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Large Graph Mining

Recent Developement, Challenges and Potential Solutions

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THE SPEAKER

PASSIONATE BY COMPUTER SCIENCE, TECHNOLOGY & RESEARCH

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Make the link between Research & Customer challenges

Supervising 3 PhD thesis, 6 Master thesis with 3 BEL Universities

Head of the EU R&D Architecture

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Guiding the transition from Telco to Service provider with new technologies

Committer on open source projects launched @ EURA NOVA

RoQ-Messaging, NAIAD, Wazaabi

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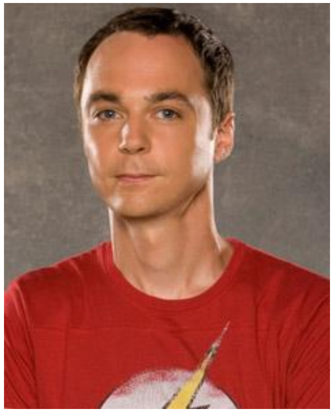
Before starting

Ramp-up test to wake-up the room after lunch a Friday afternoon …

I will use persons to illustrate the topic in this tutorial

Can you give me their names?



Leonard **Sheldon** **Moss** **Lary Page**

Looks ready to start to learn about Graph Processing !

AGENDA

1 / Introduction

2 / Focus on two graph mining algorithms

3 / Introduction of Distributed Processing Framework

4 / Graph Data warehouse – an emerging challenge

5 / Conclusion

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EXECUTIVE SUMMARY

Graph Mining needs another approach

Data Mining

Mature, algorithmic, libraries & products

- Flat data, relational data, multi-dimensional data
- No Linked data

↓

New Needs

Linked data & reasoning on relationships

- Biology
- Chemistry
- Social Networks
- Internet - Networks

↓

What do we need?

Is traditional data mining still applicable?

- Graph-based similarity
- Algorithm re-design for graphs
- Scalability for storage & processing

↓

Graph Data Warehouse

Is traditional data warehouse still applicable?

- Conceptual modeling
- Query
- Processing Stack & materialization
- Storage

LET’S START
WITH DATA MINING

Process of discovering patterns or models of data. Those patterns often consist in previously unknown and implicit information and knowledge embedded within a data set [1]

[1] M.-S. Chen, J. Han, and P. S. Yu. Data mining: An overview from a database perspective. IEEE Trans. Knowl. Data Eng., 8(6):866–883, 1996.

DATA MINING

Techniques have been developed these last 20 years

Process of analyzing data from different perspectives and summarizing it into useful information

Classification
We position data in a pre-determined group

Pattern recognition
We mine data to retrieve pre-determined patterns

Clustering
Data are grouped within partitions according criteria

Feature extraction
We transform the input data into a set of features (data set reduction)

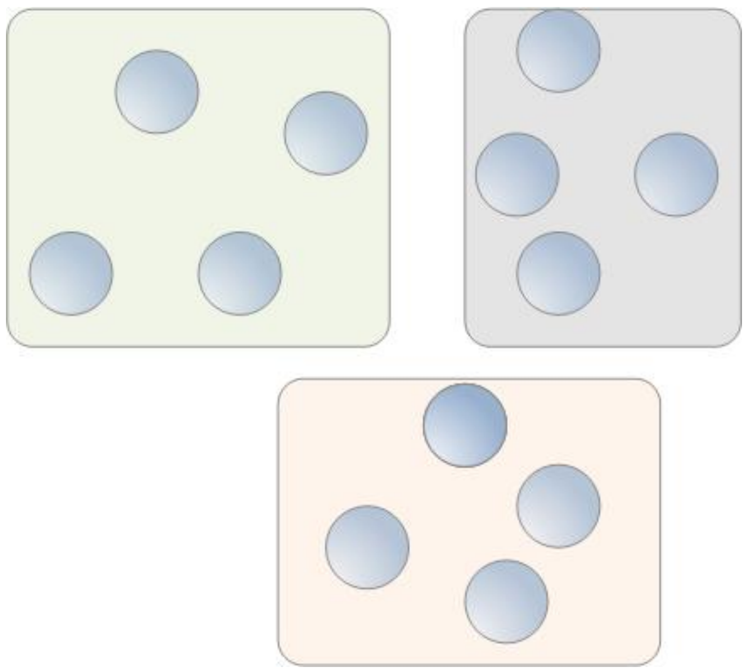
Association
Enables to link data between each other

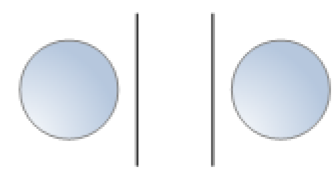
Summarization
Ranking such as page rank

DATA MINING

Manages & processes data as a collection of independent instances

The Mining usually does not consider the global relations between the objects





Almost all clustering algorithms compute the similarity between all the pair of objects in the data set

Why the relationship matters?

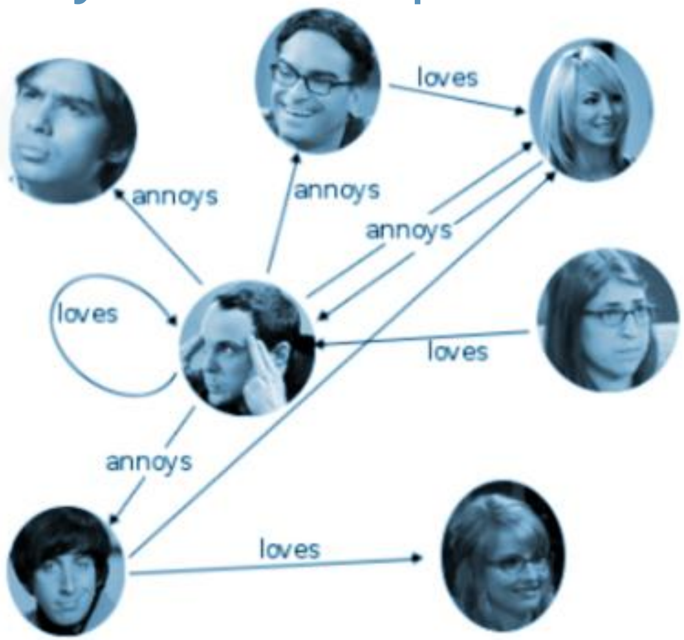
Taking into account the relation between data in mining

Imagine to cluster people from their profiles

Why the relationship matters?

Taking into account the relation between data in mining

Imagine to cluster people not only from their profiles but also … by their social interactions



- More complete Data structure
- Greater expressive power
- Better model or real-life cases

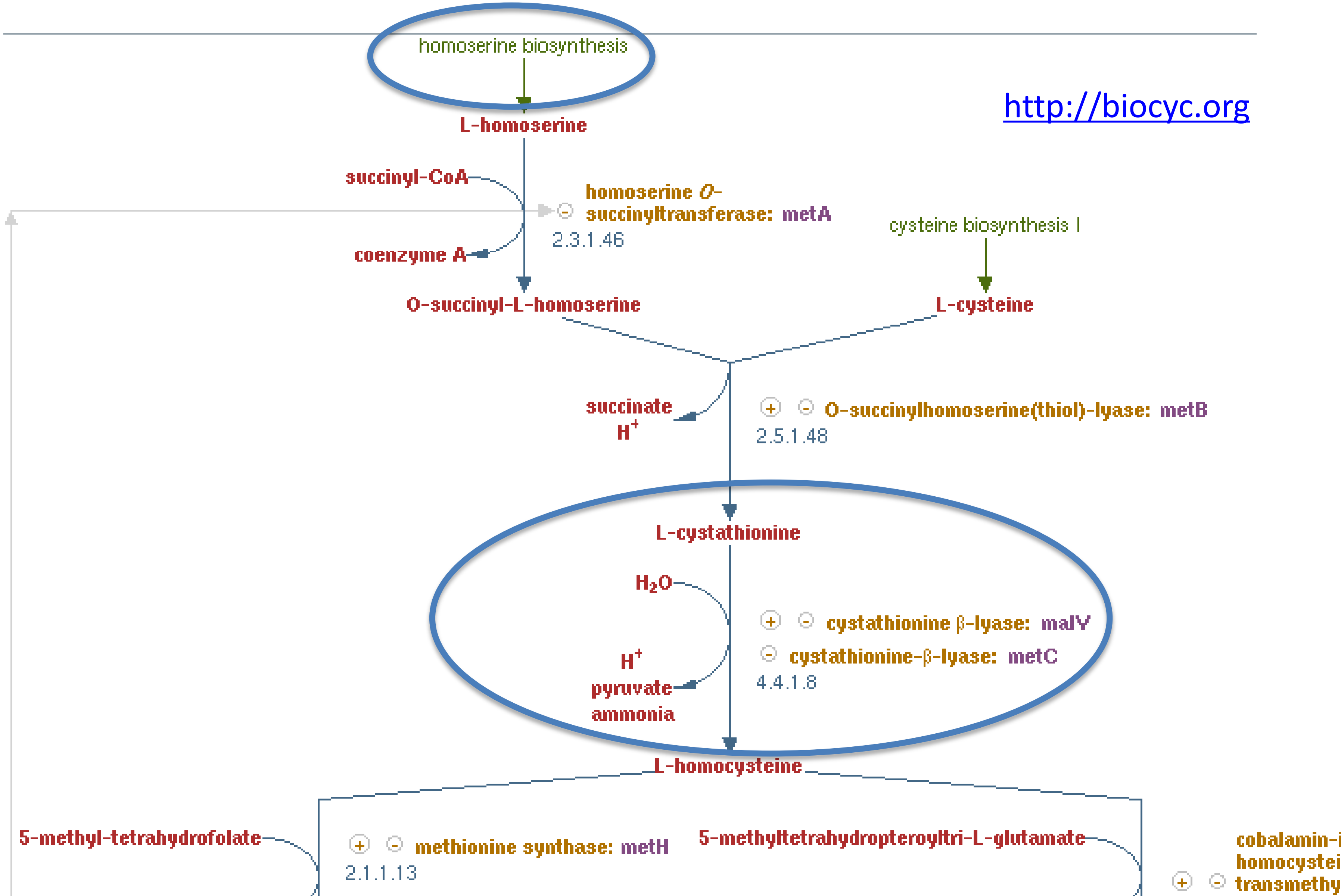
New emergent industrial needs lead to deal with this kind of structured data

New Industry requirements

Need to structure and mine structured & linked data

1. Biochemical Networks

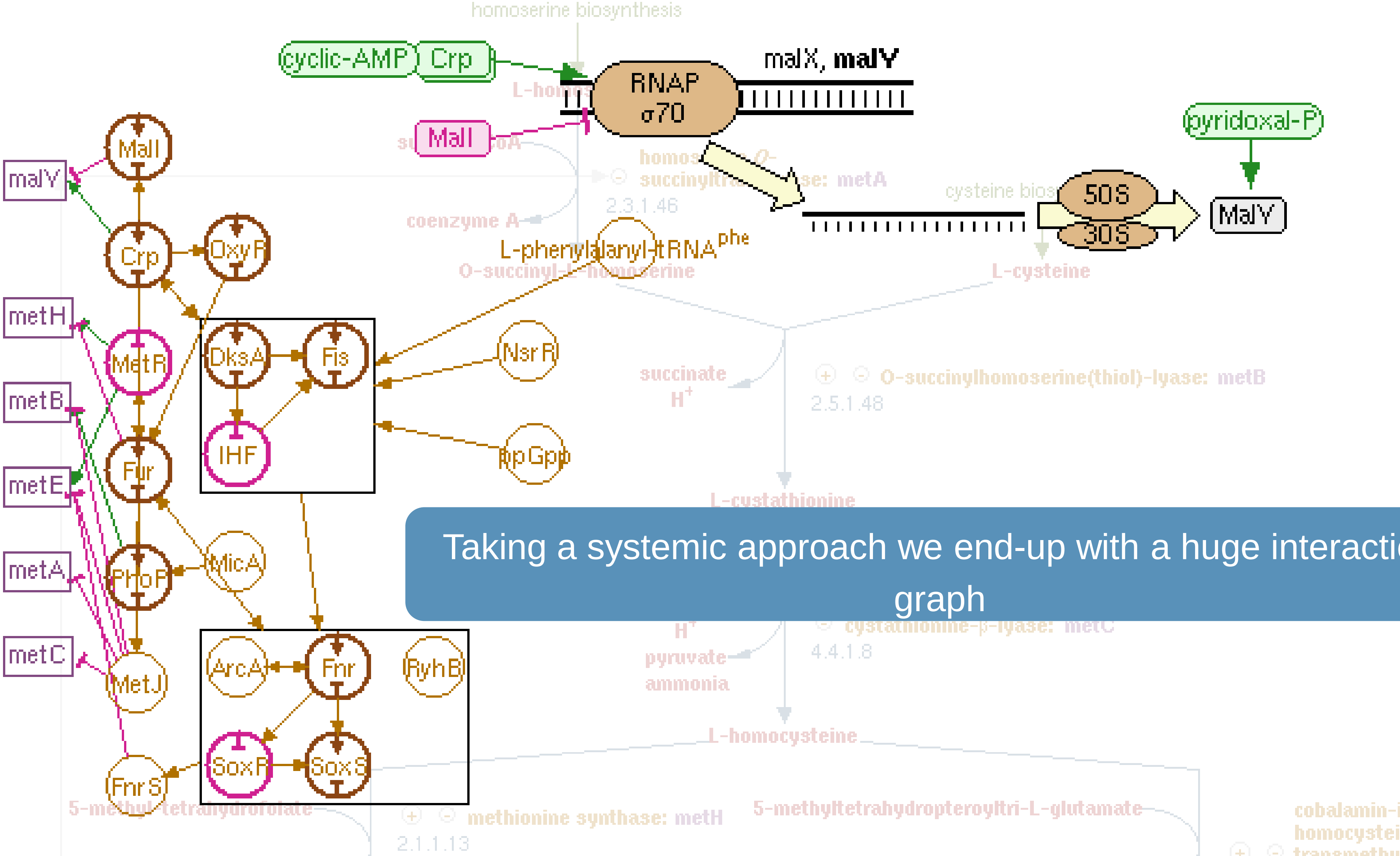
The metabolic pathways



http://biocyc.org

1. Biochemical Networks

Genetic regulation signal



Taking a systemic approach we end-up with a huge interacti
graph

1. Biochemical Networks

A biochemical network definition

$$G(V,E)$$

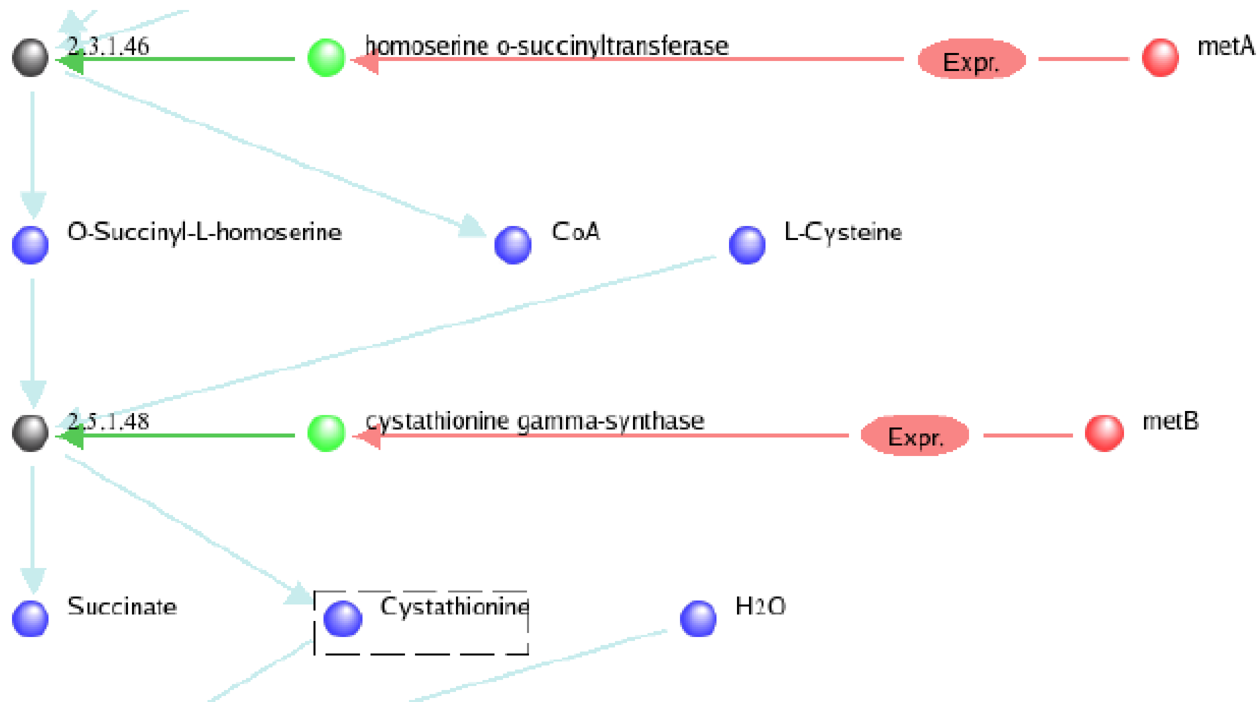
$$V = V_G \cup V_R \cup V_P \cup V_C$$

$$E = E_{Reg} \cup E_{Trans} \cup E_{React}$$

$$E_{Reg} = \{V_P \, X \, V_R\}$$

$$E_{Trans} = \{V_G \, X \, V_R\}$$

$$E_{React} = \{V_C \, X \, V_R\}$$



1. Biochemical Networks

New emergent industrial needs

What happens if I drop a compound in the system ?

