Distributional Semantics

LING 571 — Deep Processing Methods in NLP

November 4, 2019

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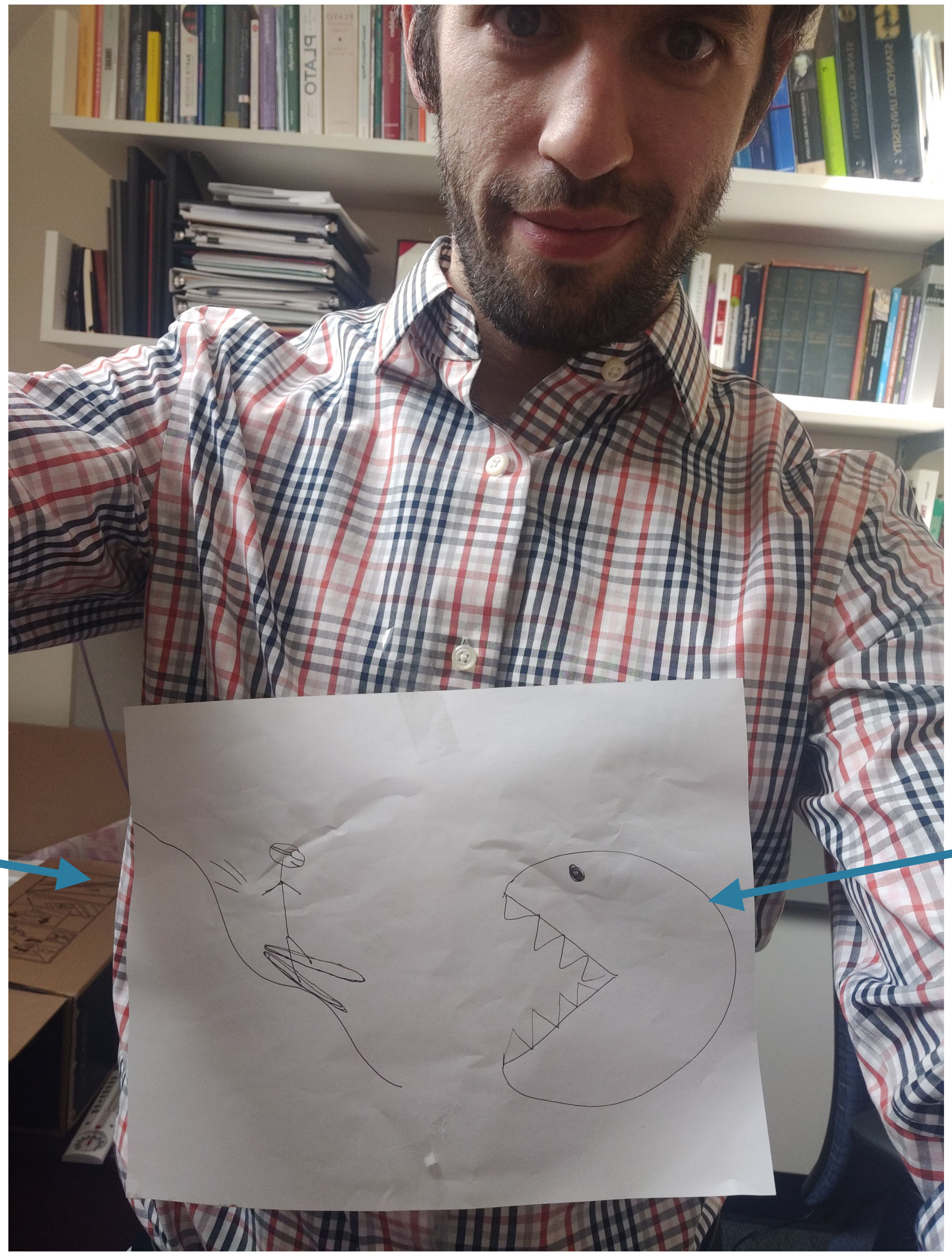
Walking the Walk

Ski



Chomp

= Chomsky!

Punny Department

Recap:
What is a word?

- Acoustically or orthographically similar → can have different meanings!
- Acoustically or orthographically different → can have similar meanings!

Recap:
What is a word?

- Words can also have relationships that cover:
  - Different ***shades*** of meaning
  - ***Part-Whole*** relationships

Recap:
What is a word?

- For now, we will set aside homonyms
  - (Specifically, *homographs*)
- Investigate word meaning as we can model it as *(dis-)**similarity***

