

# Web Reports Classification with Fuzzy Inductive Logic Programming

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## I. FUZZY INDUCTIVE LOGIC PROGRAMMING

In our application we are facing the challenge of induction and/or mining on several places. First we need an inductive procedure when extracting from web texts attributes of an accident.

Second we need an inductive procedure when trying to explain degree of seriousness of an accident by attributes of this accident (also called background knowledge).

Both places where induction has to be used have following requirements

- data are/can be fuzzy
- background knowledge is multirelational
- classification is fuzzy

Having in mind these requirements we chose Fuzzy inductive logic programming. To make the paper readable we present bellow short description of ILP techniques.

### A. Classical ILP

In our presentation of Inductive Logic Programming (ILP) we follow the book of S. Džeroski and N. Lavrač [1].

Given is a set of examples  $E = P \cup N$ , where  $P$  contains positive and  $N$  negative examples, and a background knowledge  $B$ . The task is to find a hypothesis  $H$  such that

$$(\forall e \in P)(B \cup H \models e)$$

and

$$(\forall e \in N)(B \cup H \not\models e).$$

Typically,  $E$  consists of ground instances of the target predicate which has to be classified - in our case accidents.  $B$  typically consists of several predicates (relational tables) which describe properties of object which have to be classified - in

our case properties of accidents. Background knowledge can contain also some rules. Hypothesis  $H$  typically consists of logic programming rules, which when added to  $B$ , explain all positive examples and no negative examples.

Main advantage of ILP is it's multirelational character, namely  $B$  can reside in several tables.

### B. Fuzzy and GAP induction

In our presentation of Inductive Logic Programming (ILP) we follow the Paper of T. Horvath and P. Vojtas [2] about fuzzy inductive logic programming.

We use the approach of the fuzzy logic in narrow sense developed by J. Pavelka and P. Hajek. Formulas are of the form  $\varphi, x$  ( $\varphi$  is syntactically same as in the crisp case) are graded by a truth value  $x \in [0, 1]$ . A structure  $\mathcal{M}$  consist of domain  $M$  and relations are interpreted fuzzy (we do not consider function symbols here). Evaluation  $\|\varphi\|_{\mathcal{M}}$  of a formula  $\varphi$  uses truth functions of many valued connectives (our logic is extensional and/or truth functional). Satisfaction is defined by

$$\mathcal{M} \models_f (\varphi, x) \text{ iff } \|\varphi\|_{\mathcal{M}} \geq x$$

Given is a fuzzy set of examples  $\mathcal{E} : E \rightarrow [0, 1]$  and a fuzzy background knowledge  $\mathcal{B} : B \rightarrow [0, 1]$ . The task is to find a fuzzy hypothesis  $\mathcal{H} : H \rightarrow [0, 1]$  such that

$$(\forall e, f \in \text{dom}(E))(\forall \mathcal{M})(\mathcal{M} \models_f B \cup H)$$

we have

$$E(e) > E(f) \Rightarrow \|\mathcal{E}\|_{\mathcal{M}} \geq \|\mathcal{H}\|_{\mathcal{M}}.$$

That is, it cannot happen that

$$E(e) > E(f) \wedge \|\mathcal{E}\|_{\mathcal{M}} < \|\mathcal{H}\|_{\mathcal{M}},$$

or rephrased, if  $E$  is rating  $e$  higher than  $f$ , then it can not happen in a model of  $B \cup H$  that  $e$  is rated worse than  $f$ .

Typically,  $\mathcal{E}$  consists of ground instances of the target predicate which are classified in truth degrees - in our case degree of seriousness of an accident.  $\mathcal{B}$  typically consists of several fuzzy predicates (fuzzy relational tables) which describe properties of object which have to be classified - in our case fuzzy properties of accidents - degree of injury, degree of damage, .... Background knowledge can contain also some rules, so far only crisp rules are used. Hypothesis  $H$  typically consists of a fuzzy logic program, which when added to  $B$ , prevents of misclassification (better can not be declared to be worse, nevertheless can be declared as having same degree (for more detailed discussion on this definition

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of fuzzy ILP we refer to the paper [2]). Moreover, in practise, we use GAP - Generalized Annotated Programs, so graded formulas will be sometimes understood as annotated (with crisp connectives and more complex annotation of head of rules.)

### C. Translation of fuzzy ILP task to several classical ILP tasks

As far as there is no implementation of fuzzy (GAP) ILP, we have to use a classical ILP system. Fortunately a fuzzy ILP task can be translated to several crisp ILP tasks (subject to some rounding and using finite set of truth values).

## II. SOLUTION

Citace tectogrammatical structure [3]

Citace ILP [4]

Citace Fuzzy ILP [2]

Citace Aleph:

A Learning Engine for Proposing Hypotheses (Aleph v5<sup>1</sup>)

## III. RESULTS

See fig 3.

## IV. CONCLUSION

We have presented a proposal of and experiments with a system for semantic computing of information from Czech text on Web pages. Our system relies on linguistic annotation tools from PDT [5] and the tree querying tool Netgraph [6]. Our contributions are an experimental chain of tools that enables semantic computing. In the third phase – data extraction – we formulate an inductive logic programming task over linguistically annotated data. Finally we describe transformation of these data to an ontology. Our initial experiments verified used methods and tools.

