Social Behavior and Trends

Foundations of Computational Social Science

Lecturer: **Lisette Espín-Noboa**

espin@csh.ac.at | www.lisetteespin.info | @lespin

Postdoc at Complexity Science Hub Vienna

Postdoc at Central European University

October, 29, 2024

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.

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Social behavior & trends

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Focus

Behavior refers to the actions, reactions, or conduct of individuals or groups in response to a particular situation.	Interactions of and among individuals
A **Trend** is a pattern, fashion or tendency that persists over time. Also, a direction in which something is developing or changing.	Changes in behavior or attitudes

Social behavior & trends

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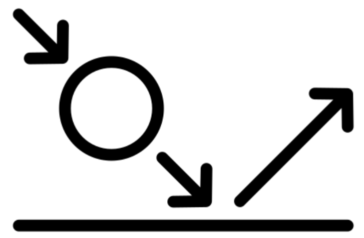
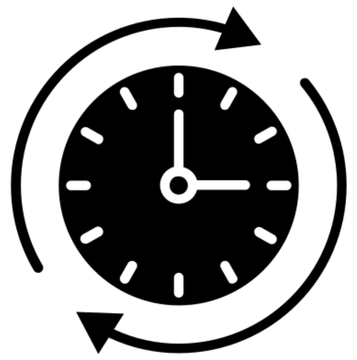
	Focus	Timeframe
Behavior refers to the actions, reactions, or conduct of individuals or groups in response to a particular situation.	Interactions of and among individuals	 Immediate action/reaction
A **Trend** is a pattern, fashion or tendency that persists over time. Also, a direction in which something is developing or changing.	Changes in behavior or attitudes	 Long-term development

Social behavior & trends

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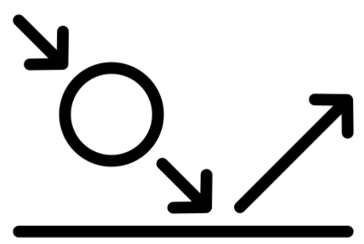
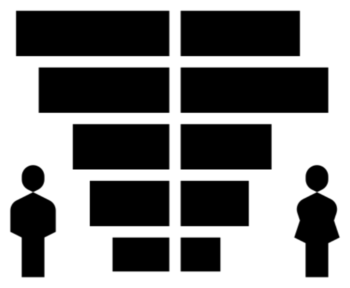
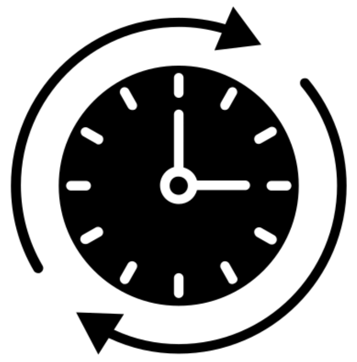
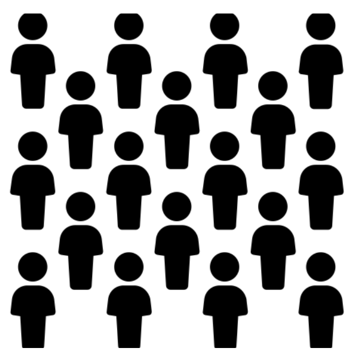
Behavior refers to the actions, reactions, or conduct of individuals or groups in response to a particular situation.	Interactions of and among individuals	 Immediate action/reaction	 Individuals or groups
A **Trend** is a pattern, fashion or tendency that persists over time. Also, a direction in which something is developing or changing.	Changes in behavior or attitudes	 Long-term development	 General population

Social behavior & trends

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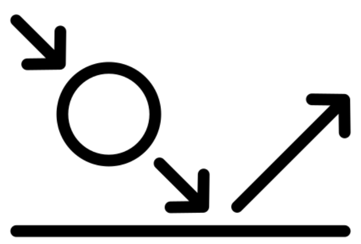
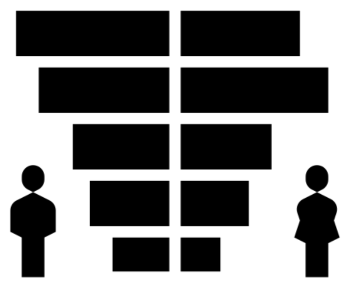
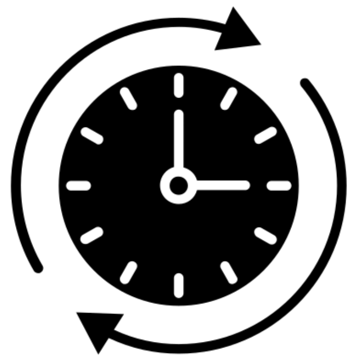
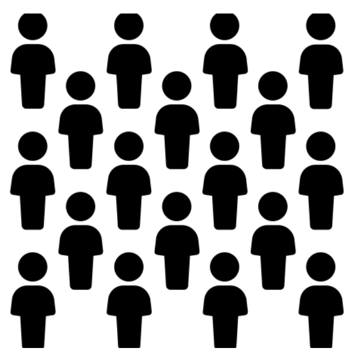
Behavior refers to the actions, reactions, or conduct of individuals or groups in response to a particular situation.	Interactions of and among individuals	 Immediate action/reaction	 Individuals or groups	Why? Intercept with social theory? What triggered it?
A **Trend** is a pattern, fashion or tendency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

Social behavior & trends

Similarities

	Focus	Timeframe	Scope	Analysis
Behavior refers to the actions, reactions, or conduct of individuals or groups in response to a particular situation.	Both involve the interaction of individuals (patterns)	Both are influenced by societal norms, cultural practices, and environmental factors		Both are within the interests of computational social scientists
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

Examples

Behavior

Trend

- How users navigate the Web, the city, etc.
- The use of ChatGPT in education & science
- Online consumer decision-making
- The increasing use of ML in CSS research
- The growing interest in understanding the ethical implications of CSS research
- 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)

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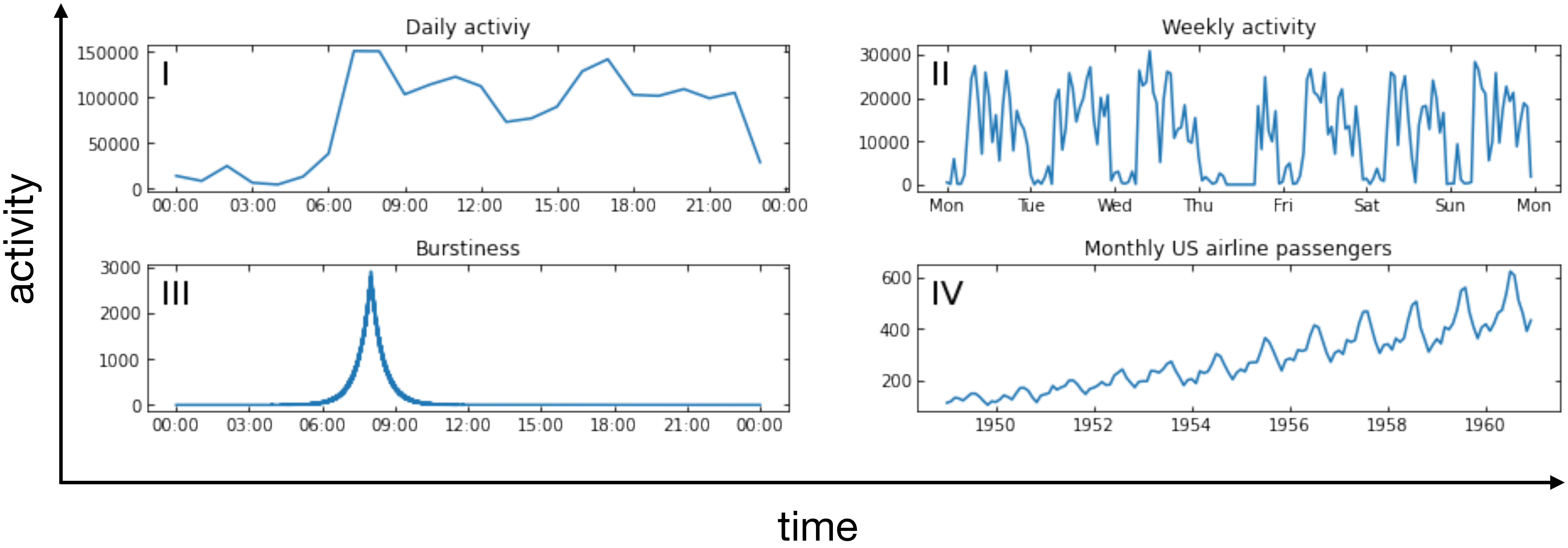

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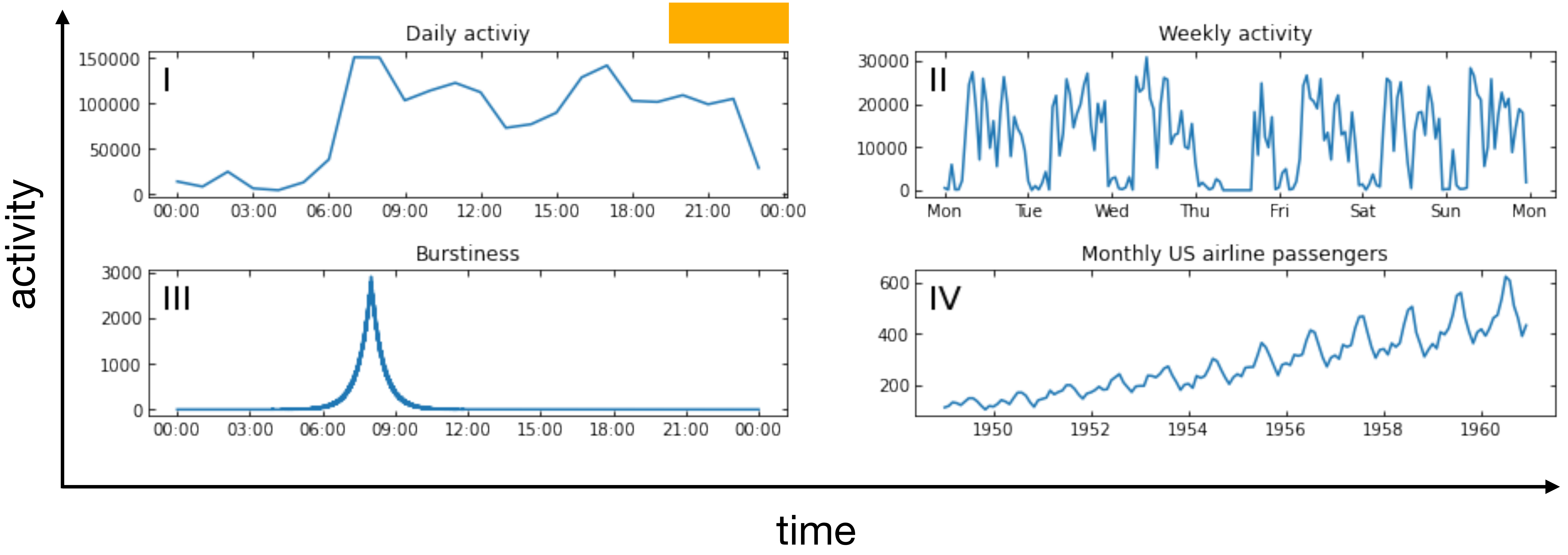

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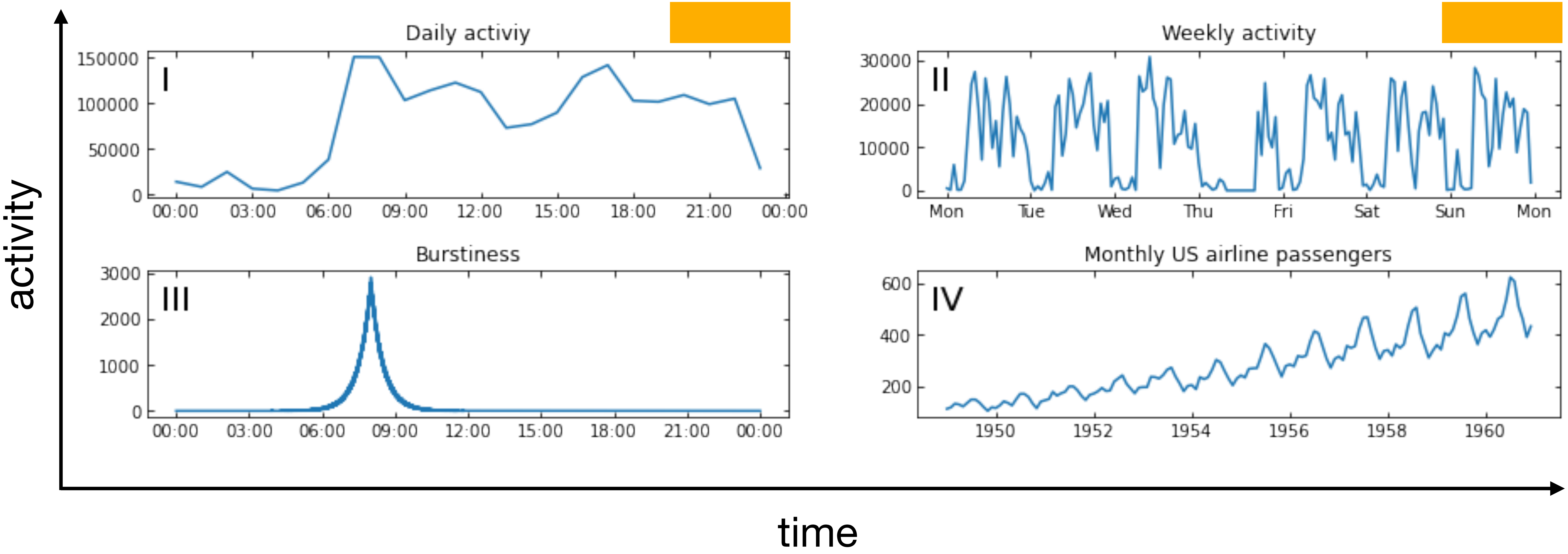

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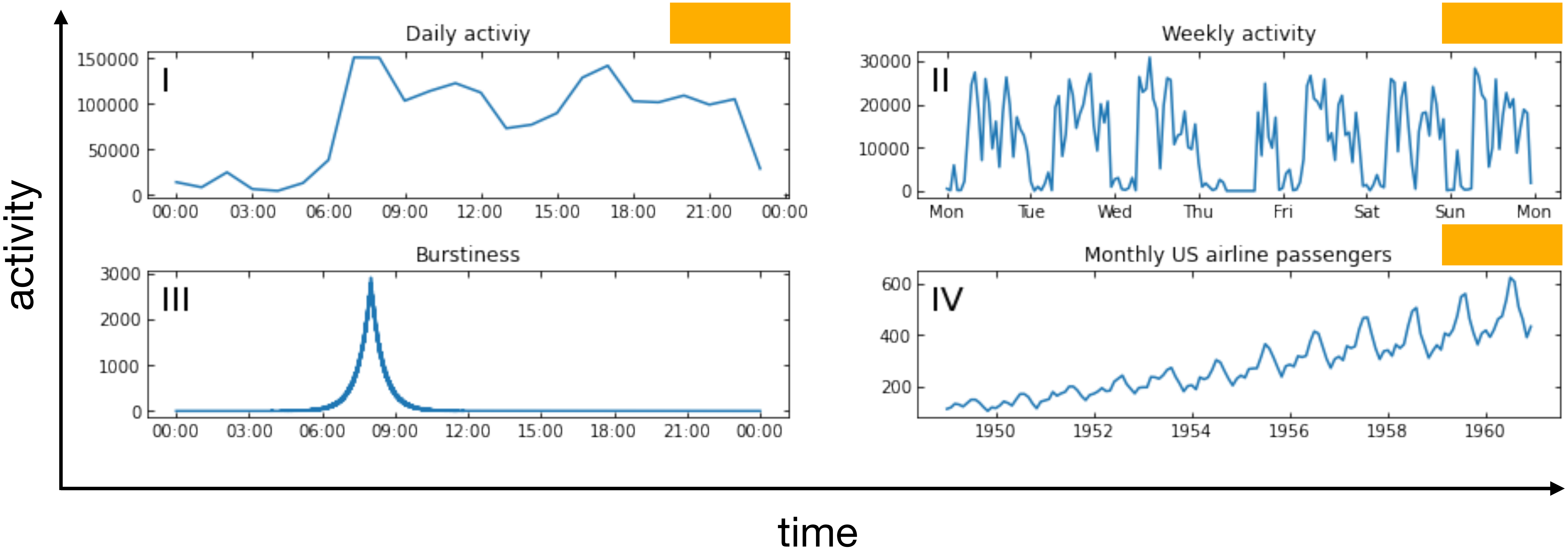

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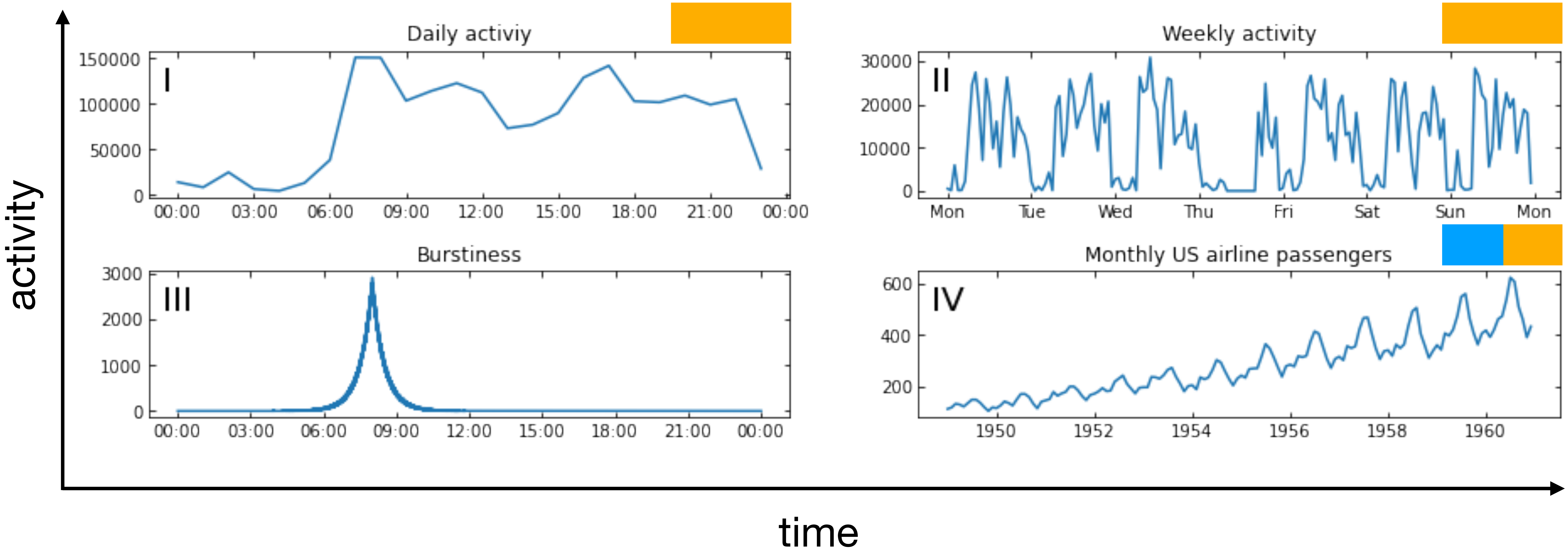

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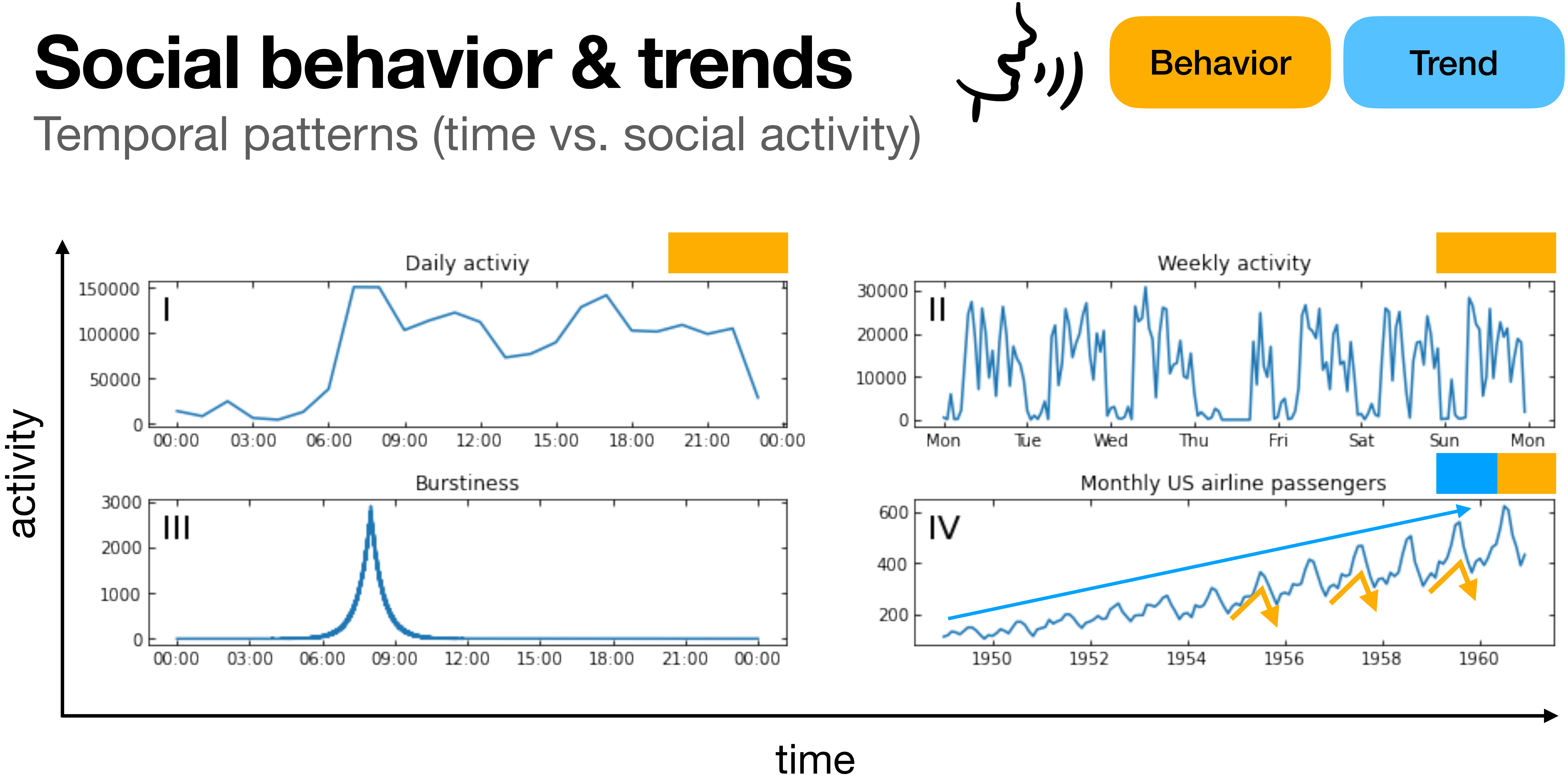

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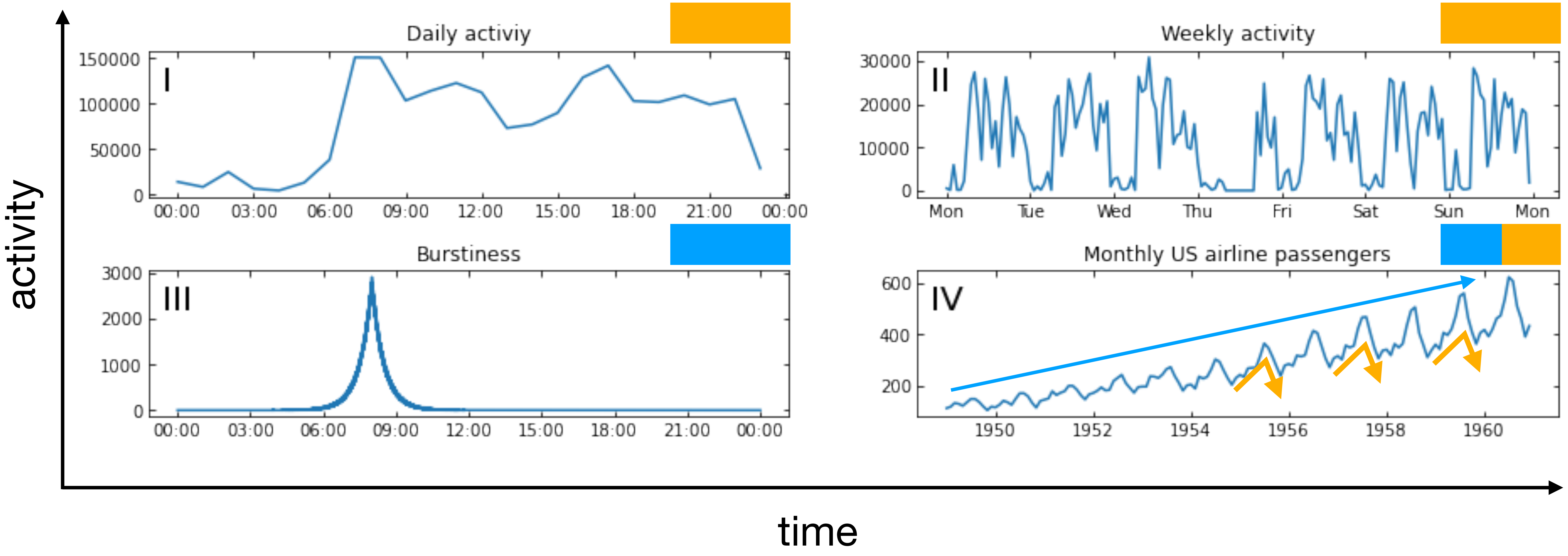

Outline

Today's class

BLOCK 1	BLOCK 2	BLOCK 3	BLOCK 4
Social Behavior	Social Trends	Quantifying Trends	Behavior & Trend Dynamics

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Social Behavior

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and the social sciences

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

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and computational social science

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

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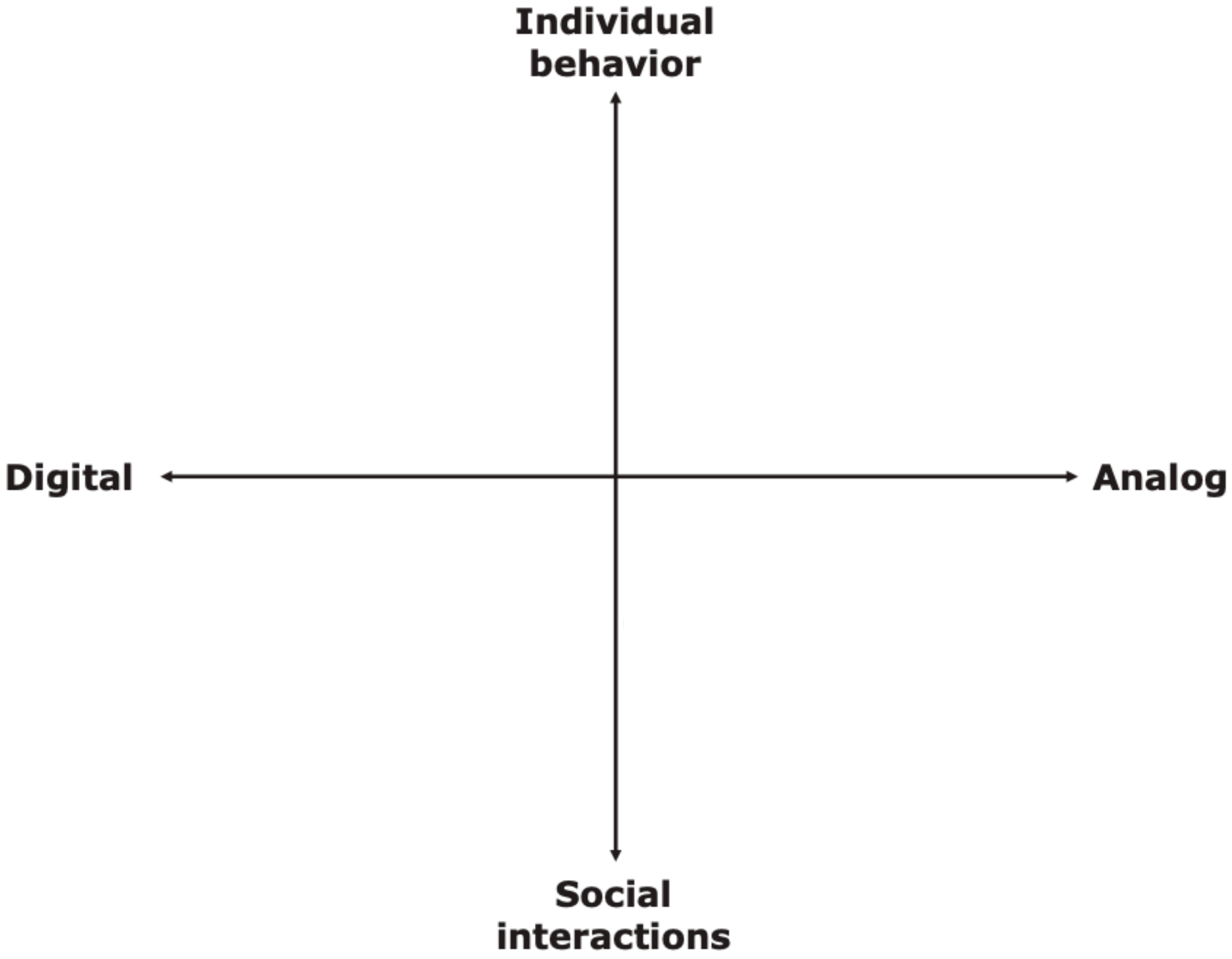

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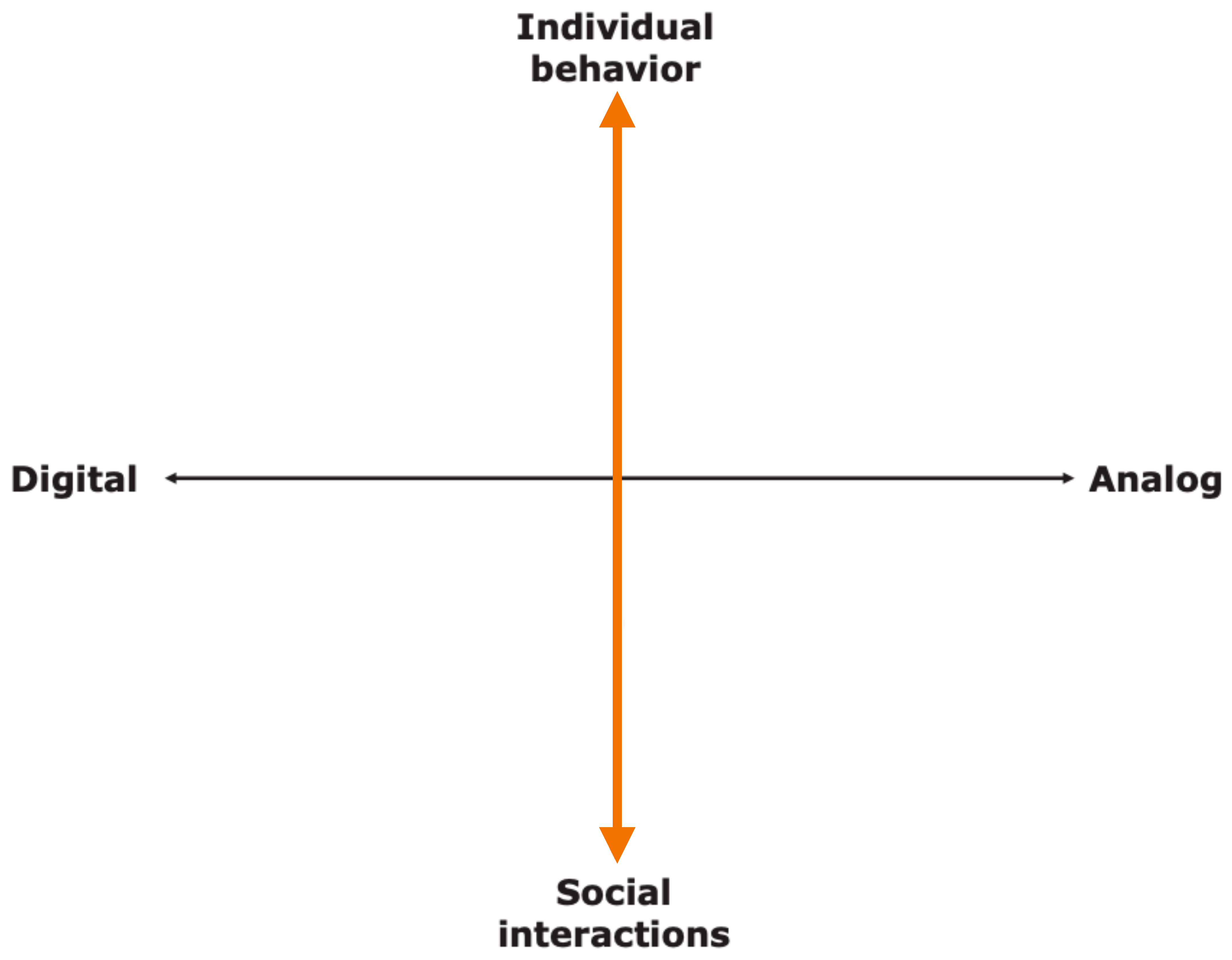

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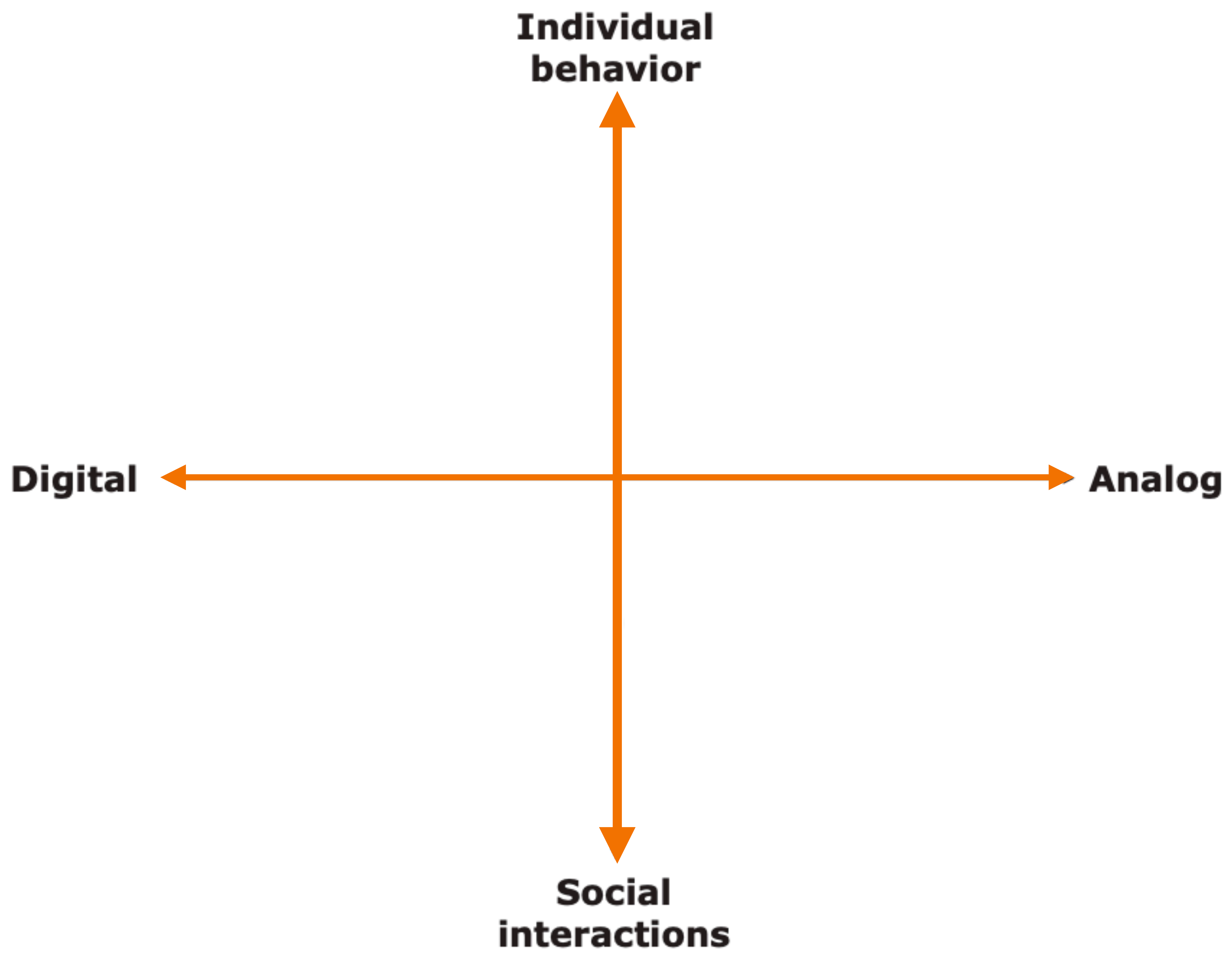

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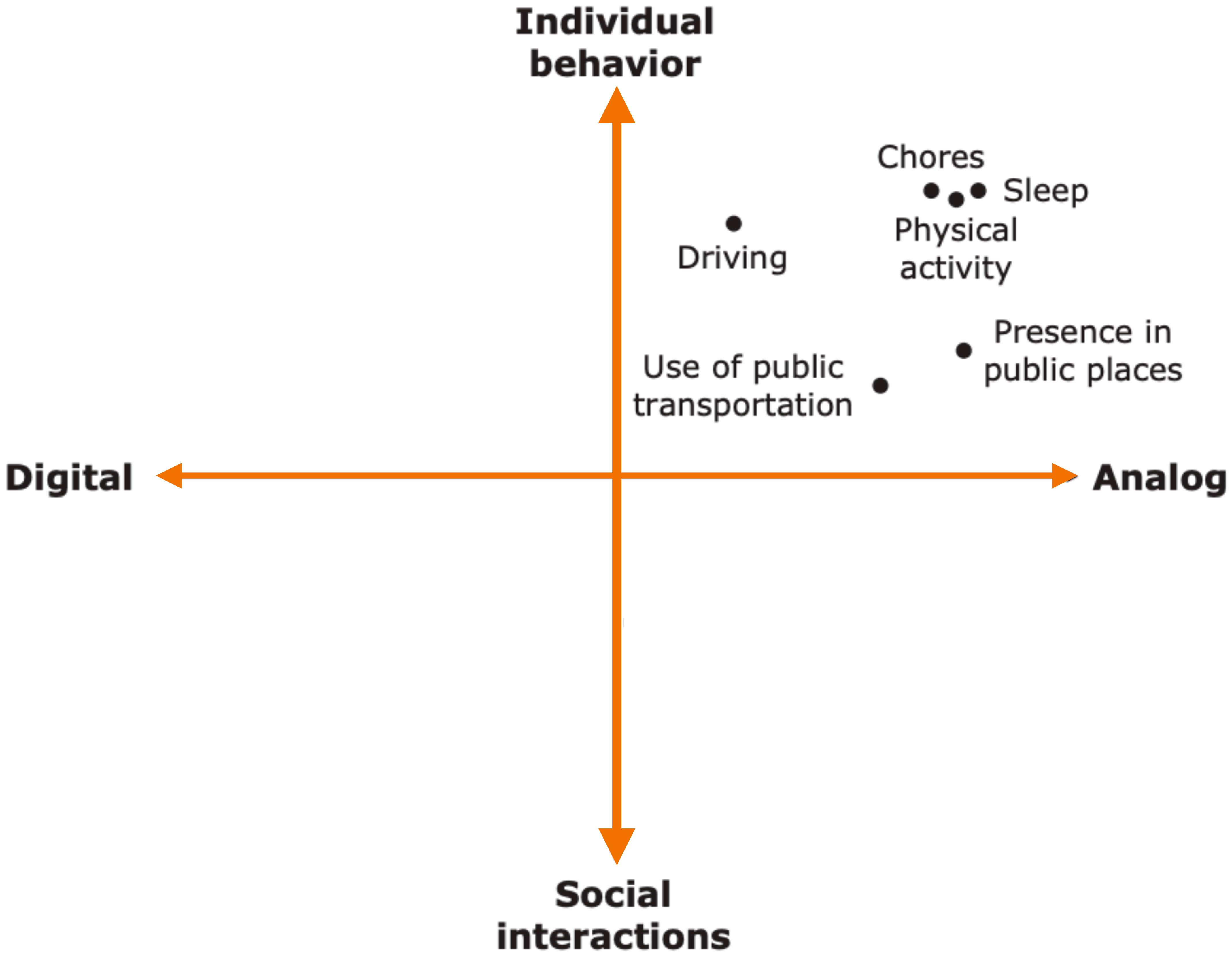

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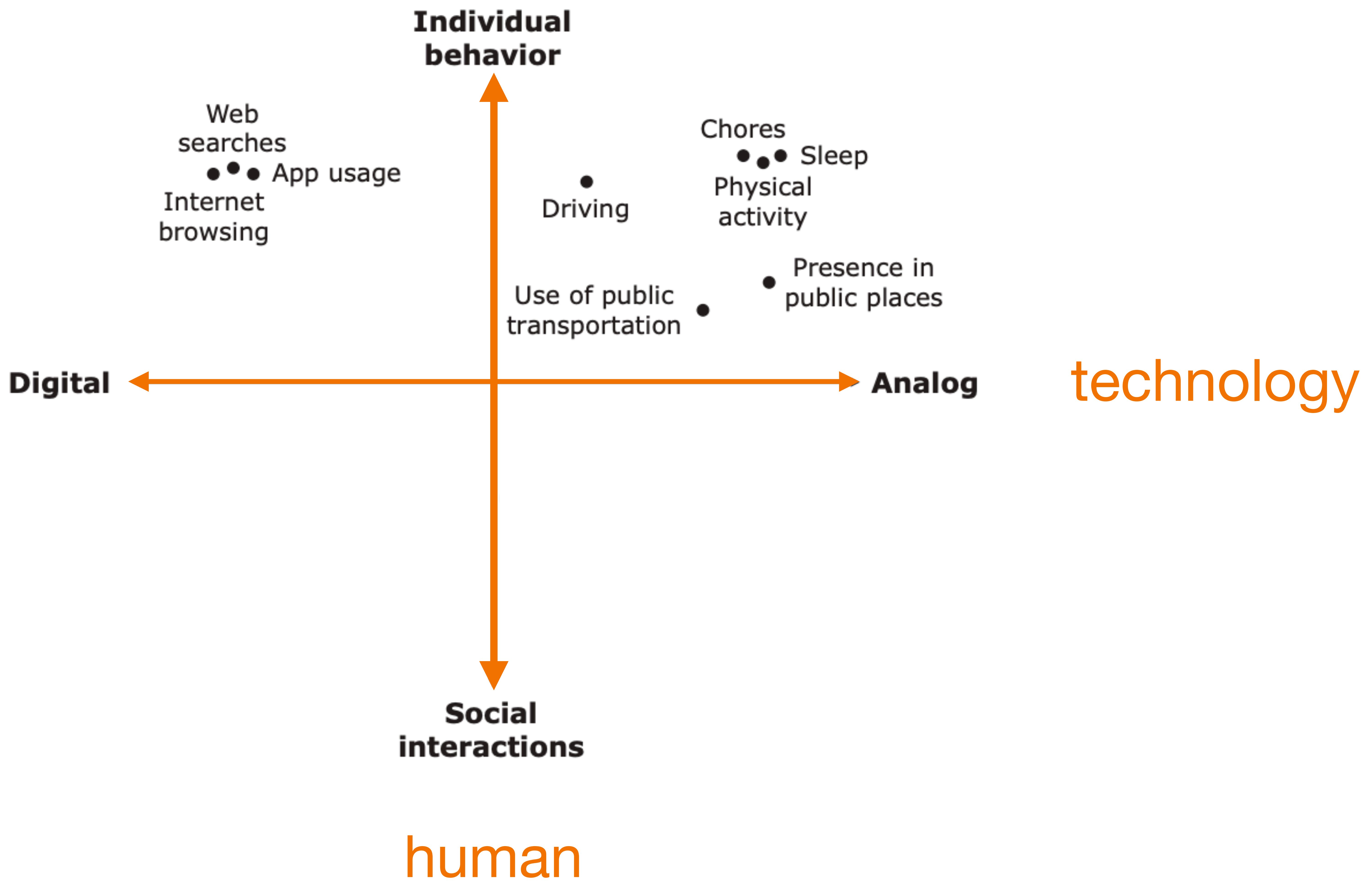

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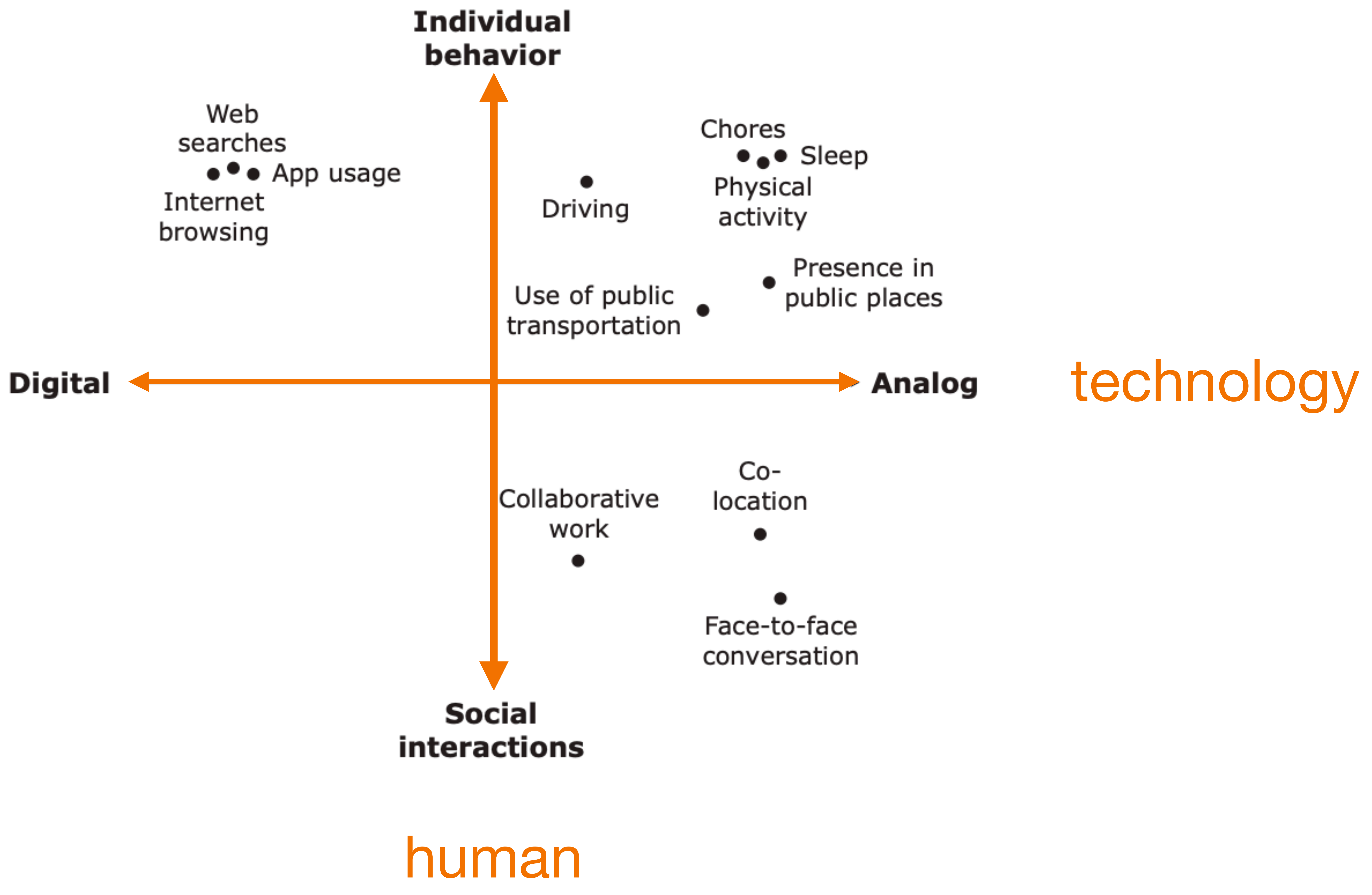

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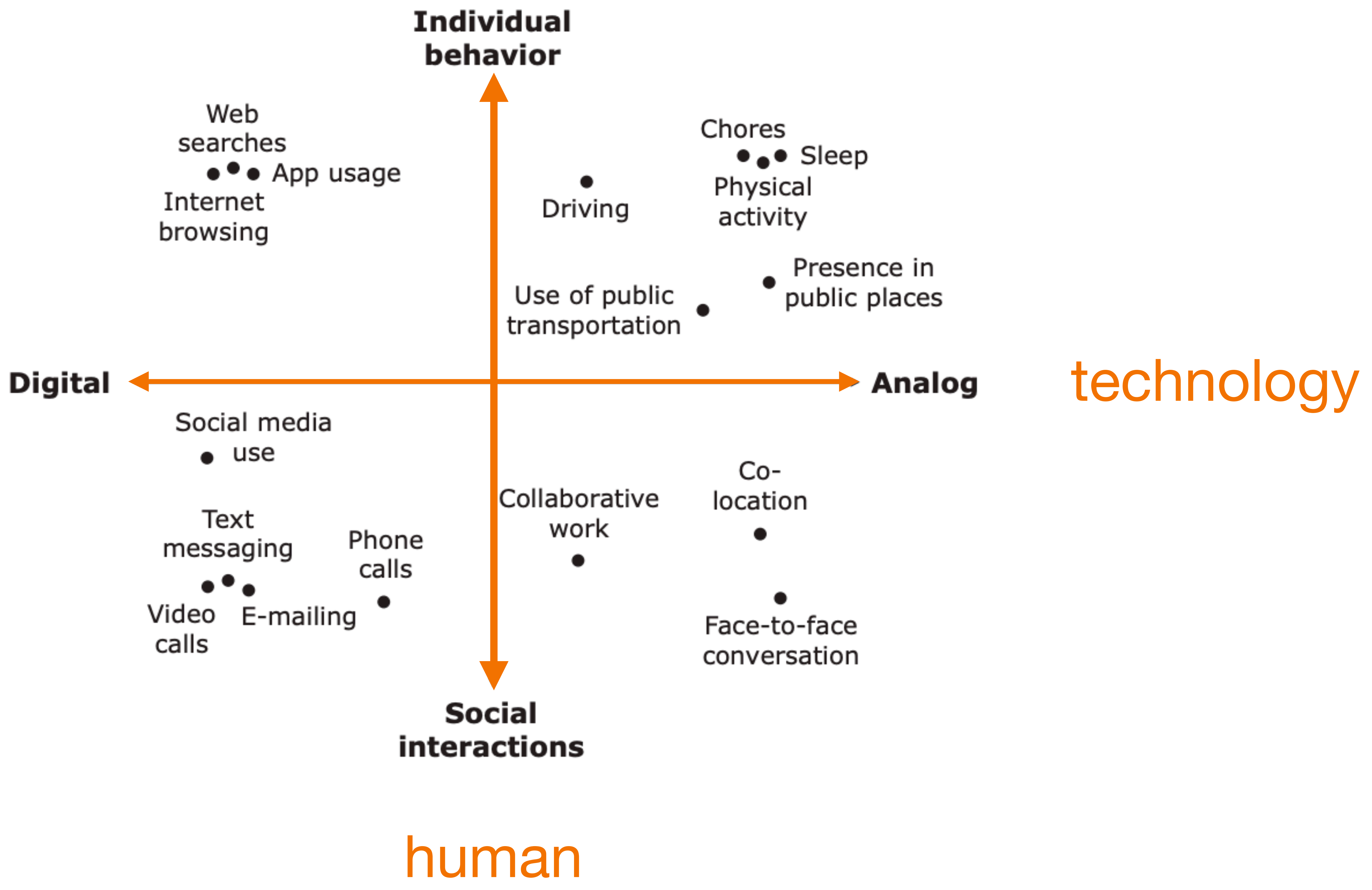

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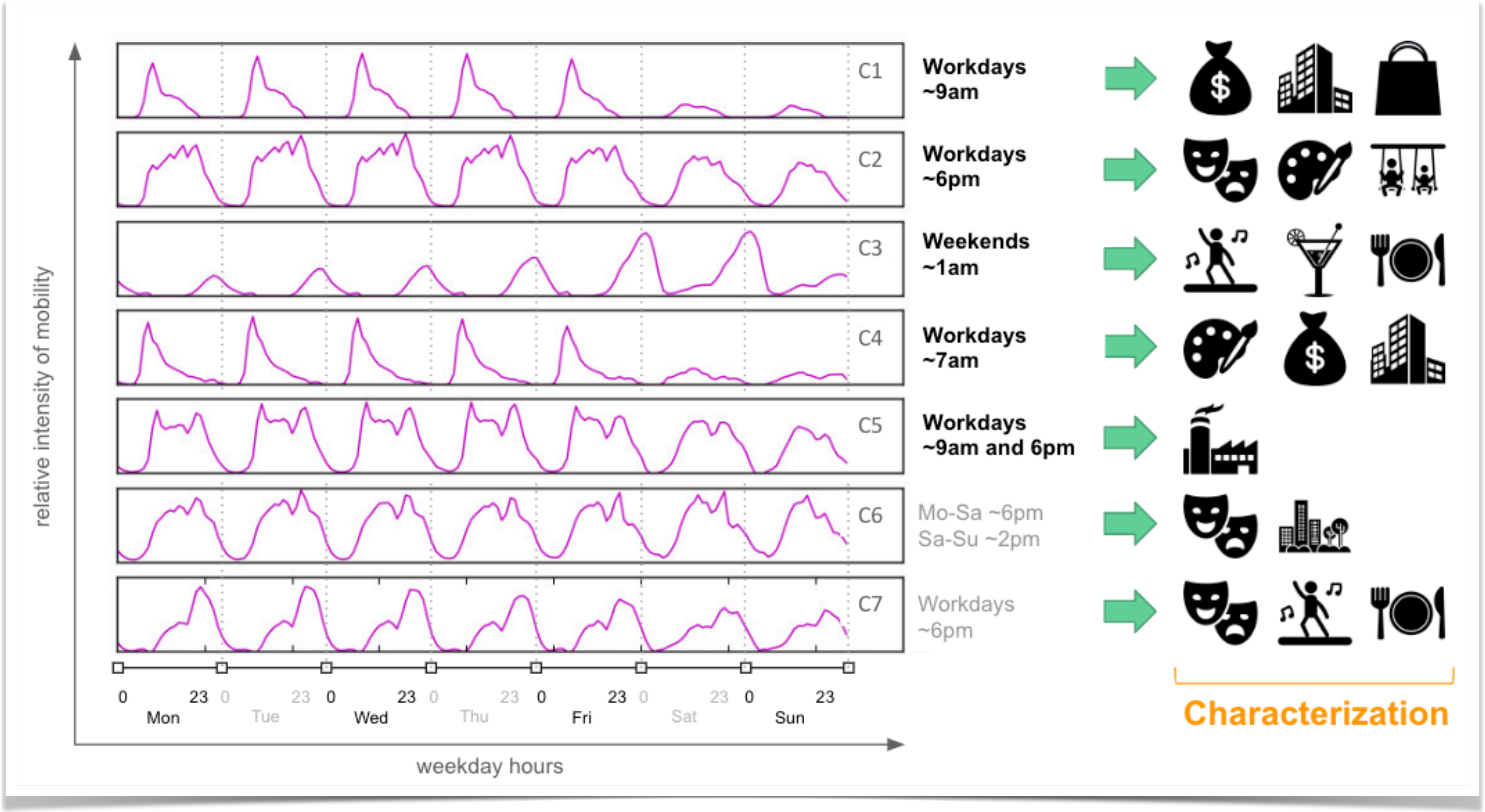

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(2017)

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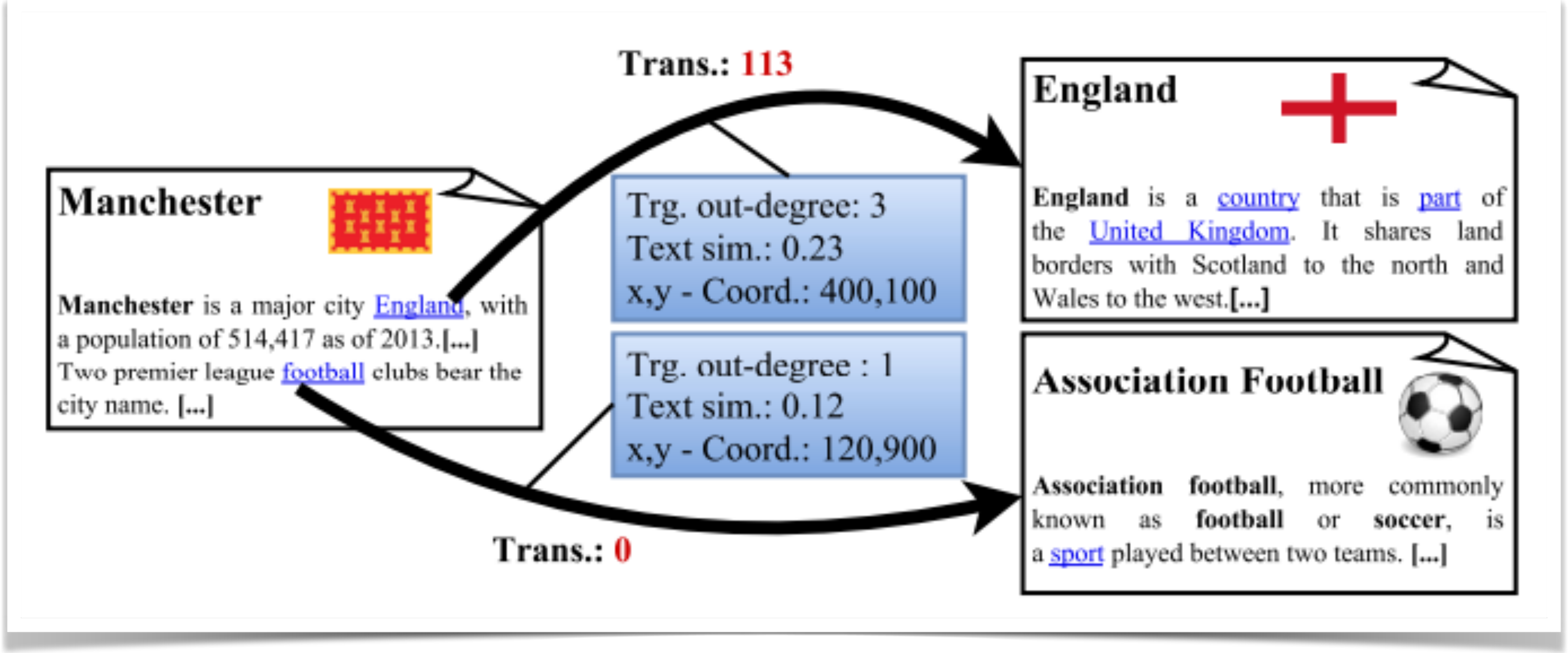

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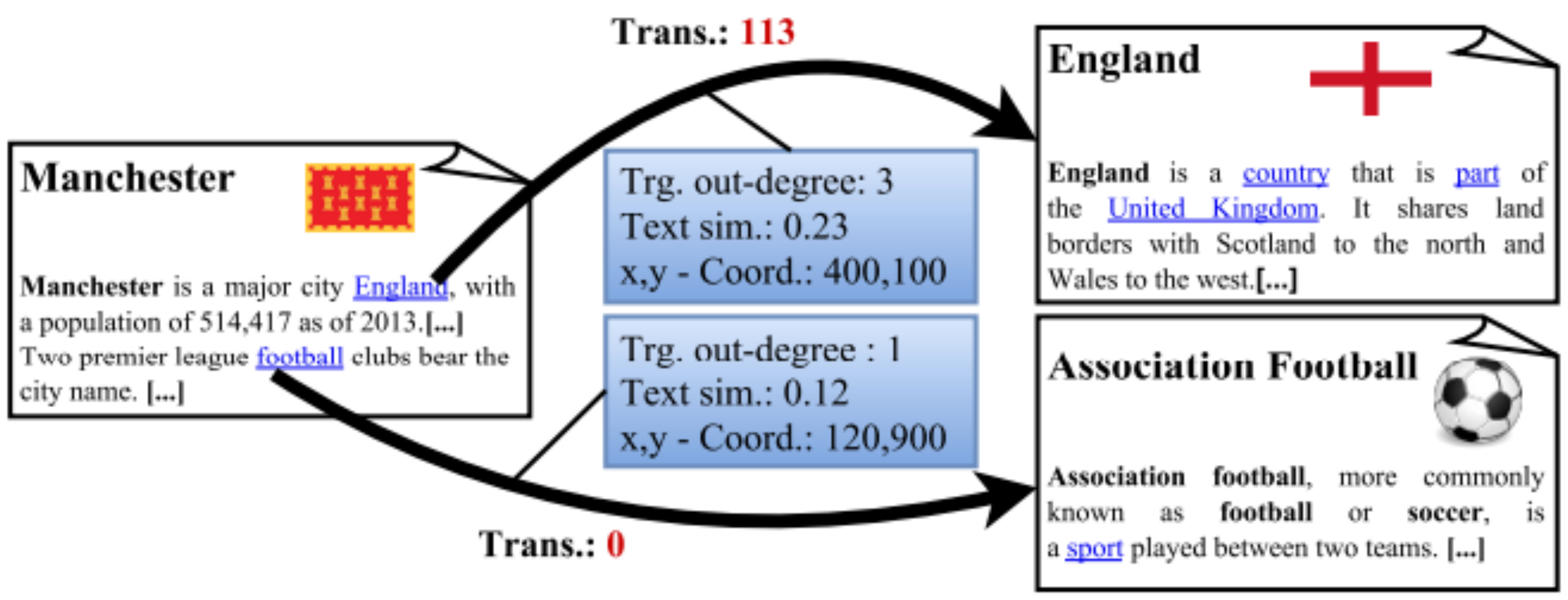

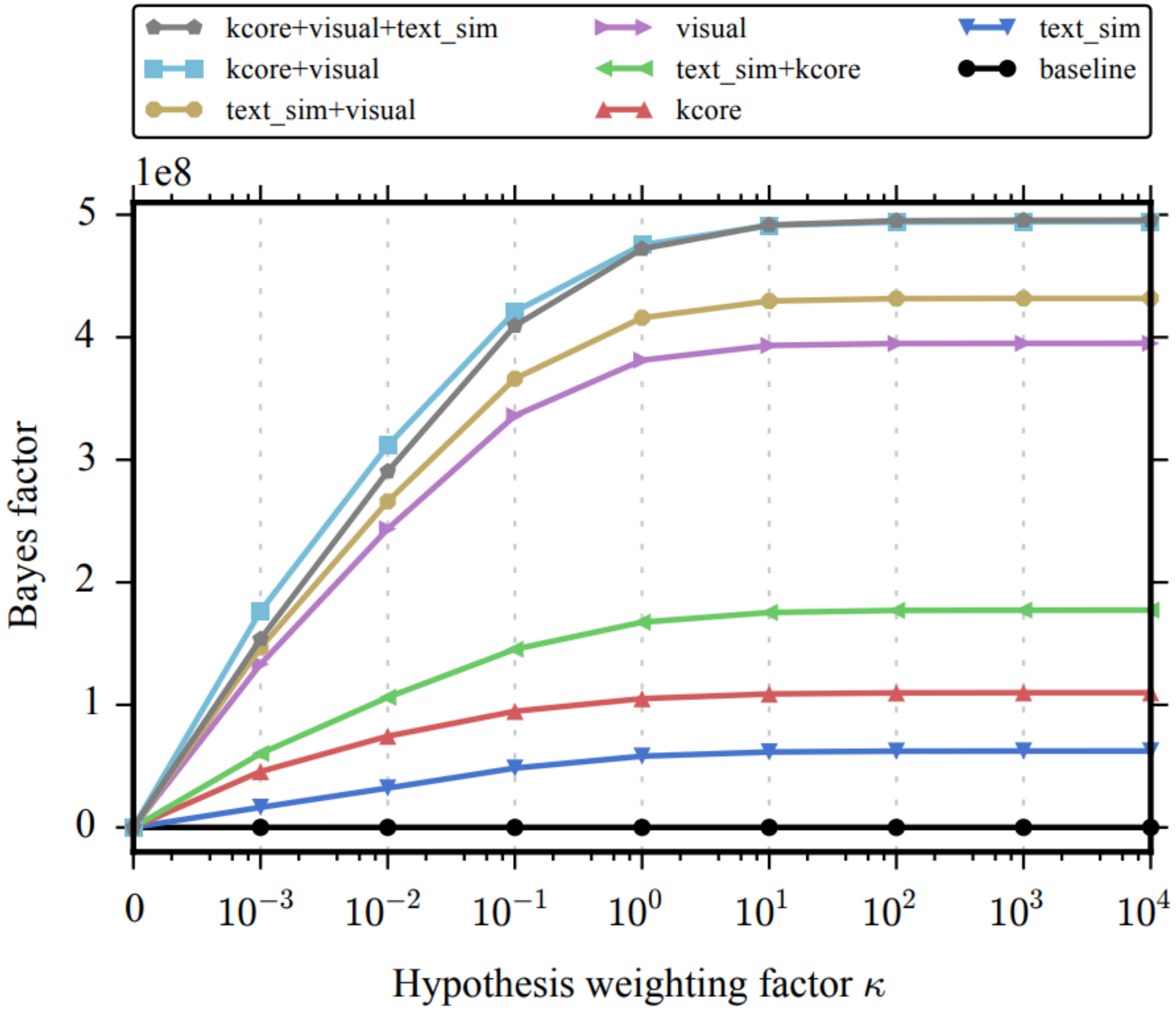

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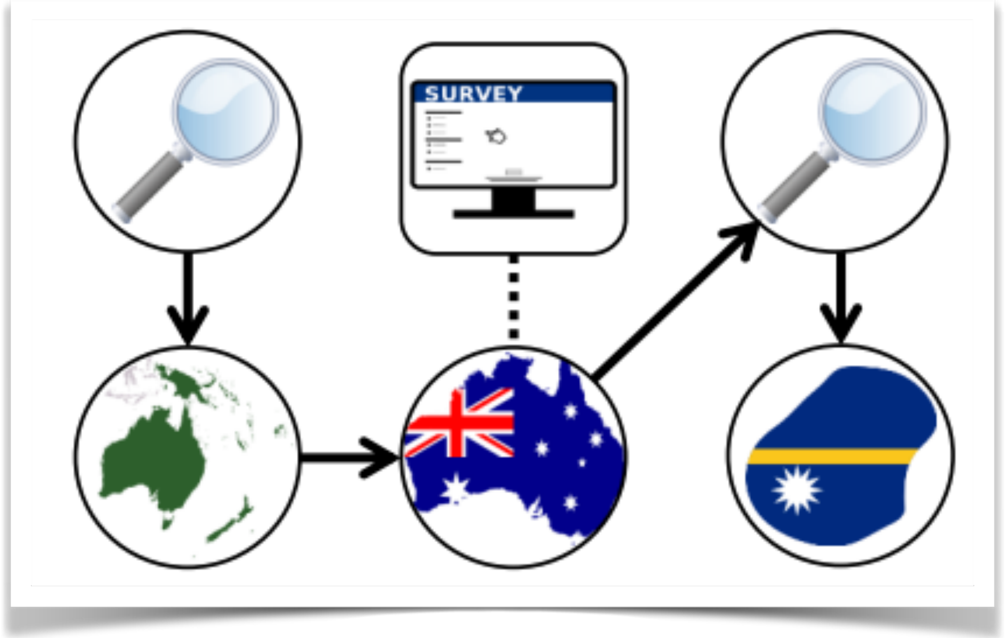

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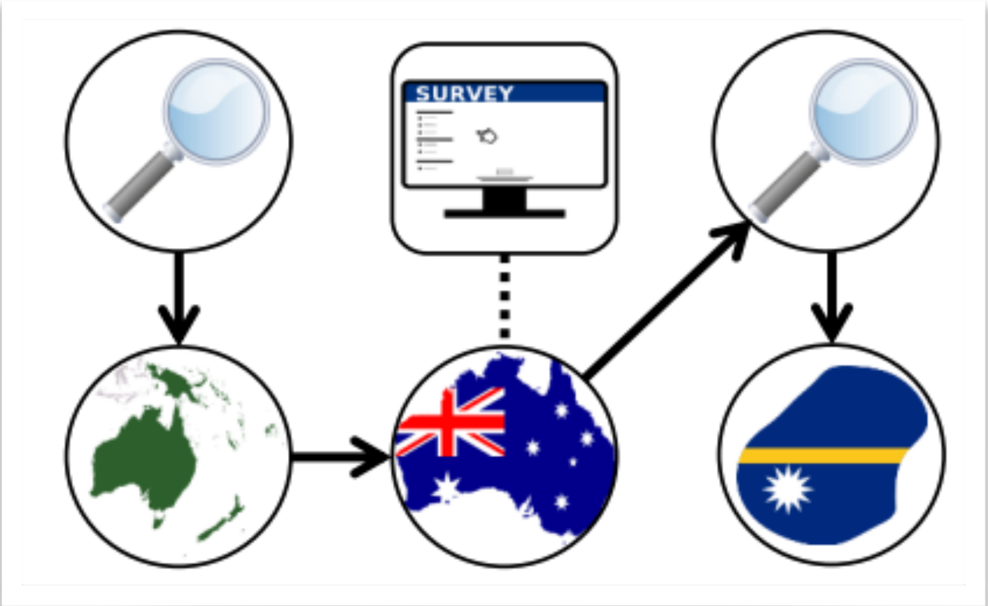

This paper uses both survey responses and web request log (navigation)

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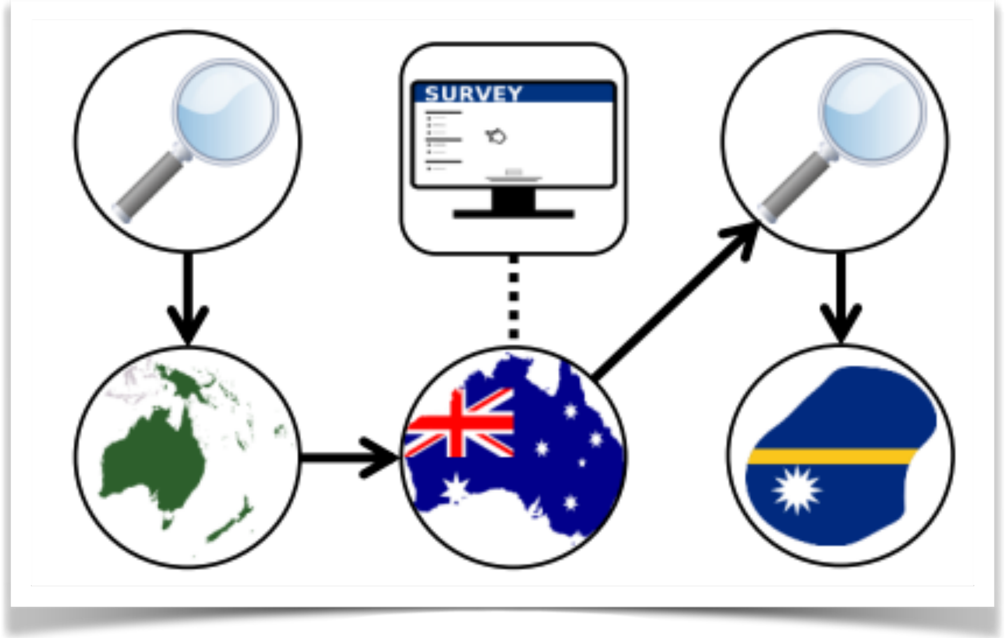
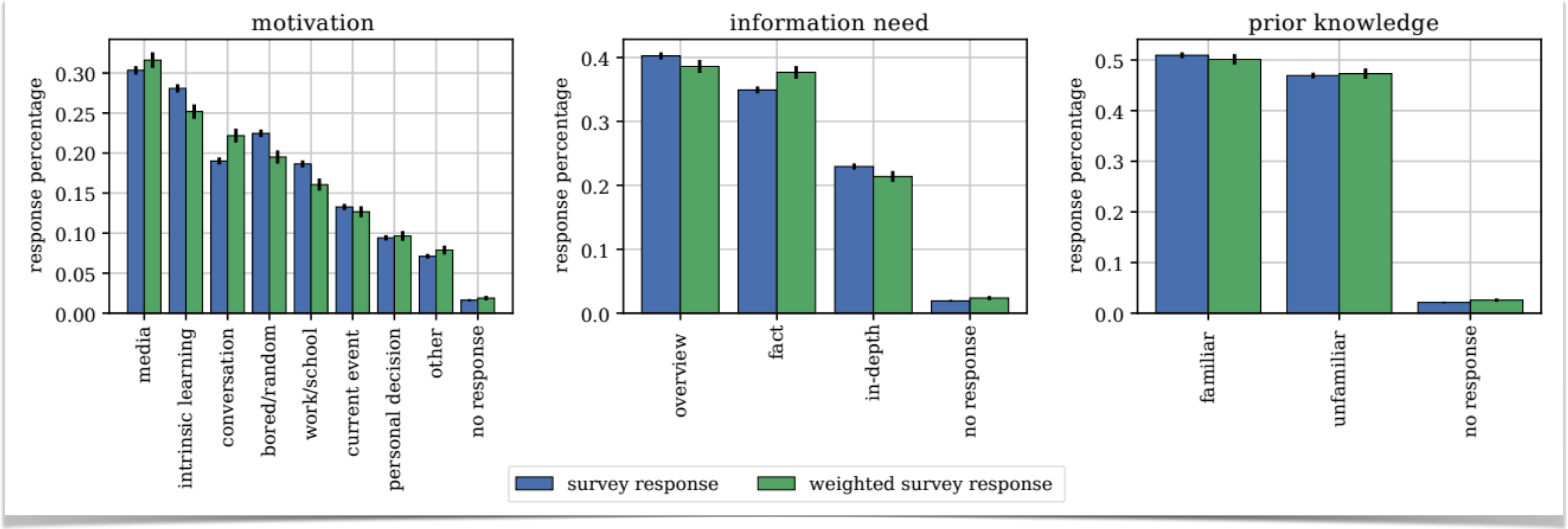
Why We Read Wikipedia

(2017)

Philipp Singer*[1], Florian Lemmerich*[1], Robert West†[2], Leila Zia[3], Ellery Wulczyn[3], Markus Strohmaier[1], Jure Leskovec[4]



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



Examples

Migration patterns from online data

Examples

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Using Facebook and LinkedIn Data to Study International Mobility

(2023)

Carolina Coimbra Vieira[1], Masoomali Fatehkia[2], Kiran Garimella[3], Ingmar Weber[2] and Emilio Zagheni[1]

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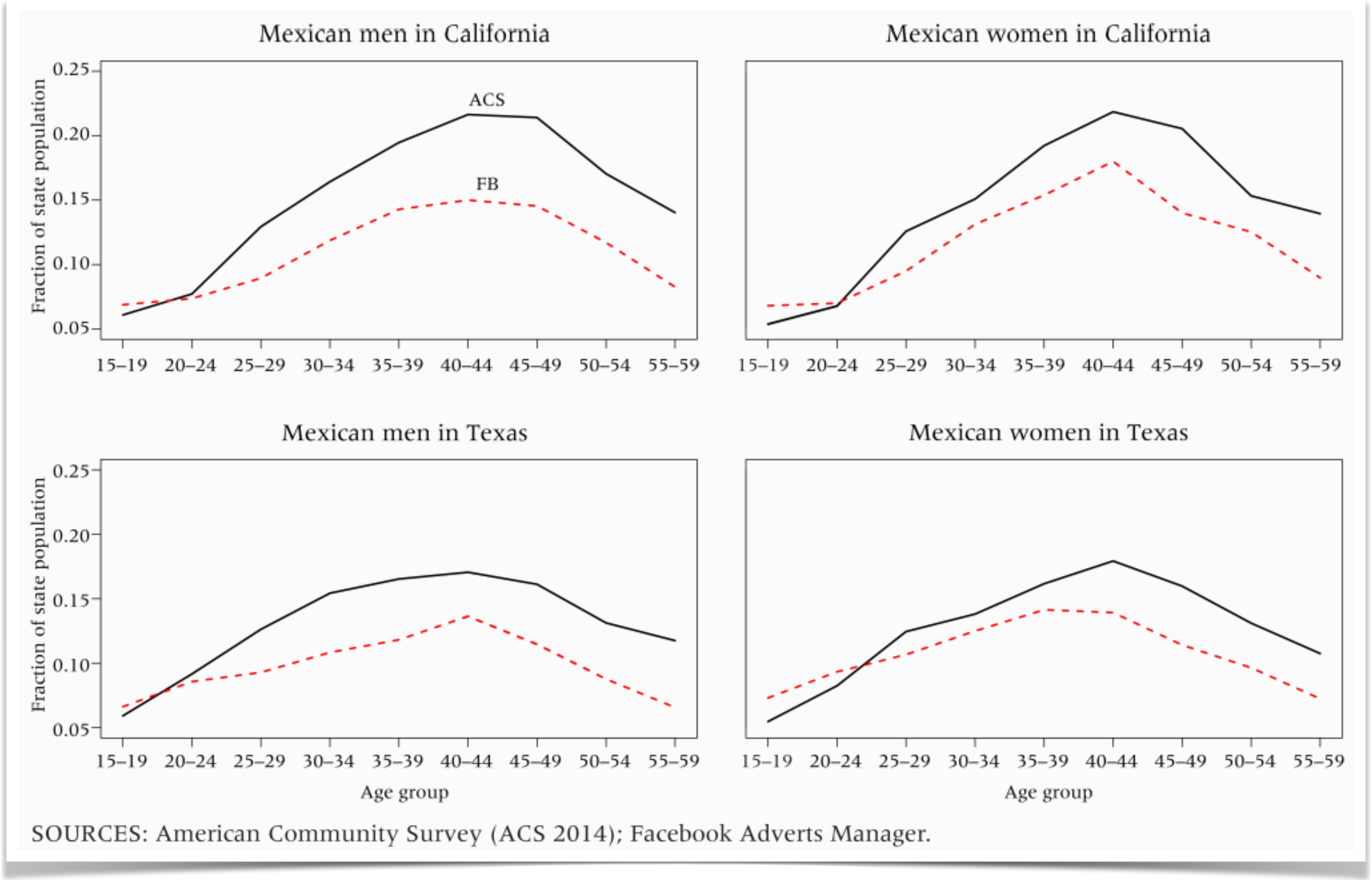

Fraction of men or women based on survey and Facebook

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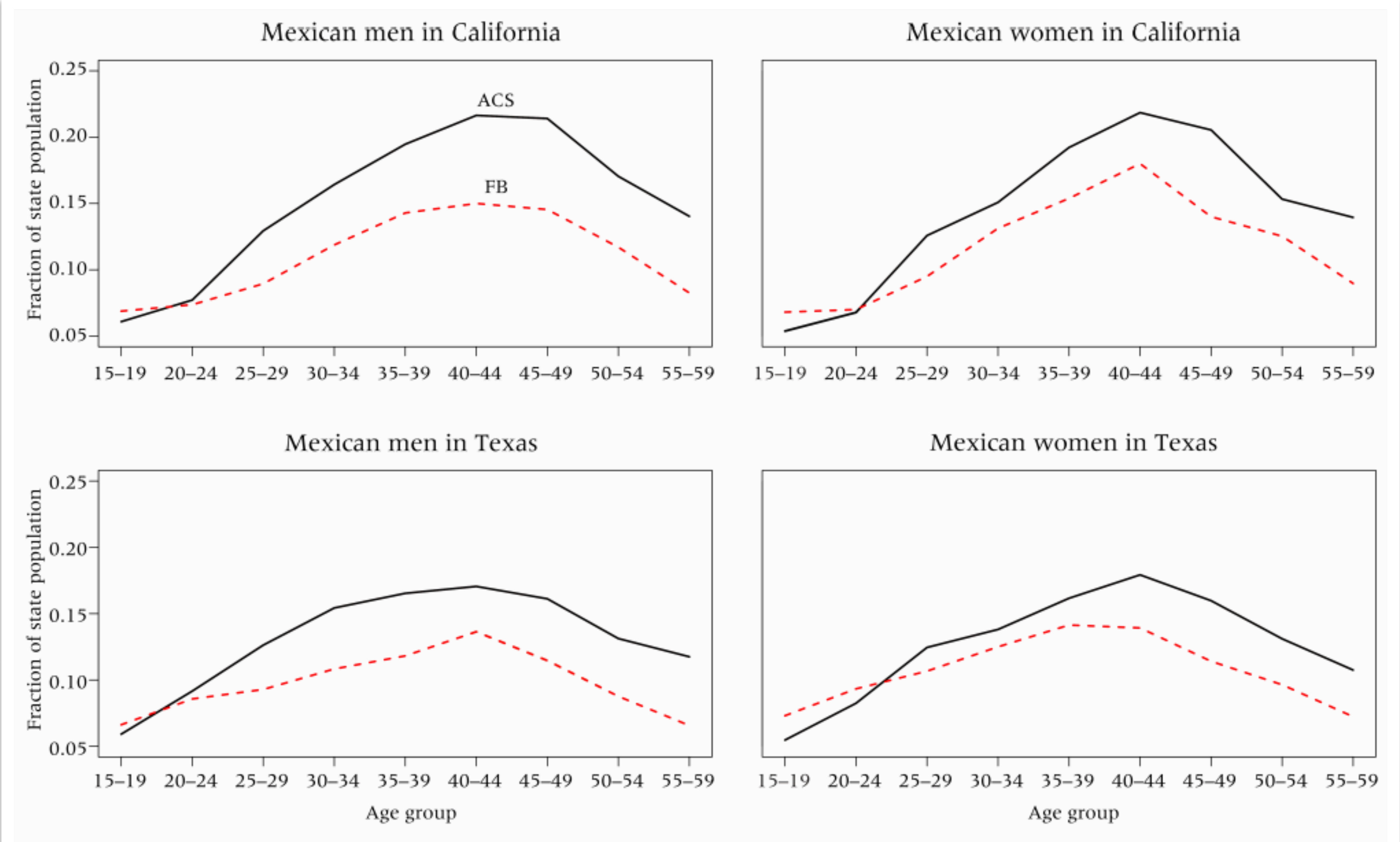
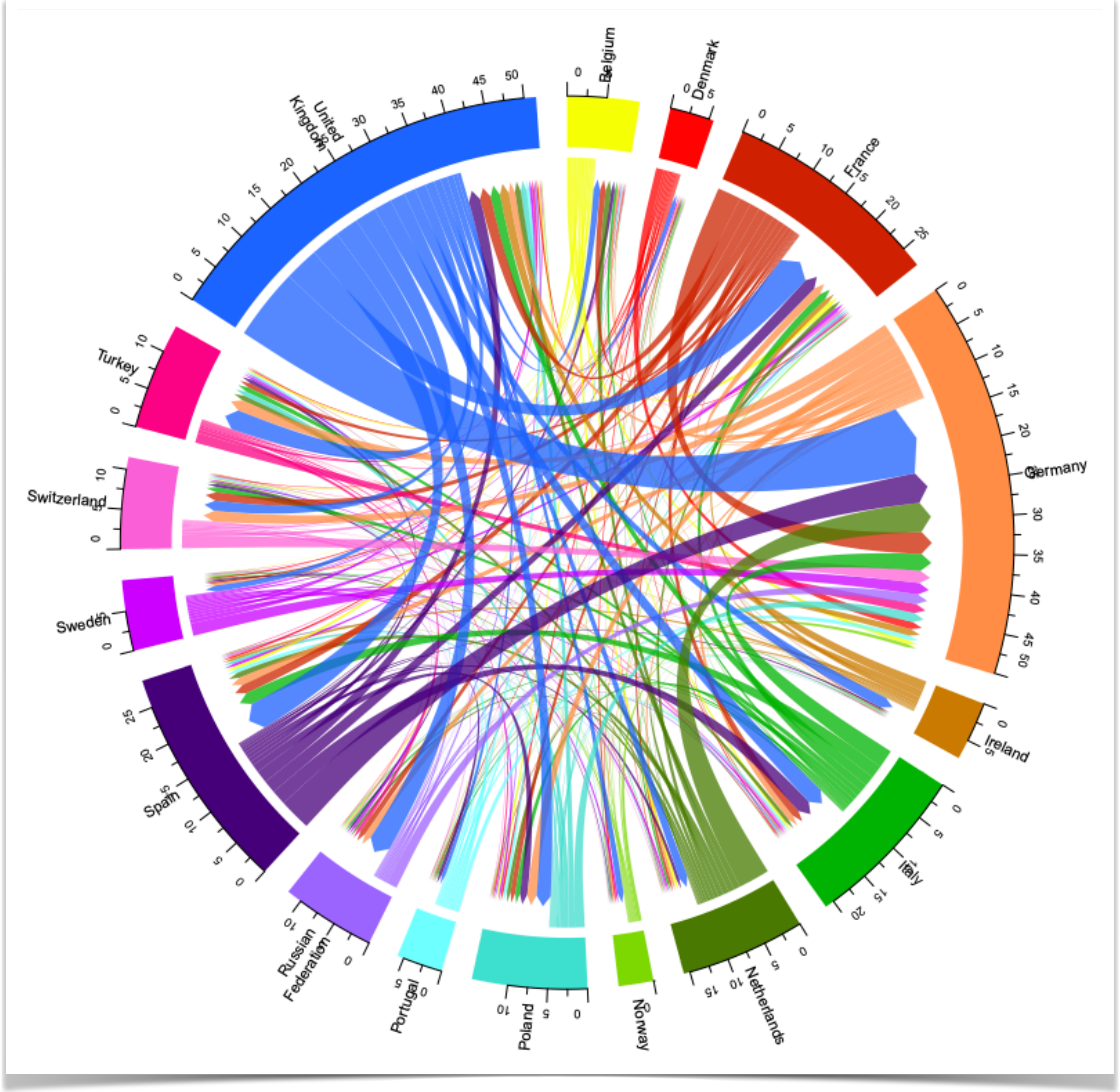


SOURCES: American Community Survey (ACS 2014); Facebook Adverts Manager.

Fraction of men or women based on survey and Facebook



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

Examples

Inferring poverty from the sky and the Web

Examples

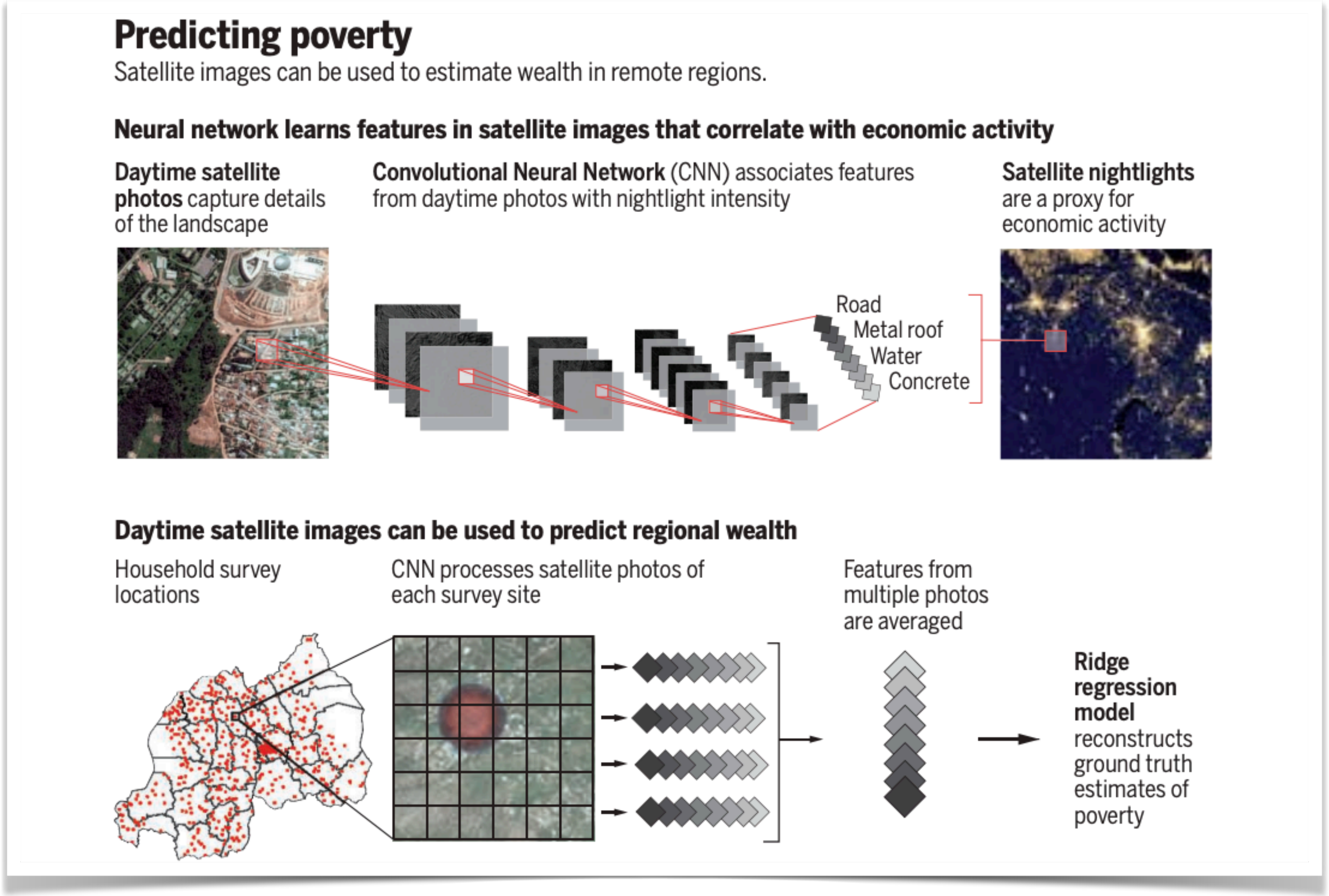
Inferring poverty from the sky and the Web

Fighting poverty with data

Machine learning algorithms measure and target poverty

(2016)

By **Joshua Evan Blumenstock**



Examples

Inferring poverty from the sky and the Web

Fighting poverty with data

Machine learning algorithms measure and target poverty

By **Joshua Evan Blumenstock**

(2016)

Interpreting wealth distribution via poverty map inference using multimodal data

Lisette Espín-Noboa
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Complexity Science Hub Vienna

János Kertész
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Complexity Science Hub Vienna

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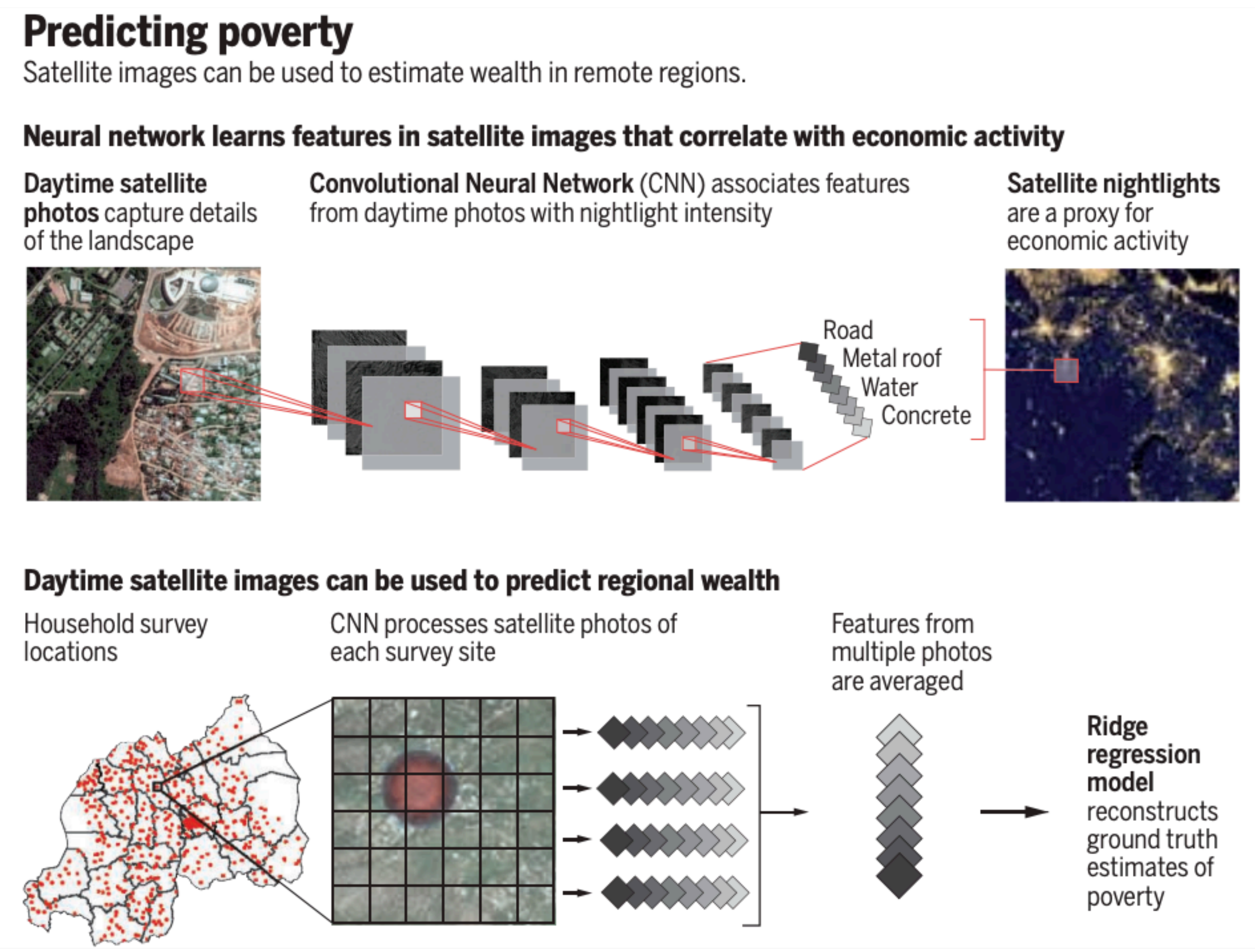
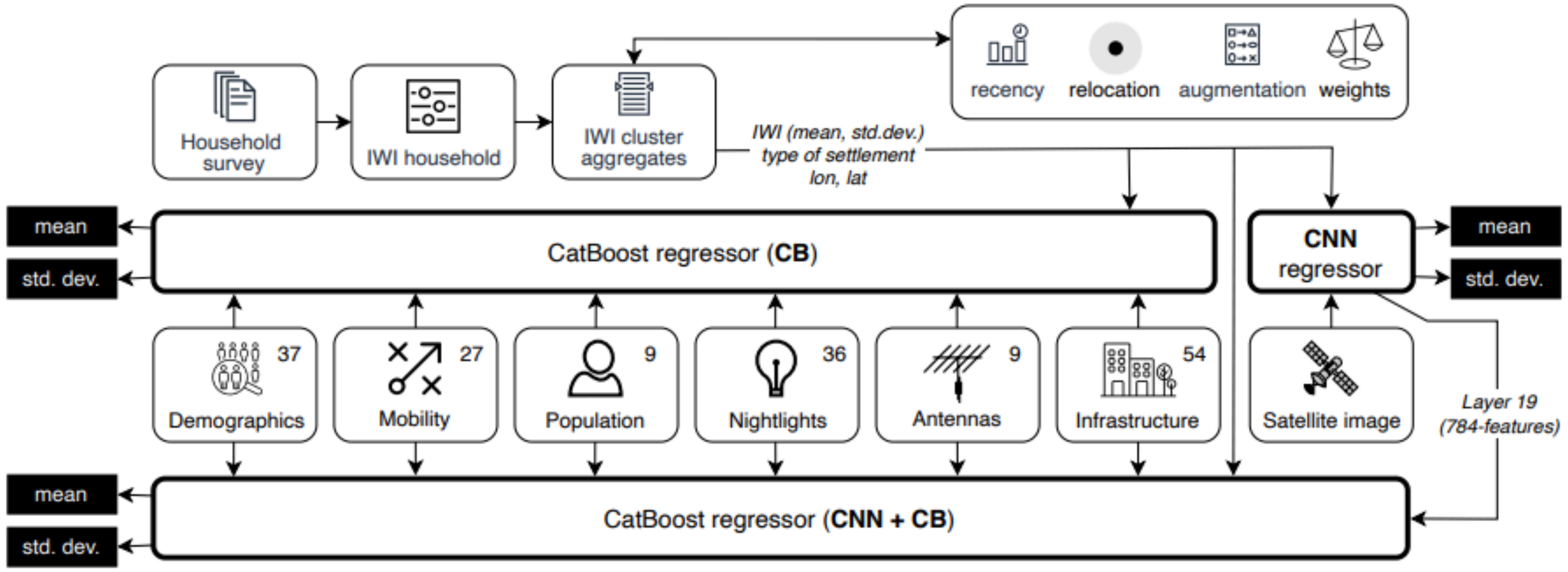
Rènyi Institute of Mathematics



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



(2023)

Examples

Health and social media

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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

(2013)

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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

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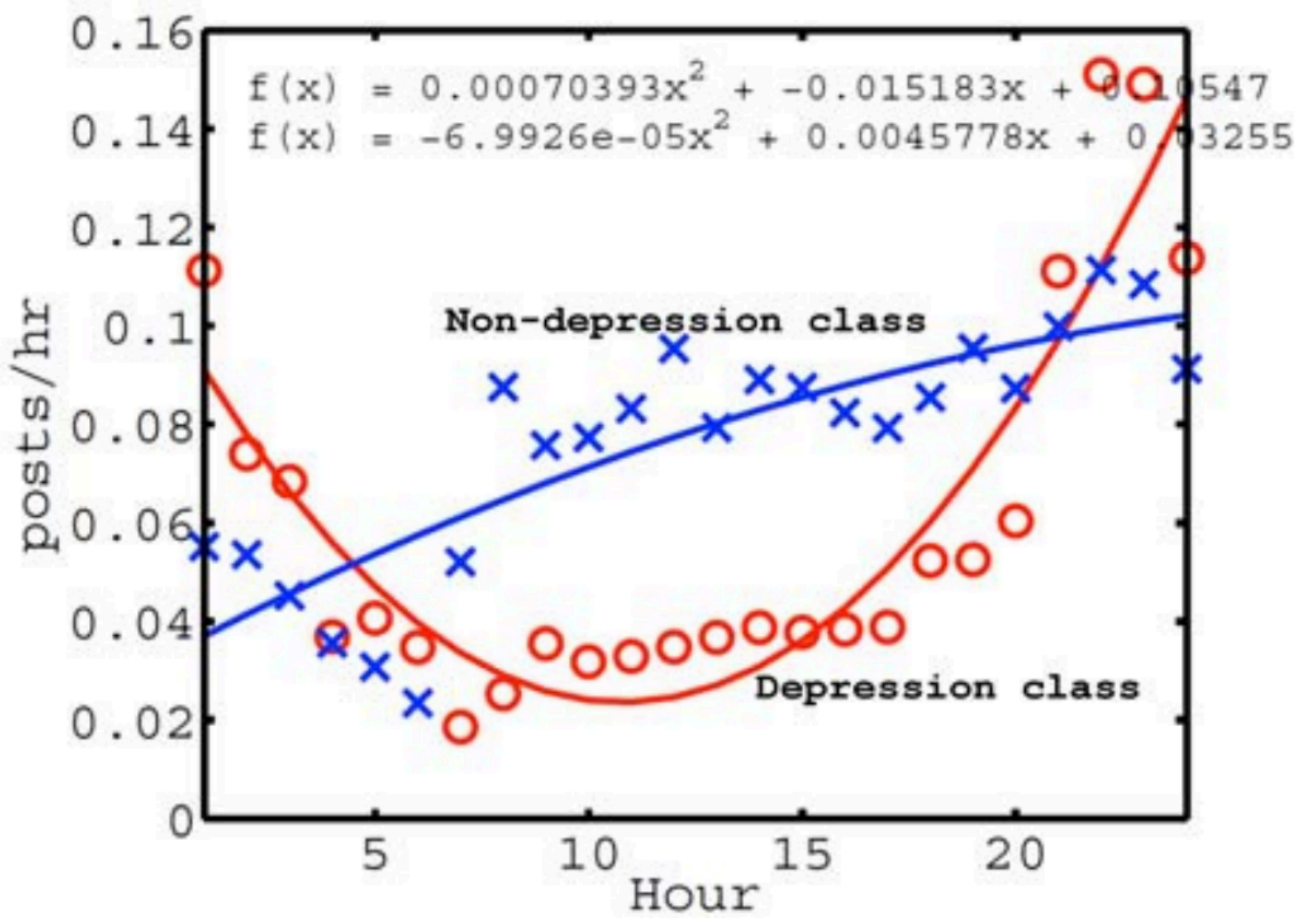

Figure 2: Diurnal trends (i.e. mean number of posts made hourly throughout a day) for the two classes. The line plots correspond to least squares fit of the trends.

