Insights from Knowledge Graphs : Introducing a new formalism

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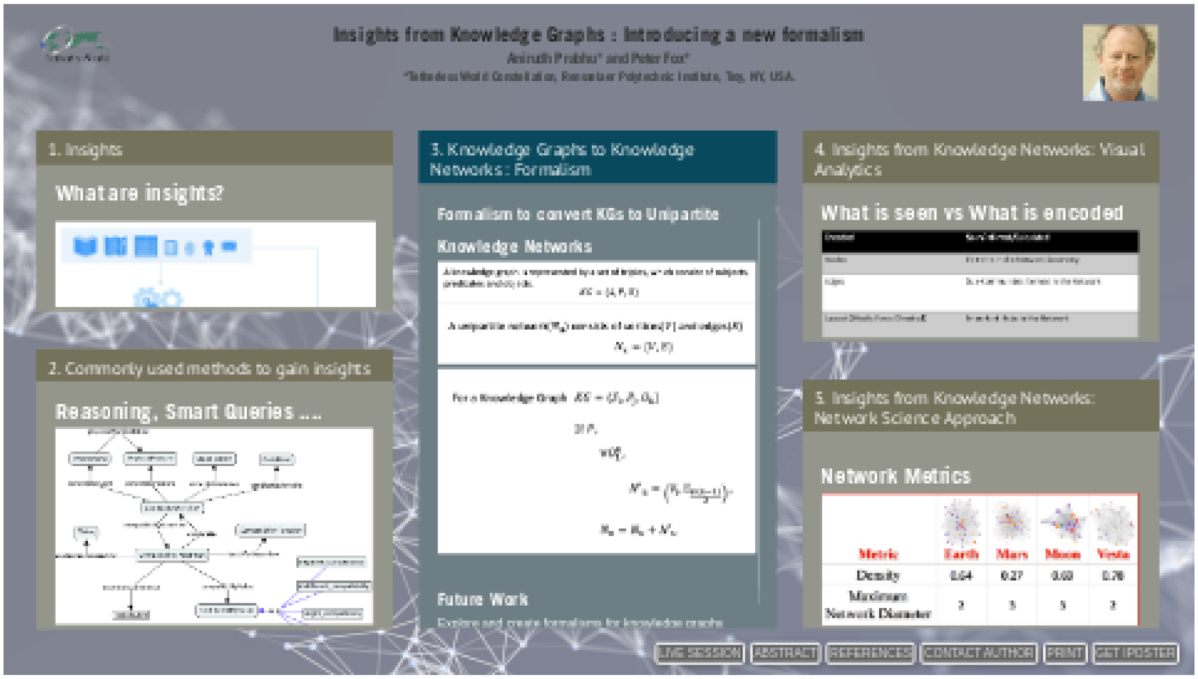
Abstract

The usage of the term Knowledge Graph (KG) has gained significant popularity since 2012, when Google introduced its own knowledge graph, and how they used it to enhance their searches and question answering systems. While various definitions and interpretations for knowledge graphs have been presented, what remains consistent is that knowledge graphs are commonly used with reasonsers to make inferences about data, based on assertions and axioms written by human experts. But knowledge graphs, which store complex, multi-dimensional data contain hidden patterns and trends that cannot be explored simply using reasoners. In such a case it becomes necessary to extract parts of the knowledge graph (focusing on the instances related to one property at a time) and analyze them individually in order to conduct a focused but tractable exploration of the domain. In this presentation, we present one way to gain insights from knowledge graphs, using network science. To achieve this goal, we have formalised the partitioning of knowledge graphs to unipartite knowledge networks, and present various ways to explore and analyse such knowledge networks to form scientific hypotheses, gain scientific insights and make discoveries.