Drug simulation in drug design

Find which genes are involved in the fat reduction pathway?

Genetic therapy

Predict a metabolic pathway given a metabolic network and seed reactions

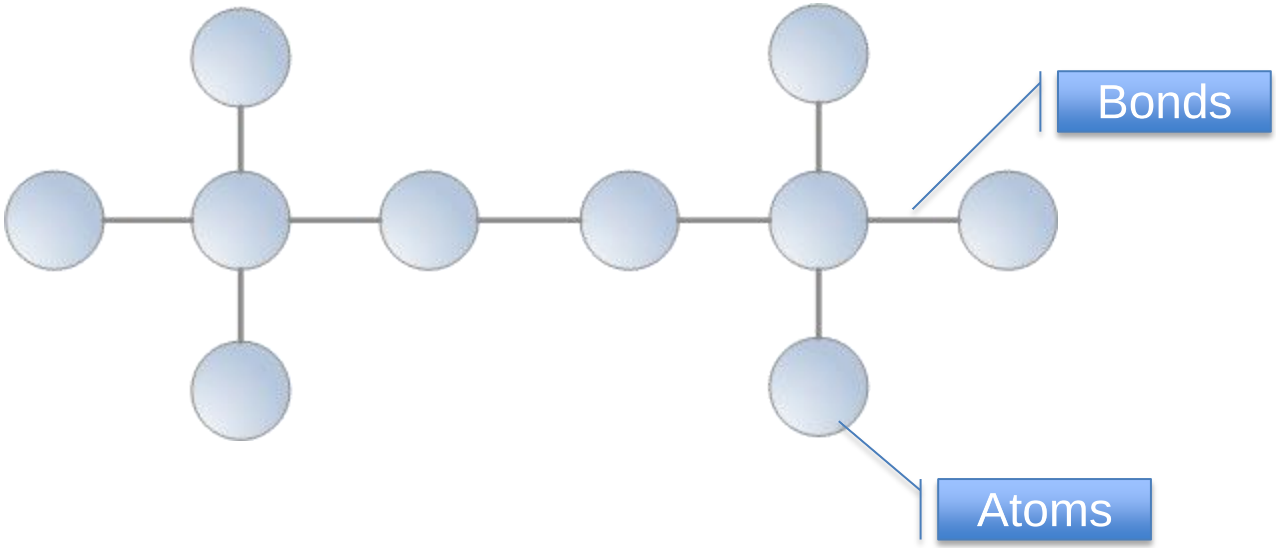
Subgraph extraction

Predict a metabolic network from a genetic signature given a protein interaction graph & a regulation network

2. Chemical Databases

New emergent industrial needs

Database specifically designed to store chemical information.



Graphs are the natural representation for chemical compounds, most of the mining algorithms focus on mining chemical graphs

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2. Chemical Databases

New emergent industrial needs

A typical request: Structural similarity search

$$G_d = (V_d, E_d)$$

Gd is the graph query

$$V_d = (\theta_1, \ldots, \theta_n)$$

The objective is to maximize the probability that the ith teta = alpha knowing the measure a, b.

$$\max_{\forall i} (P(\theta_i = \alpha \mid a, b)) \text{ with } \{\alpha \in V\}$$

2. Chemical Databases

New emergent industrial needs

Structural indexing
Indexing the structural properties of the molecules

Structural similarity search
Similar molecules will have similar effects

3D molecule conformation
Based on similar molecule conformations

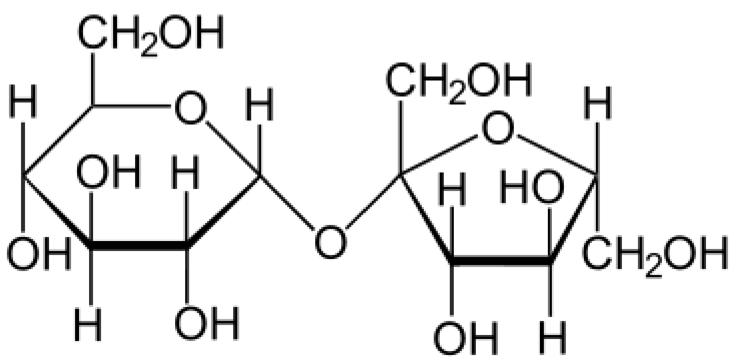
Structure-Activity-Relationship
How to modify the Structure for changing its activity

2. Chemical Databases

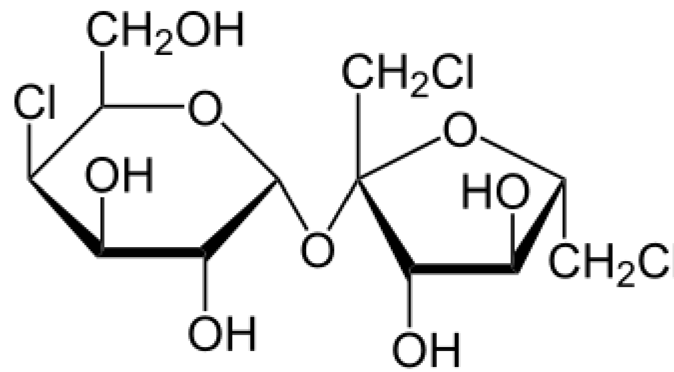
New emergent industrial needs

Structure-Activity-Relationship

Example of the sucralose where 3 hydroxyl groups have been replaced with Chloride (Cl)



Sugar $C_{12}H_{22}O_{11}$



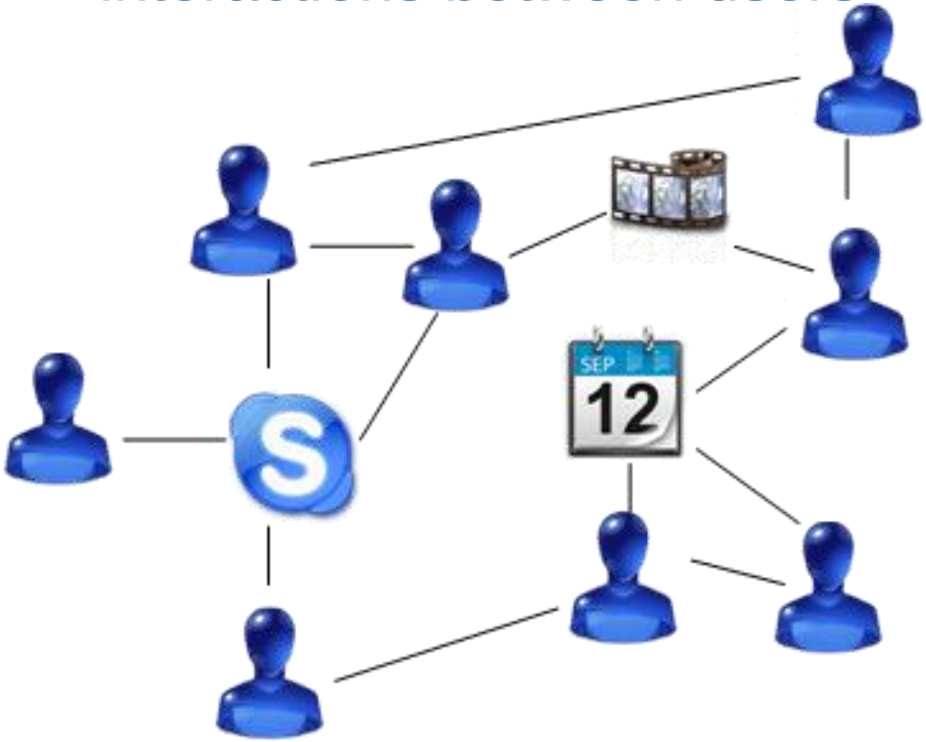
Diet Sugar $C_{12}H_{19}Cl_{3}O_{8}$

http://en.wikipedia.org/wiki/Sucralose

3. Social network anlytics

New emergent industrial needs

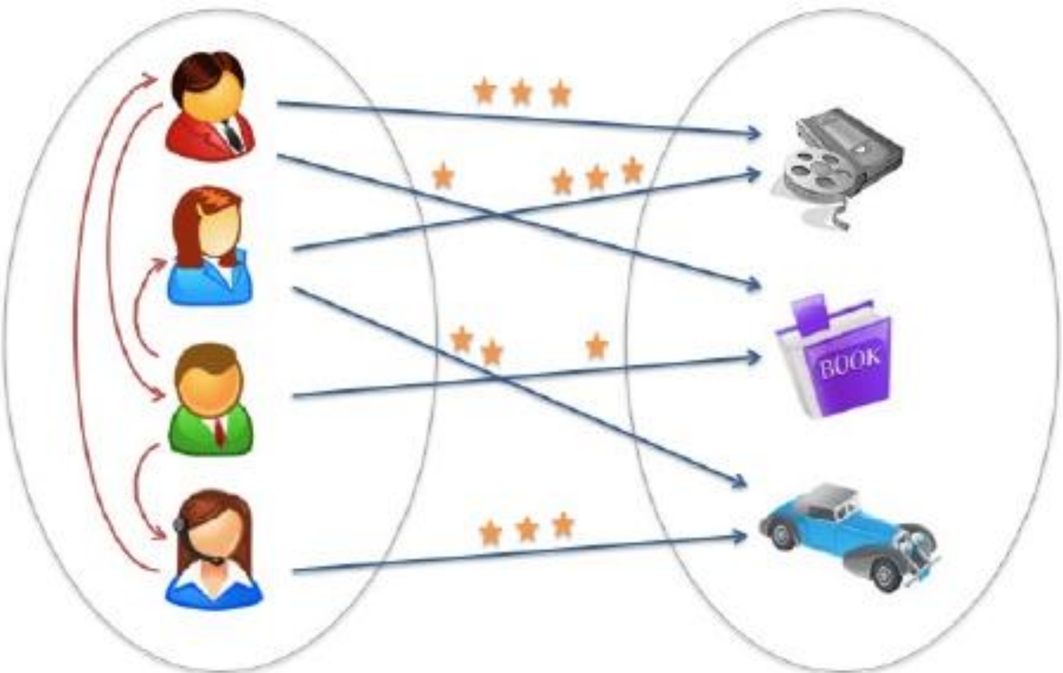
The Social Graph models the (direct or indirect) Social interactions between users



3. Social network analytics

Example of Trust from a bipartite Graph

The Goal is to infer trust connections between actors in set A only connected through Item I



Daire O'Doherty, Salim Jouili, Peter Van Roy: Towards trust inference from bipartite social networks. DBSocial 2012: 13-18

3. Social network anlytics

Example of Trust from a bi-partite Graph

The Goal is to infer trust connections between actors in set A only connected through Item I

$$J(u,v) = \frac{|N_u \cap N_v|}{|N_u \cup N_v|}$$

Measure to compare similarity and diversity

$$D(i) = \left(\frac{2}{1 + e^{(-deg(i)^{\sigma} + 2^{\sigma})}} - 1\right)$$

Highly connected shared item will have higher distance values

$$Trust(u,v) = \alpha + \beta J(u,v) + \gamma\left(1 - \frac{\sum_i^{i \in SI} D(i)}{|SI|}\right)$$

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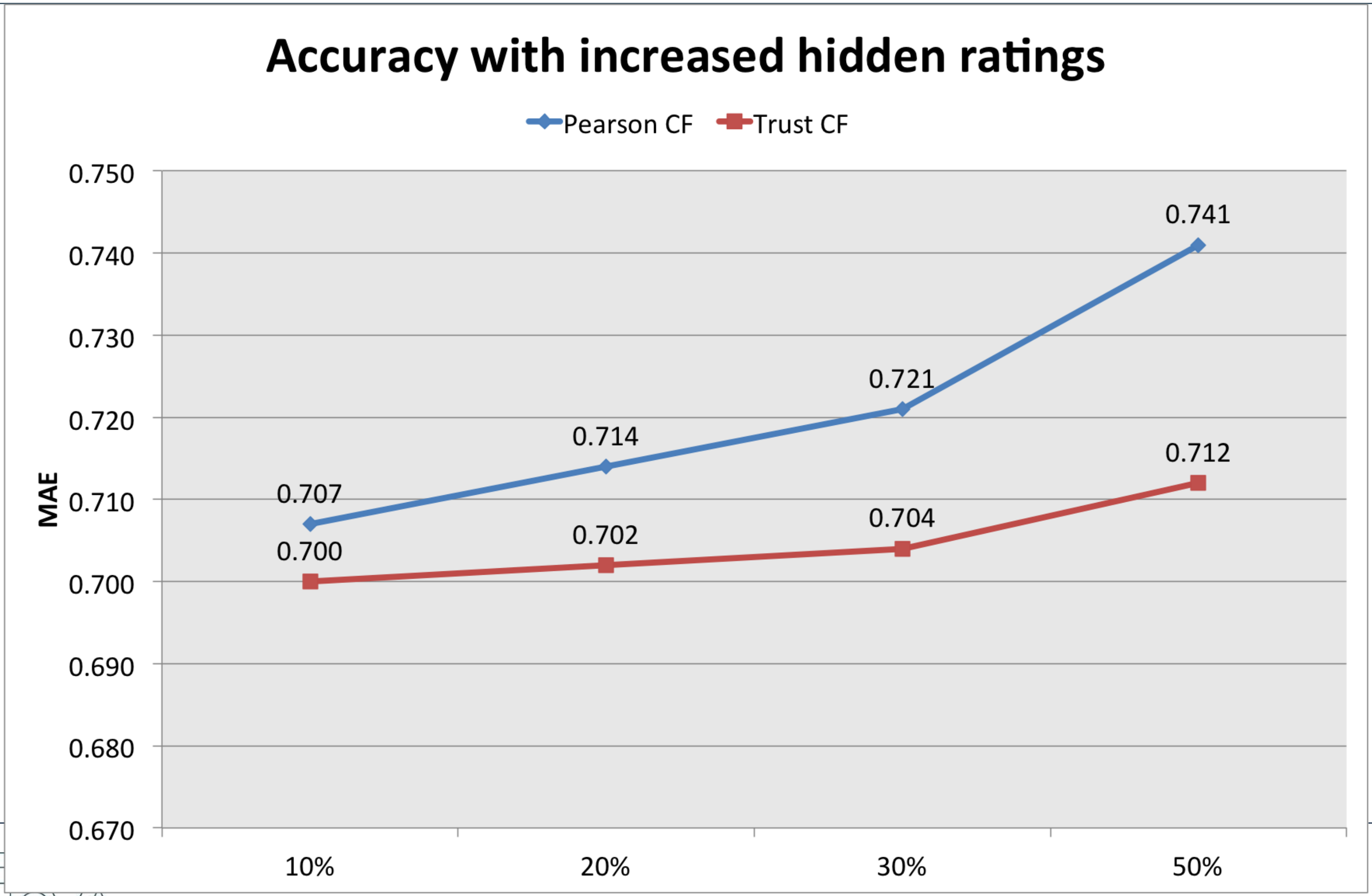
Daire O'Doherty, Salim Jouili, Peter Van Roy: Towards trust inference from bipartite social networks. DBSocial 2012: 13-18

3. Social network anlytics

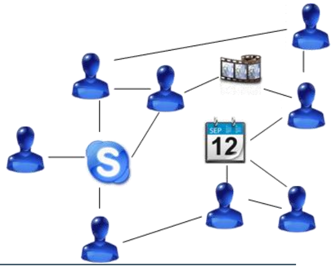
Example of Trust from a bi-partite Graph

Daire O'Doherty, Salim Jouili, and Peter Van Roy. *Trust-Based Recommendation: An Empirical Analysis*, Sixth ACM Workshop on Social Network Mining and Analysis (SNA-KDD 2012), Beijing, China, Aug. 12, 2012.



