Declarative Abstractions and Scalable Platforms for Big Data Analytics

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Big Data

- Explosion of data, in pretty much every domain
  - Sensing devices and sensor networks that can monitor everything from temperature to pollution to vital signs 24/7
  - Increasingly sophisticated smart phones
  - Internet, social networks making it very easy to publish data
  - Scientific experiments and simulations
  - Internet of Things
  - Many aspects of life being turned into data ("dataification")
- "Big Data" (= extracting knowledge and insights from data) becoming fundamental
  - Science, business, politics -- largely driven by data and analytics
  - Many others (Education, Social Good) are slowly being

Four V's of Big Data

- Big data not just about "Volume"
  - Large scale of data certainly poses many problems
  - But most datasets are pretty small…
- Variety and heterogeneity in both data and applications
  - Text, networks, time series, nested/hierarchical, multimedia, …
  - Increasingly complex and specialized analysis tasks
- Velocity
  - Data generated at very high rates and often needs to be processed in real time
- Veracity
  - What/who to trust? How to reason about data quality issues?
  - Easy to draw wrong statistical conclusions from large datasets
  - Issues becoming more important with increasing automation…

My Research

- Building data management systems to address challenges in managing and analyzing big data by..
  - Designing intuitive, formal, and <u>declarative abstractions</u> to empower users, and
  - Developing <u>scalable platforms</u> and algorithms to support those abstractions over large volumes of data

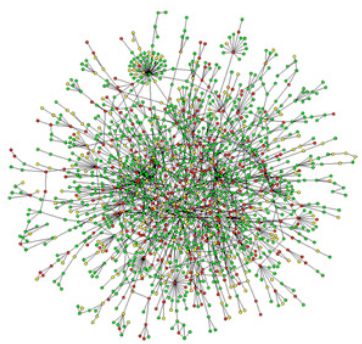
- Major research thrusts over the last 10 years
  - Uncertain and probabilistic data management
  - Graph data management
  - Data management in the cloud
  - Collaborative data analytics
  - Query processing and optimization

Outline

- Graph Data Management
  - Declarative Graph Cleaning
  - A Framework for Distributed Graph Analytics
- DataHub: A platform for collaborative data science
  - Recreation/Storage Tradeoff in Version Management *(or, why git/svn are not good at managing datasets)*

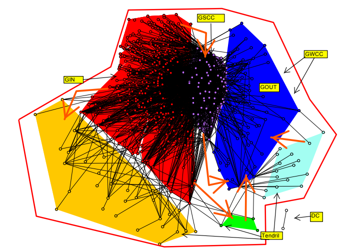
Graph Data

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



A protein-protein interaction network

Social networks



Federal funds networks

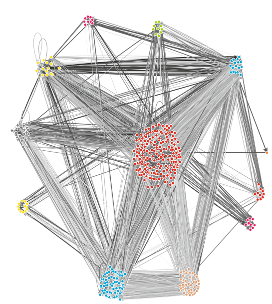
Knowledge Graph

World Wide Web

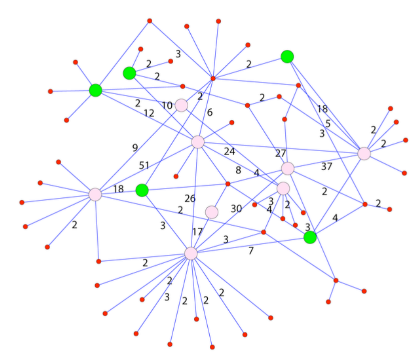
Citation networks

Communication networks

Disease transmission networks



Financial transaction networks



Stock Trading Networks

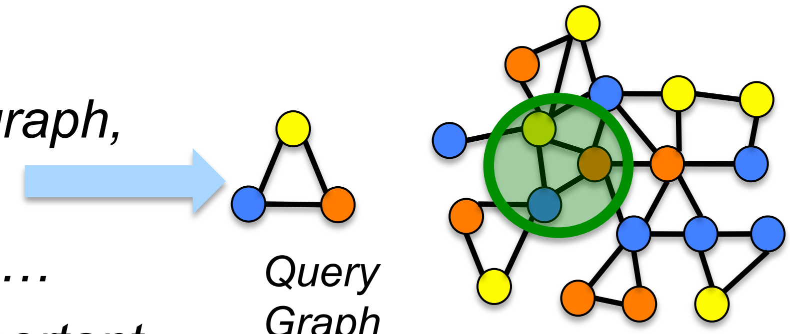
Wide Variety in Graph Queries/Analytics

Different types of "queries"

Subgraph pattern matching: Given a "query" graph, find where it occurs in a given "data" graph

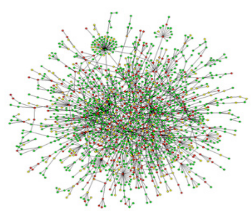
Reachability; Shortest path; Keyword search; …

Historical or Temporal queries: "Find most important nodes in a communication network in 2002?"



Query Graph

Data Grapl



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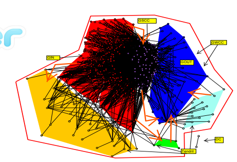

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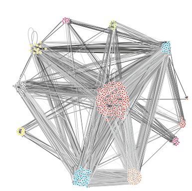

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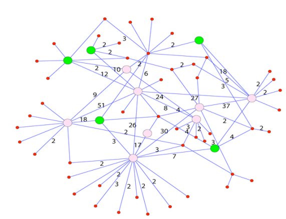


Stock Trading Networks

Wide Variety in Graph Queries/Analytics

Different types of "queries"

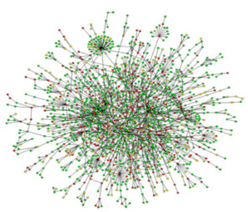
Subgraph pattern matching; Reachability; Shortest path; Keyword search; Historical or Temporal queries…

Continuous "queries" and Real-time analytics

Online prediction in response to new data

Monitoring: "Tell me when a topic is suddenly trending in my friend circle"

Anomaly/Event detection: "Alert me if the communication activity around a node changes drastically"



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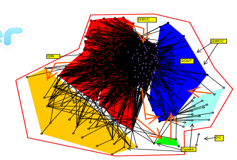

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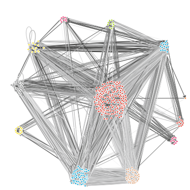

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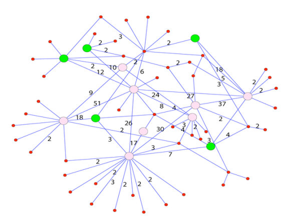

Stock Trading Networks

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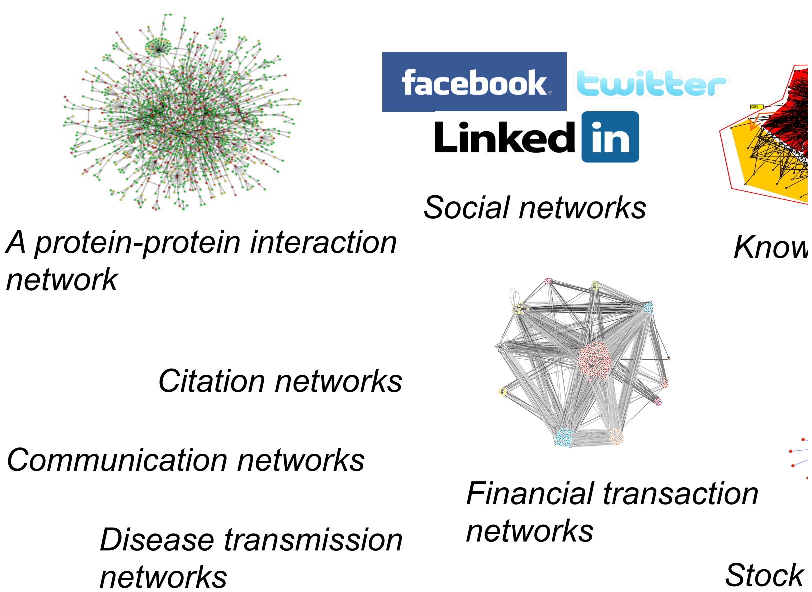
<u>Different types of "queries"</u>

Subgraph pattern matching; Reachability; Shortest path; Keyword search; Historical or Temporal queries…

<u>Continuous "queries" and Real-time analytics</u>

Online prediction; Monitoring; Anomaly/Event detection



<u>Batch analysis tasks/Network science</u>

Centrality analysis: Find the most central nodes in a network

Community detection: Partition vertices into groups with dense interactions

Network evolution: Build models for network formation and evolution

Network measurements: Measure statistical properties

Graph cleaning/inference: Remove noise in the observed network data

Wide Variety in Graph Queries/Analytics

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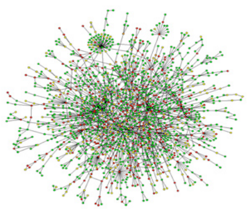
Online prediction; Monitoring; Anomaly/Event detection

Batch analysis tasks

Centrality analysis; Community detection; Network evolution; Network measurements; Graph cleaning/inference



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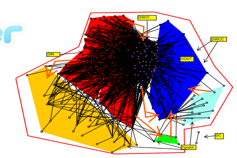

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Machine learning tasks

Many algorithms can be seen as message passing in specially constructed graphs

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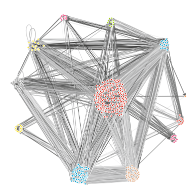

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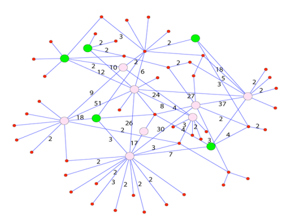

Stock Trading Networks

Graph Data Management: State of the Art

- Much prior and ongoing work – most of it outside, or on top of, general-purpose data management systems
  - Specialized indexes or algorithms for specific types of queries
  - Stand-alone prototypes for specific analysis tasks
- Emergence of specialized graph databases in recent years
  - Neo4j, Titan, OrientDB, DEX, AllegroGraph, …
  - Rudimentary declarative interfaces/query languages
- Several "vertex-centric" frameworks in recent years
  - Pregel, Giraph, GraphLab, GRACE, GraphX, …
  - Only work well for a very limited set of tasks
- Little work on continuous/real-time query processing, or on supporting evolutionary or temporal analytics

What we are doing

- Goal: A graph data management system with unified declarative abstractions for graph queries and analytics
- Work so far
  - Declarative graph cleaning [GDM'11, SIGMOD Demo'13]
  - NScale: a distributed programming framework [VLDB Demo'14]
  - Real-time continuous queries [SIGMOD'12, ESNAM'14, SIGMOD'14]
    - Techniques for continuous query processing over large dynamic graphs
    - Expressive query language for specifying anomaly detection queries
  - Historical graph data management [ICDE'13, SIGMOD Demo'13]
    - New indexing structure for retrieving historical snapshots
    - A high-level temporal/evolutionary analytics framework
  - Subgraph pattern matching and counting [ICDE'12, ICDE'14]
  - GraphGen: graph analytics over relational data [VLDB Demo'15]

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  - A Framework for Distributed Graph Analytics
- DataHub: A platform for collaborative data science
  - Recreation/Storage Tradeoff in Version Management

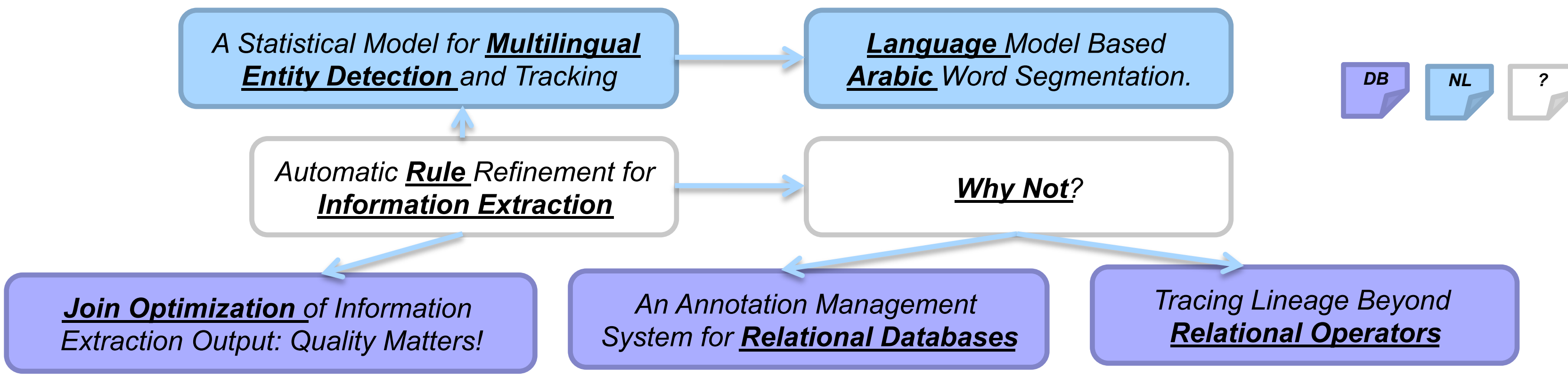
Motivation

- The *observed, automatically-extracted information networks* are often noisy and incomplete

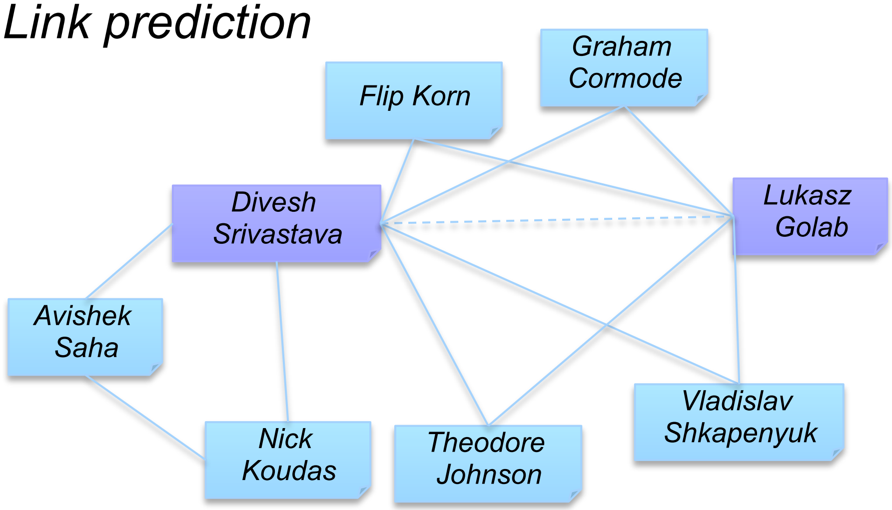
- Need to extract the underlying *true information network* through:
  - Attribute Prediction: *to predict values of missing attributes*
  - Link Prediction: *to infer missing links*
  - Entity Resolution: *to decide if two references refer to the same entity*

