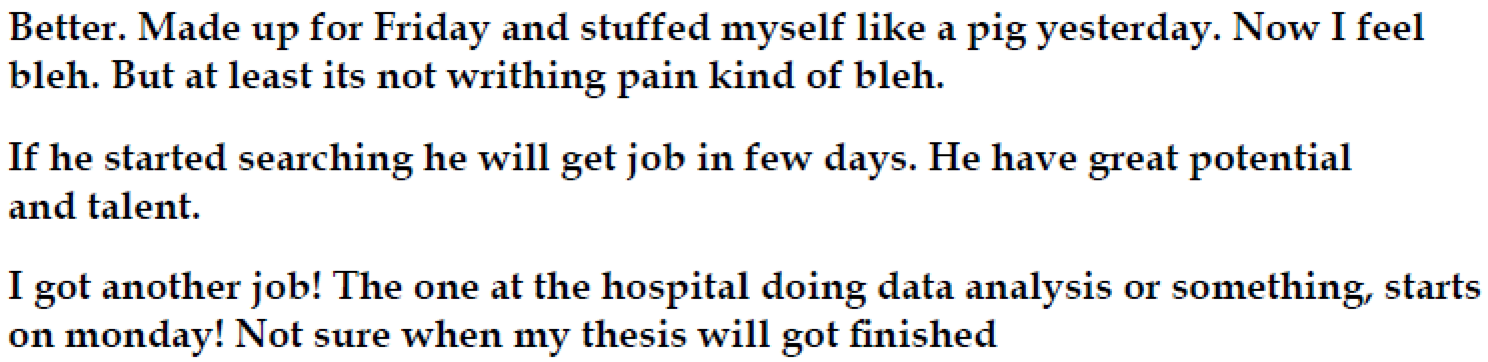


Congratulations ur awarded 500 of CD vouchers or 125gift guaranteed & Free entry 2 100 wkly draw txt MUSIC to 87066

December only! Had your mobile 11mths+? You are entitled to update to the latest colour camera mobile for Free! Call The Mobile Update Co FREE on 08002986906

Valentines Day Special! Win over £1000 in our quiz and take your partner on the trip of a lifetime! Send GO to 83600 now. 150p/msg rcvd.

  - Non-spam – ham



Better. Made up for Friday and stuffed myself like a pig yesterday. Now I feel bleh. But at least its not writhing pain kind of bleh.

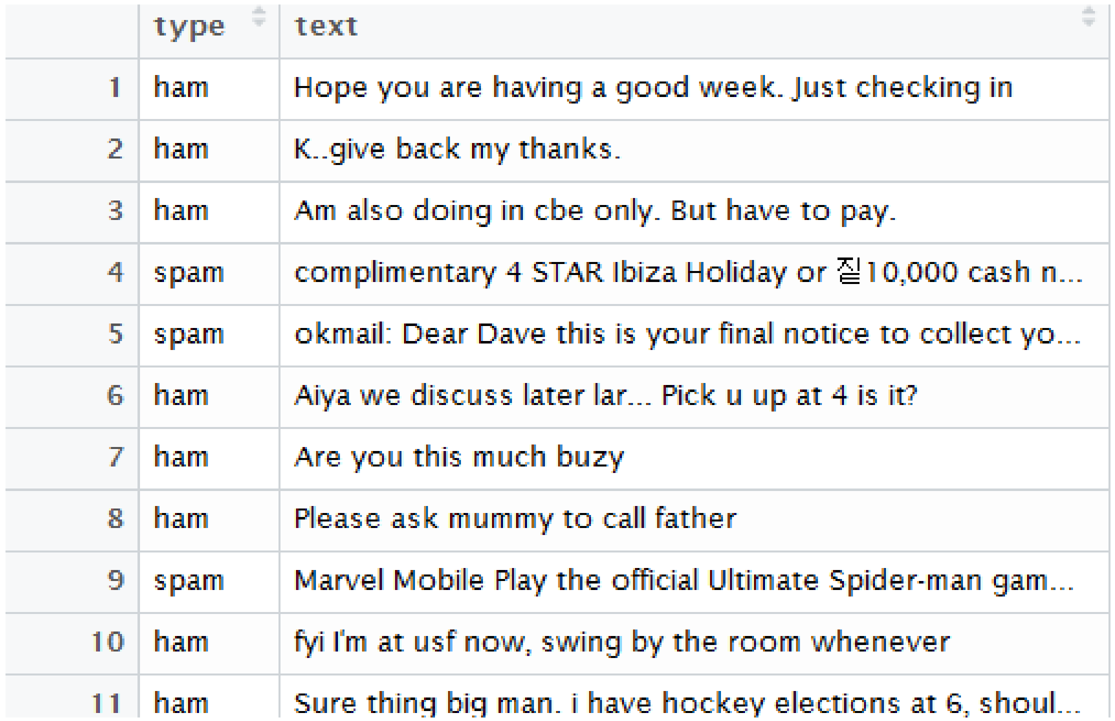
If he started searching he will get job in few days. He have great potential and talent.

