INF3580/4580 – Semantic Technologies – Spring 2017

Lecture 7: Reasoners in Jena

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Today's Plan

1. Recap: Reasoning with rules
2. Backwards and forwards reasoning
3. The Jena reasoning system
4. Built-in reasoners
5. Richer API with `OntModel`
6. External reasoners
7. A worked example

Outline

What is inference?

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    - new/inferred triples need not be materialized or persisted

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   - "All fathers are males. Martin is the father of Karl, therefore…"

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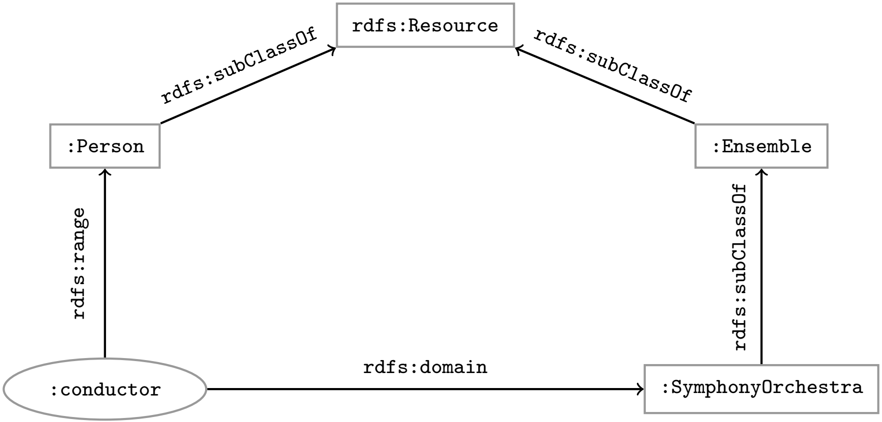
Example: Conductors and ensembles



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try to figure out why!

Outline

Forward chaining vs. backward chaining

Forward chaining:

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- reasoning from premises to conclusions of rules

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Backward chaining:

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- '. . . what needs to be true for this conclusion to hold?'
- reasoning is on-demand

Forward chaining inference

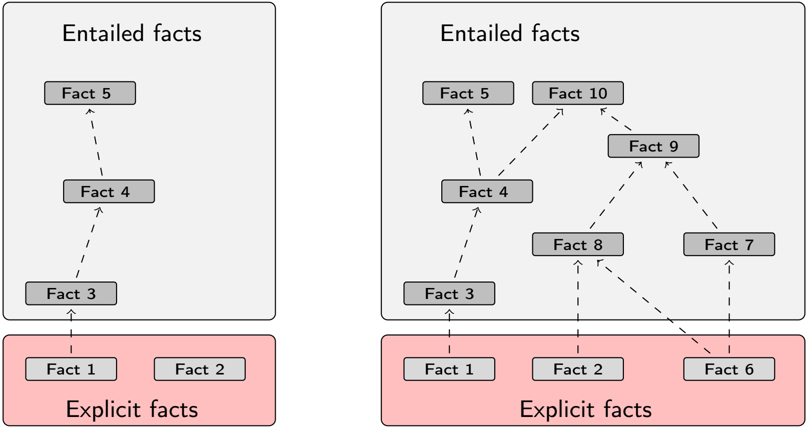

Figure: When a fact is added, all entailments are computed and stored.

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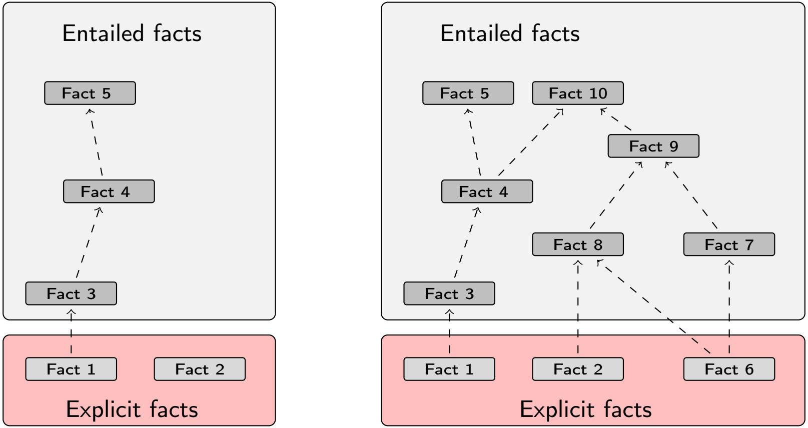
- forward chaining optimizes retrieval
- no additional inference is necessary at query time

Forward chaining and truth-maintenance



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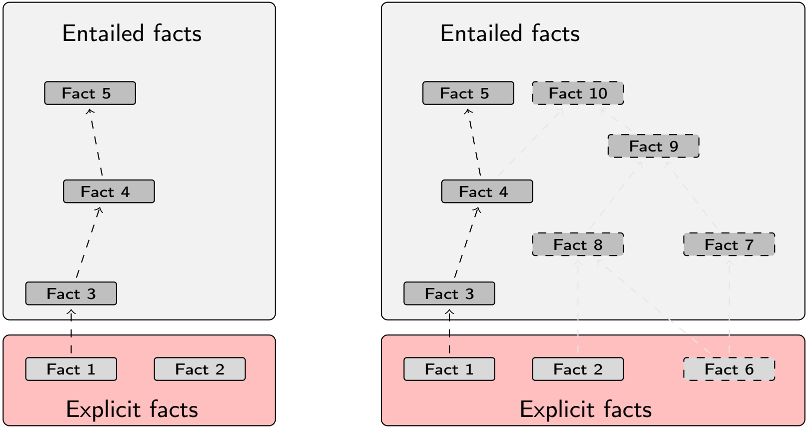

Figure: When a fact is removed, everything that comes with it must go too.

