Module-4

Semantics – Lexical semantics – Word Senses – Relation between senses – Word Sense Disambiguation- Word Similarity Analysis using Thesaurus and Distributional Methods – Word2vec – Fast text Word embedding – Lesk Algorithm – Thematic Roles – Semantic Role Labelling – Pragmatic Analysis – Anaphora Resolution

Lexical Semantics

- Lexical semantics is concerned with inherent aspects of word meaning and the semantic relations between words, as well as the ways in which word meaning is related to syntactic structure.

Lemma and Wordform

- A lemma or citation form
  - Basic part of the word, same stem, rough semantics
- A wordform
  - The "inflected" word as it appears in text

Wordform	Lemma
banks	bank
sung	sing
duermes	dormir

Word Senses

Lemmas can be polysemous (have multiple senses)

Word sense disambiguation, the task of determining which sense of a word is being used in a particular context.

- One lemma "bank" can have many meanings:

Sense 1: • …a **bank**$_1$ can hold the investments in a custodial account…

Sense 2: • "…as agriculture burgeons on the east **bank**$_2$ the river will shrink even more"

- **Sense** (or **word sense**)
  - A discrete representation of an aspect of a word's meaning.
- The lemma **bank** here has two senses

Relation between word senses

- Synonym - Two words are synonymous if they are substitutable for one another in any sentence without changing the truth conditions of the sentence. (Sense of one word is identical / near identical to the sense of another word)
  - Ex: couch / sofa
  - Perfect synonymy is rare
    - Miss Nelson became a kind of big sister to Benjamin.
    - Miss Nelson became a kind of large sister to Benjamin.
    - big has a sense that means being older, or grown up – large lacks this sense
- Homonyms: Words that share a form but have unrelated, distinct meanings
  - Bank - financial institution / sloping land (Homographs)
- Homophenes : Write and right ; Piece and peace

- Antonyms - Senses that are opposites with respect to one feature of meaning.
  - Antonyms can
    - Define a binary opposition: in/out
    - Be at the opposite ends of a scale: fast/slow
    - Be reversive: rise/fall

Hyponymy and Hypernymy

- One sense is a **hyponym** of another if the first sense is more specific, denoting a subclass of the other
  - ***car*** is a hyponym of *vehicle*
  - *mango* is a hyponym of *fruit*
- Conversely **hypernym/superordinate** ("hyper is super")
  - *vehicle* is a hypernym of *car*
  - *fruit* is a hypernym of *mango*
- Usually transitive
  - (A hypo B and B hypo C entails A hypo C)

Superordinate/hyper	vehicle	fruit	furniture
Subordinate/hyponym	car	mango	chair

Polysemy

- Multiple related meanings
  - S: (n) newspaper, paper (a daily or weekly publication on folded sheets; contains news and articles and advertisements) "he read his newspaper at breakfast“
  - S: (n) newspaper, paper, newspaper publisher (a business firm that publishes newspapers) "Murdoch owns many newspapers"
  - S: (n) newspaper, paper (the physical object that is the product of a newspaper publisher) "when it began to rain he covered his head with a newspaper"
  - S: (n) newspaper, newsprint (cheap paper made from wood pulp and used for printing newspapers) "they used bales of newspaper every day“

Word Relatedness / Association

- Word Similarity - Knowing how similar two words are can help in computing how similar the meaning of two phrases or sentences are.
  - very important component of tasks like question answering, paraphrasing, and summarization.

vanish	disappear	9.8
belief	impression	5.95
muscle	bone	3.65
modest	flexible	0.98
hole	agreement	0.3

- Word Relatedness - The meaning of two words can be related in ways other than relatedness similarity. One such class of connections is called word relatedness.
  - Ex : coffee and cup ; scalpel and surgeon

Word Relatedness / Association

- Semantic Field - A semantic field is a set of words which cover a particular semantic domain and bear structured relations with each other.
  - Ex : hospital (surgeon, scalpel, nurse, anesthetic, hospital)
- Semantic Frames and Roles - A semantic frame is a set of words that denote perspectives or participants in a particular type of event.
  - Frame – Transaction
  - Roles – buyer, seller, goods, money
- Affective meanings or connotations – represents the aspects of a word's meaning that are related to a writer or reader's emotions, sentiment, opinions, or evaluations.
  - Three important dimensions of affective meaning:
    - valence: the pleasantness of the stimulus
    - Arousal: the intensity of emotion provoked by the stimulus
    - Dominance: the degree of control exerted by the stimulus

	Valence	Arousal	Dominance
courageous	8.05	5.5	7.38
music	7.67	5.57	6.5
heartbreak	2.45	5.65	3.58
cub	6.71	3.95	4.24

Semantic field

Words that

- cover a particular semantic domain
- bear structured relations with each other.

hospitals

surgeon, scalpel, nurse, anaesthetic, hospital

restaurants

waiter, menu, plate, food, menu, chef

houses

door, roof, kitchen, family, bed

Semantic Roles

Thematic Role	Definition	Example
AGENT	The volitional causer of an event	*The waiter* spilled the soup.
EXPERIENCER	The experiencer of an event	*John* has a headache.
FORCE	The non-volitional causer of the event	*The wind* blows debris from the mall into our yards.
THEME	The participant most directly affected by an event	Only after Benjamin Franklin broke *the ice*...
RESULT	The end product of an event	The city built a *regulation-size baseball diamond*...
CONTENT	The proposition or content of a propositional event	Mona asked *"You met Mary Ann at a supermarket?"*
INSTRUMENT	An instrument used in an event	He poached catfish, stunning them *with a shocking device*.
BENEFICIARY	The beneficiary of an event	Whenever Ann Callahan makes hotel reservations *for her b*
SOURCE	The origin of the object of a transfer event	I flew in *from Boston*.
GOAL	The destination of an object of a transfer event	I drove *to Portland*.

Semantic Roles – Thematic Roles

- Semantic roles thus help generalize over different surface realizations of predicate arguments.
  - For example, while the AGENT is often realized as the subject of the sentence, in other cases the THEME can be the subject.
  - Consider these possible realizations of the thematic arguments of the verb break:

John *broke the window.*
AGENT THEME

John *broke the window with a rock.*
AGENT THEME INSTRUMENT

The rock *broke the window.*
INSTRUMENT THEME

The window broke.
THEME

The window was broken by John.
THEME AGENT

Thematic grid, θ-grid, or case frame:

These examples suggest that break has (at least) the possible arguments AGENT, THEME, and INSTRUMENT. The set of thematic role arguments taken by a verb is thematic grid often called the thematic grid, θ-grid, or case frame.

Semantic Roles – Thematic Roles

- Many verbs allow their thematic roles to be realized in various syntactic positions.
  - For example, verbs like give can realize the THEME and GOAL arguments in two different ways:

a. *Doris gave the book to Cary.*
AGENT THEME GOAL

b. *Doris gave Cary the book.*
AGENT GOAL THEME

Thematic Roles - Alternatives

- The Proposition Bank (Prop Bank) – Focuses on verbs
- NomBank – Adds annotations to noun predicates
- FrameNet – Makes inferences about the semantic commonalities across different sentences with verbs of the sentences, verbs and nouns… .
  - Ex - For example, we'd like to extract the similarity among these three sentences

[$_{\text{Arg1}}$ The price of bananas] increased [$_{\text{Arg2}}$ 5%].
[$_{\text{Arg1}}$ The price of bananas] rose [$_{\text{Arg2}}$ 5%].
There has been a [$_{\text{Arg2}}$ 5%] rise [$_{\text{Arg1}}$ in the price of bananas].

Assign the various verb arguments in the following example to their appropriate thematic roles.

1. The intense heat buckled the highway about three feet.
2. He melted her reserve with a husky-voiced paean to her eyes.
3. But Mingo, a major Union Pacific shipping center in the 1890s, has melted away to little more than the grain elevator now.

Solution

1. [FORCE The intense heat] buckled [THEME the highway] [RESULT about three feet].
2. [AGENT He] melted [THEME her reserve] [INSTRUMENT with a husky-voiced paean to her eyes].
3. But [EXPERIENCER Mingo, a major Union Pacific shipping center in the 1890s,] has melted away [RESULT to little more than the grain elevator] now.

