Graph Data Management

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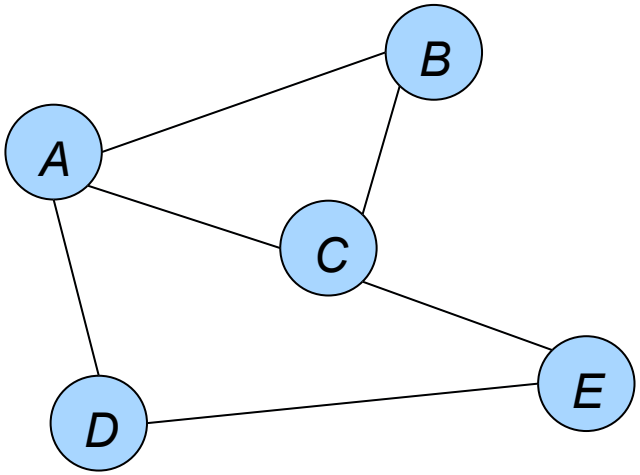
Outline

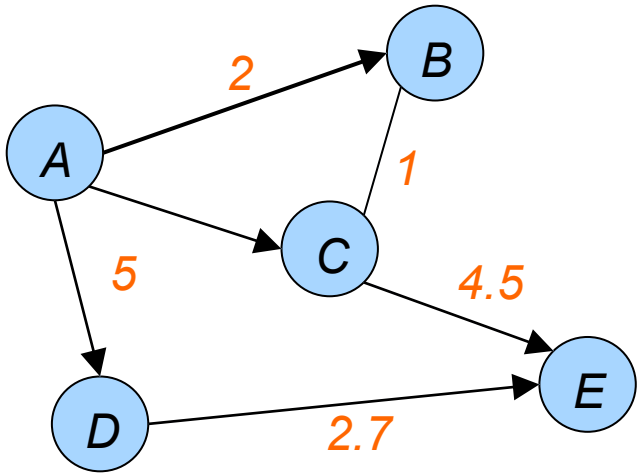
- Background and Motivation
- Graph Queries and Analysis Tasks
- Graph Data Management: Storage
- Graph Data Management: Processing
- What we are doing

Background: Graphs

- A *graph* captures a set of entities/objects, and interconnections between pairs of them
  - *Graphs* also often called *networks*
  - Entities/objects represented by *vertices or nodes*
  - Interconnections between pairs of vertices called *edges*
    - Also called *links, arcs, relationships*



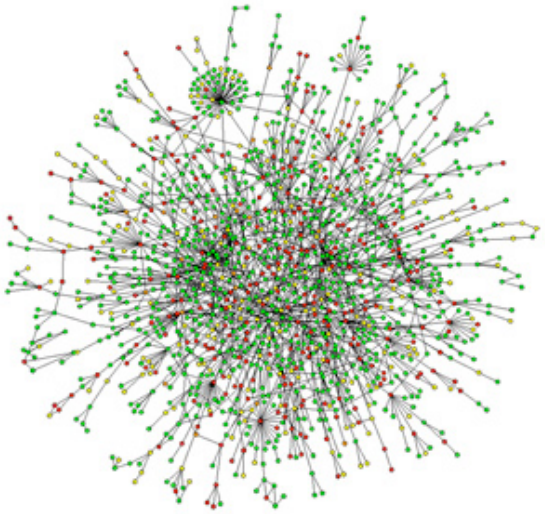
An undirected, unweighted graph



A directed, edge-weighted graph

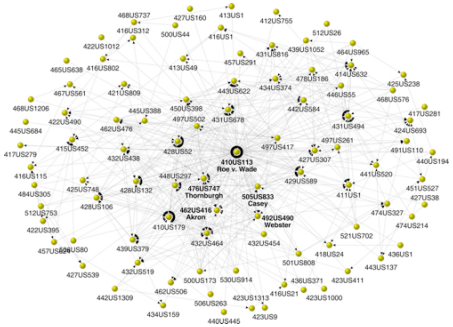
Motivation

- Increasing interest in querying and reasoning about the *underlying graph structure* in a variety of disciplines

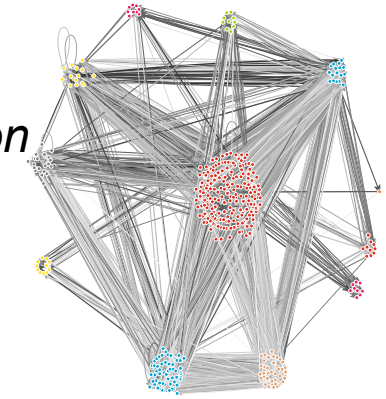


A protein-protein interaction network

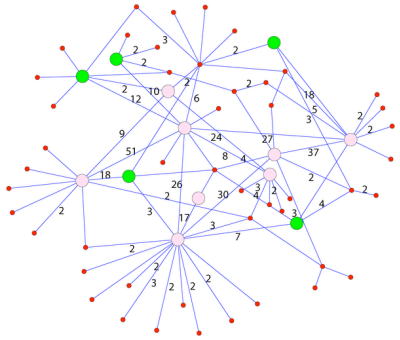
Social networks



Supreme court citation network



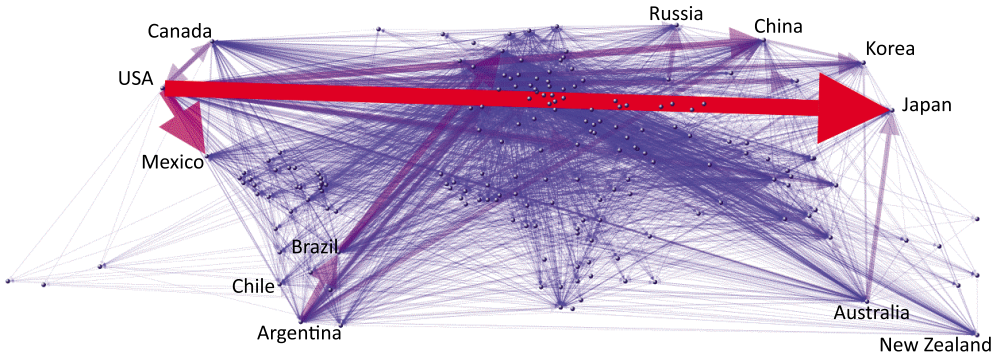
Financial transaction networks



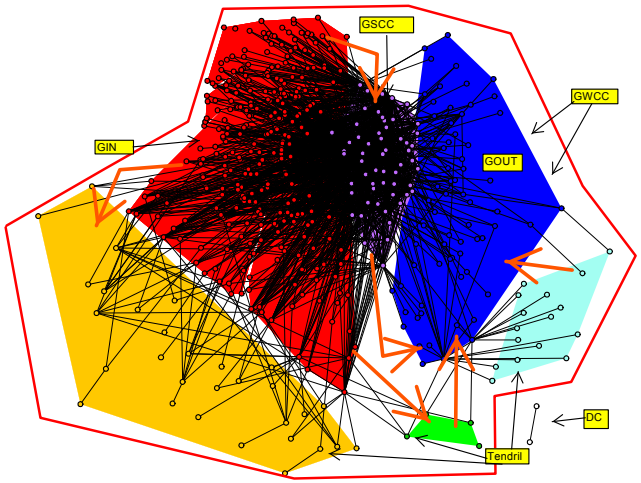
Stock Trading Networks

Motivation

- Increasing interest in querying and reasoning about *interconnected entities* in a variety of disciplines



Global virtual water trade network



Federal funds networks

Citation networks

Parcel shipment networks

Collaboration networks

Knowledge Graph

Telecommunications networks

World Wide Web

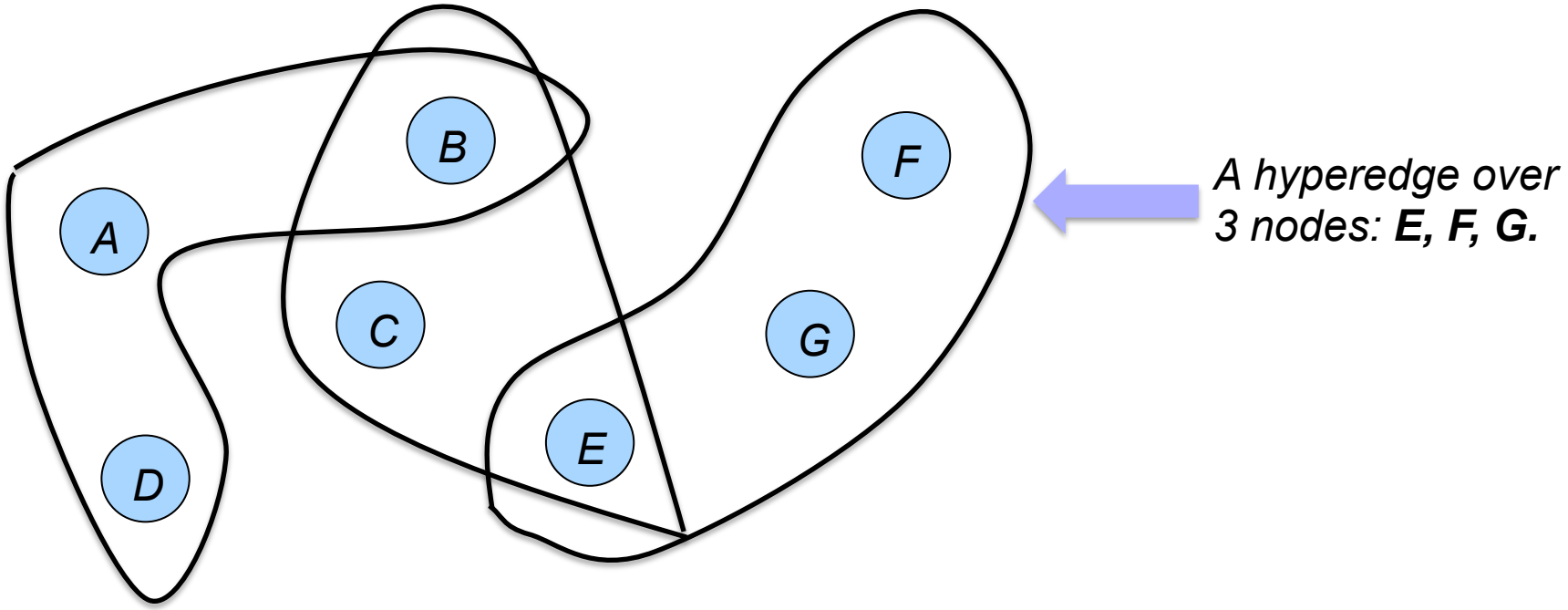
Disease transmission networks

Motivation

- Increasing interest in querying and reasoning about *interconnected entities* in a variety of disciplines
- Underlying data hasn't necessarily changed that much
  - Aside from the data volumes and easier availability
- However, several new realizations in recent years:
  - Reasoning about the graph structure can provide useful and actionable insights (*network science/complex network analysis)*
  - Lose too much information and intuitions if graph structure ignored
  - Not easy to write many natural queries or tasks using traditional tools
    - Especially relational databases like Oracle
  - Harder to efficiently process inherently graph-structured queries or complex network analysis tasks using existing tools
    - A major concern with increasingly large graphs seen in practice

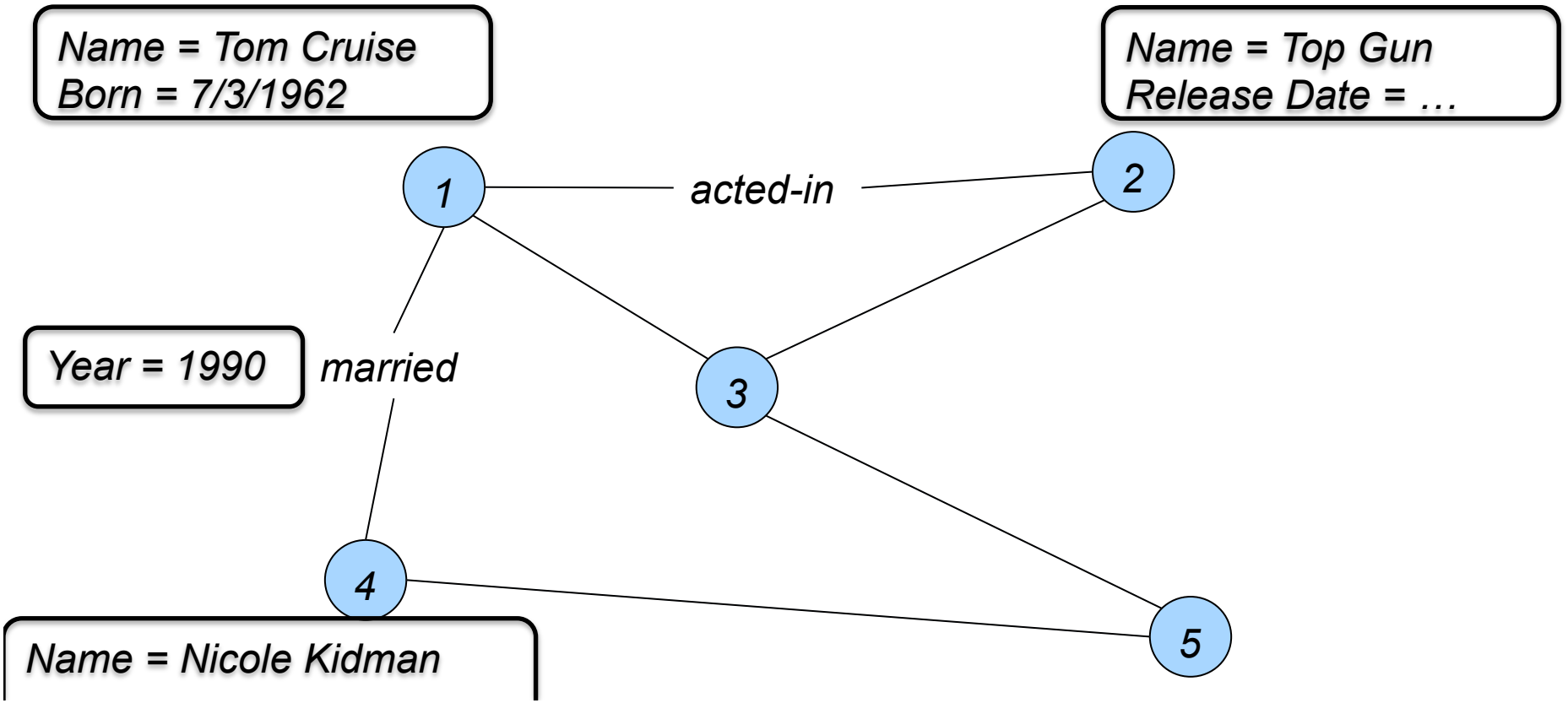
Additional Background

- Hypergraphs
  - A more powerful abstraction than graphs
  - An “edge” may connect more than two vertices
  - Enables modeling relationships/events between more than 2 entities
  - Much harder to reason about in general, but may be necessary in some domains