Distributional Similarity

Distributional Similarity

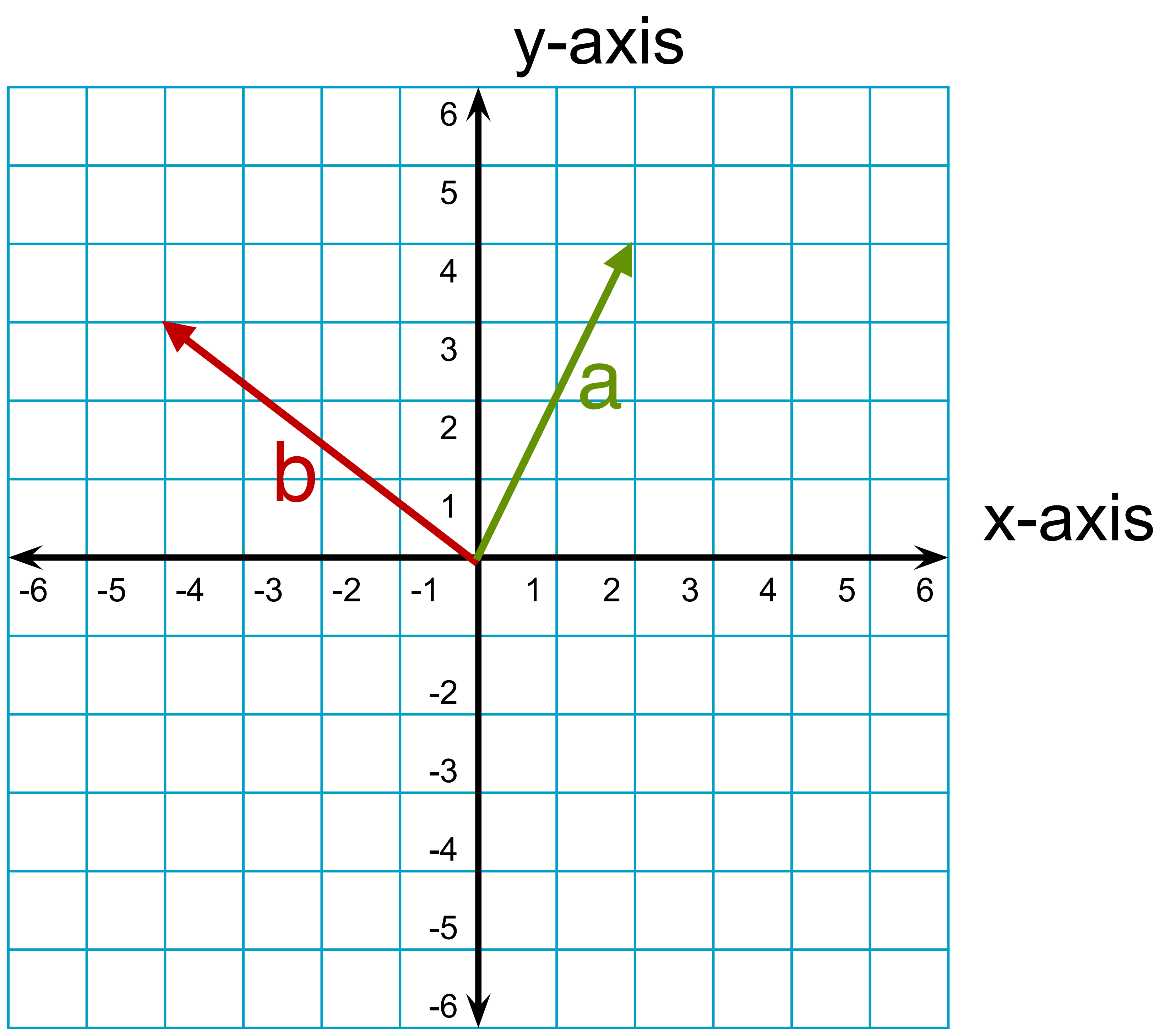
- "You shall know a word by the company it keeps!" (*Firth, 1957*)
  - A bottle of ***tezgüino*** is on the table.
  - Everybody likes ***tezgüino***.
  - ***Tezgüino*** makes you drunk.
  - We make ***tezgüino*** from corn.
- Tezguino; corn-based alcoholic beverage. (From *Lin, 1998a*)

Distributional Similarity

- How can we represent the “company” of a word?
- How can we make similar words have similar representations?

Vectors: A Refresher

- A vector is a list of numbers
- Each number can be thought of as representing a "dimension"
  - $\vec{a} = \langle 2,4 \rangle$
  - $\vec{b} = \langle -4,3 \rangle$
- What if we thought of each dimension as "quantity" of a word, rather than an arbitrary dimension?



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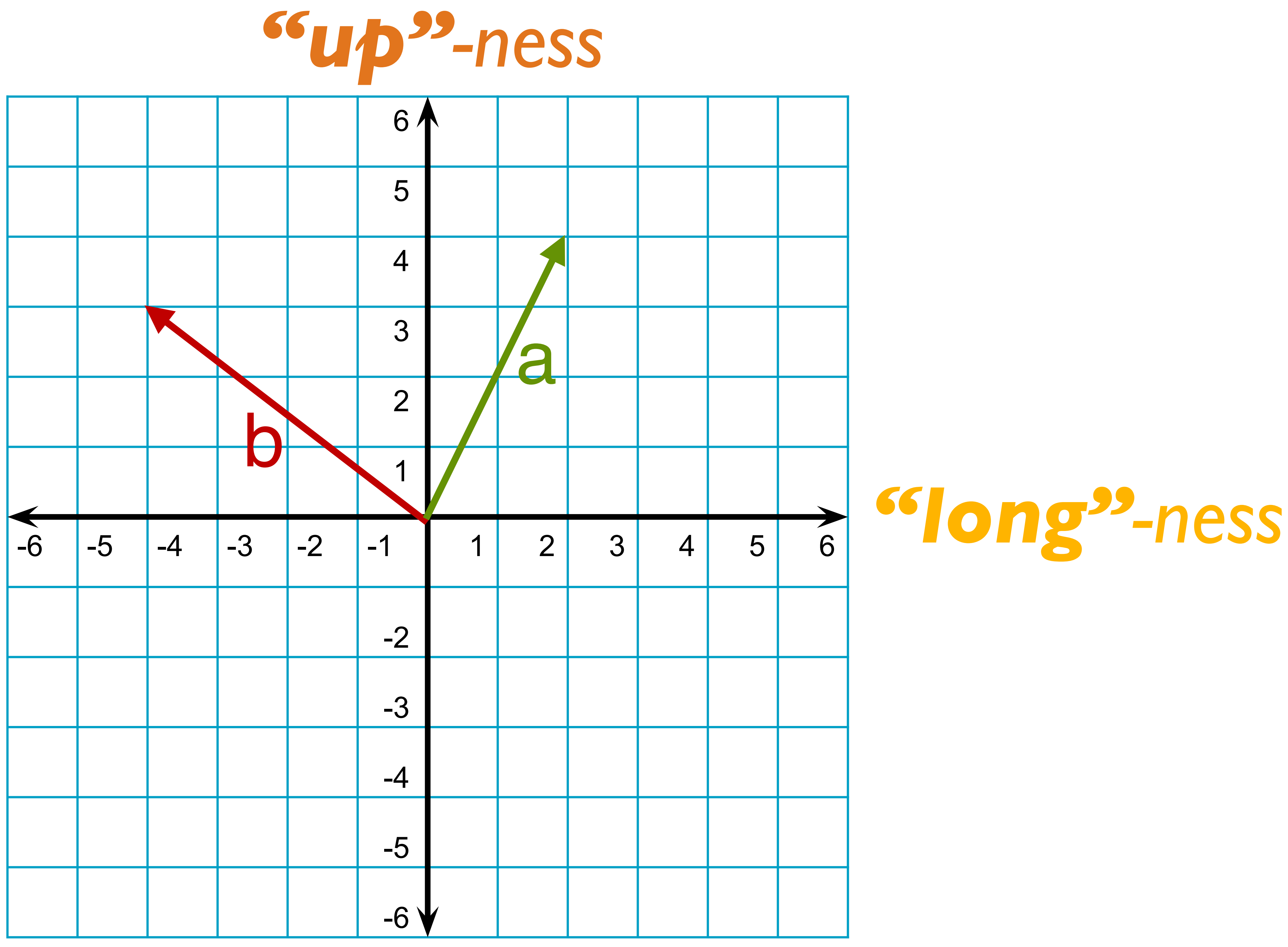

