

# Social Context as Machine Processable Knowledge Knowledge Based Text Processing



The social context (the set of facts or circumstances that surround a situation or event) is hard to represent to our formal reason



Source: Prof. Noshir Contractor



The SONIC logo is displayed in a stylized, blocky font. The letters are white with a thick black outline. The background features a network diagram with nodes (small circles) and edges (lines connecting them), suggesting a network topology.

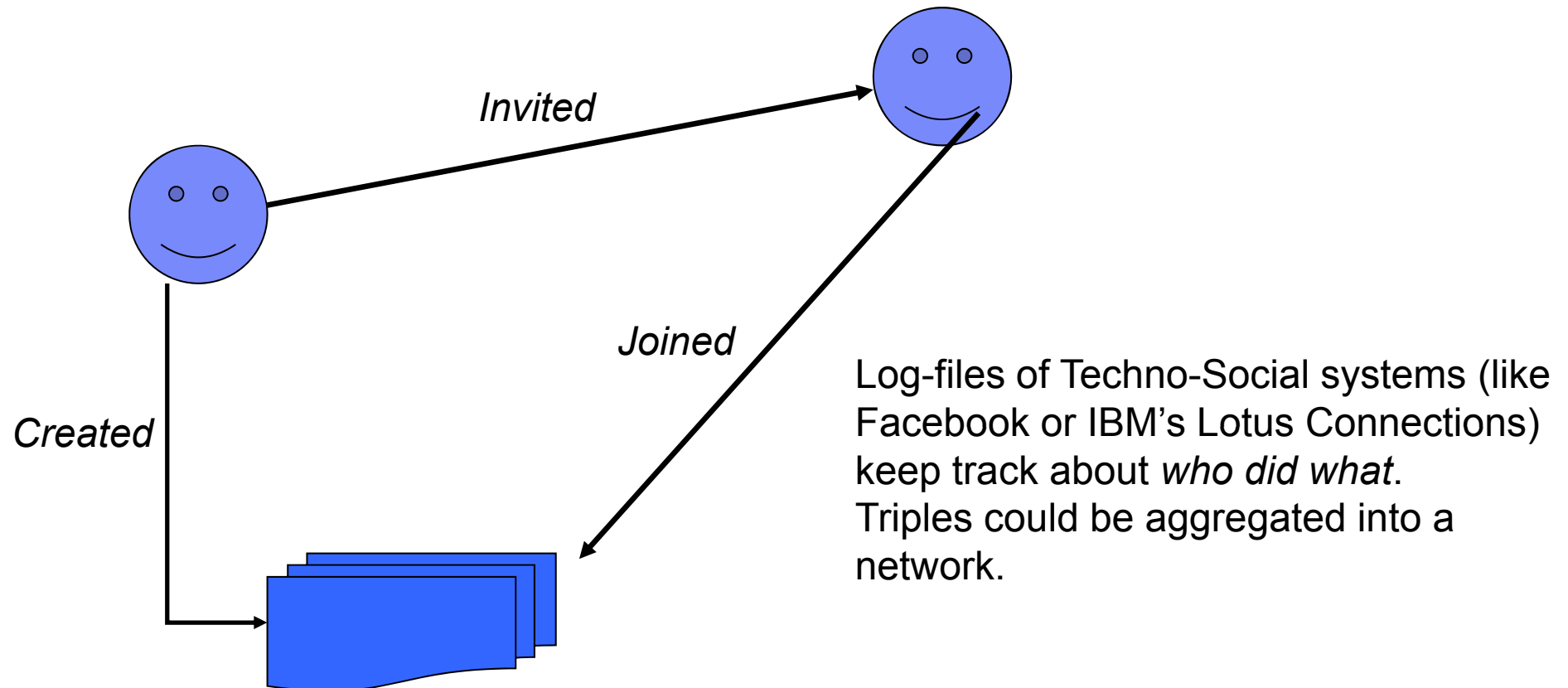
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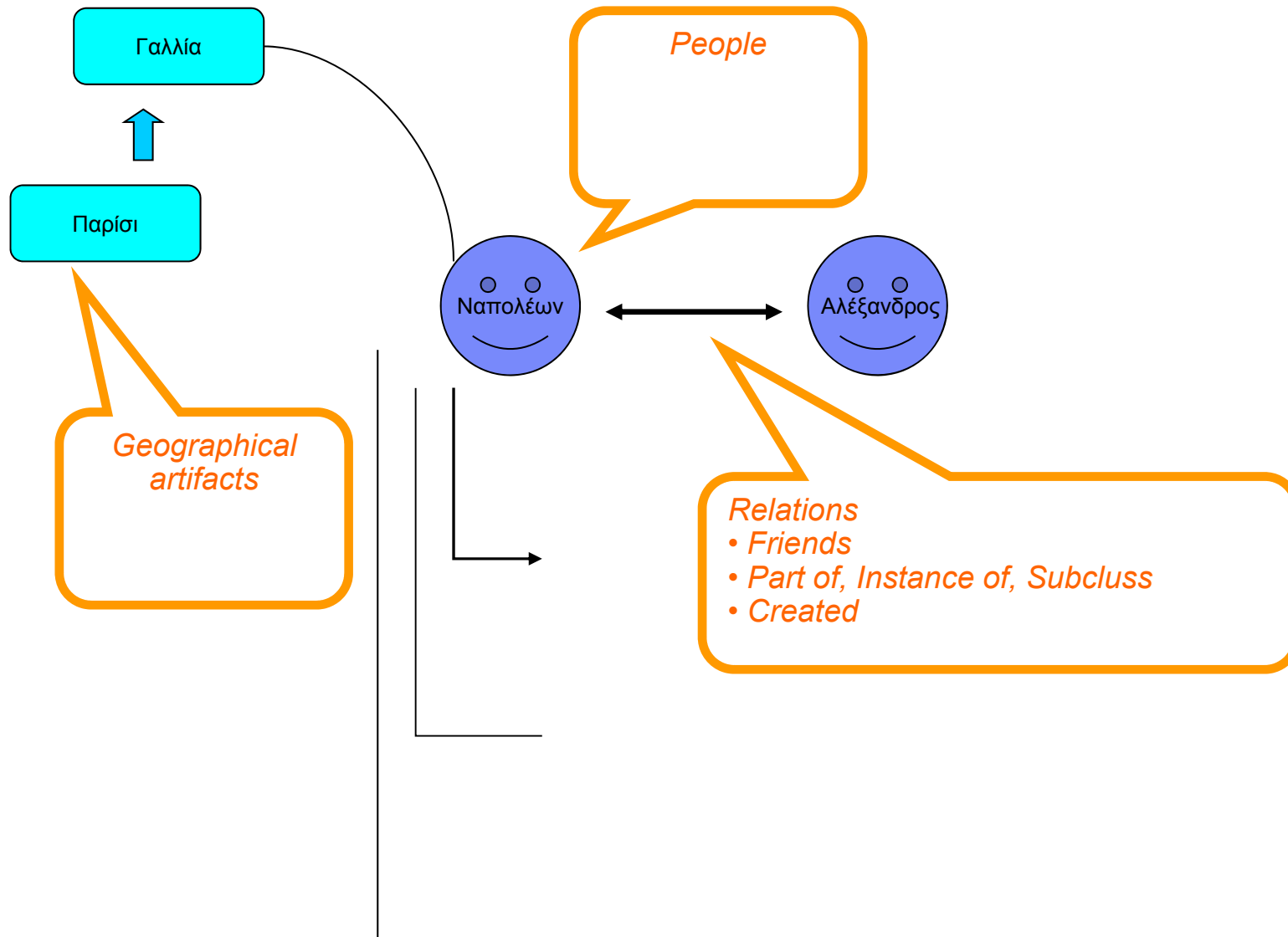
## The social context: introduction

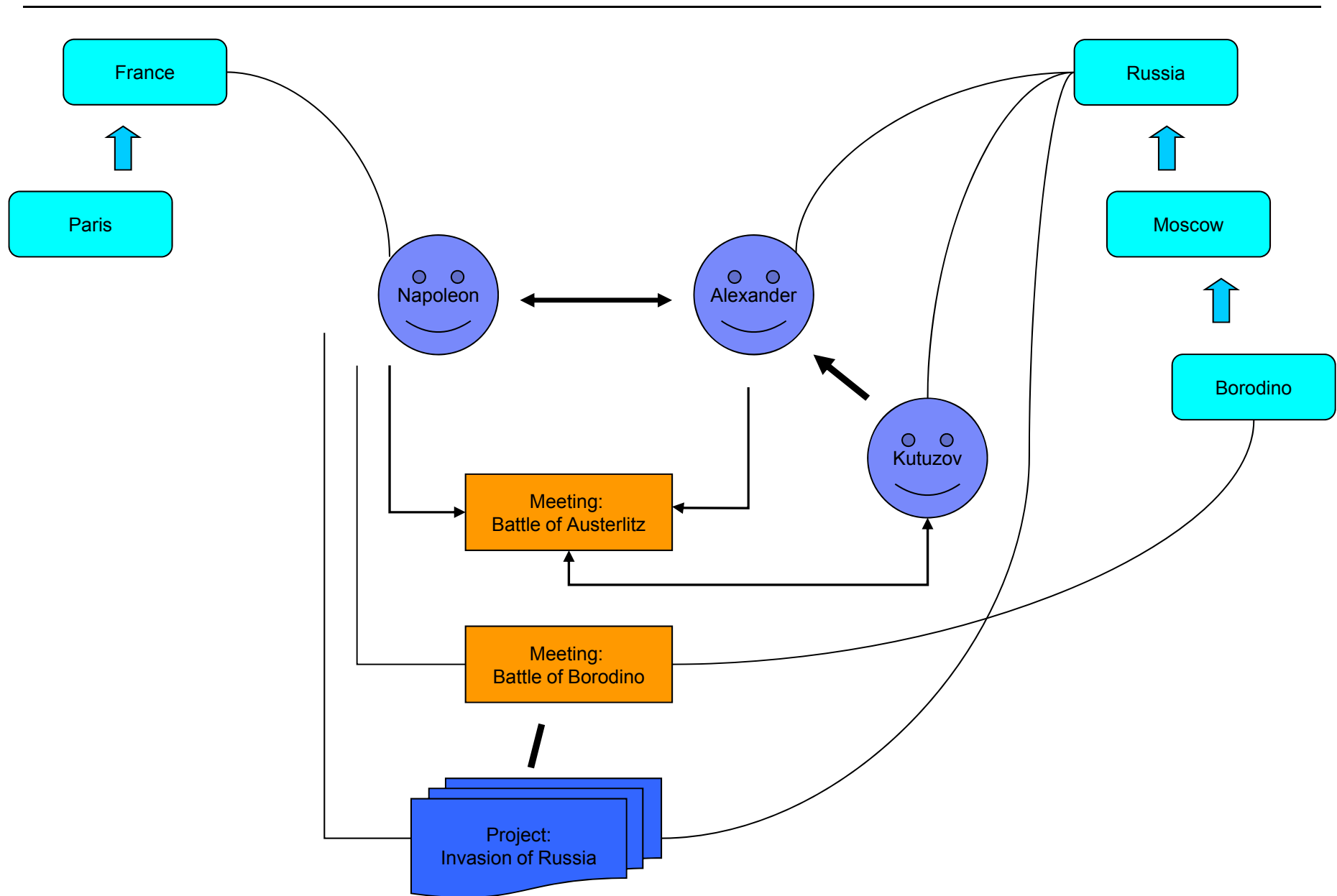
- We live in an increasingly interconnected world of techno-social systems, in which technological infrastructures composed of many layers are interoperating within a social context that drives their everyday use and development. Nowadays, most of the digital content is generated within public systems like Facebook, Delicious, Twitter, blog and wiki systems, and also enterprise environments such as Microsoft SharePoint, and IBM Lotus Connections. These applications have transformed the Web from a mere document collection into a highly interconnected social space where documents are actively exchanged, filtered, organized, discussed and edited collaboratively.
- The emergence of the Social Web opens up unforeseen opportunities for observing social behavior by tracing social interaction on the Web. In these socio-technological systems “everything is deeply intertwined” using the term coined by the pioneer of the information technologies Ted Nelson[ ]: people are connected to other people and to “non-human agents” such as documents, datasets, analytic tools, tags and concepts. These networks become increasingly multidimensional providing rich context for network mining and understanding the role of particular nodes representing people and digital content.

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## How to model the social context?



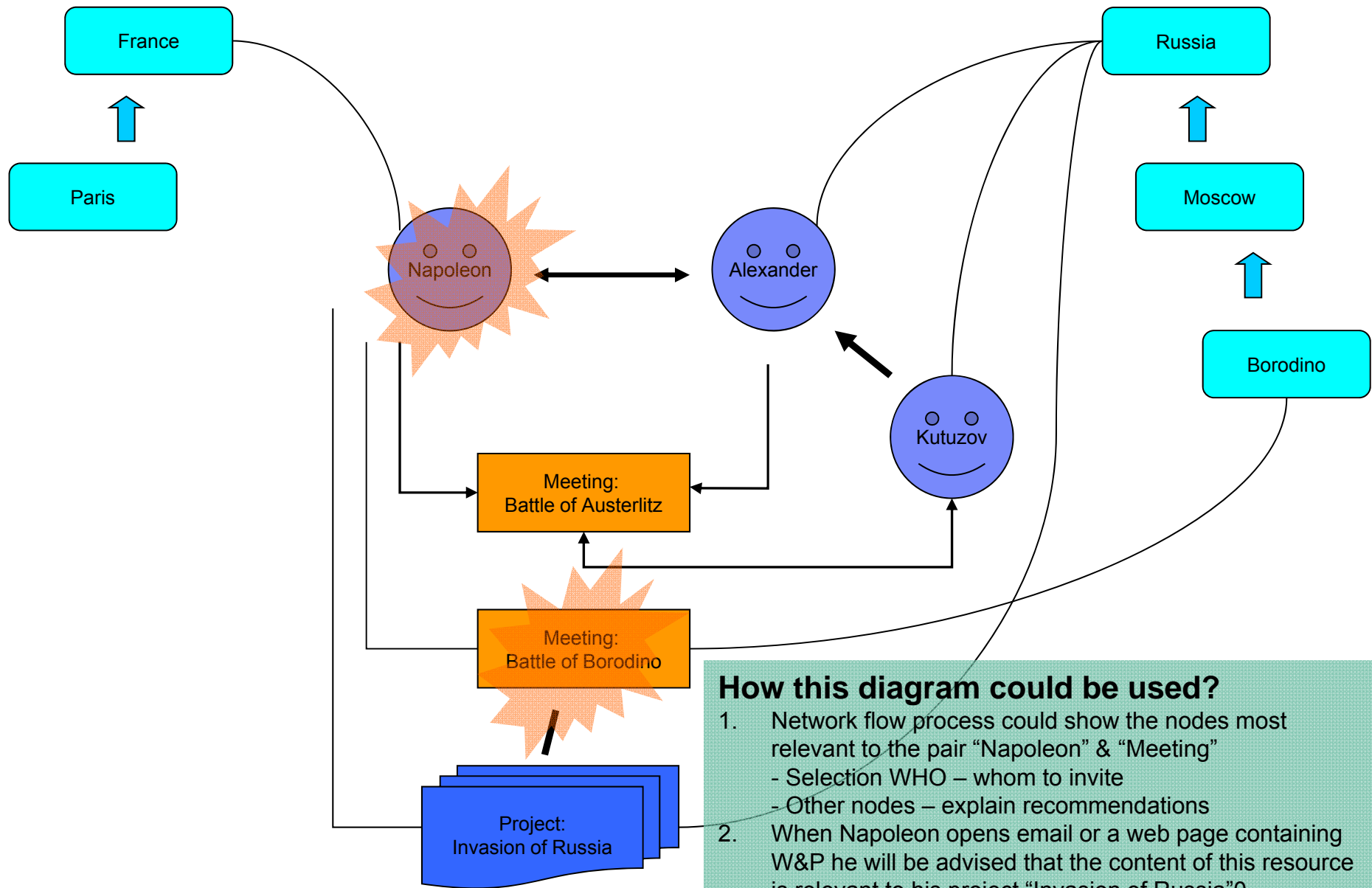




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Diagram on the previous slide ...

- What it represents ?
- How it can be used ?





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## Diagram on the previous slide ... What it represents?

- Data from Facebook, data from Napoleon's Lotus Notes calendar, structure of a Wiki, network of collocations or relations between the entities in W&P, ...
  - The proliferation of Web 2.0 and Enterprise 2.0 technologies has lead to the emergence of massive networks connecting people and various digital artifacts. These networks can be treated as a “weak” knowledge, which nevertheless might be used recommendations and even for such traditional applications as knowledge-based text processing
- Or instantiation of an ontology related to W&P by Leo Tolstoy
  - In which case we would probably know that Napoleon is emperor of France, Paris is the capital (not instantiation of a subclass) of France, etc.
- Ontology provides conceptualization, allow inferencing, but these advantages per se are useless without tedious manual work to encode the rules how to use this additional knowledge. While the knowledge encoded in the topology of the multidimensional network is ready to use provided that methods are tolerant to errors and inconsistencies in data - i.e. the methods are methods of “soft mathematic” – fuzzy inferencing, soft clustering, ...

