The Future Logging Assistant

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Luleå University of Technology

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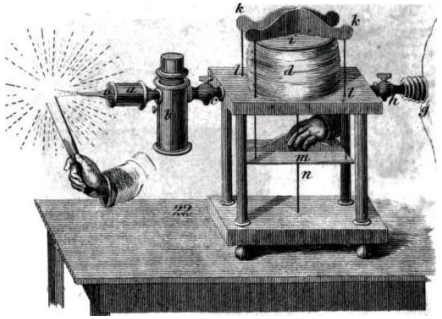
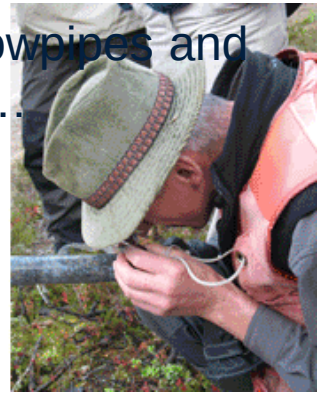
Technology development in exploration

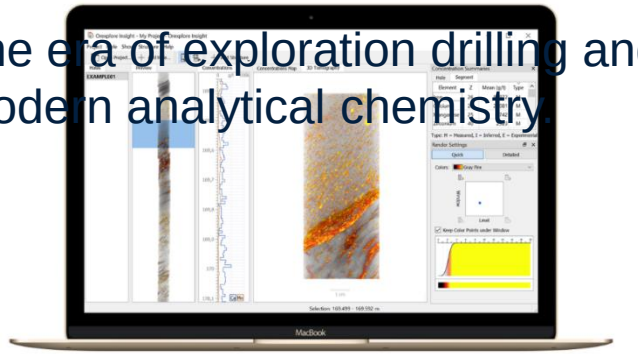


17th century

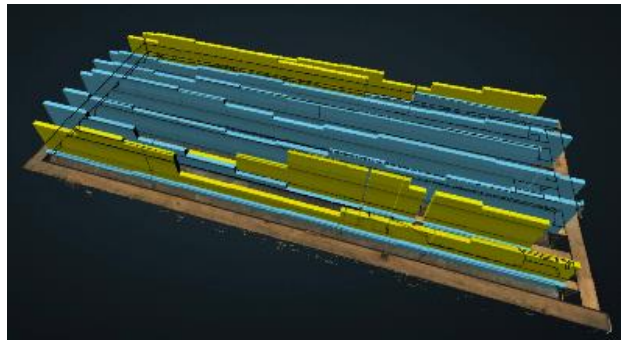


The era of blowpipes and divining rods…

20th century



The era of exploration drilling and modern analytical chemistry.



21th century

The current digital era

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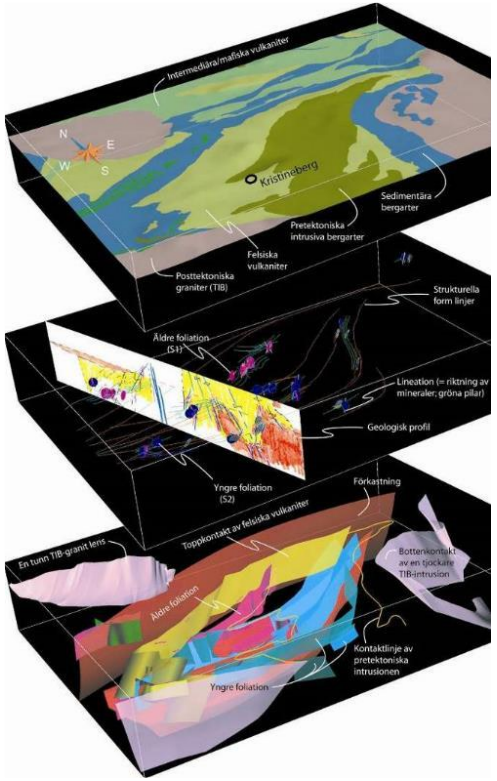
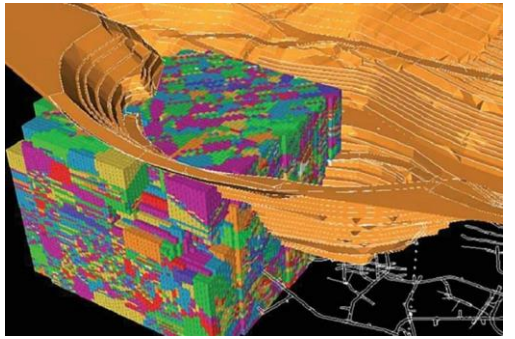
Where does the data go?



Promine 3D model, Kristineberg area

Geological models

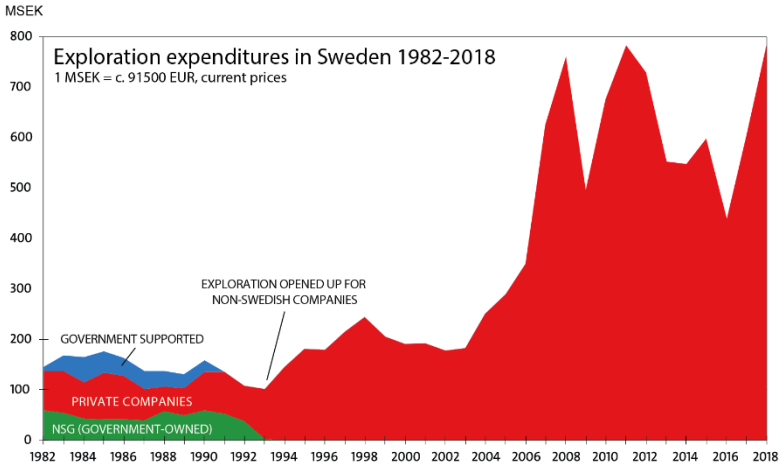
The basis for finding new mineral deposits in complex geological terrains.



https://www.mining-journal.com/events-coverage/news/1172784/geomet-leaders-head-perth

Resource models

The basis for all economic assessments, planning and technology selection.