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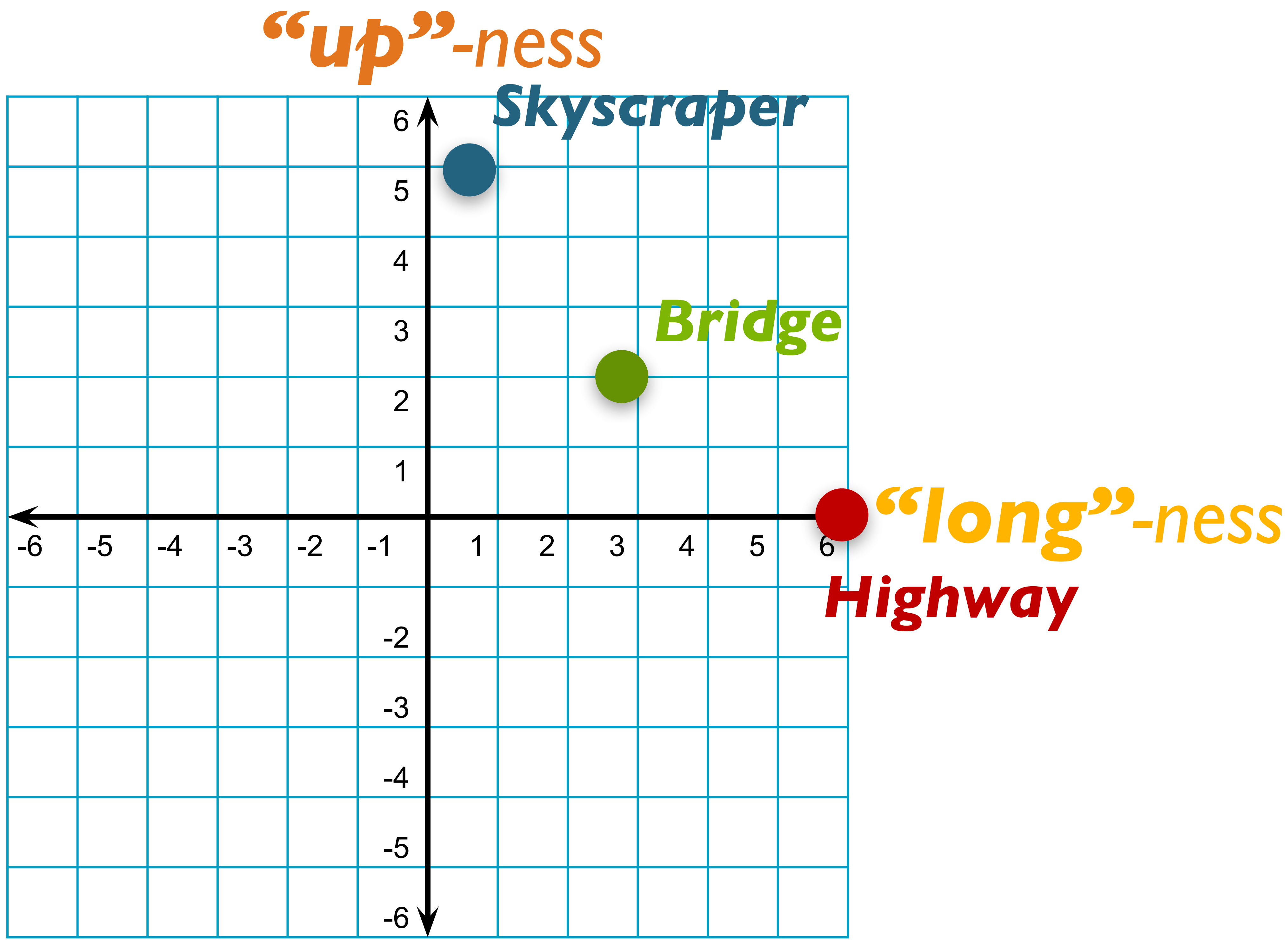