3. Social network analytics

New emergent industrial needs



People you may know
Structural similarity based

Trust computation on structural properties
Used for accurate recommendation

Collaborative filtering
Tends to like what your friends like

Influence management
Used in marketing models

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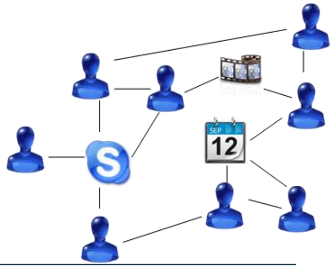
3. Social network analytics

Marketing model to influence users



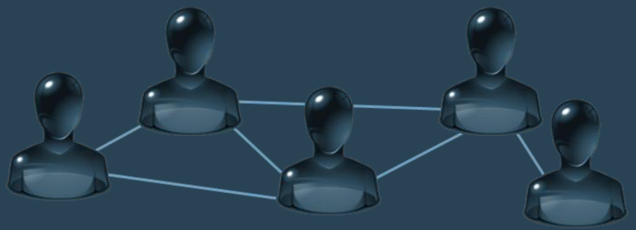
SOCIAL KNOWLEDGE

TRADITIONAL MARKETING MODELS

Bolton 1998
Bolton & Lemon 1999

SOCIAL MODELS

Nitan & Libai 2011 / Singer 2012



INFLUENCE NETWORK

Able to predict much more accurately

> How to influence influencer to reach objectives

Viral marketing maven

Accurate churners

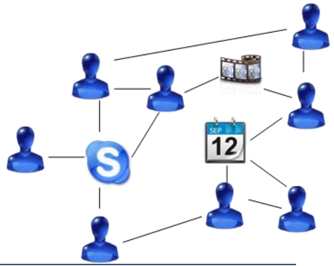
Product (content, services, etc.) adoption

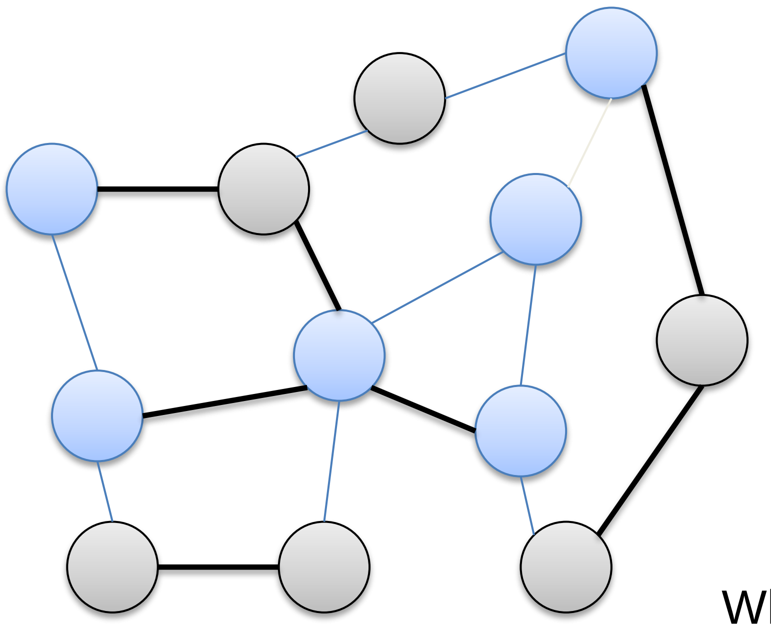
Decrease acquisition costs

Loyal user to reward to optimize the subscriber base

3. Social network analytics

Building an interaction-based model for INFLUENCE





- Vertex similarity distance
- Edge weight computing
- Betweenness centrality computation
- Temporal analysis and version at vertex/edge

When all social interaction variables are considered within the same model we end-up with a very powerful Social Profile model

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LET'S USE GRAPHS

Can I use the *traditional* data mining approaches ?

Problem Statement

What changes with graphs?

Similarity & Distances
Must be graph-based

Structural nature of the data model
Makes mining algorithm more challenging to implement

Scalability issue
Most of the graph mining problems include significant graphs

Most of the existing graph mining algorithms deal with data in the main memory-> not possible anymore

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Problem Statement

Let's position this tutorial

BSP approach
Using fully distributed approach
Google Pregel, Apache HAMA

Graph DB
Focus on storage & graph traversal
Neo4J, Dex, OrientDB

In-memory/MPI/HPC
Use multi-processors implementations
SNAP

Problem Statement

Let's position this tutorial

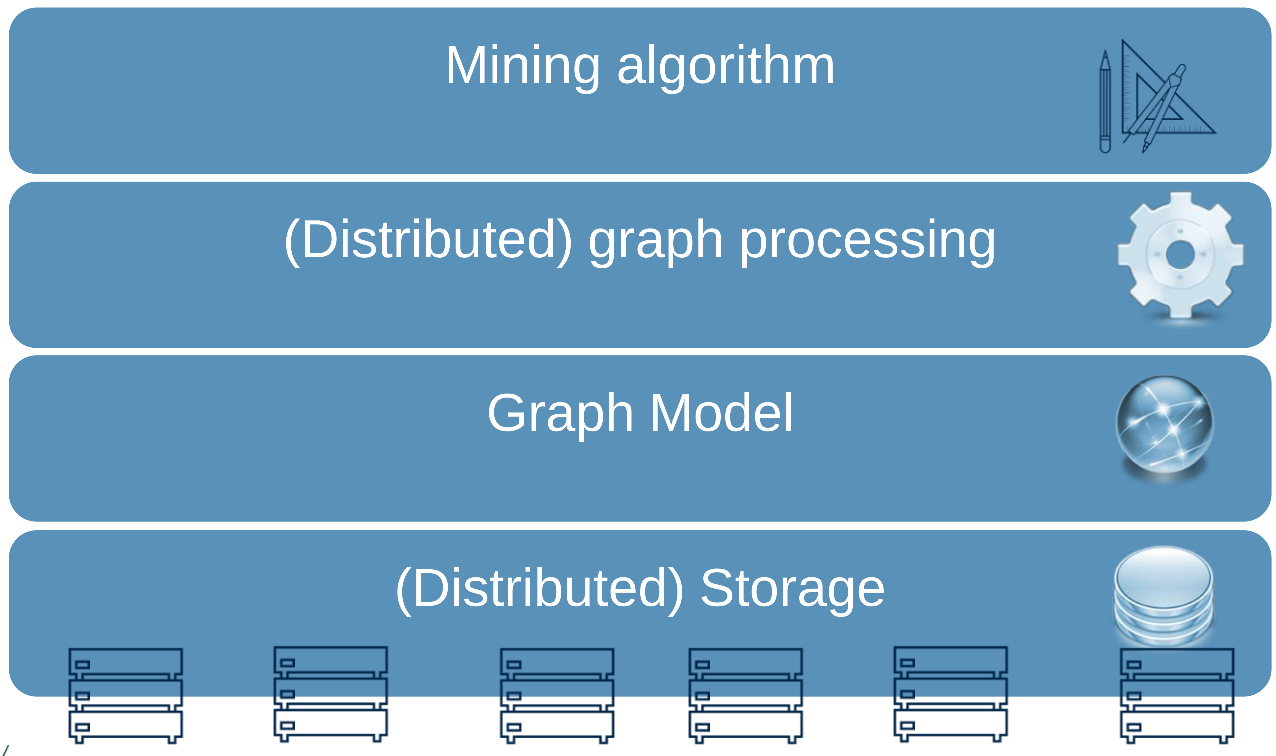
BSP approach
Using fully distributed approach
Google Pregel, Apache HAMA

Given a set of data mining algorithms, how can we adapt them to fully leverage the distributed processing approach?

Using the distributed way

The base data model is not the same anymore

The algorithm implementation will depend on the underlying distributed processing paradigm



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Graph Mining algorithms

Let’s see what a graph mining algorithm looks like

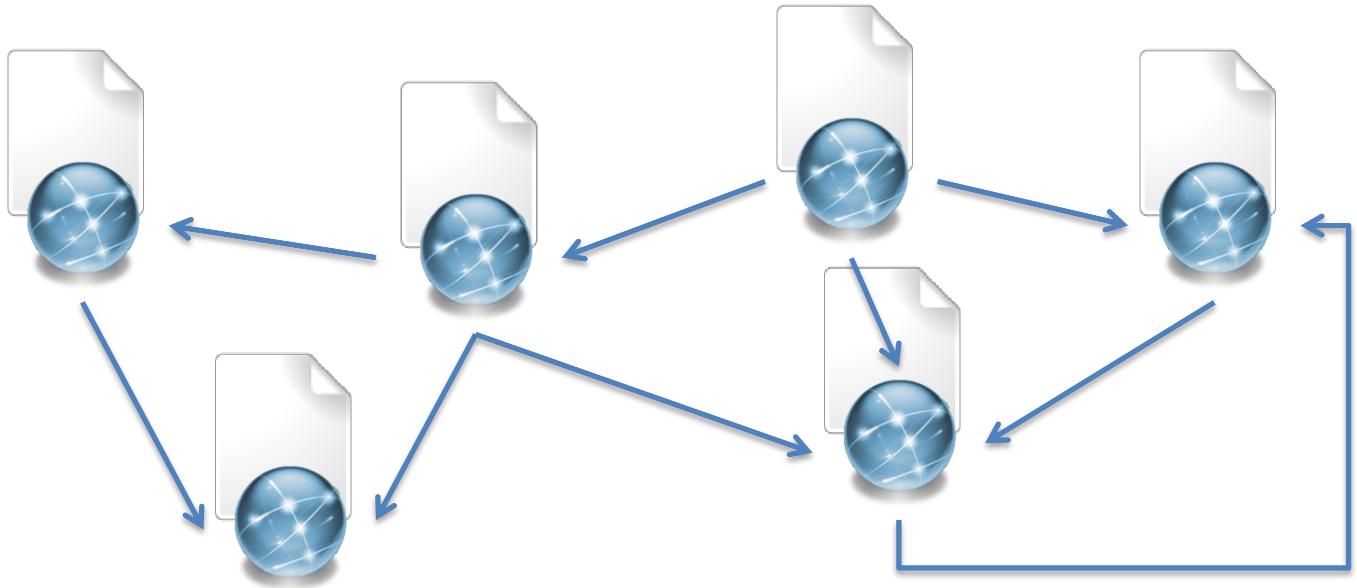
Page Rank

A ranking algorithm

Compute a ranking on every web page based only on the linkage structure

The web is a network of web pages

In addition to the page content, the page linkage represents a useful source of knowledge and information

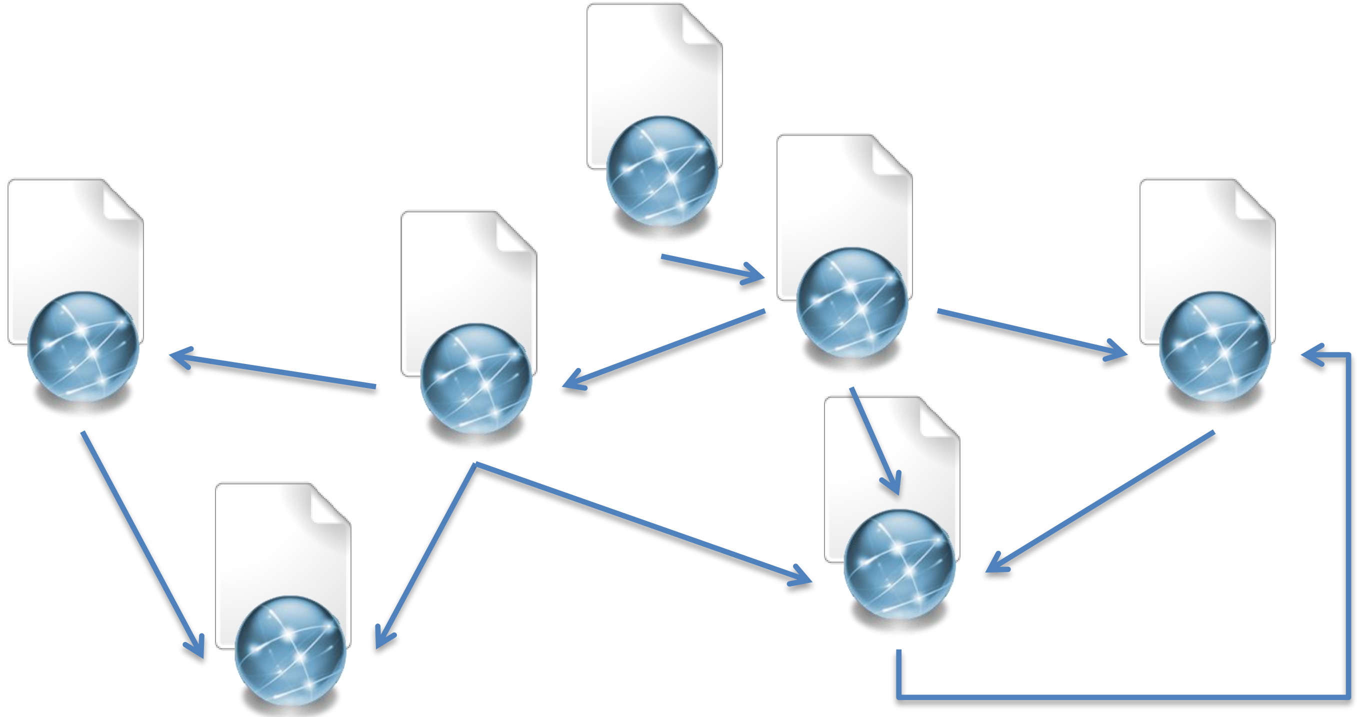


L. Page, S. Brin, R. Motwani, and T. Winograd. The pagerank citation ranking: Bringing order to the web. Technical Report 1999-66, Stanford InfoLab, November 1999. Previous number = SIDL-WP-1999-0120.

Page Rank

Basic concepts

Authority: approximate by the number & the importance of pages pointing to the considered page



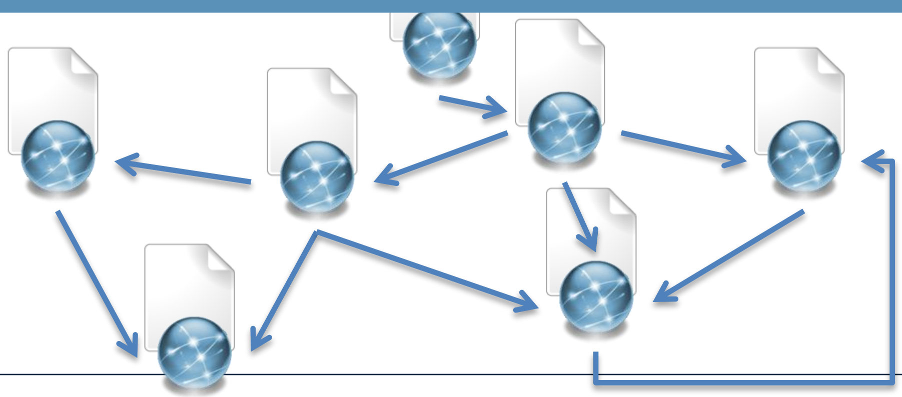
Page Rank

Random surfer who browses the pages

Either,

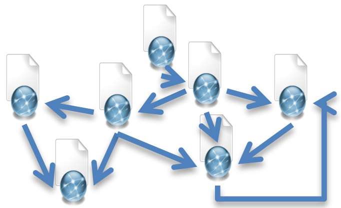
1. The surfer chooses an outgoing link of the current vertex uniformly at random, and follows that link to the destination vertex, or
2. it "teleports" to a completely random Web page, independent of the links out of the current vertex.

