A new way to evaluate association rule mining methods and its applicability to mineral association analysis

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Abstract

There has been a significant increase in the amount and accuracy of mineral data (from resources like Mindat, MED or the GEMI) and the improvements in technological resources make it possible to explore and answer large, outstanding scientific questions, such as, understanding the mineral assemblages on Earth and how they compare to assemblages and localities on other planets. In the last couple of years, affinity analysis methods have been used to:1) Predict unreported minerals at an existing locality, 2) Predict localities for a set of known minerals[1]. We've chosen to call this application "Mineral Association Analysis"[2]. Affinity analysis is an unsupervised machine learning method that uses mined association rules to find interesting patterns in the data. Most of the metrics used to evaluate market basket analysis methods focus on either the ability of the model to ingest large amounts of data[3], or using a metric based comparison of various algorithms used for association rule mining[4], or on evaluating the rules mined to more efficiently generate association rules[5]. However, when patterns generated in an unsupervised method are used to predict the occurrences of entities such as minerals, there needs to be a way to evaluate the predictions made by the model. It's in such an area that there has been very little work. In this abstract, we explore the development of a new method to evaluate the results of association rule mining algorithms specifically when used when the association rules generated are utilized in a predictive setting. [1] Prabhu et. al (2019). In AGU Fall Meeting Abstracts (EP23D-2286). [2] Morrison et al. Nat. Geo. (2021) In Prep. [3] Agrawal et al. (1993) SIGMOD'93. [4] Sharma et al. (2012) IJERT 1(06). [5] Üstündağ and Bal (2014) Proc. in Comp.

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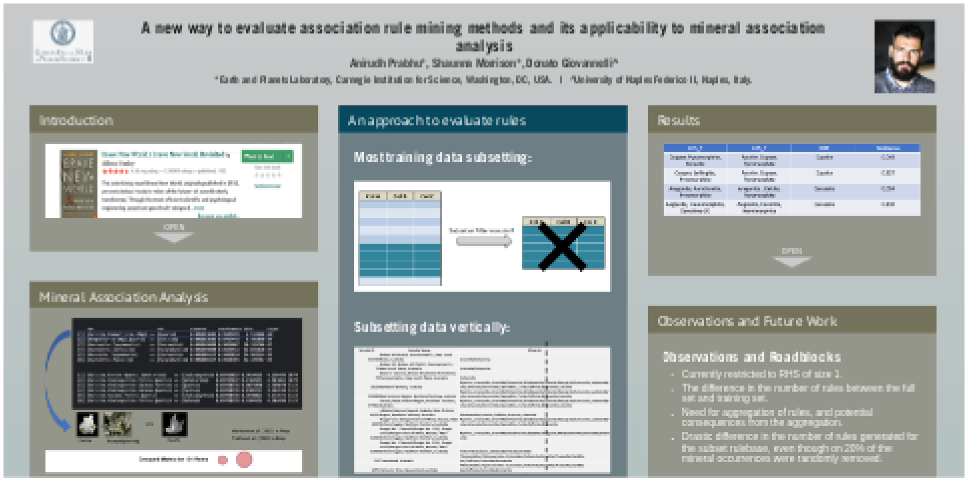

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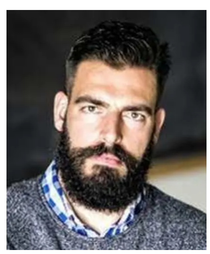


