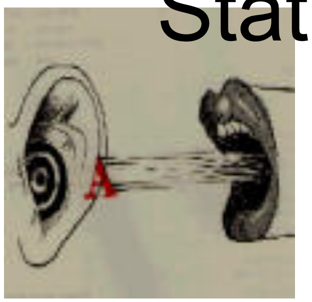
The Great (Penn Treebank) Robbery: When Statistics is Not Enough *or* The Incredible Lightness of Being a Corpus



Robert C. Berwick, Michael Coen,
Sandiway Fong & Partha Niyogi

A cognitive checklist

- Does it attain 'knowledge of human language'?
  - Grammatical/ungrammatical
  - More important: the right structures
- Does it not attain "non-knowledge" of human language (eg, Fortran, permutation language; cf Epun, Smith)
- Cognitively plausible in terms of # of input examples, kind of input data, robustness to example variation?
- Are we Fox News? (Fair and balanced) Well, consider the advertising:

Knowledge of language

- Checklist

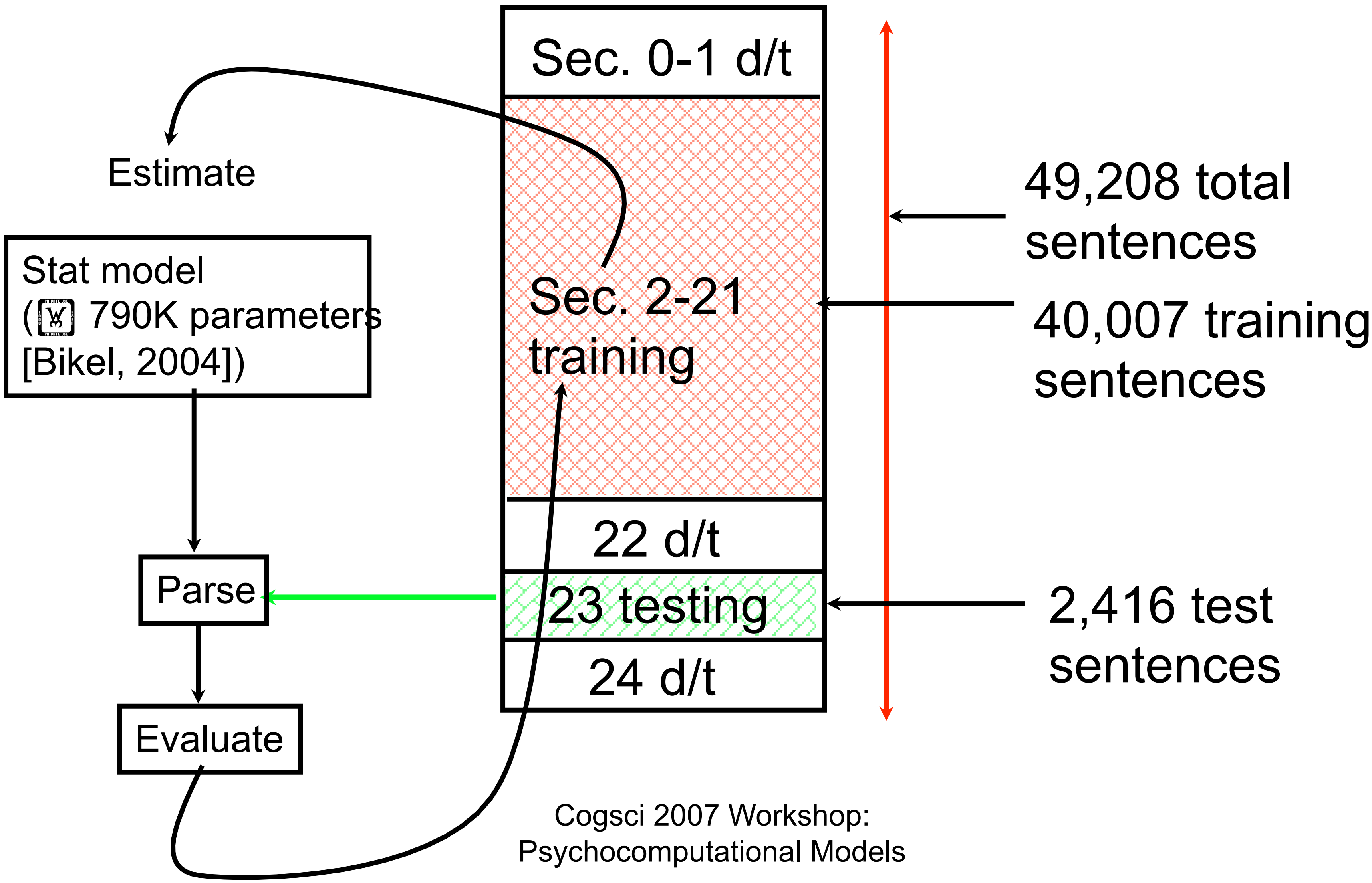
Pre Syntactic Structures

- Aux system
- Just memorizes sequences - Big Blue analogy with a very large opening book
- Berkeley parser as Pachinko machine

PTB

- The Penn Treebank (PTB) project selected 2,499 stories from a three year Wall Street Journal (WSJ) collection of 98,732 stories for syntactic annotation
- Picture: of PTB, stuffed inside kid’s head.
- Problem: license fee to LDC? Nonmembers $2500

PTB: rules of the game



KoL

= $2500/baby

???

PTB: the Discrete Charm of the

Cogsci 2007 Workshop:
Psychocomputational Models

Basic results and outline

- Don't cry over spilled milk: Excessively <u>fragile</u>
- Mirror input data

The Penn Treebank (PTB)

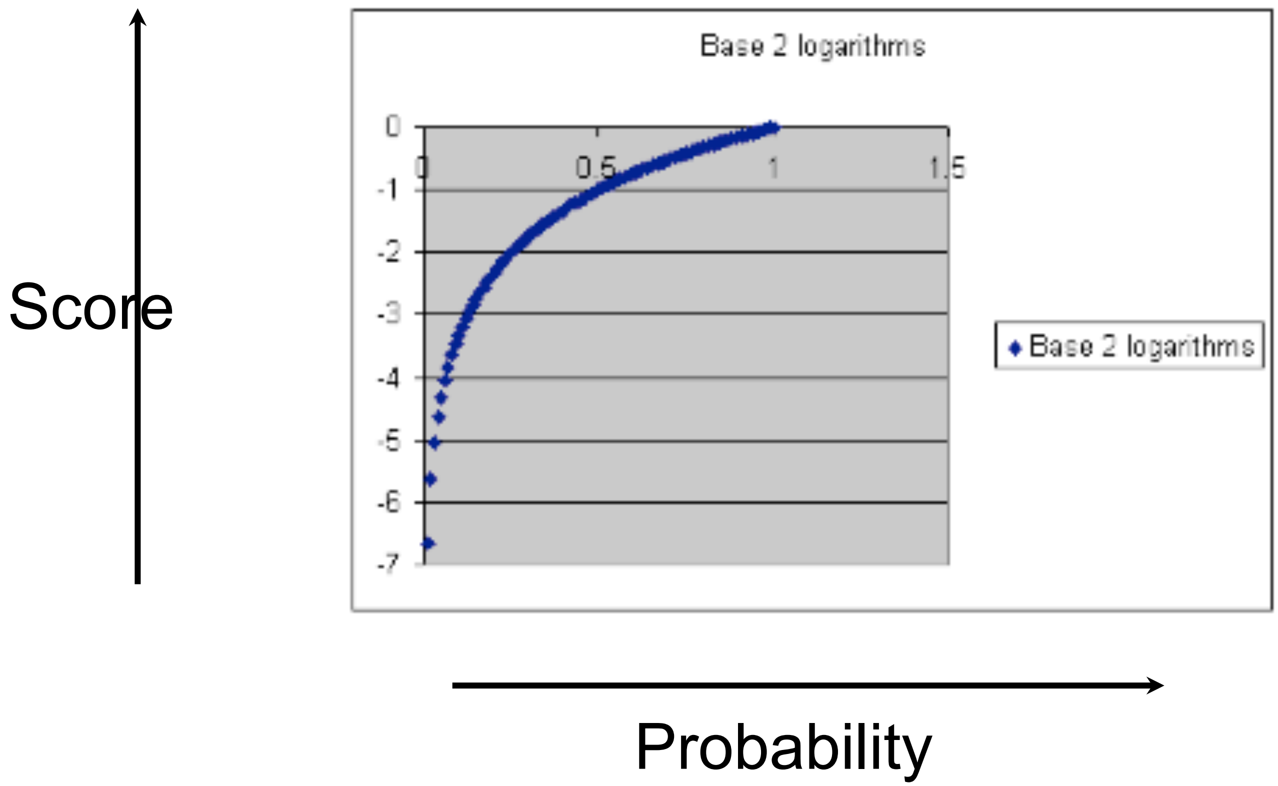
What we don’t have time to talk about here

- Conceptual issues
- Engineering/Methodological issues
  - Overtraining: no x-validation
  - Evaluation metric
  - Other G’s: CCGs.

Remember our picture of modularity

- Syntax + lexicon
- We want to avoid duplicating information
- Lexicon already has ‘semantic’ type information in it
- How does this information enter a parse?
- Do the statistical parsers enter all that’s needed?
- What information does/must the lexicon contain?

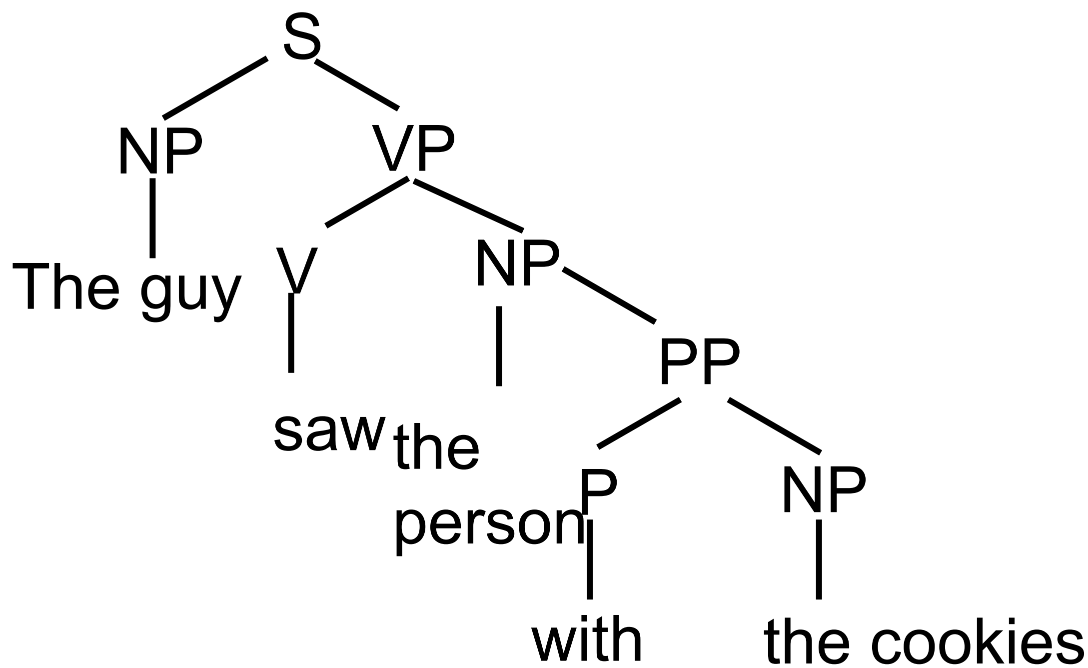
But how well does this work?


Base 2 logarithms
0
-1
-2
-3
-4
-5
-6
-7
0
0.5
1
1.5
Base 2 logarithms
Score
Probability

Does it do better? Here is the std recall & precision used

Gold standard: the guy saw the person with the cookies

1 2 3 4 5 6 7 8



NP 1 2

NP 4 5

NP 4 8

PP 6 8

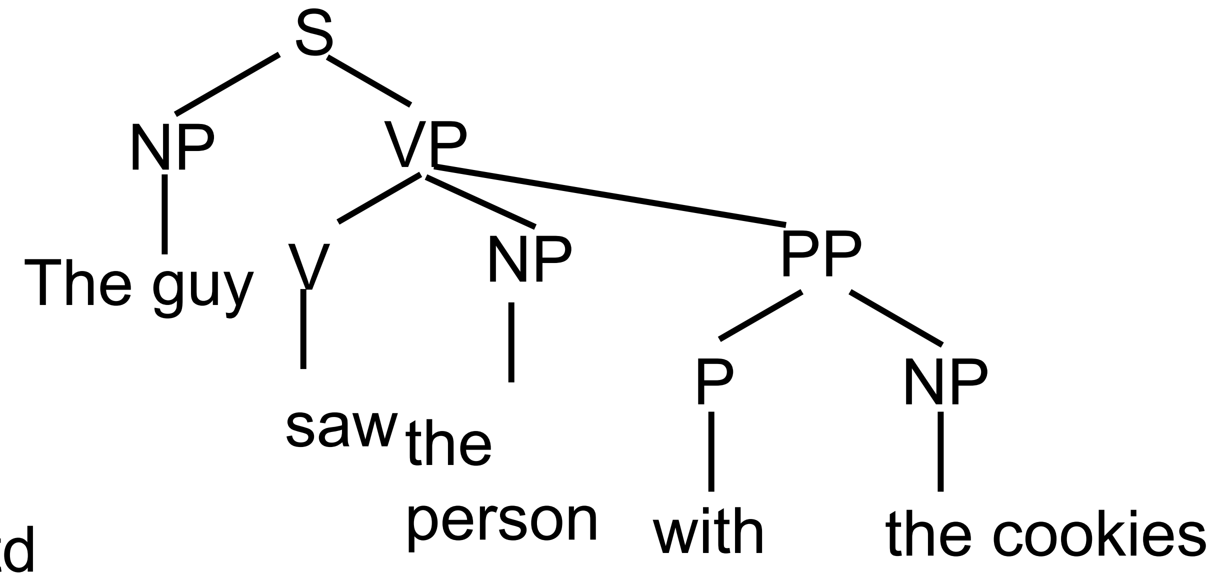
NP 7 8

VP 3 8

S 1 8

the guy saw the person with the cookies

1 2 3 4 5 6 7 8



Gold std

NP 1 2
NP 4 5
NP 4 8
PP 6 8
NP 7 8
VP 3 8
S 1 8

Actual

NP 1 2
NP 4 5
PP 6 8
NP 7 8
VP 3 8
S 1 8

G= # phrases in gold std = 7

P = # in parse output = 6

C = # correct = 6

Recall = C/G = 6/7= 86%

Precision = C/P = 6/6= 100%

Some actual results on PTB, train on 40,000 sentences, test on 2,000

Approach	Recall	Precision
SCFG	70.6%	74.8%
Lexical head dep.	85.3%	85.7
Generative lexical (what we sketched)	86.7%	86.6%

"Latest" models nearly 88-89% on both P & R…

What are the remaining issues?

Does this really work?

You will find out in the next R&R, and Lab 3a…!

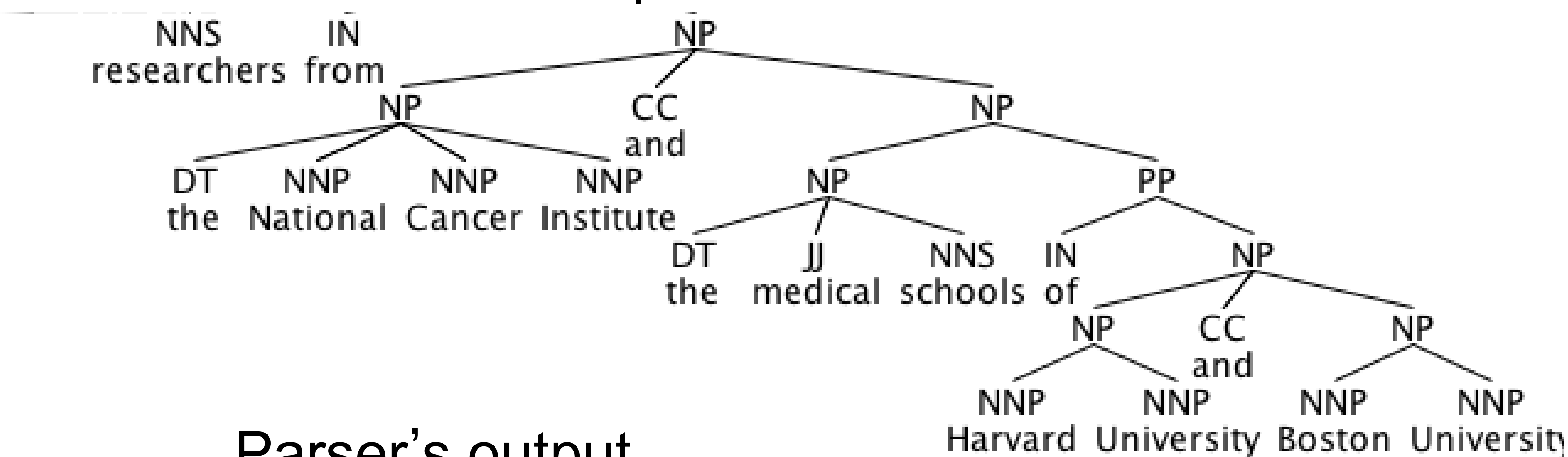
Adding Heads

Method	Recall	Precision
PCFGs (Charniak 97)	70.6%	74.8%
Conditional Models – Decision Trees (Magerman 95)	84.0%	84.3%
Lexical Dependencies (Collins 96)	85.3%	85.7%
Conditional Models – Logistic (Ratnaparkhi 97)	86.3%	87.5%
Generative Lexicalized Model (Charniak 97)	86.7%	86.6%
Model 1 (no subcategorization)	87.5%	87.7%
Model 2 (subcategorization)	88.1%	88.3%

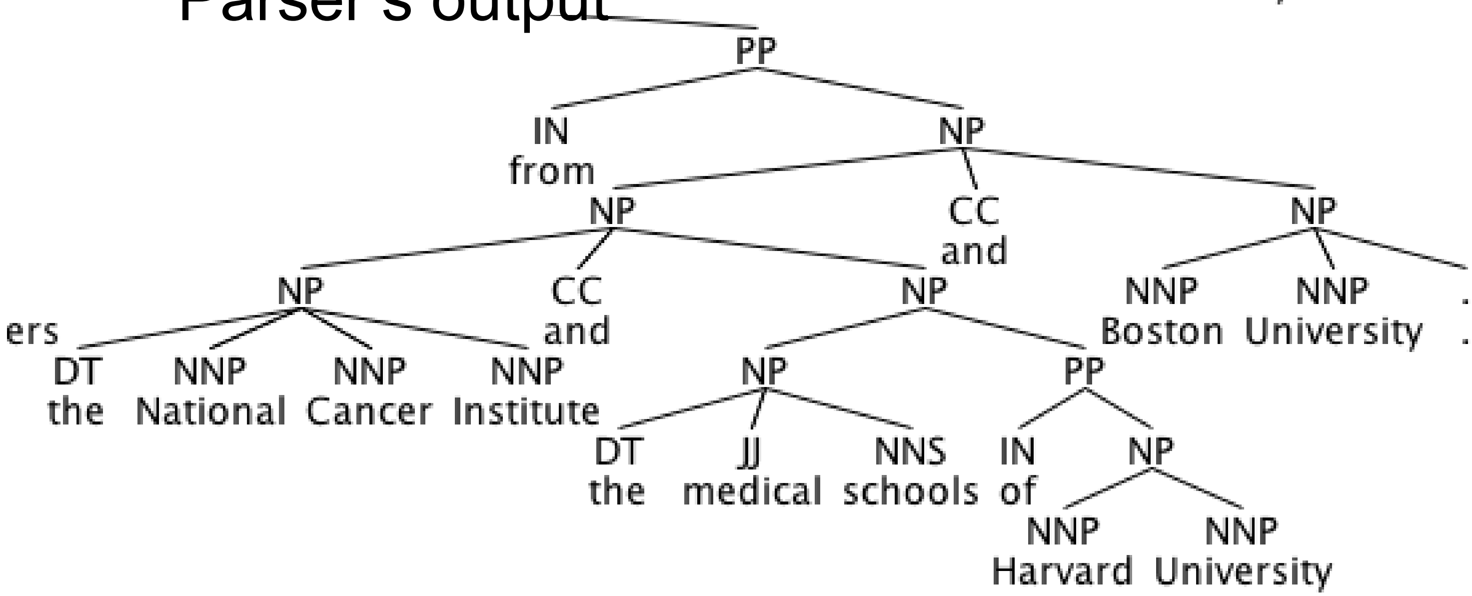
Some problems

- Conjunctions - only 50% precision & recall
- Why?

