Semantic Annotations

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Outline

Information Extraction (Problem)

- Let's have a text describing an acquisition event.

FIRST WISCONSIN <**FWB** > TO BUY MINNESOTA BANK

MILWAUKEE, Wis., March 26 - **First Wisconsin Corp** said it plans to acquire **Shelard Bancshares Inc** for **about 25 mln dlrs** in cash, its first acquisition of a Minnesota -based **bank** .

First Wisconsin said Shelard is the holding company for two banks with total assets of 168 mln dlrs.

First Wisconsin , which had assets at yearend of 7.1 billion dlrs, said the Shelard purchase price is about 12 times the 1986 earnings of the bank.

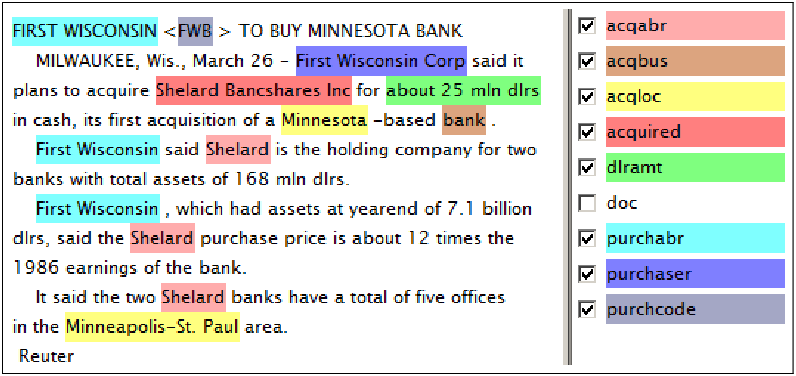
It said the two Shelard banks have a total of five offices in the Minneapolis-St. Paul area.

Reuter

- What was the object of the acquisition?
- Who was the buyer?
- What was the deal amount?

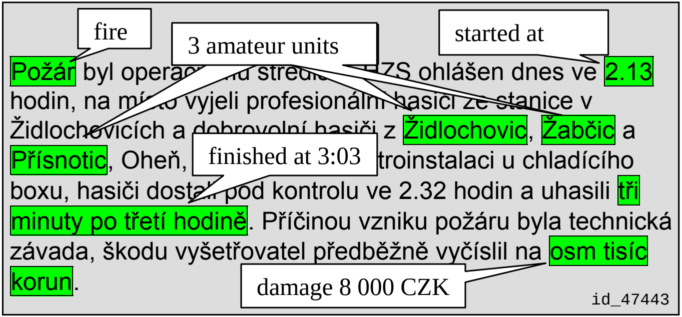
Information Extraction (Solution)

- Information Extraction tools can identify and extract such information.



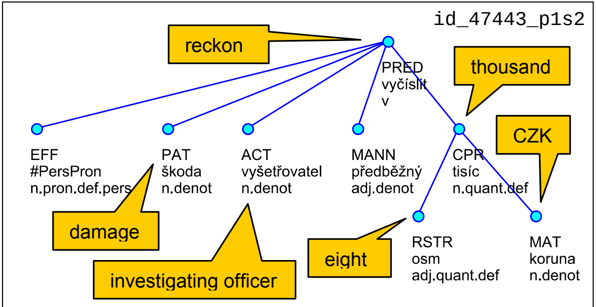
Information Extraction (Czech Example)

- Information Extraction tools can identify and extract such information.



Deep Language Parsing (Czech Example)

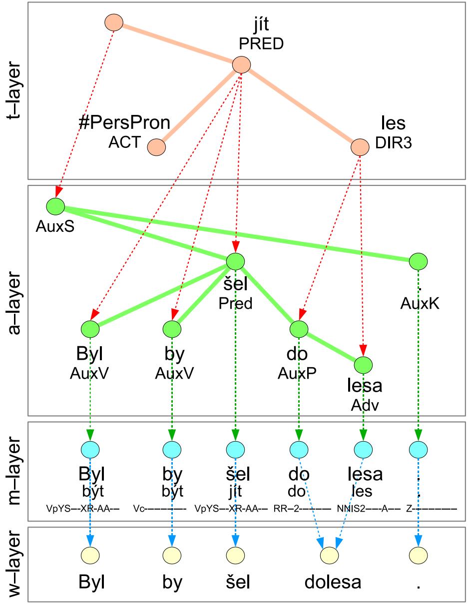
- Linguistic tools perform automated linguistic analysis.
- Producing so called *dependency trees*.



…, škodu vyšetřovatel předběžně vyčíslil na osm tisíc korun.

…, investigating officer preliminarily reckoned the damage to be 8 000 CZK.

Layers of linguistic annotation in PDT



- Tectogrammatical layer
- Analytical layer
- Morphological layer
- PDT 2.0 on-line:

`http://ufal.mff.cuni.cz/pdt2.0/`

Sentence:

Byl by šel dolesa.

He-was would went toforest.

Inductive Logic Programming

- Learning examples $E = P \cup N$ (Positive and Negative)
  - E.g. relevant and irrelevant pieces of text w.r.t. particular extraction task
- Background knowledge B
  - E.g. linguistic structure connecting individual words
- ILP task: To find logical program or hypothesis H such that all positive examples are covered and none negative

$$(\forall e \in P)(B \cup H \models e) \;\; \& \;\; (\forall n \in N)(B \cup H \not\models n).$$

  - E.g. to find common pattern (in the linguistic structure) present around every relevant piece of text and none irrelevant.