Modified after Bergverksstatistik 2018

Clear incentives

- To lower cost and leadtimes
- To increase the accuracy of the models.

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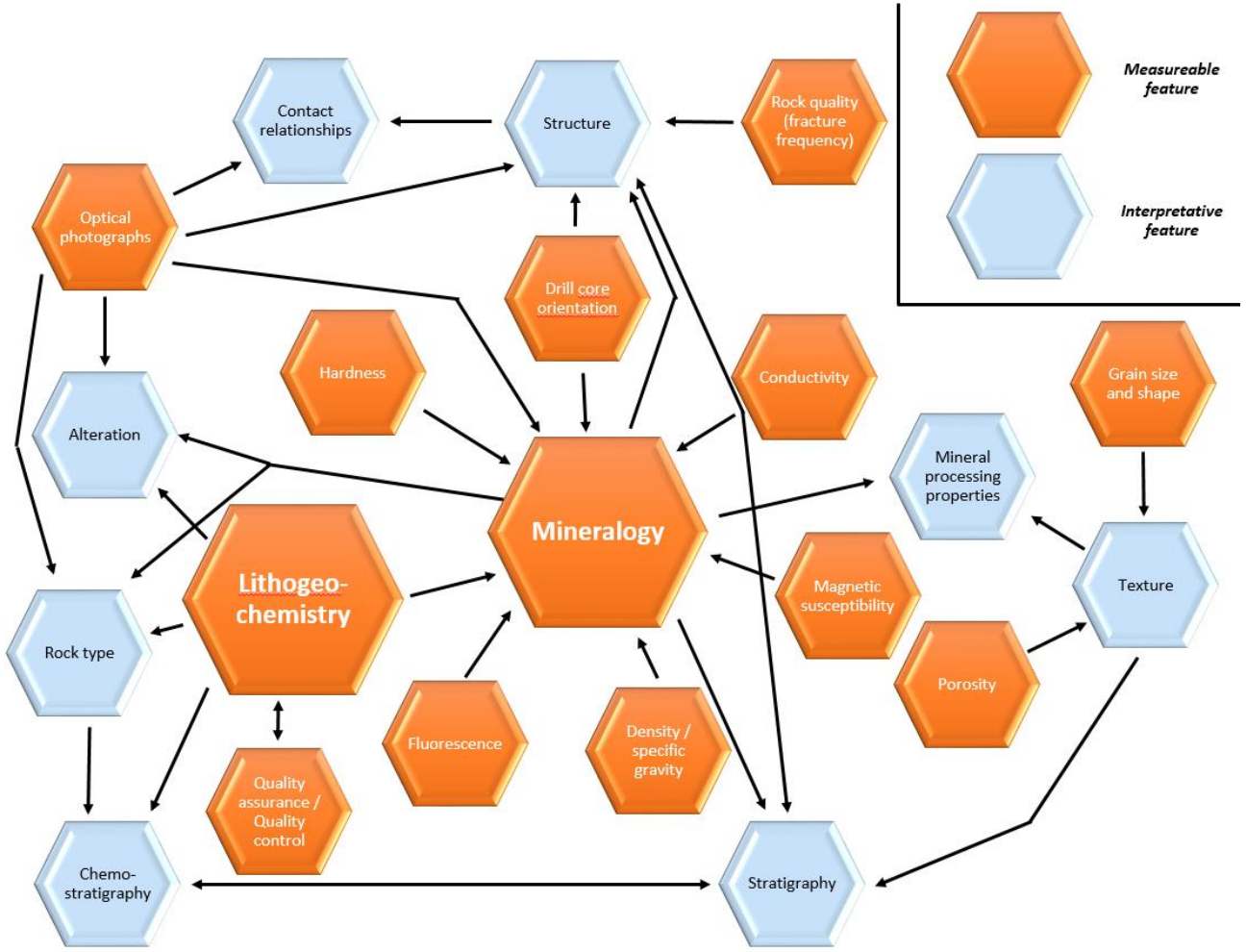
What do we log?



EnEx EIT RawMaterials project 2017-2020

Rocks are full of information, but only a fraction of this information is recorded.

Current logging routines rarely satisfies these disciplines simultaneously:

- Target generation
- Resource modelling
- Geotechnical modelling

Drill cores are commonly relogged and resampled, commonly several times.

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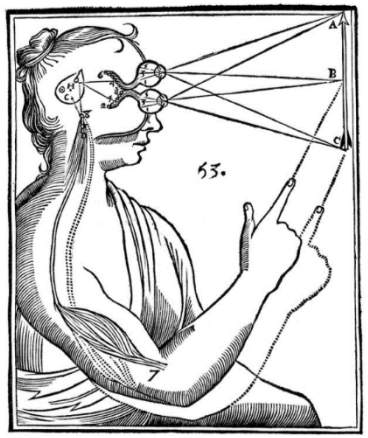

“Nothing is in the understanding, which was not first in the senses.”

John Locke (1632–1704)

FLA focuses on technology integration for semi-automated knowledge generation from drill core.

