Chunk Parsing

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- chunk parsing:
  - efficient and robust approach to parsing natural language
  - a popular alternative to the full parsing
- chunks:
  - non-overlapping regions of text
  - contain a head word (e.g. noun)
  - adjacent modifiers and function words
- motivations:
  - extract information
  - ignore information

Extracting Information: Coreference Annotation

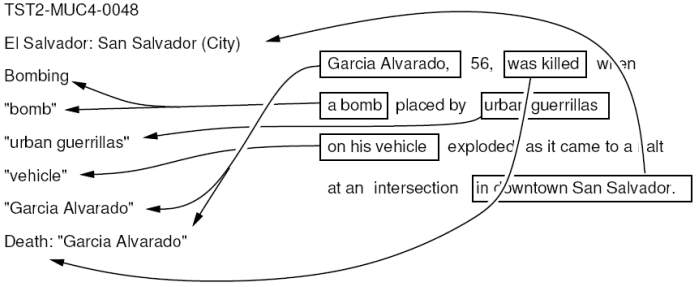
```
<COREF ID="2" MIN="woman">
  This woman
</COREF>
receives three hundred dollars a
month under
<COREF ID="5">
  General Relief
</COREF>
, plus
<COREF ID="16"
      MIN="four hundred dollars">
  four hundred dollars a month in
  <COREF ID="17"
        MIN="benefits" REF="16">
    A.F.D.C. benefits
  </COREF>
</COREF>
for
<COREF ID="9" MIN="son">
  <COREF ID="3" REF="2">
    her
  </COREF>
  son
</COREF>
, who is
```

```
<COREF ID="10" MIN="citizen" REF="9">
  a U.S. citizen
</COREF>.
<COREF ID="4" REF="2">
  She
</COREF>
's among
<COREF ID="18" MIN="aliens">
  an estimated five hundred illegal
  aliens on
  <COREF ID="6" REF="5">
    General Relief
  </COREF>
  out of
  <COREF ID="11" MIN="population">
    <COREF ID="13" MIN="state">
      the state
    </COREF>
    's total illegal immigrant
    population of
    <COREF ID="12" REF="11">
      one hundred thousand
    </COREF>
  </COREF>
</COREF>
```

```
.
<COREF ID="7" REF="5">
  General Relief
</COREF>
is for needy families and unemployable
adults who don't qualify for other public
assistance.  Welfare Department spokeswoman
Michael Reganburg says
<COREF ID="15" MIN="state" REF="13">
  the state
</COREF>
will save about one million dollars a year if
<COREF ID="20" MIN="aliens" REF="18">
  illegal aliens
</COREF>
are denied
<COREF ID="8" REF="5">
  General Relief
</COREF>
.
```

Extracting Information: Message Understanding

0.	Message: ID	TST2-MUC4-0048
3.	Incident: Location	El Salvador: San Salvador (City)
4.	Incident: Type	Bombing
6.	Incident: Instrument ID	"bomb"
9.	Perp: Individual ID	"urban guerrillas"
12.	Phys Tgt: ID	"vehicle"
18.	Hum Tgt: Name	"Garcia Alvarado"
23.	Hum Tgt: Effect of Incident	Death: "Garcia Alvarado"



Ignoring Information: Lexical Acquisition

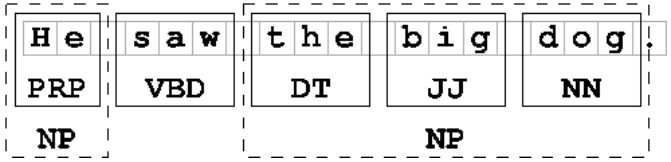
- studying syntactic patterns, e.g. finding verbs in a corpus, displaying possible arguments
- e.g. `gave`, in 100 files of the Penn Treebank corpus
- replaced internal details of each noun phrase with `NP`

```
gave NP
gave up NP in NP
gave NP up
gave NP help
gave NP to NP
```

- use in lexical acquisition, grammar development

Analogy with Tokenization and Tagging

- fundamental in NLP: segmentation and labelling
- tokenization and tagging



- other similarities: skipping material; finite-state; application specific

Chunking vs Parsing

1. Parsing

```
[
  [ G.K. Chesterton ],
  [
    [ author ] of
    [
      [ The Man ] who was
      [ Thursday ]
    ]
  ]
]
```

2. Chunking:

```
[ G.K. Chesterton ],
[ author ] of
[ The Man ] who was
[ Thursday ]
```

Chunking vs Parsing

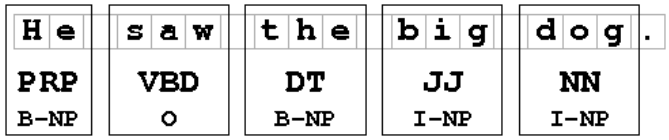
1. flat vs nested
2. context
3. robustness
4. efficiency
5. methodology

