

## 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://cox.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
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
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
as.character(sms_corpus[[1]])

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

# 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"
as.character(sms_corpus_clean[[1]])

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

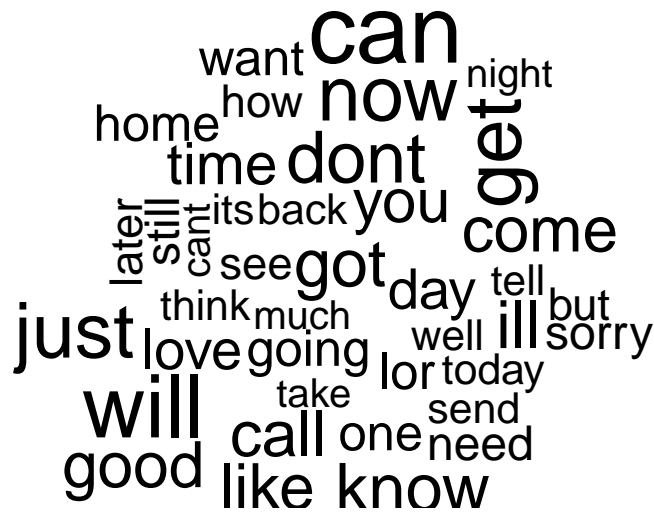
# word cloud visualization
library(wordcloud)

## Loading required package: RColorBrewer
wordcloud(sms_corpus_clean, min.freq = 50, random.order = FALSE)

```



```
## Warning in tm_map.SimpleCorpus(corpus, tm::removePunctuation): transformation
## drops documents
```



```
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"	"httpwwurawinnercom"	"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"	"rppli"	"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"	"unsubscribe"

```
## [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 |      |
## -----|-----|-----|-----|
##
##
```