Mining Google+ : TF-IDF and Bigram Analysis

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by

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ALLAHABAD
November, 2015

UNDERTAKING

We declare that the work presented in this thesis titled "*Mining Google+ : TF-IDF and Bigram Analysis*", submitted to the Computer Science and Engineering Department, Motilal Nehru National Institute of Technology, Allahabad, for the award of the ***Bachelor of Technology*** degree in ***Computer Science & Engineering***, is our original work. We have not plagiarized or submitted the same work for the award of any other degree. In case this undertaking is found incorrect, we accept that our degree may be unconditionally withdrawn.

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CERTIFICATE

Certified that the work contained in the thesis titled "*Mining Google+ : TF-IDF and Bigram Analysis*", by

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has been carried out under my supervision and that this work has not been submitted elsewhere for a degree.

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PREFACE

The Google API Console provides a means of registering an application (called a project in the Google API Console) to get OAuth credentials but also exposes an API key that you can use for simple API access. Our Project uses this API key to extract data from Google+ .

Google+ initially serves as our primary source of data because its inherently social, features content thats often expressed as longer-form notes that resemble blog entries, and is now an established staple in the social web.

Our project makes sense of textual information in documents by introducing information retrieval (IR) theory fundamentals such as TF-IDF and collocation detection. The analysis on TF-IDF and scoring methods has led us to propose our own implementation of TF-IDF that will consider order of terms in bigram and our own scoring method to rank bigrams.

ACKNOWLEDGEMENT

It is a great pleasure to thank the giants on whose shoulders we stand. First of all, we would like to thank our supervisor Dr. Ranvijay. This project would not have come into being without his kind guidance. He has been a great mentor and the best advisor we could ever have. His advice, encouragement and critique are sources of innovative ideas, inspiration, and causes behind this successful project. The confidence shown by him was the biggest source of inspiration for us. We are highly obliged to all the faculty members of Computer Science and Engineering Department for their support and encouragement. We also thank to our Department Head, Dr. R. S. Yadav for providing excellent facilities and relaxations without which this work was not easy.

Contents

Chapter 1

INTRODUCTION

This project presents the details of implementation of finding collocations in documents and applying Term Frequency Inverse Document Frequency to rank documents for each collocation. Our Thesis basically revolves around the existing implementation of TF-IDF for bigrams and Scoring Methods to Rank Bigrams. It discusses about the drawbacks in TF-IDF , our modified implementation of TF-IDF and proposal of a scoring method to rank bigrams. It also discusses about the applications of these in various fields.

