Chapter 4: Classification using Naive Bayes

This is an R Markdown Notebook. When you execute code within the notebook, the results appear beneath the code.

Try executing this chunk by clicking the *Run* button within the chunk or by placing your cursor inside it and pressing *Ctrl+Shift+Enter*.

Add a new chunk by clicking the *Insert Chunk* button on the toolbar or by pressing *Ctrl+Alt+I*.

When you save the notebook, an HTML file containing the code and output will be saved alongside it (click the *Preview* button or press *Ctrl+Shift+K* to preview the HTML file).

Example: Filtering spam SMS messages

Step 1: Download the data

```
URL <- "http://www.sci.csueastbay.edu/~esuess/classes/Statistics_6620/Presentations/ml6/sms_spam.csv"
download.file(URL, destfile = "./sms_spam.csv", method="curl")
```

Step 2: Exploring and preparing the data —-

```
# read the sms data into the sms data frame
sms_raw <- read.csv("sms_spam.csv", stringsAsFactors = FALSE)

# examine the structure of the sms data
str(sms_raw)
```

```
## 'data.frame':    5559 obs. of  2 variables:
##  $ type: chr  "ham" "ham" "ham" "spam" ...
##  $ text: chr  "Hope you are having a good week. Just checking in" "K..give back my thanks." "Am also
```

```
# convert spam/ham to factor.
sms_raw$type <- factor(sms_raw$type)

# examine the type variable more carefully
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
## 4812  747
```

```
# build a corpus using the text mining (tm) package
library(tm)
```

```
## Loading required package: NLP
```

```r
sms_corpus <- VCorpus(VectorSource(sms_raw$text))

# examine the sms corpus
print(sms_corpus)
```

```
## <<VCorpus>>
## Metadata:  corpus specific: 0, document level (indexed): 0
## Content:  documents: 5559
```

```r
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
```

```r
as.character(sms_corpus[[1]])
```

```
## [1] "Hope you are having a good week. Just checking in"
```

```r
lapply(sms_corpus[1:2], as.character)
```

```
## $`1`
## [1] "Hope you are having a good week. Just checking in"
##
## $`2`
## [1] "K..give back my thanks."
```

```r
# clean up the corpus using tm_map()
sms_corpus_clean <- tm_map(sms_corpus, content_transformer(tolower))

# show the difference between sms_corpus and corpus_clean
as.character(sms_corpus[[1]])
```

```
## [1] "Hope you are having a good week. Just checking in"
```

```r
as.character(sms_corpus_clean[[1]])
```

```
## [1] "hope you are having a good week. just checking in"
```

```r
sms_corpus_clean <- tm_map(sms_corpus_clean, removeNumbers) # remove numbers
sms_corpus_clean <- tm_map(sms_corpus_clean, removeWords, stopwords()) # remove stop words
sms_corpus_clean <- tm_map(sms_corpus_clean, removePunctuation) # remove punctuation

# tip: create a custom function to replace (rather than remove) punctuation
removePunctuation("hello...world")
```

```
## [1] "helloworld"
```

```
replacePunctuation <- function(x) { gsub("[[:punct:]]+", " ", x) }
replacePunctuation("hello...world")
```

```
## [1] "hello world"
```

```
# illustration of word stemming
library(SnowballC)
wordStem(c("learn", "learned", "learning", "learns"))
```

```
## [1] "learn" "learn" "learn" "learn"
```

```
sms_corpus_clean <- tm_map(sms_corpus_clean, stemDocument)

sms_corpus_clean <- tm_map(sms_corpus_clean, stripWhitespace) # eliminate unneeded whitespace

# examine the final clean corpus
lapply(sms_corpus[1:3], as.character)
```

