Vector Semantics

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February 5, 2021

Announcements

- **TBD**

Overview

1. Vector semantics
2. Matrix representations
3. Calculating vectors
4. Similarity measures
5. Evaluation

Vector semantics

The quest for meaning

- The realm of *lexical semantics*.
- A **lemma** can be associated with multiple **word senses** (e.g., “mouse (N)”.
- The many facets of ‘meaning’:
  - *Propositional synonymity*: two words (senses) are synonyms if the truth conditions of a sentence does not change when we swap them.
  - *Word similarity*: some features are shared, but no synonyms. E.g., ‘cat’ and ‘dog’.
  - *Word relatedness*: no features are shared, but there is a relationship. E.g., ‘water’ and ‘bottle’.
  - Semantic frames or *topics*: topical structure in documents. E.g., ‘sport’ and ‘politics’.
  - *Connotations*, e.g., sentiment (positive, negative), tone (formal or not).

Denotational vs distributional approaches

- Denotational approach: define (dictionary) meaning then apply definition. Meaning as dictionary index.
- Distributional approach: look at data to come up with meaning. **Distributional hypothesis**: “the amount of meaning difference between two words corresponds roughly to the amount of difference in their environments” (contexts of appearance). Harris, 1954.

Vector Semantics

“The meaning of a word is its use in the language.” Wittgenstein, 1953.

1. **???** *is best when cooked just right.*
2. *I prefer my* **???** *with abundant tomato sauce.*
3. *I eat* **???** *for lunch.*
4. *Would you like tomato sauce on your pizza?*
5. *We went to a pizza place for lunch.*
6. *Pizza should not be too cooked: it burns!*

Can you guess **???**

Vector Semantics

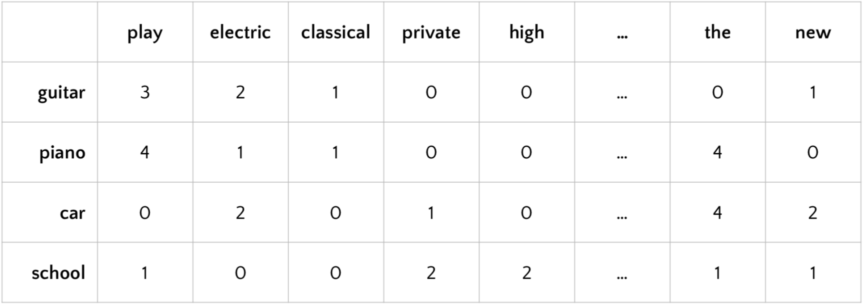
“The meaning of a word is its use in the language.” Wittgenstein, 1953.

1. *Pasta is best when cooked just right.*
2. *Pizza should not be too cooked: it burns!*
3. Vector semantics combines two intuitions:
    - **Distributional approach**: define a word by the contexts it occurs into.
    - **Vectorize it**: use vectors to represent word meaning, as a point in space.
4. **Feature engineering** for NLP: word vectors are increasingly used as features for other tasks.
5. (Word) vectors are usually referred as (word) **embeddings** in modern neural network literature.