I got another job! The one at the hospital doing data analysis or something, starts on monday! Not sure when my thesis will got finished

## Data Loading

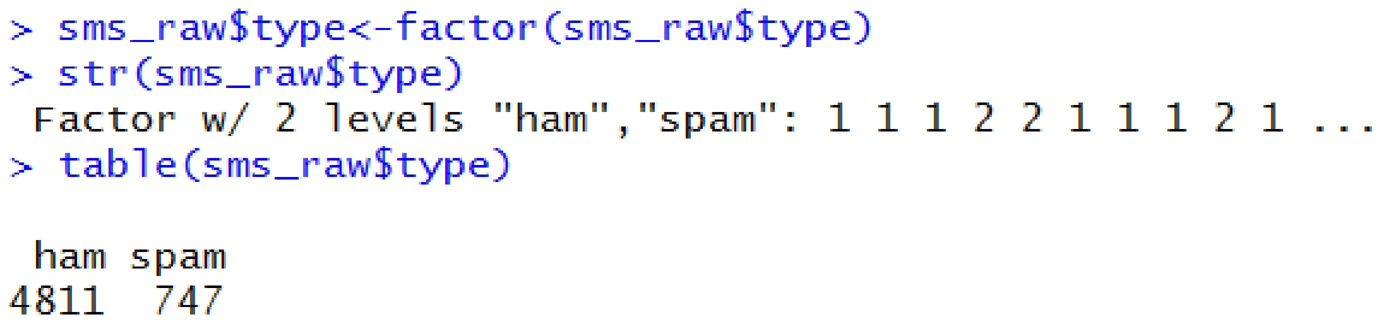
- SMS (short message service) spam filtering

```
> sms_raw<-read.csv("sms_spam.csv",stringsAsFactors = FALSE)
```



| | type | text |
|---|---|---|
| 1 | ham | Hope you are having a good week. Just checking in |
| 2 | ham | K..give back my thanks. |
| 3 | ham | Am also doing in cbe only. But have to pay. |
| 4 | spam | complimentary 4 STAR Ibiza Holiday or 질10,000 cash n... |
| 5 | spam | okmail: Dear Dave this is your final notice to collect yo... |
| 6 | ham | Aiya we discuss later lar... Pick u up at 4 is it? |
| 7 | ham | Are you this much buzy |
| 8 | ham | Please ask mummy to call father |
| 9 | spam | Marvel Mobile Play the official Ultimate Spider-man gam... |
| 10 | ham | fyi I'm at usf now, swing by the room whenever |
| 11 | ham | Sure thing big man. i have hockey elections at 6, shoul... |

## Data preparation



```
> sms_raw$type<-factor(sms_raw$type)
> str(sms_raw$type)
 Factor w/ 2 levels "ham","spam": 1 1 1 2 2 1 1 1 2 1 ...
> table(sms_raw$type)

 ham spam
4811  747
```

# Data preparation

- text -> bag of words
  - text mining package “tm”

```
> install.packages("tm")
Installing package into ‘C:/Users/Hyebong Choi/Documents/R/win-library/3.2’
(as ‘lib’ is unspecified)
also installing the dependencies ‘NLP’, ‘slam’

trying URL 'https://cran.rstudio.com/bin/windows/contrib/3.2/NLP_0.1-9.zip'
Content type 'application/zip' length 278734 bytes (272 KB)
downloaded 272 KB

trying URL 'https://cran.rstudio.com/bin/windows/contrib/3.2/slam_0.1-34.zip'
Content type 'application/zip' length 111493 bytes (108 KB)
downloaded 108 KB

trying URL 'https://cran.rstudio.com/bin/windows/contrib/3.2/tm_0.6-2.zip'
Content type 'application/zip' length 710657 bytes (694 KB)
downloaded 694 KB

package ‘NLP’ successfully unpacked and MD5 sums checked
package ‘slam’ successfully unpacked and MD5 sums checked
package ‘tm’ successfully unpacked and MD5 sums checked

The downloaded binary packages are in
        C:\Users\Hyebong Choi\AppData\Local\Temp\RtmpUHLcnN\downloaded_packages
> library(tm)
필요한 패키지를 로딩중입니다: NLP
```

