Shallow Processing & Named Entity Extraction

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(includes modified slides from
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Text

LT Components

Lexical / Morphological Analysis

Tagging

Chunking

Syntactic Analysis

Grammatical Relation Finding

Named Entity Recognition

Word Sense Disambiguation

Semantic Analysis

Reference Resolution

Discourse Analysis

Applications

OCR

Spelling Error Correction

Grammar Checking

Information retrieval

Document Classification

Information Extraction

Summarization

Question Answering

Ontology Extraction and Refinement

Dialogue Systems

Machine Translation

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From POS tagging to IE - Classification-Based Perspective

- POS tagging

The/Det woman/NN will/MD give/VB Mary/NNP a/Det book/NN

- NP chunking

The/B-NP woman/I-NP will/B-VP give/I-VP Mary/B-NP a/B-NP book/I-NP

- Grammatical Relation Finding

[NP-SUBJ-1 the woman] [VP-1 will give] [NP-I-OBJ-1 Mary] [NP-OBJ-1 a book]]

- Semantic Tagging (as for Information Extraction)

[Giver the woman][will give][Givee Mary][Given a book]

- Semantic Tagging (as for Question Answering)

Who will give Mary a book?

[Giver ?][will give][Givee Mary][Given a book]

Parsing of unrestricted text

- Complexity of parsing of unrestricted text
  - Large sentences
  - Large data sources
  - Input texts are not simply sequences of word forms
    - Textual structure (e.g., enumeration, spacing, etc.)
    - Combined with structural annotation (e.g., XML tags)
  - Various text styles, e.g., newspaper text, scientific texts, blogs, email, …
    - Demands high degree of flexibility and robustness

Motivations for Parsing

- Why parse sentences in the first place?
- Parsing is usually an intermediate stage
  - To uncover structures that are used by later stages of processing
- Full Parsing is a *sufficient* but not a *necessary* intermediate stage for many NLP tasks.
- Parsing often provides more information than we need.

Shallow Parsing Approaches

- Light (or “partial”) parsing
- Chunk parsing (a type of light parsing)
  - Introduction
  - Advantages
  - Implementations
- Divide-and-conquer parsing for German

Light Parsing

Goal: assign a *partial structure* to a sentence.

- Simpler solution space
- Local context
- Non-recursive
- Restricted (local) domain

Output from Light Parsing

- What kind of *partial structures* should light parsing construct?
- Different structures useful for different tasks:
  - Partial constituent structure
    [NP I] [VP saw [NP a tall man in the park]].
  - Prosodic segments
    [I saw] [a tall man] [in the park].
  - Content word groups
    [I] [saw] [a tall man] [in the park].

Chunk Parsing

Goal: divide a sentence into a sequence of chunks.

- Chunks are non-overlapping regions of a text

  [I] saw [a tall man] in [the park]

- Chunks are non-recursive
  - A chunk can not contain other chunks
- Chunks are non-exhaustive
  - Not all words are included in the chunks

Chunk Parsing Examples

- Noun-phrase chunking:
  - [I] saw [a tall man] in [the park].
- Verb-phrase chunking:
  - The man who [was in the park] [saw me].
- Prosodic chunking:
  - [I saw] [a tall man] [in the park].

Chunks and Constituency

Constituents: ***[[a tall man] [in [the park]]].***
Chunks: ***[a tall man] in [the park].***

- A constituent is part of some higher unit in the hierarchical syntactic parse
- Chunks are *not constituents*
  - Constituents are recursive
- But, chunks are typically sub-sequences of constituents
  - Chunks do not cross major constituent boundaries

1. [$_{NP}$ [$_{NP}$ G.K. Chesterton], [$_{NP}$ [$_{NP}$ author] of [$_{NP}$ [$_{NP}$ The Man] who was [$_{NP}$ Thursday]]]]
2. [$_{NP}$ G.K. Chesterton], [$_{NP}$ author] of [$_{NP}$ The Man] who was [$_{NP}$ Thursday]

Chunk Parsing: Accuracy

Chunk parsing achieves high accuracy

- Small solution space
- Less word-order flexibility *within* chunks than *between* chunks
  - Fewer long-range dependencies
  - Less context dependence
- Better locality
- No need to resolve ambiguity
- Less error propagation

Chunk Parsing: Domain Specificity

Chunk parsing is less domain specific

- Dependencies on lexical/semantic information tend to occur at levels “higher” than chunks:
  - Attachment
  - Argument selection
  - Movement
- Fewer stylistic differences with chunks

Psycholinguistic Motivations

- Chunks are processing units
  - Humans tend to read texts one chunk at a time
  - Eye movement tracking studies
- Chunks are phonologically marked
  - Pauses
  - Stress patterns
- Chunking might be a first step in full parsing
  - Integration of shallow and deep parsing
  - Text zooming

Chunk Parsing: Efficiency

- Smaller solution space
- Relevant context is small and local
- Chunks are non-recursive
- Chunk parsing can be implemented with a finite state machine
  - Fast (linear)
  - Low memory requirement (no stacks)
- Chunk parsing can be applied to a very large text sources (e.g., the web)

Chunk Parsing Techniques

- Chunk parsers usually ignore lexical content
- Only need to look at part-of-speech tags
- Techniques for implementing chunk parsing
  - Regular expression matching
  - Chinking
  - Cascaded Finite state transducers

Regular Expression Matching

- Define a regular expression that matches the sequences of tags in a chunk
  - A simple noun phrase chunk regrexp:
    - <DT> ? <JJ> * <NN.?>
- Chunk all matching subsequences:
    - In:
      The /DT little /JJ cat /NN sat /VBD on /IN the /DT mat /NN
    - Out:
      [The /DT little /JJ cat /NN] sat /VBD on /IN [the /DT mat /NN]
- If matching subsequences overlap, the first one gets priority
- Regular expressions can be cascaded

Chinking

- A *chink* is a subsequence of the text that is not a chunk.
- Define a regular expression that matches the sequences of tags in a chink.
  - A simple chink regexp for finding NP chunks:

(<VB.?> | <IN>)+

- Chunk anything that is *not* a matching subsequence:

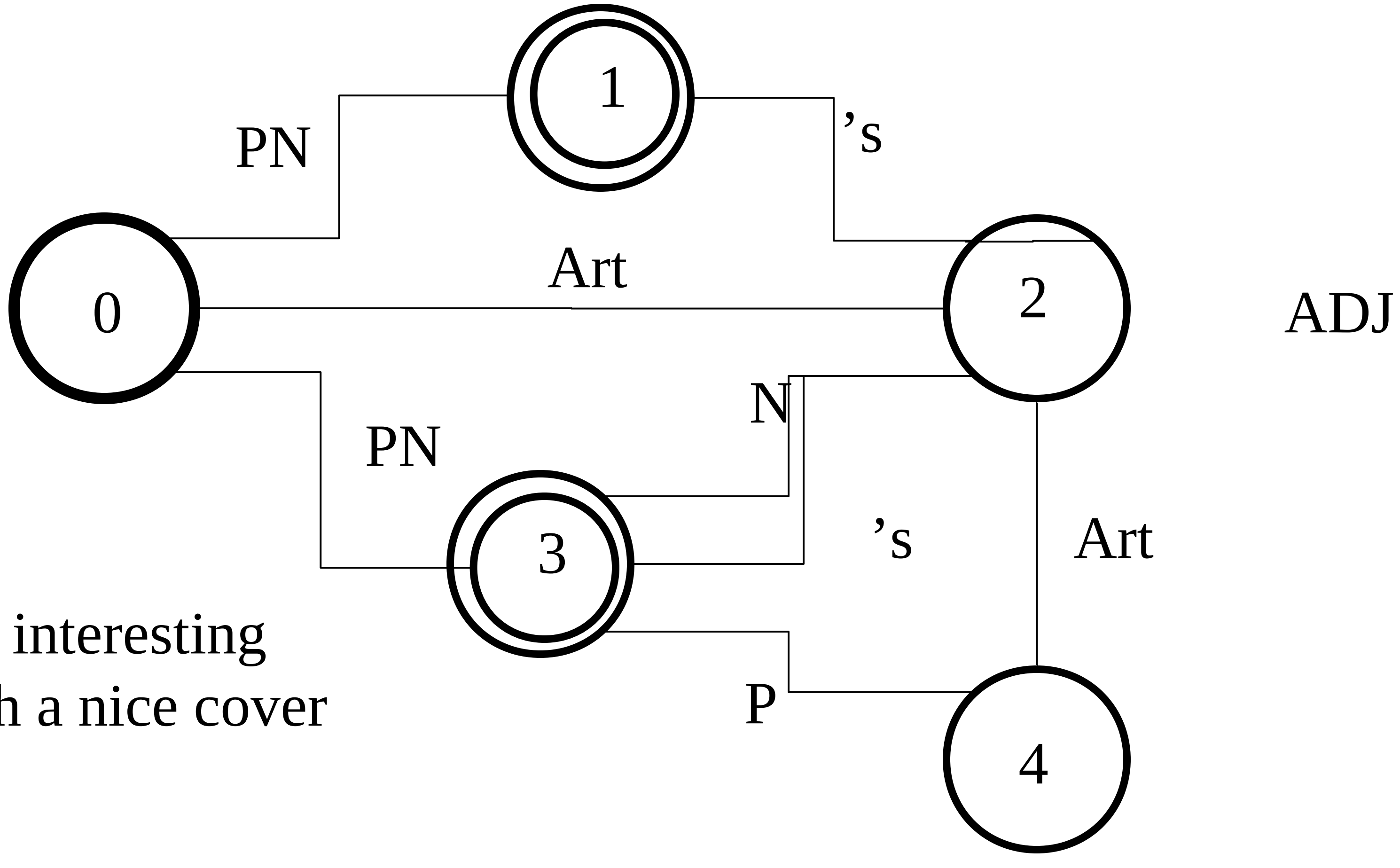
the/DT little/JJ cat/NN sat/VBD on /IN the /DT mat/NN