Collective (relational) Inference

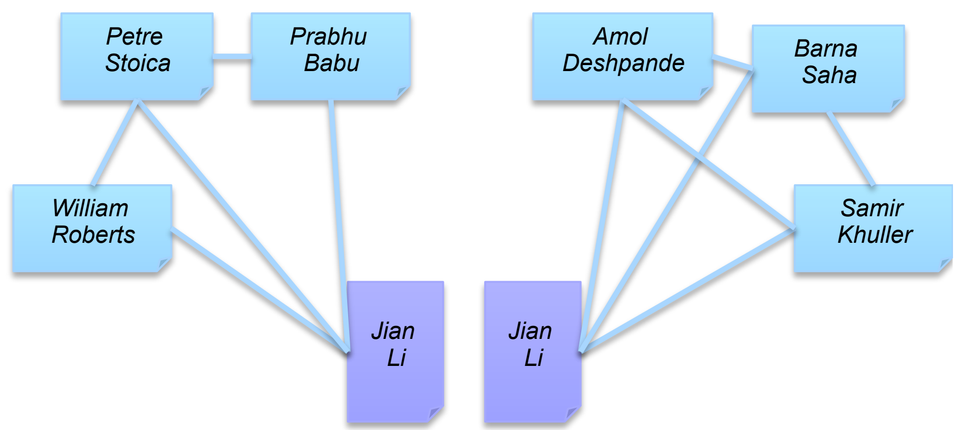
Attribute prediction: *Predict topic of the paper*



Link prediction



Entity resolution



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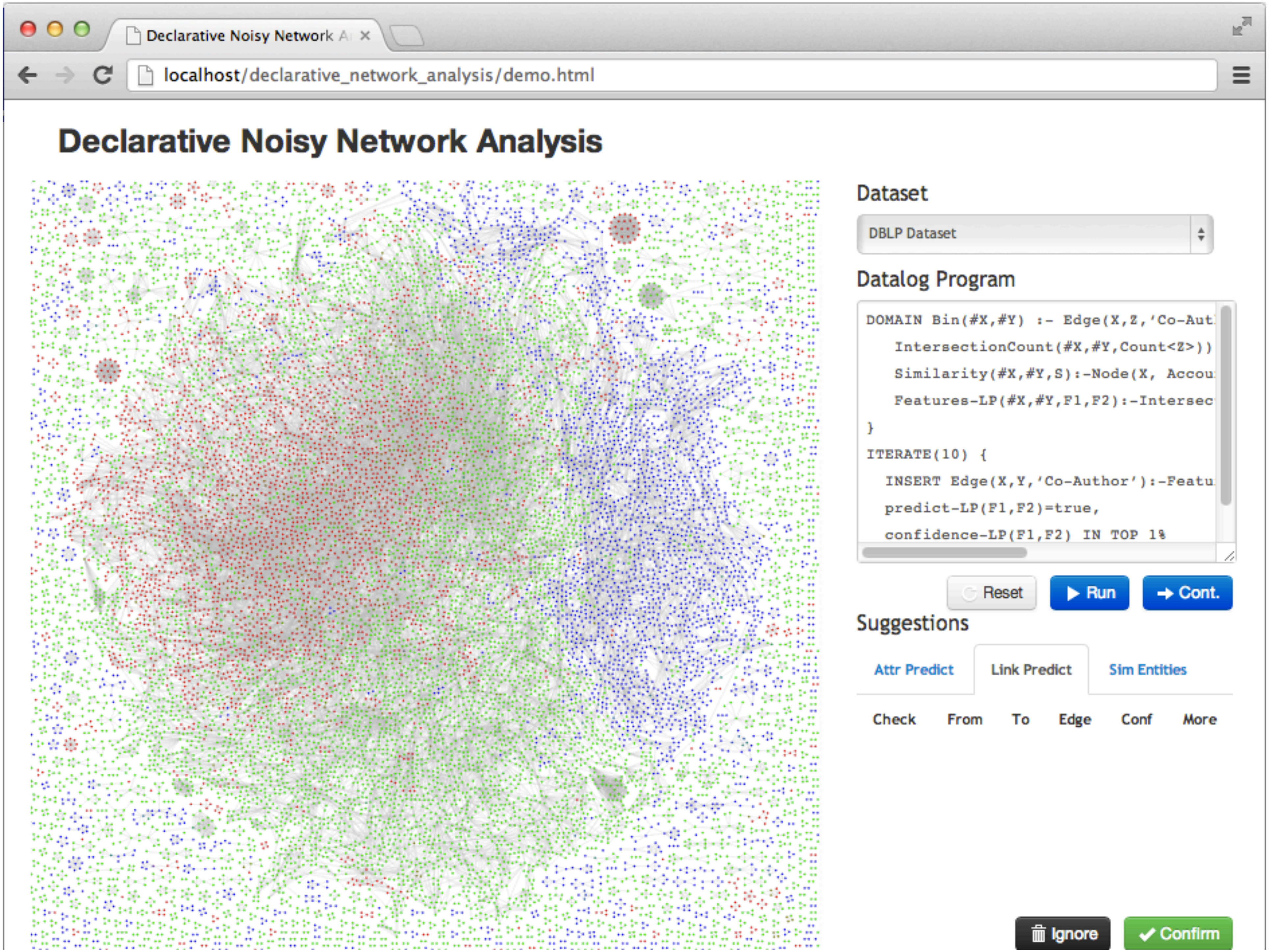
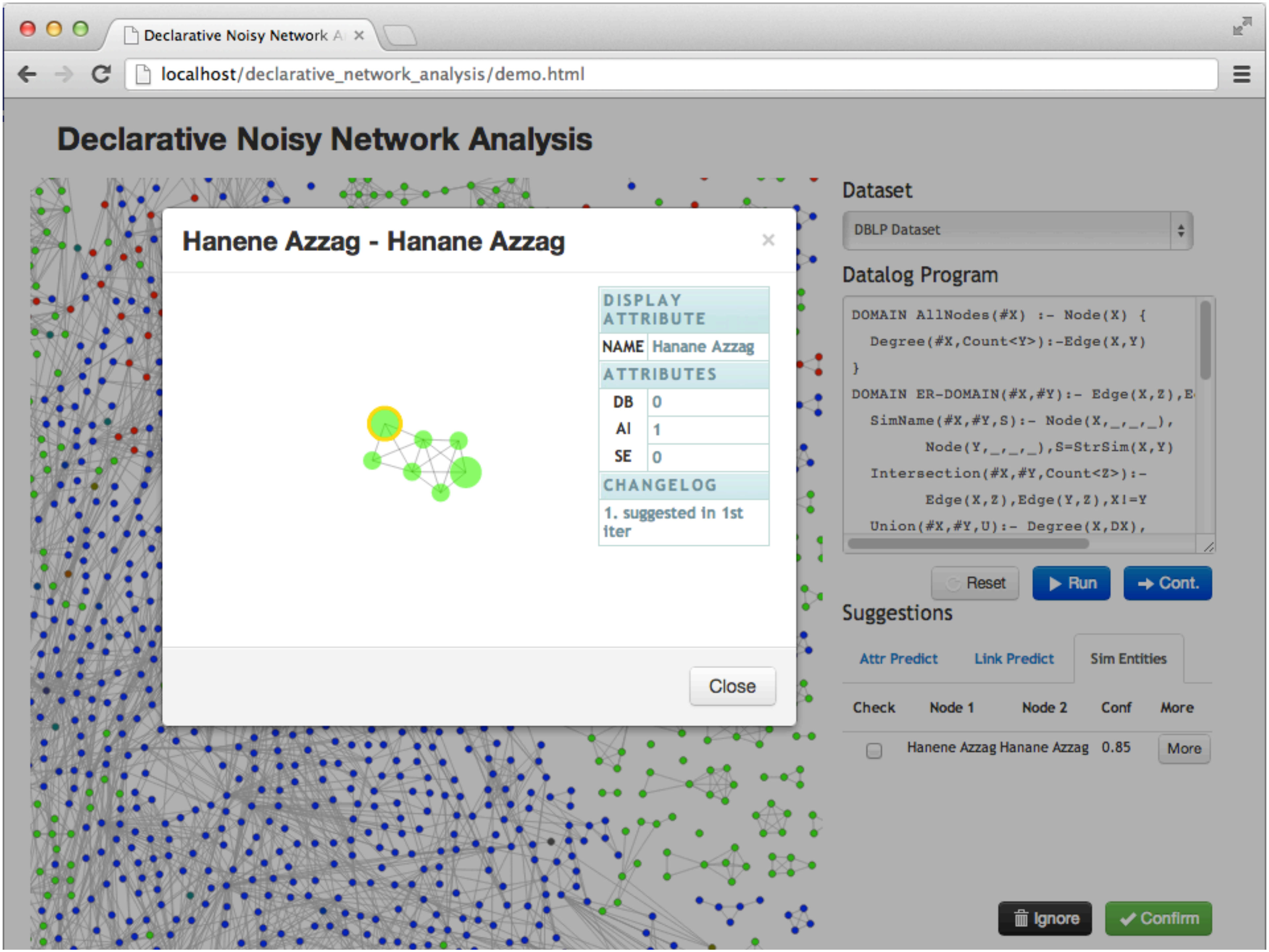
  - Entity Resolution: *to decide if two references refer to the same entity*

- Typically iterative and interleaved application of the techniques
  - Use results of one to improve the accuracy of other operations
  - Significant benefits to using graph structure ("collective" inference)

- Numerous techniques developed for the tasks in isolation
  - No support from data management systems
  - Hard to evaluate new techniques, especially for joint inference



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

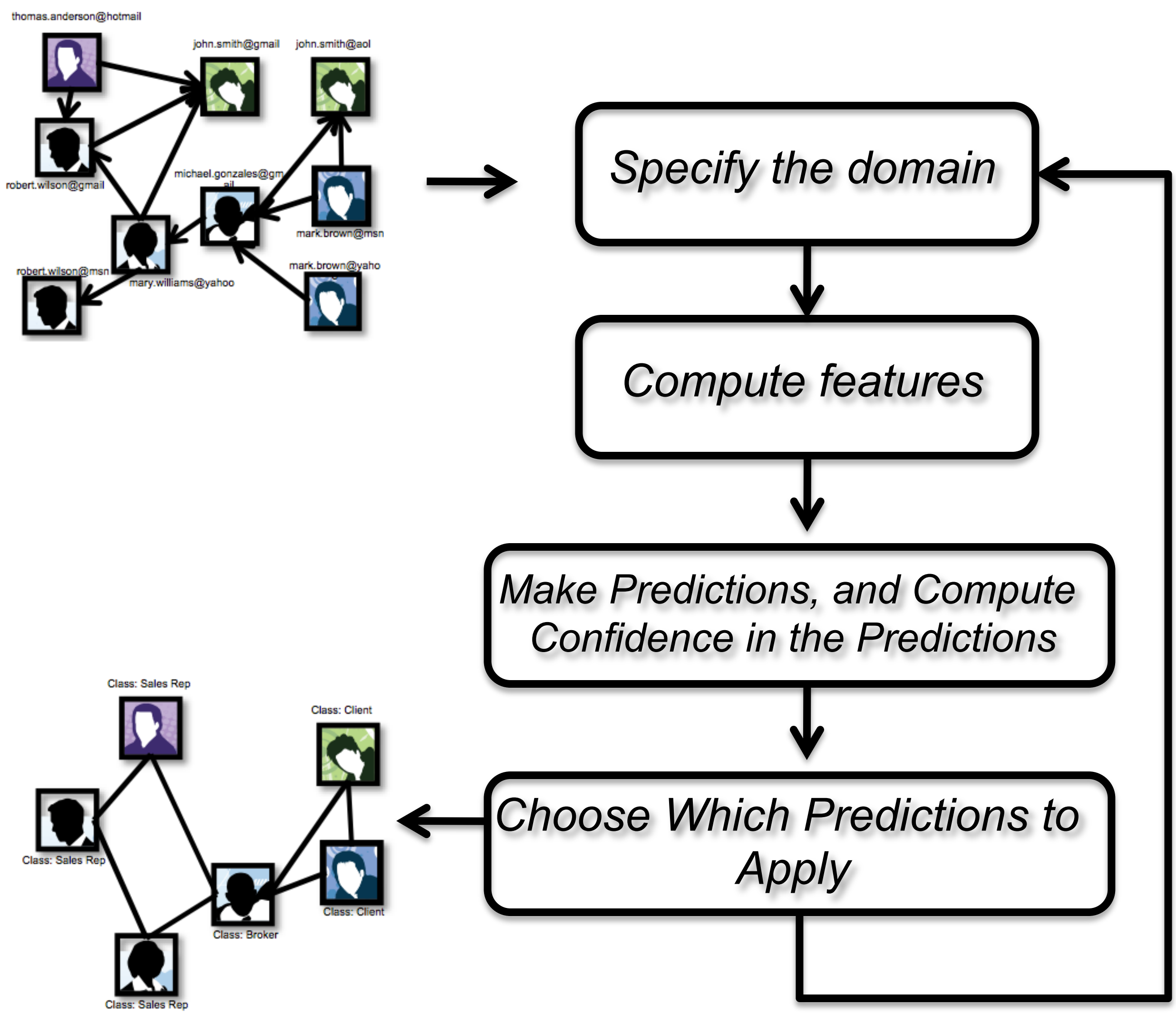


Declarative Noisy Network A
localhost/declarative_network_analysis/demo.html
Declarative Noisy Network Analysis
Hanene Azzag - Hanane Azzag
DISPLAY ATTRIBUTE
NAME Hanane Azzag
ATTRIBUTES
DB 0
AI 1
SE 0
CHANGELOG
1. suggested in 1st iter
Close
Dataset
DBLP Dataset
Datalog Program
DOMAIN AllNodes(#X) :- 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