The PropBank

- A resource of sentences annotated with semantic roles
- The English PropBank labels all the sentences in the Penn TreeBank;
- The Chinese PropBank labels sentences in the Penn Chinese TreeBank.
- Each sense of each verb thus has a specific set of roles, which are given only numbers rather than names: Arg0, Arg1, Arg2,….
- In general,
  - Arg0 represents the PROTO-AGENT
  - Arg1, the PROTO-PATIENT.
  - Arg2 is often the benefactive, instrument, attribute, or end state
  - Arg3 the start point, benefactive, instrument, or attribute, and the Arg4 the end point.

The PropBank

- PropBank also has a number of non-numbered arguments called ArgMs, which represent modification or adjunct meanings.

TMP	when?	yesterday evening, now
LOC	where?	at the museum, in San Francisco
DIR	where to/from?	down, to Bangkok
MNR	how?	clearly, with much enthusiasm
PRP/CAU	why?	because ... , in response to the ruling
REC		themselves, each other
ADV	miscellaneous	
PRD	secondary predication	...ate the meat raw

Example

agree.01

Arg0: Agreer
Arg1: Proposition
Arg2: Other entity agreeing

Ex1: [$_{Arg0}$ The group] *agreed* [$_{Arg1}$ it wouldn't make an offer].
Ex2: [$_{ArgM\text{-}TMP}$ Usually] [$_{Arg0}$ John] *agrees* [$_{Arg2}$ with Mary] [$_{Arg1}$ on everything].

Consider the Example “increase”. Apply semantic role labelling

) **increase.01** “go up incrementally”
Arg0: causer of increase
Arg1: thing increasing
Arg2: amount increased by, EXT, or MNR
Arg3: start point
Arg4: end point

- Big Fruit Co increased the price of bananas.

[$_{Arg0}$ Big Fruit Co.] increased [$_{Arg1}$ the price of bananas].

- The price of bananas was increased again by Big Fruit Co.

[$_{Arg1}$ The price of bananas] was increased again [$_{Arg0}$ by Big Fruit Co.]

- The price of bananas increased 5 %

[$_{Arg1}$ The price of bananas] increased [$_{Arg2}$ 5%].

Semantic Role Labelling - Framenet

- Framenet
  - The FrameNet project is another semantic-role-labeling project that establishes the semantic role based on the frame.
  - A frame in FrameNet is a background knowledge structure that defines
    - A set of frame elements frame-specific semantic roles, called **frame elements**
    - Includes a set of predicates that use these roles.
  - Each word evokes a frame and profiles some aspect of the frame and its elements.
  - The FrameNet dataset includes a set of frames and frame elements, the lexical units associated with each frame, and a set of labeled example sentences.

Semantic Role Labelling - Framenet

Core Roles	
ATTRIBUTE	The ATTRIBUTE is a scalar property that the ITEM possesses.
DIFFERENCE	The distance by which an ITEM changes its position on the scale.
FINAL_STATE	A description that presents the ITEM's state after the change in the ATTRIBUTE's value as an independent predication.
FINAL_VALUE	The position on the scale where the ITEM ends up.
INITIAL_STATE	A description that presents the ITEM's state before the change in the ATTRIBUTE's value as an independent predication.
INITIAL_VALUE	The initial position on the scale from which the ITEM moves away.
ITEM	The entity that has a position on the scale.
VALUE_RANGE	A portion of the scale, typically identified by its end points, along which the values of the ATTRIBUTE fluctuate.
Some Non-Core Roles	
DURATION	The length of time over which the change takes place.
SPEED	The rate of change of the VALUE.
GROUP	The GROUP in which an ITEM changes the value of an ATTRIBUTE in a specified way.

Semantic Role Labelling - Framenet

[ITEM Oil] *rose* [ATTRIBUTE in price] [DIFFERENCE by 2%].
[ITEM It] has *increased* [FINAL_STATE to having them 1 day a month].
[ITEM Microsoft shares] *fell* [FINAL_VALUE to 7 5/8].

- Note from these example sentences that the frame includes target words like rise, fall, and increase.

Selectional Restrictions and Selectional Preferences

- Used for sense disambiguation - selectional restrictions were used to rule out senses that violate the selectional restrictions of neighboring words
- For example the verb eat might have a restriction that its THEME argument be [+FOOD].

Selectional Restrictions and Selectional Preferences

- Consider the following wordnet definitions for “dish”
  - dish[1] (a piece of dishware normally used as a container for holding or serving food), with hypernyms like artifact
  - dish[2] (a particular item of prepared food) with hypernyms like food.
- Between the words eat and find, which would you expect to be more effective in selectional restriction-based sense disambiguation? Why?
  - Generally, we expect words with stricter selectional restrictions to be more useful because they allow fewer senses in their arguments. For example, if we saw eat a dish, we could rule out the sense dish#1 “a container for holding or serving food”, which we could not rule out if we saw find a dish.

WordNet: Word Relations, Senses, and Disambiguation

- WordNet includes glosses, a definition for senses in the form of a text string.

Category	Unique Strings
Noun	117,798
Verb	11,529
Adjective	22,479
Adverb	4,481

The set of near-synonyms for a WordNet sense is called a **synset** (for synonym set); synsets are an important primitive in WordNet.
The entry for bass includes synsets like

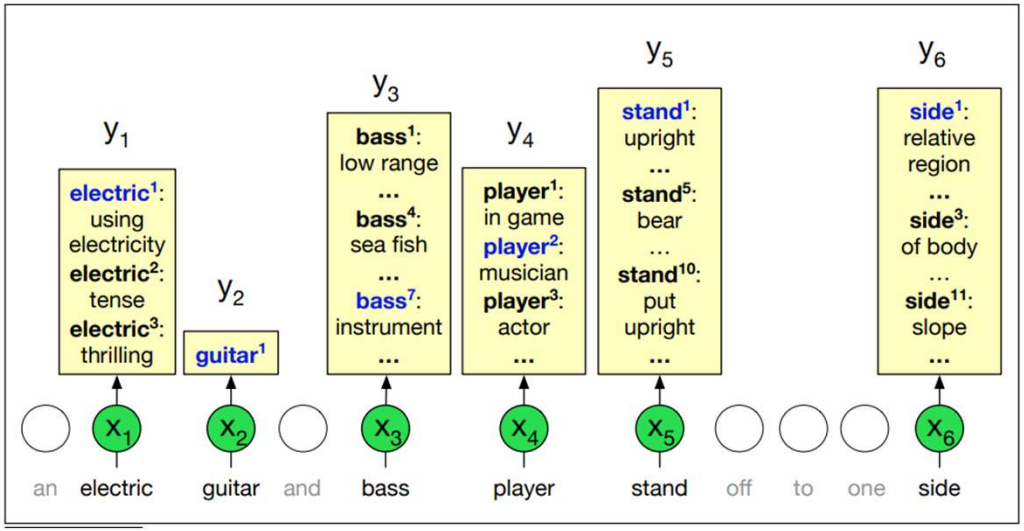
$\{bass^1, deep^6\}$, or $\{bass^6, bass\ voice^1, basso^2\}$.