Perfection is unattainable

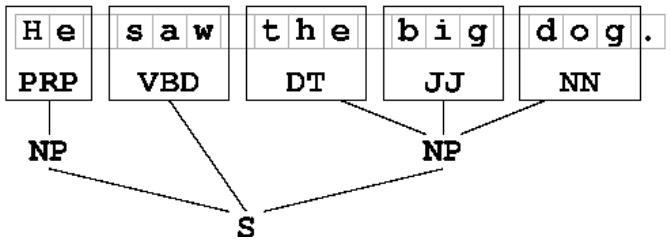
```
1. Prepositional phrase:
[
  [ I ]
  [ turned ]
  [ off the spectroroute ]
]

2. Verb-particle construction:
[
  [ I ]
  [ turned off ]
  [ the spectroroute ]
]
```

Tag Representation



Tree Representation



Chunk Structures

```
(S: (NP: 'I')
    'saw'
    (NP: 'the' 'big' 'dog')
    'on'
    (NP: 'the' 'hill'))
```

- Demonstration: reading chunk structures from Treebank and CoNLL-2000 corpora

Chunk Parsing

- regular expressions over part-of-speech tags: `parse.RegexpChunk`
- *Tag string:* a string consisting of tags delimited with angle-brackets, e.g. `<DT><JJ><NN><VBD><DT><NN>`
- *Tag pattern:* regular expression over tag strings
  - `<DT><JJ>?<NN>`
  - `<NN|JJ>+`
  - `<NN.*>`
- chunk a sequence of words matching a tag pattern: `parse.ChunkRule`

```
>>> grammar = "NP: {<DT|NN>+}  # Chunk sequences of
```

A Simple NP Chunker

```
grammar = r"""
NP:
  {<DT>?<JJ>*<NN>}     # chunk determiners, adjectives and nouns
  {<NNP>+}             # chunk sequences of proper nouns
"""
cp = chunk.Regexp(grammar)
tagged_tokens = [("the", "DT"), ("little", "JJ"), ("cat", "NN"),
     ("sat", "VBD"), ("on", "IN"), ("the", "DT"), ("mat", "NN")]

>>> cp.parse(tagged_tokens)
(S:
  (NP: ('the', 'DT') ('little', 'JJ') ('cat', 'NN'))
  ('sat', 'VBD')
  ('on', 'IN')
  (NP: ('the', 'DT') ('mat', 'NN')))
```

Developing Chunkers

```
cp1 = chunk.Regexp(r"""
NP: {<DT><JJ><NN>}      # Chunk det+adj+noun
    {<DT|NN>+}          # Chunk sequences of NN and DT
""")
cp2 = chunk.Regexp(r"""
NP: {<DT|NN>+}          # Chunk sequences of NN and DT
    {<DT><JJ><NN>}      # Chunk det+adj+noun
""")

>>> print cp1.parse(tagged_tokens, trace=1)
# Input:
 <DT>  <JJ>  <NN>  <VBD>  <IN>  <DT>  <NN>
# Chunk det+adj+noun:
{<DT>  <JJ>  <NN>} <VBD>  <IN>  <DT>  <NN>
# Chunk sequences of NN and DT:
{<DT>  <JJ>  <NN>} <VBD>  <IN> {<DT>  <NN>}
```

- tracing; rule ordering; overlapping contexts

More Chunking Rules: Chinking

- *chink:* sequence of stopwords
- *chinking:* process of removing tokens from a chunk

	Entire chunk	**Middle of a chunk**	**End of a chunk**
Input:	`[a/DT big/JJ cat/NN]`	`[a/DT big/JJ cat/NN]`	`[a/DT big/JJ cat/NN]`
Operation:	Chink `a/DT big/JJ cat/NN`	Chink `big/JJ`	Chink `cat/NN`
Output:	`a/DT big/JJ cat/NN`	`[a/DT] big/JJ [cat/NN]`	`[a/DT big/JJ] cat/NN`