Additional Background

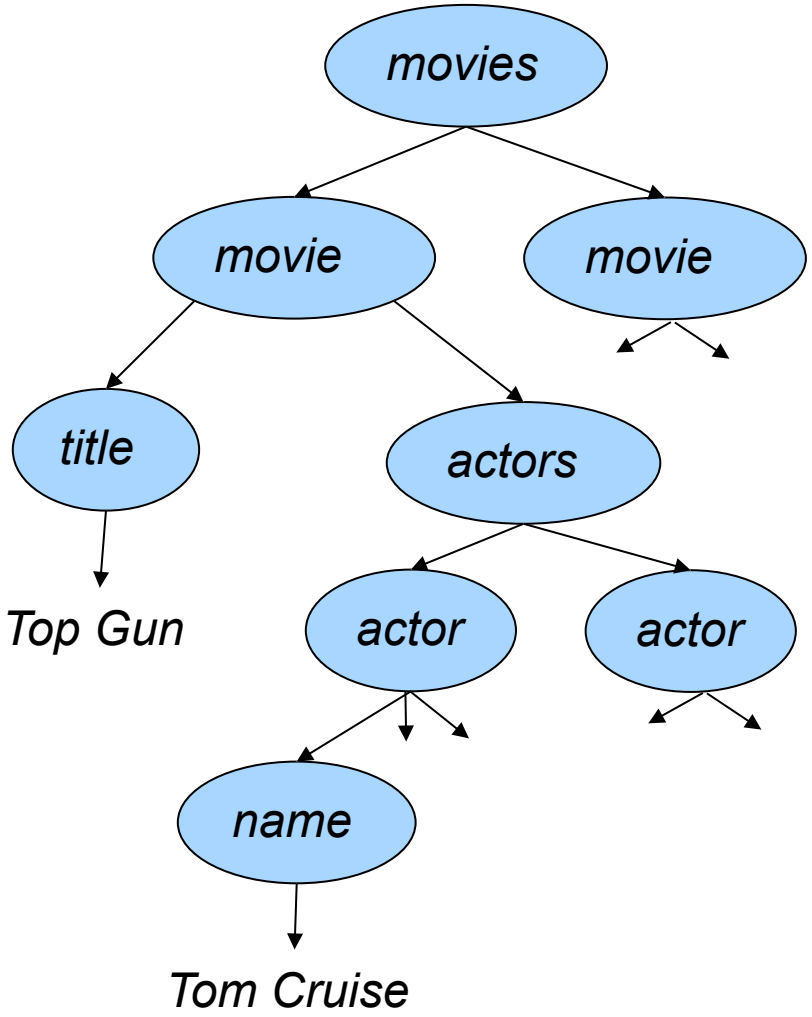
- Property Graphs
  - A graph model used by many open-source graph data management tools
  - In essence: a directed graph where each node and each edge may be associated with a set of *properties*



Additional Background

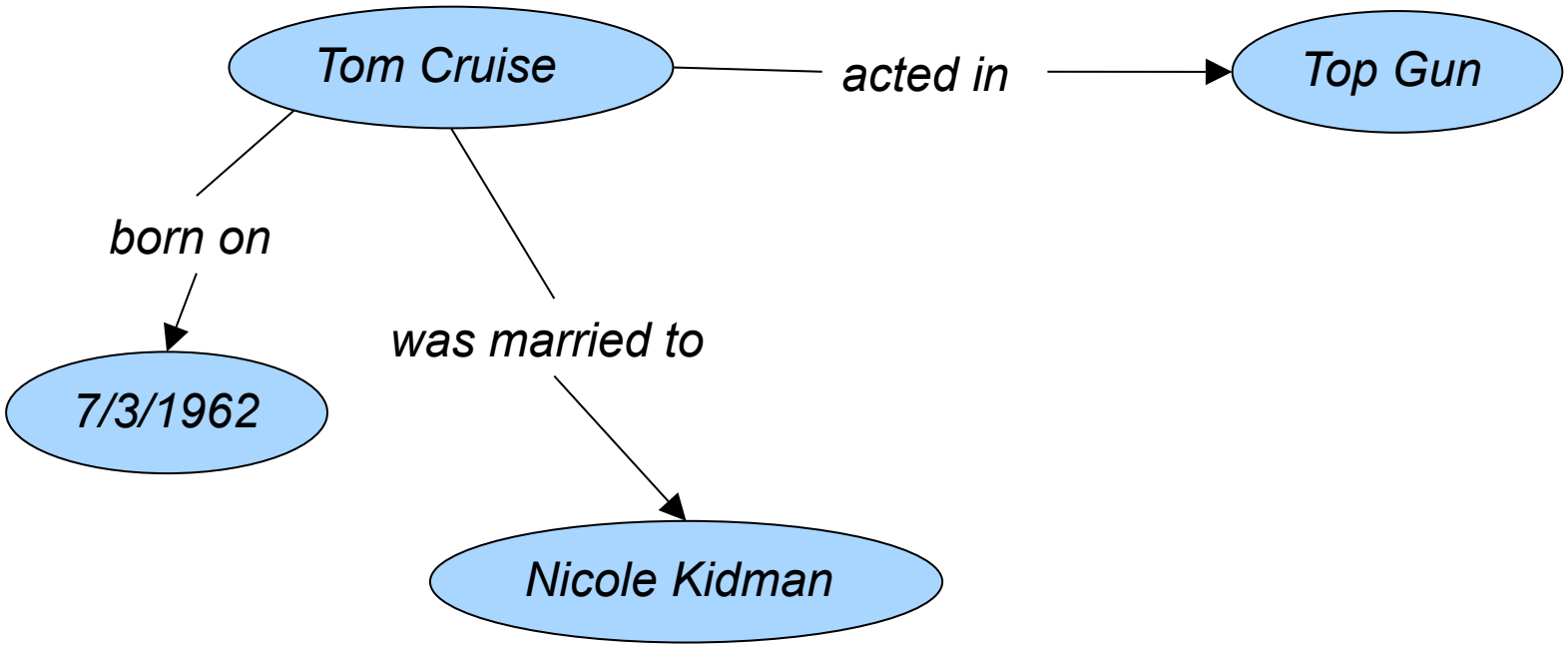
- XML
  - A commonly used data model for representing data without rigid structure
  - In essence: a directed, labeled "tree"
  - Very popular data exchange format

```
<movies>
  <movie>
      <title>Top Gun</title>
      <actors>
        <actor>
          <name>Tom Cruise</name>
          <born>7/3/1962</born>
        </actor>
        <actor>
        …
        </actor>
      </actors>
  </movie>
  …
```



Additional Background

- Resource Description Framework (RDF)
  - A commonly used data model for representing *knowledge bases*
  - In essence: a directed, labeled graph
  - Each edge (called a triple): connects a “subject”, an “object”, and is associated with a “predicate”



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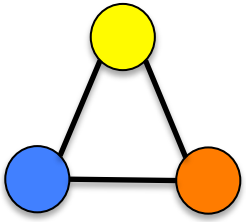
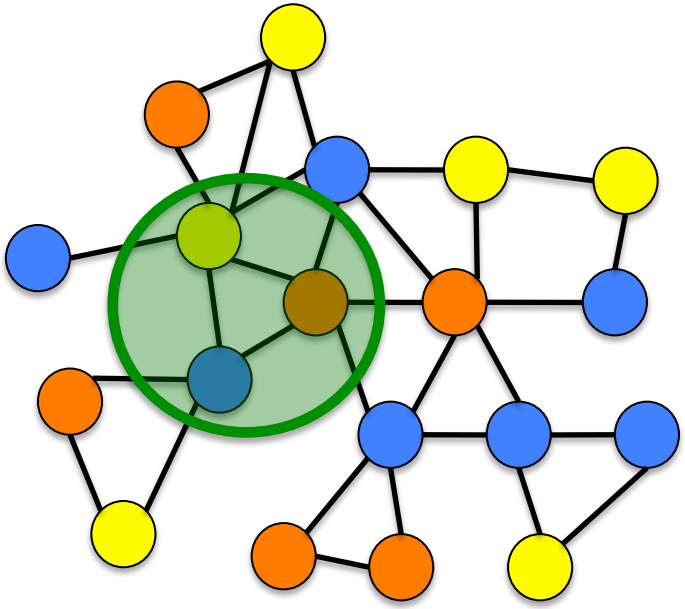
Queries: Subgraph Matching

- Given a "query" graph, find where it occurs in a given "data" graph
  - Query graph can specify restrictions on the graph structure, on values of node attributes, and so on
  - An important variation: *approximate* matching
- Alternatively, given a collection of data graphs, find the ones that contain the query graph



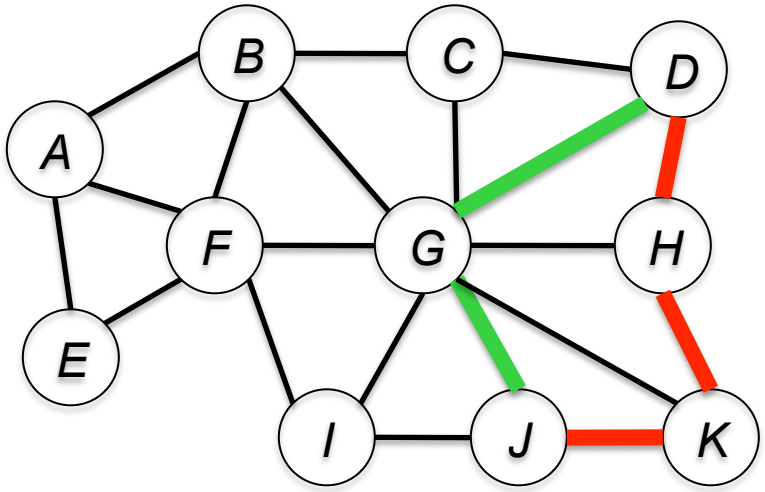
Query Graph



Data Graph

Queries: Connection Subgraphs

- Given a data graph and two (or more) nodes in it, find a small subgraph that best captures the relationship between the nodes
- Key question: How to define "best captures"?
  - E.g., "shortest path": but that may not be most informative



The "red" path between D and J maybe more informative than the "green" path

Queries

- Reachability:
  - Given two nodes, is there an undirected or directed path between them?
  - … with constraints on the types of edges that can be used?
- Shortest path:
  - Find the shortest path between two given nodes
- Keyword search:
  - Find the smallest subgraph that contains all the specified keywords
- Historical queries:
  - Given a node, find other nodes that evolved most similarly in the past
- And so on…

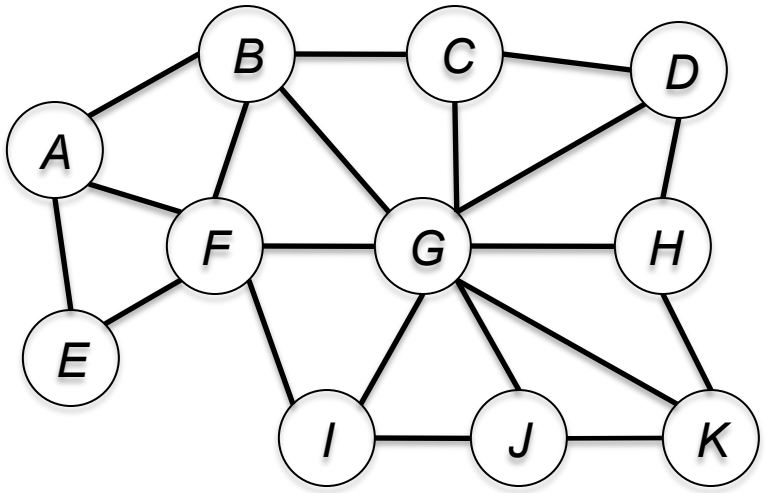
Graph Analysis: Centrality Measures

- Centrality measure: a measure of the relative importance of a vertex within a graph
- Many different centrality measures
  - … that can give fairly different results

Degree centrality of a node *u*:
*# of edges incident on **u***

Betweenness centrality of a node *u*:
*# of shortest paths between pairs of vertices that go through **u***

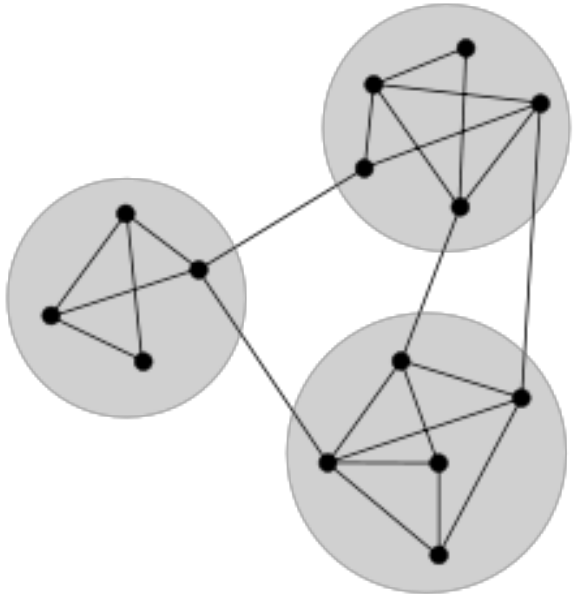
Pagerank of a node *u*:
*probability that a random surfer (who is following links randomly) ends up at node **u***



Eigenvector centrality:
Used in a recent work on analyzing Federal Funds Network

Graph Analysis: Community Detection

- Goal: partitioning the vertices into (potentially overlapping) groups based on the interconnections between them
  - Basic intuition: More connections within a community than across communities
  - Provide insights into how networks function; identify functional modules; improve performance of Web services…
- Numerous techniques proposed for community detection over the years
  - Graph partitioning-based methods
  - Maximizing some "goodness" function
  - Recursively removing high centrality edges
  - … and so on



Graph Analysis: Models of Evolution

- Two somewhat related goals:
  - Measuring different properties of networks
    - E.g., degree distributions, diameter, clustering coefficient, …
  - Using those to build models of how a network forms and evolves
    - To gain insights; for predictions about the future…
- Example:
  - Most real networks exhibit highly skewed degree distributions
  - *Preferential attachment model* explains that phenomenon
    - Basic idea: a new node is more likely to connect to a high-degree node than a low-degree node (“rich get richer”)
- Some other observed properties:
  - Shrinking diameters
  - Average degree in the network increases over time
  - High clustering coefficients