Insights from Knowledge Graphs : Introducing a new formalism



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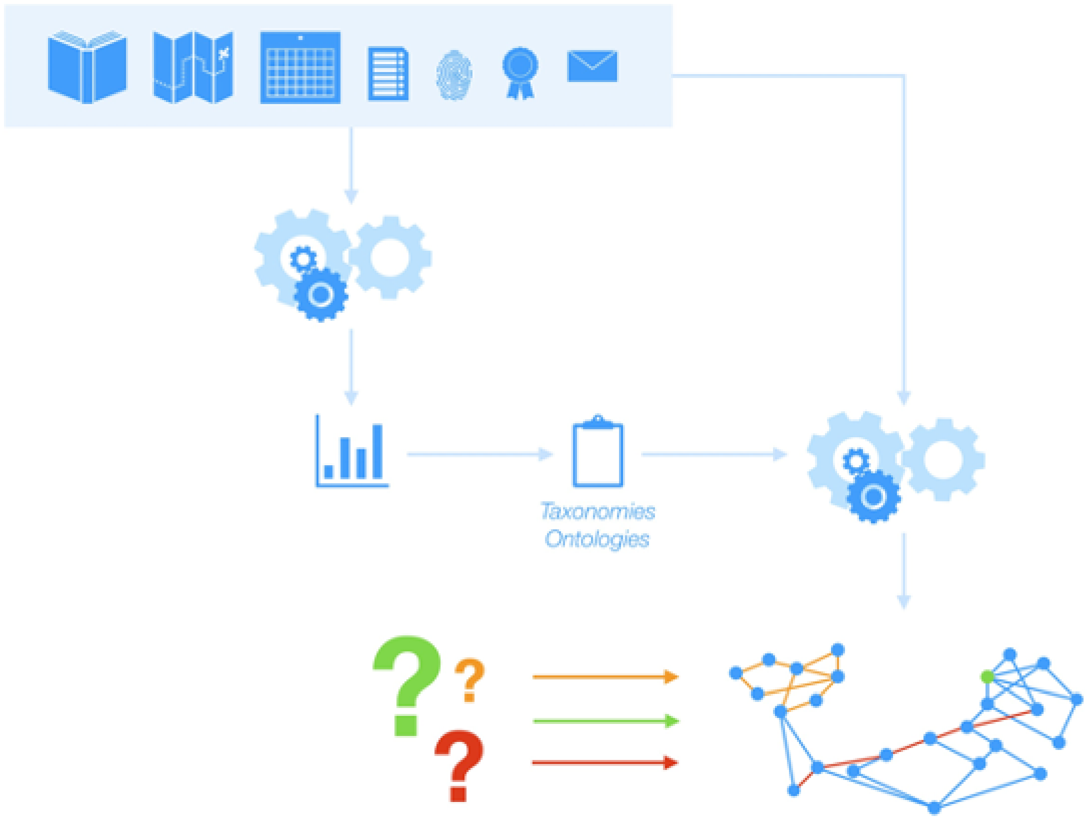
1. INSIGHTS

What are insights?



