# **Collaboration Spotting: Big Data Visual analytics**

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Wigner, Budapest, Hungary, 12 August 2016



**The Collaboration Spotting Project** 

# **Collaboration Spotting**

- Vision
- Concepts
- Modus Operandi
- Targeted performances
- Computational needs & optimization
  - Graph DB management and operations (A. Agocs)
  - Interactive visual graph processing (R. Forster)
- Future work

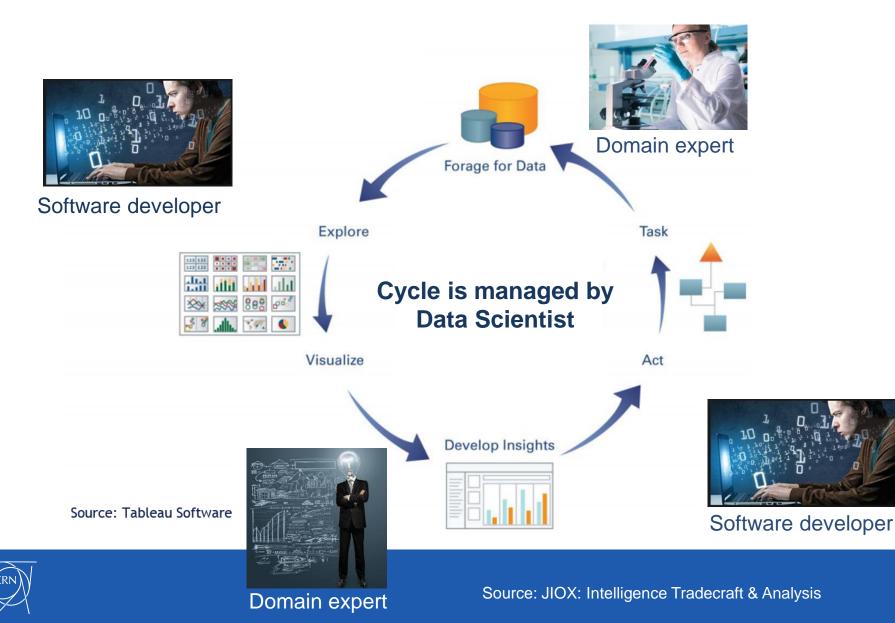


A suite to support the Visual Analytics Process

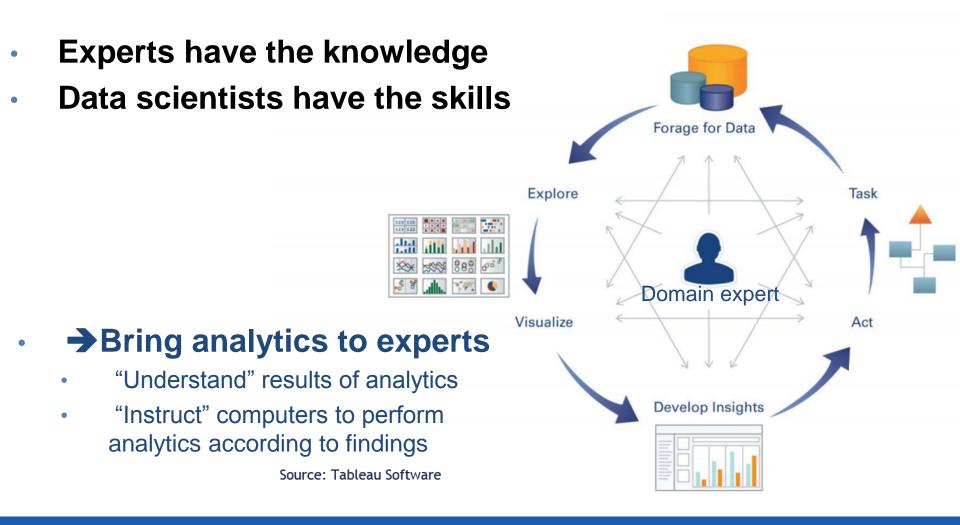
#### Vision



#### **Big Data Analytics Cycle (Today)**



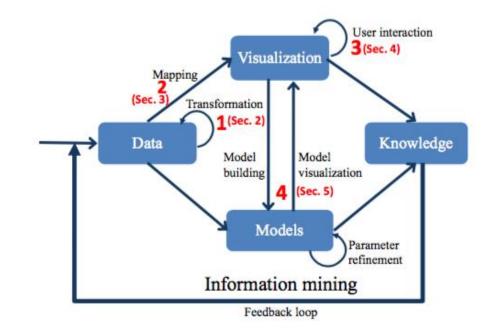
#### VISION → Expert at the centre of the cycle



 $\gg$  Data scientists to enable experts to perform analytics by themselves 5

#### Collaboration Spotting to support the Visual Analytics Process\*

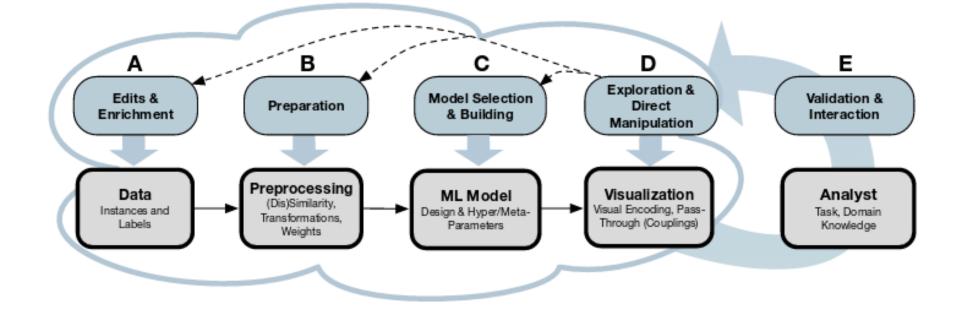
- 1. Data Pre-processing
- 2. Mapping/Layout
- 3. Visual user interactions
- 4. Model-based analysis





\*KEIM D., ANDRIENKO G., FEKETE J.-D., GÖRG C., KOHLHAMMER J., MELANCON G.: *Information Visualiza- tion*, vol. 4950 of *Lecture Notes in Computer Science*. Springer, 2008, ch. Visual Analytics: Definition, Process, and Challenges, pp. 154–175.

#### **Collaboration Spotting Framework**



The project follows the proposed conceptual framework of D. Sacha et al<sup>\*</sup>.



\*Human-Centered Machine Learning Through Interactive Visualization: Review and Open Challenges Dominik Sacha, Michael Sedlmair, Leishi Zhang, John Aldo Lee, Daniel Weiskopf, Stephen North, Daniel Keim

## A suite to support visual analytics

- Long-term project
- Iterative approach
  - First release: Publications and Patents metadata for Technology Innovation Monitoring
  - Applied to other data sources:
    - LHCb data processing
    - CERN procurement data
  - Second release: (under construction):
    - Data source pre-processing tools
    - User self-defined visual framework
    - Contextual analysis
  - Third release: The full suite



Big Data Multi-dimensional networks Graph database Interactive graph visual analysis

### **CS** Concepts



#### **Characteristics of Big Data**

Huge quantity
 Processing and storage

Distributed sources
 Access rights, security

- Complexity
  Valuable information may be hidden behind complexity
- Interconnectivity
  Unravelling new knowledge



Data scientists are instrumental to analytics
 Domain experts are at the heart of the reasoning process

#### Big Data is organised in networks

# Big Data is distributed

- Document systems with data and metadata in Database
- Database tables with metadata in schema

#### Big Data is strongly interconnected

- Networks are **not materialised** due to the distributed nature of data sources
- Ex: Publications and patents metadata



# **Building Data network**

Metadata in source contains provider specific information and format

- Ex: The Web of Knowledge (Thomson Reuters)
  - Title, Abstract, Authors and Affiliation, DOI, Citations, etc.

### Some is of interest for **analysis**

- Title, Abstract, Citations
- → Each publication metadata becomes a vertex with attributes

Some is of interest for visualisation

- Organisations, cities, keywords, journal categories, Citations, etc.
- → Each of the above becomes a vertex with attribute that is link to its publication vertices



# EX: Building a Network from publications metadata

R  $\sim$ Save to EndNote online Add to Marked List Select Page Composition of oxygen precipitates in Czochralski silicon wafers investigated by STEM with EDX/EELS **1**. and FTIR spectroscopy (Pub) By: Kot, Dawid; Kissinger, Gudrun; Schubert, Markus Andreas; et al. PHYSICA STATUS SOLIDI-RAPID RESEARCH LETTERS Volume: 9 Issue: 7 Pages: 405-409 Published: JUL 2015 Full Text from Publisher View Abstract 2. Correlation between Copper Precipitation and Grown-In Oxygen Precipitates in 300 mm Czochralski Silicon Wafer By: Dong, P.; Ma, X. Y.; Yang, D. ACTA PHYSICA POLONICA A Volume: 125 Issue: 4 Pages: 972-975 Published: APR 2014 (JCat) (Kw) (Org) Full Text from Publisher View Abstract Morphology of Oxygen Precipitates in RTA Pre-Treated Czochralski Silicon Wafers Investigated by FTIR 3. Spectroscopy and STEM By: Kot, D.; Kissinger, G.; Schubert, M. A.; et al. ECS JOURNAL OF SOLID STATE SCIENCE AND TECHNOLOGY Volume: 3 Issue: 11 Pages: P370-P375 Published: 2014 Full Text from Publisher View Abstract (Cty) (Cny) 4. Thermal deactivation of lifetime-limiting grown-in point defects in n-type Czochralski silicon wafers By: Rougieux, F. E.; Grant, N. E.; Macdonald, D. PHYSICA STATUS SOLIDI-RAPID RESEARCH LETTERS Volume: 7 Issue: 9 Pages: 616-618 Published: SEP 2013 **Full Text from Publisher** View Abstract Phosphorus gettering of iron by screen-printed emitters in monocrystalline Czochralski silicon wafers 5. By: Pletzer, Tobias M.; Suckow, Stephan; Stegemann, Elmar F. R.; et al. PROGRESS IN PHOTOVOLTAICS Volume: 21 Issue: 5 Pages: 900-905 Published: AUG 2013