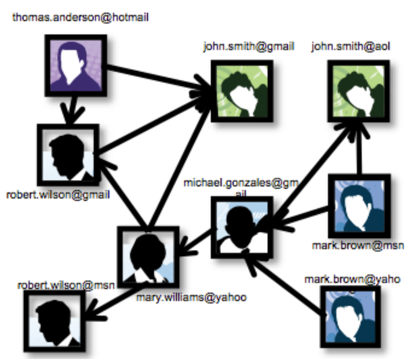
Overview of the Approach

- Declarative specification of the cleaning task
  - Datalog-based language for specifying --
    - Prediction features (including local and relational features)
    - The details of how to accomplish the cleaning task
    - Arbitrary interleaving or pipelining of different tasks

Task Specification Framework



Task Specification Framework

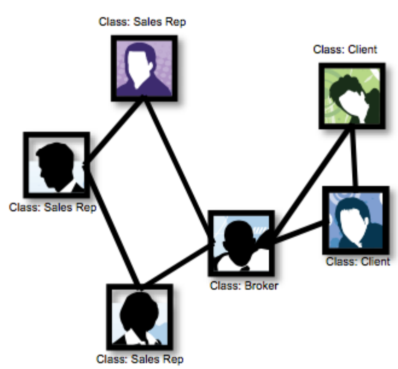


Specify the domain

Compute features

Make Predictions, and Compute Confidence in the Predictions

Choose Which Predictions to Apply

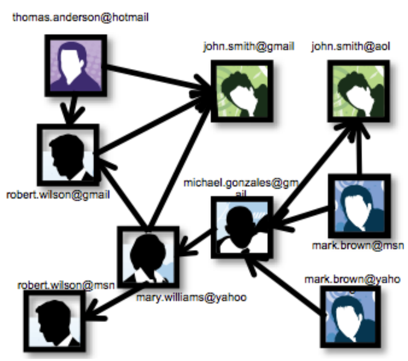


*For **attribute prediction**, the domain is a subset of the graph nodes.*

*For **link prediction** and **entity resolution**, the domain is a subset of pairs of nodes.*

***Local:** word frequency, income, etc.*
***Relational:** degree, clustering coeff., no. of neighbors with each attribute value, common neighbors between pairs of nodes, etc.*

Task Specification Framework



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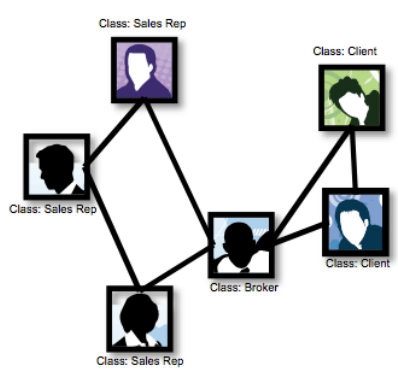

Attribute prediction: *the missing attribute*

Link prediction: *add link or not?*

Entity resolution: *merge two nodes or not?*

After predictions are made, the graph changes:
Attribute prediction *changes local attributes.*
Link prediction *changes the graph links.*
Entity resolution *changes both local attributes and graph links.*

Overview of the Approach

- Declarative specification of the cleaning task
  - Datalog-based language for specifying --
    - Prediction features (including local and relational features)
    - The details of how to accomplish the cleaning task
    - Arbitrary interleaving or pipelining of different tasks
- A mix of declarative constructs and user-defined functions to specify complex prediction functions
- Prototype implementation using Java BerkeleyDB
  - Datalog rules converted into SQL
  - Optimized the execution through caching, incremental evaluation, and pre-computed data structures

Example

- Real-world PubMed graph
  - Set of publications from the medical domain, their abstracts, and citations
- 50,634 publications, 115,323 citation edges
- Task: Attribute prediction
  - Predict if the paper is categorized as Cognition, Learning, Perception or Thinking
- Choose top 10% predictions after each iteration, for 10 iterations

```
DOMAIN Uncommitted(X):-Node(X,Committed='no')
{
  ThinkingNeighbors(X,Count<Y>):- Edge(X,Y), Node(Y,Label='Thinking')
  PerceptionNeighbors(X,Count<Y>):- Edge(X,Y), Node(Y,Label='Perception')
  CognitionNeighbors(X,Count<Y>):- Edge(X,Y), Node(Y,Label='Cognition')
  LearningNeighbors(X,Count<Y>):- Edge(X,Y), Node(Y,Label='Learning')
  Features-AP(X,A,B,C,D,Abstract):- ThinkingNeighbors(X,A), PerceptionNeighbors(X,B),
                          CognitionNeighbors(X,C), LearningNeighbors(X,D),Node(X,Abstract, _,_)
}
ITERATE(10)
{
  UPDATE Node(X,_,P,'yes'):- Features-AP(X,A,B,C,D,Text), P = predict-AP(X,A,B,C,D,Text),
                          confidence-AP(X,A,B,C,D,Text) IN TOP 10%
}
```

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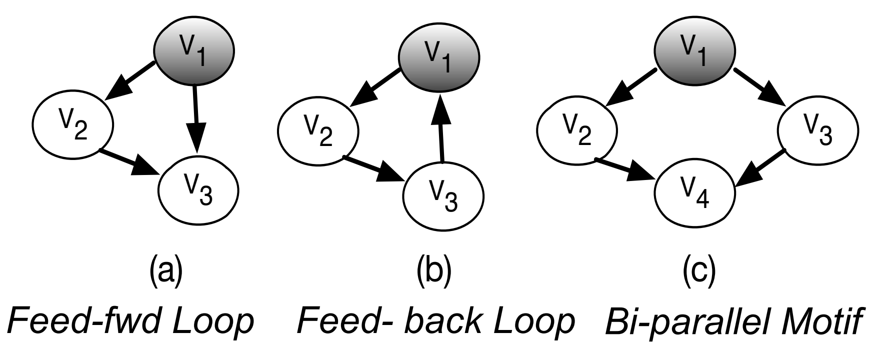
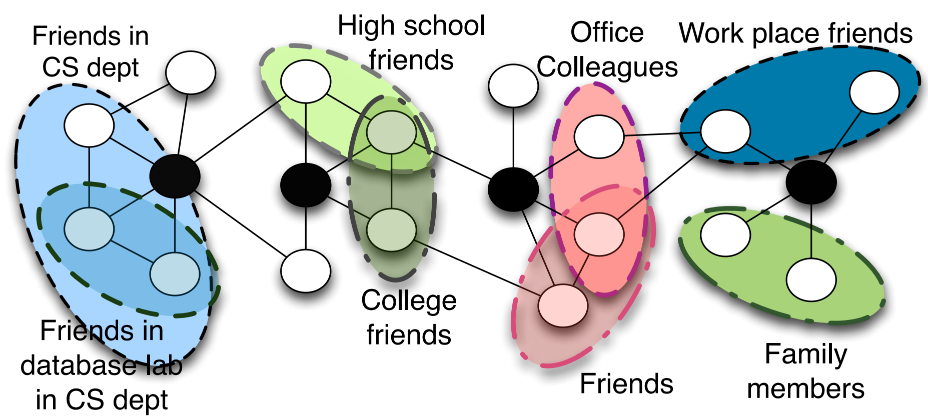
Scaling Graph Analysis Tasks

- Graph analytics/network science tasks too varied
  - Centrality analysis; evolution models; community detection
  - Link prediction; belief propagation; recommendations
  - Motif counting; frequent subgraph mining; influence analysis
  - Outlier detection; graph algorithms like matching, max-flow
  - An active area of research in itself…



Counting network motifs



Identify Social circles in a user's ego network

Scaling Graph Analysis Tasks

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  - Motif counting; frequent subgraph mining; influence analysis
  - Outlier detection; graph algorithms like matching, max-flow
  - An active area of research in itself…
- Hard to build general platforms like MapReduce
  - What is a good programming abstraction to provide?
    - Needs to cover a large fraction of use cases, and be easy to use
    - MR not a good fit for graph analytics
  - No clear winner yet, so little progress on systems
    - Especially on distributed or parallel systems
  - Application developers largely doing their own thing

“Vertex-centric” Frameworks

- Introduced by Google in a system called “Pregel”
  - Inspired by BSP (Bulk Synchronous Protocol)
- Adopted by many other systems
  - GraphLab, Apache Giraph, GraphX, Xstream, …
  - Most of the research, especially in databases, focuses on it
- “Think like a vertex” paradigm
  - User provides a single **compute()** function that operates on a vertex
  - Executed in parallel on all vertices in an iterative fashion
  - Exchange information at the end of each iteration through message passing

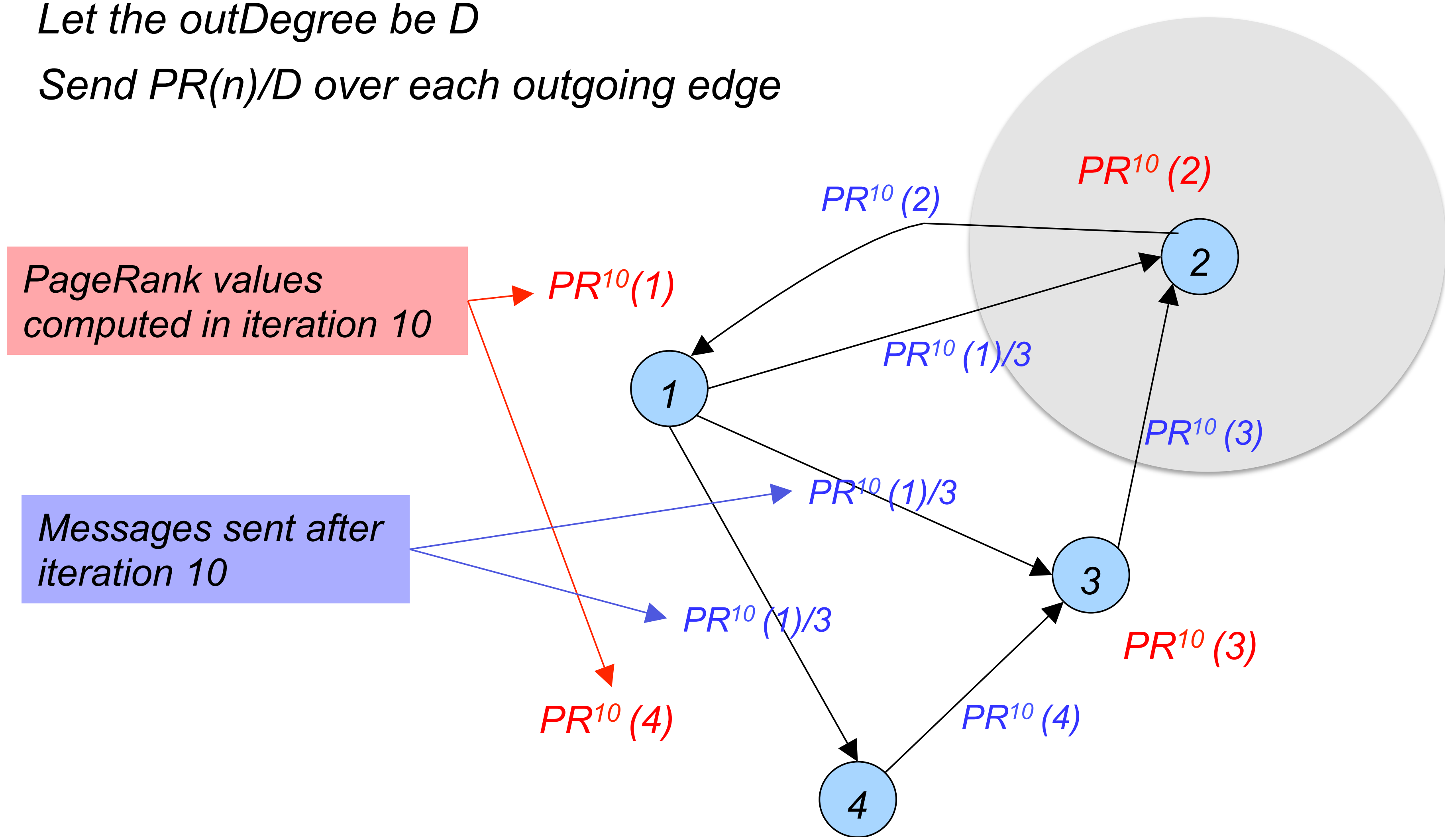
Example: PageRank

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



Programming Frameworks

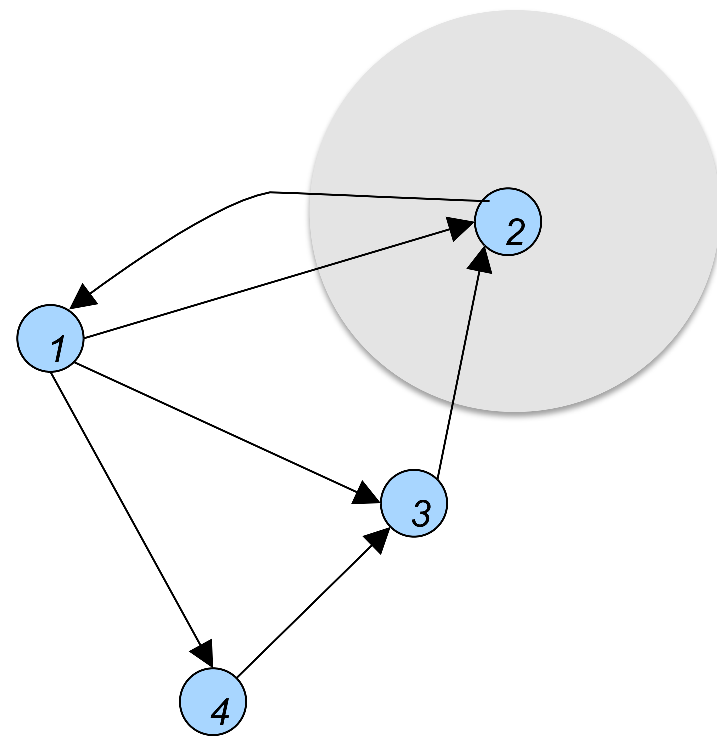
- Vertex-centric framework
  - Works well for some applications
    - Pagerank, Connected Components, …
    - Some machine learning algorithms can be mapped to it
  - However, the framework is very restrictive
    - Most analysis tasks or algorithms cannot be written easily
    - Simple tasks like counting neighborhood properties infeasible
    - Fundamentally: Not easy to decompose analysis tasks into vertex-level, independent local computations
- Alternatives?
  - Galois, Ligra, GreenMarl: Not sufficiently high-level
  - Some others (e.g., Socialite) restrictive for different reasons