```
## $`1`
## [1] "Hope you are having a good week. Just checking in"
##
## $`2`
## [1] "K..give back my thanks."
##
## $`3`
## [1] "Am also doing in cbe only. But have to pay."
```

```
lapply(sms_corpus_clean[1:3], as.character)
```

```
## $`1`
## [1] "hope good week just check"
##
## $`2`
## [1] "kgive back thank"
##
## $`3`
## [1] "also cbe pay"
```

```
# create a document-term sparse matrix
sms_dtm <- DocumentTermMatrix(sms_corpus_clean)

# alternative solution: create a document-term sparse matrix directly from the SMS corpus
sms_dtm2 <- DocumentTermMatrix(sms_corpus, control = list(
  tolower = TRUE,
  removeNumbers = TRUE,
  stopwords = TRUE,
  removePunctuation = TRUE,
  stemming = TRUE
))

# alternative solution: using custom stop words function ensures identical result
sms_dtm3 <- DocumentTermMatrix(sms_corpus, control = list(
  tolower = TRUE,
  removeNumbers = TRUE,
  stopwords = function(x) { removeWords(x, stopwords()) },
  removePunctuation = TRUE,
```

```
  stemming = TRUE
))

# compare the result
sms_dtm
```

```
## <<DocumentTermMatrix (documents: 5559, terms: 6559)>>
## Non-/sparse entries: 42147/36419334
## Sparsity           : 100%
## Maximal term length: 40
## Weighting          : term frequency (tf)
```

```
sms_dtm2
```

```
## <<DocumentTermMatrix (documents: 5559, terms: 6961)>>
## Non-/sparse entries: 43221/38652978
## Sparsity           : 100%
## Maximal term length: 40
## Weighting          : term frequency (tf)
```

```
sms_dtm3
```

```
## <<DocumentTermMatrix (documents: 5559, terms: 6559)>>
## Non-/sparse entries: 42147/36419334
## Sparsity           : 100%
## Maximal term length: 40
## Weighting          : term frequency (tf)
```

```
# creating training and test datasets
sms_dtm_train <- sms_dtm[1:4169, ]
sms_dtm_test  <- sms_dtm[4170:5559, ]

# also save the labels
sms_train_labels <- sms_raw[1:4169, ]$type
sms_test_labels  <- sms_raw[4170:5559, ]$type

# check that the proportion of spam is similar
prop.table(table(sms_train_labels))
```

```
## sms_train_labels
##       ham      spam
## 0.8647158 0.1352842
```

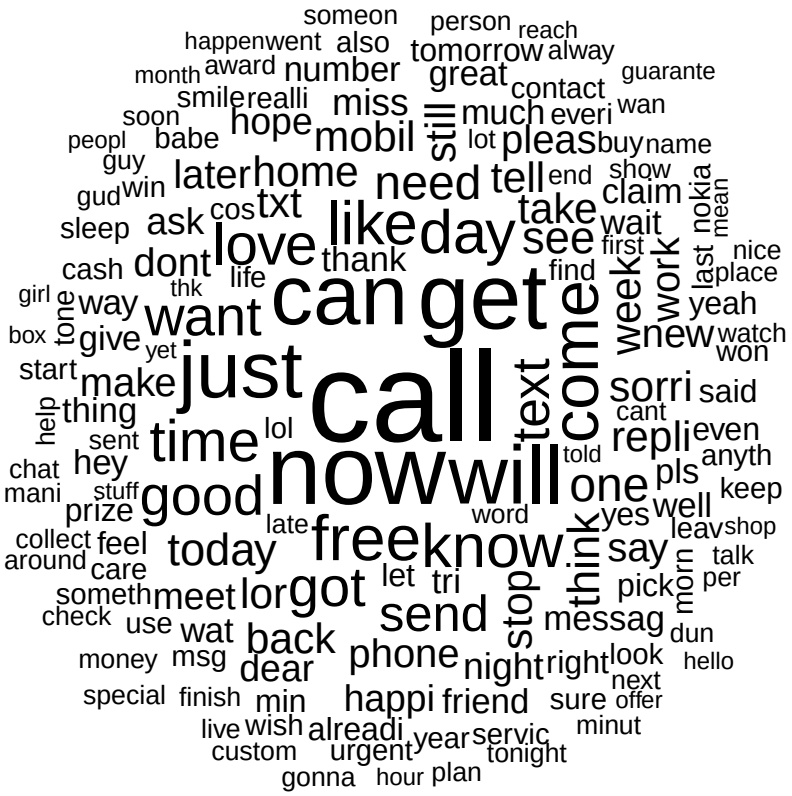
```
prop.table(table(sms_test_labels))
```

```
## sms_test_labels
##       ham      spam
## 0.8683453 0.1316547
```

```
# word cloud visualization
library(wordcloud)
```

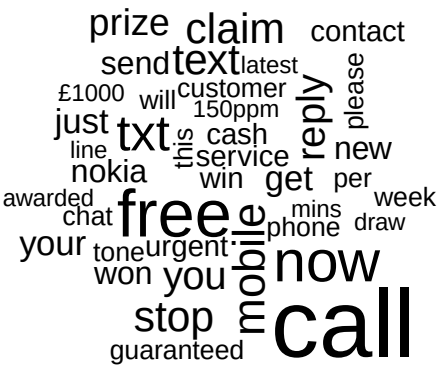
```
## Loading required package: RColorBrewer
```

```
wordcloud(sms_corpus_clean, min.freq = 50, random.order = FALSE)
```

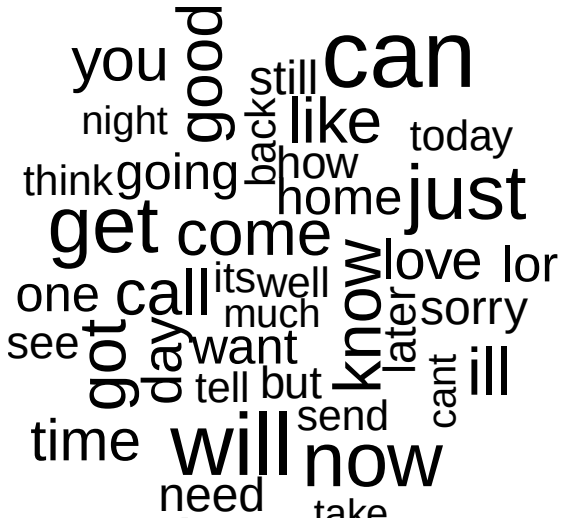



```
# subset the training data into spam and ham groups
spam <- subset(sms_raw, type == "spam")
ham  <- subset(sms_raw, type == "ham")

wordcloud(spam$text, max.words = 40, scale = c(3, 0.5))
```




```
wordcloud(ham$text, max.words = 40, scale = c(3, 0.5))
```




```
sms_dtm_freq_train <- removeSparseTerms(sms_dtm_train, 0.999)
sms_dtm_freq_train
```

```
## <<DocumentTermMatrix (documents: 4169, terms: 1104)>>
## Non-/sparse entries: 24827/4577749
## Sparsity           : 99%
## Maximal term length: 19
## Weighting          : term frequency (tf)
```

```
# indicator features for frequent words
findFreqTerms(sms_dtm_train, 5)
```

```
##    [1] "£wk"                "€~m"                "€~s"
##    [4] "abiola"             "abl"                "abt"
##    [7] "accept"             "access"             "account"
##   [10] "across"             "act"                "activ"
##   [13] "actual"             "add"                "address"
##   [16] "admir"              "adult"              "advanc"
##   [19] "aft"                "afternoon"          "age"
##   [22] "ago"                "aha"                "ahead"
##   [25] "aight"              "aint"               "air"
##   [28] "aiyo"               "alex"               "almost"
##   [31] "alon"               "alreadi"            "alright"
##   [34] "also"               "alway"              "angri"
##   [37] "announc"            "anoth"              "answer"
##   [40] "anymor"             "anyon"              "anyth"
##   [43] "anytim"             "anyway"             "apart"
##   [46] "app"                "appli"              "appreci"
##   [49] "arcad"              "ard"                "area"
##   [52] "argu"               "argument"           "armand"
##   [55] "around"             "arrang"             "arriv"
##   [58] "asap"               "ask"                "askd"
##   [61] "attempt"            "auction"            "avail"
##   [64] "ave"                "avoid"              "await"
##   [67] "awak"               "award"              "away"
##   [70] "awesom"             "babe"               "babi"
##   [73] "back"               "bad"                "bag"
##   [76] "bank"               "bare"               "basic"
```

```
##   [79] "bath"             "batteri"           "bcoz"
##   [82] "bday"             "beauti"            "becom"
##   [85] "bed"              "bedroom"           "beer"
##   [88] "begin"            "believ"            "best"
##   [91] "better"           "bid"               "big"
##   [94] "bill"             "bird"              "birthday"
##   [97] "bit"              "black"             "blank"
##  [100] "bless"            "blue"              "bluetooth"
##  [103] "bold"             "bonus"             "boo"
##  [106] "book"             "boost"             "bore"
##  [109] "boss"             "bother"            "bout"
##  [112] "box"              "boy"               "boytoy"
##  [115] "break"            "breath"            "bring"
##  [118] "brother"          "bslvyl"            "btnationalr"
##  [121] "buck"             "bus"               "busi"
##  [124] "buy"              "cabin"             "call"
##  [127] "caller"           "callertun"         "camcord"
##  [130] "came"             "camera"            "campus"
##  [133] "can"              "cancel"            "cancer"
##  [136] "cant"             "car"               "card"
##  [139] "care"             "carlo"             "case"
##  [142] "cash"             "cashbal"           "catch"
##  [145] "caus"             "celebr"            "cell"
##  [148] "centr"            "chanc"             "chang"
##  [151] "charg"            "chat"              "cheap"
##  [154] "cheaper"          "check"             "cheer"
##  [157] "chennai"          "chikku"            "childish"
##  [160] "children"         "choic"             "choos"
##  [163] "christma"         "claim"             "class"
##  [166] "clean"            "clear"             "close"
##  [169] "club"             "code"              "coffe"
##  [172] "cold"             "colleagu"          "collect"
##  [175] "colleg"           "colour"            "come"
##  [178] "comin"            "comp"              "compani"
##  [181] "competit"         "complet"           "complimentari"
##  [184] "comput"           "condit"            "confirm"
##  [187] "congrat"          "congratul"         "connect"
##  [190] "contact"          "content"           "contract"
##  [193] "cook"             "cool"              "copi"
##  [196] "correct"          "cos"               "cost"
##  [199] "cost&pm"          "costa"             "coupl"
##  [202] "cours"            "cover"             "coz"
##  [205] "crave"            "crazi"             "creat"
##  [208] "credit"           "cri"               "cross"
##  [211] "cuddl"            "cum"               "cup"
##  [214] "current"          "custcar"           "custom"
##  [217] "cut"              "cute"              "cuz"
##  [220] "dad"              "daddi"             "darl"
##  [223] "darlin"           "darren"            "dat"
##  [226] "date"             "day"               "dead"
##  [229] "deal"             "dear"              "decid"
##  [232] "decim"            "decis"             "deep"
##  [235] "definit"          "del"               "deliv"
##  [238] "deliveri"         "den"               "depend"
```

```