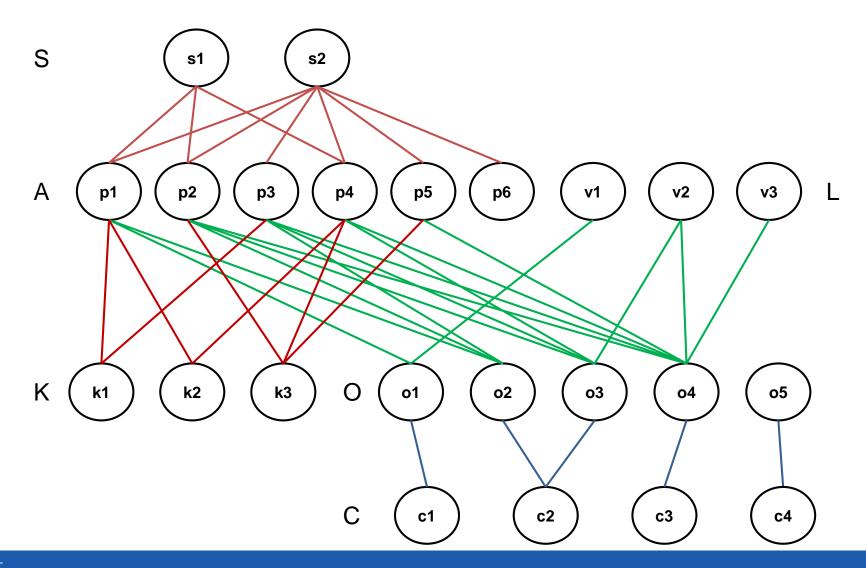
#### **Reachability Graph: Graph of data types**



JCat: Journal category, Kw: Keyword, Org: Organisation, Cny: Country, Cty: City

**Document metadata** 

### **Graph of Metadata / Data**





S: Categories, A: Pub/Pat, K: keywords, O: Organisations, C: Countries, L: Cities

# Storing network data as graphs

Graphs are natural representations of networks

- Complexity
- Interconnectivity
- Scalability
- Multi dimensional

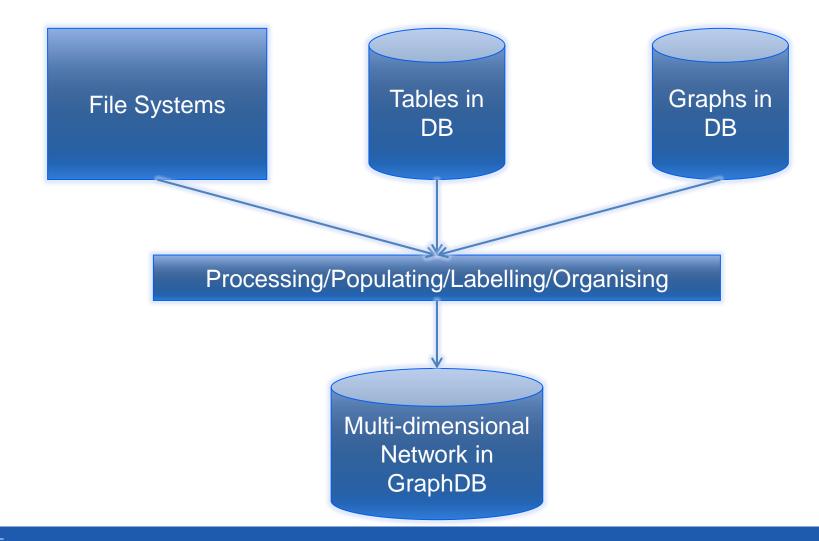
Schema is embedded in the data

- Nodes' labels
- Compact graph structure
- Graph query language
- No schema evolution



Graph Databases offer a natural support for storing network information 15

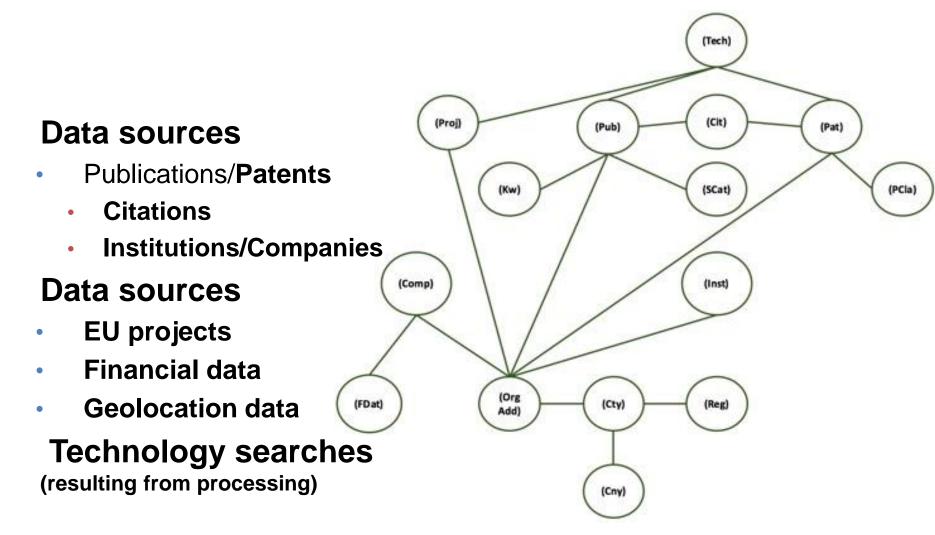
#### Building multi-dimensional networks from various data sources





#### No limit on the sixe of a network!

#### **Example: Enriching Network**



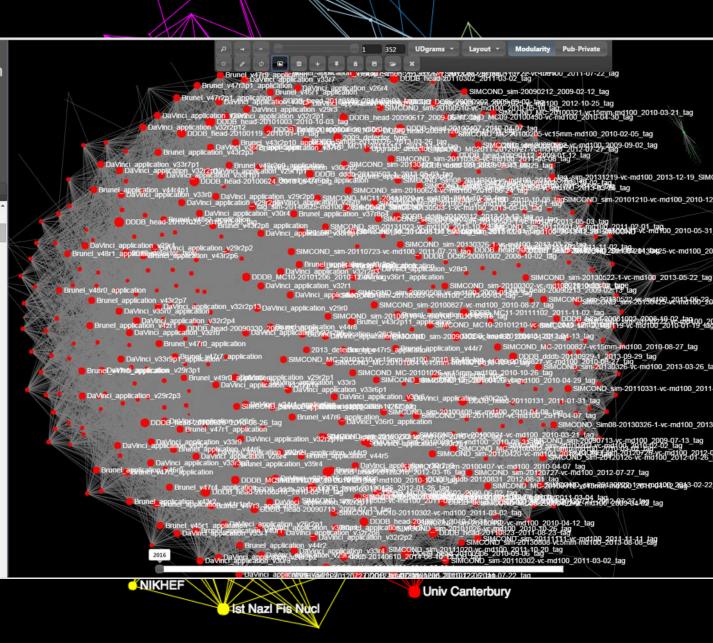


**Reachability Graph (Schema)**: Graph of linked datatypes **Dimension**: a node in the Reachability Graph (a datatype)

#### Graph of Organisations

**Collaboration** 

2016 2016 m year: 644 e\_v28r1\_application le\_v28r2\_application le\_v28r2p1\_applicatio le\_v29r0\_application e\_v29r10\_application e\_v29r11\_application le\_v29r1\_application e\_v29r1p1\_application le\_v29r2\_application e v29r2p1\_application e\_v29r3\_application v29r4\_application v29r5\_application v29r6\_application e\_v29r7\_application le\_v29r8\_application e v29r9 application application\_v37r0 el\_app lication\_v37r2p2 el\_application\_v37r3 application\_v37r8 el\_application\_v37r8p4 el\_application\_v39r4 application\_v40r0 el\_application\_v40r1 el\_application\_v41r1 el\_application\_v41r1p1 el\_application\_v42r1 el\_application\_v42r2 el\_application\_v42r2p1 l\_application\_v42r2p2



#### Setting up user analysis environment

#### **Reachability Graph**

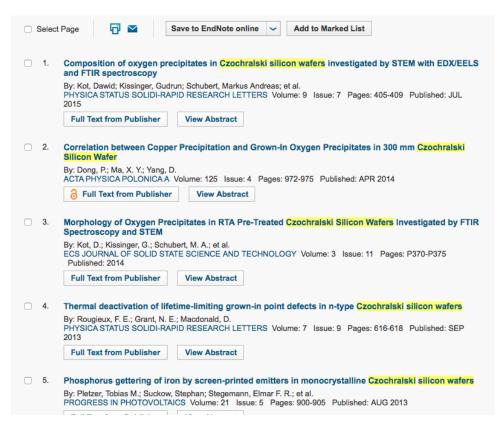
- Graph of connected dimensions
- Data analysis dimensions (user selection)
  - Ex. 1: Publications, Patents
  - Ex. 2 : Compatibility and require relationships in LHCb
- Visual analysis dimensions (user selection)
  - Ex. 1: Organisations, cities, countries, keywords, categories, etc.
  - Ex. 2: Components, Environment, conditions, etc.

