Predicting Future Scientific Research with Knowledge Graphs

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The Big Picture

Find Relevant Articles

Extract Important Data

Iterate and Store Results

Build Knowledge Graph

Create Training Data and Learn

Predict 2021 Papers from Recent Years

Knowledge Graph Construction Phase

Machine Learning Phase

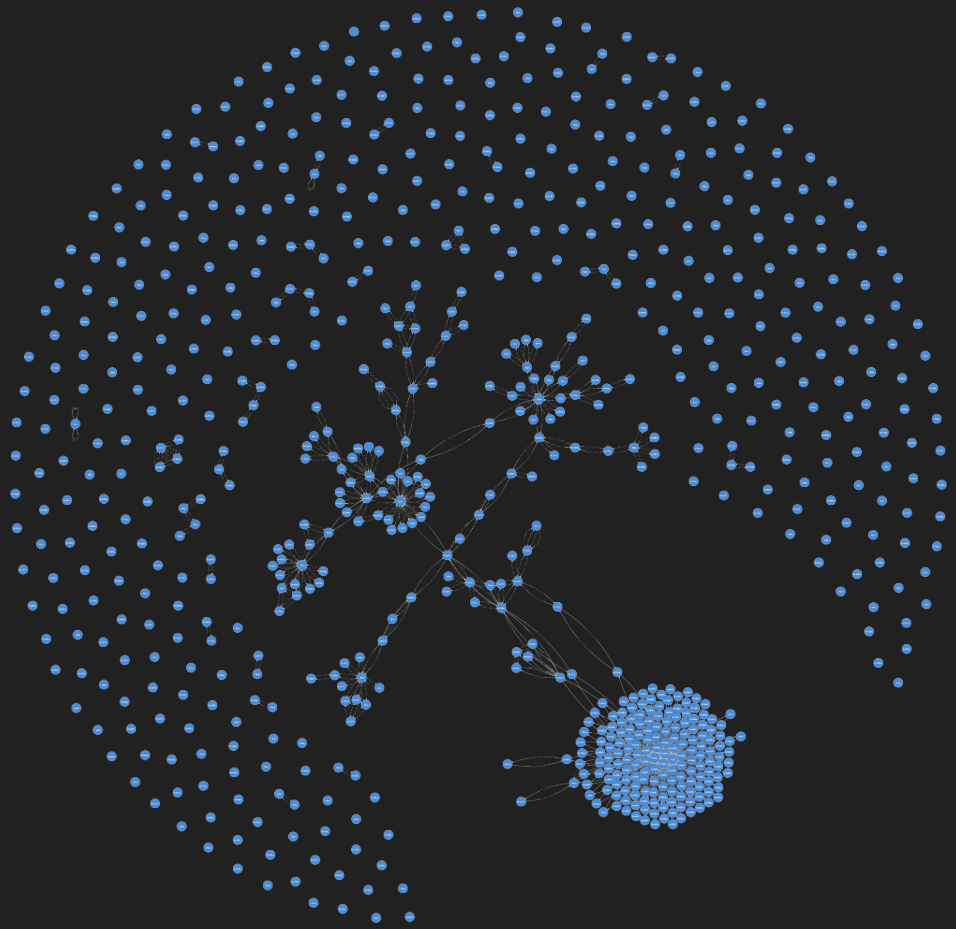
Challenges

(1) Building a connected graph:

Too much data out there, over 50k CS papers published per year on arXiv alone!

(2) Handling papers referenced in the KG but not crawled

Papers by one author:



Challenges

(3) Making plausible inferences about the future!

