Active Learning and the Irish Treebank

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Centre for Language and Communication Studies, Trinity College Dublin

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Outline

Irish Language

Treebanking

Active Learning Experiments

Conclusion
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Irish — a low density language

- Official EU language
  - VSO Celtic Language
  - inflected prepositions: *agam* ‘at me’; *agat* ‘at you’
  - progressive aspectual phrases: *tá sé ag rith* ‘he is running’
  - clefting: *is mise atá ag caint* ‘it’s me who is talking’

- National Corpus of Ireland - Irish (NCII):
  - 30 million word corpus - Foras na Gaeilge

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- Parallel Data
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  - Traslan Teoranta (data made available to NCLT, Dublin)

- META-NET. White paper published in 2012: "The Irish Language in the Digital Age"
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General Issues

- Training data for statistical parsers
- Phrase Structure vs Dependencies
- What is a sufficient size?
- Parsing experiments on 13 treebanks (Nivre, 2008):
  - training set < 1500 sentences = reasonably accurate parsing models (Arabic, Slovene)

Key Points of Talk

- Update on development of Irish Treebank
- Extent to which Active Learning can play a role
  - Bootstrapping (Passive Learning, Active Learning)
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Irish Dependency Treebank (Lynn et al., 2012)

Built upon existing NLP resources:

- Morphological analyser, POS-tagger, 225 chunked sentences (Úí Dhonnchadha, 2009, PhD Thesis)
- LFG-inspired Dependency Scheme (Çetinoğlu et al., 2010)
- Small amount of Irish LFG research (e.g. Sulger, 2009)
- Head-modifier dependency relations
  - CoNLL-X format — Form; Lemma; CPOS; FPOS; Head; Label
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Irish Dependency Treebank

Preliminary parsing experiments

- MaltParser (Nivre et al., 2006)
- Seed set of 300 gold manually annotated sentences
- 10-fold cross validation
- Test variety of feature models
- Select baseline parsing model

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Why the need for Inter-annotator agreement measure?

- Are annotators’ judgements consistent/ reliable/ trustworthy?
- Indicates usefulness of data
- Indicates replicability (e.g. clinical studies – diagnoses)
- Analysis of disagreements can be used to improve labelling scheme
- Identifies gaps in the annotation guide

How do we measure IAA?

- Kappa coefficient of agreement (Cohen, 1960)
- Labelled Attachment Score (LAS)
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IAA-1 (Lynn et al., 2012)

- Two annotators
  - Irish speaking/linguistic background
- Practice run on 30 random sentences
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- Newly updated labelling scheme and annotation guide
- Practice run on 20 random sentences
- Measured agreement on different set of 50 random sentences:

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IAA-1 analysis

Overview of Types of Disagreements

▶ interpretation disagreements
  (e.g. legislative text > 200 tokens, obscure terminology)
▶ human error
▶ gaps in annotation guide
  (e.g. lack of examples, not clearly described etc.)
▶ outstanding issues
  (e.g. unresolved or newly encountered linguistic phenomena)
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  - npred: nominal predicate
  - ppred: prepositional predicate
  - advpred: adverbial predicate
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- **relnparticle → cleftparticle:**