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The Future Logging Assistant (FLA)

- **Joint RnD project between Luleå University of Technology and Boliden, 2021-2025**

- **New tools to augment data aquisition during drill core logging**
  - Implementation of sensor technologies for automatic data aquisition
    - Visual features (e.g. textures, color)
    - Compositional features (e.g. geochemistry, mineralogy)
    - Rock mechanical features

- **New tools for semi-automated logging and data analytics at the logging table**
  - Tools for processing data generated from core for real-time decisions by human logger.
  - Focus on integration and ensemble methods

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Project team

Ore Geology & Machine Learning

Nils Jansson
Associate Professor
Ore Geology

Foteini Liwicki
Senior Lecturer
Machine Learning

Marcus Liwicki
Professor
Machine Learning

Tobias Kampmann
Associate Lecturer
Ore Geology

Jonathan Rincon
PhD student
Ore Geology

Christian Günther
Researcher
Machine Learning

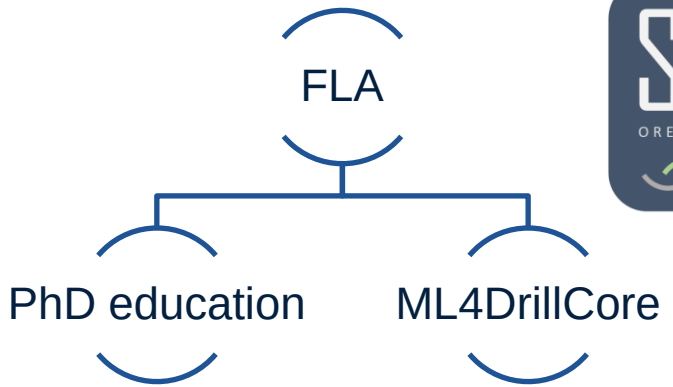
Filip Simán
PhD student
Ore Geology

Exploration

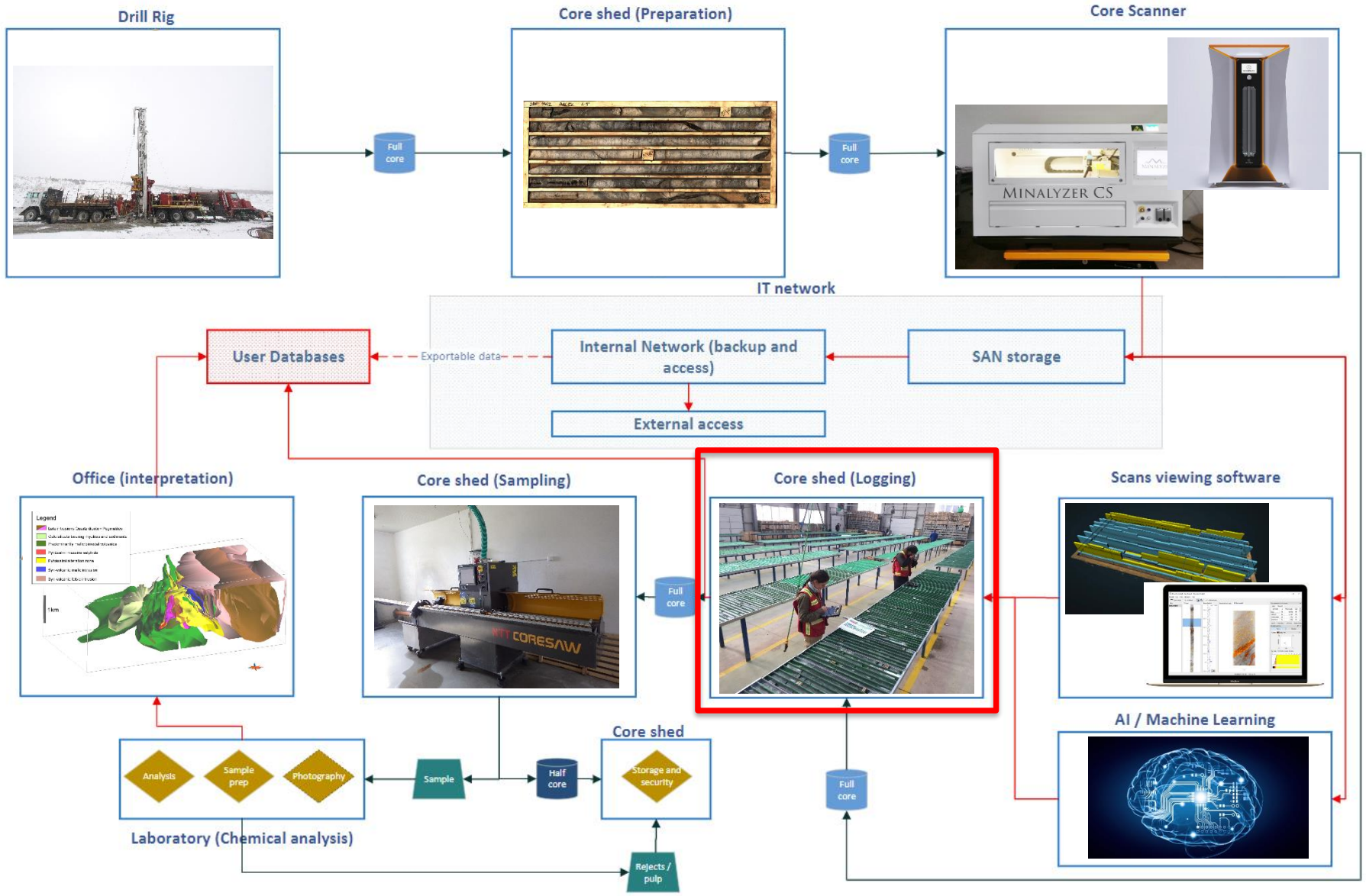
Sean Johnson
Geochemistry specialist

Tobias Hermansson
RnD manager, Exploration

Paul McDonnell
Geology data specialist



Adapting the drill core process



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Adapting the drill core process

The ambition is to have model outputs available during logging.

