

Social Behavior and Trends

Foundations of Computational Social Science

Lecturer: **Lisette Espín-Noboa**

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Postdoc at Complexity Science Hub Vienna

Postdoc at Central European University

October, 31, 2023

TU Graz

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<https://github.com/lisette-espin/TeachingMaterials>

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What is behavior?
What is a trend?



Social behavior & trends

Differences

Behavior refers to the actions, reactions, or conduct of individuals or groups in response to a particular situation.

A Trend is a pattern, fashion or tendency that persists over time. Also, a direction in which something is developing or changing.

Social behavior & trends

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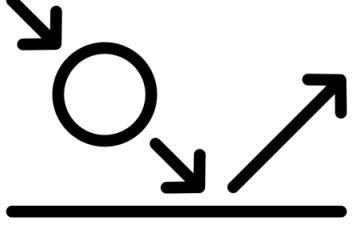
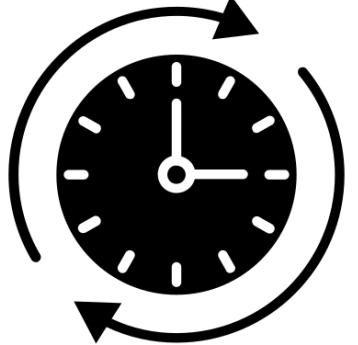
Interactions of and among individuals

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Changes in behavior or attitudes

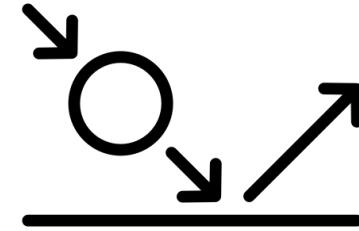
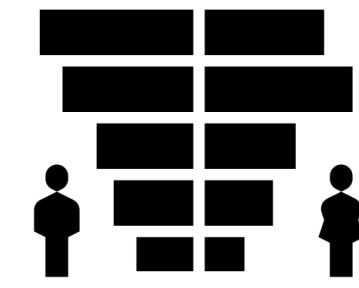
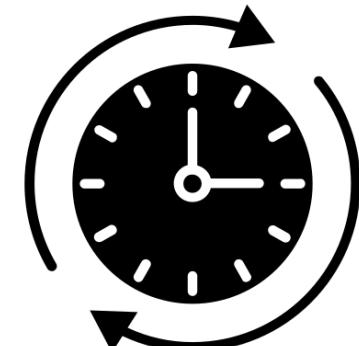
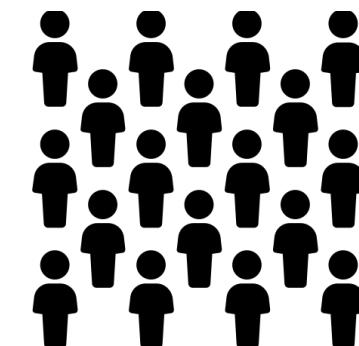
Social behavior & trends

Differences

Focus	Timeframe
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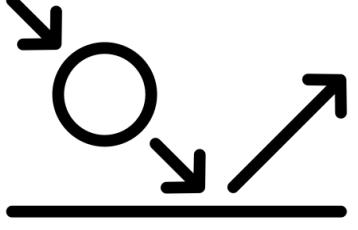
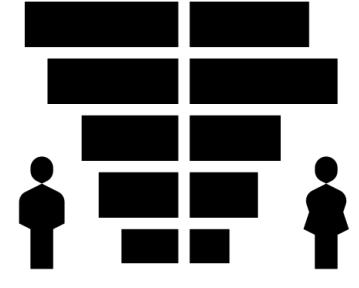
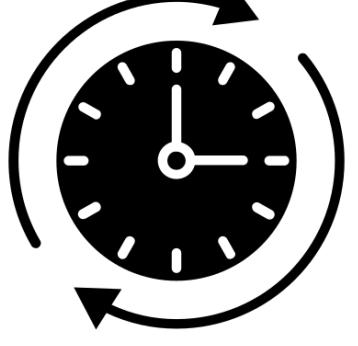
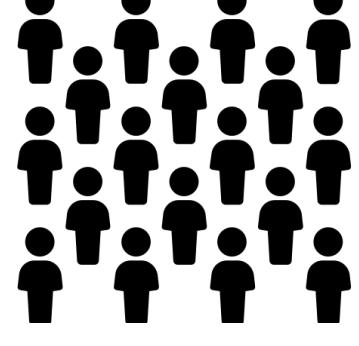
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Social behavior & trends

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Focus	Timeframe	Scope	Analysis
<p>Behavior refers to the actions, reactions, or conduct of individuals or groups in response to a particular situation.</p>	<p>Interactions of and among individuals</p>  Immediate action/reaction	 Individuals or groups	<p>Why? Intercept with social theory? What triggered it?</p>
<p>A Trend is a pattern, fashion or tendency that persists over time. Also, a direction in which something is developing or changing.</p>	<p>Changes in behavior or attitudes</p>  Long-term development	 General population	<p>Who started it? Who has adopted it? For how long will it last?</p>

Social behavior & trends

Similarities

Focus	Timeframe	Scope	Analysis
<p>Behavior refers to the actions, reactions, or conduct of individuals or groups in response to a particular situation.</p>	<p>Both involve the interaction of individuals (patterns)</p>	<p>Both are influenced by societal norms, cultural practices, and environmental factors</p>	<p>Both are within the interests of computational social scientists</p>
<p>A Trend is a pattern, fashion or tendency that persists over time. Also, a direction in which something is developing or changing.</p>			

Social behavior & trends

Examples

How users navigate the Web, the city, etc.

The use of ChatGPT in education & science

Online consumer decision-making



Behavior

Trend

The increasing focus on interdisciplinary collaboration between computer science, social sciences, and statistics.

Modeling social networks
(how edges form)

Strategies in online gaming

How scientists collaborate in academia

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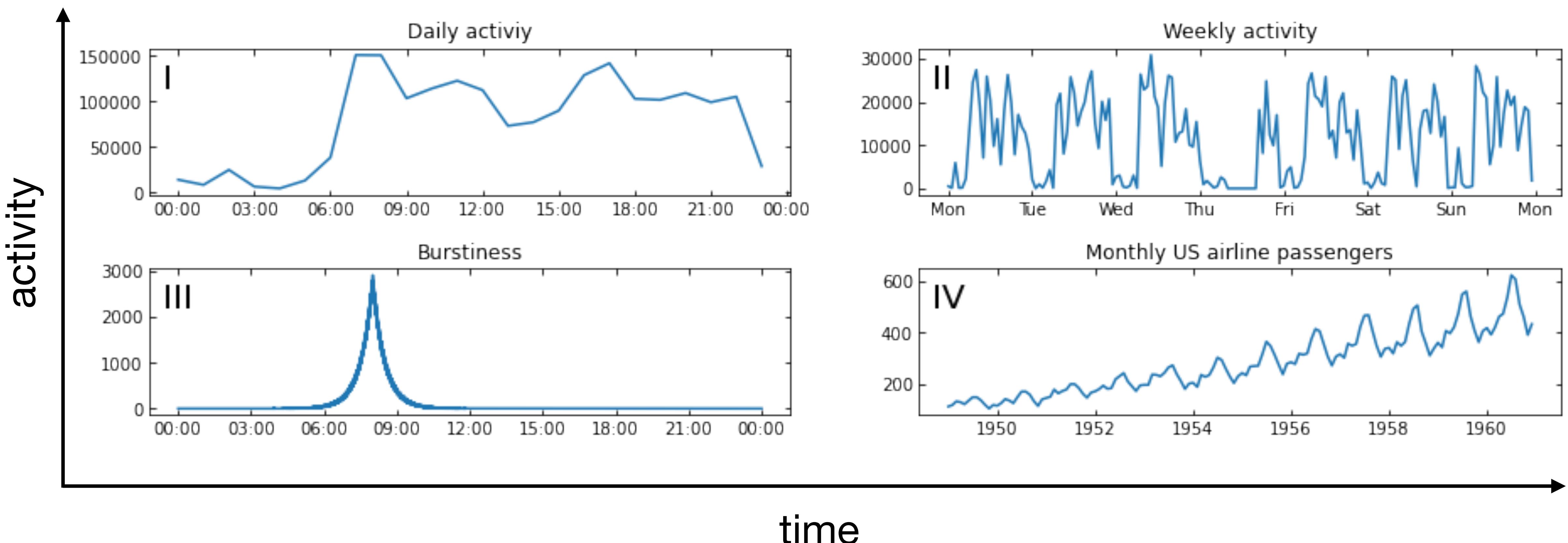
Social behavior & trends

Temporal patterns (time vs. social activity)



Behavior

Trend



Outline

Today's class

BLOCK 1

BLOCK 2

BLOCK 3

BLOCK 4

Social Behavior

Social Trends

Quantifying Trends

Behavior & Trend
Dynamics

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2. The Endo-Exo model
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Social Behavior



Social behavior

and the social sciences

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 - Key concepts: attention, memory, and decision-making.
- **Behavioral Economics** combines insights from psychology and economics to understand how people make decisions.
 - Key concepts: heuristics and biases, and how they can be applied to understand social behavior.

Social behavior

and computational social science

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- The digital revolution (BigData & AI) has affected the social sciences. Moving from data scarcity and local to large-scale, complex, and global [[Veltri 2023](#)].

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 - **New computational methods:** scalable
 - **Existing theories:** need to be revised (using more and new kinds of data)

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 - **Digital traces** in online platforms can provide new insights on human mobility, opinion and communication dynamics, human-human and human-computer interaction, mental health, disease or information spreading, political polarization, voter behavior, shopping/music/entertainment preferences, learning behavior, crime patterns and potential threats, etc.
[Keusch and Kreuter 2021]

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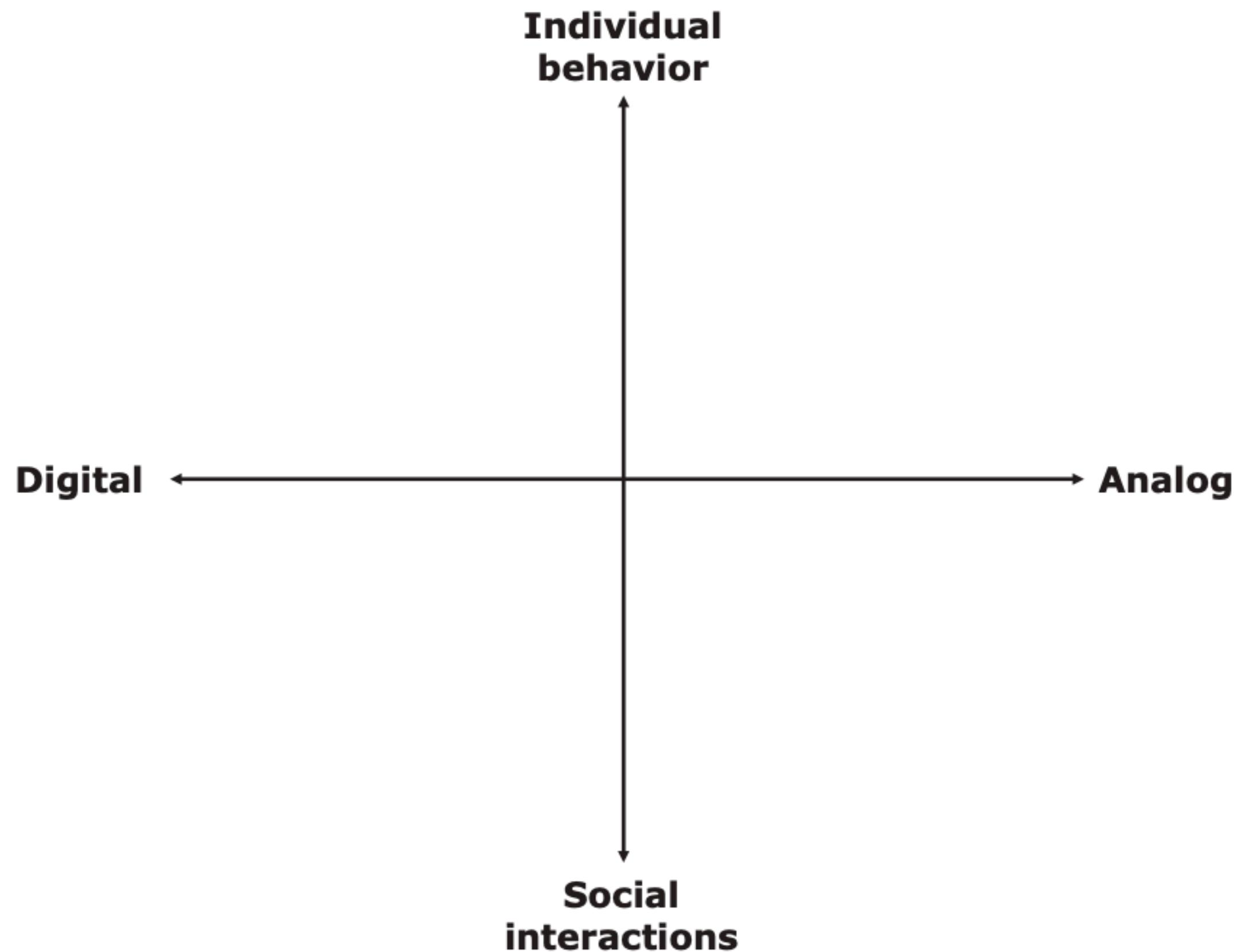
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 - Including **ethical research** to ensure transparency, data privacy, and fairness.

Social behavior

that can be studied using digital trace data

Social behavior

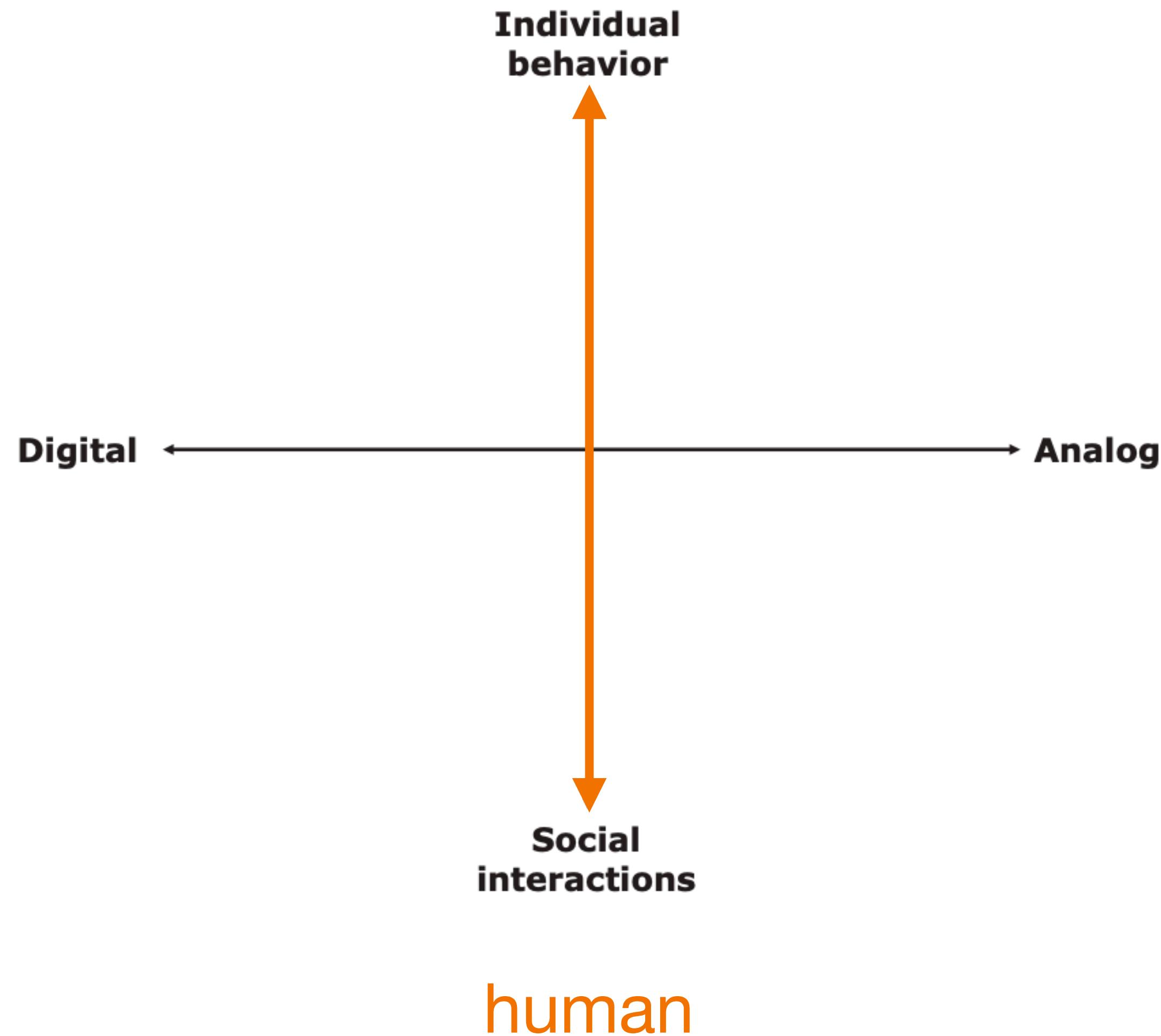
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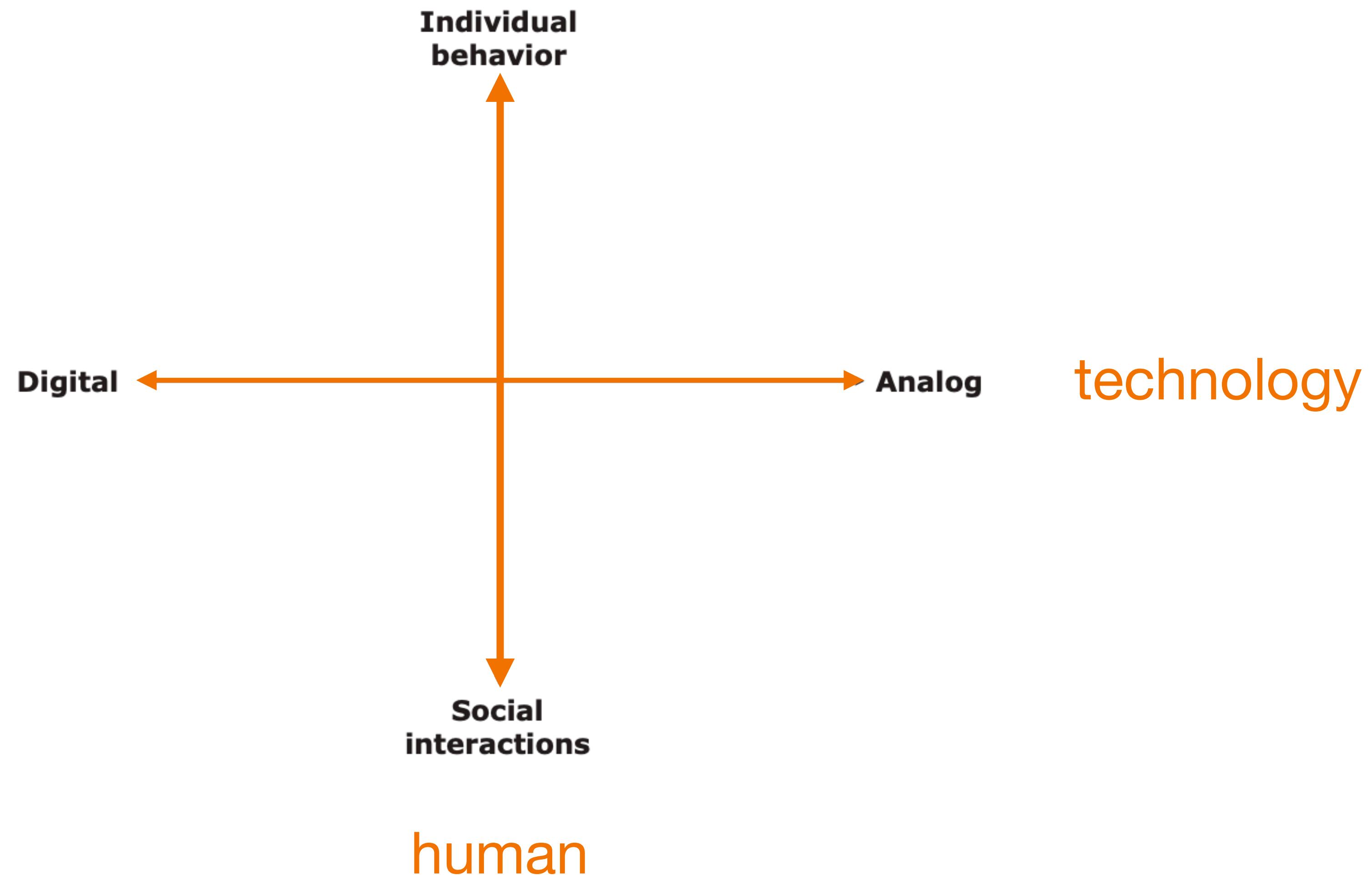
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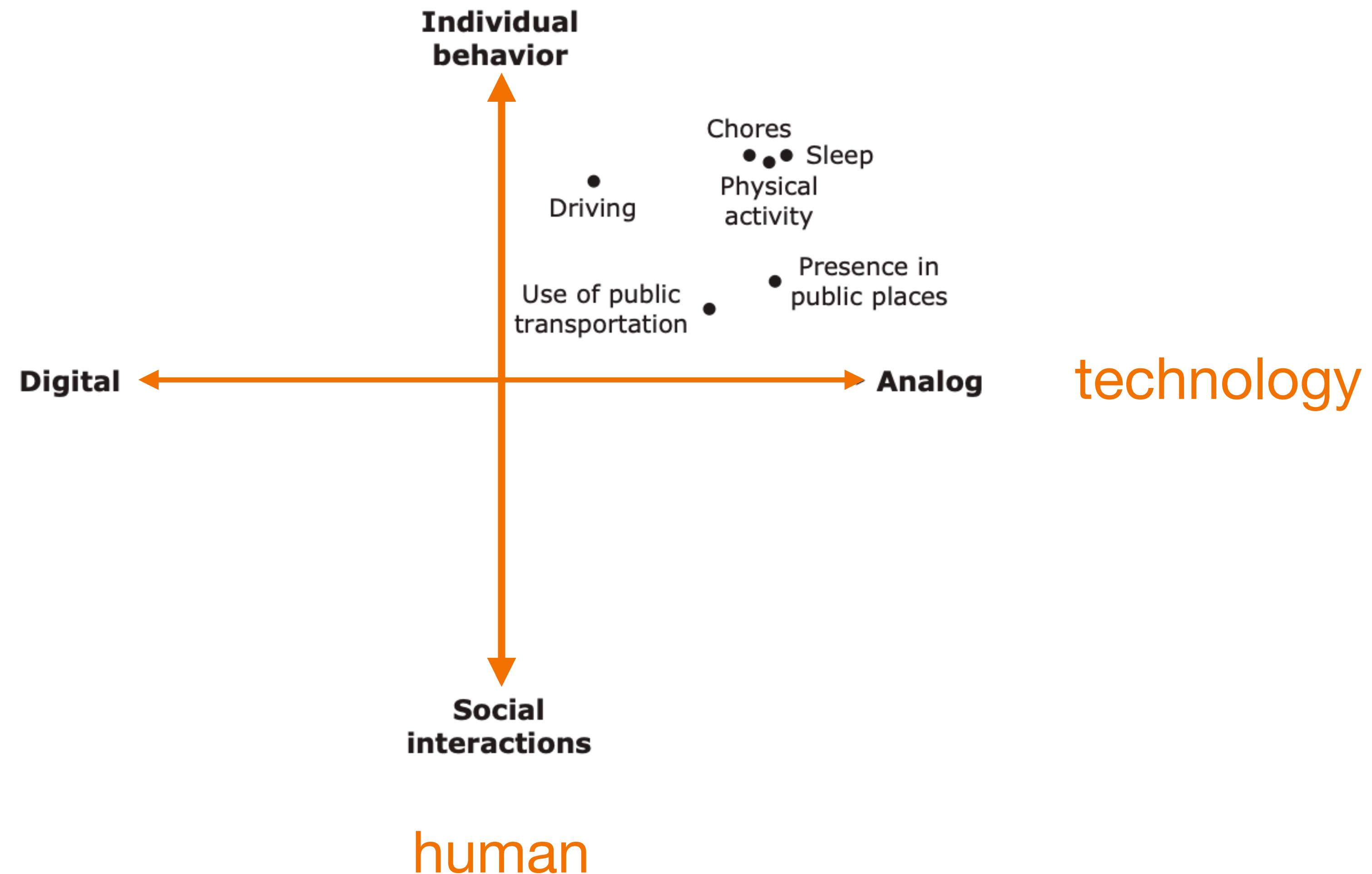


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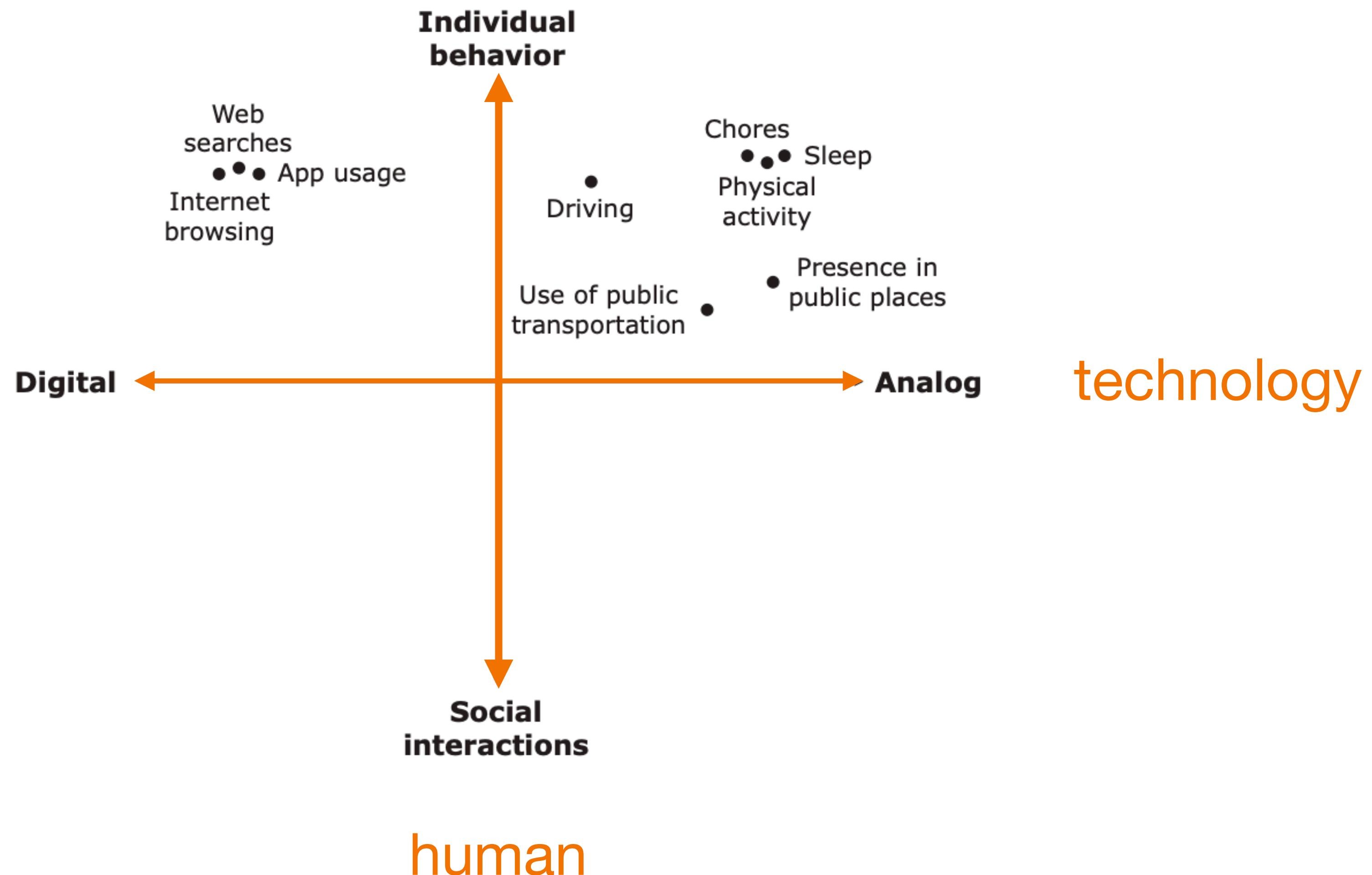
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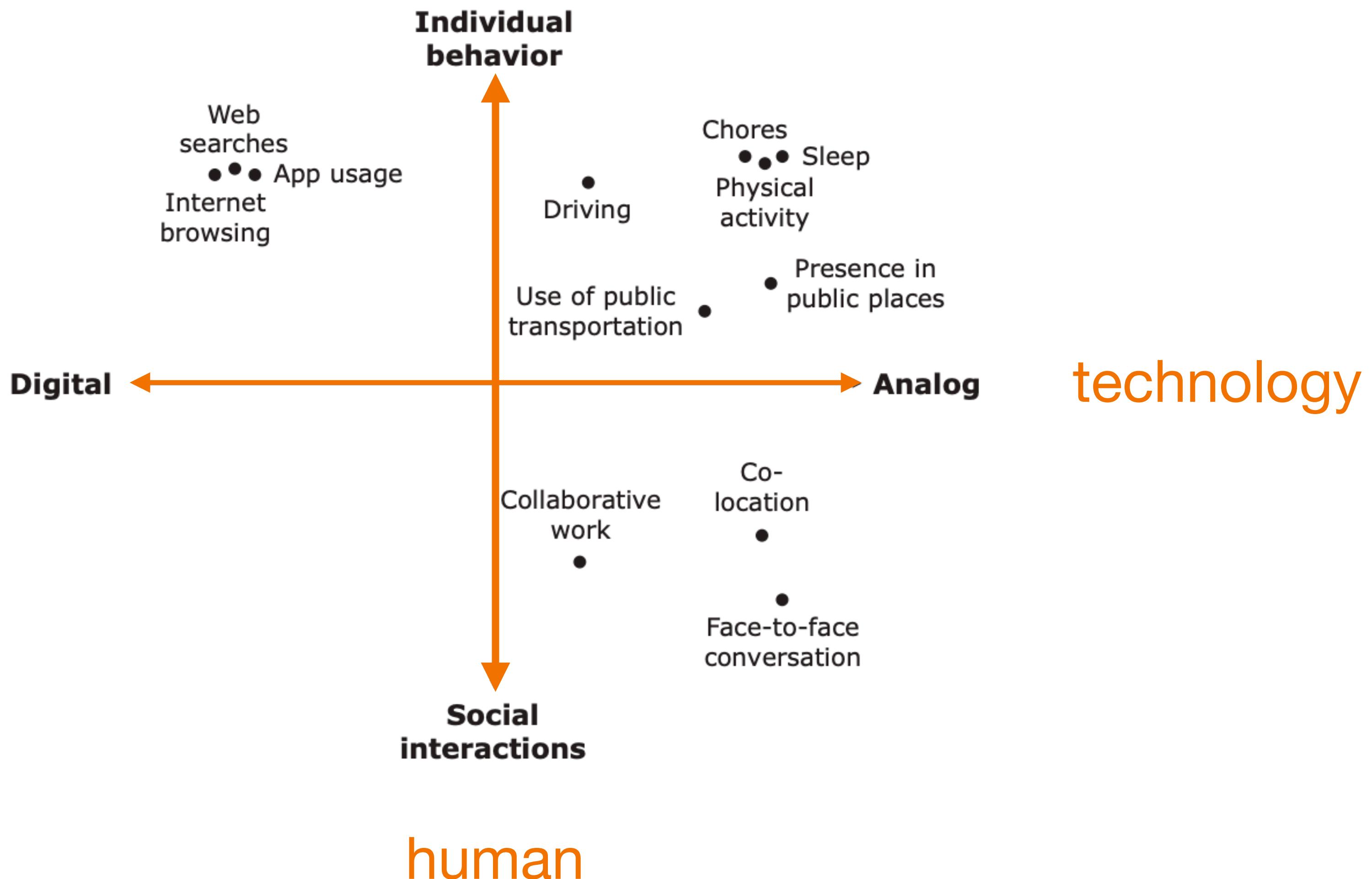
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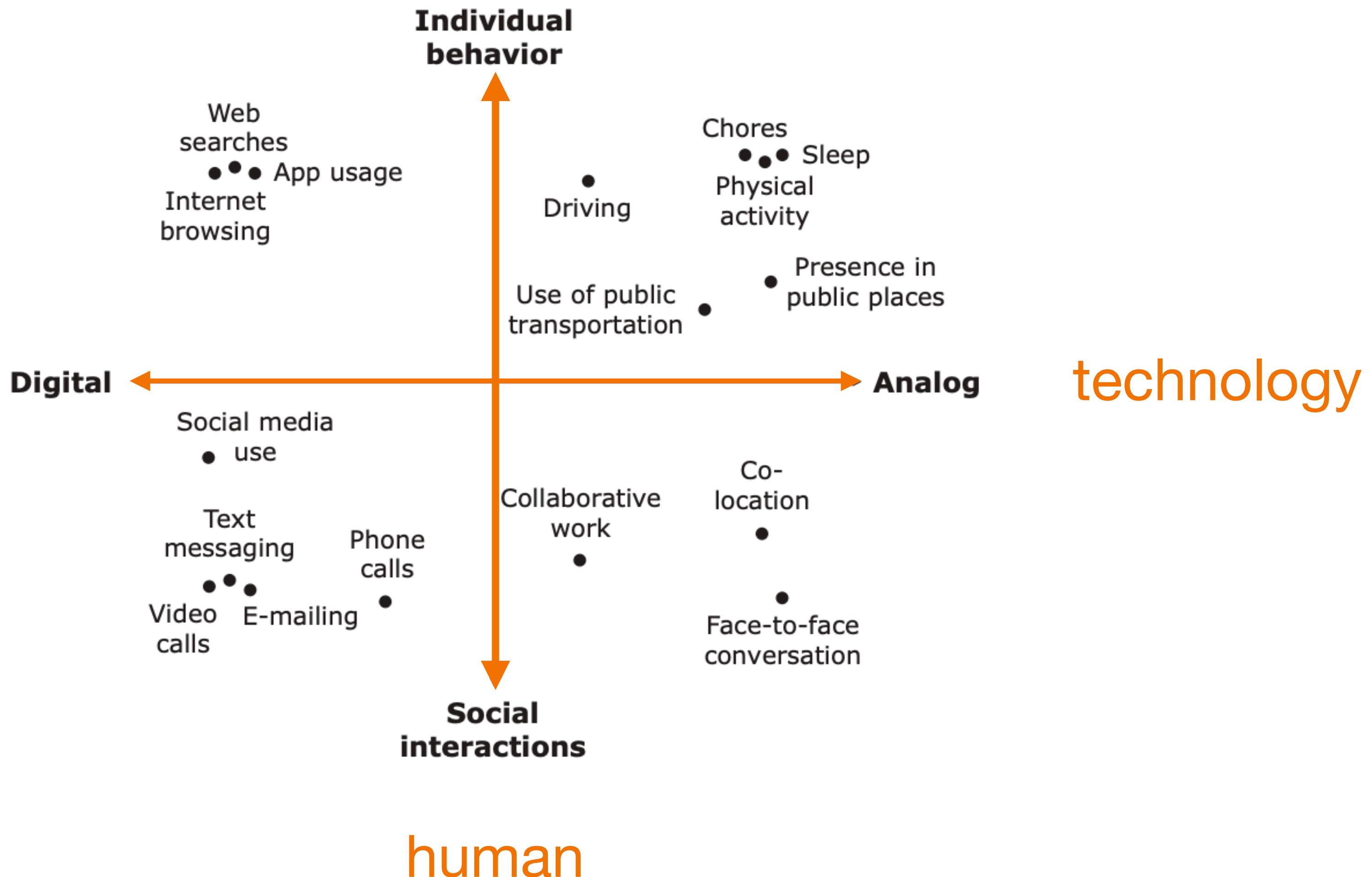
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Examples

Human mobility using taxi, census, and Foursquare data

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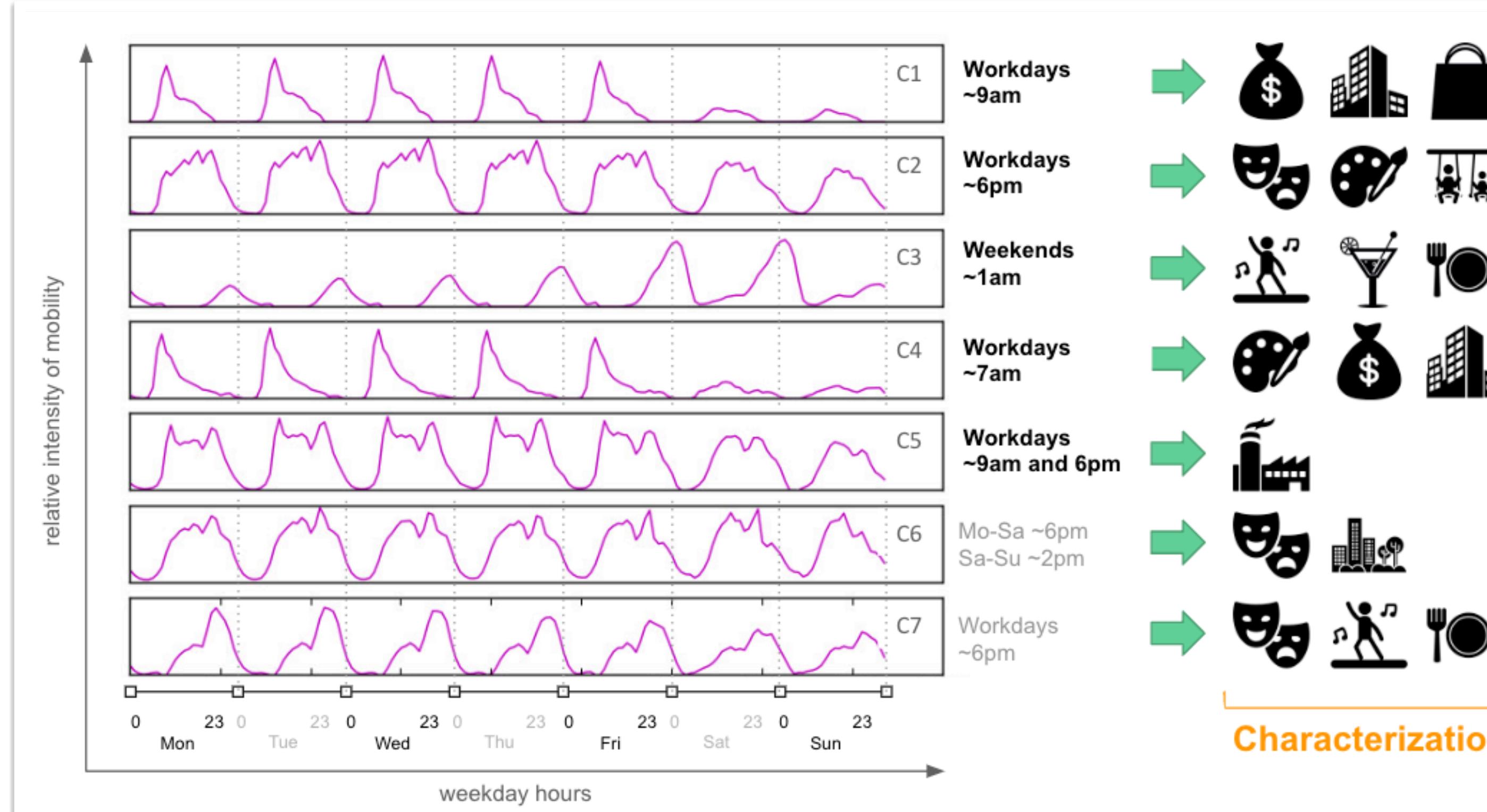
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Human (online) navigation using Wikipedia

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What Makes a Link Successful on Wikipedia?

(2017)

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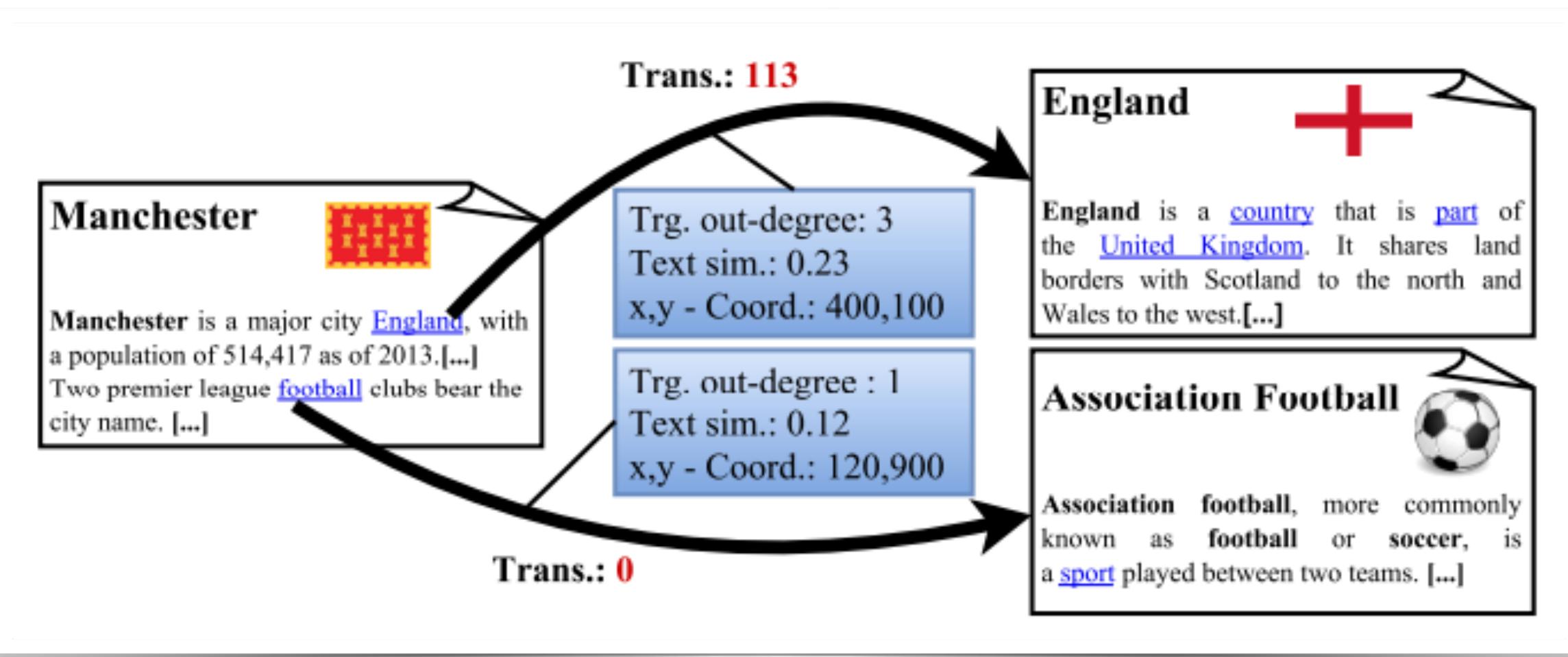
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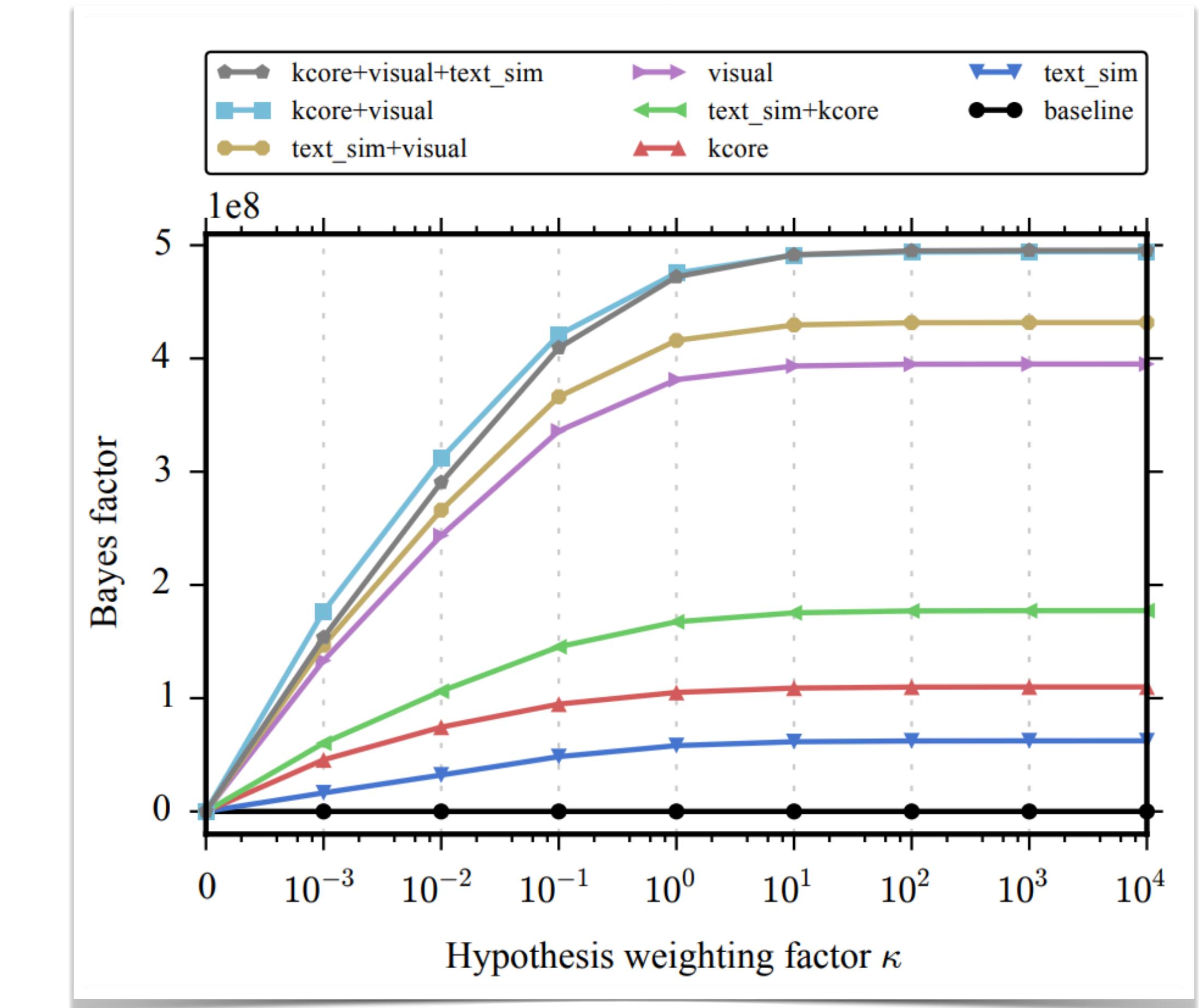
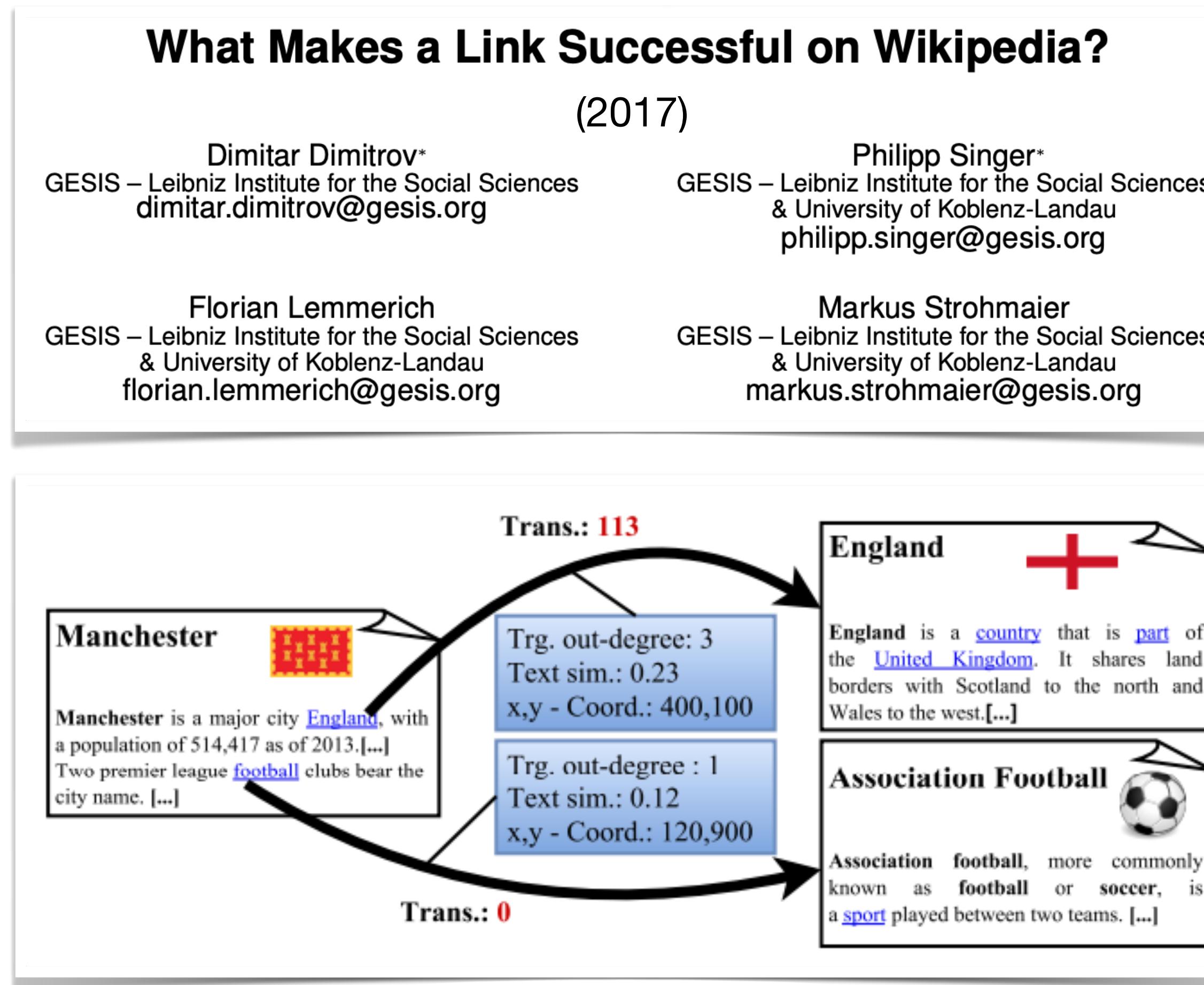
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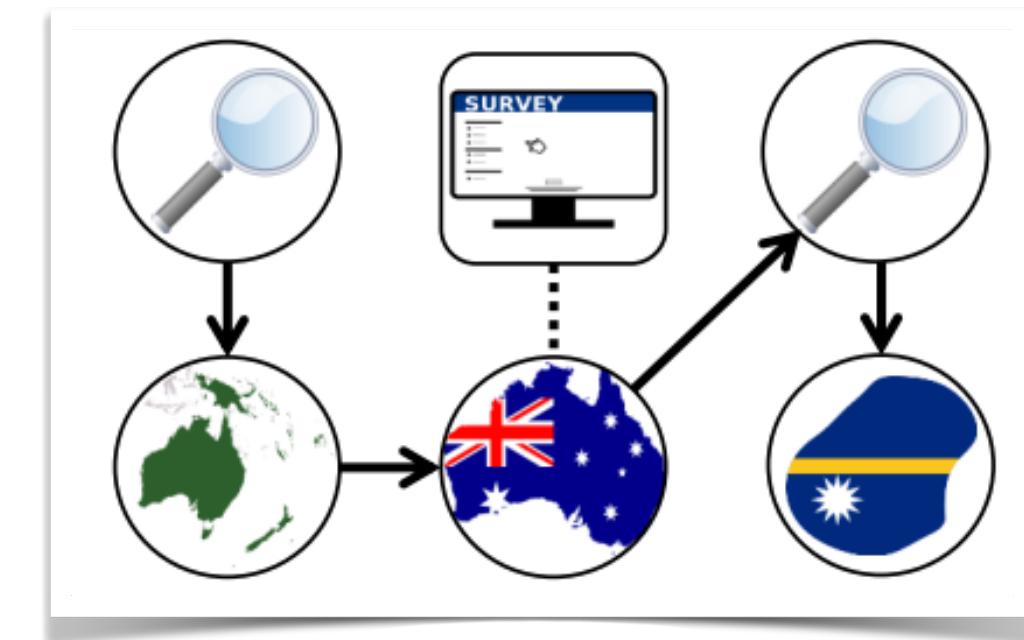
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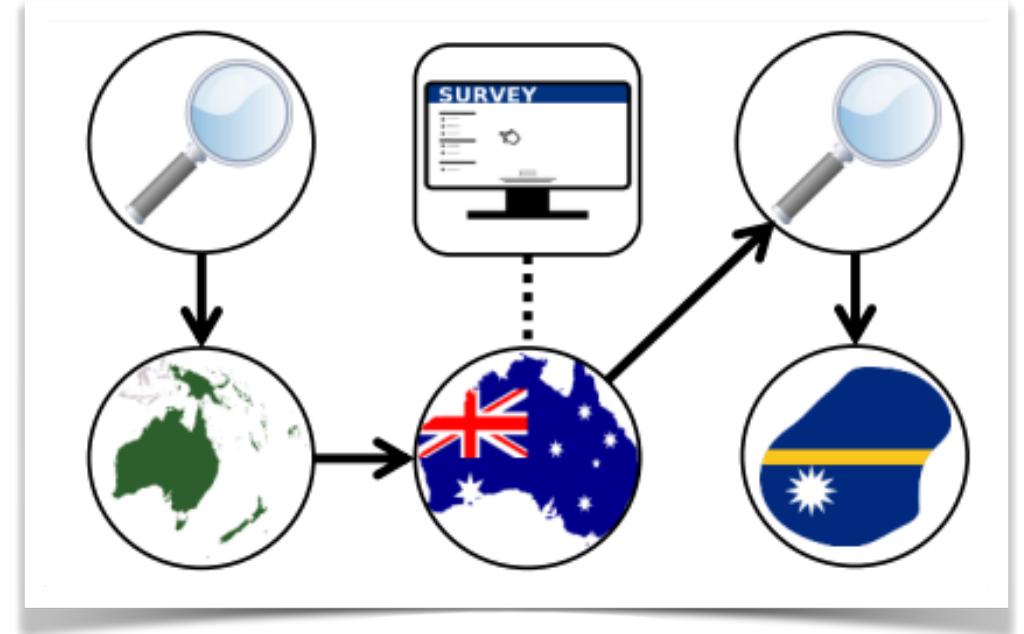


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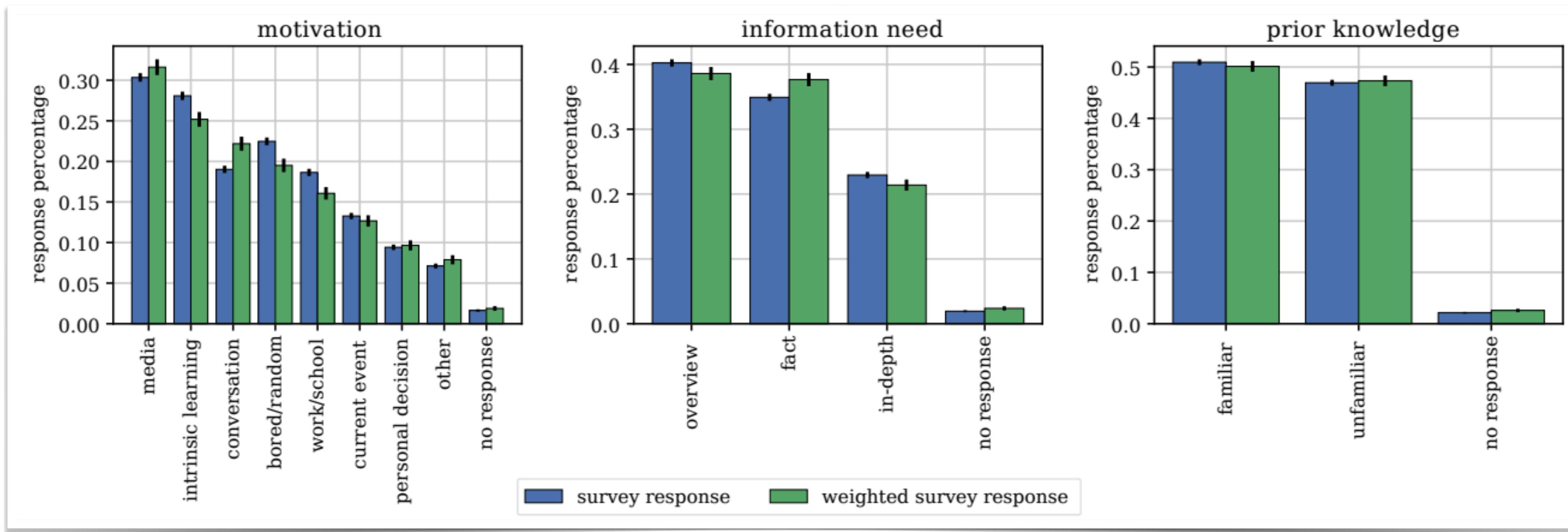
This paper uses both survey responses and web request log (navigation)

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Migration patterns from online data

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Using Facebook and LinkedIn Data to Study International Mobility (2023)

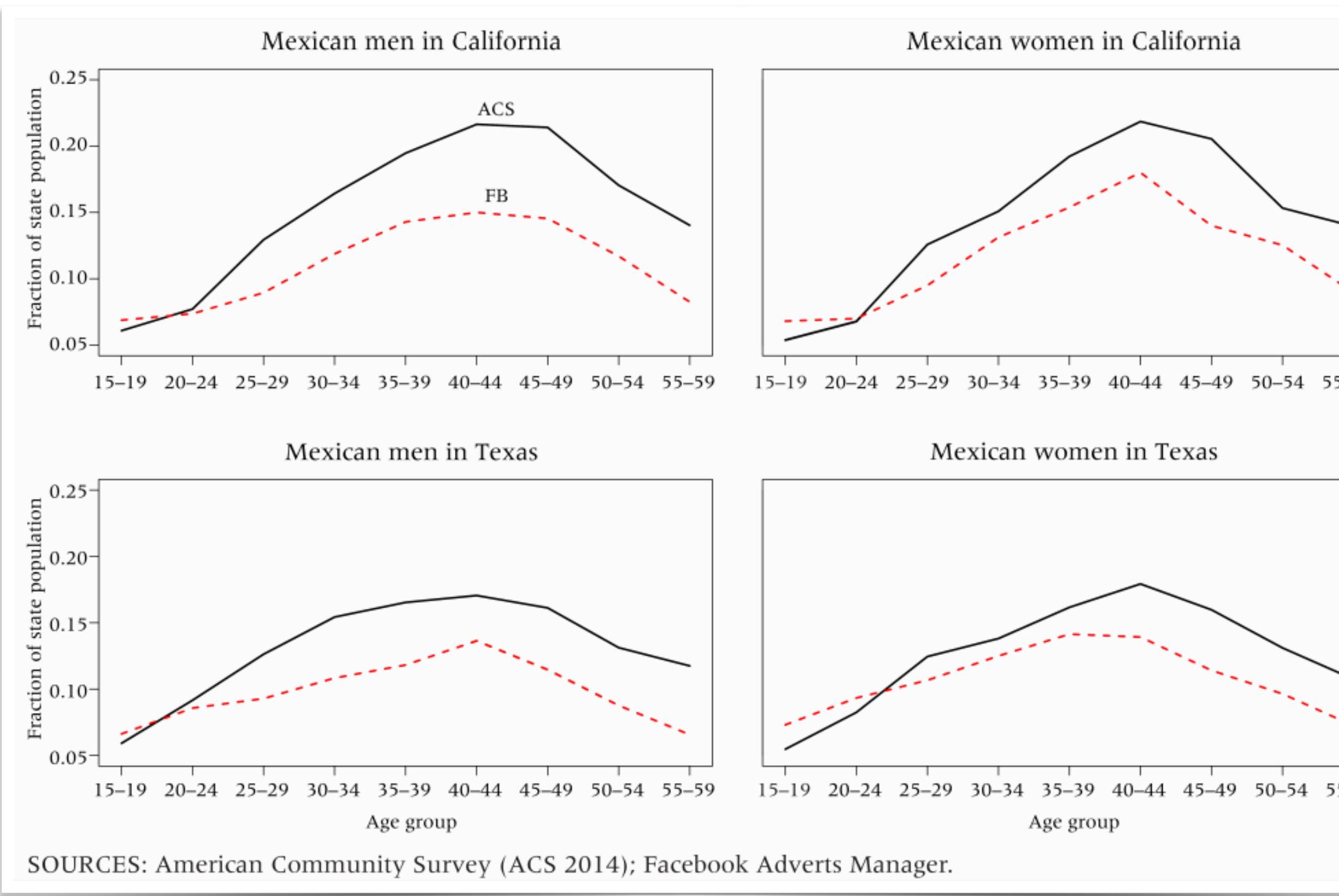
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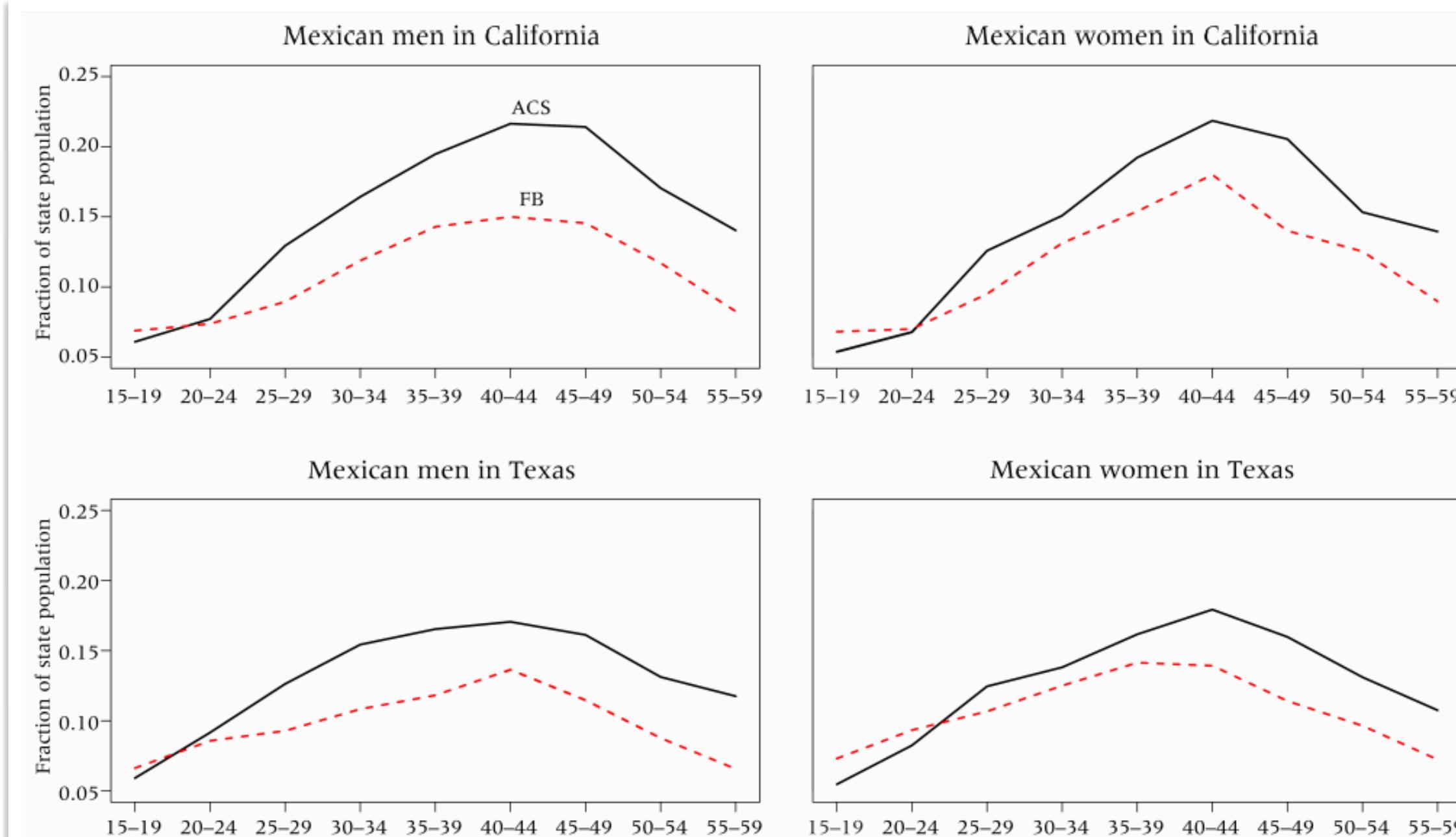
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Fraction of men or women based on survey and Facebook

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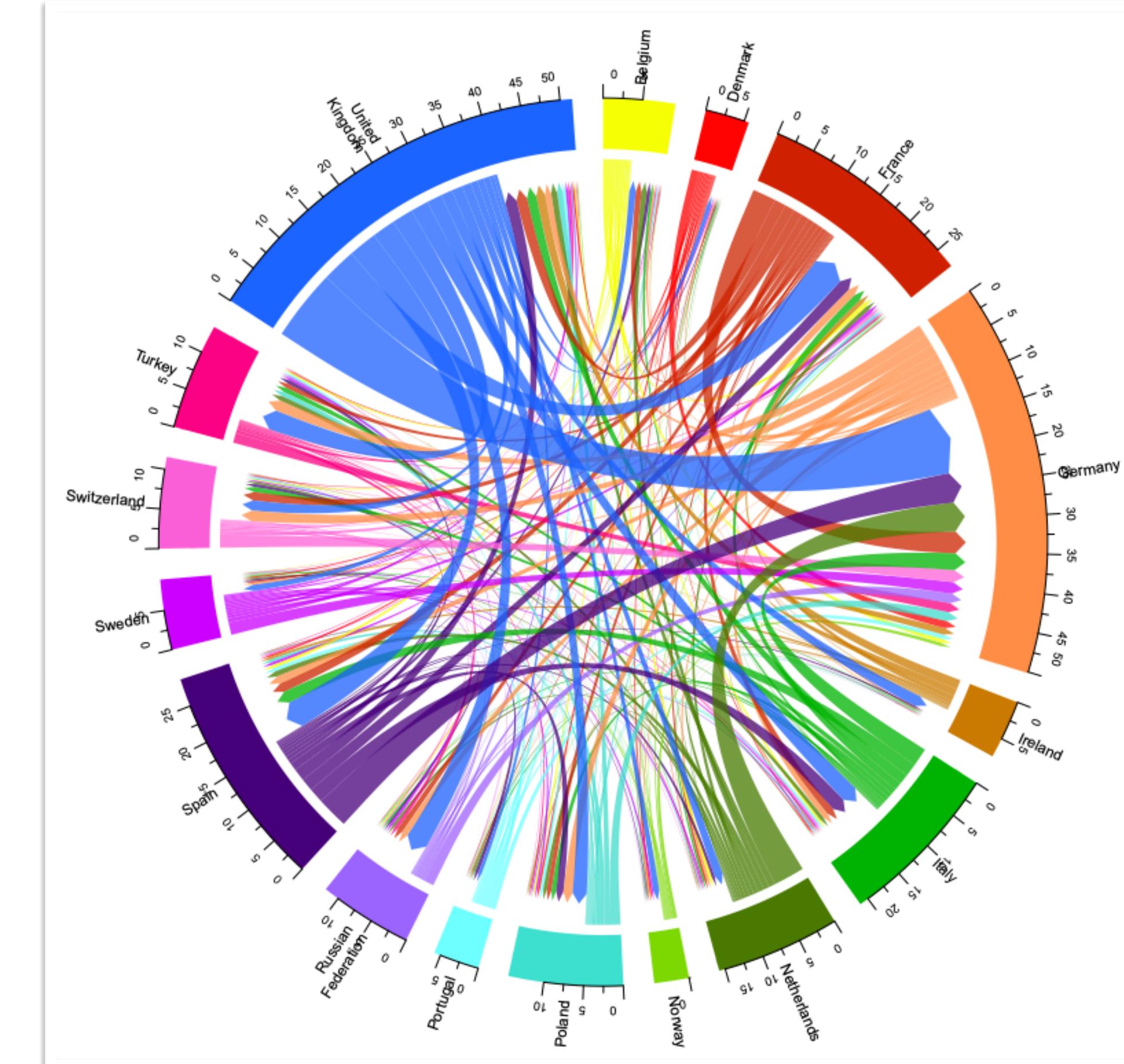


SOURCES: American Community Survey (ACS 2014); Facebook Adverts Manager.

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Migrants in 1000's (who studied in country x and live in country y)

Examples

Inferring poverty from the sky and the Web

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Fighting poverty with data

Machine learning algorithms measure and target poverty

(2016)

By Joshua Evan Blumenstock

Predicting poverty

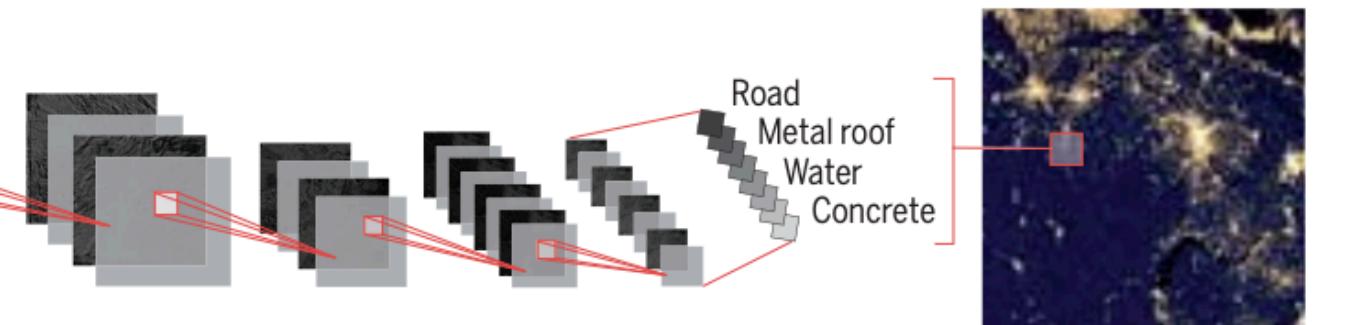
Satellite images can be used to estimate wealth in remote regions.

Neural network learns features in satellite images that correlate with economic activity

Daytime satellite photos capture details of the landscape



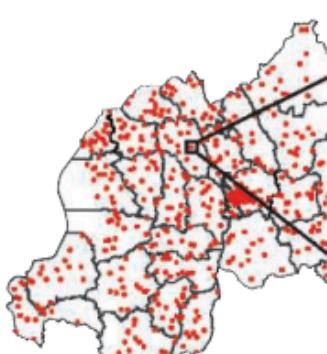
Convolutional Neural Network (CNN) associates features from daytime photos with nightlight intensity



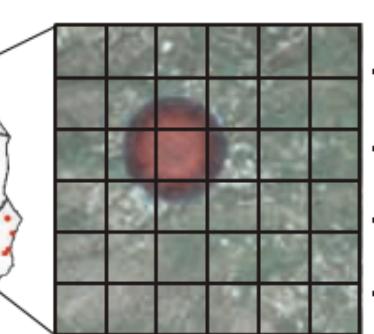
Satellite nightlights are a proxy for economic activity

Daytime satellite images can be used to predict regional wealth

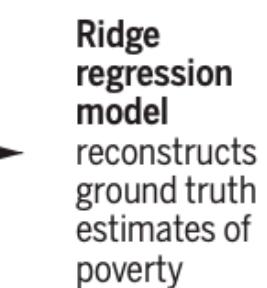
Household survey locations



CNN processes satellite photos of each survey site



Features from multiple photos are averaged



Ridge regression model reconstructs ground truth estimates of poverty

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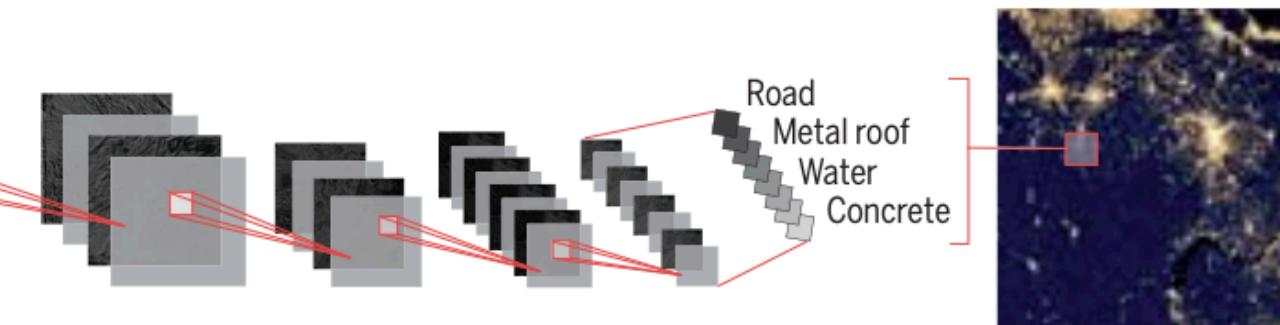
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Neural network learns features in satellite images that correlate with economic activity

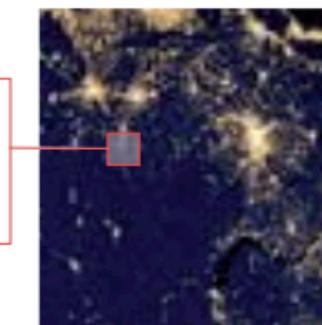
Daytime satellite photos capture details of the landscape



Convolutional Neural Network (CNN) associates features from daytime photos with nightlight intensity

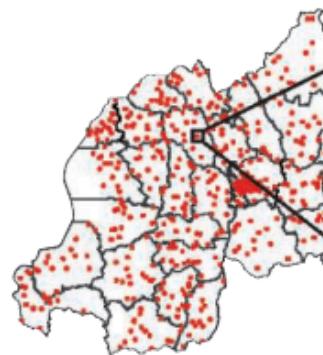


Satellite nightlights are a proxy for economic activity

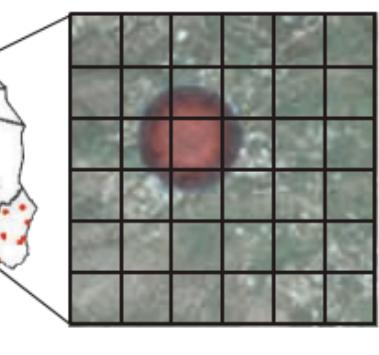


Daytime satellite images can be used to predict regional wealth

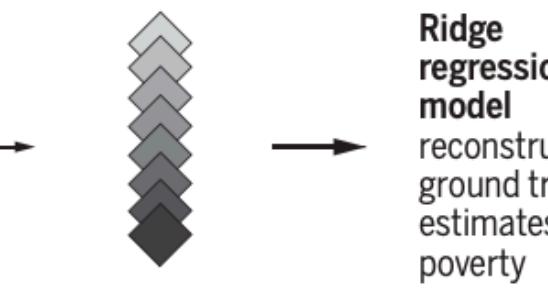
Household survey locations



CNN processes satellite photos of each survey site



Features from multiple photos are averaged



Ridge regression model reconstructs ground truth estimates of poverty

Interpreting wealth distribution via poverty map inference using multimodal data

Lisette Espín-Noboa

EspinL@ceu.edu

Central European University

Complexity Science Hub Vienna

János Kertész

KerteszJ@ceu.edu

Central European University

Complexity Science Hub Vienna

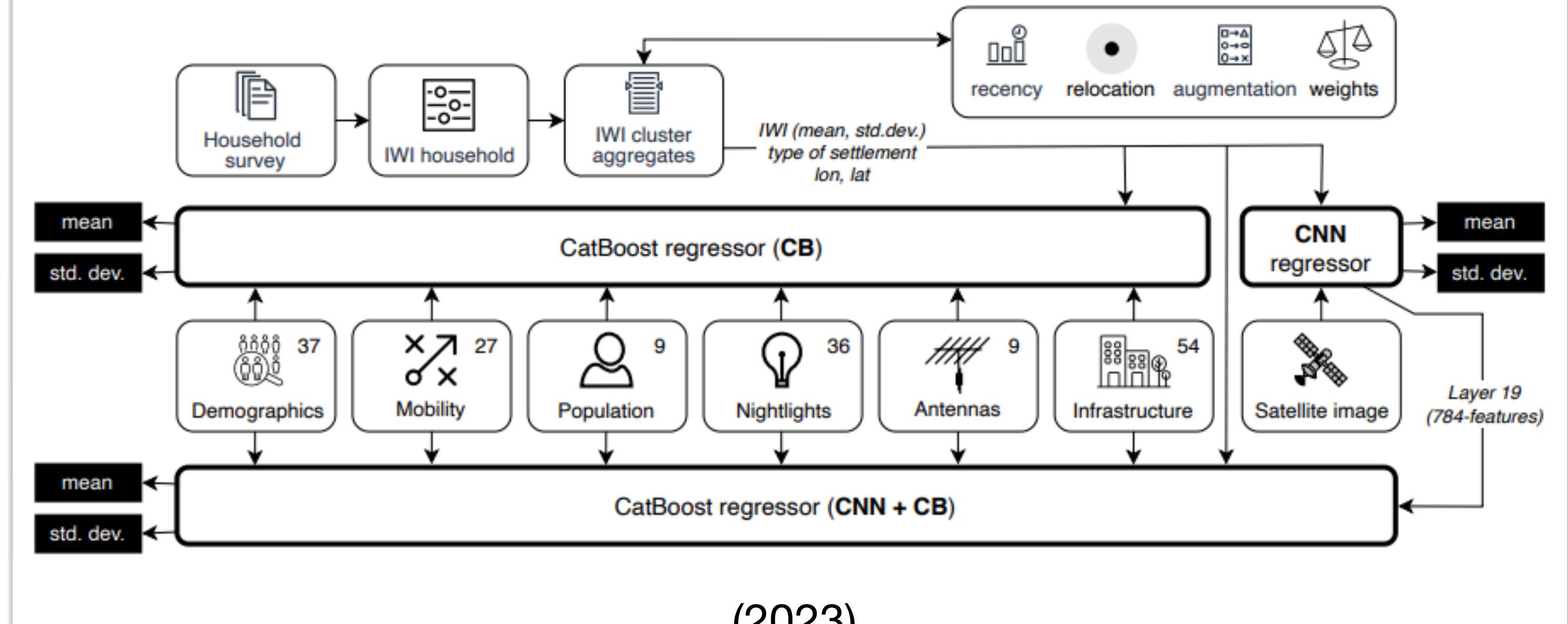
Márton Karsai

KarsaiM@ceu.edu

Central European University

Rényi Institute of Mathematics

<https://vis.csh.ac.at/poverty-maps>



(2023)

Examples

Health and social media

Examples

Health and social media

Predicting Depression via Social Media

Munmun De Choudhury

Michael Gamon

Scott Counts

Eric Horvitz

Microsoft Research, Redmond WA 98052
{munmund, mgamon, counts, horvitz}@microsoft.com

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(2013)

Having a job again makes me happy. Less time to be depressed and eat all day while watching sad movies.

“Are you okay?” Yes.... I understand that I am upset and hopeless and nothing can help me... I’m okay... but I am not alright

“empty” feelings I WAS JUST TALKING ABOUT HOW I I HAVE EMOTION OH MY GOODNESS I FEEL AWFUL

I want someone to hold me and be there for me when I’m sad.

Reloading twitter till I pass out. *lonely* *anxious* *butthurt*
frustrated *dead*

Table 2: Example posts from users in the depression class.

Examples

Health and social media

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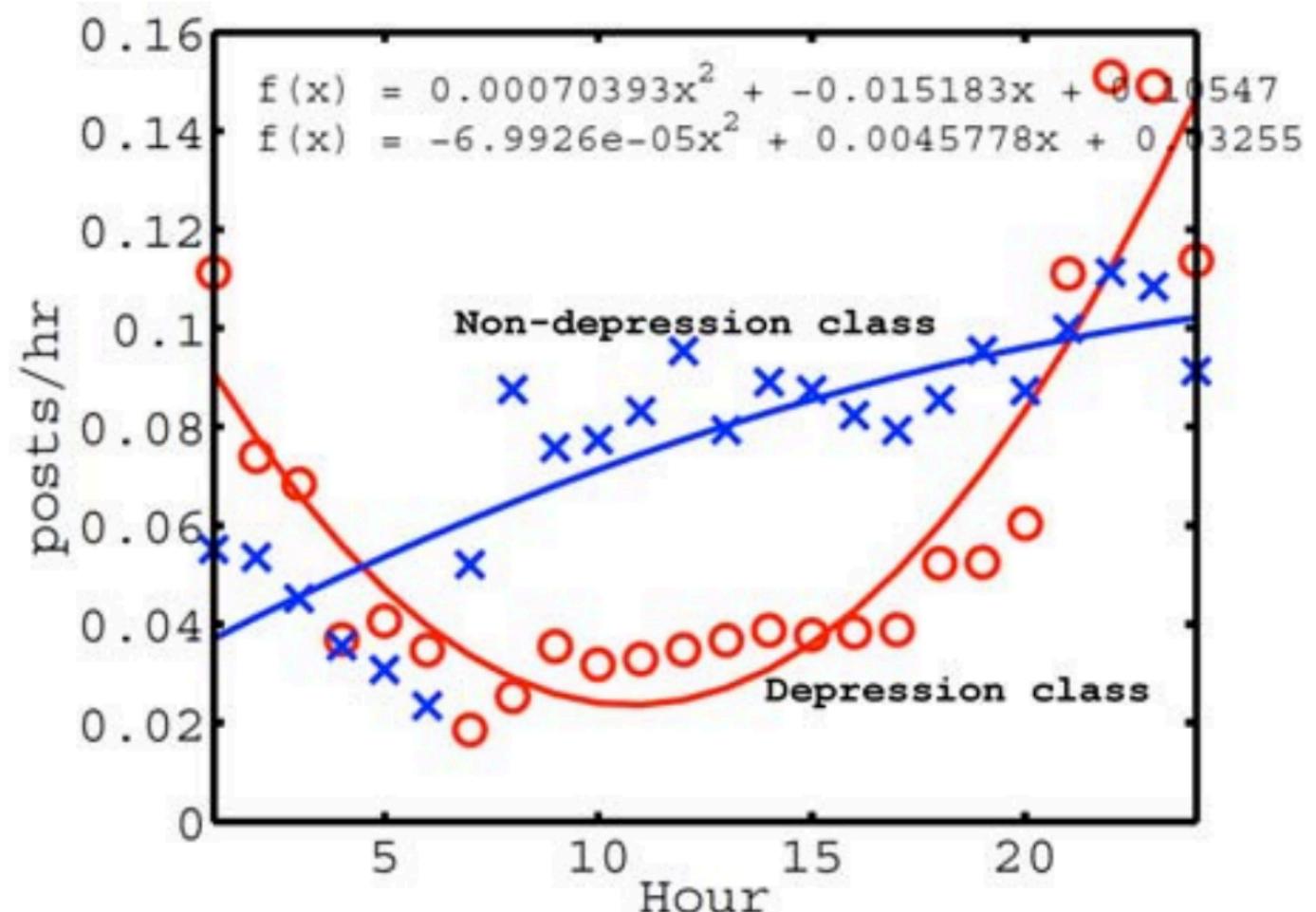


Figure 2: Diurnal trends (i.e. mean number of posts made hourly throughout a day) for the two classes. The line plots correspond to least squares fit of the trends.

