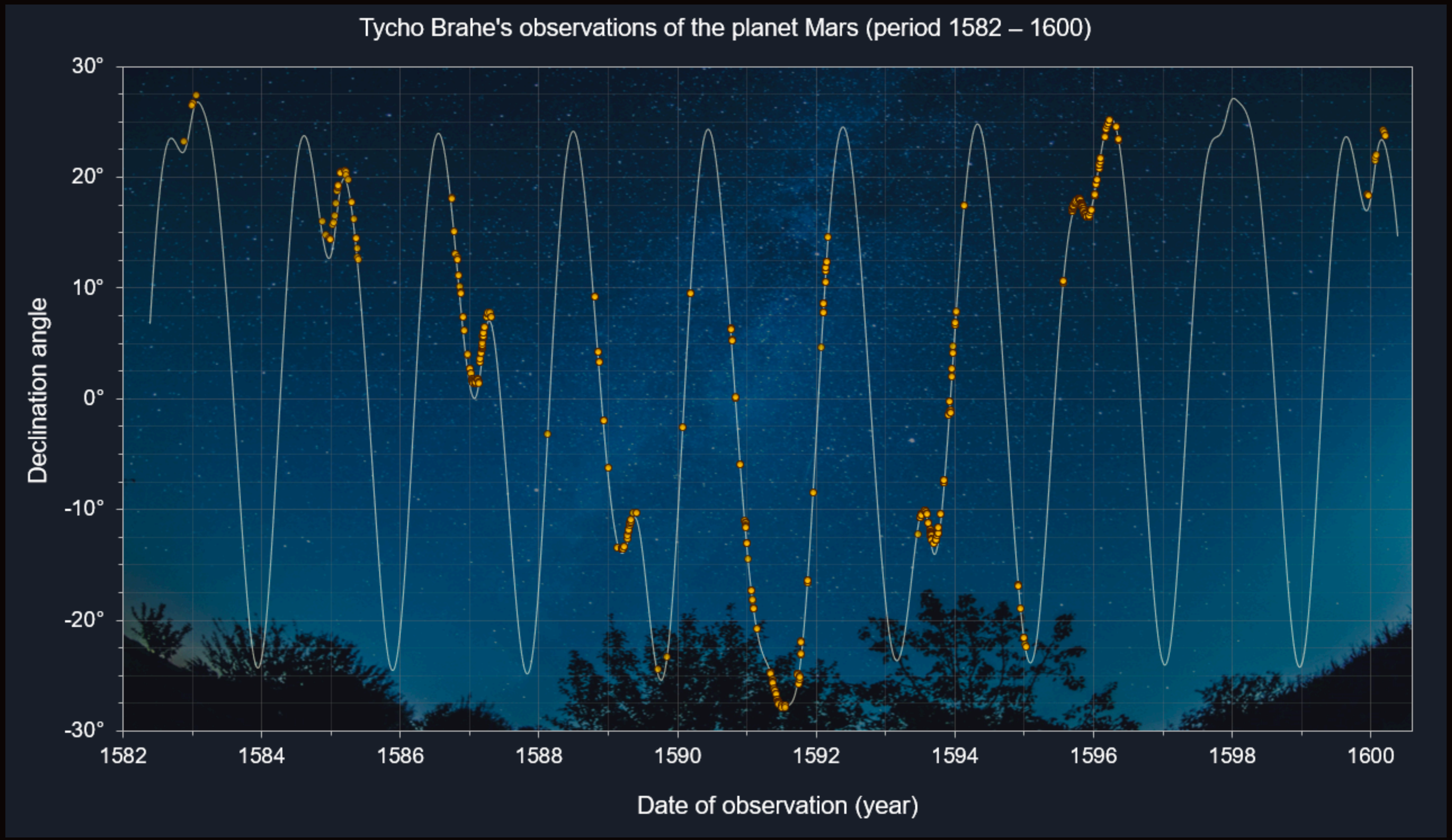
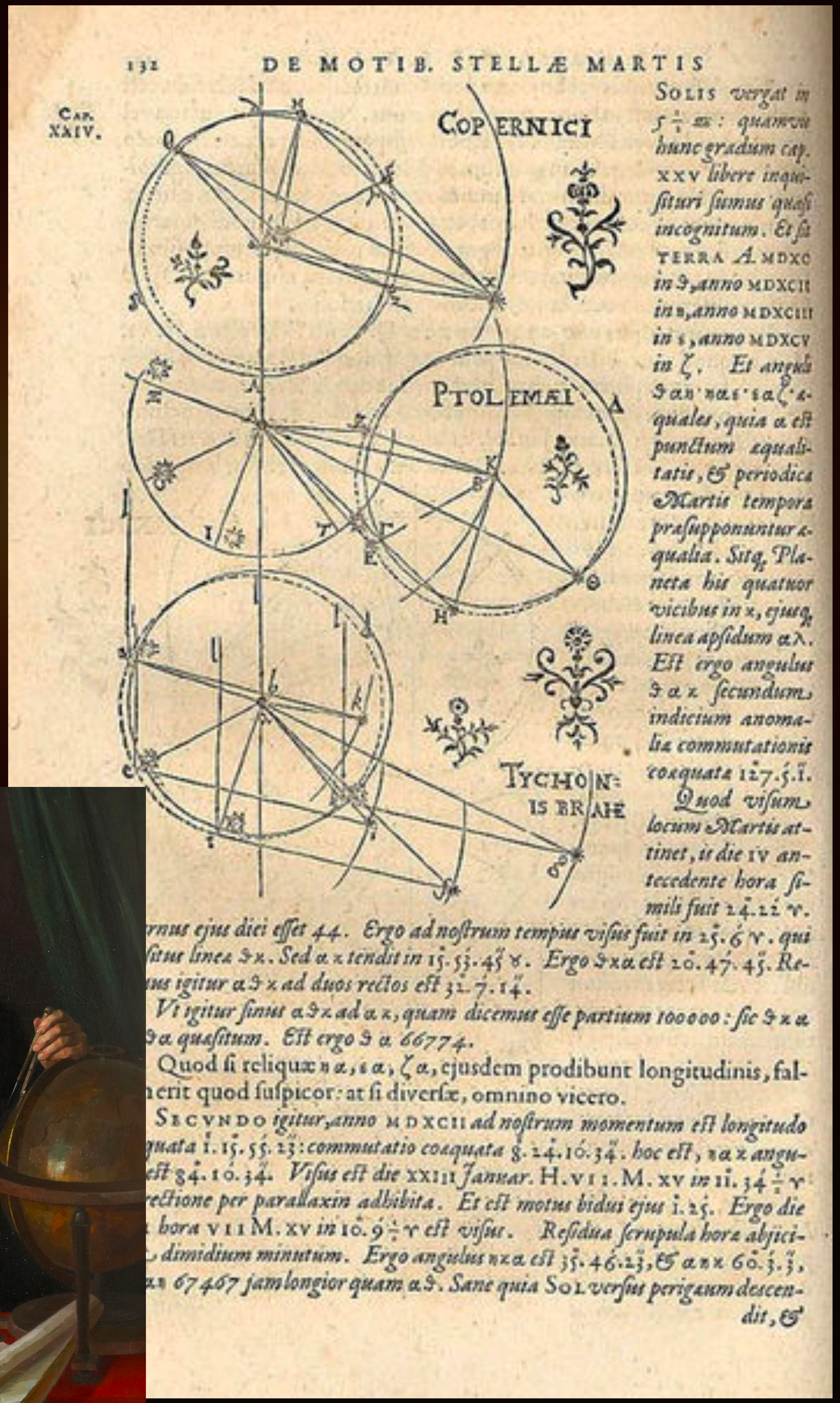
YY Ahn,
Indiana University

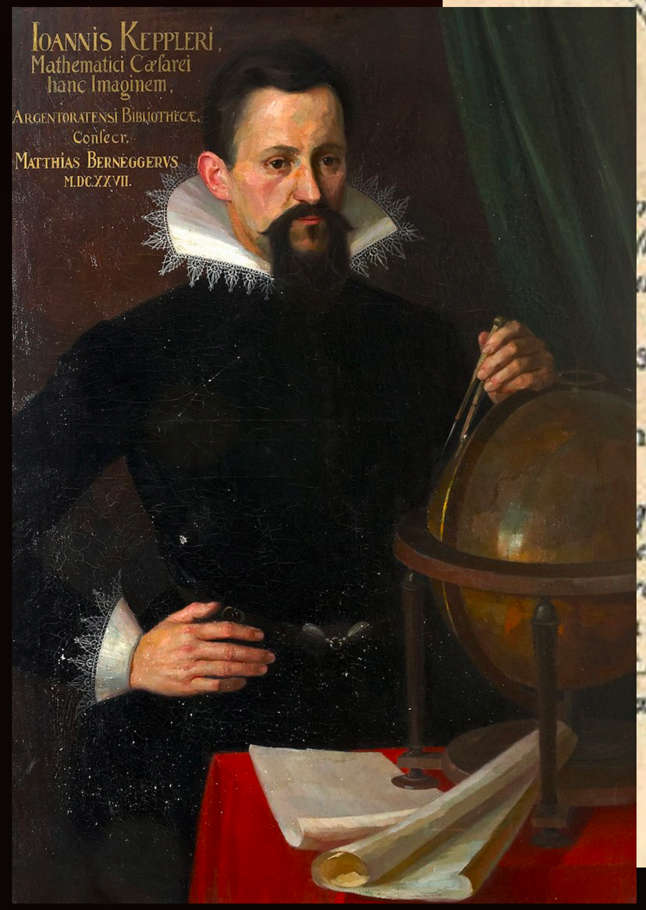
Imagining the Space of Knowledge

Observation and measurement are the bedrock of science

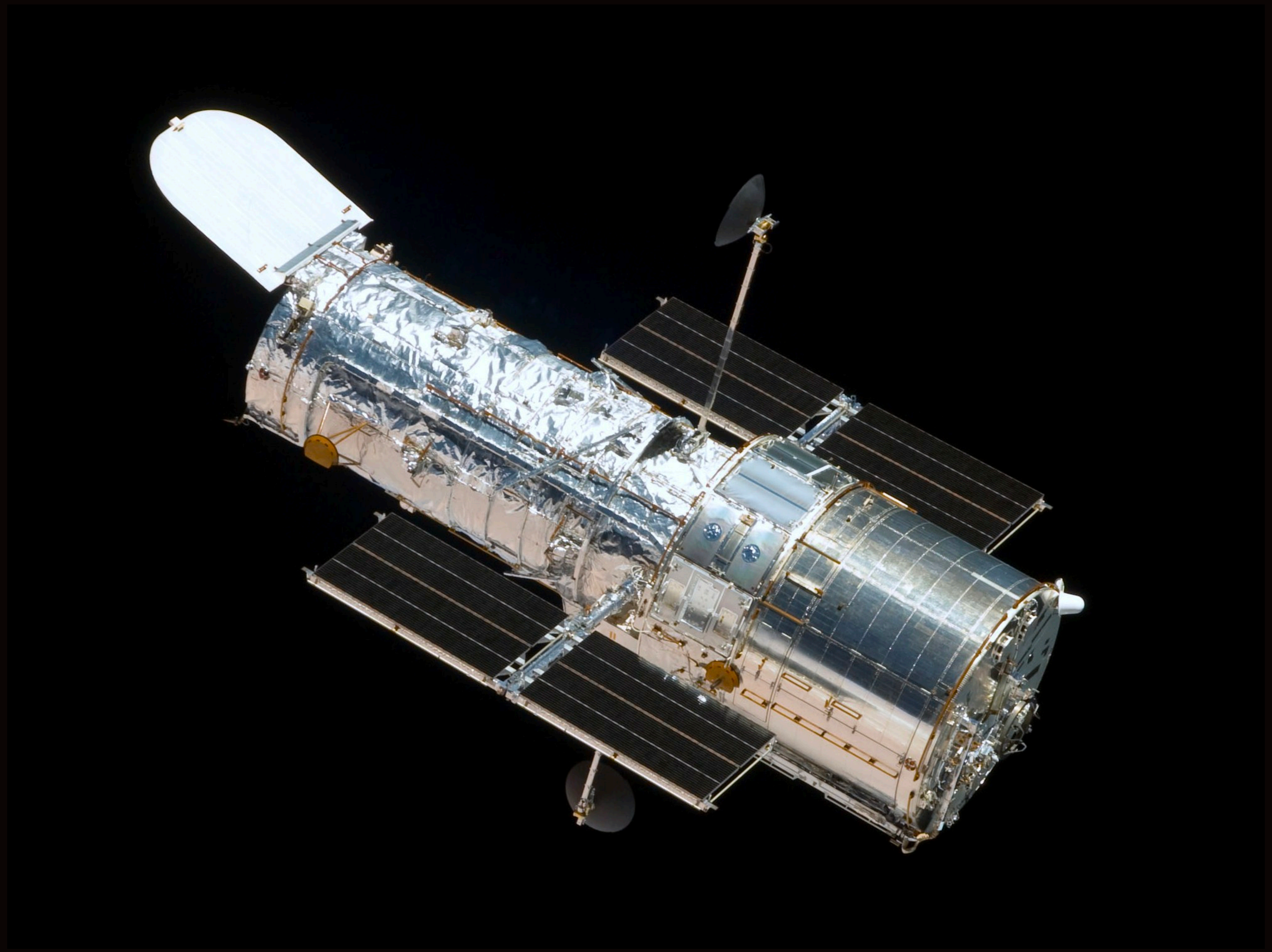


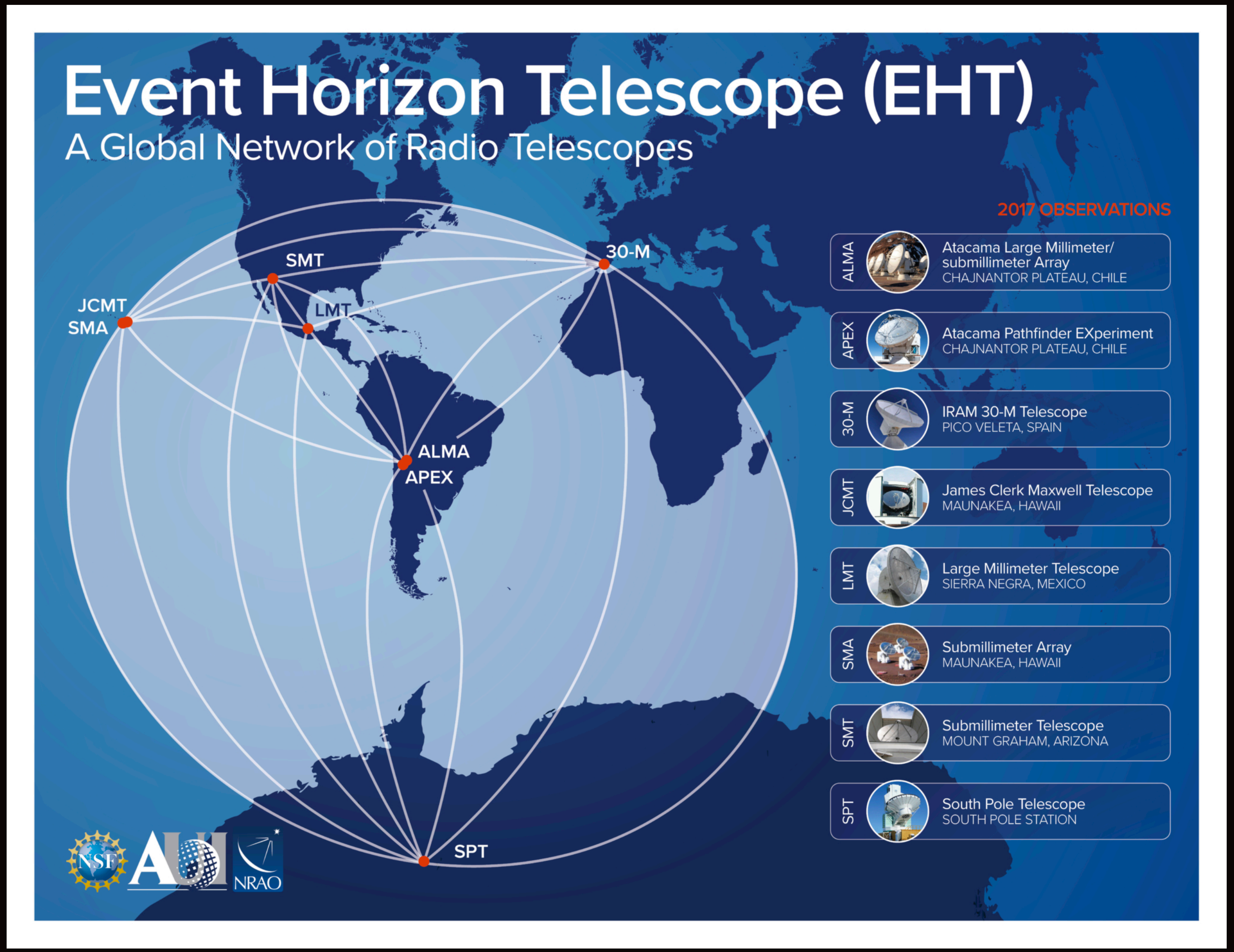
https://observablehq.com/@christophe-yamahata/visualizing-tycho-brahe-s-astronomical-observations-mars

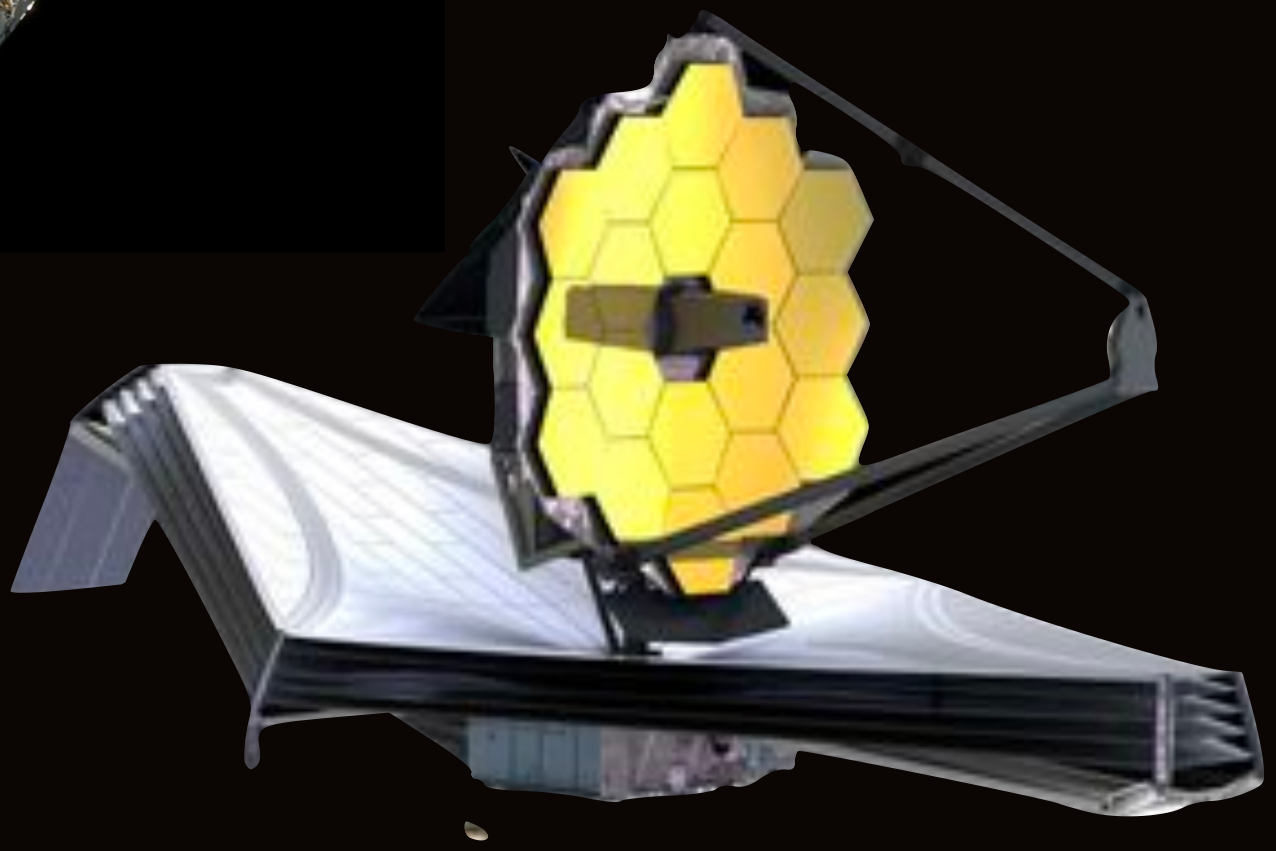




Instruments matter

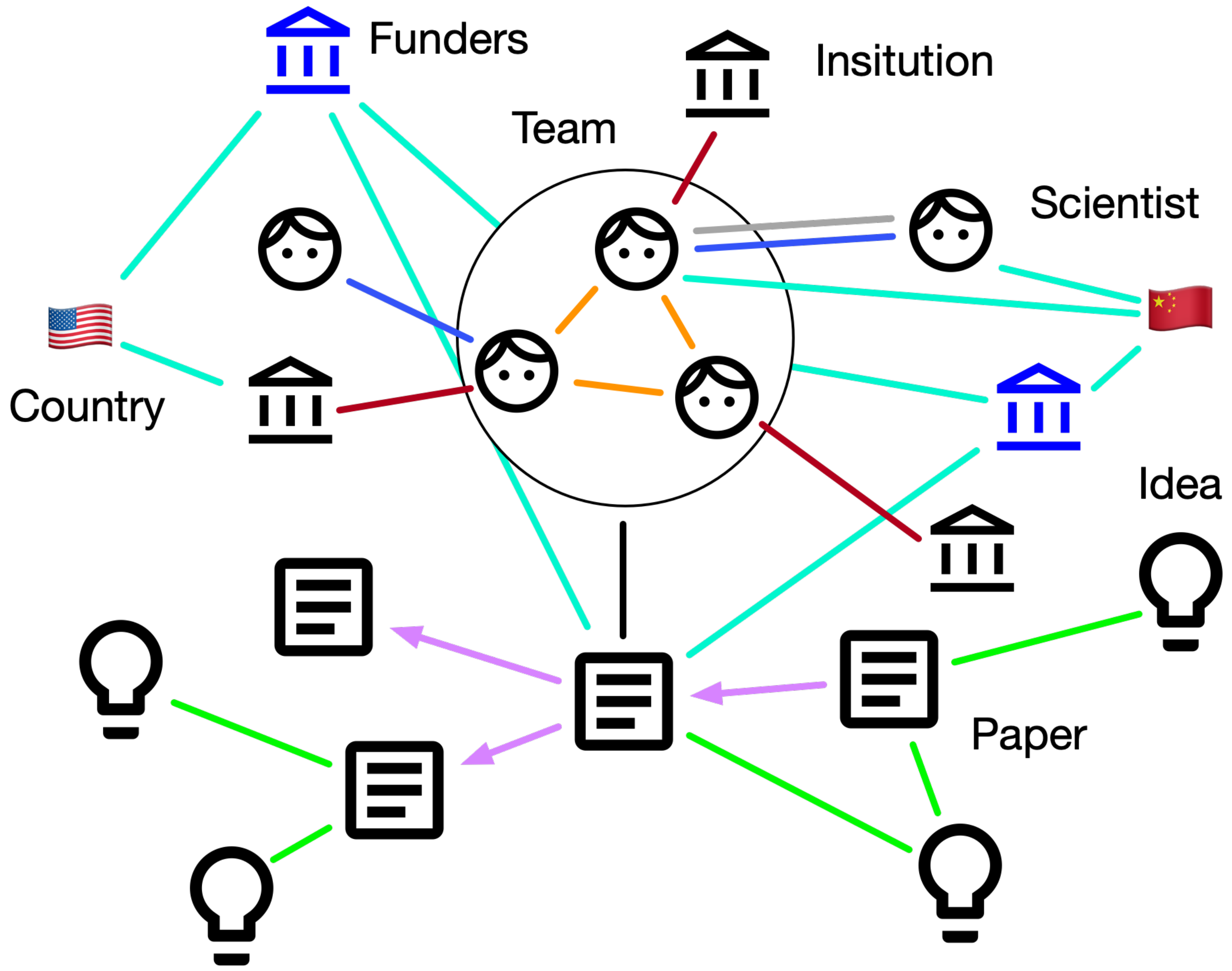


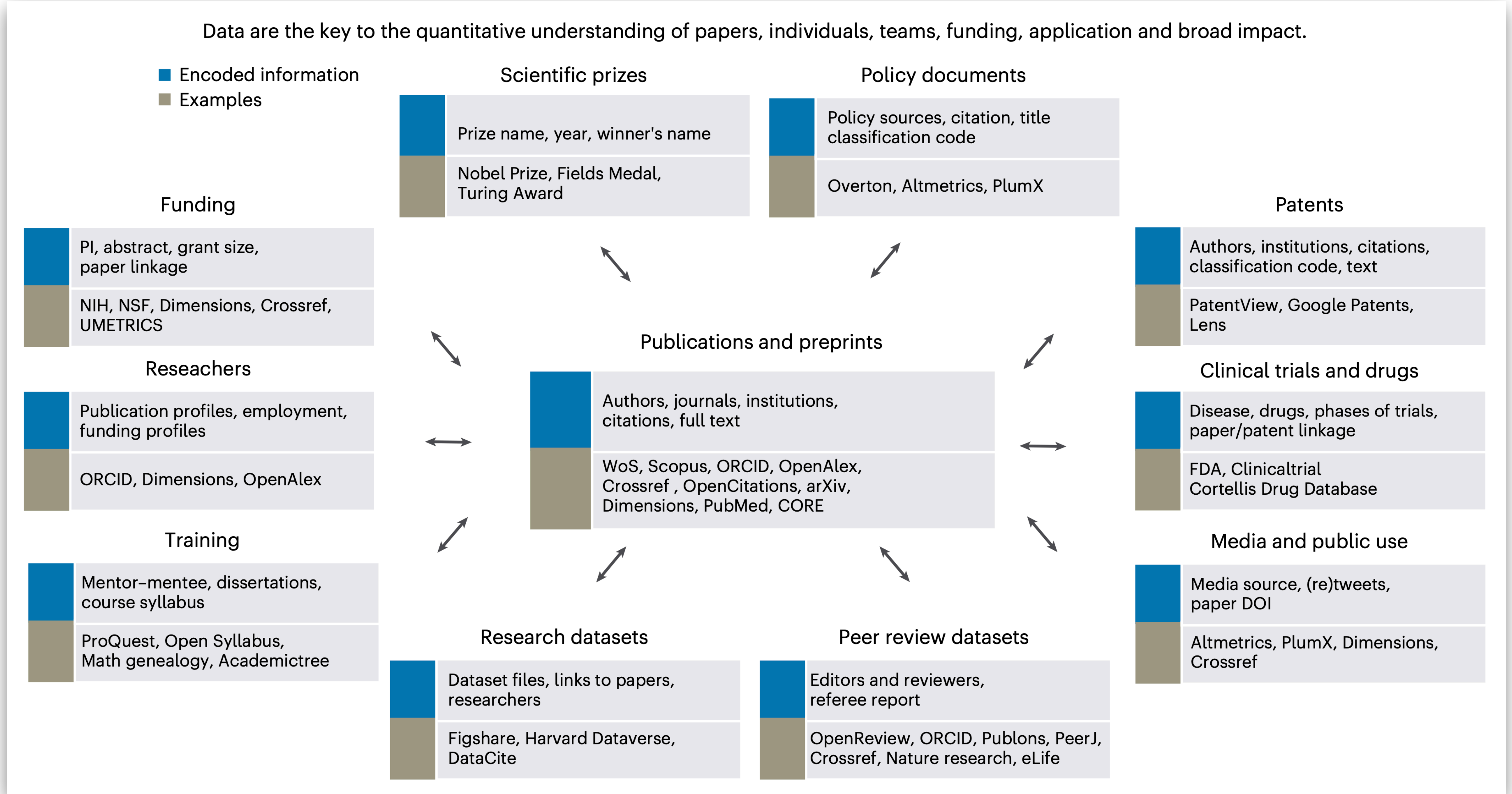




What could be the EHT/JWT for Science of Science?

More data is becoming available



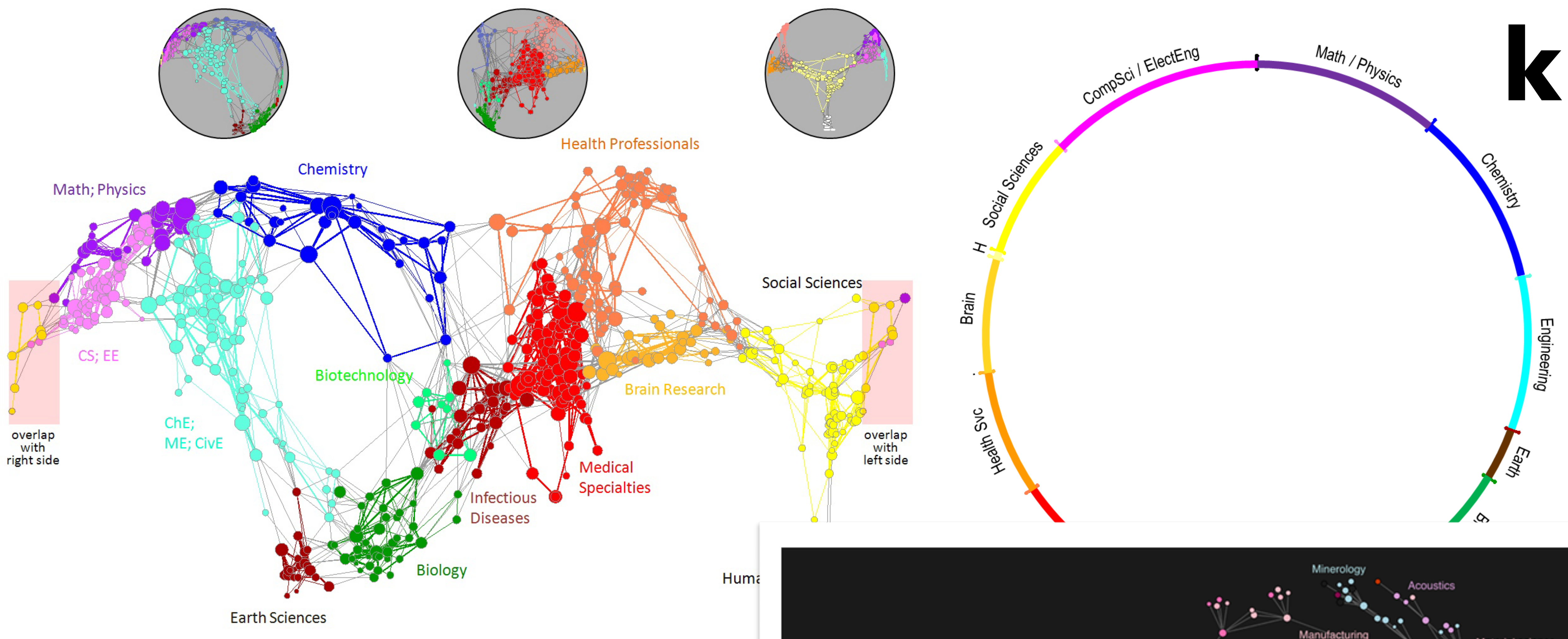


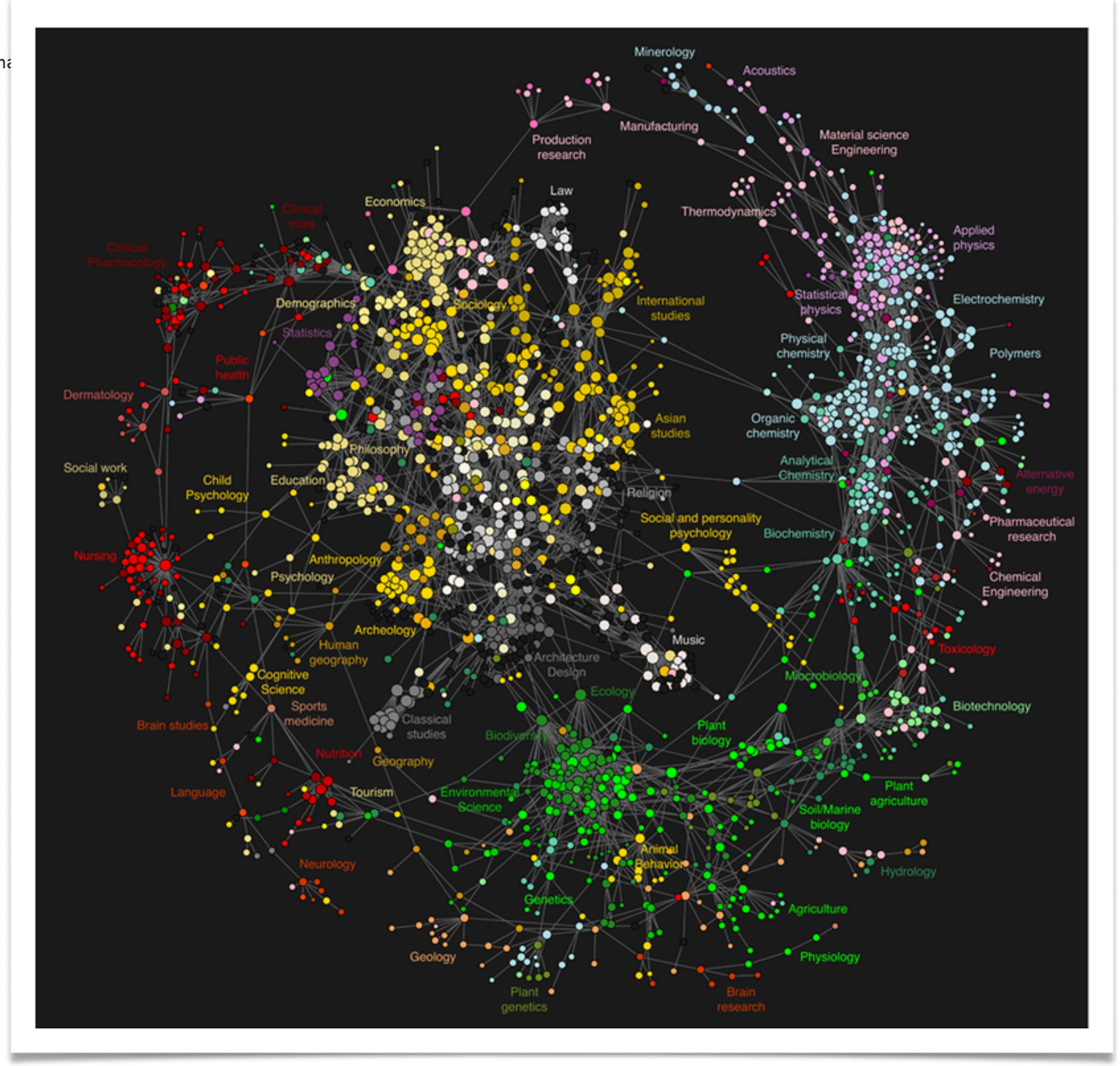
Liu, Lu, et al. "Data, measurement and empirical methods in the science of science." *Nature Human Behaviour* (2023): 1-13.

But they are complex, heterogeneous, and interconnected.