Intuitively, the random surfer traverses frequently "important" vertices with many vertices pointing to it



Page Rank

Random surfer who browses the pages



Let ***G* = *(V,E)*** be the web graph

The PageRank equation

The dumping factor (0.85)

$$PR(v) = \frac{(1-p)}{|V|} + p.\sum_{u \in d_{in}(v)} \frac{PR(u)}{d_{out}(u)}$$

Number of incoming edges to vertex V

Number of outgoing edges from vertex u

We will see how to implement it in a distributed processing framework in the 2nd part of this tutorial

Graph clustering

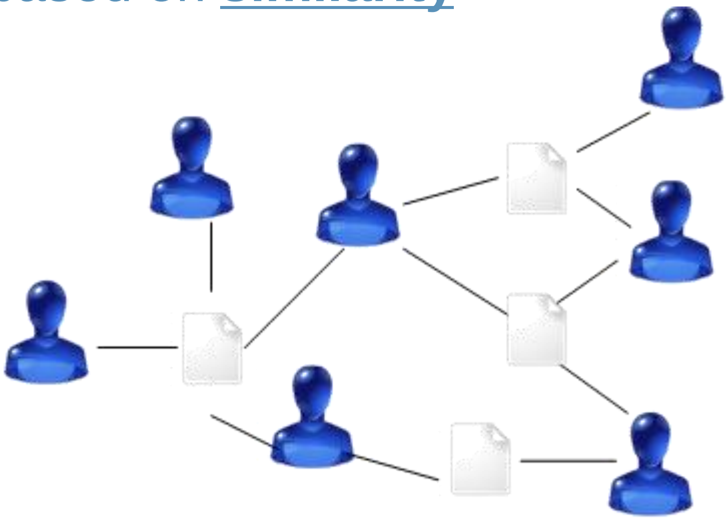
Introduction

Probably the most important topic studied in graph mining

Graph area: referred as community detection

Goal

Given a set of instances, grouping them into groups which share common **characteristics** based on **similarity**



L. Kaufman and P. J. Rousseeuw. Finding Groups in Data: An Introduction to Cluster Analysis (Wiley Series in Probability and Statistics). Wiley-Interscience, Mar. 2005.

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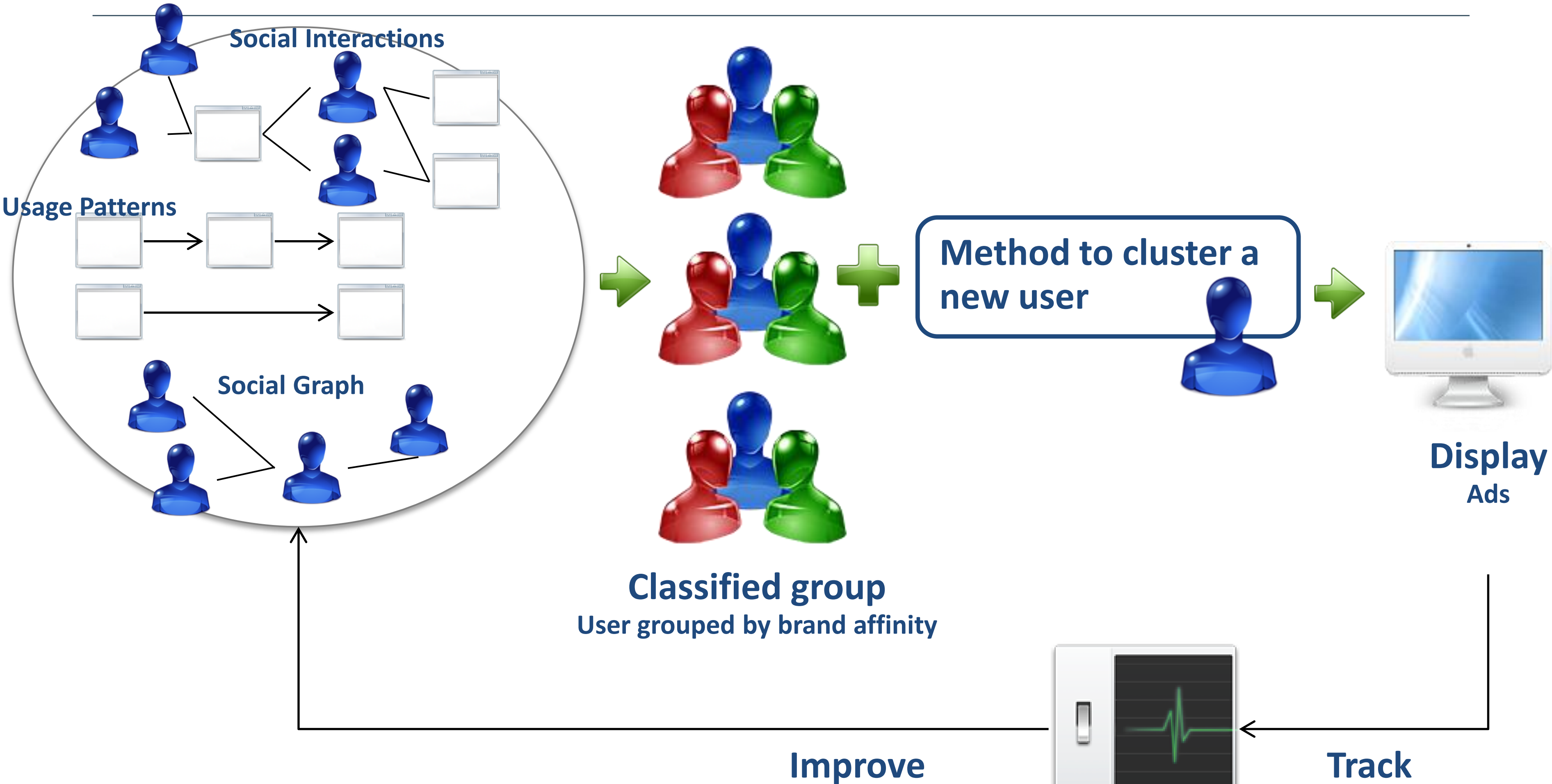
Graph clustering

Example in targeting advertisement



Let us see 2 kind of clustering algorithms

(1) Generalization of K-Means & (2) divide algorithm that uses the structure

K-Means based clustering

The original algorithm concep

Goal finding cluster by minimizing the sum of the distances between the data instances and the corresponding centroid

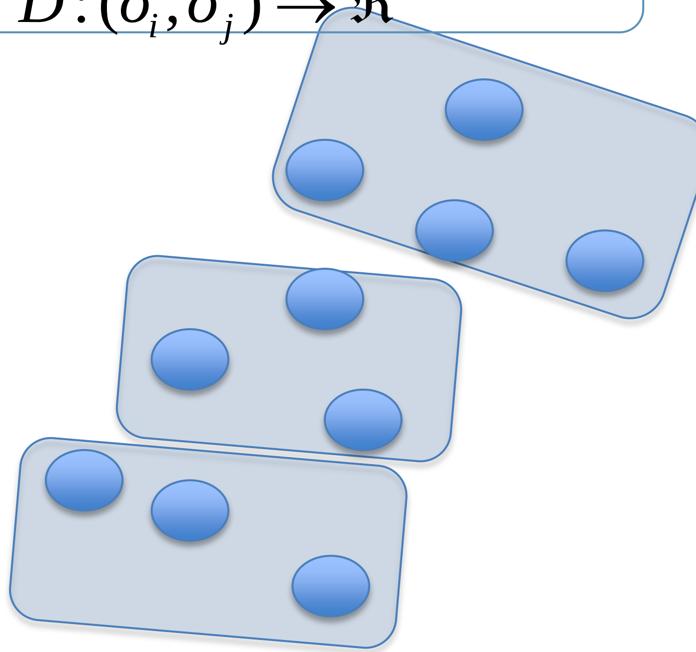
The k Number of groups

A similarity measure

$$D:(o_i,o_j)\rightarrow\Re$$

Steps

1. Select K instance as initial centroids
2. Each data instance is assigned to the nearest cluster
3. Each cluster **center** is recomputed as the average of the data instance in the cluster
4. Repeat step [2-3]



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Adapting K-Means to Graph model

What do we need to change?

Extending K-Means to take advantage of the linkage information

A Graph-aware selection of the vertex center

Median Vertex

Minimizes the sum of distances to all other vertices

$$v_m = \min_{v \in C} \sum_{u \in C} D(u,v)$$

A Graph-aware similarity measure

$$D : (o_i, o_j) \rightarrow \Re$$

The Simplest is the geodesic distance

Number of edges (hops)

Adapting K-Means to Graph model

What do we need to change?

Extending K-Means to take advantage of the linkage information

A Graph-aware selection of the vertex center

A Graph-aware similarity measure

$$D:(o_i,o_j)\rightarrow \Re$$

Closeness Centrality

a node is the more central the lower its total distance to all other nodes

The Simplest is the geodesic distance

Number of edges (hops)

$$CC(v)=\frac{|V|-1}{\sum_{v\neq u, v\in V} D(v,u)}$$

We usually take the shortest path as distance

M. J. Rattigan, M. E. Maier, and D. Jensen. Graph clustering with network structure indices. In Z. Ghahramani, editor, ICML, volume 227 of ACM International Conference Proceeding Series, pages 783–790. ACM, 2007.

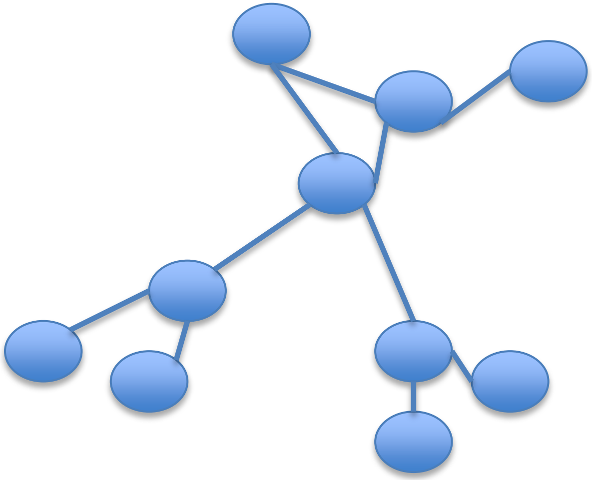
Centrality-based clustering

A divide method

From the graph, iteratively cut specific edges

Progressively cut into smaller communities

[1] proposed to use the edge betweenness centrality to select the edges to be cut



The cutting strategy should select the edges connecting as much as possible communities

M. Girvan and M. E. J. Newman. Community structure in social and biological networks. Proceedings of the National Academy of Sciences, 99(12):7821–7826,2002

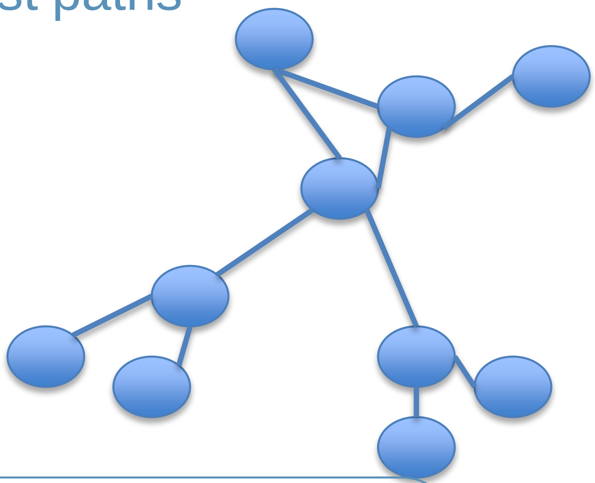
Edge betweenness centrality

Definition

Locates structurally the "well-connected" edges

If it is located on many shortest paths

$$BC(e) = \sum_{v,w \in V} \frac{b_{vw}(e)}{b_{vw}}$$



B_{vw} (e) = the number of shortest paths from V to W through e
B_{vw} = the total number of shortest paths from V to W

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S. Wasserman and K. Faust. Social Network Analysis: Methods and Applications.Number 8 in Structural analysis in the social sciences. Cambridge University Press, 1 edition, 1994.

Centrality-based clustering

Step by step description

Steps

1. Compute the betweenness of all existing edges
2. Remove the edge with the highest betweenness centrality
3. Repeat step [1,2] until the communities are suitably found

$$BC(e) = \sum_{v,w \in V} \frac{b_{vw}(e)}{b_{vw}}$$

Extremely useful for web & social graphs

Characterized by Small-World structure property

R. Kumar, J. Novak, and A. Tomkins. Structure and evolution of online social networks. In Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining, KDD ’06, pages 611–617, New York, NY, USA, 2006. ACM.

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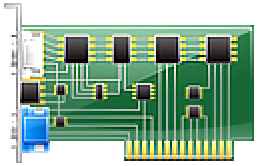
Scalability issues

Why do we need a distributed approach?

The graphs can reach a significant size ~ x100 millions nodes, x billion edges



Most of the Graph mining frameworks & libraries use in-memory graph data => we need another paradigm

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(really) Short introduction to distributed computing

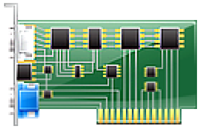
How to distribute a processing over a huge data set?

The ability to run simultaneously software in different processors in order to increase its performance while the distributed concept emphasizes the notion of loosely coupling between those processors.

Distributed architectures

From the resource sharing & the paradigm viewpoint

Shared memory



Shared Disks

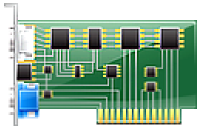
Share Nothing

Explicit parallel programming

Implicit parallel programming

Shared memory

Distributed architecture



Distributed systems that share a common memory space

Case of distributed machine, it can be a distributed cache

Pros

High speed transfer

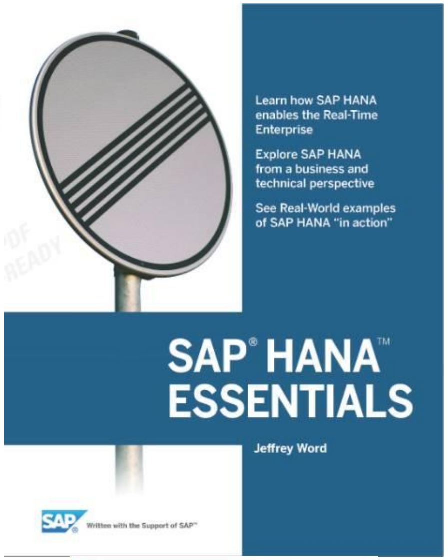
Cons

The shared memory must manage the data consistency &

The access from different clients

Can be costly when adding a new memory nodes

Can be highly expensive



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Shared disk

Distributed architecture

Distributed systems that share a common shared disk space

Typically through a LAN

Pros

Almost transparent for the applications

Less costly when adding new storage node

Cons

Access contention & data consistency issue when clients increase

Expensive

NEC

Shared Nothing

Distributed architecture

Distributed systems where each machine has its own memory space

Pros

- Can be implemented on cheap or expensive server
- With an adapted distributed processing framework the application does not need to deal with the distributed aspect
- Highly elastic

Cons

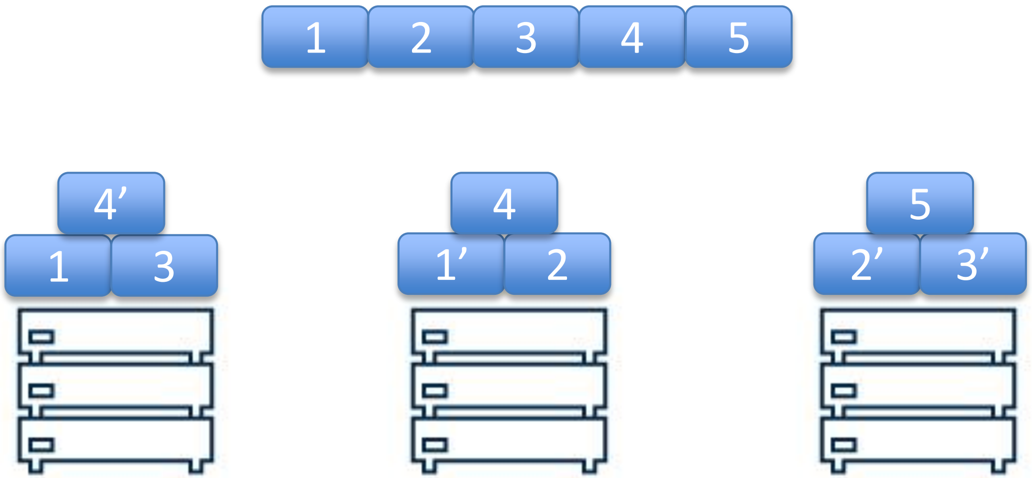
- Applications need to be re-designed

Shared Nothing

Distributed architecture

This kind of system needs to distribute the data

Partitioning policy



This leads to the interesting concept of data locality

Executing a process where the data is located

Explicit parallel programming

Distributed architecture: programming model viewpoint

The developer will have to explicitly program the parallel aspects

Create tasks, synchronization, managing threads & processes, thread safe operation, etc.