#### Entry graph (user specified)

- Visual dimension of the front graph
- Ex. 1: Technology
- Ex. 2: Processing Pass Description  $\rightarrow$  Connects to top applications



#### Selecting dimensions (Ex. 1)



#### Entry (Tech Graph (Pat) (Pub) (SCat) (Kw) (Org) (Cnv)

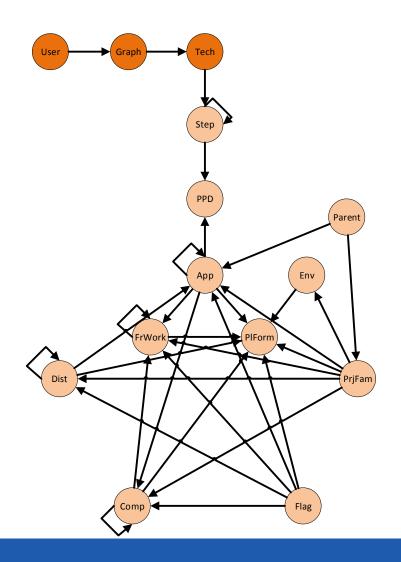
#### **Data dimensions for Analytics**

Pub: Publications, Pat: Patents (Attributes: Title and abstract are used for semantic searches) Visualisation dimensions of Analytics results:

SCat: Journal category, Kw: Keyword, Org: Organisation and Cny: Country)



### Selecting dimensions (Ex. 2)





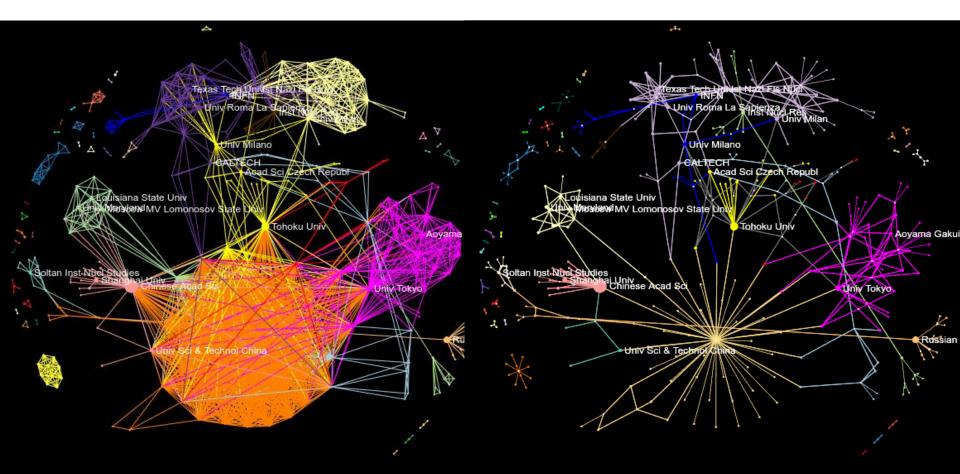
Reachability Graph for LHCb dependency data

#### CollSpotting supported Graph Visual representations

- Static graph with timeline window
- Node-link using different layout techniques
  - Clique representation (default)
    - Force Atlas (default)
    - Circular representation
  - Extra node representation (hyper-graph)
    - Force Atlas
    - Circular representation



#### Clique vs Extra node representations (ForceAtlas)



Organisation landscape graph view

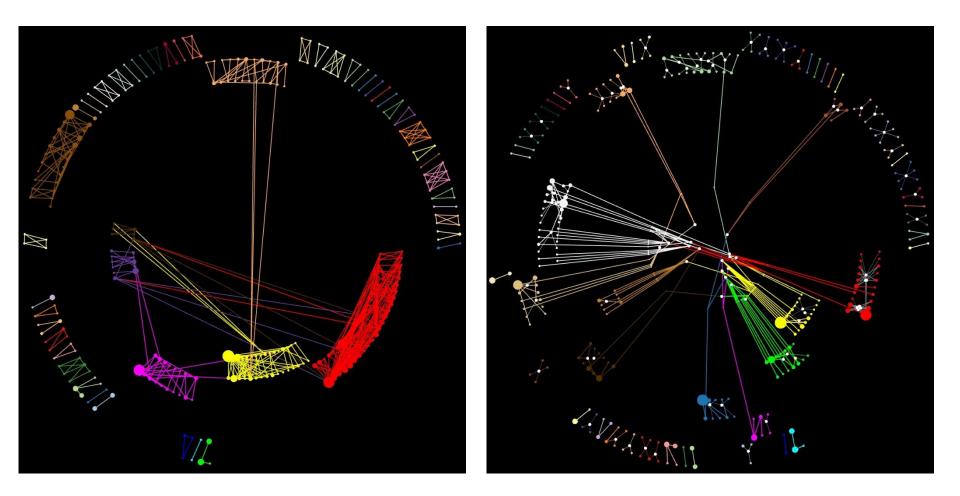
Organisation landscape hypergraph view



Technology search: BGO Crystals Pub/Pat: documents found in search results

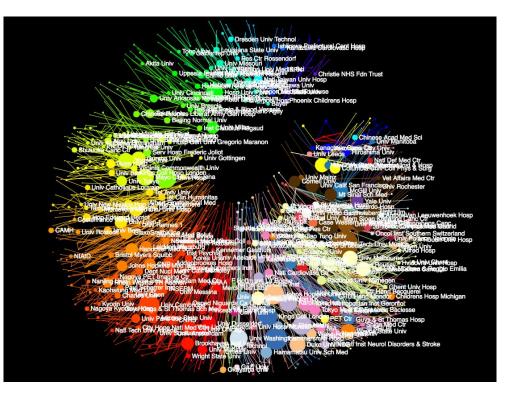
Edges vs hyper-edges

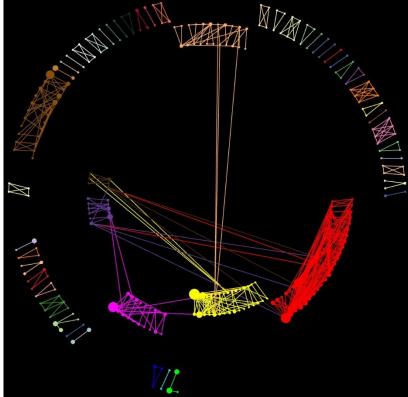
#### **Clique vs Extra Node circular representations**





