Conversions for heterogeneous treebank parsing

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Introduction

We are going to focus now on conversions for the purposes of creating more parsing data

- Fully automatic methods are preferable to rule-based ones
  - Allow for new schemes (i.e., be even more robust than last time)
- We will start with DS ↔ PS issues, but the issue is more general
  - Convert a source annotation into a target annotation
    - different representation types, different conventions, different languages
    - i.e., find a common annotation scheme to parse with

Two-step solution

1. Convert grammar formalism of source to target
2. Refine converted trees & use them as additional training data, for a target grammar parser
   - This can be iterative, retraining on converted data

Approach taken here:

- DS-to-PS conversion, to better train a PS parser
- Use existing
- Potentially ignores globally optimal conversions
  - Usually have to be hand-crafted

Other avenues which are pursued:

- pruning low-quality trees
- interpolating scores from source & target grammars
- corpus weighting

Heterogeneous treebank contains multiple treebanks in different annotation schemes (grammar formalisms)

- To parse in target formalism, we have to solve: source treebank → target treebank
- This is desirable, as it provides more labeled data

Limitations of previous approaches

- “For each head-dependent pair, only one locally optimal conversion was kept during tree-building process”
  - Potentially ignores globally optimal conversions
- Heuristic rules are used to do the conversion, when multiple possible conversions exist
  - Usually have to be hand-crafted

Grammar formalism conversion

Notation:

- \( C_{\text{DS}} \) = source treebank annotated with dependency structure (DS)
- \( C_{\text{PS}} \) = target treebank annotated with phrase structure (PS)
- Goal: convert \( C_{\text{DS}} \) to \( C_{\text{PS}} \)

Steps:

1. Train a constituency parser on \( C_{\text{PS}} \) (target)
2. Generate \( n \)-best parsers for \( C_{\text{DS}} \) (source)
3. Convert \( n \) parses (\( x_{i,t} \)) to dependency trees (\( x_{i,t}^{\text{DS}} \))
4. Compare converted dependency trees (\( x_{i,t}^{\text{DS}} \)) to gold standard tree (\( y_t \)), obtaining \( \text{Score}(x_{i,t}) \)
  - measured by parseval F-score
5. Determine the PS tree by taking the one which corresponds to the maximum \( \text{Score}(x_{i,t}) \)
Grammar formalism conversion (2)

The method as outlined above can be repeated

- Converted trees can be used as additional data to retrain the n-best parser
- Development data (CPS.d) is used to determine when iterations are no longer helping

In general, once the conversion is done, heterogeneous parsing now is the same as homogeneous parsing
- i.e., treebanks are in the same format

Target grammar parsing

Instance pruning

n-best parser may fail on some cases, i.e., give poor-quality converted trees

- **Instance pruning**: remove converted trees with low unlabeled f-scores
- Then, do parser training

Corpus weighting

One other issue to be determined: if corpora are of different sizes, how are they balanced as parser training data?

- **Corpus weighting**: reduce the weight of the larger corpus (in this case CDS) when training
- This may also reduce the influence of potentially corrupt trees

Grammar formalism conversion (3)

The conversion from DS to PS involves a step of conversion between PS to DS, in order to make the n-best (PS) trees comparable to the gold (DS) tree

- The method relies upon there being some way to objectively compare the set of parsed trees with the gold ones in the treebank
- If it were a PS-to-PS conversion, this would have to be done differently

Their method is relatively simple:
1. Find the head of each constituent, using a head table
2. Make the head of each non-head child depend on the head

Target grammar parsing

Score interpolation

Unlabeled dependency F-score measures quality from the perspective of the source (DS) grammar

- What about from the perspective of the target grammar?
- After all, there can be different ways of viewing grammar that need to be reconciled towards the target
  - “conflicts of syntactic structure definition”
  - e.g., preposition or noun as the head? (see figure 1)

The score is thus modified to take parser probability/confidence into account:

\[ \hat{\text{Score}}(x_{ij}) = \lambda \text{Prob}(x_{ij}) + (1 - \lambda) \text{Score}(x_{ij}) \]

Evaluation on WSJ

Their results in tables 2 & 3 show improvement

- The measurements correspond to accuracy of recovering the original PS trees (not parsing accuracy)
Conversions for heterogeneous treebank parsing

Introduction

Niu et al. (2009)
Smith and Eisner (2009)

References

Parsing experiments on Chinese

Used CDT and CTB, in order to parse in CTB phrase-structure style

- Corpus weighting: tried increasing the weight of CTB in merging: optimal value = 10
- Both generative and reranking parser show improvements over baseline (table 5)
  - e.g., 83.3% → 83.8%

Instance pruning

Instance pruning was done on the development set

- Result: it hurt to remove any converted trees
- Perhaps: even imperfect parses provide some useful syntactic information

Score interpolation

Used \( \widetilde{\text{Score}}(x_i, t) \) to replace \( \text{Score}(x_i, t) \)

\[ \widetilde{\text{Score}}(x_i, t) = \lambda \text{Prob}(x_i, t) + (1 - \lambda)\text{Score}(x_i, t) \]

- \( \lambda \) was tuned on the development set to be 0.4
- average index of 200-best trees increased to 2, i.e., higher up the list / more like target grammar

Results go up even further, e.g., 83.3% → 83.8% → 84.2%

Using unlabeled data as part of self-training helps even more (section 4.3)

Summary

Benefits of this approach:

- A parser generates globally-optimal syntactic structures
- No heuristic rules are needed
- Converted trees can retrain the parser and improve the conversion

Quasi-synchronous grammar features

Smith and Eisner (2009)

The general task

Additionally, these are different sentences which are annotated, so we cannot directly learn transformations

- But we can automatically obtain pairs of trees
- Train parser on source corpus, parse target, and learn from those pairings
  - Note that this is the opposite direction from Niu et al. (2009)
- Learn tree transformation model from those pairings to obtain the source corpus in the target style
Parser projection

**Parser projection** is a case of taking source annotation from one language and projecting it into a target language.

Assume these variables:
- \( w \) = target language; \( t \) = target annotation
- \( w' \) = source language; \( t' \) = source annotation
- \( a \) = alignment between languages

Goal of projection is to model \( p(t'|w', t, a) \) (or, generatively, \( p(w, t, a|w', t') \))

**Parser adaptation** is a subset of this problem, where the alignment is trivial: a word maps to itself.

Form of the Model

**Scores & features**

Score of a given tuple:

\[
(3) \quad s(t, t', a, w, w') = \sum_i w_i f_i(t, w) + \sum_j w_j g_j(t, t', a, w, w')
\]

- **target features** \( f \): based only on target words and dependencies
  - features of an edge-factored dependency parser (e.g., POS of potential relation)
- **alignment features** \( g \)
  - features for \( x \rightarrow y \) (target) consider relationship between \( x' \) and \( y' \)
  - e.g., features for monotonic projection, head-swapping, various configurations (e.g., sibling)

Adaptation

Training done with both gold and noisy trees, to gauge the effect of parser noise

- Use MSTParser to train on source & parse a (small) amount of target data
- Train edge-factored parser with QG features on target data

Source & Target are in different conditions (preposition-as-head, coordination differences):

- Results in table 1 show that even with a small amount of trees, substantial gain can be made
- Results for cross-lingual projection & adaptation also show improvement (section 6)

References