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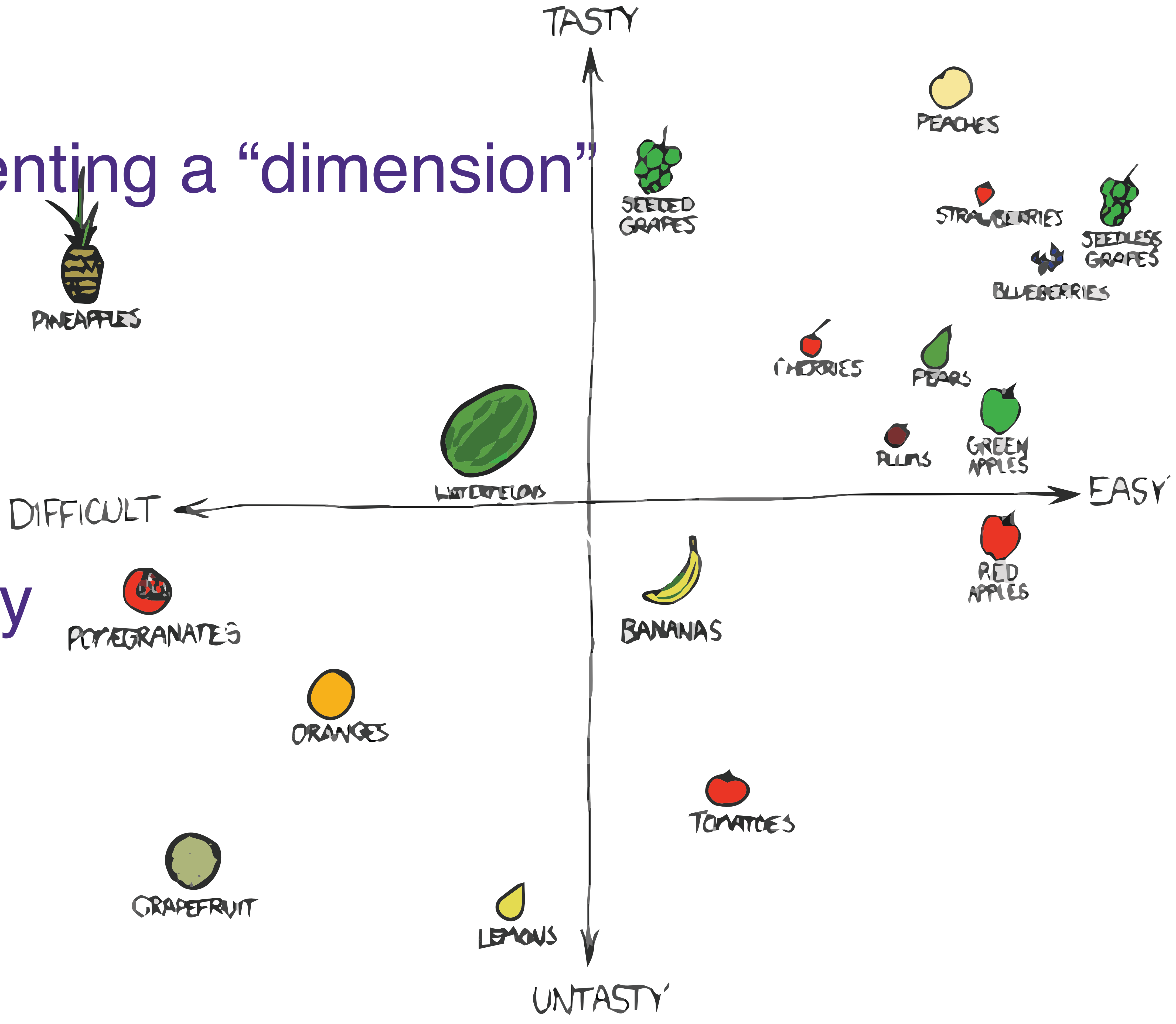
xkcd.com/388



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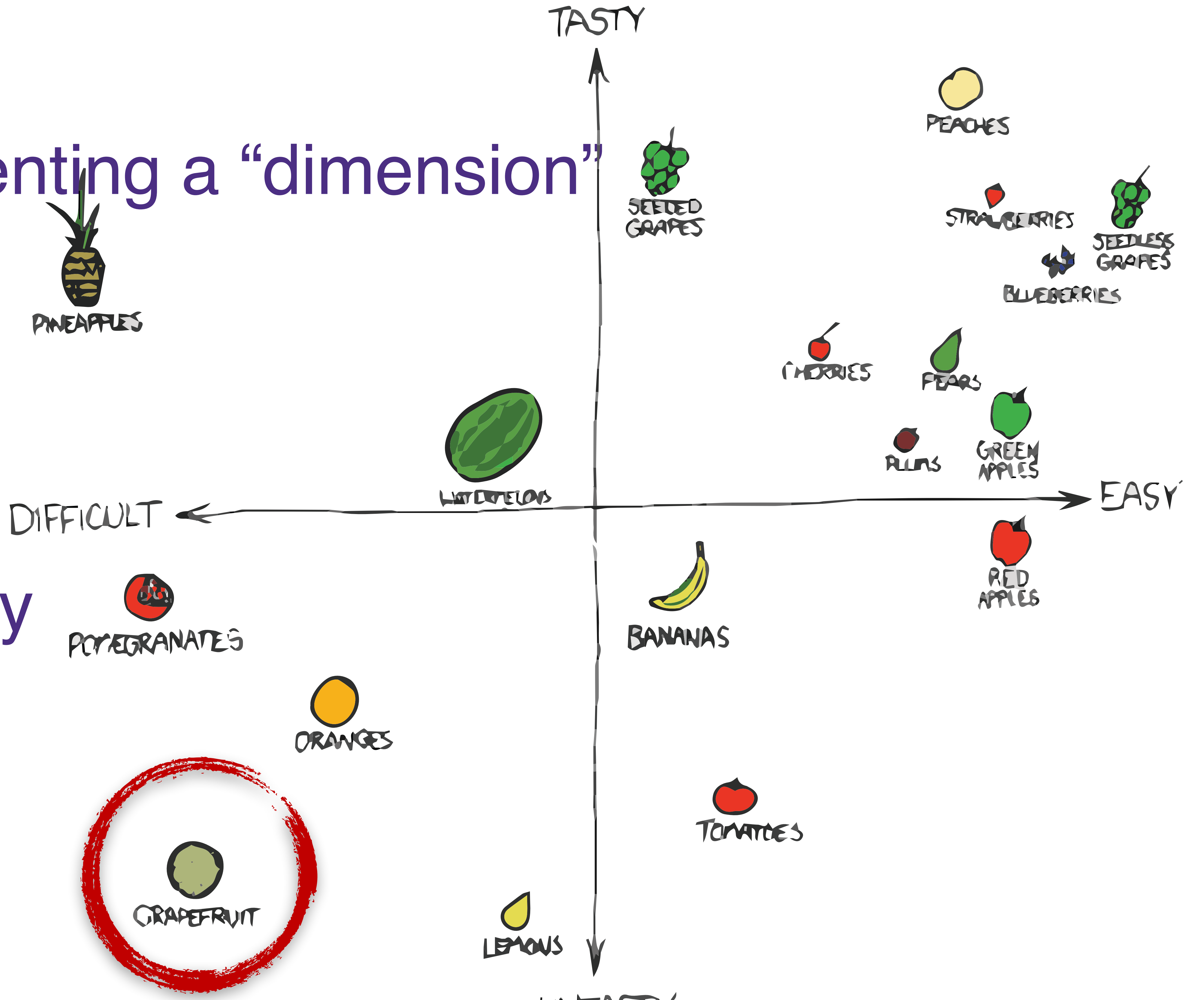

