





ABOUT ME

- Developed web apps for 5 years including e-commerce, business workflow, more.
- Worked at Google for 8 years on Google Apps, Cloud Platform
 Technologies: Python, Java, BigQuery, Oracle, MySQL, OAuth

ryan@neo4j.com @ryguyrg



Carpe Diem Data







THE PANAMA PAPERS

07

Politicians, Criminals, and the Shady System That Hides Their Cash



.



Why are YOU here today, hopefully



Power of Graph Algorithms to Understand Your Data



Power of Graph Algorithms to Understand Your Data



Graph Algorithms on ACID





Graph Algorithms on ACID

Graph Algorithms + **ACID-compliant** native graph database









Google

All	Videos	Books	Images	Shopping	More	
Abou	t 1,020,000 n	esults (0.32	seconds)			

[PDF] Basic Graph Algorithms - Stanford University

https://web.stanford.edu/class/cs97si/06-basic-graph-algorithms.pdf -

Jun 29, 2015 - Graphs. Adjacency Matrix and Adjacency List. Special Graphs. Depth-First and The most basic graph algorithm that visits nodes of a graph.

Category:Graph algorithms - Wikipedia

https://en.wikipedia.org/wiki/Category:Graph_algorithms -

T. Tarjan's off-line lowest common ancestors algorithm. Tarjan's strongly connected components algorithm. Theta* Topological sorting. Transitive closure. Transitive reduction. Travelling salesman problem. Tree traversal.

[PDF] Graph Algorithms - users.cs.umn.edu

www-users.cs.umn.edu/~karypis/parbook/Lectures/AG/chap10_slides.pdf <

In a weighted graph, the weight of a subgraph is the sum of the weights of the edges in the subgraph. A minimum spanning tree (MST) for a weighted undirected graph is a spanning tree with minimum weight. An undirected graph and its minimum spanning tree. Prim's algorithm for finding an MST is a greedy algorithm.

Graphs - Algorithms, 4th Edition

algs4.cs.princeton.edu/40graphs/ -

4.1 Undirected Graphs introduces the graph data type, including depth-first ... and two classic algorithms for solving it: Dijkstra's algorithm and Bellman-Ford.







Restructuring Transactional Data for Link Analysis in the FinCEN AI System

Henry G. Goldberg** and Raphael W.H. Wong

U.S. Department of the Treasury, Financial Crimes Enforcement Network (FinCEN), 2070 Chain Bridge Road, Vienna VA 22182 **Current address: National Association of Securities Dealers (NASD) Regulation, Inc., 9513 Key West Avenue, Rockville MD 20850 goldberh@nasd.com, wongr@fincen.treas.gov

Abstract

Due to the nature and costs of data collection, many realworld databases consist of large numbers of independent transactions. Finding evidence of structured groups of entities reflected in this data is a task aptly suited to Link Analysis. However, the databases usually must be restructured to allow effective search and analysis of the linkage structures hidden in the original transactions. The FinCEN AI System (FAIS) [Senator 1995] is an example of such an application. We briefly discuss the process of database restructuring and show how it is used to support the discovery and analysis of evidence of money laundering in a database of cash transactions.

Introduction

Transactional Databases

In our modern world, much of human activity is initially reported in terms of individual transactions. Both the

that might be used to select out the relevant ones for further analysis. In situations where we are looking for fraud in transactional data, the fraudulent activities are likely to be camouflaged to look like normal activities. The actors involved may spend much of their time in normal, uninteresting, activities and only occasionally in fraudulent ones. [Goldberg 1997] It is clear to many analysts who work with this data that the interrelationships among transactions hold the key to select the proper subset and to understand the implicit activities hidden in the data -- activities which are incompletely reflected in the recorded transactions. The analysis of these relationships, called Link Analysis, is a vital technique used by law enforcement and intelligence analysts the world over. [Andrews 1990]

Finding Hidden Structure

Statistical and other data mining methods (which often are formulated to model and characterize populations of similar intrances) can trank zo sets of the sactions to show

Anti Money Laundering

Personalized Product Recommendations with Neo4j

Recommendations

Personalized product recommendations can increase conversions, improve sales rates and provide a better experice for users. In this Neo4j Browser guide, we'll take a look at how you can generate graphbased real-time personalized product recommendations using a dataset of movies and movie ratings, but these techniques can be applied to many different types of products or content.