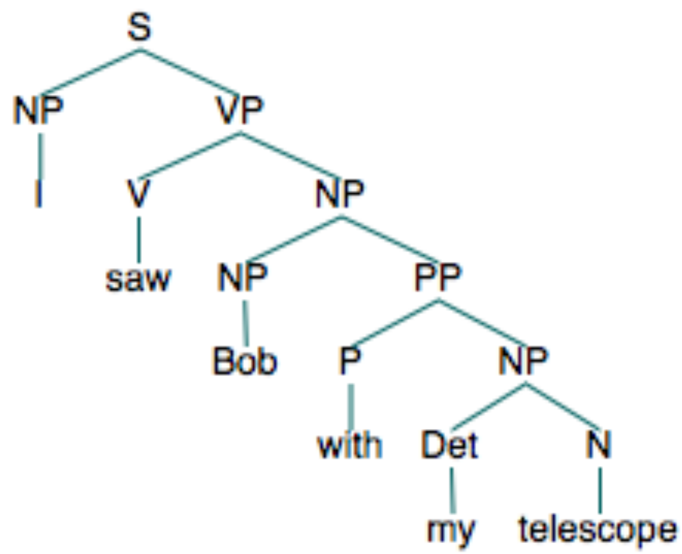
True parse

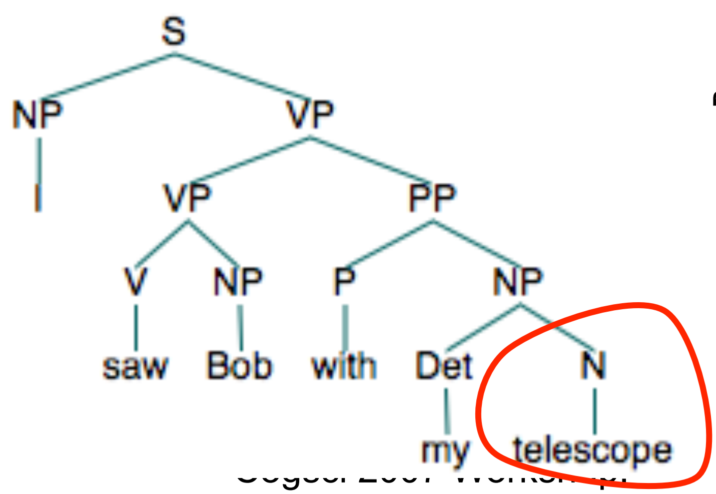


Parser's output



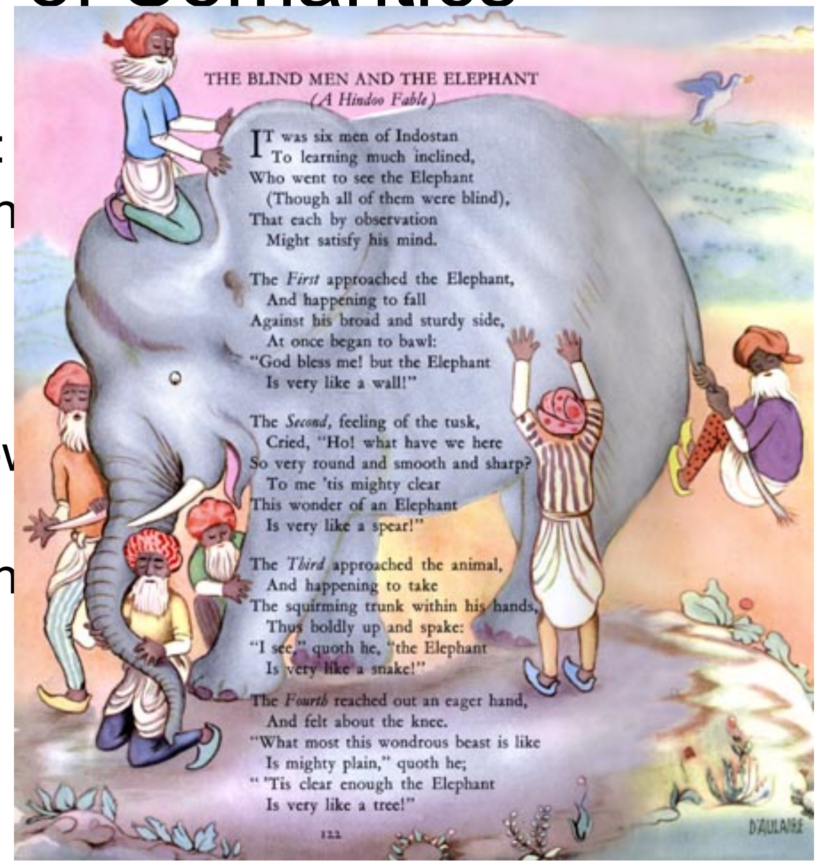
Does this fix this problem?





'telescope' should force this pref, above 'early' attachment

No “Unified Theory of Semantics”*



Different goals different semantic theories:

Syntactician: why do different words appear in different constructions?

Semanticist: what is an adequate meaning representation of a vocabulary item?

Lexicographer: what are all the things we know about a word’s meaning?

IR Engineers: what is the meaning abstraction of a piece of text?

Roboticist: how can the robot appear to understand me?

Child Dev Psych (Vocab + Grammar)

Historical linguist

*(Is there a unified theory for chemistry? physics?)

Uncertainty in terms*

- Grammar: How much semantics should be in it?
- Grammaticality: Is a semantically anomalous sentence ungrammatical?
  - He gave the book to John.
  - He thought the book to John.
- Grammatical category: What are their essences?
- Word Meaning: What is a meaning representation?
- Concepts: How are they related to words?
  - How is what we know about TIGER related to /tiger/?

*No one knows the answer! Wait: When did science know the definition of an atom, electron, proton, …?

Is Meaning About Truth?

(1) John met a unicorn.

Is (1) false because unicorns don’t exist?

(2) John met a unicorn in my dream.

How does “in my dream” change things?

Some examples to worry about…

John thought the book to Mary

John's growth of tomatoes

Sue walked in an hour

Bob shelved the windowsill with the book

Bob buttered the margarine onto the bread

Where to put the information about this???

What <u>is</u> the information about this???

Words appear in a very wide variety of constructions

He sirened her down.

The car sirened its way to NY.

She sirened Bill the message.

...

Fantasy:

VP → V142 PP

V142 → siren

A more flexible approach needed!

Does lexicon hold Subcategorization information?

(Chomsky 1965)

- Verbs have classes:

  John ate a tomato.

  A tomato was eaten.

  John resembled a tomato.

  ? A tomato was resembled.

  You have seen this in your labs!

- Use features:
  +animate, -passive, +male, +human, …
  - If we allow +human, then do we allow +good-to-eat-with-chicken?
  - Wait: where are the restrictions on these features?
  - Major problem: Blank check on features

Does lexicon hold ‘thematic roles’?

- “Who does what to whom”
- Link syntactic <u>positions</u> to <u>thematic roles</u>
- Thematic roles: Agent, Affected Object, Beneficiary, Goal, Theme (where does this list come from?)
- Example: eat

  Agent(*x*) & Theme(*y*) & Eat(*e*, *x*, *y*)

Problem: ‘rules’ linking thematic roles to structure recovered by parser can vary enormously (which is why we said before we couldn’t eliminate it from the lexicon)

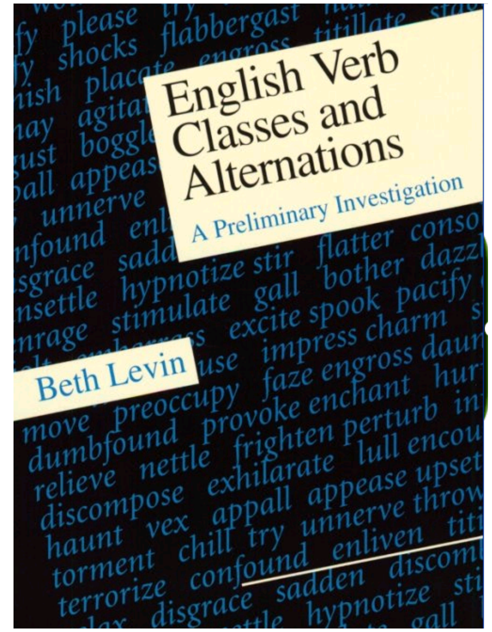
Examples: *John climbed the mountain; Who married Martha; John ate an apple; etc.*

If so…

- Then lexicon holds the subcategorization information, thematic roles <u>and</u> ‘linking rules’

- What else?

Does Lexicon hold semantically grounded classes?
(lexical-semantic structure)



- +motion +contact –effect
- Hit, touch, break, cut classes

Any notion that rules apply blindly without paying attention to “semantics” is pure wishful thinking. The question is <u>how much attention</u>.

Levin classes (3100 verbs)

- 47 top level classes, 150 second and third level
- Based on pairs of syntactic frames.

  John broke the jar. / Jars break easily. / The jar broke.

  *John cut the bread. / Bread cuts easily. / *The bread cut.*

  *John hit the wall. / *Walls hit easily. / *The wall hit.*
- Reflect underlying semantic components

  contact, directed motion,

  exertion of force, change of state
- Synonyms, syntactic patterns, relations

Other alternation examples

- Causative/inchoative
  The window broke
  John broke the window
  The rabbit suddenly appeared
  **The magician appeared the rabbit*

- Benefactive:
  Sue carved a toy out of wood for Hansel
  Sue carved Hansel a toy out of wood
  Sue carved some wood into a toy for Hansel
  **Sue carved Hansel some wood into a toy*

- Middle formation:
  The whale frightens easily
  **The whale sees easily*

Lexical-semantic structure

- Instead of:
  Agent(x) & Theme(y) & Eat(e, x, y)
- We have:
  CAUSE([Thing i], GO([Thing j], IN-MOUTH-OF([Thing i]))

Lexical semantic Structure

- Each node contains:
  - Primitive:
    - CLOSED CLASS: GO, STAY, BE, ON, IN, AT…
    - OPEN CLASS: JOHN, RUN-INGLY, …
  - Field: Analogy to motion/position in Localist approach: LOCATIONAL, POSSESSIONAL, TEMPORAL,…
  - Type: EVENT, STATE, PATH, POSITION, MANNER…

Event structure – a fuller picture

- **/Bob put –ed the book on the shelf/**

```
(cause :agent (bob) :effect (go :theme (book)
       :path (path :oper (on) :terminal+ (shelf))):tense
                                                  past))
```

- **/What did Bob put on the shelf/**

```
(cause :agent (bob) :effect (go :theme (? (what))
       :path (path :oper (on) :terminal+ (shelf))) :tense

    past))
```

- **/What did Bob put the book on/**

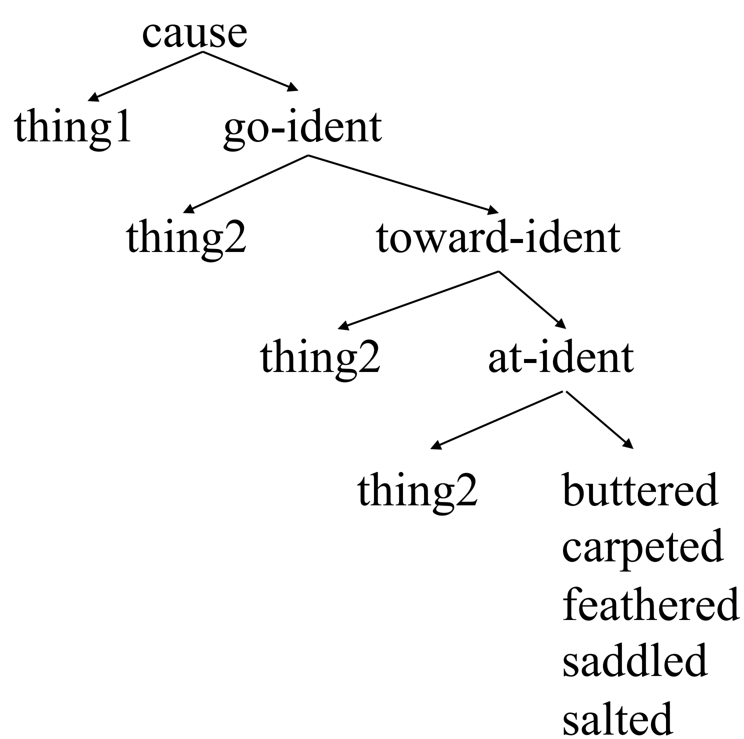
```
(query :event (cause :agent (bob) :effect (go :theme (book)
       :path (path :oper (on) :terminal+ (? (what)))) :tense
                                                  past))
```

- **/Where did Bob put the book/**

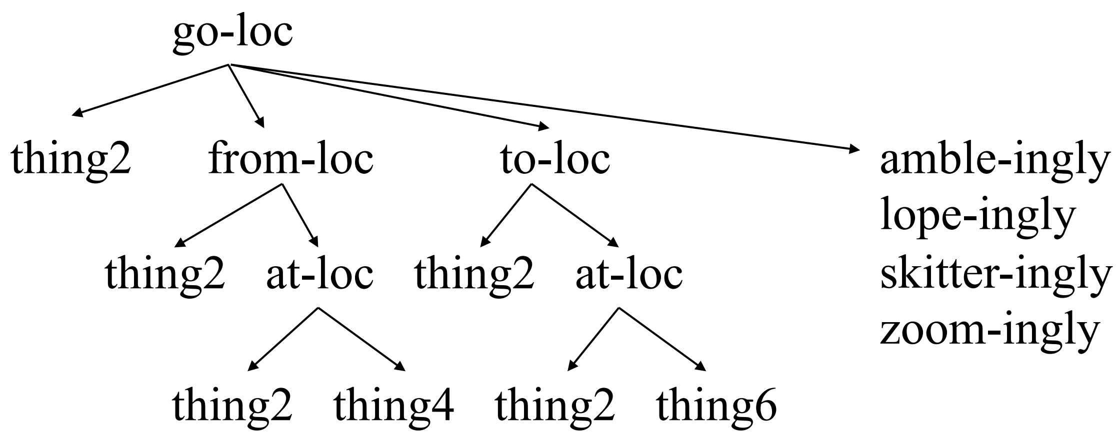
```
(query :event (cause :agent (bob) :effect (go :theme (book)
     :path (path :oper () :terminal+ (? (where)))) :tense
```

Structural vs. Content Meaning

- Verbs in a class share <u>structural</u> component
- Verbs in a class are distinguished by <u>content</u> component



Structural vs. Content Meaning



Common objections

Definition = Structure + Plus X, for <u>unknown</u> X

- Consider paint, water, butter, …:
  - She painted a house, he watered a plant, he buttered bread
- Claim: Structure is “put N on X” (Hale &Keyser 2003)
- Plus X: (story about putting)

<u>Undefinable</u> primitives:

(1) Thematic Roles: Agent, Patient, Goal, …

Remedy: Define/derive them <u>structurally</u> (Hale & Keyser 2003)

(2) Lexical Semantic Primitives: CAUSE, GO, BE, HAVE, ..

Remedy: Decompose them even more (Jackendoff 1991, 1996)

Review: What does the lexicon look like?

- Examples:

  *Bob put. *Bob put butter.

  Bob put butter on the bread.

  Butter was put on the bread

  What was put on the bread?

