Inductive Classification through Evidence-based Models and Their Ensembles

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Outline

Motivations

AIM: predicting the membership of an individual w.r.t. a query concept

- typically based on automated reasoning techniques
- Inferences are affected by the incompleteness of the Semantic Web
- decided using models induced by Machine learning methods
- The quality depends on the training data distribution
  - Given a query concept, generally, many uncertain-membership examples than individuals with a definite membership
  - **We are assuming a ternary classification problem**

Motivations

Previous solutions and the current limits

- We started to investigate the imbalance learning problem by resorting to a solution which combines (under-)sampling methods and ensemble learning models
  - for overcoming the loss of information due to the discarded instances
  - Terminological Decision Tree (TDT): a DL-based Decision Tree for concept learning and assertion prediction problems
  - combined to obtain Terminological Random Forests (TRF)
- Some limits:
  - predictions made according to simple majority vote procedure (no conflicts, no uncertainty are considered)
  - misclassifications mainly due to evenly distributed votes
- Further rules (meta-learner) required

Introduction & Motivations

Underlying idea

Using soft predictions (predictions with a confidence measure for each class value) obtained by each tree for weighting the votes

- TDTs return only hard predictions (i,.e. predicted class without any information)
- Dempster-Shafer Theory (DS) operators for information fusion
  - Solution: Resort and modify the Evidential TDTs (ETDTs)

The Dempster-Shafer Theory (DS)

- Frame of discernement Ω
  - a set of hypotheses for a domain, e.g. the membership values for an individual given a concept $\Omega = \{-1, +1\}$
- Basic Belief Assignement (BBA) $m : 2^{\Omega} \rightarrow [0, 1]$
  - the amount of belief exactly committed to $A \subseteq \Omega$
- Belief function: $\forall A, B \in 2^{\Omega} \quad Bel(A) = \sum_{B \subseteq A} m(B)$
- Plausibility function: $\forall A, B \in 2^{\Omega} \quad Pl(A) = \sum_{B \cap A \neq \emptyset} m(B)$

The Dempster-Shafer Theory (DS)

- Combination rules: used for pooling evidences for the same frame of discernment coming from various sources of information
  - Dempster's rule
    - $\forall A, B, C \subseteq \Omega \quad m_{12}(A) = m_1 \oplus m_2 = \frac{1}{1-c} \sum_{B \cap C = A} m_1(B) m_2(C)$
  - Dubois-Prade's rule
    - $\forall A, B, C \subseteq \Omega \quad m_{12}(A) = \sum_{B \cup C = A} m_1(B) m_2(C)$

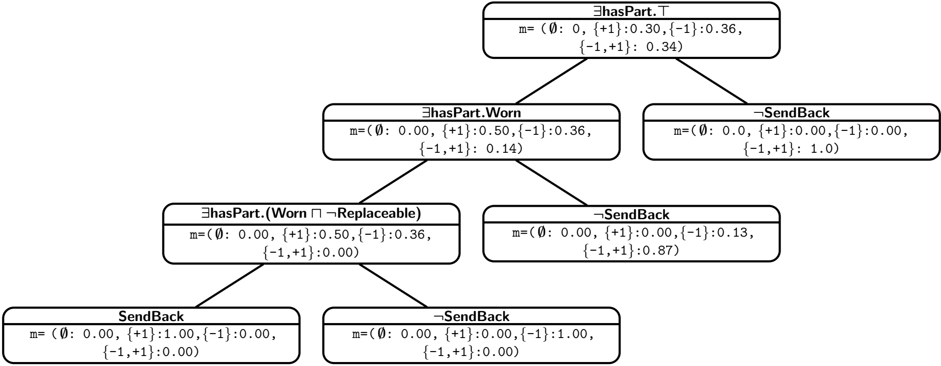
Evidential TDTs

An ETDT is a binary tree where:

- each node contains a conjunctive concept description D and a BBA m obtained by counting the positive, negative and uncertain instances;
- each departing edge is the result of instance-check test w.r.t. D, i.e., given an individual a, $\mathcal{K} \models D(a)$?
- a child node with the concept description D is obtained using a refinement operator

The model can be used for returning soft prediction

An example of ETDT



$\Omega = \{-1, +1\}$
$\{+1\} \leftrightarrow \mathcal{K} \models D(a)\ \forall a \in \mathrm{Ind}(A)$
$\{-1\} \leftrightarrow \mathcal{K} \models \neg D(b)\ \forall b \in \mathrm{Ind}(A)$
$\{-1, +1\}$ otherwise

Evidential Terminological Random Forests

- In order to tackle the imbalance learning problem, we propose Evidential Terminological Random Forest (ETRF), where
  - each ETDT returns a soft prediction in the form of BBA
  - the meta-learner is a combination rule

Learning Evidential Terminological Random Forests

Given:

- a target concept C
- the number of trees n
- a training set $\mathrm{Tr} = \langle \mathrm{Ps}, \mathrm{Ns}, \mathrm{Us} \rangle$
  - $Ps = \{a \in \mathrm{Ind}(\mathcal{A}) | \mathcal{K} \models C(a)\}$
  - $Ns = \{b \in \mathrm{Ind}(\mathcal{A}) | \mathcal{K} \models \neg C(b)\}$
  - $Us = \{c \in \mathrm{Ind}(\mathcal{A}) | \mathcal{K} \not\models C(c) \wedge \mathcal{K} \not\models \neg C(c)\}$

the algorithm can be summarized as follows:

- build a n bootstrap samples with a balanced distribution
- for each sample learn an ETDT model

Learning ETRF

Building bootstrap samples

1. a stratified sampling with replacement procedure is employed in order to represent the minority class instances in the bootstrap sample.
2. the majority class instances (either positive, negative and uncertain-membership instances) are discarded.

