Carnegie Mellon University
Heinz College

94-775 Lecture 5: Finding Possibly Related Entities

George Chen

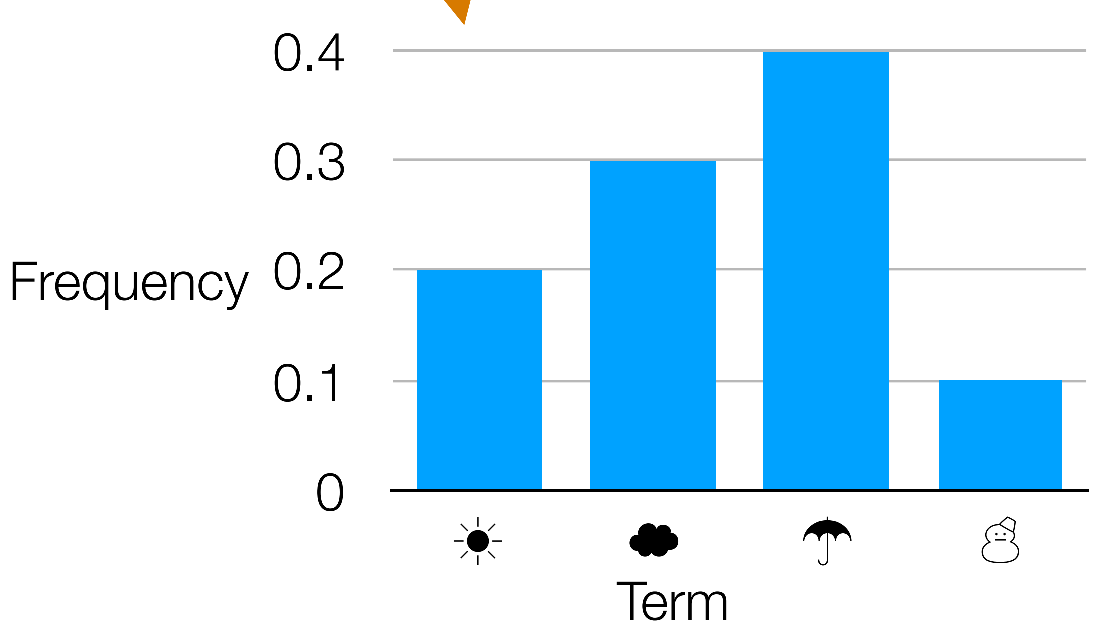
Quiz Format

- Bring a laptop that has Anaconda Python 3.6 properly installed and that you can write in a Jupyter notebook with
  - You are responsible for making sure that your laptop is working and has enough battery life! (If you need to plug it in, sit near an outlet)
- The exam will be open book, open internet
- No collaboration
- If you use external resources, cite your sources
- A mix of shorter conceptual questions (can involve code), and a longer coding question

Recap: Basic Text Analysis

- Represent text in terms of “features”
(such as how often each word/phrase appears)
  - 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

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.

Source: http://fortune.com/2017/10/16/elon-musks-tesla-powerwalls-have-landed-in-puerto-rico/

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?