  Where was the butter put?
- Traditional view - encode in rules with ‘vanilla’ nonterminals

What does the lexicon look like? Ans 1 (traditional): use lots of rules, essentially exhaustive listing

- VP → V9 NP $PP_{LOCATIVE}$ V9 → put
- VP → was VPass ; VPass → V9 $PP_{LOCATIVE}$
- VP/NP → V9 NP/NP $PP_{LOCATIVE}$
- VP/NP → V9 NP $PP_{LOCATIVE}$/NP
- $PP_{LOCATIVE}$ → $P_{LOCATIVE}$ NP ; $P_{LOCATIVE}$ → on | in |..
- $PP_{LOCATIVE}$/NP → $P_{LOCATIVE}$ NP/NP

Lexical-semantics

- **[Put V NP$_j$ PP$_k$ CAUSE([BOB]$_i$,GO([BUTTER]$_j$, TO([BREAD]$_k$)))]**

- Semantic templates mirrors alternation patterns, but are ad-hoc
- Syntax a bit simpler w/ the semantic types factored out

Hypothesis 2: Lexicon Contains Selection Criteria

`/shelf/` has $\mathbf{p}_{\mathrm{LOCATION}}$ *selection* in lexicon ($=\mathbf{p}_{\mathrm{LOCATION}}$ $=$**`d(et) V`**)

Also: **`/shelf/`** **is** $\mathbf{n}_{\mathrm{LOCATION}}$

`/butter/` has $\mathbf{p}_{\mathrm{LOCATUM}}$ *selection* in lexicon ($=\mathbf{p}_{\mathrm{LOCATUM}}$ $=$**`d(et) V`**)

Also: **`/butter/`** is $\mathbf{n}_{\mathrm{LOCATUM}}$

So then the Lexicon cannot derive:

* 1. Bob shelved the windowsill with the book.

* 2. Bob buttered the margarine onto the bread.

Information about butter and shelf – where is it located?

Hypothesis 3: Encyclopedia vs. Lexicon

Does Encyclopedia holds knowledge 'rejecting' the following “GRAMMATICAL” sentences? Or does the lexicon?

John thought the book to Mary

John's growth of tomatoes
Sue walked in an hour
Bob shelved the windowsill with the book.
Bob buttered the margarine onto the bread.

2 Language Acquisition Problems: Lexicon vs Encyclopedia

ROOT	LEXICON ENTRIES
`/shelf/`	n, =p =d V_{+cause}
`/butter/`	n, = =d V_{+cause}
`/into/`	=d +k p
`/with/`	=d +k p

LEXICON ACQUISITION:

How do LEXICAL roots
get assigned to feature set?

ROOT		ENCYCLOPEDIA ENTRIES
`/shelf/`		$n_{LOCATION}$, $=p_{LOCATION}$ =d V
`/butter/`		$n_{LOCATUM}$, $=p_{LOCATUM}$ =d V
`/into/`		=d +k $p_{LOCATION}$
`/with/`		=d +k $p_{LOCATUM}$

ENCYCLOPEDIA ACQUISITION:

How do ENCYCLOPEDIA roots
get assigned to feature set?

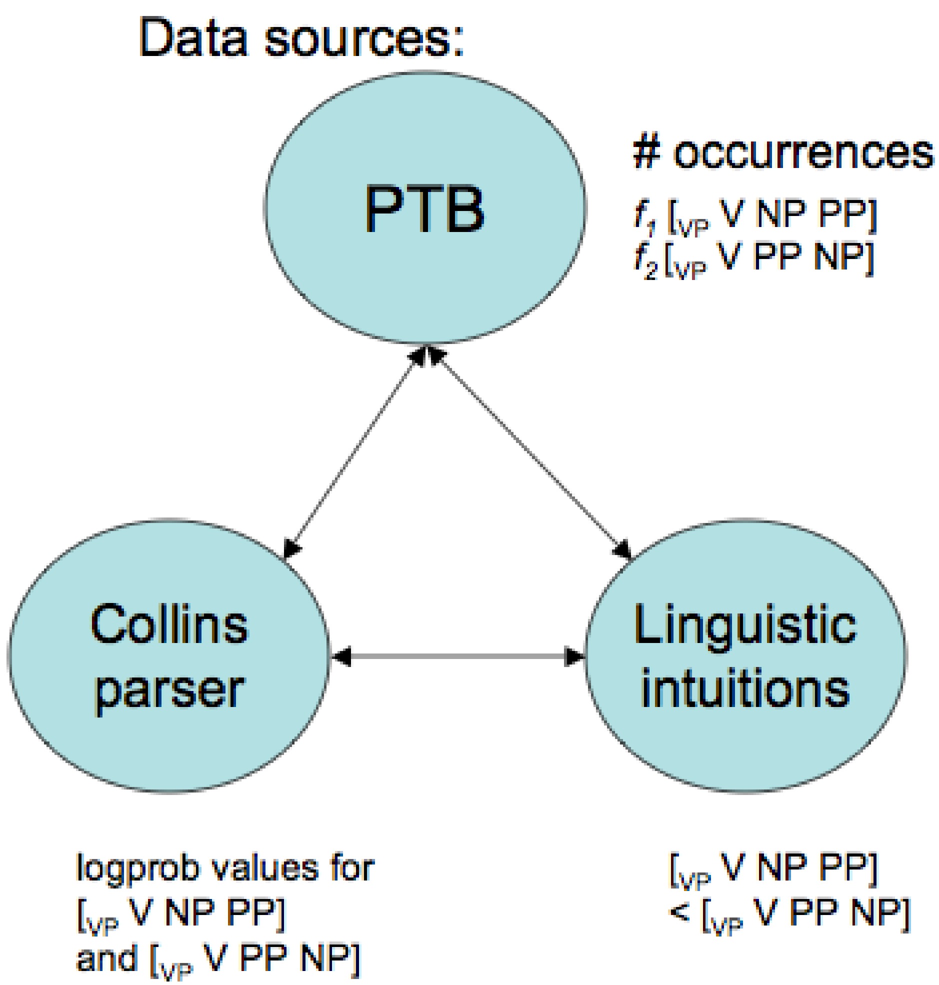
The question

- What generalizations has the parser made from being trained on the Penn Tree Banks?
- Are these the right generalizations?

Testing the parser

- Look at verbs in an alternation class (which is 'semantically' and syntactically coherent
- Find the –logprobs for the alternations, including the 'ungrammatical' ones
- Do these match up with intuitions and expectations from frequencies in the Penn Tree Bank?

- *What would you expect the Collins parser to say about a set of alternations?*
  - $[_{VP}$ V NP PP$]$
  - $[_{VP}$ V PP NP$]$



- ***join*** belongs to section 22.1 *Mix verbs*
- Syntactic frames:
  - 84 NP
  - 11 NP PP
  - 1 NP-and (together)
  - 7 PP
  - 8 []
  - ADJ PP-with
  - ADJ (together)

22 Verbs of Combining and Attaching

References: Condoravdi and Sanfilippo (1990), Gentner (1978)

These verbs are all related to combining or attaching. Their hallmark is participation in the simple reciprocal alternations, the *together* reciprocal alternations, or both. Members of this class are never found in the *apart* reciprocal alternations. The various subclasses differ according to whether the meanings of their members involve a result or means component.

22.1 *Mix* Verbs

Class Members:
with: blend, combine, commingle, concatenate, connect, fuse, join, link, merge, mingle, mix, pool
into: blend, cream, mix
to: add, connect, join, link, network

Properties:

(313) Simple Reciprocal Alternation (transitive):
a. Herman mixed the eggs with the cream. (prepositional variant)
b. Herman mixed the eggs and the cream. (reciprocal variant)

(314) Simple Reciprocal Alternation (intransitive; most verbs):
a. The eggs mixed with the cream.
b. The eggs and the cream mixed.

(315) *Together* Reciprocal Alternation (transitive):
a. Herman mixed the eggs with the cream.
b. Herman mixed the eggs and the cream together.

(316) *Together* Reciprocal Alternation (intransitive; most verbs):
a. The eggs mixed with the cream.
b. The eggs and the cream mixed together.

(317) Causative/Inchoative Alternation (most verbs):
a. I mixed the soap into the water.
The soap mixed into the water.
b. I mixed the soap and the water.
The soap and the water mixed.

(318) Middle Alternation:
a. I mixed the eggs with cream.
Eggs mix well with cream.
b. I mixed the eggs and cream (together).
Eggs and cream mix well (together).

Ps

22 Verbs of Combining and Attaching

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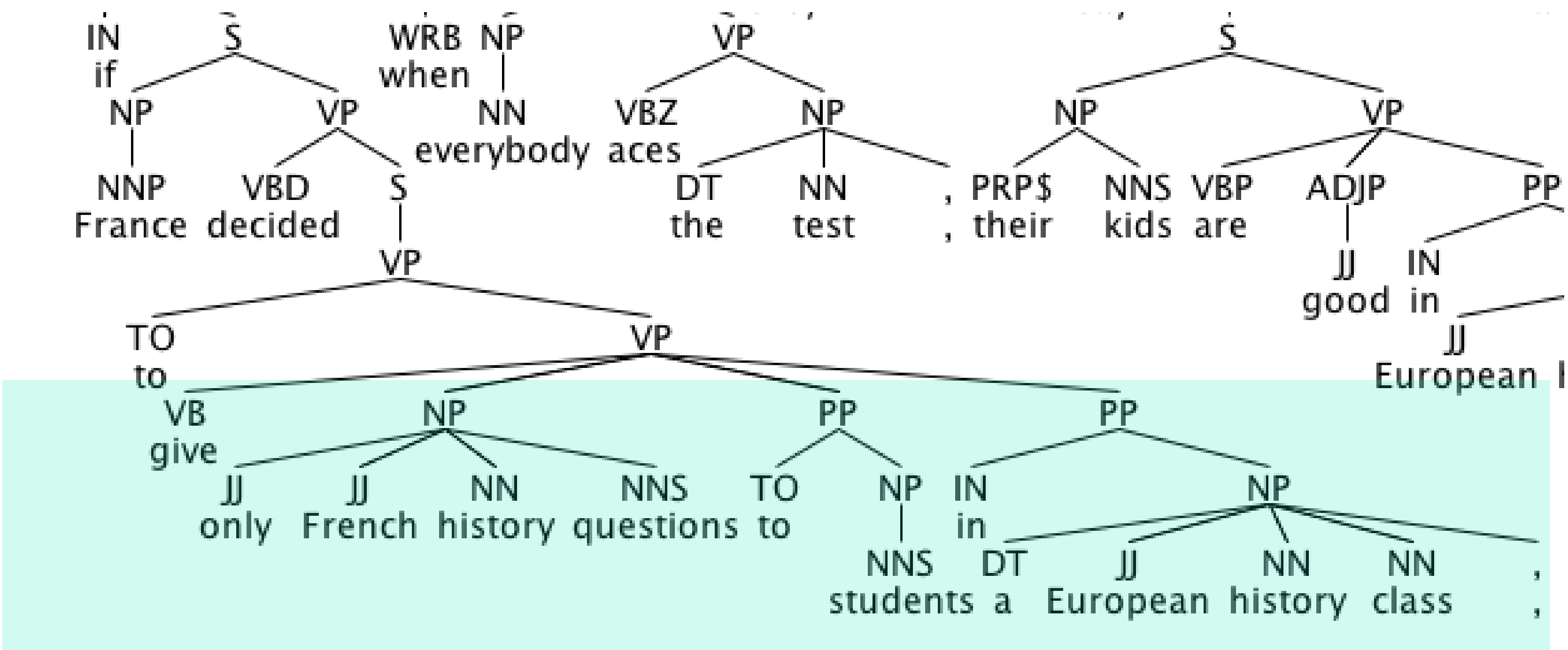
  a. I mixed the soap into the water.
  b. The soap mixed into the water.

Finding phrase patterns in corpora using nltk: VP PP NP

```
from mit.six863.parse.treebank import *
from string import join

def demog():
  give = lambda t: t.node == 'VP' and len(t)> 2
         and t[1].node == 'NP'\
         and (t[2].node == 'PP-DTC' or t[2].node == 'NP')\
         and ('gave' in t[0].leaves() or 'give' in t[0].leaves())
  for tree in g.parsed():
      for t in g.subtrees(give):
          print "%s [%s: %s] [%s: %s]" %\
                (join(t[0].leaves()),
                 t[1].node, join(t[1].leaves()),
                 t[2].node, join(t[2].leaves()))
```

‘give NP to PP’, sentence 824



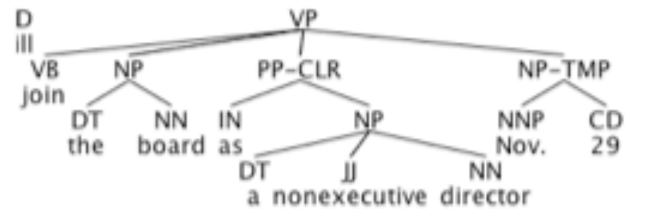
‘Give’ NP NP vs. NP PP-DTV

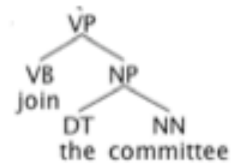
- 256 total give NP NP or NP PP-DTV in PTB
- 205 are NP NP 80%
- 51 are NP PP-DTV 20%

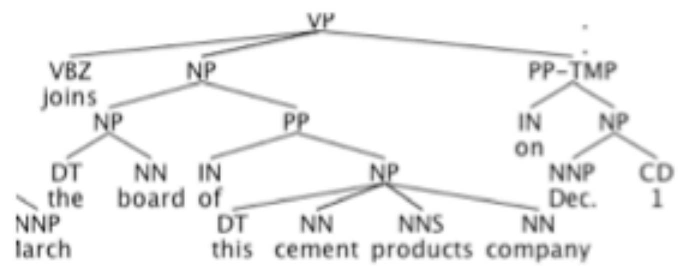
- Which frame is therefore going to be preferred?

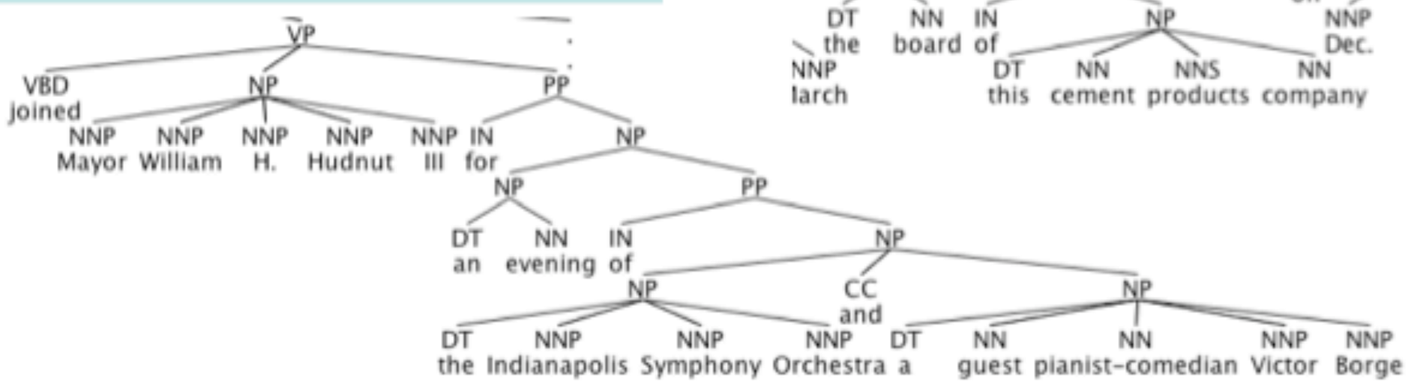
The verb “join”

- Look for VP nodes that:
  - immediately dominates VB*, and
  - that VB* is the 1st child









Matches (143)

1 join [NP,PP-CLR,NP-TMP]
76 joined [NP,PP]
486 join [NP]
488 join [NP]
952 join [NP]
993 joined [NP]
1219 joins [NP,PP-TMP]
1877 joined [NP]
1940 joining [NP,PP]
2189 joined [NP,PP-TMP]
2370 joins [NP,PP-CLR]
2401 joining [NP,PP-LOC]
2417 joining [NP,PP-CLR]
3983 joining [PP-CLR,PP-LOC]
4131 join [NP]
5027 join [NP]
5421 joined [NP,PP-TMP]
5708 joining [NP]
5710 joins [NP-TMP,,,S-ADV]
5824 joins [PRT,PP-CLR]
6044 joined [NP,PP-TMP]
6849 joined [NP]
7274 join [NP]
7673 joined [NP]
8500 joined [PP-LOC,S-PRP]
8850 joined [NP,ADVP-TMP]
8965 joined [NP]
9198 join [NP]
9213 join [NP]
9926 joins [NP,PP]
10440 joining [NP]
10443 join [NP]
10625 join [NP]
11556 joining [PP-TMP,S-PRP]
11601 joining [NP,ADVP-MNR,NP-TMP]
11625 join [SBAR-TMP]
11626 join []
12388 joined [NP]
12691 joined [NP-CLR,PP-CLR]
12842 joining [NP]
13055 joined [NP,PP]
14346 joined [ADVP-CLR,S-PRP]
14367 joining [NP,PP-TMP]
14723 join [NP]
14822 joining [NP,PP-TMP]
15150 joins [NP]
15406 joined [NP,PP-CLR,ADVP-TMP]
15466 join [NP]
15958 joined [NP,SBAR-TMP]
16113 joined [NP,PP-LOC]
16260 join [NP]
16402 join [NP]
16404 join [NP,PP]
16409 joining [SBAR-NOM]
16753 joined [NP,PP-LOC]
16916 joined [NP,PP]
16946 joined [NP,PP]
17225 join [NP,PP]
17641 join [NP]
18112 joined [NP]
18171 joined [NP]
18192 join [NP]
18521 join [PRT]
18539 joined [NP,PP-TMP]
18706 join [PP-CLR]
19135 joining [NP]
19489 join [NP]
19879 joined [NP]
19880 join [NP]
20028 join [NP-TMP]
20205 joining [NP,ADVP-TMP]
20525 joined [NP,ADVP-TMP]
21224 joined [PP-CLR,PP]
22092 joins [PP-CLR]
22339 joining [NP,PP]
22342 join [PP-CLR]
22356 joining [PRT,PP-CLR]
22678 join [NP]
23601 joined [NP,ADVP-TMP]
23618 joining [NP,PP-TMP]
23877 joined [NP]
24657 join [NP,ADVP-TMP,ADVP-PRP]
24764 joined [NP,PP,PP-TMP]
24829 join [NP]
24842 join []
24872 joined [PP-CLR,S-CLR]
26730 joined [NP,PP-TMP]
26853 joining [NP,PP-TMP]
27866 join [NP,PP,NP-TMP]
27870 join [NP,PP-LOC]
28102 joined [NP,PP]
28112 joins [NP,,,PP]
28942 join [NP]
29092 join [NP]
29616 joined [NP,PP-CLR,PP-LOC]
30526 join [NP,ADVP]
30808 joining [NP]
30981 joined [NP,PP]
31252 join [NP]
33830 joined [NP]
33954 joining [NP]
33958 joining [NP]
34093 joined [NP]
34802 join [NP,PP]
35906 joined [NP,,,S-ADV]
36282 join [NP]
36374 join [NP,PP-LOC]
36378 joined [NP]
36380 joining [NP,PP-TMP]
36694 joined [NP]
37056 join []
37167 joined [PP]
37799 joining [NP,PP-TMP,PP]
37840 joined [PP-CLR,PP]
38274 joining [NP]
38625 joined [NP]
39239 joined [NP,PP]
39289 joined [NP,PP,PP-TMP,,,PP-TMP]
39294 join [NP]
41201 join [NP,PP]
41219 join [NP]
41380 joined [NP,PP-TMP,PP]
42006 joining [NP]
42175 joined [NP]
42325 joined [PP-TMP,PP-CLR]
42850 join [NP]
42878 joined [NP,PP-LOC]
43738 joined [NP,PP-LOC]
43745 joined [NP]
44619 joined [NP,PP-CLR]
45432 joined [NP,PP-CLR,PP-TMP,ADVP-TMP]
46079 joins [NP]
46105 joins [NP,PP]
46400 joining [NP,PP-TMP,S-PRP]
46765 join [NP]
46766 join [NP,,,PP]
46779 joined [NP,PP-LOC]
47026 join [NP]
48519 join [PP-CLR,S-PRP]
48647 joining [NP,PP]
48779 join [NP,PP,PP-TMP]
48783 joined [NP,PP-CLR]
48809 joining [NP]

