EB5204 : NEW MEDIA AND SENTIMENT MINING

MODULE 2.1: TRAINING CORPUS & FEATURES

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Module Objectives 2.1

- Identify and **evaluate** methodologies for training **data sets** used in sentiment mining
- Identify and evaluate training **features** for sentiment mining
- Construct auto-learned training features from **Word Vector Representation**

Agenda

- Training **data** set generation for sentiment mining
- Training **features** for sentiment mining
- Word vectors

1. Training data for sentiment analysis

Training data set I

- The key point is to use the training data as **similar** to the test set, which applies generally for all supervised training models.

- The training and test data sets should be used from the **same domain** as far as possible. It solves problems of domain-specific terms. In most cases, best to generate a training data set for your specific objective.

- In generating training set, go for high-precision and **low recall**.
  - *High precision* means be sure those you say are positive are indeed positive. those you say are negative are indeed negative. Normally happens if you set a ‘high bar’.
  - *Low recall* means a lot of the actual positives or actual negatives are actually “ignored” as they cannot clear the ‘high bar’.
- **Balance** your dataset

Training data set II

- Ways to create training reference data:
  - dictionary corpus
  - user-generated means
  - manual (by inspection – tedious)

The training data set is usually ***not static*** but requires fine-tuning even after production.

This helps to account for changing fads in expressions, languages slangs etc as well.

A fad, trend, or craze is any form of collective behavior that develops within a culture, a generation or social group in which a group of people enthusiastically follow an impulse for a finite period.

Dictionary corpus

- Using existing dictionary corpus, egs are:
  i. SentWordNet
  ii. Public sources eg. Liu Bing, https://www.w3.org/community/sentiment/wiki/Datasets
  iii. nltk corpus

Then **expand** and **modify** the dictionary corpus.

First, a revision over synsets (revision primer from Text Mining)

Synset is a special kind of a simple interface that is present in NLTK to look up words in WordNet. Synset instances are the groupings of synonymous words that express the same concept. Some of the words have only one Synset and some have several.

Wordnet synsets

- WordNet® is a large lexical database of English. Nouns, verbs, adjectives and adverbs are grouped into sets of cognitive synonyms (synsets), each expressing a distinct concept. https://wordnet.princeton.edu/

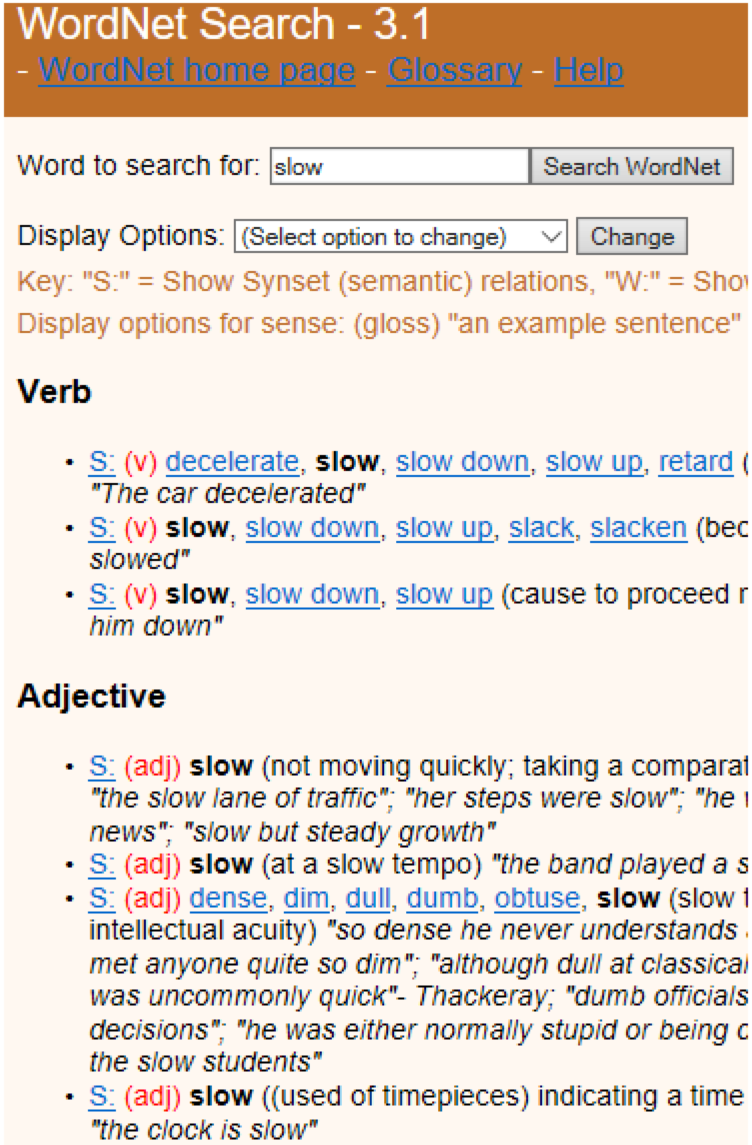
- The training corpus can be **expanded** using bootstrapping. through WordNet synsets, or related words.

- SentiWordnet adds on to WordNet by assigning sentiment polarity to these senses

More in the workshop today on ***WordNet*** and ***SentiWordNet***…

Bootstrapping synsets

- The bootstrapping of wordnet synsets can be understood in 2 steps.
  - Use a seed set of positive and negative words with their sentiment. Iterate through one by one
  - Search for the seed word's synset of records. These words then takes on the original seedset's sentiment.



WordNet Search - 3.1
- WordNet home page - Glossary - Help

Word to search for: slow [Search WordNet]

Display Options: (Select option to change) [Change]

Key: "S:" = Show Synset (semantic) relations, "W:" = Sho

Display options for sense: (gloss) "an example sentence"

Verb

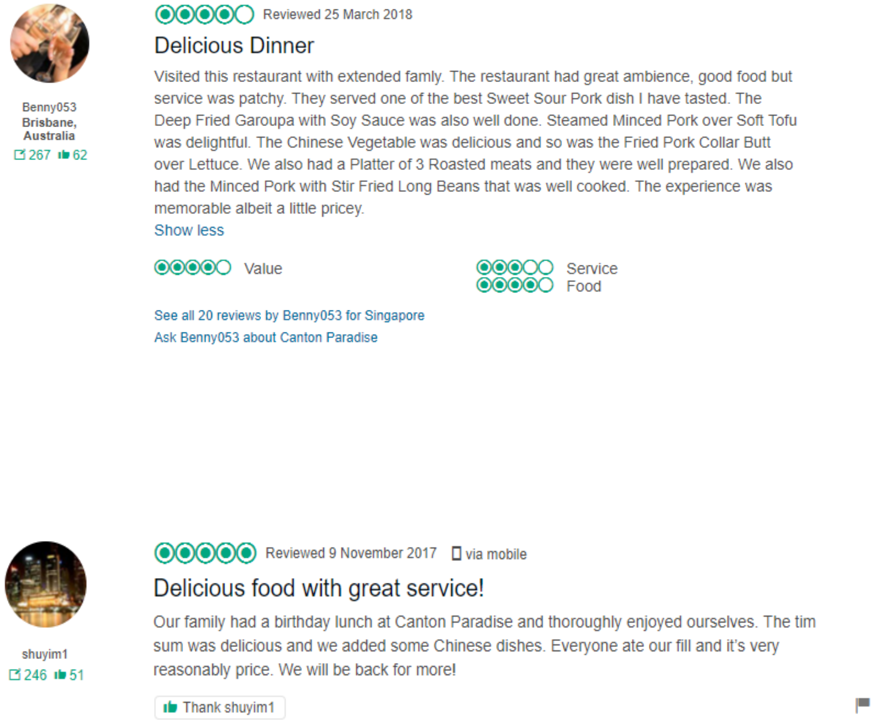
- S: (v) decelerate, **slow**, slow down, slow up, retard (*"The car decelerated"*
- S: (v) **slow**, slow down, slow up, slack, slacken (bec *slowed"*
- S: (v) **slow**, slow down, slow up (cause to proceed r *him down"*

Adjective

- S: (adj) **slow** (not moving quickly; taking a comparat *"the slow lane of traffic"; "her steps were slow"; "he news"; "slow but steady growth"*
- S: (adj) **slow** (at a slow tempo) *"the band played a s*
- S: (adj) dense, dim, dull, dumb, obtuse, **slow** (slow t intellectual acuity) *"so dense he never understands met anyone quite so dim"; "although dull at classica was uncommonly quick"- Thackeray; "dumb officials decisions"; "he was either normally stupid or being c the slow students"*
- S: (adj) **slow** ((used of timepieces) indicating a time *"the clock is slow"*

User-generated ratings

- Use the meta-data in social media to assign positive or negative ratings to the comment posts.