Graph Analysis: Cleaning/Inference

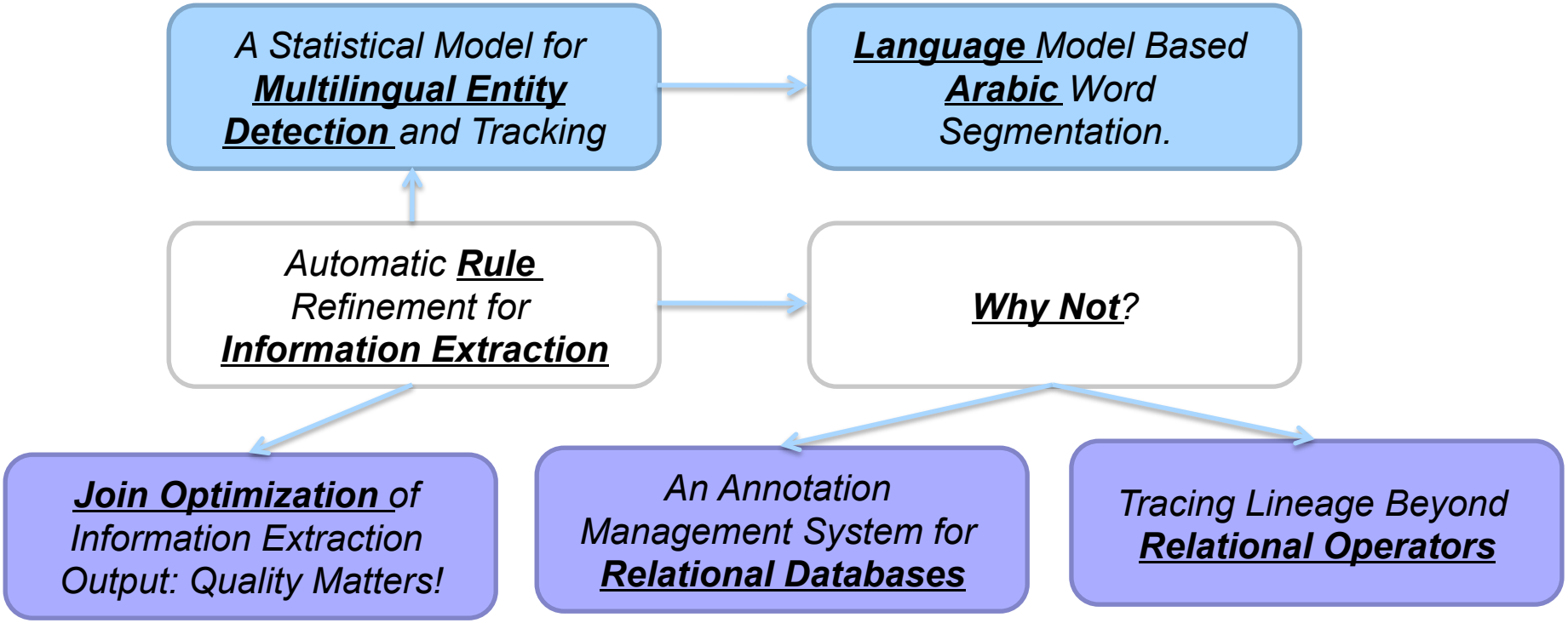
- The *observed, automatically-extracted information networks* are often noisy and incomplete
  - Missing attributes, missing links
  - Ambiguous references to the same entity

- Need to extract the underlying *true information network* through:
  - Attribute Prediction: *to predict values of missing attributes*
  - Link Prediction: *to infer missing links*
  - Entity Resolution: *to decide if two references refer to the same entity*

