T-21

Online Large-margin Weight Learning for First-order Logic-based Abduction

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Background

Abduction is inference to the best explanation

Given:
- Observation:
  {*get-gun*(*John*), *go-to-store*(*John*)}
- Background knowledge:
  $(\forall x)\ hunt(x) \rightarrow get\text{-}gun(x)$
  $(\forall x)\ go\text{-}shopping(x) \rightarrow go\text{-}to\text{-}store(x)$
  $(\forall x)\ rob(x) \rightarrow get\text{-}gun(x)$
  $(\forall x)\ rob(x) \rightarrow go\text{-}to\text{-}store(x)$

Find:
- The best explanation (≡highest-score explanation)

$score(H_1) = 4.3$
$score(H_2) = \mathbf{13.5}$
$score(H_3) = 10.8$

H_1: {*hunt*(*John*), *go-shopping*(*John*)}
H_2: {*rob*(*John*)}
H_3: {*rob*(*John*), *hunt*(*John*)}

There are many applications: natural language processing, plan recognition etc.

Tuning of score function relies on:
- Manual tuning
- Probabilistic logic-based learning (e.g. Markov Logic Networks [Richardson & Domingos 06])

Problem: inference is not scalable; learning is even harder

Weight Learning for First-order Logic Abduction

Desiderata for learning framework
- *Scalability*: computationally cheap, good results in a short time → *online*
- *Accurateness*: discriminative power → *large-margin* training
- *Usability*: learn from partially observed dataset → with *latent variables!*

Our solution

Designed by the user:
e.g. 1 if "*rob*" and "*gun*" are included in H; 0 otherwise.

The learning framework

(1) Assume weighted linear scoring model: $score(H; \mathbf{w}) = \mathbf{w} \cdot \mathbf{\Phi}(H)$

$\mathbf{w}$: weight vector
$\mathbf{\Phi}$: feature vector

(2) Learn $\mathbf{w}$ from training examples online, following the large-margin principle:

Training examples $T = \{(O_i, H_i)\}^N_{i=1}$

O_i: observation (input)
H_i: gold-standard explanation for O_i (output)

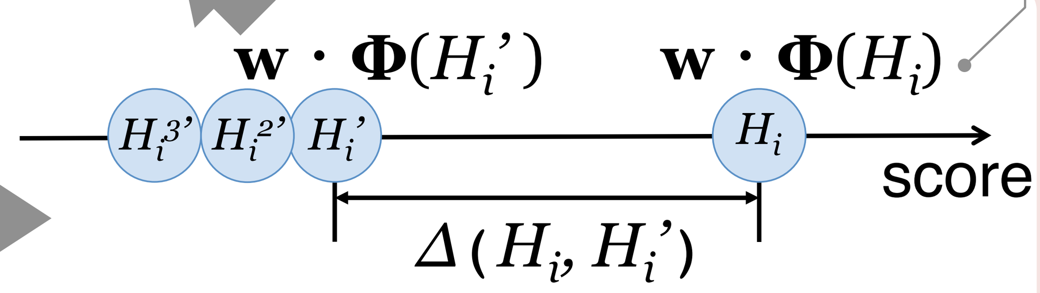
O_i: {*get-gun*(*John*), *go-to-store*(*John*)}
H_i: {*rob*(*John*)}

$(O_i, H_i) \leftarrow$ `receiveExample`(T)

H_1: {*hunt*(*John*)}
H_2: {*rob*(*John*)}
H_3: {*rob*(*John*), *hunt*(*John*)}

$H_i' \leftarrow$ `abduction`(B, O_i)

Passive Aggressive [Crammer et al. 2006]



$\Delta(H_i, H_i')$: loss function

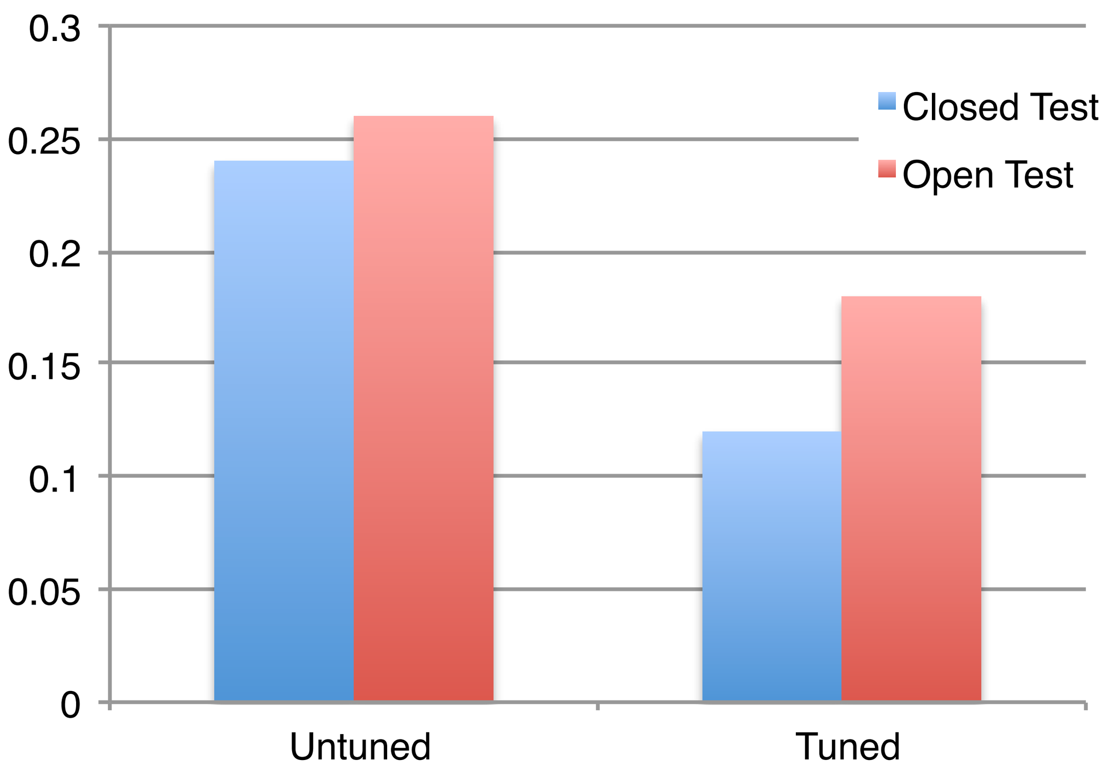
$\mathbf{w}_{t+1} \leftarrow$ `update`$(\mathbf{w}_t, H_i, H_i')$