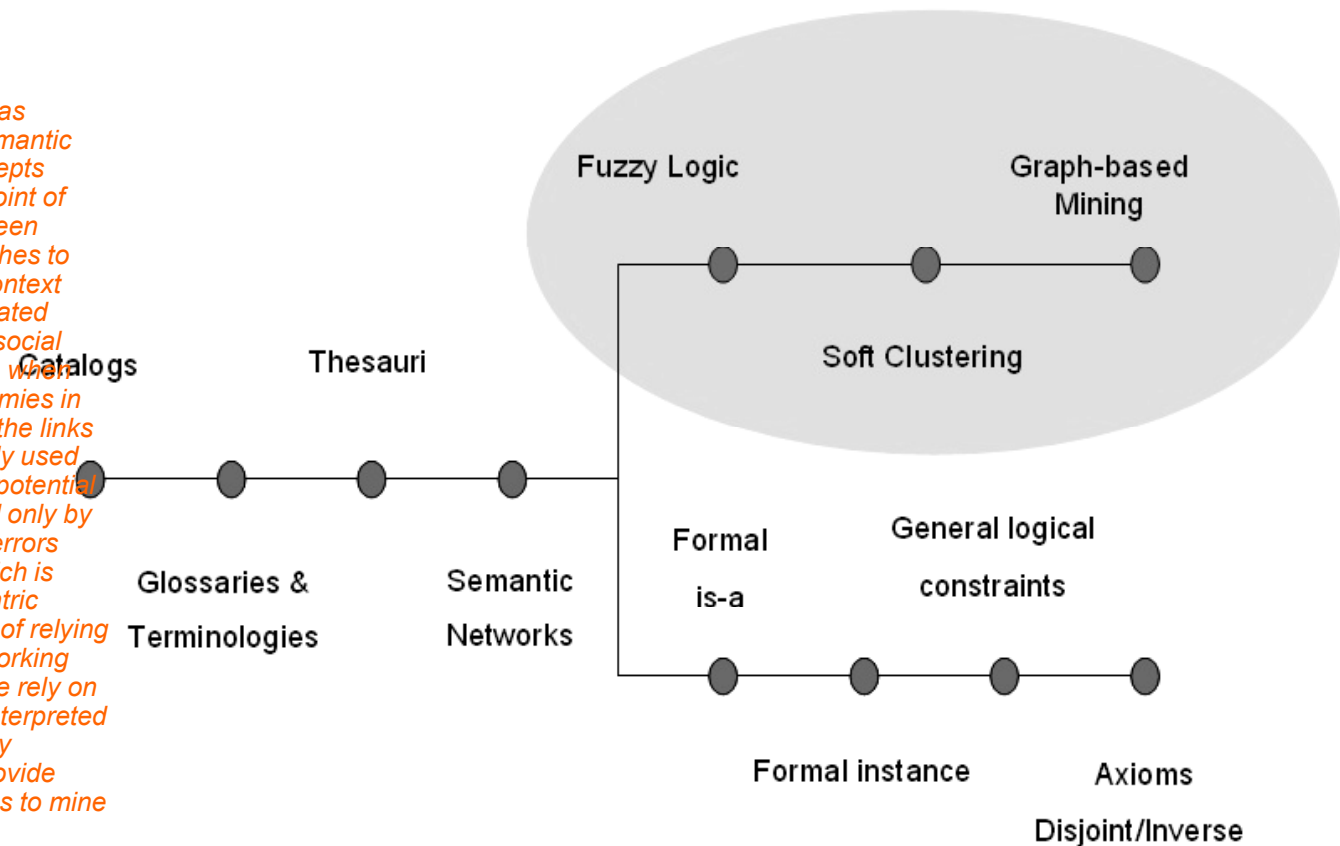
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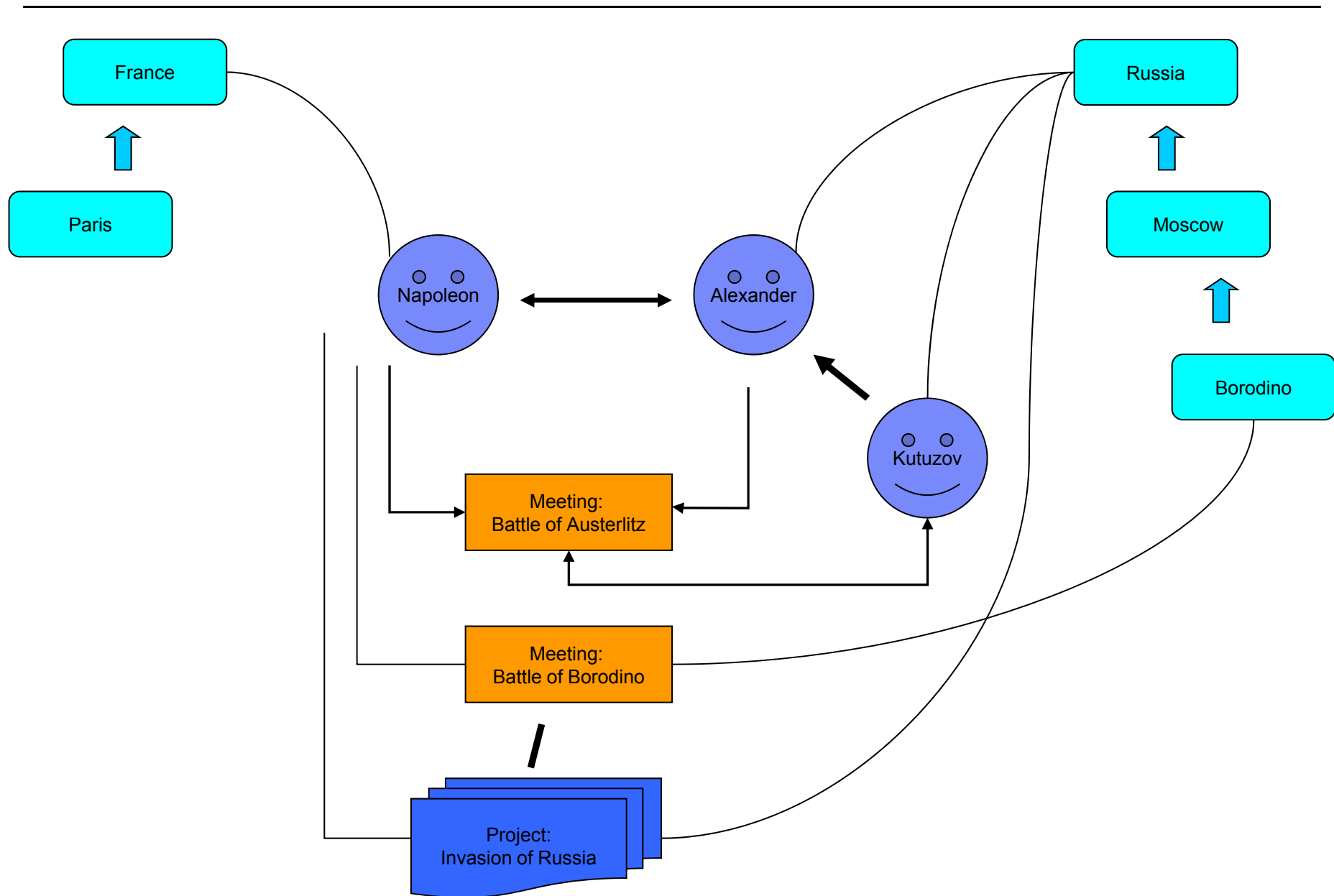
## Social Context = Social Knowledge. So what?

Representing social context as a knowledge allows us to benefit from the past experience of knowledge based applications.

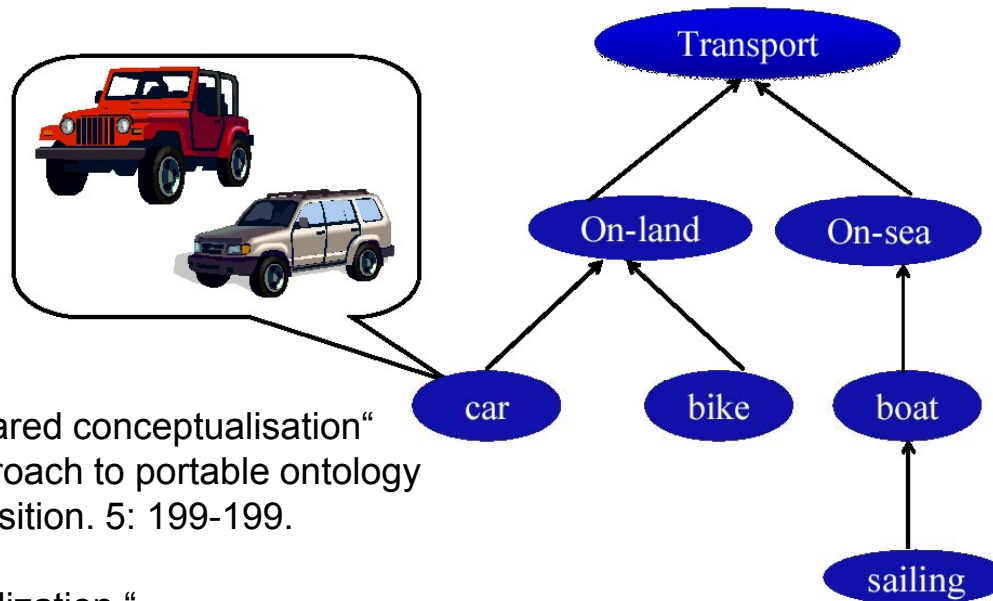
For instance, the social context modeled as a network is not much different from semantic networks which are formed from concepts represented in ontologies. And it is possible to use such networks for knowledge based text processing. Representing social context as knowledge allows us to draw experience from such mature R&D area as knowledge-based text processing

*The social context can be considered as knowledge in the same way as the semantic networks which are formed from concepts represented in ontologies. From the point of view of the traditional dichotomy between codification and collaboration approaches to knowledge management, the social context could be considered as bottom-up created social knowledge. As knowledge, the social context is a weaker type of knowledge when contrasted with ontologies and taxonomies in that it lacks proper conceptualisation, the links are usually typed and cannot be readily used for inferencing. Correspondingly, the potential of his knowledge can be fully revealed only by robust methods which are tolerant to errors and incompleteness of knowledge which is endemic in any user created, user centric knowledge system. Therefore instead of relying on the traditional logical methods of working with ontological semantic networks, we rely on graph-based methods which can be interpreted as methods of soft clustering and fuzzy inferencing. Graph-based methods provide clear intuition and elegant mathematics to mine networks.*





## “Strong” Knowledge – Ontologies



- In theory, an ontology is a

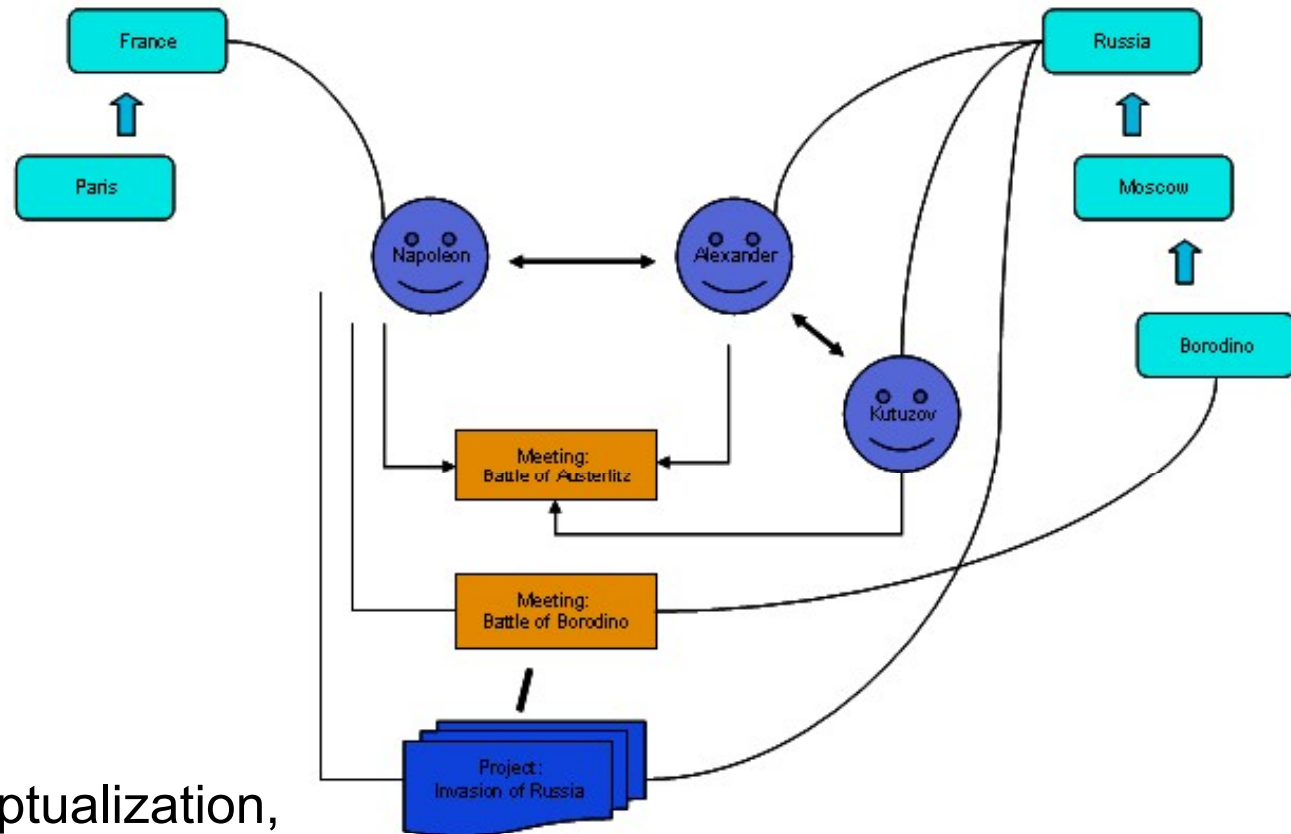
"formal, explicit specification of a shared conceptualisation"  
T. Gruber (1993). "A translation approach to portable ontology specifications". In: Knowledge Acquisition. 5: 199-199.

"explicit specification of a conceptualization,"

Gruber, T. R., Toward Principles for the Design of Ontologies Used for Knowledge Sharing. International Journal Human-Computer Studies, 43(5-6):907-928, 1995.

- An ontology provides a shared vocabulary, which can be used to model a domain — that is, the type of objects and/or concepts that exist, and their properties and relations

## “Weak” Knowledge



- No explicit conceptualization,
- Nodes and links are weakly typed.

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## “Good” Knowledge

- In certain applications manually handcrafted “Strong” knowledge is superior. However, in most modern applications strong knowledge relevant to the domain
  - simply doesn’t exist
  - is outdated
  - and even if available, not always has clear advantages over weak knowledge without additional time-consuming work to encode rules which will benefit from strong knowledge
- While “weak” knowledge is in abundance
  - The primary source - Networked models of socio-technical systems
- and therefore is “Good”

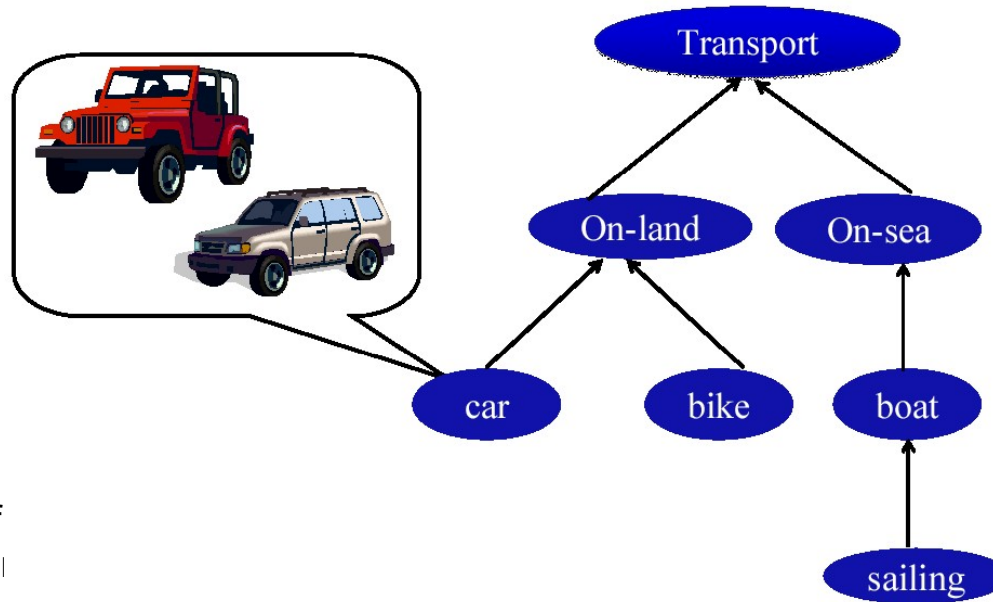
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## Summary and Conclusions of “Social Context as Machine processable knowledge”

- Social Context as Machine-Processable Knowledge
  - Troussov et al. MITACS FP-Nets Workshop on Social Networks, Vancouver, Canada. August 9-13 2010
- Social context could be represented as knowledge (as a weak knowledge as opposed to “strong” knowledge encoded in ontologies)
- Multidimensional networks are capable to model both ontologies and social context
- Social knowledge (primarily network models of techno-social systems) has practical advantages over ontologies
  - Social knowledge is relevant to the domain of applications, is up-to-date, encourages use prior to providing proper structure in full spirit of Web 2.0 business paradigm
- However, social knowledge a “weak knowledge” and its use requires methods of soft mathematics, tolerant to error and inconsistencies in data
- Soft methods actually could provide high-reliable inferencing on networks with high local density based on “weak” knowledge
  - Combinatorial effect leading to a sharp phase transition from uncertainty to certainty

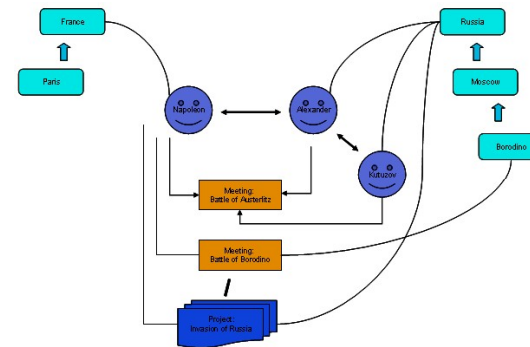


## “Strong” Knowledge – Ontologies. Taxonomies



- Ontologies, taxonomies
  - An explicit specification of world. Example of real world: GeneOntology, Amazon.com taxonomies
  - Model: a directed graph where a node represents concepts and links represent relations (ISA, ...)
  - Having an ontology doesn't imply having ANY knowledge regarding the real world
    - For example,

## “Weak” Knowledge



- No explicit conceptualisation, nodes and links are weakly typed.
  - *some nodes actually represent multiple concepts, like the tag BP could stand for Blue Pages, British Petroleum and a lot more, different nodes should actually be merged into one (remember Wikipedia moderators comments?), etc).*
- A good Example – Folksonomies (and other “crowdsourcing”)

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## What Knowledge should we use for recommenders etc?

- It depends ...
- and this problem should be properly addressed only in the view of the traditional dichotomy between top-down and bottom-up approaches in knowledge management

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## Good knowledge

- Should be relevant to the domain of the discourse
- Know realities
- Be up-to-date

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## What knowledge should we use for text analytics?

- In short:
- In certain applications manually handcrafted “Strong” knowledge is absolutely superiour. However, in most modern applications strong knowledge relevant to the domain simply doesn’t exist
  - is outdated
  - and even if available, has no clear advantages over weak knowledge
- While “weak” knowledge (including who did what to whom on the social site) is in abundance
  - The primary source - Networked models of socio-technical systems
- and therefore is “Good”

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## What knowledge should we use for text analytics?

- As a processable knowledge for understanding the documents embedded into a techno-social system, this social context has advantages over traditional ontologies. The social context is up-to-date knowledge about a subject area or community (like Facebook) which changes rapidly to reflect interests and developments in the area. It is populated with nodes representing the current state of the information and how it relates to processed texts and to the realities of a particular socio-technological system (people, projects, social groups).

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# KNOWLEDGE BASED TEXT PROCESSING

(using network models of weak knowledge)

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## Representing knowledge

- There are a number of options:
  - As *objects*, using the well-accepted techniques of object-oriented analysis and design to capture a model
  - As *clauses* going back to the early days of AI and Lisp
  - As *XML*, using the industry-standard structured mark-up language
  - As *graphs*, making use of the things we know about graph theory
  - As some combination of these
- We are looking for
  - Extensibility
  - Easy of merge heterogeneous information
  - Ease of use
- And our choice is - GRAPHS
  - Knowledge is represented by a multidimensional network which is modeled by a graph
  - And the Nepomuk-Simple will give us examples of extensibility/Easy of merge heterogeneous information/Ease of use
-



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## Graphs

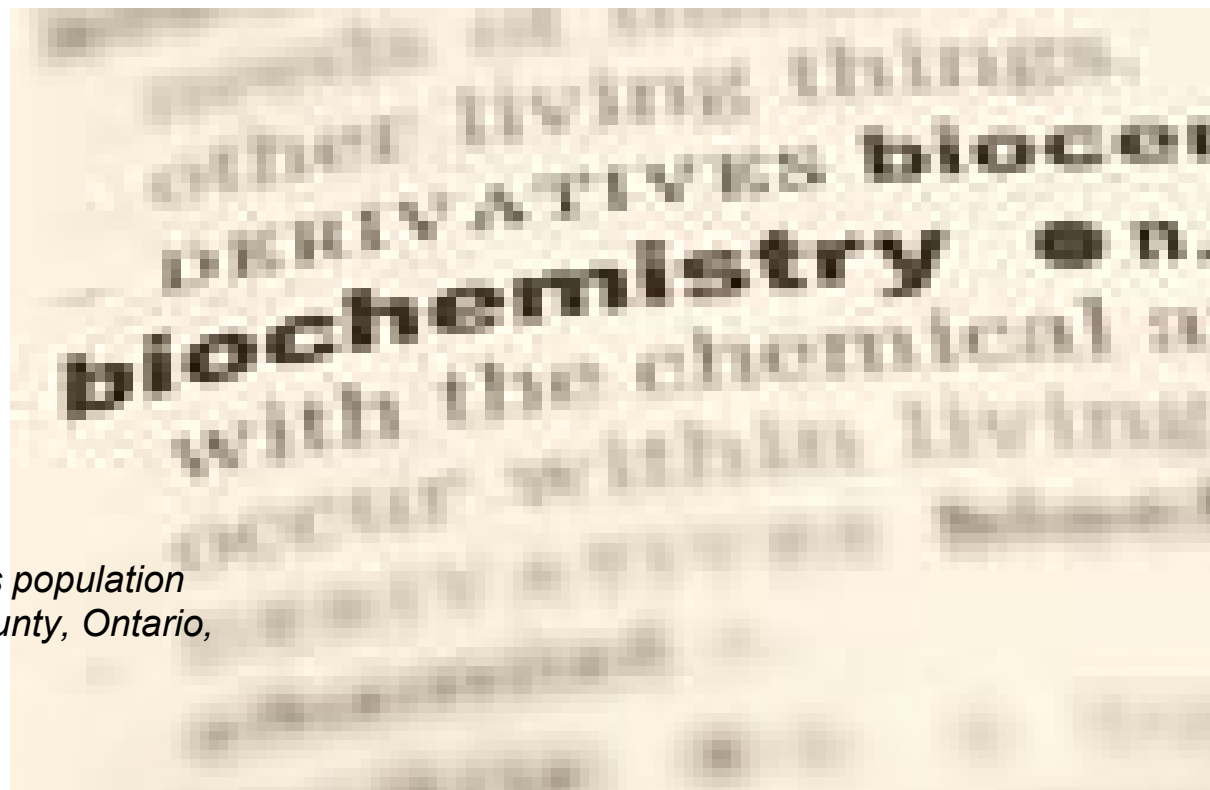
- We can use the nodes of a graph for facts, concepts, people, organisations, etc and the arcs as binary relationships between them
  - Arcs are typically called predicates or relationships in this view
  - The set of arcs intersecting a node tells us the information we know about the fact or entity

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## Natural Language Understanding is Inferencing

- From computational point of view natural language understanding is inferencing
  - Text which mentions  
*Malahide*  
is probably about  
*Canada* (??)