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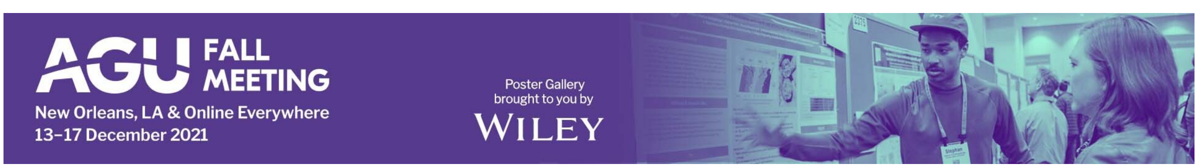
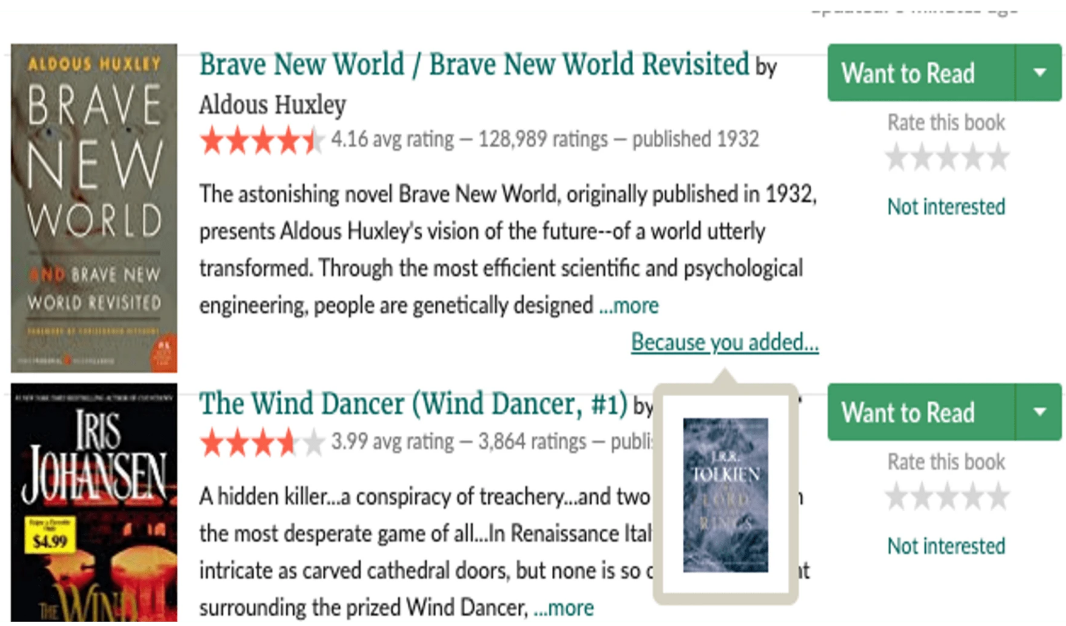


INTRODUCTION



Collaborative Filtering

Content-based Filtering

Hybrid

MINERAL ASSOCIATION ANALYSIS

```
     lhs                             rhs           support     confidence lift      count
[1] {Calcite,Pumpellyite-(Mg)} => {Quartz}      0.001013685 0.9545455   2.512686 84
[2] {Pumpellyite-(Mg),Quartz}  => {Calcite}     0.001013685 0.9767442   5.491850 84
[3] {Corvusite,Tyuyamunite}    => {Carnotite}   0.001049888 0.9666667  56.331786 87
[4] {Carnotite,Corvusite}      => {Tyuyamunite} 0.001049888 0.8529412  92.031020 87
[5] {Pascoite,Tyuyamunite}     => {Carnotite}   0.001001617 0.9431818  54.963224 83
[6] {Carnotite,Pascoite}       => {Tyuyamunite} 0.001001617 0.8556701  92.325467 83


[1] {Calcite,Pyrite,Quartz,Sphalerite}     => {Chalcopyrite} 0.03715637 0.7634515  4.258493 3079
[2] {Calcite,Chalcopyrite,Pyrite,Quartz}  => {Sphalerite}   0.03715637 0.7102653  4.901061 3079
[3] {Calcite,Chalcopyrite,Galena,Pyrite}  => {Quartz}       0.03768735 0.9075850  2.389070 3123
[4] {Calcite,Chalcopyrite,Galena,Quartz}  => {Pyrite}       0.03768735 0.9305721  3.484536 3123
[5] {Calcite,Galena,Pyrite,Quartz}        => {Chalcopyrite} 0.03768735 0.7840823  4.373571 3123
[6] {Calcite,Chalcopyrite,Pyrite,Quartz}  => {Galena}       0.03768735 0.7204152  4.202896 3123
```