Pros

Richer expressivity, give very low level control over the distributed processing (main pain point in Hadoop MR)

Cons

Serious complexity

Error-prone

Not advised solution

Implicit parallel programming

Distributed architecture: programming model viewpoint

The developer will NOT have to take of those details

The compiler or the framework handles all aspects related to parallel execution

The code to run, the scheduling, the location of execution, etc

Pros

Much more easy – hidden complexity

Highly scalable

Cons

Much less control on the execution as it is completely handled by the framework

Most of the examples we present here are Implicit programming with share nothing data resources

Let’s talk about graph processing

How can I process a graph using implicit parallel programming and a share nothing processing?

Map Reduce

The well known framework from Google & Hadoop its open source version

Created by Google to index crawled web pages

The 3 main strengths of Hadoop [1]

Data Locality
Can schedule a process where the data is

Fault Tolerant
Automatic re-scheduling of failing tasks

Parallel processing
On different chunks of data

[1)A. Bialecki, M. Cafarella, D. Cutting, and O. O'Malley. Hadoop: A framework for running applications on large clusters built of commodity hardware, http://lucene.apache.org/hadoop/, 2005

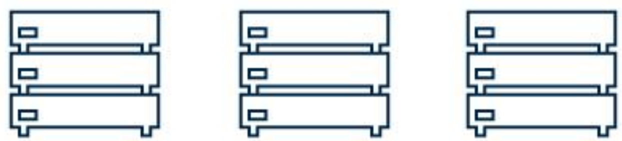
Map Reduce

Short introduction – 2 main phases Map & Reduce

Main concepts

Map Phase

The problem is partitioned into a set of smaller sub-problems



Distributed over the worker in the cluster & processed independently

Reduce Phase

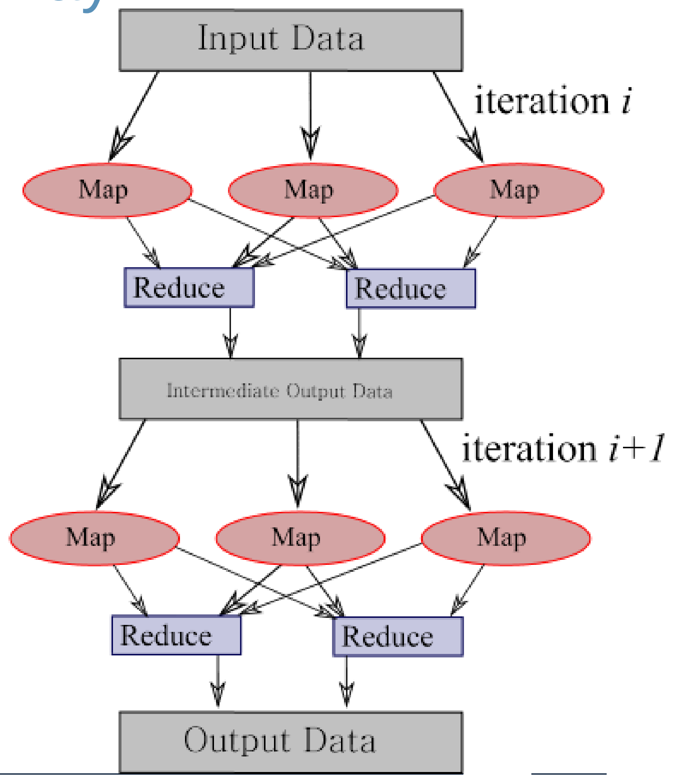
All answers to all sub-problems are gathered from the worker nodes and then merged

[1] A. Bialecki, M. Cafarella, D. Cutting, and O. O'Malley. Hadoop: A framework for running applications on large clusters built of commodity hardware, http://lucene.apache.org/hadoop/, 2005

The developer only focus on the algorithm but

Is it really suited for Graph Processing & mining?

Gives a simple way to deal with large data sets in completely distributed way



However… not really suited for Graph processing

1. Does not manipulate a Graph model – makes complex the algorithm
2. Is not suited for iterative processing

1 iteration = 1 MR

Requiring a lot of I/O, data migration, unnecessary computation

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Map Reduce Improvements

Optimizing data transfert for iterative algorithms

Few works have been done in this direction

R. Chen, X. Weng, B. He, and M. Yang. Large graph processing in the cloud. In Proceedings of the 2010 international conference on Management of data, SIGMOD '10, pages 1123–1126, New York, NY, USA, 2010. ACM.

J.Ekanayake, H. Li, B. Zhang, T. Gunarathne, S.-H. Bae, J. Qiu, and G. Fox.Twister: a runtime for iterative mapreduce. In Proceedings of the 19th ACM International Symposium on High Performance Distributed Computing, HPDC '10, pages 810–818, New York, NY, USA, 2010. ACM.

U. Kang, C. Tsourakakis, A. Appel, C. Faloutsos, and J. Leskovec. Hadi: Fast diameter estimation and mining in massive graphs with hadoop. CMU-ML-08-117, 2008.

U. Kang, C. E. Tsourakakis, and C. Faloutsos. Pegasus: A peta-scale graph mining system. In W. Wang, H. Kargupta, S. Ranka, P. S. Yu, and X. Wu, editors, ICDM, pages 229–238. IEEE Computer Society, 2009.

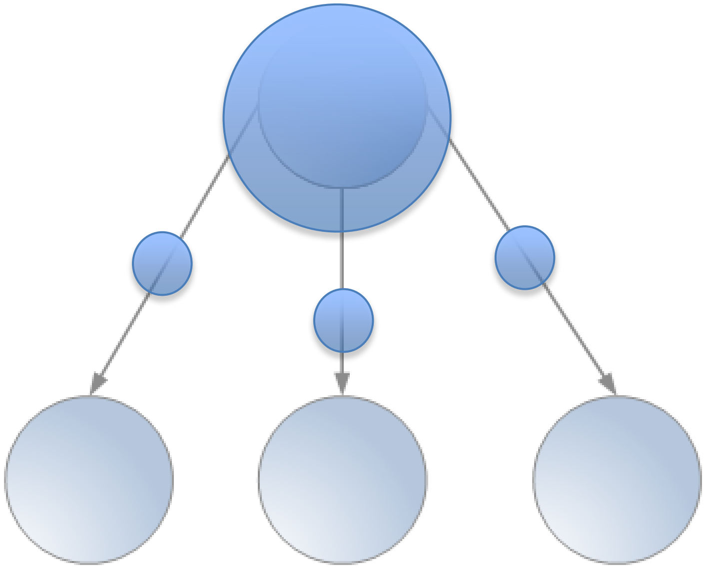
Despite the improvements these solutions lack for graph based model since they deal with multi-dimension data

Then comes Google with Pregel

Methods for dealing with linked structures using Map reduce concept

Providing a distributed computing framework dedicated to graph processing

Bulk Synchronous Processing (BSP) for graph processing



In a BSP model an algorithm is executed as a sequence a Supersteps separated by a global synch. point untill termination.

In 1 Superstep a processor can:

1. Perform computation on local data
2. Send or receive messages

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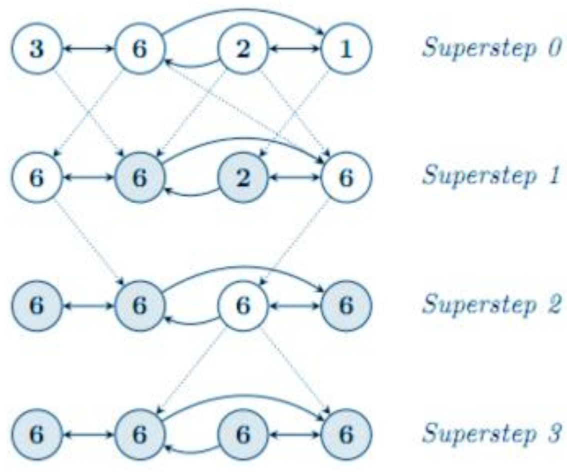
G. Malewicz, M. H. Austern, A. J. C. Bik, J. C. Dehnert, I. Horn, N. Leiser, and G. Czajkowski. Pregel: a system for large-scale graph processing. In A. K. Elmagarmid and D. Agrawal, editors, SIGMOD Conference, pages 135–146. ACM, 2010.

Concep of superstep@Pregel

Leanring distributed graph processing framework

The vertices of the graph execute the same user defined function (compute) in //

Modification of the state of a vertex or its outgoing edges
Read messages sent to the vertex from previous supersteps
Send messages to other vertices that will be received in the next supersteps
Modification of the Graph Topology



G. Malewicz, M. H. Austern, A. J. C. Bik, J. C. Dehnert, I. Horn, N. Leiser, and G. Czajkowski. Pregel: a system for large-scale graph processing. In A. K. Elmagarmid and D. Agrawal, editors, SIGMOD Conference, pages 135–146. ACM, 2010.

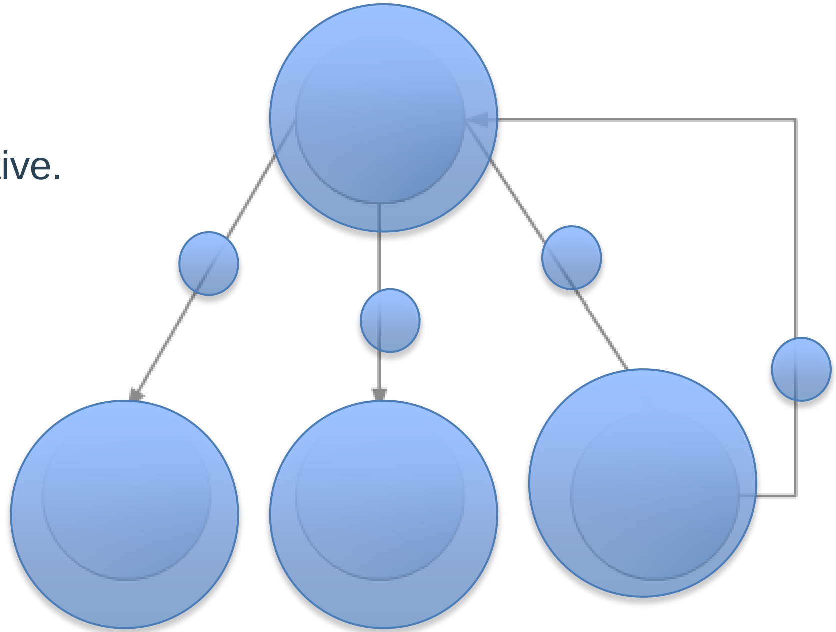
Concep of superstep@Pregel

Leanring distributed graph processing framework

How do I stop the processing?

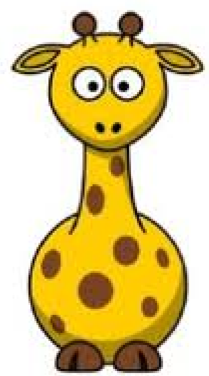
Use the “*Vertex Voting*”
Each node votes to halt -> become inactive unless it receives a non-empty message

Inactive vertices are not involved in processing anymore.
The processing stops when all vertices are inactive.



Open source implementation of Pregel

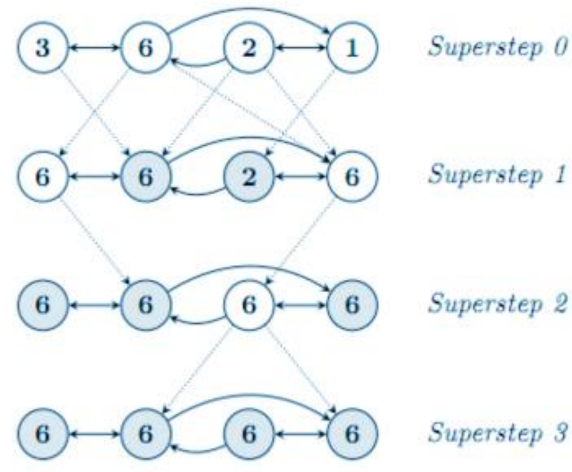
Methods for dealing with linked structures using Map reduce concept



Apache Giraph

From Google Pregel

BSP for distributed graph processing



Distributed Graph Processing

Processing

HDFS

Let’s play with Giraph

Implementing a single source shortest path (SSP)

Re-thinking the SSP for Giraph Processing

Thinking in term of supersteps & messages

Definition of the vertex value
The distance to reach the current vertex from the source

Definition of the messages
Vertex sends its current value +edge weight

1. Init vertex value to larger possible value for all vertices except the source
2. On each step
    1. The vertex reads the message from its neighbor
    2. Each message contains the distance between the source & current vertex through the last vertex
    3. We take the min value between the current value & the received value
    4. Send the message to all neighbor as min distance + weighted edge

Re-thinking the SSP for Giraph Processing

Thinking in term of supersteps & messages

```
Input   : Messages: Set of received messages
if currentVertex is the source then
|   minimumDistance ← 0;
else
|   minimumDistance ← ∞;
end
foreach message m ∈ Messages do
|   minimumDistance ← minimum(minimumDistance, valueOf(m));
end
if minimumDistance ≤ valueOf(currentVertex) then
|   valueOf(currentVertex)← minimumDistance;
|   foreach outgoing edge e from currentVertex do
|   |   sendMessageTo(targetOf(e), (minimumDistance+ valueOf(e)));
|   end
end
VoteTohalt();
```