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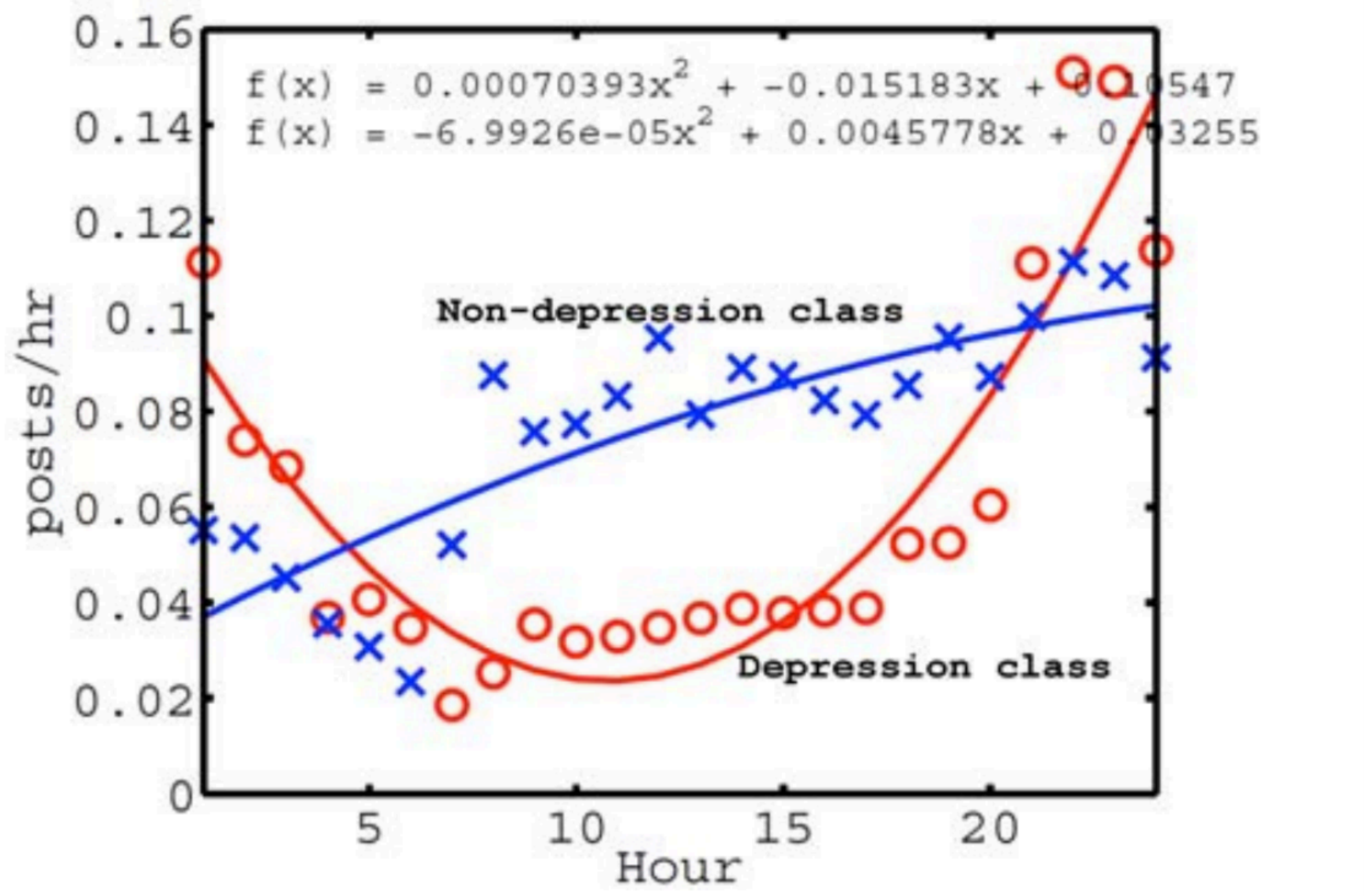

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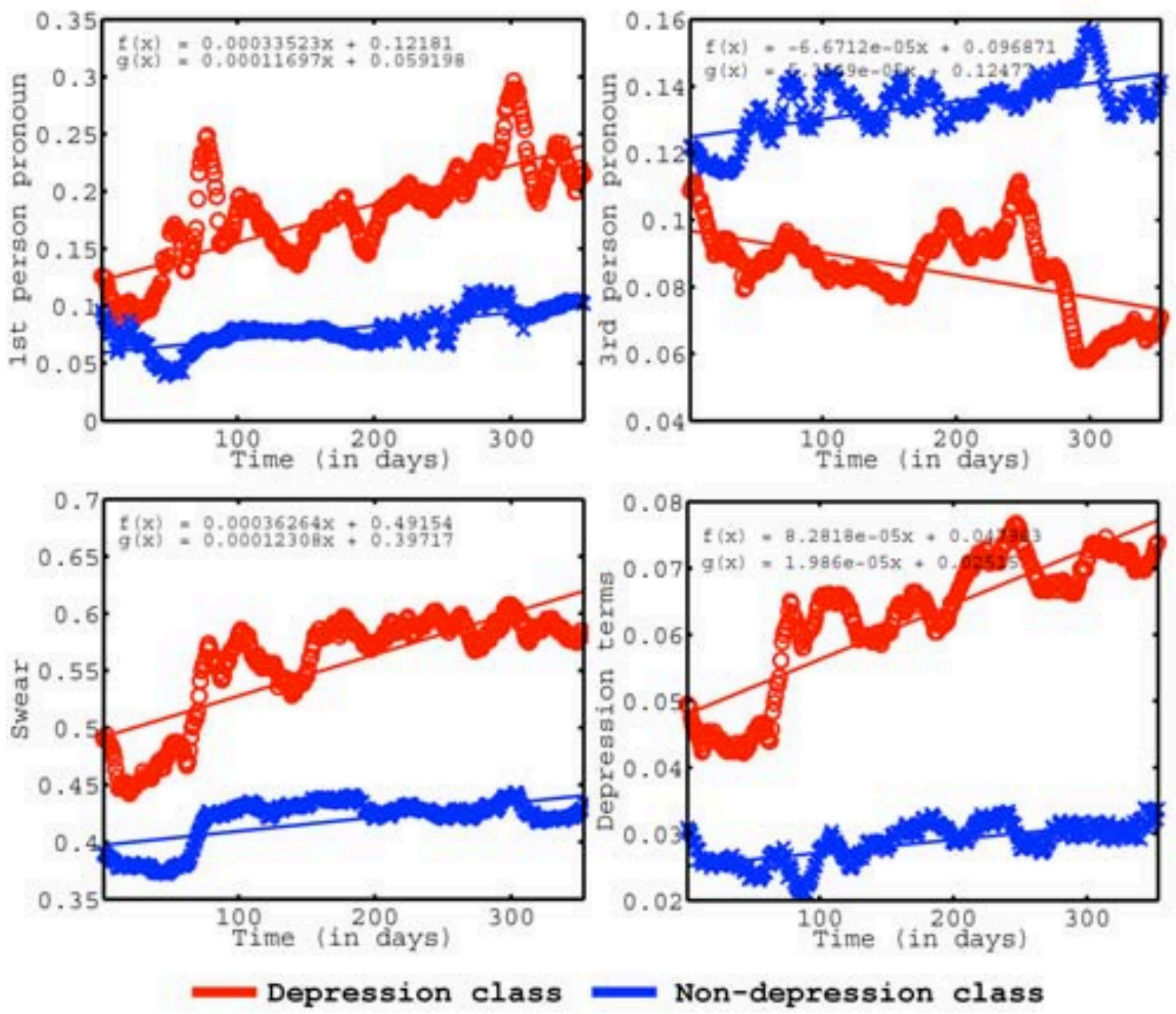


Figure 3. Trends for various features corresponding to the depression and non-depression classes. Line plots correspond to least squares fit.

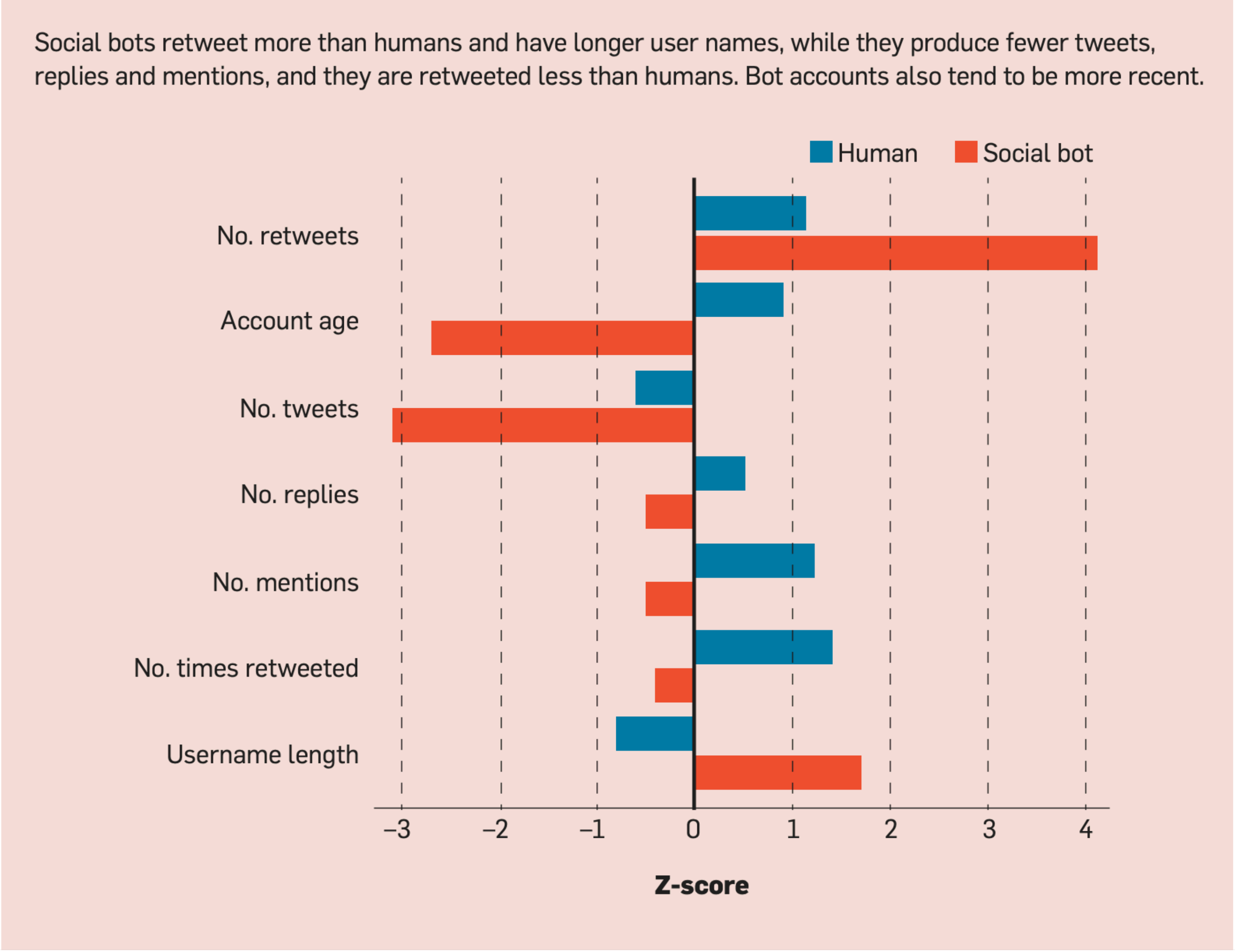
Examples

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

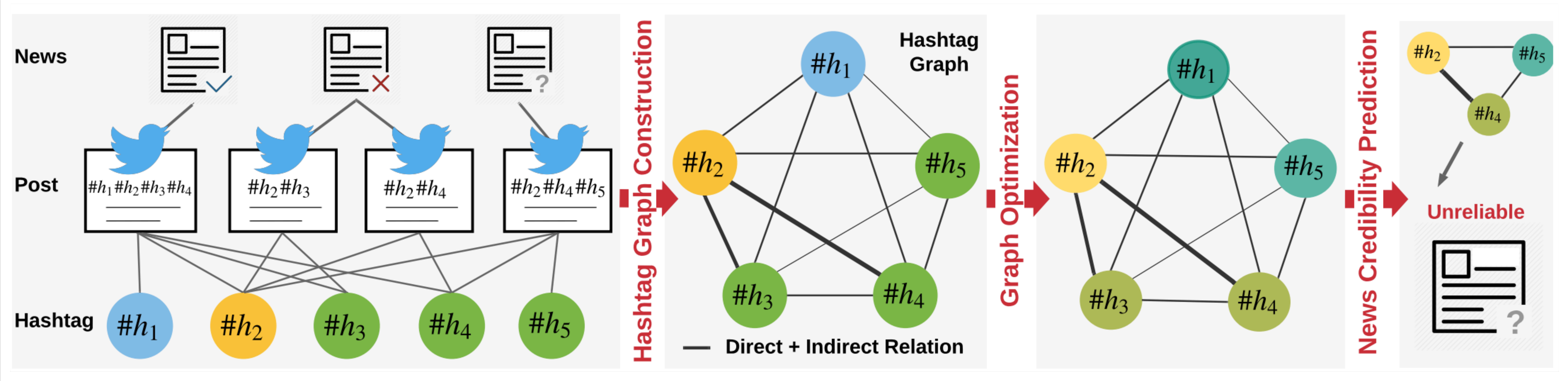
Figure 2. User behaviors that best discriminate social bots from humans.



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

Xinyi Zhou, zhouxinyi@data.syr.edu, Syracuse University, U.S.A
Reza Zafarani, reza@data.syr.edu, Syracuse University, U.S.A
Emilio Ferrara, emiliofe@usc.edu, University of Southern California, U.S.A

(2022)



Examples

Polarization

Examples

Polarization

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

Lada Adamic
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1501 Page Mill Road
Palo Alto, CA 94304
lada.adamic@hp.com

Natalie Glance
Intelliseek Applied Research Center
5001 Baum Blvd.
Pittsburgh, PA 15217
nglance@intelliseek.com

4 March 2005

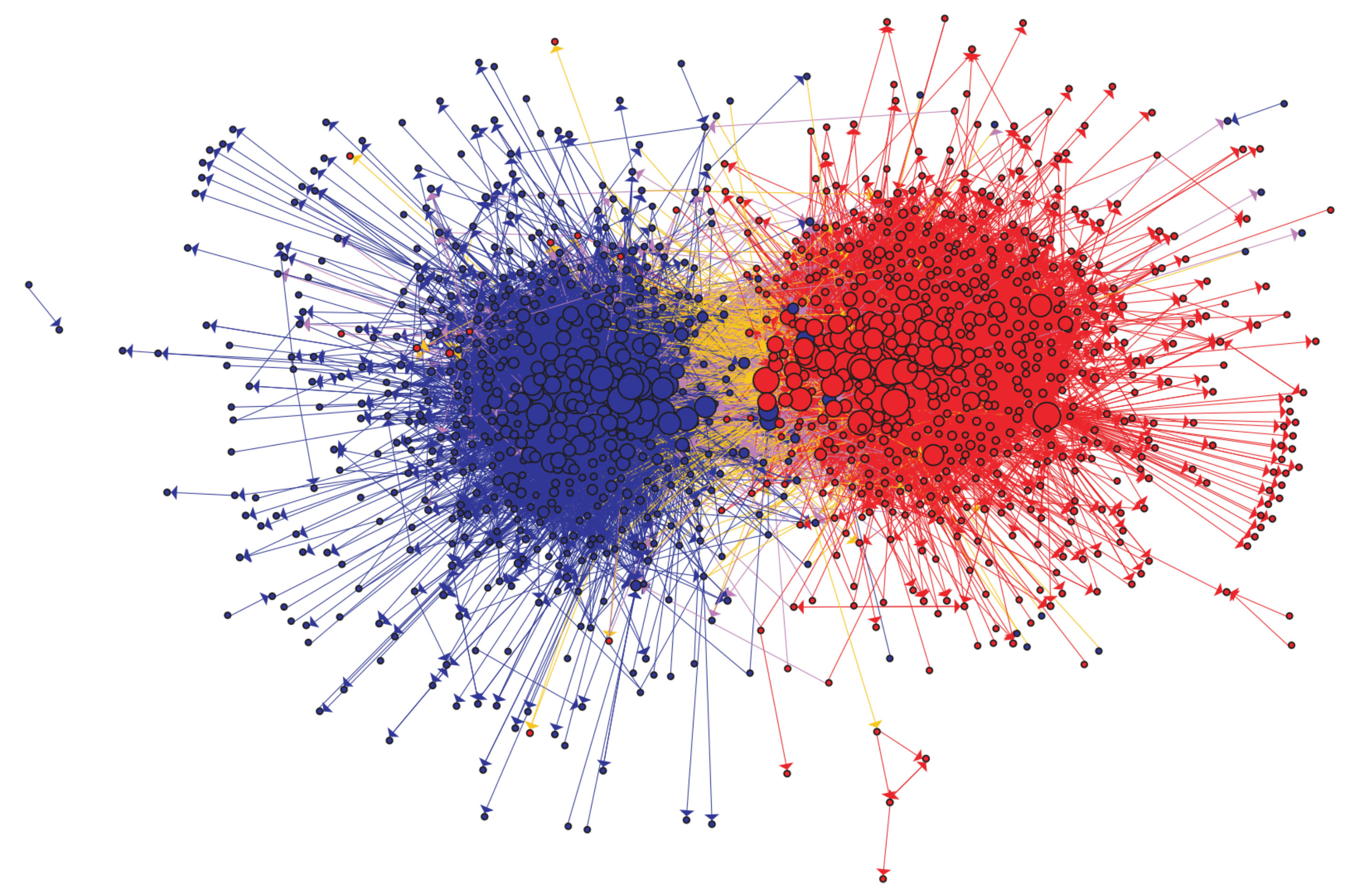

Figure 1: Community structure of political blogs (expanded set), shown using utilizing a GEM layout [11] in the GUESS[3] visualization and analysis tool. The colors reflect political orientation, red for conservative, and blue for liberal. Orange links go from liberal to conservative, and purple ones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

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4 March 2005

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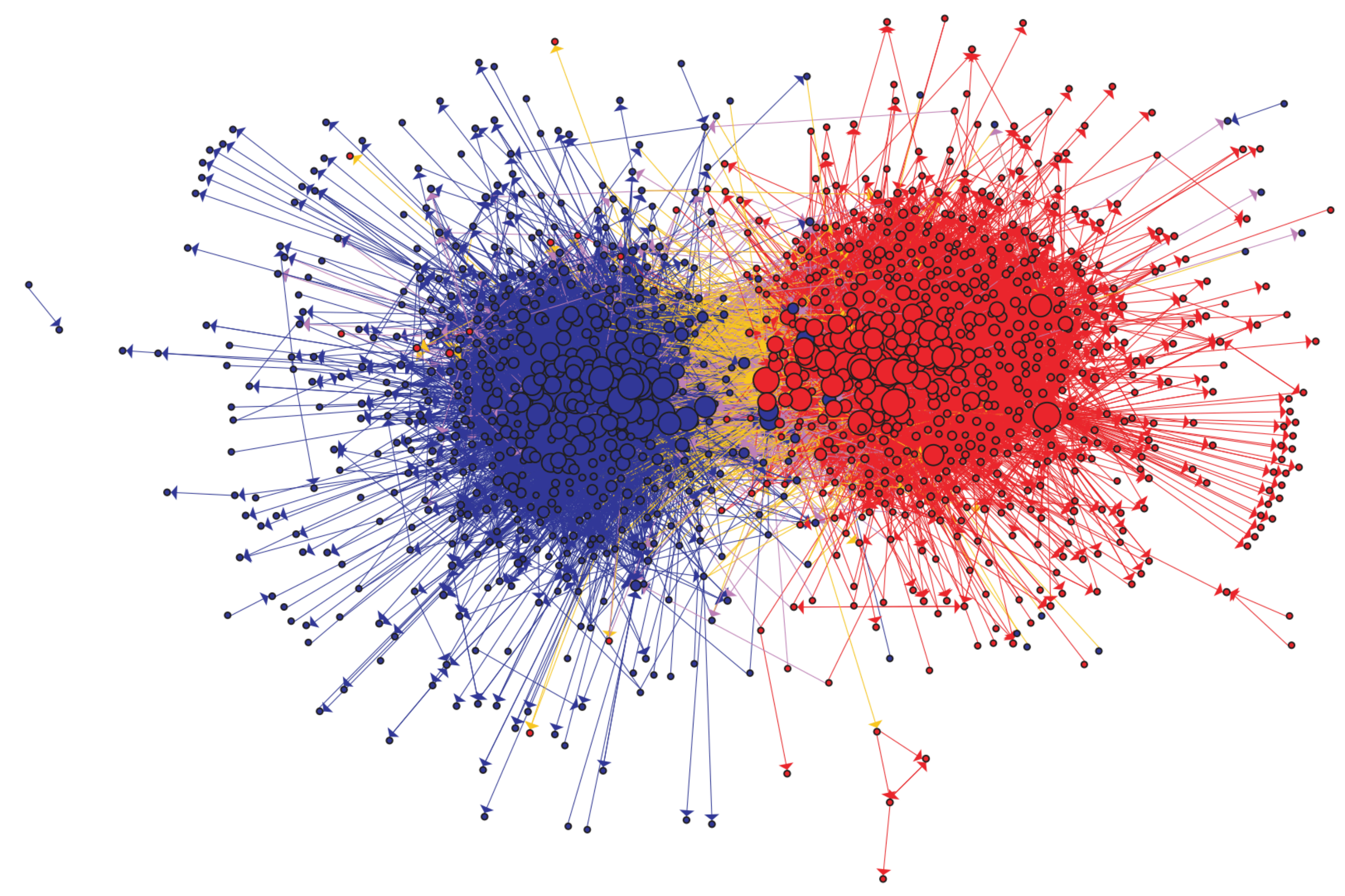
DOCTORAL DISSERTATIONS 20/2018

Polarization on Social Media

Kiran Garimella



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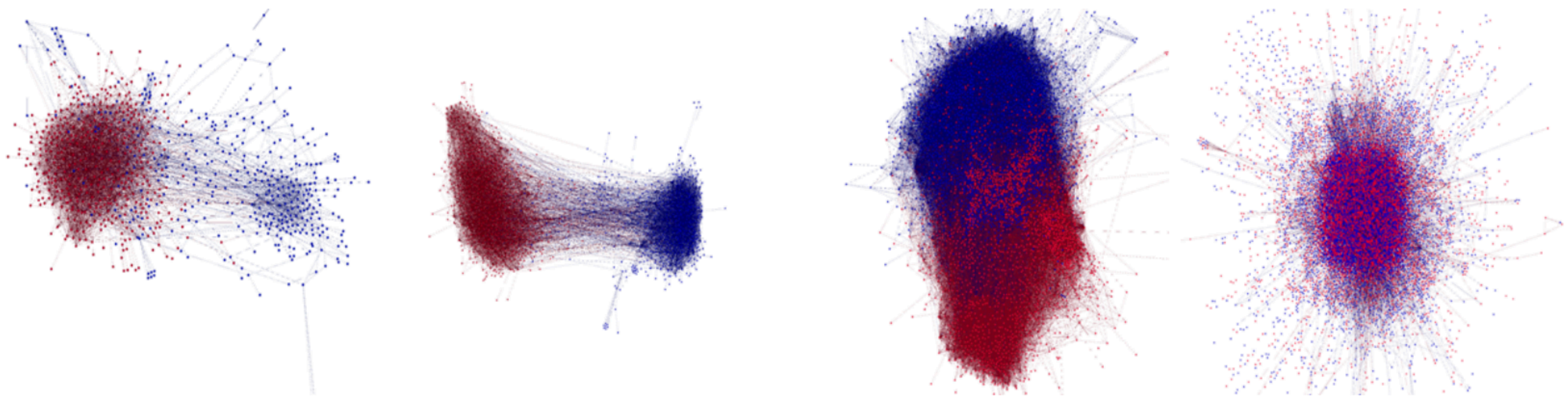


(a) (b) (c) (d)

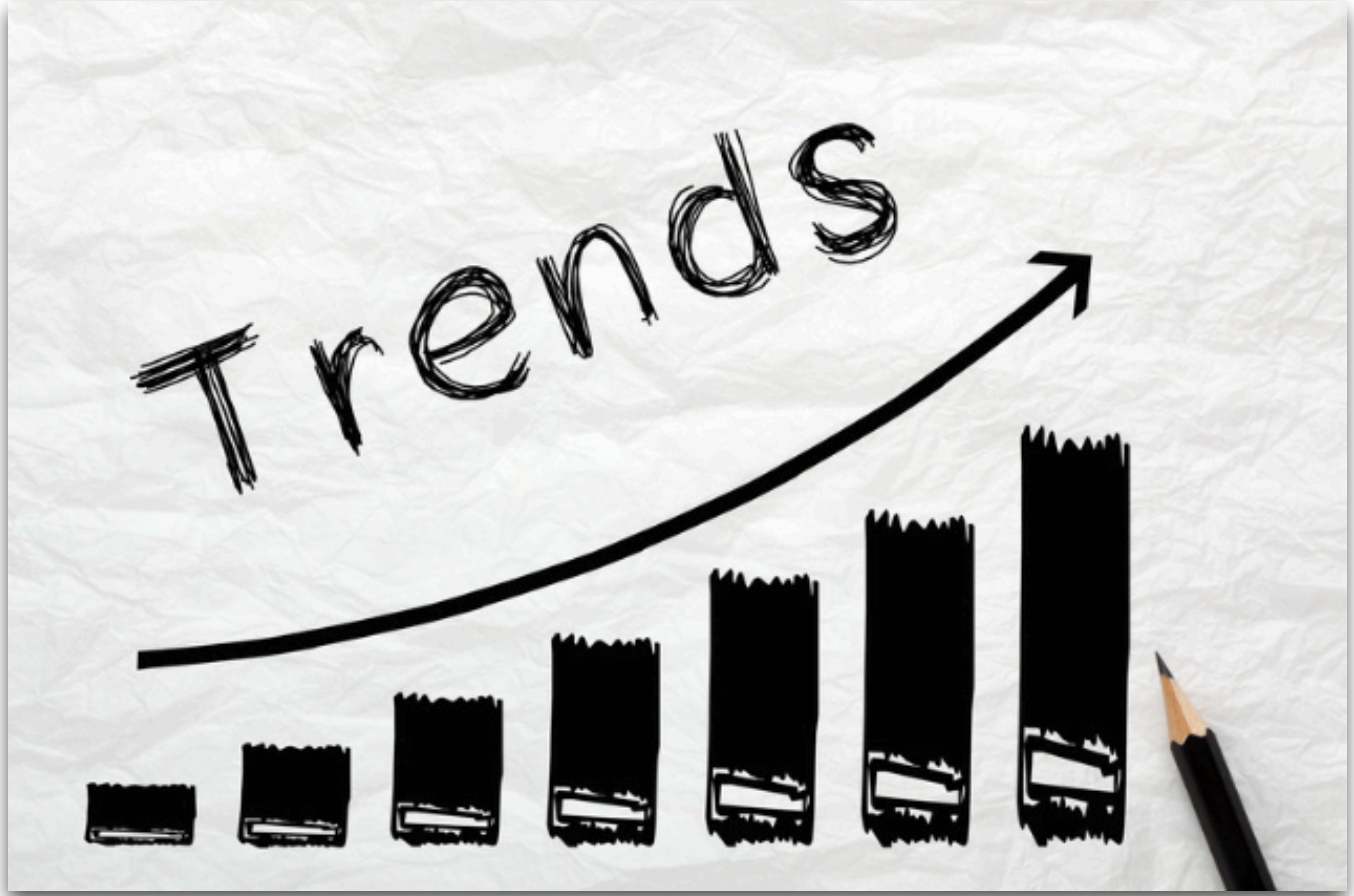
Figure 4.4. Sample follow graphs for polarized topics, (a) #beefban, (b) #russia_march, and non-polarized topics, (c) #sxsw, (d) #germanwings.

Outline

Today's class

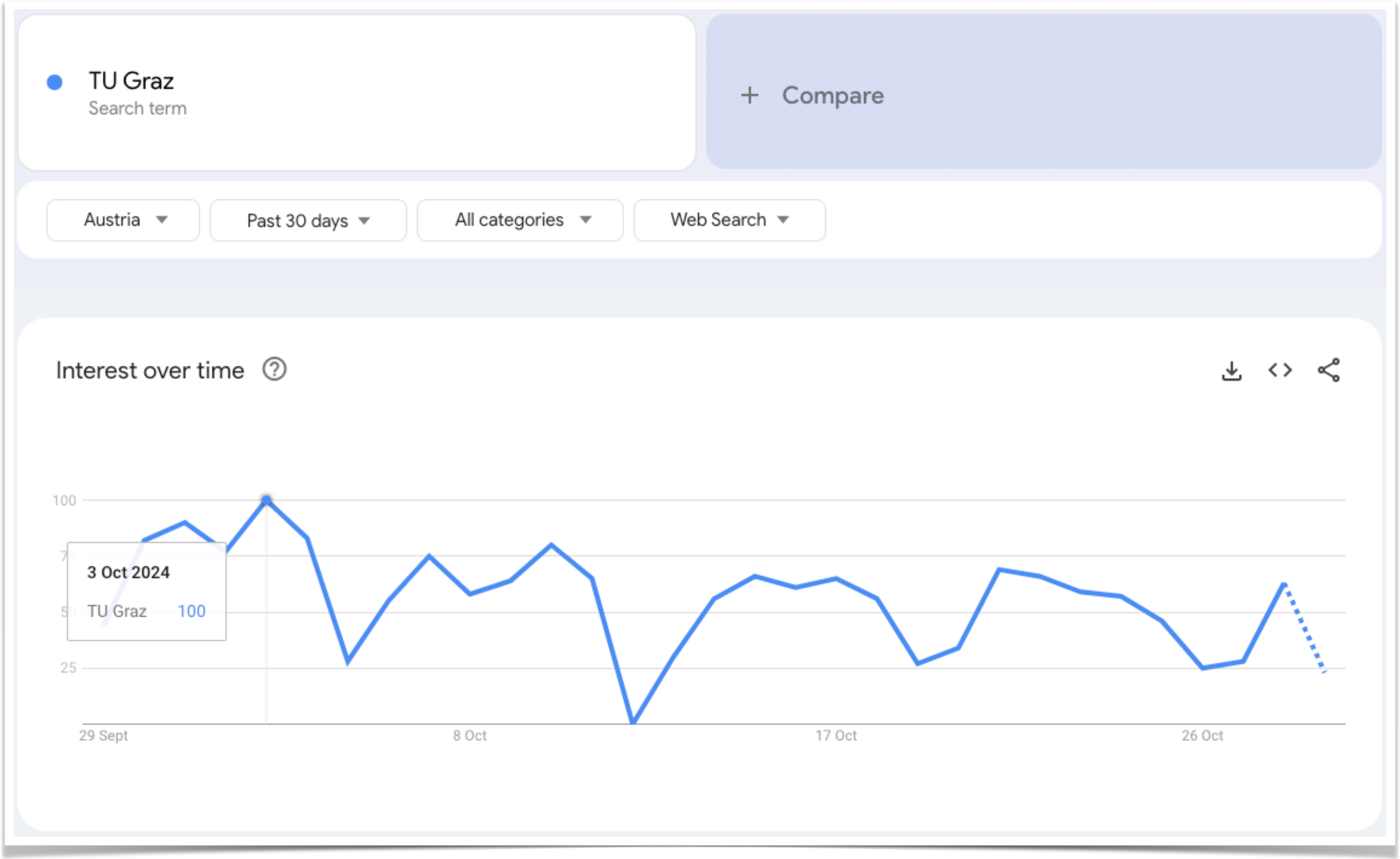
BLOCK 1	BLOCK 2	BLOCK 3	BLOCK 4
Social Behavior	Social Trends	Quantifying Trends	Behavior & Trend Dynamics
1. Social Science 2. CSS 3. Digital Traces 4. Examples	1. Google Search Trends 2. The Future Orientation Index 3. Culture and Economy	1. Correlation 2. Causation 3. Regression	1. The Theory of Fashion 2. The Endo-Exo model 3. Examples

Social Trends



Google Trends

Shows the **relative** Google search volume of a **term** within a given **time** interval and **location**



trends.google.com

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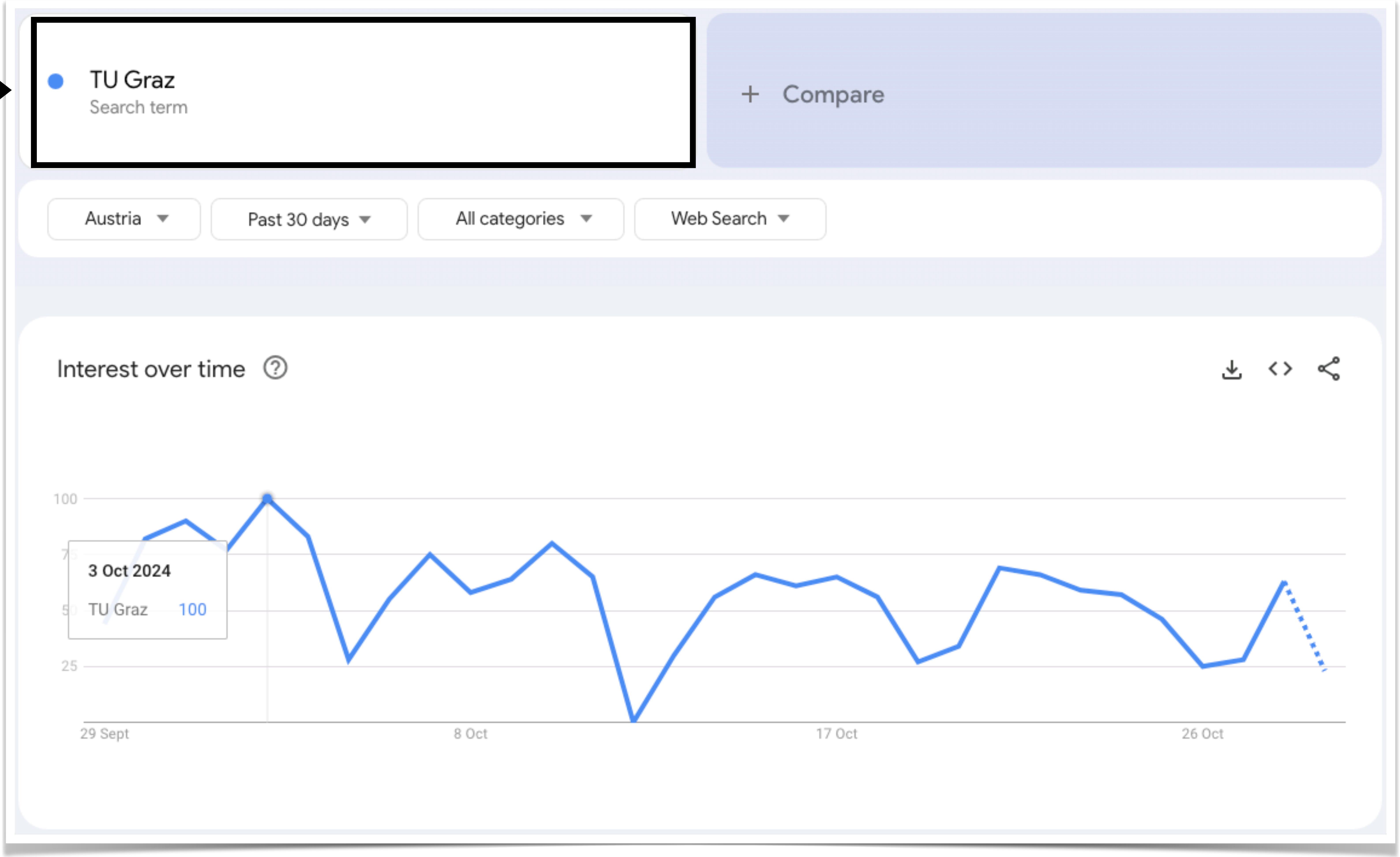
term/topic



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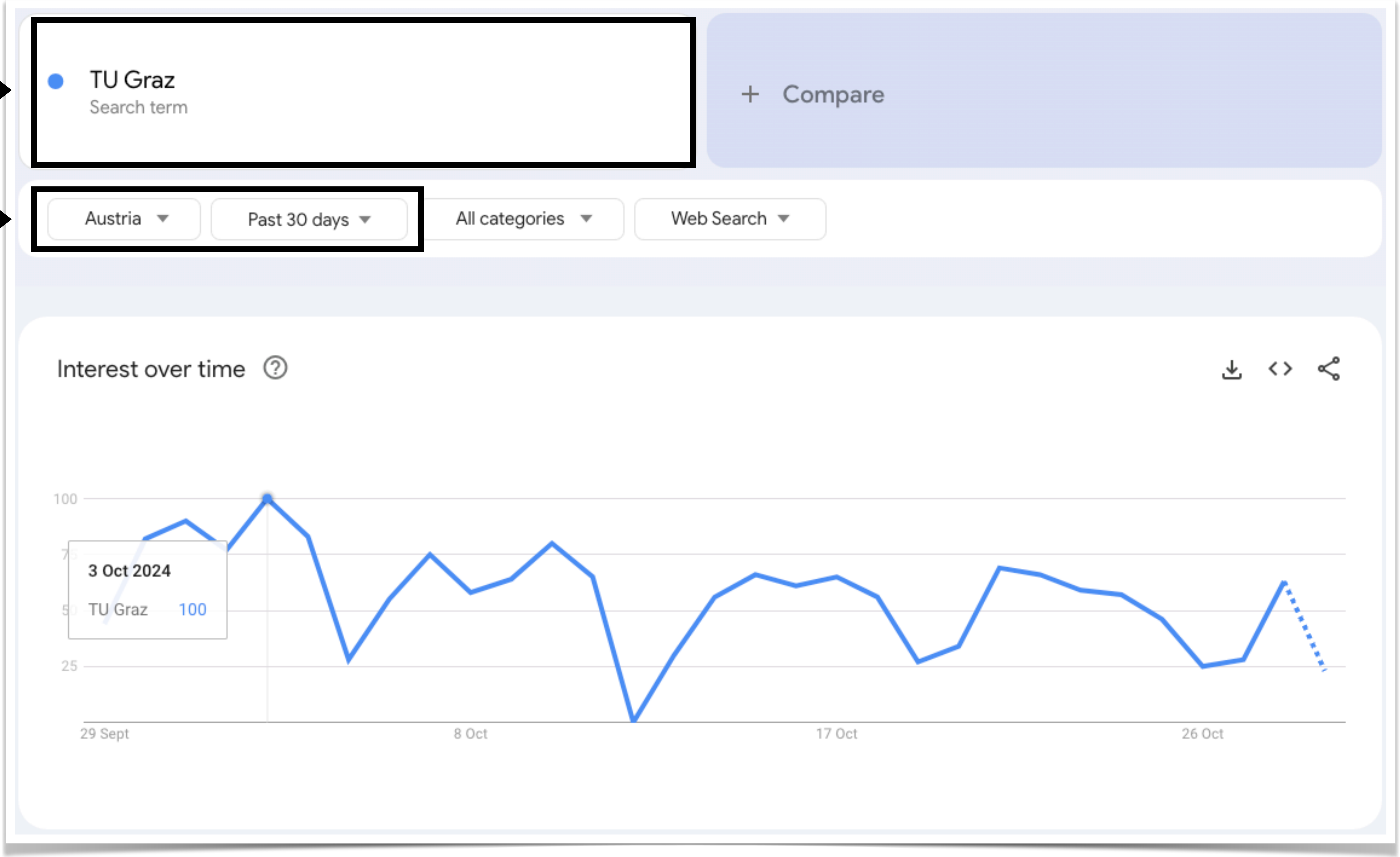
location
& time



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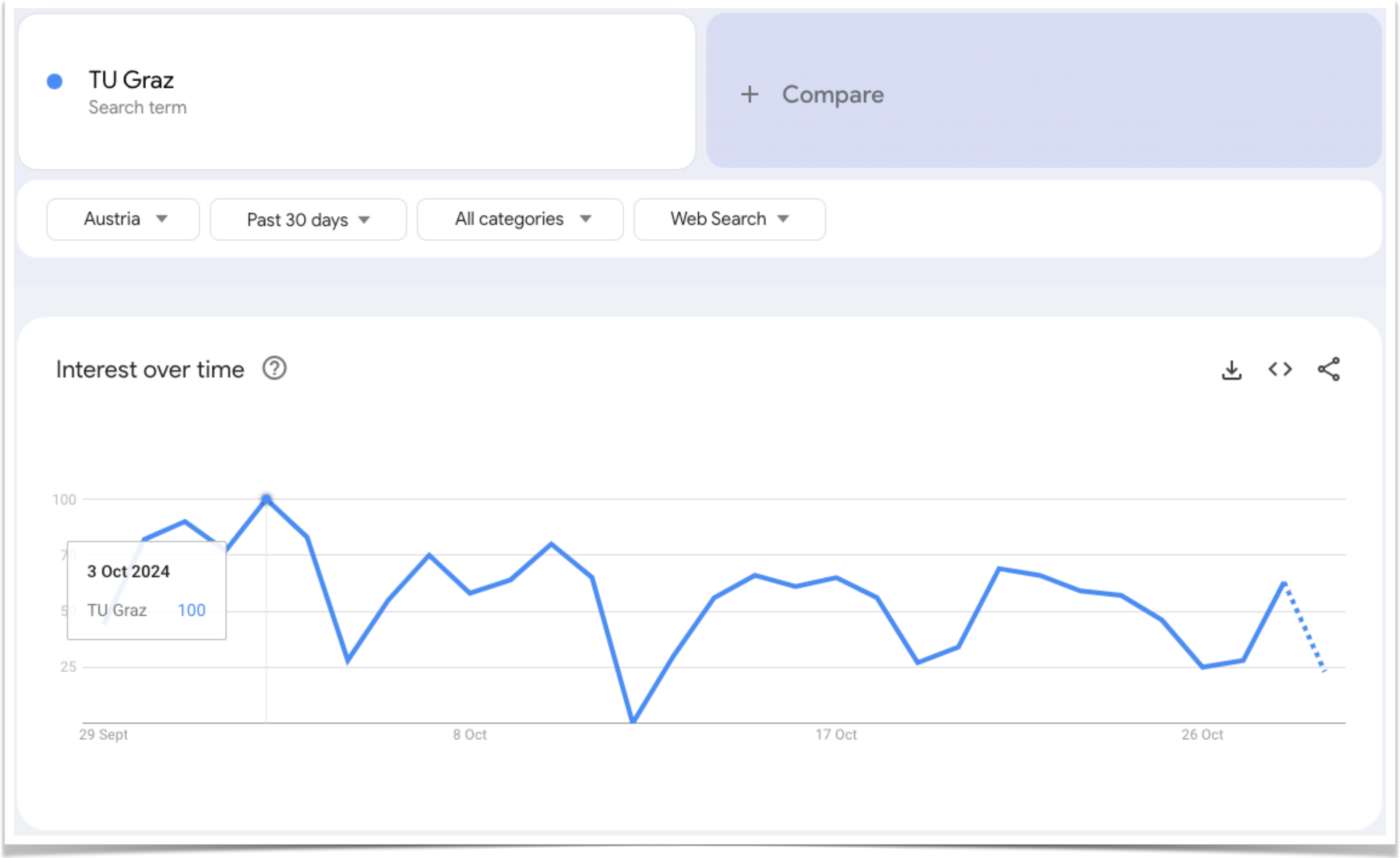

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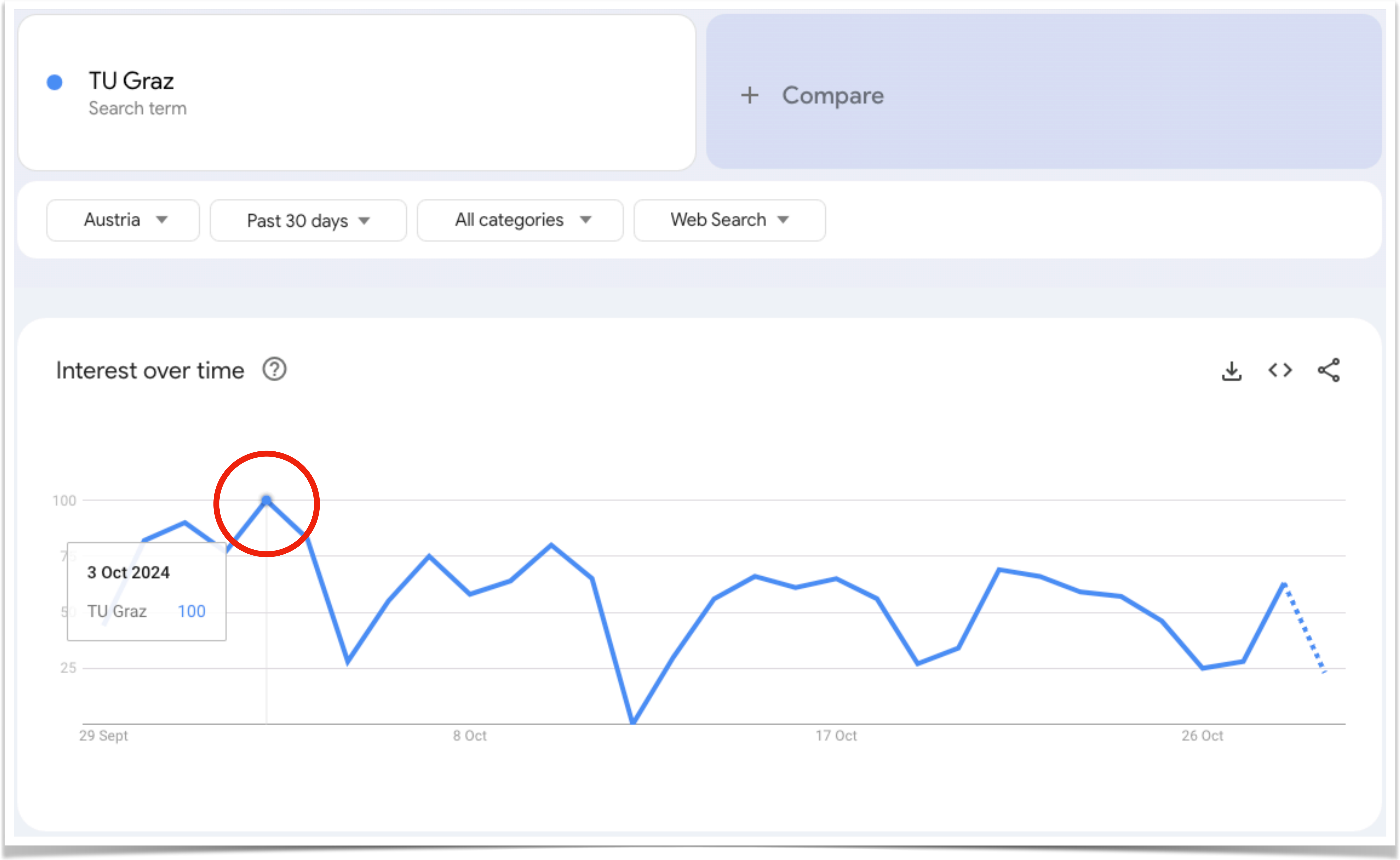

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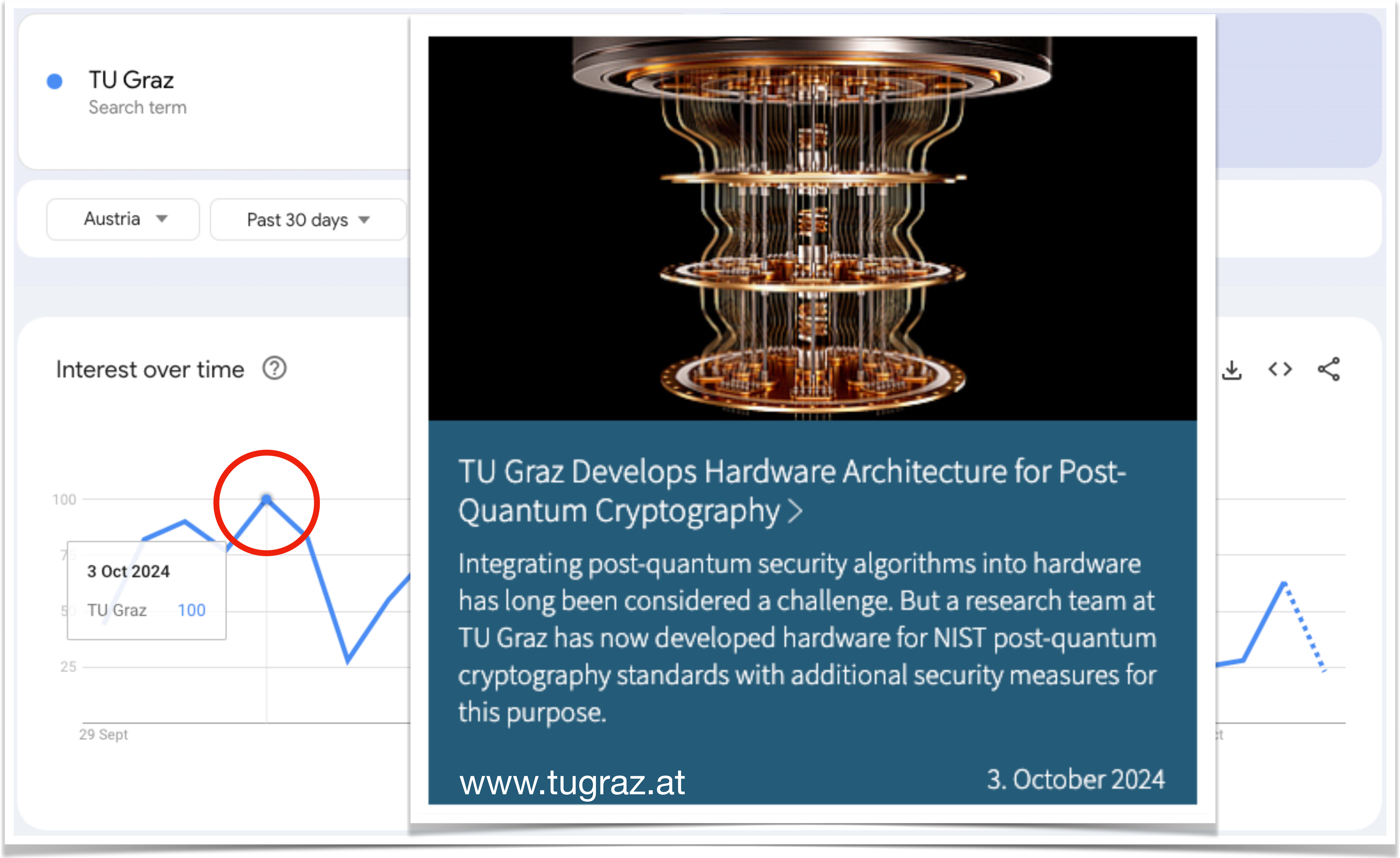

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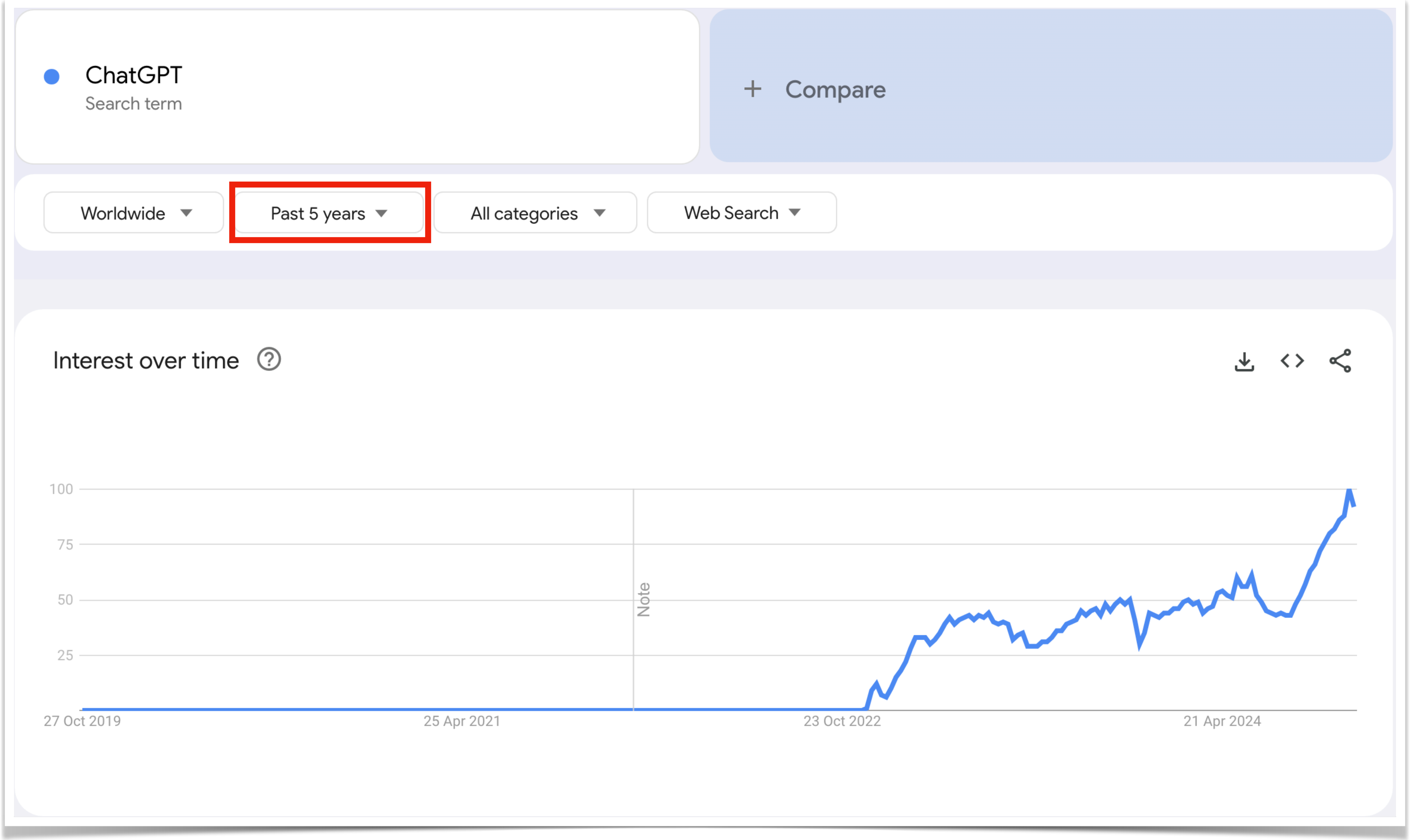

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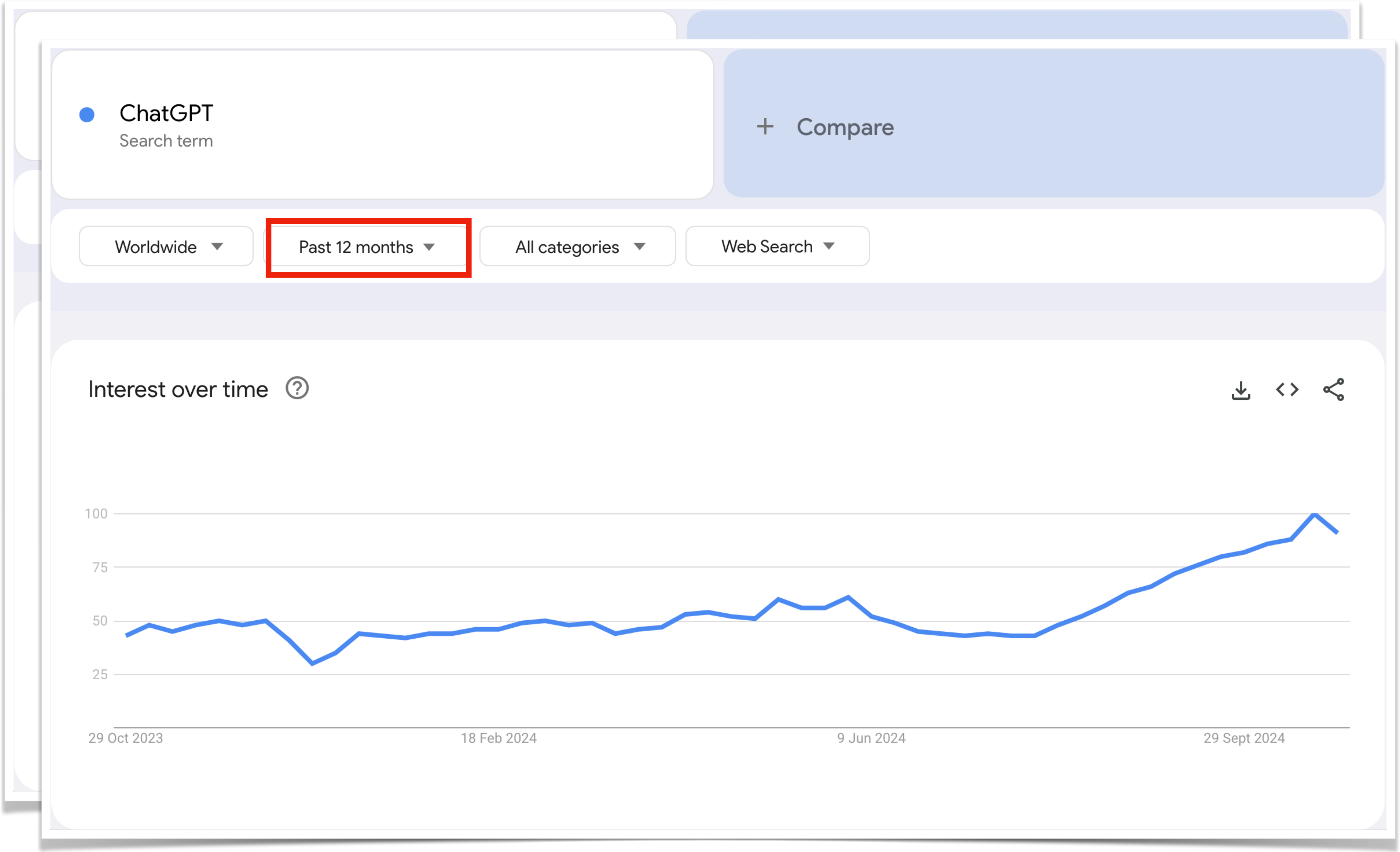

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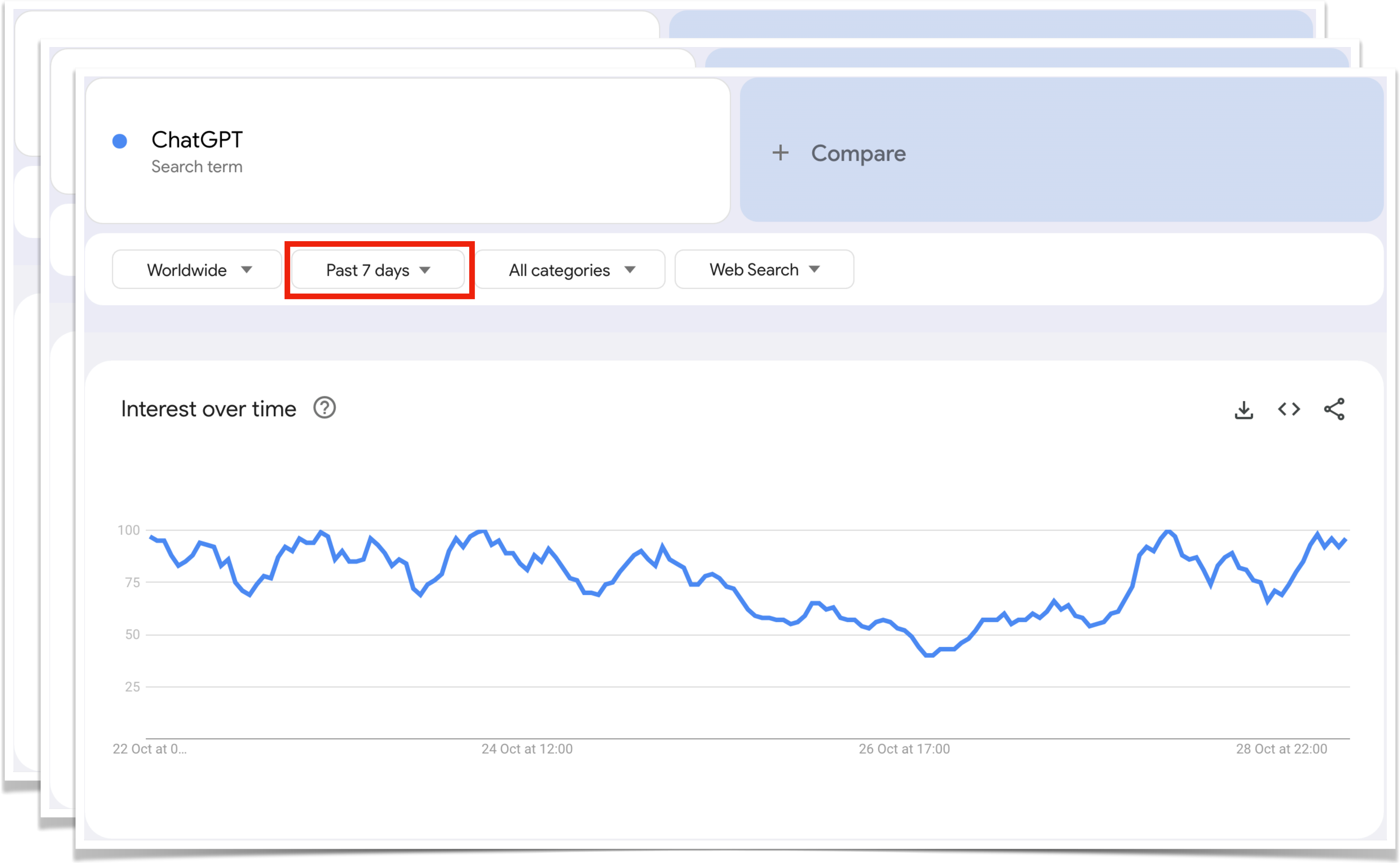

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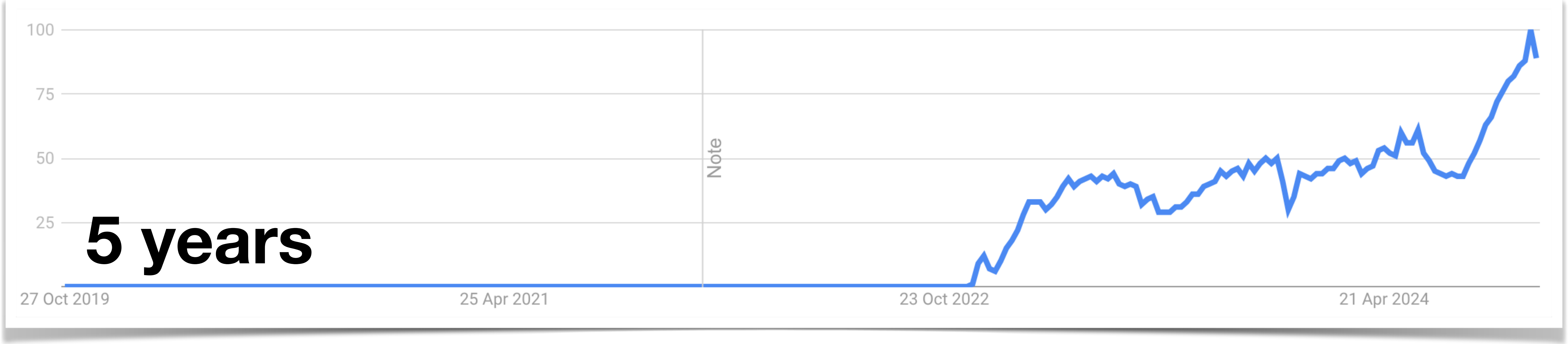

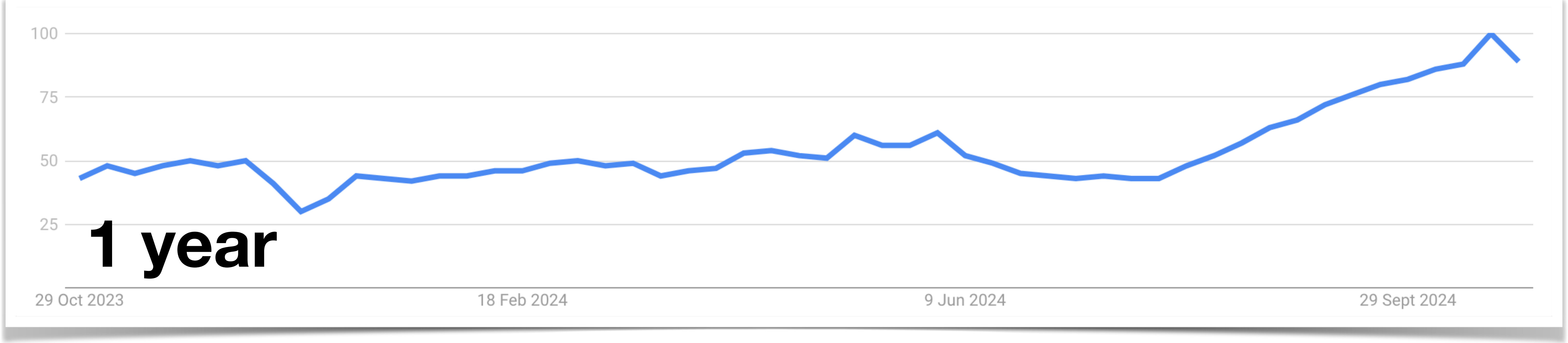

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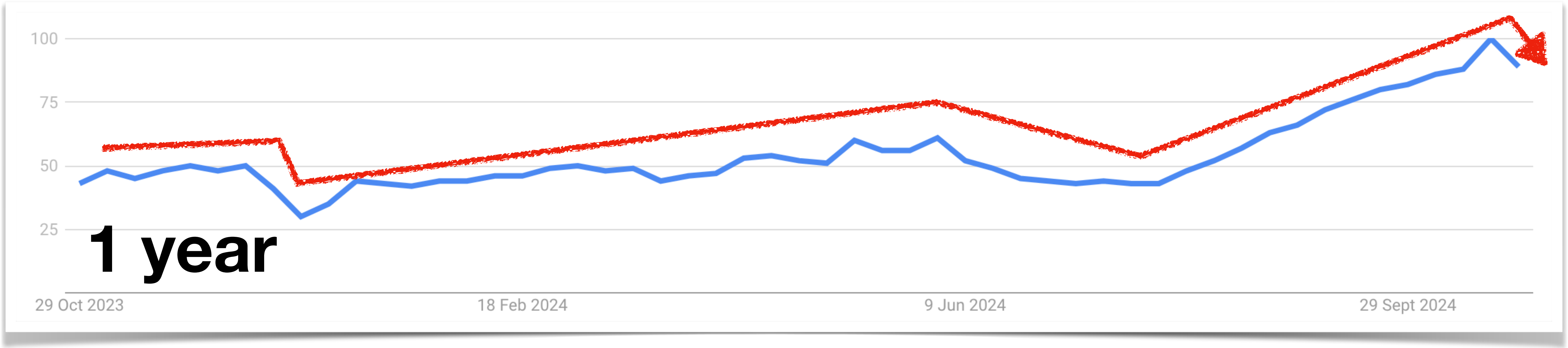

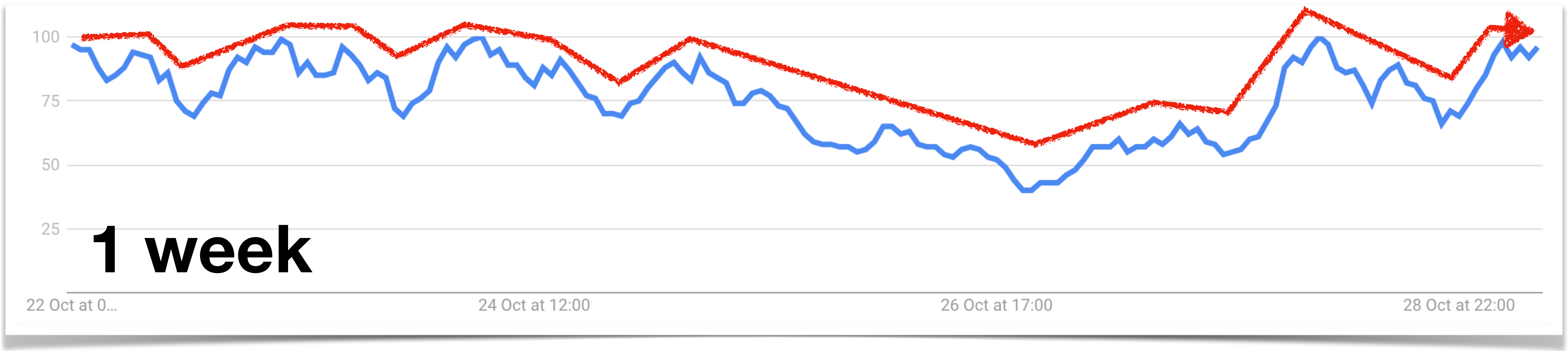

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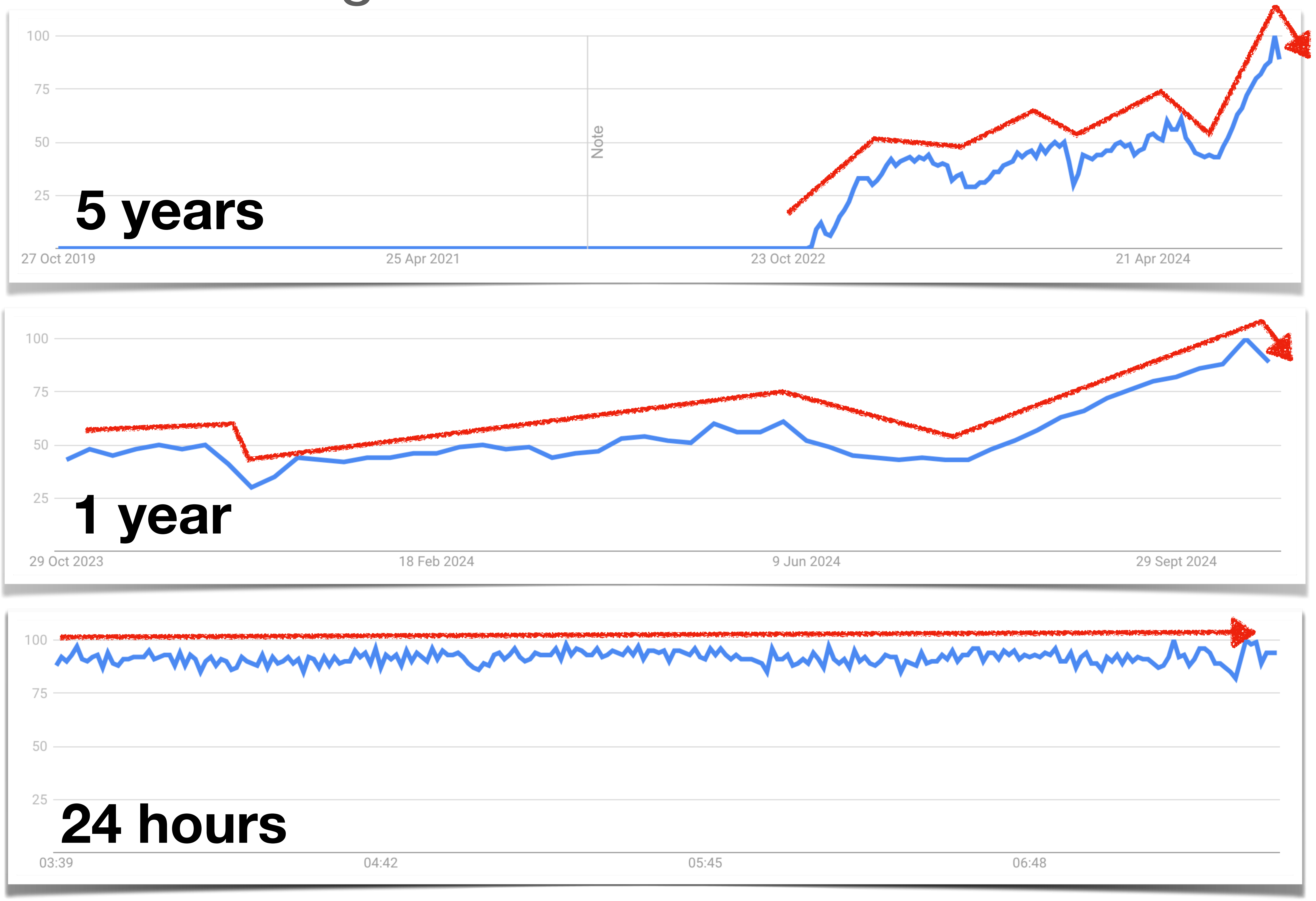
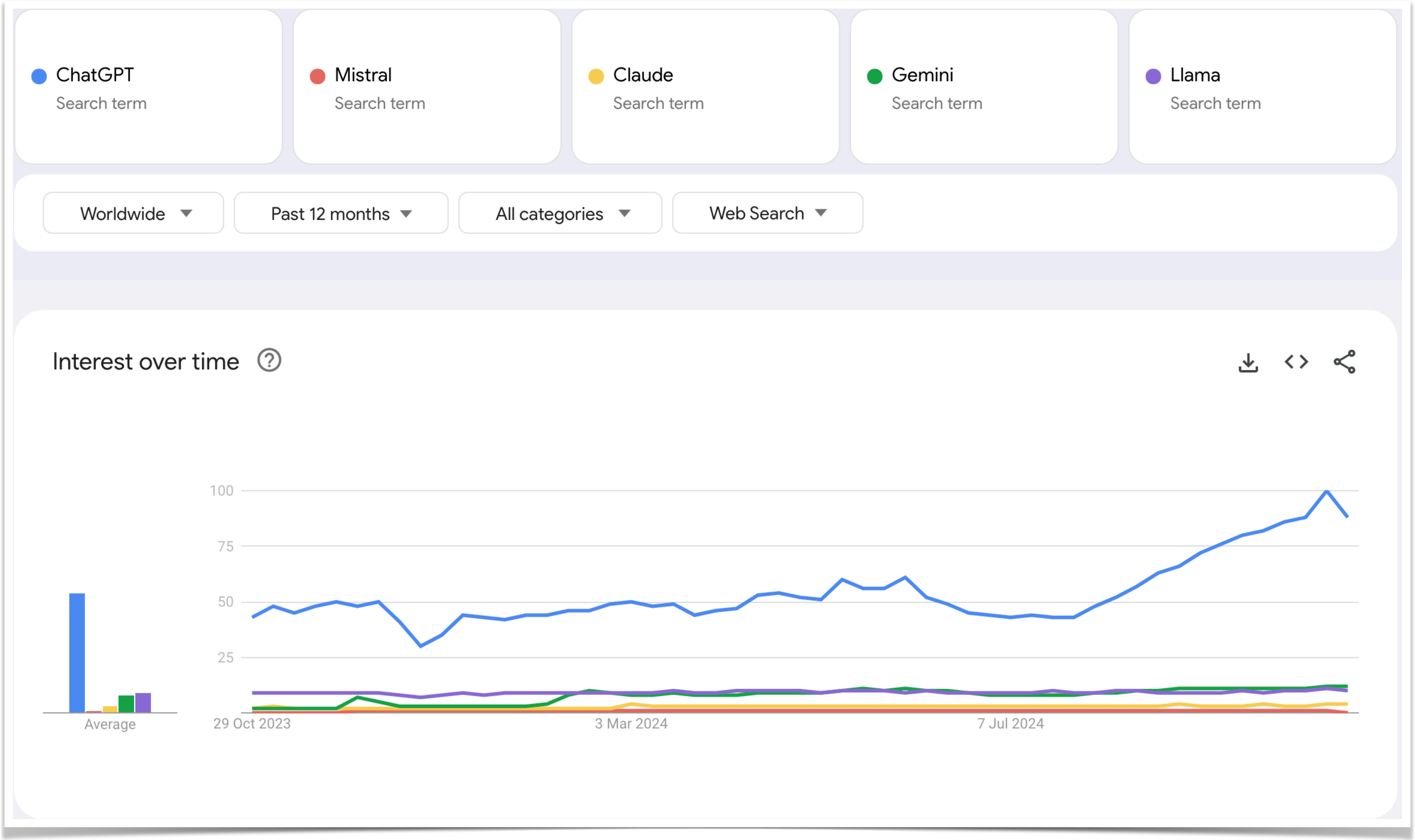


Google Trends

Searching for various trends



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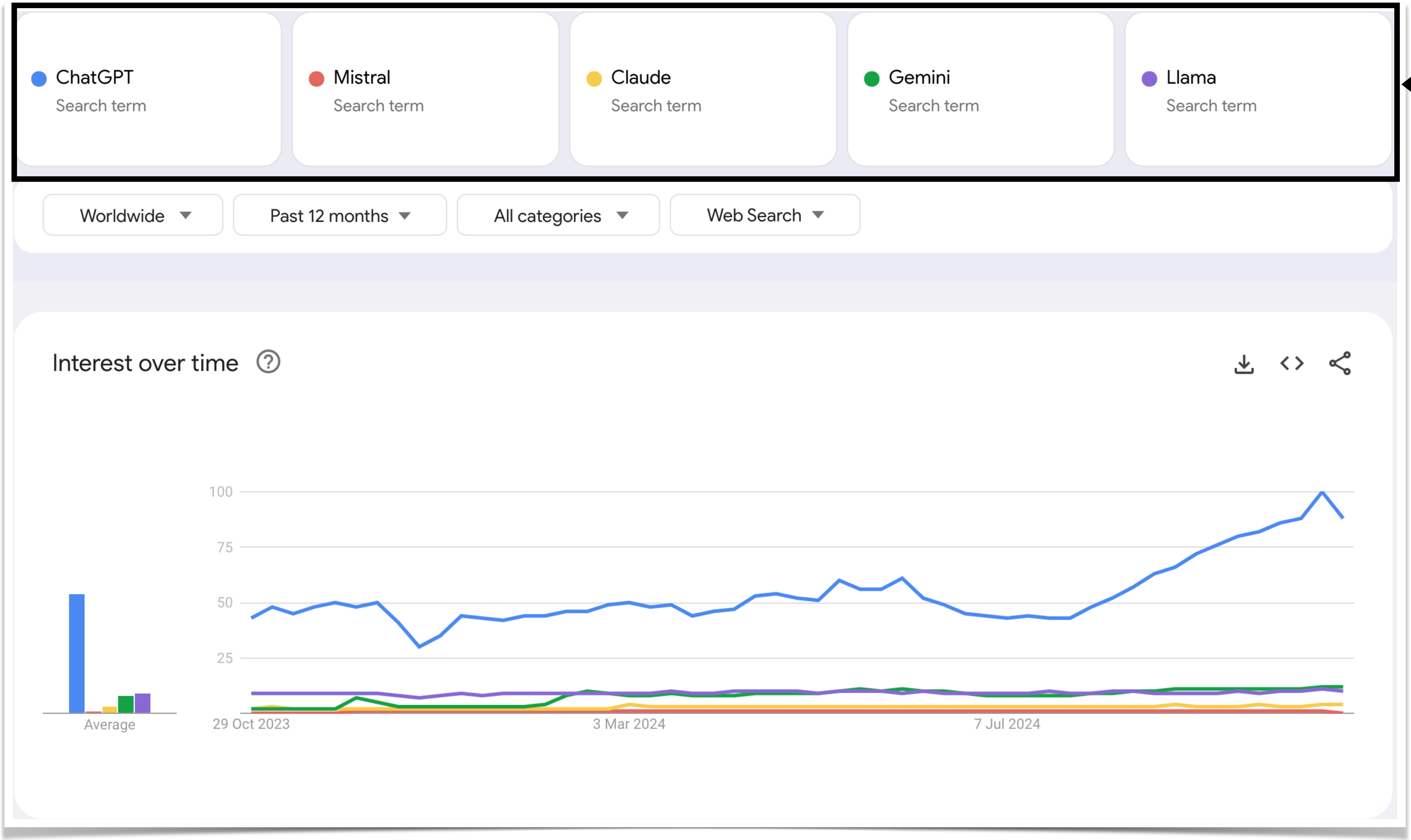
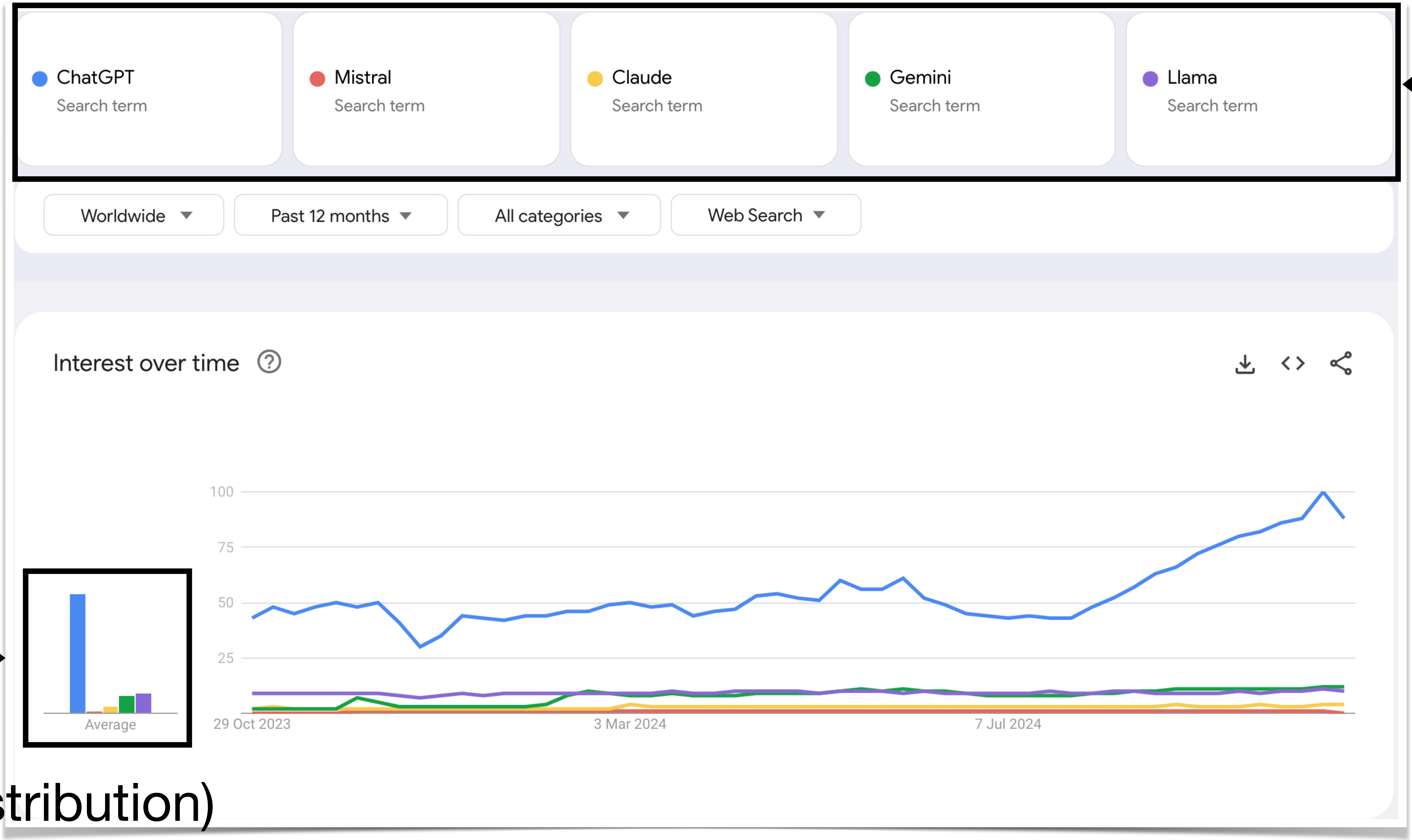


up to 5 topics

Google Trends

Searching for various trends

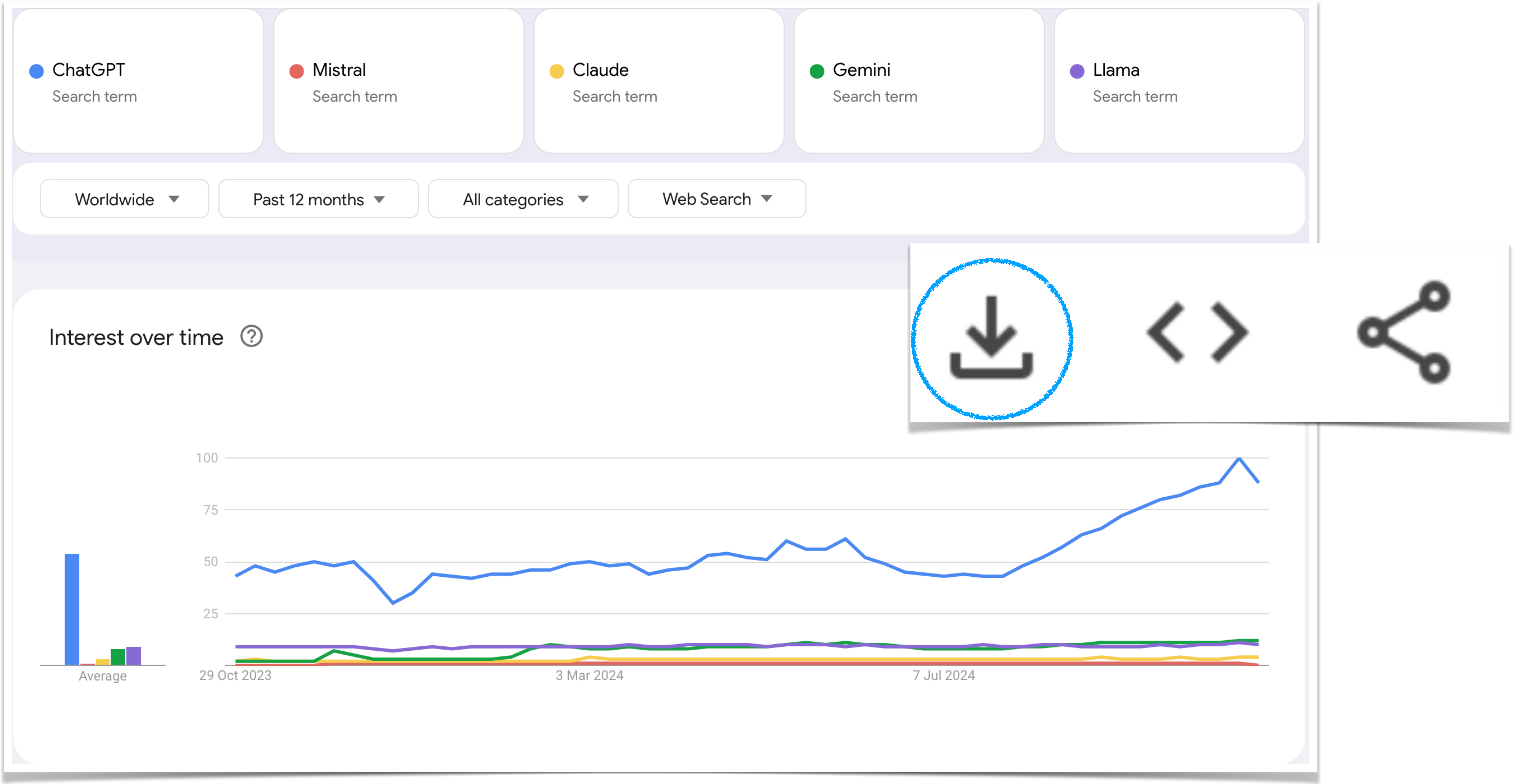


up to 5 topics

Histogram (average distribution)

Google Trends

Exporting data

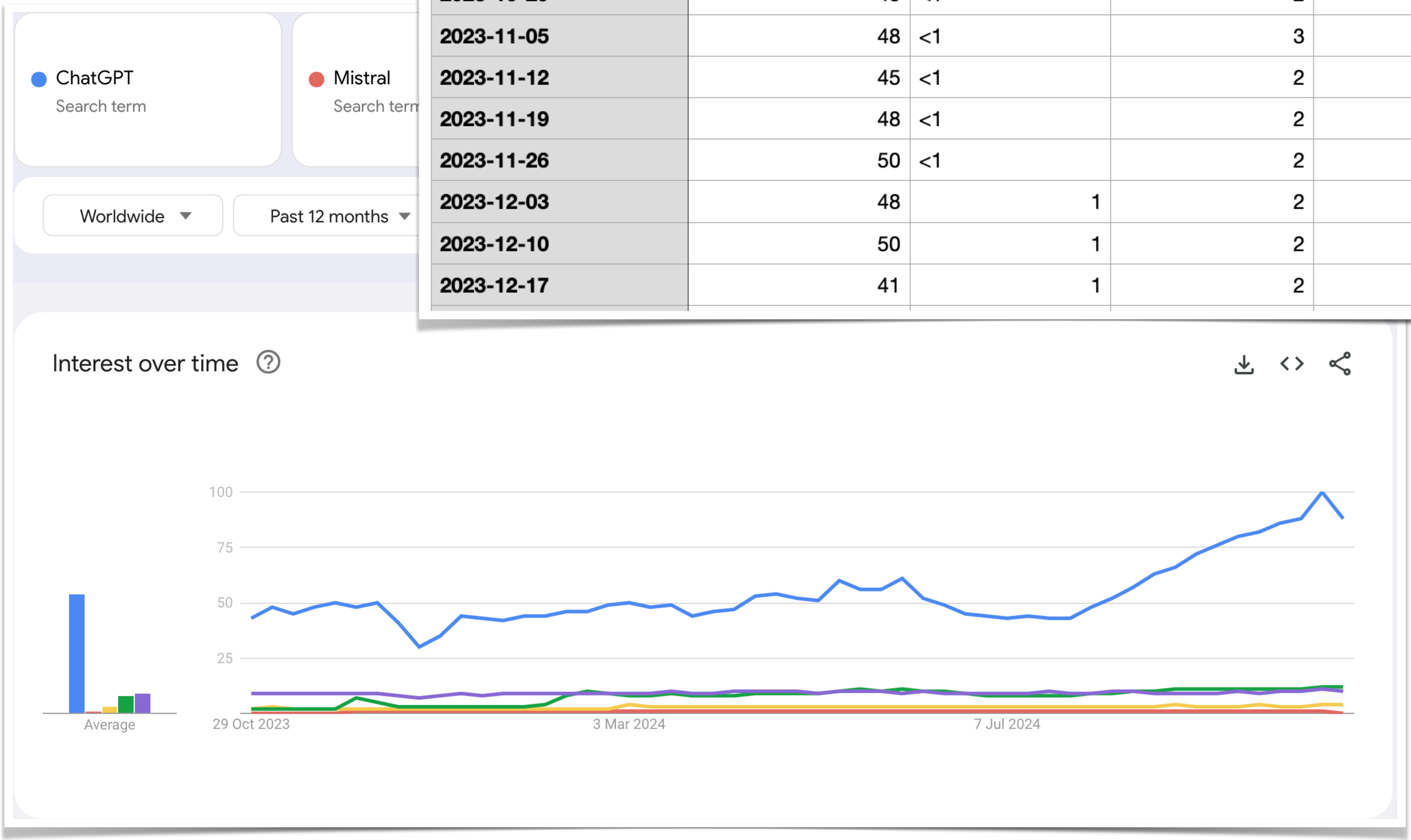


Google Trends

Export file format

multiTimeline

Category: All categories					
Week	ChatGPT: (Worldwide)	Mistral: (Worldwide)	Claude: (Worldwide)	Gemini: (Worldwide)	Llama: (Worldwide)
2023-10-29	43	<1	2	2	9
2023-11-05	48	<1	3	2	9
2023-11-12	45	<1	2	2	9
2023-11-19	48	<1	2	2	9
2023-11-26	50	<1	2	2	9
2023-12-03	48	1	2	7	9
2023-12-10	50	1	2	5	9
2023-12-17	41	1	2	3	8