●●●●○ Reviewed 25 March 2018

Delicious Dinner

Visited this restaurant with extended famly. The restaurant had great ambience, good food but service was patchy. They served one of the best Sweet Sour Pork dish I have tasted. The Deep Fried Garoupa with Soy Sauce was also well done. Steamed Minced Pork over Soft Tofu was delightful. The Chinese Vegetable was delicious and so was the Fried Pork Collar Butt over Lettuce. We also had a Platter of 3 Roasted meats and they were well prepared. We also had the Minced Pork with Stir Fried Long Beans that was well cooked. The experience was memorable albeit a little pricey.

Show less

Benny053
Brisbane, Australia
267 62

●●●●○ Value

●●●○○ Service

●●●●○ Food

See all 20 reviews by Benny053 for Singapore

Ask Benny053 about Canton Paradise

●●●●● Reviewed 9 November 2017 via mobile

Delicious food with great service!

Our family had a birthday lunch at Canton Paradise and thoroughly enjoyed ourselves. The tim sum was delicious and we added some Chinese dishes. Everyone ate our fill and it's very reasonably price. We will be back for more!

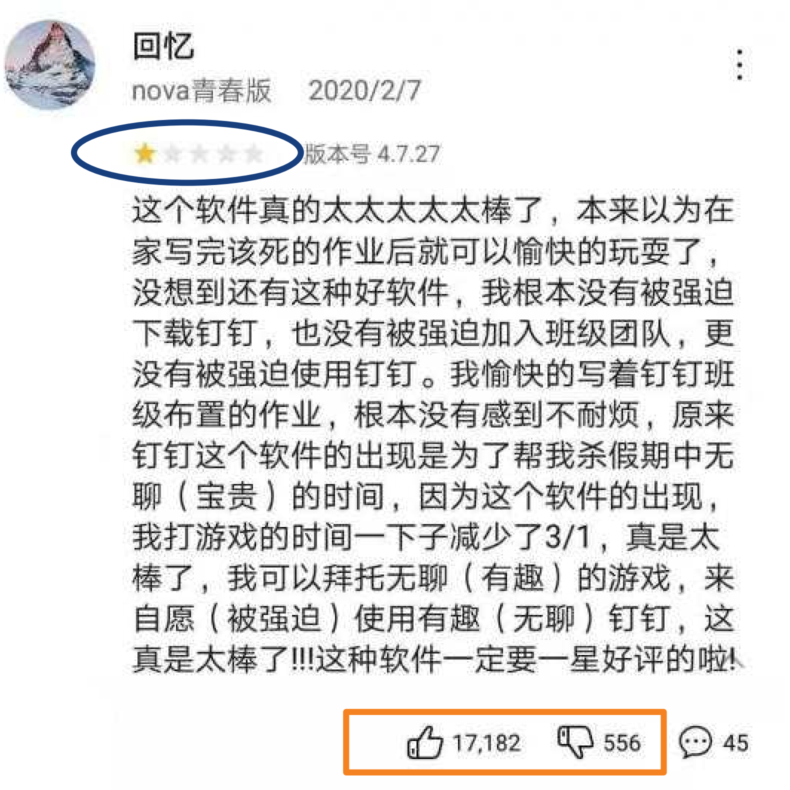
shuyim1
246 51

Thank shuyim1

Simply use high ratings this as positive labels; and low ratings as negative labels

User-generated ratings

- Mind the biased reviews.



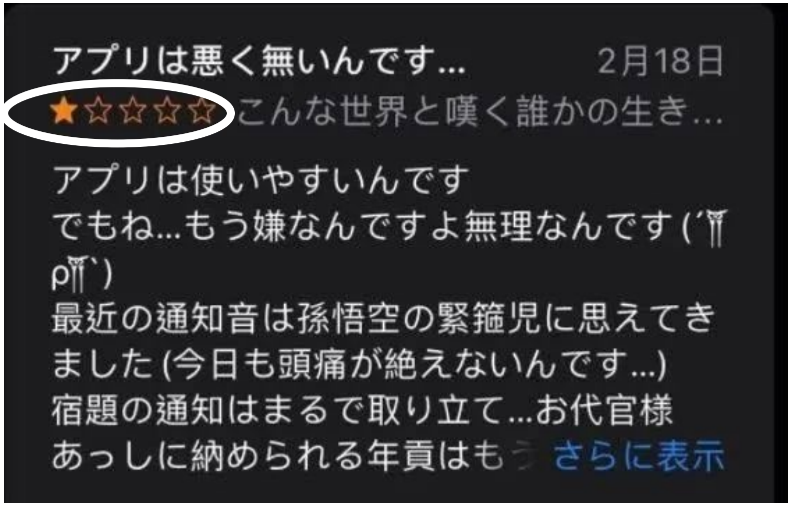
回忆

nova青春版　2020/2/7

★☆☆☆☆ 版本号 4.7.27

这个软件真的太太太太太棒了，本来以为在家写完该死的作业后就可以愉快的玩耍了，没想到还有这种好软件，我根本没有被强迫下载钉钉，也没有被强迫加入班级团队，更没有被强迫使用钉钉。我愉快的写着钉钉班级布置的作业，根本没有感到不耐烦，原来钉钉这个软件的出现是为了帮我杀假期中无聊（宝贵）的时间，因为这个软件的出现，我打游戏的时间一下子减少了3/1，真是太棒了，我可以拜托无聊（有趣）的游戏，来自愿（被强迫）使用有趣（无聊）钉钉，这真是太棒了!!!这种软件一定要一星好评的啦!

👍 17,182　👎 556　💬 45



アプリは悪く無いんです…　2月18日

★☆☆☆☆ こんな世界と嘆く誰かの生き…

アプリは使いやすいんです
でもね…もう嫌なんですよ無理なんです(´╥ρ╥`)
最近の通知音は孫悟空の緊箍児に思えてきました(今日も頭痛が絶えないんです…)
宿題の通知はまるで取り立て…お代官様
あっしに納められる年貢はも… さらに表示

2. Features for sentiment analysis

Features used in sentiment mining

- From Wikipedia:
  - **Feature engineering** is the process of using domain knowledge of the data to create features that make machine learning algorithms work.

- Represent [sentences] with a vector of numbers, which can better/best distinguish the [polarity] among all the [sentences]

Feature Engineering

- Some common features used in sentiment analysis are
  - Part of speech (POS) tags (adjectives or nouns)
  - Opinion lexicons and phrases (n-grams)
  - Negations
  - Syntactic dependency (more about this on Day 3)
  - Sentiment-aware tokens (recall 1st day)
  - Word vectors
  - Terms frequency and different information retrieval *weighting* schemes – tf-idf

What are other word features do you think will matter?

In an actual project, it is wise to look through some data sets in some detail, and identify what sets positive or negative polarity statements apart.

Features Weighting

Some are covered in Text Mining.