[the/DT little/JJ cat/NN] sat/VBD on /IN [the /DT mat/NN]

chunk   *chink*   *chunk*

Finite State Approaches to Shallow Parsing

- Finite-state approximation of sentence structures (Abney 1995)
  - finite-state cascades: sequences of levels of regular expressions
  - recognition approximation: tail-recursion replaced by iteration
  - interpretation approximation: embedding replaced by fixed levels
- Finite-state approximation of phrase structure grammars (Pereira/Wright 1997)
  - flattening of shift-reduce-recogniser
  - no interpretation structure (acceptor only)
  - used in speech recognition where syntactic parsing serves to rank hypotheses for acoustic sequences
- Finite-state approximation (Sproat 2002)
  - bounding of centre embedding
  - reduction of recognition capacity
  - flattening of interpretation structure



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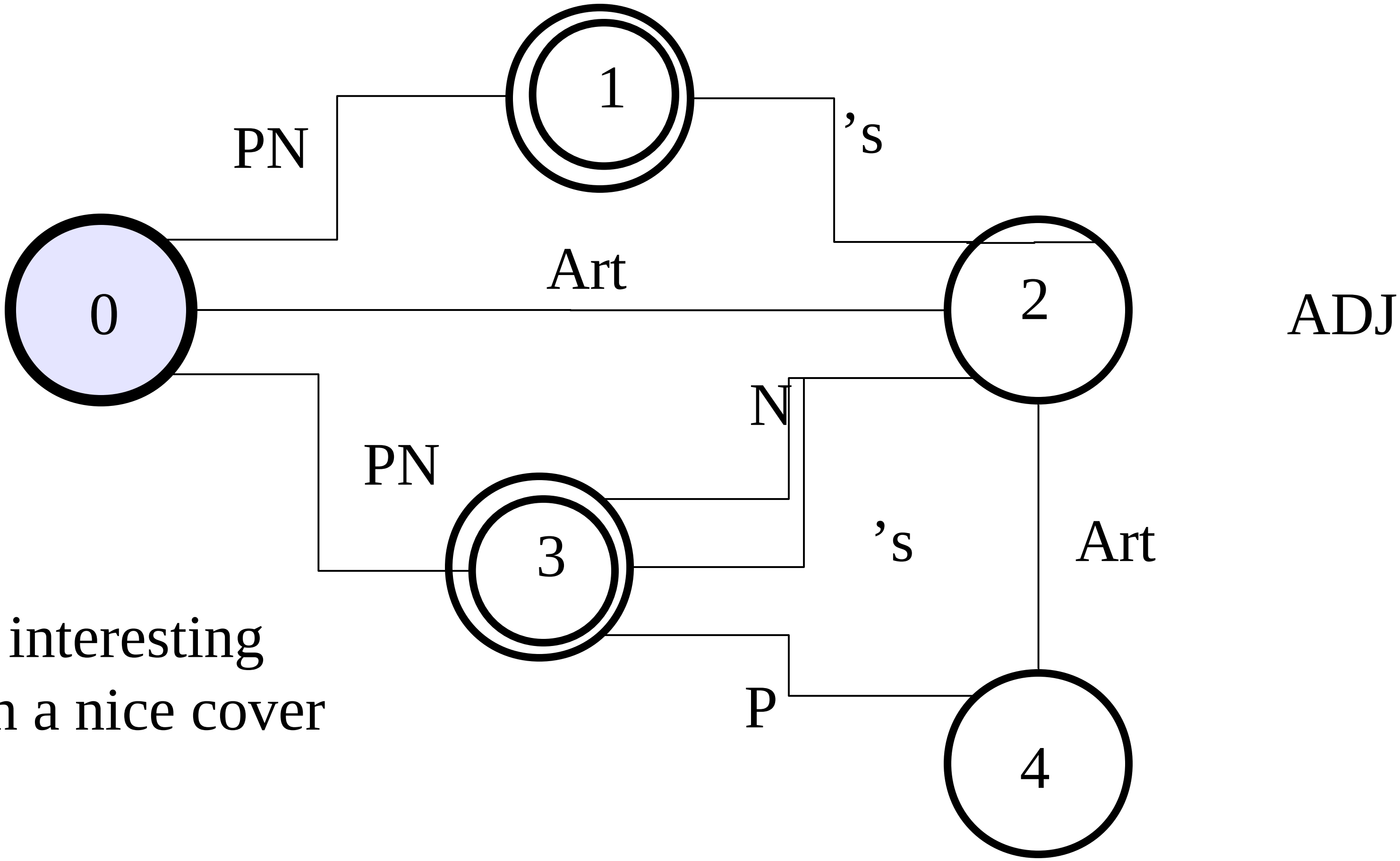
book with a nice cover



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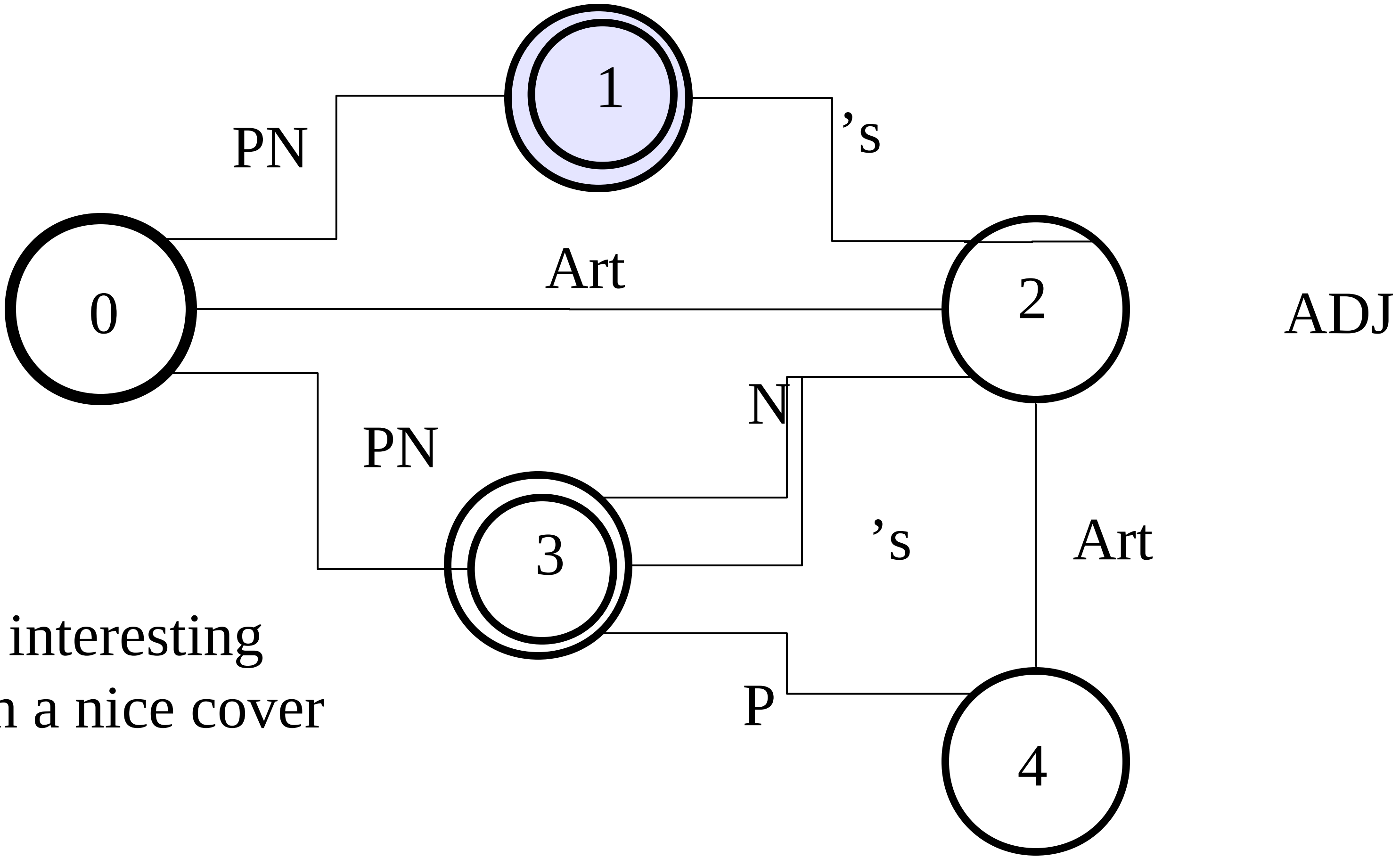

