ACS Introduction to NLP

Lecture 8: Parsing with Lexicalised PCFGs

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Chart Parsing plus Search

$$T_{\text{best}} = \arg\max_T P(T, S)$$

- The number of possible parses increases exponentially with sentence length
- For a typical newspaper sentence there are far too many possible parses to enumerate (using a treebank grammar)
- Two key ideas allow the $\arg\max_T$ to be performed efficiently:
  - dynamic programming leads to an n^5 algorithm (still not efficient enough)
  - heuristic search enables efficient parsing in practice

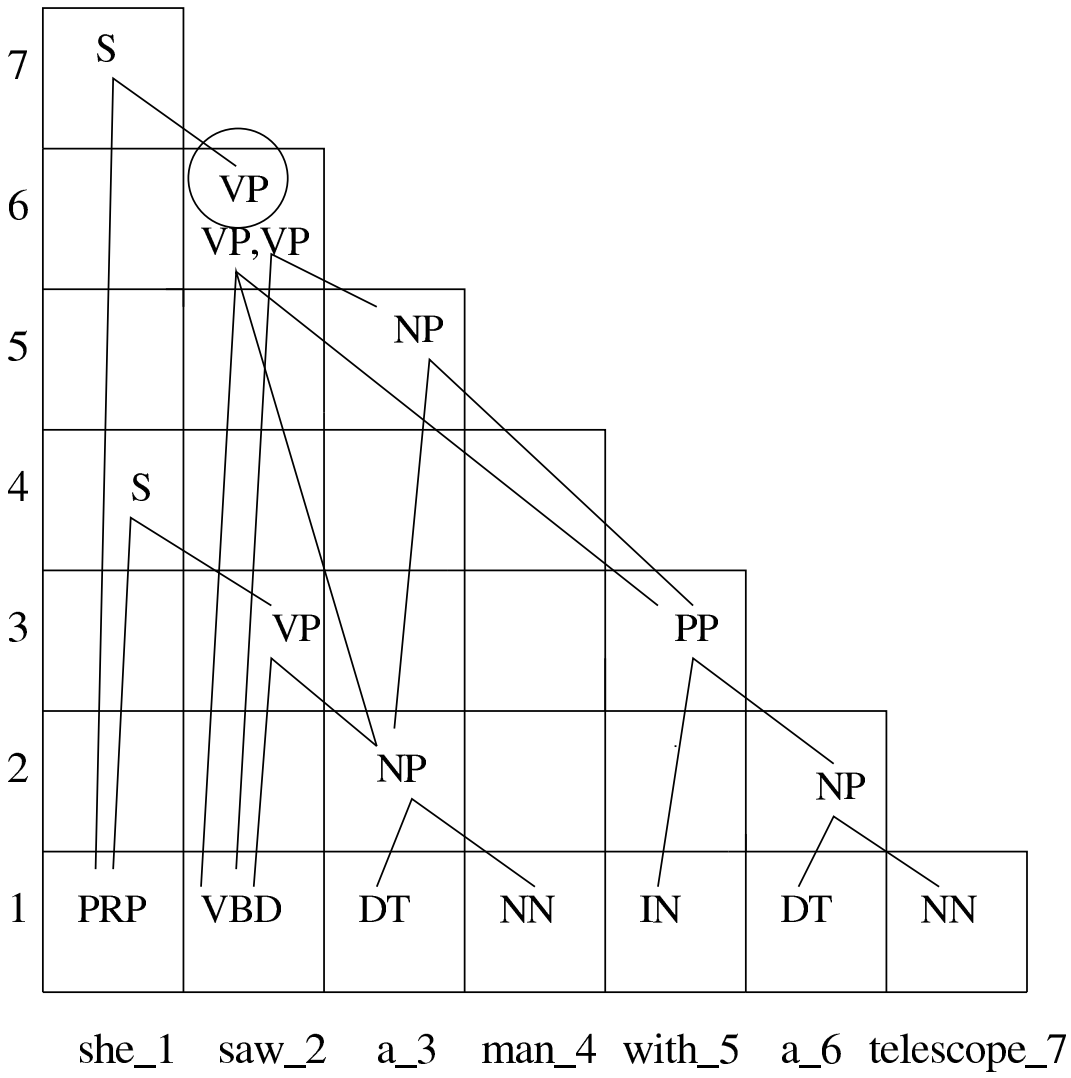
Chart Parsing with Lexicalised PCFGs

- Use a standard bottom-up chart parser, based on CKY
- The key data structure is the *chart*
  - *chart[start, end, label]* is the set of all edges in the chart spanning words *start* to *end* inclusive, with non-terminal label *label*
- We'll look at the parser for Collins Model 1
  - Model 2 just requires some extensions to deal with the modelling of subcategorisation frames