##  [241] "detail"          "didnt"           "die"
##  [244] "diet"            "differ"          "difficult"
##  [247] "digit"           "din"             "dinner"
##  [250] "direct"          "dis"             "discount"
##  [253] "discuss"         "disturb"         "dnt"
##  [256] "doc"             "doctor"          "doesnt"
##  [259] "dog"             "doin"            "don"
##  [262] "done"            "dont"            "door"
##  [265] "doubl"           "download"        "draw"
##  [268] "dream"           "drink"           "drive"
##  [271] "drop"            "drug"            "dude"
##  [274] "due"             "dun"             "dunno"
##  [277] "dvd"             "earli"           "earlier"
##  [280] "earth"           "easi"            "eat"
##  [283] "eatin"           "egg"             "either"
##  [286] "els"             "email"           "embarass"
##  [289] "end"             "energi"          "england"
##  [292] "enjoy"           "enough"          "enter"
##  [295] "entitl"          "entri"           "envelop"
##  [298] "etc"             "euro"            "eve"
##  [301] "even"            "ever"            "everi"
##  [304] "everybodi"       "everyon"         "everyth"
##  [307] "exact"           "exam"            "excel"
##  [310] "excit"           "excus"           "expect"
##  [313] "experi"          "expir"           "extra"
##  [316] "eye"             "face"            "facebook"
##  [319] "fact"            "fall"            "famili"
##  [322] "fanci"           "fantasi"         "fantast"
##  [325] "far"             "fast"            "fat"
##  [328] "father"          "fault"           "feb"
##  [331] "feel"            "felt"            "fetch"
##  [334] "fight"           "figur"           "file"
##  [337] "fill"            "film"            "final"
##  [340] "find"            "fine"            "finger"
##  [343] "finish"          "first"           "fix"
##  [346] "flag"            "flat"            "flight"
##  [349] "flower"          "follow"          "fone"
##  [352] "food"            "forev"           "forget"
##  [355] "forgot"          "forward"         "found"
##  [358] "freak"           "free"            "freemsg"
##  [361] "freephon"        "fren"            "fri"
##  [364] "friday"          "friend"          "friendship"
##  [367] "frm"             "frnd"            "frnds"
##  [370] "full"            "fullonsmscom"    "fun"
##  [373] "funni"           "futur"           "gal"
##  [376] "game"            "gap"             "gas"
##  [379] "gave"            "gay"             "gentl"
##  [382] "get"             "gettin"          "gift"
##  [385] "girl"            "girlfrnd"        "give"
##  [388] "glad"            "god"             "goe"
##  [391] "goin"            "gone"            "gonna"
##  [394] "good"            "goodmorn"        "goodnight"
##  [397] "got"             "goto"            "gotta"
##  [400] "great"           "grin"            "guarante"
```

```
##  [403] "gud"              "guess"              "guy"
##  [406] "gym"              "haf"                "haha"
##  [409] "hai"              "hair"               "half"
##  [412] "hand"             "handset"            "hang"
##  [415] "happen"           "happi"              "hard"
##  [418] "hate"             "hav"                "havent"
##  [421] "head"             "hear"               "heard"
##  [424] "heart"            "heavi"              "hee"
##  [427] "hell"             "hello"              "help"
##  [430] "hey"              "hgsuiteland"        "hit"
##  [433] "hiya"             "hmm"                "hmmm"
##  [436] "hmv"              "hol"                "hold"
##  [439] "holder"           "holiday"            "home"
##  [442] "hook"             "hop"                "hope"
##  [445] "horni"            "hospit"             "hot"
##  [448] "hotel"            "hour"               "hous"
##  [451] "how"              "howev"              "howz"
##  [454] "hrs"              "httpwwwurawinnercom" "hug"
##  [457] "huh"              "hungri"             "hurri"
##  [460] "hurt"             "ice"                "idea"
##  [463] "identifi"         "ignor"              "ill"
##  [466] "immedi"           "import"             "inc"
##  [469] "includ"           "india"              "info"
##  [472] "inform"           "insid"              "instead"
##  [475] "interest"         "invit"              "ipod"
##  [478] "irrit"            "ish"                "island"
##  [481] "issu"             "ive"                "izzit"
##  [484] "januari"          "jay"                "job"
##  [487] "john"             "join"               "joke"
##  [490] "joy"              "jst"                "jus"
##  [493] "just"             "juz"                "kate"
##  [496] "keep"             "kept"               "kick"
##  [499] "kid"              "kill"               "kind"
##  [502] "kinda"            "king"               "kiss"
##  [505] "knew"             "know"               "knw"
##  [508] "ladi"             "land"               "landlin"
##  [511] "laptop"           "lar"                "last"
##  [514] "late"             "later"              "latest"
##  [517] "laugh"            "lazi"               "ldn"
##  [520] "lead"             "learn"              "least"
##  [523] "leav"             "lect"               "left"
##  [526] "leh"              "lei"                "less"
##  [529] "lesson"           "let"                "letter"
##  [532] "liao"             "librari"            "lie"
##  [535] "life"             "lift"               "light"
##  [538] "like"             "line"               "link"
##  [541] "list"             "listen"             "littl"
##  [544] "live"             "lmao"               "load"
##  [547] "loan"             "local"              "locat"
##  [550] "log"              "lol"                "london"
##  [553] "long"             "longer"             "look"
##  [556] "lookin"           "lor"                "lose"
##  [559] "lost"             "lot"                "lovabl"
##  [562] "love"             "lover"              "loyalti"
```

```
##  [565] "ltd"          "luck"          "lucki"
##  [568] "lunch"        "luv"           "mad"
##  [571] "made"         "mah"           "mail"
##  [574] "make"         "malaria"       "man"
##  [577] "mani"         "march"         "mark"
##  [580] "marri"        "match"         "mate"
##  [583] "matter"       "maxim"         "maxmin"
##  [586] "may"          "mayb"          "meal"
##  [589] "mean"         "meant"         "med"
##  [592] "medic"        "meet"          "meetin"
##  [595] "meh"          "member"        "men"
##  [598] "merri"        "messag"        "met"
##  [601] "mid"          "midnight"      "might"
##  [604] "min"          "mind"          "mine"
##  [607] "minut"        "miracl"        "miss"
##  [610] "mistak"       "moan"          "mob"
##  [613] "mobil"        "mobileupd"     "mode"
##  [616] "mom"          "moment"        "mon"
##  [619] "monday"       "money"         "month"
##  [622] "morn"         "mother"        "motorola"
##  [625] "move"         "movi"          "mrng"
##  [628] "mrt"          "mrw"           "msg"
##  [631] "msgs"         "mths"          "much"
##  [634] "mum"          "murder"        "music"
##  [637] "must"         "muz"           "nah"
##  [640] "nake"         "name"          "nation"
##  [643] "natur"        "naughti"       "near"
##  [646] "need"         "net"           "network"
##  [649] "neva"         "never"         "new"
##  [652] "news"         "next"          "nice"
##  [655] "nigeria"      "night"         "nite"
##  [658] "nobodi"       "noe"           "nokia"
##  [661] "noon"         "nope"          "normal"
##  [664] "normpton"     "noth"          "notic"
##  [667] "now"          "num"           "number"
##  [670] "nyt"          "obvious"       "offer"
##  [673] "offic"        "offici"        "okay"
##  [676] "oki"          "old"           "omg"
##  [679] "one"          "onlin"         "onto"
##  [682] "oop"          "open"          "oper"
##  [685] "opinion"      "opt"           "optout"
##  [688] "orang"        "orchard"       "order"
##  [691] "oredi"        "oso"           "other"
##  [694] "otherwis"     "outsid"        "pack"
##  [697] "page"         "paid"          "pain"
##  [700] "paper"        "parent"        "park"
##  [703] "part"         "parti"         "partner"
##  [706] "pass"         "passion"       "password"
##  [709] "past"         "pay"           "peopl"
##  [712] "per"          "person"        "pete"
##  [715] "phone"        "photo"         "pic"
##  [718] "pick"         "pictur"        "pin"
##  [721] "piss"         "pix"           "pizza"
##  [724] "place"        "plan"          "play"
```

