

Exploring the Strong Coupling Through Natural Language Processing

Patrick L.S. Connor, **Antonin Sulc**

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- > Strong coupling increases at lower energies, in contrast to the electromagnetic and weak forces.
- > The behavior of the strong coupling constant is an important feature of the strong force in the Standard Model. Yet it is one of the least known parameters (only known at percent-level accuracy).



Approaches

Embedding

Analysis of semantic similarity through vector representation of abstracts.

...Space-Time Geometry Using Young diagrams... $\rightarrow \mathbf{e} = [0.1, 0.3, -0.2\dots]$

...Status of NNLO 3-jet calculations.. $\rightarrow \mathbf{e} = [0.1, -0.3, 0.2\dots]$

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Topic Modeling

"Clustering" of abstracts and extraction of their most characteristic words.

...Space-Time Geometry Using Young diagrams... $\rightarrow Topic_1 = \{young, diagram\}$

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Citation Graph

Building a directed graph on citations and identification of context from reference list.

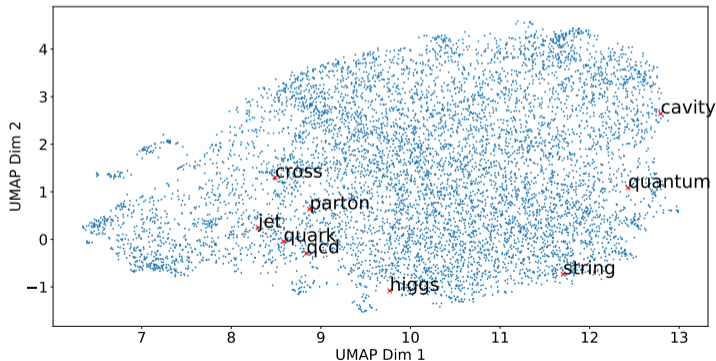
Word Embedding

Representing individual words as vectors.

cavity $\rightarrow \mathbf{w} = [0.1, -1, 2, \dots]$

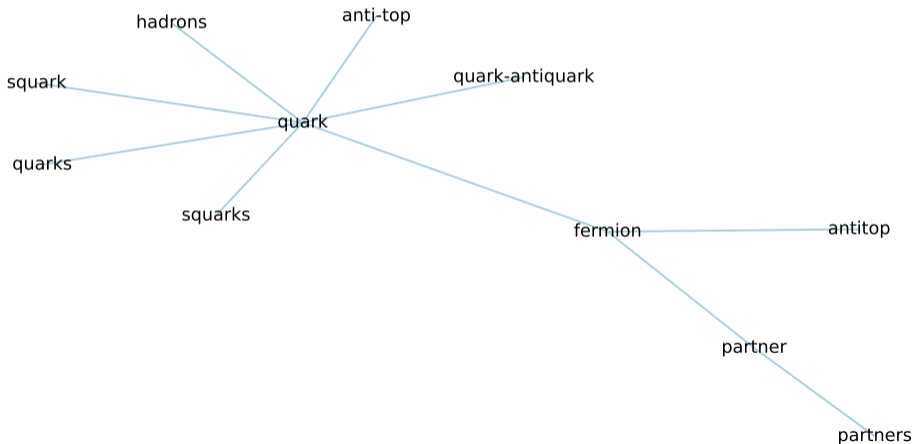
qcd $\rightarrow \mathbf{w} = [0.2, 0.8, 1.8, \dots]$