Caveats

- Some verbs have multiple senses
- Not all instances of a category label hold the same ‘semantic’ or ‘thematic’ role
- To be completely accurate, we’d have to review each and every tree and label each node with a semantic role, very carefully
- But as a first approximation, let’s conflate category labels

Patterns (39)

- 1 [NP,PP-CLR,NP-TMP]
- 1 [PP-CLR,PP-LOC]
- 1 [NP-TMP,,,S-ADV]
- 1 [PP-LOC,S-PRP]
- 1 [PP-TMP,S-PRP]
- 1 [NP,ADVP-MNR,NP-TMP]
- 1 [SBAR-TMP]
- 1 [NP-CLR,PP-CLR]
- 1 [ADVP-CLR,S-PRP]
- 1 [NP,PP-CLR,ADVP-TMP]
- 1 [NP,SBAR-TMP]
- 1 [SBAR-NOM]
- 1 [PRT]
- 1 [NP-TMP]
- 3 [PP-CLR]
- 2 [PRT,PP-CLR]
- 4 [NP,ADVP-TMP]
- 1 [NP,ADVP-TMP,ADVP-PRP]
- 1 [PP-CLR,S-CLR]
- 1 [NP,PP,NP-TMP]
- 1 [NP,PP-CLR,PP-LOC]
- 1 [NP,ADVP]
- 1 [NP,,,S-ADV]
- 11 [NP,PP-TMP]
- 3 []
- 1 [PP]
- 2 [PP-CLR,PP]
- 1 [NP,PP,PP-TMP,,,PP-TMP]
- 2 [NP,PP-TMP,PP]
- 1 [PP-TMP,PP-CLR]
- 1 [NP,PP-CLR,PP-TMP,ADVP-TMP]
- 1 [NP,PP-TMP,S-PRP]
- 2 [NP,,,PP]
- 8 [NP,PP-LOC]
- 1 [PP-CLR,S-PRP]
- 16 [NP,PP]
- 2 [NP,PP,PP-TMP]
- 4 [NP,PP-CLR]
- 58 [NP]

Delete ‘TMP’ nodes

- Why?
- Temporal PPs, etc.

Patterns (27)

- 1 [PP-CLR,PP-LOC]
- 1 [,,S-ADV]
- 1 [PP-LOC,S-PRP]
- 1 [S-PRP]
- 1 [NP,ADVP-MNR]
- 1 [NP-CLR,PP-CLR]
- 1 [ADVP-CLR,S-PRP]
- 1 [SBAR-NOM]
- 1 [PRT]
- 2 [PRT,PP-CLR]
- 1 [NP,ADVP-PRP]
- 1 [PP-CLR,S-CLR]
- 1 [NP,PP-CLR,PP-LOC]
- 1 [NP,ADVP]
- 1 [NP,,,S-ADV]
- 5 []
- 1 [PP]
- 2 [PP-CLR,PP]
- 1 [NP,PP,,]
- 4 [PP-CLR]
- 1 [NP,S-PRP]
- 2 [NP,,,PP]
- 8 [NP,PP-LOC]
- 1 [PP-CLR,S-PRP]
- 21 [NP,PP]
- 7 [NP,PP-CLR]
- 74 [NP]

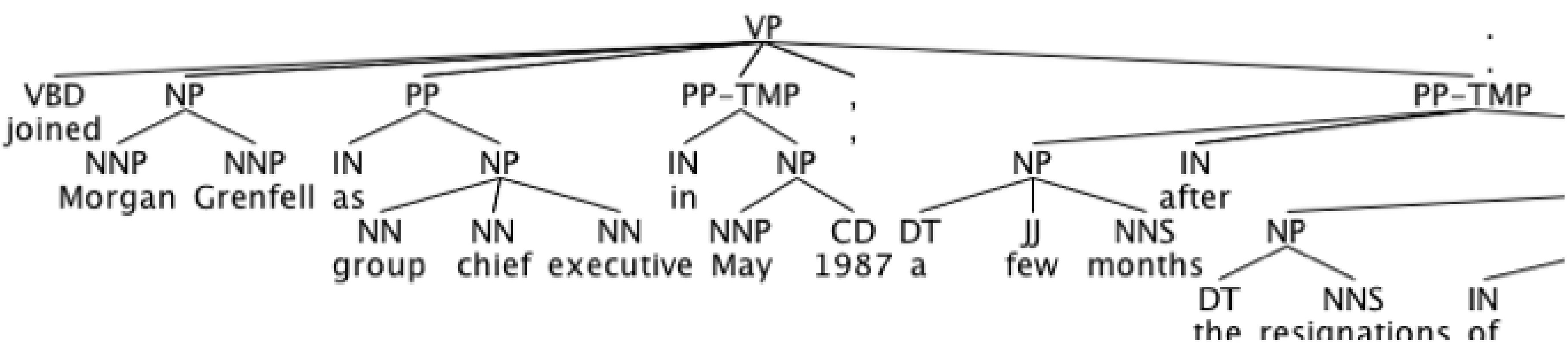
1 [NP,PP,,]

- 1 [NP,PP,,]
- 1 [NP,PP,PP-TMP,,,PP-TMP]

Delete the extra ‘commas’

Case 39289

- Mr. Craven joined Morgan Grenfell as group chief executive in May 1987 , a few months after the resignations of former Chief Executive Christopher Reeves and other top officials because of the merchant bank 's role in Guinness PLC 's controversial takeover of Distiller 's Co. in 1986 .



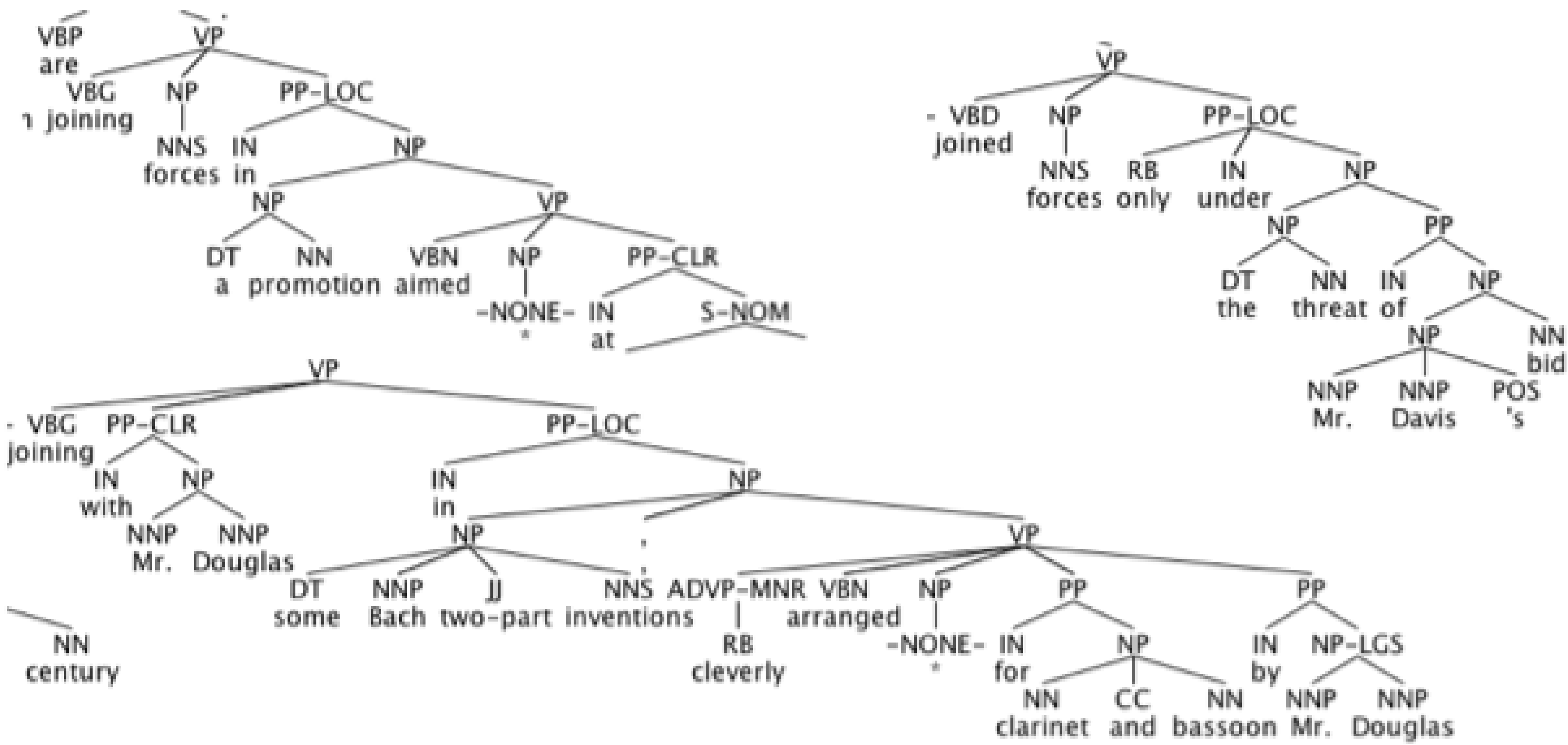
[$_{VP}$ *joined* NP PP PP-TMP , PP-TMP]

Patterns (25)

- 1 [PP-CLR,PP-LOC]
- 1 [S-ADV]
- 1 [PP-LOC,S-PRP]
- 1 [S-PRP]
- 1 [NP,ADVP-MNR]
- 1 [NP-CLR,PP-CLR]
- 1 [ADVP-CLR,S-PRP]
- 1 [SBAR-NOM]
- 1 [PRT]
- 2 [PRT,PP-CLR]
- 1 [NP,ADVP-PRP]
- 1 [PP-CLR,S-CLR]
- 1 [NP,PP-CLR,PP-LOC]
- 1 [NP,ADVP]
- 1 [NP,S-ADV]
- 5 []
- 1 [PP]
- 2 [PP-CLR,PP]
- 4 [PP-CLR]
- 1 [NP,S-PRP]
- 8 [NP,PP-LOC]
- 1 [PP-CLR,S-PRP]
- 24 [NP,PP]
- 7 [NP,PP-CLR]
- 74 [NP]

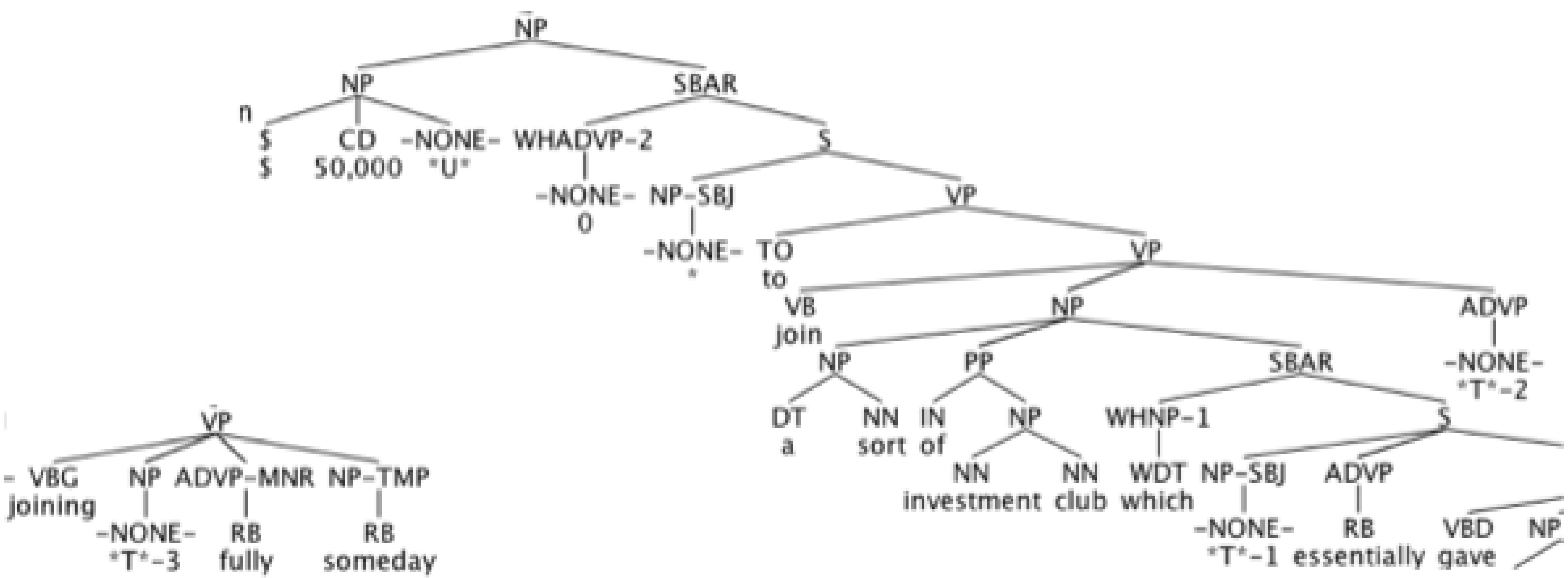
PP-LOC

- Cases 2401, 3983 and 43738



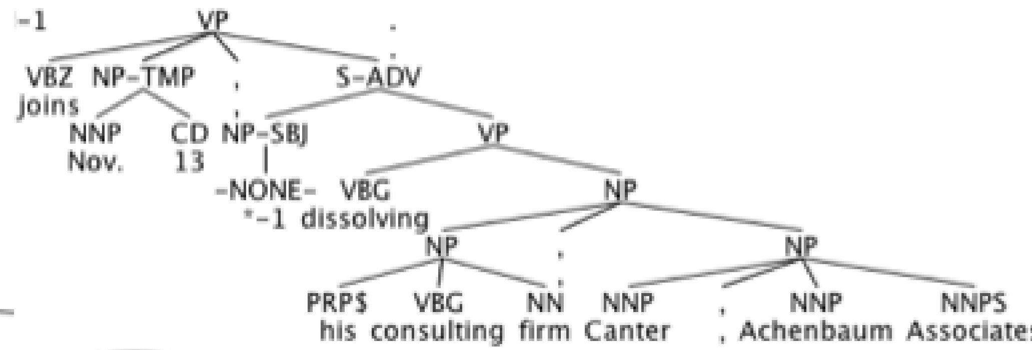
ADVP and -MNR

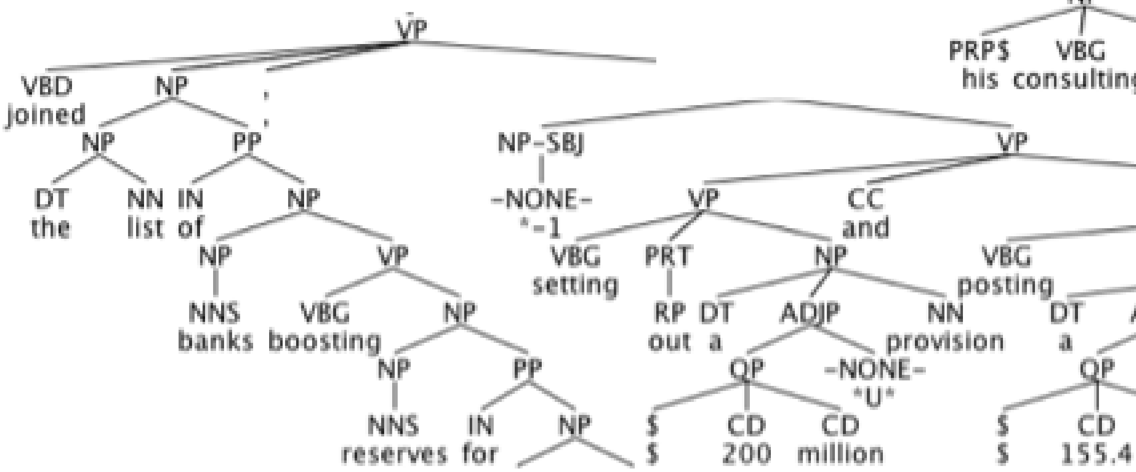
- Cases 11601 (ADVP-MNR) and 30526 (ADVP)