Four Main Topics

- **Manual Design of Extraction Rules**
- **Induction of Extraction Rules**
- **Shareable Extraction Ontologies**
- **Fuzzy ILP Document Classification**

Manual Design of Extraction Rules

Slides about the topic *Manual Design of Extraction Rules* will have **brown** headline background.

Induction of Extraction Rules

Slides about the topic *Induction of Extraction Rules* will have **green** headline background.

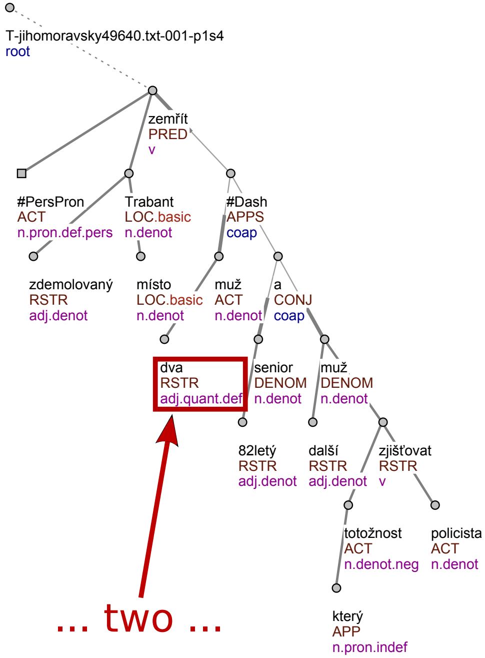
Shareable Extraction Ontologies

Slides about the topic *Shareable Extraction Ontologies* will have **cyan** headline background.

Fuzzy ILP Document Classification

Slides about the topic *Fuzzy ILP Document Classification* will have **magenta** headline background.

Ordinary

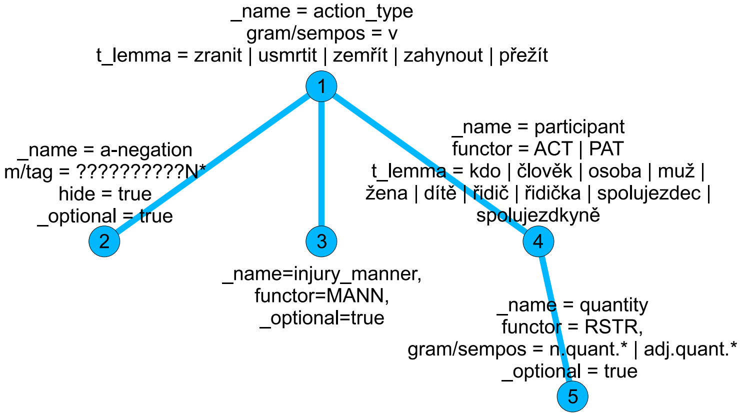


- How to extract the information about two dead people?
- *Sentence:*

  Ve zdemolovaném trabantu na místě zemřeli dva muži -- 82letý senior a další muž, jehož totožnost zjišťují policisté.

  Two men died on the spot in demolished trabant -- …

Extraction rules -- Netgraph queries



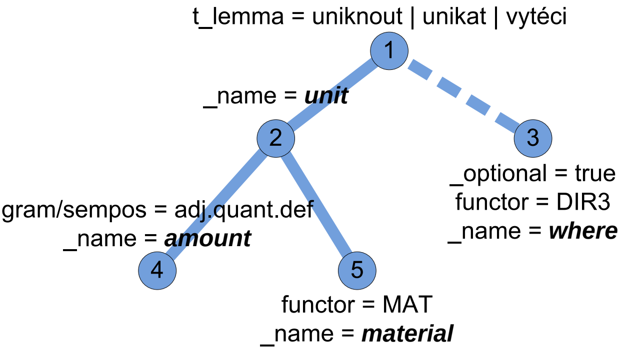
- Tree patterns on shape and nodes (on node attributes).
- Evaluation gives actual matches of particular nodes.
- Names of nodes allow use of references.

Raw data extraction output


```
<QueryMatches>
  <Match root_id="T-vysocina63466.txt-001-p1s4" match_string="2:0,7:3,8:4,11:2">
    <Sentence>
      Při požáru byla jedna osoba lehce zraněna - jednalo se
      o majitele domu, který si vykloubil rameno.
    </Sentence>
    <Data>
      <Value variable_name="action_type" attribute_name="t_lemma">zranit</Value>
      <Value variable_name="injury_manner" attribute_name="t_lemma">lehký</Value>
      <Value variable_name="participant" attribute_name="t_lemma">osoba</Value>
      <Value variable_name="quantity" attribute_name="t_lemma">jeden</Value>
    </Data>
  </Match>
  <Match root_id="T-jihomoravsky49640.txt-001-p1s4" match_string="1:0,13:3,14:4">
    <Sentence>
      Ve zdemolovaném trabantu na místě zemřeli dva muži - 82letý senior
      a další muž, jehož totožnost zjišťují policisté.
    </Sentence>
    <Data>
      <Value variable_name="action_type" attribute_name="t_lemma">zemřít</Value>
      <Value variable_name="participant" attribute_name="t_lemma">muž</Value>
      <Value variable_name="quantity" attribute_name="t_lemma">dva</Value>
    </Data>
  </Match>
  <Match root_id="T-jihomoravsky49736.txt-001-p4s3" match_string="1:0,3:3,7:1">
    <Sentence>Čtyřiatřicetiletý řidič nebyl zraněn.</Sentence>
    <Data>
      <Value variable_name="action_type" attribute_name="t_lemma">zranit</Value>
      <Value variable_name="a-negation" attribute_name="m/tag">VpYS---XR-NA---
      </Value>
      <Value variable_name="participant" attribute_name="t_lemma">řidič</Value>
    </Data>
  </Match>
</QueryMatches>
```