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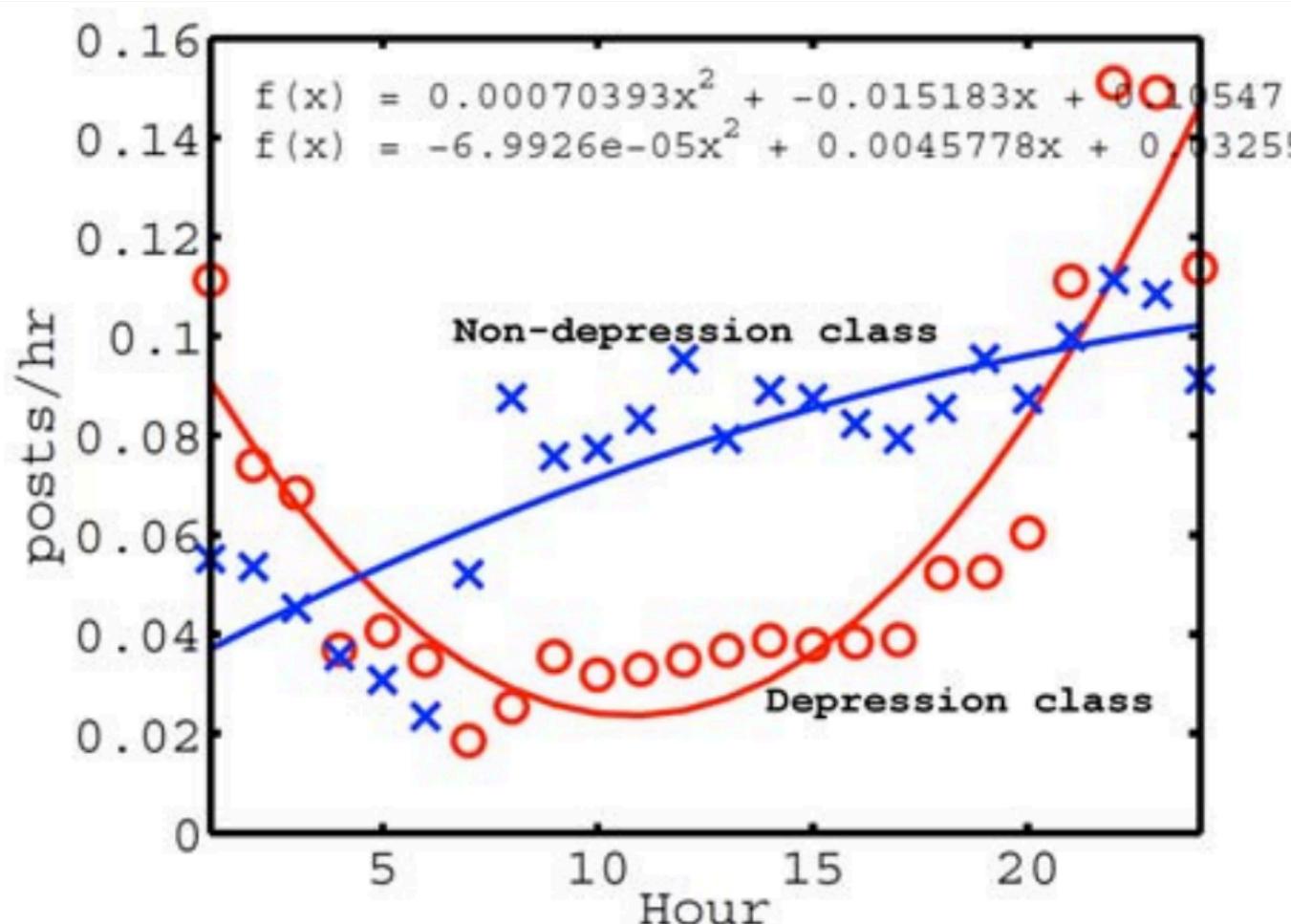


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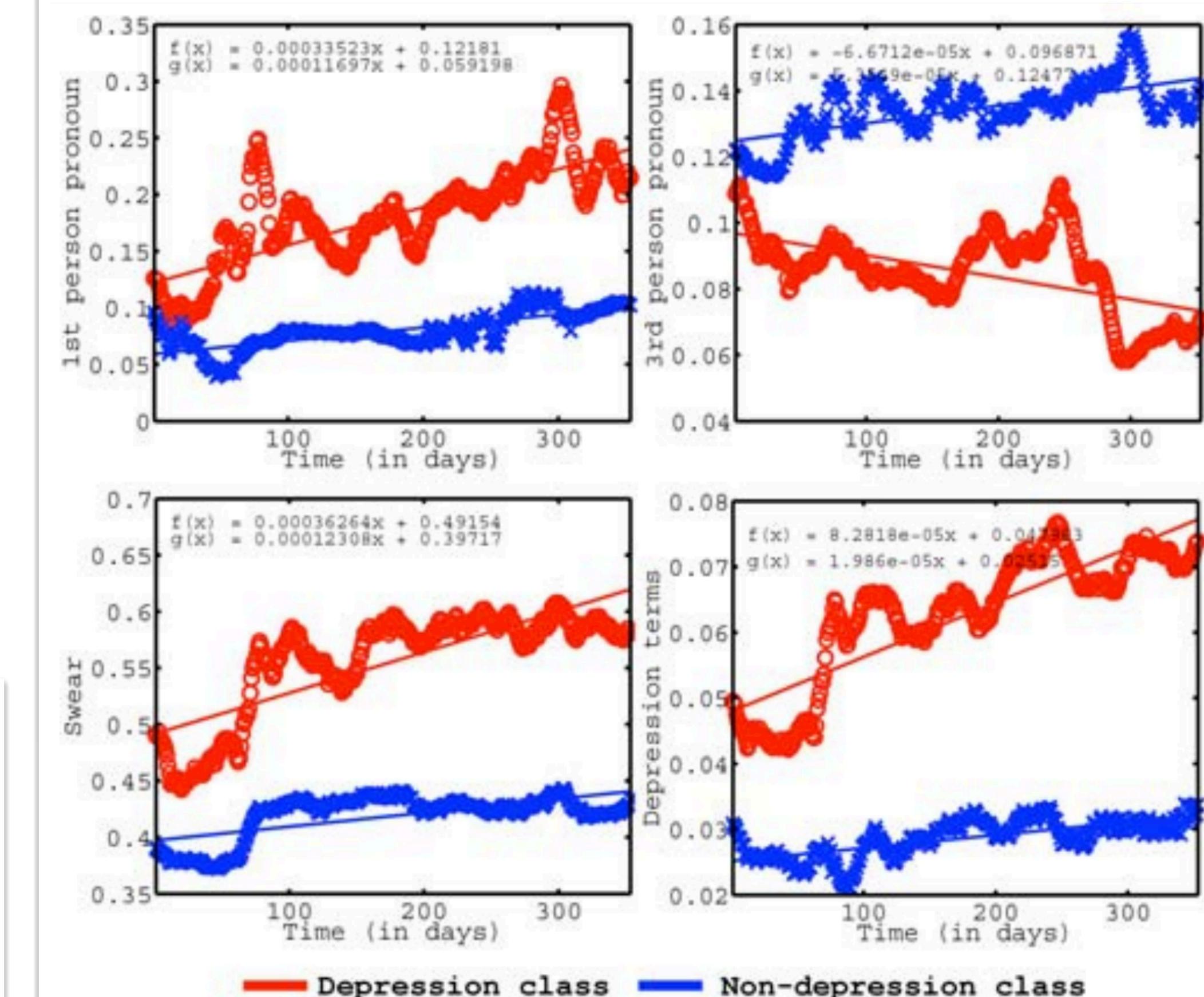


Figure 3. Trends for various features corresponding to the depression and non-depression classes. Line plots correspond to least squares fit.

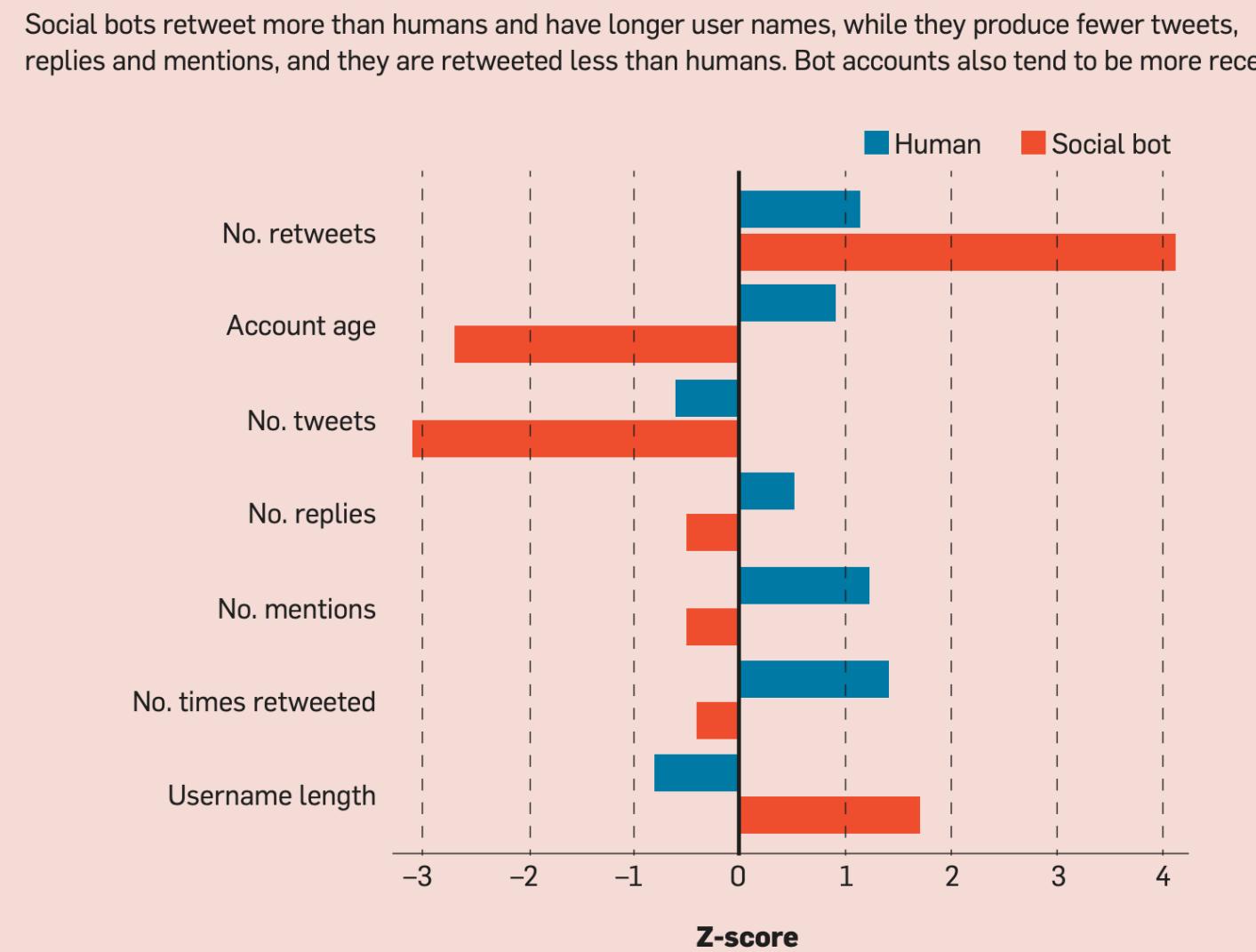
Examples

Bots and fake news in social media

BY EMILIO FERRARA, ONUR VAROL, CLAYTON DAVIS,
FILIPPO MENCZER, AND ALESSANDRO FLAMMINI (2016)

The Rise of Social Bots

Figure 2. User behaviors that best discriminate social bots from humans.



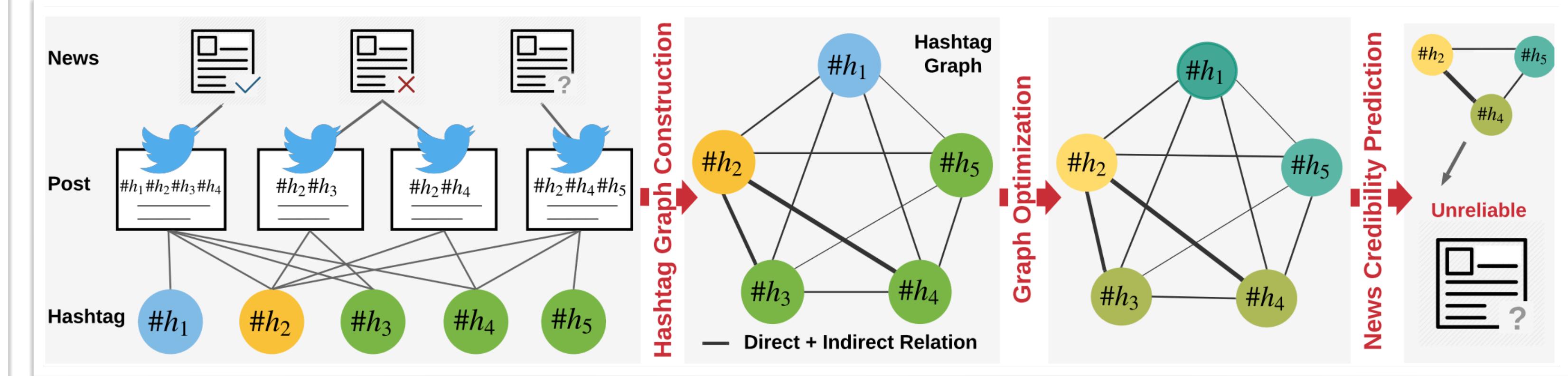
From Fake News to #FakeNews: Mining Direct and Indirect Relationships among Hashtags for Fake News Detection

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(2022)



Examples

Polarization

Examples

Polarization

The Political Blogosphere and the 2004 U.S. Election:
Divided They Blog

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Natalie Glance

Intelliseek Applied Research Center

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Pittsburgh, PA 15217

n glance@intelliseek.com

4 March 2005

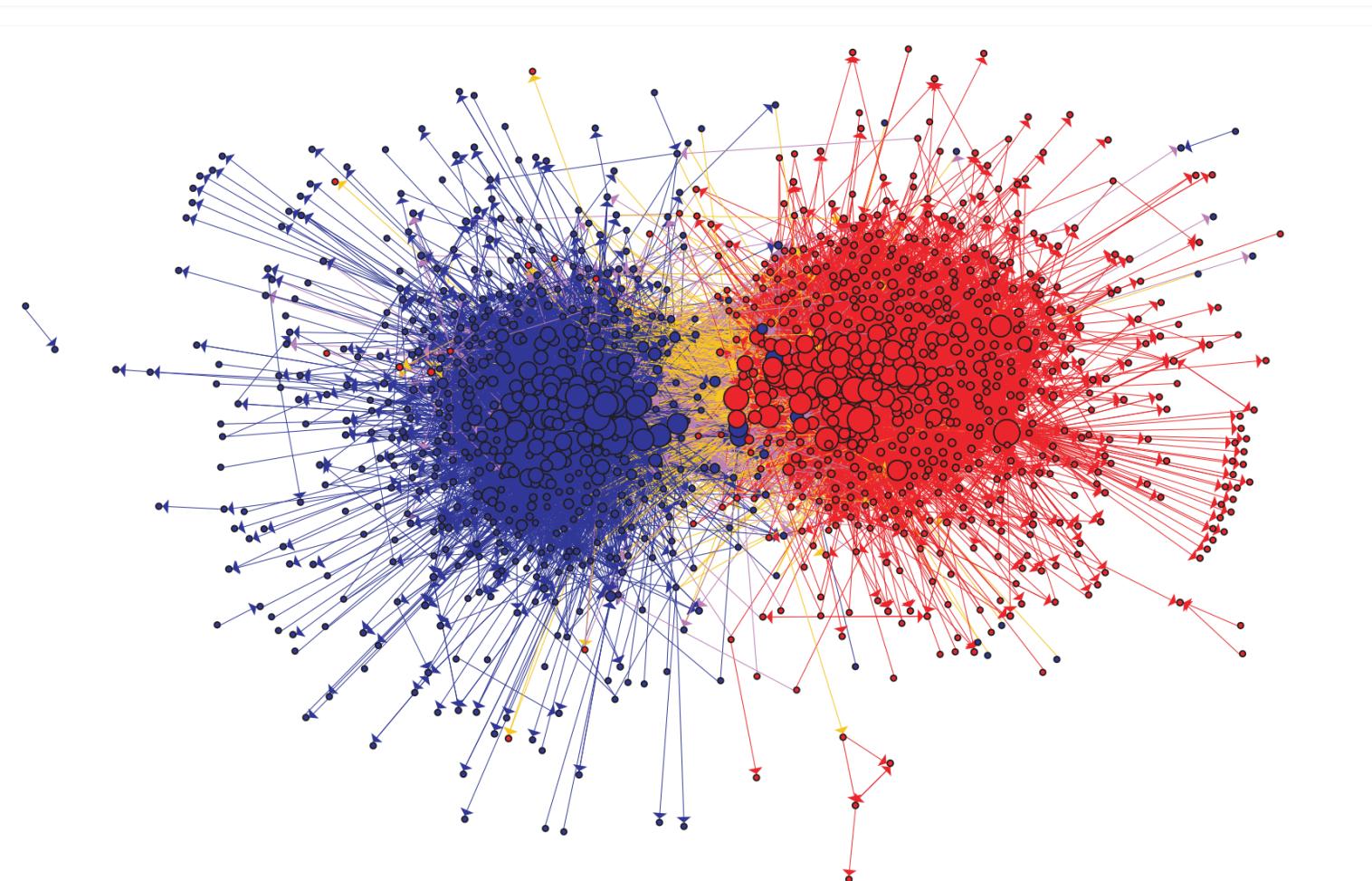


Figure 1: Community structure of political blogs (expanded set), shown using utilizing a GEM layout [11] in the GUESS[3] visualization and analysis tool. The colors reflect political orientation, red for conservative, and blue for liberal. Orange links go from liberal to conservative, and purple ones from conservative to liberal. The size of each blog reflects the number of other blogs that link to it.

Examples

Polarization

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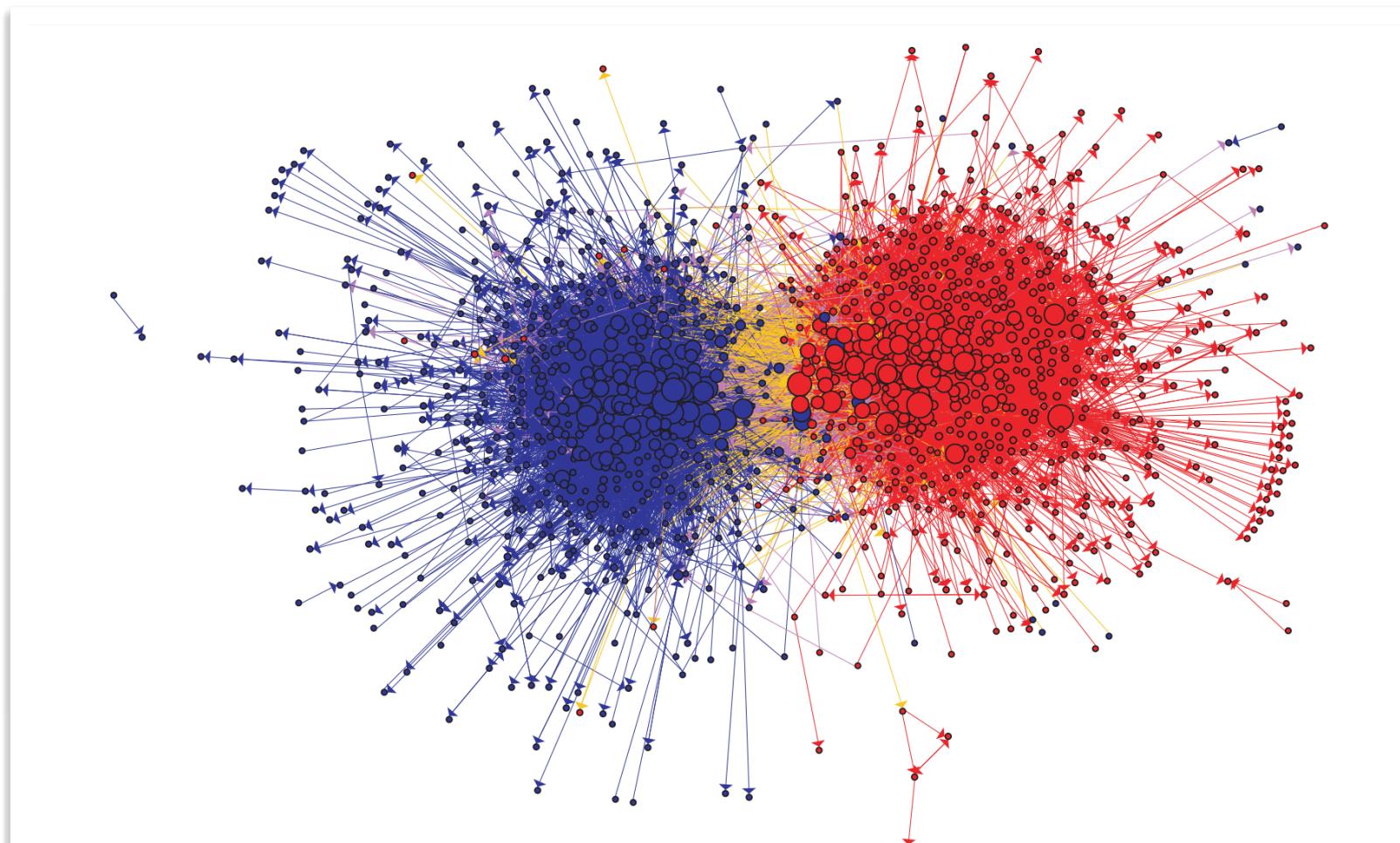


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Aalto University publication series
DOCTORAL DISSERTATIONS 20/2018

Polarization on Social Media

Kiran Garimella

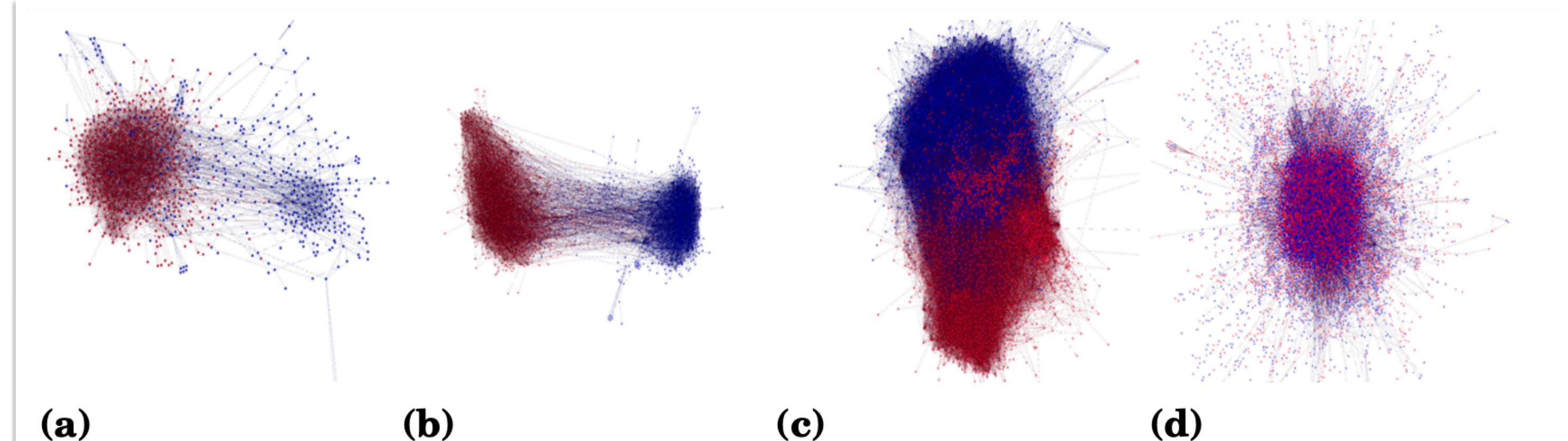


Figure 4.4. Sample follow graphs for polarized topics, (a) #beefban, (b) #russia_march, and non-polarized topics, (c) #sxsw, (d) #germanwings.

Outline

Today's class

BLOCK 1

BLOCK 2

BLOCK 3

BLOCK 4

Social Behavior

- 1. Social Science
- 2. CSS
- 3. Digital Traces
- 4. Examples

Social Trends

- 1. Google Search Trends
- 2. The Future Orientation Index
- 3. Culture and Economy

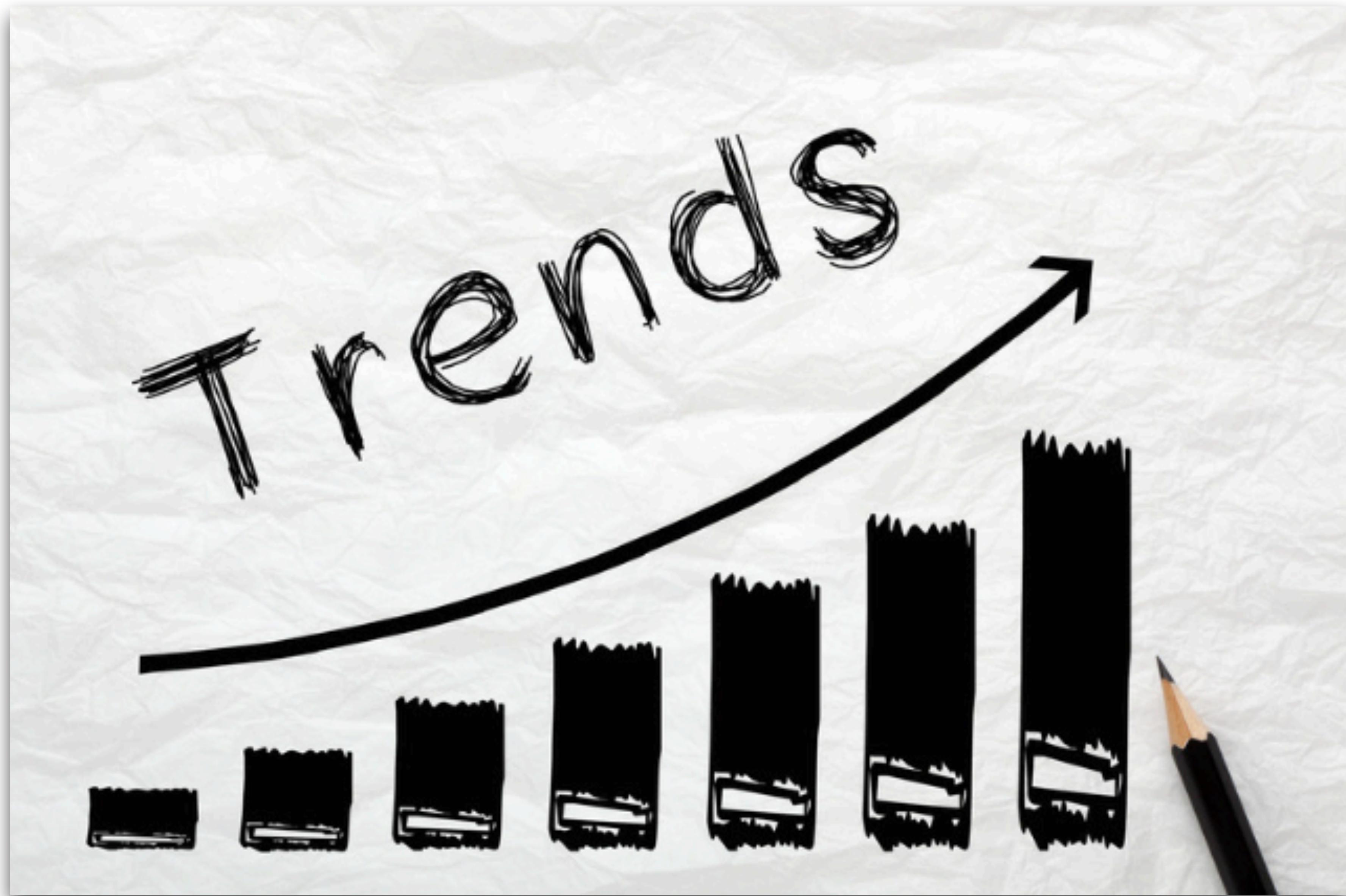
Quantifying Trends

- 1. Correlation
- 2. Causation
- 3. Regression

Behavior & Trend Dynamics

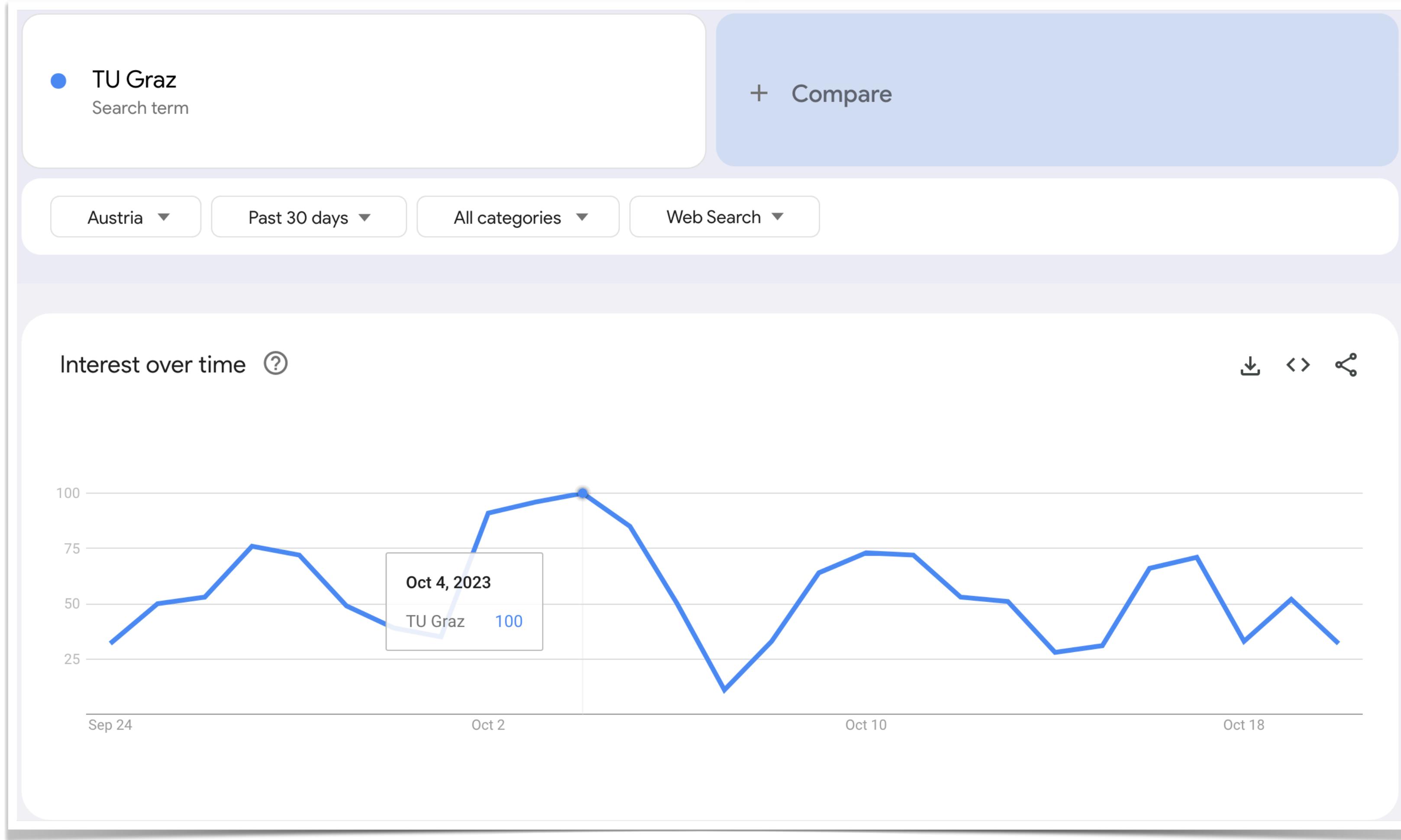
- 1. The Theory of Fashion
- 2. The Endo-Exo model
- 3. Examples

Social Trends



Google Trends

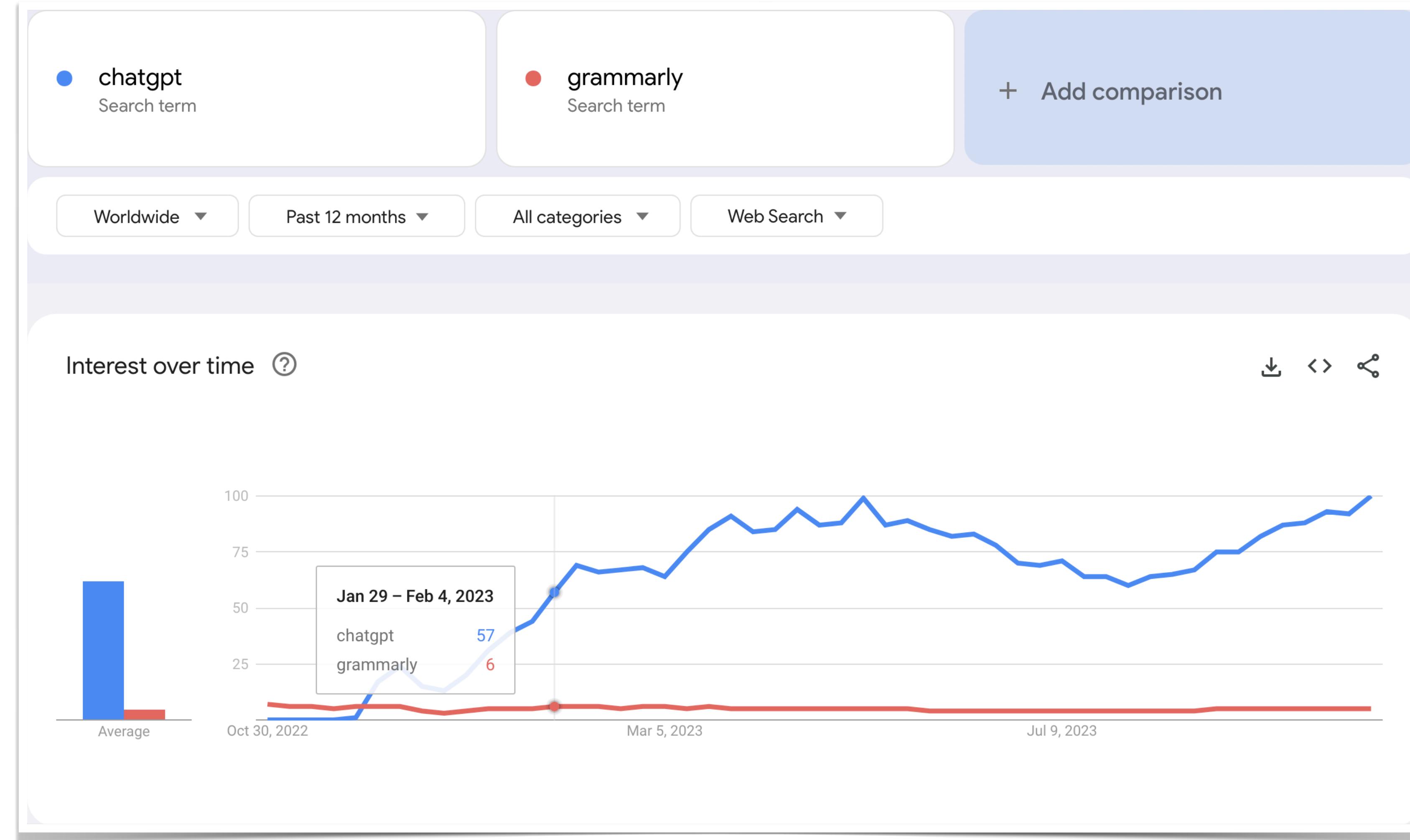
Shows the Google search volume of a term within a given time interval



trends.google.com

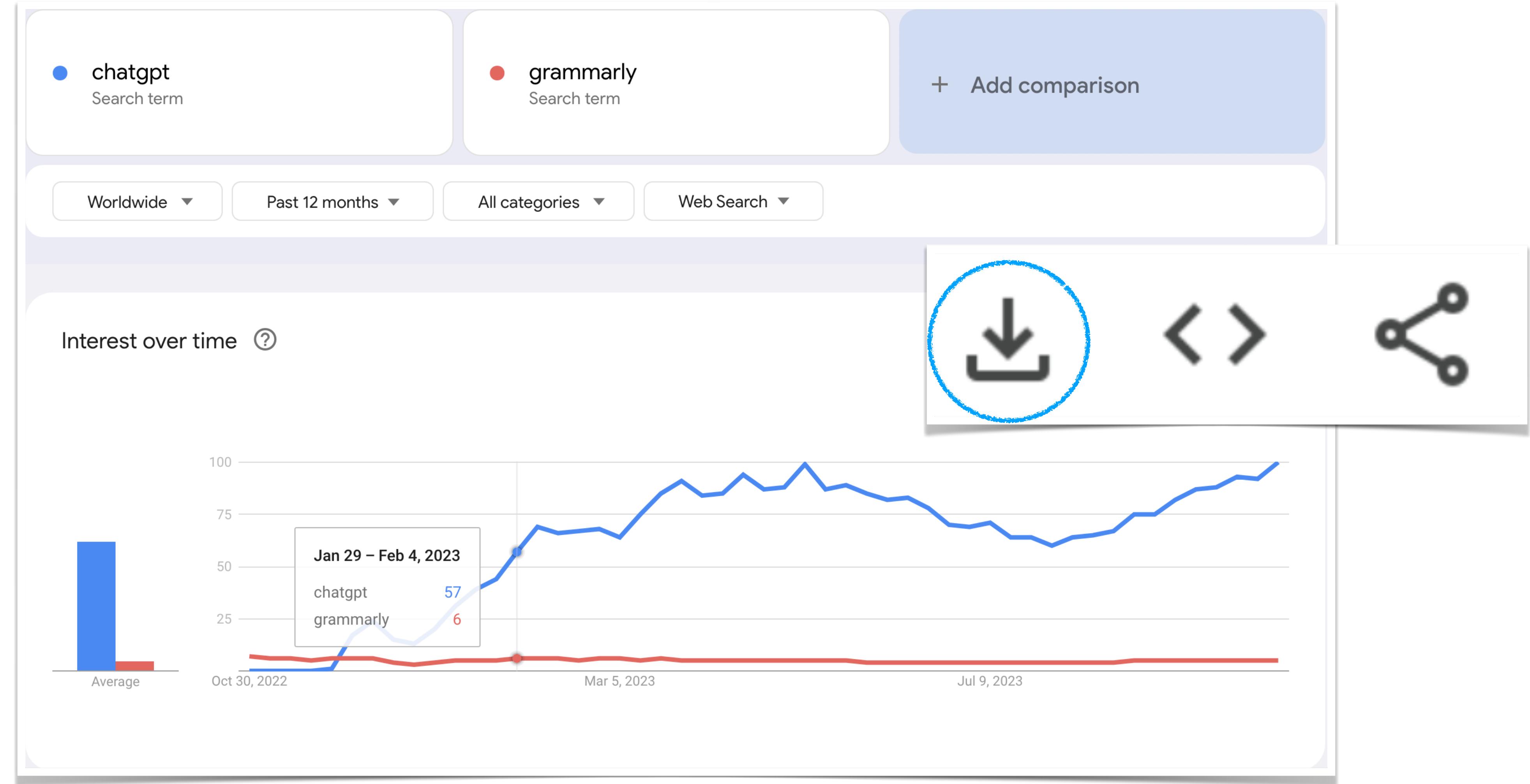
Google Trends

Searching for various trends



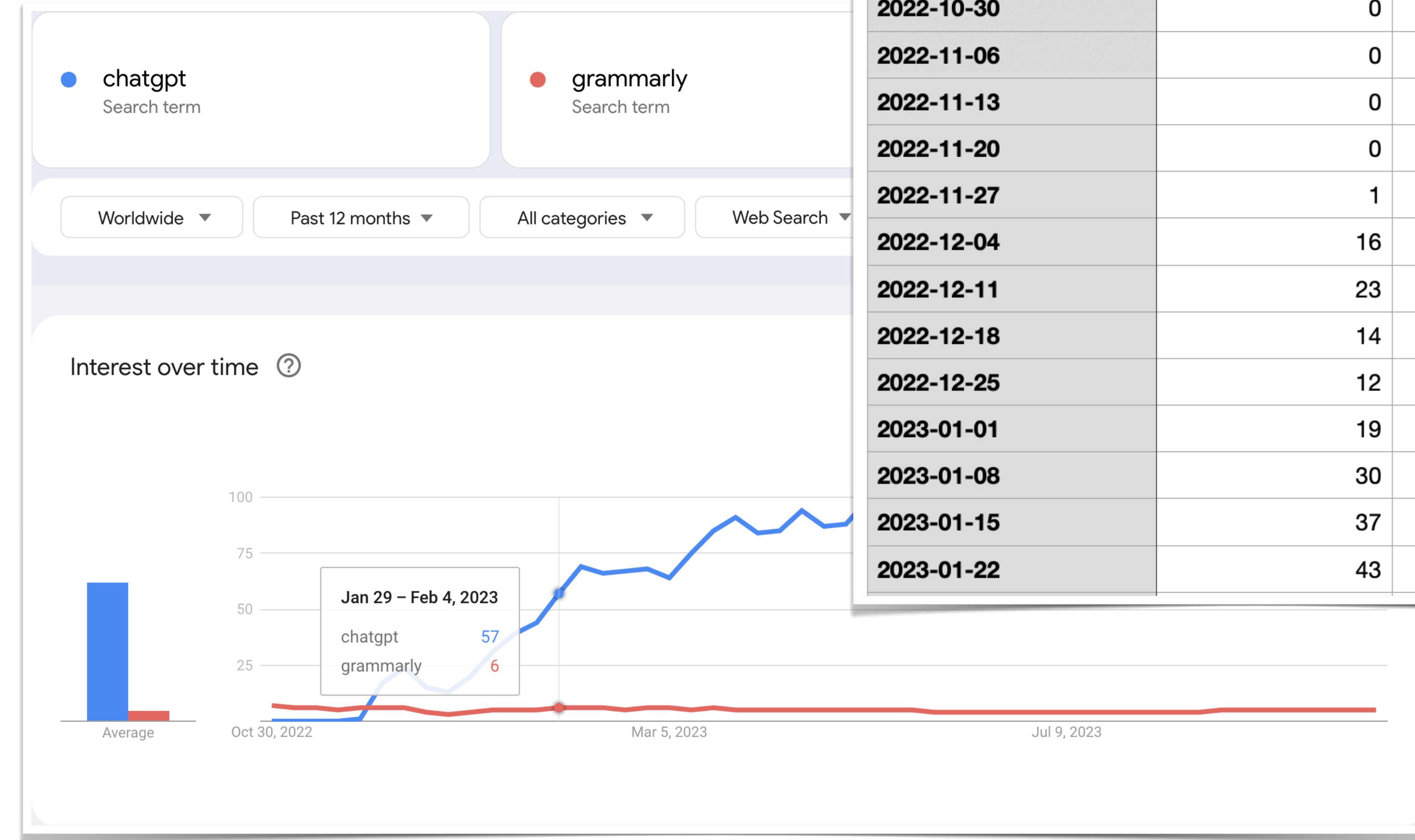
Google Trends

Exporting data



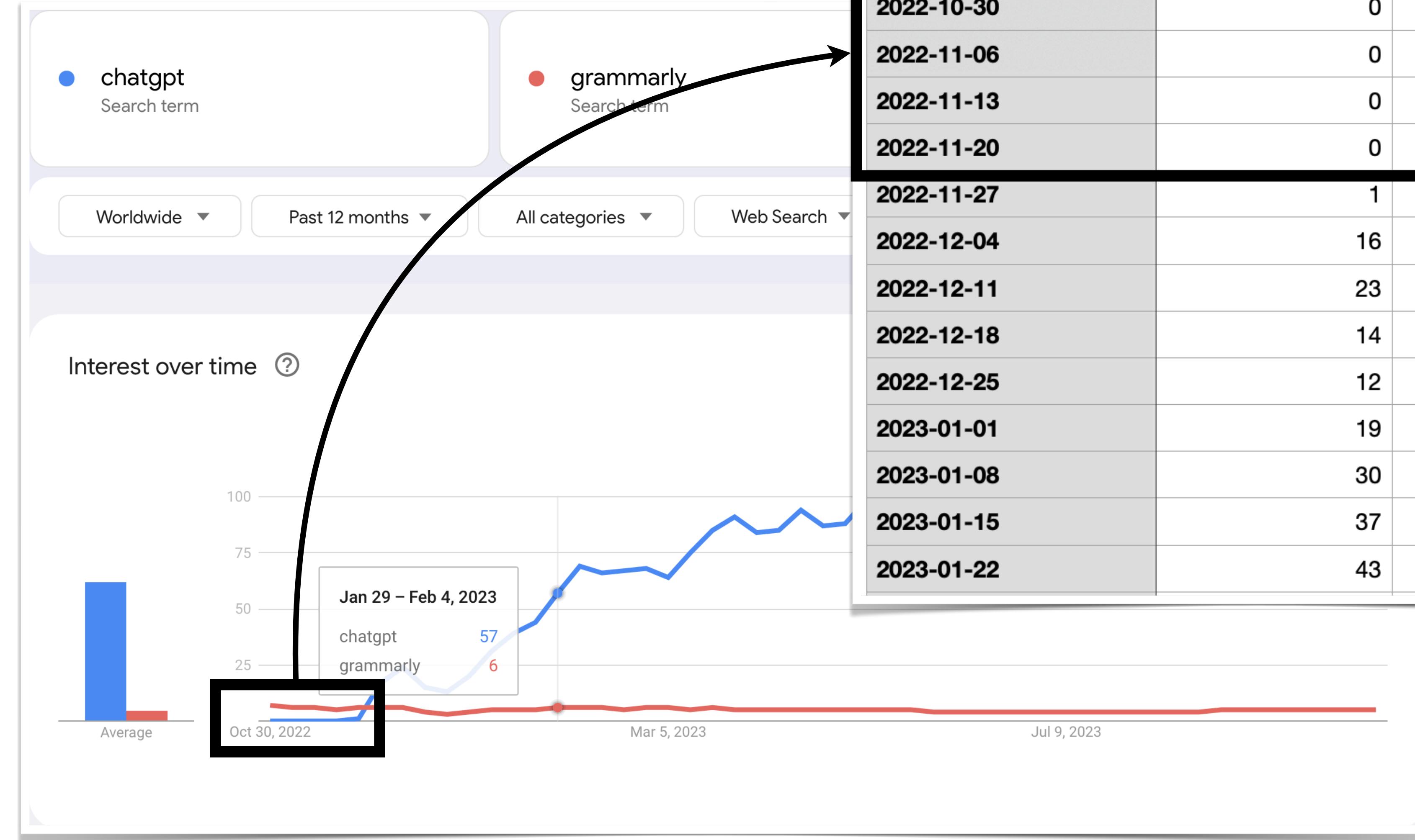
Google Trends

Export file format



Google Trends

Export file format



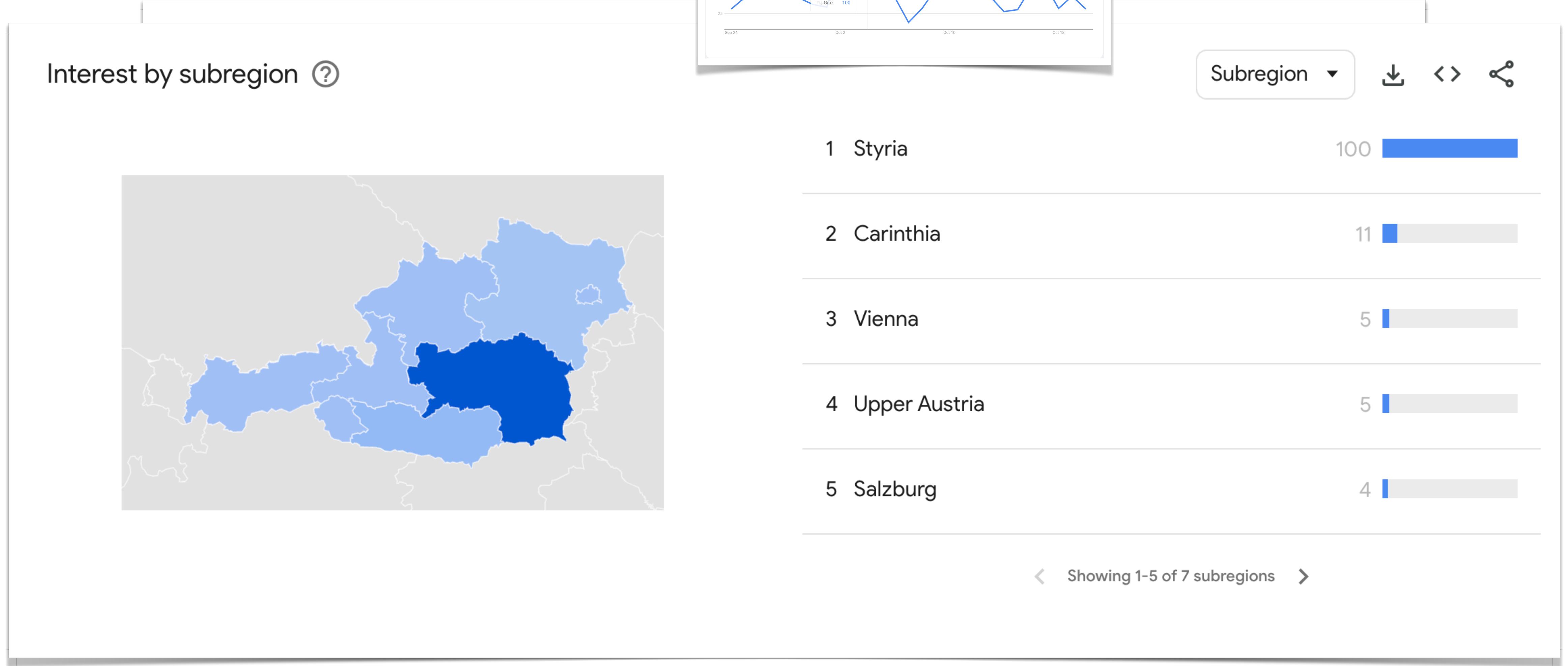
Google Trends

Comparing regions



Google Trends

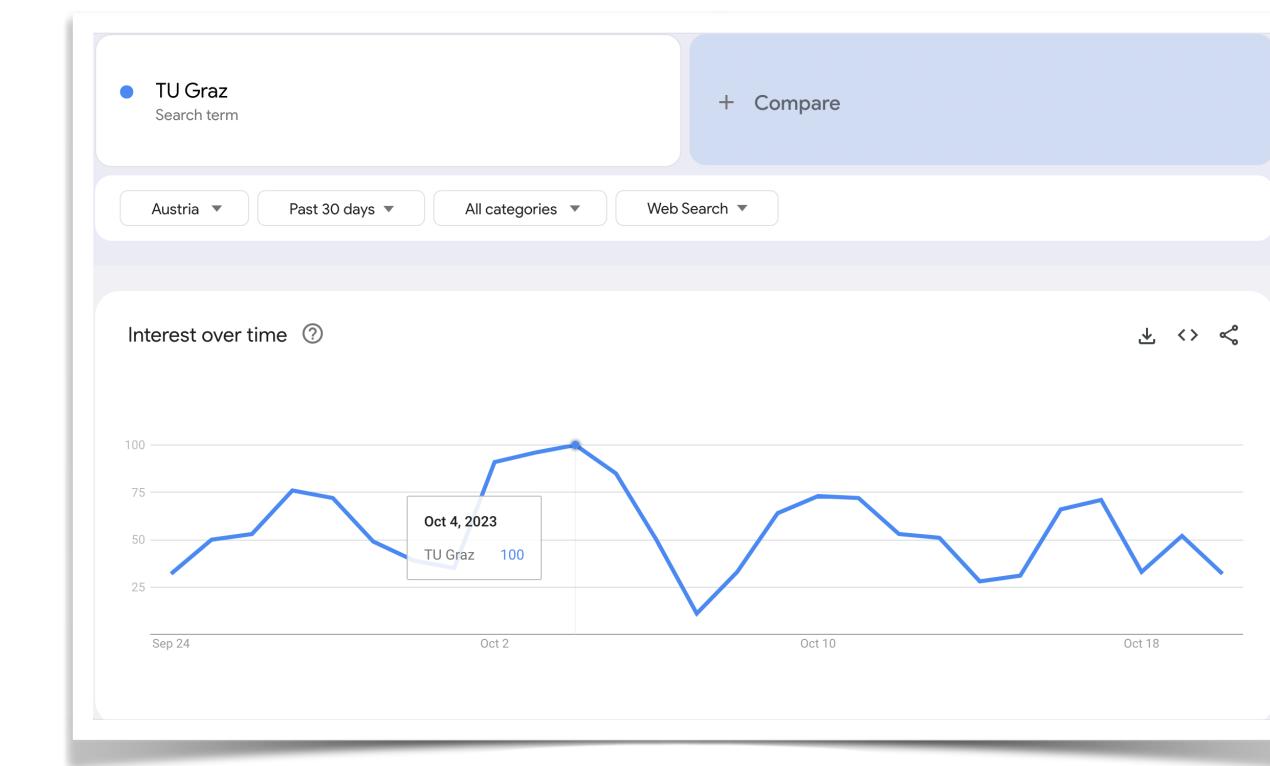
Comparing regions



Google Trends

Related topics and queries

search term: TU Graz



Related topics [?](#) Rising ▾ Download Compare Share

1 Professor - Job title	Breakout	⋮
2 Institut für angewandte Informationsverarb...	Breakout	⋮
3 university cafeteria - Topic	Breakout	⋮
4 Virtual private network - Topic	Breakout	⋮
5 Research - Organization type	Breakout	⋮

Showing 1-5 of 7 topics < >

Related queries [?](#) Rising ▾ Download Compare Share

1 tu fest graz	Breakout	⋮
2 tu graz welcome days	Breakout	⋮
3 teach center tu graz	Breakout	⋮
4 tu fest graz 2023	Breakout	⋮
5 tc tu graz	Breakout	⋮

Showing 1-5 of 9 queries < >

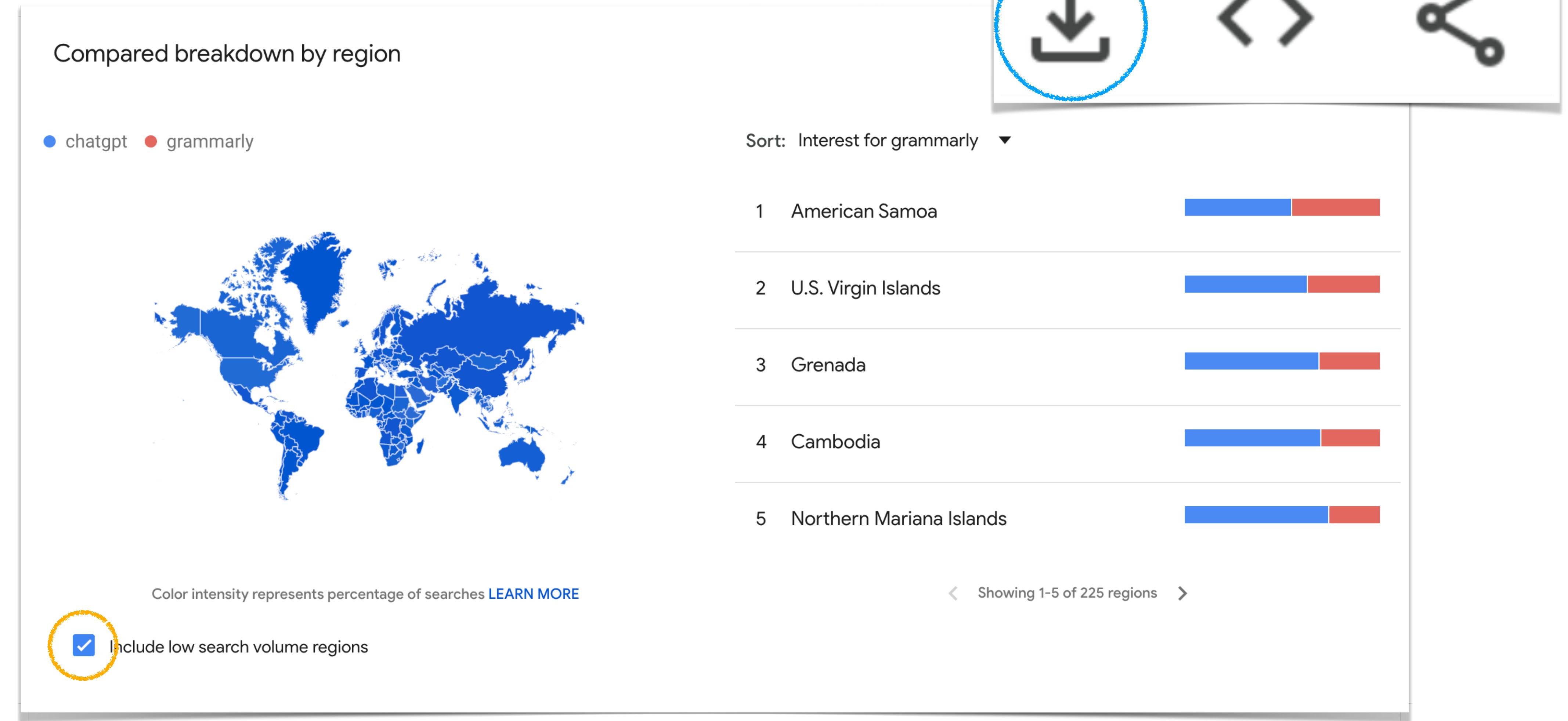
Google Trends

Exporting map data



Google Trends

Exporting map data



Google Trends

Export file format for maps



geoMap

Category: All categories		
Country	chatgpt: (10/24/22 - 10/24/23)	grammarly: (10/24/22 - 10/24/23)
China	97 %	3 %
Bhutan	97 %	3 %
Malawi	98 %	2 %
Solomon Islands	100 %	
Nepal	97 %	3 %
Madagascar	99 %	1 %
Djibouti	100 %	
Philippines	84 %	16 %
Singapore	95 %	5 %
Sri Lanka	93 %	7 %
Pakistan	93 %	7 %
Vanuatu	100 %	

< Showing 1-5 of 225 regions >

What can we do with
Google Trends data?

The Future Orientation Index (FOI)

Preis et al. 2012

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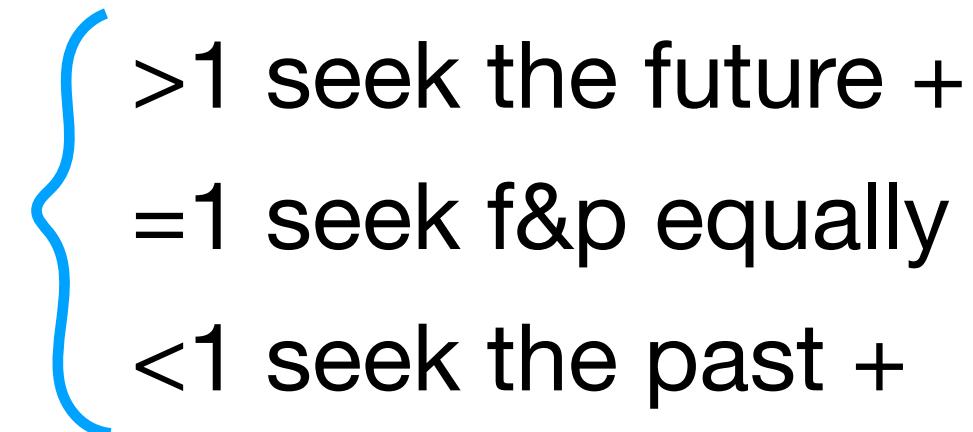
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{
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 =1 seek f&p equally
 <1 seek the past +

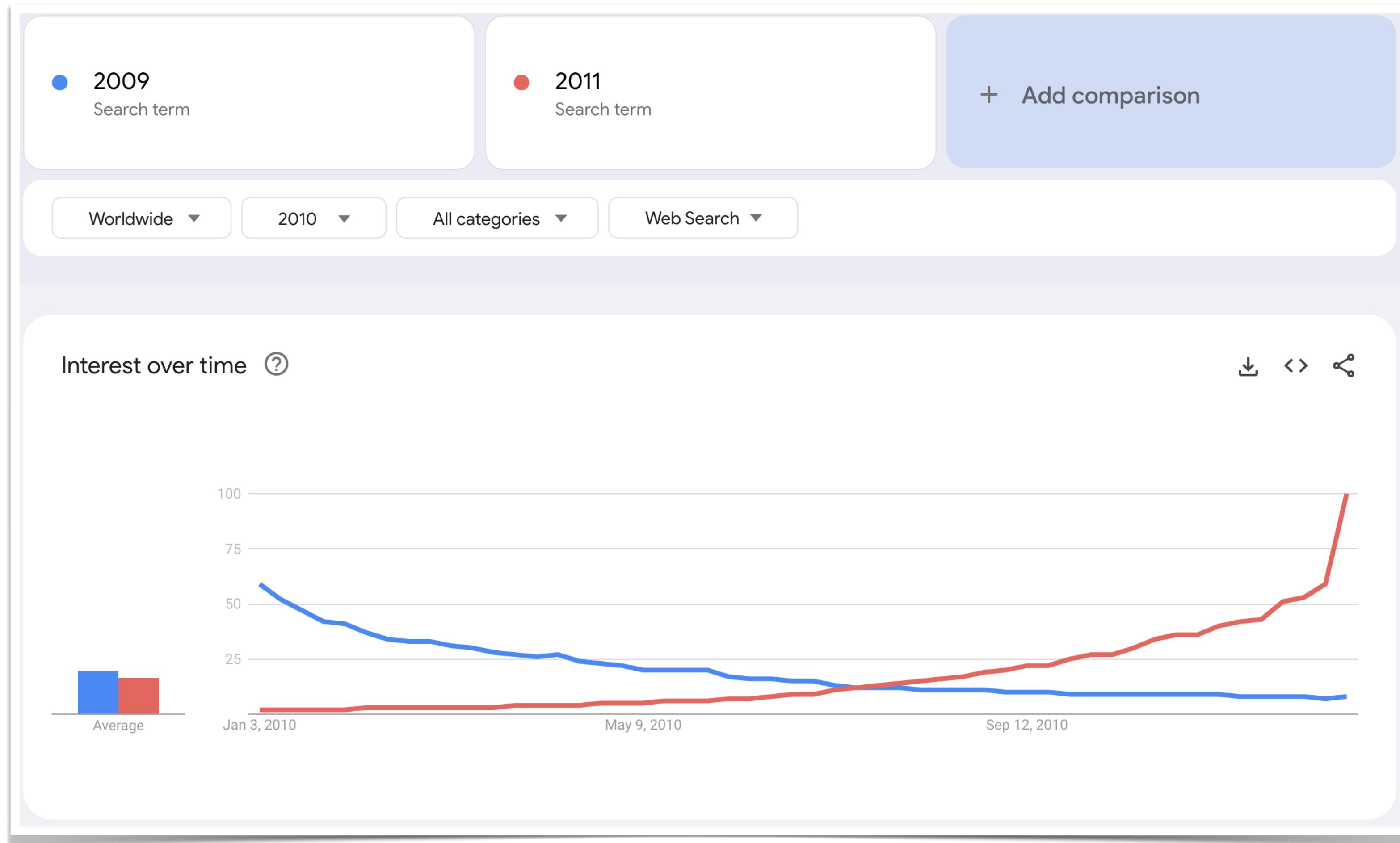
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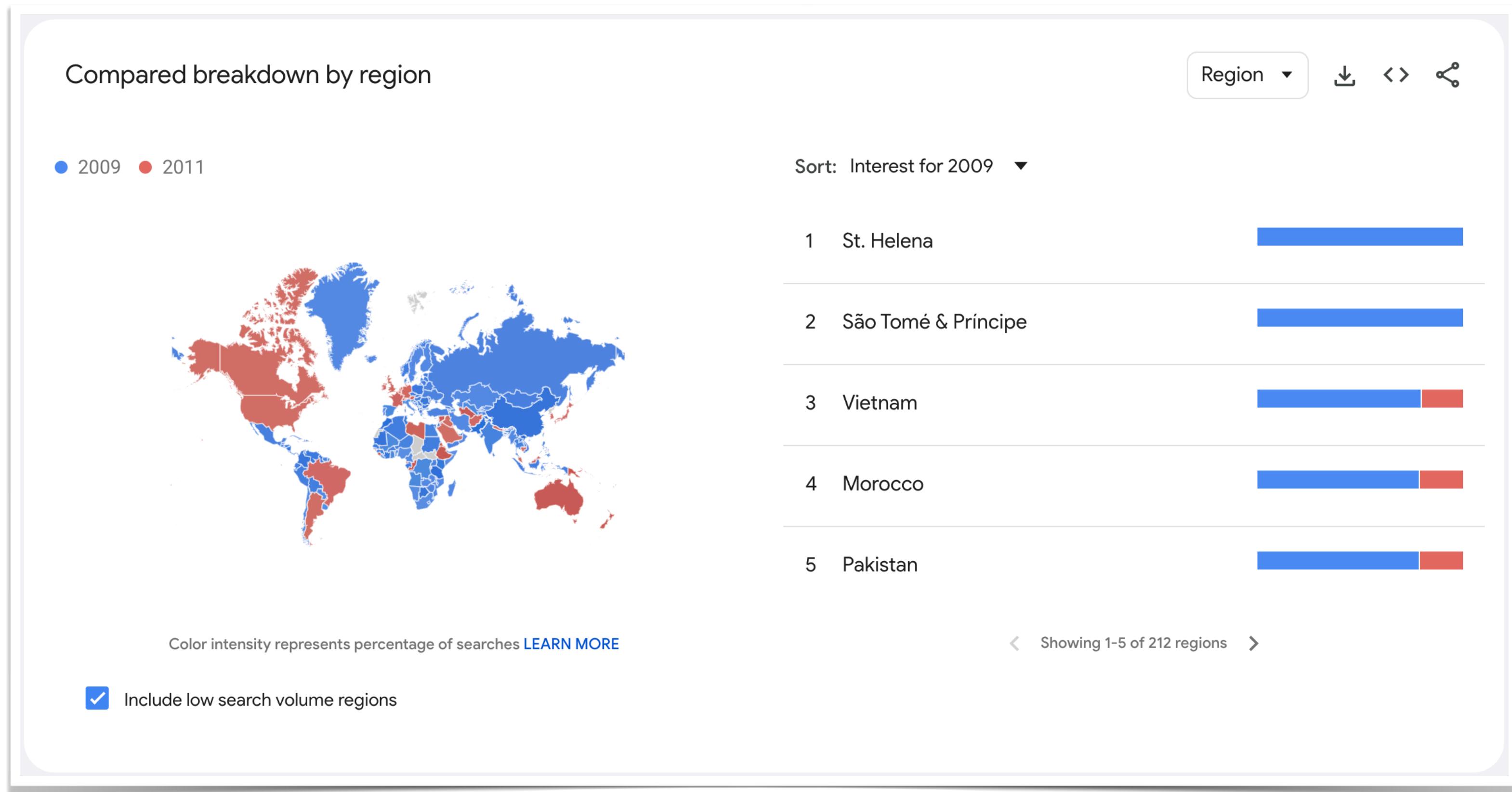
Examples of FOI

using Google Trends (per region, map data)



Examples of FOI

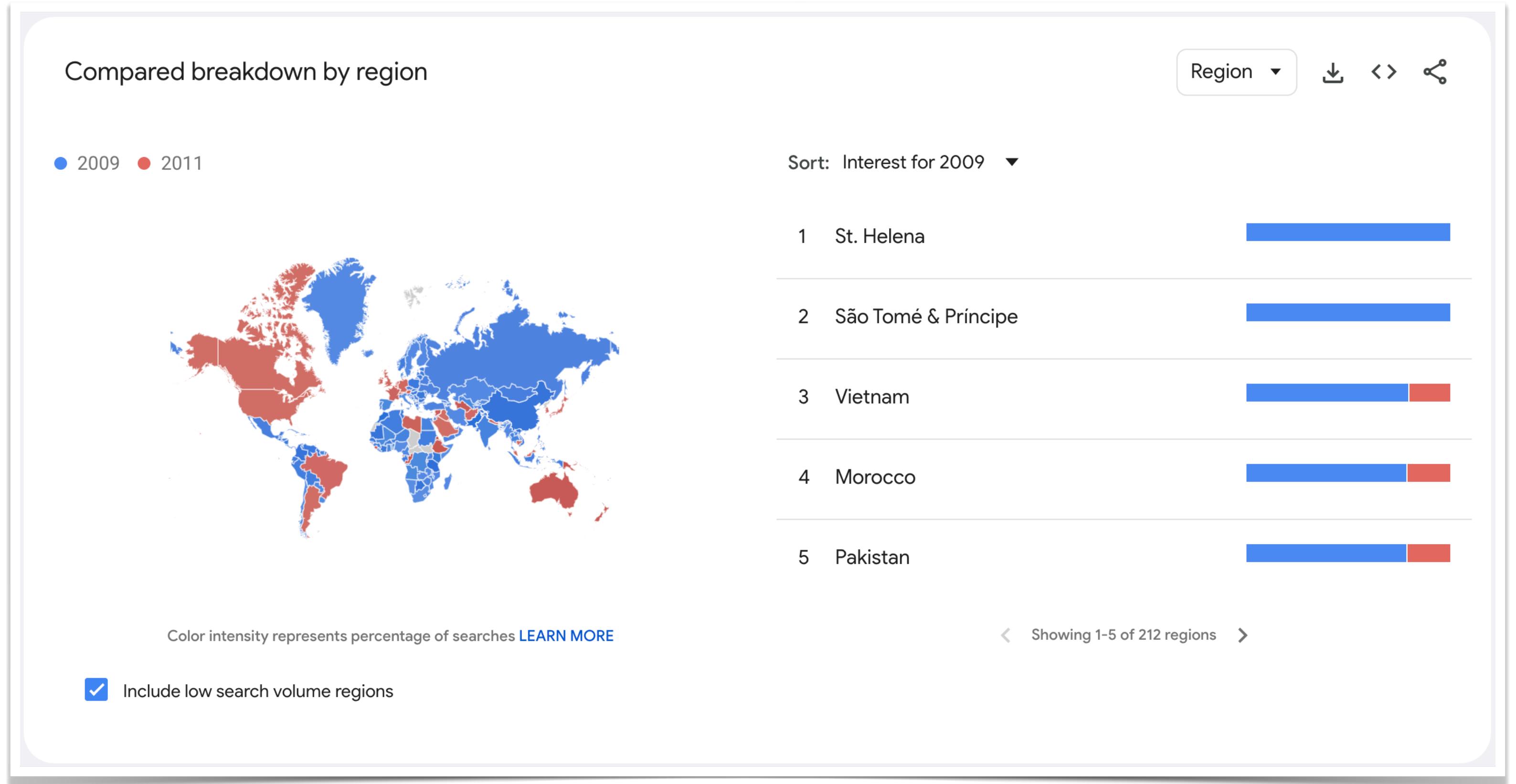
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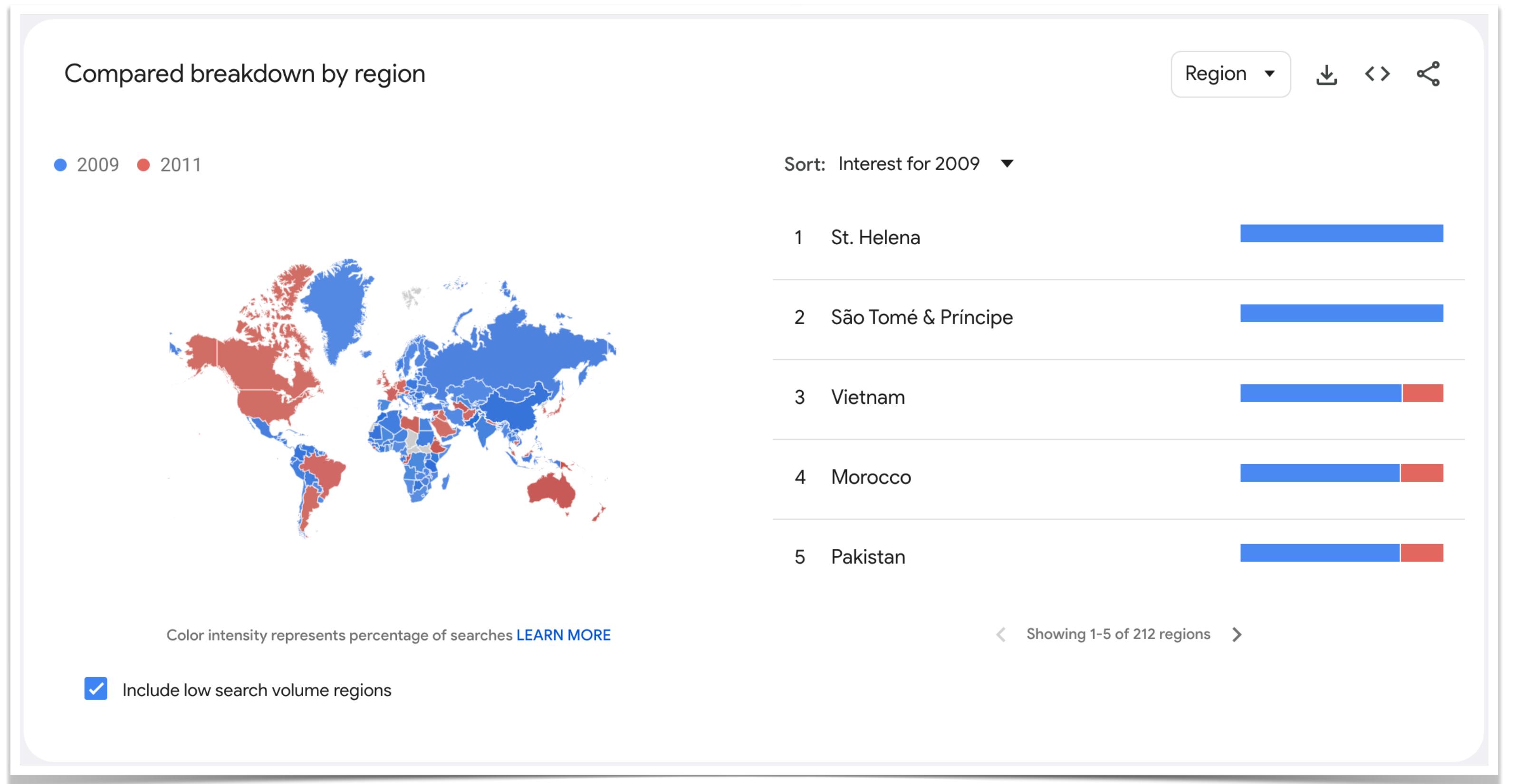
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Country	2009	2011
Germany	46.0	54.0
Austria	46.0	54.0
Ecuador	63.0	37.0

Examples of FOI

using Google Trends (per region, map data)



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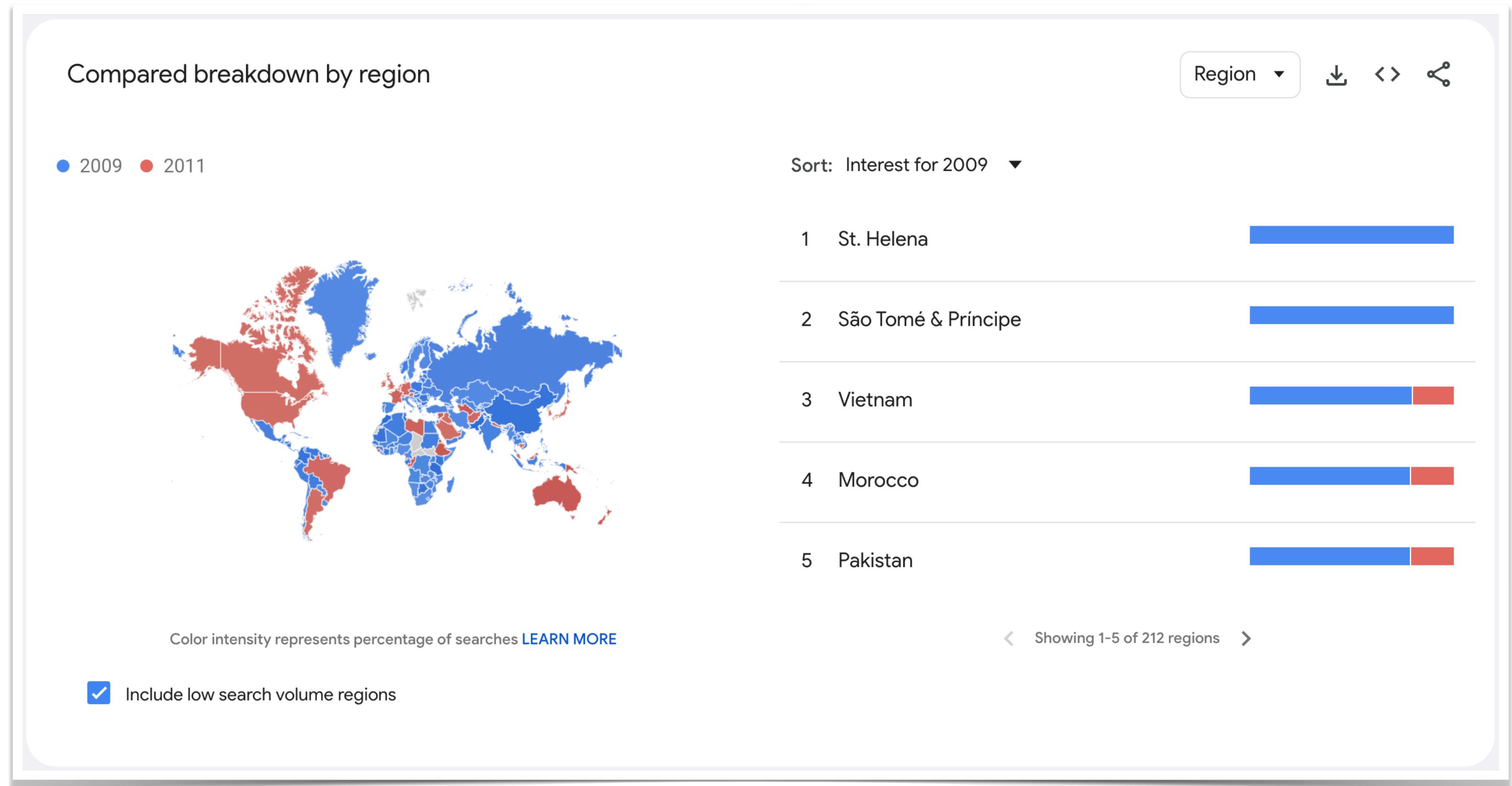
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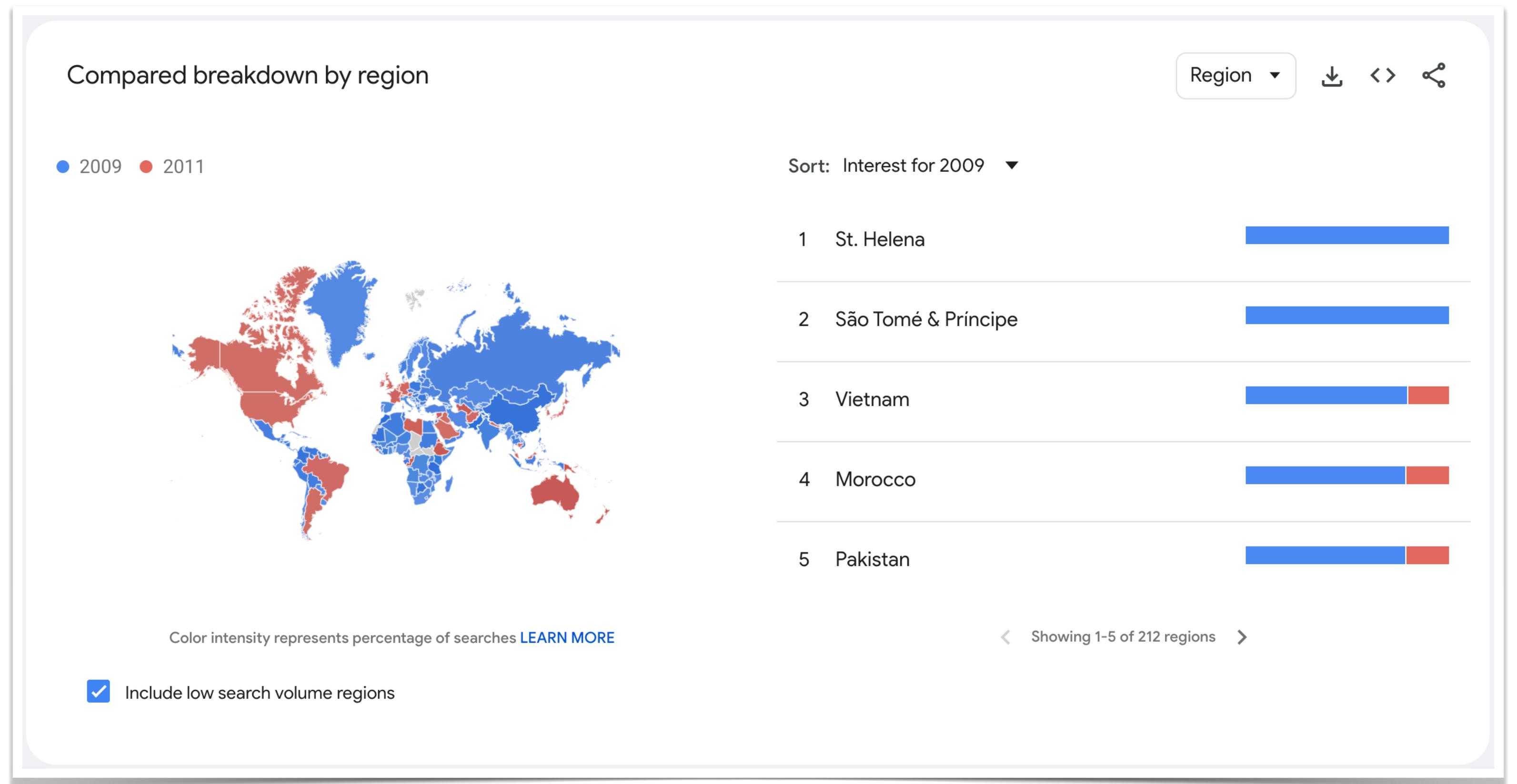
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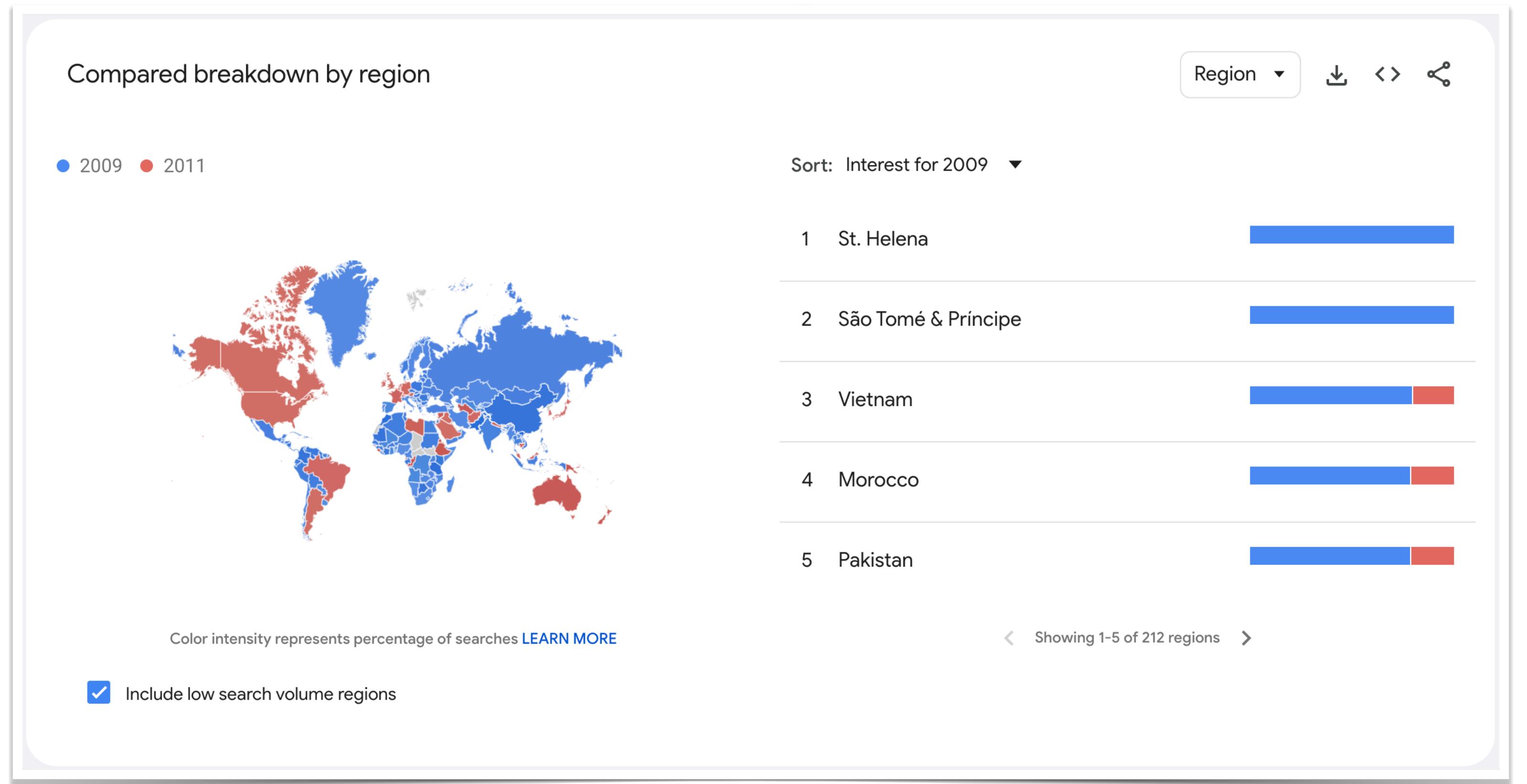
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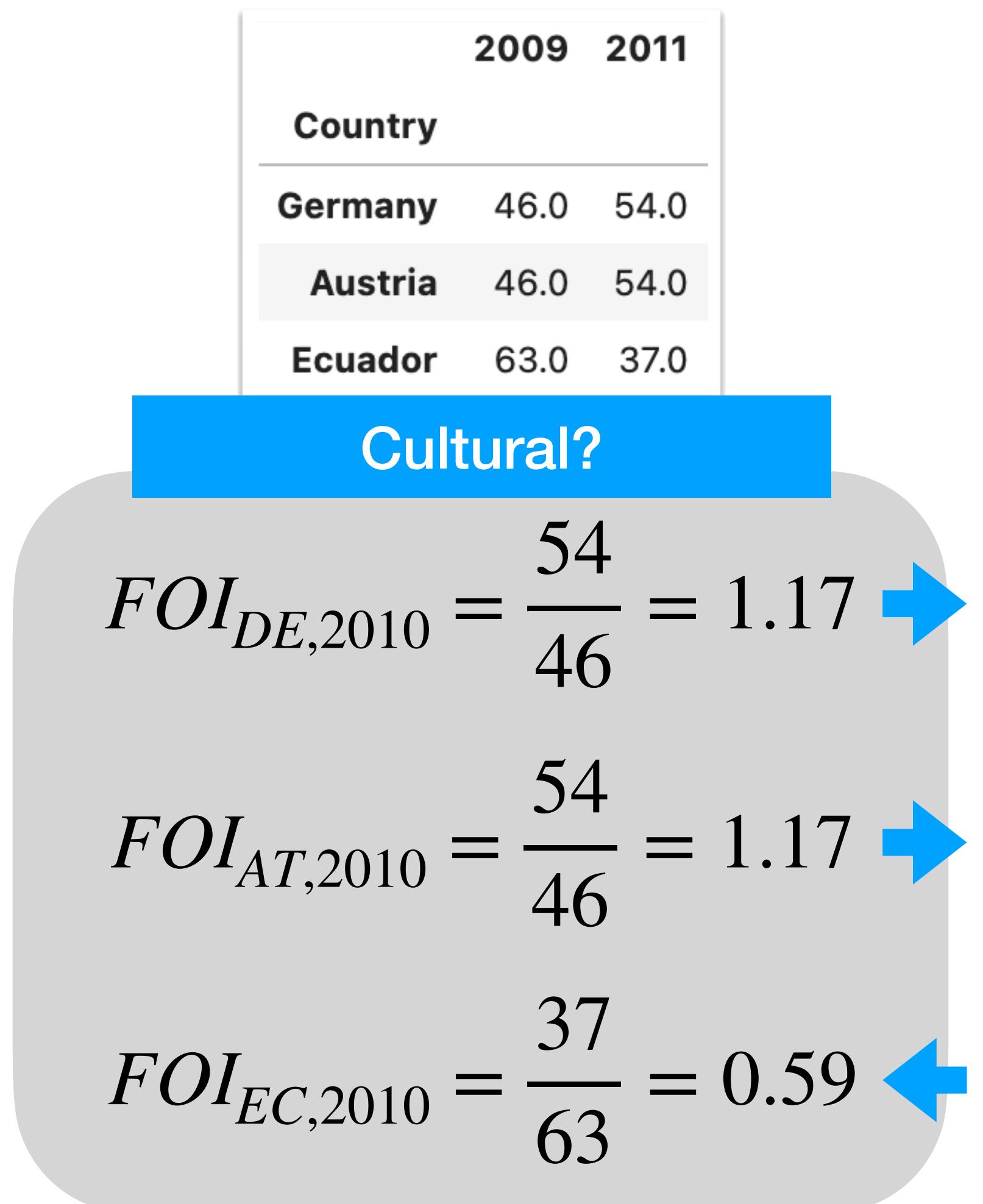
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So what?

