Unsupervised Natural Language Parsing

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Tutorial Overview

1.	Introduction	(Kewei)
2.	Generative Approaches	(Kewei, Yong)
3.	Discriminative Approaches	(Wenjuan)
4.	Special Topics	(Yanpeng)
5.	Summary	(Kewei)

2. Generative Approaches

Generative Approaches

A generative approach models the joint generation of sentence x and parse tree z.

- Main approach: learning a probabilistic generative grammar
  - Context-free grammar (CFG)
  - Dependency model with valence (DMV)
  - Other:
    - Tree substitution grammar (Bod, 2006a,b; Cohn et al., 2010; Blunsom & Cohn, 2010)
    - Combinatory categorial grammar (Bisk & Hockenmaier, 2012, 2013; Bisk et al., 2015)
- Other generative approaches
  - Constituent Context Model (Klein and Manning, 2002; Golland et al., 2012)
  - Language model with structural constraints (Shen et al., 2017; 2018)

The focus of part 2

To be discussed in part 4

Outline

- Structure Learning (Kewei)
- Parameter Learning (Yong)

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- Structure Learning (Kewei)
- Parameter Learning (Yong)

Structure Learning

- Context-free grammar (CFG)
  - Σ: terminal symbols
  - N: nonterminal symbols
  - S: start symbol
  - R: production rules

Vocabulary of the language; no learning required

“Structure” of the grammar; must be learned

- Structure learning
  - Finding an optimal set of production rules
- Two classes of approaches
  - Heuristic approaches
  - Optimization-based approaches

Heuristic approaches

- Create nonterminals and production rules using heuristic criteria and rules
- No explicit learning objective

Three typical steps in a heuristic approach:

- Constituent filtering
- Nonterminal creation
- Reduce and repeat

Heuristic approaches - Constituent filtering

Goal: identify substrings in the training sentences that are likely constituents

Methods:

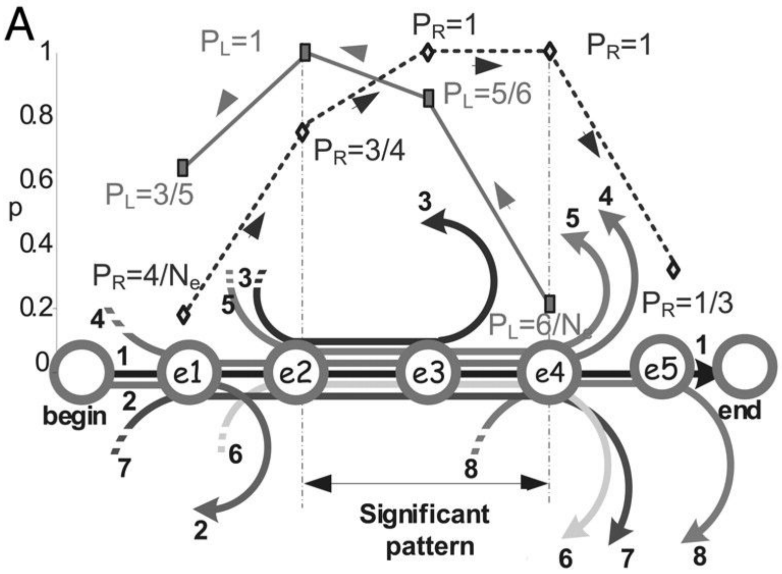
1. Frequency of a substring
2. Mutual information between the symbols occurring *before* and *after* a substring (Clark, 2001)
    - Constituents often have high MI

Heuristic approaches - Constituent filtering

Goal: identify substrings in the training sentences that are likely constituents

Methods:

3. Ratio of fan-through to fan-in
   (Solan et al., 2005)



Heuristic approaches - Nonterminal creation

Goal: create a new nonterminal representing a set of constituents

Methods:

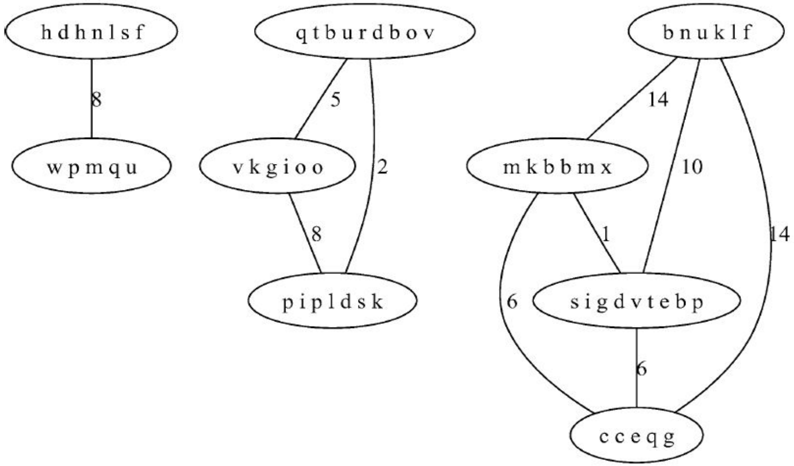
1. Substitutability heuristic (Adriaans et al., 2000; van Zaanen, 2000; Solan et al., 2005; Clark, 2007)
    - “Constituents of the same type can be replaced by each other” (Harris, 1951)
    - Create a nonterminal for substrings that appear in the same context (i.e., these substrings are substitutable)

Heuristic approaches - Nonterminal creation

Goal: create a new nonterminal representing a set of constituents

Methods:

1. Substitutability heuristic (Adriaans et al., 2000; van Zaanen, 2000; Solan et al., 2005; Clark, 2007)
   - Substitution-graph