[picture of chart]

- Charts naturally and efficiently represent an exponential number of derivations for a sentence given a CFG
- Key idea: sub-derivations headed by the same non-terminal, spanning the same subsequence, can be represented by one instance of the non-terminal
- Key idea (written another way): when parsing bottom-up, only need to insert one instance of the same non-terminal spanning the same subsequence
- *We can do this because of the context-free assumption*

- Suppose now we want to find the highest-scoring derivation in the chart, using a PCFG
- Key idea: parsing bottom-up, we only need to keep the single highest scoring sub-derivation for a particular non-terminal spanning a particular subsequence
- This leads to the Viterbi algorithm for trees ($O(n^3)$)
- *We can do this because of the (probabilistic) context-free assumption*


7
6
5
4
3
2
1
S
VP
VP,VP
NP
S
VP
PP
NP
NP
PRP
VBD
DT
NN
IN
DT
NN
she_1
saw_2
a_3
man_4
with_5
a_6
telescope_7

The *edge* Datatype

label	non-terminal label
headlabel	non-terminal label of head child of the edge
headword	the head word
headtag	part of speech tag of the head word
start	index of first word in edge’s span
end	index of last word in edge’s span
stop	TRUE if the edge has received its stop probabilities
prob	log probability of the edge
children	list of the children of the edge (left to right)

Dynamic Programming for Collins Model 1

- If we're only looking for the highest scoring parse, no need to keep all edges in an equivalence class
- If two edges are equivalent for the purposes of future parsing, *and in terms of the probability model*, then the edge with the lowest score can be discarded
- Same idea as the Viterbi algorithm for PCFGs

The Equivalence Test


```
// assume e1 and e2 have the same start and end indices

boolean edges_eqivalent(edge e1, edge e2)
{
  if(e1.label     != e2.label      OR
     e1.headlabel != e2.headlabel  OR
     e1.headword  != e2.headword   OR
     e1.headtag   != e2.headtag    OR
     e1.stop      != e2.stop)
    return FALSE;
  else
    return TRUE;
}
```

Adding Edges to the Chart


```
void add_edge(edge e, int start, int end)
{
  foreach edge x in chart[start, end, e.label]
    if(edges_equivalent(e,x))
    {
      if(e.prob > x.prob)
        replace x with e
      return;
    }

  add e to chart[start, end, e.label]
}
```

Combining Edges


```
// e1 is adjacent and to the left of e2; e2 is a modifier of e1

void join_2_edges_follow(edge e1, edge e2)
{
  edge e3;

  e3.label      = e1.label;
  e3.headlabel  = e1.headlabel;
  e3.headword   = e1.headword;
  e3.headtag    = e1.headtag;
  e3.start      = e1.start;
  e3.end        = e2.end;
  e3.stop       = FALSE;
  e3.children   = e1.children ++ e2;
  e3.prob = e1.prob + e2.prob + log P_r(e1,e2);
  // P_r calculates the additional probability when the modifier
  // is to the right

  add_edge(e3,e1.start,e2.end);
}
```

Combining Edges II


```
// e1 is adjacent and to the left of e2; e1 is a modifier of e2

void join_2_edges_precede(edge e1, edge e2)
{
  edge e3;

  e3.label      = e2.label;
  e3.headlabel  = e2.headlabel;
  e3.headword   = e2.headword;
  e3.headtag    = e2.headtag;
  e3.start      = e1.start;
  e3.end        = e2.end;
  e3.stop       = FALSE;
  e3.children   = e1.children ++ e2;
  e3.prob = e1.prob + e2.prob + log P_l(e1,e2);
  // P_l calculates the additional probability when the modifier
  // is to the left

  add_edge(e3,e1.start,e2.end);
}
```