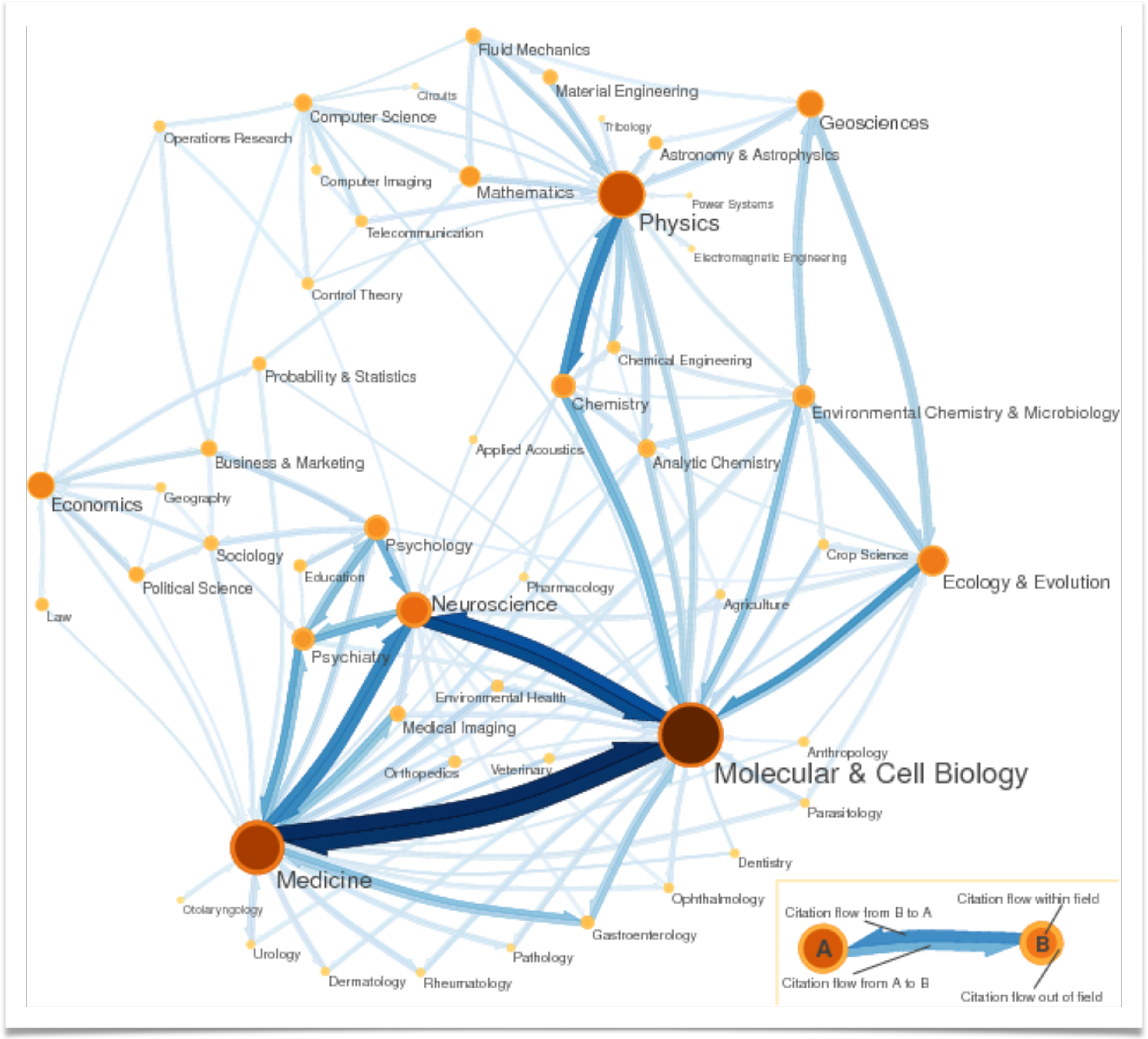
Maps of Science—imagining the knowledge space

Börner, Klavans, Boyak, et al., 2012





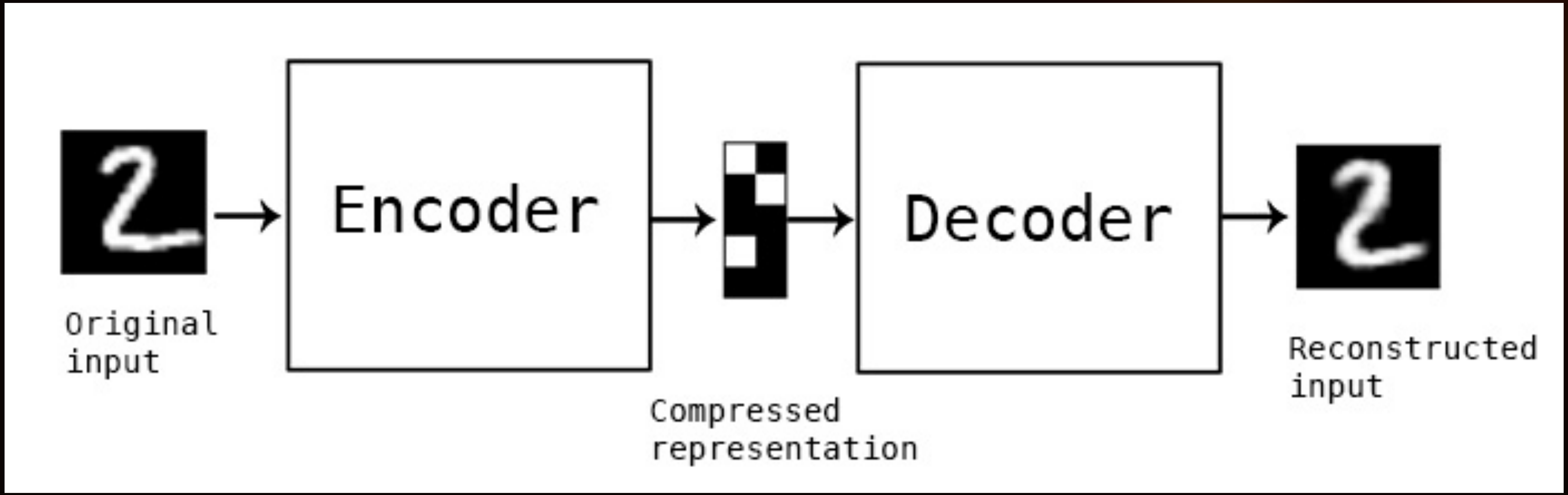
Bollen et al., 2009



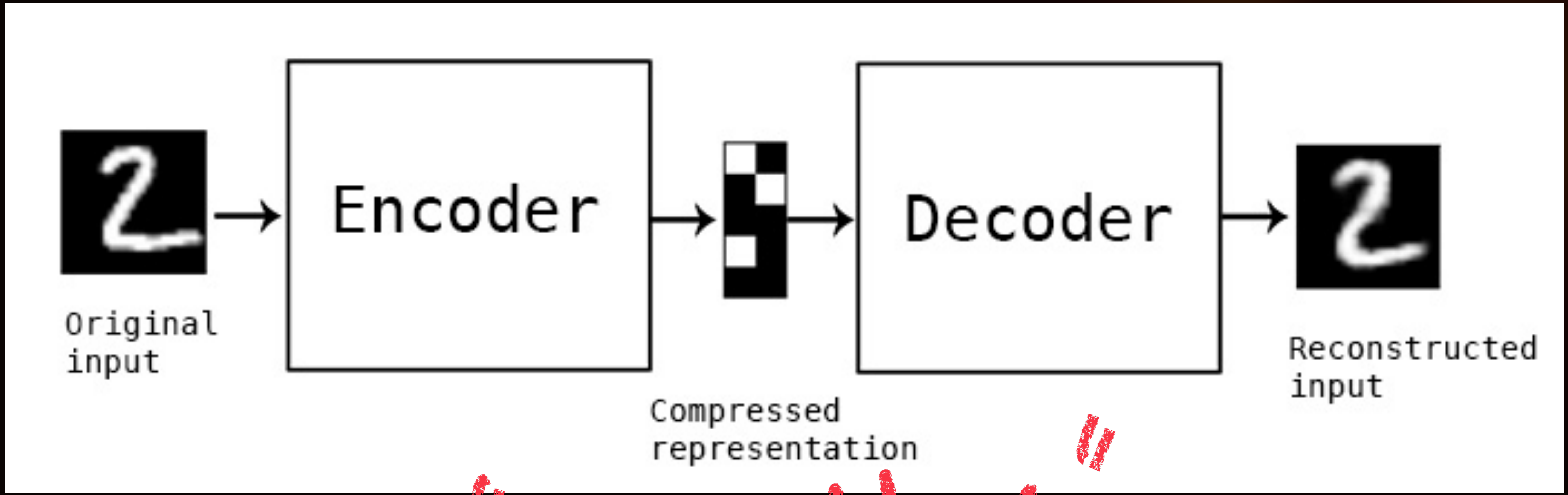
Rosvall & Bergstrom

Can we really push the analogy of knowledge “space”?

Deep learning is **representation learning**

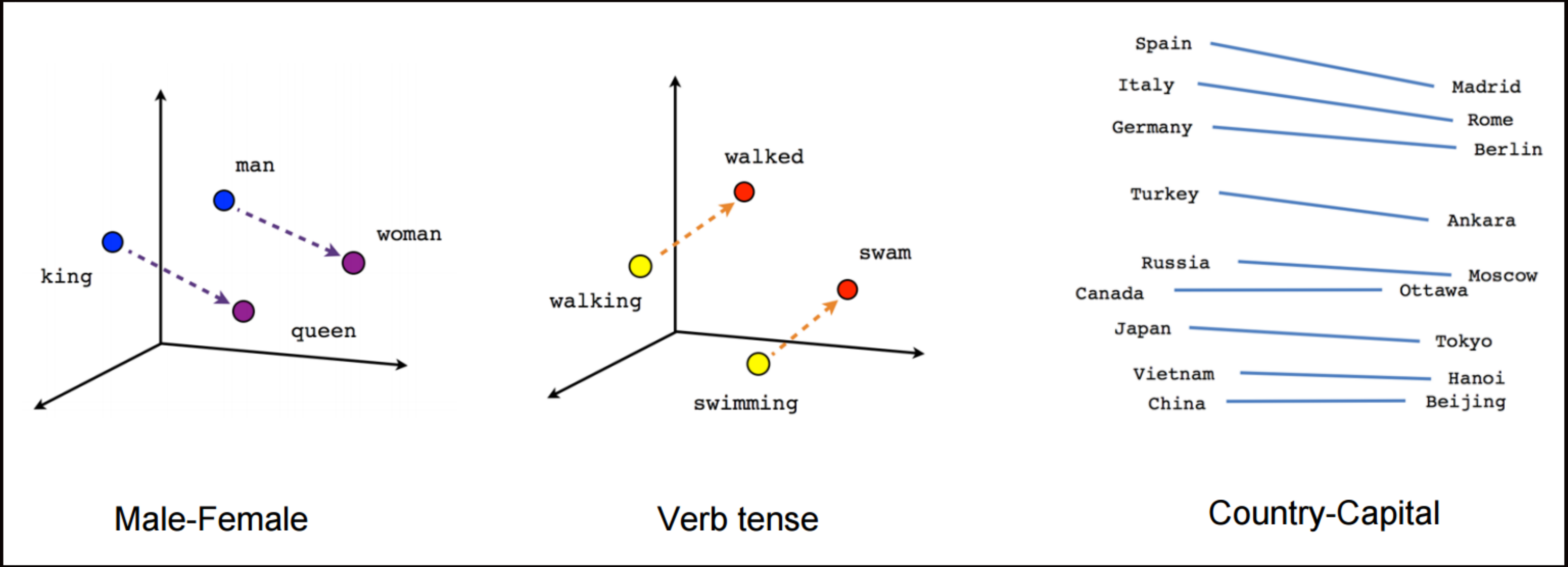


Deep learning is **representation learning**



"embedding"

Representation learning can produce interpretable "space"



Mikolov, Tomas, Ilya Sutskever, Kai Chen, Greg Corrado, and Jeffrey Dean. "Distributed representations of words and phrases and their compositionality." arXiv preprint arXiv:1310.4546 (2013).

"**Space**" of Words,

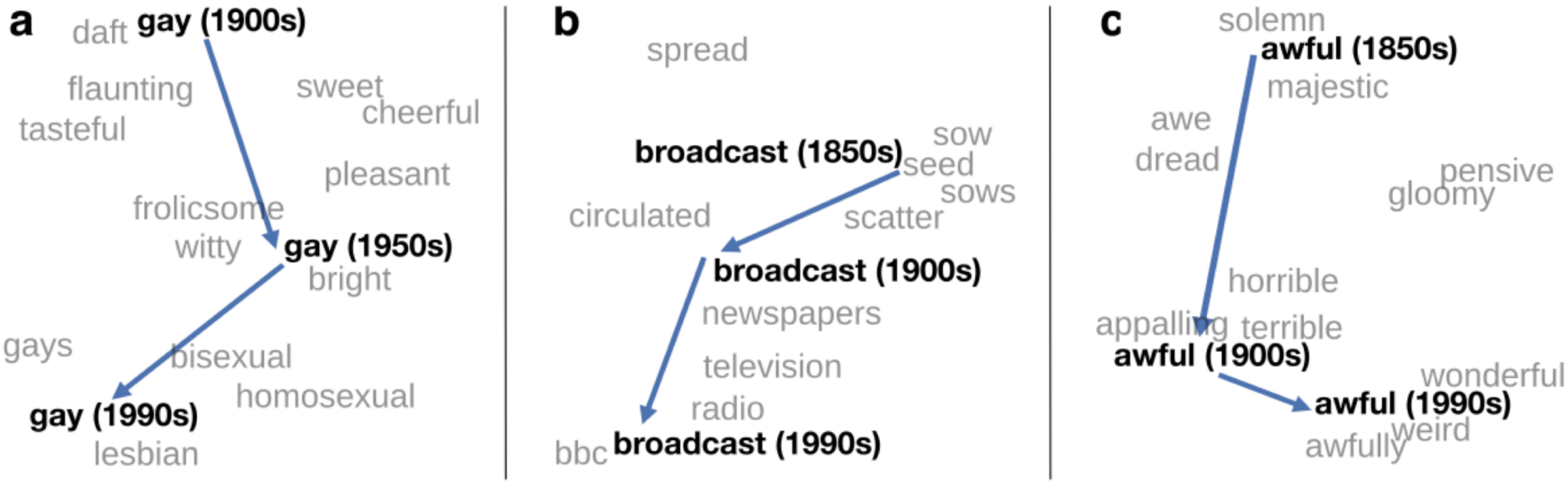
"**Space**" of Materials,

"**Space**" of Images,

"**Space**" of Knowledge,

…

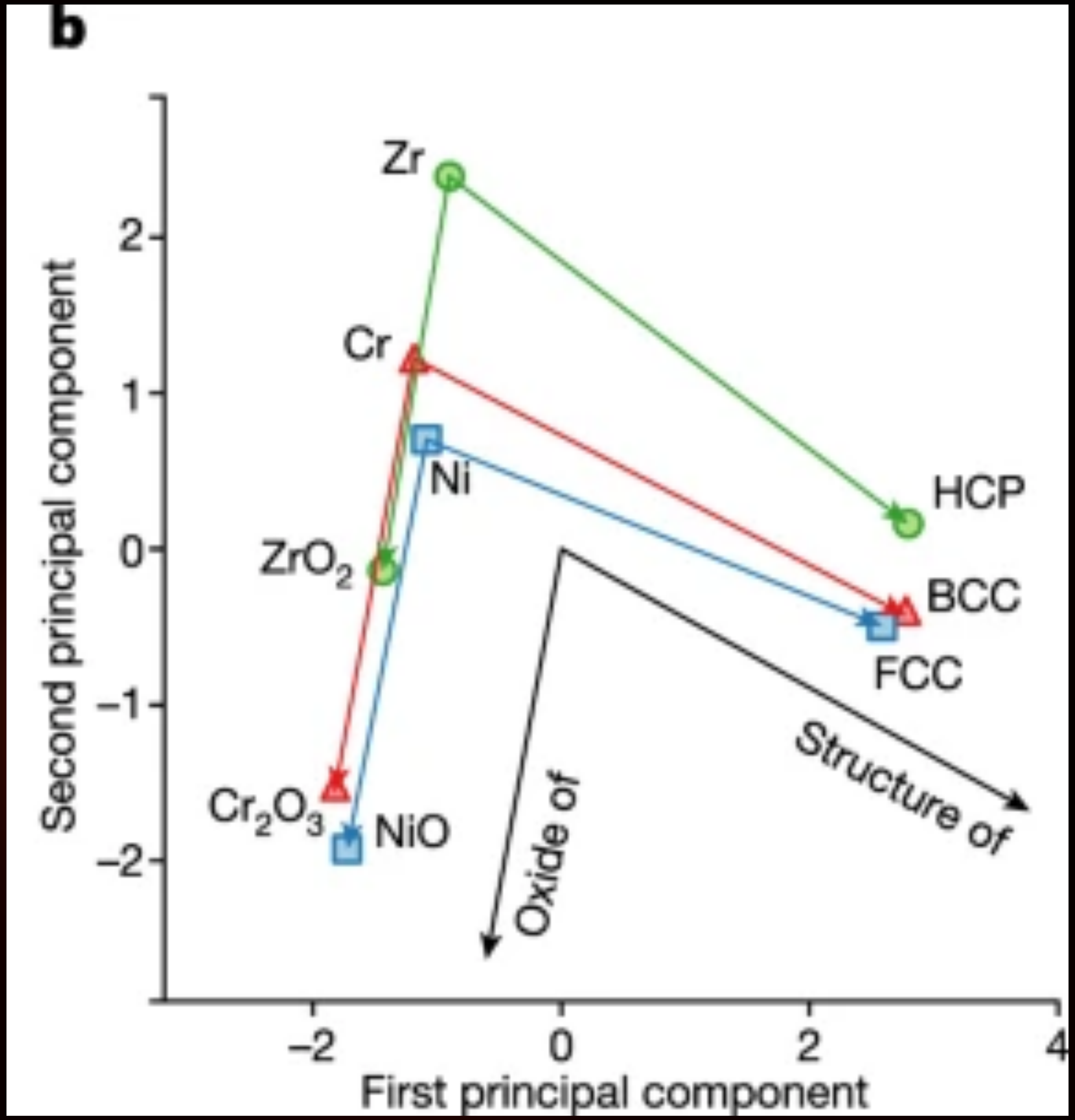
Word embedding → how do words move?
A natural way to trace temporal changes



William L. Hamilton, Jure Leskovec, and Dan Jurafsky. ACL 2016. Diachronic Word Embeddings Reveal Statistical Laws of Semantic Change.

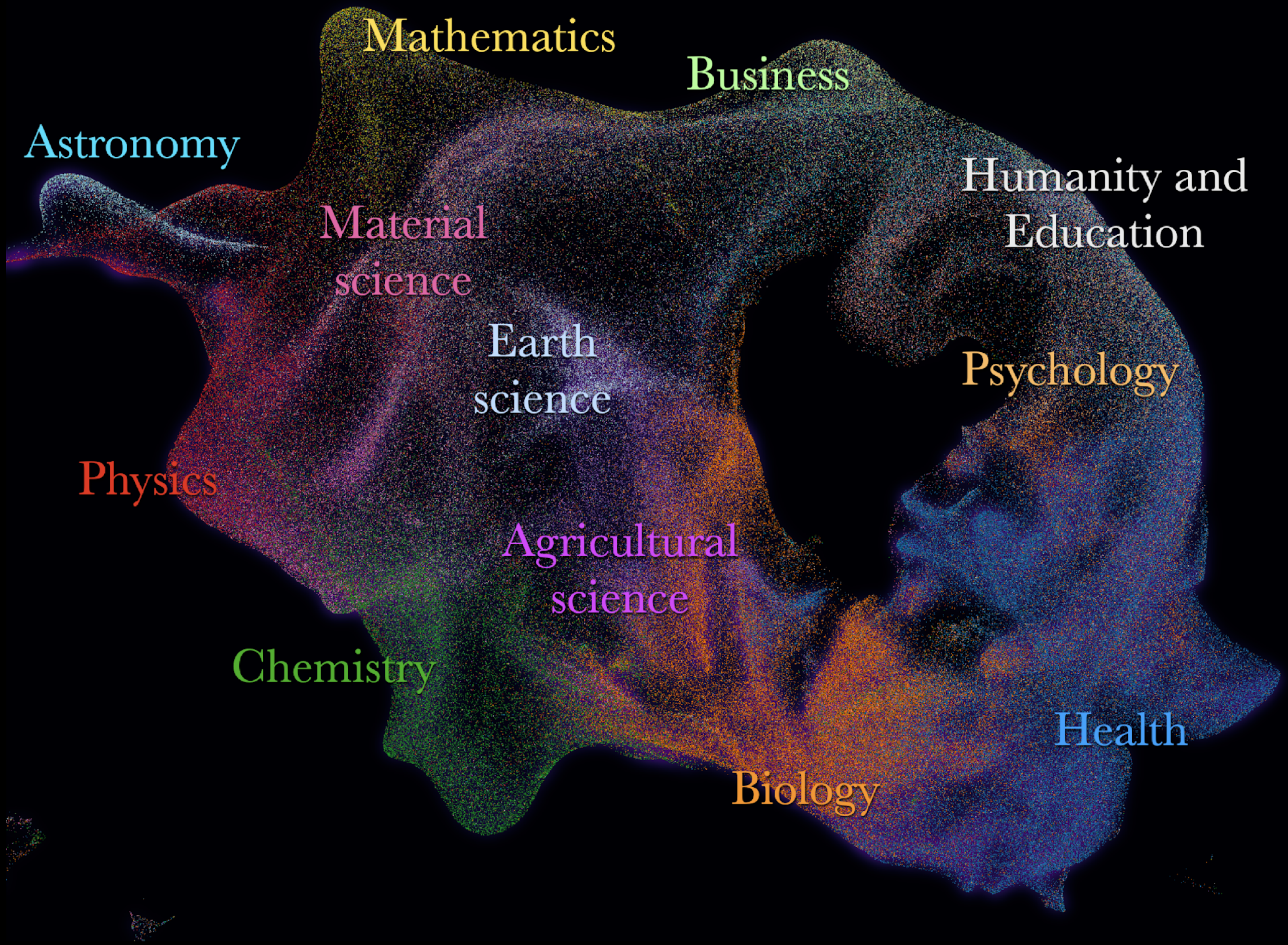
$$Zr - ZrO2 + Cr2O3 \approx Cr$$

$$\overrightarrow{\text{ferromagnetic}} - \overrightarrow{\text{NiFe}} + \overrightarrow{\text{IrMn}} \approx \overrightarrow{\text{antiferromagnetic}}$$



Tshitoyan, V. et al. Nature 571, 95–98 (2019).

Can we imagine the "space of knowledge" as a real "space"?




Can we model the scientific enterprise
like we model a murmuration of birds?


Can we study knowledge foraging
as we study animal foraging?

Can we *imagine and observe* a “blackhole” in the space of knowledge?

Imagining knowledge space to model universal citation dynamics across systems

Law

Science

Patents

	Law (US)	Science	Patents
Participation criteria	Law school, Appointment by president	Anyone in principle, mostly through training	
Choice of subject	Random	Largely driven by personal interests, chosen by participants	
Collaboration	Rare	Common	
Reference discovery	Search engine	Search engine	Search engine
Needs for securing funding	Low	High	?
Publication process	Unilateral	Peer review	USPTO review
Hierarchy	Binding and strict	Not strict	Not strict
Author growth	Slow	High	High
Incentive for citation			Some perverse (?) incentive not to cite the most relevant patents

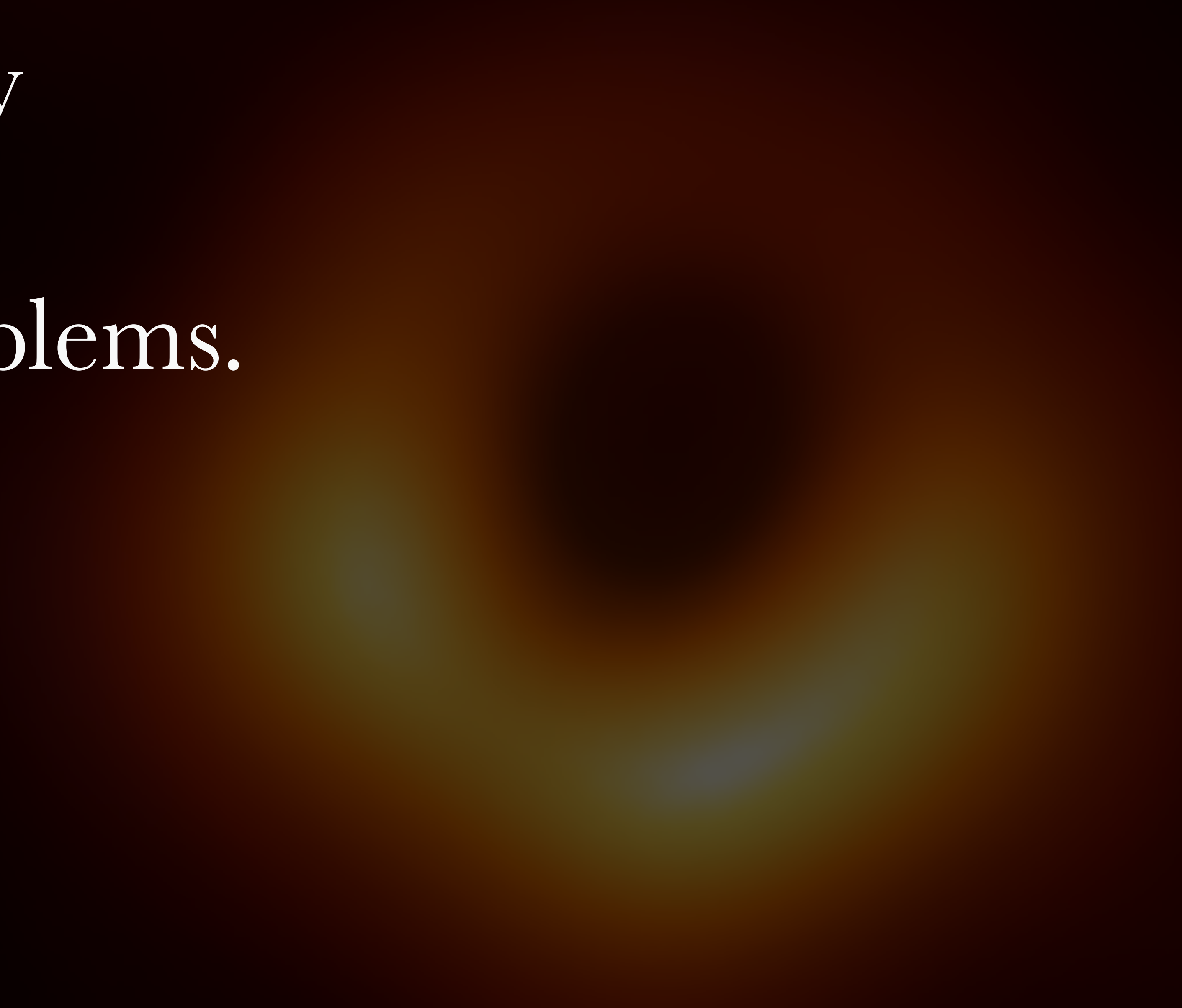
Law (US) vs. Science

Law (US) vs. Science

- Codified & bounding hierarchy vs. organic hierarchy

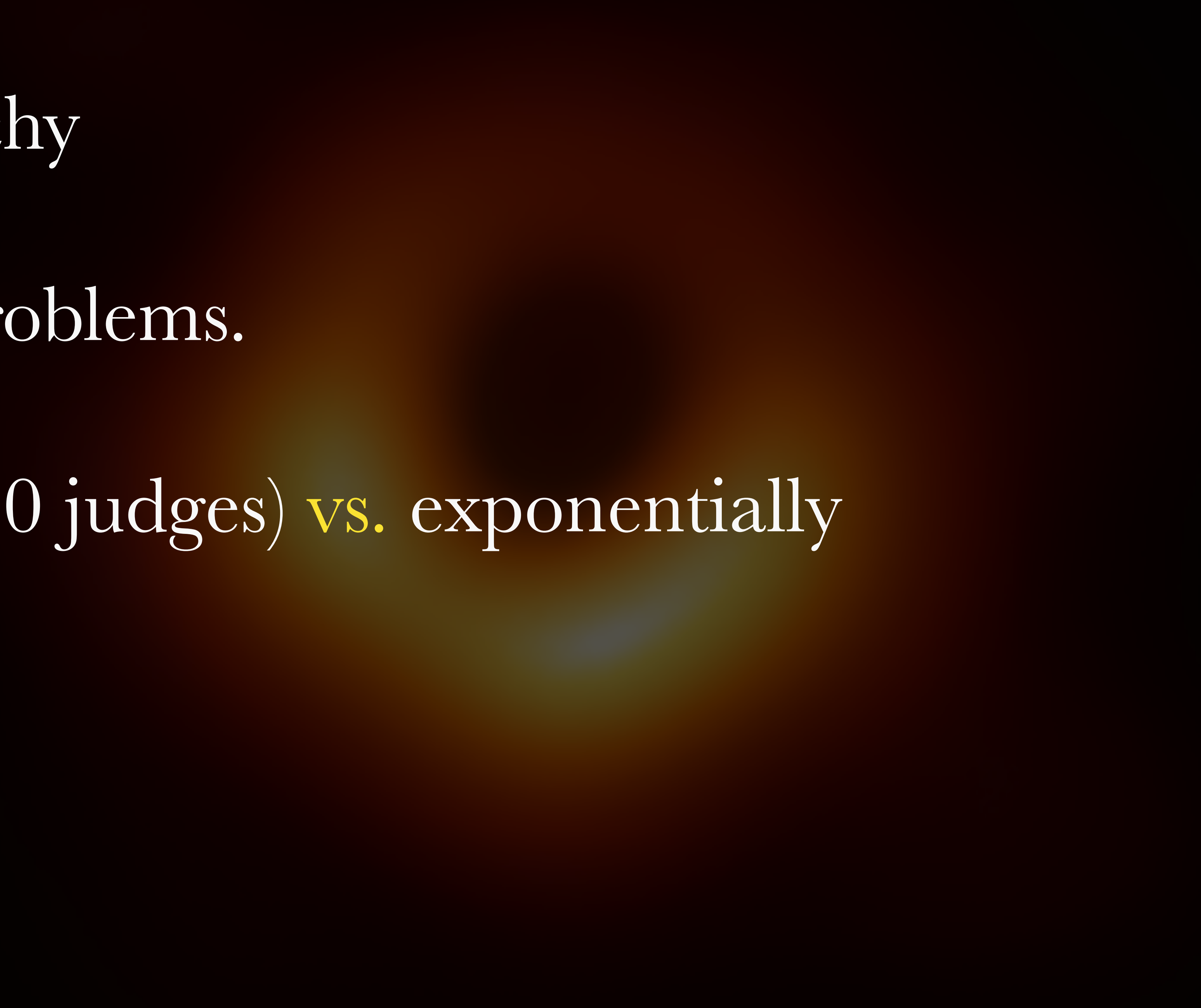
Law (US) vs. Science

- Codified & bounding hierarchy vs. organic hierarchy
- Randomly assigned cases vs. personal choice of problems.