Attribute Prediction

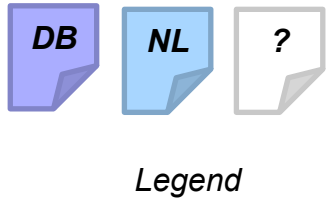
Task: *Predict topic of the paper*

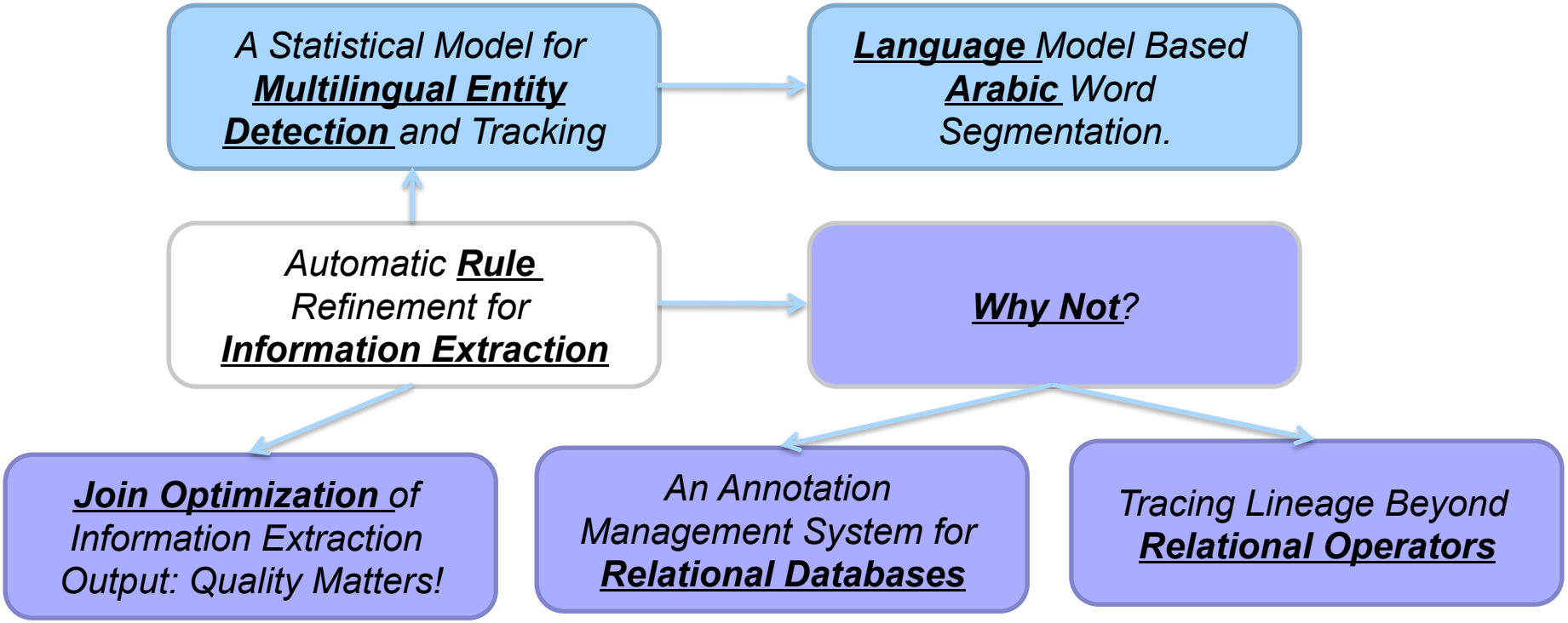
Legend



Attribute Prediction

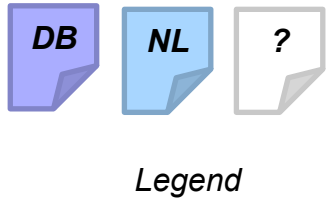
Task: *Predict topic of the paper*

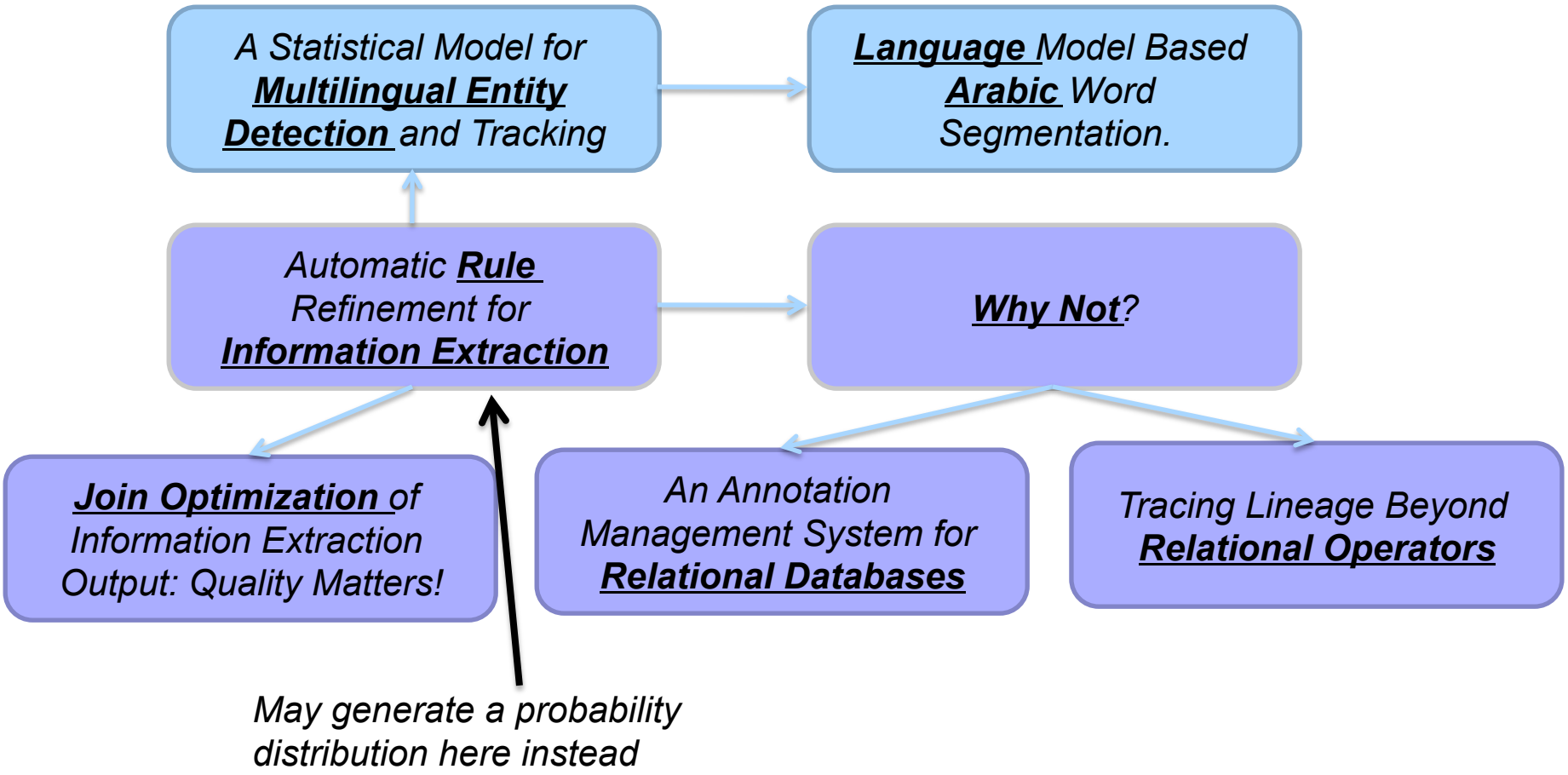




Attribute Prediction

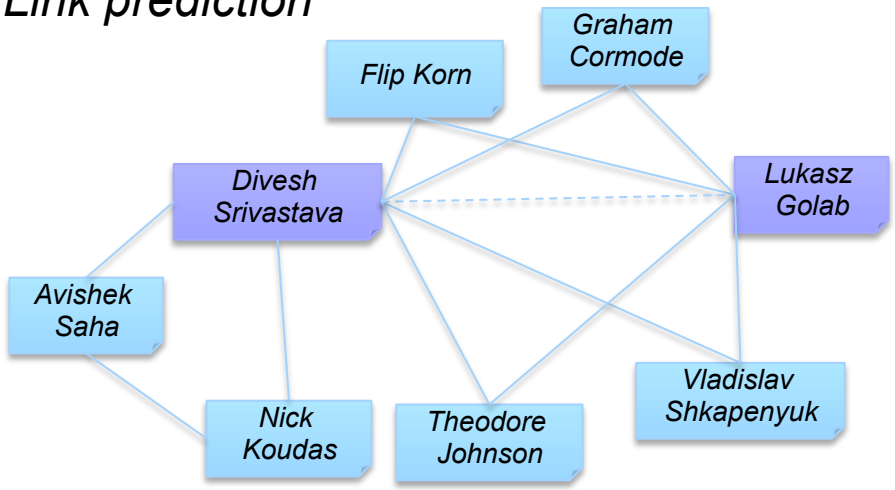
Task: *Predict topic of the paper*



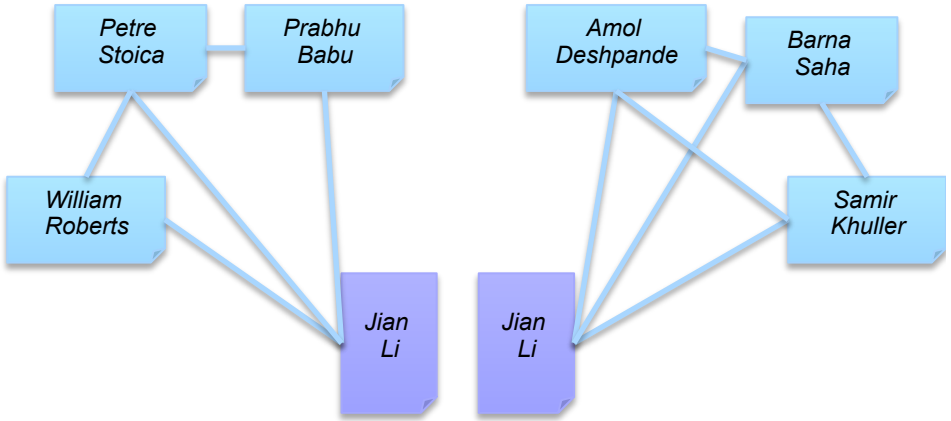


Collective (relational) Inference

Link prediction



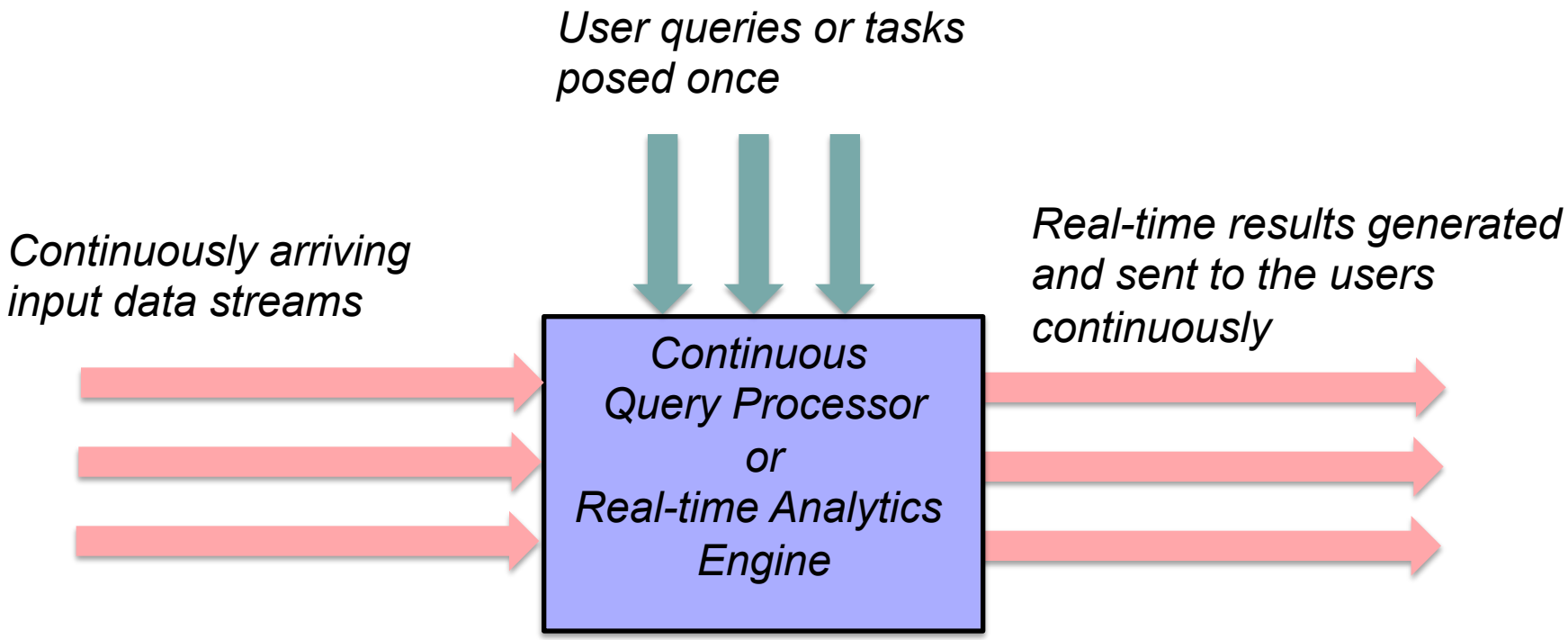
Entity resolution



- Many collective techniques have been developed over the years

Real-time Graph Queries and Analytics

- Most of the queries/analysis so far focus on a static graph datasets
- Increasing need for doing those in real-time on "data streams"



Real-time Graph Queries and Analytics

- Most of the queries/analysis so far focus on a static graph dataset
- Increasing need for doing those in real-time on "data streams"
- Examples:
  - Update me when a friend posts a message on a social network
  - Alert me when a topic is suddenly "trending" in my friend circle
  - Anomaly detection:
    - Alert me if the communication activity in the network changes drastically
    - Monitor constraints on the data being generated by the nodes
- Data streams very well studied for relational data, but not in the context of graph querying or analytics
- An ongoing research focus for my group

Graph Queries and Analysis

- Eigenvalue analysis
- Clustering coefficients
- Ego-centric analysis
- Visualizations
- Summarization
- Motif Counting
- …

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Options for Storing Graph Data

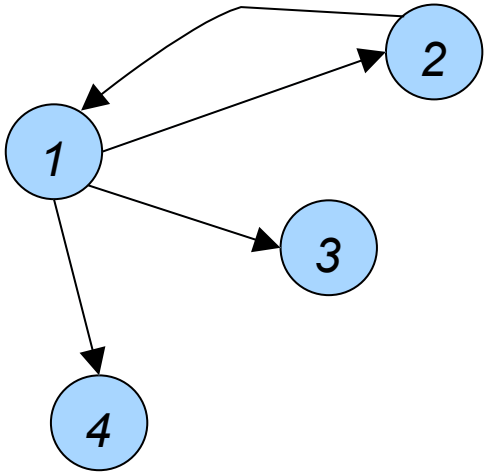
1. Use file systems
   - \+ Very simple, and no (practical) limits on how large a dataset to manage
   - − No support for transactions; minimal functionality
2. Use a *relational* database (e.g., Oracle, IBM DB2, etc.)
   - \+ Mature technology – much of the data is already in them anyway
   - \+ All the goodies (SQL, transactions, toolchains) available
   - − Almost no support for traversing the graph structure
3. Use NoSQL *key-value* stores
   - \+ Can handle very large datasets efficiently, in a distributed fashion
   - − Minimal functionality – must build the analysis/querying tools on top
4. Use a persistent *graph database*
   - \+ Efficiently support *graph traversals*
   - − But even the most mature products not as a mature as RDBMSs
   - − Typically no declarative languages (a la SQL), so must write programs

Storage 1: File Systems

- Simplest to get started, and widely used in practice
  - Especially since the other options don't really help that much anyway for graph querying or analytics
- Many *cloud computing* programming frameworks read data from file systems
  - E.g., Hadoop Distributed File System (HDFS) used by Apache Hadoop and others
- Key disadvantages:
  - Almost no data management functionality
    - Everything from parsing to analyzing must be done by the programmer
  - No support for updates, or transactions
  - Hard to do "queries" without building auxiliary structures

Storage 2: Relational Databases

- Store the entities in a set of tables, and encode the connections between them in separate tables
  - E.g., RDF and XML data predominantly stored in relational databases
- Can use SQL to query the data, and other DBMS analytic tools
- However, no support for graph traversals
  - Must extract the relevant data, & write code to construct/process the graph
  - Can be much much slower than specialized solutions for traversal operations



Banks

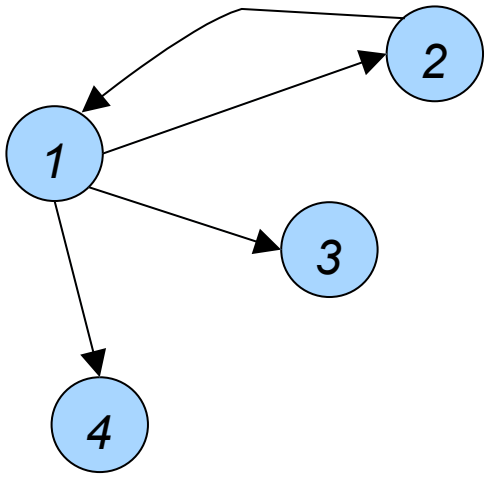
ID	Name	…
1	…	…
2	…	…
3	…	…
4	…	…

Trades

Bank1	Bank2	Date	…
1	2	…	
2	1	…	
3	1	…	
4	1	…	

Storage 3: Key-value Stores

- A recent, and wildly popular solution, to manage large datasets
  - Examples: Apache HBase, Cassandra, Amazon Dynamo, Redis
- Very basic functionality
  - Put(*k, v*): Store the value *v,* and associate it with key *k*
  - Get(*k*): Get the value associated with key *k*



One way to store it in a key-value store

Key	Value
Bank1	Information about the bank
Bank2	…
Bank1.outTrades	A list of all the trades where Bank1 is the seller
Bank1.inTrades	A list of all the trades where Bank1 is the buyer
…	…

Storage 3: Key-value Stores

- A recent, and wildly popular solution, to manage large datasets
  - Examples: Apache HBase, Cassandra, Amazon Dynamo, Redis
- Key-value stores manage the data in a distributed fashion
  - Can handle very large datasets with very low latencies
  - Underlie many Web applications (many Google products, Facebook, etc.)
- Advantages:
  - Support efficient updates (must be careful about consistency)
  - Fast retrieval → easy to traverse the graph structure
  - We chose this option for the first prototype implementation of our distributed graph data management system for dynamic graphs
- Disadvantages:
  - Everything outside of graph traversals must be built on top

Storage 4: Specialized Graph Databases

- Built to manage and query graph-structured data
- Many built over the years, and increasing interest in recent years
  - Neo4j: Perhaps the most mature product out there
  - InfiniteGraph: Originally an object-oriented database
  - DEX: Quite similar to Neo4j in functionality
  - AllegroGraph: An RDF database
  - HyperGraphDB: Allowing modeling hypergraphs
  - Wikipedia page on graph databases lists many more
- Key disadvantages:
  - Fairly rudimentary declarative interfaces -- most applications need to be written using programmatic interfaces
  - Or using provided toolkits/libraries

Neo4j

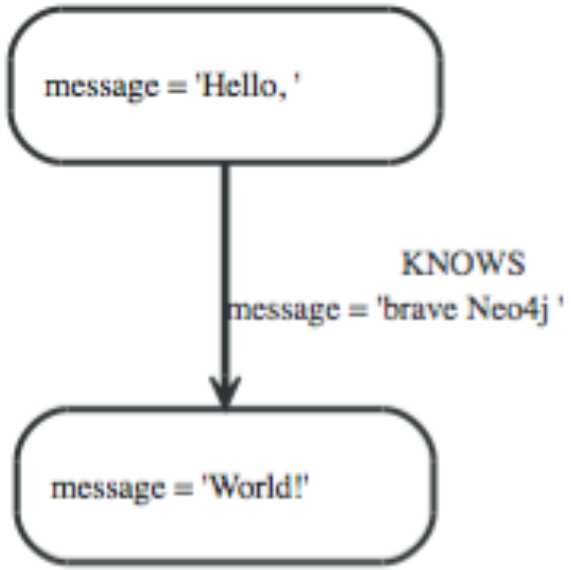
- Open-source graph database supported by Neo Technology
  - Uses the *property graph* model
  - The data stored on disks (unlike key-value stores)
  - Full ACID support (i.e., consistent and reliable updates)
  - Can scale to billions of nodes and edges
  - Supports many different APIs to access the data, and to retrieve the data
  - Highly efficient retrieval of nodes of interest through “indexing”

Neo4j

- Feature-rich Programmatic API to access a Neo4j database

```
firstNode = graphDb.createNode();
firstNode.setProperty( "message", "Hello, " );
secondNode = graphDb.createNode();
secondNode.setProperty( "message", "World!" );

relationship = firstNode.createRelationshipTo( secondNode, RelTypes.KNOWS );
relationship.setProperty( "message", "brave Neo4j " );
```

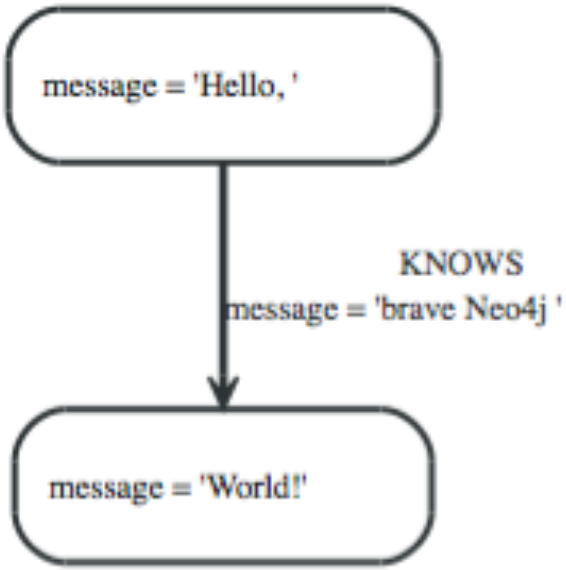


Source: http://www.neo4j.org

Neo4j

- Feature-rich Programmatic API to access a Neo4j database

```
System.out.print( firstNode.getProperty( "message" ) );
System.out.print( relationship.getProperty( "message" ) );
System.out.print( secondNode.getProperty( "message" ) );
```



Source: http://www.neo4j.org

Neo4j

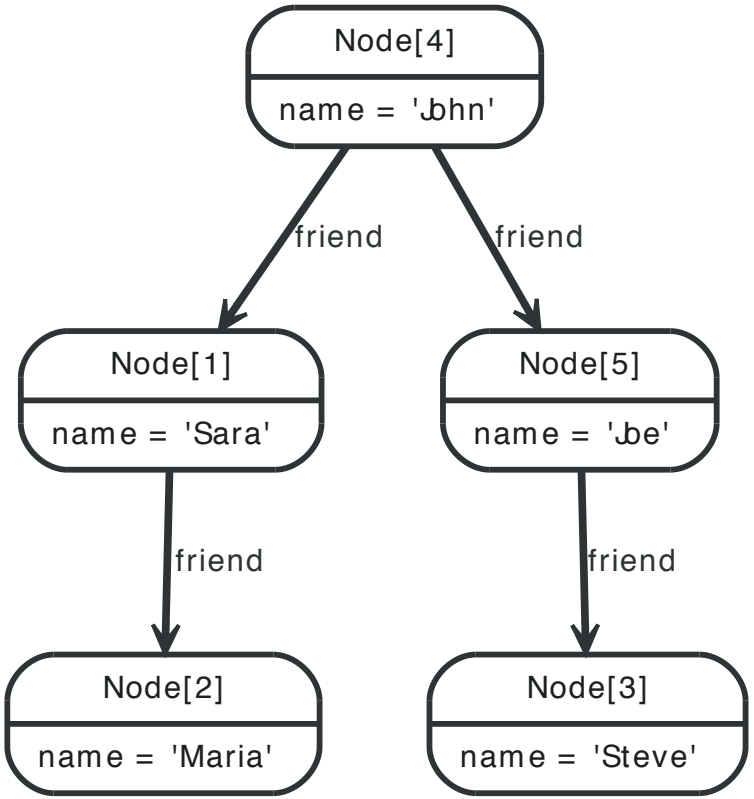
- Feature-rich Programmatic API to access a Neo4j database
  - Supports different types of indexes to quickly find “start” nodes
    - E.g., find the node for a particular person in a social network
  - Support different types of “traversals” to traverse the local neighborhoods

Source: http://www.neo4j.org

Neo4j

- Also supports a high-level language, called **cypher**, for traversing and searching

Figure 15.1. Example Graph



Finds friends of John's friends

```
START john=node:node_auto_index(name = 'John')
MATCH john-[:friend]->()-[:friend]->fof
RETURN john, fof
```

Source: http://www.neo4j.org

Neo4j

- Also supports a high-level language, called **cypher**, for traversing and searching
- Can use **cypher** on its own (in a console), or in an embedded fashion (e.g., from within Java)

Source: http://www.neo4j.org

AllegroGraph

- Aimed at Semantic Web Applications
- Triple-store: stores RDF assertions of the form
  - <subject, predicate, object>
  - E.g., <“sky”, “has-color”, “blue” >
- Full support for transactions, concurrency, recovery
- Several different ways to query:
  - Query patterns (specify the types of triples)
  - Has a Social Network Analysis Toolkit
    - Search methods, Centrality computations, etc.
  - Supports querying using Prolog
  - Supports SPARQL query language
  - …