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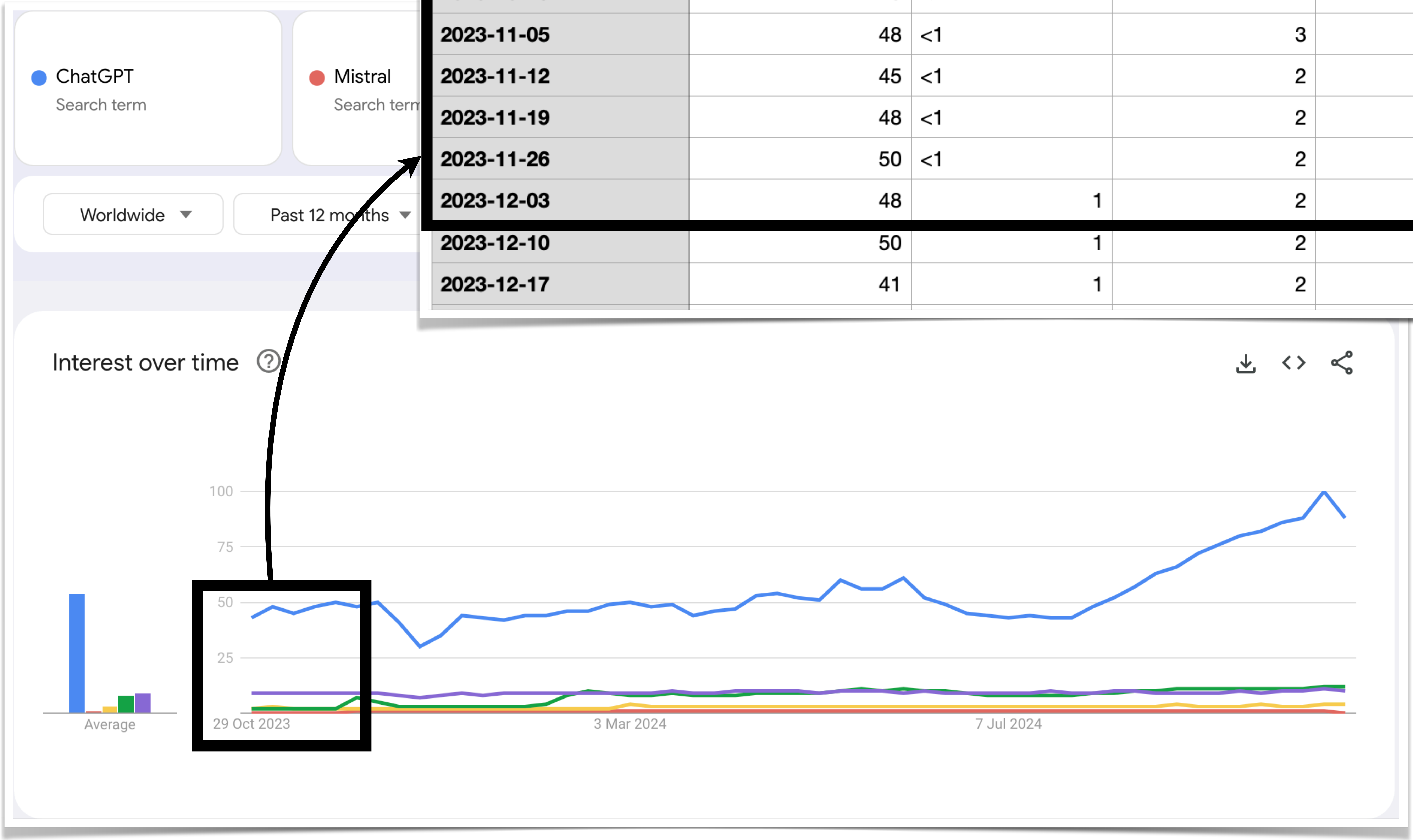
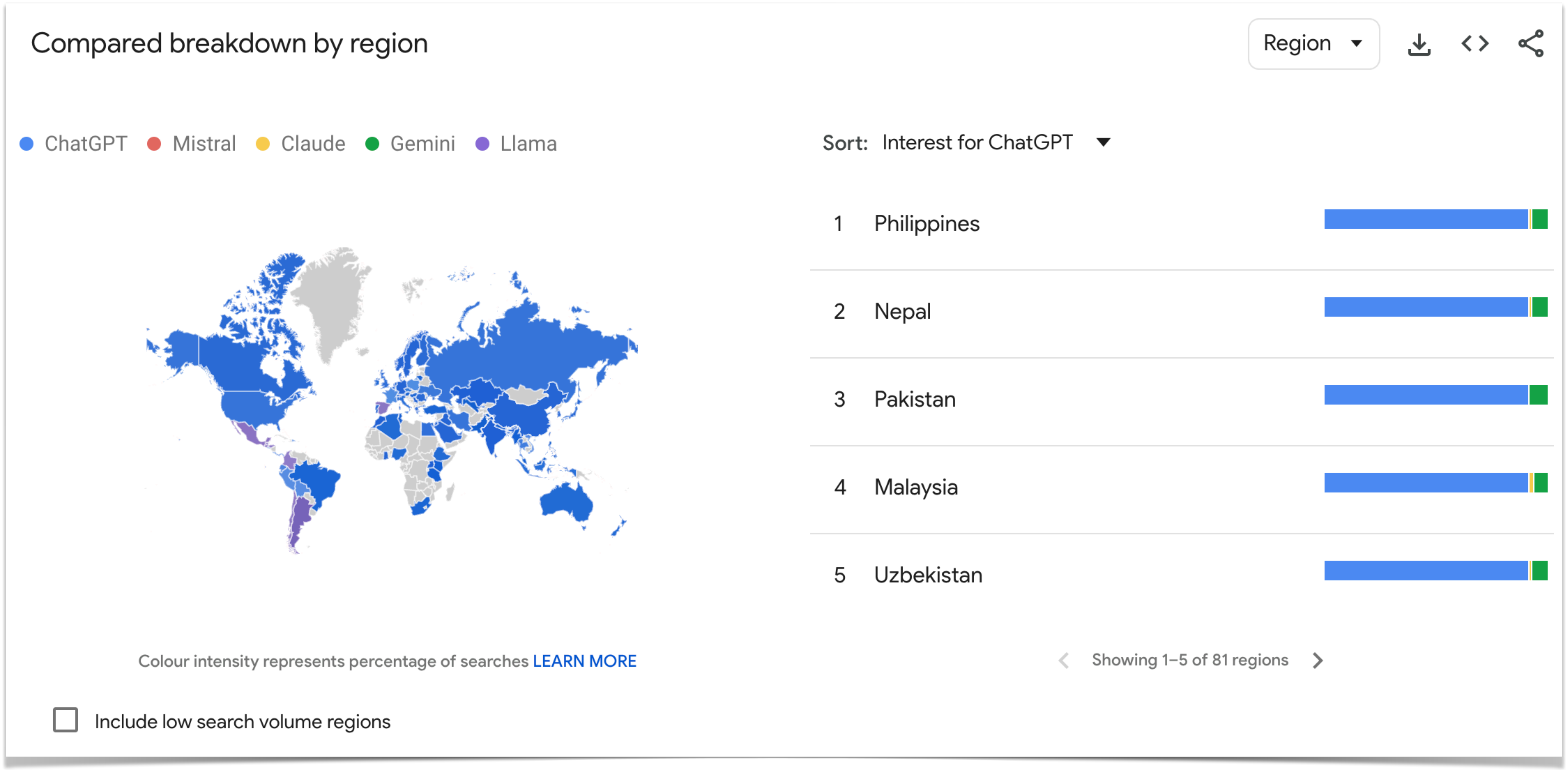


Google Trends

Comparing regions



Google Trends

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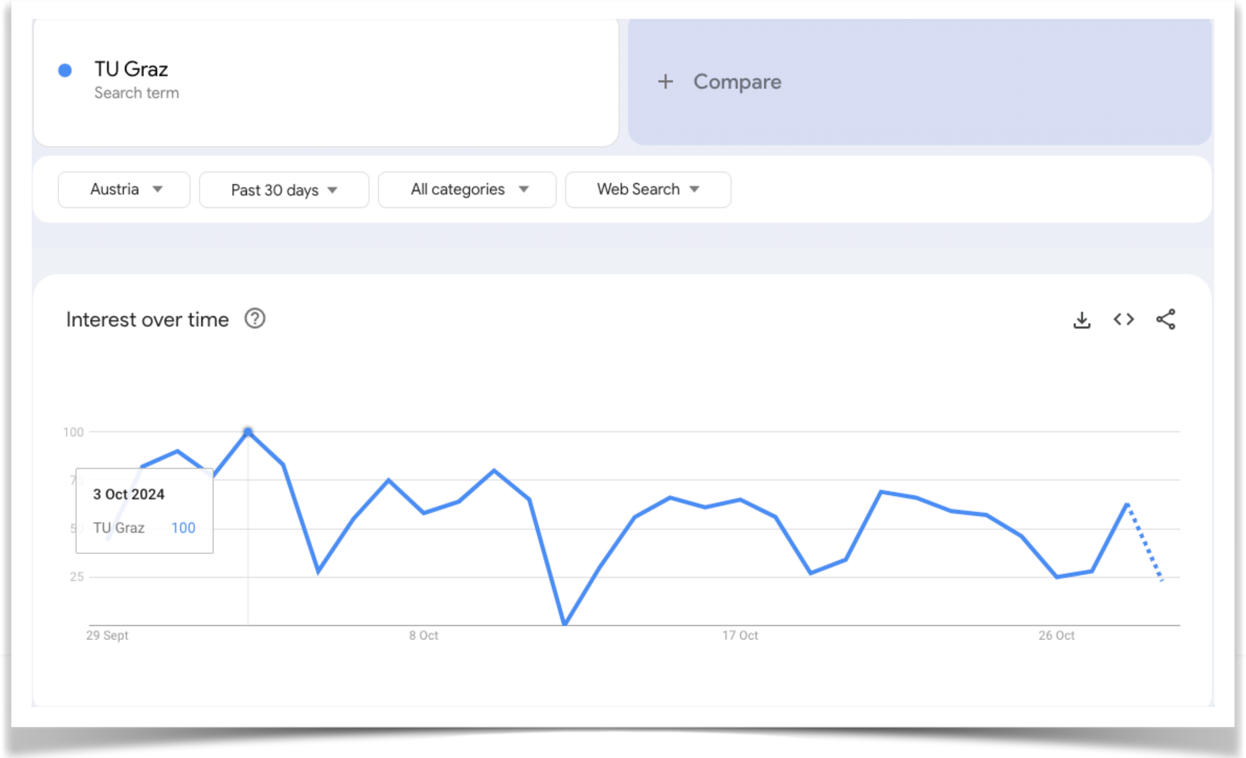
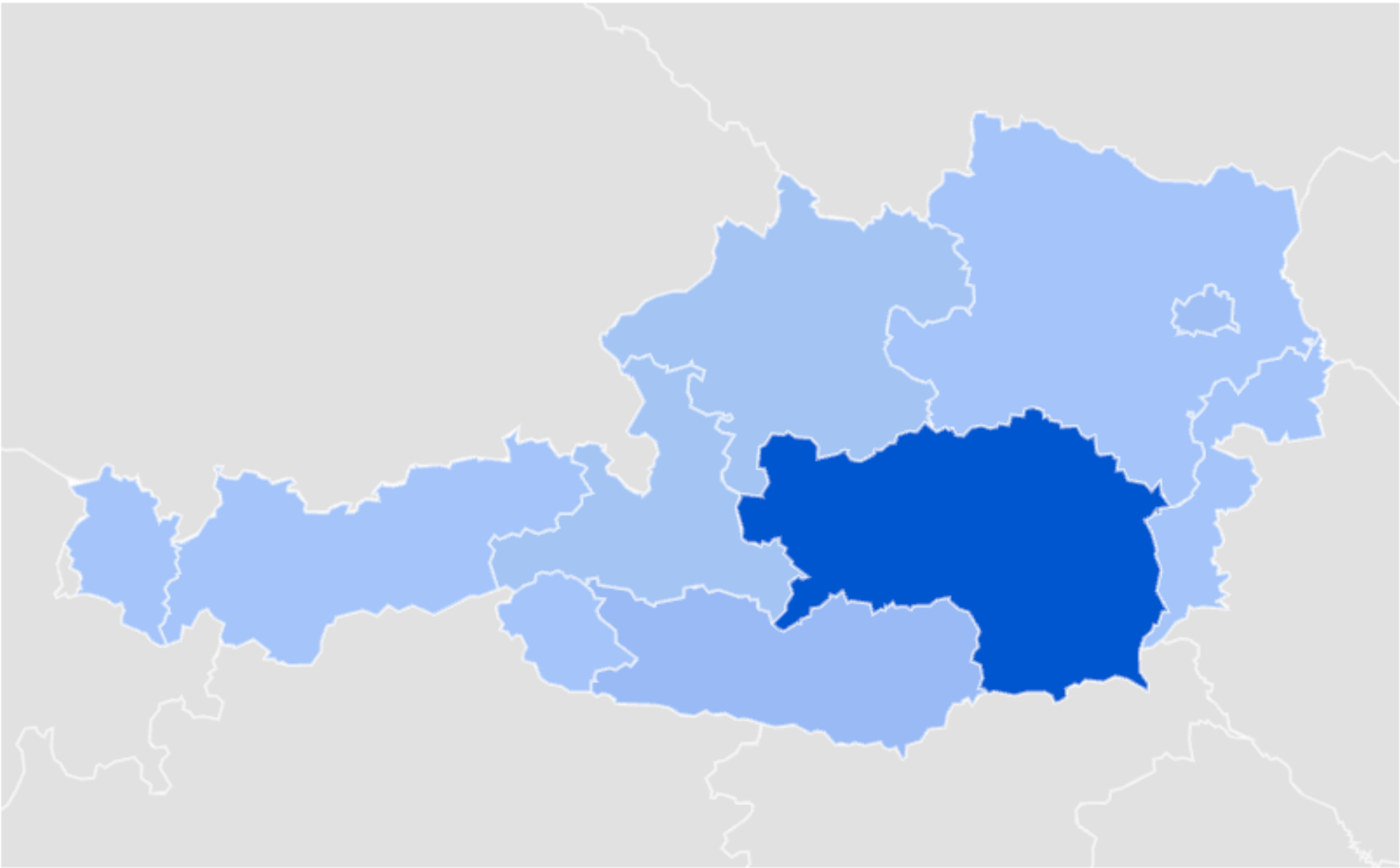


search term: **TU Graz**

Interest by sub-region

Sub-region

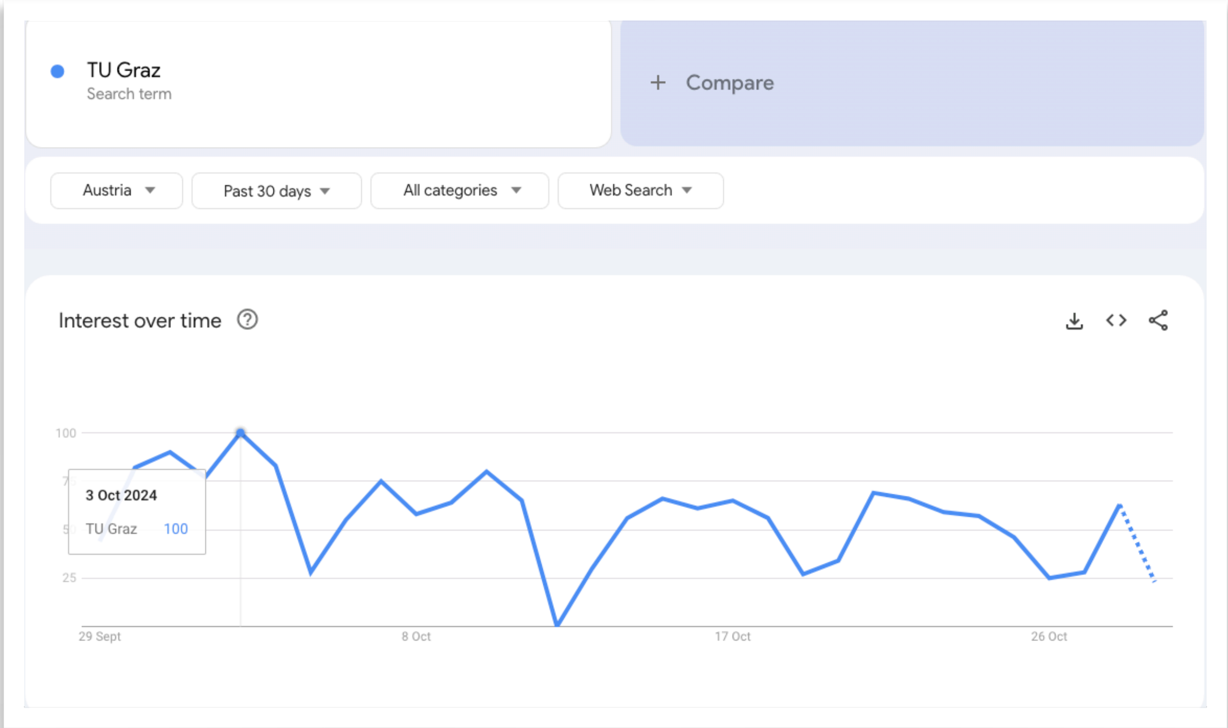


1	Styria	100
2	Carinthia	9
3	Vienna	5
4	Salzburg	3
5	Upper Austria	3

Showing 1–5 of 9 subregions

Google Trends

Related topics and queries



search term: **TU Graz**

Related topics — Rising

1	AnyConnect - Software	Breakout
2	Academic term - Topic	Breakout
3	Doctoral school - Topic	Breakout
4	GitLab - Software	Breakout
5	One-time password - Topic	Breakout

Showing 1–5 of 16 topics

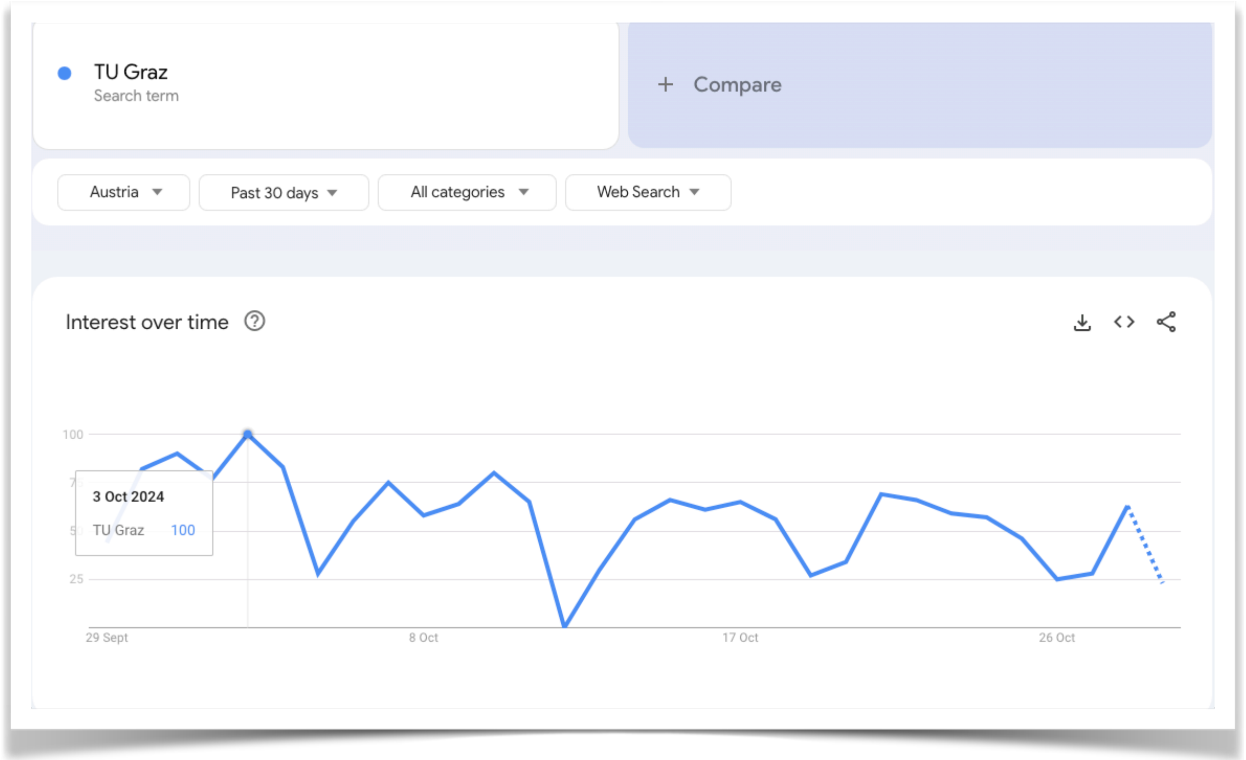
Related queries — Rising

1	teachcenter	Breakout
2	tu fest graz 2024	Breakout
3	fh campus 02	Breakout
4	teach center	Breakout
5	egiraffe tu graz	Breakout

Showing 1–5 of 13 queries

Google Trends

Related topics and queries



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Showing 1–5 of 16 topics

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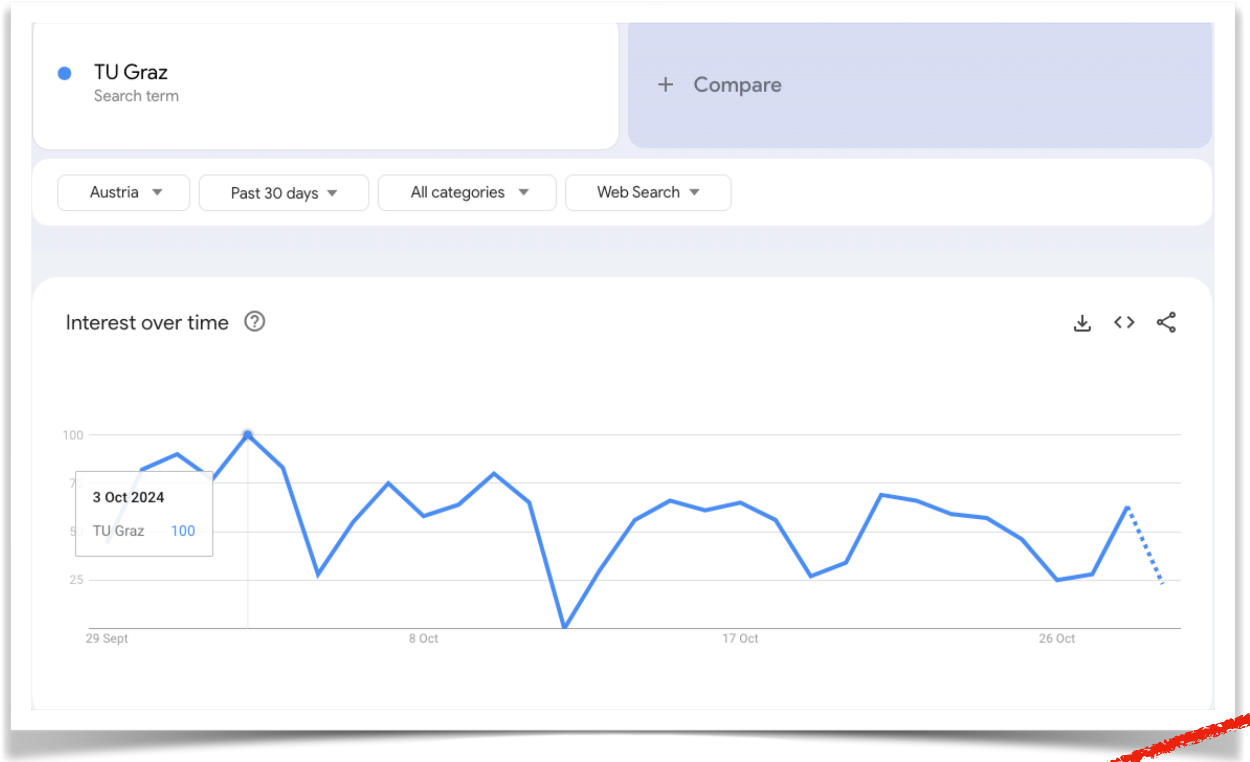
Showing 1–5 of 13 queries

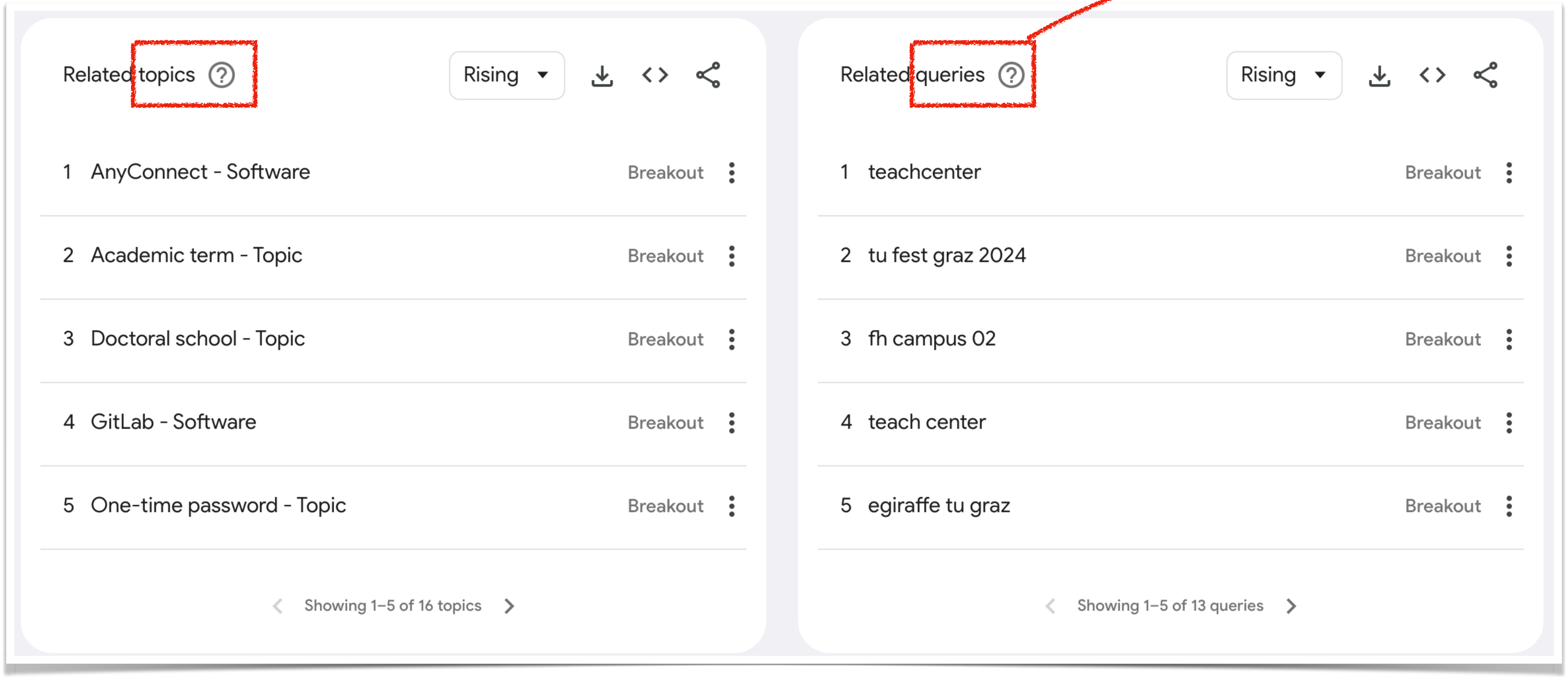
Google Trends

Related topics and queries



search term: **TU Graz**

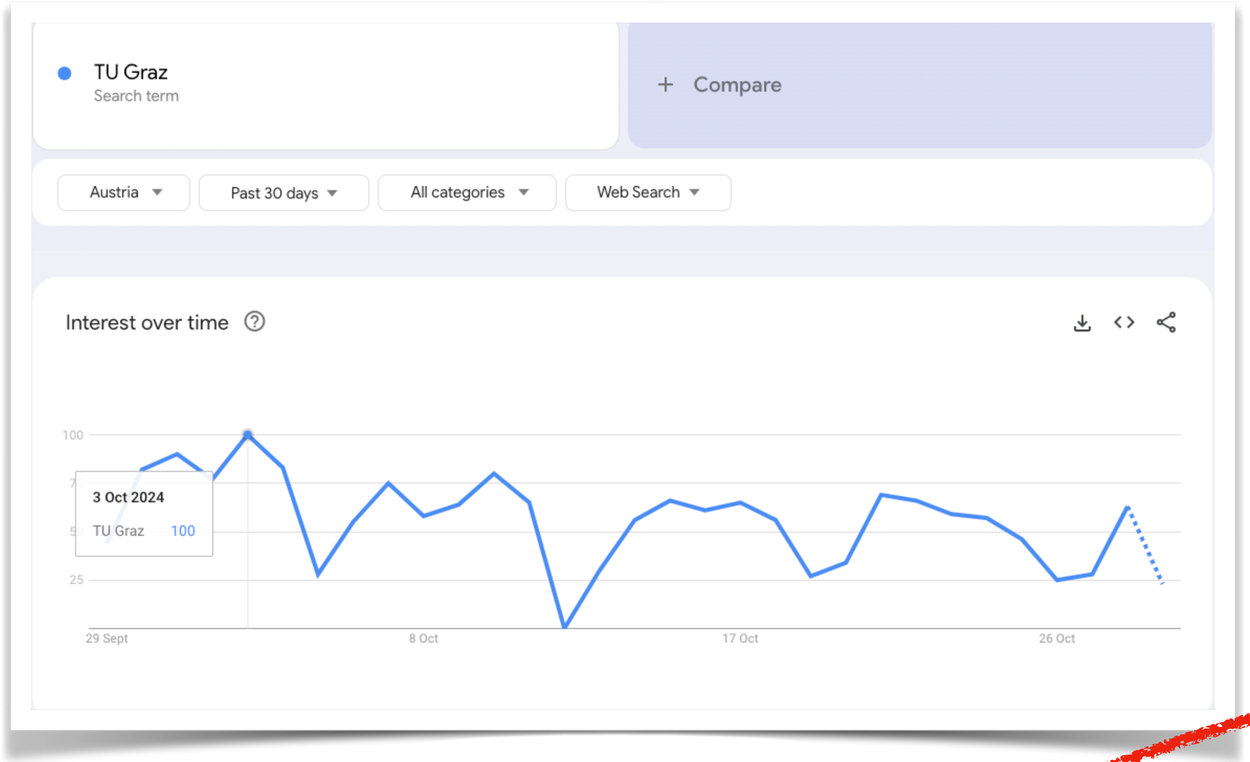
Exact search terms!



Google Trends

Related topics and queries

Encompass multiple search terms!



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Related topics — Rising

1	AnyConnect - Software	Breakout
2	Academic term - Topic	Breakout
3	Doctoral school - Topic	Breakout
4	GitLab - Software	Breakout
5	One-time password - Topic	Breakout

Showing 1–5 of 16 topics

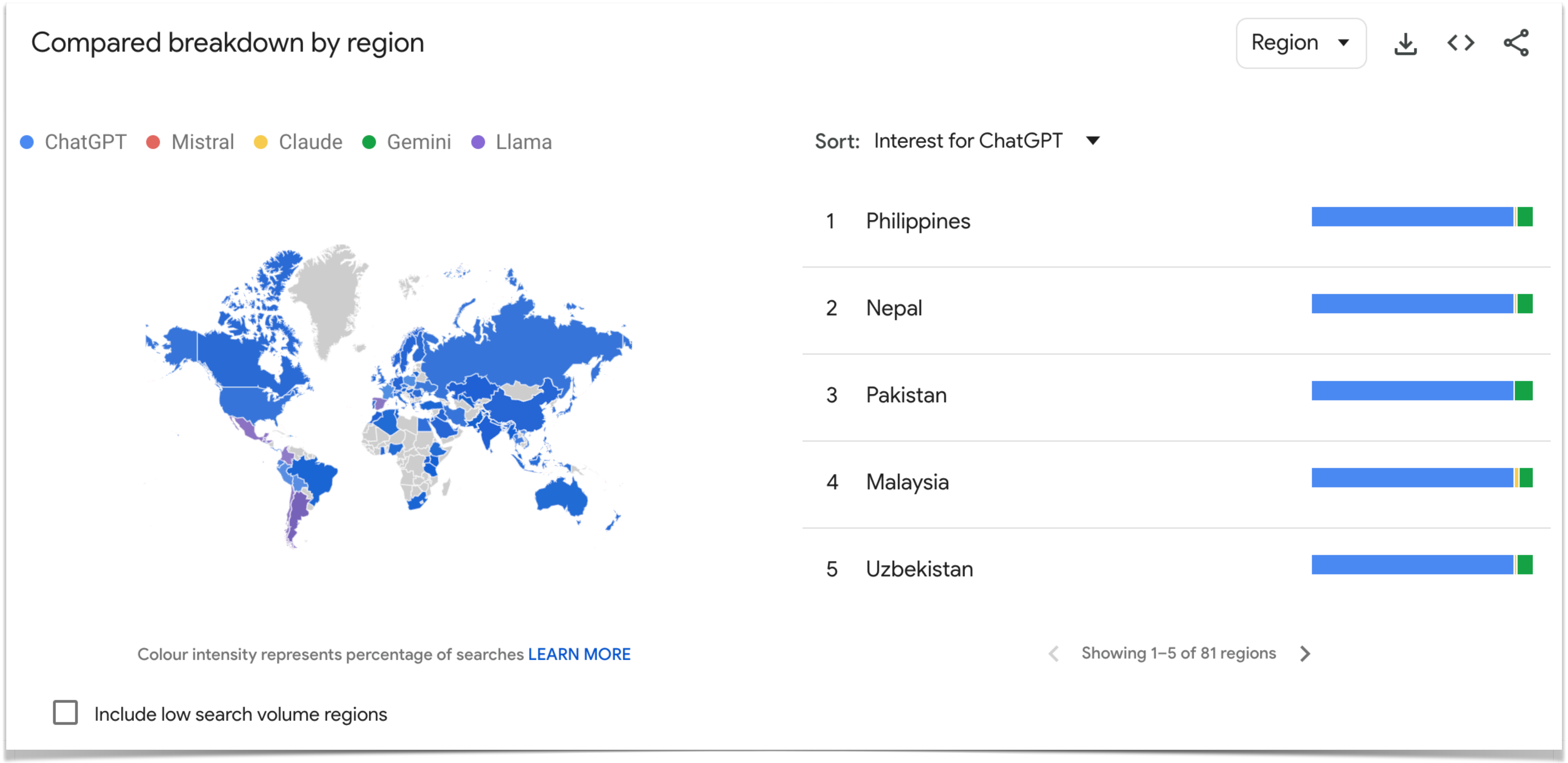
Related queries — Rising

1	teachcenter	Breakout
2	tu fest graz 2024	Breakout
3	fh campus 02	Breakout
4	teach center	Breakout
5	egiraffe tu graz	Breakout

Showing 1–5 of 13 queries

Google Trends

Exporting map data



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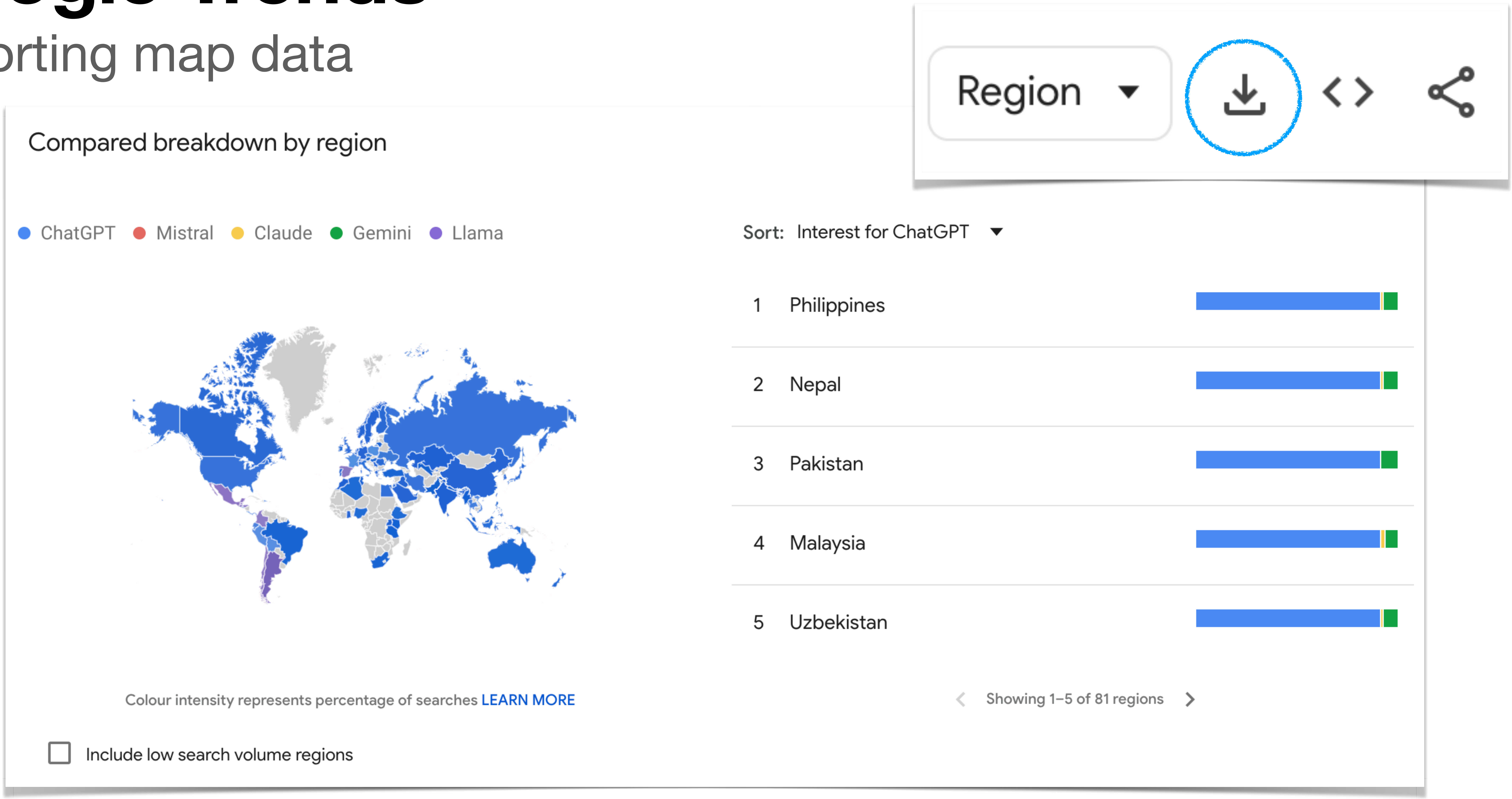

Google Trends

Export file format for maps

Compared breakdown by region

Region

geoMap

Category: All categories					
Country	ChatGPT: (29/10/2023 - 29/10/2024)	Mistral: (29/10/2023 - 29/10/2024)	Claude: (29/10/2023 - 29/10/2024)	Gemini: (29/10/2023 - 29/10/2024)	Llama: (29/10/2023 - 29/10/2024)
Bhutan					
Vanuatu					
Solomon Islands					
China	85 %	<1%	4 %	8 %	3 %
Botswana					
Philippines	92 %	<1%	1 %	7 %	<1%
Sri Lanka	91 %	<1%	1 %	8 %	<1%

Colour intensity represents percentage of searches LEARN MORE

Showing 1–5 of 81 regions

Include low search volume regions

What can we do with Google Trends data?

The Future Orientation Index (FOI)

Preis et al. 2012

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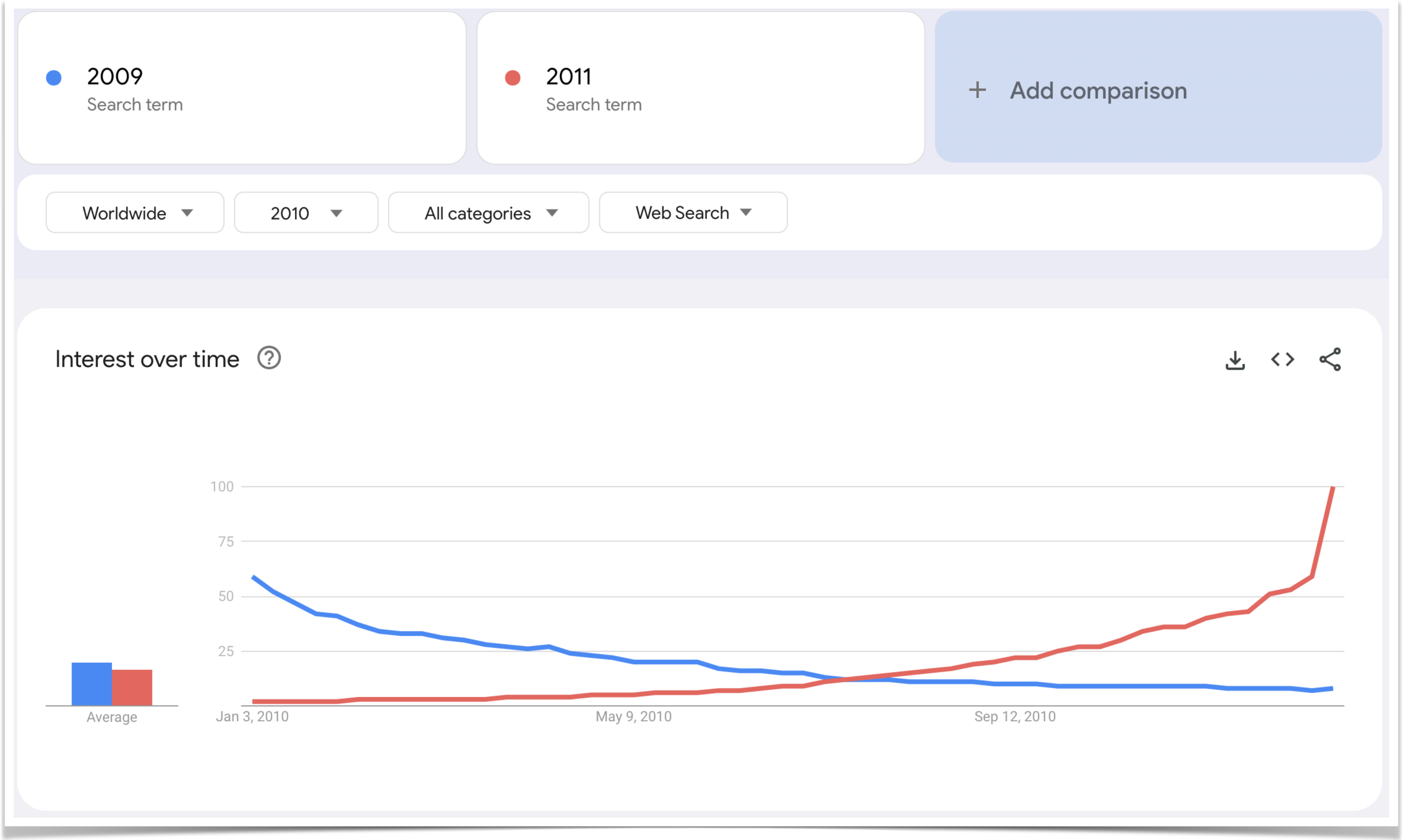
Examples of FOI

using Google Trends in **2010** (per region, map data)



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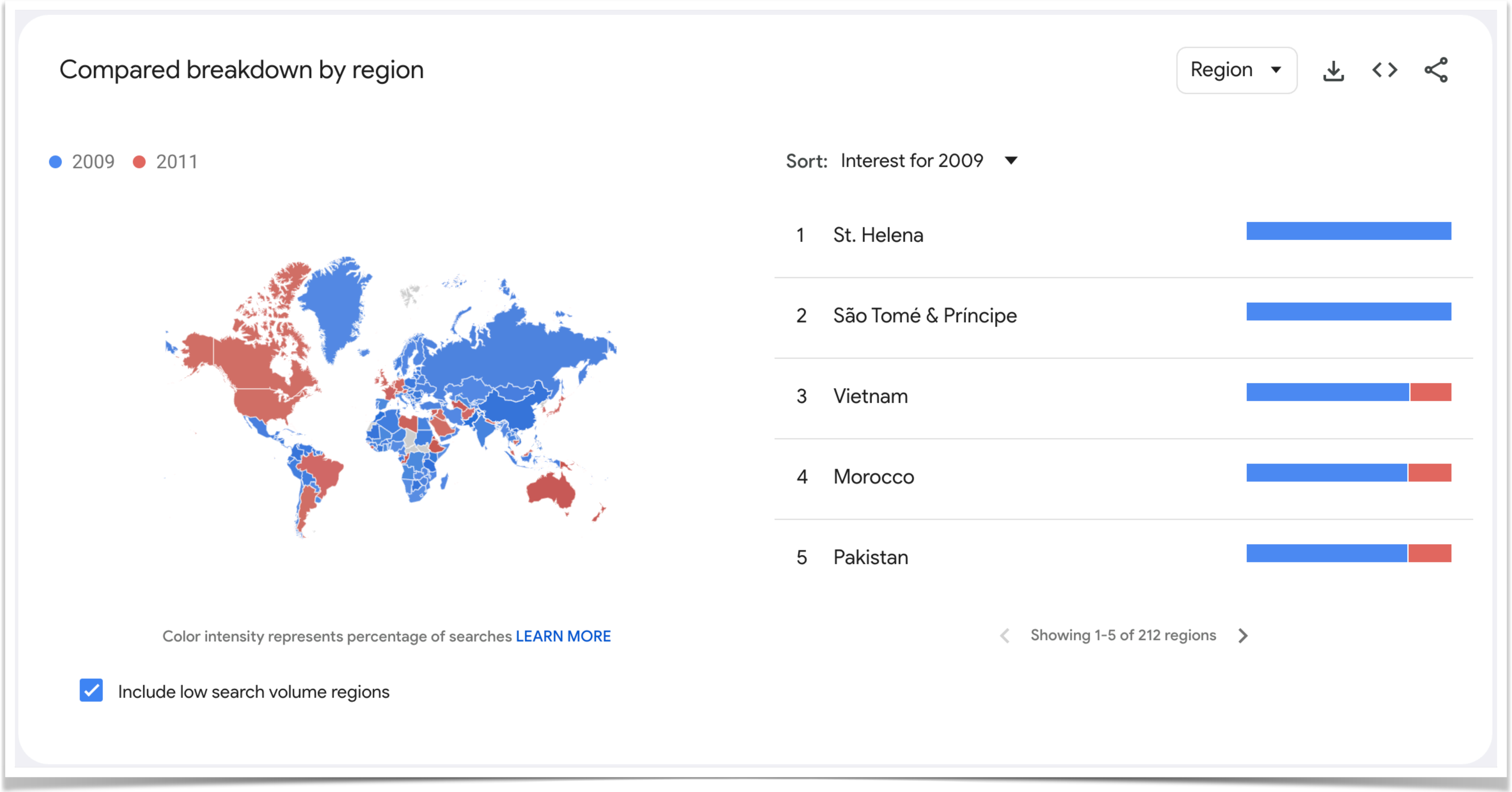

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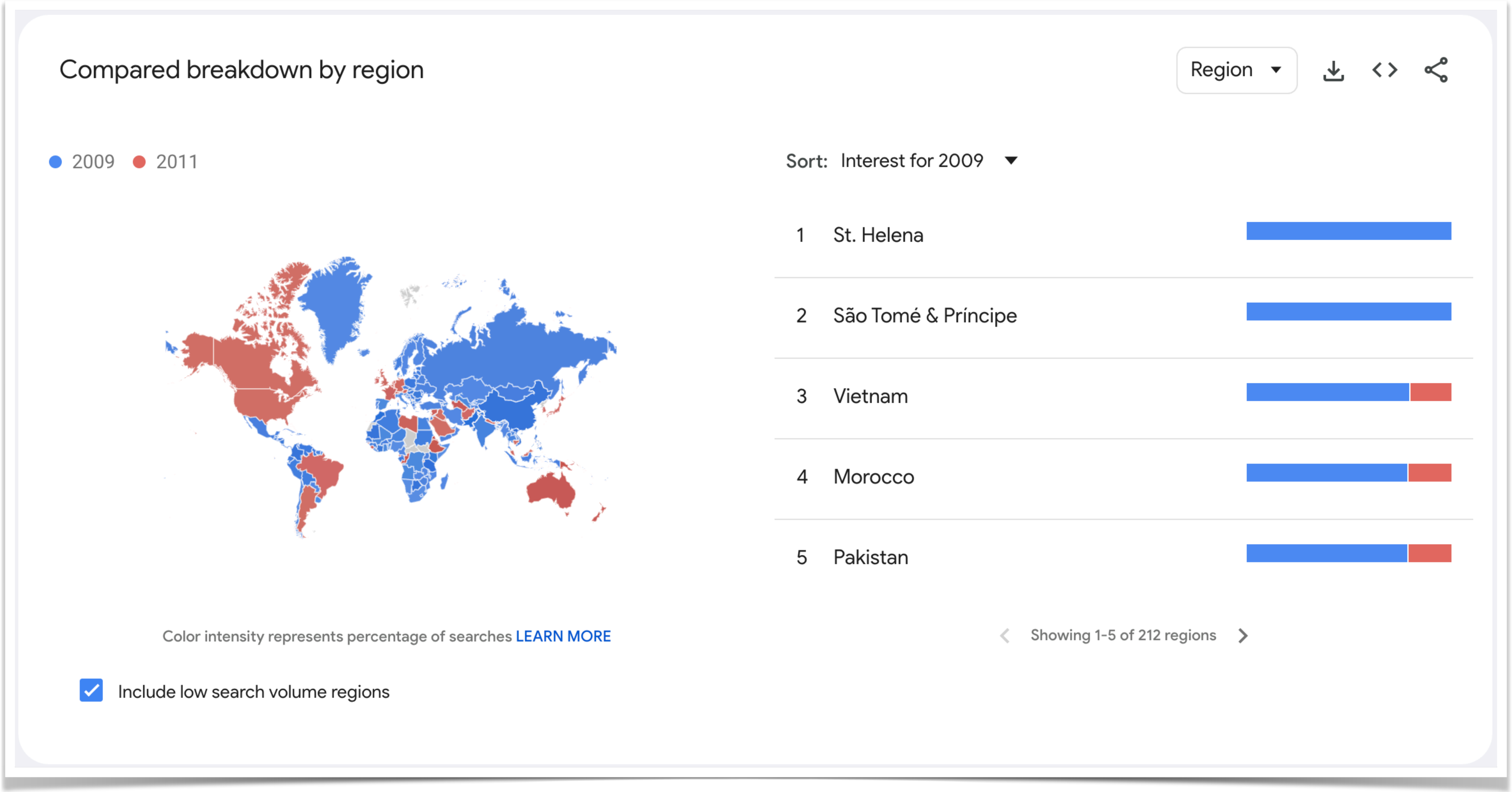

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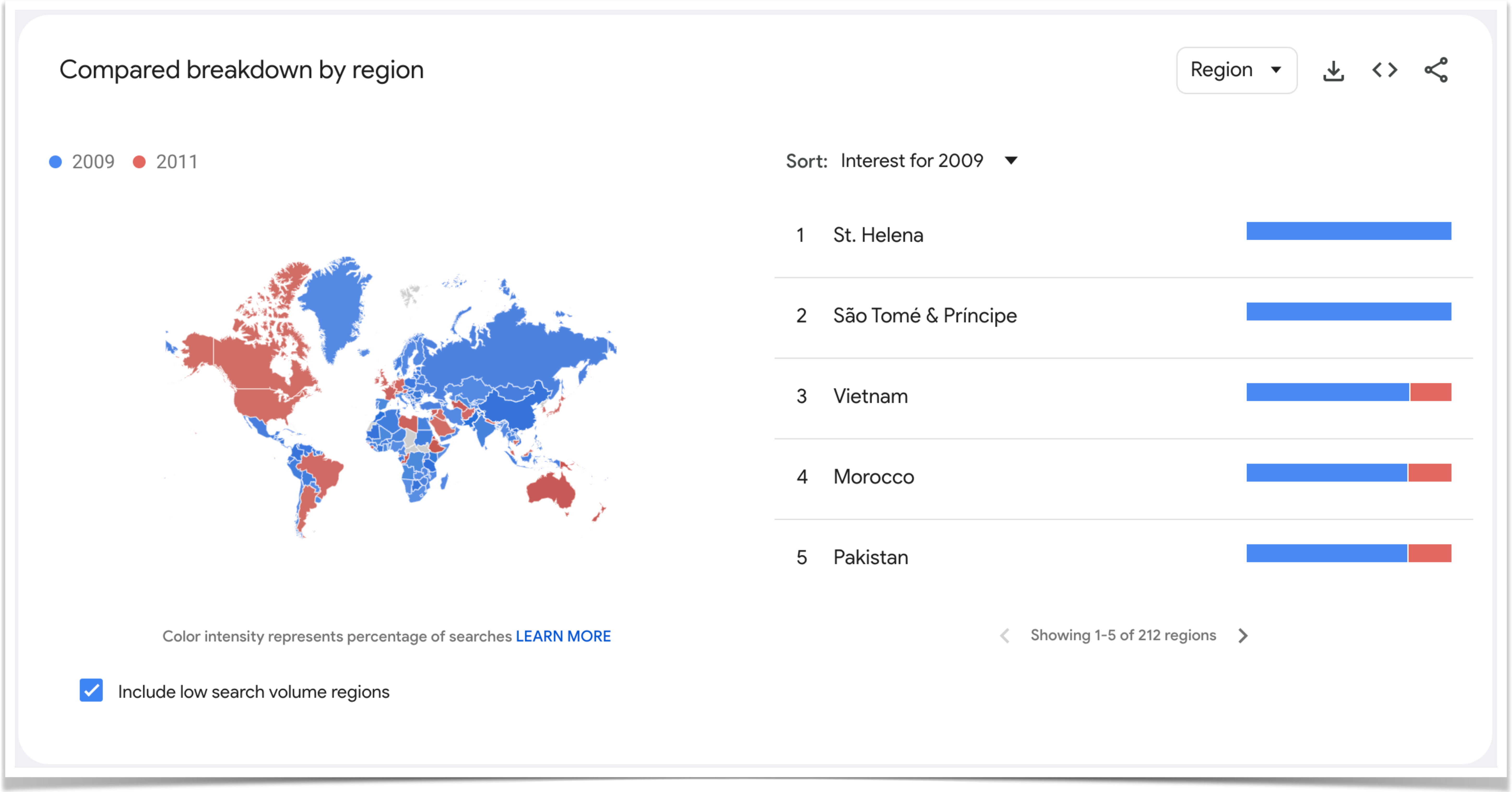

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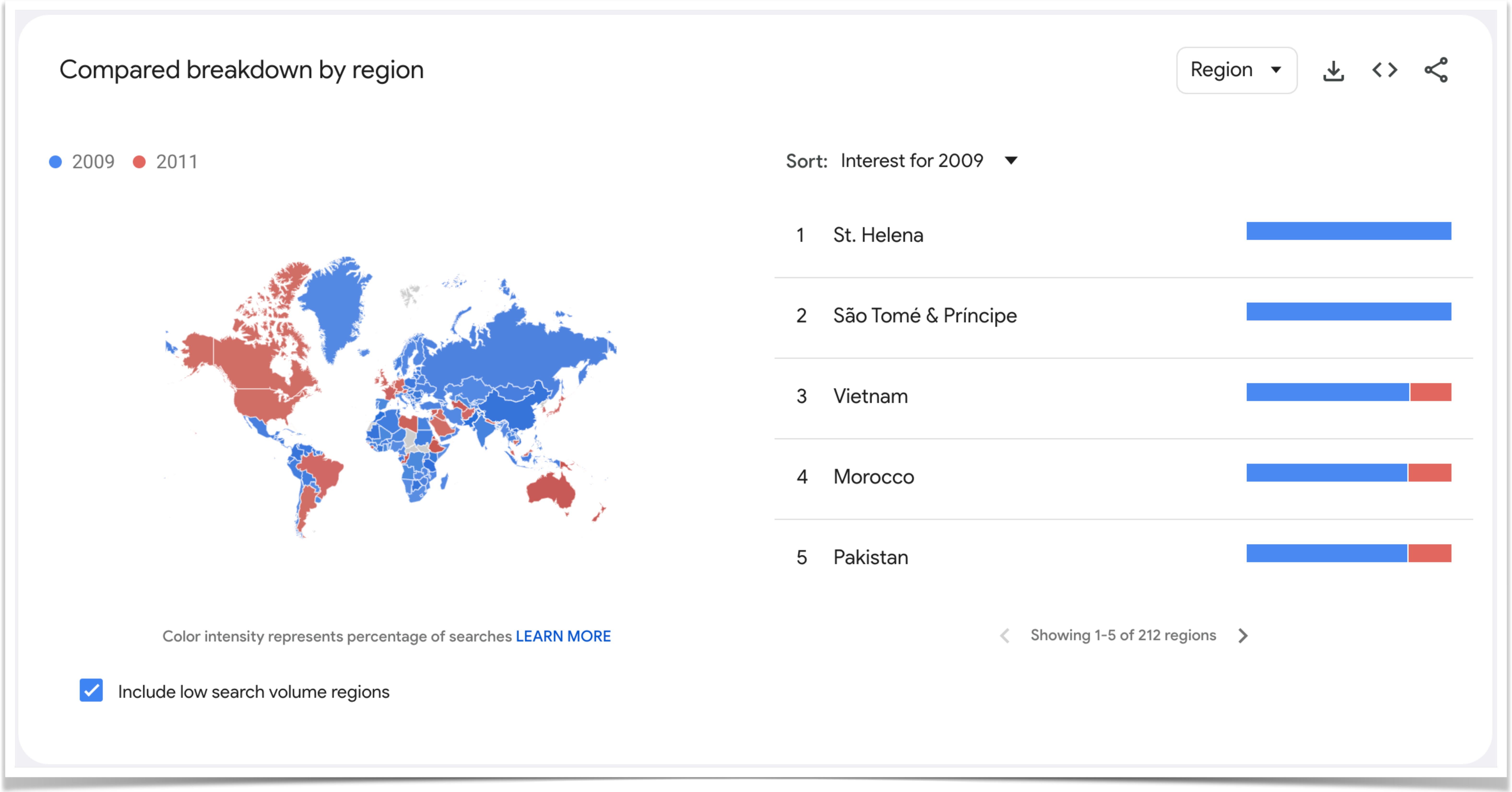

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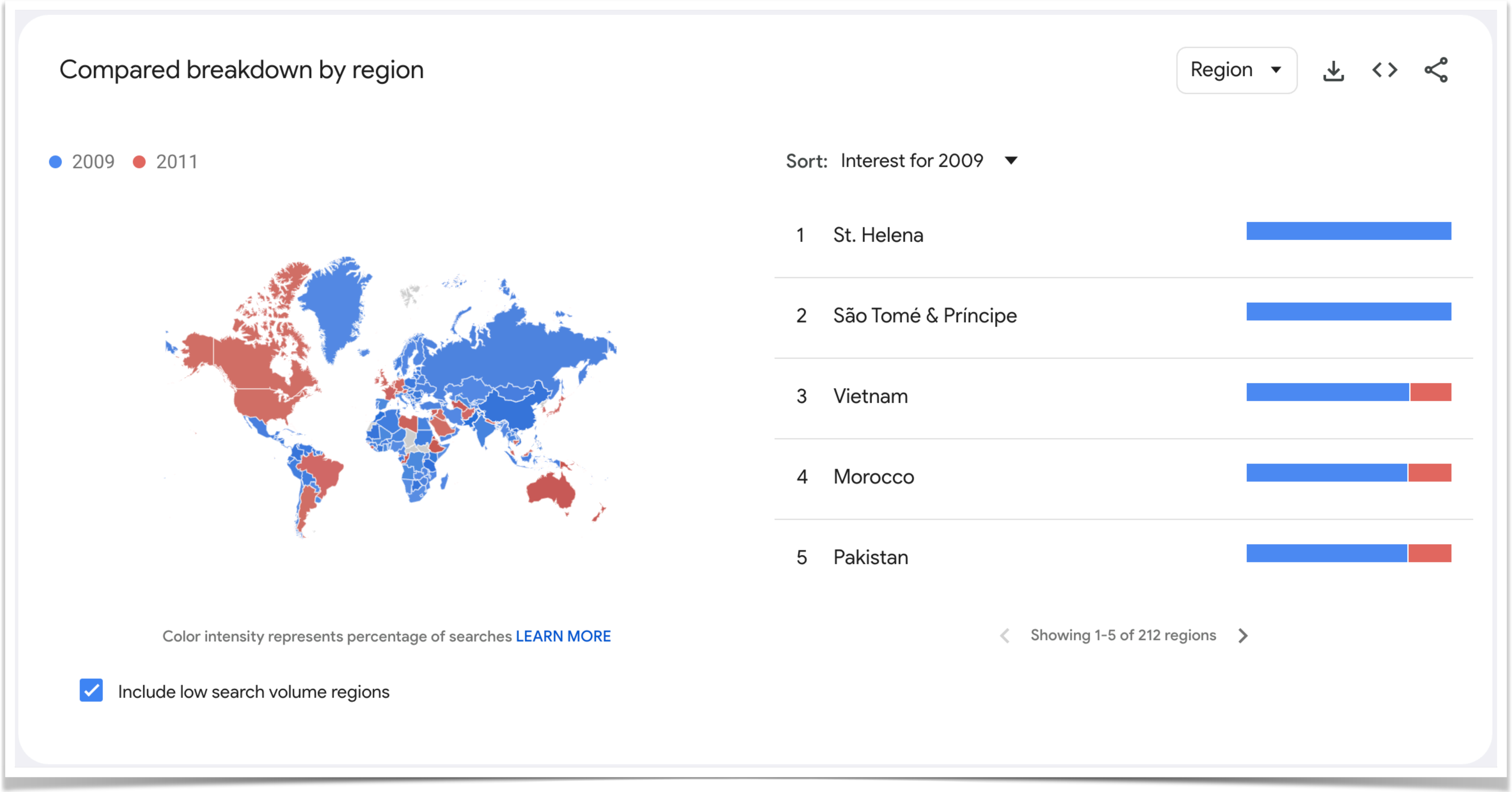

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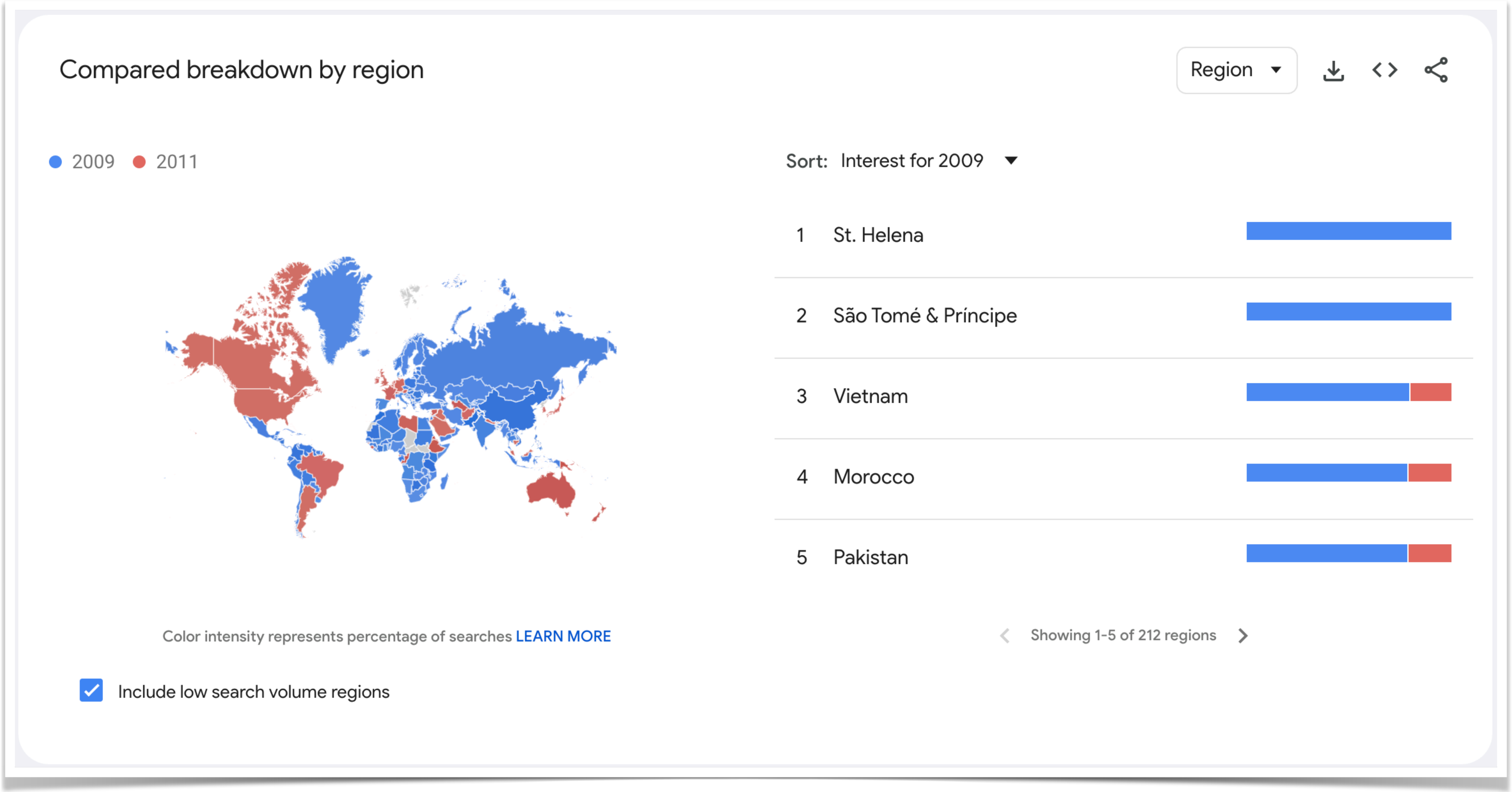

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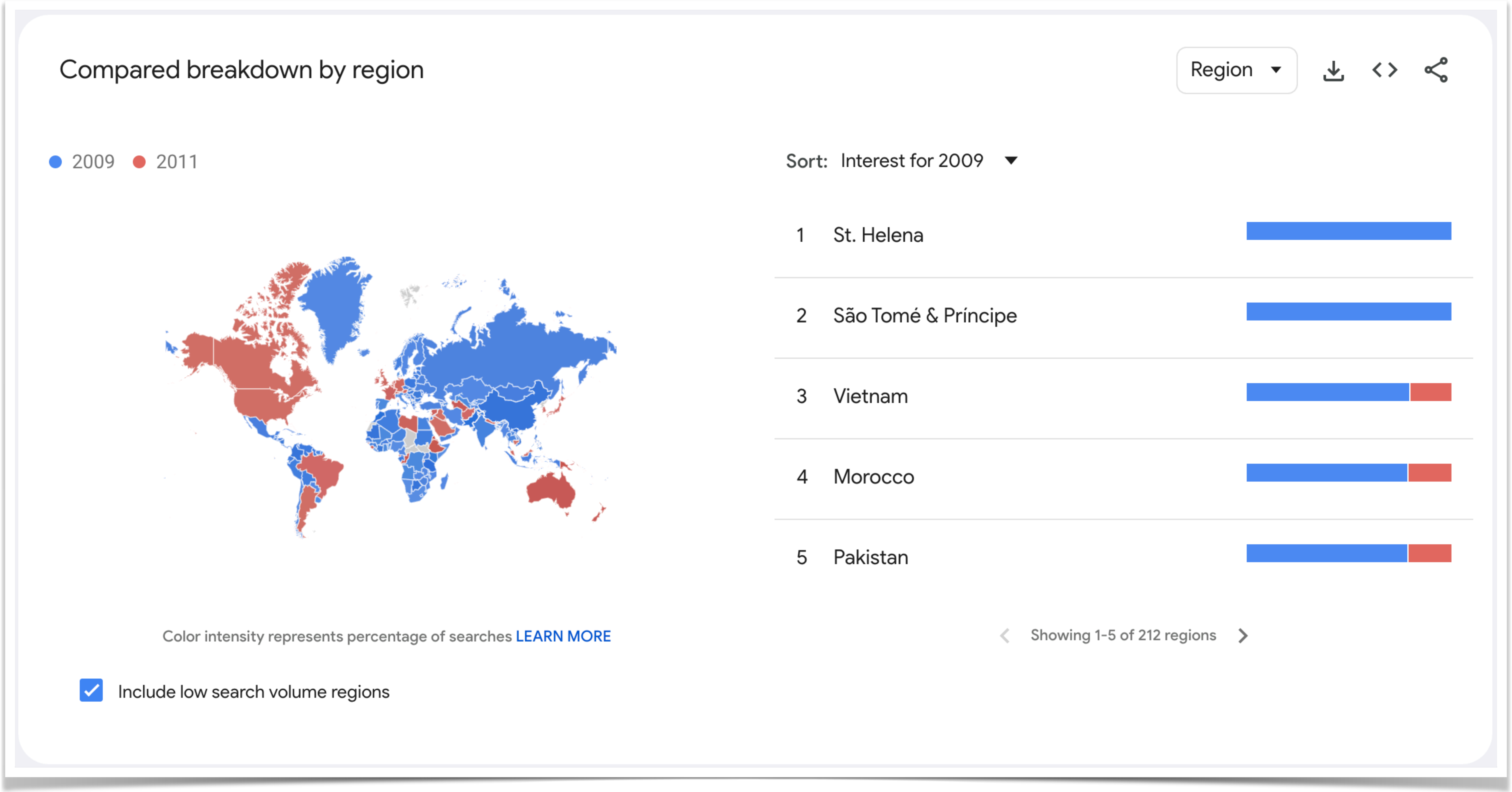

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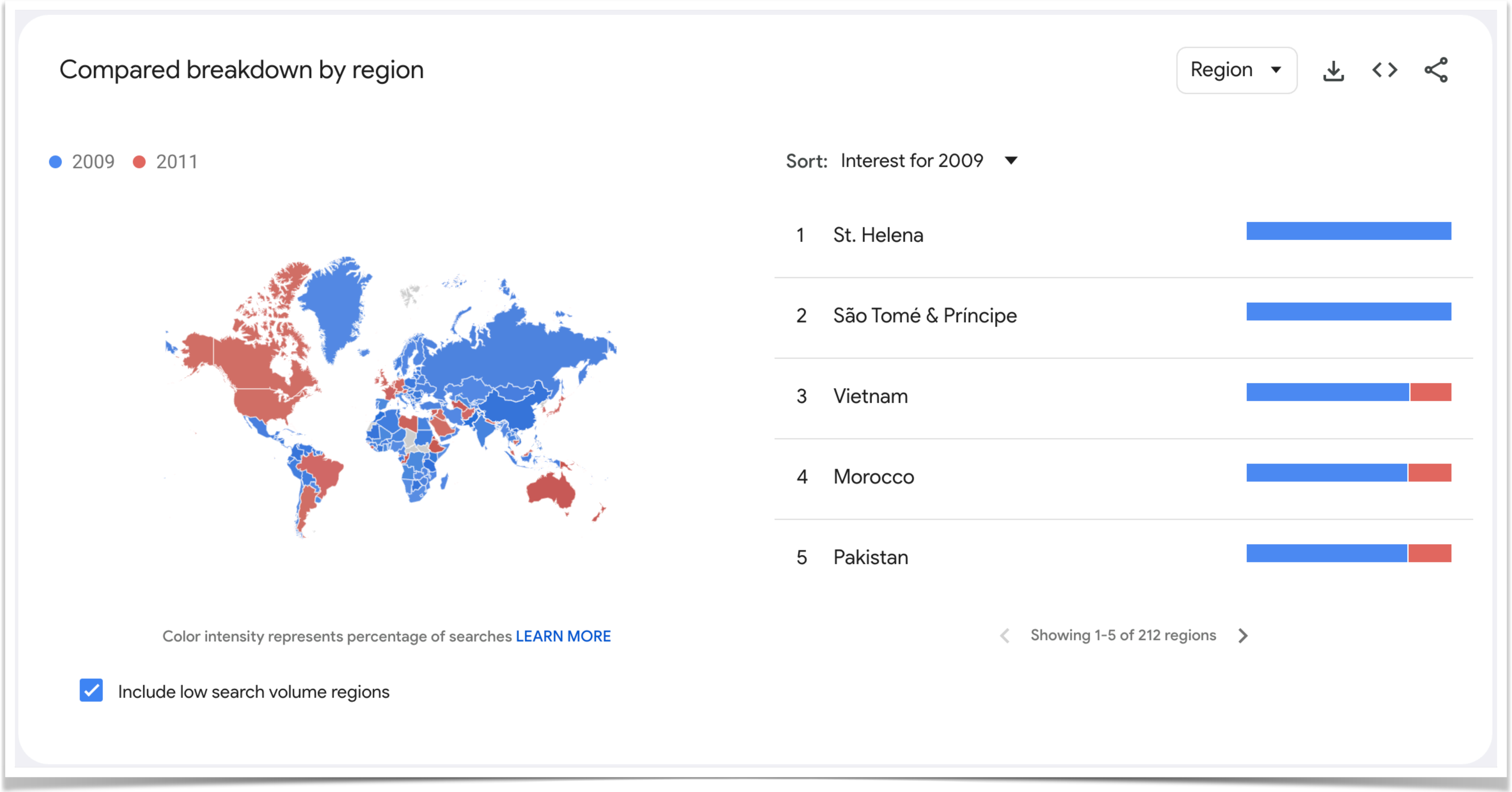

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Cultural?

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So what?

Culture vs. Economy

Long-term orientation by Geert Hofstede

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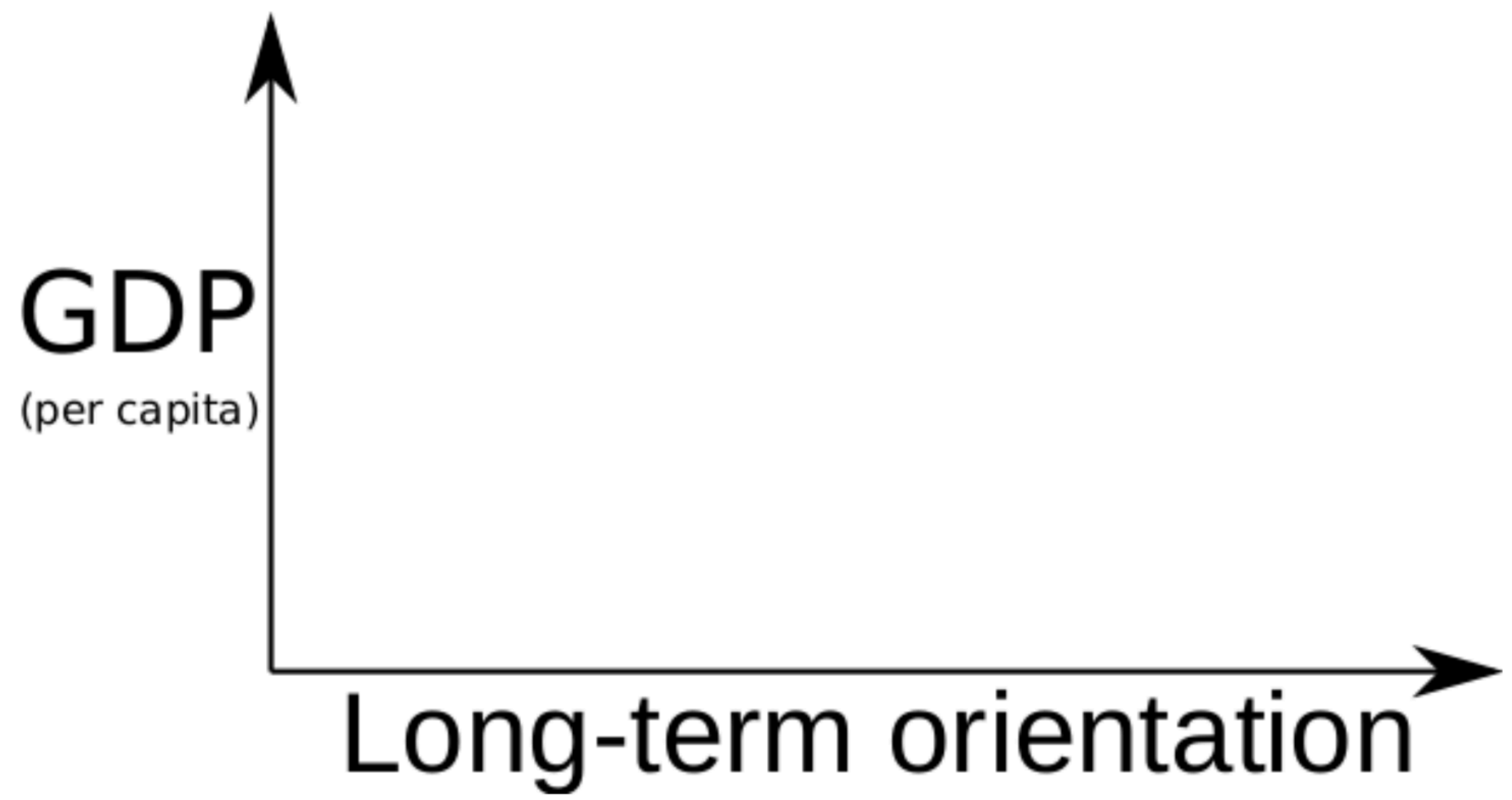

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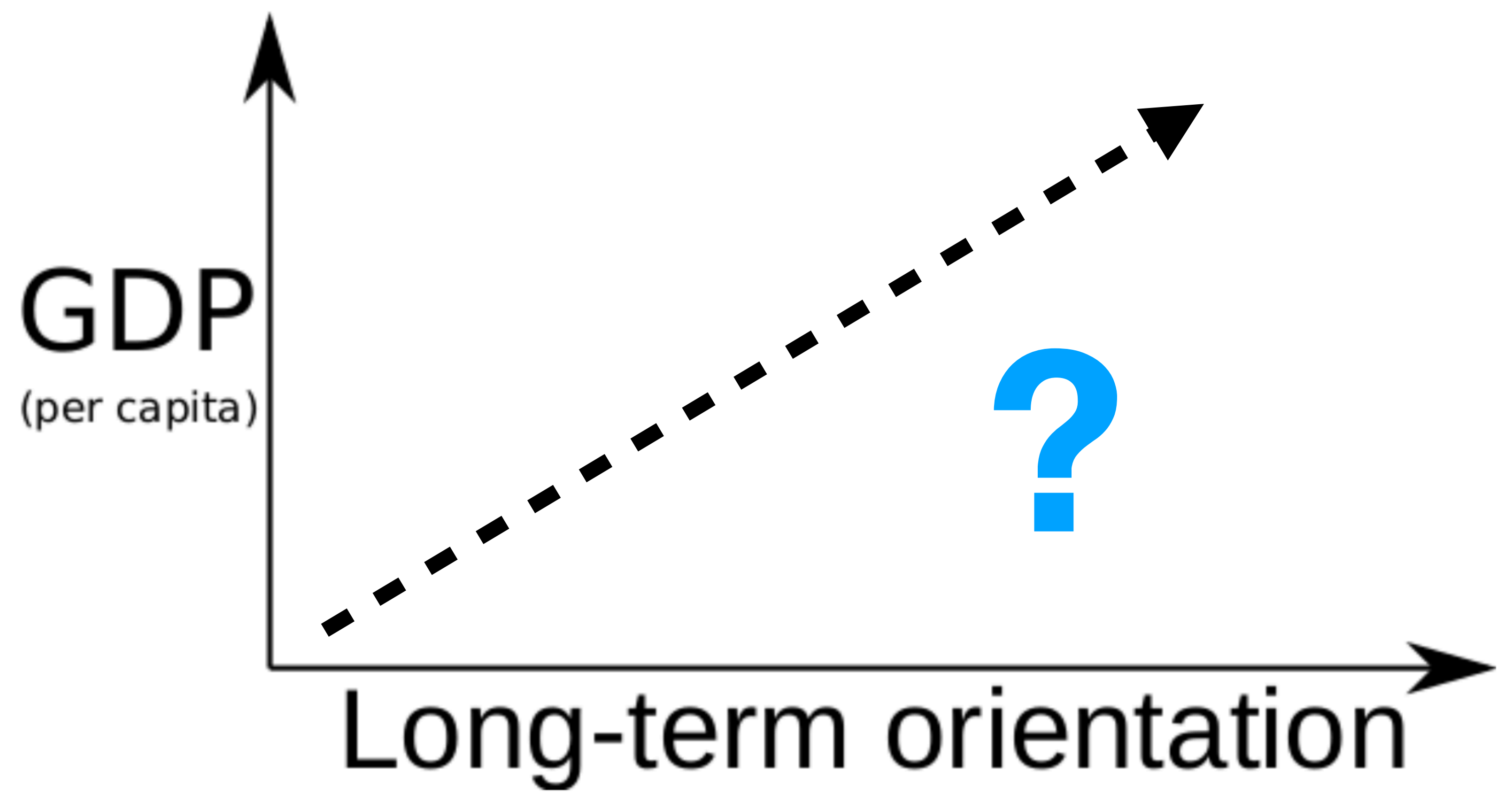

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- In other words: The FOI measures the ratio of search volume within a country for the next year divided by the search volume of the previous year in the same country.
- Using Google Trends, Preis et al. found that **users from countries with a higher GDP (gross domestic product) 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)

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Country Name	GDP_2010	FOI_2010
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GDP: https://wits.worldbank.org/CountryProfile/en/country/by-country/startyear/LTST/endyear/LTST/indicator/NY-GDP-PCAP-KD

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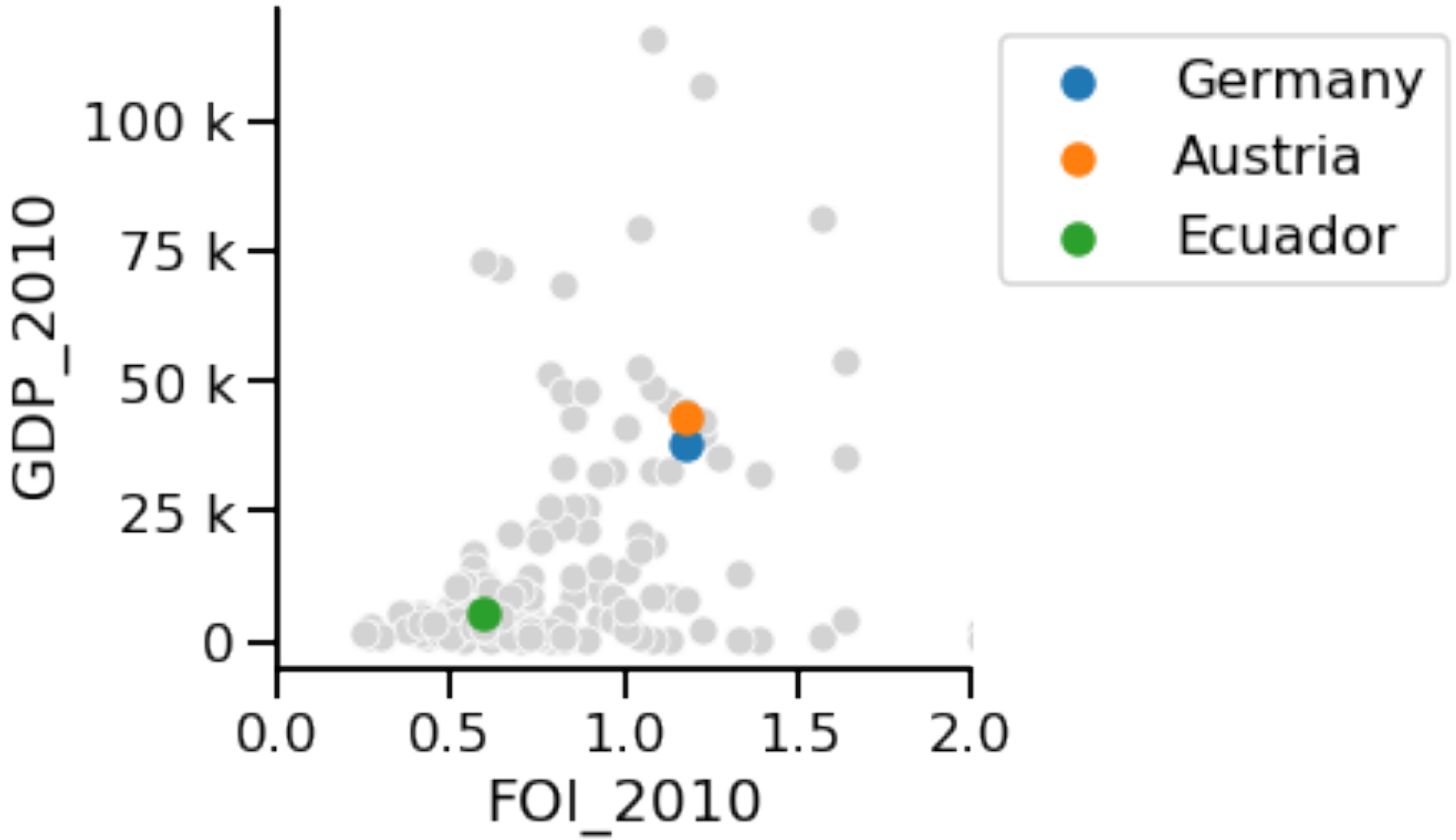

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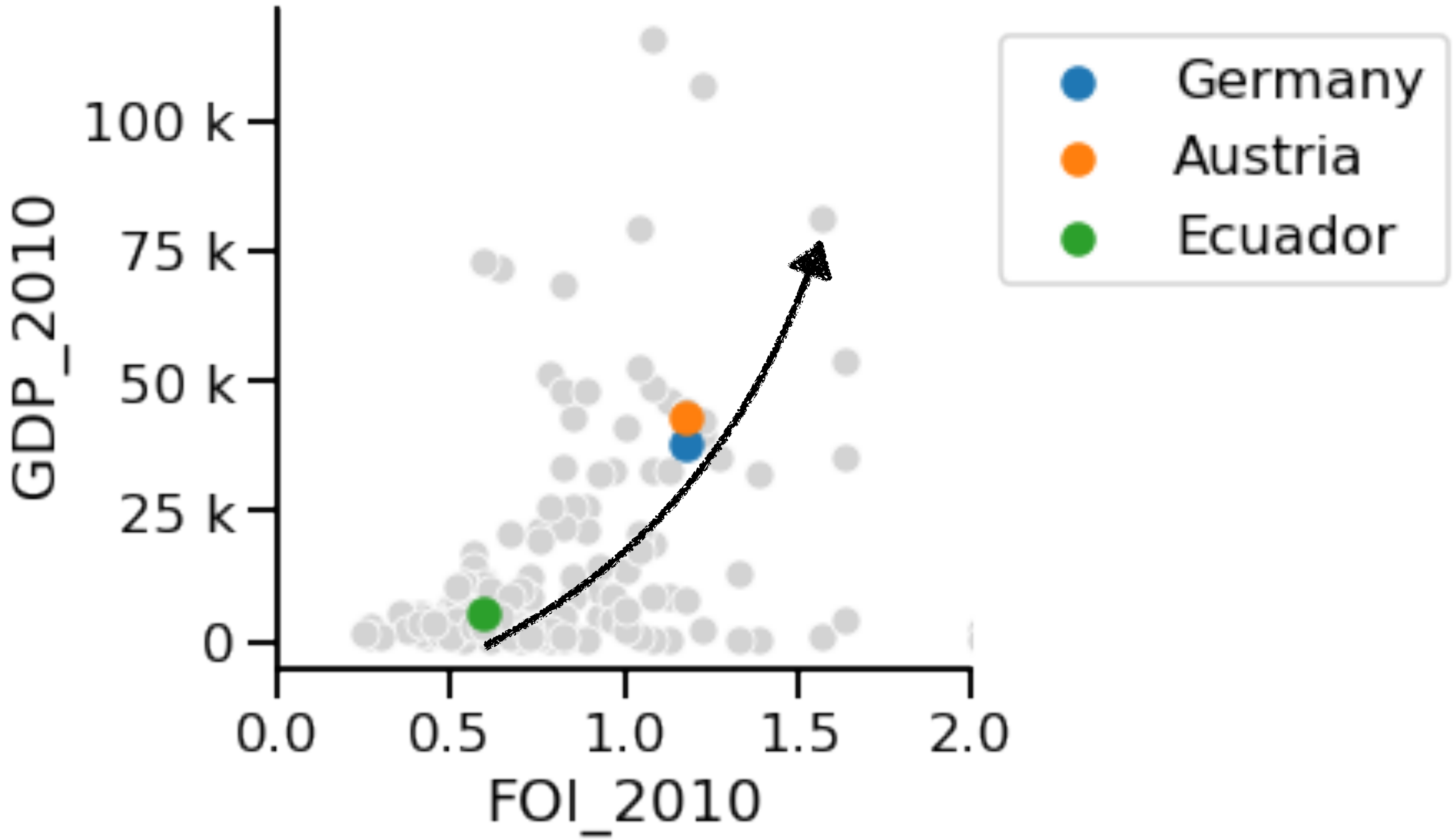

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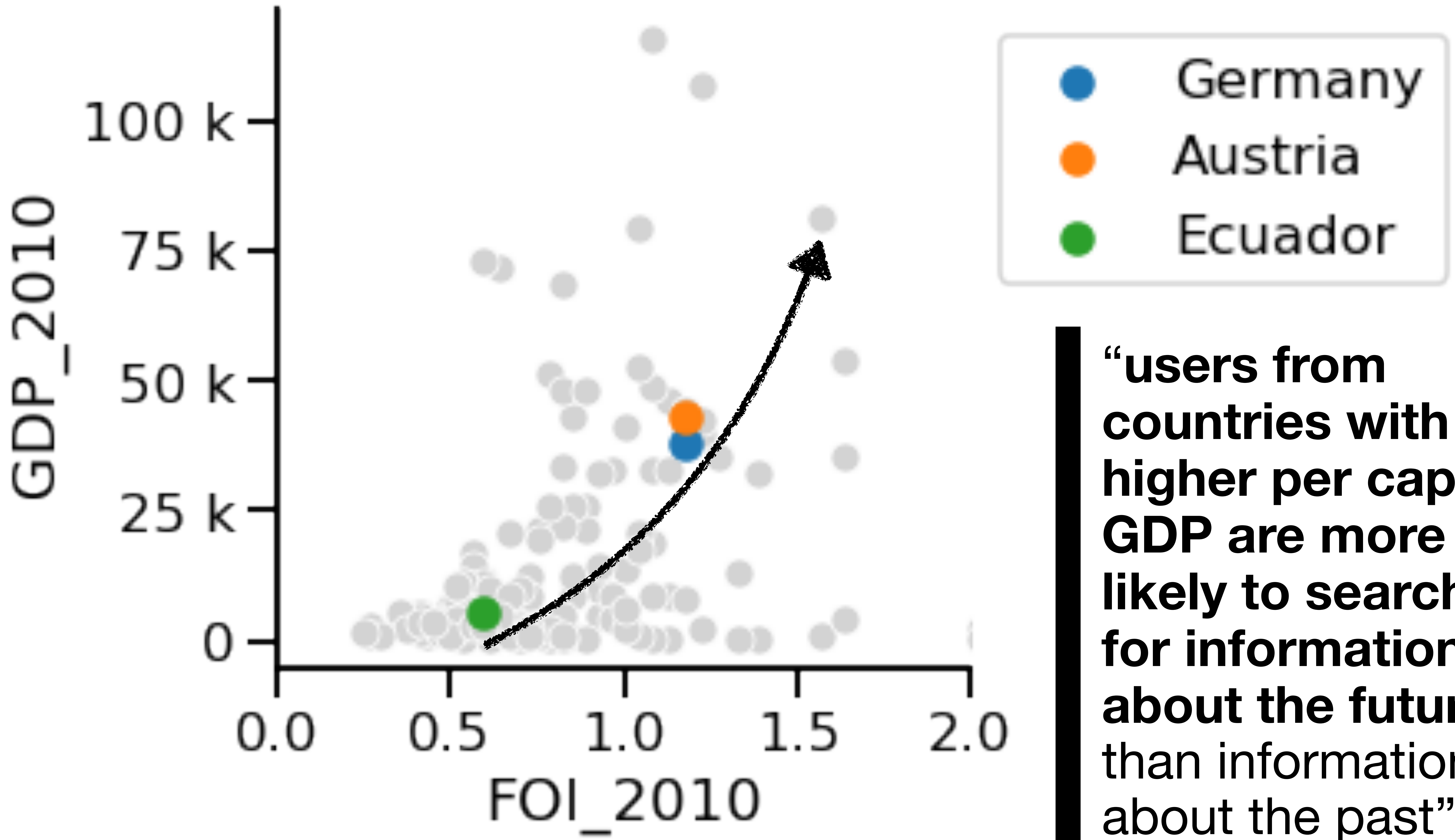

"users from countries with a higher per capita GDP are more likely to search for information about the future than information about the past"
Preis et al. 2012

Examples of FOI

Replicating results from Preis et al. 2012

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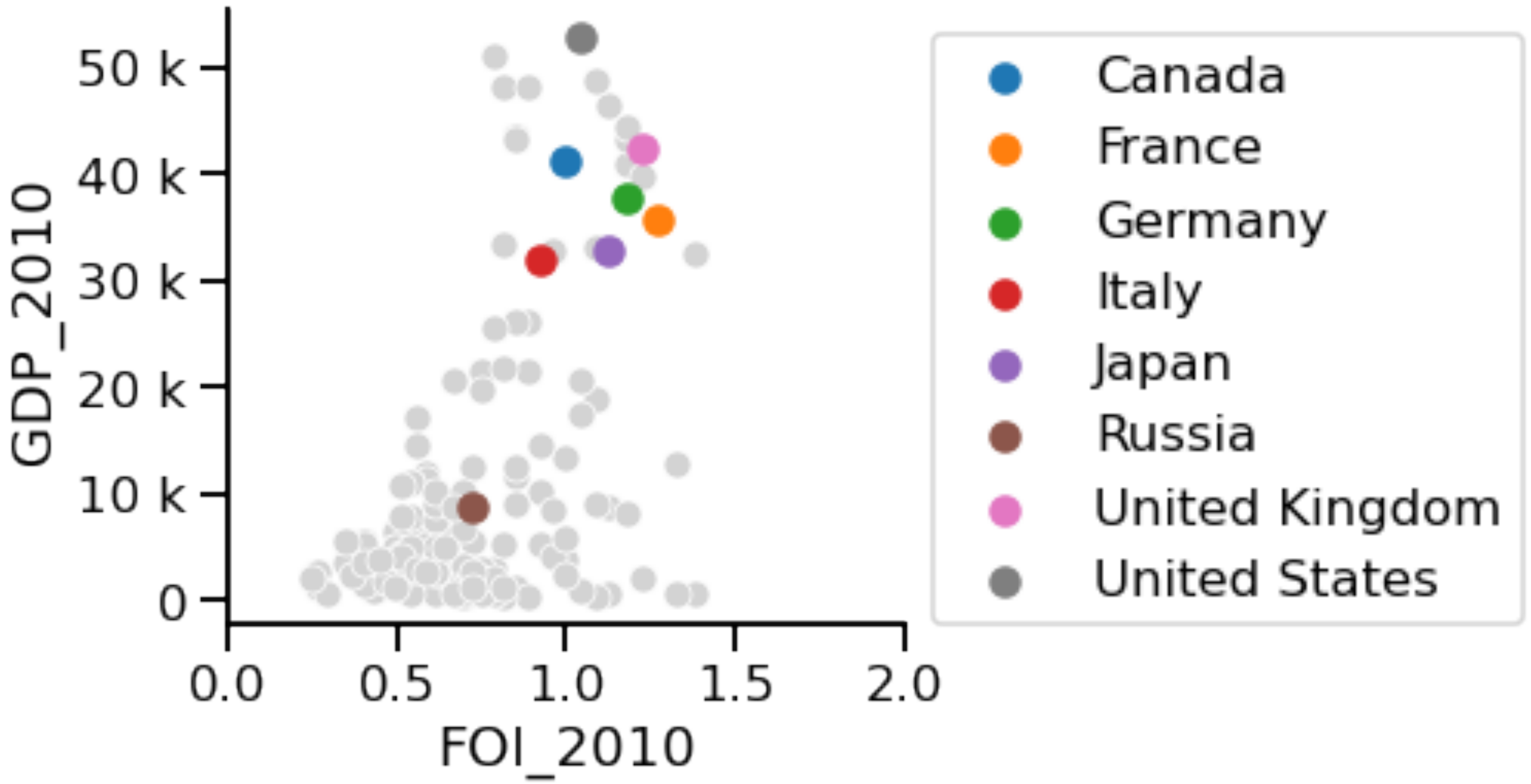

My replication
140 countries

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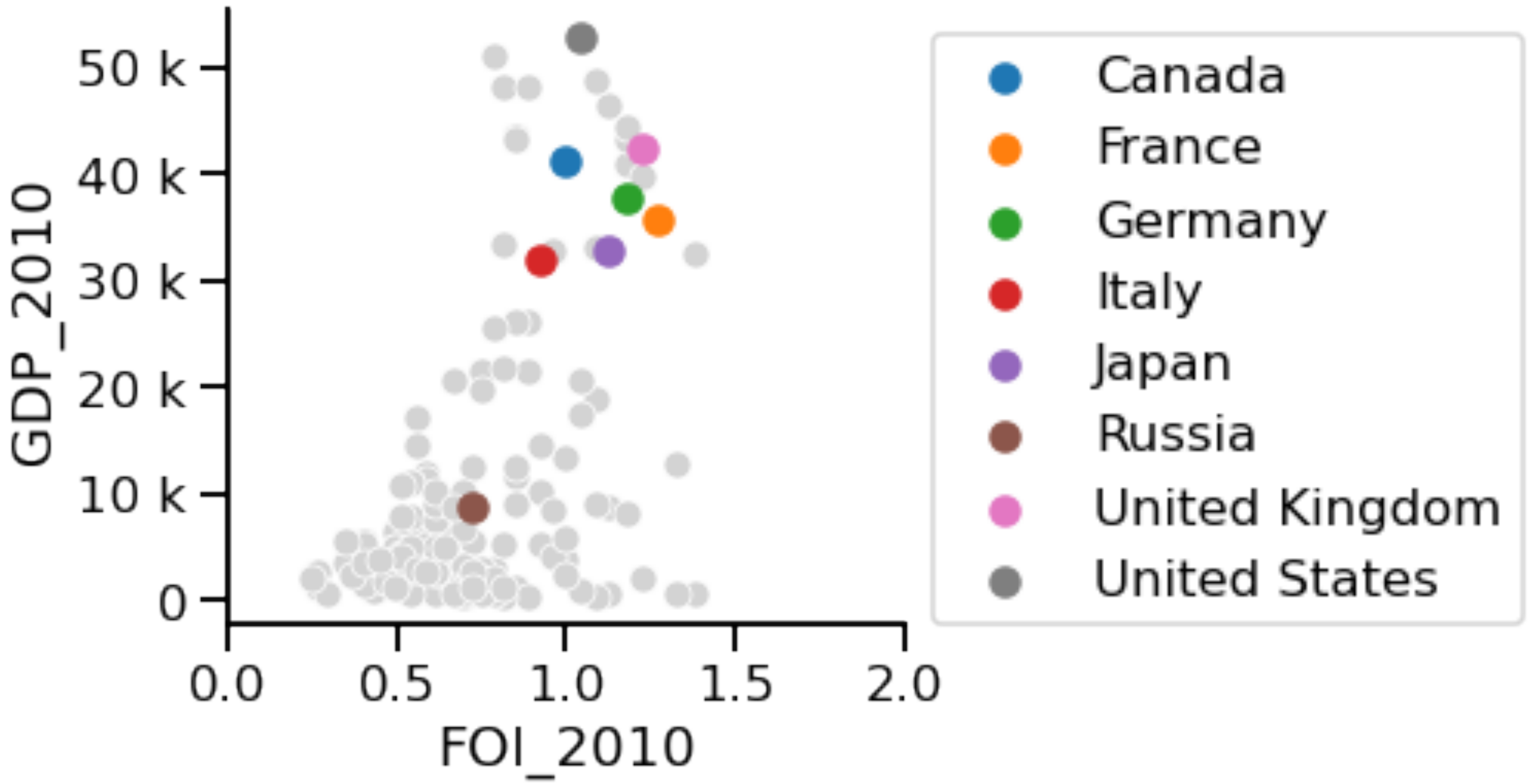