#### ForceAtlas vs Circular

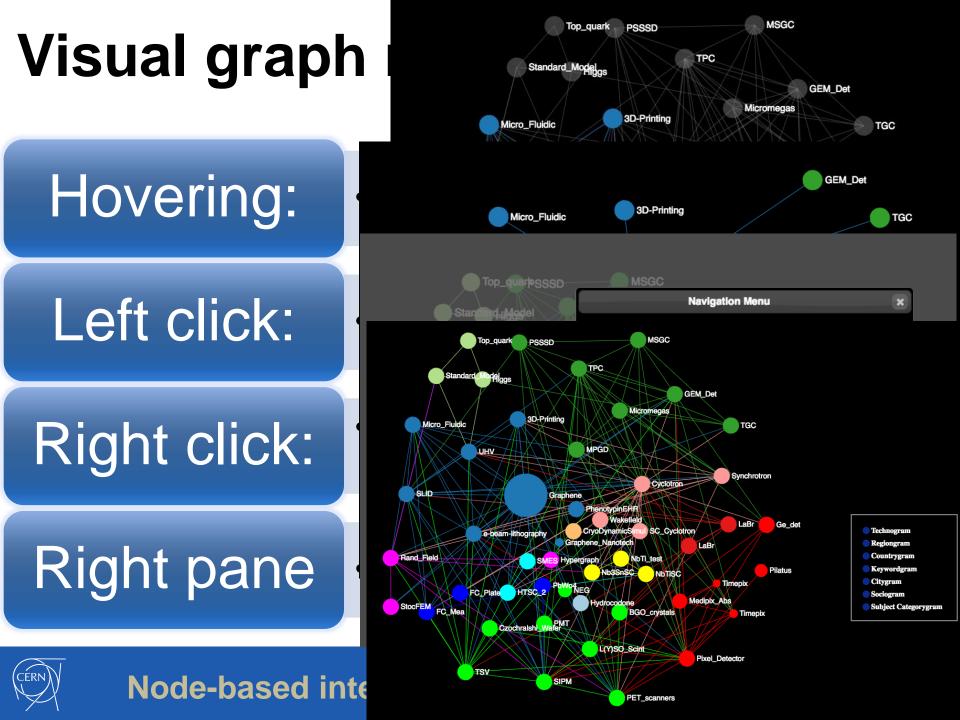




#### Clique view with ForceAtlas2

Cluster circular distribution according to cluster interconnectivity





**Dataset: Publications and Patents** 

# Illustration of visual interactive graph features



**Collaboration Spotting** 

## **CS Graph visualisation features**

#### Maximizing human understanding

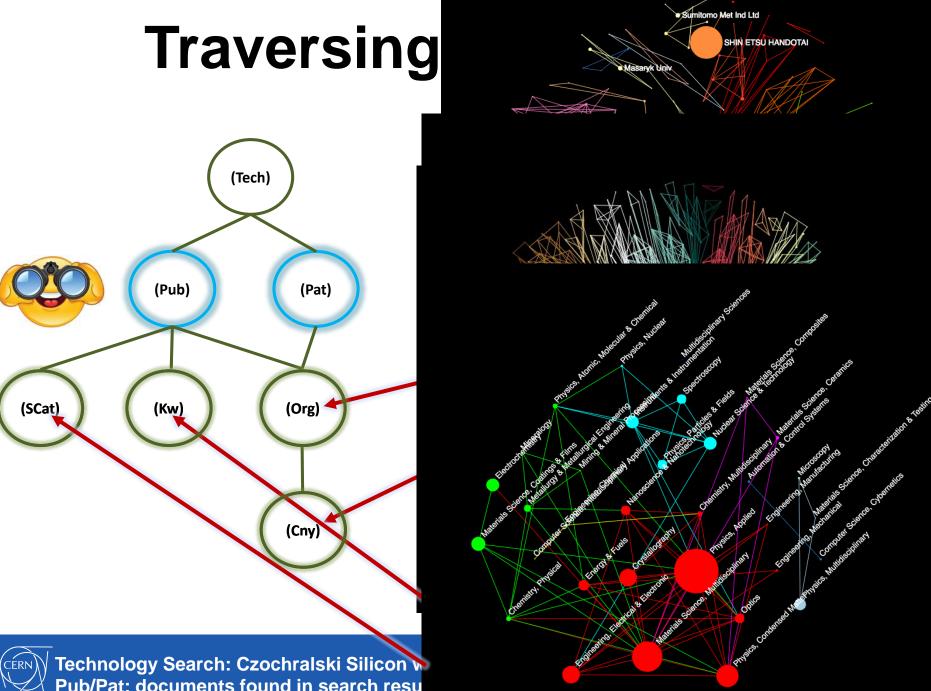
- Selecting network dimensions
- Traversing network dimensions
- Graphical queries
- Time/Frequency evolution

# Enhancing reasoning

- Viewing multiple data sources
- Looking for collaborations
- Sorting data
- Contextual visualisation & analytics

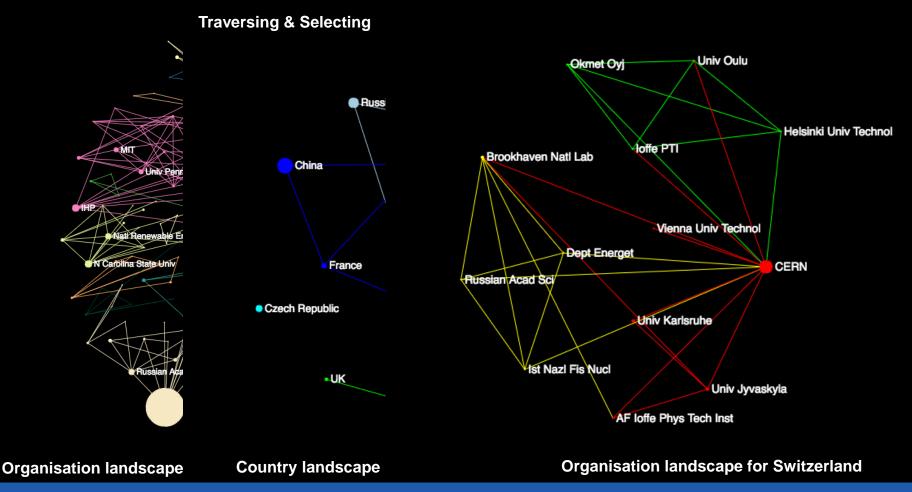


→ Features illustrated in the following slides using publications/patents <sup>28</sup>



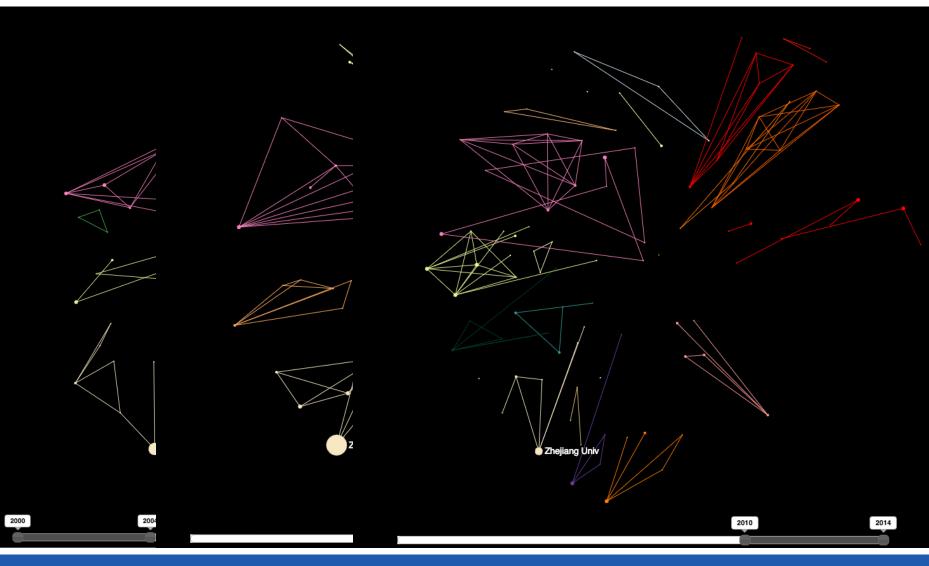
Pub/Pat: documents found in search resu

### **Graphical Queries**



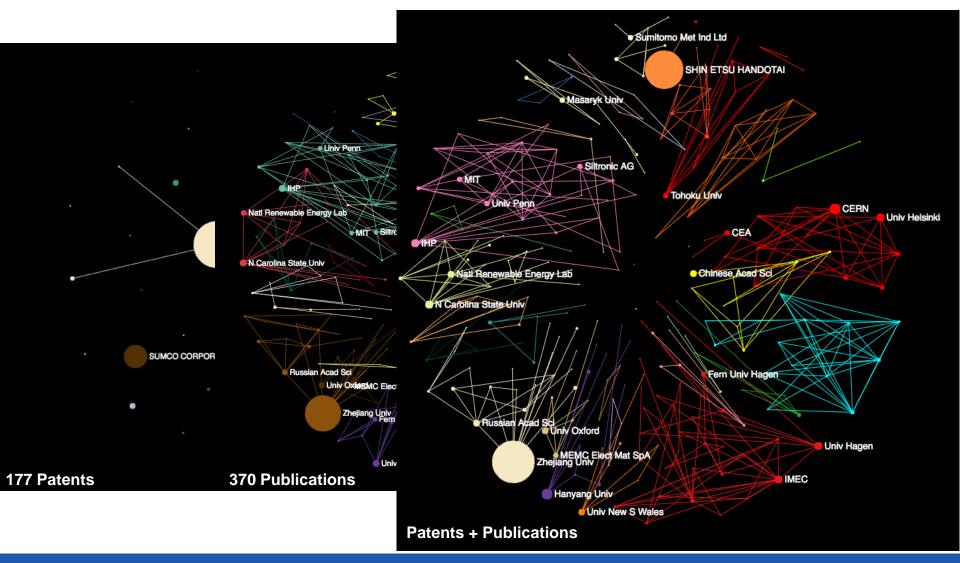


### **Time/Frequency evolution**





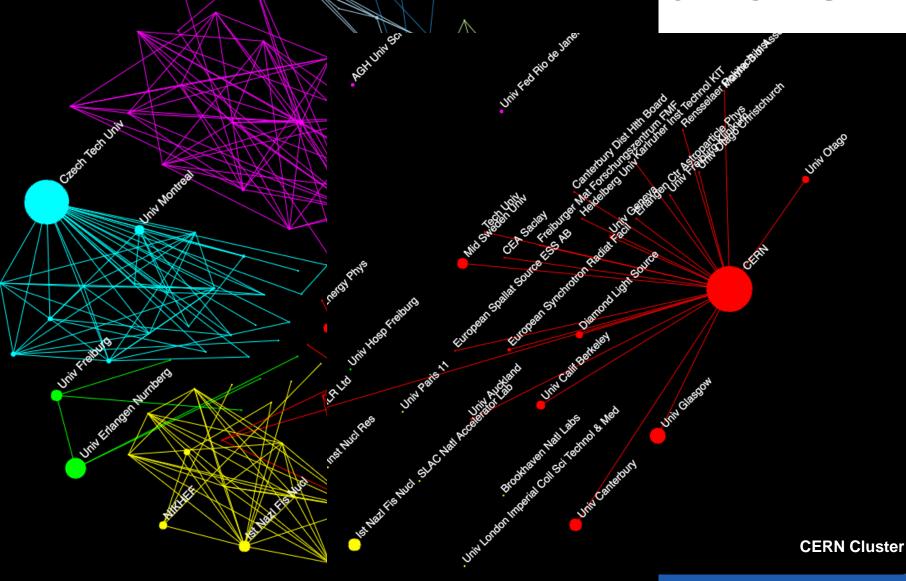
### **Combining data sources**





#### **Organisation landscape**

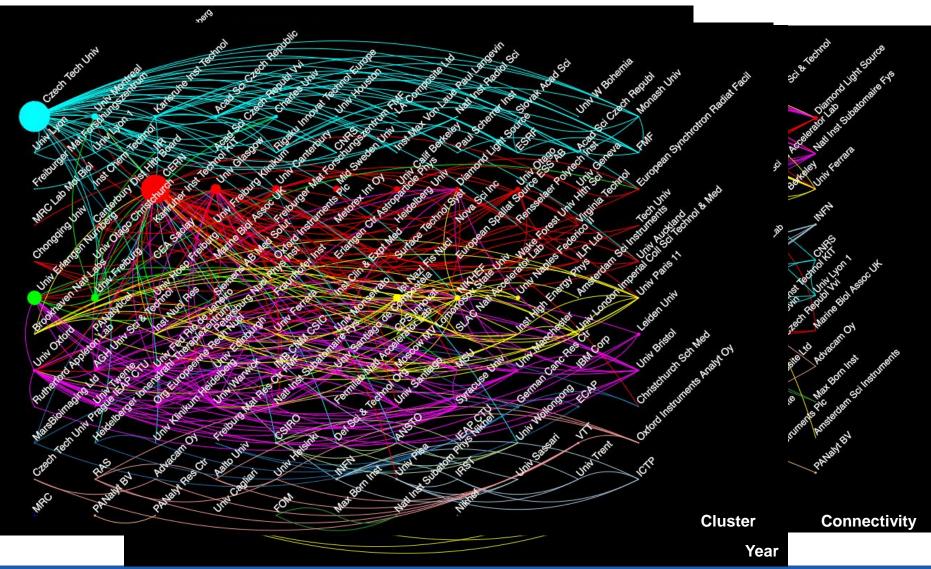
### ations





Technology Search: Pixelated detector (Medipix)Cluster: Organisations that tend to collaboratePub/Pat: Documents found in search resultsmore together than with others3