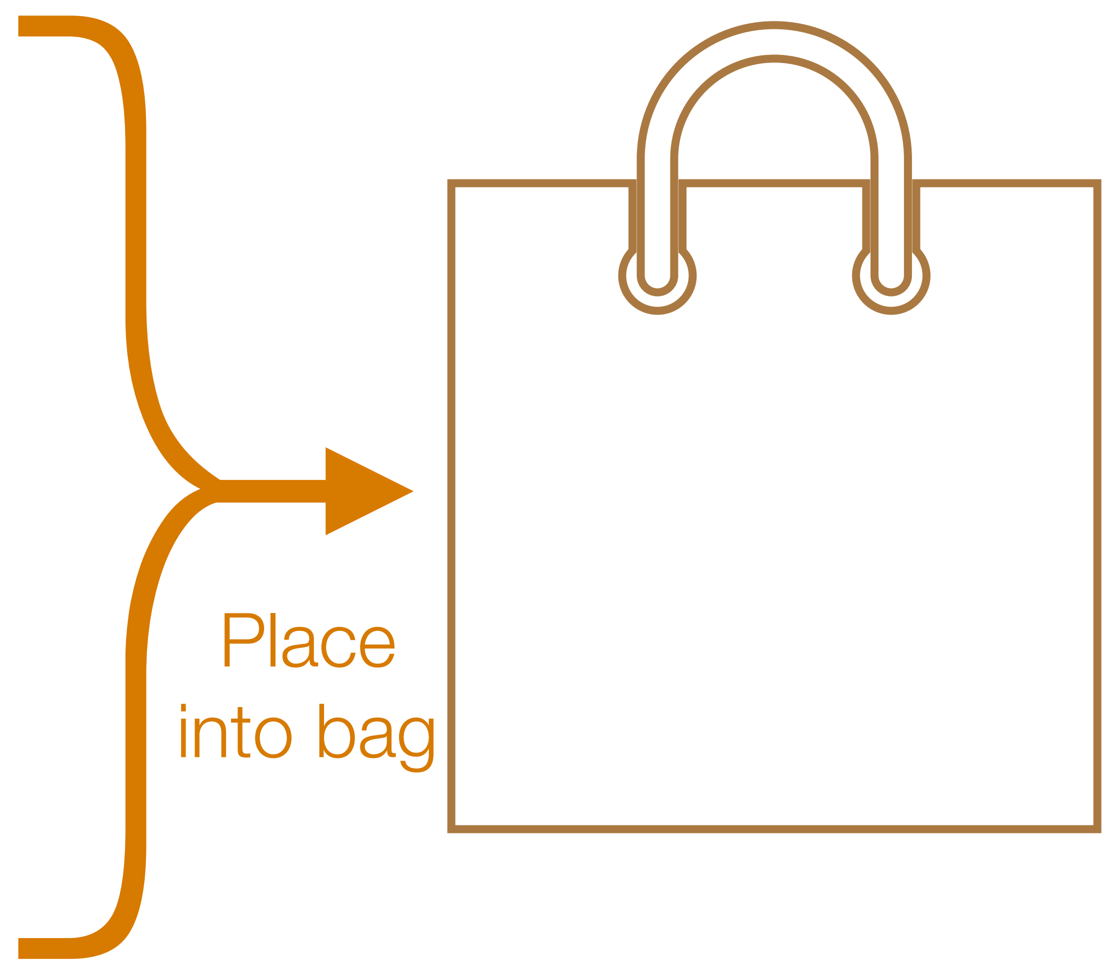
10 of these cards: Elon Musk, Apple

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(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

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

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

if equal to 1
➔ A, B are indep.

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:

$$\frac{[\ P(A, B) - P(A)\ P(B)\ ]^2}{P(A)\ P(B)}$$

Phi-square is between 0 and 1

0 ➔ pairs are all indep.

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

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

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

N = sum of all co-occurrence counts (in upper right of triangle earlier)

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/
  re
  -
- If y
  an ased/
  re
  -
- If y
  cr curs
  - Crime reports & locations

