Graph Similarity Computations on Large Graph Databases

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Introduction
Graph theory has been around since the 18th century. However, in recent times, the range of problems that require graph processing has grown rapidly. With the ever-evolving needs of users and the rise of big data, understanding the relationships between interconnected data has grown in importance.

Graphs are ideal for a wide variety of applications, including natural language processing, geospatial analysis, medical records, social networks, ecommerce, and cybersecurity.

Graph Similarity
Graph similarity is a way of measuring how similar two graphs are. This is done using intricate algorithms that analyze the graph’s structure in addition to its properties. These algorithms generally return a number as a measure of the similarity between a pair of graphs. This similarity metric can then be used to group similar entities, such as webpages, products, malware, or medical patients.

Motivation
- Processing large numbers of complex graphs is a challenging task, and an ongoing problem.
- Data size and complexity continuously evolves over time. Graph databases are well-suited for this.
- Prior work designed for small-scale graph processing, and is not intuitive to use for large volumes of data.
- Performance and usability are major challenges.
- We need a comprehensive solution that can handle large-scale data, as well as data from different sources.

Datasets
- Randomly generated graphs
- Electronic Medical Records (EMR)
- E-business
- E-learning data
Need uniform schema for each dataset, and data loaders for real world data.

Graph Processing Components
- Graph database: Neo4j
  - Meets our requirements to store and process the datasets.
  - Is an open source project, written in Java.
- Random graph generator
  - We are developing a flexible tool that allows us to generate graphs or trees, with the characteristics that we need.
  - Supports weighted and labeled property graphs.
  - Outputs results in the GraphML format.
- Parallel computing framework: Nvidia CUDA, JCUDA
  - GPGPU framework will be used to accelerate complex operations.
- Data Loader
  - Implement tool to filter and convert graph data to a format import tools can understand.
- Graph Visualization Tools: Gephi, yEd

Queries
- Nodes
- Relationships
- Paths
- Neighborhoods
- Distances
A combination of metrics

Proposed Framework
- Powerful graph processing framework based around a graph database.
- Handle importing/exporting data in various formats, and visualizing the graphs.
- Some similarity algorithms will be implemented based on related work in [1][2][3].
- Cypher query language can satisfy some tasks, and computationally intensive workloads can be offloaded to GPU.

Future Work
- Implement data loaders to import non-graph data.
- Improve performance by utilizing high performance computing (GPUs, clusters, cloud computing, etc.).
- Explore new techniques and data structures to reduce graph memory usage in parallel applications.
- Explore indexing techniques for graph databases.

Data Characteristics
- Large: Upwards of millions of discrete graphs
- Complex: Nodes are labeled and have additional properties. Edges are directed, and have weights and labels.
- Dynamic: Need to be able to add, remove, or modify nodes and relationships, at any time. Some graph types have additional rules that must be satisfied.
- Index-free adjacency: find adjacent nodes without the need for indexes or database scans. Performance doesn’t degrade like relational databases.
- Labels are more important than properties, and are given preferential treatment in the database. Properties are stored separately, but cached.