SELECT action_type.t_lemma, a-negation.mtag, injury_manner.t_lemma, participant.t_lemma, quantity.t_lemma **FROM** ****extraction rule****

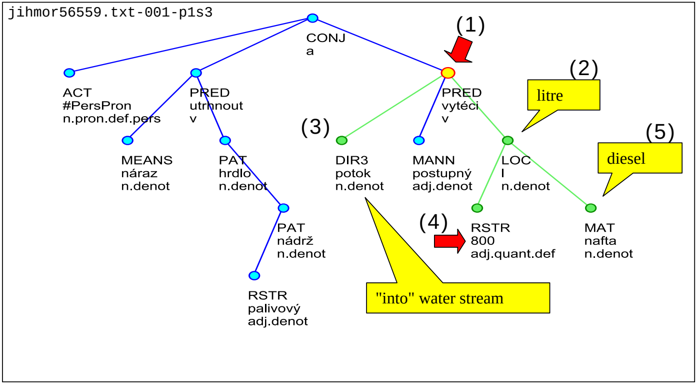
Extraction rules -- Environment Protection Use Case



Matching Tree

"Due to the clash the throat of fuel tank tore off and 800 litres of oil (diesel) has run out to a stream."

“Nárazem se utrhl hrdlo palivové nádrže a do potoka postupně vyteklo na 800 litrů nafty.”



Raw data extraction output

```xml
<QueryMatches>
  <Match root_id="jihmor56559.txt-001-p1s3" match_string="15:0,16:4,22:1,23:2,27:3">
    <Sentence>Nárazem se utrhl hrdlo palivové nádrže a do potoka postupně vyteklo na
800 litrů nafty.</Sentence>
    <Data>
      <Value variable_name="amount" attribute_name="t_lemma">800</Value>
      <Value variable_name="unit" attribute_name="t_lemma">l</Value>
      <Value variable_name="material" attribute_name="t_lemma">nafta</Value>
      <Value variable_name="where" attribute_name="t_lemma">potok</Value>
    </Data>
  </Match>
  <Match root_id="jihmor68220.txt-001-p1s3" match_string="3:0,12:4,21:1,22:2,27:3">
    <Sentence>Z palivové nádrže vozidla uniklo do půdy v příkopu vedle silnice zhruba
350 litrů nafty, a proto byli o události informováni také pracovníci odboru životního
prostředí Městského úřadu ve Vyškově a České inspekce životního prostředí.</Sentence>
    <Data>
      <Value variable_name="amount" attribute_name="t_lemma">350</Value>
      <Value variable_name="unit" attribute_name="t_lemma">l</Value>
      <Value variable_name="material" attribute_name="t_lemma">nafta</Value>
      <Value variable_name="where" attribute_name="t_lemma">půda</Value>
    </Data>
  </Match>
...
```

litre

water stream

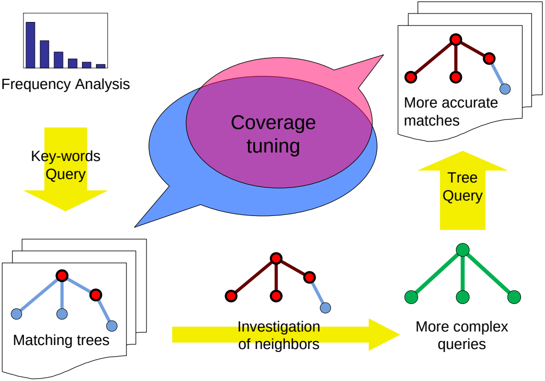
diesel

soil

SELECT amount.t_lemma, unit.t_lemma, material.t_lemma, where.t_lemma

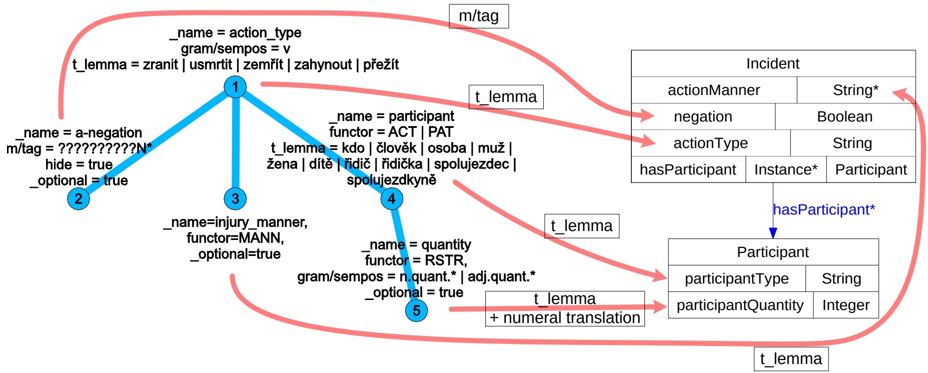
FROM ****extraction rule****

Design of extraction rules -- iterative process



1. Frequency analysis $\rightarrow$ representative key-words.
2. Investigating of matching trees $\rightarrow$ tuning of tree query.
3. Complexity of the query $\cong$ complexity of extracted data.