The noun "bass" has 8 senses in WordNet.
1. bass[1] - (the lowest part of the musical range)
2. bass[2], bass part[1] - (the lowest part in polyphonic music)
3. bass[3], basso[1] - (an adult male singer with the lowest voice)
4. sea bass[1], bass[4] - (the lean flesh of a saltwater fish of the family Serranidae)
5. freshwater bass[1], bass[5] - (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
6. bass[6], bass voice[1], basso[2] - (the lowest adult male singing voice)
7. bass[7] - (the member with the lowest range of a family of musical instruments)
8. bass[8] - (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)

The adjective "bass" has 1 sense in WordNet.
1. bass[1], deep[6] - (having or denoting a low vocal or instrumental range)
"a deep voice"; "a bass voice is lower than a baritone voice"; "a bass clarinet"

Word Sense Disambiguation(WSD)

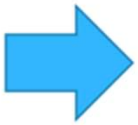
- The task of selecting the correct sense for a word is called word sense disambiguation (WSD)
- Input : word in context , fixed inventory of potential word senses(wordnet)
- Output: correct word sense in context



Function Words / Content Words

- **Function words (closed class words)**
  - words that have little lexical meaning
  - express grammatical relationships with other words
  - Prepositions (in, of, etc), pronouns (she, we, etc), auxiliary verbs (would, could, etc), articles (a, the, an), conjunctions (and, or, etc)
- **Content words (open class words)**
  - Nouns, verbs, adjectives, adverbs etc
  - Easy to invent a new word (e.g. “google” as a noun or a verb)
- **Stop words**
  - Similar to function words, but may include some content words that carry little meaning with respect to a specific NLP application

(Machine Learning) Approaches for WSD



- Dictionary-based approaches
  - Simplified Lesk
  - Corpus Lesk
- Supervised-learning approaches
  - Naïve Bayes
  - Decision List
  - K-nearest neighbor (KNN)
- Semi-supervised-learning approaches
  - Yarowsky's Bootstrapping approach
- Unsupervised-learning approaches
  - Clustering

Baselines

- Most frequent sense
- The Lesk algorithm

Most Frequent Sense

- WordNet senses are ordered in frequency order
- So "most frequent sense" in WordNet = "take the first sense"
- Sense frequencies come from the *SemCor* corpus

Freq	Synset	Gloss
338	plant[1], works, industrial plant	buildings for carrying on industrial labor
207	plant[2], flora, plant life	a living organism lacking the power of locomotion
2	plant[3]	something planted secretly for discovery by another
0	plant[4]	an actor situated in the audience whose acting is rehearsed but seems spontaneous to the audience

Dictionary-based approaches

- Rely on machine readable dictionaries
- Initial implementation of this kind of approach is due to Michael Lesk (1986)
- "Lesk algorithm"
  - Given a word *W* to be disambiguated in context C
    - Retrieve all of the sense definitions, *S*, for *W* from the MRD
    - Compare each *s* in *S* to the dictionary definitions D of all the remaining words c in the context C
    - Select the sense *s* with the most overlap with D (the definitions of the context words C)

The Simplified Lesk algorithm

- Let's disambiguate "**bank**" in this sentence:

  The **bank** can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.

- given the following two WordNet senses:

bank[1]	Gloss:	a financial institution that accepts deposits and channels the money into lending activities
	Examples:	"he cashed a check at the bank", "that bank holds the mortgage on my home"
bank[2]	Gloss:	sloping land (especially the slope beside a body of water)
	Examples:	"they pulled the canoe up on the bank", "he sat on the bank of the river and watched the currents"

The Simplified Lesk algorithm

Choose sense with most word overlap between gloss and context
(not counting function words)

The **bank** can guarantee deposits will eventually cover future tuition costs because it invests in adjustable-rate mortgage securities.

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bank[2]	Gloss:	sloping land (especially the slope beside a body of water)
	Examples:	"they pulled the canoe up on the bank", "he sat on the bank of the river and watched the currents"

Simulate the original Lesk word overlap disambiguation algorithm on the phrase "Time flies like an arrow". Assume that the words are to be disambiguated one at a time, from left to right.

A subset of the WordNet senses:

time#n#5	(the continuum of experience in which events pass from the future through the present to the past)
time#v#1	(measure the time or duration of an event or action or the person who performs an action in a certain period of time) "he clocked the runners"
flies#n#1	(two-winged insects characterized by active flight)
flies#v#8	(pass away rapidly) "Time flies like an arrow"; "Time fleeing beneath him"
like#v#4	(feel about or towards; consider, evaluate, or regard) "How did you like the President's speech last night?"
like#a#1	(resembling or similar; having the same or some of the same characteristics; often used in combination) "suits of like design"; "a limited circle of like minds"; "members of the cat family have like dispositions"; "as like as two peas in a pod"; "doglike devotion"; "a dream-like quality"
arrow#n#1	(a mark to indicate a direction or relation)
arrow#n#2	(a projectile with a straight thin shaft and an arrowhead on one end and stabilizing vanes on the other; intended to be shot from a bow)

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arrow#n#1	(a mark to indicate a direction or relation)
arrow#n#2	(a projectile with a straight thin shaft and an arrowhead on one end and stabilizing vanes on the other; intended to be shot from a bow)

Disambiguating *arrow*:

- arrow#n#1 shares nothing with any other signatures
- arrow#n#2 shares nothing with any other signatures

Since there is a tie, we select the most frequent sense, arrow#n#1.

Disambiguating *time*:

- time#n#5 shares *pass* with flies#v#8
- time#v#1 shares *time* with flies#v#8

There is a tie, so we should select the most frequent sense. But WordNet does not compare sense frequencies between nouns and verbs, so we cannot select a sense for *time*.

Disambiguating *flies*:

- flies#n#1 shares *two* with like#a#1
- flies#v#8 shares *pass* with time#n#5, *time* with time#v#1 and *like* with like#v#4 and like#a#1

So we select flies#v#8.

Disambiguating *like*:

- like#v#4 shares *like* with flies#v#8
- like#a#1 shares *like* with flies#v#8 (and *two* with flies#n#1, but we have already decided on flies#v#8)

There is a tie, so we should select the most frequent sense. But WordNet does not compare sense frequencies between verbs and adjectives, so we cannot select a sense for *like*.

Vector Semantics & Embeddings

Vector Semantics

Computational models of word meaning

Can we build a theory of how to represent word meaning, that accounts for at least some of the desiderata?

We'll introduce **vector semantics**

- The standard model in language processing!
- Handles many of our goals!

Ludwig Wittgenstein

PI #43:

"The meaning of a word is its use in the language"

Let's define words by their usages

One way to define "usage":

words are defined by their environments (the words around them)

Zellig Harris (1954):

If A and B have almost identical environments we say that they are synonyms.

What does recent English borrowing *ongchoi* mean?

Suppose you see these sentences:

- Ong choi is delicious **sautéed with garlic**.
- Ong choi is superb **over rice**
- Ong choi **leaves** with salty sauces

And you've also seen these:

- …spinach **sautéed with garlic over rice**
- Chard stems and **leaves** are **delicious**
- Collard greens and other **salty** leafy greens

Conclusion:

- Ongchoi is a leafy green like spinach, chard, or collard greens
  - We could conclude this based on words like "leaves" and "delicious" and "sauteed"

Ongchoi: *Ipomoea aquatica "Water Spinach"*

空心菜
kangkong
rau muống
…

Yamaguchi, Wikimedia Commons, public domain

Idea 1: Defining meaning by linguistic distribution

Let's define the meaning of a word by its distribution in language use, meaning its neighboring words or grammatical environments.

Idea 2: Meaning as a point in space (Osgood et al. 1957)

3 affective dimensions for a word

- **valence**: pleasantness
- **arousal**: intensity of emotion
- **dominance**: the degree of control exerted

	Word	Score		Word	Score
Valence	love	1.000		toxic	0.008
	happy	1.000		nightmare	0.005
Arousal	elated	0.960		mellow	0.069
	frenzy	0.965		napping	0.046
Dominance	powerful	0.991		weak	0.045
	leadership	0.983		empty	0.081

NRC VAD Lexicon
(Mohammad 2018)

Hence the connotation of a word is a vector in 3-space

Idea 1: Defining meaning by linguistic distribution

Idea 2: Meaning as a point in multidimensional space

Defining meaning as a point in space based on distribution

Each word = a vector (not just "good" or "w_{45}")

Similar words are "**nearby in semantic space**"

We build this space automatically by seeing which words are **nearby in text**

We define meaning of a word as a vector

Called an "embedding" because it's embedded into a space (see textbook)

The standard way to represent meaning in NLP

Every modern NLP algorithm uses embeddings as the representation of word meaning

Fine-grained model of meaning for similarity

Intuition: why vectors?