Law (US) vs. Science

- Codified & bounding hierarchy vs. organic hierarchy
- Randomly assigned cases vs. personal choice of problems.
- Much fewer, rather fixed number of judges (~6,000 judges) vs. exponentially growing pool of scientists



Law (US) vs. Science

- Codified & bounding hierarchy vs. organic hierarchy
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Law (US) vs. Science

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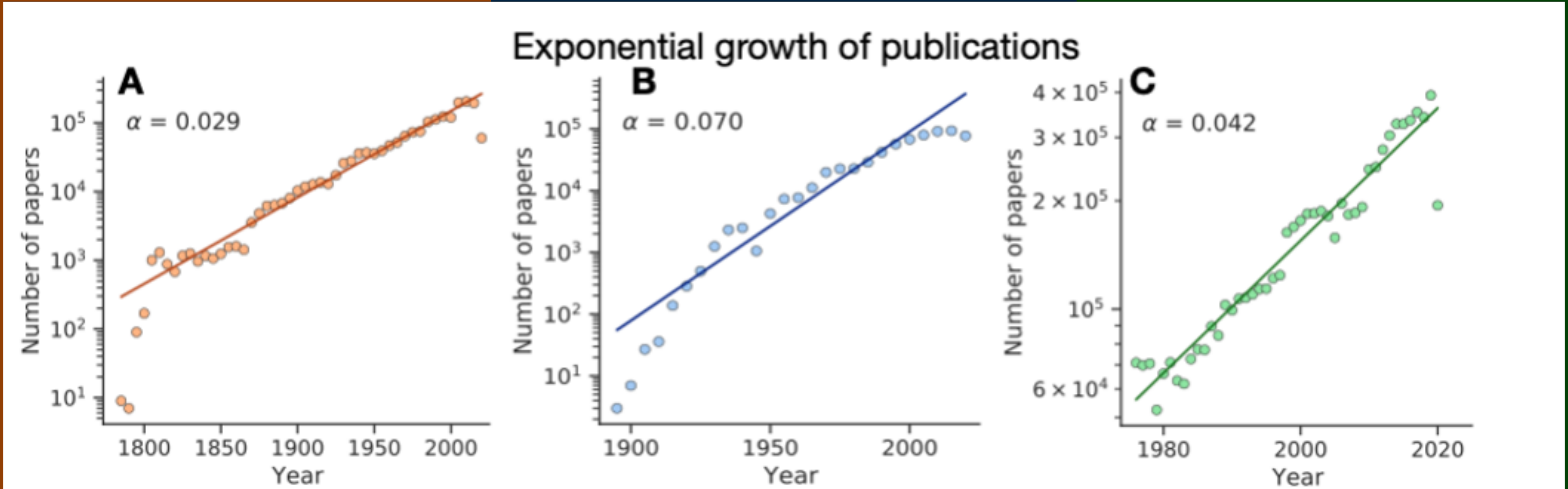
- Life-term appointments and no direct motivation to get citations vs. publish (and get cited) or perish
- …

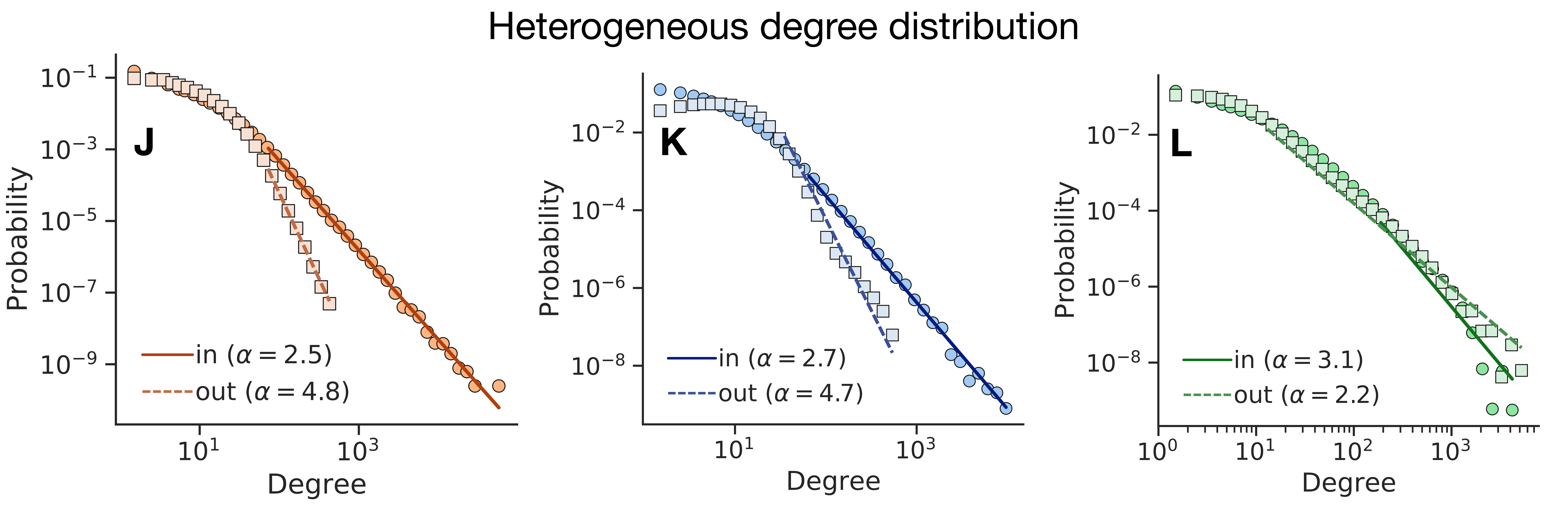
Different modes of operation, yet

Exponential growth

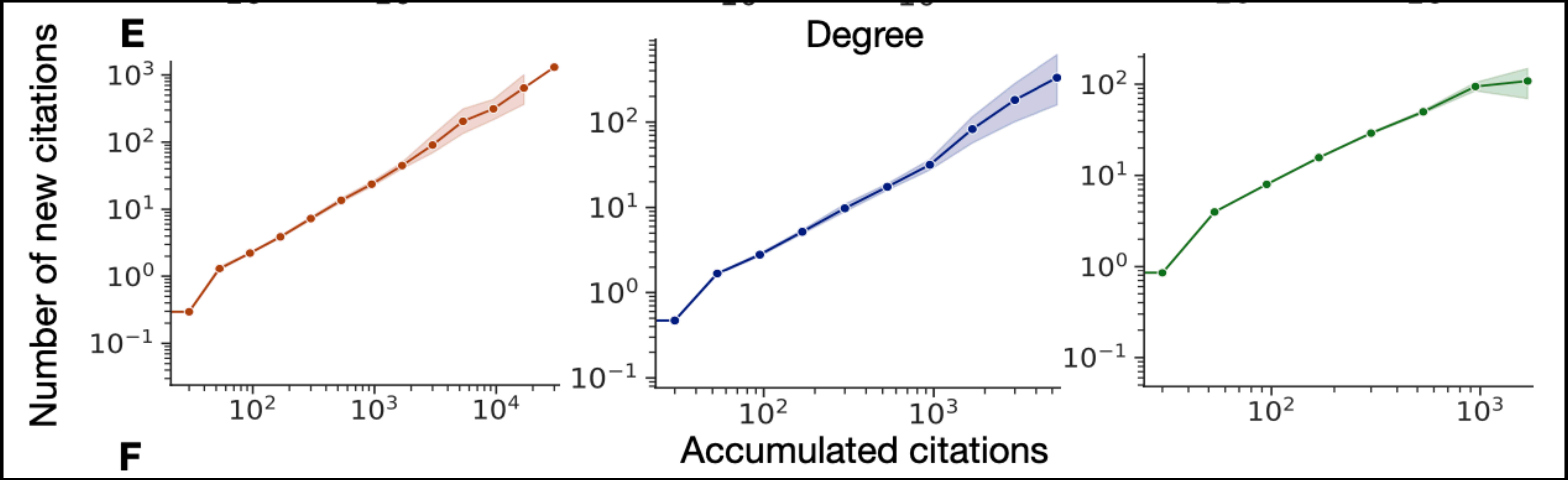


Law Science Patents

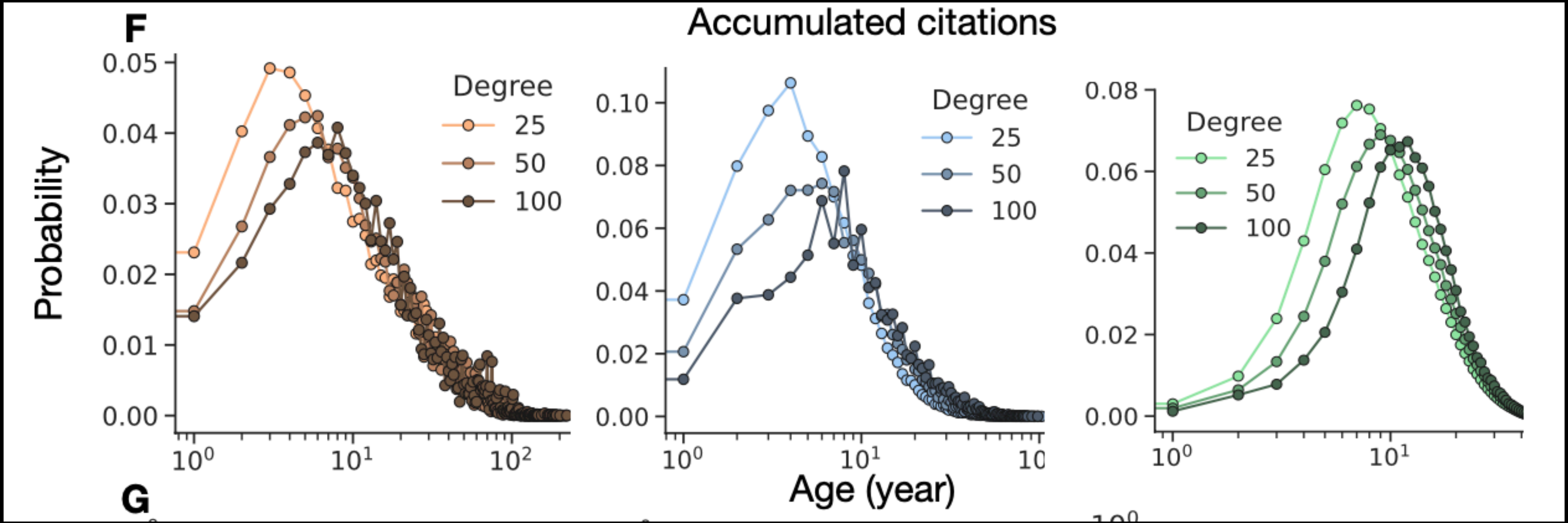
Degree distribution



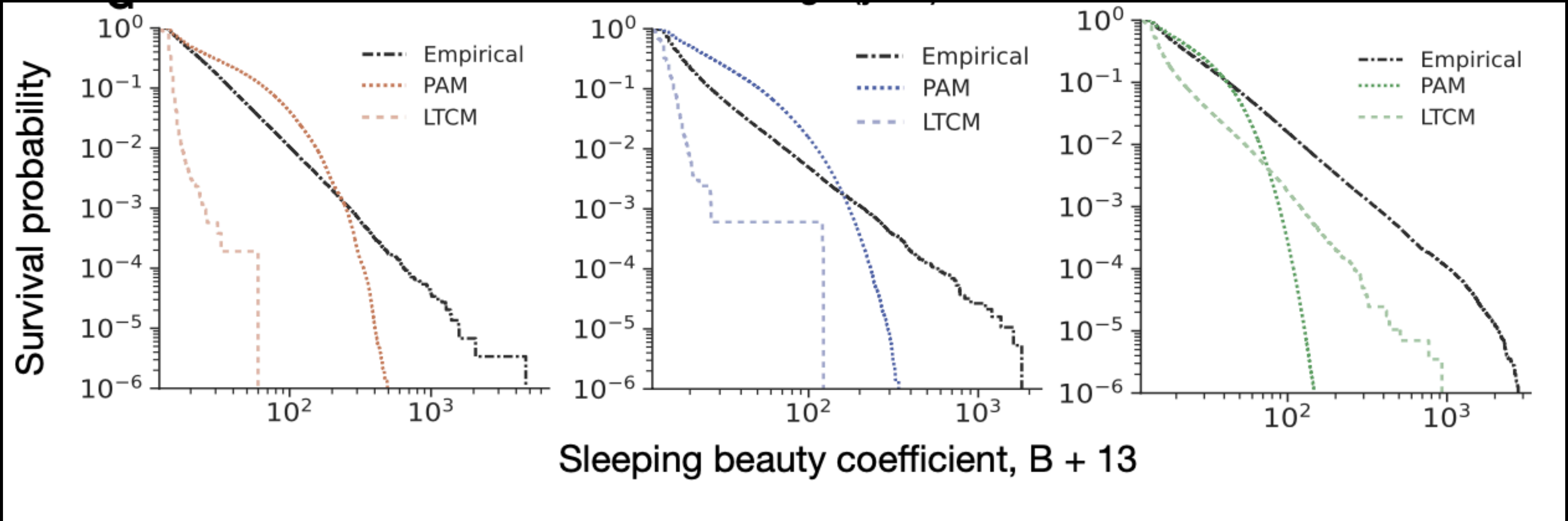
Preferential Attachment



Citation recency



Delayed recognition



Then, what is the underlying mechanism?

$$\Pi_i(t) \sim \eta_i c_i^t P_i(t)$$

Wang, Dashun, Chaoming Song, and Albert-László Barabási. "Quantifying long-term scientific impact." *Science* 342.6154 (2013): 127-132.

$$\Pi_i(t) \sim \underline{\eta_i} c_i^t P_i(t)$$

Fitness

Wang, Dashun, Chaoming Song, and Albert-László Barabási. "Quantifying long-term scientific impact." *Science* 342.6154 (2013): 127-132.

$$\Pi_i(t) \sim \underbrace{\eta_i}_{\text{Fitness}} \overbrace{c_i^t}^{\text{Citation (PA)}} P_i(t)$$

Wang, Dashun, Chaoming Song, and Albert-László Barabási. "Quantifying long-term scientific impact." *Science* 342.6154 (2013): 127-132.

Citation (PA)

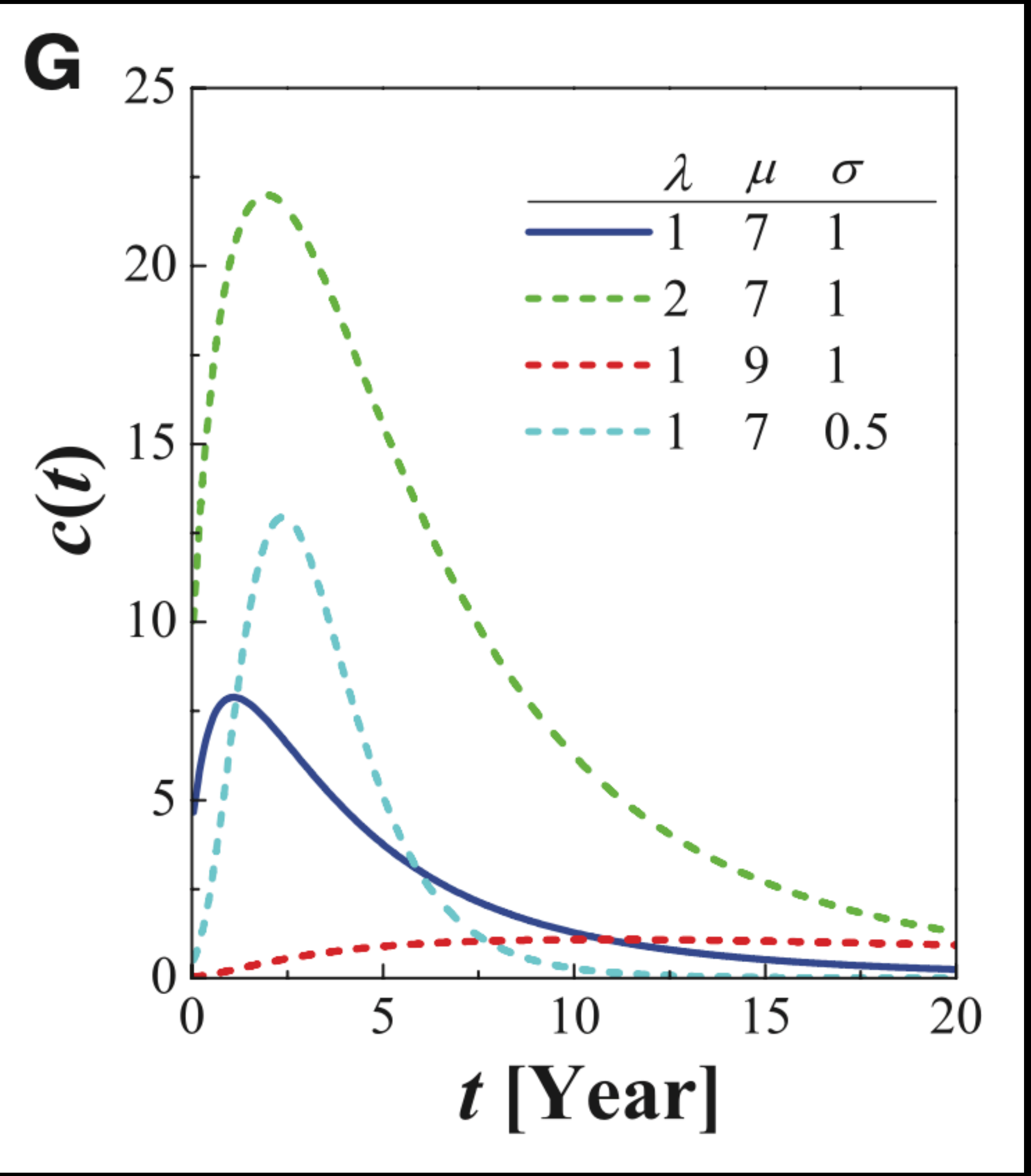
$$\Pi_i(t) \sim \underbrace{\eta_i}_{\text{Fitness}} \overbrace{c_i^t}^{\text{Citation (PA)}} \underbrace{P_i(t)}_{\text{Aging}}$$

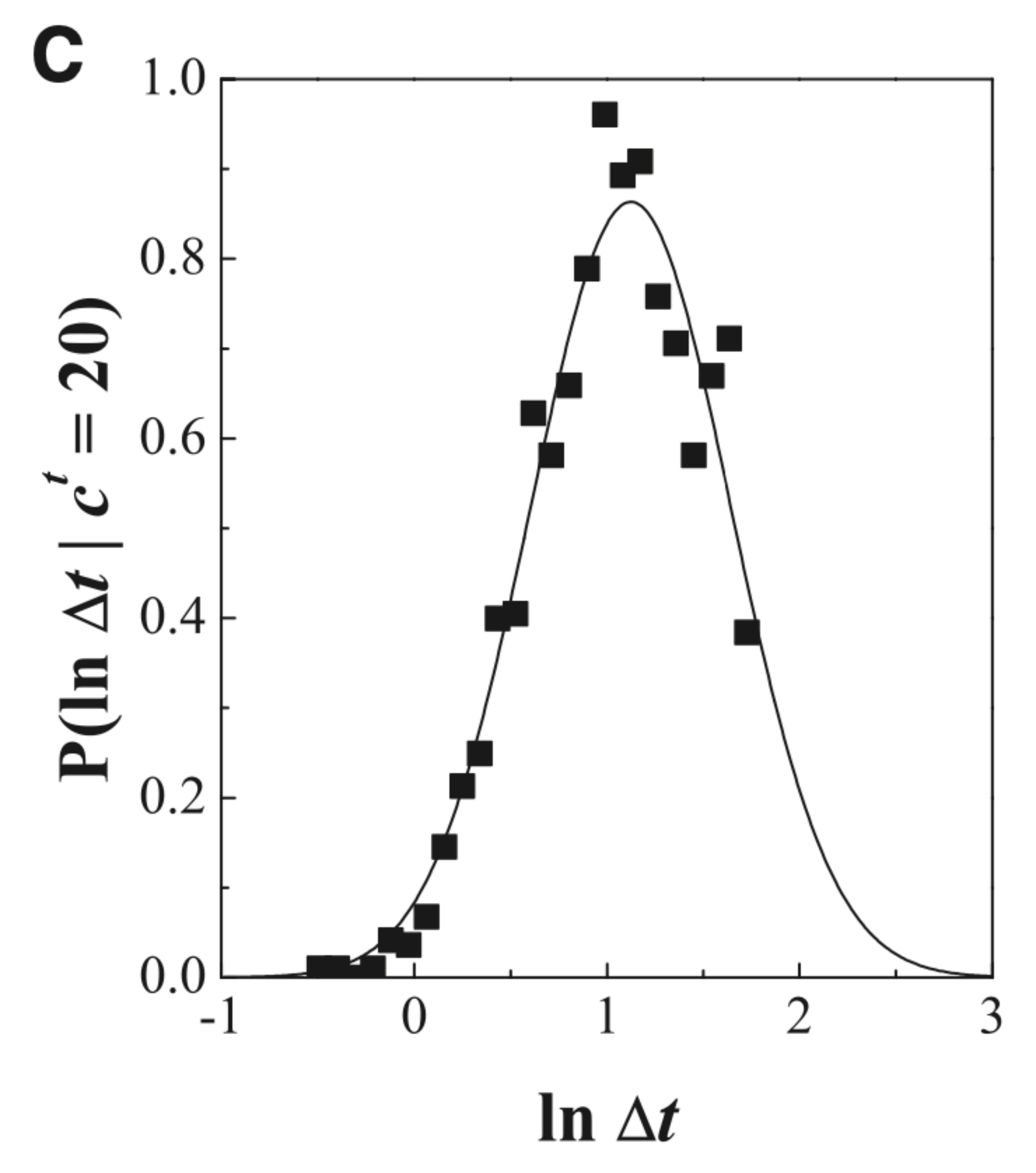
Fitness

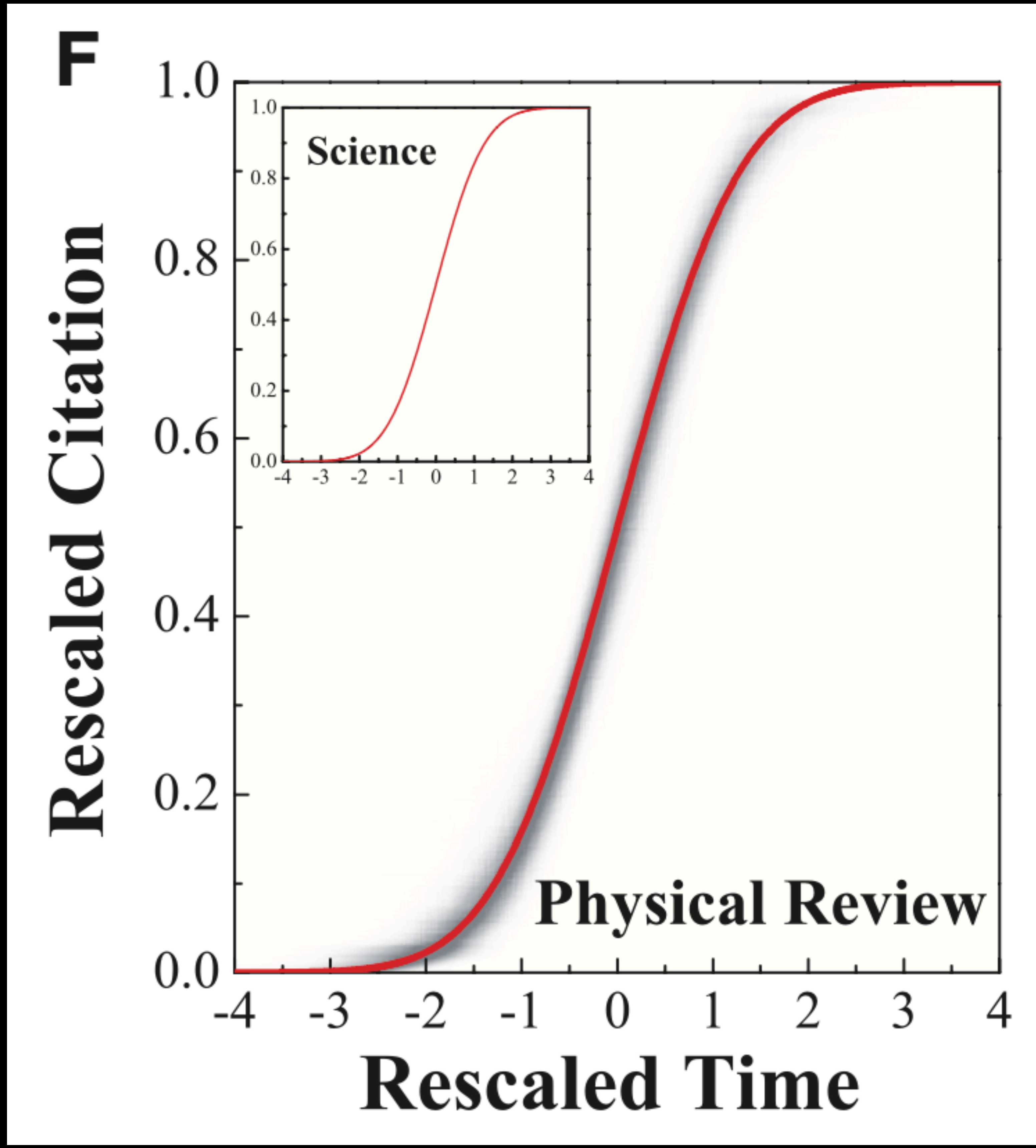
Aging

Wang, Dashun, Chaoming Song, and Albert-László Barabási. "Quantifying long-term scientific impact." *Science* 342.6154 (2013): 127-132.

Long-term citation model







Wang, Dashun, Chaoming Song, and Albert-László Barabási. "Quantifying long-term scientific impact." *Science* 342.6154 (2013): 127-132.

But,

"Performance is about ***you****. …*
Success, however, is about ***us****."*

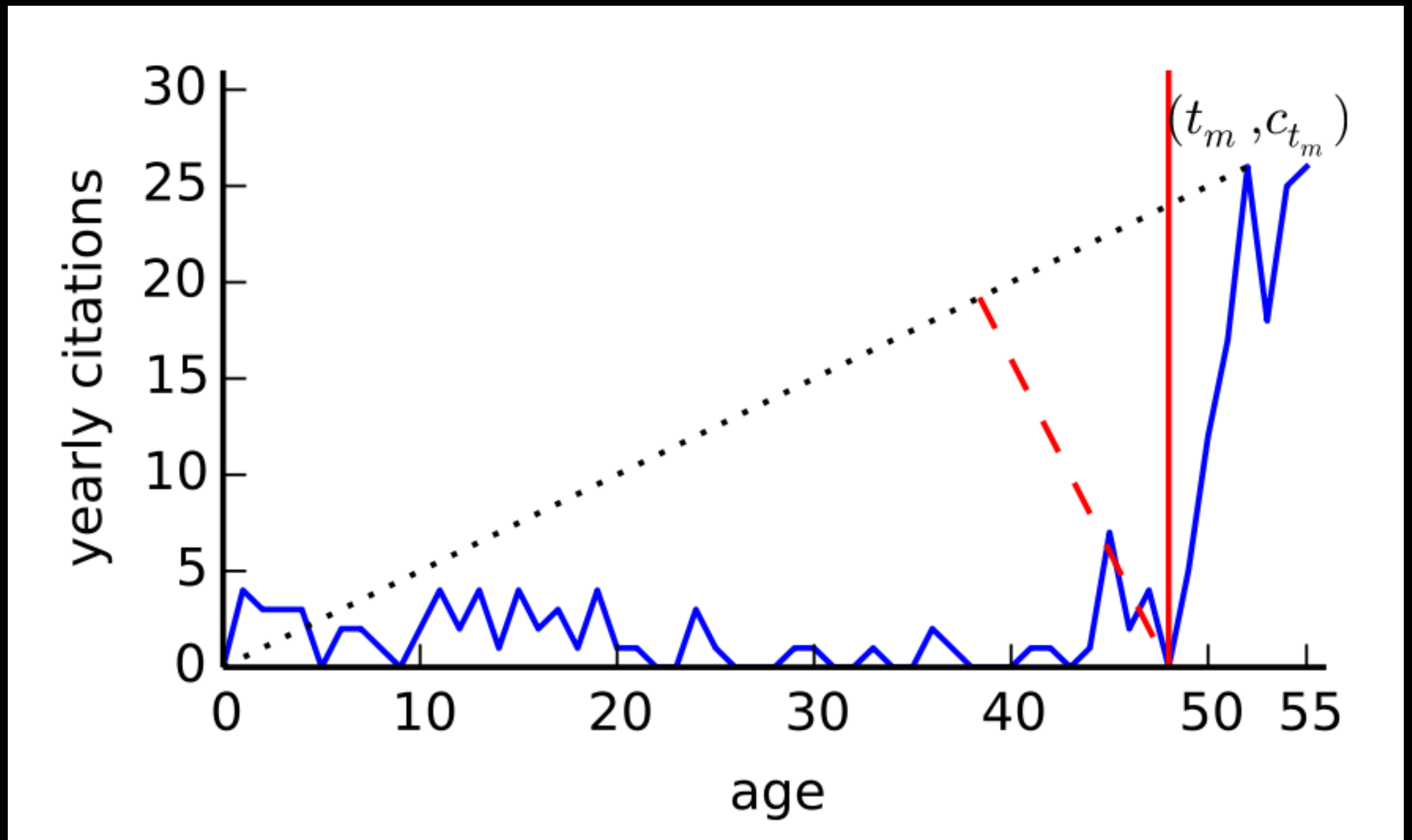
–Albert-László Barabási

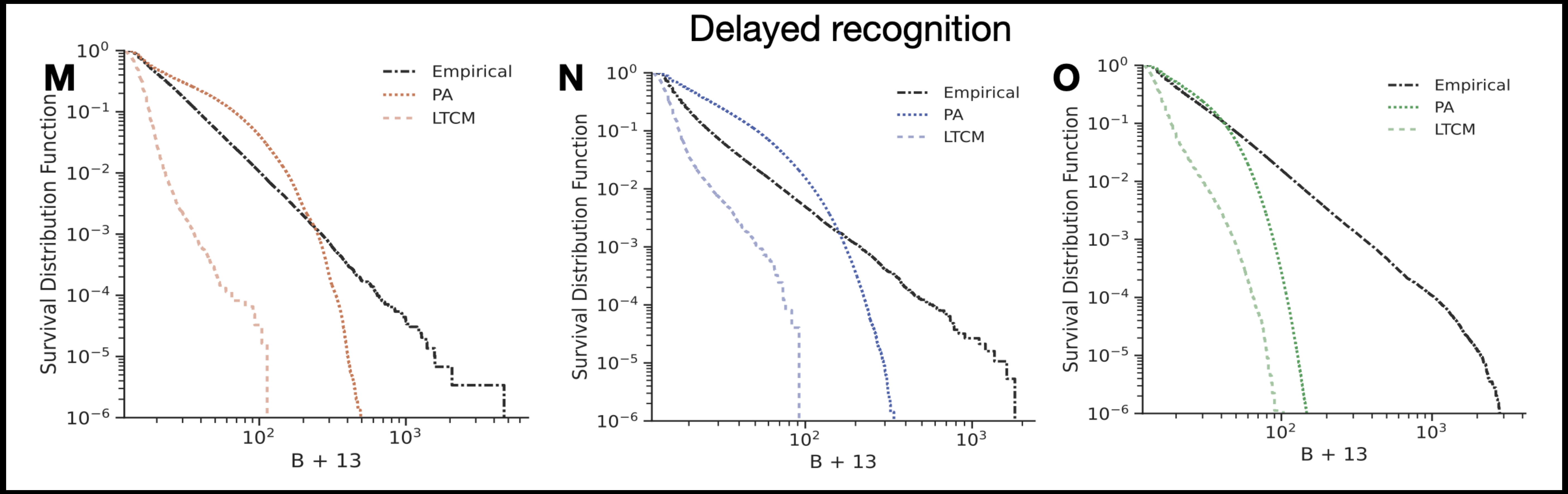
Citation ~ success?

Then, is it really enough to only focus on the *paper* (you), not the *collective/community* (us)?

Shouldn't the citation dynamics be inherently collective?

An example: **delayed recognition**
(“sleeping beauties”)





$$\Pi_i(t) \sim \eta_i c_i^t P_i(t)$$

?

Community citation model

Community citation model

- **Paper-centric view**: the success is determined by its *intrinsic quality, age, and luck*.

Community citation model

- **Paper-centric view**: the success is determined by its *intrinsic quality, age, and luck*.
- **Collective/community-centric view**: the success (citations) is determined by the *collective attention of the community*.

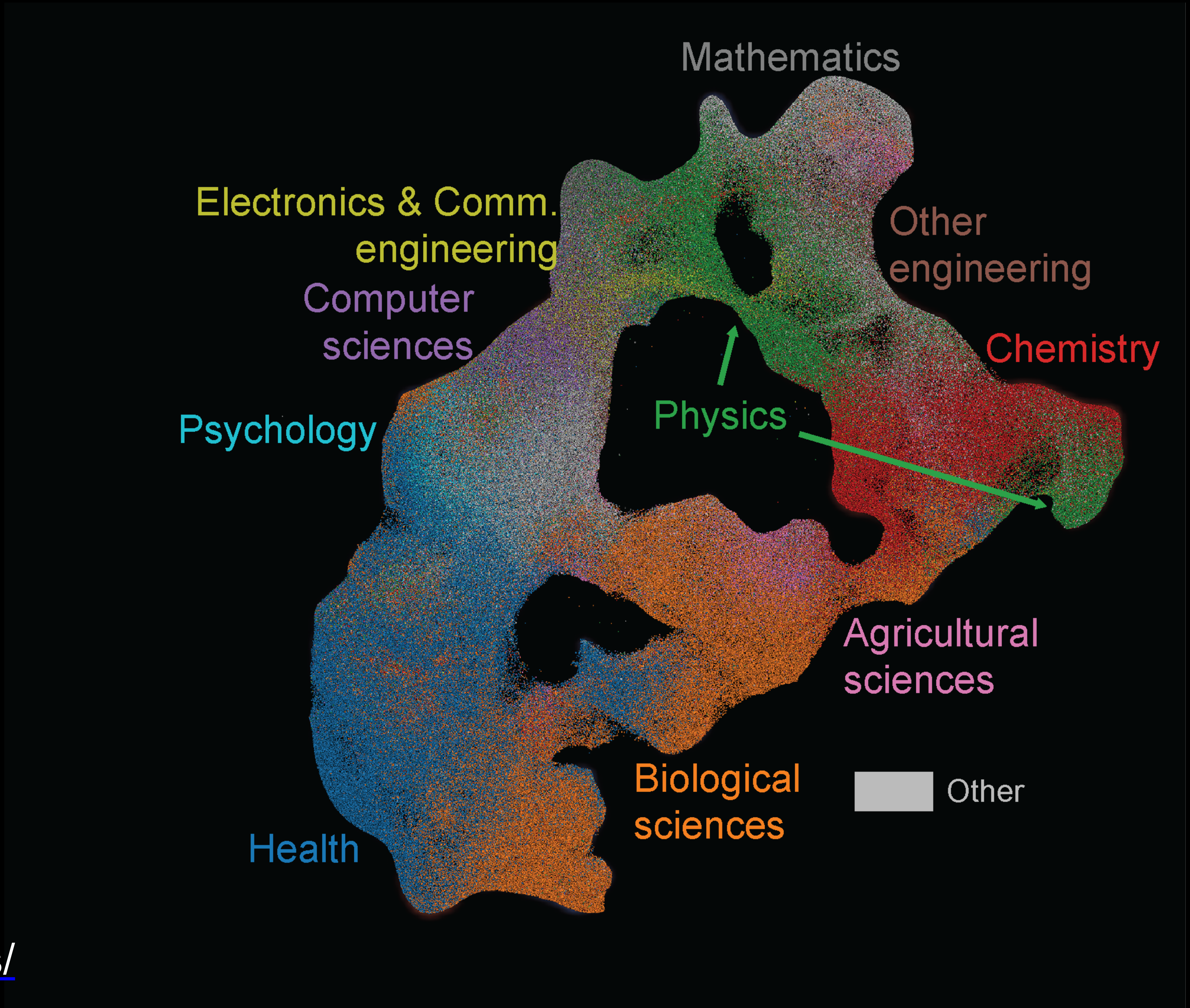
How can we model the "*community*"?