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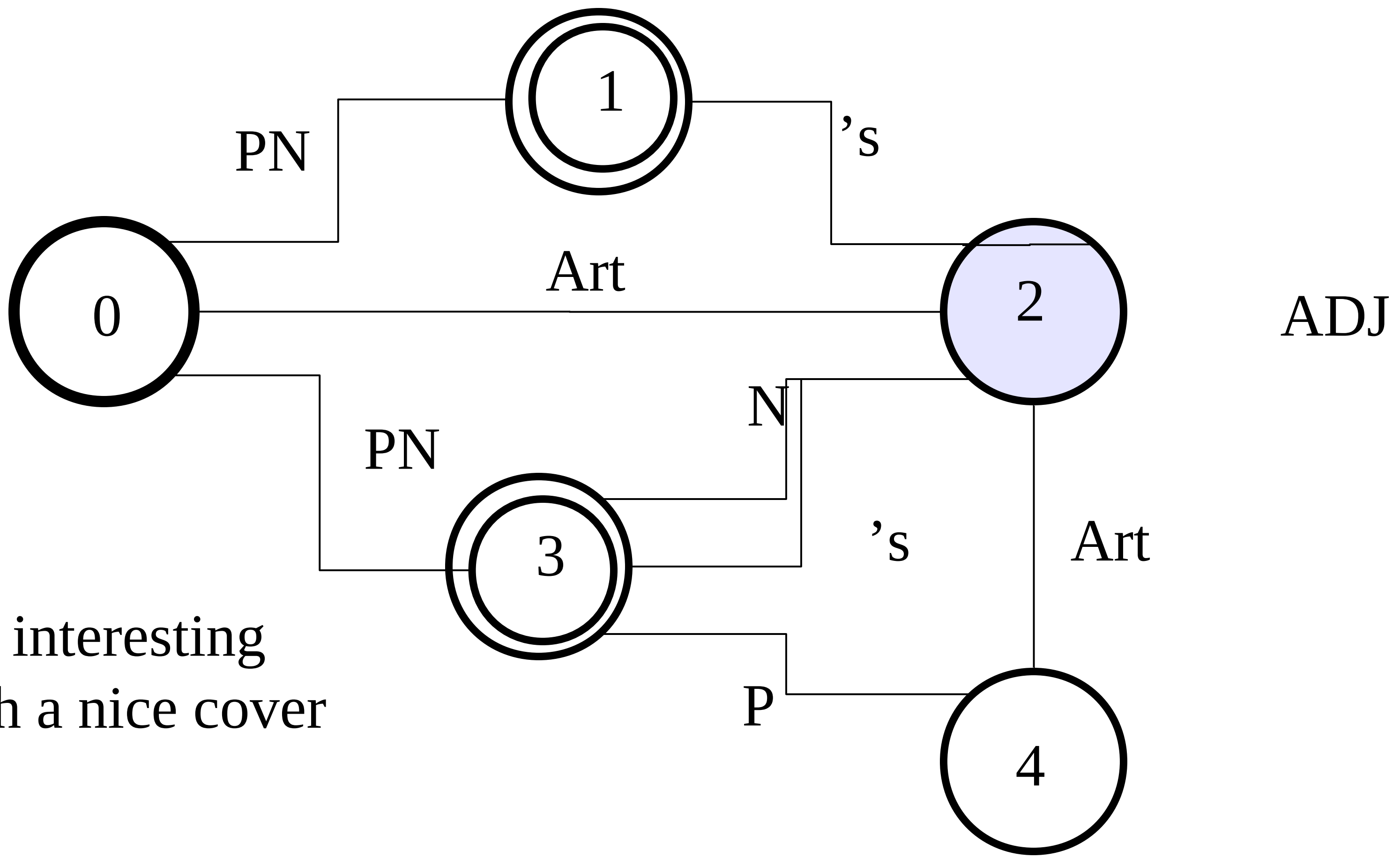

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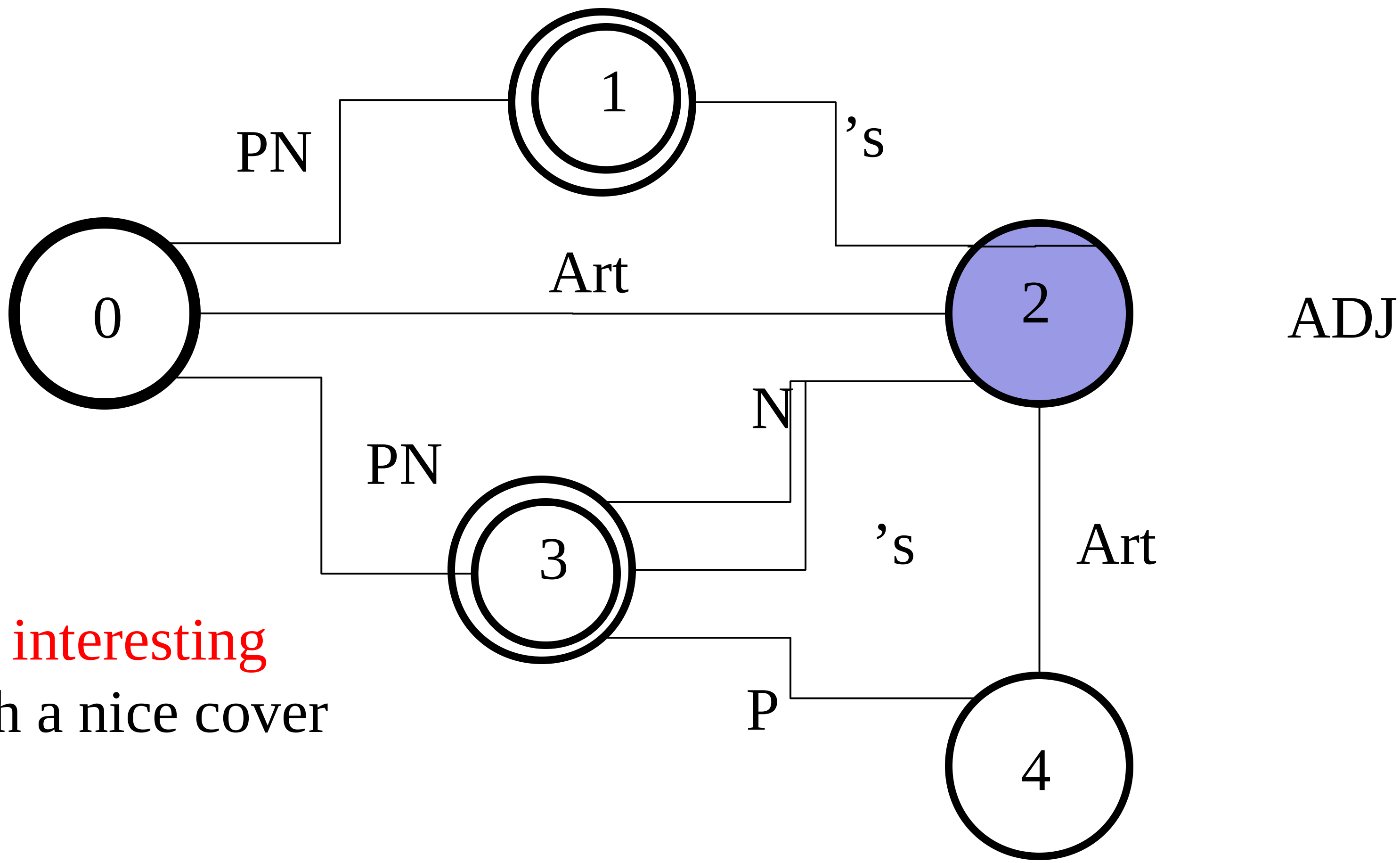

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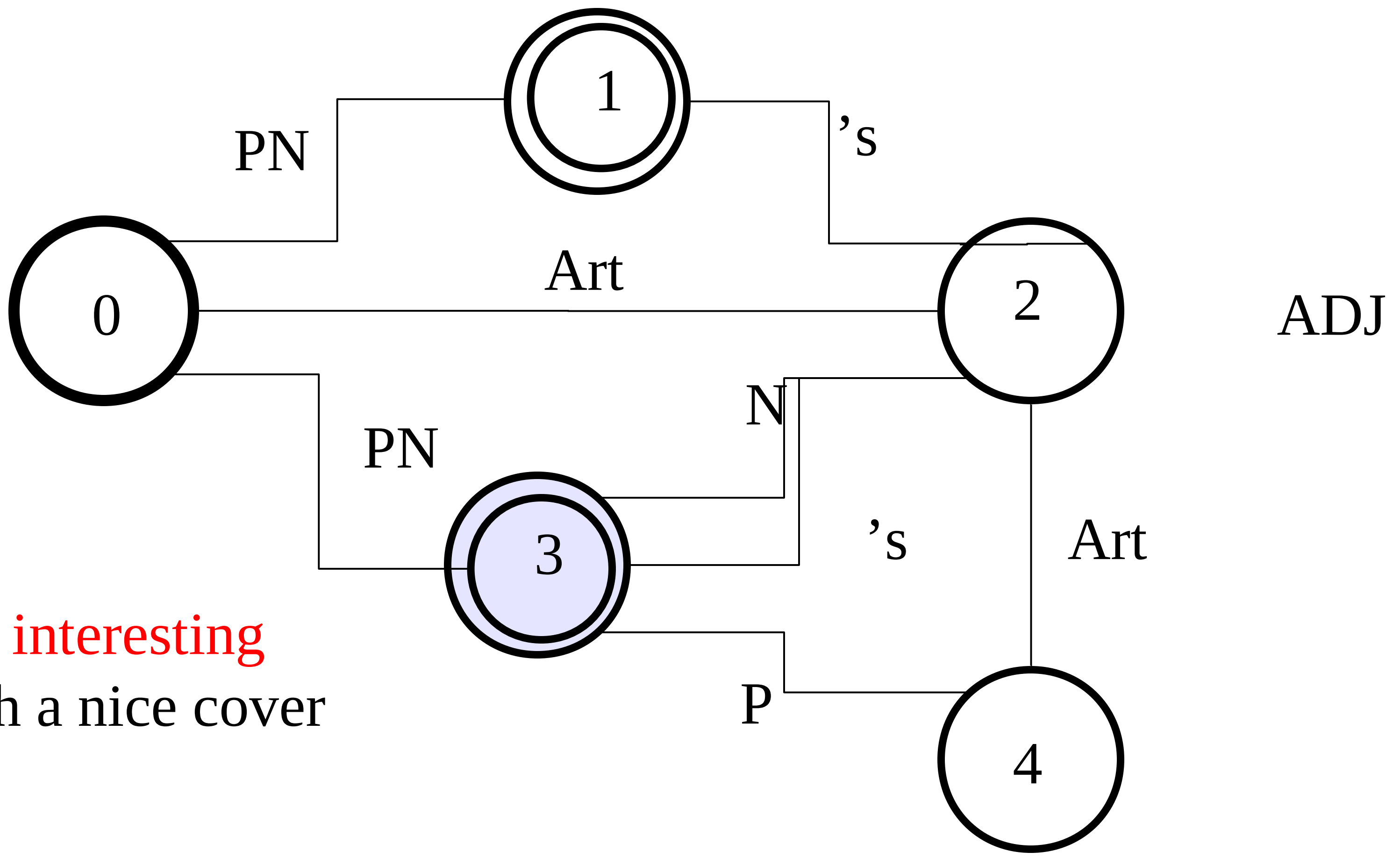

