

# Exploring Importance Measures for Summarizing RDF/S KBs

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# Structure

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**01** Introduction

**02** Objectives

**03** Methods

**04** Experimental Setup

**05** Results

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# Problem Definition

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Explosion of the Web Data and the associated Linked Open Data creates:

1. Huge volume of data stored as graphs.
2. Extremely complex schemas.

Problems:

1. Difficult to comprehend.
2. Limiting the exploration and the exploitation potential of the information.

The idea

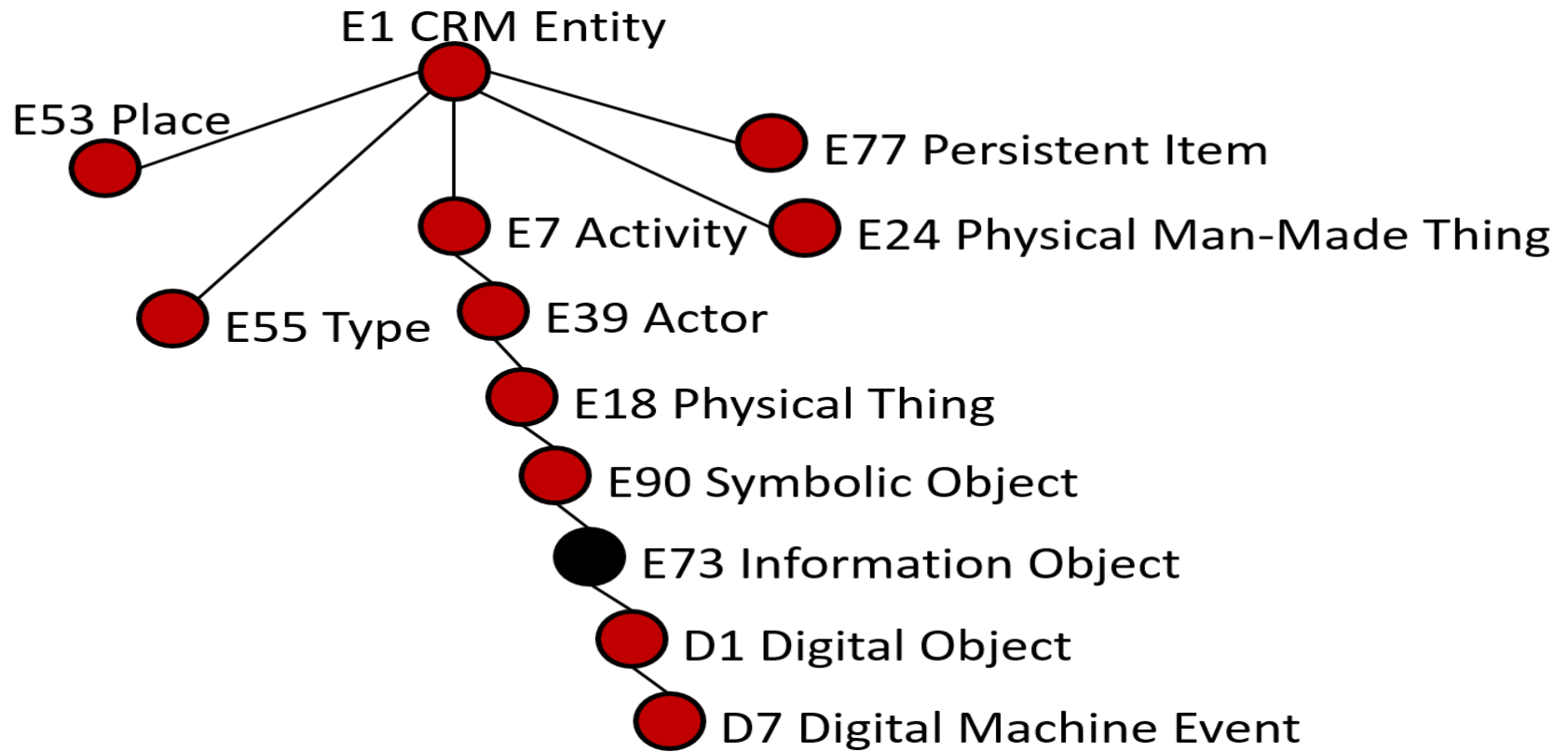
# Summarization

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The process of distilling knowledge from an ontology in order to produce an abridged version.







## Central questions to the process of summarization

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1. How to identify the most important nodes
2. How to link those nodes to produce a valid sub-schema graph.

