Statistical Machine Translation by Parsing

final presentation

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Statistical Machine Translation by Parsing

The Team
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The Supporting Team
Motivation for SMT by Parsing

- State-of-the-art SMT often produces word salad.
- Bolting trees onto FST-based (IBM-style) SMT doesn't seem to help.
- SMT is very compute-intensive (slow).
- SMT systems getting very complicated, making them hard to study and improve.
The Engineering Motivation for Syntax

- Need fewer parameters to express ordering preferences.
  - E.g.: Arabic adjectives always follow their nouns.
- Fewer parameters are easier to learn, given limited training data and/or computing resources.
- Less training data needed to reach a given level of accuracy.
- Better accuracy on fixed amount of data.
- All parameters interact during learning, so better estimates for syntactic parameters lead to better estimates for other types.
But isn’t syntax too expensive?

- **Myth**: Translation models involving syntax are computationally too expensive to train.
- **Fact**: Finite-state models are *more* expensive! (more parameters)
- Of course, bolting syntax on top of a finite state model incurs the combined cost of both. (So we avoided that.)
- In machine learning with structured inference (most of NLP), better models should train *faster.*
Motivations for our team’s work

- short-term
  - lower the entry barriers to the field
  - demonstrate feasibility of SMT by Parsing
- short- and long-term
  - answer fundamental scientific questions
  - educate the next generation
  - accelerate progress in MT
- long-term
  - help to reunite MT with NLP
following precedent

**SMT @ WS’99**
- EGYPT toolkit
  - incl. GIZA
  - no decoder
- Cairo
- N. Smith & M. Jahr
- feasibility of SMT

**SMT @ WS’05**
- GenPar toolkit
  - incl. “sandboxes”
  - no sep. decoder required
- MultiTreeViewer
- A. Burbank, P. Fox, and other educational achievements
- feasibility of SMT by Parsing
more precedent

<table>
<thead>
<tr>
<th>SMT @ WS’99</th>
<th>SMT @ WS’05</th>
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</thead>
<tbody>
<tr>
<td>• 1 week of data prep</td>
<td>• 1 week of data prep</td>
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<tr>
<td>• 3 weeks of software engineering</td>
<td>• 3 weeks of software engineering</td>
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<td>• 1 week of system integration</td>
<td>• 1 week of system integration</td>
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<td>• 1 week of research</td>
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</tbody>
</table>
Outline of the rest of the talk

- data preparation
- the GenPar toolkit
  - motivations
  - key algorithms
  - core system design
  - extensions
  - sandboxes: robust system integration
- feasibility of SMT by Parsing
- 2 proposals for follow-on research
- an empirical study
data preparation

1. obtain corpora (not easy)
2. tokenize
3. lemmatize
4. re-tokenize (re-lemmatize)
5. adapt text format to external taggers and parsers (Diab, Bikel)
6. tag & parse
7. partition into training/dev/test sets
8. filter out sentence pairs rejected by parser
9. induce word-to-word translation model (TM)
10. filter out sentence pairs rejected by TM
11. install improved taggers & parsers
12. repeat from step 2
The GenPar ToolKit

- a toolkit for generalized parsing
- integrated end-to-end system for translation by parsing, which is easy to obtain, understand, use, study, modify, extend, and improve
- relatively simple yet general architecture
- intuitive, flexible, object-oriented design
- 3 kinds of documentation: user, design, system
- dynamically configurable
- easily extendable
- freely downloadable!

http://www.clsp.jhu.edu/ws2005/groups/statistical/
The GenPar toolkit: outline

- main challenge
- key algorithm
- core system design
- design extensions
- robust system integration
DFD for SMT by Parsing
Challenges of complex systems

- Hard to study
  - Difficult to do controlled experiments.
  - Difficult to assign credit/blame for changes in performance.

- Hard to modify/extend
  - Research prototypes are often not well-designed, with many features hard-coded.

- Hard to replicate
  - Most papers on syntax-driven SMT compare their results only to systems with no syntax.

- Hard for the community to make progress
Lowering entry barriers: Reducing system complexity

The core algorithms are all generalized parsers.
How to do everything by parsing?

- multitrees
- multiparsing
- alignment by parsing
- translation by parsing
- later: MT evaluation by parsing
What’s a multitree?