## Data preparation

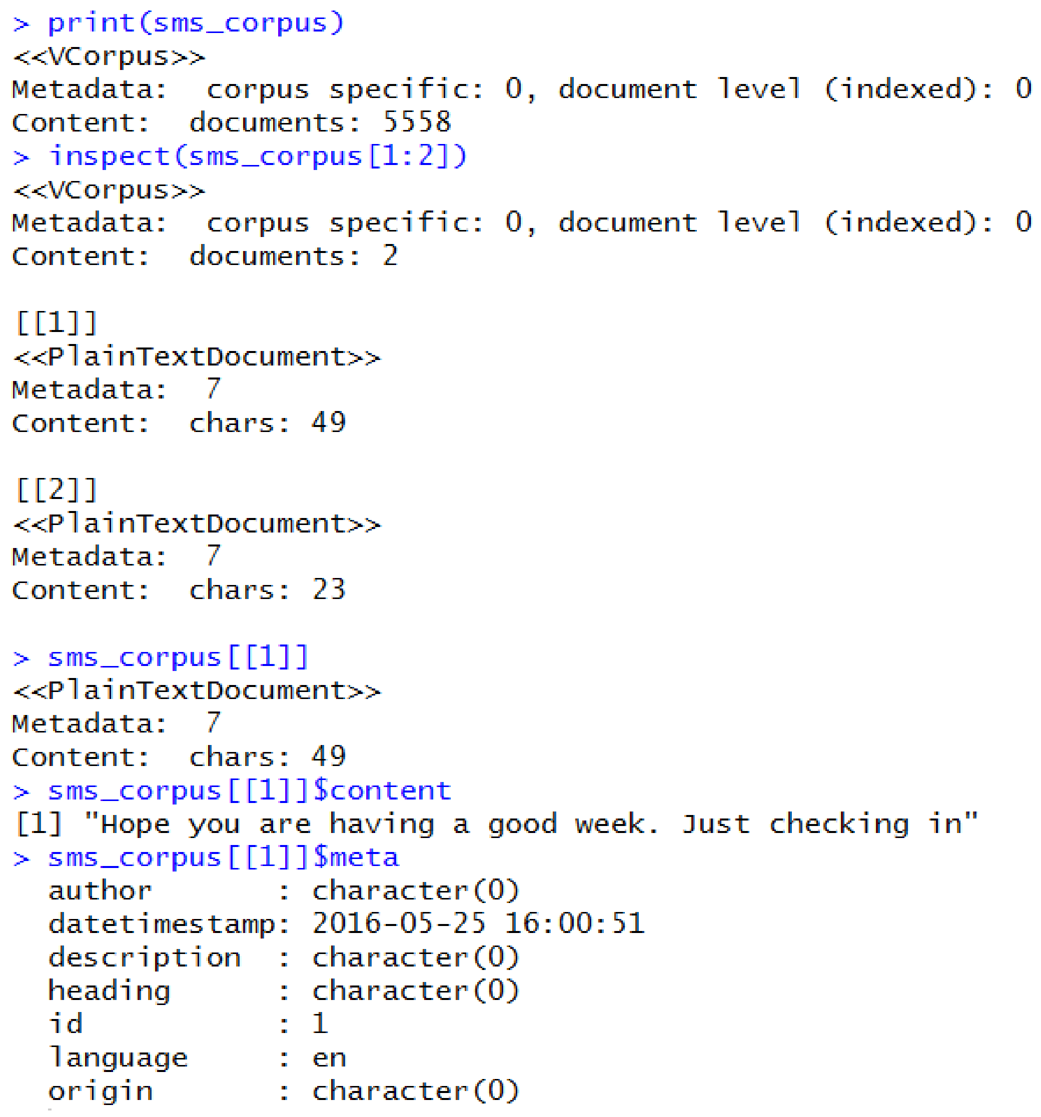
- text -> bag of words
  - text mining package “tm”

```
> sms_corpus <- Corpus(VectorSource(sms_raw$text))
```

This command uses two functions. First, the `Corpus()` function creates an R object to store text documents. This function takes a parameter specifying the format of the text documents to be loaded. Since we have already read the SMS messages and stored them in an R vector, we specify `VectorSource()`, which tells `Corpus()` to use the messages in the vector `sms_train$text`. The `Corpus()` function stores the result in an object named `sms_corpus`.

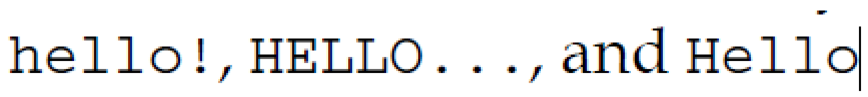
The `Corpus()` function is extremely flexible and can read documents from many different sources such as PDFs and Microsoft Word documents. To learn more, examine the *Data Import* section in the `tm` package vignette using the command: `print(vignette("tm"))`

## Data preparation



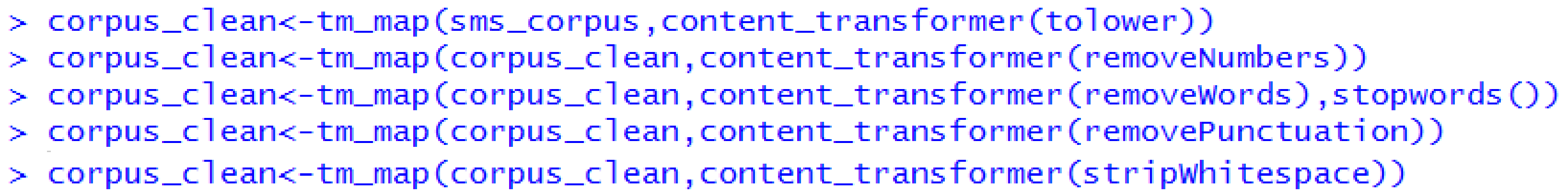
```
> print(sms_corpus)
<<VCorpus>>
Metadata:  corpus specific: 0, document level (indexed): 0
Content:  documents: 5558
> inspect(sms_corpus[1:2])
<<VCorpus>>
Metadata:  corpus specific: 0, document level (indexed): 0
Content:  documents: 2

[[1]]
<<PlainTextDocument>>
Metadata:  7
Content:  chars: 49

[[2]]
<<PlainTextDocument>>
Metadata:  7
Content:  chars: 23

> sms_corpus[[1]]
<<PlainTextDocument>>
Metadata:  7
Content:  chars: 49
> sms_corpus[[1]]$content
[1] "Hope you are having a good week. Just checking in"
> sms_corpus[[1]]$meta
  author       : character(0)
  datetimestamp: 2016-05-25 16:00:51
  description  : character(0)
  heading      : character(0)
  id           : 1
  language     : en
  origin       : character(0)
```