The space of knowledge

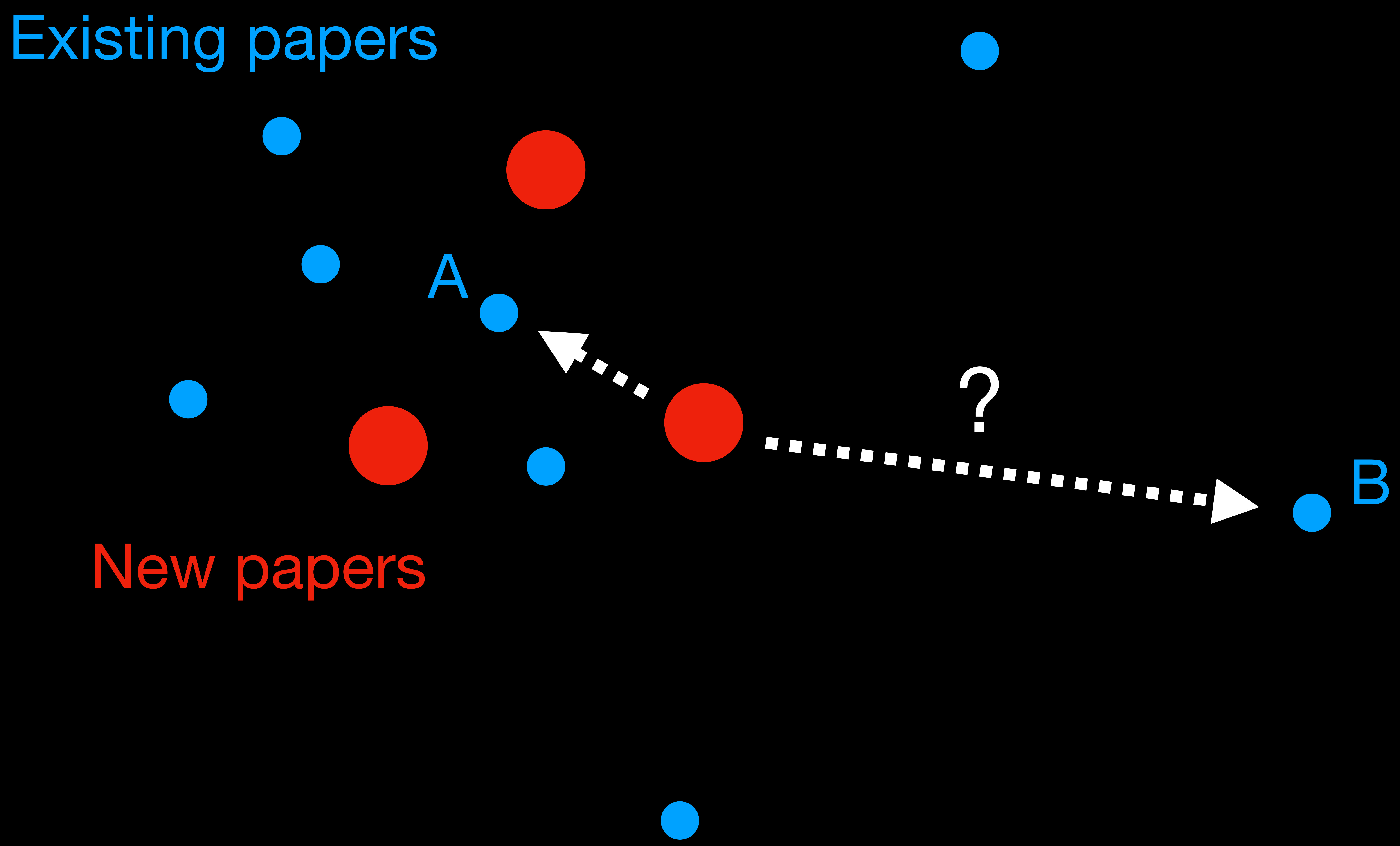
Filipi Silva

Sadamori Kojaku

Lili Miao



https://sg.iu.edu/visualization/sciencemaps/



The space of knowledge

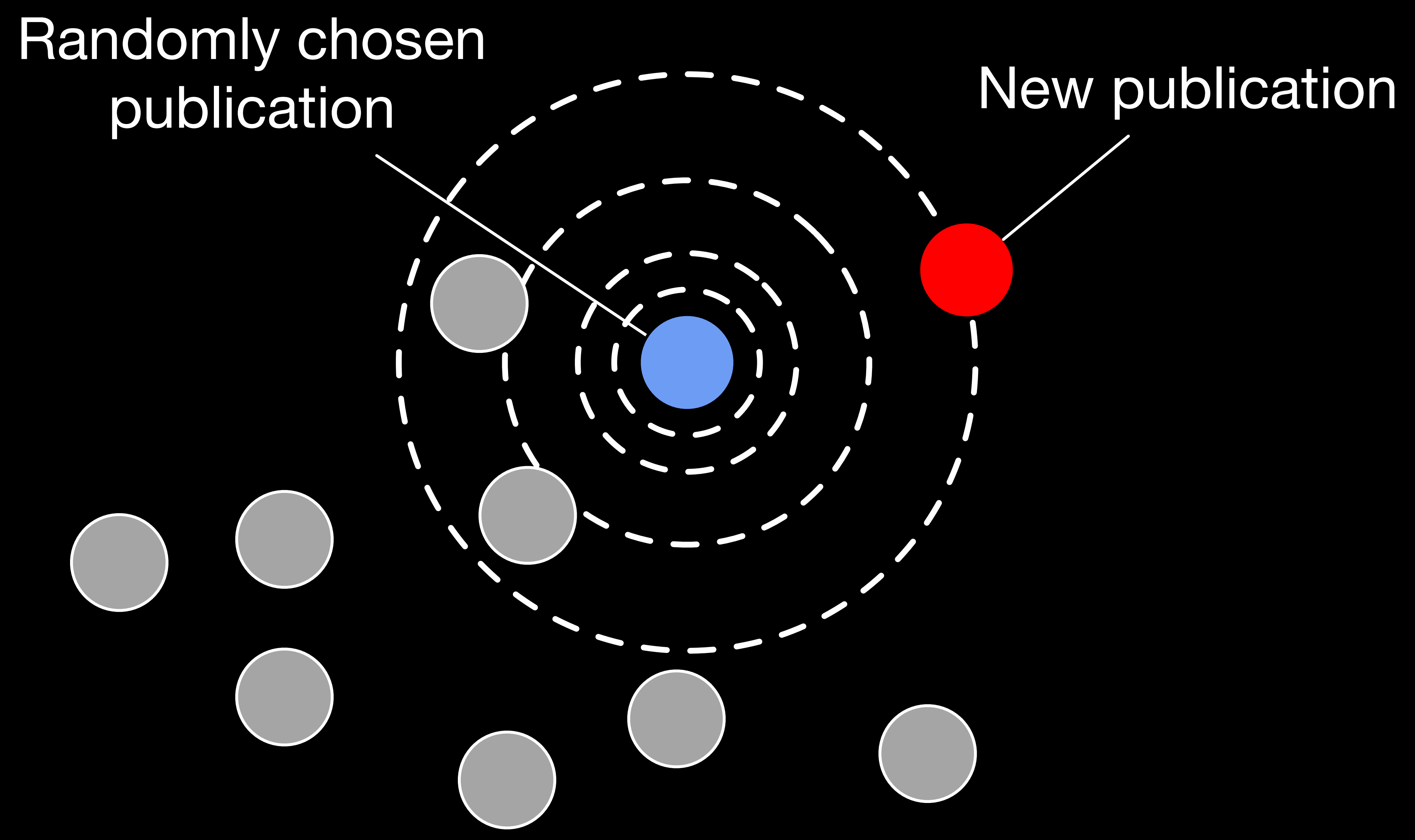
Community citation model

1. New knowledge (papers) *get created somewhere* in the space of knowledge

2. Each paper *identifies relevant existing literature* and cite them.

Adjacent production model

A existing paper is randomly chosen, and then a new paper appears near the chosen paper:



$$P(u_i \mid u_j) \propto \exp(-\lambda d(\mathbf{u}_i, \mathbf{u}_j))$$

von Mises–Fisher distribution

How do they identify relevant knowledge?

How do they identify relevant knowledge?

$$\Pi_i(t) \sim \underbrace{\eta_i}_{\text{Fitness}}\overbrace{c_i^t}^{\text{Citation (PA)}}\underbrace{P_i(t)}_{\text{Aging}}$$

Community citation model

$$P(j\,|\,i) = \frac{1}{Z_{t_i}}\eta_j\left(c_j(t_i) + c_0\right)f(t_i - t_j)\cdot\exp\left(-\kappa d(\mathbf{u_j}, \mathbf{u_i})\right)$$

Community citation model

$$P(j \mid i) = \frac{1}{Z_{t_i}} \underline{\eta_j} \Big(c_j(t_i) + c_0 \Big) f(t_i - t_j) \cdot \exp\Big(-\kappa d(\mathbf{u_j}, \mathbf{u_i}) \Big)$$

Fitness

Community citation model

$$P(j\,|\,i) = \frac{1}{Z_{t_i}} \underbrace{\eta_j}_{\text{Fitness}} \Big(\overbrace{c_j(t_i) + c_0}^{\text{Citation (PA)}} \Big) f(t_i - t_j) \cdot \exp\Big(-\kappa d(\mathbf{u_j}, \mathbf{u_i}) \Big)$$

Community citation model

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Community citation model

Citation (PA)

$$P(j\,|\,i) = \frac{1}{Z_{t_i}}\eta_j\left(\overline{c_j(t_i) + c_0}\right)\underline{f(t_i - t_j)} \cdot \exp\left(-\kappa d(\underline{\mathbf{u_j}, \mathbf{u_i}})\right)$$

Fitness

Aging*

Embedding vectors

Community citation model

Citation (PA)

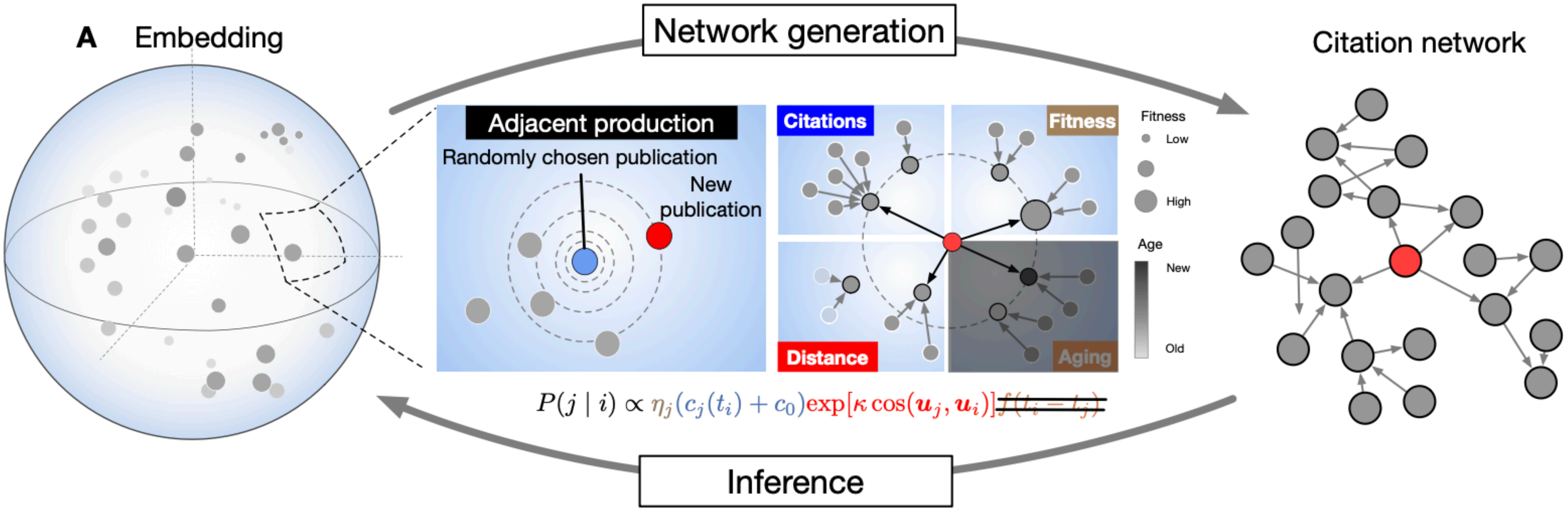
$$P(j \mid i) = \frac{1}{Z_{t_i}} \underbrace{\eta_j}_{\text{Fitness}} \Big(\overbrace{c_j(t_i) + c_0}^{\text{Citation (PA)}} \Big) \underbrace{f(t_i - t_j)}_{\text{Aging*}} \cdot \exp\Big(-\kappa d(\underbrace{\mathbf{u_j}, \mathbf{u_i}}_{\text{Embedding vectors}}) \Big)$$

Fitness

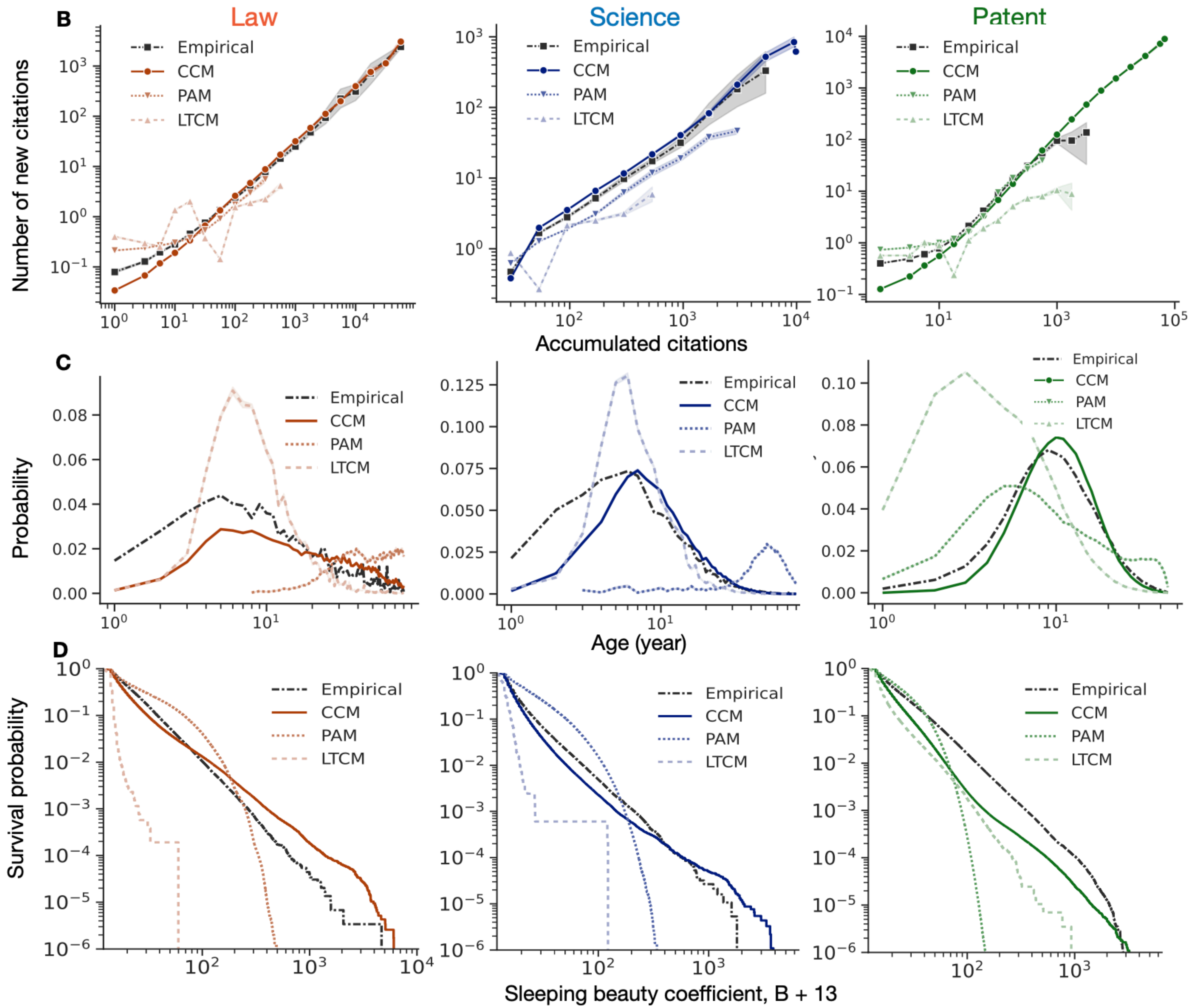
Aging*

Embedding vectors

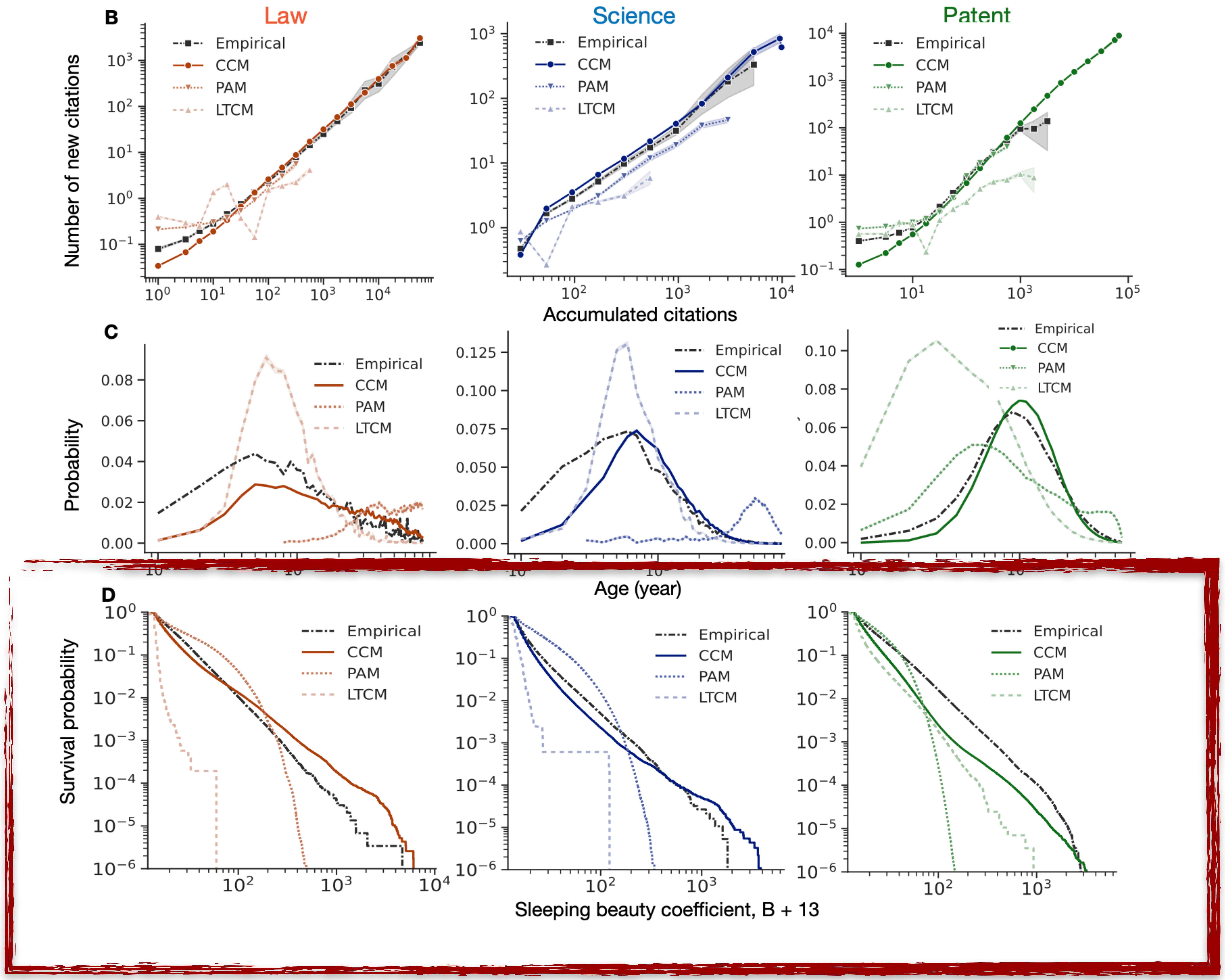
* Aging turns out to be not necessary.



A
Embedding
Network generation
Citation network
Adjacent production
Randomly chosen publication
New publication
Citations
Fitness
Distance
Aging
Fitness
Low
High
Age
New
Old
$P(j \mid i) \propto \eta_j(c_j(t_i) + c_0)\exp[\kappa \cos(\boldsymbol{u}_j, \boldsymbol{u}_i)]\cancel{f(t_i - t_j)}$
Inference



B
Law
Science
Patent
Number of new citations
Accumulated citations
Empirical
CCM
PAM
LTCM
C
Probability
Age (year)
D
Survival probability
Sleeping beauty coefficient, B + 13



B
Law
Science
Patent
Empirical
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Number of new citations
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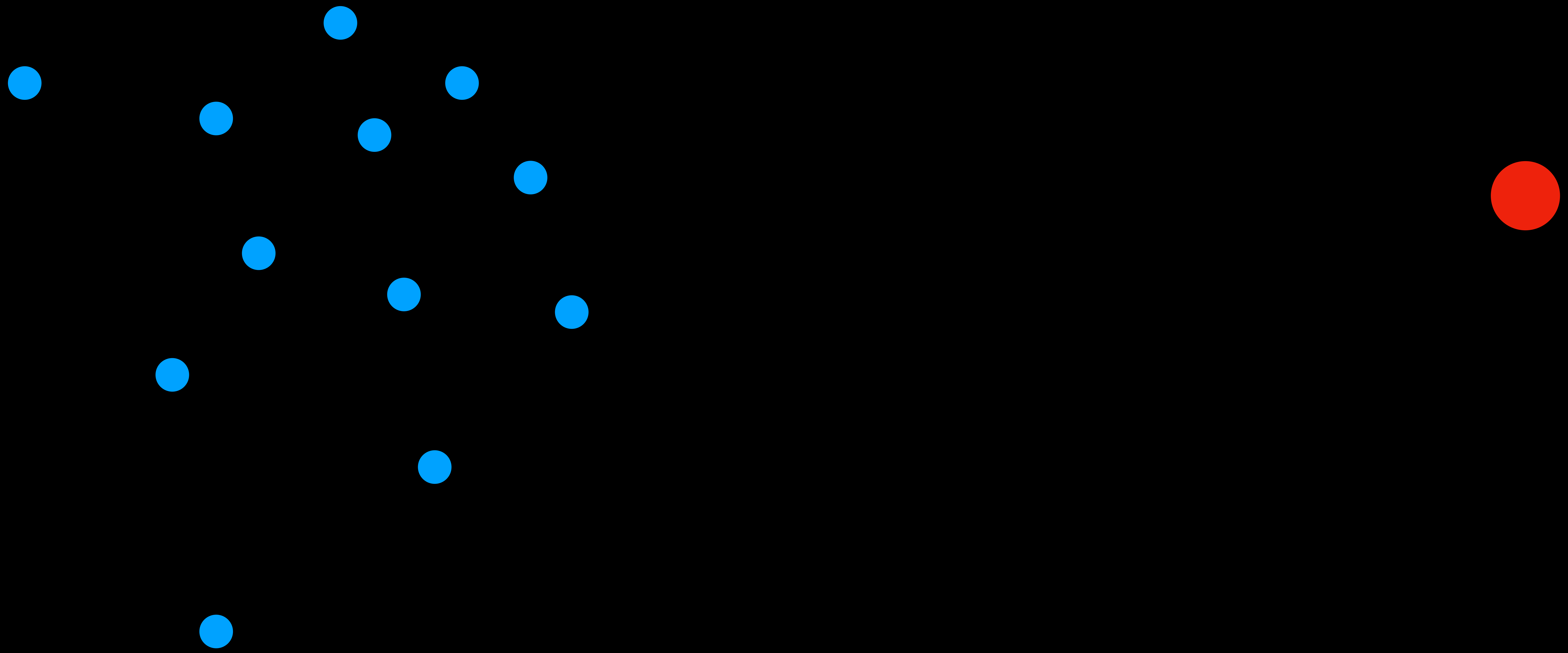
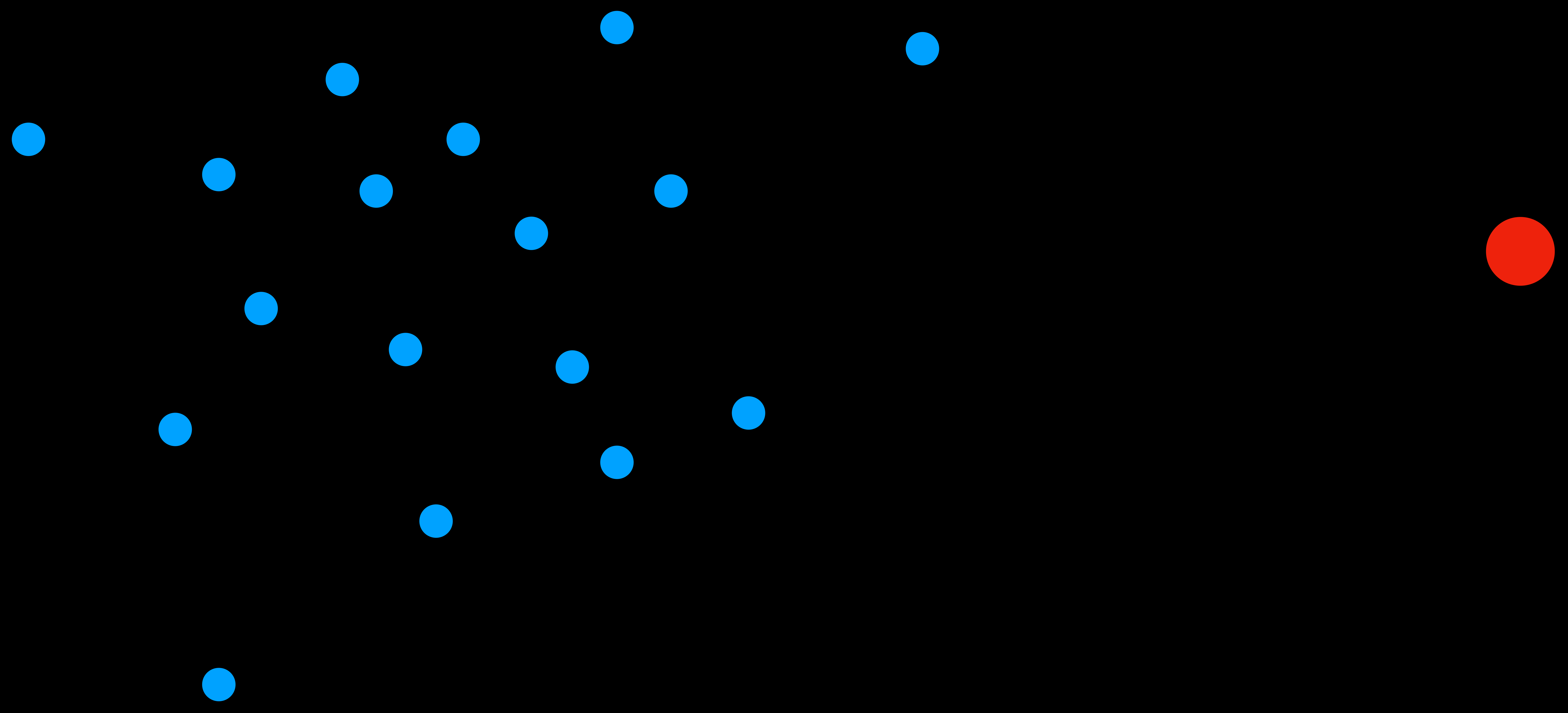
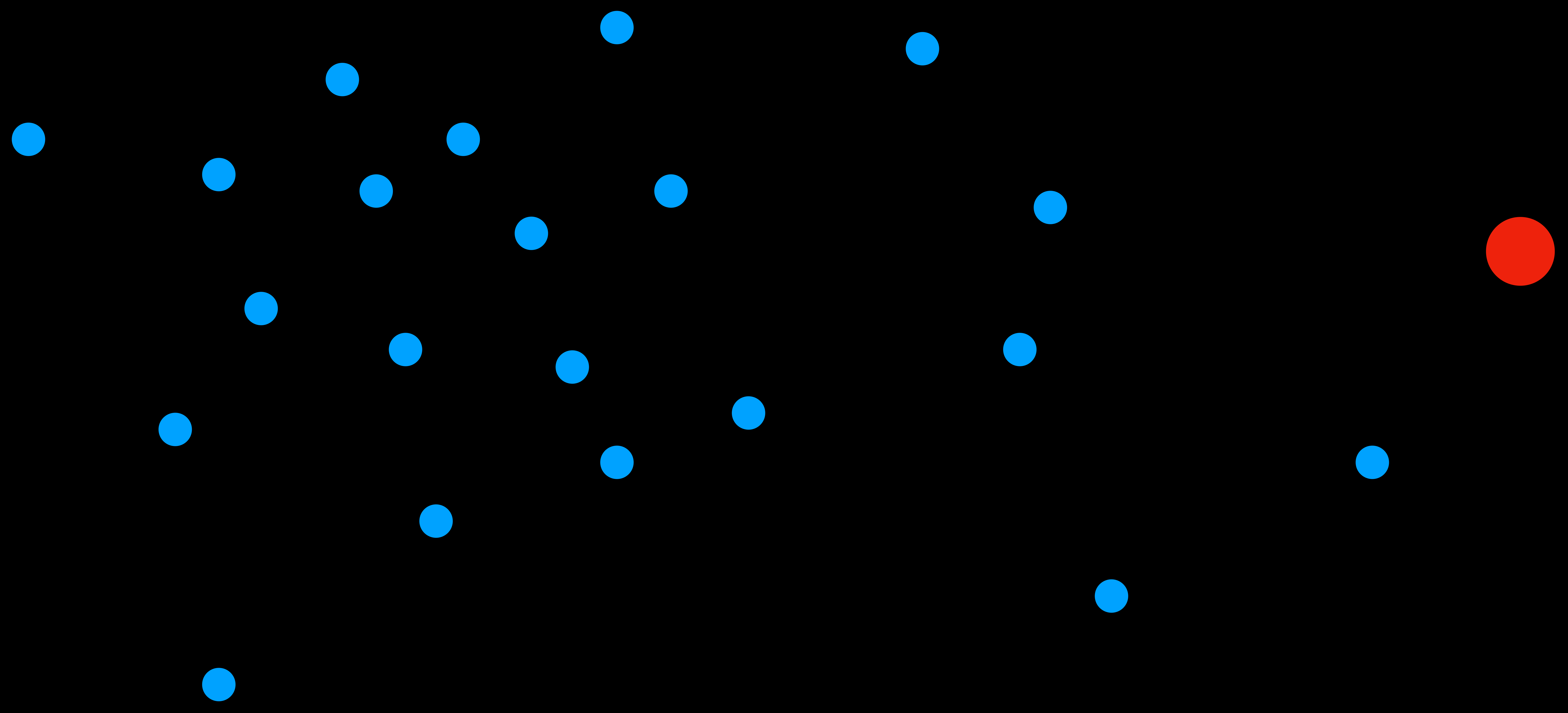
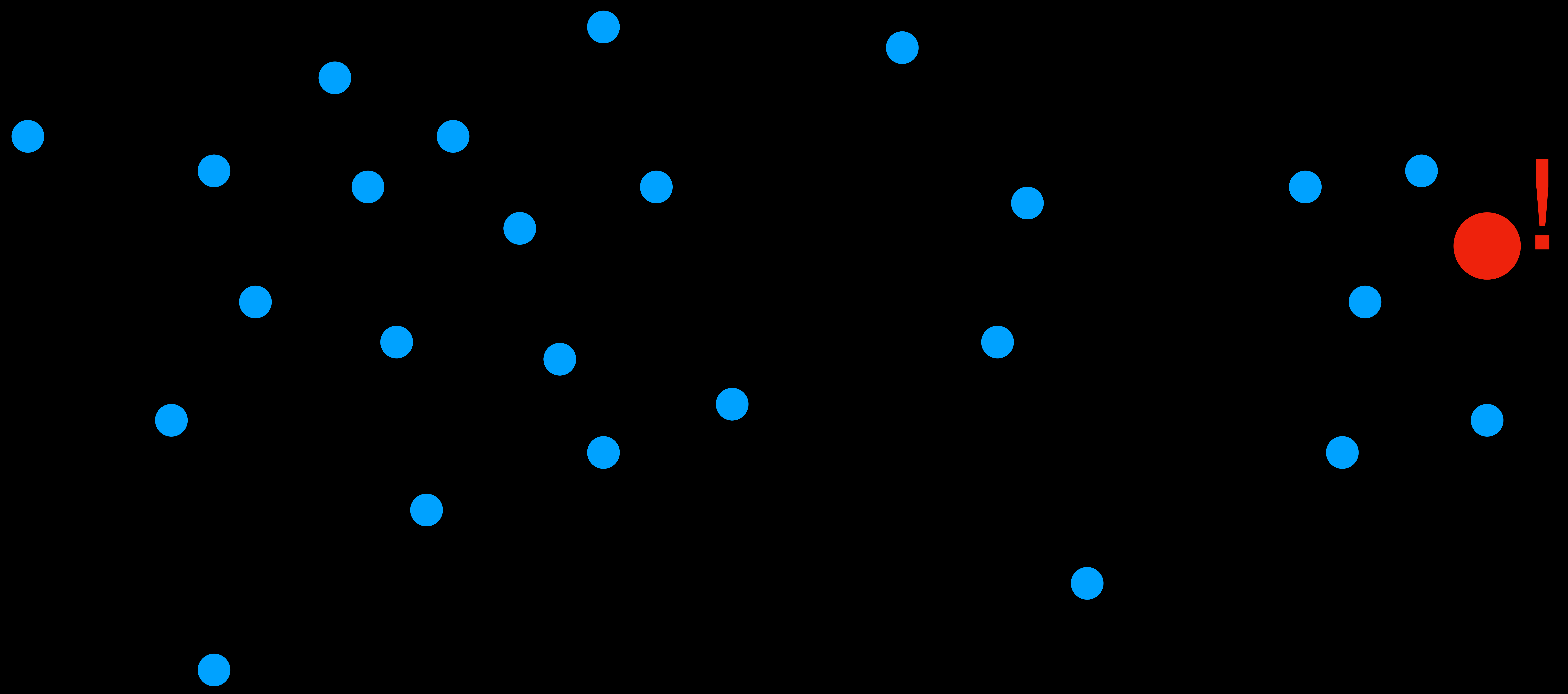


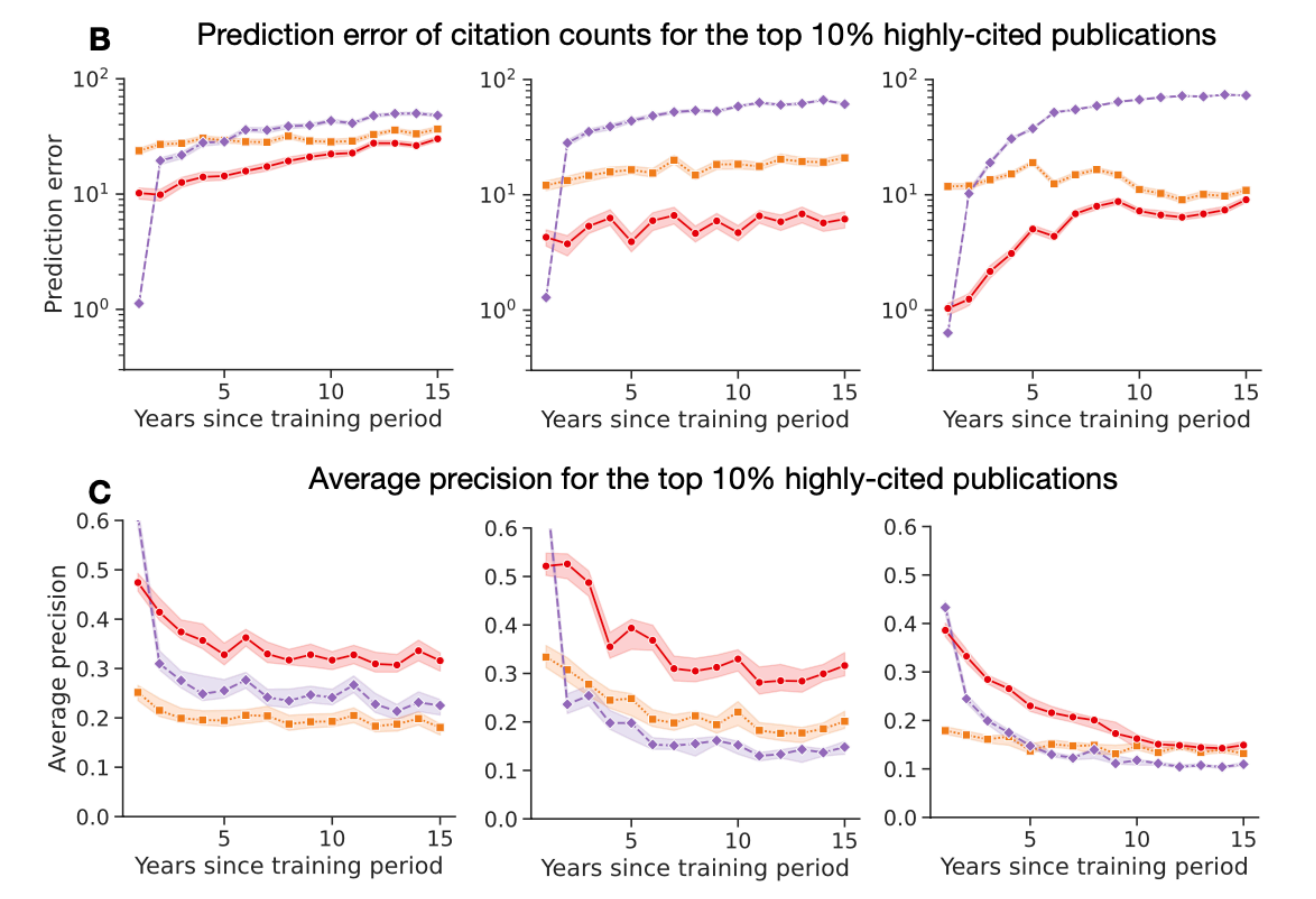






It allows us to "simulate" the whole system.

It better predicts the future "hits"



Summary

- Citation-based knowledge systems exhibit many universal citation dynamics even with distinct modes of operations.
- Imagining the knowledge space allows us to shift the perspective from individual papers to the whole community.
- This shift lets us explain phenomena like sleeping beauties and better predict future citation patterns.