Example

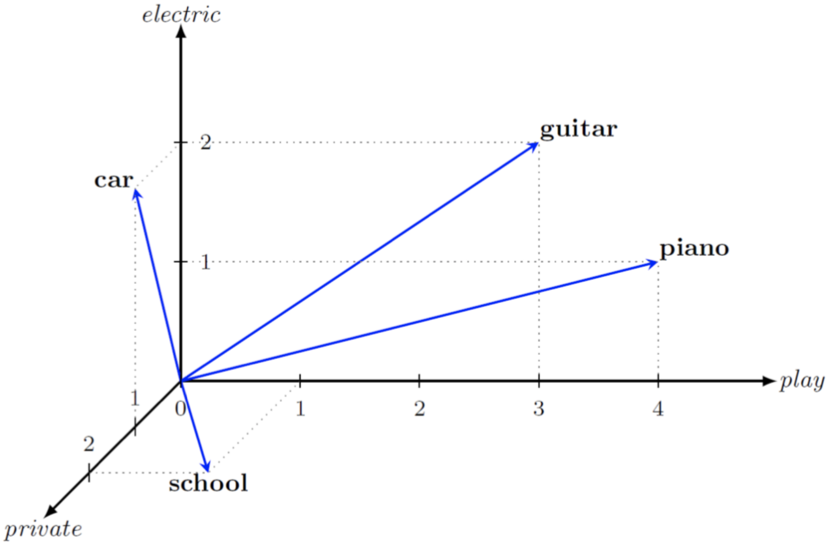
```
…ound and sonic power of a [new electric  guitar  played through] a guitar amp has play…
                         …[Some electric  guitar  models feature] piezoelectric pickups…
                               …[Playing  guitar  with a] pick produces a bright sound …
…ings, he is known for [playing fretless  guitar  in his] performances…
               …the neck of [a classical  guitar  is too] wide and the normal position …
…t in the centre of Bristol [playing the  piano   , I was] punched in the head while, a…
…r in Houston, Texanstagram [playing the  piano   in his] flooded home after Hurrican H…
… some supplies, he stopped to [play the  piano   that was] sitting in knee-high water …
…te and one black, who [played classical  piano   together]…
                    …The [first electric  pianos  from the] late 1920s used metal strin…
…technologies, for example [the electric   car    and the] integration of mobile commun…
…study had each driver of [each electric   car    drive unimpeded], perform a task whil…
…Honda to commence testing of [their new   car    and the] American was no doubt more t…
…mary design considerations for [the new   car    were "safety] innovations, performanc…
…would be possible if almost [all private  cars   requiring drivers], which are not in …
… who donate to groups [providing private school  scholarships have] written pieces att…
… that students participating [in private school  choice programs] graduate high school…
…s in the establishment of this [new high school  , named the] Gavirate Business School…
         …Anna heads into her [final high school  year before] university wanting somet…
… but he can prevent them from [playing at school]
```

Example

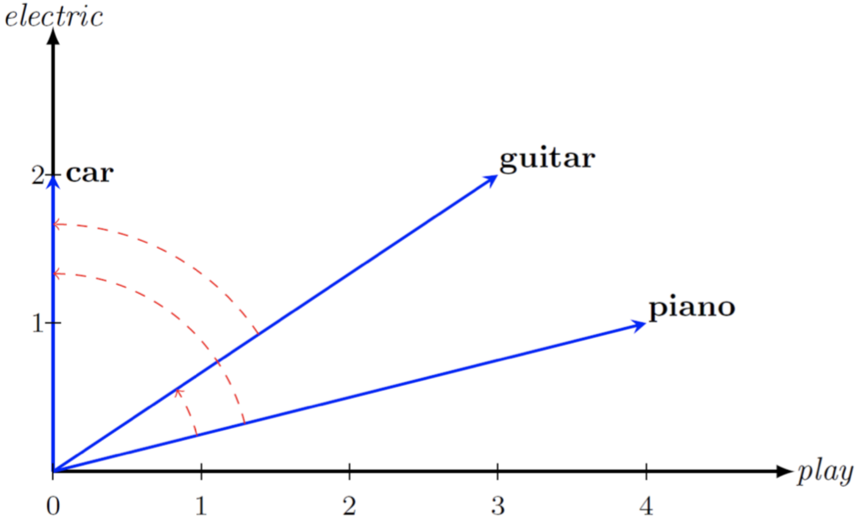


	play	electric	classical	private	high	...	the	new
guitar	3	2	1	0	0	...	0	1
piano	4	1	1	0	0	...	4	0
car	0	2	0	1	0	...	4	2
school	1	0	0	2	2	...	1	1

Example



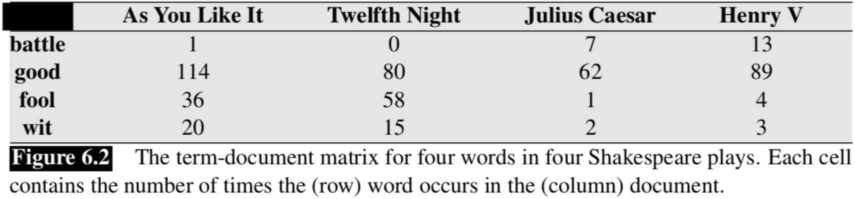
Example



Matrix representations

Word-Document matrix

- We have a set of documents D and a vocabulary V. X is a $|V| \times |D|$ matrix with word occurrences in documents.



	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

Figure 6.2 The term-document matrix for four words in four Shakespeare plays. Each cell contains the number of times the (row) word occurs in the (column) document.

Credit: J&M, ch. 6.