(And not generating predictions that are merely a reshuffling of their sources' abstracts)

(4) Making the graph useful

(You don't need a KG to look up papers by author or title)

Data Sources

dblp
computer science bibliography

Extract citations and references

Popular articles

arXiv

Abstracts for the popular articles

“Seed trail” crawling

Web Scraping

Entity Resolution

43 Million Pairs
Reduction Ratio: 0.93
3M pairs compared

Result: 20534 records

(1) Link Using
Title
Author
Date

Final Dataset

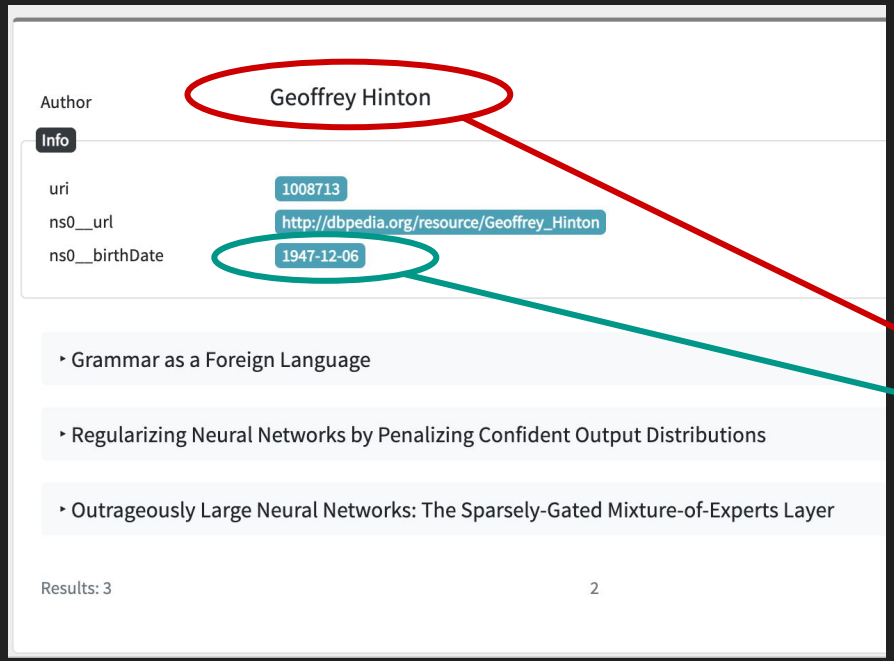
(2) Link Using
DOI

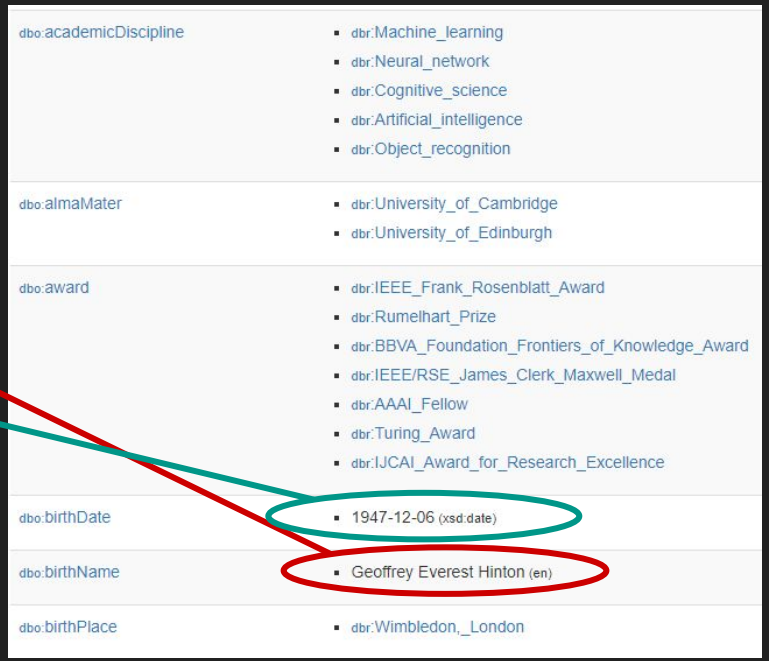
(3) Link Using
Title
Author
DOI

dblp
computer science bibliography

External KG Linkage

Our Knowledge Graph





Triple Generation

453k Paper URIs (incl. references)