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    - rules could apply to premisses on different disks, etc.

Backward chaining inference

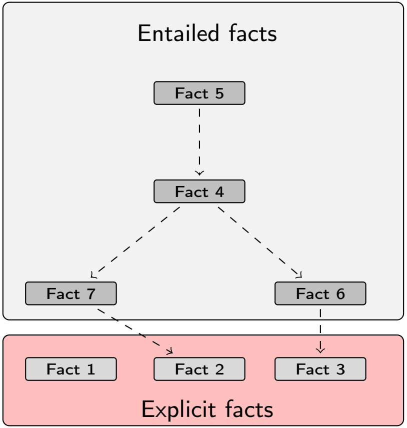

Figure: Backward chaining uses rules to expand queries.

Backward chaining: Example

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semantic web framework Jena

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- `config` is a `Resource` that describes requested features for the reasoner.

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- Most reasoners can be configured before binding them to a model, to change various details of their behaviour.

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Simplified overview

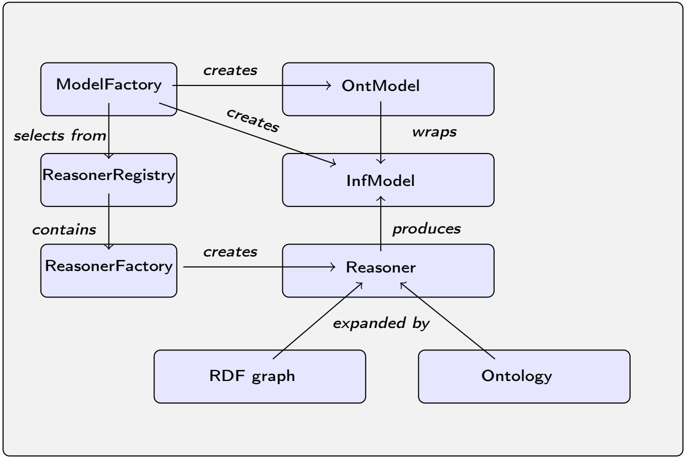

Figure: The structure of the reasoning system

Outline

Built-in reasoners

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    - covered in connection with external reasoners later

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using ModelFactory.createInfModel

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OntModel model = ModelFactory.createOntologyModel(spec, model);
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An OntModel is created by calling a method in ModelFactory

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- some reasoners supply their own such API, e.g. Pellet

Question

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— why do we need reasoners?

Many reasons:

- Separate logic (All symphony orchestras are ensembles) from control (when to add which triples): declarative programming.
- Can use ontology reasoners to check that the logic is OK. Much easier than checking that a Java program is OK.
- Getting the control right (and efficient) is not always easy. Using a generic reasoner reuses this know-how.

Outline

Plugging in third-party reasoners

Jena's reasoning-system architecture makes it easy...

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External reasoners usually

- check in a `ReasonerFactory` in the `ReasonerRegistry`, and
- supply a `OntModelSpec` to be handed to the `ModelFactory`

Some better known ones

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- hyper-tableaux (HermiT)
- only rule reasoners have a notion of forwards vs. backwards

Using an external reasoner

- retrieve an instance of the reasoner:

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- Or: create an `OntModel` for a richer API:

```
OntModel m;
m = ModelFactory.createOntologyModel(
    PelletReasonerFactory.THE_SPEC);
```

Outline

Integrating information from DBpedia

Quick facts about the DBpedia project:

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- set relevant prefixes:

```
String ont = "http://dbpedia.org/ontology/";
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String ex = "http://www.example.org/";
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```

- connect to DBpedia, describe J. Ullman:

```
String dbpedia = "http://dbpedia.org/sparql";
String describe = "DESCRIBE <" + res + "Jeffrey_Ullman>";
QueryExecution qexc =
  QueryExecutionFactory.sparqlService(dbpedia, describe);
Model ullman = qexc.execDescribe();
```

- build an ontology of collaborators (or better, read it from file):

```
Model ontology = ModelFactory.createDefaultModel();
Property collab = ontology.createProperty(ex + "collaborator");
Property phds = ontology.createProperty(prop + "doctoralStudents");
Property phd = ontology.createProperty(ont + "doctoralStudent");
Property adv = ontology.createProperty(ont + "doctoralAdvisor");
ontology.add(phds, RDFS.subPropertyOf, collab);
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- wrap it in an `OntModel` if you need a richer API

- write the query:

```
String qStr =
"PREFIX ont:  <" + ont + ">" +
"PREFIX res:  <" + res + ">" +
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"SELECT ?collaborator WHERE {" +
" res:Jeffrey_Ullman ex:collaborator ?collaborator." +
"}";
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Query query = QueryFactory.create(qStr);
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- and, if, you like, print out the results

```
ResultSetFormatter.out(res, query);
```

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- you need a reasoner capable of doing backwards reasoning
- i.e. a rule reasoner
- and a way to configure it
- let's use the built-in `RDFSRuleReasoner`
- first create a configuration specification:

```
# A config spec is itself an RDF graph
Resource config = ontology.createResource();
```

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config.addProperty(ReasonerVocabulary.PROPruleMode, "backward");
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- proceed as before. . .

Next Weeks

- (Simplified) Model Semantics for RDF and RDFS
- Relationship Reasoning $\Longleftrightarrow$ Semantics
- OWL, semantics of that, etc.