Source: http://www.franz.com/agraph/allegrograph/

SPARQL

- Standardized RDF query language
- Basic functionality quite similar to *subgraph pattern matching*
  - But recent extensions attempt to go quite a bit beyond that

Find names and emails of every person in the dataset

```
PREFIX foaf: <http://xmlns.com/foaf/0.1/>
SELECT ?name ?email
WHERE {
  ?person a foaf:Person.
  ?person foaf:name ?name.
  ?person foaf:mbox ?email.
}
```

SPARQL

- Standardized RDF query language
- Basic functionality quite similar to *subgraph pattern matching*
  - But recent extensions attempt to go quite a bit beyond that

Find me all landlocked countries with a population greater than 15 million (revisited), with the highest population country first.

```
PREFIX type: <http://dbpedia.org/class/yago/>
PREFIX prop: <http://dbpedia.org/property/>

SELECT ?country_name ?population
WHERE {
        ?country a type:LandlockedCountries ;
                 rdfs:label ?country_name ;
                 prop:populationEstimate ?population .
         FILTER (?population > 15000000 &&
                  langMatches(lang(?country_name), "EN")) .
} ORDER BY DESC(?population)
```

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- Graph Queries and Analysis Tasks
- Graph Data Management: Storage
- Graph Data Management: Processing
- What we are doing

Options for Processing Graph Data

1. Write your own programs
   - Extract the relevant data, and construct an in-memory graph
   - Different storage options help to different degrees with this
2. Write queries in a declarative language
   - Works for a very small class of graphs queries/tasks today
   - Ongoing research work (including in my group) on generalizing that
3. Use a general-purpose distributed programming framework
   - E.g.: Hadoop or MapReduce
   - Hard to program most graph analysis tasks this way
4. Use a graph-specific programming framework
   - Goal is to simplify writing graph analysis tasks, and scale them to very large volumes at the same time
   - Still ongoing work – wide applicability still to be proven

Option 2: Declarative Interfaces

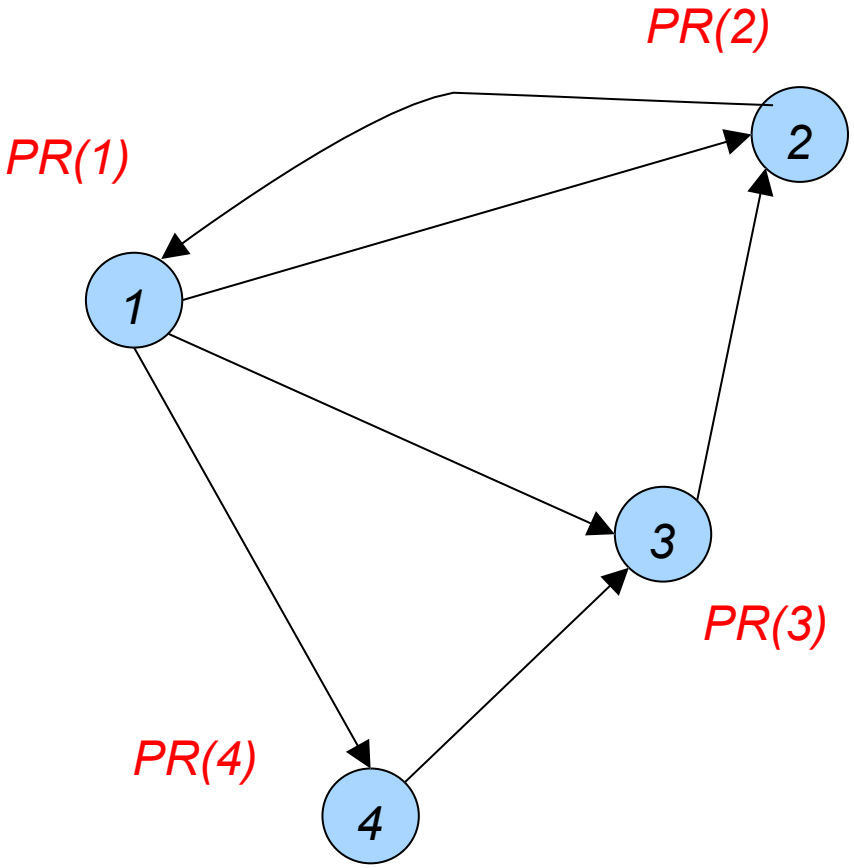
- No consensus on declarative, high-level languages (like SQL) for either querying or for analysis
  - Too much variety in the types of queries/analysis tasks
  - Makes it hard to find and exploit commonalities
- Some limited solutions:
  - XQuery for XML
    - Limited to tree-structured data
  - SPARQL for RDF
    - Standardized query language, but limited functionality
  - Cypher by Neo4j
  - Datalog-based frameworks for specifying analysis tasks
    - Mostly research prototypes, typically specific to some analysis task

Option 3: Map Reduce

- A very popular option for (batch) processing very large datasets
  - More specifically: Hadoop, the open source implementation
- Two key advantages:
  - Scalability without worrying about scheduling, distributed execution, fault tolerance, and so on…
  - Simple programming framework
- Disadvantages:
  - Hard to use this for graph analysis tasks
  - Each “traversal” effectively requires a new “map-reduce” phase
    - Map-reduce framework not ideal for large numbers of phases
- However, much work on showing how different graph analysis tasks can be done using MapReduce

Background: PageRank

- PageRank: A measure of *centrality* of a node
- PR(node) = Probability that a random *surfer* ends up at that node



Probability of jumping to a random node

$PR(2) = \alpha/4 + (1 - \alpha)\,(PR(1)/3 + R(3)$

PageRank of node 1

This formula defines a probability distribution over the nodes.

PageRank of node 3 distributed over its out-edges

Background: PageRank

- PageRank: A measure of *centrality* of a node
- PR(node) = Probability that a random *surfer* ends up at that node
- Damping factor α needed to handle nodes with 0 out-degree and other special cases
  - Surfer may jump to a random page with probability α and restart
- How to compute?
  - Algebraically: using Gaussian Elimination
    - Not scalable to large graphs
  - Iteratively:
    - For the first iteration: PR(n) = 1/N for all nodes
    - Repeatedly apply the formula using the PR() values from the previous iteration
    - Typically 25-50 iterations enough to converge

Background: PageRank

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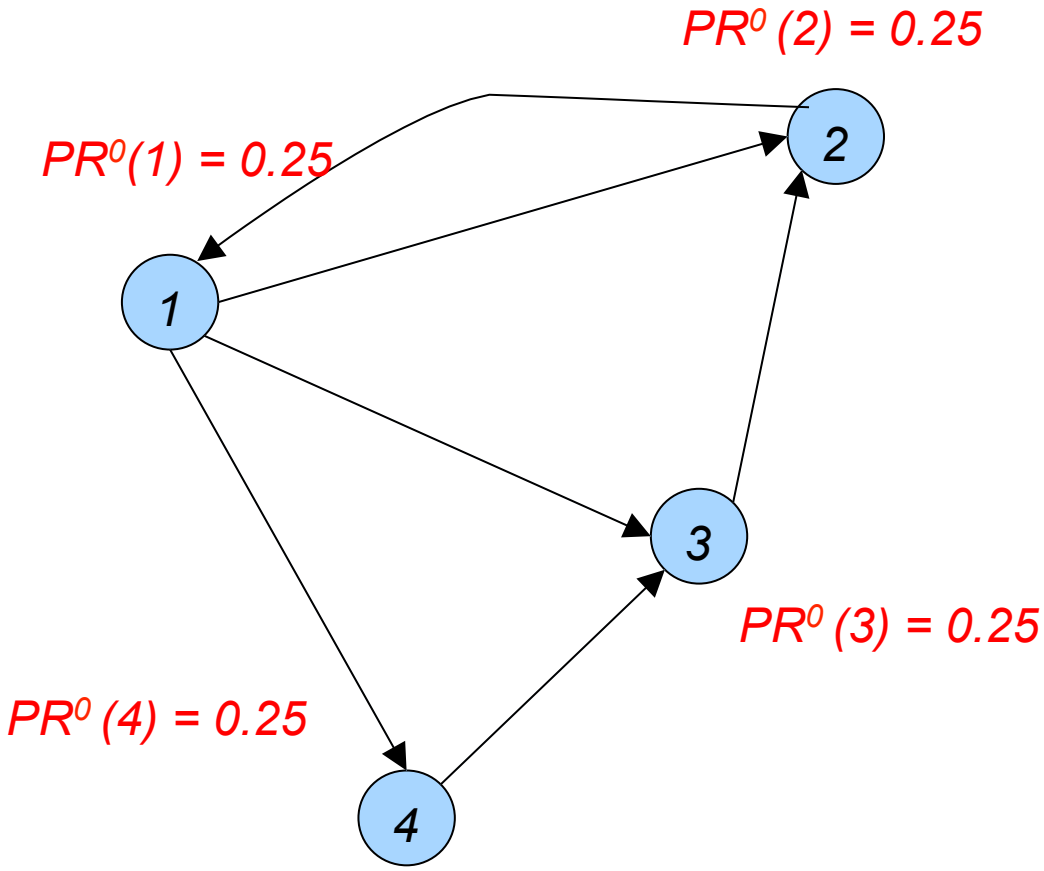
- Iterative approach:



Compute $PR^1(1), \ldots,$ *using* $PR^0(1), \ldots$

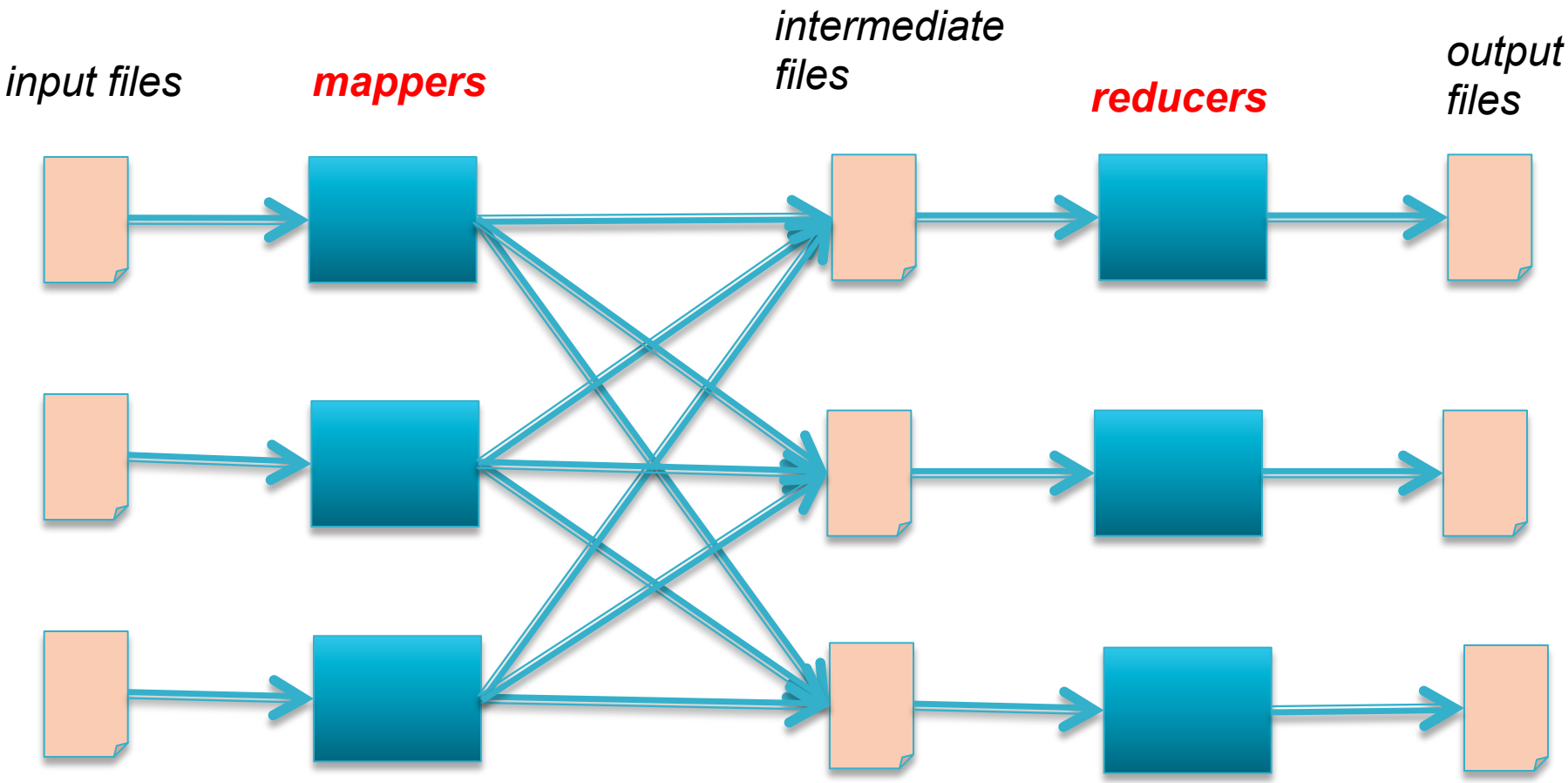
E.g.,

$$PR^1(2) = \alpha/4 + (1 - \alpha)\,(PR^0(1)/3 + PR^0(3))$$

Option 3: Map Reduce

- Programmers write a pipeline of functions, called *map* or *reduce*
  - map programs
    - **inputs**: a list of "records" (record defined arbitrarily – could be images, genomes etc…)
    - **output**: for each record, produce a set of "(key, value)" pairs
  - reduce programs
    - **input**: a list of "(key, {values})" grouped together from the mapper
    - **output**: no specific restrictions – depends on what next
  - Both can do arbitrary computations on the input data as long as the basic structure is followed