51k Author URIs

298 DBpedia Matches

383 Predicted Papers

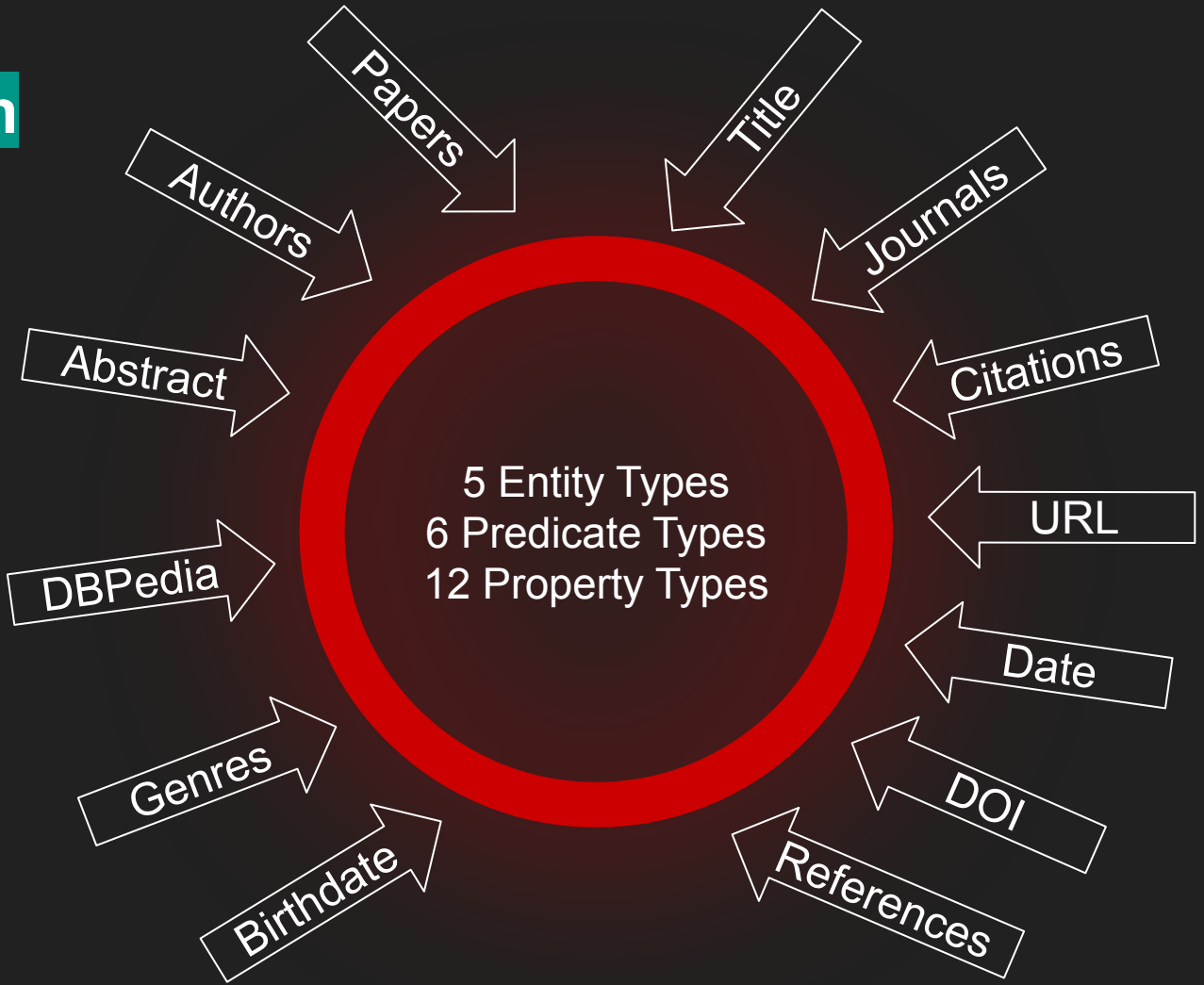
207 Genres