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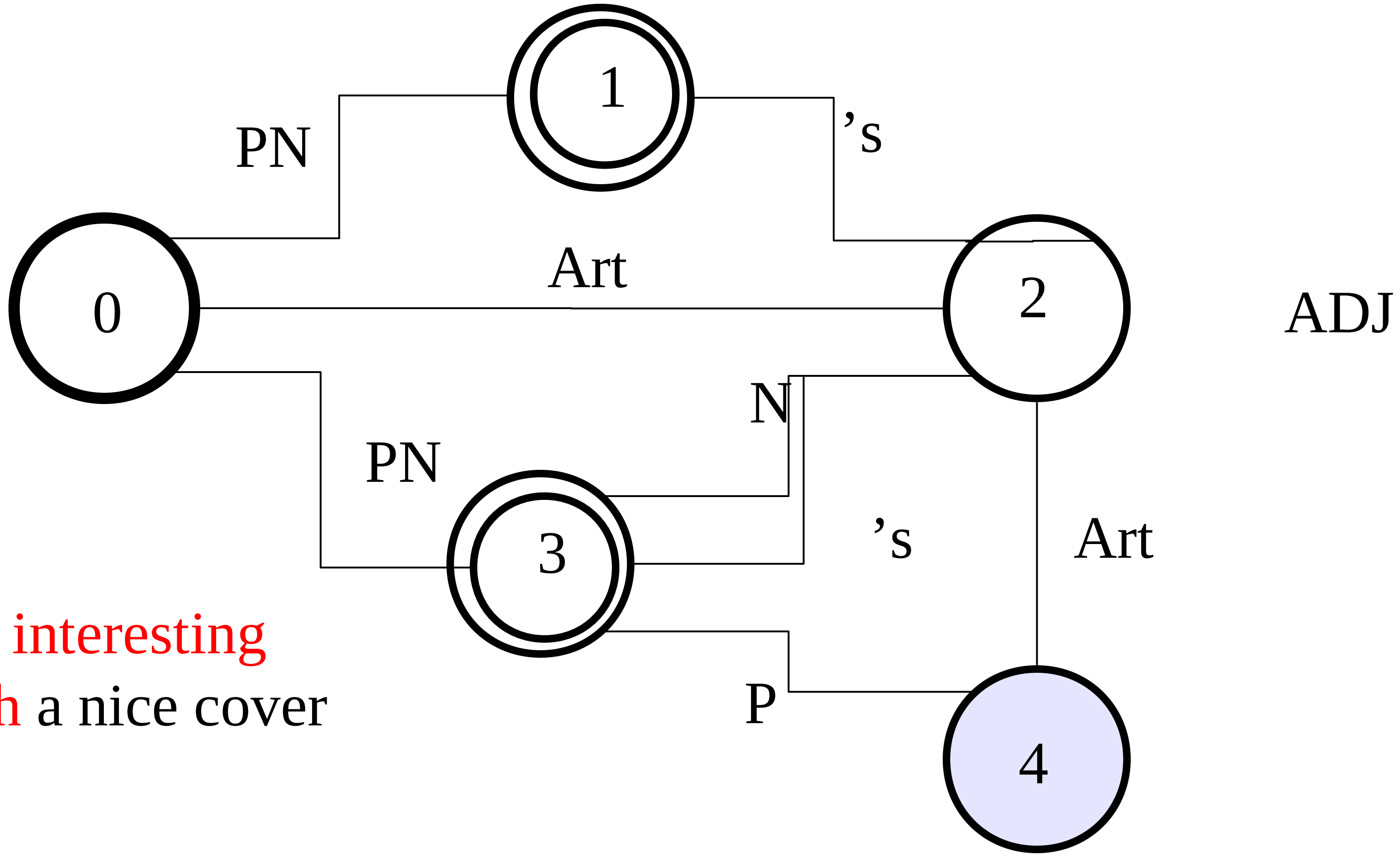

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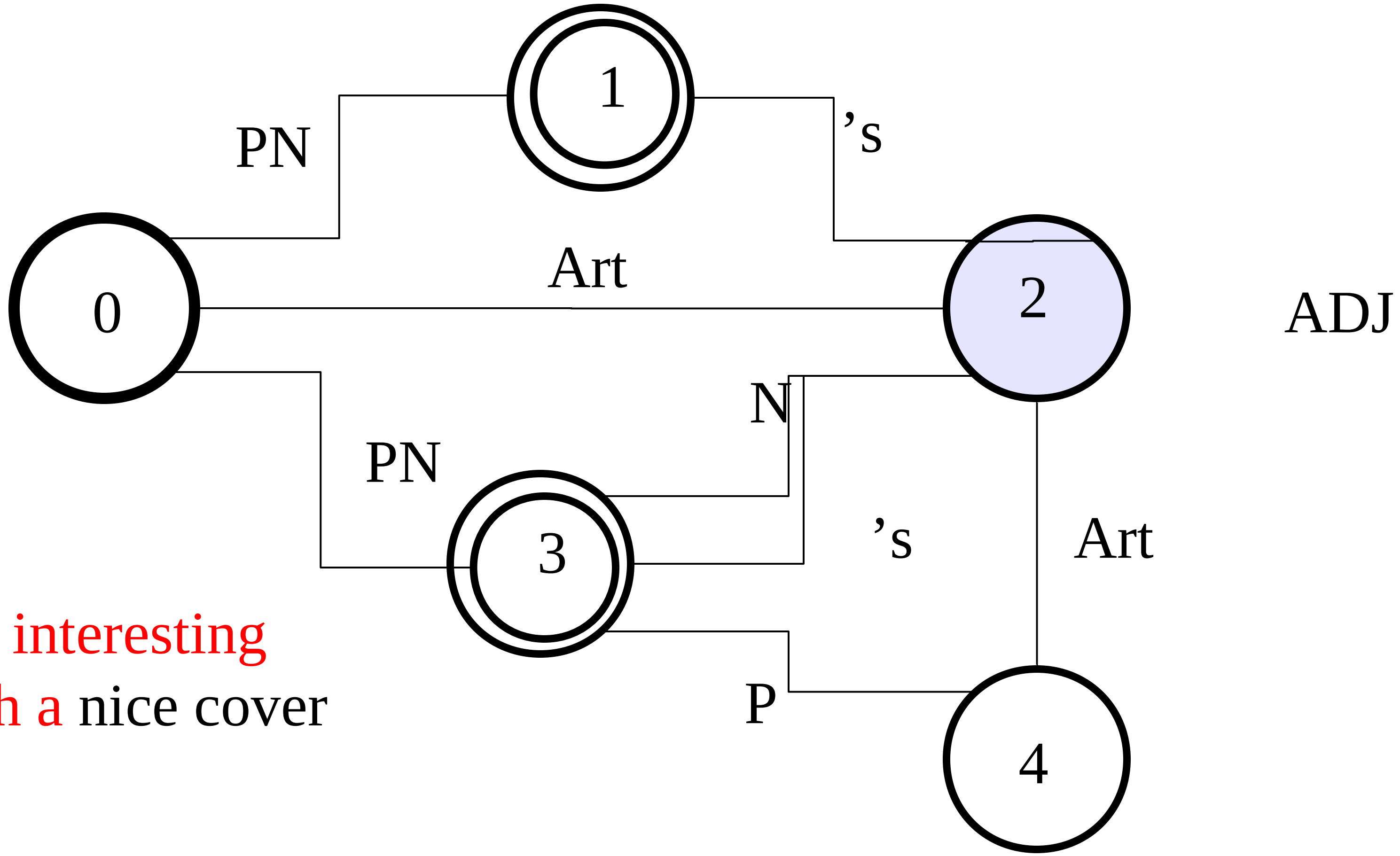

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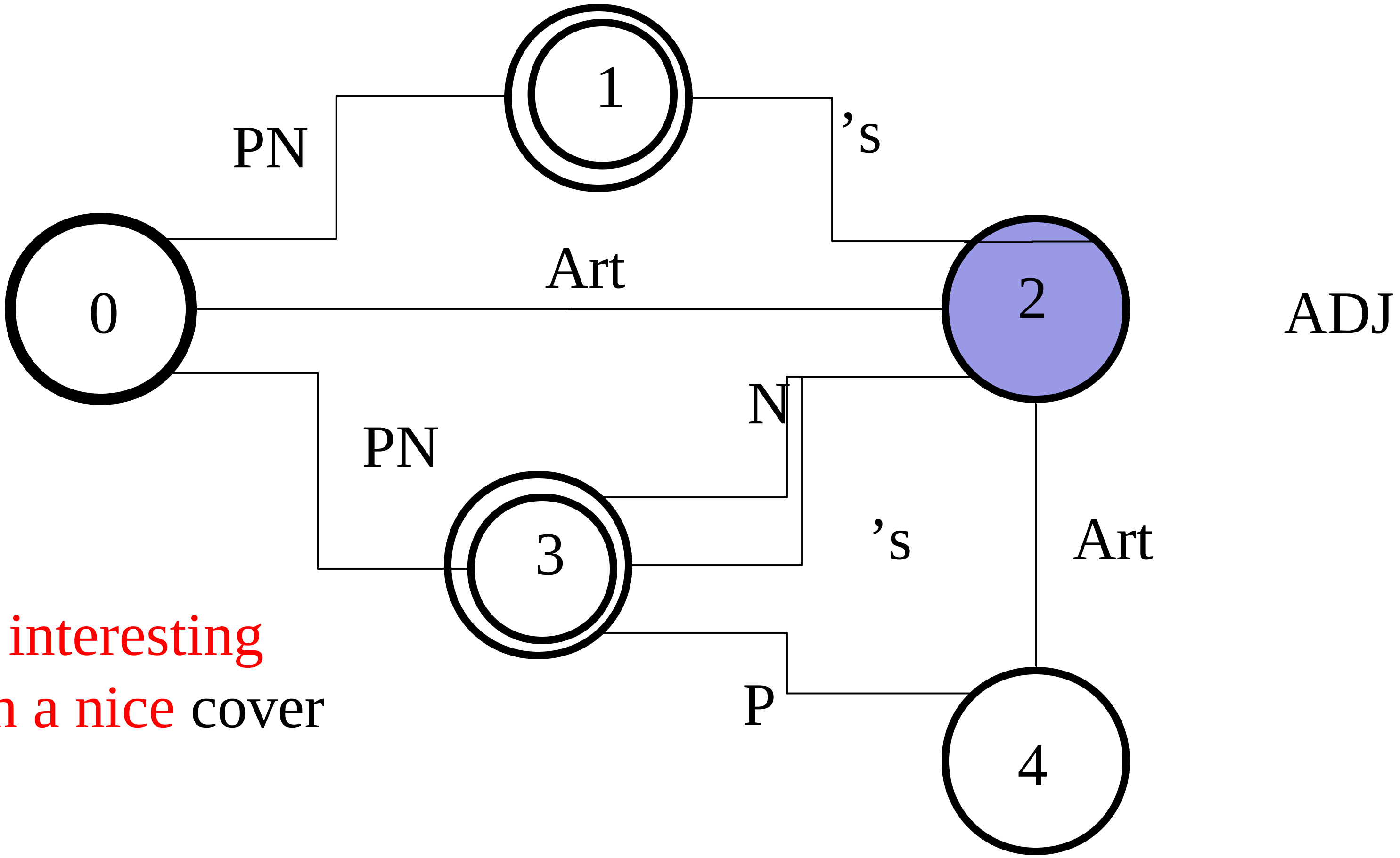