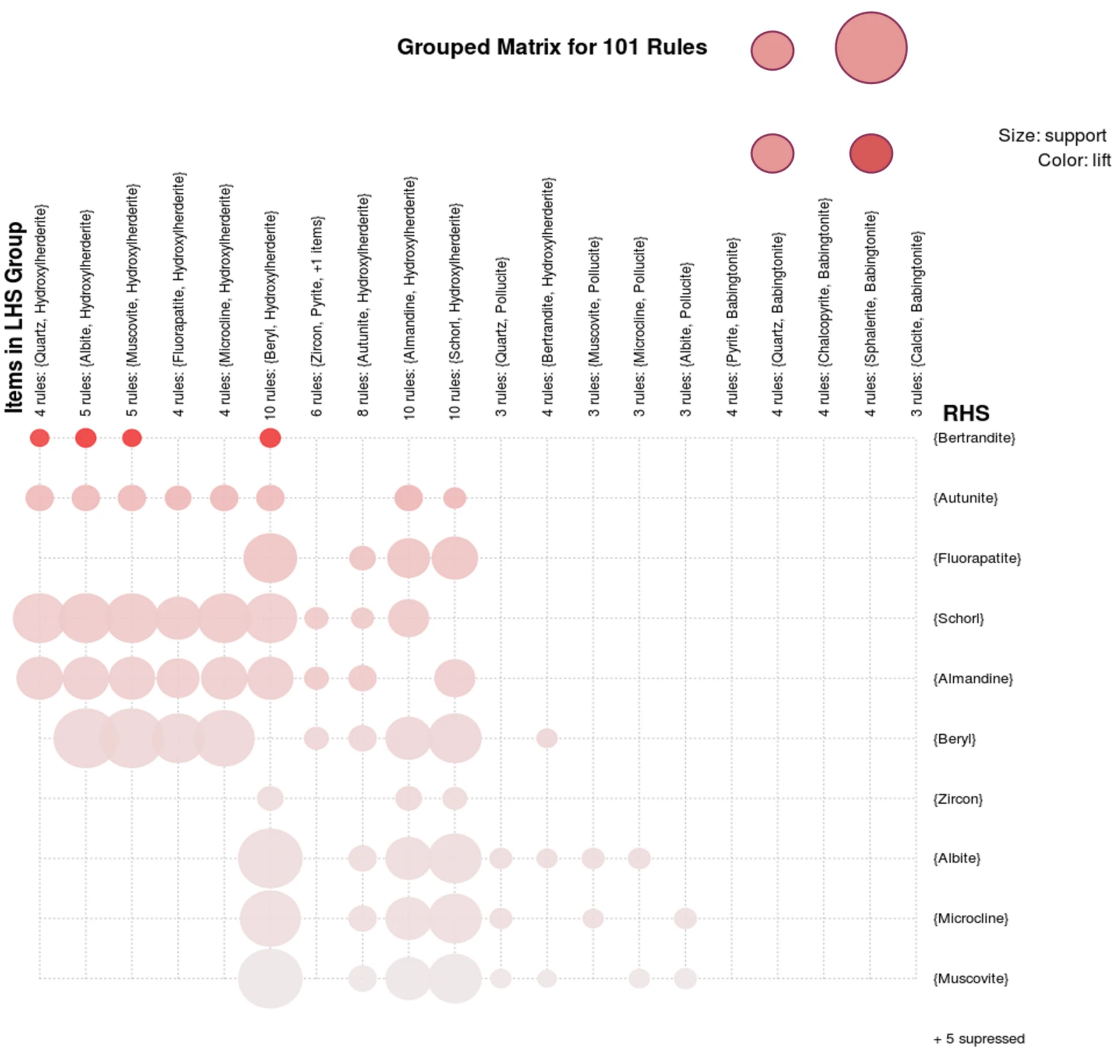

Calcite

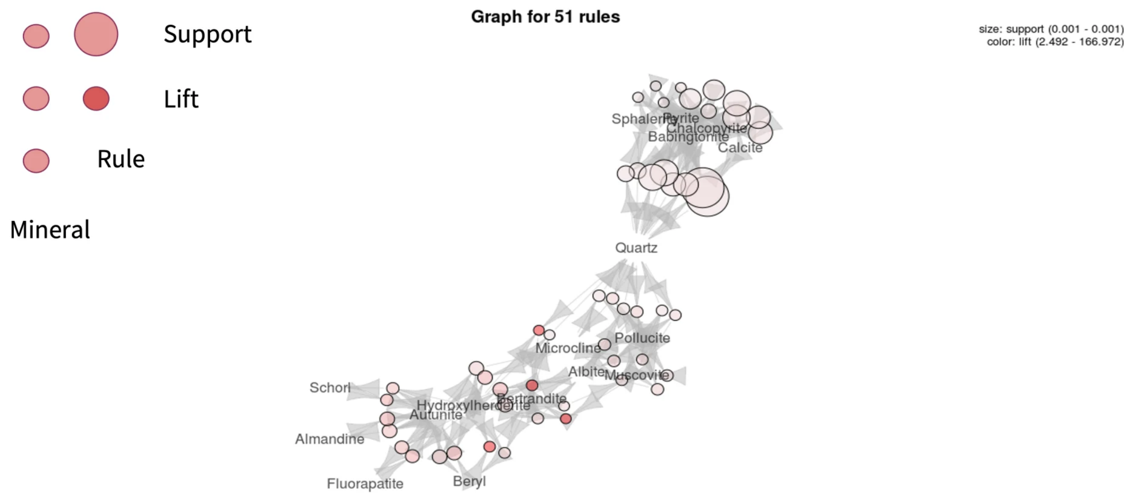

Pumpellyite-Mg

=>


Quartz

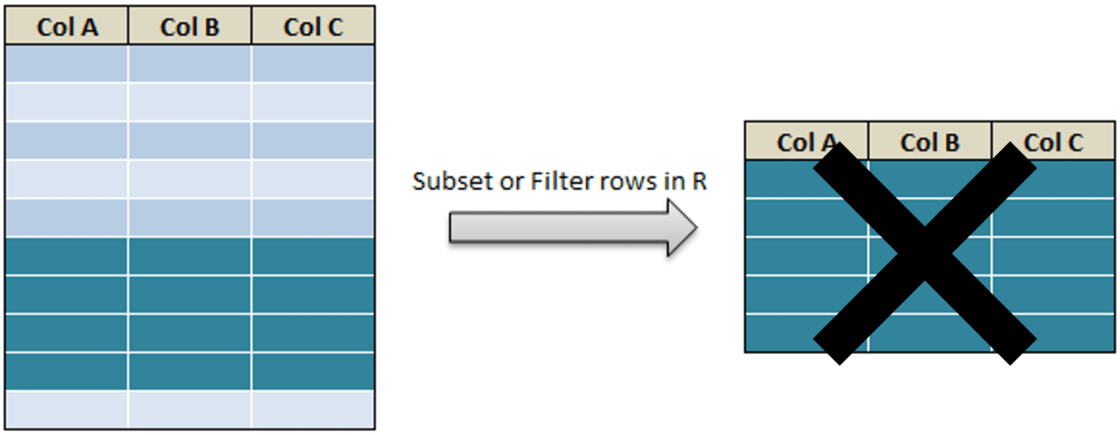
Morrison et al. (2022) in Prep
Prabhu et al. (2022) in Prep




Support
Lift
Rule
Mineral
Graph for 51 rules
size: support (0.001 - 0.001)
color: lift (2.492 - 166.972)
Sphalerite
Pyrite
Chalcopyrite
Babingtonite
Calcite
Quartz
Pollucite
Microcline
Albite
Muscovite
Schorl
Hydroxylherderite
Autunite
Bertrandite
Almandine
Fluorapatite
Beryl