photon $\rightarrow \mathbf{w} = [0.18, 1.1, 1.8, \dots]$



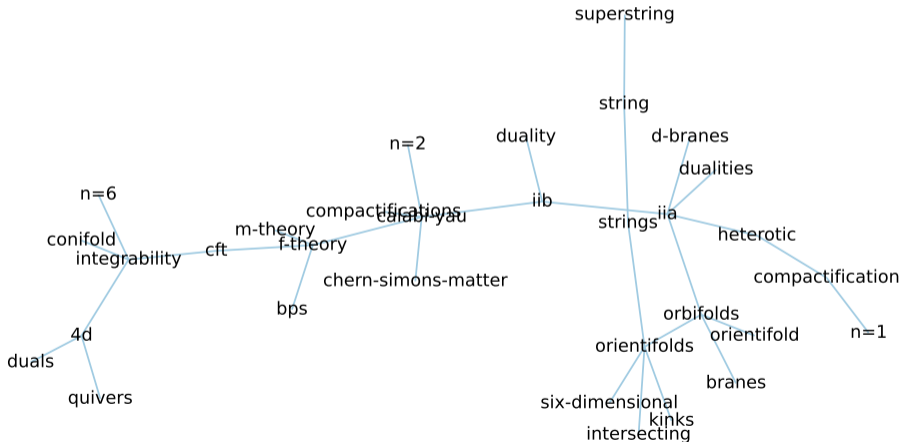
Word Embedding - Quark Similarity Graph

Quark



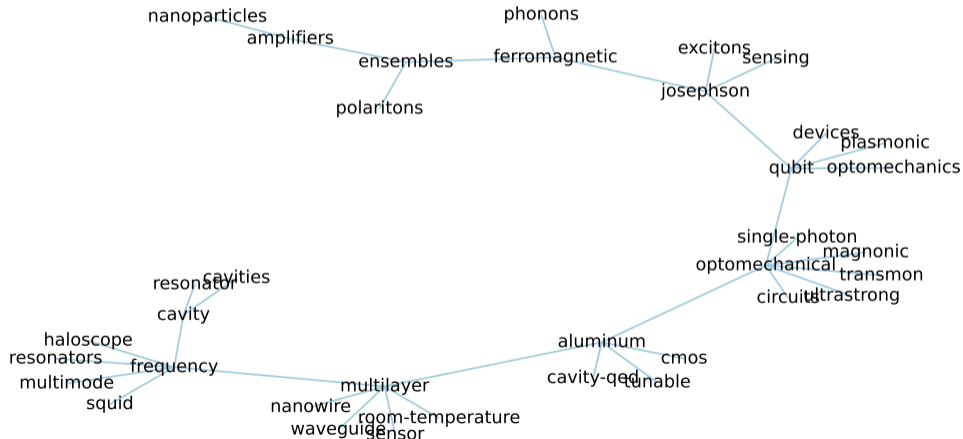
Word Embedding - String Similarity Graph