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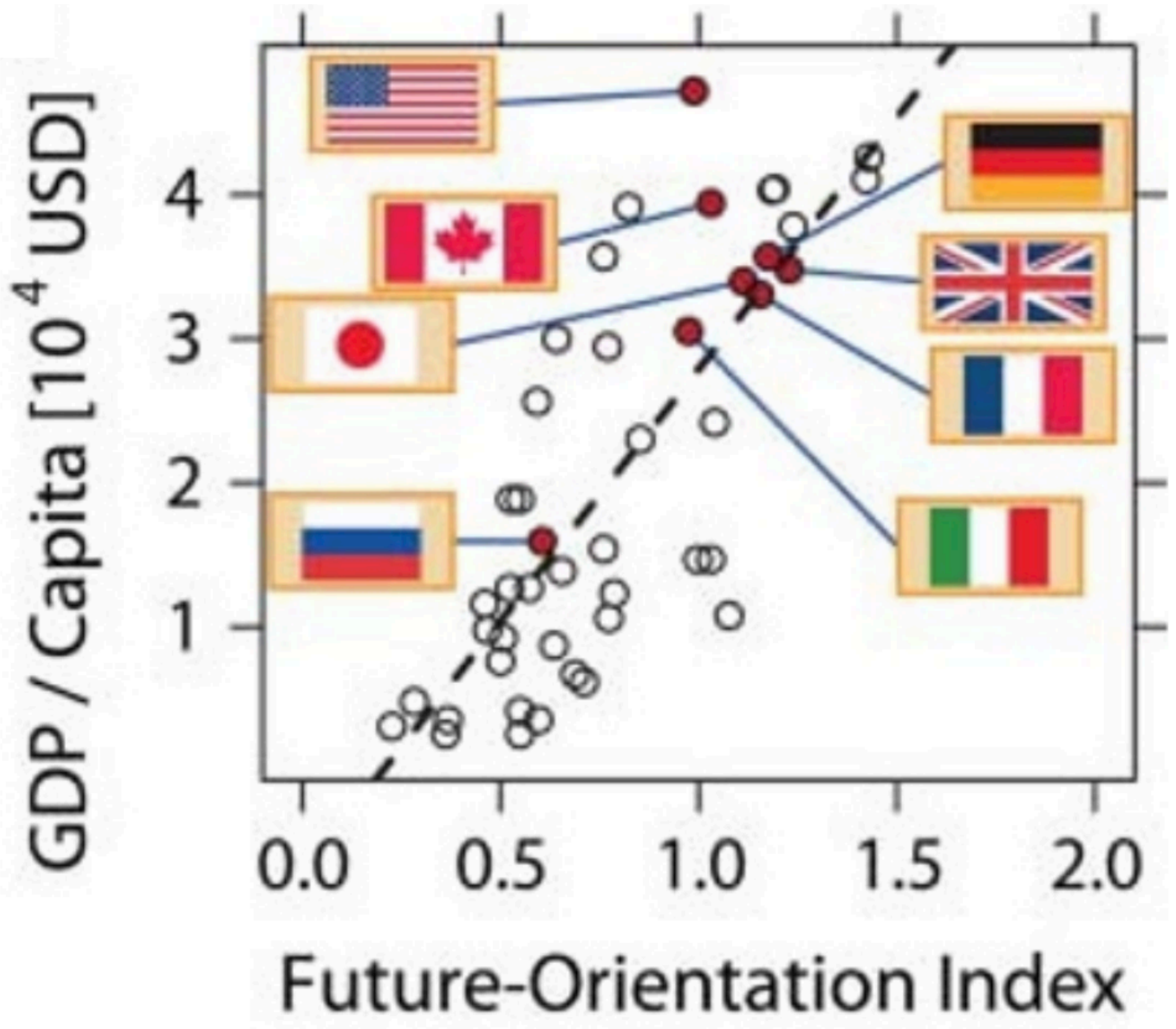

Preis et al. 2012
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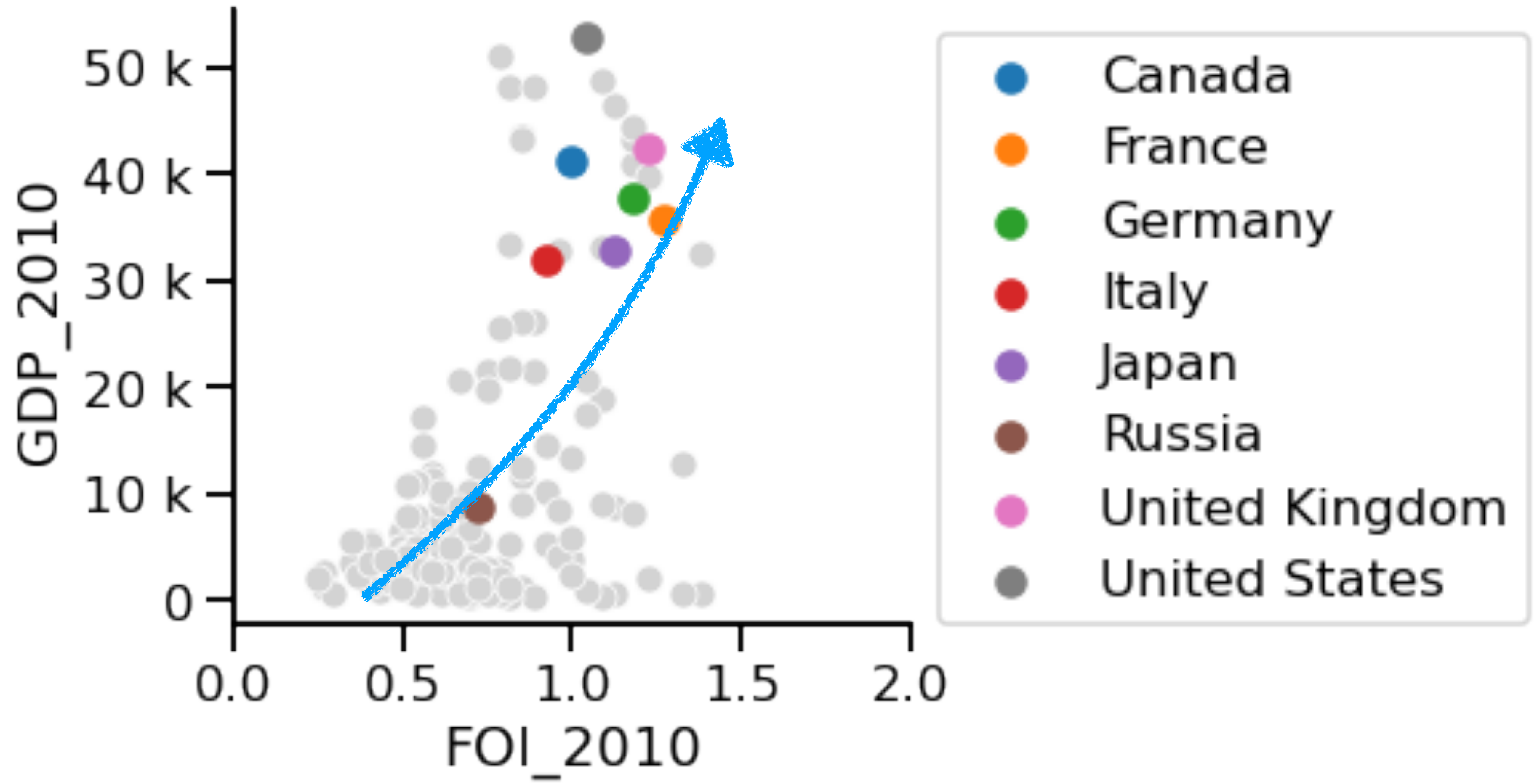

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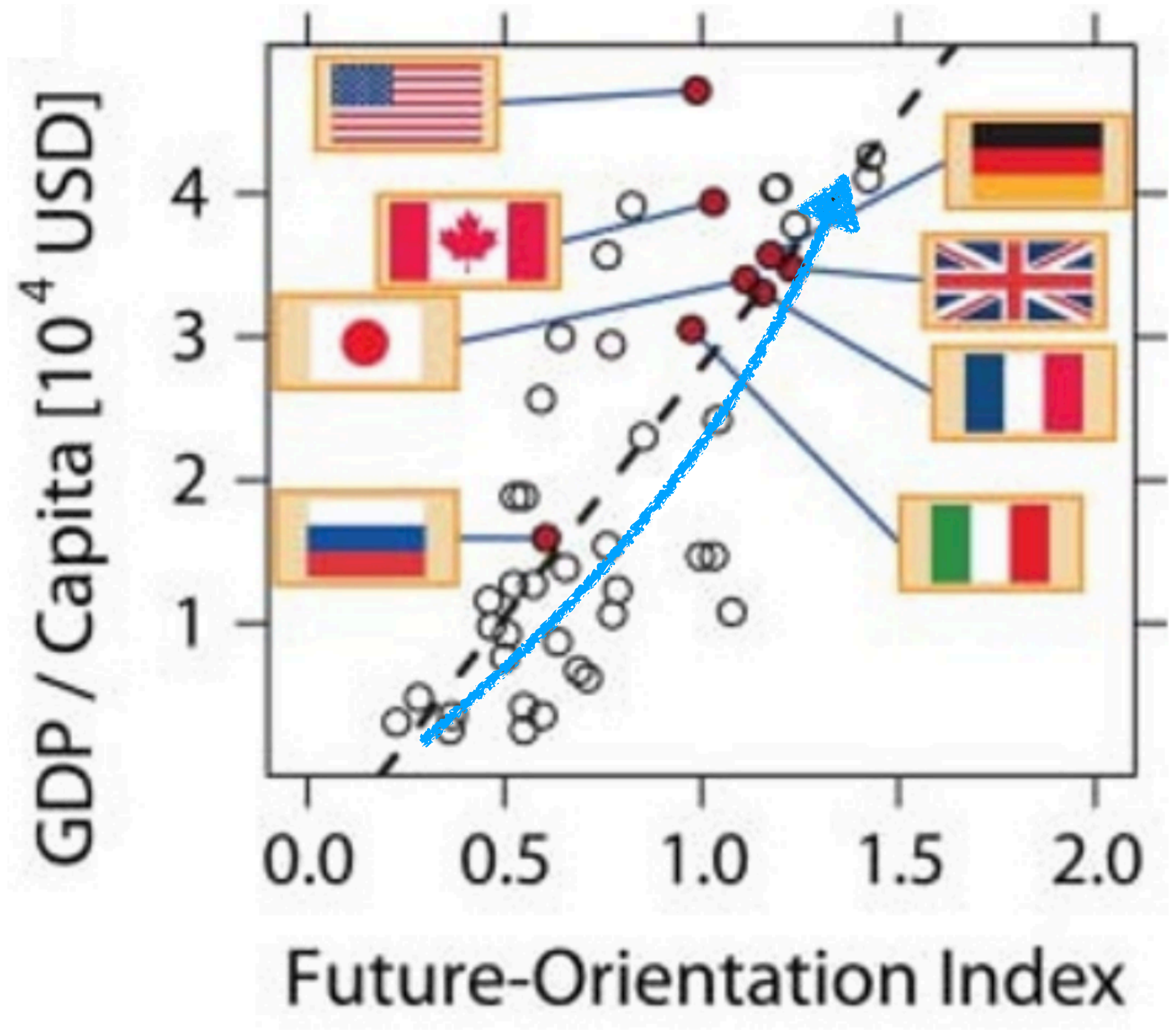

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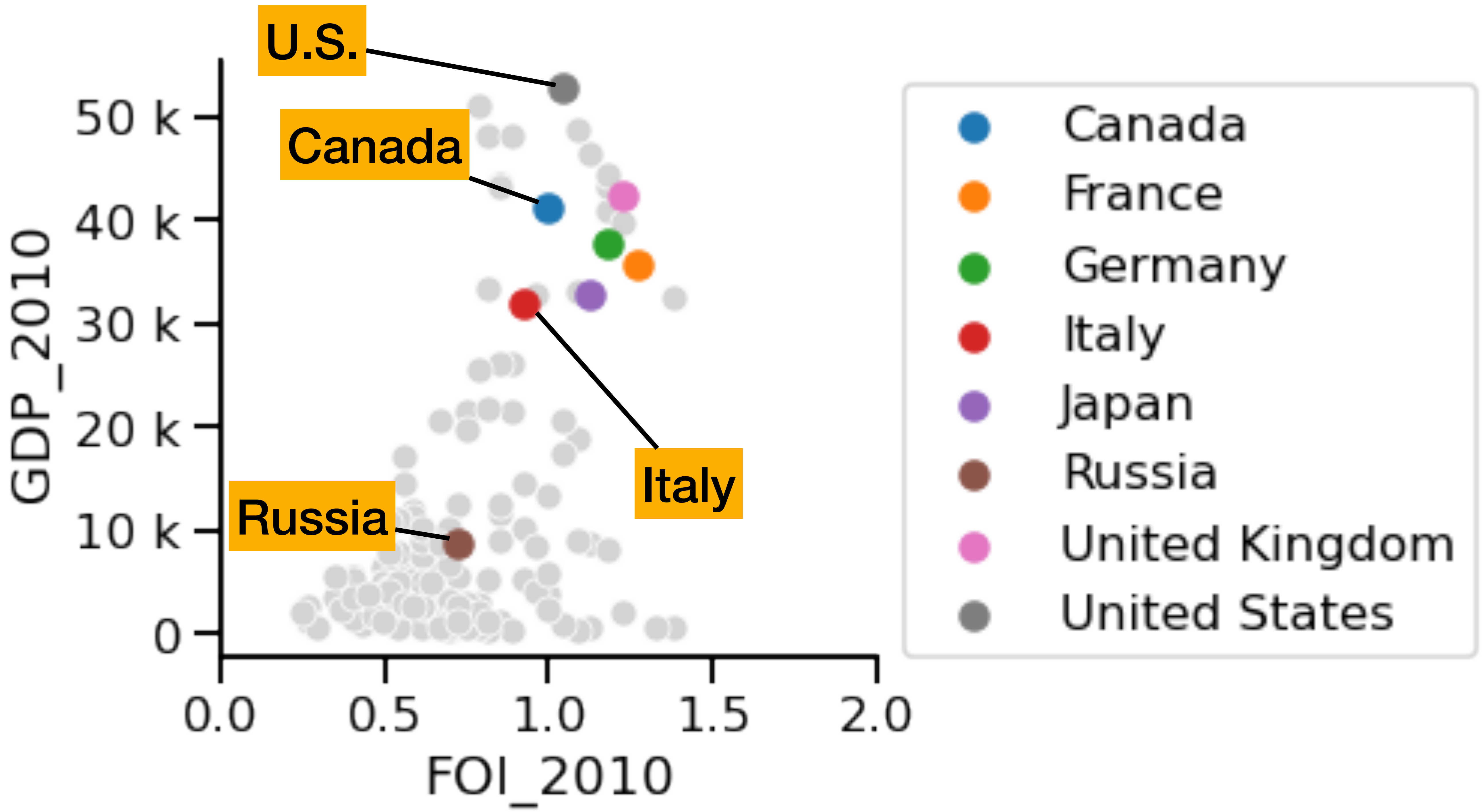

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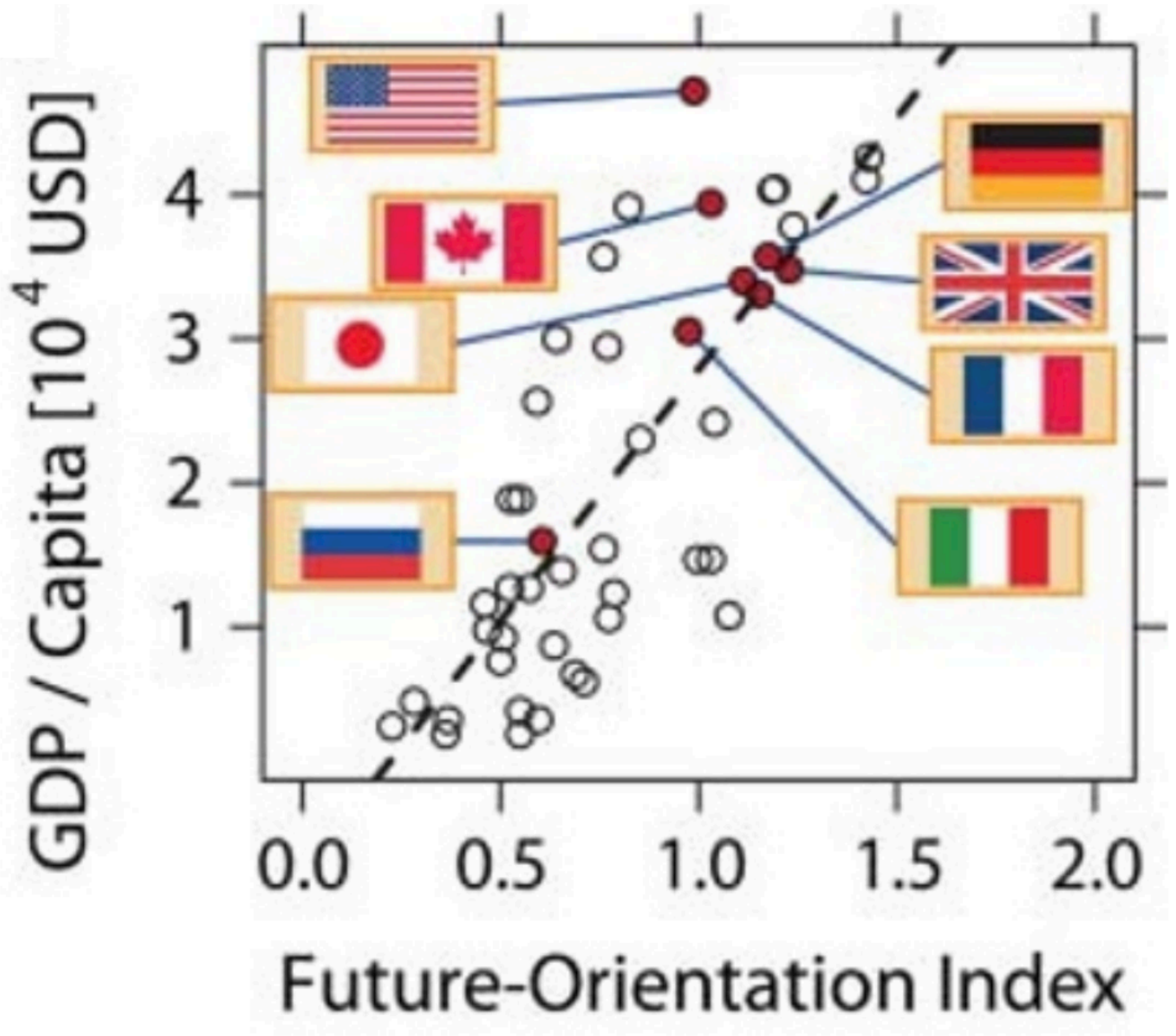

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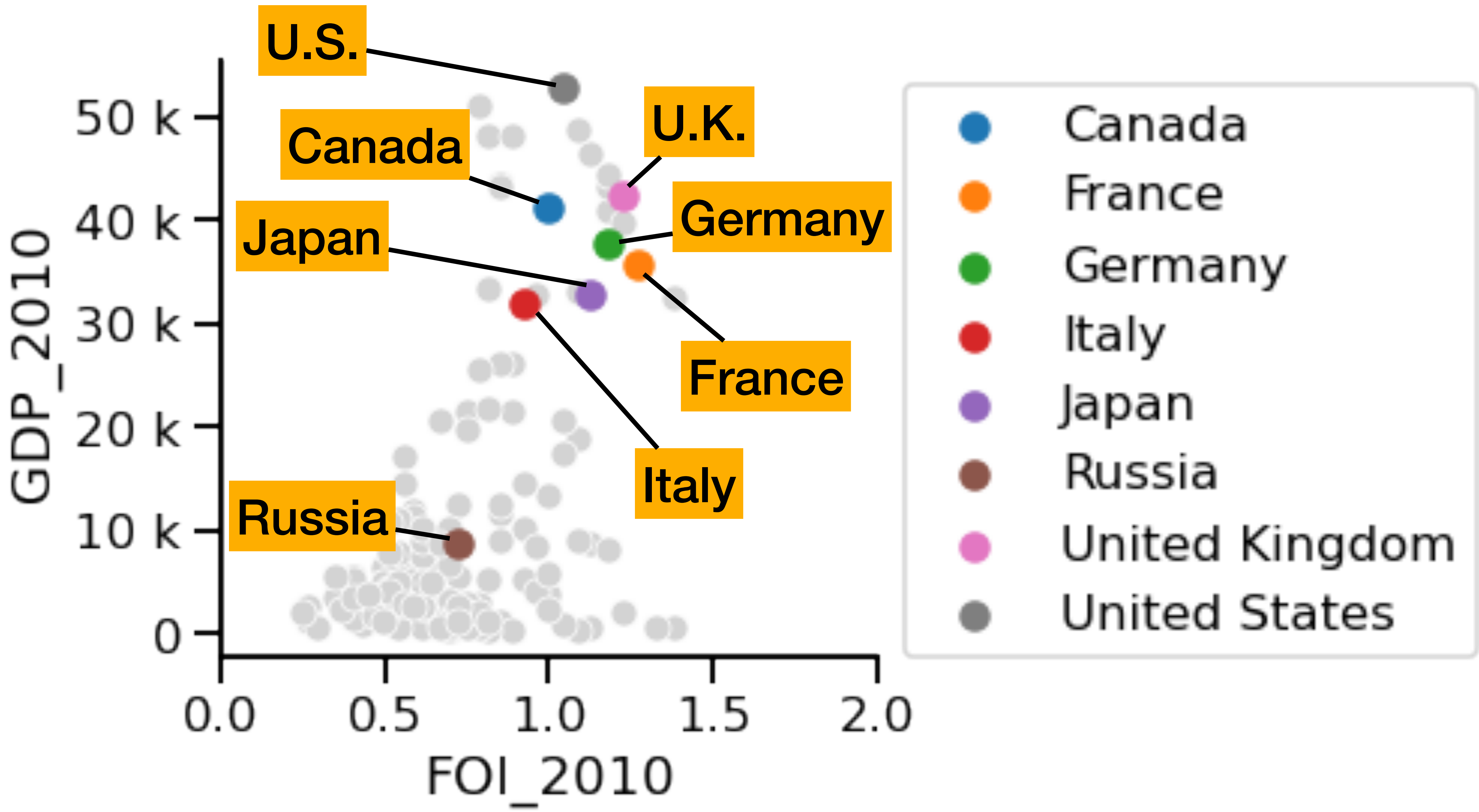

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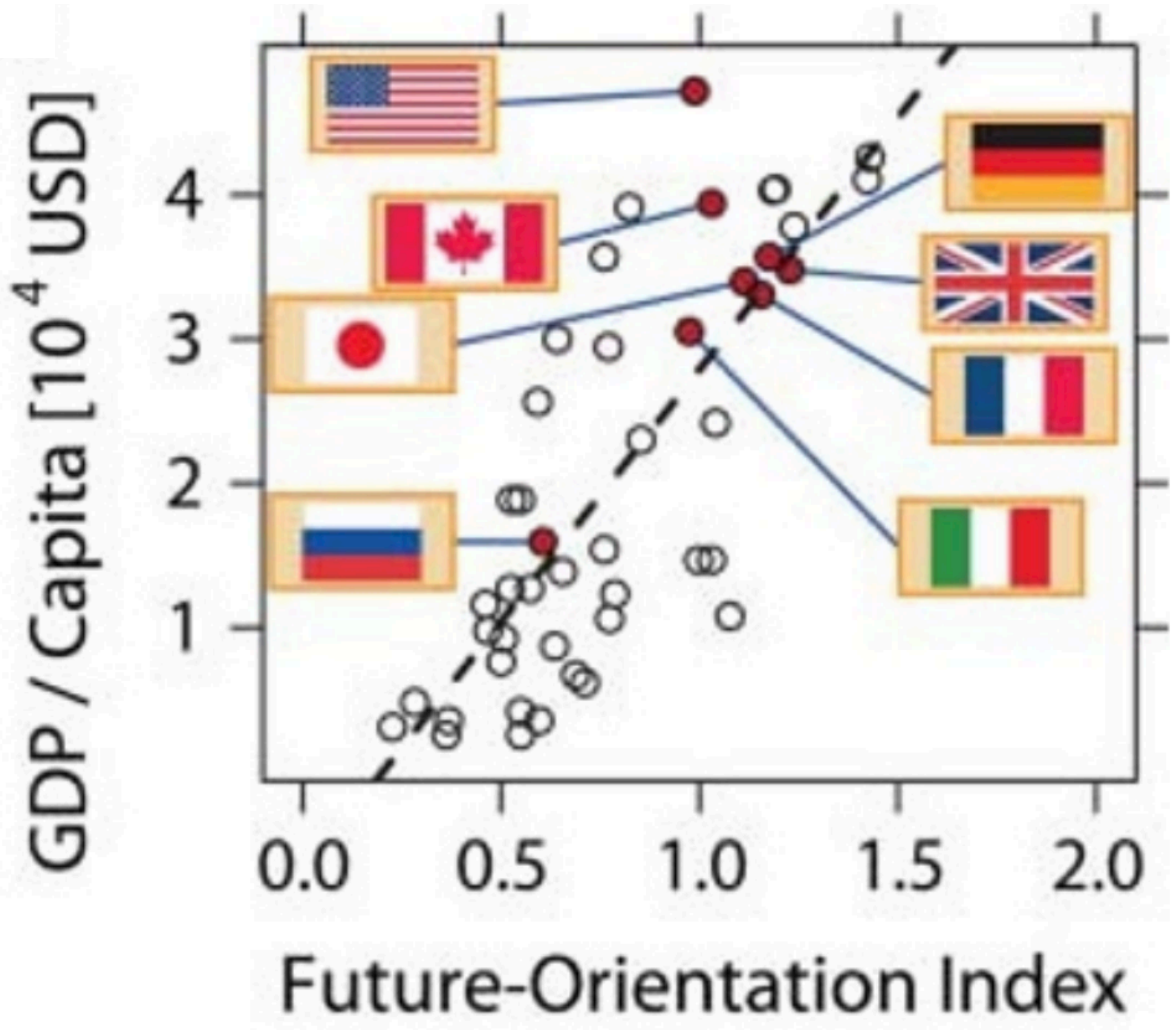

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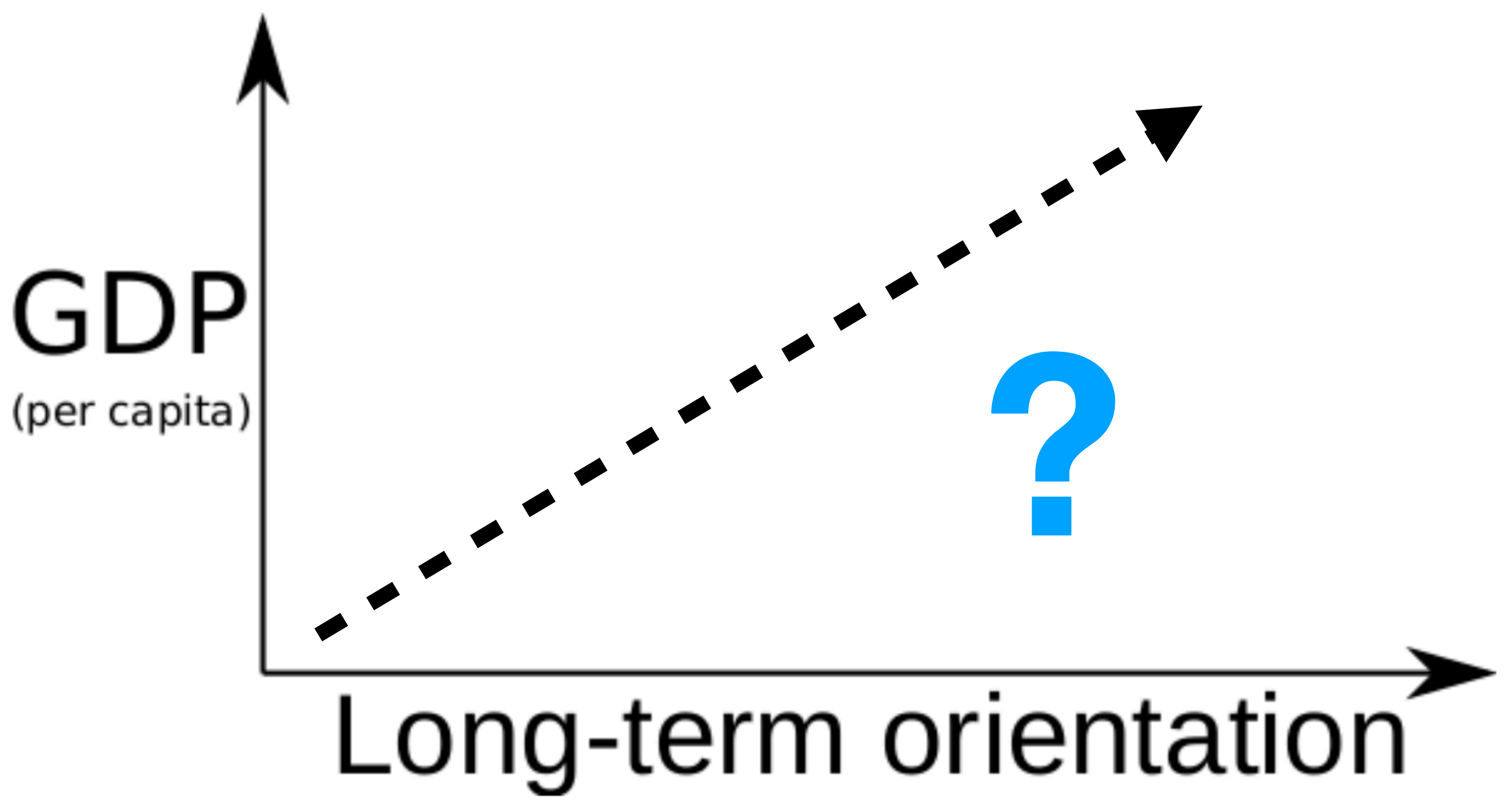
Can this relationship (pattern) be numerically measured?



Outline

Today's class

BLOCK 1	BLOCK 2	BLOCK 3	BLOCK 4
Social Behavior	Social Trends	Quantifying Trends	Behavior & Trend Dynamics
1. Social Science 2. CSS 3. Digital Traces 4. Examples	1. Google Search Trends 2. The Future Orientation Index 3. Culture and Economy	1. Correlation 2. Causation 3. Regression	1. The Theory of Fashion 2. The Endo-Exo model 3. Examples

Measuring Correlation

What is correlation?

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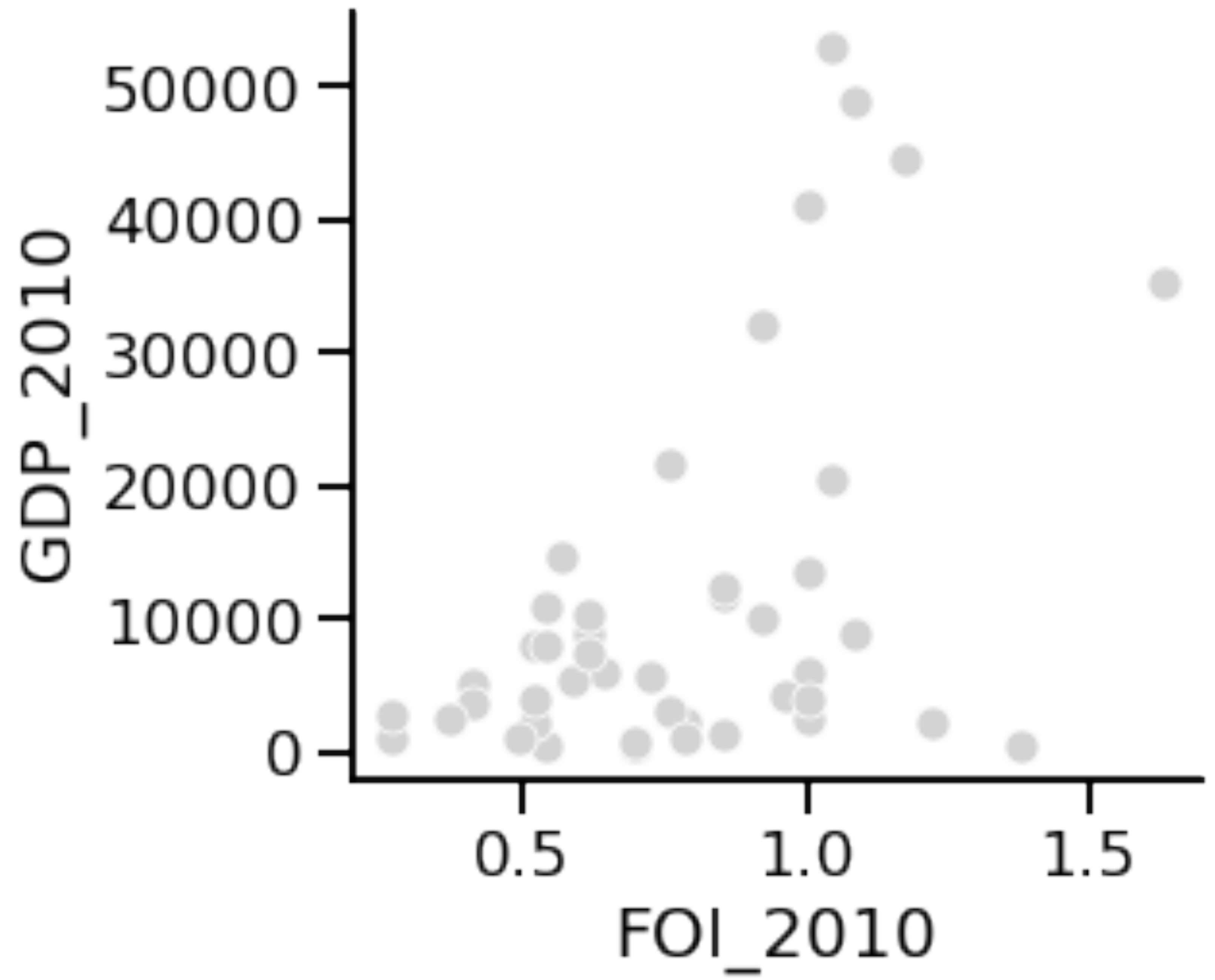

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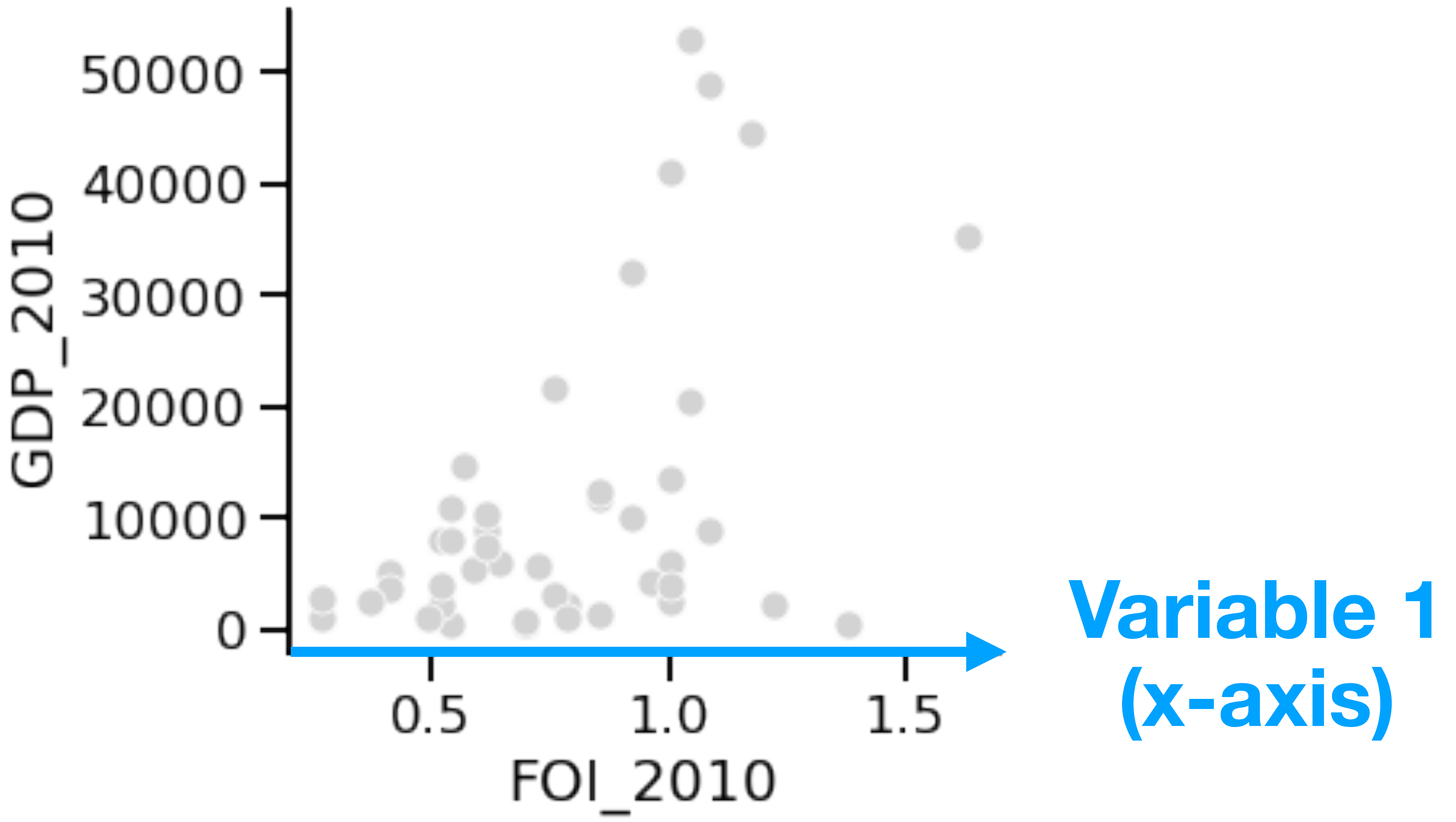

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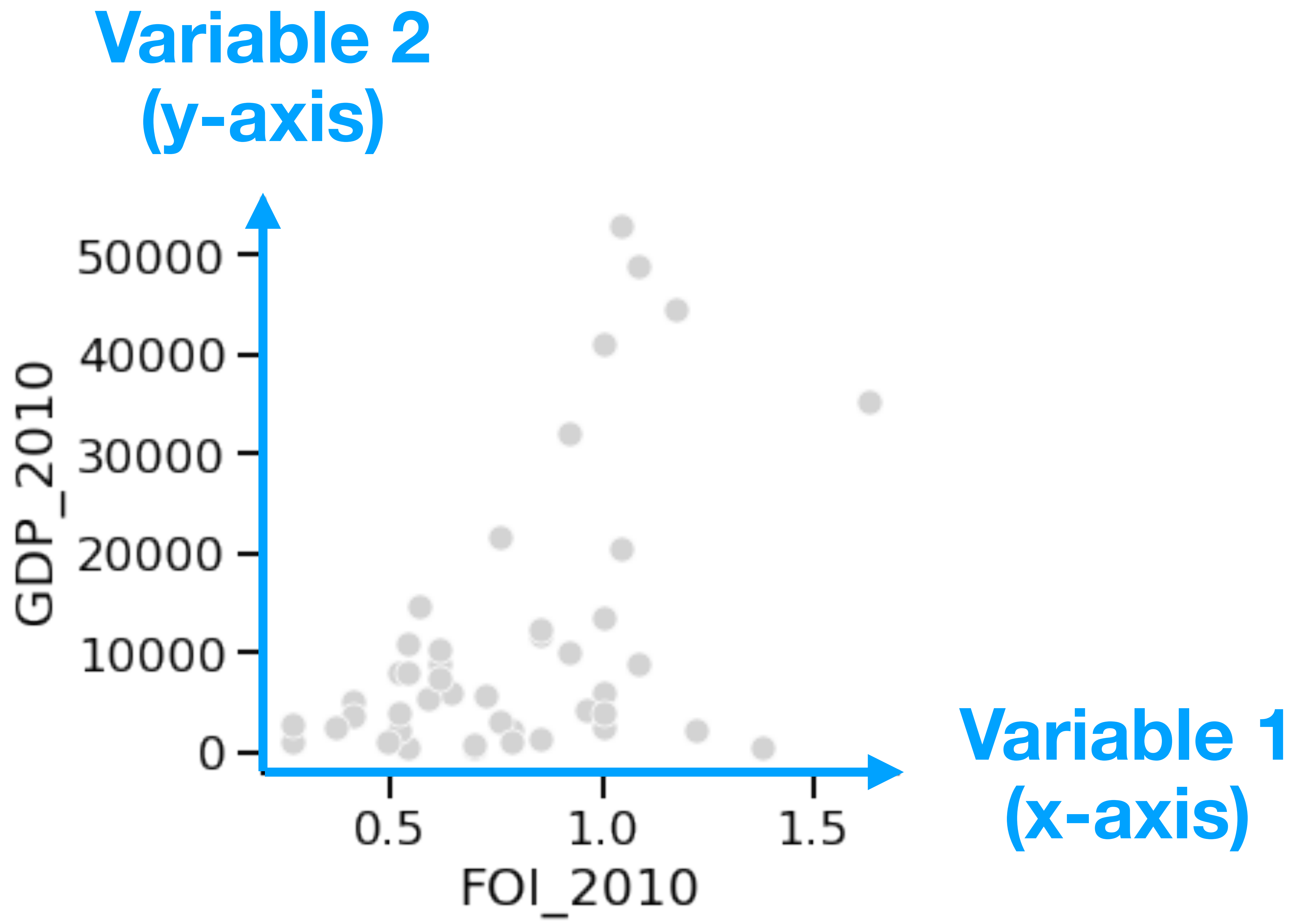

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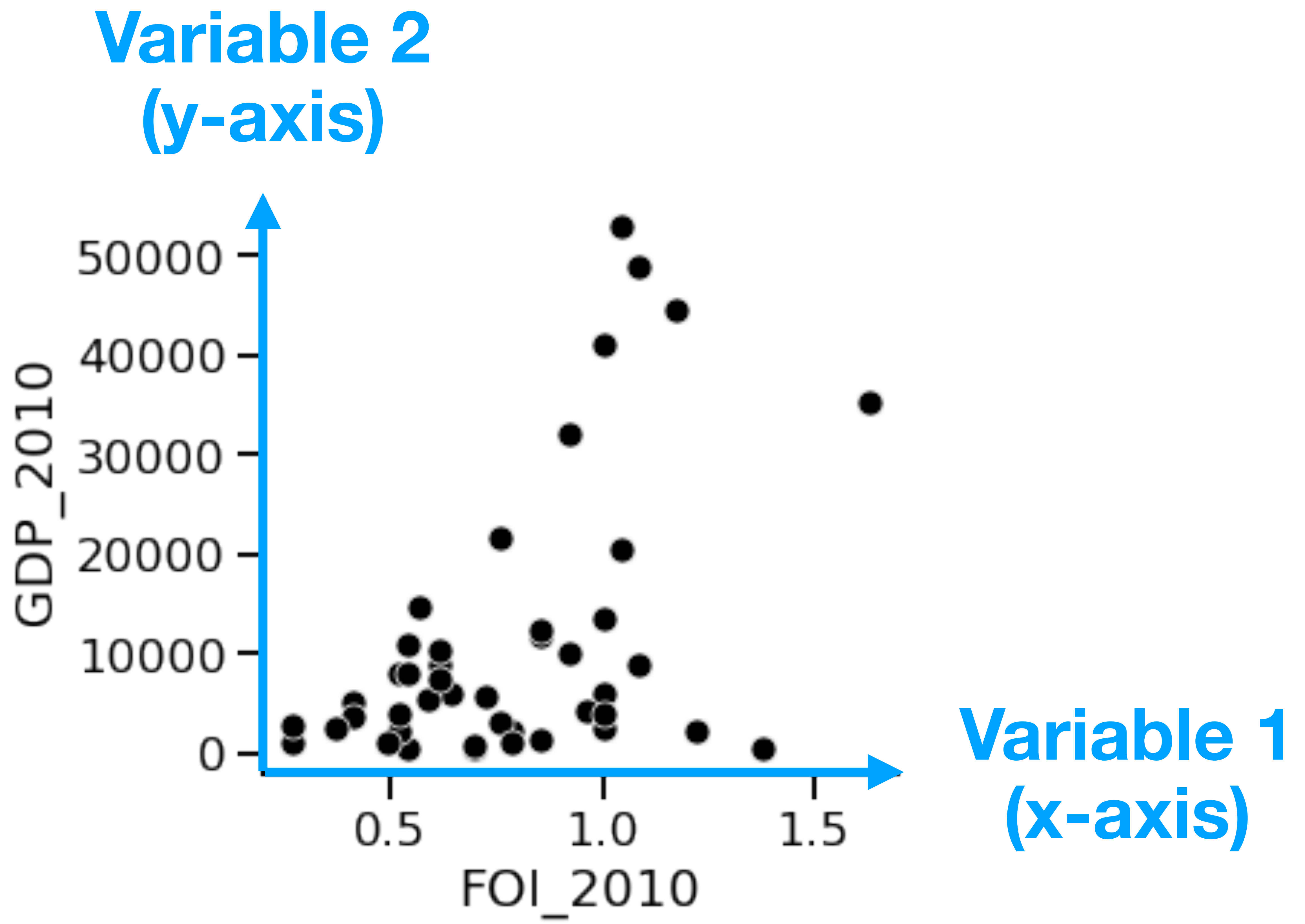

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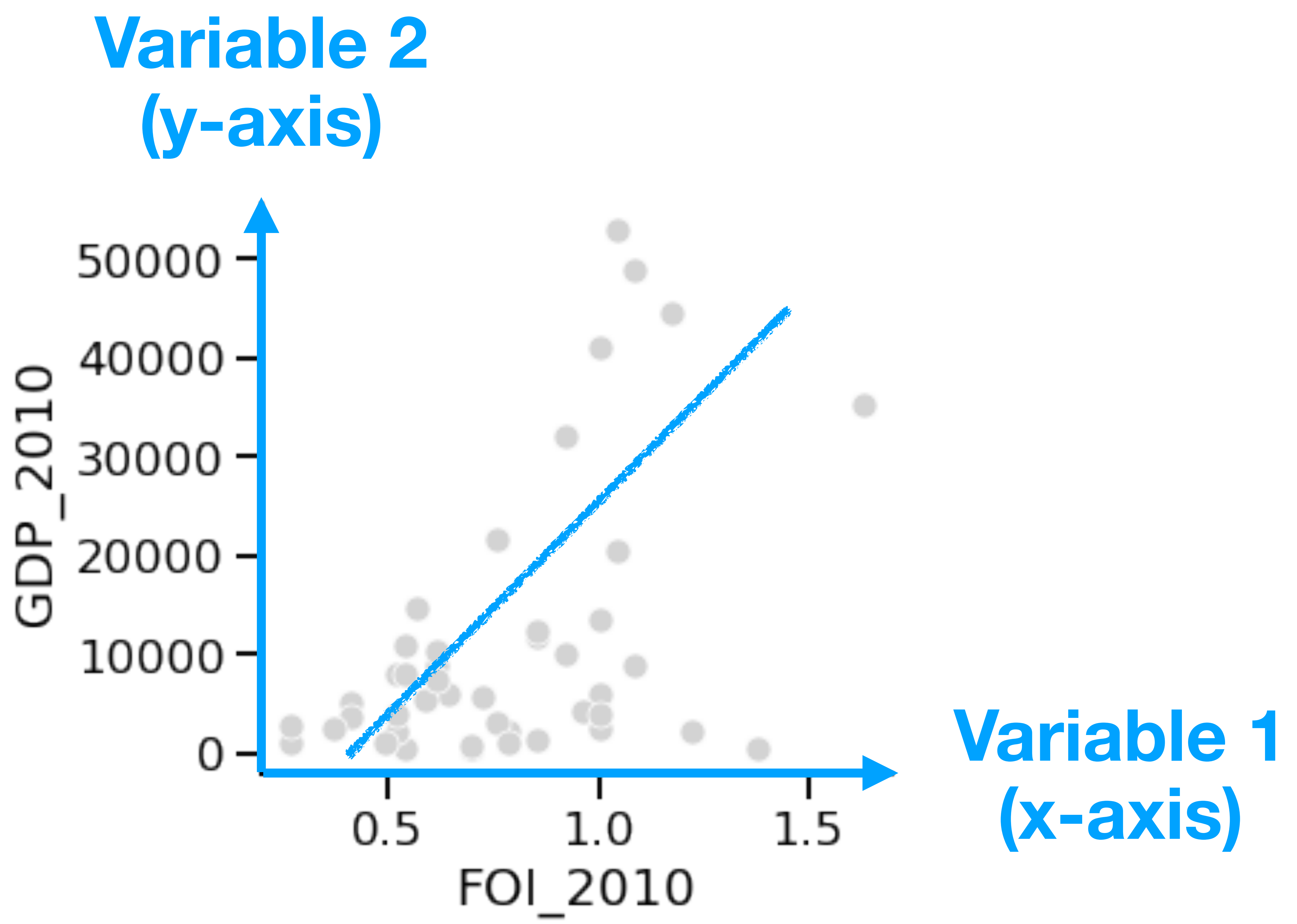

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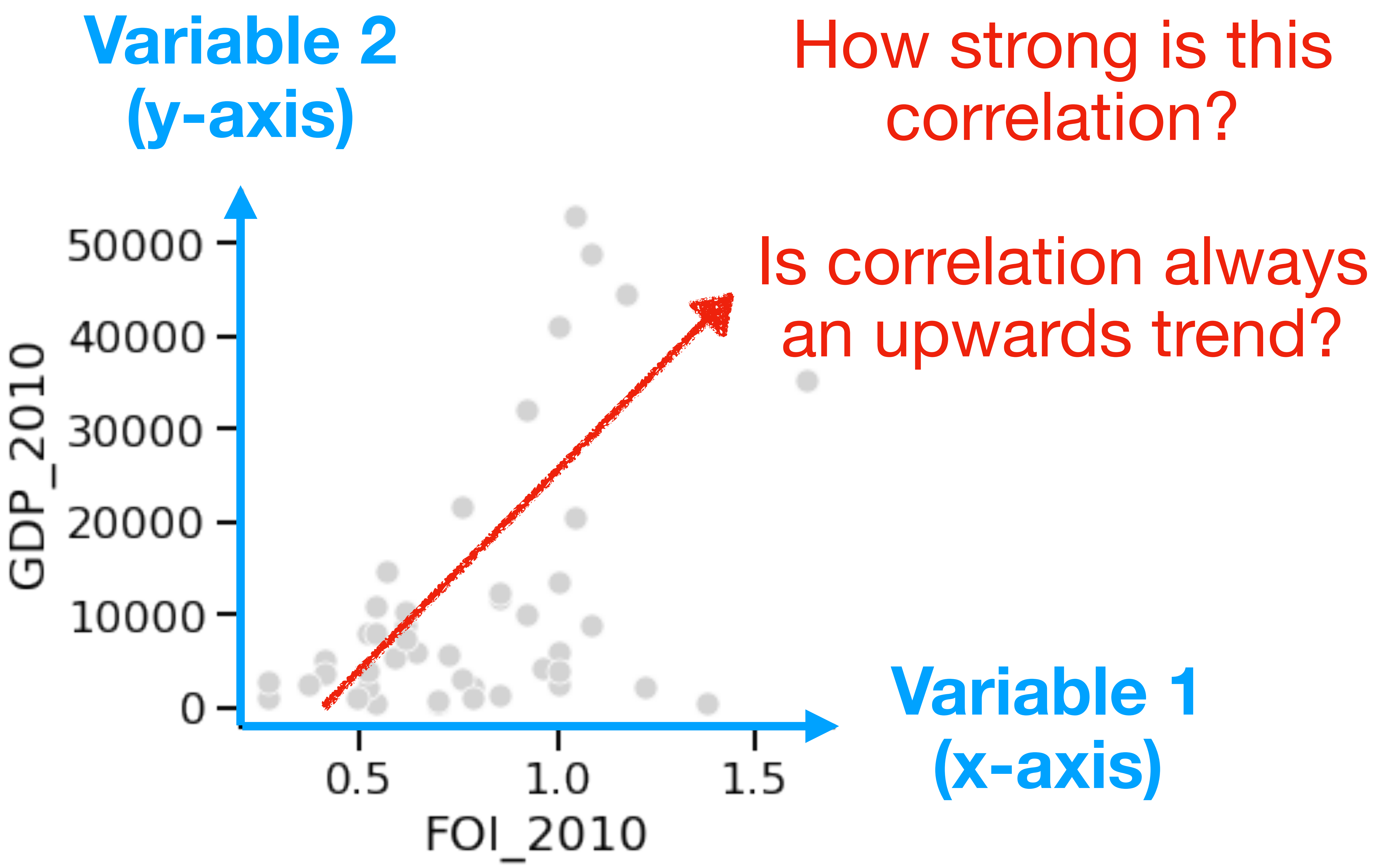

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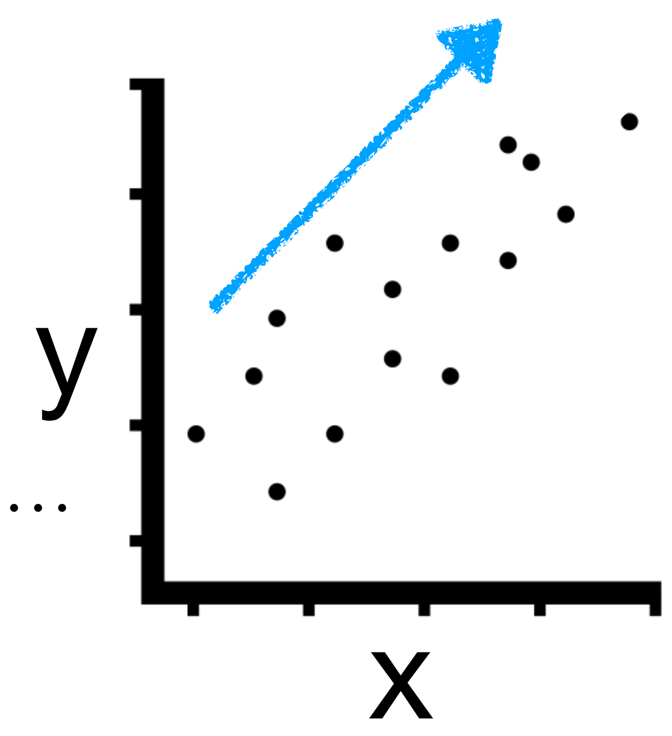

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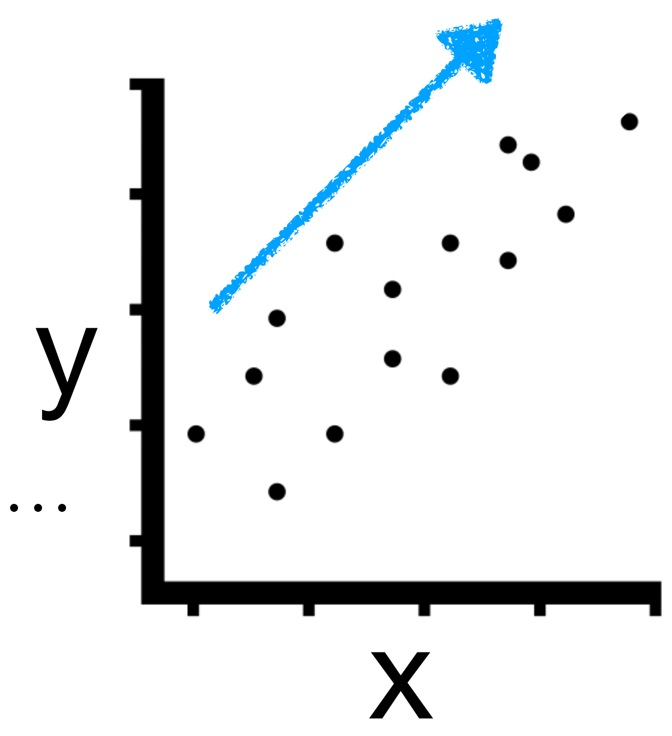

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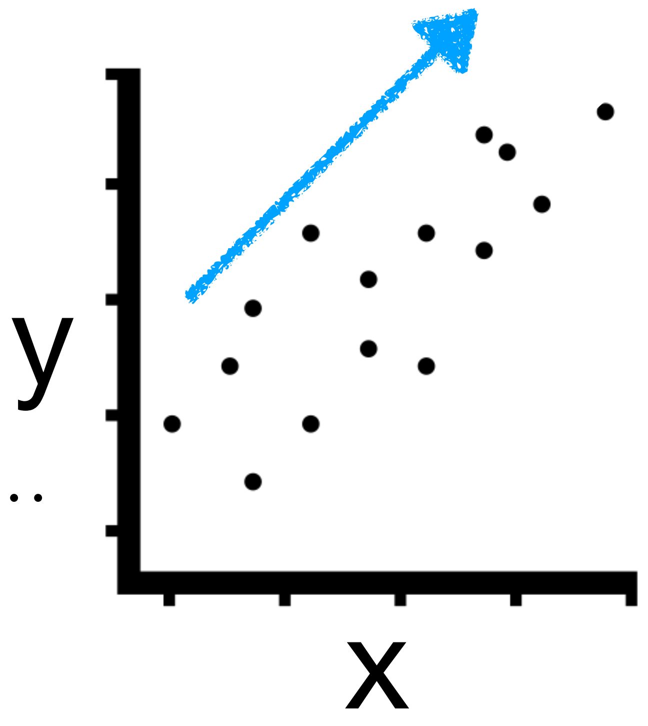

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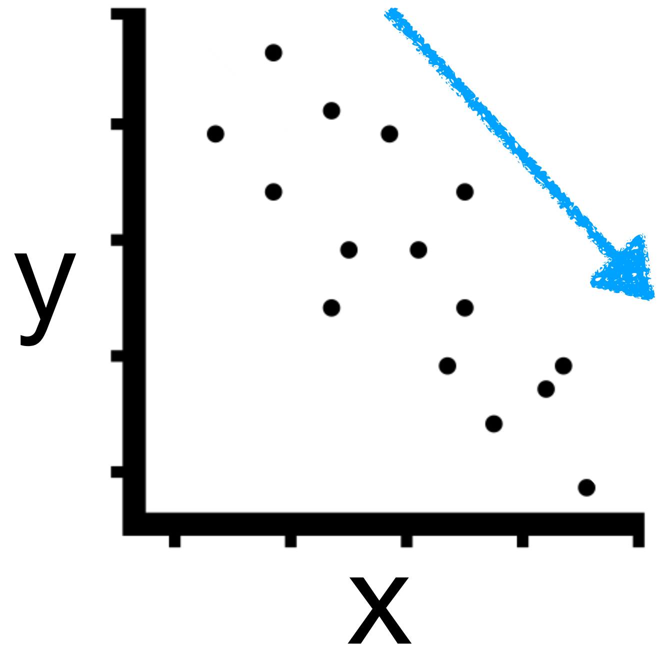

Types of correlation

Direction of the trend

Correlation also measures the **direction** of the relationship:

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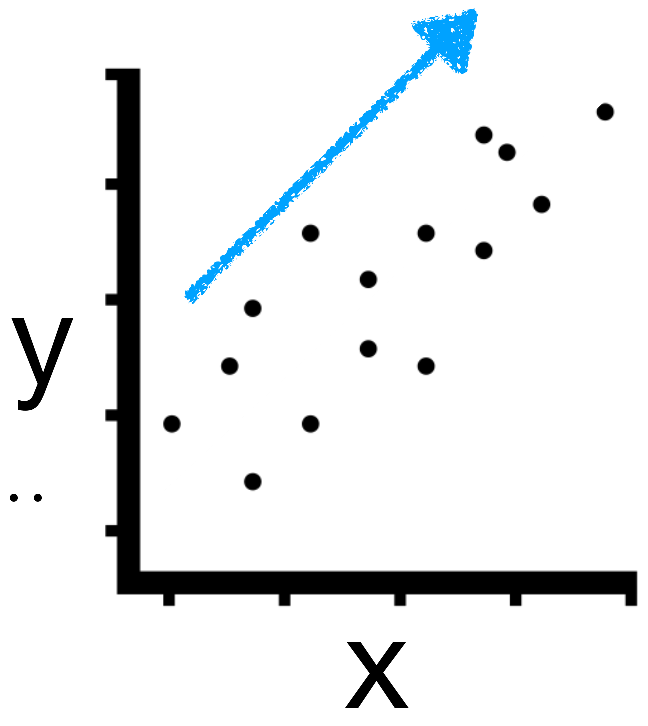

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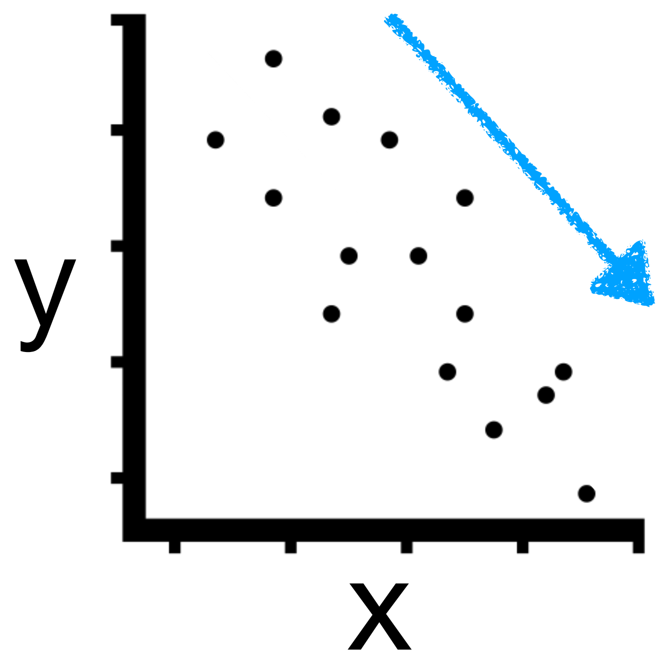

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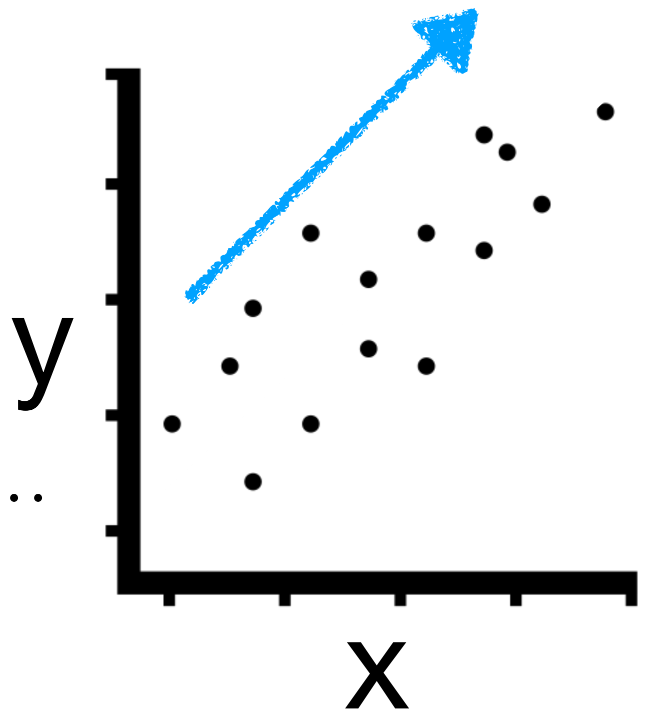
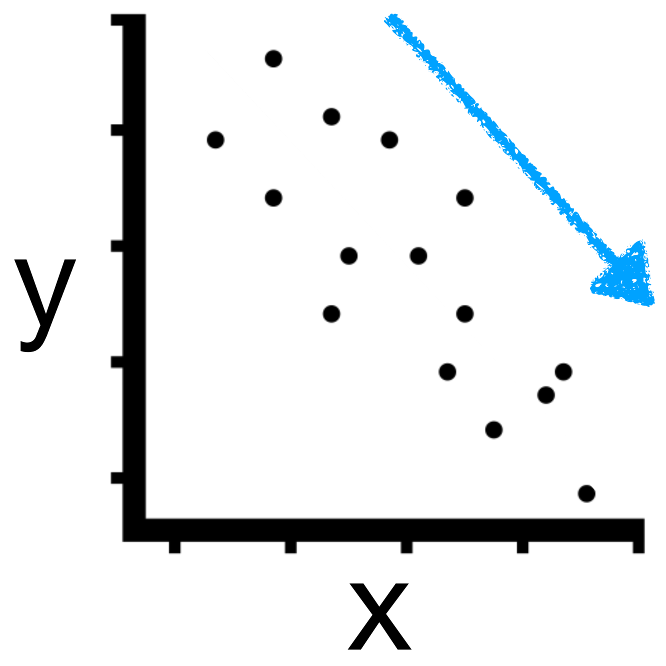
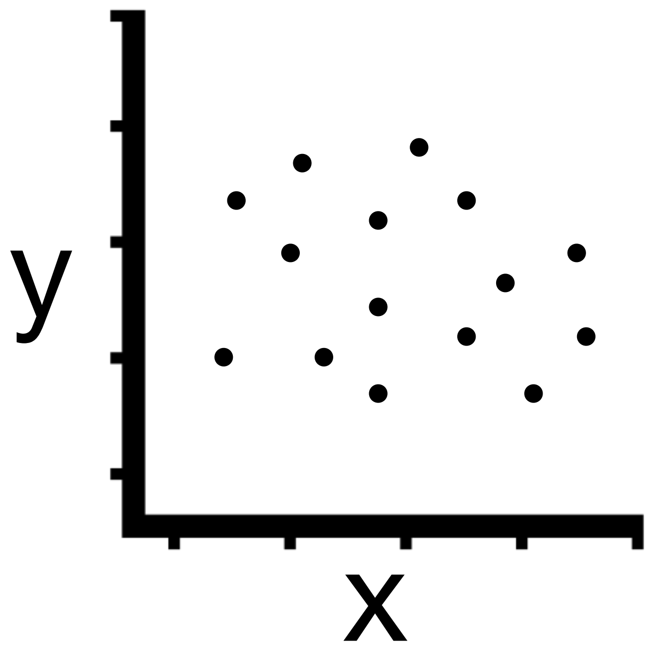
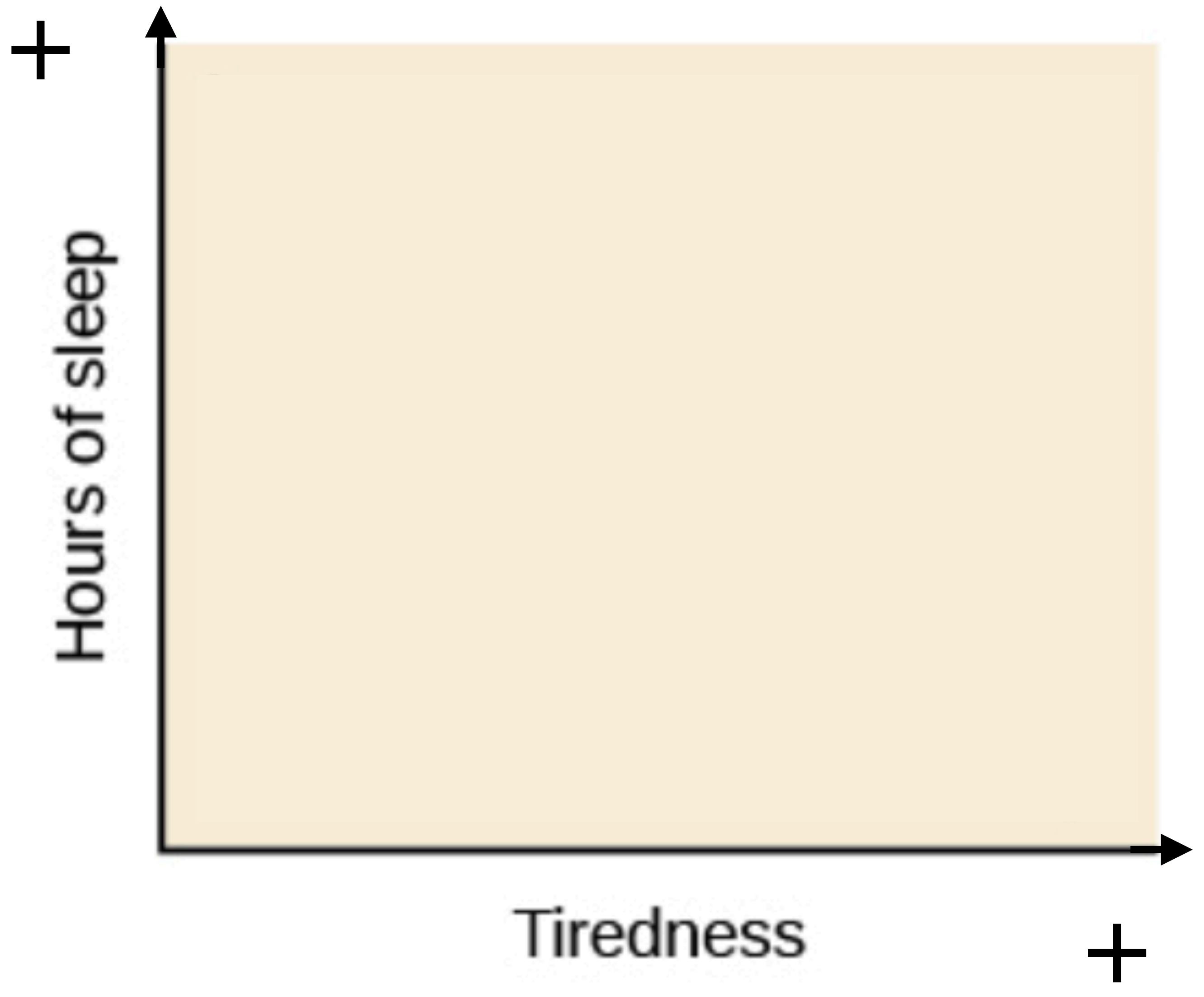


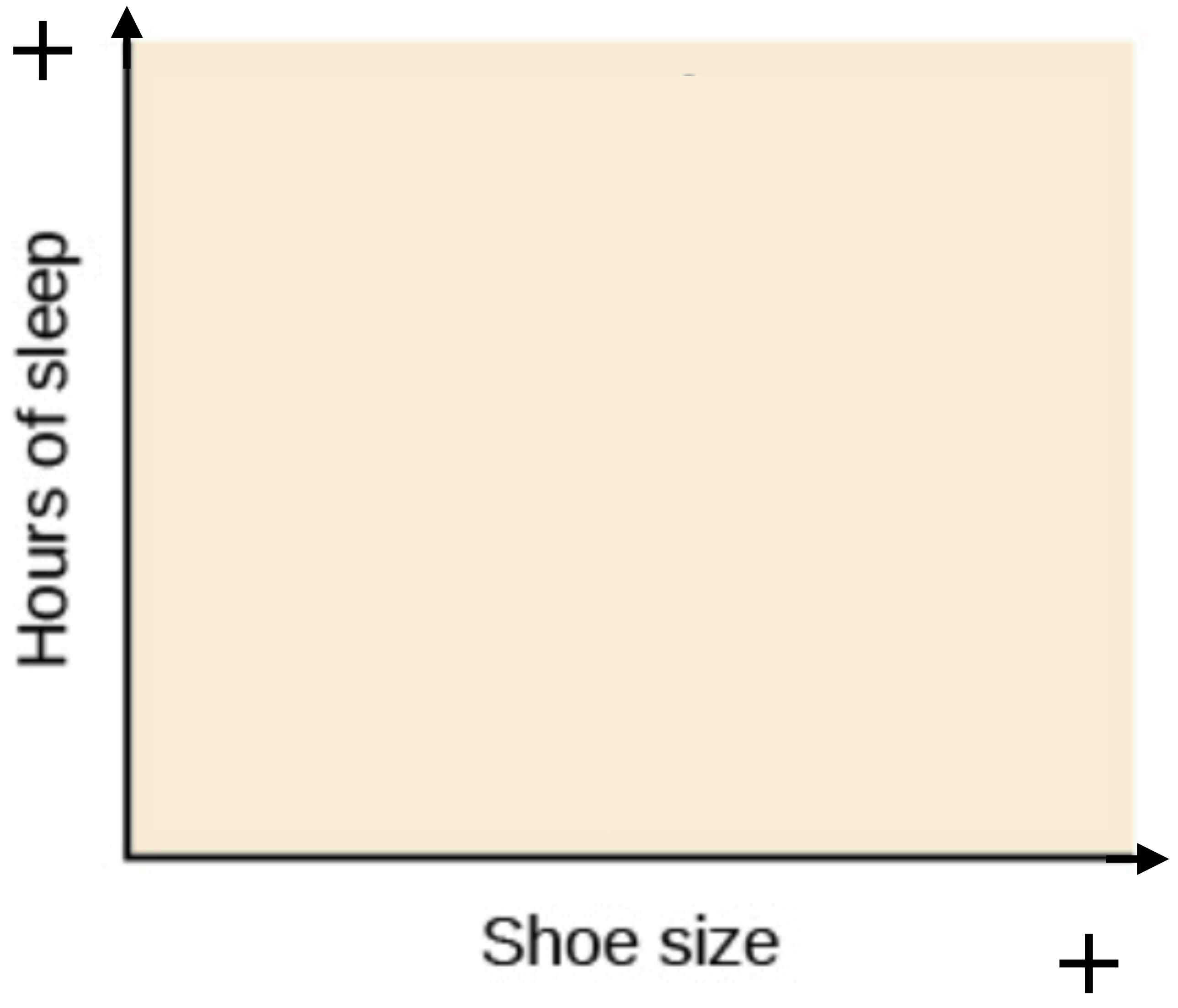


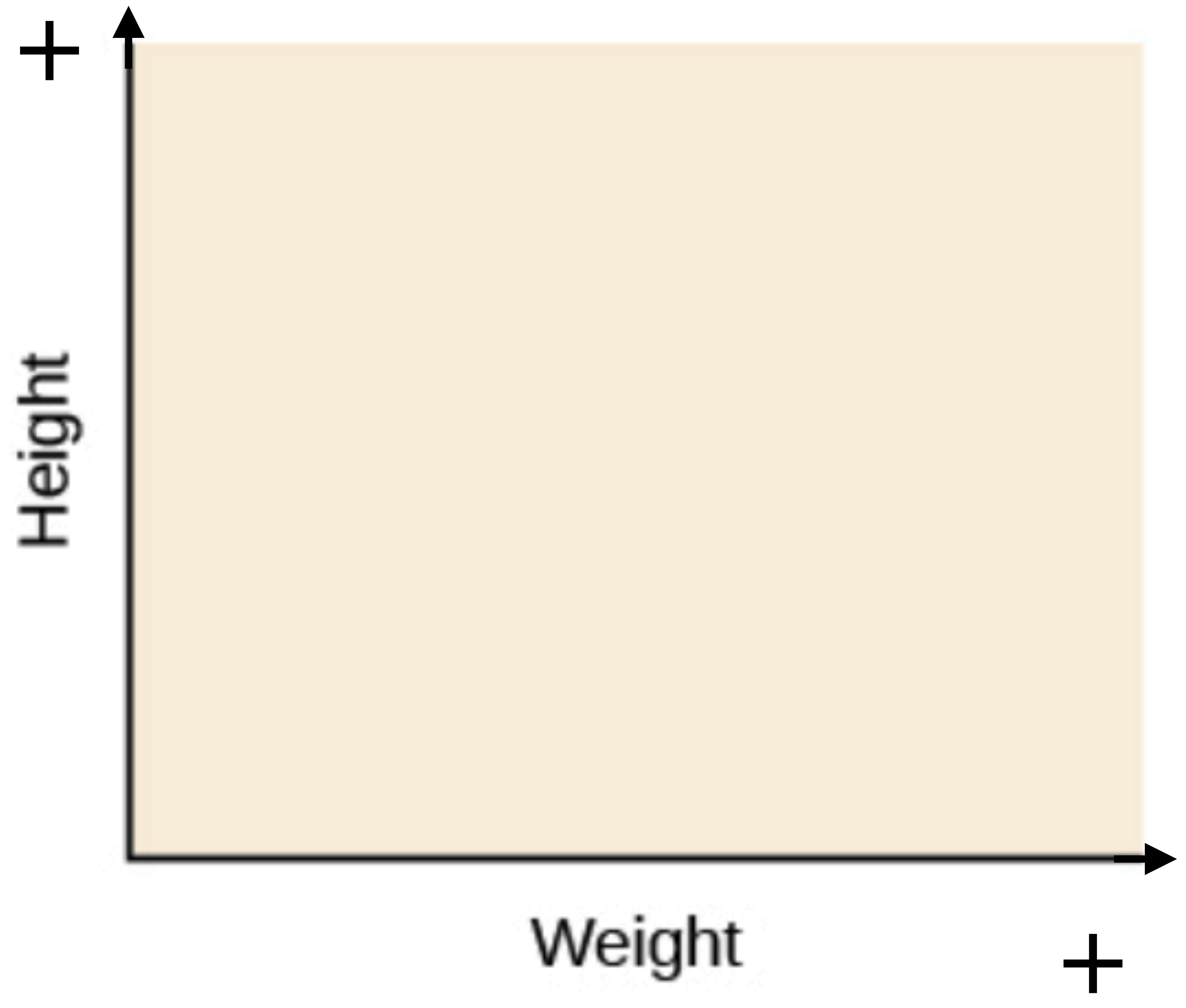


Examples of correlation

Positive? Negative? None?







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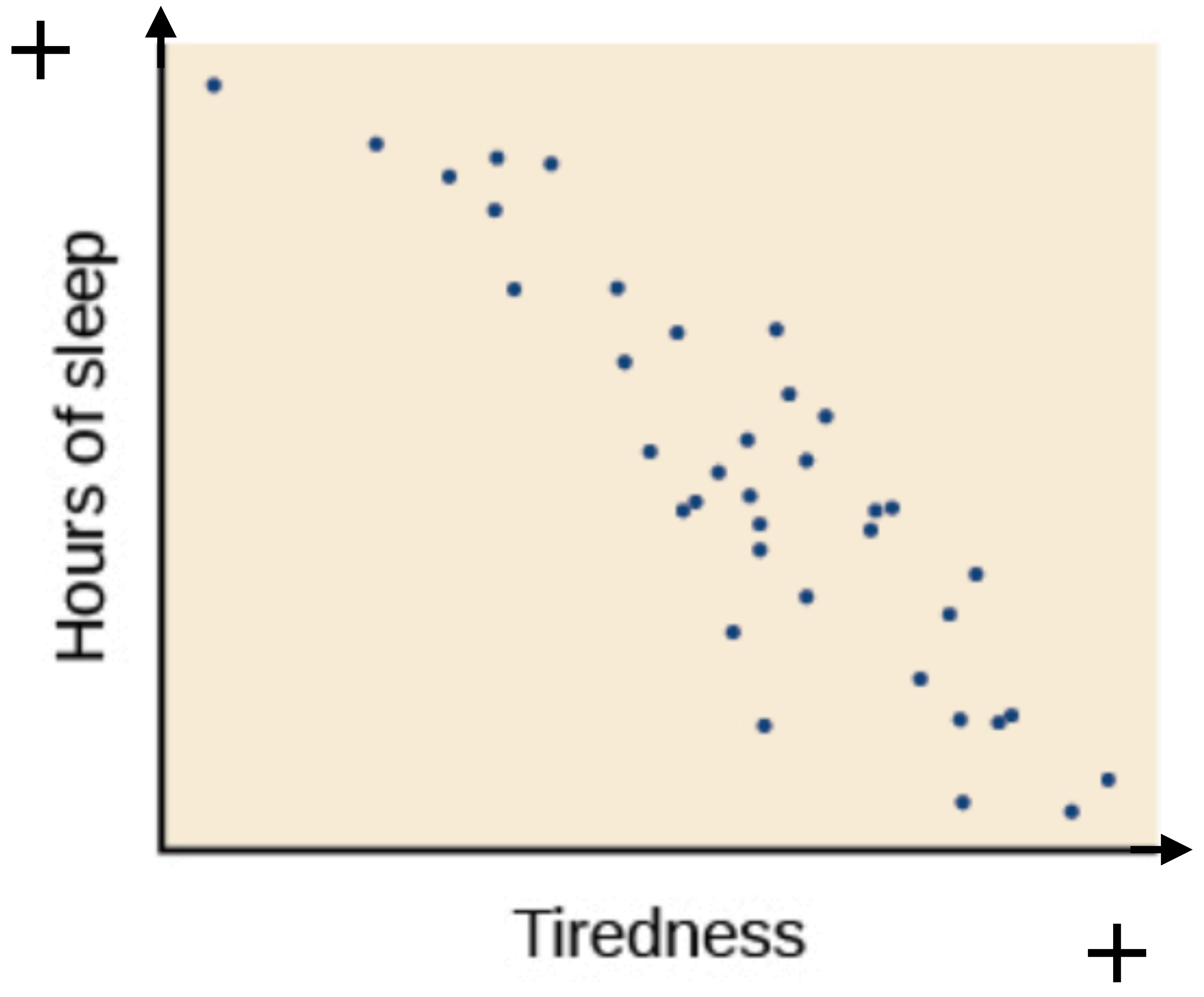

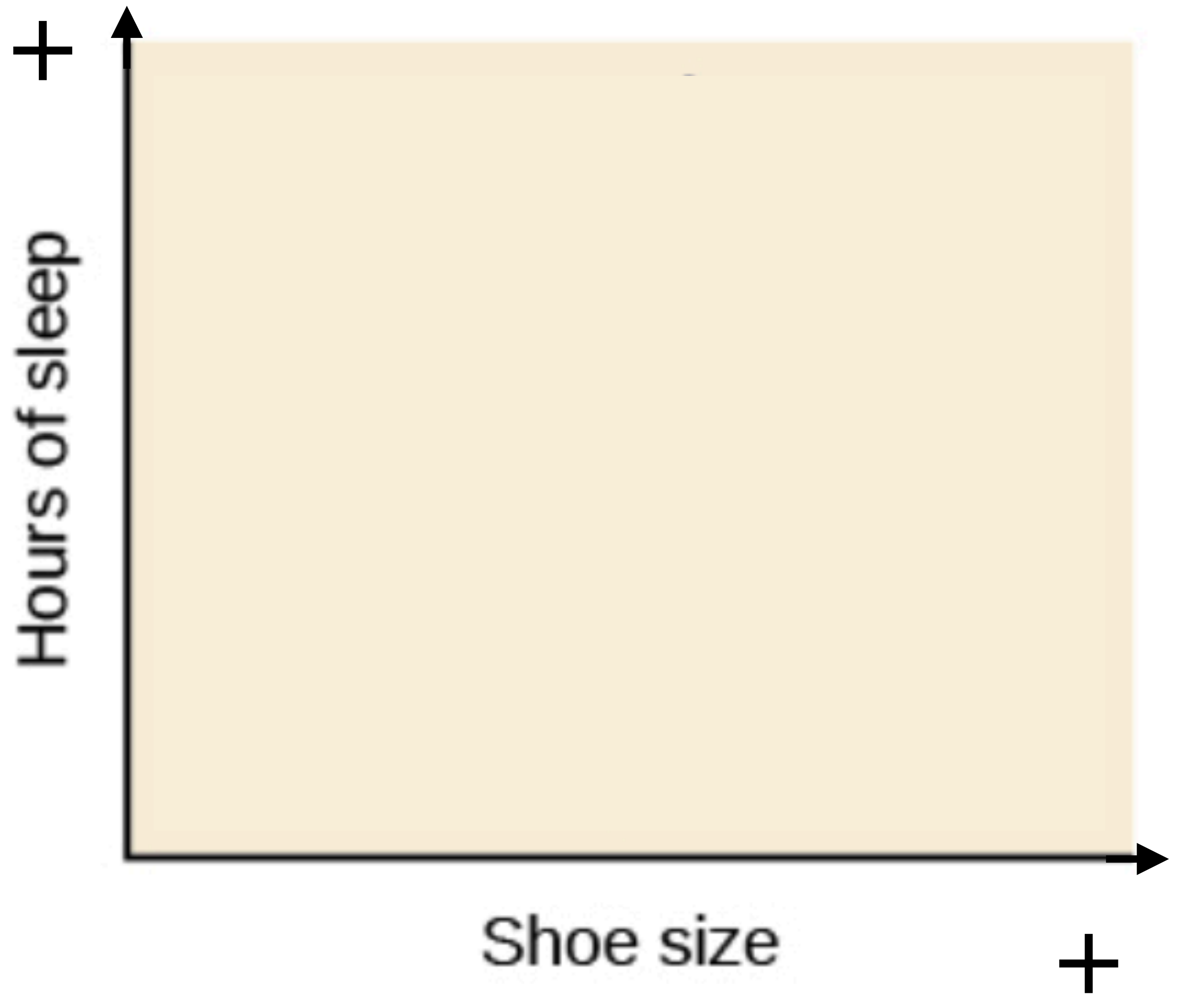

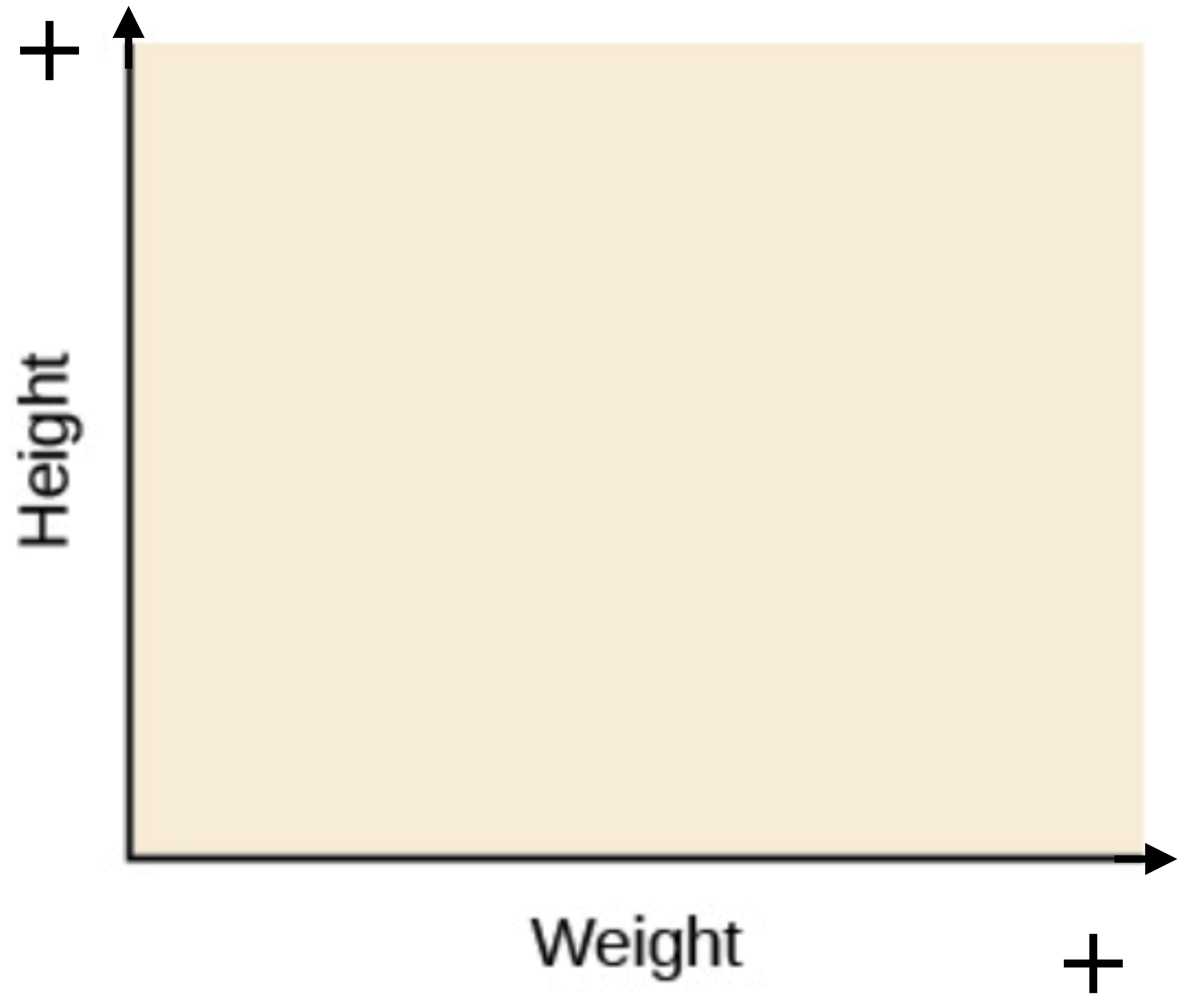

Negative
correlation

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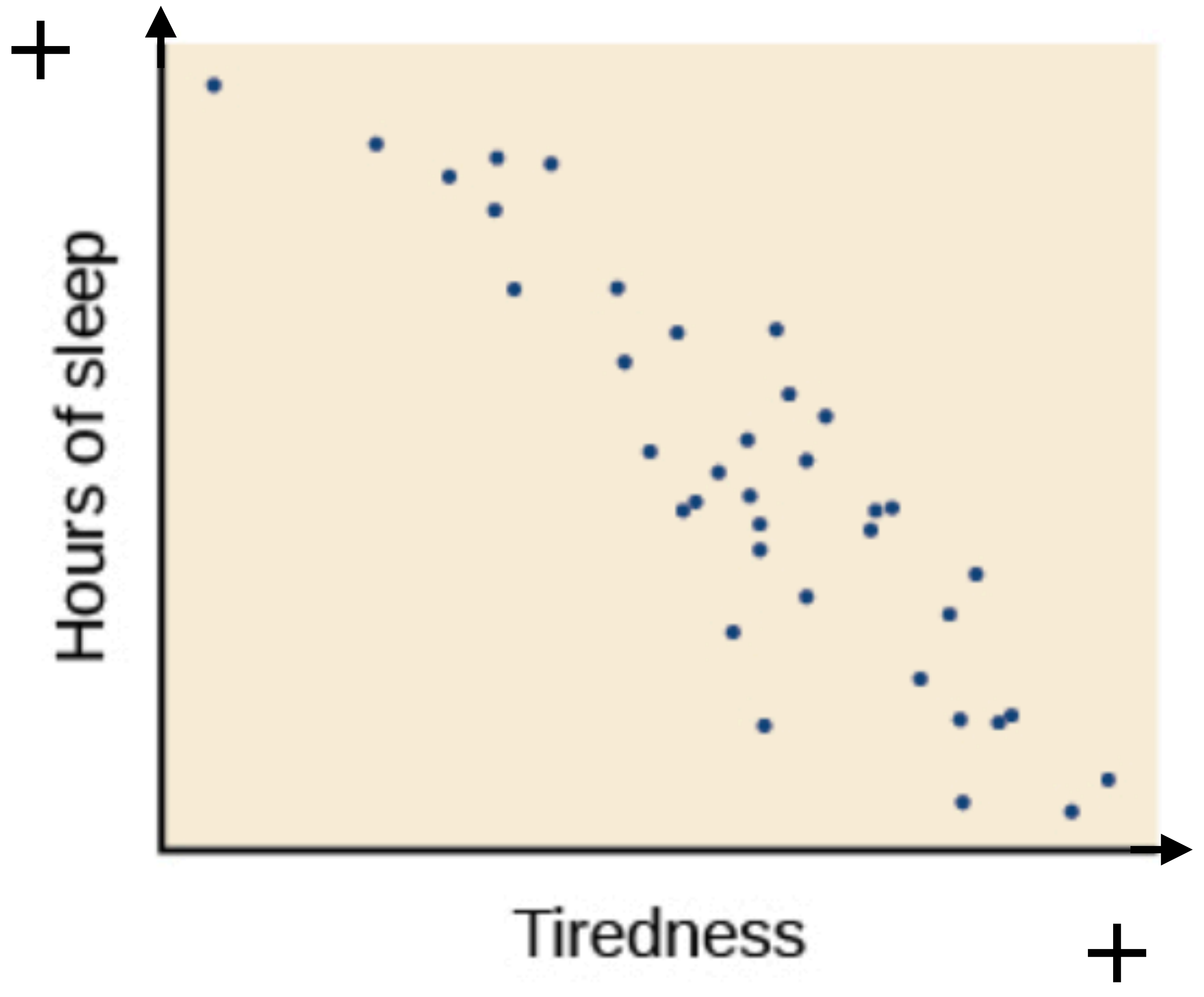

