

Text mining

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curiositybits.cc

A couple of reminders...

1. Tutorial for W6 and W7 (submit your complete report before 11 PM, March 7th)
2. Assignment 2: Friday, March 8, 2019, 12:00 AM

Related:

https://curiositybits.shinyapps.io/PH_Tracker_dashboard/

Insights from text

IBM Watson

<https://personality-insights-demo.ng.bluemix.net>

Personality Portrait

28145 words analyzed: **Very Strong Analysis**

Summary

You are particular, explosive and expressive.

You are self-controlled: you have control over your desires, which are not particularly intense. You are adventurous: you are eager to experience new things. And you are dutiful: you take rules and obligations seriously, even when they're inconvenient.

Experiences that give a sense of efficiency hold some appeal to you.

You are relatively unconcerned with both taking pleasure in life and helping others. You prefer activities with a purpose greater than just personal enjoyment. And you think people can handle their own business without interference.

You are likely to_____

- ☒ be sensitive to ownership cost when buying automobiles
- ☒ like historical movies
- ☒ volunteer for social causes

You are unlikely to_____

- ☐ be influenced by social media during product purchases
- ☐ prefer style when buying clothes
- ☐ like rap music

How did we get this?

Insights from text

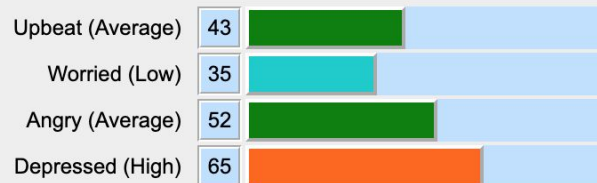
Analyze Words

AnalyzeWords.com

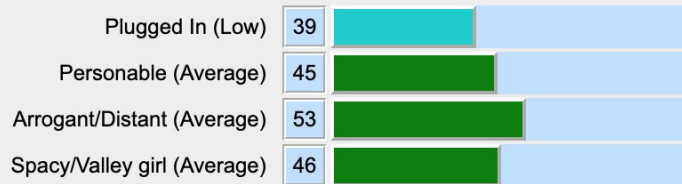


Analysis of tweets from weaiwayne (995 most recent words - 4th March, 2019)

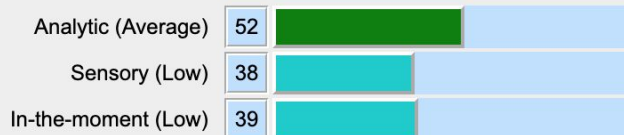
Emotional Style



Social Style



Thinking Style



The science behind the algorithm

“A well-accepted theory of psychology, marketing, and other fields is that human language reflects personality, thinking style, social connections, and emotional states. The frequency with which people use certain categories of words can provide clues to these characteristics.”

More at

<https://cloud.ibm.com/docs/services/personality-insights?topic=personality-insights-science#science>