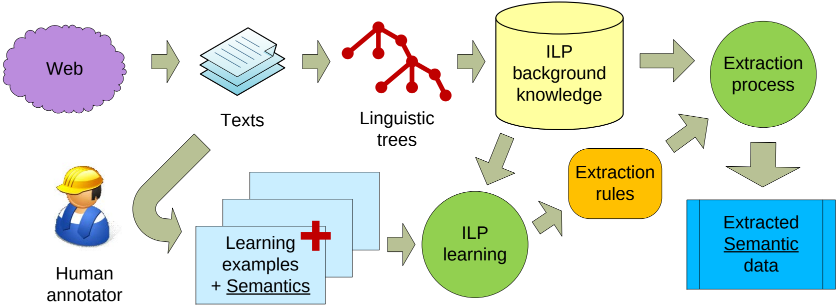
Semantic interpretation of extraction rules



- Determines how particular values of attributes are used.
- Gives semantics to extraction rule.
- Gives semantics to extracted data.
- Only proposal

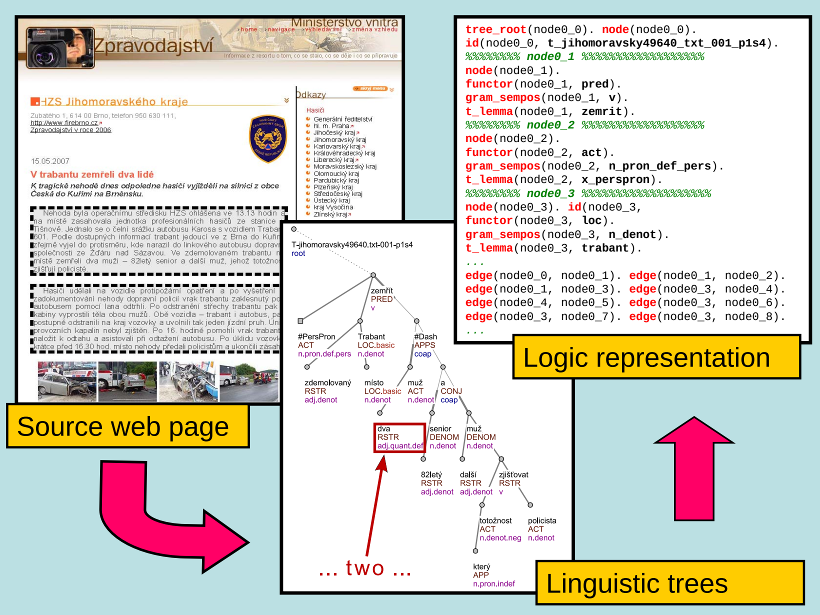
Induction of Extraction Rules

Integration of ILP in our extraction process

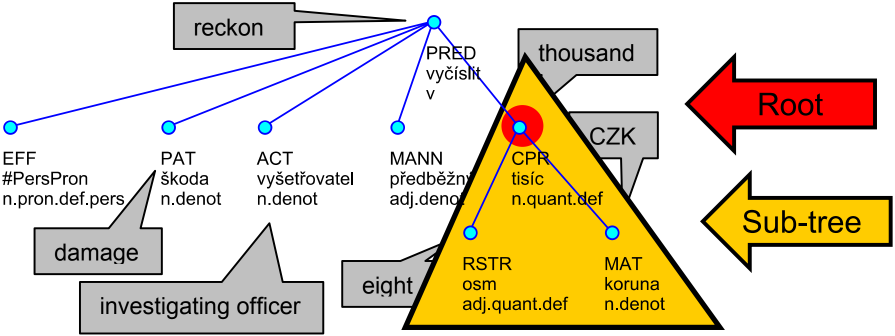


- Main point: transformation of trees to logic representation.
- Human annotator does not need to be a linguistic expert.

Logic representation of linguistic trees



Root/Subtree Preprocessing/Postprocessing



…, škodu vyšetřovatel předběžně vyčíslil na osm tisíc korun.

…, investigating officer preliminarily reckoned the damage to be eight thousand Crowns (CZK).

- Multi-word expressions

Rules with largest coverage (Czech fireman dataset)

```
% [cars - Rule 3] [Pos cover = 5 Neg cover = 0]
mention(cars,A) :-
   'lex.rf'(B,A), sempos(B,'n.denot'), tDependency(C,B), t_lemma(C,vozidlo),
   functor(C,'ACT'), number(C,sg).   % vozidlo ~ vehicle
% [damage - Rule 1] [Pos cover = 14 Neg cover = 0]
mention(damage,A) :-
   'lex.rf'(B,A), sempos(B,'n.quant.def'), tDependency(C,B), tDependency(C,D),
   t_lemma(D,'vyšetřovatel').   % vyšetřovatel ~ investigating officer
% [end_subtree - Rule 7] [Pos cover = 6 Neg cover = 0]
mention(end_subtree,A) :-
   'lex.rf'(B,A), sempos(B,'n.quant.def'), tDependency(C,B), t_lemma(C,'ukončit').
       % ukončit ~ finish
% [start - Rule 2] [Pos cover = 15 Neg cover = 0]
mention(start,A) :-
   'lex.rf'(B,A), functor(B,'TWHEN'), tDependency(C,B), tDependency(C,D),
   t_lemma(D,ohlásit).   % ohlásit ~ report (e.g. a fire)
% [injuries - Rule 1] [Pos cover = 7 Neg cover = 0]
mention(injuries,A) :-
   'lex.rf'(B,A), functor(B,'PAT'), tDependency(B,C), t_lemma(C,'zraněný'),
   tDependency(D,B), aspect(D,cpl).   % zraněný ~ injured
% [fatalities - Rule 1] [Pos cover = 3 Neg cover = 0]
mention(fatalities,A) :-
   'lex.rf'(B,A), functor(B,'PAT'), tDependency(C,B), t_lemma(C,srazit).
       % srazit ~ knock down
% [professional_unit - Rule 1] [Pos cover = 17 Neg cover = 0]
mention(professional_unit,A) :-
   'lex.rf'(B,A), functor(B,'LOC'), gender(B,fem), tDependency(C,B),
   functor(C,'CONJ'), overlap_Lookup_tToken(D,B).
% [amateur_unit - Rule 1] [Pos cover = 19 Neg cover = 0]
mention(amateur_unit,A) :-
   'lex.rf'(B,A), tDependency(C,B), tDependency(D,C), tDependency(D,E),
   t_lemma(E,dobrovolný).   % dobrovolný ~ voluntary
```

