Lecture 17
More constituency parsing and dependency parsing

Intro to NLP, CS585, Fall 2014

http://people.cs.umass.edu/~brenocon/inlp2014/

Brendan O'Connor

- Projects
  - No exercise this week
- Constituent parsing continued
  - Better PCFG’s
  - Whole-tree features
  - Shift-reduce parsers
- Start dependency parsing
- Thursday: examples of what you do with parsing

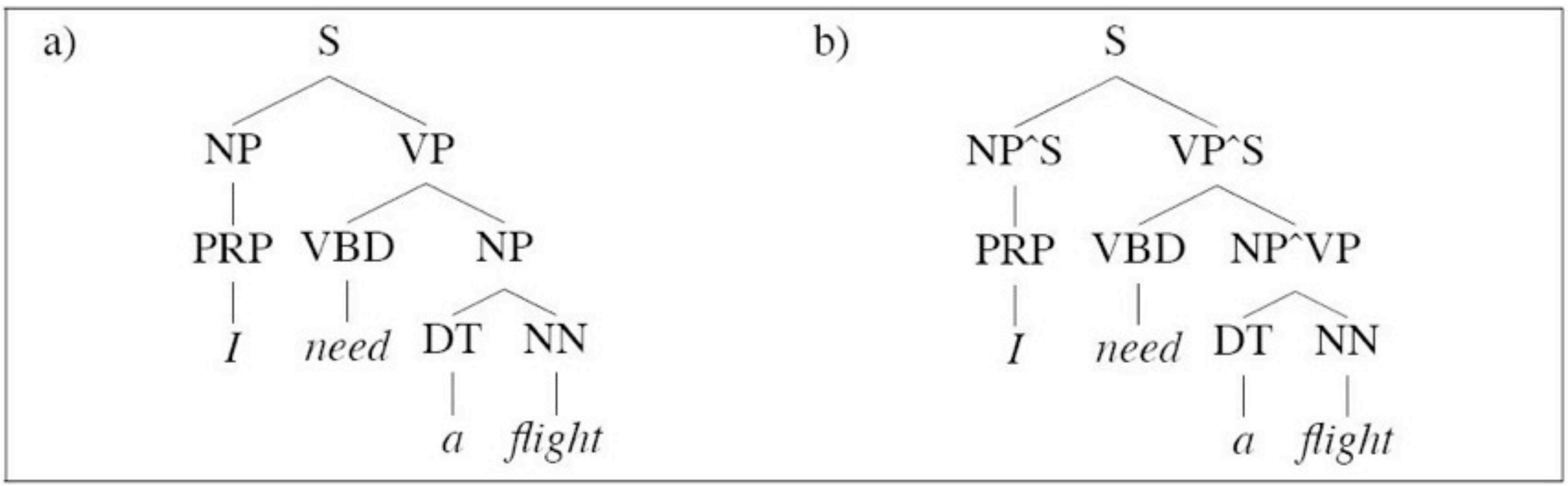
Modern statistical parsers

- PCFG assumptions are too strong.
  How to improve?
  - Transform the training data
    - splitting/“annotating” non-terminals
  - Automatically learn better splits with EM *(Berkeley parser)*
  - Discriminative whole-tree features -- need to use re-ranking (*BLIPP parser*)