-ADV

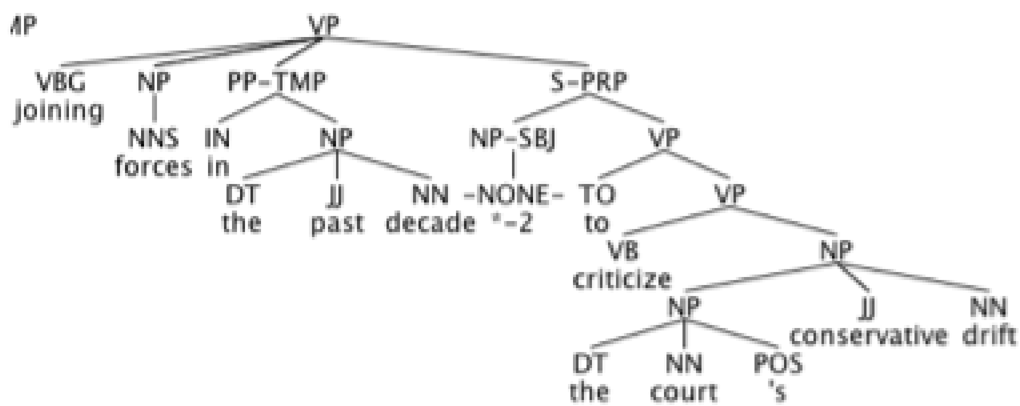
- adverbial
- Cases 5710 (S-ADV) and 35906 (S-ADV)





-PRP

- purpose
- Case 46400 (S-PRP)



Patterns

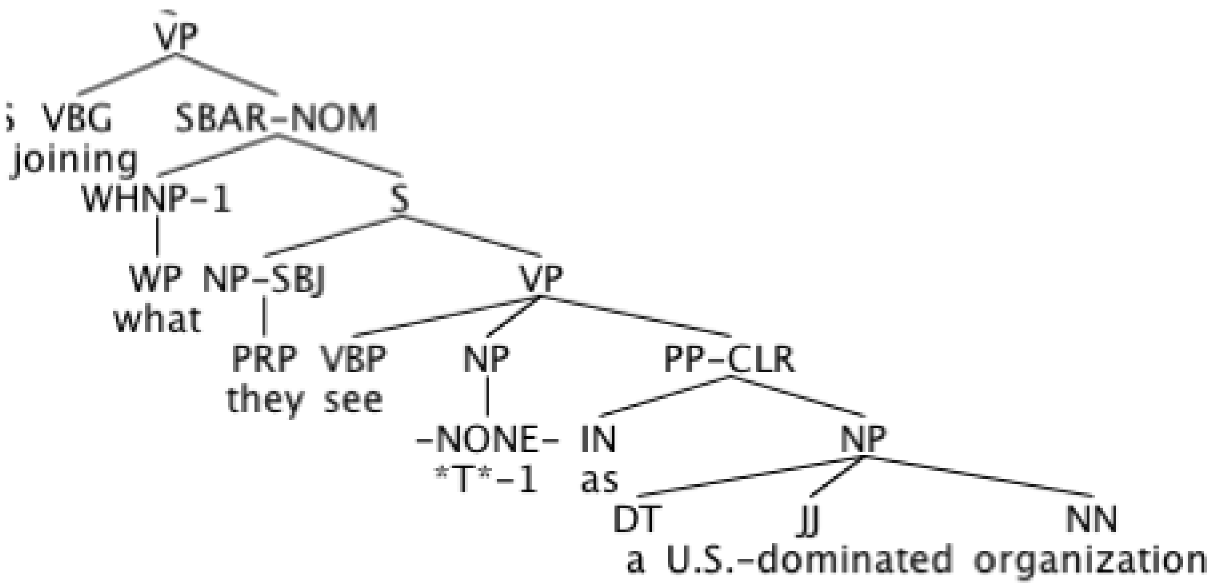
- Delete ADV(P), -LOC, -MNR, _PRP
  - 1 [NP-CLR,PP-CLR]
  - 1 [SBAR-NOM]
  - 1 [PRT]
  - 2 [PRT,PP-CLR]
  - 1 [PP-CLR,S-CLR]
  - 9 []
  - 1 [PP]
  - 2 [PP-CLR,PP]
  - 6 [PP-CLR]
  - 24 [NP,PP]
  - 8 [NP,PP-CLR]
  - 87 [NP]

- Delete ADV(P) but not anything with -CLR, -LOC, -MNR, _PRP
  - 1 [NP-CLR,PP-CLR]
  - 1 [ADVP-CLR]
  - 1 [SBAR-NOM]
  - 1 [PRT]
  - 2 [PRT,PP-CLR]
  - 1 [PP-CLR,S-CLR]
  - 8 []
  - 1 [PP]
  - 2 [PP-CLR,PP]
  - 6 [PP-CLR]
  - 24 [NP,PP]
  - 8 [NP,PP-CLR]
  - 87 [NP]

can't simply delete ADV everywhere

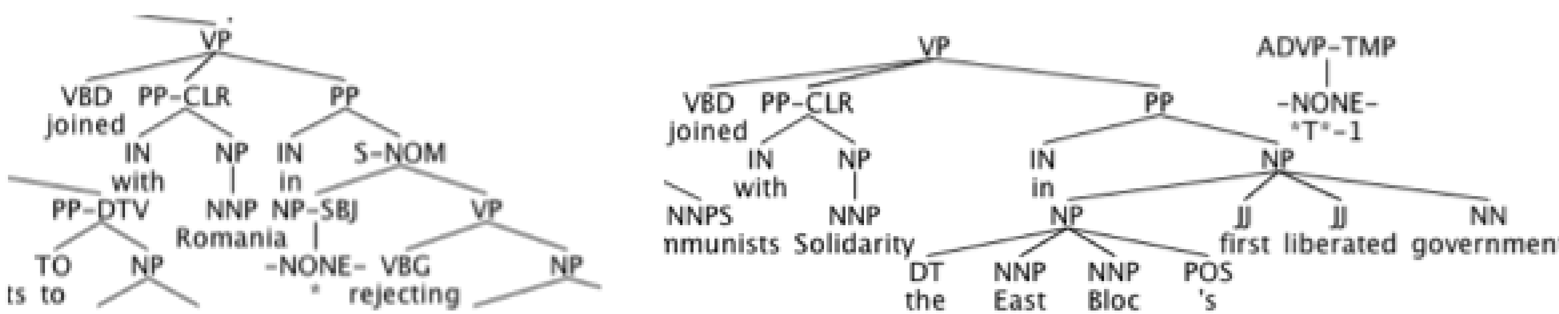
SBAR-NOM

- headless relative
- Case 16409



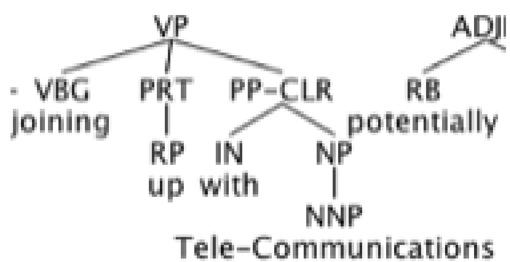
-CLR

- closely related ("*middle ground between arguments and adjuncts*")
- Cases 37840 and 21224 (PP-CLR PP)

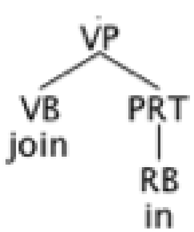


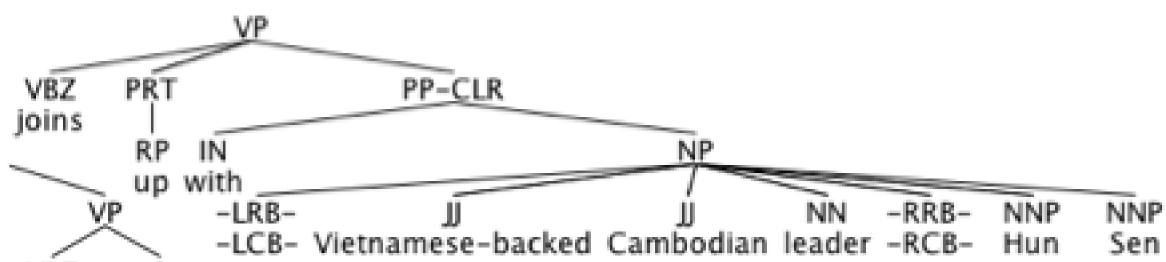
PRT

- particle
- Cases 18521, 22356 and 5824



do we treat
join up/in as
different from *join*?





- ***join*** belongs to section 22.1 *Mix verbs*
- Syntactic frames:
  - 84 NP
  - 11 NP PP
  - 1 NP-and (together)
  - 7 PP
  - 8 []
  - ADJ PP-with
  - ADJ (together)

22 Verbs of Combining and Attaching

References: Condoravdi and Sanfilippo (1990), Gentner (1978)

These verbs are all related to combining or attaching. Their hallmark is participation in the simple reciprocal alternations, the *together* reciprocal alternations, or both. Members of this class are never found in the *apart* reciprocal alternations. The various subclasses differ according to whether the meanings of their members involve a result or means component.

22.1 *Mix* Verbs

Class Members:

with: blend, combine, commingle, concatenate, connect, fuse, join, link, merge, mingle, mix, pool

into: blend, cream, mix

to: add, connect, join, link, network

Properties:

(313) Simple Reciprocal Alternation (transitive):
a. Herman mixed the eggs with the cream. (prepositional variant)
b. Herman mixed the eggs and the cream. (reciprocal variant)

(314) Simple Reciprocal Alternation (intransitive; most verbs):
a. The eggs mixed with the cream.
b. The eggs and the cream mixed.

(315) *Together* Reciprocal Alternation (transitive):
a. Herman mixed the eggs with the cream.
b. Herman mixed the eggs and the cream together.

(316) *Together* Reciprocal Alternation (intransitive; most verbs):
a. The eggs mixed with the cream.
b. The eggs and the cream mixed together.

(317) Causative/Inchoative Alternation (most verbs):
a. I mixed the soap into the water.
The soap mixed into the water.
b. I mixed the soap and the water.
The soap and the water mixed.

(318) Middle Alternation:
a. I mixed the eggs with cream.
Eggs mix well with cream.
b. I mixed the eggs and cream (together).
Eggs and cream mix well (together).

WSJ PTB vs. EVCA

- WSJ PTB
  - 1 [NP-CLR,PP-CLR]
  - 1 [ADVP-CLR]
  - 1 [PP-CLR,S-CLR]
  - 8 []
  - 1 [PP]
  - 2 [PP-CLR,PP]
  - 6 [PP-CLR]
  - 24 [NP,PP]
  - 8 [NP,PP-CLR]
  - 87 [NP]
- EVCA
  - NP PP-with
  - PP-with
  - []
  - NP-and (together)
  - ADJ PP-with
  - ADJ (together)
- **Note**: ADJ is JJ in PTB tagset

Further work on WSJ PTB

- WSJ PTB [ADVP-CLR]
  - Recently, *some 60 environmental and outdoor groups representing such divergent points of view as the Sierra Club, the League of Women Voters and the National Rifle Association* joined together to request a reassessment of the environmentally unsound Central Utah Project.

- EVCA
  - NP-and (together)

Further work on WSJ PTB

- PP-CLR for *join* always headed by *with*?
  - *in* 4
  - *with* 11
  - *as* 5

with is always a PP-CLR for *join*

- PP for *join* headed by?
  - *for* 1
  - *upon* 1
  - *by* 3
  - *on* 1
  - *from* 4
  - *in* 8
  - *as* 8

Further work on WSJ PTB

- Intransitive cases
- 37056,24842,20028, 11626,11625,11556, 8500,5710

  - other carriers to join
  - others to join
  - several other companies to join
  - to join
  - Britain would join SBAR-TMP
  - Several of the New York Stock Exchange's own listed companies, led by giant Contel Corp., are joining
  - most of the smaller makers joined [PP-LOC under the Microsoft Corp. umbrella]
  - he joins [NP-TMP Nov. 13th]

- What would you expect the Collins parser to say about the verb alternations?

- **Example**:
  - Collins parser is trained on the PTB
  - we might expect logprob rankings to reflect frequencies of the various VP frames in the PTB
  - *if they don't, why not?*
- **Example:**
  - do the logprob values reflect your personal intuitions or expectations about the sentences?
- **Example**:
  - are the differences between logprob values noise or significant?
  - e.g. -99.1/-99.7 vs. -99.1/-200.4
  - what is the general effect of sentence length?
  - e.g. *what is the typical penalty for adding a word to a sentence?*
  - e.g. are ungrammatical sentences assigned radically different logprobs?
  - e.g. can the Collins parser distinguish valid and invalid alternations for a given verb?

- What would you expect the Collins parser to say about the alternations?

- **Focus on discrepancies**:
  - Collins vs. PTB
  - Collins vs. Linguistic Intuition
  - PTB vs. Linguistic Intuition
- **Question:**
  - are the discrepancies regular or random?
  - e.g. one verb patterns one way, another a different way

A case study: *join, merge*

- "Bristol-Meyers agreed to merge with Sun Microsystems"
- "Boeing and Sun Microsystems agreed to merge"
- Which would be more likely? Which is more likely? Which 'should be' more likely (according to linguistic accounts)

Some counts

- join - 49 VB
- mix - 1
- water 114 NN
- 24 milk NN
- 14 toys NN
- 207 computers NNS

Some sentences

- John NNP mixed VBD the DT water NN and CC the DT milk NN
- John NNP mixed VBD the DT milk NN and CC the DT water NN
- John NNP mixed VBD the DT water NN with IN the DT milk NN
- John NNP mixed VBD the DT milk NN with IN the DT water NN

- John NNP joined VBD the DT water NN and CC the DT milk NN
- John NNP joined VBD the DT milk NN and CC the DT water NN
- John NNP joined VBD the DT water NN with IN the DT milk NN
- John NNP joined VBD the DT milk NN with IN the DT water NN

- John NNP joined VBD the DT water NN and CC the DT water NN
- John NNP joined VBD the DT water NN with IN the DT water NN
- John NNP joined VBD the DT computers NNS and CC the DT computers NNS
- John NNP joined VBD the DT computer NNS with IN the DT computer NNS

The envelope please…

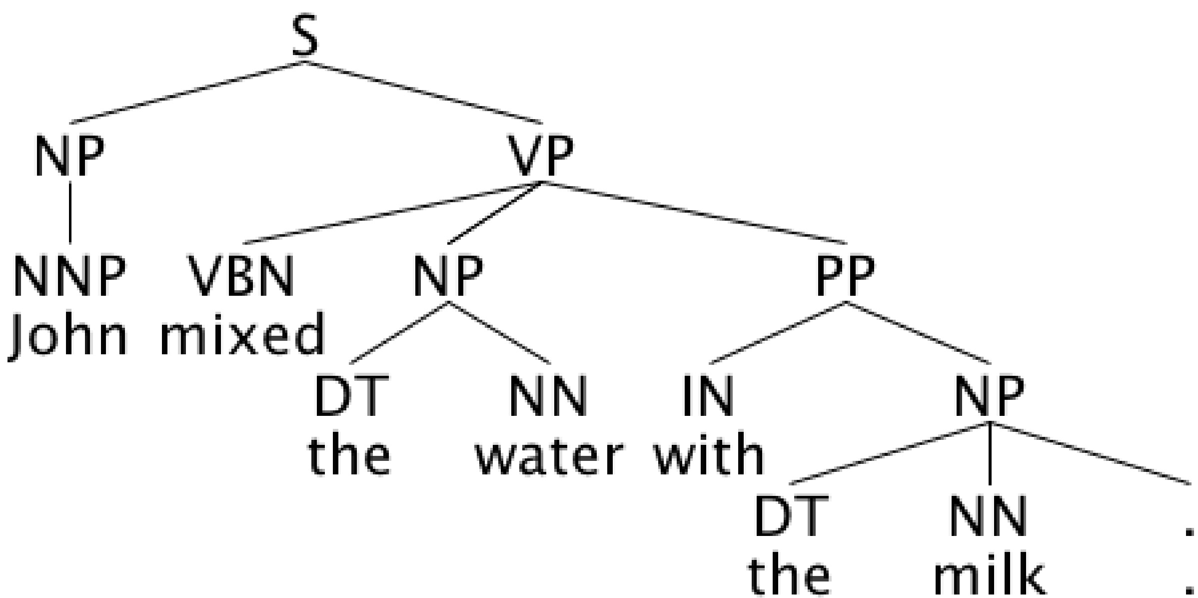
	–log prob: (closer to 0 = more likely)
• J. mixed the water and the milk	–55.6292
• J. mixed the milk and the water	–54.307
• J. mixed the water with the milk	–54.3957
• J. mixed the milk with the water	–51.2094
• J. joined the water and the milk	–48.4139
• J. joined the water with the milk	–46.1579
• J. joined the milk with the water	–46.1015
• J. joined the water with the milk	–43.0599

And more

- John joined the computers and the computers –39.699
- John joined the computers with the computers –43.054
- John joined the milk and the milk –48.0987
- John joined the milk with the milk –46.3324