Learning ETRF

Learning ETDTs

- Divide-and-conquer algorithm for learning an ETDT [Rizzo et al.@IPMU, 2014]
- Steps:
  1. refinement of the concept description installed into the current node
  2. Random selection of a subset of candidates
  3. A BBA for each selected description
  4. The concept having the most definite membership (and its BBA) installed into the new node.
- Stop conditions: the node is pure w.r.t. the membership

Predicting membership for unseen individuals

- Given a forest F and a new individual a, the algorithm collects BBAs returned by each ETDT
- The BBA returned by an ETDT is decided by following a path according to the instance check test result.
- For a concept description installed as node D
  - if $\mathcal{K} \models D(a)$ the left branch is followed
  - if $\mathcal{K} \models \neg D(a)$ the right branch is followed
  - otherwise both branches are followed
  - Various leaves can be reached and the corresponding BBAs are pooled according to the combination rule

Predicting membership for unseen individuals

- The set of BBAs returning from all the ETDTs are combined through the combination rule
- After a pooled BBA $\overline{m}$ is obtained, Bel (resp. Pl) function is derived
- Final membership assignement: hypothesis which maximizes belief (resp. plausibility) function
  - Bel and Pl function are monotonic : uncertain-memberhip is more probable
  - Return the uncertain-membership value when the belief for the positive- and negative-membership are approximately equal

Experiments

- 15 query concepts randomly generated
- 10-fold cross validation
- number of candidates randomly selected: $\sqrt{|\rho(\cdot)|}$
- Comparison w.r.t. TDTs, ETDTs, TRFs
- Forest sizes: 10, 20, 30 trees
- Stratified Sampling rates: 50%, 70 %, 80 %
- Metrics:
  - match: individuals for which the inductive model and a reasoner predict the same membership
  - commission: cases of opposite predictions
  - omission: individuals having a definite membership that cannot be predicted inductively;
  - induction: predictions that are not logically derivable.

Some results...

Ontology index		TDT	ETDTs
BCO	M%	**80.44 ± 11.01**	**90.31 ± 14.79**
	C%	**07.56 ± 08.08**	**01.86 ± 02.61**
	O%	**05.04 ± 04.28**	**00.00 ± 00.00**
	I%	**06.96 ± 05.97**	**07.83 ± 15.35**
BIOPAX	M%	**66.63 ± 14.60**	**87.00 ± 07.15**
	C%	**31.03 ± 12.95**	**11.57 ± 02.62**
	O%	**00.39 ± 00.61**	**00.00 ± 00.00**
	I%	**01.95 ± 07.13**	**01.43 ± 08.32**
NTN	M%	**68.85 ± 13.23**	**23.87 ± 26.18**
	C%	**00.37 ± 00.30**	**00.00 ± 00.00**
	O%	**09.51 ± 07.06**	**00.00 ± 00.00**
	I%	**21.27 ± 08.73**	**75.13 ± 26.18**
HD	M%	**58.31 ± 14.06**	**10.69 ± 01.47**
	C%	**00.44 ± 00.47**	**00.07 ± 00.17**
	O%	**05.51 ± 01.81**	**00.00 ± 00.00**
	I%	**35.74 ± 15.90**	**89.24 ± 01.46**

Some results...

Ontology	*index*	*Sampling rate 50 %* TRF *10 trees*	ETRF *10 trees*
BCO	M%	**86.27 ± 15.79**	**91.31 ± 06.35**
	C%	**02.47 ± 03.70**	**02.91 ± 02.45**
	O%	**01.90 ± 07.30**	**00.00 ± 00.00**
	I%	**09.36 ± 13.96**	**05.88 ± 06.49**
BIOPAX	M%	**75.30 ± 16.23**	**96.92 ± 08.07**
	C%	**18.74 ± 17.80**	**00.79 ± 01.22**
	O%	**00.00 ± 00.00**	**00.00 ± 00.00**
	I%	**01.97 ± 07.16**	**02.29 ± 08.13**
NTN	M%	**83.41 ± 07.85**	**05.38 ± 07.38**
	C%	**00.02 ± 00.04**	**06.58 ± 07.51**
	O%	**13.40 ± 10.17**	**00.00 ± 00.00**
	I%	**03.17 ± 04.65**	**88.05 ± 08.50**
HD	M%	**68.00 ± 16.98**	**10.29 ± 00.00**
	C%	**00.02 ± 00.05**	**00.26 ± 00.26**
	O%	**06.38 ± 02.03**	**00.00 ± 00.00**
	I%	**25.59 ± 18.98**	**89.24 ± 00.26**

Discussion

- improved performance of ETRFs w.r.t. the other models
  - higher match rate and induction rate
  - a lower standard deviation
- smallest changes of performance w.r.t. the forest size
  - weak diversification(overlapping) between trees by increasing the number of trees
- refinement operator is a bottleneck for learning phase

Conclusions and Further Extensions

- We proposed an ensemble solution based on DS to improve the predictiveness of the models for class-membership prediction with imbalanced training data distribution
- Extensions:
  - Development and reuse of refinement operators
  - Further ensemble techniques and combination rules
  - Experiments with larger ontologies
  - Parallelization of the current implementation

Thank you!

Questions?