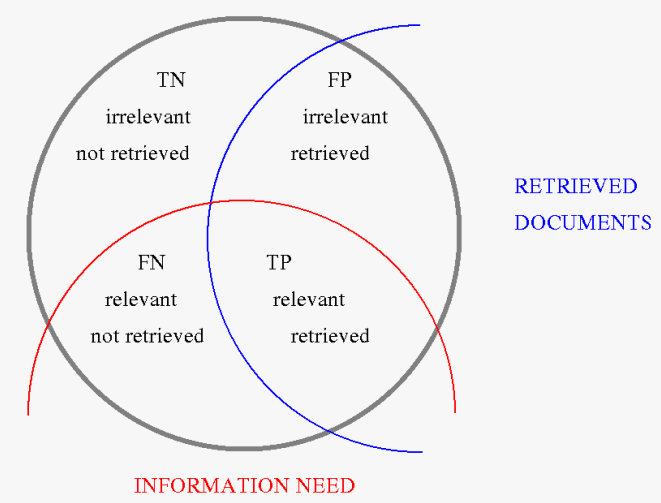
Chinking Example

```
>>> grammar = r"""
... NP:
...   {<.*>+}          # Chunk everything
...   }<VBD|IN>+{      # Chink sequences of VBD and IN
... """
>>> cp = chunk.Regexp(grammar)
>>> print cp.parse(tagged_tokens)
(S:
  (NP: ('the', 'DT') ('little', 'JJ') ('cat', 'NN'))
  ('sat', 'VBD')
  ('on', 'IN')
  (NP: ('the', 'DT') ('mat', 'NN')))
>>> print chunk.accuracy(cp, conll2000.chunked(files='test', chunk_type
0.581041433607
```

Evaluating Chunk Parsers

- Process:
  1. take some already chunked text
  2. strip off the chunks
  3. rechunk it
  4. compare the result with the original chunked text
- `ChunkScore.score()`
  - *precision*: what fraction of the returned chunks were correct?
  - *recall*: what fraction of correct chunks were returned?

Precision and Recall



Chunker evaluation in NLTK

```
>>> rule = parse.ChunkRule('<DT|JJ|NN>+', "Chunk sequences of DT, JJ, an
>>> chunkparser = parse.RegexpChunk([rule], chunk_node='NP', top_node='S
>>> chunkscore = parse.ChunkScore()
>>> for chunk_struct in islice(treebank.chunked(), 10):
...     test_sent = chunkparser.parse(chunk_struct.leaves())
...     chunkscore.score(chunk_struct, test_sent)
>>> print chunkscore
ChunkParse score:
    Precision:  48.6%
    Recall:     34.0%
    F-Measure:  40.0%
```

Error Analysis: Missed Chunks

```
>>> from random import randint
>>> missed = chunkscore.missed()
>>> for i in range(15):
...     print missed[randint(0,len(missed)-1)]
(('A', 'DT'), ('Lorillard', 'NNP'), ('spokewoman', 'NN'))
(('it', 'PRP'),)
(('symptoms', 'NNS'),)
(('even', 'RB'), ('brief', 'JJ'), ('exposures', 'NNS'))
(('its', 'PRP$'), ('Micronite', 'NN'), ('cigarette', 'NN'), ('filters', 'NN
(('30', 'CD'), ('years', 'NNS'))
(('workers', 'NNS'),)
(('preliminary', 'JJ'), ('findings', 'NNS'))
(('Medicine', 'NNP'),)
(('cancer', 'NN'), ('deaths', 'NNS'))
(('Consolidated', 'NNP'), ('Gold', 'NNP'), ('Fields', 'NNP'), ('PLC', 'NNP'
(('Medicine', 'NNP'),)
(('its', 'PRP$'), ('Micronite', 'NN'), ('cigarette', 'NN'), ('filters', 'NN
(('a', 'DT'), ('forum', 'NN'))
(('researchers', 'NNS'),)
```

Error Analysis: Incorrect Chunks

```
>>> incorrect = chunkscore.incorrect()
>>> for i in range(15):
...     print incorrect[randint(0,len(incorrect)-1)]
(('New', 'JJ'), ('York-based', 'JJ'))
(('Micronite', 'NN'), ('cigarette', 'NN'))
(('a', 'DT'), ('forum', 'NN'), ('likely', 'JJ'))
(('later', 'JJ'),)
(('later', 'JJ'),)
(('brief', 'JJ'),)
(('preliminary', 'JJ'),)
(('New', 'JJ'), ('York-based', 'JJ'))
(('resilient', 'JJ'),)
(('group', 'NN'),)
(('cancer', 'NN'),)
(('the', 'DT'),)
(('cancer', 'NN'),)
(('Micronite', 'NN'), ('cigarette', 'NN'))
(('A', 'DT'),)
```

Evaluation Methodology

- Baseline:
  - How hard is chunking?
  - What is a good baseline for evaluation?
- Bake-off

Development Methodology

- approaches
  - different rules and combinations
  - hand-crafted vs automatic
- focus on diagnosis:
  - manual
  - utility functions
  - error analysis
  - evaluation

Conclusion

- light-weight methods: as seen in tagging
- applications: extraction, lexical acquisition
  (aside: chunking as a utility method in parsing)
- next: parsing
- but first: switch to application focus