Word-Document matrix

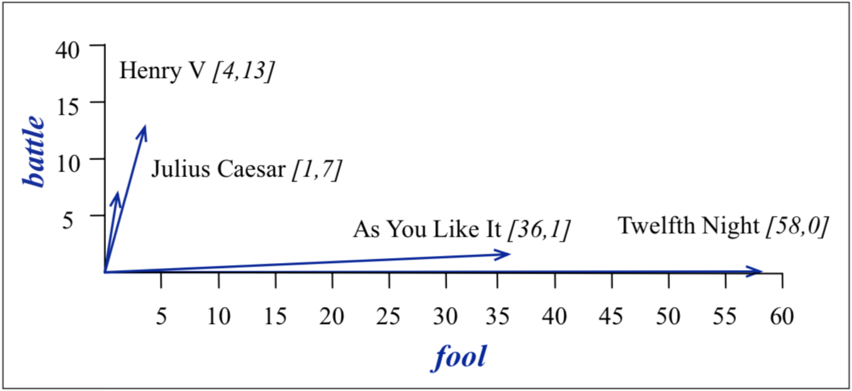
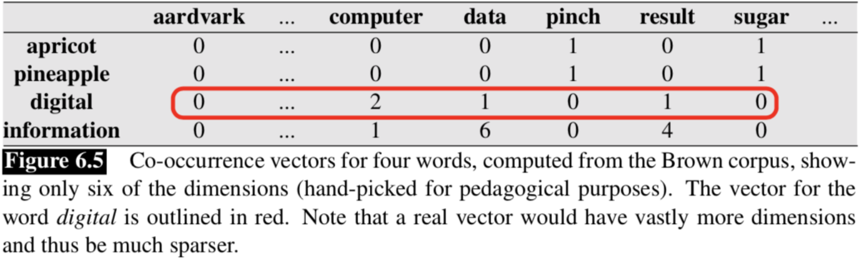


Figure 6.4 A spatial visualization of the document vectors for the four Shakespeare play documents, showing just two of the dimensions, corresponding to the words *battle* and *fool*. The comedies have high values for the *fool* dimension and low values for the *battle* dimension.

Credit: J&M, ch. 6.

Word-Context matrix

- We have a set of words V and a set of contexts they occur into C, taken from our corpus of documents. X in this case is a $|V| \times |C|$ matrix with word occurrences in contexts.
- The most intuitive context are co-occurrences with other words in V, within a certain **window**. In this case, X would be a $|V| \times |V|$ matrix.



	aardvark	...	computer	data	pinch	result	sugar	...
apricot	0	...	0	0	1	0	1	
pineapple	0	...	0	0	1	0	1	
digital	0	...	2	1	0	1	0	
information	0	...	1	6	0	4	0	

Figure 6.5 Co-occurrence vectors for four words, computed from the Brown corpus, showing only six of the dimensions (hand-picked for pedagogical purposes). The vector for the word *digital* is outlined in red. Note that a real vector would have vastly more dimensions and thus be much sparser.

Credit: J&M, ch. 6.

Word-Context matrix

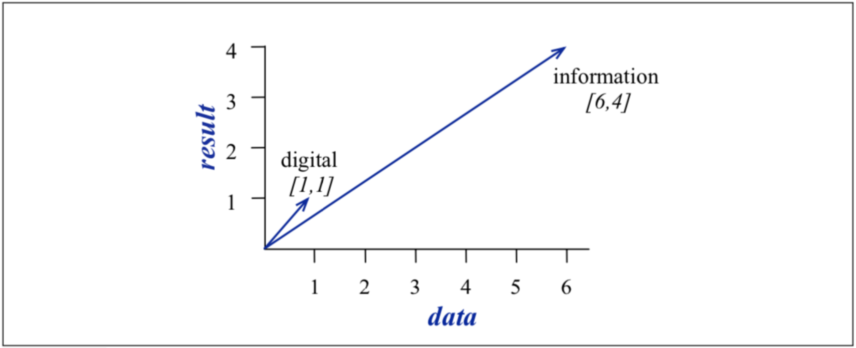


Figure 6.6 A spatial visualization of word vectors for *digital* and *information*, showing just two of the dimensions, corresponding to the words *data* and *result*.