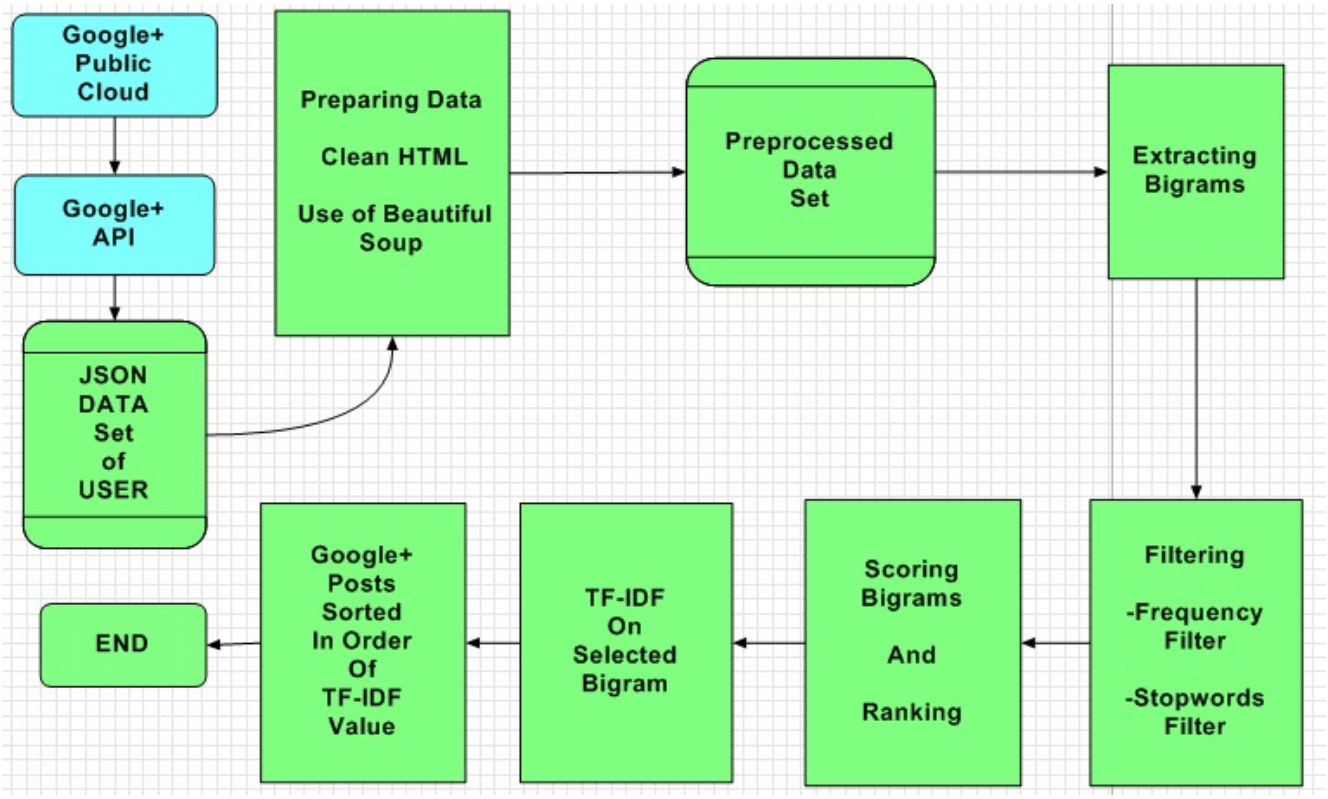
1.1 Motivation

Rapid advances in data collection and storage technology have enabled organizations to accumulate vast amounts of data. However, extracting useful information has proven extremely challenging. Mining is a technology that blends traditional data analysis methods with sophisticated algorithms for processing large volumes of data. It has also opened up exciting opportunities for exploring and analyzing new types of data and for analyzing old types of data in new ways.
From startups to the Fortune 500, smart companies are getting on data-driven insight, seizing the opportunities of other technologies.

1.2 Objective

The posts here in google+ resemble blog entries. We aim to get relevant reviews of a search query. Additionally we can find out the things which any particular user or other users he may be connected with is talking about . We aim to build an interface that provides user the option to query any person by name or google plus Id , the system will display the N topmost bigrams related to that person.Moreover, the user also has an option of choose one of the selected bigram and find out the posts which contains the bigram.
We aim to remove the drawbacks in the existing TF-IDF and contribute to bigram scoring methods by proposing a new scoring method.

1.3 Project Outline



Chapter 2

DESCRIPTION

In this chapter we describe about all the concepts used in this project.

2.1 Google+ API

Anyone with a Gmail account can trivially create a Google+ account and start collaborating with friends. From standpoint of product, Google+ has evolved rapidly and used some of the most compelling features of existing social network platforms. In Google+ API parlance, social interactions are framed in terms of people, activities, comments, and moments[7].

People : Google+ search API provides the facility to search any user on Google+. Either the username or the Google+ ID stripped out of URL can be used to explore any profile.

Activity : Activities are the things that people do on Google+. An activity is essentially a note and can be as long or short as the author likes: it can be as long as a blog post, or it can be devoid of any real textual meaning.

Comments : Through comments users of Google+ interact with each other. Simple analysis of comments on Google+ would potentially reveal a lot of insights into a persons social circles or the virality of content.