- Inference tricks at runtime

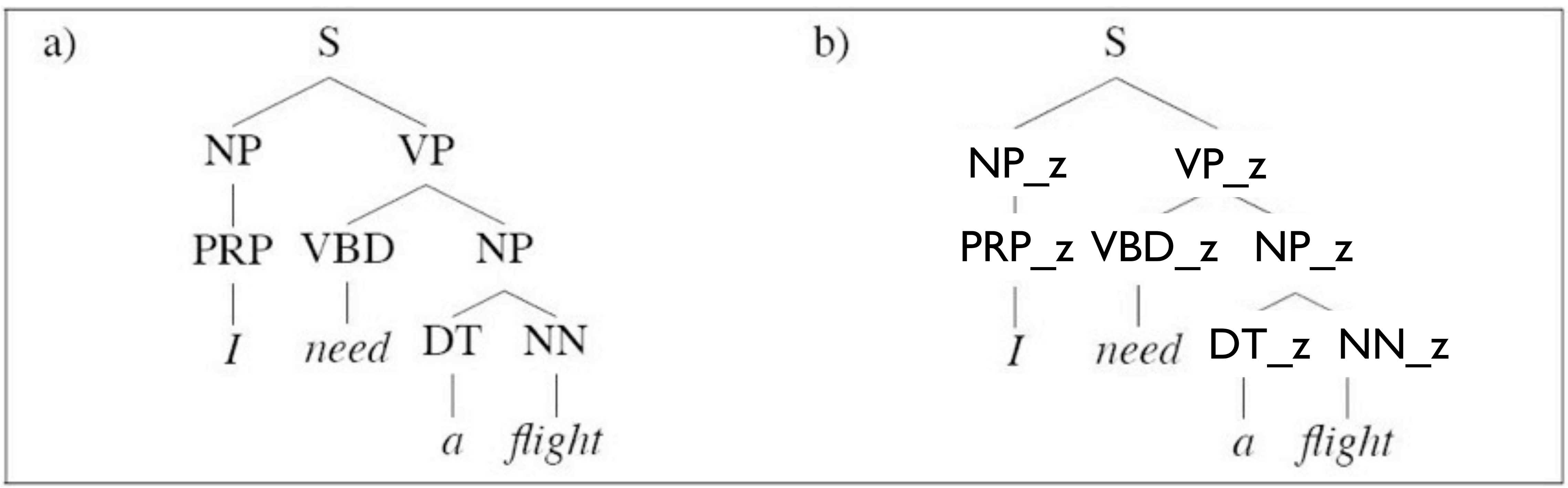
Non-terminal splits

- Annotate a nonterminal symbol its parent/ grandparent/sibling
  - Relaxes PCFG independence assumptions



Latent-variable PCFG

- Automatically ***learn*** useful splits.
- Latent-variable PCFG: augment training data with latent states. Learn with EM. Use "split-merge" training to vary number of latent states.
  - NP_1, NP_2, NP_3....
- [Petrov (2009), used today in open-source Berkeley parser]
  - The software is pretty easy to use



Discriminative re-ranking

- This is the most accurate method known so far (for English constituent parses on WSJ PTB...)
    - BLIPP parser, open-source
- No more PCFG: Why not use a log-linear model with *whole-tree* features?
    - Does this NP contain 15-20 words?
    - Right-branching tendencies?
    - PP object is “telescope” and VP verb is “see” (bilexical features: sparse but very useful!)
    - Now CKY is no longer possible. Why?
- Make it fast with **re-ranking**:
    - Take top-K trees from a PCFG. (Variant of CKY can do this)
    - Extract features for each, and re-rank them.
- Re-ranking is a very powerful general technique in NLP
    - Simple, fast model generates candidates
    - Slow, more accurate model decides the best one

Shift-reduce parsing

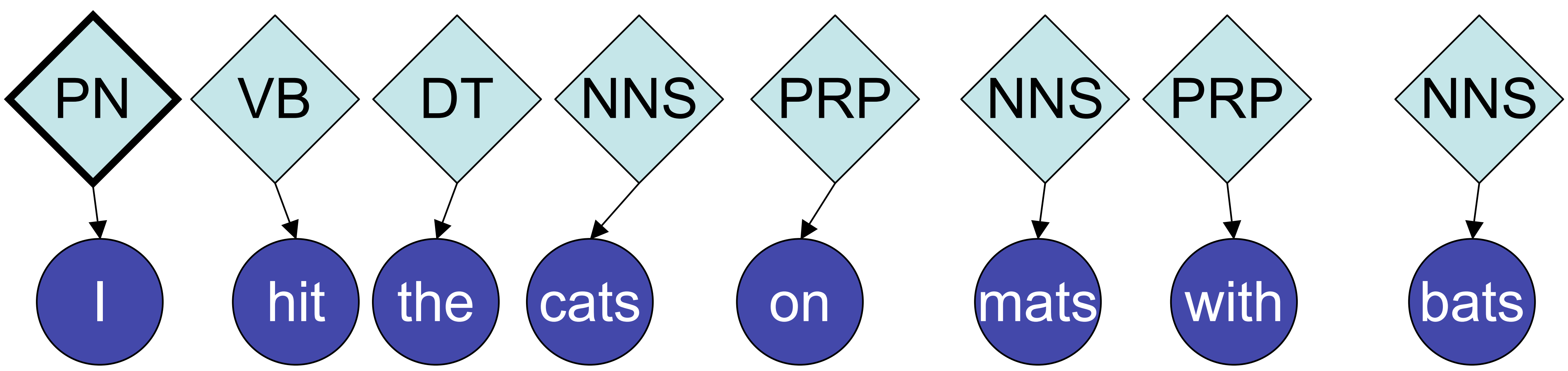
- Totally different paradigm.
- Incrementally build up the parse tree left-to-right.
- Eat words as you go along: for each word, decide what to do with it ... add to current subtree, or pop the stack and attach to a higher one.
    - Make these decisions according to a classifier.
- Think of the parser as an automaton.
- No dynamic programming! O(n) runtime!
- Potentially related to cognitive processing?