## Importance Measures

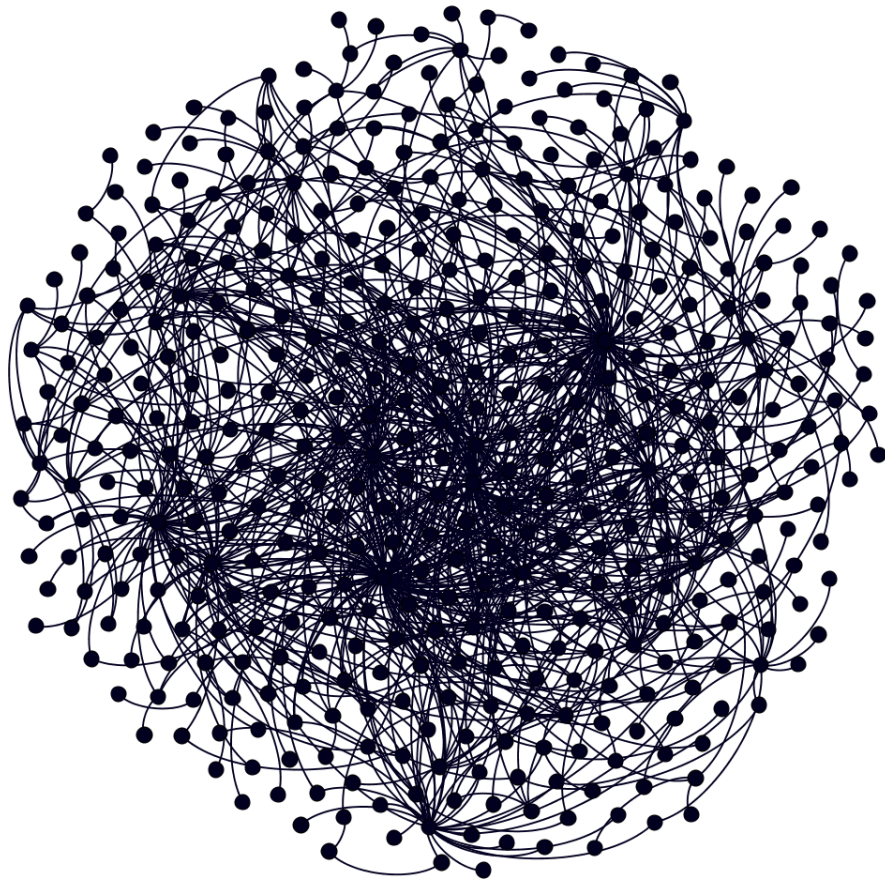
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Importance measures, produce rankings which seek to identify the role and importance of any vertex in a graph.

"There is certainly no unanimity on exactly what centrality is or on its conceptual foundations, and there is little agreement on the proper procedure for its measurement "

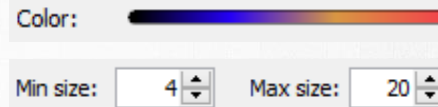
*-Freeman 1978*





# Graph Instance

## Nodes Ranking



Tool:

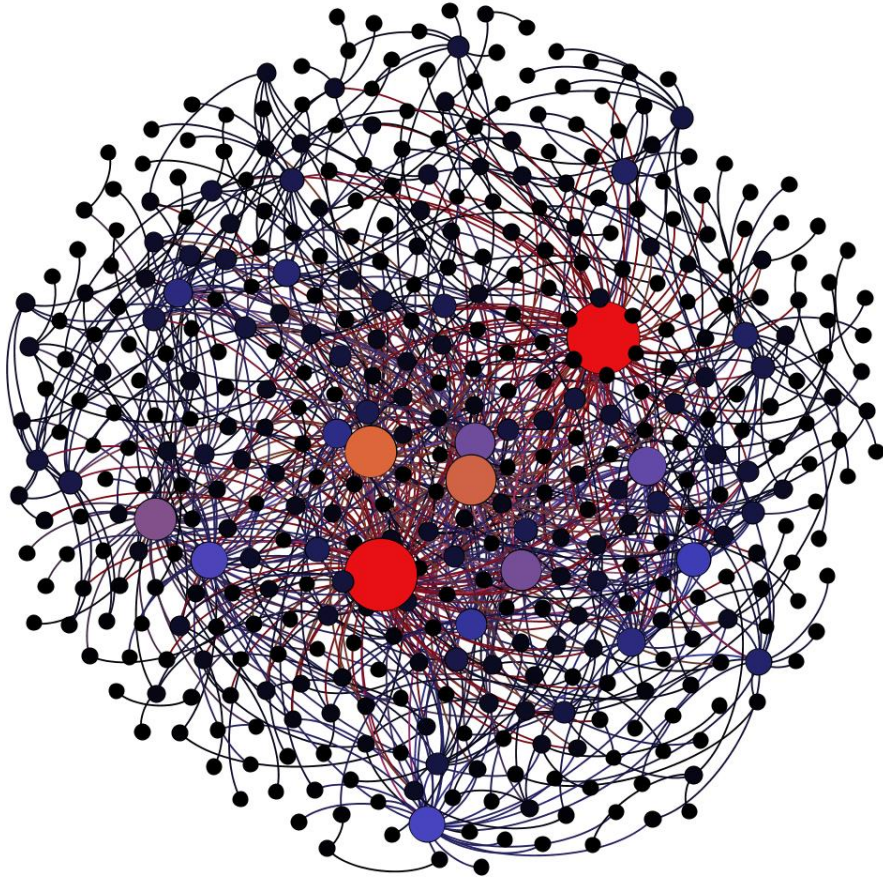


## CENTRALITIES (1/6)

### Degree



Counts the number of edges incident to a node.