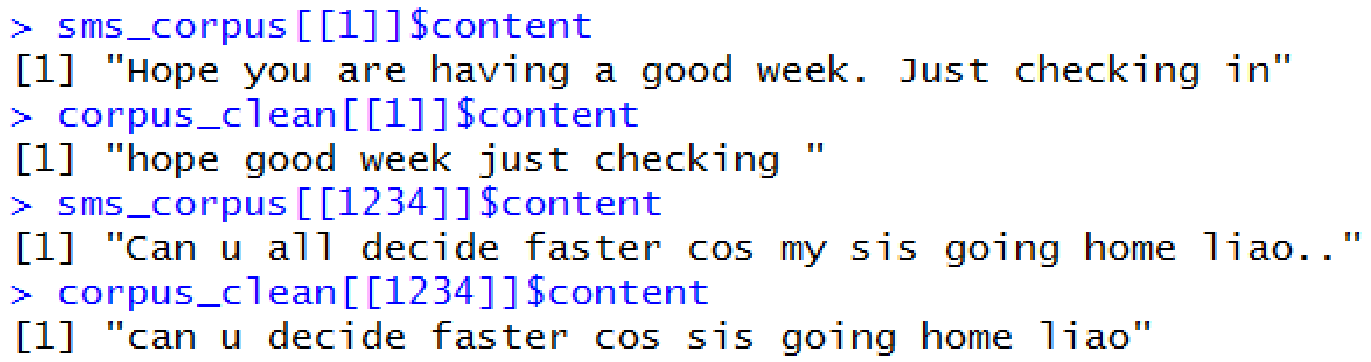
## Data preparation


hello!, HELLO..., and Hello

count as all “hello”

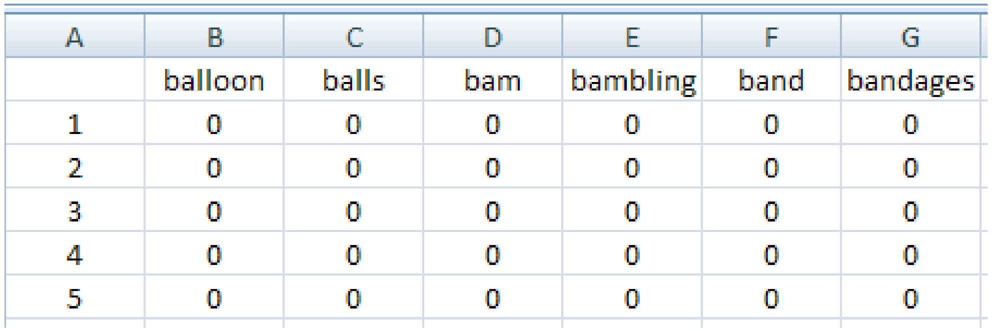
- remove numbers, punctuation, white space, and stop words.
- to make all lower-cased


```
> corpus_clean<-tm_map(sms_corpus,content_transformer(tolower))
> corpus_clean<-tm_map(corpus_clean,content_transformer(removeNumbers))
> corpus_clean<-tm_map(corpus_clean,content_transformer(removeWords),stopwords())
> corpus_clean<-tm_map(corpus_clean,content_transformer(removePunctuation))
> corpus_clean<-tm_map(corpus_clean,content_transformer(stripWhitespace))
```


```
> sms_corpus[[1]]$content
[1] "Hope you are having a good week. Just checking in"
> corpus_clean[[1]]$content
[1] "hope good week just checking "
> sms_corpus[[1234]]$content
[1] "Can u all decide faster cos my sis going home liao.."
> corpus_clean[[1234]]$content
[1] "can u decide faster cos sis going home liao"
```

# Data preparation

- to document and term matrix (tokenizing)



| A | B | C | D | E | F | G |
|---|---|---|---|---|---|---|
| | balloon | balls | bam | bambling | band | bandages |
| 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| 2 | 0 | 0 | 0 | 0 | 0 | 0 |
| 3 | 0 | 0 | 0 | 0 | 0 | 0 |
| 4 | 0 | 0 | 0 | 0 | 0 | 0 |
| 5 | 0 | 0 | 0 | 0 | 0 | 0 |

```
> sms_dtm <- DocumentTermMatrix(corpus_clean)
```

```
> inspect(sms_dtm[1:10, 1000:1010])
<<DocumentTermMatrix (documents: 10, terms: 11)>>
Non-/sparse entries: 0/110
Sparsity           : 100%
Maximal term length: 10
Weighting          : term frequency (tf)

    Terms
Docs caps captain captaining car card cardiff cardin cards care careabout cared
   1    0       0          0   0    0       0      0     0    0         0     0
   2    0       0          0   0    0       0      0     0    0         0     0
   3    0       0          0   0    0       0      0     0    0         0     0
   4    0       0          0   0    0       0      0     0    0         0     0
   5    0       0          0   0    0       0      0     0    0         0     0
   6    0       0          0   0    0       0      0     0    0         0     0
```

```
> dim(sms_dtm)
[1] 5558 7989
```