Can we concretely *interpret* *the "distance" in the knowledge embedding space?*

PNAS

RESEARCH ARTICLE | SOCIAL SCIENCES

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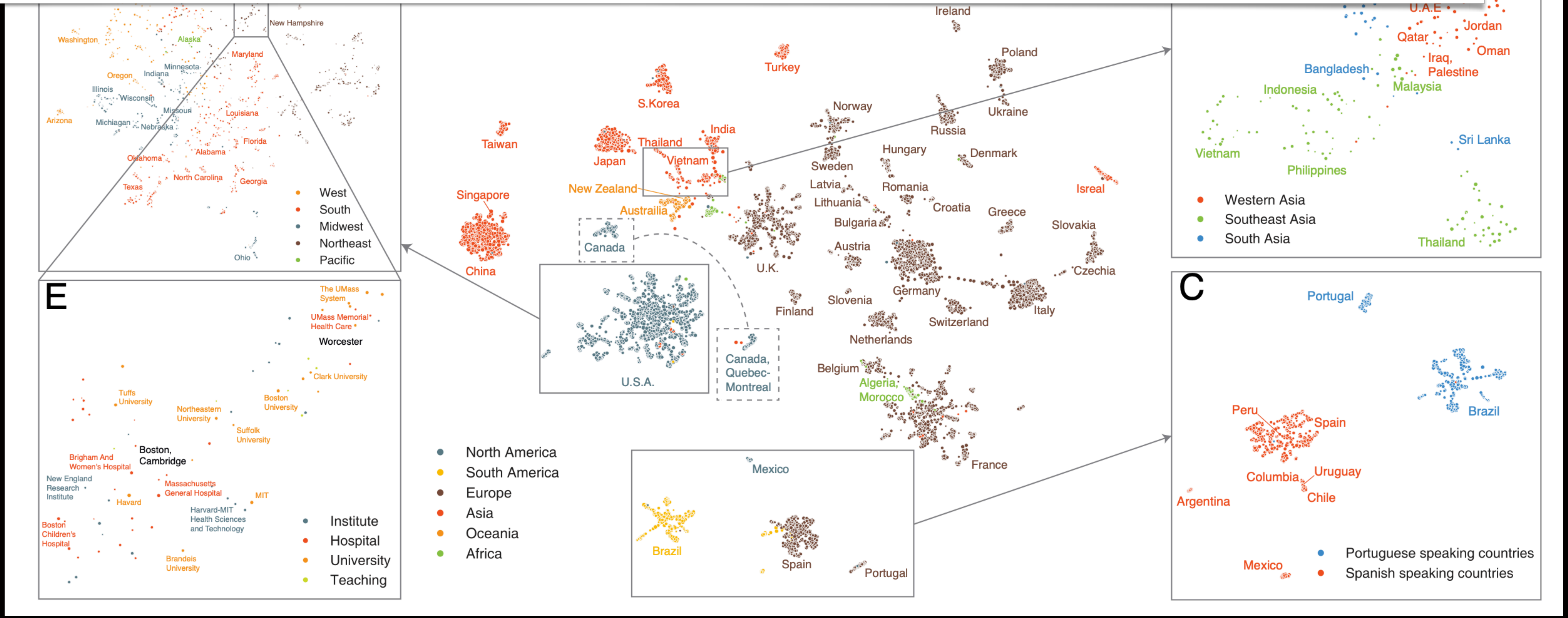
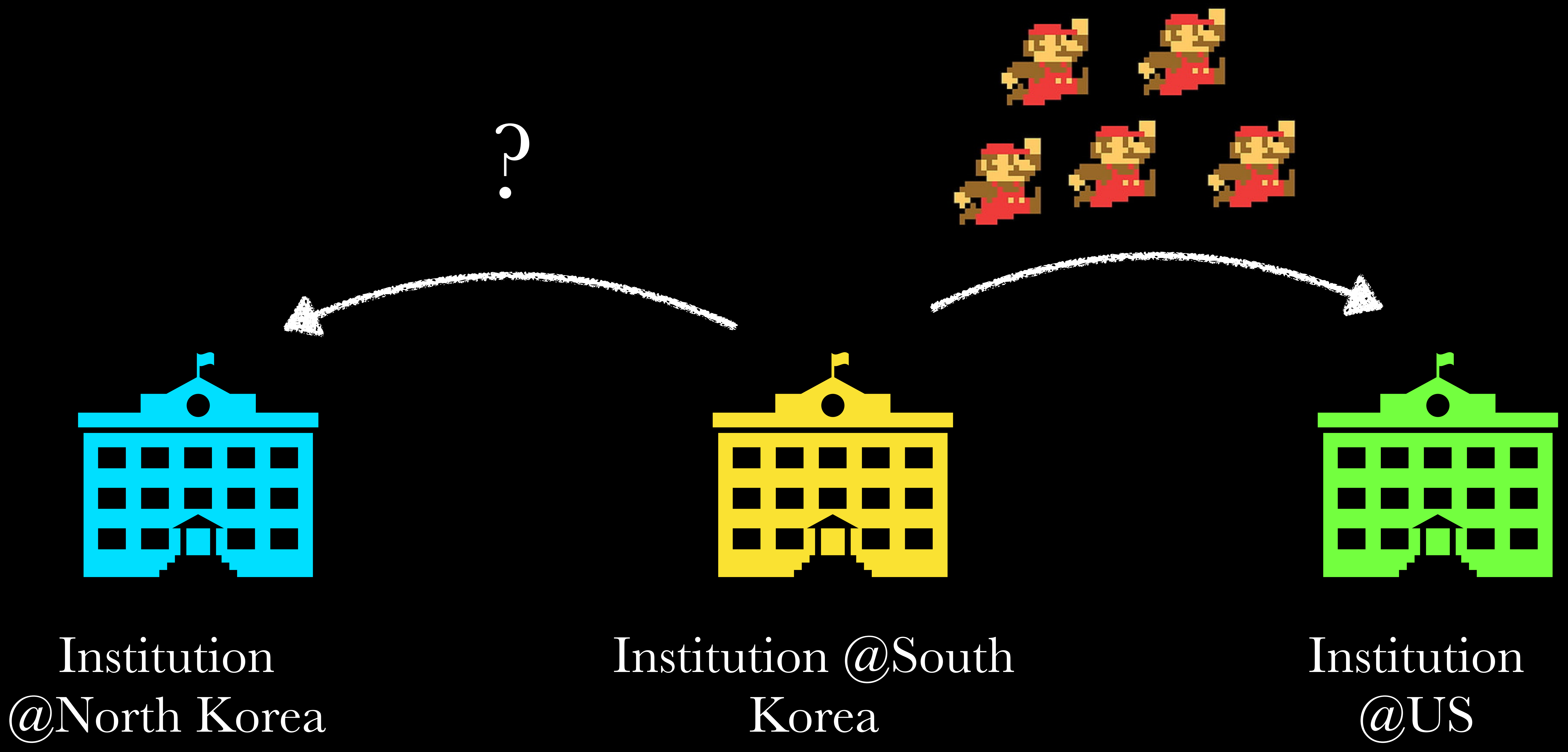
Unsupervised embedding of trajectories captures the latent structure of scientific migration

Dakota Murray[a,b,1], Jisung Yoon[a,c,d,1], Sadamori Kojaku[a,1], Rodrigo Costas[e,f], Woo-Sung Jung[g,h], Staša Milojević[a,2], and Yong-Yeol Ahn[a,2]

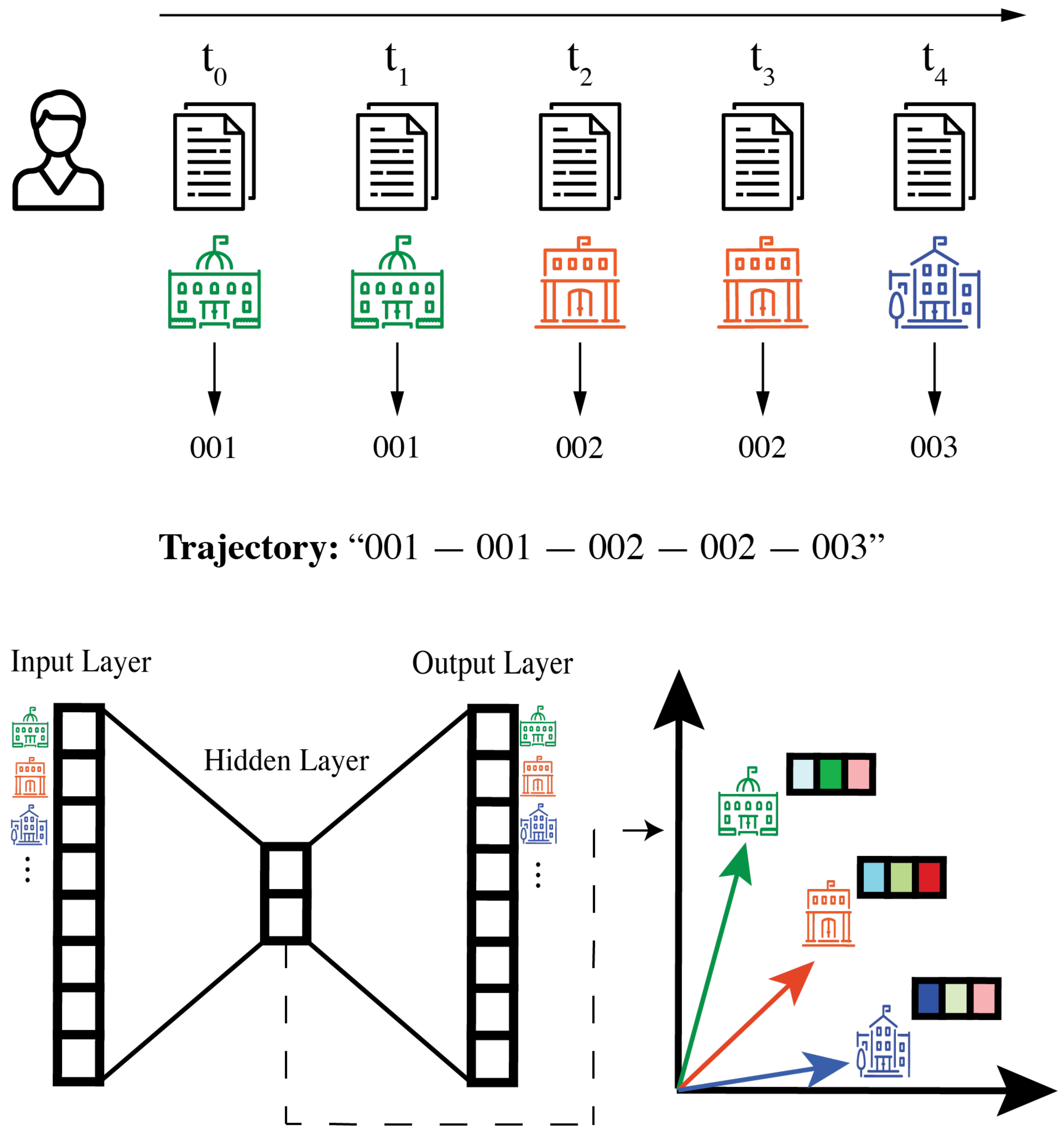



QUÉBECARTOGRAPHIE...
QUÉBEC
LES AUTRES
ÉTATS-UNIS
FRANCE
PARIS
YUL
OLD ORCHARD
PLATTSBURGH
WILDWOOD
MEXIQUE
FLORIDE
FT. LAUDERDALE
HOLLYWOOD
MIAMI
N
O
E
S
Tim Burke '82
MONTREAL GAZETTE

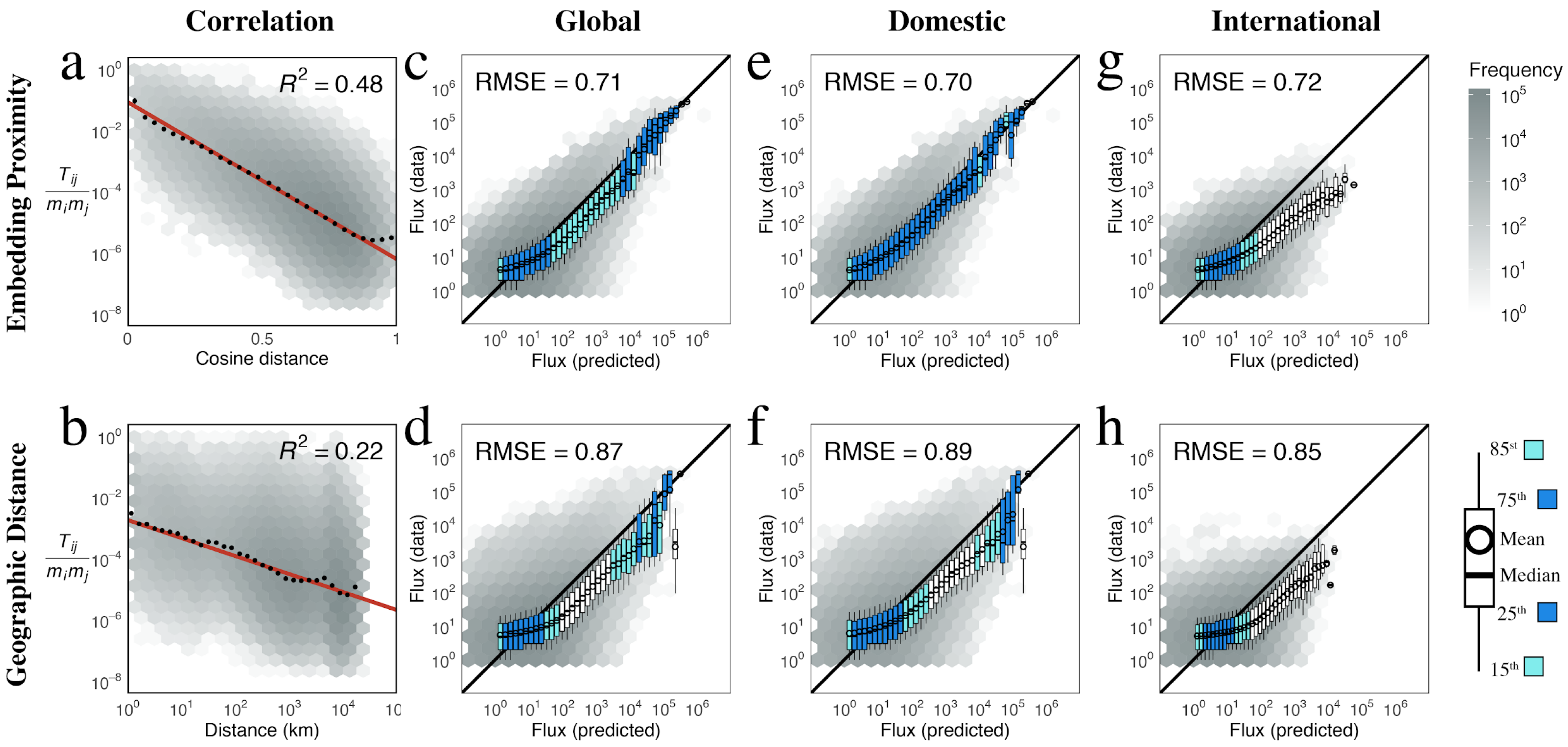


Social proximities do matter in human mobility

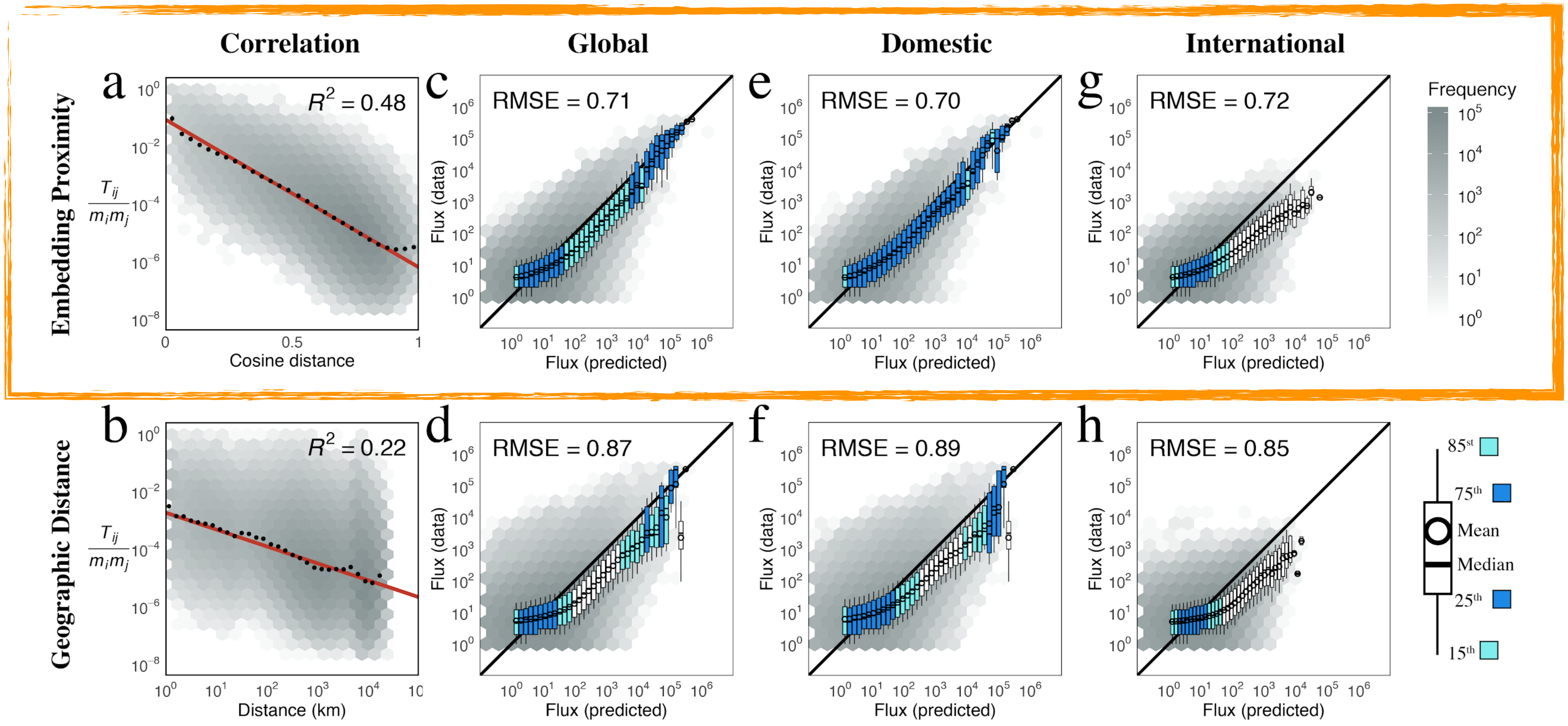
What happens if we use mobility of scientists to obtain the embedding?

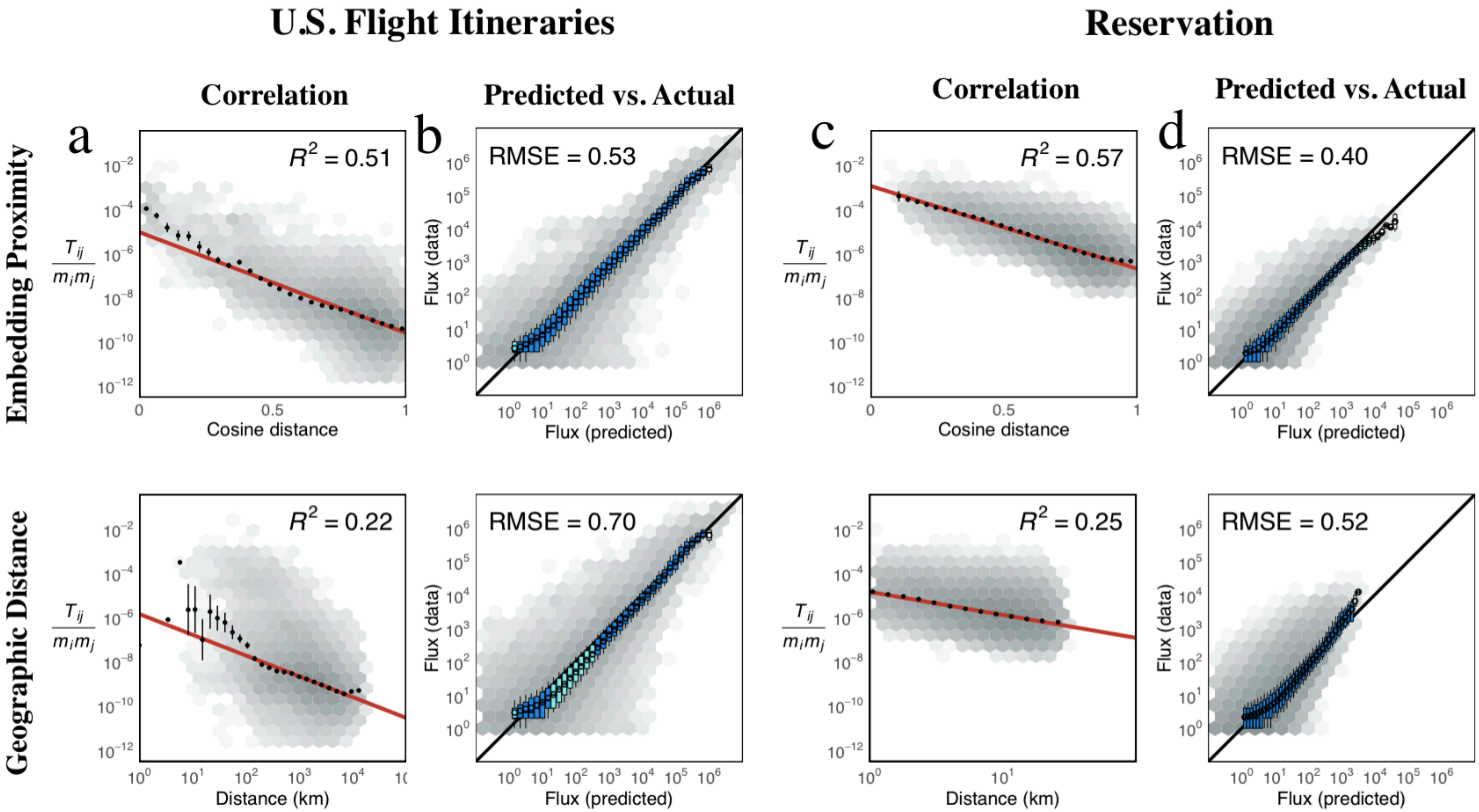


Embedding fits the gravity law much better!



Embedding fits the gravity law much better!

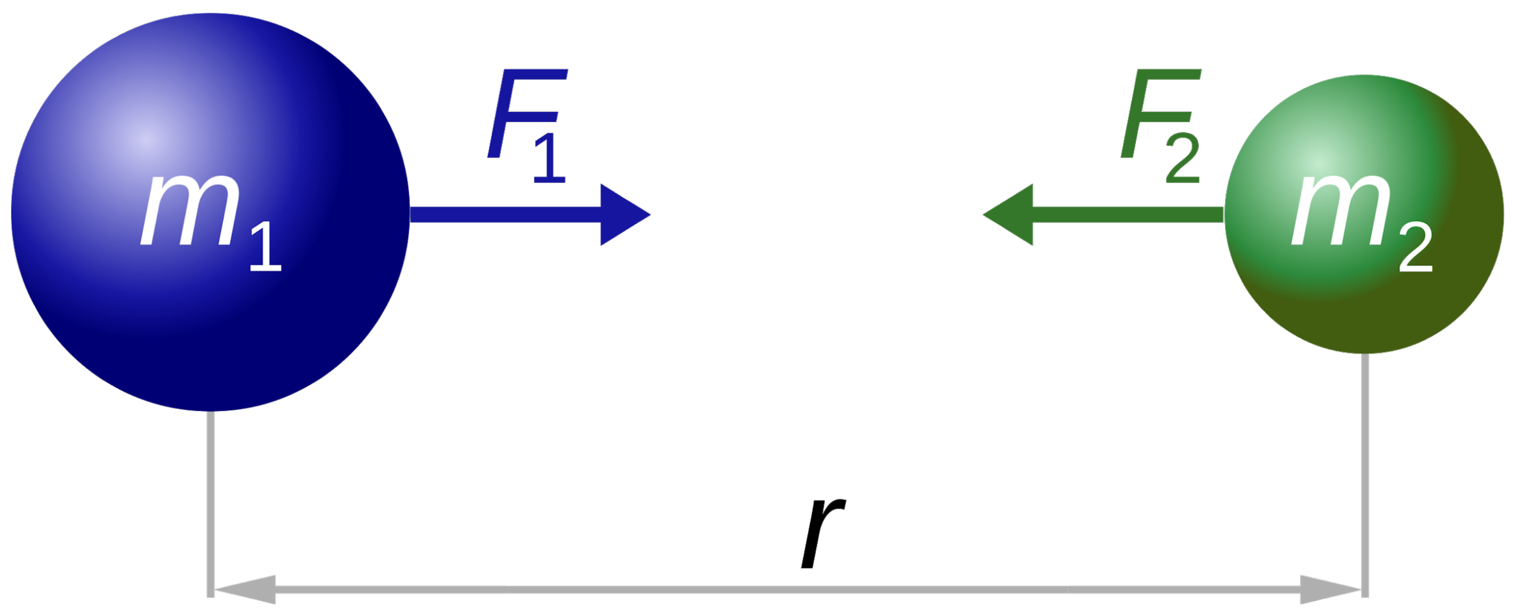




U.S. Flight Itineraries
Reservation
Correlation
Predicted vs. Actual
Embedding Proximity
Geographic Distance
a
b
c
d
$R^2 = 0.51$
RMSE = 0.53
$R^2 = 0.57$
RMSE = 0.40
$R^2 = 0.22$
RMSE = 0.70
$R^2 = 0.25$
RMSE = 0.52
$\frac{T_{ij}}{m_i m_j}$
Cosine distance
Distance (km)
Flux (data)
Flux (predicted)

Gravity law of mobility

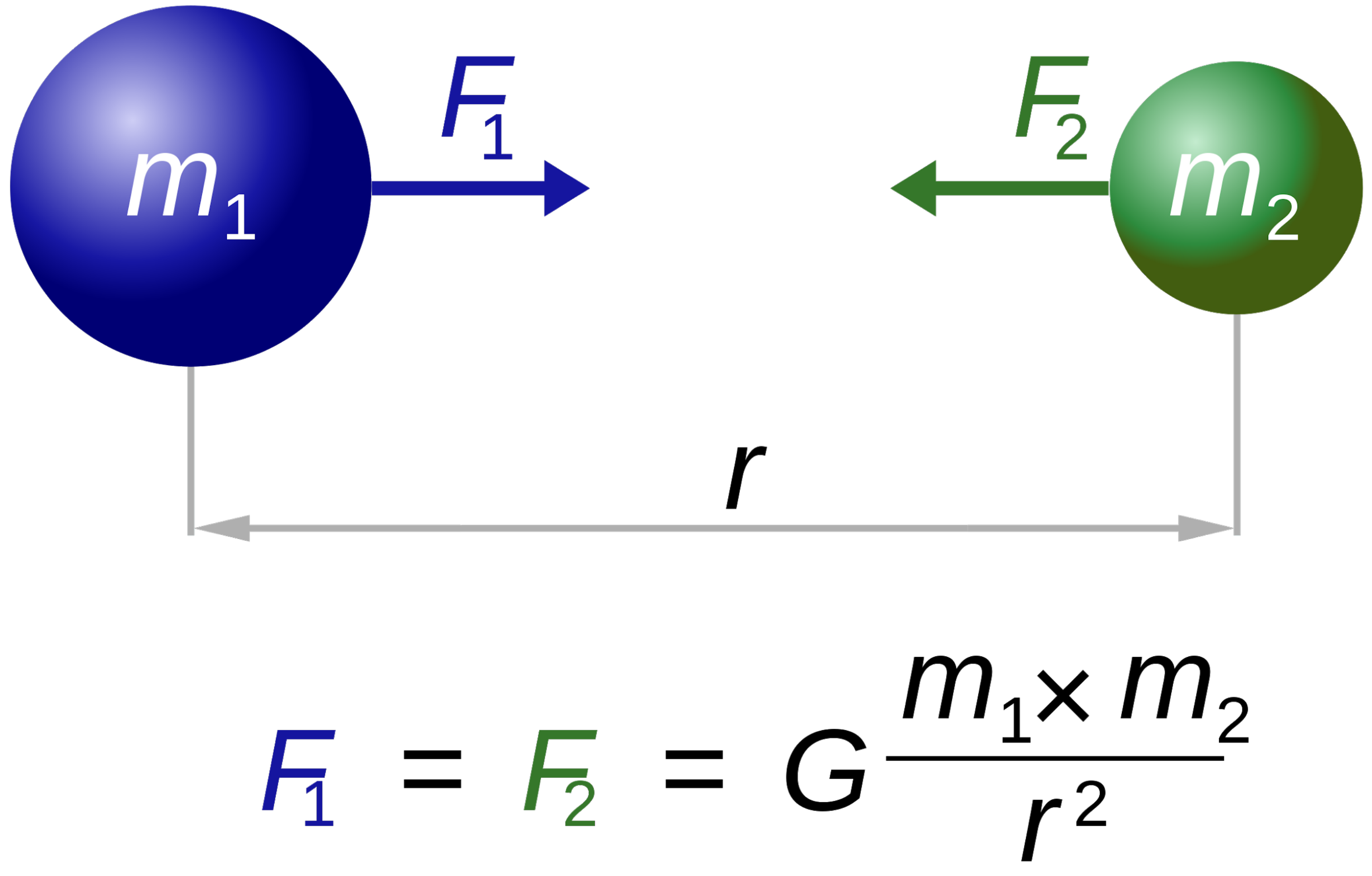
Gravity law of mobility



$$F_1 = F_2 = G\frac{m_1 \times m_2}{r^2}$$

Wikipedia user Dennis Nilsson

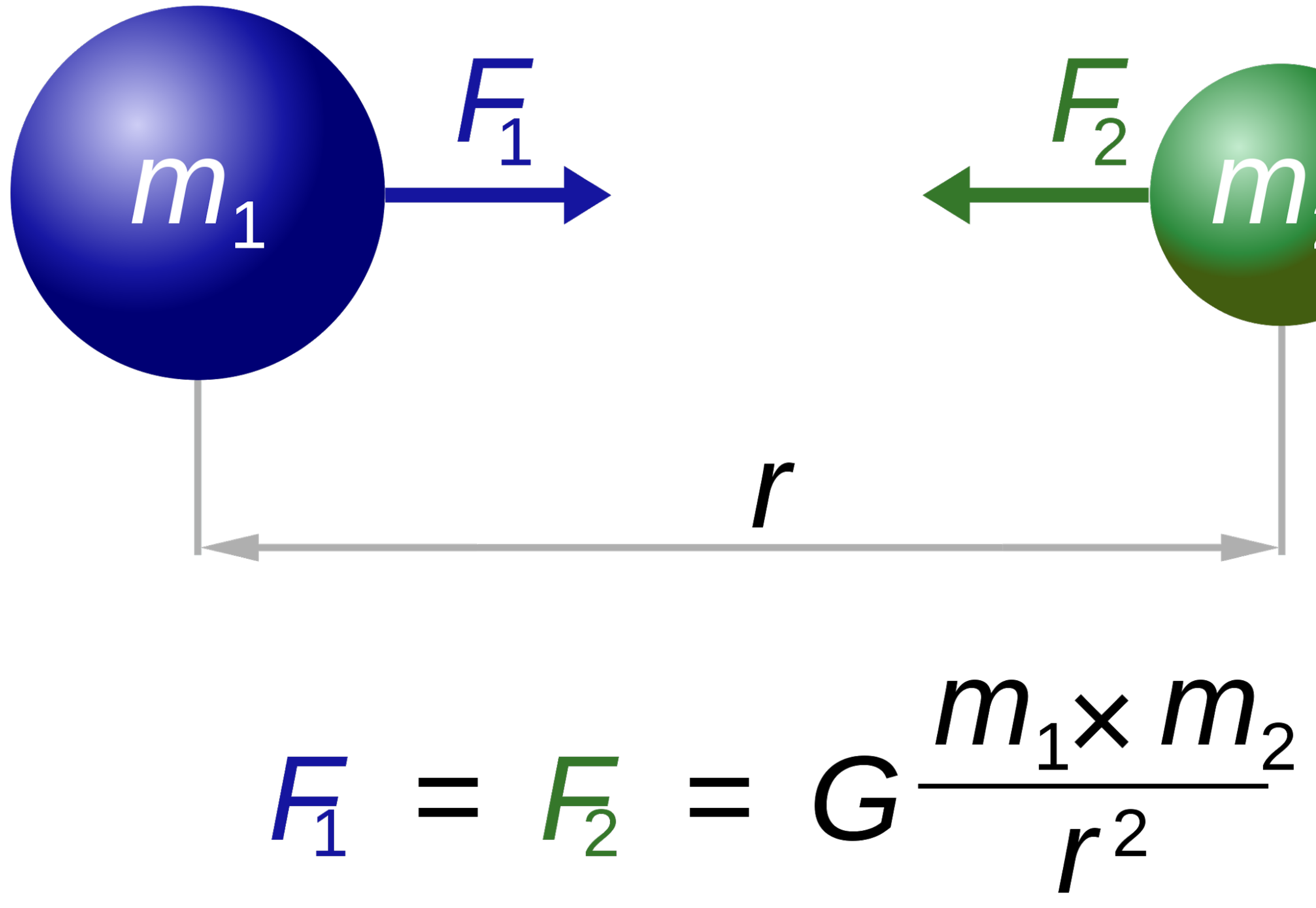
Gravity law of mobility



"You are less likely to go somewhere farther away than somewhere close."