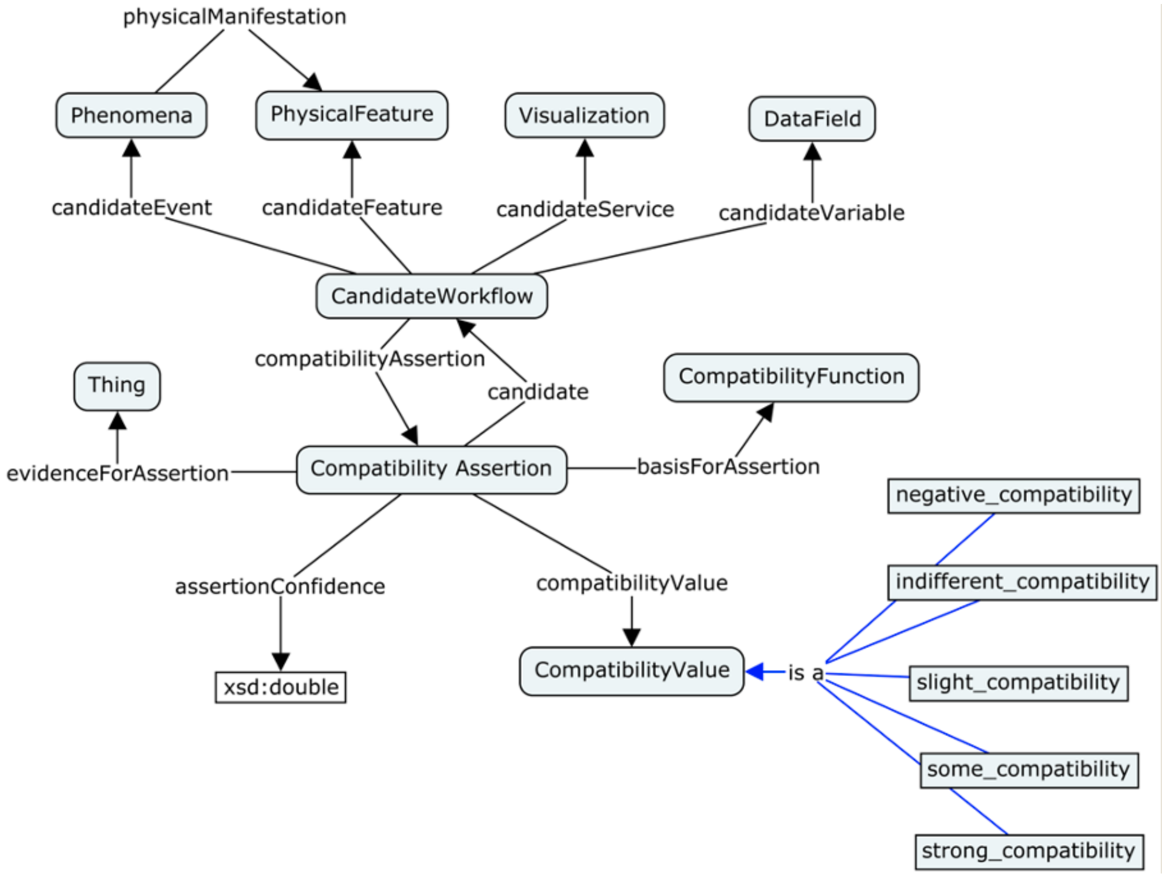
How to gain insights?

How do we gain insights?

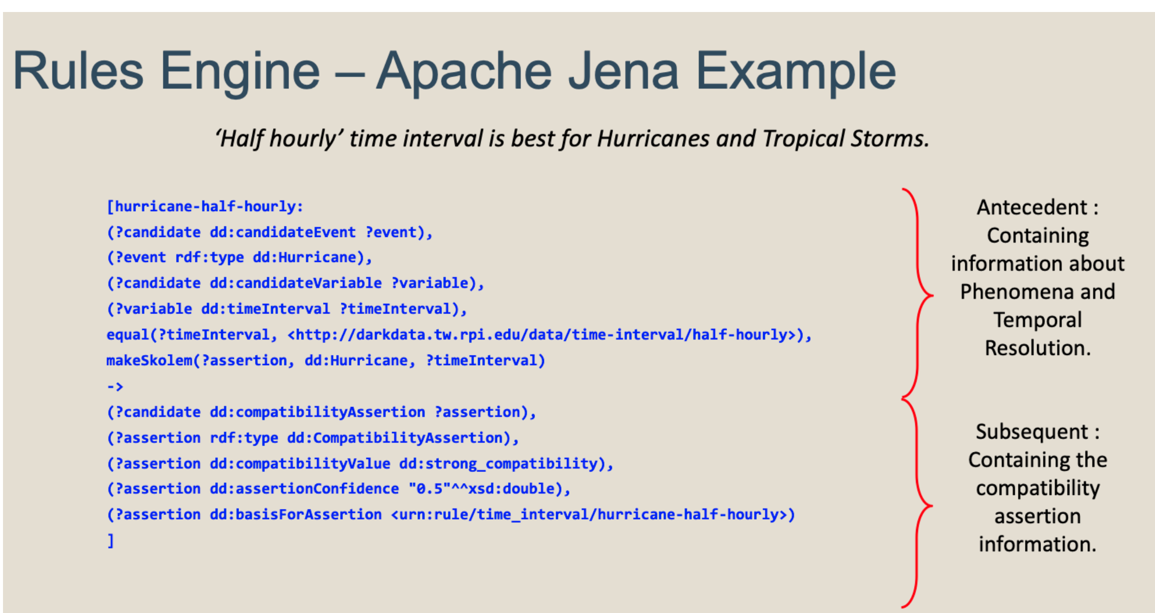
- Reasoners
- Visual Analytics
- Network Science Approach