AN APPROACH TO EVALUATE RULES

Most training data subsetting:



Subsetting data vertically:

Mindat ID	Locality Name	Minerals
235733	Broken Hill District, Yancowinna Co., New South Wales, Australia	Uraninite,Torbernite
72	Broken Hill, Broken Hill District, Yancowinna Co., New South Wales, Australia	Uraninite,Torbernite
73	Block 14 Opencut, Broken Hill, Broken Hill District, Yancowinna Co., New South Wales, Australia	Torbernite
15622	Northern Territory, Australia	Wyartite,Uranopilite,Uraninite,Torbernite,Sklodowskite,Saleeite,Rabejacite,Parsonsite,Metatorbernite,Johannite,Dumontite,Dewindtite,Curite,Coffinite,Brannerite,Autunite
263589	West Arnhem Region, Northern Territory, Australia	Wyartite,Uranopilite,Uraninite,Torbernite,Sklodowskite,Saleeite,Rabejacite,Parsonsite,Metatorbernite,Johannite,Dumontite,Dewindtite,Curite,Coffinite,Brannerite,Autunite
277956	Kakadu, West Arnhem Region, Northern Territory, Australia	Wyartite,Uranopilite,Uraninite,Torbernite,Sklodowskite,Saleeite,Rabejacite,Parsonsite,Metatorbernite,Johannite,Dumontite,Dewindtite,Curite,Coffinite,Brannerite,Autunite
41611	Jabiluka Uranium Deposit, Kakadu, West Arnhem Region, Northern Territory, Australia	Sklodowskite,Saleeite,Coffinite,Autunite,Uraninite
4622	Ranger Mine (Ranger Uranium Mine), Kakadu, West Arnhem Region, Northern Territory, Australia	Wyartite,Uranopilite,Uraninite,Torbernite,Sklodowskite,Saleeite,Rabejacite,Parsonsite,Metatorbernite,Johannite,Dumontite,Dewindtite,Curite,Coffinite,Brannerite
41442	Ranger No. 1 Deposit (Ranger No. 1 Pit), Ranger Mine (Ranger Uranium Mine), Kakadu, West Arnhem Region, Northern Territory, Australia	Wyartite,Uranopilite,Uraninite,Sklodowskite,Saleeite,Rabejacite,Metatorbernite,Dewindtite,Brannerite
41443	Ranger No. 3 Deposit (Ranger No. 3 Pit), Ranger Mine (Ranger Uranium Mine), Kakadu, West Arnhem Region, Northern Territory, Australia	Torbernite,Saleeite,Metatorbernite,Dewindtite
127	Queensland, Australia	Yttrotantalite-(Y),Uranocircite-II,Uraninite,Torbernite,Richetite,Phurcalite,Davidite-(La),Coffinite,Carnotite,Brannerite
6471	Cloncurry Shire, Queensland, Australia	Yttrotantalite-(Y),Uranocircite-II,Uraninite,Torbernite,Richetite,Phurcalite,Davidite-(La),Coffinite,Carnotite,Brannerite
133	Cloncurry, Cloncurry Shire, Queensland, Australia	Uraninite,Torbernite,Richetite,Phurcalite,Coffinite,Brannerite

Association Rules Example:

Full Set	Subset
$M_1M_2M_4 \rightarrow M_6$	$M_1M_4 \rightarrow M_6$
$M_2M_4 \rightarrow M_5$	$M_2M_4 \rightarrow M_5$
$M_8M_7 \rightarrow M_3$	$M_6 \rightarrow M_3$
$M_5M_2M_9 \rightarrow M_7$	$M_1 \rightarrow M_8$
$M_1 \rightarrow M_8$	
$M_3 \rightarrow M_5$	

Resilience of a Rule:

For $\exists RHS_i$,

- If no matches on LHS skip rule.
- Else, create a full set of items from the LHS of both rules.