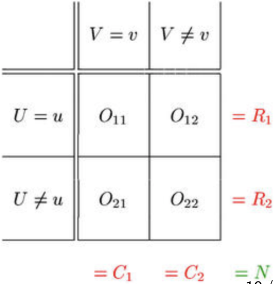
Credit: J&M, ch. 6.

Types of co-occurrences

- **Surface co-occurrence**:
  - a contextual word co-occurs with the target word as many times as the former appears in a collocational span (window) surrounding the latter.
  - The span may be symmetric ([-5w, +5w]) or asymmetric ([-5w, 0]).
- **Textual co-occurrence**:
  - words co-occur if they appear in the same text segment (e.g., a sentence, a paragraph, a web page ...).
  - It usually does not matter how many times each word occur in each document.
- **Syntactic co-occurrence**:
  - count word co-occurrences in a specific syntactic relation (e.g., verb-object, adjective-noun ...).

Contingency tables

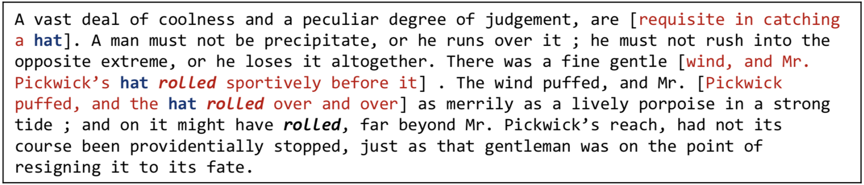
- Tabular representation of the observed frequencies between the variable whose values are reported in rows and the variable whose values are reported in columns.
- Intermediate step for some calculations we will see.
- If u is our target word and v is a contextual word:
  - O_{11} – observed frequency of u and v (i.e., $f(u, v)$).
  - R_1, R_2, C_1, C_2 – marginal frequencies.
  - R_1 – absolute frequency of u (i.e. $f(u)$).
  - C_1 – absolute frequency of v (i.e. $f(v)$).
  - $N = O_{11} + O_{12} + O_{21} + O_{22}$ – sample size.



	$V = v$	$V \neq v$	
$U = u$	O_{11}	O_{12}	$= R_1$
$U \neq u$	O_{21}	O_{22}	$= R_2$
	$= C_1$	$= C_2$	$= N$

Contingency tables – Surface co-occurrences

- w1 = “hat”; w2 = “roll”.
- Collocational span: ±4 words (i.e. [-4w, +4w]).
- Spans cannot cross sentence boundaries.



A vast deal of coolness and a peculiar degree of judgement, are [requisite in catching a **hat**]. A man must not be precipitate, or he runs over it ; he must not rush into the opposite extreme, or he loses it altogether. There was a fine gentle [wind, and Mr. Pickwick’s **hat** ***rolled*** sportively before it] . The wind puffed, and Mr. [Pickwick puffed, and the **hat** ***rolled*** over and over] as merrily as a lively porpoise in a strong tide ; and on it might have ***rolled***, far beyond Mr. Pickwick’s reach, had not its course been providentially stopped, just as that gentleman was on the point of resigning it to its fate.

Contingency tables – Surface co-occurrences

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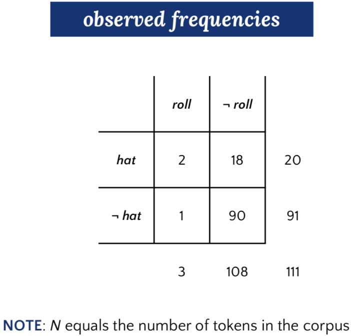


observed frequencies

	roll	*¬ roll*	
hat	2	18	20
¬ hat	1	90	91
	3	108	111

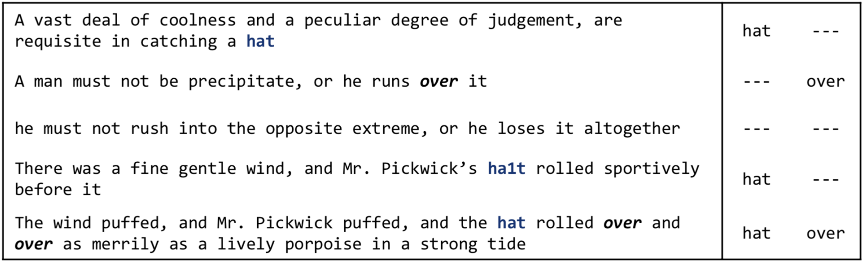
NOTE: *N* equals the number of tokens in the corpus

Error in the example

Row 1 column 2 (hat, not roll) should take value 1.