Wikipedia user [Dennis Nilsson]

Gravity law of mobility

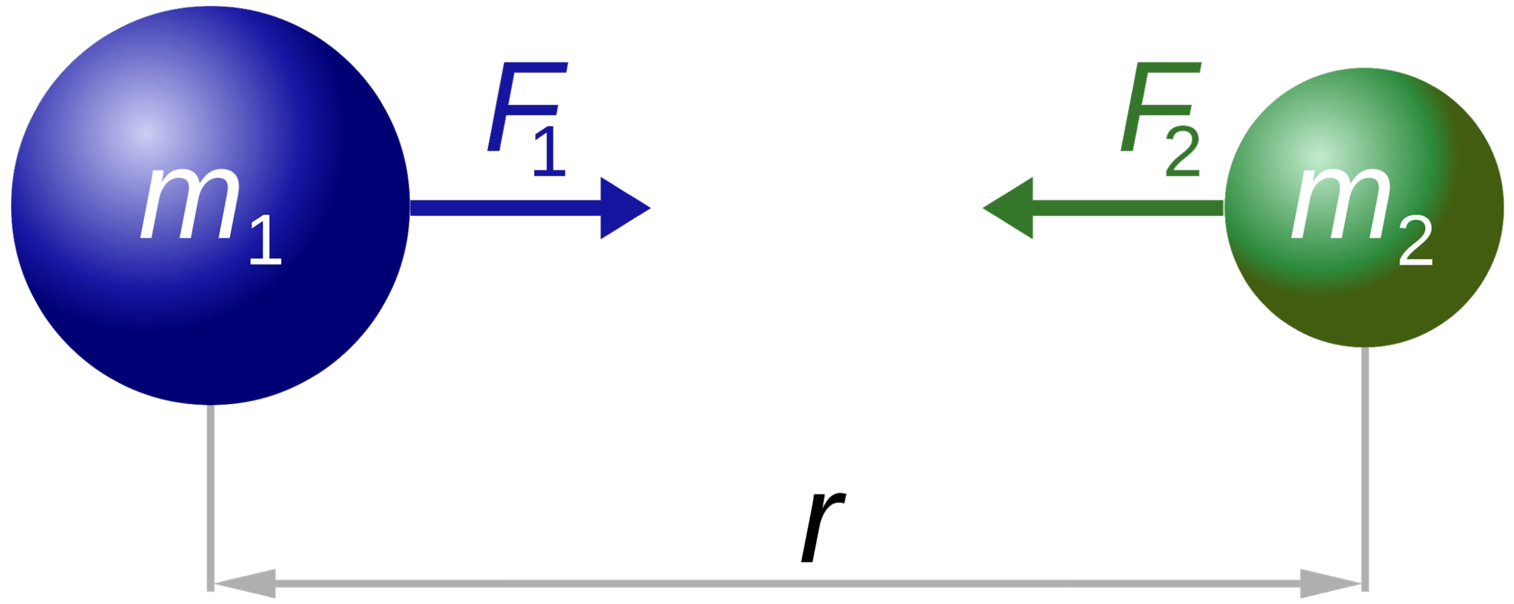


Wikipedia user [Dennis Nilsson]

"You are less likely to go somewhere farther away than somewhere close."

$$\hat{T}_{ij} = C m_i m_j f(r_{ij})$$

Gravity law of mobility



$$F_1 = F_2 = G\frac{m_1 \times m_2}{r^2}$$

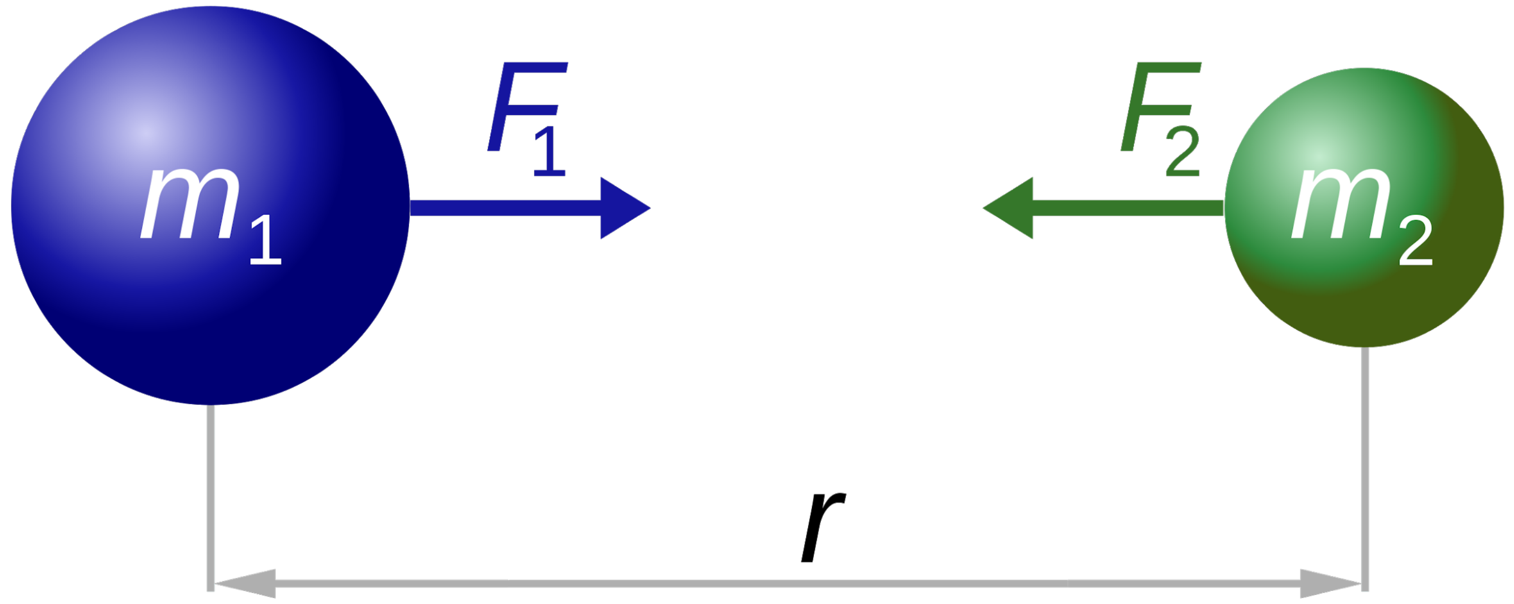
Wikipedia user [Dennis Nilsson]

"You are less likely to go somewhere farther away than somewhere close."

$$\hat{T}_{ij} = C m_i m_j f(r_{ij})$$

Flux

Gravity law of mobility



$$F_1 = F_2 = G\frac{m_1 \times m_2}{r^2}$$

Wikipedia user [Dennis Nilsson]

"You are less likely to go somewhere farther away than somewhere close."

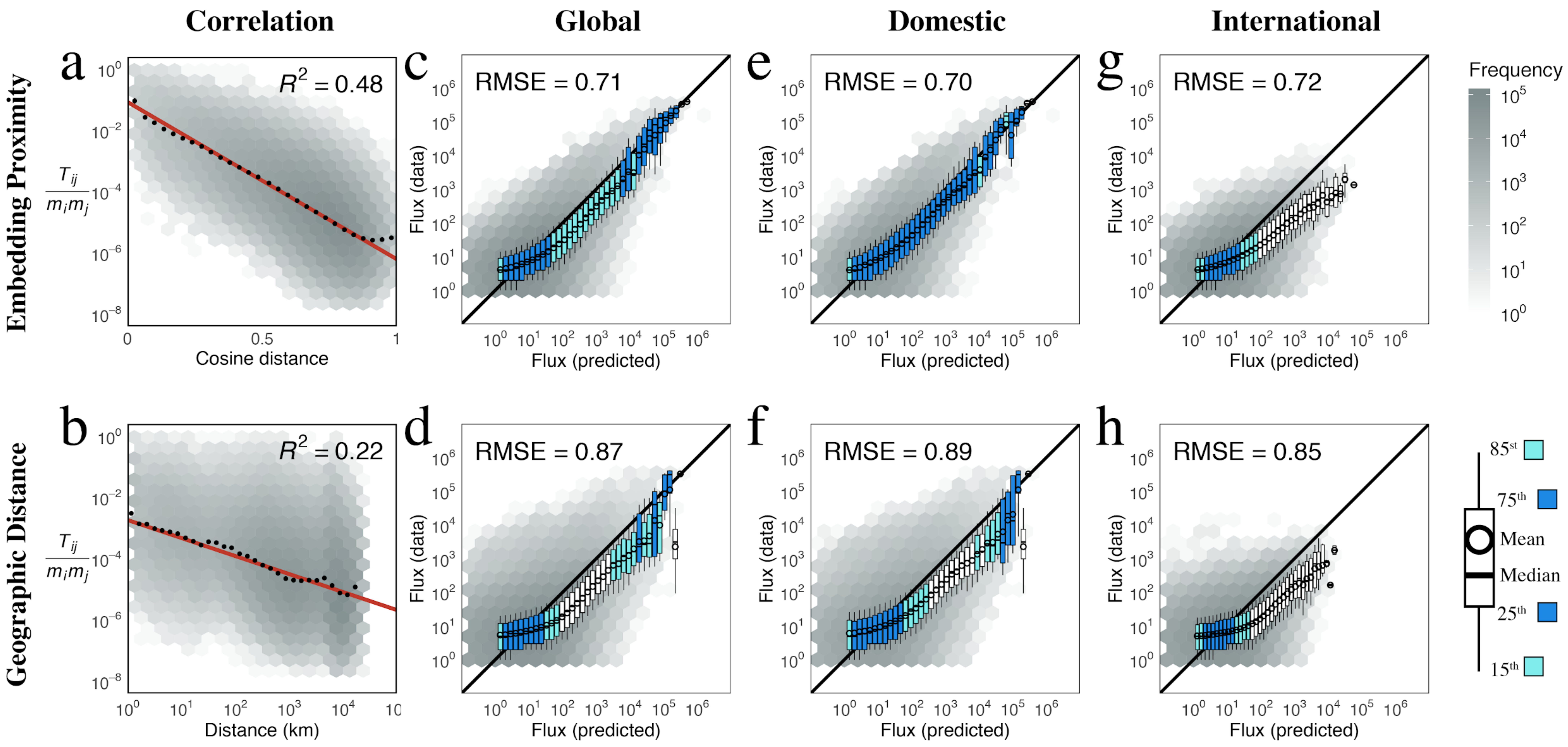
$$\hat{T}_{ij} = C m_i m_j f(r_{ij})$$

Flux

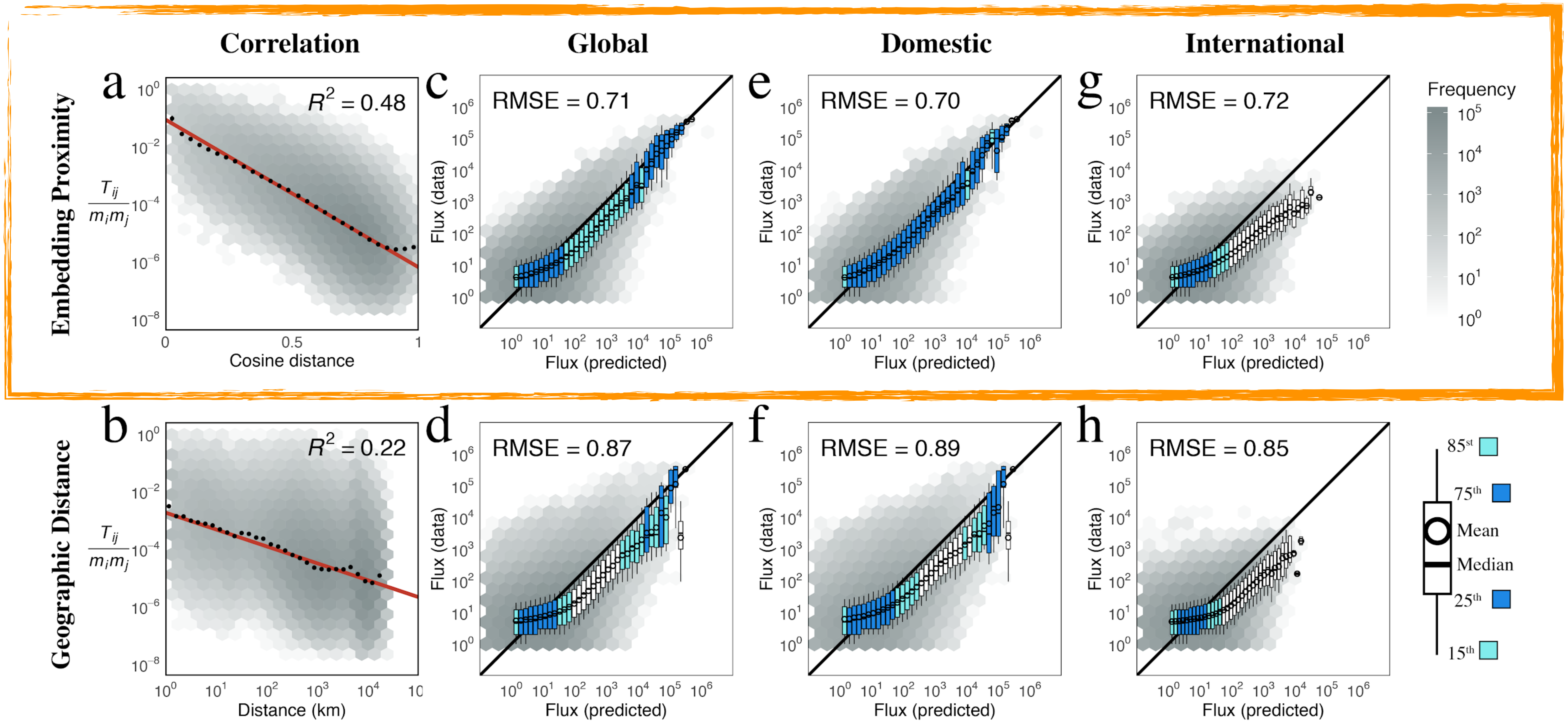
Population

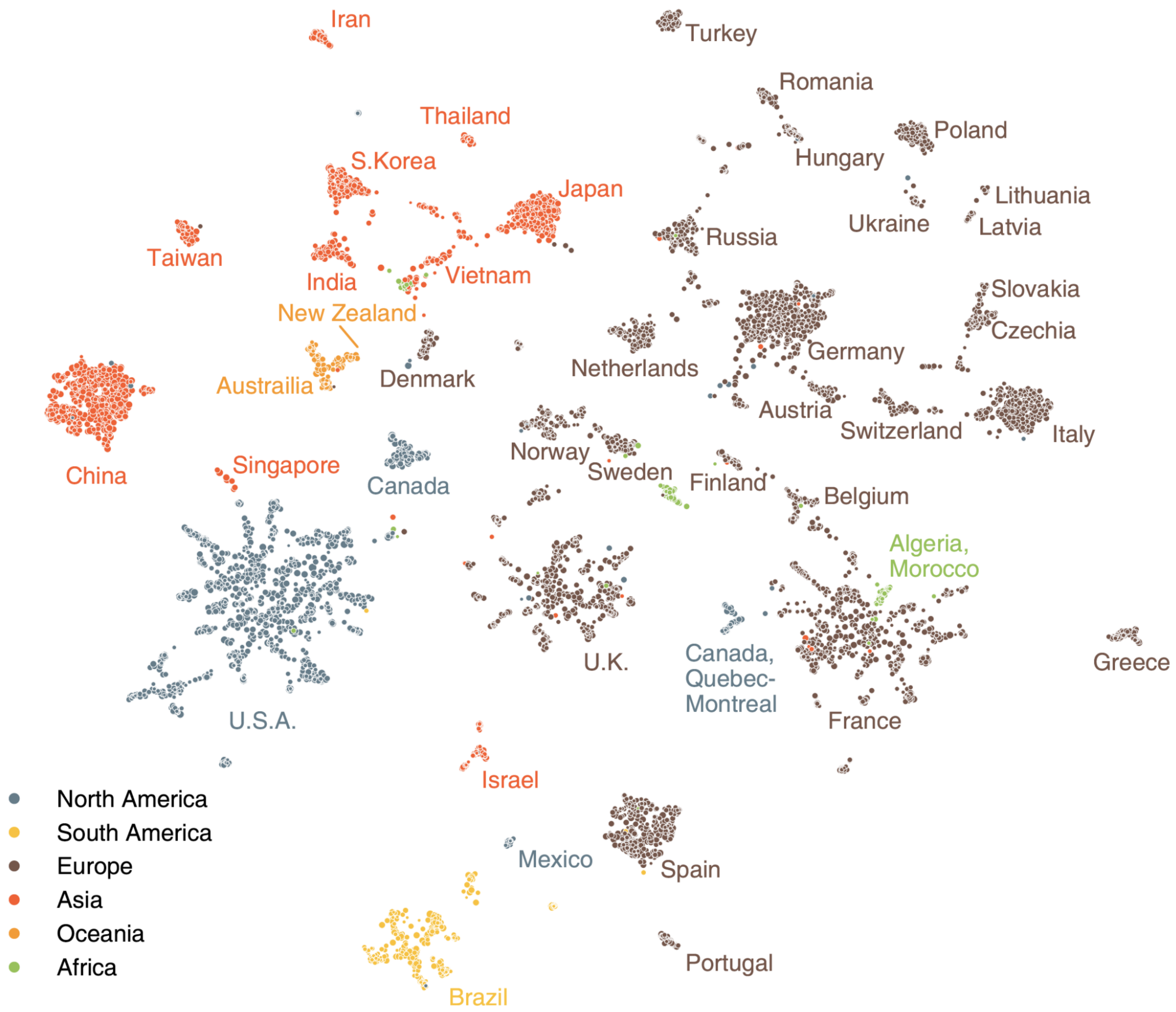
a decay function

Embedding fits the gravity law much better!



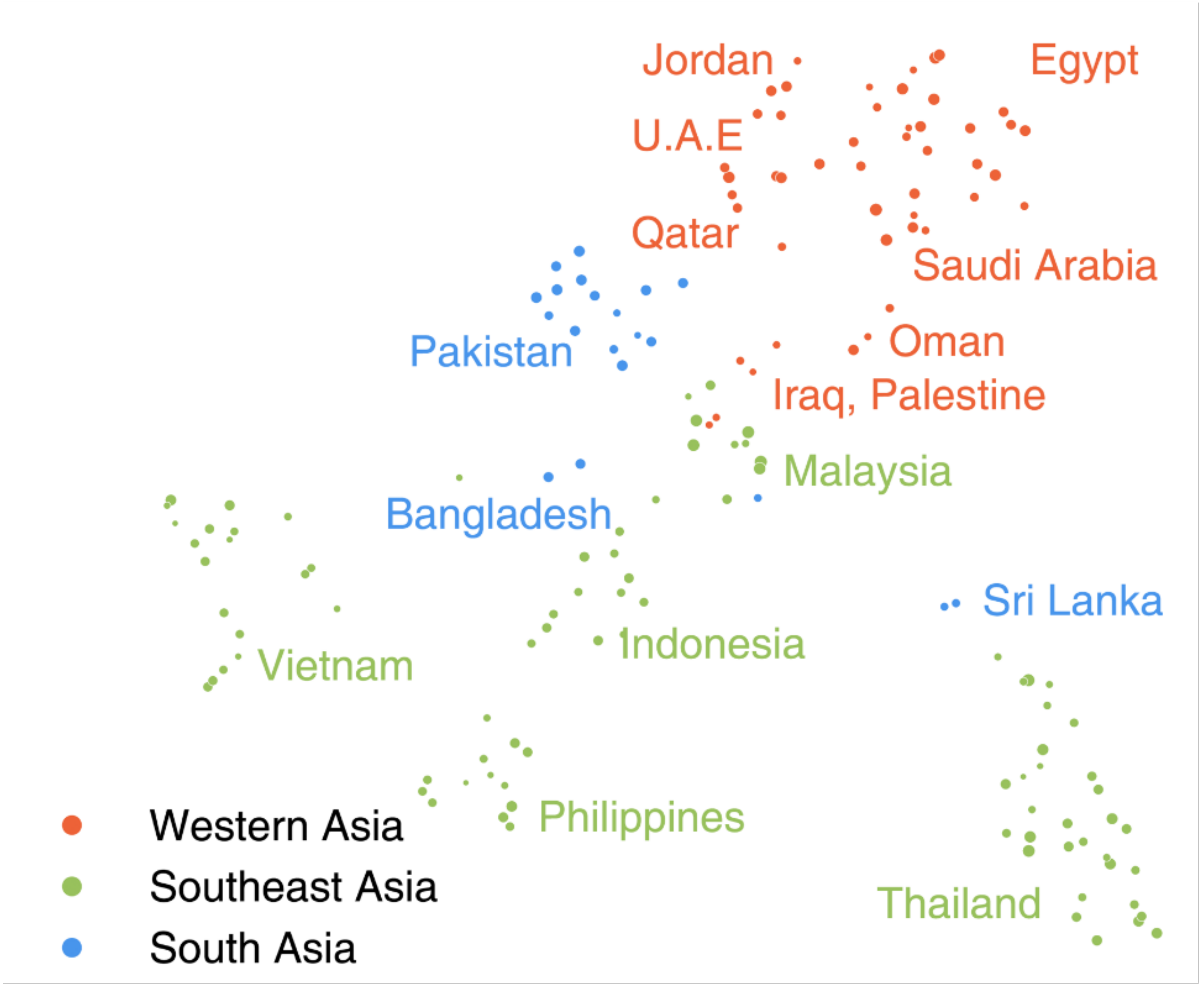
Embedding fits the gravity law much better!

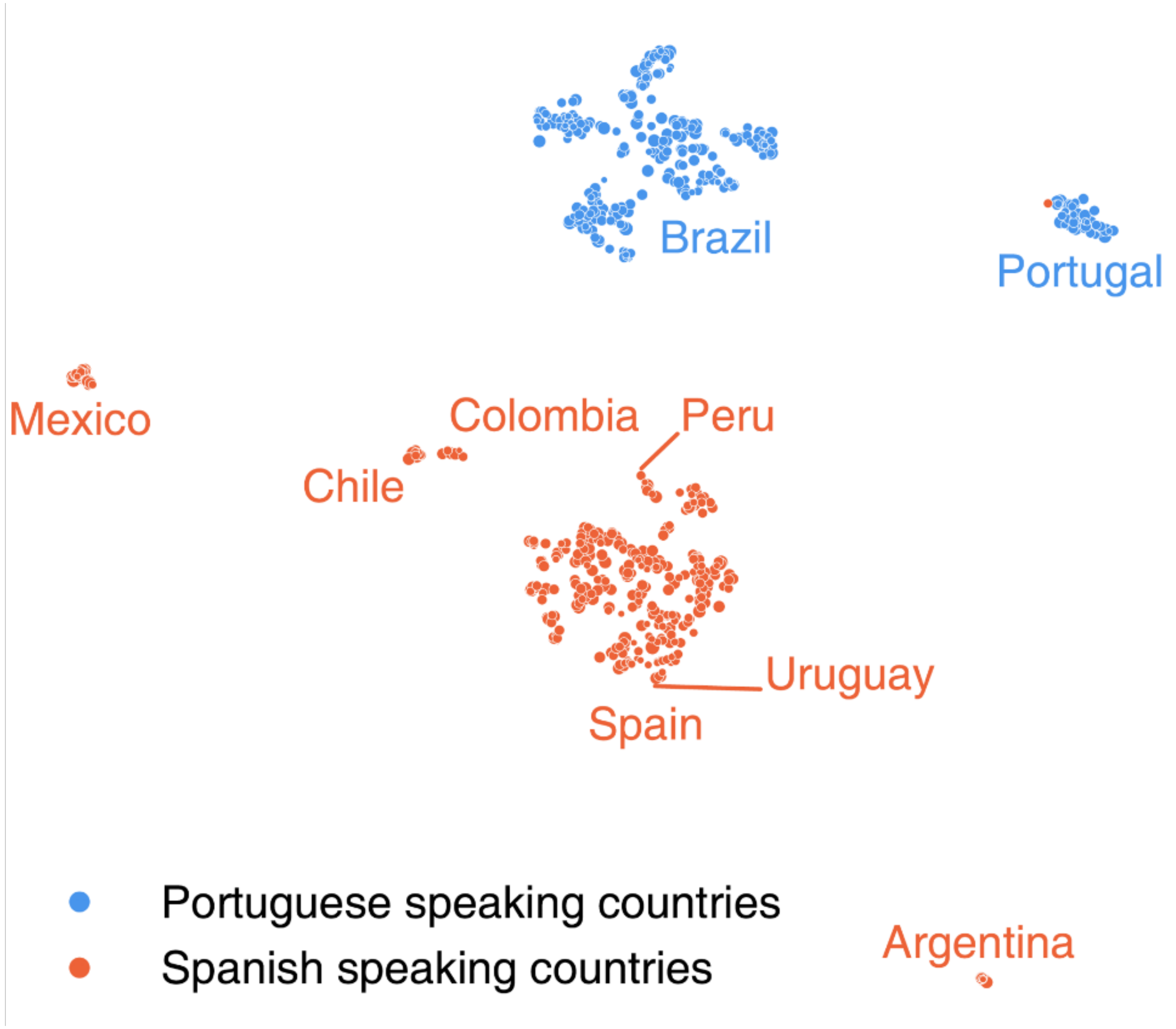




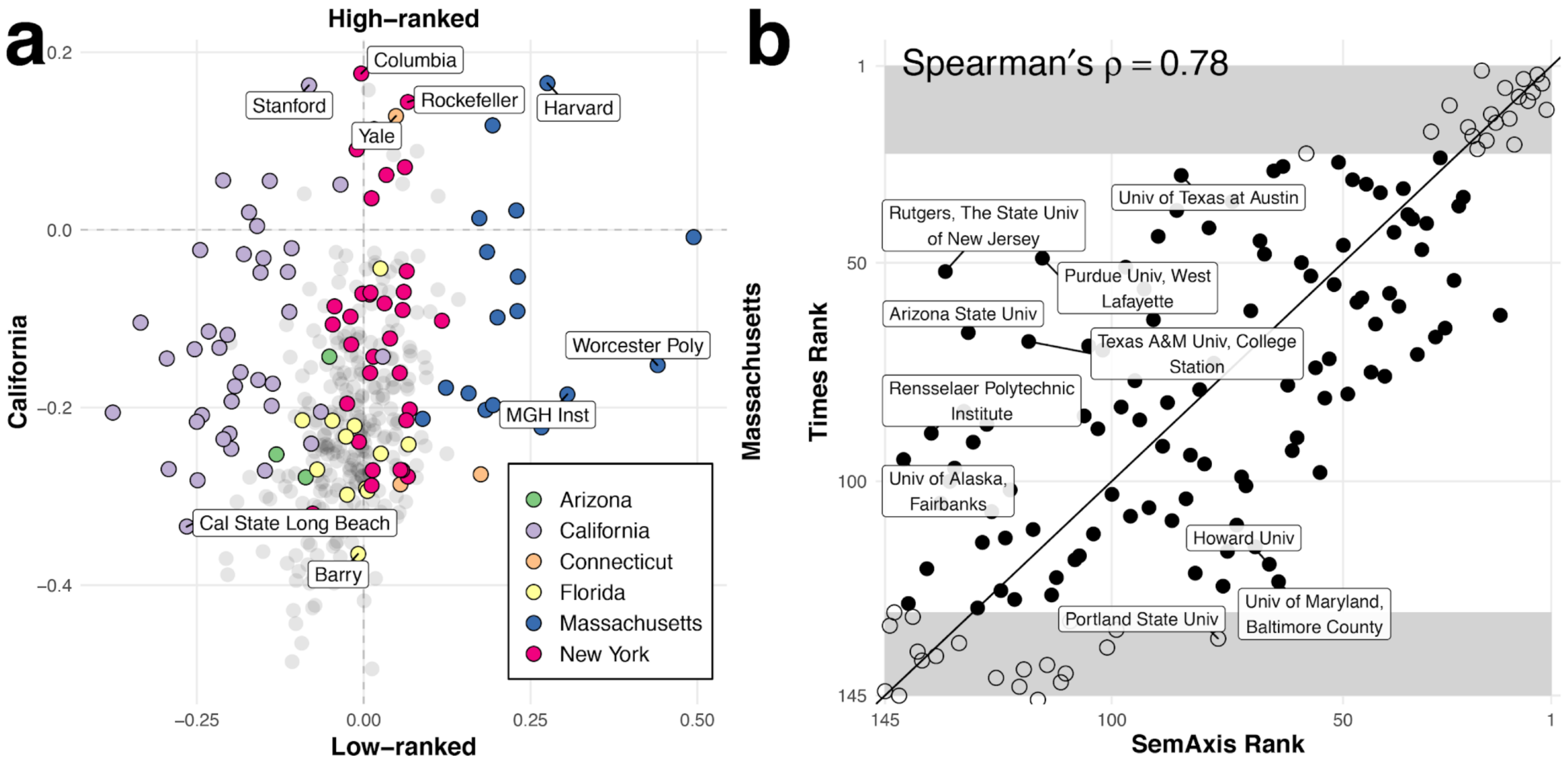
Iran
Turkey
Romania
Thailand
Poland
Hungary
S.Korea
Japan
Lithuania
Ukraine
Latvia
Taiwan
Russia
India
Vietnam
Slovakia
New Zealand
Czechia
Germany
Netherlands
Denmark
Austrailia
Austria
Switzerland
Italy
China
Norway
Singapore
Sweden
Canada
Finland
Belgium
Algeria,
Morocco
Canada,
Quebec-
Montreal
U.K.
Greece
U.S.A.
France
Israel
North America
South America
Europe
Asia
Oceania
Africa
Mexico
Spain
Portugal
Brazil

It encodes regional & cultural structures





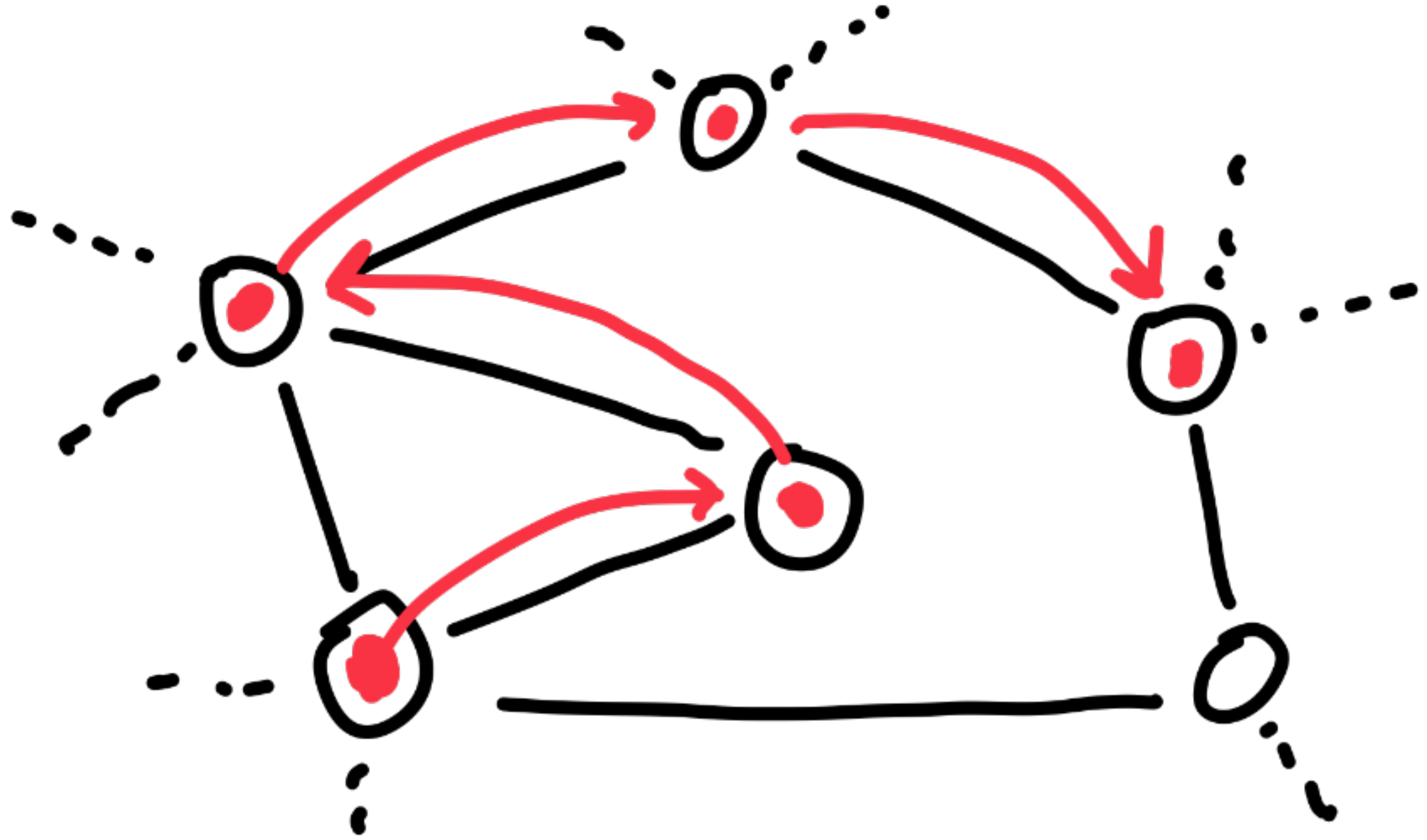
It encodes prestige



Why?

But most surprisingly, we found that, with some maths...

$$P(w_t \mid w_c) \approx \frac{p_n(t)\exp(\mathbf{k}_t \cdot \mathbf{q}_c)}{\sum_i p_n(i)\exp(\mathbf{k}_i \cdot \mathbf{q}_c)}$$



flux

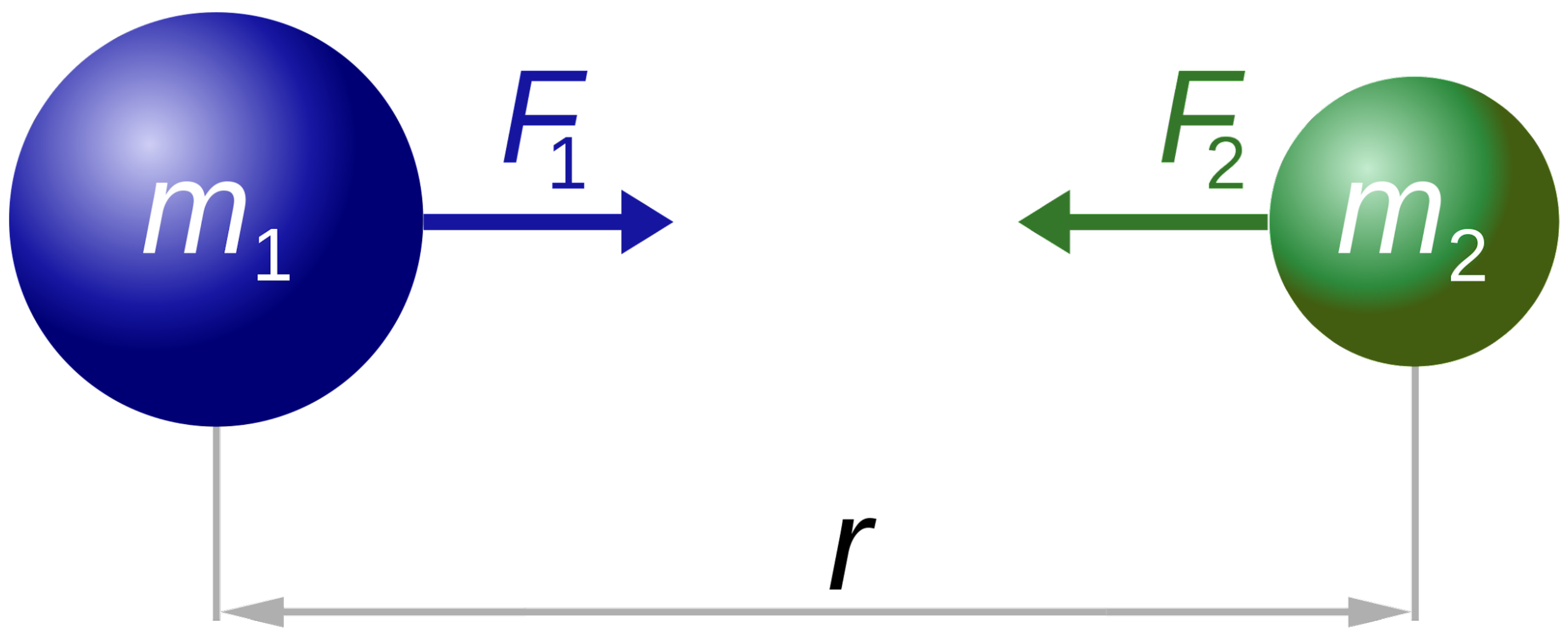
$$\hat{T}_{ij} \propto P(j \mid i)P(i) \propto \frac{P(i)P(j)\exp(\mathbf{k}_j \cdot \mathbf{q}_i)}{\sum_{j'} P(j')\exp(\mathbf{k}_{j'} \cdot \mathbf{q}_i)}$$

when embedding dimension is sufficiently large

$$\hat{T}_{ij} = \hat{T}_{ji} \propto P(i)P(j)\exp(\mathbf{k}_i \cdot \mathbf{k}_j)$$

Gravity law!