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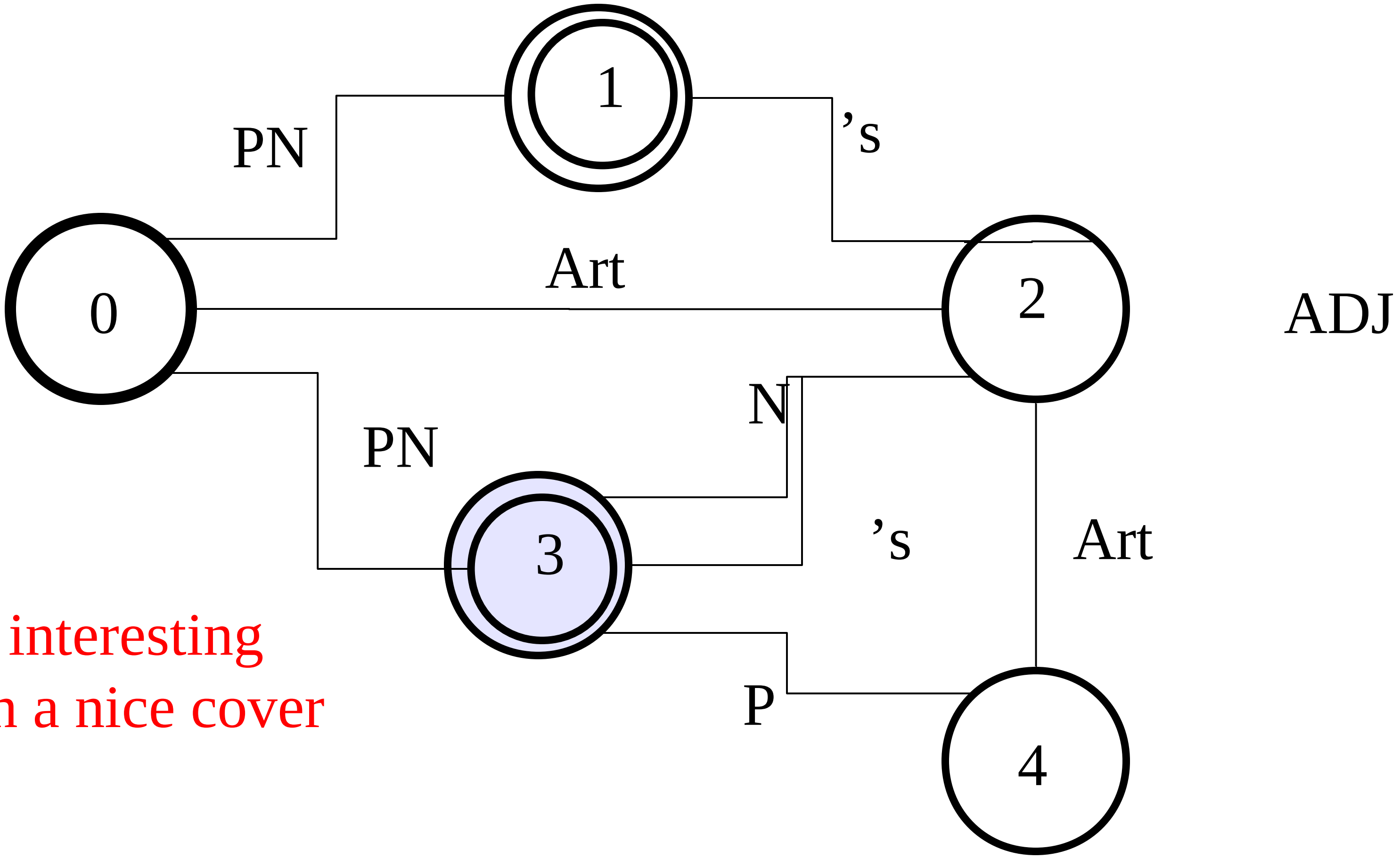

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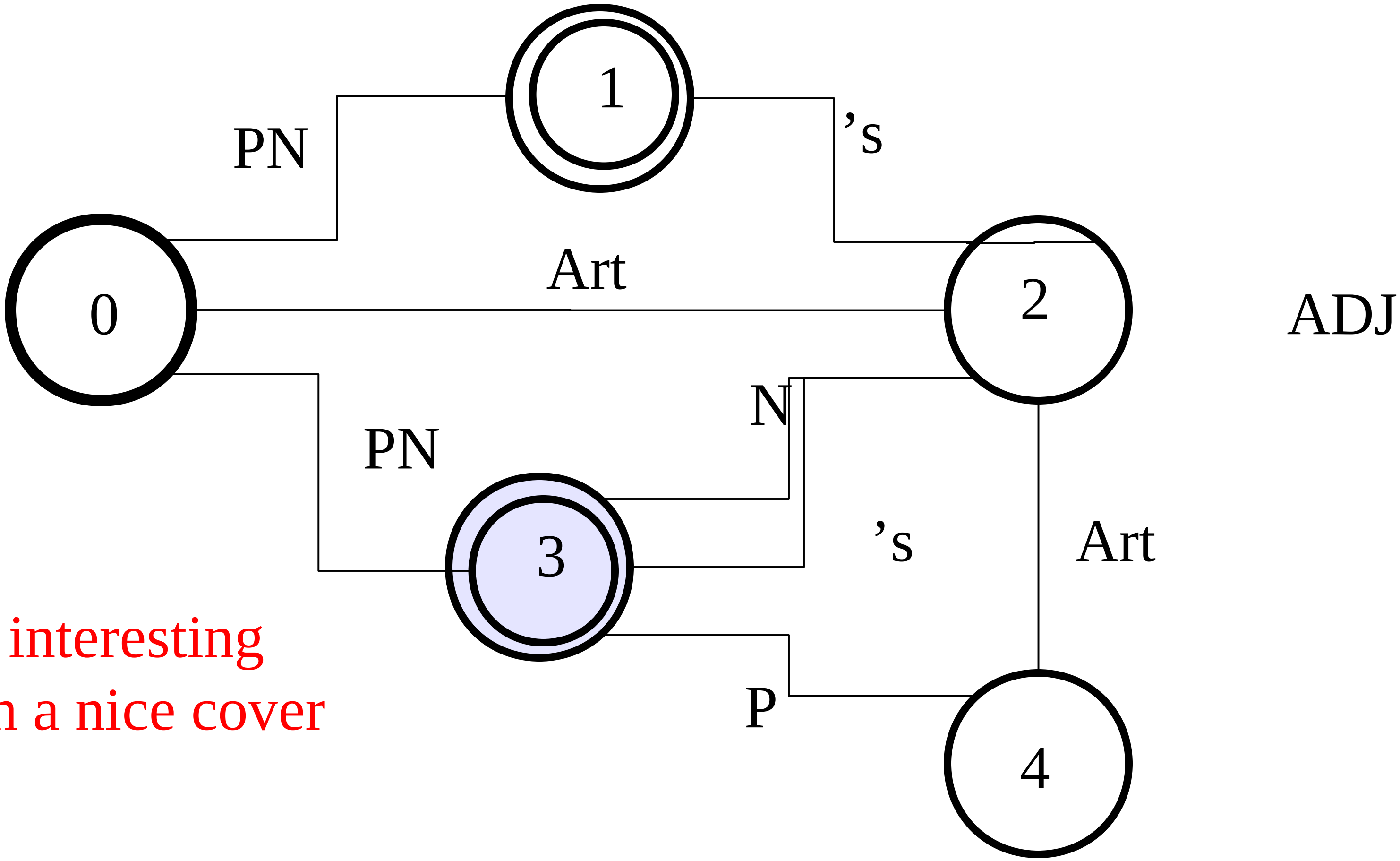
Pattern-maching