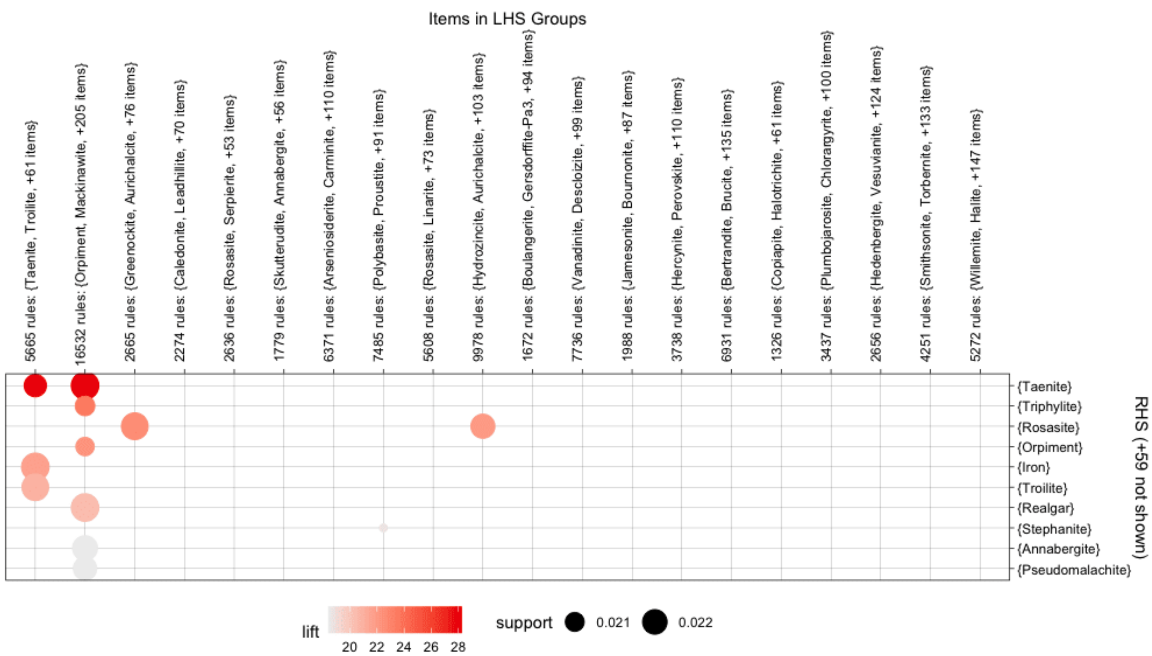
$$\frac{N_{LHS_F}}{N_{LHS_T}} \times |L_F - L_T| \times \frac{1}{N_{LHS_{F \cap T}}}$$

The ideal resilience of a rule is 0. The higher the score, the lower the resilience of the rule.