Contingency tables – Textual co-occurrences

- w1 = “hat”; w2 = “over”.
- Unit is sentence (multiple occurrence is the same unit are ignored).



A vast deal of coolness and a peculiar degree of judgement, are requisite in catching a **hat**	hat	---
A man must not be precipitate, or he runs ***over*** it	---	over
he must not rush into the opposite extreme, or he loses it altogether	---	---
There was a fine gentle wind, and Mr. Pickwick’s **ha1t** rolled sportively before it	hat	---
The wind puffed, and Mr. Pickwick puffed, and the **hat** rolled ***over*** and ***over*** as merrily as a lively porpoise in a strong tide	hat	over

Contingency tables – Textual co-occurrences

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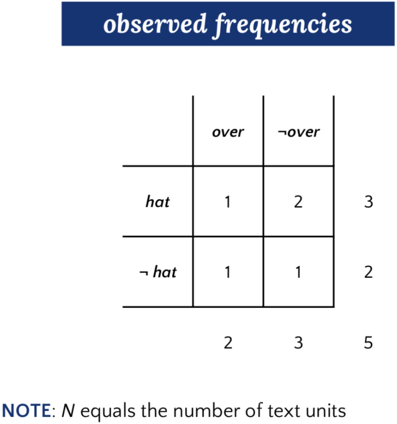


observed frequencies

	over	*¬over*	
hat	1	2	3
¬ hat	1	1	2
	2	3	5

NOTE: *N* equals the number of text units

Calculating vectors

Families of vectors

- **Sparse vectors**: many zero values and high-dimensional spaces. E.g., weighted co-occurrence matrices (this class).
- **Dense vectors**: no zero values and comparatively smaller-dimensional spaces.
  - Dimensionality reduction (Singular Value Decomposition, Random indexing, Non-negative matrix factorization): next lab.
  - Neural-networks (Skigp-gram, CBOW, GloVe): future class.

(Better) quantifying association

Raw co-occurrence frequency is not of the optimal measure of association between a word and a context:

- we need a way to estimate to what extent a context word is particularly informative about a target word;
- frequencies are very skewed.
- A couple of solutions: **tf-idf** and **PPMI**.

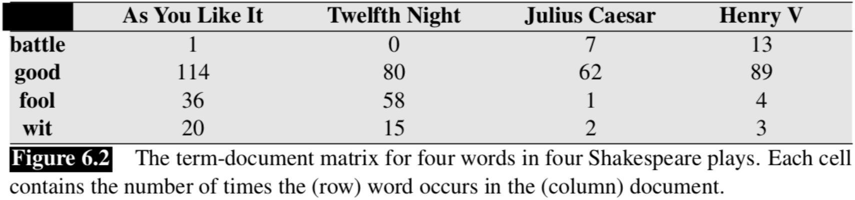
Term frequency - Inverse document frequency

- Tf-idf is the standard weighting scheme for term-document matrices.
- It is likely the most used weighting scheme in Information Retrieval.
- **Term frequency** $tf(t,d) =$ the number of times term t occurs in document d. M any variants exist (e.g., using a log transform). It accounts for how frequent t is within the document collection.
- **Inverse document frequency** $idf(t) = log\left(\frac{|D|}{|D_t|}\right)$; where D is the collection of documents and D_t is the subset where term t appears once or more. It accounts for how 'discriminative' t is with respect to the document collection.

$$tfidf(t,d) = tf(t,d) \times idf(t)$$

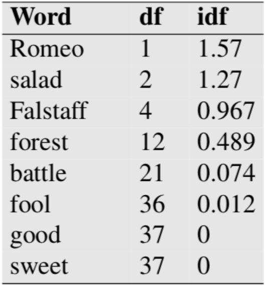
- Recall: this is the same trade-off we discussed between the *multinomial* and the *multivariate Bernoulli* Naïve Bayes variants w.r.t. calculating $P(w|c)$. Tf-idf brings the two sides of the coin together in a single measure.