## Spliting Training and Test set

```
> sms_raw_train <- sms_raw[1:4169, ]
> sms_raw_test  <- sms_raw[4170:5559, ]
```

Then the document-term matrix:

```
> sms_dtm_train <- sms_dtm[1:4169, ]
> sms_dtm_test  <- sms_dtm[4170:5559, ]
```

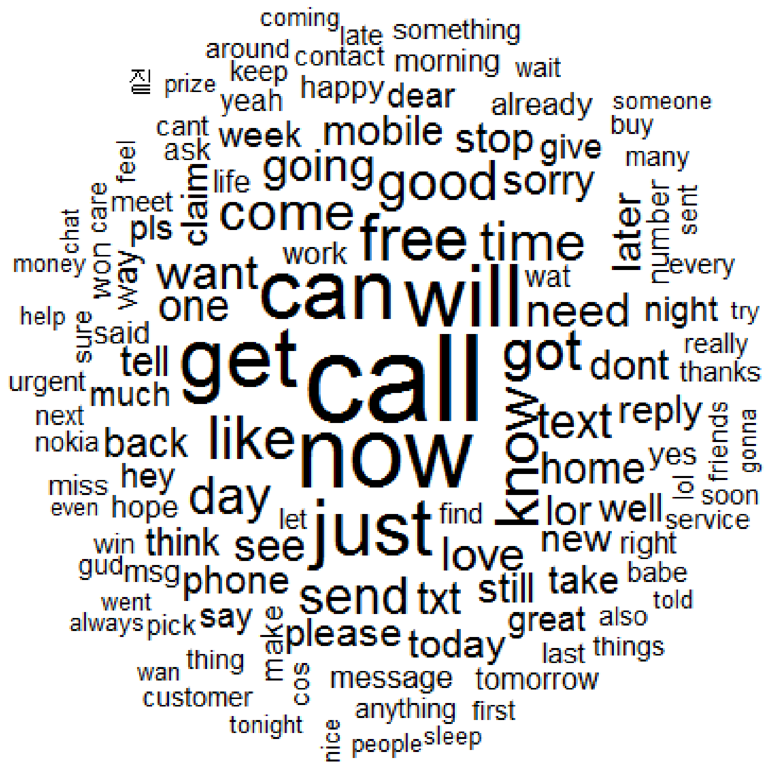
And finally, the corpus:

```
> sms_corpus_train <- corpus_clean[1:4169]
> sms_corpus_test  <- corpus_clean[4170:5559]
```

```
> prop.table(table(sms_raw_train$type))
      ham      spam
0.8647158 0.1352842
> prop.table(table(sms_raw_test$type))
      ham      spam
0.8683453 0.1316547
```

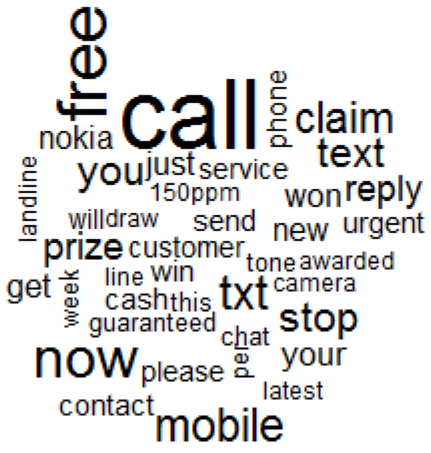
## Visualization - word cloud

```
> install.packages("wordcloud")

The downloaded binary packages are in
        C:\Users\Hyebong Choi\AppData\Local\Temp\RtmpUHLcnN\downloaded_packages
> library(wordcloud)
필요한 패키지를 로딩중입니다: RColorBrewer
Warning message:
패키지 'wordcloud'는 R 버전 3.2.5에서 작성되었습니다
> wordcloud(sms_corpus_train,min.freq = 40,random.order = FALSE)
```

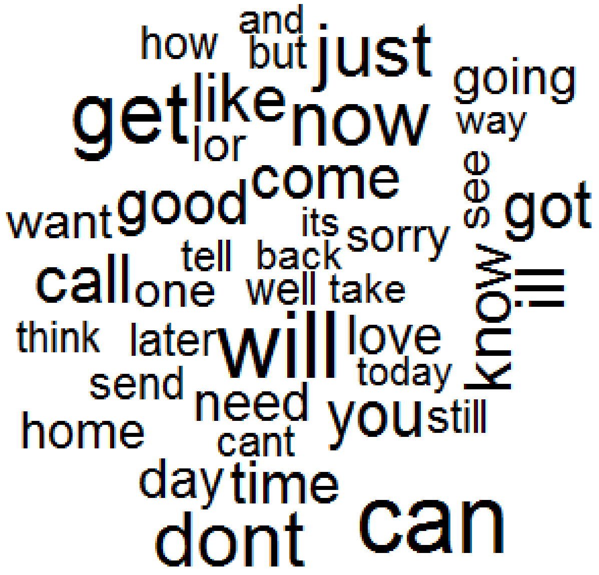


# Visualization - word cloud

```
> spam<-subset(sms_raw_train,type=="spam")
> ham<-subset(sms_raw_train,type=="ham")
> wordcloud(spam$text,min.freq=20,max.words = 40,scale=c(3,0.5))
> wordcloud(ham$text,max.words = 40,scale=c(3,0.5))
```