86 Publishers

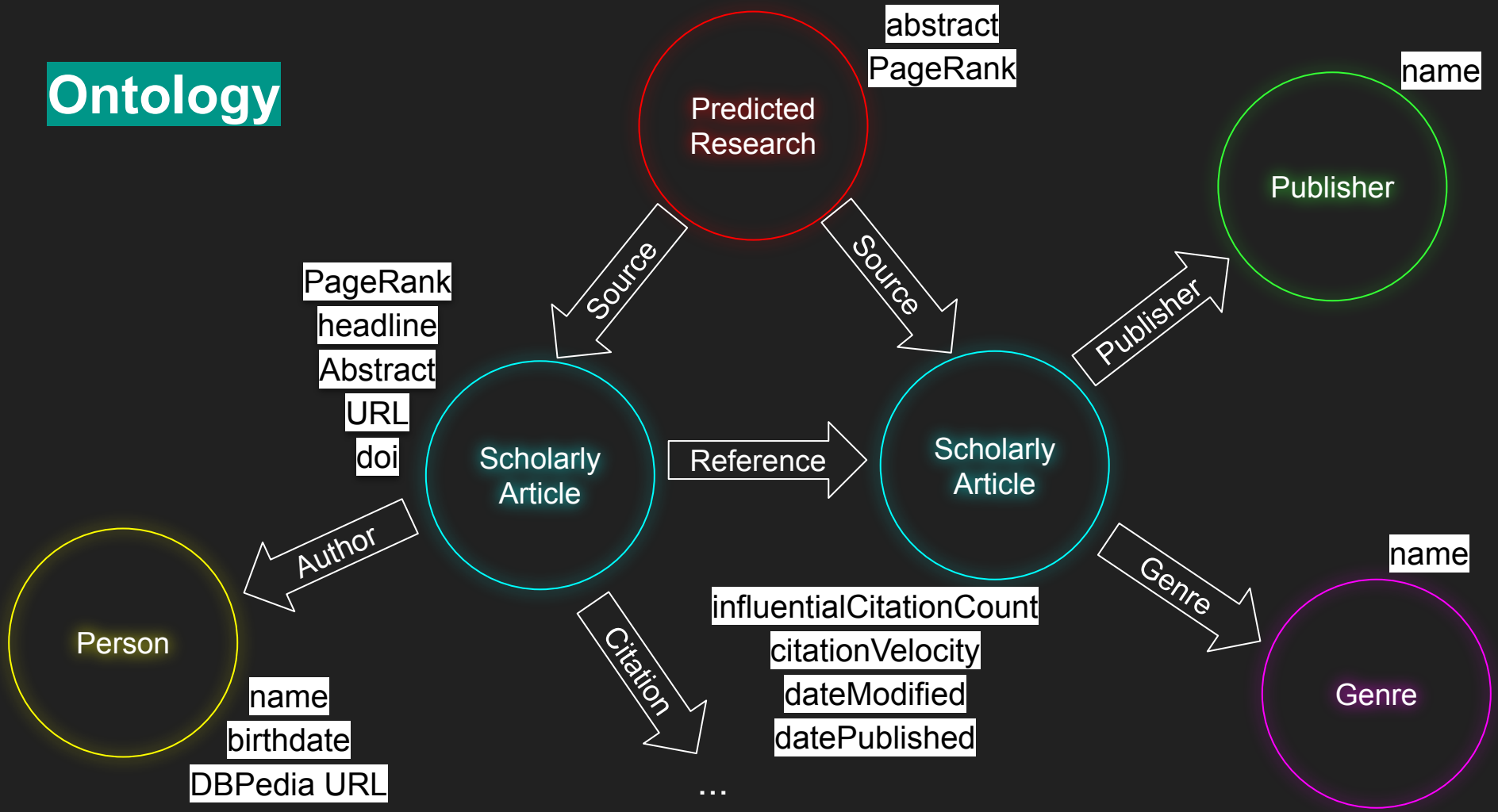
1.5M Relationships

505k Nodes

2.65M Triples!