- Pre-classification
- Suggestions
- Feature recognition

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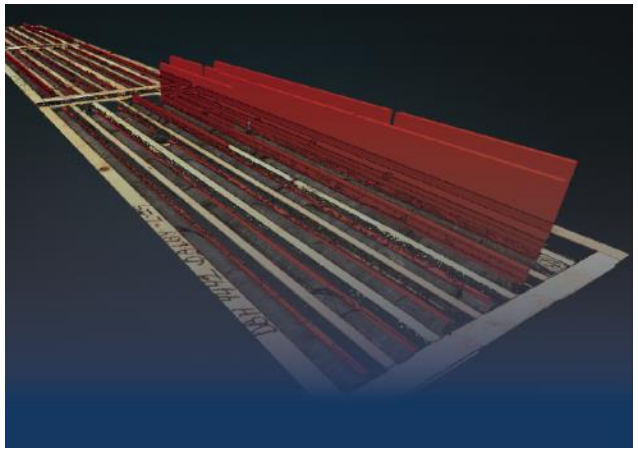
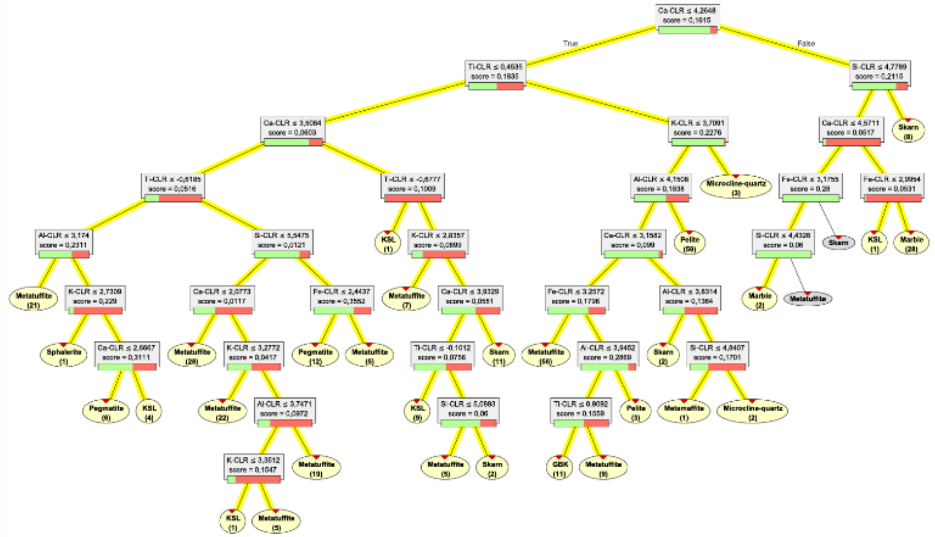
Semi-automated lithology classification

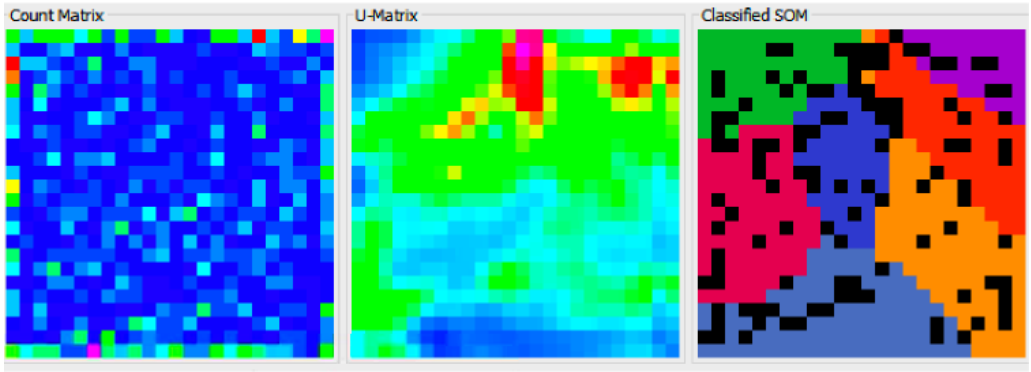
Continuous XRF corescan data



Supervised learning



Unsupervised learning



Chemically distinct lithologies can nowadays easily be grouped from compositional data.

How good are the results?