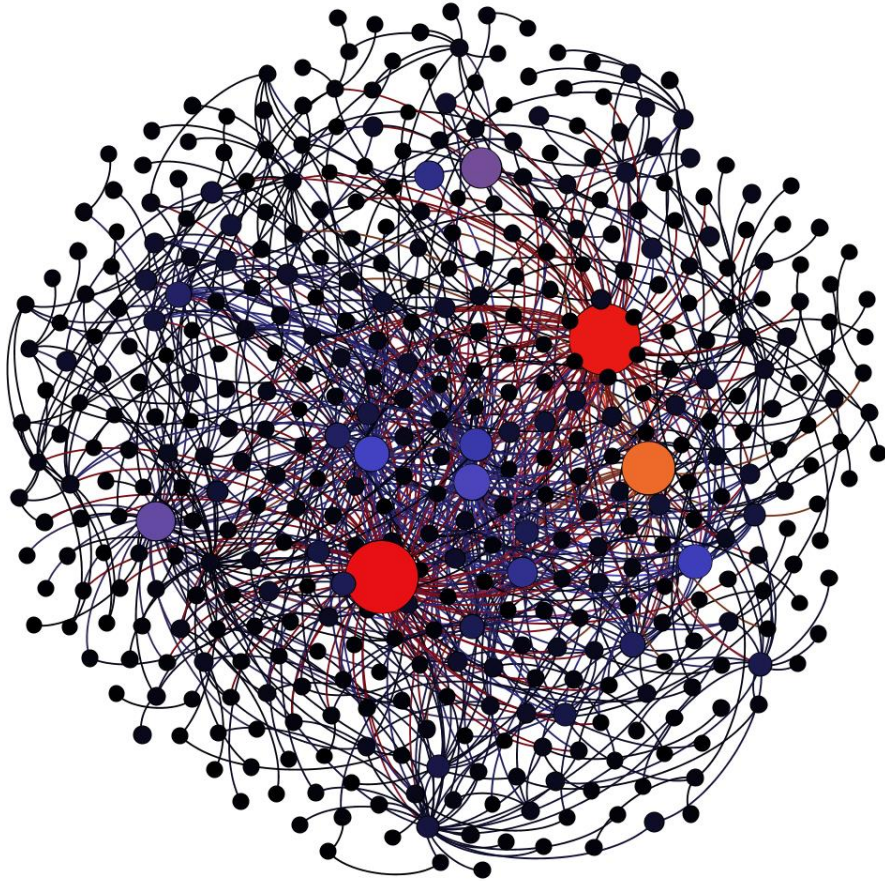


## Ego

Defines how important a node is to his neighborhood.

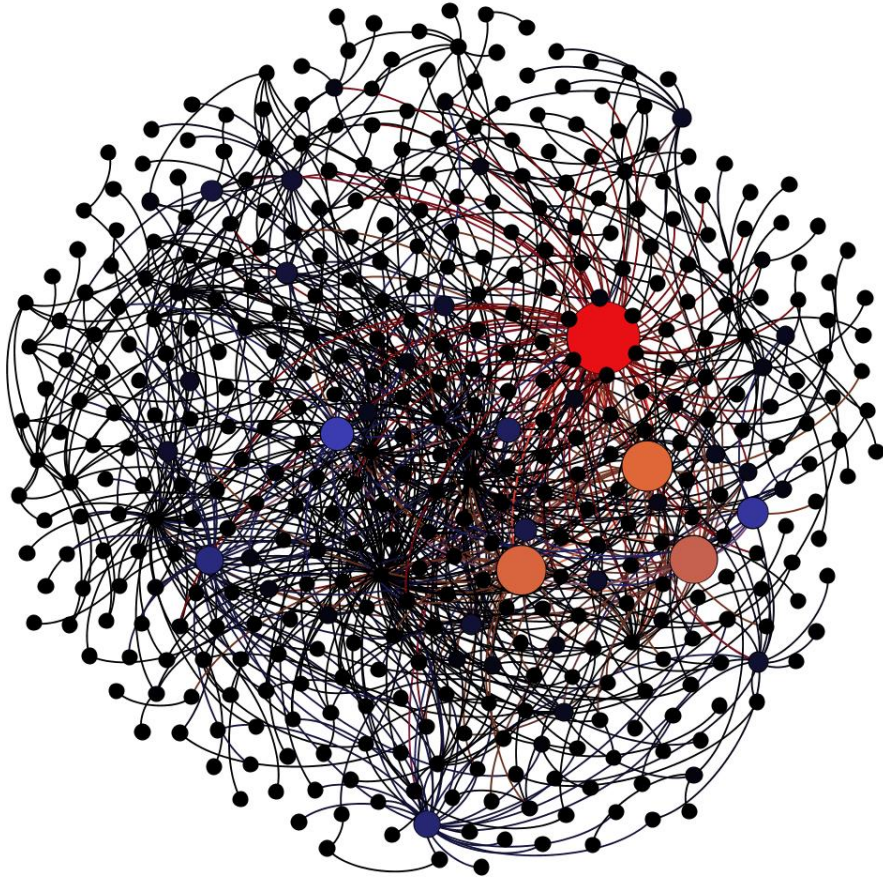
The importance of a node  $v$  to a neighbor node  $u$  is defined as:

$$Im(v, u) = \frac{1}{Degree(u)}$$



## Betweenness

Quantifies the number of times a node acts as a bridge along the shortest path between two other nodes.