[S
  [NP
    [N pasudu]
  ]
  [V moy]
]

[S
  [NP
    [N wash]
  ]
  [D the]
  [N DISH dishes]
]
MultiTreeViewer (MTV)
More perspectives on multitrees

Ya  kota  kormil  eosh

I fed the cat eosh
More perspectives on multitrees

<table>
<thead>
<tr>
<th></th>
<th>Ya</th>
<th>kota</th>
<th>kormil</th>
<th>eosh</th>
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<td>eosh</td>
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</tbody>
</table>
More perspectives on multitrees
More perspectives on multitrees
head-switching multitrees

El bebé acaba de comer eosh

The baby just ate eosm
head-switching multitrees

<table>
<thead>
<tr>
<th></th>
<th>El</th>
<th>bebé</th>
<th>acaba</th>
<th>de</th>
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</table>
How does a multiparser work?

Grammar:

N -> DISH
N -> PAS
NP -> D N
S -> V NP
NP -> N
S -> V NP

Input:

PAS pasudu
MIT moy

WASH wash
D the
DISH dishes

0 1 2 3
Multiparsing (1/4)

N  DISH

N  PAS

PAS
pasudu

MIT
moy

WASH
wash

D
the

DISH
dishes

0 1 2 3
Multiparsing (1/4)

N \rightarrow DISH

N \rightarrow PAS

N

PAS pasudu

MIT moy

WASH wash

D the

DISH dishes

0 1 2 3

0 1 2 3
Multiparsing (2/4)

V          WASH
V          MIT

N
PAS  
pasudu
MIT  
moy

WASH  wash  D  the  DISH  dishes

0  1  2  3
0  1  2
Multiparsing (2/4)

V    WASH
V    MIT

N    PAS pasudu
V    MIT moy

V    WASH
    wash
    the
    dishes

0 1                               2                      3
Multiparsing (3/4)
Multiparsing (3/4)
Multiparsing (4/4)

The diagram illustrates the process of parsing a sentence into its constituent parts.

The sentence structure is represented as follows:

- **S**: Sentence
- **NP**: Noun Phrase
- **V**: Verb
- **PAS**: Part-of-Speech
- **moy**: MIT

The diagram breaks down the sentence into its components:

- **WASH**: Verb (wash)
- **D**: Determiner (the)
- **DISH**: Noun (dishes)
- **pasudu**: Part-of-Speech
- **MIT**: Noun (moy)

The diagram visually represents the sentence structure and the parsing process.
Multiparsing (4/4)
Alignment

word-to-word model:
dishes = pasudu
wash = moy
the = ∅
Translation (1)

\[
\begin{array}{c|c|c}
\text{WASH} & \text{MIT} \\
0 & 1 \\
\end{array}
\]

\[
\begin{array}{c|c|c}
V & V \\
0 & 1 \\
\end{array}
\]
Translation (2, 3, 4)
Result of translation is a multitree

```
NP  
  V
     PAS
     MIT

NP  
  V
     WASH
     D
     DISH
```

0  1                      2                      3
Result of translation is a multitree?

- But we want a string!
- Trivial: Output string can be read off the multitree leaves by a trivial postprocess.
- Information about relative order of constituents is inferred as part of the parsing process.
- No separate “decoder” required.
How to do everything by parsing

- single inference algorithm
- varying constraints:
  - production rules
  - pre-existing monolingual tree(s)
  - input string
  - etc.
- easier said than done...
GenPar design goals

1. powerful and configurable
   - can instantiate many kinds of SMTbyP systems
   - abstract classes interact in a fixed but generic way
   - concrete variants chosen at runtime via config files:
     - parsing algorithm
     - type of grammar
     - pruning strategy
     - etc., etc., etc.

2. easy to understand

3. easy to extend
   - new functionality added by subclassing abstract components -- surprisingly flexible!
   - OO design facilitates concurrent development of multiple components
The core of the design

- Parsing Goal
- Multitree
- Grammar
- Chart
- Item
- Inference
- Logic
- OutsideCostEstimator
- Agenda
- Comparator
- PruningStrategy

X → Y: X knows about Y
X ↔ Y: X contains Y
Generic agenda-based parsing algorithm

Input: logic L (with grammar inside), pruning strategy P, sentence tuple, parsing goal, etc.

