

95-865

Unstructured Data Analytics
Lecture 2: Basic Text Analysis
Wrap-up, Co-occurrence Analysis

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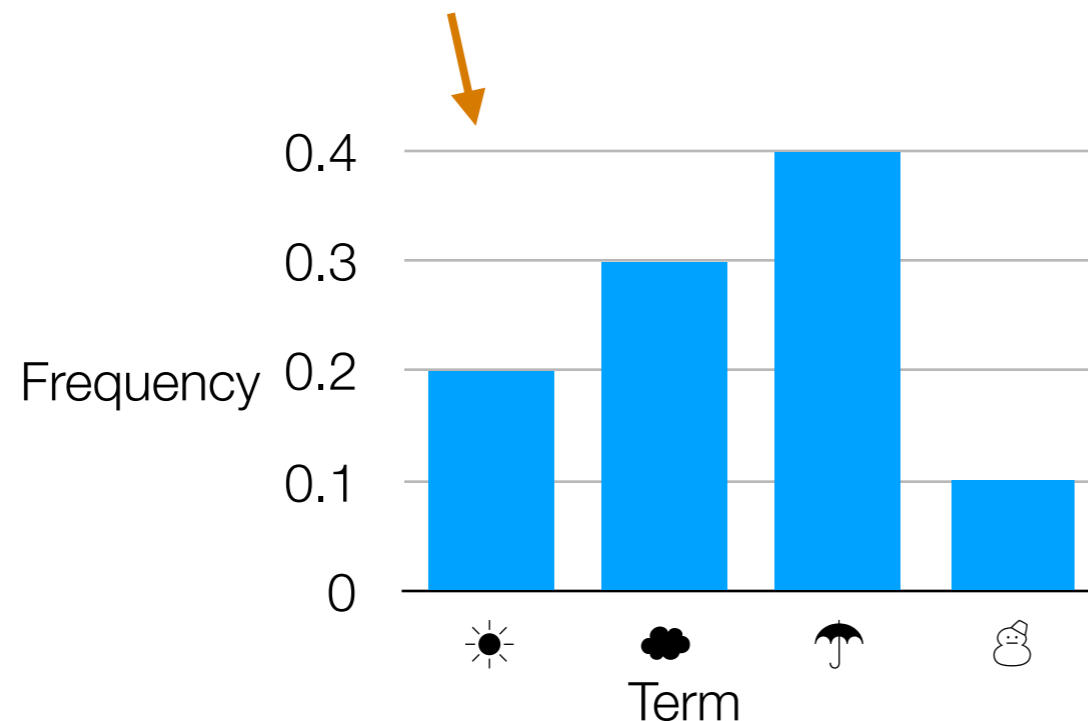
The spaCy Python Package

Demo

Recap: Basic Text Analysis

- Represent text in terms of “features” (e.g., how often each word/phrase appears, whether it’s a named entity, etc)
- Can repeat this for different documents:
represent each document as a “feature vector”