Term frequency - Inverse document frequency



[redacted]	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	1	0	7	13
good	114	80	62	89
fool	36	58	1	4
wit	20	15	2	3

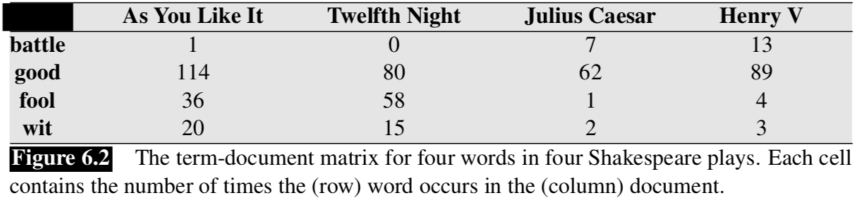
Figure 6.2 The term-document matrix for four words in four Shakespeare plays. Each cell contains the number of times the (row) word occurs in the (column) document.



Word	df	idf
Romeo	1	1.57
salad	2	1.27
Falstaff	4	0.967
forest	12	0.489
battle	21	0.074
fool	36	0.012
good	37	0
sweet	37	0

Credit: J&M, ch. 6.

Term frequency - Inverse document frequency



	As You Like It	Twelfth Night	Julius Caesar	Henry V
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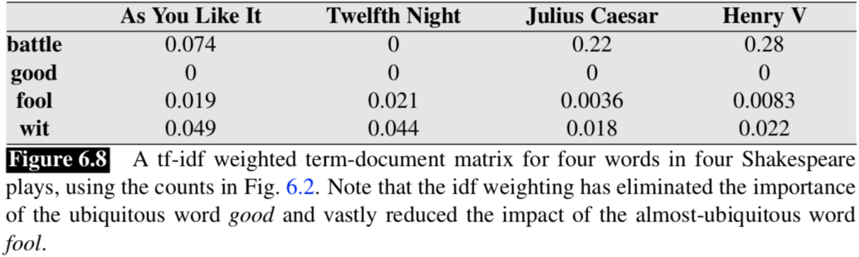


	As You Like It	Twelfth Night	Julius Caesar	Henry V
battle	0.074	0	0.22	0.28
good	0	0	0	0
fool	0.019	0.021	0.0036	0.0083
wit	0.049	0.044	0.018	0.022

Figure 6.8 A tf-idf weighted term-document matrix for four words in four Shakespeare plays, using the counts in Fig. 6.2. Note that the idf weighting has eliminated the importance of the ubiquitous word *good* and vastly reduced the impact of the almost-ubiquitous word *fool*.

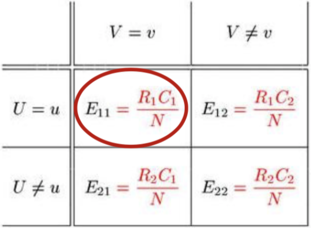
Credit: J&M, ch. 6.

(Positive) Pointwise Mutual Information

Intuition: in order to discriminate between informative and uninformative word-context associations, let us **take the expected frequency into account as a baseline**.

- The **expected frequency** of a (word, context) pair is a measure of how often a word would occur in a context if the two linguistic entities were statistically independent (i.e., if they were occurring by chance).
- The expected frequency can be estimated from the marginals in the contingency table:

$$E_{11} = \frac{f(u)f(v)}{N}$$



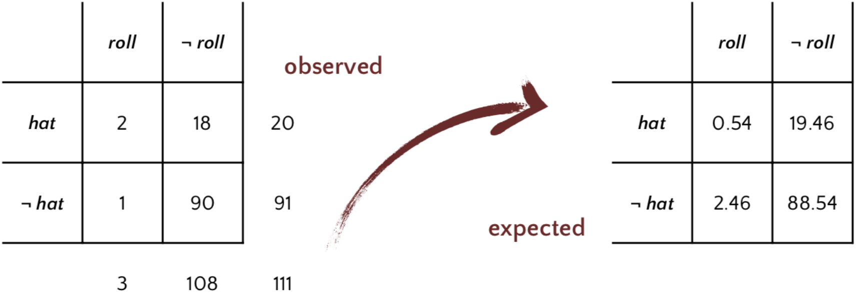
	$V = v$	$V \neq v$
$U = u$	$E_{11} = \frac{R_1 C_1}{N}$	$E_{12} = \frac{R_1 C_2}{N}$
$U \neq u$	$E_{21} = \frac{R_2 C_1}{N}$	$E_{22} = \frac{R_2 C_2}{N}$