Consider sentiment analysis:

- With **words**, a feature is a word identity
  - Feature 5: 'The previous word was "terrible"'
  - requires **exact same word** to be in training and test
- With **embeddings**:
  - Feature is a word vector
  - 'The previous word was vector [35,22,17…]
  - Now in the test set we might see a similar vector [34,21,14]
  - We can generalize to **similar but unseen** words!!!

We'll discuss 2 kinds of embeddings

tf-idf

- Information Retrieval workhorse!
- A common baseline model
- **Sparse** vectors
- Words are represented by (a simple function of) the **counts** of nearby words

Word2vec

- **Dense** vectors
- Representation is created by training a classifier to **predict** whether a word is likely to appear nearby
- Later we'll discuss extensions called **contextual embeddings**

From now on:
Computing with meaning representations instead of string representations

荃者所以在鱼，得鱼而忘荃　Nets are for fish;
Once you get the fish, you can forget the net.
言者所以在意，得意而忘言　Words are for meaning;
Once you get the meaning, you can forget the words

庄子(Zhuangzi), Chapter 26

Vector Semantics & Embeddings

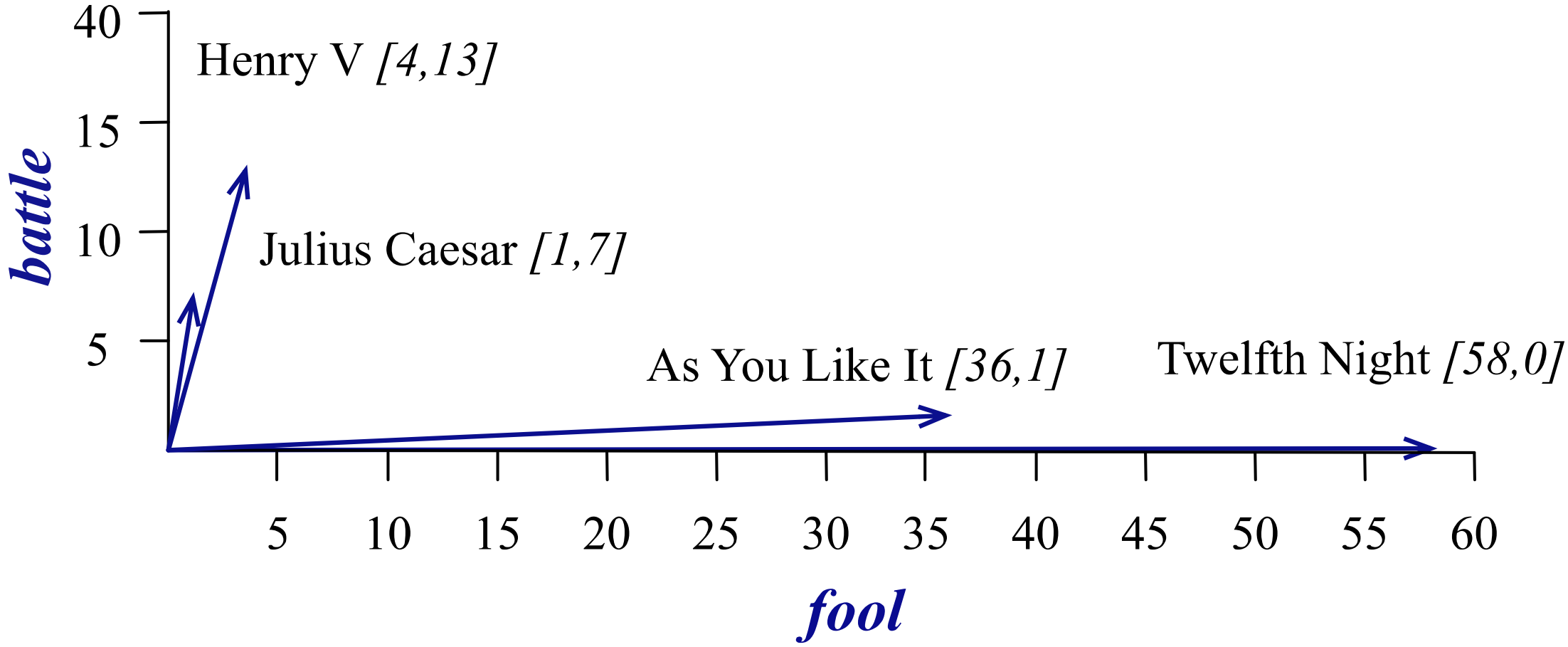
Words and Vectors

Term-document matrix

Each document is represented by a vector of words

	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

Visualizing document vectors



Vectors are the basis of information retrieval

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

Vectors are similar for the two comedies

But comedies are different than the other two

Comedies have more *fools* and *wit* and fewer *battles*.

Idea for word meaning: Words can be vectors too!!!

	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

battle is "the kind of word that occurs in Julius Caesar and Henry V"

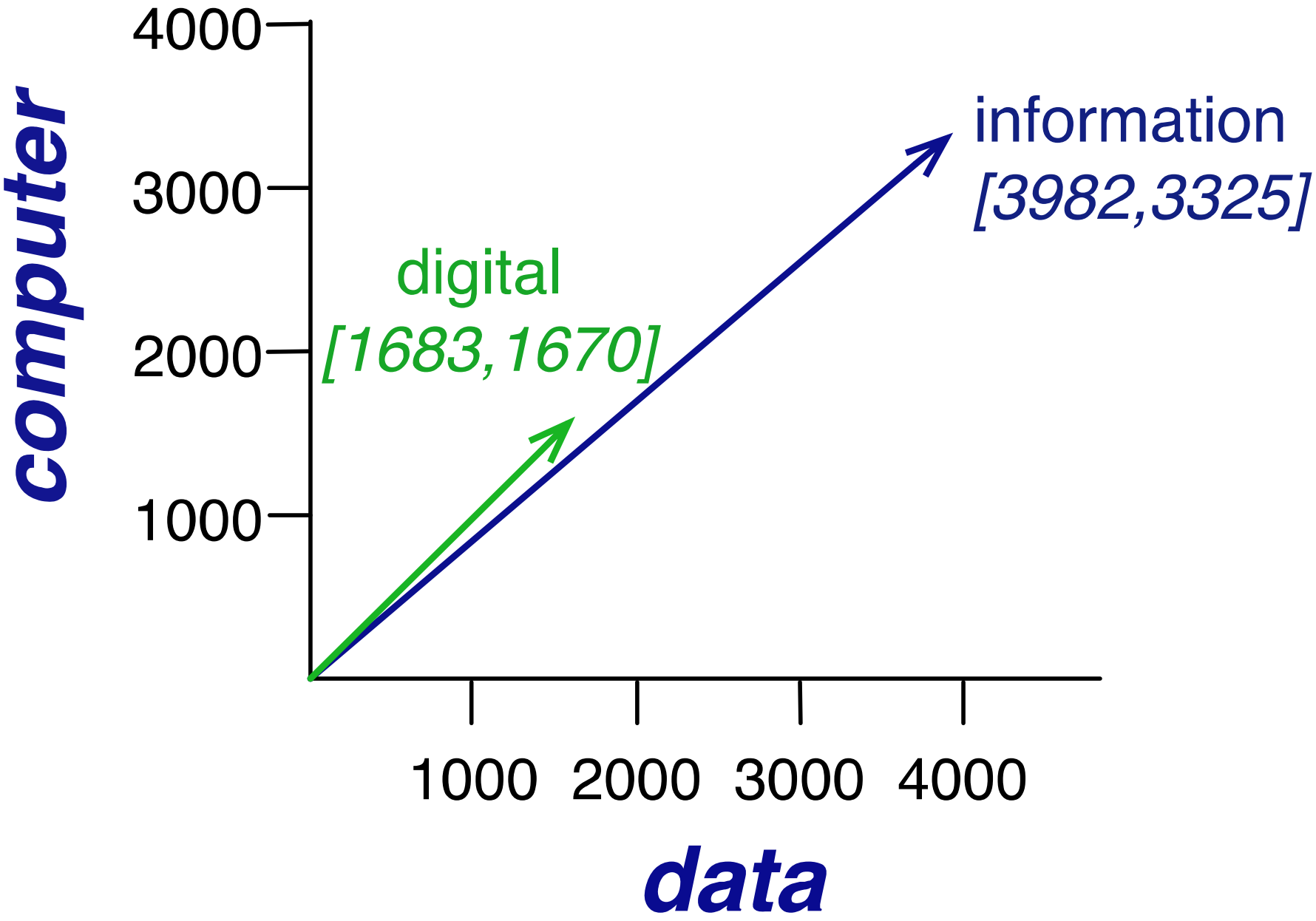
fool is "the kind of word that occurs in comedies, especially Twelfth Night"

More common: word-word matrix (or "term-context matrix")

Two **words** are similar in meaning if their context vectors are similar

is traditionally followed by	**cherry**	pie, a traditional dessert
often mixed, such as	**strawberry**	rhubarb pie. Apple pie
computer peripherals and personal	**digital**	assistants. These devices usually
a computer. This includes	**information**	available on the internet

	aardvark	...	**computer**	**data**	**result**	**pie**	**sugar**	...
cherry	0	...	2	8	9	442	25	...
strawberry	0	...	0	0	1	60	19	...
digital	0	...	1670	1683	85	5	4	...
information	0	...	3325	3982	378	5	13	...