2.2 Introduction of TF -IDF

TF-IDF, short for Term FrequencyInverse Document Frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus. It is often used as a weighting factor in information retrieval and text mining. The tf-idf value increases proportionally to the number of times a word appears in the document, but is offset by the frequency of the word in the corpus, which helps to adjust for the fact that some words appear more frequently in general.

Term Frequency:
A terms frequency could simply be represented as the number of times it occurs in the text, but it is more commonly the case that you normalize it by taking into account the total number of terms in the text, so that the overall score accounts for document length relative to a terms frequency.

TF(term) = number of occurrences of term in a document / length of document

Inverse Document Frequency: The inverse document frequency is a measure of how much information the word provides, that is, whether the term is common or rare across all documents . In this calculation stop-words are not taken into account. IDF score for a term is the logarithm of a quotient that is defined by the number of documents in the corpus divided by the number of texts in the corpus that contain the term.

$$\mathbf{IDF(term) = 1 + Log(N/\ M)}$$

N=Number of documents in overall corpus
M=Number of documents that contain that term
A term frequency score is calculated on a per-document basis, an inverse document frequency score is computed on the basis of the entire corpus.

TF-IDF FORMULA : TF-IDF = tf * idf
To compute the TF-IDF of a Bigram(token1,token2) ,the TF-IDF value of each token is computed and then values of both of them are summed up.

2.3 Bi-Grams and N-Grams

Bigrams of a sentence are the two words that appear together in a text/corpus . Similarly n-grams are the n words occurring in a text together in a fixed order[7].

2.4 Collocations

A collocation is a sequence of words or terms that co-occur more often than would be expected by chance . We find collocations using collocation finder functionality in NLTK library[7].

2.5 Scoring Methods

There are certain methods that are used to give scores to all bigrams and then rank bigrams in order of their importance in the document. Evaluating and determining the best method to apply in any particular situation is often as much art as science. We discuss here few methods of scoring[5][4][6].

Raw frequency : As its name implies, raw frequency is the ratio expressing the frequency of a particular n-gram divided by the frequency of all n-grams. It is useful for examining the overall frequency of a particular collocation in a text.

Jaccard Index : The Jaccard Index is a ratio that measures the similarity between sets. As applied to collocations, it is defined as the frequency of a particular collocation divided by the total number of collocations that contain at least one term in the collocation of interest. It is useful for determining the likelihood of whether the given terms actually form a collocation, as well as ranking the likelihood of probable collocations. Using notation consistent with previous explanations, this formulation would be mathematically defined as:

$$\frac{freq(term1, term2)}{freq(term1, term2) + freq(\widetilde{term1}, term2) + freq(term1, \widetilde{term2})}$$

Dices coefficient : Dices coefficient is extremely similar to the Jaccard Index. The fundamental difference is that it weights agreements among the sets twice as heavily

as Jaccard. It is defined mathematically as:

$$\frac{2 * freq(term1, term2)}{freq(*, term2) + freq(term1, *)}$$

Mathematically, it can be shown fairly easily that:
Dice = 2 * Jaccard / 1 + Jaccard

Point Mutual Index :

An information-theoretic motivated measure for discovering interesting collocations is point-wise mutual information.

Let the total number of words in the document be 1000.Therefore the number of unigrams are 1000 and number of bigrams are (1000-1)=999. Let the bigram be (token1,token2) The probability of the unigrams are evaluated.

$$\mathbf{P1} = probability(token1) = \frac{frequencyoftoken1}{numberofunigrams}$$

$$\mathbf{P2} = probability(token2) = \frac{frequencyoftoken2}{totalnumberofunigrams}$$

$$\mathbf{P3} = probability(token1, token2) = \frac{frequencyof(token1, token2)}{totalnumberofbigrams}$$

$$\mathbf{PMI} = \frac{P3}{P1 * P2}$$

Since the evaluated value might be large hence we take the log of the evaluated value which is declared as the PMI.