Graph-Based Recommendations

Generating personalized recommendations is one of the most common use cases for a graph database. Some of the main benefits of using graphs to generate recommendations include:

- 1. Performance. Index-free adjacency allows for calculating recommendations in real time, ensuring the recommendation is always relevant and reflecting up-to-date information.
- 2. Data model. The labeled propety graph model allows for easily combining datasets from multiple sources, allowing enterprises to unlock value from previously separated data silos.



Product Recommendations

Recommended for you See more recommendations >



Rosie Revere's Big Project

Book for Bold Engineers

Paperback

\$12.04 **vprime**

Andrea Beaty, David Roberts



Brain Rules for Baby : How to Raise a Smart and... John Medina, Pear Press

Audiobook

\$14.95



Iggy Peck's Big Project Book

Andrea Beaty, David Roberts

for Amazing...

\$10.39 **vprime**

Paperback



(Baby Loves Science) Ruth Spiro, Irene Chan Board book ★★★★★★★★★★★★ \$8.09 ✓ prime



Baby Loves Thermodynamics! (Baby Loves Science)

Explore material handling supplies See more





Sports

Who Is the Best Player Ever? A Complex Network Analysis of the History of Professional Tennis

Filippo Radicchi

Matjaz Perc, Editor

Author information
Article notes
Copyright and License information

This article has been cited by other articles in PMC.

Abstract

We considered all matches played by professional tennis players between 1968 and2010, and, on the basis of this data set, constructed a directed and weighted network of contacts. The resulting graph showed complex features, typical of many real networked systems studied in literature. We developed a diffusion algorithm and applied it to the tennis contact network in order to rank professional players. *Jimmy Connors* was identified as the best player in the history of tennis according to our ranking procedure. We performed a complete analysis by determining the best players on specific playing surfaces as well as the best ones in each of the years covered by the data set. The results of our technique were compared to those of two other well established methods. In general, we observed that our ranking method performed better: it had a higher predictive power and did not require the arbitrary introduction of external criteria for the correct assessment of the quality of players. The present work provides novel evidence of the utility of tools and methods of network theory in real applications.

Introduction

Go to: 🕑

Go to: 🖂

Social systems generally display complex features [1]. Complexity is present at the individual level: the behavior of humans often obeys complex dynamical patterns as for example demonstrated by the rules governing electronic correspondence [2]–[5]. At the same time, complexity is present also at the global level. This can be seen for example oben social systems are mathematically represented in terms of oranhs.



Literature



BIZ & IT -

Novel text analysis uses PageRank to identify influential Victorian authors

Searching for the Adam and Eve of 20th century authors.

LIAT CLARK, WIRED.CO.UK - 8/18/2012, 8:47 AM



Urban Planning

Ranking Spaces for Predicting Human Movement in an Urban Environment

Bin Jiang

Department of Land Surveying and Geo-informatics The Hong Kong Polytechnic University, Hung Hom, Kowloon, Hong Kong Email: bin.jiang@polyu.edu.hk

(February 2008 version 3)

Abstract

A city can be topologically represented as a connectivity graph, consisting of nodes representing individual spaces and links if the corresponding spaces are intersected. It turns out in the space syntax literature that some defined topological metrics can capture human movement rates in individual spaces. In other words, the topological metrics are significantly correlated to human movement rates, and individual spaces can be ranked by the metrics for predicting human movement. However, this correlation has never been well justified. In this paper, we study the same issue by applying the weighted PageRank algorithm to the connectivity graph or space-space topology for ranking the individual spaces, and find surprisingly that (1) the PageRank scores are better correlated to human movement rates than the space syntax metrics, and (2) the underlying space-space topology demonstrates small world and scale free properties. The findings provide a novel justification as to why space syntax, or topological analysis in general, can be used to predict human movement. We further conjecture that this kind of analysis is no more than predicting a drunkard's walking on a small world and scale free network.

Keywords: Space syntax, topological analysis of networks, small world, scale free, human movement, and PageRank

Toxic Waste Management

WIRED

CALEB GARLING BUSINESS 02.16.12 04:20 PM

ESEARCHERS FIGHT TOXIC WASTE WITH GOOGLE PAGERANK





Historical Tooling





igraph is a collection of network analysis tools with the emphasis on efficiency, portability and ease of use. igraph is open source and free. igraph can be programmed in R, Python and C/C++.

igraph R package

🔥 igraph

python-igraph

igraph C library





Download Libraries - Documentation -

Examples

Community -**Developers** -

GraphX is Apache Spark's API for graphs and graph-parallel computation.

Flexibility

Seamlessly work with both graphs and collections.