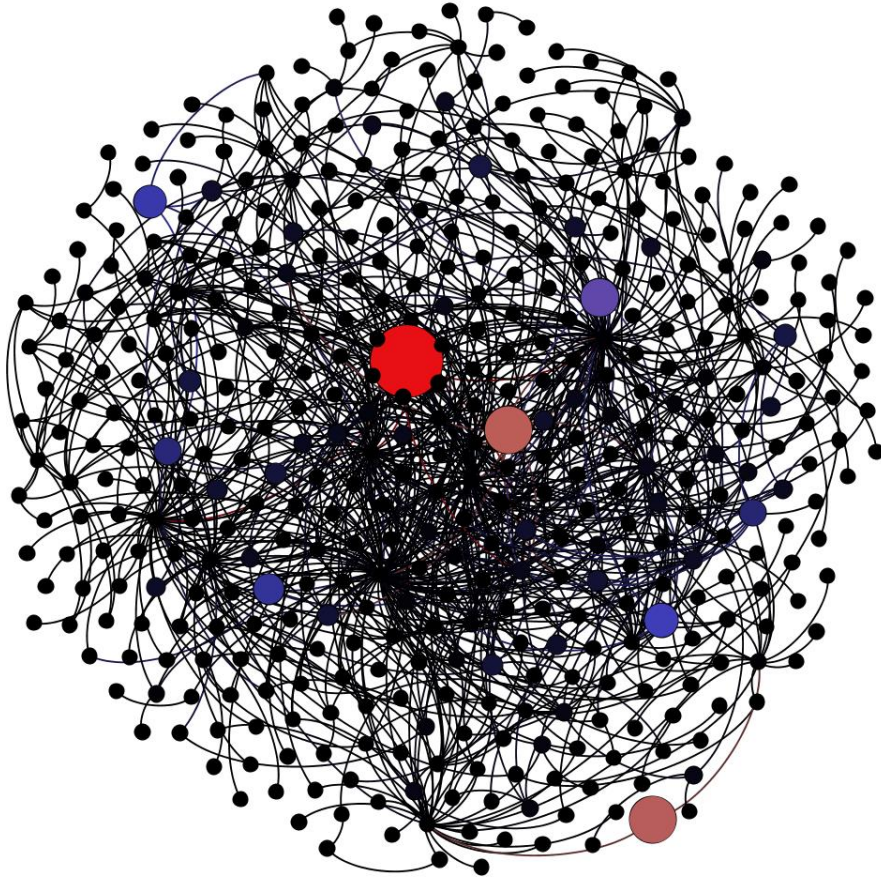




## Bridging Centrality

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Identifies the information flow and the topological locality of a node in a Graph.

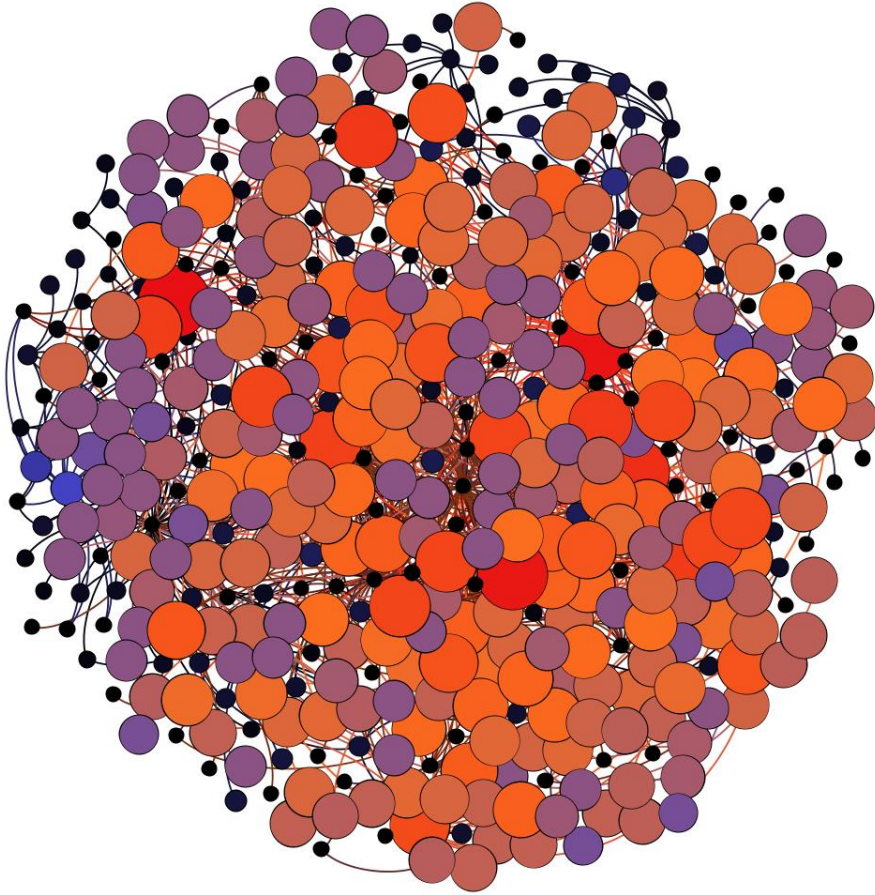




## Harmonic

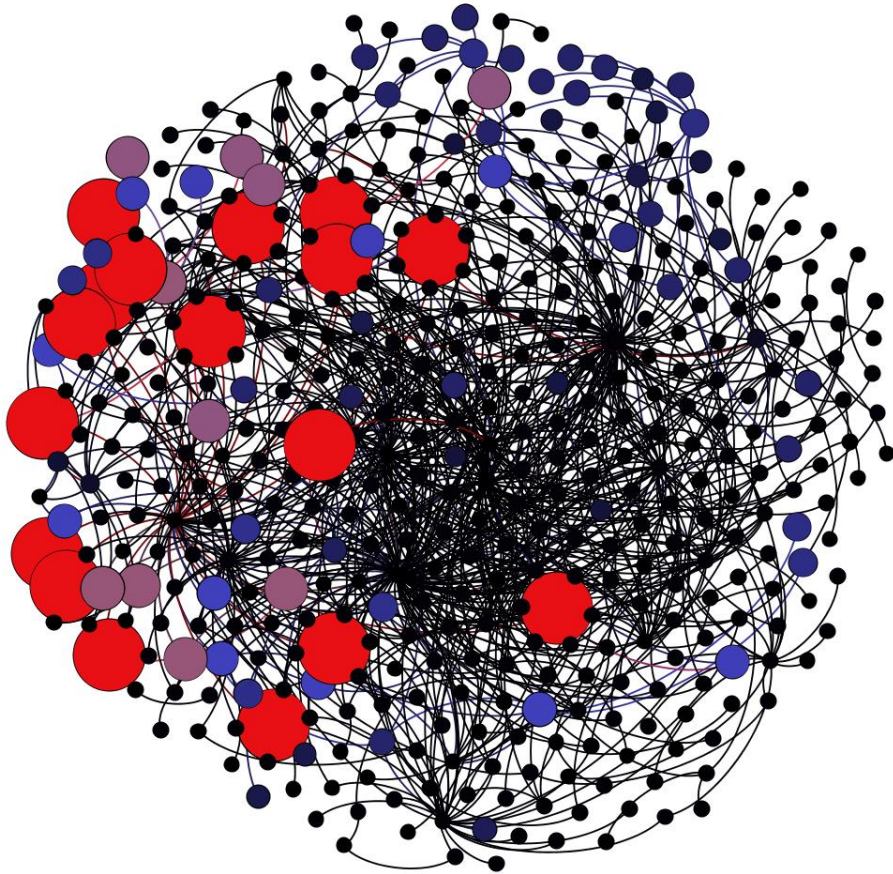
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Identifies the centrality of a node in a Graph, in terms of distance.