4000
3000
2000
1000
computer
information
[3982,3325]
digital
[1683,1670]
1000
2000
3000
4000
data

Vector Semantics & Embeddings

Cosine for computing word similarity

Computing word similarity: Dot product and cosine

The dot product between two vectors is a scalar:

$$\text{dot product}(\mathbf{v},\mathbf{w}) = \mathbf{v}\cdot\mathbf{w} = \sum_{i=1}^{N} v_i w_i = v_1 w_1 + v_2 w_2 + \ldots + v_N w_N$$

The dot product tends to be high when the two vectors have large values in the same dimensions

Dot product can thus be a useful similarity metric between vectors

Problem with raw dot-product

Dot product favors long vectors

Dot product is higher if a vector is longer (has higher values in many dimension)

Vector length:

$$|\mathbf{v}| = \sqrt{\sum_{i=1}^{N} v_i^2}$$

Frequent words (of, the, you) have long vectors (since they occur many times with other words).

So dot product overly favors frequent words

Alternative: cosine for computing word similarity

$$\text{cosine}(\vec{v},\vec{w}) = \frac{\vec{v}\cdot\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

Based on the definition of the dot product between two vectors a and b

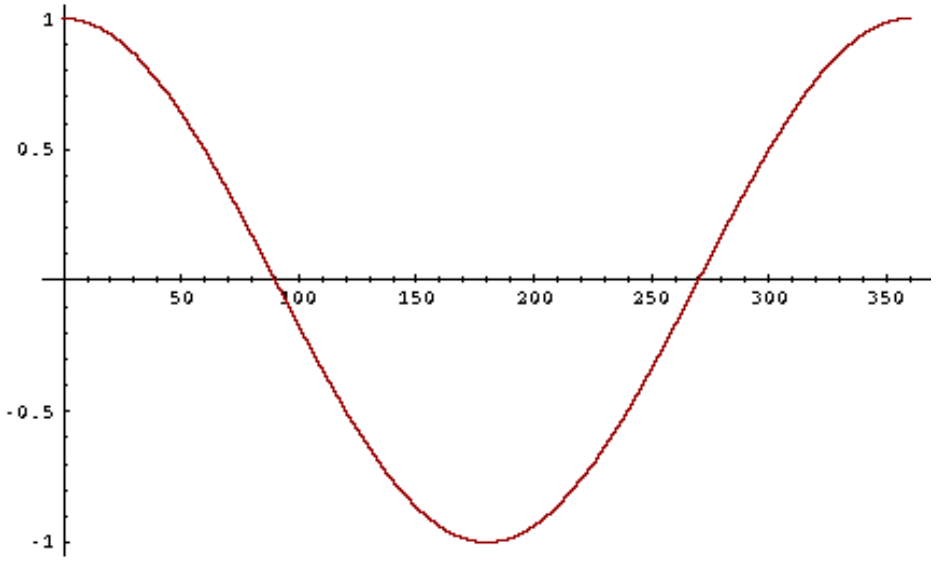
$$\mathbf{a}\cdot\mathbf{b} = |\mathbf{a}||\mathbf{b}|\cos\theta$$
$$\frac{\mathbf{a}\cdot\mathbf{b}}{|\mathbf{a}||\mathbf{b}|} = \cos\theta$$

Cosine as a similarity metric

-1: vectors point in opposite directions

+1: vectors point in same directions

0: vectors are orthogonal



But since raw frequency values are non-negative, the cosine for term-term matrix vectors ranges from 0–1

Cosine examples

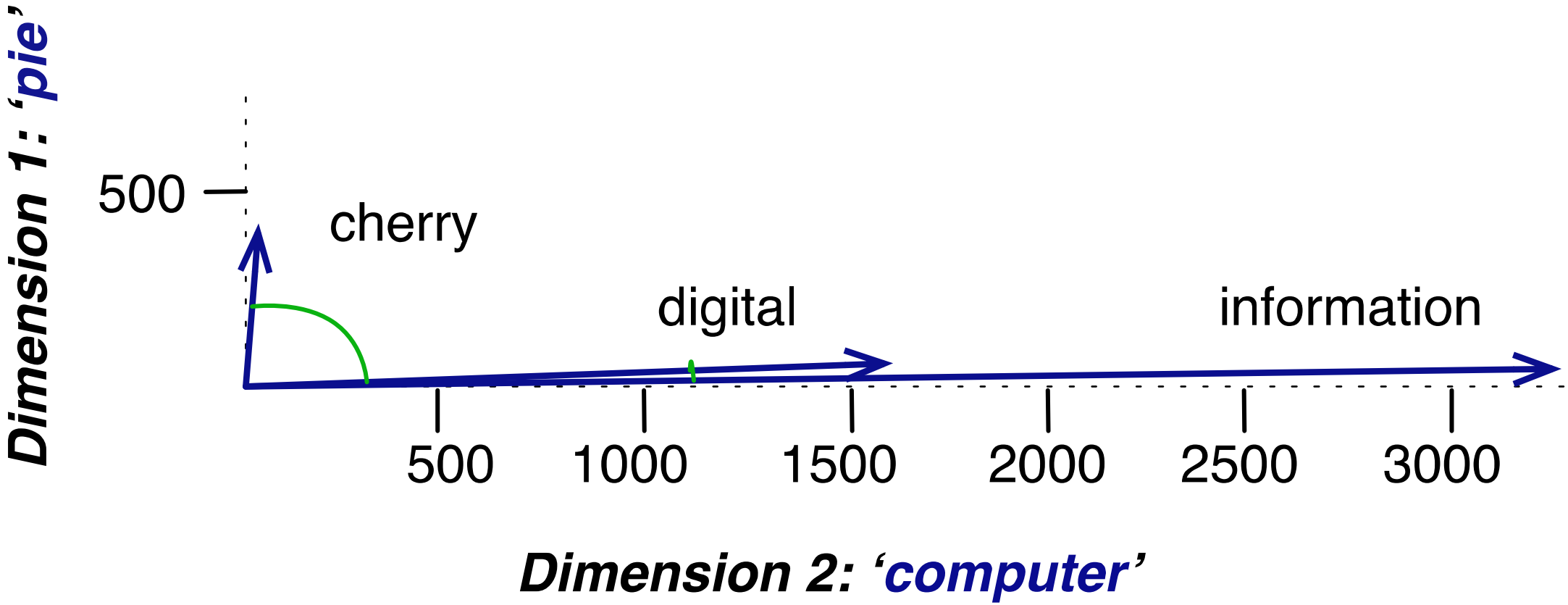
$$\cos(\vec{v},\vec{w}) = \frac{\vec{v}\cdot\vec{w}}{|\vec{v}||\vec{w}|} = \frac{\vec{v}}{|\vec{v}|}\cdot\frac{\vec{w}}{|\vec{w}|} = \frac{\sum_{i=1}^{N} v_i w_i}{\sqrt{\sum_{i=1}^{N} v_i^2}\sqrt{\sum_{i=1}^{N} w_i^2}}$$

	pie	data	computer
cherry	442	8	2
digital	5	1683	1670
information	5	3982	3325

$$\cos(\text{cherry},\text{information}) = \frac{442*5+8*3982+2*3325}{\sqrt{442^2+8^2+2^2}\sqrt{5^2+3982^2+3325^2}} = .017$$

$$\cos(\text{digital},\text{information}) = \frac{5*5+1683*3982+1670*3325}{\sqrt{5^2+1683^2+1670^2}\sqrt{5^2+3982^2+3325^2}} = .996$$

Visualizing cosines (well, angles)



TF-IDF - Example

- Given the corpus

D1 : A quick brown fox jumps over the lazy dog. What a fox!