Word2vec model is equivalent to the **Gravity law of mobility!**



$$F_1 = F_2 = G\frac{m_1 \times m_2}{r^2}$$

Wikipedia user [Dennis Nilsson]

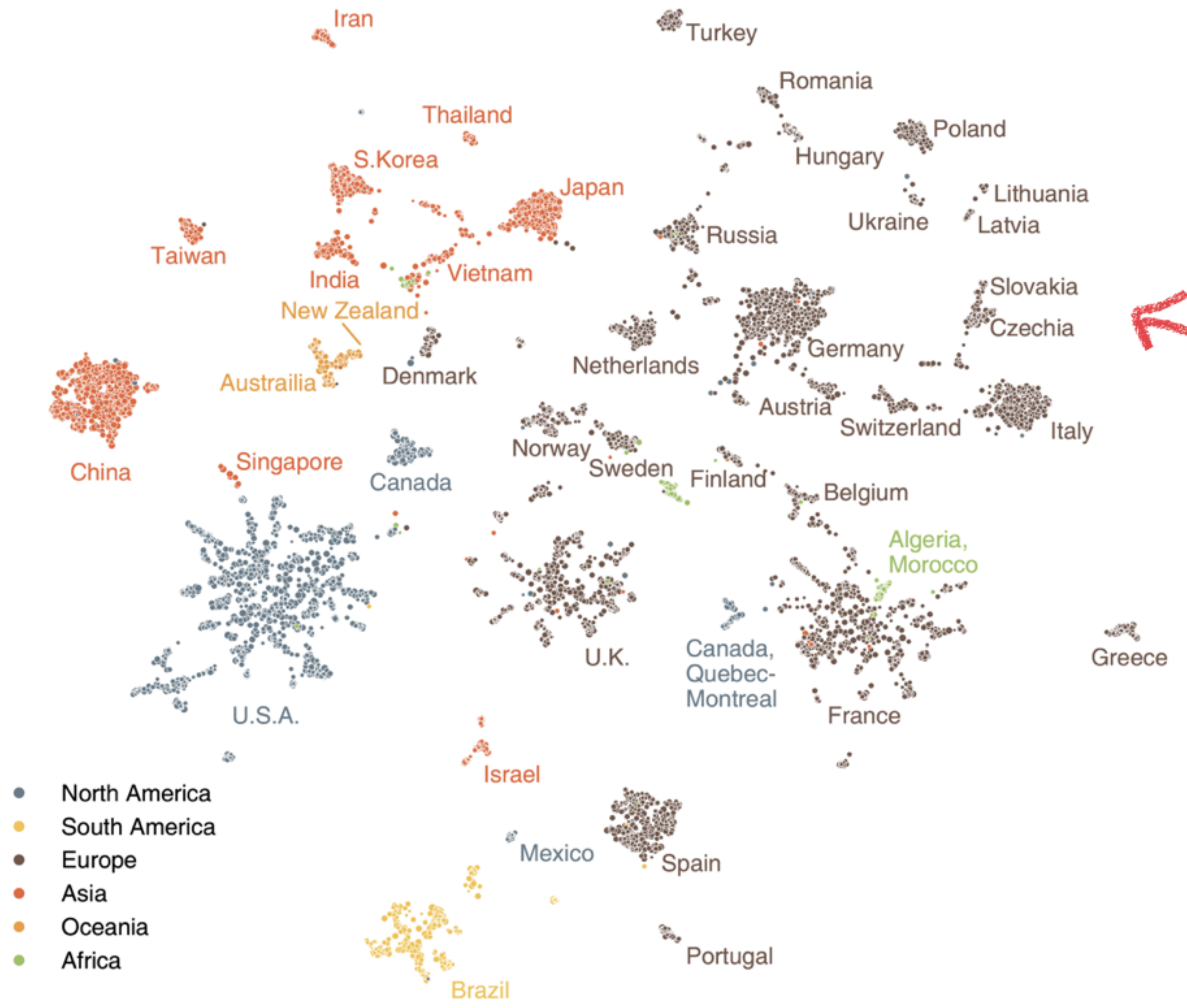
$$\hat{T}_{ij} = C m_i m_j f(r_{ij})$$

Flux

Population

A decay function

word2vec model ~ gravity law



The embedding distance has a concrete, interpretable meaning.

The space where the institutions are arranged so that the flux and distance between them satisfies the gravity law of mobility!

Interestingly…

Gravity law of embedding

$$F = G\frac{m_1 m_2}{r^2}$$

Mass

$$m_i \sim P(i)$$

Closeness

$$\frac{1}{r^2} \sim \exp(u_i^\top v_j)$$

This law is model agnostic!

Gravity law of embedding

$$F = G\frac{m_1 m_2}{r^2}$$

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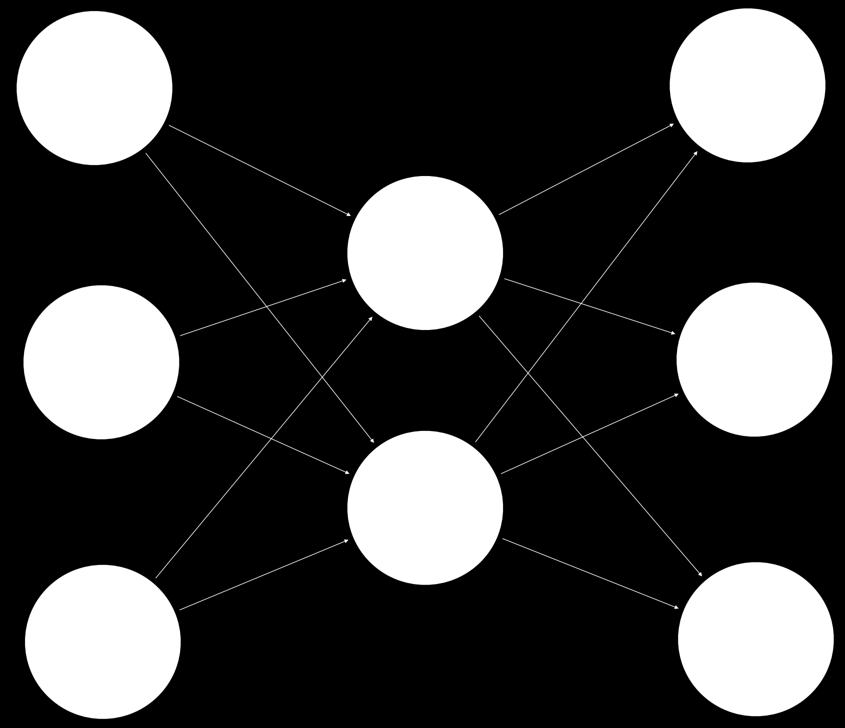
This law is model agnostic!

Affiliation trajectories

Univ. A Univ. B Gov. A Gov. A College. A

word2vec



Gravity law of embedding

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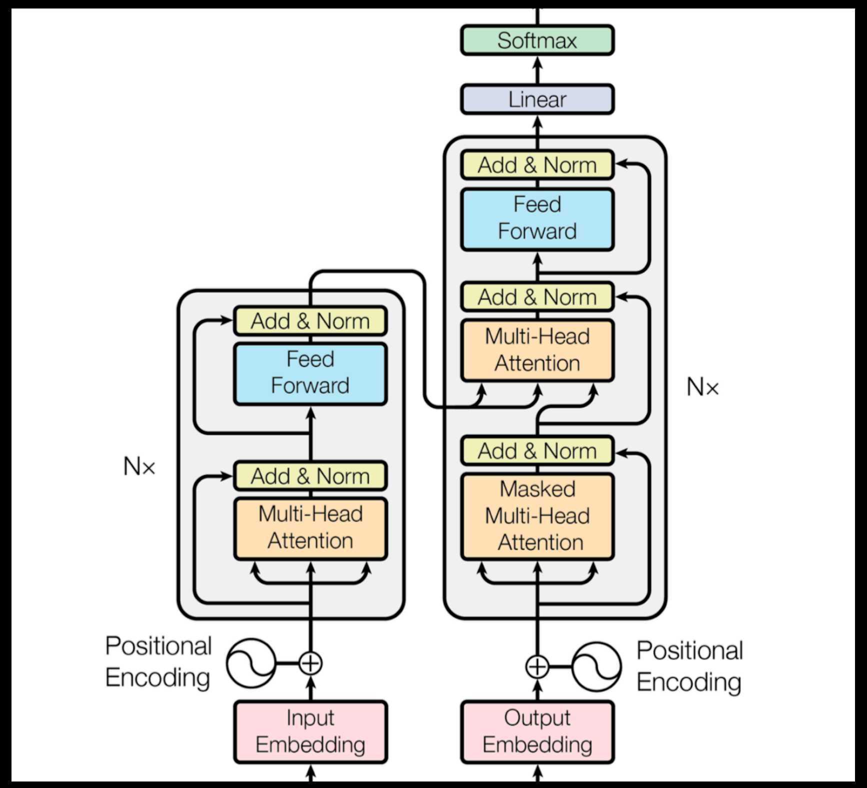
Affiliation trajectories

Univ. A Univ. B Gov. A Gov. A College. A

Transformers



Gravity law of embedding

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Mass

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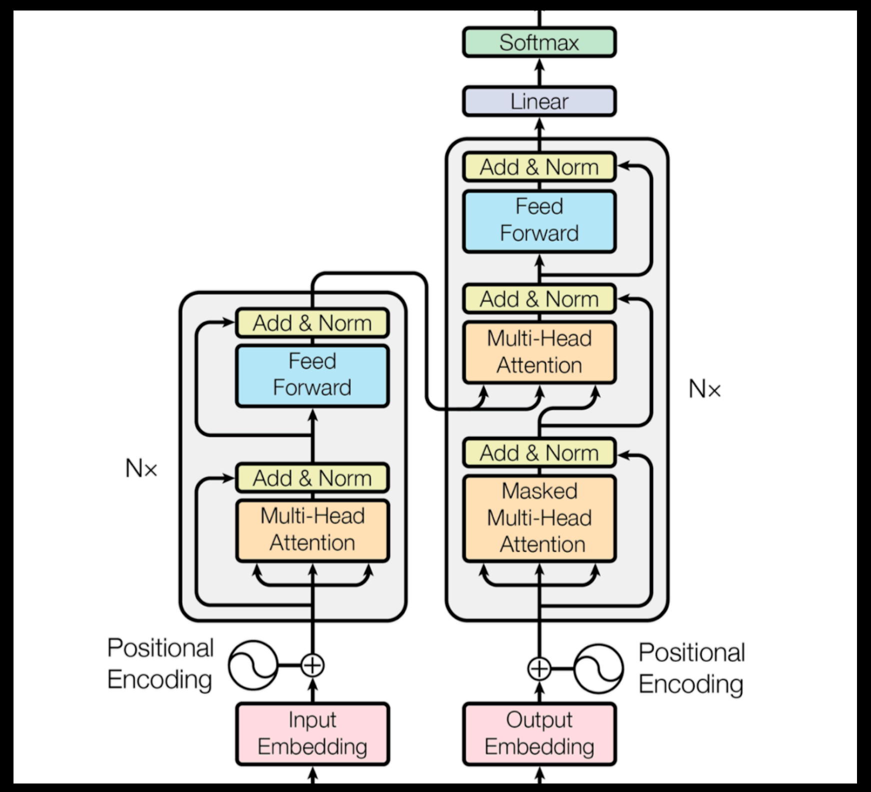
Closeness

$$\frac{1}{r^2} \sim \exp(u_i^\top v_j)$$

This law is model agnostic.

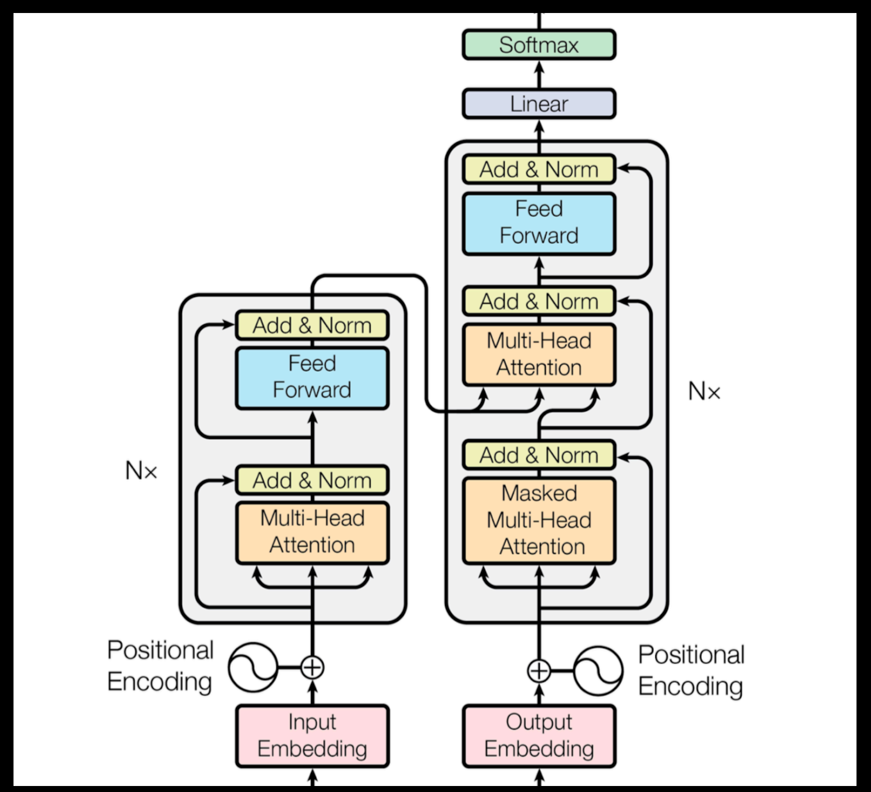
Paper text trajectories

Transformers



Paper text trajectories

Transformers



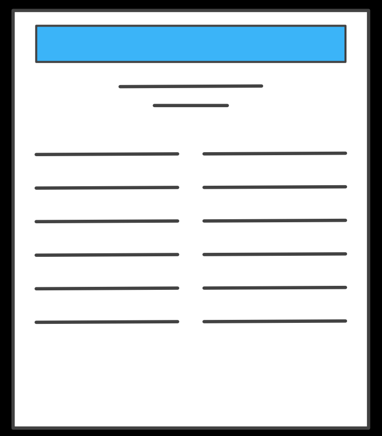
Paper title

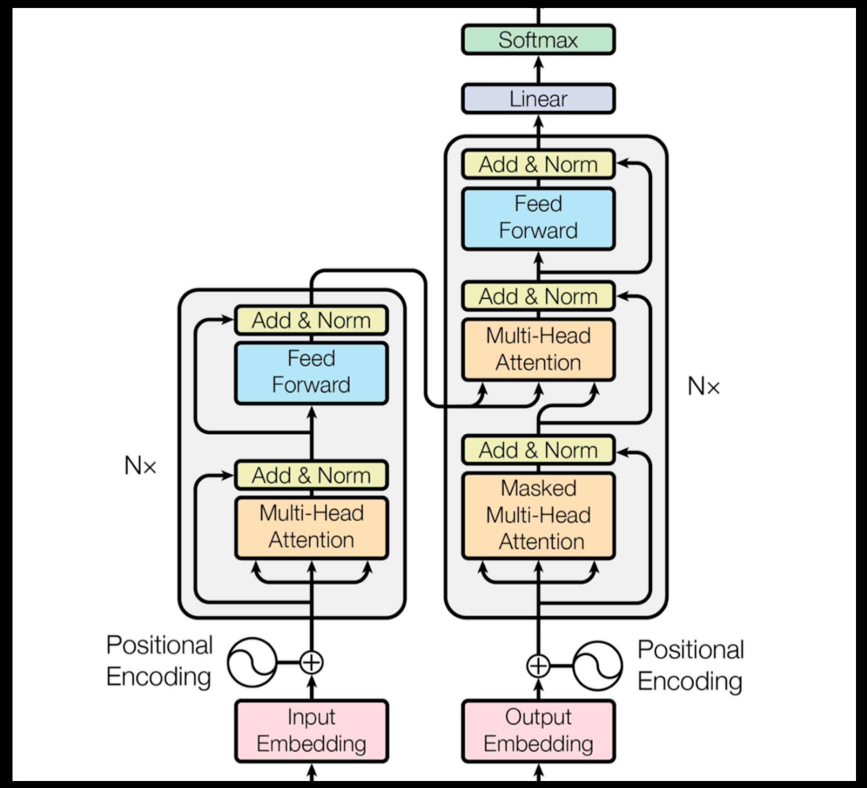
Training

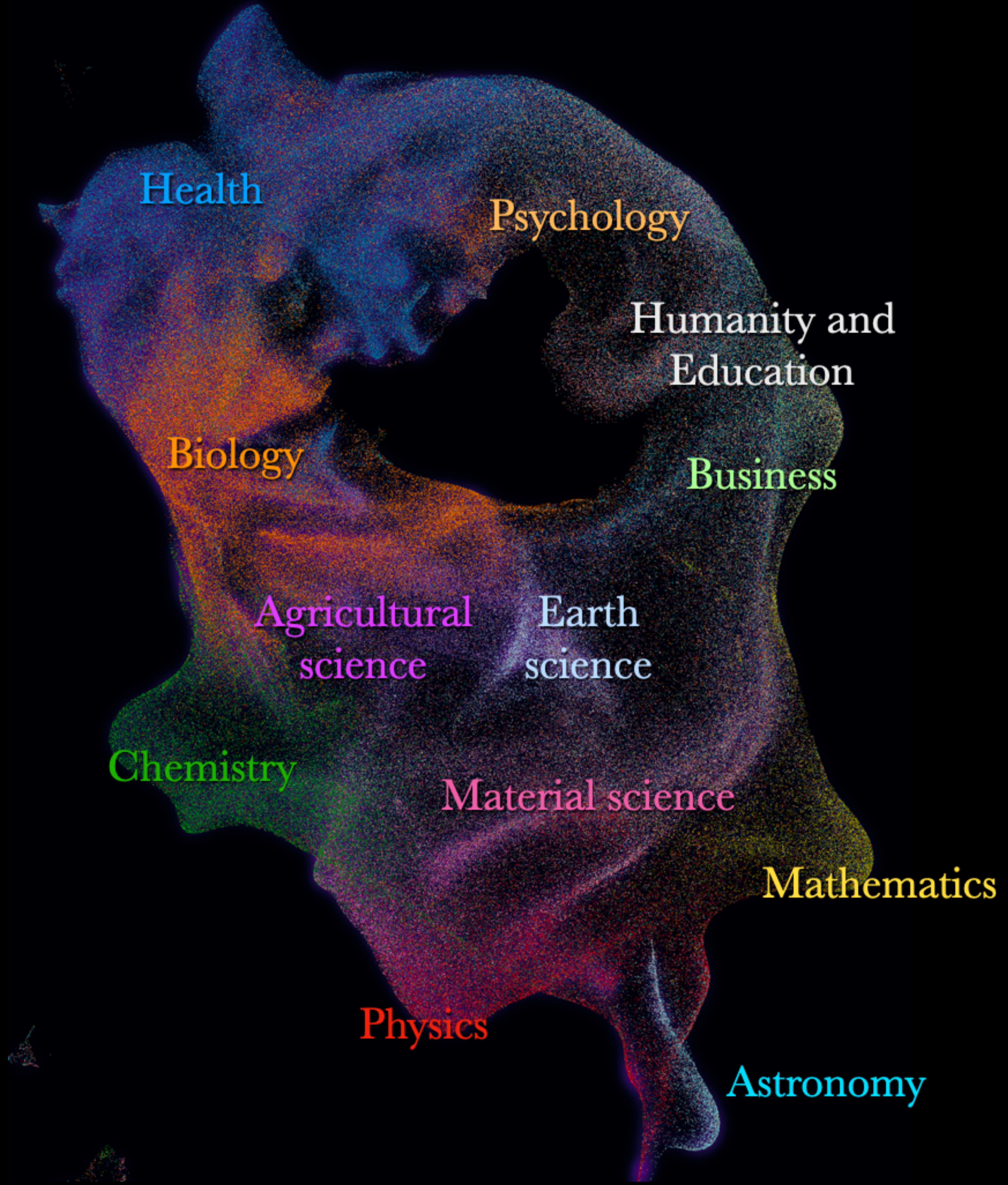
RoBERTa transformers

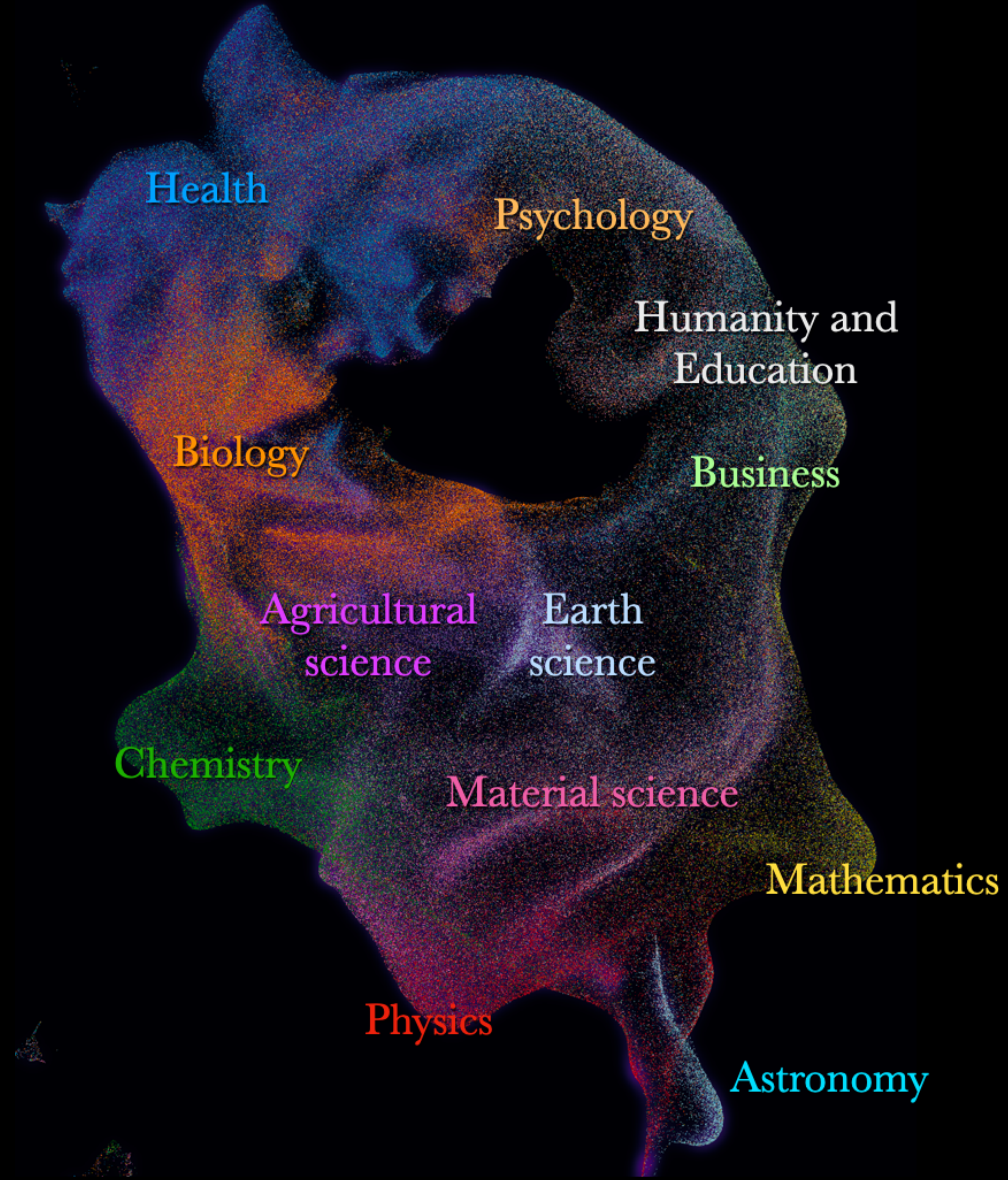
SciSciNet data

(134M papers published before 2022)




Softmax
Linear
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Add & Norm
Masked Multi-Head Attention
Nx
Add & Norm
Feed Forward
Add & Norm
Multi-Head Attention
Nx
Positional Encoding
Positional Encoding
Input Embedding
Output Embedding


Health
Psychology
Humanity and Education
Biology
Business
Agricultural science
Earth science
Chemistry
Material science
Mathematics
Physics
Astronomy


Health
Psychology
Humanity and Education
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Earth science
Chemistry
Material science
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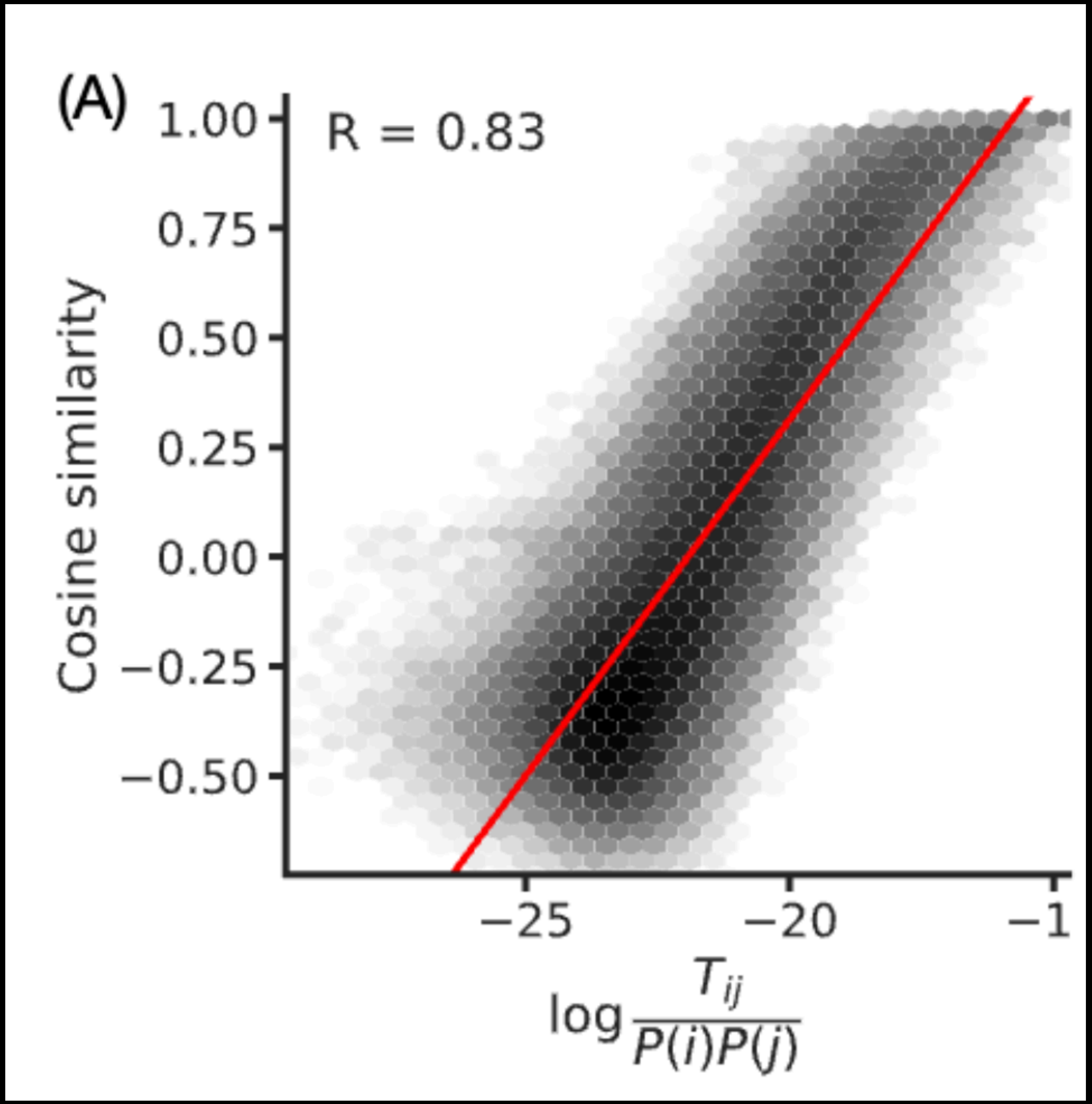
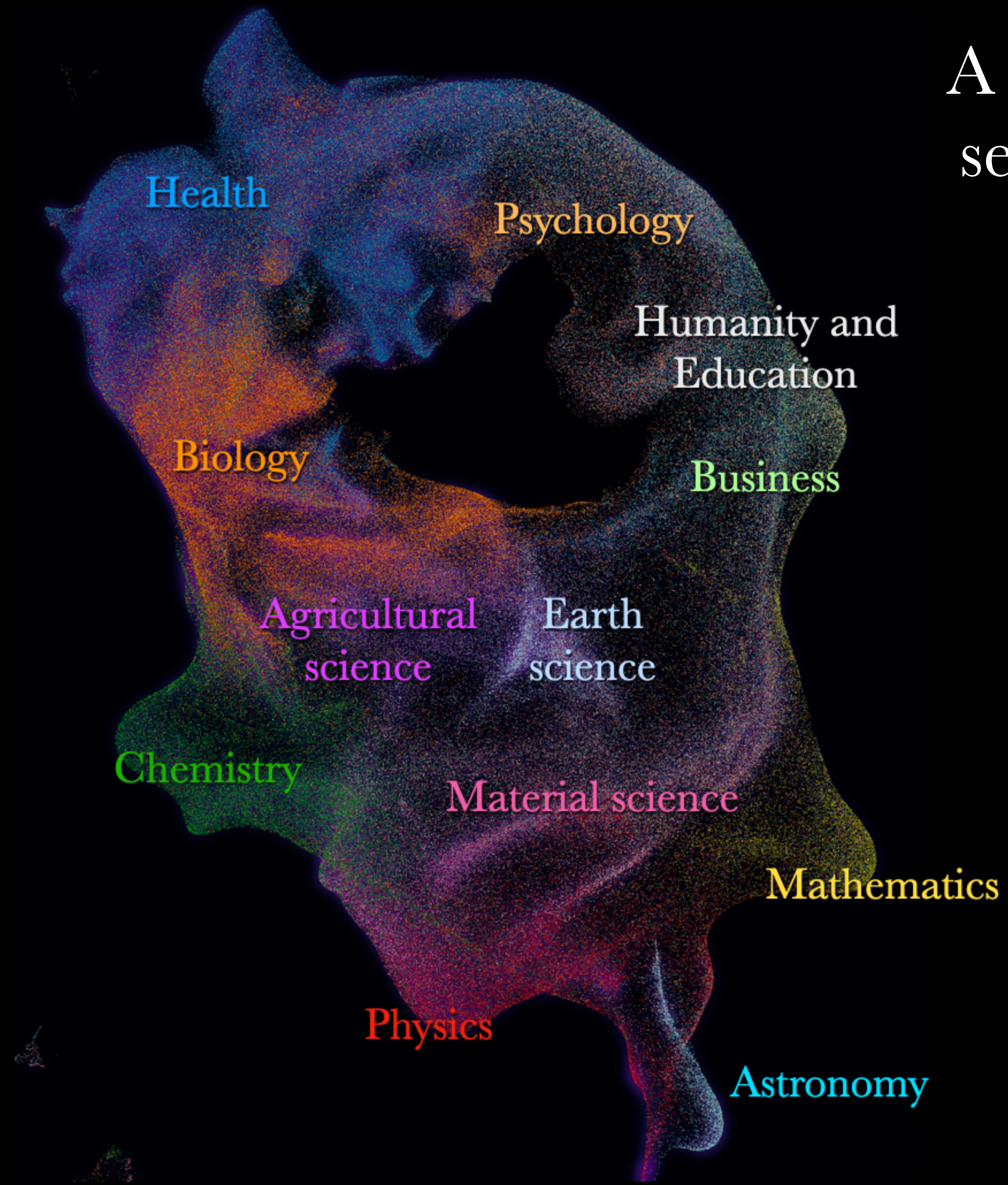
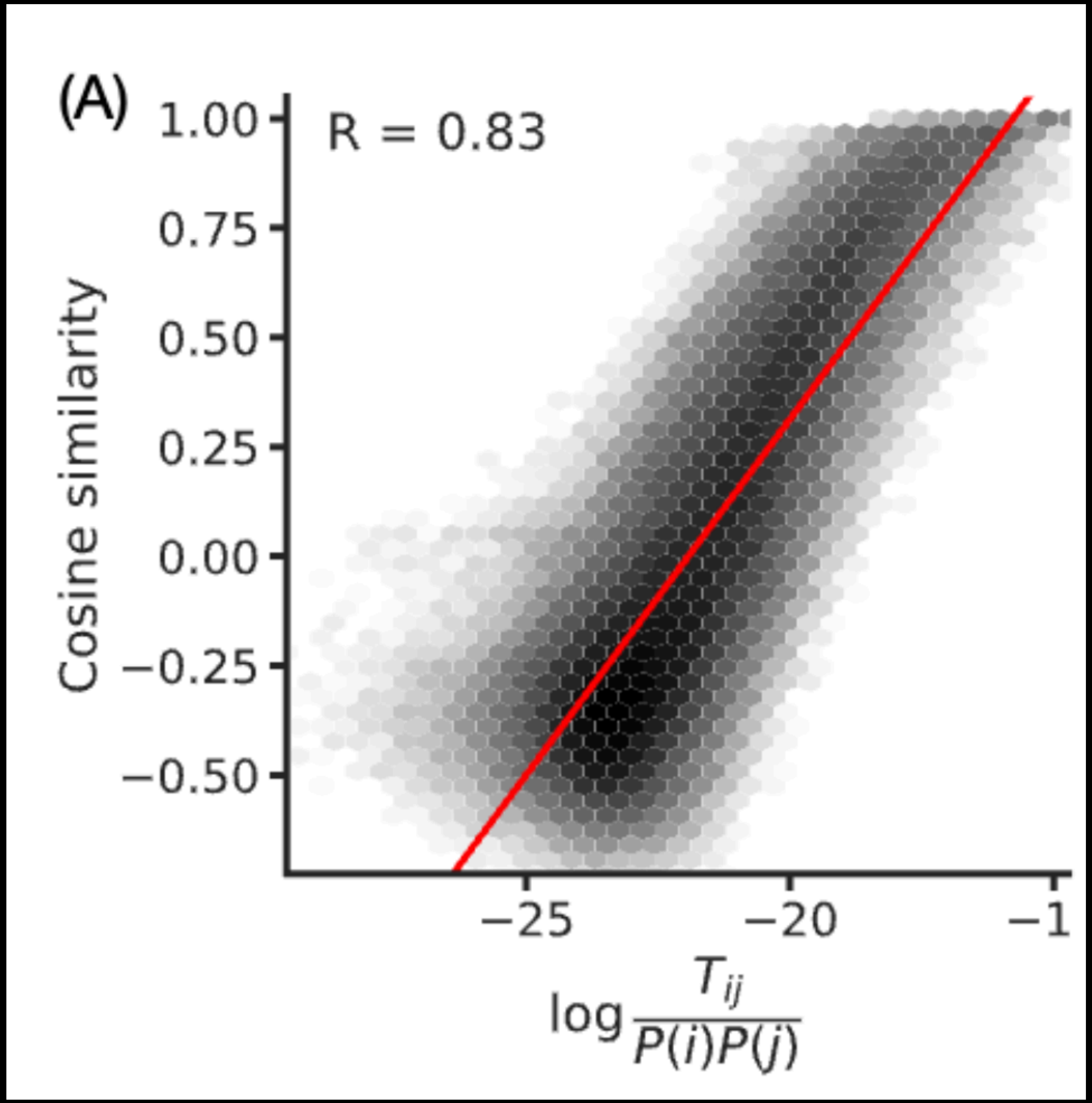
Physics
Astronomy


(A)
R = 0.83
Cosine similarity
1.00
0.75
0.50
0.25
0.00
−0.25
−0.50
−25
−20
−1
$\log \frac{T_{ij}}{P(i)P(j)}$

A representation space for any possible sentences, where the gravity law holds






Health
Psychology
Humanity and
Education
Biology
Business
Agricultural
science
Earth
science
Chemistry
Material science
Mathematics
Physics
Astronomy

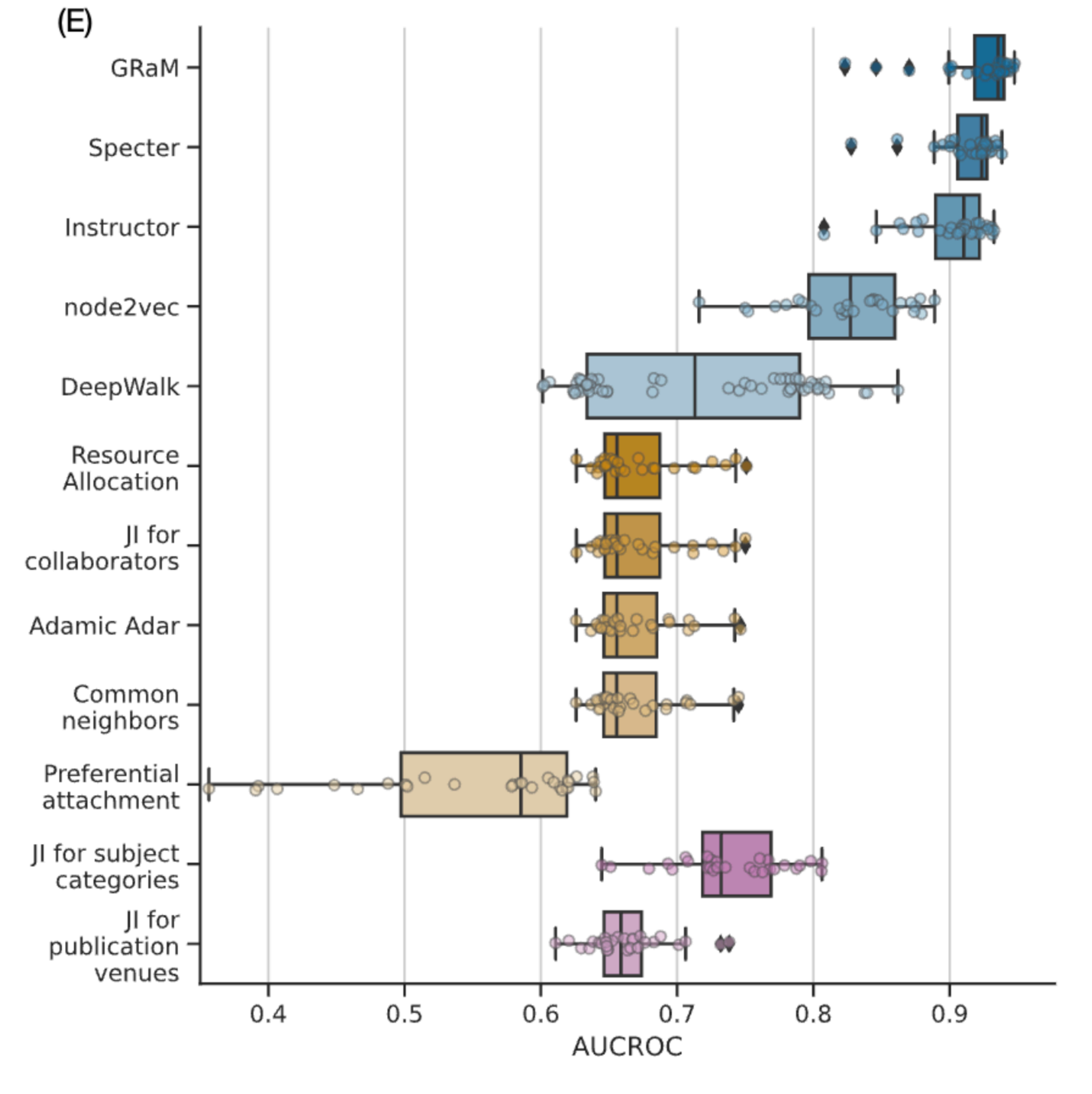
An LLM that produces embeddings of any paper titles, where distance captures how easy for scientists to make the jump

We can use intuitive space analogy.