## Radiality

Average tendency to node proximity or isolation.





# Summarized Importance Value

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- Normalization of importance Value is defined as:

$$normal(IM_i(v)) = \frac{IM_i(v) - \min(IM_i(g))}{\max(IM_i(g)) - \min(IM_i(g))}$$

- Similarly, we normalize the number of instances ( $Inst(v)$ ) that belong to a schema node.
- The summarized importance value of each node is defined as:

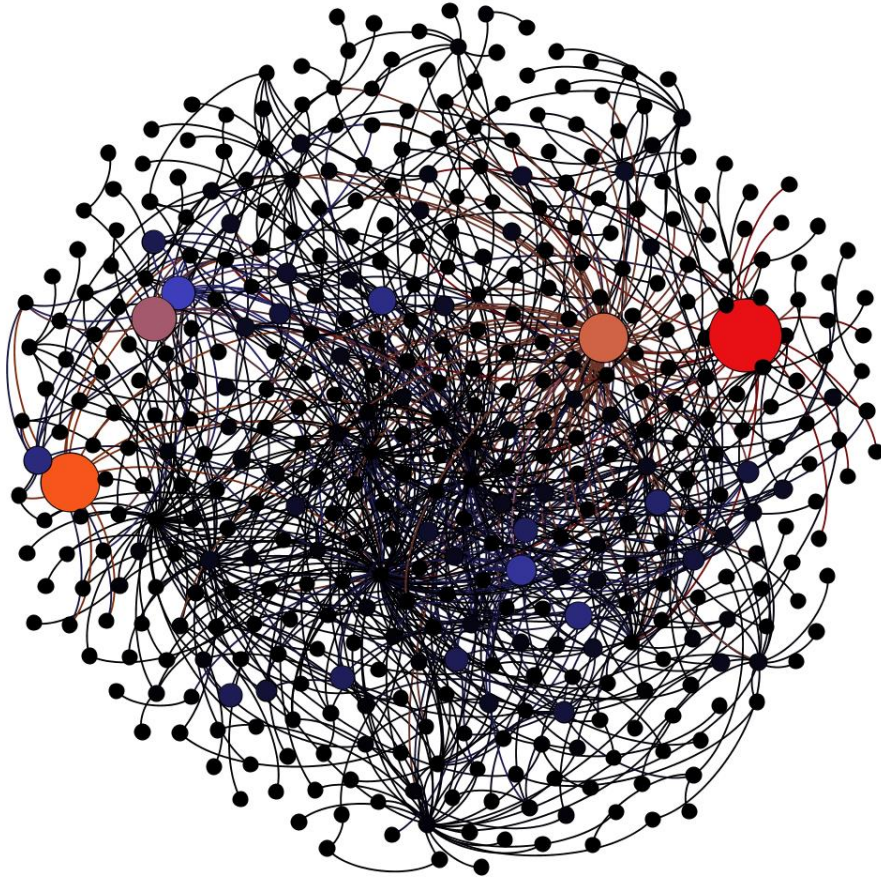
$$SIM_i(v) = normal(IM_i(v)) + normal(Inst(v))$$

## Related Work - Relevance

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Determined by:

- Connectivity in the schema
- Cardinality of the instances



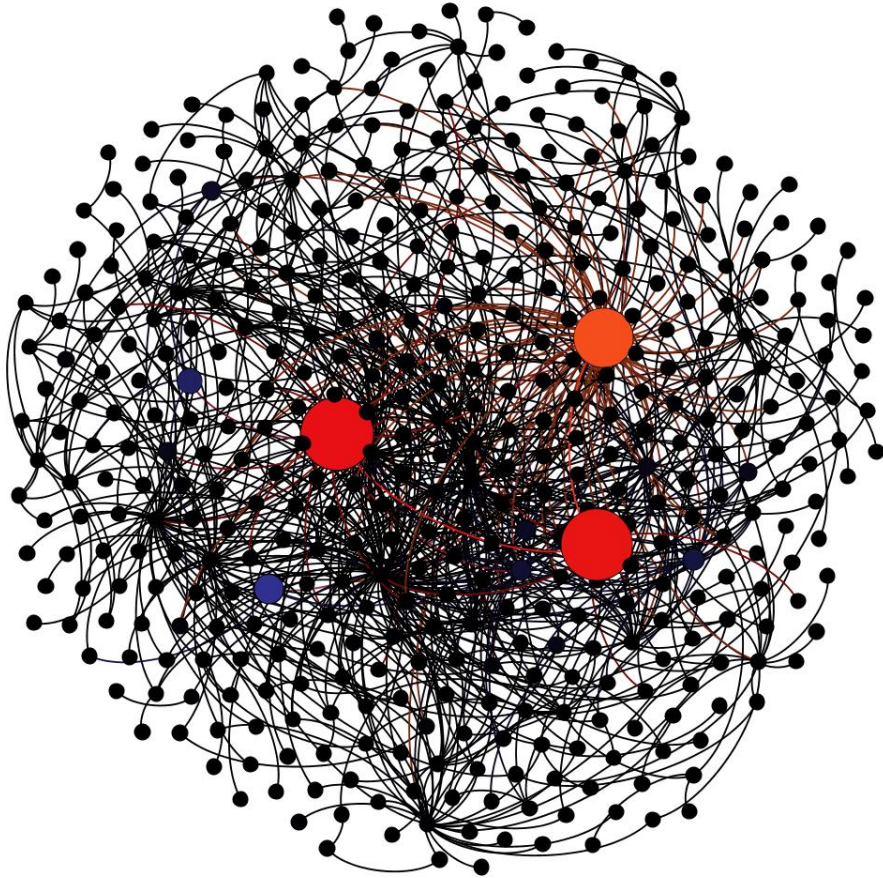


Hybrid CENTRALITIES (2/2)

## Related Work – KCE importance

Determined by:

- Connectivity in the schema
- Cardinality of the instances
- Psycho-linguistic criteria





# Construction of the RDF/S Summary Schema Graph

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Focus on the paths that link the most important nodes:

The Graph Steiner Tree Problem

The idea

# The Steiner Tree Problem

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Given an undirected graph  $G = (V, E)$ , with edge weights  $w: E \rightarrow \mathbb{R}^+$  and a node set of terminals  $S \subseteq V$ , find a minimum-weight tree  $T \in \mathcal{G}$  such that  $S \subseteq V_t$  and  $E_t \subseteq E$ .

# Algorithms, Approximation & Heuristics

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1. SDISTG
2. CHINS
3. HEUM

Worst case bound of 2 *Deviation*  $= \frac{(Z_t - Z_{opt})}{Z_{opt} \times 100}$

Where  $Z_t$  and  $Z_{opt}$  denotes the objective function values of a feasible solution and an optimal solution respectively.

# Complexity of Algorithms

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Algorithm	Un-weighted graph
MST	$O( V + E )$
SDISTG	$O(Q \times  V + E )$
CHINS	$O(Q \times  V + E )$
HEUM	$O(V \times  V + E )$



## The competitor - The Maximum-Cost Spanning Tree (MST)

Given an undirected graph  $G = (V, E)$ , with edge weights  $w: E \rightarrow \mathbb{R}^+$  find a spanning tree  $T \in \mathcal{G}$  of maximum total edge cost, where  $E_t \subseteq E$ .



# Evaluation - Data Sets

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- Dbpedia 3.8: 359 classes, 1323 properties and more that 2.3M instances
- Dbpedia 3.9: 552 classes, 1805 properties and more than 3.3M instances

Ontology	Density	Diameter	Avg path length
DBpedia 3.8	0.00472	9	3.80
DBpedia 3.9	0.00298	13	4.36

## Evaluation - Gold Standard

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**Frequency:** To identify the most important nodes of those ontologies we rely on the corresponding SPARQL endpoint query logs, created by users queries

- DBpedia 3.8 more than 50K queries
- DBpedia 3.9 more than 110K queries

# Evaluation - Measures

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## 1. Evaluation of Measures for Assessing vertices' Importance

- Spearman's rank correlation coefficient
- The Similarity Measure

## 2. Evaluating Summaries

- Graph edit distance
- Additional vertices Introduced

# Spearman's rank correlation coefficient

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Statistical dependence between the ranking of:

- Important measures
- Gold Standard



# The Similarity Measure

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Ontologies can be compared at two different levels:

- The number of classes that exists in gold standard
- For those that does not exists, asses their distance in the taxonomic structure



# Graph edit distance

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- Measure of similarity between two graphs.
- Count the minimum number of operations required to transform a graph  $G$  into (a graph isomorphic to)  $G'$

# Additional vertices Introduced

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Overhead imposed by the algorithms for linking the most important vertices in terms of the additional vertices that are introduced.