*Malahide (Canada 2006 Census population 8,828) is a township in Elgin County, Ontario, Canada*



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## However ...

- Terms are ambiguous, and our knowledge is never “the truth, the whole truth, and nothing but the truth”
  - Malahide, Co. Dublin
  - Malahide is a township in Elgin County, Ontario, Canada.
  - Malahide (Irish: Mullach Íde) is an affluent coastal suburban town, near Dublin city.
  - Malahide United F.C. are a football club from Malahide, County Dublin
  - Malahide Road, Malahide Viaduct, ...
  - Paradis Gisenyi Malahide is a hotel in Rwanda
  - Malahide.Net - is an on-line vendor of hot stamp stamping foil.
  - Patrick Malahide - Actor

■

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## Fuzzy Inferencing from Multiple Concepts is a Solution

- One of the successful solutions for this problem in the previous art, is the use of spreading activation (SA) algorithms.
- In our interpretation of this previous art, the success of this methods should be explained as follows:
  - SA effectively provides inferencing from multiple concepts, for instance, the initial seed for the activation propagation starts at two nodes in a geographical taxonomy: *Malahide (Ontario)* and *Malahide (Co. Dublin)* as well as from other concepts mentioned in the text
    - Text which mentions *Malahide* and *Europe* – is a little bit more likely to be about Ireland than about Canada
    - Text which mentions *Malahide* and *Clontarf* – is more likely to be about *Ireland* than about *Canada*
    - ...
    - Cohesive coherent text which mentions: *Malahide*, *Mulhuddart*, *Lansdowne*, *Clontarf*, *Donabate* - is almost for sure about *Dublin*
- Such rapid “phase transition” from uncertainty to certainty is similar to the transition related to percolation threshold

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## Percolation Threshold

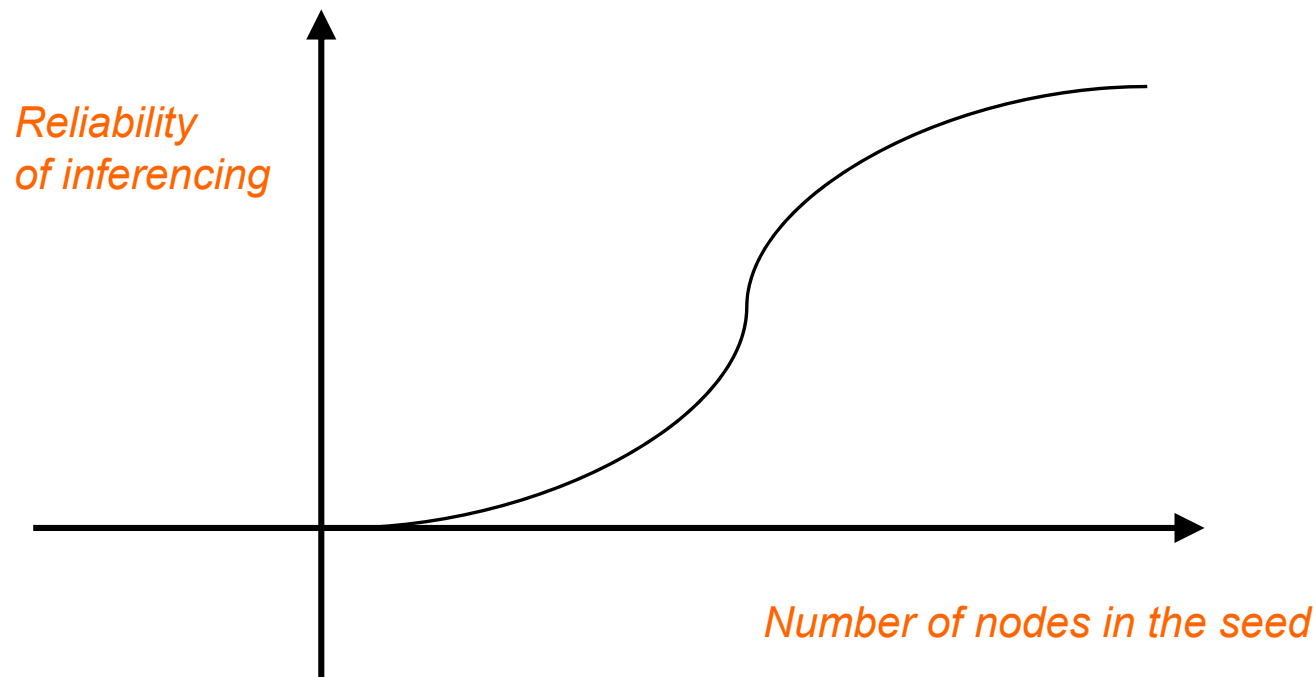
- In physics, chemistry and materials science, percolation concerns the movement and filtering of fluids through porous materials. Percolation threshold is a mathematical term related to percolation theory, which is the formation of long-range connectivity in random systems.
  - Think of a cube of plastic with metal shavings suspended inside. Some of these metal shavings touch; others don't. A high concentration of metal shavings gives you a greater chance of a conductive connection between opposing sides of a cube; lower concentration of metal shavings reduce that chance.

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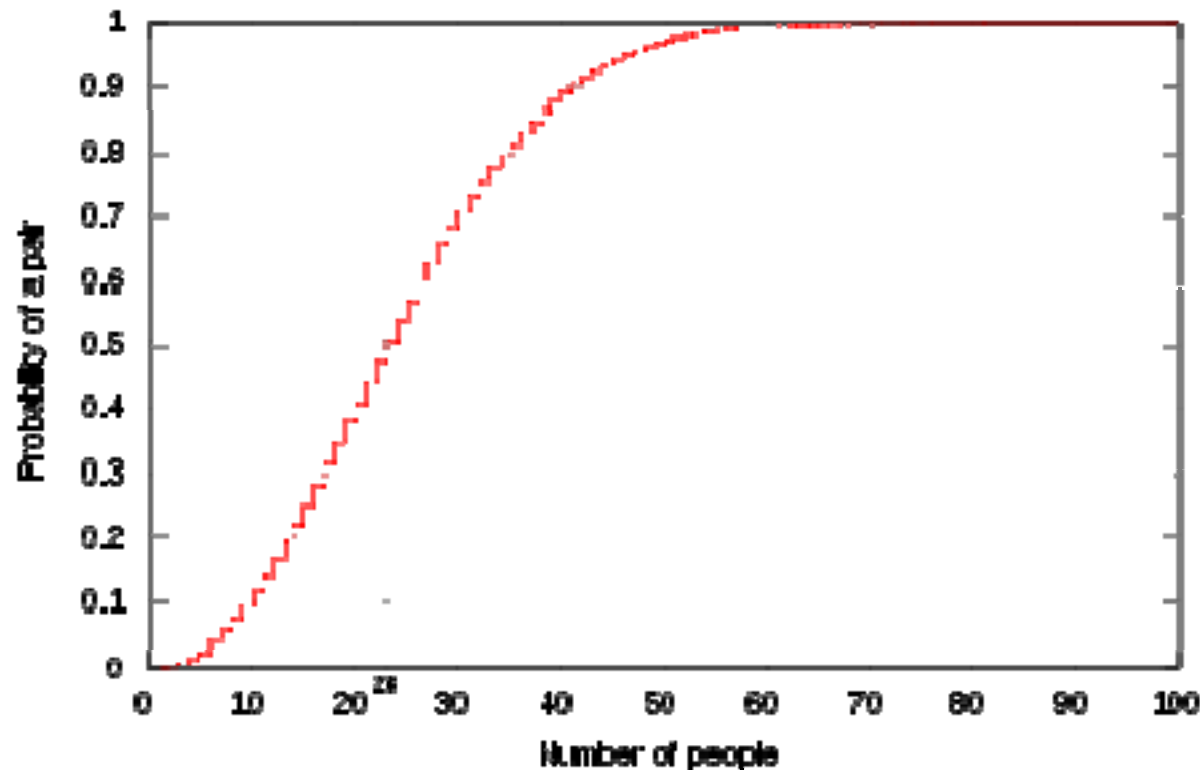
## from Uncertainty to Certainty in Inferencing: phase transitions as a function of seed size in analogy to ones in percolation

- In (semantic) networks with high local density the reliability of inferencing from a single concept is almost never sufficient, reliability could be low when inferencing starts from a small number of seed concepts, but inferencing becomes very reliable at some level of the number of the initial seed concepts (which could be explained by combinatorics)



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and probably could be explained by combinatorics



- A graph showing the approximate probability of at least two people sharing a birthday amongst a certain number of people.
- In probability theory, the birthday problem, or birthday paradox[1] pertains to the probability that in a set of randomly chosen people some pair of them will have the same birthday. By the pigeonhole principle, the probability reaches 100% when the number of people reaches 366 (ignoring February 29 births). But perhaps counter-intuitively, 99% probability is reached with a mere 57 people, and 50% probability with 23 people.

Alexander Trousov, Ph.D., IBM Dublin Software Lab

4th Russian Summer School in Information Retrieval, September 13-18, 2010, Voronezh

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# Using Social Context for Text Processing





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In this lecture we'll show how the social context could be efficiently used for traditional tasks of natural language text processing, such as automated large scale semantic annotation, term disambiguation, search of similar documents, as well as for novel applications such as social recommender systems which aim to alleviate information overload over social media users by presenting the most attractive and relevant content.

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## Bigger context, Individual context

- The current trend in corpus linguistics is for bigger and bigger corpora in order to draw more general analyses.
- In order to provide the type of text analysis needed to drive the development of the social web, we need to look beyond the corpora and documents themselves and draw upon the individual context within which the documents exist.
  - Instead considering how documents in the system relate to each other and also entities (people, tasks, ideas....) outside the scope of the traditional corpus but which have relevance when it comes to analysing the data in the text itself. In addition to word-level, paragraph-level and corpus-level text processing, text analytics on the techno-social level yields a wealth of interesting and useful data and will play increasingly important role in future advances in this area.

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## World of techno-social systems

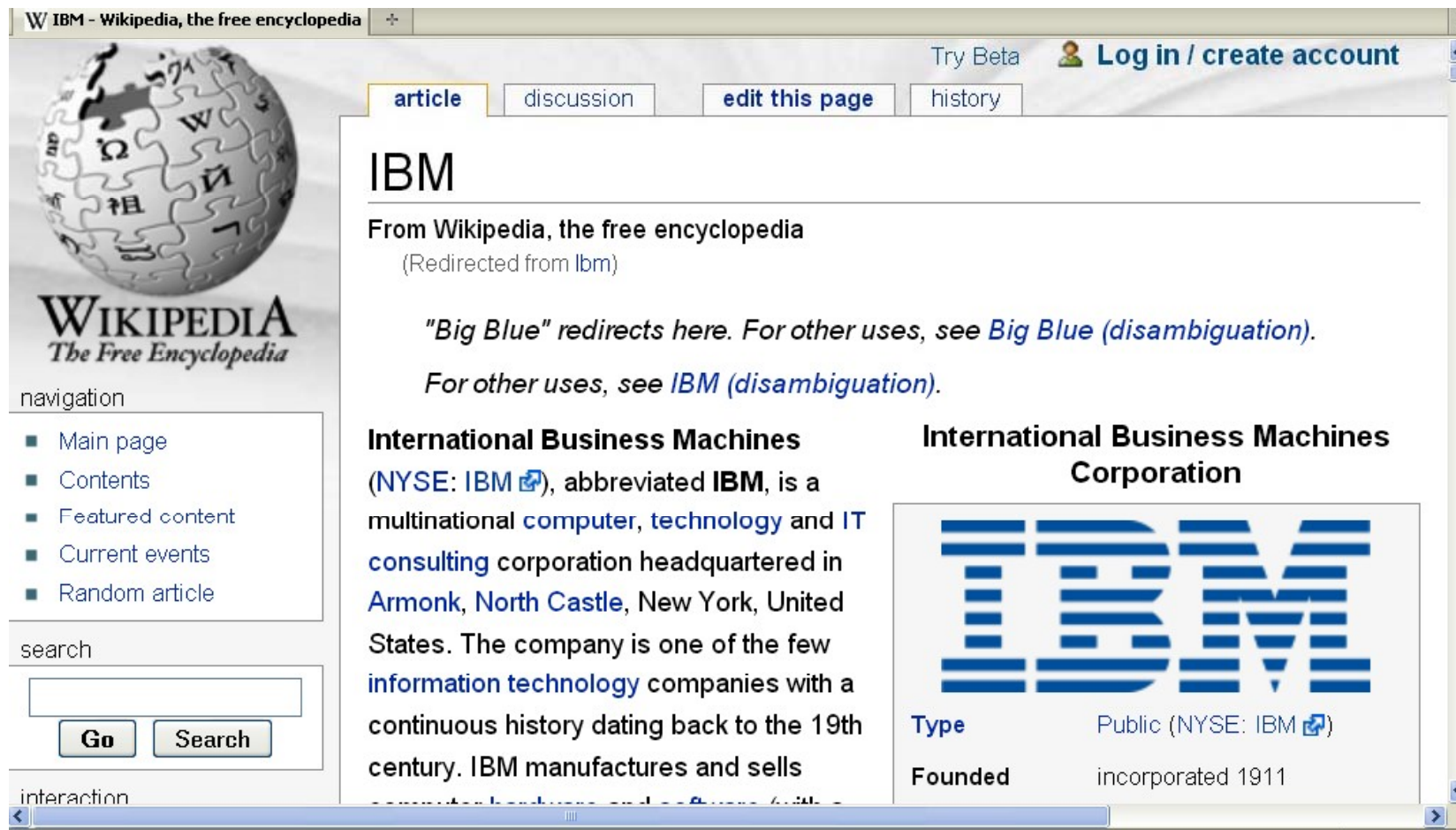
- We live in an increasingly interconnected world of techno-social systems, in which infrastructures composed of different technological layers are interoperating within the social component that drives their use and development.
  - Nowadays, most of the digital content and metadata is generated within systems like Facebook, Delicious, Twitter, blog and wiki systems, Microsoft SharePoint, and IBM Lotus Connections. These applications have transformed the Web from a mere document collection into a social space where documents are actively exchanged, filtered, organized and discussed.

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## World of techno-social systems (cont.)

- In these techno-social systems “everything is deeply intertwined” using the term coined by the pioneer of the information technologies Ted Nelson: people are connected to other people and to “non-human agents” such as documents, datasets, analytic tools, tags and concepts. And these networks become more and more “multidimensional” providing rich context for processing of embedded natural language texts.

## Wikipedia – a knowledge repository



W IBM - Wikipedia, the free encyclopedia

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# IBM

From Wikipedia, the free encyclopedia  
(Redirected from *Ibm*)

*"Big Blue" redirects here. For other uses, see [Big Blue \(disambiguation\)](#).*


*For other uses, see [IBM \(disambiguation\)](#).*


## International Business Machines

(NYSE: [IBM](#) )

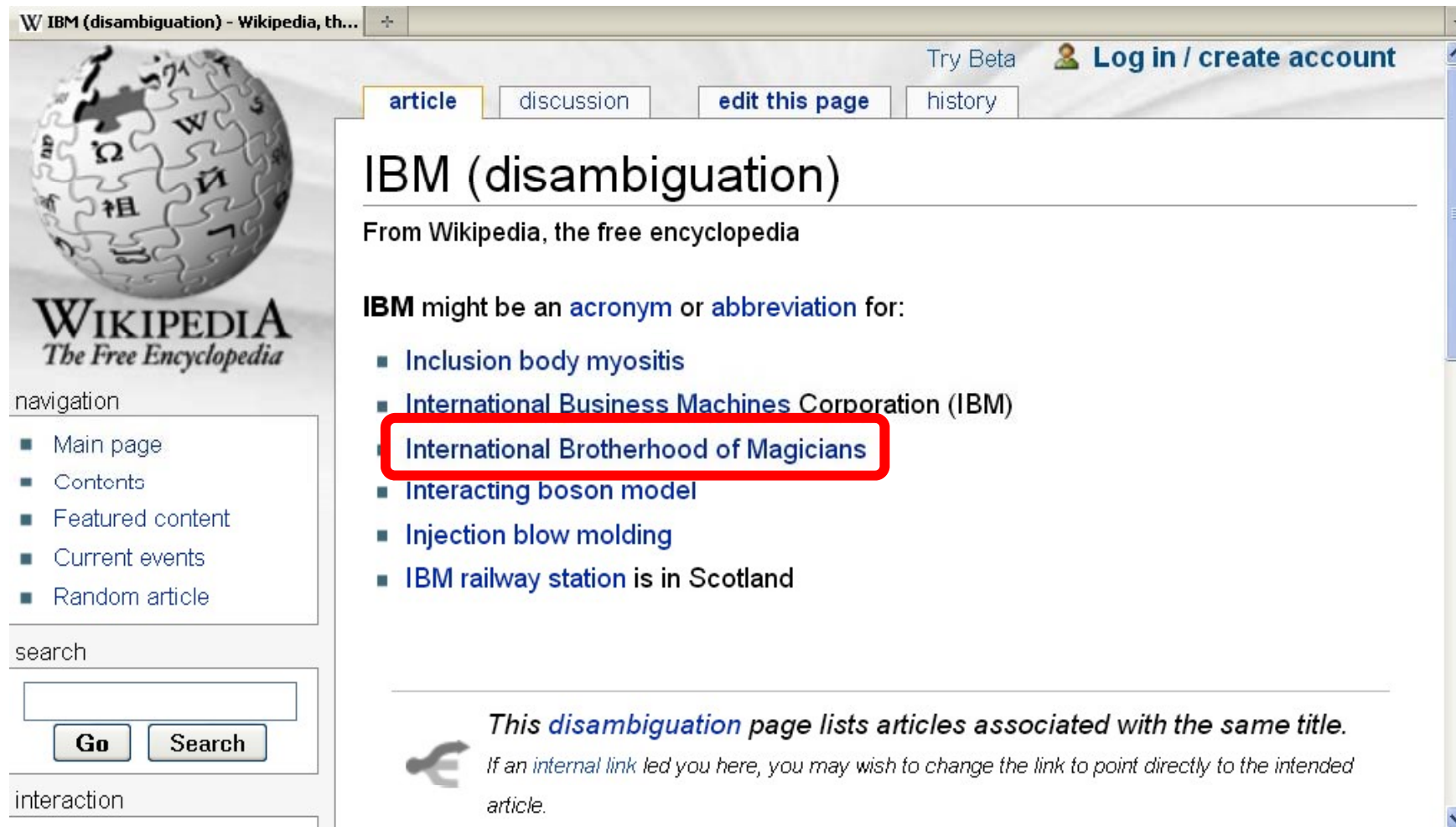
abbreviated **IBM**, is a multinational [computer](#), [technology](#) and [IT consulting](#) corporation headquartered in [Armonk](#), [North Castle](#), New York, United States. The company is one of the few [information technology](#) companies with a continuous history dating back to the 19th century. IBM manufactures and sells

## International Business Machines Corporation



|         |   |
|---------|---|
| Type    | Public (NYSE: <a href="#">IBM</a>  ) |
| Founded | incorporated 1911   |

## Wikipedia cont. – a lexico-semantic resource



W IBM (disambiguation) - Wikipedia, th... Try Beta Log in / create account

article discussion edit this page history

# IBM (disambiguation)

From Wikipedia, the free encyclopedia

**IBM** might be an [acronym](#) or [abbreviation](#) for:

- [Inclusion body myositis](#)
- [International Business Machines Corporation \(IBM\)](#)
- [International Brotherhood of Magicians](#)
- [Interacting boson model](#)
- [Injection blow molding](#)
- [IBM railway station](#) is in Scotland

*This [disambiguation](#) page lists articles associated with the same title.*

*If an internal link led you here, you may wish to change the link to point directly to the intended article.*

navigation

- Main page
- Contents
- Featured content
- Current events
- Random article

search

Go Search

interaction








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## Wikipedia is a techno-social system

- It is based on the technology “wiki” which allows to quickly create and edit pages.
- It is a social systems based on “crowdsourcing”
  - Crowdsourcing is a neologistic compound of Crowd and Outsourcing for the act of taking tasks traditionally performed by an employee or contractor, and outsourcing them to a group of people or community, through an "open call" to a large group of people (a crowd) asking for contributions. The term has become popular with businesses, authors, and journalists as shorthand for the trend of leveraging the mass collaboration enabled by Web 2.0 technologies to achieve business goals.