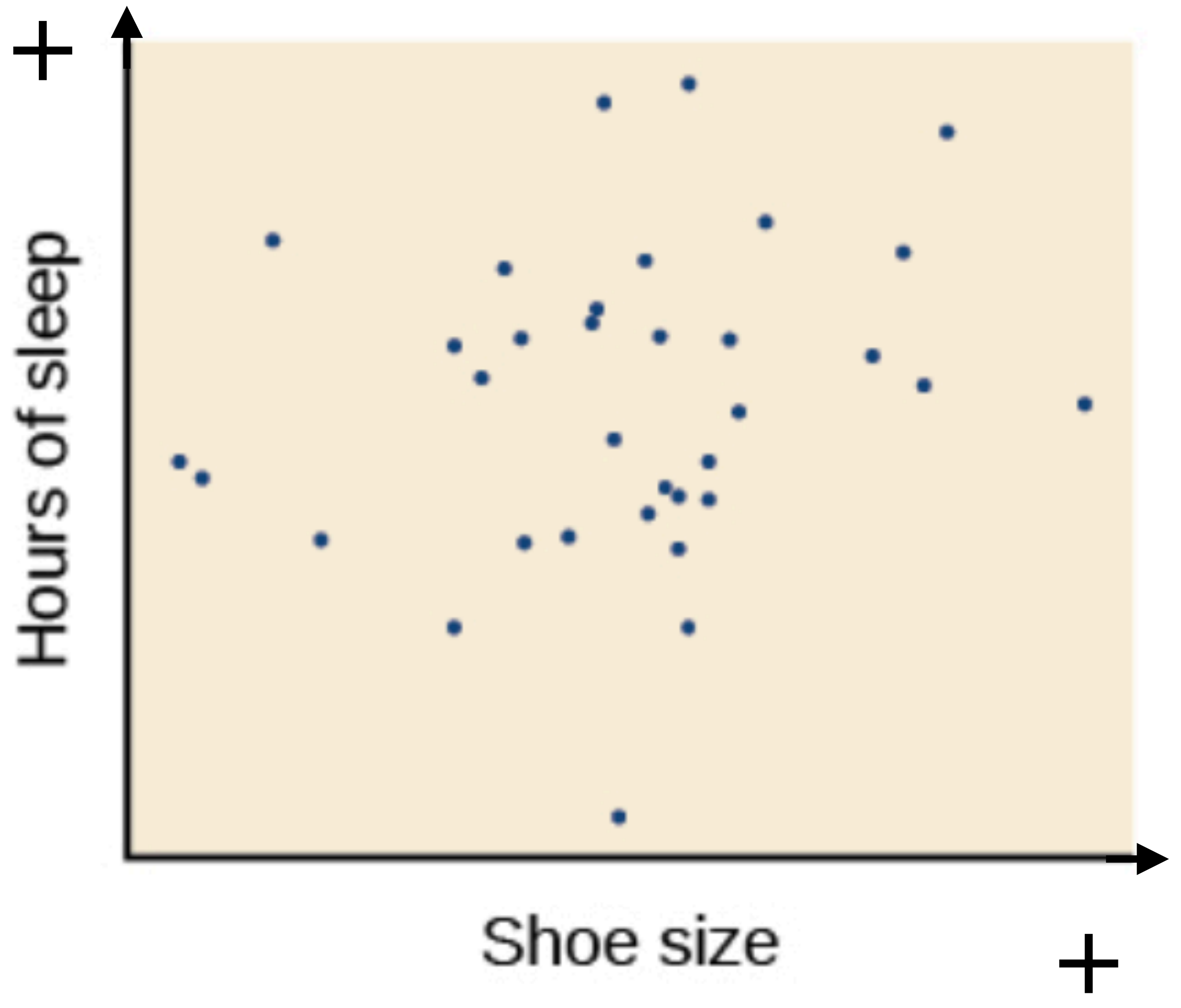

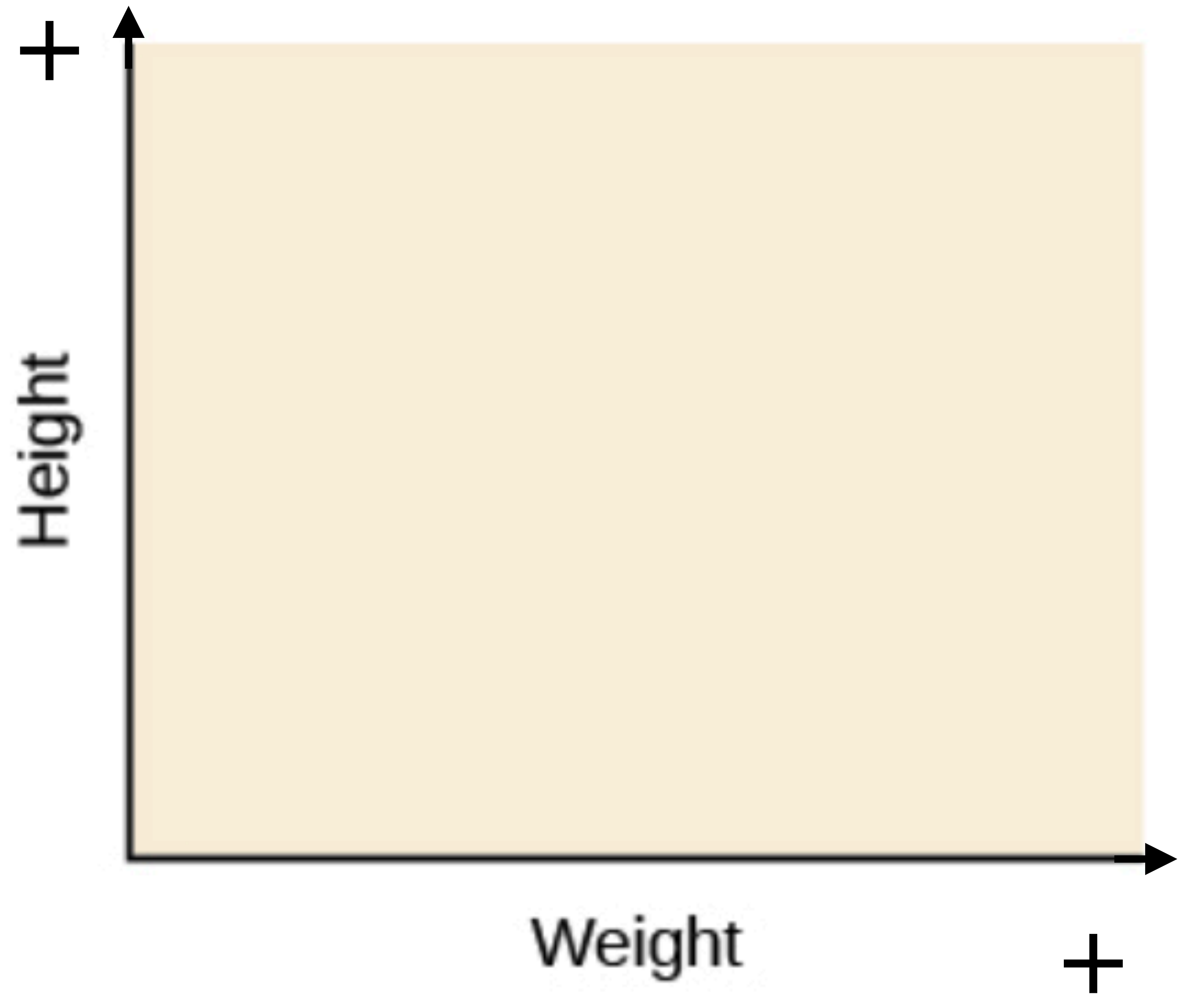

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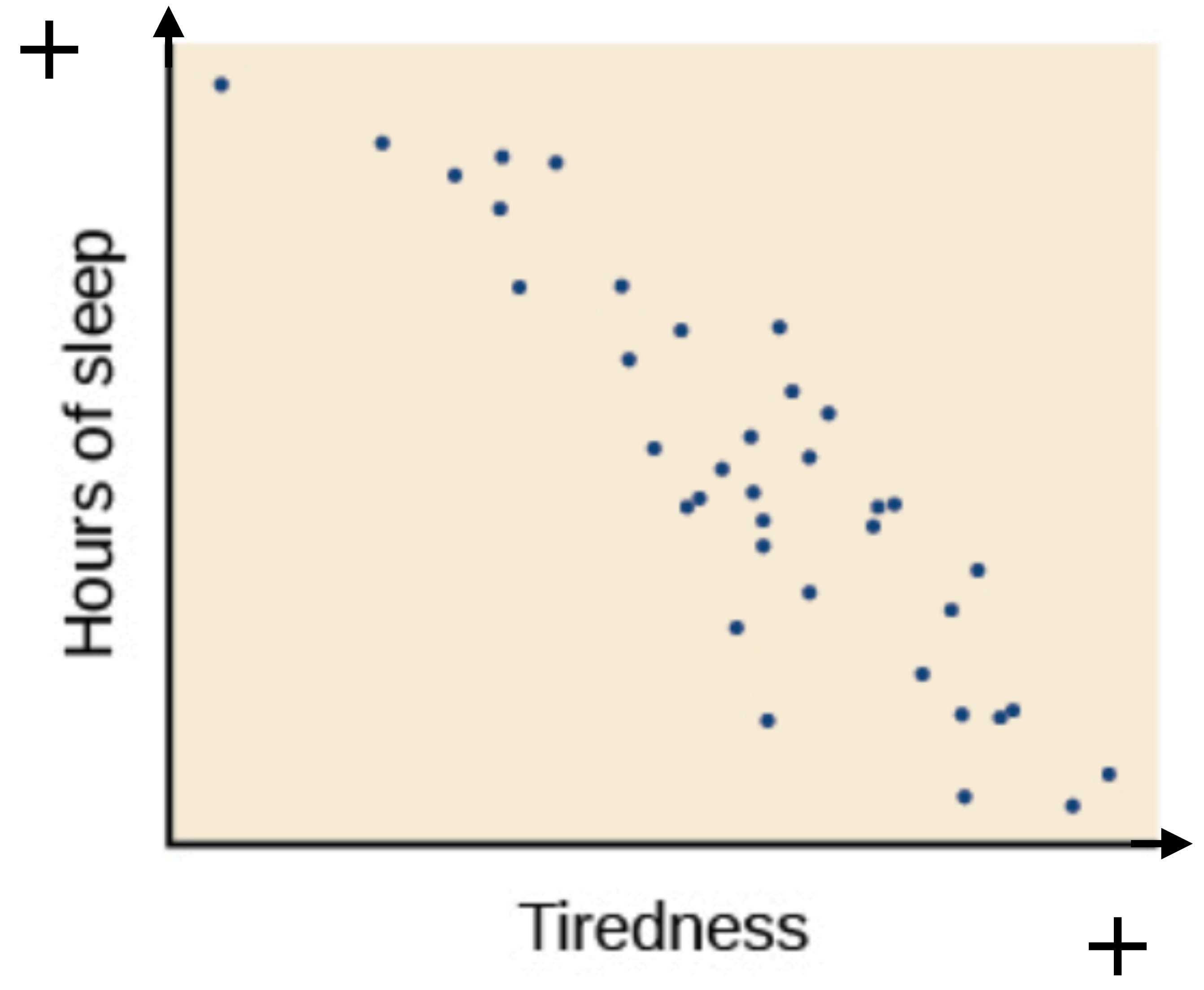

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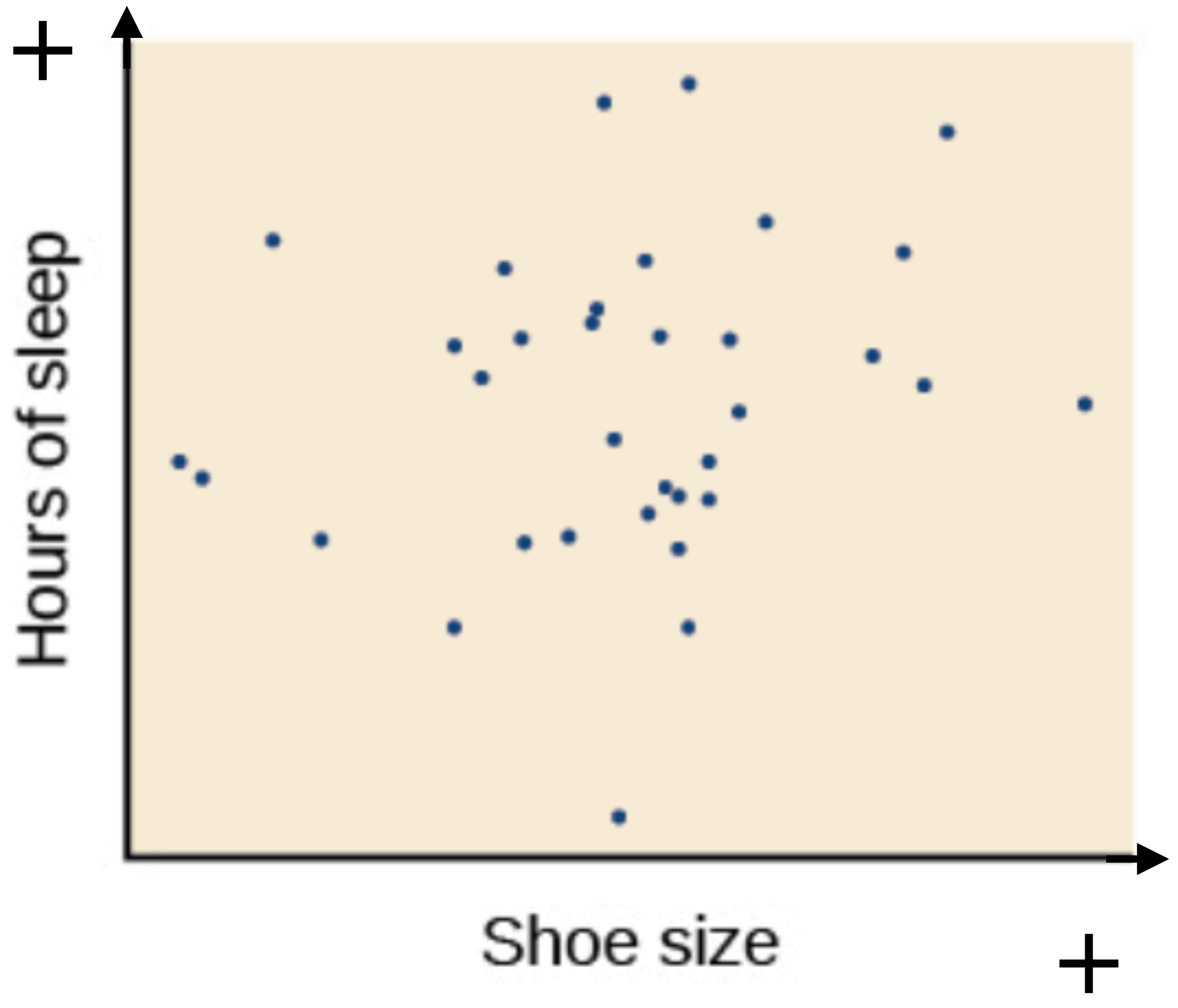

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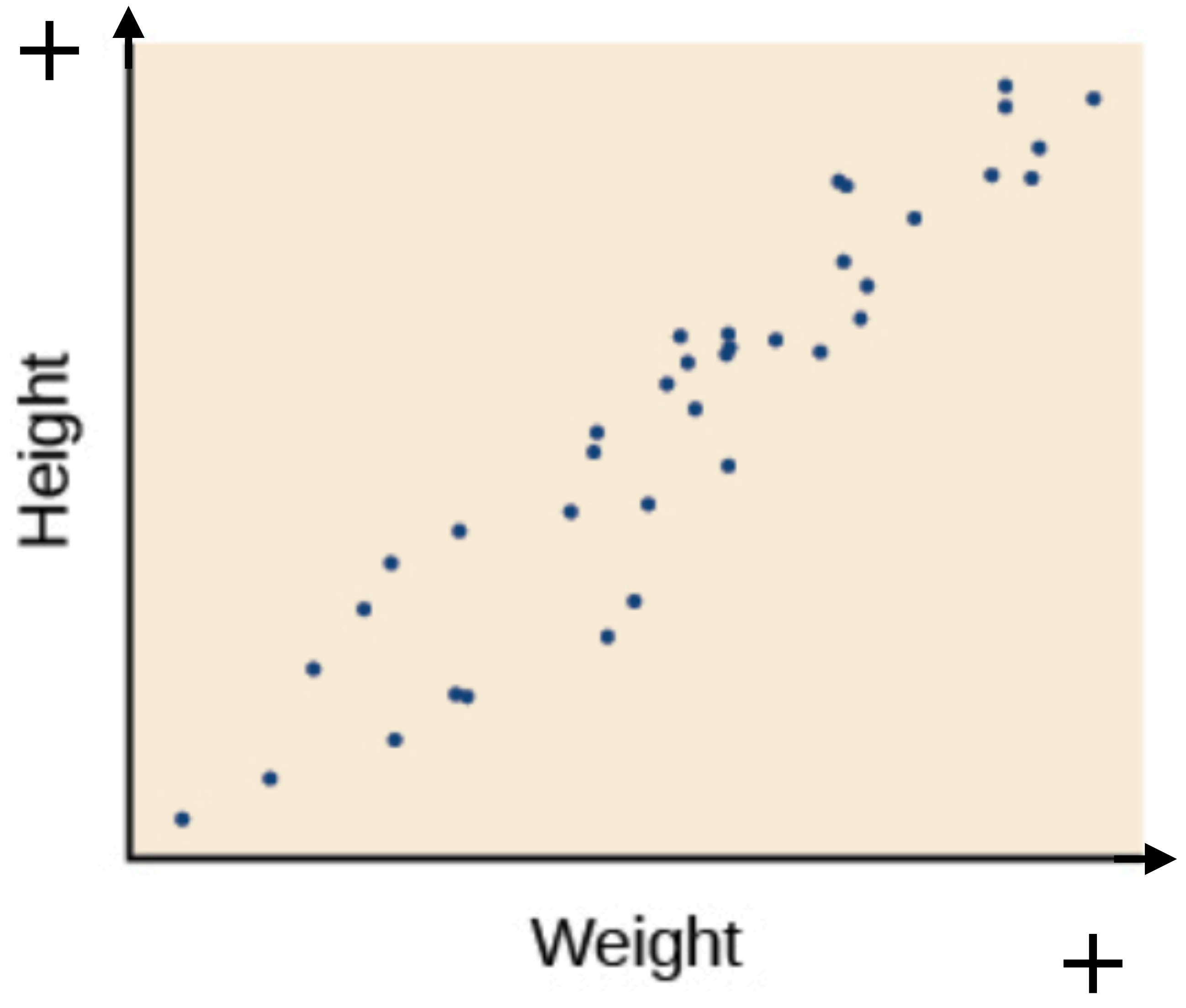

Positive
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Measuring correlation

Strength and direction

Measuring correlation

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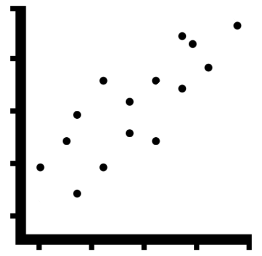
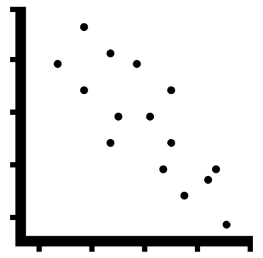
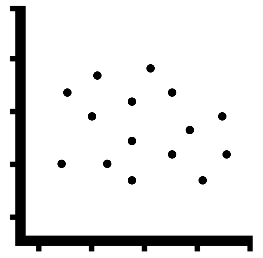
  - $\rho > 0$ positive correlation 
  - $\rho < 0$ negative correlation 
  - $\rho \approx 0$ no correlation 

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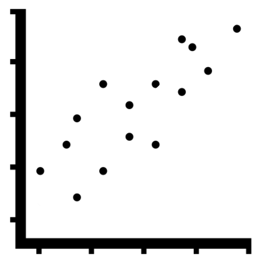
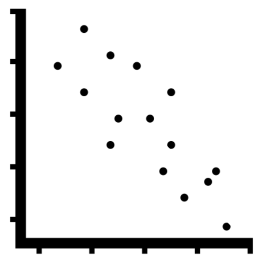
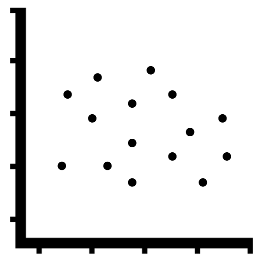
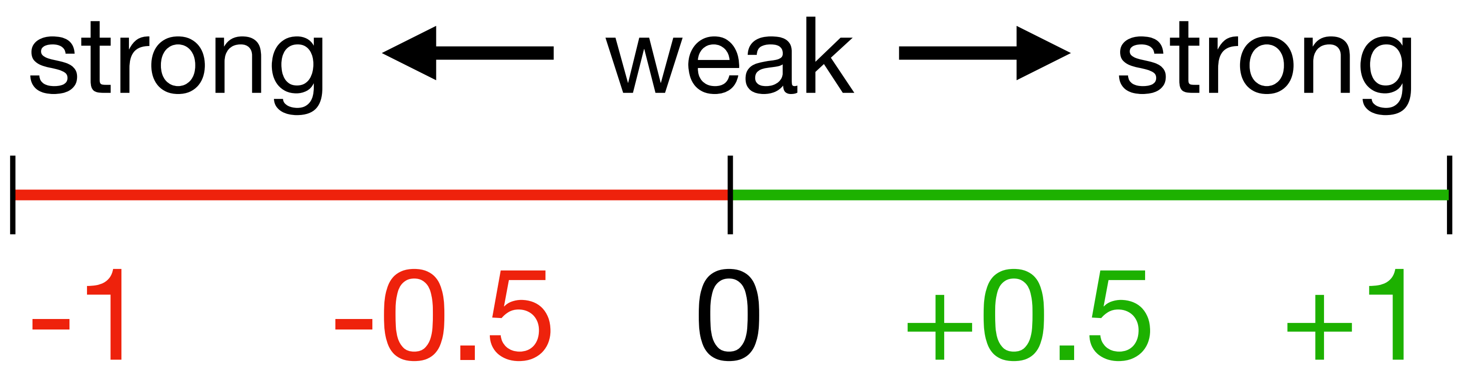
    - $\rho > 0$ positive correlation 
    - $\rho < 0$ negative correlation 
    - $\rho \approx 0$ no correlation 



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    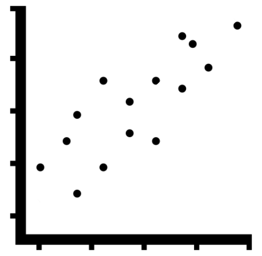
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    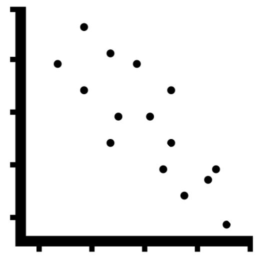
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    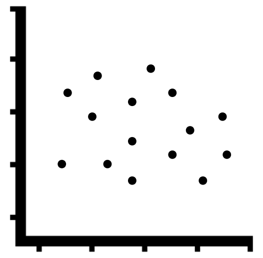

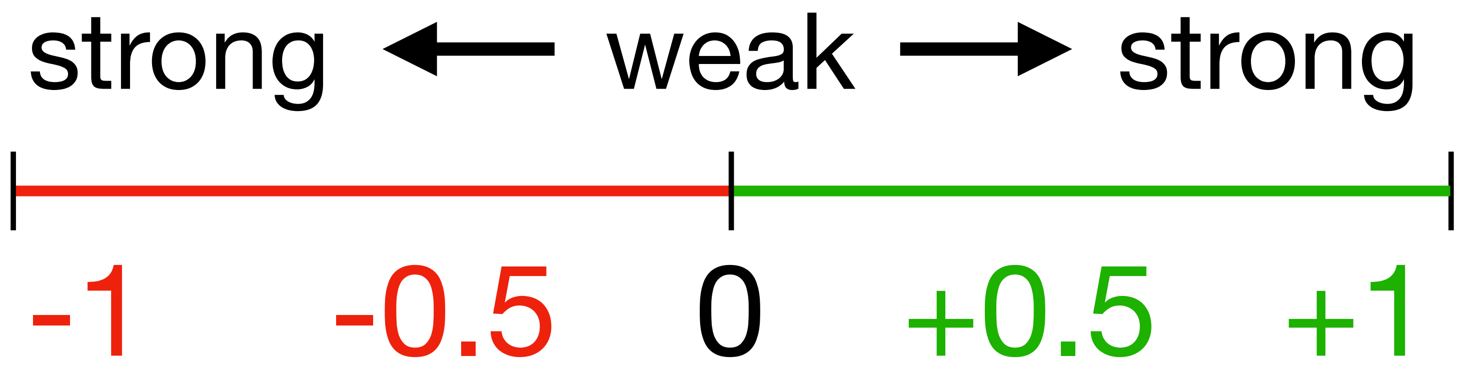

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- The correlation coefficient is usually represented by the letter r or greek letter ρ (rho).

Pearson's correlation coefficient

$\rho(X, Y)$

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to understand the Pearson's correlation coefficient

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  - We estimate the expected value as the mean of X:

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lower-case x

upper-case (capital) X

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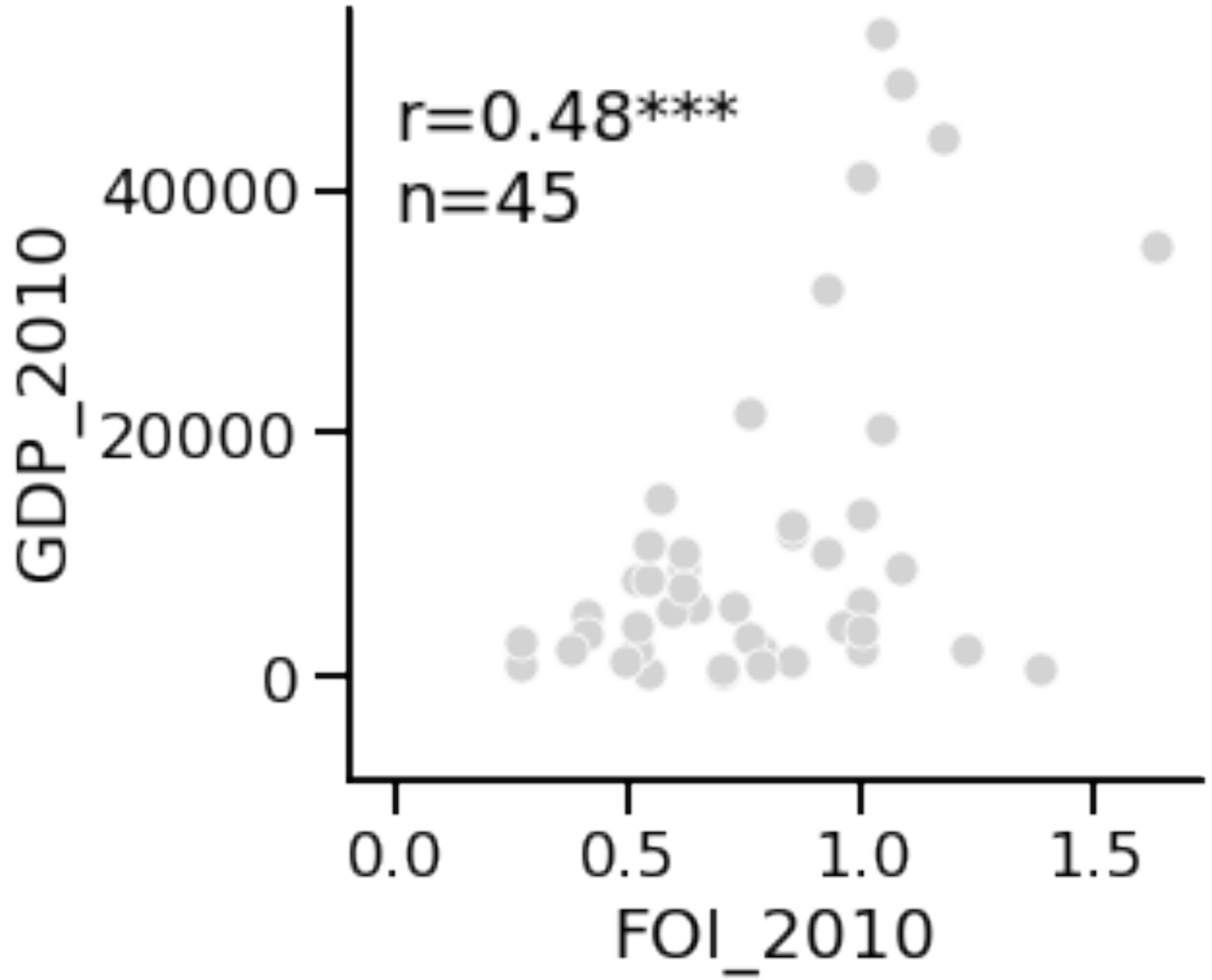
- The principle: correlation as the deviation from $E[XY] - E[X]E[Y] = 0$ *(no correlation)*
- The absolute value of this difference can be at most $\sigma_X \sigma_Y$ *(normalizing factor)*
- Thus, $\sigma_X \sigma_Y$ rescales the difference to be between –1 and 1

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

Pearson's correlation between X and Y

Correlation between FOI and GDP

Pearson's correlation coefficient



Correlation between FOI and GDP

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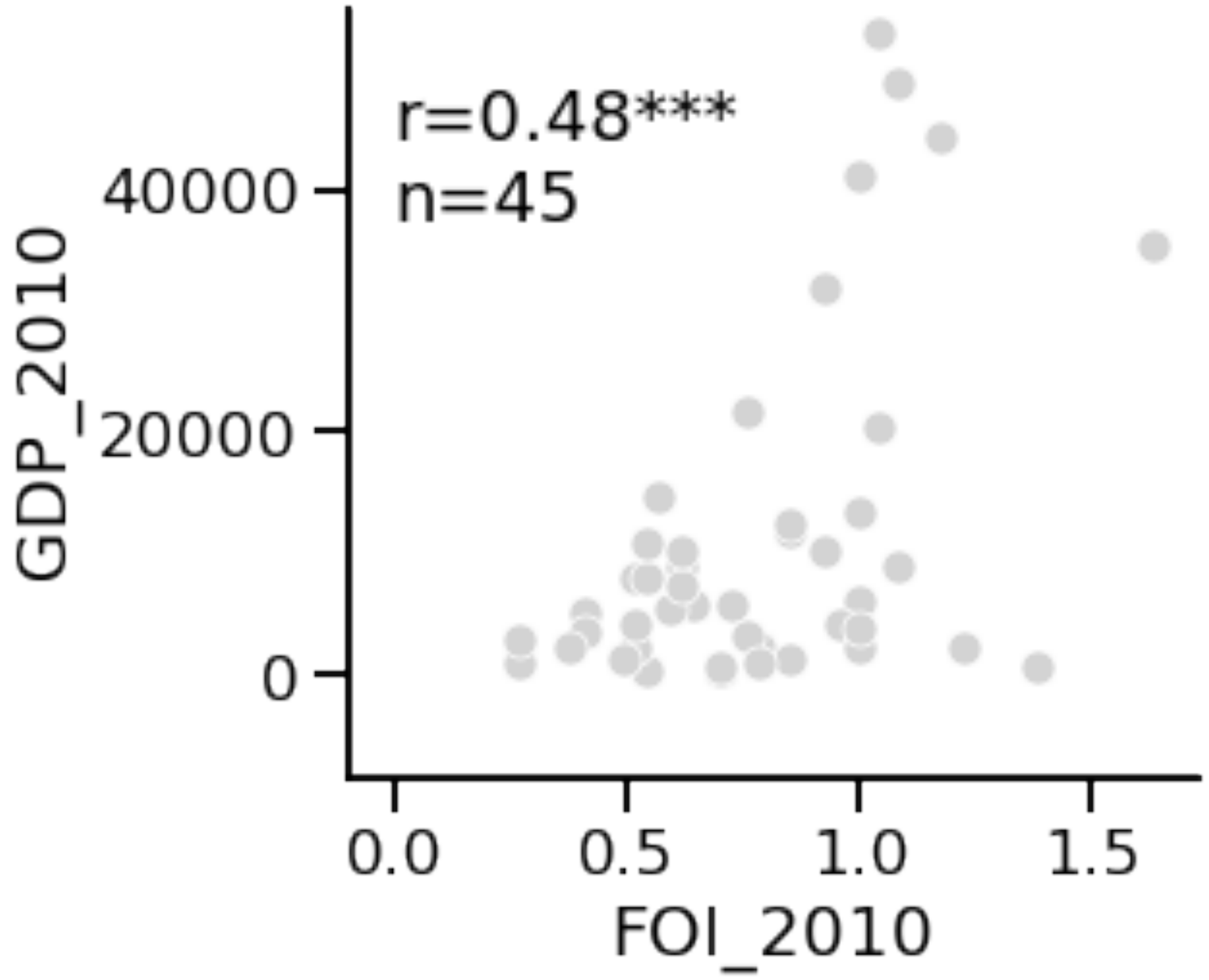
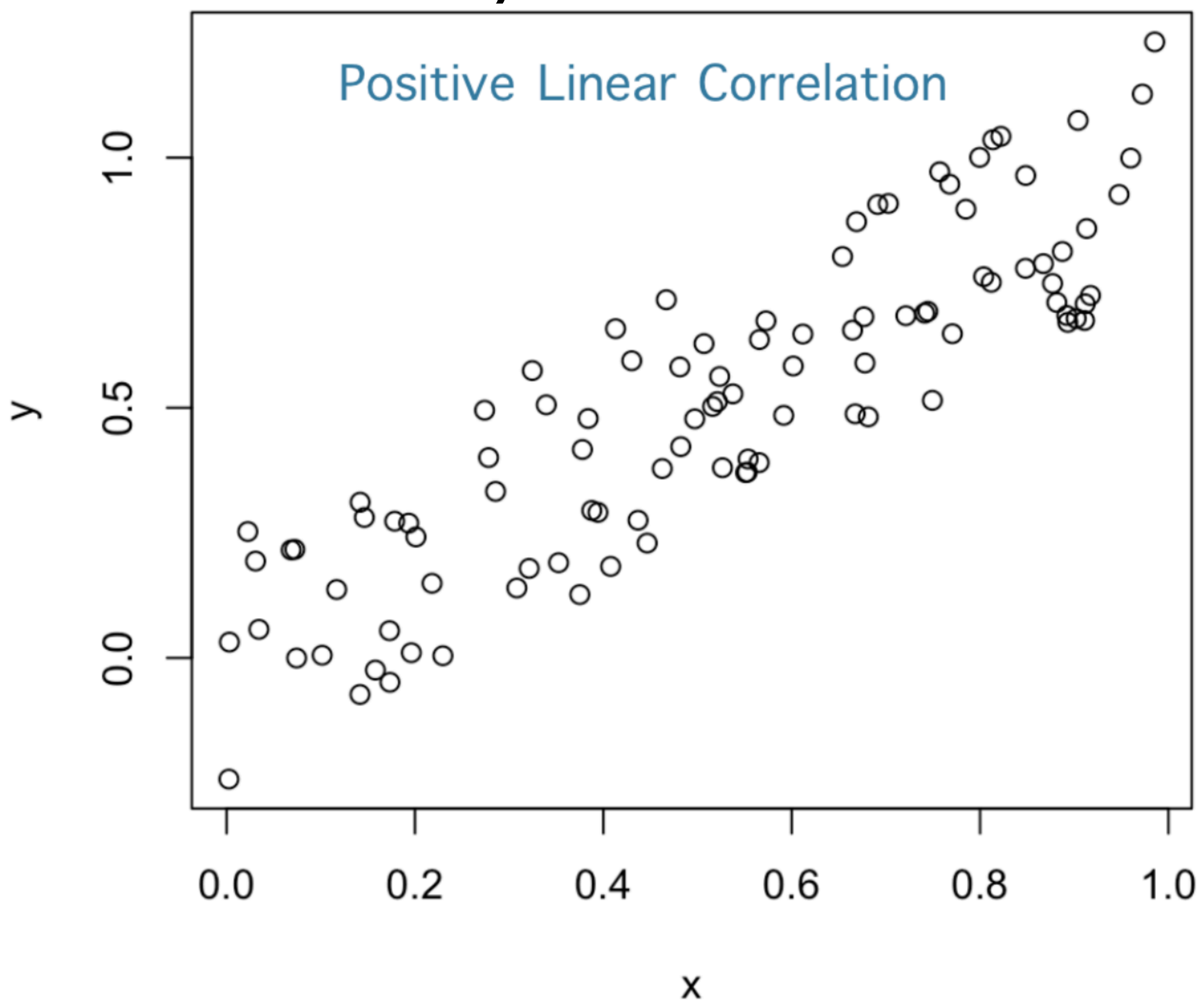
Positive and moderate correlation



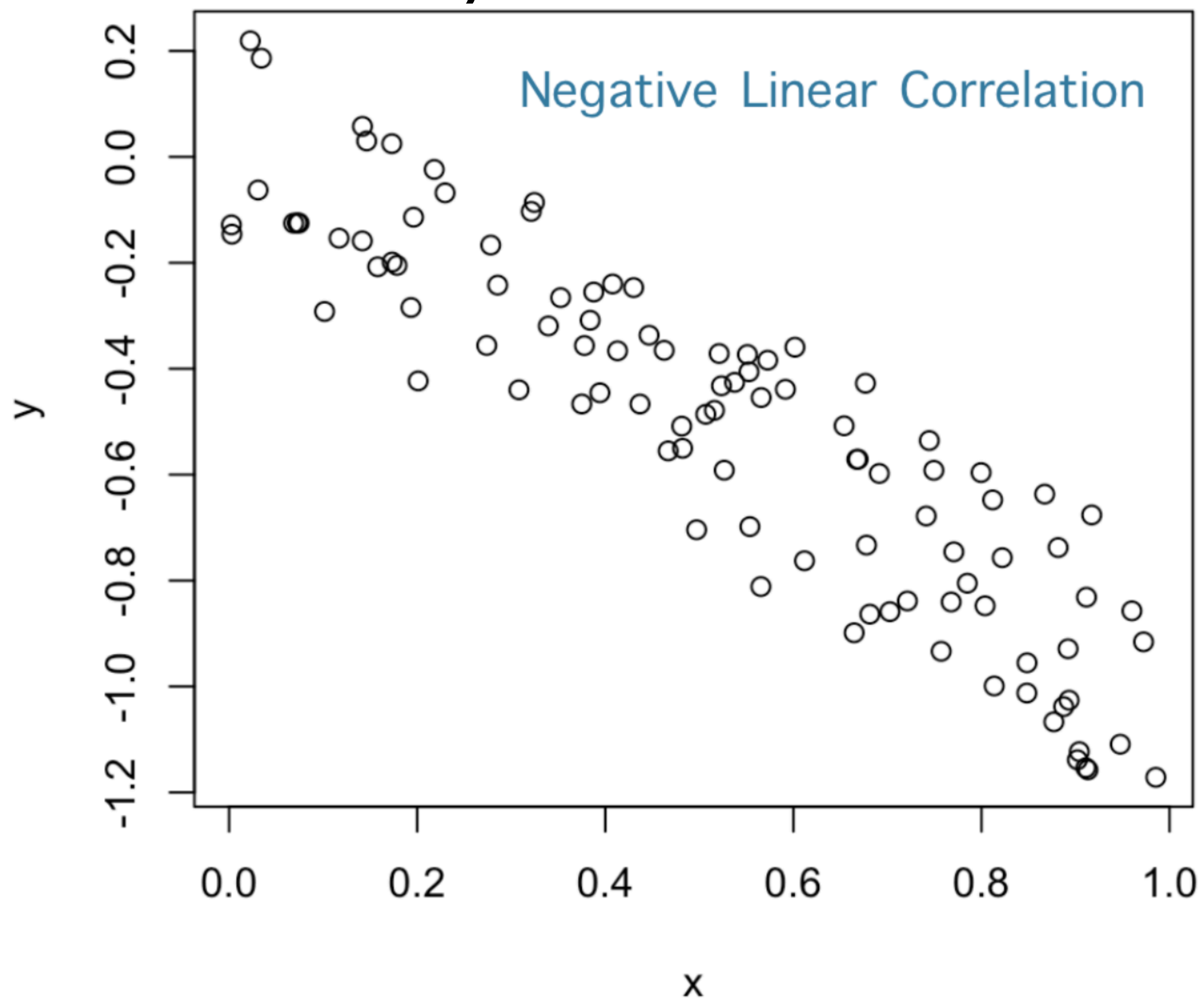
More examples

Pearson's correlation coefficient

$\rho = 0.8765$



$\rho = -0.9046$



More examples

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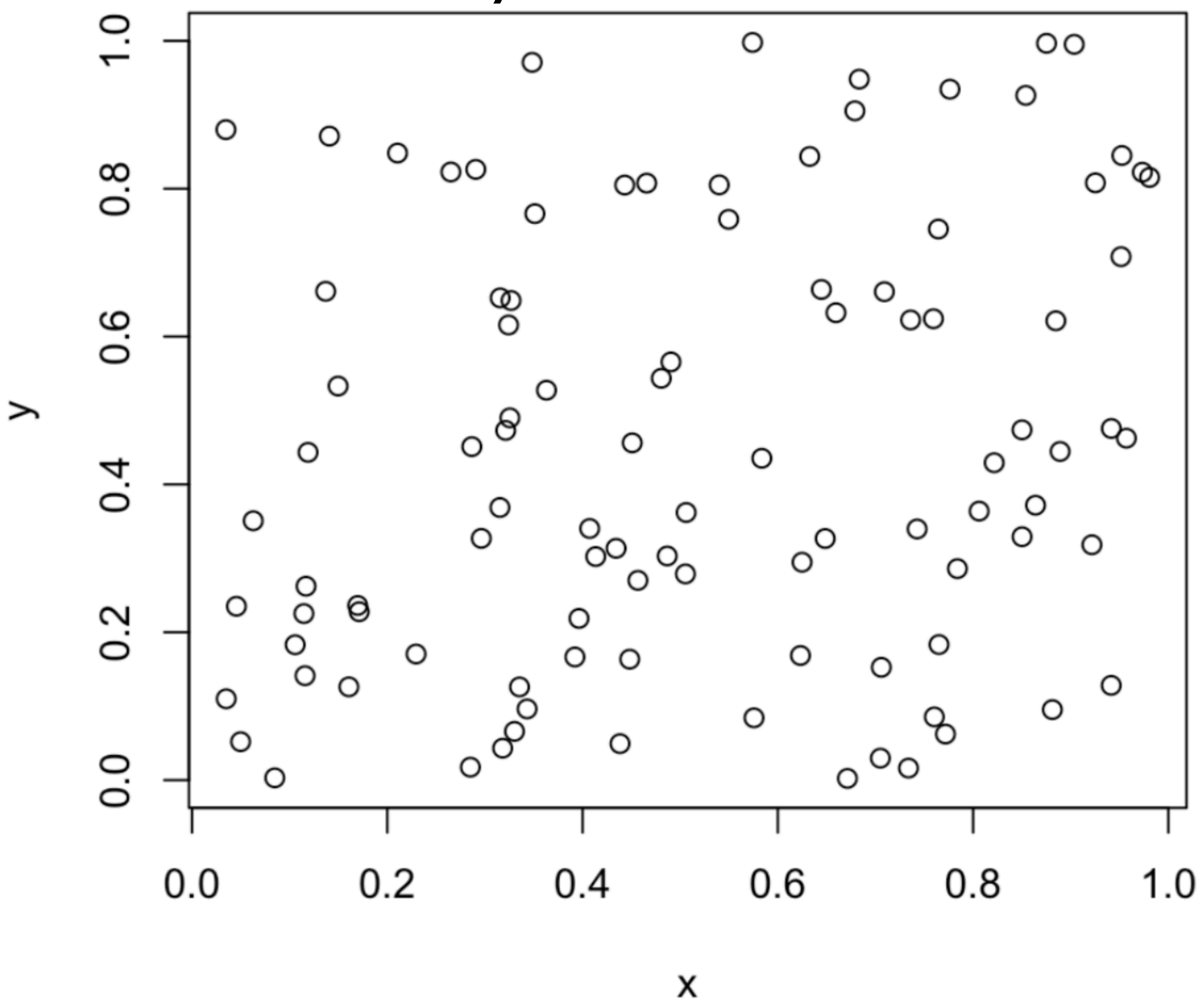

More examples

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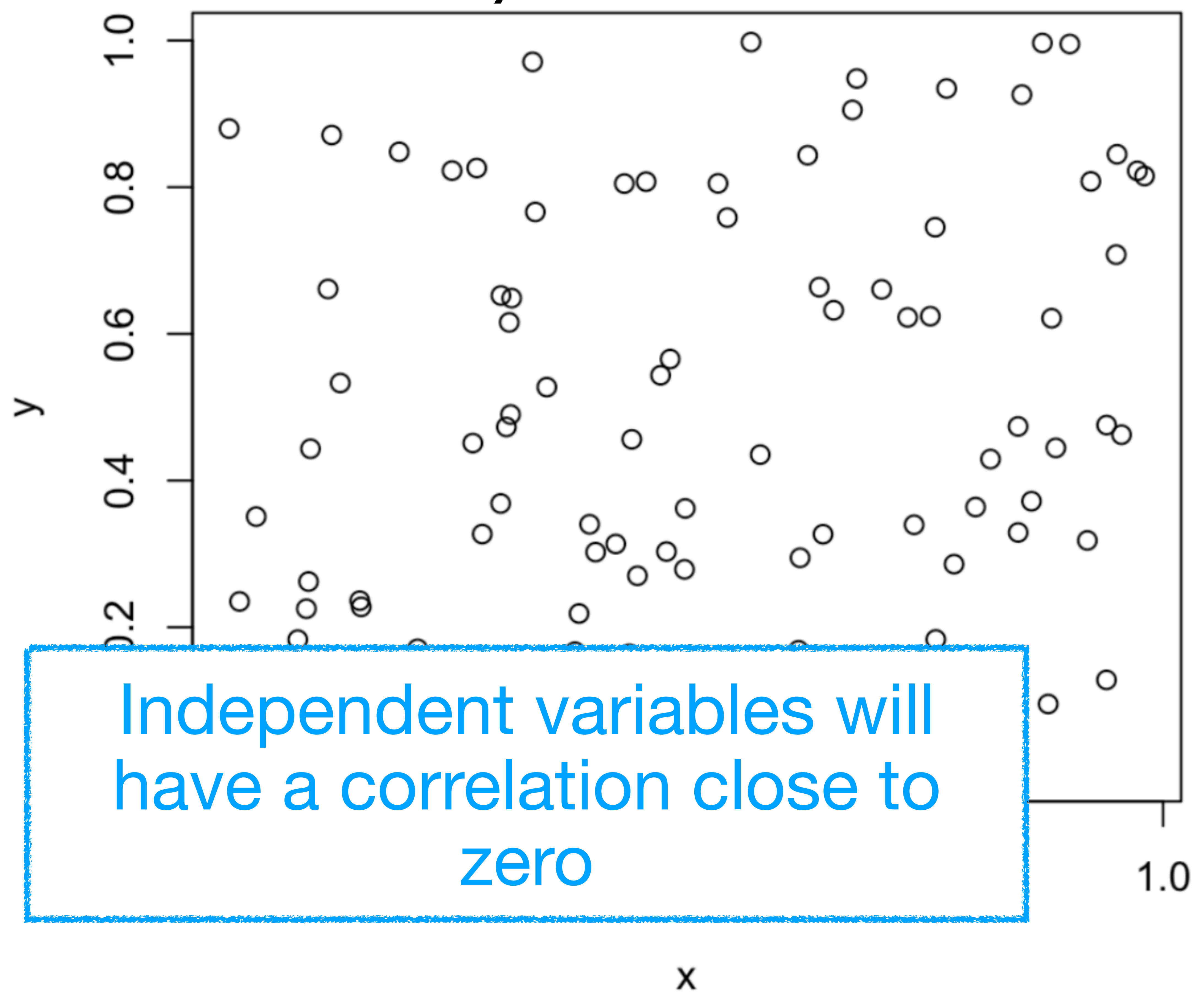

Independent variables will have a correlation close to zero

More examples

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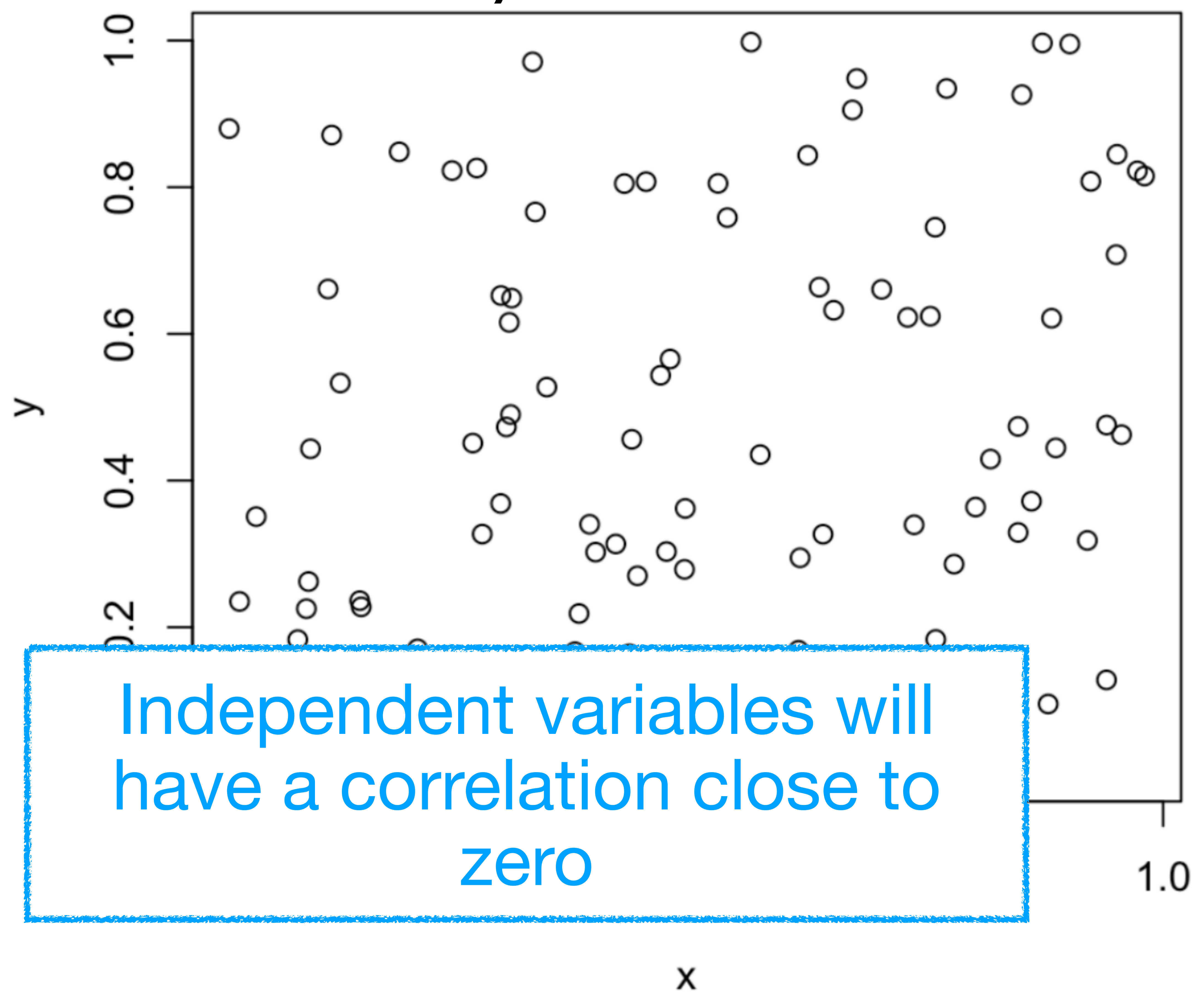

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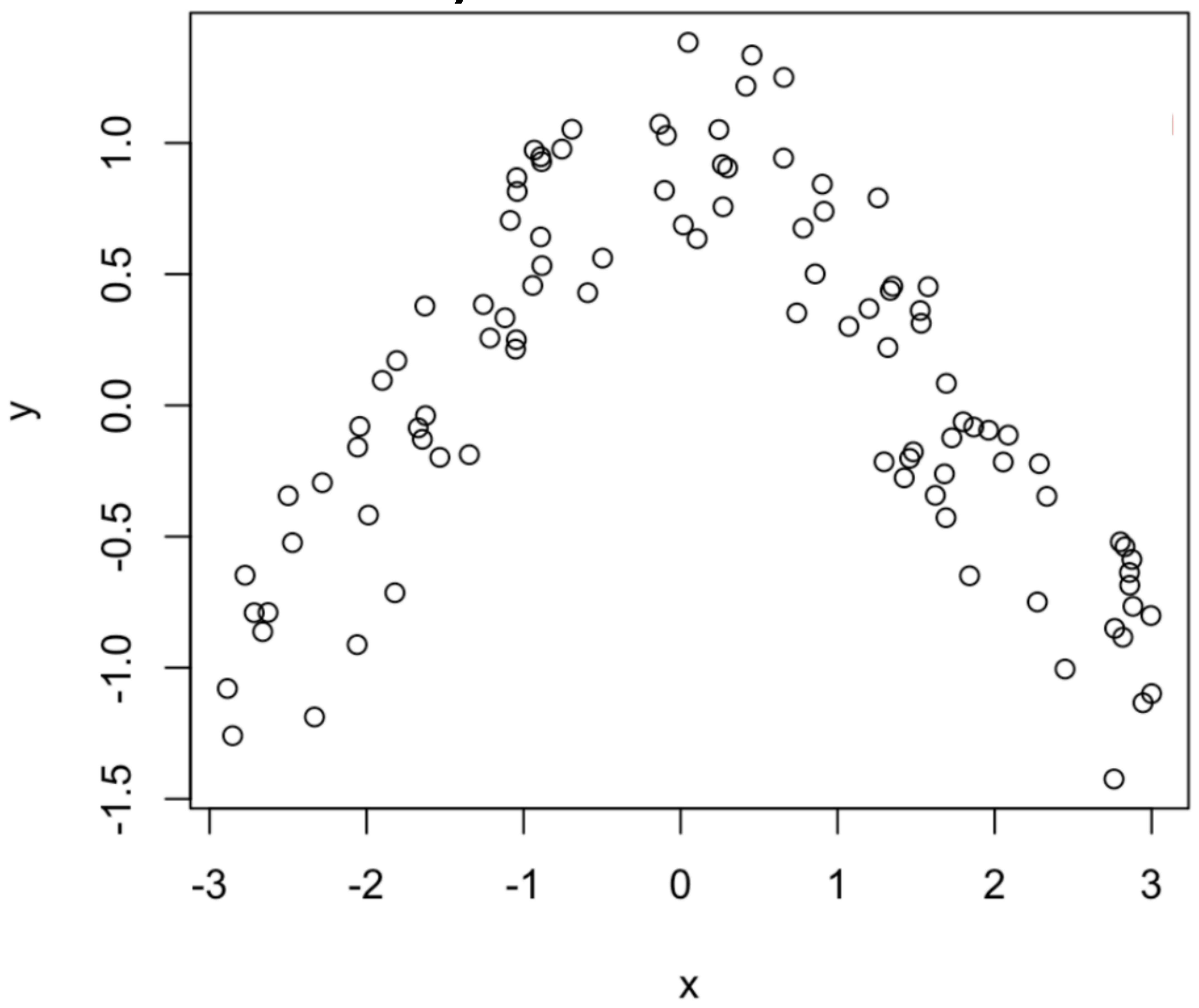

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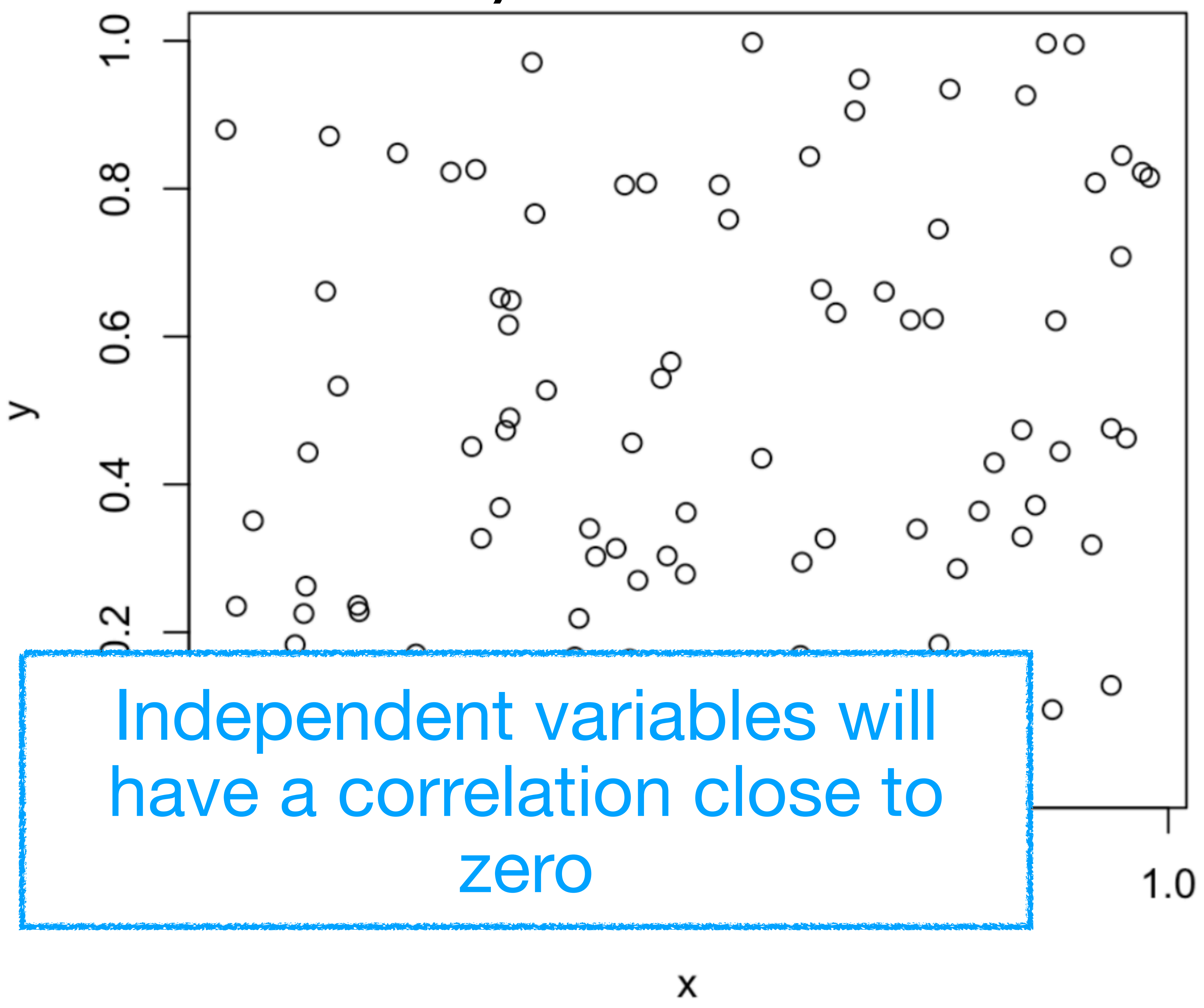

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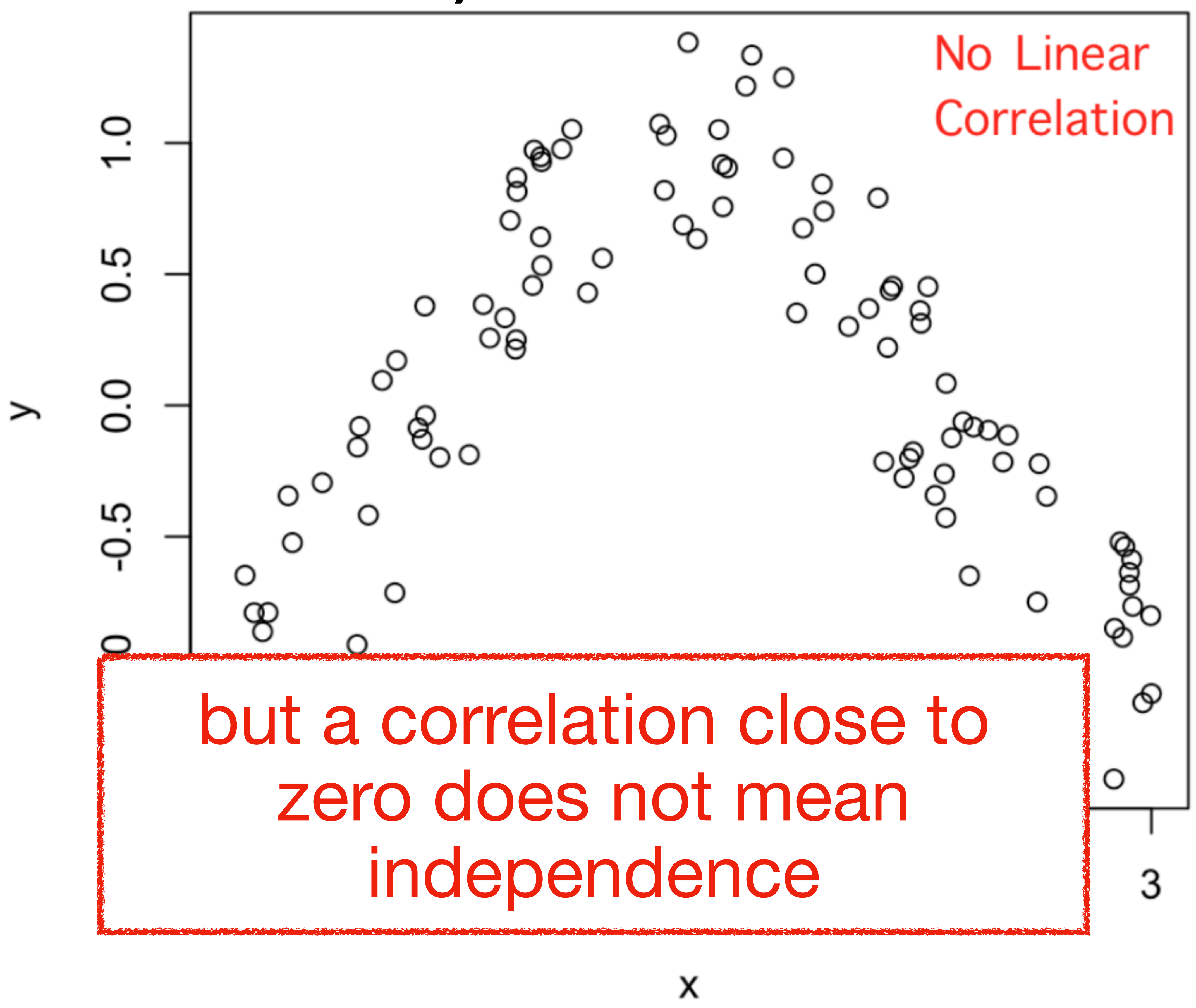


but a correlation close to zero does not mean independence

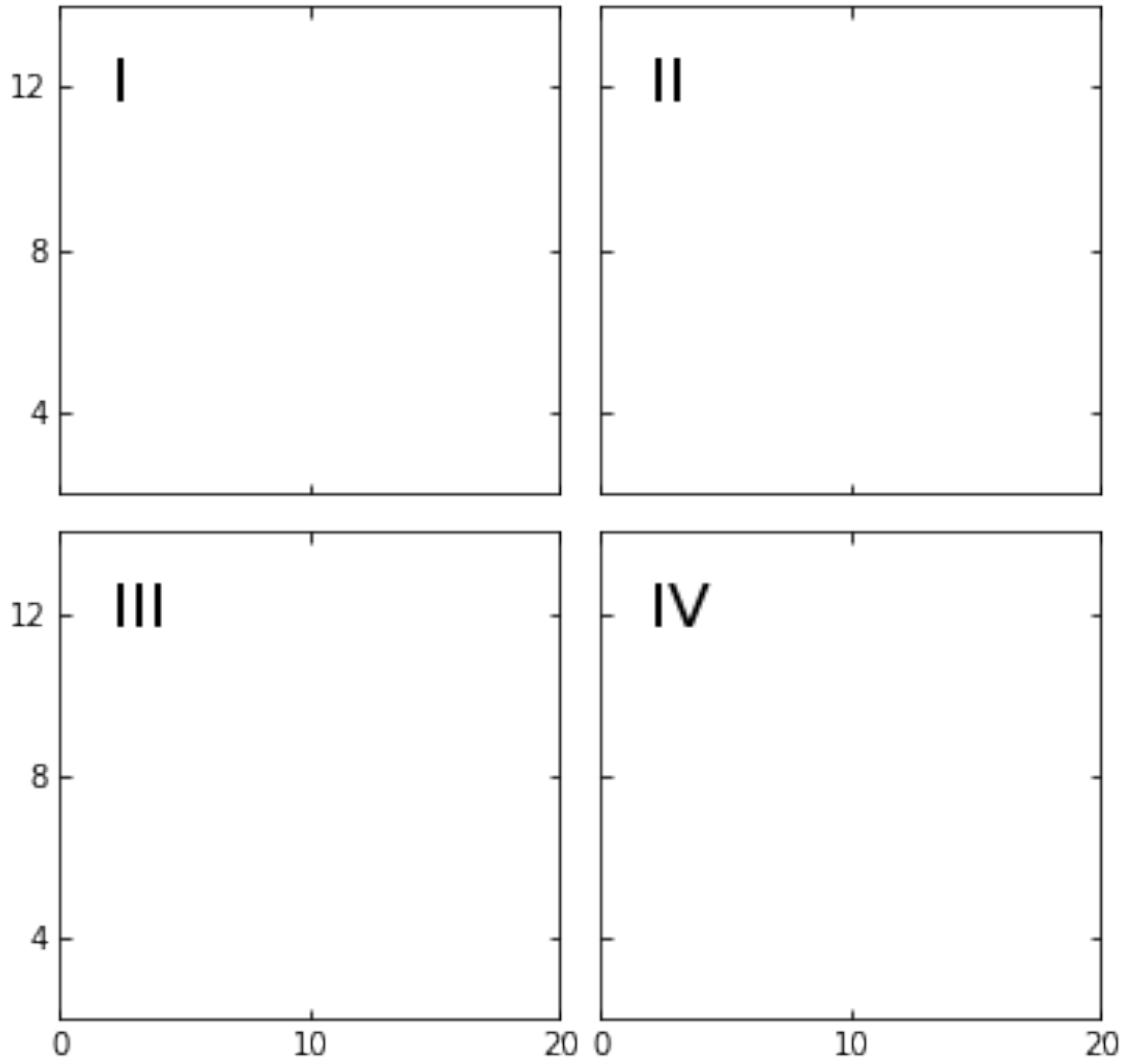
Anscombe's quartet

"numerical calculations are exact, but graphs are rough"

Anscombe's quartet

"numerical calculations are exact, but graphs are rough"

- These are 4 different datasets (X, Y)



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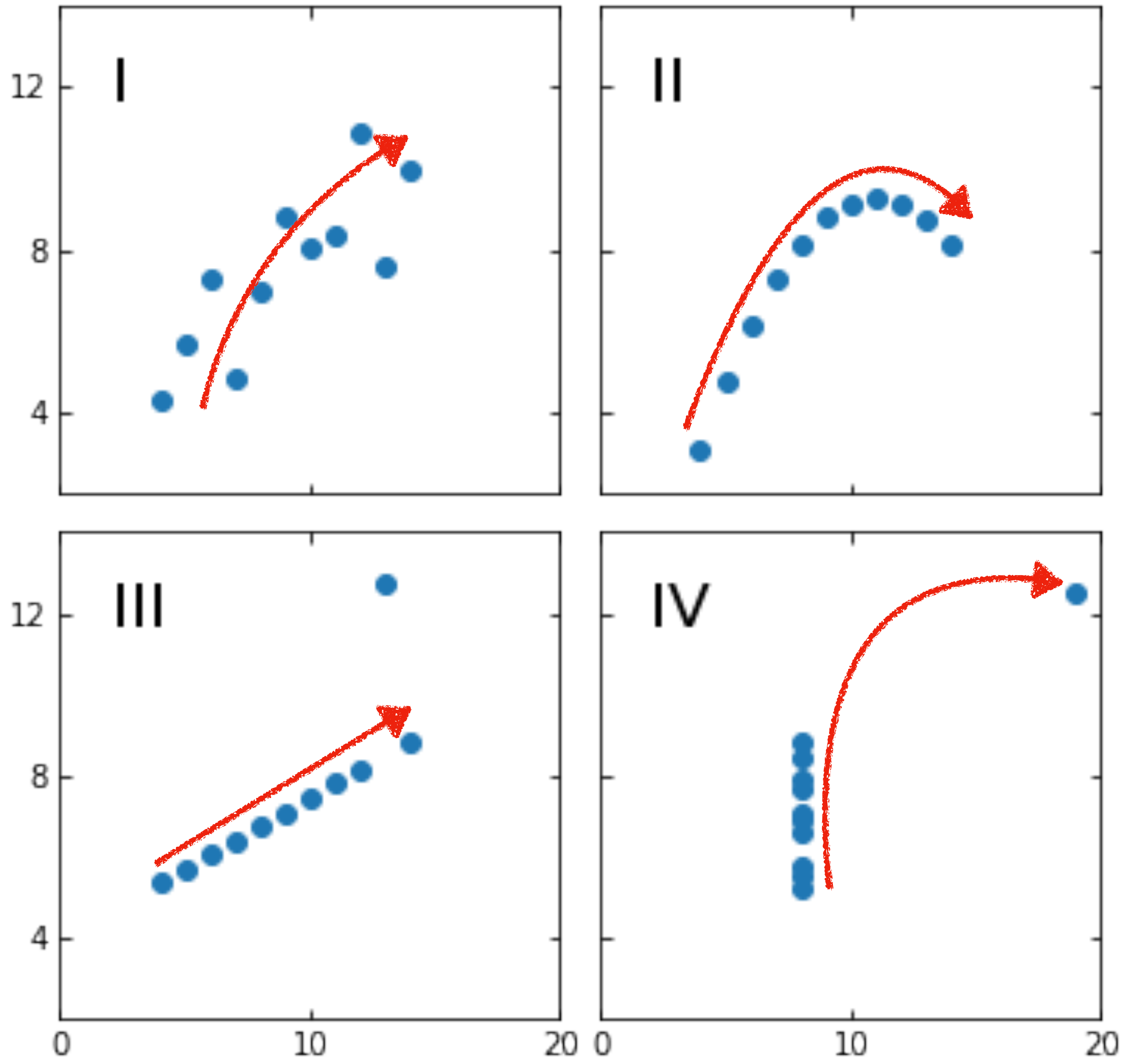

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- These are 4 different datasets (X, Y)
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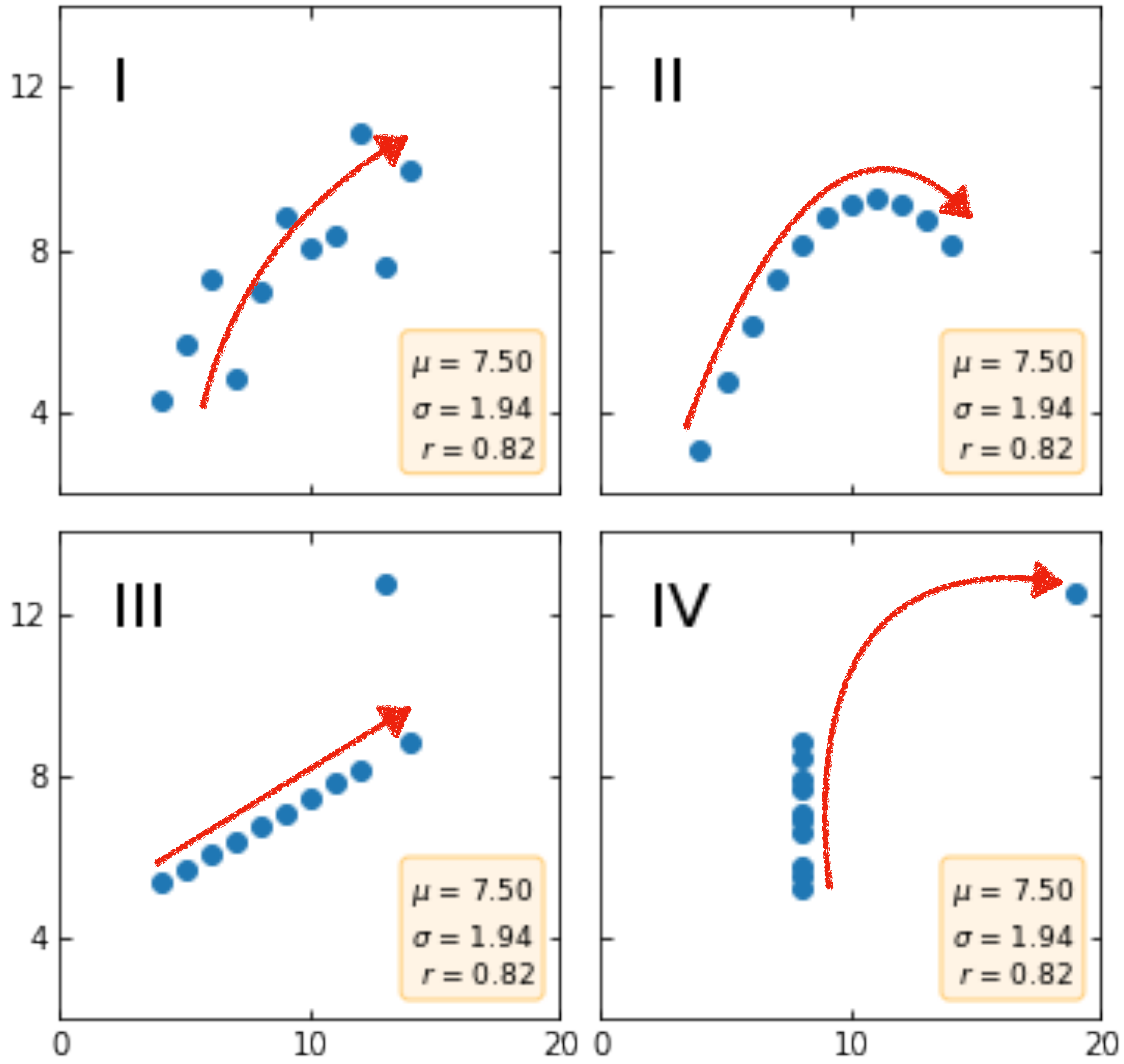
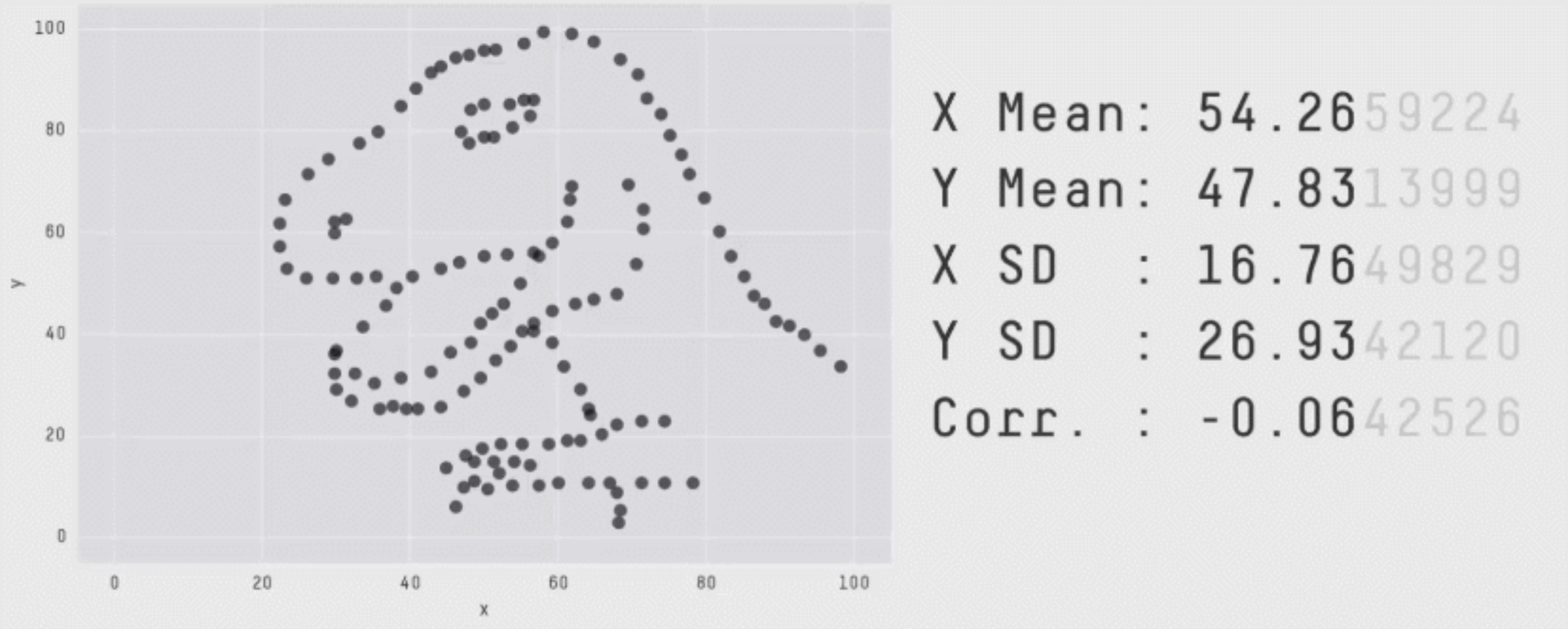
- Quantitative, they are the same: they have the same mean, standard deviation, and Pearson correlation



The Datasaurus dozen

Same Stats, different Graphs



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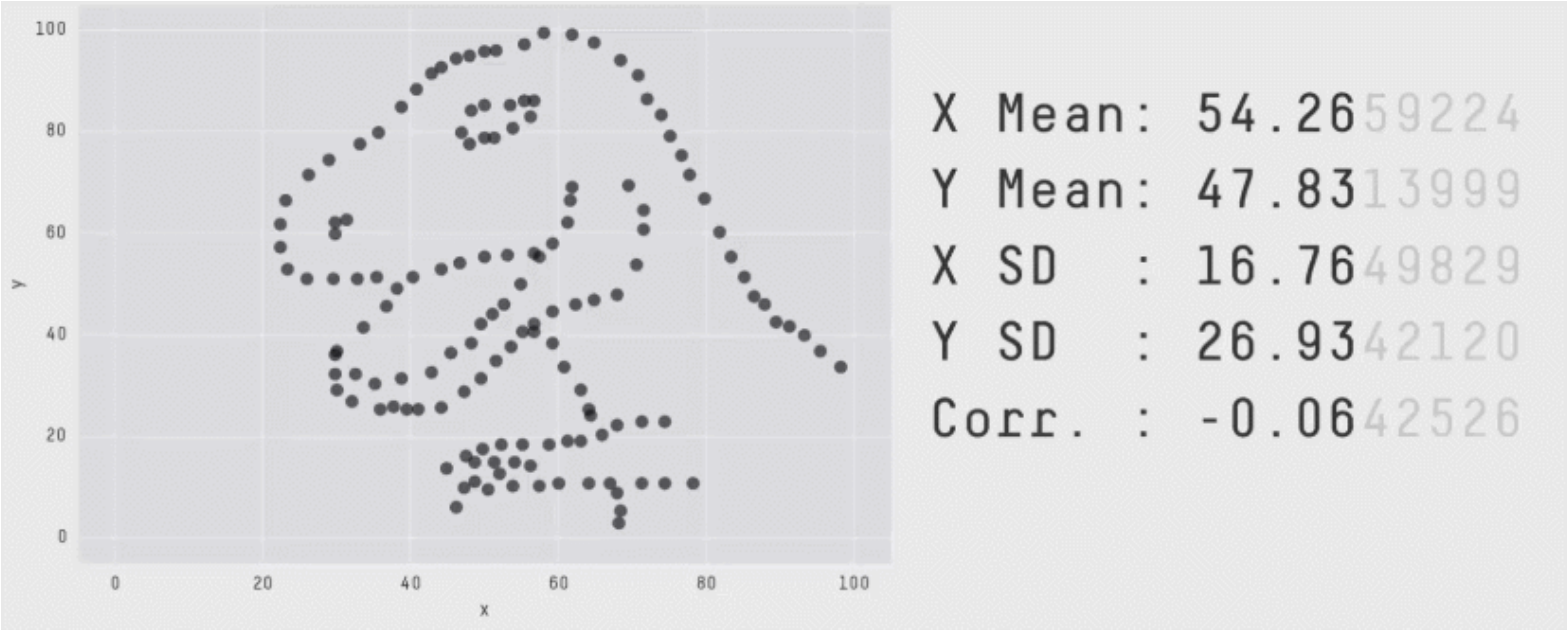
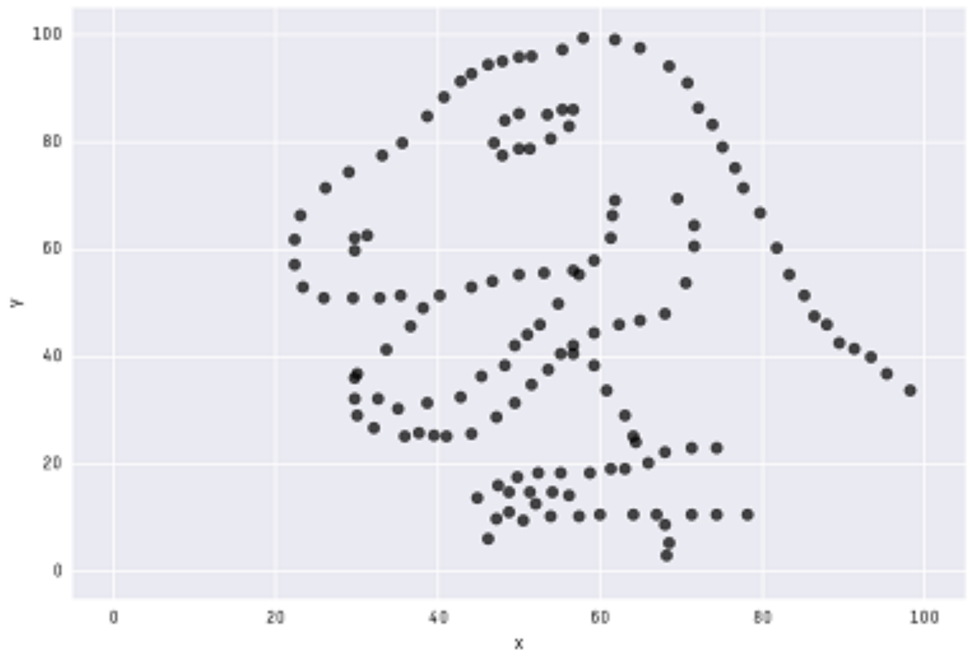
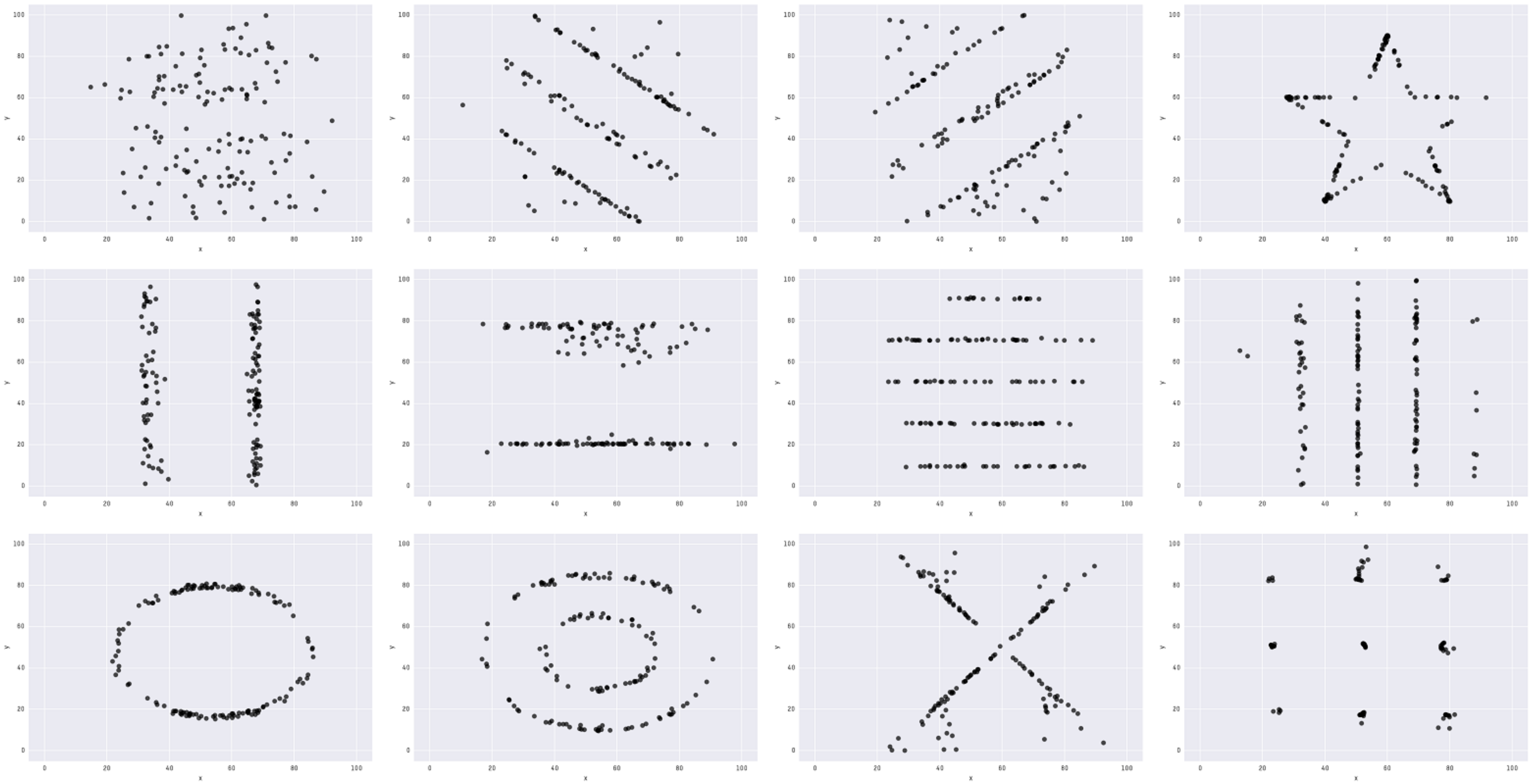




X Mean: 54.26
Y Mean: 47.83
X SD : 16.76
Y SD : 26.93
Corr. : -0.06



Limitations of Correlation

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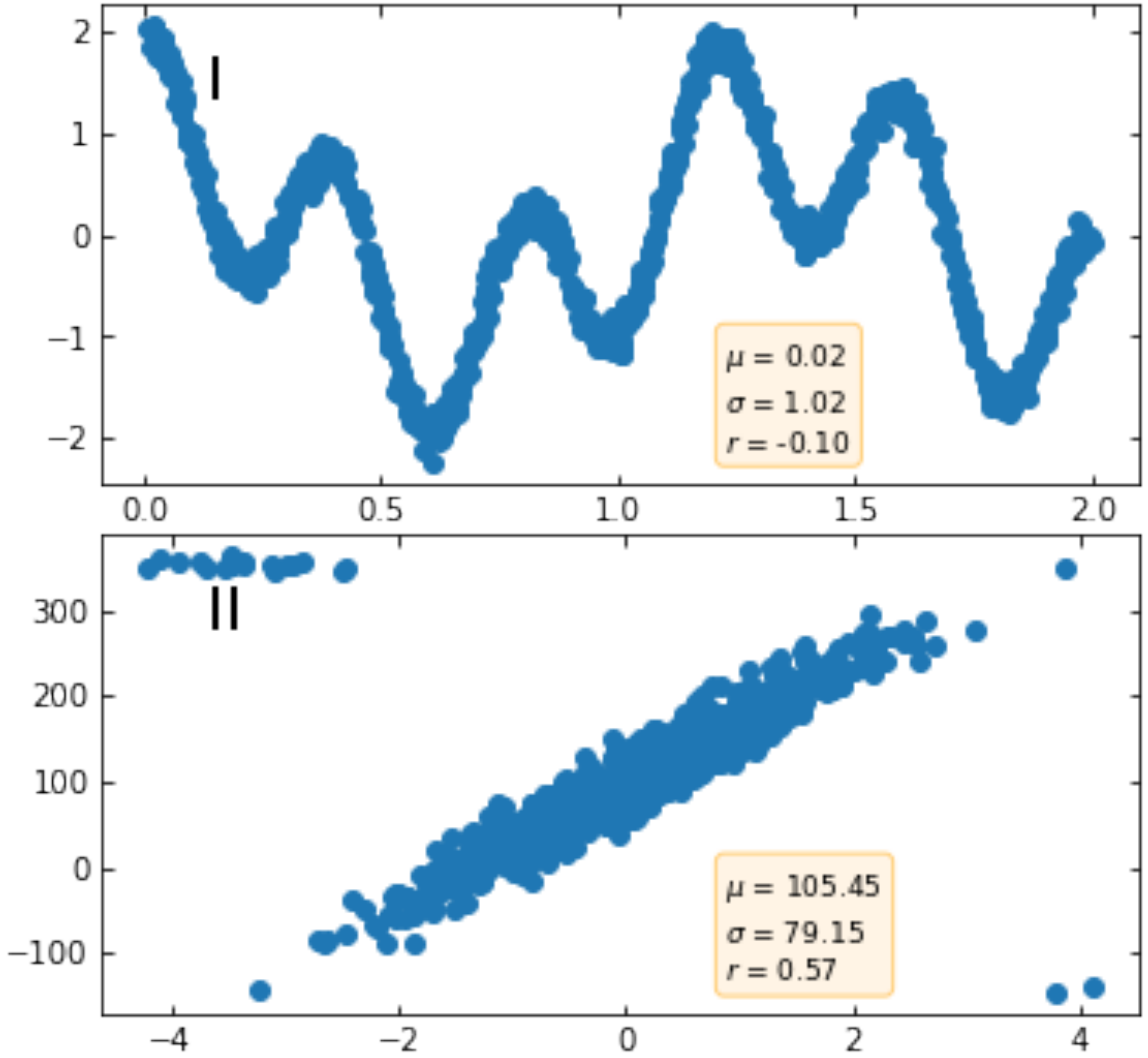
- Correlation can be influenced by **non-linear** relationships or **outliers**



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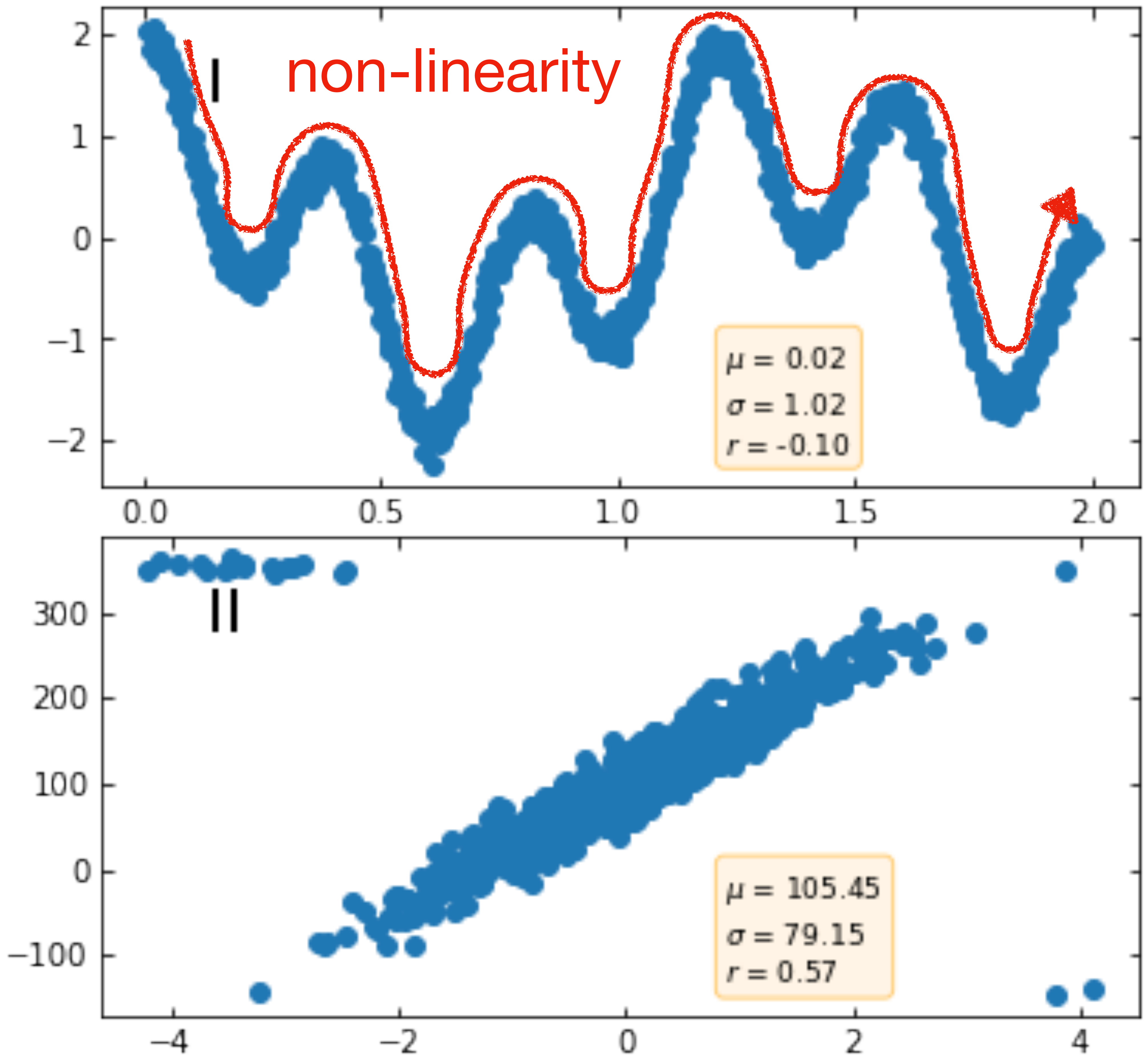

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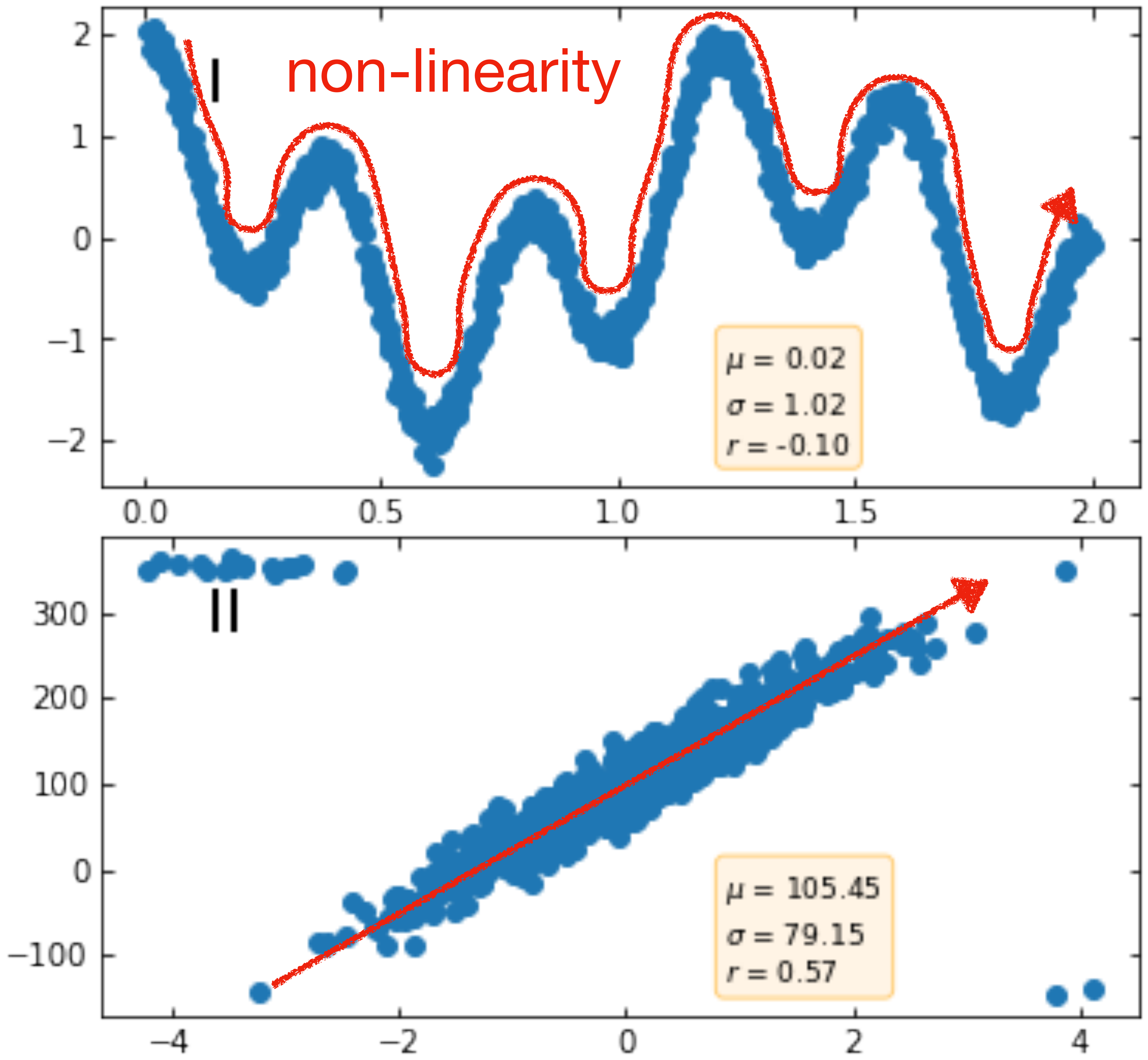

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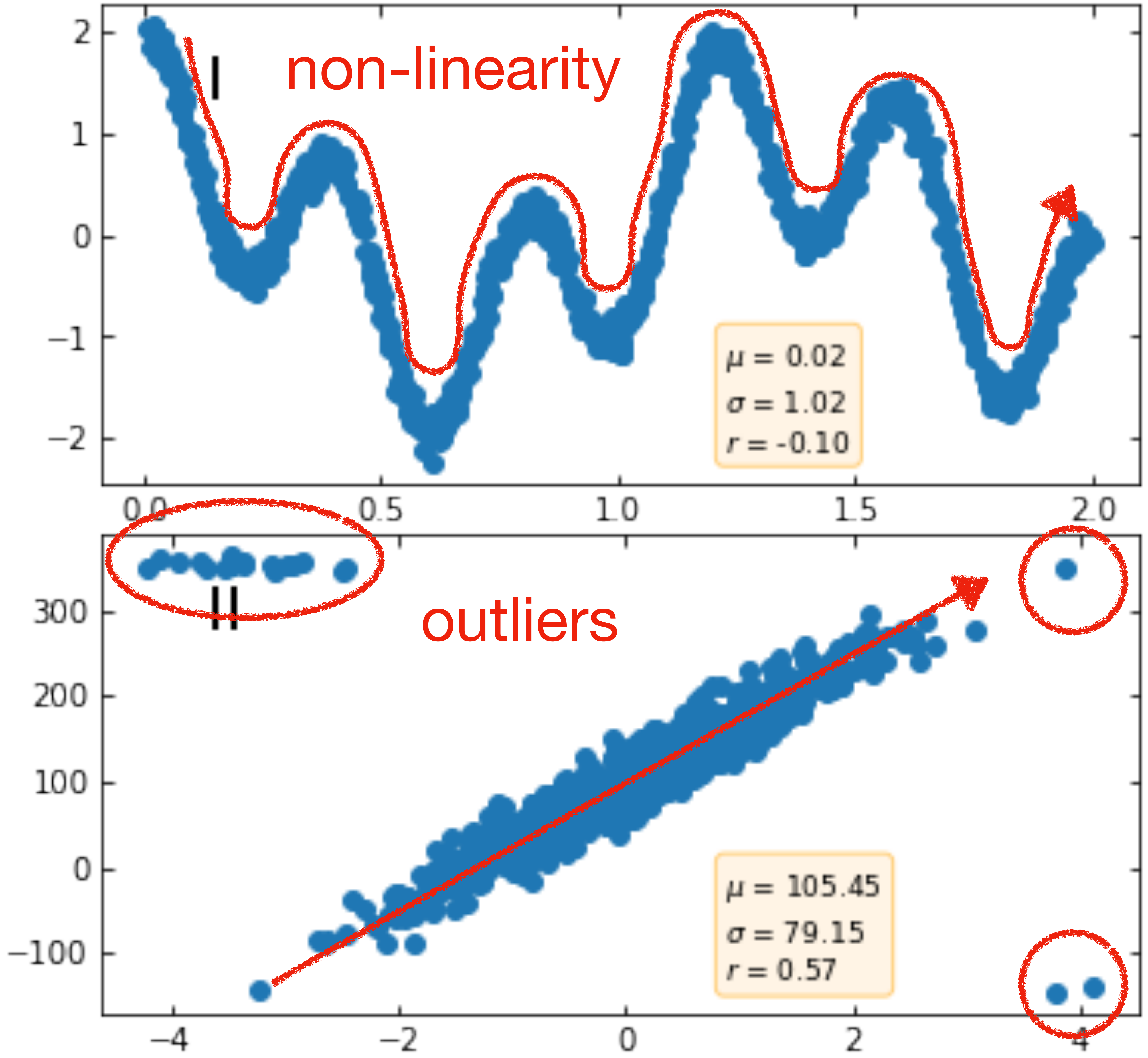
- Correlation can be influenced by **non-linear** relationships or **outliers**



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If you want to divorce, then drink whole milk!