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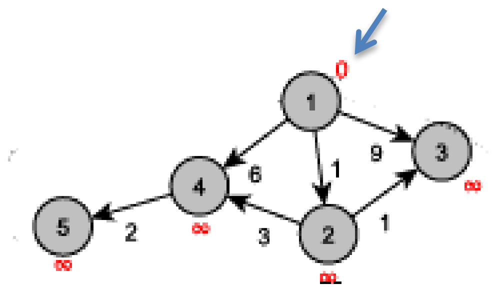
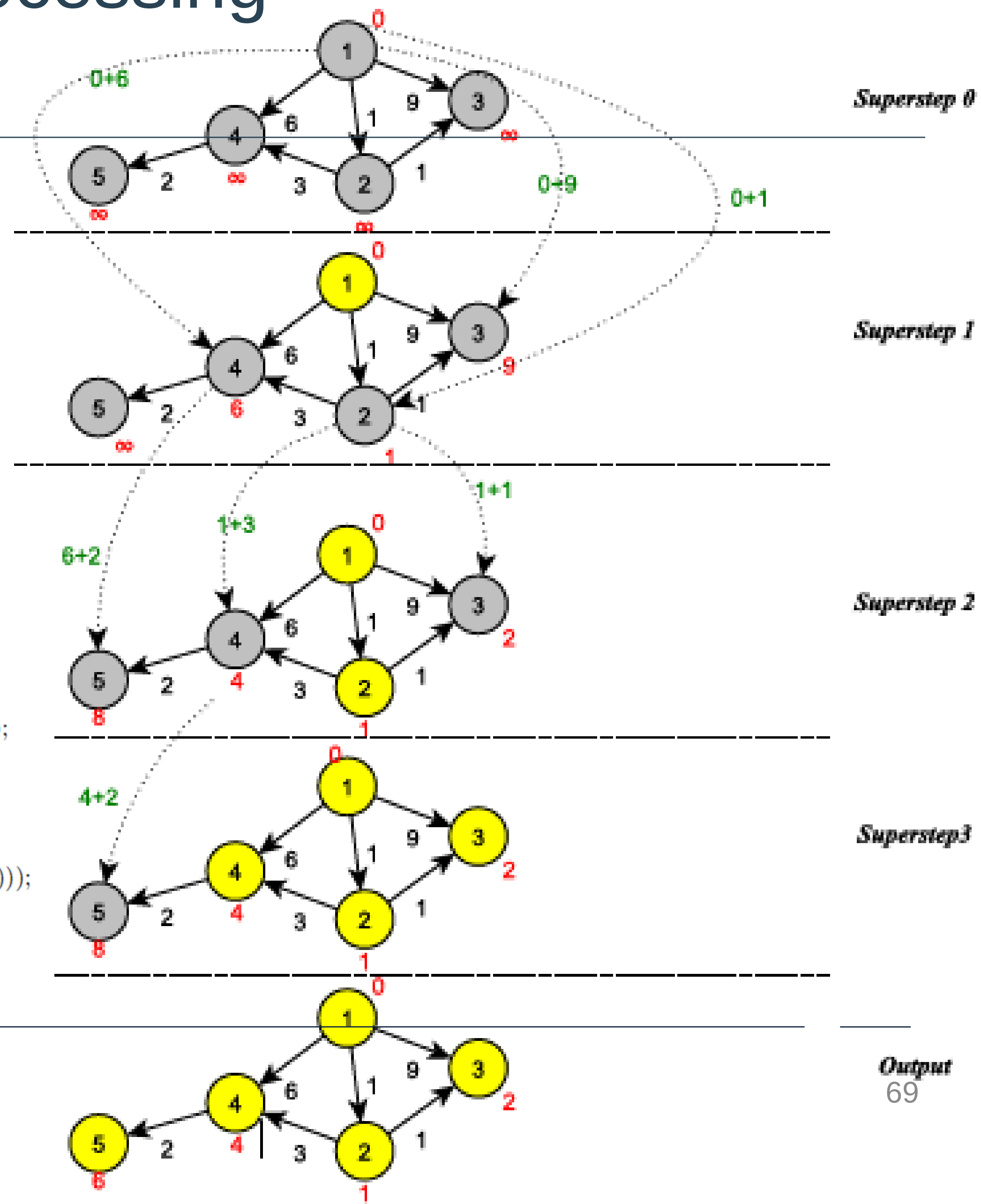
SSP for Giraph Processing

Let's dive into the supersteps





Input : Messages: Set of received messages
if *currentVertex is the source* **then**
  minimumDistance ← 0;
else
  minimumDistance ← ∞;
end
foreach *message* $m \in$ *Messages* **do**
  minimumDistance ← minimum(minimumDistance, valueOf(m));
end
if *minimumDistance* $\leq$ *valueOf(currentVertex)* **then**
  valueOf(currentVertex)← minimumDistance;
  foreach *outgoing edge e from currentVertex* **do**
    sendMessageTo(targetOf(e), (minimumDistance+ valueOf(e)));
  end
end
VoteTohalt();

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SSP for Giraph Processing

For a Geek like me, code is easier to get

```
@Override
public void compute(Iterator<DoubleWritable> msgIterator) {
    //1. init value
    if (getSuperstep() == 0) {
        setVertexValue(new DoubleWritable(Double.MAX_VALUE));
    }
    //2. set the minimum distance to MAX
    double minDist = isSource() ? 0d : Double.MAX_VALUE;
    //3. Read the messages and update the min distance
    //Check wether one of the previous node is nearer than the others
    while (msgIterator.hasNext()) {
        minDist = Math.min(minDist, msgIterator.next().get());
    }
    //4. Check wether the current value is > than the min distance sent by a previous vertex
    if (minDist < getVertexValue().get()) {
        setVertexValue(new DoubleWritable(minDist));
        //5. Send to my neighbor my shortest distance + weight on edge
        for (LongWritable targetVertexId : this) {
            FloatWritable edgeValue = getEdgeValue(targetVertexId);
            sendMsg(targetVertexId, new DoubleWritable(minDist + edgeValue.get()));
        }
    }
    voteToHalt();
}
```

https://github.com/apache/giraph

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Launching the code in Giraph

Just for information & Fun

```
@Override
public int run(String[] argArray) throws Exception {
    if (argArray.length != 4) {
        throw new IllegalArgumentException(
            "run: Must have 4 arguments <input path> <output path> " +
            "<source vertex id> <# of workers>");
    }
    GiraphJob job = new GiraphJob(getConf(), getClass().getName());
    job.setVertexClass(getClass());
    job.setVertexInputFormatClass(SimpleShortestPathsVertexInputFormat.class);
    job.setVertexOutputFormatClass(SimpleShortestPathsVertexOutputFormat.class);
    FileInputFormat.addInputPath(job, new Path(argArray[0]));
    FileOutputFormat.setOutputPath(job, new Path(argArray[1]));
    job.getConfiguration().setLong(SimpleShortestPathsVertex.SOURCE_ID, Long.parseLong(argArray[2]));
    job.setWorkerConfiguration(Integer.parseInt(argArray[3]), Integer.parseInt(argArray[3]), 100.0f);
    if (job.run(true) == true) {
        return 0;
    } else {
        return -1;
    }
}
```


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Let’s play with Giraph II

Implementing Page Rank

Re-thinking PageRank for Giraph Processing

Thinking in term of supersteps & messages

Definition of the vertex value

?

Definition of the messages

?

Remember the PageRank equation

$$PR(v) = \frac{(1-p)}{|V|} + p.\sum_{u \in d_{in}(v)} \frac{PR(u)}{d_{out}(u)}$$

3 Mins to think !

Re-thinking PageRank for Giraph Processing

Thinking in term of supersteps & messages

Definition of the vertex value
The PageRank tentative

Definition of the messages
The PageRank tentative divided by #out edges

Remember the PageRank equation

$$PR(v) = \boxed{\frac{(1-p)}{|V|} + p.\sum_{u \in d_{in}(v)} \boxed{\frac{PR(u)}{d_{out}(u)}}}$$

PageRank in Giraph

Dive into the algorithm

One could find a suitable setup to run until convergence of values [1]

Definition of the vertex value
The PageRank tentative

Definition of the messages
The PageRank tentative divided by #out edges

1. Init vertex value with 1/Size of the Grpah
2. On each step
   1. The vertex read the message from its neighbor
   2. Each message contains PR tentative of ingoing vertex
   3. Compute the page rank for the current vertex with p=0.85
   4. Send the message to all outgoing edges
   5. After a fixed number of supersteps (iterations), Vertex vote to halt

$$PR(v) = \frac{(1-p)}{|V|} + p. \sum_{u \in d_{in}(v)} \frac{PR(u)}{d_{out}(u)}$$

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[1]L. Page, S. Brin, R. Motwani, and T. Winograd. The pagerank citation ranking: Bringing order to the web. Technical Report 1999-66, Stanford InfoLab, November 1999. Previous number = SIDL-WP-1999-0120.

PageRank algorithm distilled

A deeper look at the algorithm

```
Input   : Messages: Set of received messages
if NumberOfSuperstep ≥ 1 then
    sum ← 0;
    foreach message m ∈ Messages do
        sum ← sum + valueOf(m);
    end
    valueOf(currentVertex)← 0.15 / SizeOfGraph + 0.85 × sum;
end
if NumberOfSuperstep < MaximumNumberOfIteration then
    N = SizeOf({outgoing edges from currentVertex})
    sendMessageToAllNeighbors(valueOf(currentVertex) / N);
else
    VoteTohalt();
end
```

PageRank for Giraph Processing

For a Geek like me, code is easier to get

```
@Override
public void compute(Iterator<DoubleWritable> msgIterator) {
    if (getSuperstep() >= 1) {
        double sum = 0;
        //Read the message from last step and sum them (second term in the equation)
        while (msgIterator.hasNext()) {
            sum += msgIterator.next().get();
        }
        //Compute the equation
        DoubleWritable vertexValue = new DoubleWritable((0.15f / getNumVertices()) + 0.85f * sum);
        //Set the page rank value
        setVertexValue(vertexValue);
    }
    //Check iteration
    if (getSuperstep() < MAX_SUPERSTEPS) {
        long edges = getNumOutEdges();
        sendMsgToAllEdges(new DoubleWritable(getVertexValue().get() / edges));
    } else {
        voteToHalt();
    }
}
```

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https://github.com/apache/giraph

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PageRank for Giraph Processing

For the Geekers - what's the meaning of the sendMesgToAllEdges ?

```
@Override
 public final void sendMsgToAllEdges(final DoubleWritable msg) {
   if (msg == null) {
     throw new IllegalArgumentException(
         "sendMsgToAllEdges: Cannot send null message to all edges");
   }
   final MutableVertex<LongWritable, DoubleWritable, FloatWritable,
   DoubleWritable> vertex = this;
   verticesWithEdgeValues.forEachKey(new LongProcedure() {
     @Override
     public boolean apply(long destVertexId) {
       vertex.sendMsg(new LongWritable(destVertexId), msg);
       return true;
     }
   });
 }
```

https://github.com/apache/giraph

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Test: Write a classification Example

Up to you guys – Classification of customer by product

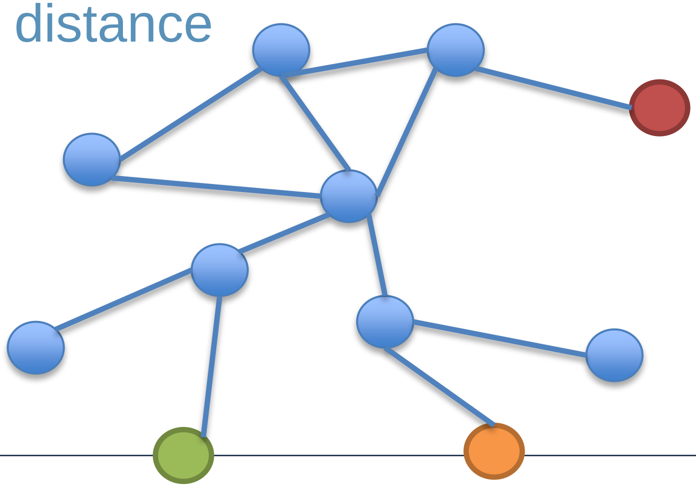
15 mins

Definition of the vertex value
?

Definition of the messages
?

1. Starting from n root nodes, each having one color
2. Propagate the color to all neighbor nodes
3. The color is propagated if there is no nearest root colored node
4. Use the SSSP to define the distance

```
public enum Color {
    GREEN, RED, ORANGE
}
```



Test: Write a classification Example

Up to you guys – Classification of customer by product

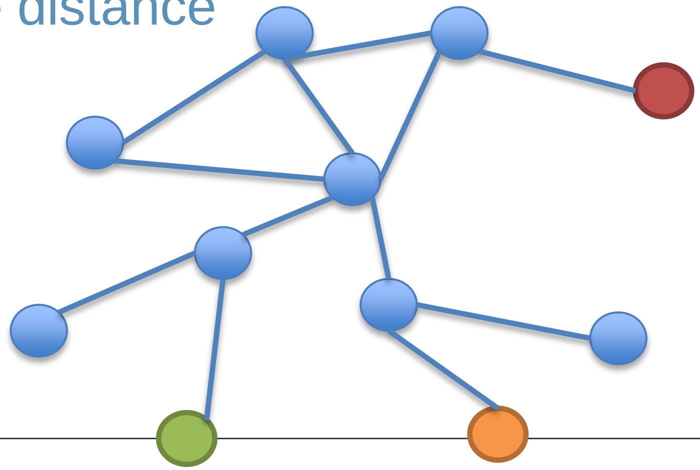
10 mins

Definition of the vertex value
[Color Label, Distance to the root node of this color]

Definition of the messages
[Color, Distance to the root node of this color]

1. Starting from n root nodes, each having one color
2. Propagate the color to all neighbor nodes
3. The color is propagated if there is no nearest root colored node
4. Use the SSSP to define the distance

```
public enum Color {
    GREEN, RED, ORANGE
}
```



Test: Write a classification Example

Up to you guys – Classification of customer by product

8 mins

Definition of the vertex value

[Color Label, Distance to the root node of this color]

Definition of the messages

[Color, Distance to the root node of this color]

```
public class ColorDistance implement Writable{
    private long distance=0;
    private Color color = Color.RED;

    /***
    * Default constructor
    **/
    public ColorDistance(Color color, long distance){
        this.color = color;
        this.distance = distance;
    }

    /** return the distance between source color node and the current node*/
    public long getDistance(){ return this.distance;}

    /** return the color of the vertex*/
    public Color getColor(){ return this.color;}

    @Override
    public void readFields(DataInput in) throws IOException {
        //...
    }

    @Override
    public void write(DataOutput out) throws IOException {
        //...
    }
```

```
public abstract class LongLongNullModifiedBloomVertex extends
MutableVertex<LongWritable, ColorMessage, NullWritable, Modifiec
  /** Int represented vertex id */
  private long id;
  /** ColorDistance represented vertex value */
  private ColorMessage value;
  /** Int array of neighbor vertex ids */
  private long[] neighbors;
  /** ColorDistance array of messages */
  private List<ColorDistance> messages;

@Override
  public LongWritable getVertexId() {
    return new LongWritable(id);
  }

  @Override
  public ColorDistance getVertexValue() {
    return new this.value;
  }

  @Override
  public void setVertexValue(ColorDistance vertexValue) {
    this.value = vertexValue;
  }
```

Test: Write a classification Example

Up to you guys – Classification of customer by product

Definition of the vertex value
[Color Label, Distance to the root node of this color]

Definition of the messages
[Color, Distance to the root node of this color]

1. Init vertex value to larger possible value for all vertices except the source colored vertices
2. On each step
   1. The vertex read the message from its neighbor
   2. Each message contains the distance between the source & current vertex through the last vertex and the propagated color
   3. If the value is less than the received value we update the value and set the color
   4. Send the message to all neighbor as min distance + weighted edge

Test: Write a classification Example

Up to you guys – Classification of customer by product

```
@Override
 public void compute(Iterator<ColorDistance> msgIterator) {
     //Initiatialisation phase
     if (getSuperstep() == 0) {
         if(!isSource()){
             setVertexValue(new ColorDistance(Color.RED, Double.MAX_VALUE));
         }
    }
    double minDist = isSource() ? 0d : Double.MAX_VALUE;
    Color propagatedColor =Color.RED;

    //2. Define the nearest Color recieved
    while (msgIterator.hasNext()) {
        ColorDistance msg_i =msgIterator.next().get();
        if(msg_i.getDistance()<minDist){
            propagatedColor =msg_i.getColor();
            minDist = msg_i.getDistance();
        }
    }

    //3. Check the Vertext value
    if (minDist < getVertexValue().get()) {
        setVertexValue(new ColorDistance(msg_i.getColor(), minDist));
        //4. Send to all neighbor the new distance and the color to propagate
        sendMsgToAllEdges(getVertexValue(propagatedColord, minDist + 1));
    }
    voteToHalt();
 }
```

Intermediate Conclusion

Can I use graph mining algorithm on huge graphs using distributed framework coming from the web?

Intermediate Conclusion

Can we do graph mining on large graphs using the distributed approach?

Yes you can, but …

1. Need to choose a implicit distributed framework
2. This will constraint **the programming model** & the **storage**
3. Need **to re-design** the algorithm to fully exploit the framework

If I can mine the graph - does it mean that I have a data warehouse?

What do we miss to have a full graph data warehouse?

AGENDA

1 / Introduction

2 / Focus on two graph mining algorithms

3 / Introduction of Distributed Processing Framework

4 / Graph Data warehouse – an emerging challenge

5 / Conclusion

Links between Data Warehouse & Data Mining

Is it the same?

Data warehouse & mining

Definition of interactions

Data Mining algorithms are involved in many steps of the DW

1. Identifying key attributes
2. Finding related measures
3. Limiting the scope of queries

OLAP framework are often integrated with mining frameworks

-> **OLAM (On-Line Analytic Mining)** & exploratory multi-dimensional mining [1]

Mining space
Multi-dimensional cube space for mining

Generating features & target
By using OLAP queries

Multi-step OLAP process
Using data mining as building blocs

Speeding up model construction
Using data cube computation

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[1] J. Han and M. Kamber. Data Mining: Concepts and Techniques. Morgan Kaufmann, 2000.