Example: Local Clustering Coefficient

LCC(n) = *neighborhood density around n*

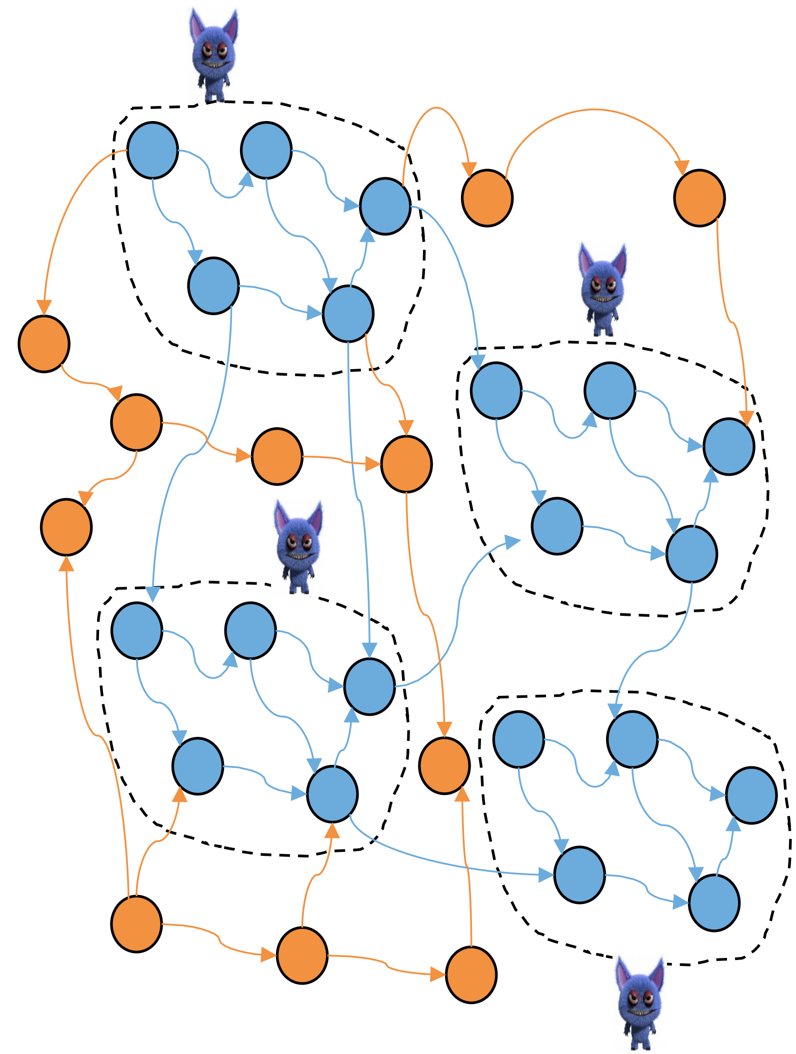
Compute() at Node n:

- *Need to count the no. of edges between neighbors*
- *But does not have access to that information*
- *Option 1: Each node transmits its list of neighbors to its neighbors*
  - *Huge memory consumption*
- *Option 2: Allow access to neighbors' state*
  - *Neighbors may not be local*
  - *What about computations that require 2-hop information?*



NScale Programming Framework

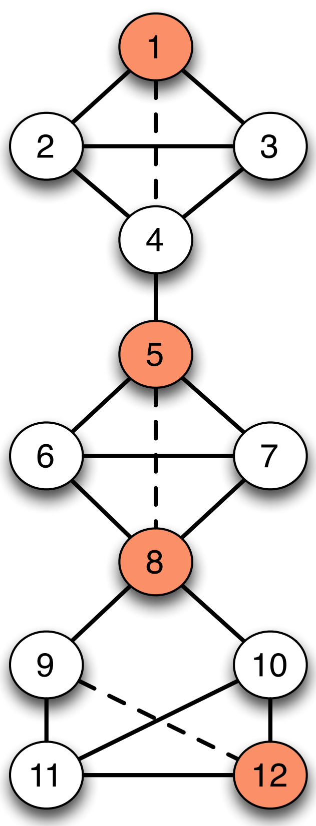
- An end-to-end distributed graph programming framework
- Users/application programs specify:
  - Neighborhoods or subgraphs of interest
  - A kernel computation to operate upon those subgraphs
- Framework:
  - Extracts the relevant subgraphs from underlying data and loads in memory
  - Execution engine: Executes user computation on materialized subgraphs
  - Communication: Shared state/ message passing



NScale: LCC Computation Walkthrough

NScale programming model

Underlying graph data on HDFS



Subgraph extraction query:

Compute (LCC) on
Extract ({Node.color=orange}
{k=1}
{Node.color=white}
{Edge.type=solid}
)

Query-vertex predicate

Neighborhood Size

Neighborhood vertex predicate

Neighborhood edge predicate

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NScale programming model

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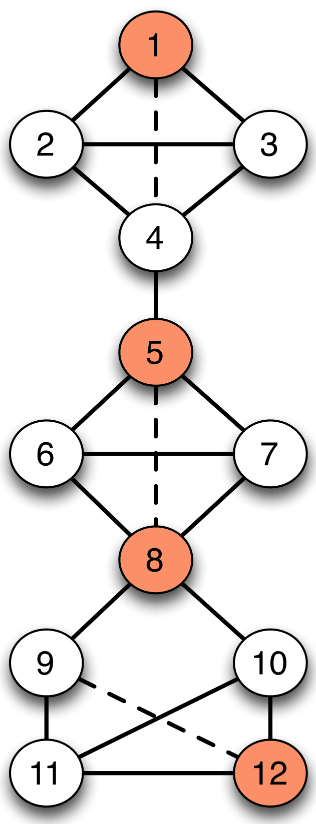


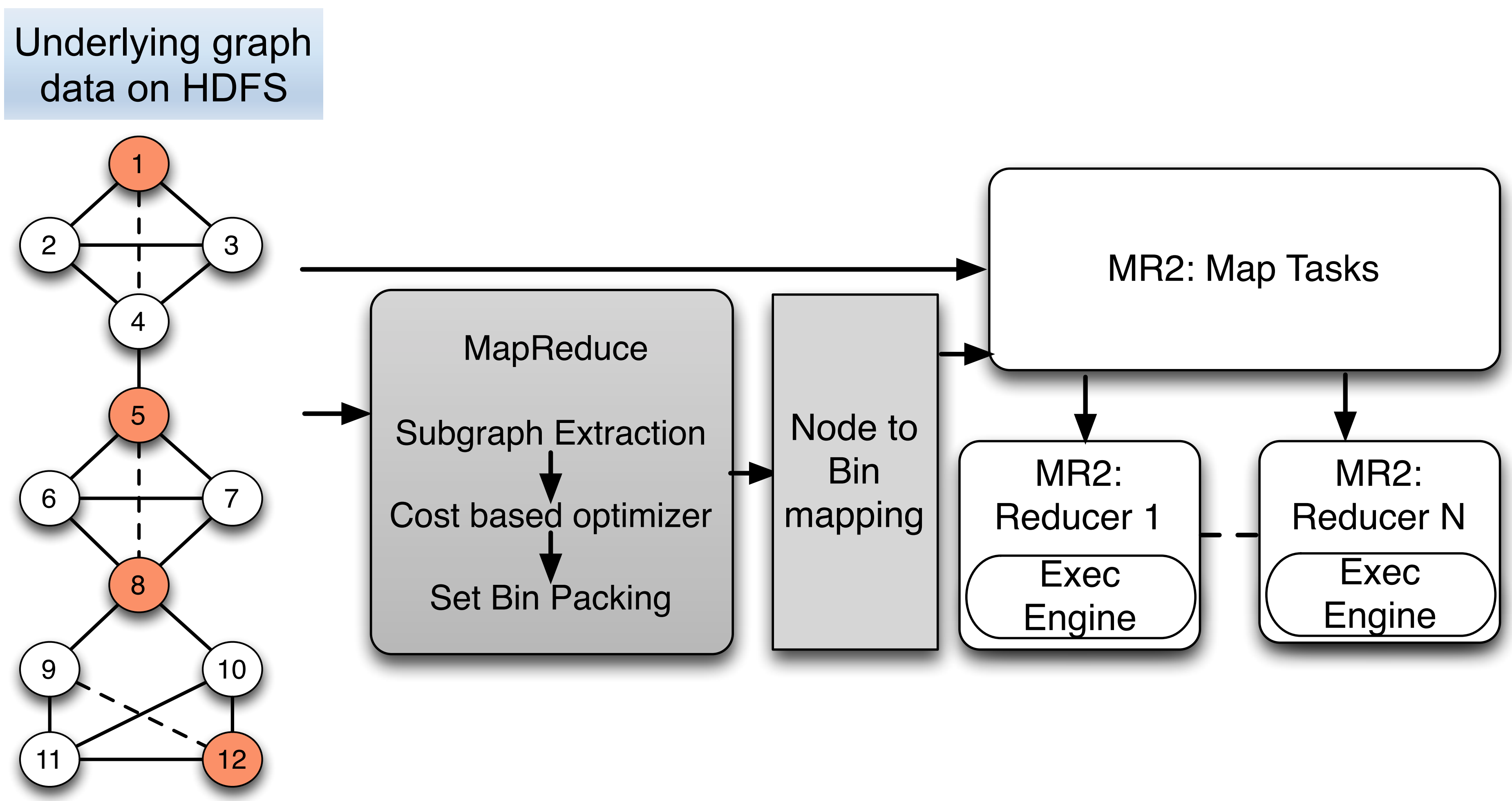
Specifying Computation: BluePrints API

```
ArrayList<RVertex> n_arr = new ArrayList<RVertex>();
for(Edge e: this.getQueryVertex().getOutEdges)
     n_arr.add(e.getVertex(Direction.IN));

int possibleLinks = n_arr.size()* (n_arr.size()-1)/2;

// compute #actual edges among the neighbors
for(int i=0; i < n_arr.size()-1; i++)
   for(int j=i+1; j < n_arr.size(); j++)
      if(edgeExists(n_arr.get(i), n_arr.get(j)))
         numEdges++;
```

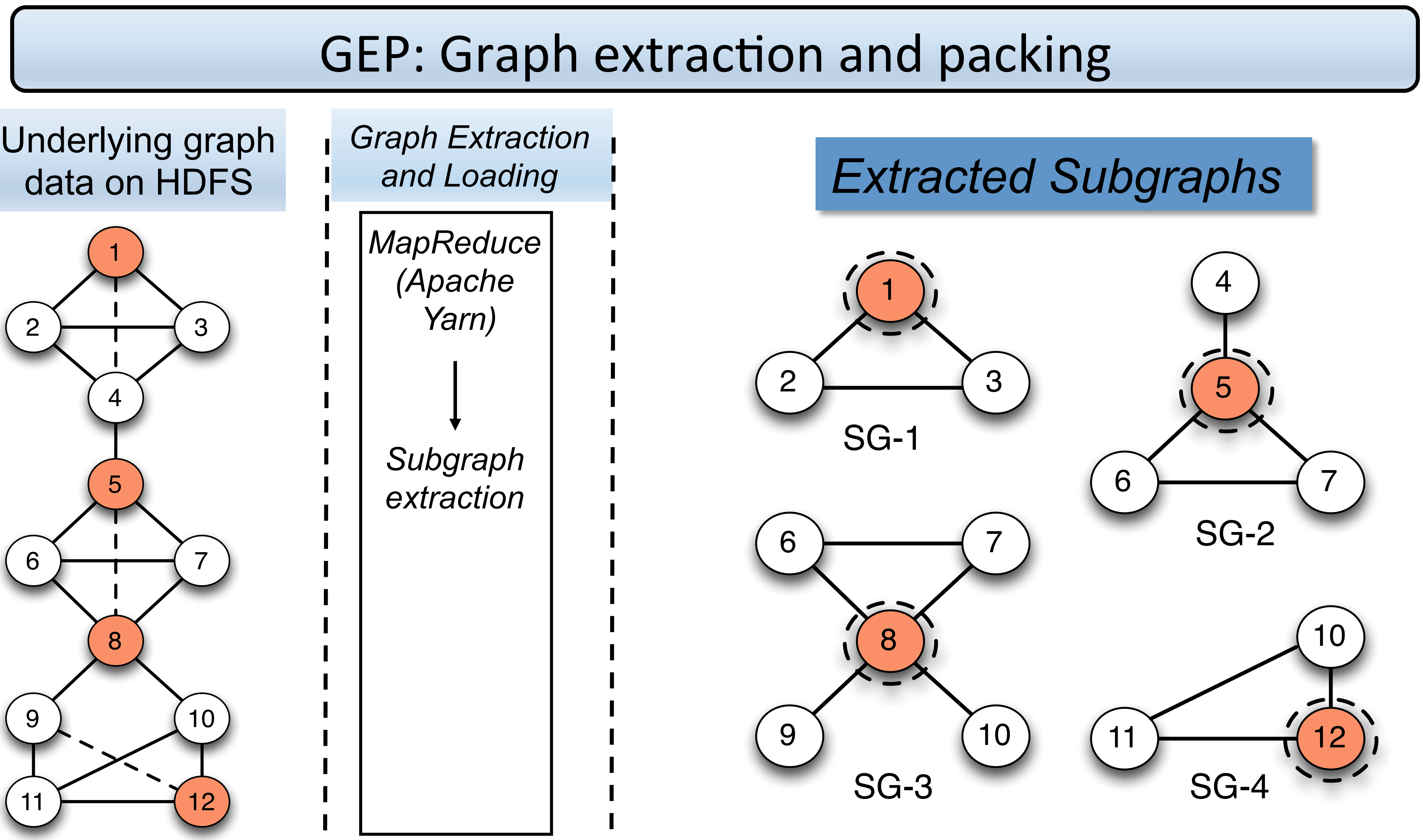
Program cannot be executed as is in vertex-centric programming frameworks.