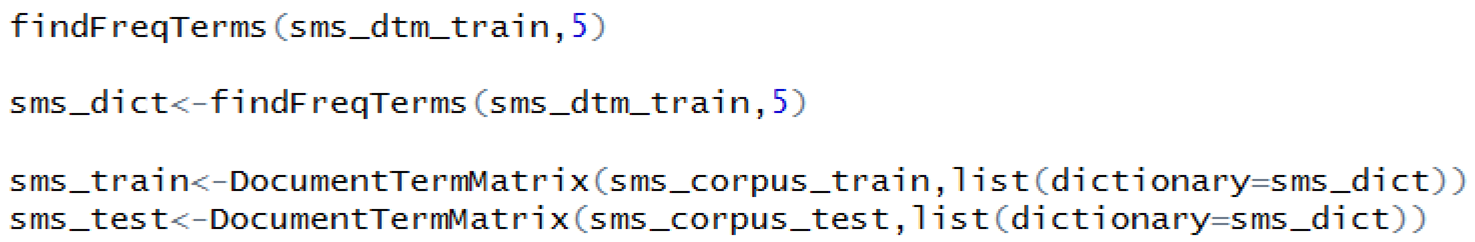
spam



ham

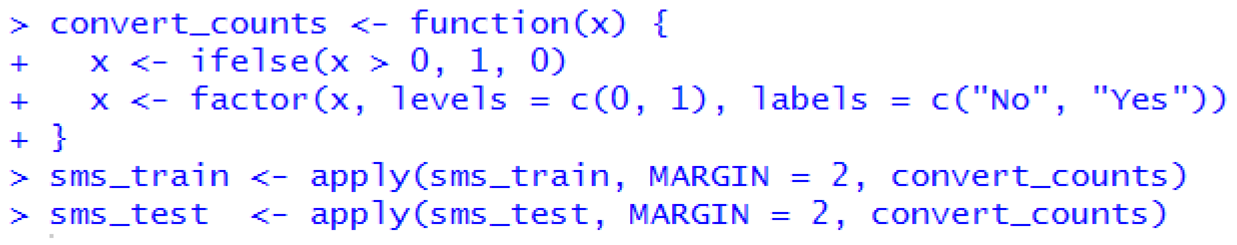
## Filtering frequent terms

- Remove terms that appear less than 5 times



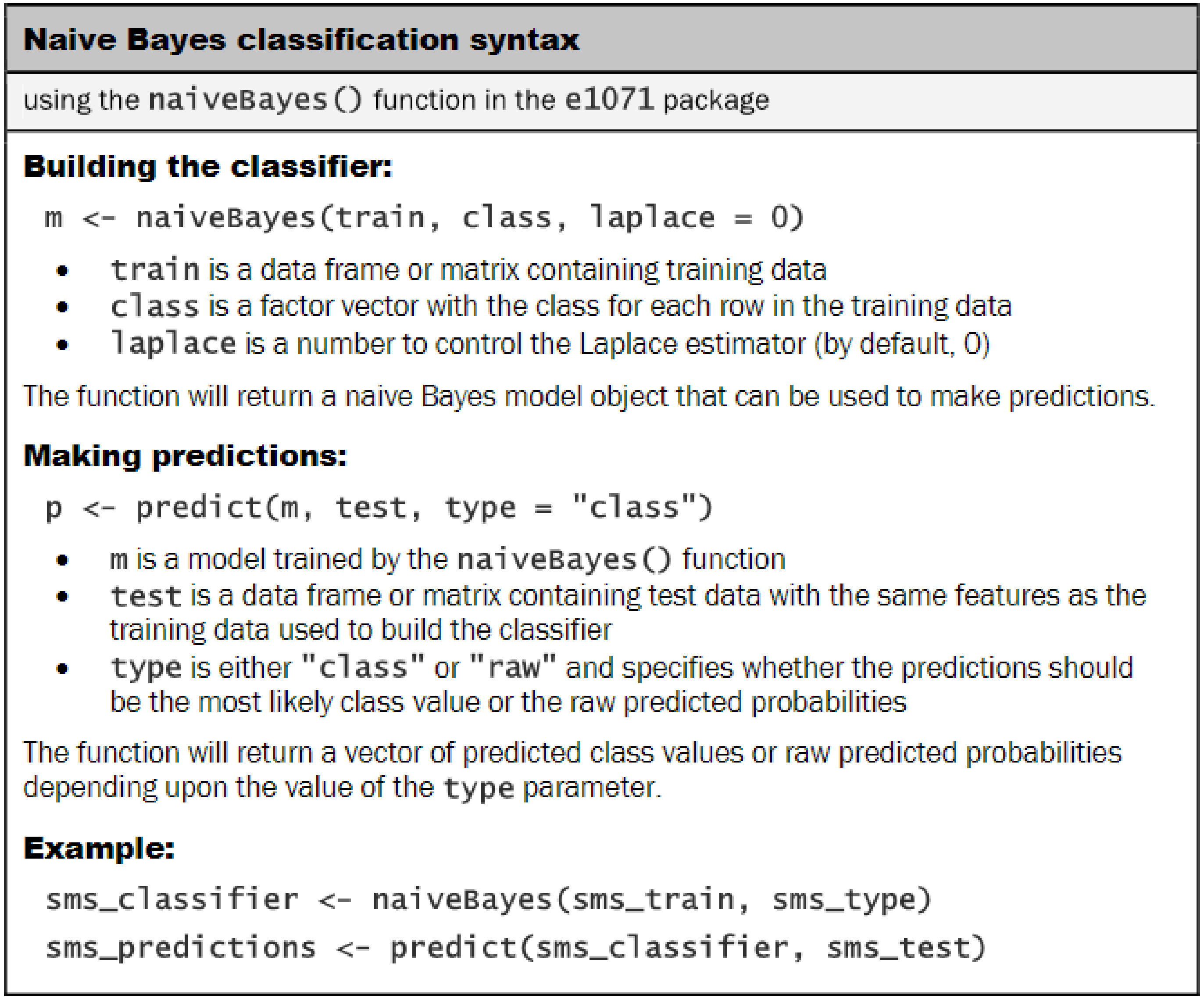
```
findFreqTerms(sms_dtm_train,5)

sms_dict<-findFreqTerms(sms_dtm_train,5)

sms_train<-DocumentTermMatrix(sms_corpus_train,list(dictionary=sms_dict))
sms_test<-DocumentTermMatrix(sms_corpus_test,list(dictionary=sms_dict))
```