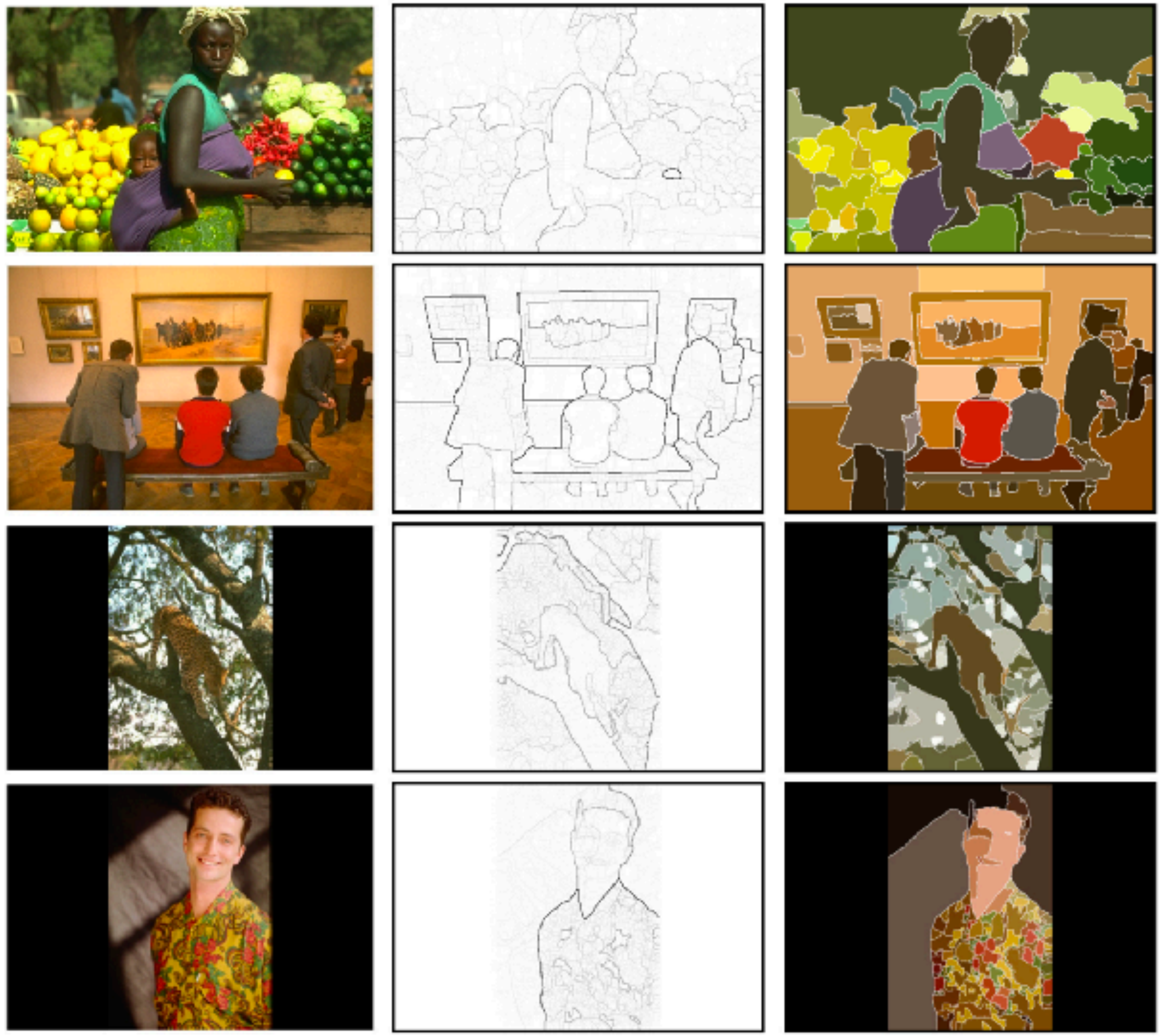
Examples of data to take advantage of:

- data collected by your organization
- social networks
- news websites
- blogs

Web scraping frameworks can be helpful:

- Scrapy
- Selenium (great with JavaScript-heavy pages)