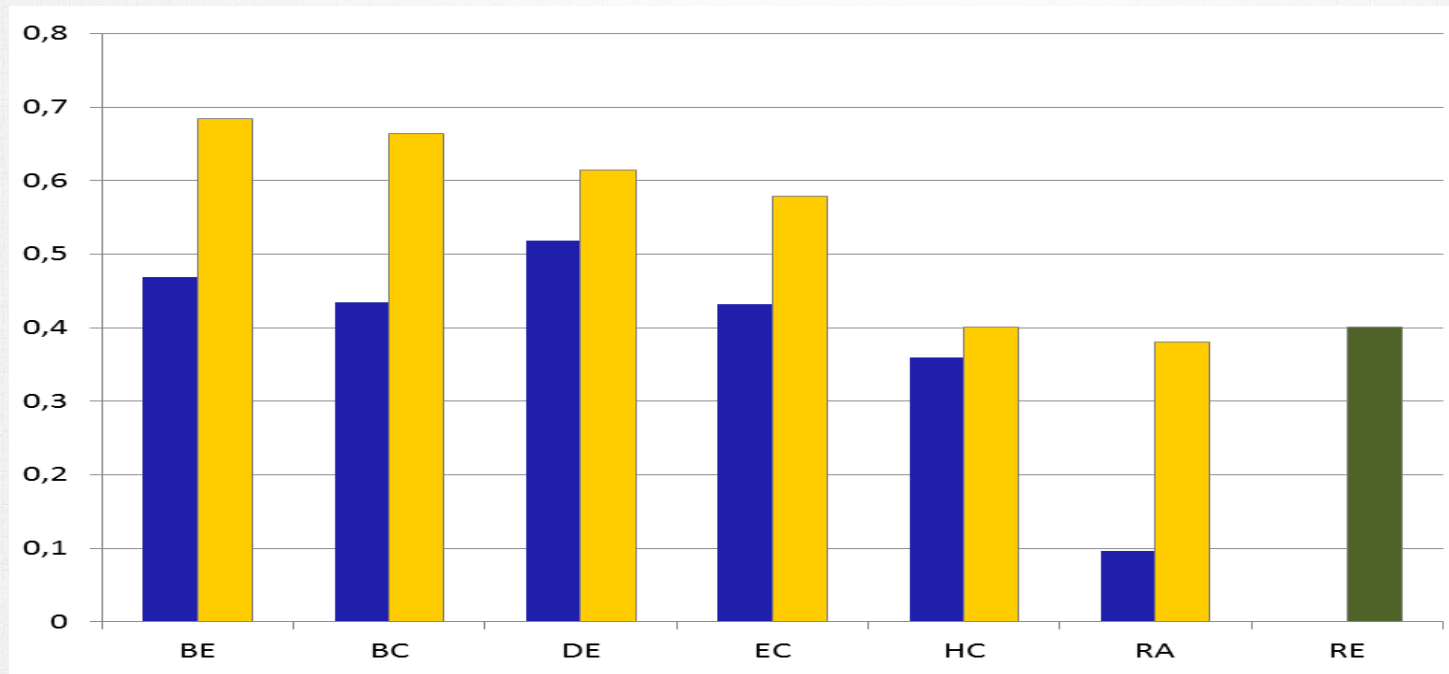
## Execution Time

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- Performance and scalability with graph sizes
- Average time of 50 executions

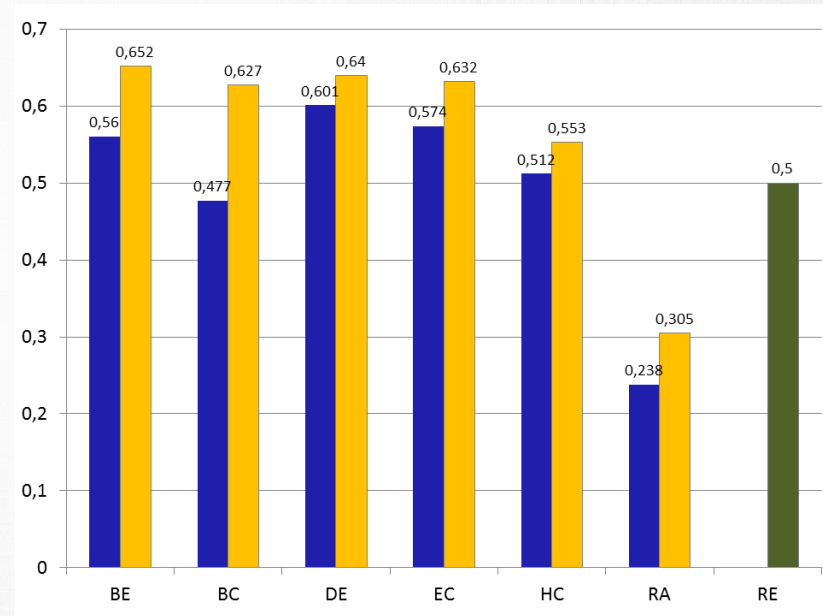
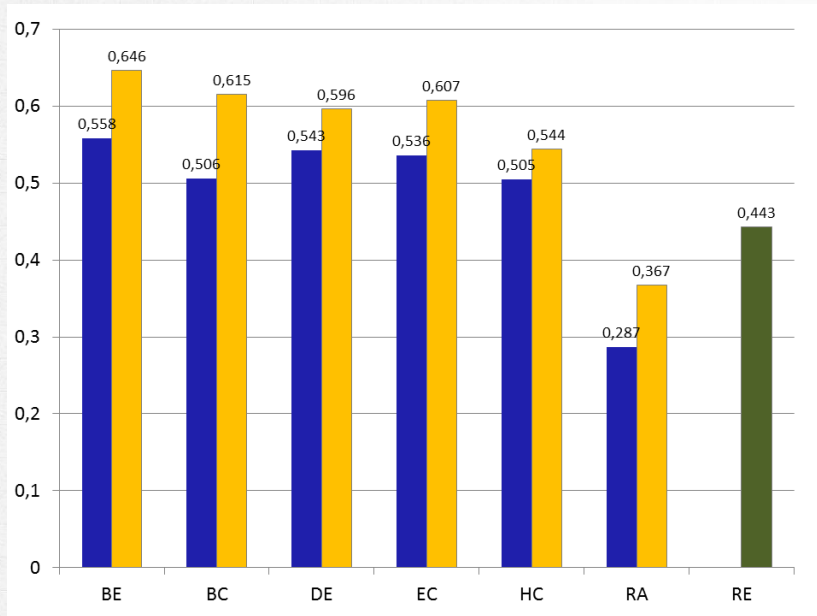
# Spearman's rank correlation coefficient