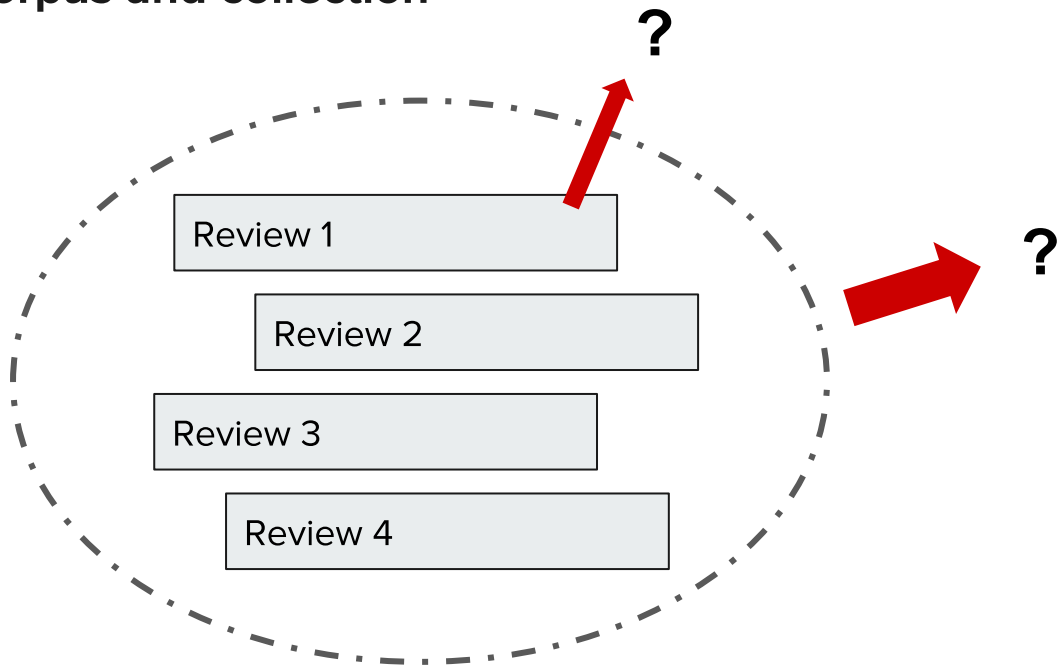
The science behind the algorithm



Search: James W. Pennebaker and Jeff Hancock

Review of concepts

Corpus and collection



Review of concepts

?

features

docs	awesome	projector	traditional	boston	experience
Boston	120	1	2	862	143
Denver	215	2	0	0	106
Rhode Island	113	0	3	10	158

Review of concepts

?

"Awesome projector. Traditional Boston experience, with a great location!"



[1]	"Awesome"	"projector"	". "	"Traditional"	"Boston"
[6]	"experience"	", "	"with"	"a"	"great"
[11]	"location"	"!"			

New concepts

Stop words

Stop words: filter words because they are extremely common words but appear to be of little value.



New concepts

There are standard stop word lists for most languages

<https://stopwords.quanteda.io/>

a	12 a	1 a	1 akin
about	13 actualmente	2 ab	2 aking
above	14 acuerdo	3 aber	3 ako
across	15 adelante	4 ach	4 alin
after	16 ademas	5 acht	5 am
afterwards	17 además	6 achte	6 amin
again	18 adrede	7 achten	7 aming
against	19 afirmó	8 achter	8 ang
all	20 agregó	9 achtet	9 ano
almost	21 ahi	10 ag	10 anumang
alone	22 ahora	11 alle	11 apat
along	23 ahí	12 allein	12 at
already	24 al	13 allem	13 atin
also	25 algo	14 allen	14 ating
although	26 alguna	15 aller	15 ay
always	27 algunas	16 allerdings	16 bababa
am	28 alguno	17 alles	17 bago
among	29 algunos	18 allgemeinen	18 bakit
	30 algún	19 als	19 bawat
	31 alli	20 also	20 bilang
	32 allí	21 am	21 dahil
	33 alrededor	22 an	
	34 ambos	23 ander	
	35 ampleamos	24 andere	
	36 antano	25 anderem	
	37 antaño	26 anderen	
	38 ante	27 anderer	
	39 anterior	28 anderen	
	40 antes	29 anderen	

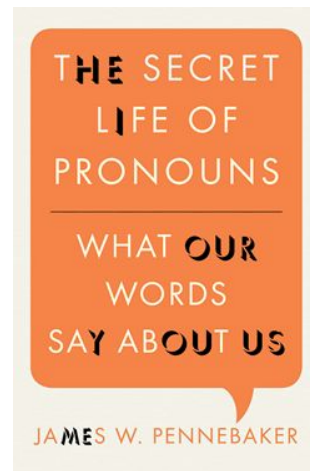
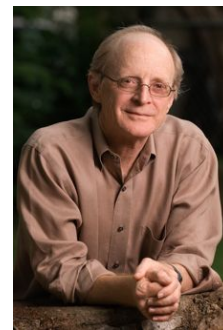
New concepts



A case against filtering stop words

- Smallish words, or function words (articles, prepositions, pronouns), as opposed to content words
- Linguistic Inquiry and Word Count (LIWC)
- People of different gender, age, and social groups, and with different personality traits use function words differently.

"The more similar [they were] across all of these function words, the higher the probability that [they] would go on a date in a speed dating context," Pennebaker says. "And this is even cooler: We can even look at ... a young dating couple... [and] the more similar [they] are ... using this language style matching metric, the more likely [they] will still be dating three months from now."