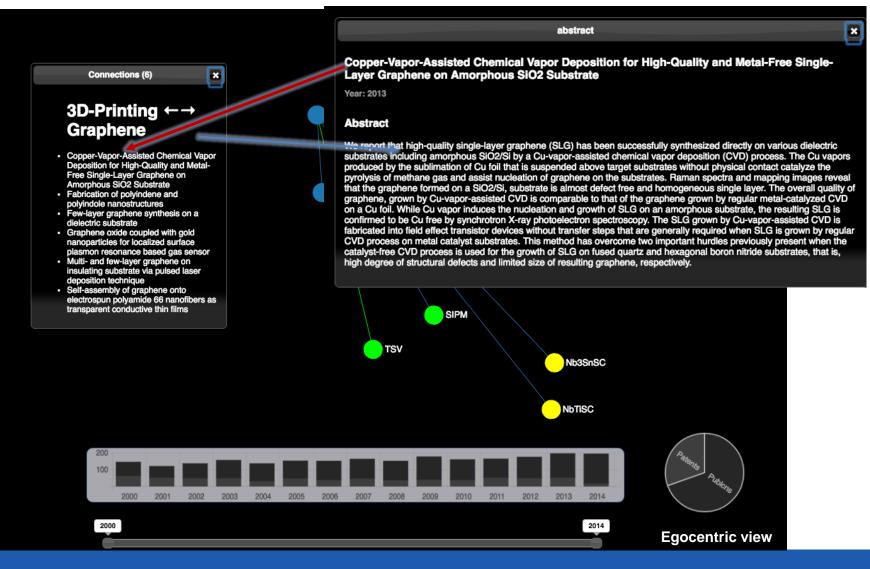
## **Sorting information**





Technology Search: Pixelated detector (Medipix) Pub/Pat: Documents found in search results

### **Contextual visualisation**





Technology search: 3-D Printing Pub/Pat: documents found in search results

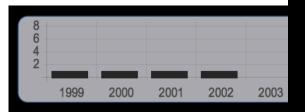
#### Contextual access to publications & patents 35

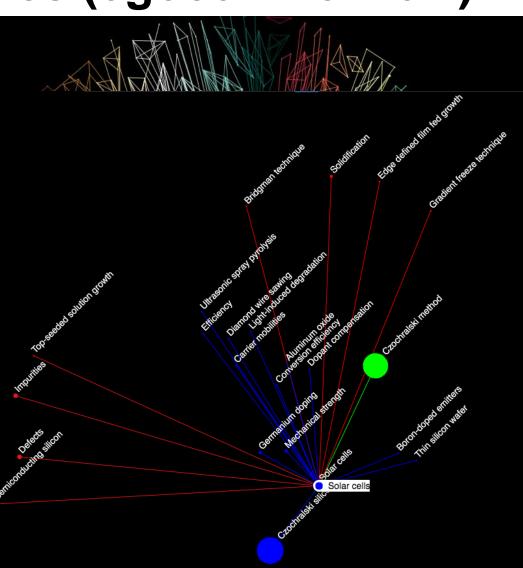
#### **Contextual Analytics (egocentric view)**

Look at the distribution of publications related to the keywords:

#### Solar cells

In Czochralski Silicon wafer over the years.