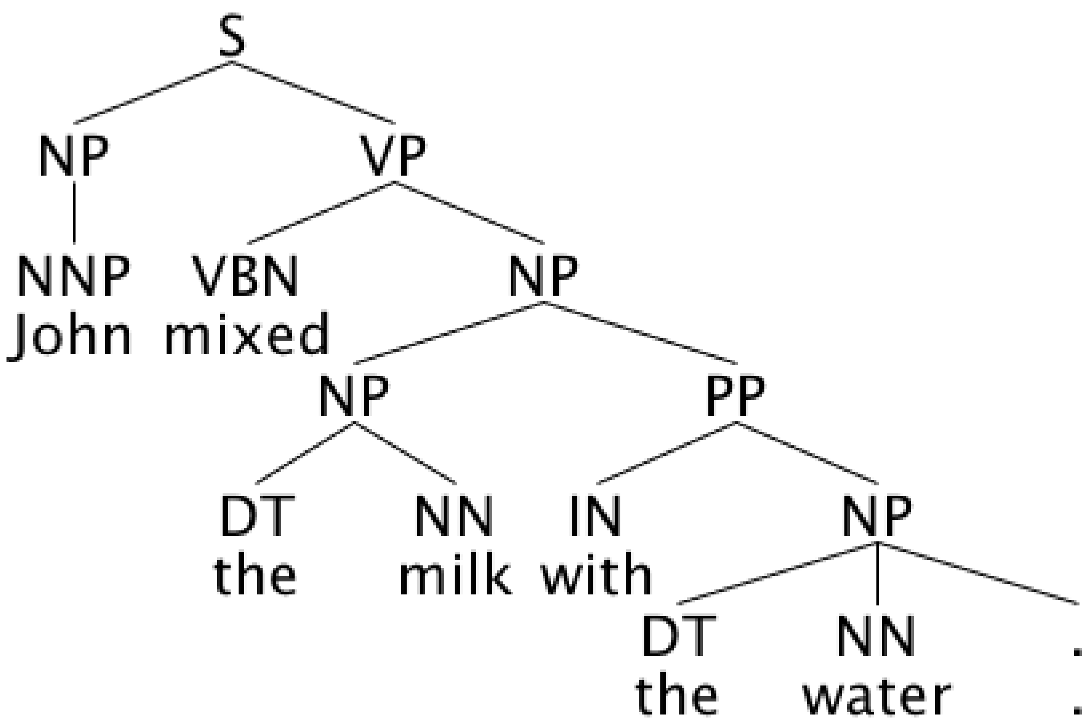
First of all…

- John mixed the water with the milk



Then

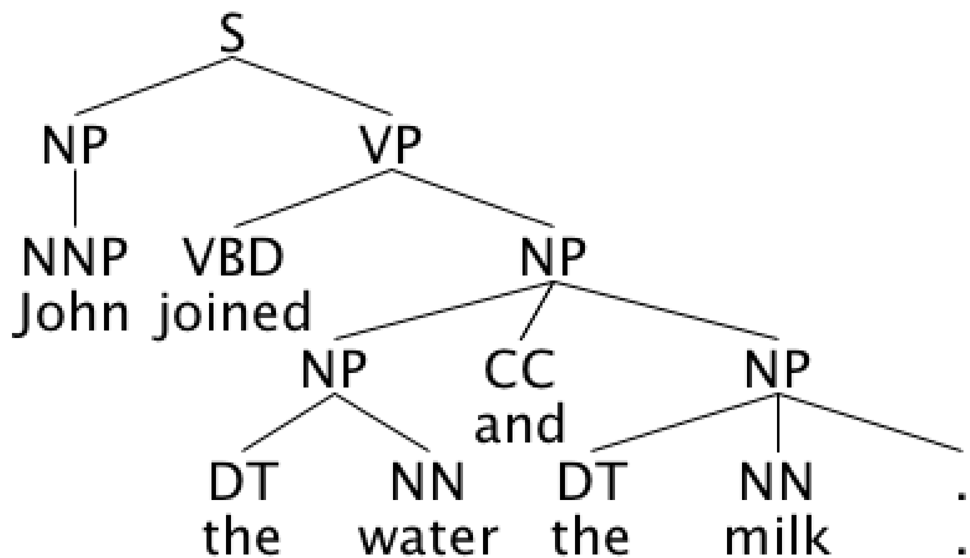
- John mixed the milk with the water



Hmm… what about ‘mixed’? Try ‘join’

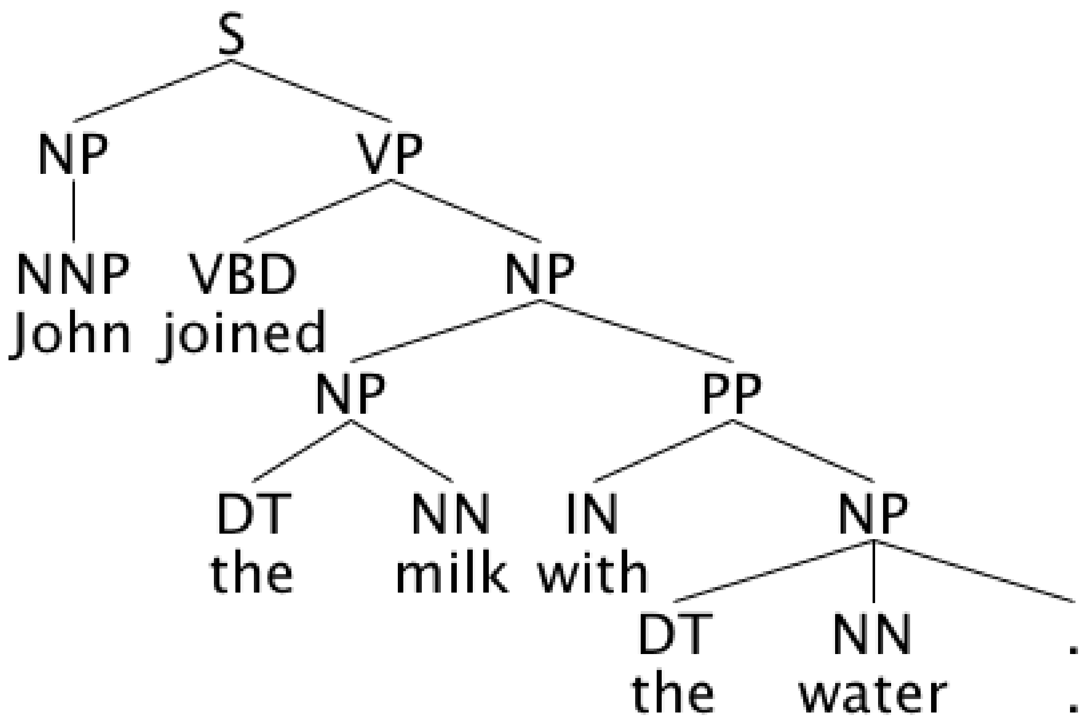
‘Join’

- J. joined the water and the milk



‘Join’

- John joined the milk with the water

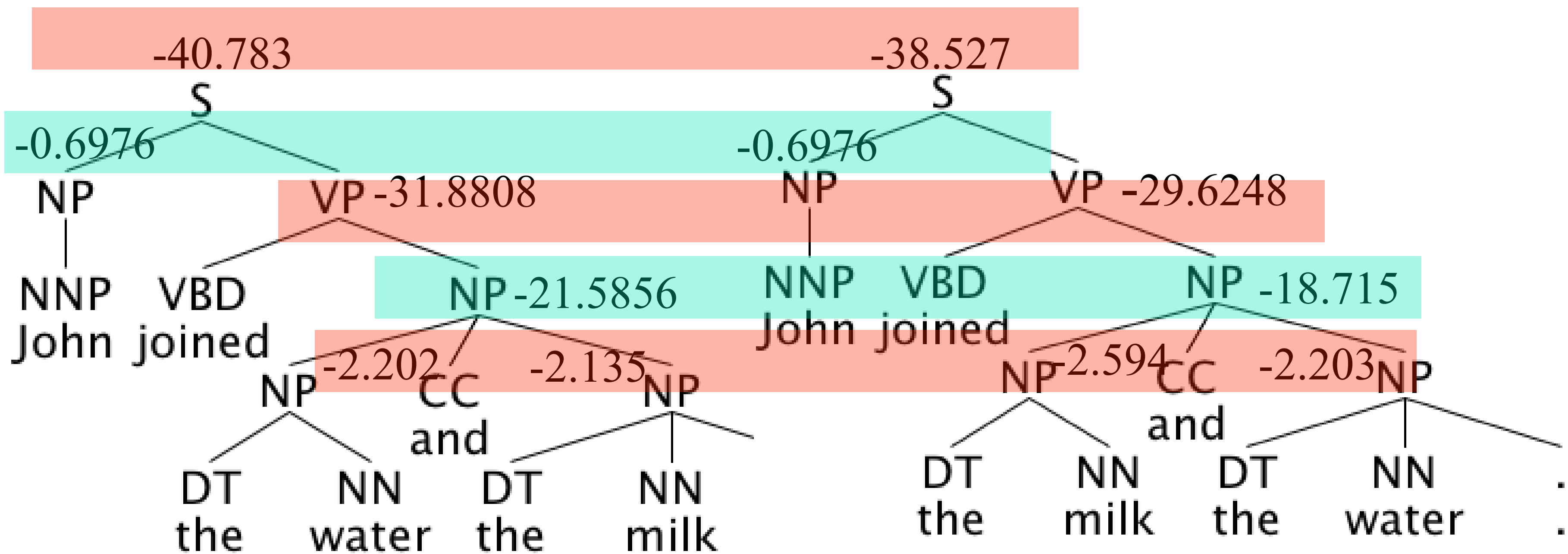


In fact…

- No <u>matter</u> what lexical item we choose, ‘milk’ (but not ‘water’ or ‘toys’ or ‘computer’) forces a low attachment like this – all the others, in all other combinations, force the high PP attachment…

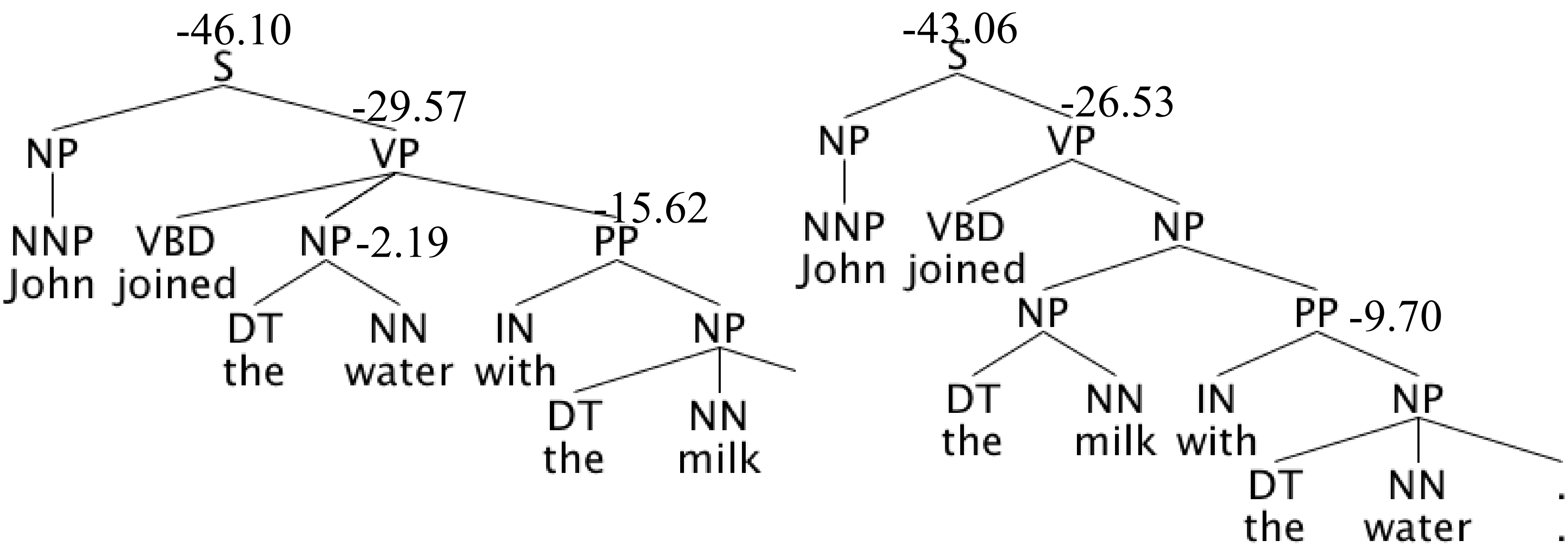
Where do the numbers come from? A breakdown

- John joined the water and the milk
- John joined the milk and the water

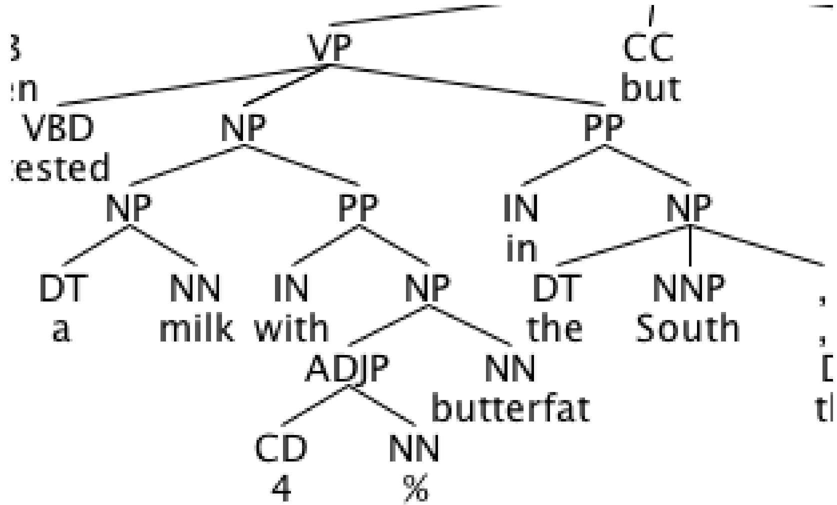


Where do the numbers come from?

- J. joined the water with the milk
- J. joined the milk with the water



24 ‘milk’ sentences, only a few as a noun…



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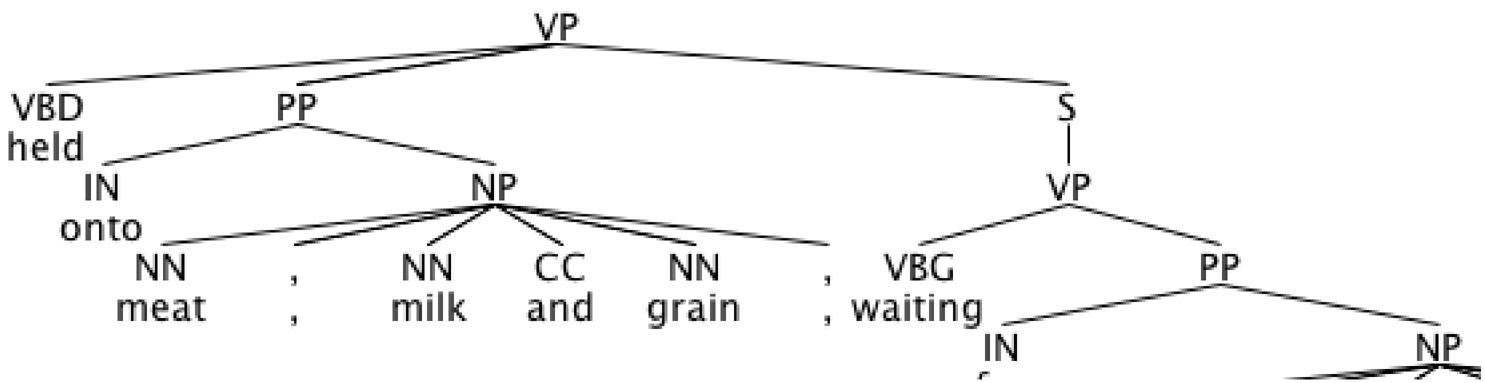

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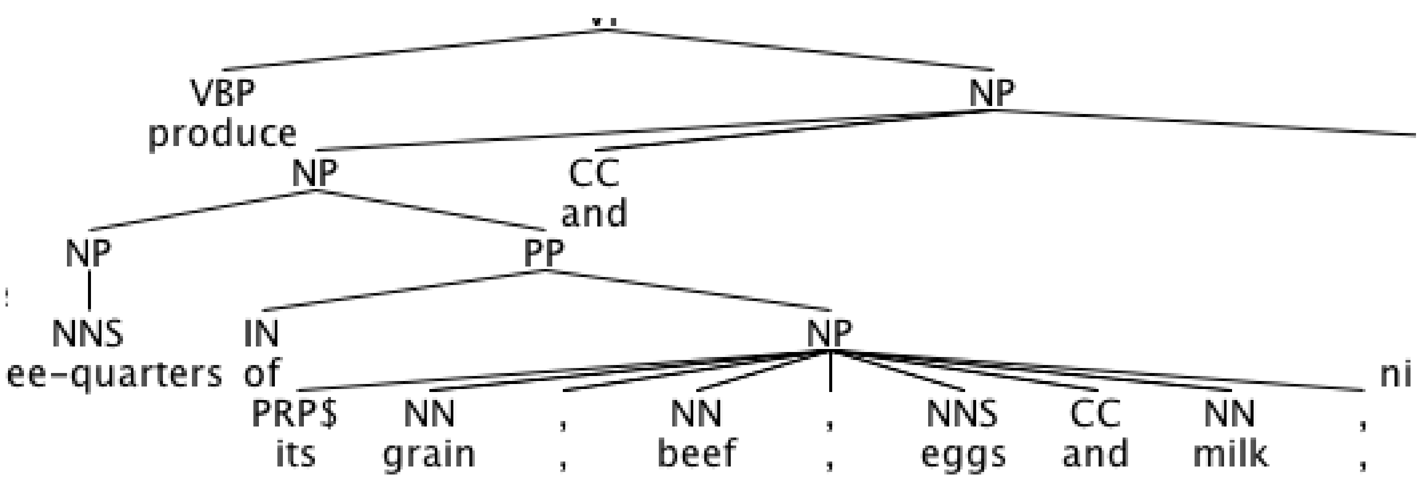
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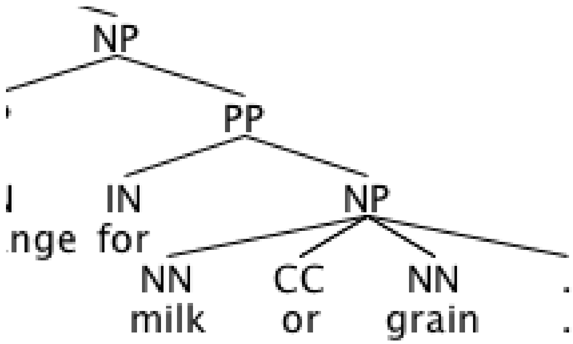

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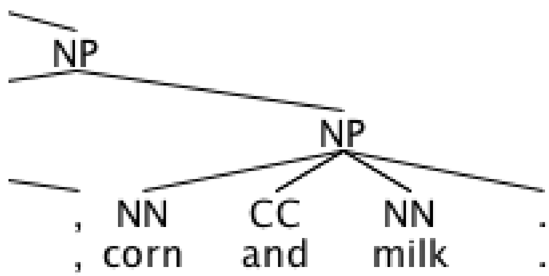

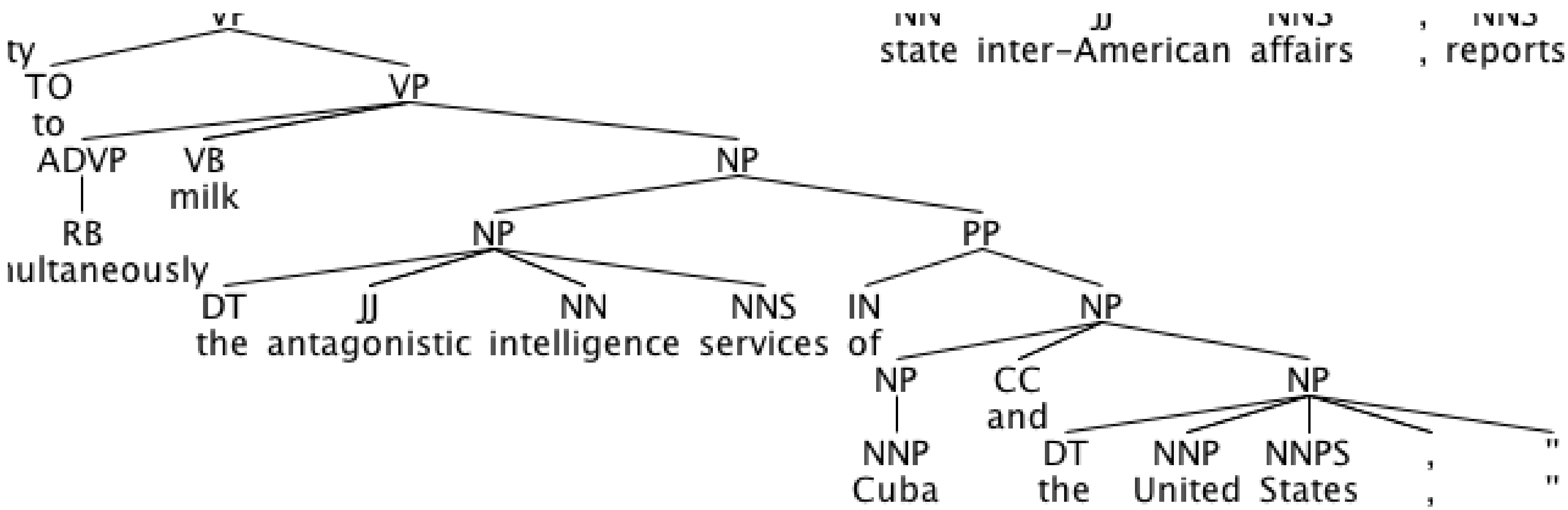
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affairs
,
reports

Another example: ‘bark’

(a) The dog barked to Mary.