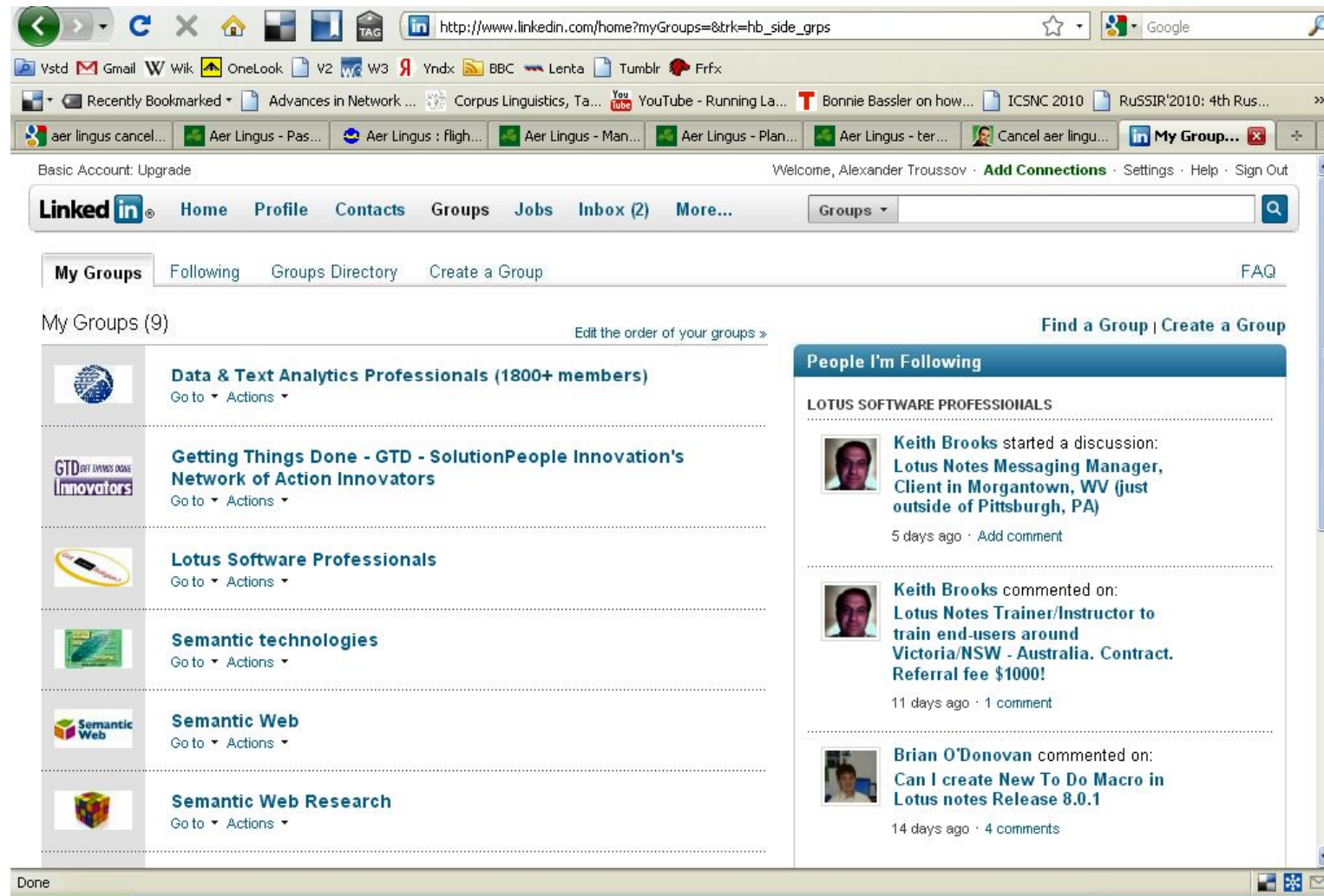
Source is reliable – Wikipedia 😊

## Wikis – popular workplace choice

|   |   |   |   |
|---|---|---|---|
|  <a href="#">About Project</a>         |  <a href="#">Project homepage</a>        |  <a href="#">Wiki Categories</a>             |  <a href="#">Wiki User Guide and FAQ</a> |
|  <a href="#">Useful info</a>           |  <a href="#">People</a>                  |  <a href="#">Project - related Links</a>     |  <a href="#">Tutorials</a>               |
|  <a href="#">Integration Committee</a> |  <a href="#">Scientific Committee</a>    |  <a href="#">Intellectual Property</a>       |  <a href="#">Executive Committee</a>     |
|  <a href="#">Demonstrators</a>        |  <a href="#">Education and Outreach</a> |  <a href="#">Commercialisation Committee</a> |  <a href="#">Entrepreneurship</a>       |
| <a href="#">ILT: meetings activities</a>  | <a href="#">DCM: meetings</a>   | <a href="#">LOC</a>   | <a href="#">SF: meetings</a>  |
| <a href="#">ILT.1: meetings activities Submitted Papers</a>   | <a href="#">DCM.1</a>   | <a href="#">LOC.1</a>   | <a href="#">SF.1: meetings activities</a>   |
| <a href="#">ILT.2</a>   | <a href="#">DCM.2</a>   | <a href="#">LOC.2</a>   | <a href="#">SF.2: meetings activities</a>   |
| <a href="#">ILT.3: meetings activities</a>  | <a href="#">DCM.3</a>   | <a href="#">LOC.3</a>   |   |



## LinkedIn – Social Net + Groups + ...



## ... + Discussions in Groups + ...

The screenshot shows a web browser with two tabs: 'Gmail - Inbox (1659) - troussov@gmail.com' and 'Text Analytics Group | LinkedIn'. The LinkedIn page is for the 'Text Analytics' group, which has 1800+ members. The navigation bar includes 'Home', 'Profile', 'Contacts', 'Groups' (selected), 'Jobs', 'Inbox (2)', and 'More...'. A search bar with 'People' and an 'Advanced' search option is also present. The group's overview shows tabs for 'Overview', 'Discussions', 'News', and 'Jobs'. Below these are links to 'Start a Discussion', 'Submit news', and 'Share group'. The 'Discussions' section is active, showing a list of recent discussions with titles like 'EVENTS2010 Second Call for Papers', 'Have you ever hired a reliable development partner?', 'Help required: Personalized Search', 'Summarization Algorithm', and 'What is the best web-scraping tool available?'. Each discussion entry includes the author's name, a profile picture, and the time it was posted. On the right side of the page, there is a 'Group Profile' section and a sidebar with a 'Take a tour' button and a 'TOP LEADS' badge. At the bottom, there is an 'Updates: Last 7 Days' section showing recent activity within the group.

Basic Account: Upgrade

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**Text Analytics**

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Discussions

Recent Activity Recent Discussions More

**EVENTS2010 Second Call for Papers**  
By Georgios Peliouras 2 hours ago  
[Follow discussion](#) | [Add comment](#) »

**Have you ever hired a reliable development partner?**  
By Nikolay Z 16 minutes ago  
[Follow discussion](#) | [Add comment](#) »

**Help required: Personalized Search**  
By Nicolaas Matthijs 5 days ago  
[Follow discussion](#) | 3 comments »

**Summarization Algorithm**  
By Abhishek Gunjan 7 days ago  
[Follow discussion](#) | 1 comment »

**What is the best web-scraping tool available?**  
By Tathagata Mukhopadhyay 18 days ago

My Groups  
Following  
Groups Directory  
Create a Group  
Data & Text Analytics Professionals (1800+ members)  
Getting Things Done - GTD - SolutionPeople Innovation's Network of Action Innovators  
Lotus Software Professionals  
[See all groups »](#)

Group Profile

grow your business

Take a tour

Updates: Last 7 Days

**Nikolay Z** started a discussion:  
**Have you ever hired a reliable development partner?**  
16 minutes ago · [Add comment](#)

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Friends  
Applications  
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**Groups** + Create a Group

**Linkedin Innovators & LinkedIn Innovation Groups**  
6,877 members  
4 Wall Posts

**Computational Linguistics Applications**  
864 members  
1 link

Groups help

**Sponsored**  
**Cyprus Easter Hotels**  
Book with Get when Easter  
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**Online Forex Trading**  
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**quick-step stair system**  
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Facebook with its 400,000 M users is the most popular social networking site in several English-speaking countries, including Canada, UK, and US

Facebook directs more online users than Google  
(Benny Evangelista February 15, 2010)

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## Facebook (from Wikipedia)

- Users can create profiles with photos, lists of personal interests, contact information and other personal information. Communicating with friends and other users can be done through private or public messages or a chat feature. Users can also create and join interest and fan groups, some of which are maintained by organizations as a means of advertising.
- Users can add friends and send them messages, and update their personal profiles to notify friends about themselves. Additionally, users can join networks organized by city, workplace, and school or college.
- "How on earth did we stalk our exes, remember our co-workers' birthdays, bug our friends, and play a rousing game of Scrabulous before Facebook?"
- Facebook Notes - a blogging feature that allowed tags and embeddable images.
- By November 3, 2007, seven thousand applications had been developed on the Facebook Platform
- Many new smartphones offer access to the Facebook services either through their web-browsers or applications. Google's Android 2.0 OS automatically includes an official Facebook app.



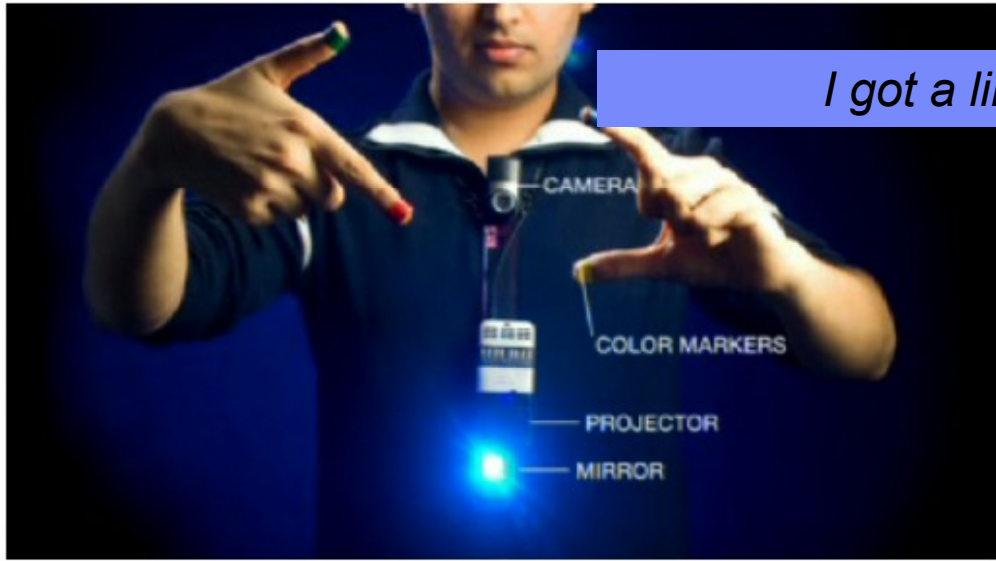


## Sharing, bookmarking, tagging

### TALKS

#### Pranav Mistry: The thrilling potential of SixthSense technology

TEDIndia 2009, Filmed Nov 2009; Posted Nov 2009



VIDEO PLAYER CONTROLS: Play button, Progress bar (05:26 / 13:51), Volume, Share, Rate

#### About this talk


[Open interactive transcript »](#)

At TEDIndia, Pranav Mistry demos several tools that allow the real world interact with the world of data -- from a "laptop" that looks at his SixthSense device and a new, paradigm-shifting paper "laptop." In an onstage Q&A, Mistry says he'll open-source the software behind SixthSense, to open its possibilities to all.

#### About Pranav Mistry

Pranav Mistry is the inventor of SixthSense, a wearable device that enables new interactions between the real world and the world of data. [Full bio and more links](#)

#### What to watch next



**TED2009**  
**Pattie Maes and Pranav Mistry demo SixthSense**  
08:42 Posted: Mar 2009  
Rated:  
**Jaw-dropping Fascinating**  
Ingenious...

I bookmarked the link on a collaborative tagging service

The screenshot shows a web browser window with the address bar displaying the URL: [http://www.ted.com/talks/pranav\\_mistry\\_the\\_thrilling\\_potential\\_of\\_sixthsense\\_technology](http://www.ted.com/talks/pranav_mistry_the_thrilling_potential_of_sixthsense_technology). The browser's toolbar includes icons for back, forward, home, and search, along with a Google search bar. The browser's address bar shows the URL. The browser's toolbar includes icons for back, forward, home, and search, along with a Google search bar. The browser's address bar shows the URL. The browser's toolbar includes icons for back, forward, home, and search, along with a Google search bar.

The main content area of the browser shows the TED website. The TED logo is prominently displayed with the tagline "Ideas worth spreading". Below the logo, the text "TALKS" is visible, followed by the title "Pranav Mistry: The thrilling potential of SixthSense technology". A video player is partially visible, showing a person holding a device. The video player is partially visible, showing a person holding a device. The video player is partially visible, showing a person holding a device.

Overlaid on the right side of the browser window is a "delicious Edit Bookmark" dialog box. The dialog box contains the following fields:

- URL:** [http://www.ted.com/talks/pranav\\_mistry\\_the\\_thrilling\\_potential\\_of\\_sixthsense\\_technology.html](http://www.ted.com/talks/pranav_mistry_the_thrilling_potential_of_sixthsense_technology.html)
- TITLE:** Pranav Mistry: The thrilling potential of SixthSense technology | Video on TED.com
- KEYWORD:** (empty)
- NOTES:** from Mikhail (highlighted with a red box)
- TAGS:** video \*\*\*\*\* (highlighted with a red box)
- SEND:** Send your bookmarks

Below the "SEND" button, there are two tabs: "Tags" and "Send". The "Tags" tab is active, showing a list of recommended tags: "ted", "technology", "video", "inspiration", "digital", "innovation", "design", "computer". The "video" tag is highlighted with a red box. Below the recommended tags, there are "Popular Tags" which include "ted", "technology", "video", "sixthsense", "interface", "future", "inspiration", "digital".

---

## Tagging – as a part of the Social Context

- Bottom-up approach to semantics to build Folksonomies as the alternative to formal taxonomies (or ontologies)
- Tags reflect all dimensions of human life (see next slide)



---

## Tags reflect dimensions of human life

- Semantics
  - After all, we call ourselves “***homo sapiens***” meaning “Man the Wise”
  - Semantics
    - Semantic web technologies
    - Traditional AI, including Natural Language Understanding
- Social
  - We are social beings as well as individuals / “To live in a society and be free from it is impossible” / Sometimes we want to be “***homo ludens***” (the “playing man”)
- Activities management
  - “***Homo faber***” (Latin for “Man the Smith” or “Man the Maker”)
  - This is about evocation, “getting things done”, action management, etc

# Tags are ambiguous

Search:

Tags 3 By Alpha A-Z

adapted 1

faceted 1

ted 2

Our Mission (You can help)

TEDTalks

Subscribe to TEDTalks

TEDTalks on social networks

TED transcript text analysis

History

Who we are

TED staff

TED Brain Trust

Who owns TED

Jobs at TED

What people say

What attendees say

What the press says

What bloggers say

What sponsors say

Is TED elitist?\*


Contact us

Press and media information

Bookmarks 2 By Last Added

Ted Nelson Quotes

TED | About TED



From left: Al Gore at TED2006; Jane Goodall at TED2003; Brian Greene at TED2005

TED is a small nonprofit devoted to Ideas Worth Spreading. It started out as a conference bringing together people from three worlds: **Technology, Entertainment, Design**. Since then its scope has become ever broader with the annual TED Conference in Long Beach, California, and the TED confere

Delicious

Search:

Tags 3 By Alpha A-Z

adapted 1

faceted 1

ted 2

Home - Quote Topics - Quotes of the Day - Quote Keywords - Author Types - Quotation Trivia

Authors: [A](#) [B](#) [C](#) [D](#) [E](#) [F](#) [G](#) [H](#) [I](#) [J](#) [K](#) [L](#) [M](#) [N](#) [O](#) [P](#) [Q](#) [R](#) [S](#) [T](#) [U](#) [V](#) [W](#) [X](#) [Y](#) [Z](#)

Google Custom Search

Ted Nelson Quotes


SHARE

Brazil

Eucalyptus Plantations

Investments from 5 to 8 years

€7,695 for



But it seemed to me that as soon as you have computer storage you could put every point you wanted in - make the ones that are less relevant to your central topic, further away or allow the central topic to move as the reader proceeded.

[Ted Nelson](#)

Computers are hierarchical. We have a desktop and hierarchical files which have to mean everything.

[Ted Nelson](#)

I am looking at it from the point of view of a harried user, which I am, and I believe that I am much more like the typical non-technical harried user than I am like the people who smoothly operate everything.

[Ted Nelson](#)

I thought I was going to be a filmmaker but at the same time I was an intellectual and I felt that I could make a contribution to some field, as yet, not invented.

[Ted Nelson](#)

I was very intensely concerned with all kinds of new media.

Bookmarks 2 By Last Added

Ted Nelson Quotes

TED | About TED

avt on Delicious

---

## Social Software

- **Social services are new way of collaboration**
- **Vox populi**
  - Is the Facebook imperative really so great for Corporate America?
  - March 1st, 2010 Posted by Larry Dignan <http://blogs.zdnet.com/BTL/?p=31350&tag=nl.e550>
    - The question is why is all enterprise software not like Facebook. On Facebook you don't waste time searching for the right data going from app to app, **the data finds you in real time**. That's what customer is getting, not from outdated **collaboration applications** like Microsoft Sharepoint and Lotus Notes.  
Sharepoint is owned by a lot of businesses, used by far fewer, and enjoyed practically by none. When was the last time everyone said they really loved using Microsoft Sharepoint or Lotus Notes? The reality is customers want to attract their coworkers who matter to them, the most critical conversations, the apps they depend on, the concept they create and share, all using the new mobile devices that they are carrying around in their hand. They want to **collaborate without the cost**, complexity and flexibility and overall enterprise dead weight of enterprise software, hardware and data centers.

---

# Social Context = Knowledge ?

## A New Mathematical Model of Horse Racing

- Assume, without the loss of generality, that each horse in the horse racing is modelled by a wooden ball of radius  $R_i$ .