In future work we would like to test our method on another languages and compare our results with similar solutions. Our work is very close to domain dependent information extraction such as relation and event extraction. These tasks were considered as Semantic Evaluation in the first place in

<sup>1</sup><http://www.comlab.ox.ac.uk/activities/machinelearning/Aleph/>

attribute name	distinct values	missing values	monotonic
size (of file)	49	0	yes
type (of accident)	3	0	no
damage	18	30	yes
dur_minutes	30	17	yes
fatalities	4	0	yes
injuries	5	0	yes
cars	5	0	yes
amateur_units	7	1	yes
profesional_units	6	1	yes
pipes	7	8	yes
lather	3	2	yes
aqualung	3	3	yes
fan	3	2	yes
ranking	14	0	yes

Fig. 1. Characteristics of accident attributes.

the MUC-6 conference 1995 [7]. Contemporary results of the ACE competition<sup>2</sup> show the difficulty of these problems, which are very close to ours.

## ACKNOWLEDGMENT

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<sup>2</sup><http://www.nist.gov/speech/tests/ace/>

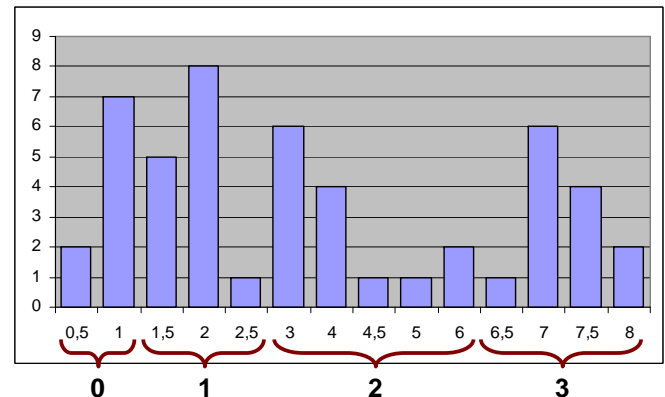


Fig. 2. Frequency histogram of accidents ranking.

		Raw ILP	Fuzzy ILP
<b>Fuzzy test set</b>	TP:	42	57
positive: 64	FP:	7	6
negative: 36	Precision:	0,857	0,905
sum: 100	Recall:	0,656	0,891
	F-measure:	0,743	0,898
<b>Crisp test set</b>	TP:	12	15
positive: 25	FP:	13	10
negative: 75	Precision:	0,480	0,600
sum: 100	Recall:	0,480	0,600
	F-measure:	0,480	0,600

Fig. 3. Evaluation results

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

Fig. 4. Conversion of results: monotone  $\rightarrow$  crisp.

```
serious_atl_0(ID) :- serious_3(ID).
serious_atl_1(ID) :- serious_3(ID).
serious_atl_2(ID) :- serious_3(ID).
serious_atl_3(ID) :- serious_3(ID).
```

Fig. 5. Conversion of results: crisp  $\rightarrow$  monotone.

```
damage_atl(ID,N) :-
    damage(ID,N), not(integer(N)).
damage_atl(ID,N) :-
    damage(ID,N2), integer(N2),
    damage(N), integer(N), N2>=N.
```

Fig. 6. Monotonization of attributes (damage  $\rightarrow$  damage\_atl).

```
serious_0(A):-dur_minutes(A,8).
serious_0(A):-type(A,fire), pipes(A,0).
serious_0(A):-fatalities(A,0), pipes(A,1),
               lather(A,0).
serious_1(A):-amateur_units(A,1).
serious_1(A):-amateur_units(A,0), pipes(A,2),
               aqualung(A,1).
serious_1(A):-damage(A,300000).
serious_1(A):-damage(A,unknown), type(A,fire),
               profesional_units(A,1).
serious_1(A):-dur_minutes(A,unknown),
               fatalities(A,0), cars(A,1).
serious_2(A):-lather(A,unknown).
serious_2(A):-lather(A,0), aqualung(A,1),
               fan(A,0).
serious_2(A):-amateur_units(A,2),
               profesional_units(A,2).
serious_2(A):-dur_minutes(A,unknown),
               injuries(A,2).
serious_3(A):-fatalities(A,1).
serious_3(A):-fatalities(A,2).
serious_3(A):-injuries(A,2), cars(A,2).
serious_3(A):-pipes(A,4).
```

Fig. 7. Crisp rules

```
serious_atl_0(A).
serious_atl_1(A):-injuries_atl(A,1).
serious_atl_1(A):-lather_atl(A,1).
serious_atl_1(A):-pipes_atl(A,3).
serious_atl_1(A):-dur_minutes_atl(A,unknown).
serious_atl_1(A):-size_atl(A,764),
               pipes_atl(A,1).
serious_atl_1(A):-damage_atl(A,8000),
               amateur_units_atl(A,3).
serious_atl_1(A):-type(A,car_accident).
serious_atl_1(A):-pipes_atl(A,unknown),
               randomized_order_atl(A,35).
serious_atl_2(A):-pipes_atl(A,3),
               aqualung_atl(A,1).
serious_atl_2(A):-type(A,car_accident),
               cars_atl(A,2), profesional_units_atl(A,2).
serious_atl_2(A):-injuries_atl(A,1),
               profesional_units_atl(A,3), fan_atl(A,0).
serious_atl_2(A):-type(A,other),
               aqualung_atl(A,1).
serious_atl_2(A):-dur_minutes_atl(A,59),
               pipes_atl(A,3).
serious_atl_2(A):-injuries_atl(A,2),
               cars_atl(A,2).
serious_atl_2(A):-fatalities_atl(A,1).
serious_atl_3(A):-fatalities_atl(A,1).
serious_atl_3(A):-dur_minutes_atl(A,unknown),
               pipes_atl(A,3).
```

Fig. 8. Monotonised rules