Predictive Keyboard - Reproducible Report

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Friday, October 10, 2014

Modeling the Predictive Keyboard

Problem statement

This document describes the steps I took for building the model for the project. The **main requirement** of this project is **"PREDICTIVE KEYBOARD: ... use the knowledge you gained in data products to build a predictive text product..."**. Basically, based on a pre-constructed predictive model and the current text written in a simulated mobile input box, the *predictive keyboard* should propose believable *following* words. The user can choose (if the prediction does suggest a good word) a word from the choices, and add it to the text already put in.

Deliverables for the project:

- A predictive text model to test on a real data set (this is a set of data.tables in R, which store the N-Grams analysis results).
- A reproducible R markdown document describing your model building process (this document)
- A data product built with Shiny or Yhat to demonstrate the use of your product (https://spopa74.shinyapps.io/PredictiveKeyboard/)

What do we have

- For data, we start with a set of texts (blogs, tweets, news) collected from HC Corpora (www.corpora.heliohost.org).
- For software and libraries, I'll use R, tm library (text mining), RWeka (R library for accessing Weka algorithms), data.table library (for fast data manipulation). A quick check with the files reveals they are somewhat big files:

```
  lines       words     file
...
 899288    37334690    .//en_US/en_US.blogs.txt
1010242    34372720    .//en_US/en_US.news.txt
2360148    30374206    .//en_US/en_US.twitter.txt
...
```

The workflow

As a general approach, I'll follow these steps:

Initial data manipulation

1. Remove profanities from files, clean them of numbers and dates and punctuation marks. Save the files somewhere else.

- A new set of files in a folder called **1__clean**, called "clean__en__US.blogs.txt", etc.

- At same time, remove numbers, dates, most punctuation, and lower case everything (prepare for N-grams analysis).

2. Break the files, get a training corpus, a test corpus, and a smaller corpus for a possible cross-validation step.

- A new set of files, in folders **2_train**, **2_test**, **2_cross**. The sizes will follow the percentages 70% for training, 20% for testing, 10% for cross validation.
- The process of splitting will be a simple one, break the files in somewhat equal 10 sizes. Pick randomly from these pieces, 2 for testing and 1 for cross-validation, the rest will be the training set. In this case I think this method will be enough, meaning that the collection of blogs/news/tweets is already pretty mixed, more like a "cluster" than a "stratum". Picking "clusters" (chunks) from files will keep the variability of the possible features constant (and high).

Create simple models

3. Get a language model based on the training corpus. Create 1-, 2-, 3-, 4-, 5-grams. Check what's the distribution of frequencies (at some point the difference between frequencies will probably plateau, meaning that the N-grams will be unique, so no decision power at that point). There will be a set of files, in the folders *3_grams* (with the basic N-gram frequencies) and *4_models* (which contains a set of files for each N-grams, including an index of words, a vector of frequencies, and pointers towards the N-1 and 1-gram associated, as "prior" and "posterior").
4. Measure the accuracy of the model on the *test* corpus.