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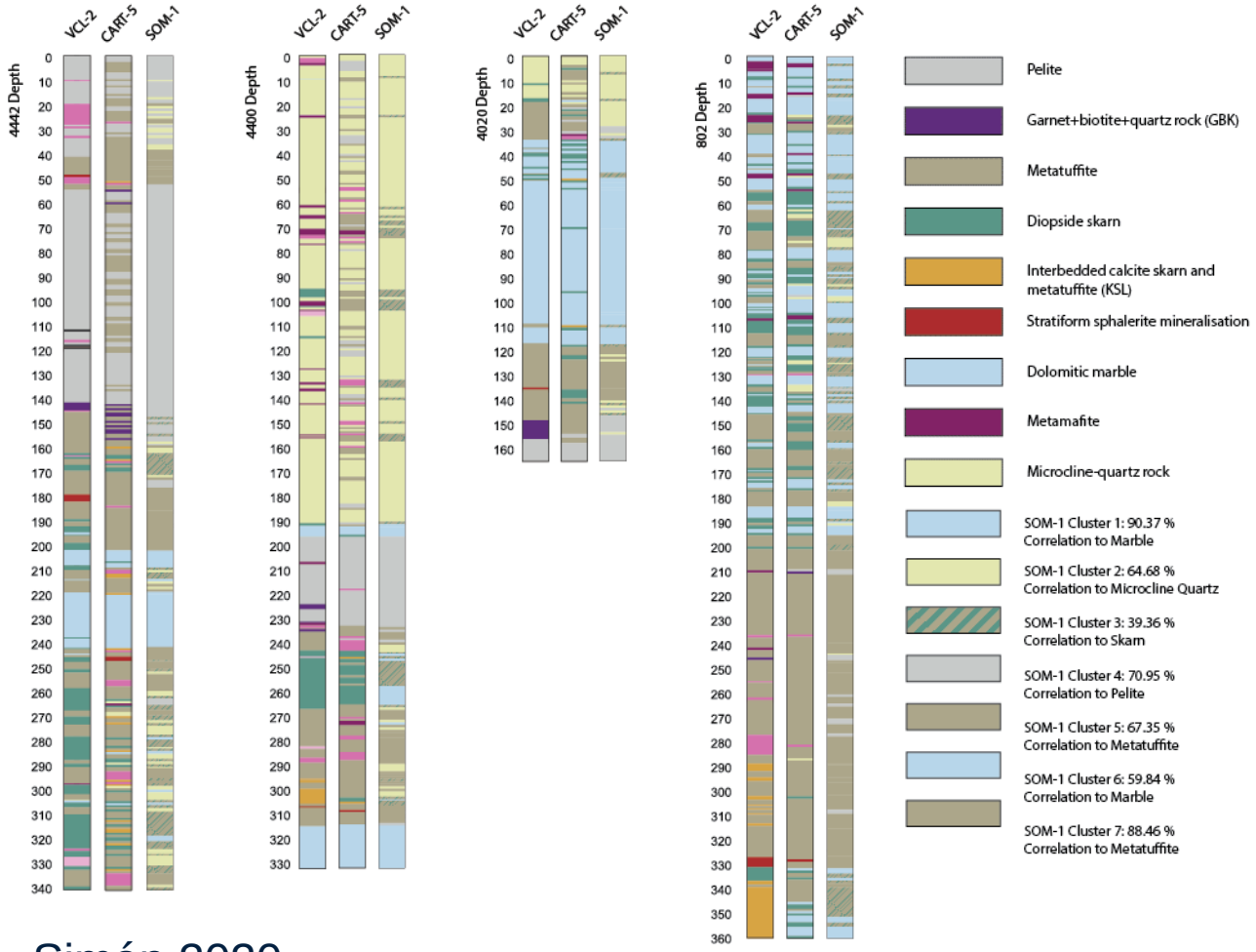
Semi-automated lithology classification



Simán 2020

Different models applied to the same data yield different results.

Simán (2020): up to 60-70 % classification accuracy at Zinkgruvan.

Not all lithologies differ in chemistry.

Way forward

- Integration with computer vision.
- Ensemble models.

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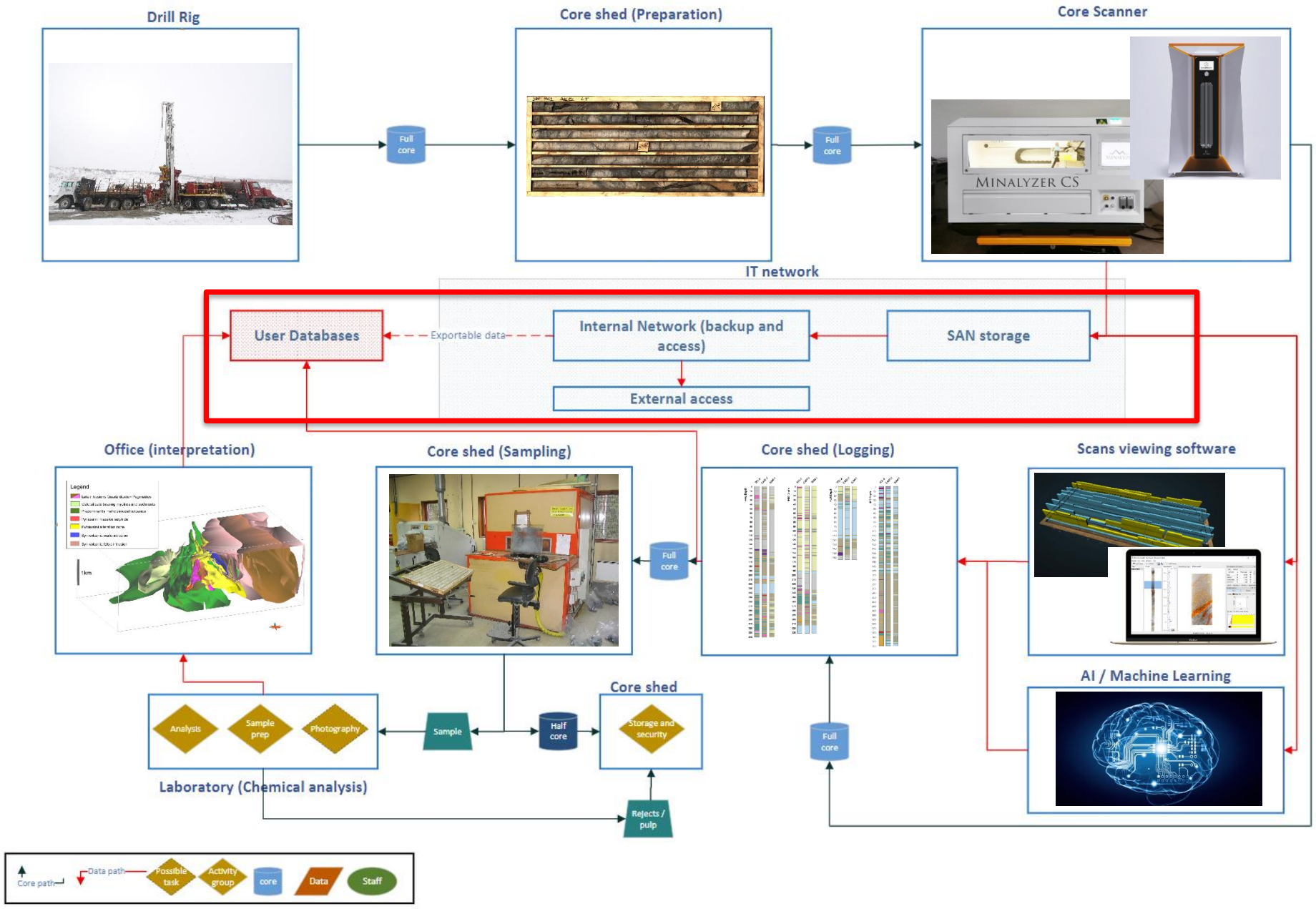
Ensemble methods for improved classification