Ontology


abstract
PageRank
Predicted Research
name
Publisher
Source
Source
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PageRank
headline
Abstract
URL
doi
Scholarly Article
Reference
Scholarly Article
Author
Person
name
birthdate
DBPedia URL
Citation
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citationVelocity
dateModified
datePublished
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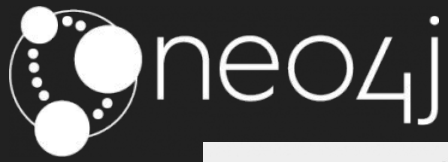
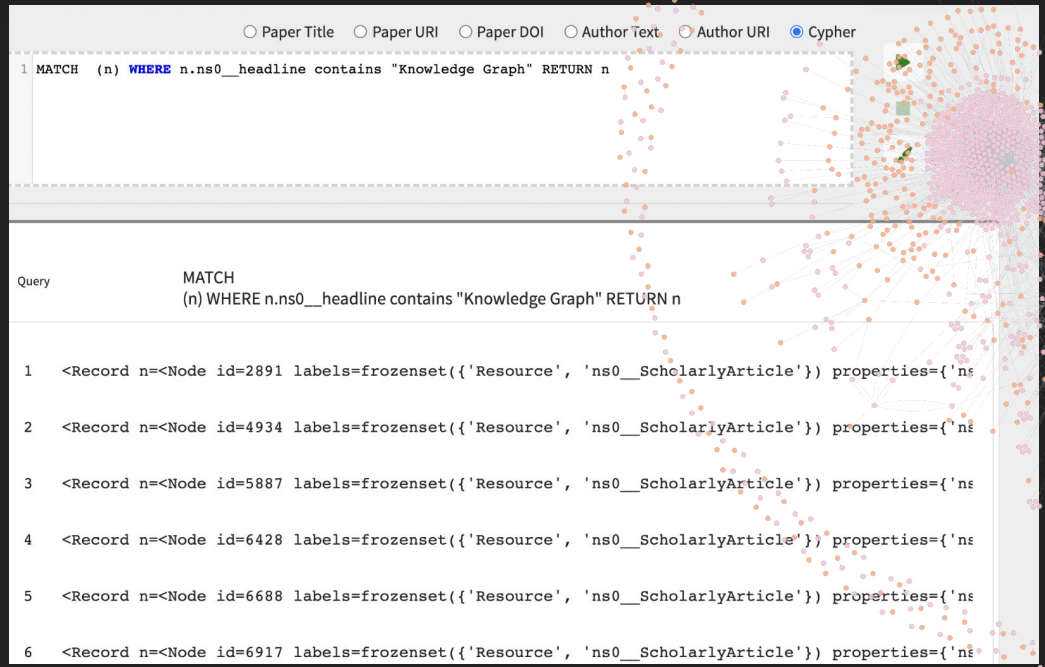
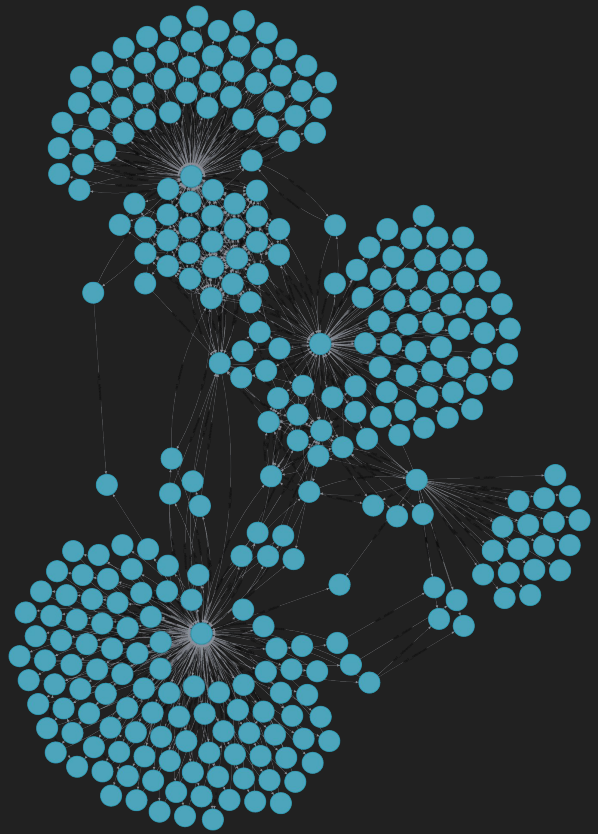
Genre
name
Genre

Graph Database





PageRank



Sample Endpoint Query:

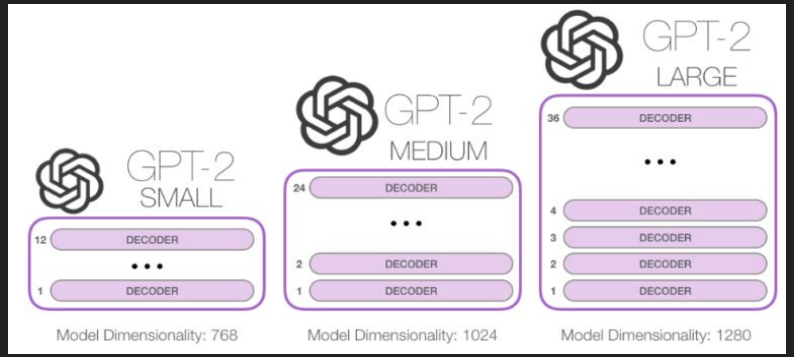
Title	Representation Learning: A Review and New Perspectives
URI	221
ns1__doi	10.1109/TPAMI.2013.50
ns0__datePublished	2013
ns0__url	https://www.semanticscholar.org/paper/184ac0766262312ba76bbdece4e7ffad0aa8180b
pagerank	21.52842592122827
ns1__citationVelocity	1384
ns1__b_influentialCitati	372
onCount	
Authors	Yoshua Bengio, P. Vincent, Aaron C. Courville
Abstract	The success of machine learning algorithms generally depends on data repres because different representations can entangle and hide more or less the diff behind the data. Although specific domain knowledge can be used to help de generic priors can also be used, and the quest for AI is motivating the design c algorithms implementing such priors. This paper reviews recent work in the a deep learning, covering advances in probabilistic models, autoencoders, mar motivates longer term unanswered questions about the appropriate objectiv computing representations (i.e., inference), and the geometrical connections estimation, and manifold learning.

Predicting Future Research

OpenAI

Transformers

build passing | license Apache-2.0 | website online | release v2.0.0



CO PRO

Predicting Future Research

(1) Reading the reference abstracts (priming the model)

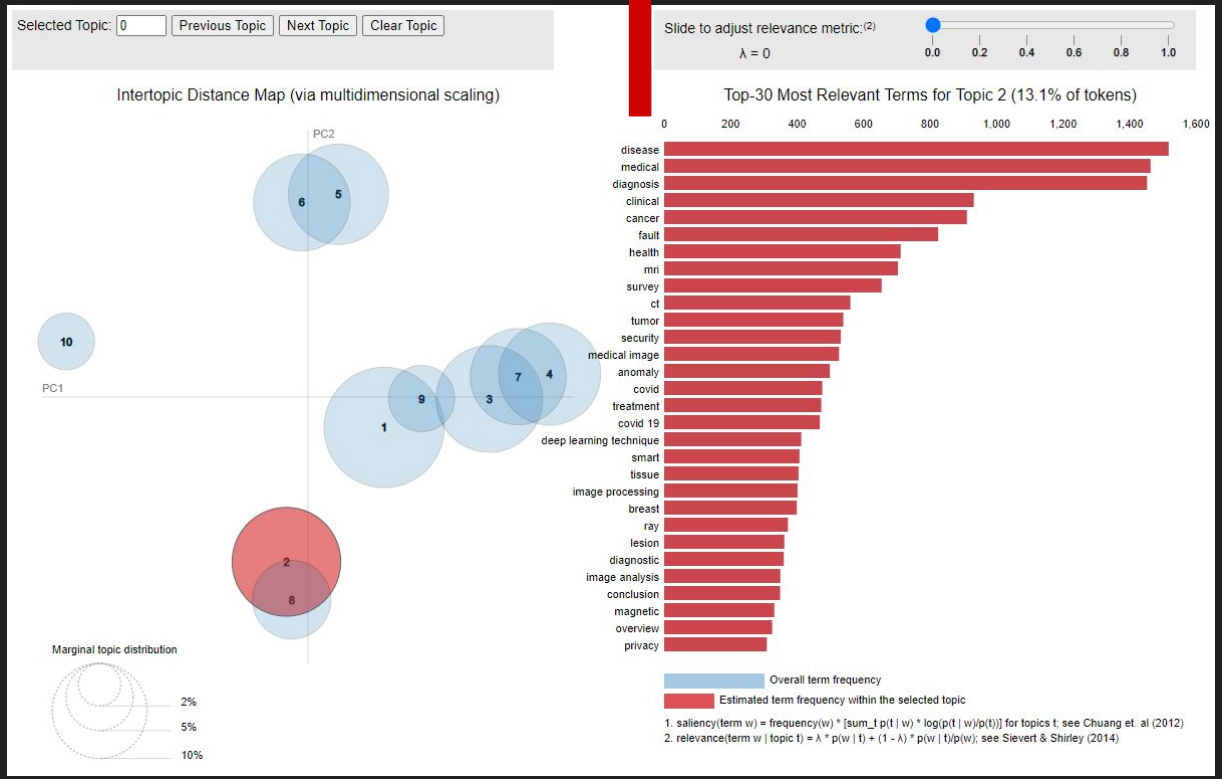
(2) Writing an entire new paper (text generation)