Graph is fine but stop to play, be an adult

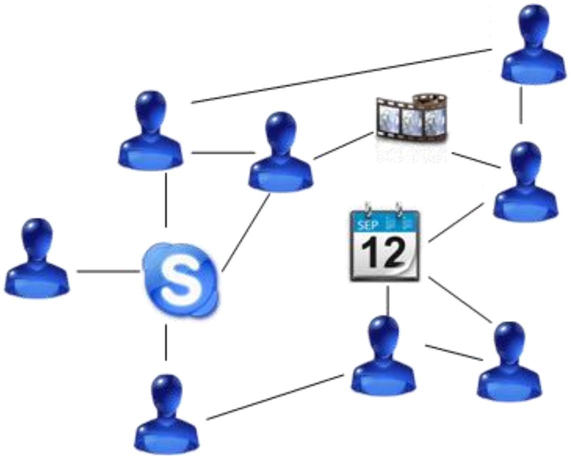
Come back in a professional & Business environment, come back to relational DB

The graph is a constraint

It is not because it is fun, it is because the relationship model brings a value

Let's take the Social Network example

1. We can model a friend relationship in a m-n
2. In Average ~ 100 Friends
3. Friends of Friends request – 100^2 join requests



Storing a SN in a Relational DB is not a problem

Unless you need traversal queries for mining

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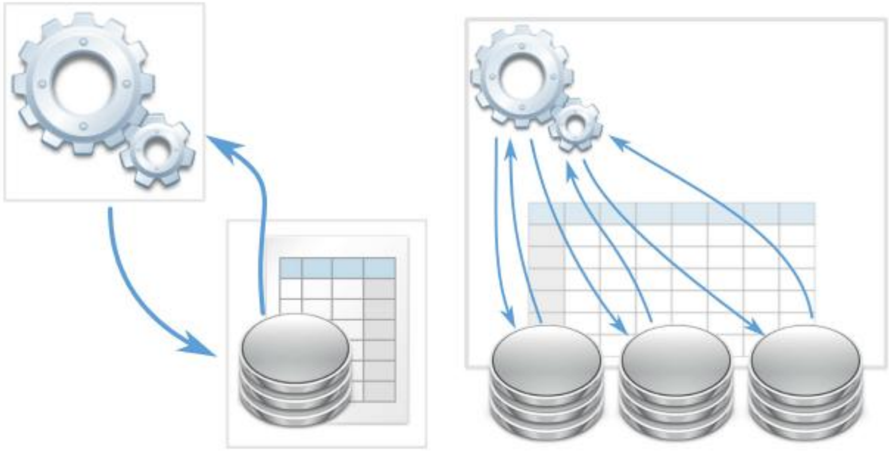
A Graph in a relational DB

Two main important issues

1. Cost of Joins when traversing
2. Almost transfering the totality of the graph between the client and the DB



(a) (b)

We have seen that Distributed Graph Processing frameworks use the data locality to minimize the cost

Data Application Server

I got a distributed processing framework & mining algorithms

Now do I have a Graph Data warehouse?

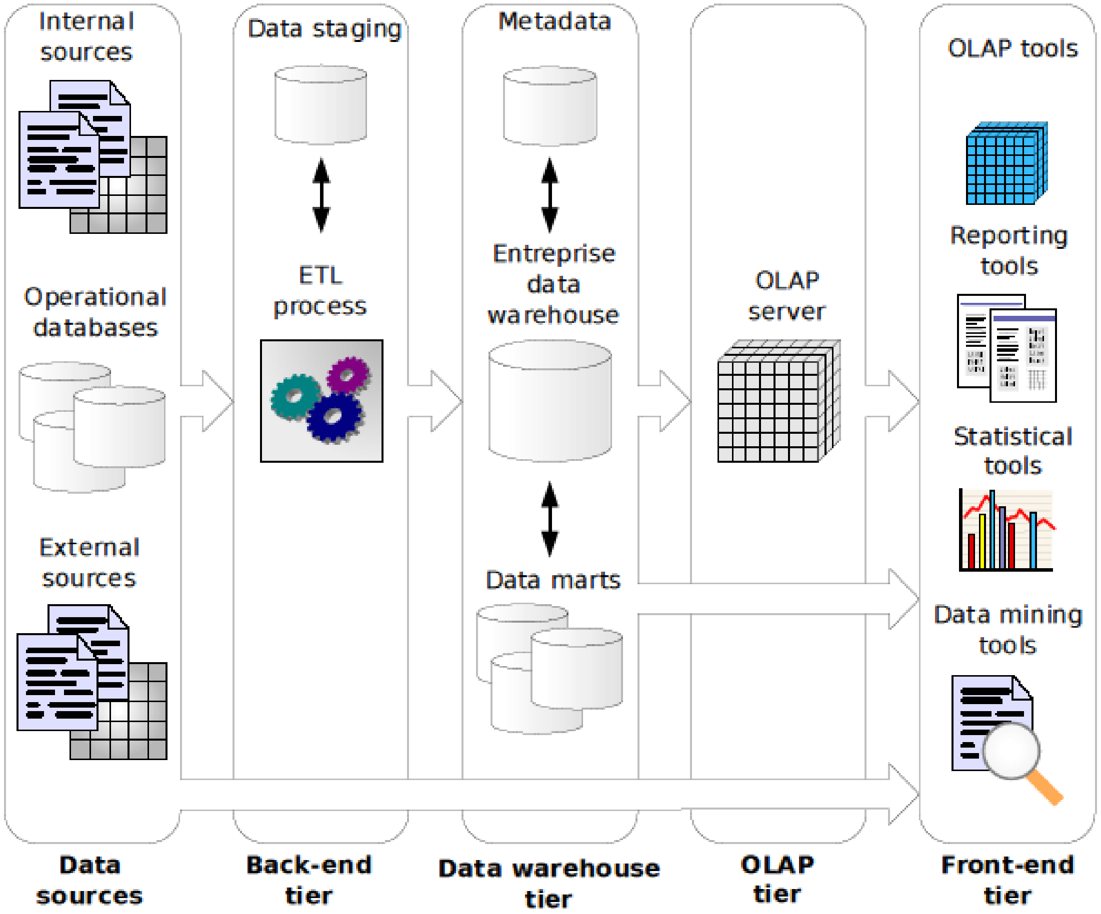
…BTW what is exactly a Data warehouse?

Traditional Data warehouse

Let's take a look

E. Malinowski and E. Zimanyi. Advanced data warehouse design: From conventional to spatial and temporal applications. Springer-Verlag, 2008.

Aim at providing software, modeling approaches & tools to analyze a set of data in a collection of DB



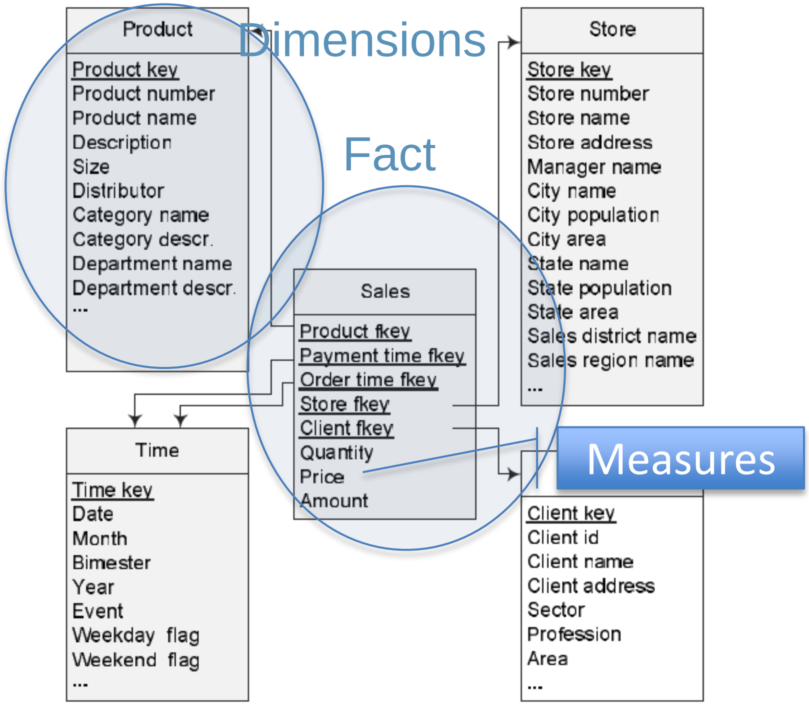
Conceptual modeling

An important topic of research

Aim at providing software, modeling approaches & tools to analyze a set of data in a collection of DB

Research topic focus

1. Improvement of the Snowflake & Star model
2. Models enabling the to define levels of hierarchies
3. Role played by a measure in different dimension
4. Properties such as additive, derive



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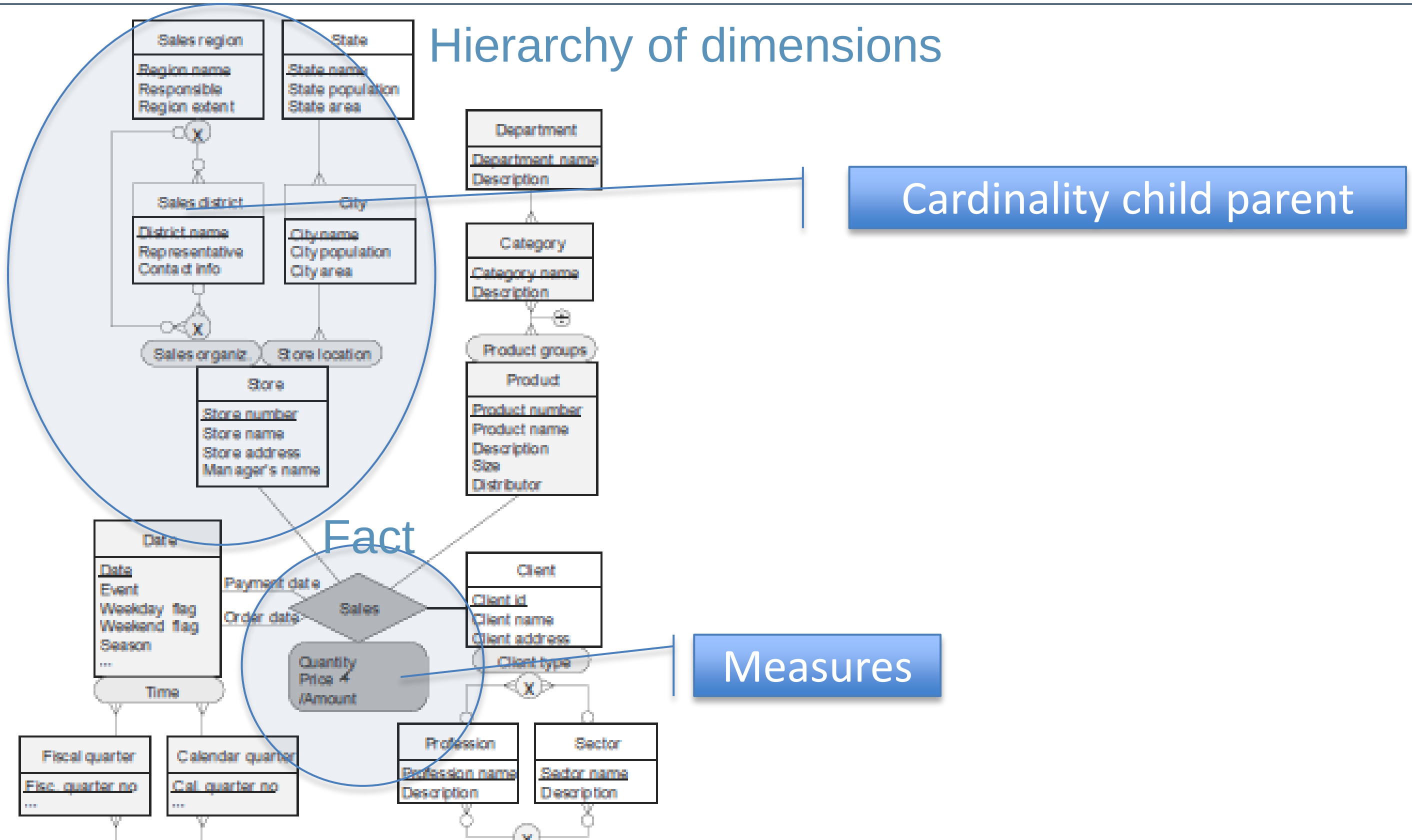
E. Malinowski and E. Zimanyi. Multidimensional conceptual modeling. In J. Wang, editor, Encyclopedia of Data Warehousing and Mining, pages 293–300. IGI Global, second edition, 2008.

Conceptual modeling

The multiDim model – a conceptual model for Data Warehouse & OLAP Applications



Conceptual modeling reached a certain level of maturity

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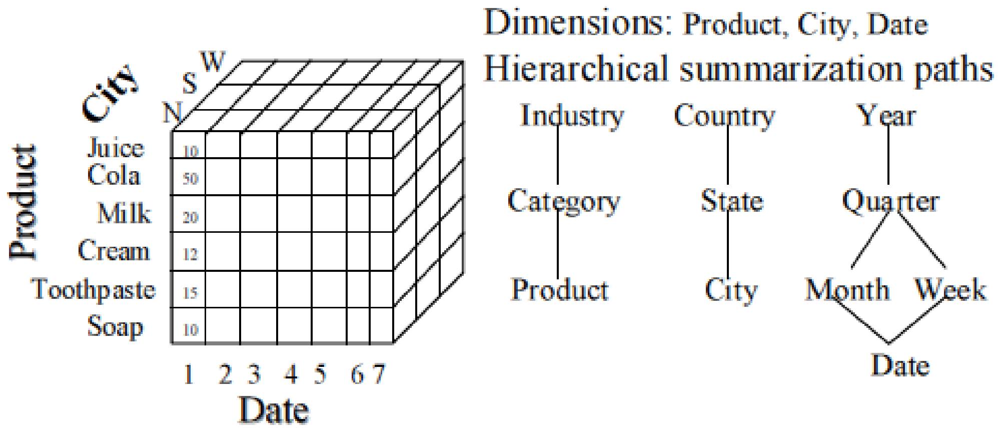
E. Malinowski and E. Zimanyi. Multidimensional conceptual modeling. In J. Wang, editor, Encyclopedia of Data Warehousing and Mining, pages 293–300. IGI Global, second edition, 2008.

OLAP queries

Operations & queries on the model

Extracting information by Queries



1. Rollup (increasing the level of aggregation)
2. Drill-down (decreasing the level of aggregation or increasing detail) along one or more dimension hierarchies
3. Slice and dice (selection and projection)
4. Pivot (re-orienting the multidimensional view of data).

S. Chaudhuri and U. Dayal. An overview of data warehousing and olap technology. SIGMOD Record, 26(1):65–74, 1997

Summary

Functional layers for OLAP

QUERY LAYER	**OLAP Cube** Snowflake Models & SQL request
TRANSLATION LAYER	**OLAP** OLAP Processing framework
PROCESSING FRAMEWORK	
STORAGE	**Relational** Traditional storage

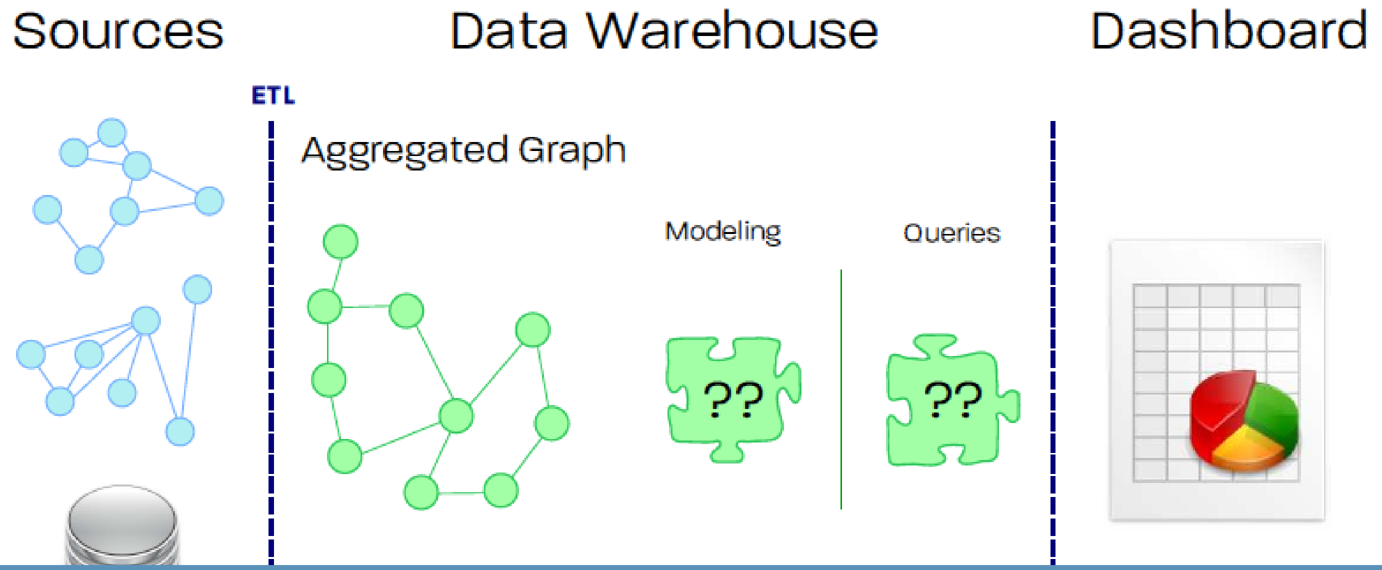
I got a distributed processing framework & mining algorithms

Now do I have a Graph Data warehouse?!