<https://www.npr.org/sections/health-shots/2012/04/30/151550273/to-predict-dating-success-the-secrets-in-the-pronouns>

New concepts

Ngrams

N-gram: contiguous sequence of n items

Google Books Ngram Viewer

Graph these comma-separated phrases: ☐ case-insensitive

between and from the corpus with smoothing of .

[Search lots of books](#)

[Tweet](#)

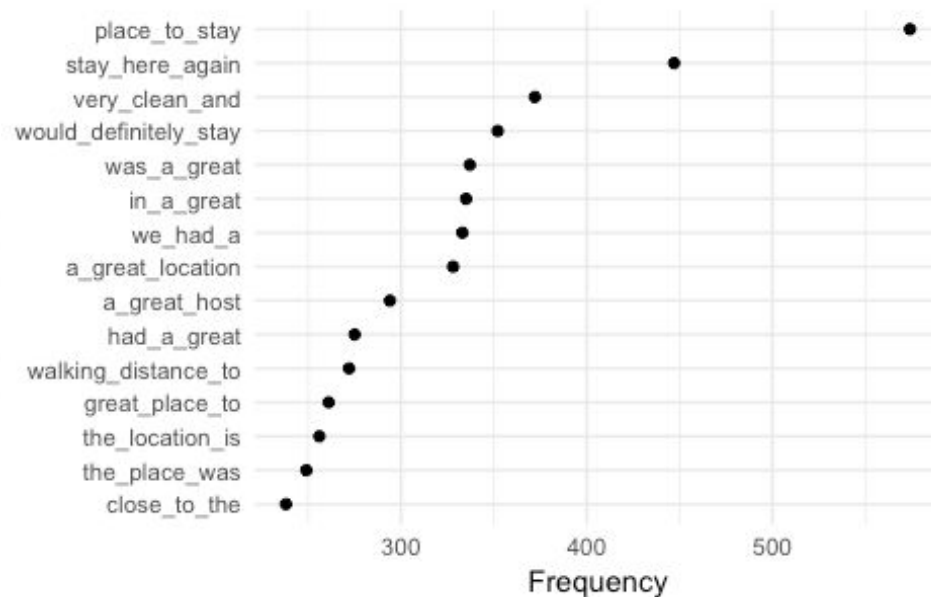
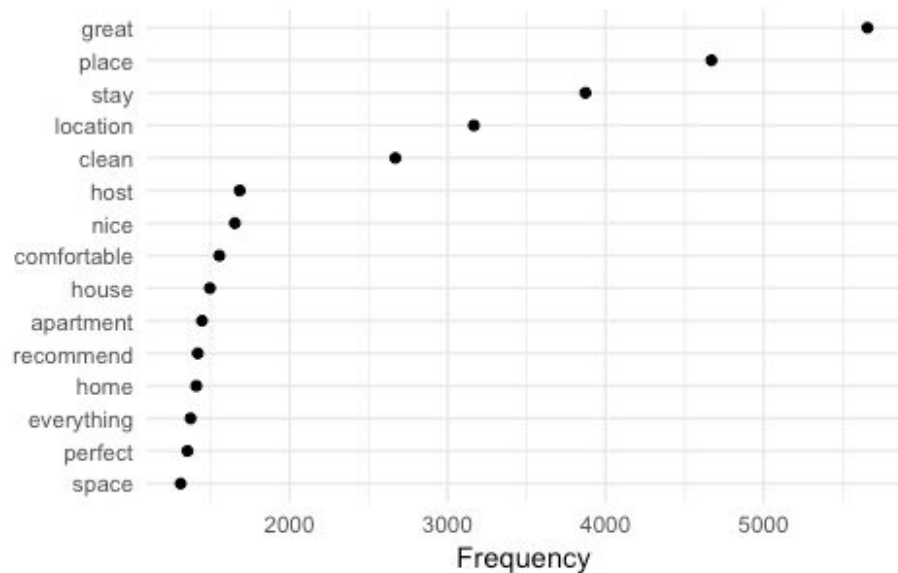
[Embed Chart](#)