1. Item $I = \text{null}$;
2. repeat
3. if (not agenda.empty()) then
4. $I = \text{agenda.pop()}$;
5. set<Item> $E = L.\text{expand}(G, I)$ // initialize if $I$ is null
6. for ($J \in E$) do
7. if (not $P(J)$) // check if pruning
8. agenda.push($J$);
9. until (agenda.empty() or parsing goal reached)

Output: L.result() // multitree(s) with cost(s)
Key abstraction: Parsing Logics

- Nondeterministic parsing algorithm
- Specifies which items can compose with which other items into which other items
- Does not fully specify the order of compositions -- a separate search strategy can do that
- Search strategy expressed by agenda’s comparator
- Degree of nondeterminism can vary from a lot to none
Key abstraction: Parsing Logics

- partially based on Shieber et al. (1995)
- E.g., CKY algorithm:
  - logic = bottom up
  - search strategy = shortest span first
- Different item comparator gives different parsing algorithms with same logic:
  - best first
  - left-to-right
  - random
- The comparator is a relatively tiny piece of code, easy to write.
Key Abstraction: Grammar encapsulation

- grammars evaluate partial parses
  - `getPossibleCons(item1, item2)`: decide if two items can compose
  - `getCost(inference)`: compute inference cost
- can be based on production rules
- can be based on some completely different system of constraints

Diagram:

- Grammar
  - Weighted Multitext Grammar (WMTG)
    - your grammar here
  - Bilexical Probabilistic MTG
    - your grammar here
  - Two-Tree-Constrained MTG
Extensions

- New variants are easy to implement, sometimes surprisingly easy!
- new logics for:
  - faster translation
  - multiparsing with no agenda
- new grammars for
  - alignment with one constraining tree
  - “phrases”
New functionality: faster translation

Logic

Bottom-Up Logic

abstract

implements expand() with genScans() and genComposes()

Bottom-Up Translation Logic

extends expand() with genLoads()

Faster Bottom-Up Translation Logic

overrides genLoads() to filter loads based on input sentence
Effects of a single method override

Inference counts for translation of 10 sentences using tiny grammar

<table>
<thead>
<tr>
<th>Language pair</th>
<th>Inferences under naïve logic</th>
<th>Inferences under faster logic</th>
<th>Reduction factor</th>
</tr>
</thead>
<tbody>
<tr>
<td>English to English</td>
<td>998</td>
<td>646</td>
<td>1.55</td>
</tr>
<tr>
<td>French to English</td>
<td>1092</td>
<td>974</td>
<td>1.12</td>
</tr>
<tr>
<td>Arabic to English</td>
<td>2341</td>
<td>996</td>
<td>2.35</td>
</tr>
</tbody>
</table>

On larger grammar: reduced by 2 orders of magnitude.
New functionality: translation without agenda

- overrides `expand()` to implement deterministic CKY translation algorithm
- after translation, `expand()` returns the empty set, so agenda never used
- still uses superclass’s methods for `genScans()`, `genLoads()`, `genComposes()`
Generic agenda-based parsing algorithm

Input: logic L (with grammar inside), pruning strategy P, sentence tuple, parsing goal, etc.

1. Item I = null;
2. repeat
3. if (not agenda.empty()) then
4.   I = agenda.pop();
5. set<Item> E = L.expand(G, I)  // initialize if I is null
6. for (J ∈ E) do
7.   if (not P(J))                              // check if pruning
8.     agenda.push(J);
9. until (agenda.empty() or parsing goal reached)

Output: L.result()        // multitree(s) with cost(s)
New functionality: alignment with one constraining tree

- overrides `getPossibleCons()` to consult only one constraining tree
- completely transparent to logic
Possible new functionality: “phrases”

- assume we have a phrase list for one or both languages
- easy case: contiguous n-grams
- (treegrams a bit trickier, but not much)
- e.g., “kick the bucket”, “there is”, “account for”
- solution:
  - treat each phrase as a possible constituent, with unique nonterminal label
  - attach to or identify with lowest subsuming node in constraining tree during alignment
  - slash sibling nonterminal labels
Possible new functionality: “phrases”

E.g., phrase = “ab”

constraining tree =

use trie for efficient phrase recognition during scanning of the input

span of scanned word can be wider than 1

no other changes for retraining and translation

all changes encapsulated in grammar
System integration
Lowering entry barriers: Sandboxes

A sandbox is...