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so c ... crime. When i ... ales
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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

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- Correlation does not provide information about the presence of **confounding** variables

- Correlation does not imply **causation**

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

Definition

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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).

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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 $X \to Y$ relationship.

How is causality measured?

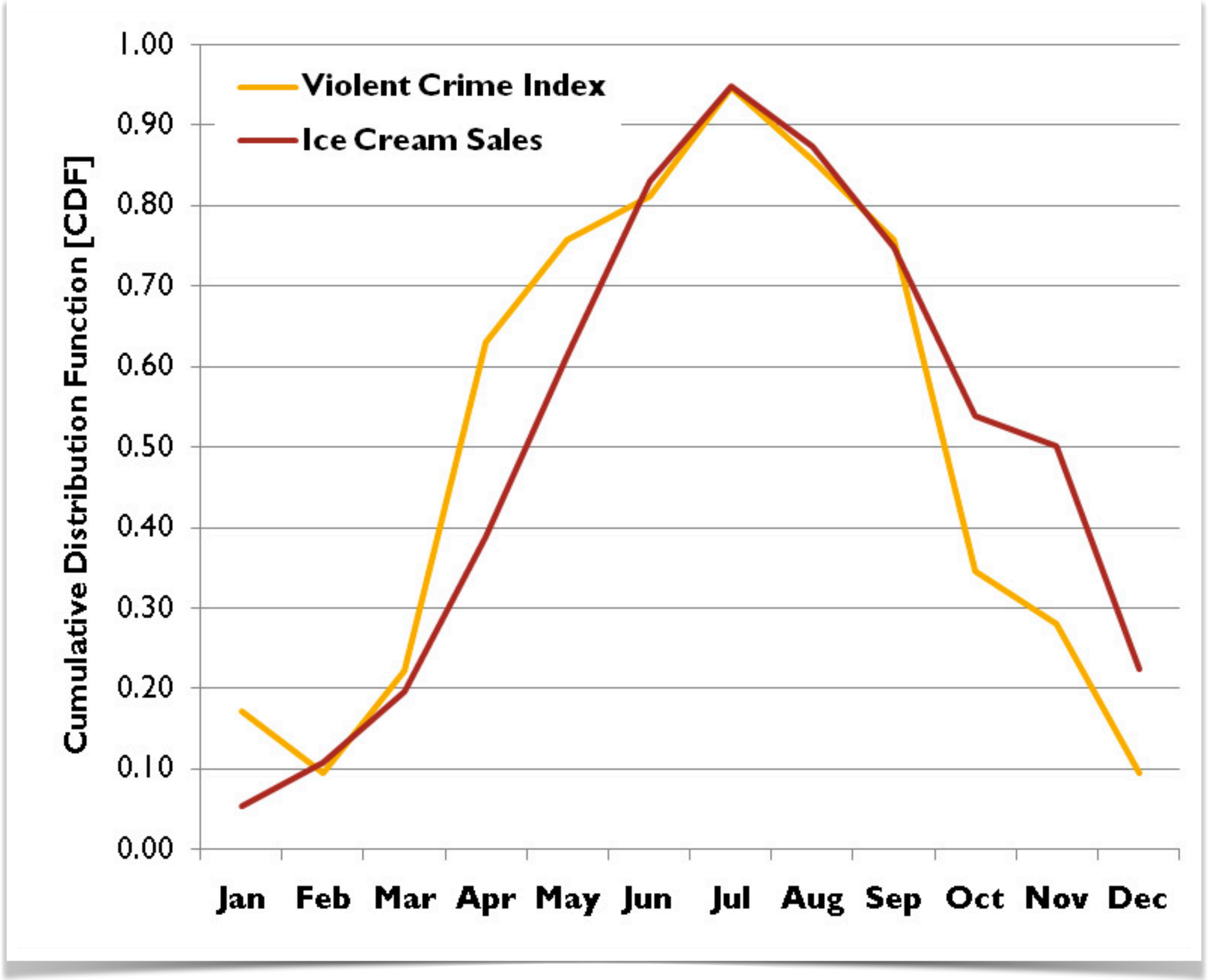
- **Experimentation:** A controlled experiment, where the independent variable X is manipulated (controlled), and the effect on the dependent variable Y is measured.
    - Randomized controlled trials (RCTs) are often used in clinical medical research to demonstrate causality.
        - Also known as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

Examples

of causality

Examples

of causality



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

Examples

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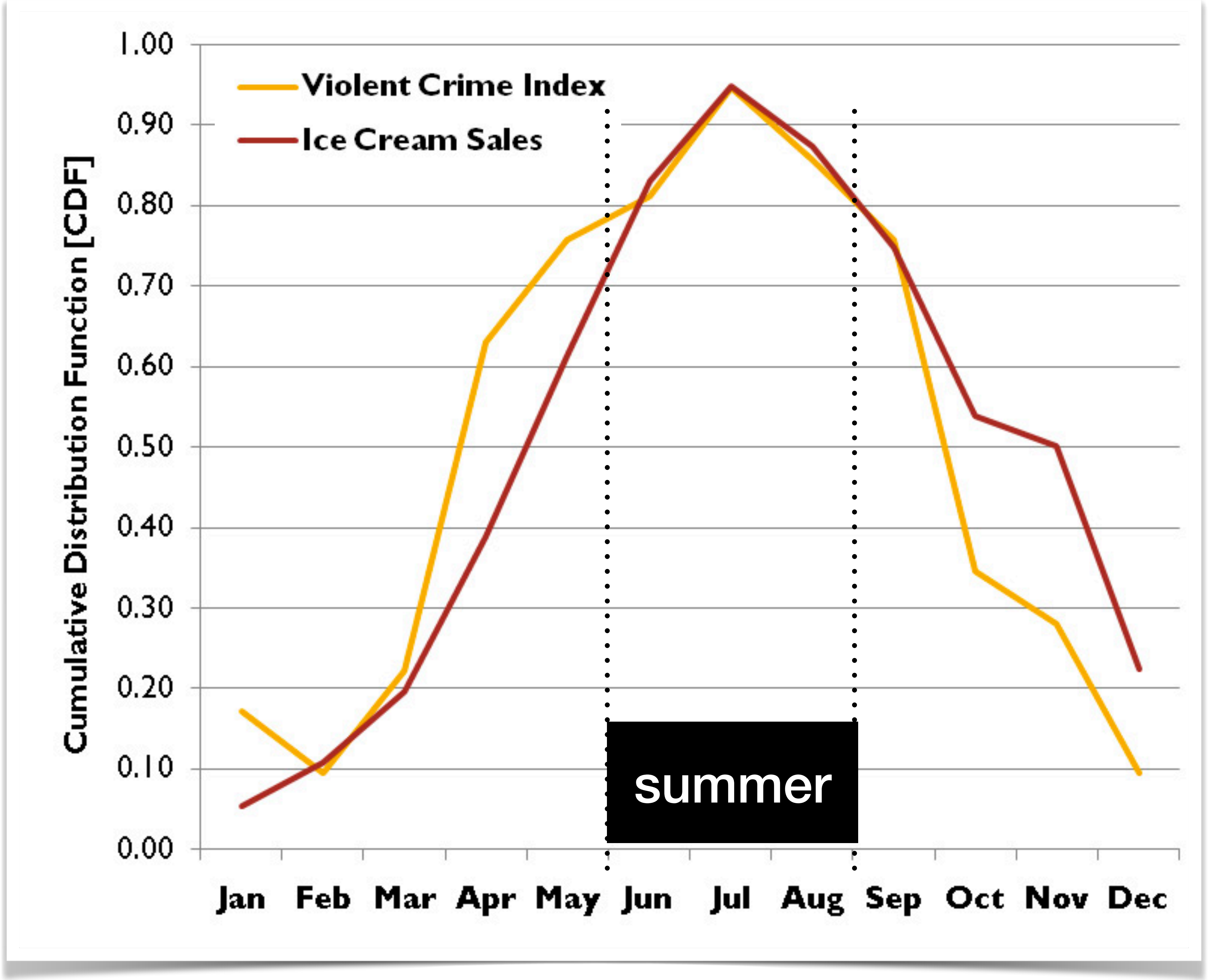

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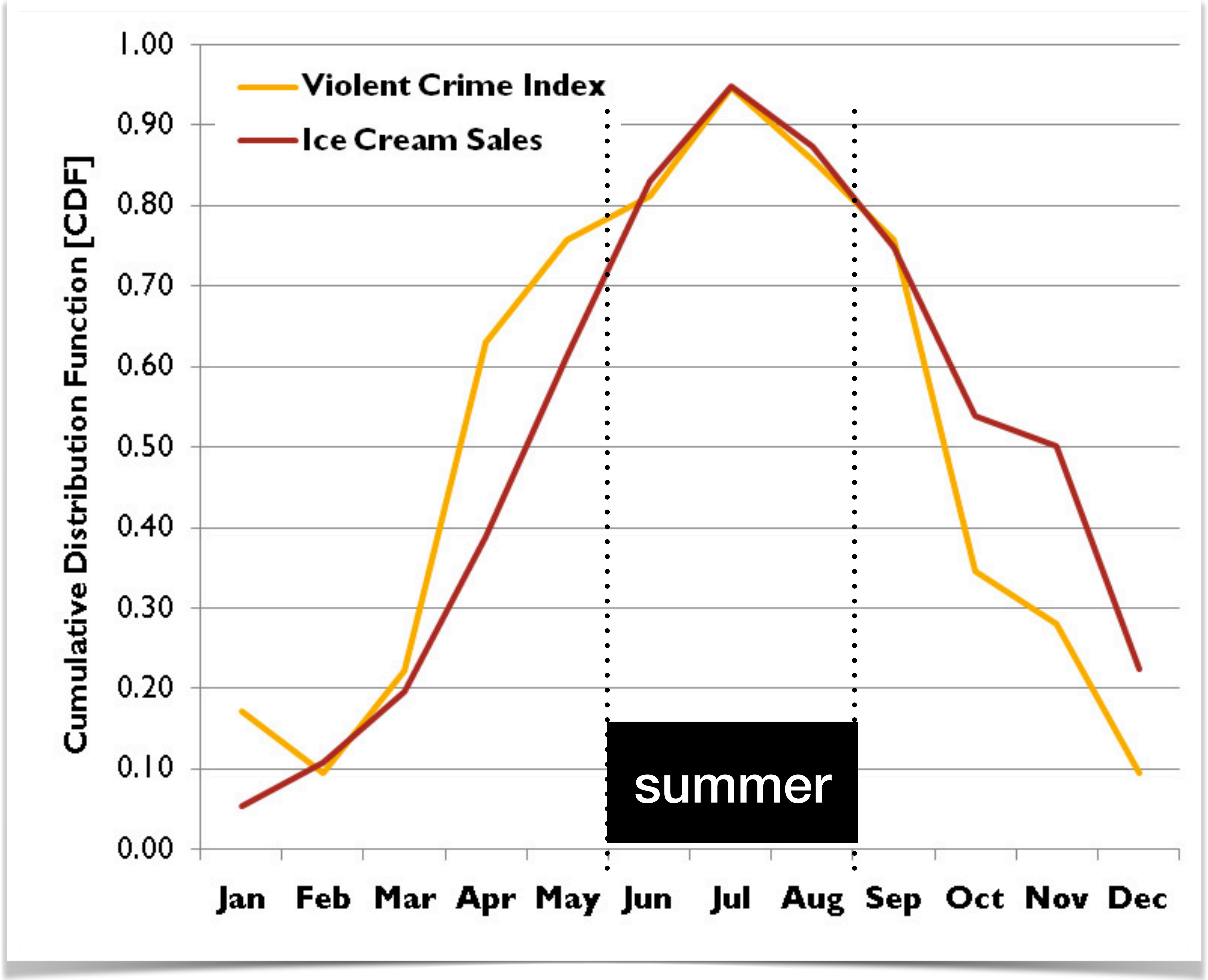

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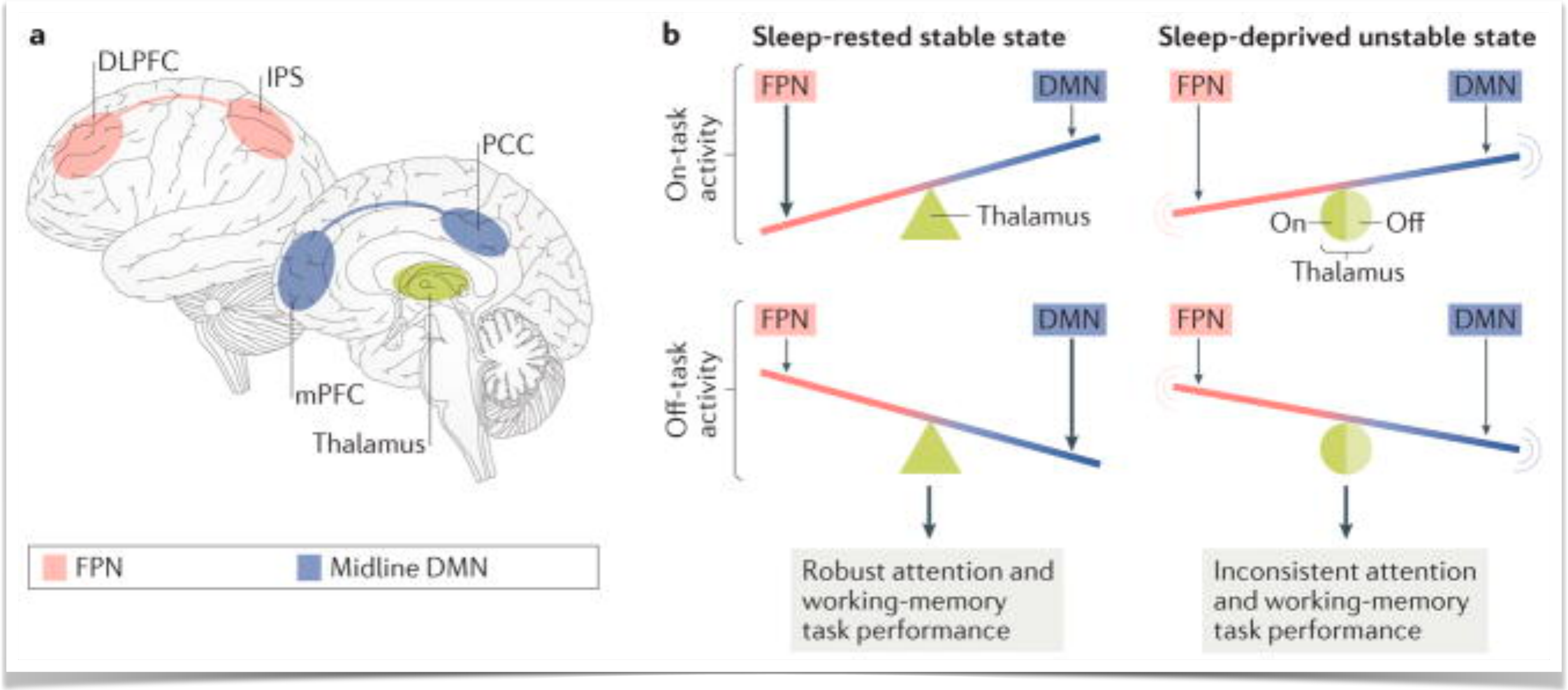

Sleep deprivation causes deficit in attention and working memory [Krause et al. 2017]

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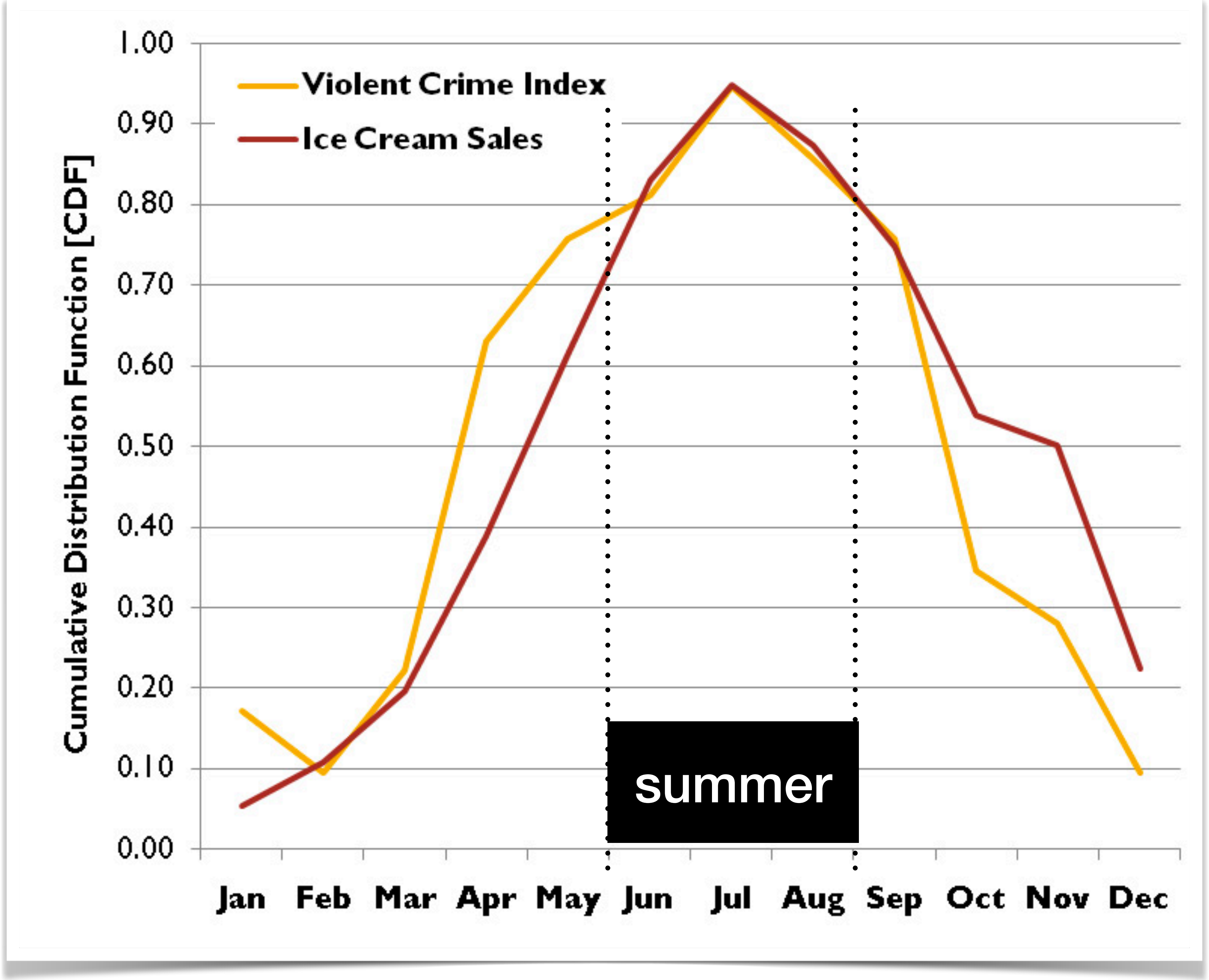

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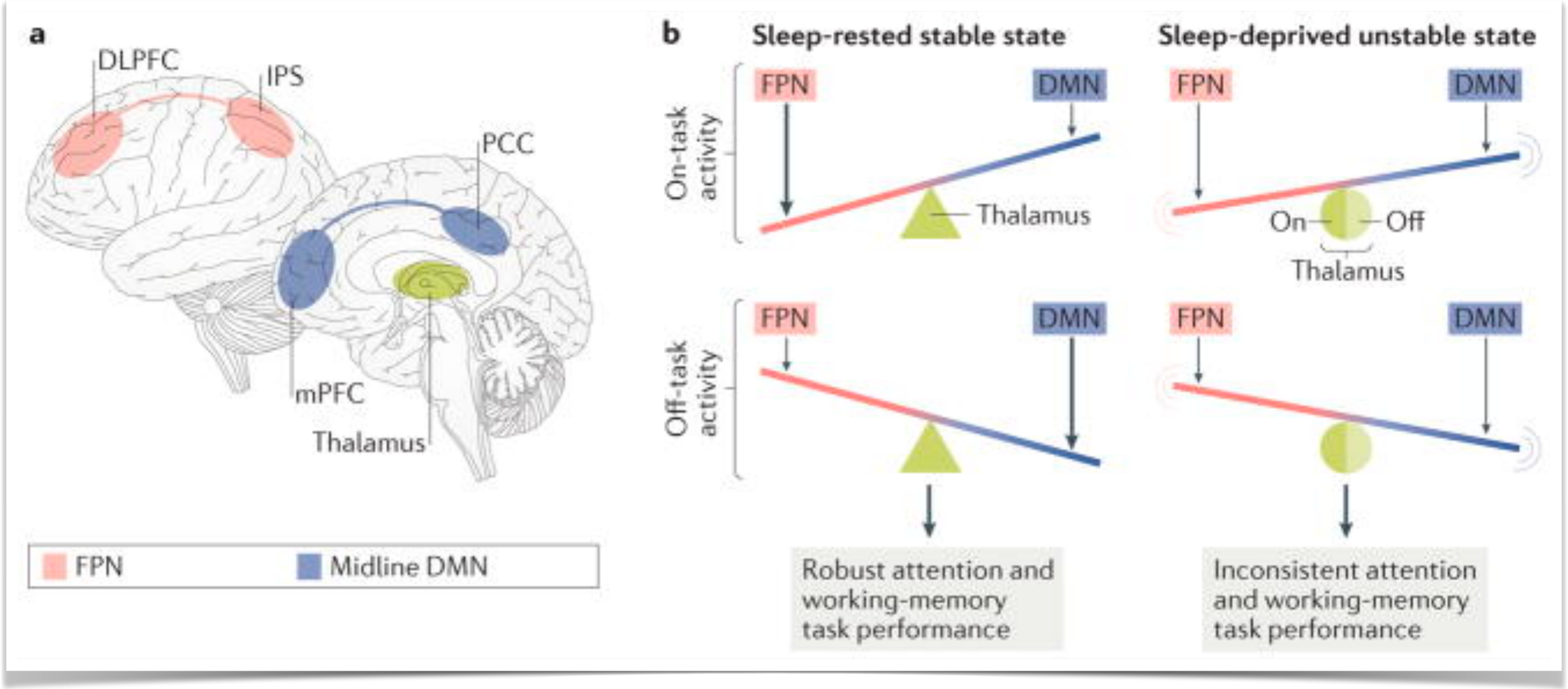
control group

treatment group



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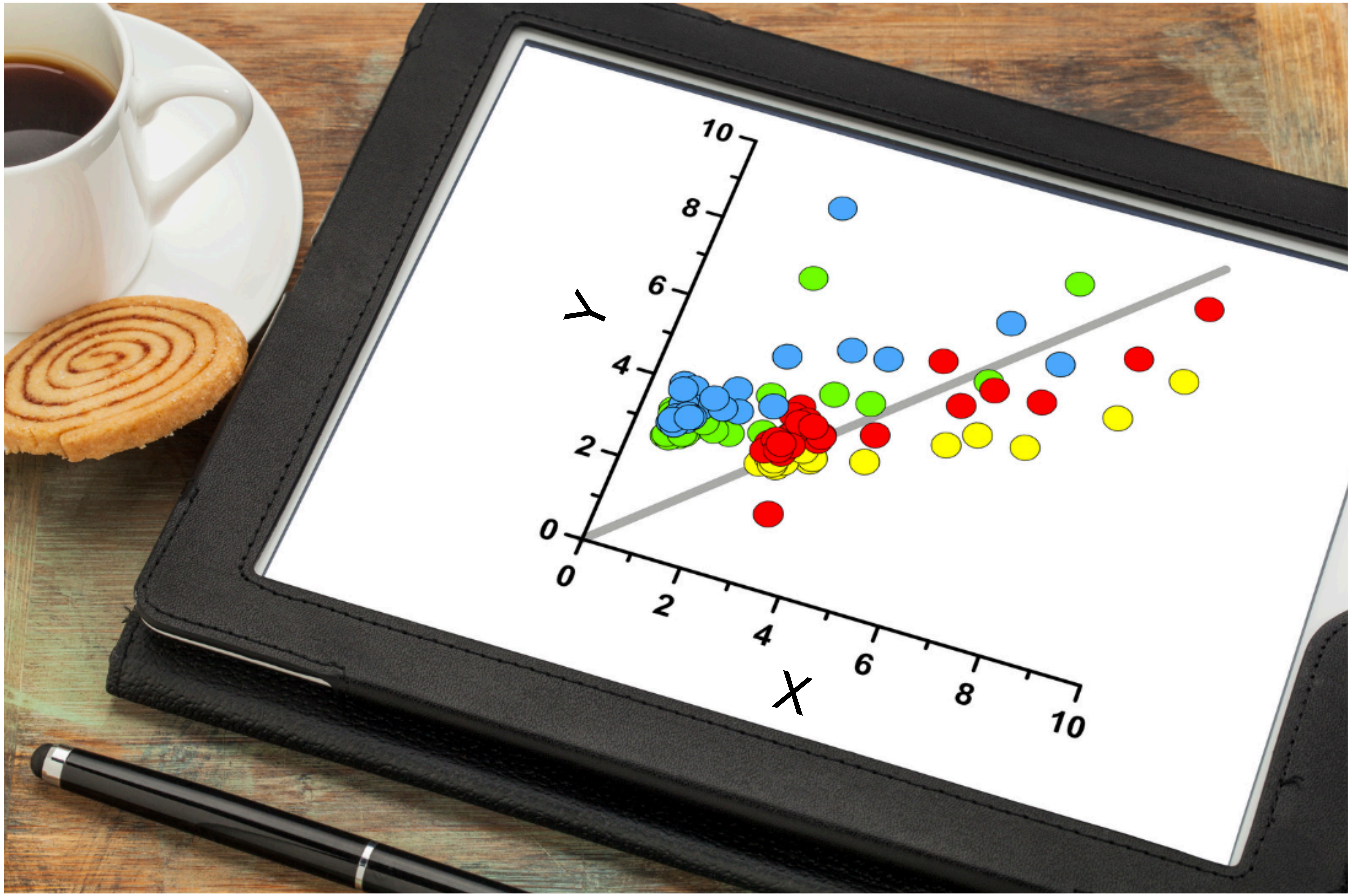
Linear Regression



Linear regression

Basics

Linear regression

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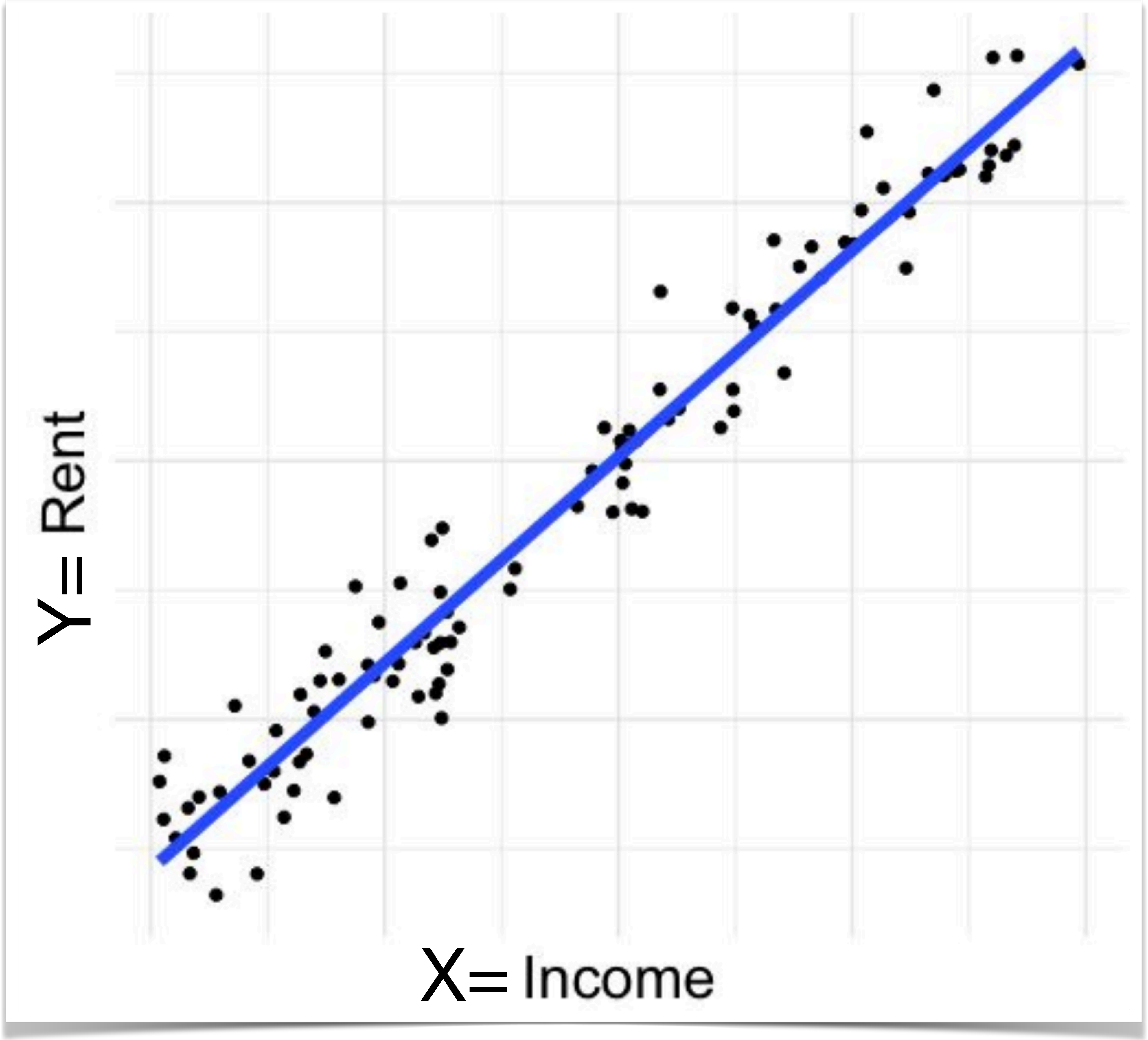
- It predicts a continuous variable Y using one or multiple variables X's (can be continuous, categorical, or both).



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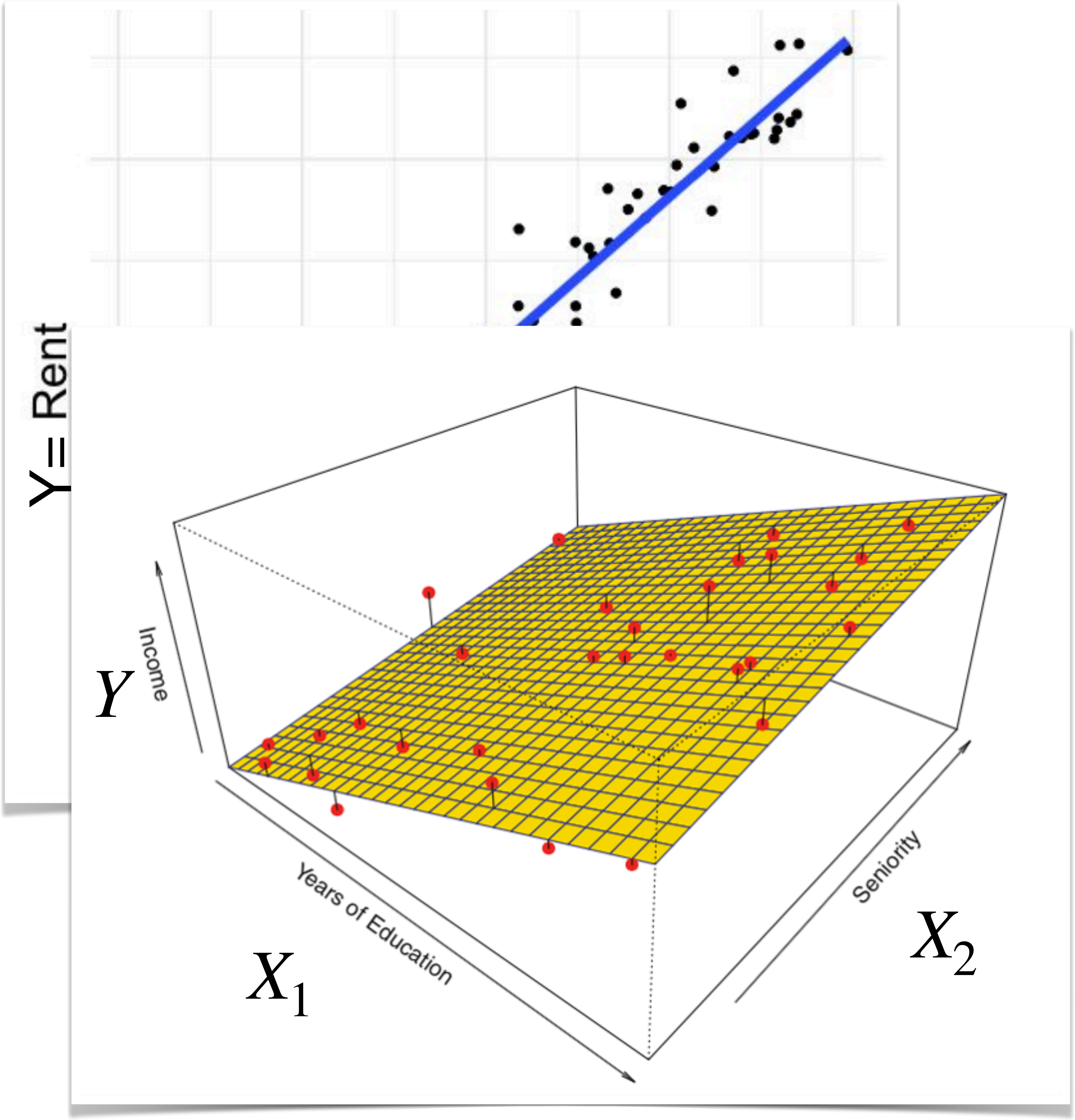

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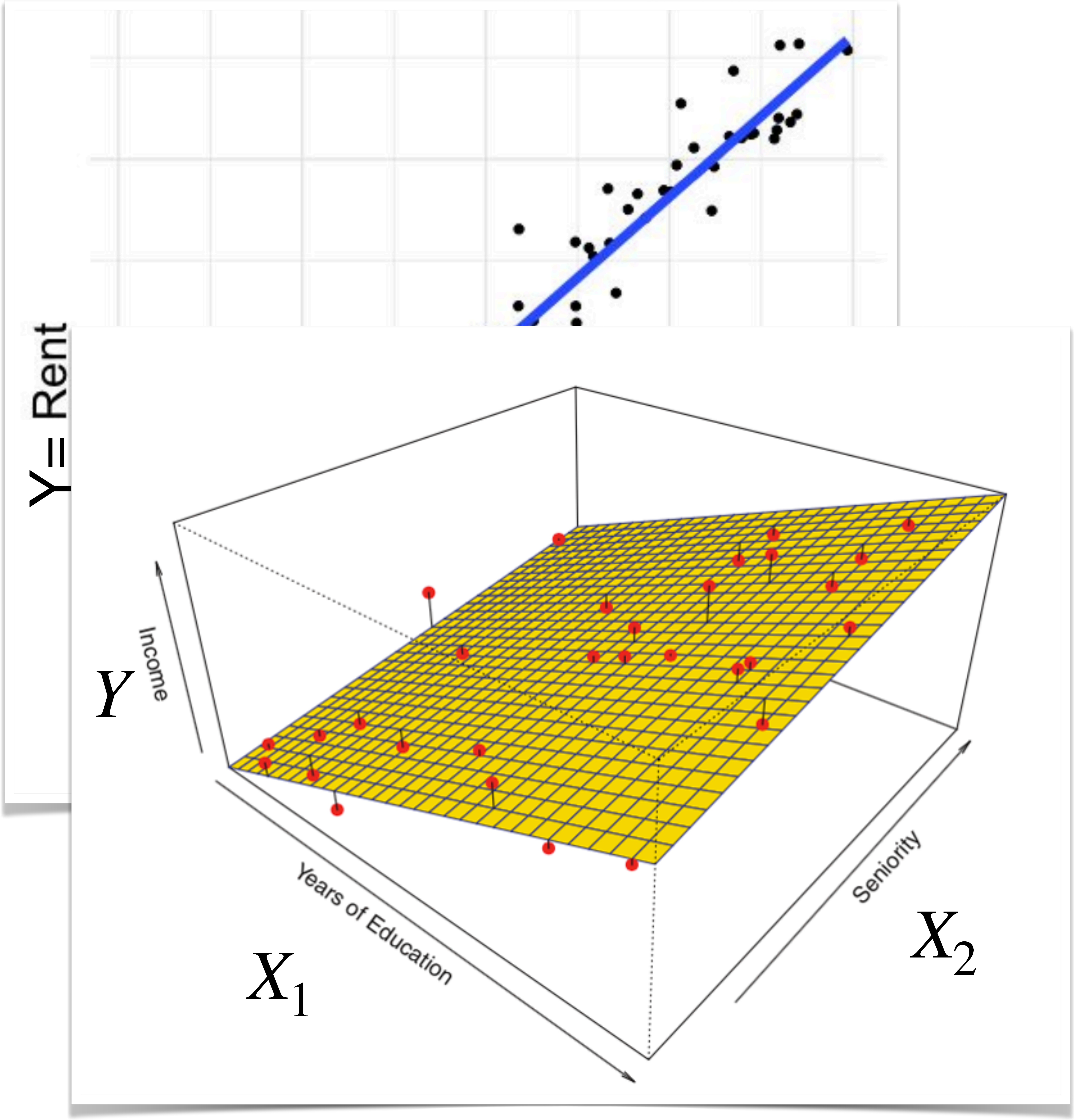
- It describes the relationship between these variables using a line (2D) or a plane (3D)
  - Similar to correlation, but **correlation** measures the strength and direction of a linear relationship between two variables, and **regression** measures how those variables affect each other using an equation (it estimates the best straight line that summarizes the relation).



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

Linear regression

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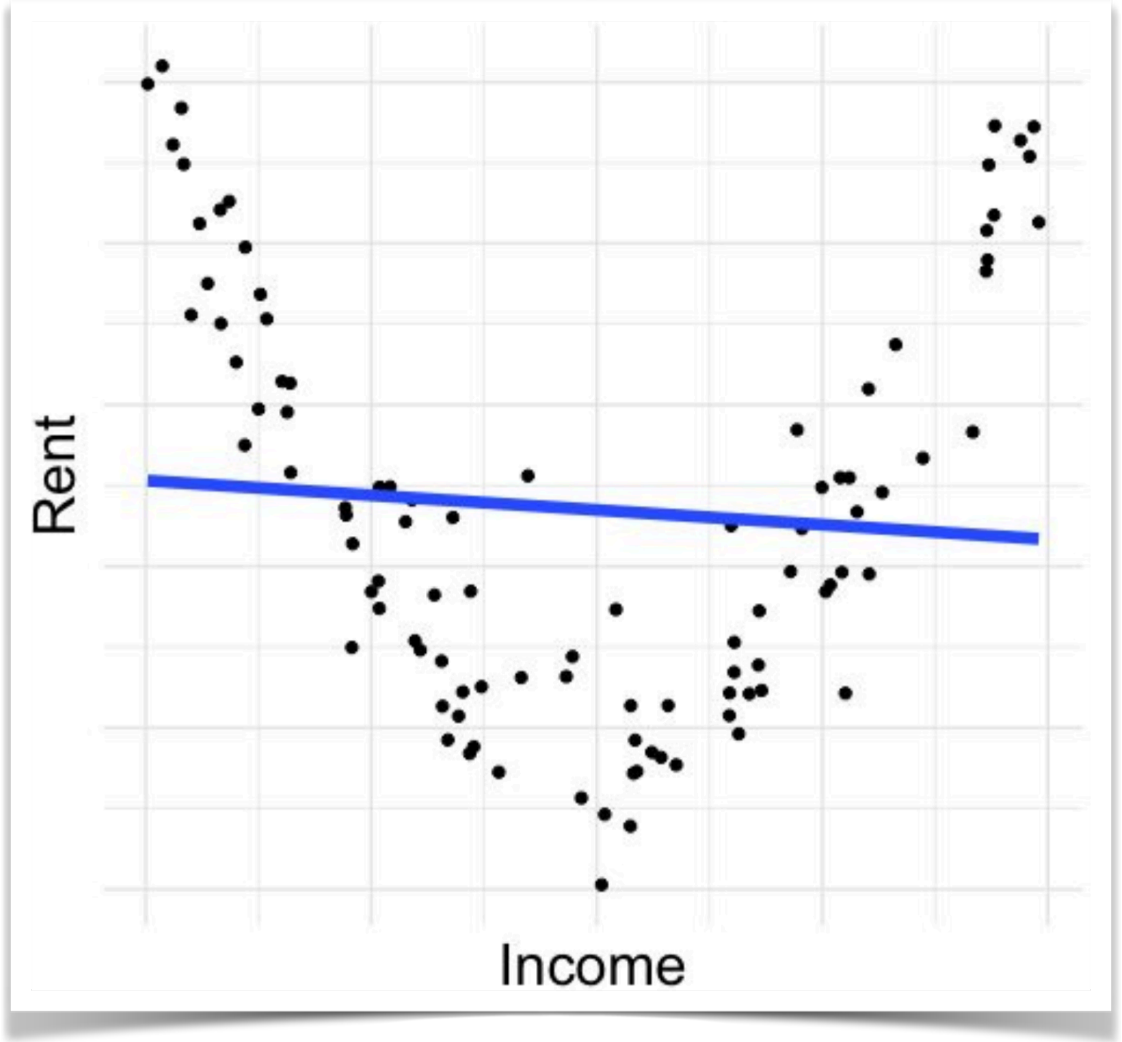

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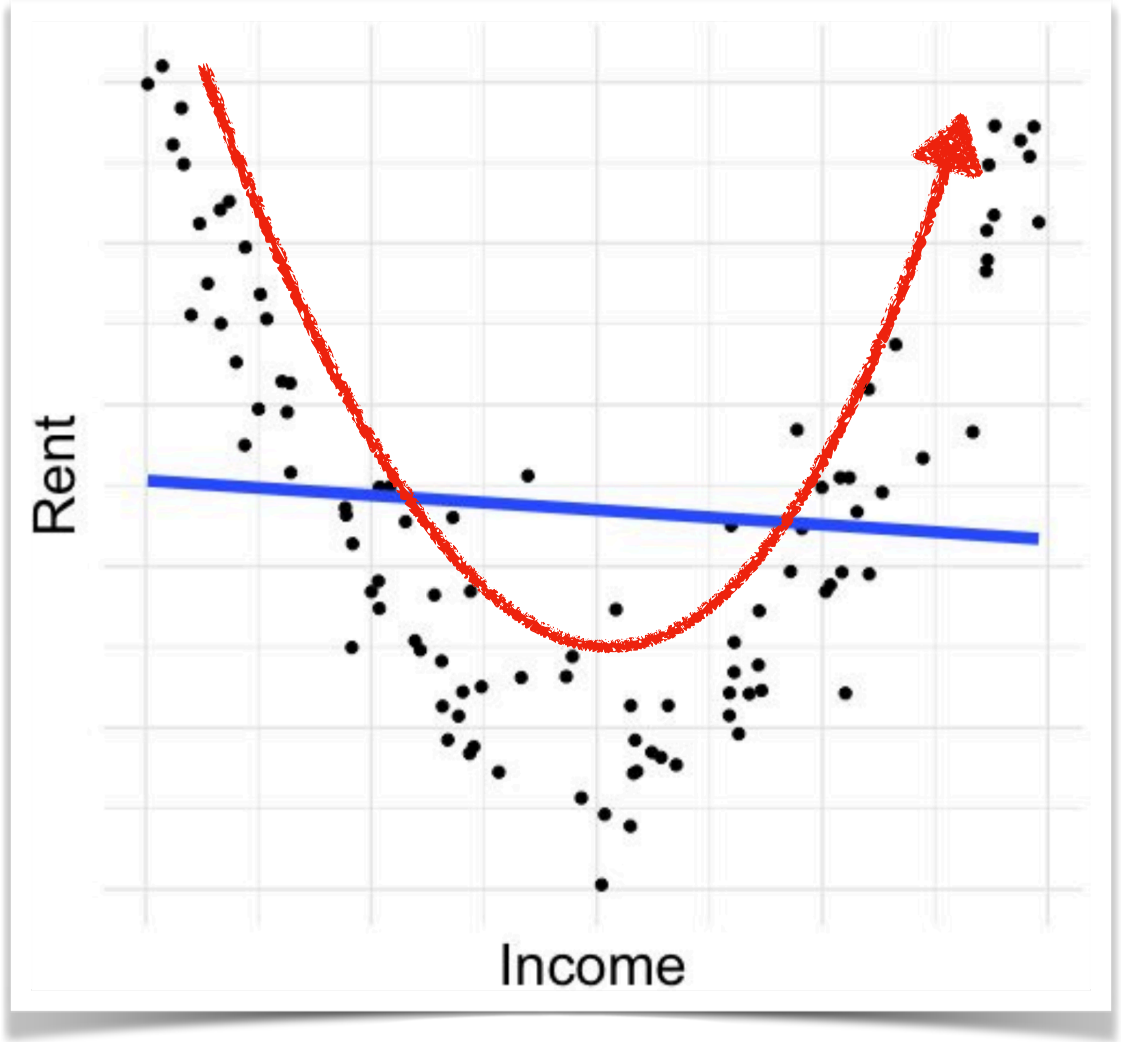

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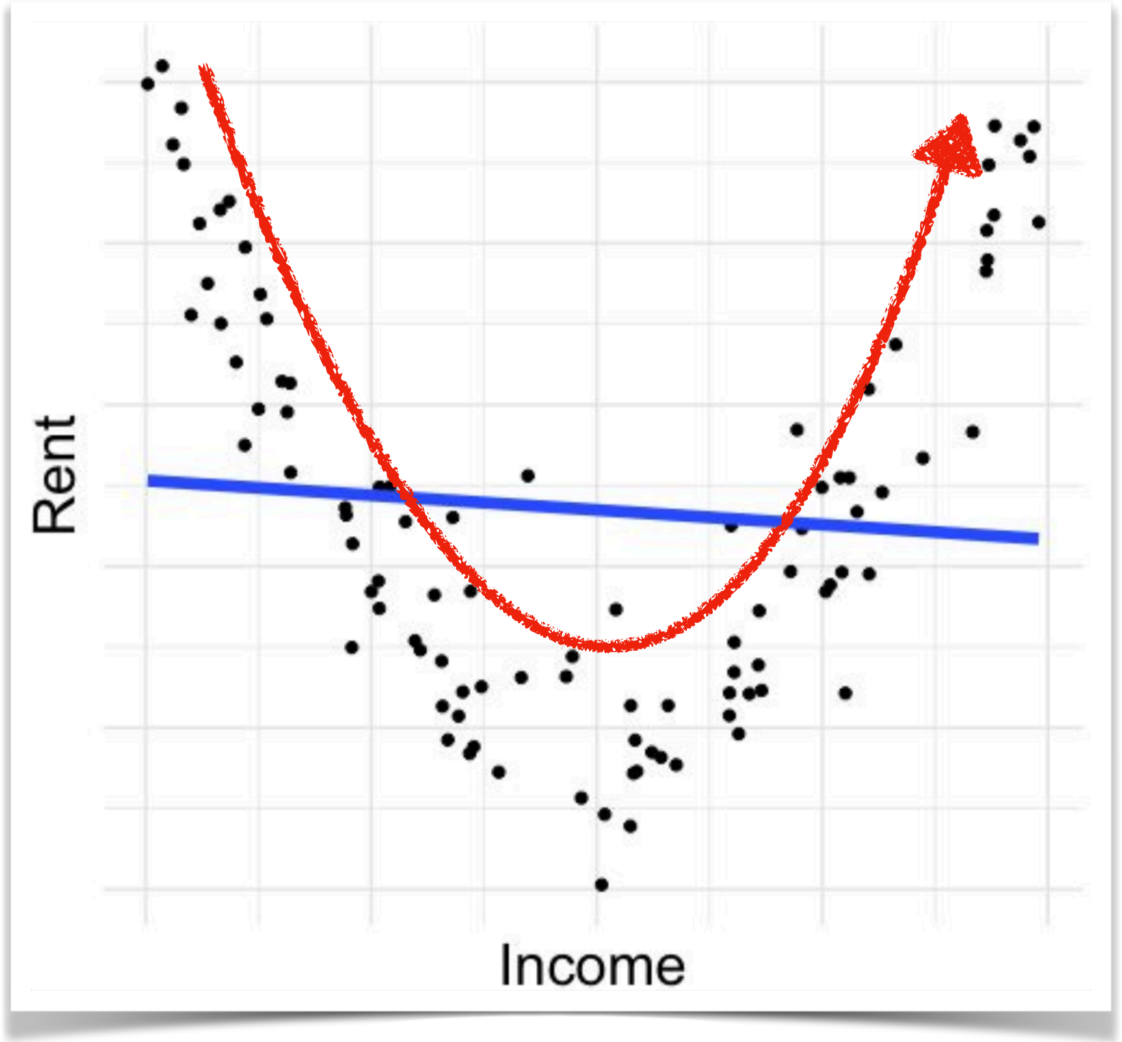

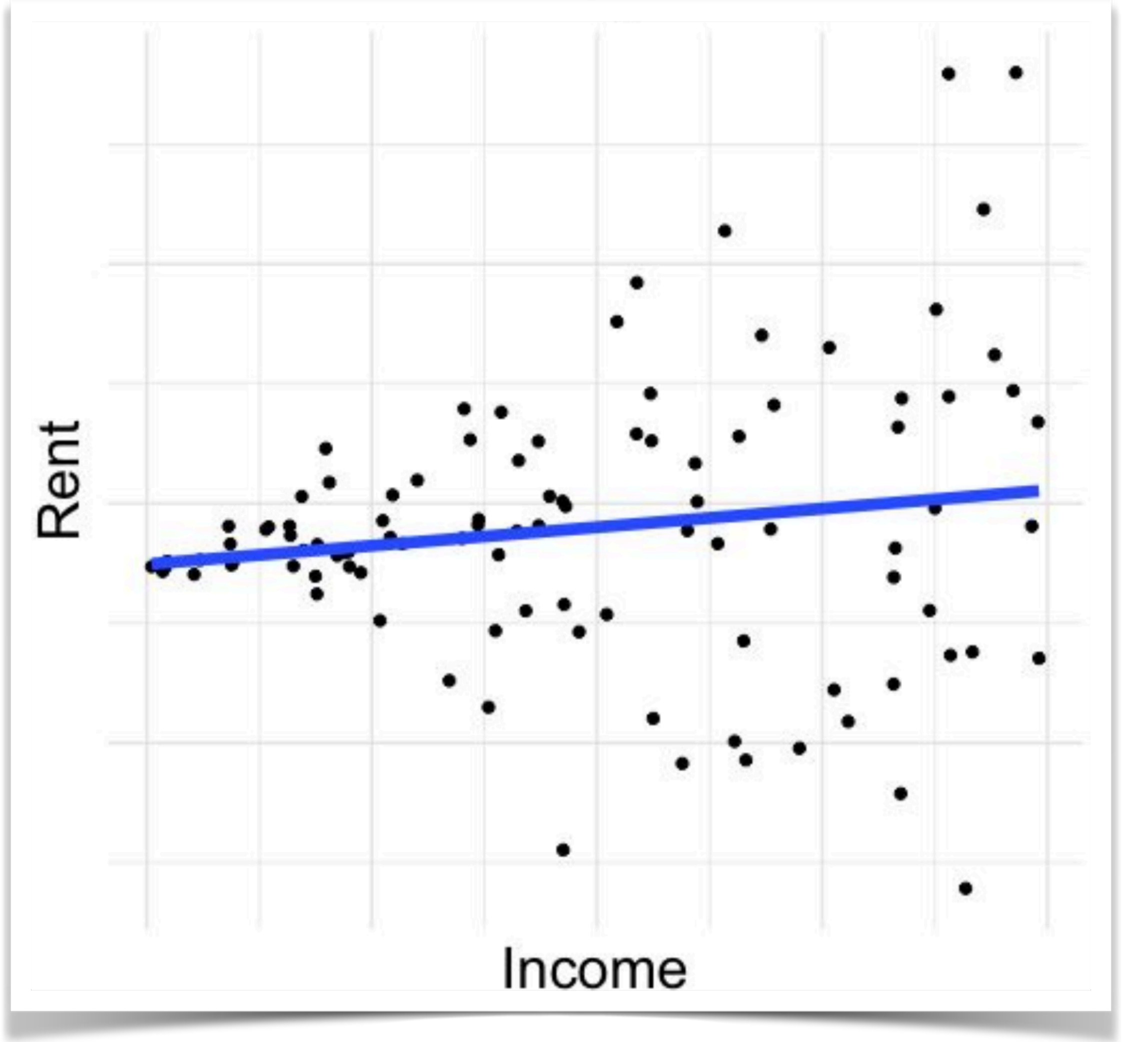

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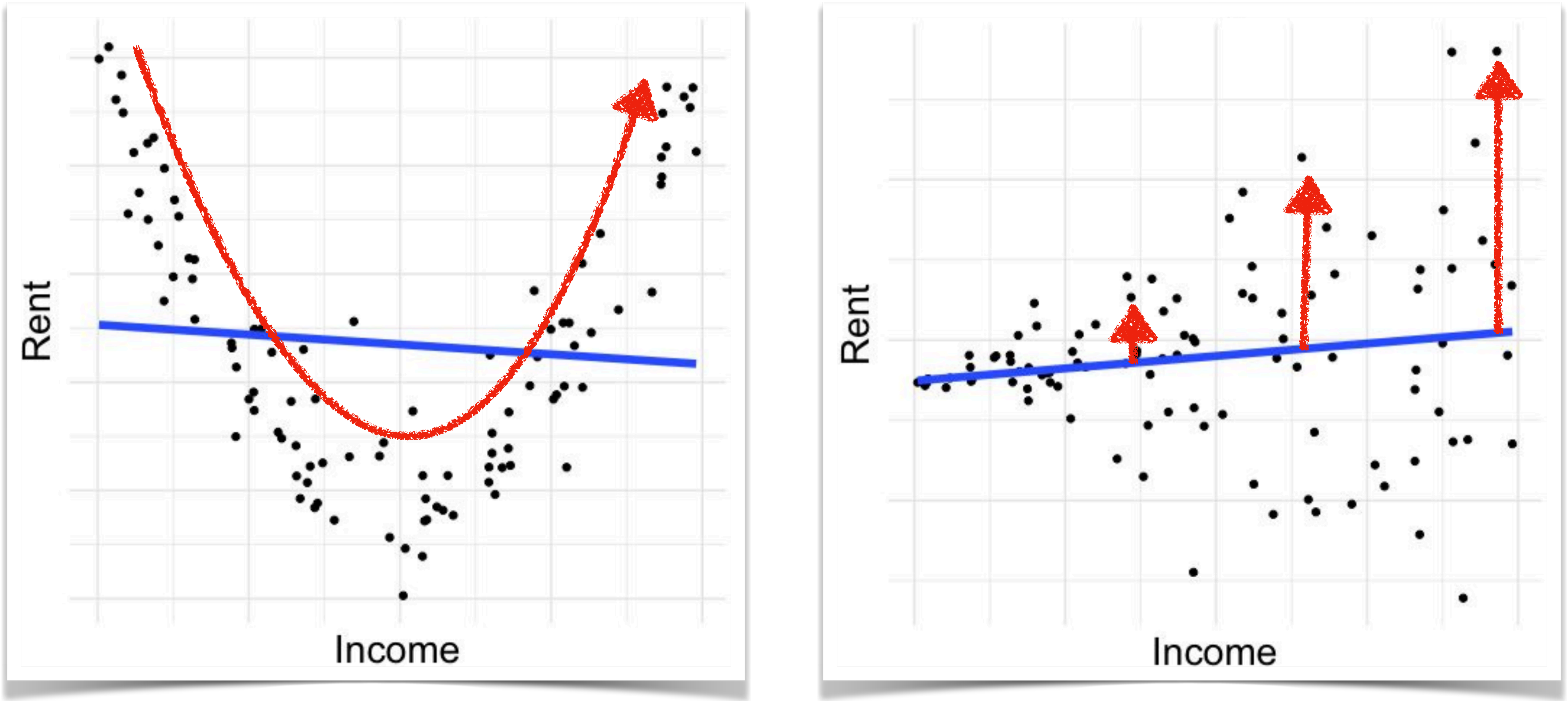

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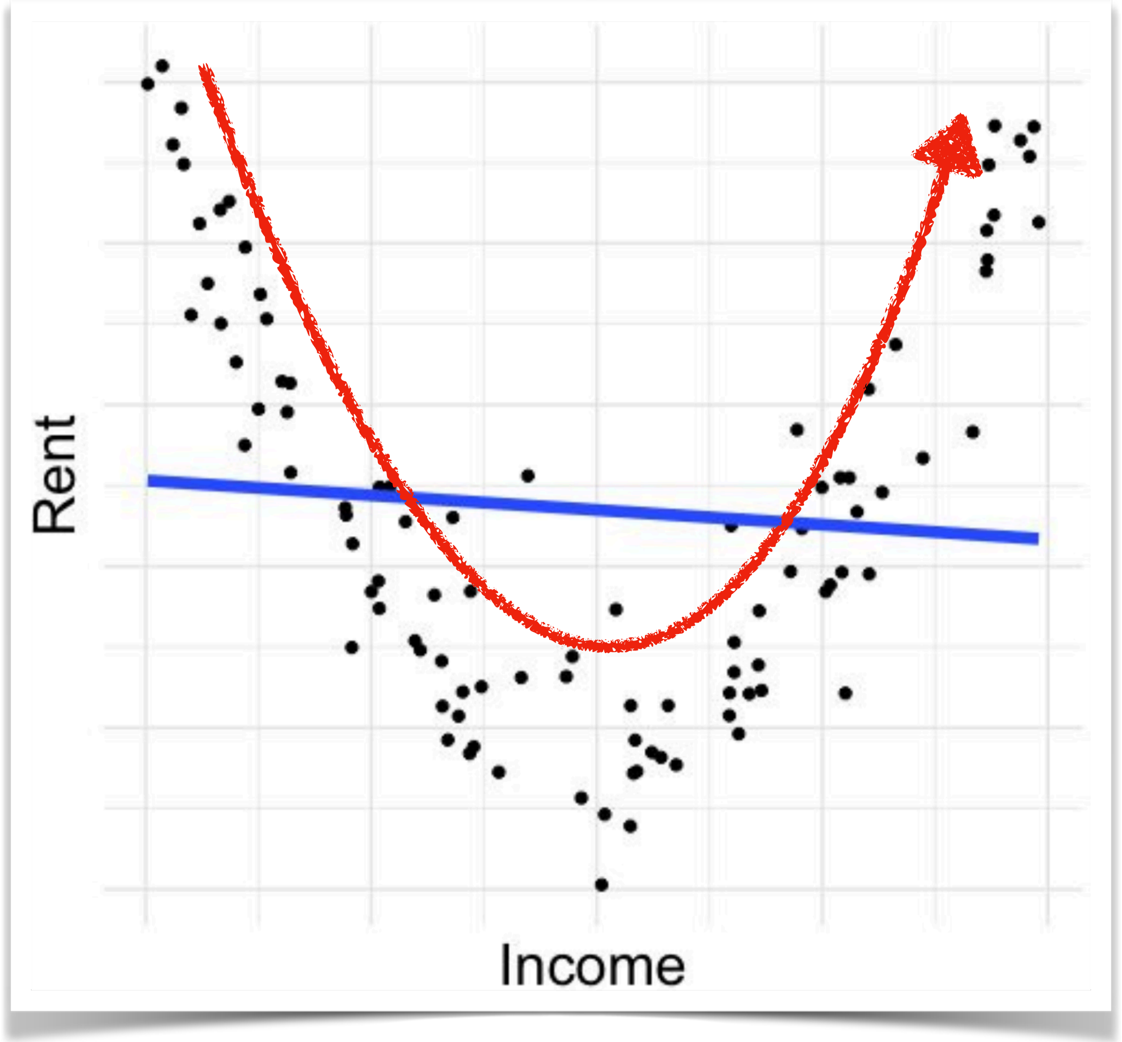

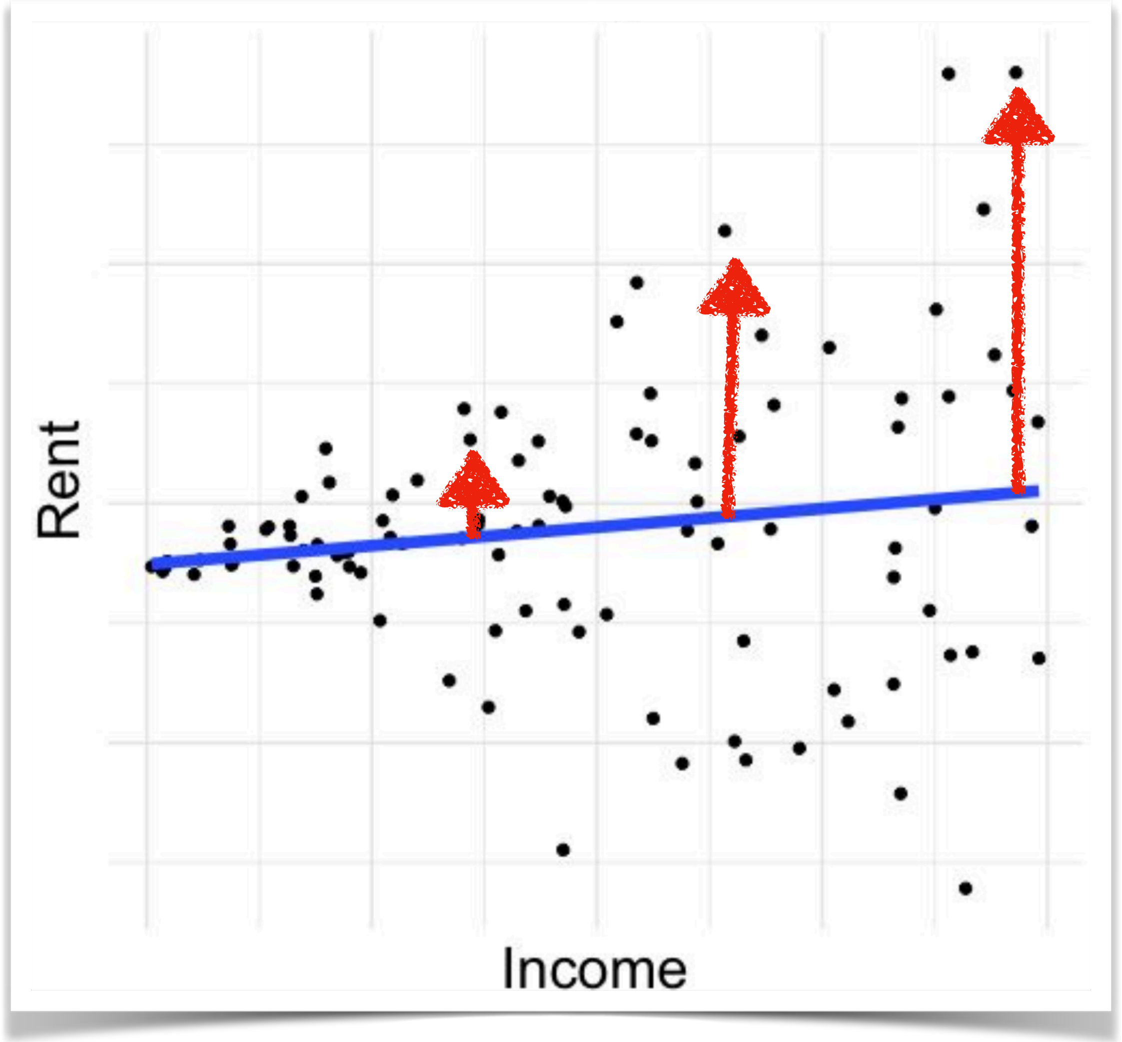

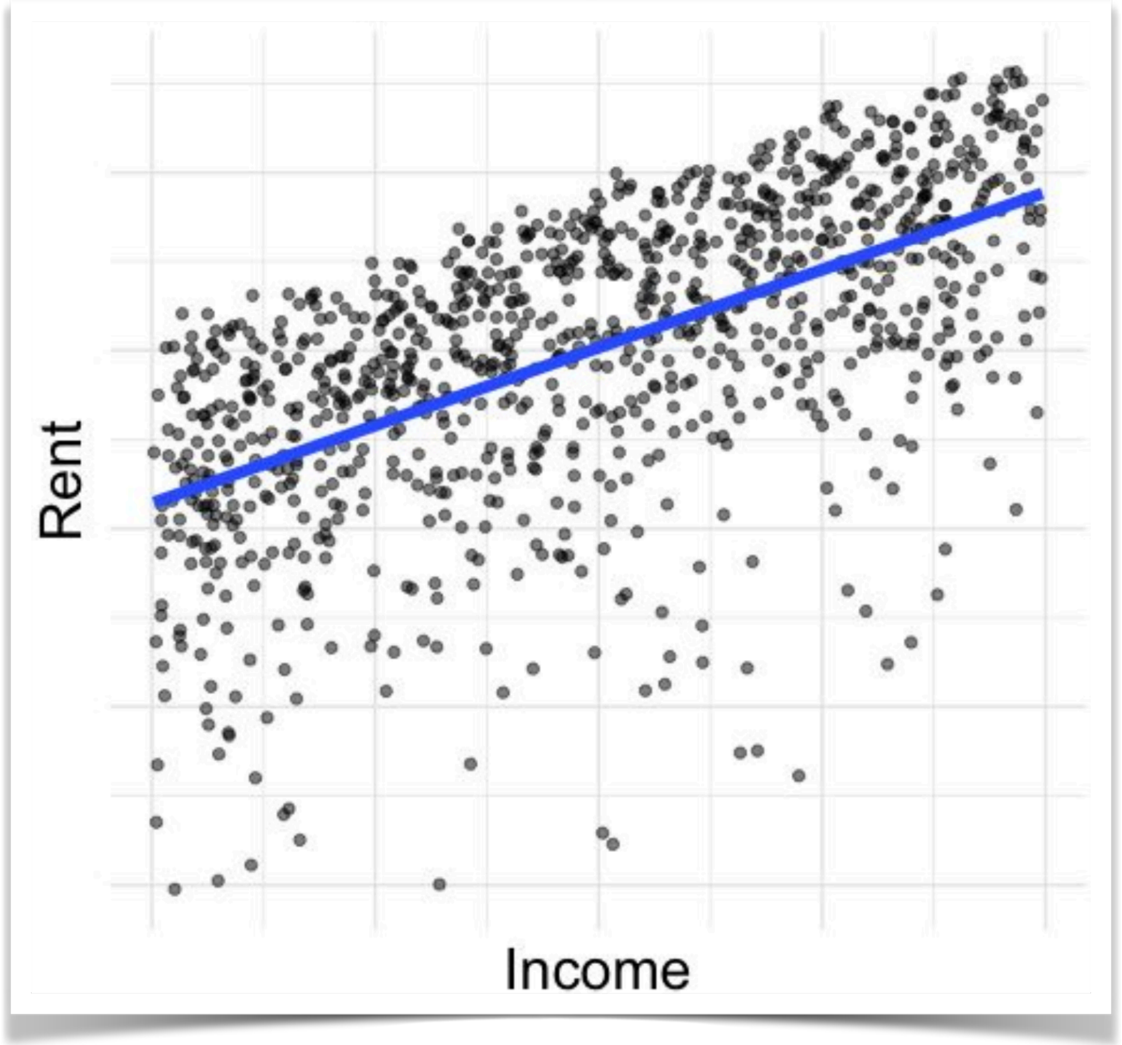

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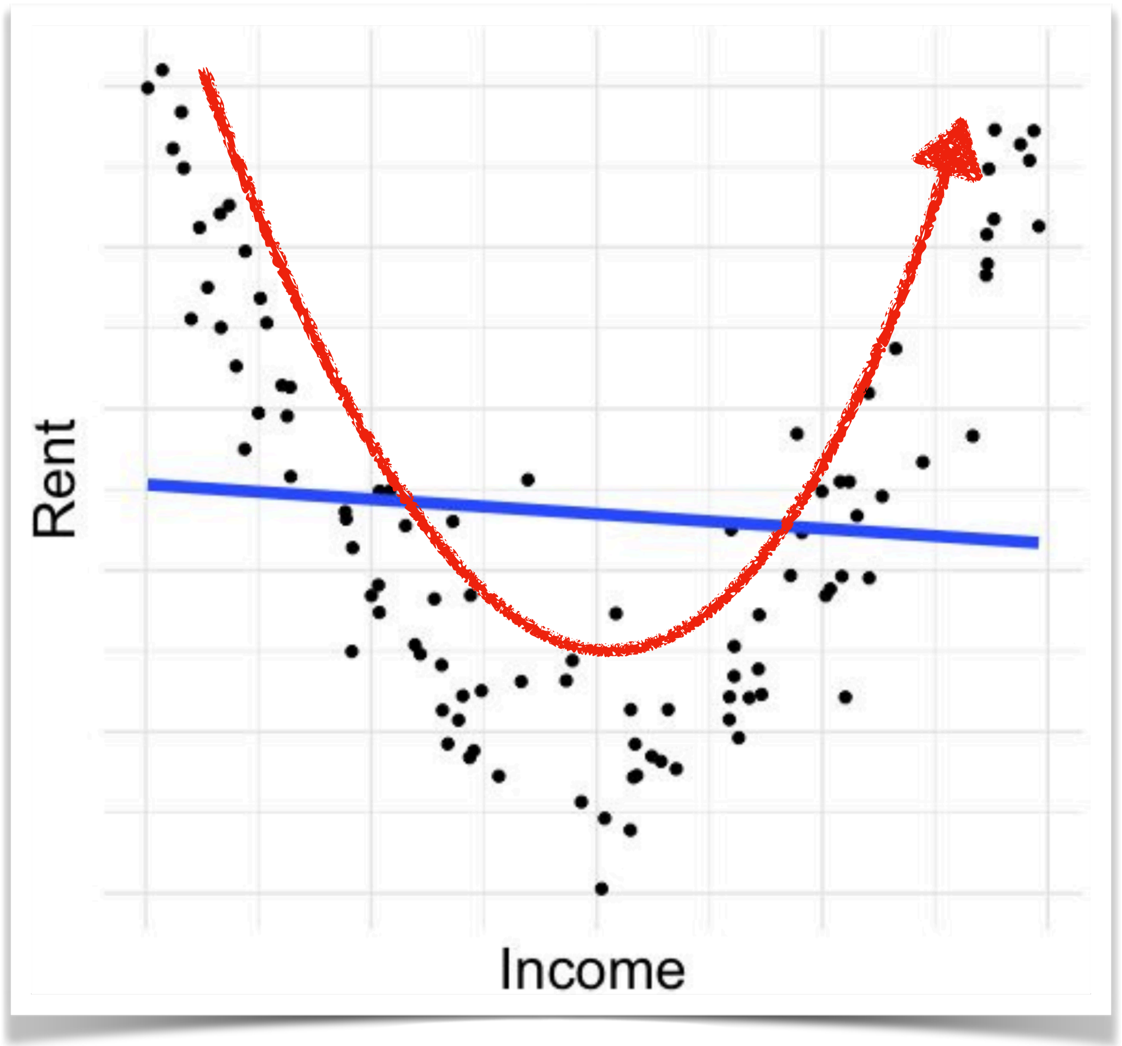

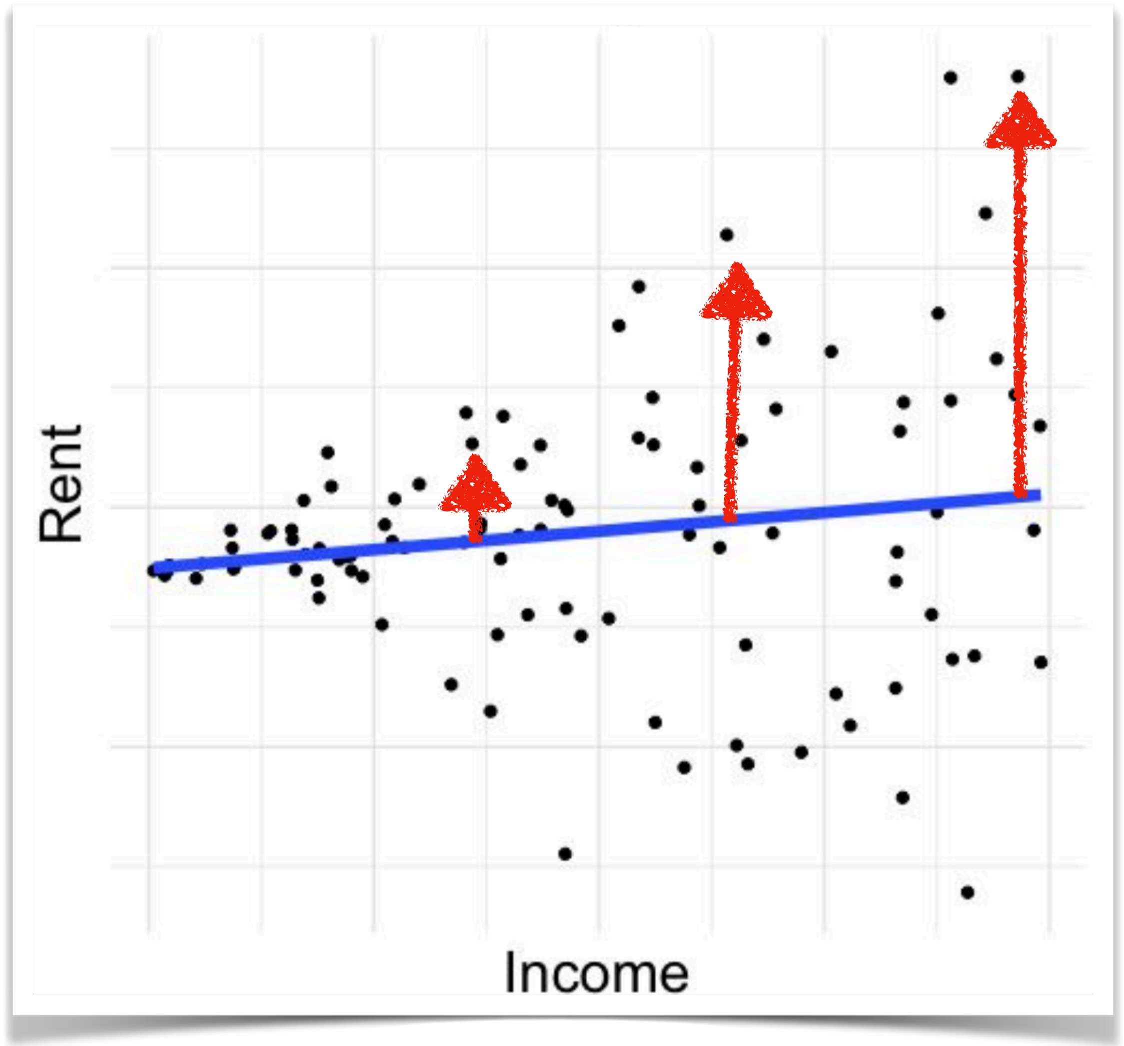

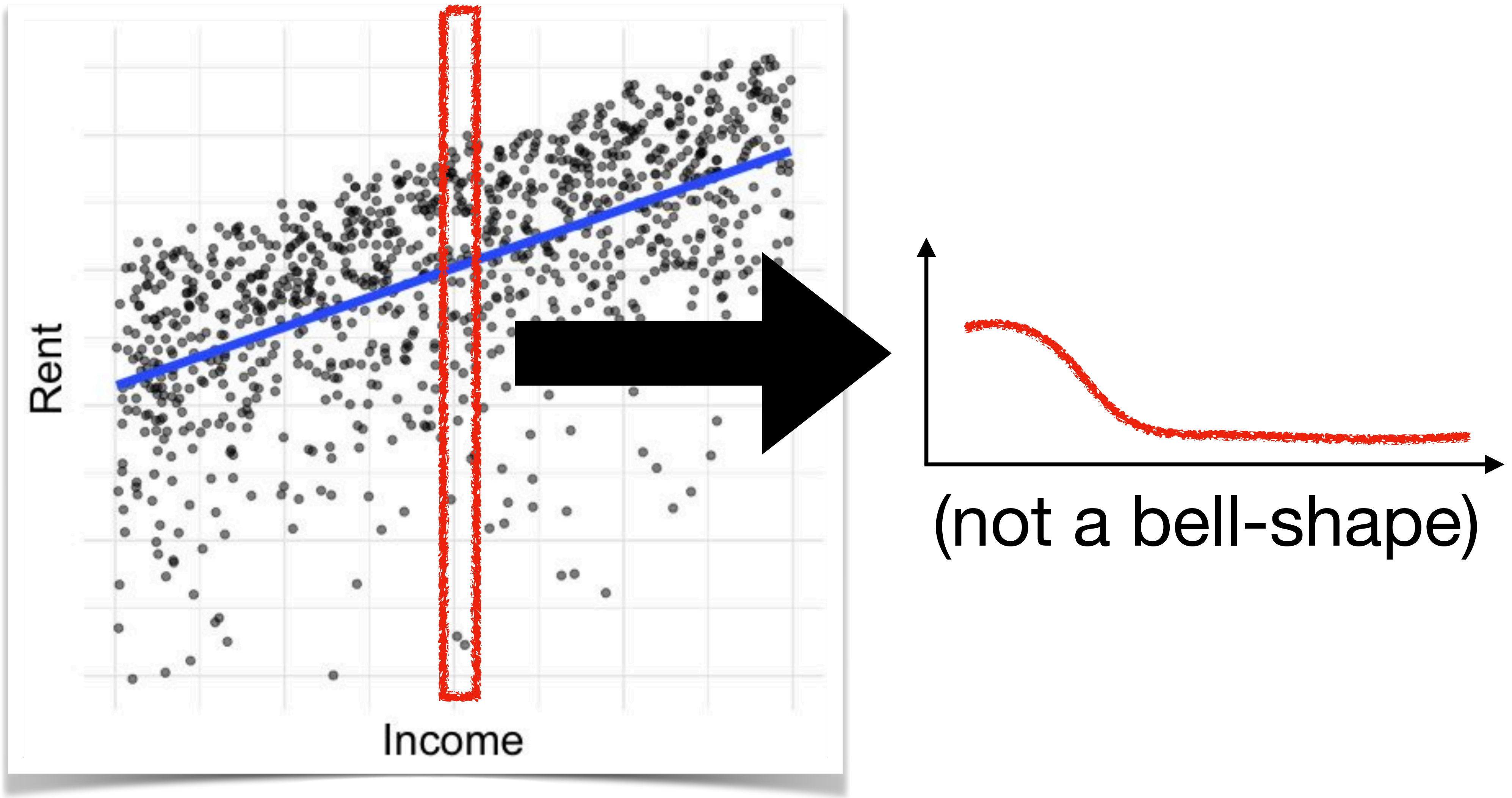

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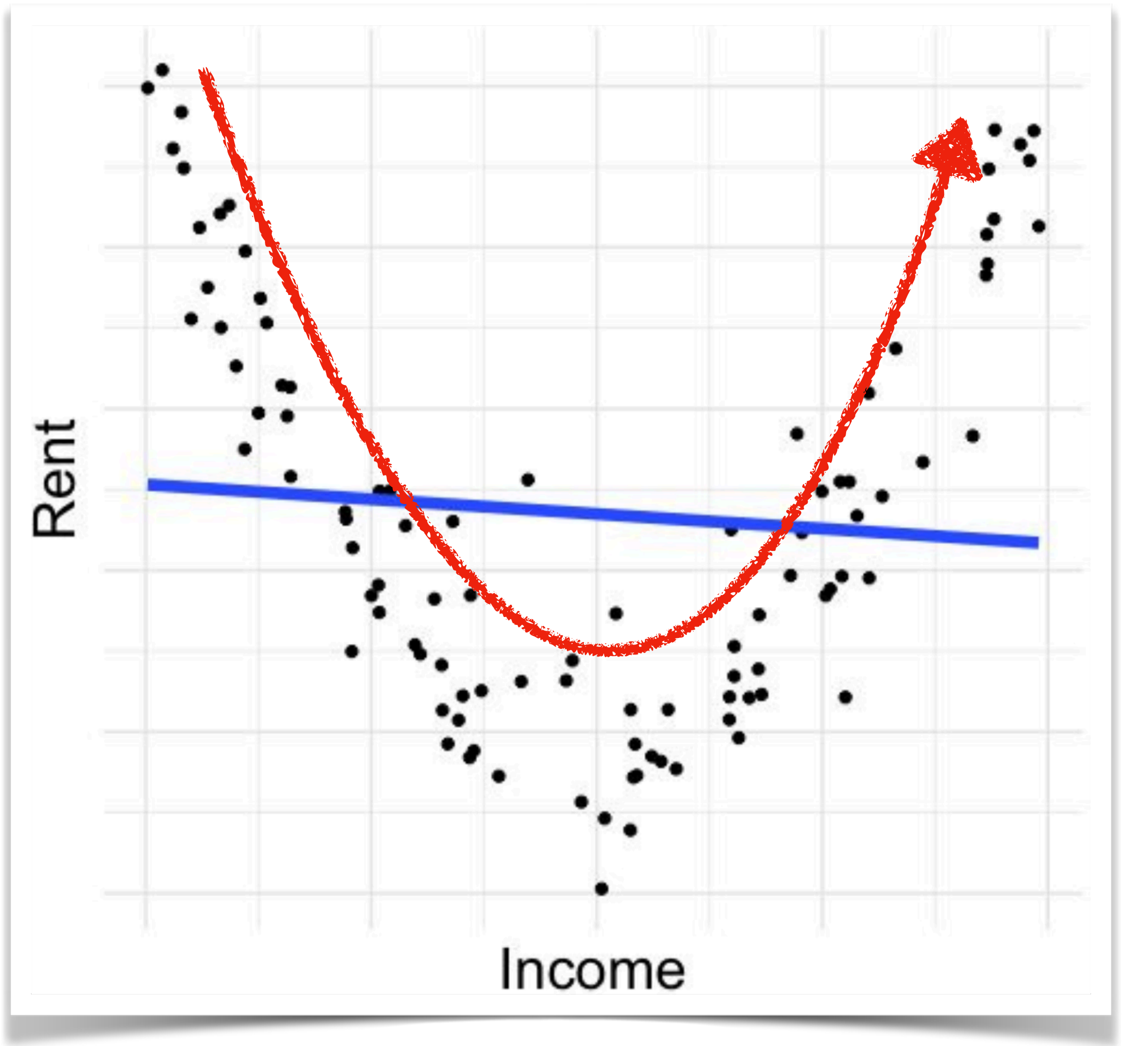
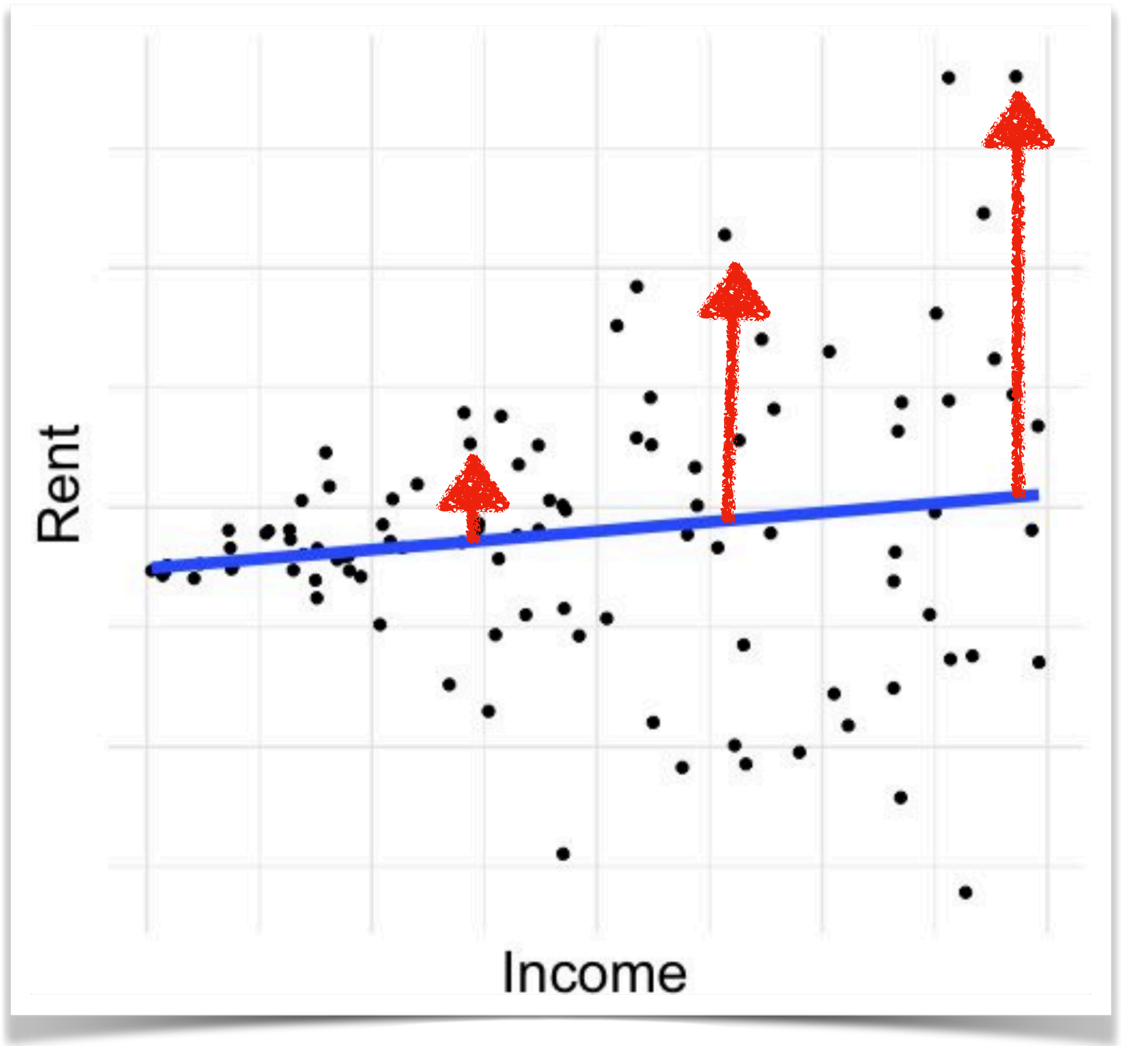
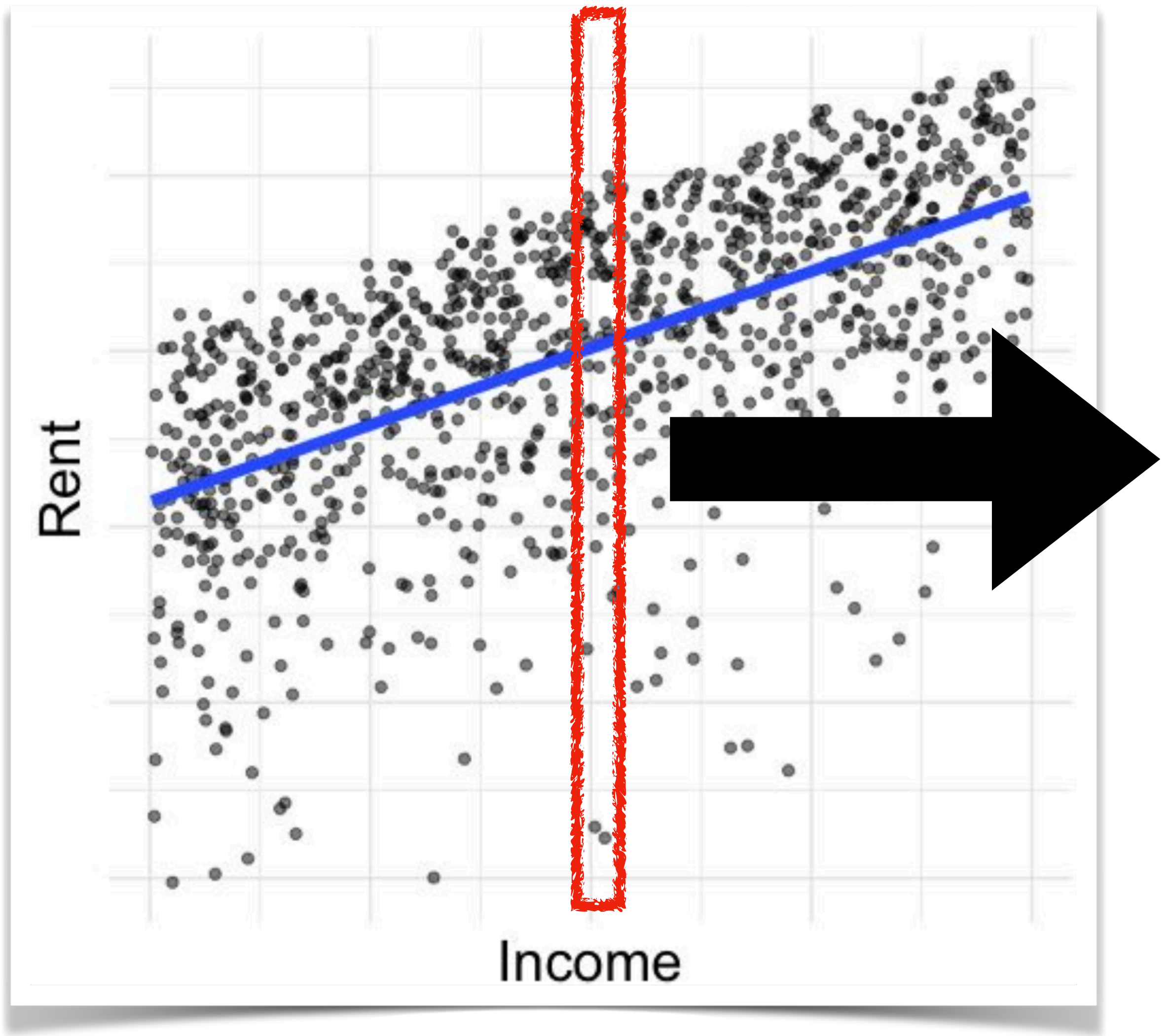
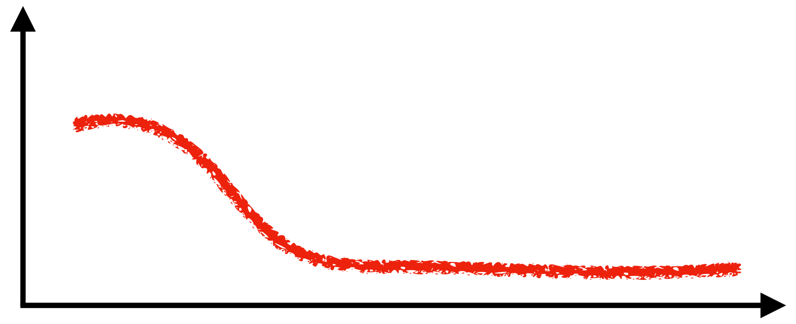
- **Independence:** Observations are independent of each other.