String

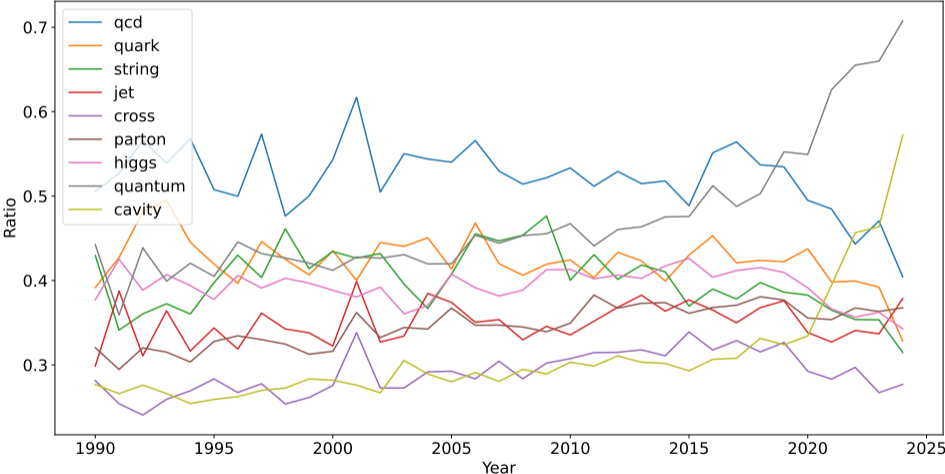


Word Embedding - Cavity Similarity Graph

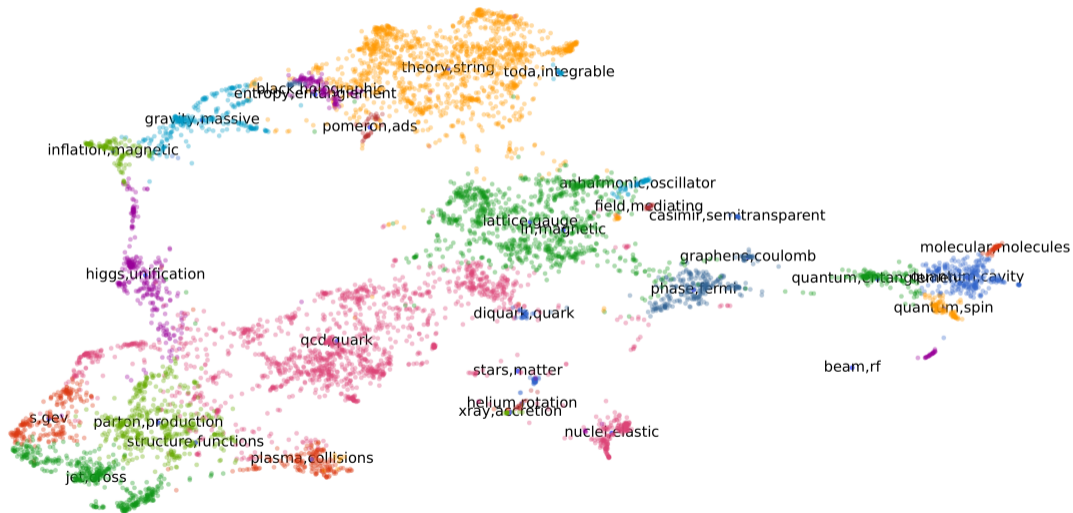
Cavity



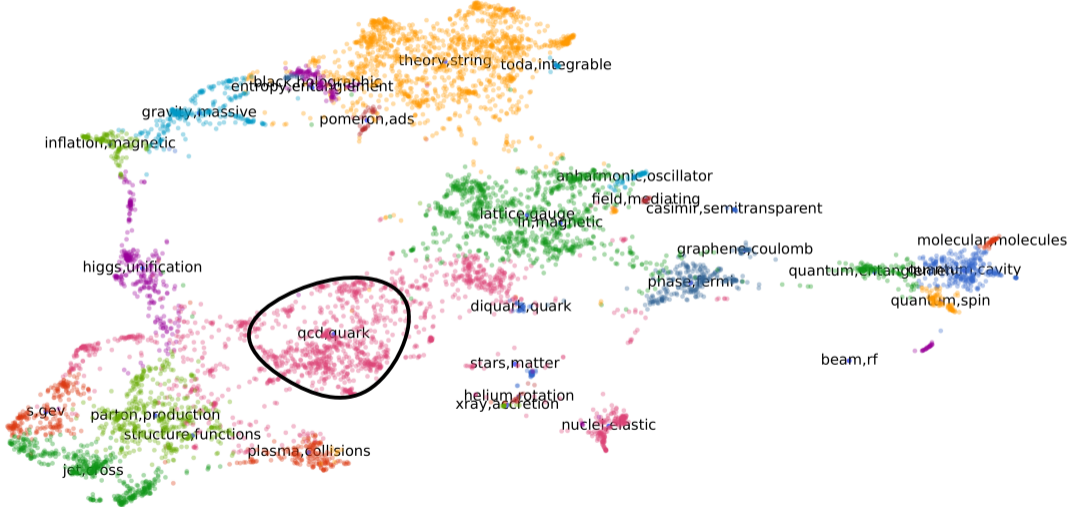
Trends of Selected Words



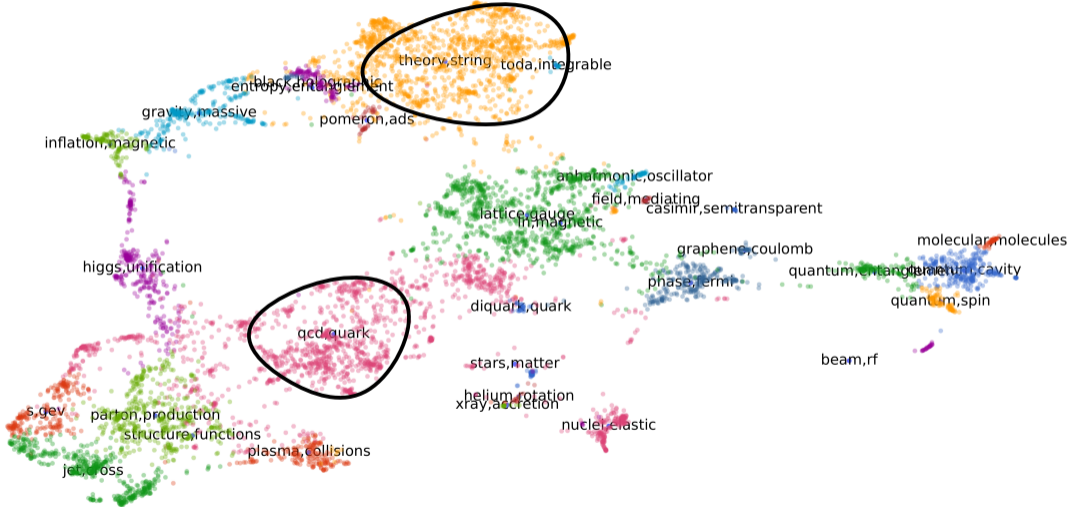
Topic Modelling



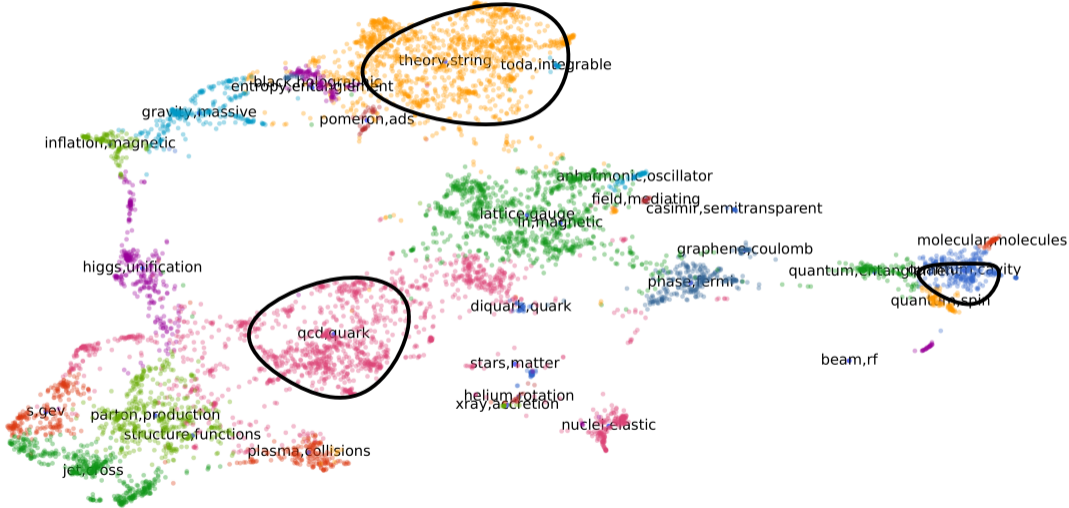
Topic Modelling - QCD, Quark



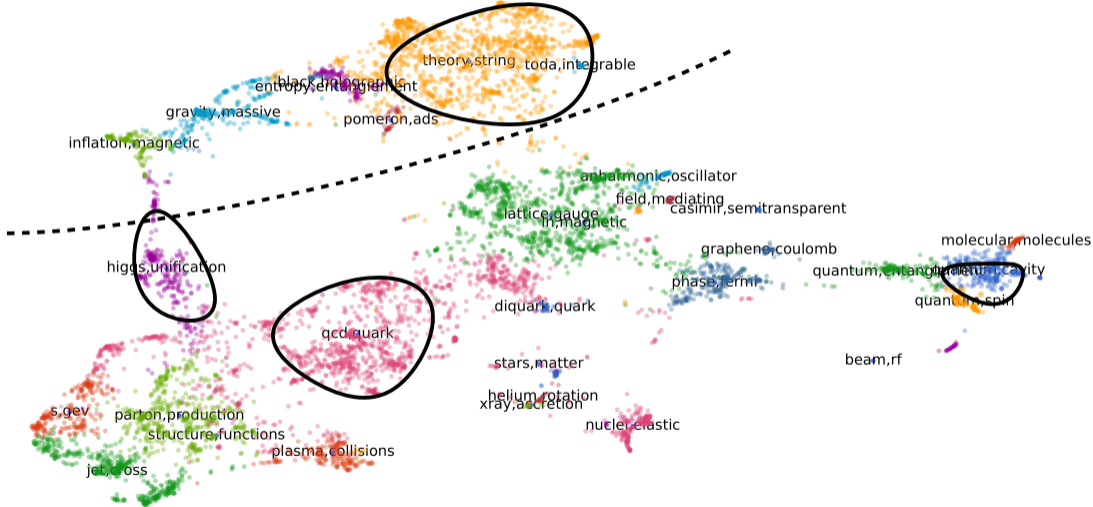
Topic Modelling - String Theory



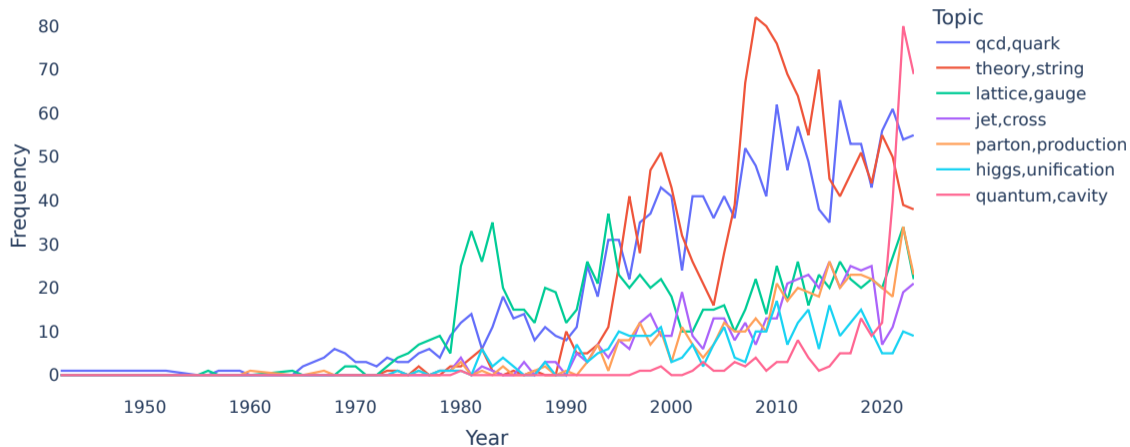
Topic Modelling - Quantum