2. COMMONLY USED METHODS TO GAIN INSIGHTS

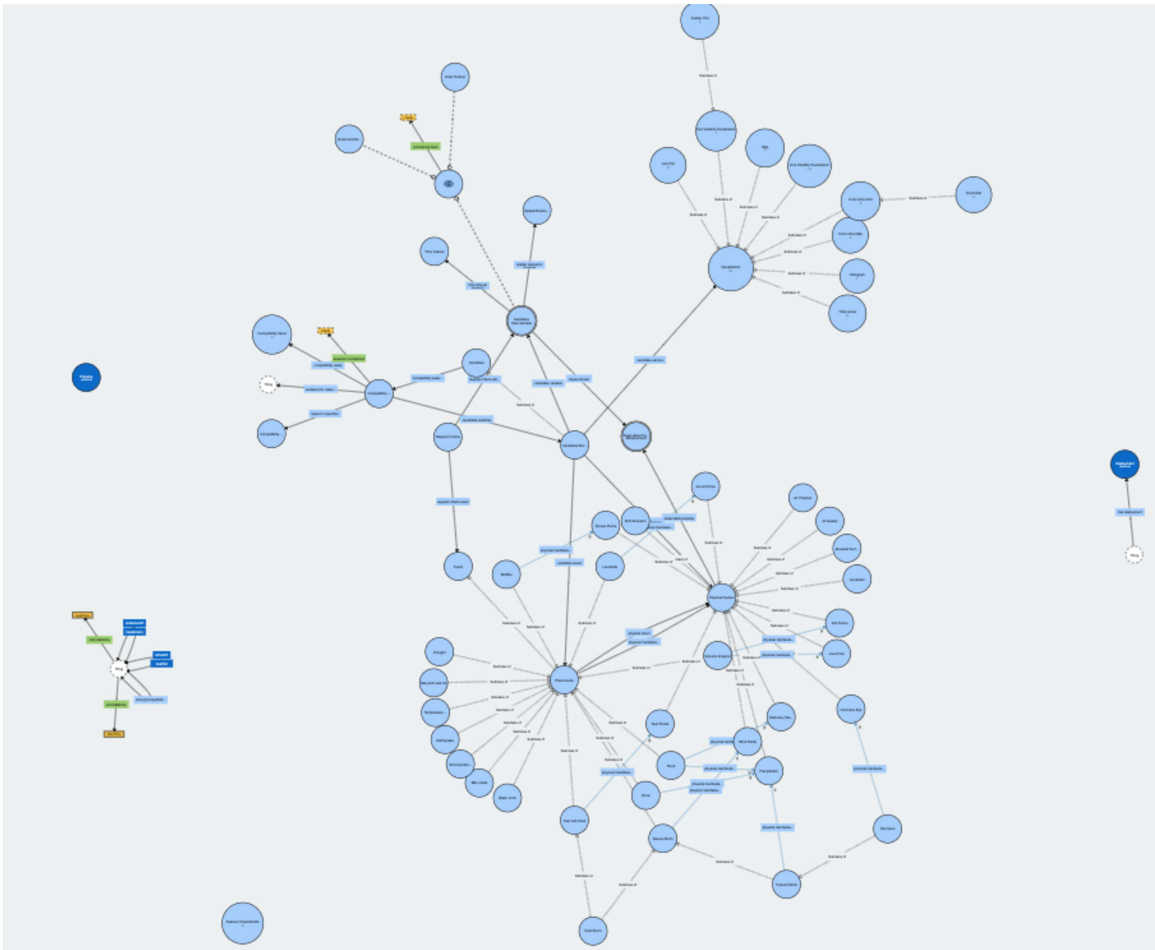
Reasoning, Smart Queries ....