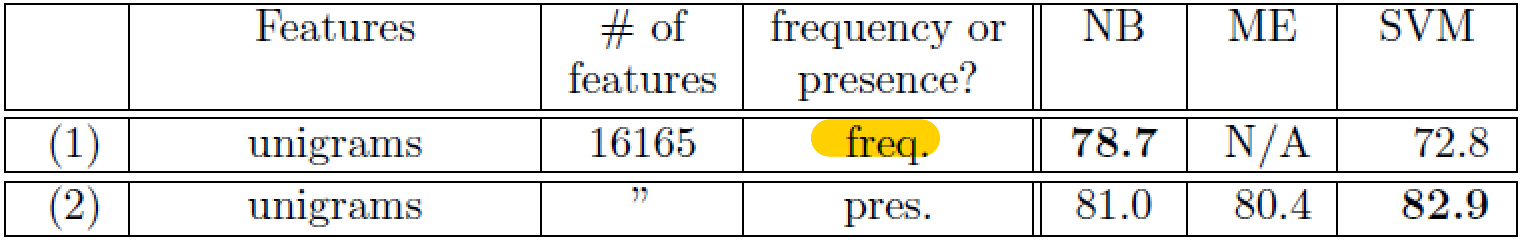
- Binary
  - 0 or 1, simply indicating whether a word has occurred in the document.
- Frequency-based
  - ***term frequency***, the frequency of words in the document.
- *tf-idf* weighting: (considers document set)
  - $tf_{t,d}$: term frequency – number of occurrences of term *t* in document *d*
  - idf_t : inverted document frequency of term *t*
  - df_t : the ***document frequency*** of term *t*, i.e., the number of documents that contain the term.
  - *N* : the total number of documents in the corpus

$$tf\text{-}idf_{t,d}=tf_{t,d}*idf_t$$

$$idf_t = \log \frac{N}{df_t}$$

Frequency or presence?

- Pang et al 2002 found out that better performance of sentiment classification on movie review data is achieved by accounting only for feature presence, not feature frequency



	Features	# of features	frequency or presence?	NB	ME	SVM
(1)	unigrams	16165	freq.	**78.7**	N/A	72.8
(2)	unigrams	”	pres.	81.0	80.4	**82.9**

Feature Engineering

- **Pointwise Mutual Information**
  - Do the two words **co-occur** very often for a reason? or just by random

$$\mathrm{PMI}(w_1,w_2)=\log_2\frac{P(w_1,w_2)}{P(w_1)P(w_2)}$$

$$P(w)=\frac{Freq(w)}{totalWordCount}$$

  - Positive PMI

$$PPMI=\begin{cases} PMI & if\ PMI>0 \\ 0 & else \end{cases}$$

Feature Engineering

- **PMI for first 50 millions of words in Wikipedia**
  - Total word count is 50,000,952

word 1	word 2	count word 1	count word 2	count of co-occurrences	**PMI**
puerto	rico	1938	1311	1159	**10.0349081703**
hong	kong	2438	2694	2205	**9.72831972408**
los	angeles	3501	2808	2791	**9.560676150**
to	and	1025659	1375396	1286	**-3.08825363041**
to	in	1025659	1187652	1066	**-3.12911348956**
of	and	1761436	1375396	1190	**-3.70663100173**

Term-document matrix

- Many text mining applications are based on vector representation of documents (term-document matrix) using “bag-of-words” approach

$$\left(\begin{array}{ccccc} & F_1 & F_2 & \cdots & F_t \\ D_1 & w_{11} & w_{21} & \cdots & w_{t1} \\ D_2 & w_{12} & w_{22} & \cdots & w_{t2} \\ \vdots & \vdots & \vdots & & \vdots \\ \vdots & \vdots & \vdots & & \vdots \\ D_n & w_{1n} & w_{2n} & \cdots & w_{tn} \end{array}\right)$$

F: features
D: document
w: value of the features

- Usually only content words (adjectives, adverbs, nouns, and verbs) are used as unigram vector features.

Classic NLP: Feature Engineering

- **Count-based vectors are**
  - e.g. TF-IDF, PPMI
  - long (|V| > 100,000)
  - sparse (lots of zero)

In information retrieval, tf–idf, TF*IDF, or TFIDF, short for term frequency–inverse document frequency, is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus.

	he	drink	hold	…	*tfidf* drink apple	*tfidf* hold apple	*tfidf* apple juice	…	*PPMI* drink apple	*PPMI* hold apple	*PPMI* apple juice
sent0	0.01	0.38	0.00	…	0.87	0.00	0.92	…	4.23	0.00	8.90
sent1	0.01	0.00	0.28	…	0.00	0.87	0.00	…	0.00	2.45	0.00

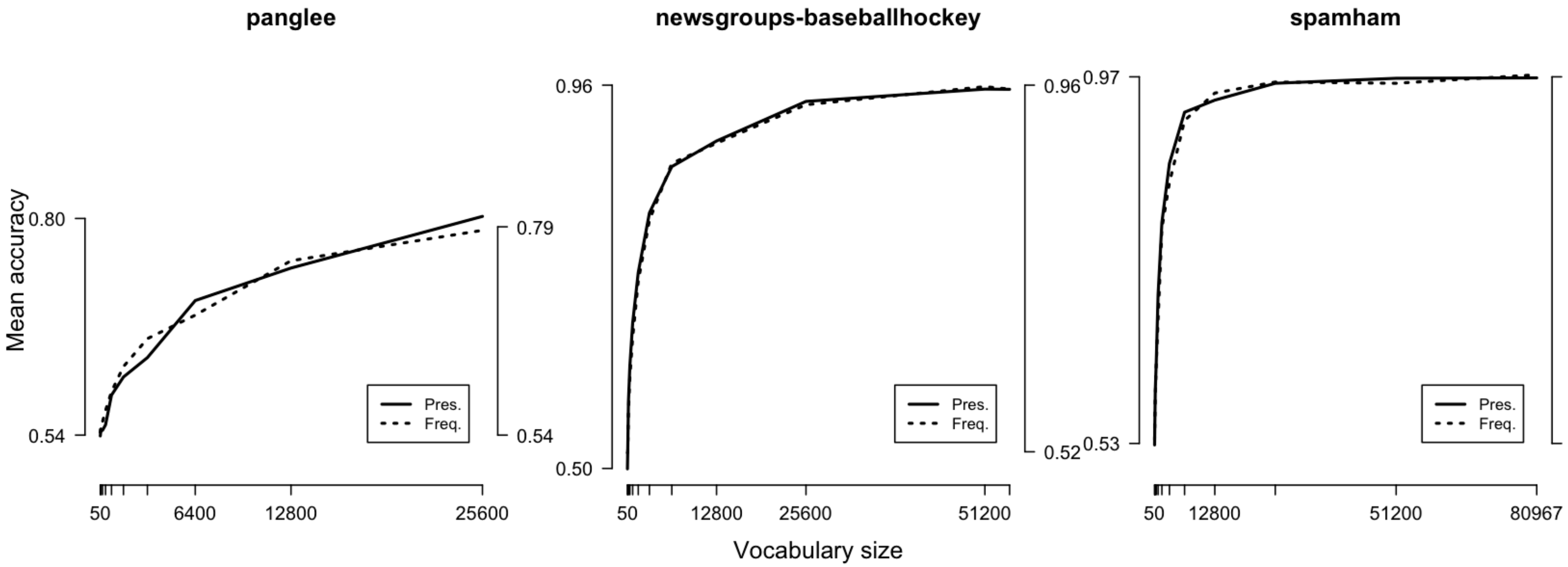
The higher the numerical weight value, the rarer the term. The smaller the weight, the more common the term.
For TF-IDF

The Curse of Dimensionality

- The feature-document matrix lies in **high-dimensional spaces**, (100,000+ features from variations of “Ngrams”).
- High-dimensional data requires an amount of time and memory that increases exponentially.
- Irrelevant “noise” features affect the performance of the algorithms – overfitting!
- Data sparsity – a lot of features with presence in very few documents.