- Open-source implementations: Yue Zhang's *zpar* is extremely fast, and quite accurate. (Also see recent Stanford NLP releases...)

Example from a similar incremental parser (slightly different than current work)

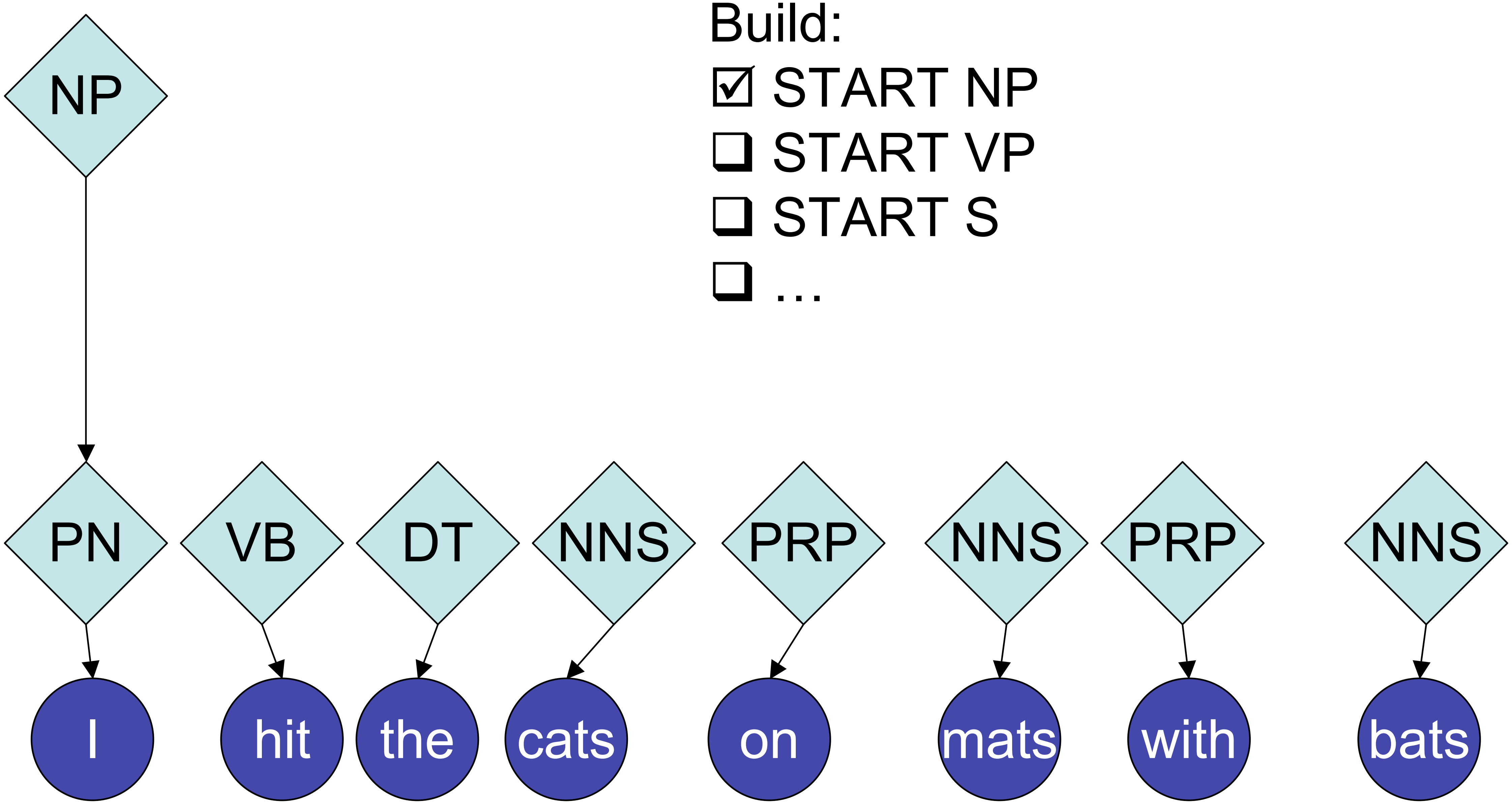
Ratnaparkhi (1998)