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Is ise a chonaic mé inné
'COP she REL saw I yesterday'
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- **relparticle** → **cleftparticle:**

```plaintext
Irish:  
"Is ise a chonaic mé inne" 
"COP she REL saw I yesterday"

English:  
"It is she whom I saw yesterday"
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IAA-1 analysis

- adjunct $\rightarrow$ obl
- subj $\rightarrow$ csubj

'I expect they will return'
IAA-1 analysis

- adjunct $\rightarrow$ obl
- subj $\rightarrow$ csubj

Be expectation with-me COMP return-FUT they
'I expect they will return'
Re-running parsing experiments

- LAS-1/ UAS-1: original treebank
- LAS-2/ UAS-2: post-workshop updated treebank

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- Passive vs Active
  - Passive — select next set of parse trees for manual correction
  - Active — select ‘problematic’ parses for manual correction
- Active Learning previously used in NLP:
  - information extraction (Scheffer et al., 2001)
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Useful for building a resource?

- Some evidence of this with Interlinear Glossed Texts (Baldridge and Palmer, 2009)
- Treebanks?
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  - Passive — select next set of parse trees for manual correction
  - Active — select 'problematic' parses for manual correction
- Active Learning previously used in NLP:
  - information extraction (Scheffer et al., 2001)
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  - word-sense disambiguation (Chen et al., 2006)
  - parsing (Osborne and Baldridge, 2004)

Useful for building a resource?

- Some evidence of this with Interlinear Glossed Texts (Baldridge and Palmer, 2009)
- Treebanks?
Overview of Active Learning

General

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How to identify 'problematic' (informative) parses?

Query By Uncertainty (QBU) - (Cohn et al., 1994)
- select for manual correction when learner is least confident

Query By Committee (QBC) - (Seung et al., 1992)
- select based on disagreement among committee of learners
Bootstrapping Algorithm

\[ t \leftarrow \text{seed training set} \]
Train a parsing model, \( p \), using the trees in \( t \)

**repeat**

\[ u \leftarrow \text{a set of } X \text{ unlabelled sentences} \]
Parse \( u \) with \( p \) to yield \( u_p \)
\[ u' \leftarrow \text{a subset of } Y \text{ sentences from } u \]
Hand-correct \( u'_p \) to yield \( u'_\text{gold} \)
\[ t \leftarrow t + u'_\text{gold} \quad \text{(Add } u'_\text{gold} \text{ to } t) \]
Train a parsing model, \( p \), using the trees in \( t \)

**until** convergence

\[ u = 200 \]
\[ u' = 50 \]
Bootstrapping Algorithm (Passive vs Active)

The difference in versions lies in how $u'$ is chosen.

**Passive**

$u'$ is random selection of 50 sentences from $u$.

**Active - (QBC)**

$u'$ is top 50 most 'disagreed upon' sentences from $u$. 
Active Learning Experiment Setup

Details

- 450 Gold Trees = seed training (150); development set (150); test set (150)
- Two versions of bootstrapping algorithm: Active & Passive
- Four iterations (50 sentences manually corrected each time)
- Active Committee = MaltParser (Nivre et al., 2006) & Mate parser (Bohnet, 2010)
- Disagreement between two trees, $t_1$ and $t_2$ is defined as $1 - LAS(t_1, t_2)$. 
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Results: Passive vs Active (UAS)

x-axis = the number of training iterations
y-axis = unlabelled attachment score
Results: Passive vs Active (LAS)

- x-axis = the number of training iterations
- y-axis = labelled attachment score
Differences between Active and Passive sentences

<table>
<thead>
<tr>
<th>Average Sentence Length</th>
<th>Lt. 1</th>
<th>Lt.2</th>
<th>Lt.3</th>
<th>Lt.4</th>
</tr>
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<tbody>
<tr>
<td>Passive</td>
<td>18.6</td>
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<td>23.9</td>
<td>24.5</td>
</tr>
<tr>
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<td>25.5</td>
<td>24.8</td>
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| Correction Effort       | Passive | 23.8 | 30.2 | 27.0 | 23.8 |
|                         | Active  | 36.7 | 37.6 | 32.4 | 32.8 |

- Correction $\Rightarrow$ gold parse trees
- Correction effort $=$ disagreement between the automatic parse and its correction (1-LAS)
- Modest gains - worth the effort?
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Irish Language

Treebanking

Active Learning Experiments

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Summary

- Used IAA to finalise annotation scheme
- Bootstrapping parser => bootstrapping the treebank
- Explored the role of AL in treebank development
  - How will this picture change over time?
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Go raibh maith agaibh
Thank you
Merci