"Sentence": ☀️☔☁☁☁☔👶☔☔☀️



$$\begin{bmatrix} 0.2 \\ 0.3 \\ 0.4 \\ 0.1 \end{bmatrix}$$

This is a point in
4-dimensional
space, \mathbb{R}^4

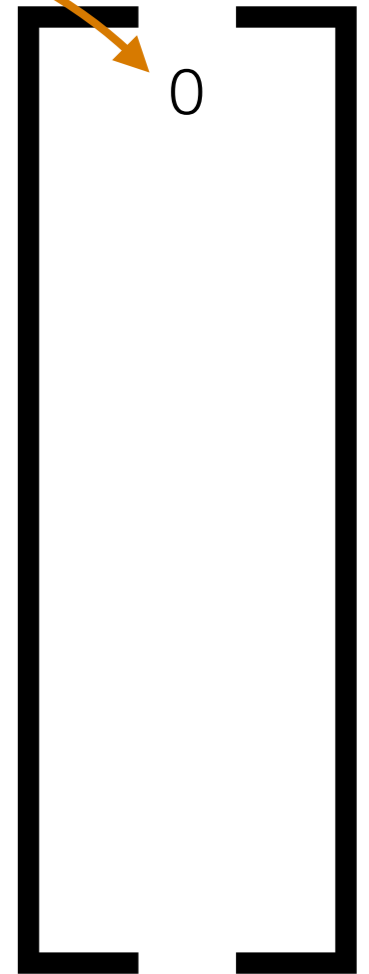
dimensions = number of terms

In general (not just text): first represent data as feature vectors