Feature Selection

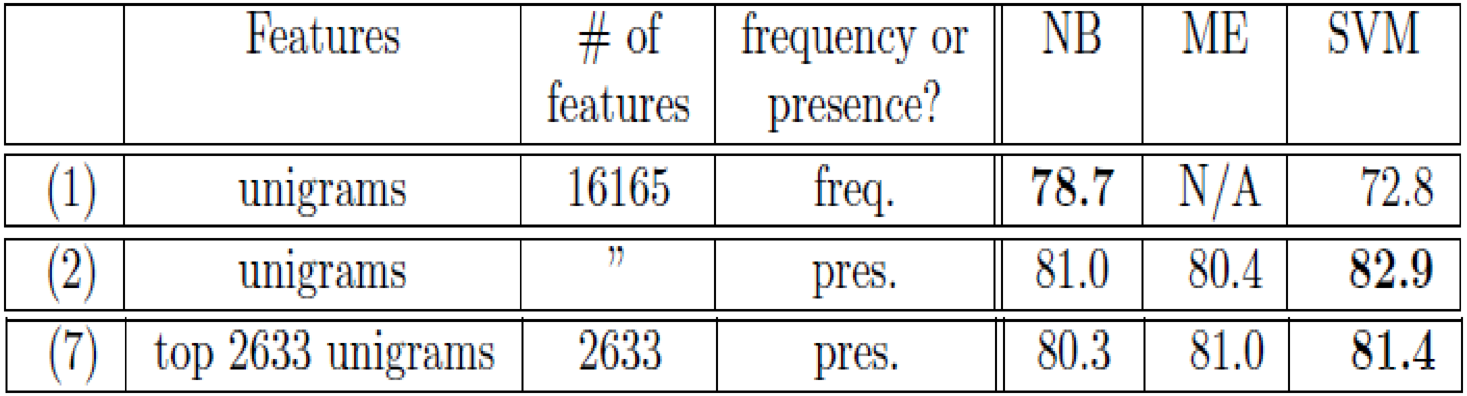
- Overall sentiment classifier accuracy increases steadily with the no of features (e.g., size of the vocabulary), but risk over-fitting, not generalize well to new data.



Potts, 2011

Feature Selection – more or less features?

- Pang et al 2002 found that simply using the 2633 most frequent unigrams can yield performance comparable to that of using all 16165.



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(1)	unigrams	16165	freq.	**78.7**	N/A	72.8
(2)	unigrams	”	pres.	81.0	80.4	**82.9**
(7)	top 2633 unigrams	2633	pres.	80.3	81.0	**81.4**

Naive Bayes(NB)
Support Vector Machine(SVM)
Maximum Entropy (ME)

Feature Selection (or extraction)

- To select relevant features and reduce the number of features used in the matrix
- Various ways (trial-and-error):
  - Remove **features that appear rarely** in the documents
  - Select **top *K*** number of most **frequent** features
  - Leverage on the labels to pick ***K* most useful** features

More about it in workshop.

Summary

- Two key steps before building a sentiment analysis are:
  i. *Training data (corpus)* selection/ generation
  ii. *Features selection*

These pre-steps are key to the success of a sentiment analysis and usually **more important than the training algorithms** themselves.

Training data selection needs to be as similar as possible to the production data. The features selection requires domain expertise.

Features from WordToVec

- Feature generation and selection could be tedious
- How might we generate “*universal*” features automatically?
- Zooming into word level vector representation

Word2vec is a technique for natural language processing. The word2vec algorithm uses a neural network model to learn word associations from a large corpus of text. Once trained, such a model can detect synonymous words or suggest additional words for a partial sentence.

Features from Word Vectors

- **Count from Data**
  - Word Co-occurrence + SVD
  - Count-based model

In linear algebra, the singular value decomposition (SVD) is a factorization of a real or complex matrix that generalizes the eigendecomposition of a square normal matrix to any. matrix via an extension of the polar decomposition.

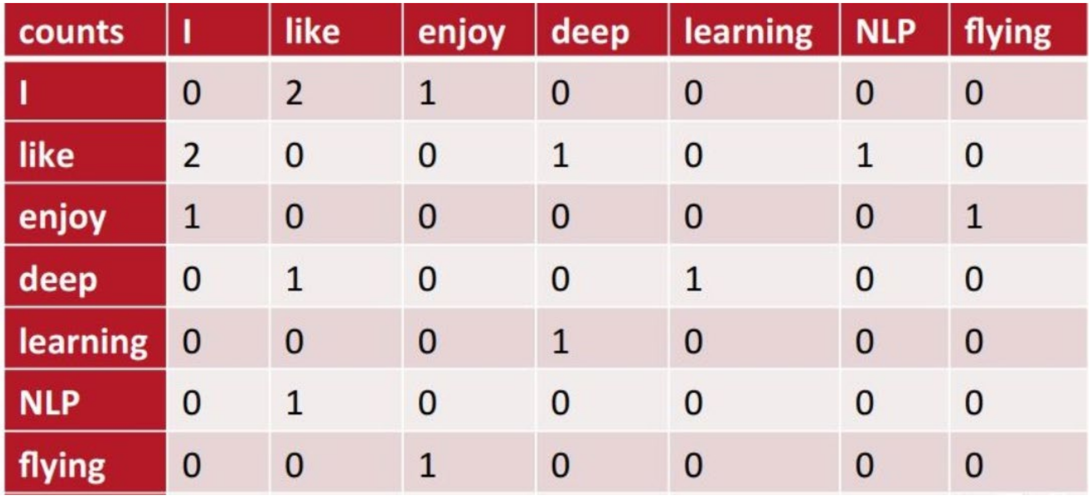
- **Learn from Data**
  - CBOW and SKIPGRAM
  - NN Methods
  - Predictive Model
- **Count and Learn from Data**
  - GLOVE: Global Vectors for Word Representation
  - Count + SGD

Count from Data

- **Word-level representation**
- **Counting context-words within a window_size**

Sent_1: *I like deep learning*
Sent_2: *I like NLP*
Sent_3: *I enjoy flying*

Window_size=1

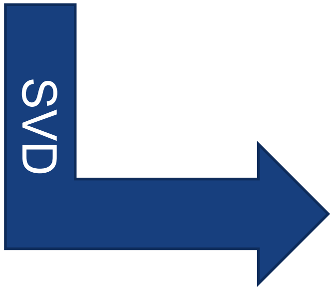


counts	I	like	enjoy	deep	learning	NLP	flying
I	0	2	1	0	0	0	0
like	2	0	0	1	0	1	0
enjoy	1	0	0	0	0	0	1
deep	0	1	0	0	1	0	0
learning	0	0	0	1	0	0	0
NLP	0	1	0	0	0	0	0
flying	0	0	1	0	0	0	0

Count From Data

counts	I	like	enjoy	deep	learning	NLP	flying
I	0	2	1	0	0	0	0
like	2	0	0	1	0	1	0
enjoy	1	0	0	0	0	0	1
deep	0	1	0	0	1	0	0
learning	0	0	0	1	0	0	0
NLP	0	1	0	0	0	0	0
flying	0	0	1	0	0	0	0

(7,7)



SVD

	S1	S2
I	1.5	.1
like	3.14	.23
enjoy	2.7	-.98
Deep	.55	.1
learning	.8	2.5
NLP	-2.5	3
flying	4.5	4.9

(7,N)

Sorted Singular Values		
12.29		
	6.2	
		…

(N,N)

	I	like	..	..	..	..
S1	.1	2	3	4	6	7
S2	.5	6	7	3	1	8

(N,7)

Count From Data

vec(I) =
vec(like) =
vec(enjoy) =
vec(deep) =
vec(learning) =
vec(NLP) =
vec(flying) =

	S1	S2
I	1.5	.1
like	3.14	.23
enjoy	2.7	-.98
Deep	.55	.1
learning	.8	2.5
NLP	-2.5	3
flying	4.5	4.9

(7,N)

●

Sorted Singular Values		
12.29		
	6.2	
		…

(N,N)

Features from Word Vectors

- **Count from Data**
  - Word Co-occurrence + SVD
  - Count-based model
- **Learn from Data**
  - Word2Vec
  - NN Methods
  - Predictive Model
- **Count and Learn from Data**
  - GLOVE: Global Vectors for Word Representation
  - Count + SGD

Learn From Data

One-Hot Encoding (Sparse Representation)

Vocabulary of the corpus (big enough)