= a ball ? 😊

---

## What kind of knowledge?

- As a knowledge – “the social context” – is a rather “weak” knowledge as compared to “traditional” ontologies
  - *some nodes actually represent multiple concepts, like the tag BP could stand for Blue Pages, British Petroleum and a lot more, different nodes should actually be merged into one (remember Wikipedia moderators comments?), etc).*
- However, “the social context” is up-to-date knowledge about a universe (like Facebook) which changes every second. Therefore as a resource for processing of messages on Facebook it is better than an ontology
  - which has no concepts of Web, Blog, Wiki, and is not populated with instances of global multinationals (Microsoft, Google), influential people (Barak Obama, Tim Berners-Lee, ...),
  - and doesn’t know my friends and colleagues,
  - and doesn’t know concepts within the scope of my interests

---

## Weak knowledge ☹️

- Social knowledge is a weak knowledge.
- The knowledge encoded in ontologies is the truth ?
  - *"the truth, the whole truth, and nothing but the truth"*
- *Probably not*
  - *After many years as an expert, I've become more and more uncomfortable about swearing to tell the truth, the whole truth and nothing but the truth, especially when I've looked back on cases in which two experts have said exactly the opposite and one's bound to ask which one was telling the truth? ...*

Professor Max Sussman, The Expert Witness Institute
  - *The truth is rarely pure and never simple.*

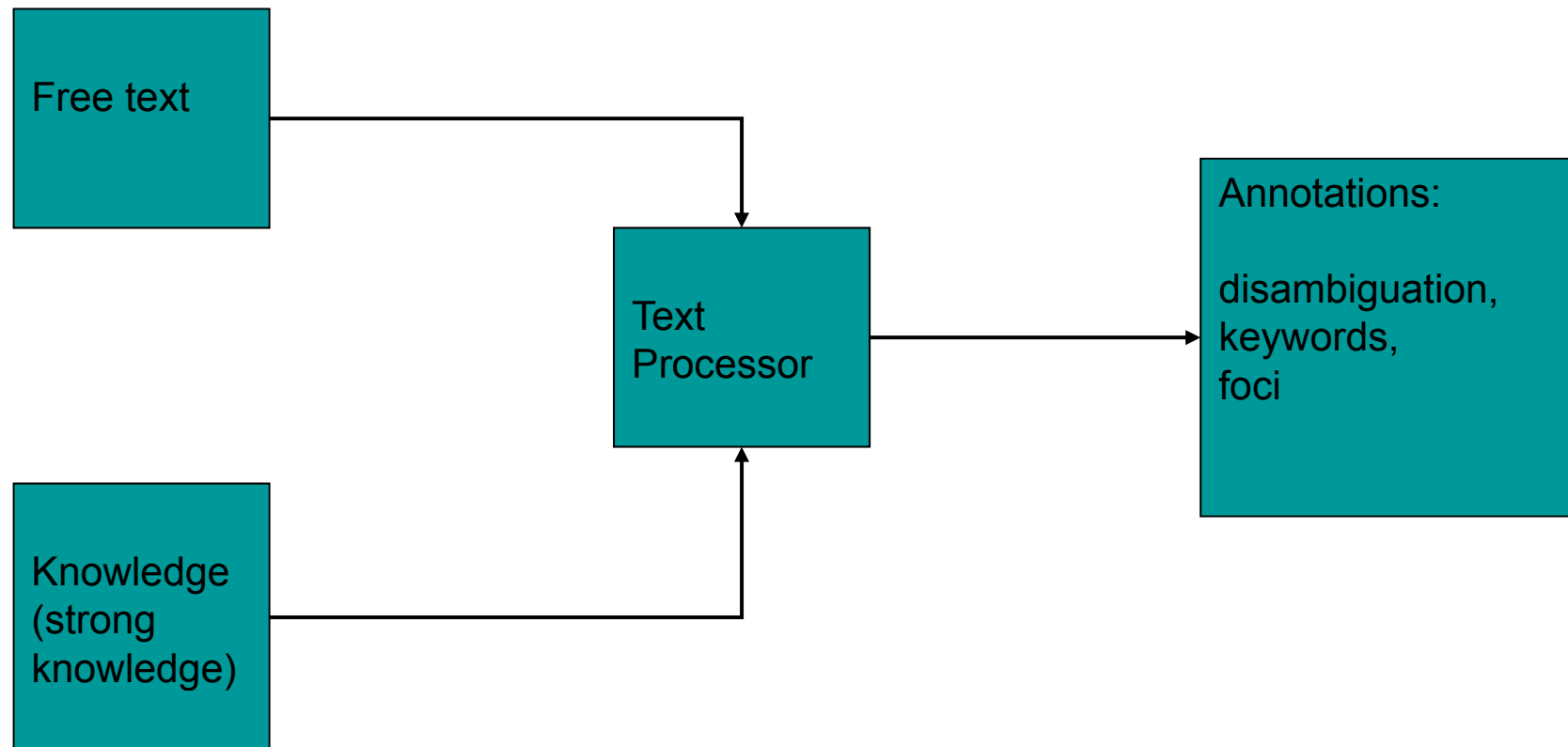
Oscar Wilde, Irish dramatist, novelist, & poet

---

How such knowledge could be used for text analytics

---

## Traditional knowledge-based text processing

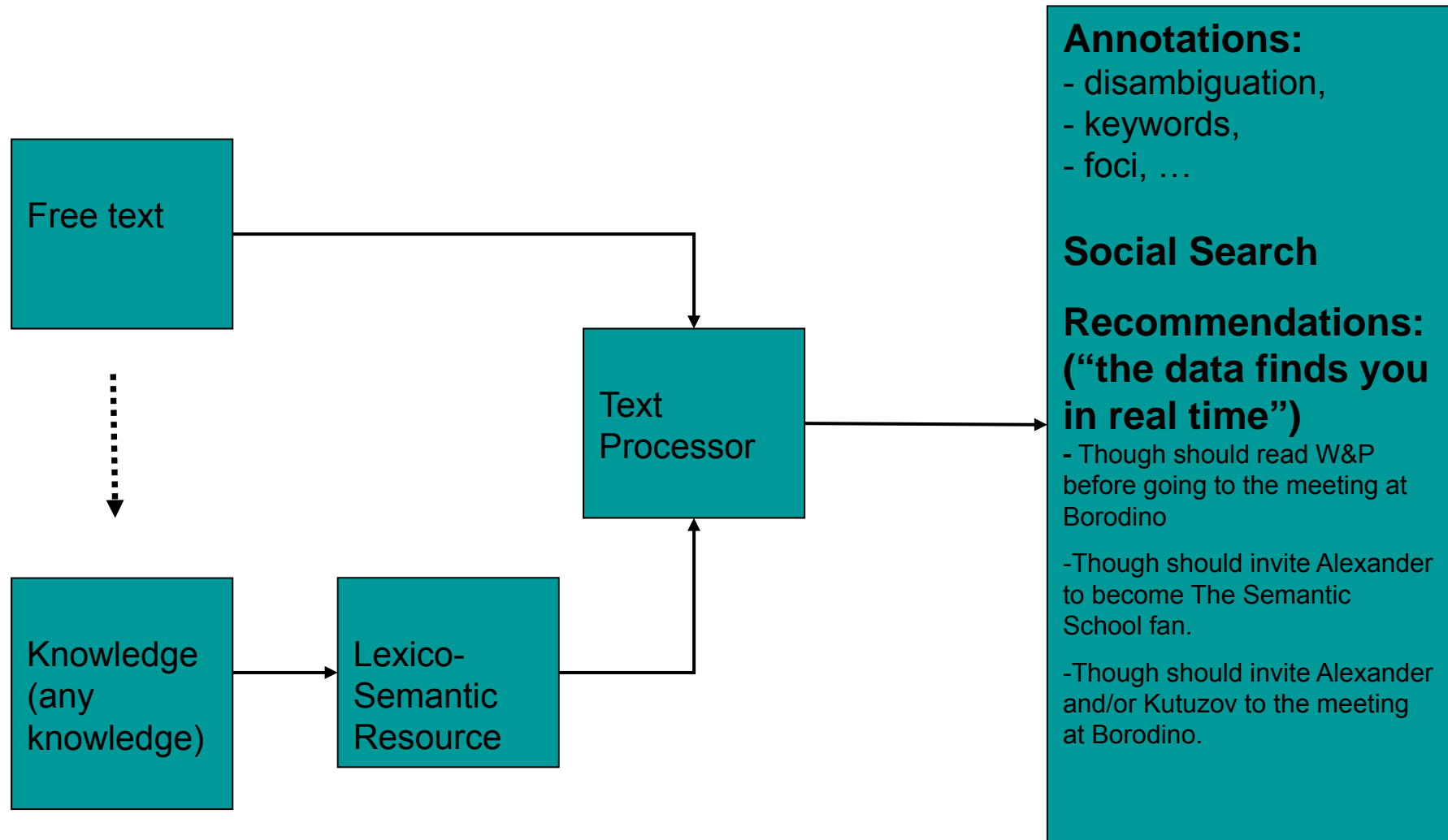




## If weak knowledge is a good knowledge?



- COLONS ~ ONTOLOGIES
- SEMICOLONS ~ SOCIAL CONTEXT
- Suitable capital fonts and colons are hard to find, while small fonts and semicolons are now in abundance and DO JUST FINE if properly used.



---

## New types of text annotations are needed

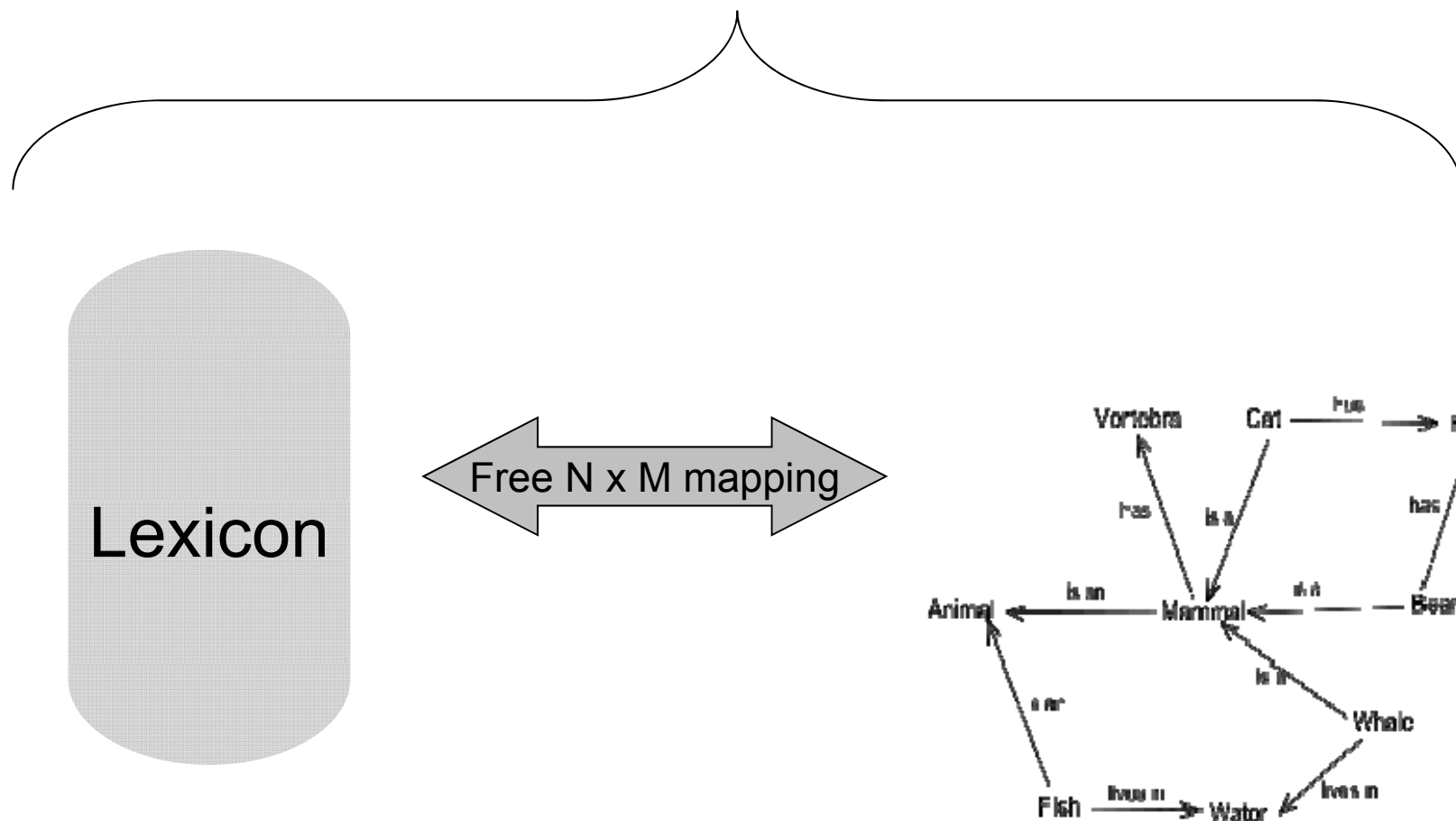
- Semantics
- Social
- Activities management
  - This is about evocation, “getting things done”, action management, etc

---

## Knowledge and Lexico-Semantic Resources

# Layered organisation

Layered organisation of lexico-semantic knowledge  
for automatic text processing

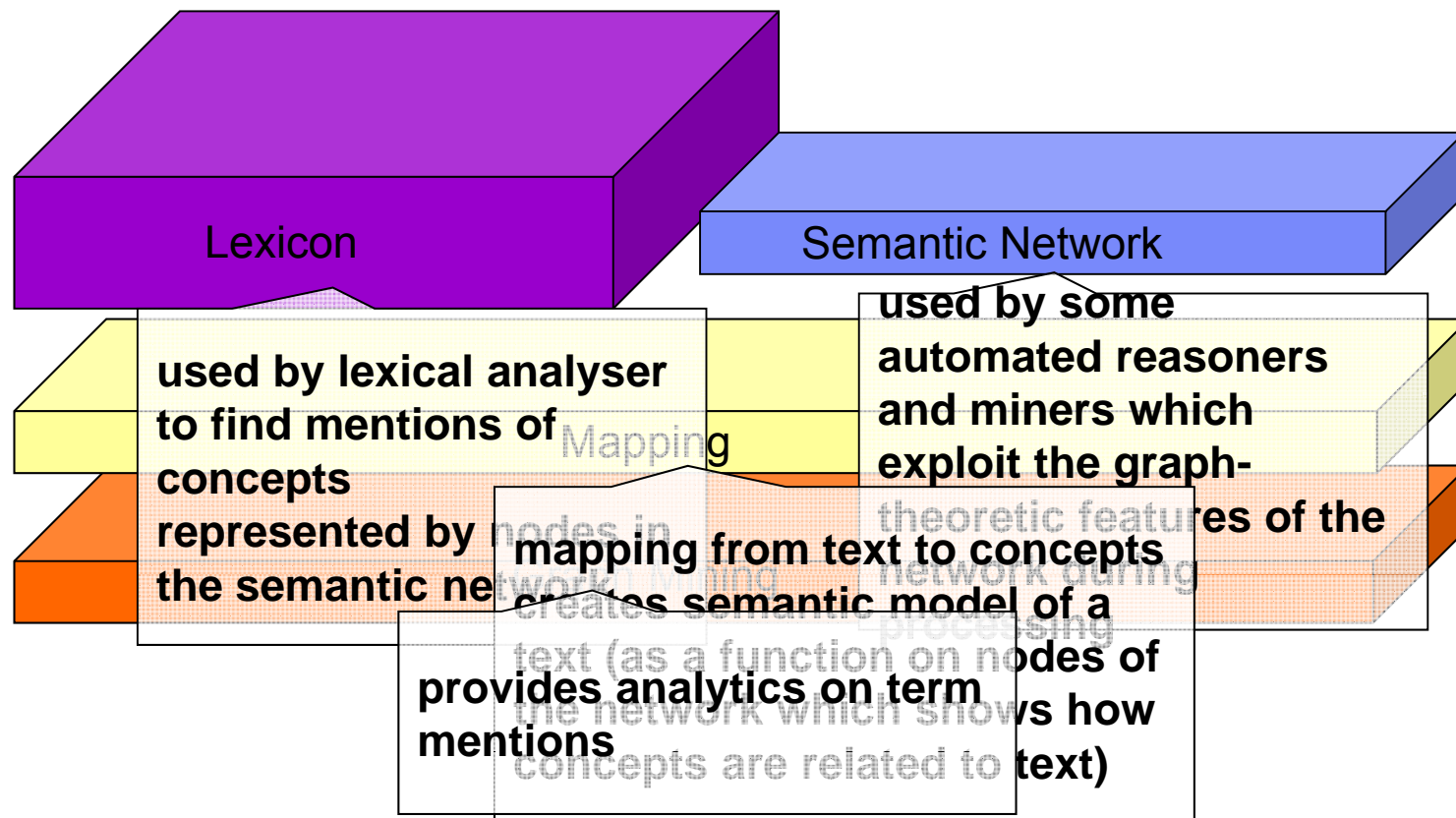


---

## Layered organisation

- Key principles of the organization of lexico-semantic knowledge into a lexically enriched ontology for automatic text processing implemented in IBM Galaxy:
  - Use of two layers: lexical entries and concepts
  - No distinctions between conceptual layer and instances layer
    - which are merged into semantic network
  - Labels != lexical entries
  - Lexical entries – any names of concepts, terms, MWU, ...
  - Free  $N \times M$  mappings between lexical expressions and concepts

... and processing resources



---

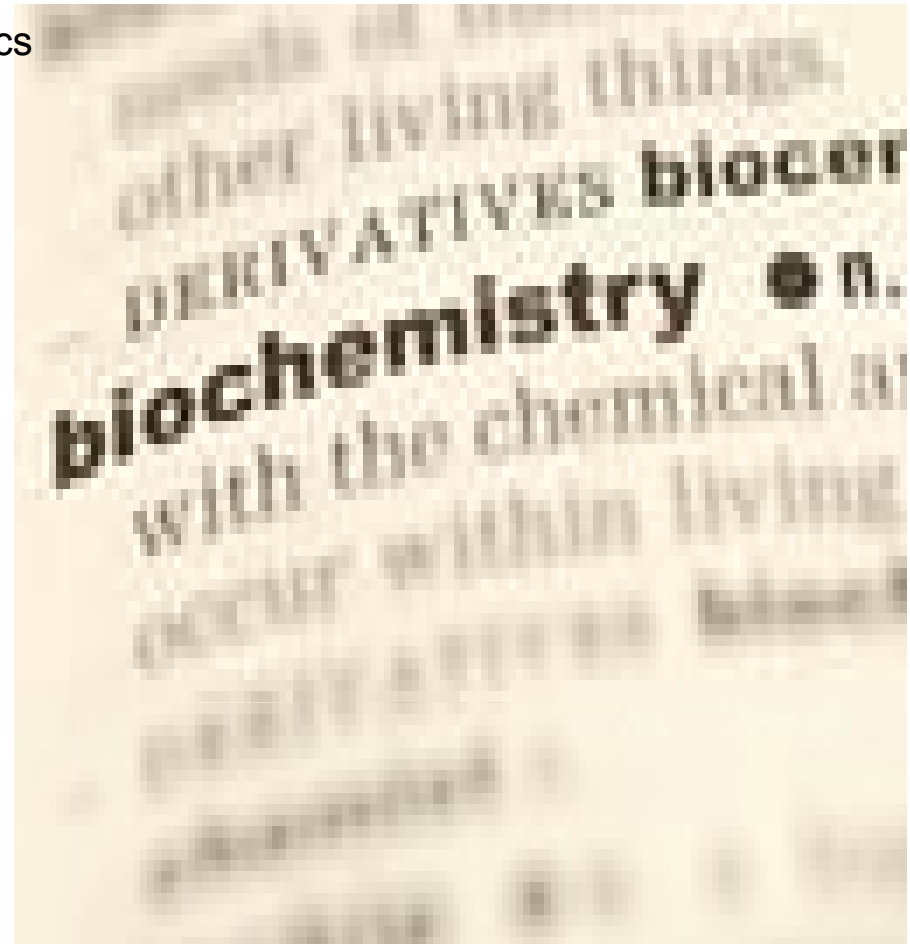
# Text processing



---

## Knowledge-based text processing

- IBM library Galaxy is an example of robust analytics on term mentions
- Galaxy as a product for semantic text analysis:
  - Reads the text
  - Memorises all the concepts
  - Uses networks of words to analyse which concepts sit well together
- Text which mentions  
*Mulhuddart, Lansdowne, Clontarf*  
is probably about  
*Dublin / Ireland / Europe*