Example: Representing an Image



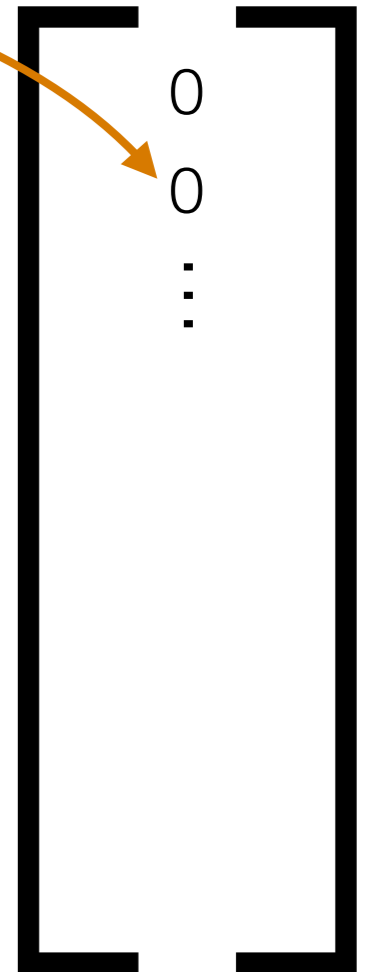
0: black
1: white



Go row by row and look at pixel values

Example: Representing an Image

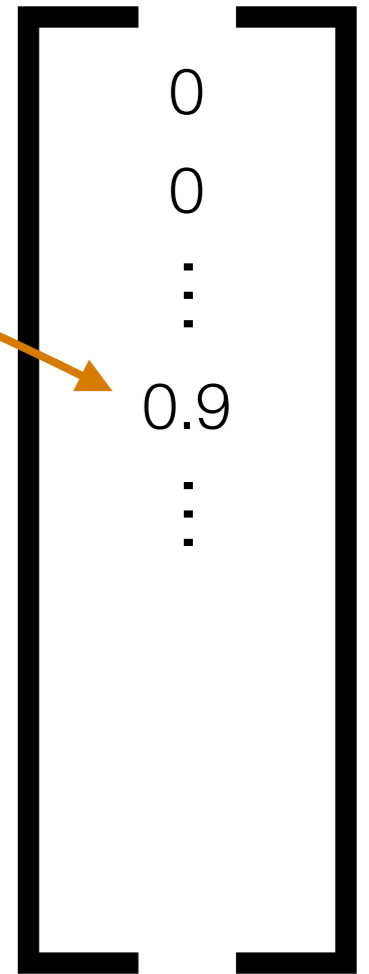
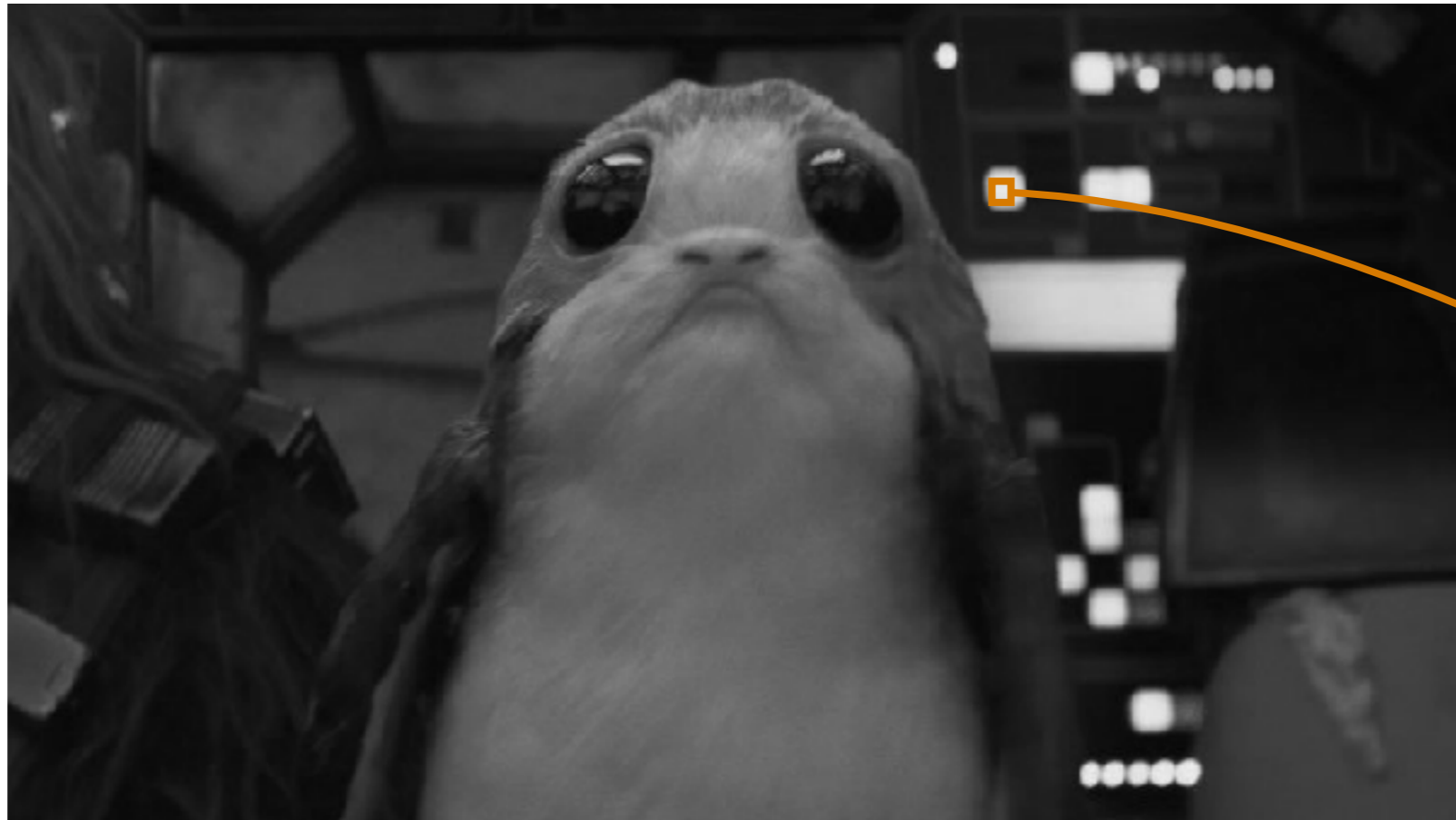
0: black
1: white



