Master on Artificial Intelligence

Natural Language Research Group

Constituency parsing with NLTK

Dependency parsing with NLTK

Introduction to Human Language Technologies 8. Parsing

Natural Language Research Group



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Outline

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Constituency parsing with NLTK

- 1 Constituency parsing with NLTK
 - Non-probabilistic parsers
 - Mandatory Exercise
 - Probabilistic parsers
- 2 Dependency parsing with NLTK
 - CoreNLP
 - Paraphrases

Constituency parsing with NLTK

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Constituency parsing with NLTK

Dependency parsing with NLTK

Non-probabilistic parsers:

- ChartParser (default parser is BottomUpLeftCornerChartParser)
- BottomUpChartParser, LeftCornerChartParser
- TopDownChartParser, EarleyChartParser

...

Probabilistic parsers:

- InsideChartParser, RandomChartParser, LongestChartParser (they are bottom-up parsers)
- ViterbiParser
- CoreNLPParser (third-party's parser)

- -

Example:

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Constituency parsing with NLTK

Non-probabilistic parsers

Dependency parsing with NLTK

number of trees: 2

Output I:

```
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```

Constituency parsing with NLTK

Non-probabilistic parsers

```
In [3]:
         print(ts[0])
         ts[0]
         (NP (JJ small) (NNS (NNS cats) (CC and) (NNS mice)))
Out[3]:
                  NP
                        NNS
         small
                 NNS
                              NNS
                 cats
                        and
                              mice
         print(ts[1])
In [4]:
         ts[1]
         (NP (NP (JJ small) (NNS cats)) (CC and) (NP (NNS mice)))
Out[4]:
                       NP
              NP
                               NP
           JJ
                  NNS
                        and
                              NNS
         small
                 cats
                              mice
```

Output II:

```
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```

Constituency parsing with NLTK

Non-probabilistic parsers

```
In [5]: # achieve the list of applied edges
        parse = parser.chart parse(['small', 'cats', 'and', 'mice'])
        print("TD num edges = ".parse.num edges())
        TD num edges = 28
In [6]: parse.edges()
Out[6]: [[Edge: [0:1] 'small'].
          [Edge: [1:2] 'cats'].
          [Edge: [2:3] 'and'],
          [Edge: [3:4] 'mice'],
          [Edge: [0:1] JJ -> 'small' *],
          [Edge: [0:1] NP -> JJ * NNS].
          [Edge: [1:2] NNS -> 'cats' *].
          [Edge: [1:2] NP -> NNS *],
          [Edge: [1:2] NNS -> NNS * CC NNS],
          [Edge: [0:2] NP -> JJ NNS *],
          [Edge: [0:2] NP -> NP * CC NP],
          [Edge: [1:2] NP -> NP * CC NP].
          [Edge: [2:3] CC -> 'and' *].
          [Edge: [1:3] NNS -> NNS CC * NNS],
          [Edge: [0:3] NP -> NP CC * NP],
          [Edge: [1:3] NP -> NP CC * NP],
          [Edge: [3:4] NNS -> 'mice' *],
          [Edge: [3:4] NP -> NNS *].
          [Edge: [3:4] NNS -> NNS * CC NNS]
```

Main differences of non-probabilistic chart parsers:

- BottomUpChartParser: bottom-up strategy
- BottomUpLeftCornerChartParser (ChartParser): bottom-up strategy filtering out edges without any word subsumtion (e.g., [0,0]: X→. Y Z)
- LeftCornerChartParser: bottom-up strategy filtering out edges without new word subsumptions (e.g., if we already got [0,1] Y→y. and [1,2] Z→z. then [0,1] A→Y.Z is filtered out whereas [0,2] A→Y Z. is fired)
- TopDownChartParser: top-down strategy
- EarleyChartParser: incremental top-down strategy (more efficient)

```
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```

Constituency parsing with NLTK

Non-probabilistic parsers

Mandatory Exercise

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Constituency parsing with NLTK

Mandatory Exercise

Dependency parsing with NLTK

Statement:

- Consider the following sentence: Lazy cats play with mice.
- Expand the grammar of the example related to non-probabilistic chart parsers in order to subsume this new sentence.
- Perform the constituency parsing using a BottomUpChartParser, a BottomUpLeftCornerChartParser and a LeftCornerChartParser.
- For each one of them, provide the resulting tree, the number of edges and the list of explored edges.
- Which parser is the most efficient for parsing the sentence?
- Which edges are filtered out by each parser and why?

Example: inside chart parser

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Constituency parsing with NLTK

Probabilistic parsers

Dependency parsing with NLTK

number of trees: 2

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Probabilistic parsers

Dependency parsing with NLTK

```
Output:

In [3]: 1 print(ts[0]) 2 ts[0] (NP (JJ small) (NNS (NNS cats) (CC and) (NNS mice))) (p=0.001944)
```

Out[3]:



In [4]: 1 print(ts[1]) 2 ts[1]

(NP (NP (JJ small) (NNS cats)) (CC and) (NP (NNS mice))) (p=0.000486)

Out[4]:



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Probabilistic parsers

Dependency parsing with NLTK Main differences of probabilistic chart parsers:

- They use the bottom-up strategy
- InsideChartParser: select edges in decreasing order of their trees' inside probs. $p\rightarrow A,B \Rightarrow Prob=P(p)P(A)P(B)$
- RandomChartParser: select edges in random order.
- LongestChartParser: select longer edges before shorter ones.

Probabilistic parsers: Viterbi

Example: Probabilistic Viterbi parser

Output:

```
In [2]: 1 tree = next(parse)
2 print(tree)
3 tree
(NP (JJ small) (NNS (NNS cats) (CC and) (NNS mice))) (p=0.001944)
Out[2]:
```



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Constituency parsing with NLTK

Probabilistic parsers

Probabilistic parsers: Viterbi

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Constituency parsing with NLTK

Probabilistic parsers