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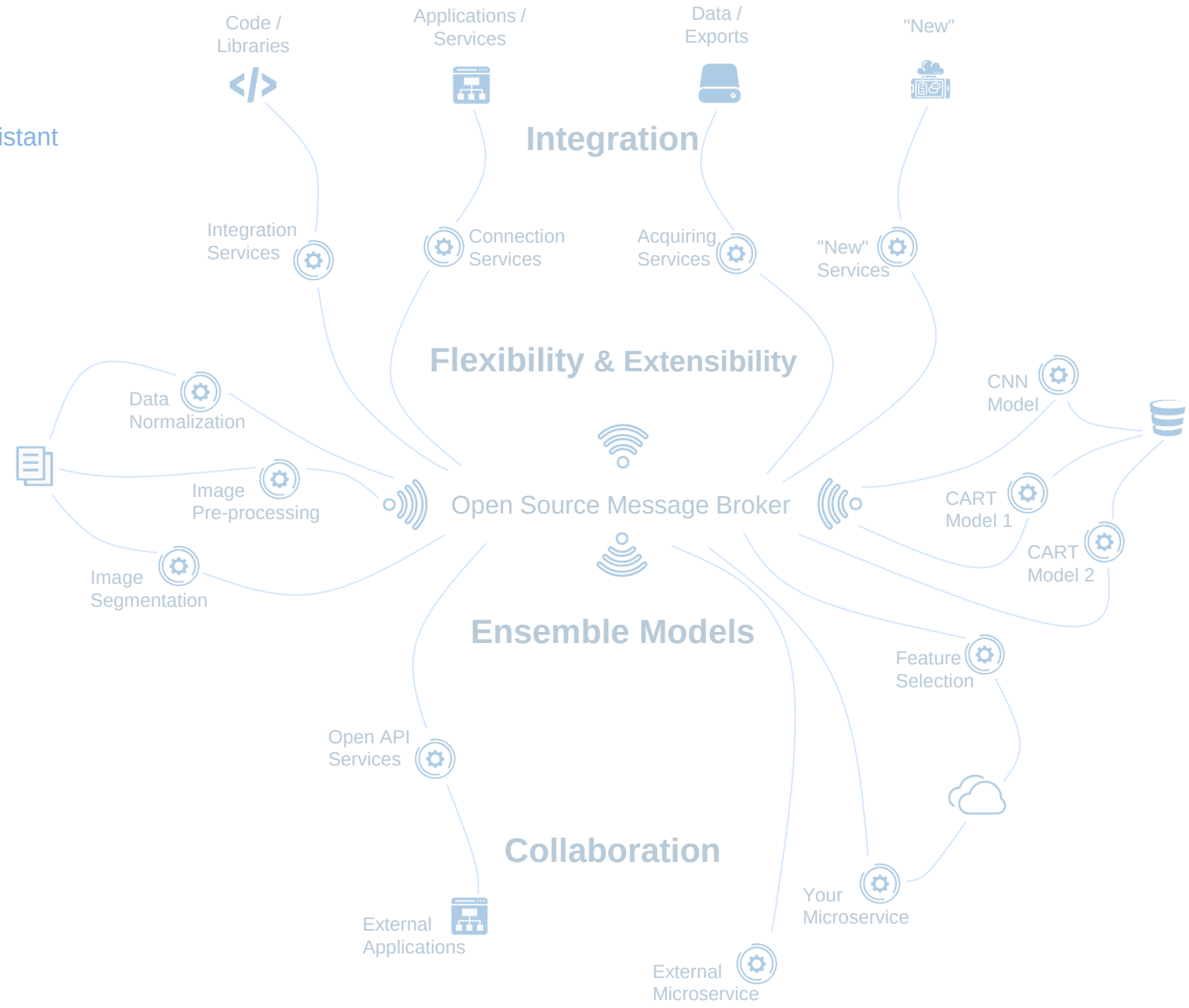