Culture vs. Economy

Long-term orientation by Geert Hofstede

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Research Question:

Are long-term oriented societies wealthier?

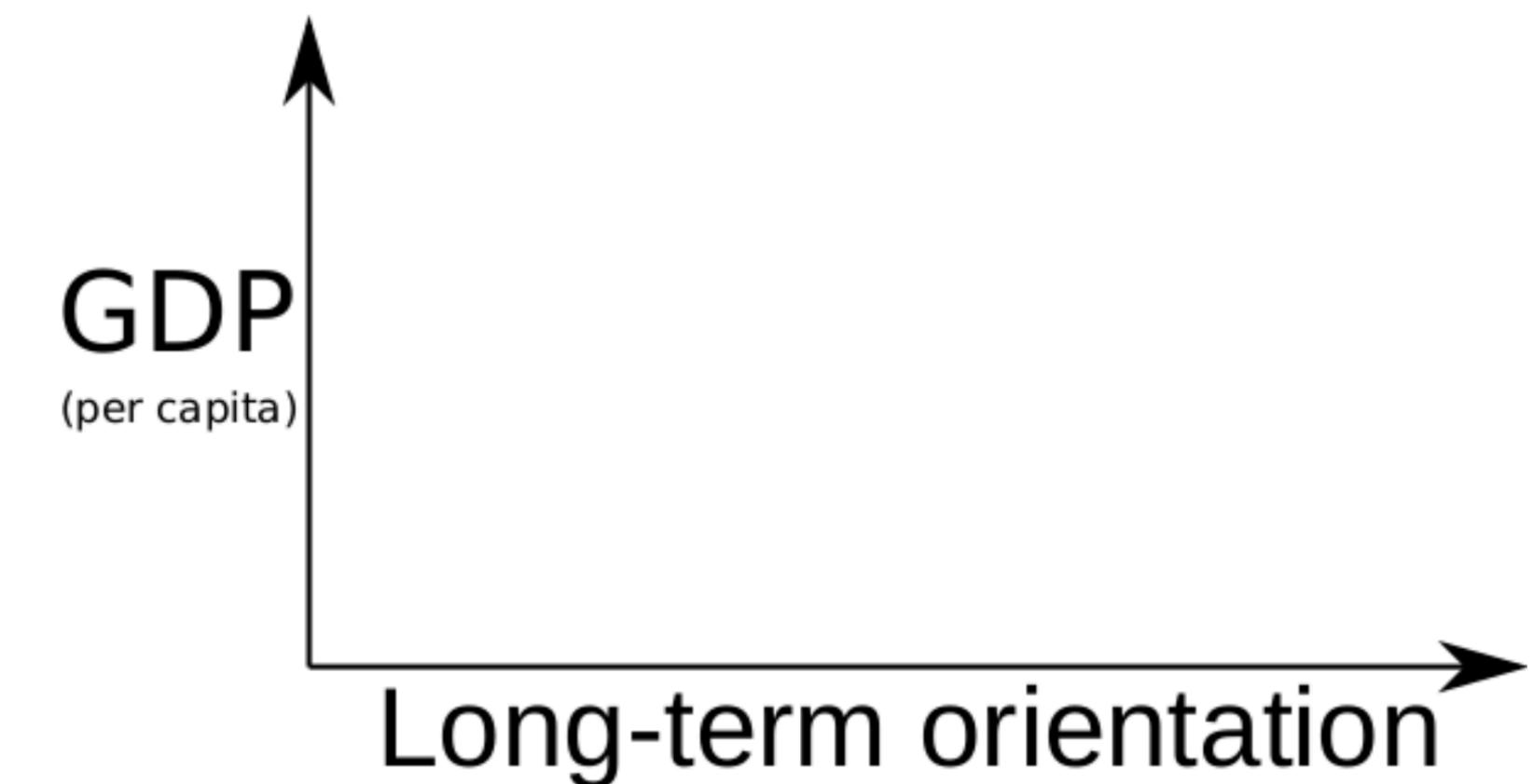
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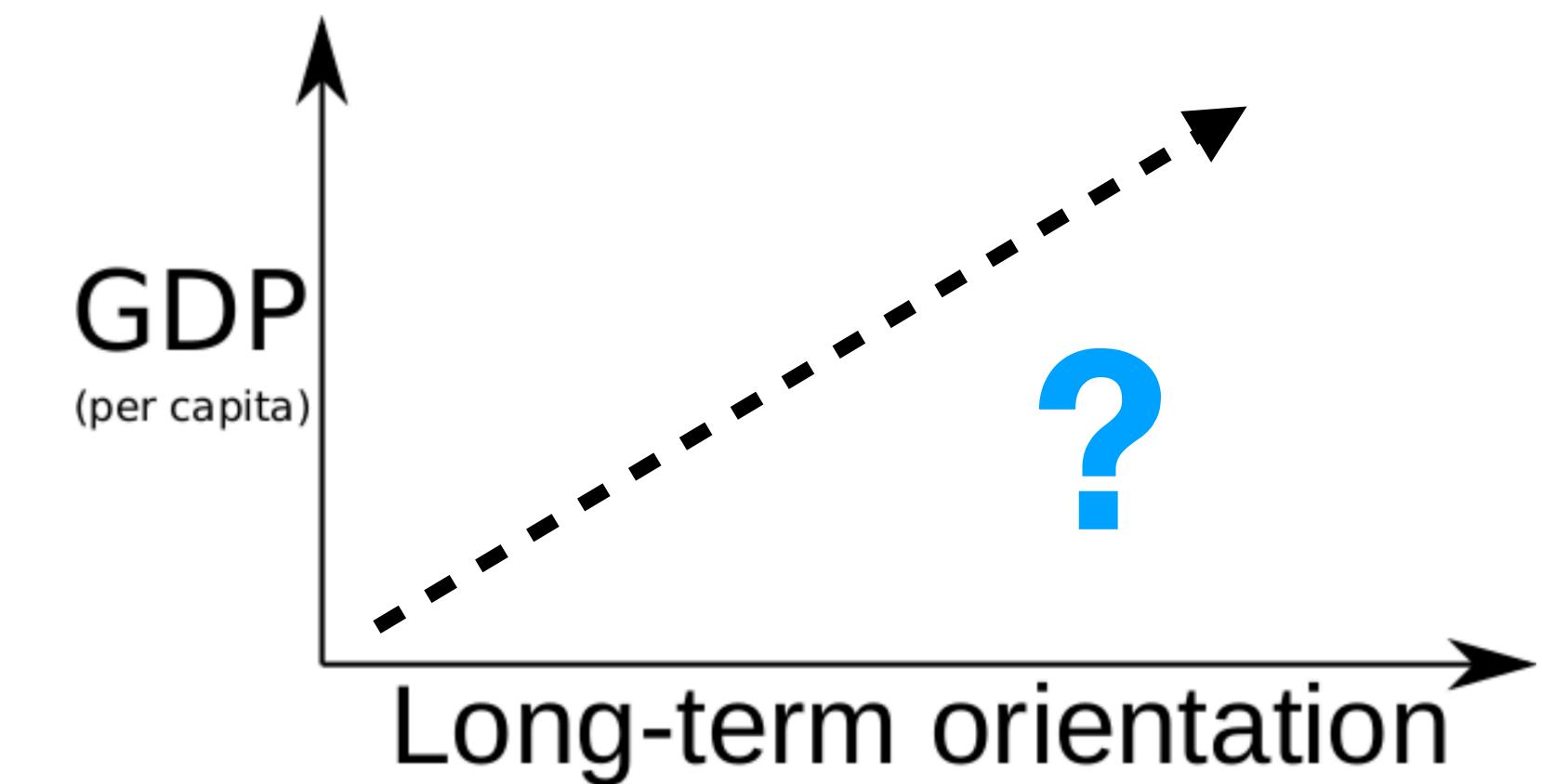
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- In other words: The FOI measures the ratio of search volume within a country for the next year divided by the search volume of the previous year in the same country.
- Using Google Trends, Preis et al. found that **users from countries with a higher per capita GDP are more likely to search for information about the future** than information about the past.

Examples of FOI

using Google Trends (per region, map data)

Examples of FOI

using Google Trends (per region, map data)

	GDP_2010	FOI_2010
Country Name		
Germany	37760.91	1.17
Austria	43334.51	1.17
Ecuador	5331.38	0.59

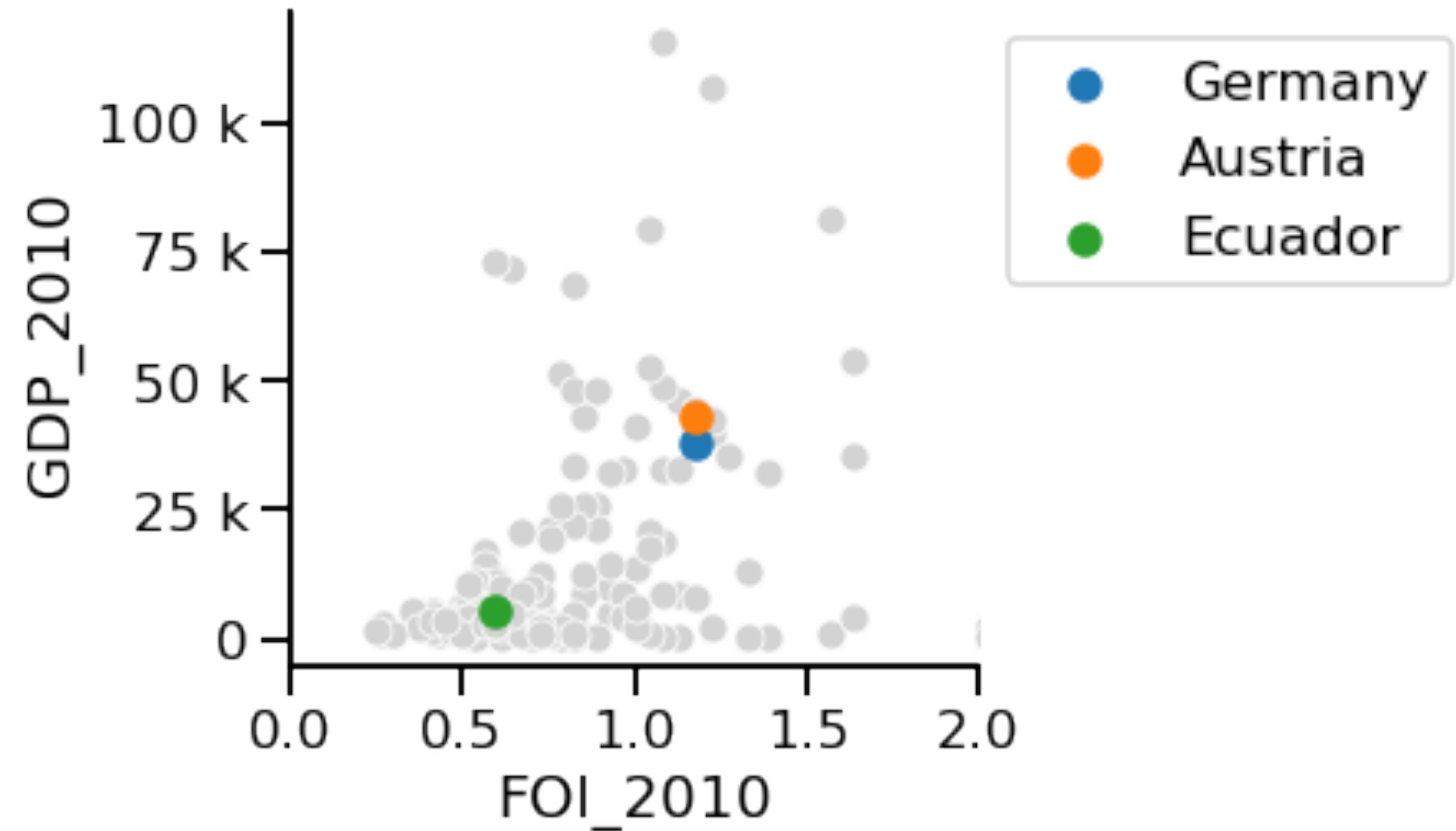
GDP: [https://wits.worldbank.org/
CountryProfile/en/country/by-country/
startyear/LTST/endyear/LTST/
indicator/NY-GDP-PCAP-KD](https://wits.worldbank.org/CountryProfile/en/country/by-country/startyear/LTST/endyear/LTST/indicator/NY-GDP-PCAP-KD)

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CountryProfile/en/country/by-country/
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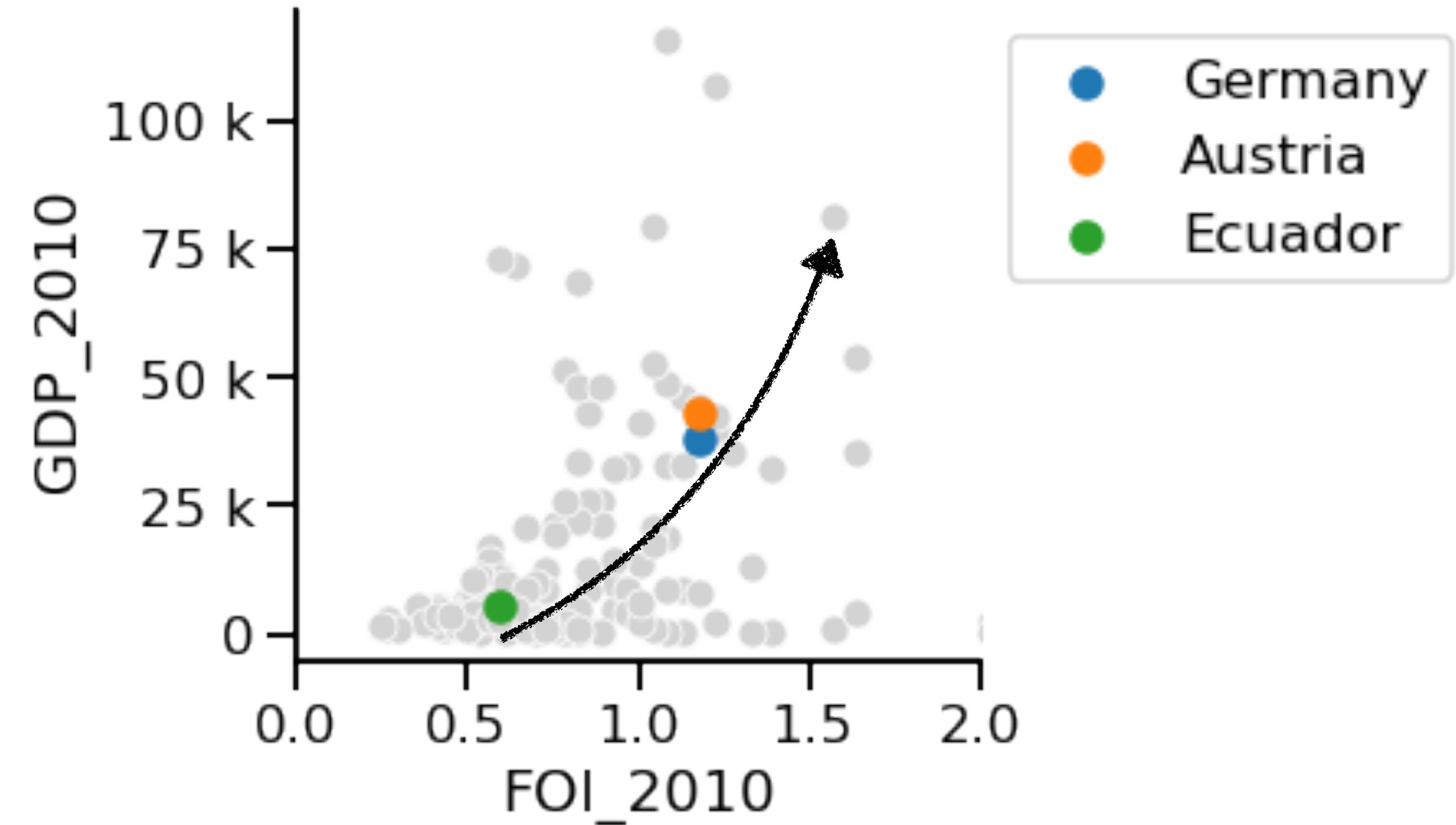


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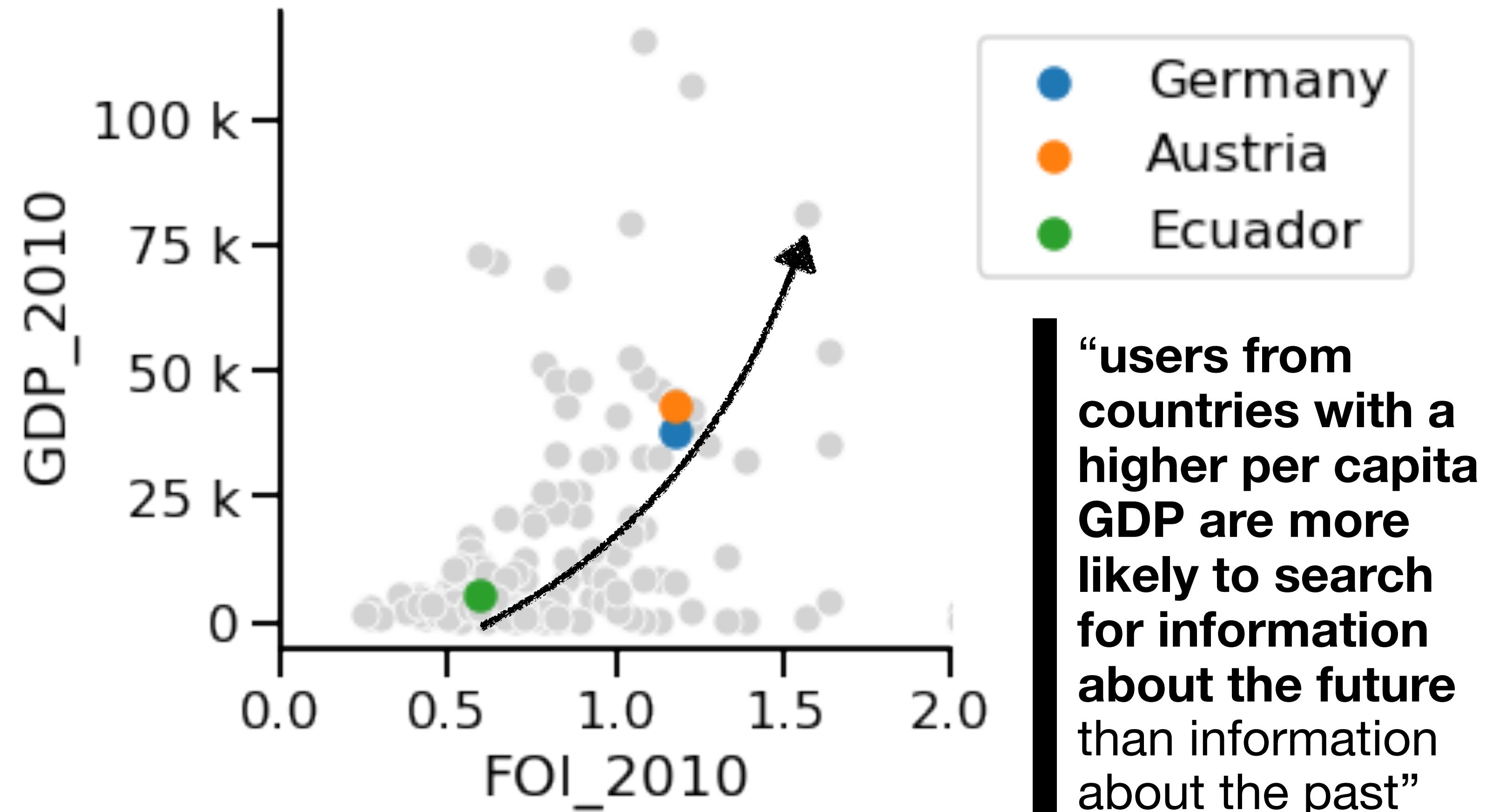


Examples of FOI

using Google Trends (per region, map data)

Country Name	GDP_2010	FOI_2010
Germany	37760.91	1.17
Austria	43334.51	1.17
Ecuador	5331.38	0.59

GDP: [https://wits.worldbank.org/
CountryProfile/en/country/by-country/
startyear/LTST/endyear/LTST/
indicator/NY-GDP-PCAP-KD](https://wits.worldbank.org/CountryProfile/en/country/by-country/startyear/LTST/endyear/LTST/indicator/NY-GDP-PCAP-KD)



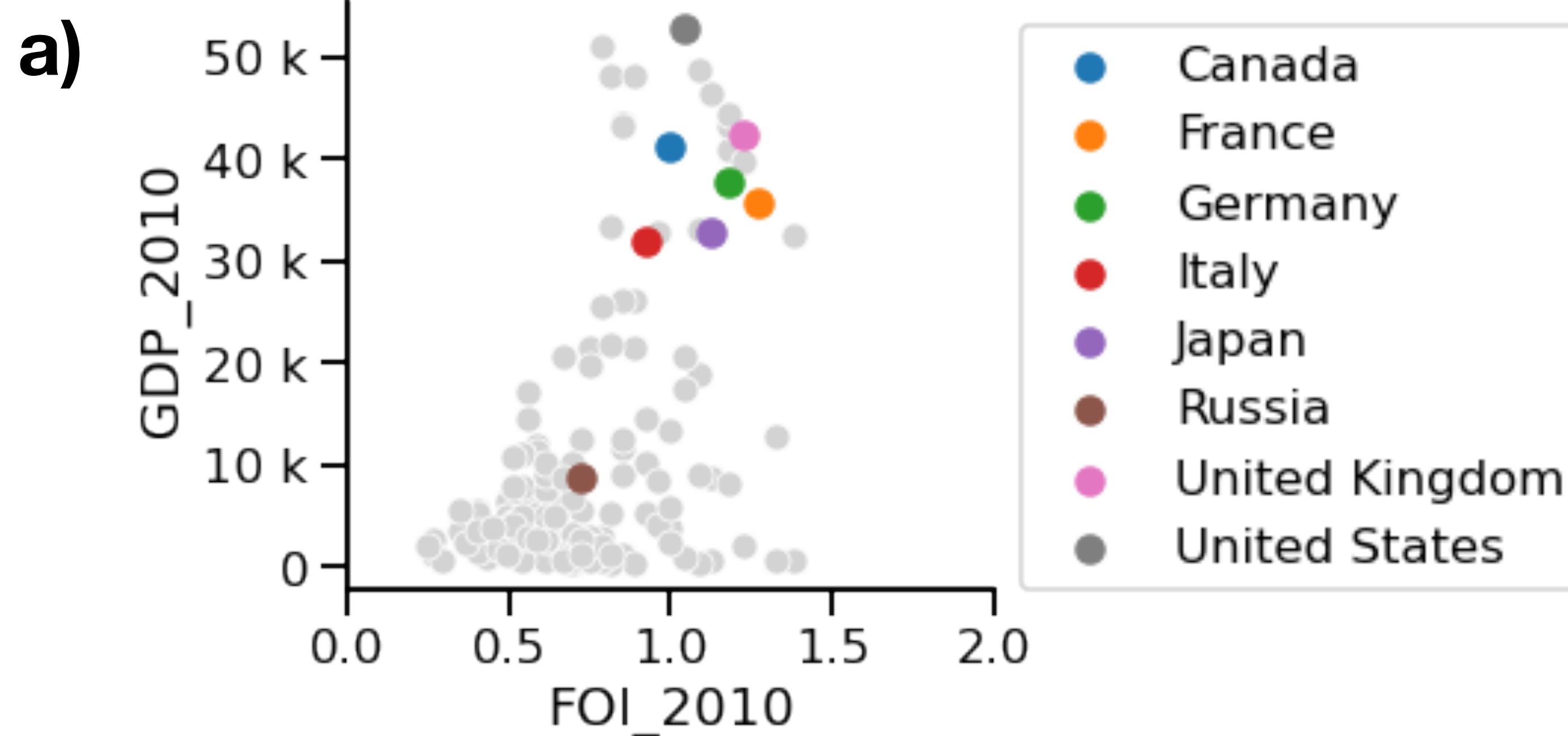
“users from countries with a higher per capita GDP are more likely to search for information about the future than information about the past”
Preis et al. 2012

Examples of FOI

Replicating results from Preis et al. 2012

Examples of FOI

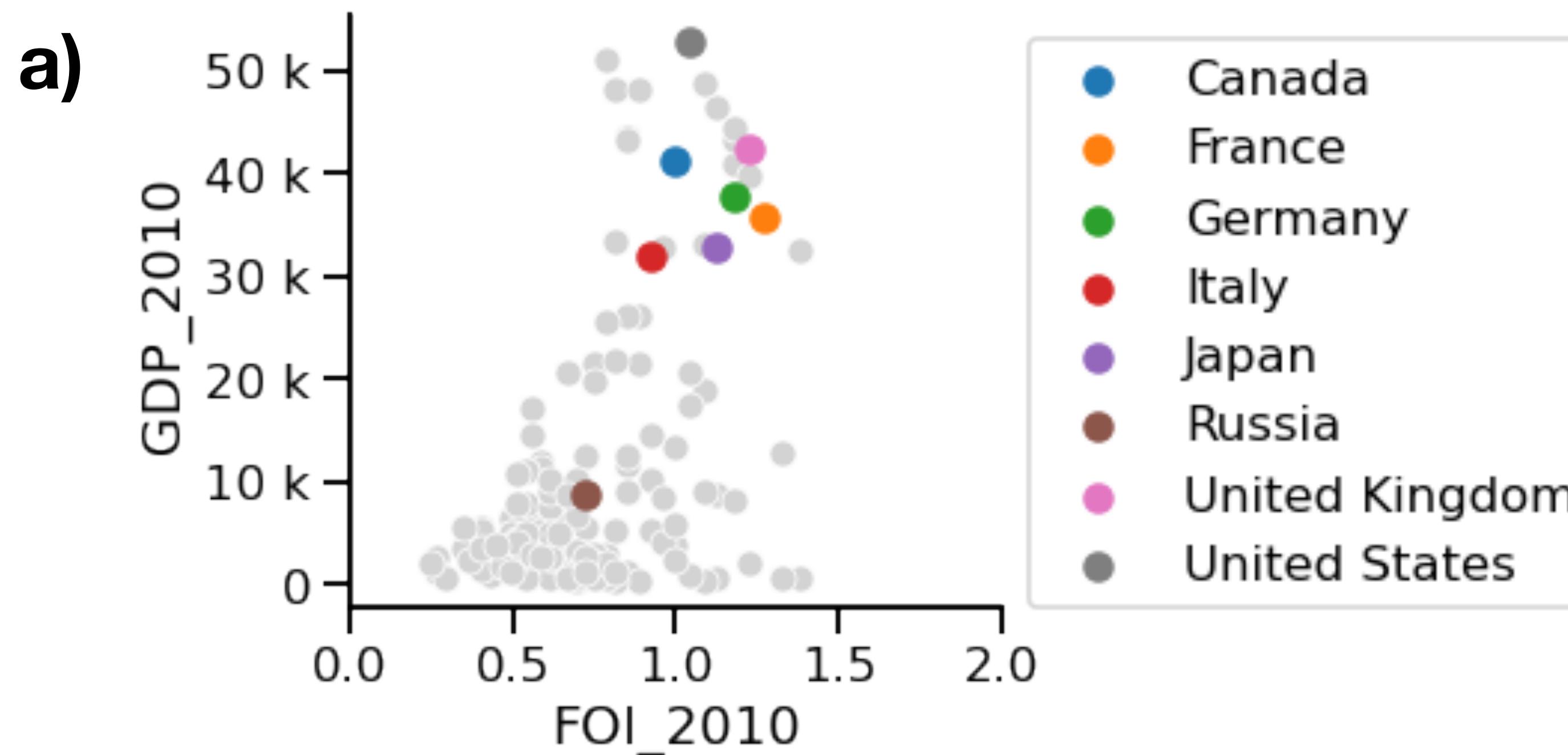
Replicating results from Preis et al. 2012



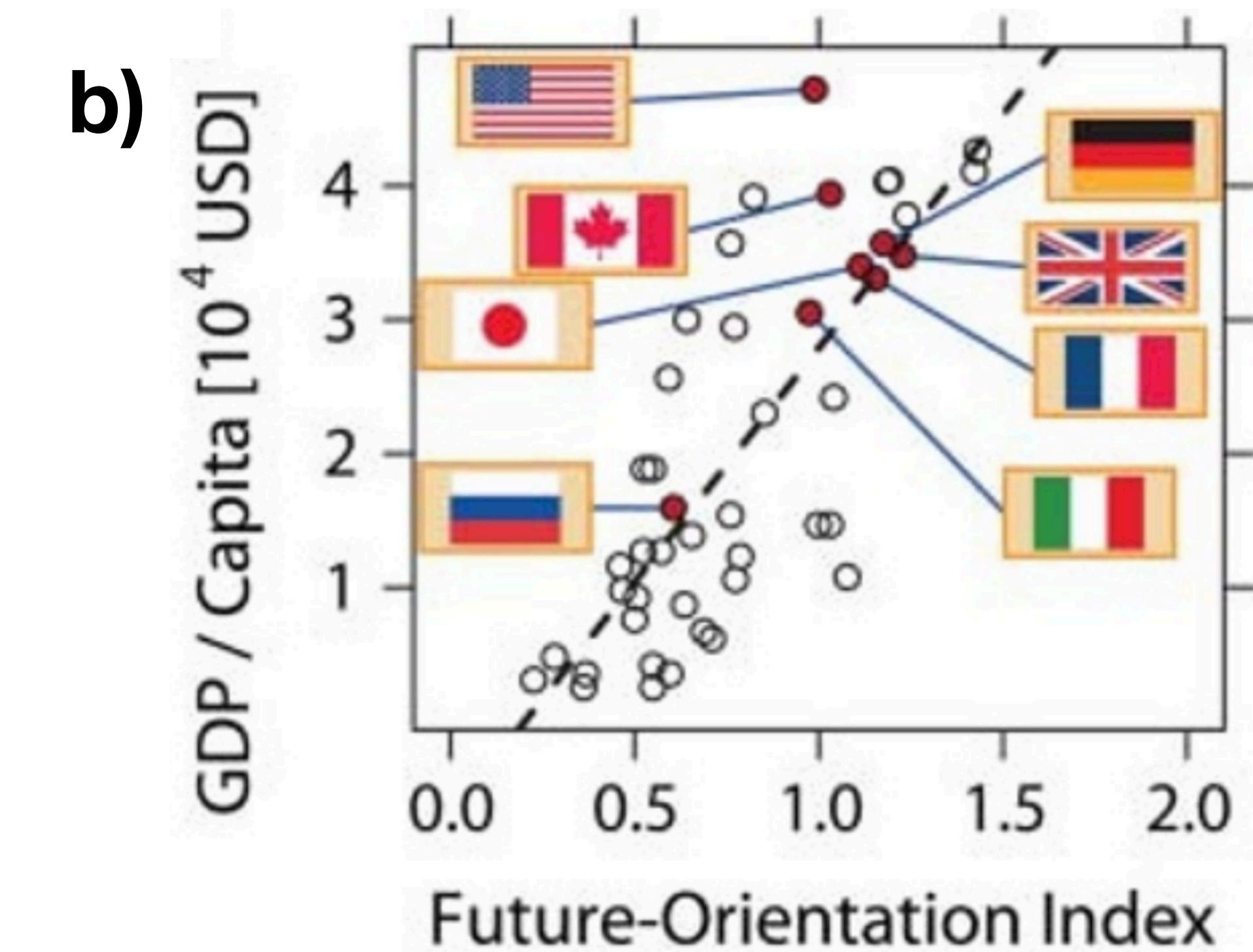
My replication
140 countries

Examples of FOI

Replicating results from [Preis et al. 2012](#)



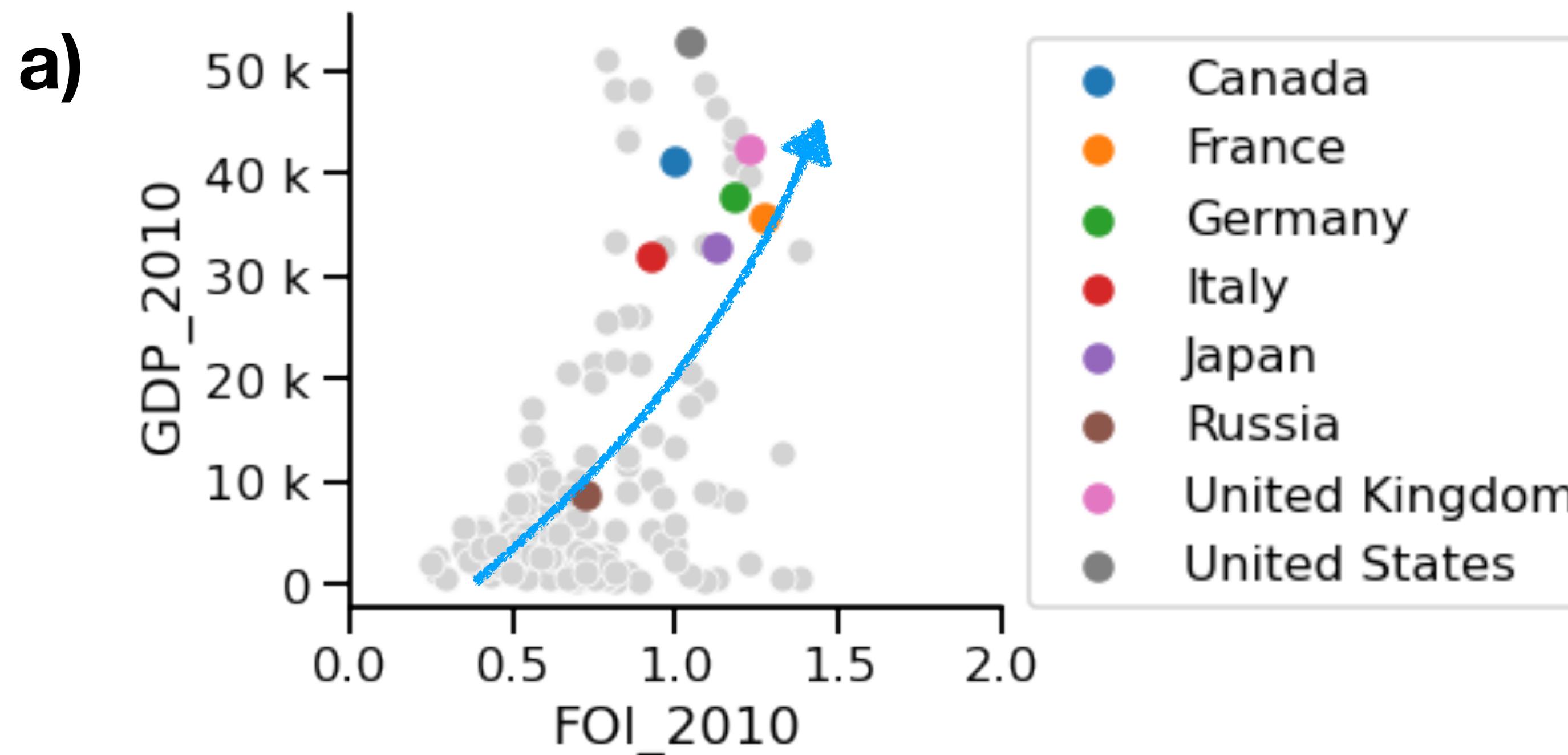
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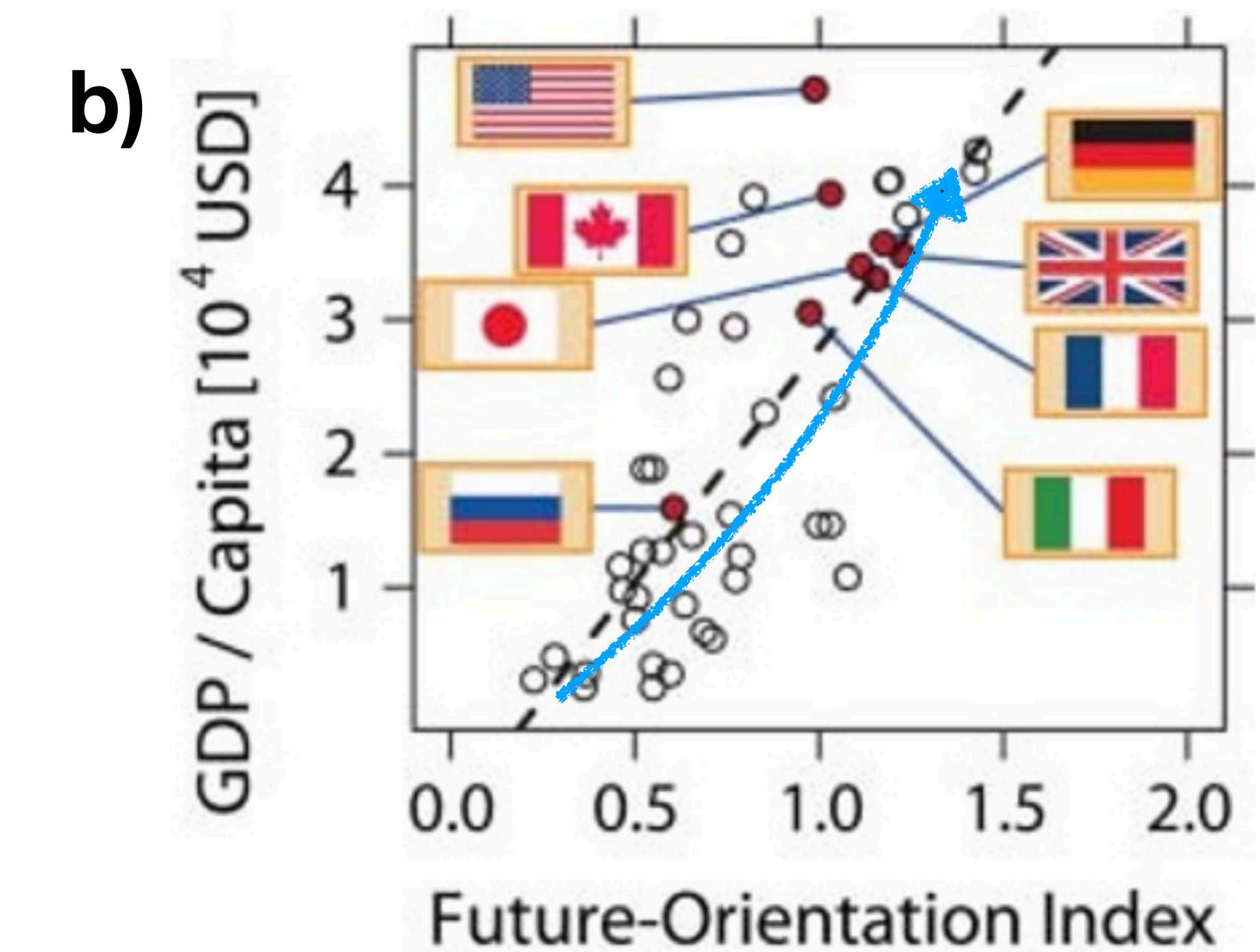
Preis et al. 2012
45 countries

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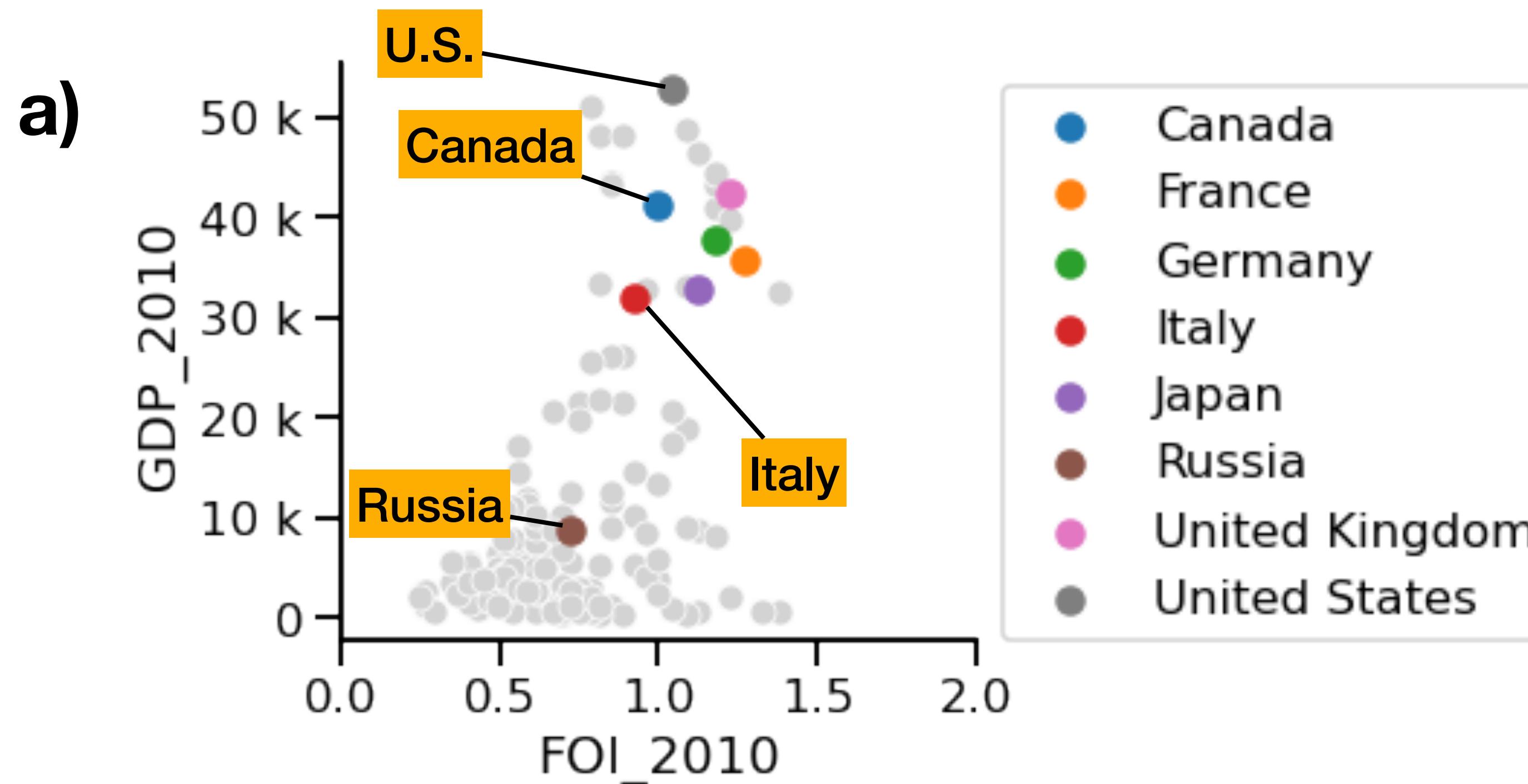
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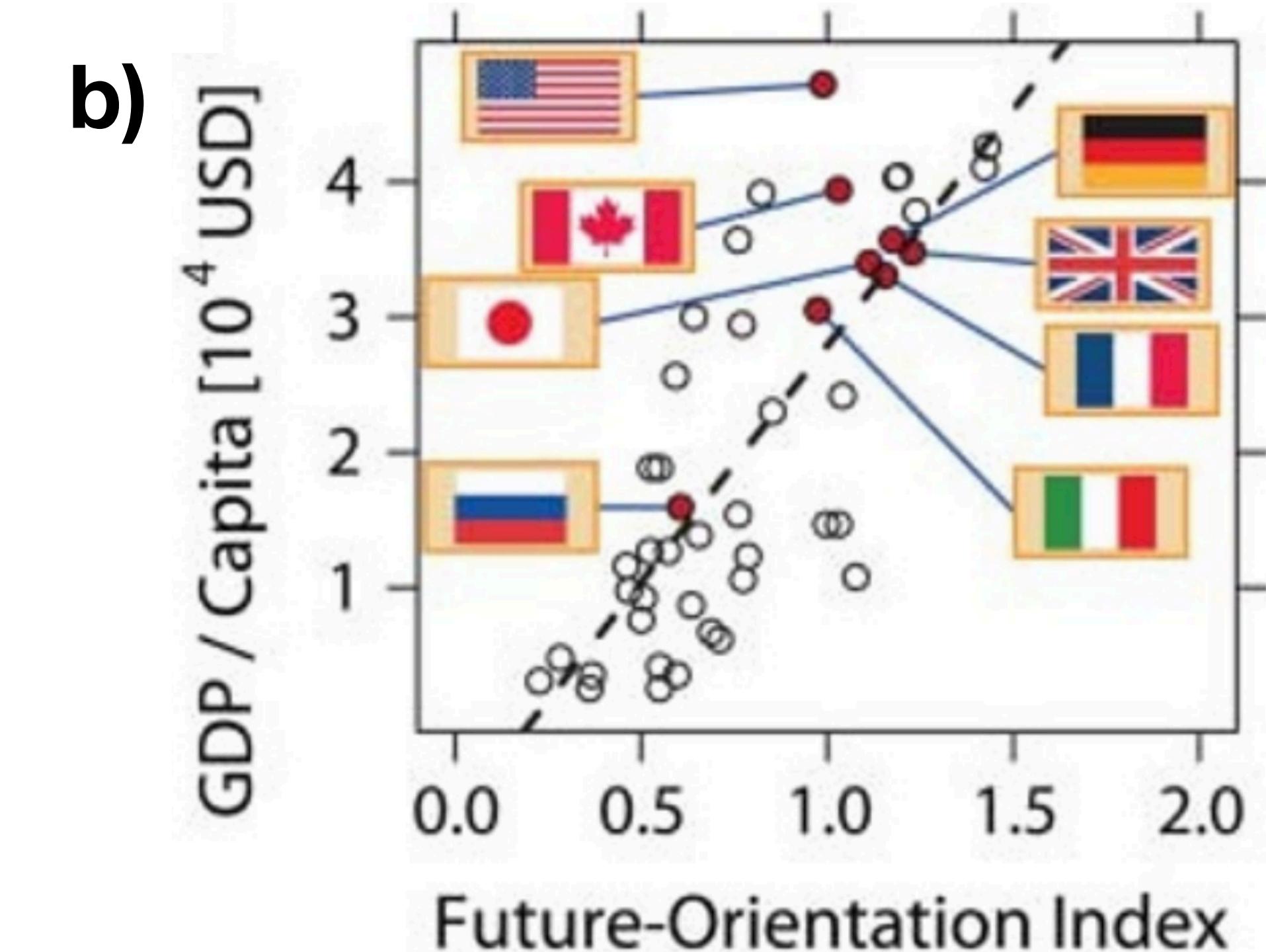
Preis et al. 2012
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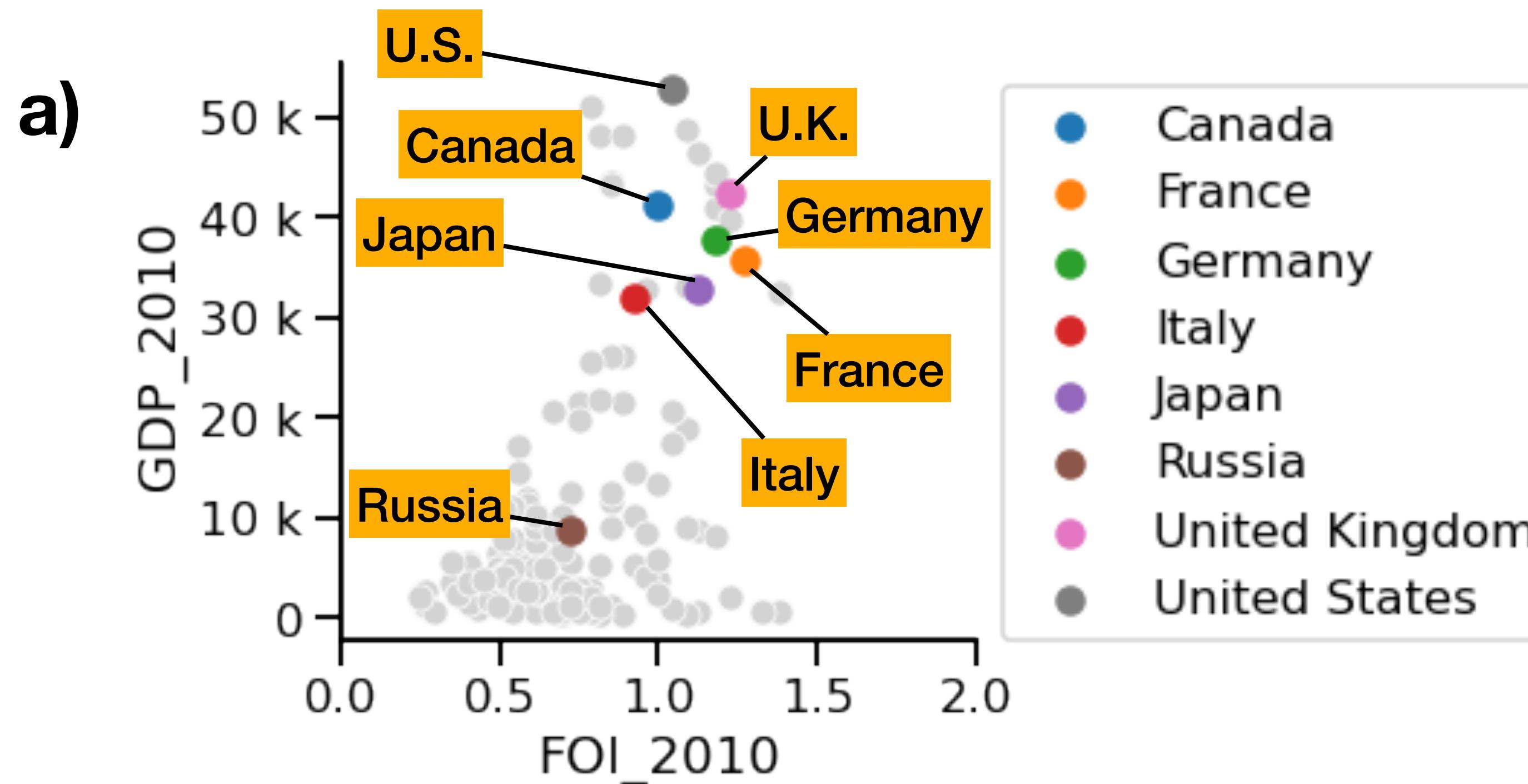
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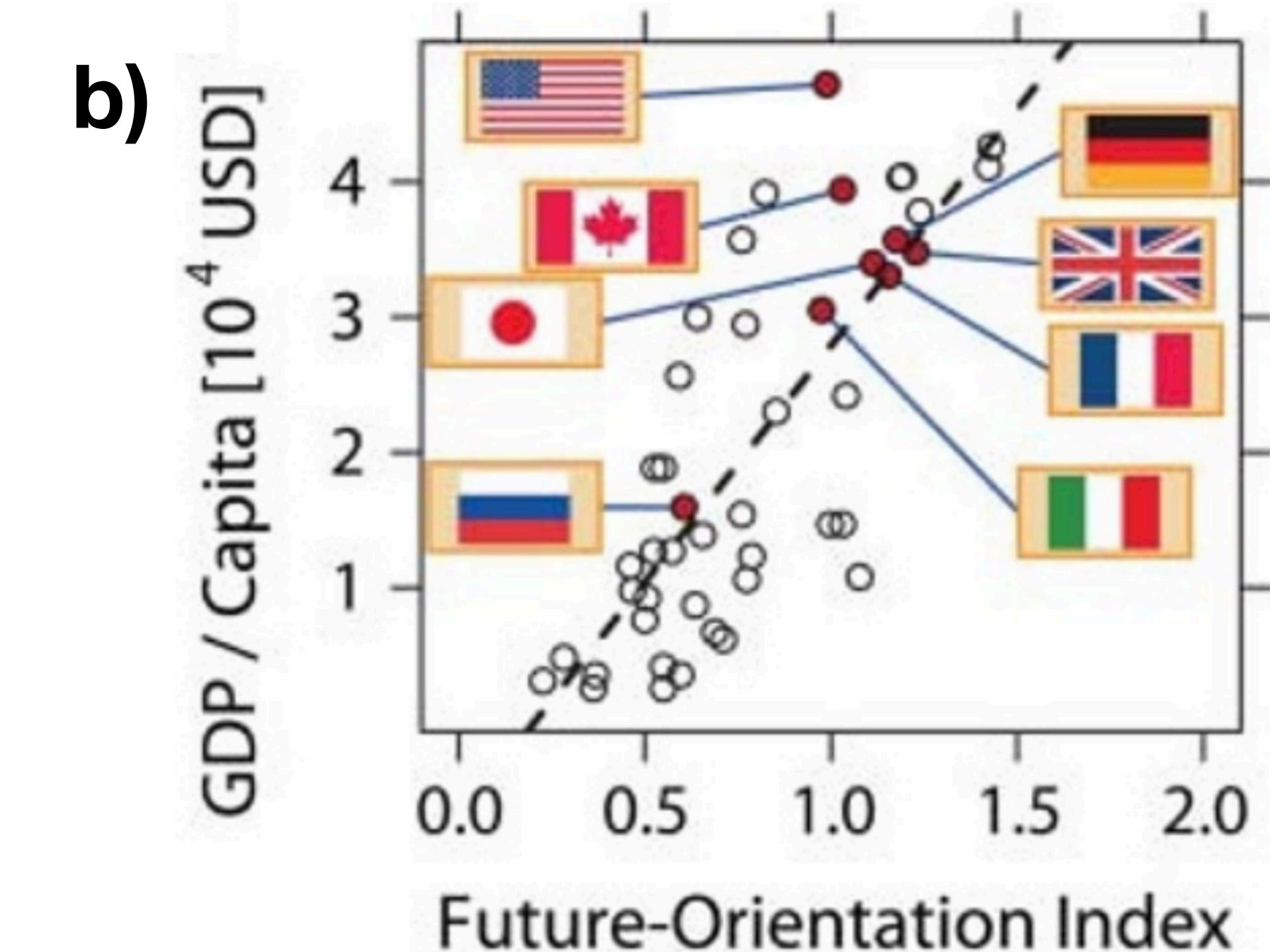
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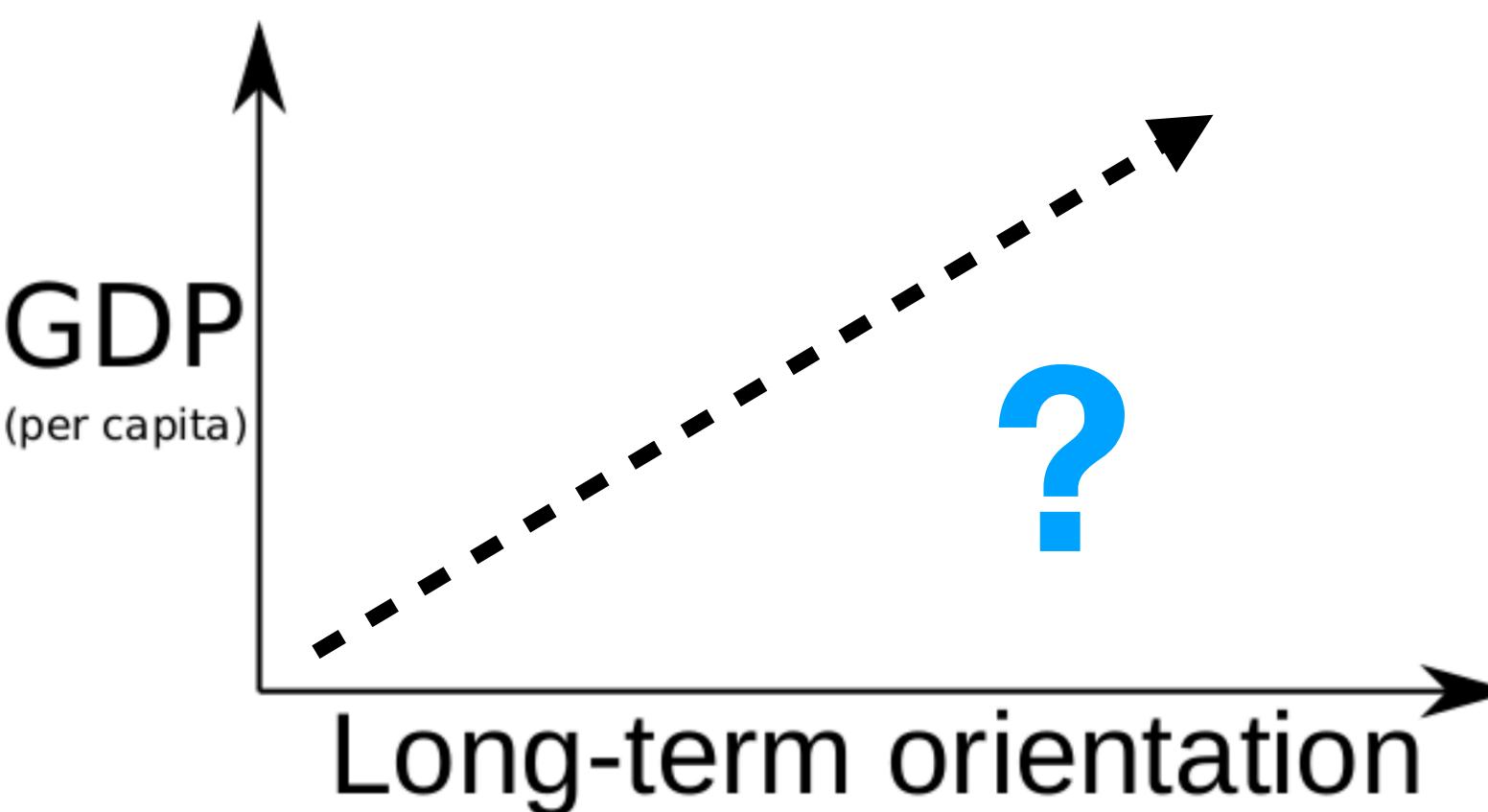


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Preis et al. 2012
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Can this **relationship** (pattern)
be numerically measured?



Outline

Today's class

BLOCK 1

Social Behavior

- 1. Social Science
- 2. CSS
- 3. Digital Traces
- 4. Examples

BLOCK 2

Social Trends

- 1. Google Search Trends
- 2. The Future Orientation Index
- 3. Culture and Economy

BLOCK 3

Quantifying Trends

- 1. Correlation
- 2. Causation
- 3. Regression

BLOCK 4

Behavior & Trend Dynamics

- 1. The Theory of Fashion
- 2. The Endo-Exo model
- 3. Examples

Measuring Correlation



What is correlation?

Definition

What is correlation?

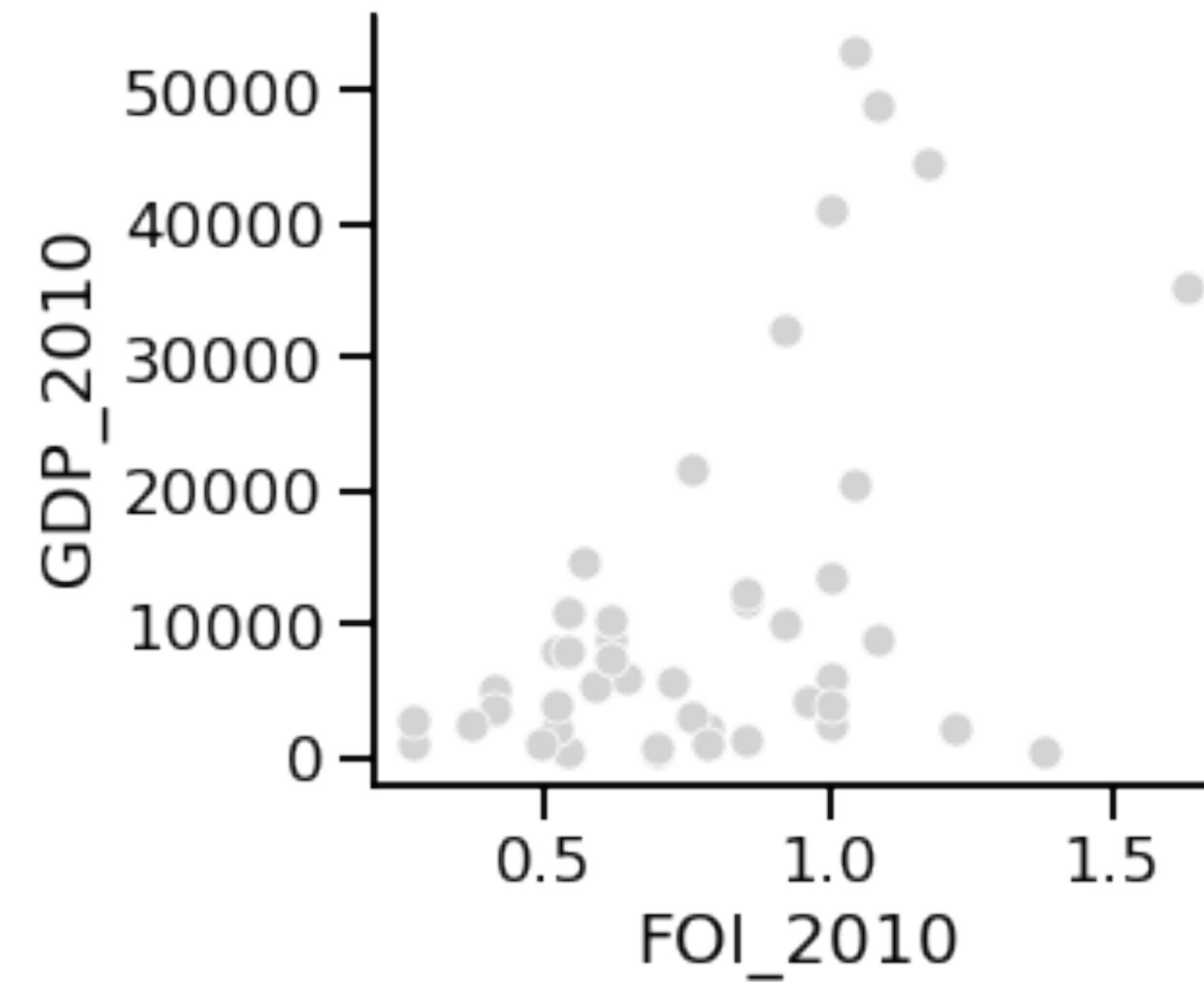
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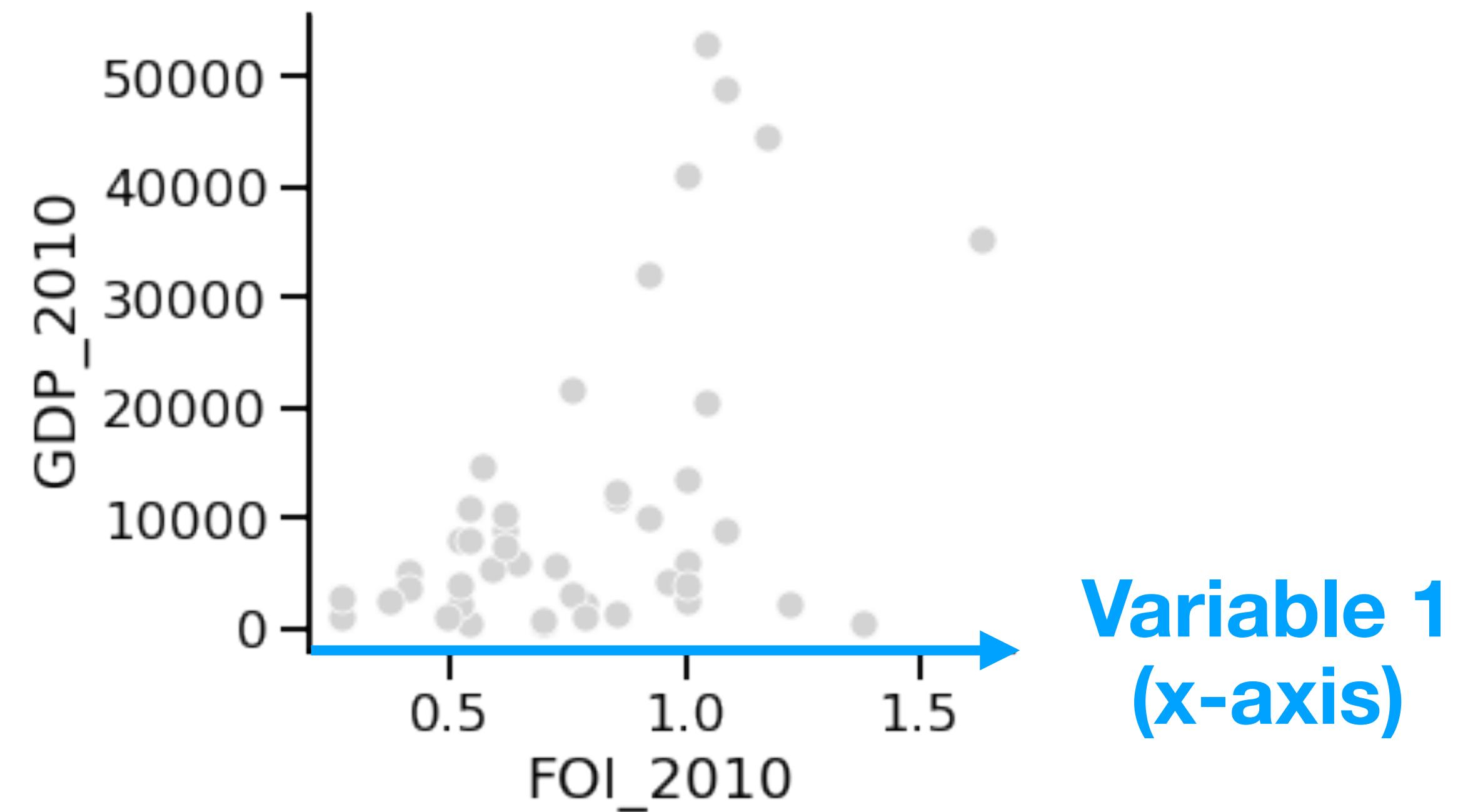
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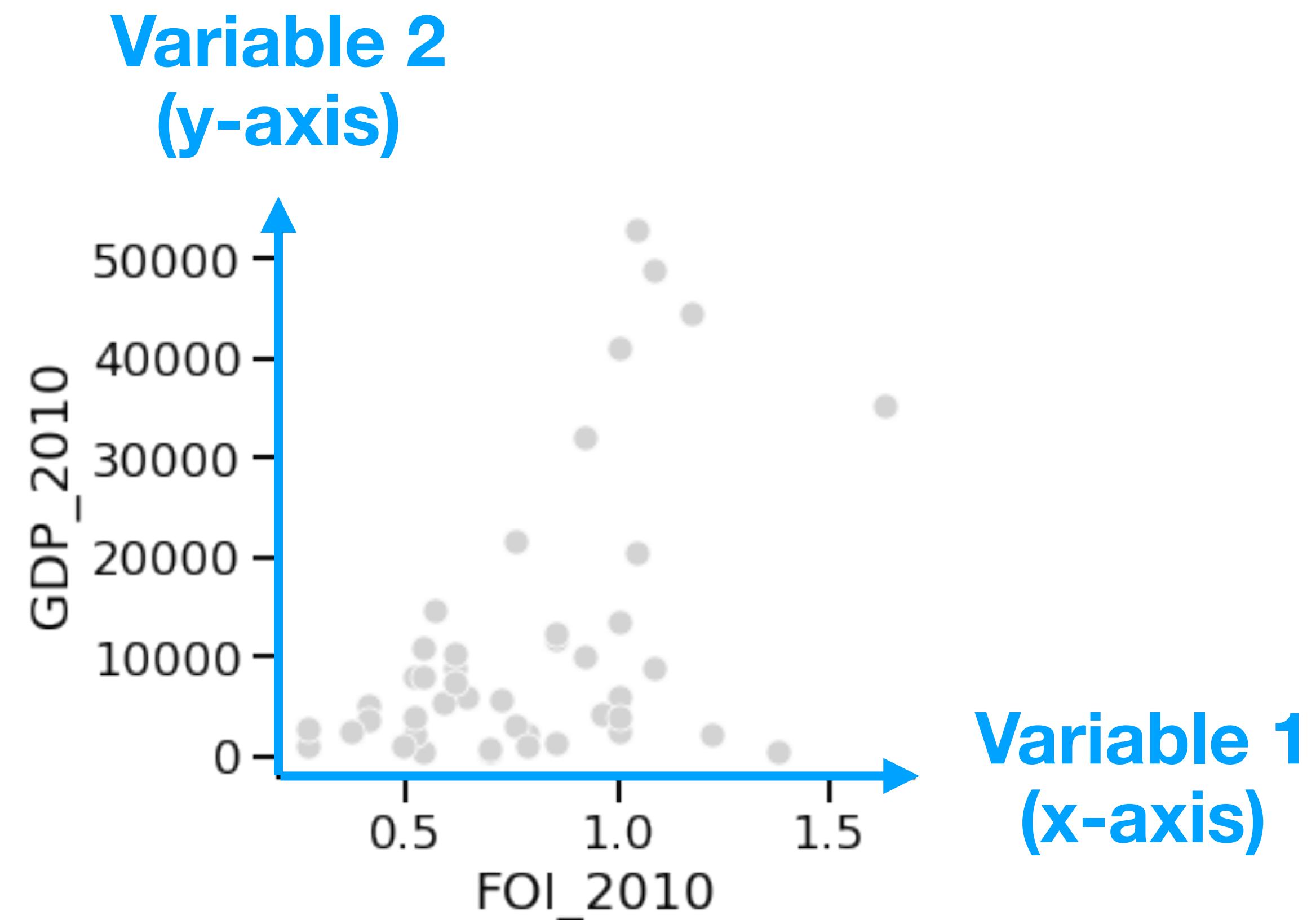
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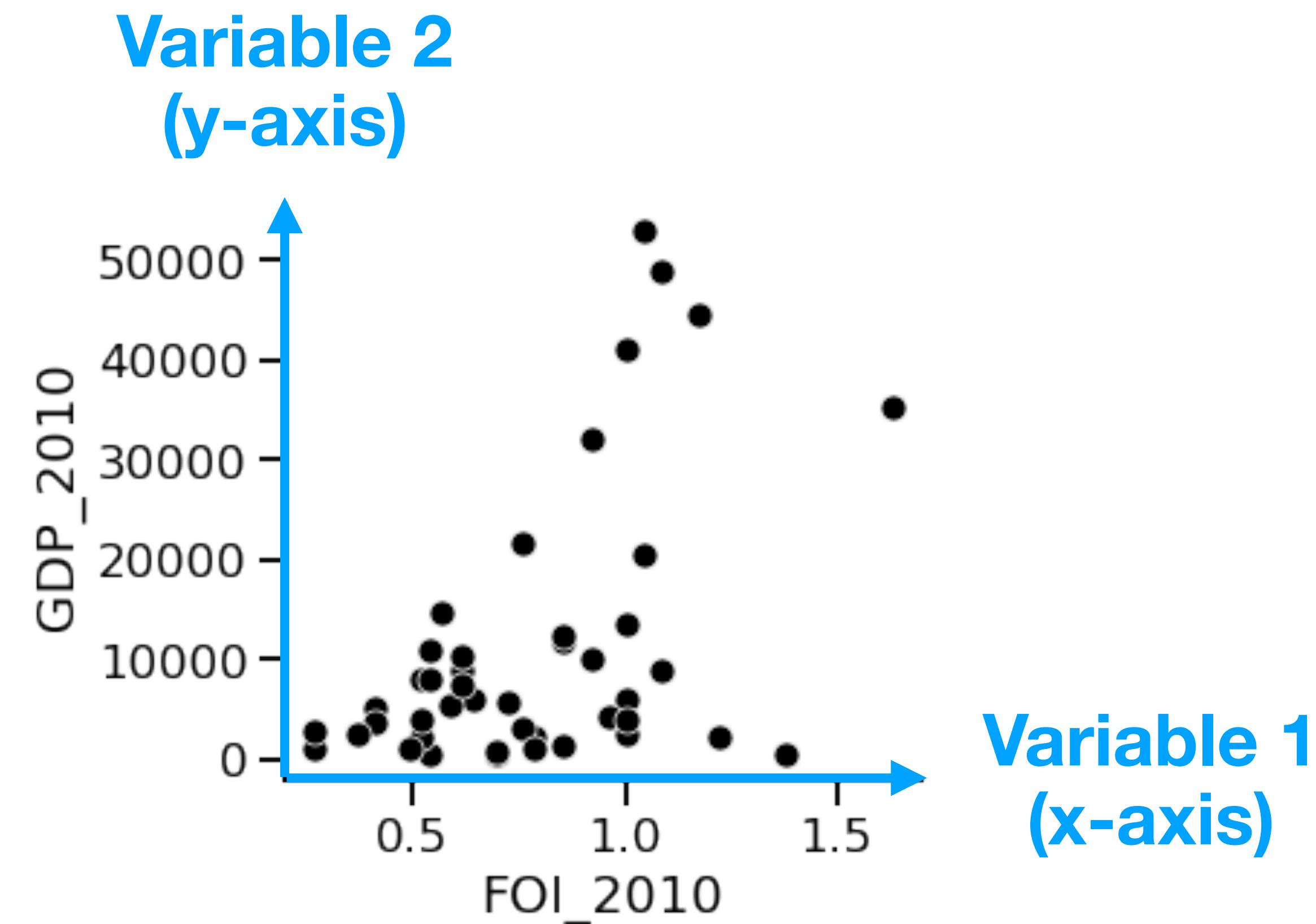
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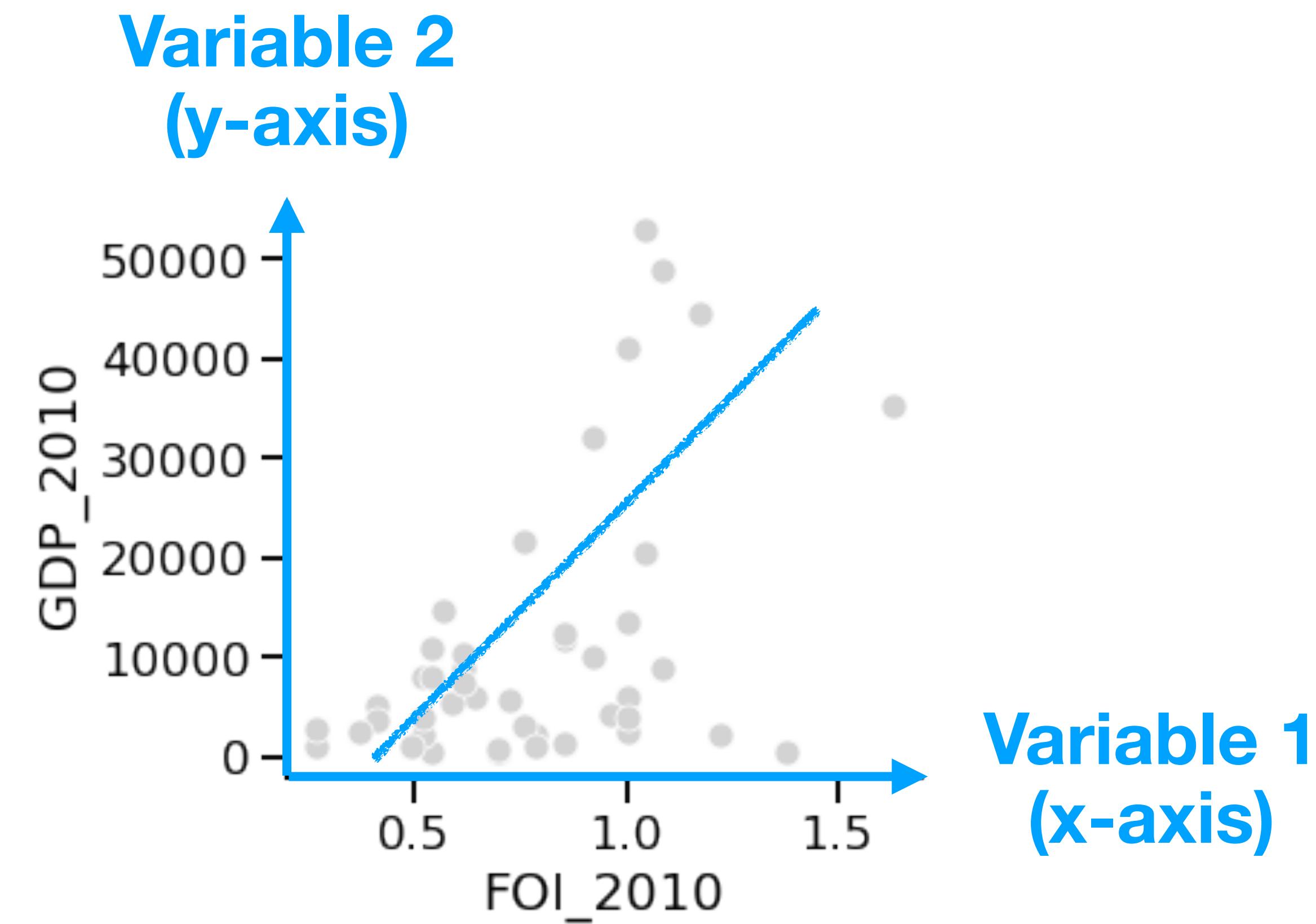
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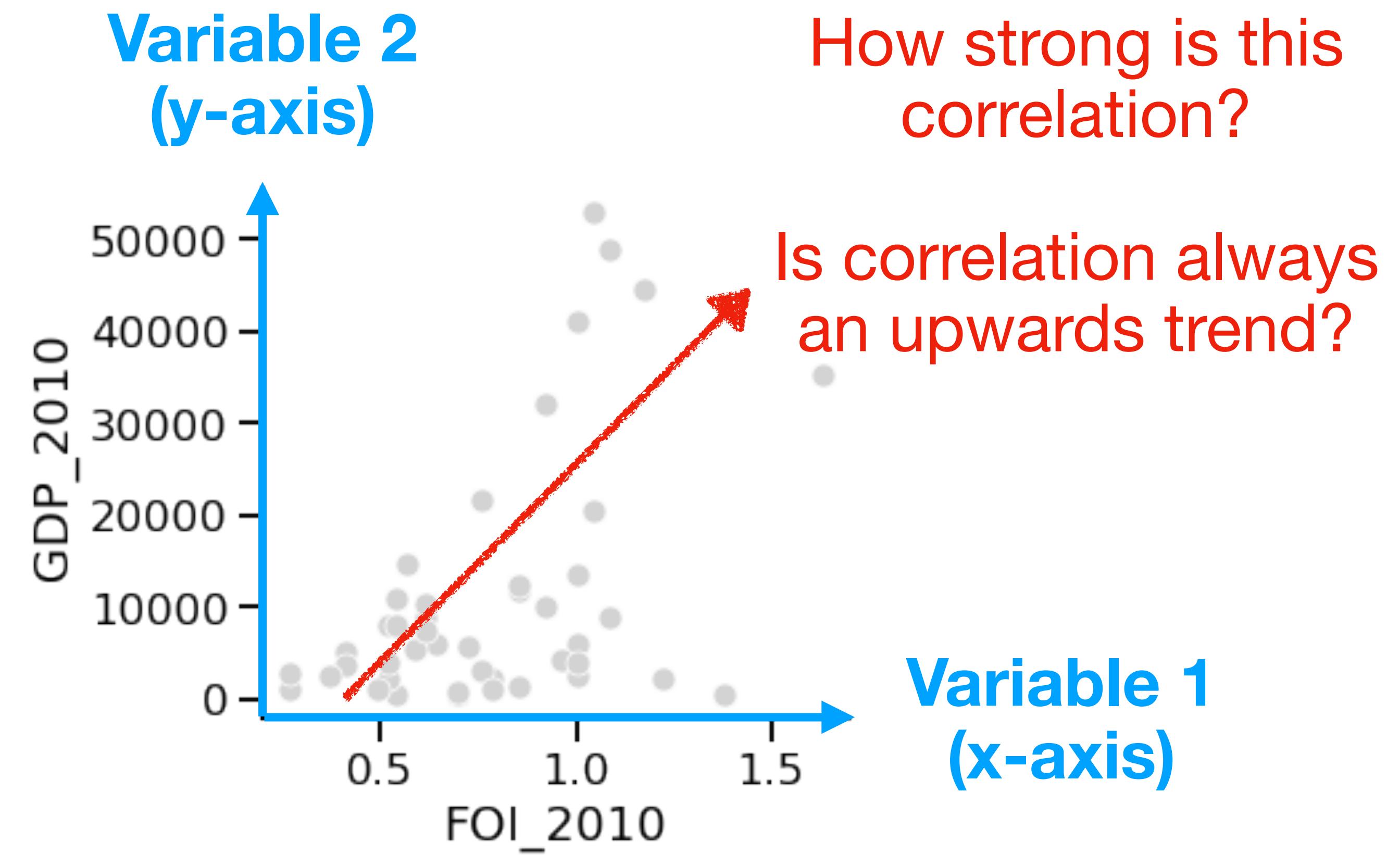
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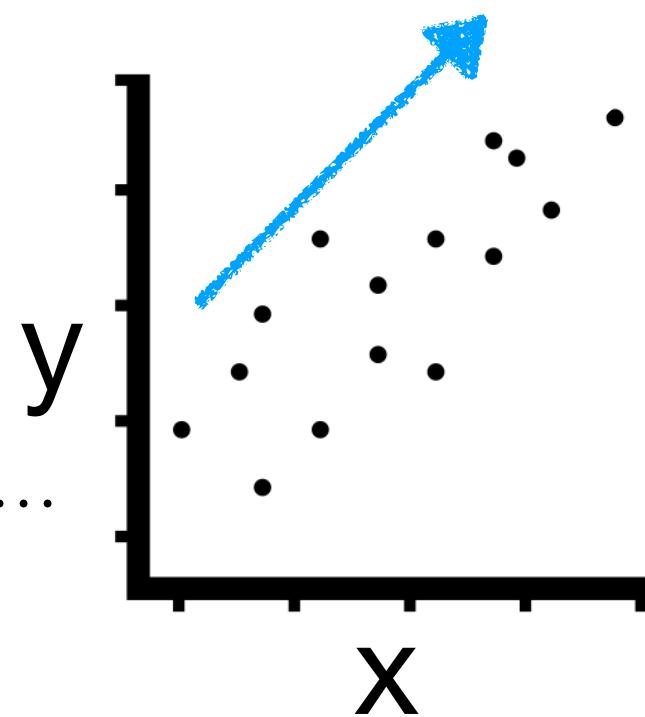
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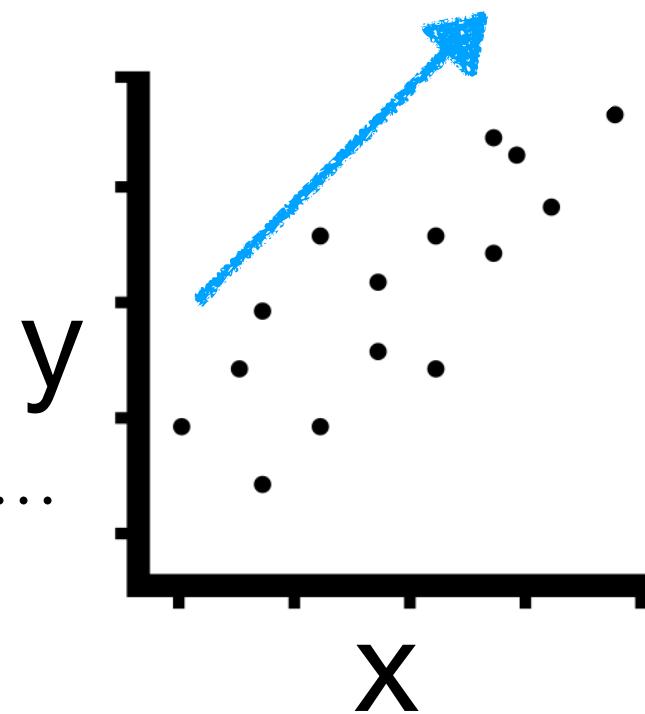


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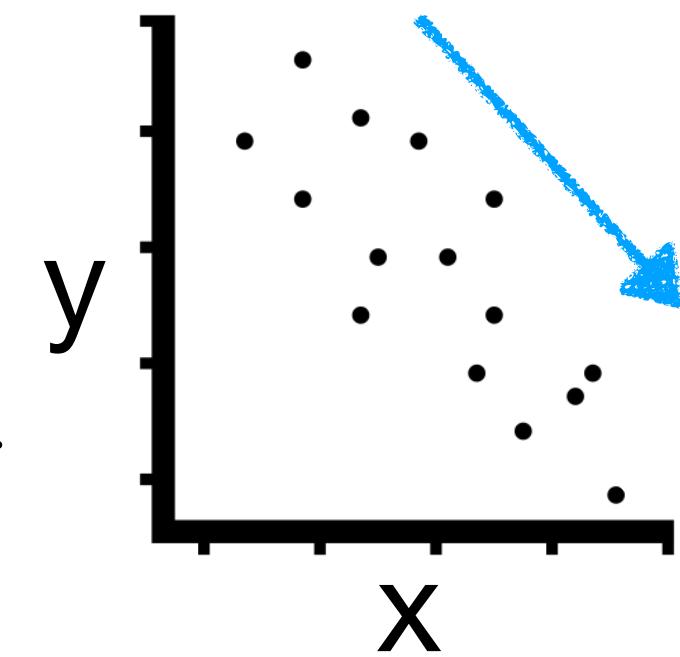
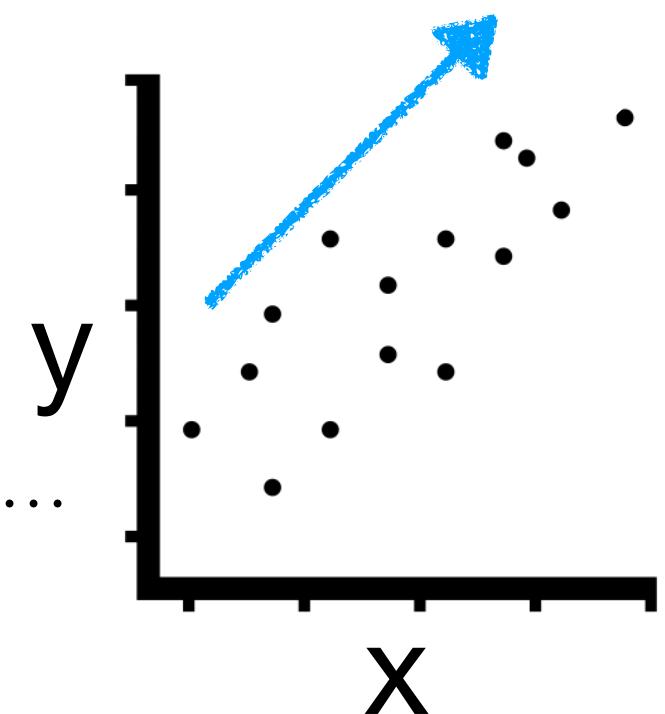