WTF, Grapefruit?

Vector Space: Documents

- We can represent documents as vectors, with each dimension being a count of a particular word

Shakespeare Plays x Counts of Words

	As You Like It	***Twelfth Night***	***Julius Caesar***	***Henry V***
battle	1	1	8	15
soldier	2	2	12	36
fool	37	58	1	5
clown	5	117	0	0

Vector Space: Documents

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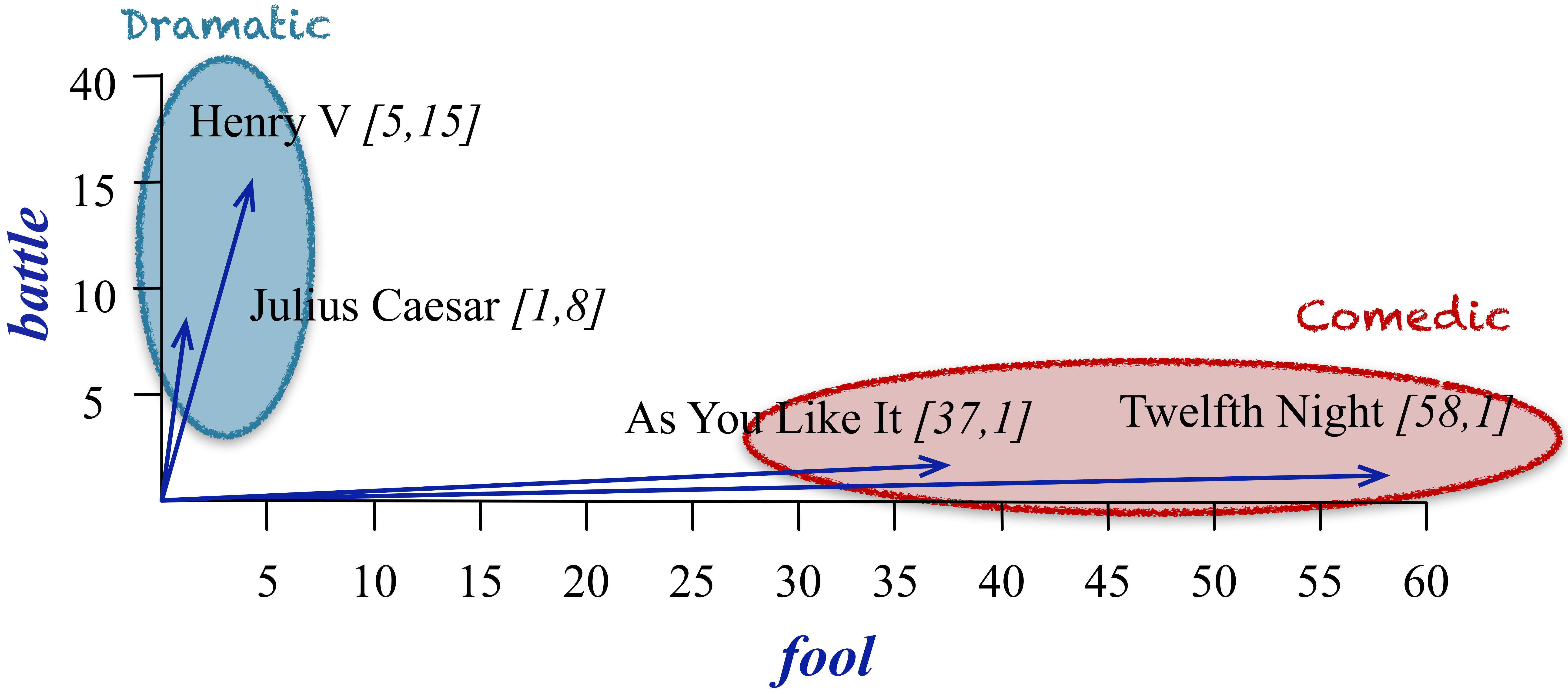


J&M 3rd ed, 6.3.1 [link]

Vector Space: Words

- Find thematic clusters for ***words*** based on words that occur ***around*** them.