PN ’s (ADJ)* N P Art (ADJ)* N



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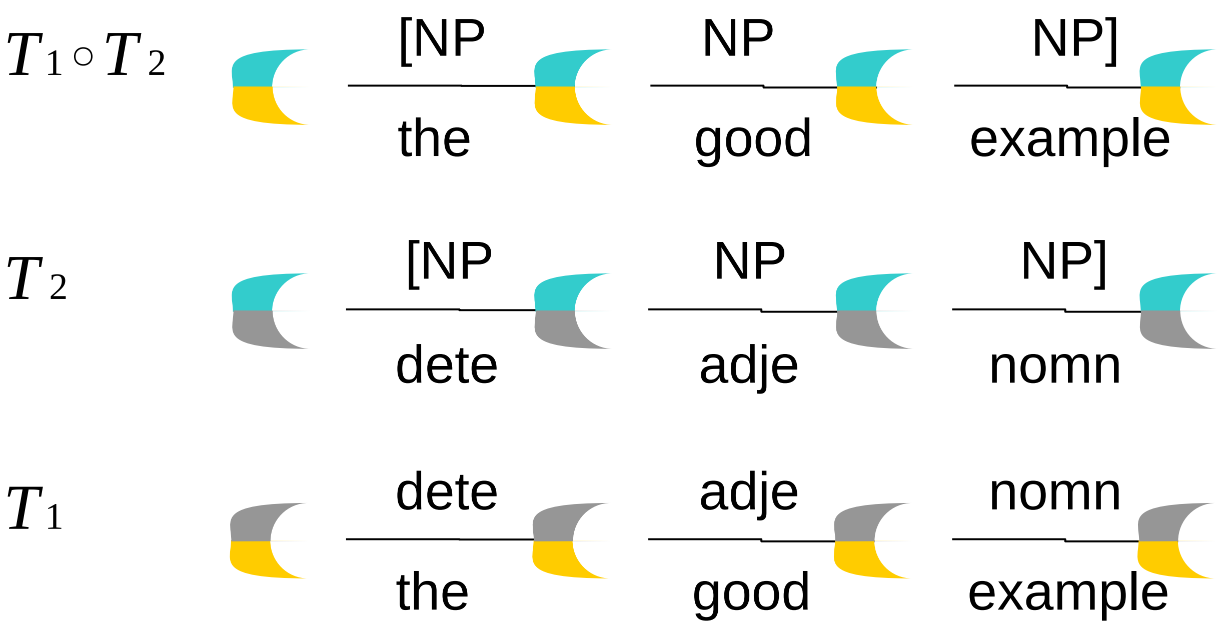
Syntactic Structure:
Finite State Cascades

- functionally equivalent to composition of transducers,
  - but without intermediate structure output
  - the individual transducers are considerably smaller than a composed transducer



Syntactic Structure:
Finite-State Cascades (Abney)

Finite-State Cascade

<table>
<tr><td>L_3 ----</td><td colspan="7">S</td><td colspan="3">S</td></tr>
<tr><td>T_3</td><td colspan="10"></td></tr>
<tr><td>L_2 ----</td><td colspan="2">NP</td><td colspan="4">PP</td><td>VP</td><td>NP</td><td colspan="2">VP</td></tr>
<tr><td>T_2</td><td colspan="10"></td></tr>
<tr><td>L_1 ----</td><td colspan="2">NP</td><td>P</td><td colspan="3">NP</td><td>VP</td><td>NP</td><td colspan="2">VP</td></tr>
<tr><td>T_1</td><td colspan="10"></td></tr>
<tr><td>L_0 ----</td><td>D</td><td>N</td><td>P</td><td>D</td><td>N</td><td>N</td><td>V-tns</td><td>Pron</td><td>Aux</td><td>V-ing</td></tr>
<tr><td></td><td>the</td><td>woman</td><td>in</td><td>the</td><td>lab</td><td>coat</td><td>thought</td><td>you</td><td>were</td><td>sleeping</td></tr>
</table>

Regular-Expression Grammar

$$L_1 : \left\{ \begin{array}{l} NP \rightarrow D?\, N*\, N \\ VP \rightarrow V - tns \mid Aux\, V\text{-}ing \end{array} \right\}$$

$$L_2 : \{ PP \rightarrow P\ NP \}$$

$$L_3 : \{ S\ PP*\ NP\ PP*\ VP\ PP* \}$$

NOTE:
No recursion allowed

Syntactic Structure:
Finite-State Cascades (Abney)

- cascade consists of a sequence of levels
- phrases at one level are built on phrases at the previous level
- no recursion:
  - phrases never contain same level or higher level phrases
- two levels of special importance
  - chunks: non-recursive cores (NX, VX) of major phrases (NP, VP)
  - simplex clauses: embedded clauses as siblings
- patterns:
  - reliable indicators of bits of syntactic structure

An alternative FST cascade for German (free word order), Neumann et al.

Most partial parsing approaches following a bottom-up strategy:

Major steps

lexical processing

including morphological analysis, POS-tagging, Named Entity recognition

phrase recognition

general nominal & prepositional phrases, verb groups

clause recognition via domain-specific templates

templates triggered by domain-specific predicates attached to relevant verbs;

expressing domain-specific selectional restrictions for possible argument fillers

Bottom-up chunk parsing

perform clause recognition after phrase recognition is completed

However a bottom-up strategy showed to be problematic in case of German free text processing

Crucial properties of German

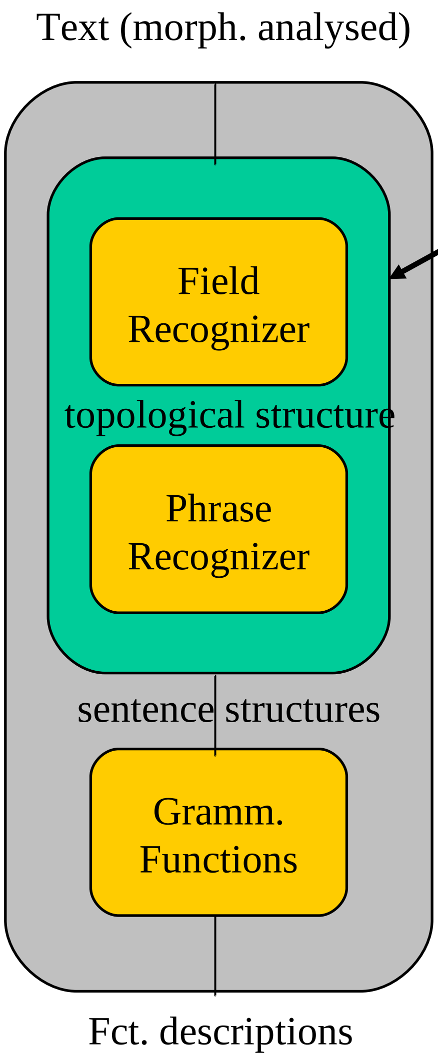
1. highly ambiguous morphology (e.g., case for nouns, tense for verbs)
2. free word/phrase order
3. splitting of verb groups into separated parts into which arbitrary phrases an clauses can be spliced in (e.g., *Der Termin findet morgen statt*. *The date takes place tomorrow.)*

Main problem in case of a bottom-up parsing approach:
Even recognition of simple sentence structure
depends heavily on performance of phrase recognition.

NP ist gängige Praxis.
[NP Die vom Bundesgerichtshof und den Wettbewerbern als Verstoß gegen das Kartellverbot gegeisselte zentrale TV-Vermarktung] ist gängige Praxis.

NP ist gängige Praxis.
[NP Central television marketing censured by the German Federal High Court and the guards against unfair competition as an infringement of anti-cartel legislation] is common practice.

In order to overcome these problems we propose the following two phase divide-and-conquer strategy



Divide-and-conquer strategy

1. Recognize verb groups and topological structure (*fields*) of sentence domain-independently;

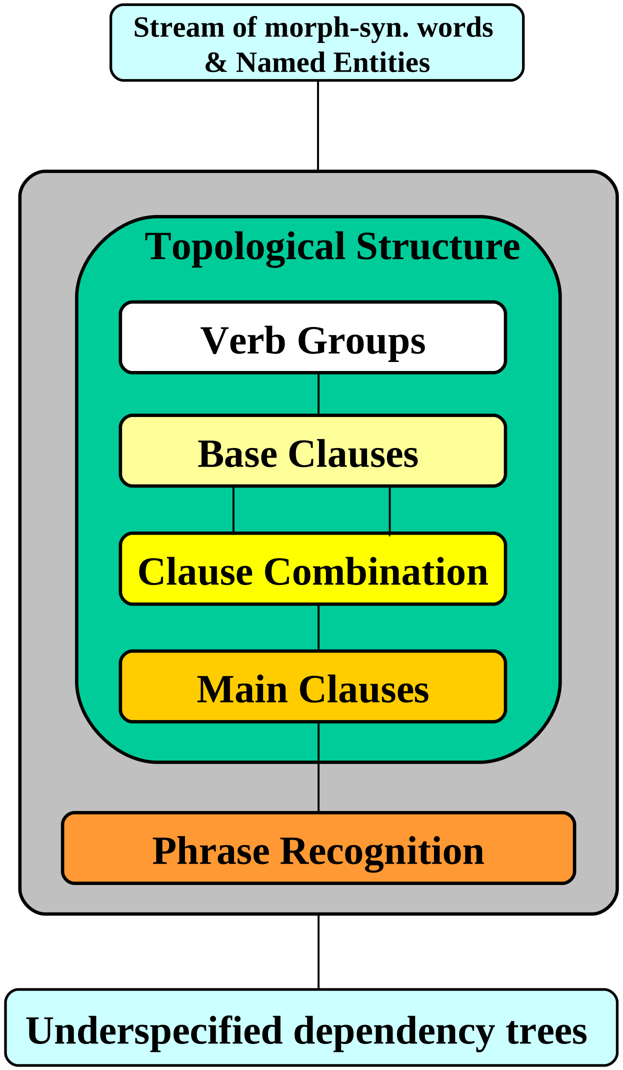
FrontField LeftVerb MiddleField RightVerb RestField

2. Apply general as well as domain-dependent phrasal grammars to the identified fields of the main and sub-clauses

[CoordS [CSent *Diese Angaben konnte der Bundesgrenzschutz aber nicht bestätigen*], [CSent *Kinkel sprach* von Horrorzahlen, [Relcl *denen er keinen Glauben schenke*]]].

This information couldn‘t be verified by the Border Police, Kinkel spoke of horrible figures that he didn‘t believe.