---

## Semantic Function Space Models for Texts

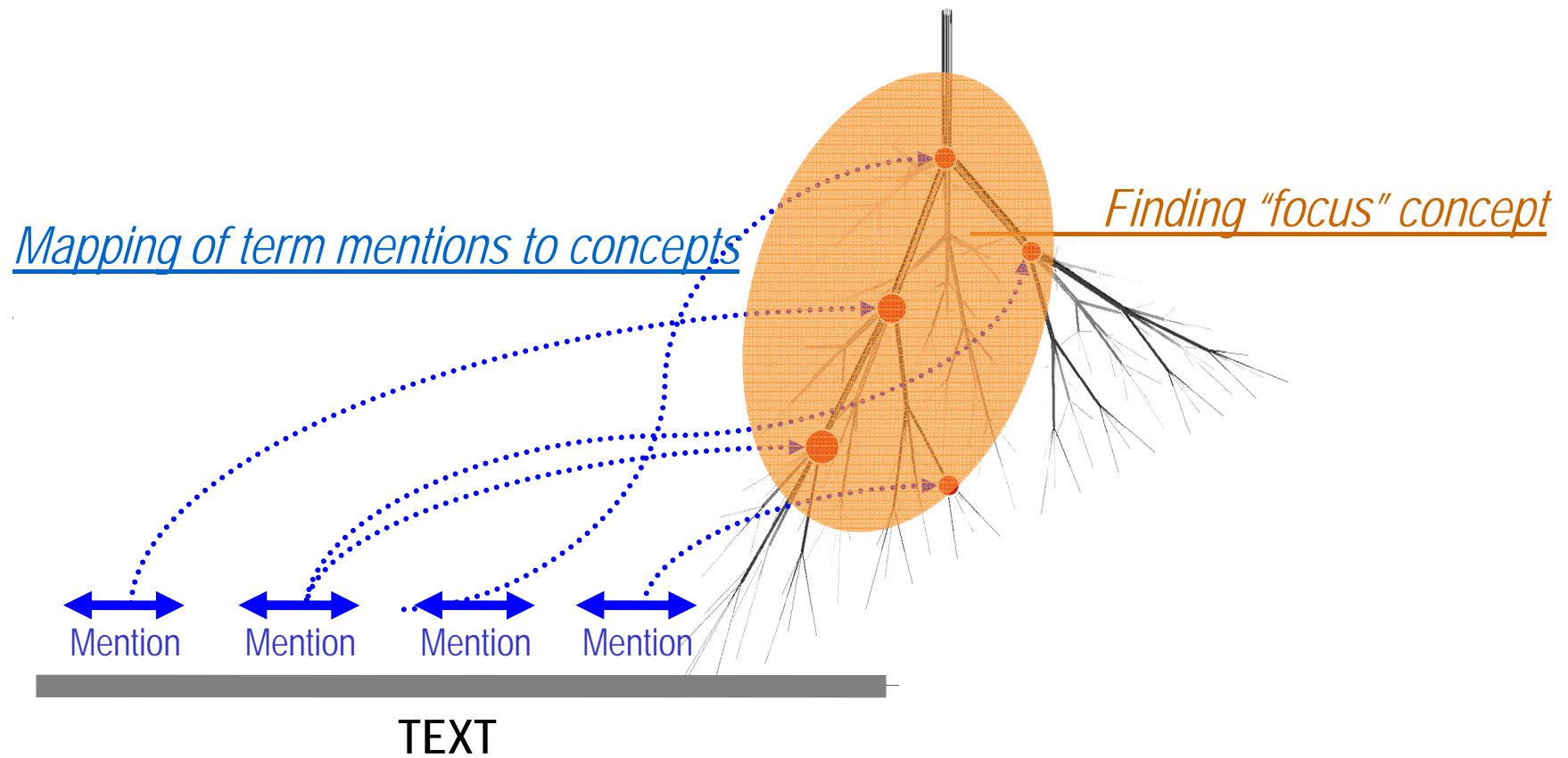
---

## Semantic Function Space Models for Representing Text Documents

- TRADITIONAL: Vector Space Model (VSM)
  - Traditional Vector Space Model of Information Retrieval
- NOVEL: Semantic Function Space Model
  - Model we introduce which covers Vector Space Models and is somewhat similar to it
  - However, VSM is an algebraic model,
  - while Function Space Model can be studied by the methods of function analysis: make function more smooth, find local maximums, etc. involving graphmining

## How it works: modelling and mining

### NETWORK OF CONCEPTS

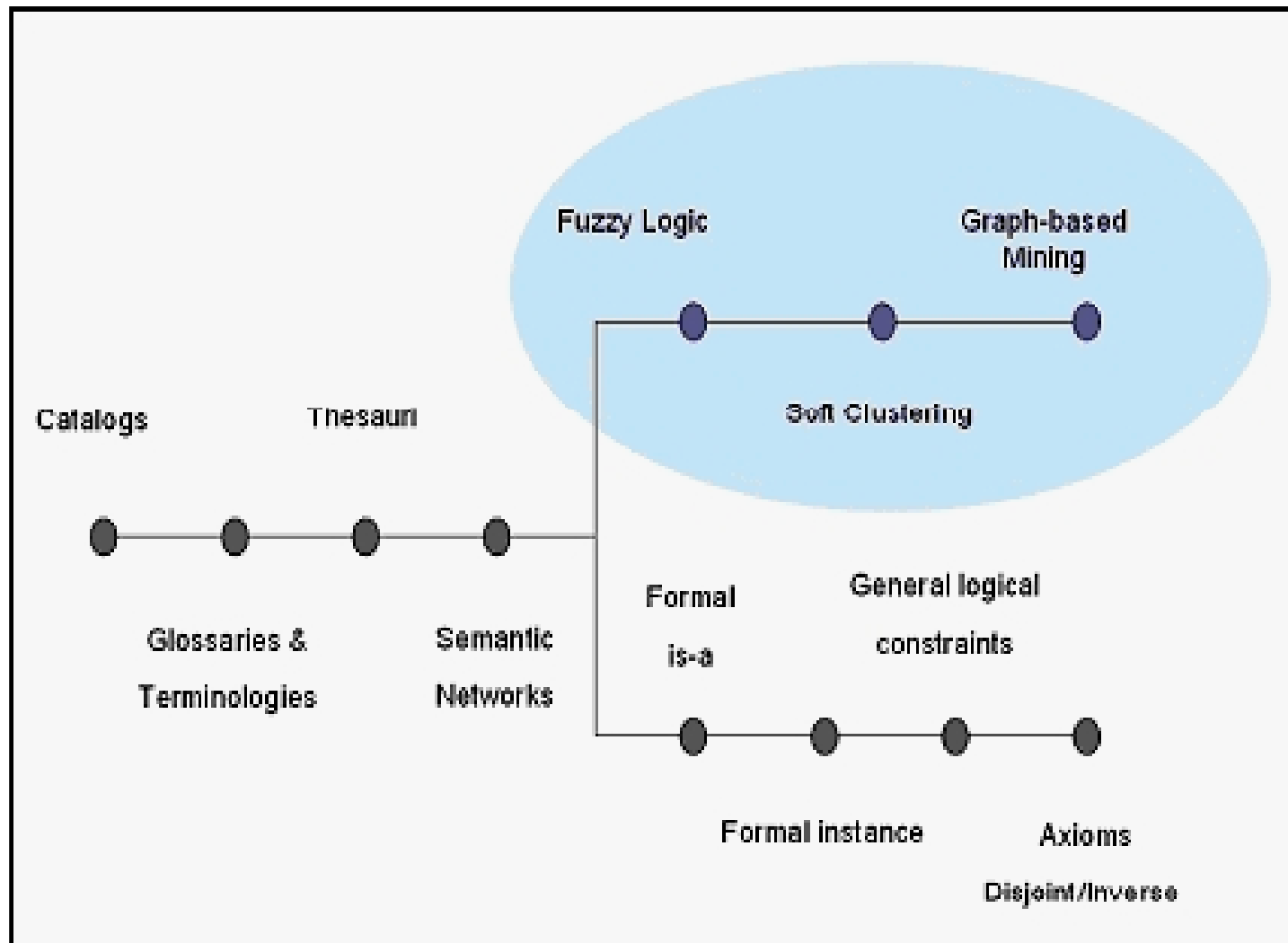


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## Semantic Function Space Model

- We model a text by mapping term mentions onto the knowledge network
- Cohesive coherent text is different from random list of terms. Smoothing the function helps to understand topicality, finding local maximums helps us to see the foci of the text
- Later we will talk about diffusion processes which allow to “smooth” the model

## Graph-based approach to use “knowledge”



---

## “Strong” and “Weak” Knowledge

---

## What Knowledge should we use for text analytics?

- It depends ...
- and this question should be properly addressed only in the view of the traditional dichotomy between top-down and bottom-up approaches in knowledge management



---

## Good knowledge

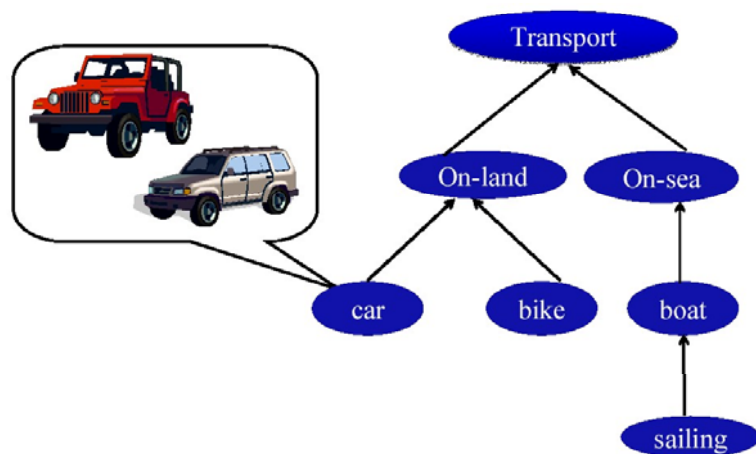
- Should be relevant to the domain of the discourse
- Should know the realities of the domain
- Should be up-to-date

---

## Where we can find “the right” knowledge?

- Where we can find “the right” knowledge for text processing?
  - Right for the domain
    - Knowledge about Symantec Client Firewall is not suitable to process W&P
  - Right for computers
- In the Social Knowledge

## NLU as inferencing



The concept of a car is relevant to a text.

Car IS-A “on-land travel” (?)

Therefore “on-land travel” is somewhat relevant to the text, ...

---

## NLU as an inferencing

The notion of relevancy ( text – concept “car”) with some ad hoc measure is introduced (explicitly or implicitly)

The concept of a car is relevant to the processed text

inferencing is used to propagate this relevancy measure to other concepts

“car” IS A “on-land travel” ? Therefore “on-land travel” is somewhat relevant, ... (ok)

### Problems

“car” IS A “on-land travel”, “bike” IS A “on-land travel”

Therefore “bike” is relevant (?)

“Napoleon” IS A “person”, “Newton” IS A “person”

Therefore “Newton” is relevant (???)

When the knowledge is “weak” -problems with inferencing become severe

### Solutions:

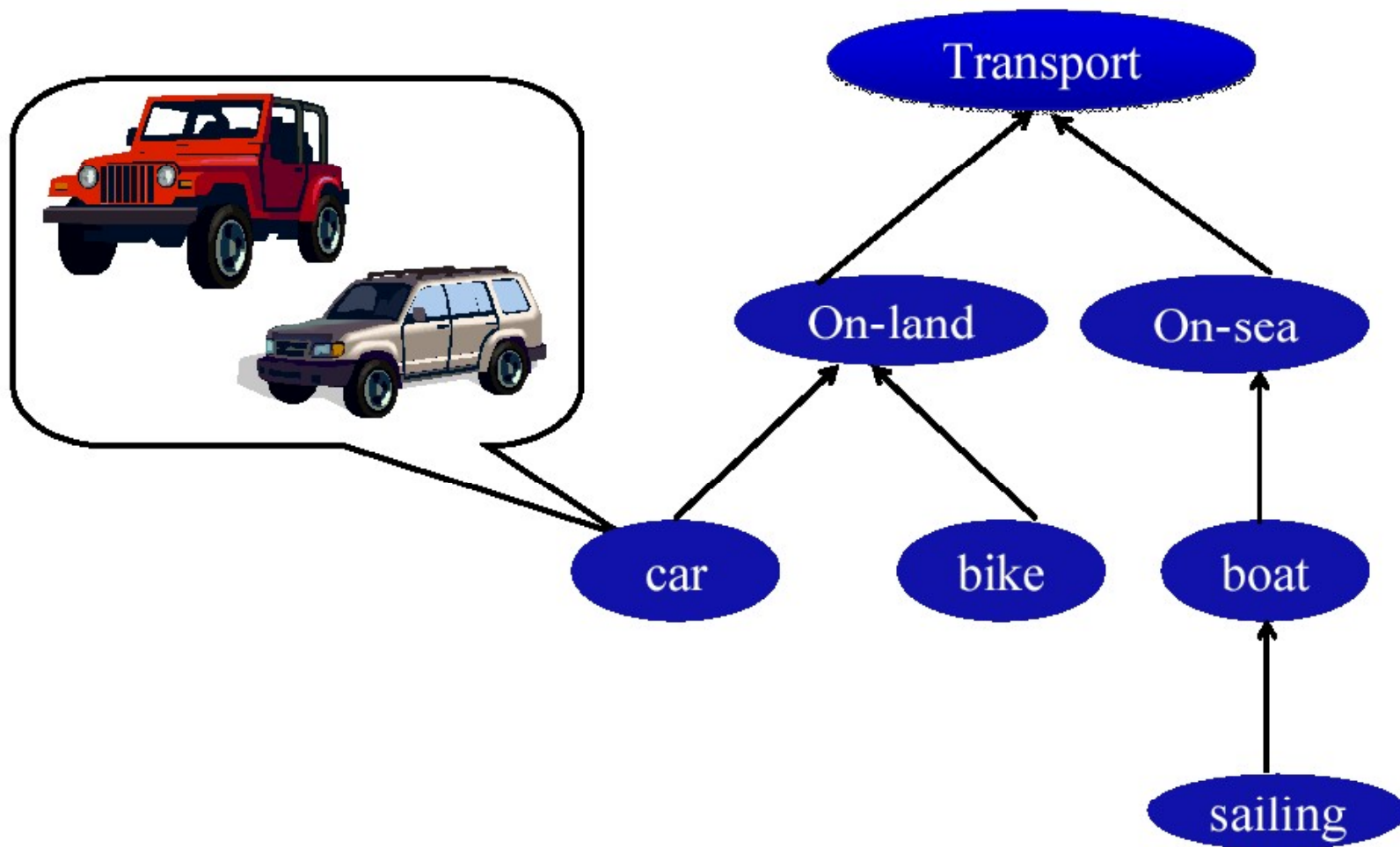
- fuzzy logic

- look for inspiration from other domains:

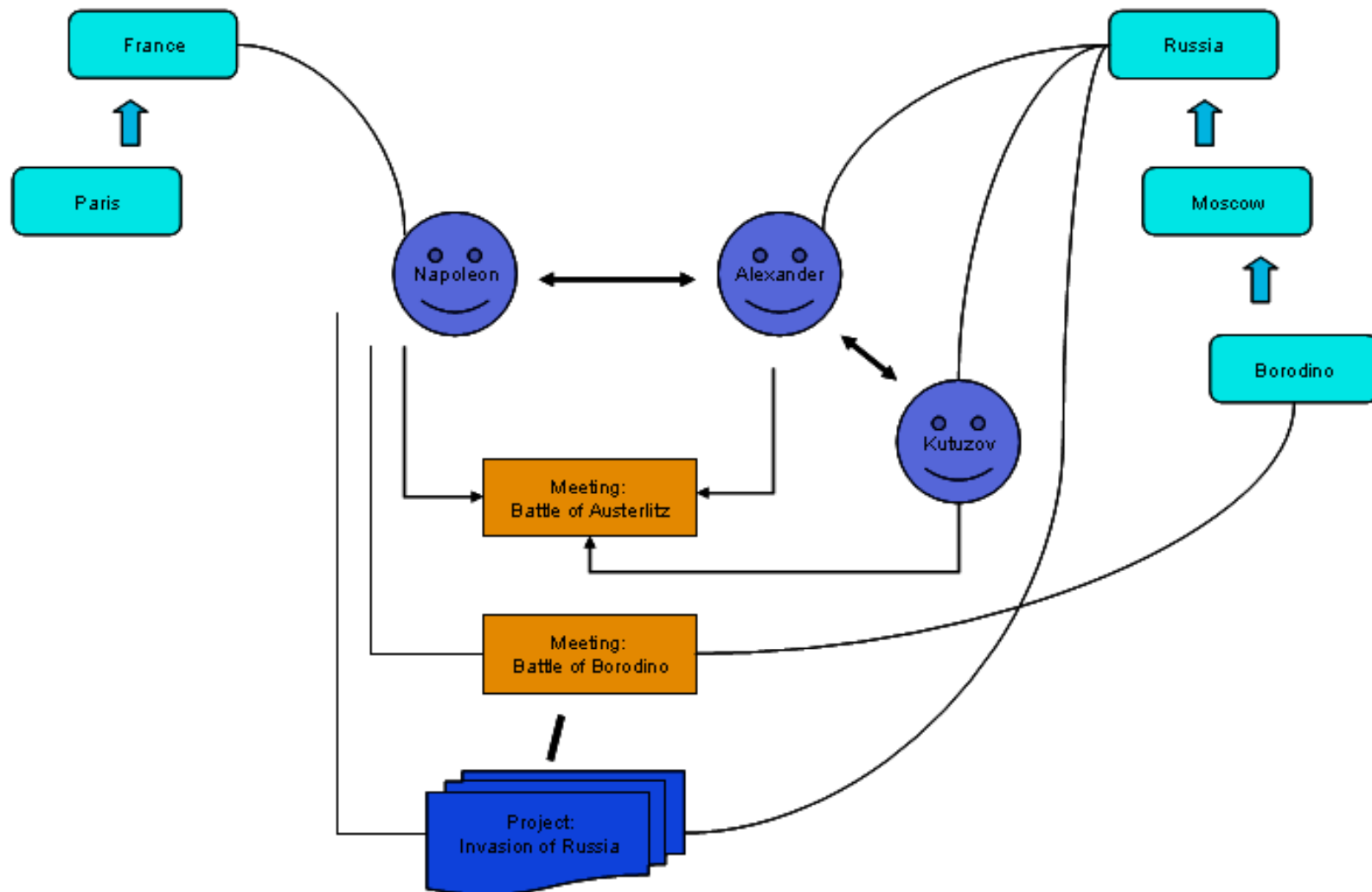
- including the use of diffusion methods to propagate

- trust, knowledge, information, deceases, ...

## NLU as inferencing



## NLU as inferencing



---

## Diffusion like methods

- Diffusion –
  - the spread of social institutions (and myths and skills) from one society to another
  - (physics) the process of diffusing; the intermingling of molecules in gases and liquids as a result of random thermal agitation
  - the act of dispersing or diffusing something ("The diffusion of knowledge")
- Diffusion methods are actively used for trust, risk, web-page importance propagation.
- Following this approach:
  - “car” – relevancy 1.0
- we propagate the relevancy measure
  - “on-line transportation” – relevancy 0.5 (or 0.9, or 0.1)
  - Etc

---

## Diffusion like methods (cont.)

- Diffusion-like methods are increasingly applied to social networks, hyperlink structures on the Web, electric grids etc.
  - functioning of many networks in nature is defined mainly through elementary interactions between primitive elements.
- At the same time, many of the measures in network analysis have very different interpretations in networks of different kinds.
  - Interpretations of these measures should take into account demonstrate how to make these methods aware of dimensions of networks where people are involved, including social, semantics, and activity management dimensions.
  - In the following, we will also talk about networks in general, but it should be clear from the text that many of the measures in network analysis can only be strictly interpreted in the context of social networks or have very different interpretations in networks of other kinds.