(Positive) Pointwise Mutual Information

	roll	*¬ roll*	
hat	2	18	20
¬ hat	1	90	91
	3	108	111

observed

(Positive) Pointwise Mutual Information



	roll	*¬ roll*	
hat	2	18	20
¬ hat	1	90	91
	3	108	111

observed
expected

	roll	*¬ roll*
hat	0.54	19.46
¬ hat	2.46	88.54

(Positive) Pointwise Mutual Information

- Mutual Information provides a measure of independence of two random variables X and Y:

$$MI(X,Y) = \sum_{x \in X} \sum_{y \in Y} P(x,y) log \frac{P(x,y)}{P(x)P(y)}$$

- Pointwise Mutual Information is the part related to two outcomes x and y:

$$PMI(x,c) = log \frac{P(x,y)}{P(x)P(y)}$$

- Us, we are interested in a word-context pair, w and c:

$$PMI(w,c) = log \frac{P(w,c)}{P(w)P(c)}$$

Positive Pointwise Mutual Information

- We are not interested in joint events more unlikely than independent ones, thus we usually just consider the positive values of **PPMI**:

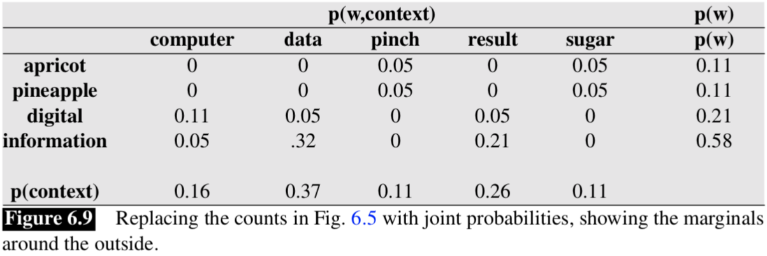
$$PPMI(w,c) = max\Big(0, log\,\frac{P(w,c)}{P(w)P(c)}\Big)$$

- Many variants to account for minor issues:
  - **Positive Local Mutual Information**: deals with the tendency of PPMI to emphasize rare events over frequent ones:

$$PLMI(w,c) = max\Big(0, f(w,c) \times PMI(w,c)\Big)$$

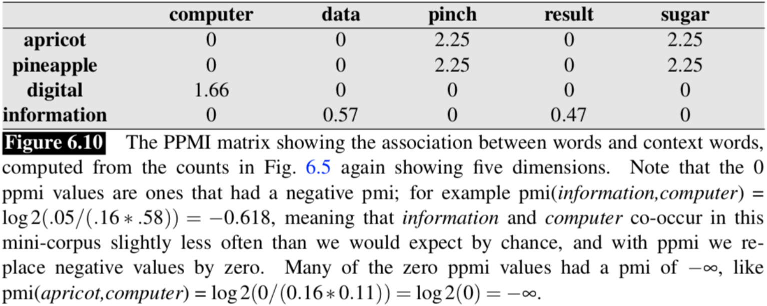
  - More in the labs and assignment 3.

PPMI



	p(w,context)					p(w)
	computer	**data**	**pinch**	**result**	**sugar**	**p(w)**
apricot	0	0	0.05	0	0.05	0.11
pineapple	0	0	0.05	0	0.05	0.11
digital	0.11	0.05	0	0.05	0	0.21
information	0.05	.32	0	0.21	0	0.58
p(context)	0.16	0.37	0.11	0.26	0.11	

Figure 6.9 Replacing the counts in Fig. 6.5 with joint probabilities, showing the marginals around the outside.



	computer	**data**	**pinch**	**result**	**sugar**
apricot	0	0	2.25	0	2.25
pineapple	0	0	2.25	0	2.25
digital	1.66	0	0	0	0
information	0	0.57	0	0.47	0

Figure 6.10 The PPMI matrix showing the association between words and context words, computed from the counts in Fig. 6.5 again showing five dimensions. Note that the 0 ppmi values are ones that had a negative pmi; for example pmi(*information,computer*) = $\log 2(.05/(.16 * .58)) = -0.618$, meaning that *information* and *computer* co-occur in this mini-corpus slightly less often than we would expect by chance, and with ppmi we replace negative values by zero. Many of the zero ppmi values had a pmi of $-\infty$, like pmi(*apricot,computer*) $= \log 2(0/(0.16 * 0.11)) = \log 2(0) = -\infty$.

Credit: J&M, ch. 6.