Topic Modelling - Higgs, Unification



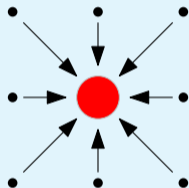
Topics over Time



Analysis of Citation Graph - Degree Centrality

Degree centrality

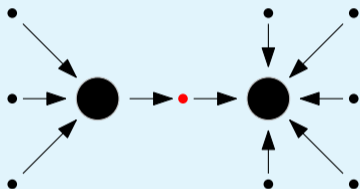
Most cited papers



- > **0.043** Gauge theory correlators from noncritical string theory
- > **0.015** Confinement of Quarks
- > **0.014** The Shear viscosity of strongly coupled N=4 supersymmetric Yang-Mills plasma

Analysis of Citation Graph - Between-ness Centrality

Between-ness centrality

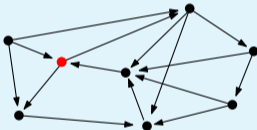


- > **0.22** Confinement of Quarks
- > **0.21** Gauge theory correlators from noncritical string theory
- > **0.08** The QCD Running Coupling

Analysis of Citation Graph - PageRank

PageRank centrality

A node with high PageRank means: routes to other nodes, and has many visits over iterative passes.



- > **0.005** Gauge theory correlators from noncritical string theory
- > **0.003** Cavity quantum electrodynamics
- > **0.002** Confinement of Quarks