Improve on the model

5. Get a model based on back-off. Get a measure of accuracy on the test corpus.

Draw conclusion
Create a data product

Initial data manipulation

I'll start with cleaning the files of profanities, transforming them into a version easy to analyze from a N-Gram model point of view. The dates, numbers, punctuation will be removed, the profanities replaced with "(…)". I used the list at https://github.com/shutterstock/List-of-Dirty-Naughty-Obscene-and-Otherwise-Bad-Words/blob/master/en (a simplified subset of it). I used simple replacement instead of regular expression matching, for two reasons. First, the regular expressions matching will still be prone to errors (" *uck" or similar will also filter "duck"). Second, the straight replacement will be much faster. Used the RWeka AlphabeticTokenizer, for simplicity.

```
library(stringi)
library(RWeka)

## Java stuff
Sys.setenv(JAVA_HOME="") ## ugly error without this
options(java.parameters="-Xmx14g")  ## give Weka as much memory as possible

## function will parse a file and will write clean lines of that file in other file.
## e.g. A call like cleanFile("meh.txt", "clean") will create the folder "clean" and inside
## a files - clean_meh.txt etc. This should not contain profanities (as defined above).
```

```
## NOTE - please careful with the param, the function doesn't check them at all.
cleanFile <- function(fileInput, folderOutput) {
  if (!file.exists(folderOutput)){
    ## create the folder if it doesn't exist
    dir.create(folderOutput)
  }
  ## get the lines from the file.
  input <- file(fileInput, "rb", encoding = "UTF-8")
  lines <- readLines(input, skipNul = TRUE, encoding = "UTF-8")
  close(input)
  ## open a file for writing
  output <- file(paste(folderOutput, "/clean_", fileInput, sep=""), "w", encoding = "UTF-8")
  for (line in lines){
    line <- iconv(line, to = "UTF-8")
    ## readlines, clean them, write them in the new file.
    cleanLine <- removeProfanities(line)
    writeLines(text = cleanLine, con = output)
  }
  close(output)
}

## list of profanities, reduced here for readability. The actual list used is much longer.
## the list in the actual code does contain the actual profanities, shortened here.
profanities <- c("acroto...", "an..", "ana...", "ars...") ## etc

## function, will remove profanities from a line and will return the line with no punctuation,
removeProfanities <- function(line) {
  tokens <- AlphabeticTokenizer(line)
  newline <- ""
  for (token in unlist(tokens))
    if (token %in% profanities) newline <- paste(newline, "(...)")
    else newline <- paste(newline, stri_trans_tolower(token), sep=" ")
  return(newline)
}
```

After running the code above on ALL files, I get in the folder 2_clean, the cleaned version of the initial files. I used the Unix split command (*split -l*) to break the files into 10 chunks each, approximately equal sizes (based on the number of lines of each file - Unix *wc -l* command). I picked at random 1 file for cross training, 2 for testing, 7 for training, for each of the tweets/blogs/news. Moved them into different folders (2_train for training set, 2_test for testing set). Now the data is ready for analysis.

Create simple models

At this point I want to create the N-Grams (1 to 5). I'll save the results in a different folder, where I'll start building the model. Using tm and RWeka, the code will look like (do this for all of the 1 to 5-Grams):

```
## Java stuff
Sys.setenv(JAVA_HOME="")
options(java.parameters="-Xmx14g")
```

```r
## create a tokenizer in RWeka, for this example do only the 5-Grams
tokenizer <- function(x) NGramTokenizer(x, Weka_control(min = 5, max = 5))
## load a corpus from a folder
en_texts <- VCorpus(DirSource(directory="data/en_US/2_train", encoding="UTF-8"),
                    readerControl=list(language="en"))
## options(mc.cores=1)
## create a term document matrix, with the frequencies
tdm <- TermDocumentMatrix(en_texts, control=list(tokenizer=tokenizer))

## process the TDM
tdmMatrix <- as.matrix(tdm)

## get the sums over rows, sort the grams decreasingly by frequency
tf1grams <- rowSums(tdmMatrix)
tf1sorted <- sort(tf1grams, decreasing = TRUE)

## save the vector, has as element names the N-grams (.tf stands for term frequencies)
save(tf1grams, file="3_model/5Grams.tf")
save(tf1sorted, file="3_model/5Sorted.tf")
```

Note: loading in parallel on RWeka/MacOS TermDocumentMatrix crashes with some obscure errors. Suggestion to use option mc.cores=1.
Note: working on a "bigger" TermDocumentMatrix crashes the JVM behind RWeka, OutOfMemory. Suggestion to use option java.parameters="-Xmx14g" (heap size up to 14G)
Note: rJava library has problems if the environment variable JAVA_HOME is set. So unset it before loading rJava or RWeka (Sys.setenv(JAVA_HOME="“"))

Some stats with regards to time required to analyze the whole corpus (English):