New concepts

Ngrams

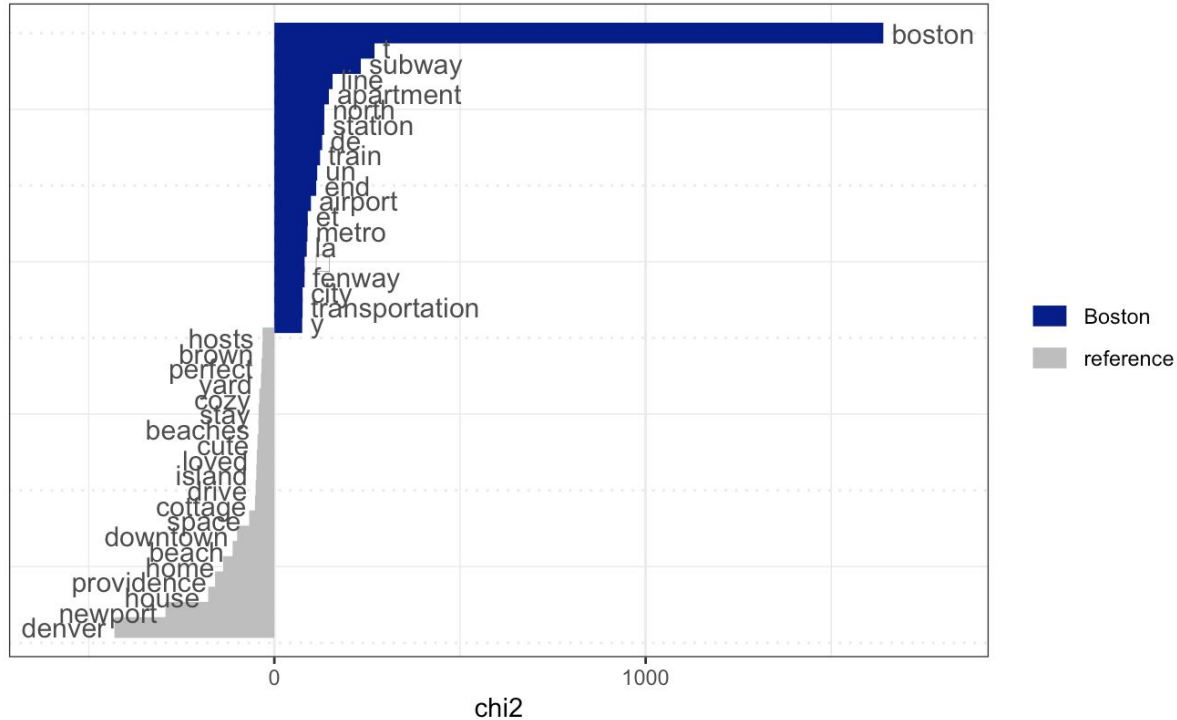
N-gram: contiguous sequence of n items



New concepts

Keyness

Keyness words (or key words): words which occur significantly more often in one group of texts than in another



Tf-idf (term frequency-inverse document frequency):

New concepts

Tf-idf (term frequency-inverse document frequency)

A measure of weighting term based on how important a word is to a corpus.

great	place	stay	location	clean	host	nice
5657	4670	3872	3166	2669	1684	1653
comfortable	house	apartment				
1555	1495	1445				