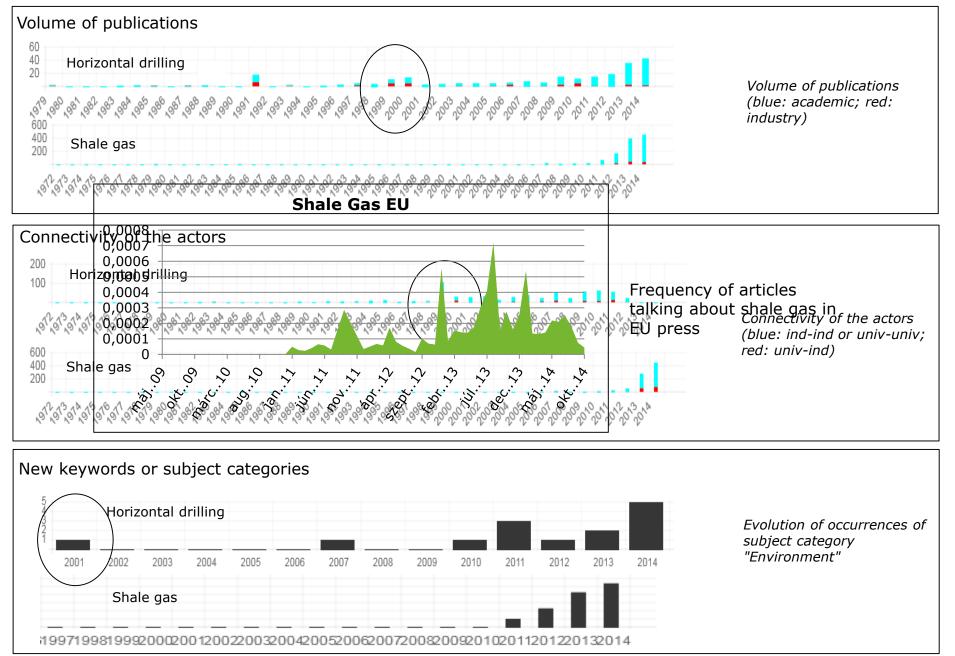






**Contextual Analytics** 

#### Early signals – Horizontal drilling Vs shale gas



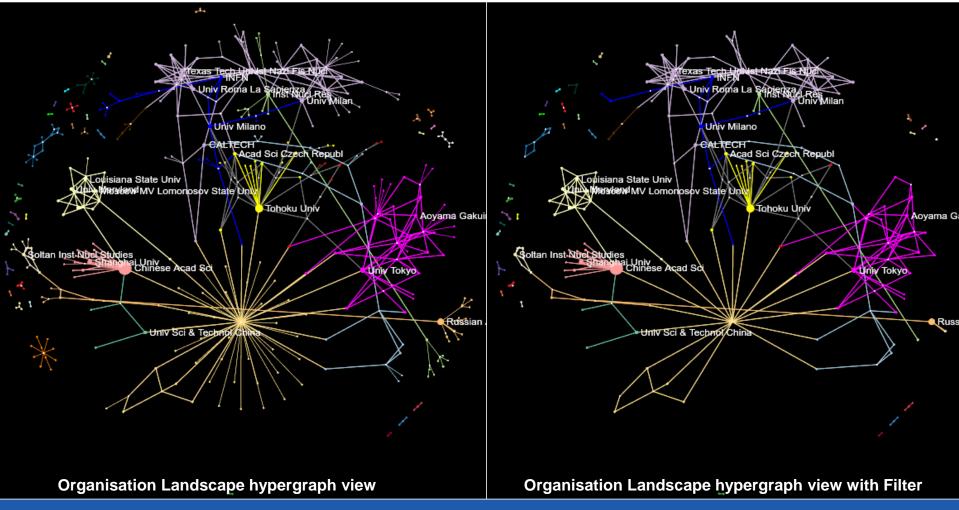
Courtesy: O. Eulaert/EC-JRC

Filtering User-triggered operations

## **Operations on visual graphs**



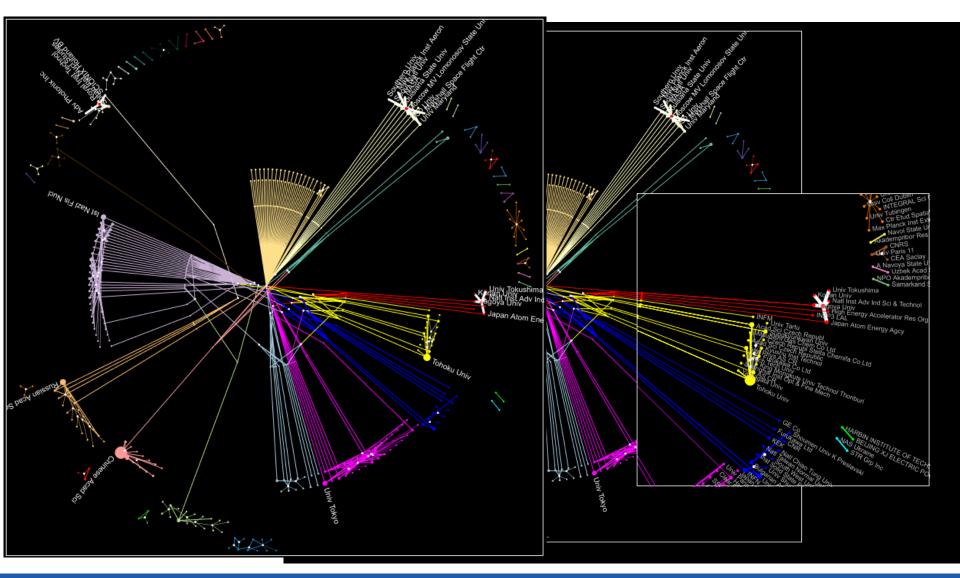
# Filtering





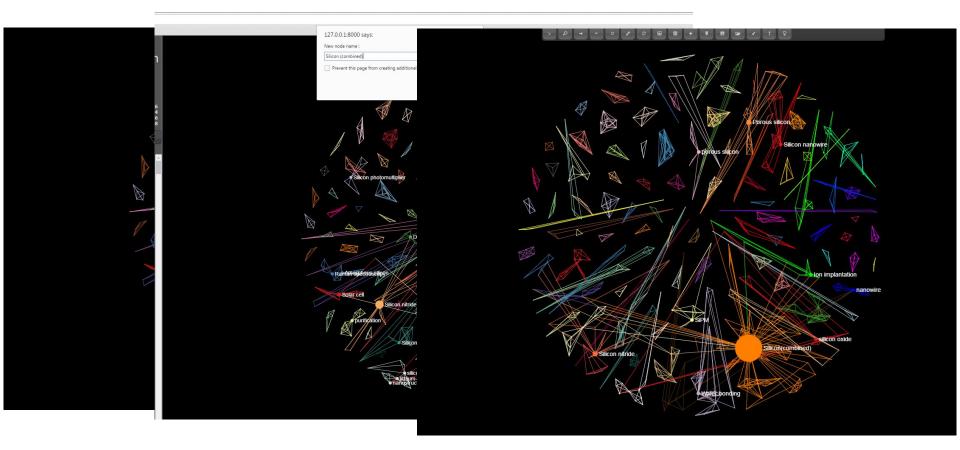
Technology search: BGO Crystals Pub/Pat: documents found in search results

# Zooming





# **Merging vertices**





User triggered operations are not affecting the data in the Graph DB! Collaboration Spotting 4

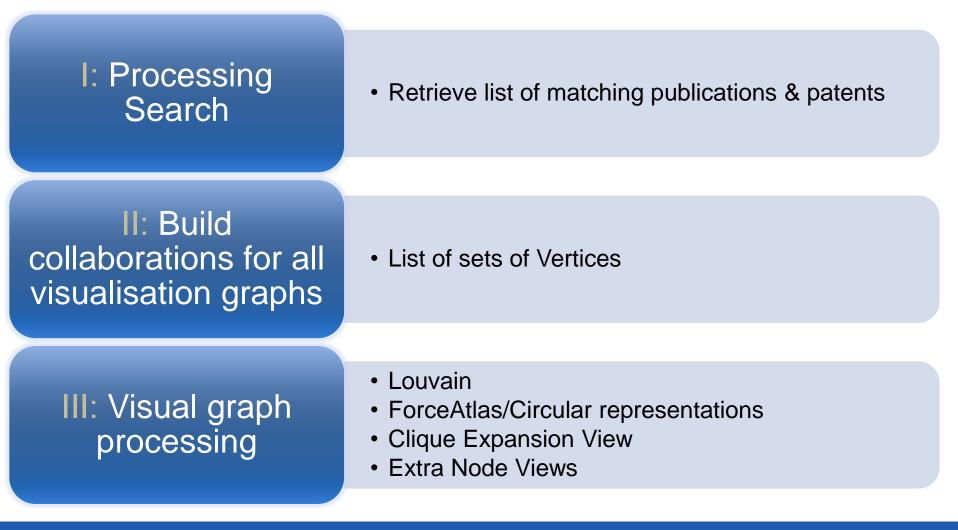
Reachability Graph Analytics dimensions

Visualisation dimensions

# **CS Modus Operandi**



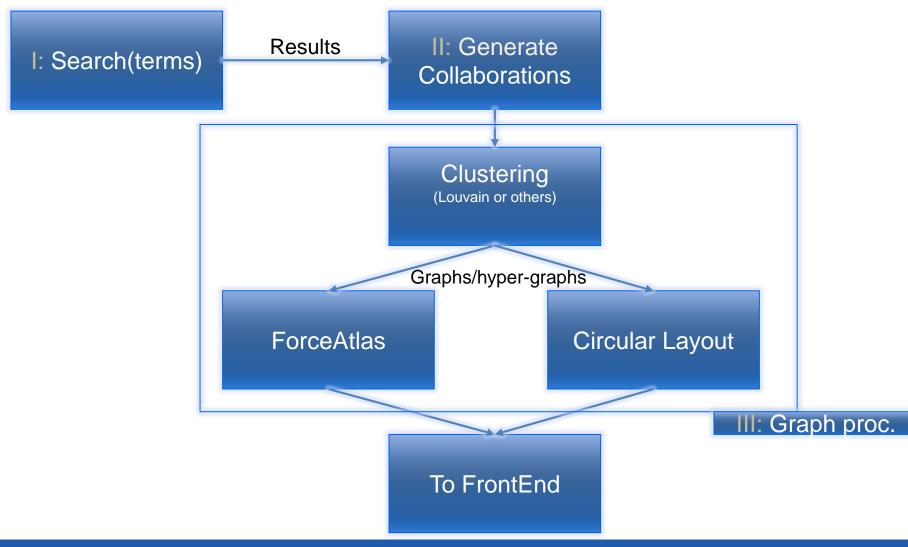
# **Processing Steps**





## **Processing sequence**

(Building new visualization graphs from data analysis)





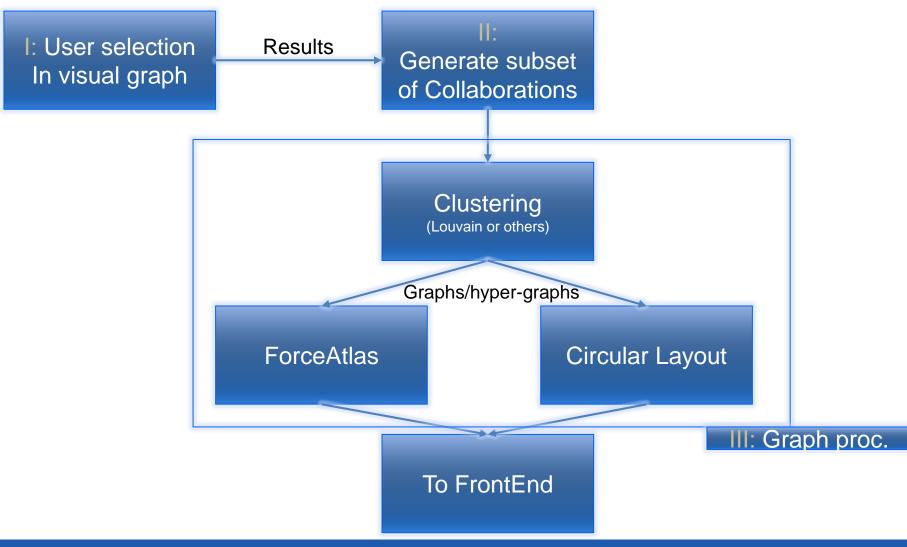
## **Processing Sequence**

Velcome, Jean-Marie Le Gof	poration ing			
Home Create Gr	uph Page List of Graphs List of Users Search Aber Please input your query: title:(high AND temp* AND super OR obstract(high AND temp* AND super		2015	Retrieve
	• 2 Web of Knowledg • 2 PatStat Graph:	set you would like to search: je		Pub  &  Pat
Jser selects	• • TechnogramJMLJ • • TechnogramDem Search			Refine Search 2
/isual graph subset	Y	es .		Yes
Build visual graphs	Large graph ?		Compute collaborations for each graph	



## **Processing sequence**

(During user exploration)





Concurrent users Data Analysis Visual Interactions and Analysis

## **Performance Target**



# **Performance target**

### Concurrent users

- Ex. 1: 100 interactive users
- Ex. 2: TBD

### • User-triggered analysis (~ seconds)

- Ex. 1: Keyword- based search
- Ex. 2: Compatibility search for a given data analysis process.
- Visual interactions (~ seconds, special provisions for large graphs)
  - Graphical queries (deterministic graph filtering)
  - Analysis of query results (incl. other visualisation modalities)



Neo4j graph DB Cypher queries Reachability Graph Longer paths vs additional edges Data records examples

### **Computational needs & optimization** Graph DB management and operations (A. Agocs)



**Collaboration Spotting** 

# Overview

- Neo4j DB
- Cypher + Visual operations
- Multi-navigation on the reachability graph
- Longer paths vs. additional edges



## Neo4j database 1.

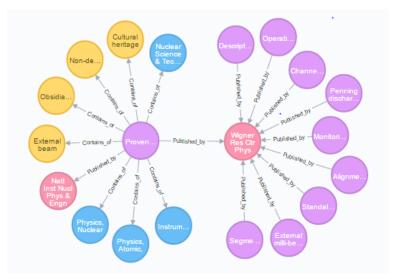
- Uses Labelled Property Graph Data model
- Nodes and relationships (with labels and properties) instead of tables, tuples and attributes
- Two big advantages:
  - Easier to adapt to another graph models (Feynman diagram)
  - Relationships can represent one-to-one, many-toone, one-to-many and many-to-many relationships



# Neo4j database 2.

Short example:

- Red: Organisations
- Purple: Publications or Patents
- Orange: Author Keywords
- Blue: Subject Categories





## Neo4j database 3.

Type of nodes	Number of nodes
Patents	15.000.442
Publications	20.087.904
Organisations	2.918.060
Author Keywords	8.193.604
Subject Categories	230
Cities	7.741
Regions	946
Countries	128
Σ	46.209.055

	Patents	Publications	Σ
Organisations	12.440.903	36.672.677	49.113.580
Author Keywords	-	48.941.098	48.941.098
Subject Categories	-	32.566.806	32.566.806
Cities	3.193.709	8.826.222	12.019.931
Regions	265.421	2.504.441	2.769.862
Countries	3.156.449	8.020.648	11.177.097
Σ	19.056.482	137.531.892	156.588.374

### Statistics on Patent & Publication database (2000-2014): Nodes (left) and edges (right)



# Cypher

- Inspirited by SparQL (SQL based query language for semantic data, stored in RDF)
- The biggest advantages:
  - Pattern matching:
    - Define a subgraph via Cypher
    - Database finds all occurrences of it in the graph.
- Question: How should we create a pattern?



