Fuzzy ILP classifier for Weka

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http://www.ksi.mff.cuni.cz/~dedek/fuzzyILP/

Fuzzy ILP

Fuzzy ILP

- Introd. example, theory, architecture and an experiment
- Fuzzy ILP Implementation
- Evaluation

Introd, example, theory, architecture and an experiment

ILP Example

Types of ground variables

```
animal(dog). animal(dolphin) ... animal(penguin).
class(mammal). class(fish). class(reptile). class(bird).
covering(hair). covering(none). covering(scales).
habitat(land). habitat(water). habitat(air).
```

Background knowledge

```
has_covering(dog, hair). has_covering(crocodile, scales). has_legs(dog,4)... has_legs(penguin, 2). etc. has_milk(dog)... has_milk(platypus). etc. homeothermic(dog)... homeothermic(penguin). etc. habitat(dog, land)... habitat(penguin, water). etc. has_eggs(platypus)... has_eggs(eagle). etc. has_gills(trout)... has_gills(eel). etc.
```

Introd. example, theory, architecture and an experiment

ILP Example

Positive examples

```
class(lizard, reptile).
class(trout, fish).
class(bat, mammal).
```

Negative examples

```
class(trout, mammal).
class(herring, mammal).
class(platypus, reptile).
```

Induced rules

Classical ILP and Fuzzy ILP principles

- Learning examples $E = P \cup N$ (Positive and Negative)
- Background knowledge B
- ILP task to find hypothesis H such that:

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

- Fuzzy learning examples $\mathcal{E}: E \longrightarrow [0,1]$
- Fuzzy background knowledge $\mathcal{B}: B \longrightarrow [0, 1]$
- Fuzzy ILP task to find hyp. $\mathcal{H}: H \longrightarrow [0,1]$ such that:

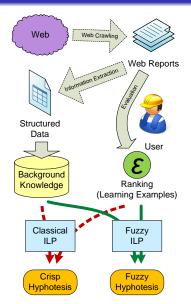
$$(\forall e_1, e_2 \in E)(\forall \mathcal{M})(\mathcal{M} \models_f \mathcal{B} \cup \mathcal{H}) \ : \ \mathcal{E}(e_1) > \mathcal{E}(e_2) \Rightarrow \|e_1\|_{\mathcal{M}} \geq \|e_2\|_{\mathcal{M}}$$

Generalized Annotated Programs

- Fuzzy ILP is equivalent to Induction of Generalized Annotated Programs¹
- For implementation we use GAP or strictly speaking:
 Definite Logic Programs with monotonicity axioms (also equivalent)
- Basic paradigm: deal with values as with degrees.
 - We don't have to normalize values, they order is enough.
- For example with monotonicity axioms we can use rule: serious(A, 4) ← fatalities(A, 10). and from the fact fatalities(id_123, 1000) deduce serious_alt(id_123, 4).

¹See in S. Krajci, R. Lencses and P. Vojtas: "A comparison of fuzzy and annotated logic programming", Fuzzy Sets and Systems, vol.144, pp.173–192, 2004.

Schema of the whole system



- Web Crawling
- Information Extraction and User Evaluation
- Logic representation
 - Construction of background knowledge
 - Construction of learning examples
- ILP Learning
 - Crisp
 - Fuzzy
- Comparison of results

Accident attributes

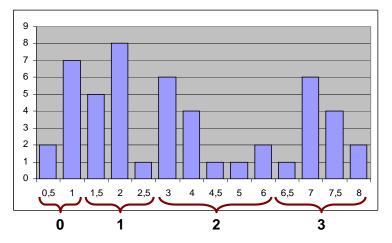
	distinct	missing	
attribute name	values	values	monotonic
size (of file)	49	0	yes
type (of accident)	3	0	no
damage	18	30	yes
dur_minutes	30	17	yes
fatalities	4	0	yes
injuries	5	0	yes
cars	5	0	yes
amateur_units	7	1	yes
profesional_units	6	1	yes
pipes	7	8	yes
lather	3	2	yes
aqualung	3	3	yes
fan	3	2	yes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

- Information that could be extracted.
- Missing values.
- Almost all attributes are numeric.
 - So monotonic
 - This will be used for "fuzzyfication"
- Artificial target attribute seriousness ranking.