Conceptual Map of Ontology



Example of rules used in Ontology



Ontology visualized using VOWL (http://www.visualdataweb.de/webvowl/ (http://www.visualdataweb.de/webvowl/))

3. KNOWLEDGE GRAPHS TO KNOWLEDGE NETWORKS : FORMALISM

Formalism to convert KGs to Unipartite Knowledge Networks

A knowledge graph is represented by a set of triples, which consist of subjects, predicates and objects.

$$KG = (S, P, O)$$

A unipartite network(N_u) consists of vertices(V) and edges(E)

$$N_u = (V, E)$$

For a Knowledge Graph $KG = (S_i, P_j, O_k)$

$$\exists!\, P,$$

$$\forall O_1^k,$$

$$N'_{\mathrm{u}} = \left(\mathrm{V_i}, \mathrm{E}_{\frac{\mathrm{n(n-1)}}{2}}\right),$$

$$N_u = N_u + N'_u$$

Future Work

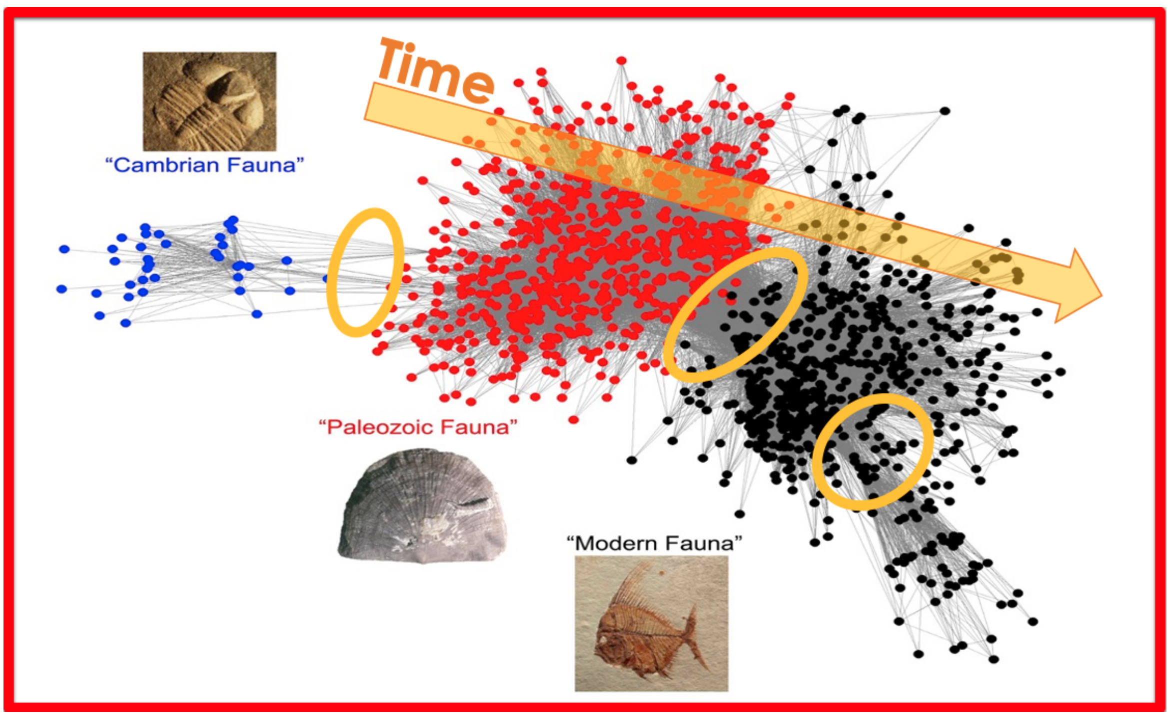
Explore and create formalisms for knowledge graphs to bipartite and other k-partitie networks.