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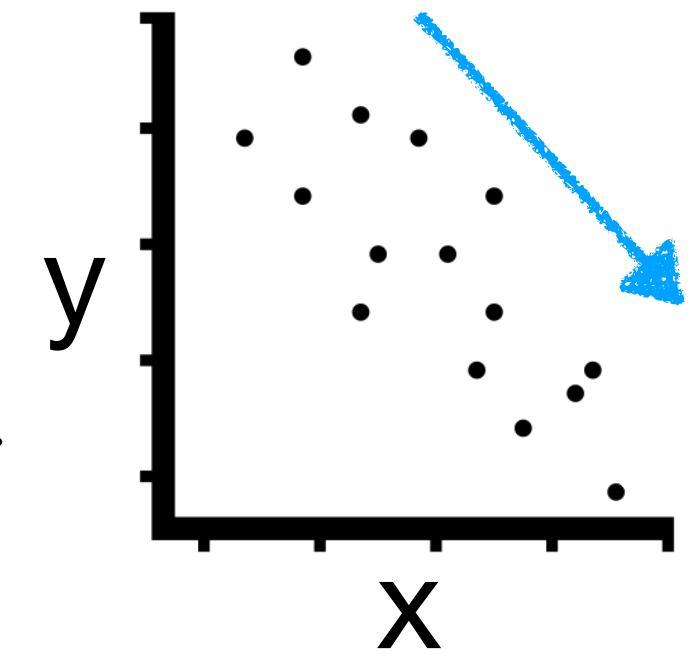
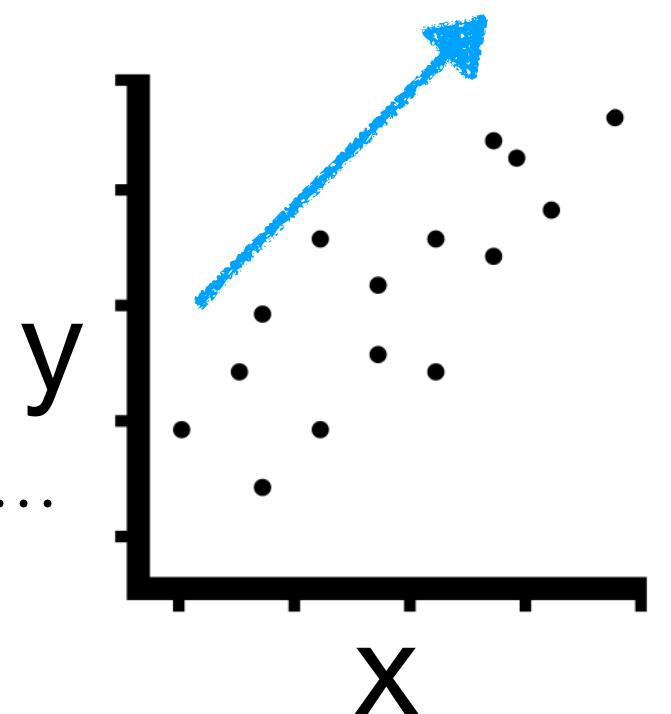


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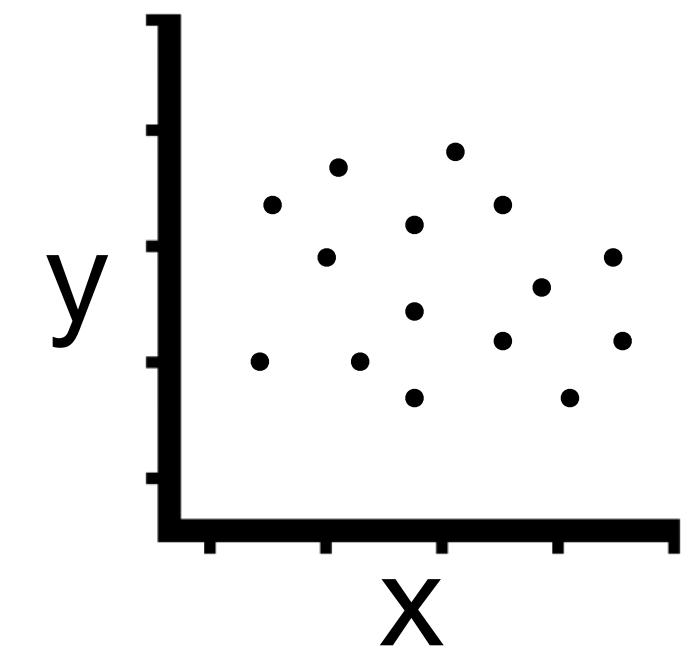
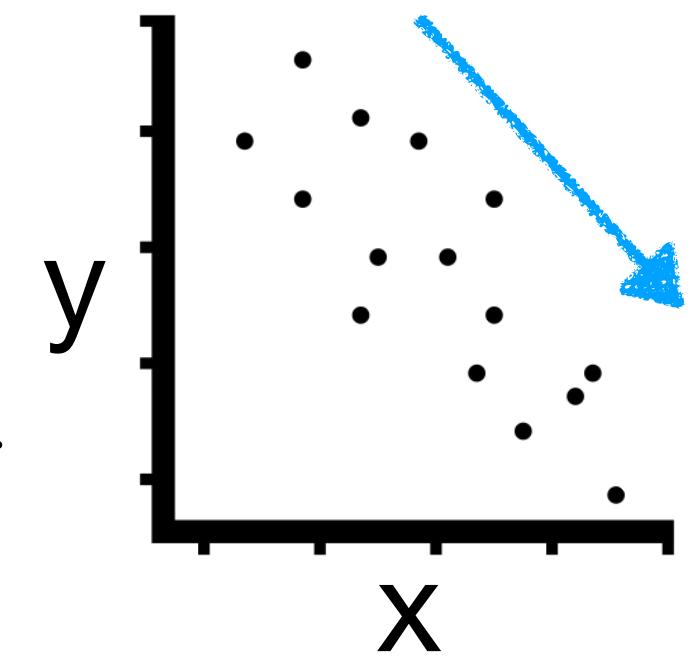
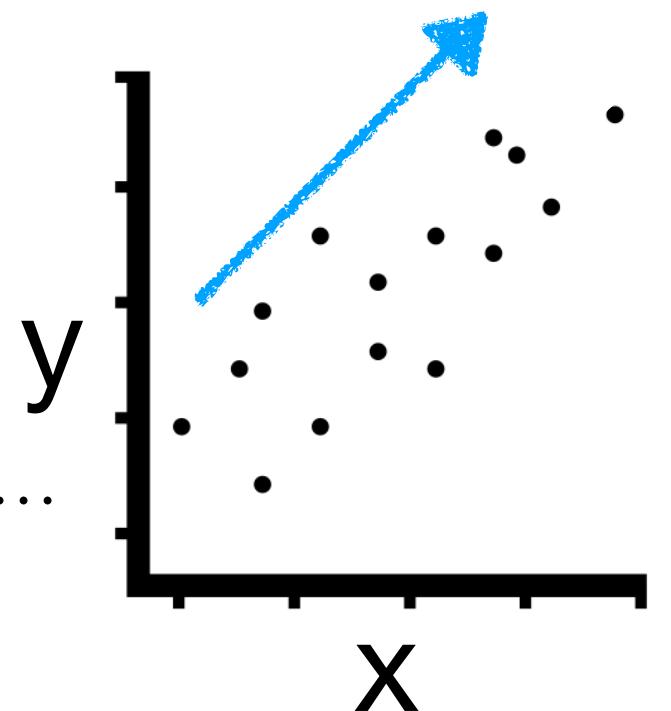


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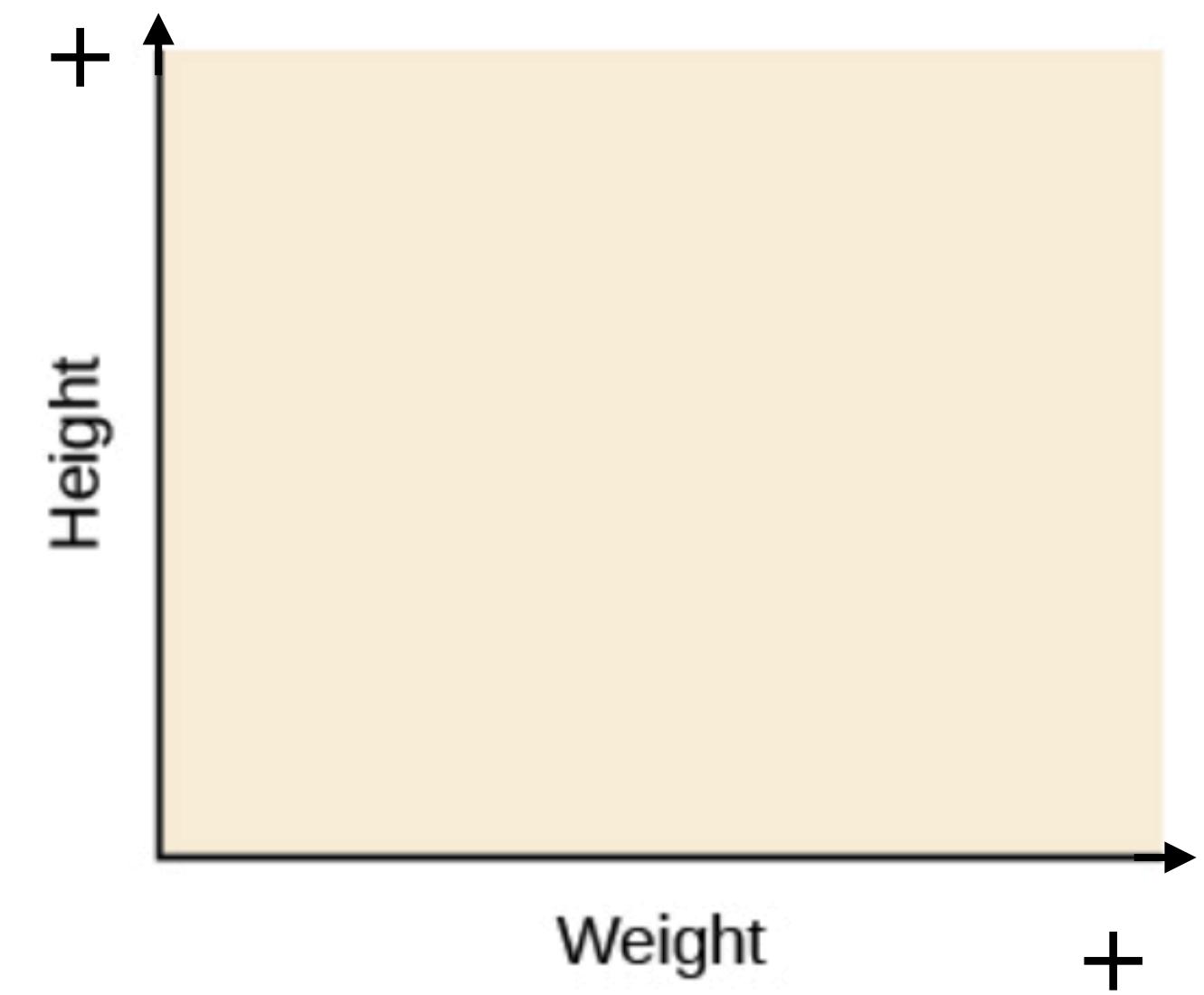
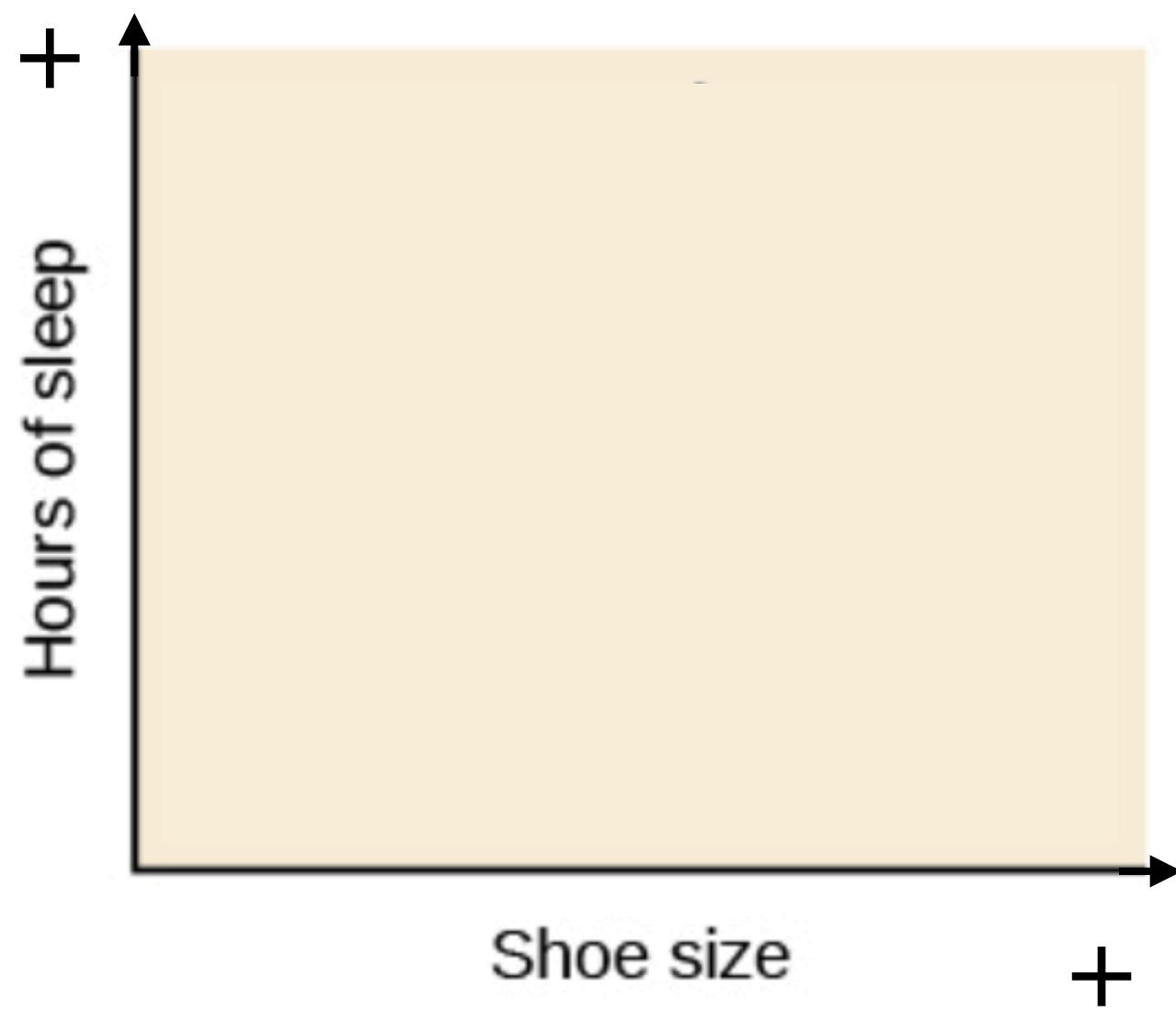
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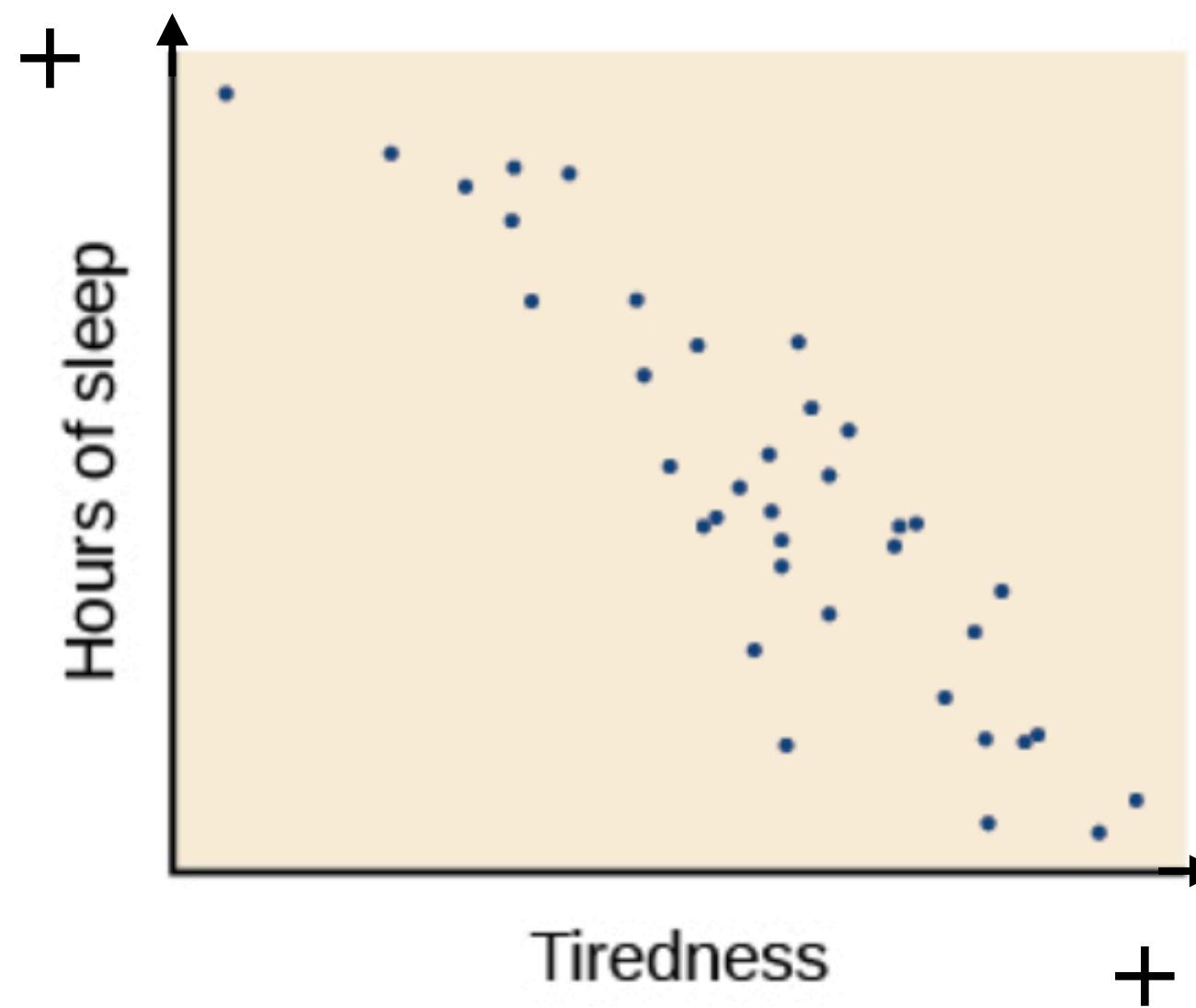
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Positive? Negative? None?

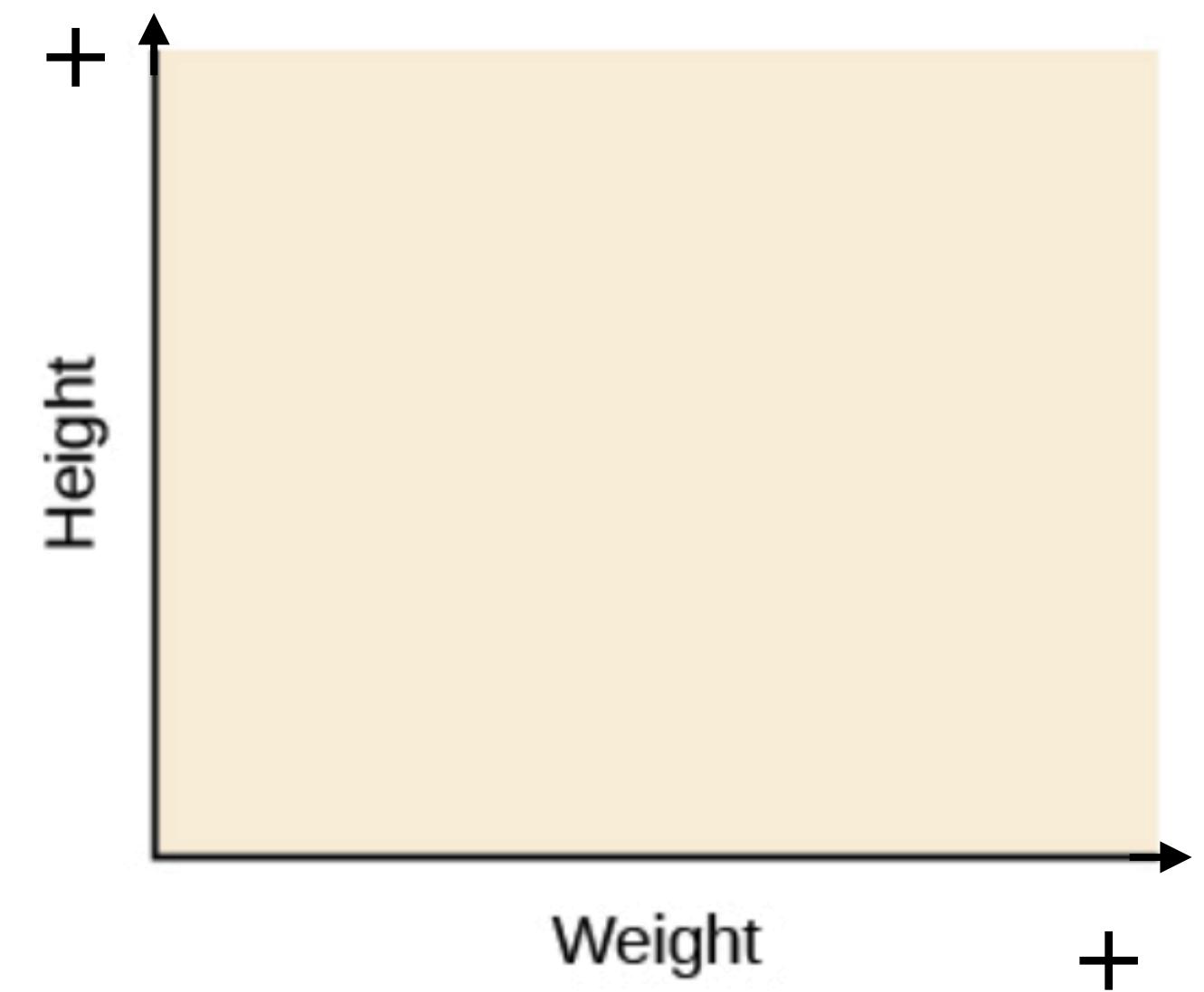
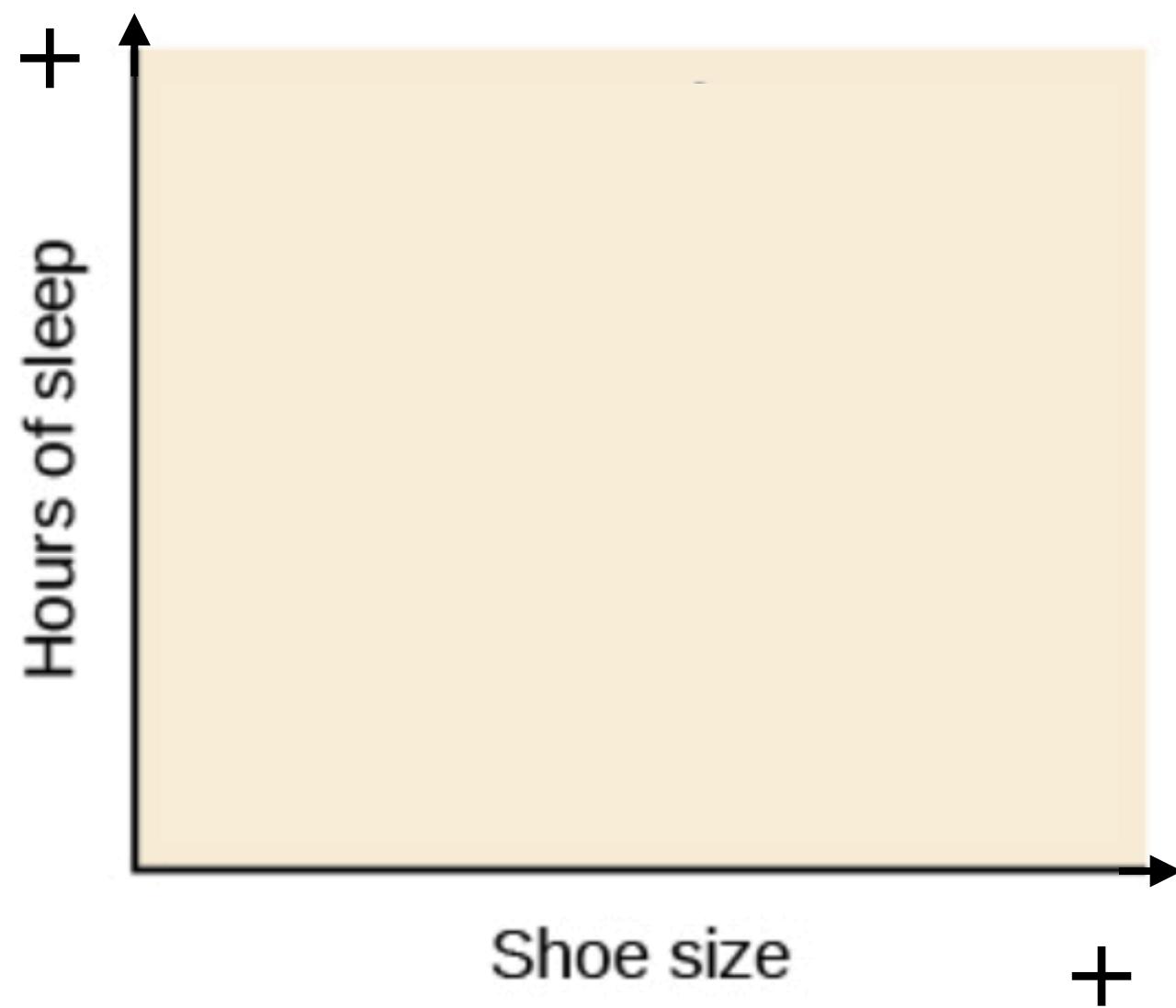


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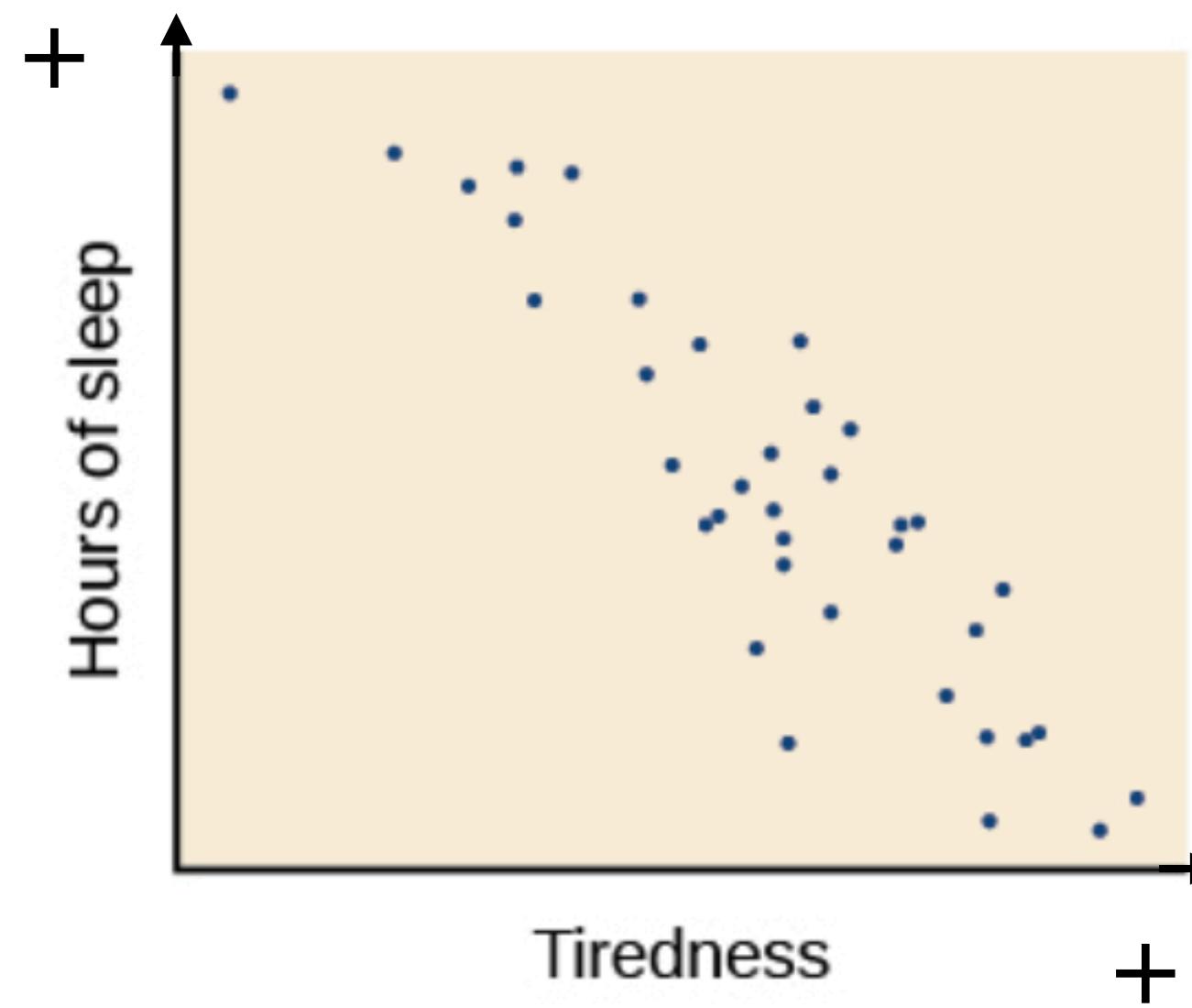


Negative
correlation

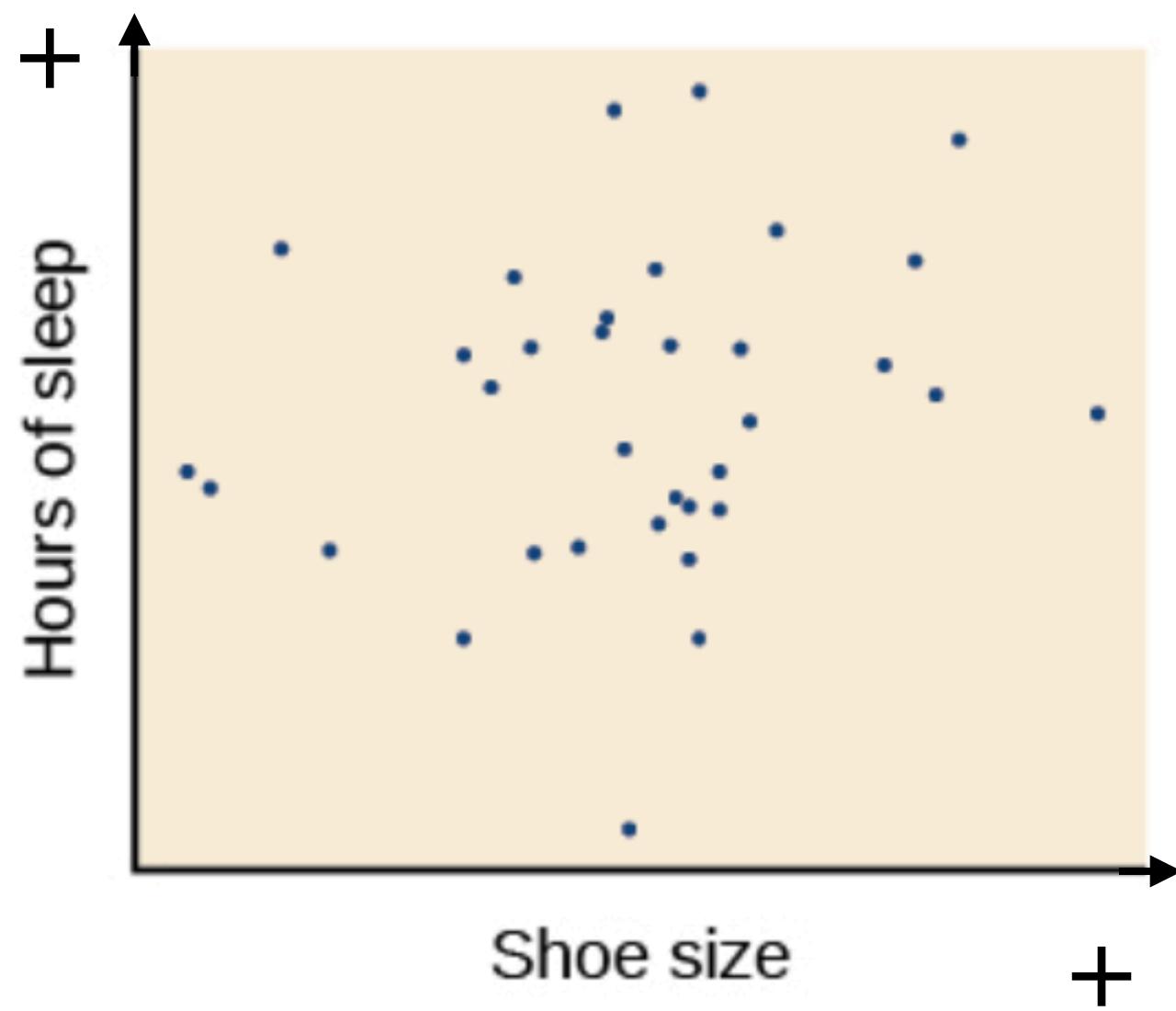


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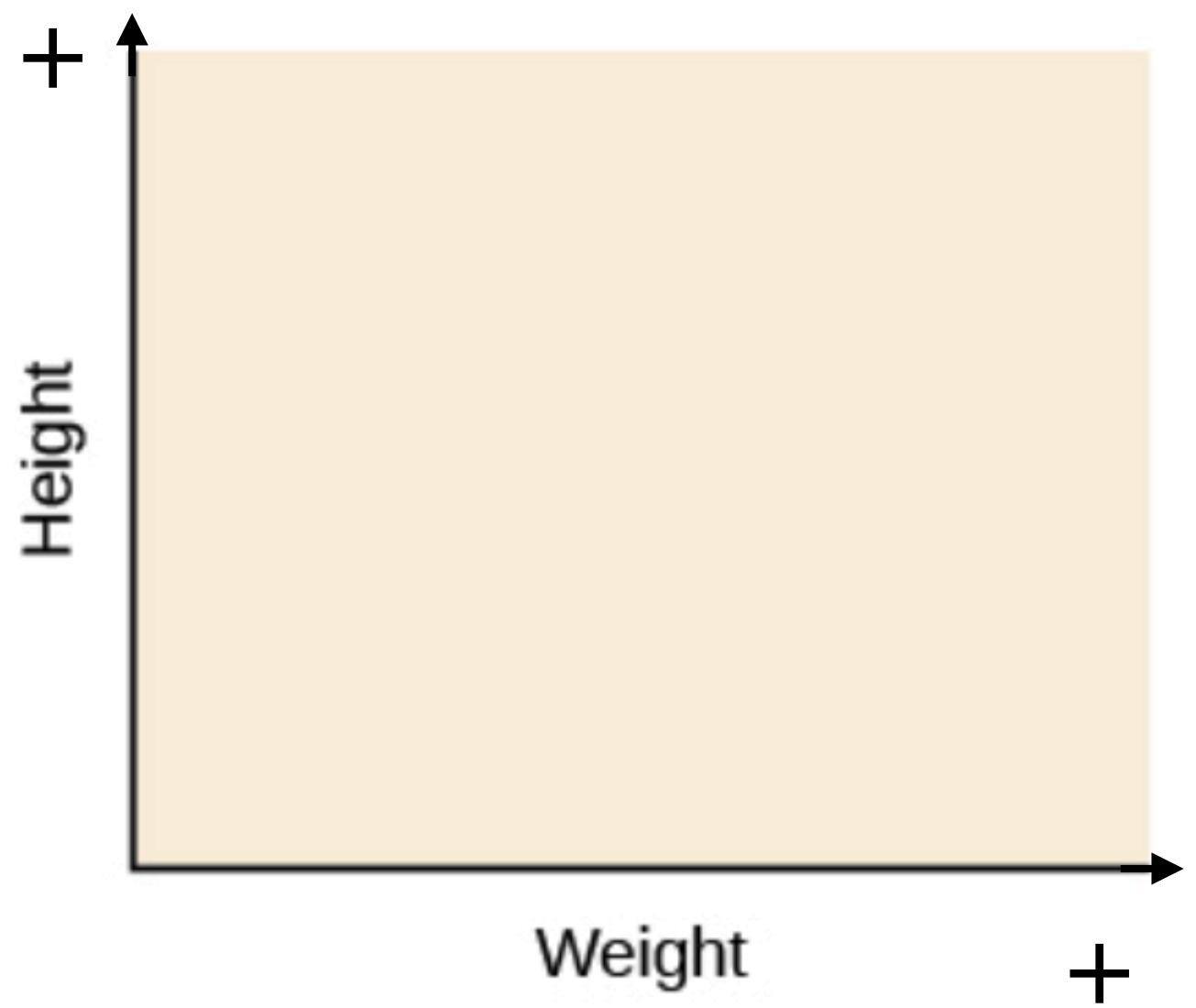
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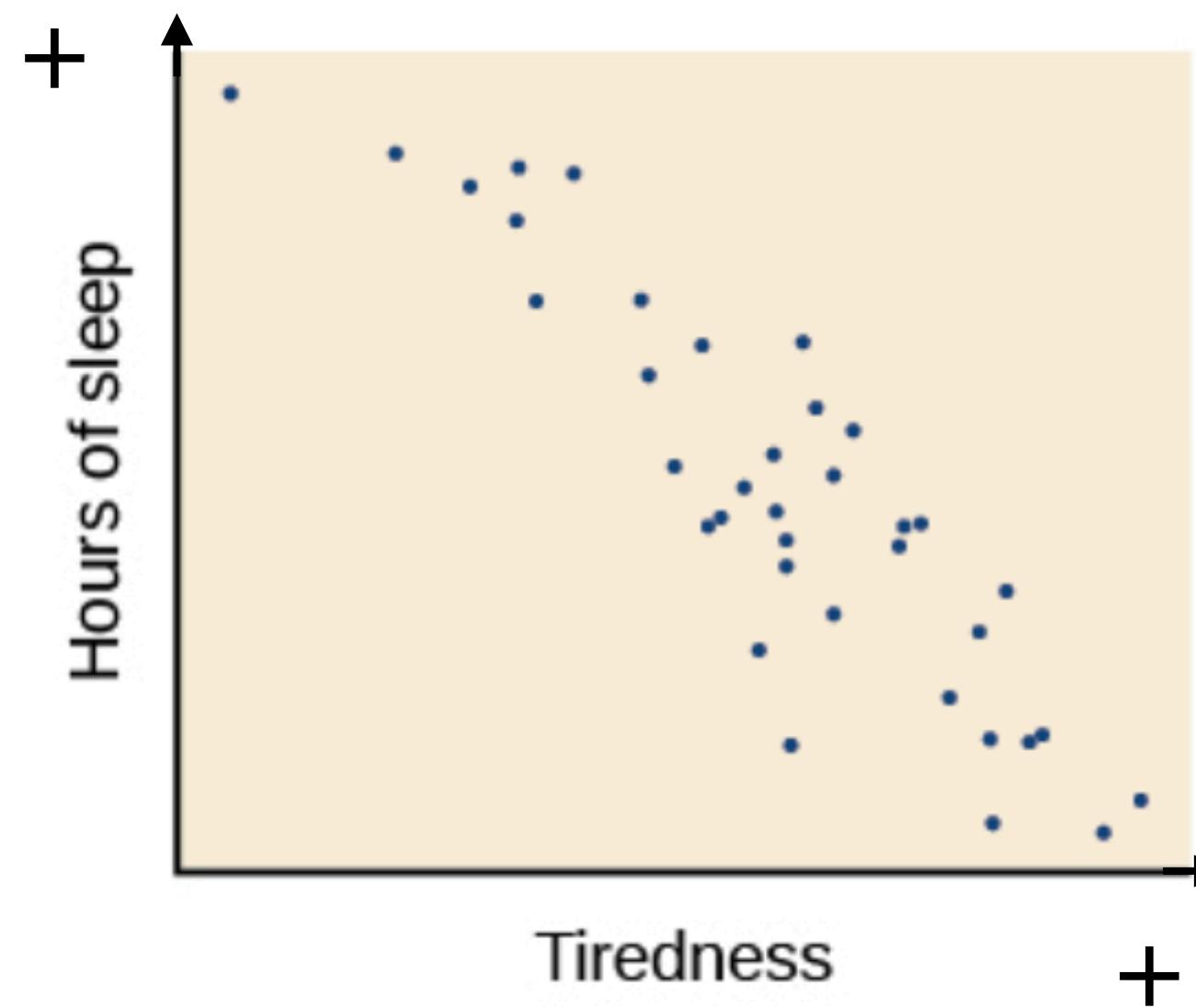


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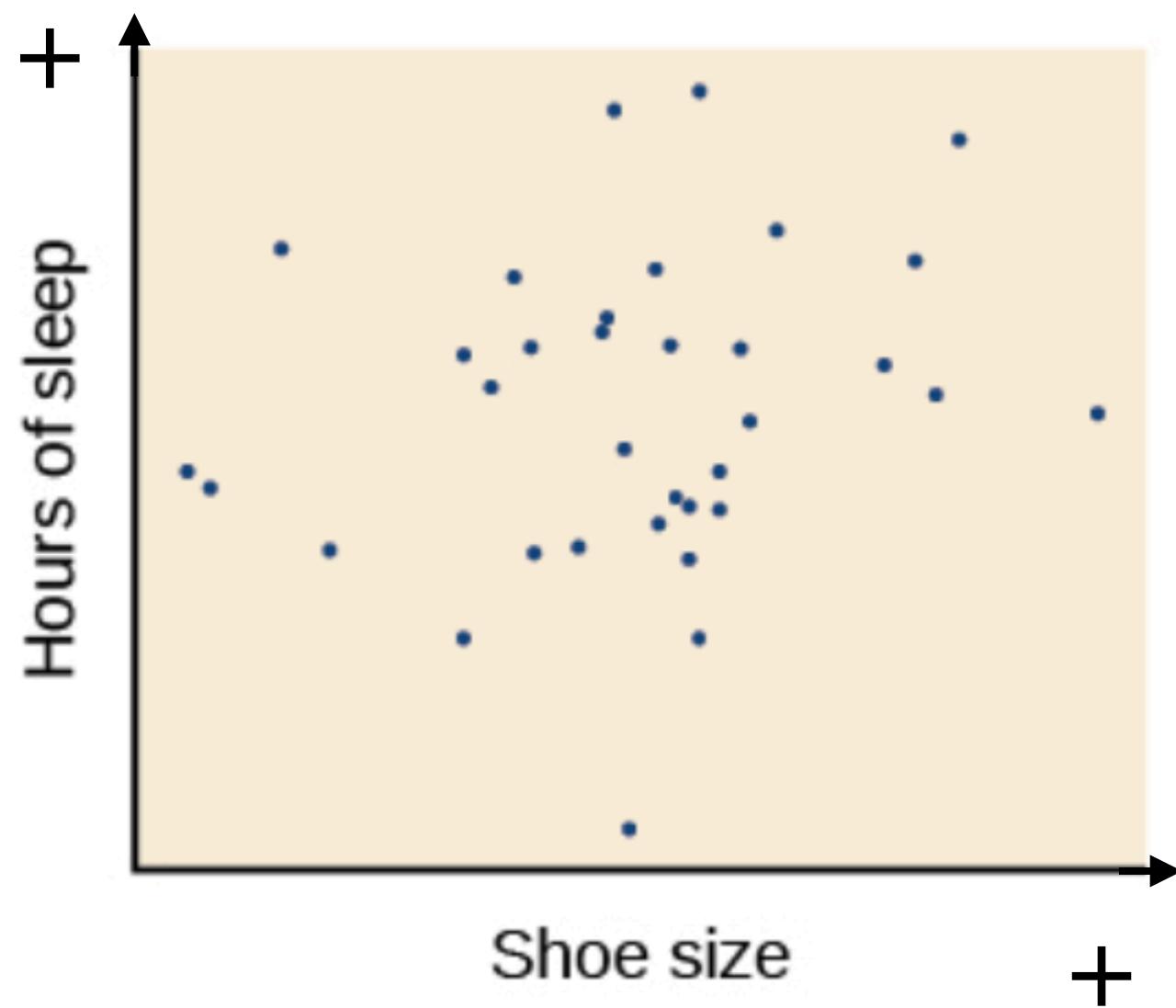


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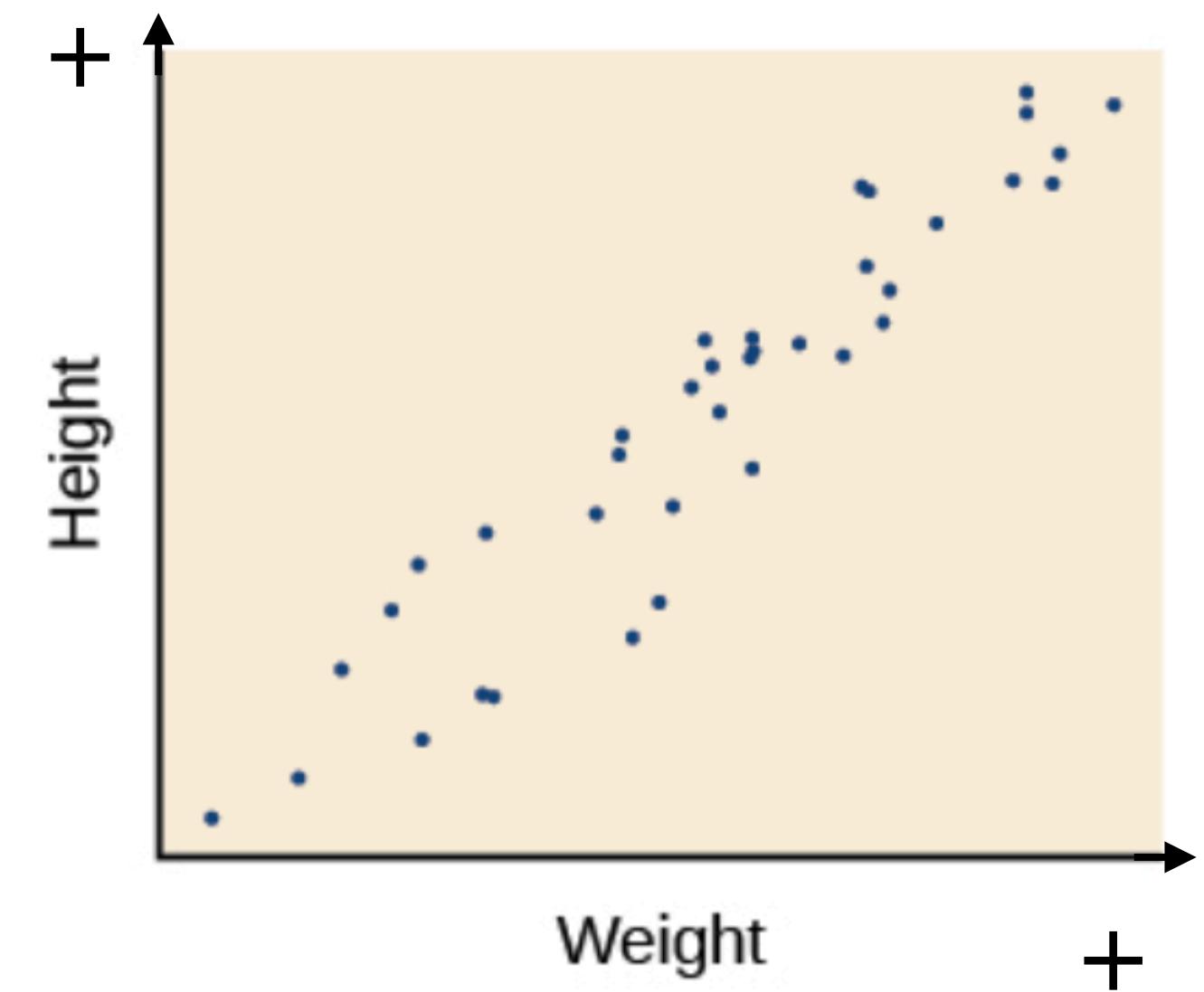
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Negative
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Positive
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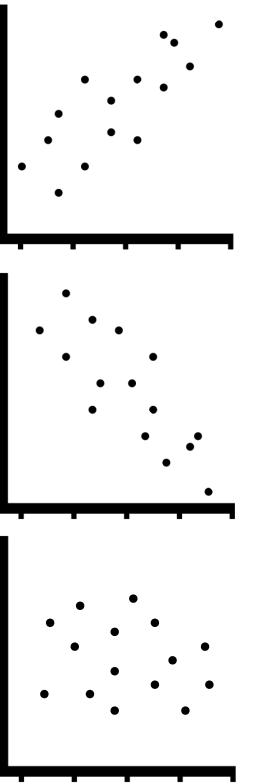
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Measuring correlation

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- $\rho > 0$ positive correlation
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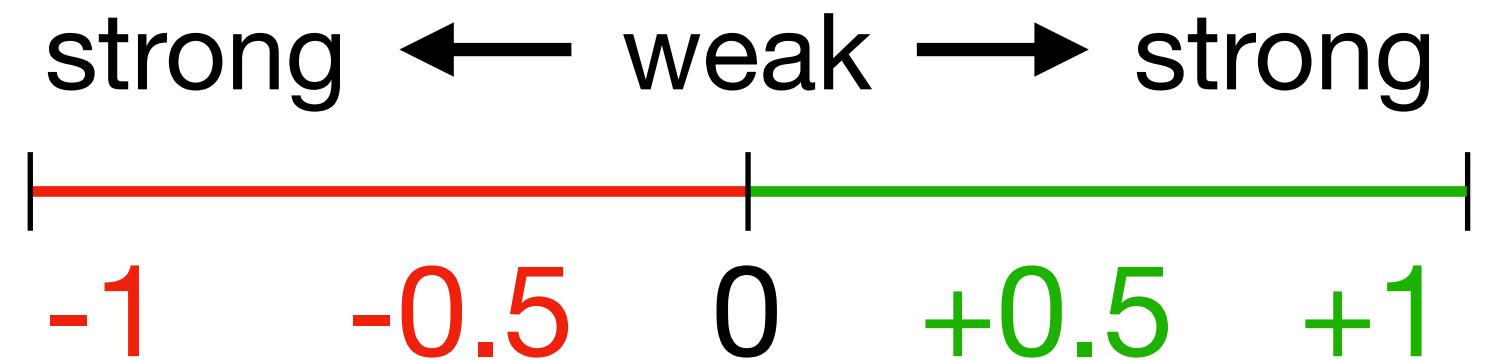
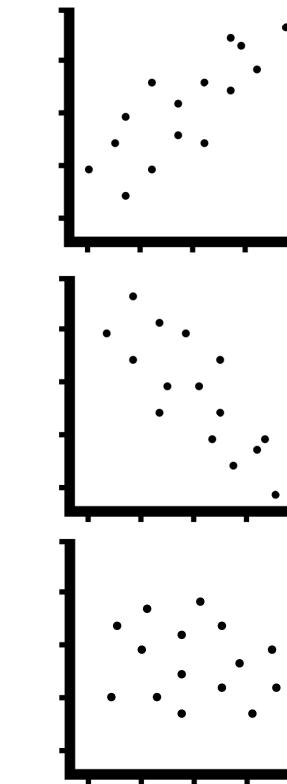


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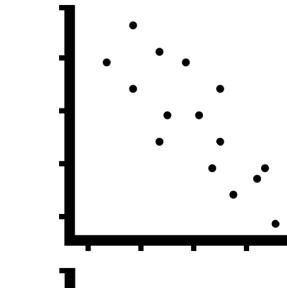
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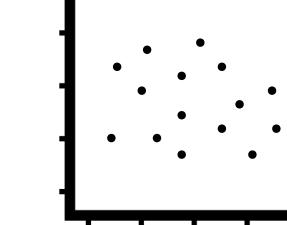
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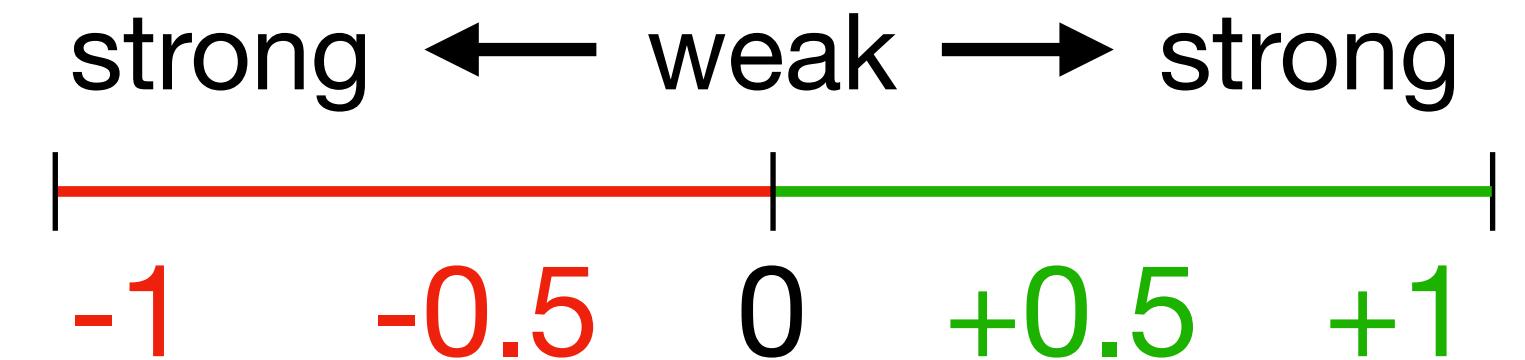


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- The correlation coefficient is usually represented by the letter r or greek letter ρ (rho).



Pearson's correlation coefficient

$$\rho(X, Y)$$

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The diagram illustrates the formula for Pearson's correlation coefficient, $\rho(X, Y)$. A blue arrow points from the text 'Pearson's correlation between X and Y ' to the symbol $\rho(X, Y)$. Another blue arrow points from the text 'Expected values of the product' to the term $E[XY] - E[X]E[Y]$. A third blue arrow points from the text 'The product of the standard deviations of X and Y ' to the denominator $\sigma_X \sigma_Y$.

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Some univariate statistics notation

to understand the Pearson's correlation coefficient

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- It is measured in squared units of X
- σ_X is the standard deviation of X
 - $\sigma_X = \sqrt{V[X]}$, which is convenient because it measures dispersion in the same units as X
 - You can calculate it with the functions `std()` from `numpy` or `stdev()` from `statistics`

Some univariate statistics notation (iii)

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- If X and Y are **independent**, then they satisfy that the expectation of the product equals the product of expectations:

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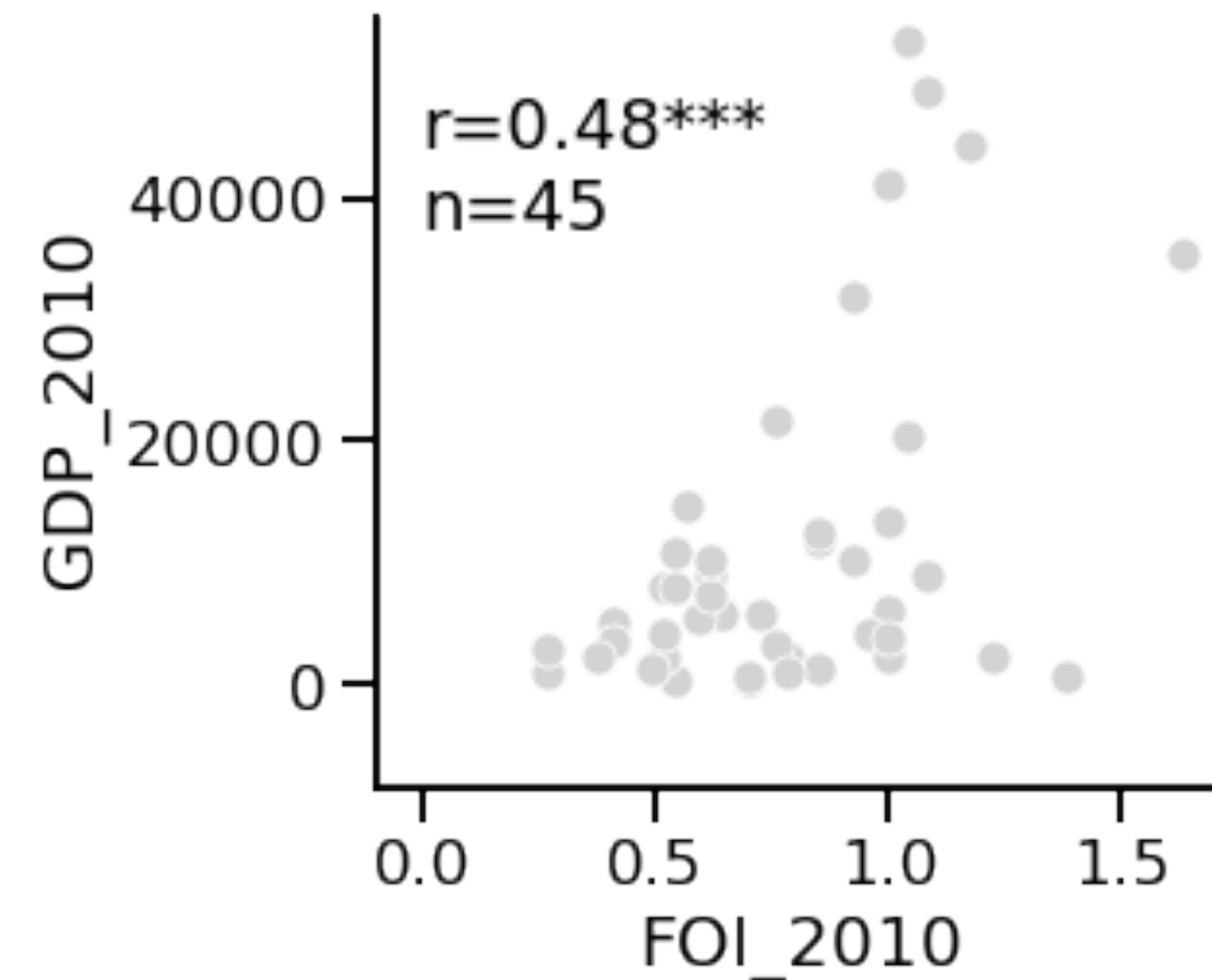
- The principle: correlation as the deviation from $E[XY] - E[X]E[Y] = 0$ (*no correlation*)
- The absolute value of this difference can be at most $\sigma_X\sigma_Y$ (*normalizing factor*)
- Thus, $\sigma_X\sigma_Y$ rescales the difference to be between -1 and 1

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$$\rho(X, Y) = \frac{E[XY] - E[X]E[Y]}{\sigma_X\sigma_Y}$$

Correlation between FOI and GDP

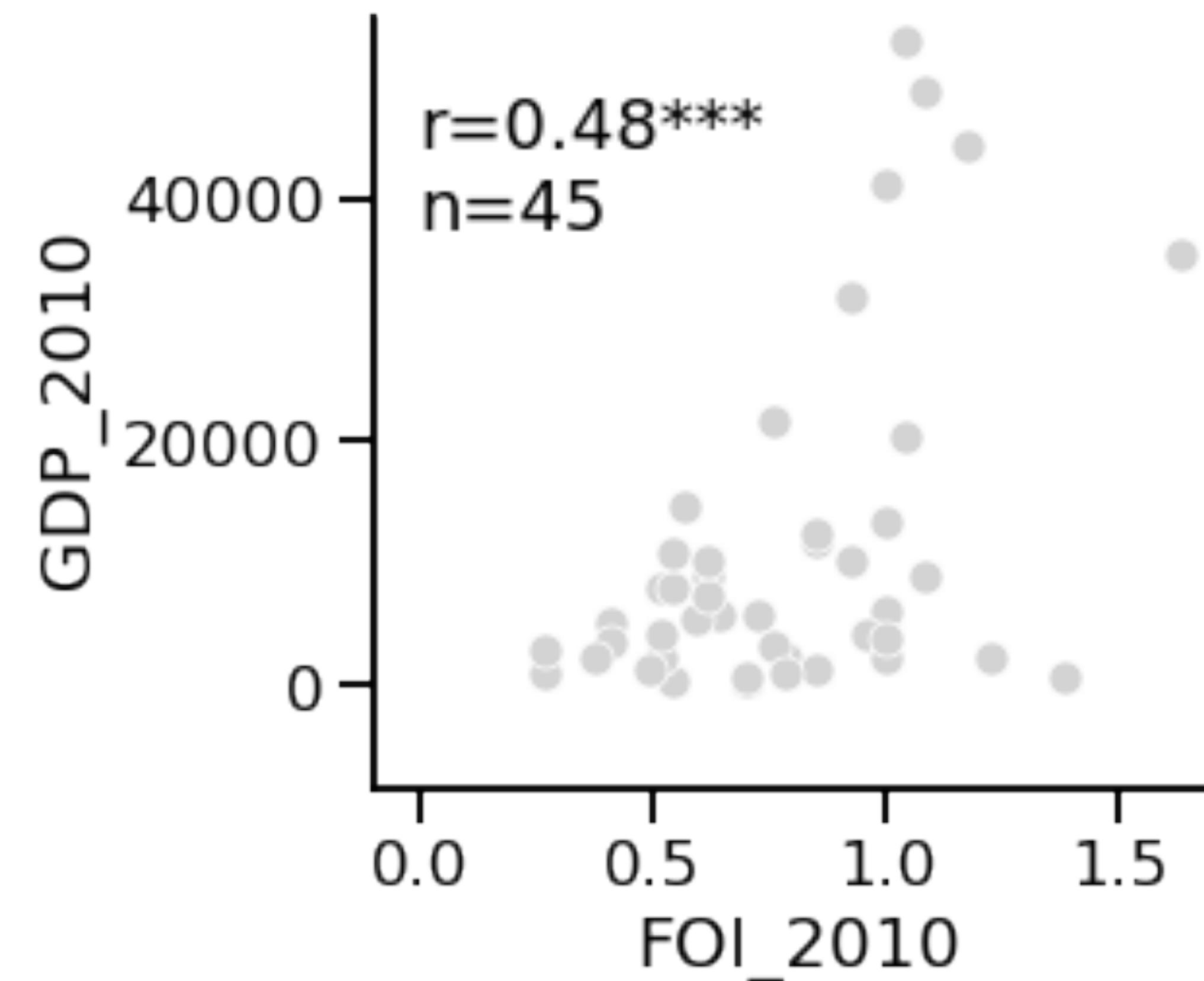
Pearson's correlation coefficient



Correlation between FOI and GDP

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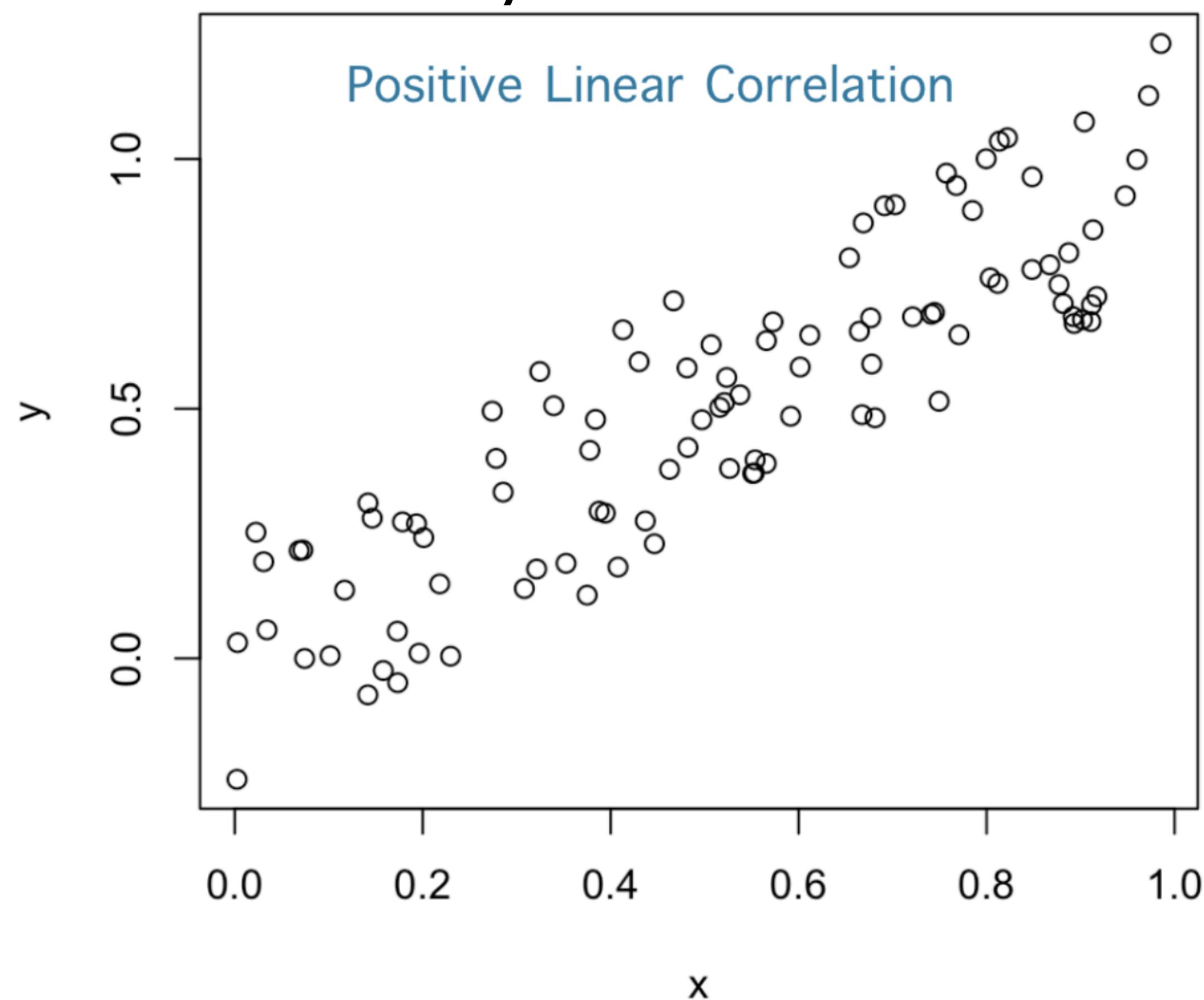
Positive and moderate correlation



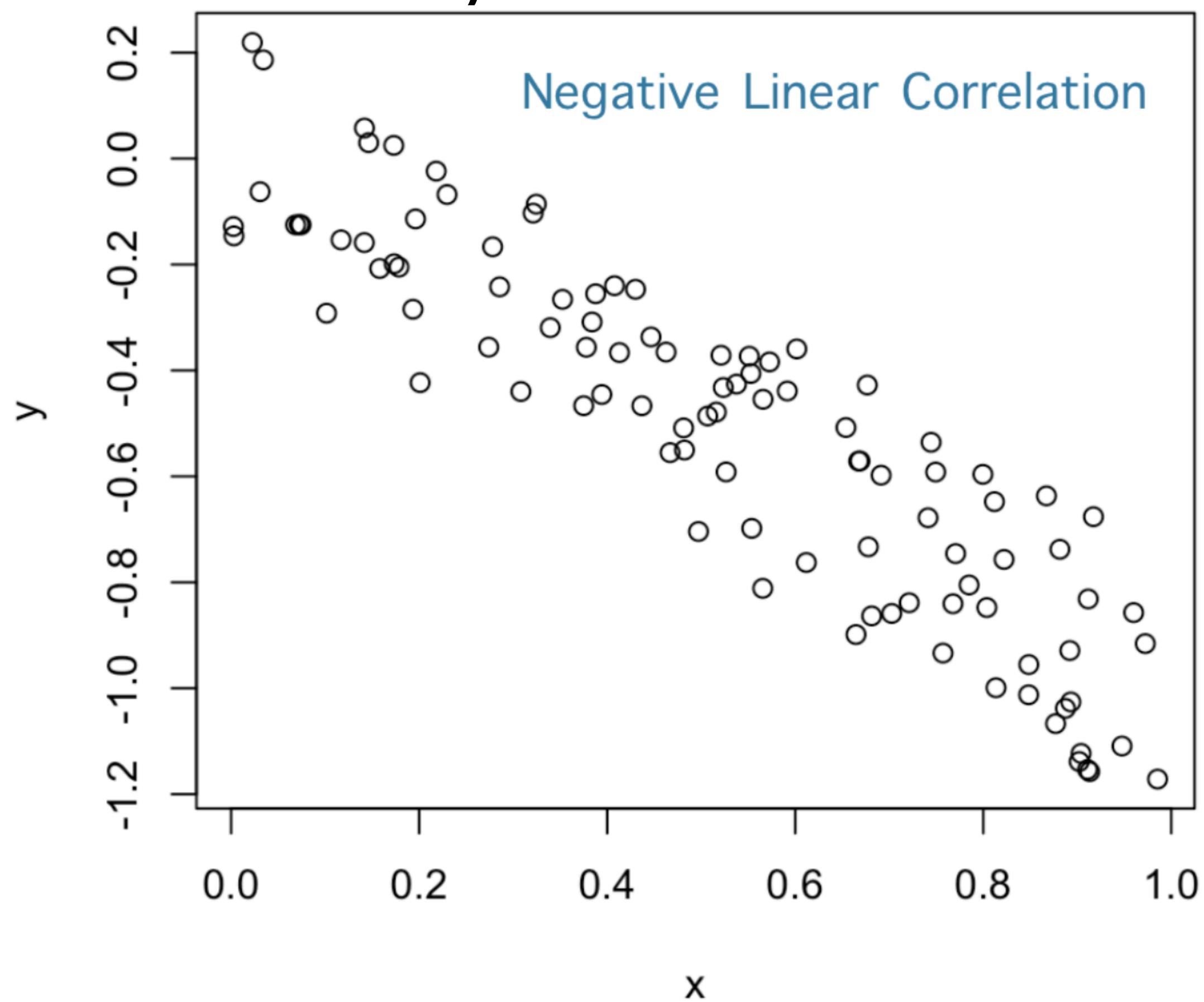
More examples

Pearson's correlation coefficient

$$\rho = 0.8765$$



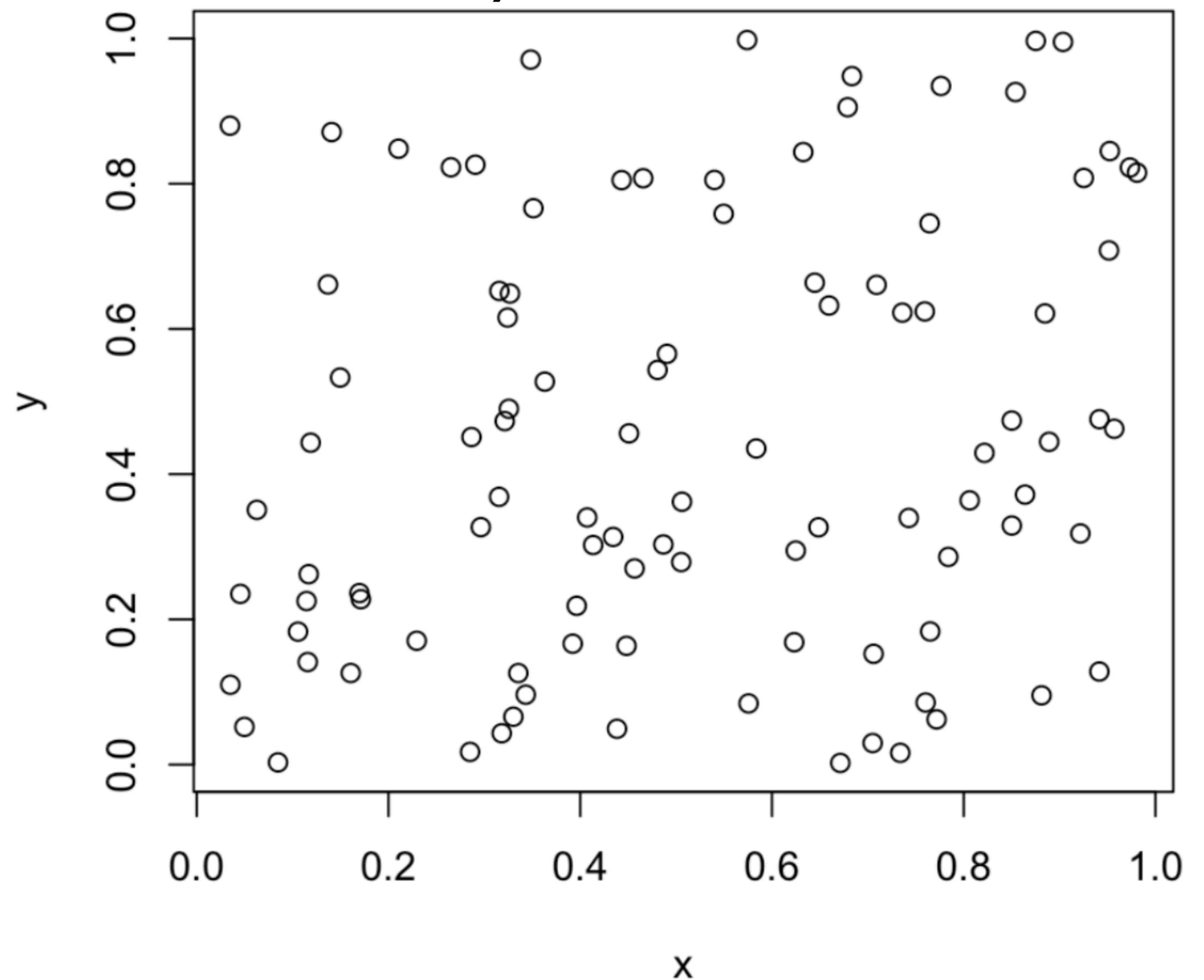
$$\rho = -0.9046$$



More examples

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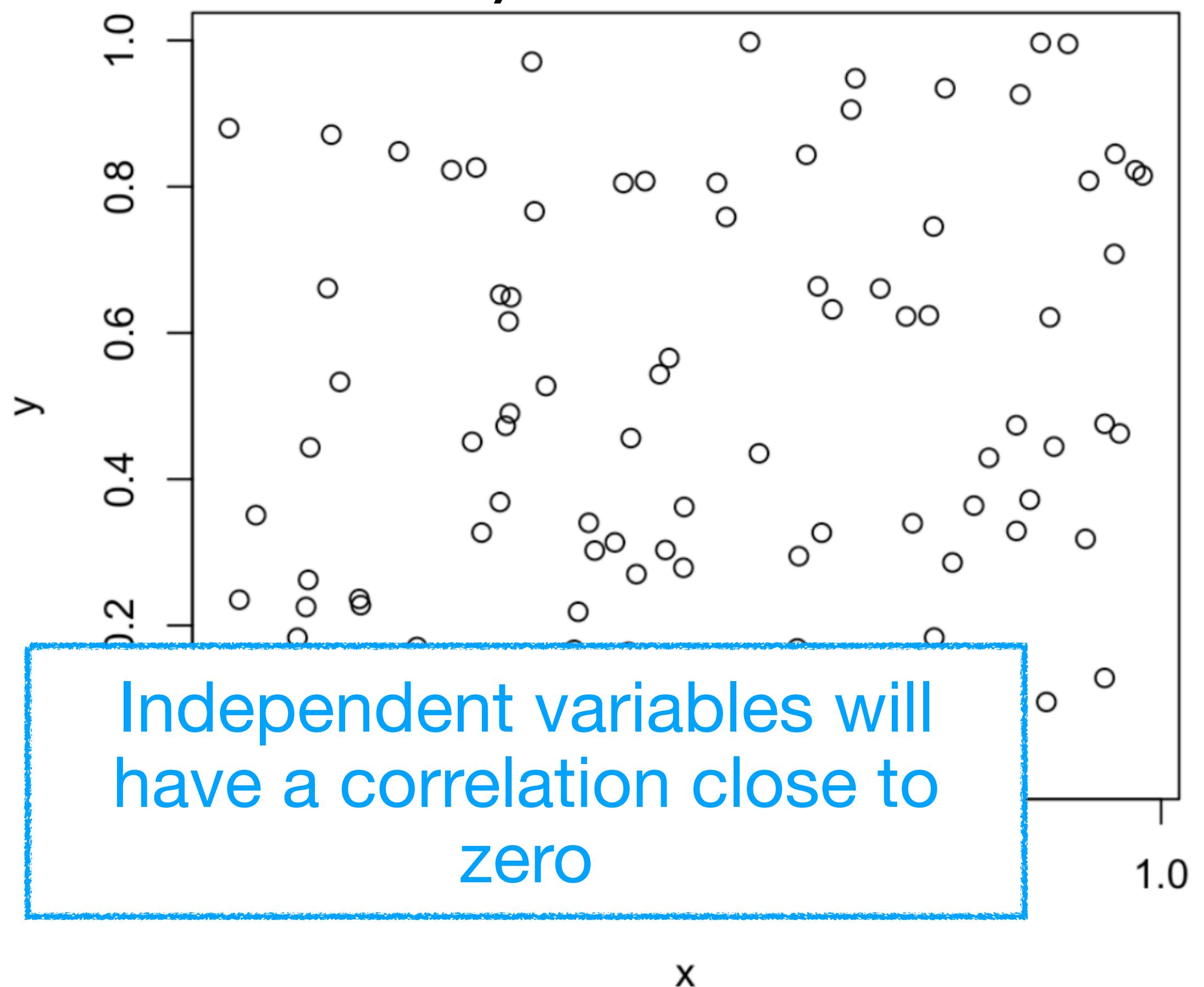
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More examples

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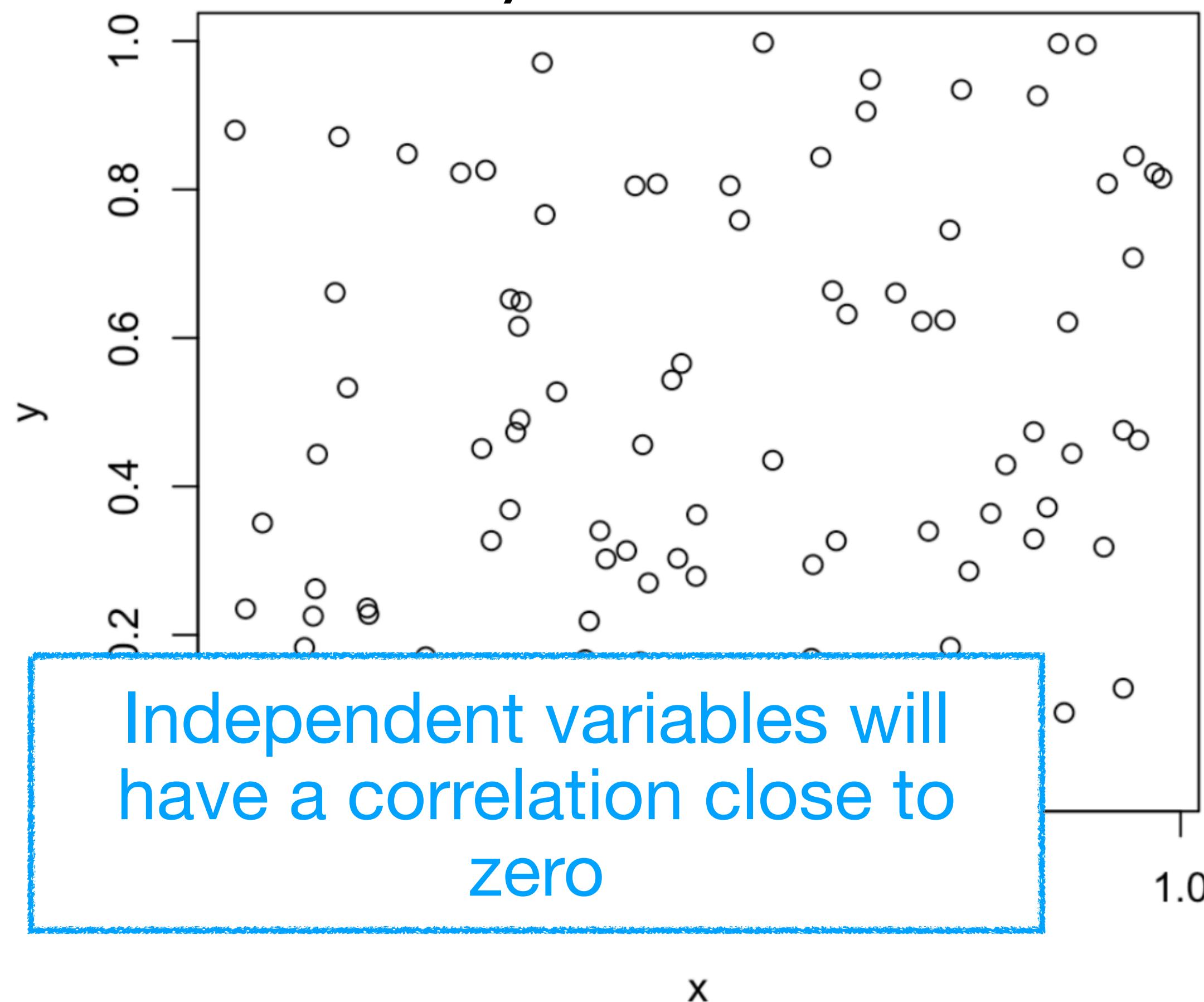
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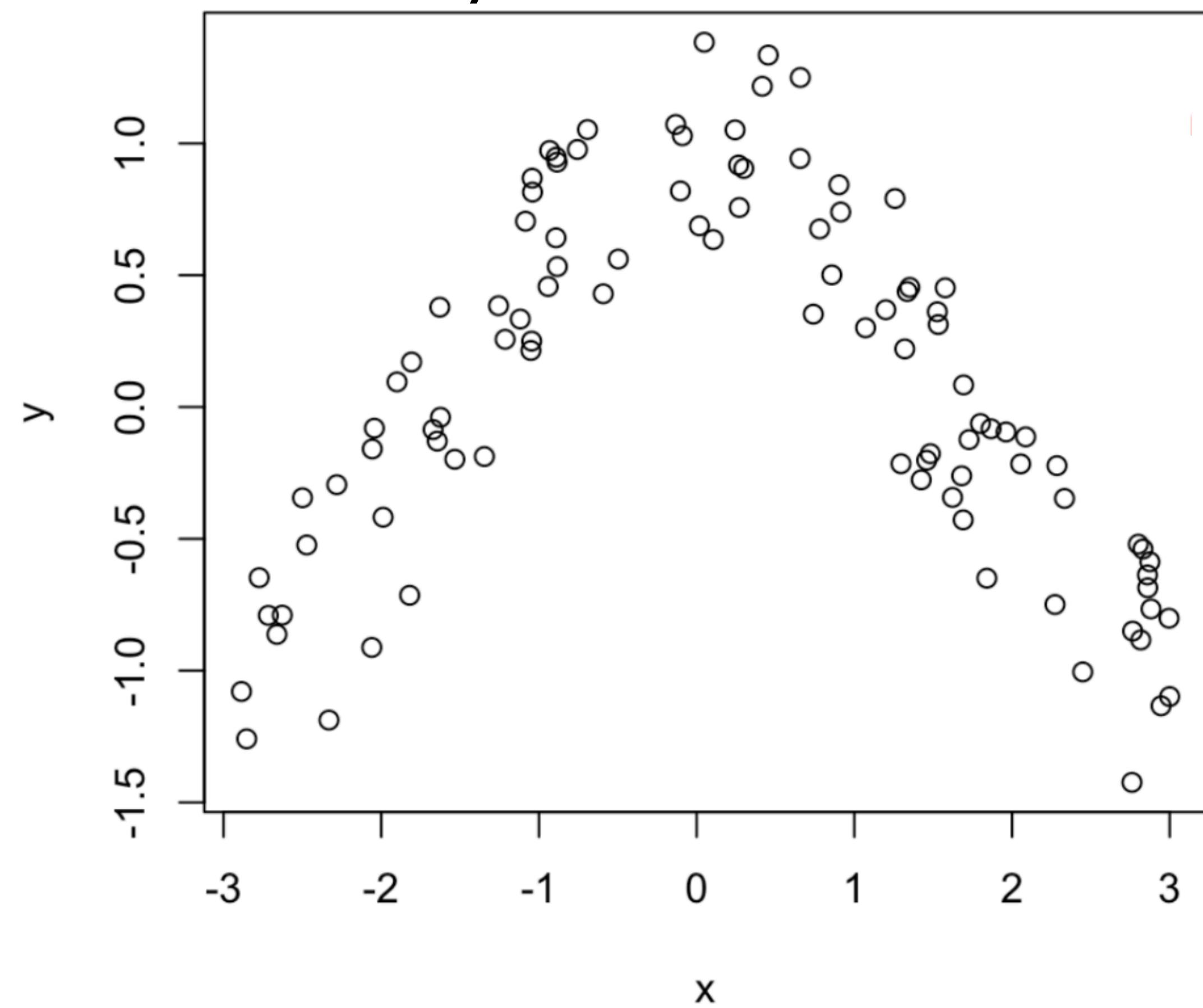
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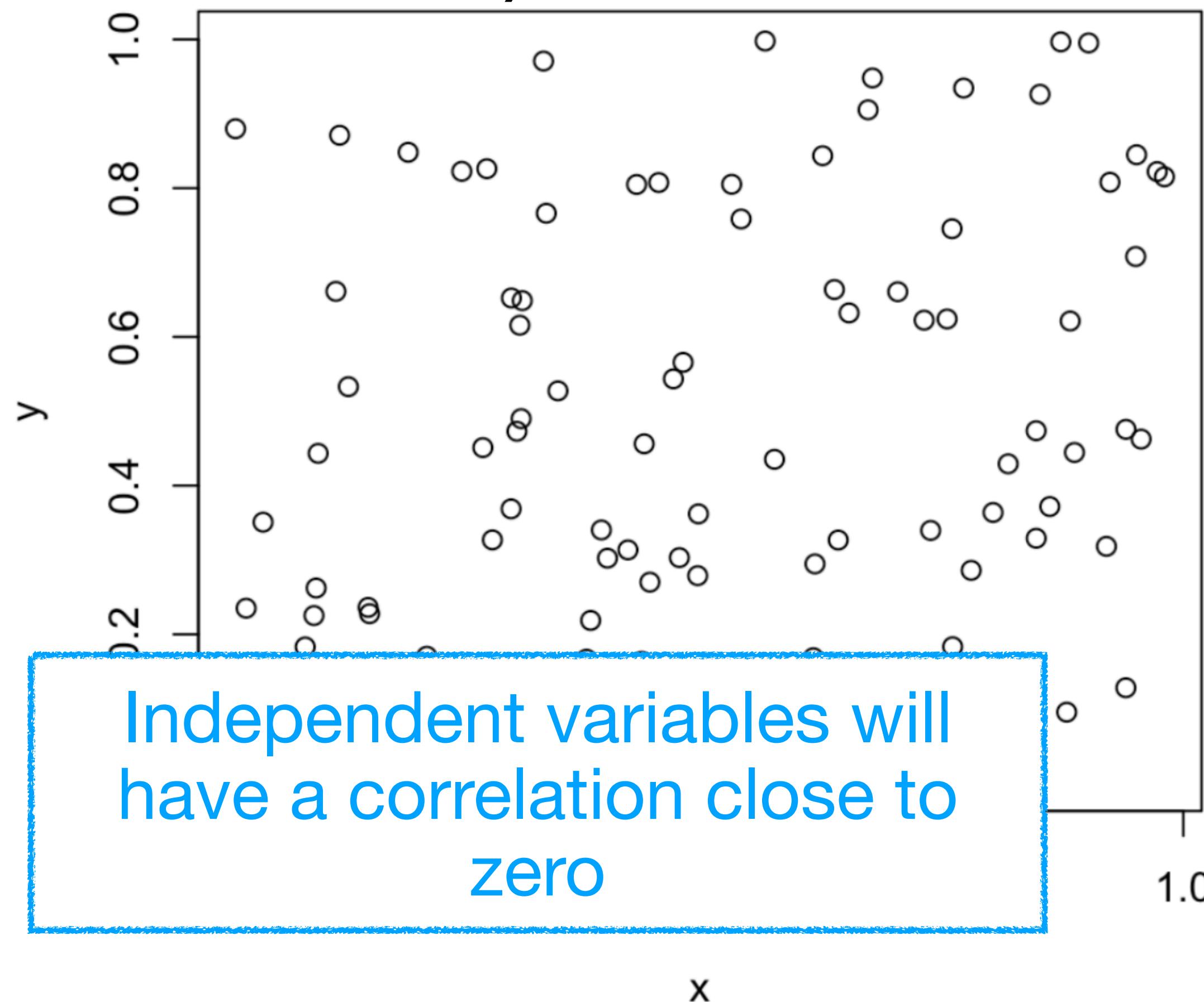
$$\rho = -0.1245$$