Similarity measures

Comparing vectors: the dot product

- Now we know how to calculate the first-order associations between words and how to use this information to create a *distributional signature* of each word.
- **Similarity measures** can be used to quantify the distance between two vectors in a space, and this can be used to estimate how similar the represented words are.
- Most vector similarity measure are based on the **dot (inner) product**:

$$\vec{u} \cdot \vec{v} = \sum_{i=1}^{d} u_i v_i = u_1 v_1 + u_2 v_2 + \cdots + u_d v_d$$

Comparing vectors: the dot product

- When used as a similarity metric, the dot product has a huge problem: it favors long vectors.

$$|\vec{v}| = \sqrt{\sum_{i=1}^{d} v_i^2}$$

- Vectors are longer if they have more or higher values in each dimension. This means that frequent words will have higher dot products.
- A similarity measure that is too sensitive to frequency often performs badly.

Comparing vectors: Cosine

- Solution 1: divide thee dot product by the length of the two vectors,

$$\frac{\vec{u} \cdot \vec{v}}{|\vec{u}||\vec{v}|}$$

- Solution 2: divide each vector by its length, thus using unit vectors before taking the dot product.
- The two solutions are equivalent, in both cases we find the **cosine of the angle between the two vectors**:

$$cosine(\vec{u}, \vec{v}) = \frac{\vec{u} \cdot \vec{v}}{|\vec{u}||\vec{v}|} = \frac{\sum_{i=1}^{d} u_i v_i}{\sum_{i=1}^{d} u_i^2 \sum_{i=1}^{d} v_i^2}$$

- The cosine ranges between 1 and -1, taking value 0 for orthogonal vectors. Due to the fact that PPMIs and other frequencies are always non-negative, cosine ranges from 0 to 1 (identically directed vectors).

Cosine

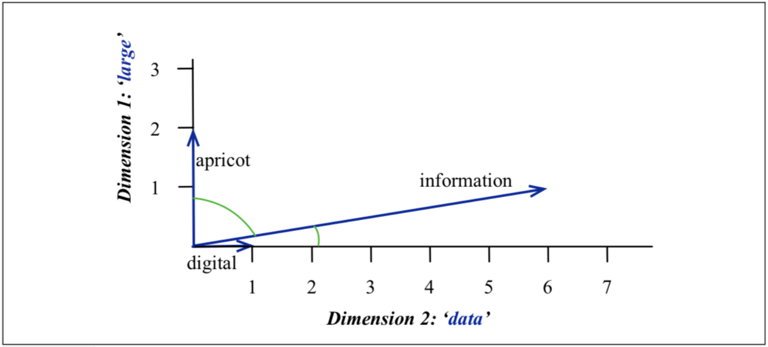


Figure 6.7 A graphical demonstration of cosine similarity, showing vectors for three words (*apricot*, *digital*, and *information*) in the two dimensional space defined by counts of the words *data* and *large* in the neighborhood. Note that the angle between *digital* and *information* is smaller than the angle between *apricot* and *information*. When two vectors are more similar, the cosine is larger but the angle is smaller; the cosine has its maximum (1) when the angle between two vectors is smallest (0°); the cosine of all other angles is less than 1.

Credit: J&M, ch. 6.

Evaluation

Association/Similarity

Two words or a word and a context, may have two kinds of associations:

- **Syntagmatic associations** (first-order co-occurrence): how much two words appear one next to the other.
    1. E.g., the association between a verb and its typical complements;
    2. what is represented in a co-occurrence matrix.
- **Paradigmatic associations** (second-order co-occurrence) is similarity of context: how similar are the neighbors of the two words.
    1. E.g., the association between two synonyms, or “wrote”, “said”, “remarked”.
    2. what is estimated by calculating (first-order) vectors similarity.

Evaluation of vectors

- The most common evaluation is to test their performance on similarity tasks.
- Correlation between algorithm and human word similarity ratings:
  1. *WordSim-353*: 353 noun pairs rated on a 0-10 scale. sim("plane", "car") = 5.77.
  2. *SimLex-999*: similarity of noun, adjectives and adjectives pairs. *Assignment 3*.
- Taking *TOEFL* multiple-choice vocabulary tests
  1. Levied is closest in meaning to: imposed, believed, requested, correlated.
- Judgments in context
  1. *Stanford Contextual Word Similarity* (SCWS) dataset: human judgments on 2,003 pairs of nouns, verbs, and adjectives in their sentence context.