Ontology Acquisition for Automatic Building of Scientific Portals

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1. Introduction — PortaGe architecture
2. The role of ontologies in portal building

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- what “relevant” means in each particular case

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It is one of the tasks of the ontology extraction engine.

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The automatic classification process can base its decision on the knowledge extracted from other documents in a previous run, such as the fact that a particular method is used for machine learning in other fields.

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The OLE framework interlinks individual pieces of such knowledge with lexico-syntactic patterns able to identify the relations in the retrieved documents.

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The user profiles and the ontologies also cover the availability of the resources for a particular user, user-specified amount of documents that should be presented and processing time requirements.

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- The produced ontologies must reflect the stepwise development of the PortaGe system. If there is no current need for a particular kind of knowledge, the extraction should be postponed to later phases.

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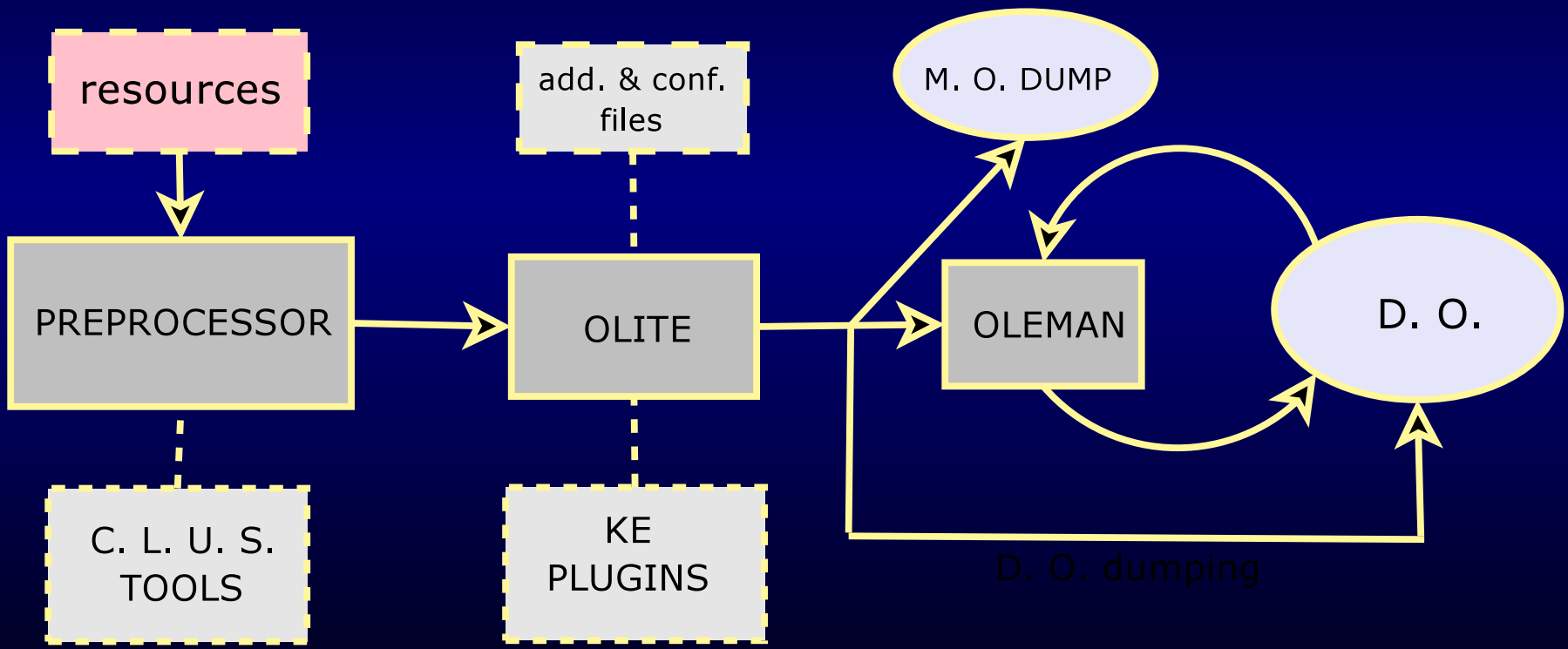