Citation Graph Embedding - {Theory, String,...} Topic



Citation Graph Embedding - {QCD, Quark,...} Topic



Citation Graph Embedding - {Jet, Cross,...} Topic



Citation Graph Embedding - {Parton, Production,...} Topic



Citation Graph Embedding - {Higgs, Unification,...} Topic



Citation Graph Embedding - {Lattice, Gauge,...} Topic

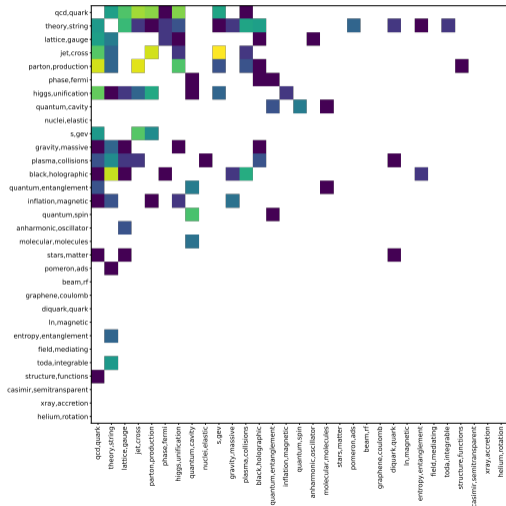


Citation Graph Embedding - {Phase, Fermni,...} Topic

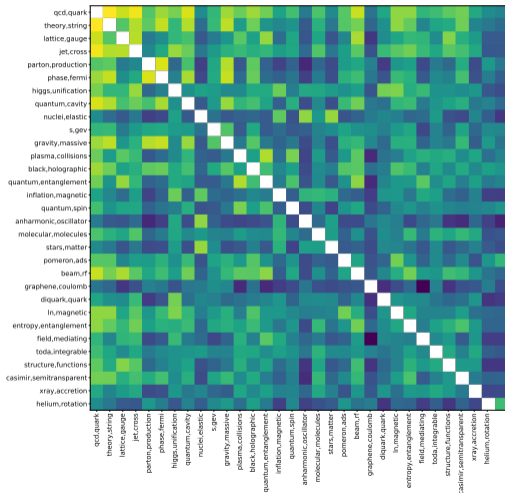


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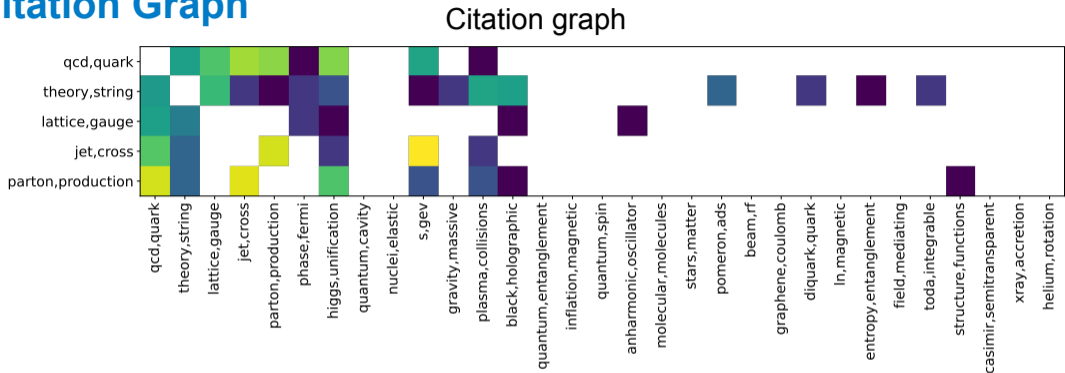
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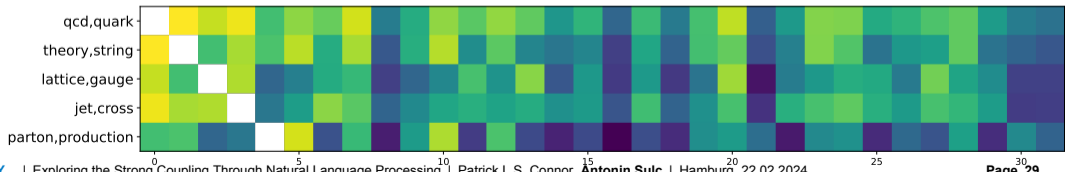
Topics



Citation Graph



Topics



Conclusion & Summar

- > You heard about embedding of abstracts into vectors.
- > You learned about (unsupervised) topic modelling of the current dark matter publication landscape from InspireHEP.
- > You saw that you can built knowledge graph just based data from abstracts.
- > You learned something about about community and citations.



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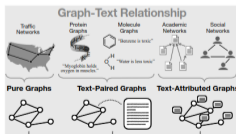
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Large Language Models on Graphs: A Comprehensive Survey

Bowen Jin*, Gang Liu*, Chi Han*, Meng Jiang, Heng Ji, Jiawei Han

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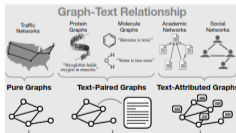
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By [Jonathan Larson](#), Senior Principal Data Architect; [Steven Truitt](#), Principal Program Manager

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- > Link, Predict, Associate?

Article

Mathematical discoveries from program search with large language models

<https://doi.org/10.1038/s41586-023-06924-6>

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Thank you!

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