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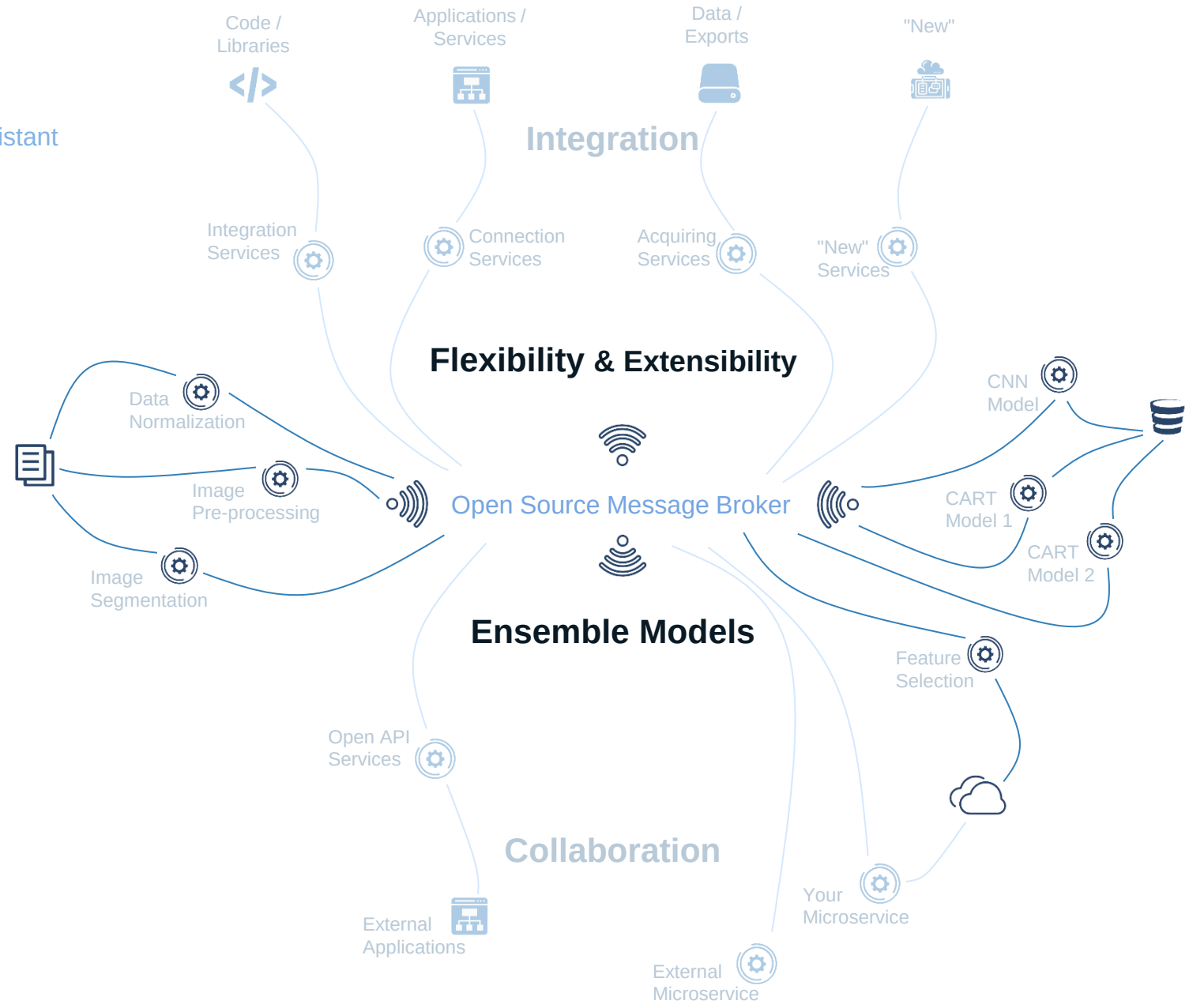

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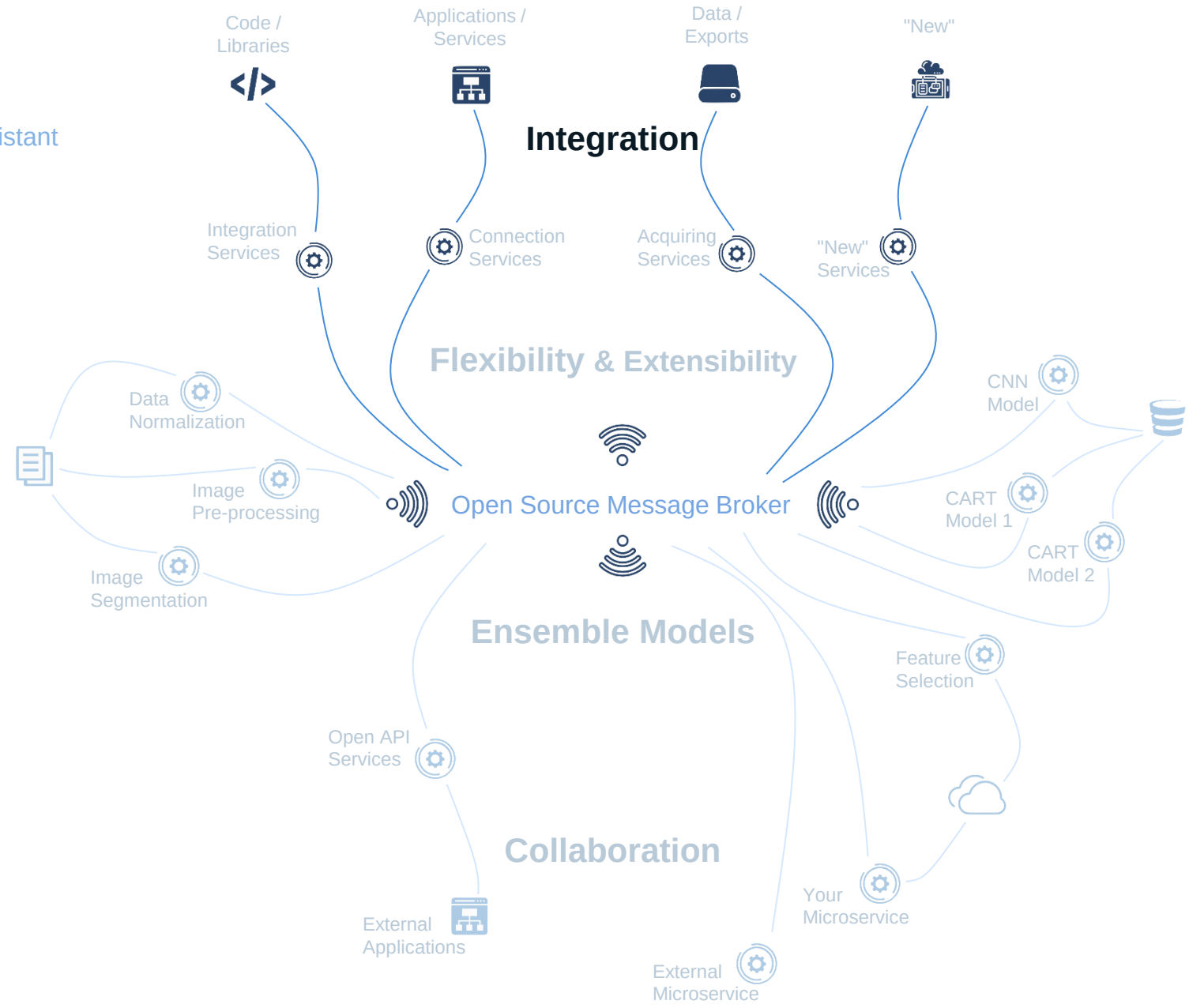