- term frequency -> term occurrence



```
> convert_counts <- function(x) {
+   x <- ifelse(x > 0, 1, 0)
+   x <- factor(x, levels = c(0, 1), labels = c("No", "Yes"))
+ }
> sms_train <- apply(sms_train, MARGIN = 2, convert_counts)
> sms_test  <- apply(sms_test, MARGIN = 2, convert_counts)
```

## Naïve Bayes



**Naive Bayes classification syntax**

using the `naiveBayes()` function in the `e1071` package

**Building the classifier:**

```
m <- naiveBayes(train, class, laplace = 0)
```

- `train` is a data frame or matrix containing training data
- `class` is a factor vector with the class for each row in the training data
- `laplace` is a number to control the Laplace estimator (by default, 0)

The function will return a naive Bayes model object that can be used to make predictions.

**Making predictions:**

```
p <- predict(m, test, type = "class")
```

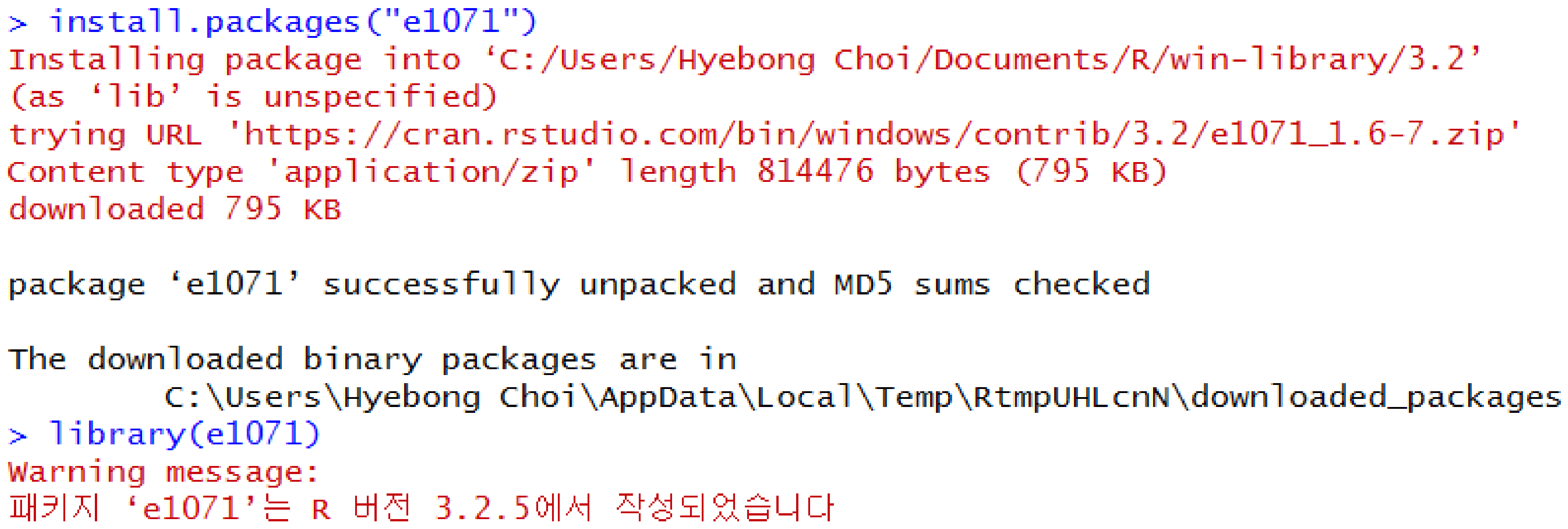
- `m` is a model trained by the `naiveBayes()` function
- `test` is a data frame or matrix containing test data with the same features as the training data used to build the classifier
- `type` is either `"class"` or `"raw"` and specifies whether the predictions should be the most likely class value or the raw predicted probabilities

The function will return a vector of predicted class values or raw predicted probabilities depending upon the value of the `type` parameter.