(b) The dog barked about Mary.

(c) The dog barked at Mary.

bark: 1

the: 33164

dog: 12

: to: 20655

: Mary: 31

: about: 2508

: at: 5364

Table 26: *(26a) The dog barked to Mary.*

Model	Probability of Sentence	Probability of VP
1	-36.5968	-17.117
2	-36.4098	-17.0518
3	-36.4164	-17.0758

Table 27: *(26b) The dog barked about Mary.*

Model	Probability of Sentence	Probability of VP
1	-40.5624	-21.0827
2	-40.4081	-21.0501
3	-40.3831	-21.0425

Table 28: *(26c) The dog barked at Mary.*

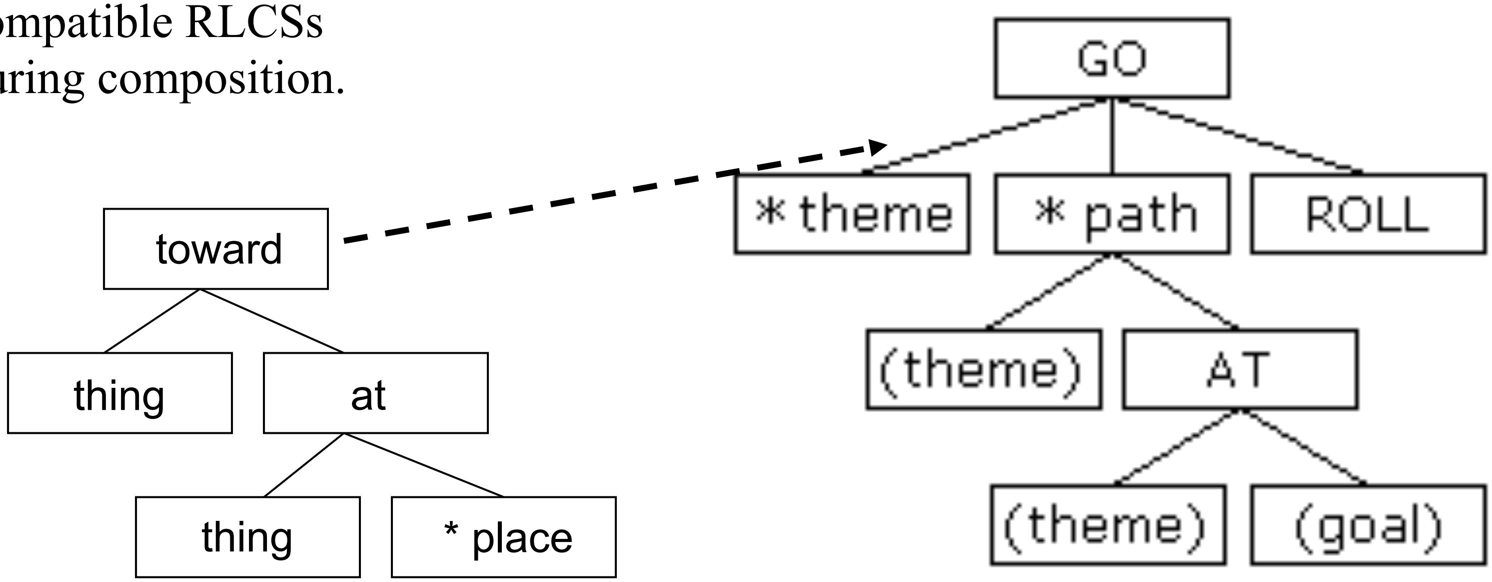
Model	Probability of Sentence	Probability of VP
1	-37.4994	-18.0197
2	-37.2983	-17.9403
3	-37.3178	-17.9772

Lexical Conceptual Structure (LCS)

Entries in the lexicon are Root Lexical Conceptual Structures, RLCS

*-marked positions are unified with other compatible RLCSs during composition.

Roll:



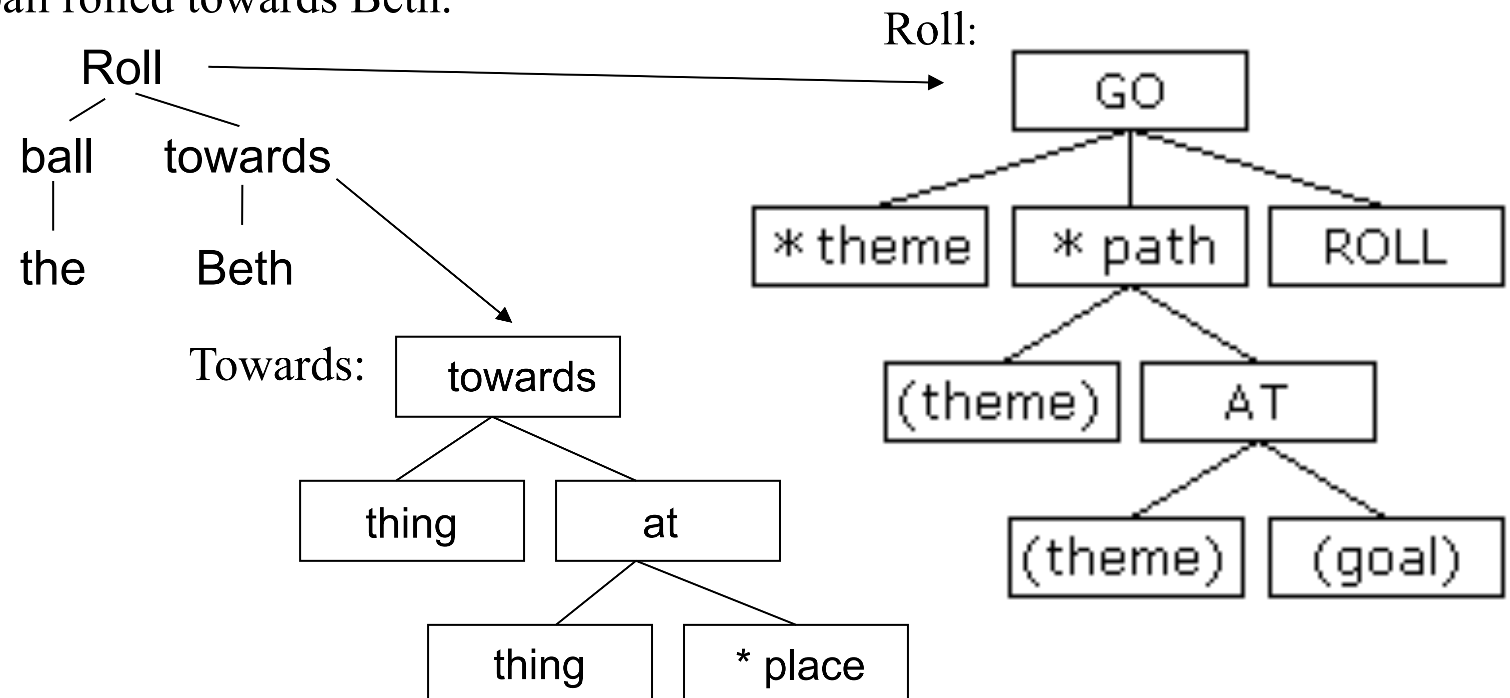
Lexical Conceptual Structure

- Each node contains:
  - Primitive:
    - CLOSED CLASS: GO, STAY, BE, ON, IN, AT…
    - OPEN CLASS: JOHN, RUN-INGLY, …
  - Field: Analogy to motion/position in Localist approach: LOCATIONAL, POSSESSIONAL, TEMPORAL,…
  - Type: EVENT, STATE, PATH, POSITION, MANNER…

LCS Structure & Composition

Recursively compose the children, then assign the composed children to *-marked positions in the current RLCS. This yields a Composed LCS, CLCS.

The ball rolled towards Beth.



Language of Thought (LOT) (Fodor 1975)

- Children acquiring a language are mapping words onto internal language
- This internal language <u>cannot</u> be induced on the basis of language learning – Why?
- Are the lexical semantics primitives the LOT?

Structural vs. Content Meaning Component

- Verbs in a class share a <u>structural</u> component
- Verbs in a class distinguished by <u>content</u> component

What information is in the lexicon?

Answer 1: structural info encodes agent, patient, goal,… (Hale & Keyser)

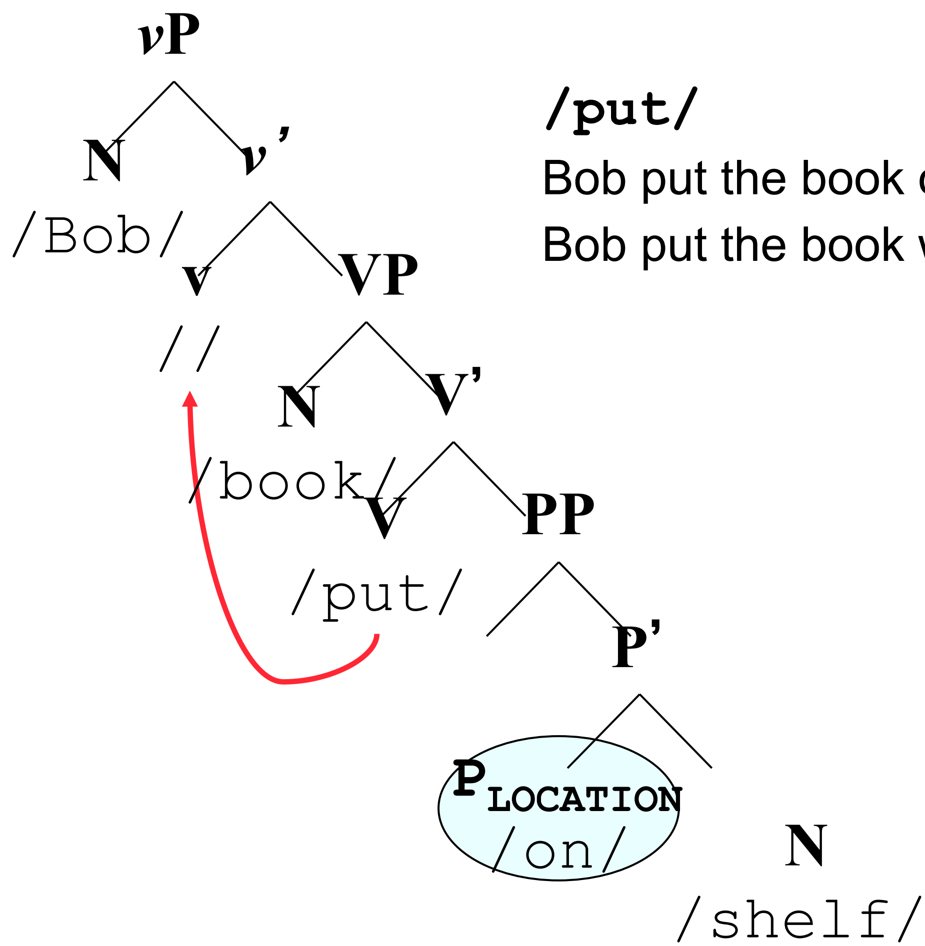
Answer 2: nothing but vanilla syntactic categories (N, V, P, …)

Hypothesis 1 Problem

Problem: How does Lexicon acquire the following:

/shelf/	$n_{LOCATION}$	$=p_{LOCATION}$ $=d$ V
/butter/	$n_{LOCATUM}$	$=p_{LOCATUM}$ $=d$ V
/shovel/	$n_{INST-MOT}$	$=p_{INST-MOT}$ $=p_{LOCATION}$ $=d$ V
/pencil/	$n_{INST-IMP}$	$=p_{INST-IMP}$ $=p_{LOCATION}$ $=d$ V
/mop/	$n_{INST-REMOVAL}$	$=p_{INST-REMOVAL}$ $=p_{SOURCE}$ $=d$ V
/email/	$n_{INST-COMM}$	$=p_{INST-COMM}$ $=p_{HAVE}$ $=d$ V $=p_{INST-COMM}$ $=p_{DEST}$ $=d$ V
etc.		

Hypo 1: /put/ vs. /shelf/ vs. /butter/



/put/

Bob put the book on the shelf.

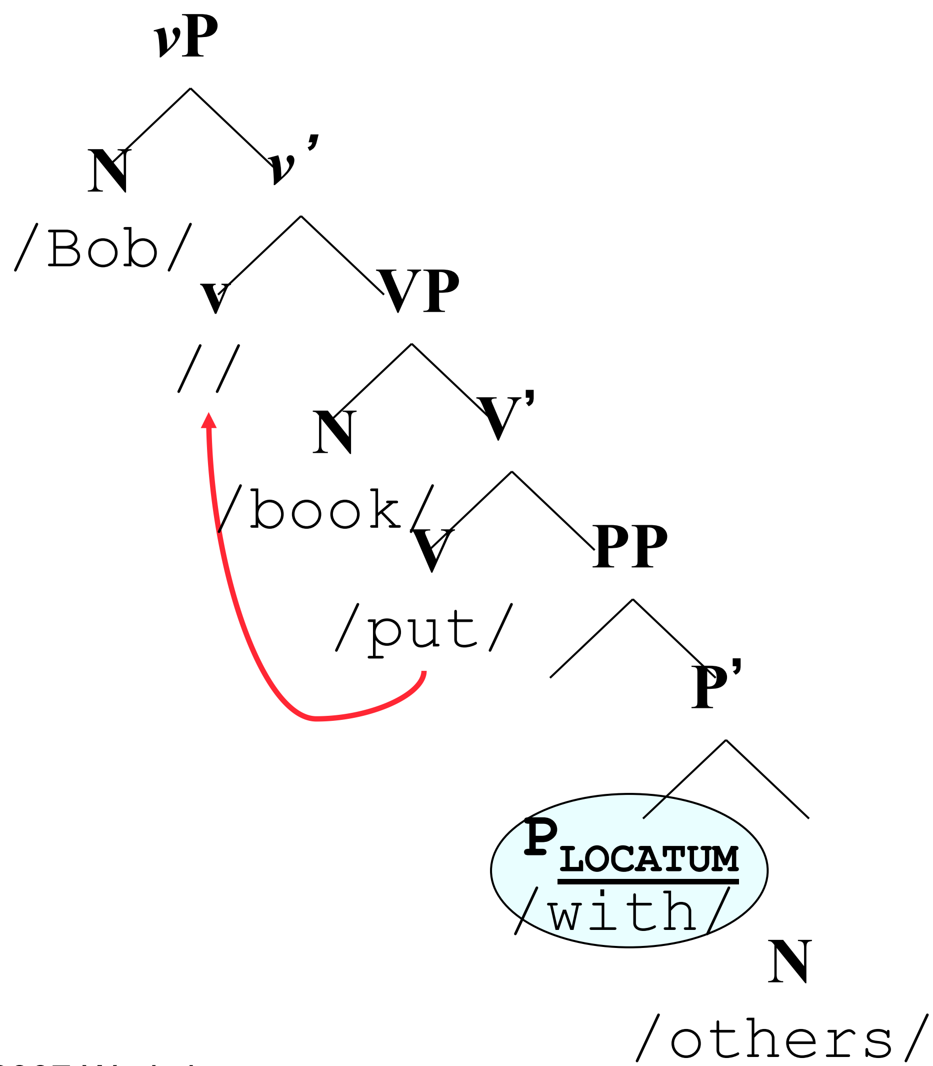
Bob put the book with the others.