Go row by row and look at pixel values

Example: Representing an Image

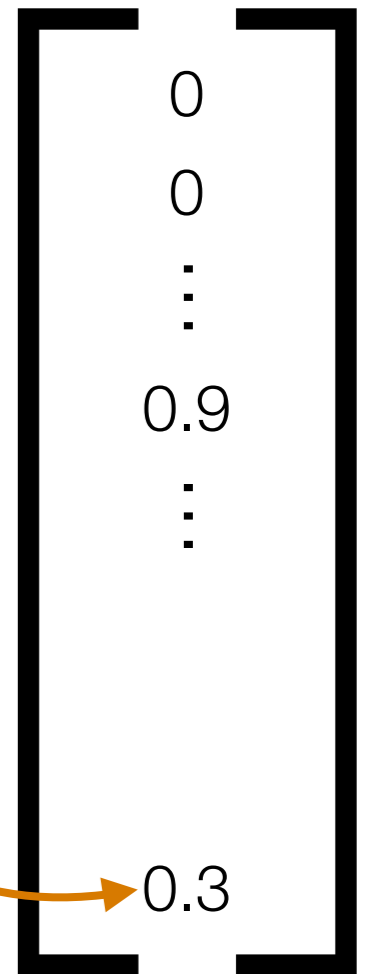
0: black
1: white



Go row by row and look at pixel values

Example: Representing an Image

0: black
1: white



Go row by row and look at pixel values

dimensions = image width × image height

Very high dimensional!

Image source: starwars.com

Back to Text

Unigram bag of words model is already quite powerful:

- Enough to learn topics
(each text doc: raw word counts without stopwords)
- Enough to learn a simple detector for email spam

These are HW2 problems

Finding Possibly Related Entities

Elon Musk's Tesla Powerwalls Have Landed in Puerto Rico



How to automatically figure out Elon Musk and Tesla are related?

The solar batteries have reportedly been spotted in San Juan's airport.

By **John Patrick Pullen** October 16, 2017

Exactly one week after **Tesla CEO Elon Musk** suggested his company could help with Puerto Rico's electricity crisis in the aftermath of Hurricane Maria, more of the company's Powerwall battery packs have arrived on the island, according to a photo snapped at San Juan airport Friday, Oct. 13.

Co-Occurrences

For example: count # news articles that have different named entities co-occur

	Apple	Facebook	Tesla
Elon Musk	10	15	300
Mark Zuckerberg	500	10000	500
Tim Cook	200	30	10

Big values → *possibly* related named entities

Different Ways to Count

- Just saw: for all doc's, count # of doc's in which two named entities co-occur
 - This approach ignores # of co-occurrences *within a specific document* (e.g., if 1 doc has “Elon Musk” and “Tesla” appear 10 times, we count this as 1)
 - Could instead add # co-occurrences, not just whether it happened in a doc
- Instead of looking at # doc's, look at co-occurrences within a *sentence*, or a *paragraph*, etc

Bottom Line

- There are many ways to count co-occurrences
- You should think about what makes the most sense/is reasonable for the problem you're looking at

Co-Occurrences

For example: count # news articles that have different named entities co-occur

	Apple	Facebook	Tesla
Elon Musk	10	15	300
Mark Zuckerberg	500	10000	500
Tim Cook	200	30	10

Big values → *possibly* related named entities

How to downweight “Mark Zuckerberg” if there are just way more articles that mention him?

Key idea: what would happen if people and companies had nothing to do with each other?

	Apple	Facebook	Tesla
Elon Musk	10	15	300
Mark Zuckerberg	500	10000	500
Tim Cook	200	30	10

Probability of drawing
“Elon Musk, Apple”?

Probability of drawing
a card that says
“Apple” on it?

10 of these cards:

Elon Musk, Apple

15 of these cards:

Elon Musk, Facebook

300 of these cards:

Elon Musk, Tesla

⋮

10 of these cards:

Tim Cook, Tesla



Co-occurrence table

	Apple	Facebook	Tesla
Elon Musk	10	15	300
Mark Zuckerberg	500	10000	500
Tim Cook	200	30	10

Total: 11565

Joint probability table

	Apple	Facebook	Tesla
Elon Musk	10 /11565	15 /11565	300 /11565
Mark Zuckerberg	500 /11565	10000 /11565	500 /11565
Tim Cook	200 /11565	30 /11565	10 /11565

sum to get
 $P(\text{Elon Musk})$

Total: 11565

Joint probability table

	Apple	Facebook	Tesla	
Elon Musk	0.00086	0.00130	0.02594	0.02810
Mark Zuckerberg	0.04323	0.86468	0.04323	0.95115
Tim Cook	0.01729	0.00259	0.00086	0.02075
	0.06139	0.86857	0.07004	