Let's take the Data warehouse process

Define what is missing if we have a graph model instead of a relational model

Global process overview



Need to be able to model intermediate structure keeping the relationship as a central place while Defining navigation path, roles in navigation, summarization pros, etc.

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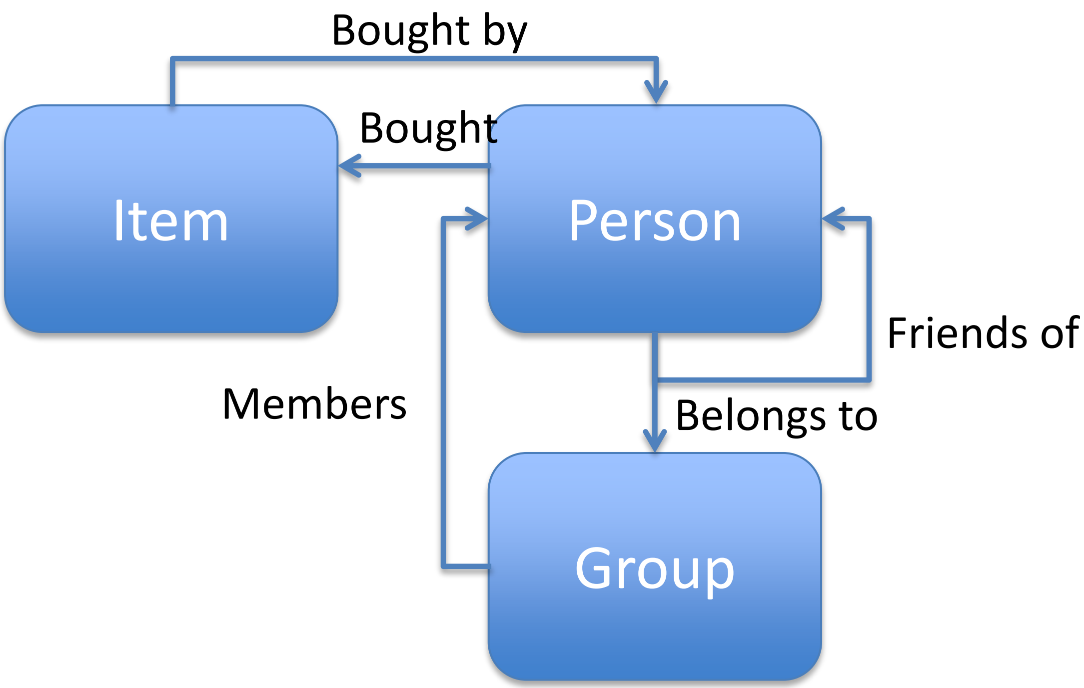
Why navigation path matters?

Central element in the traversal and then in graph mining

Define the way one could traverse the graph



Used in

1. Classification
2. Ranking
3. Collaborative filtering

Roles in paths

Hierarchies in paths

Additivity in paths

Processing layers

Dealing with distributed frameworks while keeping an high level query layer

QUERY LAYER

TRANSLATION LAYER

DISTRIBUTED PROCESSING FRAMEWORK

GRAPH STORAGE

Challenges @Processing layers

Dealing with distributed frameworks while keeping an high level query layer

QUERY LAYER

What kind of query language to expose ?

SQL - PigLatin – SPARQL ?

TRANSLATION LAYER

How to infer a physical execution plan ?

Data materialization issue is completely different from OLAP

DISTRIBUTED PROCESSING FRAMEWORK

How to deal with the distributed aspects ?

Integration of the processing FWK ?

GRAPH STORAGE

How to deal with the graph nature ?

If I have a graph DB how do I use Giraph ?

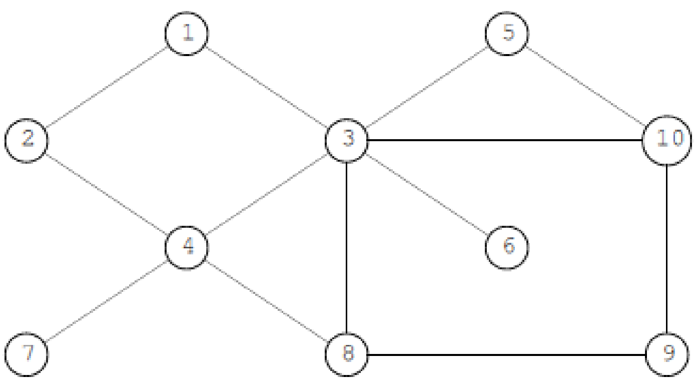
The most advanced research

From Google & Microsoft Research

New Warehousing & OLAP multi-dimensional network model

A graph on which vertex = tuple in a table

Attributes of this table = multi-dimensional spaces



(a) Graph

ID	Gender	Location	Profession	Income
1	Male	CA	Teacher	\$70,000
2	Female	WA	Teacher	\$65,000
3	Female	CA	Engineer	\$80,000
4	Female	NY	Teacher	\$90,000
5	Male	IL	Lawyer	\$80,000
6	Female	WA	Teacher	\$90,000
7	Male	NY	Lawyer	\$100,000
8	Male	IL	Engineer	\$75,000
9	Female	CA	Lawyer	\$120,000
10	Male	IL	Engineer	\$95,000

(b) Vertex Attribute Table

Combining Social Interaction information with user profiles

Target ads, marketing, etc.

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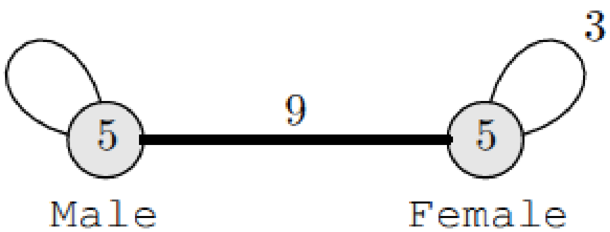
Attributes of this table = multi-dimensional spaces

1. Shown we can execute **standard OLAP operations** while leveraging the graph aspects
2. Defined the algorithm to obtain the **aggregated networks** from queries
3. Present a **materialization approach**

Zhao and al., Graph cube: on warehousing and OLAP multidimensional networks, in Proceedings of the 2011 international conference on Management of data

Showing structural behaviors

Examples for operation on multi-dimensional networks



(a) Aggregate Network

Gender	COUNT(*)
Male	5
Female	5

(b) Aggregate Table

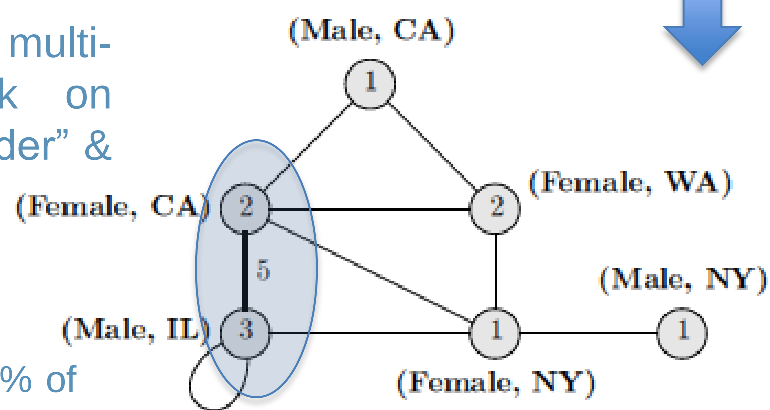
Summarizing on the multi-dimensional network on the dimension "Gender"

Drill-down operation

What is the network structure as grouped by both gender & location?

Summarizing on the multi-dimensional network on the dimensions "Gender" & "Location"

2 females in CA take 55.6% of the total Male-Female connections



(a) Aggregate Network

Gender	Location	COUNT(*)
Male	CA	1
Female	CA	2
Female	WA	2
Male	IL	3
Male	NY	1
Female	NY	1

(b) Aggregate Table

EURA NOVA

Zhao and al., Graph cube: on warehousing and OLAP multidimensional networks, in Proceedings of the 2011 international conference on Management of data

Queries on GraphCube

1. The cuboid queries

Has as output the aggregate network corresponding to a specific aggregation of the multi-dimensional network

What is the network structure between various location & profession combinations?

The answer = the aggregated network in the desired cuboid in the graph cube

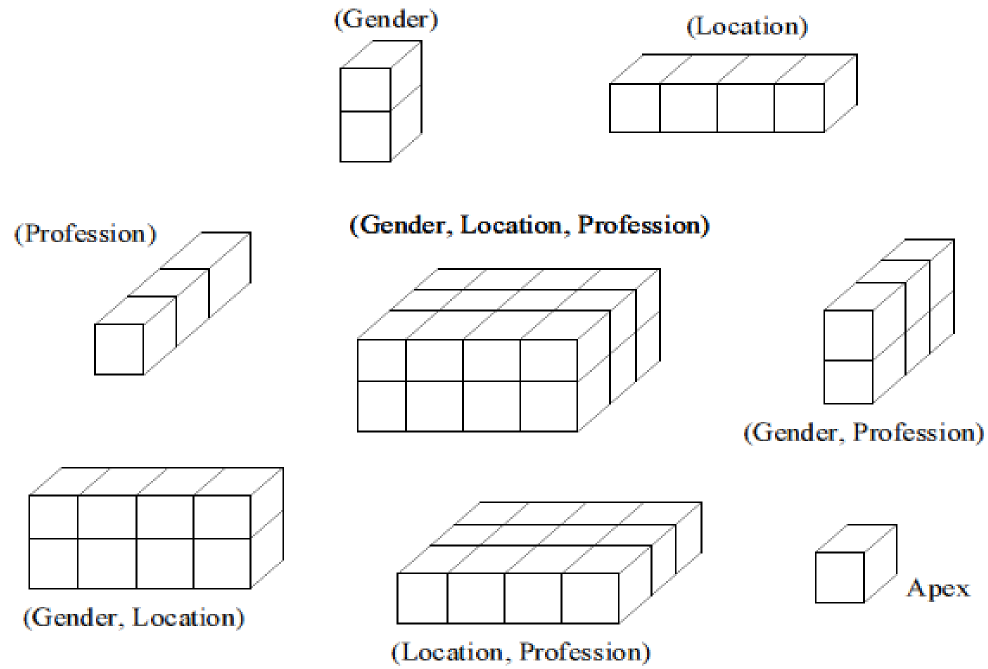


Figure 6: Traditional Cuboid Queries

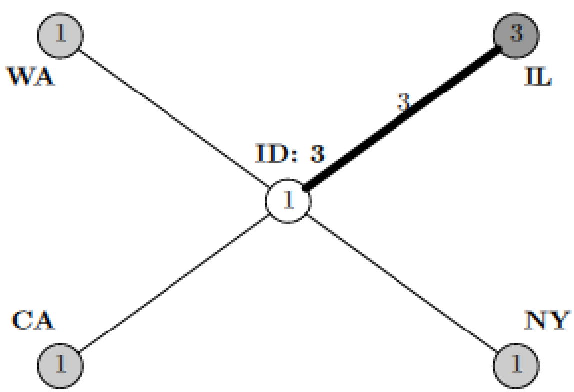
Zhao and al., Graph cube: on warehousing and OLAP multidimensional networks, in Proceedings of the 2011 international conference on Management of data

Queries on GraphCube

2. Crossboid query

Queries which crosses multiple multi-dimensional spaces of the networks (Cuboids)

What is the network structure between the user “3” and various locations?



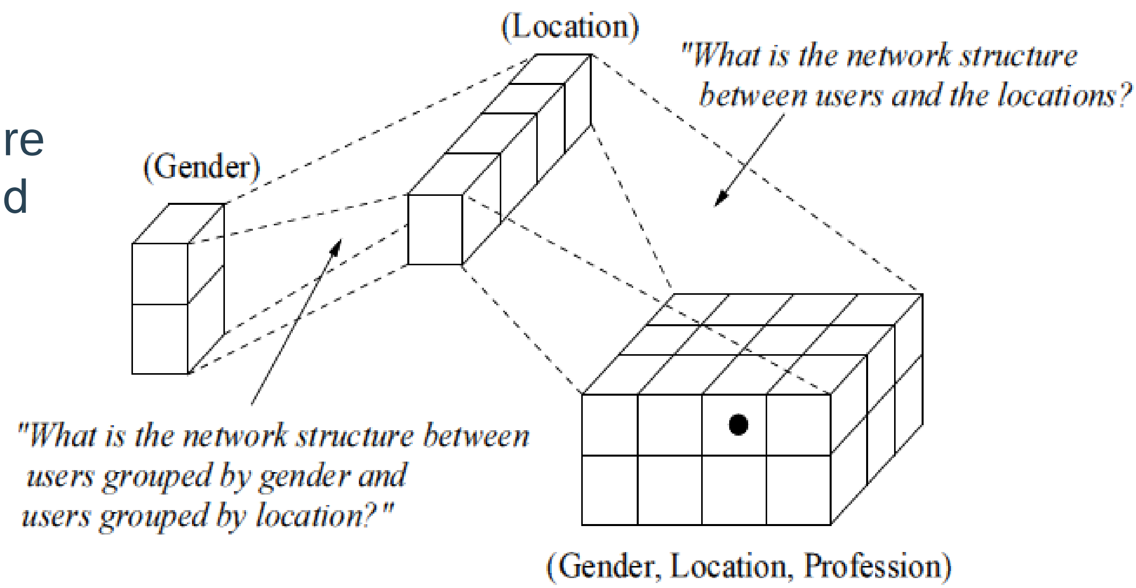


Figure 7: Crossboid Queries Straddling Multiple Cuboids

Zhao and al., Graph cube: on warehousing and OLAP multidimensional networks, in Proceedings of the 2011 international conference on Management of data

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A graph on which vertex = tuple in a table

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1. Shown we can execute standard OLAP operation while leveraging the graph aspects
2. Defined the algorithm to obtain the aggregated networks from queries
3. Present a materialization approach

Only consider vertex of the same type

Only centralized processing

Then materialization policy is inspired by legacy central DW

Zhao and al., Graph cube: on warehousing and OLAP multidimensional networks, in Proceedings of the 2011 international conference on Management of data

AGENDA

Conclusion

Today building **blocs exist** to mine large graphs

Up to you to assemble them for a dedicated purpose

mahout

MapReduce

GOLDENORB

MINING LIBRARIES

NON-GRAPH BASED

DISTRIBUTED PROCESSING FRAMEWORK

GRAPH STORAGE

hadoop

Cassandra

OrientDB

Neo4j the graph database

Conclusion

Structuring linked data as graph is an **emerging & important** requirement

Important challenges for Mining algorithms

Adapting the logic to include the global relationship

Important challenges for the processing layer

Re-design algorithms – integrating the storage layer - using emerging Big data frameworks

However implicit distributed graph processing frameworks are emerging

Still far from the concept of Graph Data Warehouse

Lack of modeling – uniform stack –Query language – Re-design the materialization

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THANK YOU

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