D2 : A quick brown fox jumps over the lazy fox. What a fox!

- How is fox relevant to Corpus D?

Term Frequency		
Term	D1	D2
Fox	2/12 0.17	3/12 0.25

Document Frequency		
Term	Collection Frequency	Document Frequency
Fox	2	2

Term Frequency		
Term	D1	D2
Fox	2/12 0.17	3/12 0.25

- idf = $\log_{10}(N/df) = \log_{10}(2/2) = 0$

Calculate the TF-IDF for the given DT matrix

Document/Term	T1	T2	T3	T4	T5	T6
D1	5	9	4	0	5	6
D2	0	8	5	3	10	8
D3	3	5	6	6	5	0
D4	4	6	7	8	4	4

$$TF - IDF(T1\ in\ D1) = 5 * \log\left(\frac{4}{3}\right) = 0.625$$

$$TF - IDF(T2\ in\ D1) = 9 * \log\left(\frac{4}{4}\right) = 0.0$$

$$TF - IDF(T3\ in\ D1) = 4 * \log\left(\frac{4}{4}\right) = 0.0$$

$$TF - IDF(T4\ in\ D1) = 0 * \log\left(\frac{4}{3}\right) = 0.0$$

$$TF - IDF(T5\ in\ D1) = 5 * \log\left(\frac{4}{4}\right) = 0.0$$

$$TF - IDF(T6\ in\ D1) = 6 * \log\left(\frac{4}{3}\right) = 0.7496$$

Word Embedding

Word Embedding

- Word embedding is a technique in natural language processing (NLP) that represents words as vectors in a continuous vector space. This allows for capturing semantic relationships and similarities between words based on their context in large text corpora.
- Some word embedding models are Word2vec (Google), Glove (Stanford), and fastest (Facebook).

Word Embedding

- Word Embedding is also called a distributed semantic model or distributed represented or semantic vector space or vector space model.
- The similar words can be grouped together. For example, fruits like apples, mango, and banana should be placed close whereas books will be far away from these words.
- In a broader sense, word embedding will create the vector of fruits which will be placed far away from the vector representation of books.

Importance - Word Embedding

- **Semantic Understanding -** semantic meaning of words
- **Contextual Relationships -** Embeddings can capture the context in which words appear.
- **Dimensionality Reduction -** Word embeddings reduce the dimensionality, making computations more efficient and models faster.
- **Transfer Learning**: Pre-trained word embeddings can be used.
- **Improved Performance**: Using word embeddings often leads to better performance in various NLP tasks such as text classification, sentiment analysis, and machine translation. They help models generalize better by capturing nuanced relationships between words.

Applications

- **NLP Tasks**: Used in sentiment analysis, machine translation, information retrieval, and more.
- **Transfer Learning**: Pre-trained models can be fine-tuned for specific tasks, leveraging knowledge from vast corpora.
- **Word Embedding Limitations**
  - **Out-of-Vocabulary Words**: Word2Vec does not handle words that were not present in the training data well.
  - **Lack of Contextual Awareness**: It generates a single vector for each word regardless of its context (e.g., "bank" in "river bank" vs. "financial bank").

Word2Vec

- Word2Vec is a popular technique for creating word embeddings, developed by a team at Google led by Tomas Mikolov. It represents words in a continuous vector space, allowing machines to understand their meanings based on context. Here are the main components of Word2Vec:

Word2Vec - **Architectures**

- **Continuous Bag of Words (CBOW)**:
  - Predicts the target word from the surrounding context words.
  - For example, given the context words "the," "sat," "on," it predicts "cat."
  - Generally faster and more suitable for smaller datasets.
- **Skip-gram Model**:
  - Predicts surrounding context words given a target word.
  - For example, given the target word "cat," it tries to predict words like "sat," "on," "the," etc.
  - Effective for capturing semantic relationships and works well with large datasets.

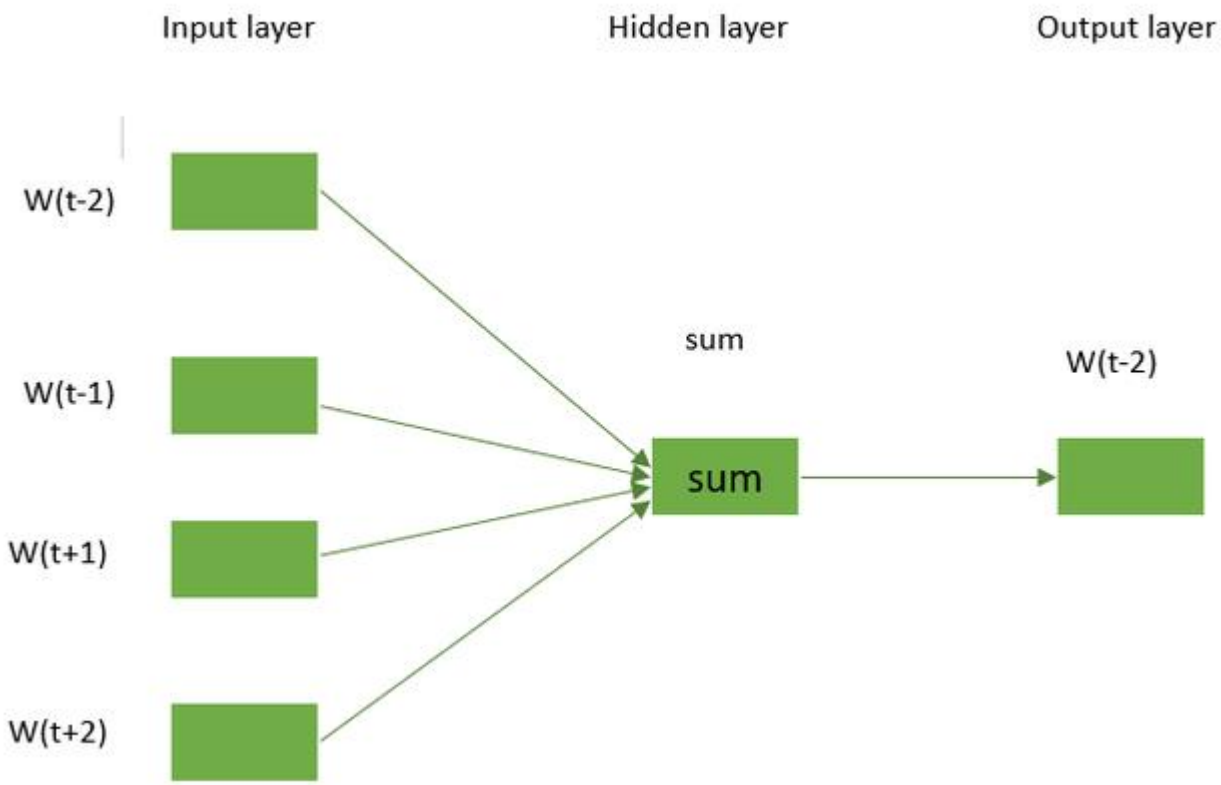
Word2vec

- Instead of **counting** how often each word *w* occurs near "*apricot*"
  - Train a classifier on a binary **prediction** task:
    - Is *w* likely to show up near "*apricot*"?
- We don’t actually care about this task
    - But we'll take the learned classifier weights as the word embeddings
- Big idea: **self-supervision**:
    - A word c that occurs near apricot in the corpus cats as the gold "correct answer" for supervised learning
    - No need for human labels
    - Bengio et al. (2003); Collobert et al. (2011)