Distributional Similarity

- Represent 'company' of word such that similar words will have similar representations
  - 'Company' = context
- Word represented by context feature vector
  - Many alternatives for vector
- Initial representation:
  - 'Bag of words' feature vector
  - Feature vector length N, where N is size of vocabulary
    - f_i+=1 if $word_i$ within window size w of $word$

There are more kinds of **plants** and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plants** and animals in the rainforest that we have not yet discovered.

Biological Example

The Paulus company was founded in 1938. Since those days the product range has been the subject of constant expansions and is brought up continuously to correspond with the state of the art. We're engineering, manufacturing and commissioning world-wide ready-to-run **plants** packed with our comprehensive know-how. Our Product Range includes pneumatic conveying systems for carbon, carbide, sand, lime and many others. We use reagent injection in molten metal for the…

Industrial Example

Label the First Use of "Plant"

-1 +1

There are more kinds of **of plants and** animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plants** and animals in the rainforest that we have not yet discovered.

plant: (and: 1, of: 1)

-2 +2

There are more kinds of **plants** and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plants** and animals in the rainforest that we have not yet discovered.

plant: (and: 1, animal: 1, kind: 1, of: 1)

-3 +3

There are more kinds of **plants** and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plants** and animals in the rainforest that we have not yet discovered.

plant: (and: 1, animal: 1, in: 1, kind: 1, more: 1, of: 1)

-4 +4

There are more kinds of **plants** and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plants** and animals in the rainforest that we have not yet discovered.

plant: (and: 1, animal: 1, are: 1, in: 1, kind: 1, more: 1, of: 1, the: 1)

-5 +5

There are more kinds of **plants** and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plants** and animals in the rainforest that we have not yet discovered.

plant: (and: 1, animal: 1, are: 1, in: 1, kind: 1, more: 1, of: 1, rainforest: 1, the: 1, there: 1)

There are more kinds of **plants** and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plants** and animals in the rainforest that we have not yet discovered.

plant: (and: 1, animal: 2, are: 1, in: 1, kind: 1, more: 1, of: 1, rainforest: 1, the: 1, there: 1, species: 1)

There are more kinds of **plants** and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plants** and animals in the rainforest that we have not yet discovered.

plant: (and: 1, animal: 3, are: 2, in: 1, kind: 1, more: 1, of: 1, rainforest: 1, the: 1, there: 1, species: 1)

There are more kinds of **plants** and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plants** and animals in the rainforest that we have not yet discovered.

plant: (and: 1, animal: 3, are: 2, in: 1, kind: 1, more: 1, of: 1, rainforest: 2, the: 1, there: 1, species: 1, nowhere: 1)

There are more kinds of **plants** and animals in the rainforests than anywhere else on Earth. Over half of the millions of known species of **plants** and animals live in the rainforest. Many are found nowhere else. There are even **plants** and animals in the rainforest that we have not yet discovered.

plant: (and: 1, animal: 3, are: 2, in: 1, kind: 1, more: 1, of: 1, rainforest: 2, the: 1, there: 1, species: 1, nowhere: 1)

Context Feature Vector

	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

Distributional Similarity Questions

What is the right neighborhood?

How should we weight the features?

How can we compute the similarity between vectors?

Similarity “Neighborhood”

1. Fixed window

- How many words in the neighborhood?
  - +/– 500 words: ‘topical context’
  - +/– 1 or 2 words: collocations, predicate-argument

2. Only words in some grammatical relation (Hindle, 1990)

- Parse text (dependency)
  - Include *subj-verb*; *verb-obj*; *adj-mod*
  - $N \times R$ vector: word × relation

Similarity “Neighborhood”: Fixed Window

- Same corpus, different windows
  - British National Corpus (BNC)
  - Nearest neighbors of “dog”
- 2-word window:
  - *Cat, horse, fox, pet, rabbit, pig, animal, mongrel, sheep, pigeon*
- 30-word window:
  - *Kennel, puppy, pet, terrier, Rottweiler, canine, cat, to bark, Alsatian*

Similarity “Neighborhood”: Grammatical Relations

- Build a vector from dependency triples: (Lin, 1998)
  - `(w1 dep_rel w2)`

	subj-of, absorb	subj-of, adapt	subj-of, behave	…	pobj-of, inside	pobj-of, into	…	nmod-of, abnormality	nmod-of, anemia	nmod-of, architecture	…	obj-of, attack	obj-of, call	obj-of, come from	obj-of, decorate	…	nmod, bacteria	nmod, body	nmod, bone marrow
cell	1	1	1		16	30		3	8	1		6	11	3	2		3	2	2

Dependency vector for “cell,” counts from 64M word corpus.

“Neighborhood”: Window vs. Grammatical Relations

- Grammatical relations:
  - Richer representation
  - Much more POS information
- Window:
  - Only need text!
  - Scales very, very well. (Maybe too well.)
  - Adding explicit supervision from parsers often doesn’t help dramatically

Distributional Similarity Questions

What is the right neighborhood?

How should we weight the features?

How can we compute the similarity between vectors?

Weighting Features: Binary vs. Nonbinary?