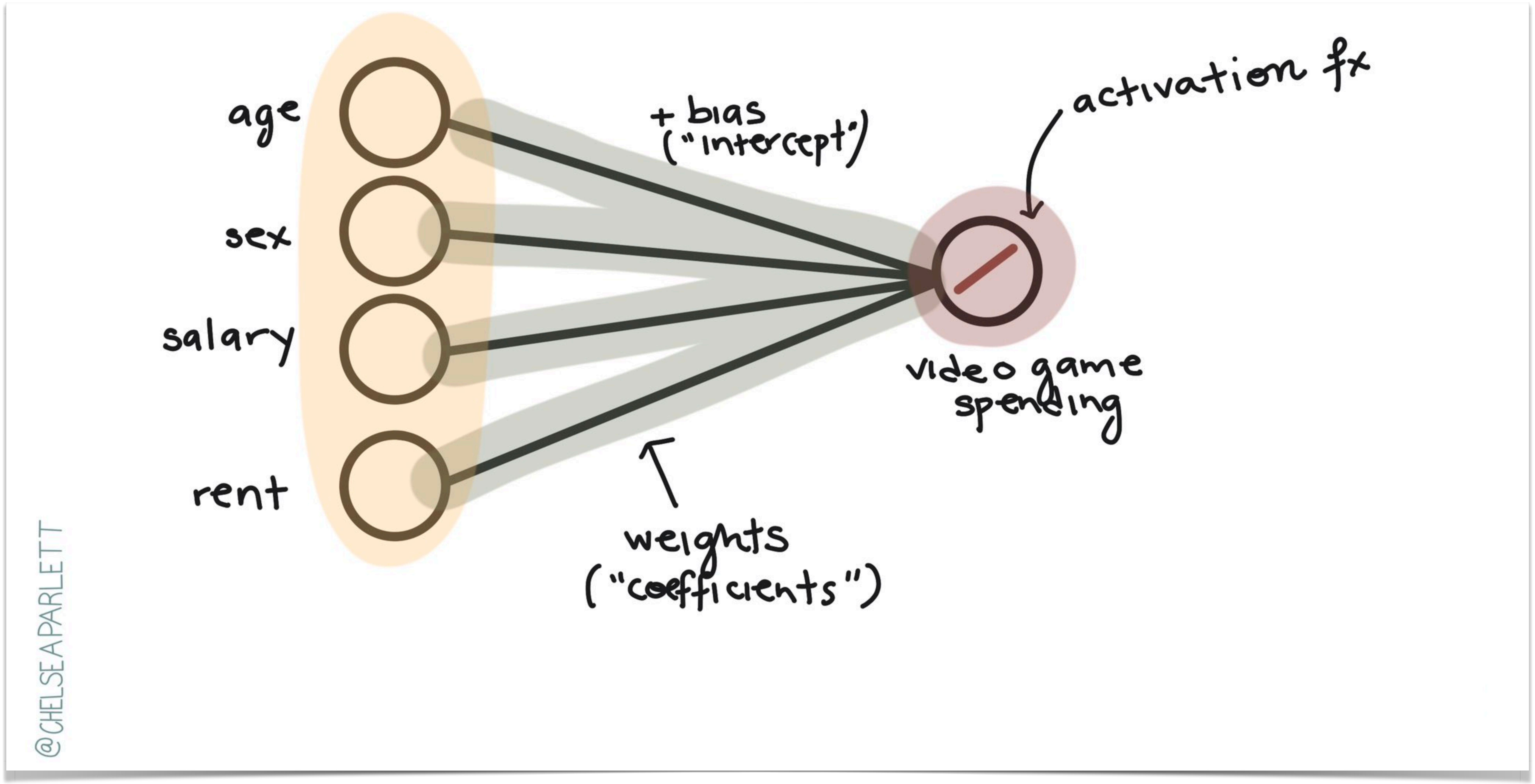




(not a bell-shape)

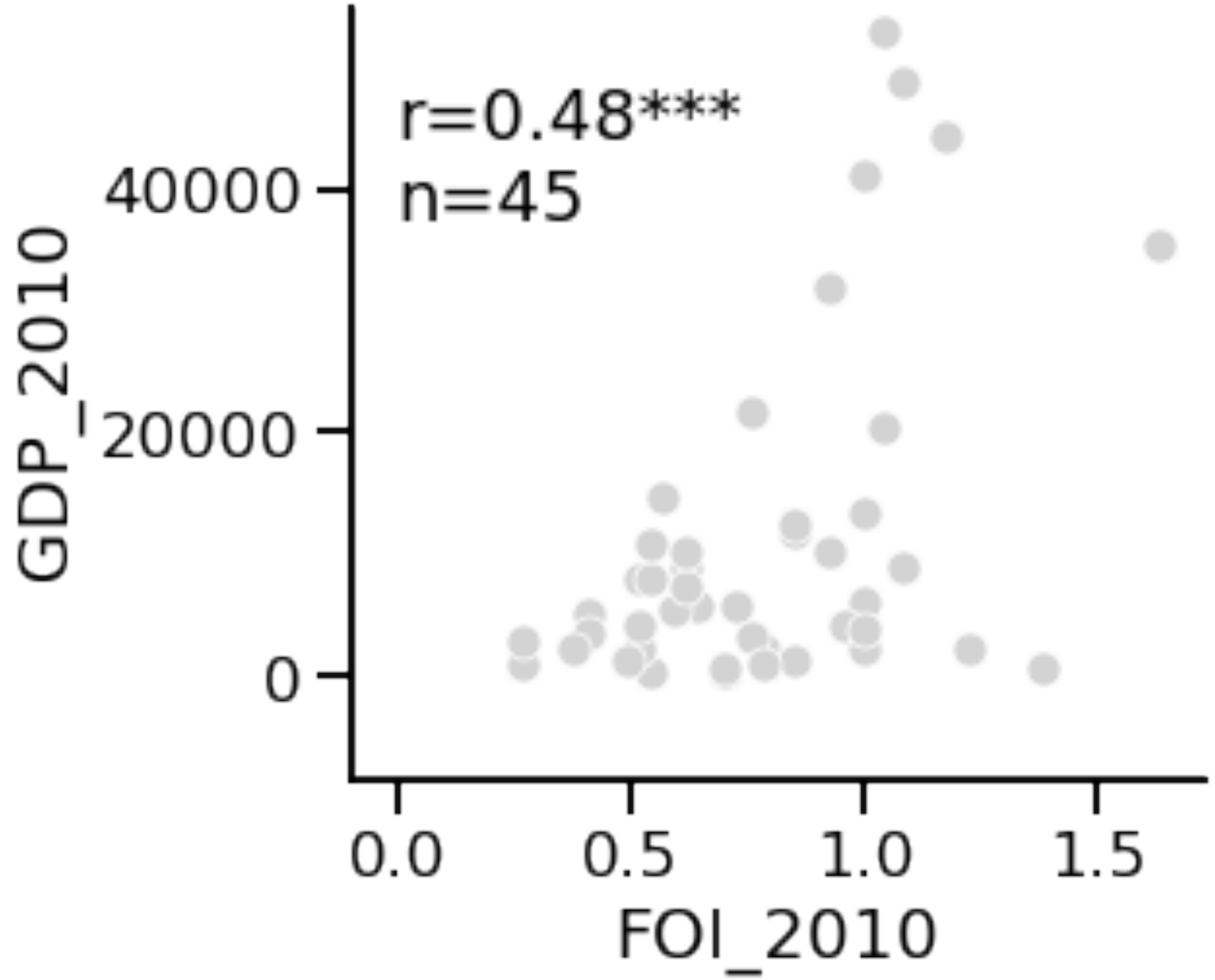
Linear regression

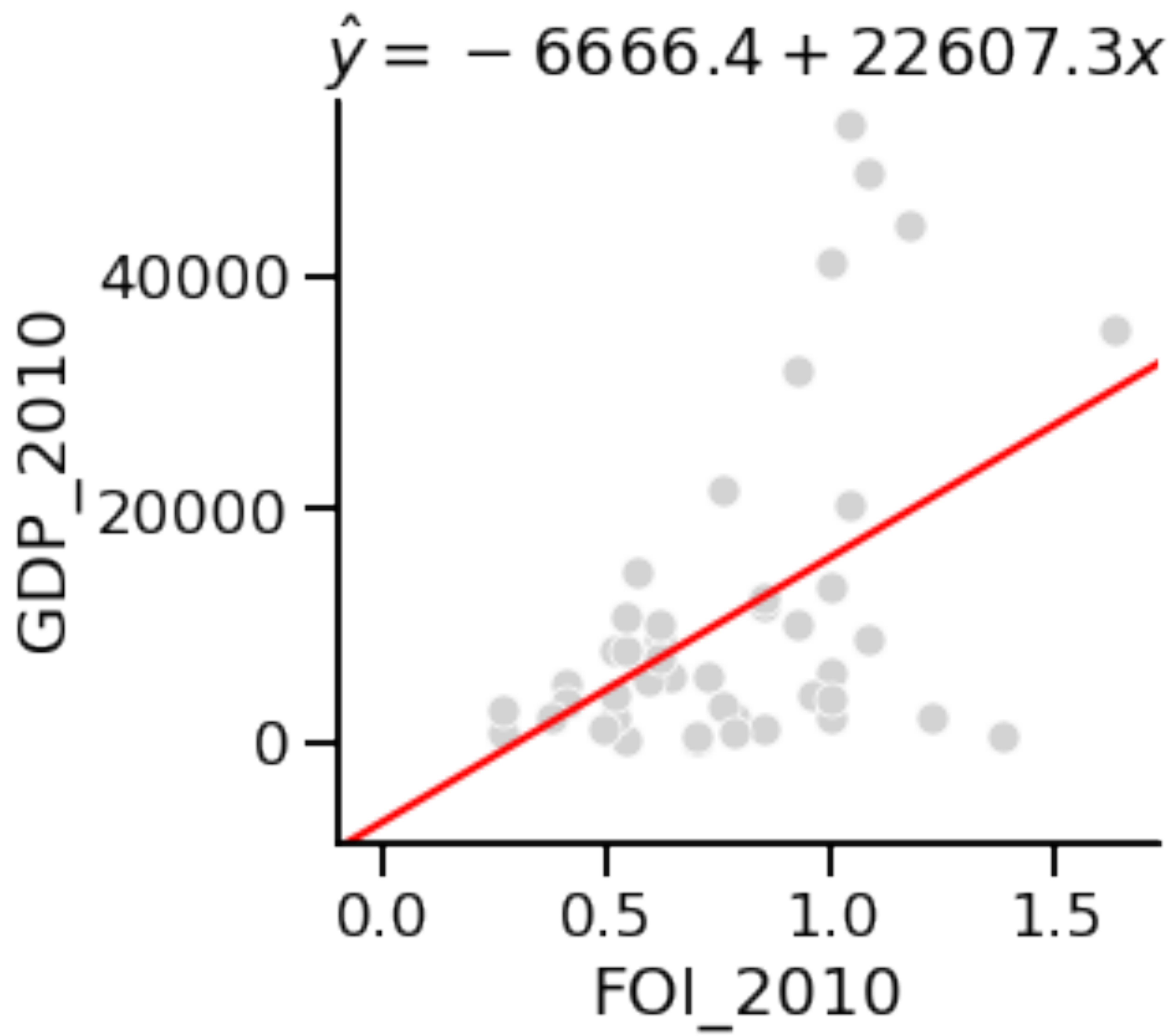
as a neural network



Example FOI and GDP

Correlation vs. Linear regression





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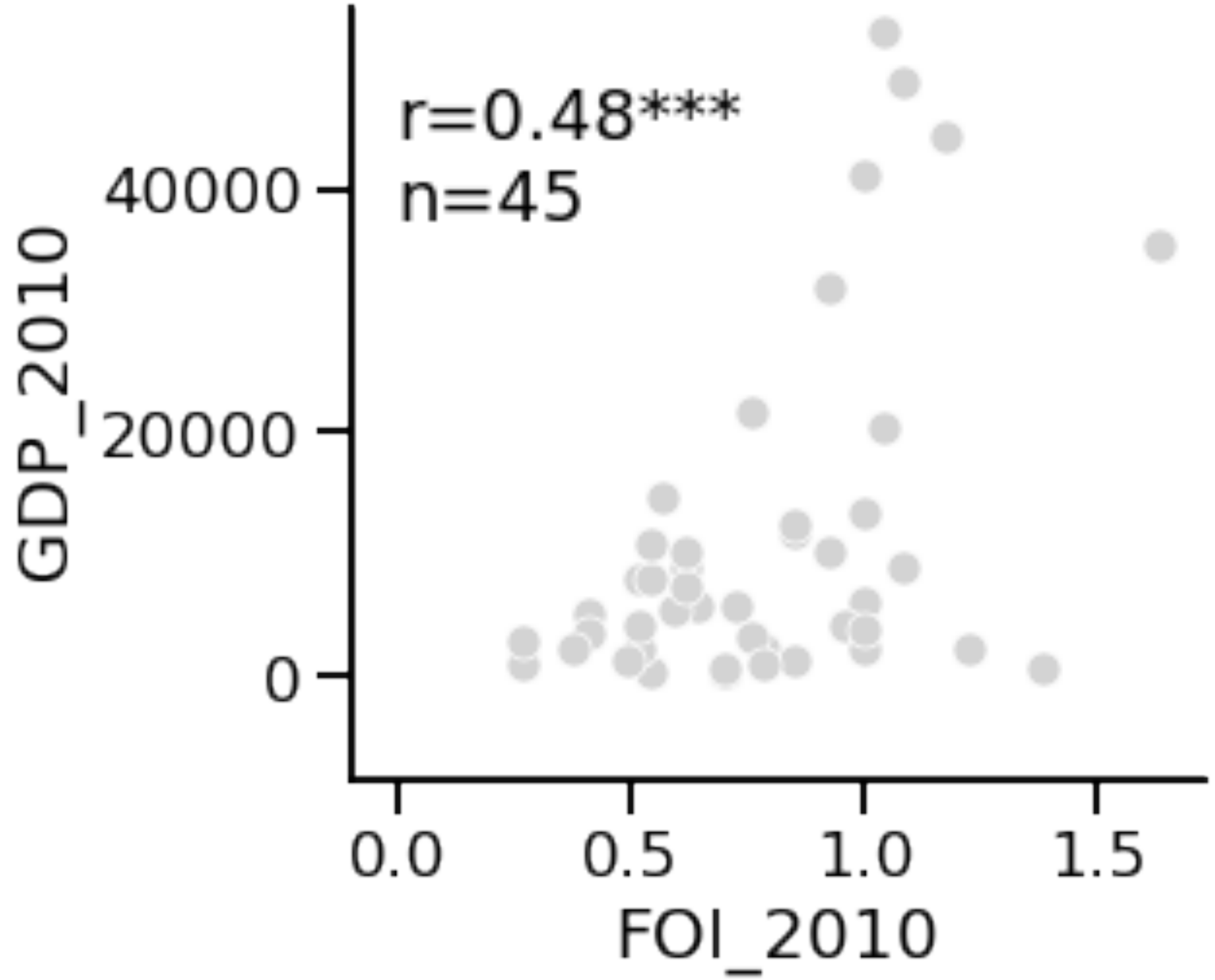
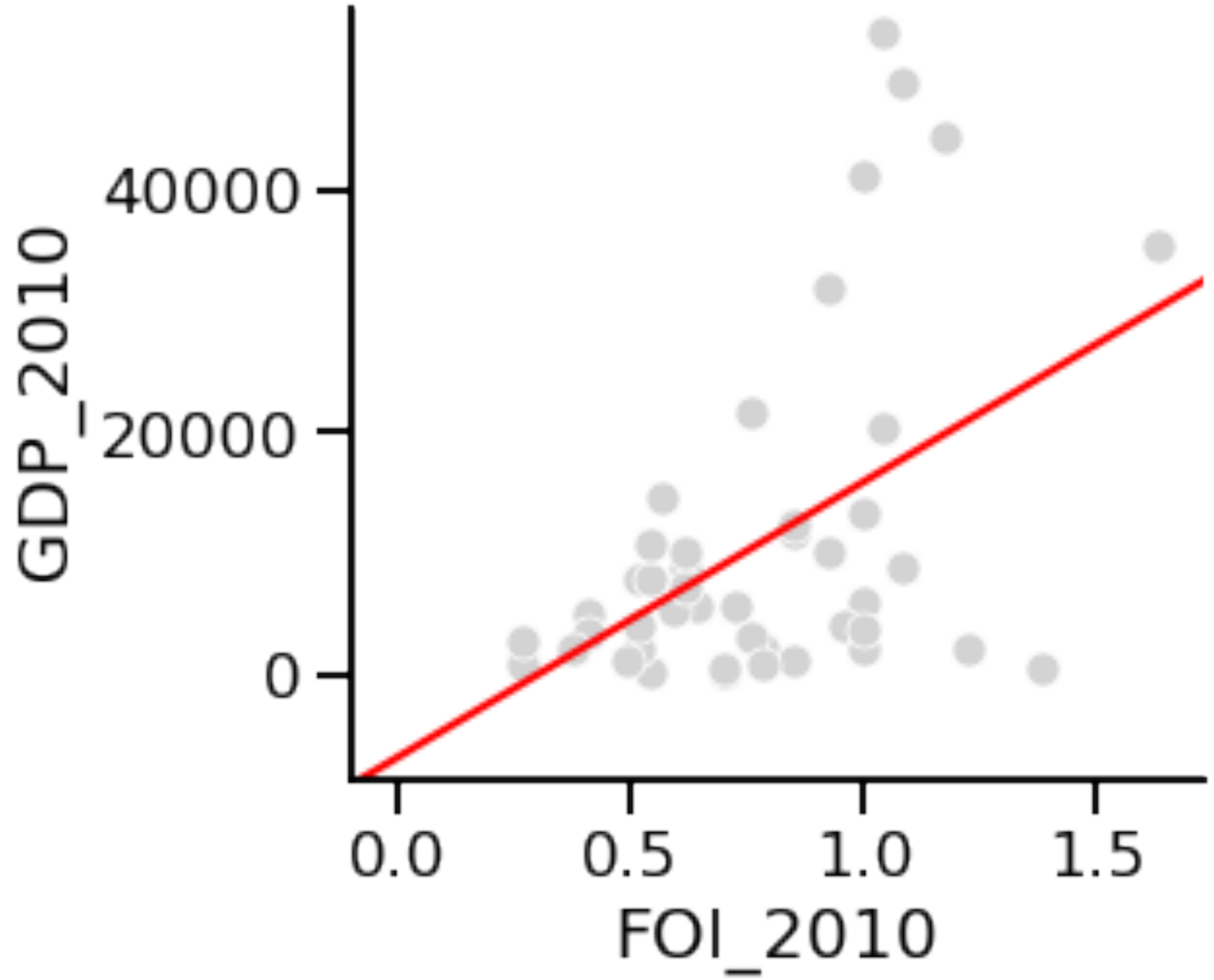


Intercept a

$\hat{y} = -6666.4 + 22607.3x$



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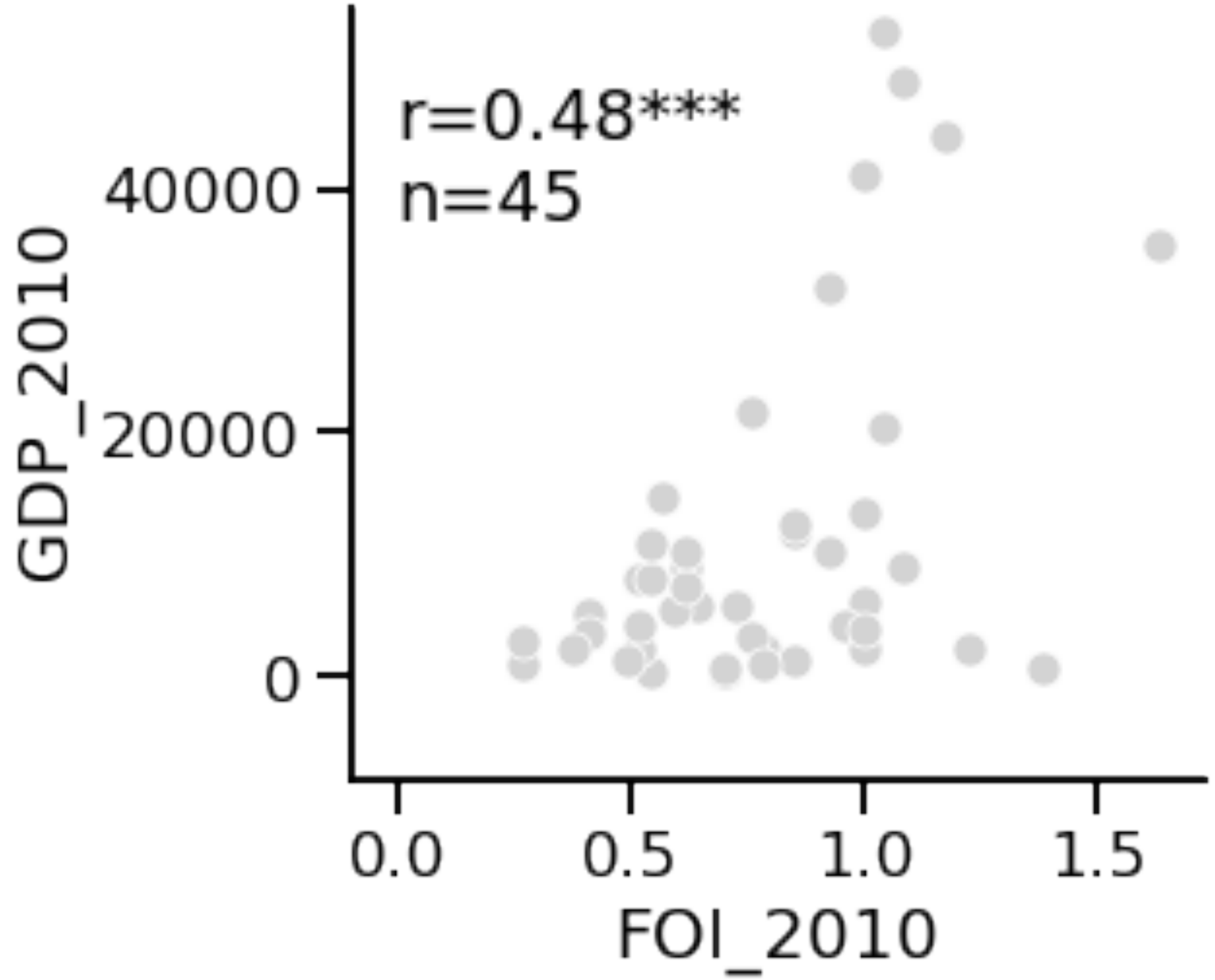
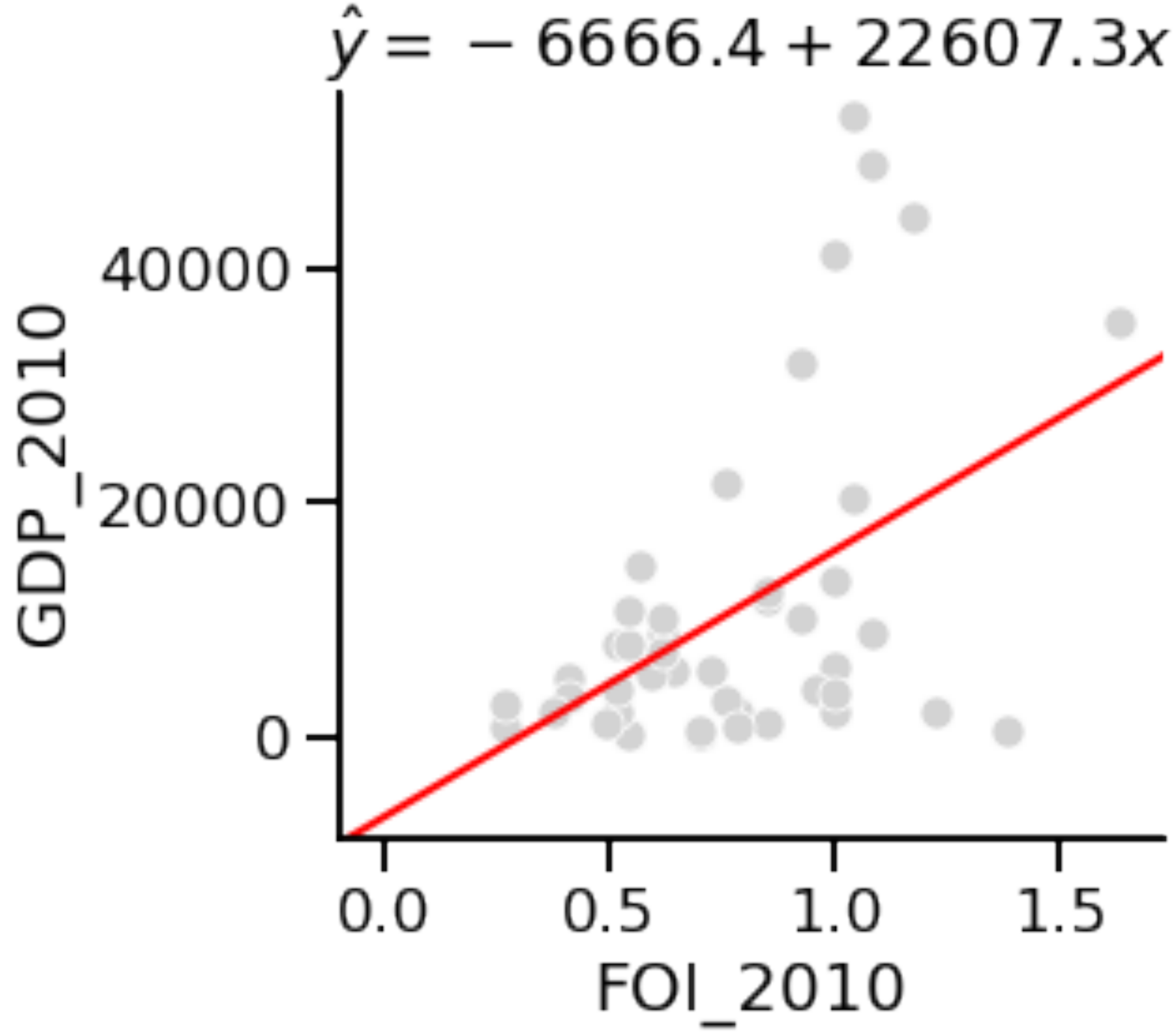


Intercept a Slope β_{FOI}



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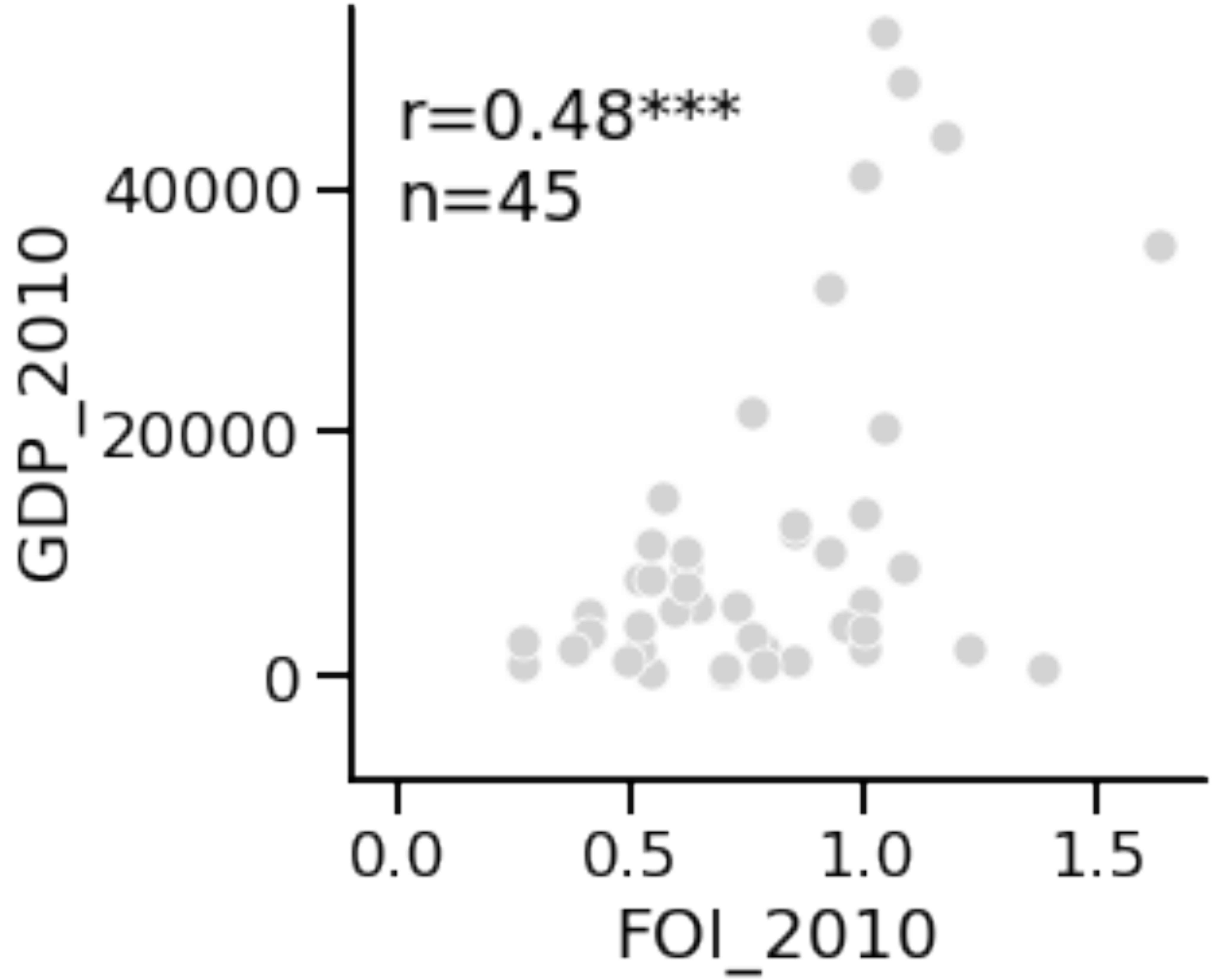

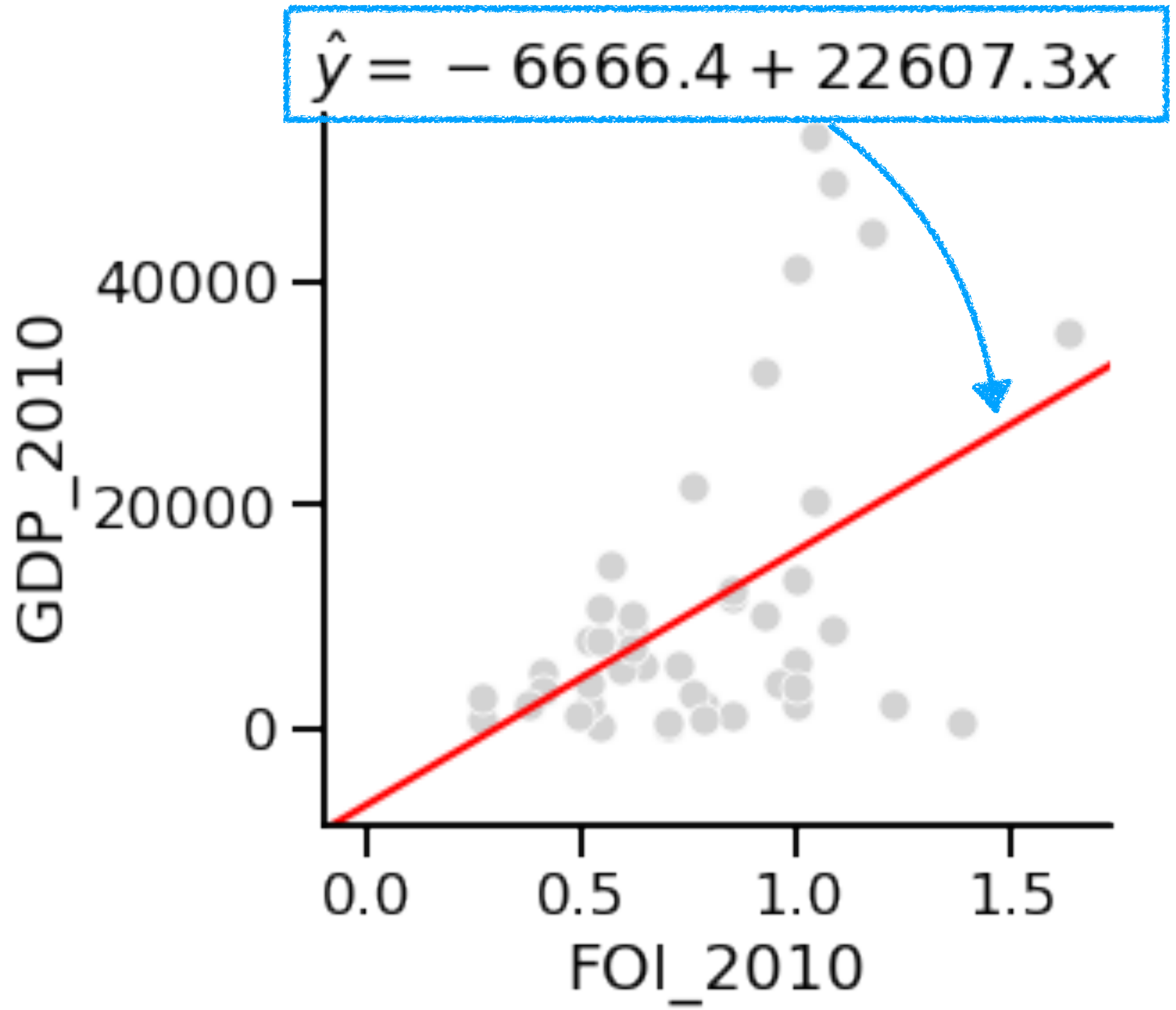

Regression residuals

Error term: ϵ

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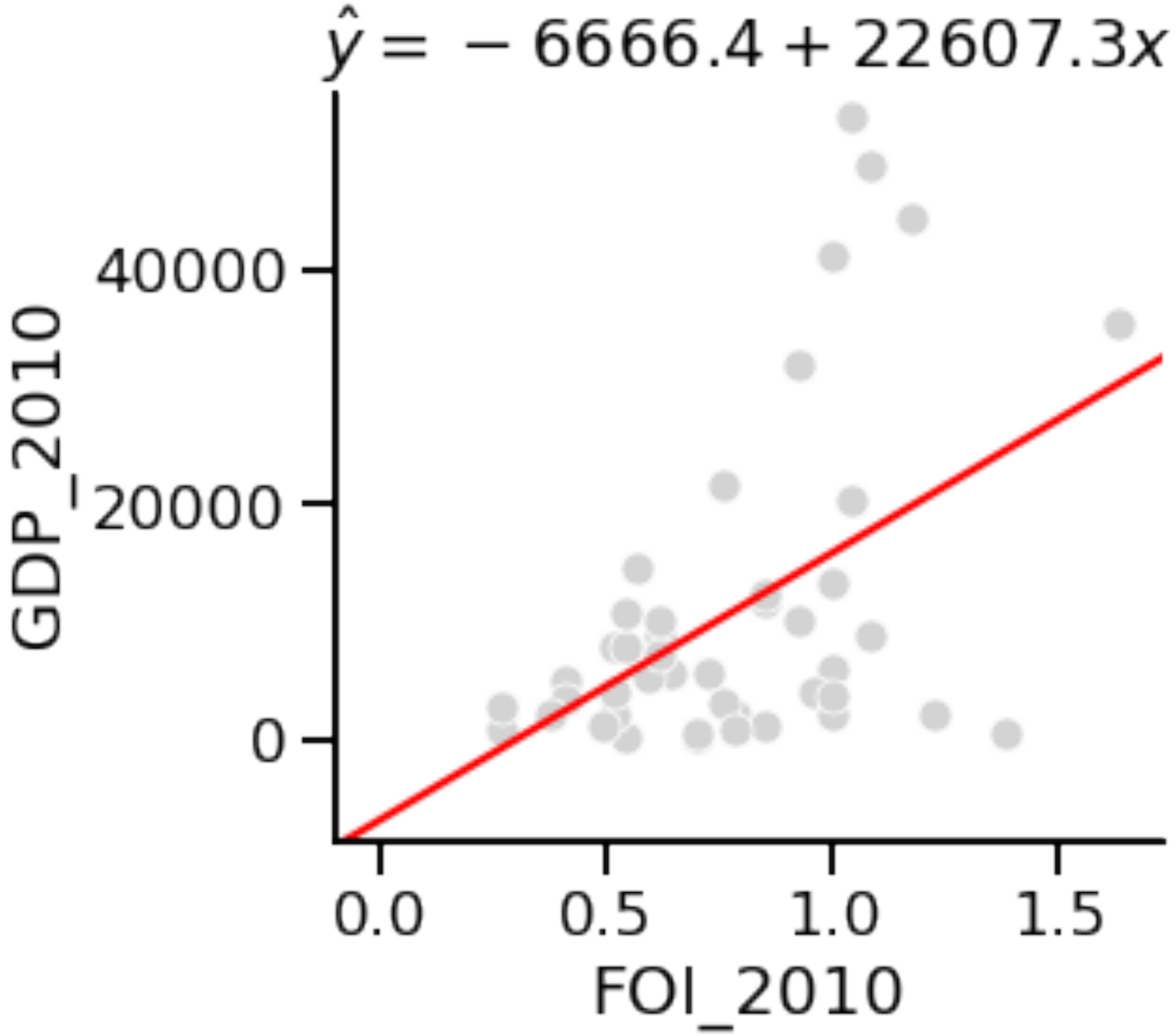

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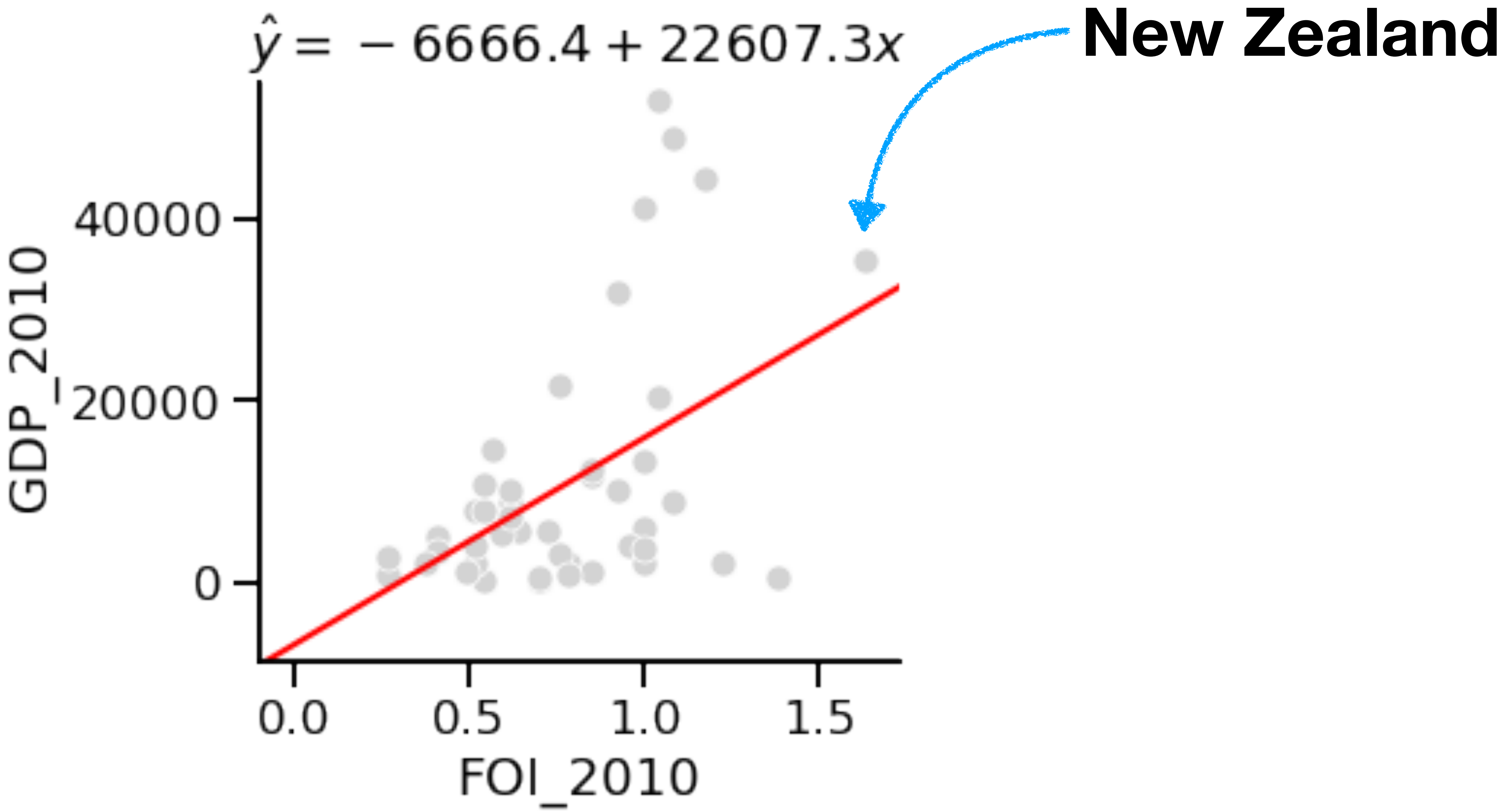

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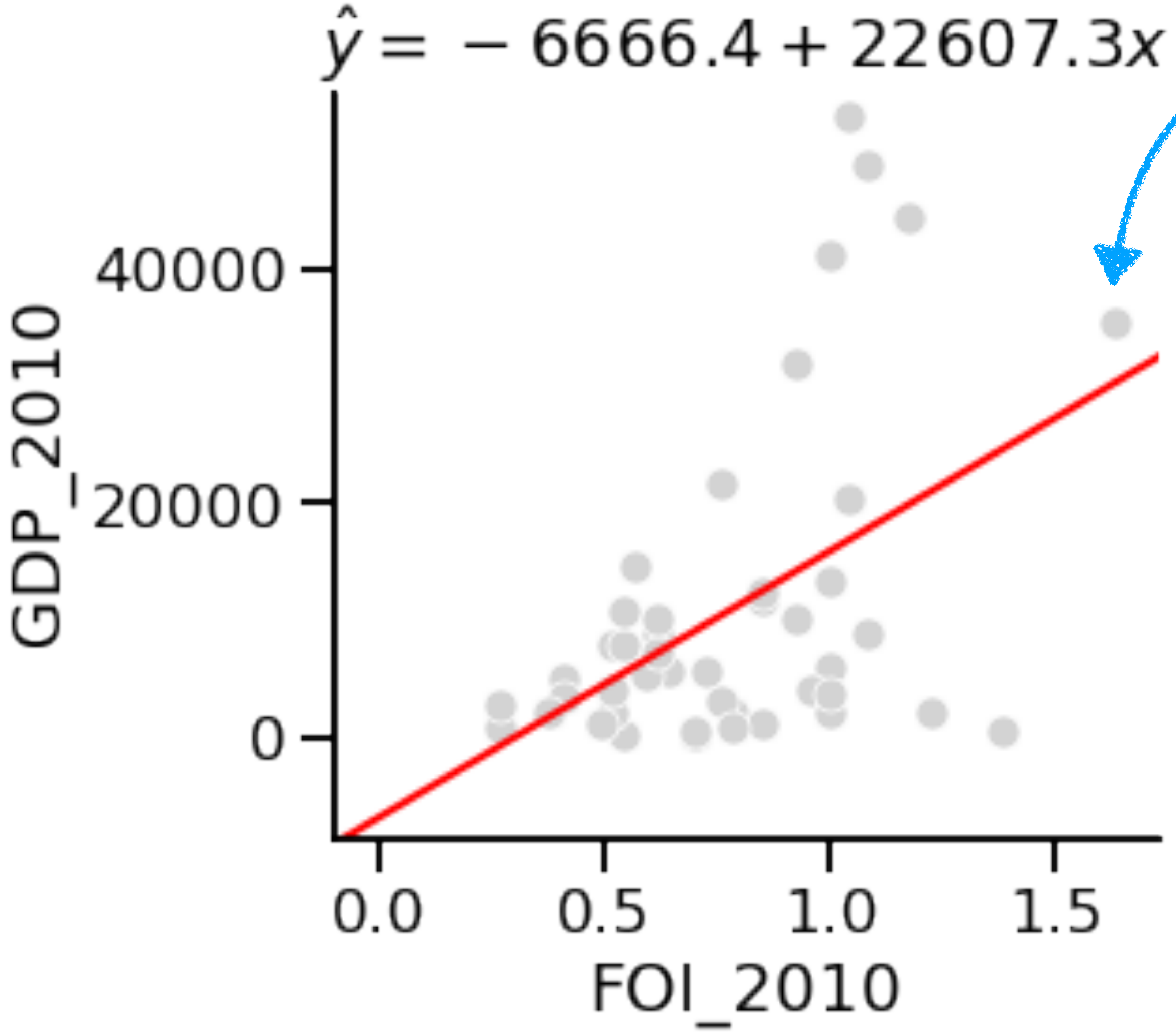

New Zealand

$x = 1,631579$

$y = 35.374,93$

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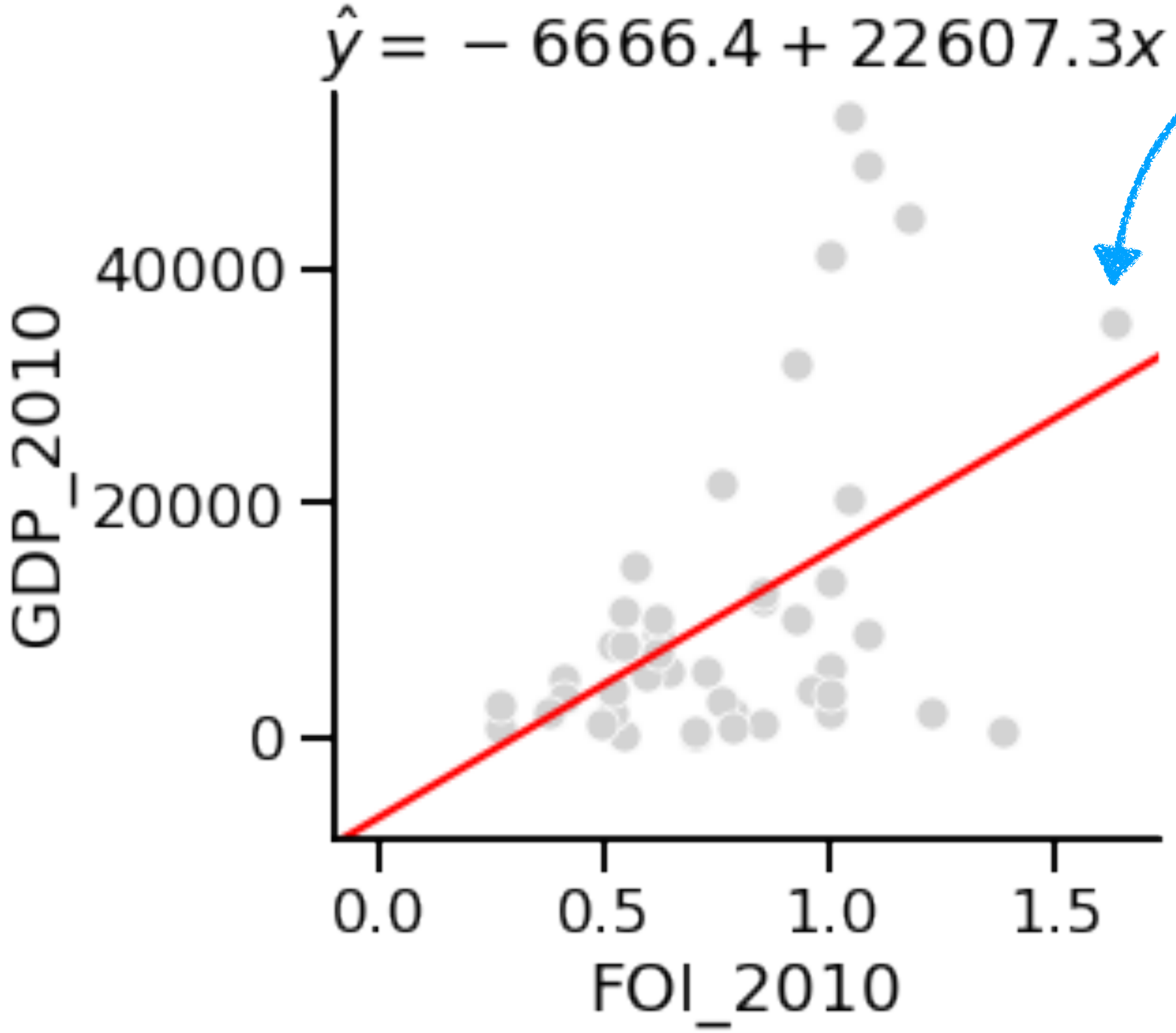

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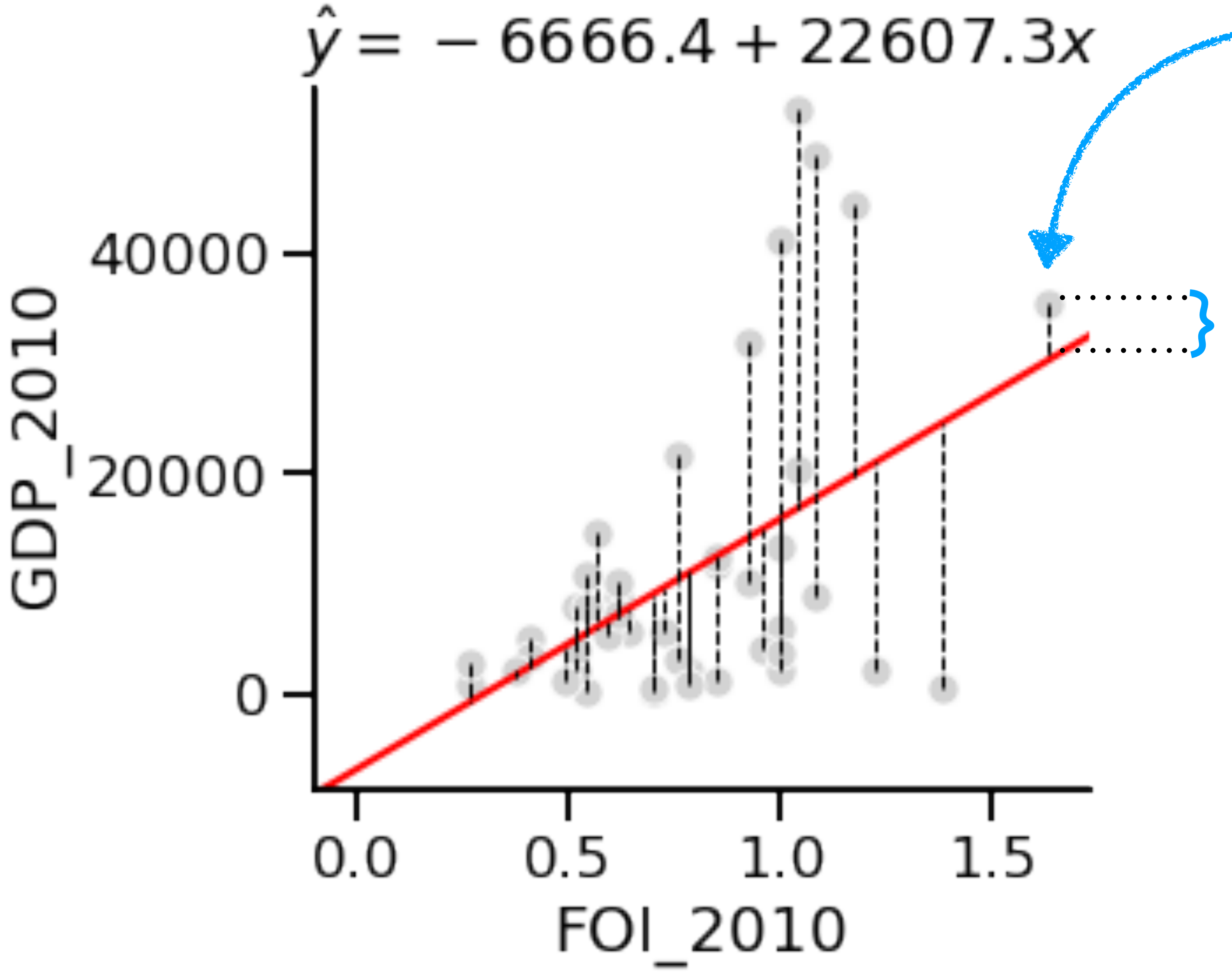

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$\epsilon = y - \hat{y} = 5.155{,}73$

Ordinary Least Squares (OLS)

Model fitting

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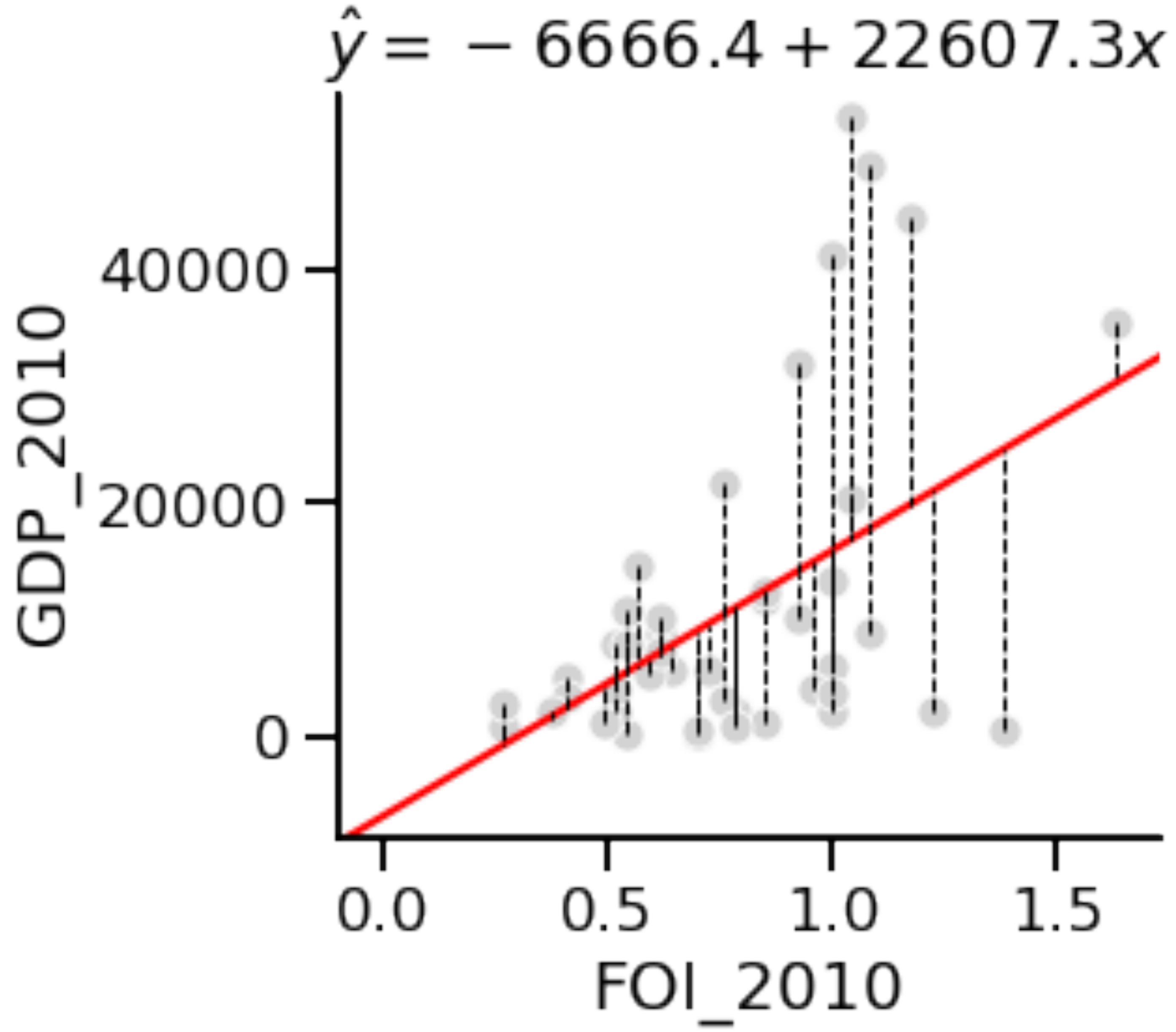

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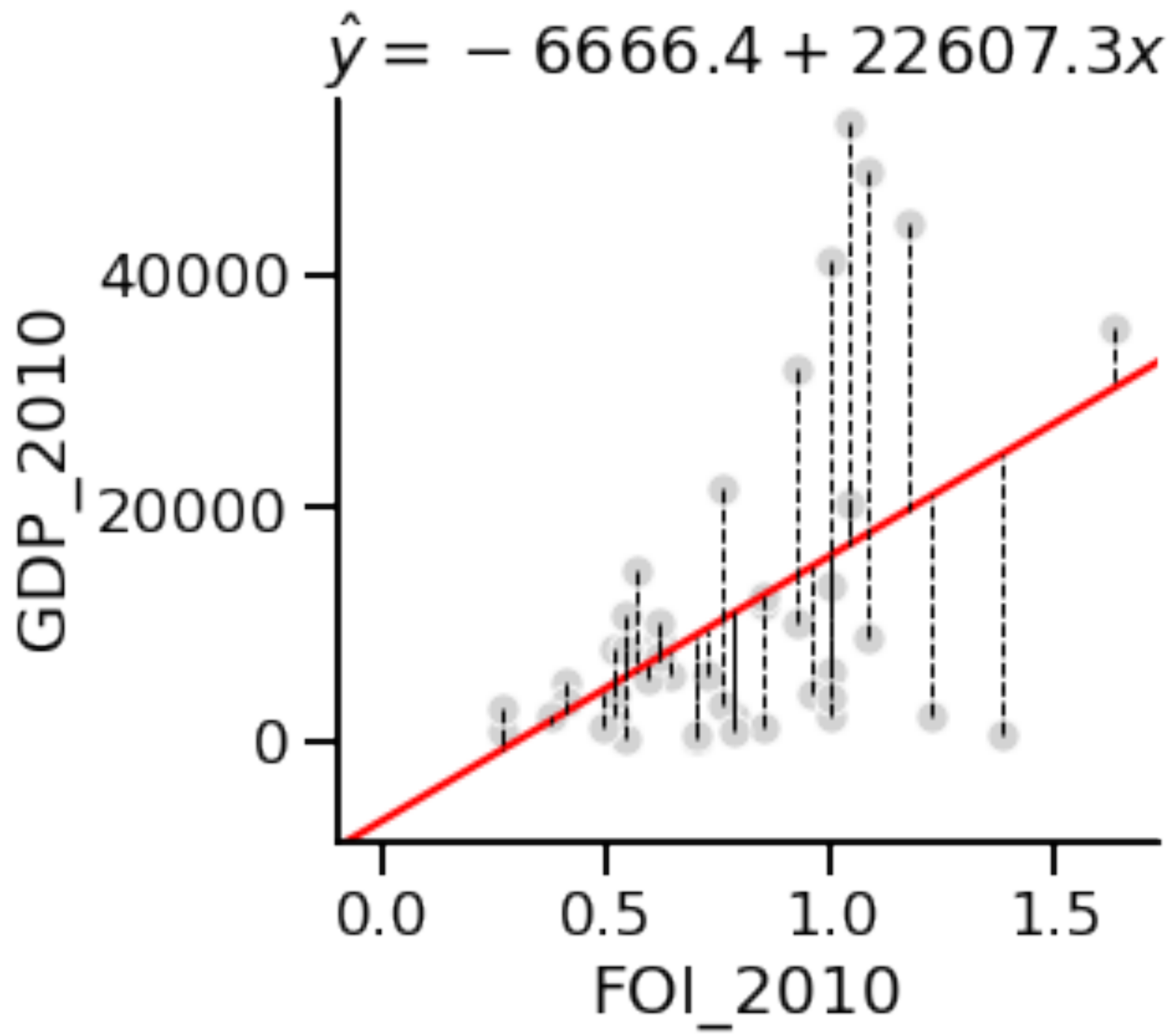
Fitted model



Ordinary Least Squares (OLS)

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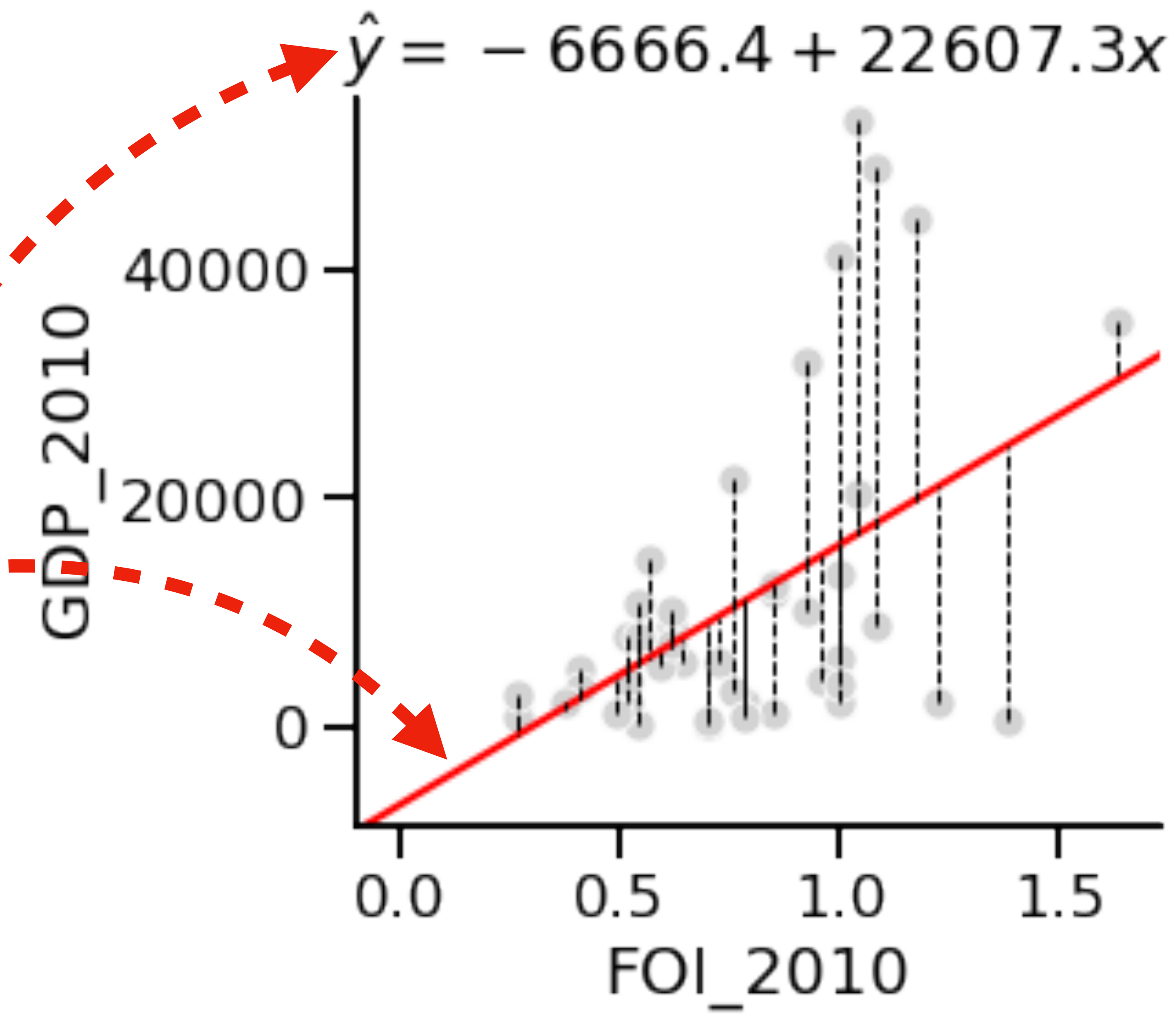

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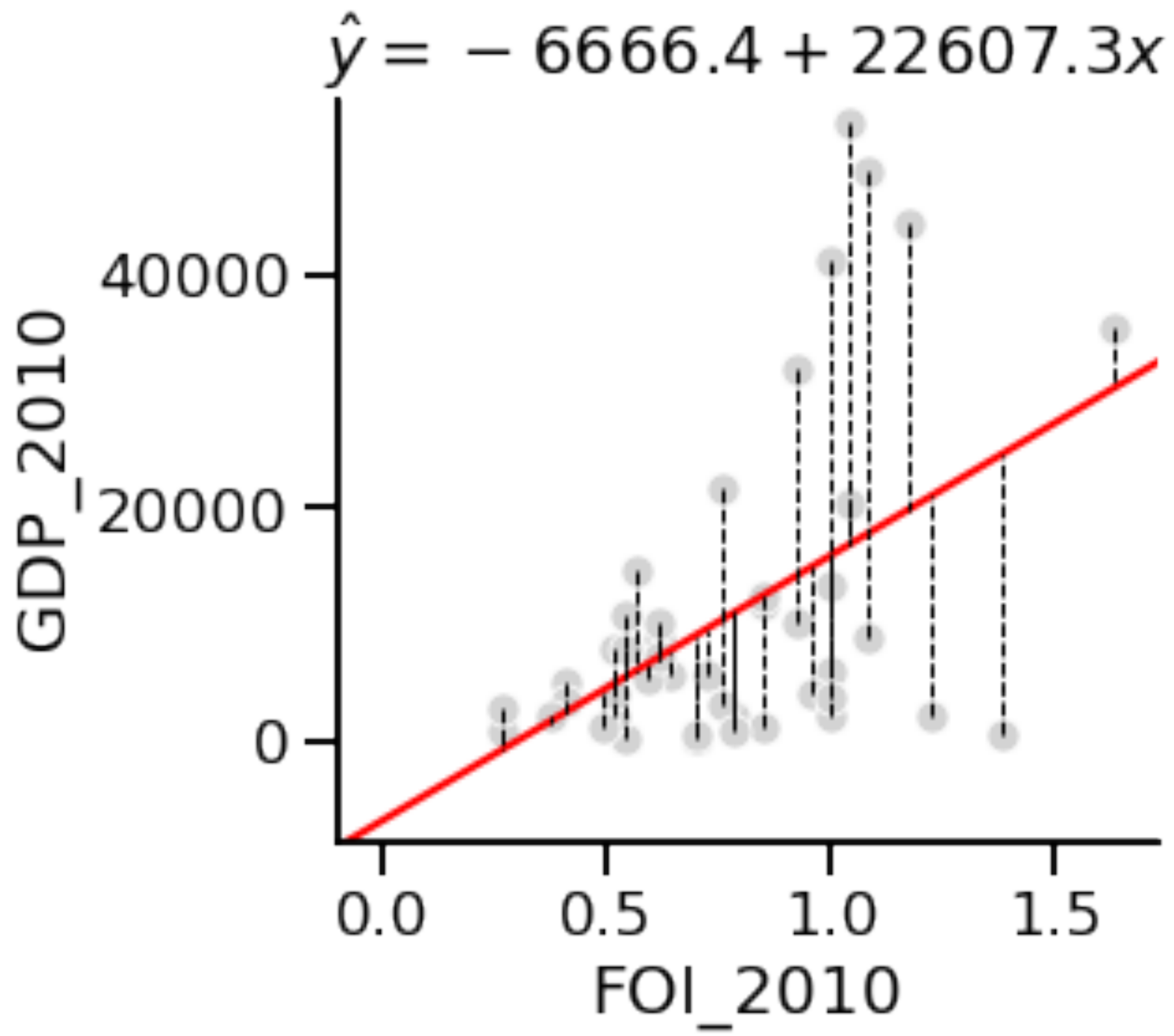

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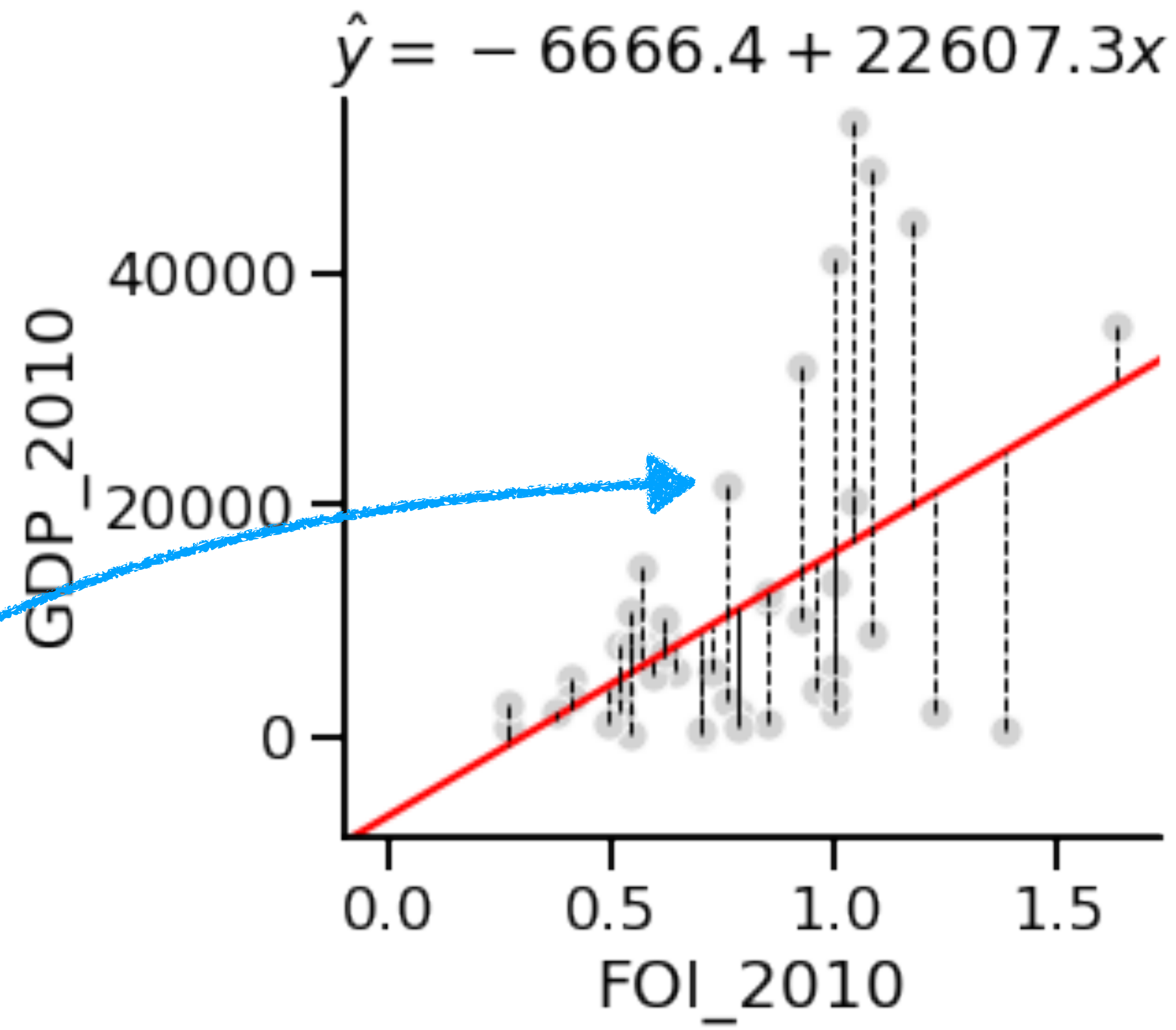

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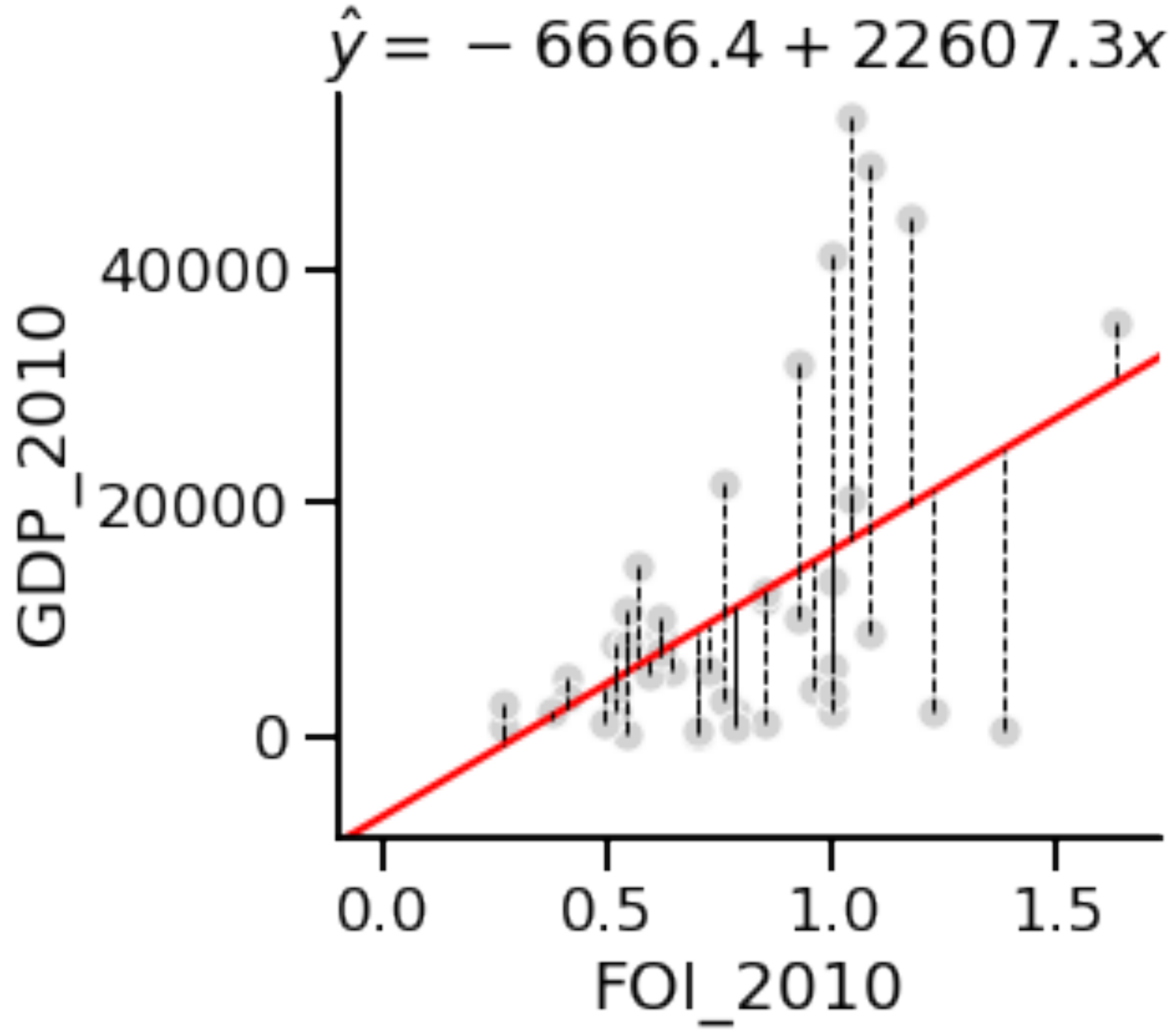

- The Ordinary Least Squares method (OLS) looks for the values of coefficients that minimize the RSS. This way, you can think about the OLS result as the line that minimizes the sum of squared lengths of the vertical lines in the figure.

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.
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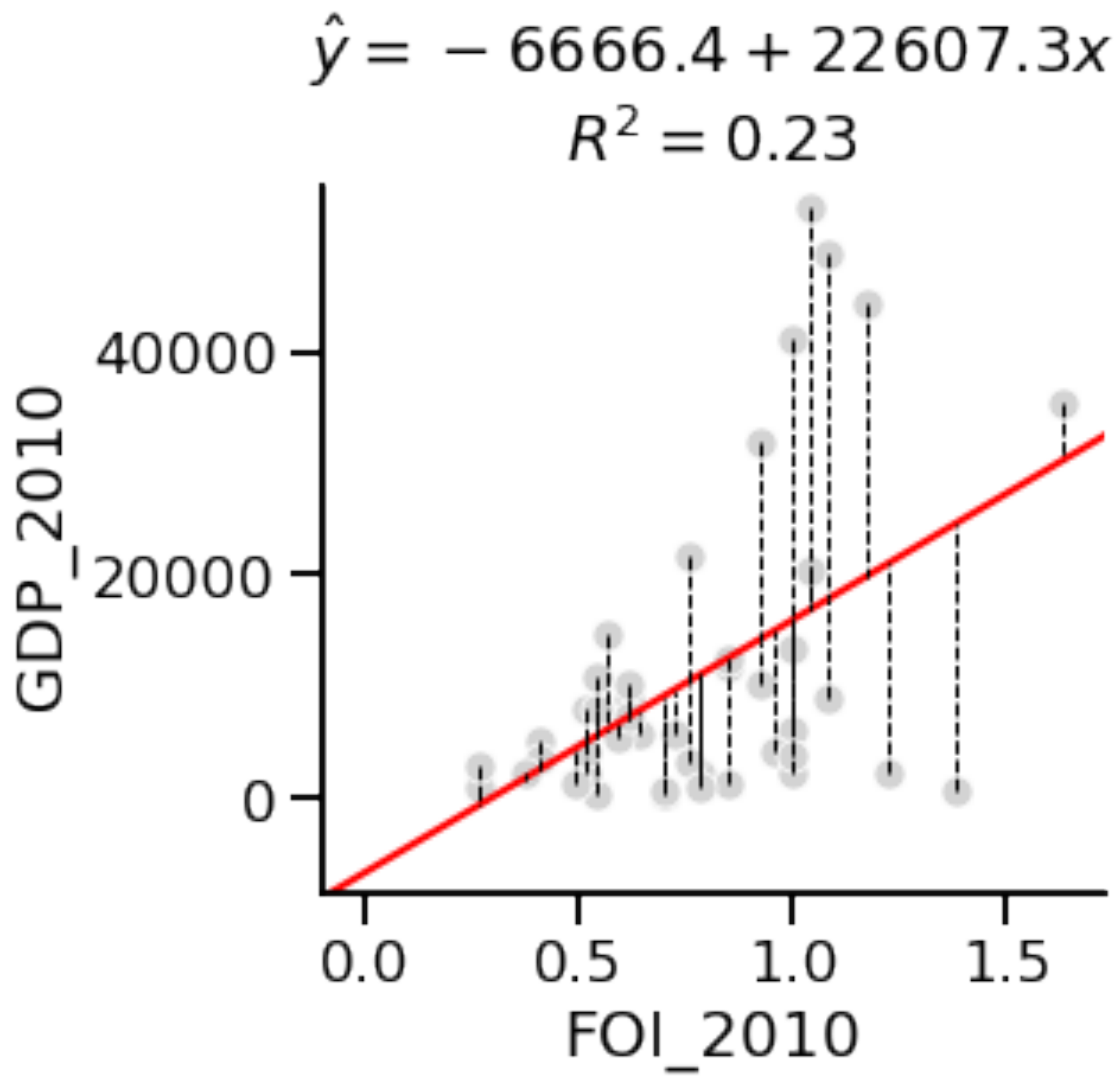

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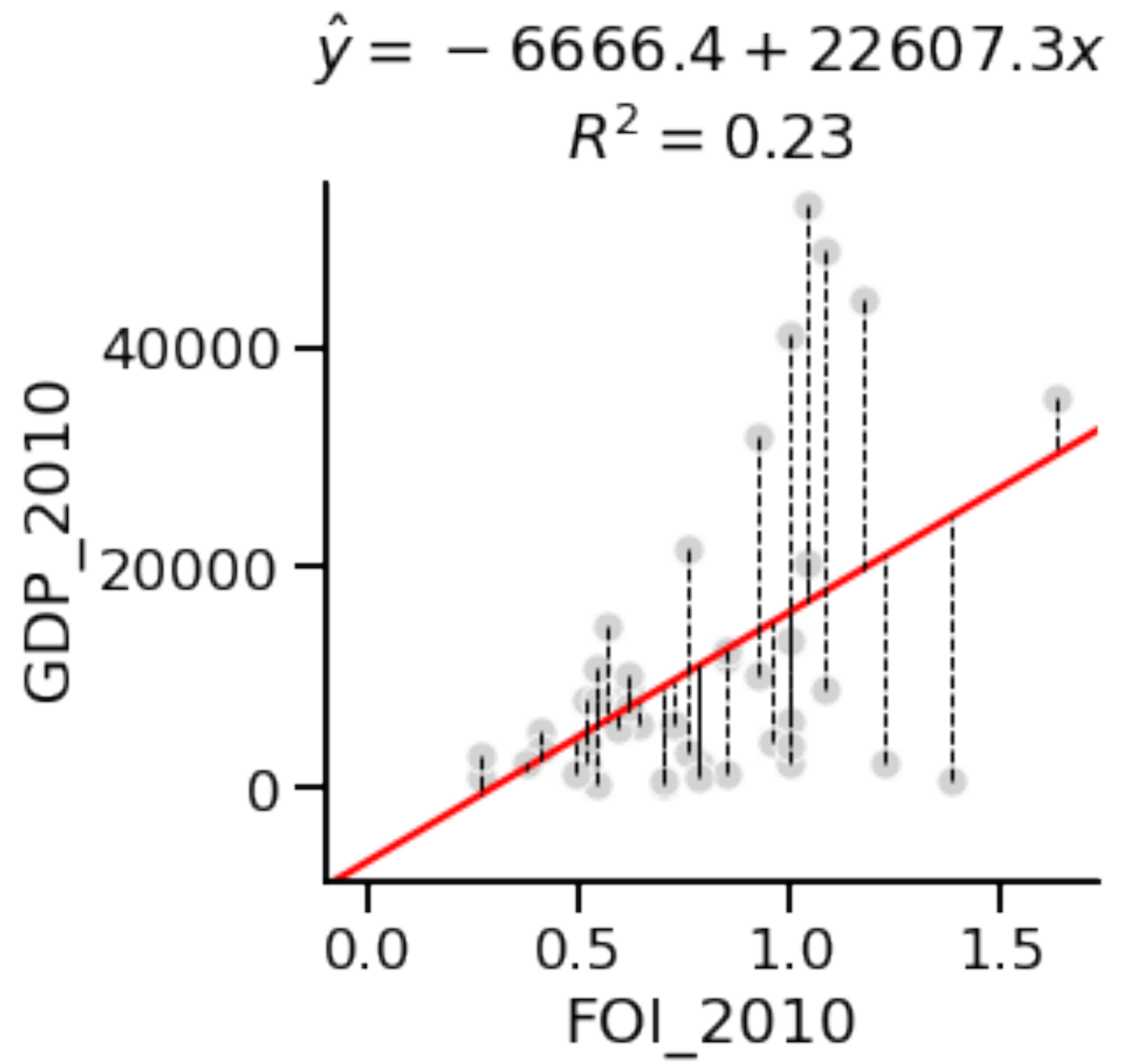

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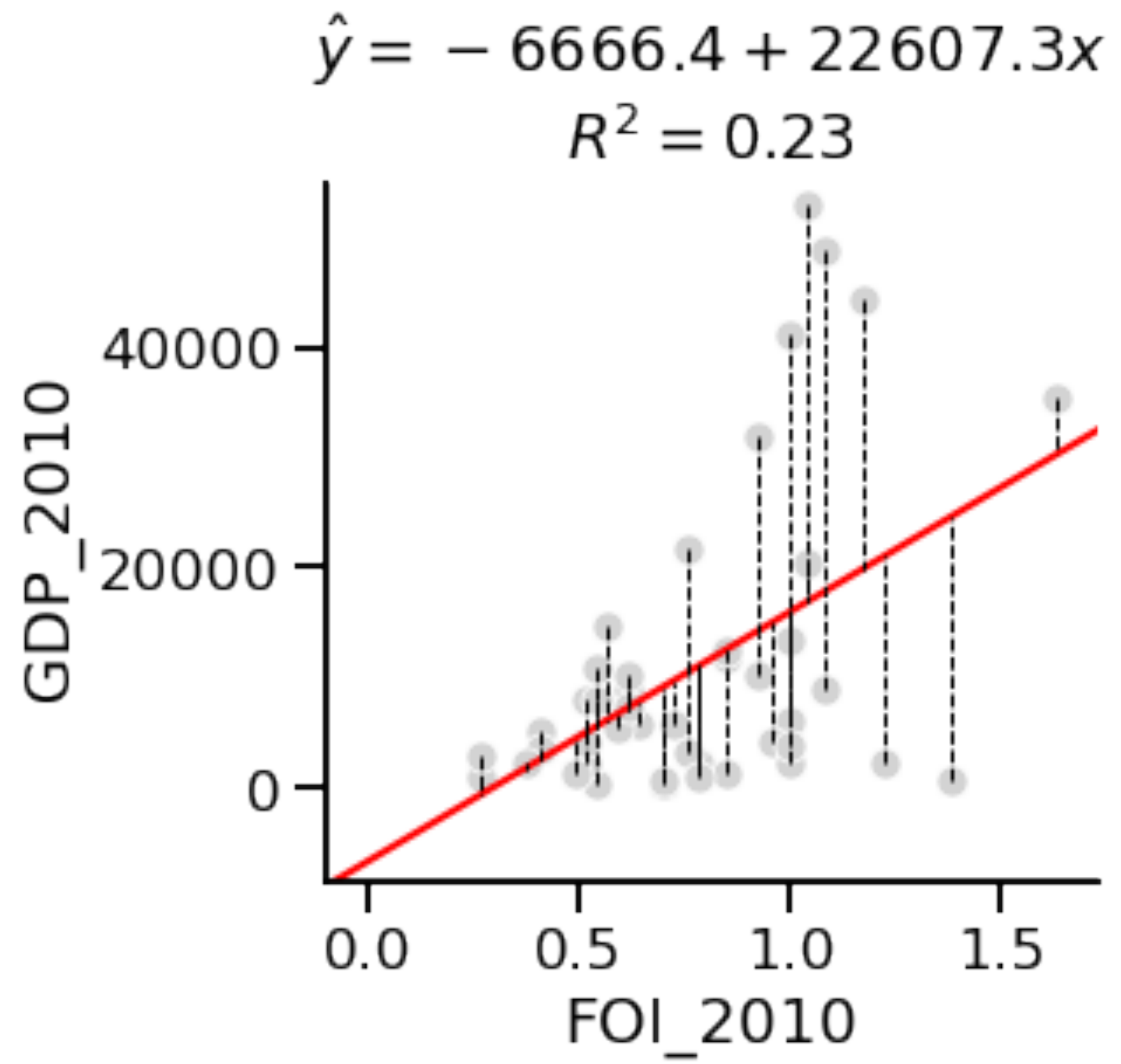

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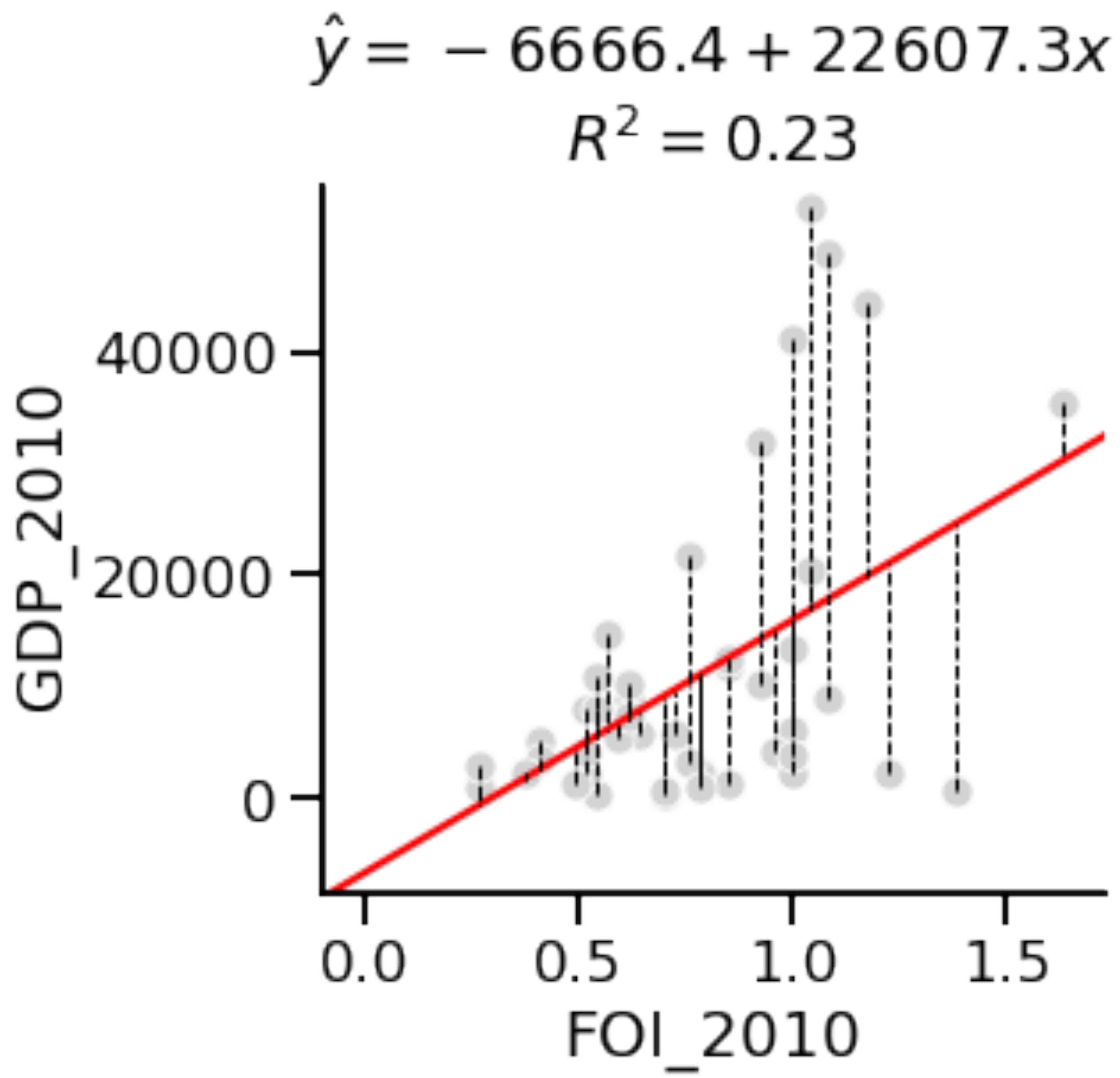

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Other metrics of "model success"

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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	BLOCK 2	BLOCK 3	BLOCK 4
Social Behavior	Social Trends	Quantifying Trends	Behavior & Trend Dynamics
1. Social Science 2. CSS 3. Digital Traces 4. Examples	1. Google Trends 2. The Future Orientation Index 3. Culture and Economy	1. Correlation 2. Causation 3. Regression	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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  - 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

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Imitation and distinctiveness

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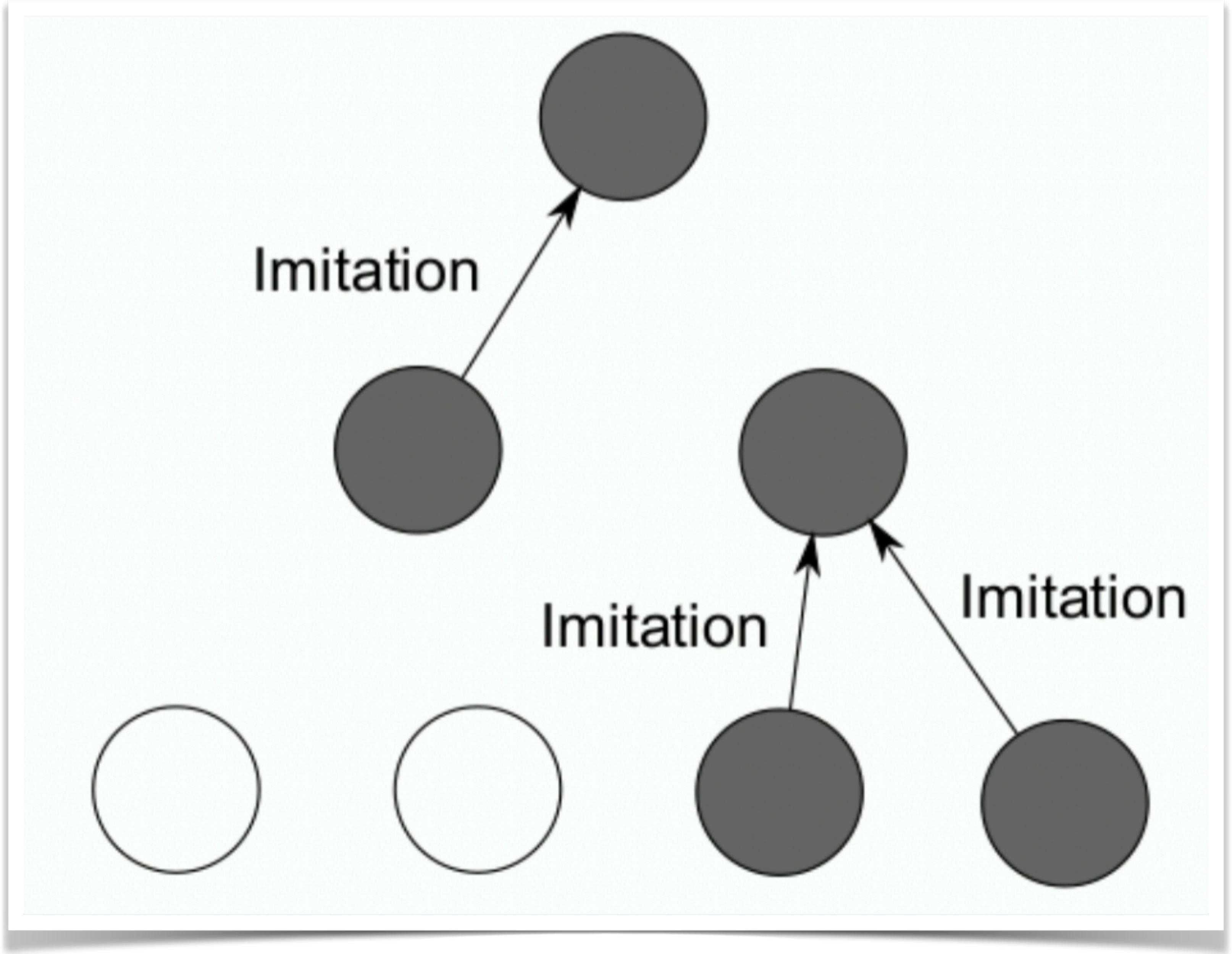

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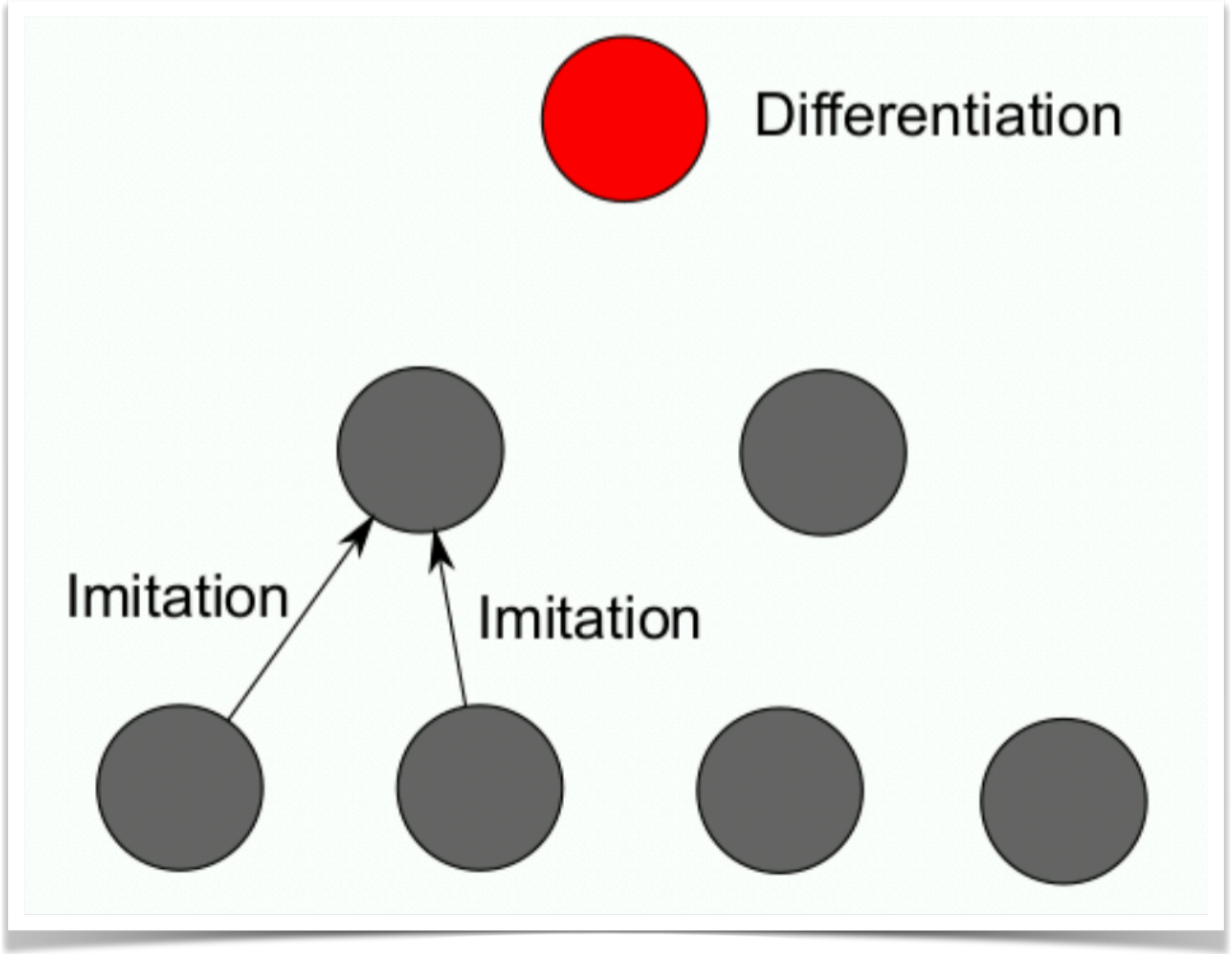

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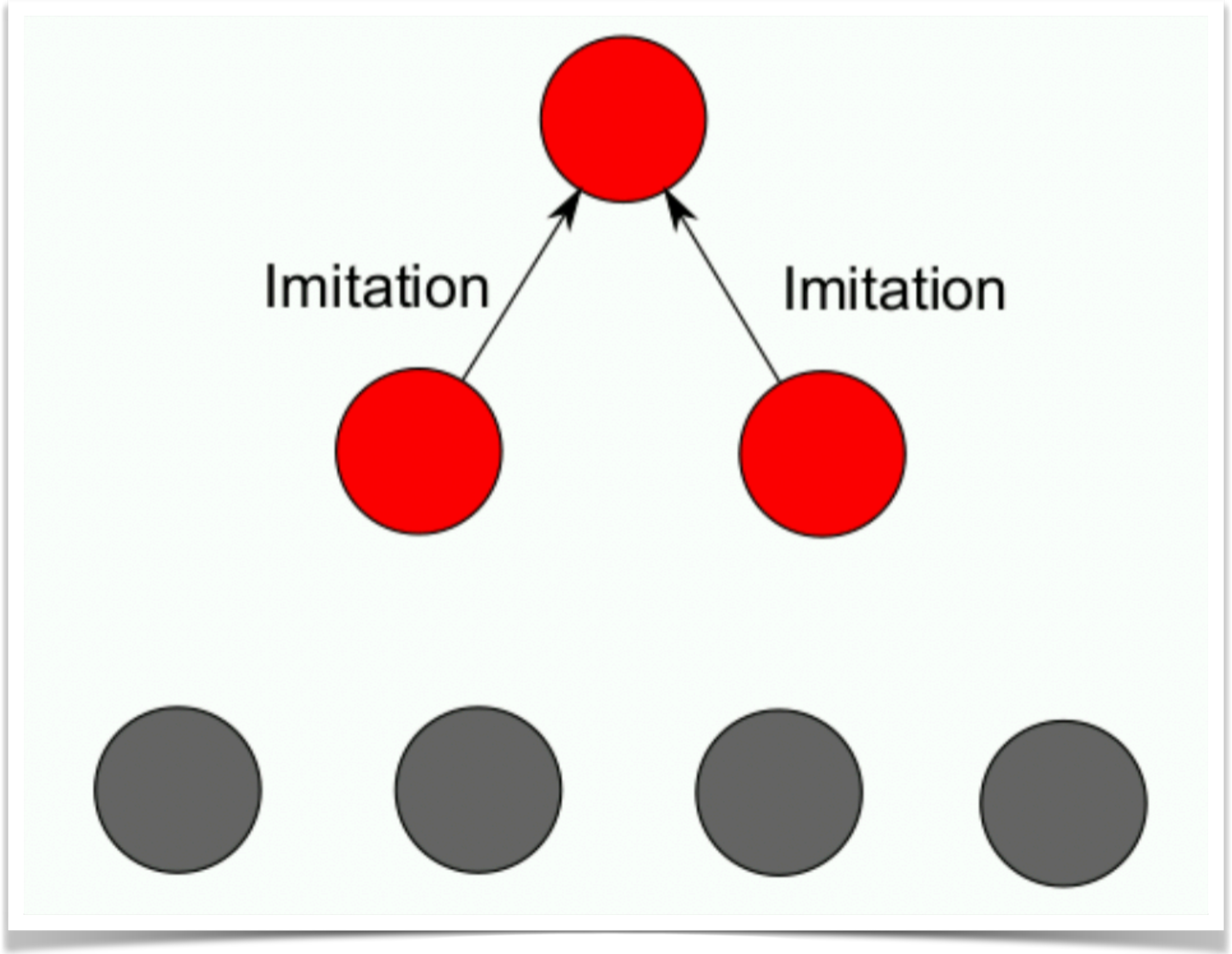

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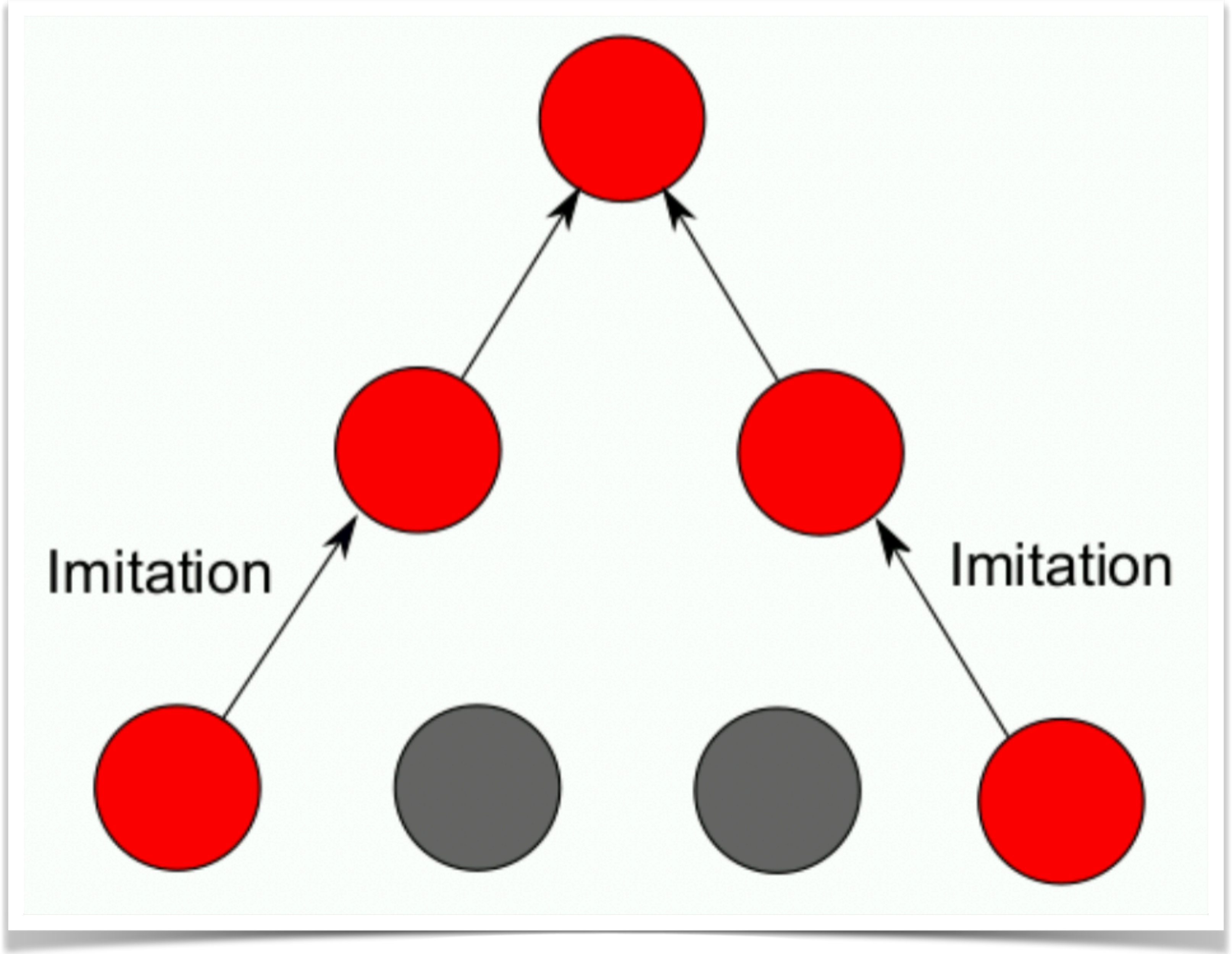