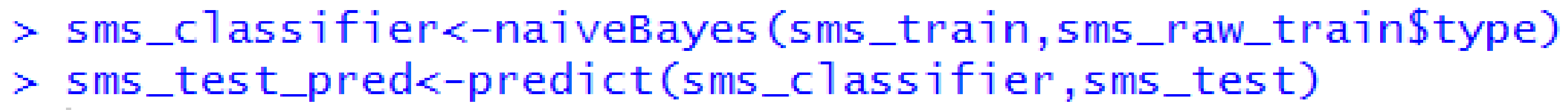
**Example:**

```
sms_classifier <- naiveBayes(sms_train, sms_type)
sms_predictions <- predict(sms_classifier, sms_test)
```

## Naïve Bayes



```
> install.packages("e1071")
Installing package into ‘C:/Users/Hyebong Choi/Documents/R/win-library/3.2’
(as ‘lib’ is unspecified)
trying URL 'https://cran.rstudio.com/bin/windows/contrib/3.2/e1071_1.6-7.zip'
Content type 'application/zip' length 814476 bytes (795 KB)
downloaded 795 KB

package ‘e1071’ successfully unpacked and MD5 sums checked

The downloaded binary packages are in
        C:\Users\Hyebong Choi\AppData\Local\Temp\RtmpUHLcnN\downloaded_packages
> library(e1071)
Warning message:
패키지 ‘e1071’는 R 버전 3.2.5에서 작성되었습니다
```

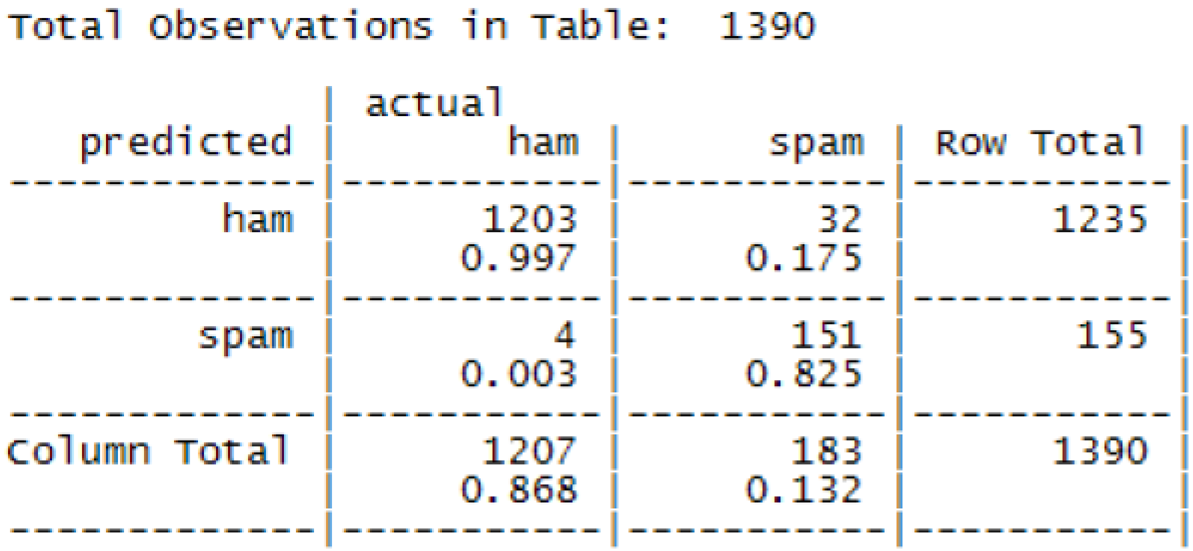


```
> sms_classifier<-naiveBayes(sms_train,sms_raw_train$type)
> sms_test_pred<-predict(sms_classifier,sms_test)
```

## Naïve Bayes

```
> library(gmodels)
> CrossTable(sms_test_pred, sms_raw_test$type,
    prop.chisq = FALSE, prop.t = FALSE,
    dnn = c('predicted', 'actual'))
```

This produces the following table:



```
Total Observations in Table:  1390

             | actual
   predicted |       ham |      spam | Row Total |
-------------|-----------|-----------|-----------|
         ham |      1203 |        32 |      1235 |
             |     0.997 |     0.175 |           |
-------------|-----------|-----------|-----------|
        spam |         4 |       151 |       155 |
             |     0.003 |     0.825 |           |
-------------|-----------|-----------|-----------|
Column Total |      1207 |       183 |      1390 |
             |     0.868 |     0.132 |           |
-------------|-----------|-----------|-----------|
```

## Improvement

```
> sms_classifier2 <- naiveBayes(sms_train, sms_raw_train$type, laplace = 1)
> sms_test_pred2 <- predict(sms_classifier2, sms_test)
> CrossTable(sms_test_pred2, sms_raw_test$type,
+            prop.chisq = FALSE, prop.t = FALSE, prop.r = FALSE,
+            dnn = c('predicted', 'actual'))
```

```
Total Observations in Table:  1390

             | actual
   predicted |       ham |      spam | Row Total |
-------------|-----------|-----------|-----------|
         ham |      1204 |        31 |      1235 |
             |     0.998 |     0.169 |           |
-------------|-----------|-----------|-----------|
        spam |         3 |       152 |       155 |
             |     0.002 |     0.831 |           |
-------------|-----------|-----------|-----------|
Column Total |      1207 |       183 |      1390 |
             |     0.868 |     0.132 |           |
-------------|-----------|-----------|-----------|
```