## Diffusion-like methods



- Spreading activation is one of the diffusion-like methods. The algorithm is inspired by the phenomena observed in the nervous systems of living organisms
- In physical analogy we replace the notion of activation by the notion degree of illumination and spread of activation by the notion of light propagation
- Each node of interest within the graph emits an amount of “light” which propagates around the graph along its links
- “Light” from multiple sources combines eventually leading to a point which is illuminated to a greater degree
  - Physical analogy allows to see that the most illuminated nodes are not necessarily those nodes which were originally chosen as light emitters, but rather the overlapping areas
- This is from known to unknown, from seen to unseen  
“Je ne cherche pas, je trouve”

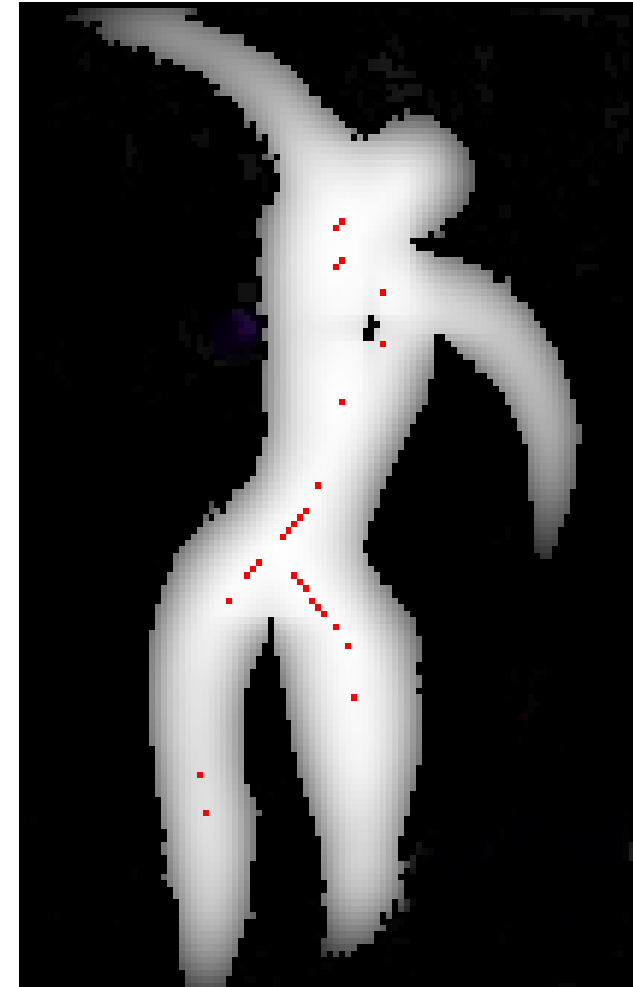
Pablo Picasso

---

## Are capable to analyse massive networks

- Detect structure of networks at different time slices
  - With complex topology (not necessarily “grids” as in image processing)
- Applications:
  - trend analysis, risk assessment
    - The component “left leg” became more prominent
    - The component “Head” become less prominent

*Numerical simulation on the scanned image with 6000 pixels done by IBM Galaxy tool*



# Applications of network flow graph-based methods for mining and using network models of social context



---

## Previous art in use of network models of weak knowledge

- Troussov et al. "Social Context as Machine-Processable Knowledge" MITACS FP-Nets Workshop on Social Networks, August 2010, Vancouver, Canada.
  - We examined previous art in use of network models of weak knowledge (see the list on the next slide)
  - We found (demonstrated) that graph-based methods used there were used mainly for fuzzy inferencing and soft clustering.
  - and we created a set of “atomic” network flow operations
  - Which allow to generalize the approach taken in previous art

---

## Summary and Conclusions (Cont.)

- The same methods actually perform well with simplified multidimensional network models of instantiations of ontologies without the need for encoding the rules how to use proper conceptualisation
- We revised previous art in use of network models of weak knowledge, and we described the algorithms and the architecture of the hybrid recommender system in the activity centric environment Nepomuk-Simple (EU 6th Framework Project NEPOMUK):
- The applications constituting previous art were monolithic software applications. In this paper we present a novel computational paradigm which breaks these applications into “atomic” components, where the computational methods for propagation are separated as distinct “atomic” network flow engines. This approach provides a unified view of previous applications. From the software engineering prospective the advantages of such an approach includes easy software maintenance, reuse and optimization of network flow engines, and the guide for new applications.
  - We created a set of “atomic” network objects
  - And the set of network flow-based operations with such objects
  - And described efficient scalable implementations of such operations.
- Performance – subsecond for networks with several hundreds K nodes

---

## Representing knowledge

- There are a number of options:
  - As *objects*, using the well-accepted techniques of object-oriented analysis and design to capture a model
  - As *clauses* going back to the early days of AI and Lisp
  - As *XML*, using the industry-standard structured mark-up language
  - As *graphs*, making use of the things we know about graph theory
  - As some combination of these
- We are looking for
  - Extensibility
  - Easy of merge heterogeneous information
  - Ease of use
- And our choice is - GRAPHS
  - Knowledge is represented by a multidimensional network which is modeled by a graph
  - And the Nepomuk-Simple will give us examples of extensibility/Easy of merge heterogeneous information/Ease of use
-

---

## Graphs

- We can use the nodes of a graph for facts, concepts, people, organisations, etc and the arcs as binary relationships between them
  - Arcs are typically called predicates or relationships in this view
  - The set of arcs intersecting a node tells us the information we know about the fact or entity

---

## Nepomuk

- NEPOMUK (Networked Environment for Personalized, Ontology-based Management of Unified Knowledge) is an open-source software specification that is concerned with the development of a social semantic desktop that enriches and interconnects data from different desktop applications using semantic metadata stored as RDF.
- Initially, it was developed in the EU 6th framework integrated project Nepomuk (2006-2008) - 17 million euros, of which 11.5 million was funded by the European Union
- Partners
  - German Research Center for Artificial Intelligence DFKI GmbH Germany
  - International Business Machines (IBM) Ireland
  - SAP AG Germany
  - Hewlett-Packard Galway Ltd Ireland
  - Thales SA TRT France
  - PRC Group The Management House S.A Greece
  - Mandriva Edge-IT France
  - Cognium Systems SA France
  - National University of Ireland, Galway Ireland
  - Ecole Polytechnique Fédérale de Lausanne Switzerland
  - Forschungszentrum Informatik an der Universität Karlsruhe Germany
  - L3S Research Center Germany
  - Institute of Communication and Computer Systems of the National Technical University of Athens, Greece
  - Kungliga Tekniska Högskolan Sweden
  - Università de la Svizzera Italiana Switzerland
  - Irion Management Consulting GmbH Germany



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## Nepomuk hybrid recommender

- We present the architecture of the hybrid recommender system in the activity centric environment Nepomuk-Simple (EU 6th Framework Project NEPOMUK).
- “Real” desktops usually have piles of things on them where the users (consciously or unconsciously) grouped together items which are related to each other or to a task. The so called “Pile” UI, used in the Nepomuk-Simple imitates this type of data and metadata organization which helps to avoid premature categorization and reduces the retention of useless documents.
- Metadata describing the user data are stored in the Nepomuk personal information management ontology (PIMO). Proper recommendations, such as recommendation of additional items to add to the pile, apparently should be based on the PIMO, on the textual content of the items in the pile. Although methods of natural language processing for information retrieval could be useful, the most important type of textual processing are those which allows to related concepts in PIMO to the processed texts. Since PIMO changes over the time, this type of natural language processing can’t be performed as preprocessing of all textual context related to the user. Hybrid recommendation needs on-the fly textual processing with the ability to aggregate the current instantiation of PIMO with the results of textual processing.
- Representing and modeling this ontology as a multidimensional network allows to augment the ontology on the fly by new information, such as the “semantic” content of the textual information in user documents. Recommendations in the Nepomuk-Simple are computed on the fly by graph-based methods performing in the unified multidimensional network of concepts from the personal information management ontology augmented with concepts extracted from the documents pertaining to the activity in question. In this paper, we classify Nepomuk-Simple recommendations into two major types. The first type of recommendations is recommendation of the additional items to the pile, when the user is working on an activity. The second type of recommendations arises, for instance, when the user is browsing Web; the Nepomuk-Simple can recommend that current resource might be relevant to one or more activities performed by the user. In both cases there is a need to operate with Clouds (fuzzy sets of PIMO nodes): Clouds describe topicality of documents in terms of PIMO, the pile itself is a Cloud.

# Pile UI

Nepomuk – Your Semantic Desktop

NepomukSimple

CID project CID shared

Task prototype (Pile)

Dirk Hageman (Person)

cidpeople.png (Image)

Open Print Share

Reset Image Fileinfo Person Calendar Music Tag Message All details

☒ Group by subjects ☐ High metadata Order by Subject

|             |                      |                                       |
|-------------|----------------------|---------------------------------------|
| CID project | preferred label      | CID project                           |
| D8.2 CID    | belongs to container | 2008                                  |
|             | file last modified   | Friday, 31 October 2008 17:11:01 CET  |
|             | file name            | D8.2 CID project meeting – report.doc |
|             | file size            | 125440                                |
|             | has topic            | Claudia                               |

CID project Add tag

Search Pile Recommendations Timeline Google Maps

| Suggestions for adding to this pile: | Relevance |
|--------------------------------------|-----------|
| CID shared                           | +++++     |
| Claudia                              | +++++     |
| London meeting                       | +++++     |
| CID_logo.png                         | +++++     |
| Preliminary tasklist                 | +++++     |
| Klaus                                | +++++     |
| Prototypes task                      | +++++     |

98 triples

## Nepomuk use case: activity management

A user started to work on a new project CID. Using the Nepomuk SSD, she collects a “pile” of resources she needs while working on the project: *MS-Word documents, contacts, etc* by drag-and-dropping resources from her desktop, by linking resources from e-mail (Mozilla Thunderbird) and web browser (Firefox) applications.

| Suggestions for adding to this pile:  | Relevance |
|---------------------------------------|-----------|
| CID shared                            | +++++     |
| Integrated project proposalIST Call 4 | +++++     |
| Claudia                               | +++++     |
| CID_logo.png                          | +++++     |
| London meeting                        | +++++     |
| Klaus                                 | +++++     |

## Nepomuk use case: activity management

The screenshot shows the Nepomuk application window titled "Nepomuk - Your Semantic Desktop". The interface includes a menu bar (Nepomuk, File, Pile, Resources, Developer, Actions, Window, Help) and a toolbar with icons for NepomukSimple and PIMO. The main area displays a "Pile" of items, including "meeting minutes - CID" (Word Document) and "D8.2 CID project meeting - report" (Word Document). A sidebar on the left shows "Dirk Hageman" (Person) and "cidpeople.png" (Image). A red speech bubble highlights the text: "Galaxy (IBM hybrid recommender) analyses the pile content and linkage structure as a multidimensional network of concepts extracted from documents and links between concepts, projects, project participants, meetings, document authors, ... and provides handy recommendations of resources she might possibly need". At the bottom, a red-bordered pane titled "Suggestions for adding to this pile:" displays a table of recommendations.

| Suggestions for adding to this pile:  | Relevance |
|---------------------------------------|-----------|
| CID shared                            | +++++     |
| Integrated project proposalIST Call 4 | +++++     |
| Claudia                               | +++++     |
| CID_logo.png                          | +++++     |
| London meeting                        | +++++     |
| Klaus                                 | +++++     |



## Nepomuk use case: activity management

The screenshot shows the Nepomuk web interface. The main content area displays a wiki page titled "Claudia: Appointment". The page text includes a goal: "Goal: To organise an appointment (Previous Scenario - First Draft Not Valid Anymore)". It describes a scenario where Dirk's schedule is full, and he needs to meet Claudia. The text mentions "CID" (Context Identifier) and "WP3000". A red speech bubble with a grey background and a red border contains the text: "Galaxy can spot what the user might miss: 'This web page might be relevant to your CID activity' - Galaxy is very fast (hundreds of msc for most of the applications)". A red rectangular box highlights the bottom status bar, which shows "CID\_shared" followed by a series of plus signs and a blue icon.

Galaxy can spot what the user might miss:  
"This web page might be relevant to your CID activity"  
- Galaxy is very fast  
(hundreds of msc for most of the applications)

## Pile recommendation for a webpage

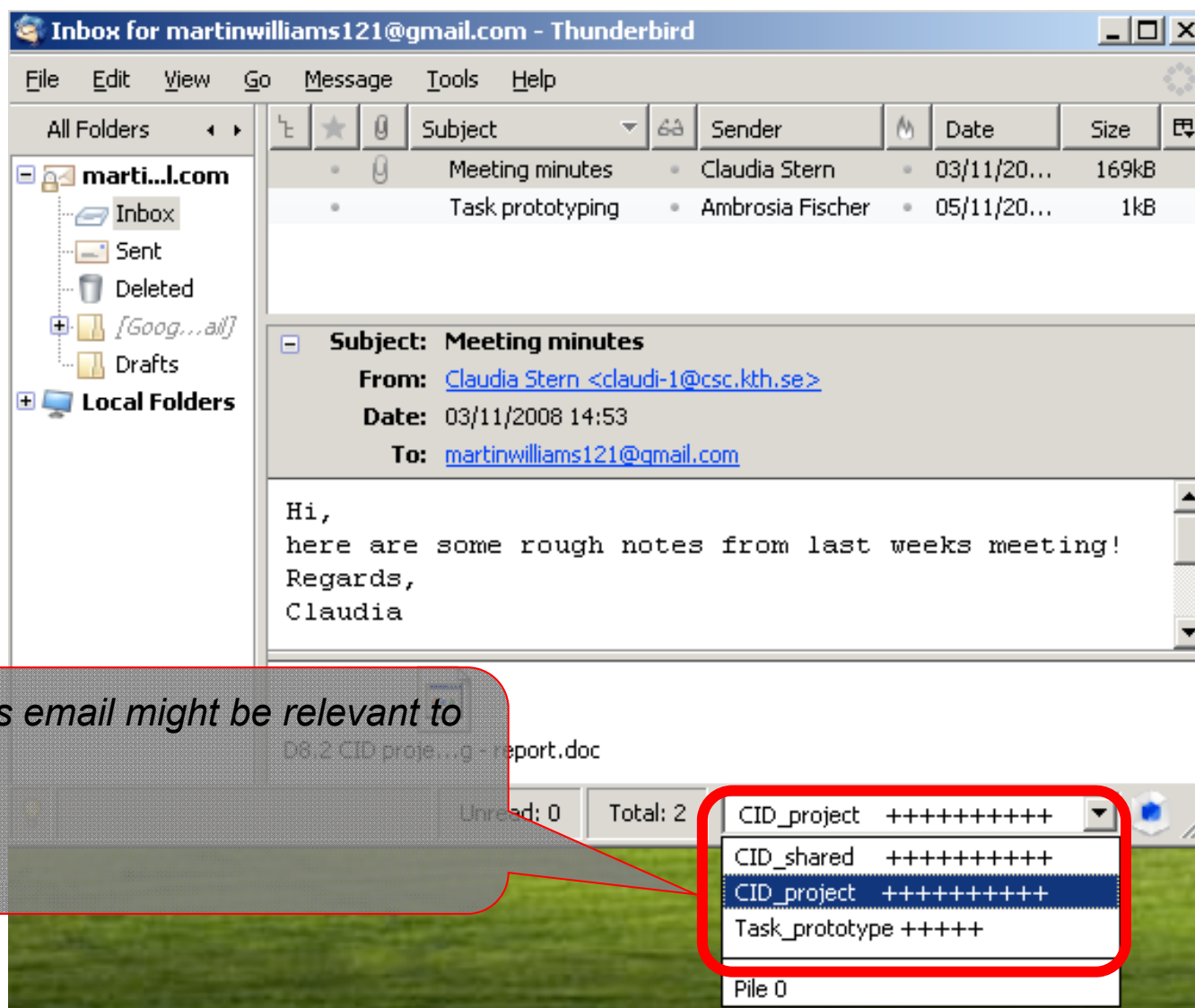
The screenshot shows a web browser window displaying the NEPOMUK application. The browser's address bar shows the URL `http://nepomuk.semanticdesktop.org/xwiki/bin/view/Main/DirkPlanTimeForWork`. The NEPOMUK logo is visible in the top left, and the Information Society Technologies logo is in the top right. A navigation bar contains links like Home, News, Wiki, IST, What's New, Search, Help, ParLannero, and Logout. Below the navigation bar, there are links for editing the wiki page: Edit (wiki), Edit objects, Rename, Add an attachment (1), History, and Print.

The main content area is titled "Claudia: Appointment". It features a goal statement: "Goal: To organise an appointment (Previous Scenario - First Draft Not Valid Anymore)". Below the goal, there is a paragraph of text describing Dirk's schedule and a meeting invitation from Claudia. A timeline diagram is shown at the bottom of the main content area, with stages: Idea, Proposal done, Kick-off, D1, D2, and Done. A red dot is placed on the D1 stage.

On the left side, there is a sidebar with a list of links under the heading "NEPOMUK". The links include Consortium, Calendar, Mailing lists, Slides template, Deliverable templates, Wiki guidelines, Wiki wish list, Publications, Tag manager, All pages, and Document manager. Below this, there is a "Tags" section with a list of tags: Bbitem, ChatLog, CleanMe, Component, ContributeNow, Deadline, Definition, Deliverable, DeliverableDraft, Demo, Demo2008, Deprecated, DesignIdea, DisseminationMaterial, Draft, Eclipse, ExternalPartner, FinalReview08, FunctionalRequirement, Functionality, Meeting, Minutes, NonFunctionalRequirement, Organization, Person, Persona, PhD, Prototype, Scenario, School, Security, Summer, Task, TaskForce, Telco, and TeleCon.

On the right side, there is a sidebar with two sections: "Page tags" and "Backlinks". The "Page tags" section contains a list of tags: WP3000, Scenario, and WP10000. Below the tags is a text box containing the text "WP3000|Scenario|WP10000" and an "Update tags" button. The "Backlinks" section contains a list of links: Hugo: Organizing his time, High-level Functionalities, Scenario, Design idea: Overview, Check required time, Task Planning, Shared information wrt meetings, Design idea: Perspective, Compute and Configure Relevance Prototype, Requirements Material for TF-Functionalities, Tailor, TF-Functionalities Group 4, Desktop Sharing, Query Related Items, and Dirk Hageman.

## Nepomuk use case: activity management



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## Network flow methods

- Social context modeled as a multidimensional network can be used as an efficient machine processable knowledge representation for various tasks. The application of this method includes such traditional areas of knowledge usage as knowledge based text understanding, and the recently emerged area of recommender systems.
- We analyse several applications and show that computational methods used in these applications are based on the network flow process, “that focuses on the outcomes for nodes in a network where something is flowing from node to node across the edges” (Borgatti and Everett, M. 2006 ]
- We interpret this “something” as a relevancy measure; for instance, the initial seed input value which shows nodes of interest in the network. Propagating the relevancy measure through outgoing links allows us to compute the relevancy measure for other network nodes and dynamically rank these nodes according to the relevancy measures.
- The same paradigm could be used to address the centrality measurements in social network analysis. Centralisation of the network can be achieved when we assume that all the nodes are equally important, and iteratively recompute the relevancy measure based on the connections between nodes. In addition to “global” centralisation, “local” centralisation could be performed if the initial seed values represent the nodes of interest.



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## Network flow as relevancy propagation / redistribution

- Our definition of a network flow:
  - A discrete process when on each iteration the value of a relevancy measure at a node is recomputed based on the connections between nodes.
- Dual interpretation:
  - Relevancy measure could be interpreted as a membership function which defines the fuzzy set of nodes. In this interpretation the network flow provides transformation of the fuzzy set into the sequence of fuzzy sets (expanding, shrinking,...). When the operation is “expanding” the process is usually called spreading activation.
  - Alternatively, the process is iterative redistribution of the relevancy measure and frequently is the process of computation numerical approximation to the solution of a partial differential equation
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## Network objects – operands of network flow

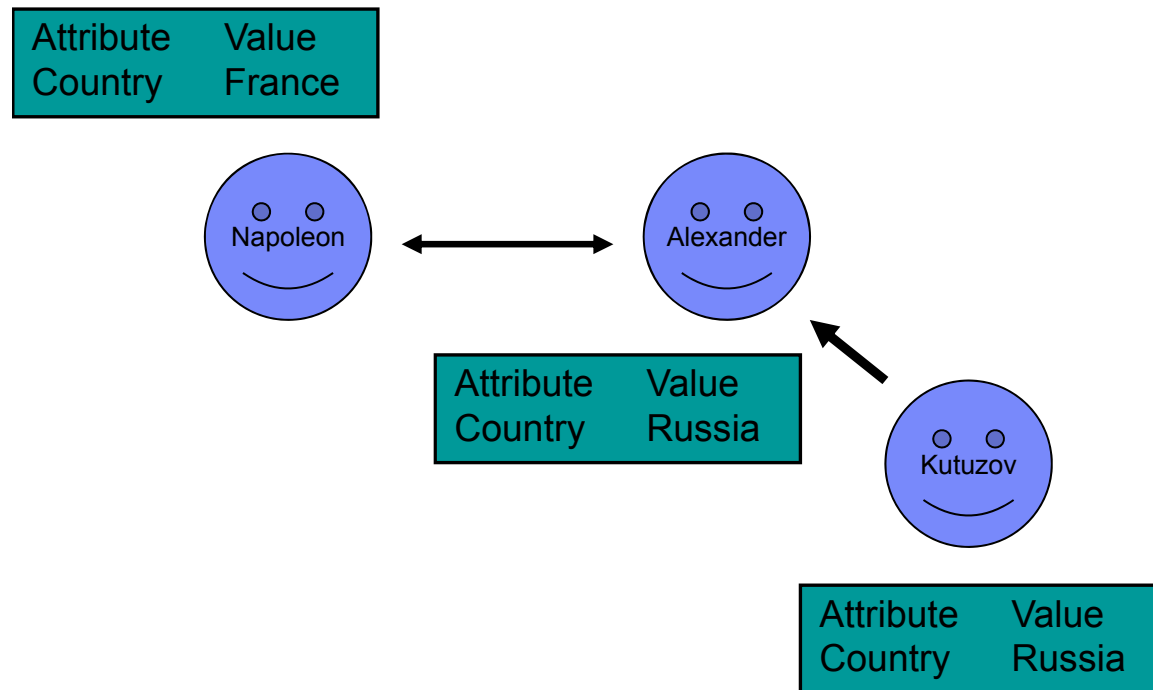
- Object (Network object) – is a node or a (fuzzy) set of nodes on the network . Fuzzy sets are characterized by a membership function  $M$  which shows the degree of belongings of an element to the set.
- We also use term cloud where we want to emphasize the fact that the membership function is non-negative real-valued function, not Boolean valued.