4. INSIGHTS FROM KNOWLEDGE NETWORKS: VISUAL ANALYTICS

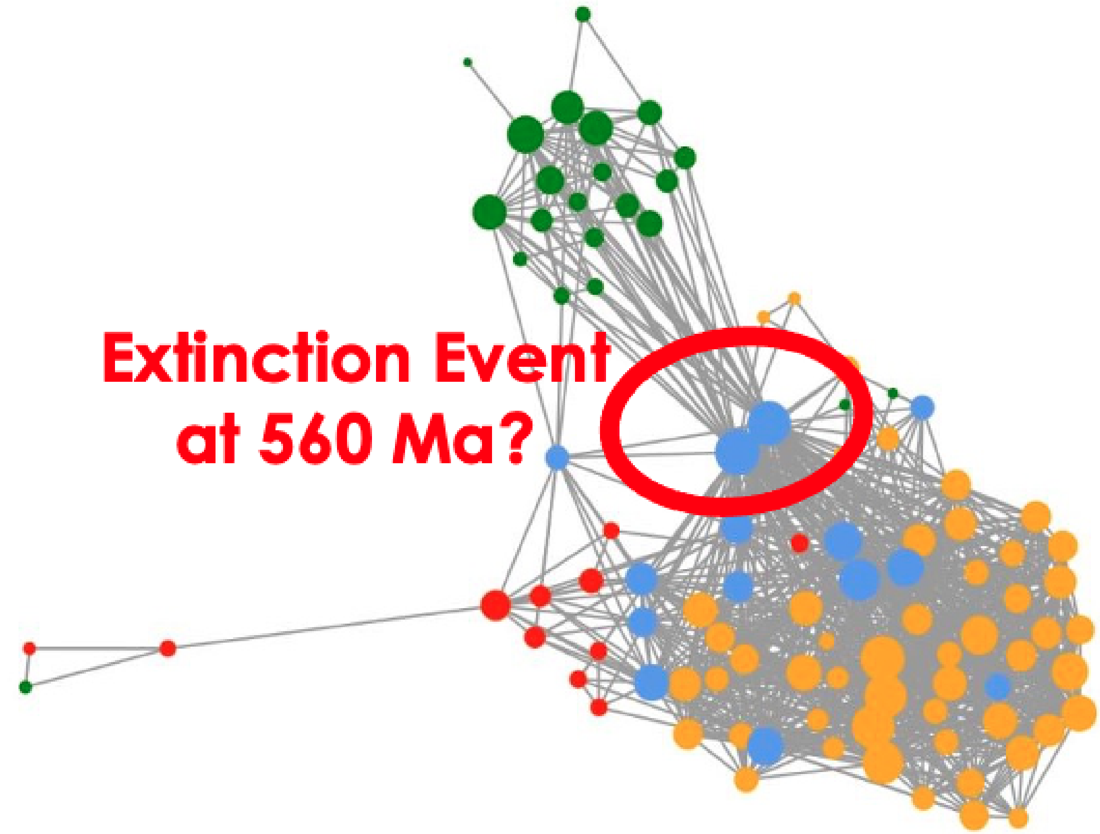
What is seen vs What is encoded

Encoded	Seen/Inferred/Calculated
Nodes	Patterns in the Network Geometry
Edges	Sub-Communities formed in the Network
Layout (Mostly Force Directed)	Important Hubs in the Network
Additional Parameters for Nodes (Optional)	Additional metrics that explain the complexity of the environment (assortativity, betweenness, centrality etc.)

In the visual layout



Animal Family Fossil Network (from 542 Ma - present)



Ediacaran Fossil Network (From 635 Ma to 541 Ma)

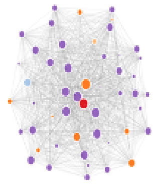
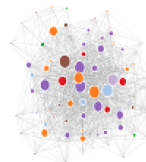
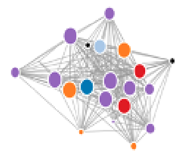
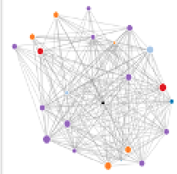
Evolving Networks

[VIDEO] https://www.youtube.com/embed/x1P3FZhWALw?rel=0&fs=1&modestbranding=1&rel=0&showinfo=0

Network of Copper Minerals evolving through time. (3.7 Ga to 2.4 Ga)