partially-specified update:
update $\mathbf{w}$ s.t. any explanation that includes H_i is the best
(×) H_1: {*hunt*(*John*), *go-shopping*(*John*)}
(○) H_2: {*rob*(*John*)}
(○) H_3: {*rob*(*John*), *hunt*(*John*)}

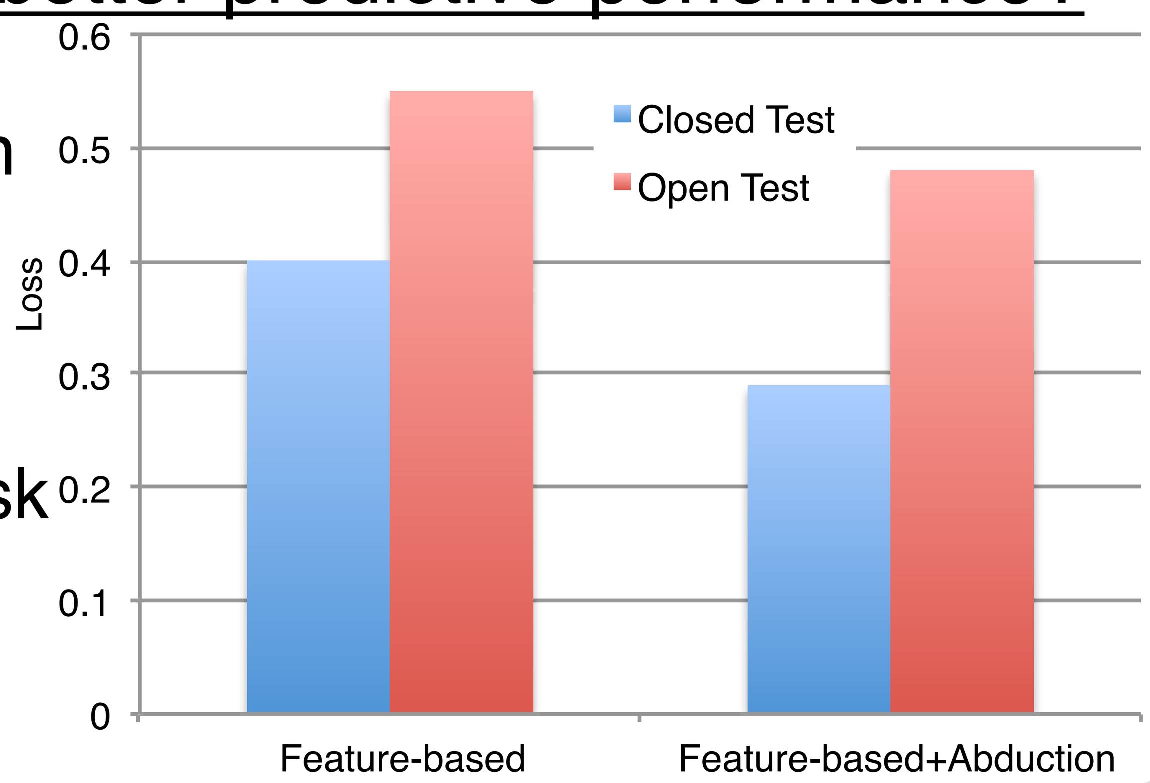
$H_i \leftarrow$ `abduction`(B, O_i) s.t. H_i is included [Yamamoto et al. 12]

Evaluation

Q1: Does learning have positive impact?
- Task: Plan recognition
- Gold-standard: plan literals
- Dataset: Ng & Mooney [92]
- Training/Testing: 25 examples
- BK: 107 axioms



Q2: Does combining logic-based reasoning with existing classifier give better predictive performance?
- Task: Coreference resolution
- Gold-standard: equalities
- Dataset: CoNLL-2011 Shared Task
- Training/Testing: 100 documents
- BK: 300,000 axioms



Findings

- Weight learning reduces predictive loss
- Combining abductive reasoning with feature-based classifier reduces predictive loss
- Generalization ability on unseen dataset

Publicly available at: http://github.com/naoya-i/henry-n700/

Future work

- Use k-best explanations for update
- Comparison with feature-based classifier exploiting world knowledge as features

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