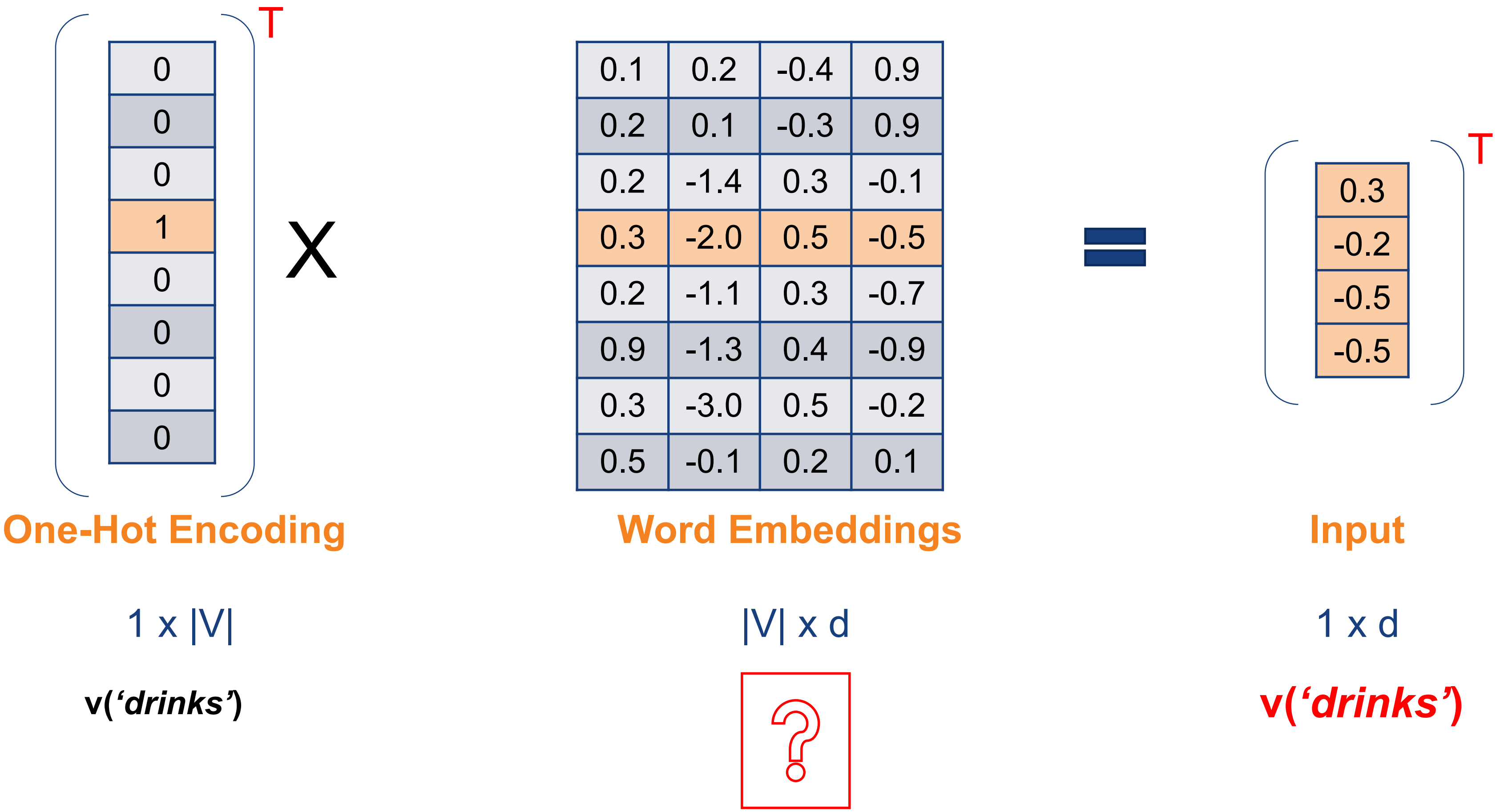
	he	she	eats	drinks	sushi	ramen	hungry	coffee
he	1	0	0	0	0	0	0	0
drinks	0	0	0	1	0	0	0	0
	0	0	0	0	1	0	0	0
coffee	0	0	0	0	0	0	0	1
	0	0	0	0	0	0	1	0
	0	0	1	0	0	0	0	0

v(‘*drinks*’)

simple machine learning application
count vectorizer / tf-idf do not preserve any relationship between words, word embedding preserve relationship

Word2Vec

Word embedding is any of a set of language modeling and feature learning techniques in natural language processing where words or phrases from the vocabulary are mapped to vectors of real numbers.



$$\begin{pmatrix}0\\0\\0\\1\\0\\0\\0\\0\end{pmatrix}^T \times \begin{pmatrix}0.1 & 0.2 & -0.4 & 0.9\\0.2 & 0.1 & -0.3 & 0.9\\0.2 & -1.4 & 0.3 & -0.1\\0.3 & -2.0 & 0.5 & -0.5\\0.2 & -1.1 & 0.3 & -0.7\\0.9 & -1.3 & 0.4 & -0.9\\0.3 & -3.0 & 0.5 & -0.2\\0.5 & -0.1 & 0.2 & 0.1\end{pmatrix} = \begin{pmatrix}0.3\\-0.2\\-0.5\\-0.5\end{pmatrix}^T$$

One-Hot Encoding

1 x |V|

v(*‘drinks’*)

Word Embeddings

|V| x d

?

Input

1 x d

v(*‘drinks’*)

https://www.youtube.com/watch?v=UqRCEmrv1gQ&t=307s&ab_channel=TheSemicolon

Word2Vec (CBOW)

Continuous Bag of Words

Learn the Matrix through “classification” task,

Sentence: the bulk of linguistic questions concern the distinction between a and m. a linguistic account of phenomenon …

of	the bulk ______ linguistic questions
linguistic	bulk of ______ questions concern
questions	of linguistic ______ concern the
concern	linguistic questions ______ the dis-
the	questions concern ______ dis- tinction
dis-	concern the ______ tinction between
tinction	the dis- ______ between a
between	dis- tinction ______ a and
a	tinction between ______ and m.
and	between a ______ m. a
m.	a and ______ a linguistic
a	and m. ______ linguistic account
linguistic	m. a ______ account of
account	a linguistic ______ of a
of	linguistic account ______ a phenomenon
a	account of ______ phenomenon gen-
phenomenon	of a ______ gen- erally

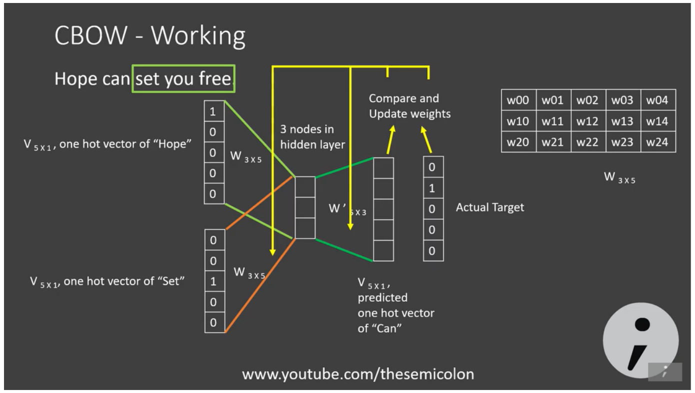
The window size is the maximum context location at which the words need to be predicted. The window size is denoted by c. For example, in the given architecture image the window size is 2, therefore, we will be predicting the words at context location (t-2), (t-1), (t+1) and (t+2).

window_size = 2

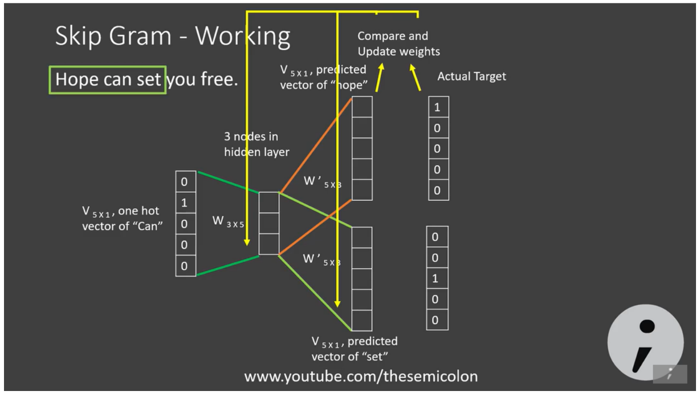
More depth in TPML

Features from WordToVec

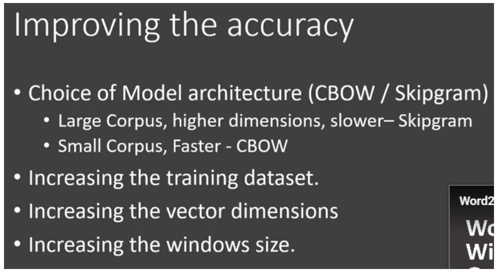
- **Count from Data**
  - Word Co-occurrence + SVD
  - Count-based model