The divide-and-conquer parser is realized by means of a cascade of finite state grammars



Weil die Siemens GmbH, die vom Export lebt, Verluste erlitt, mußte sie Aktien verkaufen.
Because the Siemens Corp which strongly depends on exports suffered from losses they had to sell some shares.

Weil die Siemens GmbH, die vom Export Verb-FIN, Verluste Verb-FIN, Modv-FIN sie Aktien FV-Inf.

Weil die Siemens GmbH, Rel-Clause Verluste Verb-FIN, Modv-FIN sie Aktien FV-Inf.

Subconj-Clause,
Modv-FIN sie Aktien FV-Inf.

Clause

Semantic Analysis
Selected Approaches (1)

- *Chunk linking and chunk attachment (Abney)*
  - Interpretation steps in partial parsing
  - linking of hitherto unconnected structures (attachment of modifiers, prepositional phrases, determination of subject and object)
  - interpretation basis: case frames, corpus examples
- *Finite state filtering (Grefenstette, 1999)*
  - layered finite-state parser
  - groups adjacent syntactically related units
  - extracts non-adjacent n-ary grammatical relations.
  - high level specifications of regular expressions or describing the patterns to be extracted.

Semantic Analysis
Selected Approaches (2)

- *head-modifier-pairs*
  - mass data parsing with identifying pairs like
    [H: extraction, M: information]
  - used in information retrieval for enriching the document index and improving retrieval efficiency (Strzalkowski/Lin/Ge/Perez-Carballo, Jose (1999)).
- *fact extraction in fixed domains*
  - information patterns in highly standardized text types (weather forecasts, stock market reports)
  - example: biography
    - [A-Z][a-z]*“, “[A-Z][a-z]*“, *“[0-9]{4}“ in “[A-Z][a-z]*“, † „[0-9]{4}“ in “[A-Z][a-z]*
    - *Buonarroti, Michelangelo, *1475 in Caprese , † 1564 in Roma*

Semantic Analysis
Selected Approaches (3)

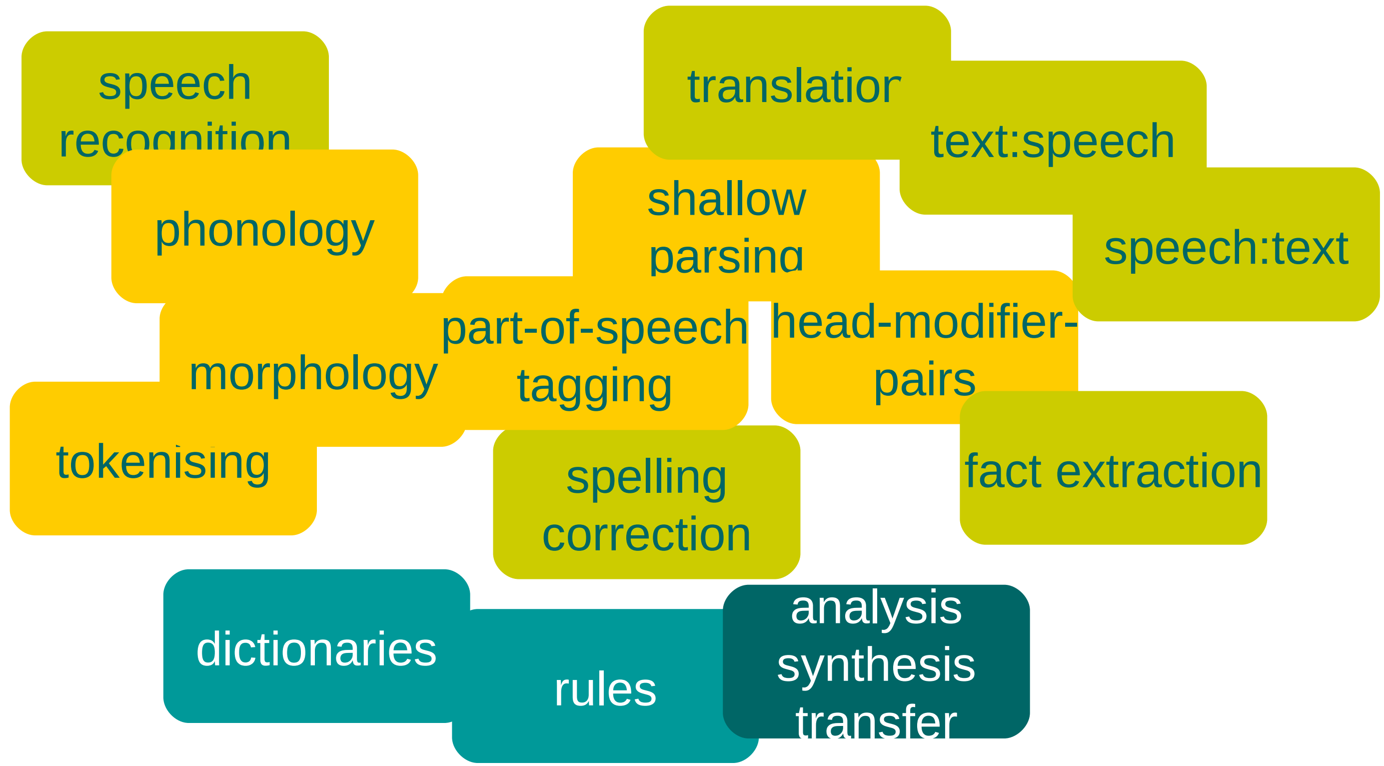
- *message understanding/information extraction*
  - filling in relational database templates from newswire texts
  - approach of FASTUS [1)]: cascade of five transducers
    - recognition of names,
    - fixed form expressions,
    - basic noun and verb groups
    - patterns of events
      - <company> <form><joint venture> with <company>
      - "Bridgestone Sports Co. said Friday it has set up a joint venture in Taiwan with a local concern and a Japanese trading house to produce golf clubs to be shipped to Japan."
    - identification of event structures that describe the same event

Relationship	TIE-UP
Entities	Bridgestone Sports Co. a local concern a Japanese trading house
JV Company	-
Capitalization	-

[1)] Hobbs/Appelt/Bear/Israel/Kehler/Martin/Meyers/Kameyama/Stickel/Tyson (1997)

Application Perspective

- Introduction
- Morphology
- Syntax
- Semantics
- Summary



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Named Entity Extraction

Machine Learning for
Named Entity
Extraction

The who, where, when & how much in a sentence

- The task: identify lexical and phrasal information in text which express references to named entities NE, e.g.,
  - person names
  - company/organization names
  - locations
  - dates&times
  - percentages
  - monetary amounts
- Determination of an NE
  - Specific type according to some taxonomy
  - Canonical representation (template structure)

Example of NE-annotated text

Delimit the named entities in a text and tag them with NE types:

<ENAMEX TYPE=„LOCATION“>Italy</ENAMEX>‘s business world was rocked by the announcement <TIMEX TYPE=„DATE“>last Thursday</TIMEX> that Mr. <ENAMEX TYPE=„PERSON“>Verdi</ENAMEX> would leave his job as vice-president of <ENAMEX TYPE=„ORGANIZATION“>Music Masters of Milan, Inc</ENAMEX> to become operations director of <ENAMEX TYPE=„ORGANIZATION“>Arthur Andersen</ENAMEX>.

- „Milan“ is part of organization name
- „Arthur Andersen“ is a company
- „Italy“ is sentence-initial $\Rightarrow$ capitalization useless

NE and Question-Answering

- Often, the expected answer type of a question is a NE
  - *What was the name of the first Russian astronaut to do a spacewalk?*
    - Expected answer type is PERSON
  - *Name the five most important software companies!*
    - Expected answer type is a list of COMPANY
  - *Where is does the ESSLLI 2004 take place?*
    - Expected answer type is LOCATION (subtype COUNTRY or TOWN)
  - *When will be the next talk?*
    - Expected answer type is DATE

Difficulties of Automatic NEE

- Potential set of NE is too numerous to include in dictionaries/Gazetteers
- Names changing constantly
- Names appear in many variant forms
- Subsequent occurrences of names might be abbreviated

> - list search/matching does not perform well
> - context based pattern matching needed

Difficulties for Pattern Matching Approach

Whether a phrase is a named entity, and what name class it has, depends on

- Internal structure:
  „<u>Mr.</u> Brandon“
- Context:
  „The new <u>company</u>, SafeTek, will make air bags.“
- Feiyu Xu, <u>researcher </u>at DFKI, Saarbrücken

NE is an interesting problem

- Productivity of name creation requires lexicon free pattern recognition
- NE ambiguity requires resolution methods
- Fine-grained NE classification needs fined-grained decision making methods
  - Taxonomy learning
- Multi-linguality
  - A text might contain NE expressions from different languages
  - New pilot challenge in ACE'2007
    - Extract all NEs mentioned in a Mandarin/Arabic text
    - Translate them to English

NE Co-reference

Norman Augustine ist im Grunde seines Herzens ein friedlicher Mensch."Ich könnte niemals auf irgend etwas schiessen", versichert der 57jährige Chef des US-Rüstungskonzerns Martin Marietta Corp. (MM). ... Die Idee zu diesem Milliardendeal stammt eigentlich von GE-Chef JohnF. Welch jr. Er schlug Augustine bei einem Treffen am 8. Oktober den Zusammenschluss beider Unternehmen vor. Aber Augustine zeigte wenig Interesse, Martin Marietta von einem zehnfach grösseren Partner schlucken zu lassen.

- Martin Marietta can be a person name or a reference to a company
- If MM is not part of an abbreviation lexicon, how do we recognize it?
  - Also by taking into account NE reference resolution.

Why Machine Learning NE?