- Binary?
  - Minimally informative
  - Can’t capture intuition that frequent features more indicative of relationship.
- Frequency
  - Or rather, probability: $assoc_{prob}(w, f) = P(f|w)$
  - …but how do we know which words are informative?
  - *the, it, they* — not likely to help differentiate target word

Weighting Features: Pointwise Mutual Information

- PMI is measure of how often two events x and y occur, vs. expected frequency if they were independent (Fano, 1961)

$$PMI(x, y) = \log_2 \frac{P(x, y)}{P(x) \cdot P(y)}$$

Weighting Features: Pointwise Mutual Information

- We can formulate for word/feature occurrence: $assoc_{PMI}(w,f) = \log_2 \frac{P(w,f)}{P(w) \cdot P(f)}$
- Generally only use positive values
  - Negatives inaccurate unless corpus huge
- Can also rescale/smooth context values

Weighting Features: (Positive) Pointwise Mutual Information

$$assoc_{PMI}(w,f) = \log_2 \frac{P(w,f)}{P(w) \cdot P(f)}$$

$$p_{ij} = \frac{f_{ij}}{\sum_{i=1}^{W} \sum_{j=1}^{C} f_{ij}}$$

probability of feature f relating i to j

$$p_{i*} = \frac{\sum_{j=1}^{C} f_{ij}}{\sum_{i=1}^{W} \sum_{j=1}^{C} f_{ij}}$$

probability of feature f relating i to *anything*

$$p_{*j} = \frac{\sum_{i=1}^{W} f_{ij}}{\sum_{i=1}^{W} \sum_{j=1}^{C} f_{ij}}$$

probability of feature f relating *anything* to j

$$PPMI_{ij} = \max(\log_2 \frac{p_{ij}}{p_{i*} \cdot p_{*j}}, 0)$$

Get (non-negative) ratio

Weighting Features: (Positive) Pointwise Mutual Information

- For pure word co-occurrence, feature f is the colocated word.

Weighting Features: Pointwise Mutual Information

- Total words (sum of whole table) $=$ **19**

	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

Weighting Features: Pointwise Mutual Information

- Total words (sum of whole table) $= 19$
  - $P(w)$, where w is *information* = **11**/19 = **.579**

	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

Weighting Features: Pointwise Mutual Information

- Total words (sum of whole table) $=$ 19
  - $P(w)$, where w is *information* = 11/19 = .579
  - $P(f)$, where f is *data* = **7**/19 = **.368**

	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

Weighting Features: Pointwise Mutual Information

- Total words (sum of whole table) $=$ 19
  - $P(w)$, where w is *information* = 11/19 = .579
  - $P(f)$, where f is *data* = 7/19 = .368
  - $P(w,f)$, where (w,f) is (*information*,*data*) = **6**/19 = **.316**

	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	$\boxed{6}$	0	4	0

Weighting Features: Pointwise Mutual Information

- Total words (sum of whole table) $=$ 19
  - $P(w)$, where w is *information* = 11/19 = .579
  - $P(f)$, where f is *data* = 7/19 = .368
  - $P(w,f)$, where (w,f) is (*information*,*data*) = 6/19 = .316

$$PPMI_{assoc} = \log_2 \frac{P(w,f)}{P(w) \cdot P(f)}$$

$$= \log_2 \frac{0.316}{0.579 \cdot 0.368}$$

$$= 0.568$$

	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

PPMI re-scaling

	computer	data	result	pie	sugar	count(w)
cherry	2	8	9	442	25	486
strawberry	0	0	1	60	19	80
digital	1670	1683	85	5	4	3447
information	3325	3982	378	5	13	7703
count(context)	4997	5673	473	512	61	11716

Figure 6.9 Co-occurrence counts for four words in 5 contexts in the Wikipedia corpus, together with the marginals, pretending for the purpose of this calculation that no other words/contexts matter.

J&M 3rd ed. [sec. 6.7]

PPMI re-scaling

	computer	data	result	pie	sugar
cherry	0	0	0	4.38	3.30
strawberry	0	0	0	4.10	5.51
digital	0.18	0.01	0	0	0
information	0.02	0.09	0.28	0	0

Figure 6.11 The PPMI matrix showing the association between words and context words, computed from the counts in Fig. 6.10. Note that most of the 0 PPMI values are ones that had a negative PMI; for example PMI(*cherry,computer*) = -6.7, meaning that *cherry* and *computer* co-occur on Wikipedia less often than we would expect by chance, and with PPMI we replace negative values by zero.

J&M 3rd ed. sec. 6.7

Weighting Features: Pointwise Mutual Information

- Downside:
  - PPMI favors rare events
- Solutions:
  - Change the $P(f)$ to be raised to the power of α
    - Increases the probability assigned to rare contexts
  - Laplace smoothing (add-n)

Distributional Similarity Questions

What is the right neighborhood?

How should we weight the features?

How can we compute the similarity between vectors?