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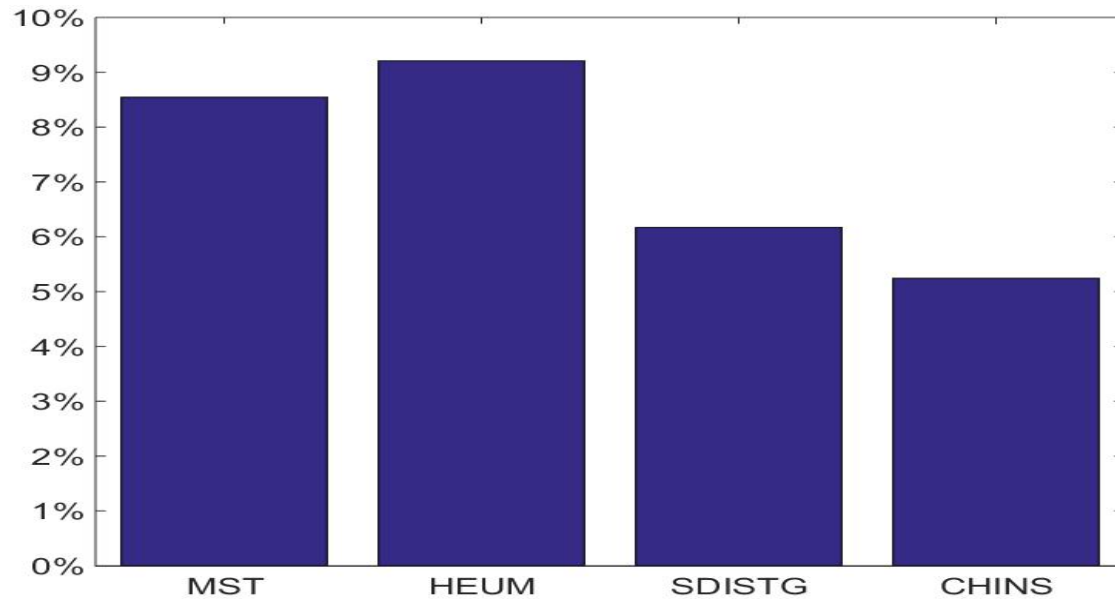
# The Similarity Measure



Average similarity DBpedia 3.8 and DBpedia 3.9 for a summary of 1-50%.

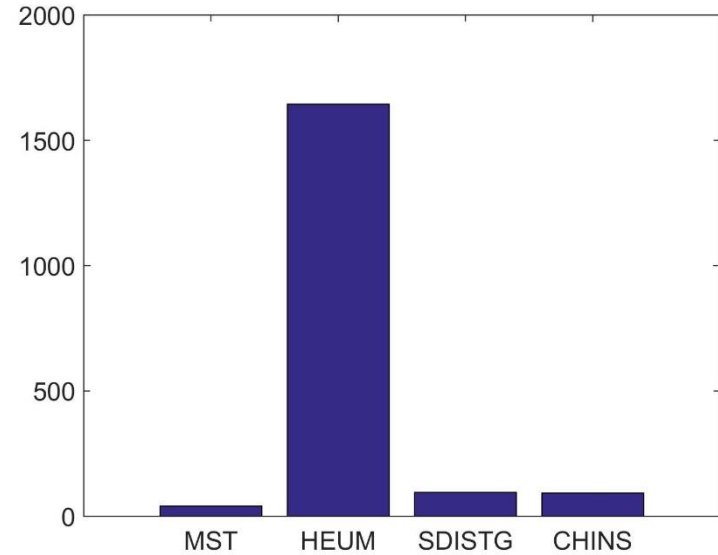
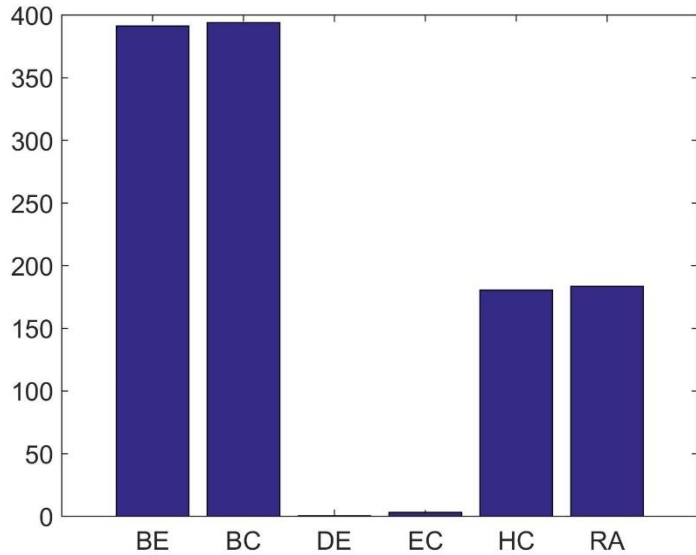
# Additional vertices Introduced

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# Average Execution Time in milliseconds

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## Discussion & Conclusion

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- Structural measures have better results in most of the cases.
  - Betweenness and the Ego Centrality
- Steiner-Tree approximation algorithms produce better summaries and introduce less additional nodes to the result schema graph
  - CHINS seems to achieve an optimal trade-off between quality and execution time.

# Future Work

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1. Combine the various measures in order to achieve the best results according to the specific characteristics of the input ontologies.
2. Extend our approach to handle more constructs from OWL(not only ontologies)
3. Index coverage in the sense of frequent sub-graph problem has to be further examined.
4. Smaller index size and improvement of query performance over graph databases is a growing need.
5. Exploit summaries for Query Answering

THANK YOU for your attention

"Graphs are everywhere  
and their possibilities are endless."

*-Mark Cryer*

Questions?