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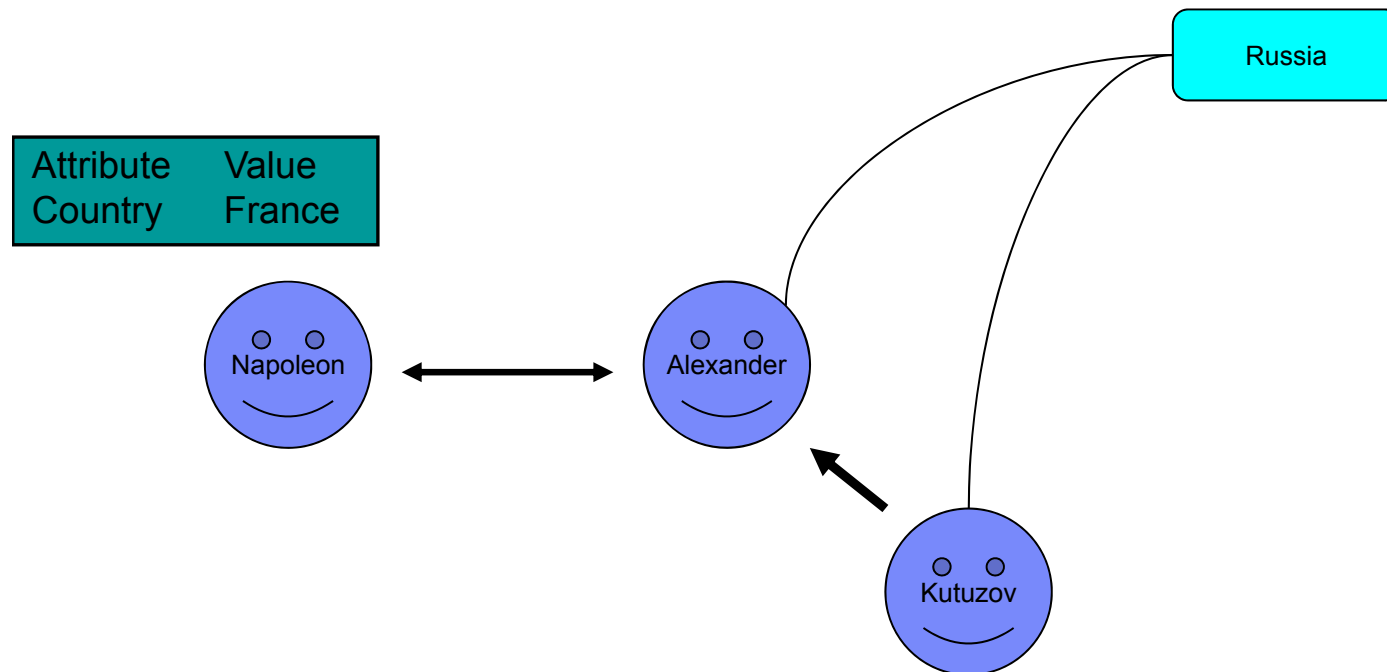
## Clouds

- Clouds per se are not part of the network, although they could be encoded into the topology of the network

## Attribute–value pairs



## Attribute–value pairs → Topology



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## Clouds (cont.)

- Clouds frequently are task specific and created dynamically:
  - Text could be modeled as cloud of concepts from a static semantic network
  - Activities (as in the Nepomuk-Simple)

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## Notations

- *Object* (Network object) – is a node or a (fuzzy) set of nodes on the network. Fuzzy sets are characterized by a membership function  $M$  which shows the degree of belongings of an element to the set.
- $M$  – the membership function for fuzzy sets which is a non-negative real-valued function.
- *Activation* – the membership function when it is not interpreted in the fuzzy sets paradigm. We use the activation (the activation of nodes, or objects) as an abstract relevancy measure.
- *Cloud* (cloud object) – we use the term cloud where we want to emphasize the fact that the membership function is non-negative real-valued function, not Boolean valued. As usual, we assume that a node  $e$  belongs to the fuzzy set  $C$ , or in mathematical notations  $e \in C$  - if  $M(e) \geq 0$ .
- $|\dots|$  - cardinality of sets. In case of clouds we define  $|C| = \sum M(e)$  for all nodes  $e$  such that  $e \in C$ .
- *Query* – an object used as a seed for local ranking (defined below)

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## Operations with one argument

- *Expansion* – is a unary operation which transform a cloud into another cloud: *Expansion*:  $C1 \rightarrow C2$ . If  $C1$  and  $C2$  are crisp sets, we assume that  $C1$  is a proper subset of  $C2$ :  $C1 \subset C2$ . If general, we assume that this operation increases the number of the nodes with non-zeroed membership function values, doesn't change significantly the values of the membership functions on the nodes in  $C1$ , and that  $|C1| \leq |C2|$ .
  - *Useful to compare “sparse” clouds*
- *Smoothing* – is formally the same as expansion, however the interpretation of this operation can't be done in the framework of fuzzy sets, instead, it roots in the operations with functions in calculus. We assume that smoothing makes the difference between the values of the function  $M()$  on neighbor nodes smaller.
  - *a blend of fuzzy inferencing and soft clustering useful for text processing)*
- *Local ranking* - is formally the same as expansion. The purpose of this operation is to get the value of the activation which shows the proximity, or relevance, of objects to a query.
- *Shrinking* – is a unary operation which transform a cloud into another cloud: *Shrinking*:  $C2 \rightarrow C1$ . If  $C1$  and  $C2$  are crisp sets, we assume that  $C1$  is a proper subset of  $C2$ , i.e.  $C1 \subset C2$ . If general, we assume that this operation decreases the number of the nodes with non-zeroed membership function values, doesn't change significantly the values of the membership functions on the nodes in  $C1$ , and that  $|C2| \leq |C1|$ . Shrinking is a kind of inverse operation to expansion, although we don't necessarily assume that for any pair of such operations  $C1 \equiv \text{Shrinking}(\text{Expansion}(C1))$  for each object  $C1$ .



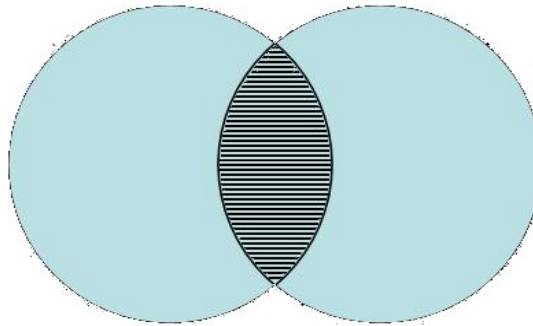
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## Operations with two and more arguments – Similarity, Search

- Similarity (Dissimilarity) of Sets of Nodes and Search for Similar Sets
  - Discussion on the distinction between similarity and proximity of network nodes is outside of the scope of this paper. In this Section we present empirical approach to computation of similarity based on a network flow process. Similarity of network nodes, or more generally similarity of two network objects (like clouds which are fuzzy sets of network nodes) could be described in terms of their ability to affect various parts of the network (like in viral marketing applications. In other words, similarity of two sets  $A_0$  and  $B_0$  should be defined as similarity of two fuzzy sets  $A = \text{Expanding}(A_0)$  and  $B = \text{Expanding}(B_0)$ , where the operation *Expanding* is done by network flow methods compatible with the targeted applications. For instance, if the target applications is in the area of “viral marketing”, than we expect that the *Expanding* is done by network flow methods which model “viral marketing”.
- In section 4.1 we provide additional arguments to justify our approach to similarity and introduce the similarity of two fuzzy sets on a network. In Section 4.2 we describe efficient and scalable implementation of search for similar sets.

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## Similarity metrics in Set Theory



▪ Venn Diagram

- Set theory: The measure of similarity - how much in common two sets have is measured in terms of an "exact" match. The similarity value is a number in the range 0 to 1, 0 – no common elements, 1 – the sets are equal.
- Using fuzzy logic operations we define similarity as:

$$S(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

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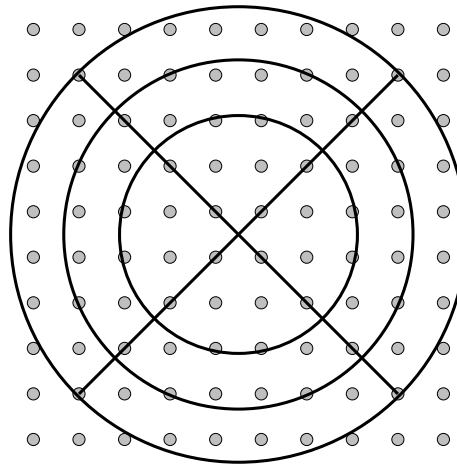
## Similarities/Dissimilarities in Set Theory

- Similarity of users in techno-social systems is used for so called community based recommendations.
- Techno-social systems are different:
  - In contrast to the behavior of users in classic recommender systems, the users of bookmarking systems are opportunistic - users randomly bookmark items rather than trying to rate as much as they can as in classic recommenders.
    - It means that the fact that two users bookmarked same 10 items is important, but the fact that each has 50 other items not bookmarked by the other is not that important. Usage of popular similarity measures (like cosine similarity, Pearson correlation and Jaccard index [6]) to measure similarity between users of collaborative tagging systems provides the results which are overly affected by dissimilarities.
- In this section we propose a novel method which allows flexibility for taking into account similarities/dissimilarities.
  - Firstly, users are modeled by fuzzy sets of related nodes on a network model. Secondly, comparison of user models is done by the use of fuzzy logic which allows us to control the importance . We define a new metric for nodes similarity which shows flexibility for taking into account similarities/dissimilarities. With some choose of logical AND and OR operations the above mentioned formula gives the results insensitive to the dissimilarities.

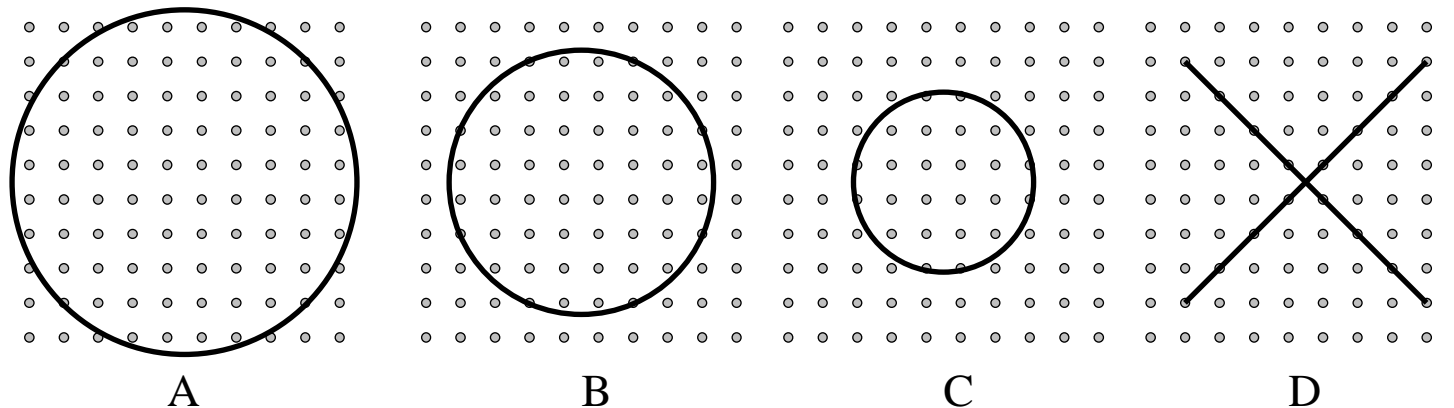
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## Similarity between two groups of nodes

- However, our sets are actually sets of nodes in a network of concepts. Because the links between concepts indicate the semantic proximity of concepts (including synonymy relations), these relations must be taken into account when comparing the sets. Instead of the degree of exact match, we need to use a "fuzzy" matching technique.
- To illustrate this "fuzzy" matching, let us consider a contrived geometrical example, where the network of concepts is the grid on two dimensional plane like the one on the Fig. 2.



- 
- Let us consider four sets of nodes (semantic models) with the shape depicted on the Fig 3 (with centers of symmetry place at the origin of the grid)



- Which two sets of nodes are most similar? If our matching strategy is to look for an exact match, then the pair A and D would be most similar because they have the most nodes in common. However, intuitively, A and B are closest. How do we make a computation based on this intuition which will show us that A and B are very similar?

- 
- Our approach for "fuzzy" matching is to expand all the sets by making their boundaries less well defined and more "fluffy" and as the measure of similarity between original pair we choose the exact match (i.e. overlap) of their expanded variants.



- Fig. 4. To provide "fuzzy" comparison of original sets, we perform their "fuzzyfication" first by the operation which we denoted previously as *Expanding*.
- From the Fig 4 we see that A and C still do not have common area, and hence the measure of their similarity is still zero. Sets A and B became practically indistinguishable, and their measure of similarity is close to 1, while sets A and D have common areas only in the four corners.

- 
- The method we suggested to compare two “clouds” (fuzzy sets of nodes) is very close to the simplified version described above. The difference is that the nodes in the original sets are provided with membership function

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## Querying Collection of N Clouds

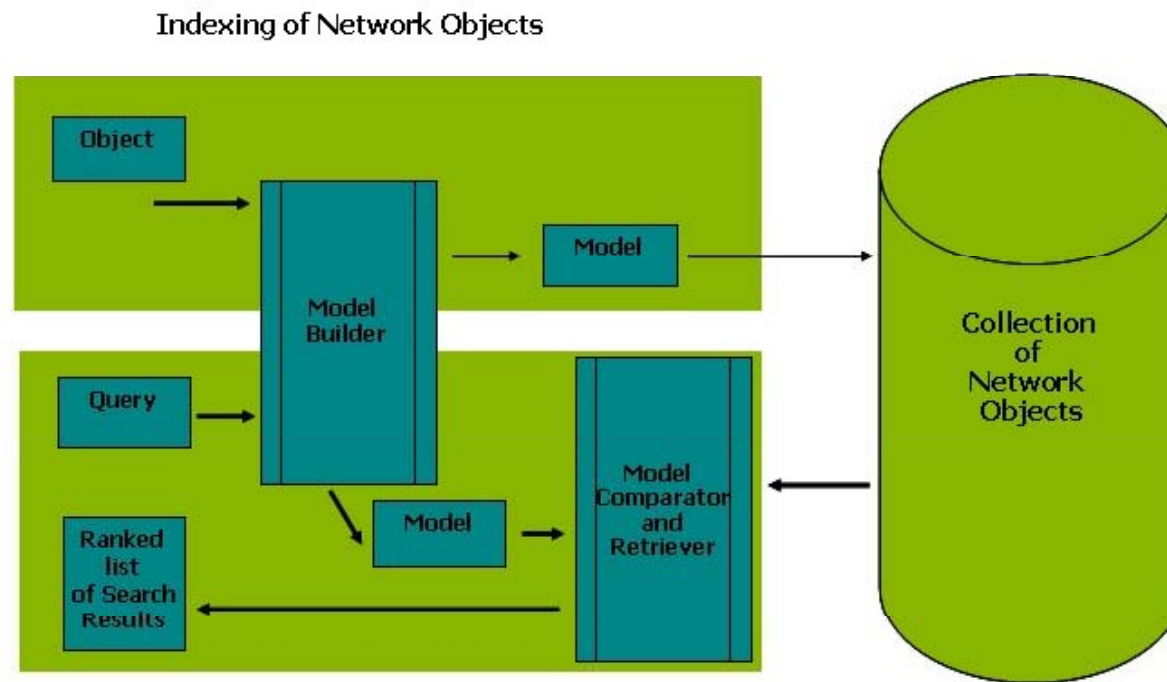
### retrieval of a similar sets in a collection - n-ary operation

- Computing of similarity of two sets above - is really fast (100msc)
- But retrieval of a similar cloud from a collection of 100 clouds will be 100 times slower if done straightforwardly. We created scalable solution Here we briefly outline that method.



## Querying Collection of N Clouds (Cont.)

- The retrieval process takes a user query as input. A semantic model of the query is created by the model builder. This query model is then passed to the retrieval module which compares the query model to the document collection and retrieves a ranked list of documents according to the set similarity measures described above.



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## Outline of the algorithm

- **Step 1.** Building the model of a cloud.
- This technical step aims to increase the storage capacity by modeling a cloud A by *Shrinking*(A); alternatively, the operation *Expanding*(A) could be used to improve recall.
- **Step 2.** This model is added to the repository ((collection) of processed network objects, which is a node-by-object matrix, each element of which is the weight of node  $i$  in the object  $j$ .
- **Step 3.** The model *Expanding*(B) of a query B can be compared against other models stored in the repository. Similarity score of document  $j$  and document  $k$  is calculated, for instance, using cosine similarity function:

$$S(d_j, d_k) = \frac{\sum_{i=1}^N w_{ij} \cdot w_{ik}}{\sqrt{\sum_{i=1}^N w_{ij}^2} \cdot \sqrt{\sum_{i=1}^N w_{ik}^2}}$$

- If row-wise matrix storage is used, semantic models that do not have common non-zero weight nodes with the target semantic model (and therefore guaranteed to produce zero similarity), are eliminated before a similarity score is calculated, this speeds processing.

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## Network-flow based Computational Systems for Mining and Use of the Social Context

- In this Section we present novel software architecture for mining and use of network models of social context based on a set of atomic software engines implementing one of the basic network flow operations described above. Arguments (operands) of these operations are network objects which we define as fuzzy sets of network nodes.
- This architecture generalizes the design of systems constituting the previous art without introducing new components which could potentially hamper performance and scalability. We show that efficient and scalable implementations for each of the atomic software engines actually exist (although as part of monolithic software applications). For instance, the paper Judge et al. 2007 describes the system which perform atomic operations on network with several hundreds nodes in 200msc on an ordinary PC. The paper Troussov et al. 2008 describes the large scale multifunctional application where various recommendations are done using hybrid methods including natural text processing. Therefore we conclude that the architecture described in this Section could be successfully used to mine and exploit the social context.

Judge, J., Sogrin, M., and Troussov, A. "Galaxy: IBM Ontological Network Miner". *Proceedings of the 1st Conference on Social Semantic Web (CSSW)*, September 26-28, 2007, Leipzig, Germany.

Troussov, A., Judge, J., Sogrin, M., Bogdan, C., Lannero, P., Edlund, H., and Sundblad, Y. "Navigation Networked Data using Polycentric Fuzzy Queries and the Pile UI Metaphor". *Proceedings of the International SoNet Workshop (2008)*, pp. 5-12.

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## Network-flow based Computational Systems for Mining and Use of the Social Context (Cont.)

- Major steps involved in building the software application based on principles described in this paper are:
  - Modeling the social context (such as instantiations of techno-social systems) using multidimensional networks.
  - Task is modeled as a cloud - fuzzy set of nodes which performs the role of the *Query*
  - Task dependent enhancement of the model of the social context
    - the network is enhanced on the fly by new objects and new links between node, and augmented by new task dependent objects
  - Local ranking using *Query* as the initial seed provides the ranked list of network objects relevant to the *Query*
- The previous sections provide examples of these steps. For instance, in the Nepomuk-Simple the underlying network is enhanced on the fly by concepts extracted from the textual content of pile items.