# Coursera Capstone Project: Word prediction

#### David Pham

September 19, 2014

### 1 Introduction

Within the data specialization track offered by Coursera, instructors challenged us, the students, to produce a statistical data-product using Rable to predict the end of sentence of sequence of words. This has extremely useful application in text input on smartphones as the new feature of iOS 8 allowing for alternative keyboards demonstrates. In this report, a summary of the data, presenting the main challenge of the project, and main methods will be introduced.

#### 2 Data

Although other languages (among German and Russian) were available, only English has been chosen for this study. Reasons for this choice are that there are already several challenge and choice that need to be addressed before going in more difficult territories.

Three types of raw texts (english news, blogs entries, users' tweets) have been made available to download (about 500mb of data). Each observation being separated by an end of line.

Thanks to the huge number of observations per text, number of words per observation after a log-transformation are well summarized by gaussian distribution.

Quantitatively speaking, one observes that number of words on blogs entries have a bigger variance than english news, although they have approximately the same number of words in mean to the contrary the *twitter* dataset, with a lot less number of words. Concerning the type of text, preliminary exploratory analysis did not reveal anything in particular, they seems to display the same level of english complexity.

One remarks that although these data sets are labeled English, there have a lot of uncommon (non-ascii) characters (Japanese, Korean and Chinese as well) which makes the analysis harder. Note that as the data are raw, spelling mistakes are still in the text, adding noise (or information depending on which point of view).

### 3 Methodology

**Data cleaning** The following procedures have performed:

- Removal of bad words using the dictionary shared with the other students;
- Almost all punctuation has been removed: "-" and "' " has been kept as they have a different meaning in English;
- As English is the main language of study, all letters have been transformed to lower cases;
- Numbers have been removed;
- White space have stripped from observations;
- All non-ascii character have been deleted.

1 1010242 31 19.27 184 117.13 news   2 899288 29 32.62 158 180.88 blogs   3 2360148 12 7.41 65 45.96 twitte		messages	med.words	mad.words	med.chars	mad.chars	dataset
	1	1010242	31	19.27	184	117.13	news
3 2360148 12 7.41 65 45.96 twitte	2	899288	29	32.62	158	180.88	blogs
	3	2360148	12	7.41	65	45.96	twitter

**Table 1:** Summary statistics of the data sets, based on a sample of  $10^5$  observations for each text.

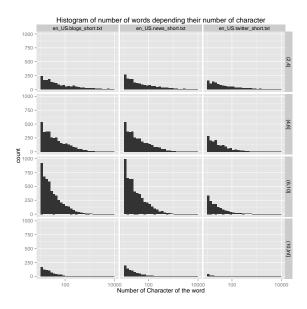


Figure 1: Count of number of words by text type and number of characters

**Technological choices** To lead the project, Rhas been chosen/imposed as the default choice. Several packages will be useful:

tm An environment to clean and manage text file data

tau Library allowing to make really fast text counting for natural language processing technics.

Matrix Sparse matrix data structure

ggplot2 Data visualization

parallel Speed improvement;

data.table Data structure mimicking the data.frame, but with thousand times faster performance.

The main problem with using Ris it does not provide a convenient dictionary structure as python for example. One could certainly use the environment data structure or even lists, however looking up demand a huge amount of time to perform the analysis.

# 4 Learning and Prediction Methods

The main challenge are the following:

- What data structure to use in order to summarize the data?
- How to predict words we did not yet observe?
- How complex will the model be? What are the trade-off between biais and variance?
- What is the performance in real time situation of the model?

To begin with, models with tri- and bigram will be used (sequence of three and two words). Good-Turing and Back-off techniques will used to adjust for non observed realizations. Good-Turing correction basically corrects the observation biais while the Back-off algorithm provides a smart way to smooth the data to account for unseen observation. These steps require a lot of look-up operations which are really slow in R, making one of the bottleneck of the learning process.

A first result will provide a static model (the model will learn only once and be run for a certain amount of time to see how well it performs.)

#### 5 Conclusion

As the structure of the data is quite uncommon for a statistician, the challenge offered by this project is tremendous. Even though we are at the genesis of the project, we have a lot of hope that the products of our analysis will be displayable online and testable by other people. Finally, let us not that R is not the most appropriate language to create a good word prediction device.