Predicting new collaborations

Pick two scientists who have never collaborated

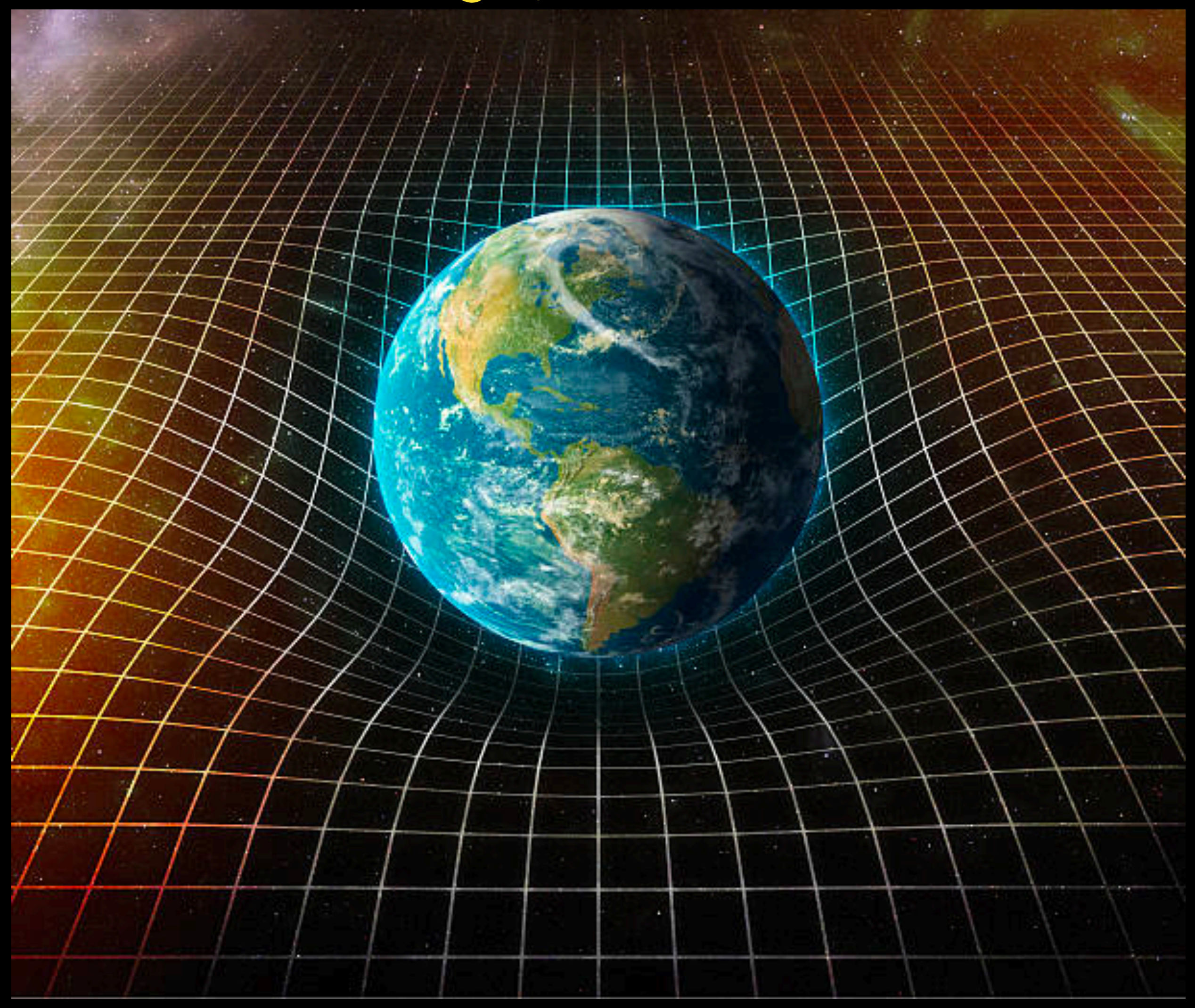
Measure the distance in the given year



We can bring tools from physics

New attraction area

Gravity potential



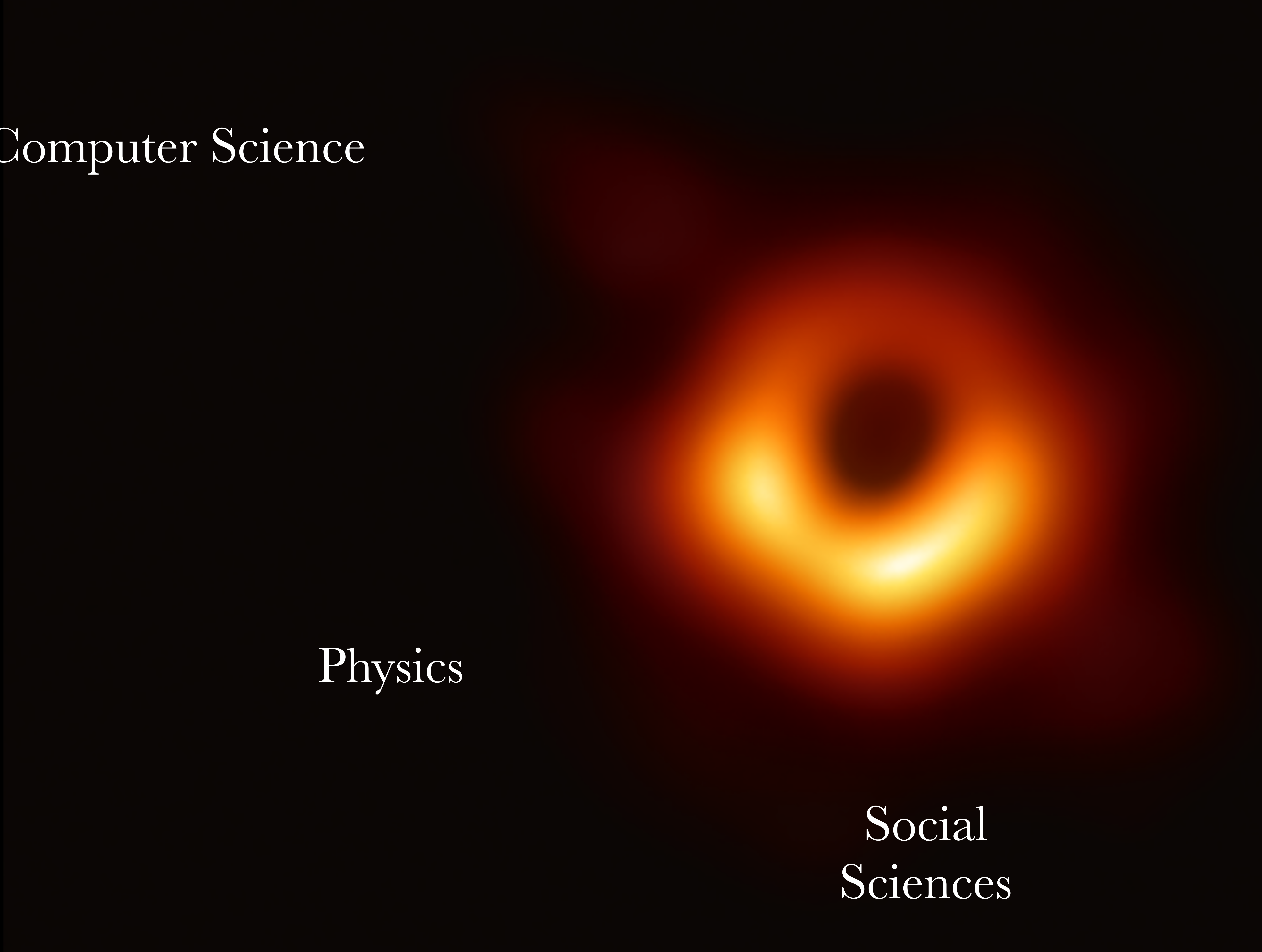
Gravity law of embedding

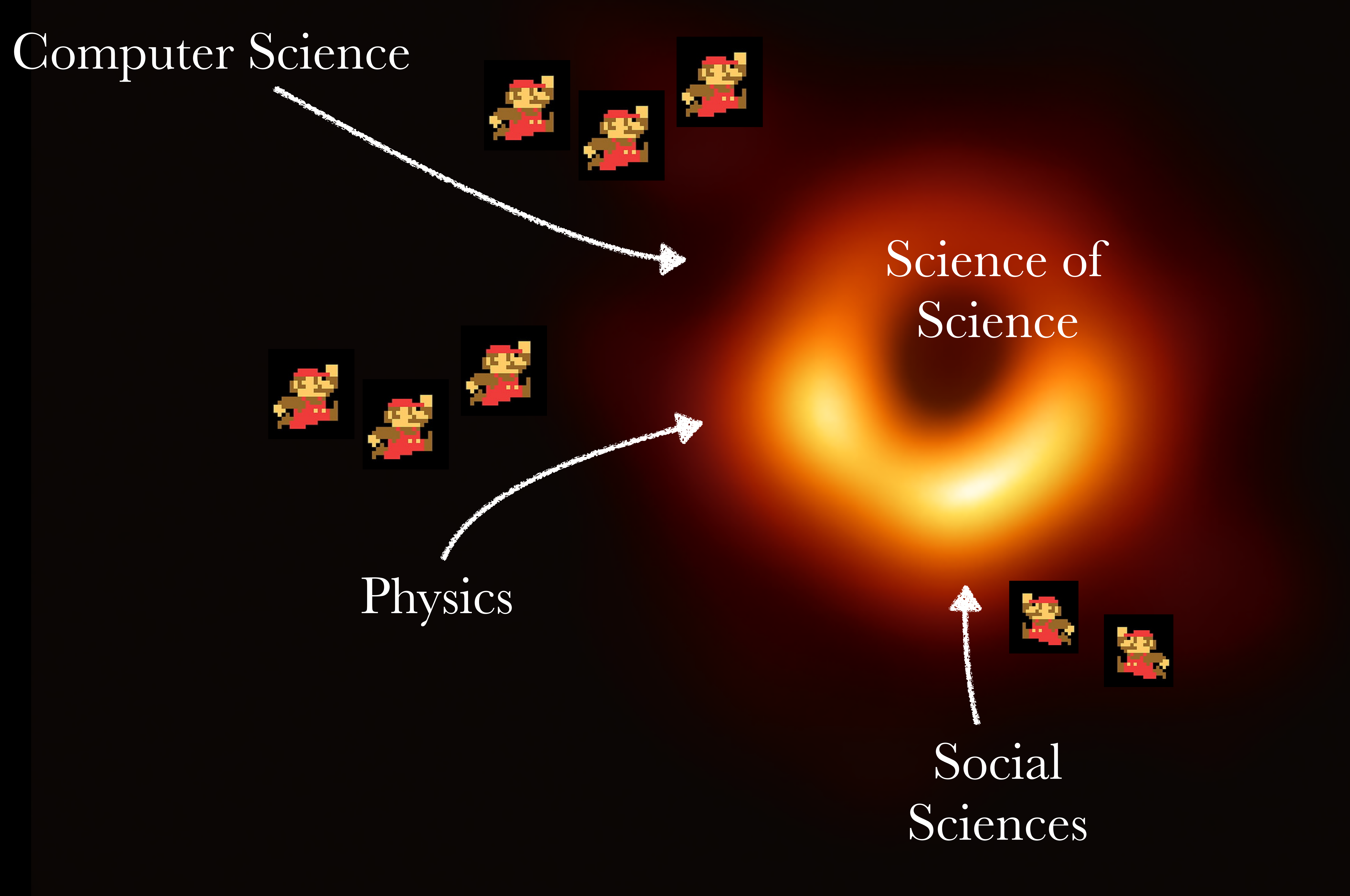
$$P(i,j) = \frac{1}{Z} P(i) P(j) \exp\left(v_j^\top u_i\right)$$

Gravity potential

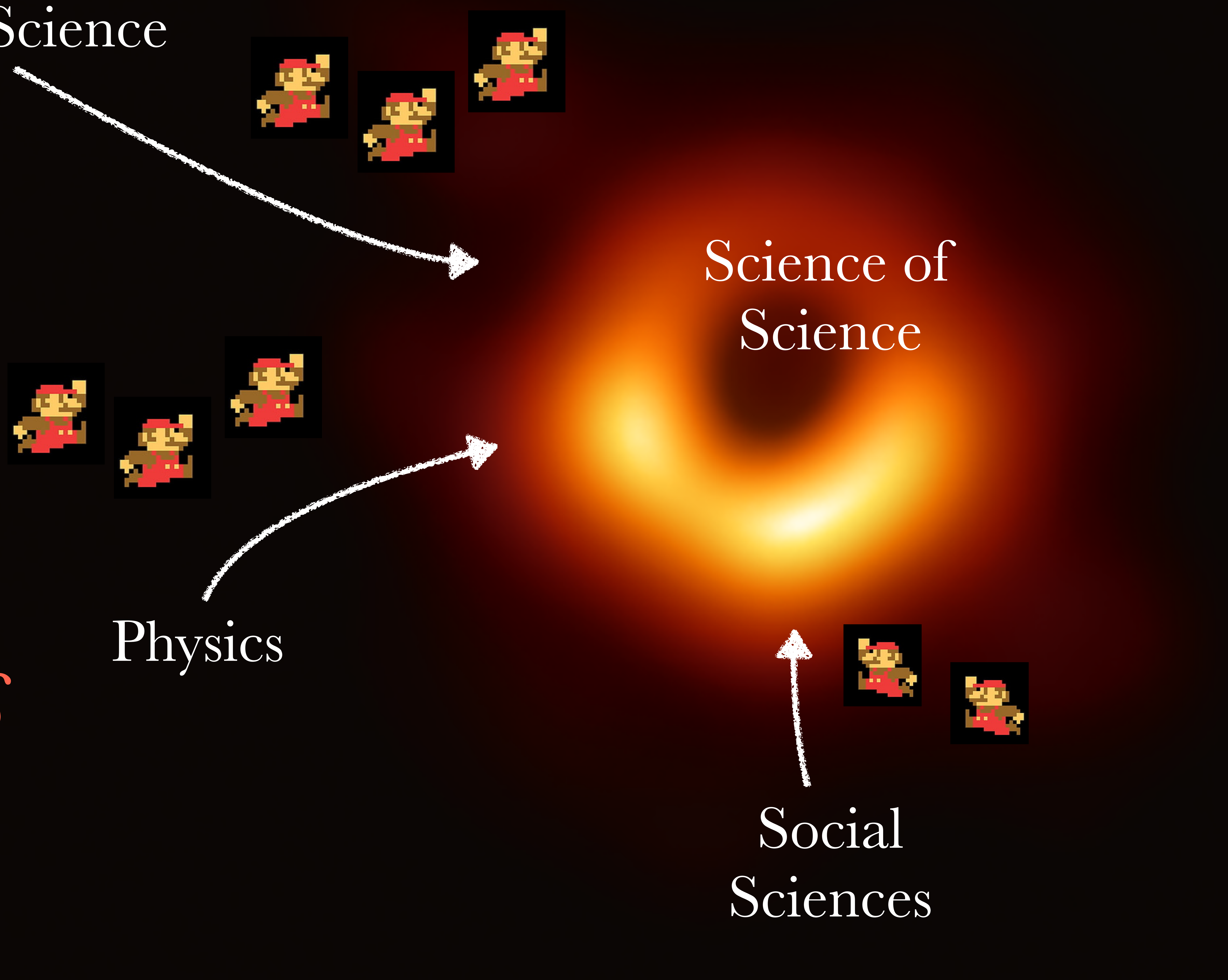
$$\Phi(u) = -\frac{1}{Z} \sum_j P(j) \exp\left(v_j^\top u\right)$$

Gravity potential operationalizes how many scientists an area attracts

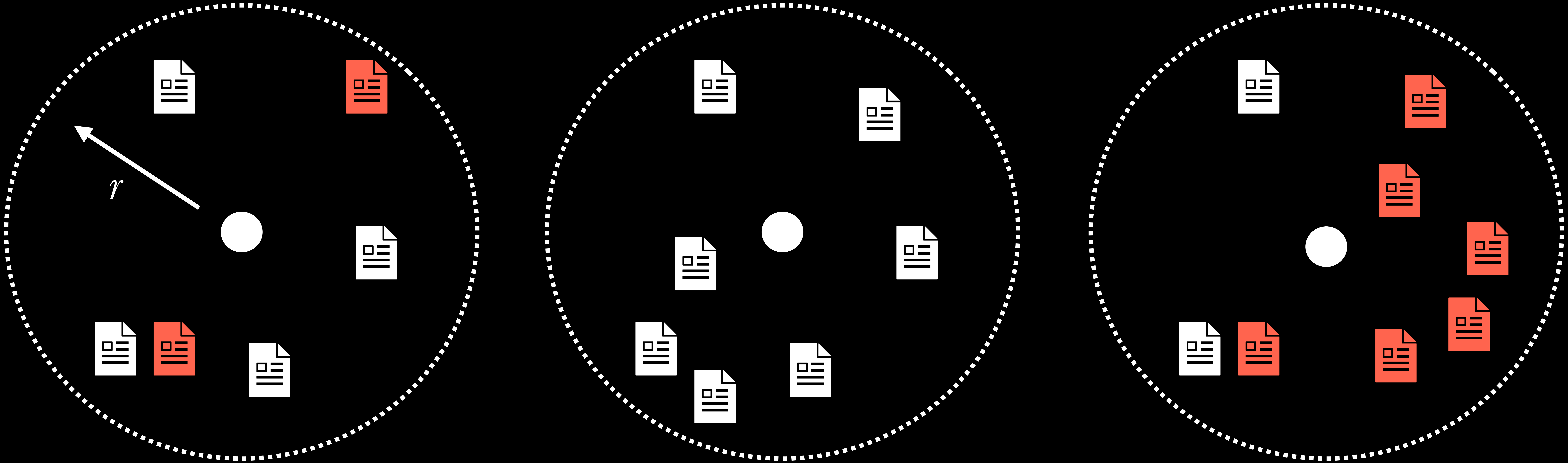

Computer Science
Physics
Social
Sciences


Computer Science
Science of
Science
Physics
Social
Sciences

Emerging fields ~ black holes?



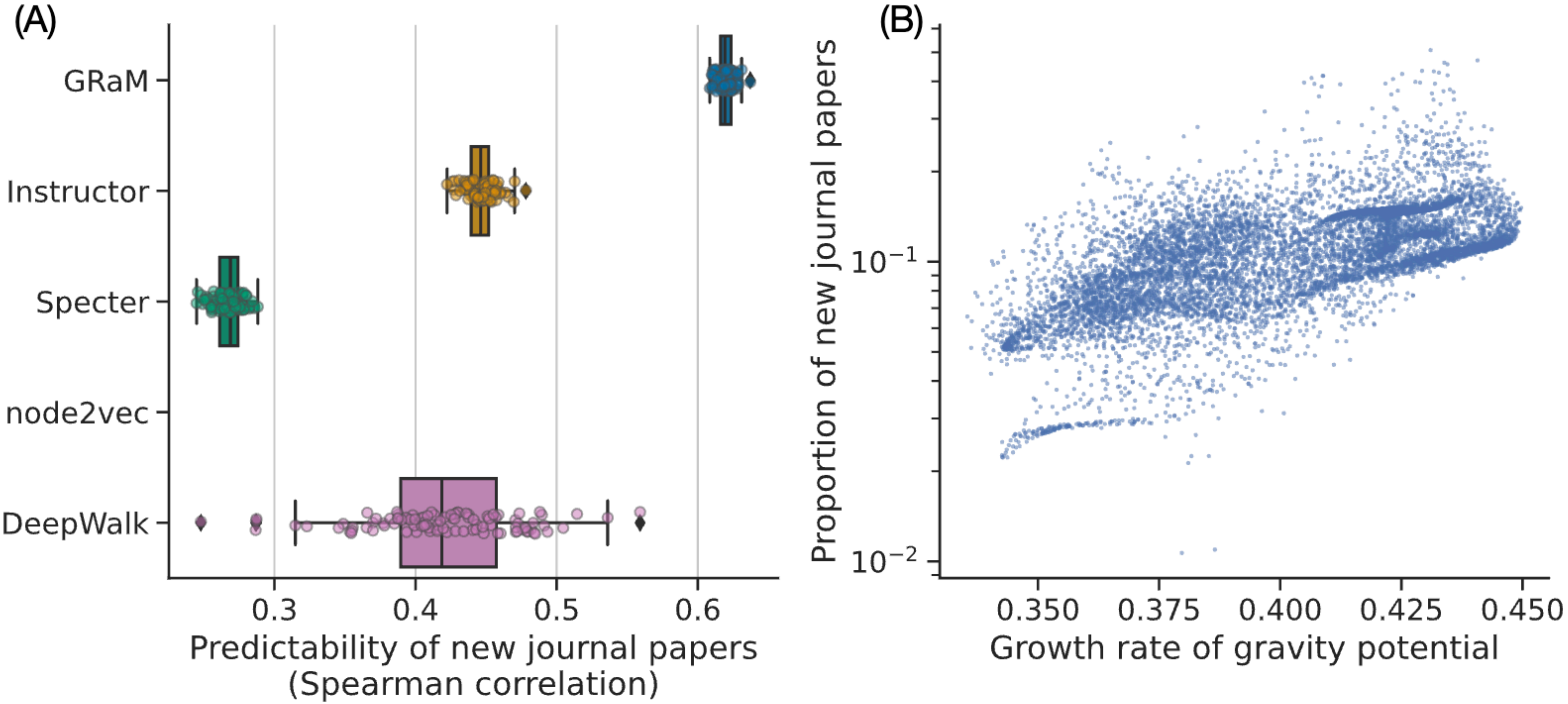
Can our gravity potential predict new journals?

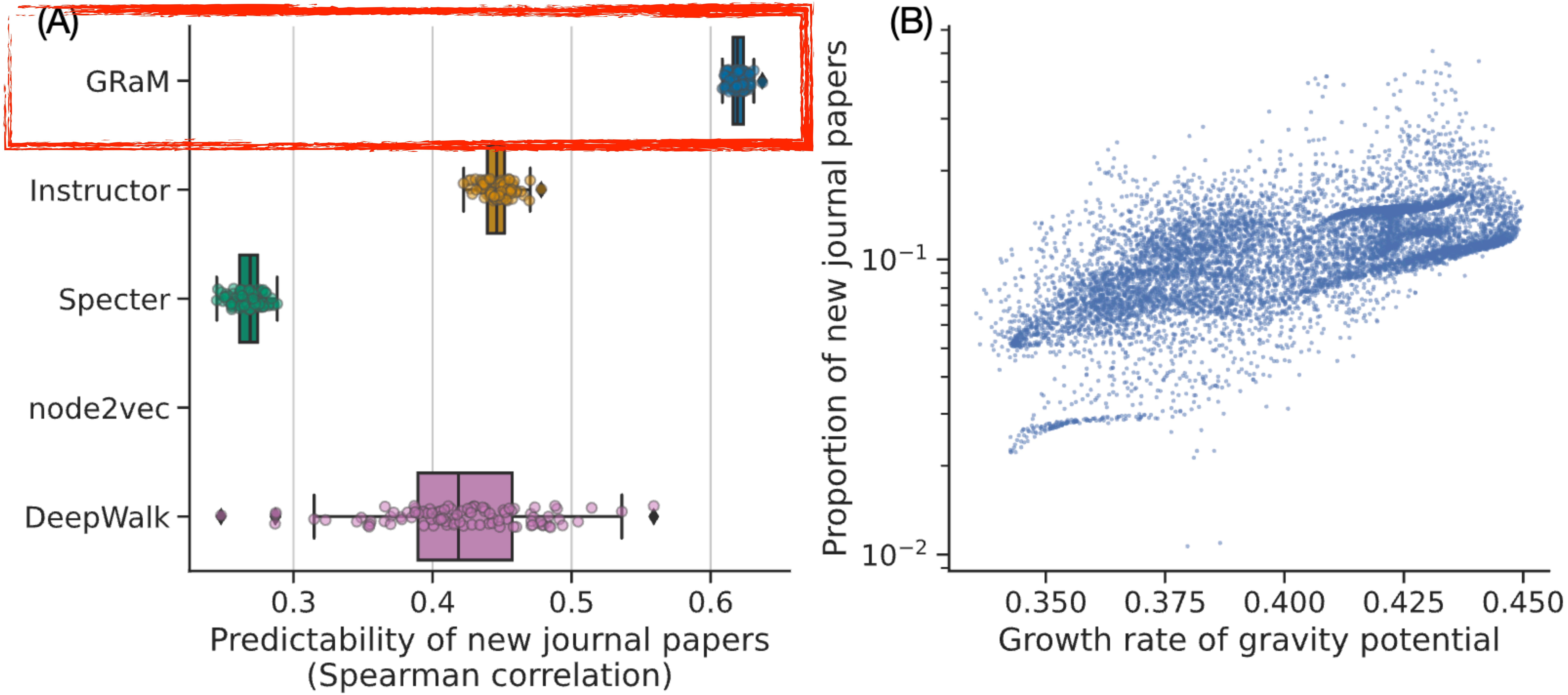


Our prediction score

$$\log \frac{\Phi_{[2006,2010]}(u)}{\Phi_{[2000,2005]}(u)}$$

Evaluation metric ~ Proportion of new journal papers within a radius r


(A)
GRaM
Instructor
Specter
node2vec
DeepWalk
0.3
0.4
0.5
0.6
Predictability of new journal papers
(Spearman correlation)
(B)
Proportion of new journal papers
10^{-1}
10^{-2}
0.350
0.375
0.400
0.425
0.450
Growth rate of gravity potential



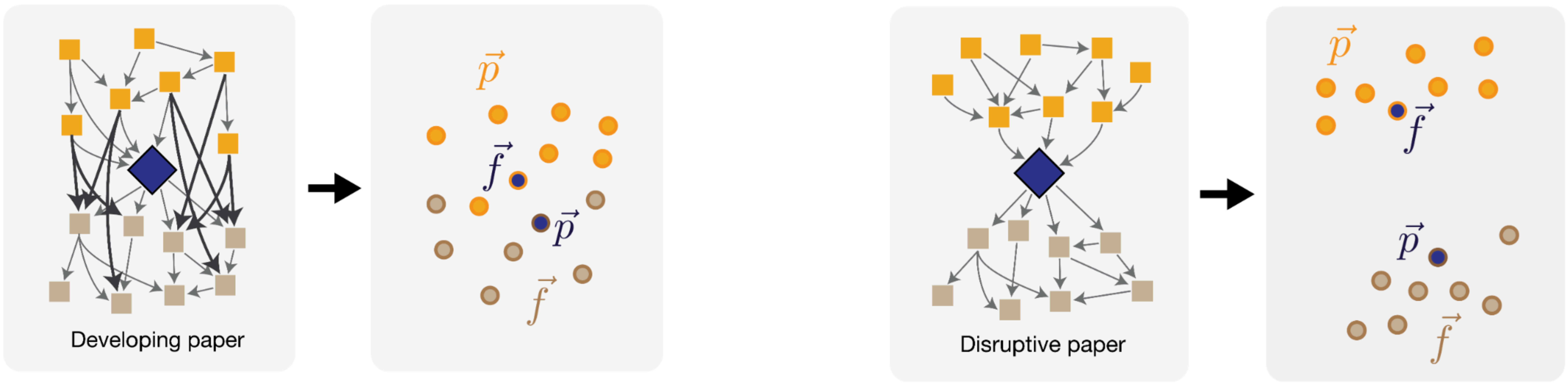
(A)
GRaM
Instructor
Specter
node2vec
DeepWalk
0.3
0.4
0.5
0.6
Predictability of new journal papers
(Spearman correlation)
(B)
Proportion of new journal papers
10^{-1}
10^{-2}
0.350
0.375
0.400
0.425
0.450
Growth rate of gravity potential

Summary

- Understanding of embedding model → Interpretable embedding space.
- Transition probability and gravity law can guide the creation of interpretable knowledge space models.

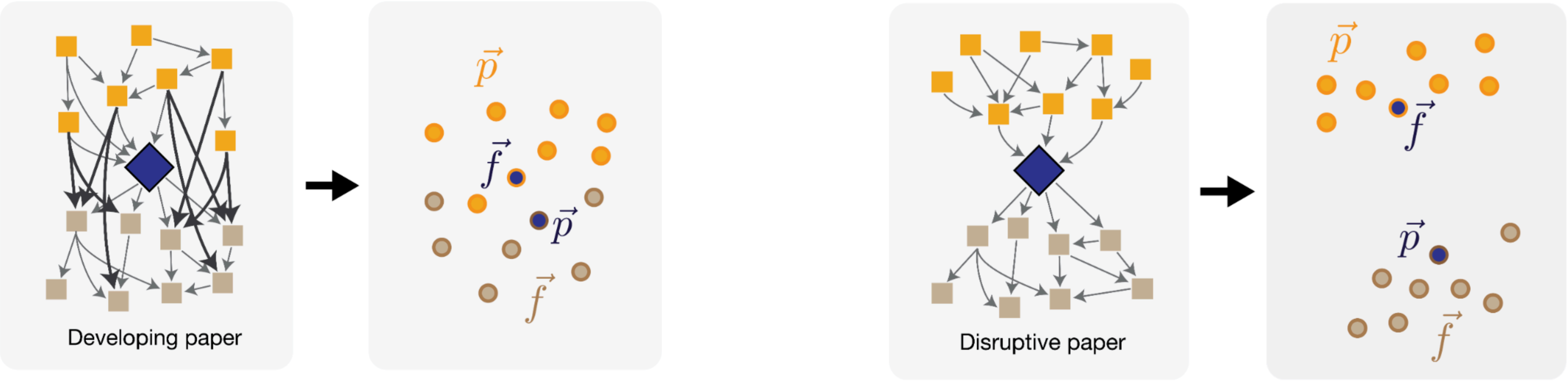
Thinking disruptiveness in knowledge space

Imagining the knowledge space allows us to define a powerful continuous measure of disruption.



Check out the poster!

Imagining the knowledge space allows us to define a powerful continuous measure of disruption.



Summary

- Imagining the space of knowledge help us conceptualize:
  - A continuous measure of disruptiveness
  - A community-centric model of long term citation patterns
- We can create a representation model of knowledge space that can be concretely interpretable with the gravity law.


Staša Milojević, IU


Alessandro Flammini, IU


Filippo Menczer, IU


Sriraam Natarajan, UT Dallas


Hao Peng


Sadamori Kojaku


Robert Mahari


Sandro Lera


Sandy Pentland


Clara Boothby


Esteban Moro


Rodrigo Costas


Ceren Budak

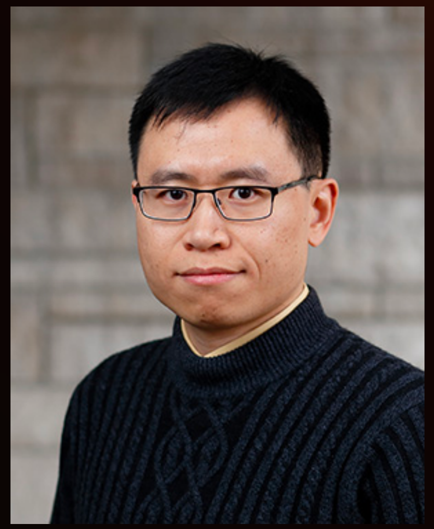

Daniel Romero


Filipi Silva


Lili Miao


Dakota Murray


Jisung Yoon


Xiaoran Yan


Woo-Sung Jung


Cassidy Sugimoto

Thanks!


Vincent Lariviere


Attila Varga