Fuzzy ILP

Introd. example, theory, architecture and an experiment

Histogram of the seriousness ranking attribute



- 14 different values, range 0.5 8
- Divided into four approximately equipotent groups.

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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):

- 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

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



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```
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),prof_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),prof_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).
serious_3(A):-injuries(A,2).

serious O(A):-dur minutes(A,8).

serious_3(A):-injuries(A,2), cars(A,2). serious_3(A):-pipes(A,4).

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_attl_1(A):-pipes_attl(A,unknown), randomized_order_attl(A,35).
serious_attl_2(A):-pipes_attl(A,3), aqualung_attl(A,1).
serious_attl_2(A):-type(A,car_accident), cars_attl(A,2),prof_units_attl(A,2).

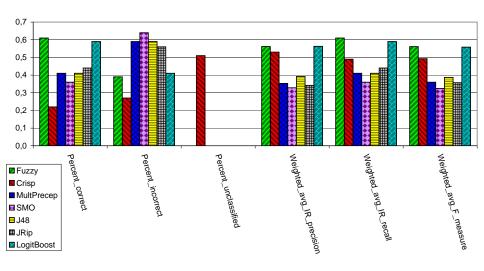
serious_atl_2(A):-injuries_atl(A,1),prof_units_atl(A,3),fan_atl(A,0). serious_atl_2(A):-type(A,other), aqualung_atl(A,1). serious_atl_2(A):-dur_minutes_atl(A,59), pipes_atl(A,3).

serious_atl_2(A):-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). Crisp hypothesis

- Monotonized hypothesis
 - Monotonicity axioms
 - Monotonized learning examples

Evaluation and Comparison of Results – graph



	Fuzzy	Crisp	MultPerc	SMO	J48	JRip	LBoost		
Corr	$0.61 \pm .19$.22±.17 •	.41±.19 •	.36±.24 ●	.41±.22 ●	.44±.17 ●	.59±.26		
Incor	$.39 \pm .19$	$.27 \pm .24$.59±.19 ∘	.64±.24 o	.59±.22 ∘	.56±.17 ∘	.41±.26		
Uncl	$.00 \pm .00$.51±.29 ∘	$.00 \pm .00$	$.00 \pm .00$	$.00 \pm .00$	$.00 \pm .00$.00±.00		
Prec	$.56 \pm .24$	$.53 \pm .37$.35±.20 ●	$.33 {\pm} .26$	$.39 \pm .22$.34±.21 ●	.56±.28		
Rec	$.61 \pm .19$	$.49 {\pm} .32$.41±.19 ●	.36±.24 ●	.41±.22 ●	.44±.17 ●	$.59 \pm .26$		
F	$.56 \pm .20$	$.49 {\pm} .33$.36±.19 ●	.32±.24 ●	$.39 \pm .21$.36±.19 ●	.56±.27		
o, ◆ statistically significant improvement or degradation									
Fuzzyczsem.ILP.FuzzyILPClassifier " Crispczsem.ILP.CrispILPClassifier " MultPercfunctions.MultilayerPerceptron '-L 0.3 -M 0.2 -N 500 -V 0 -S 0 -E 20 -H a' SMOfunctions.SMO '-C 1.0 -L 0.0010 -P 1.0E-12 -N 0 -V -1 -W 1 -K \"functions.supportVector.PolyKernel -C 250007 -E 1.0\"' J48trees.J48 '-C 0.25 -M 2' JRiprules.JRip '-F 3 -N 2.0 -O 2 -S 1' LBoostmeta.LogitBoost '-P 100 -F 0 -R 1 -L -1.7976931348623157E308 -H 0.1 -S 1 -I 10 -W trees.DecisionStump'									
CorrPercent correct InorPercent incorrect UnclPercent unclassified PrecWeighted avg IR precision RecWeighted avg IR recall FWeighted avg F measure									

Conversion of Results

crisp ← **monotone** (**select max**)

monotone ← crisp

```
serious_atl_0(ID) :- serious_2(ID).
serious_atl_1(ID) :- serious_2(ID).
serious atl 2(ID) :- serious 2(ID).
```