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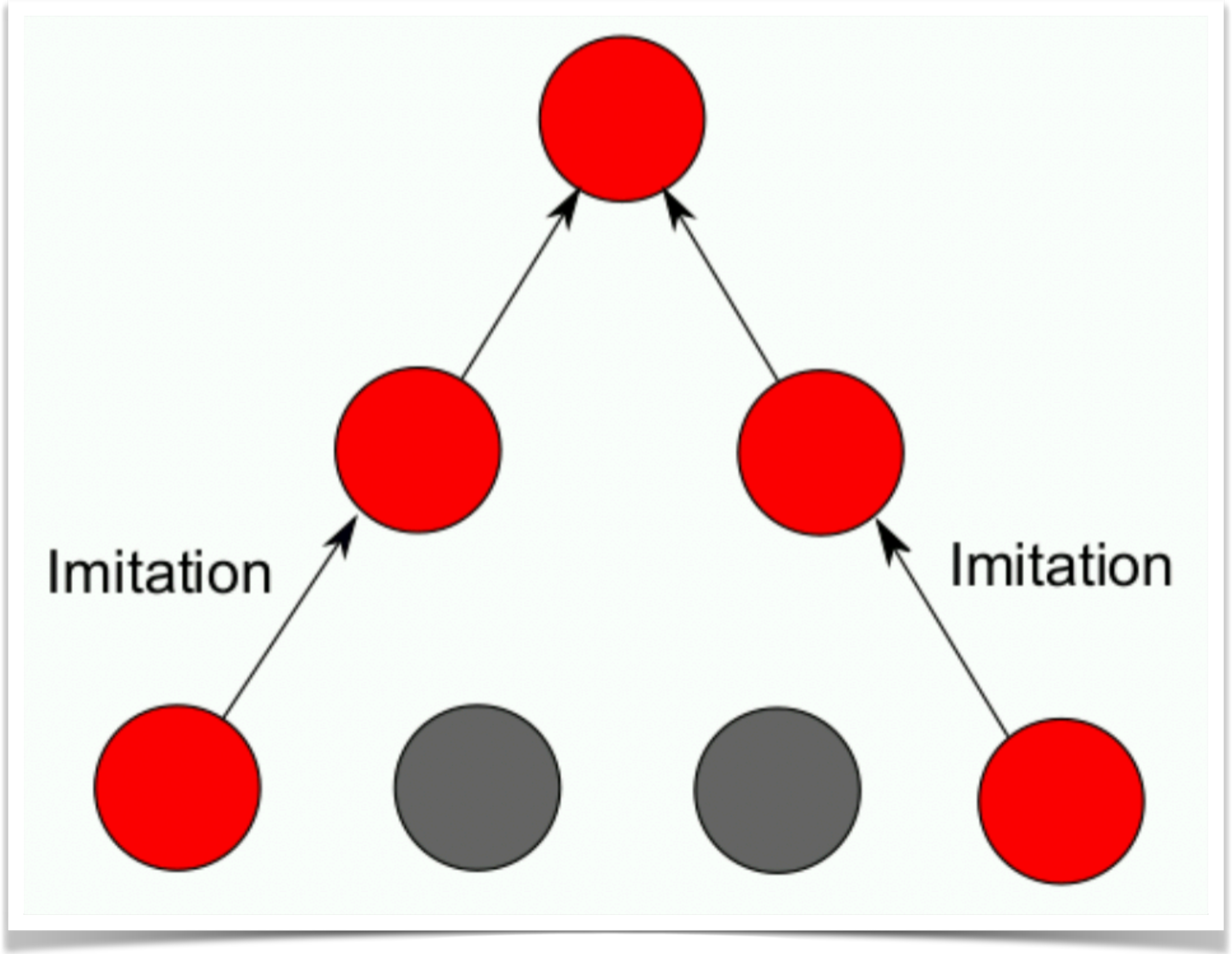

- Jeans were invented in 1871
    - Originally created for miners.
    - Popularized in 1950 in films.
    - 1960 widespread adoption.
- White sneakers were invented in 1916
    - Made popular by Adidas in 1970?
- Music challenge videos on TikTok

The case of baby names

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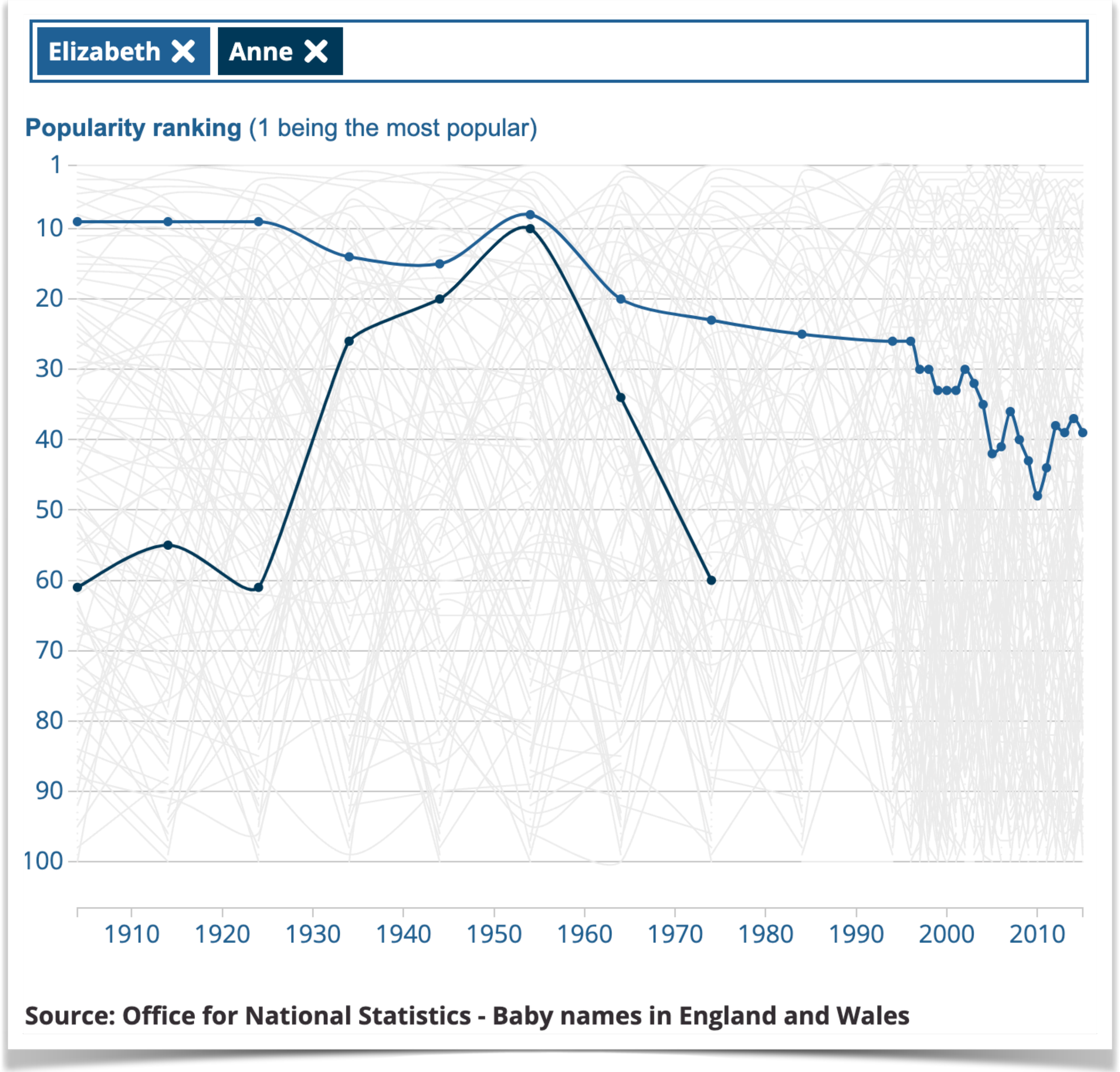

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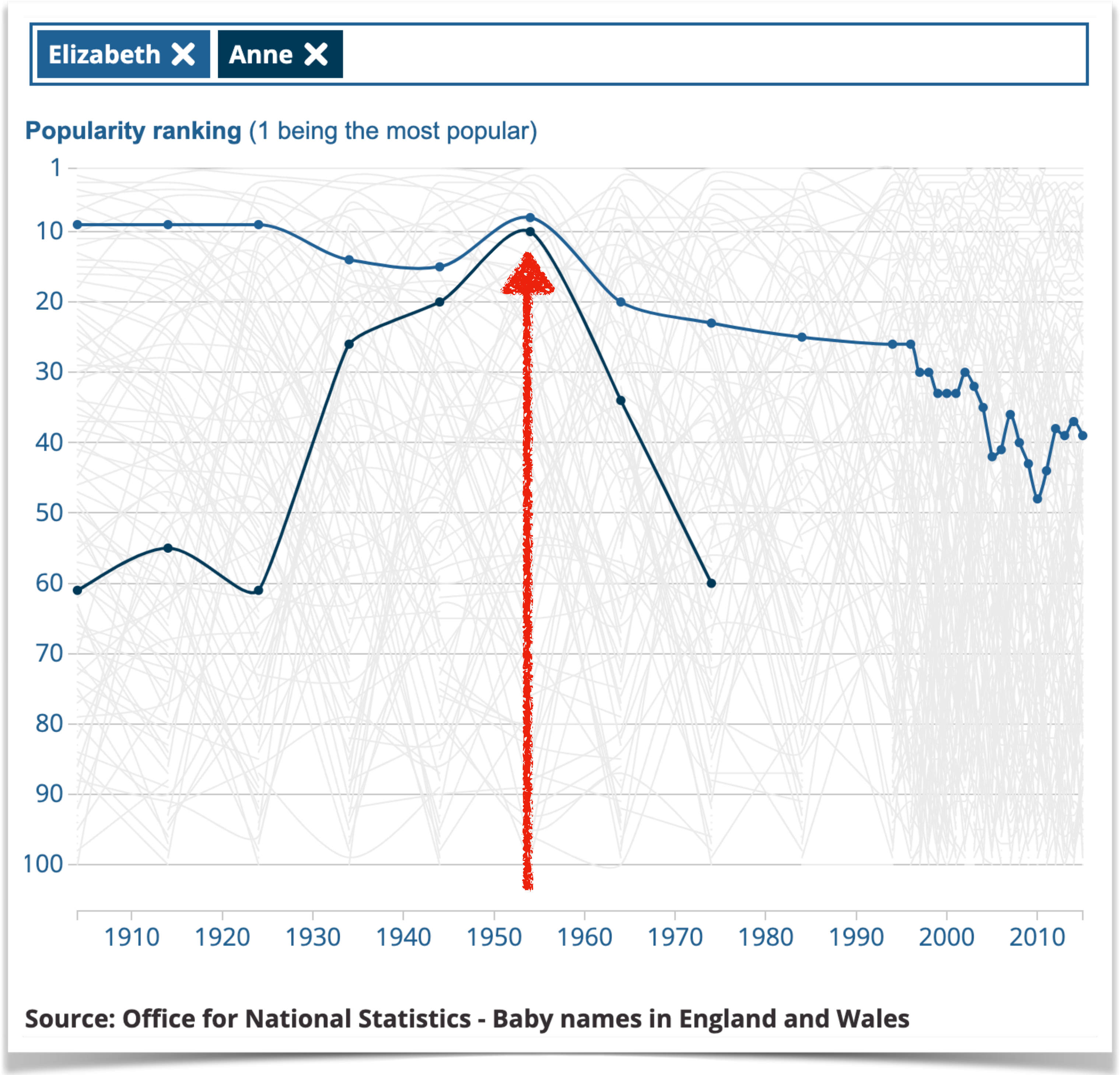

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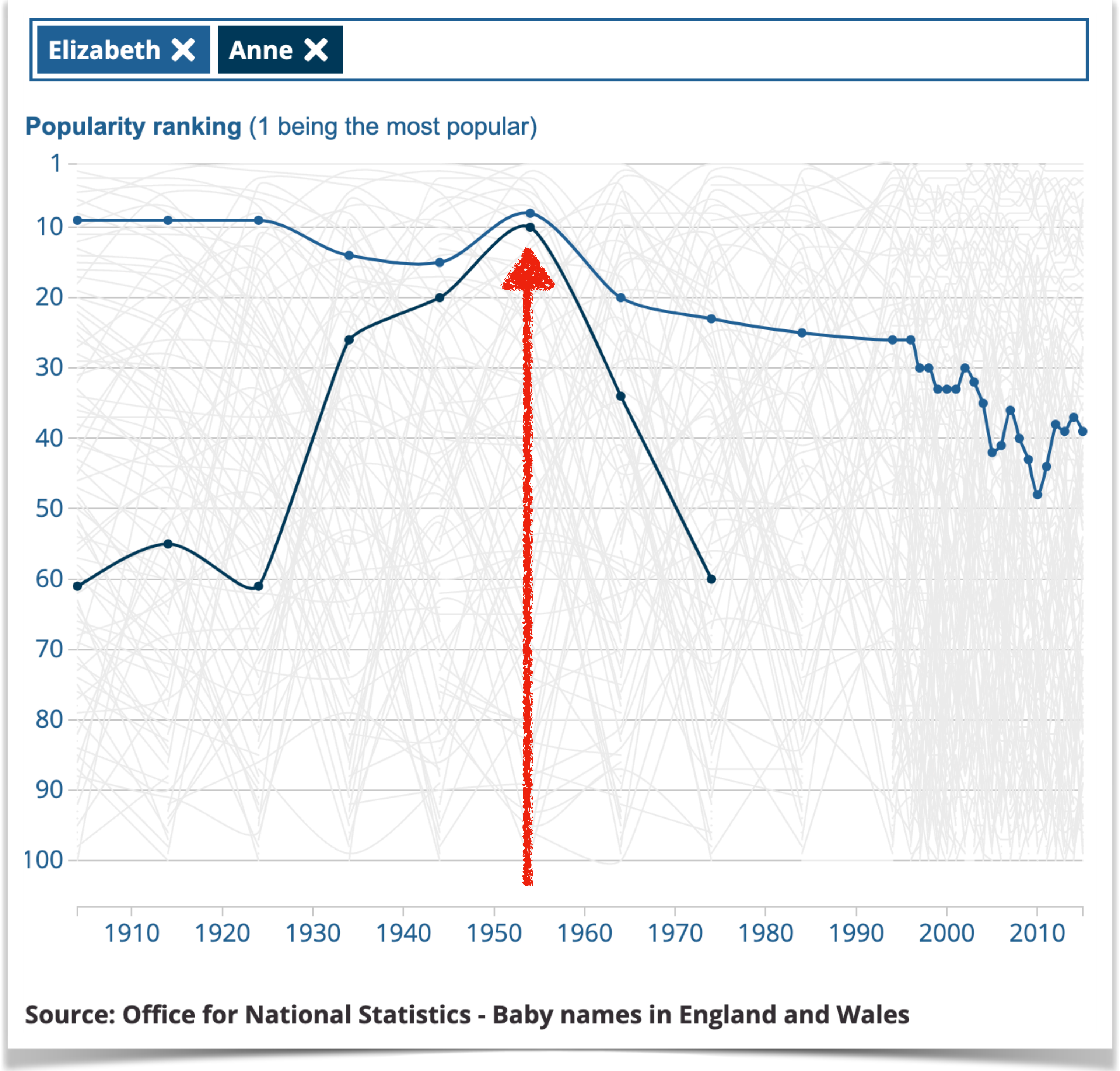

What happened around 1950 in the UK?

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

Social trends in online platforms

Google Search Trends

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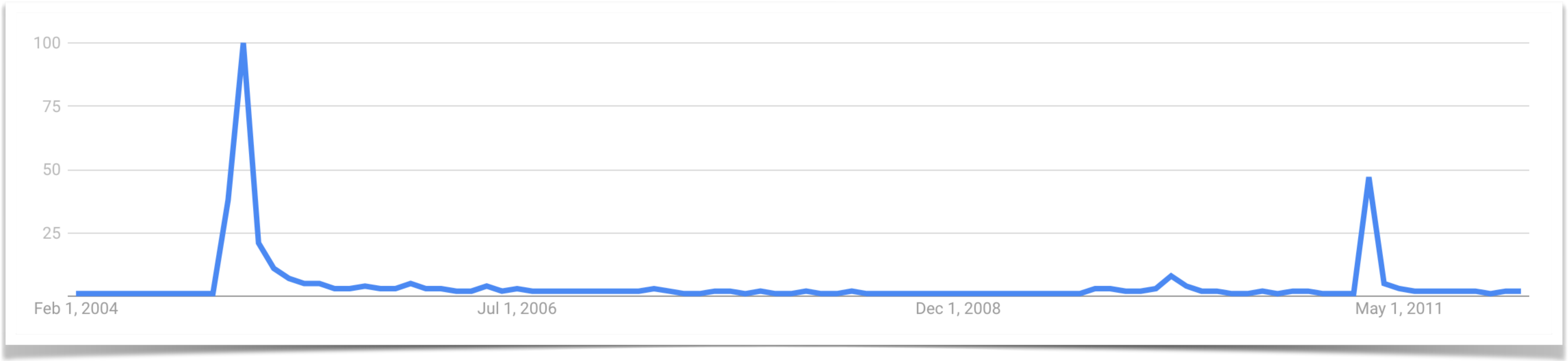

“Tsunami”

Social trends in online platforms

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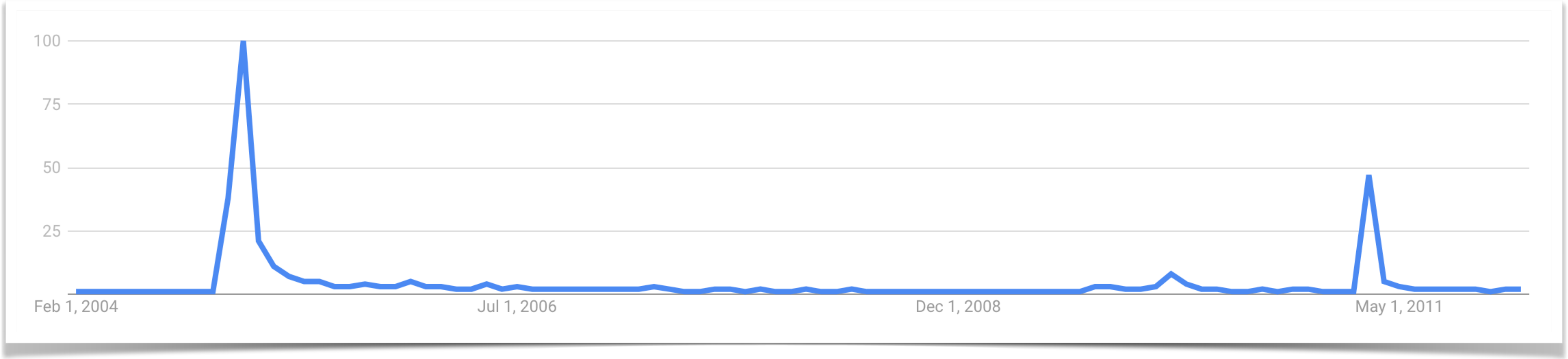

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December 26 **2004**
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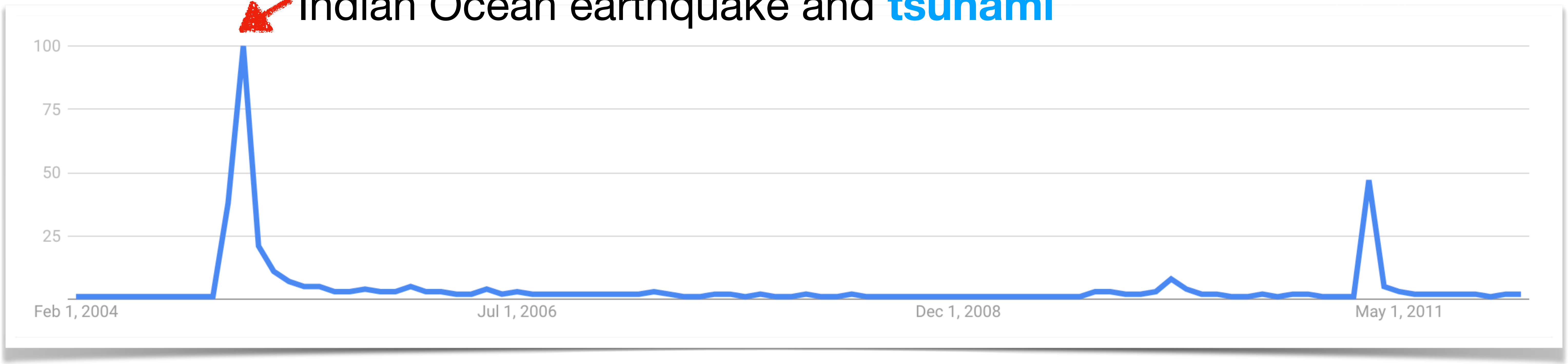

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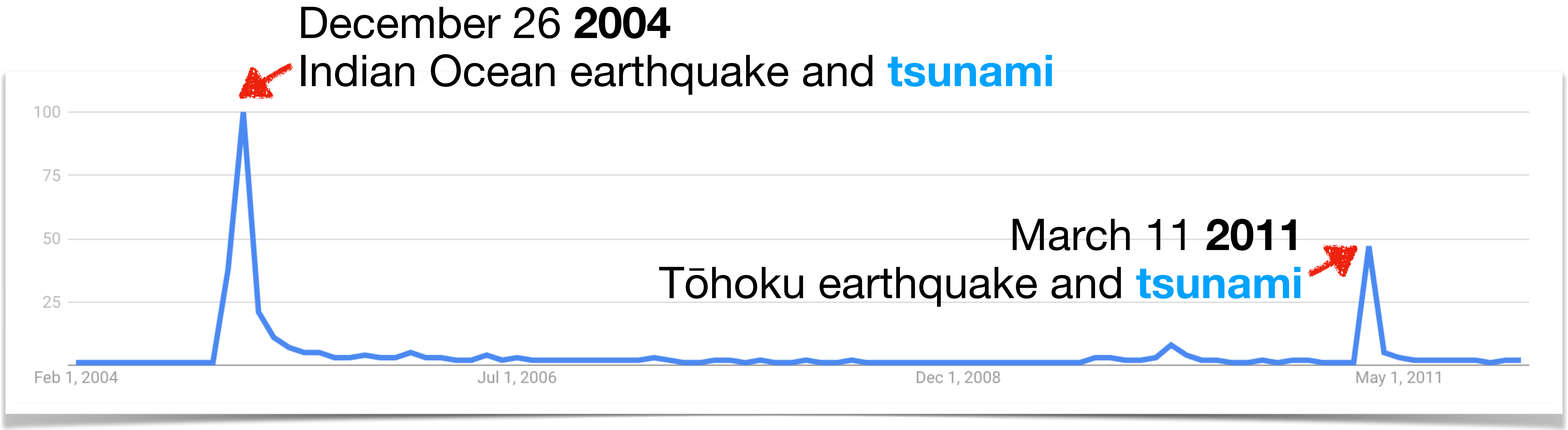

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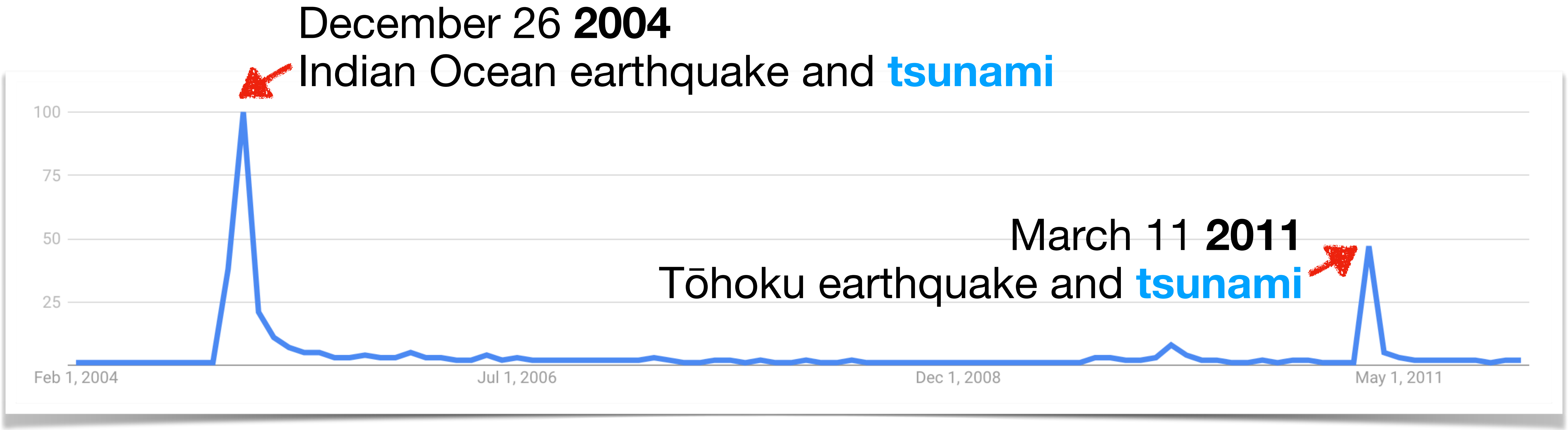

“Tsunami”
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“Harry Potter”

Social trends in online platforms

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December 26 **2004**
Indian Ocean earthquake and **tsunami**

March 11 **2011**
Tōhoku earthquake and **tsunami**

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

Harry Potter and the Order of the Phoenix was released in summer **2007** worldwide (movie #5).

"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]

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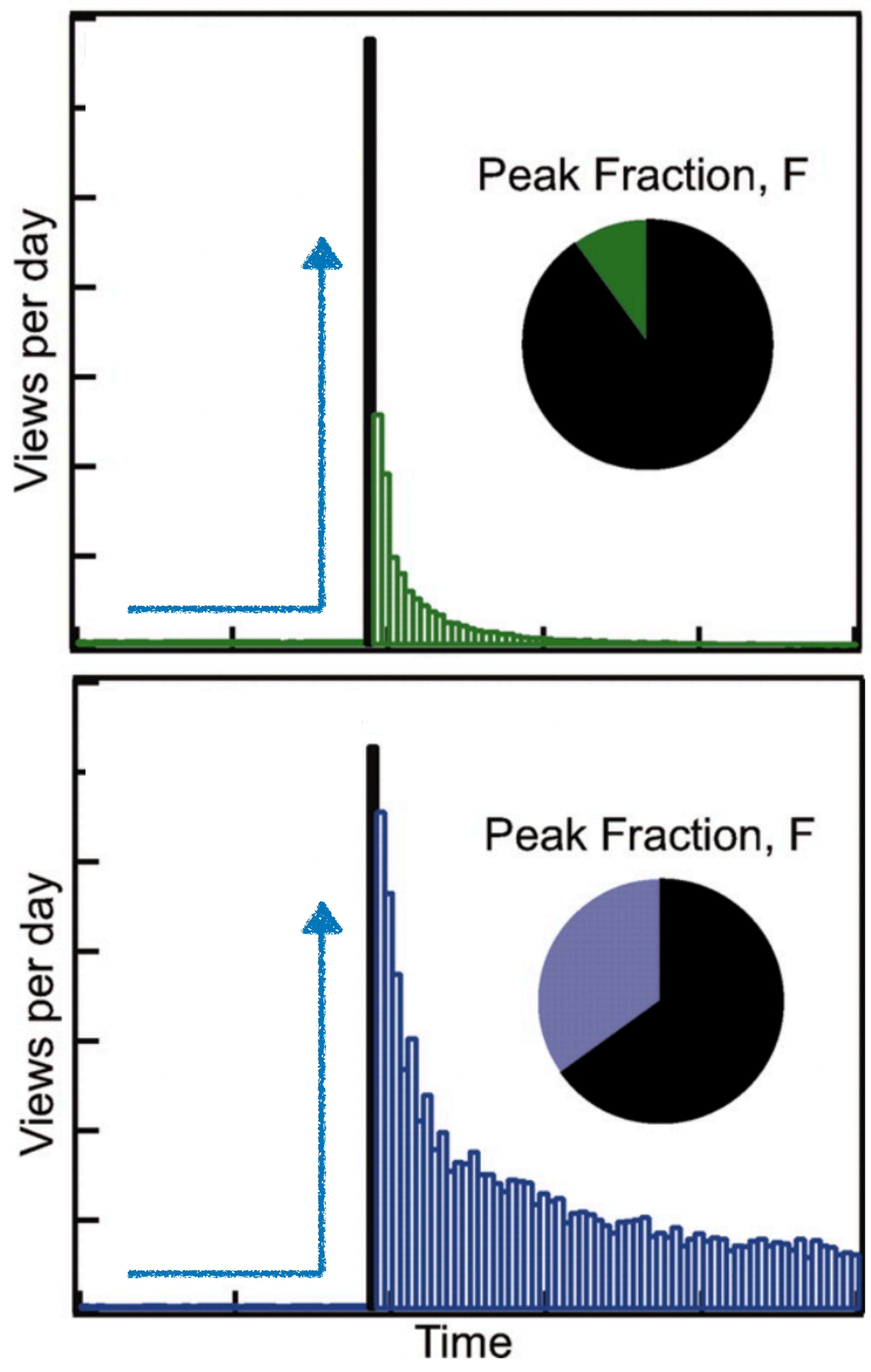
Exogenous behavior



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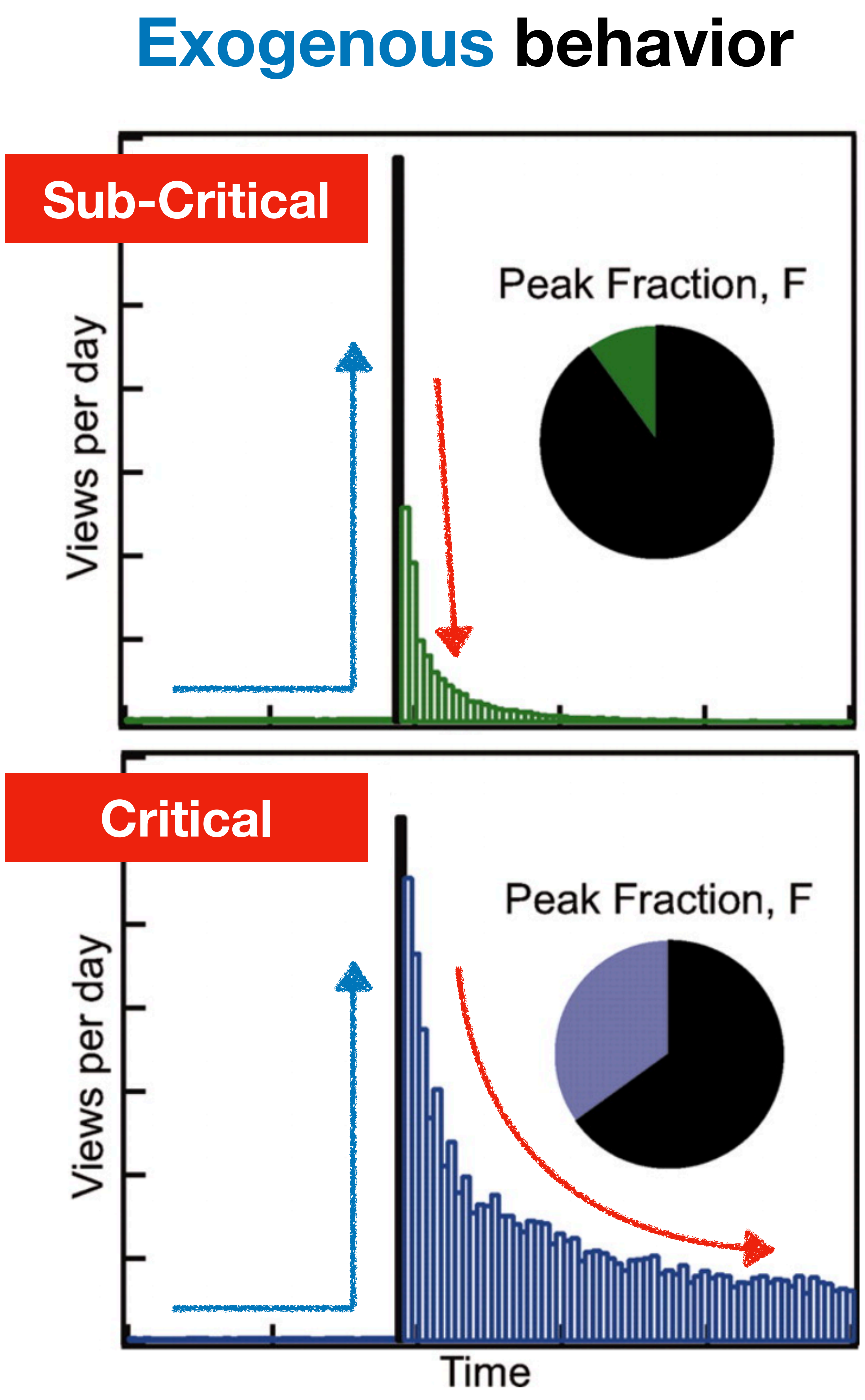
  - **Critical:** when the social interaction between individuals leads to further responses and it is stronger than the rate of losing interest.



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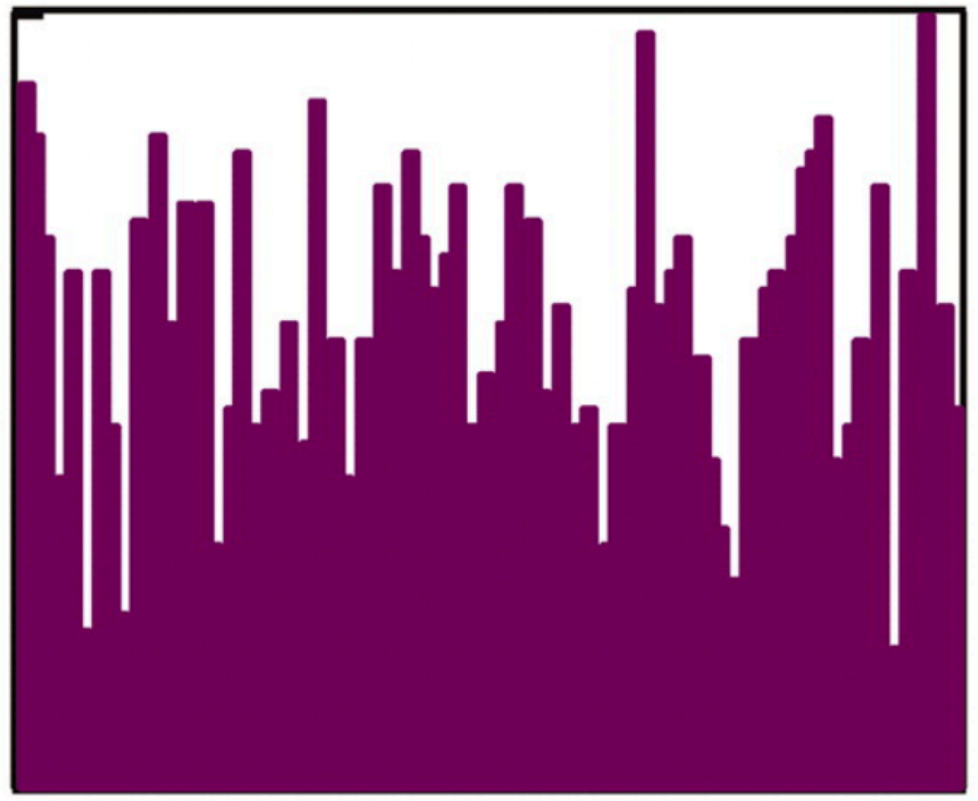
Sub-Critical		
Critical		

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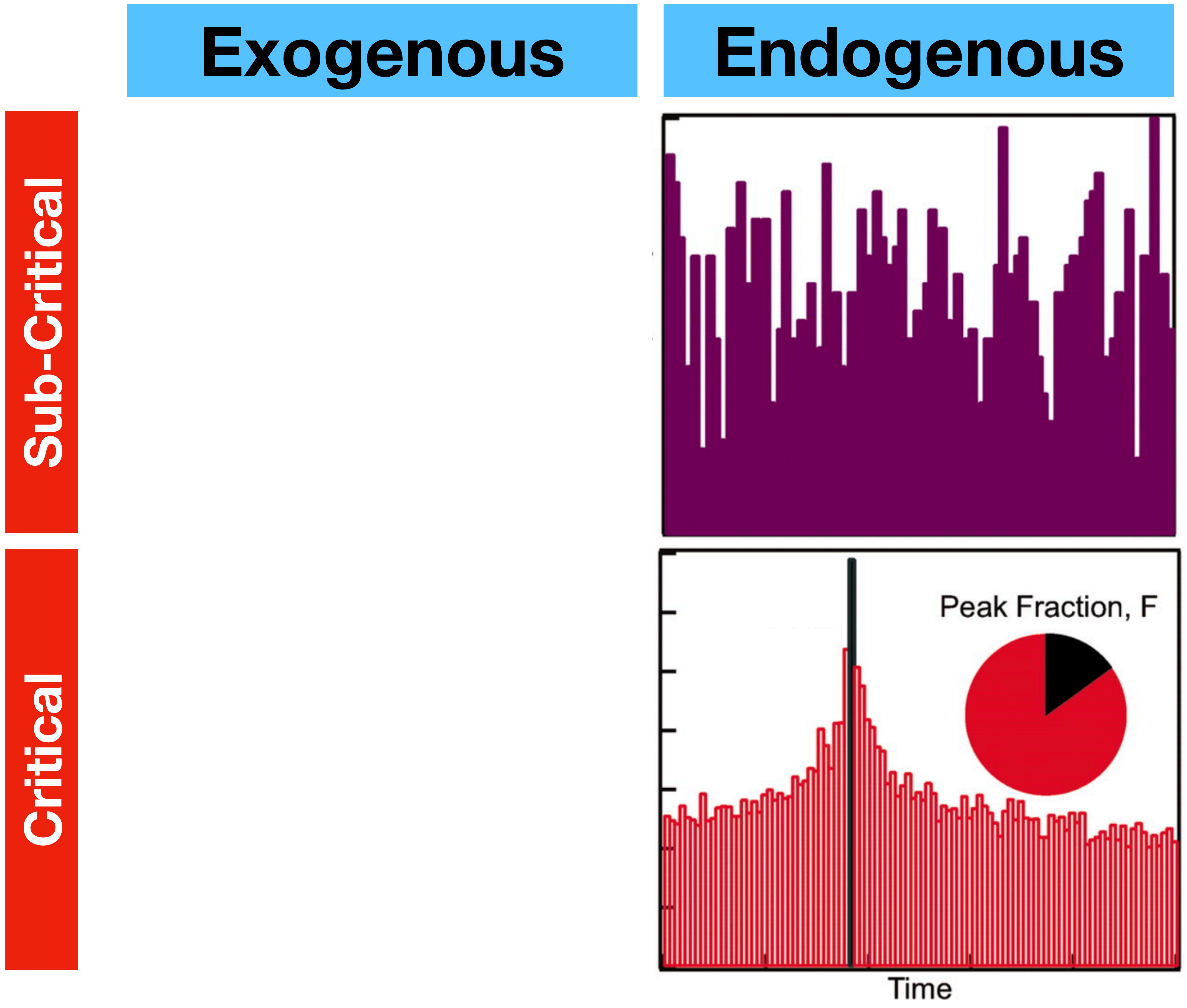

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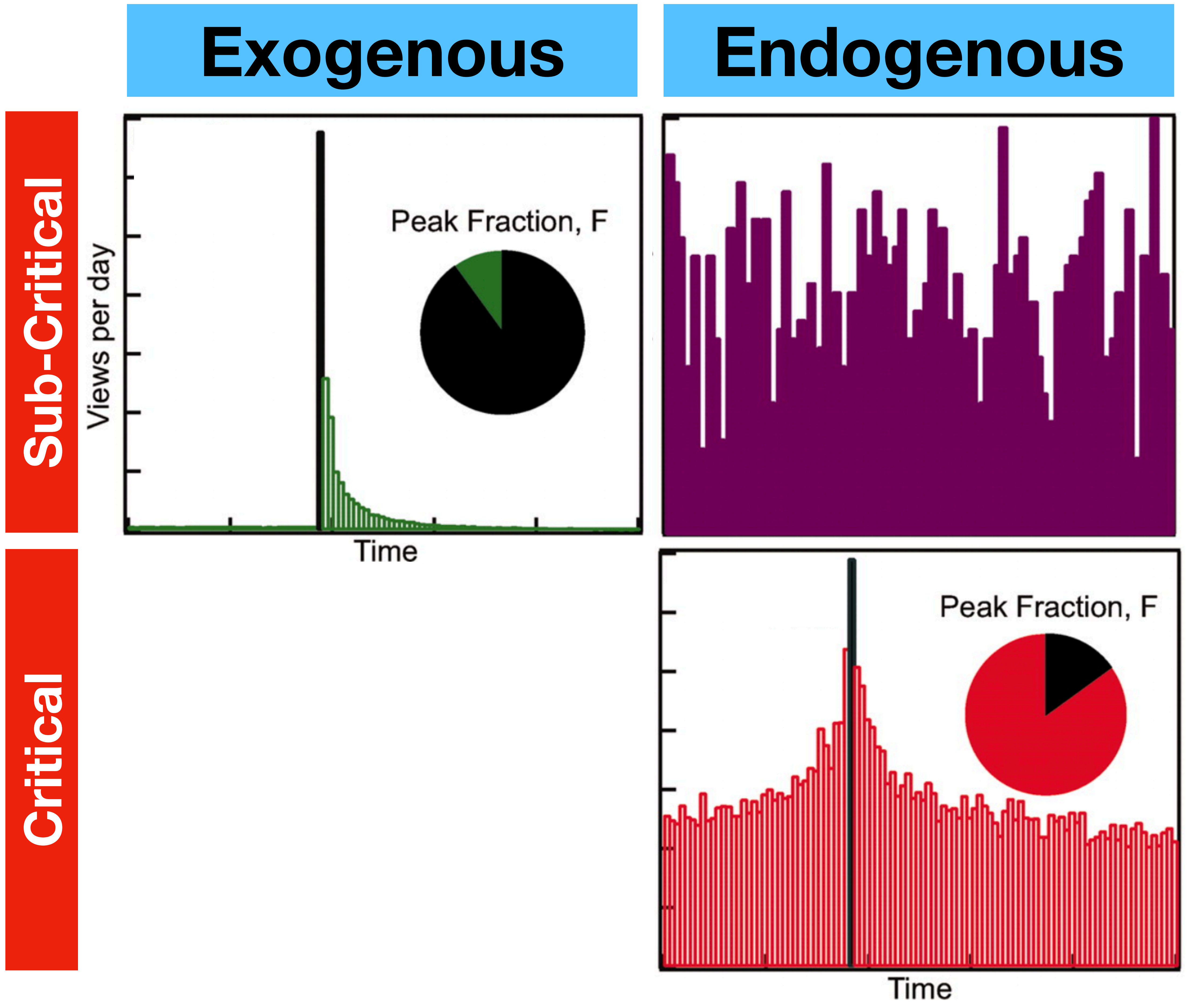

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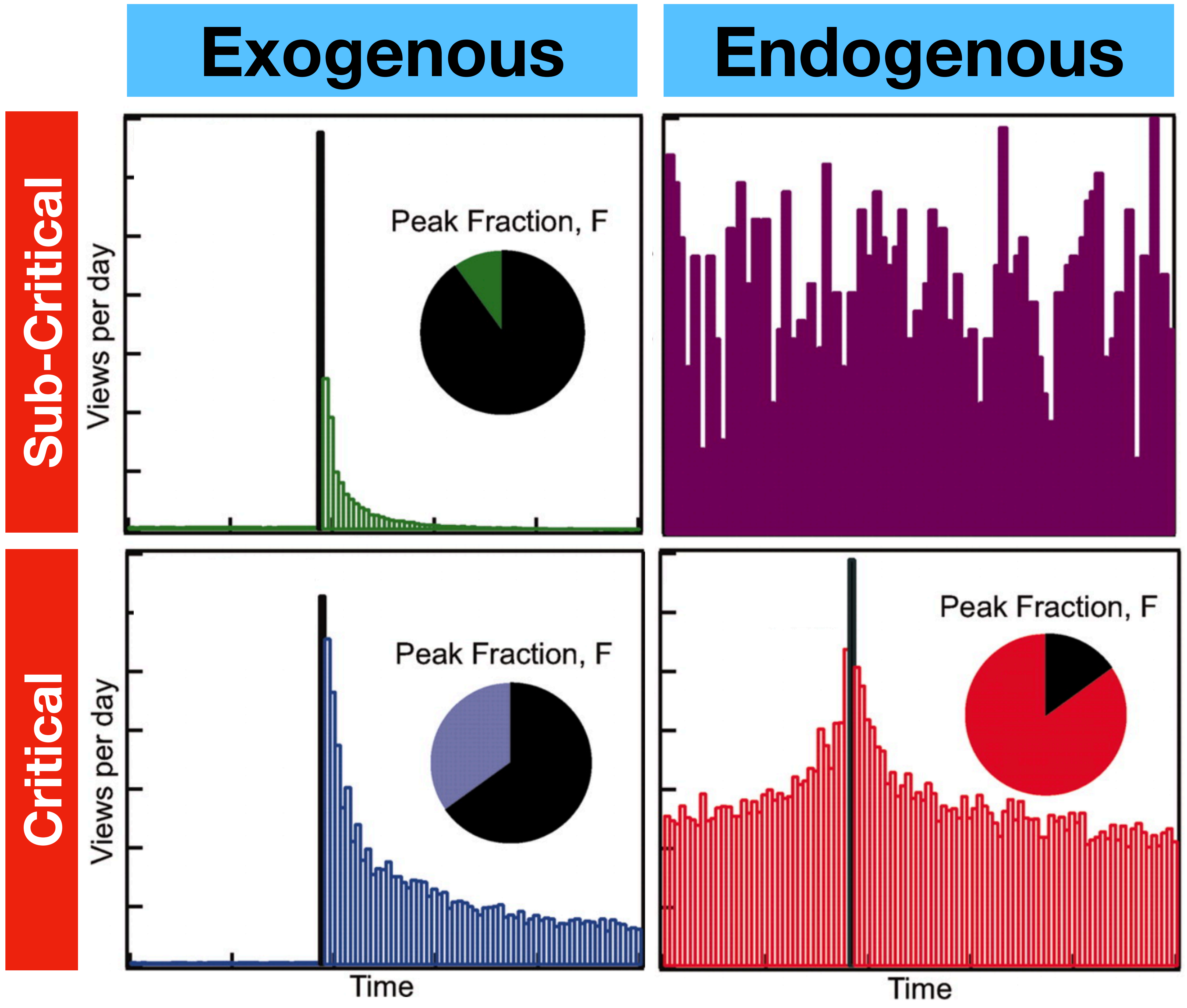

Trends on Twitter

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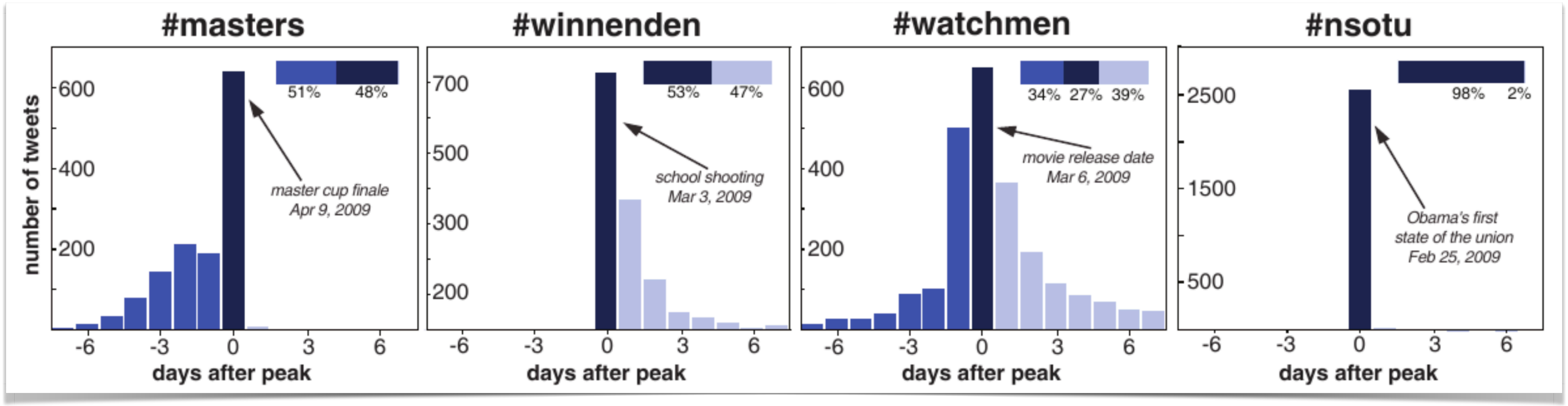

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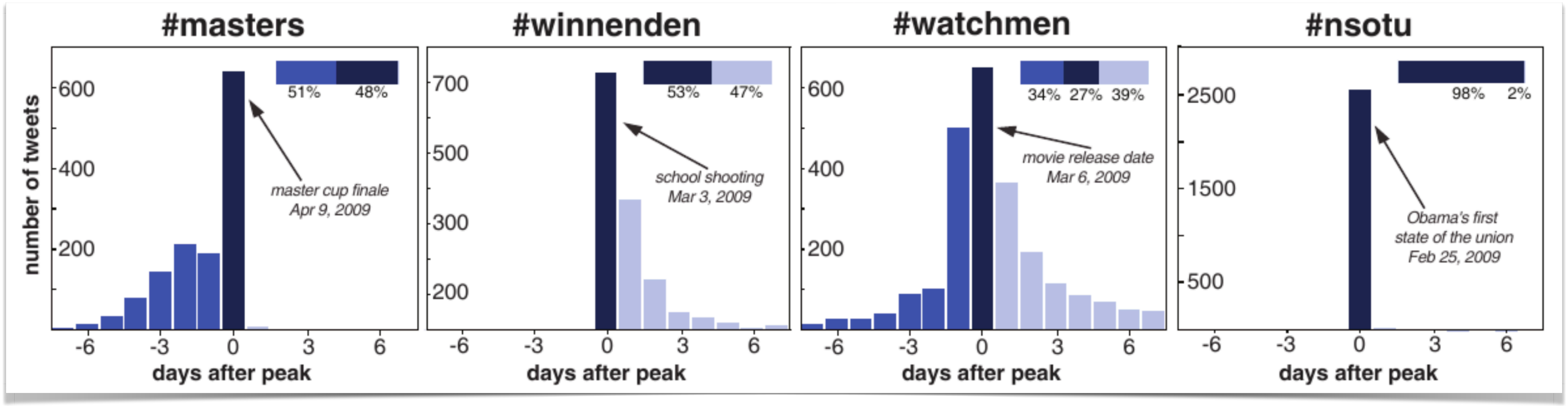

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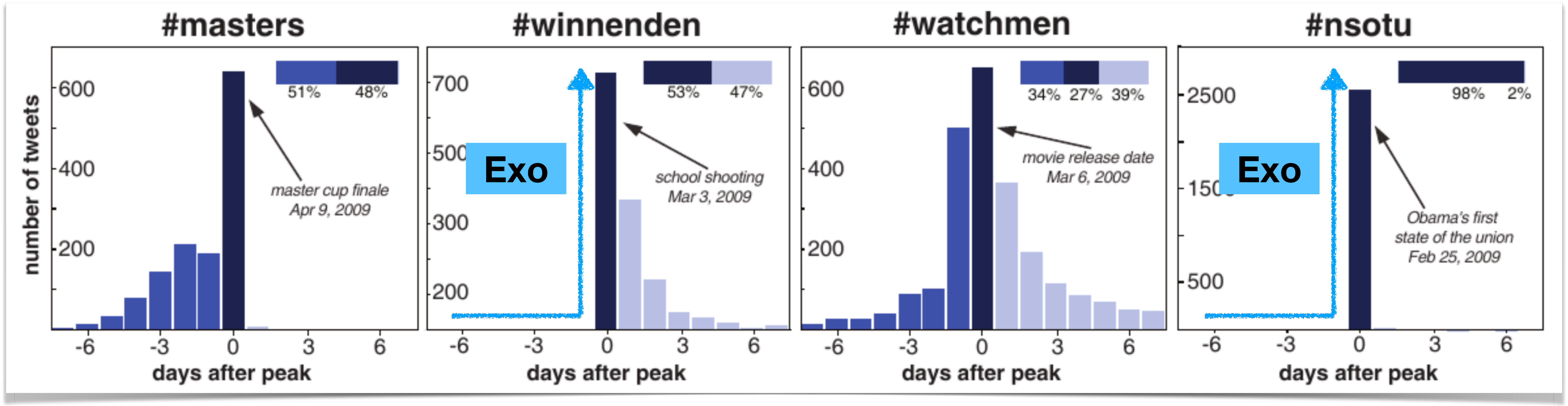

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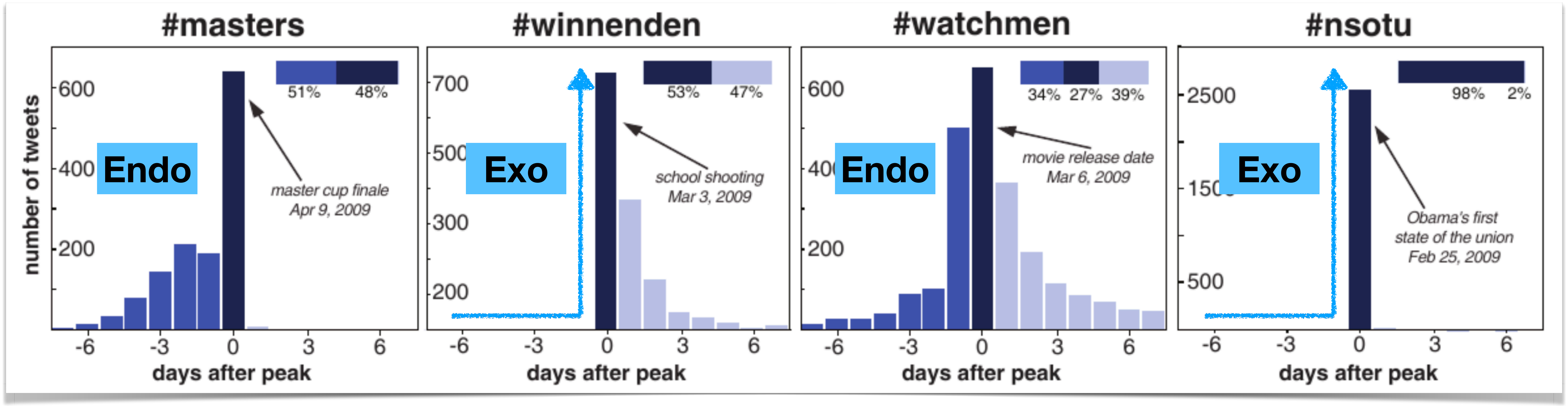

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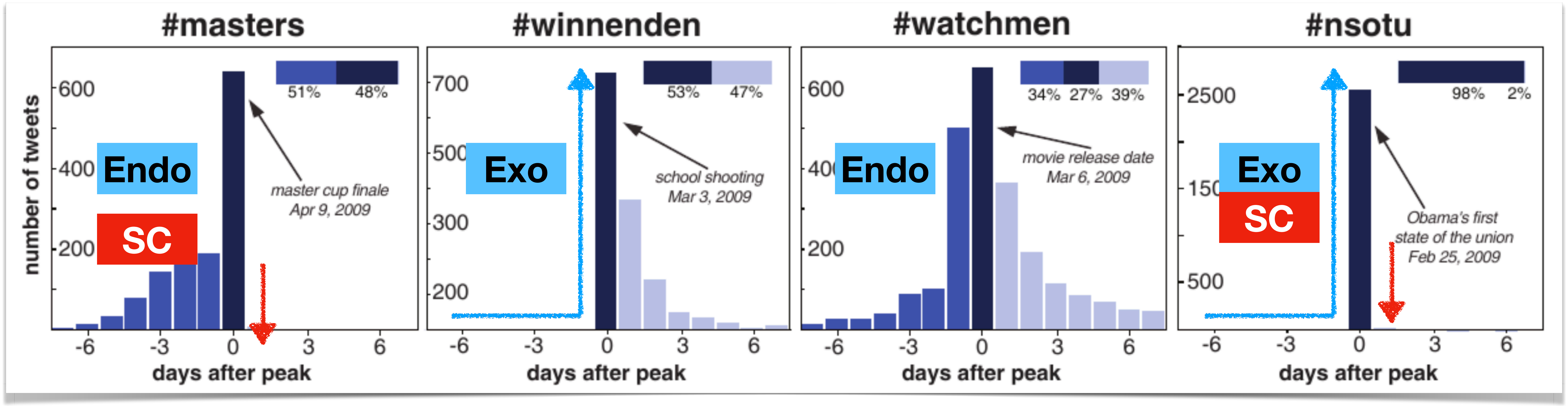

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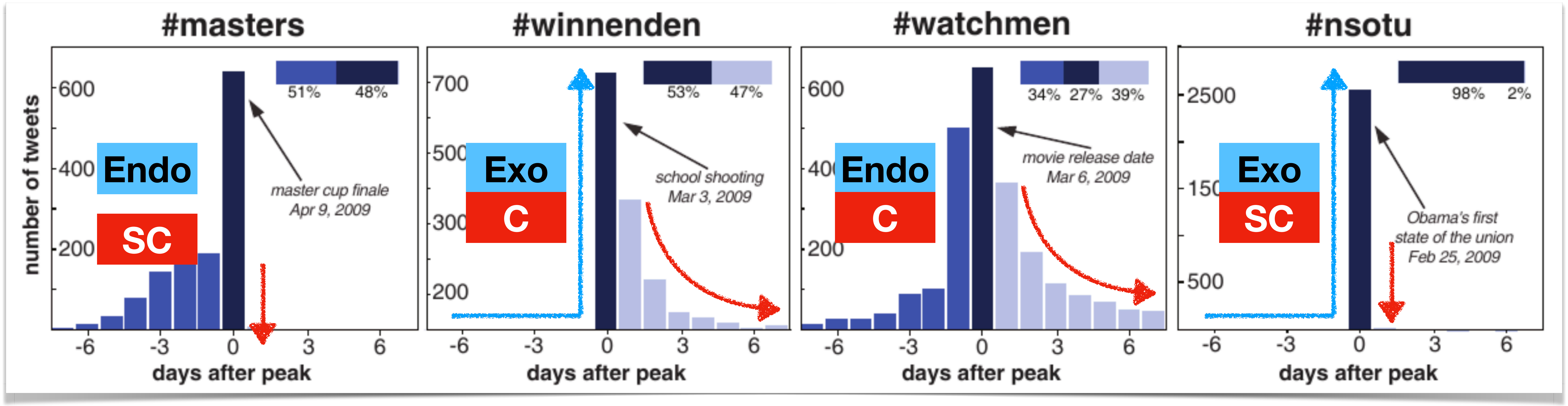

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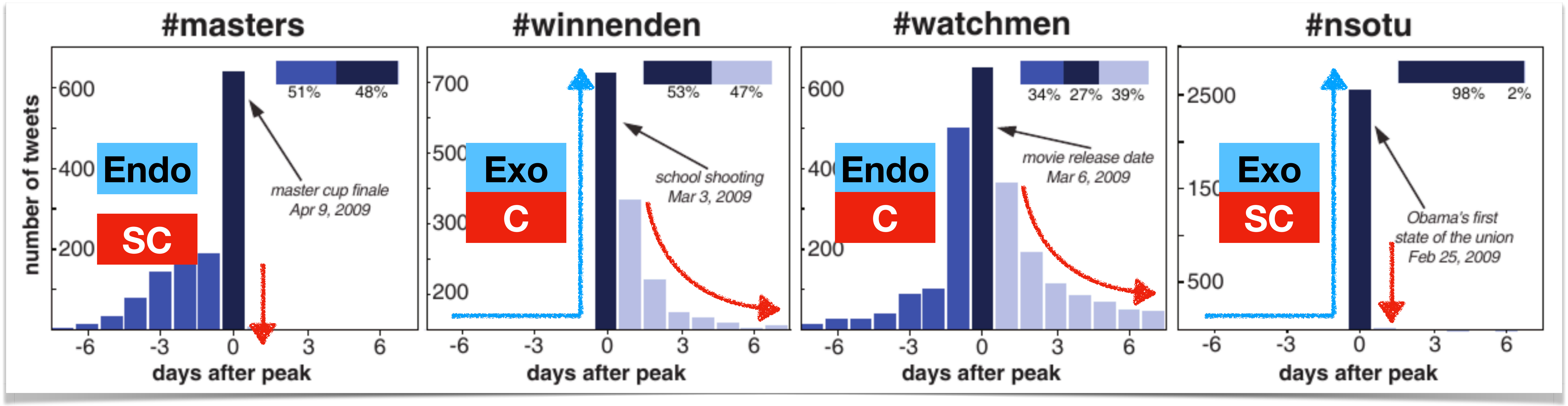
Endo/Exo?
Critical/Subcritical?

- This model has been applied to classify Twitter hashtag trends by Lehmann et al.



Gathering this kind of volume data is best done by using the Twitter API v2 (https://developer.x.com/en/docs/x-api/rate-limits)

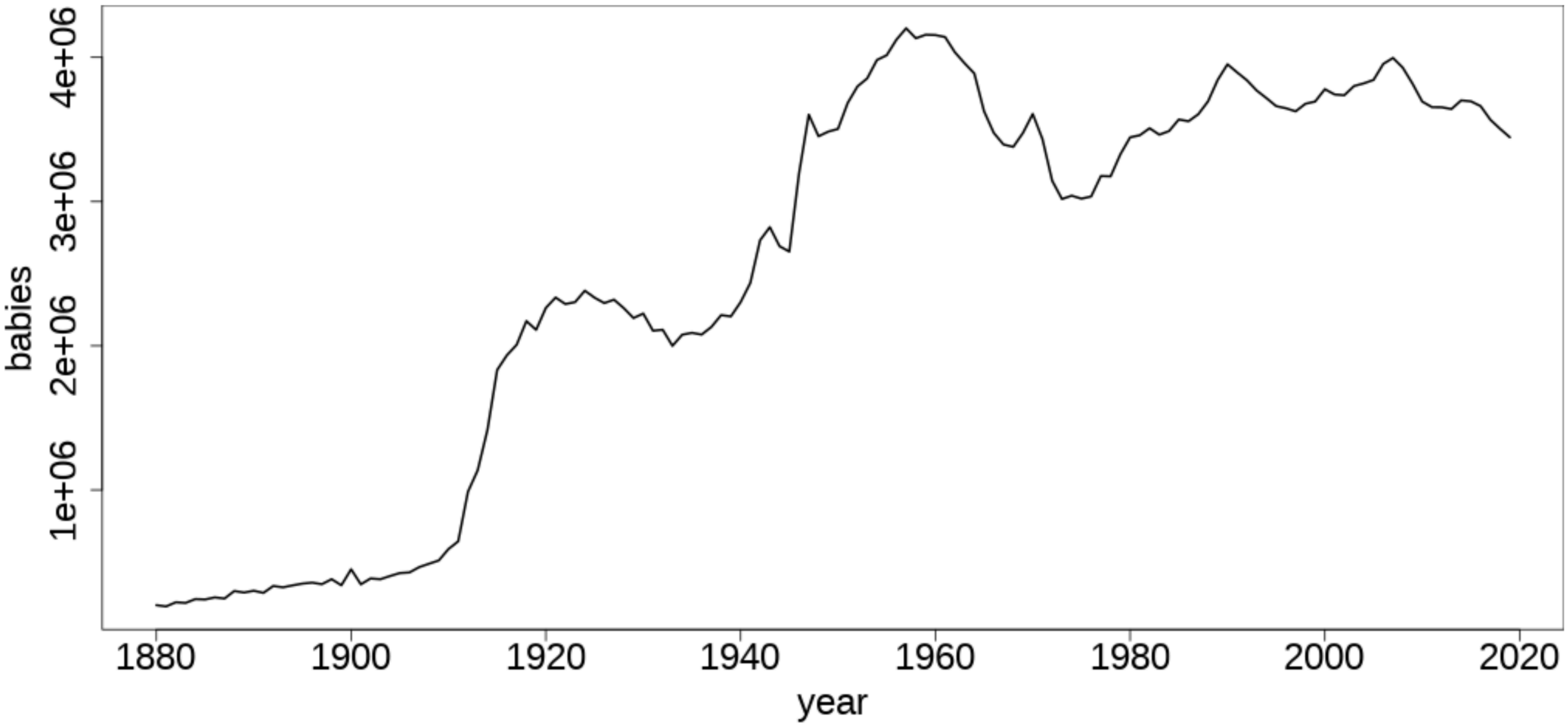
- Free access: up to 1500 tweets per month
- Basic (100 USD/month): up to 10K tweets per month
- Pro (5000 USD/month): up to 1M tweets per month

Old BigData

Baby name trends

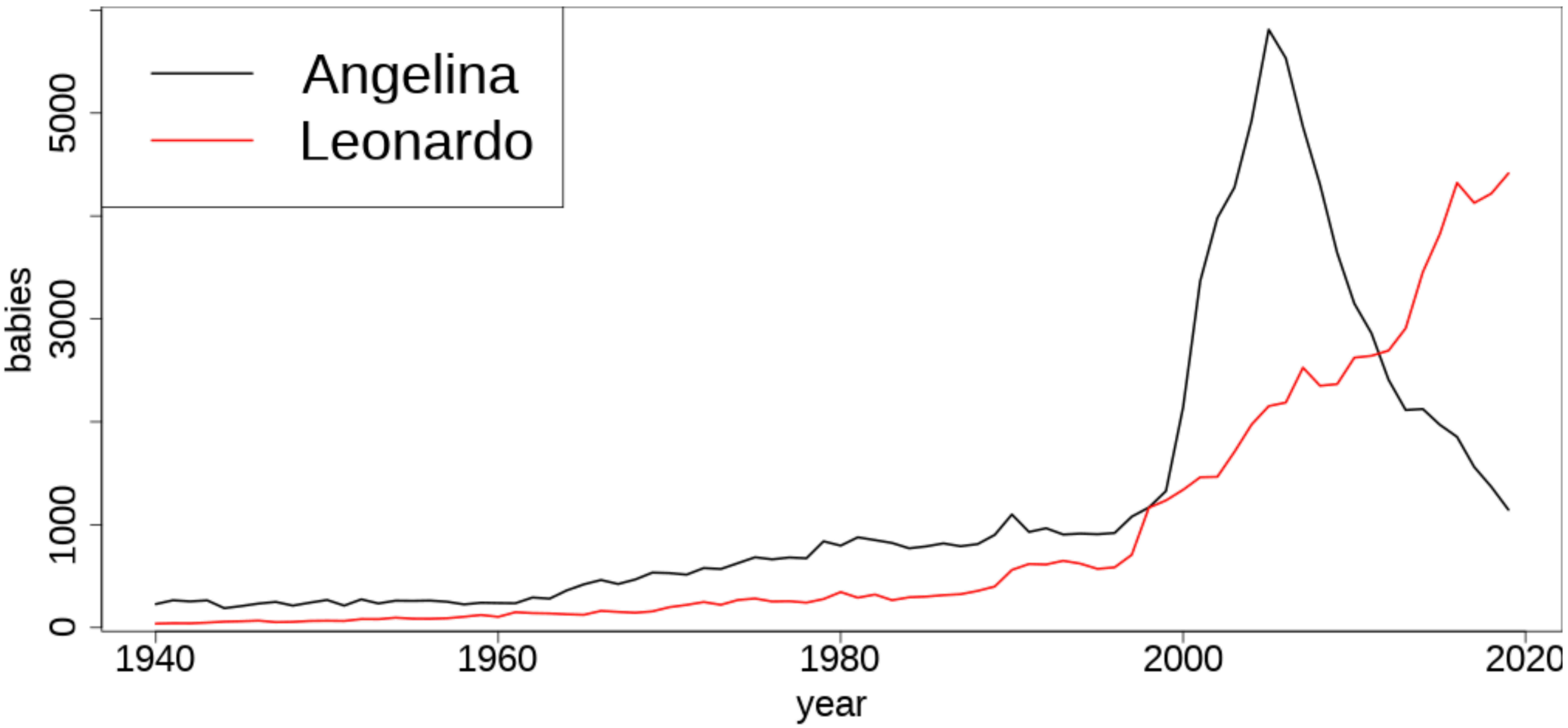
USA SSA baby name data

(Social Security Administration)



Baby name trends

Examples

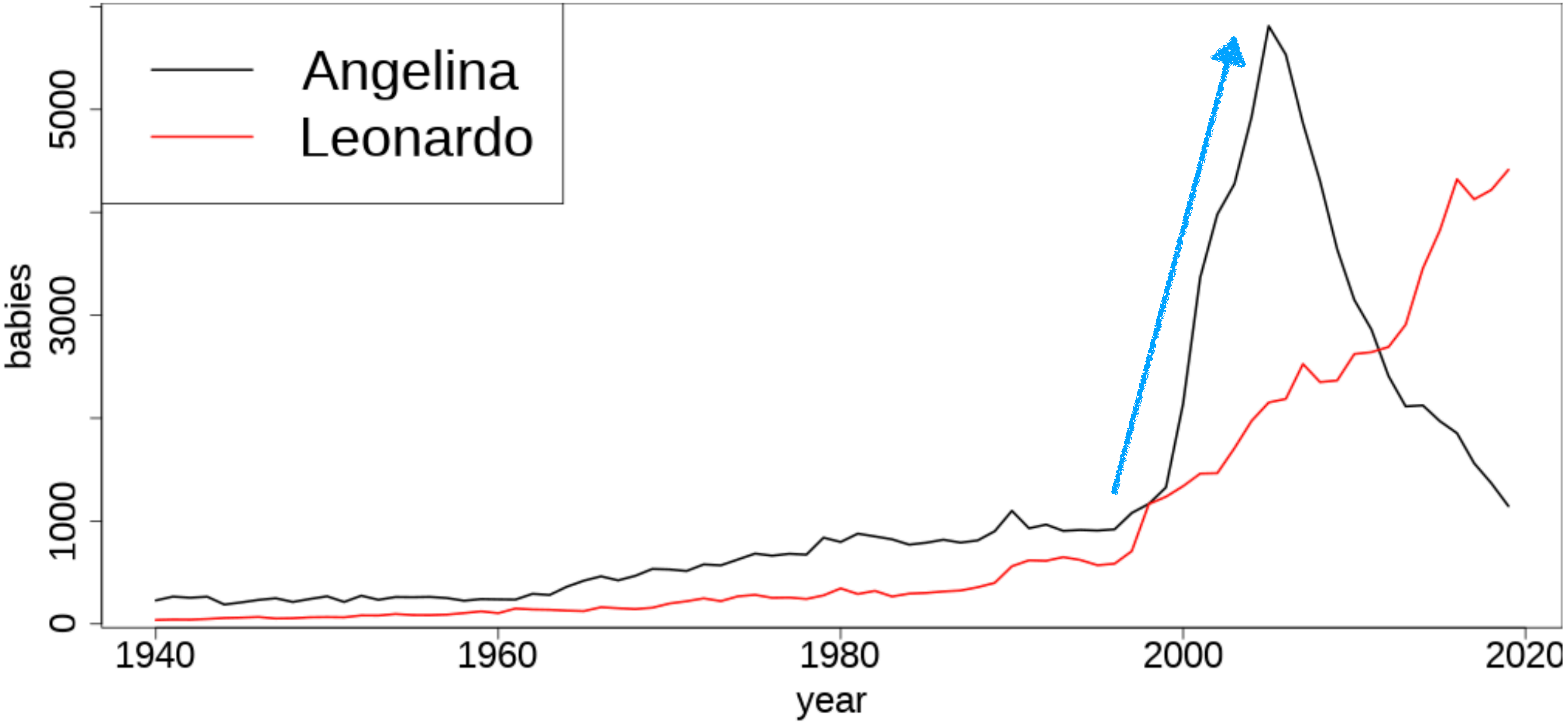


Baby name trends

Examples

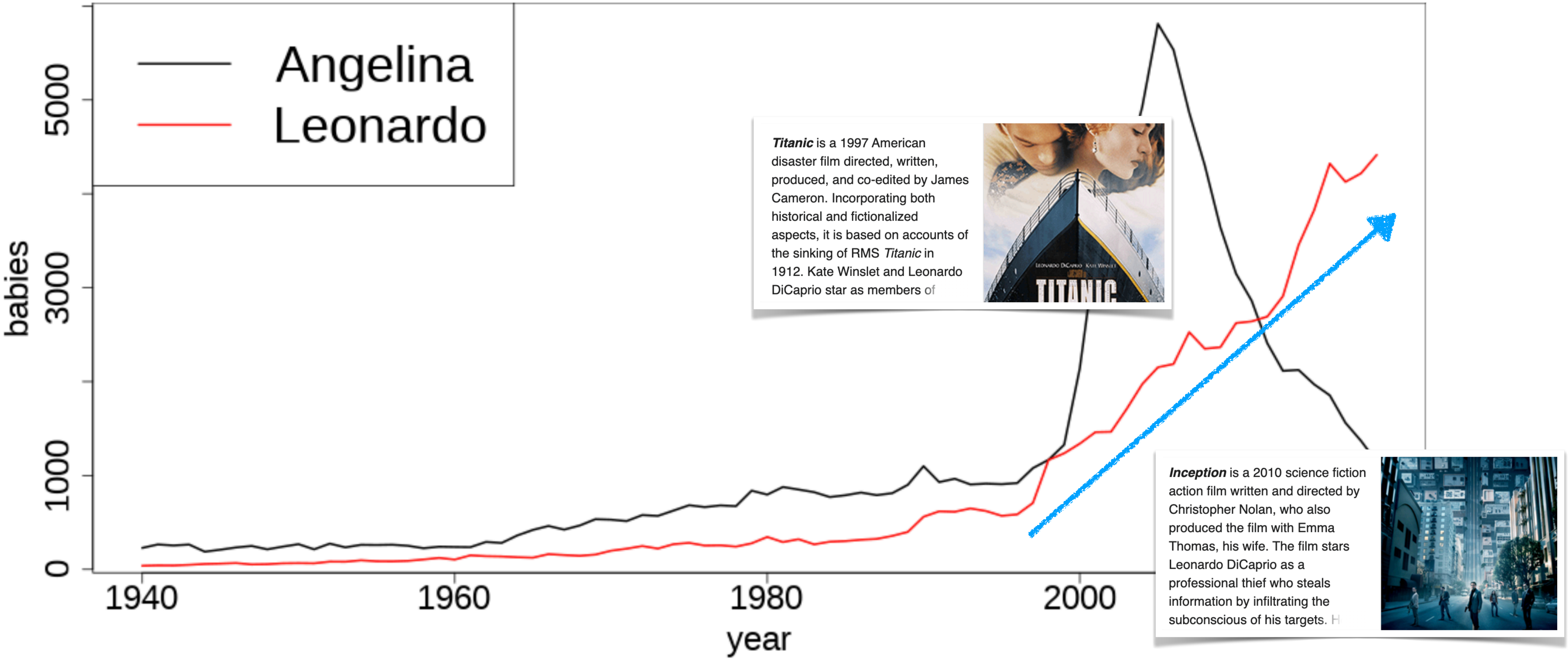
The Bone Collector is a 1999 American crime thriller film directed by Phillip Noyce and starring Denzel Washington and Angelina Jolie. The film is based on the 1997 crime novel of the same name written by Jeffery Deaver, concerning the tetraplegic detective Lincoln Rhyme.

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,



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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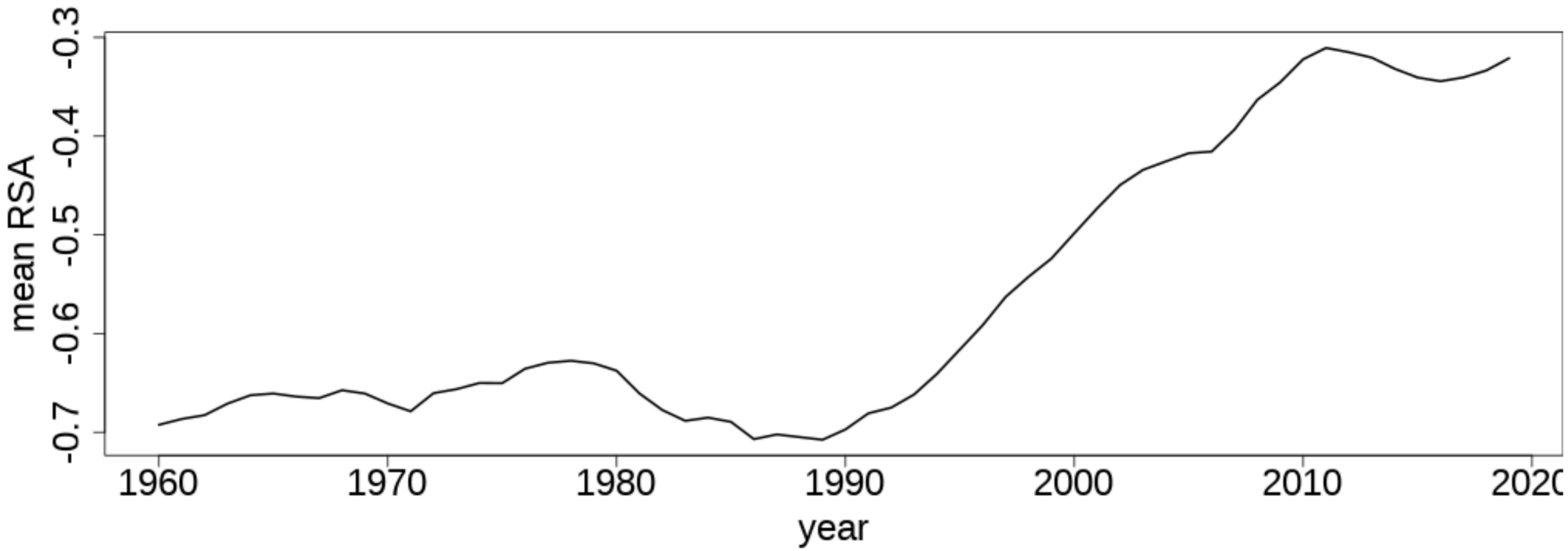

* RSA (right-side advantage) = (# right-side letters) - (# left-side letters)

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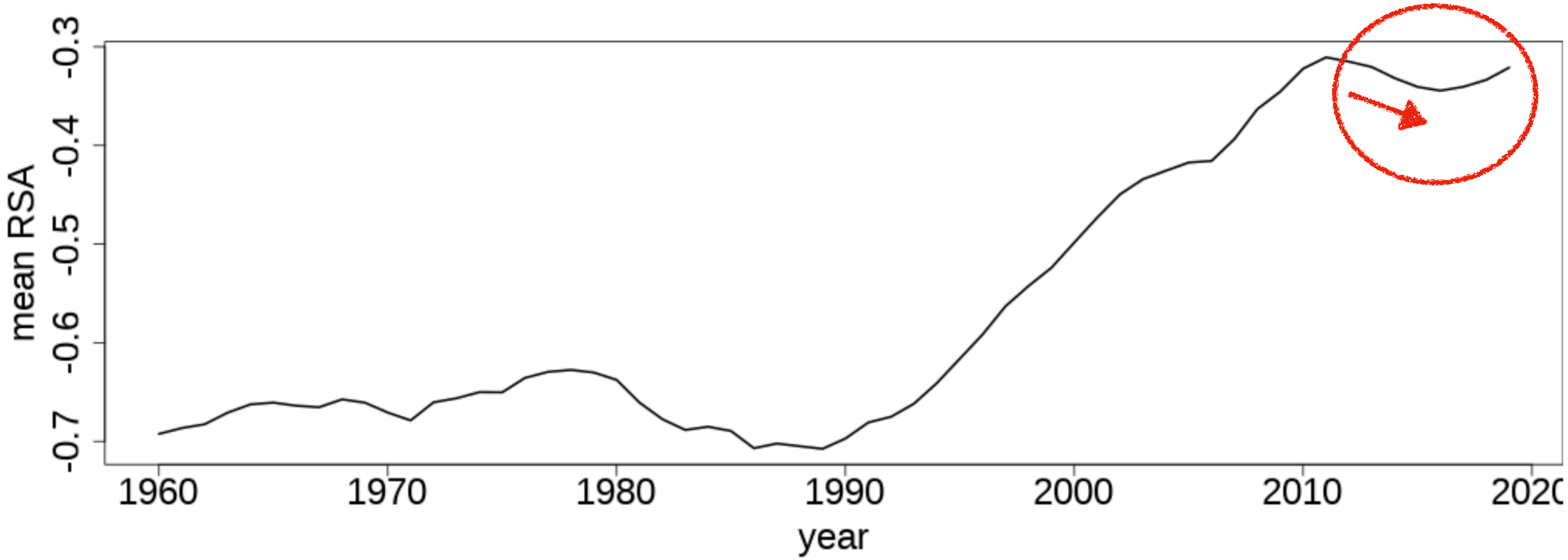

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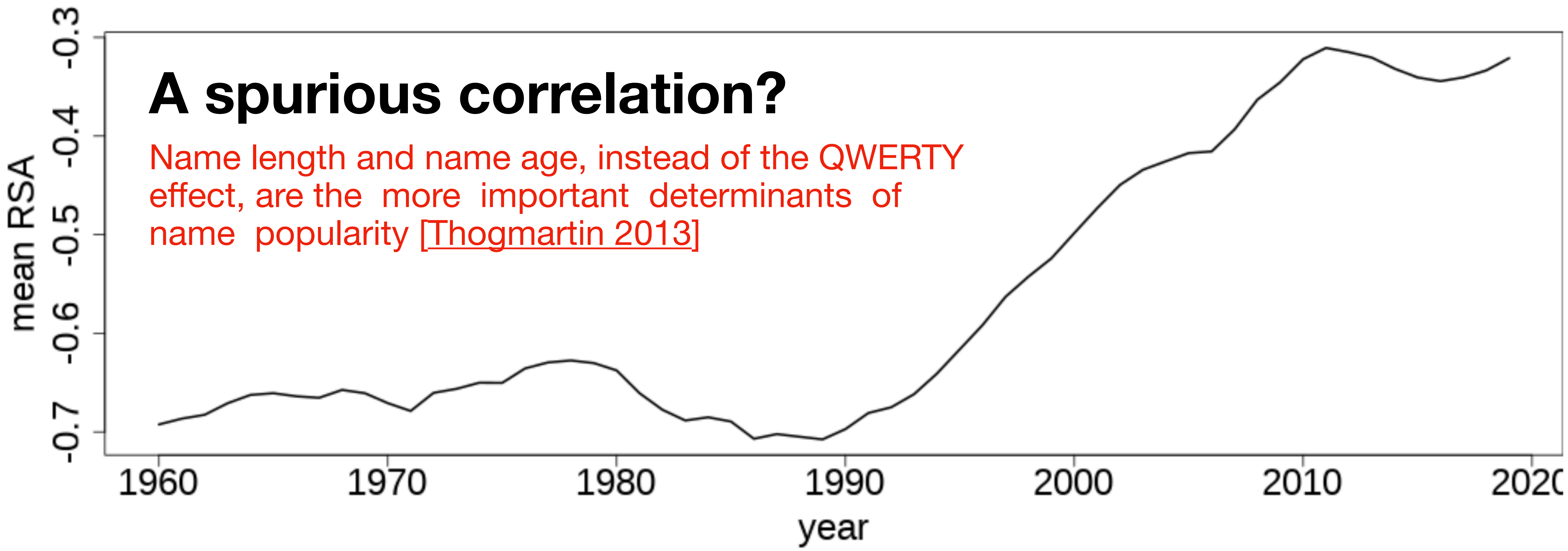

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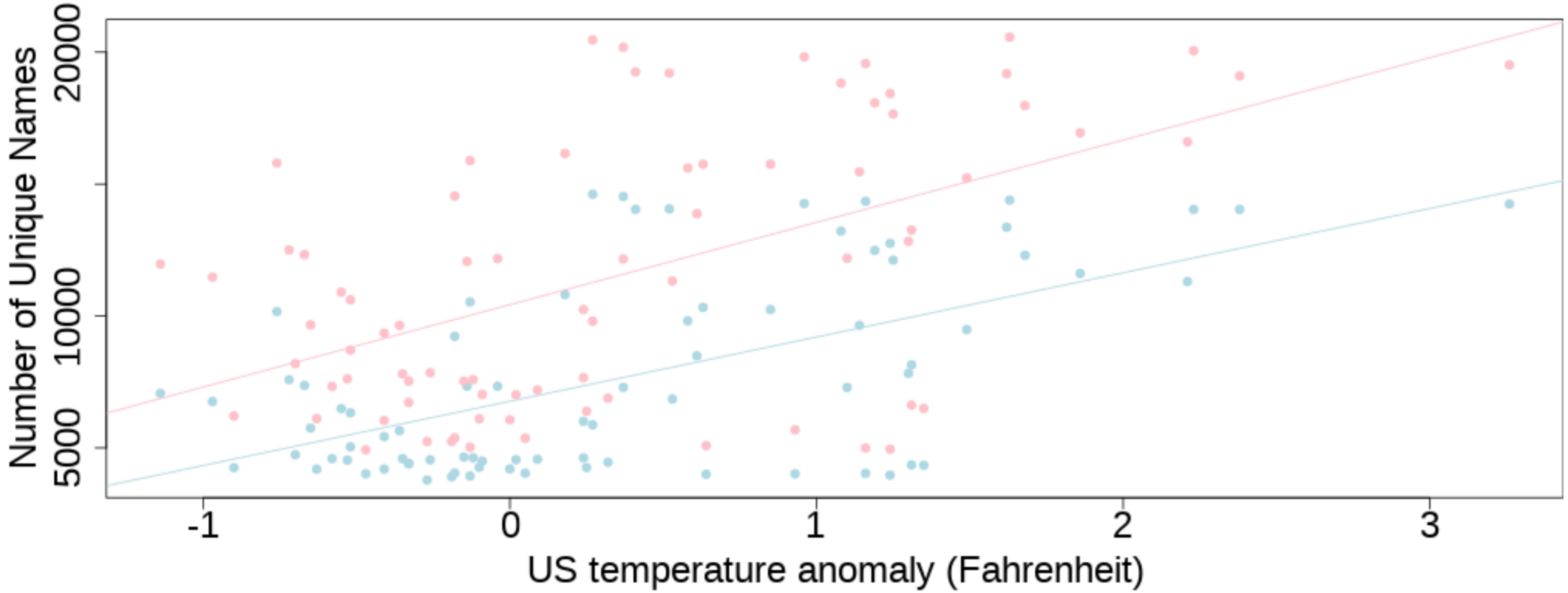
Wacky baby name research

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

- A parody paper titled "We are entering an unprecedented age in baby name flux" reported; "baby name diversity also seems to have risen with the increasing annual temperature of the US (i.e., climate change)."



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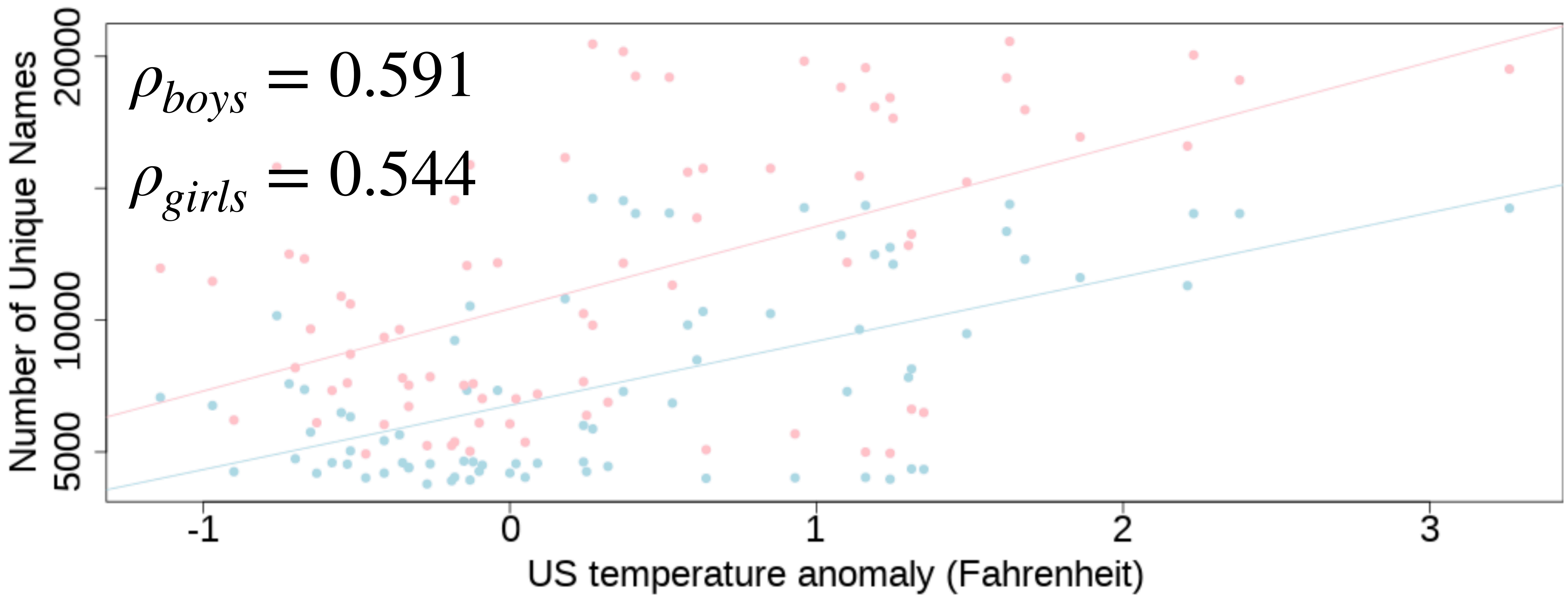

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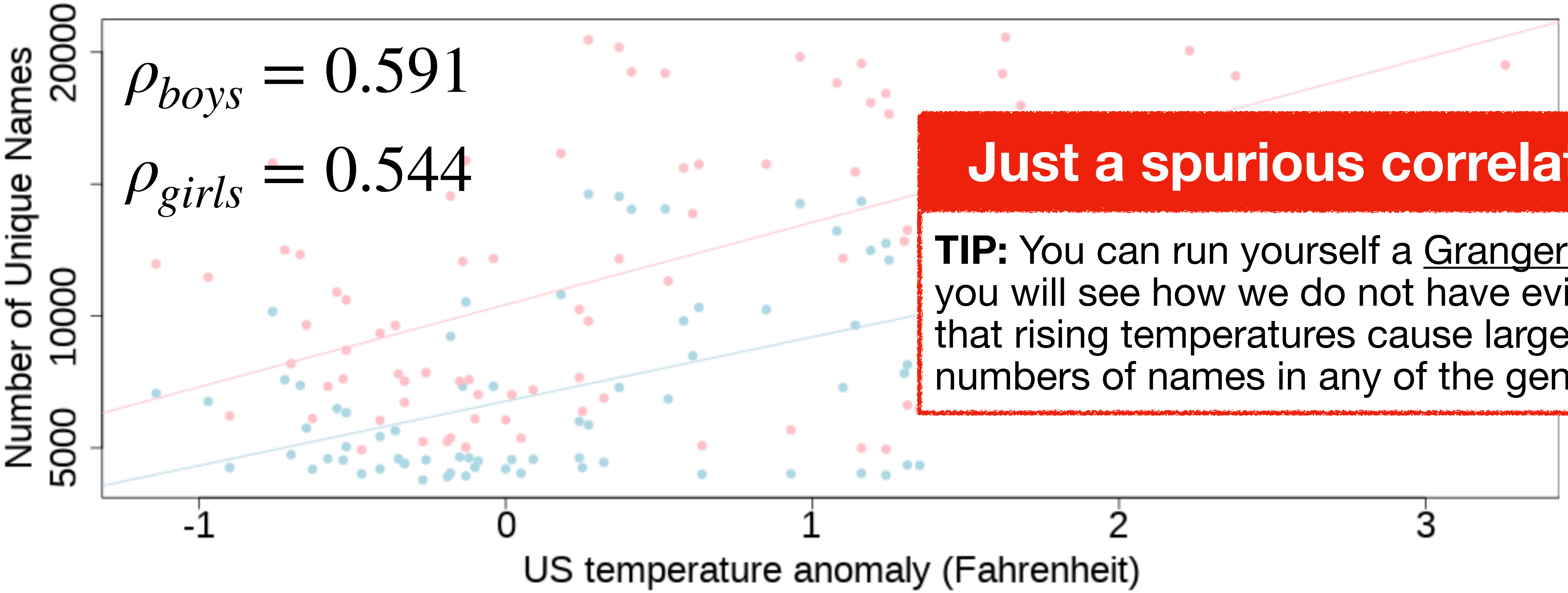

Just a spurious correlation!!!

TIP: You can run yourself a Granger test and you will see how we do not have evidence that rising temperatures cause larger numbers of names in any of the genders.

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?

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

MOST POPULAR BOYS' NAMES OF 2015?

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

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	

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

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Annika	Clementine	Flannery	Linden	Phoebe
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$$acc = \frac{7}{24} = 0{,}29$$

Real

Abigail	**Avery**	Emily	**Isabella**	**Sofia**
Addison	Charlotte	**Emma**	Madison	**Sophia**
Amelia	Chloe	Evelyn	Mia	Victoria
Aubrey	Elizabeth	Grace	Olivia	Zoey
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The limits of baby name predictability

Most popular **boy** names in 2015 (and the prediction)

Prediction

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

Real

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)

Prediction

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

$$acc = \frac{6}{22} = 0{,}27$$

Real

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

Predicting is hard

Prediction vs. Explanation

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Prediction vs. Explanation

- There is not much overlap between the prediction and the results for 2015.

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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	BLOCK 2	BLOCK 3	BLOCK 4
Social Behavior	Social Trends	Quantifying Trends	Behavior & Trend Dynamics
1. Social Science 2. CSS 3. Digital Traces 4. Examples	1. Google Trends 2. The Future Orientation Index 3. Culture and Economy	1. Correlation 2. Causation 3. Regression	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

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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]

Backups

Granger test

Using python

```
import statsmodels.api as sm
from statsmodels.tsa.stattools import grangercausalitytests
import numpy as np
data = sm.datasets.macrodata.load_pandas()
data = data.data[["realgdp", "realcons"]].pct_change().dropna()
gc_res = grangercausalitytests(data, [4])
```

https://www.statsmodels.org/dev/generated/statsmodels.tsa.stattools.grangercausalitytests.html
https://www.statsmodels.org/dev/datasets/generated/macrodata.html

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```
Granger Causality
number of lags (no zero) 4
ssr based F test:         F=10.9646 , p=0.0000  , df_denom=189, df_num=4
ssr based chi2 test:   chi2=45.9467 , p=0.0000  , df=4
likelihood ratio test: chi2=41.3192 , p=0.0000  , df=4
parameter F test:         F=10.9646 , p=0.0000  , df_denom=189, df_num=4
{4: ({'ssr_ftest': (10.964552417824168, 5.124118568651298e-08, 189.0, 4),
   'ssr_chi2test': (45.94669584612032, 2.526564876838052e-09, 4),
   'lrtest': (41.31917679499497, 2.308367546679231e-08, 4),
   'params_ftest': (10.964552417824136, 5.1241185686514934e-08, 189.0, 4.0)},
  [<statsmodels.regression.linear_model.RegressionResultsWrapper at 0x7d7ba228e4a0>,
   <statsmodels.regression.linear_model.RegressionResultsWrapper at 0x7d7ba228e7d0>,
   array([[0., 0., 0., 0., 1., 0., 0., 0., 0.],
          [0., 0., 0., 0., 0., 1., 0., 0., 0.],
          [0., 0., 0., 0., 0., 0., 1., 0., 0.],
          [0., 0., 0., 0., 0., 0., 0., 1., 0.]])])}
```

https://www.statsmodels.org/dev/generated/statsmodels.tsa.stattools.grangercausalitytests.html
https://www.statsmodels.org/dev/datasets/generated/macrodata.html