Recall: if events A and B are independent, $P(A, B) = P(A)P(B)$

Joint probability table **if people and companies were independent**

	Apple	Facebook	Tesla	
Elon Musk	0.00173	0.02441	0.00197	0.02810
Mark Zuckerberg	0.05839	0.82614	0.06662	0.95115
Tim Cook	0.00127	0.01802	0.00145	0.02075
	0.06139	0.86857	0.07004	

Recall: if events A and B are independent, $P(A, B) = P(A)P(B)$

What we
actually observe

	Apple	Facebook	Tesla
Elon Musk	0.00086	0.00130	0.02594
Mark Zuckerberg	0.04323	0.86468	0.04323
Tim Cook	0.01729	0.00259	0.00086

What should be the
case if people are
companies are
independent

	Apple	Facebook	Tesla
Elon Musk	0.00173	0.02441	0.00197
Mark Zuckerberg	0.05839	0.82614	0.06662
Tim Cook	0.00127	0.01802	0.00145

Pointwise Mutual Information (PMI)

Probability of A and B co-occurring

$$\frac{P(A, B)}{P(A) P(B)}$$

if equal to 1

→ A, B are indep.

Probability of A and B co-occurring *if they were independent*

PMI(A, B) is defined as the log of the above ratio

PMI measures (the log of) a ratio that says how far A and B are from being independent

Example PMI Calculation

Demo

Looking at All Pairs of Outcomes

- PMI measures how $P(A, B)$ differs from $P(A)P(B)$ using a **log ratio**
- **Log ratio** isn't the only way to compare!
- Another way to compare:

$$\text{Phi-square} = \sum_{A, B} \frac{[P(A, B) - P(A)P(B)]^2}{P(A)P(B)}$$

$$\text{Chi-square} = N \times \text{Phi-square}$$

N = sum of all co-occurrence counts

Phi-square is between 0 and 1
 $0 \rightarrow$ pairs are all indep.

Measures how close *all* pairs of outcomes are close to being indep.

Phi-Square/Chi-Square Calculation

Demo

Summary: Co-Occurrences

- Joint probability $P(A, B)$ can be poor indicator of whether A and B co-occurring is “interesting”
- Find interesting relationships between pairs of items by looking at PMI
- Intuition: “Interesting” co-occurring events should occur more frequently than if they were to co-occur independently