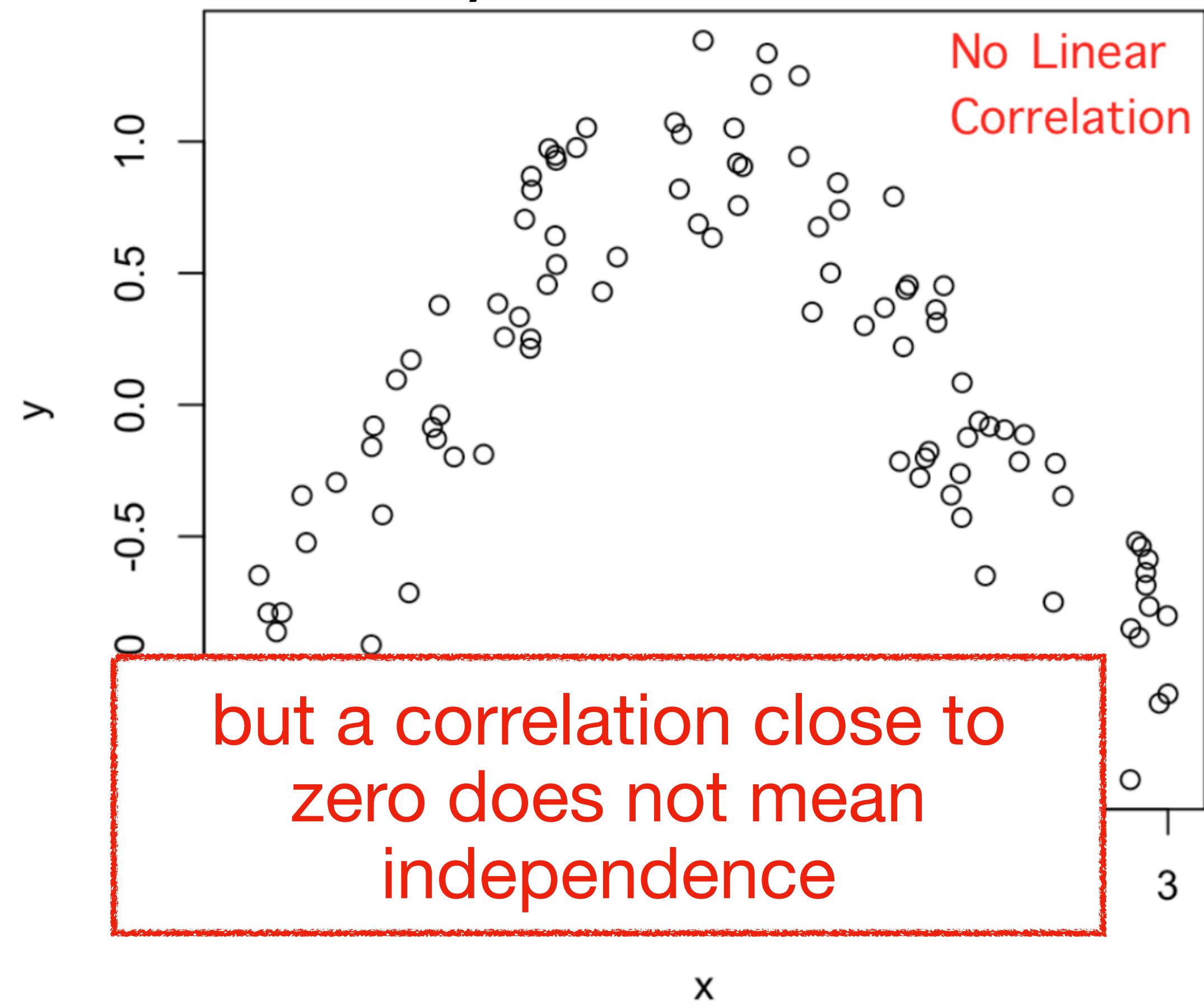
More examples

Pearson's correlation coefficient

$$\rho = 0.2253$$



$$\rho = -0.1245$$



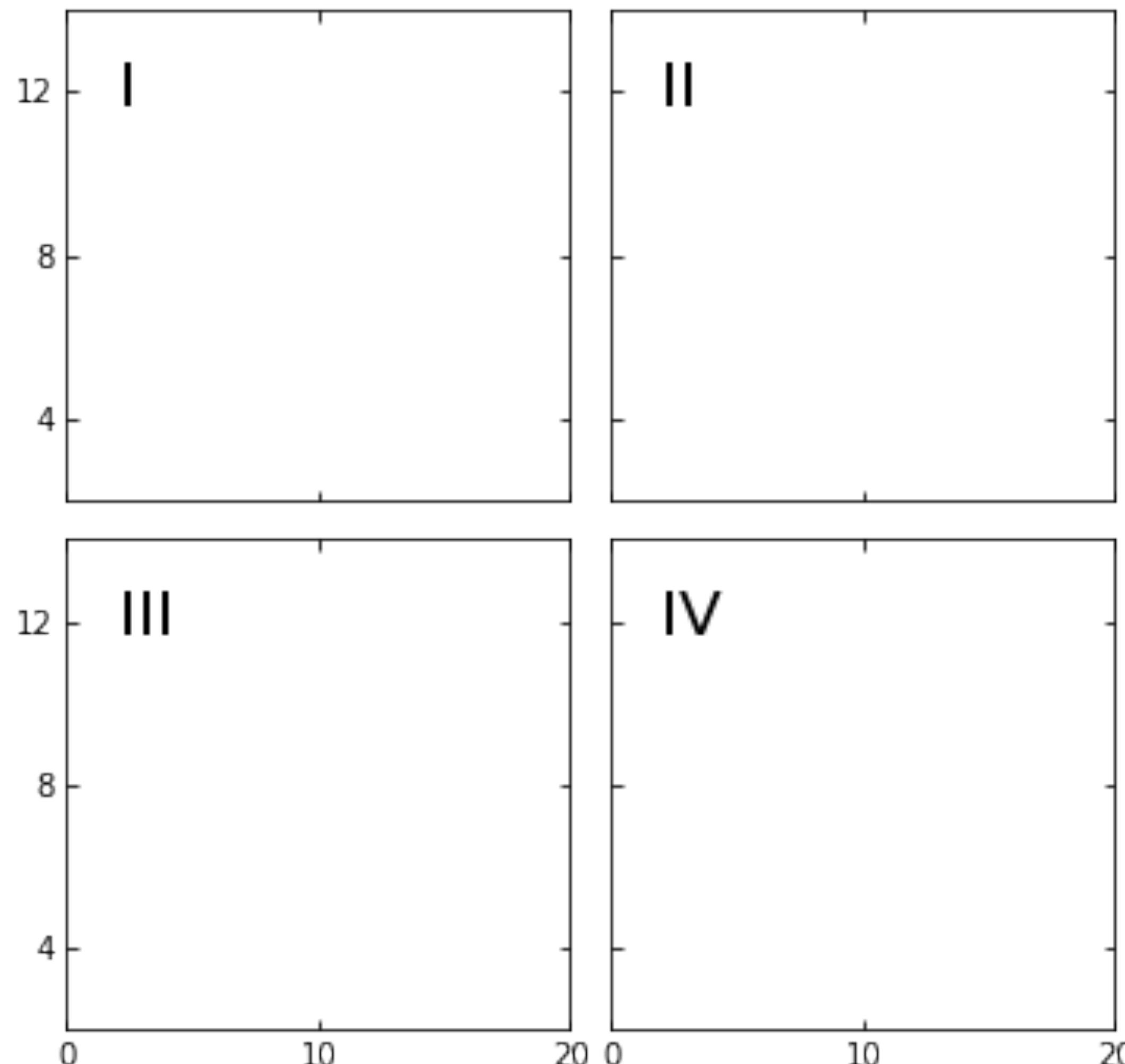
Anscombe's quartet

"numerical calculations are exact, but graphs are rough"

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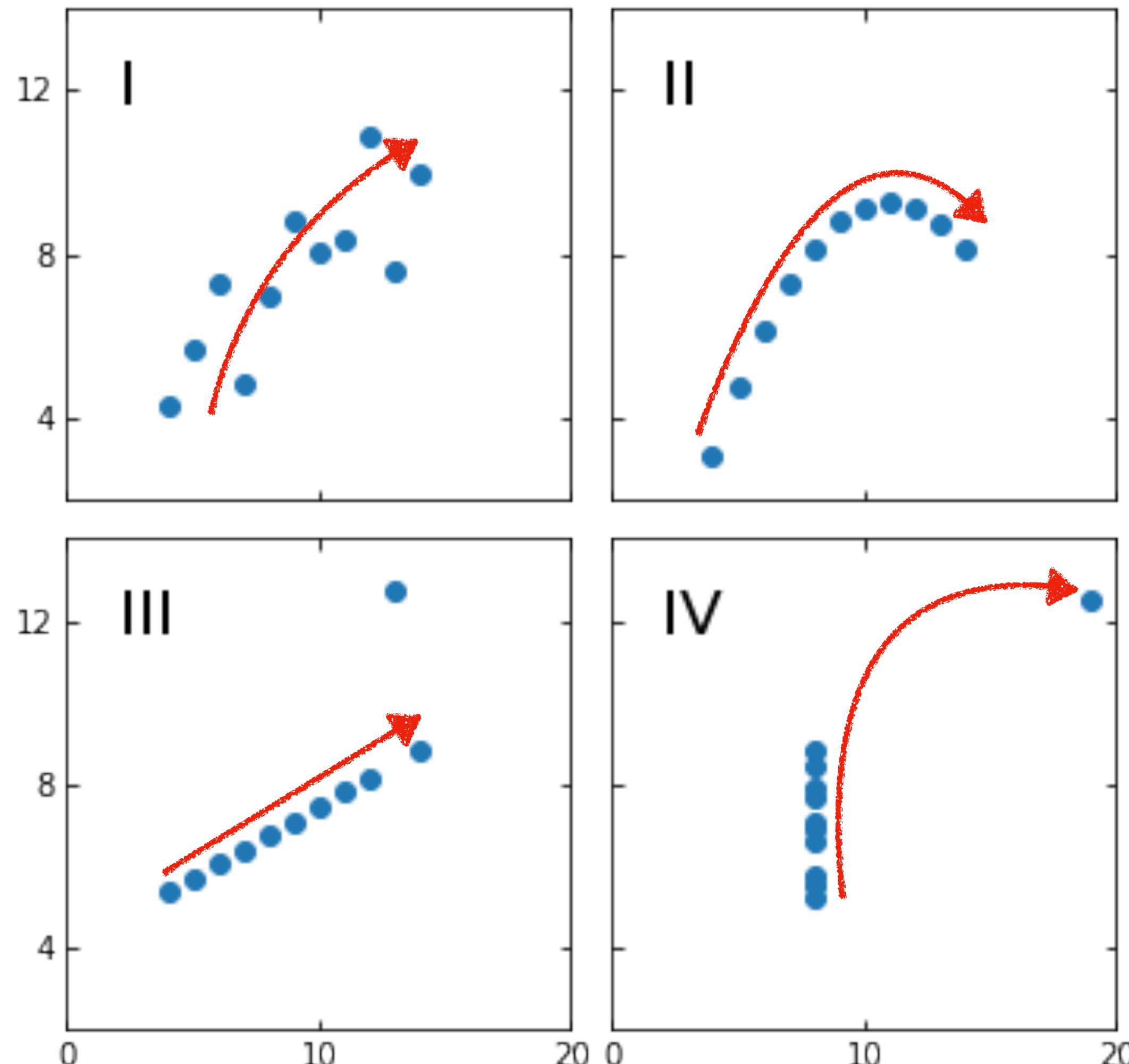
- These are 4 different datasets (X, Y)



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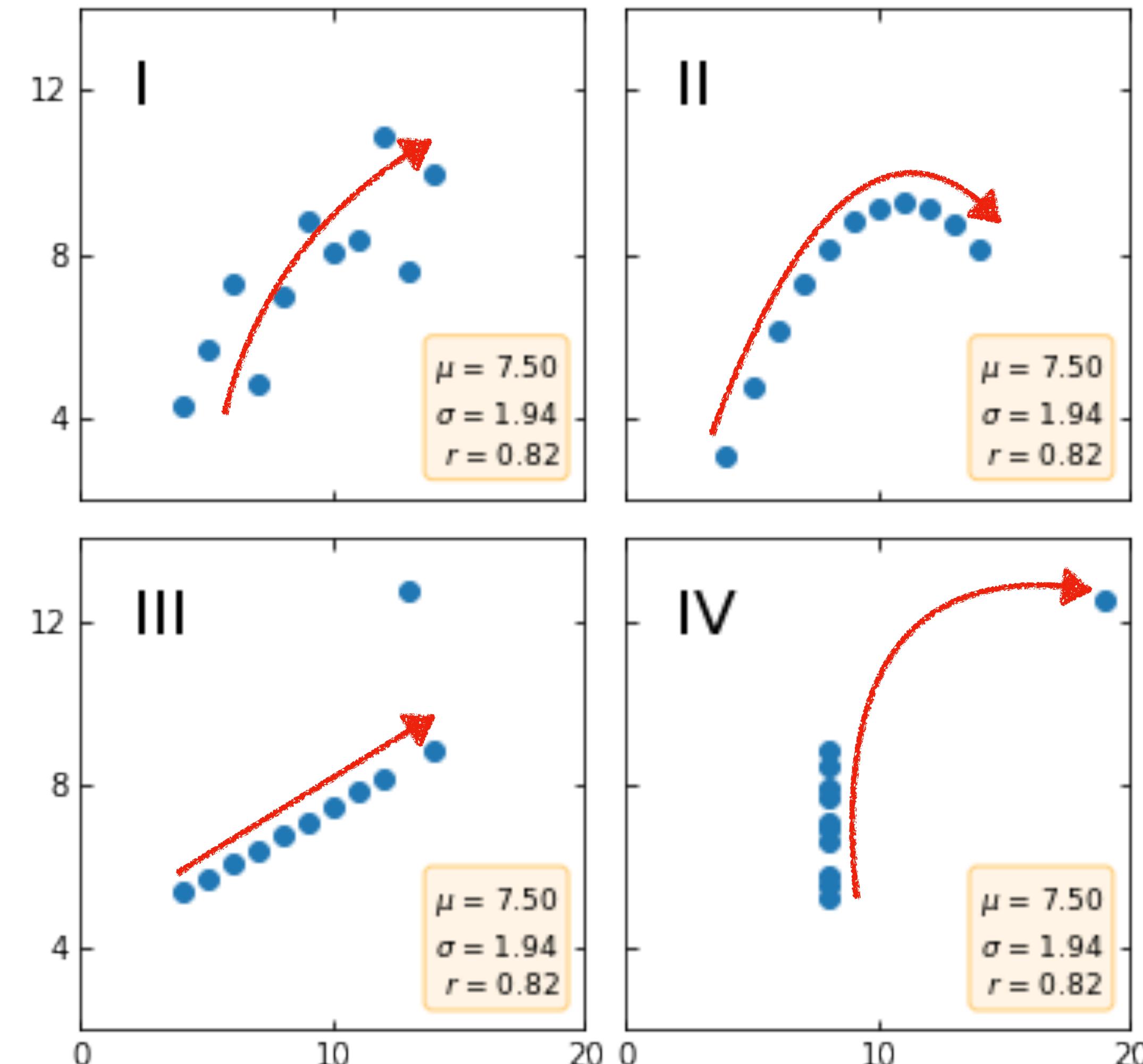
- These are 4 different datasets (X, Y)
- Qualitatively, they are very different



Anscombe's quartet

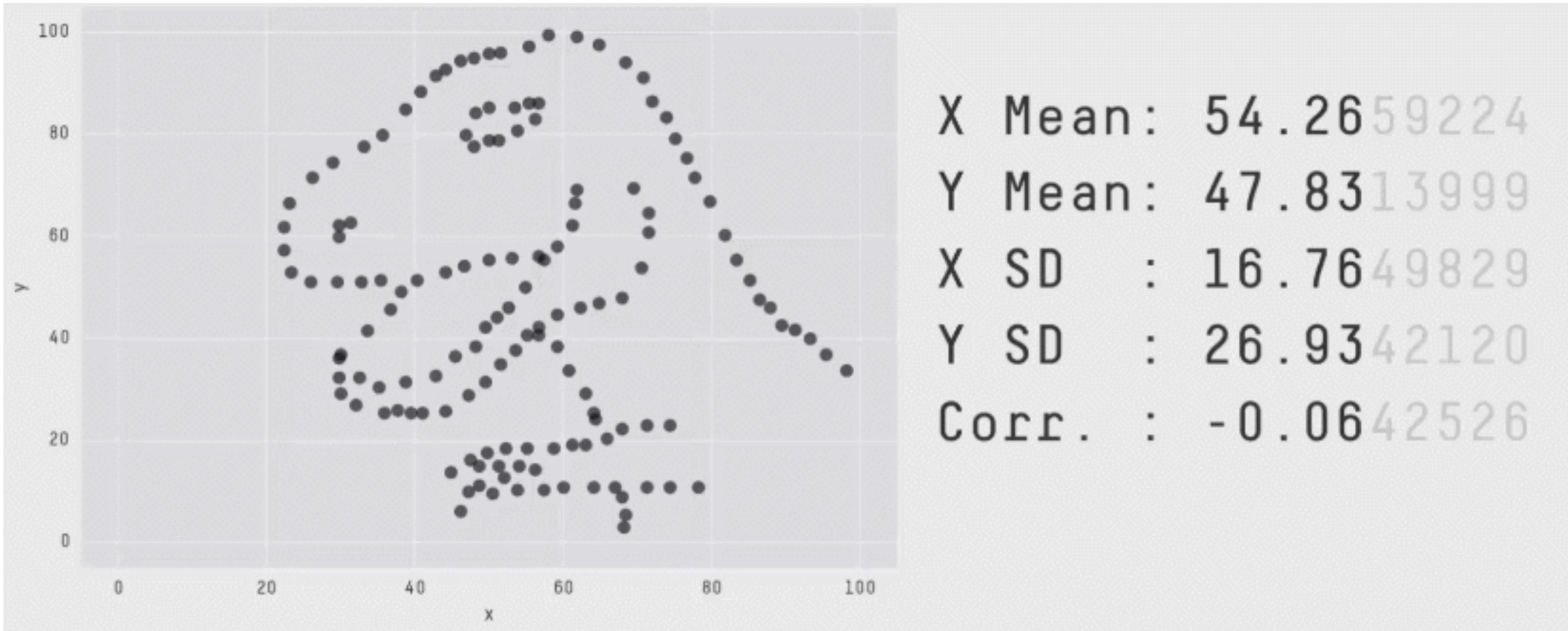
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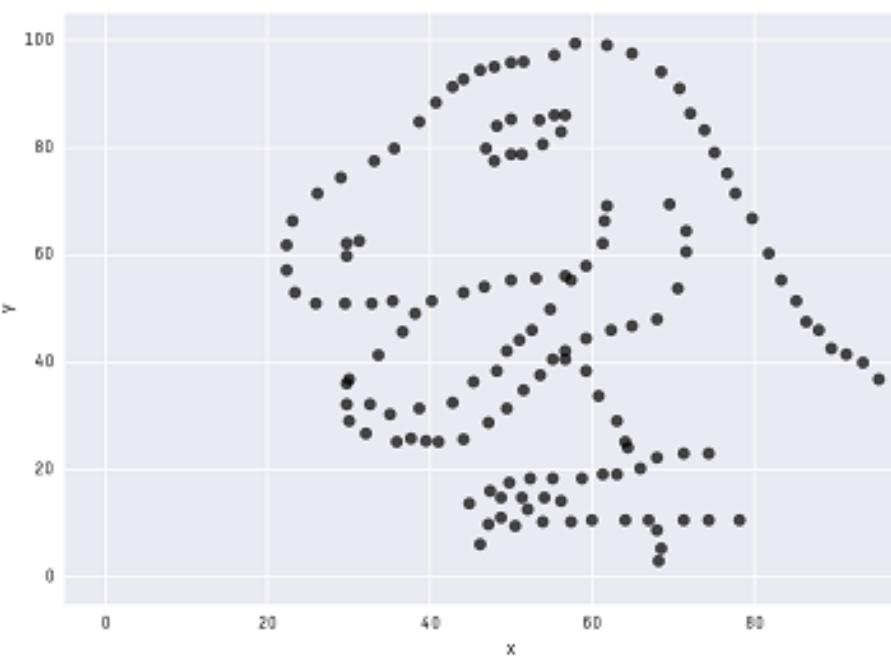
- These are 4 different datasets (X, Y)
- Qualitatively, they are very different
- Quantitative, they are the same: they have the same mean, standard deviation, and Pearson correlation



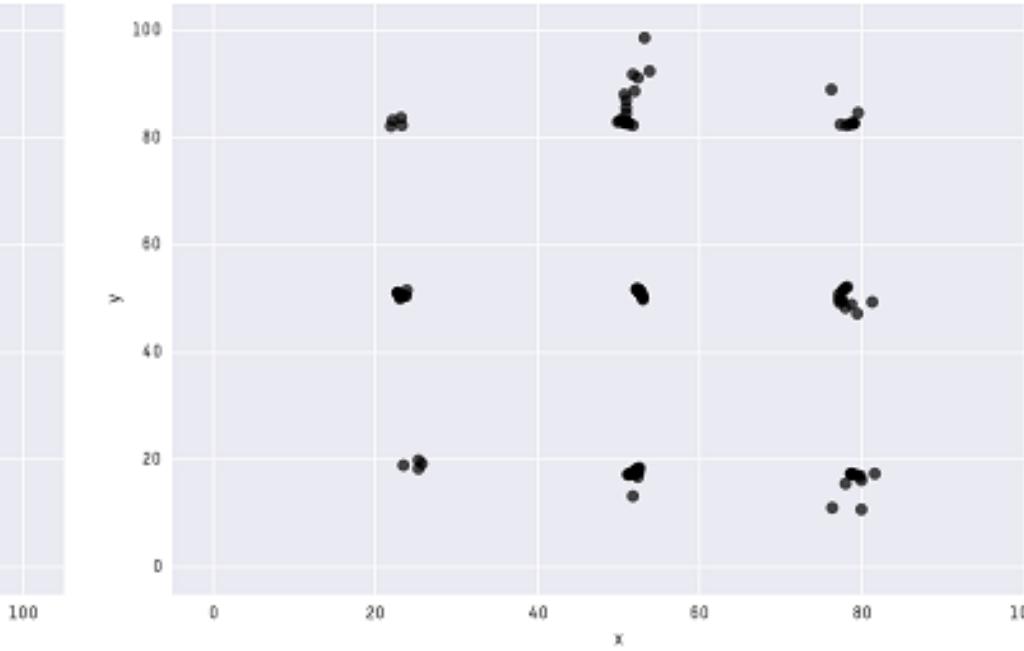
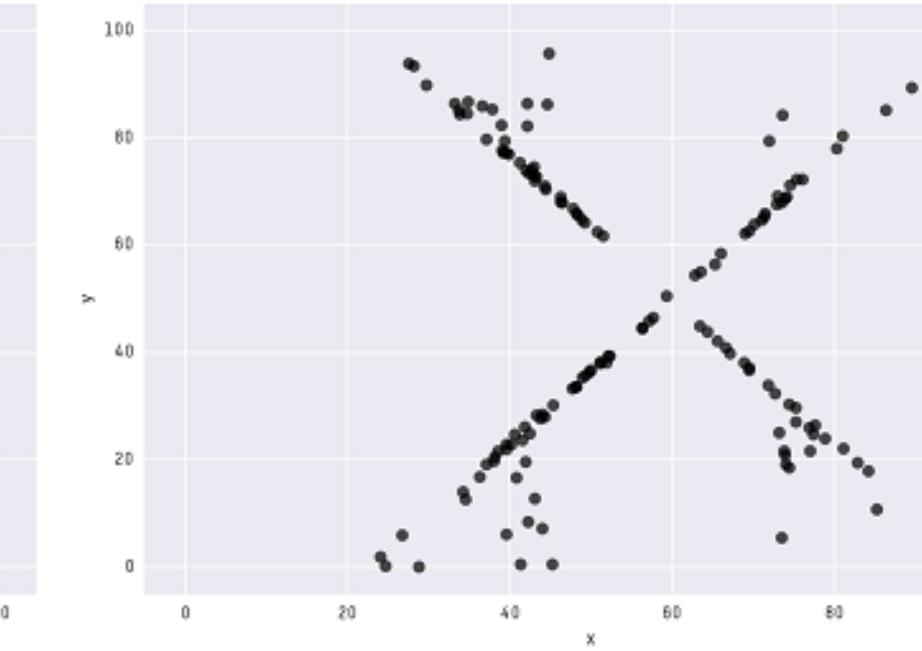
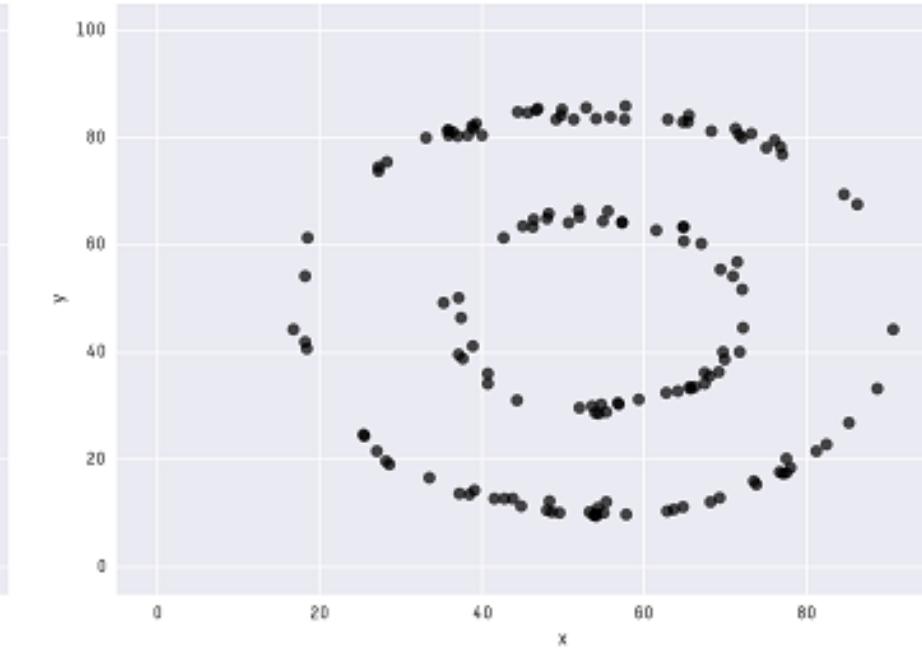
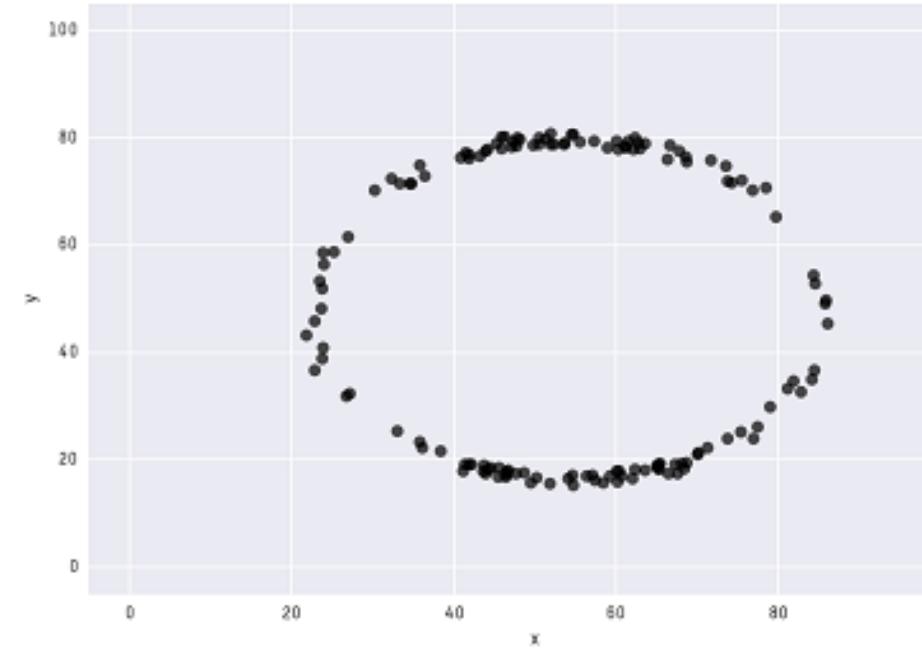
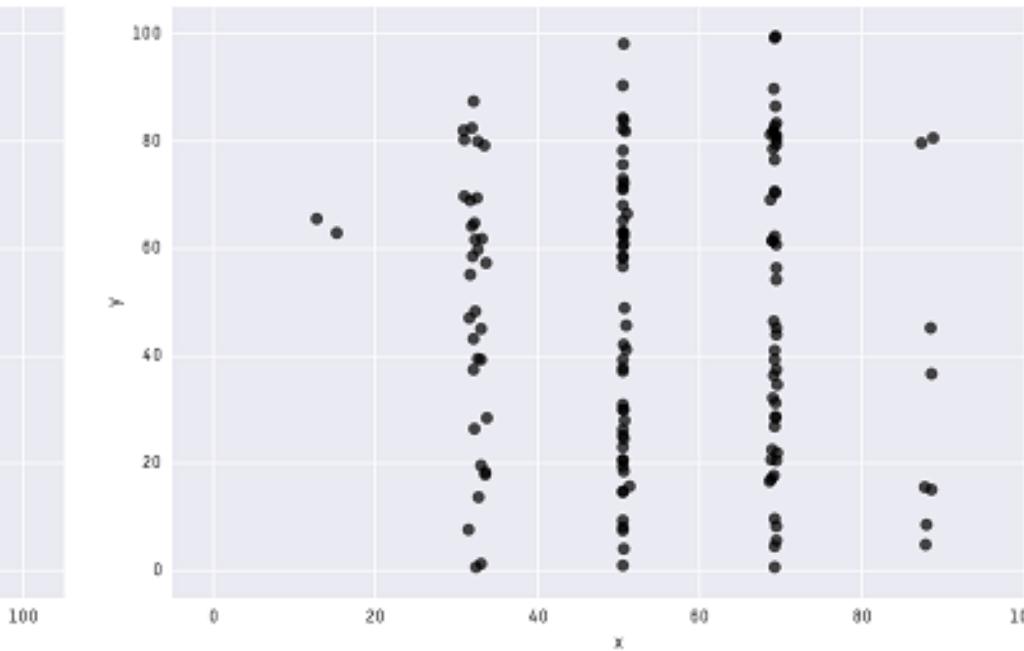
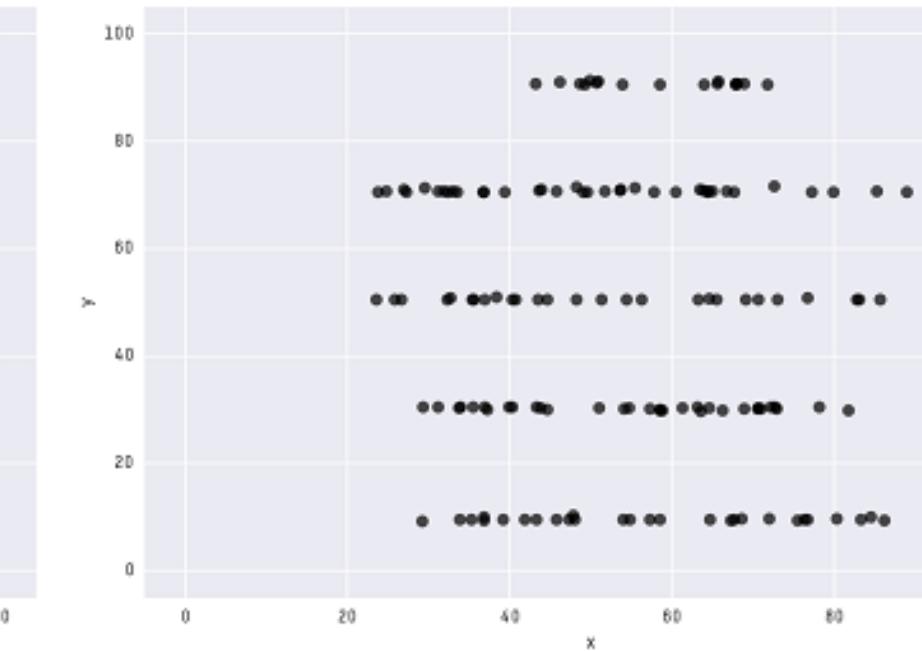
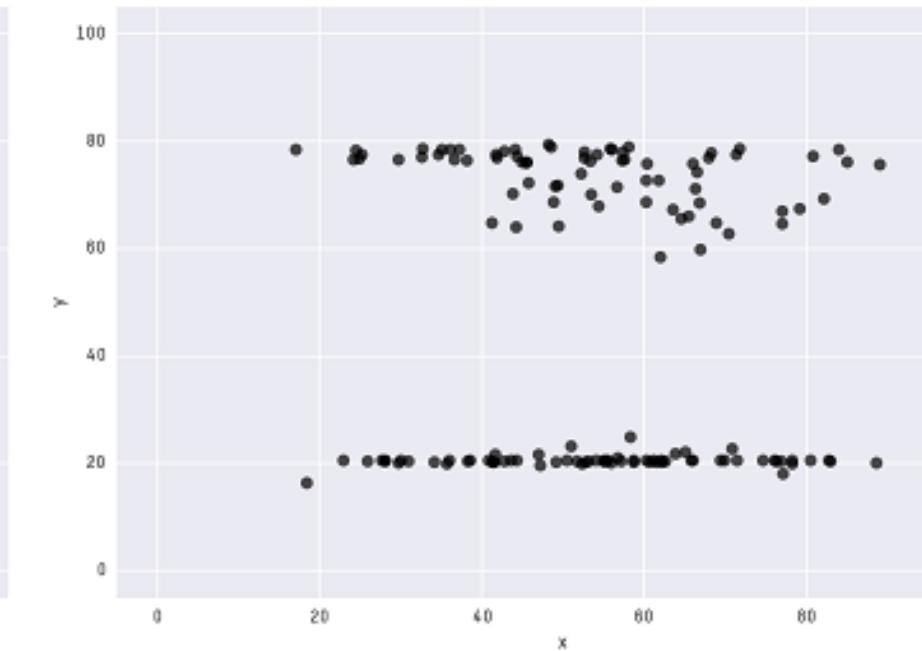
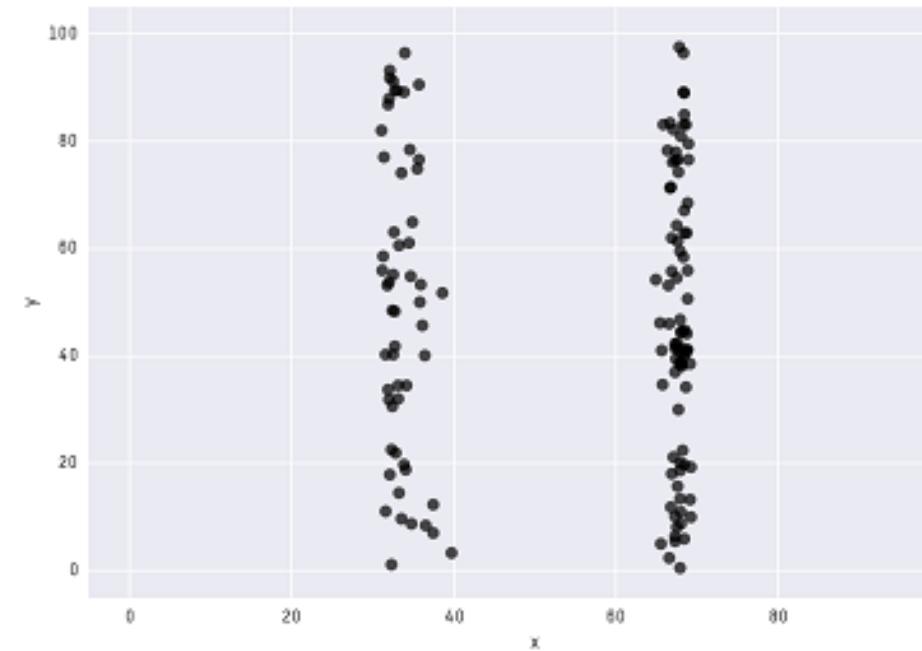
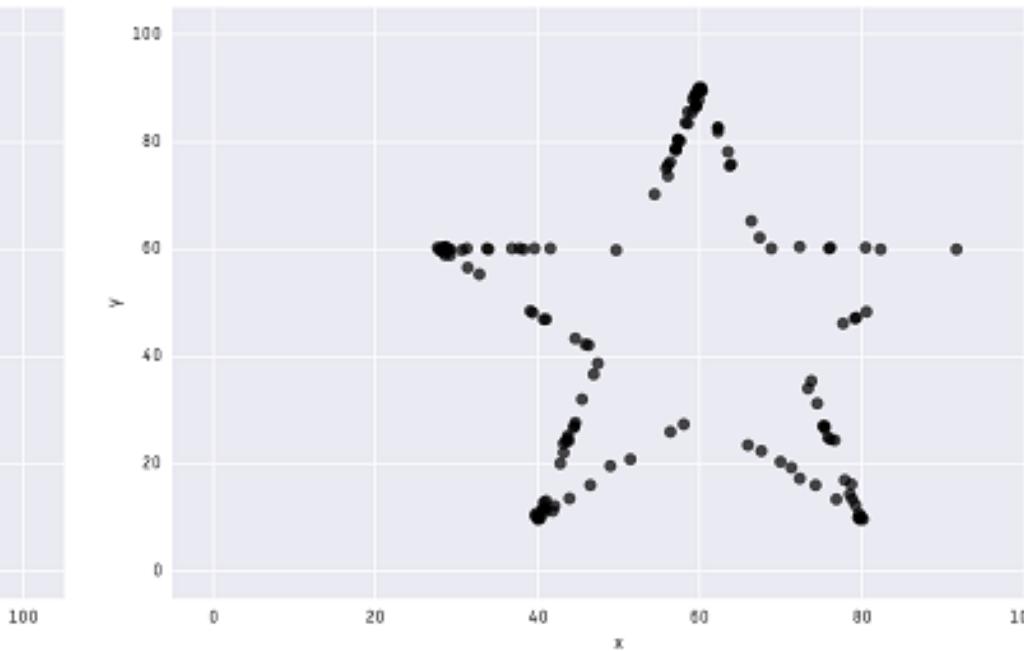
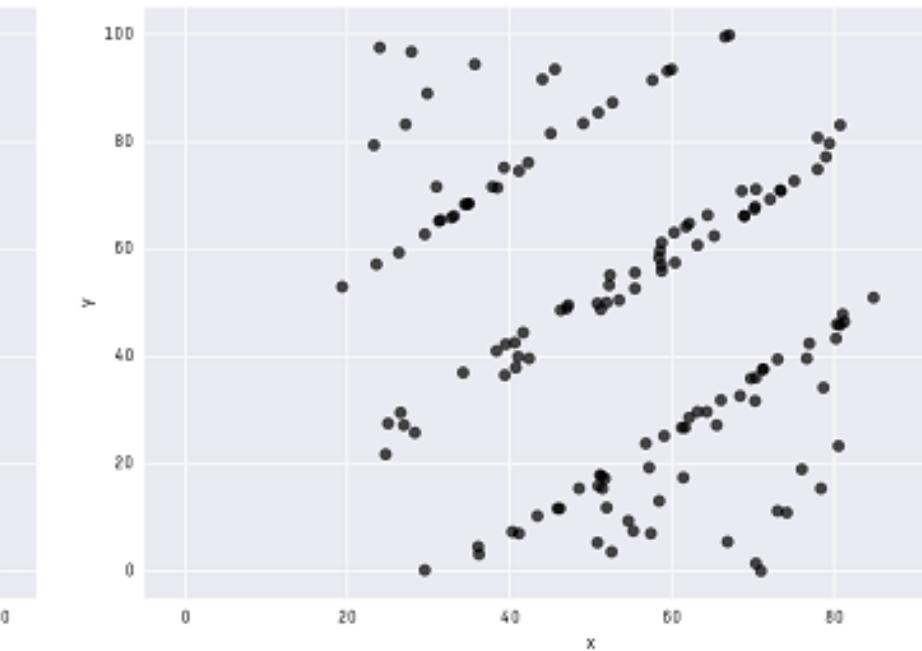
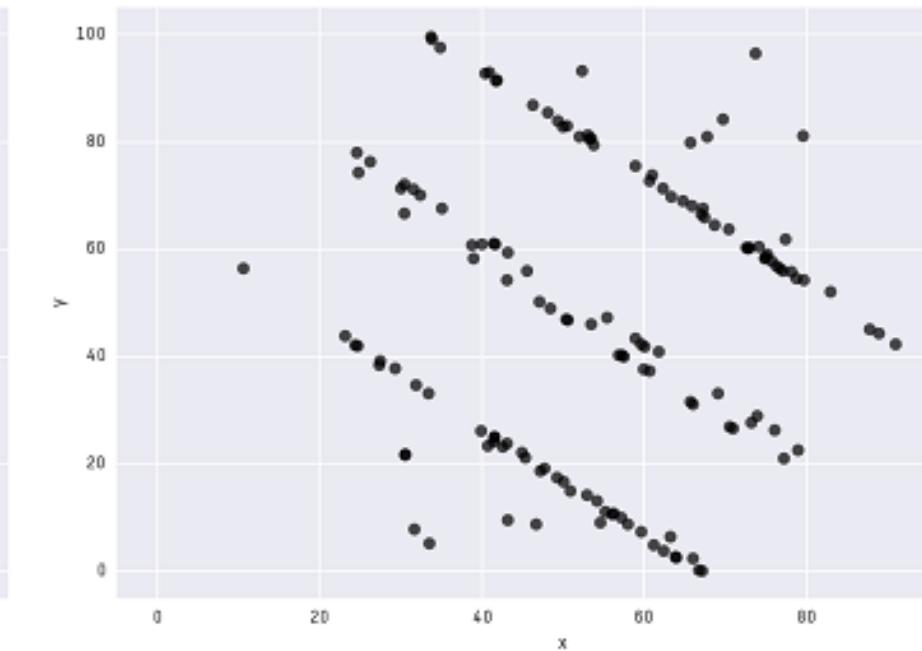
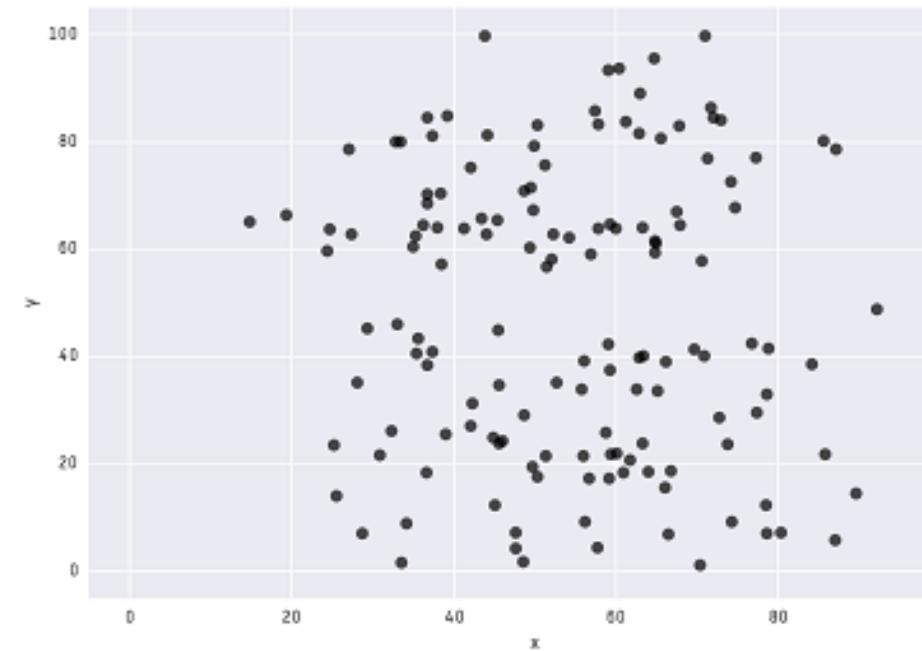
The Datasaurus dozen

Same Stats, different Graphs





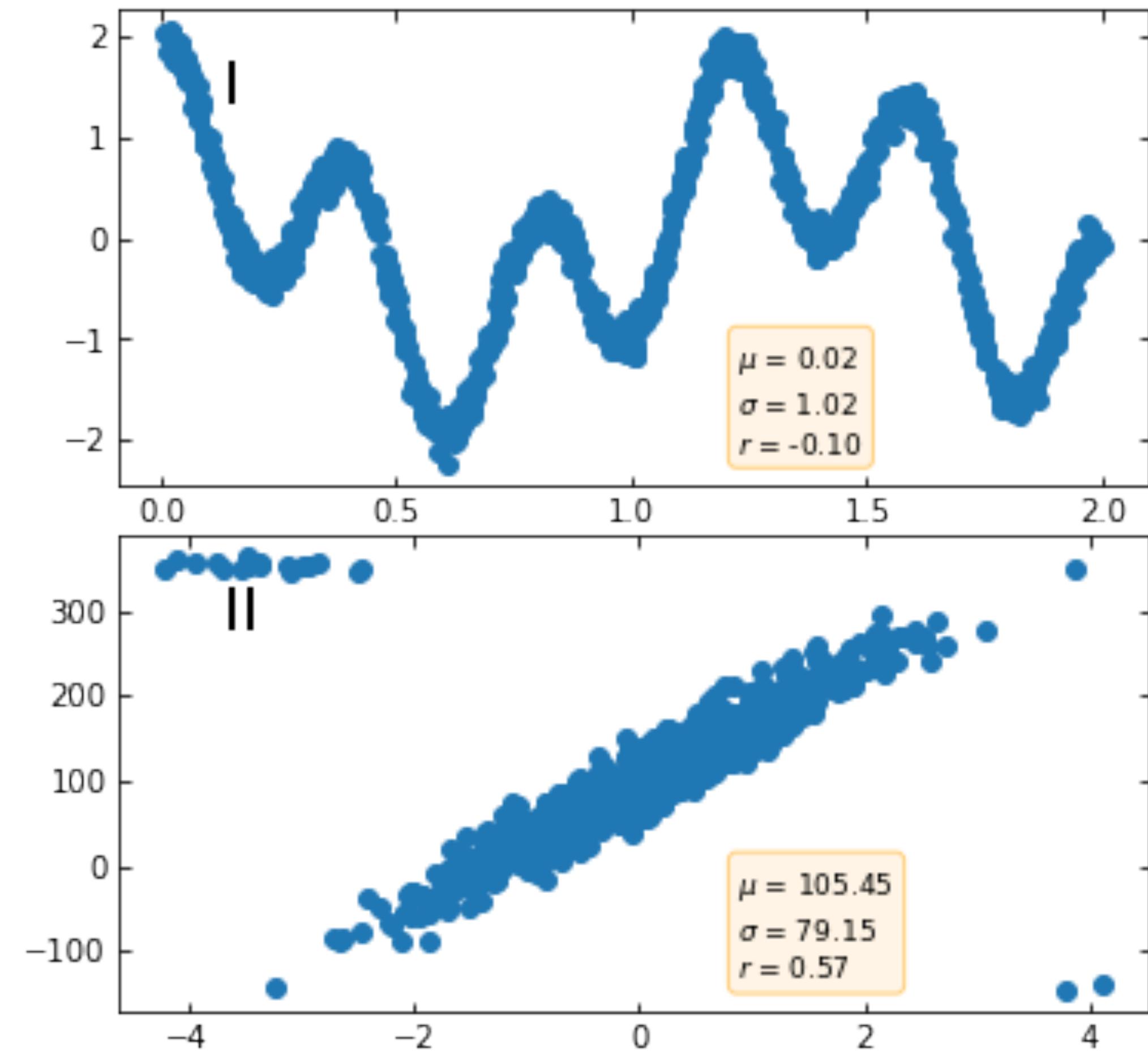
X Mean: 54.26
Y Mean: 47.83
X SD : 16.76
Y SD : 26.93
Corr. : -0.06



Limitations of Correlation

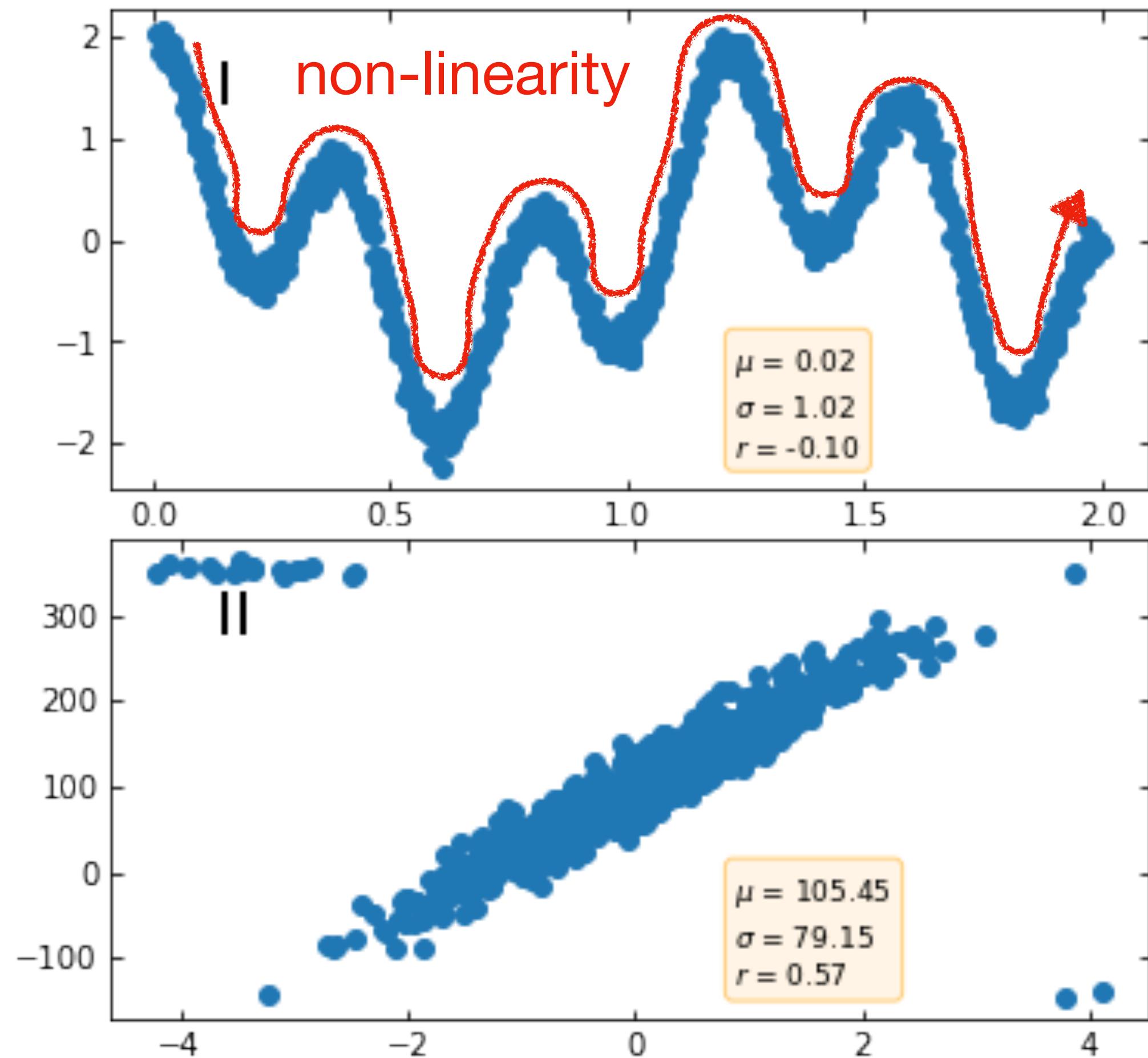
Limitations of Correlation

- Correlation can be influenced by **non-linear relationships or outliers**



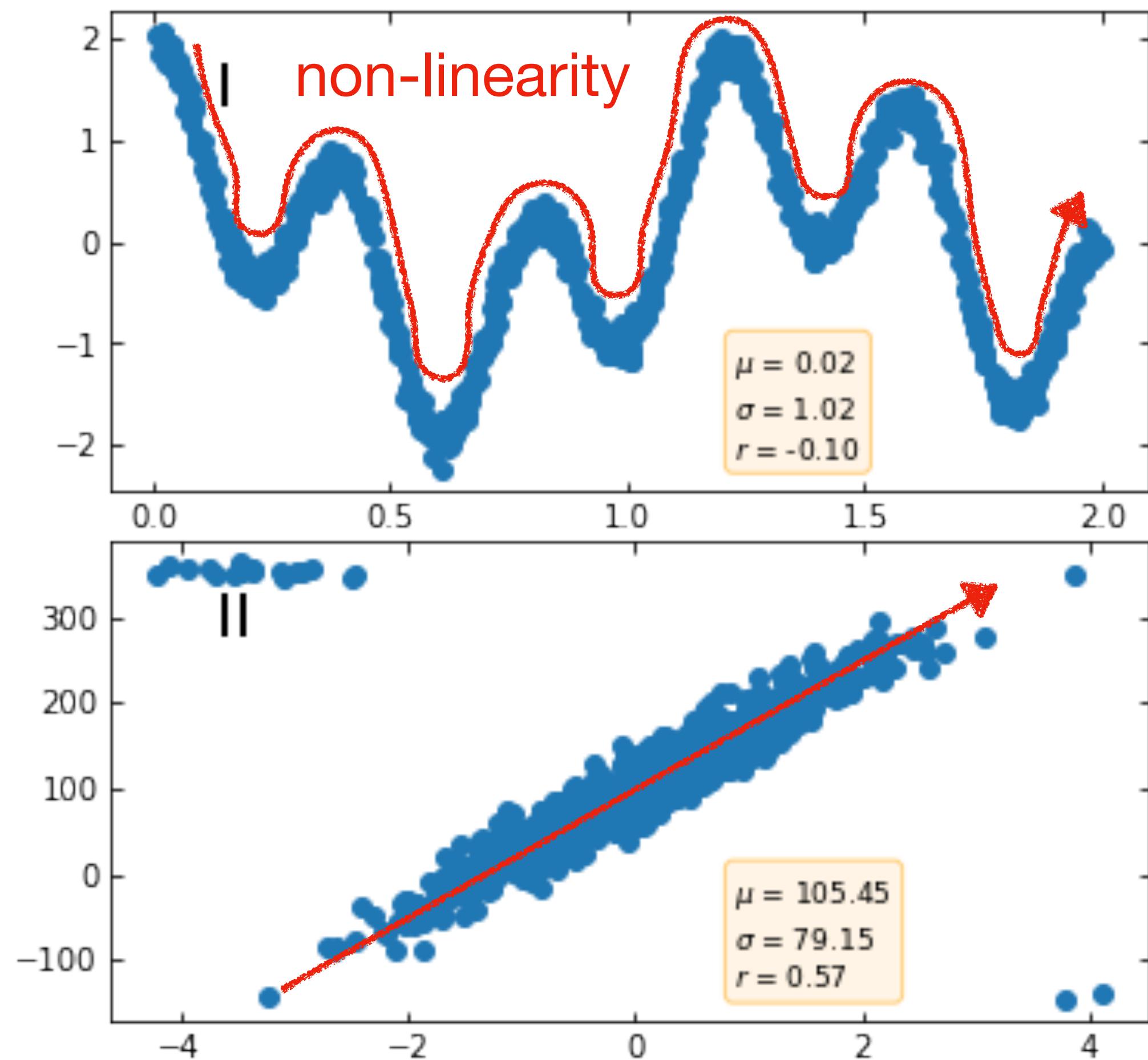
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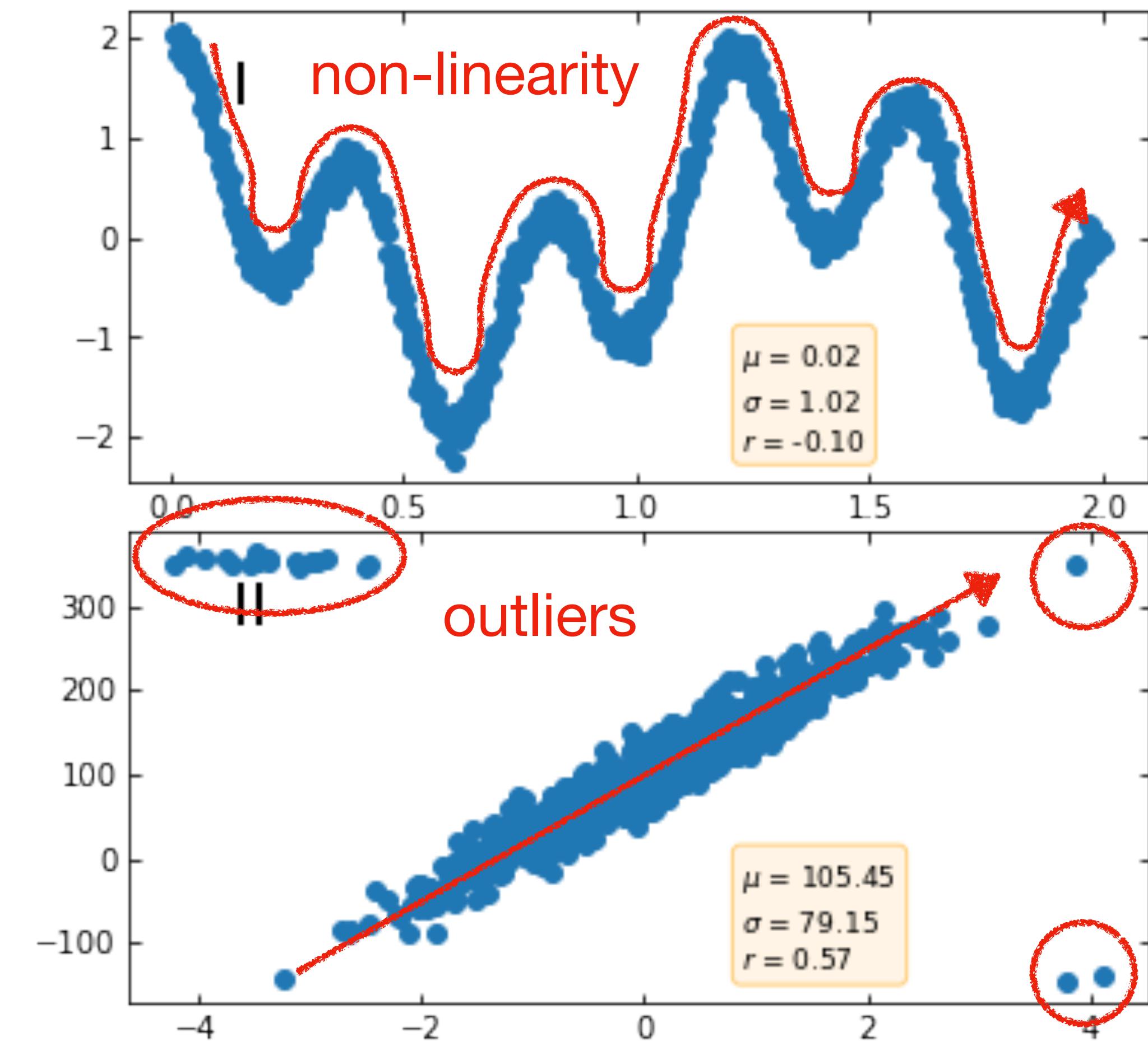
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If you want to divorce, then drink whole milk!

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These are just spurious correlations

Did you know that as ice cream sales increase, so does the rate of crime. When it's hot outside, people buy more ice cream and commit more crimes.

So it seems people who eat more ice cream causes people to commit more crimes. Right?

Did you know that there is positive correlation between the number of people who drink whole milk in Oregon and the number of divorces per capita? The correlation of whole milk consumption and divorce rates is $r = 0.9$.

If you want to divorce, then drink whole milk!

Limitations of Correlation

- Correlation can be influenced by non-linear relationships or outliers
- Correlation does not provide information about the presence of confounding variables

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Both ice cream sales and violent crime are associated with a **third variable**: seasonality (summer)

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Limitations of Correlation

- Correlation can be influenced by **non-linear relationships or outliers**
- Correlation does not provide information about the presence of **confounding variables**
- Correlation does not imply **causation**

These are just spurious correlations

Both ice cream sales and violent crime are associated with a **third variable**: seasonality (summer)

Whole milk and divorces are only related by **coincidence**.

Studying Causality

(brief overview)



What is causality

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- Causality is the relationship between **cause** and **effect**, where a change in one variable (the cause) leads to a change in another variable (the effect).
- Establishing causality requires three essential conditions:
 - **Temporal** sequencing: X must come before Y in time.
 - **Non-chance** relationship: The observed relationship between X and Y did not happen by chance alone.
 - **No alternative** explanation: There is nothing else that accounts for the $X \rightarrow Y$ relationship.

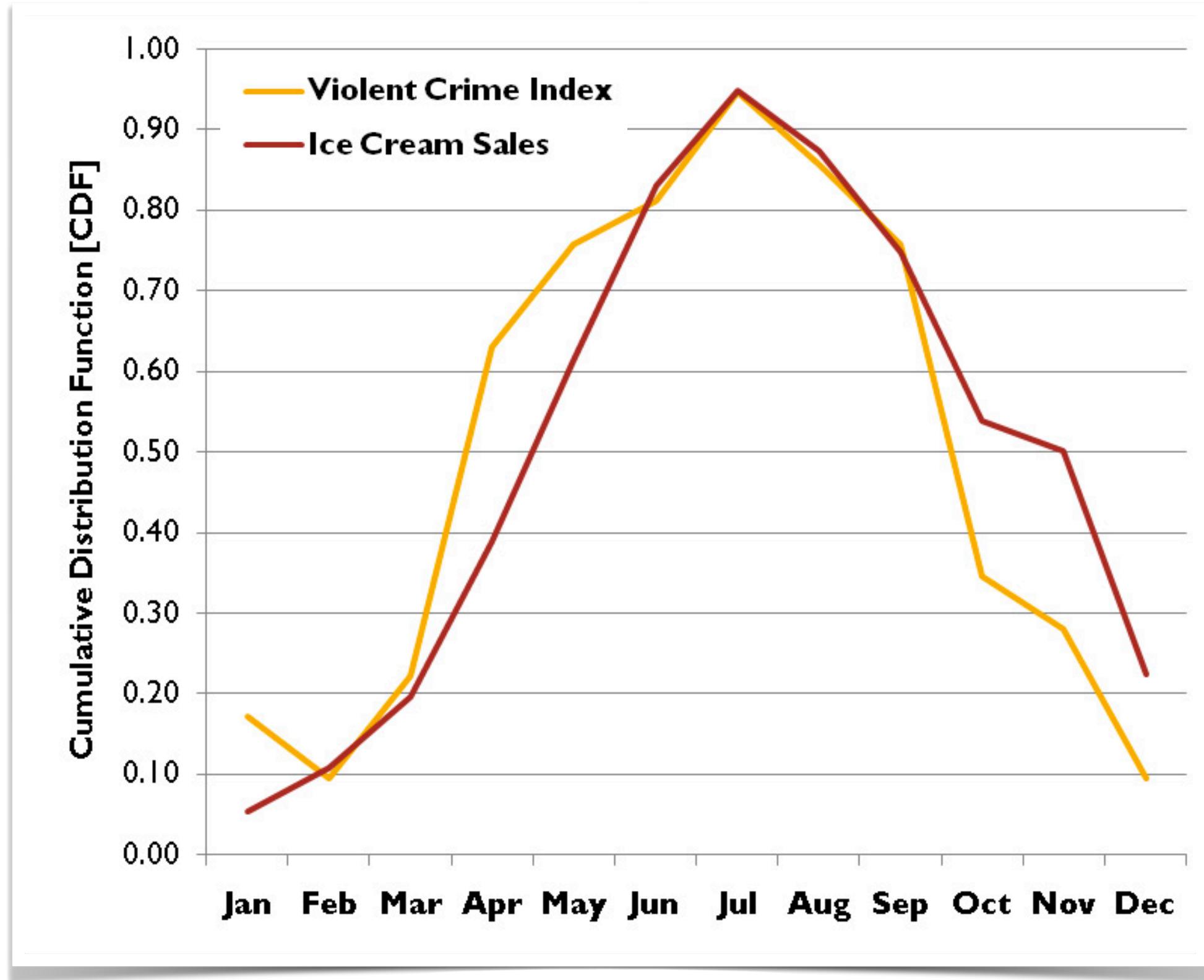
How is causality measured?

- **Experimentation:** A controlled experiment, where the independent variable X is manipulated (controlled), and the effect on the dependent variable Y is measured.
 - Randomized controlled trials (RCTs) are often used in clinical medical research to demonstrate causality.
 - Also known as “counterfactuals” in computer science (AI/ML & fairness)

Examples

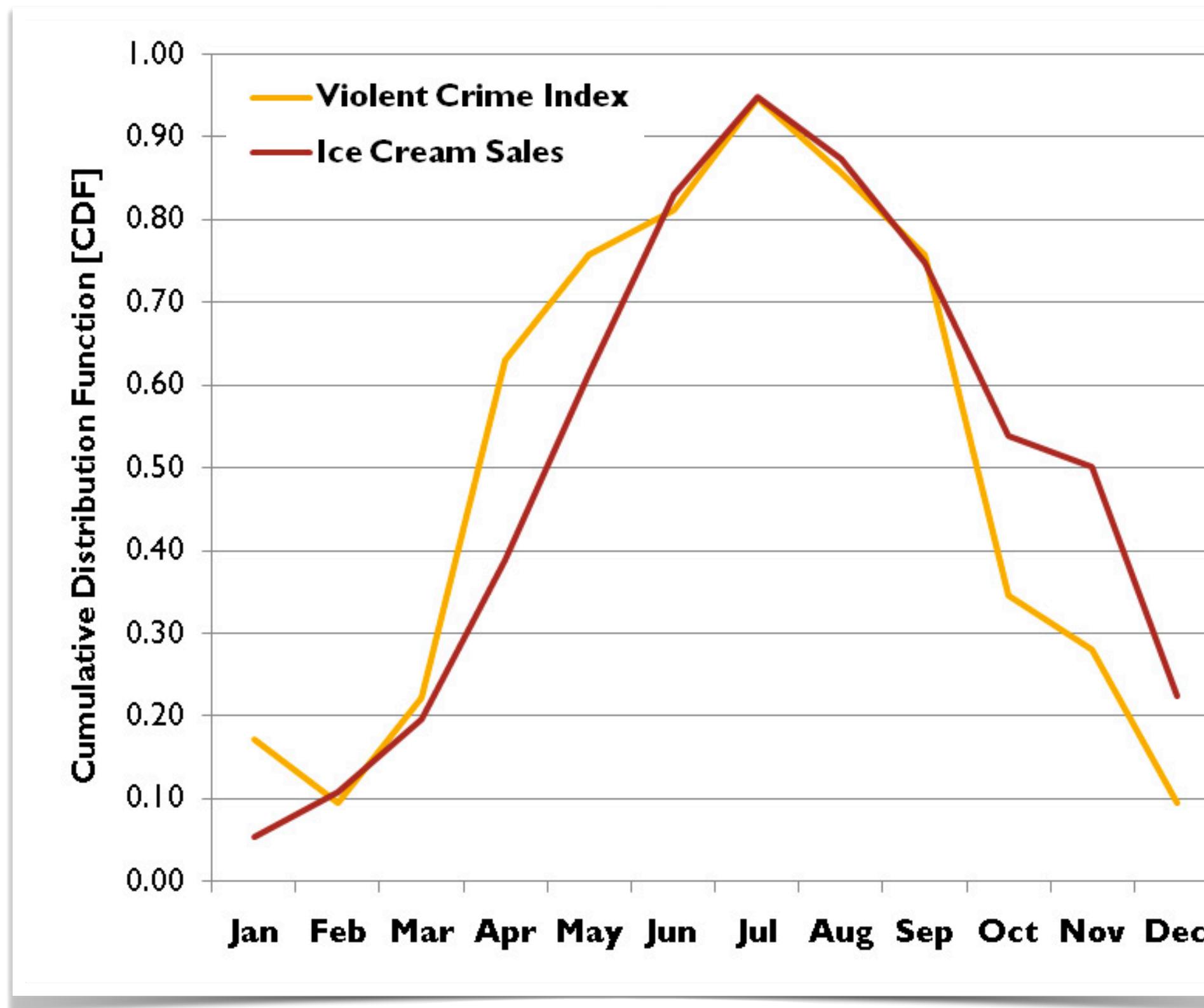
of causality

Examples of causality

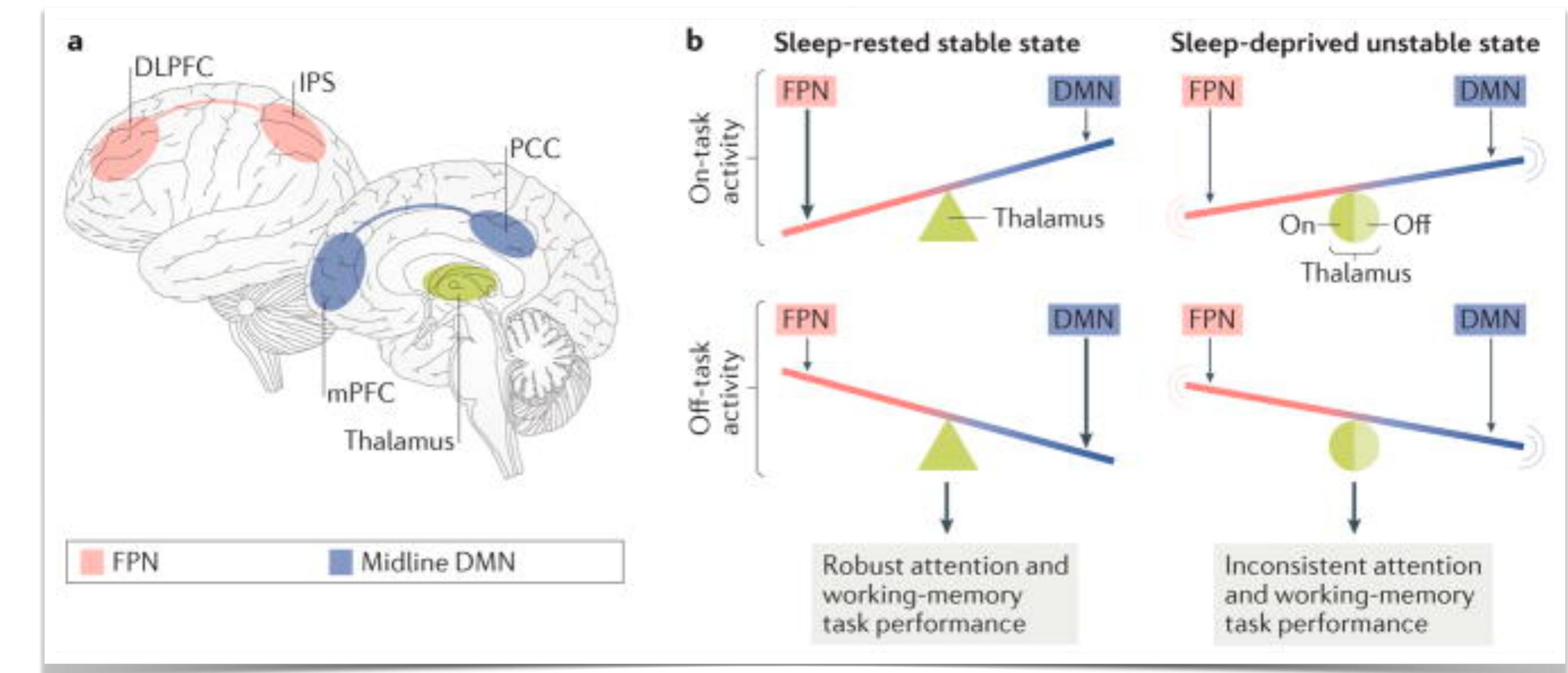


High temperature increases ice cream consumption and crime
[Drescher 2014]

Examples of causality

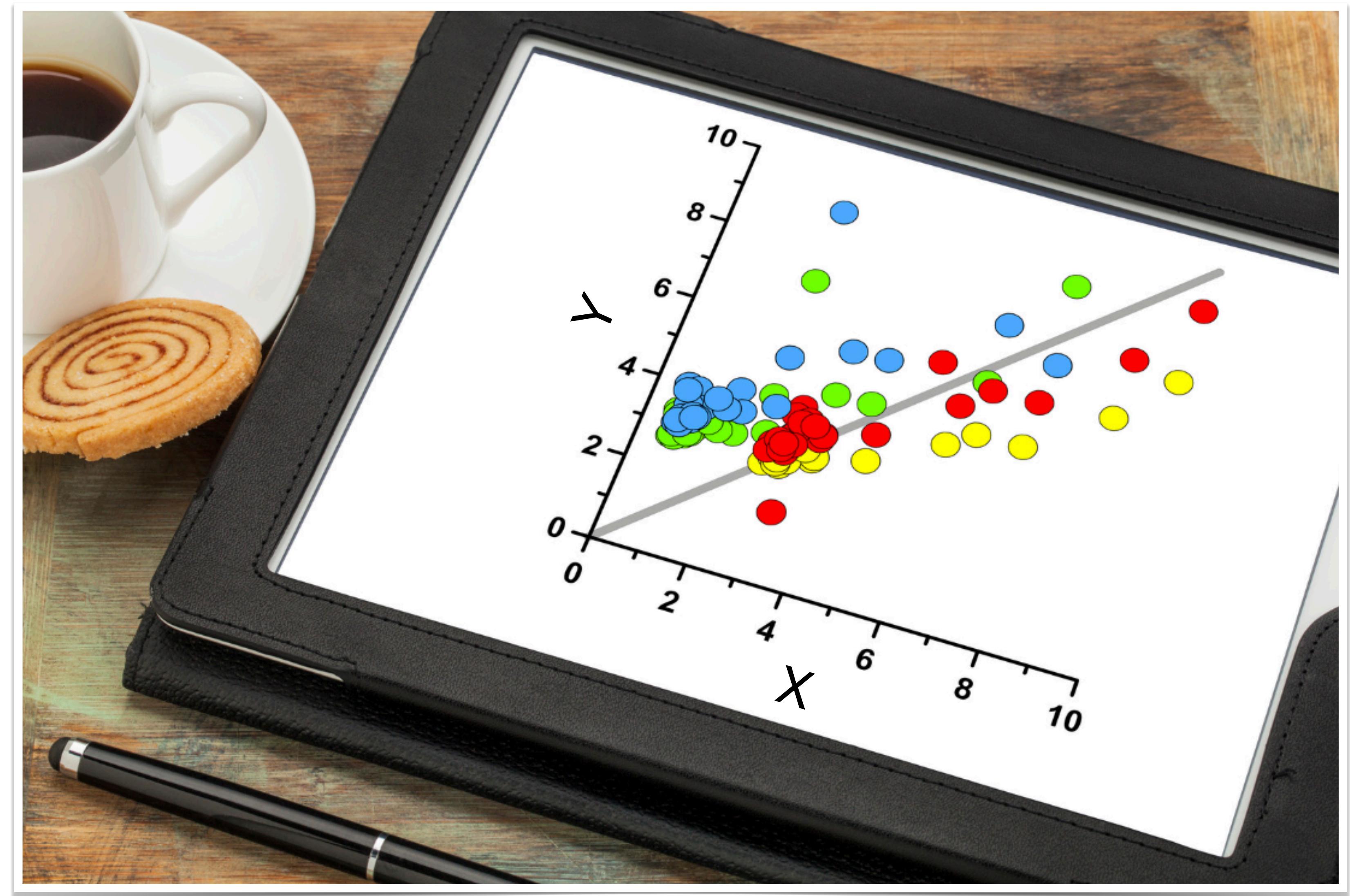


High temperature increases ice cream consumption and crime [Drescher 2014]



Sleep deprivation causes deficit in attention and working memory [Krause et al. 2017]

Linear Regression



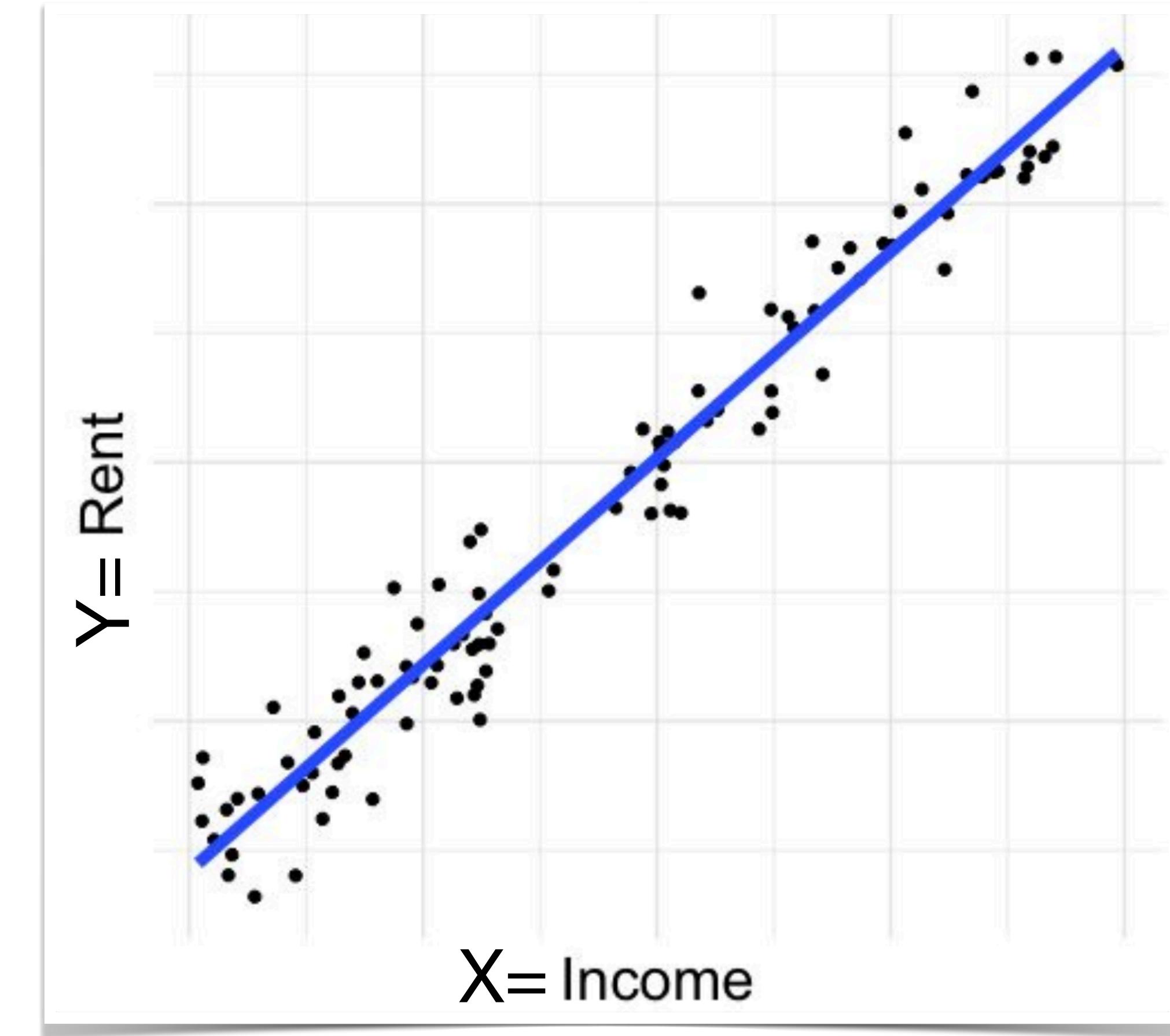
Linear regression

Basics

Linear regression

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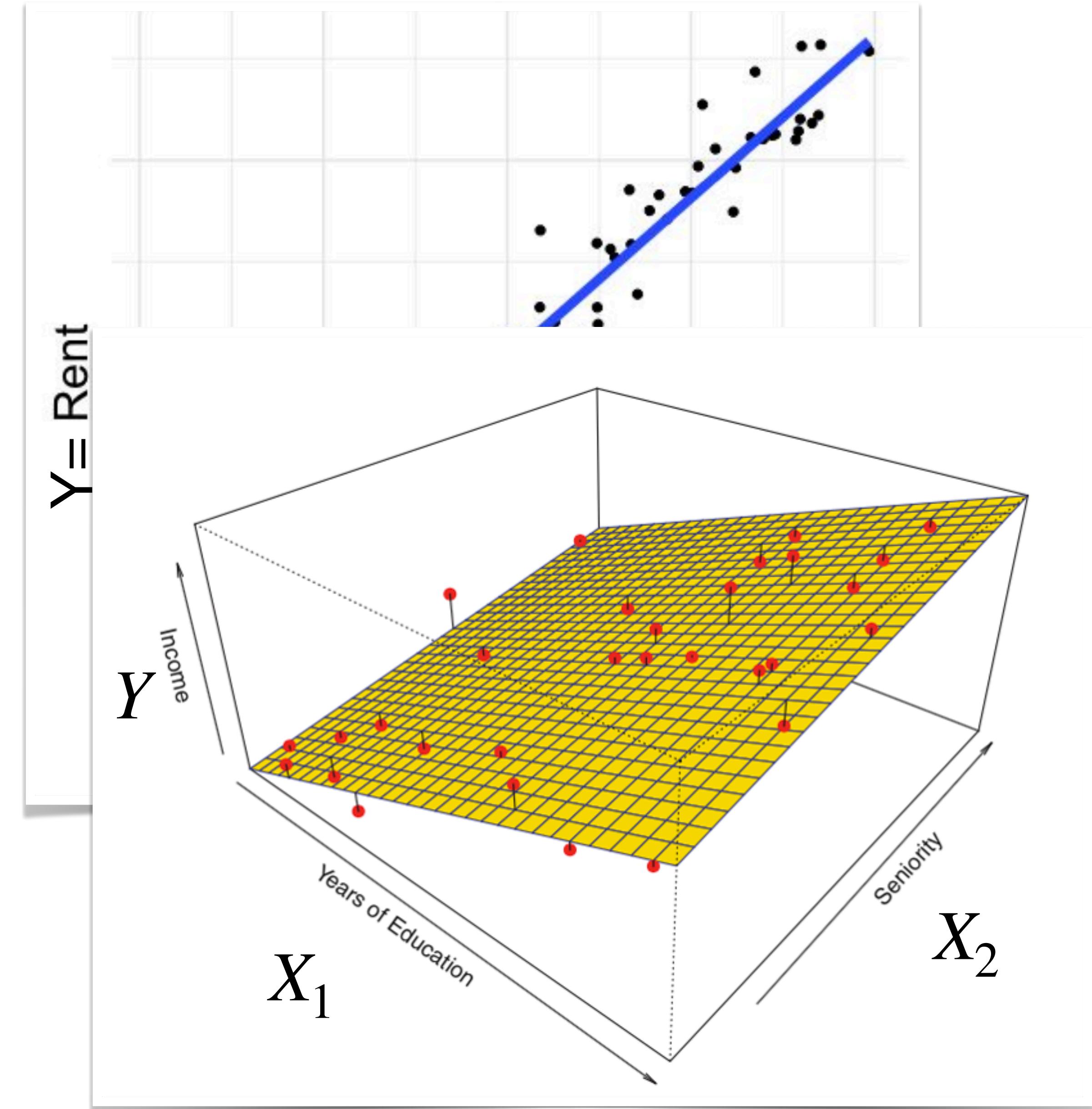
- It predicts a continuous variable Y using one or multiple variables X 's (can be continuous, categorical, or both).