```
##  [727] "player"          "pleas"          "pleasur"
##  [730] "plenti"          "pls"            "plus"
##  [733] "plz"             "pmin"           "pmsg"
##  [736] "pobox"           "point"          "poli"
##  [739] "polic"           "poor"           "pop"
##  [742] "possess"         "possibl"        "post"
##  [745] "pound"           "power"          "ppm"
##  [748] "pray"            "present"        "press"
##  [751] "pretti"          "previous"       "price"
##  [754] "princess"        "privat"         "prize"
##  [757] "prob"            "probabl"        "problem"
##  [760] "project"         "promis"         "pub"
##  [763] "put"             "qualiti"        "question"
##  [766] "quick"           "quit"           "quiz"
##  [769] "quot"            "rain"           "random"
##  [772] "rang"            "rate"           "rather"
##  [775] "rcvd"            "reach"          "read"
##  [778] "readi"           "real"           "reali"
##  [781] "realli"          "reason"         "receipt"
##  [784] "receiv"          "recent"         "record"
##  [787] "refer"           "regard"         "regist"
##  [790] "relat"           "relax"          "remain"
##  [793] "rememb"          "remind"         "remov"
##  [796] "rent"            "rental"         "repli"
##  [799] "repres"          "request"        "respond"
##  [802] "respons"         "rest"           "result"
##  [805] "return"          "reveal"         "review"
##  [808] "reward"          "right"          "ring"
##  [811] "rington"         "rite"           "road"
##  [814] "rock"            "role"           "room"
##  [817] "roommat"         "rose"           "round"
##  [820] "rowwjhl"         "rpli"           "rreveal"
##  [823] "run"             "rush"           "sad"
##  [826] "sae"             "safe"           "said"
##  [829] "sale"            "sat"            "saturday"
##  [832] "savamob"         "save"           "saw"
##  [835] "say"             "sch"            "school"
##  [838] "scream"          "sea"            "search"
##  [841] "sec"             "second"         "secret"
##  [844] "see"             "seem"           "seen"
##  [847] "select"          "self"           "sell"
##  [850] "semest"          "send"           "sens"
##  [853] "sent"            "serious"        "servic"
##  [856] "set"             "settl"          "sex"
##  [859] "sexi"            "shall"          "share"
##  [862] "shd"             "ship"           "shirt"
##  [865] "shop"            "short"          "show"
##  [868] "shower"          "sick"           "side"
##  [871] "sigh"            "sight"          "sign"
##  [874] "silent"          "simpl"          "sinc"
##  [877] "singl"           "sipix"          "sir"
##  [880] "sis"             "sister"         "sit"
##  [883] "situat"          "skxh"           "skype"
##  [886] "slave"           "sleep"          "slept"
```

```
##  [889] "slow"             "slowli"           "small"
##  [892] "smile"            "smoke"            "sms"
##  [895] "smth"             "snow"             "sofa"
##  [898] "sol"              "somebodi"         "someon"
##  [901] "someth"           "sometim"          "somewher"
##  [904] "song"             "soni"             "sonyericsson"
##  [907] "soon"             "sorri"            "sort"
##  [910] "sound"            "south"            "space"
##  [913] "speak"            "special"          "specialcal"
##  [916] "spend"            "spent"            "spoke"
##  [919] "spree"            "stand"            "start"
##  [922] "statement"        "station"          "stay"
##  [925] "std"              "step"             "still"
##  [928] "stockport"        "stone"            "stop"
##  [931] "store"            "stori"            "street"
##  [934] "student"          "studi"            "stuff"
##  [937] "stupid"           "style"            "sub"
##  [940] "subscrib"         "success"          "suck"
##  [943] "suit"             "summer"           "sun"
##  [946] "sunday"           "sunshin"          "sup"
##  [949] "support"          "suppos"           "sure"
##  [952] "surf"             "surpris"          "sweet"
##  [955] "swing"            "system"           "take"
##  [958] "talk"             "tampa"            "tariff"
##  [961] "tcs"              "tea"              "teach"
##  [964] "tear"             "teas"             "tel"
##  [967] "tell"             "ten"              "tenerif"
##  [970] "term"             "test"             "text"
##  [973] "thank"            "thanx"            "that"
##  [976] "thing"            "think"            "thinkin"
##  [979] "thk"              "tho"              "though"
##  [982] "thought"          "throw"            "thru"
##  [985] "tht"              "thur"             "tick"
##  [988] "ticket"           "til"              "till"
##  [991] "time"             "tire"             "titl"
##  [994] "tmr"              "toclaim"          "today"
##  [997] "togeth"           "told"             "tomo"
## [1000] "tomorrow"         "tone"             "tonight"
## [1003] "tonit"            "took"             "top"
## [1006] "torch"            "tot"              "total"
## [1009] "touch"            "tough"            "tour"
## [1012] "toward"           "town"             "track"
## [1015] "train"            "transact"         "travel"
## [1018] "treat"            "tri"              "trip"
## [1021] "troubl"           "true"             "trust"
## [1024] "truth"            "tscs"             "ttyl"
## [1027] "tuesday"          "turn"             "twice"
## [1030] "two"              "txt"              "txting"
## [1033] "txts"             "type"             "ufind"
## [1036] "ugh"              "ull"              "uncl"
## [1039] "understand"       "unless"           "unlimit"
## [1042] "unredeem"         "unsub"            "unsubscrib"
## [1045] "updat"            "ure"              "urgent"
## [1048] "urself"           "use"              "user"
```

```
## [1051] "usf"                "usual"              "uve"
## [1054] "valentin"           "valid"              "valu"
## [1057] "via"                "video"              "vikki"
## [1060] "visit"              "vodafon"            "voic"
## [1063] "vomit"              "voucher"            "wait"
## [1066] "wake"               "walk"               "wan"
## [1069] "wana"               "wanna"              "want"
## [1072] "wap"                "warm"               "wast"
## [1075] "wat"                "watch"              "water"
## [1078] "way"                "weak"               "wear"
## [1081] "weather"            "wed"                "wednesday"
## [1084] "weed"               "week"               "weekend"
## [1087] "welcom"             "well"               "wen"
## [1090] "went"               "what"               "whatev"
## [1093] "whenev"             "whole"              "wid"
## [1096] "wif"                "wife"               "wil"
## [1099] "will"               "win"                "wine"
## [1102] "winner"             "wish"               "wit"
## [1105] "within"             "without"            "wiv"
## [1108] "wkli"               "wks"                "wnt"
## [1111] "woke"               "won"                "wonder"
## [1114] "wont"               "word"               "work"
## [1117] "workin"             "world"              "worri"
## [1120] "wors"               "worth"              "wot"
## [1123] "wow"                "write"              "wrong"
## [1126] "wwq"                "wwwgetzedcouk"      "xmas"
## [1129] "xxx"                "yahoo"              "yar"
## [1132] "yeah"               "year"               "yep"
## [1135] "yes"                "yesterday"          "yet"
## [1138] "yoga"               "yup"
```

```
# save frequently-appearing terms to a character vector
sms_freq_words <- findFreqTerms(sms_dtm_train, 5)
str(sms_freq_words)
```