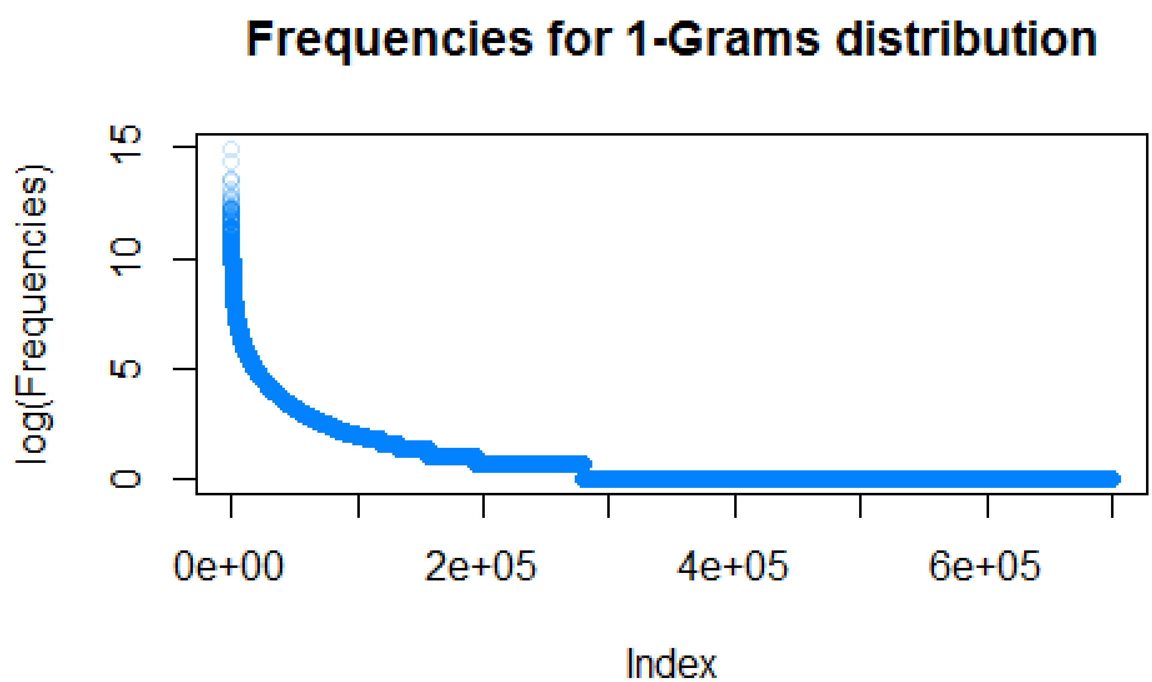
N-grams	User / System / Elapsed
1-Gram	773.86 / 1.77 / 775.69
2-Gram	916.21 / 5.79 / 902.12
3-Gram	2179.20 / 8.42 / 2153.49
4-Gram	2999.19 / 8.60 / 2969.92
5-Gram	3285.18 / 8.86 / 3258.52

With the sorted term/frequencies, I can look at some basic statistics for the N-Grams.

1. 1-Grams:
   - Total different: ~443,000
   - Highest frequency: ~3.3 millions
   - Number of 1's (frequency == 1): ~229,000
   - 6 Most used: *the*, *to*, *and*, *a*, *i*, *of*, *in*, *it*, *that*
2. 2-Grams:
   - Total different: ~10 millions
   - Highest frequency: ~300,000
   - Number of 1's (frequency == 1): ~7.1 millions
   - 6 Most used: *of the*, *in the*, *it's*, *i'm*, *to the*, *for the*

3. 3-Grams:
    - Total different: ~32.7 millions
    - Highest frequency: ~40,000
    - Number of 1's (frequency == 1): ~27 millions
    - 6 Most used: *i don't*, *one of the*, *a lot of*, *it's a*, *i can't*, *thanks for the*
4. 4-Grams:
    - Total different: ~50 millions
    - Highest frequency: 7898
    - Number of 1's (frequency == 1): ~45.7 millions
    - 6 Most used: *i don't know*, *i'm going to*, *can't wait to*, *the end of the*, *I don't think*, *don't want to*
5. 5-Grams:
    - Total different: ~55.7 millions
    - Highest frequency: 2630
    - Number of 1's (frequency == 1): 53.7 millions (most of them are encountered only once)
    - 6 Most used: *at the end of the*, *i don't want to*, *can't wait to see*, *it's going to be*, *i can't wait to*, *don't know that*

As for a plot, I'll put just the 1-Grams plot (logarithm so I can see the "elbow"). The plots for the rest of the N-Grams will look VERY SIMILAR (except they have lower and lower starting frequencies, and longer and longer tails to the right - meaning more and more Grams with very low counts).