- **Learn from Data**
  - Word2Vec
  - NN Methods
  - Predictive Model



- **Count and Learn from Data**
  - **GLOVE**: Global Vectors for Word Representation
  - Count + SGD



Improving the accuracy

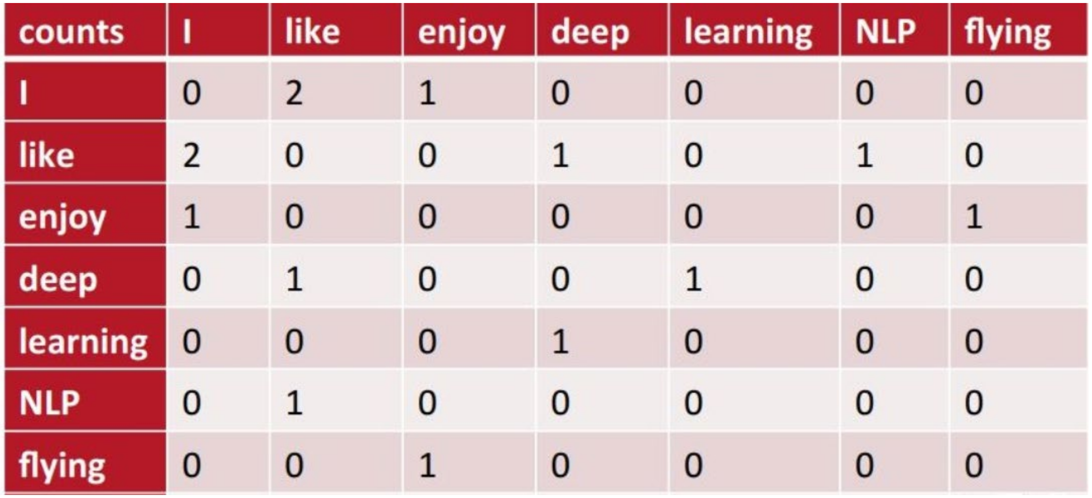
- Choice of Model architecture (CBOW / Skipgram)
  - Large Corpus, higher dimensions, slower– Skipgram
  - Small Corpus, Faster - CBOW
- Increasing the training dataset.
- Increasing the vector dimensions
- Increasing the windows size.

GLOVE-Global Vectors for Word Representation

- **Word-level representation**
- **Counting context-words within a window_size**

Sent_1: *I like deep learning*
Sent_2: *I like NLP*
Sent_3: *I enjoy flying*

Window_size=1



counts	I	like	enjoy	deep	learning	NLP	flying
I	0	2	1	0	0	0	0
like	2	0	0	1	0	1	0
enjoy	1	0	0	0	0	0	1
deep	0	1	0	0	1	0	0
learning	0	0	0	1	0	0	0
NLP	0	1	0	0	0	0	0
flying	0	0	1	0	0	0	0

(# of “***like***” as “***I***’s” context-words) = 2

(# of “***I***” as “***like***’s” context-words) = 2

GLOVE-Global Vectors for Word Representation

- **Word-level representation**
- **Counting context-words within a window_size**

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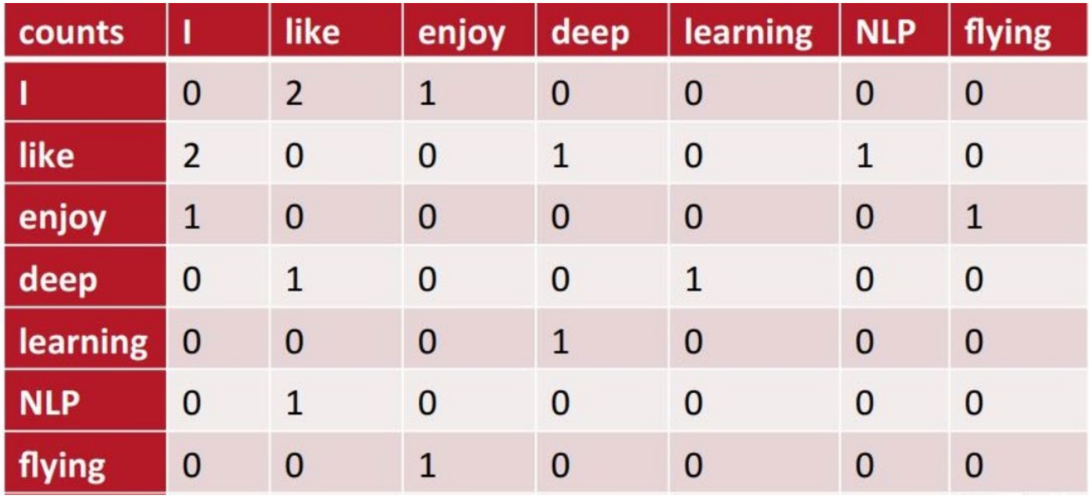

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like	2	0	0	1	0	1	0
enjoy	1	0	0	0	0	0	1
deep	0	1	0	0	1	0	0
learning	0	0	0	1	0	0	0
NLP	0	1	0	0	0	0	0
flying	0	0	1	0	0	0	0

P(I,like)= P(like | I) = Count(# of “***like***” as “***I***’s” context-words)
/ Count(total # of “***I***’s” context-words)

$$= C_{I,like} / C_I \quad = 2/3$$

$$\log (P (I,like)) = \log(C_{I,like} / C_I) = \log (C_{I,like}) - \log(C_I) \quad = \log 2 - \log 3$$

GLOVE-Global Vectors for Word Representation

Sent_1: *I like deep learning*
Sent_2: *I like NLP*
Sent_3: *I enjoy flying*

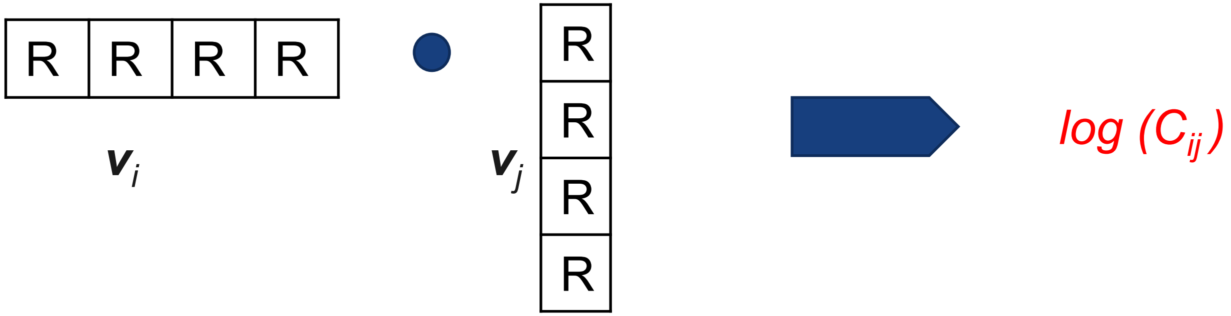
Window_size=1

counts	I	like	enjoy	deep	learning	NLP	flying
I	0	2	1	0	0	0	0
like	2	0	0	1	0	1	0
enjoy	1	0	0	0	0	0	1
deep	0	1	0	0	1	0	0
learning	0	0	0	1	0	0	0
NLP	0	1	0	0	0	0	0
flying	0	0	1	0	0	0	0

$$\log(P(I,like)) = \log(C_{I,like} / C_I) = \log(C_{I,like}) - \cancel{\log(C_I)} = \mathbf{\log 2} - \cancel{\log 3}$$

Let $\mathbf{v}_i$ *= the vector representing "I"* *i refers to "I"*
$\mathbf{v}_j$ *= the vector representing "like"* *j refers to "like"*