NScale: LCC Computation Walkthrough

GEP: Graph extraction and packing



NScale: LCC Computation Walkthrough



NScale: LCC Computation Walkthrough

GEP: Graph extraction and packing

Goal:

- Group graphs with high similarity
- Minimizes memory consumption

Techniques explored

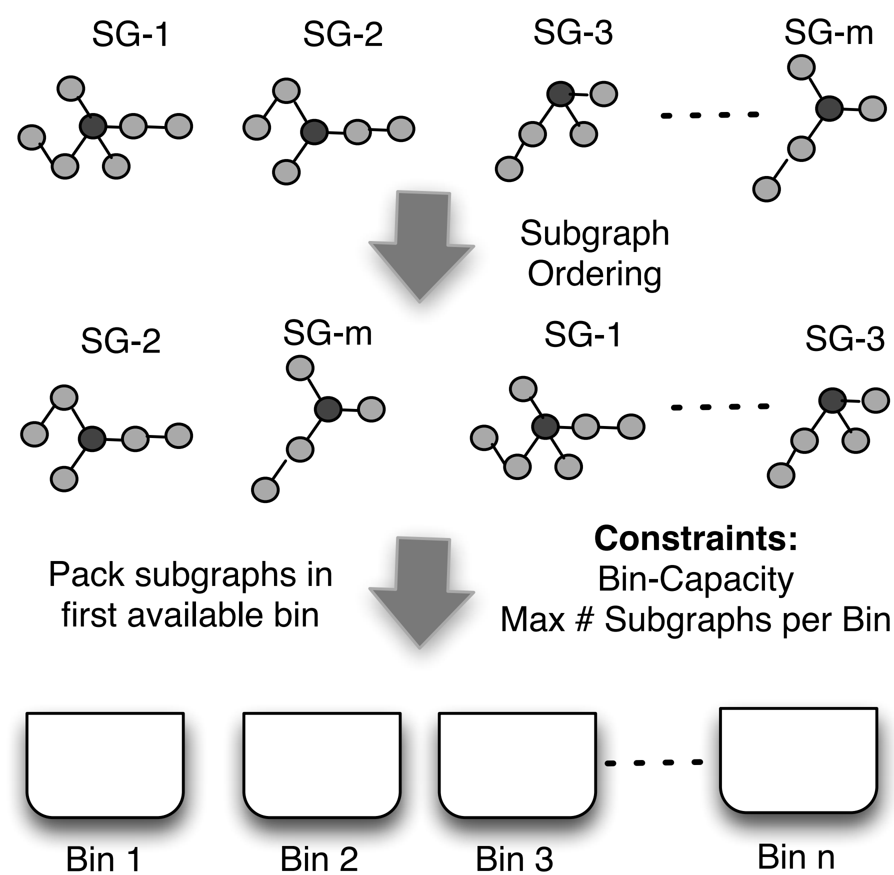
- Set bin packing, graph partitioning, clustering

Shingle based set bin packing

- **Min-hash signatures** based sorting
- Grouping based on **Jaccard** similarity

Bin Packing

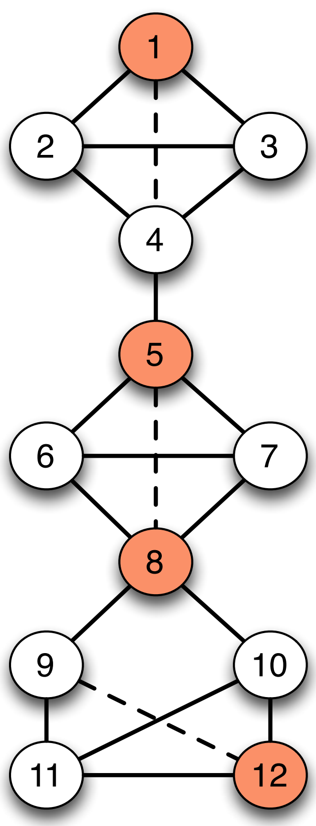
- Set union operation
- Bin Capacity: **Elastic resource allocation**
- Max # Subgraphs: **Handles Skew**



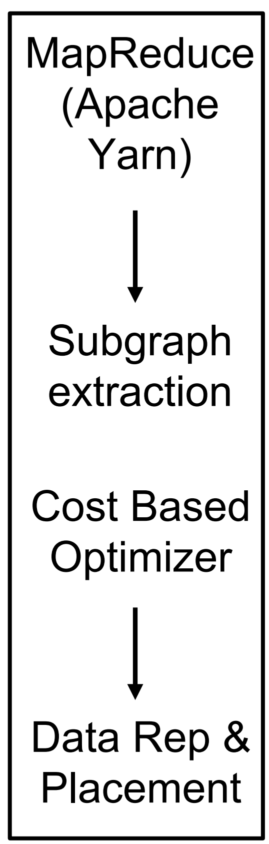
NScale: LCC Computation Walkthrough

GEP: Graph extraction and packing

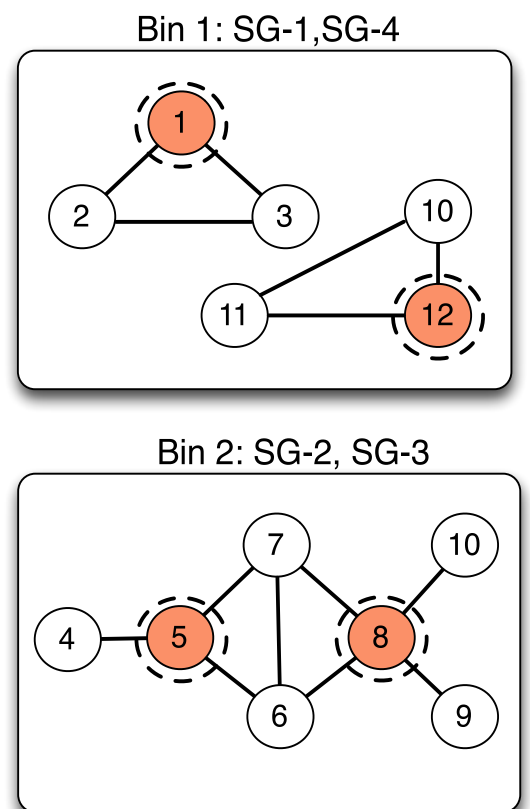
Underlying graph data on HDFS



Graph Extraction and Loading

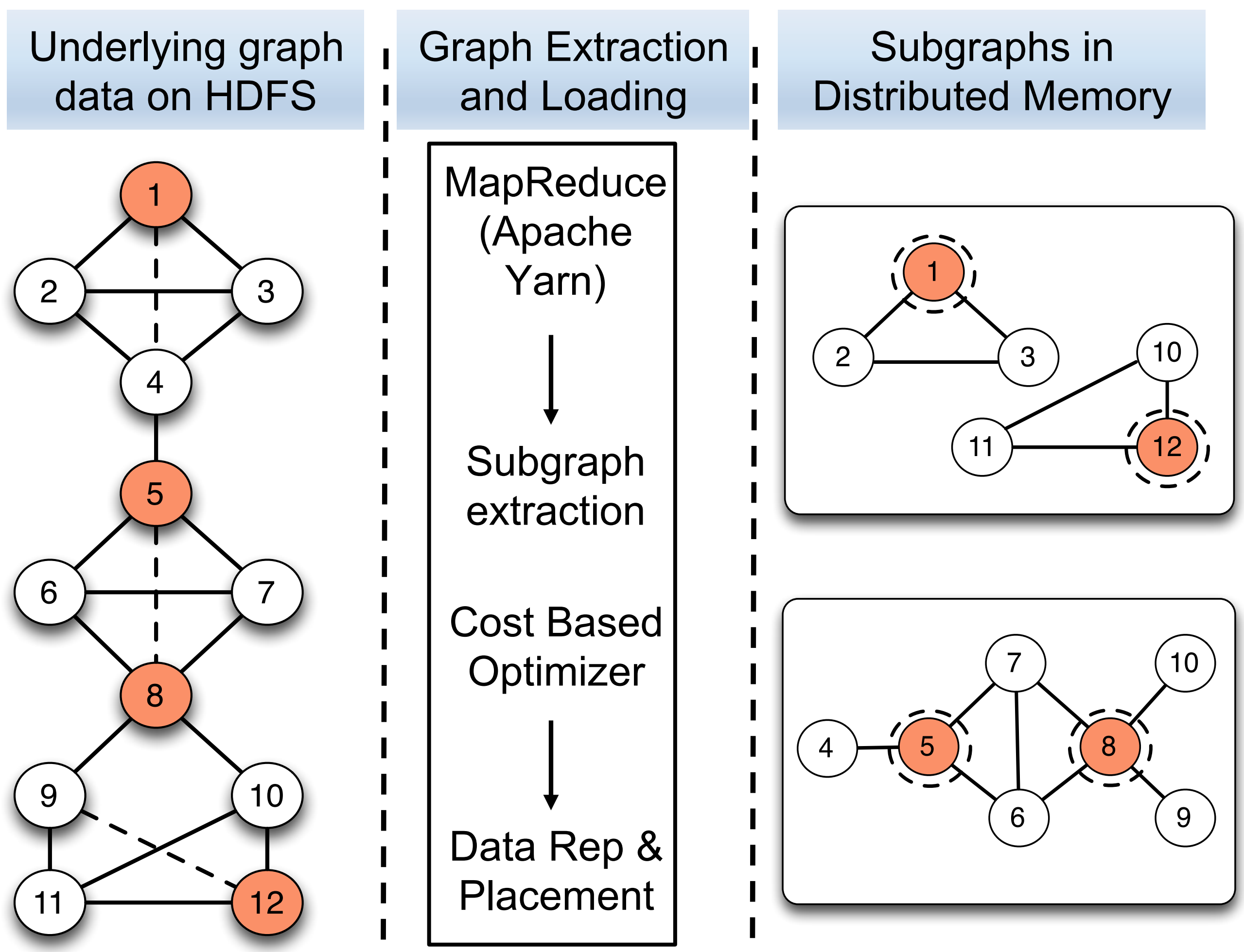


Sample bin packing using Shingles

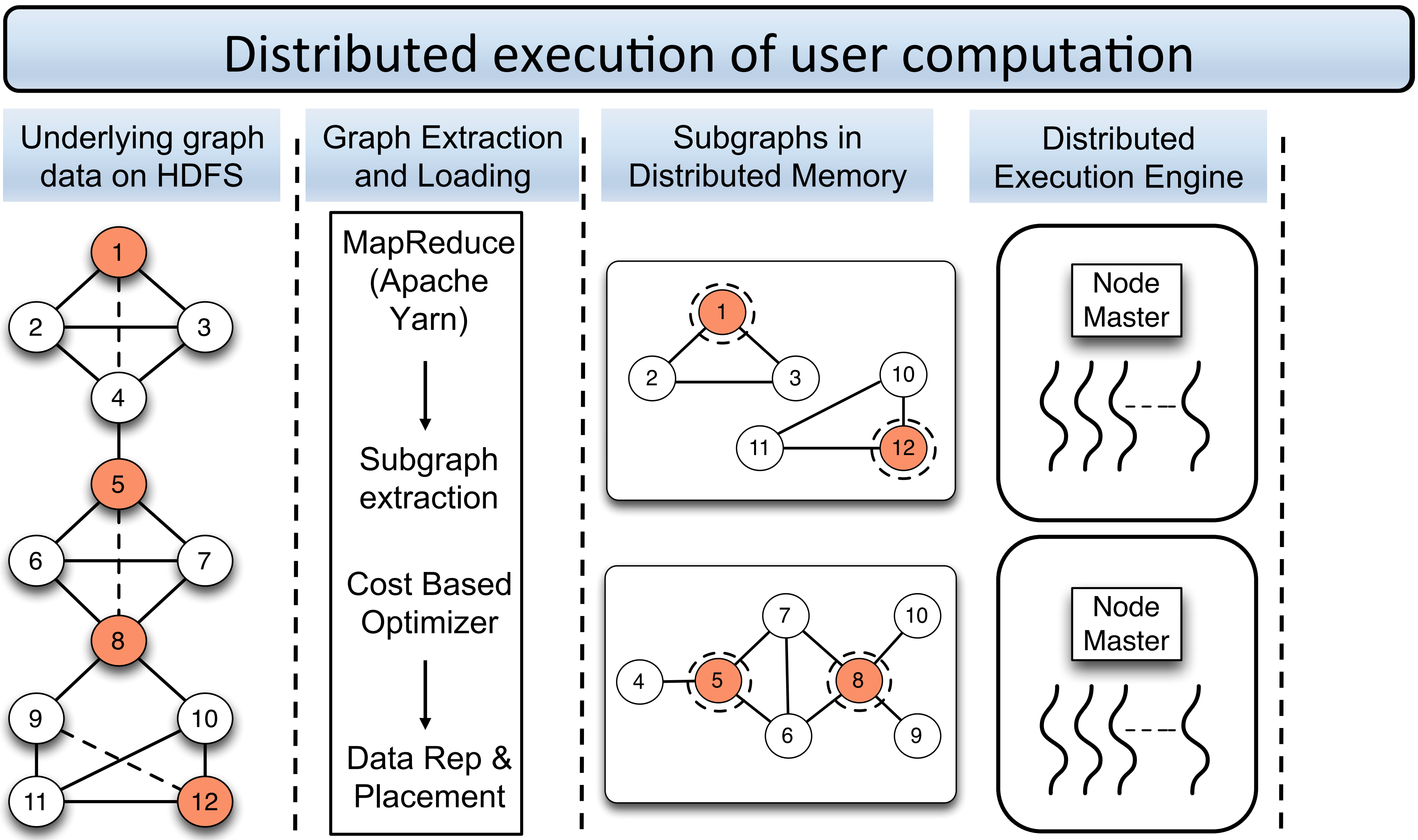


NScale: LCC Computation Walkthrough

GEP: Graph extraction and packing



NScale: LCC Computation Walkthrough



NScale: Summary

- Users write programs at the abstraction of a graph
  - More intuitive for graph analytics
  - Captures mechanics of common graph analysis/cleaning tasks
- Generalization: Flexibility in subgraph definition
  - Subgraph = vertex and associated edges: vertex-centric programs
  - Subgraph = an entire graph: global programs
- Scalability
  - Only relevant portions of the graph data loaded into memory
    - User can specify subgraphs of interest, and select nodes or edges based on properties
  - Carefully partition (pack) nodes across machines so that:
    - Every subgraph is entirely in memory on a machine, while using very few machines