With above data, one could draw the conclusion that starting with a frequency sorted dictionary with the 1-Grams collected, the quantiles for 0.5, 0.9 and 0.99 (See the *calculateQuantile* function underneath) are: **107 (high frequency) words to cover 50% of the word instances (in this case ~400,000), 6363 words to cover 90%, and 75607 to cover 99% of the word instances.**

```
## calculate quantiles, quick and dirty method. I have already a probability distribution,
## in a vector, sorted decreasingly by probability. Loop through the elements, stop when
## the desired quantile is achieved.
calculateQuantile <- function(distribution, quantile) {## careful, no param checking here.
  prob <- 0
  for (i in 1:length(distribution)) {
    prob <- prob + distribution[i]
    if (prob > quantile){
      print(prob)
      return(i)
}}}
```

At this point I have all of the 1- to 5-Grams constructed, saved separately as files in the folder 3_model. Some are >6GB when loaded in R, so playing with them becomes quickly a problem. I might need to filter all of the N-Grams, so they contain only the Grams with frequencies > 1 (exception the 1-Grams, I'll use those as dictionary).

In order to build the N-gram, I'll process the N-grams by breaking them in several different indexes. Each of the N-grams will be saved as intermediary files, as follows:

- a file for the "n-gram" to "index" mapping (since the words take most of the memory space, I'll keep them in only one place)
- a file for the "n-1 gram", the prior. This has the indexes in the N-1 "n-gram to index" mapping (calculated in a prev step)
- a file for the "1-gram" posterior. This has the indexes in the 1-gram "n-gram to index" mapping (calculated in first step)
- a file with the calculated probabilities, mapping N-gram to calculated probabilities (sorted decreasingly by probability).
- PUT ALL OF THEM IN A DATA.TABLE (gives us keys and faster searches)

So, the code underneath does:

- load the "term frequency" file, sorted decreasingly in a previous step by frequency
- extract the "N-gram to index" vector, save
- extract the priors (N-1-Grams), posteriors (1-Grams), save
- calculate the conditional probabilities for the N-Grams | N-1-Grams, using MLE
  - P(wn|w1w2..wn-1) = C(w1w2…wn) / C(w1w2..wn-1)
- with all above, create a data.table, work on the data.table from here on (easy to order, etc)

```
library(data.table)

##..... code removed, left only the 5-Grams.

## load the 5-grams
load("3_grams/5Sorted.tf")  ## loads the sorted N-Gram to counts map
len5 <-length(tf5Sorted)
indexes5Gram <- 1:len5
names(indexes5Gram) <- names(tf5Sorted)
save(indexes5Gram, file="5_models/indexes5Gram.tf") ## MAPPING N-GRAM TO INDEX

## find prior, posterior
```

```
allNames5 <- names(tf5Sorted)
freq5Gram <- unname(tf5Sorted)
save(freq5Gram, file="5_models/freq5Gram.tf")       ## MAPPING INDEX TO COUNTS
allNamesCollapsed5 <- paste(allNames5, collapse = " ")
allNamesVector5 <- unlist(strsplit(allNamesCollapsed5, split = " "))
prior5_1 <- allNamesVector5[seq.int(1, len5 * 5, 5)]
prior5_2 <- allNamesVector5[seq.int(2, len5 * 5, 5)]
prior5_3 <- allNamesVector5[seq.int(3, len5 * 5, 5)]
prior5_4 <- allNamesVector5[seq.int(4, len5 * 5, 5)]
post5 <- allNamesVector5[seq.int(5, len5 * 5, 5)]
prior5 <- paste(prior5_1, prior5_2, prior5_3, prior5_4, sep = " ")
prior5Ix <- indexes4Gram[prior5]
post5Ix <- indexes1Gram[post5]
save(prior5Ix, file="5_models/prior5Gram.tf")     ## MAPPING INDEX TO PRIOR
save(post5Ix, file="5_models/posterior5Gram.tf")  ## MAPPING INDEX TO POSTERIOR

## calculate probabilities for these, use the N-1 probability
prob5Gram <- vector(mode = "integer", length = length(freq5Gram))
for(i in 1:length(indexes5Gram))
  prob5Gram[i] <- (freq5Gram[i] / freq4Gram[prior5Ix[i]])
names(prob5Gram) <- names(indexes5Gram)
save(prob5Gram, file="5_models/prob5GramSimple.tf") ## MAPPING N-GRAM TO PROBABILITY

## put all together in a data.table
dt5Grams <- data.table(grams = names(indexes5Gram),
                       index = indexes5Gram,
                       frequency = freq5Gram,
                       prior = prior5Ix,
                       posterior = post5Ix,
                       probabilities = prob5Gram)
## most of the searches and operations will be done on priors
save(dt5Grams, file="5_models/dt5Gram.dt")

## sort by prior (increasing) and probability (decreasing)
dt5SortedPriorProb <- dt5Gram[order(prior, -probabilities)]
save(dt5SortedPriorProb, file="5_models/dt5SortedPriorProb.dt")
```