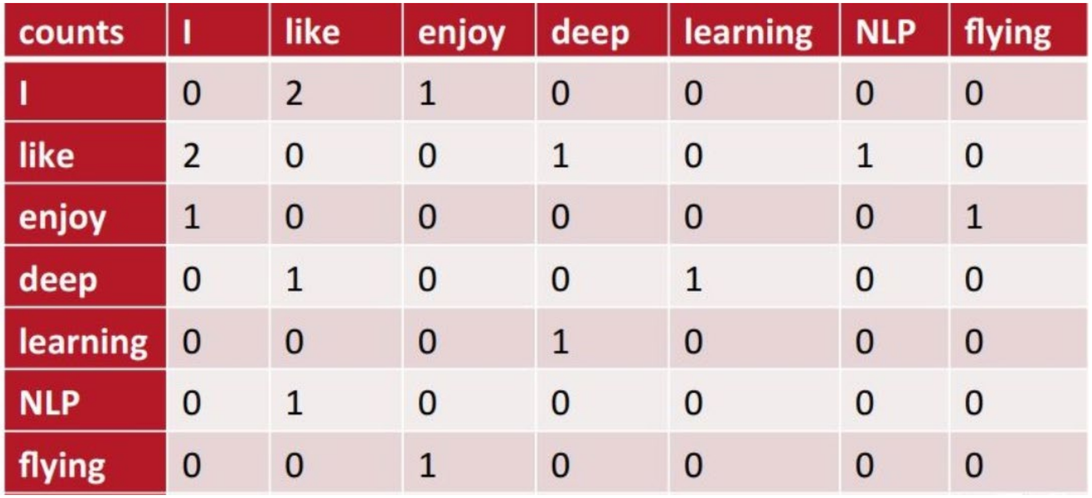
Then we Expect : mapping $\mathbf{v}_i \bullet \mathbf{v}_j$ *to* $\log(C_{ij})$



GLOVE-Global Vectors for Word Representation

Sent_1: *I like deep learning*
Sent_2: *I like NLP*
Sent_3: *I enjoy flying*

Window_size=1



counts	I	like	enjoy	deep	learning	NLP	flying
I	0	2	1	0	0	0	0
like	2	0	0	1	0	1	0
enjoy	1	0	0	0	0	0	1
deep	0	1	0	0	1	0	0
learning	0	0	0	1	0	0	0
NLP	0	1	0	0	0	0	0
flying	0	0	1	0	0	0	0

Let $\mathbf{v}_i$ *= the vector representing "I"* *i refers to "I"*
$\mathbf{v}_j$ *= the vector representing "like"* *j refers to "like"*

Then we Expect : mapping $\mathbf{v}_i \bullet \mathbf{v}_j$ *to* $\log(C_{ij})$

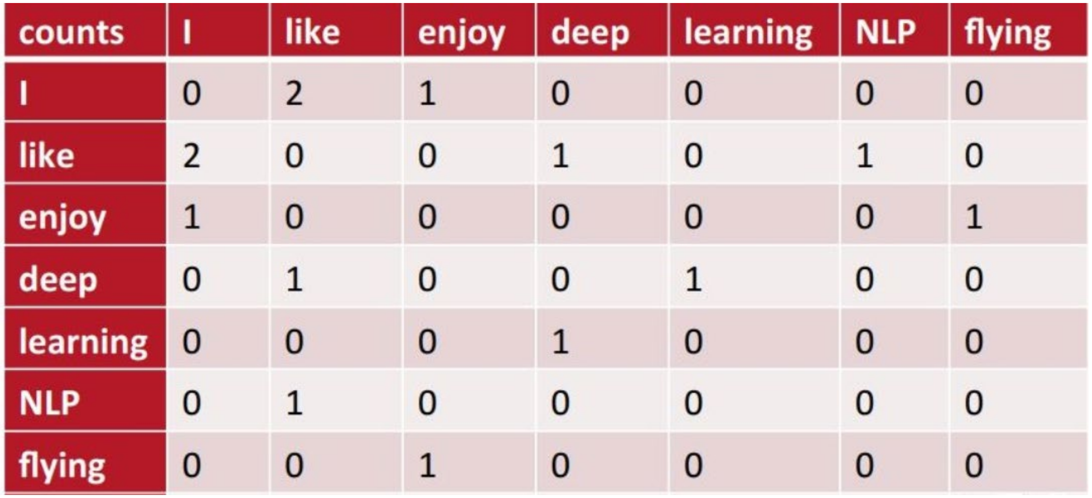
Thus we Define: Least Square Loss Function : $L = \sum_{ij} [\, \log(C_{ij}) - (\mathbf{v}_i \bullet \mathbf{v}_j + v_{bias})\,]^2$

$$L2LossFunction = \sum_{i=1}^{n} (y_{true} - y_{predicted})^2$$

GLOVE-Global Vectors for Word Representation

Sent_1: *I like deep learning*
Sent_2: *I like NLP*
Sent_3: *I enjoy flying*

Window_size=1



counts	I	like	enjoy	deep	learning	NLP	flying
I	0	2	1	0	0	0	0
like	2	0	0	1	0	1	0
enjoy	1	0	0	0	0	0	1
deep	0	1	0	0	1	0	0
learning	0	0	0	1	0	0	0
NLP	0	1	0	0	0	0	0
flying	0	0	1	0	0	0	0

Moreover we Define: weighted least square Loss Function :

$$L = \sum_{i,j} [\log(C_{ij}) - (\mathbf{v}_i \bullet \mathbf{v}_j + v_{bias})]^2 \bullet Weight\_Func(C_{ij})$$

Constrains:

$Weight\_Func(0) = 0$
Bigger C_{ij} *leads to Bigger* $Weight\_Func(C_{ij})$
$Weight\_Func(C_{ij})$ *should have a upper bound as* C_{ij} *can be a big number*

Thus we Define: Least Square Loss Function : $L = \sum_{ij} [\log(C_{ij}) - (\mathbf{v}_i \bullet \mathbf{v}_j + v_{bias})]^2$

GLOVE-Global Vectors for Word Representation

Sent_1: *I like deep learning*
Sent_2: *I like NLP*
Sent_3: *I enjoy flying*

Window_size=1

counts	I	like	enjoy	deep	learning	NLP	flying
I	0	2	1	0	0	0	0
like	2	0	0	1	0	1	0
enjoy	1	0	0	0	0	0	1
deep	0	1	0	0	1	0	0
learning	0	0	0	1	0	0	0
NLP	0	1	0	0	0	0	0
flying	0	0	1	0	0	0	0

$$L = \sum_{i,j} [\log(C_{ij}) - (\mathbf{v}_i \bullet \mathbf{v}_j + v_{bias})]^2 \bullet Weight\_Func(C_{ij})$$

$$Weight\_Func(C_{ij}) = \begin{cases} 1, & when\ C_{ij} >= 100 \\ (C_{ij}/100)^{0.75}, & otherwise \end{cases}$$

Constrains:

$Weight\_Func(0) = 0$

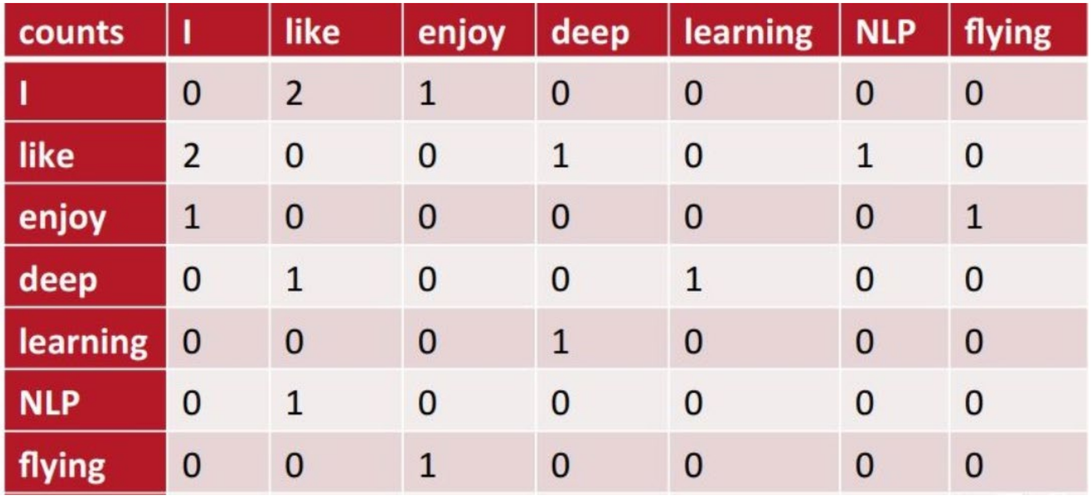
Bigger C_{ij} leads to Bigger $Weight\_Func(C_{ij})$