Linear regression

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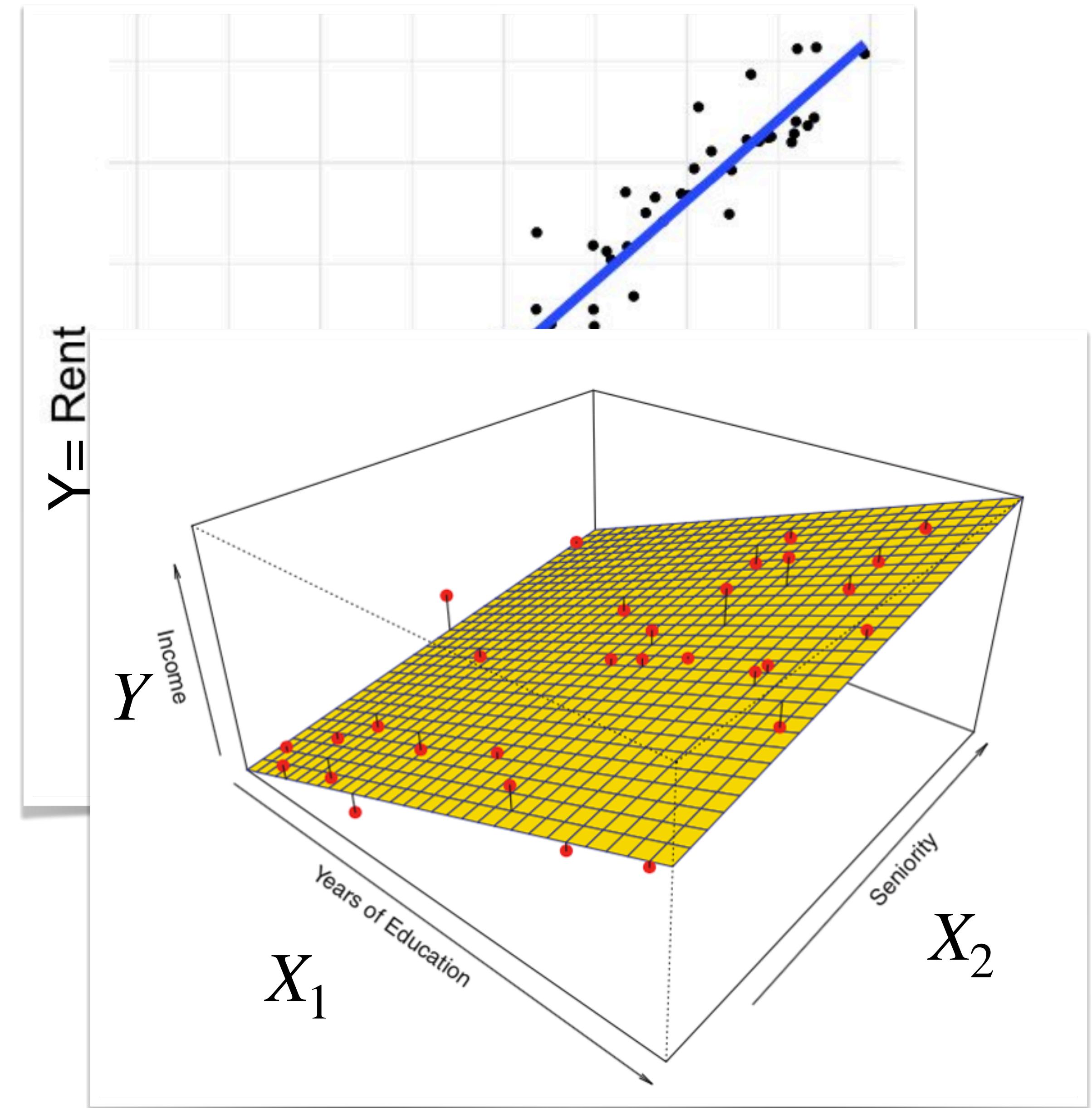
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- It describes the relationship between these variables using a line (2D) or a plane (3D)



Linear regression

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- It predicts a continuous variable Y using one or multiple variables X 's (can be continuous, categorical, or both).
- It describes the relationship between these variables using a line (2D) or a plane (3D)
 - Similar to correlation, but **correlation** measures the strength and direction of a linear relationship between two variables, and **regression** measures how those variables affect each other using an equation (it estimates the best straight line that summarizes the relation).



Linear regression

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- ϵ are the residuals, the errors of the equation in the data

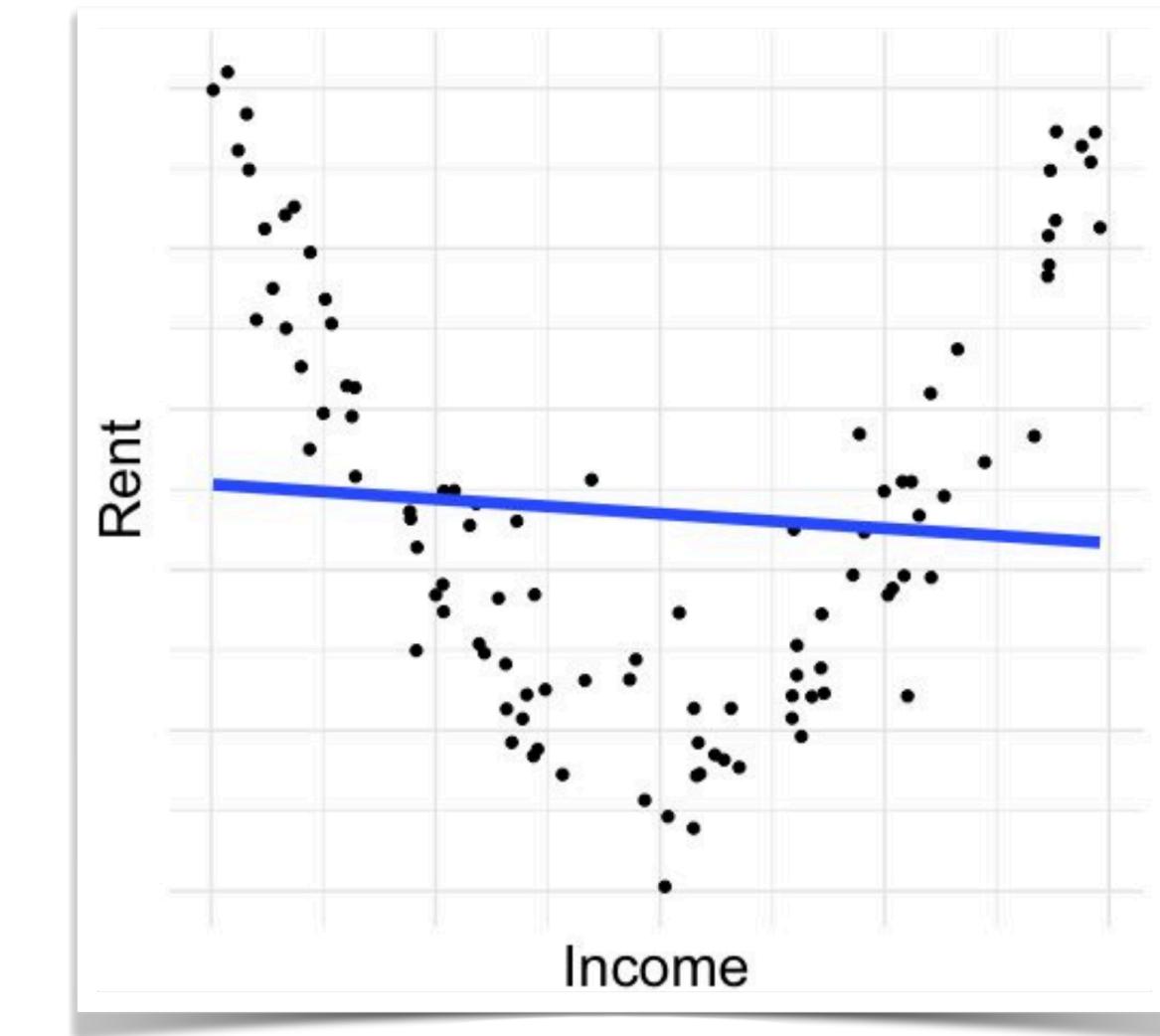
Linear regression

Assumptions

Linear regression

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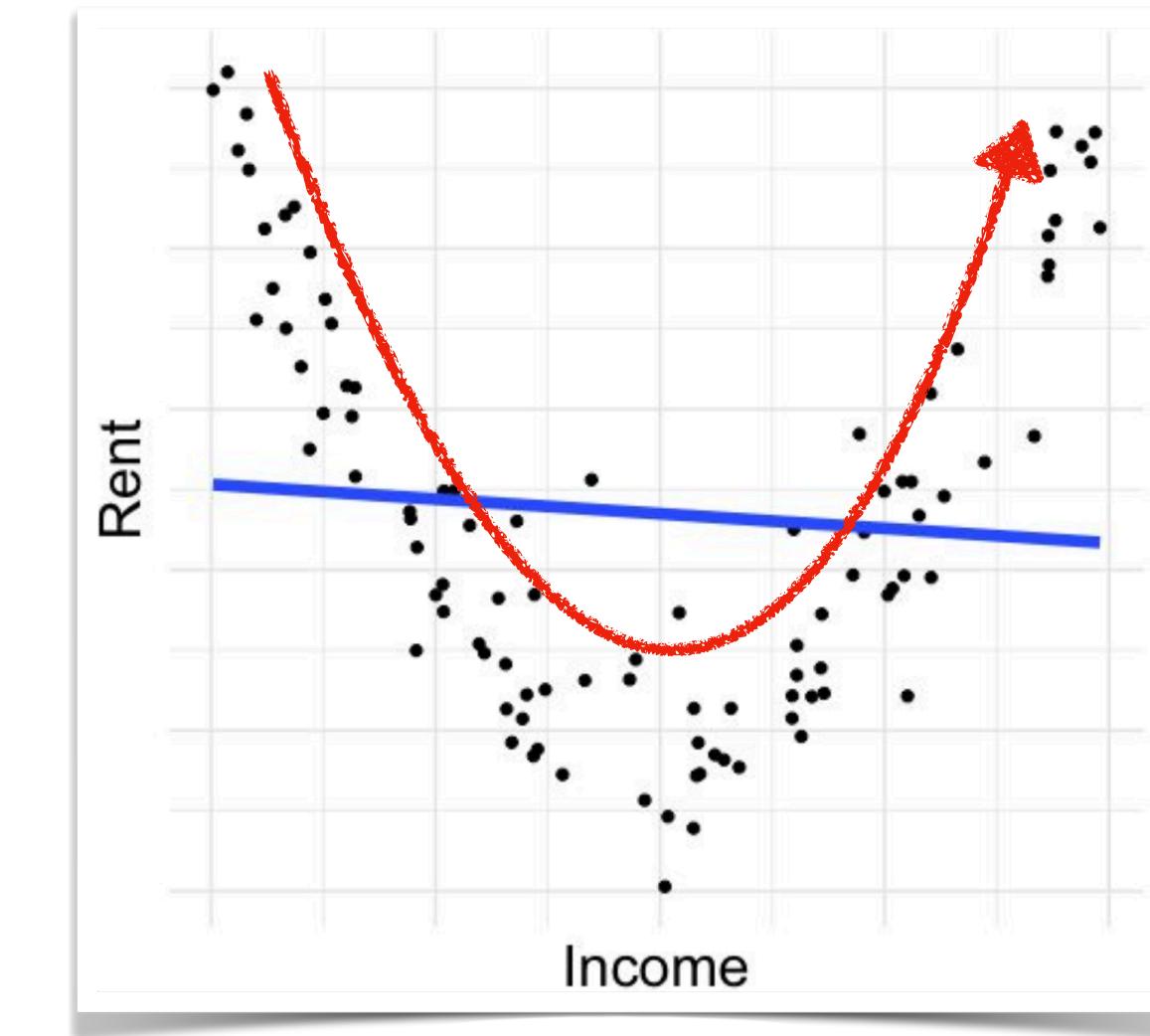
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Linear regression

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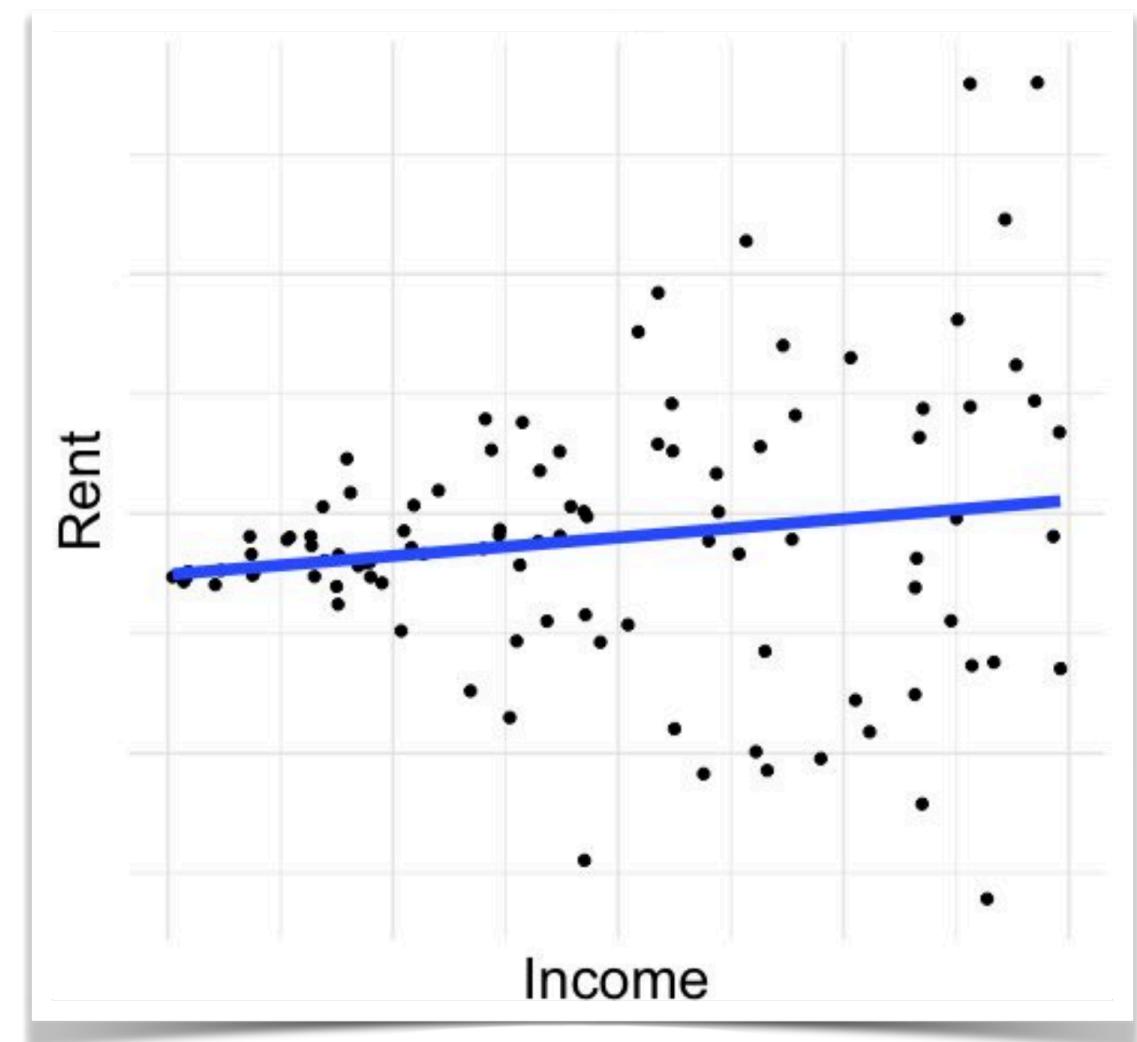
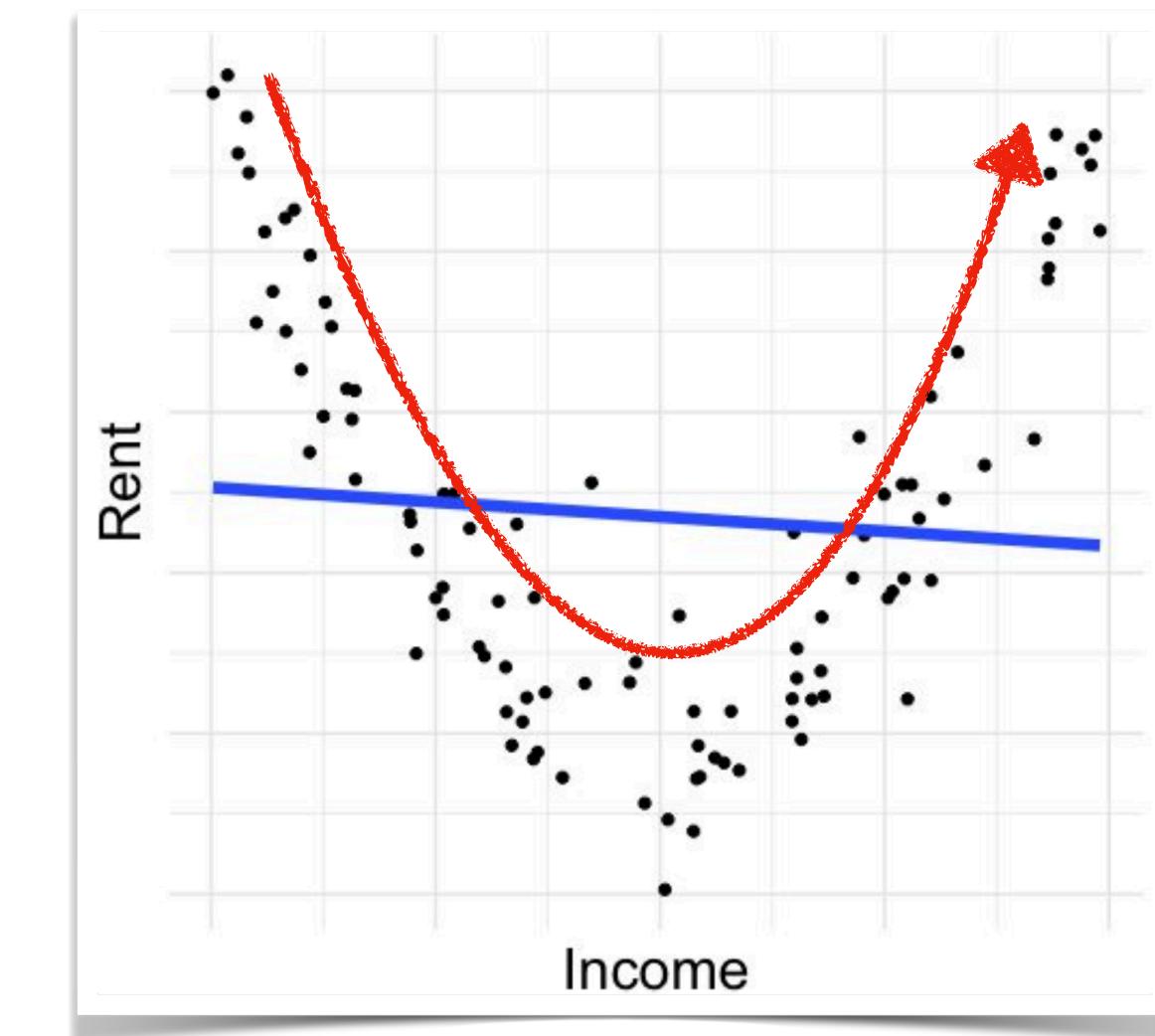
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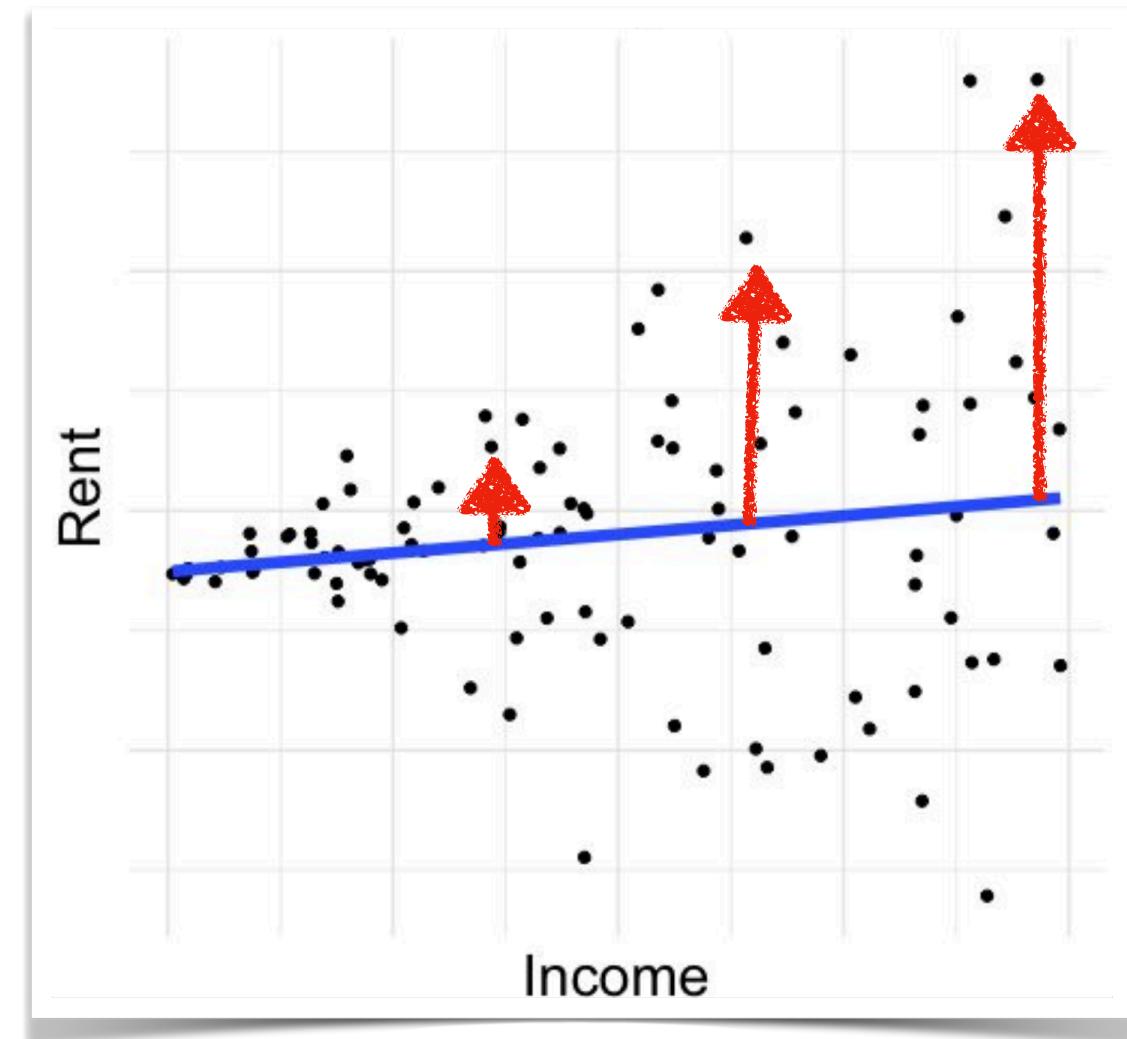
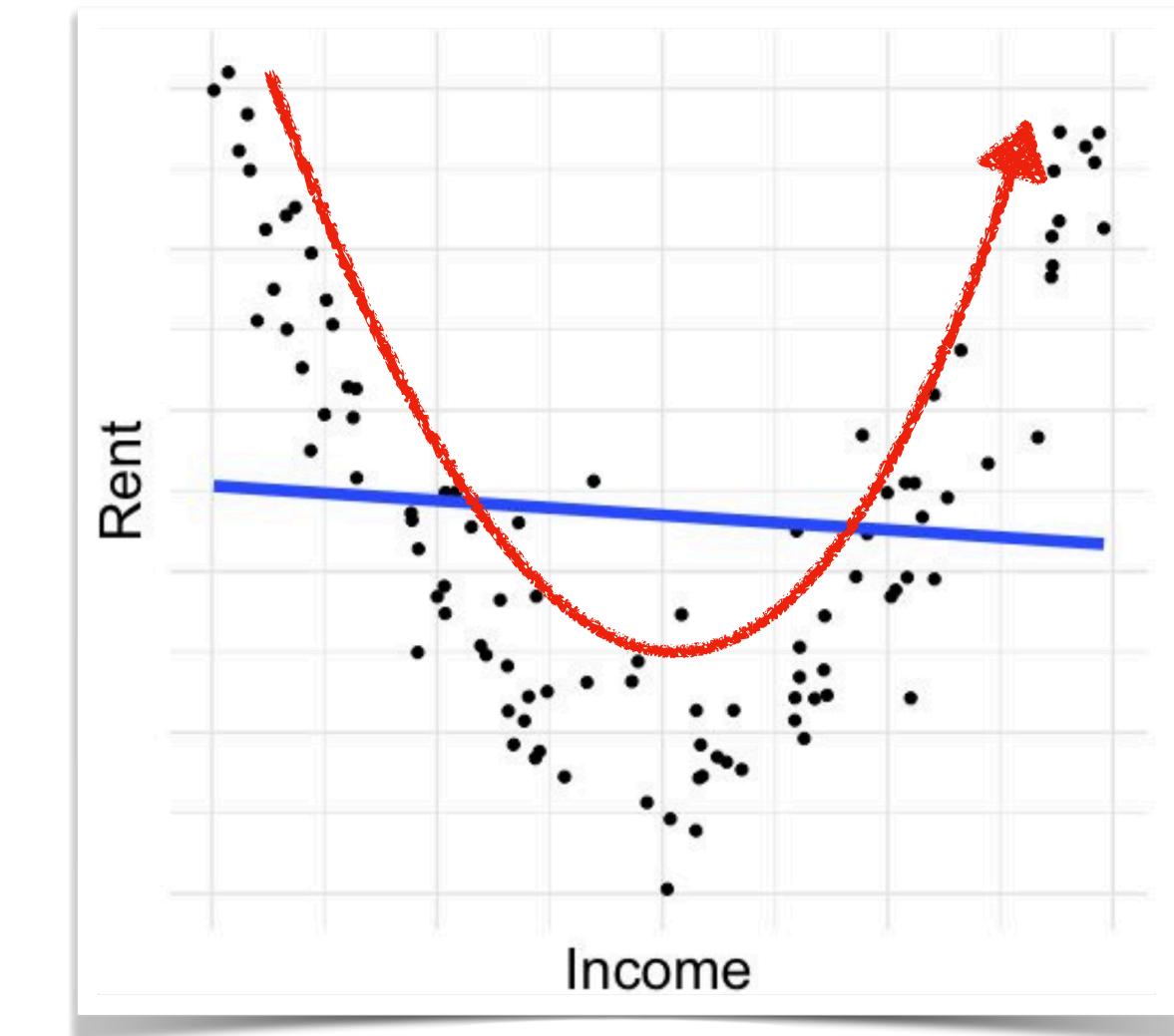
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Linear regression

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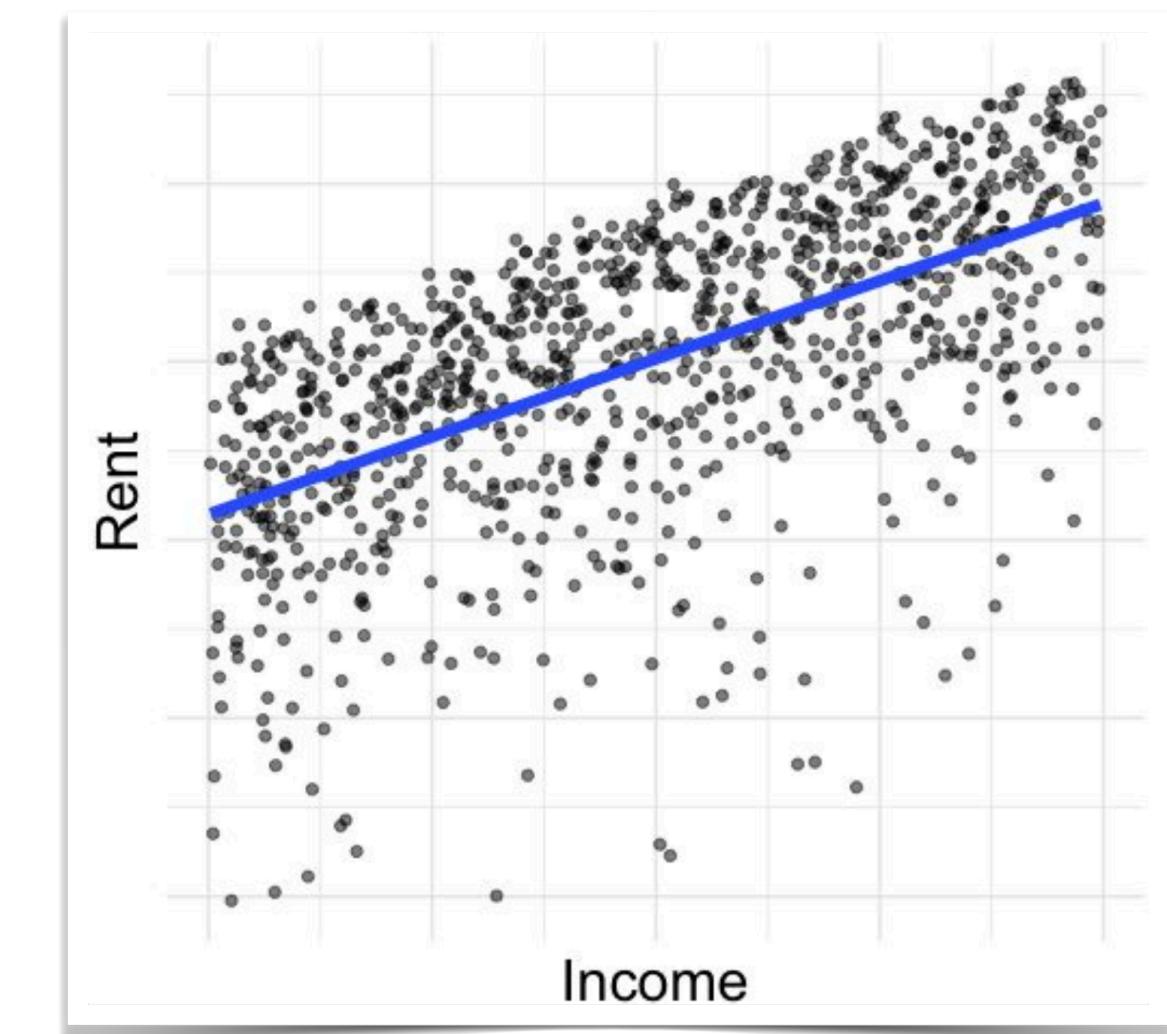
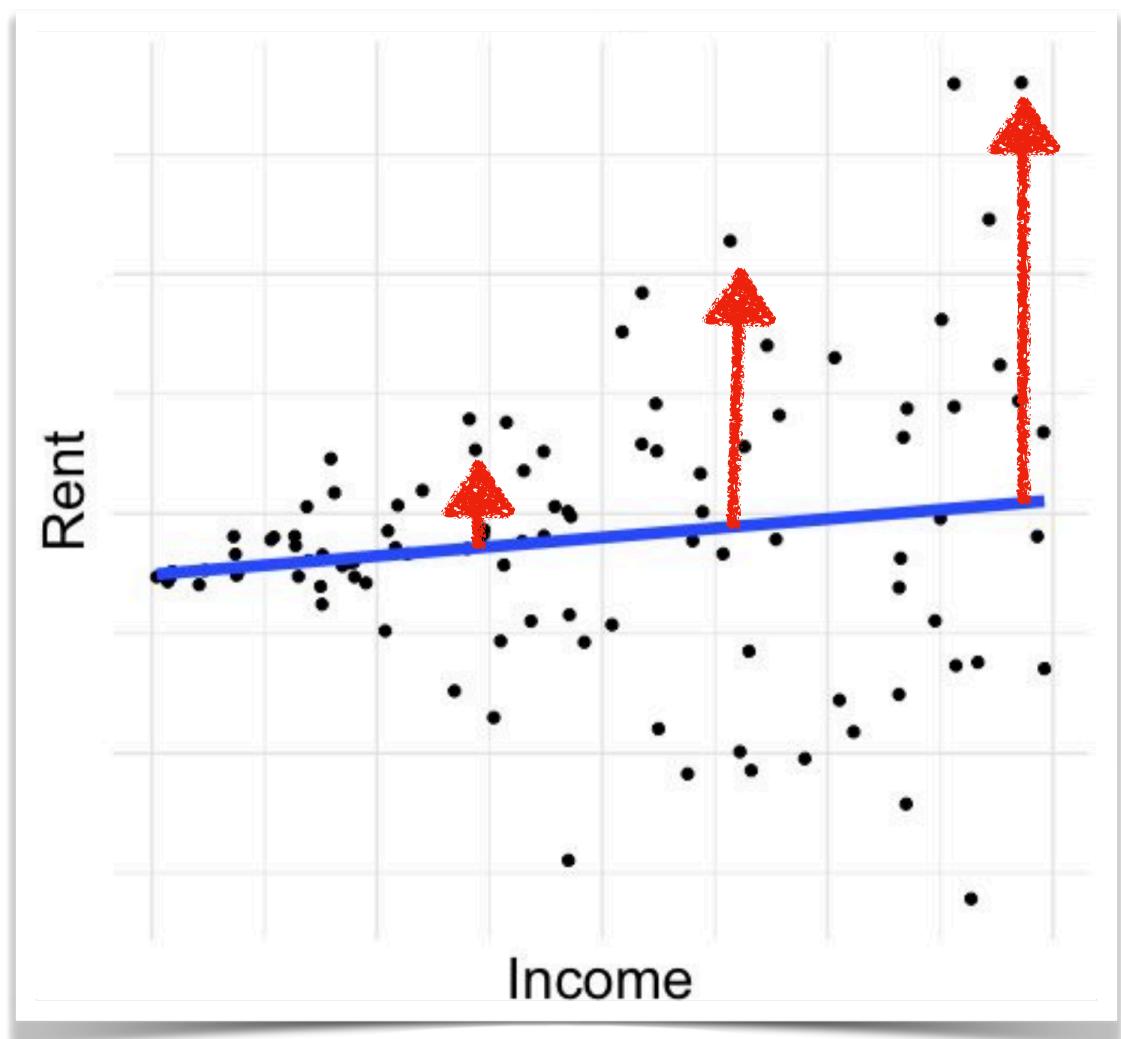
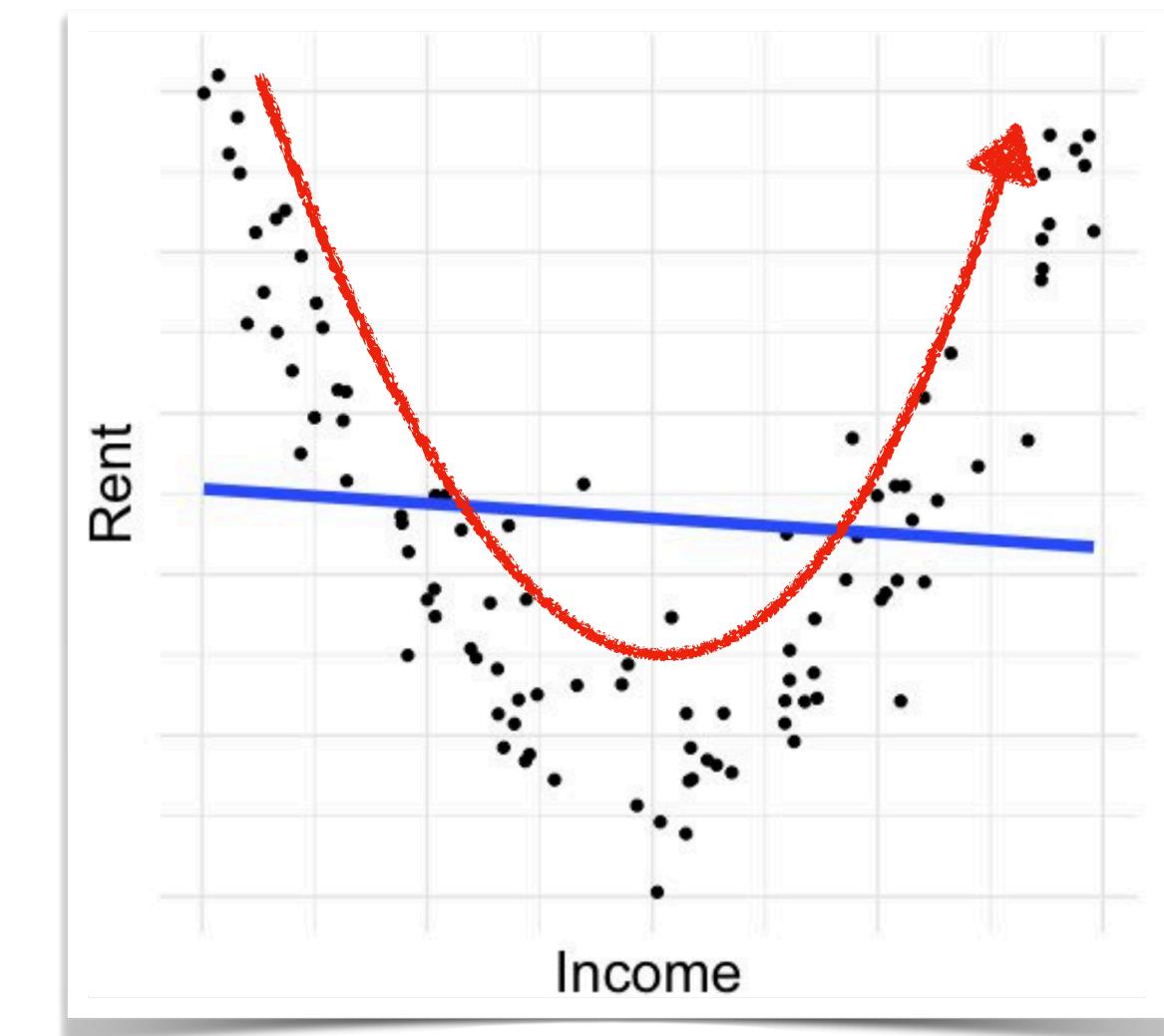
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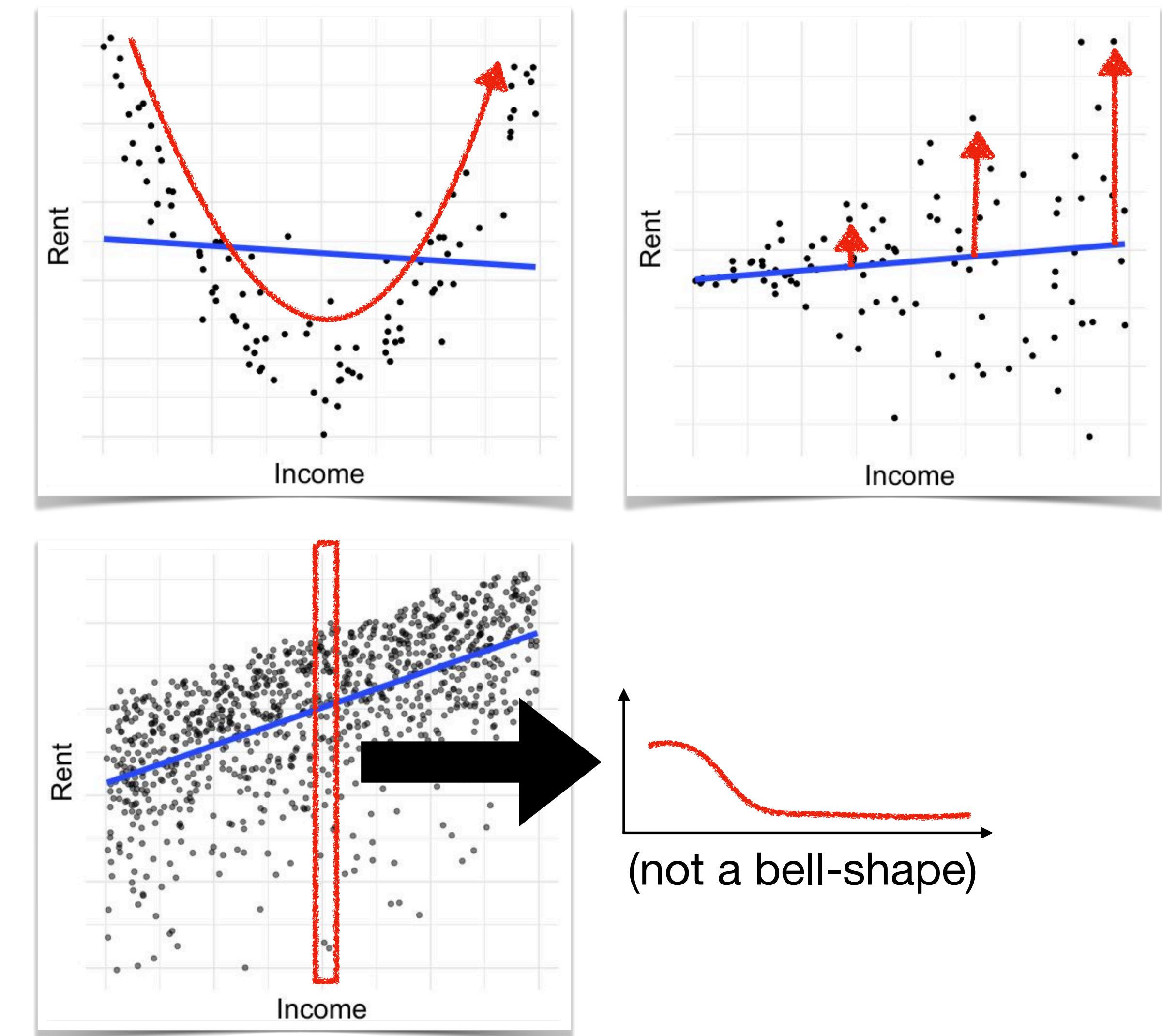
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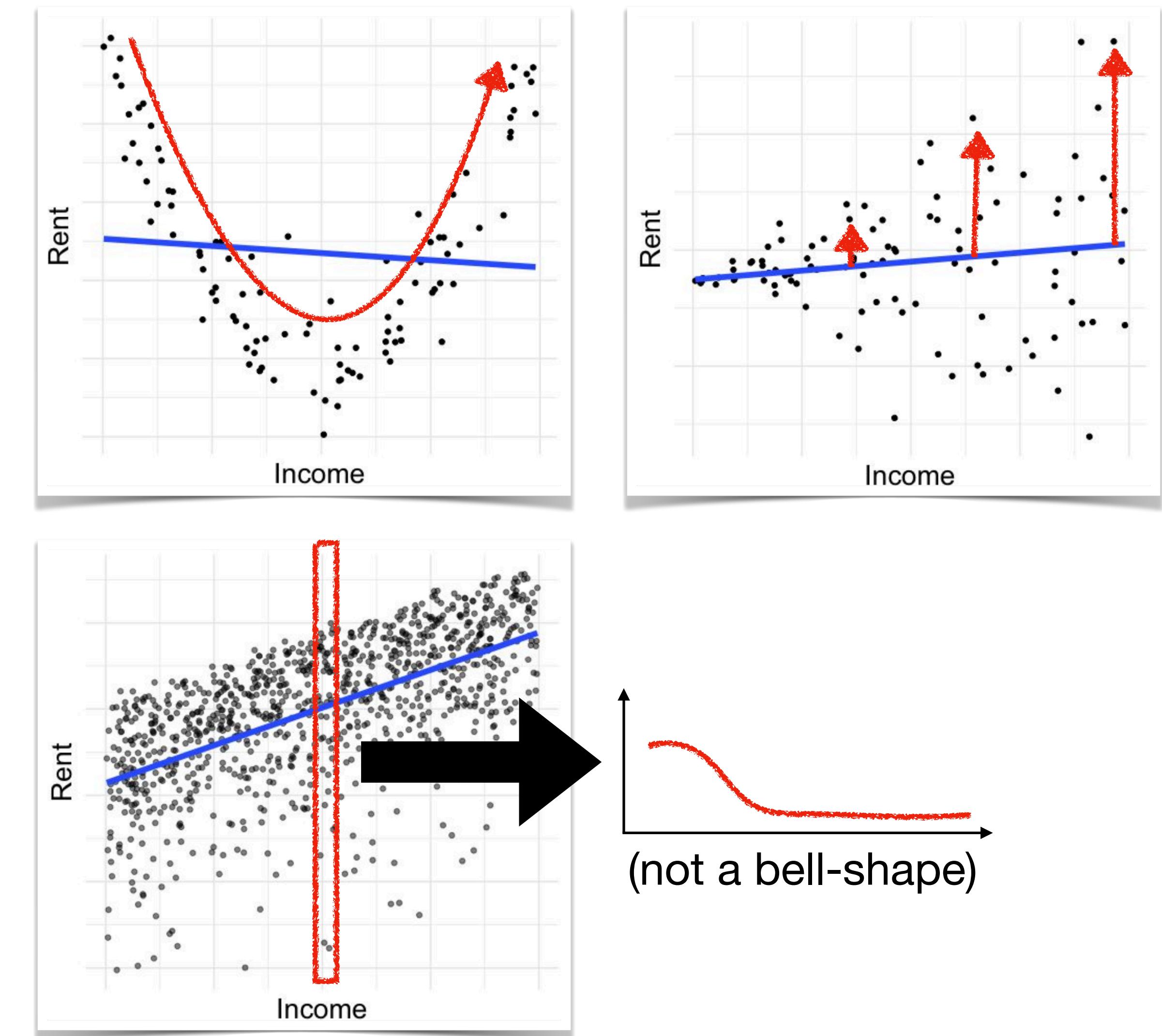
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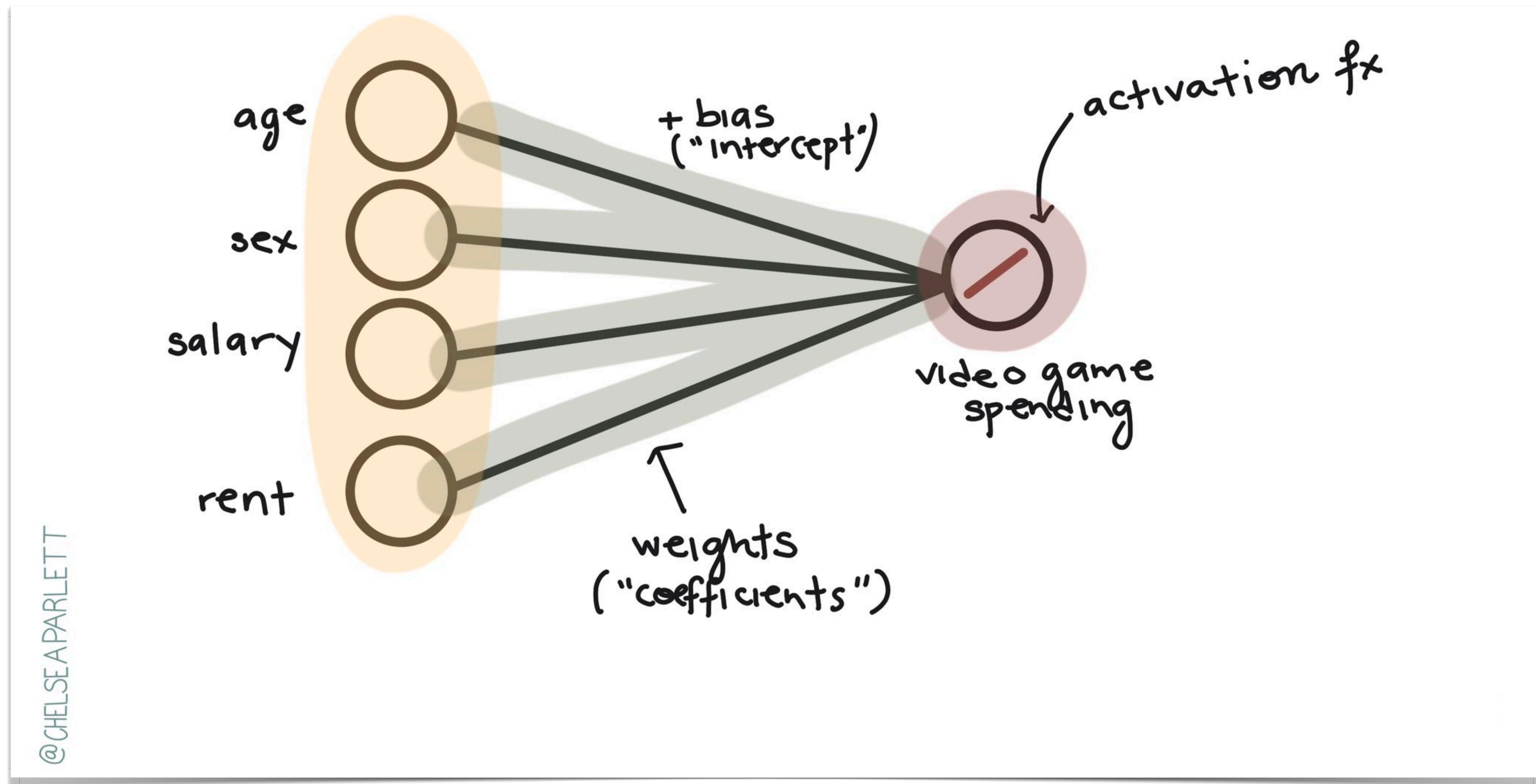
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- **Independence:** Observations are independent of each other.



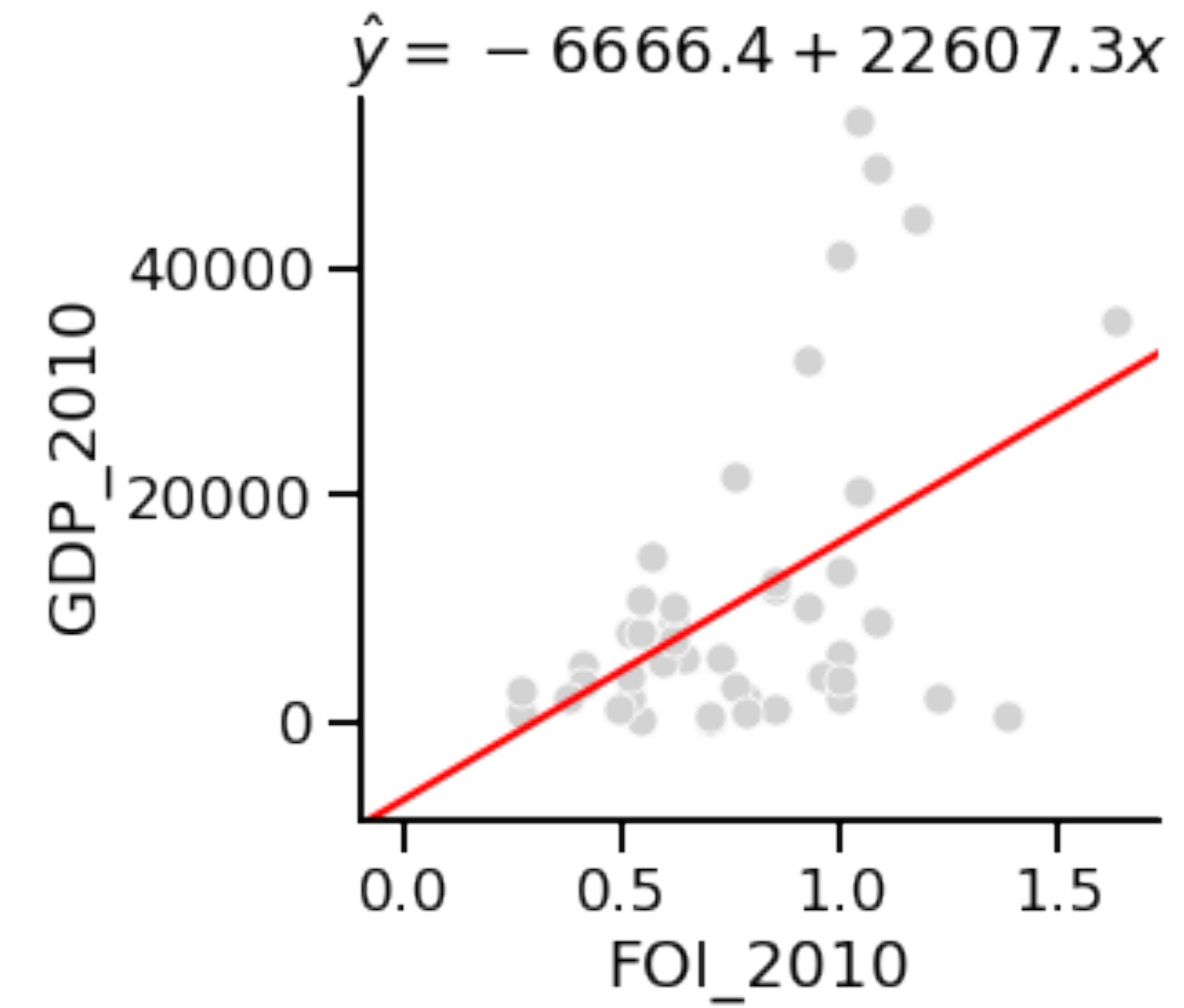
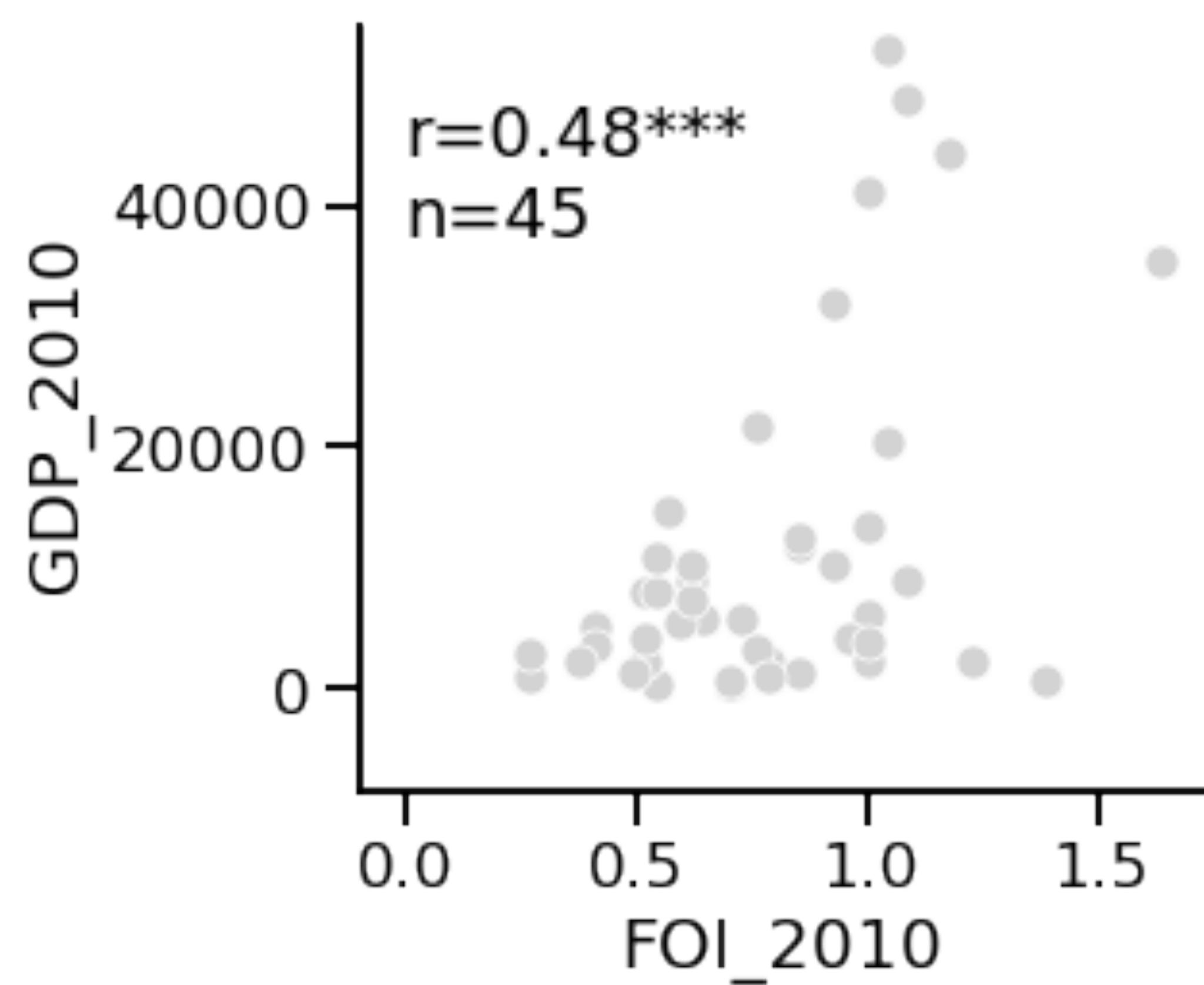
Linear regression

as a neural network



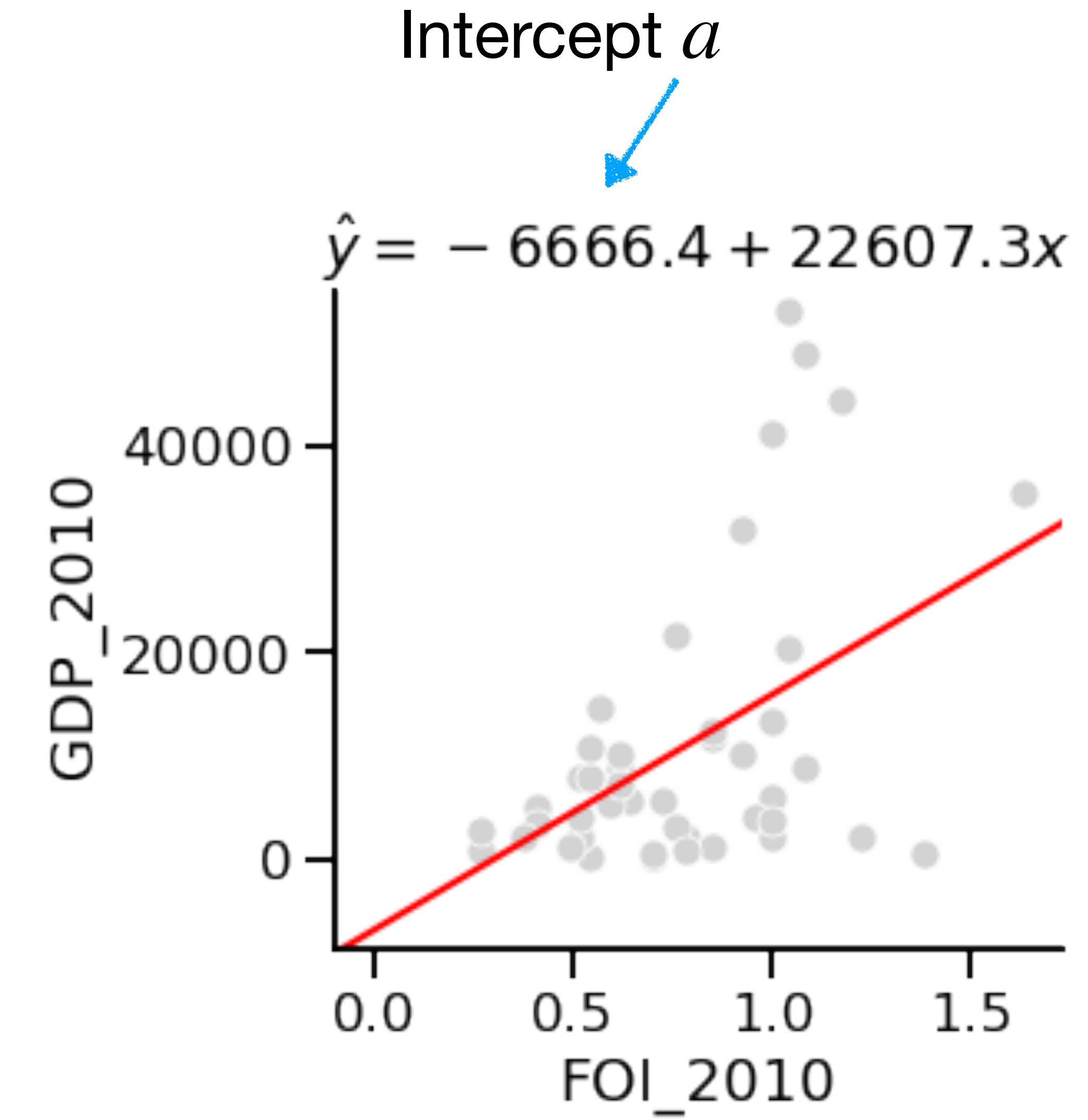
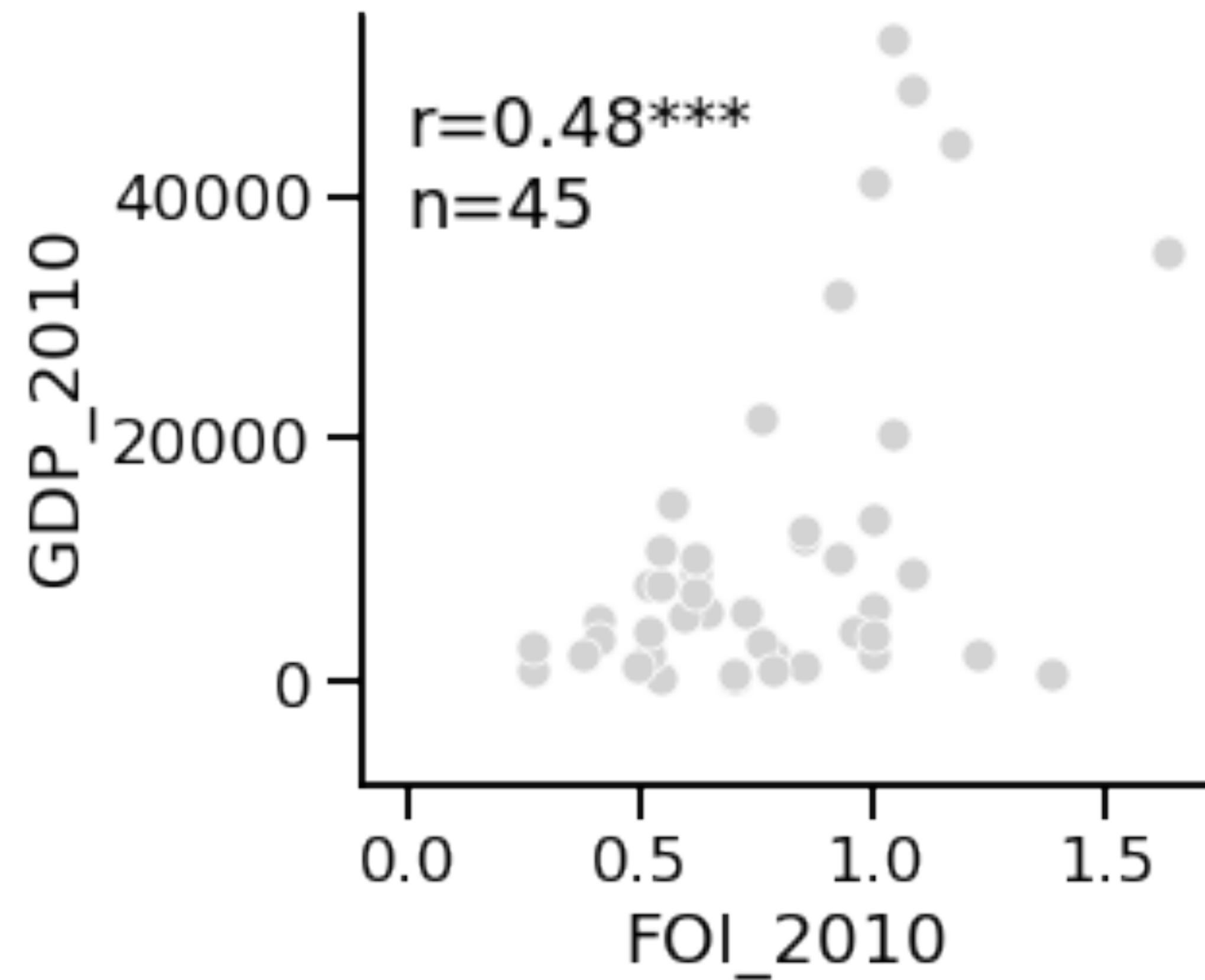
Example FOI and GDP

Correlation vs. Linear regression



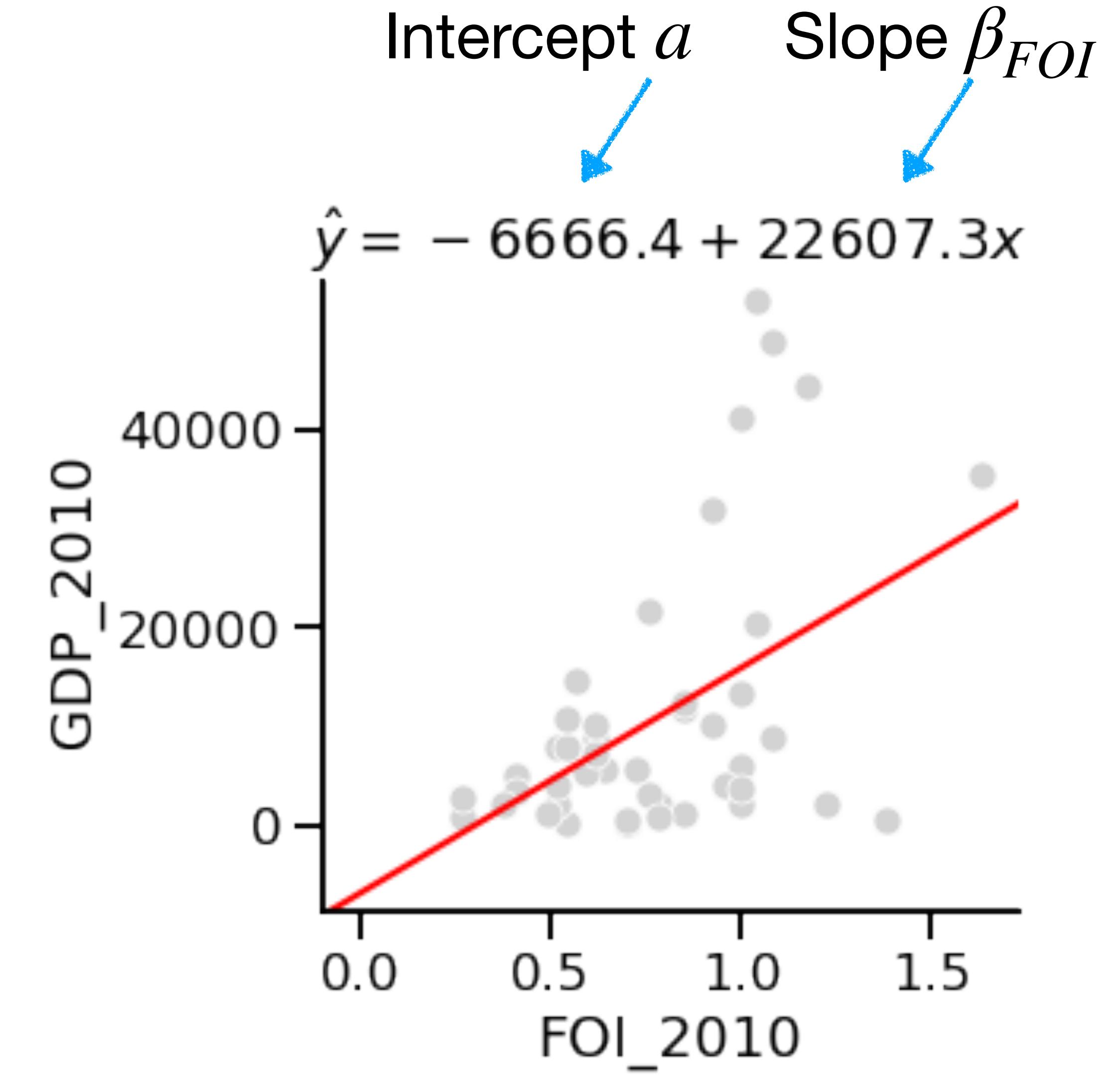
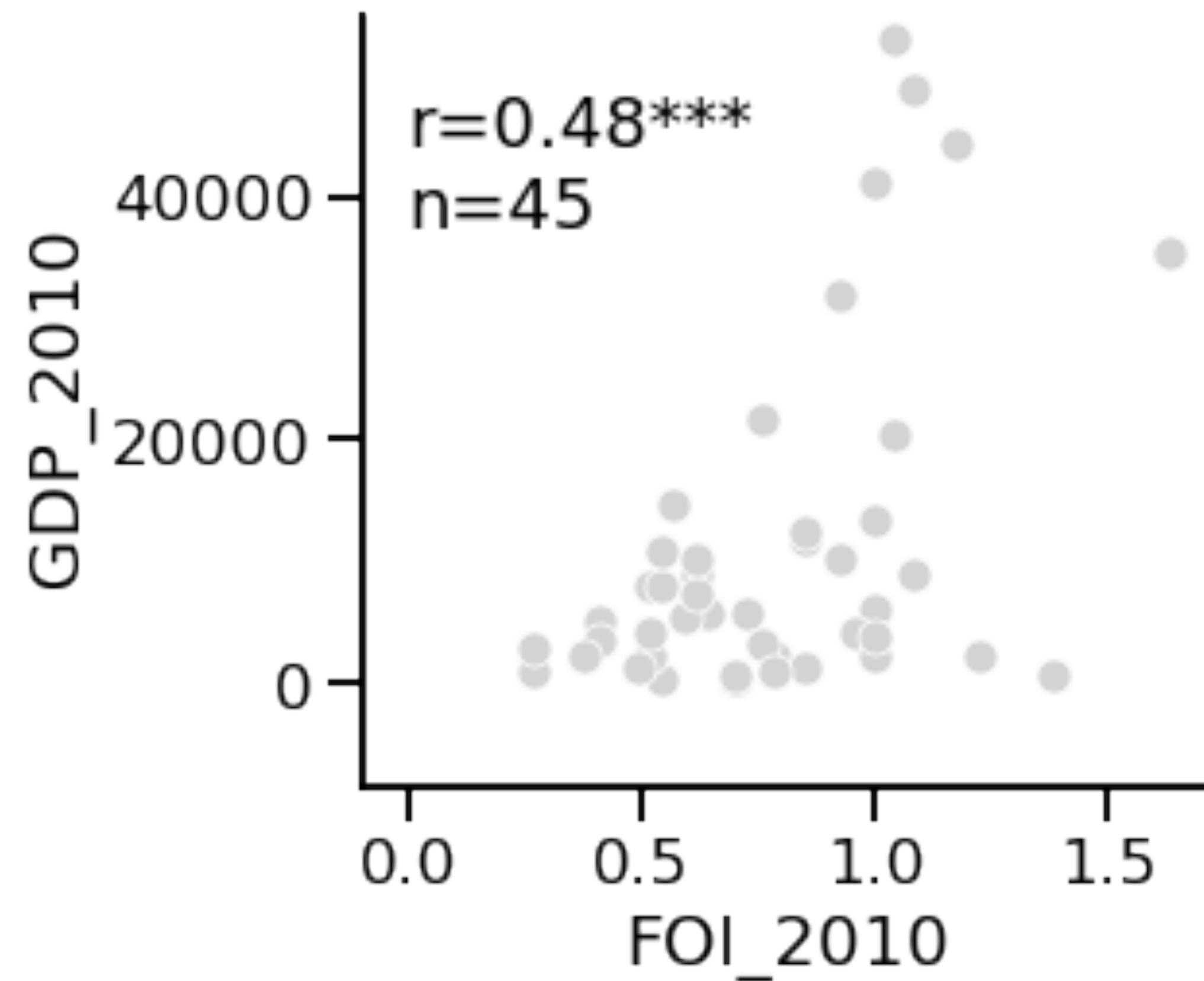
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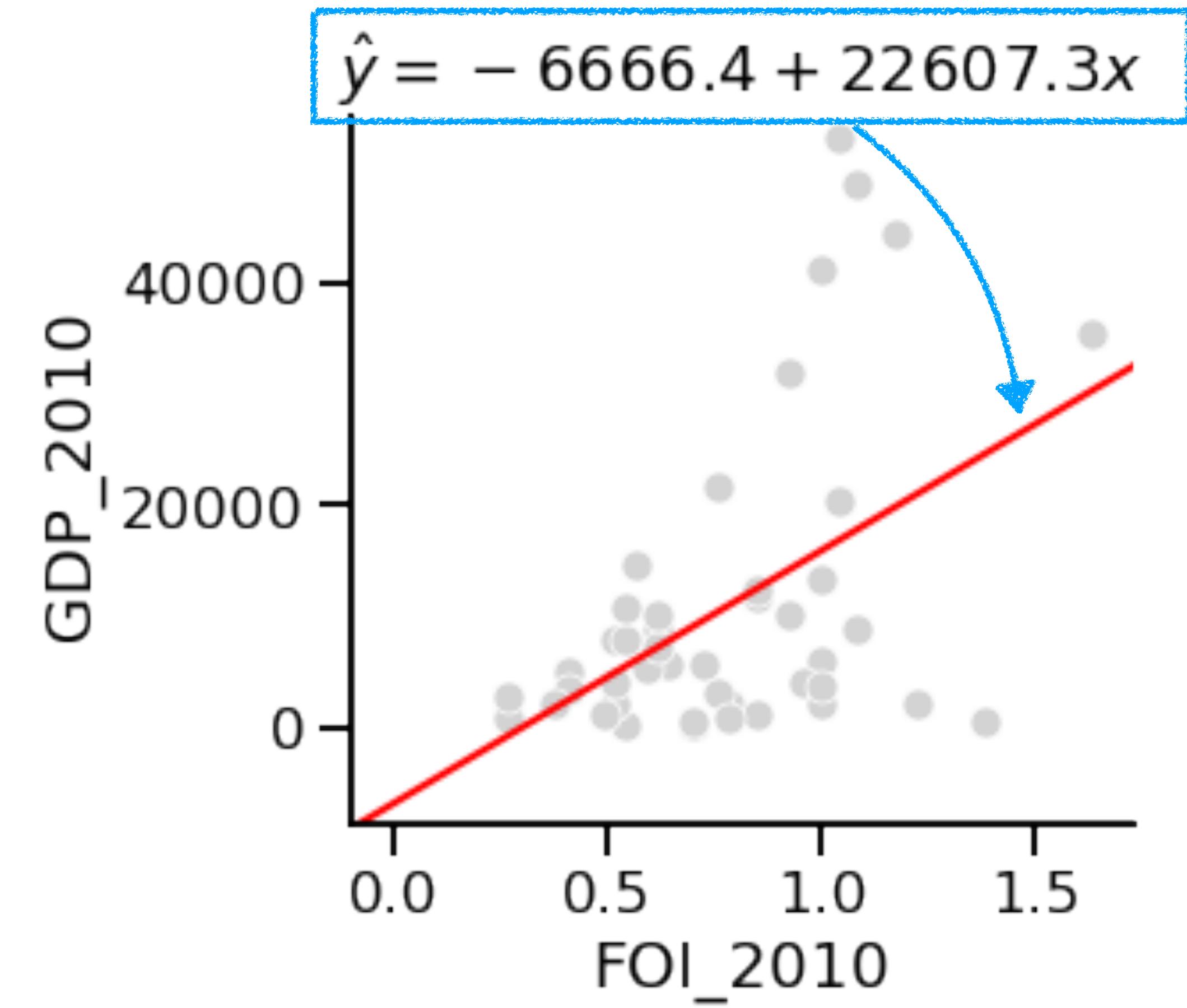
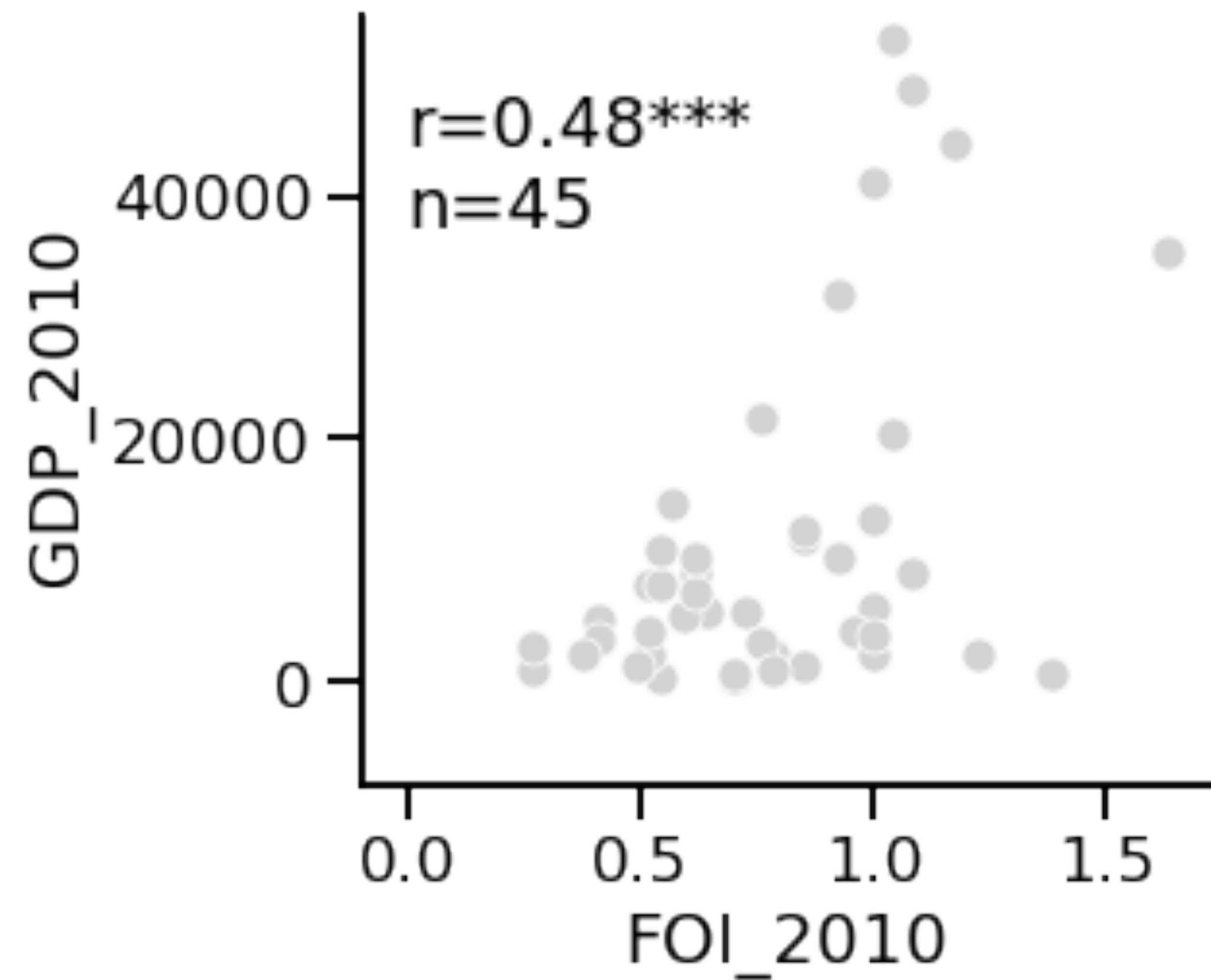
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Regression residuals

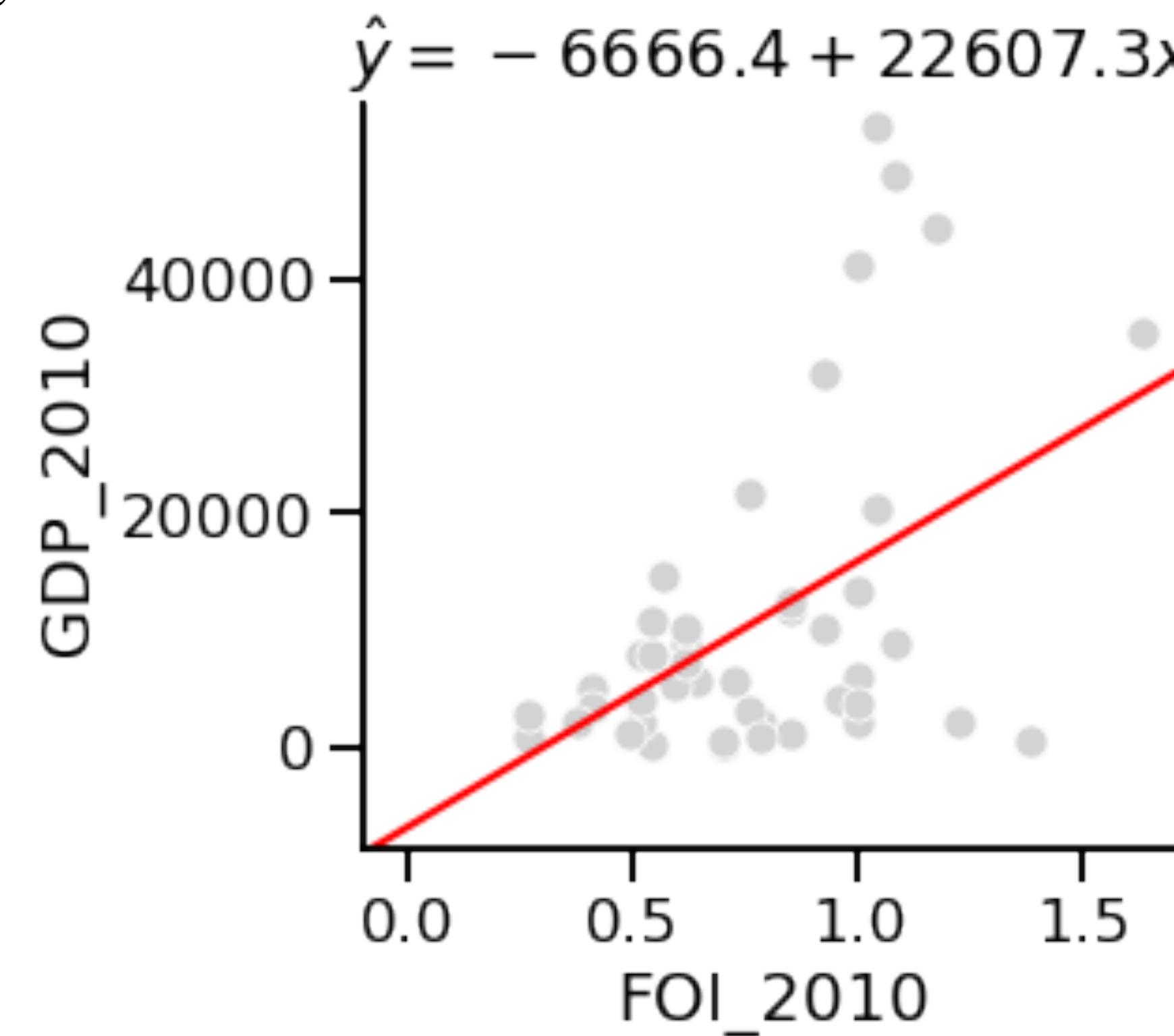
Error term: ϵ

- Residuals (ϵ) are the differences in between the empirical values y_i and their fitted values \hat{y}_i

Regression residuals

Error term: ϵ

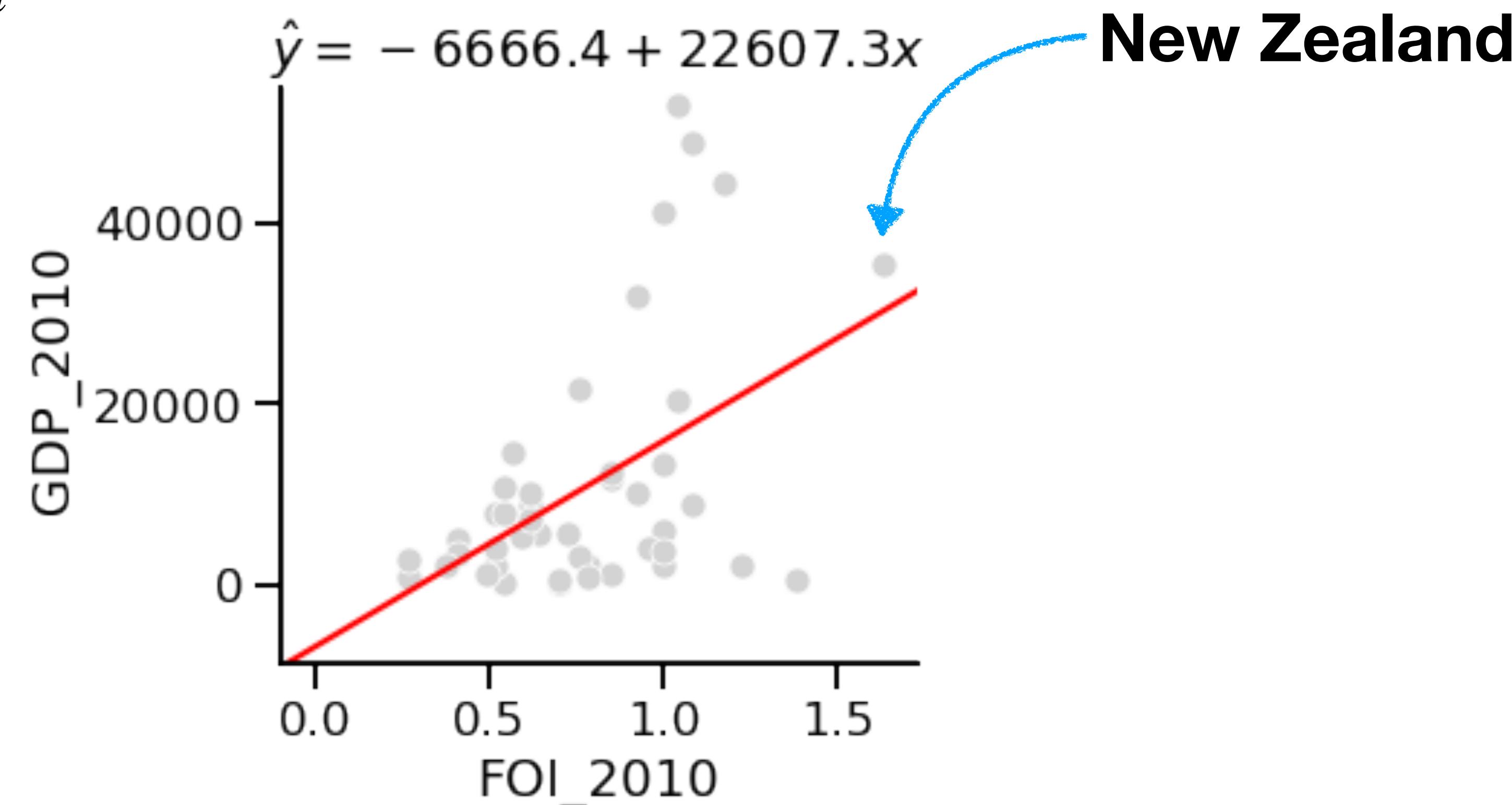
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Regression residuals

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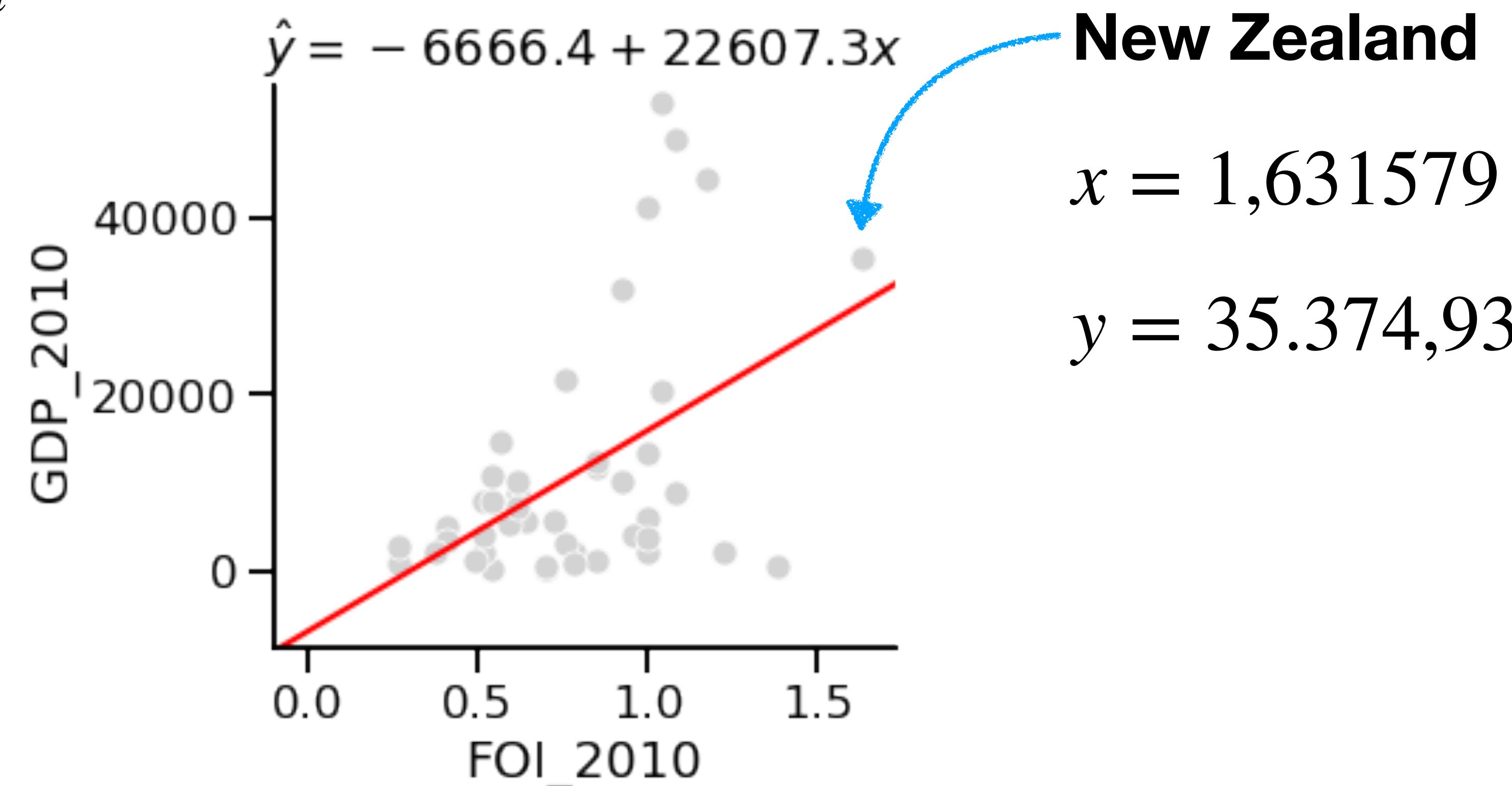
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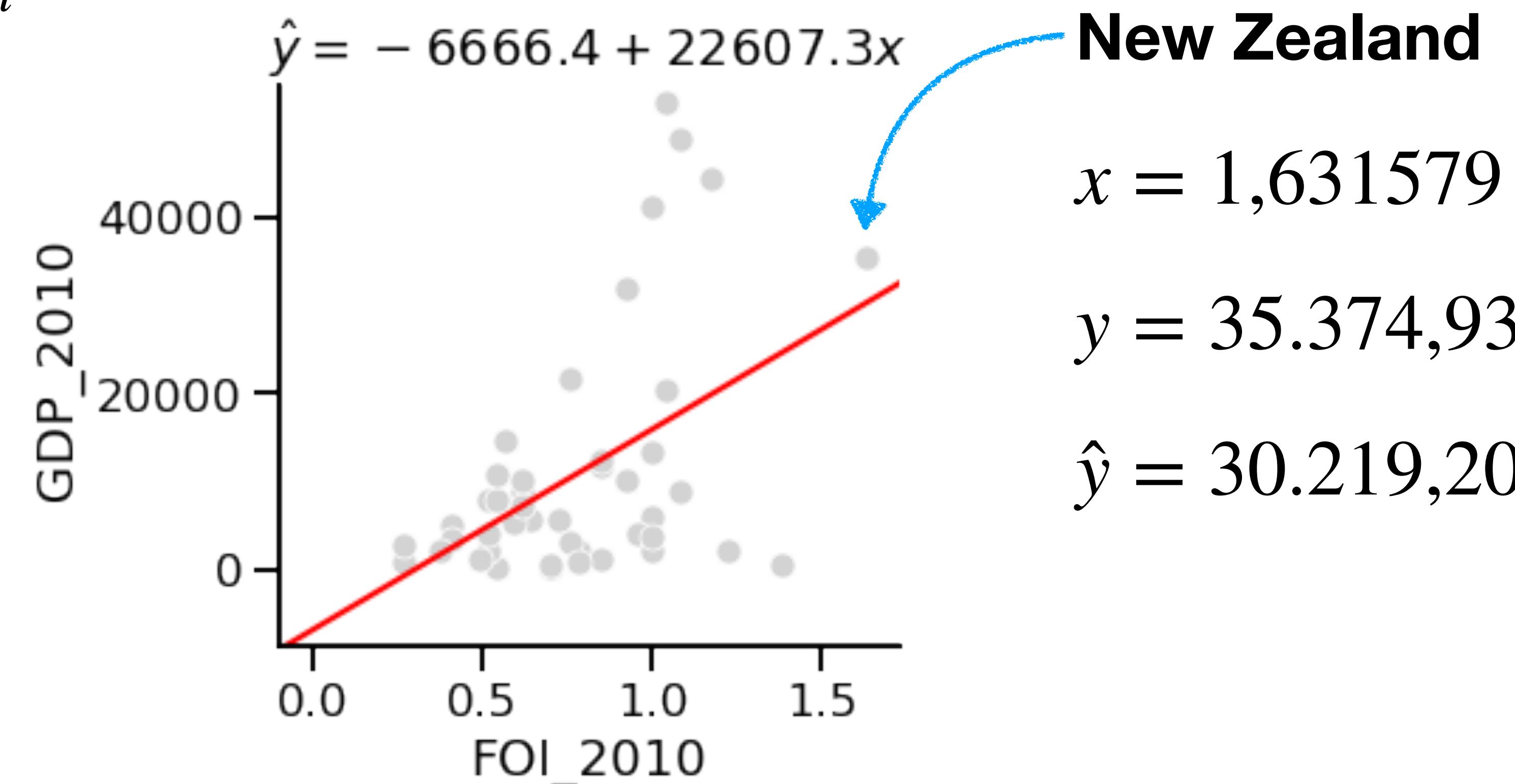
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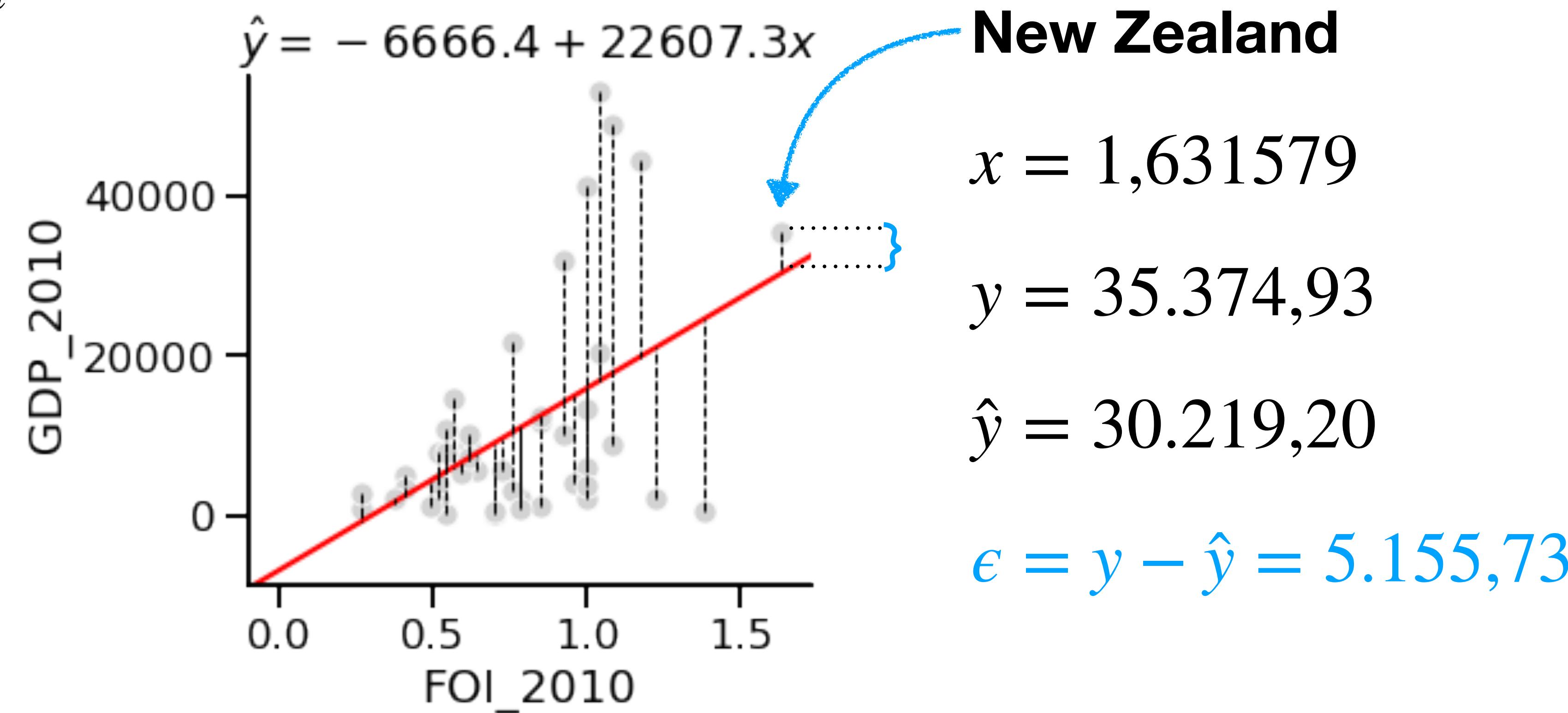
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Ordinary Least Squares (OLS)

Model fitting

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- Fitting a regression model is the task of finding the values of the coefficients $(a, \beta_1, \beta_2, \dots, \beta_k)$ in a way that minimizes the sum of residuals of the model.