Heuristic approaches - Nonterminal creation

Goal: create a new nonterminal representing a set of constituents

Methods:

1. Substitutability heuristic (Adriaans et al., 2000; van Zaanen, 2000; Solan et al., 2005; Clark, 2007)

	John (.) tea	John (.) coffee	John (.) eating	John makes (.)	John likes (.)	John is (.)
makes	x	x				
likes	x	x	x			
is			x			
tea				x	x	
coffee				x	x	
eating					x	x

Heuristic approaches - Nonterminal creation

Goal: create a new nonterminal representing a set of constituents

Methods:

2. Biclustering (Adriaans et al., 2000)
    - Simultaneously group substrings and their contexts

	John (.) tea	John (.) coffee	John (.) eating	John makes (.)	John likes (.)	John is (.)
makes	x	x				
likes	x	x	x			
is			x			
tea				x	x	
coffee				x	x	
eating					x	x

Heuristic approaches - Nonterminal creation

Goal: create a new nonterminal representing a set of constituents

Methods:

3. Distributional clustering (Harris, 1954; Clark, 2001; Scicluna and de la Higuera,2014)
   - Cluster substrings based on their distributions over possible contexts
   - Based on co-occurrence frequencies, not just yes/no. Hence more robust.
   - Can be extended to biclustering (Tu&Honavar, 2008)

Heuristic approaches - Nonterminal creation

Goal: create a new nonterminal representing a set of constituents

Methods:

3. Distributional clustering (Harris, 1954; Clark, 2001; Scicluna and de la Higuera,2014)

Different contextual distributions

	John (.) tea	John (.) coffee	John (.) eating	John makes (.)	John likes (.)	John is (.)
makes	1	2				
likes	1	1	2			
is			1			
tea				1	1	
coffee				2	1	
eating					2	1

Distributional biclustering can be more robust (Tu&Honavar, 2008)

Heuristic approaches - Reduce & repeat

Once a nonterminal is created, along with a set of production rules, reduce the training sentences using the rules and then repeat the previous steps.

V → makes | likes

John makes tea .
John likes tea .
John makes coffee .
John likes coffee .

John V tea .
John V tea .
John V coffee .
John V coffee .

Optimization-based approaches

Optimizing an explicit objective function of the grammar structure by local search:

- Start with a trivial grammar
- Search with a set of structure-change operations

Optimization-based approaches

Objective functions

- Posterior probability (Stolcke and Omohundro, 1994; Chen, 1995; Tu&Honavar, 2008)

$$P(G|X) \propto \underline{P(X|G)}\,\underline{P(G)}$$

Likelihood, computed by parsing corpus *X* using grammar *G*.

Rule probabilities in *G* are either heuristically assigned or learned.

Prior probability. A typical choice is the *universal a priori probability*

$$P(G) = 2^{-L(G)}$$

L(*G*) is the description length of *G* in bits

Trade-off between data fitting and model complexity (generalizability)

Optimization-based approaches

Objective functions

- Description length (Langley&Stromsten, 2000)
  - Equivalent to posterior probability with the above prior
- Free energy (negative evidence lower bound) (Kurihara&Sato, 2006)

Optimization-based approaches

Start point of local search

1. Union of training sentences (Stolcke and Omohundro, 1994; Langley&Stromsten, 2000; Tu&Honavar, 2008)

Ex: S -> John makes tea
S -> John makes coffee
...
S -> John is eating

all the training sentences

➢ Perfect fitting of training data
➢ No generalizability

Optimization-based approaches

Start point of local search

2. Most general grammar (Chen, 1995; Kurihara&Sato, 2006)

Ex: S -> S X | X
X -> a | b | c | ...

all the terminals

- ➢ Bad fitting of training data
- ➢ Can generate any sentence

Optimization-based approaches

Structure-change operations

1. AND (a.k.a. composition, chunk) (Stolcke and Omohundro, 1994; Chen, 1995; Langley&Stromsten, 2000)

Add a new rule: A -> B C

a new symbol

existing symbols

Replace “BC” with A in the right-hand side of other rules

Ex: “X -> B C D” becomes “X -> A D”

Optimization-based approaches

Structure-change operations

2. OR (i.e., alternatives) (Chen, 1995)

Add a new rule: A -> B | C

a new symbol existing symbols

Replace B and C with A in the right-hand side of other rules

Ex: “X -> C D” becomes “X -> A D”

Optimization-based approaches

Structure-change operations

3. AND-OR (Tu&Honavar, 2008)

O_1 -> B_1 | B_2 | ...
Add new rules: A -> O_1 O_2 ... and O_2 -> C_1 | C_2 | ...
...

new symbols

existing symbols

Replace sequences "B_i C_j ..." with A in the right-hand side of other rules
Ex: "X -> B_2 C_1 ..." becomes "X -> A"

Optimization-based approaches

Structure-change operations

4. Merging two existing symbols (Stolcke and Omohundro, 1994; Langley&Stromsten, 2000; Kurihara&Sato, 2006)
5. Splitting an existing symbol to two and making copies of rules involving the symbol (Kurihara&Sato, 2006)
6. Deleting a rule (Kurihara&Sato, 2006)

Optimization-based approaches

Reevaluating the objective function after each structure-change operation

- A complete reevaluation is time-consuming
  - Requires re-parsing of all the training sentences
- Simple formulas may exist for computing the change of the objective function value
  - Only require computation on local changes
  - May be approximate

Structure Learning - Summary

- Goal: Finding an optimal set of production rules
- Two classes of approaches
  - Heuristic approaches
  - Optimization-based approaches

- Empirical results
  - Poor accuracies on real data, often below simple baselines 😟

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