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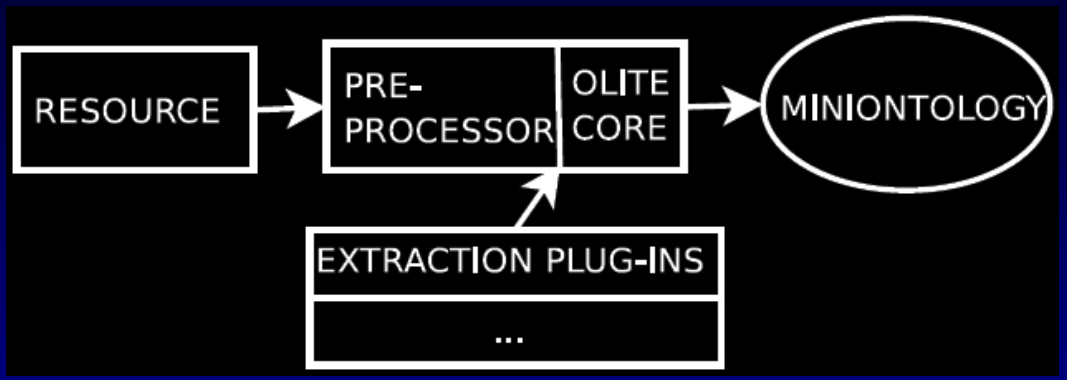

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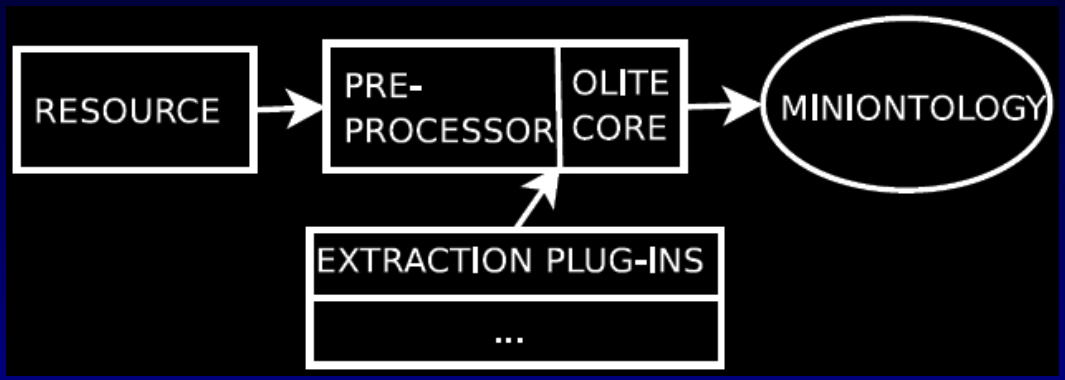

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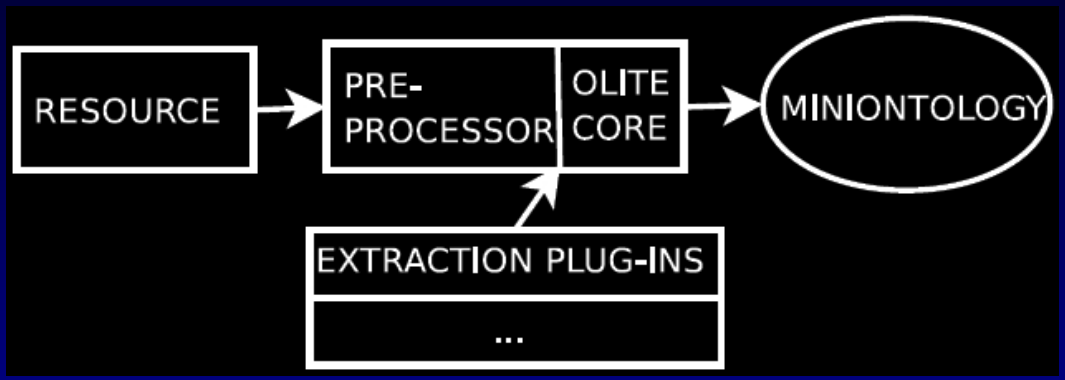