Evaluation -- Czech fireman -- Precision (optimistic example)

Strict Precision

Task	ILP			PAUM		
cars	0.324	$\pm$	0.387	0.380	$\pm$	0.249
damage	0.901	$\pm$	0.178	0.860	$\pm$	0.176
end subtree	0.529	$\pm$	0.381	0.499	$\pm$	0.242
start	0.929	$\pm$	0.109	0.651	$\pm$	0.152 •
injuries	0.667	$\pm$	0.291	0.398	$\pm$	0.205 •
fatalities	0.814	$\pm$	0.379	0.307	$\pm$	0.390 •
rofessional unit	0.500	$\pm$	0.241	0.677	$\pm$	0.138 ◦
amateur unit	0.863	$\pm$	0.256	0.546	$\pm$	0.293 •
overall	0.691	$\pm$	0.358	0.540	$\pm$	0.297 •

◦, • statistically significant improvement or degradation

Evaluation -- Corporate acquisitions -- Overall

Task	Annotations ver. A	Annotations ver. B	Extraction Method SRV	HMM	Elie	SVM+ILP	ILP	PAUM
acquired	**683**	651	38.5	*30.9*	43.5	41.8	31.3	**47.3**
acqabr	**1450**	1494	38.1	40.1	39.7	42.6	*25.8*	**45.6**
purchaser	**624**	594	45.1	48.1	46.2	45.4	*36.7*	**51.1**
purchabr	1263	**1347**	**48.5**	n/a	28.7	35.4	*17.2*	44.3
seller	267	**707**	23.4	n/a	*15.6*	**51.5**	17.0	23.2
sellerabr	431	**458**	**25.1**	n/a	13.4	21.7	*8.5*	20.2
dlramt	**283**	206	61.8	55.3	59.0	53.0	*28.0*	**65.9**
Total/Overall	5001	**5457**	41.1	n/a	33.5	40.8	*23.9*	**44.0**

- F_1 measure
- Two versions of the dataset (A - white / B - gray)
- Results taken form the literature (except ILP and PAUM)
- ``Baseline experiments'', see also the discussion slide (57) about future experimenting possibilities

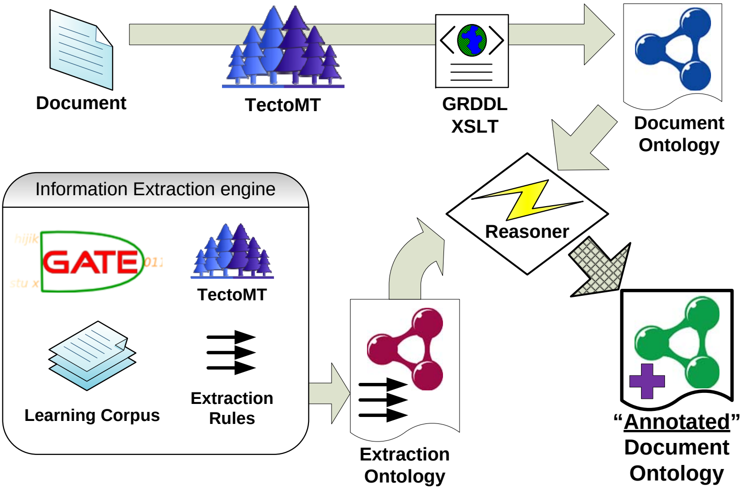
Extraction Ontology

- The knowledge (extraction model) used in the extraction process can itself be saved in an ontology.
  - So called Extraction Ontology

- D. W. Embley, ``Toward semantic understanding: an approach based on information extraction ontologies,'' in *ADC '04*. Darlinghurst: ACS, 2004, pp. 3--12.
- M. Labský et al., ``The Ex Project: Web Information Extraction Using Extraction Ontologies,'' in *Knowledge Discovery Enhanced with Semantic and Social Information*, ser. Studies in Comput. Intellig. Springer, 2009, vol. 220, pp. 71--88.

- But these Extraction Ontologies can only be used with the original tool.
- They are not shareable!