Initialising the Chart


```
void initialise()
{
  edge e;
  for i = 1 to n  // n is number of words in input sentence
  {
    if(word_i is an ‘‘unknown’’ word)
      set X = {POS tag from tagger for word_i}
    else
      set X = {set of all tags seen for word_i in training data}

    foreach POS tag T in X
    {
      e.label     = T;    e.headword  = word_i; e.headtag   = T;
      e.stop      = TRUE; e.start     = i;      e.end       = i+1;
      e.prob      = 0;

      add_edge(e,i,i+1);
    }
  }
}
```

All Edge Combinations


```
void complete(int start, int end)
{
  for split = start to end-1
  {
    foreach edge e1 in chart[start,split] such that e1.stop == FALSE
      foreach edge e2 in chart[split+1,end] such that e2.stop == TRUE
        join_2_edges_follow(e1,e2);

    foreach edge e1 in chart[start,split] such that e1.stop == TRUE
      foreach edge e2 in chart[split+1,end] such that e2.stop == FALSE
        join_2_edges_precede(e1,e2);
  }
}
```

The Final Parsing Algorithm


```
edge parse()
{
  initialise();

  // n is the number of words in the sentence
  for span = 2 to n
    for start = 1 to n-span+1
    {
      end = start + span - 1;
      complete(start, end);
    }

  // assume TOP is the start symbol
  X = edge in chart[1,n,TOP] with highest probability;

  return X;
}
```

Parsing Complexity

- Calls to join_2_edges_[precede|follow] take $O(1)$ time
- These calls are buried within 5 loops:

Complexity	Loop
$O(n)$	for span = 2 to n
$O(n)$	for start = 1 to n-span+1
$O(n)$	for split = start to end-1
$O(n)$	foreach edge e1 in chart[start,split] s.t. e1.stop == FALSE
$O(n)$	foreach edge e2 in chart[split+1,end] s.t. e2.stop == TRUE

- Parsing algorithm is essentially an n^5 algorithm
- I've ignored some constants along the way (related to size of tag set etc)

Heuristic Beam Search

- n^5 (plus some non-neglible constants) is inefficient for practical parsing
- We need to prune low-probability constituents in the chart
- This is a “lossy” strategy since we may throw away the correct parse
  - so there are now two sources of possible error in the parser: model error and search error
  - Viterbi finds the optimal solution so does not lead to search errors
- But in practice we can obtain great increases in efficiency with very small losses in accuracy

Figures of Merit

- What score should we use for a partial parse (constituent)?
- Obvious score to use is `prob` - the (log) conditional probability of the constituent: $P(\text{subtree}|\text{label,head-word,head-tag})$
- This doesn't work too well
  - problem is that the conditional probability does not account for the *prior* probability of seeing the particular (label,head-word,head-tag) triple

Prior for a Figure of Merit

$$\begin{aligned}\text{Score(subtree)} &= P(\text{subtree}|\text{label,head-tag,head-word}) \\ &\times P_{\text{prior}}(\text{label,head-tag,head-word})\end{aligned}$$

- One way to calculate the prior (Collins):

$$\begin{aligned}P_{\text{prior}}(\text{label,head-tag,head-word}) &= P(\text{head-tag,head-word}) \\ &\times P(\text{label}|\text{head-tag,head-word})\end{aligned}$$

- Probabilities estimated using relative frequency from counts in the corpus; second probability smoothed with interpolation

The Beam

- Let bestprob(start,end) be the highest score for any constituent spanning start..end
- Discard all constituents with span start..end and with log prob $< \alpha$ bestprob(start,end)
- α is the beam width; typical value is $\frac{1}{10000}$

Pros and Cons of the Generative Model

- Pros:
  - Conceptually easy to understand; well understood techniques
  - Estimation is easy (max. likelihood = relative frequencies)
  - Produces good results
- Cons:
  - Models S when the sentence is given
  - Independence assumptions required
  - Locality restrictions on features required for efficient estimation and decoding
  - Guarantees on estimation (e.g. soundness) only apply with unlimited training data
  - Choosing the order for the chain rule, and independence assumptions plus smoothing, something of a “black art”

References

- Appendix B, D and E of Collins' thesis
- Caraballo and Charniak (1998), New Figures of Merit for best-first probabilistic chart parsing. Computational Linguistics, 24(2), pages 275-298

all available from the web; Collins thesis from Collins' web page