2.6 Spearman's rank correlation coefficient or Spearman's rho

Spearman rank correlation is a non-parametric test that is used to measure the degree of association between two variables. It was developed by Spearman, thus it is called the Spearman rank correlation. Spearman rank correlation test does not assume any assumptions about the distribution of the data and is the appropriate correlation analysis when the variables are measured on a scale that is at least ordinal.

The following formula is used to calculate the Spearman rank correlation:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}.$$

Where:

P= Spearman rank correlation.

di= the difference between the ranks of corresponding values Xi and Yi.

n= number of value in each data set.

In statistics, the value of the correlation coefficient varies between +1 and -1. When the value of the correlation coefficient lies around 1, then it is said to be a perfect degree of association between the two variables. As the correlation coefficient value goes towards 0,the relationship between the two variables will be weaker.

Chapter 3

HYPOTHESIS

3.1 Problem Description

The problem we are trying to solve is that while TF-IDF is a powerful tool thats easy to use,it has a few important limitations that have been conveniently overlooked :

1. It treats a document as a bag of words, which means that the order of terms in both the document and the query itself does not matter.

   For example, querying for Green Mr. would return the same results as Mr. Green if we didnt implement logic to take the query term order into account or interpret the query as a phrase as opposed to a pair of independent terms. But obviously, the order in which terms appear is very important.

2. Even if one of the unigrams in the Bigram is not present in a post, yet that post will have a positive value of TF-IDF for that bigram.

3. In performing an n-gram analysis to account for collocations and term ordering,the existing TF-IDF still face the underlying issue that all tokens with the same text value mean the same thing

4. A homonym is a word that has identical spellings and pronunciations to another word but whose meaning is driven entirely by context, and any homonym of your choice is a counterexample. Homonyms such as book, match, cave, and

cool are a few examples that should illustrate the importance of context in determining the meaning of a word.

5. String comparisons are case-sensitive, so its important to normalize terms so that frequencies can be calculated as accurately as possible. However, blindly normalizing to lowercase can also complicate the situation since the case used in certain words and phrases can be important. For example- Mr. Green and Web 2.0 are two examples worth considering. In the case of Mr. Green, maintaining the title case in Green could potentially be advantageous since it could provide a useful clue to a query algorithm that this term is not referring to an adjective and is likely part of a noun phrase.

Apart from the above mentioned problems, evaluating the rank of collocations and determining the best scoring method to apply in any particular situation is often as much art as a science.

3.2 Proposed Solution

Proposed TF-IDF :
In the existing TF-IDF we sum up the individual TF-IDF of the terms.Hence the order of terms is not being preserved.So, in our proposed solution we have considered the bi-gram as a whole.
To calculate the TF of Bigram in a particular post/document, the steps are :

1. The number of occurrence of Bigram in a post is calculated.Let the count be t.

2. The total number of Bigrams in post will be total number of words - 1.Let this count be T1.

3. The number of bigrams which contains stopwords are removed.Let the count be T2.

4. The effective total number of bigrams in post = T1 - T2.

$$TF of the bigram = \frac{t}{T1 - T2}$$

To calculate the IDF of Bigram in a particular post/document, the steps are :

1. Calculate the number of posts in which the Bigram is present.Let the value be L1.
2. Calculate the total number of post, i.e the length of the corpus.Let the value be L2.
3. IDF of the bigram = 1 + Log(L1/L2)

The improved TF-IDF of the Bigram = Improved TF * IDF.
proposed method preserves the order of the term.

Proposed Scoring Method : This method gives more importance to those bigrams in which the occurring unigrams do not occur with any other bigram.
Let the bigram be (token1,token2)

$$Score = \frac{f(token1, token2)}{f(token1) * f(token1, \widetilde{token2}) + f(token2) * f(\widetilde{token1}, token2) + f(token1, token2)}$$

where
f(token1,token2) = frequency of the bigram
f(token1) = frequency of the unigram token1
f(token2) = frequency of the unigram token2
f(token1, $\widetilde{token2}$) = frequency of bigrams in which token1 appears without token2
f($\widetilde{token1}$, token2) = frequency of bigrams in which token2 appears without token1
Steps:

1. Calculate the bigram frequency f(token1,token2) and the the frequency of unigrams occurring in that bigram , i.e , f(token1) and f(token2).
2. To find number of occurrences of token1 as a bigram with any other token except token2 , i.e, f(token1, $\widetilde{token2}$) = f(token1) - f(token1,token2).
3. Similarly we evaluate f($\widetilde{token1}$,token2).