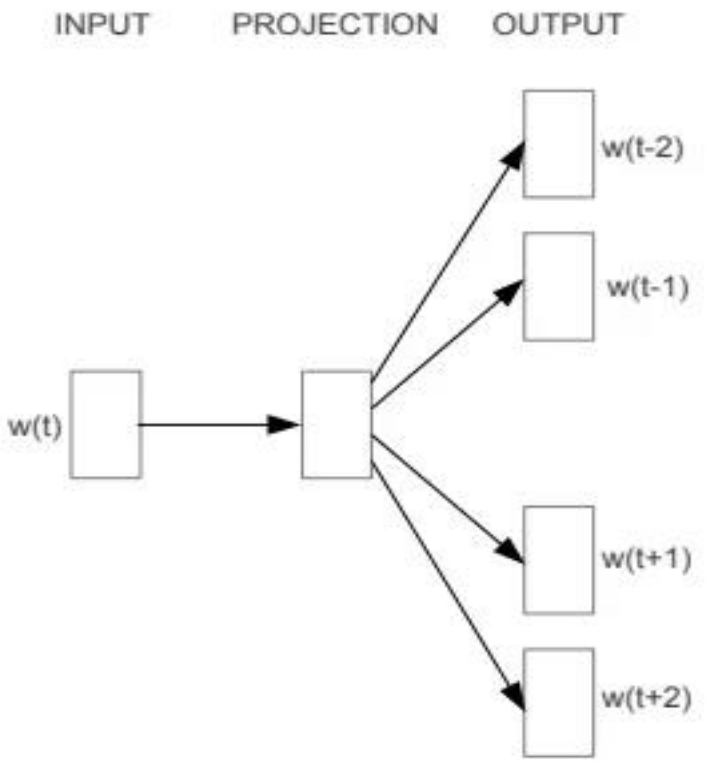
Approach: predict if candidate word *c* is a "neighbor"

1. Treat the target word *t* and a neighboring context word *c* as **positive examples**.
2. Randomly sample other words in the lexicon to get negative examples
3. Use logistic regression to train a classifier to distinguish those two cases
4. Use the learned weights as the embeddings

Architecture of the CBOW model



Architecture of Skip-gram Model

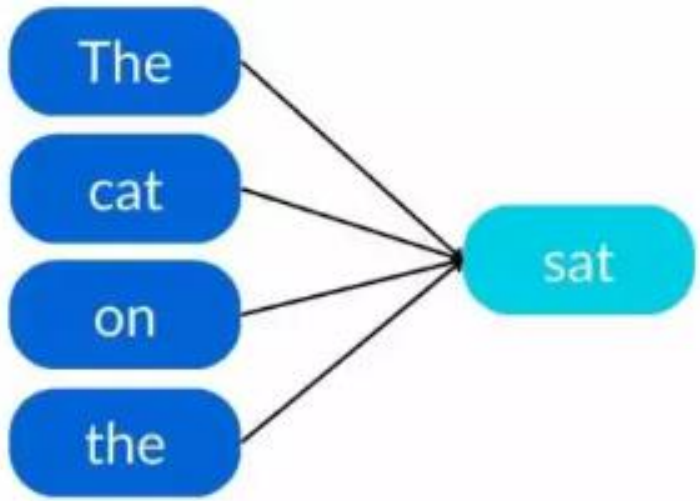


Skip-gram

Example Sentence: The cat sat on the mat.

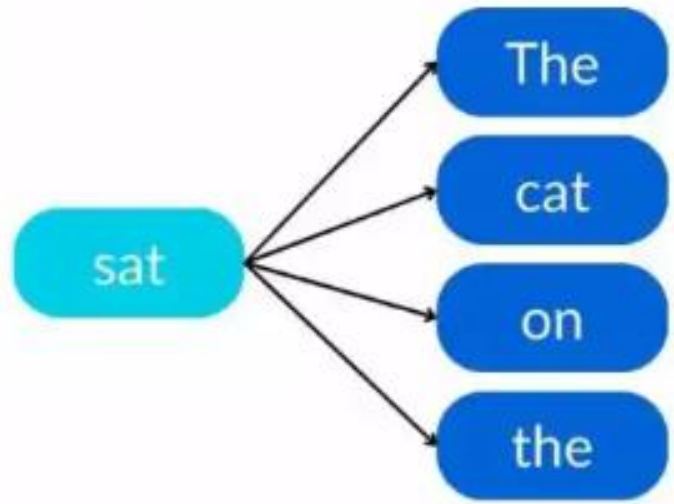
Continuous Bag-of-Words (CBOW)

Goal: Given context words,
predict the target word.



Skip-gram Model

Goal: Given a word,
predict the surrounding context words.



Similarity is computed from dot product

- Remember: two vectors are similar if they have a high dot product
  - Cosine is just a normalized dot product
- So:
  - Similarity(w,c) $\propto w \cdot c$
- We'll need to normalize to get a probability

CBOW - Example

Step 1: Define the Example

Sentence: "The man and woman are discussing about the king and queen."

Step 2: Identify the Target and Context Words

- **Target Word**: **"king"**
- **Context Words**: **["man", "woman"]**

Step 3: Assign 4-Dimensional Vectors

Let's assign random 4-dimensional vectors to each of the relevant words:

- "king" → [0.6, 0.8, 0.5, 0.9]
- "queen" → [0.5, 0.7, 0.4, 0.8]
- "man" → [0.2, 0.3, 0.6, 0.1]
- "woman" → [0.3, 0.5, 0.7, 0.4]

CBOW – Example Cont…

Step 4: Average the Context Vectors

Now, calculate the average vector of the context words "man" and "woman."

1. **Vectors for Context Words**:
   - "man" → [0.2, 0.3, 0.6, 0.1]
   - "woman" → [0.3, 0.5, 0.7, 0.4]
2. **Calculate the Average**:

$$\text{Average} = \frac{1}{2}\left([0.2, 0.3, 0.6, 0.1] + [0.3, 0.5, 0.7, 0.4]\right)$$

$$= \frac{1}{2}\left([0.5, 0.8, 1.3, 0.5]\right) = [0.25, 0.4, 0.65, 0.25]$$

CBOW – Example Cont…

Step 5: Compute Scores

Now, we'll compute the scores for each word in the vocabulary by calculating the dot product between the average vector and the weight vectors for each word.

Example Weights

Assuming we have learned weight vectors for each word:

- Weights for "king" → [0.7, 0.8, 0.6, 0.9]
- Weights for "queen" → [0.6, 0.7, 0.5, 0.8]
- Weights for "man" → [0.4, 0.3, 0.5, 0.4]
- Weights for "woman" → [0.5, 0.6, 0.7, 0.3]

CBOW – Example Cont…

Calculate the Scores

1. Score for "king":

$$\text{Score}_{king} = (0.25 \times 0.7) + (0.4 \times 0.8) + (0.65 \times 0.6) + (0.25 \times 0.9)$$
$$= 0.175 + 0.32 + 0.39 + 0.225 = 1.110$$

2. Score for "queen":

$$\text{Score}_{queen} = (0.25 \times 0.6) + (0.4 \times 0.7) + (0.65 \times 0.5) + (0.25 \times 0.8)$$
$$= 0.15 + 0.28 + 0.325 + 0.2 = 0.955$$

3. Score for "man":

$$\text{Score}_{man} = (0.25 \times 0.4) + (0.4 \times 0.3) + (0.65 \times 0.5) + (0.25 \times 0.4)$$
$$= 0.1 + 0.12 + 0.325 + 0.1 = 0.645$$

4. Score for "woman":

$$\text{Score}_{woman} = (0.25 \times 0.5) + (0.4 \times 0.6) + (0.65 \times 0.7) + (0.25 \times 0.3)$$
$$= 0.125 + 0.24 + 0.455 + 0.075 = 0.895$$

CBOW – Example Cont…

Step 6: Apply Softmax Function

Next, convert the scores to probabilities using the softmax function.