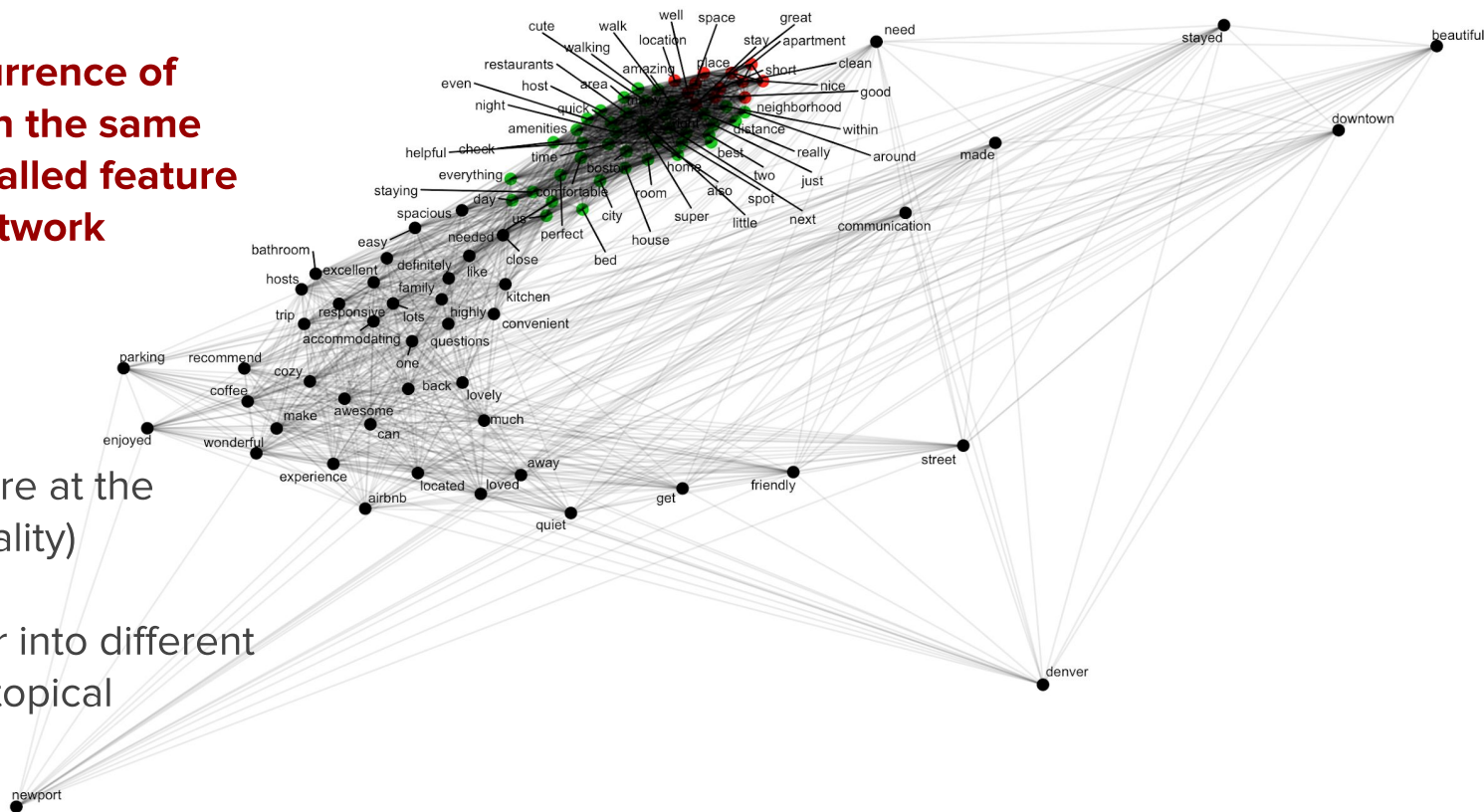
denver	boston	providence	newport	subway	beaches	t
396.96488	153.55158	147.43047	100.90029	57.25455	39.60106	25.53323
thames	fenway	ri				
20.51621	20.03909	20.03909				

Semantic networks

Based on co-occurrence of terms (features) in the same document. Also called feature co-occurrence network

Important words are at the center (high centrality)

Words may cluster into different groups based on topical similarity



Topic models

Automated clustering of the text based on topical similarity

A live demo based on Russia's IRA tweets

<https://www.cascadia-analytics.com/2018/08/12/ira-tweets1.html>



Topic models

LDA (Latent Dirichlet Allocation (LDA) model) is a commonly used topic modeling algorithm.

The pitfalls of topic modeling

- Finding the *best* k (k = the number of topics)
- interpretability

	Topic 1	Topic 2	Topic 3
[1,]	"great"	"great"	"great"
[2,]	"place"	"place"	"place"
[3,]	"location"	"stay"	"stay"
[4,]	"stay"	"location"	"location"
[5,]	"clean"	"clean"	"clean"
[6,]	"boston"	"house"	"denver"
[7,]	"apartment"	"host"	"home"
[8,]	"nice"	"comfortable"	"space"
[9,]	"host"	"home"	"house"
[10,]	"comfortable"	"newport"	"nice"
[11,]	"easy"	"nice"	"recommend"
[12,]	"recommend"	"perfect"	"comfortable"
[13,]	"room"	"us"	"host"
[14,]	"everything"	"everything"	"definitely"
[15,]	"definitely"	"recommend"	"everything"
[16,]	"close"	"apartment"	"easy"
[17,]	"good"	"space"	"perfect"
[18,]	"perfect"	"room"	"close"
[19,]	"walk"	"definitely"	"downtown"
[20,]	"really"	"easy"	"super"