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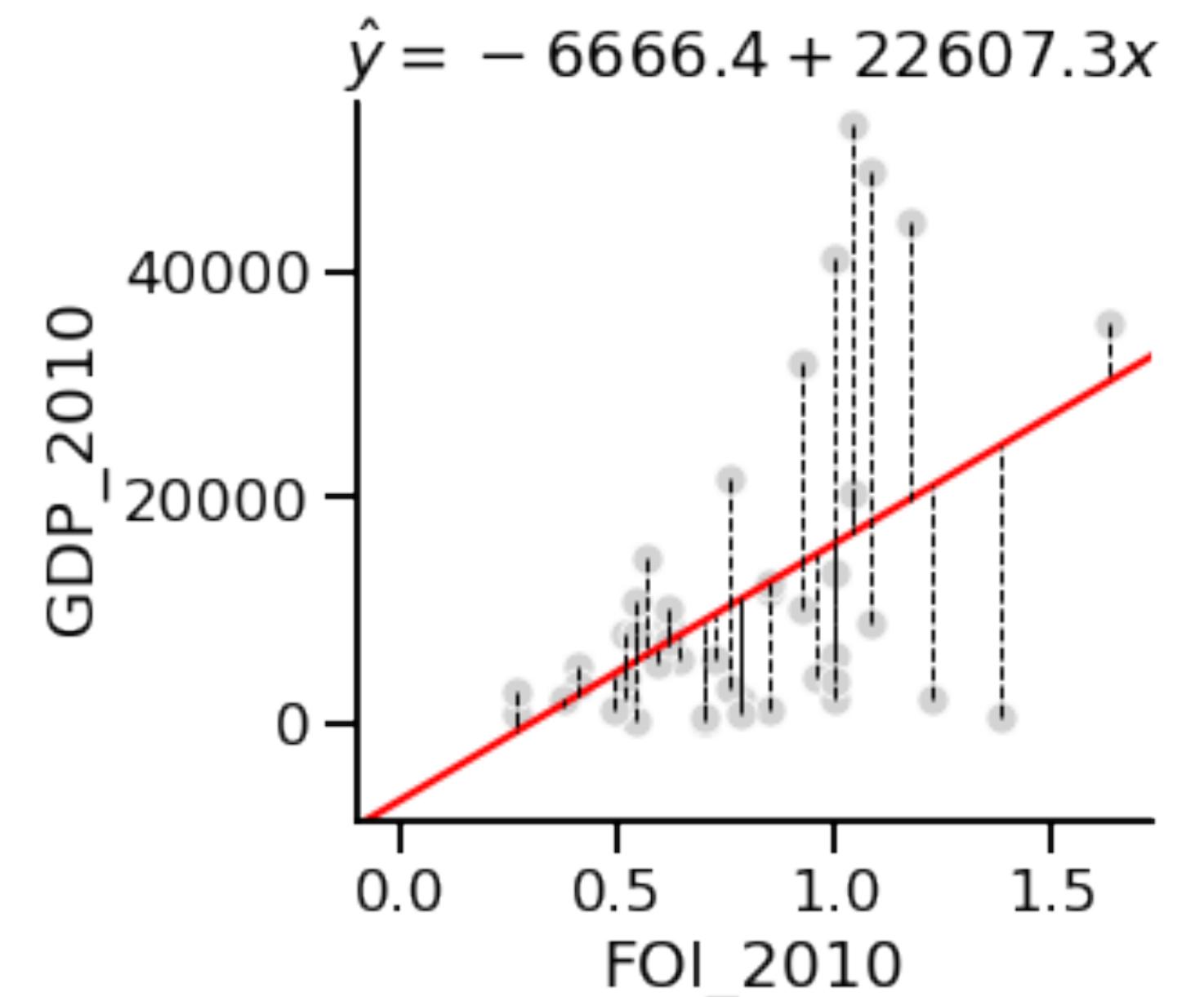
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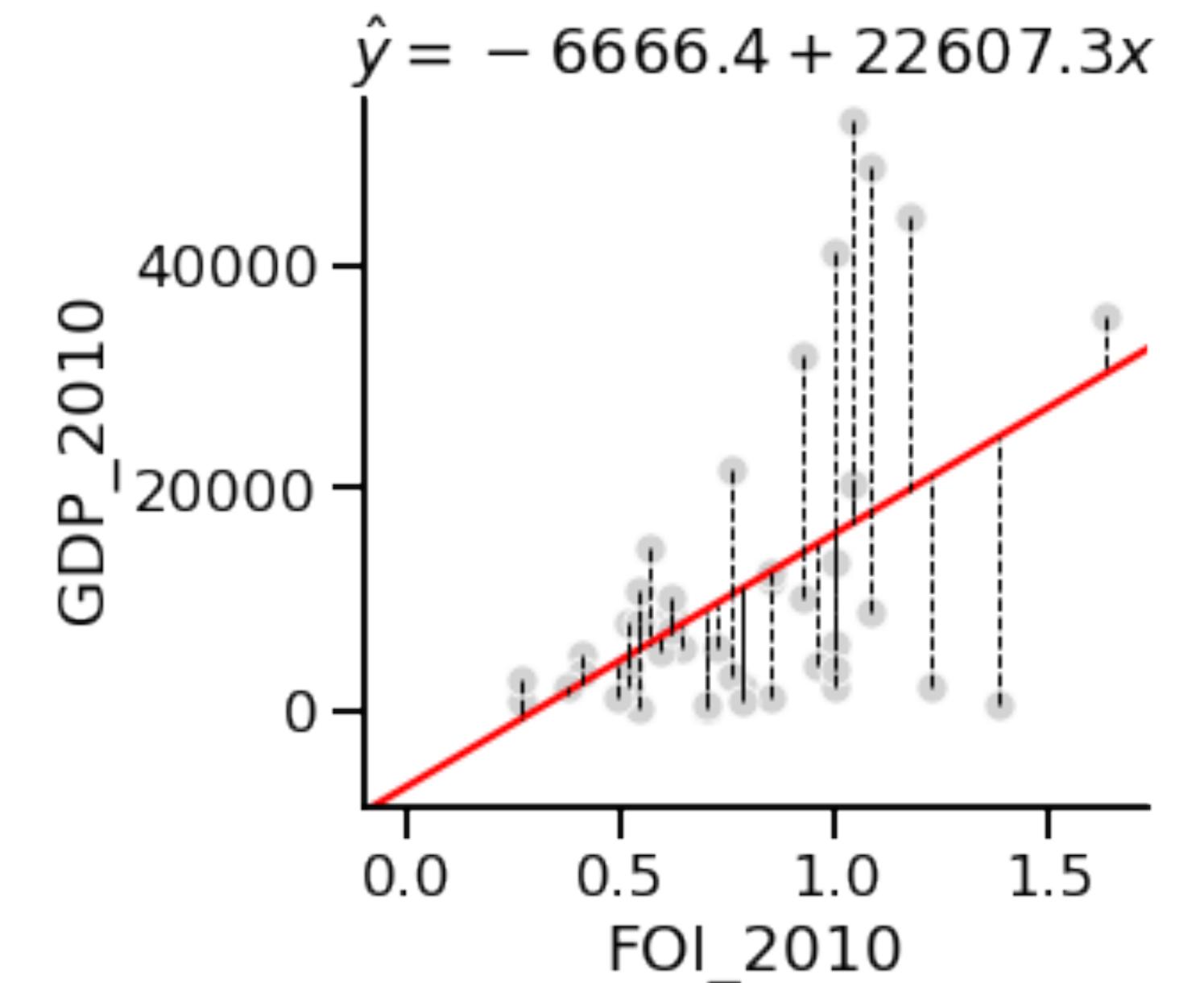
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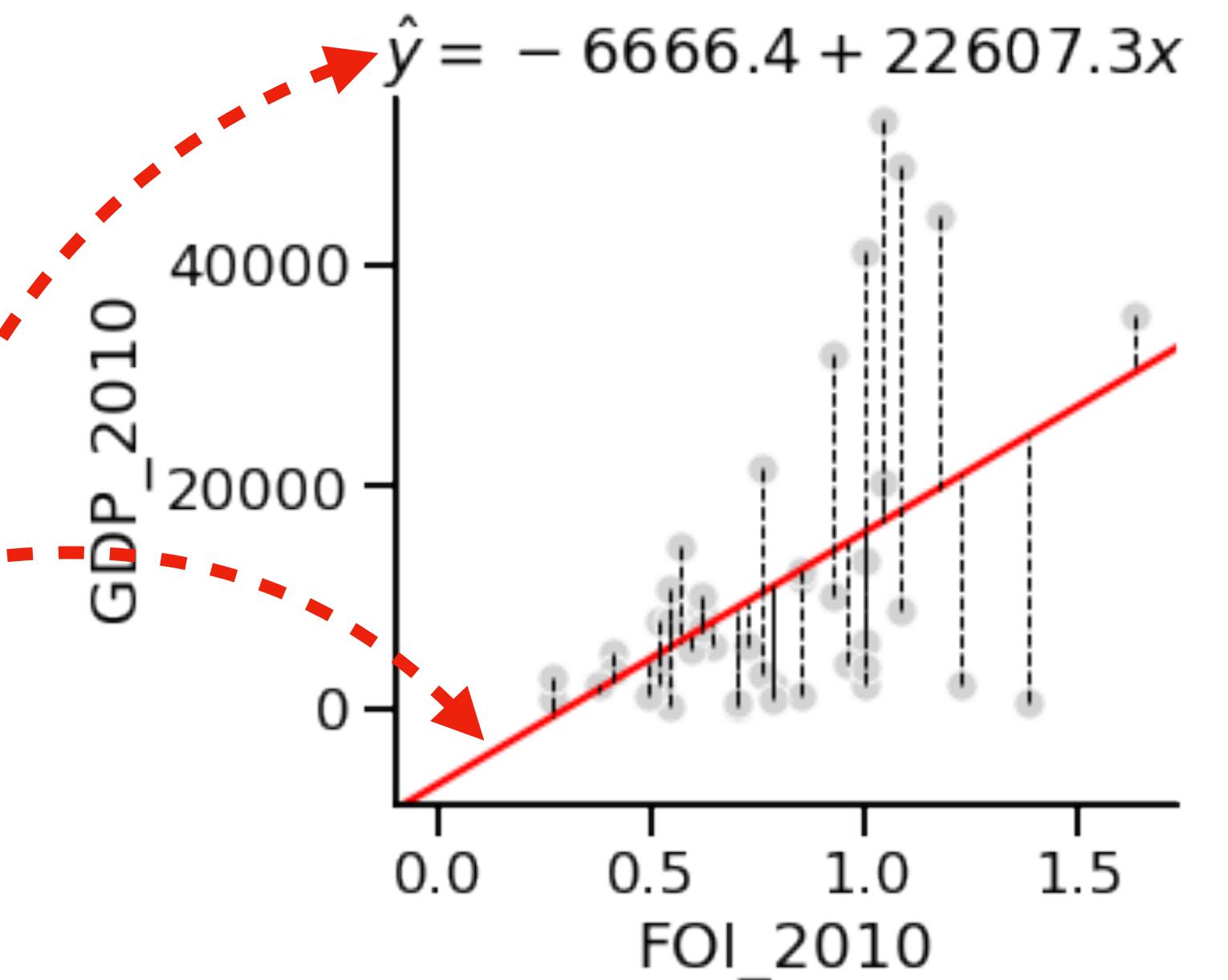


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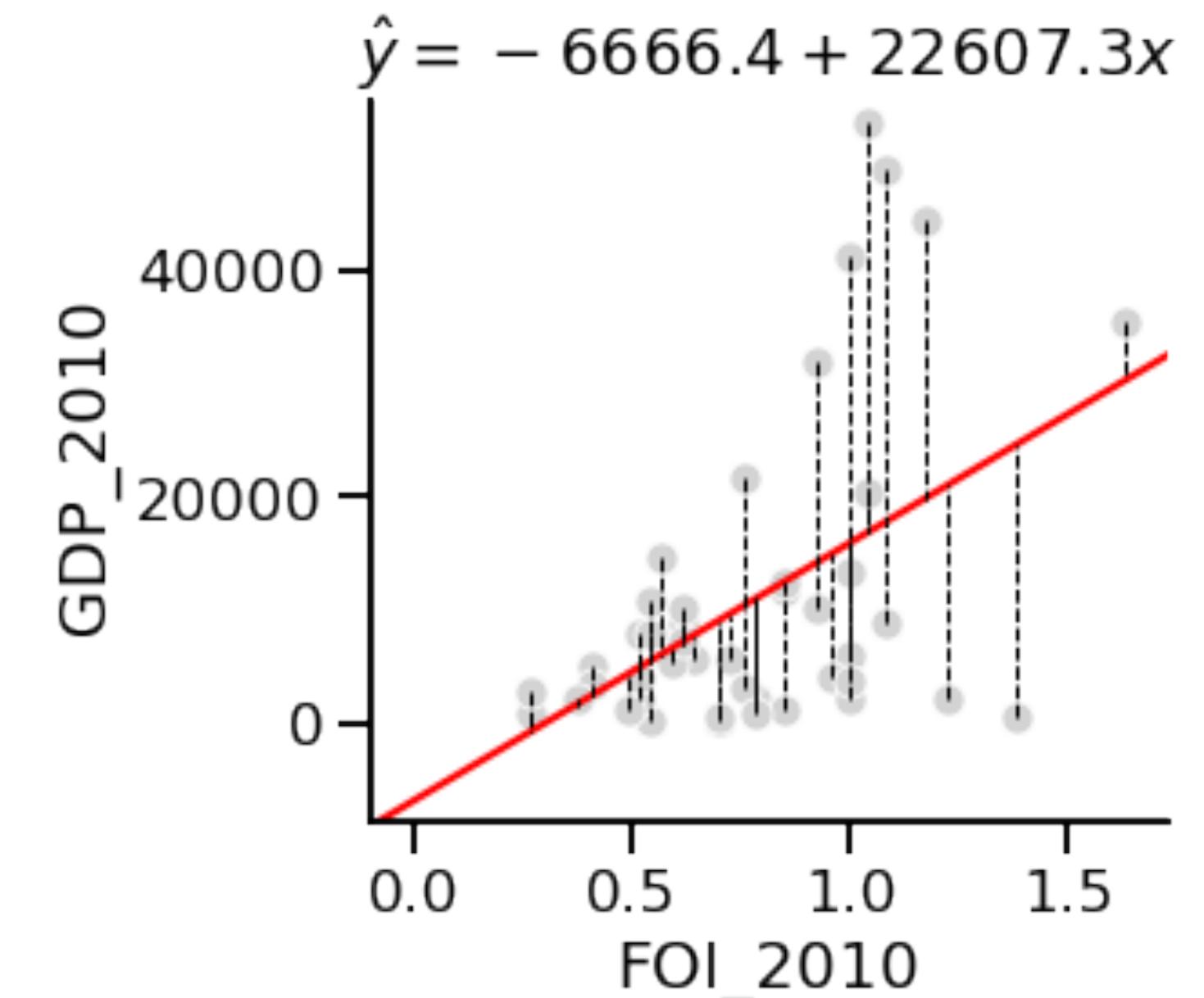
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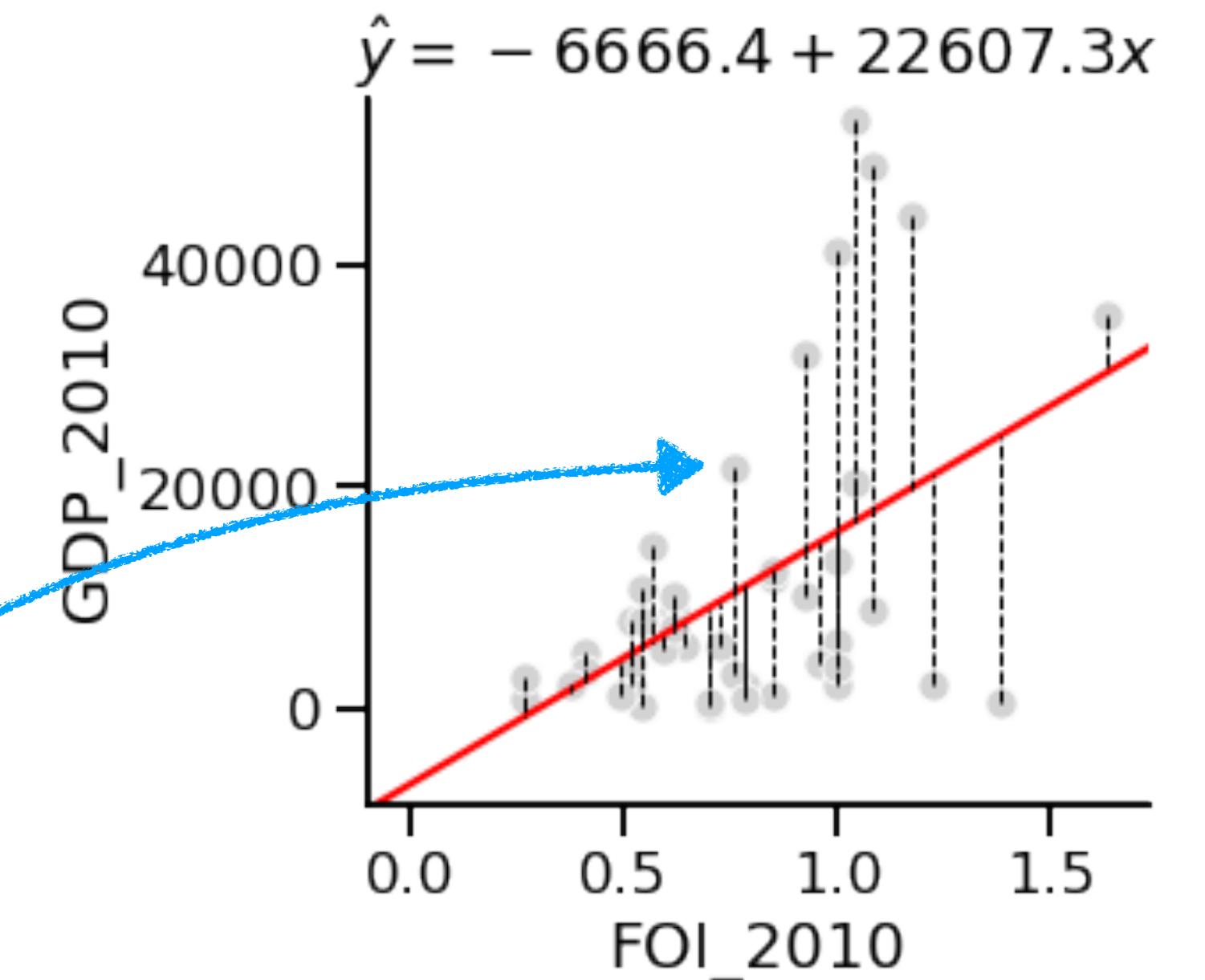
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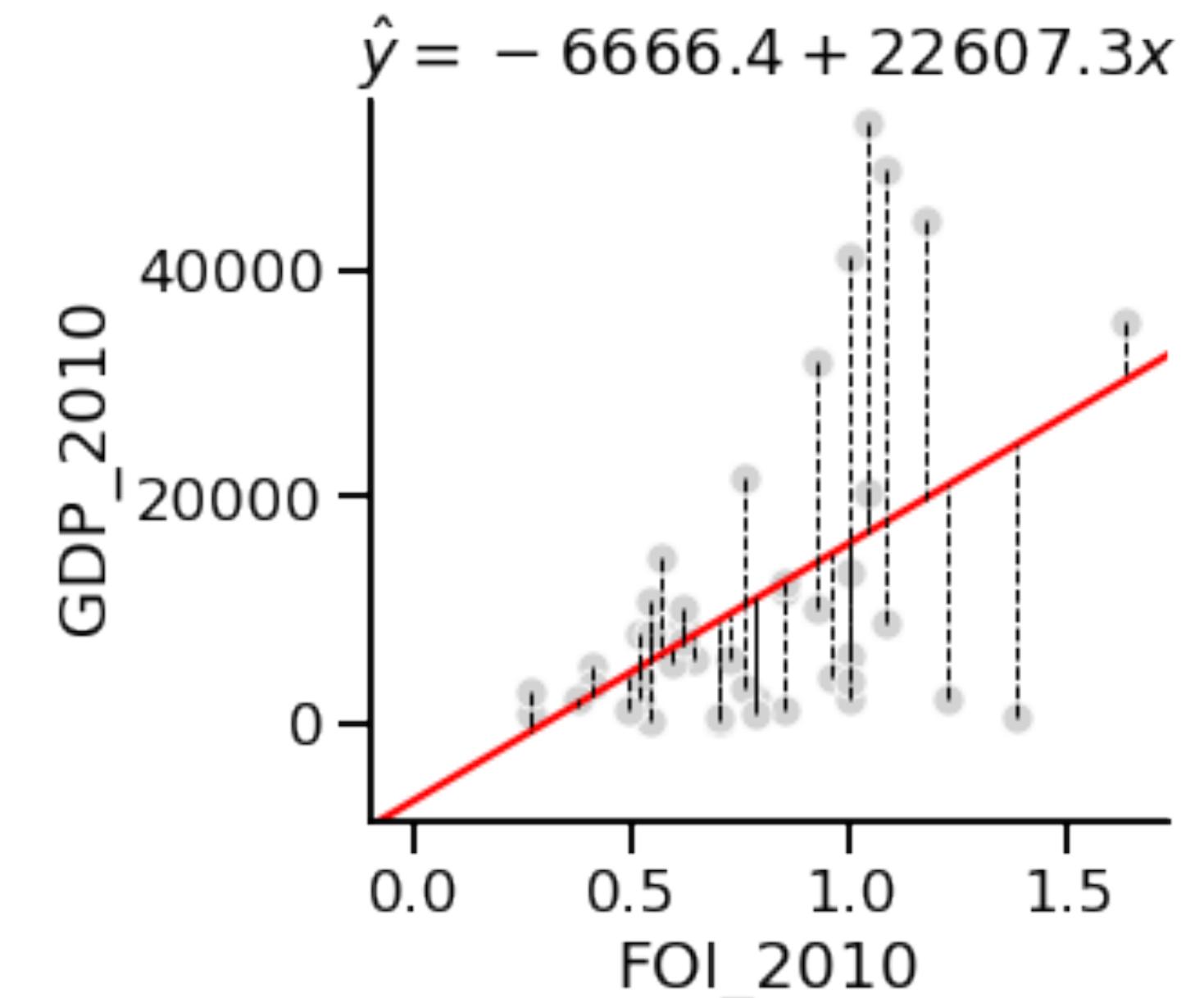
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Fitted model

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- The Ordinary Least Squares method (OLS) looks for the values of coefficients that minimize the RSS. This way, you can think about the OLS result as the line that minimizes the sum of squared lengths of the vertical lines in the figure.



Goodness of fit

Model fitting

- A way to measure the quality of a model fit is to calculate the proportion of variance of the dependent variable ($V[Y]$) that is explained by the model.
- We can do this by comparing the variance of residuals ($V[\epsilon]$) to the variance of Y .
- This is captured by the coefficient of determination, also known as R^2 :

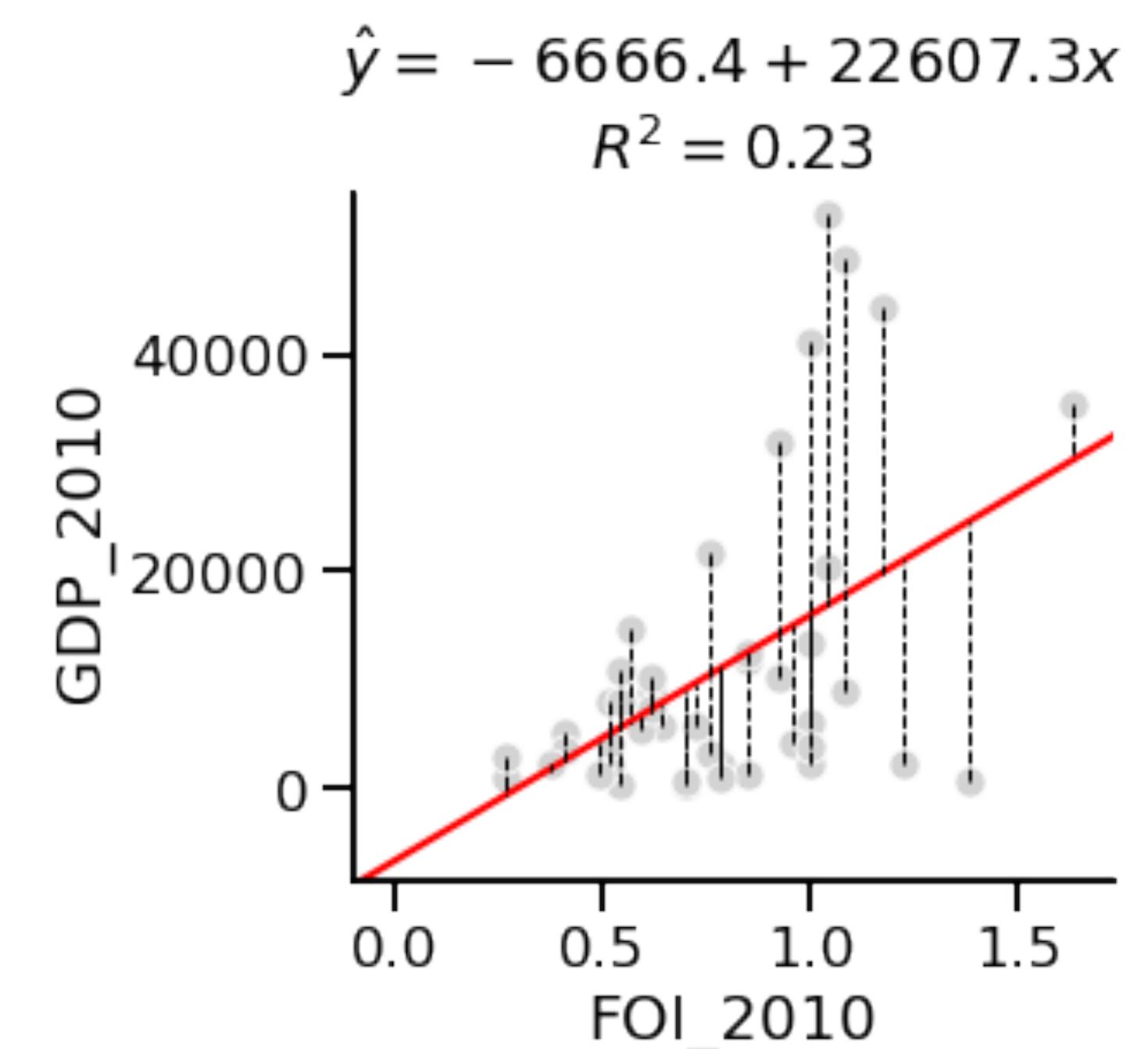
$$R^2 = 1 - \frac{V[\epsilon]}{V[Y]} = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2}$$

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Other metrics of “model success”

Model fitting

- Adjusted R squared: $R_{adj}^2 = 1 - \left[\frac{(1 - R^2)(N - 1)}{(N - k - 1)} \right]$
- Mean average error: $MAE = \frac{1}{N} \sum_i |y_i - \hat{y}_i|$
- Mean square error: $MSE = \frac{1}{N} \sum_i (y_i - \hat{y}_i)^2$
- Root mean square error: $RMSE = \sqrt{\frac{1}{N} \sum_i (y_i - \hat{y}_i)^2}$
- Mean absolute percentage error: $MAPE = \frac{1}{N} \sum_i \left| \frac{y_i - \hat{y}_i}{y_i} \right|$

In the formulas N is the number of observations and k is the number of the independent variables in the data.

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For comparing the accuracy among different linear regression models, $RMSE$ is a better choice than R^2 .

Outline

Today's class

BLOCK 1

Social Behavior

1. Social Science
2. CSS
3. Digital Traces
4. Examples

BLOCK 2

Social Trends

1. Google Trends
2. The Future Orientation Index
3. Culture and Economy

BLOCK 3

Quantifying Trends

1. Correlation
2. Causation
3. Regression

BLOCK 4

Behavior & Trend Dynamics

1. The Theory of Fashion
2. The Endo-Exo model
3. Examples

How does social behavior spread in society?



The Simmel effect

Theory of fashion (1895)

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- The Simmel effect refers to the dynamics of **status symbols** in hierarchically ordered societies.
 - Status symbols are externally displayed traits or cultural features associated with high social class, e.g. surnames, clothing, sport, food, etc.

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 - Simmel noticed that *fashions come and go*, but fashion is always present. When something becomes popular, it is bound to lose its popularity.
- Simmel hypothesized that the *instability* of fashion results from the combined action of **imitation** and **distinction**.
 - Simmel hypothesized that status symbols spread through the population downwards, from the highest to the lowest status. As they spread, old symbols are replaced with new ones. Thereby, social differentiation persists under the instability of status symbols.

The mechanisms of Simmel's theory

Imitation and distinctiveness

The mechanisms of Simmel's theory

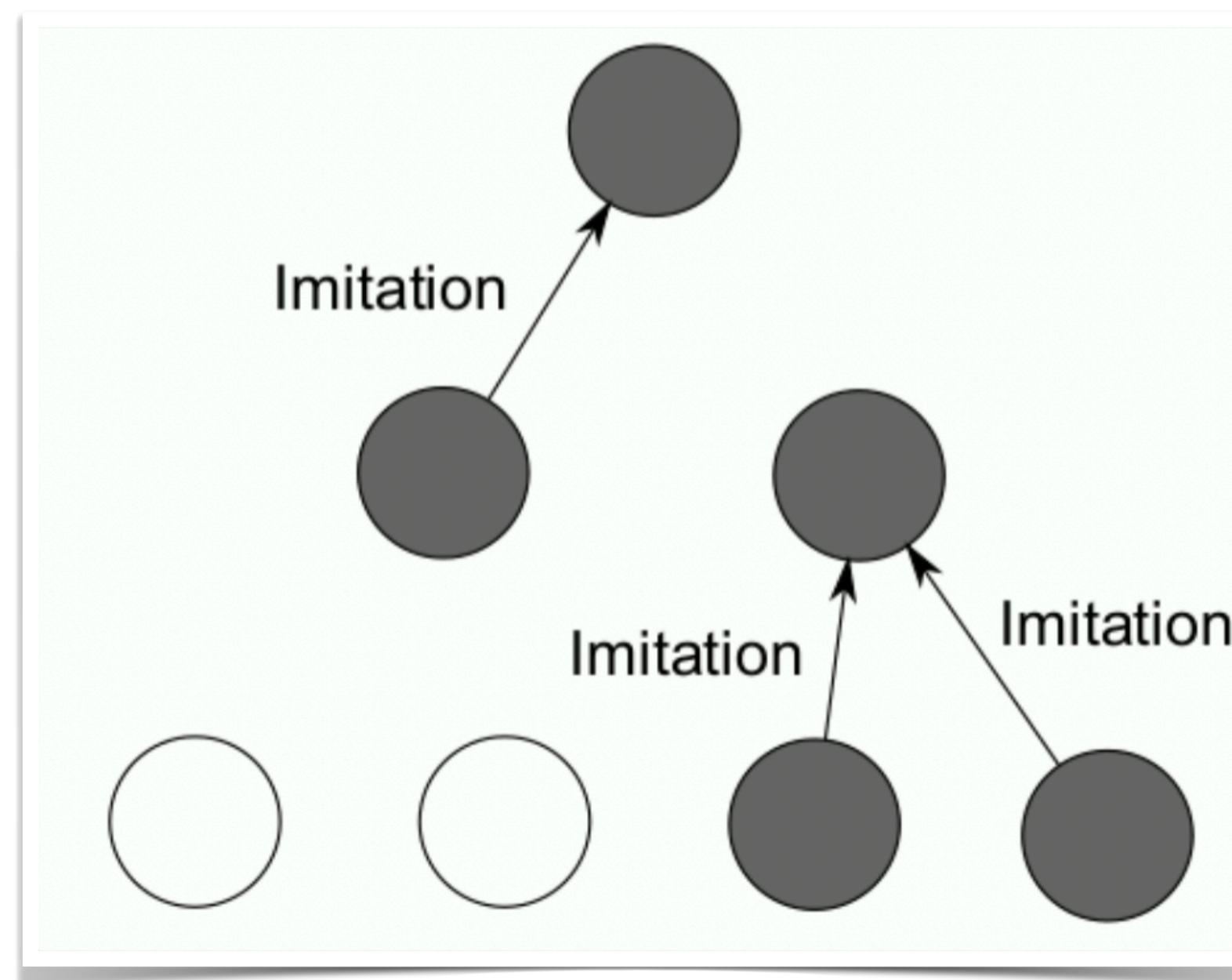
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- On one hand, each of us has tendency to **imitate others**. On the other, we also have a tendency to **distinguish ourselves from others**.
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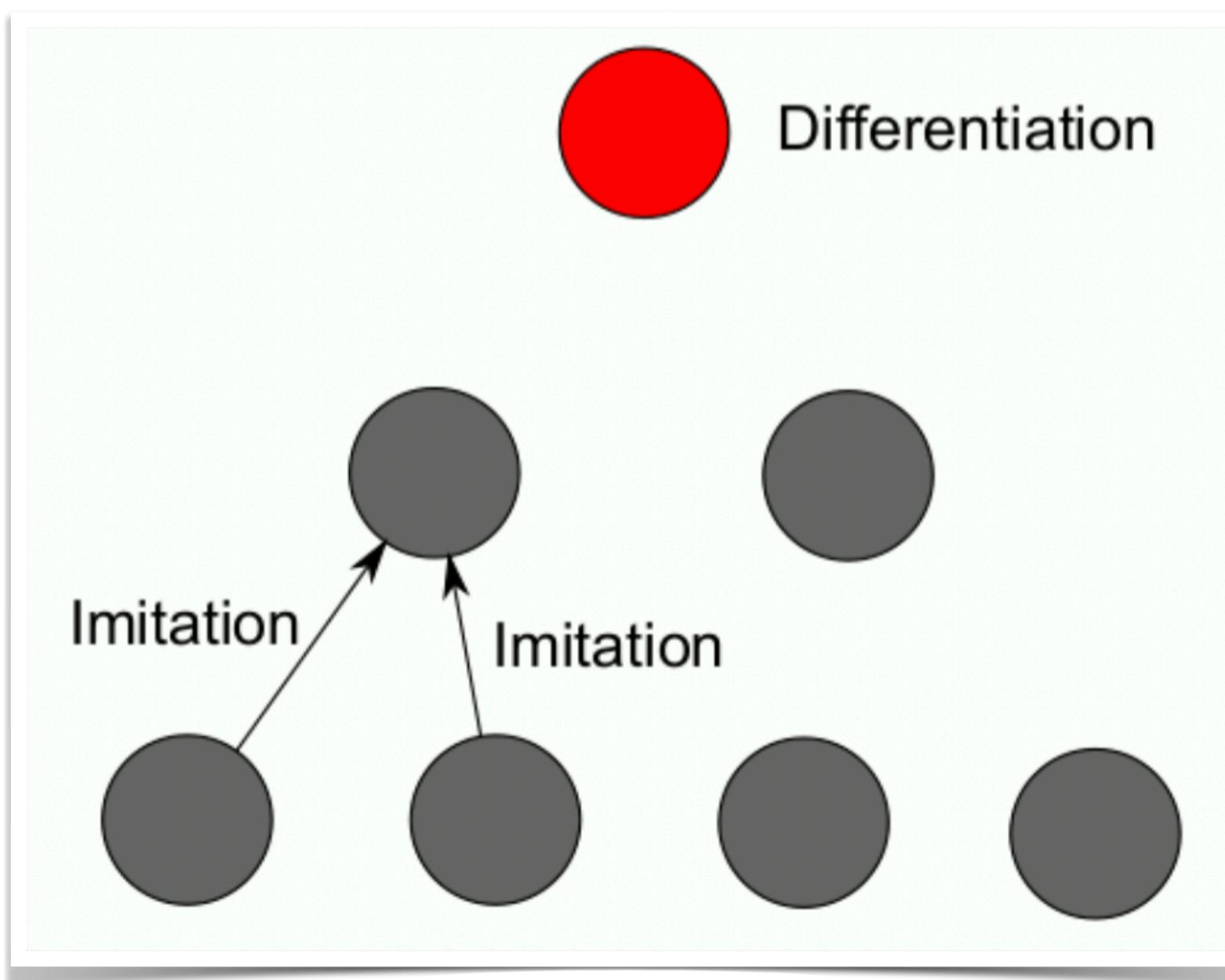
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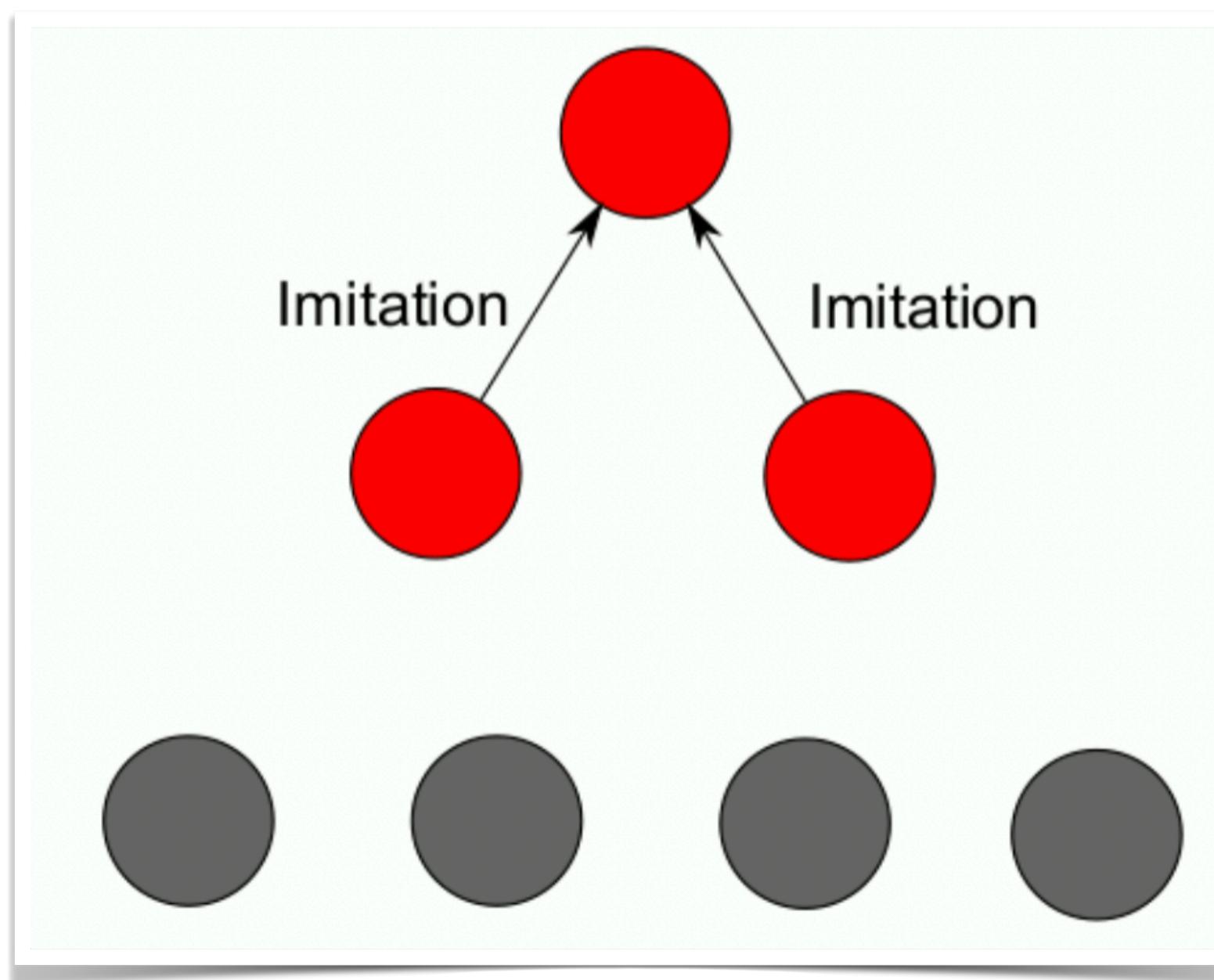
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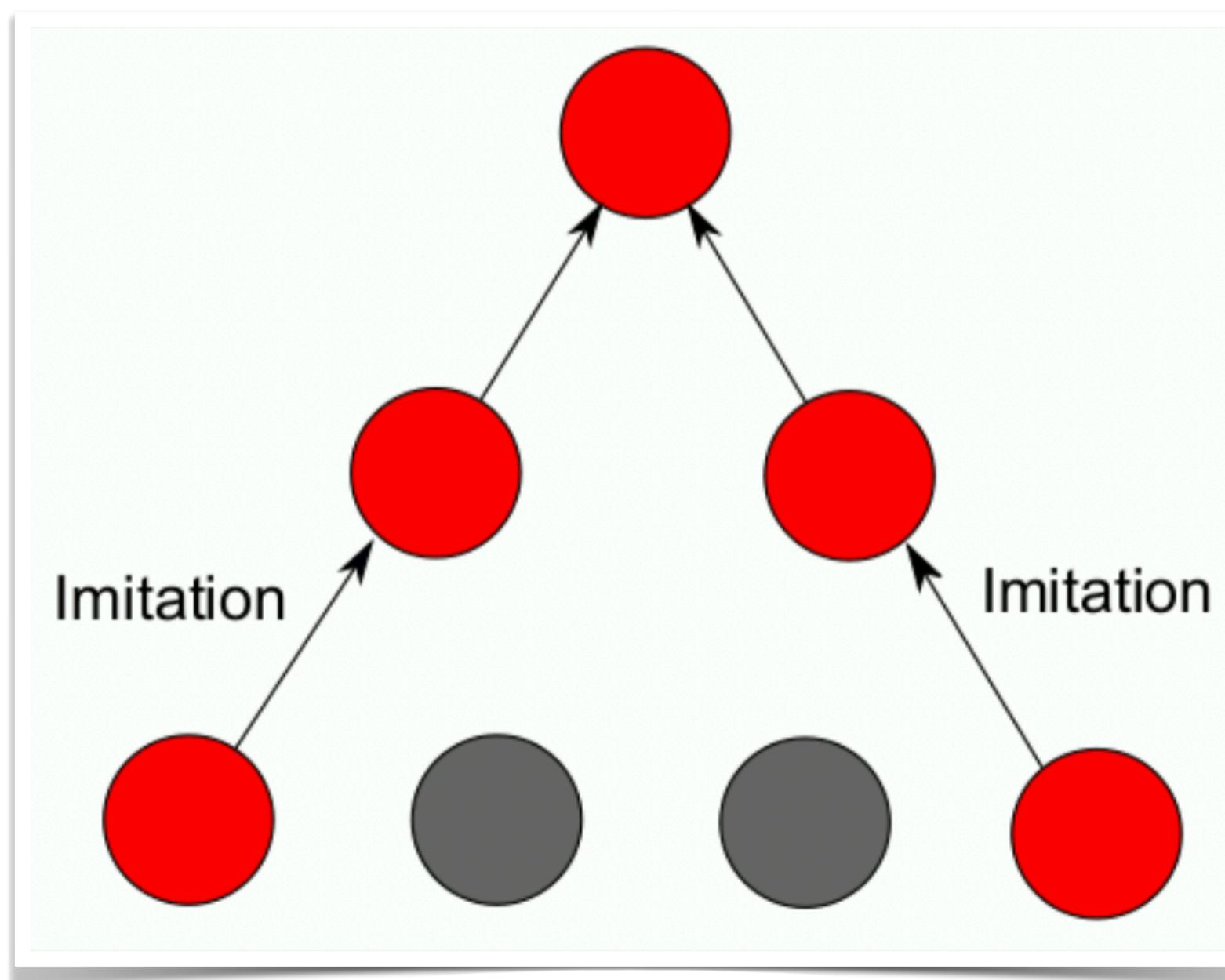
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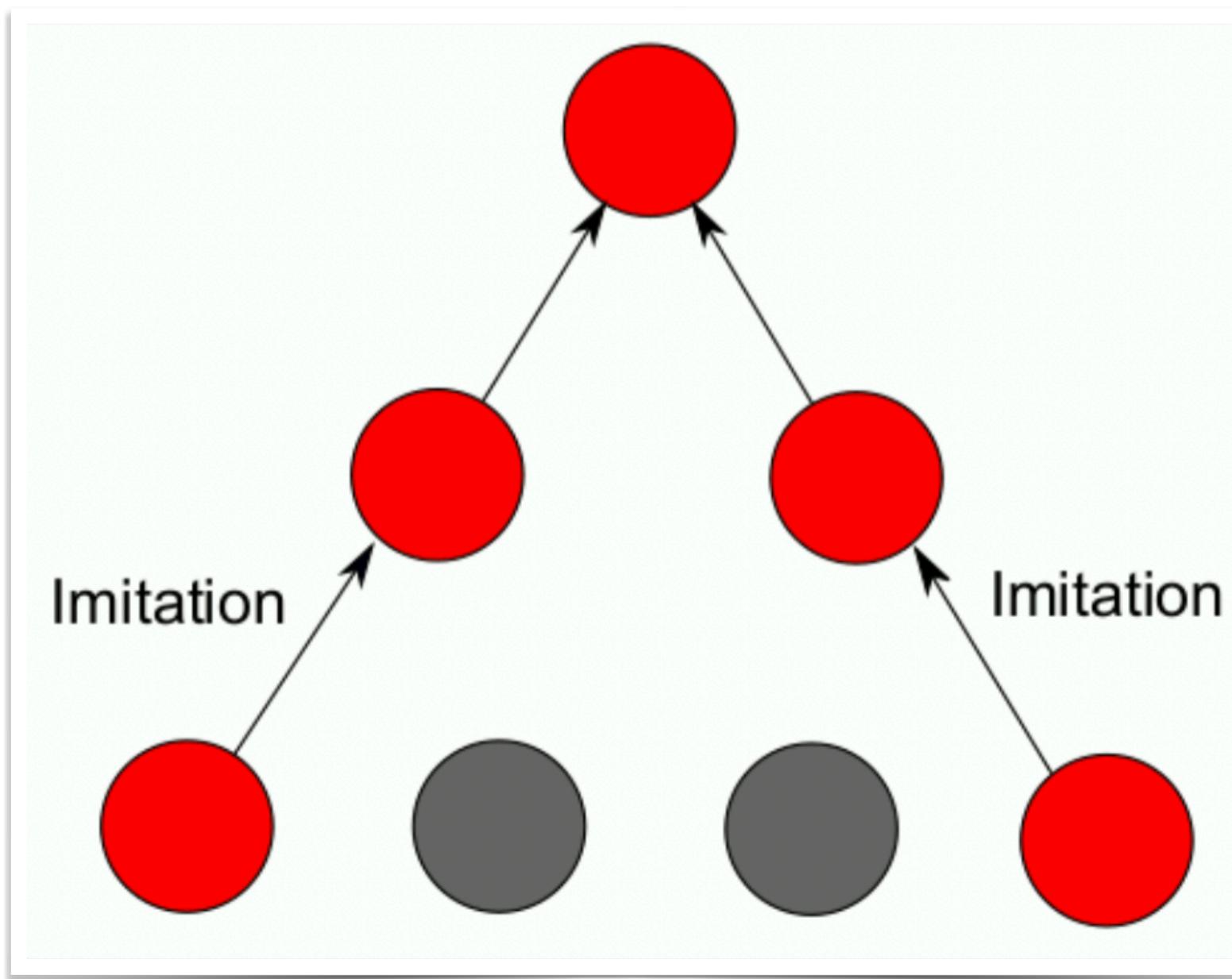
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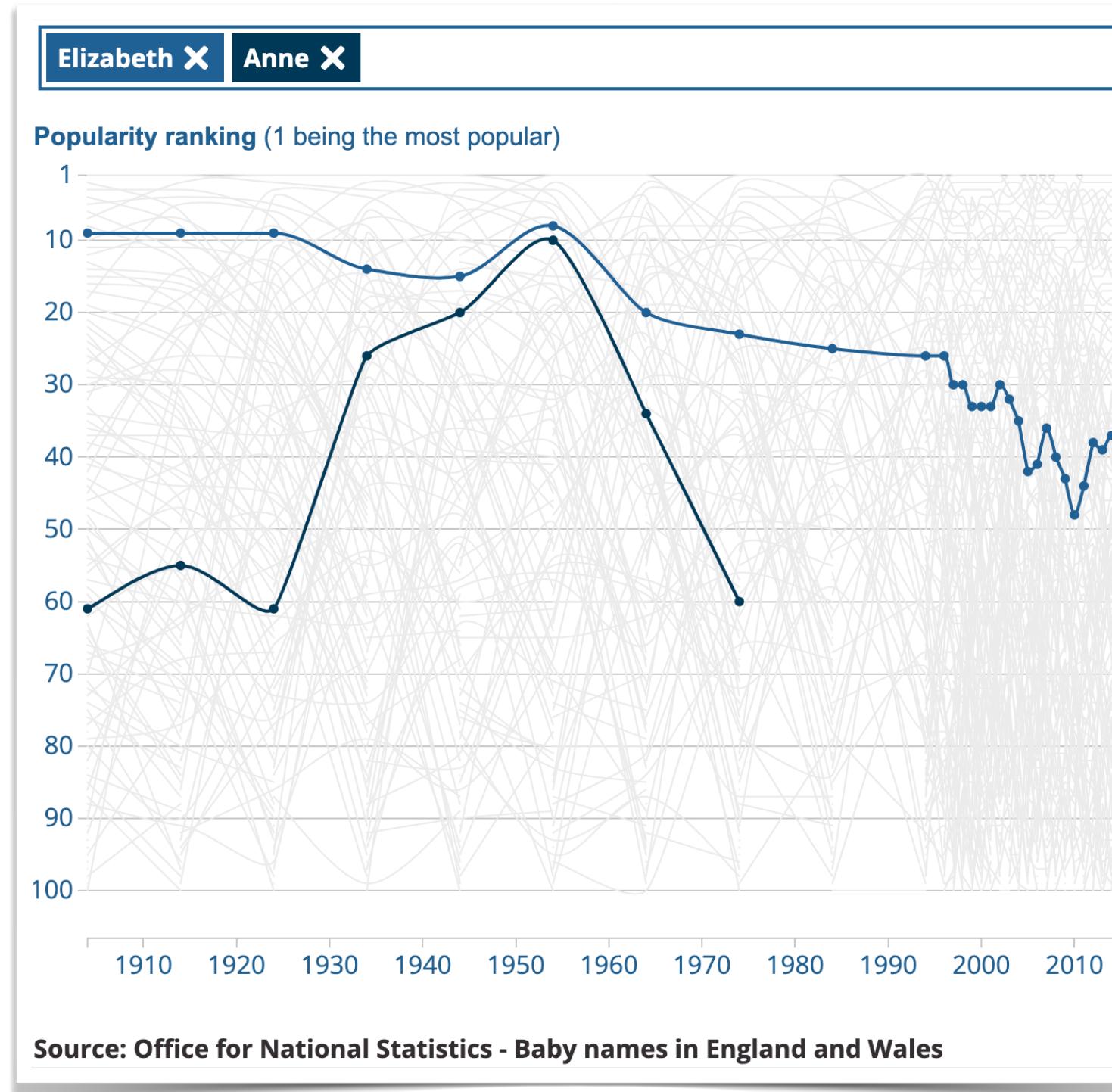
- Jeans were invented in 1871
 - Originally created for miners.
 - Popularized in 1950 in films.
 - 1960 widespread adoption.
- White sneakers were invented in 1916
 - Made popular by Adidas in 1970?
- Music challenge videos on TikTok

The case of baby names

- First names can be status symbols and carry subjective and social values.
- Copying the name of your baby from someone else is an example of **imitation**.

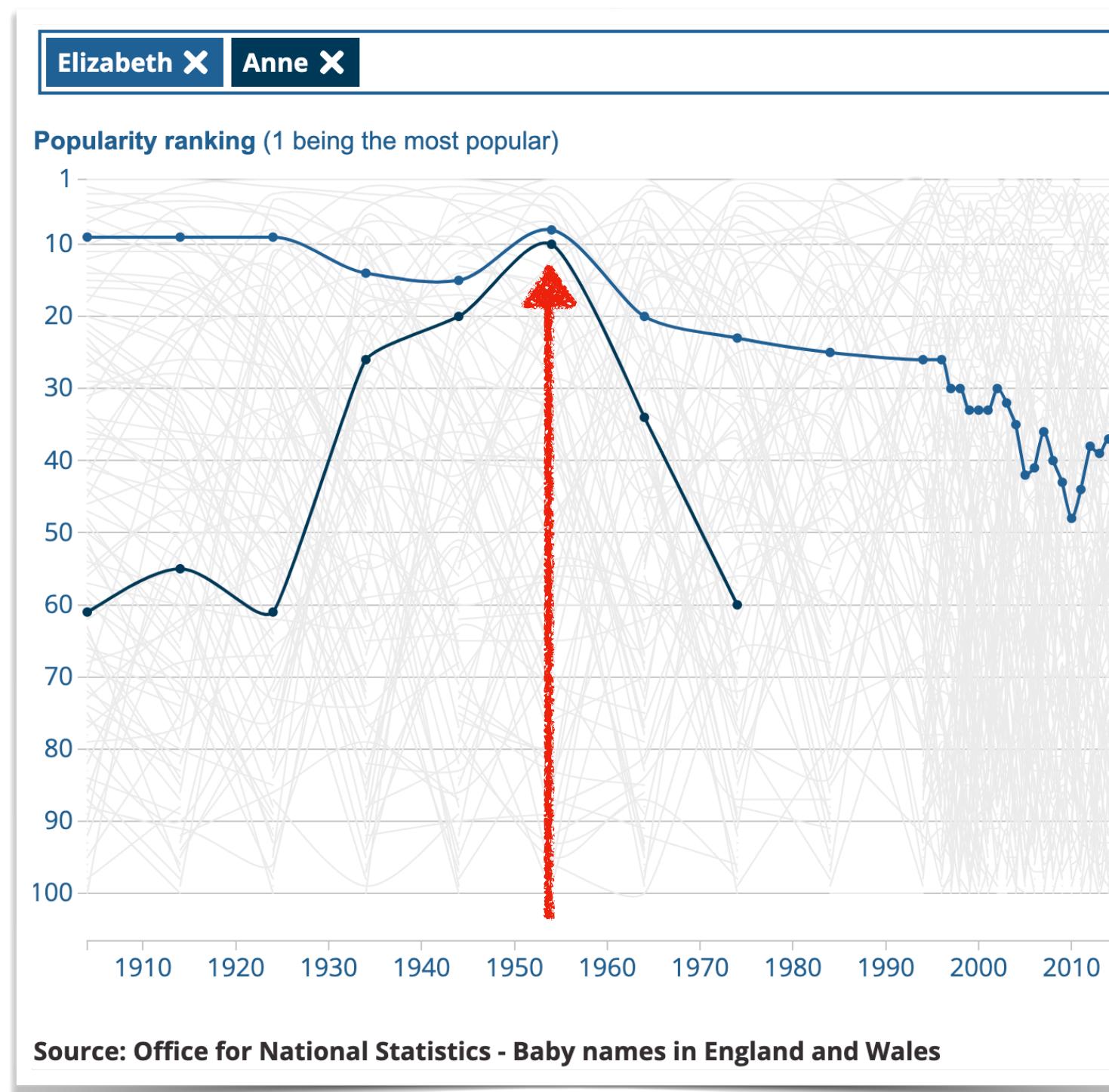
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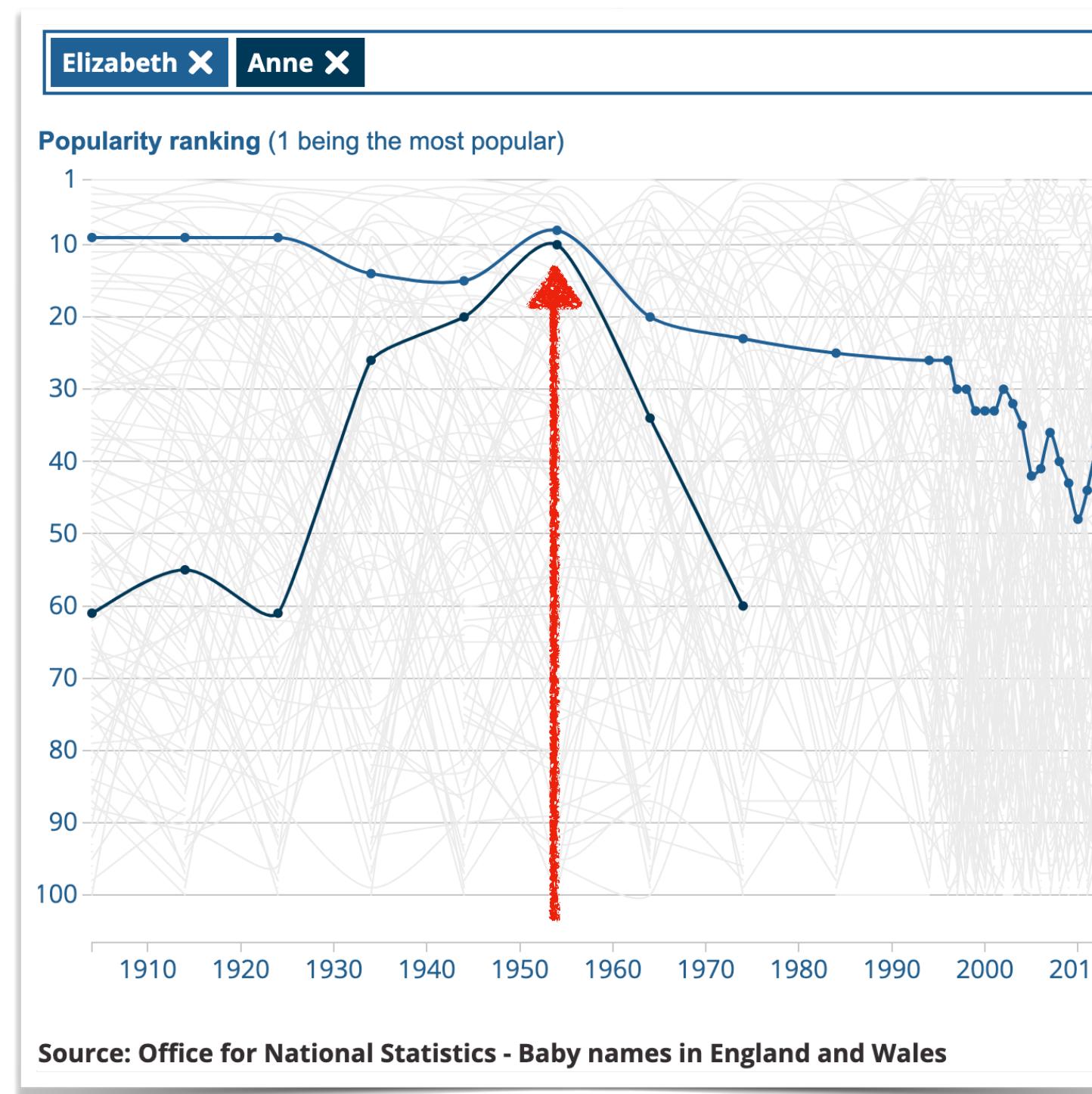
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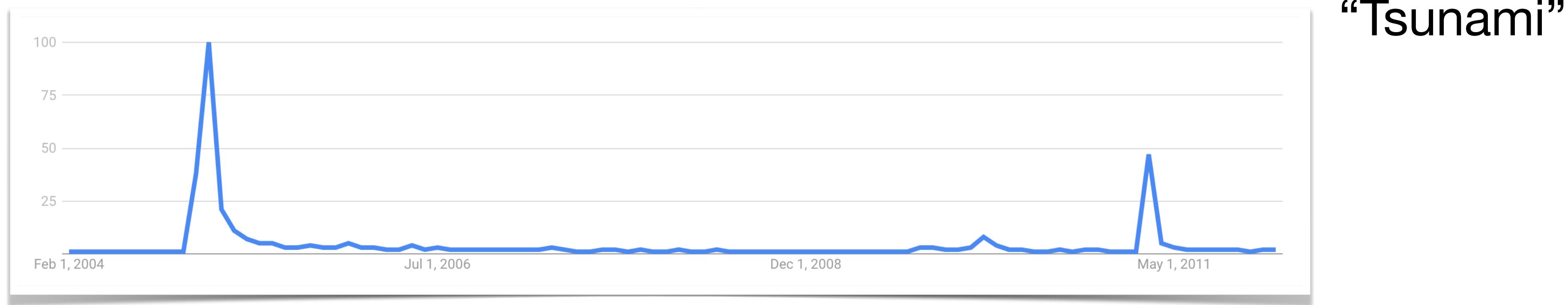
- 1950 Princess Anne was born
- 1953 Queen Elizabeth II was crowned

Social trends in online platforms

Google Search Trends

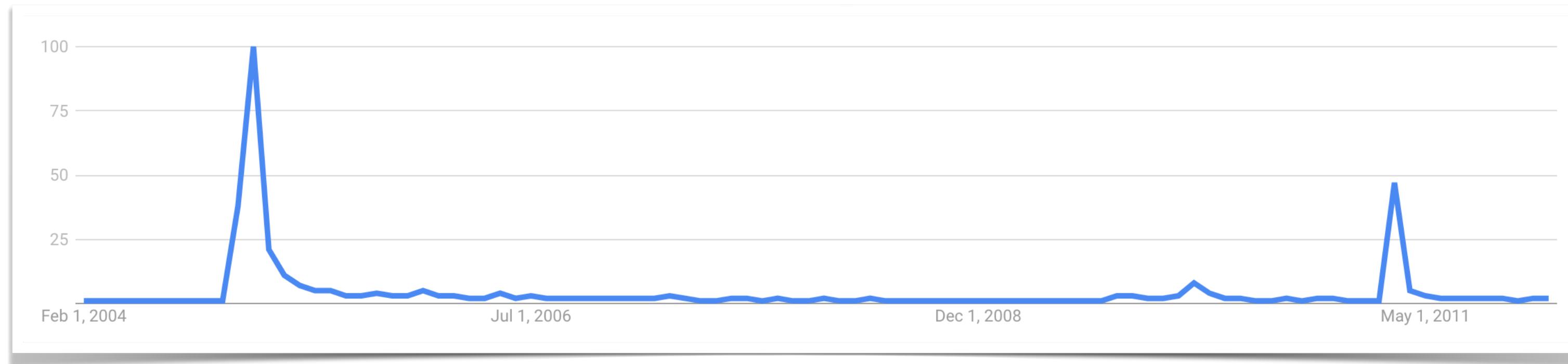
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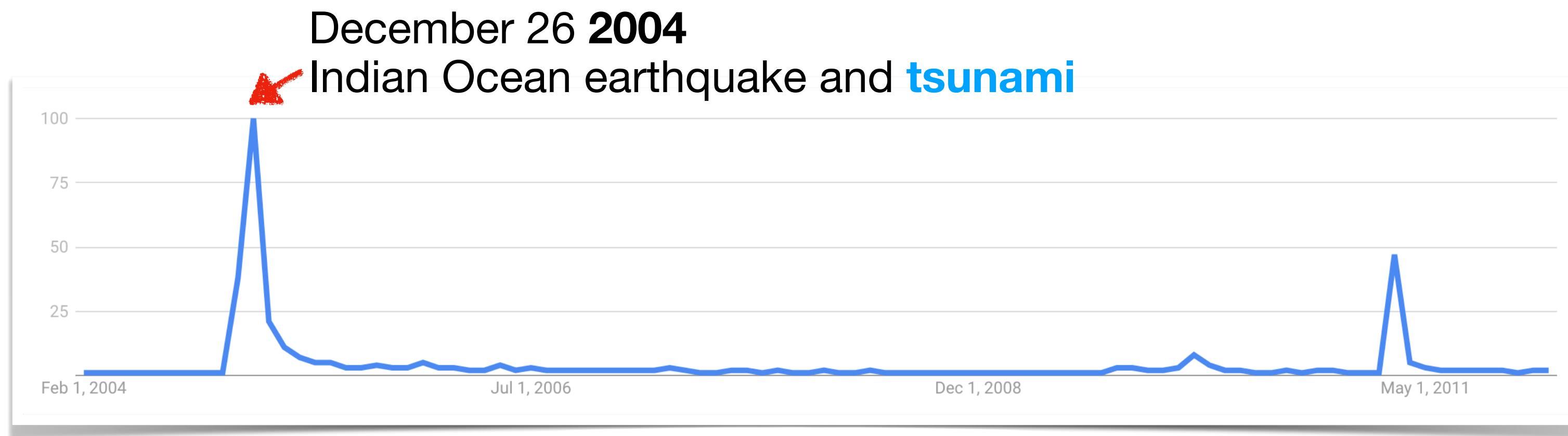


“Tsunami”

An **exogenously** (sudden)
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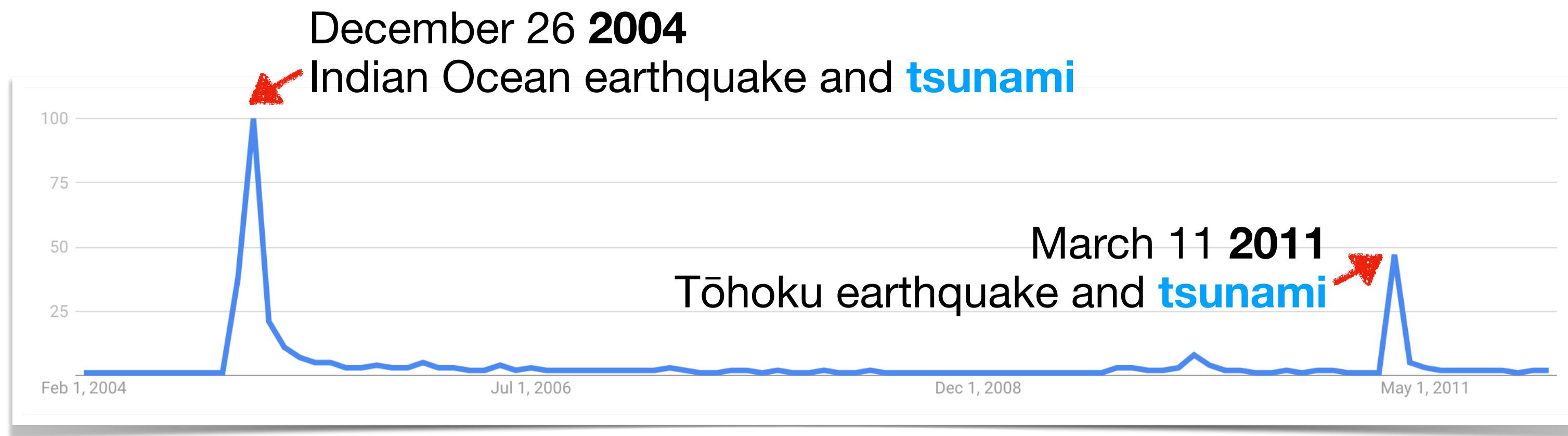


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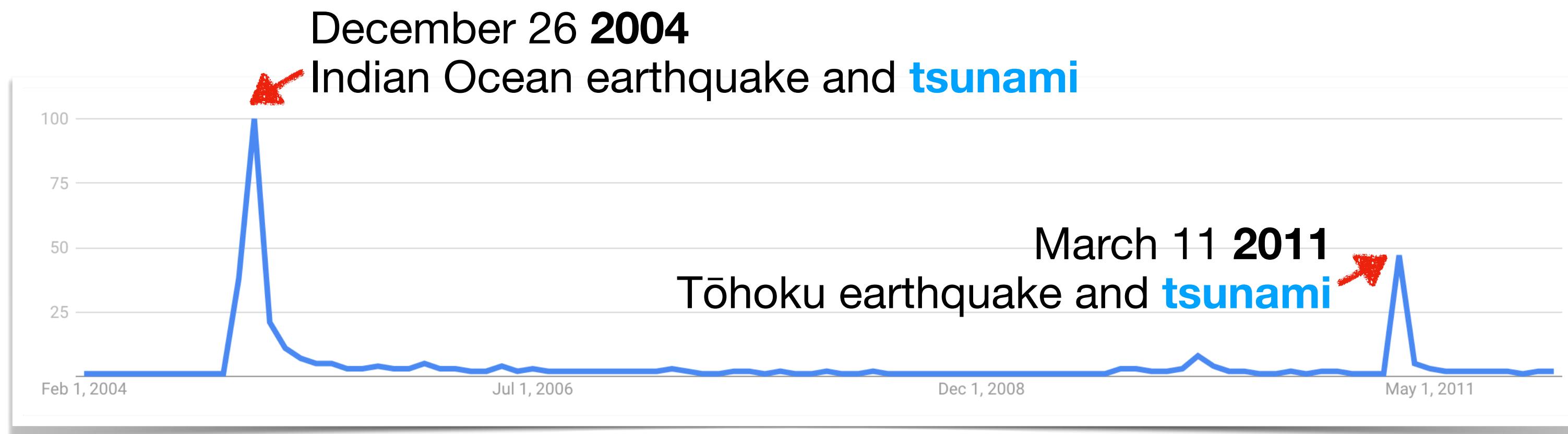


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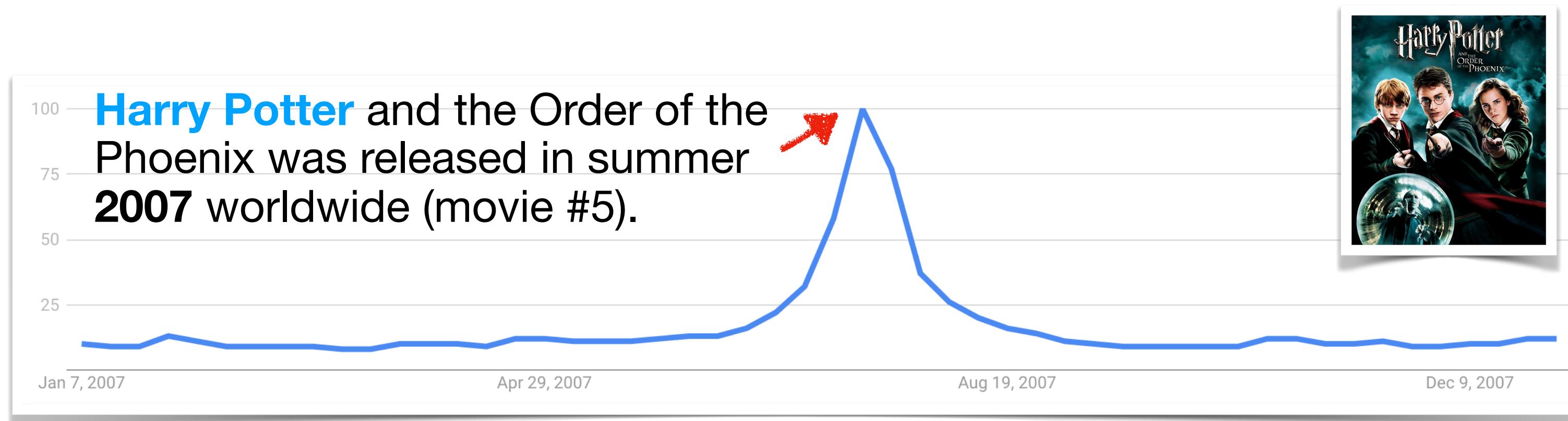
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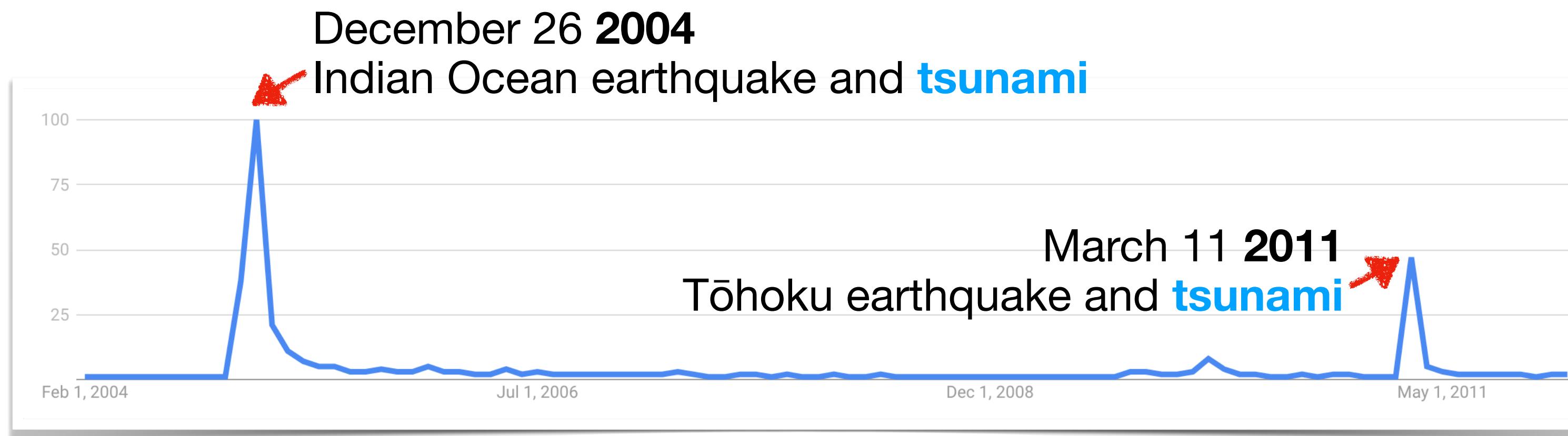
An **exogenously** (sudden) triggered search volume



“Harry Potter”

Social trends in online platforms

Google Search Trends



“Tsunami”
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“Harry Potter”
An **endogenously** (gradual)
driven search

Harry Potter was first introduced in the novel Harry Potter and the Philosopher's Stone in 1997, and released four movies prior to 2007: in 2001, 2002, 2004, 2005.
... ←

The endo-exo model

[Crane and Sornette 2008]