3.3 Working of Interface Implementing proposed method

INPUT :

1. The Google+ ID or the Google+ Username.
2. Maximum number of collocations required.
3. Number of topmost posts of interest.

OUTPUT :

1. Required collocations.
2. Topmost posts for selected collocation.

STEPS :

1. Click the Google+ label to enter the Google+ ID or the Google+ Username.
2. Enter the corresponding detail and Submit.
3. Now click on the Result G+ option to get the list of the users related to the query.
4. Select the desired Userid to mine.
5. Click on Mine this User to let the system collect the required data.
6. Click on Collocations to enter the number of collocations required.
7. Submit the number to get the desired collocations.
8. Click on List of Bigrams to get the bigrams ranked on the basis of scoring method.
9. Select the Bigram for which the corresponding posts need to be extracted.
10. The corresponding posts will be obtained.

3.4 Applications Of Proposed Method

The Modified TF-IDF as proposed by us can be used in :

1. Categorization applications to texts written in programming languages. Applying bigrams in this setup would lead to a significant success[3].
2. Feature wise Product Ranking from Reviews.

Implementation of Programming Language Classifier :

Training data
Set of files of each programming language

Testing data
Source code file to be classified.

Output
Type of Source code file.

Steps:

1. Build a python dictionary by traversing the training data keeping bigrams as key and the language to which it belongs as value.
2. Those Bigrams that occur in more than one language data set are discarded.
3. Traverse the testing code file and find out the bigrams in it.
4. The result is the language that has the maximum number of bigrams matched with the bigrams of the testing data.