Extraction Rules Interpreted by OWL Reasoner



- Tool independent extraction ontologies

Extraction rules in OWL/XML syntax for Rules

```xml
<?xml version="1.0" encoding="UTF-8"?>
<!DOCTYPE Ontology [
  <!ENTITY pml "http://ufal.mff.cuni.cz/pdt/pml/" >
]>
<Ontology xmlns="http://www.w3.org/2002/07/owl#"
  ontologyIRI="http://czsem.berlios.de/ontologies/...rules.owl">
  <DLSafeRule>
    <Body>
      <ObjectPropertyAtom> <ObjectProperty IRI="&pml;lex.rf"/>
        <Variable IRI="urn:swrl#b"/> <Variable IRI="urn:swrl#a"/>
      </ObjectPropertyAtom>
      <DataPropertyAtom> <DataProperty IRI="&pml;sempos"/>
        <Variable IRI="urn:swrl#b"/> <Literal>n.quant.def</Literal>
      </DataPropertyAtom>
      <ObjectPropertyAtom> <ObjectProperty IRI="&pml;tDependency"/>
        <Variable IRI="urn:swrl#c"/> <Variable IRI="urn:swrl#b"/>
      </ObjectPropertyAtom>
      <ObjectPropertyAtom> <ObjectProperty IRI="&pml;tDependency"/>
        <Variable IRI="urn:swrl#c"/> <Variable IRI="urn:swrl#d"/>
      </ObjectPropertyAtom>
      <DataPropertyAtom> <DataProperty IRI="&pml;t_lemma"/>
        <Variable IRI="urn:swrl#d"/> <Literal>vyšetřovatel</Literal>
      </DataPropertyAtom>
    </Body>
    <Head>
      <DataPropertyAtom> <DataProperty IRI="&pml;mention_root" />
        <Literal>damage</Literal> <Variable IRI="urn:swrl#a" />
      </DataPropertyAtom>
    </Head>
  </DLSafeRule>
</Ontology>
```

Extraction rules in Protégé

```
#[Rule 1]
lex.rf(?b, ?a), sempos(?b, "n.quant.def"), tDependency(?c, ?b),
tDependency(?c, ?d), t_lemma(?d, "vyšetřovatel") #investigator
      -> mention_root(?a, "damage")

#[Rule 2]
lex.rf(?b, ?a), functor(?b, "TOWH"), tDependency(?c, ?b),
tDependency(?c, ?d), t_lemma(?d, "škoda") #damage
      -> mention_root(?a, "damage")
```

Extraction rules in Jena

```
@prefix pml: <http://ufal.mff.cuni.cz/pdt/pml/>.
[rule-1:
        ( ?b pml:lex.rf ?a )
        ( ?b pml:sempos 'n.quant.def' )
        ( ?c pml:tDependency ?b )
        ( ?c pml:tDependency ?d )
        ( ?d pml:t_lemma 'vyšetřovatel' )
     ->
        ( ?a pml:mention_root 'damage' )
]
```

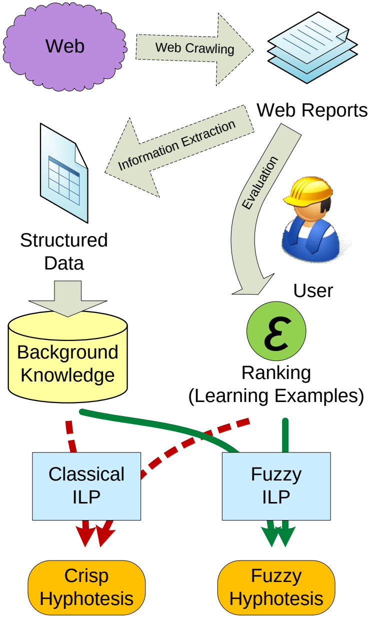
Performance Evaluation -- Datasets & Reasoners

dataset	domain	language	num of files	data size (MB)	num of rules
czech_fireman	accidents	Czech	50	16	2
acquisitions	finance	English	600	126	113

reasoner	**czech_fireman**	stdev	**acquisitions-v1.1**	stdev
Jena	161 s	0.226	1259 s	3.579
HermiT	219 s	1.636	$\gg$ 13 hours	
Pellet	11 s	0.062	503 s	4.145
FaCT++	Does not support rules.			

- Poor performance...
- Because these tools are not optimized for these taks (yet?)

Schema of the whole system



1. Web Crawling
2. Information Extraction and User Evaluation
3. Logic representation
   - Construction of background knowledge
   - Construction of learning examples
4. ILP Learning
   - Crisp
   - Fuzzy
5. Comparison of results

Essential difference between learning examples

Crisp learning examples

```
serious_2(id_47443). %positive

serious_0(id_47443). %negative
serious_1(id_47443). %negative
serious_3(id_47443). %negative
```

Monotonized learning examples

```
serious_atl_0(id_47443). %positive
serious_atl_1(id_47443). %positive
serious_atl_2(id_47443). %positive

serious_atl_3(id_47443). %negative
```

- For one evidence (occurrence, e.g. one accident)
- Crisp:
  Always one positive and three negative learning examples
- Monotonized:
  Up to the observed degree positive, the rest negative.

Monotonization of attributes

damage_atl ← damage

```
damage_atl(ID,N) :- damage(ID,N), not(integer(N)). %unknown values

damage_atl(ID,N) :- damage(ID,N2), integer(N2), %numeric values
                    damage(N), integer(N), N2>=N.
```

- We infer all lower values as sufficient.
- Treatment of unknown values.
- Negation as failure.