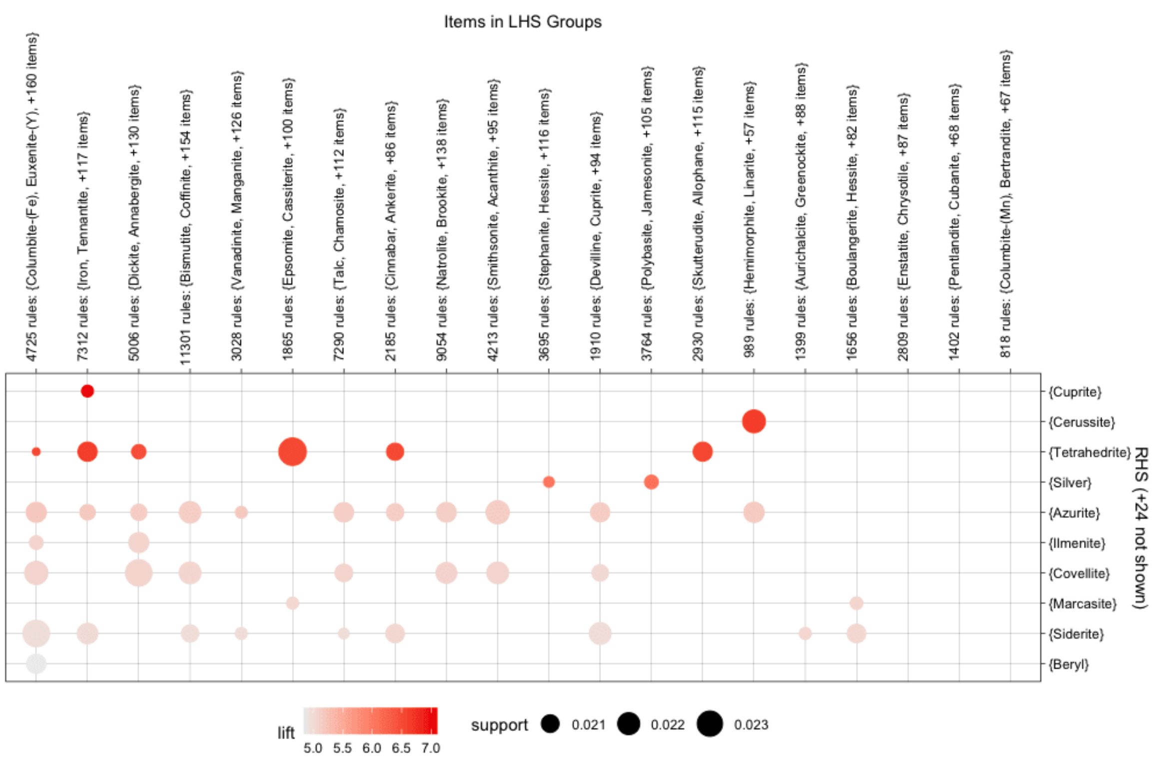
RESULTS

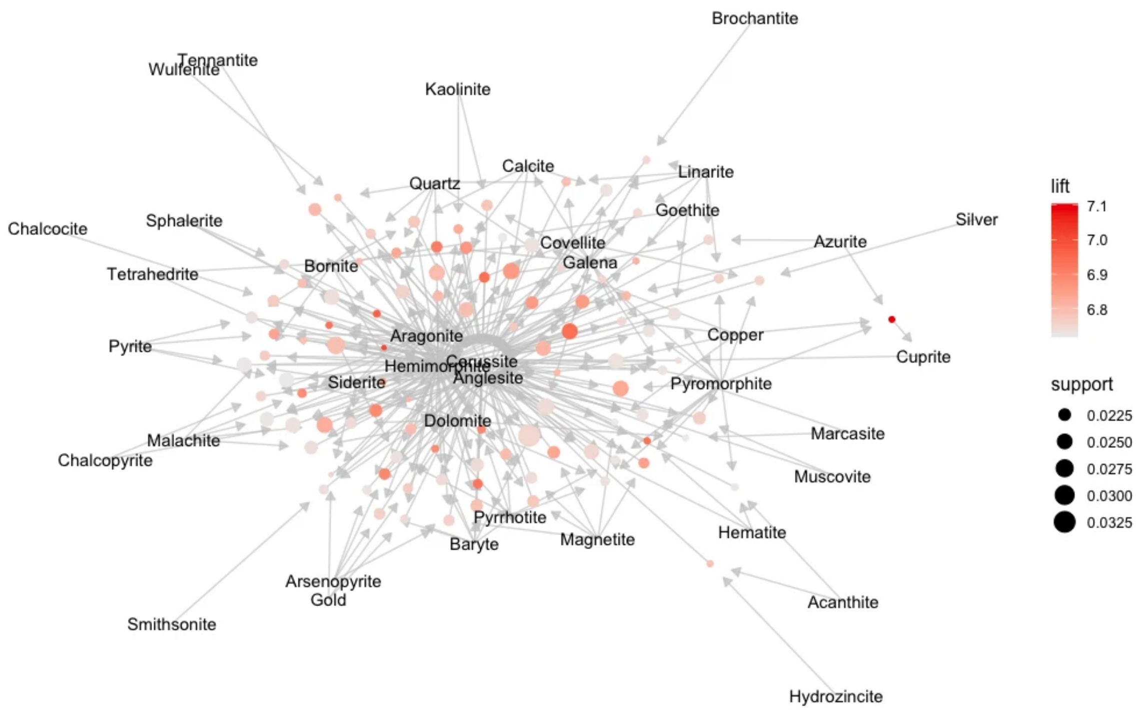
LHS_F	LHS_T	RHS	Resilience
Copper, Pyromorphite, Tenorite	Azurite, Copper, Pyromorphite	Cuprite	0.045
Copper, Lollingite, Pyromorphite	Azurite, Copper, Pyromorphite	Cuprite	0.227
Aragonite, Aurichalcite, Pyromorphite	Aragonite , Calcite, Pyromorphite	Cerussite	0.054
Anglesite, Hemimorphite, Xenotime-(Y)	Anglesite, Covellite, Hemimorphite	Cerussite	0.110