Experimental Evaluation

- **Datasets**
  - Web graphs
  - Communication/interaction graphs
  - Social networks
- **Graph applications**
  - Local Clustering Coefficient
  - Motif counting
  - Identifying weak ties
  - Triangle Counting
  - Personalized Page Rank
- **Baselines**
  - Apache Giraph
  - GraphLab
  - GraphX
- **Evaluation Metrics**
  - Computational Effort
  - Execution Time
  - Cluster Memory
- **Cluster Setup**
  - 16 Node Cluster
  - Apache YARN (MRv2)
  - Each Node:
    - 2 x 4-core Intel Xeon
    - 24GB RAM, 3 x 2 TB disks

Experimental Evaluation

	Local Clustering Coefficient							
Dataset	**NScale**		**Giraph**		**GraphLab**		**GraphX**	
	CE (Node-Secs)	Cluster Mem (GB)	CE (Node-Secs)	Cluster Mem (GB)	CE (Node-Secs)	Cluster Mem (GB)	CE (Node-Secs)	Cluster Mem (GB)
EU Email	377	9.00	1150	26.17	365	20.10	225	4.95
NotreDame	620	19.07	1564	30.14	550	21.40	340	9.75
Google Web	658	25.82	2024	35.35	600	33.50	1485	21.92
WikiTalk	726	24.16	DNC	OOM	1125	37.22	1860	32.00
LiveJournal	1800	50.00	DNC	OOM	5500	128.62	4515	84.00
Orkut	2000	62.00	DNC	OOM	DNC	OOM	20175	125.00

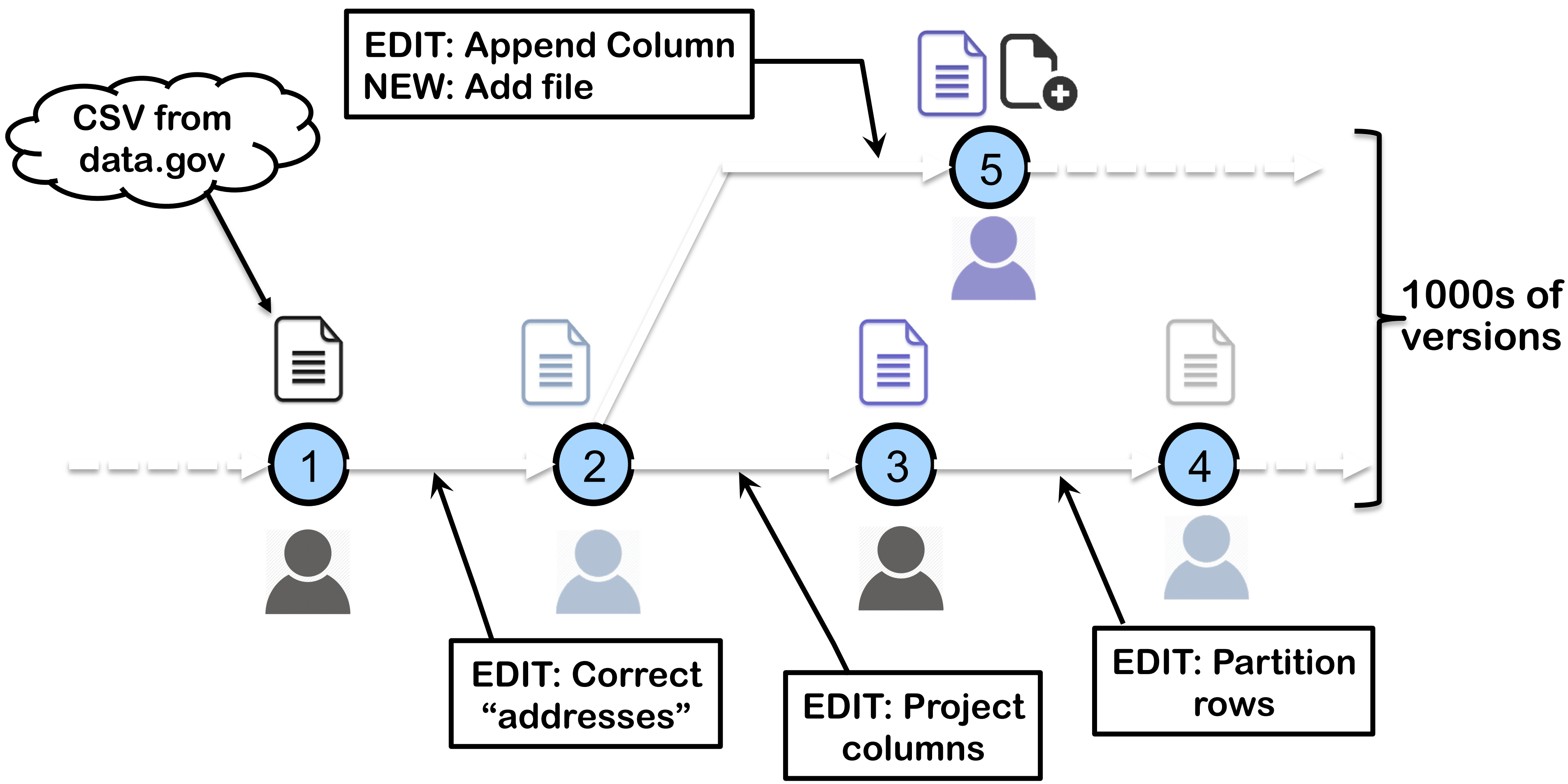
		Personalized Page Rank on 2-Hop Neighborhood							
Dataset		**NScale**		**Giraph**		**GraphLab**		**GraphX**	
	#Source Vertices	CE (Node-Secs)	Cluster Mem (GB)	CE (Node-Secs)	Cluster Mem (GB)	CE (Node-Secs)	Cluster Mem (GB)	CE (Node-Secs)	Cluster Mem (GB)
EU Email	3200	52	3.35	782	17.10	710	28.87	9975	85.50
NotreDame	3500	119	9.56	1058	31.76	870	70.54	50595	95.00
Google Web	4150	464	21.52	10482	64.16	1080	108.28	DNC	-
WikiTalk	12000	3343	79.43	DNC	OOM	DNC	OOM	DNC	-
LiveJournal	20000	4286	84.94	DNC	OOM	DNC	OOM	DNC	-
Orkut	20000	4691	93.07	DNC	OOM	DNC	OOM	DNC	-

Outline

- Graph Data Management
  - Declarative Graph Cleaning
  - A Framework for Distributed Graph Analytics
- DataHub: A platform for collaborative data science
  - Recreation/Storage Tradeoff in Version Management

Collaborative Data Science

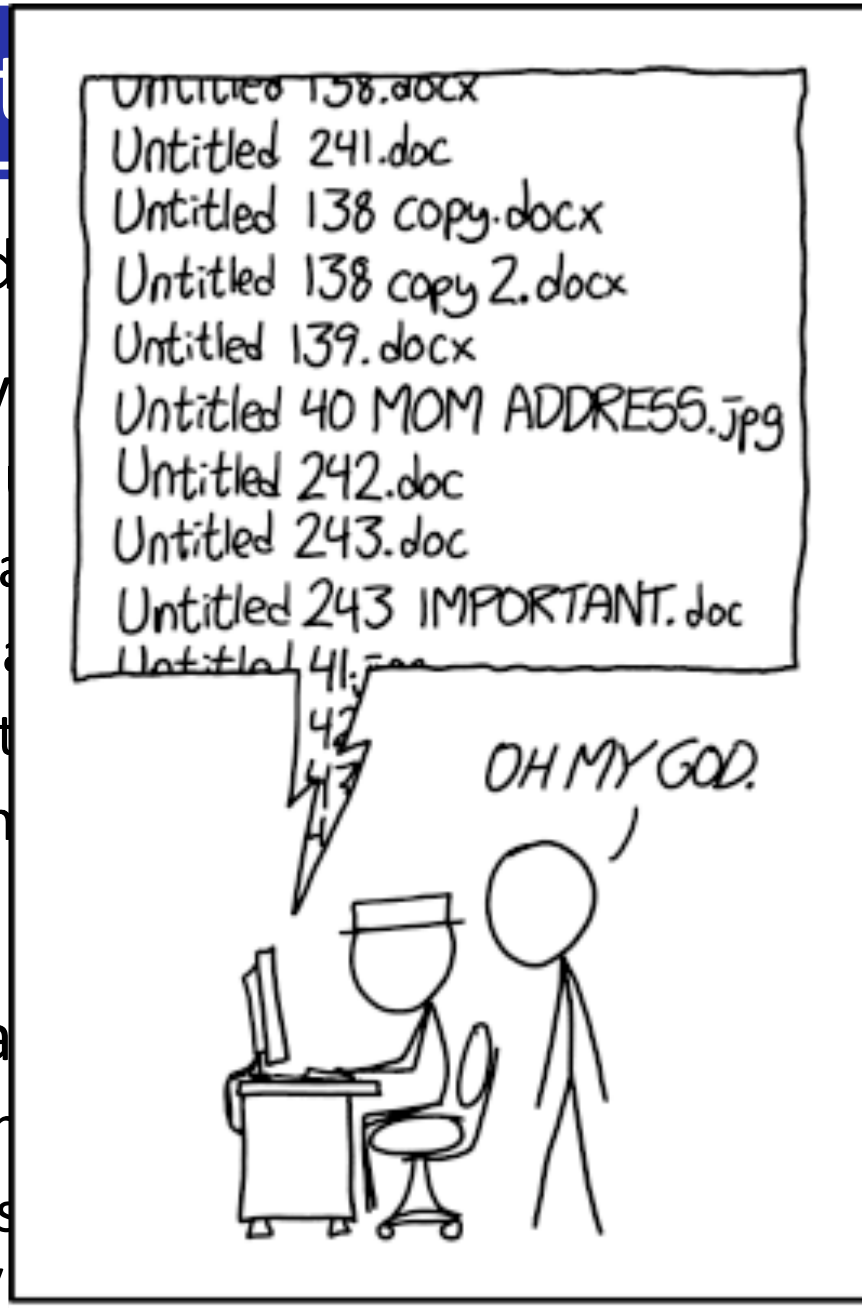
- Widespread use of “data science” in many many domains



A typical data analysis workflow

Collaborat

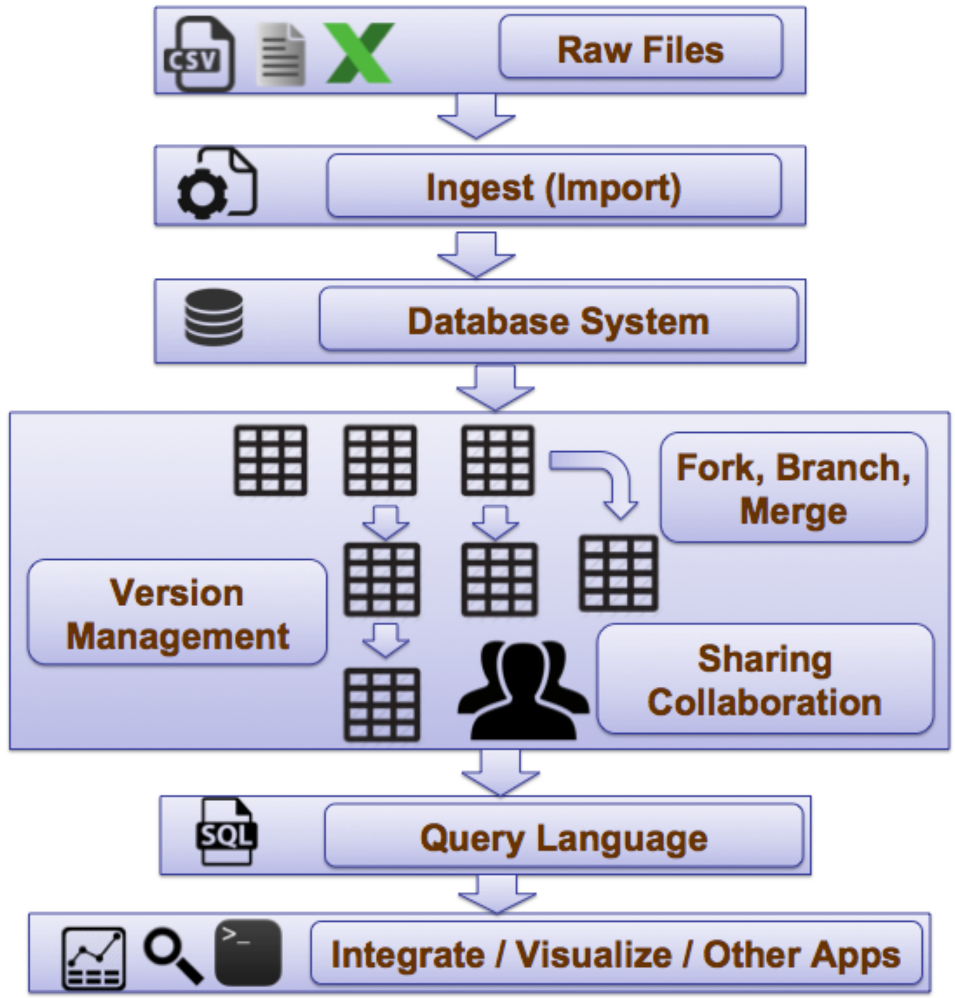
- Widespread ... ny many domains
- Increasingly ... g the *process*, especially d...
  - Many priva ... sive redundancy
  - No easy w ... between datasets
  - Manual int ... onflicts
  - No efficien ... f datasets
  - No way to ... of a dataset
- Ad hoc data ... Dropbox) used
  - Much of th ... y can't use DBs
  - The proces ... hoc and exploratory
  - Scientists/ ... uch on their own



PROTIP: NEVER LOOK IN SOMEONE ELSE'S DOCUMENTS FOLDER.