(3) Writing the paper's abstract (text summarization)

BONUS!

Topic Modeling

Medicine



Latent Dirichlet Allocation

BONUS!

Recommender System

```
%%time

INPUT_STRING = "Deep Support Vector Quantum Neural Graph Networks"

get_recommendation(INPUT_STRING,
                   NUM_RECOMMENDATIONS=10,
                   vectorizer = vectorizer,
                   LDA_obj = LDA_obj,
                   LDA_data = LDA_data,
                   topic_names = topic_names,
                   papers = papers)
```

```
Wall time: 1.07 s
```

	ID	Cosine Distance	Title	Modeled Topic	Citations
1	4751	0.011244	Underwater Target Classification Using Deep Ne...	feature; deep; classification; neural; neural ...	0.0
2	768	0.013166	Deep Learning for Monotonic Support Vector Mac...	feature; deep; classification; neural; neural ...	0.0
3	5567	0.013761	Stacked Sparse Autoencoder (SSAE) based framew...	feature; deep; classification; neural; neural ...	13.0
4	8586	0.020387	DeepGene: an advanced cancer type classifier b...	feature; deep; classification; neural; neural ...	13.0
5	6171	0.021423	Extract Features Using Stacked Denoised Autoen...	feature; deep; classification; neural; neural ...	0.0
6	4641	0.024708	Hybrid shallow and deep learned feature mixtur...	feature; deep; classification; neural; neural ...	0.0
7	4335	0.025183	DeepPPI: Boosting Prediction of Protein-Protei...	feature; deep; classification; neural; neural ...	20.0
8	3423	0.027645	Human emotion recognition using deep belief ne...	feature; deep; classification; neural; neural ...	36.0
9	7712	0.030773	A deep learning method for lincRNA detection u...	feature; deep; classification; neural; neural ...	0.0
10	1302	0.031278	ECG assessment based on neural networks with p...	feature; deep; classification; neural; neural ...	6.0

Trained on the entire graph

Paper recommendations using LDA similarity between input and abstracts

Not reliant on searching keywords in the database

Even hosted on a local machine can return query in 1 second

Validation

Validation Set: 98.4% TPR on DBpedia authors

Novelty in Generated Abstracts:

Only 7% of synthetic papers find their sources on the top 5 recommendations

Full dataset: 0.02% self-evident FPs (impossible 3-way matches)