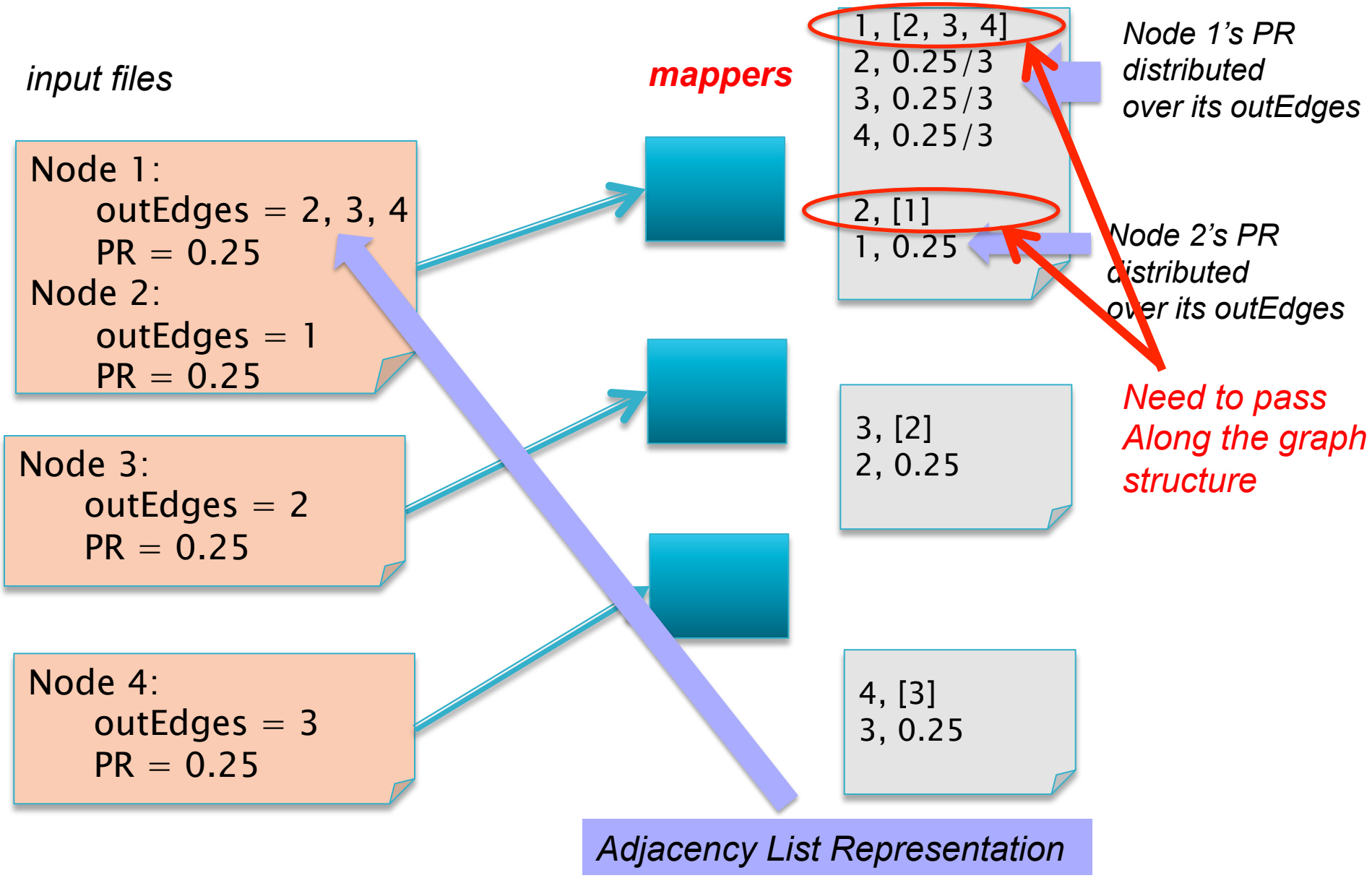
Option 3: Map Reduce – PageRank



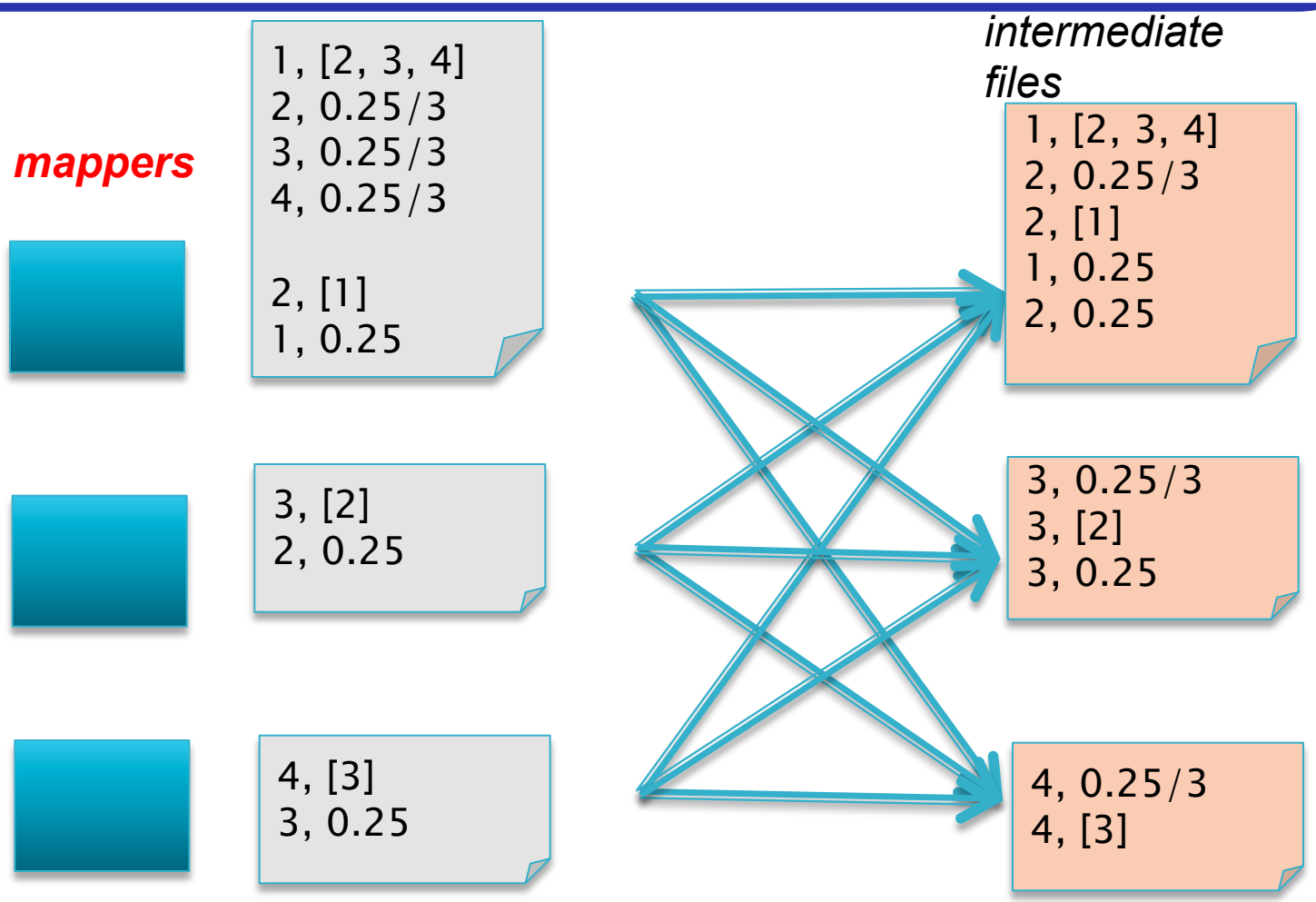
- *All mappers run in parallel, typically on separate machines*
Then all reducers run in parallel, typically on separate machines

- *All the files are stored in a distributed file system*

Option 3: Map Reduce – PageRank

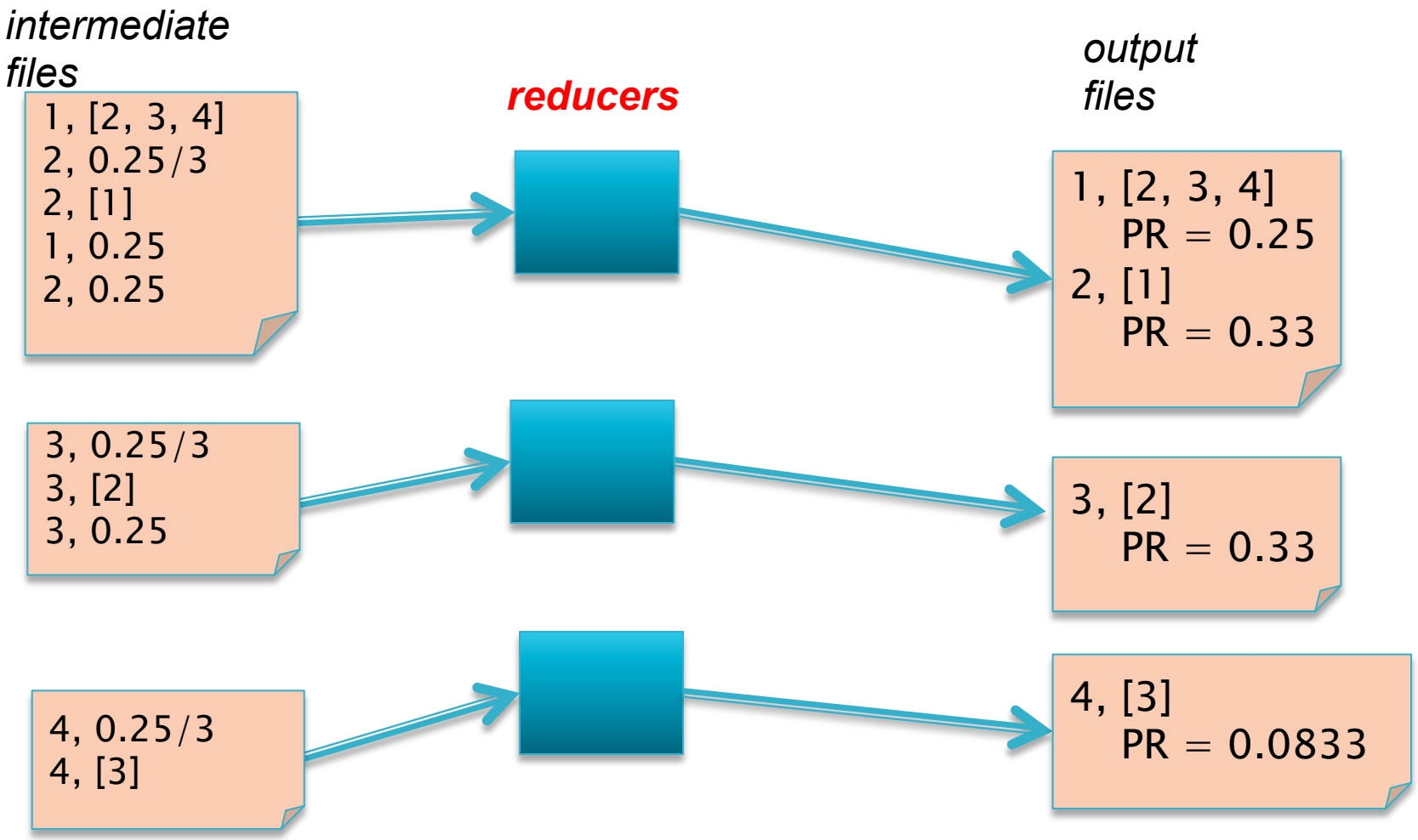


Option 3: Map Reduce – PageRank



"Shuffle" so that all the records with the same "key" end up in the same file

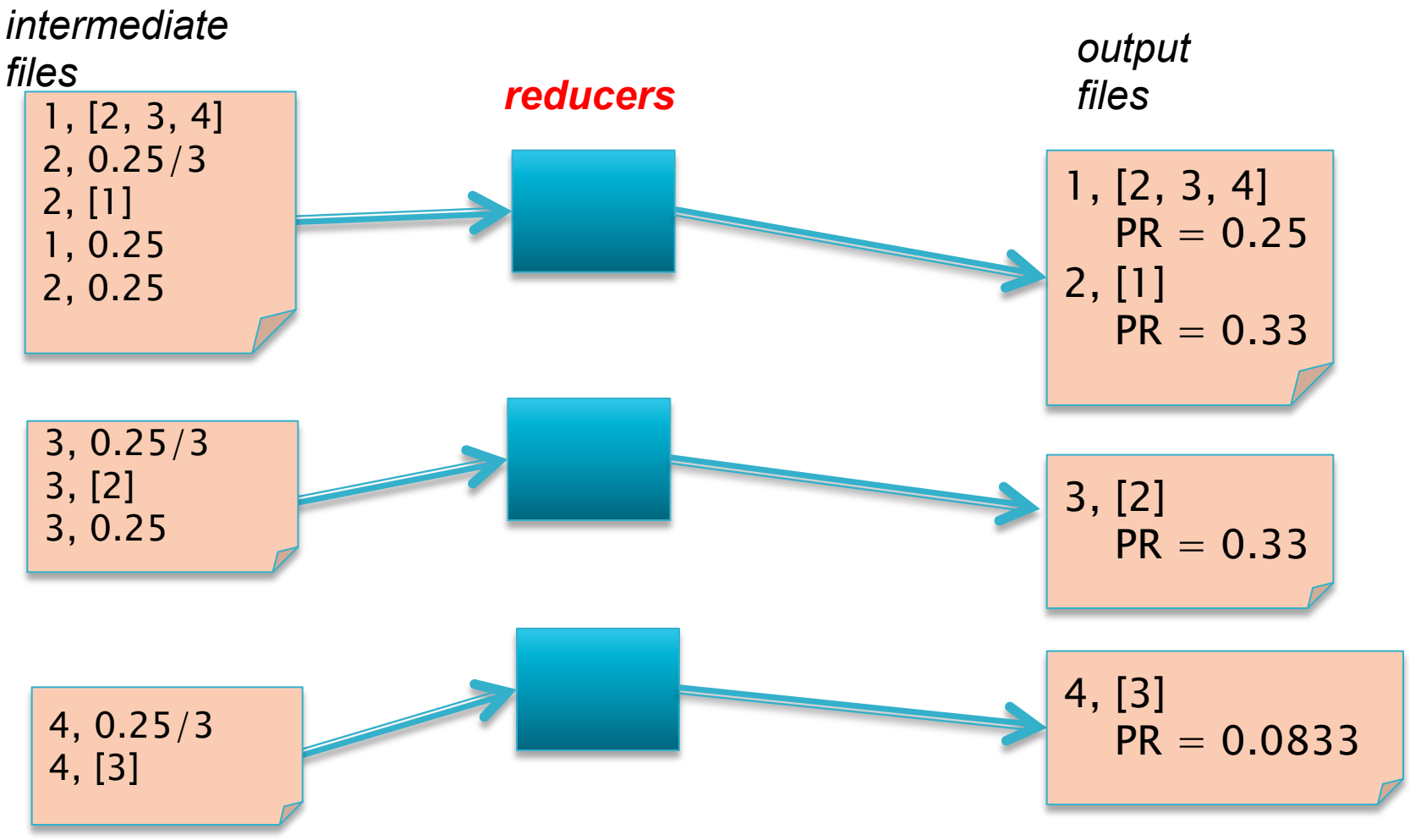
Option 3: Map Reduce – PageRank



Reduce:

Compute the new PageRank (assume α = 0)
Write out: graph structure + PageRank

Option 3: Map Reduce – PageRank



REPEAT UNTIL CONVERGENCE

Option 3: Map Reduce

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  - Each “traversal” effectively requires a new “map-reduce” phase
    - Map-reduce framework not ideal for large numbers of phases
  - Not efficient – too much redundant work
    - In PageRank example: repeated reading and parsing of the inputs

Option 4: Graph Programming Frameworks

- Analogous frameworks proposed for analyzing large volumes of graph data
  - An attempt at addressing limitations of MapReduce
  - Most are *vertex-centric*
    - Programs written from the point of view of a vertex
  - Most based on message passing between nodes

- Pregel: original framework proposed by Google
  - Based on "Bulk Synchronous Protocol" (BSP)
- Giraph: an open-source implementation of Pregel
- GraphLab: asynchronous execution

Option 4: Pregel

- Programmers write one program: **compute()**
- Typical structure of **compute()**:
  - **Inputs**: current values associated with the node
  - **Inputs**: messages sent by the neighboring nodes
  - Do something…
  - Modify current values associated with the node (if desired)
  - **Outputs**: send messages to neighbors

- Execution framework:
  - Execute *compute()* for all the nodes in parallel
  - Synchronize (for all messages to be delivered)
  - Repeat

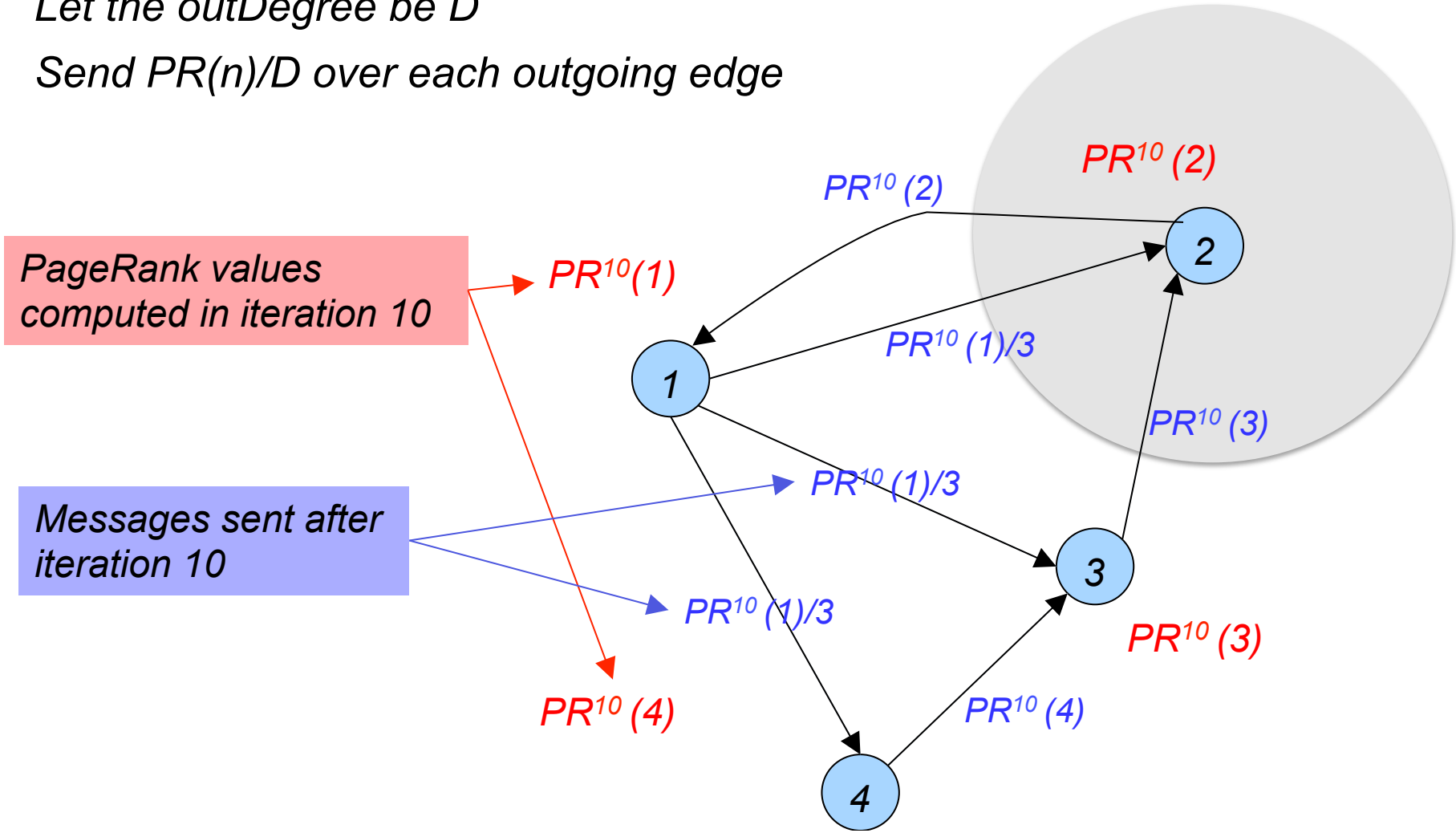
Option 4: Pregel – PageRank

Compute() at Node n:

PR(n) = sum up all the incoming weights

Let the outDegree be D

Send PR(n)/D over each outgoing edge



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- Vertex-centric frameworks somewhat limited and inefficient
  - Unclear how to do many complex graph analysis tasks
  - Not widely used yet
- An ongoing active area of research
  - Including in my group at UMD

Outline

- Background and Motivation
- Graph Queries and Analysis Tasks
- Graph Data Management: Storage
- Graph Data Management: Processing
- What we are doing

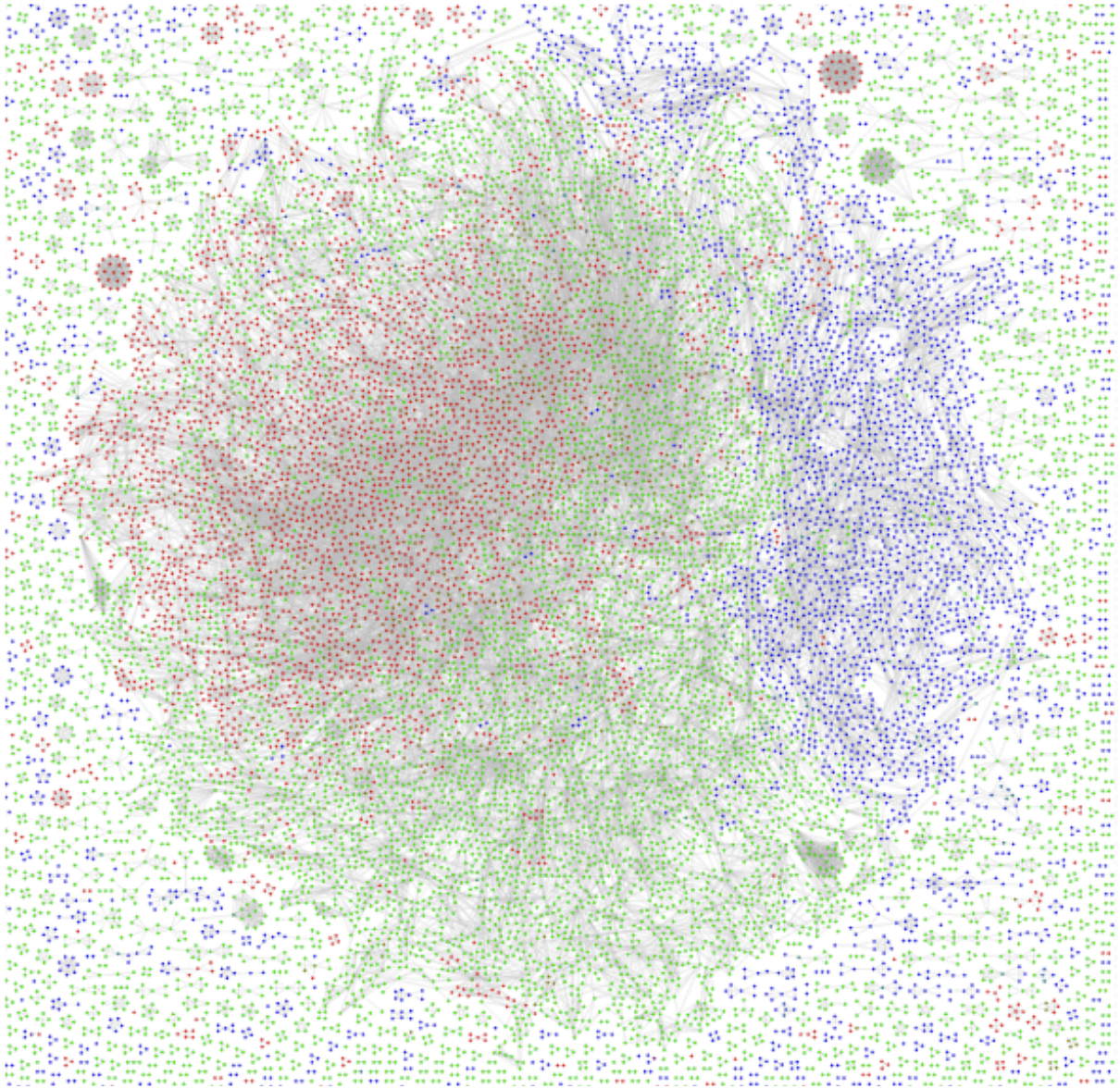
1. Declarative Graph Cleaning

- Enable declarative specification of *graph cleaning* tasks
  - Attribute Prediction: *to predict values of missing attributes*
  - Link Prediction: *to infer missing links*
  - Entity Resolution: *to decide if two references refer to the same entity*
- A mix of declarative constructs and user-defined functions to specify complex prediction functions
- *Interactive* system for executing them over large datasets
- Optimize the execution through caching, incremental evaluation, pre-computed data structures …
  - Prototype implementation using BerkeleyDB + SQL
  - Currently changing the backend to scale to larger volumes

Declarative Noisy Network A ×

localhost/declarative_network_analysis/demo.html

Declarative Noisy Network Analysis



Dataset

DBLP Dataset

Datalog Program

```
DOMAIN Bin(#X,#Y) :- Edge(X,Z,'Co-Aut
   IntersectionCount(#X,#Y,Count<Z>))
   Similarity(#X,#Y,S):-Node(X, Accou
   Features-LP(#X,#Y,F1,F2):-Intersec
}
ITERATE(10) {
  INSERT Edge(X,Y,'Co-Author'):-Featu
  predict-LP(F1,F2)=true,
  confidence-LP(F1,F2) IN TOP 1%
```

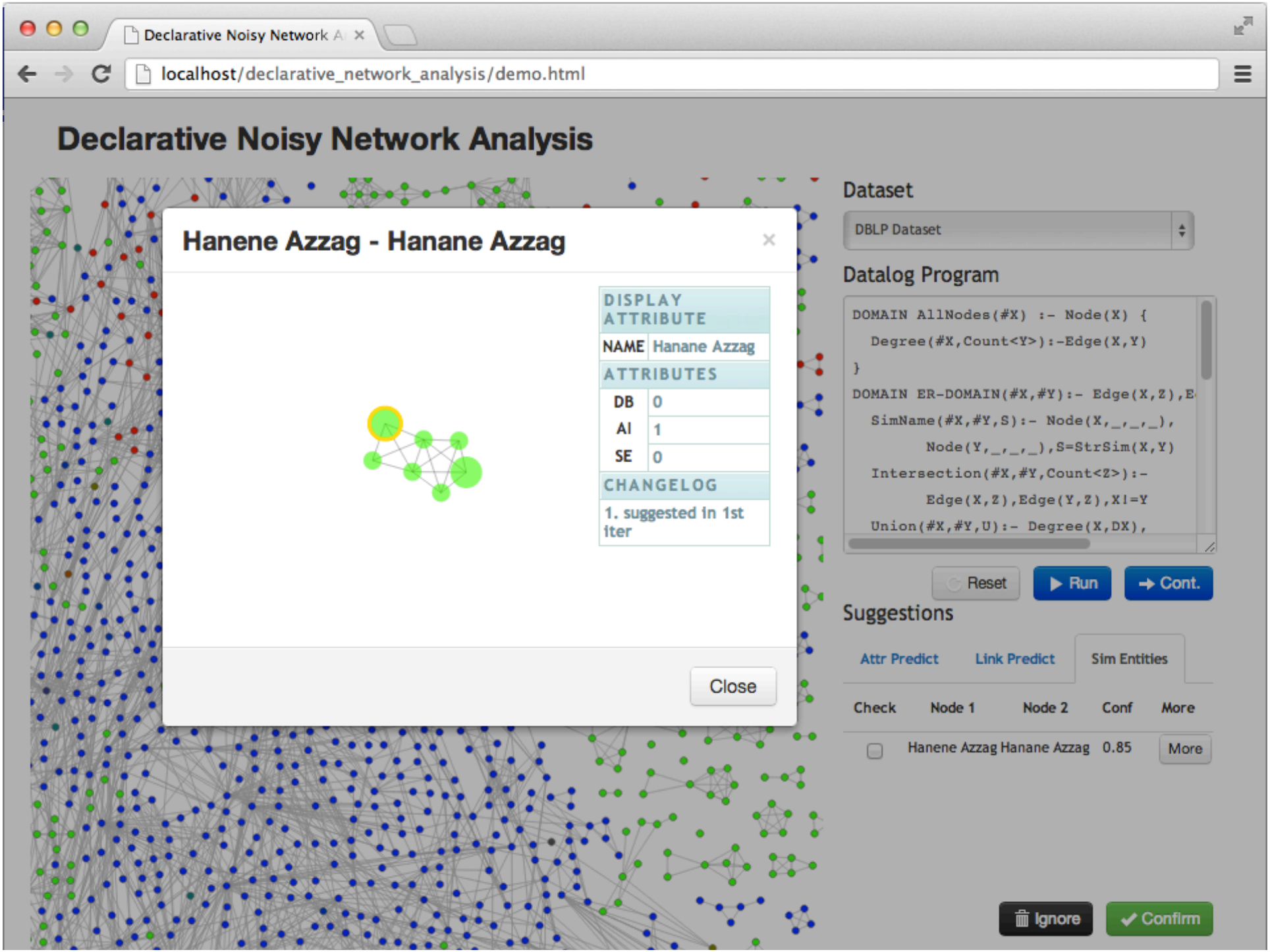
Reset ▶ Run → Cont.