Rules for the whole Czech fireman dataset

```
% Crisp
serious_0(A) :- fatalities(A,0), injuries(A,0), cars(A,1),
                amateur_units(A,0), lather(A,0).
serious_0(A) :- fatalities(A,0), cars(A,0), amateur_units(A,0),
                professional_units(A,1).
serious_1(A) :- amateur_units(A,1).
serious_1(A) :- damage(A,300000).
serious_1(A) :- type(A,fire), amateur_units(A,0), pipes(A,2).
serious_1(A) :- type(A,car_accident), dur_minutes(A,unknown),
                fatalities(A,0), injuries(A,1).
serious_2(A) :- lather(A,unknown).
serious_2(A) :- cars(A,0), lather(A,0), aqualung(A,1), fan(A,0).
serious_2(A) :- amateur_units(A,2).
serious_3(A) :- fatalities(A,2).
serious_3(A) :- type(A,fire), dur_minutes(A,unknown), cars(A,0), fan(A,0).
serious_3(A) :- injuries(A,2), cars(A,2).
serious_3(A) :- fatalities(A,1).

% Monotonized
serious_atl_0(A).
serious_atl_1(A) :- injuries_atl(A,1).
serious_atl_1(A) :- dur_minutes_atl(A,21), pipes_atl(A,1), aqualung_atl(A,0).
serious_atl_1(A) :- damage_atl(A,8000), amateur_units_atl(A,3).
serious_atl_1(A) :- dur_minutes_atl(A,197).
serious_atl_1(A) :- dur_minutes_atl(A,unknown).
serious_atl_2(A) :- dur_minutes_atl(A,50), pipes_atl(A,3).
serious_atl_2(A) :- size_atl(A,1364), injuries_atl(A,1).
serious_atl_2(A) :- fatalities_atl(A,1).
serious_atl_2(A) :- size_atl(A,1106), professional_units_atl(A,3).
serious_atl_3(A) :- fatalities_atl(A,1).
serious_atl_3(A) :- damage_atl(A,1500000).
```

Conversion of Results

serious_t ← serious_atl_t (selecting maximum)

```
serious_0(ID) :- serious_atl_0(ID),
                 not(serious_atl_1(ID)), not(serious_atl_2(ID)),
                 not(serious_atl_3(ID)).
serious_1(ID) :- serious_atl_1(ID),
                 not(serious_atl_2(ID)), not(serious_atl_3(ID)).
serious_2(ID) :- serious_atl_2(ID),
                 not(serious_atl_3(ID)).
serious_3(ID) :- serious_atl_3(ID).
```

Evaluation -- Czech fireman dataset

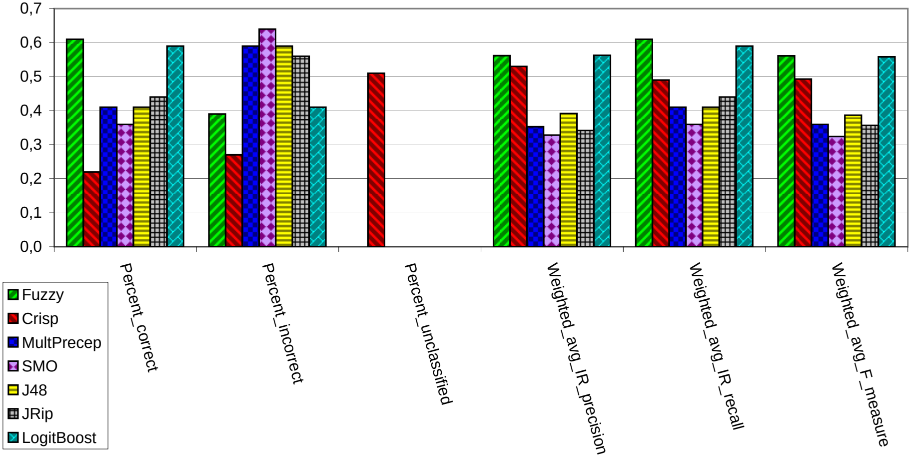
	Fuzzy	Crisp	MultPerc	SMO	J48	JRip	LBoost
Corr	0.61±.19	.22±.17 ●	.41±.19 ●	.36±.24 ●	.41±.22 ●	.44±.17 ●	.59±.26
Incor	.39±.19	.27±.24	.59±.19 ○	.64±.24 ○	.59±.22 ○	.56±.17 ○	.41±.26
Uncl	.00±.00	.51±.29 ○	.00±.00	.00±.00	.00±.00	.00±.00	.00±.00
Prec	.56±.24	.53±.37	.35±.20 ●	.33±.26	.39±.22	.34±.21 ●	.56±.28
Rec	.61±.19	.49±.32	.41±.19 ●	.36±.24 ●	.41±.22 ●	.44±.17 ●	.59±.26
F	.56±.20	.49±.33	.36±.19 ●	.32±.24 ●	.39±.21	.36±.19 ●	.56±.27

○, ● statistically significant improvement or degradation

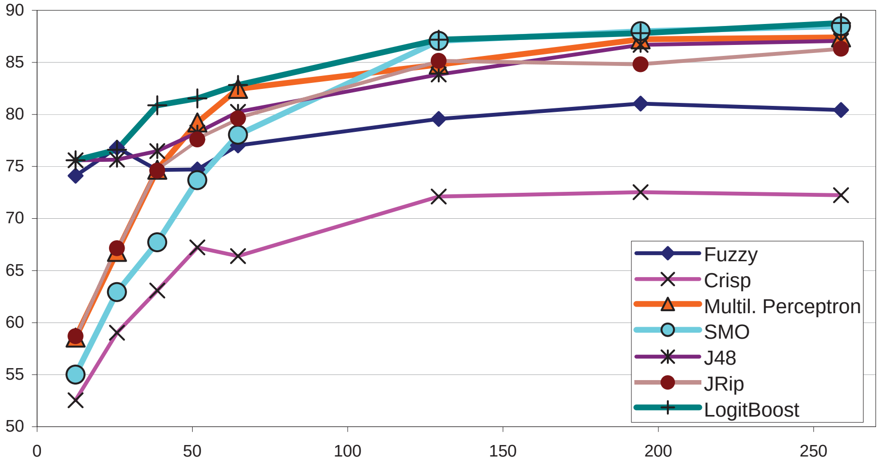
Fuzzy . . . . czsem.ILP.FuzzyILPClassifier
Crisp . . . . czsem.ILP.CrispILPClassifier
MultPerc . . . . functions.MultilayerPerceptron
SMO . . . . functions.SMO
J48 . . . . trees.J48
JRip . . . . rules.JRip
LBoost . . . . meta.LogitBoost