Chapter 4

CONCLUSION AND FUTURE WORK

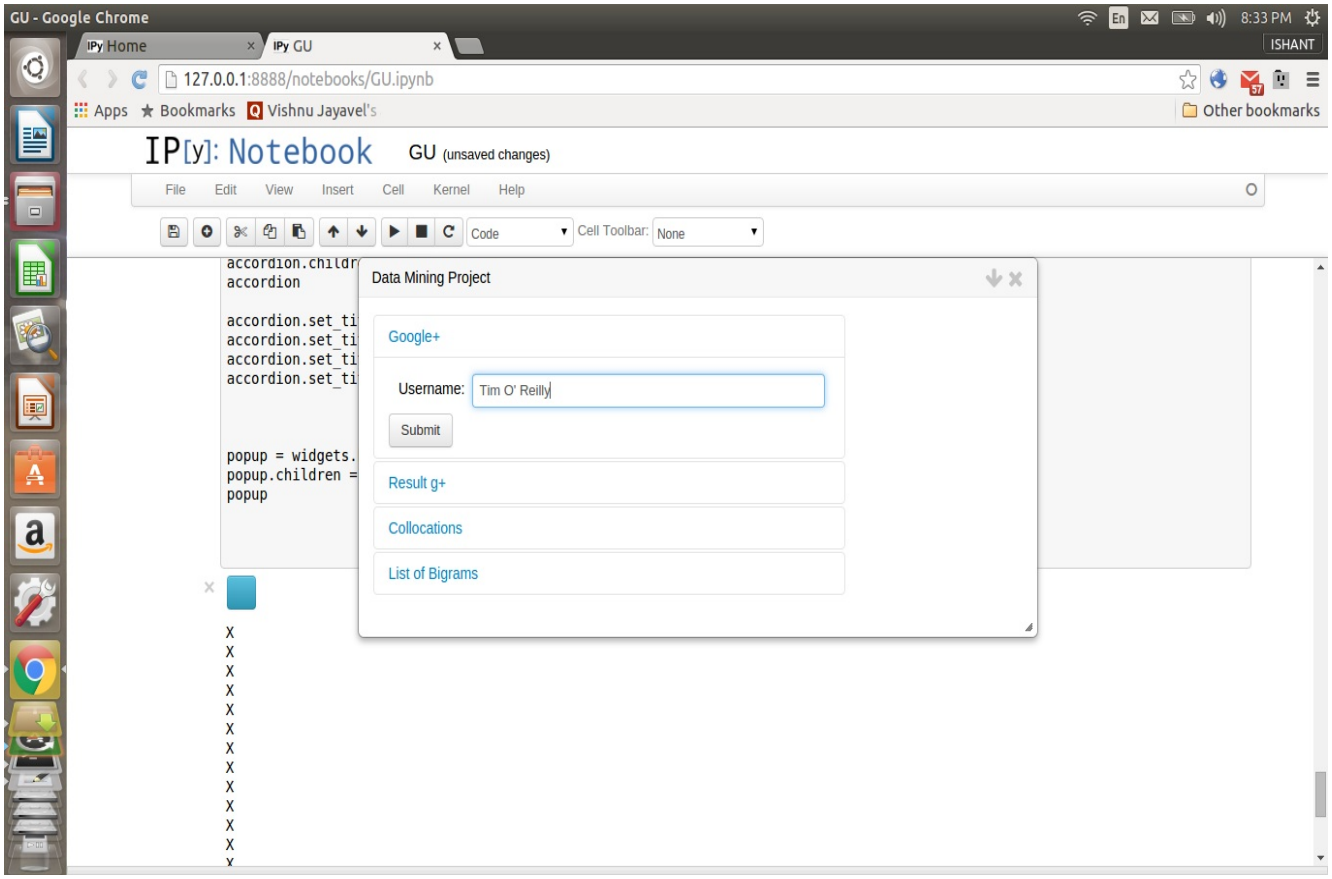
TF-IDF:
Since we have considered bigram itself while calculating the TF-IDF instead of unigrams , the TF-IDF value will be zero for posts that has a unigram but no relevant bigram. The query "Mr. Green" and "Green Mr." will be treated differently as order of terms in considered.
The Complexity of the proposed method is O(N),
where N= Total Corpus length.
Scoring Method Comparison with Existing Methods:

1. **Spearman correalaton coefficient with jaccard and dice is 0.796020318207**
2. **Spearman correalaton coefficient with pmi is 0.736470775601**

This project has a lot of future prospects. The TF-IDF can be further optimized to consider contextual meaning and case sensitivity by applying advanced parsing with NLP.

Chapter 5

SNAPSHOTS



[1] [2]

In [4]:
```
from IPython.core.display import HTML

html = []

for p in people_feed['items']:
    html += ['<p><img src="%s" /> %s: %s</p>' % \
             (p['image']['url'], p['id'], p['displayName'])]

HTML(''.join(html))
```

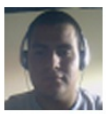
Out[4]:

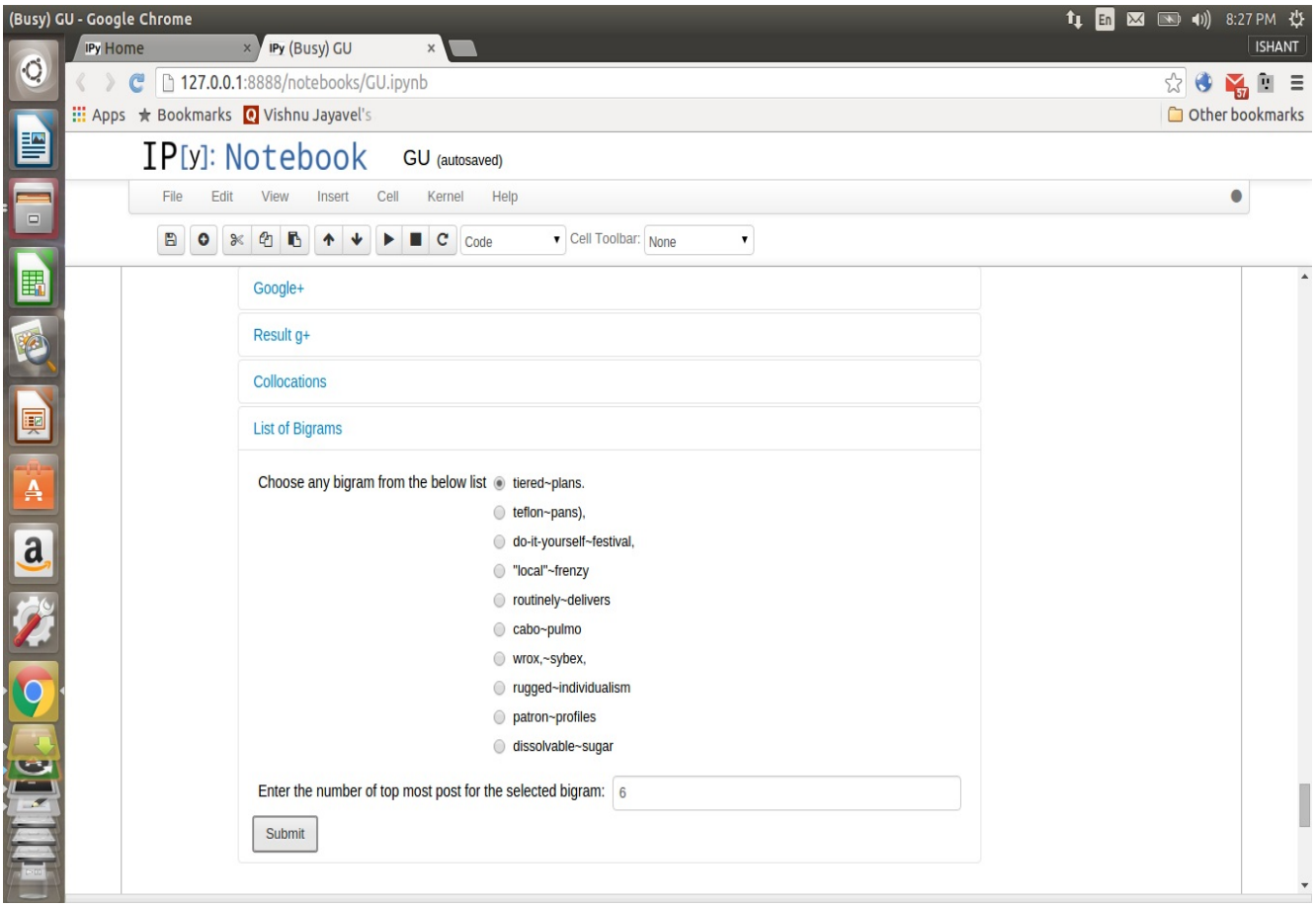

10703373124620068102 4: Tim O'Reilly


10741562989610870052 6: Timothy O'Reilly


11566571170551699336 9: Tim O'Reilly


10418940544237939636 9: Timothy O'Reilly


10299444709793247799 1: Timothy O'Reilly


(Busy) GU - Google Chrome
8:27 PM
ISHANT
IPy Home
IPy (Busy) GU
127.0.0.1:8888/notebooks/GU.ipynb
Apps
Bookmarks
Vishnu Jayavel's
Other bookmarks
IP[y]: Notebook
GU (autosaved)
File
Edit
View
Insert
Cell
Kernel
Help
Code
Cell Toolbar:
None
Google+
Result g+
Collocations
List of Bigrams
Choose any bigram from the below list
tiered~plans.
teflon~pans),
do-it-yourself~festival,
"local"~frenzy
routinely~delivers
cabo~pulmo
wrox,~sybex,
rugged~individualism
patron~profiles
dissolvable~sugar
Enter the number of top most post for the selected bigram:
6
Submit

[1] [2]

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