Validation Set: 99.53% TPR on record linkage

Reduction Ratio: 0.93

Final Result

Recommender System

Text Query

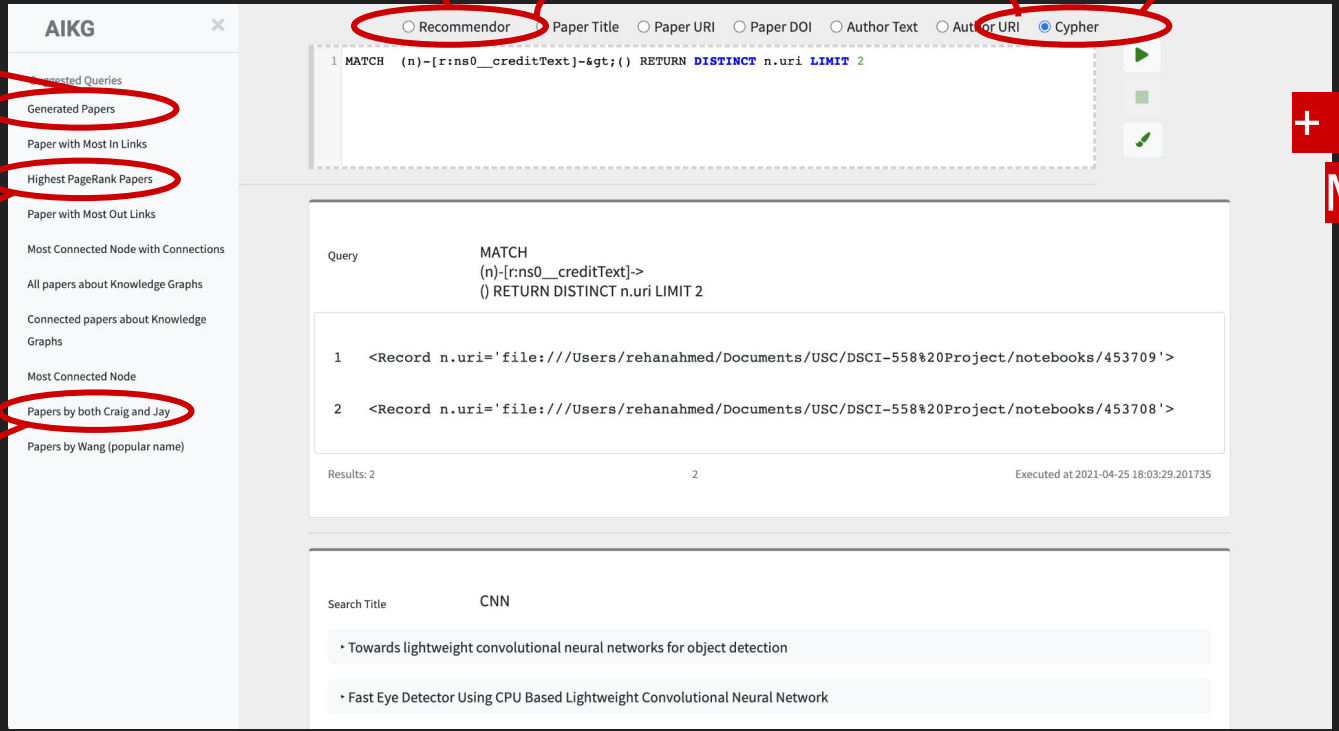
Neo4J Endpoint

Research Predictions

PageRank

DBpedia

+ LDA Topic Modeling



Neural-Net for Traffic Control on Foggy Days

'A sparse deep belief network with efficient fuzzy learning framework The algorithm is based on a deep neural network that is able to learn to distinguish between different types of blurred scenes . The algorithm can be applied to any scene, including static and dynamic ones, and it can also be used to improve the performance of existing algorithms . The authors demonstrate the use of deep learning in traffic prediction by using a network trained on real traffic data to train a model that could predict how fast a particular vehicle would be traveling at any given time of day, based on its speed in relation to other vehicles, such as cars, trucks, buses, motorcycles, bicycles, etc. In this way, the researchers demonstrate how deep networks can be used in a wide range of problems, including traffic management, vehicle safety, traffic congestion, urban planning, transportation planning and transportation planning . They hope that this work will inspire other researchers to explore the potential of this approach in other areas of this type of engineering . The work was supported by the U.S. National Science Foundation (NSF)'

Training a Facial Recognition Neural-Net from Brain Activity

"The reconstructions capture individual-specific information, such as the location of the eyes, nose, mouth, and other facial features, as well as their shape and size . This information can be used to improve the model's performance in a number of ways . For example, it is possible to use the reconstructed images to train a model to recognize faces . In this way, we are able to capture the individual features of a face and use them to predict the face's identity . We also use this information to enhance the performance of our model in other ways, for instance, by using it to detect faces that are not in the image . Our method is based on a combination of two approaches: (1) the use of a network-based approach and (2) a neural network based approach . Our model is able to extract features from the neural activity of a human subject, including the shape and shape of their dendritic trees . We show that our method can also be used as a tool for reconstruct"

typo

Thank You!

Questions?