- System-based adaptation for new domains
  - Fast development cycle
  - Manual specification too expensive
  - Language-independence of learning algorithms
  - NL-tools for feature extraction available, often as open-source
- Current approaches already show near-human-like performance
  - Can easily be integrated with externally available Gazetteers
- High innovation potential
  - Core learning algorithms are language independent, which supports multi-linguality
  - Novel combinations with relational learning approaches
  - Close relationship to currently developed ML-approaches of reference resolution

Different approaches of Preprocessing

- Character-level features
  - (Whitelaw&Patrick, CoNLL, 2003)
- Tokenization
  - (Bikel et al., ANLP 1997)
- POS + lemmatization
  - (Yangarber et al. Coling 2002)
- Morphology
  - (Cucerzan&Yarowsky, EMNLP 1999)
- Full parsing
  - (Collins&Singer, EMNLP 1999)

Different approaches

- Supervised learning
  - Training is based on available very large annotated corpus
  - Mainly statistical-based methods used
    - HMM, MEM, connectionists models, SVM, hybrid ML-methods (cf. http://www.cnts.ua.ac.be/conll2003/ner/)
- Semi-supervised learning
  - Training only needs very few seeds and
  - very large un-annotated corpus, usually larger than for supervised learning
- Unsupervised Learning
  - Typical approach is clustering, e.g., cluster NEs on basis of similar context (common syntagmatic relationship), Problem: naming the clusters, e.g., WordNet-labels, cf. (Alfonseca and Mandandhar, 2004)
  - Hypernym rules, “X such as A, B, C” -> A,B,C are NEs of type X, cf. (Evans 2003)

Performance of supervised methods (CoNLL, 2003)*

English	precision	recall	F
[FIJZ03]	88.99%	88.54%	88.76±0.7
[CN03]	88.12%	88.51%	88.31±0.7
[KSNM03]	85.93%	86.21%	86.07±0.8
[ZJ03]	86.13%	84.88%	85.50±0.9
[CMP03b]	84.05%	85.96%	85.00±0.8
[CC03]	84.29%	85.50%	84.89±0.9
[MMP03]	84.45%	84.90%	84.67±1.0
[CMP03a]	85.81%	82.84%	84.30±0.9
[ML03]	84.52%	83.55%	84.04±0.9
[BON03]	84.68%	83.18%	83.92±1.0
[MLP03]	80.87%	84.21%	82.50±1.0
[WNC03]*	82.02%	81.39%	81.70±0.9
[WP03]	81.60%	78.05%	79.78±1.0
[HV03]	76.33%	80.17%	78.20±1.0
[DD03]	75.84%	78.13%	76.97±1.2
[Ham03]	69.09%	53.26%	60.15±1.3
baseline	71.91%	50.90%	59.61±1.2

German	precision	recall	F
[FIJZ03]	83.87%	63.71%	72.41±1.3
[KSNM03]	80.38%	65.04%	71.90±1.2
[ZJ03]	82.00%	63.03%	71.27±1.5
[MMP03]	75.97%	64.82%	69.96±1.4
[CMP03b]	75.47%	63.82%	69.15±1.3
[BON03]	74.82%	63.82%	68.88±1.3
[CC03]	75.61%	62.46%	68.41±1.4
[ML03]	75.97%	61.72%	68.11±1.4
[MLP03]	69.37%	66.21%	67.75±1.4
[CMP03a]	77.83%	58.02%	66.48±1.5
[WNC03]	75.20%	59.35%	66.34±1.3
[CN03]	76.83%	57.34%	65.67±1.4
[HV03]	71.15%	56.55%	63.02±1.4
[DD03]	63.93%	51.86%	57.27±1.6
[WP03]	71.05%	44.11%	54.43±1.4
[Ham03]	63.49%	38.25%	47.74±1.5
baseline	31.86%	28.89%	30.30±1.3

Produced by a system which only identified entities which had a unique class in the training data.

*http://www.cnts.ua.ac.be/conll2003/ner/

Main features used by CoNLL 2003 systems

	lex	pos	aff	pre	ort	gaz	chu	pat	cas	tri	bag	quo	doc
Florian	+	+	+	+	+	+	+	-	+	-	-	-	-
Chieu	+	+	+	+	+	+	-	-	-	+	-	+	+
Klein	+	+	+	+	-	-	-	-	-	-	-	-	-
Zhang	+	+	+	+	+	+	+	-	-	+	-	-	-
Carreras (a)	+	+	+	+	+	+	+	+	-	+	+	-	-
Curran	+	+	+	+	+	+	-	+	+	-	-	-	-
Mayfield	+	+	+	+	+	-	+	+	-	-	-	+	-
Carreras (b)	+	+	+	+	+	-	-	+	-	-	-	-	-
McCallum	+	-	-	-	+	+	-	+	-	-	-	-	-
Bender	+	+	-	+	+	+	+	-	-	-	-	-	-
Munro	+	+	+	-	-	-	+	-	+	+	+	-	-
Wu	+	+	+	+	+	+	-	-	-	-	-	-	-
Whitelaw	-	-	+	+	-	-	-	-	+	-	-	-	-
Hendrickx	+	+	+	+	+	+	+	-	-	-	-	-	-
De Meulder	+	+	+	-	+	+	+	-	+	-	-	-	-
Hammerton	+	+	-	-	-	+	+	-	-	-	-	-	-

Table 3: Main features used by the the sixteen systems that participated in the CoNLL-2003 shared task sorted by performance on the English test data. Aff: affix information (n-grams); bag: bag of words; cas: global case information; chu: chunk tags; doc: global document information; gaz: gazetteers; lex: lexical features; ort: orthographic information; pat: orthographic patterns (like Aa0); pos: part-of-speech tags; pre: previously predicted NE tags; quo: flag signing that the word is between quotes; tri: trigger words.

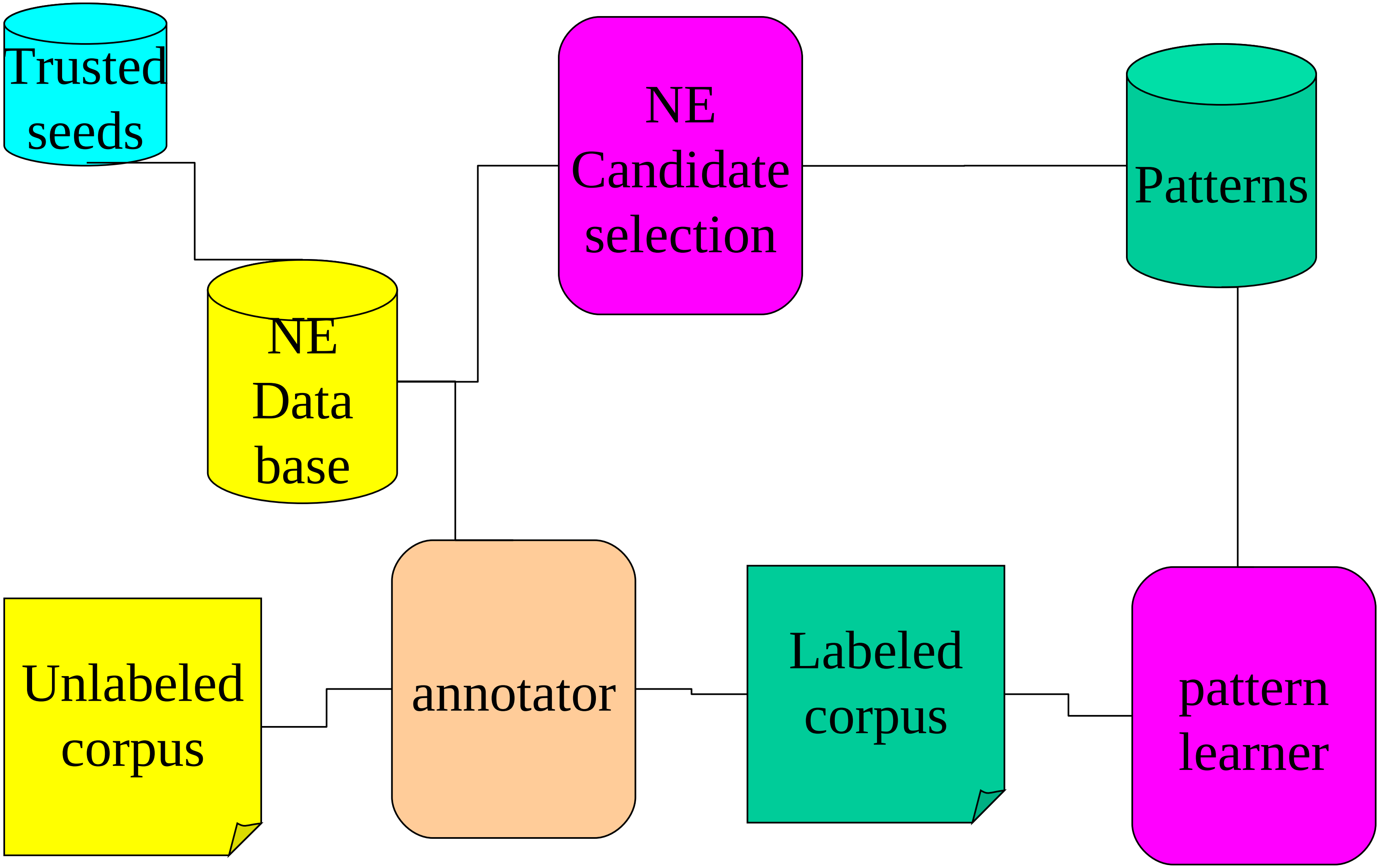
Learning Approaches in CoNLL

- Most systems used
  - Maximum entropy modeling (5)
  - Hidden-Markov models (4)
  - Connectionists methods (4)
- Near all systems used external resources, e.g., gazetteers
- Best systems performed hybrid learning approach

Semi-supervised NE: idea

- Define manually only a small set of trusted seeds
- Training then only uses un-labeled data
- Initialize system by labeling the corpus with the seeds
- Extract and generalize patterns from the context of the seeds
- Use the patterns to further label the corpus and to extend the seed set (bootstrapping)
- Repeat the process until no new terms can be identified

Semi-supervised NE-learning: idea



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