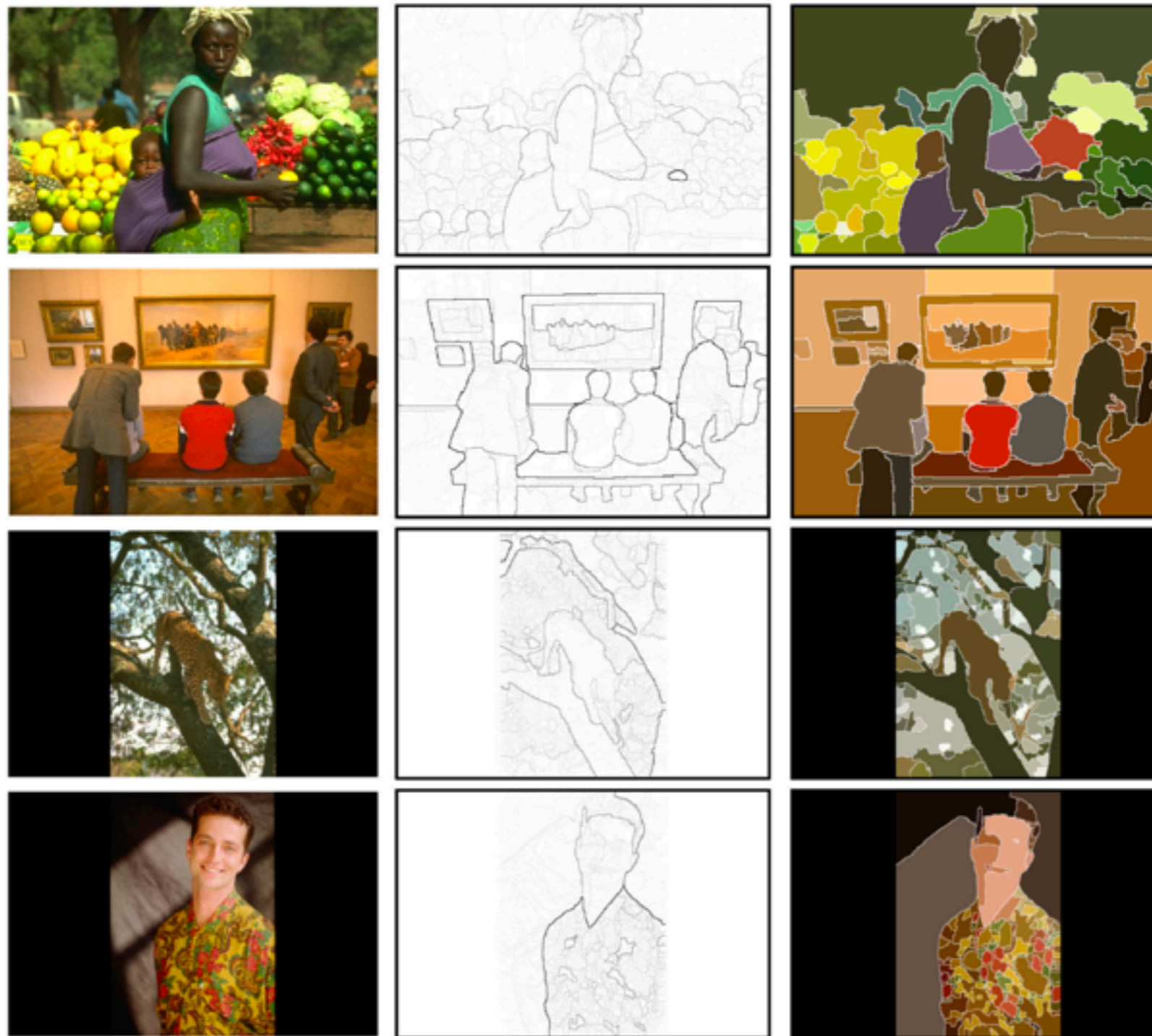
Co-occurrence Analysis Applications

- If you're an online store/retailer:
anticipate *when* certain products are likely to be purchased/
rented/consumed more
 - Products & dates
- If you have a bunch of physical stores:
anticipate *where* certain products are likely to be purchased/
rented/consumed more
 - Products & locations
- If you're the police department:
create "heat map" of where different criminal activity occurs
 - Crime reports & locations

Co-occurrence Analysis Applications

- If you're an online store/retailer:
 - anticipate when certain products are likely to be purchased/reordered
- Examples of data to take advantage of:
 - data collected by your organization
 - social networks
 - news websites
 - blogs
- If you are an analyst/researcher:
 - Web scraping frameworks can be helpful:
 - Scrapy
 - Selenium (great with JavaScript-heavy pages)
- If you are a law enforcement officer:
 - Crime reports & locations

Example Application of PMI: Image Segmentation



Phillip Isola, Daniel Zoran, Dilip Krishnan, and Edward H. Adelson. Crisp boundary detection using pointwise mutual information. ECCV 2014.