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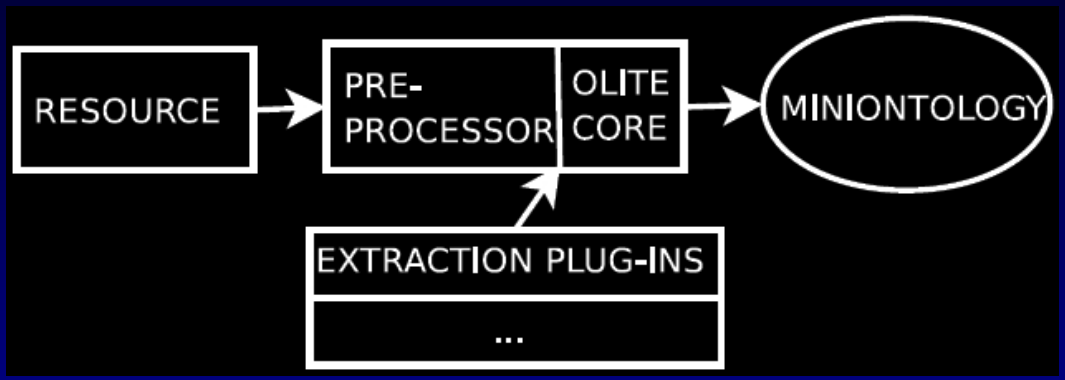

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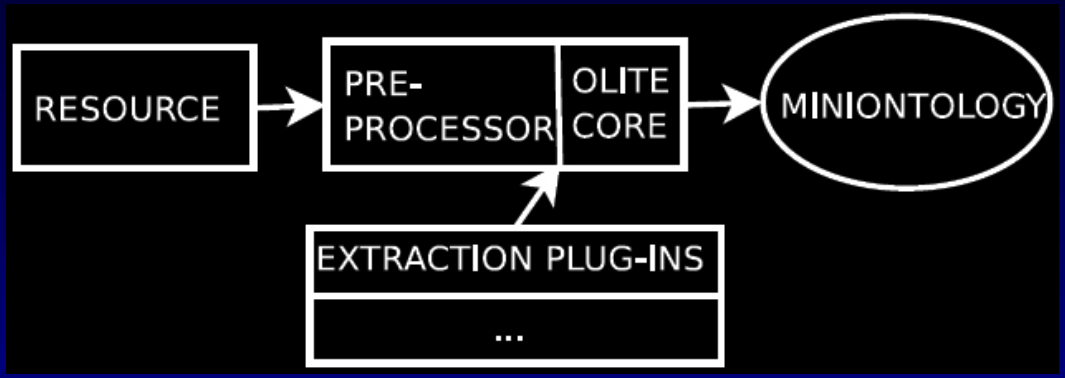

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- **Miniontology** covers the concepts and their relations identified in the respective resource.

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- Plug-ins of particular extraction methods

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- Chunker trainer employs a treebank-like corpus to learn how to chunk the input tagged sentences.

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3. Transformation layer provides transformational rules for immediate miniontology output in various formats (such as OWL or our fuzzy OWL extension – (F)OWL); it also passes the unmodified extracted miniontology further to the integration module OLEMAN

Possible Extraction Methods

- pattern-driven extraction of semantic relations – well known and easy to implement method coined by Marti Hearst; utilizes matching of given patterns that are significant for particular semantic relations; mostly effective for the *is-a* relation but applicable for other semantic or ad hoc relations (such as *method-of* or *described-in* relations that are useful when analyzing scientific materials)

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- various other kinds of semantic clustering or (F)FCA methods can be easily plugged in