DataHub: A Collaborative Data Science Platform

The one-stop solution for collaborative data science and dataset version management



http://data-hub.org

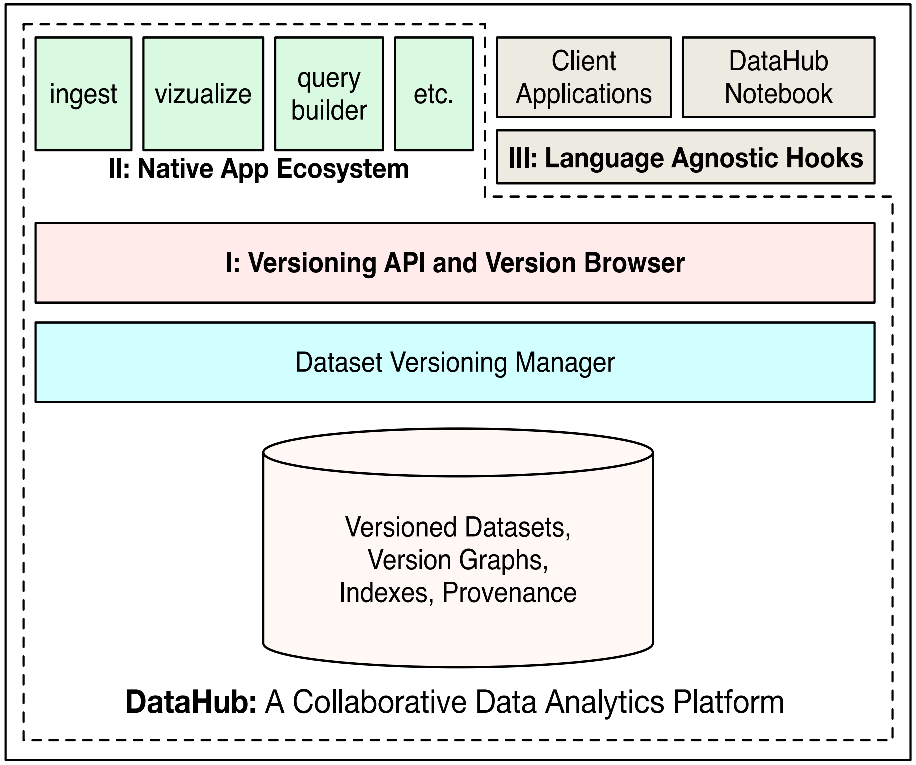
DataHub: A Collaborative Data Science Platform

The one-stop solution for collaborative data science and dataset version management

• a dataset management system – import, search, query, analyze a large number of (public) datasets

• a dataset version control system – branch, update, merge, transform large structured or unstructured datasets

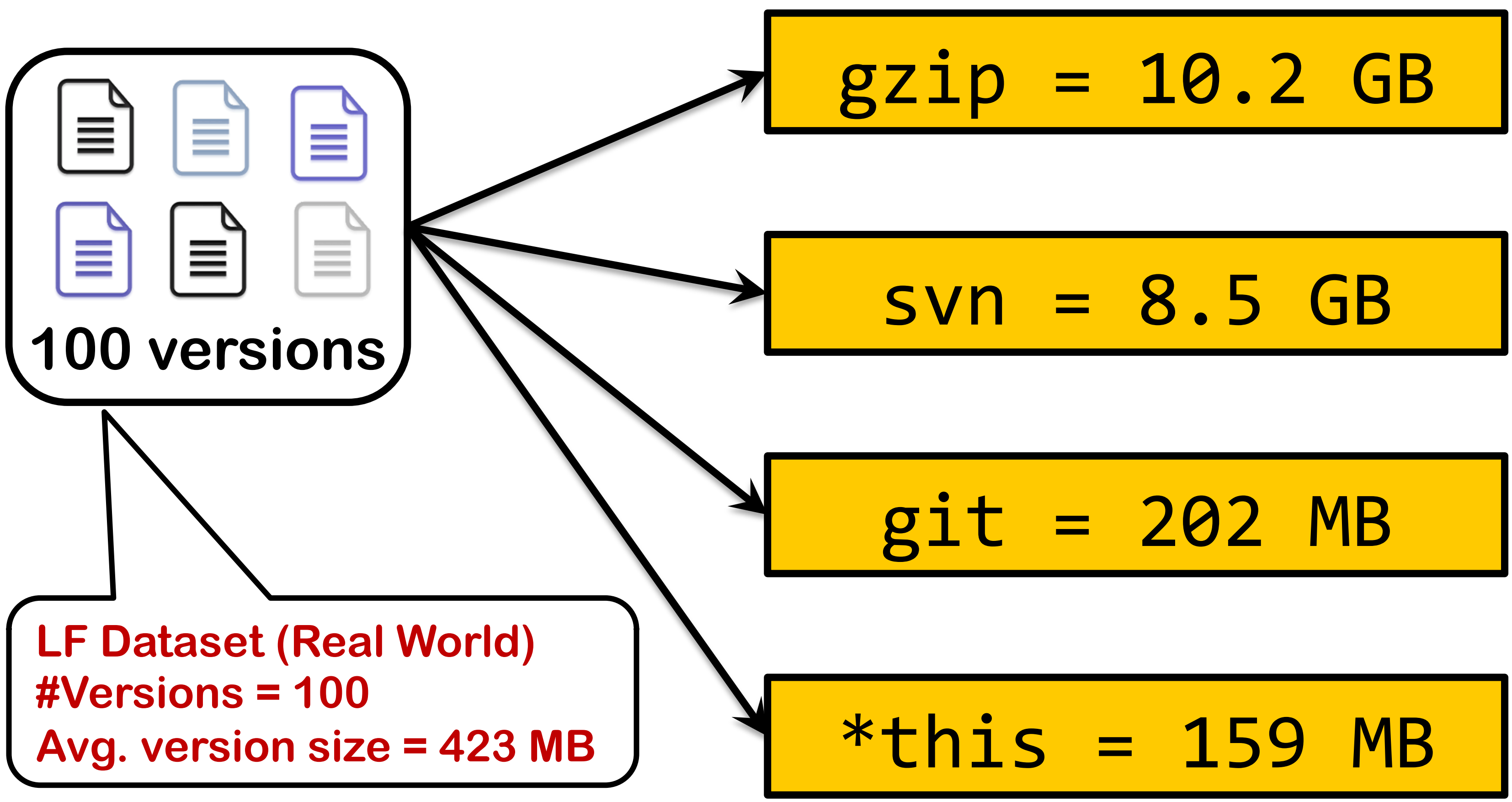
• an app ecosystem and hooks for external applications (Matlab, R, iPython Notebook, etc)



DataHub Architecture

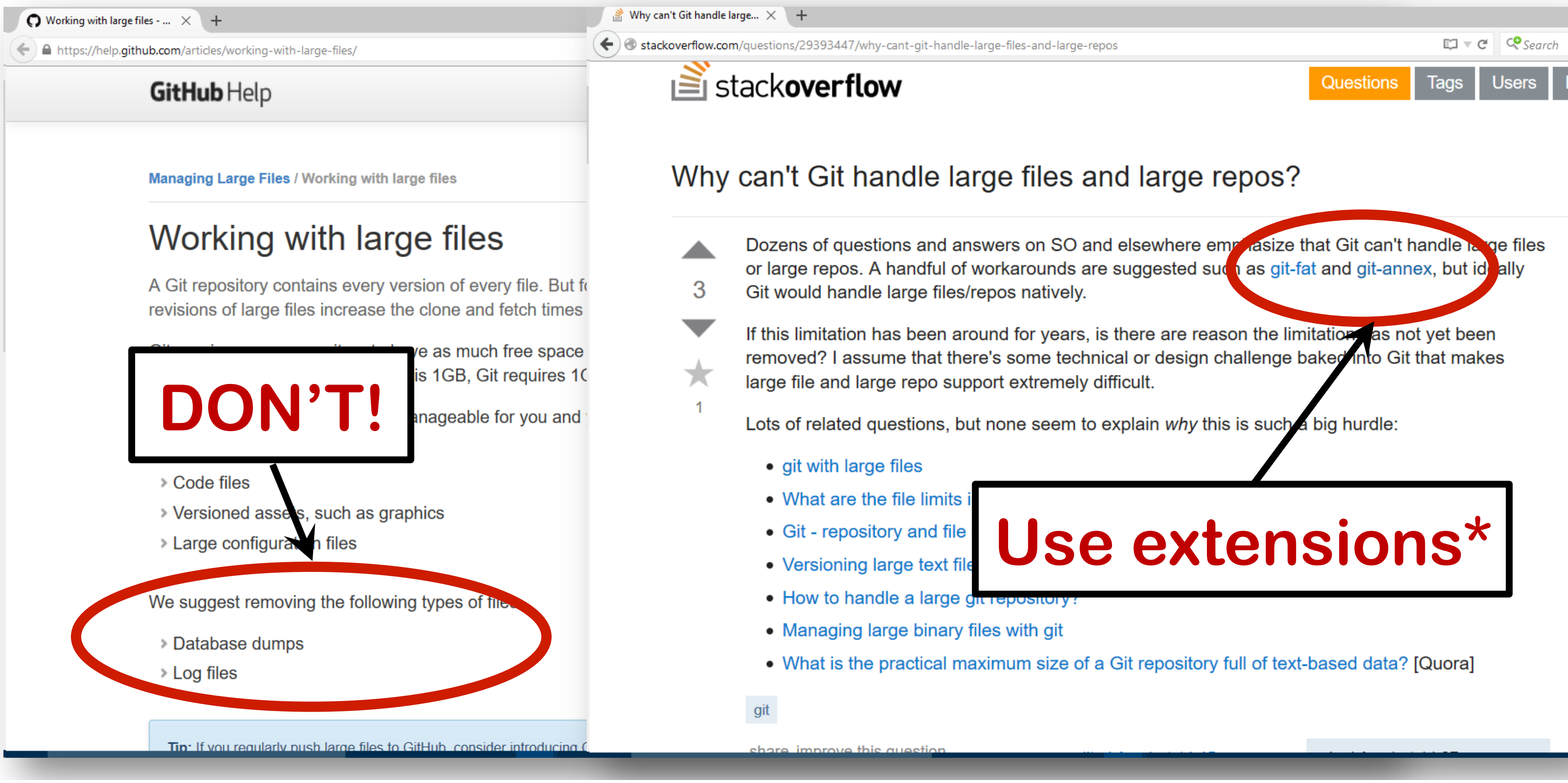
Can we use Version Control Systems (e.g., Git)?

- **No, because they typically use fairly simple algorithms and are optimized to work for code-like data**



Can we use Version Control Systems (e.g., Git)?

- ✘ No, because they typically use **fairly simple algorithms** and are optimized to work for code-like data
- ✘ Git ends up using **large amounts of RAM** for large files



Can we use Version Control Systems (e.g., Git)?

- **No, because they typically use fairly simple algorithms and are optimized to work for code-like data**
- **Git ends up using large amounts of RAM for large files**
- **Querying and retrieval functionalities are primitive, and revolve around single version and metadata retrieval**
- **No way to specify queries like:**
  - *identify all datasets derived of dataset A that satisfy property P*
  - *identify all predecessor versions of version A that differ from it by a large number of records*
  - *rank a set of versions according to a scoring function*
  - *find the version where the result of an aggregate query is above a threshold*
  - *find parent records of all records in version A that satisfy certain property*

Can we use Version Control Systems (e.g., Git)?

- **No, because they typically use fairly simple algorithms and are optimized to work for code-like data**
- **Git ends up using large amounts of RAM for large files**

VQuel: A Unified Query Language for querying versioning and derivation information [USENIX TAPP'15]

Example: What commits did Alice make after January 01, 2015?

```
range of V is Version
retrieve V.all
where V.author.name = "Alice" and
      V.creation_ts >= "01/01/2015”
```

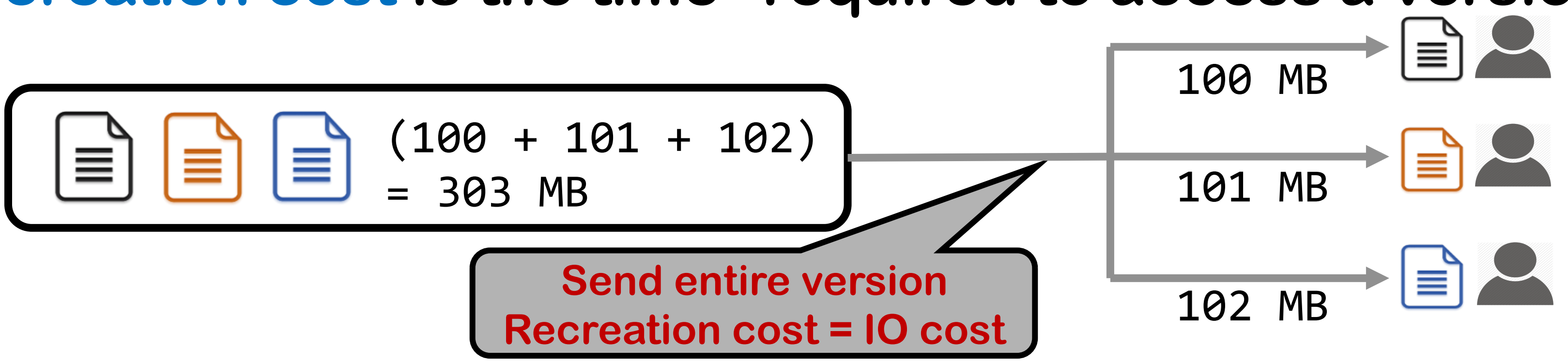
- *find the version where the result of an aggregate query is above a threshold*
- *find parent records of all records in version A that satisfy certain property*

Outline

- Graph Data Management
  - Declarative Graph Cleaning
  - A Framework for Distributed Graph Analytics
- DataHub: A platform for collaborative data science
  - Recreation/Storage Tradeoff in Version Management