Full Rulebase:



Subsetted Rulebase:




Brochantite
Tennantite
Wulfenite
Kaolinite
Calcite
Quartz
Linarite
Goethite
Silver
Chalcocite
Sphalerite
Covellite
Azurite
Galena
Tetrahedrite
Bornite
Pyrite
Aragonite
Copper
Cuprite
Cerussite
Hemimorphite
Anglesite
Siderite
Pyromorphite
Dolomite
Marcasite
Malachite
Chalcopyrite
Muscovite
Pyrrhotite
Magnetite
Hematite
Baryte
Arsenopyrite
Gold
Acanthite
Smithsonite
Hydrozincite
lift
7.1
7.0
6.9
6.8
support
0.0225
0.0250
0.0275
0.0300
0.0325

OBSERVATIONS AND FUTURE WORK

Observations and Roadblocks

- Currently restricted to RHS of size 1.

- The difference in the number of rules between the full set and training set.

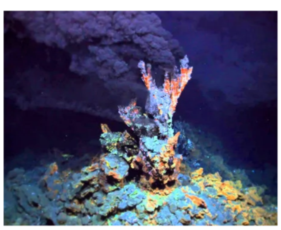
- Need for aggregation of rules, and potential consequences from the aggregation.

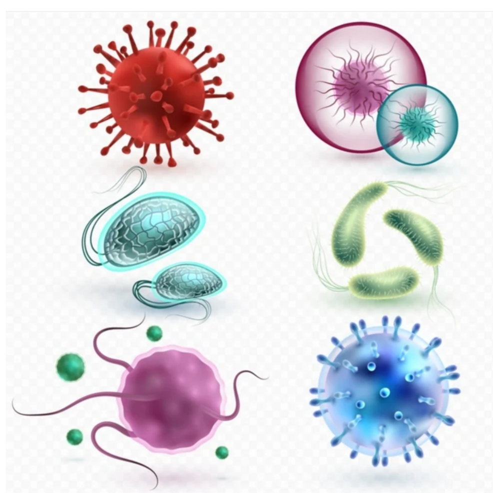
- Drastic difference in the number of rules generated for the subset rulebase, even though on 20% of the mineral occurrences were randomly removed.

Future Work:

- Increase the size of RHS above 1. (In order to predict more complex mineral assemblages)
- Develop a method to aggregate rules.
- Improve and fine tune evaluation method.

Exploring Microbial Association Analysis:





ABSTRACT

There has been a significant increase in the amount and accuracy of mineral data (from resources like Mindat, MED or the GEMI) and the improvements in technological resources make it possible to explore and answer large, outstanding scientific questions, such as, understanding the mineral assemblages on Earth and how they compare to assemblages and localities on other planets. In the last couple of years, affinity analysis methods have been used to:1) Predict unreported minerals at an existing locality, 2) Predict localities for a set of known minerals[1]. We've chosen to call this application "Mineral Association Analysis"[2].

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[5] Üstündağ and Bal (2014) Proc. in Comp.

[6] https://medium.com/futurist-zone/the-future-directions-of-recommender-systems-72beae7c2dd2

[7] https://www.datasciencemadesimple.com/filter-subsetting-rows-r-using-dplyr/