$Weight\_Func(C_{ij})$ should have a upper bound as C_{ij} can be a big number

GLOVE-Global Vectors for Word Representation

Sent_1: *I like deep learning*
Sent_2: *I like NLP*
Sent_3: *I enjoy flying*

Window_size=1

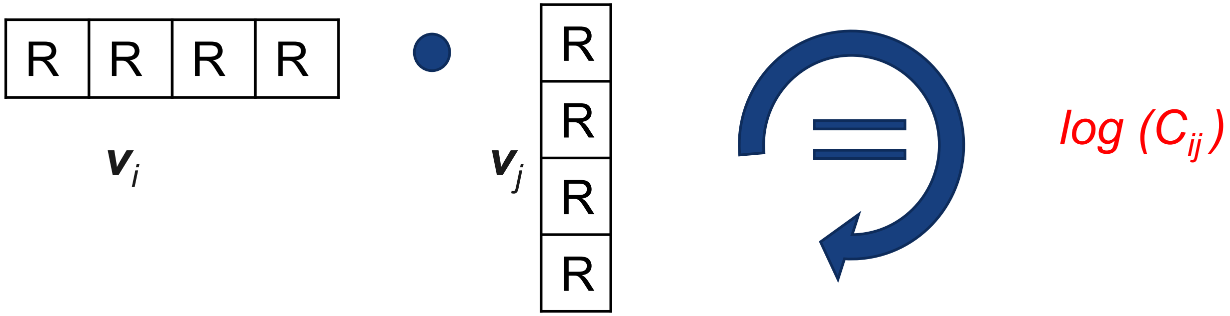


counts	I	like	enjoy	deep	learning	NLP	flying
I	0	2	1	0	0	0	0
like	2	0	0	1	0	1	0
enjoy	1	0	0	0	0	0	1
deep	0	1	0	0	1	0	0
learning	0	0	0	1	0	0	0
NLP	0	1	0	0	0	0	0
flying	0	0	1	0	0	0	0

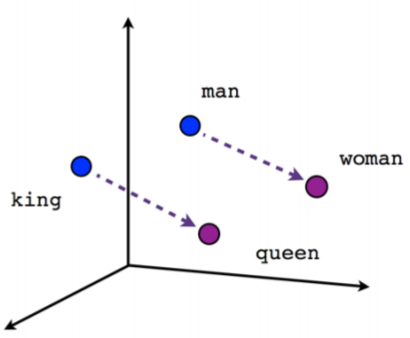
$\log (P(I,like)) = \log(C_{I,like} / C_I) = \log(C_{I,like})$ – ~~$\log(C_I)$~~ = **log2** – ~~log3~~

Let $\mathbf{v}_i$ = *the vector representing "I"* *i refers to "I"*
$\mathbf{v}_j$ = *the vector representing "like"* *j refers to "like"*

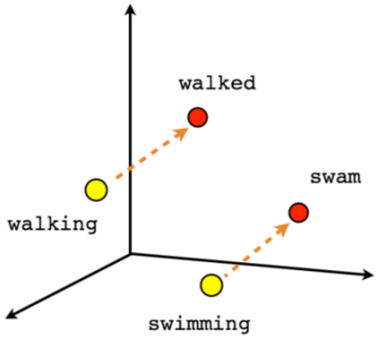
Then we Expect : mapping $\mathbf{v}_i \bullet \mathbf{v}_j$ *to* $\log(C_{ij})$



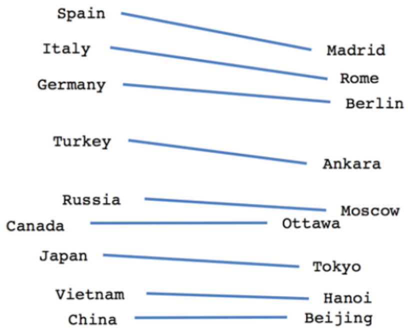
Properties of Word Vectors



Male-Female



Verb tense



Country-Capital

Ingredients

Corpus of text	As large as possible
Annotations	0
Initialize weights (aka Embeddings)	1x per word
Deep Learning Model	1x
Cost Function	Appropriately
GPU	Lotsa of it

Features from WordToVec

- **Count from Data (SVD)**
  - Best for **Word-level Similarity**
  - significantly outperformed word2vec and GLOVE
  - Computational cost is High
  - Difficult to handle huge matrix
  - Keep window short (window_size = 2)
- **Learn from Data (Word2Vec)**
  - Cheap to train and Scales with corpus size
  - Generate improvements on other predictive tasks
  - Capture complex patterns beyond word level similarity
- **Count and Learn from Data (GLOVE)**
  - Fast to Train
  - Believed to have advantages from both
  - Differences are not obvious
  - Widely used (pre-trained model from Wikipedia and Twitter)

Sentence Embedding

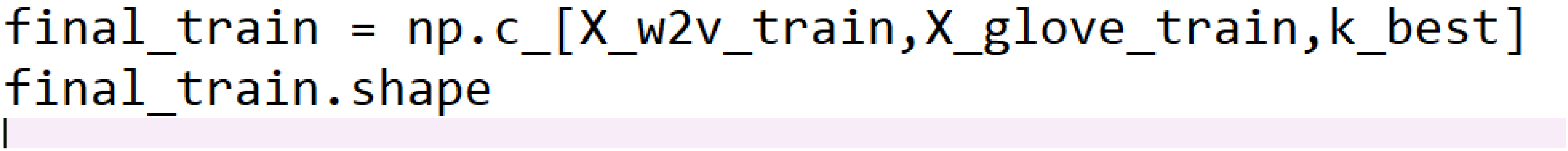
v(*'he'*)	0.5	-1.3	0.6	1.1
v(*'drinks'*)	0.3	-0.2	0.5	0.5
v(*'coffee'*)	1.3	2.1	-0.8	1.1
	AVG()/MAX()/MIN()/Concat()			
Sent0 ("he drinks coffee")	0.7	0.2	0.1	0.9

Instead of picking *K* most useful features,
here take **N** dimensional Word Embedding

Combine Feature Sets

v(*‘he’*)	0.5	-1.3	0.6	1.1
v(*‘drinks’*)	0.3	-0.2	0.5	0.5
v(*‘coffee’*)	1.3	2.1	-0.8	1.1
	AVG()			
Sent0 (“he drinks coffee”)	0.7	0.2	0.1	0.9

	he	drink	coffee	*tfidf* drink coffee	*tfidf* he drink	*PPMI* he drink	*PPMI* drink coffee	…	Sent Vector			
sent0	0.01	0.38	0.00	0.87	0.00	4.23	0.00	…	0.7	0.2	0.1	0.9



```
final_train = np.c_[X_w2v_train,X_glove_train,k_best]
final_train.shape
```

How to Choose Context?

- **Different contexts lead to different embeddings**

- **Small context window:** more syntax related

- **Large context window:** more semantics related

Semantics is the study of meaning, reference, or truth.

Limitations

- **Sensitive to “tokens”** (cat vs cats)
- **Inconsistent across space**, embeddings for the same words trained with different data are different
- **Can encode bias** (stereotypical gender roles, racial bias)
- **Not interpretable**

Summary

- Key steps before building a sentiment analysis are:
  i. *Training data (corpus)* selection/ generation
  ii. *Features selection*
  iii. *Features from embedding*

These pre-steps are key to the success of a sentiment analysis and usually **more important than the training algorithms** themselves.

Training data selection needs to be as similar as possible to the production data. The features selection requires domain expertise.

Word Embeddings can be retrained with domain data or downloaded from pre-trained data