To repeat, at this point I have structures (data.tables) which represent N-grams with:

- indexes
- frequencies
- priors
- posteriors
- probabilities

With the above, I can create a new structure for each N-Grams, which is a mapping "prior to best choices for posterior". I'll use the data.tables obtained above.

```
## keep only 3 posterior choices for each prior, the ones with the higher probability
dt5Priors <- dt5SortedPriorProb$prior
dt5Keep <- cmpMarkFirstN(dt5Priors, 3)                ## <- cmpMarkFirstN is a compiled function
dt5SortedPriorProb$keep <- dt5Keep                    ## <- add the keep vector as a column
```

```
dt5SortedFirst3 <- dt5SortedPriorProb[keep == TRUE]  ## <- filter based on keep
dt5GramFinal <- dt5SortedFirst3                      ## <- this is the structure I'll use for the matchi
save(dt5GramFinal, file="4_models/dt5GramFinal.dt")  ## <- save in a file
```

This structure has only the 3 best choices for *following word*, for each prior, in each N-Gram set. So it's a small set. I'll use these to start the basic N-Gram tests.

Some tests with the N-gram models. For these tests, I'll use 2 *accuracy measurements*:

- First, *estimate next word*. Loop through the test corpus, for each word use the model to estimate next word. Use the model to return ONLY the highest probability one. Compare the model given answer with the actual word. Count the hits/misses, get accuracy.
- Second, *estimate next possible 3 words*. This is different, in the way that a software keyboard could give the user several options in regards to the next possible word. In my case, I'll use 3 options. With this in mind, the process will be: parse the testing corpus, and for each word use the model to return 3 possibilities. If the actual next word is in those 3, consider it a "hit". Count hits and misses, calculate accuracy.

Not going to use perplexity measurements. While in general, would give a somewhat accurate measure of "how probable is a certain sentence" (using 5-Grams in this model), would not measure IF the keyboard would be actually useful. Our interest here is to give the user "good options", not necessarily a "high probability of sentence". It's very possible that a model with a lower perplexity would give NO useful predictions to the user. Otherwise, should be trivial to calculate following the steps:

- loop through the test text.
- for each word calculate the probability of that word in the context (5-Grams if I have 4 previous words, etc).
- log the probability, add it and then calculate the mean - this would be the perplexity.