The endo-exo model

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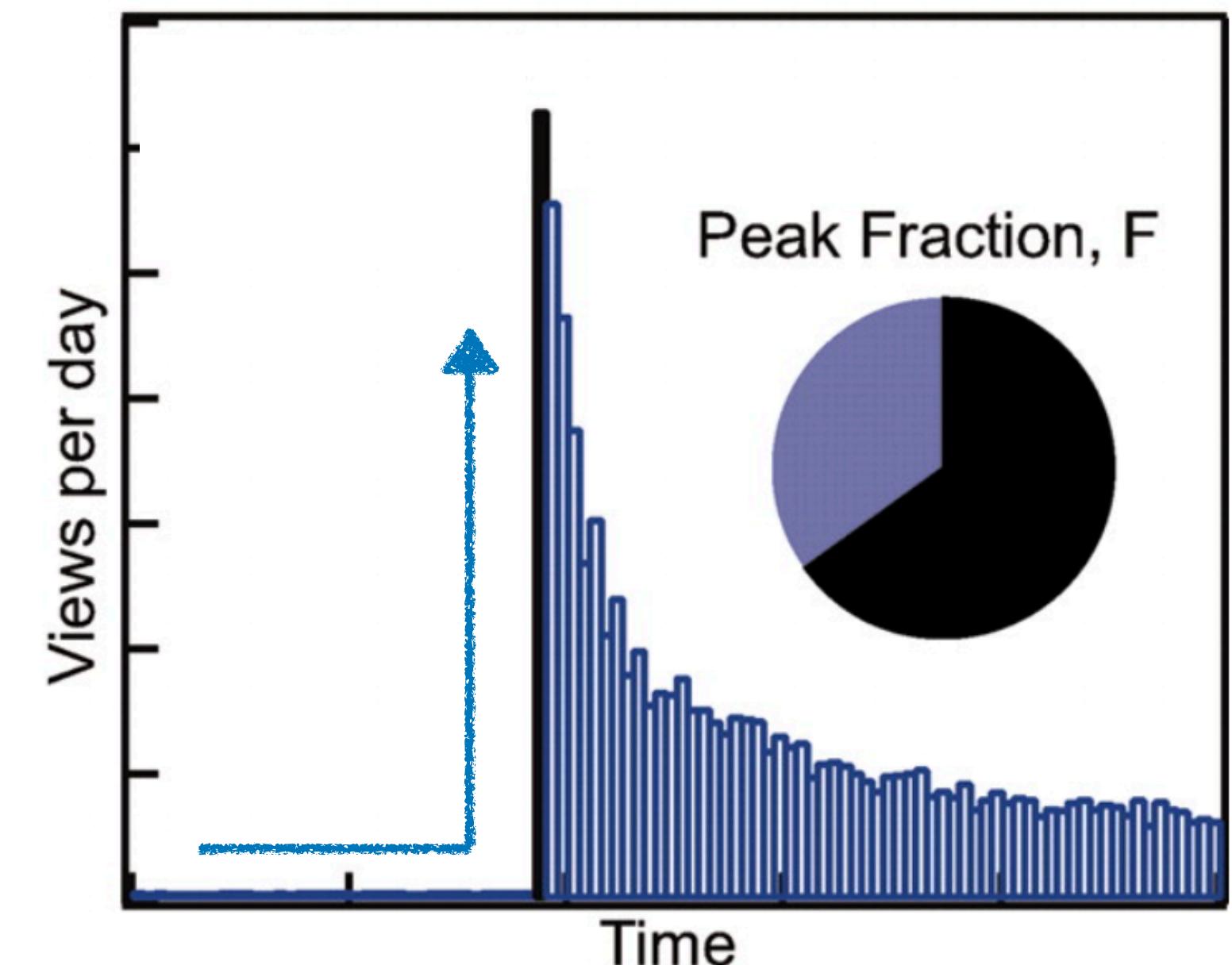
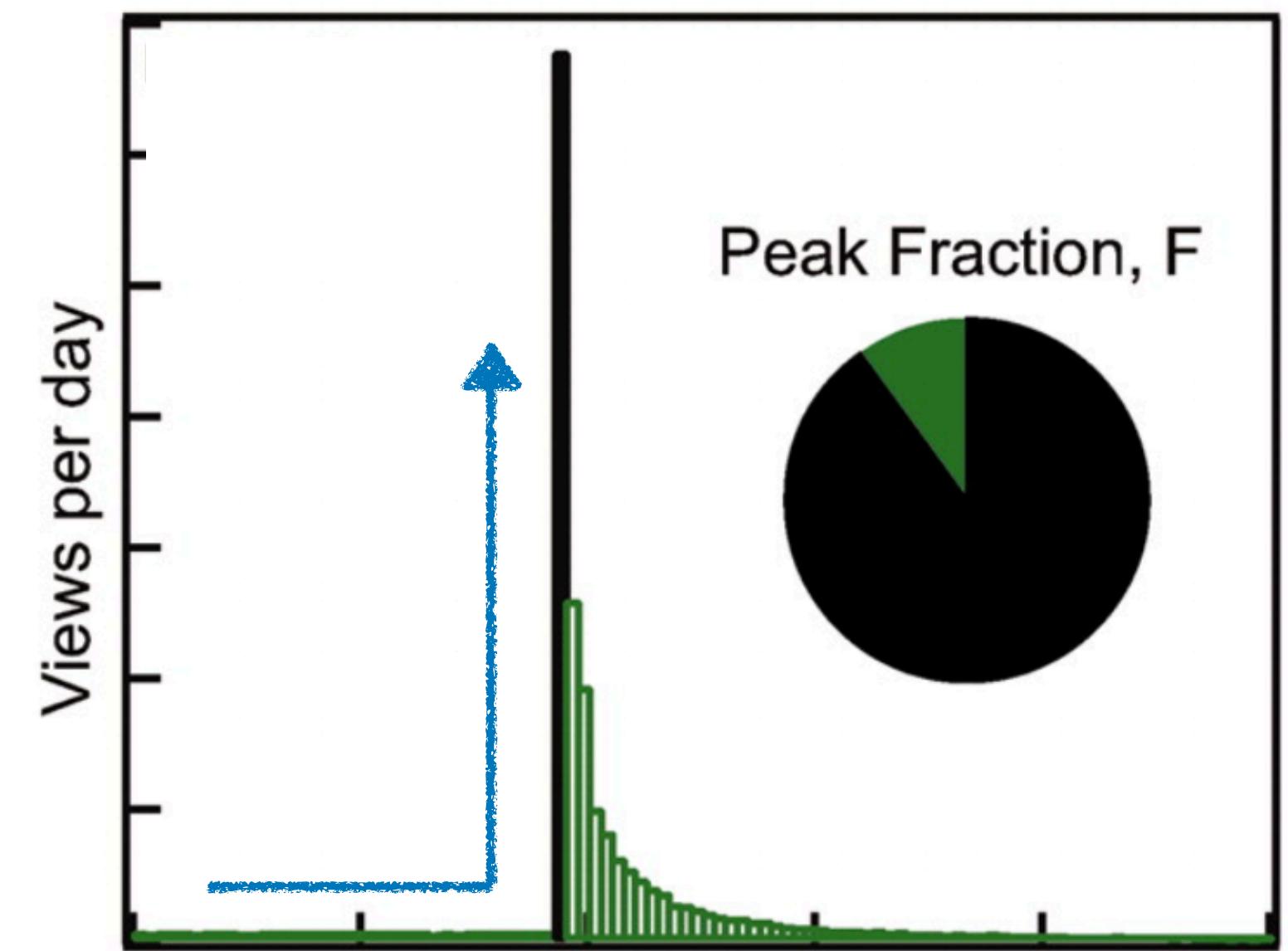
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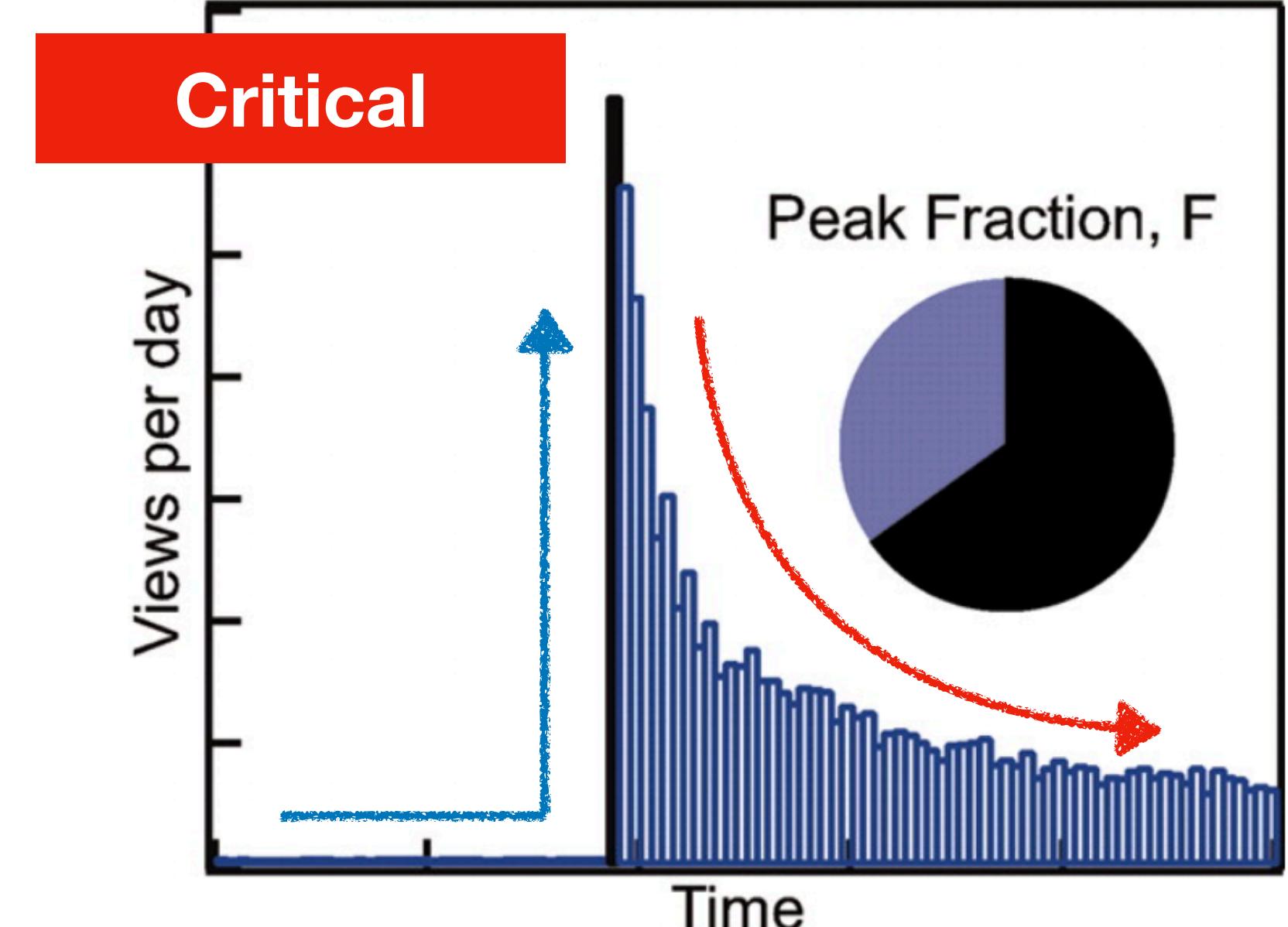
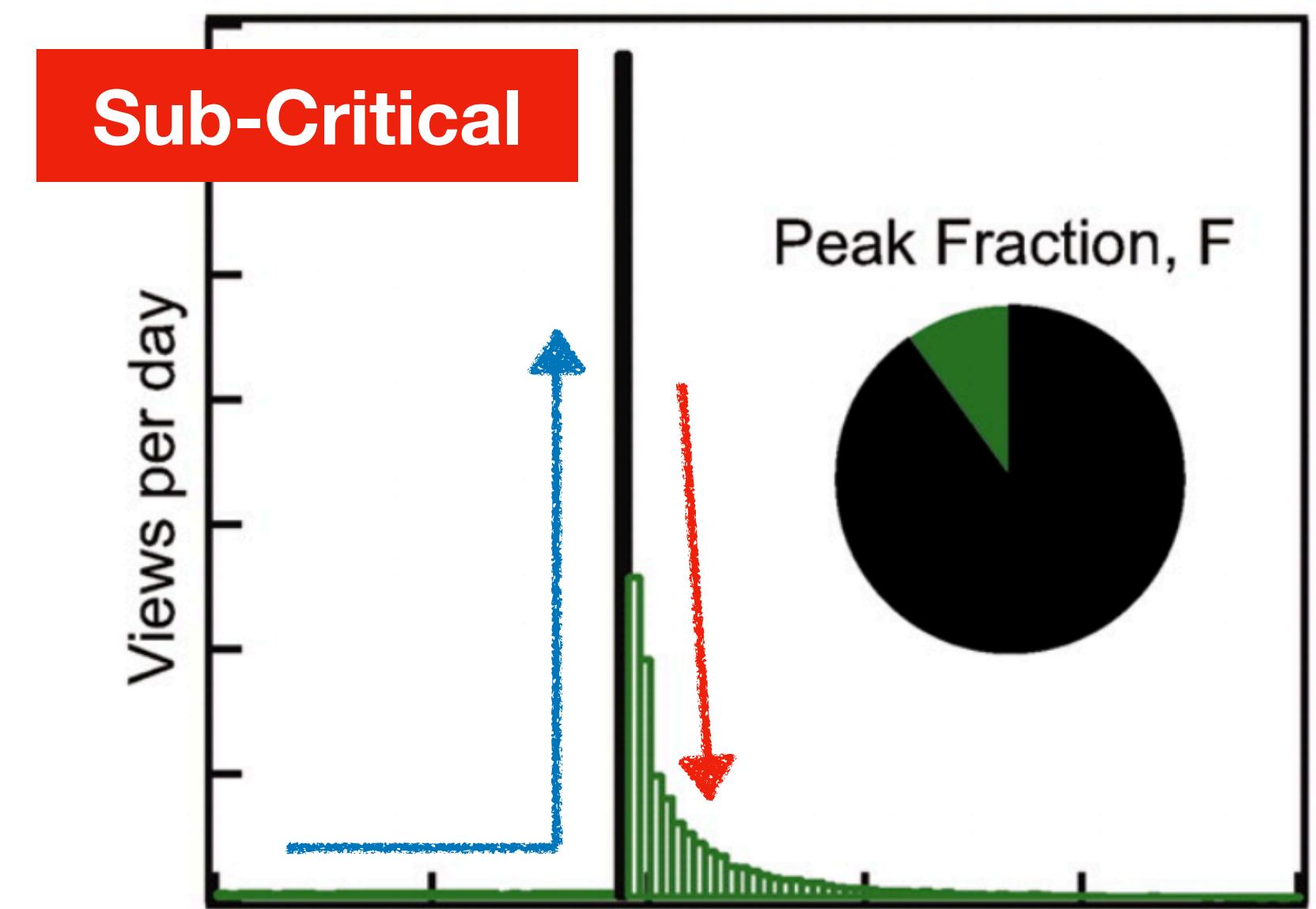


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 - Critical:** when the social interaction between individuals leads to further responses and it is stronger than the rate of losing interest.



The endo-exo model

[Crane and Sornette 2008]

The endo-exo model

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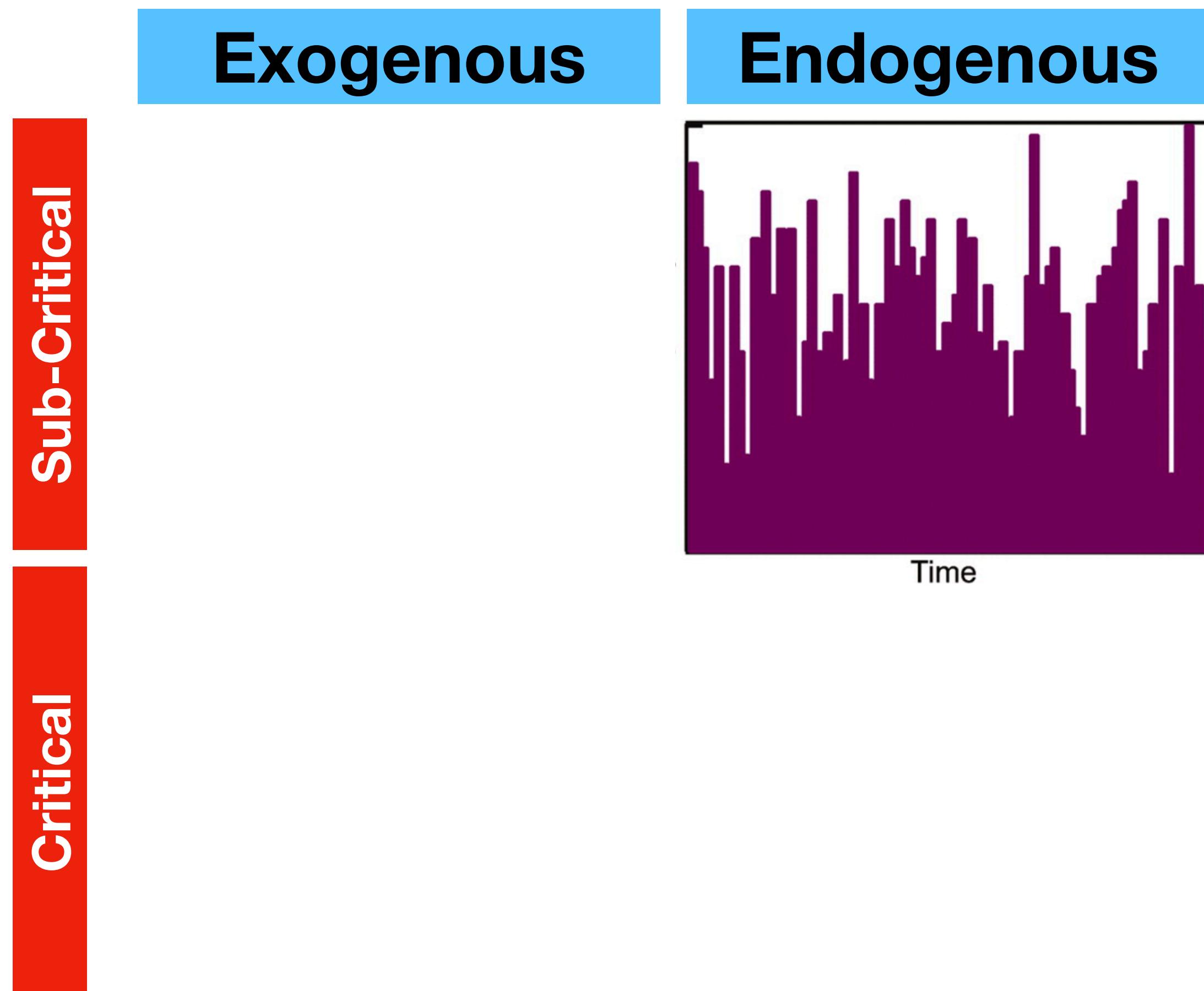
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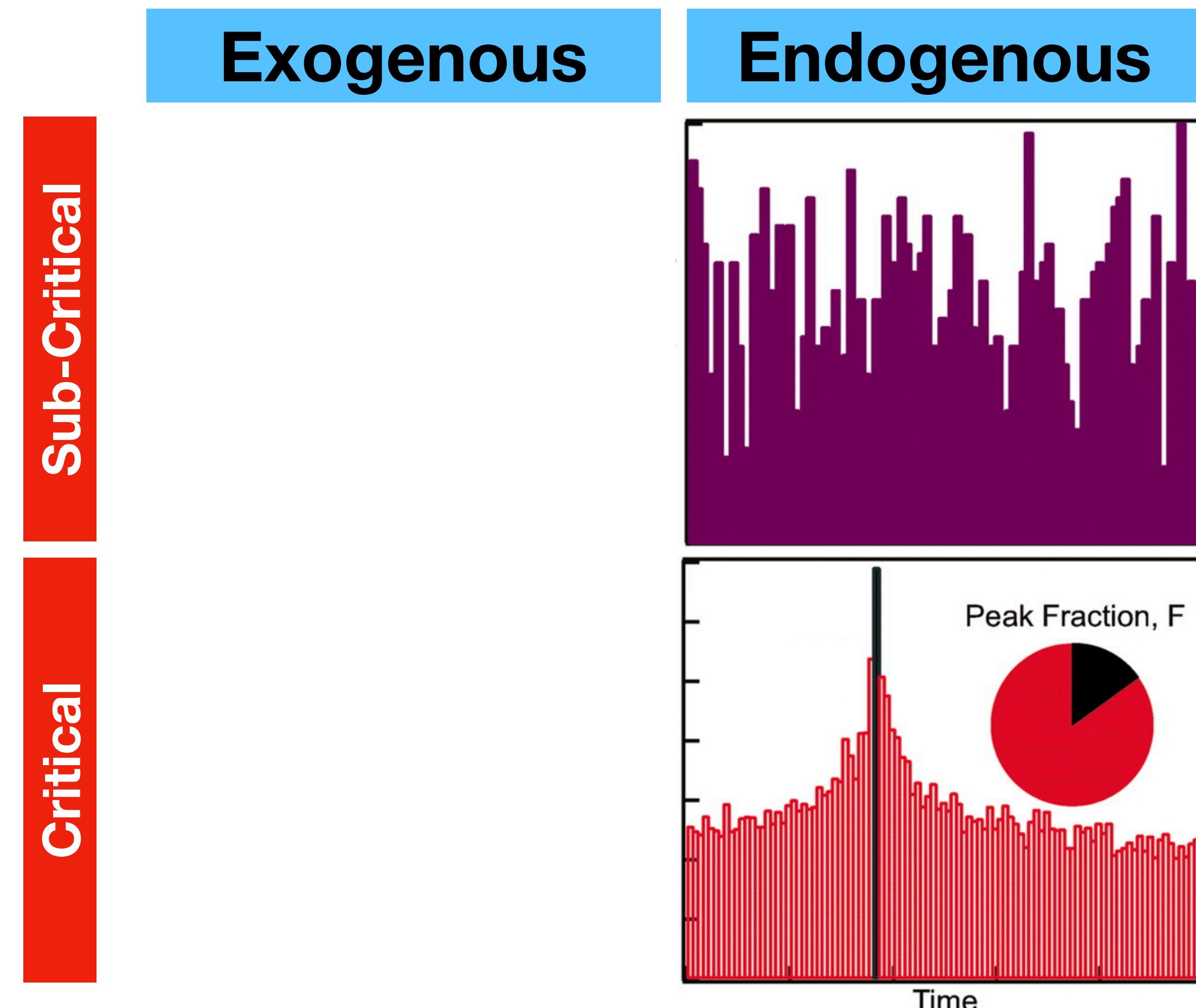
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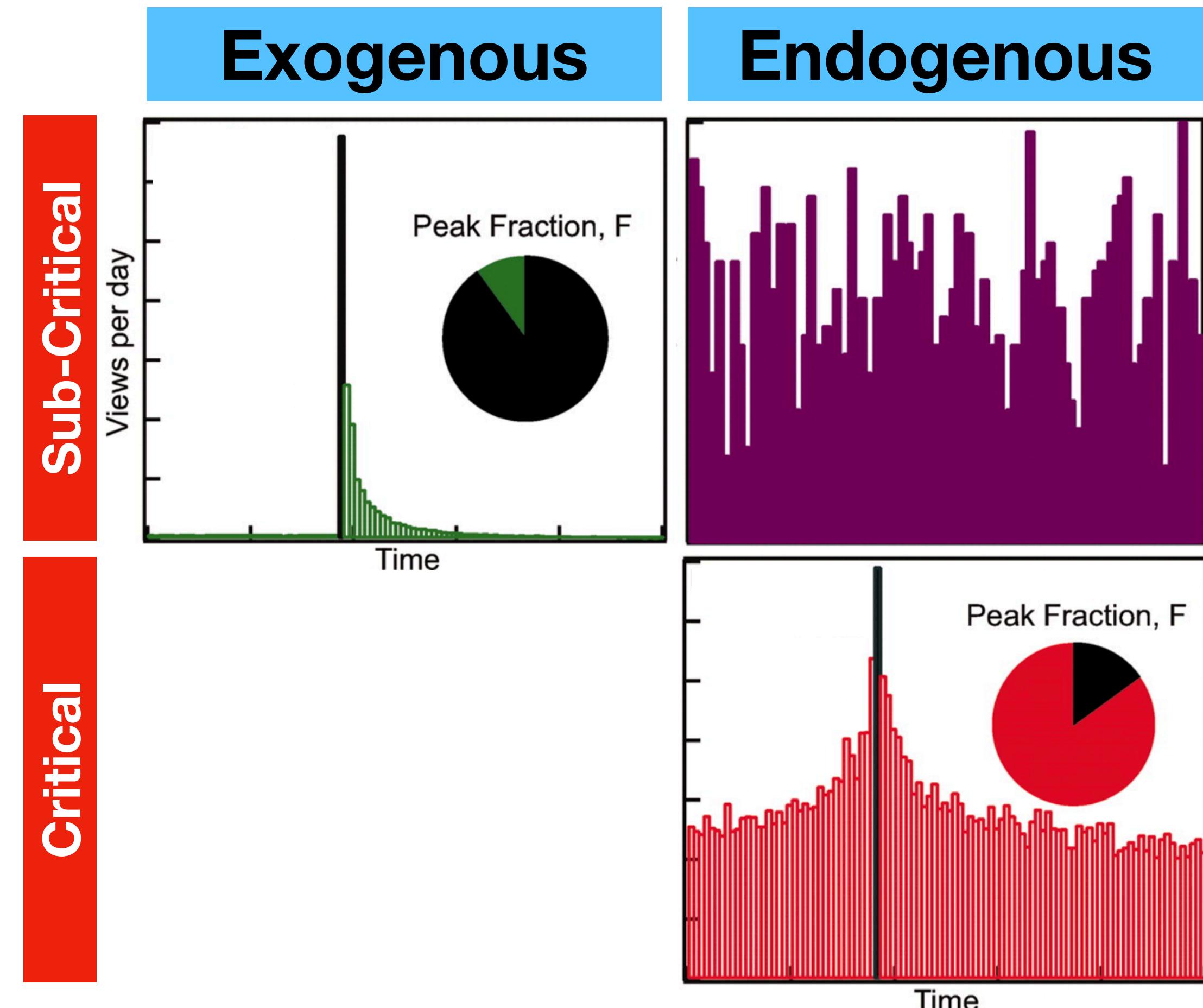
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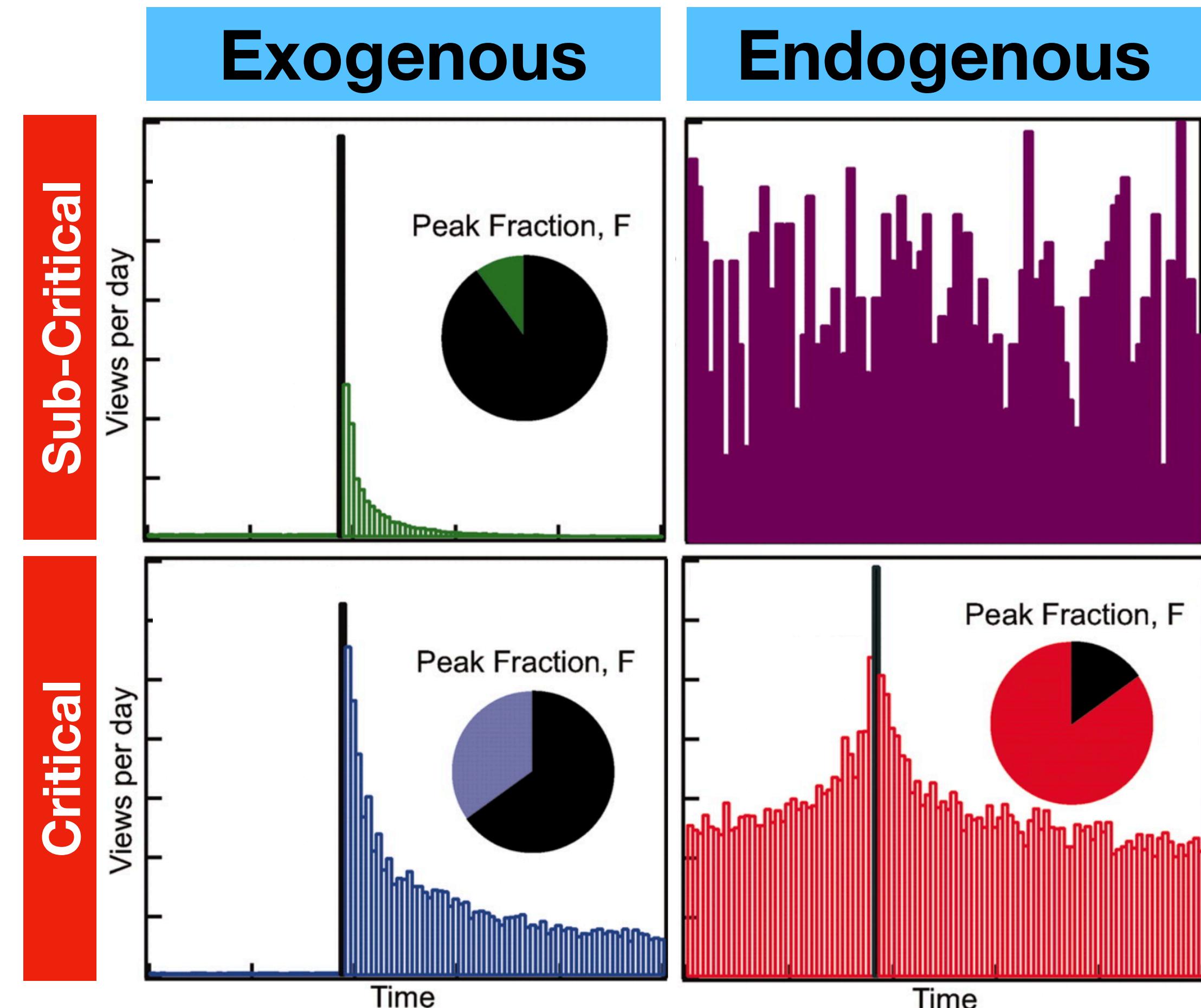
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 - 4. Exogenous critical:** sharp peak but slow decay due to strong interaction after shock.



Trends on Twitter

#hashtags

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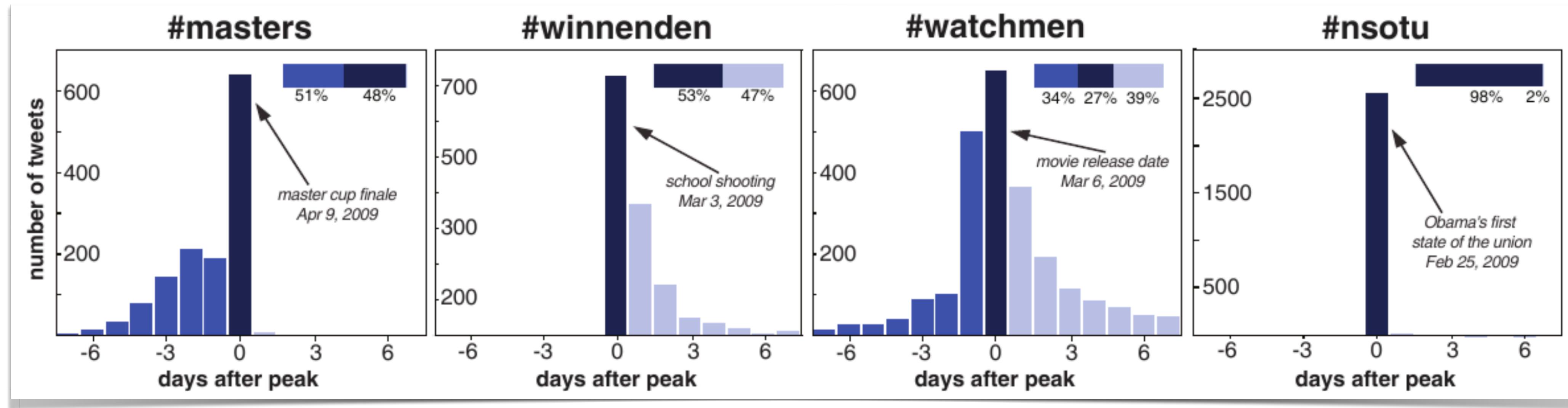
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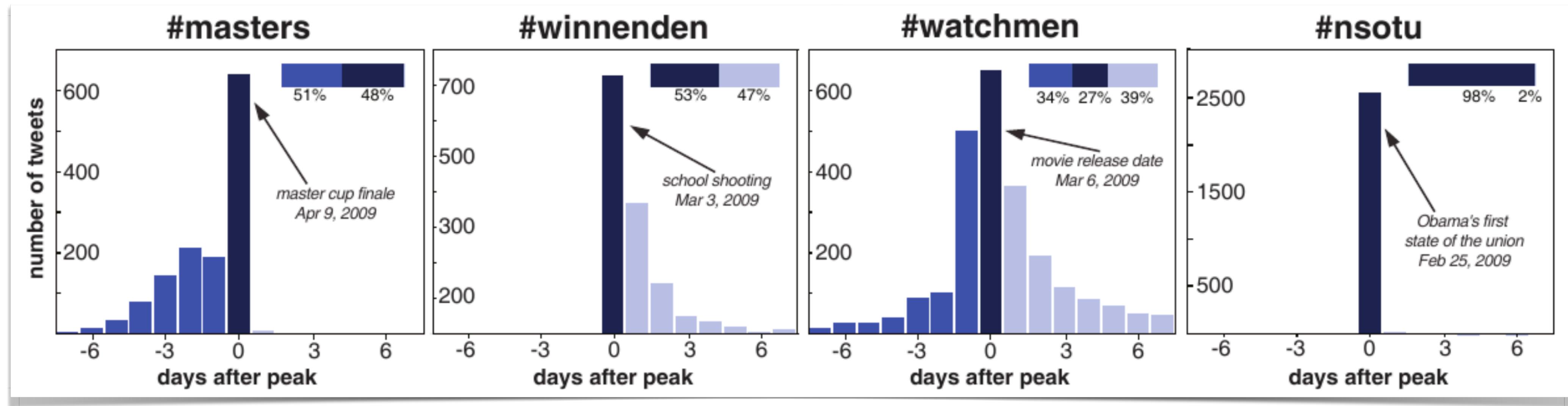


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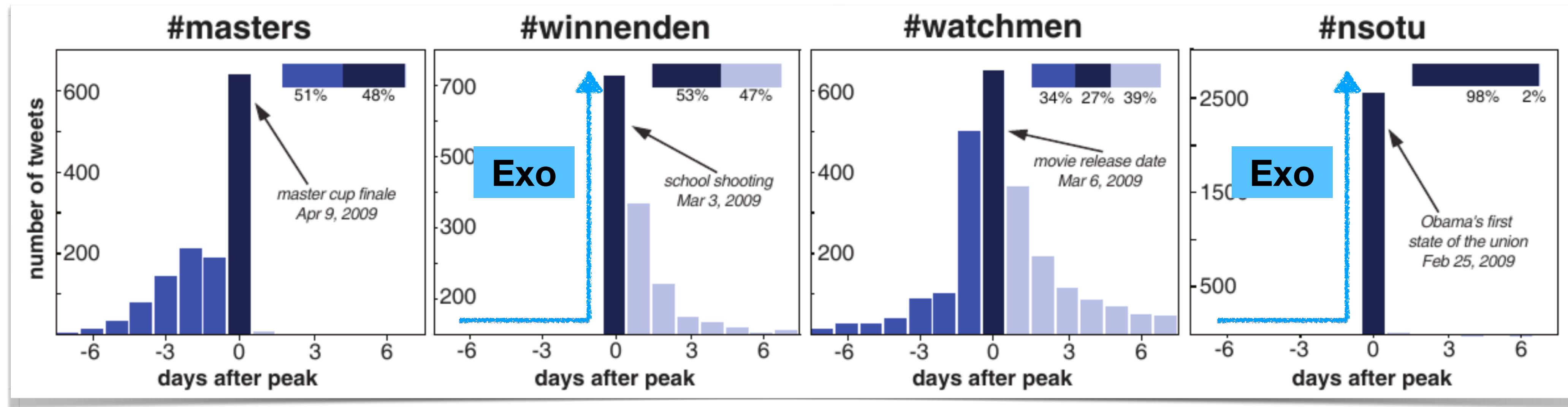


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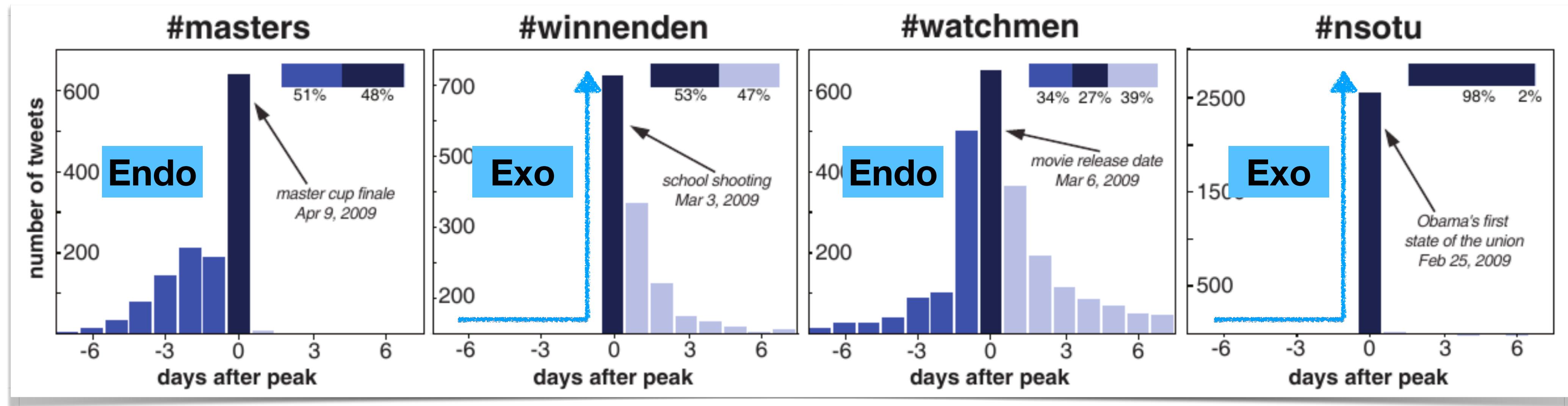


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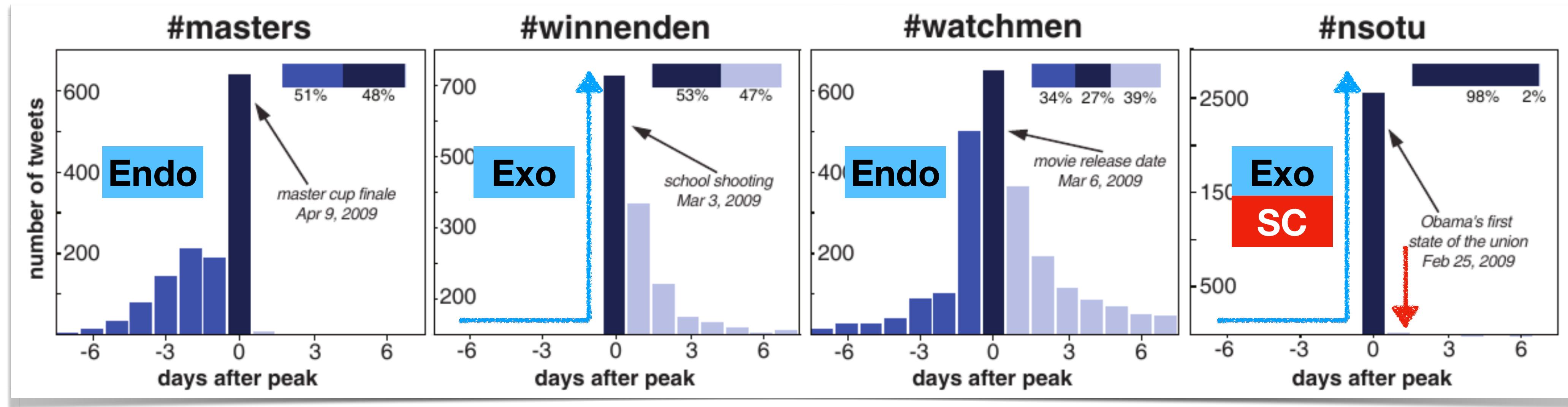


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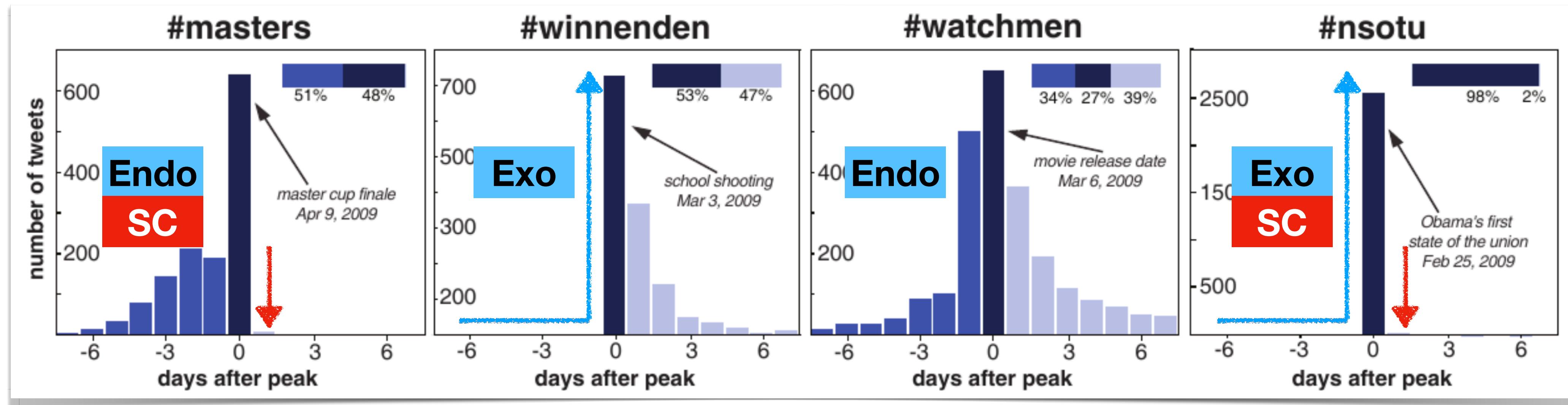


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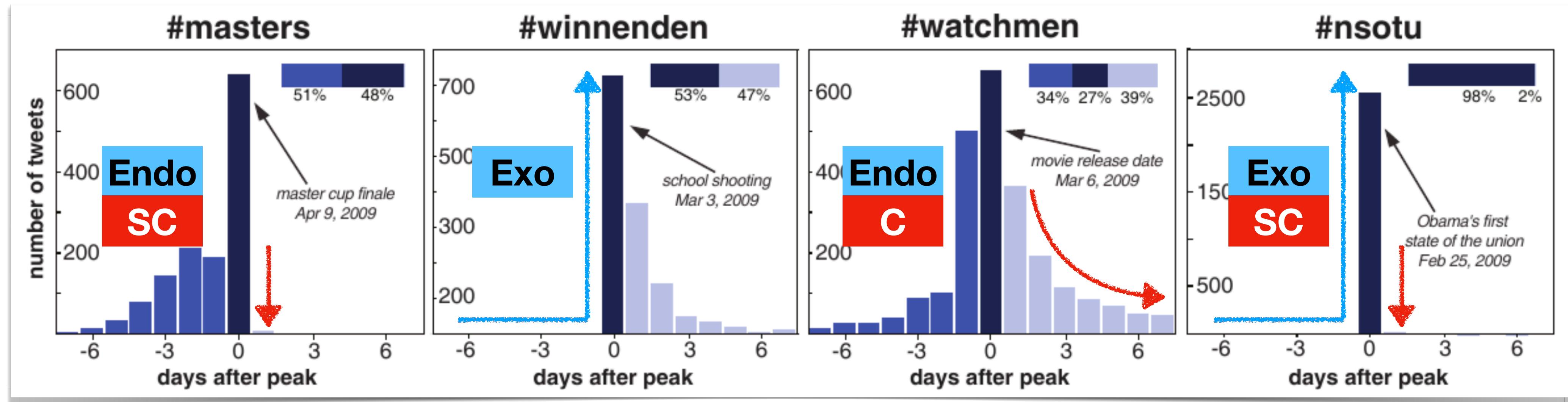


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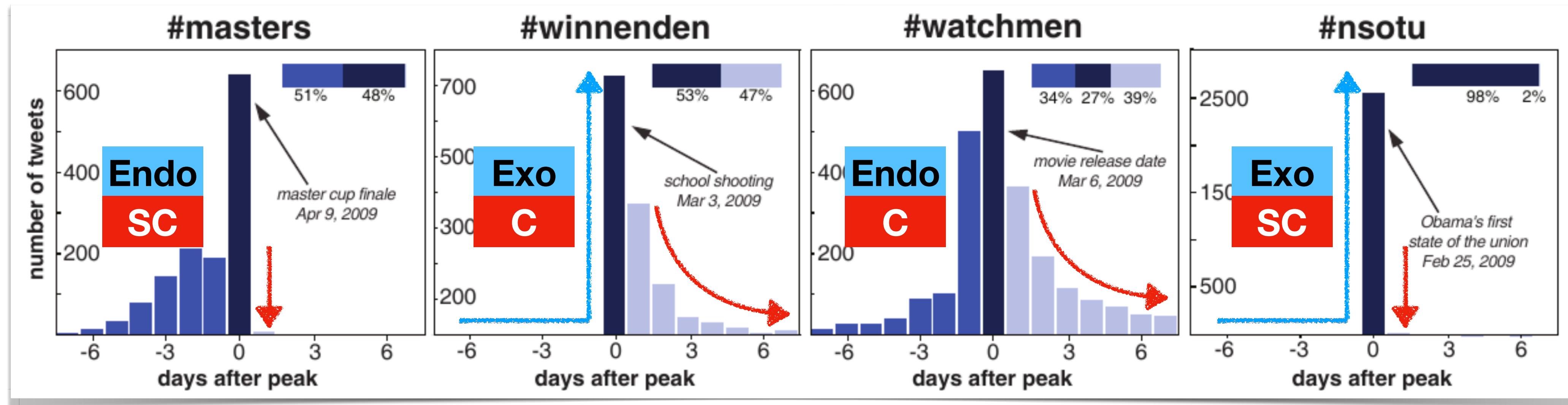


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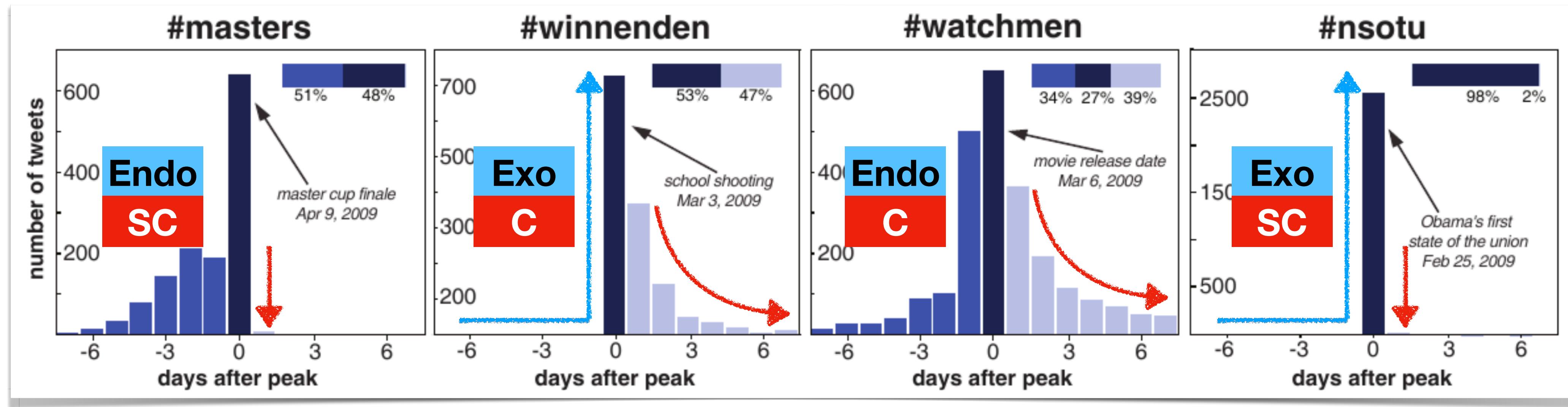


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Gathering this kind of volume data is best done by using the Twitter API v2.

- Free access: up to 1500 tweets per month
- Basic (100 USD/month): up to 10K tweets per month
- Pro (5000 USD/month): up to 1M tweets per month

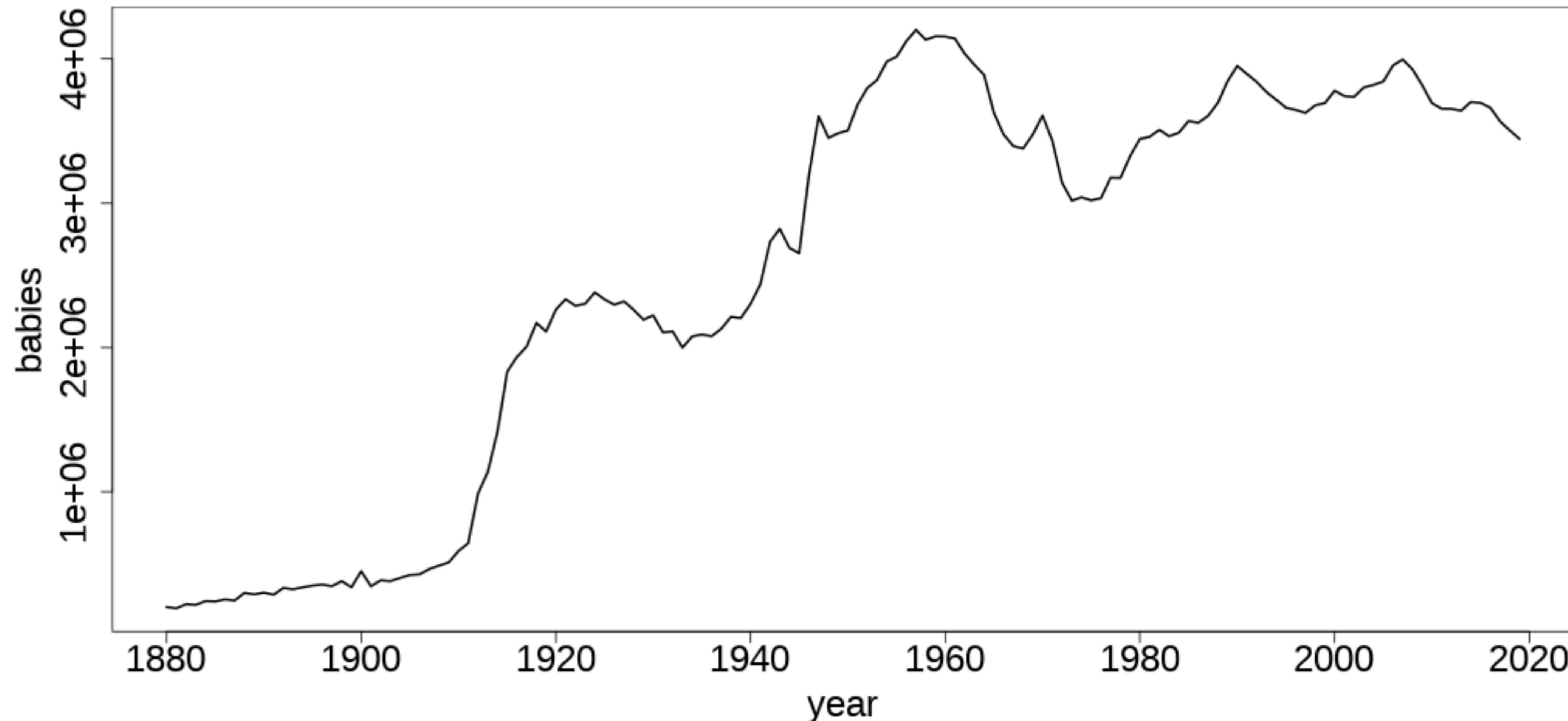
Old BigData

Baby name trends



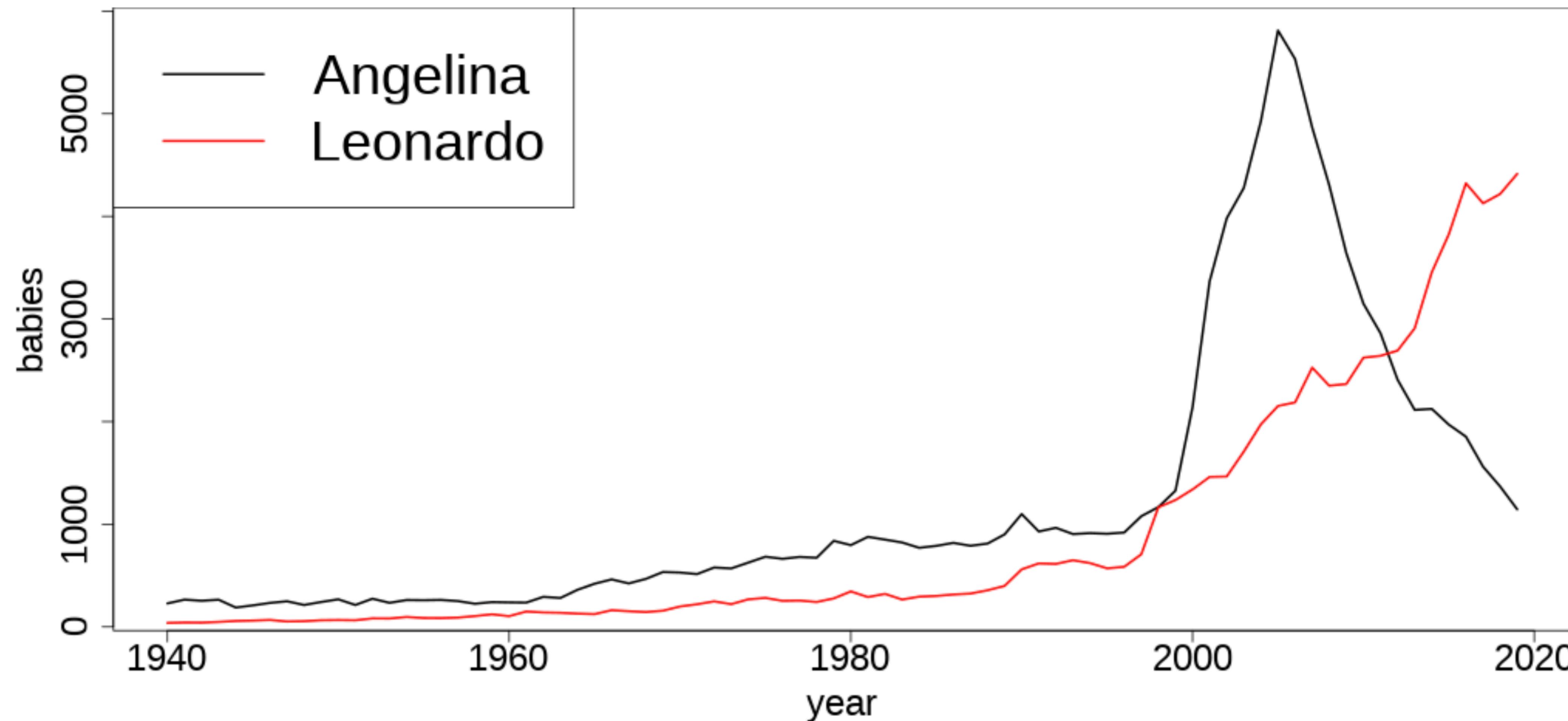
USA SSA baby name data

(Social Security Administration)



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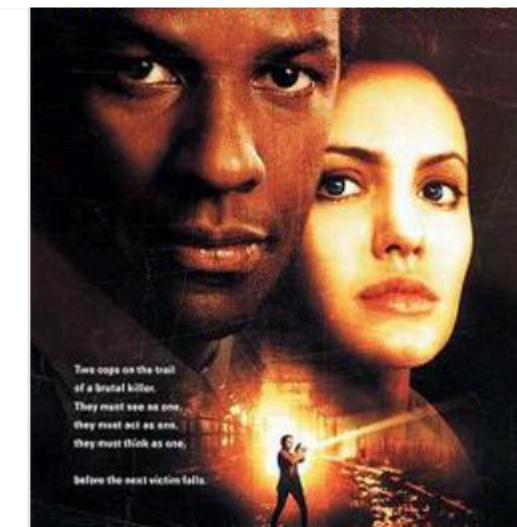
Examples



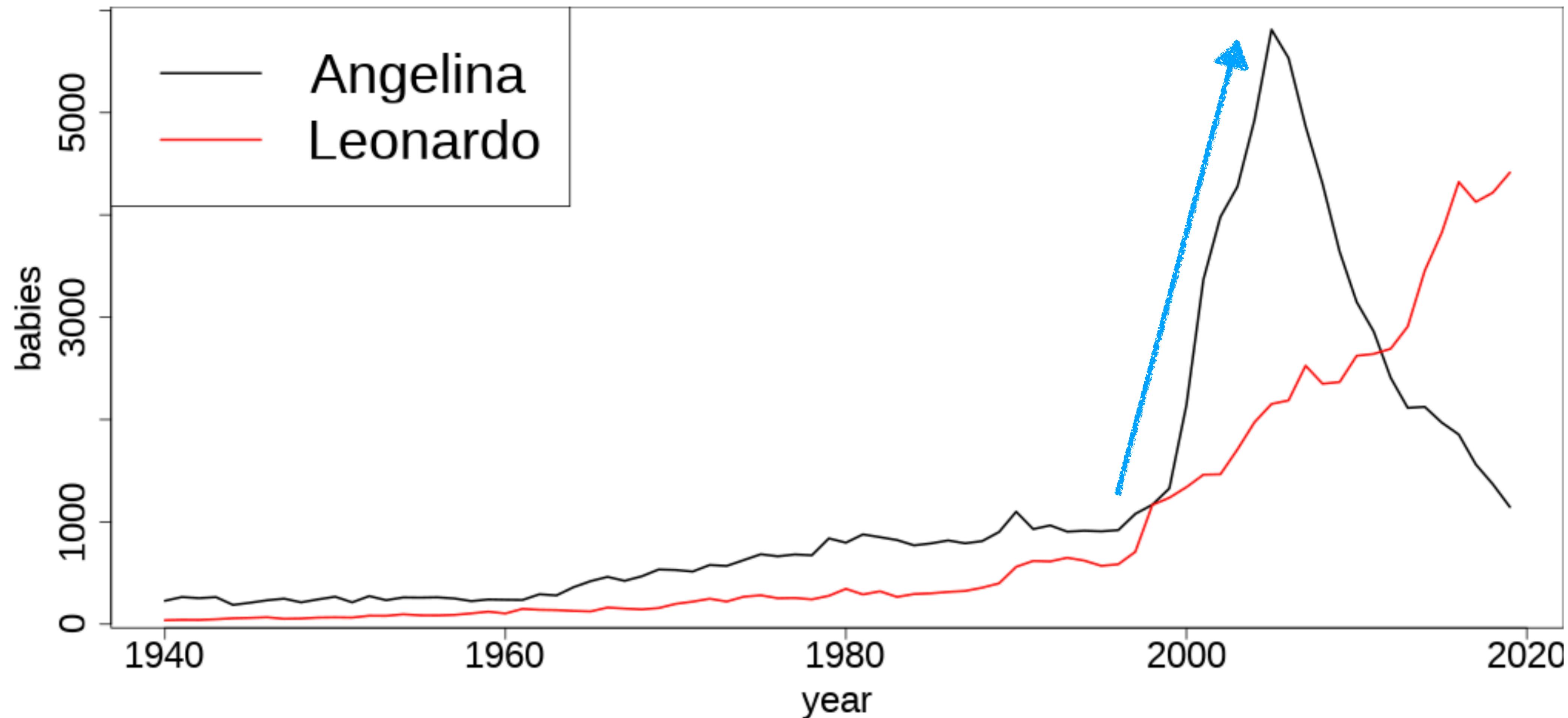
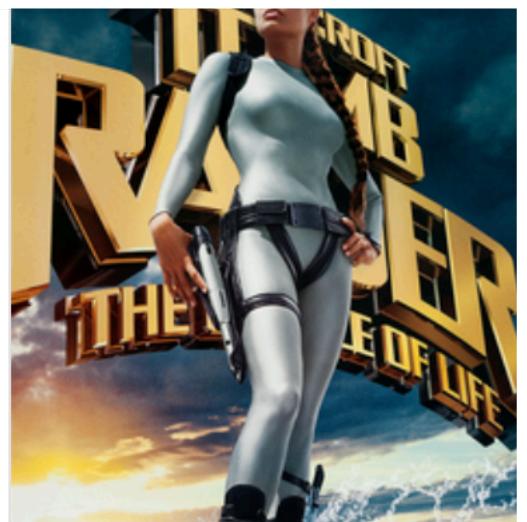
Baby name trends

Examples

The Bone Collector is a 1999 American crime thriller film directed by Phillip Noyce and starring Denzel Washington and Angelina Jolie. The film is based on the 1997 crime novel of the same name written by Jeffery Deaver, concerning the tetraplegic detective Lincoln Rhyme.

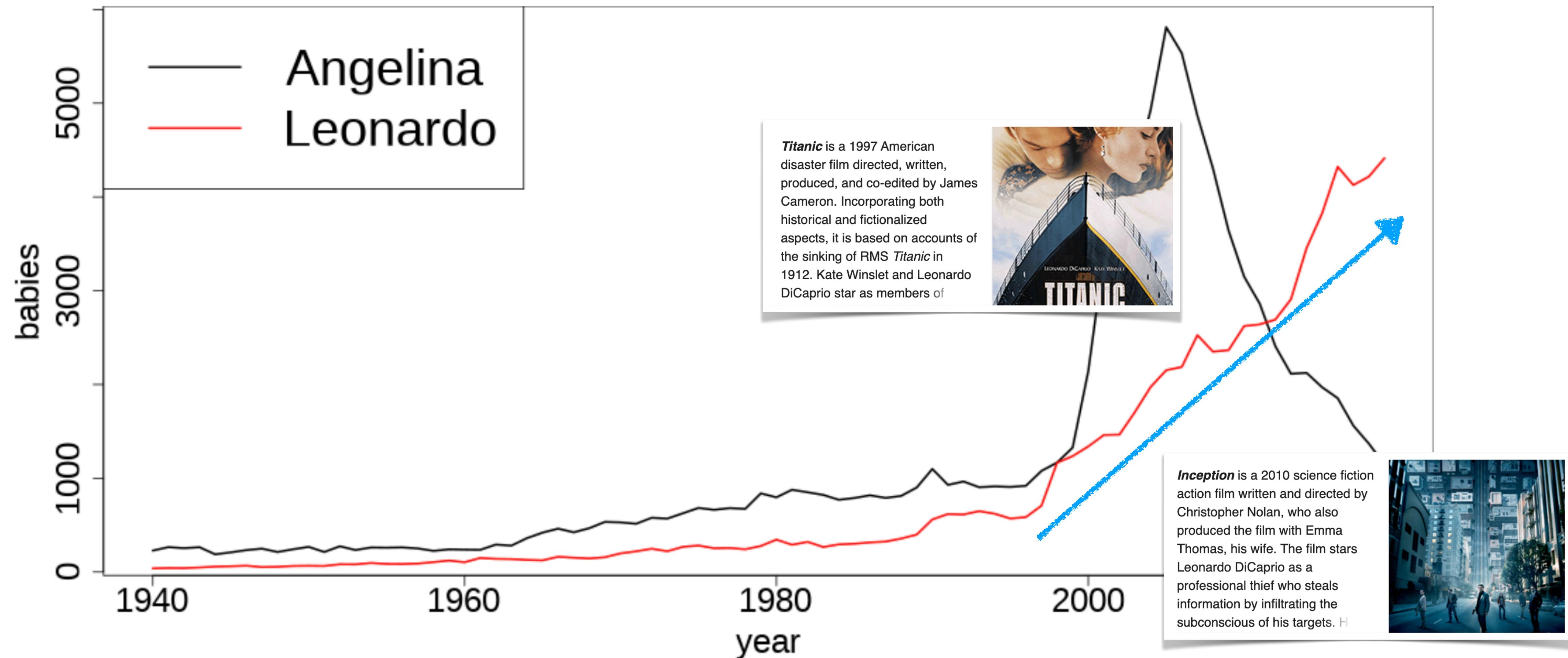


Lara Croft: Tomb Raider – The Cradle of Life is a 2003 action adventure film directed by Jan de Bont and based on the *Tomb Raider* video game series. Angelina Jolie stars as the titular character Lara Croft with supporting performances from Gerard Butler, Ciarán Hinds, C



Baby name trends

Examples



The QWERTY effect in baby names

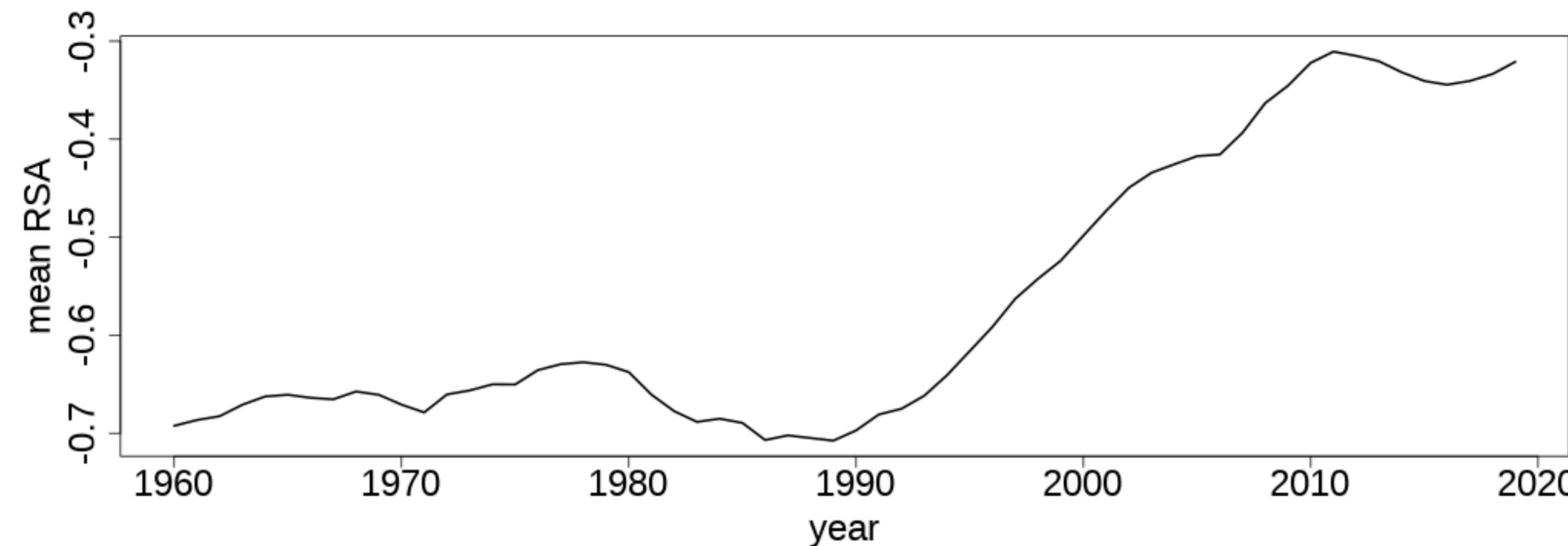
[Casasanto et al. 2014]

- The QWERTY effect is a hypothesis in Psychology that postulates that words that are written with more **right-hand** letters of the keyboard are, on average, **more positive** than words that are written with more left-hand letters of the keyboard. The fraction of right-hand letters in US baby names has been increasing:

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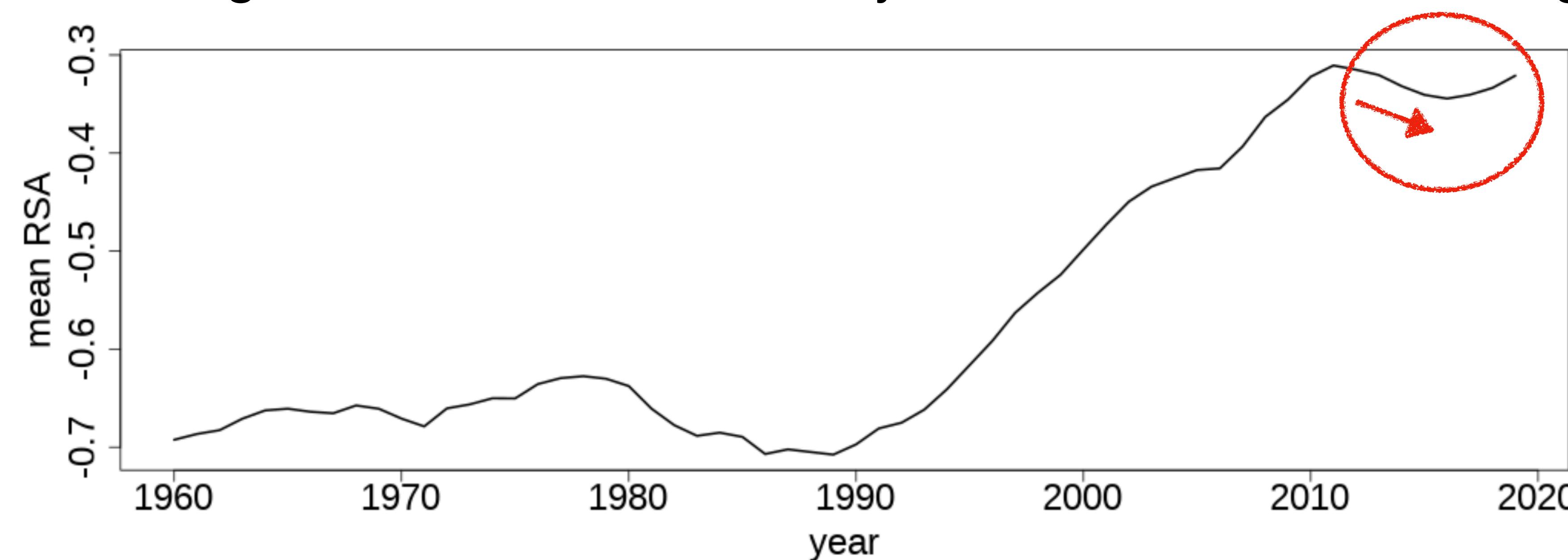


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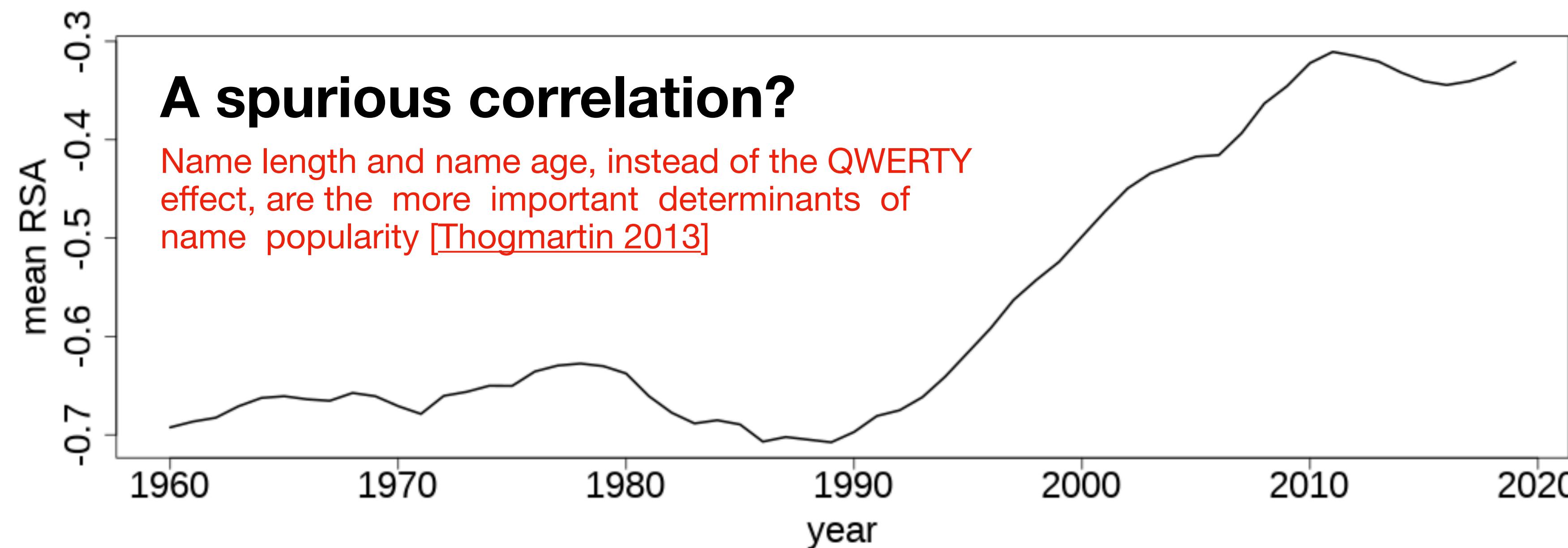


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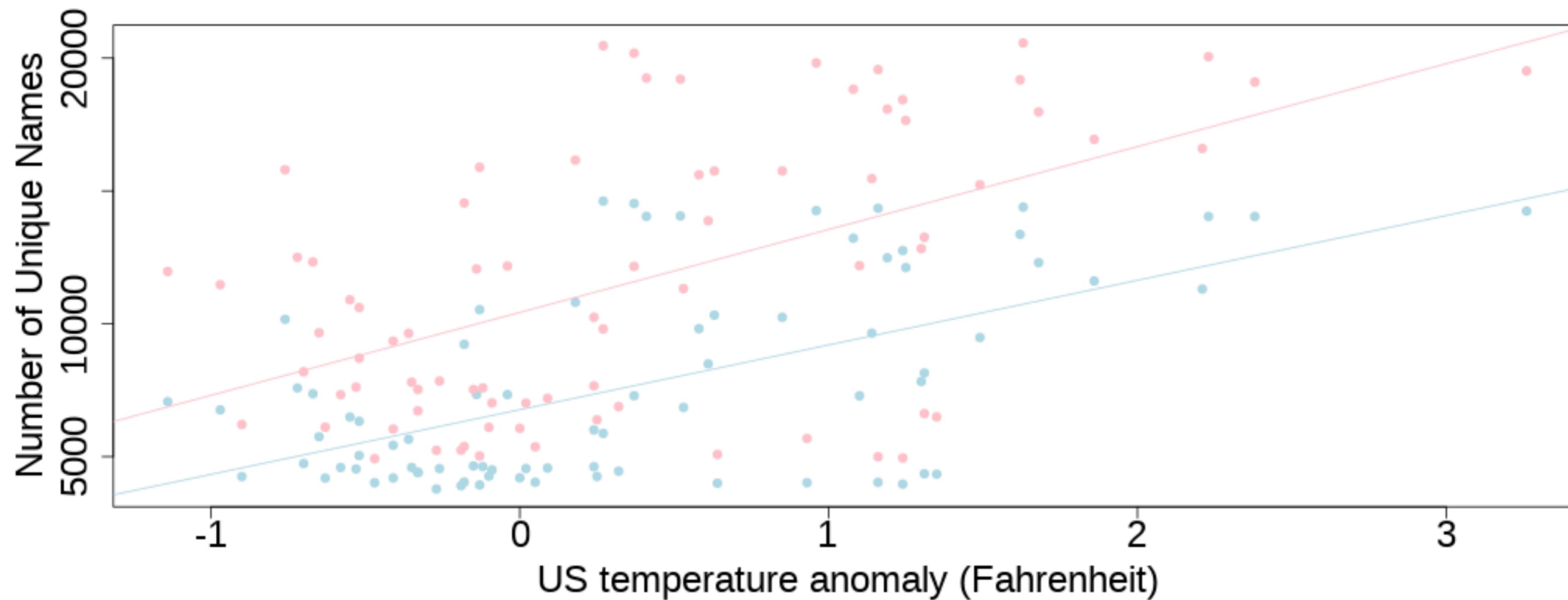


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Wacky baby name research

Proceedings of the Natural Institute of Science (a real parody)

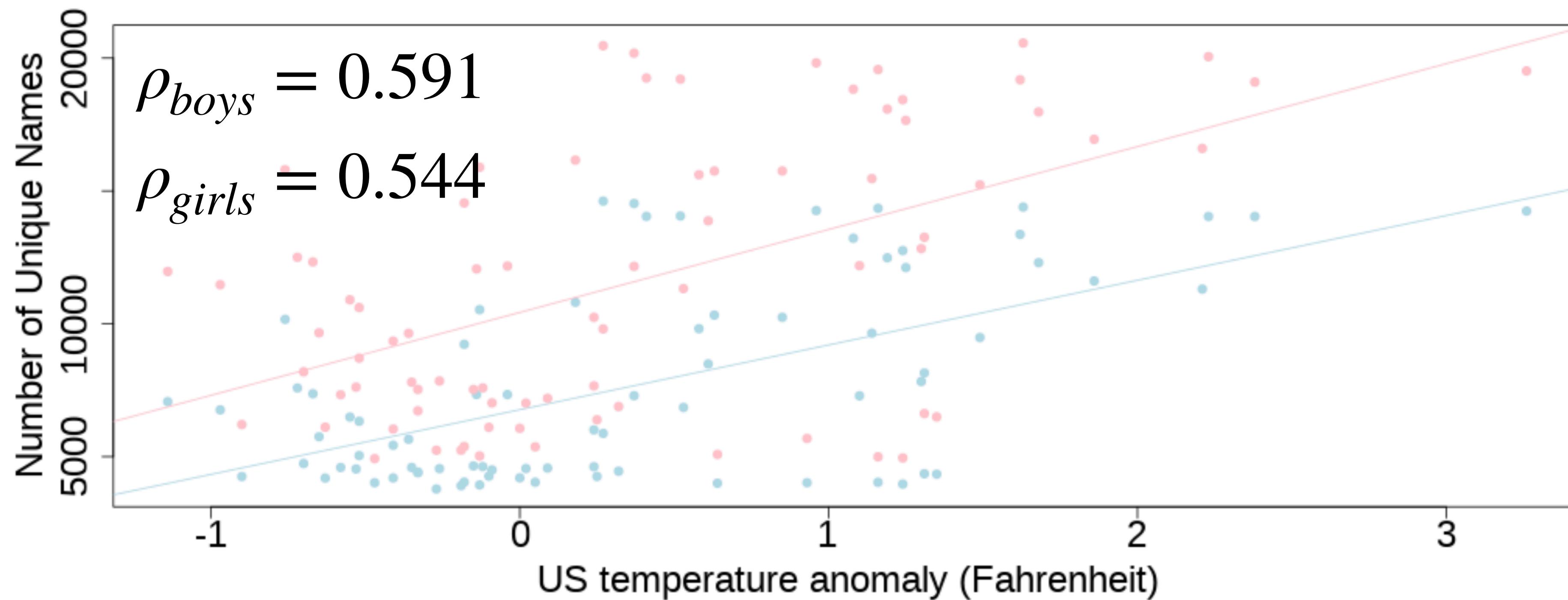
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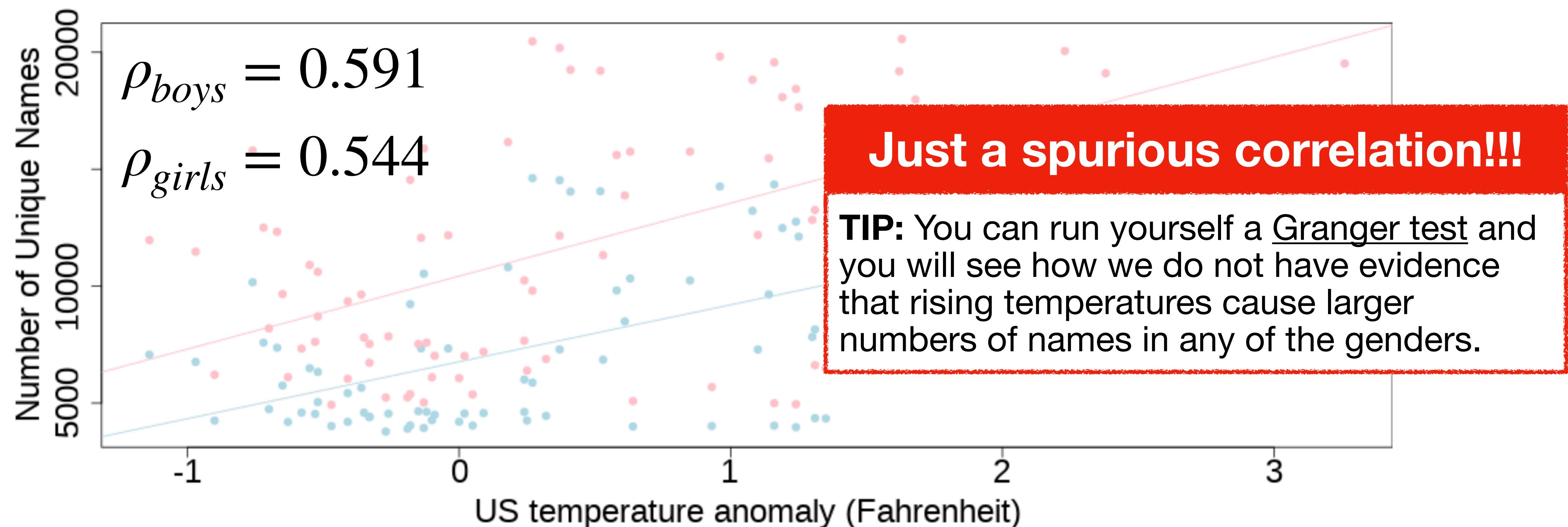
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The limits of baby name predictability

Simmel effect in baby name popularity

- The book Freakonomics (2004) explains the **imitation** part of the **Simmel effect** and explains how **people imitate their richer neighbors when naming their babies**. The book goes as far as making a prediction of what will be the top US baby names in 2015, based on a data analysis exercise that is never explained in detail in the article. Here is the prediction:

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MOST POPULAR GIRLS' NAMES OF 2015?				MOST POPULAR BOYS' NAMES OF 2015?			
Annika	Eleanora	Isabel	Maya	Aidan	Bennett	Johan	Reagan
Ansley	Ella	Kate	Philippa	Aldo	Carter	Keyon	Sander
Ava	Emma	Lara	Phoebe	Anderson	Cooper	Liam	Sumner
Avery	Fiona	Linden	Quinn	Ansel	Finnegan	Maximilian	Will
Aviva	Flannery	Maeve	Sophie	Asher	Harper	McGregor	
Clementine	Grace	Marie-Claire	Waverly	Beckett	Jackson	Oliver	

The limits of baby name predictability

Most popular girl names in 2015 (and the prediction)

Annika	Clementine	Flannery	Linden	Phoebe
Ansley	Eleanora	Grace	Maeve	Quinn
Ava	Ella	Isabel	Marie-Claire	Sophie
Avery	Emma	Kate	Maya	Waverly
Aviva	Fiona	Lara	Philippa	

Prediction

Abigail	Avery	Emily	Isabella	Sofia
Addison	Charlotte	Emma	Madison	Sophia
Amelia	Chloe	Evelyn	Mia	Victoria
Aubrey	Elizabeth	Grace	Olivia	Zoey
Ava	Ella	Harper	Scarlett	

Real

The limits of baby name predictability

Most popular girl names in 2015 (and the prediction)

					Prediction
Annika	Clementine	Flannery	Linden	Phoebe	
Ansley	Eleanora	Grace	Maeve	Quinn	
Ava	Ella	Isabel	Marie-Claire	Sophie	
Avery	Emma	Kate	Maya	Waverly	
Aviva	Fiona	Lara	Philippa		$acc = \frac{7}{24} = 0,29$
					Real
Abigail	Avery	Emily	Isabella	Sofia	
Addison	Charlotte	Emma	Madison	Sophia	
Amelia	Chloe	Evelyn	Mia	Victoria	
Aubrey	Elizabeth	Grace	Olivia	Zoey	
Ava	Ella	Harper	Scarlett		

The limits of baby name predictability

Most popular boy names in 2015 (and the prediction)

Aidan	Beckett	Harper	Maximilian	Summer
Aldo	Bennett	Jackson	McGregor	Will
Anderson	Carter	Johan	Oliver	
Ansel	Cooper	Keyon	Reagan	
Asher	Finnegan	Liam	Sander	

Aiden	David	Jacob	Logan	Noah
Alexander	Elijah	James	Lucas	Oliver
Benjamin	Ethan	Jayden	Mason	Samuel
Carter	Gabriel	Joseph	Matthew	William
Daniel	Jackson	Liam	Michael	

The limits of baby name predictability

Most popular boy names in 2015 (and the prediction)

Aidan	Beckett	Harper	Maximilian	Summer	
Aldo	Bennett	Jackson	McGregor	Will	
Anderson	Carter	Johan	Oliver		
Ansel	Cooper	Keyon	Reagan		
Asher	Finnegan	Liam	Sander	$acc = \frac{6}{22} = 0,27$	Prediction

Aiden	David	Jacob	Logan	Noah	
Alexander	Elijah	James	Lucas	Oliver	
Benjamin	Ethan	Jayden	Mason	Samuel	
Carter	Gabriel	Joseph	Matthew	William	
Daniel	Jackson	Liam	Michael		Real

Predicting is hard

Prediction vs. Explanation

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Prediction vs. Explanation

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Prediction vs. Explanation

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- What you see is that predicting which names in particular will be the most popular is a very difficult task. **The Simmel effect describes forces that create observable patterns, but that does not mean that the model is predictive to tell us which of all names will become popular ten years from now**, even if we had data of the social status of parents.

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- This is the difference between **explanatory** and **predictive** power of a model. A model can explain phenomena without being useful to make predictions, as in this case, but can also be predictive without giving explanations, like in the case of deep learning or other black-box approaches.

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Take home message: understanding does not imply predictive power and vice versa

To recap...

Today's class

BLOCK 1

Social Behavior

1. Social Science
2. CSS
3. Digital Traces
4. Examples

BLOCK 2

Social Trends

1. Google Trends
2. The Future Orientation Index
3. Culture and Economy

BLOCK 3

Quantifying Trends

1. Correlation
2. Causation
3. Regression

BLOCK 4

Behavior & Trend Dynamics

1. The Theory of Fashion
2. The Endo-Exo model
3. Examples

Summary

Part 1 & 2: Behavior and trends

Social behavior and trends are both important aspects of human behavior that involve the interactions of individuals, and are influenced by societal and environmental factors.

Social **behavior** focuses on the interactions of individuals (between them, or between external factors such as a website, a technology, etc.)

Social **trends** are more broad and can be observed at the group or societal level, focusing on the larger patterns and changes in behavior or attitudes.

Summary

Part 3: Correlation, causation, and linear regression

The Future Orientation Index (FOI) measures the relationship between culture (Google Search Trends) and the economy (GDP)

Correlation measures the strength and direction of the relationship between two variables, but it does not explain “why” (correlation is not causation)

A regression model formalizes how one quantity depends on a linear combination of others. We can evaluate its “goodness-of-fit”.

Summary

Part 4: Simmel effect and baby names

Fashion always changes but there is always a fashion.
It is explained by imitation and distinctiveness.

The endo-exo model to explain social trends in online platforms.

Trends are hard to predict but show patterns of behavior.

Summary

Today's class

BLOCK 1

BLOCK 2

BLOCK 3

BLOCK 4

Social Behavior	Social Trends	Quantifying Trends	Behavior & Trend Dynamics
<ul style="list-style-type: none">1. Social Science2. CSS3. Digital Traces4. Examples	<ul style="list-style-type: none">1. Google Trends2. The Future Orientation Index3. Culture and Economy	<ul style="list-style-type: none">1. Correlation2. Causation3. Regression	<ul style="list-style-type: none">1. The Theory of Fashion2. The Endo-Exo model3. Examples

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Resources

Other materials used to prepared these slides

- Digital traces [[GESIS](#)]
- Correlation and Causation [[KhanAcademy](#)] [[icecream-crime](#)]
- Establishing Causality by Brian Anderson [[Blog](#)]
- Foundations of CSS by David Garcia [[GitHub](#)]
- Correlational research [[University of Central Florida](#)]
- Graphs in Statistical Analysis by J. S. Anscombe [[article](#)] [[matplotlib](#)]
- The datasaurus R package [[website](#)]
- Fashion trends [[white sneakers](#)] [[jeans](#)] [[UK baby names](#)]
- Linear regression [[ChelseaParlett](#)] [[R Tutorial](#)]