Suggestions

Attr Predict | Link Predict | Sim Entities

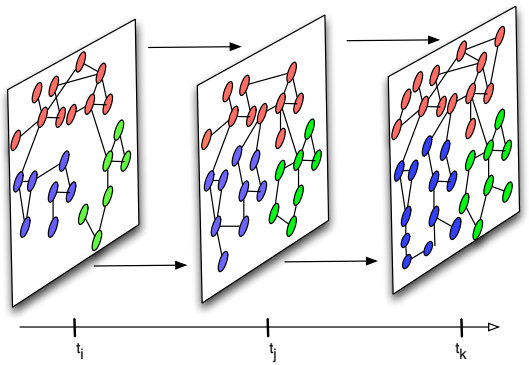
Check	From	To	Edge	Conf	More

🗑 Ignore ✔ Confirm


Declarative Noisy Network A
localhost/declarative_network_analysis/demo.html
Declarative Noisy Network Analysis
Hanene Azzag - Hanane Azzag
DISPLAY ATTRIBUTE
NAME Hanane Azzag
ATTRIBUTES
DB 0
AI 1
SE 0
CHANGELOG
1. suggested in 1st iter
Close
Dataset
DBLP Dataset
Datalog Program
DOMAIN AllNodes(#X) :- Node(X) {
Degree(#X,Count<Y>):-Edge(X,Y)
}
DOMAIN ER-DOMAIN(#X,#Y):- Edge(X,Z),E
SimName(#X,#Y,S):- Node(X,_,_,_),
Node(Y,_,_,_),S=StrSim(X,Y)
Intersection(#X,#Y,Count<Z>):-
Edge(X,Z),Edge(Y,Z),X!=Y
Union(#X,#Y,U):- Degree(X,DX),
Reset
Run
Cont.
Suggestions
Attr Predict
Link Predict
Sim Entities
Check
Node 1
Node 2
Conf
More
Hanene Azzag Hanane Azzag 0.85
More
Ignore
Confirm

2. Historical Graph Data Management

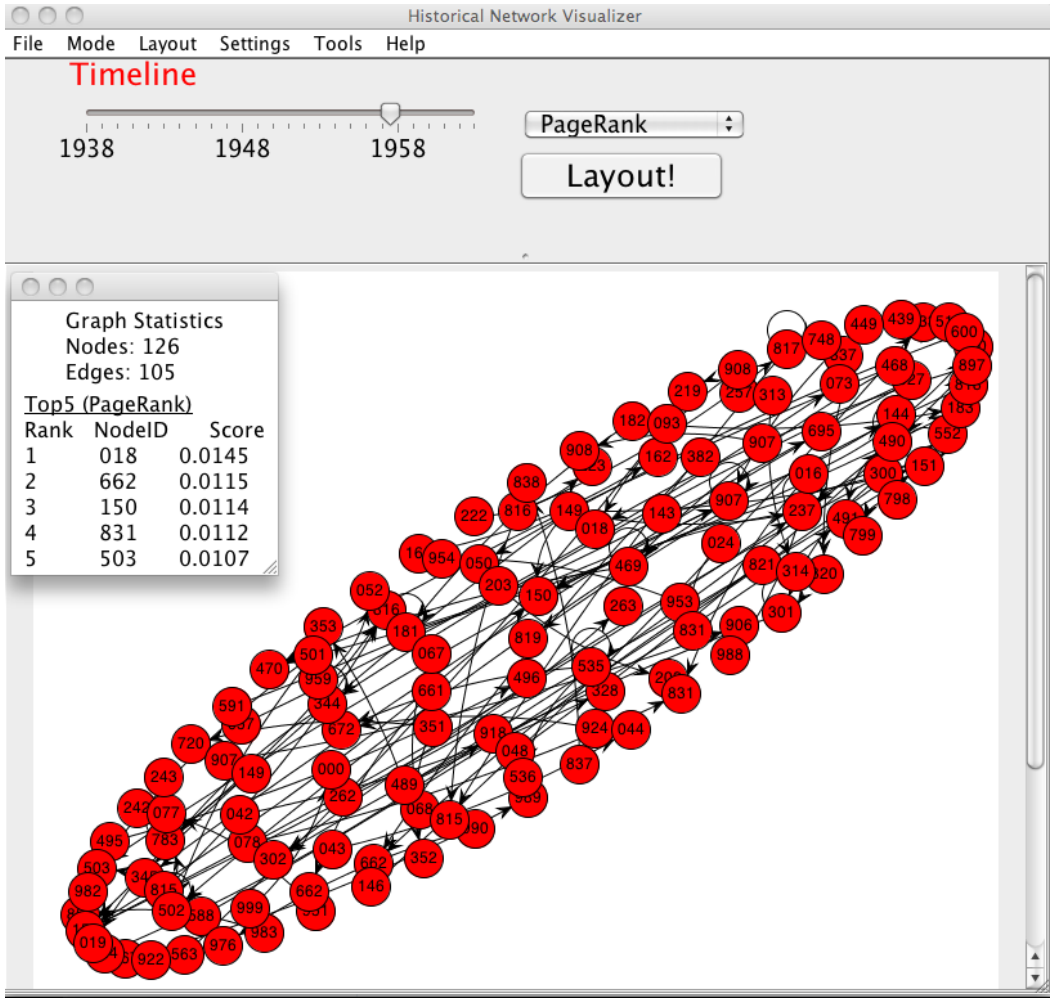
- Increasing interest in temporal analysis of information networks to:
  - Understand evolutionary trends (e.g., how communities evolve)
  - Perform comparative analysis and identify major changes
  - Develop models of evolution or information diffusion
  - Visualizations over time
  - For better predictions in the future



- Focused exploration and querying
  - *"Who had the highest PageRank in a citation network in 1960?"*
  - *"Identify nodes most similar to* X *as of one year ago"*
  - *"Identify the days when the network diameter (over some transient edges like messages) is smallest"*
  - *"Find a temporal subgraph pattern in a graph"*

2. Historical Graph Data Management

- We are building a system for visualizing, analyzing, and querying historical trace data



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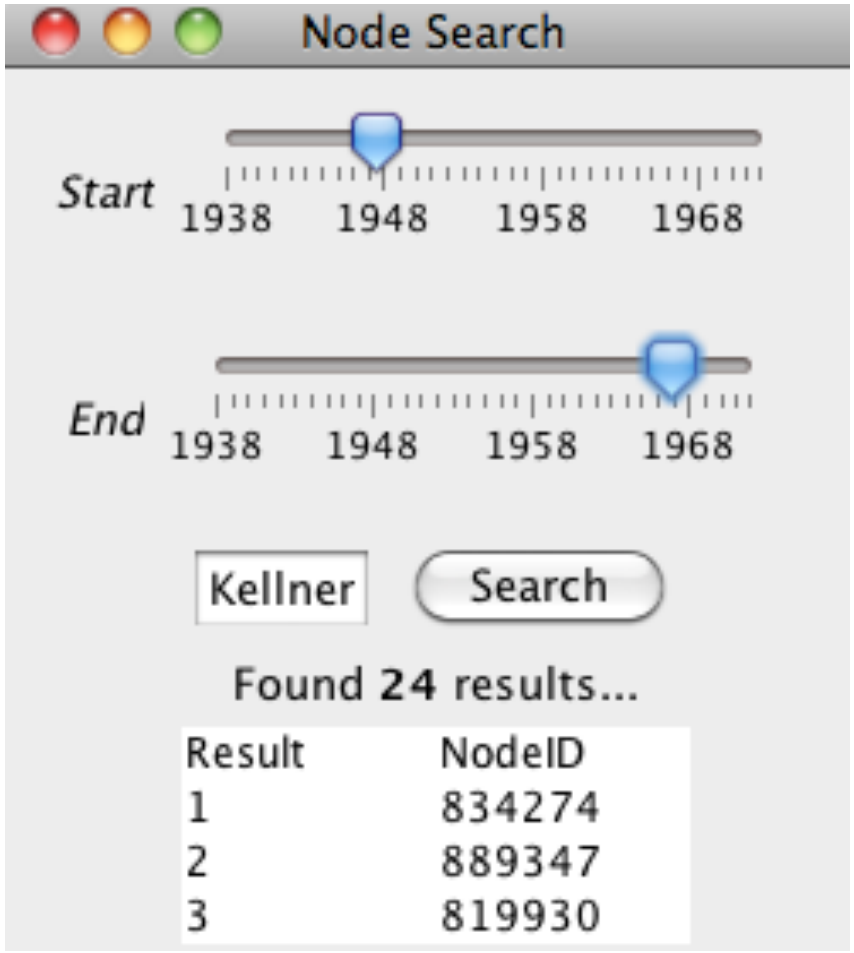

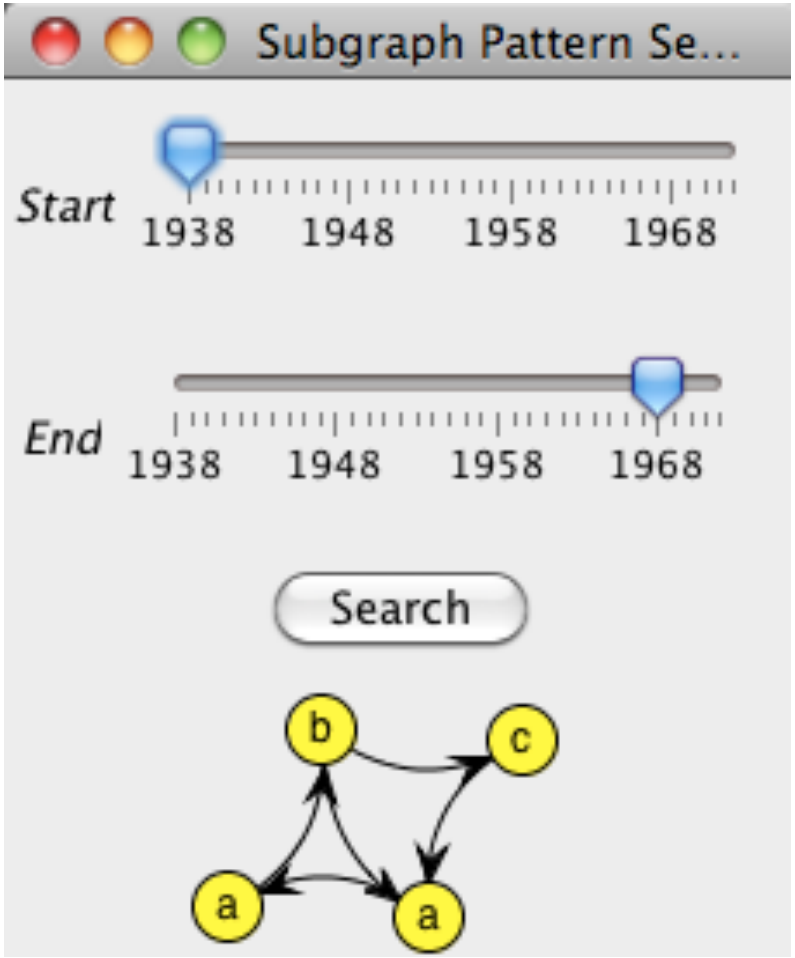

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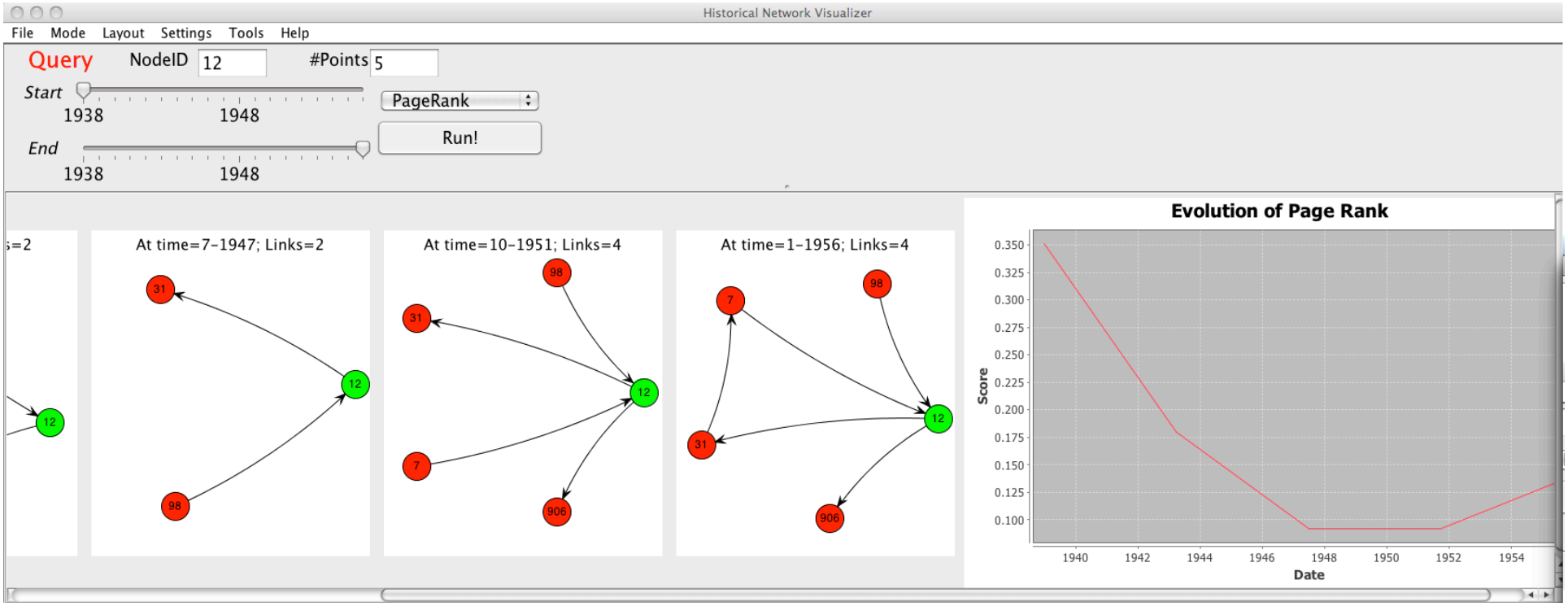

What we are doing

3. Real-time Analytics over Graphs

- Designing a system to support *continuous* queries and analytics over large, dynamic graphs
- Ranging from simple "monitor updates in the neighborhood" to complex "trend discovery" and "anomaly detection" queries
- A major research challenge to handle the high data volumes while guaranteeing low latencies

4. NScale: Neighborhood-based Graph Programming Framework

- Address some of the limitations of Pregel/Giraph by allowing users to write queries in a neighborhood-centric way
- Aimed at handling a larger class of queries and analysis tasks efficiently

Thank you !!