Build:
- ❑ START NP
- ❑ START VP
- ❑ START S
- ❑ …



[Slides: Noah Smith]

Ratnaparkhi (1998)



Build:
- ☑ START NP
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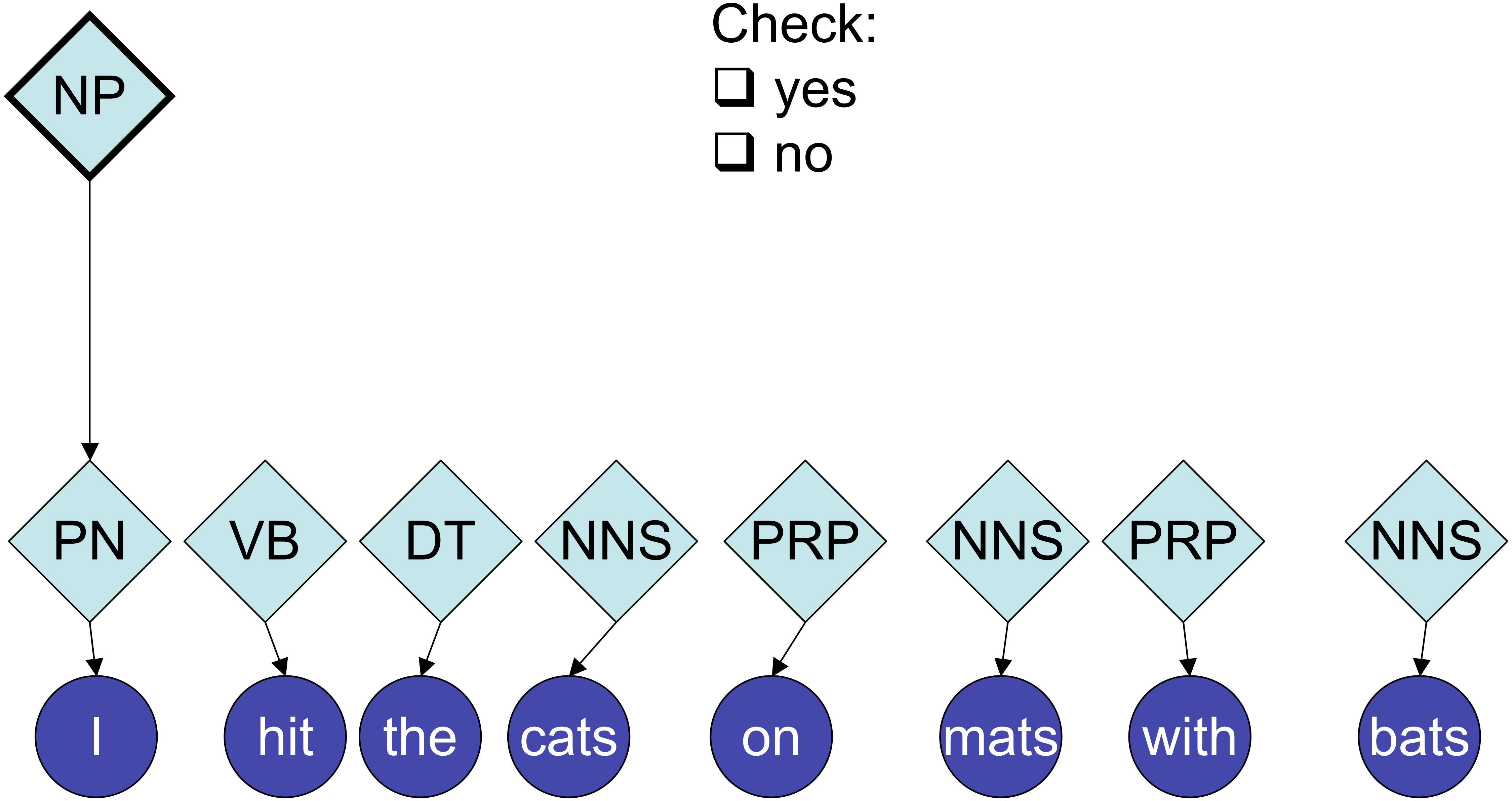
[Slides: Noah Smith]