So, with the accuracy measurements described above, I can go on and run a test against EACH of the N-Grams (these are just basic tests). The code is similar to the following:

```
## Run the 2-Gram Model. Parameters:
## data - vector of words to be tested with
## n - number of possibilities to check
## models - the data.tables with the 2-Grams (prior and posterior,
## 3 options for each prior), and the dictionary
run2GramModel <- function(data, n, model2, model1) {

  ## if interested in only 1 possibility, filter the model2
  if (n == 1) model2 <- model2[!duplicated(model2$prior),]

  ## index model1 by grams
  setkey(model2, grams)
  setkey(model1, grams)
  ## to return:
  hits <- 0
  misses <- 0
  notin <- 0
  ## loop through the test data
  for(i in 1:(length(data)-1)) {
    ## get the current and next words
```

```
    currentWord <- data[i]
    nextWord <- data[i+1]
    ## create a bigram
    g2Gram <- paste(currentWord, nextWord)
    ## check if we have it in our 2-Gram model
    dt <- model2[grams == g2Gram]
    ## interpret
    if (length(dt$index) > 0)
      hits <- hits + 1
    else {
      ## why wasn't found? Prior, or posterior, not in the models?
      ## find the prior
      mdt <- model1[grams == currentWord]
      if (length(mdt$index) == 0) notin <- notin + 1
      else misses <- misses + 1
    }
  }
  return(c("hits" = hits, "misses" = misses, "notin" = notin))
}
```

I arrive to the following results on the test text (**not involved** in training - about 350,000 words ~ 2MB, taken from a random piece of blogs data):
NOTE: these tests are done with a *strictly* N-gram model, not with a combination of models.

```
Type of test | Accuracy
```

1-Gram 1 choice	5.5% (basically this model just counts the "the" words in the test vector)
1-Gram 3 choices	8% (this time counts "the", "to", "and")
2-Gram 1 choice	15.5%
2-Gram 3 choices	23% (~1200 priors not in model)
3-Gram 1 choice	8% (going down from 2-Grams, ~250000 priors not in model)
3-Gram 3 choices	24% (going up from -Grams, ~200000 priors not in model)
4-Gram 1 choice	8% (same as with only 3)
4-Gram 3 choices	16% (worse than with only 3)
5-Gram 1 choice	2.5% (a lot worse)
5-Gram 3 choices	4% (a lot worse)

Obviously, the accuracy is expected to start going down further (for higher N-Grams, the probability of getting an unknown word will go up with the N).

Improve on the model

At this point it becomes obvious that the basic N-Gram model is not enough, we miss enough of the common groups. So a better model is a backoff model, very simple one, a *trivial* back-off. Check for 5-Grams, if found count as hit, if not, check for 4-Grams (4 last words *typed*), etc. If not found anywhere, is a miss (is a little more complicated than this, but not a lot more). Ran on the same test file, the results are obviously better.

```
Type of test | Accuracy
```

Trivial backoff 1 choice	26% (not bad for a 1 choice model), ~800 not in dictionary
Trivial backoff 3 choice	37% (for some reason I expected better)

Now, a big issue is the size of the model: 400,000 1-Grams, 750,000 2-Grams, 14 million 3-Grams, 40 million 4-Grams, over 50 million 5-Grams (this was artificially truncated). This size is already into 16GB RAM, which puts stress on the machine. Growing the model even larger would force the machine to swap, which would make the processing significantly longer.
I'll try to reduce the size, by trimming the N-grams. I'll use a strategy of removing the 1 time found 1-Grams (misspellings, ad-hoc words or foreing languages), then going through the 2- to 5-Grams and eliminating the ones which correspond to N-1-Grams eliminated earlier (go through the 2-Grams and eliminate the ones with the prior or posterior in the eliminated 1-Grams, then go through the 3-Grams and eliminate.. etc).
With the trimmed data, I get the reduction in sizes:

N-Gram	Size of data
1-Grams	~200,000 (instead of 400,000)
2-Grams	~225,000 (instead of 10 million)
3-Grams	~2 million (instead of 15 million)
4-Grams	~2.5 million (instead of 40 million)
5-Grams	<2 million (instead of 10 million)

. . . and the accuracies measurements.

```
Type of test | Accuracy
```

Trivial backoff 1 choice	24.5% (slightly worse than above)
Trivial backoff 3 choice	35% (slightly worse as well)