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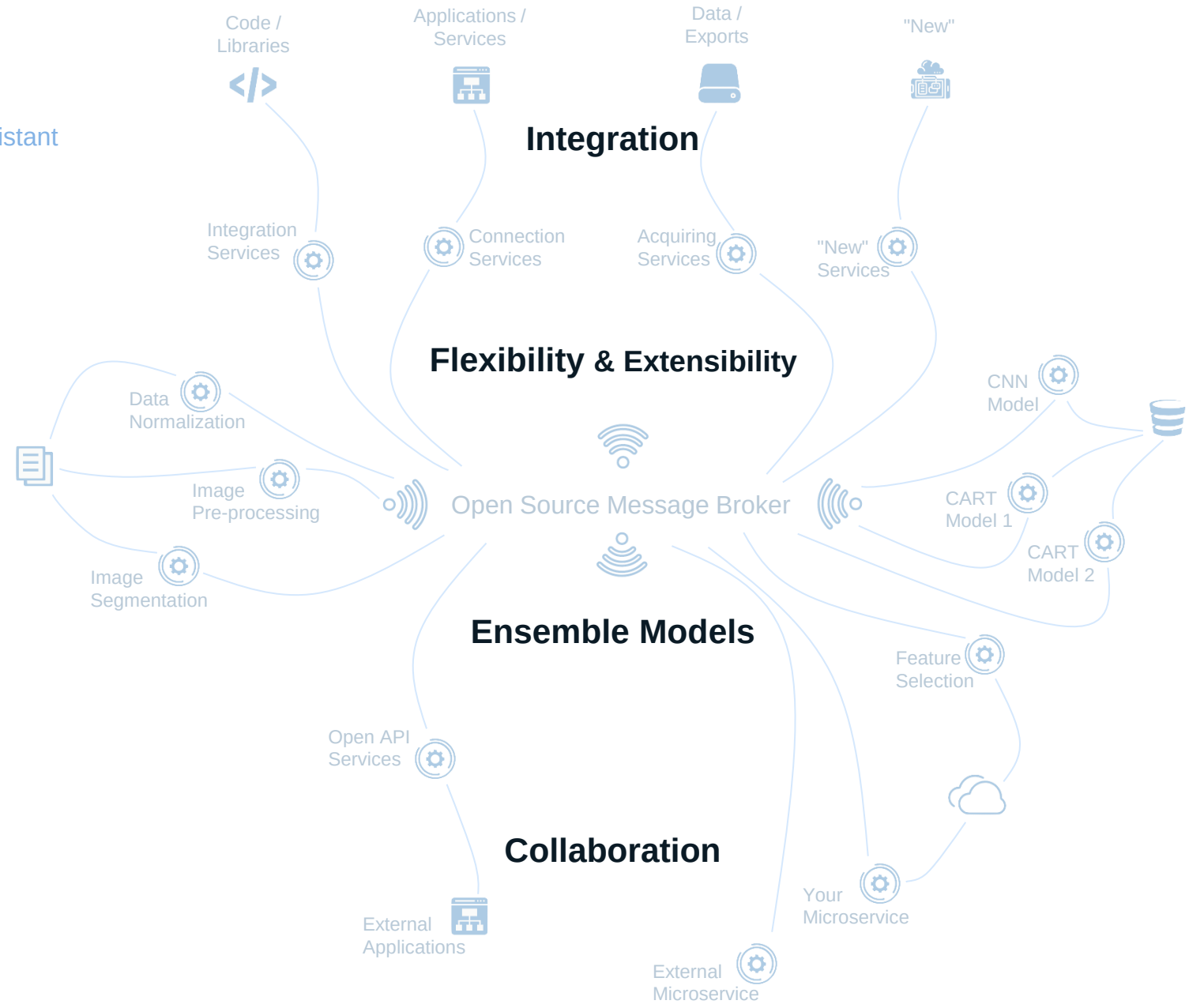

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