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

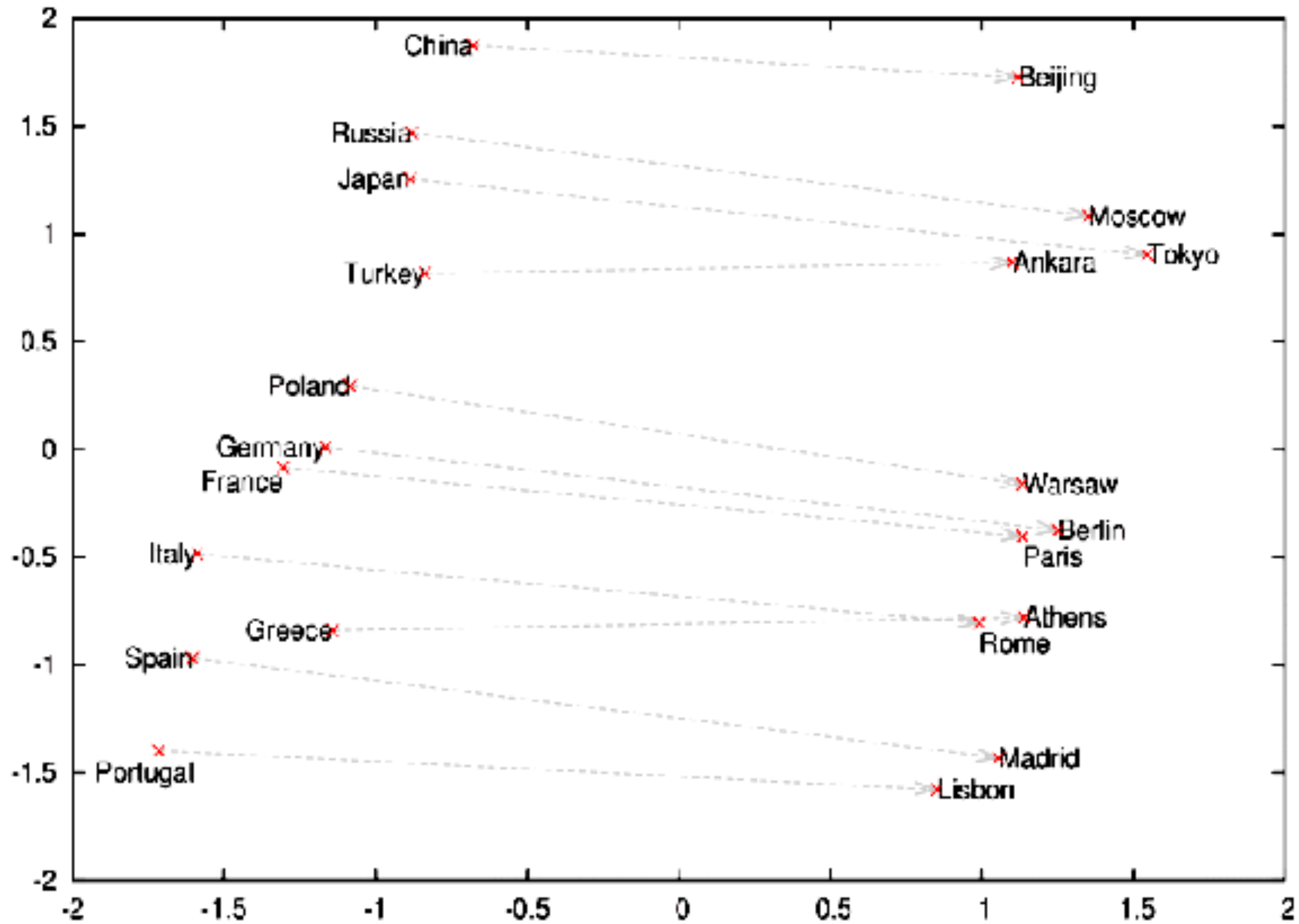
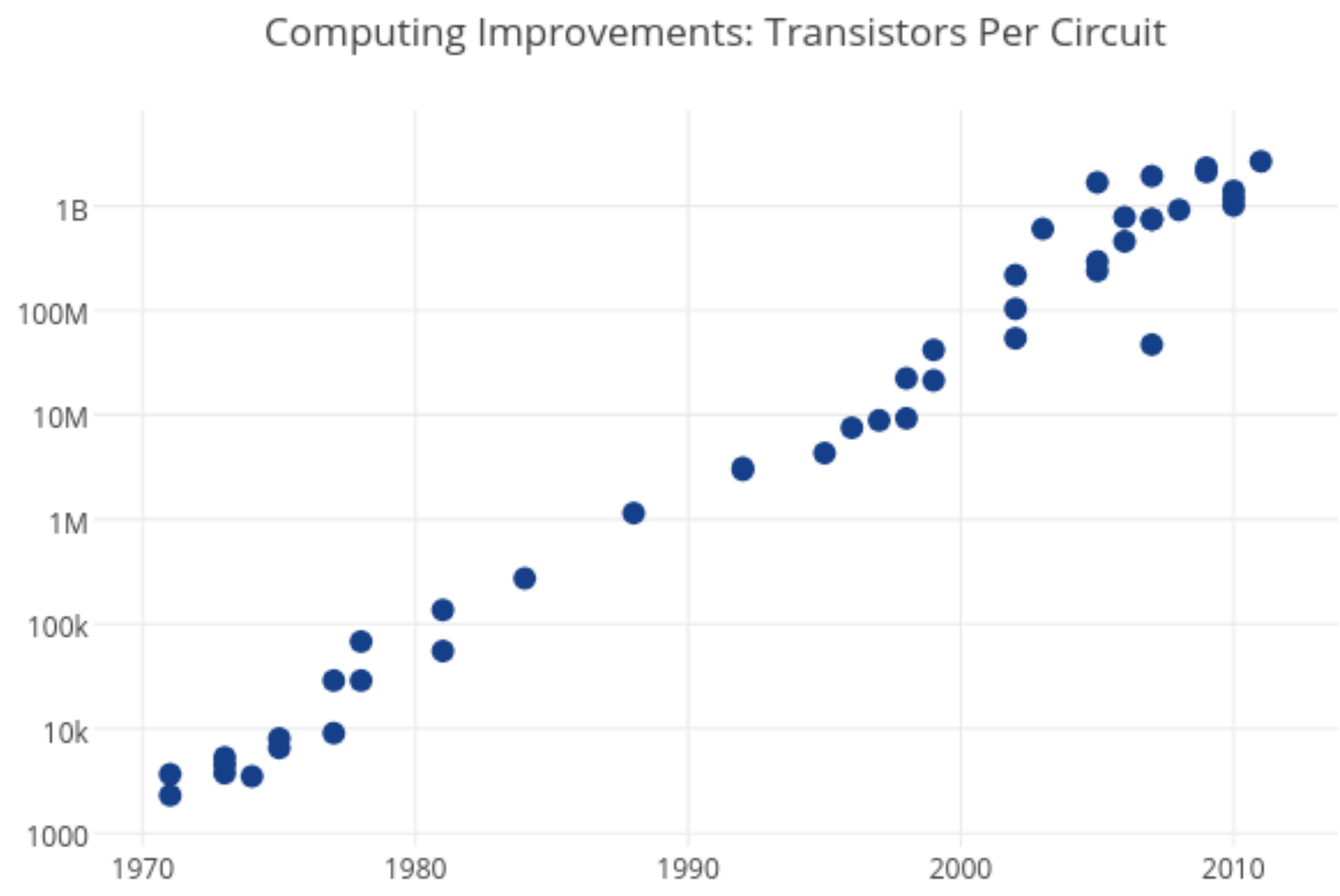


Image source: https://deeplearning4j.org/img/countries_capitals.png

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

Continuous Measurements

- So far, looked at relationships between *discrete* outcomes
- For pair of *continuous* outcomes, use a **scatter plot**



Of course, not all trends look like a line

(so don't just do linear regression!)

Image source: https://plot.ly/~MattSundquist/5405.png