



most contributed articles **(extended version)**

Big Data Computing Final Project

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September 2023



Introduction

Task: Graph Analysis + Information Retrieval System

We are looking for: given a query, retrieve the most relevant articles

Data: .json file containing article information such as title and list of references. Data can be found [here](#).

Approaches:

- Degree Centrality
- PageRank
- TF-IDF + Cosine similarity
- Cosine similarity + PageRank -> ContentLink score

Components used:

- PySpark 3.4.1
- Python 3.10
- Google Colab Pro
- Google Drive



Data

Json

File type

≈ 12GB

File size

4,894,504

Articles

45,564,149

Citations



Data Pre-processing

01

Json

12GB file size

02

Pickle

Dictionary storing the
relevant data
(id, title, references)
≈ 660 MB file size

03

Csv

- Filtering **top 500,000** articles
- **Article.csv** (id, title)
≈ 40 MB file size
- **Citations.csv** (citations)
≈ 120 MB file size
5,635,143

Graph Structure



Nodes

Articles



Edges

Citation relationship

a to b (a -> b)
if article a has cited
article b



Unweighted



Directed

Approaches

Degree centrality

- *Undirected graph*: defines the importance of a node v as the **number of the neighbors of node v**
- *Directed graph*: defines the importance of a node v based on the **number of the incoming and outgoing edges**
- In our case, the **higher the number of the incoming edges**, the **higher is the importance of the node**.

PageRank

- PageRank works by counting the **number** and **quality** of links to a page to determine a **rough estimate of how important the website** is. “Google”
- The PageRank algorithm outputs a **probability distribution** used to represent the **likelihood that a person randomly** clicking on links will arrive **at any particular page**.
- Initial probability (rank) = $1/N$, $N = \# \text{ nodes}$
- The rank of a node would be updated at the end of each iteration based on the **rank of the preceding nodes** and the **probability of being randomly chosen**.
- **Stopping criteria:** when we reach a point of convergence



Example



- Setting the decay factor $d = 0.85$
- The **new rank of page A** would be updated to:
$$d \cdot (0.25/1) + d \cdot (0.25/1) + d \cdot (0.25/1) + (1 - d)/4 = 0.675$$

Results

The background is a gradient from dark blue on the left to bright orange on the right. It features several decorative elements: white wavy lines in the top-left and bottom-right corners; three colorful (blue-to-orange gradient) diagonal bars in the top-left; a white paperclip and two more colorful diagonal bars in the top-right; a white circle with a plus sign in the bottom-left; and two more colorful diagonal bars in the bottom-left.

Degree centrality results

InDegree



**Distinctive Image Features from
Scale-Invariant Keypoints**

Citations received: **10,123**

OutDegree



Deep Reinforcement Learning

Citations given: **307**



In our work, the **higher a node's InDegree**, the **more important** that specific node is.

PageRank results

PageRank



**Learnability and the
Vapnik-Chervonenkis dimension**

Rank: **0.00269**

Iterations: 10



Comparison

InDegree



**Distinctive Image Features from
Scale-Invariant Keypoints**

Citations **10,123**

Rank: **0.0013**

PageRank



**Learnability and the
Vapnik-Chervonenkis dimension**

Citations: **296**

Rank: **0.00269**





Search Engine



TF-IDF

- It evaluates the **importance** of a word (or term) within a document relative to a collection of documents (corpus).

$$\text{ Tf_Idf } (t, d, D) = \text{ Tf } (t, d) * \text{ Idf } (t, D)$$

- **Tf (t,d):** # occurrences of a term t in a document d

$$\text{ Tf } (t, d) = \log (1 + \text{freq } (t, d))$$

- **Idf (t, D):** quantifies how common a term is among a set of documents D

$$\text{ Idf}(t, D) = \log(|D| / \text{count}(d \in D : t \in d))$$

Text preprocessing

- We are going to focus on the terms in the title of the articles. In order to make our data suitable for our work we have to go through a text preprocessing:
 - **Tokenization**
 - **Lowercasing**
 - **Stopwords removal**
 - **Punctuations removal**
 - **Stemming**



Cosine similarity

- Given a query and a set of documents with their terms' TF-IDF, we define the cosine similarity between each query and a document as follows:

$$\text{cosine similarity (q, d)} = \text{dot_product(q,d)} / (\|q\| * \|d\|)$$

- The **higher the cosine similarity**, the **more relevant** the document is for the given query

Note: we have assumed that we have the TF-IDF of the terms in the query and the document in a vector.

Results

The background features a smooth gradient from deep blue on the left to bright orange on the right. Decorative elements include several sets of thin, white, wavy lines that flow across the top and bottom. Scattered throughout are various geometric shapes: elongated capsules and circles with a blue-to-orange gradient, and a white circle containing a plus sign in the bottom-left corner.

Cosine similarity results

Our query “**Big Data Computing**”

Retrieved articles with their cosine similarity :

- “Big Data – A State-of-the-Art” : **0.86**
- “Big data” : **0.86**
- “Big Data over Networks” : **0.81**
- “Content-Centric and Software-Defined Networking with Big Data” : **0.81**
- “Efficient computation of the well-founded semantics over big data” : **0.79**



ContentLink score



ContentLink score

We have defined a score that will combine the cosine similarity and the pageRank metrics.

Steps:

- **Filtering:** Filtering the articles that have at least one of the terms in the given query in their title.
- **Scaling:** Scaling the similarities and the pageRanks for these articles to be in $[0, 1]$

$$\text{ContentLink score} = \text{alpha} * \text{cosine_similarity}(q, d) + \text{beta} * \text{pageRank}(d)$$

alpha, beta in $[0,1]$ are the rate of the contributions

Results

The background features a smooth gradient from deep blue on the left to bright orange on the right. Decorative elements include several sets of thin, white, wavy lines that flow across the top and bottom of the frame. Scattered throughout are various geometric shapes: elongated capsules with a blue-to-orange gradient, a white paperclip-like shape in the top right, and a white circle containing a plus sign in the bottom left.

ContentLink score

- Our query **“Big Data Computing”**
- **alpha = 0.5, beta = 0.5**

Retrieved articles with their score :

- “Computer Processing of Line-Drawing Images” : **0.65**
- “Big data” : **0.50**
- “Big Data – A State-of-the-Art” : **0.50**
- “Big Data over Networks” : **0.47**
- “Content-Centric and Software-Defined Networking with Big Data” : **0.47**



ContentLink score

- Our query **“Big Data Computing”**
- **alpha = 0.6, beta = 0.4**

Retrieved articles with their score :

- “Big data” : **0.60**
- “Big Data – A State-of-the-Art” : **0.60**
- “Computer Processing of Line-Drawing Images” : **0.58**
- “Big Data over Networks” : **0.56**
- “Content-Centric and Software-Defined Networking with Big Data” : **0.56**



ContentLink score

- Our query **“Big Data Computing”**
- **alpha = 0.4, beta = 0.6**

Retrieved articles with their score :

- “Computer Processing of Line-Drawing Images” : **0.72**
- “Specification and implementation of resilient, atomic data types” : **0.49**
- “A Survey of Data Structures for Computer Graphics Systems” : **0.42**
- “Clustering categorical data: an approach based on dynamical systems” : **0.42**
- “Big data” : **0.40**





**Thank you
for your attention**