/put/ vs. /shelf/ vs. /butter/

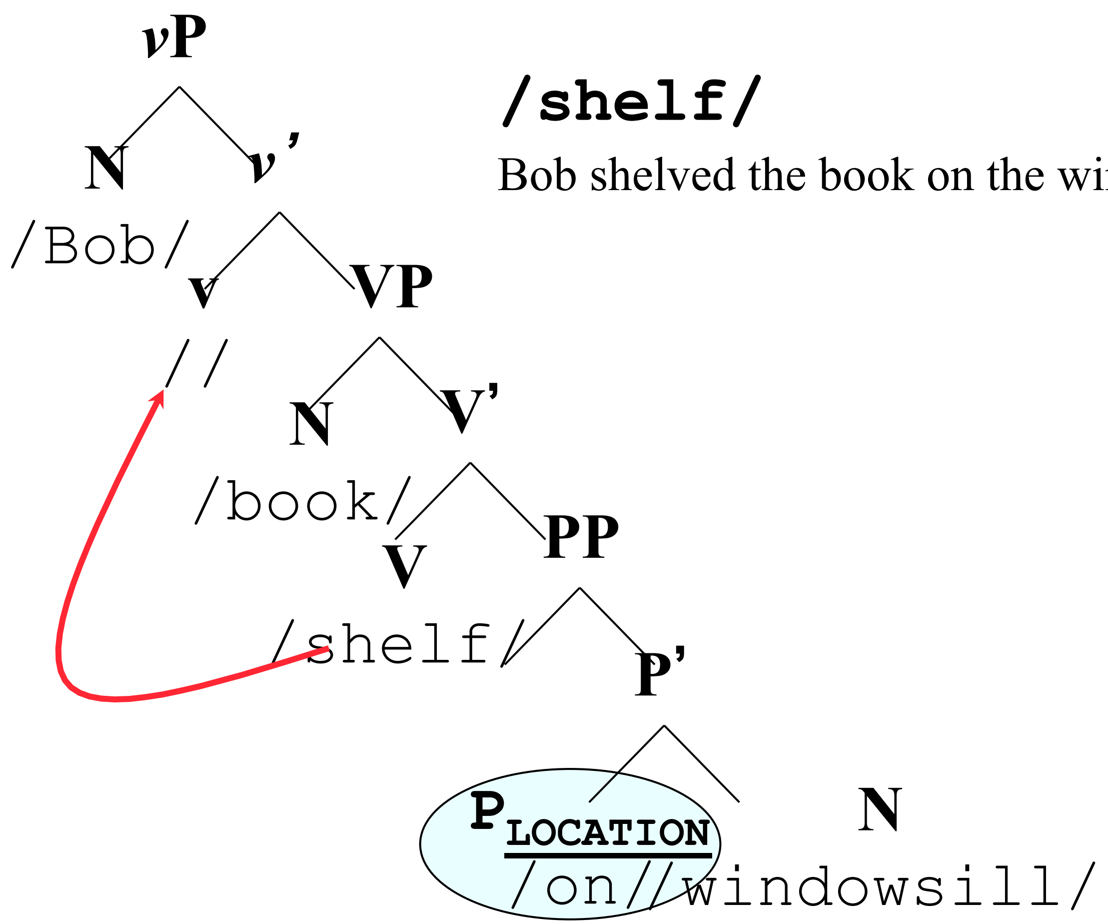
/put/

Bob put the book on the shelf.

Bob put the book with the others.



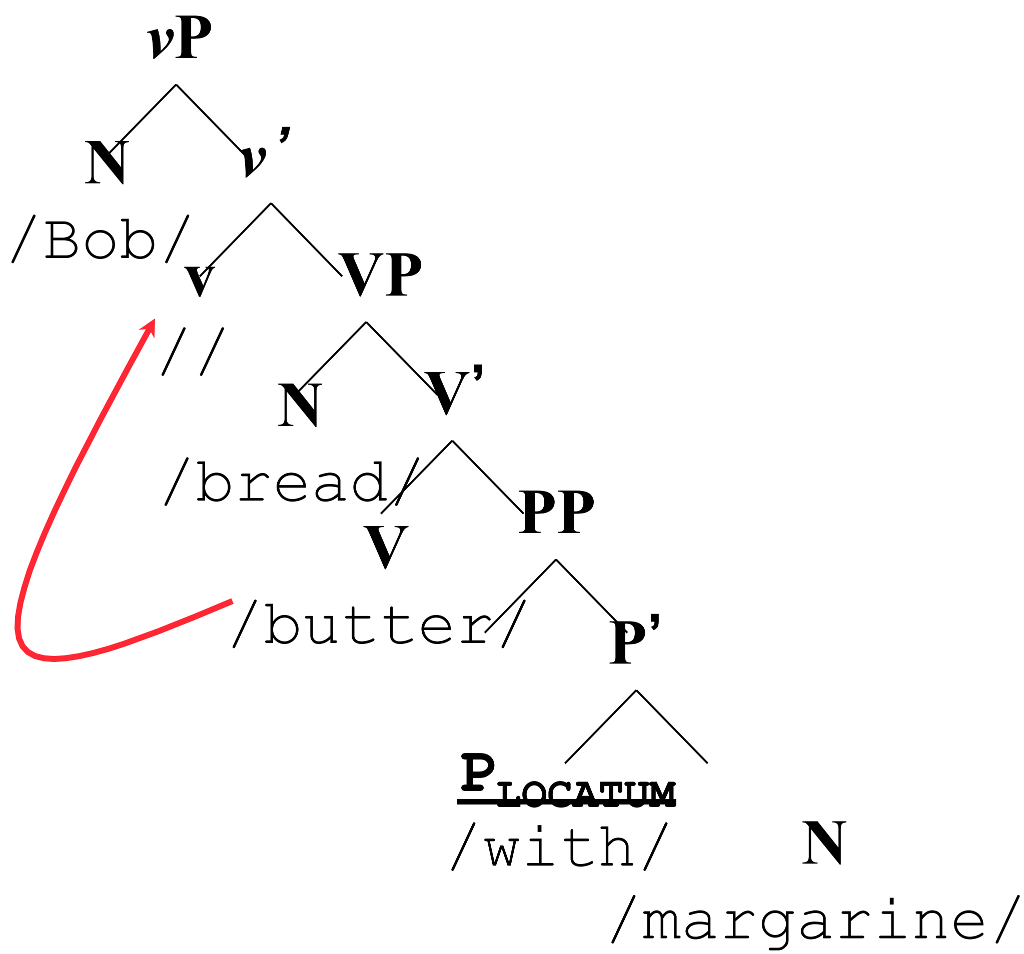
/put/ vs. /shelf/ vs. /butter/



/shelf/

Bob shelved the book on the windowsill.

/put/ vs. /shelf/ **vs.** /butter/



/shelf/ vs. /put/ vs. /butter/

/shelf/

Bob shelved the book on the windowsill.

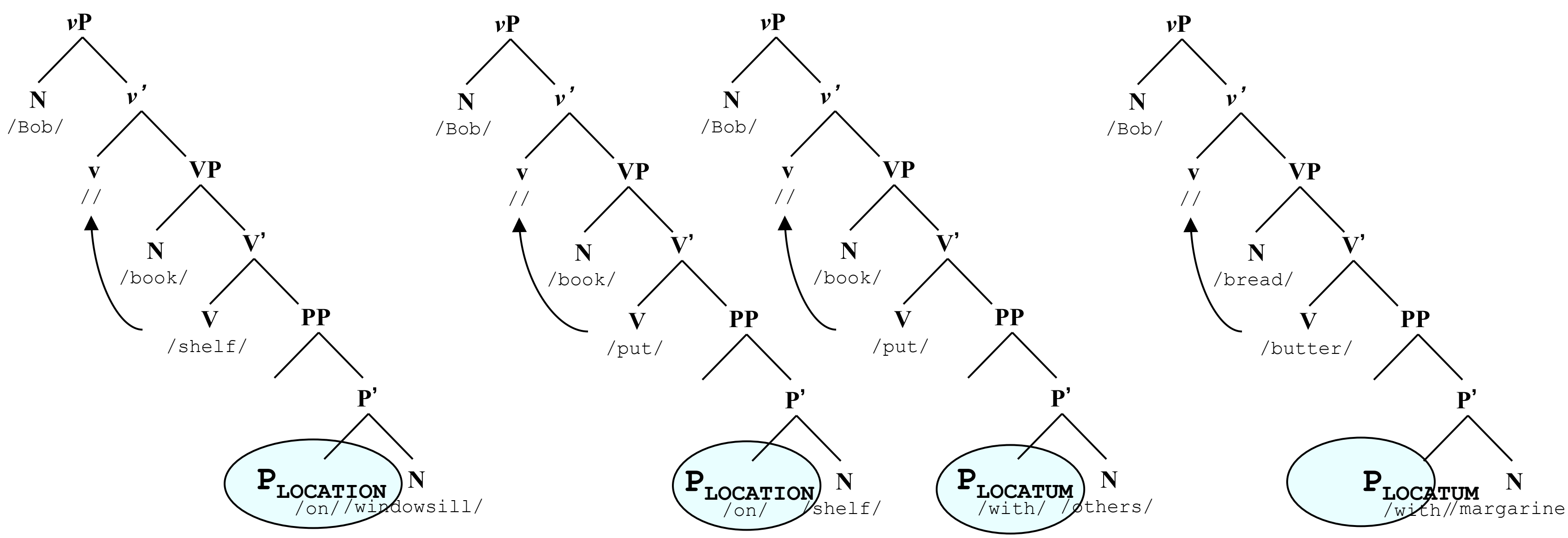
/put/

Bob put the book on the shelf.

Bob put the book with the others.

/butter/

He buttered the bread with margarine.



/put/, /shelf/ imposes $\mathbf{p}_{\text{LOCATION}}$ on arguments

/put/, /butter/ imposes $\mathbf{p}_{\text{LOCATUM}}$ on arguments

Hypothesis 1: <u>Lexicon</u> Contains Selection Criteria

/shelf/ has $\mathbf{p}_{\mathrm{LOCATION}}$ *selection* in lexicon ($=\mathbf{p}_{\mathrm{LOCATION}}$ $=$**d(et) V**)

Also: **/shelf/ is** $\mathbf{n}_{\mathrm{LOCATION}}$

/butter/ has $\mathbf{p}_{\mathrm{LOCATUM}}$ *selection* in lexicon ($=\mathbf{p}_{\mathrm{LOCATUM}}$ $=$**d(et) V**)

Also: **/butter/** is $\mathbf{n}_{\mathrm{LOCATUM}}$

So then the <u>Lexicon</u> cannot derive:

* 1. Bob shelved the windowsill with the book.

* 2. Bob buttered the margarine onto the bread.

Information about butter and shelf – <u>where</u> is it located?

What to do?

Solution 1: Solve the above problem

Solution 2: Push problem OUT of Lexicon and
INTO Encyclopedia

Solution 2: Push problem OUT of Lexicon and INTO Encyclopedia

Encyclopedia, not lexicon, is *source* of 'Oddness' of:

(1) Bob shelved the windowsill with the book

(2) Bob buttered the margarine onto the bread

Lexicon is NOT:

/shelf/ =$p_{LOCATION}$ =d(et) V **/butter/ =d +k $p_{LOCATUM}$**

/into/ =d +case $p_{LOCATION}$ **/with/ =d +case $p_{LOCATUM}$**

But instead:

/shelf/ =p =d V **/butter/ =d +case p**

/into/ =d +case p **/with/ =d +case p**

Thus insofar as the lexicon is concerned,
(1) and (2) are <u>GRAMMATICAL</u>

WordNet
(Miller et al 1998)

- Widely used in computational linguistics
- Dictionary-like definitions organized by links:
  - Nouns: X is a kind-of/part-of Y
  - Verbs: X involves doing Y
    - Also with *common* syntactic frames
  - Other than the above, no conceptual structure, no meaning postulates
- Enumerates lists of senses, does not relate these senses

Senses

- How many senses per a word? WordNet examples:
  - bank – 10 noun senses, 8 verb senses
  - have – 1 noun sense, 19 verb senses
  - smoke – 8 noun sense, 2 verb senses
- Are these different senses? How are they structurally related?
  - relating them structurally requires <u>conceptual metalanguage</u>

Meaning isn’t (always) at the Word Level

pick up, throw up, turn on does NOT have
picking, throwing, turning (at least not directly)

Antidisestablishmentarism

(morphosemantics theory very poor)

And there is pragmatics (too large a topic)

Idioms / Constructions

- Are idioms to be stored in the lexicon?
  - Examples:
    - Kicked the bucket, Paint the town red
    - Spic-and-span, kit and kaboodle
    - What's X doing Y? The X-er, The Y-er
  - H1: Yes
    - BUT then: how do you treat Tense, agreement, …
  - H2: No
    - BUT then: then where is "meaning" stored?
      - Answer: the encyclopedia
        - But that is a non-answer

Failure to Compose

- Defeasability:

  He climbed the mountain vs He climbed down the mountain
- Red hair vs red Porsche
  - Does this work? Red(x) & Hair(x)
  - Meaning of RED in context > outside context?
- Former friend
  - Does this work? Former(x) & Friend(x)
- Good knife vs good book vs good life
  - Does this work? Good(x) & Knife(x)
  - Good knives cut well, Good books …, Good lives …

Metaphoric Meanings

- “No silver bullet on 9/11”
- “My surgeon is a butcher” vs “My butcher is a surgeon”
- “Don’t get high on Montague grammar”

- Appears way more often than you think.

Meanings are highly private

Before they become adults, children think:

/uncle/ is a friendly middle-aged man

/island/ is a beachy area with palm trees

/two/ is some small number greater than one

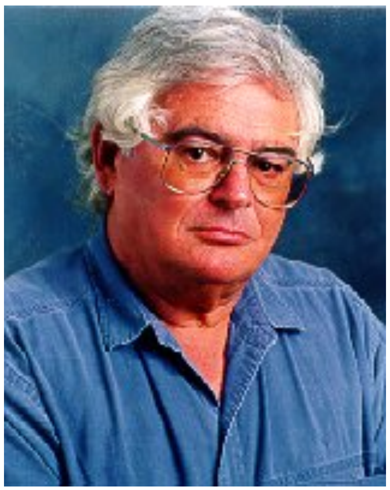
and not anything like

Blind children's meaning of LOOK

What can one do?

Let's …

Show why everyone is wrong (Fodor 1998)



Promise: negative control

Unpromise: Has atypical ideas on what it means to "have" a concept

Summarize corpora statistically

P(V142|D) = .011
P(V143|D) = .004
P(V144|D) = .0014

Promise: Helps parsing.

Unpromise:

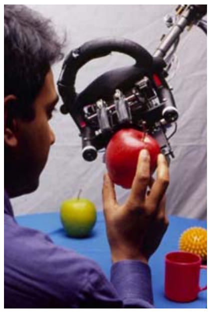
(1) Why parse?

(2) This is a mere redescription

- I thought the book to Mary.

Let's …

Build robots



Promise: Machine Learning used to get /apple/ associated to RED, …

Unpromise: only as good as your concept metalanguage, which is sensorimotor by nature. Reading minds is much harder.

Collect knowledge from people

Teach Computers

Promise: If machines could understand what is collected, Plus-X goes away.

Unpromise: (1) IF

(2) Data without a theory.

Let's

- Figure out how children learn

- John joined the eggs with the cream
- John joined the eggs and the cream

How robust is the Collins Parser?

Would lexical selection be a factor in comparing logprobs?

- John joined the cream with the eggs
- $[_{PP}$ P(*with*) $[_{NP}$ DET *cream*$]]$
- $[_{PP}$ P(*with*) $[_{NP}$ DET *eggs*$]]$
- *how about noun complements of preposition with that actually occur in the WSJ PTB vs. those that don't?*

- WSJ PTB frequencies:
  - 5 Herman
  - 442 John
  - 28 eggs
  - 3 cream

File:

```
Herman joined the eggs with the
   cream .
Herman joined the eggs and the
   cream .
Herman joined the cream with the
   eggs .
Herman joined the cream and the
   eggs .
John joined the eggs with the
   cream .
John joined the eggs and the cream
   .
John joined the cream with the
   eggs .
John joined the cream and the eggs
   .
```

- MXPOST:

```
Herman_NNP joined_VBD the_DT eggs_NNS
   with_IN the_DT cream_NN ._.
Herman_NNP joined_VBD the_DT eggs_NNS
   and_CC the_DT cream_NN ._.
Herman_NNP joined_VBD the_DT cream_NN
   with_IN the_DT eggs_NNS ._.
Herman_NNP joined_VBD the_DT cream_NN
   and_CC the_DT eggs_NNS ._.
John_NNP joined_VBD the_DT eggs_NNS
   with_IN the_DT cream_NN ._.
John_NNP joined_VBD the_DT eggs_NNS
   and_CC the_DT cream_NN ._.
John_NNP joined_VBD the_DT cream_NN
   with_IN the_DT eggs_NNS ._.
John_NNP joined_VBD the_DT cream_NN
   and_CC the_DT eggs_NNS ._.
```

Analyzing the probabilities

Collins input format:

```
8 Herman NNP joined VBD the DT
  eggs NNS with IN the DT cream
  NN . .
8 Herman NNP joined VBD the DT
  eggs NNS and CC the DT cream NN
  . .
8 Herman NNP joined VBD the DT
  cream NN with IN the DT eggs
  NNS . .
8 Herman NNP joined VBD the DT
  cream NN and CC the DT eggs NNS
  . .

8 John NNP joined VBD the DT eggs
  NNS with IN the DT cream NN . .
8 John NNP joined VBD the DT eggs
  NNS and CC the DT cream NN . .
8 John NNP joined VBD the DT cream
  NN with IN the DT eggs NNS . .
8 John NNP joined VBD the DT cream
  NN and CC the DT eggs NNS . .
```

- Output (model 1):

```
PROB 762 -36.766 0
PROB 888 -39.1046 0
PROB 935 -35.825 0
PROB 873 -36.8356 0

PROB 746 -40.9796 0
PROB 863 -43.3183 0
PROB 909 -40.0386 0
PROB 841 -41.0492 0
```

- **Sample Analysis**:
  - Herman/John change doesn't affect the logprob rankings (as expected)
  - *NP with NP < NP and NP*
  - *cream* then *eggs*

But too few Hermans!

Encyclopedia vs. Lexicon

Lexicon does NOT hold real-world knowledge, only:

ROOT	Lexicon	Examples
arrive	**+v, +DP, –cause**	John arrived. The arrival of John
big	**–v, +DP**	The big X.
open	**±v, +DP, ±cause**	John opened X. X opened.
destroy	**+v, +DP, +cause**	John destroyed X. John's destruction of X.
grow	**+v, +DP, ±cause**	Tomatoes grew. John grew tomatoes. John's growth of tomatoes.