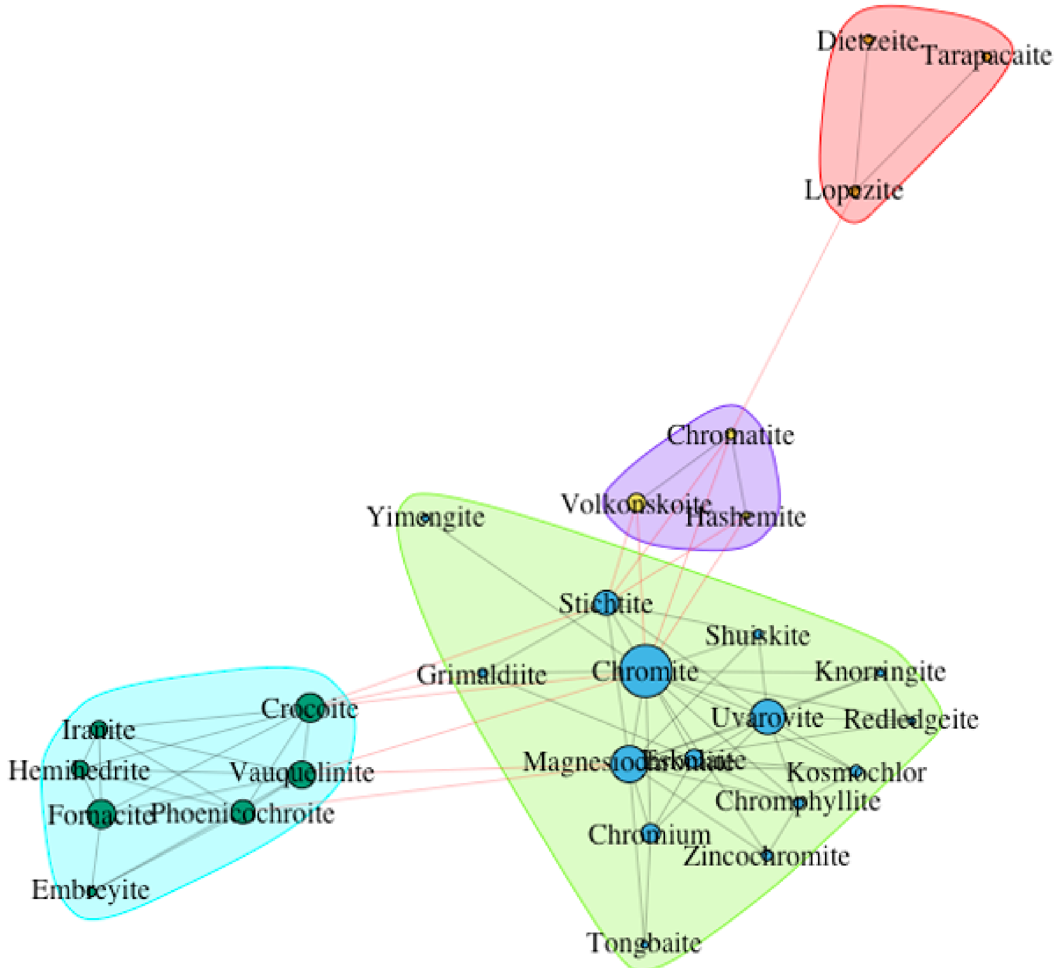
5. INSIGHTS FROM KNOWLEDGE NETWORKS: NETWORK SCIENCE APPROACH

Network Metrics

Metric	 Earth	 Mars	 Moon	 Vesta
Density	0.64	0.27	0.69	0.78
Maximum Network Diameter	2	3	3	2
Mean Network Diameter	1.36	1.69	1.26	1.22
Degree Central.	0.34	0.62	0.23	0.22
Betweenness Centralization	0.02	0.09	0.03	0.02

Comparing Global Metrics in mineral networks of planetary bodies

Community Detection Algorithms



Walktrap algorithm applied to Chromium Mineral Network.

- Groups correspond to Paragenetic Mode.
- Paragenetic Mode : Formation Conditions.
- How and when the Minerals were formed.

ABSTRACT

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