Example Application of PMI: Word Embeddings

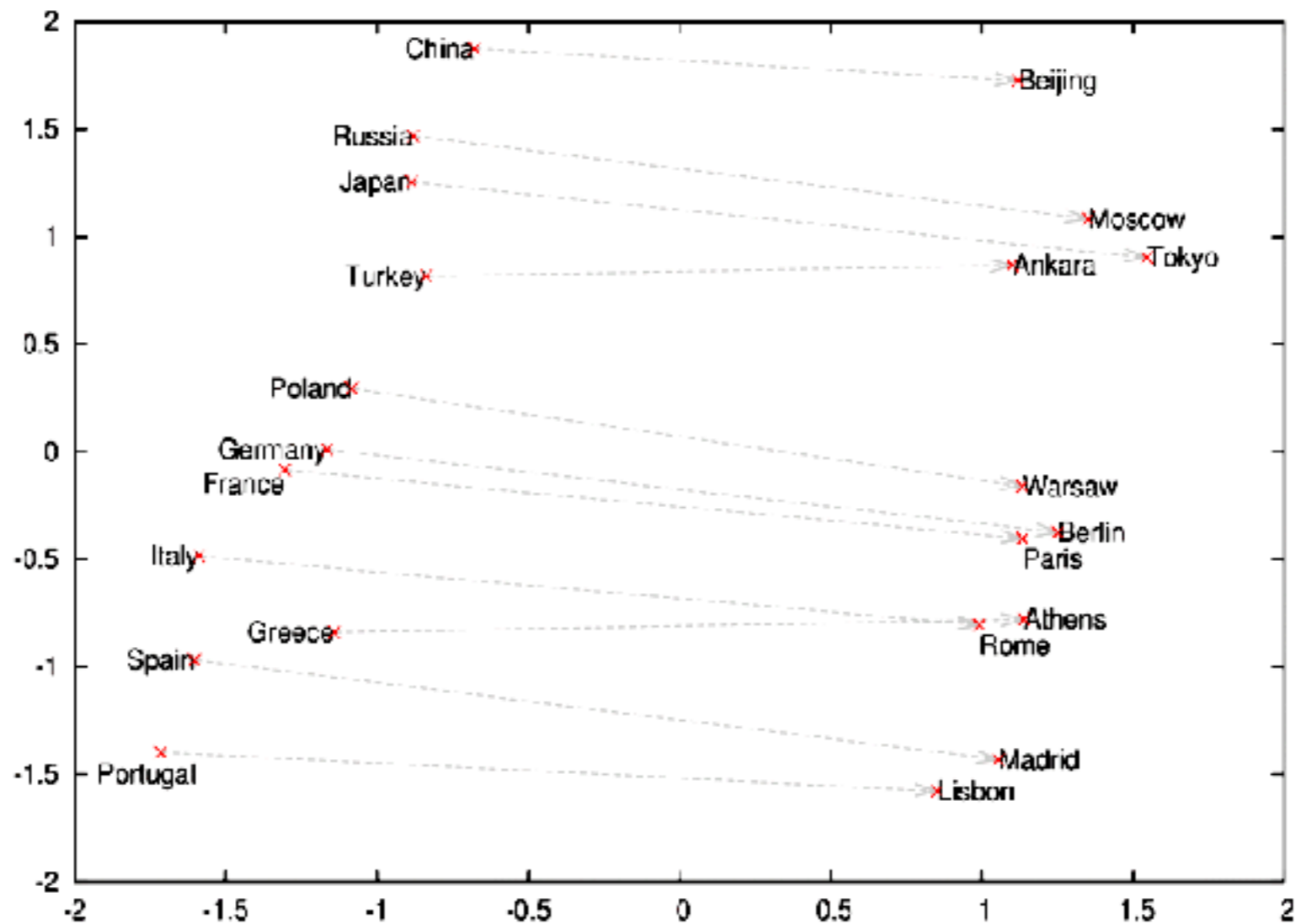


Image source: https://deeplearning4j.org/img/countries_capitals.png

Omer Levy and Yoav Goldberg. Neural word embeddings as implicit matrix factorization. NIPS 2014.