# Cypher – Operation from GUI

- Support:
  - Selection on a graph view (GUI solves it)
  - Extension on a graph view (DB call)
  - Navigation from one graph view to another one. (DB call)
- We got from GUI: list of selected nodes and navigation purpose



# Cypher – Pattern builder

- Goal 1: the pattern has to contain labels of the selected nodes + basic label + navigation label
- Goal 2: create a pattern which use the minimal amount of labels
- Solution: Steiner tree problem NP-hard
  →use minimal spanning tree



# Challenges on database level

- Data: 46M nodes + 156M edges (Pats&Pubs)
  - It can be increased by:
    - Using different sources
    - Using more dimensions (example: authors, journals, etc.)
    - Making time interval wider (from 2000-2014 to 1970-2016)
- Complex patterns (spec. with extra dimensions)
- Solution: Neo4j Cluster (Master-Clients)



## Multi-nav. on the reachability graph

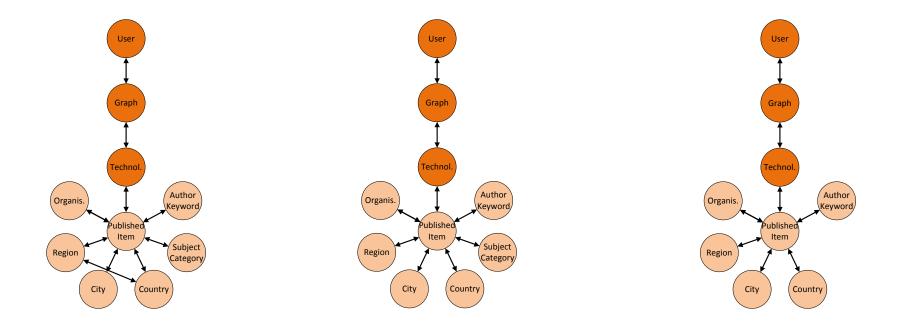
Reachability graph:

- "Schema" of the graph based on node labels
- Pb1: Different paths from one node to another can mean different things:
  - Example: Publication & Patent; (EU) Region; Country
- Pb2: Sensitive data

Solution: Use multiple navigations



## Multi-nav. on the reachability graph



### Ex: Modified Pub&Pat reachability graph with two navigation options

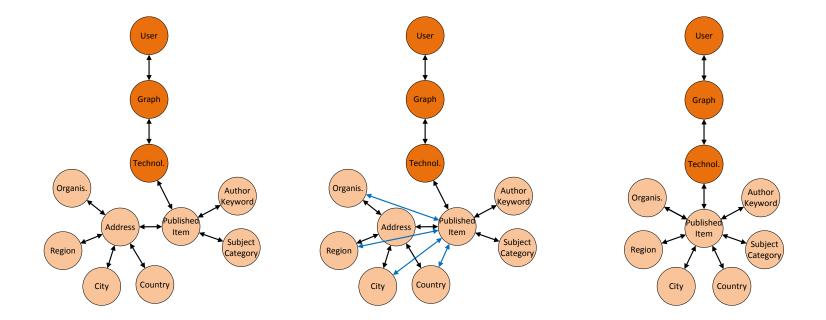


## Long paths vs. additional rel.ships

- Long Paths:
  - Disadvantage: Costly
- Additional (generated) relationships:
  - Advantage: Solve execution time problem.
- Problem: They answer two different questions.



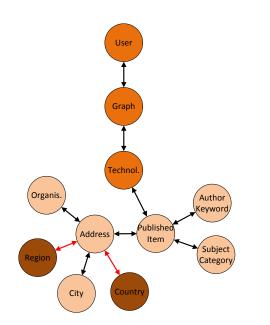
## Long paths vs. additional rel.ships



Ex: The future reachability graph (Pats&Pub DB) (left); Adding additional relationships (middle); Navigation with additional relationships (right)



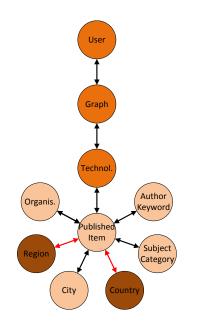
## Example: Long paths vs. add. rels.



- Question: How many regions does Hungary has?
- Answer: 11 (NUTS3)



## Example: Long paths vs. add. rels.



- Question: How many EU regions does Hungary publish with?
- Answer: 198 (NUTS3)



Support user visual interactions Collaborations Louvain ForceAtlas Circular layout Graph and hypergraph visual representations

### **Computational needs & optimization** Interactive visual graph processing (R. Forster)



#### AGENDA

- Graph generation
- Community Detection
- ForceAtlas
- Performance results
- Future work

### **GRAPH GENERATION**

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### GRAPH GENERATION

- This is a process required for every single graph by any user
- First, database returned data needs to be transformed
- Have to generate:
  - Collaborations
  - Nodes
  - Edges

#### **GRAPH GENERATION**

	Silicon	Database	3D	СТ
Collaborations	33,45	13,85	18,64	12,65
Nodes	0,69	0,65	2,48	0,38
Edges	1,48	1,87	0,71	0,69

Computation time for specific parts of the graph generation in seconds

### COMMUNITY DETECTION

### COMMUNITY DETECTION

- Used to reveal groups in real world data
- Louvain method
- Parallel heuristics

#### LOUVAIN METHOD

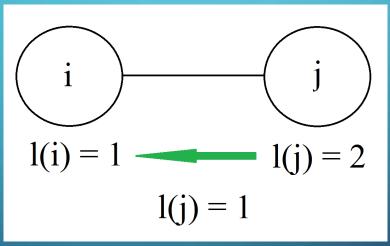
- Multi-phase, iterative, greedy algorithm
- Monotonically increasing modularity
- Inherently sequential

### LOUVAIN PARALLEL HEURISTICS

- Singlet minimum label heuristic
- Generalized minimum label heuristic

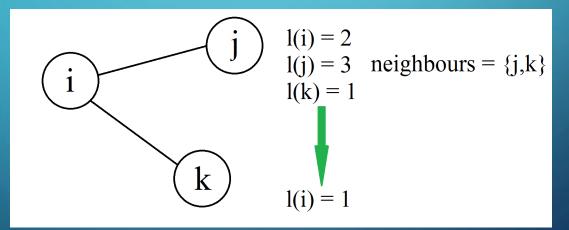
### SINGLET MINIMUM LABEL HEURISTIC

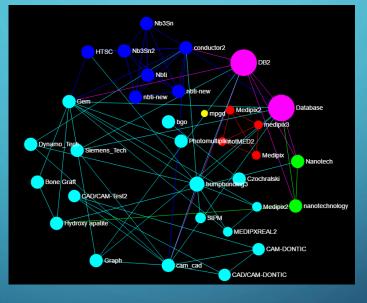
• Move node (j) only if: I(C(i)) < I(C(j))



#### GENERALIZED MINIMUM LABEL HEURISTIC

• Move node (i) to neighbour community only if:  $\min_{n \in neighbours} l(C(n)) < l(C(i))$ 







#### FORCEATLAS

- Force-directed layout based on n-body simulation
- Repulsion-attraction
- Makes visual interpretation easier
- Result depends on starting state

### PARALLEL FORCEATLAS

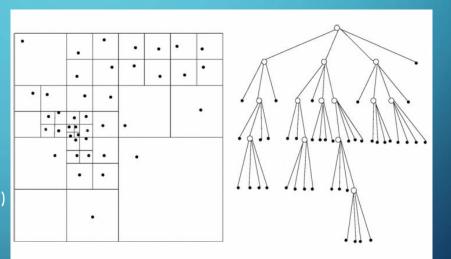
- Repulsion in parallel
- Attraction in parallel

### PARALLEL REPULSION

• Barnes-Hut algorithm

- Repulsion on regions
  - Complexity:

O(N\*LOG(N)) instead of  $O(N^2)$ 

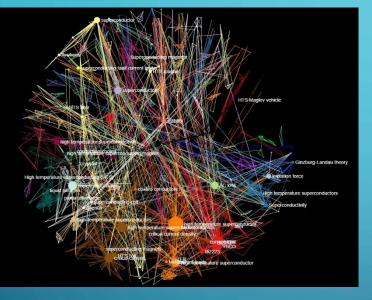


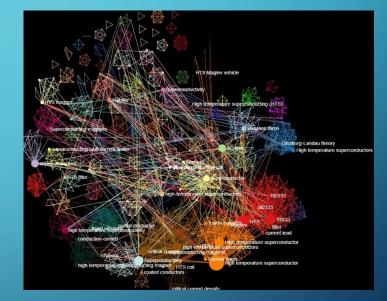
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### PARALLEL ATTRACTION