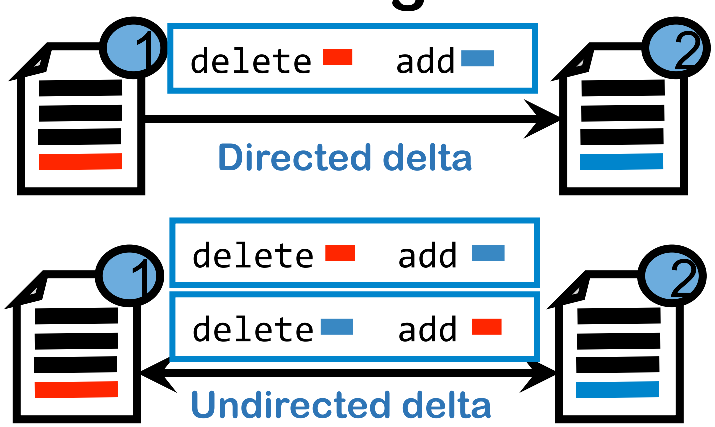
Storage cost is the space required to store a set of versions

Recreation cost is the time* required to access a version



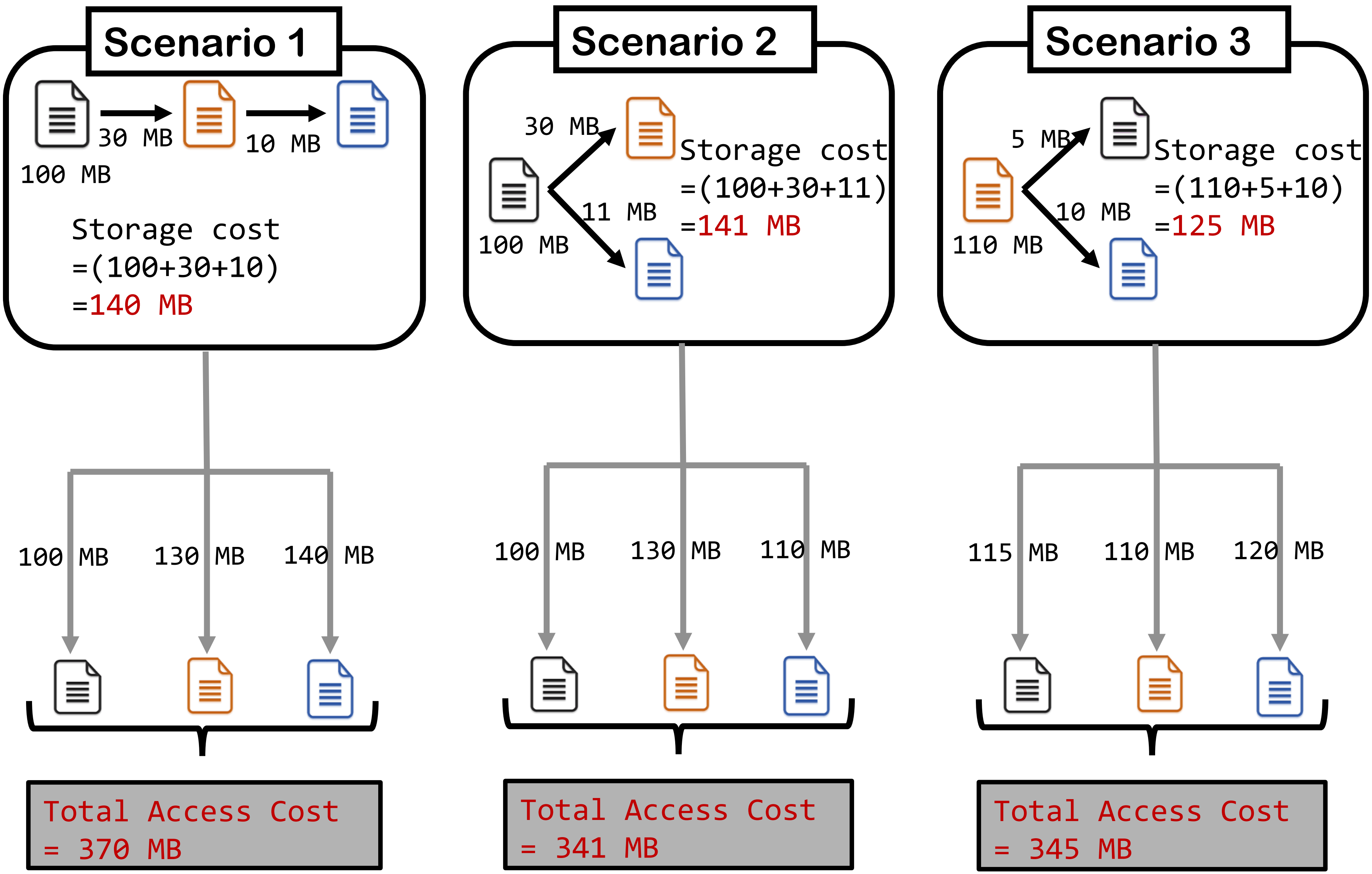
A delta between versions is a file which allows constructing one version given the other

Example: Unix diff, xdelta, XOR, etc.



A delta has its own storage cost and recreation cost, which, in general, are independent of each other

Storage-Recreation Tradeoff



Storage-Recreation Tradeoff

Given

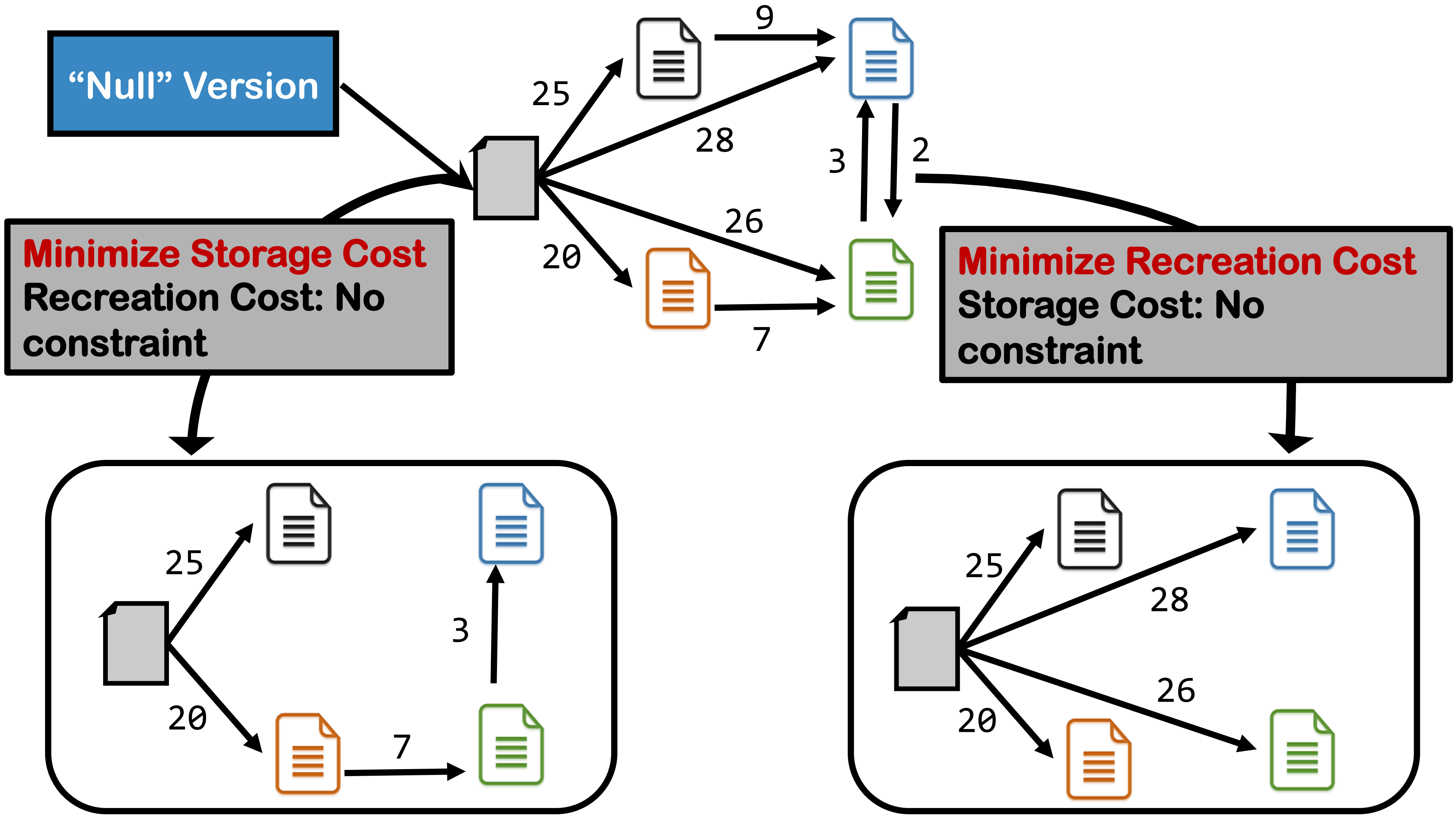
1) a set of versions
2) partial information about deltas between versions

Find a Storage Solution that:

- minimizes total recreation cost given a storage budget, or
- minimizes max recreation cost given a storage budget

	Storage Cost	Recreation Cost	Undirected Case, $\Delta = \Phi$	Directed Case, $\Delta = \Phi$	Directed Case, $\Delta \neq \Phi$
P1	min C	$R_i < \infty, \forall i$	PTime, Minimum Cost Arborescence (MCA)		
P2	$C < \infty$	$\min \{\max \{R_i \mid 1 \leq i \leq n\}\}$	PTime, Shortest Path Tree (SPT)		
P3	$C \leq \beta$	$\min \{ \sum_{i=1}^{n} R_i \}$	NP-hard, LAST* Alg	NP-hard, LMG Algorithm	
P4	$C \leq \beta$	$\min \{\max \{R_i \mid 1 \leq i \leq n\}\}$		NP-hard, MP Algorithm	
P5	min C	$\sum_{i=1}^{n} R_i \leq \theta$	NP-hard, LAST* Alg	NP-hard, LMG Algorithm	
P6	min C	$\max \{R_i \mid 1 \leq i \leq n\} \leq \theta$		NP-hard, MP Algorithm	

Baselines

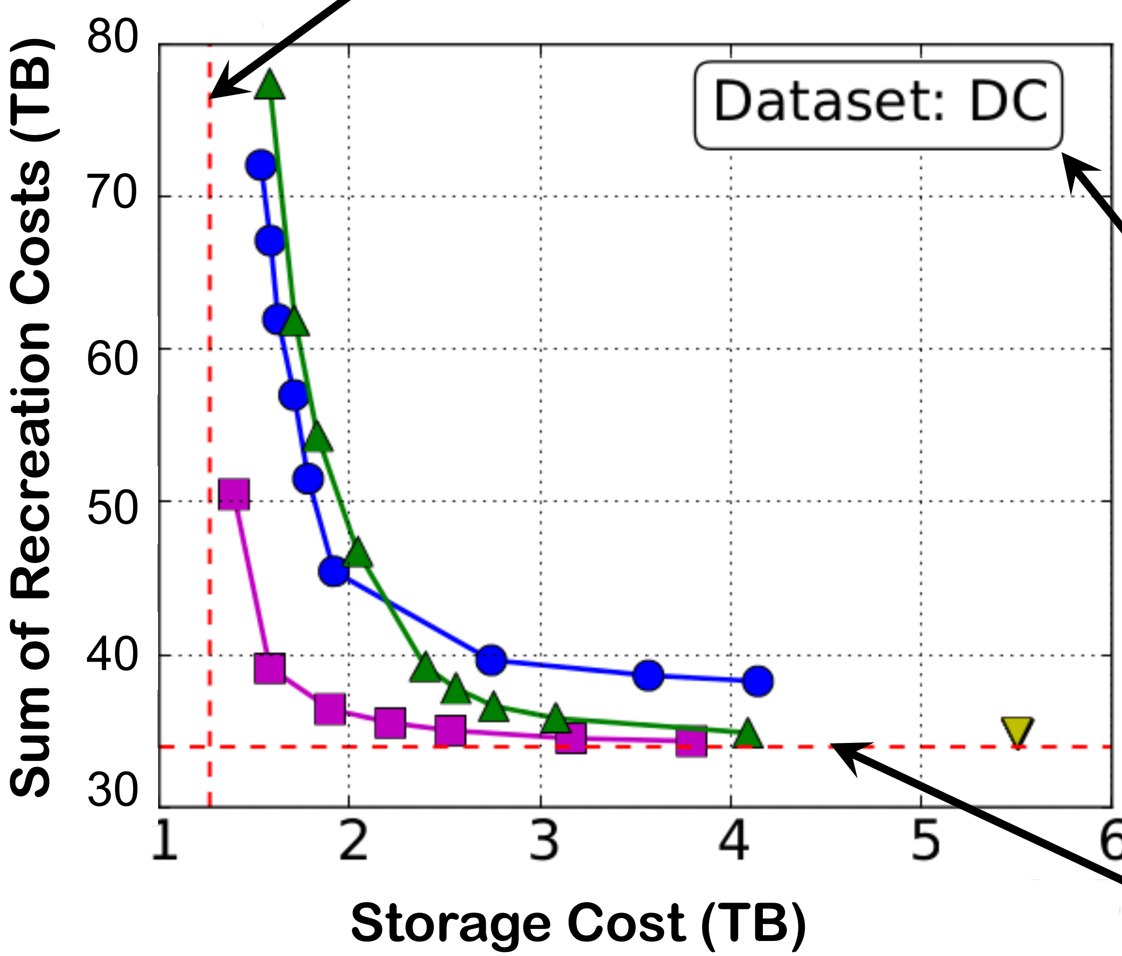


Minimum Cost Arborescence (MCA)
Edmonds' algorithm
Time complexity = O(E + V logV)

Shortest Path Tree (SPT)
Dijkstra's algorithm
Time complexity = O(E logV)

Comparing Different Solutions

MCA Storage Cost



Type = CSV files
#Versions = **100010**
#Deltas = **18086876**
Average version size = **347.65 MB**
MCA Recreation Cost = **11.5 PB**
SPT Storage Cost = **34 TB**

SPT Recreation Cost

Storage budget of 1.1X the MCA reduces total recreation cost by 1000X