- a directory structure where a single command will run the end-to-end system on a toy-sized corpus
  - simply go to base directory and type “make”
- a validation suite for developers
  - after each change of code, make sure nothing broke
- an educational tool for SMT
  - seeing some data run through the pipeline is a good way to get familiar with the system
- a blueprint for experiments
  - change config files, and run your own data through it
- toolkit includes sandboxes for 3 language pairs
Feasibility of SMT by Parsing

- parameter estimation in GenPar
- highlights of configuration used
- the data
- automatic evaluation method
- preliminary results
parameter estimation in GenPar

So far, very primitive: Viterbi estimation.

Machine learning toolkits can be integrated.
configuration used for experiments

- Logic: Bottom Up
- Search Strategy: Best First
- Grammar:
  - for alignment: tree-constrained MTG
  - for retraining & translation:
    - bilexical (headed) probabilistic MTG
    - fine-grained generative process with strong independence assumptions but no smoothing
- N.B: first-cut model and training method
data used for experiments

- English tagger (Ratnaparkhi) & parser (Bikel) trained on PTB
- French to English
  - subset of EuroParl corpus (Koehn’02)
  - pretokenized, except for some missing periods
  - stop-lists off the web
  - train/dev set from standard training partition
- Arabic to English
  - tagger from Diab@HLT’04
  - Bikel parser, trained on part of Arabic treebank (ATB)
  - training data: A/E parallel news corpus
  - test data: NIST MTEval’03 test set
MT evaluation: measuring text overlap

To avoid double-counting, the overlap is a maximum matching.
Rewards for longer matches

Reward diagonal runs more than linearly in their length. E.g., run weight is the area of its minimum enclosing square.
MT evaluation: the standard measures

- maximum match size (MMS) = maximum combined area of non-overlapping squares
- take square root to linearize
- normalize by lengths of the candidate (C) and reference (R) to get a score between 0 and 1:
  - $P = \text{precision} = \frac{\text{MMS}}{|C|}$
  - $R = \text{recall} = \frac{\text{MMS}}{|R|}$
  - F-measure = harmonic mean of P and R
    \approx \text{the fraction of the grid covered by matches}
- measure not developed here, but the software is part of toolkit
preliminary evidence for empirical feasibility

- approx speed (without much optimization)
  - alignment, retraining: about 1 sentence pair per second
  - translation: 1 sentence per minute with no LM
- learning curve (Declan)
New functionality:
Target language models

A proposal for follow-on research
(Markus)
MT Evaluation by Parsing

A proposal for follow-on research
(Ben)
The ITG Hypothesis for Arabic/English

(Dekai)
Take-home messages

- **Findings:**
  - Multiparsing can be fast.
  - Typical models fit in the memory of typical machines.
  - Our first-cut system is comparable in accuracy to an off-the-shelf FST-based SMT system.
    - On the only corpus on which we could make a direct comparison, which was small.
  - Much low-hanging fruit ready to be picked, to improve speed and accuracy.

- **Conjectures:**
  - All processes are easily parallelizable at the sentence level.
  - Processing typical bitext sizes is no more difficult than for FST-based SMT.
Take-home software

• On our team’s homepage
  http://www.clsp.jhu.edu/ws2005/groups/statistical
• MTV

• GenPar
  – sign onto genpar-announce@cs.nyu.edu to be notified of updates
(near) future directions

- target language models
- MT evaluation by parsing
- phrases
- other grammar formalisms (CCG, TSG, ...)
- smoothing methods for generative transduction grammars
- machine learning beyond EM
- more sophisticated pruning
- beyond single-best translations
Review

- **short-term**
  - lower the entry barriers to the field
  - demonstrate feasibility of SMT by Parsing

- **short- and long-term**
  - answer fundamental scientific questions
  - educate the next generation
  - accelerate progress in MT

- **long-term**
  - help to reunite MT with NLP
Helping to reunite MT with NLP

- Recently, MT research has been borrowing more from machine learning than from NLP.
- Strong connection between MT and parsing should make both subfields pay more attention to each other.
- Then, MT can improve by parsing.
- Parsing can claim another application.
- A Good Thing, long term.
## Looking forward

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<tr>
<th></th>
<th>SMT</th>
<th>SMT by Parsing</th>
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<tbody>
<tr>
<td>first proposed</td>
<td>1988</td>
<td>1995</td>
</tr>
<tr>
<td>publicly available toolkit</td>
<td>+11 years = 1999</td>
<td>+10 years = 2005</td>
</tr>
<tr>
<td>dominant approach</td>
<td>+3 years = 2002</td>
<td>??</td>
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