Vector Distances: Manhattan & Euclidean

- **Manhattan Distance**

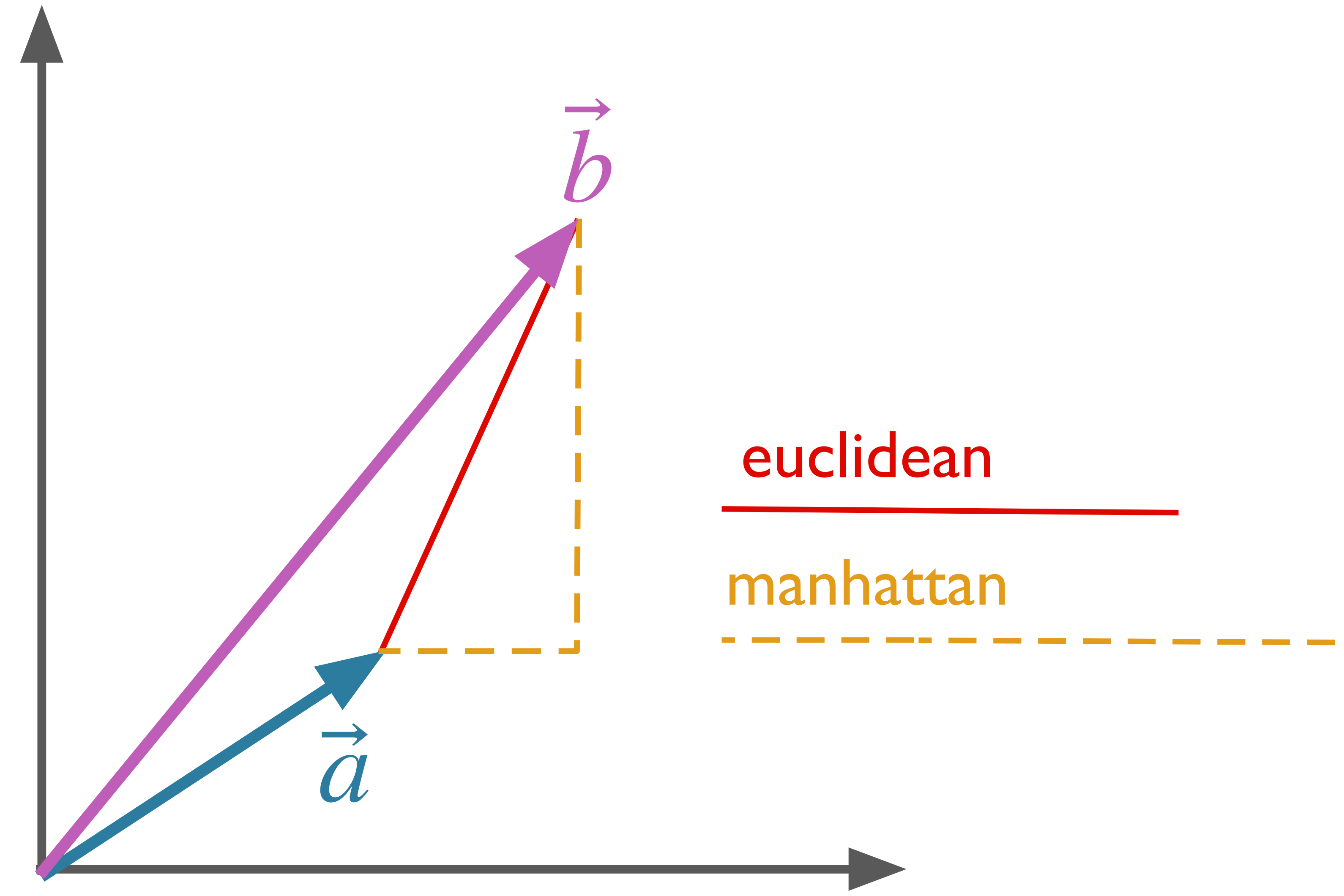
$$dist_{manhattan} = (\vec{x}, \vec{y}) = \sum_{i=1}^{N} |x_i - y_i|$$

  - (Distance as cumulative horizontal + vertical moves)

- **Euclidean Distance**

$$dist_{euclidean} = \sqrt{\sum_{i=1}^{N} (x_i - y_i)^2}$$

- Too sensitive to extreme values



Vector Similarity: Dot Product

- Produces real number scalar from product of vectors' components

$$sim_{dot-product}(\vec{v}, \vec{w}) = \vec{v} \cdot \vec{w} = \sum_{i=1}^{N} v_i \times w_i$$

- Biased toward ***longer*** (larger magnitude) vectors
  - In our case, vectors with fewer zero counts

Vector Similarity: Cosine

- If you normalize the dot product for vector magnitude…
- …result is same as cosine of angle between the vectors.

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

Sample Results

- Based on Lin dependency model
  - **Hope (N)**: optimism, chance, expectation, prospect, dream, desire, fear
  - **Hope (V)**: would like, wish, plan, say, believe, think

  - **Brief (N)**: legal brief, affidavit, filing, petition, document, argument, letter
  - **Brief (A)**: lengthy, hour-long, short, extended, frequent, recent, short-lived, prolonged, week-long

Recap

- We can build feature vectors to represent context of a word

- These features could be:
  1. Occurs before *drunk*
  2. Occurs after *bottle*
  3. Is direct object of *likes*
  4. Is direct object of *make*

A. A bottle of ***tezgüino*** is on the table.
B. Everybody likes ***tezgüino***.
C. ***Tezgüino*** makes you drunk.
D. We make ***tezgüino*** from corn.

	1	2	3	4
tezgüino	1	1	1	1
tequila	1	1	1	1
apricots	0	0	1	0
pizza	0	0	1	1

Recap

- These feature vectors can be as simple as co-occurrence
- …for vocabulary V
  - …for each element i
  - is word v_i within window w of target?

A. A bottle of ***tezgüino*** is on the table.
B. Everybody likes ***tezgüino***.
C. ***Tezgüino*** makes you drunk.
D. We make ***tezgüino*** from corn.

bottle	drunk	matrix	table
1	1	0	0

Context matrix for *tezgüino* with w=3

Recap

- Intuition:
  - These co-occurrence vectors should be able to tell us something about words' similarities

	arts	boil	data	function	large	sugar	summarized	water
Apricot	0	1	0	0	1	1	0	1
Pineapple	0	1	0	0	1	1	0	1
Digital	0	0	1	1	1	0	1	0
Information	0	0	1	1	1	0	1	0

Problem: Sparse Vectors!

- Big problem:
  - The vast majority of word pairs will be zero!
  - This leads to very sparse vectors.
- In the exercise:
  - (*election*, *primary*) is 2
  - (*election, midterm*) is 0
- …how can we generalize better?

Problem: Sparse Vectors!

- Term x document:

	c1	c2	c3	c4	c5	m1	m2	m3	m4
human	1	0	0	1	0	0	0	0	0
interface	1	0	1	0	0	0	0	0	0
computer	1	1	0	0	0	0	0	0	0
user	0	1	1	0	1	0	0	0	0
system	0	1	1	2	0	0	0	0	0
response	0	1	0	0	1	0	0	0	0
time	0	1	0	0	1	0	0	0	0
EPS	0	0	1	1	0	0	0	0	0
survey	0	1	0	0	0	0	0	0	1
trees	0	0	0	0	0	1	1	1	0
graph	0	0	0	0	0	0	1	1	1
minors	0	0	0	0	0	0	0	1	1