Corr . . . . Percent correct
Inor . . . . Percent incorrect
Uncl . . . . Percent unclassified
Prec . . . . Weighted avg IR precision
Rec . . . . Weighted avg IR recall
F . . . . Weighted avg F measure

Evaluation -- Czech fireman dataset



The impact of dataset size on classification performance



- `nursery' dataset from UCI ML Repository
- x-axis: number of training instances
- y-axis: percent of correctly classified instances
- average values from 10 repetitions

The Title

- Nobody is happy with the title!
  - Including the author himself ...
- But it is quite difficult to find better one.
- ``Use of deep language parsing for generation of extraction rules''
  - The last two topics are not cowered
- ``How ILP and ontologies can help information extraction''
  - The first and the last topic is not cowered

1. Introduction
   - Information Extraction
   - Deep Language Parsing
   - Inductive Logic Programming
   - Organization of this Presentation
2. Contents
   - Manual Design of Extraction Rules
   - Induction of Extraction Rules
   - Shareable Extraction Ontologies
   - Fuzzy ILP Document Classification
3. Questions and Comments from Reviews
   - Review 1 (Filip Železný)
   - Review 2 (Diana Maynard)

Topic of the question / comment

- The thesis consists of four equally important topics
- We cannot concentrate on a single one (**Induction of Extraction Rules)**

- It was really had work to prepare and evaluate the baseline method
- And make it directly comparable with the state-of-the-art solutions
- The framework is now open to everybody
- ``Infinite'' amount of experiments can be performed
  - See also the discussion slide (57) about future experimenting possibilities

The Task of Information Extraction

> *The task of IE should be clearly defined, making clear what it involves, why it is needed, and why it is hard. ... Sections on IE components ... are much too short. ... I would expect these issues to be covered and discussed in depth, with appropriate references (these issues have all been discussed many times in the literature), ...*

- Is it really necessary to discuss all these topics?
  - It concerns only 2 of 4 main topics of the thesis.
  - We are not creating a text book, are we?
  - What is the contribution in it?
- What reference is actually missing?
- Is the used terminology lacking something important?

Dědek	MUC-6 1995, Appelt & Israel 1999
Entity Recognition	Named Entity Recognition
Relation Extraction	Template Element Construction
Event Extraction	Template Relation Construction
Event Extr. Encoded as Ent. Rec.	Template Unification
Instance Resolution	Scenario Template Production

Future Experimenting Possibilities

- Cartesian product of many factors:
  - Doplnit!

Available Resources Criterion: Time, Effort, Allocated Capabilities

- One common answer to comments like:
  - ``Chapter, section, etc. is too short.''
  - ``Problem, solution, etc. should be more discussed.''
  - ``The techniques could easily be described and motivated in much more detail.''
  - ``More examples should be given.''
  - ``Evaluation dataset is rather too small.''
- The answer is:
  - Yes, that is reasonable comment, but there were no more available resources for it.
  - Is the work as a whole too short?
  - Are there parts that should have been omitted?
  - We did our best to include the most important and relevant things.
  - But then, oops, the time was up!
- Let's look at this in more detail on the next slides...

Work Performed -- Implementation

- Nontrivial extensive implementation
- Use and integration of following tools and technologies:
  - Linguistics
    - PDT 2.0 analysis tools + TectoAnalysis by Václav Klimeš
    - TectoMT (Treex currently also supported)
    - Perl/brted programming of first *procedural* extraction rules
    - Netgraph by Jiří Mírovský, *declarative* extraction rules
    - GATE
  - Semantic Web
    - OWL API + Pellet, HermiT and FaCT++
    - Jena (including Jena Rules)
    - SweetRules
    - PML $\rightarrow$ RDF (OWL) transformation (XSLT $\approx$ GRDDL)
    - ILP Extraction rules $\rightarrow$ SWRL transformation
  - Data Mining
    - **ILP** (Progol, Prolog + Aleph):
      Integration with GATE (IE Rules Induction) and
      Weka (Fuzzy ILP Classifier)
    - **Weka:** Fuzzy ILP Classifier and Statistical significance of GATE experiments
  - XML RPC (Perl server, Java client)

Work Performed -- Other

- Construction (or contribution) of new datasets:
  - Czech Fireman Reports without Annotations
  - Czech Fireman Reports Manually Annotated
  - RDF Dataset Based on Czech Fireman Reports
  - RDF Dataset Based on Corporate Acquisition Events
  - Classification Dataset Based on Czech Fireman Reports

- Evaluation experiments
  - **Direct** comparison with state-of-the-art
- Publications:
  - Including E-Environment and Economics (Crisis prediction)
- Development of the idea of **Web Semantization**
  - Finally not included in the thesis
  - But published in selected papers