```
Trace:
In [3]:
          parser = ViterbiParser(grammar)
          parser.trace(3)
          3 parse = parser.parse(sent)
          4 next(parse)
         Inserting tokens into the most likely constituents table...
            Insert: I=...I small
            Insert: | .=..| cats
            Insert: | ..=. | and
            Insert: |...=| mice
         Finding the most likely constituents spanning 1 text elements...
            Insert: |=...| JJ -> 'small' [0.6]
                                                             0.60000000000
            Insert: | .=.. | NNS -> 'cats' [0.1]
                                                             0.1000000000
            Insert: | .=.. | NP -> NNS [0.5]
                                                             0.0500000000
            Insert: |..=.| CC -> 'and' [0.9]
                                                             0.9000000000
            Insert: |...=| NNS -> 'mice' [0.3]
                                                             0.3000000000
            Insert: |...=| NP -> NNS [0.5]
                                                             0.1500000000
         Finding the most likely constituents spanning 2 text elements...
            Insert: |==..| NP -> JJ NNS [0.3]
                                                             0.0180000000
         Finding the most likely constituents spanning 3 text elements...
            Insert: | .===| NP -> NP CC NP [0.2]
                                                             0.0013500000
            Insert: |.===| NNS -> NNS CC NNS [0.4]
                                                             0.0108000000
            Insert: | .===| NP -> NNS [0.5]
                                                             0.0054000000
           Discard: | .===| NP -> NP CC NP [0.2]
                                                             0.0013500000
           Discard: | .===| NP -> NP CC NP [0.2]
                                                             0.0013500000
         Finding the most likely constituents spanning 4 text elements...
            Insert: |====| NP -> JJ NNS [0.3]
                                                             0.0019440000
           Discard: |====| NP -> NP CC NP [0.2]
                                                             0.0004860000
           Discard: | ==== | NP -> NP CC NP [0.2]
                                                             0.0004860000
```

Probabilistic parsers: learn a PCFG

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Constituency parsing with NLTK

Probabilistic parsers

Dependency parsing with NLTK

Example: learn a treebank grammar

```
In [4]: 1 import nltk
2 from nltk.corpus import treebank
3 productions = []
4 S = nltk.Nonterminal('S')
5 for f in treebank.fileids():
6 for tree in treebank.parsed sents(f):
7 productions += tree.productions()
8 grammar = nltk.induce pcfg(S, productions)
9 grammar.productions()[10:15]

Out[4]: [NN -> 'evit' [7.59532e-05],
NN -> 'powder' [7.59532e-05],
SBAR -> WHNP-167 S [0.000424628],
VDN -> 'drawn' [0.00140581],
NN -> 'senior' [0.000151906]]
```

Probabilistic parsers: learn a PCFG

Example: apply the learnt PCFG to Viterbi parser

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Constituency parsing with NLTK

Probabilistic parsers

```
In [5]: sent = ['it', 'is', 'a', 'small', 'group', 'of', 'workers', 'and', 'researchers']
         parser = ViterbiParser(grammar)
         parse = parser.parse(sent)
         tree = next(parse)
         print(tree)
         tree
         (S
           (NP-SBJ (PRP it))
           (VP
             (VBZ is)
             (NP-PRD
               (NP (DT a) (JJ small) (NN group))
               (PP
                 (IN of)
                 (NP (NNS workers) (CC and) (NNS researchers)))))) (p=2.64379e-21)
Out[5]:
         NP-SBJ
           PRP
                  VBZ
                                       NP-PRD
           it
                                     NN
                                           IN
                                                          NP
                            small
                                    group
                                           of
                                                  NNS
                                                                   NNS
                                                workers
                                                         and
                                                                researchers
```

Probabilistic parsers: CoreNLP parser

Example:

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Constituency parsing with NLTK

Probabilistic parsers

```
In [6]: # run in a shell:
        # java -mx4g -cp "*" edu.stanford.nlp.pipeline.StanfordCoreNLPServer -port 9000 -timeout 15000
        import nltk
        from nltk.parse.corenlp import CoreNLPParser
        parser = CoreNLPParser(url='http://localhost:9000')
        parse = parser.raw parse('Smith jumps over lazy dogs')
        tree = next(parse)
        print(tree)
        tree
        (ROOT
          (S
            (NP (NNP Smith))
            (VP (VBZ jumps) (PP (IN over) (NP (JJ lazv) (NNS dogs))))))
Out[6]:
                ROOT
          NNP
                  VBZ
         Smith
                 jumps
                         over
                               lazy
                                    dogs
```

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Dependency parsing: CoreNLP dependency parser

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Constituency parsing with NLTK

Dependency parsing with NLTK CoreNLP

Example:

Dependency parsing: CoreNLP dependency parser

Showing the graph:

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Constituency parsing with NLTK

Dependency parsing with NLTK CoreNLP

```
In [3]:
             # Graphviz is needed
             # sudo pip3 install graphviz
             tree
Out[3]:
                0 (None)
                     ROOT
                2 (jumps)
                  nsubj
           1 (Smith)
                          6 (dog)
                                    amod
            3 (over)
                                      5 (lazy)
                          4 (the)
```

Mandatory exercise

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Constituency parsing with NLTK

Dependency parsing with NLTK

Paraphrases

Statement:

- Read all pairs of sentences of the trial set within the evaluation framework of the project.
- 2 Compute the Jaccard similarity of each pair using the dependency triples from *CoreNLPDependencyParser*.
- 3 Show the results. Do you think it could be relevant to use NEs to compute the similarity between two sentences?

 Justify the answer.