- Connected nodes are attracted to each other
- Attraction intensity controlled by the user

#### FORCEATLAS LAYOUT TYPES





Original layout

Community based layout

Search: in title or abstract (high AND temp\* AND supercond\*)

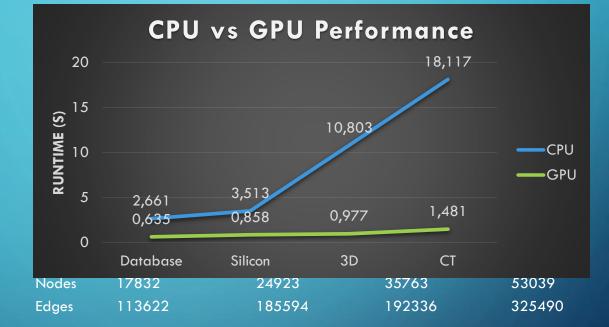
### PERFORMANCE RESULTS

#### PERFORMANCE RESULTS

- Graphs used: 3D, CT, Database and Silicon technologies
- Implementation in C++
- 8 threads in parallel execution
- System:
  - Intel Core i7 4710HQ
  - 24 GB DDR3
  - GeForce GTX 980M

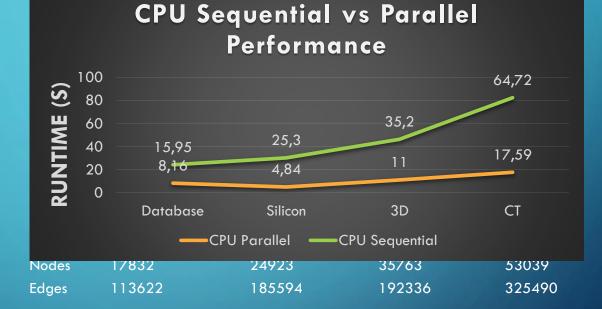
#### RESULTS (COMMUNITY DETECTION)

- Database: 4x
- Silicon: 4x
- 3D: 11x
- CT: 12x



#### RESULTS (FORCEATLAS)

- Database: 1,95x
- Silicon: 5,22x
- 3D: 3,2x
- CT: 3,68x



#### FUTURE WORK

- Further optimization of the graph data generation
- GPU implementation of ForceAtlas

Explore other data sources

Advanced analytics

### **Future Work**



## **Deployment & collaborations**

- CollSpotting on Publications and Patents under tests on Open Stack @ CERN
  - Limited performance; could be improved with GPUs
  - Cores with max RAM to store graph of DB in memory needed
- System will be available to HEPTech members
  - CERN login required (Licence issues)
  - Additional data sources according to HEPTech needs
- Exploration of collaborations with CERN
  - EPFL  $\rightarrow$  Big Data to be identified
  - UN-UNICRI (Interregional Crime and Justice Research Institute) → Big Data analytics to reinforce security



### Advanced visual analytics

- → More value to users when analysing Clusters
- Contextual analytics
  - While navigating across dimensions
  - While performing operations on visual graphs
- Support to the visualisation of very large graphs in the nodelink representation
- Multi-dimensional visual graphs and cluster optimization
- Dynamic visual dimensions selection to optimize cluster visualisation
- Major performance optimization efforts to maintain acceptable processing time for users, irrespective of the graph's size.



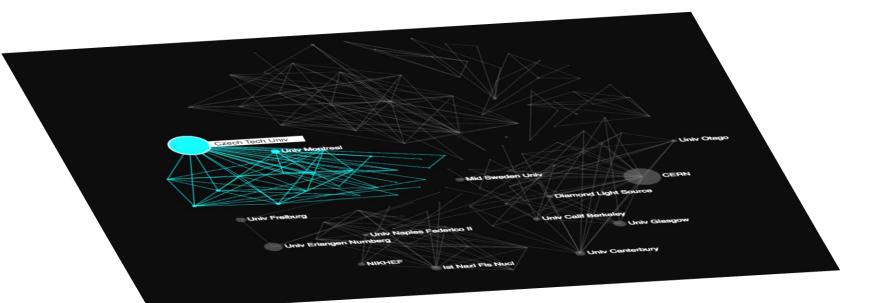
# Compound graphs(\*)

- <u>Compound graphs</u>: C=(G,T) is defined as a graph G=(V, E<sub>G</sub>) and a rooted tree T=(V, E<sub>T</sub>, r) that share the same set of vertices such as:
- $\forall e = (v_1, v_2) \in E_G, v_1 \notin path_T(r, v_2) \land v_2 \notin path_T(r, v_1)$
- Relationships between vertices are expressed by T:
- Vertices sharing a common parent in T belong to the same group.
- When two vertices sharing a common parent are connected in G, they share a generic relationship.



### Map Cluster to single vertex

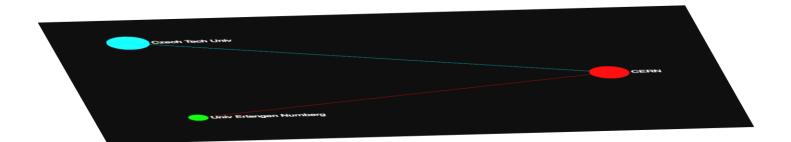


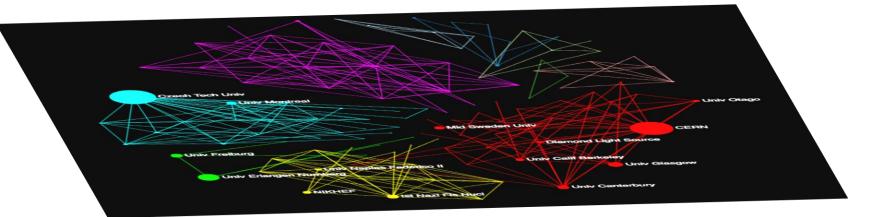




Technology: Medipix/Sociogram

### **Replacing clusters with vertices**

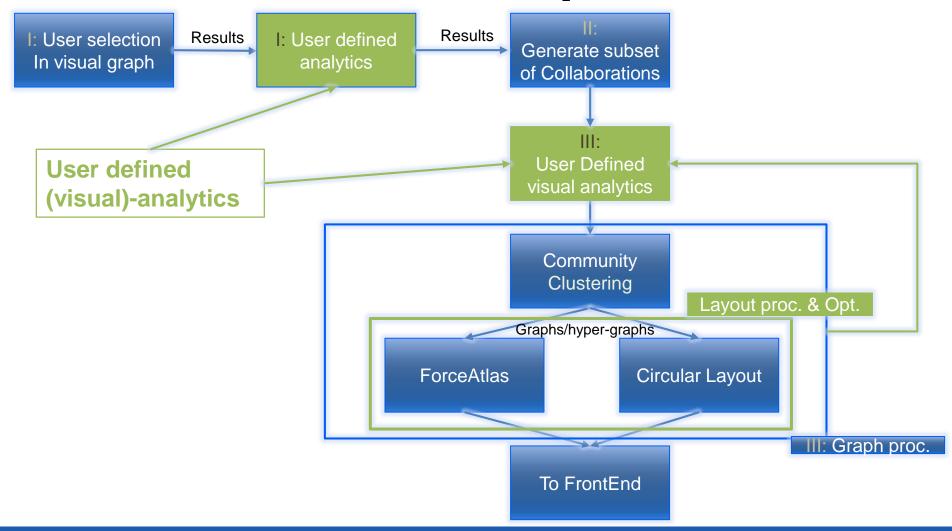






Technology: Medipix/Sociogram

# Introducing Analytics in the visualisation process





### **Explore other datasets**

- To validate development and support future work we need to team with domain experts to gather
   <u>Use Cases</u>, in particular <u>to explore</u> <u>multi-dimensional visual analytics</u>
- Possible sources (Collaboration required!)
  - Particle Physics
  - Biotech
    - Ex: Phenotyping



### Conclusion

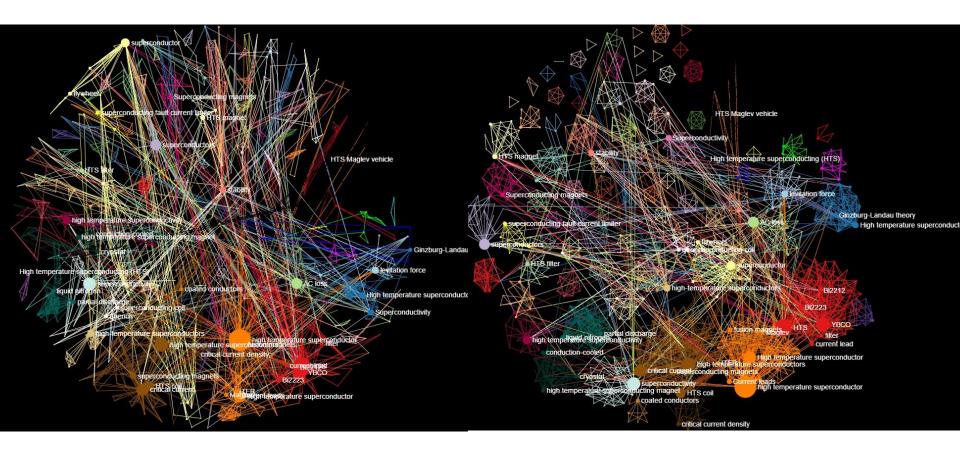
- Big Data visual Analytics bring the expert at the centre of the analytics cycle
- Interactive and multi-dimensional graph-based tools provide strong support to analytics
- Techniques applicable to any kind of data!





### Thank you for your attention!

### ForceAtlas is computing savvy





Different computation strategies on graphs of keywords



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