Calculate Exponentials

1. $e^{1.110} \approx 3.033$
2. $e^{0.955} \approx 2.598$
3. $e^{0.645} \approx 1.905$
4. $e^{0.895} \approx 2.446$

Total:

$$\text{Total} = 3.033 + 2.598 + 1.905 + 2.446 \approx 10.982$$

CBOW – Example Cont…

Softmax Probabilities:

1. Probability for "king":

$$P(\text{king}) = \frac{3.033}{10.982} \approx 0.276$$

2. Probability for "queen":

$$P(\text{queen}) = \frac{2.598}{10.982} \approx 0.237$$

3. Probability for "man":

$$P(\text{man}) = \frac{1.905}{10.982} \approx 0.174$$

4. Probability for "woman":

$$P(\text{woman}) = \frac{2.446}{10.982} \approx 0.223$$

Softmax Calculation:

$$\text{Softmax}(x_i) = \frac{e^{x_i}}{\sum e^{x_j}}$$

Why Softmax? - Probabilities can be compared directly, helping to identify which word has the highest likelihood of being the target.

CBOW – Example Cont…

- **Step 7: Identify the Predicted Word**
- The predicted word is the one with the highest probability. In this case, if "king" has the highest probability (approximately 0.276), it will be the predicted target word.
- **Summary of Steps**
  1. **Identify the Target**: Target word "king" and context words "man" and "woman."
  2. **Vector Representation**: Assign 4D vectors to all words.
  3. **Average Context**: Calculate the average of context word vectors.
  4. **Score Calculation**: Compute dot products with weights for each word.
  5. **Softmax**: Convert scores to probabilities.
  6. **Prediction**: Identify the word with the highest probability.

Summary

- In CBOW, context words are chosen based on proximity to the target word, which is determined by the window size.
- Including additional words like "queen" depends on expanding the context window.
- By adjusting the context, you can influence the prediction, capturing more semantic relationships.

Skip-gram model - Ex

Step 1: Define the Example

Sentence: "The man and woman are discussing about the king and queen."

Step 2: Identify the Target and Context Words

- **Target Word**: "king"
- **Context Words**: ["man," "woman," "queen"] (depending on the context window size)

Skip-gram model – Ex Cont...

Step 3: Assign 4-Dimensional Vectors

Assign random 4-dimensional vectors to each of the relevant words:

- "king" → [0.6, 0.8, 0.5, 0.9]
- "queen" → [0.5, 0.7, 0.4, 0.8]
- "man" → [0.2, 0.3, 0.6, 0.1]
- "woman" → [0.3, 0.5, 0.7, 0.4]

Skip-gram model – Ex Cont...

Step 4: Prepare Input for Skip-gram

In Skip-gram, the target word is used to predict the context words. Here, **"king"** will be used to predict its surrounding context words **["man," "woman," "queen"]**.

Step 5: Compute Scores for Context Words

1. **Input Vector**: The vector for the target word "king" is $[0.6, 0.8, 0.5, 0.9]$.
2. **Calculate Scores**: Compute dot products with the weight vectors for the context words.

Skip-gram model – Ex Cont...

Example Weights for Context Words

Assuming the same weight vectors for the context words:

- Weights for "man" → [0.2, 0.3, 0.6, 0.1]
- Weights for "woman" → [0.3, 0.5, 0.7, 0.4]
- Weights for "queen" → [0.5, 0.7, 0.4, 0.8]

Skip-gram model – Ex Cont...

Calculate the Scores

1. Score for "man":

$$\text{Score}_{man} = (0.6 \times 0.2) + (0.8 \times 0.3) + (0.5 \times 0.6) + (0.9 \times 0.1)$$

$$= 0.12 + 0.24 + 0.30 + 0.09 = 0.75$$

2. Score for "woman":

$$\text{Score}_{woman} = (0.6 \times 0.3) + (0.8 \times 0.5) + (0.5 \times 0.7) + (0.9 \times 0.4)$$

$$= 0.18 + 0.40 + 0.35 + 0.36 = 1.29$$

3. Score for "queen":

$$\text{Score}_{queen} = (0.6 \times 0.5) + (0.8 \times 0.7) + (0.5 \times 0.4) + (0.9 \times 0.8)$$

$$= 0.30 + 0.56 + 0.20 + 0.72 = 1.78$$

Skip-gram model – Ex Cont...

Step 6: Apply Softmax Function

Next, convert the scores to probabilities using the softmax function.

Calculate Exponentials

1. $e^{0.75} \approx 2.117$
2. $e^{1.29} \approx 3.615$
3. $e^{1.78} \approx 5.892$

Total:

$$\text{Total} = 2.117 + 3.615 + 5.892 \approx 11.624$$

Skip-gram model – Ex Cont...

Softmax Probabilities:

1. Probability for "man":

$$P(\text{man}) = \frac{2.117}{11.624} \approx 0.182$$

2. Probability for "woman":

$$P(\text{woman}) = \frac{3.615}{11.624} \approx 0.311$$

3. Probability for "queen":

$$P(\text{queen}) = \frac{5.892}{11.624} \approx 0.506$$

Skip-gram model – Ex Cont...

Step 7: Identify the Predicted Context Words

The context words predicted from the target word "king" will be based on the highest probabilities. In this case, "queen" would have the highest probability, followed by "woman" and "man."

Summary of Steps

1. **Identify the Target:** Target word "king" and context words ["man," "woman," "queen"].
2. **Vector Representation:** Assign 4D vectors to all words.
3. **Score Calculation:** Compute dot products between the target word vector and context word vectors.
4. **Softmax:** Convert scores to probabilities.
5. **Prediction:** Identify context words based on the highest probabilities.

Identify the Predicted Context Words:

Threshold: You can set a threshold to consider only those context words whose probabilities exceed a certain value.
Top-N Selection: Alternatively, you can select the top-N context words with the highest probabilities. This is common when you expect multiple context words.

Step 1: Set a Threshold (Optional)

You can define a probability threshold, for example, 0.2. In this case, all three context words exceed the threshold.

Step 2: Select Top-N Context Words

If you want to select the top 2 context words based on probabilities, you would:

1. **Sort the Probabilities:**
   - "queen" → 0.506
   - "woman" → 0.311
   - "man" → 0.182
2. **Choose Top-N:**
   - Top 2 context words: **"queen"** and **"woman"**.

fasText

- fastText introduces a pivotal shift by considering words as composed of character n-grams, enabling it to build representations for words based on these subword units
- This approach allows the model to understand and generate embeddings for words not seen in the training data, offering a substantial advantage in handling morphologically rich languages and rare words.

Difference Between fastText and Word2Vec

- **Handling of Out-of-Vocabulary (OOV) Words**
  - **Word2Vec:** Word2Vec operates at the word level, generating embeddings for individual words. It struggles with out-of-vocabulary words as it cannot represent words it hasn’t seen during training.
  - **fastText:** In contrast, fastText introduces subword embeddings by considering words to be composed of character n-grams. This enables it to handle out-of-vocabulary words effectively by breaking terms into subword units and generating embeddings for these units, even for unseen words. This capability makes fastText more robust in dealing with rare or morphologically complex expressions.

Representation of Words

- **Word2Vec:** Word2Vec generates word embeddings based solely on the words without considering internal structure or morphological information.
- **fastText:** fastText captures subword information, allowing it to understand word meanings based on their constituent character n-grams. This enables fastText to represent words by considering their morphological makeup, providing a richer representation, especially for morphologically rich languages or domains with specialised jargon.

Training Efficiency

- **Word2Vec:** The training process in Word2Vec is relatively faster than older methods but might be slower than fastText due to its word-level approach.
- **fastText:** fastText is known for its exceptional speed and scalability, especially when dealing with large datasets, as it operates efficiently at the subword level.

Use Cases

- **Word2Vec:** Word2Vec's word-level embeddings are well-suited for tasks like finding similar words, understanding relationships between words, and capturing semantic similarities.
- **fastText:** fastText's subword embeddings make it more adaptable in scenarios involving out-of-vocabulary words, sentiment analysis, language identification, and tasks requiring a deeper understanding of morphology.