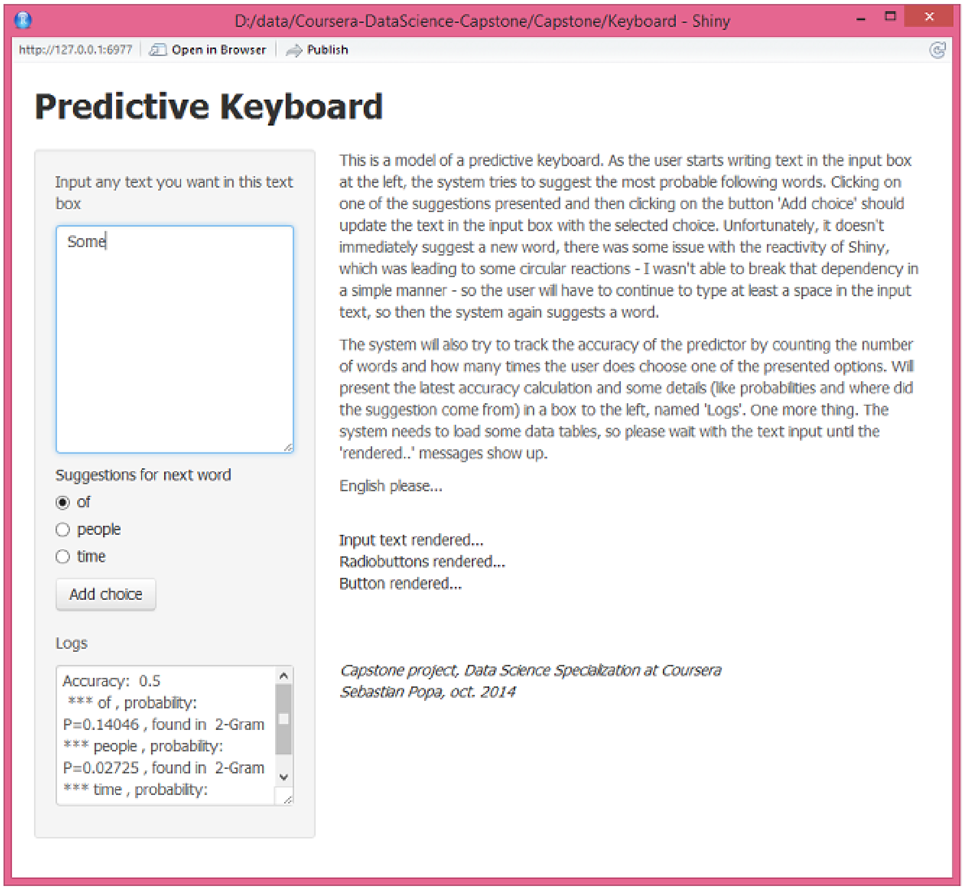
So the drastic reduction in dimension resulted in a small reduction in accuracy.

One could calculate a confidence interval for the proportions I obtained (binomial distribution for a sample). Taking for example the last result, 35% for a 300,000 words corpus (take the small text I tested with, not the large one), I get the following:

```
* P = 0.35
* N = 300,000
* the confidence interval is P_estimated +/- z * sqrt(P_estimated * (1 - P_estimated) / N)
* this gets me, for a 95% confidence level (z = 1.96), to the **confidence interval = (34.8%, 35.1%)**
```

Data Product

With some methods which use the reduced model above, I created a Shiny app - https://spopa74.shinyapps.io/PredictiveKeyboard/ The app simulates an input into some mobile application. The application will let the user input text, and will suggest possible next words to the words put in. The user can click on the respective suggestions, and a measure of accuracy (how many times clicked vs. total number of words in text) will be measured. Include an image..



What can be improved upon?

There are many ways in which this model can be improved. Probably the best one would be letting the application LEARN from the user. For this, a separate set of N-Grams could be kept and analyzed, the model could be tested against the actual user input (learn for a couple of days, test for a couple more) and it could be compared with the generic model. An interpolation model between the two could be imagined.

References

- [1] Natural Language Processing - Dan Jurafsky, Christopher Manning - https://class.coursera.org/nlp/lecture
- [2] Mining the Web, discovering knowledge from hypertext data - Soumen Chakrabarti
- [3] Wikipedia
- [4] Stemming algorithms, stopwords and resources at http://snowball.tartarus.org