GraphX unifies ETL, exploratory analysis, and iterative graph computation within a single system. You can view the same data as both graphs and collections, transform and join graphs with RDDs efficiently, and write custom iterative graph algorithms using the Pregel API.

```
graph = Graph(vertices, edges)
messages =
spark.textFile("hdfs://...")
graph2 = graph.joinVertices(messages)
  (id, vertex, msg) => ...
```

Using GraphX in Scala

Apache Software Foundation -

Latest News

- Spark Summit (June 5-7th, 2017, San Francisco) agenda posted (Mar 31, 2017)
- Spark Summit East (Feb 7-9th, 2017, Boston) agenda posted (Jan 04, 2017)
- Spark 2.1.0 released (Dec 28, 2016)
- Spark wins CloudSort
- Benchmark as the most
- efficient engine (Nov 15, 2016)

Archive

Download Spark



Global analysis PageRank, Centrality, etc.

4

Real-time queries

6









The New World





Reuters UK

ConservativesIN

Adrian Monck

Space in Space

Jona has Portes

Out do Ven

Robert

Patronette

John Rentoul Jim Pickard

Keiran Pedley

James Murray

Nicholas Soames

Maighan QC Jill Rutter Damian Collins

Will Straw

Paul A

Strong

sleve richards

MarquaChown





Hit a wall with igraph/R

Need to scale graph algorithms











OPTIMIZED FOR







GREAT FOR



Subgraph Queries





POSTS

MENTIONS

WORKING ON











	홎 + - 💽-		
★ Star	87 ¥ Fork 13		
	Edit		
	কাুঁ GPL-3.0		
Find file	Clone or download -		
atest com	mit 146b229 2 days ago		
	a day ago		
	8 days ago		
	a day ago		
	3 days ago	+(
	a day ago	\mathbf{x}	
	5 months ago		
	4 months ago		

Neo4j Graph Algorithms







Cypher Query Language

Wide Range of APOC Procedures



Finds the optimal path availability and quality

> Evaluates how a group is clustered or partitioned

Usage

1.Call as Cypher procedure 2. Pass in specification (Label, Prop, Query) and configuration 3.~.stream variant returns (a lot) of results CALL algo.<name>.stream('Label','TYPE',{conf}) YIELD nodeId, score 4.non-stream variant writes results to graph returns statistics CALL algo.<name>('Label','TYPE',{conf})

Pathfinding

Centrality

Community Detection

What about Virtual Graphs?

Pass in Cypher statement for node- and relationship-lists.

```
CALL algo.<name>(
'MATCH ... RETURN id(n)',
'MATCH (n) \rightarrow (m)
 RETURN id(n) as source,
        id(m) as target', {graph:'cypher'
```

Pathfinding

Centrality

Communit\ Detection

Supported Centrality Algos

- PageRank (baseline)
- Betweeness
- Closeness
- Degree

Pathfinding

Centrality

Community Detection

Supported Centrality Algos

CALL algo.pageRank.stream ('Page', 'LINKS', {iterations:20, dampingFactor:0.85}) YIELD node, score RETURN node, score ORDER BY score DESC LIMIT 20

CALL algo.pageRank('Page', 'LINKS', {iterations:20, dampingFactor:0.85, write: true, writeProperty:"pagerank"})

YIELD nodes, loadMillis, computeMillis, writeMillis

Supported Pathfinding Algos

- Single Source Short Path
- All-Nodes SSP
- Parallel BFS / DFS



Pathfinding

Centrality

Community Detection

Goal: Iterate Quickly

- Combine data from sources into one graph
- Project to relevant subgraphs
- Enrich data with algorithms
- Traverse, collect, filter aggregate with queries
- Visualize, Explore, Decide, Export
- From all APIs and Tools

Transactions

Discovery and Design Operational Activities

Analytics

A note on Performance 500 416



Twitter 2010 Dataset

- 1.47 Billion Relationships
- 41.65 Million Nodes

Spark GraphX results publicly available

- Amazon EC2 cluster running 64-bit Linux
- 128 CPUs with 68 GB of memory, 2 hard disks





Neo4j

PageRank

Neo4j Configuration

 Physical machine running 64-bit Linux 128 CPUs with 55 GB RAM, SSDs

What's the Future Look Like?

Improved Performance & Testing

Tim = necematis. //in//sac/nec4/community/shell = ssh = 230x89	
1 1.1	þ
Physical (1) V/V V/V	

Scaling via Parallel Processing





Scaling Across the Cluster



THANK YOU!

ryan@neo4j.com @ryguyrg