```
##  chr [1:1139] "£wk" "€~m" "€~s" "abiola" "abl" "abt" "accept" "access" ...
```

```
# create DTMs with only the frequent terms
sms_dtm_freq_train <- sms_dtm_train[ , sms_freq_words]
sms_dtm_freq_test <- sms_dtm_test[ , sms_freq_words]

# convert counts to a factor
convert_counts <- function(x) {
  x <- ifelse(x > 0, "Yes", "No")
}

# apply() convert_counts() to columns of train/test data
sms_train <- apply(sms_dtm_freq_train, MARGIN = 2, convert_counts)
sms_test  <- apply(sms_dtm_freq_test, MARGIN = 2, convert_counts)
```

Step 3: Training a model on the data —-

```
library(e1071)
sms_classifier <- naiveBayes(sms_train, sms_train_labels)
```

Step 4: Evaluating model performance —-

```
sms_test_pred <- predict(sms_classifier, sms_test)

head(sms_test_pred)
```

```
## [1] ham  ham  ham  ham  spam ham
## Levels: ham spam
```

```
library(gmodels)
CrossTable(sms_test_pred, sms_test_labels,
           prop.chisq = FALSE, prop.t = FALSE, prop.r = FALSE,
           dnn = c('predicted', 'actual'))
```

```
##
##
##    Cell Contents
## |-------------------------|
## |                       N |
## |           N / Col Total |
## |-------------------------|
##
##
## Total Observations in Table:  1390
##
##
##              | actual
##    predicted |       ham |      spam | Row Total |
## -------------|-----------|-----------|-----------|
##          ham |      1201 |        30 |      1231 |
##              |     0.995 |     0.164 |           |
## -------------|-----------|-----------|-----------|
##         spam |         6 |       153 |       159 |
##              |     0.005 |     0.836 |           |
## -------------|-----------|-----------|-----------|
## Column Total |      1207 |       183 |      1390 |
##              |     0.868 |     0.132 |           |
## -------------|-----------|-----------|-----------|
##
##
```

Step 5: Improving model performance —-

```
sms_classifier2 <- naiveBayes(sms_train, sms_train_labels, laplace = 1)
sms_test_pred2 <- predict(sms_classifier2, sms_test)
CrossTable(sms_test_pred2, sms_test_labels,
           prop.chisq = FALSE, prop.t = FALSE, prop.r = FALSE,
           dnn = c('predicted', 'actual'))
```

```
##
```

```
##
##    Cell Contents
## |-------------------------|
## |                       N |
## |           N / Col Total |
## |-------------------------|
##
##
## Total Observations in Table:  1390
##
##
##              | actual
##    predicted |       ham |      spam | Row Total |
## -------------|-----------|-----------|-----------|
##          ham |      1202 |        28 |      1230 |
##              |     0.996 |     0.153 |           |
## -------------|-----------|-----------|-----------|
##         spam |         5 |       155 |       160 |
##              |     0.004 |     0.847 |           |
## -------------|-----------|-----------|-----------|
## Column Total |      1207 |       183 |      1390 |
##              |     0.868 |     0.132 |           |
## -------------|-----------|-----------|-----------|
##
##
```