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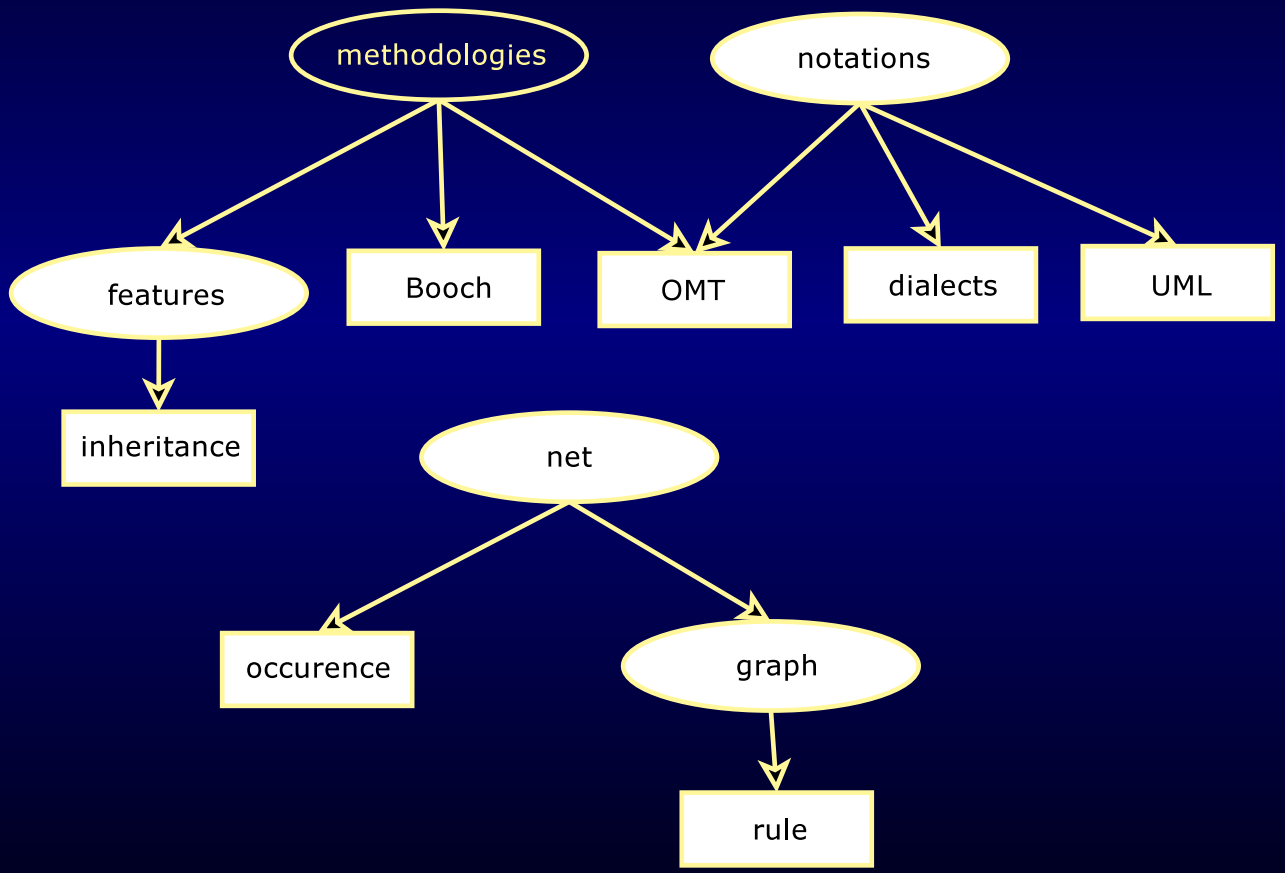
- speed of about $10,000$ words per second
- no "gold standard" for the domain was available, so an orientational semi–automatic evaluation was performed on a random sample of 10 miniontologies:

File	File sz. (words)	No. of conc.	No. of rel.	Prec. (%)	Rec. (%)	I (%)
1	3330	7	5	60.00	23.52	840.34
2	2606	9	5	80.00	5.21	1438.85
3	5387	33	24	62.50	5.88	4401.41
4	2274	16	11	63.63	3.31	2179.11
5	3936	25	14	71.43	7.51	4277.25
6	4943	27	18	61.11	5.84	3892.36
7	3937	22	15	46.67	4.27	3070.39
8	7438	25	16	68.75	7.37	3756.83
9	1826	10	5	60.00	6.19	1801.80
10	5250	52	32	37.50	18.42	8333.33
average	4093	22.6	14.5	61.16	8.75	3399.17

Sample Portion of an Ontology Gained by OLE



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- WordNet, SUMO, MILO to define the directions for kinds of relations

Conclusions and Future Directions

- the flexible OLE system has been presented as a base for future purely–autonomous acquisition of ontologies for automatic building of scientific portals
- more extraction plug-ins to increase the coverage of the OLITE module
- defeasible mechanisms for ontology merging and their combination with fuzzy logic
- development and integration of advanced reasoning engines
- coin and apply a framework for proper evaluation
- WordNet, SUMO, MILO to define the directions for kinds of relations
- uncertainty via subjective language analysis