Ratnaparkhi (1998)

Check:
- ❑ yes
- ❑ no



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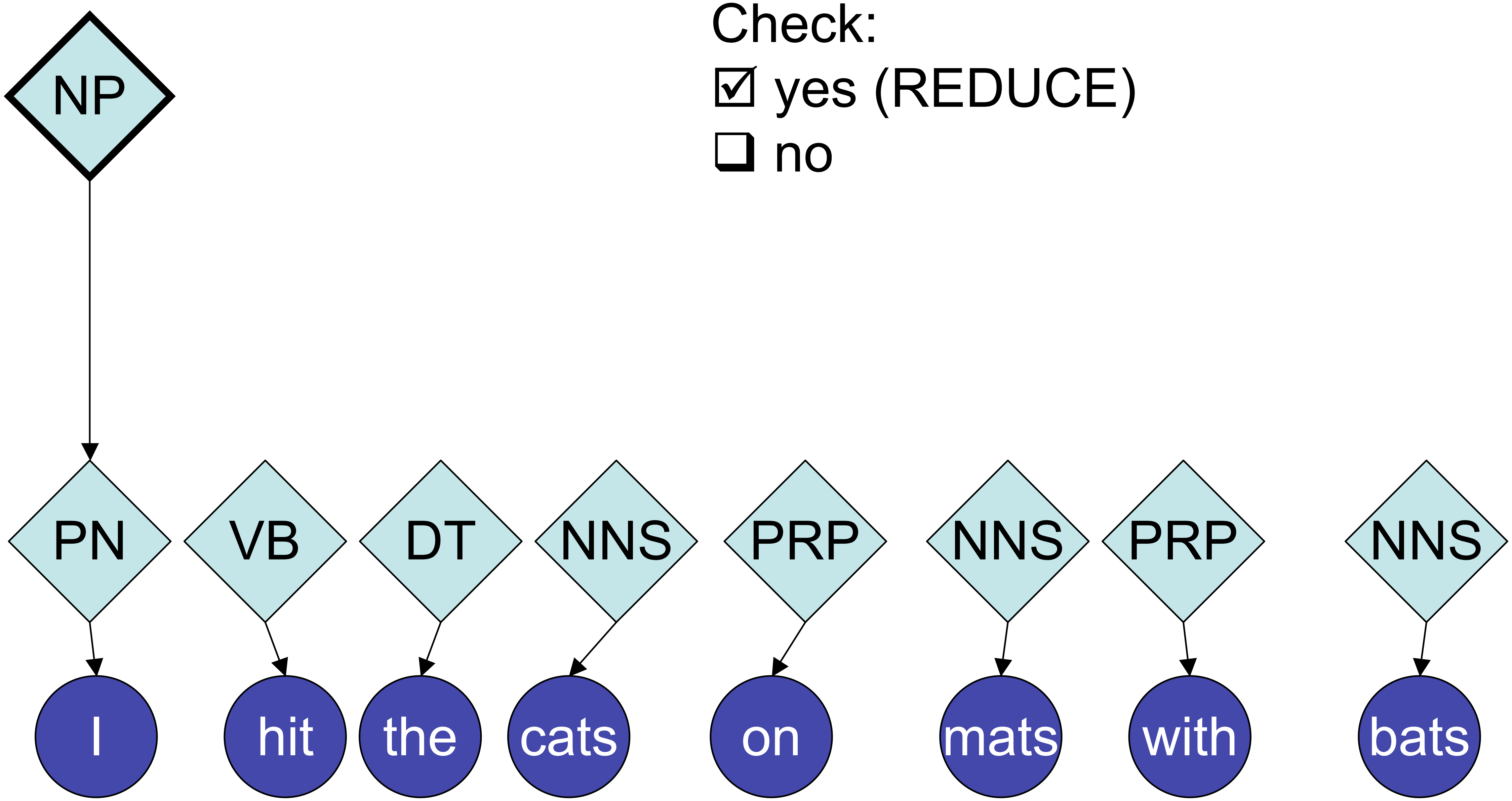

Check:
☑ yes (REDUCE)
❑ no

[Slides: Noah Smith]

Ratnaparkhi (1998)

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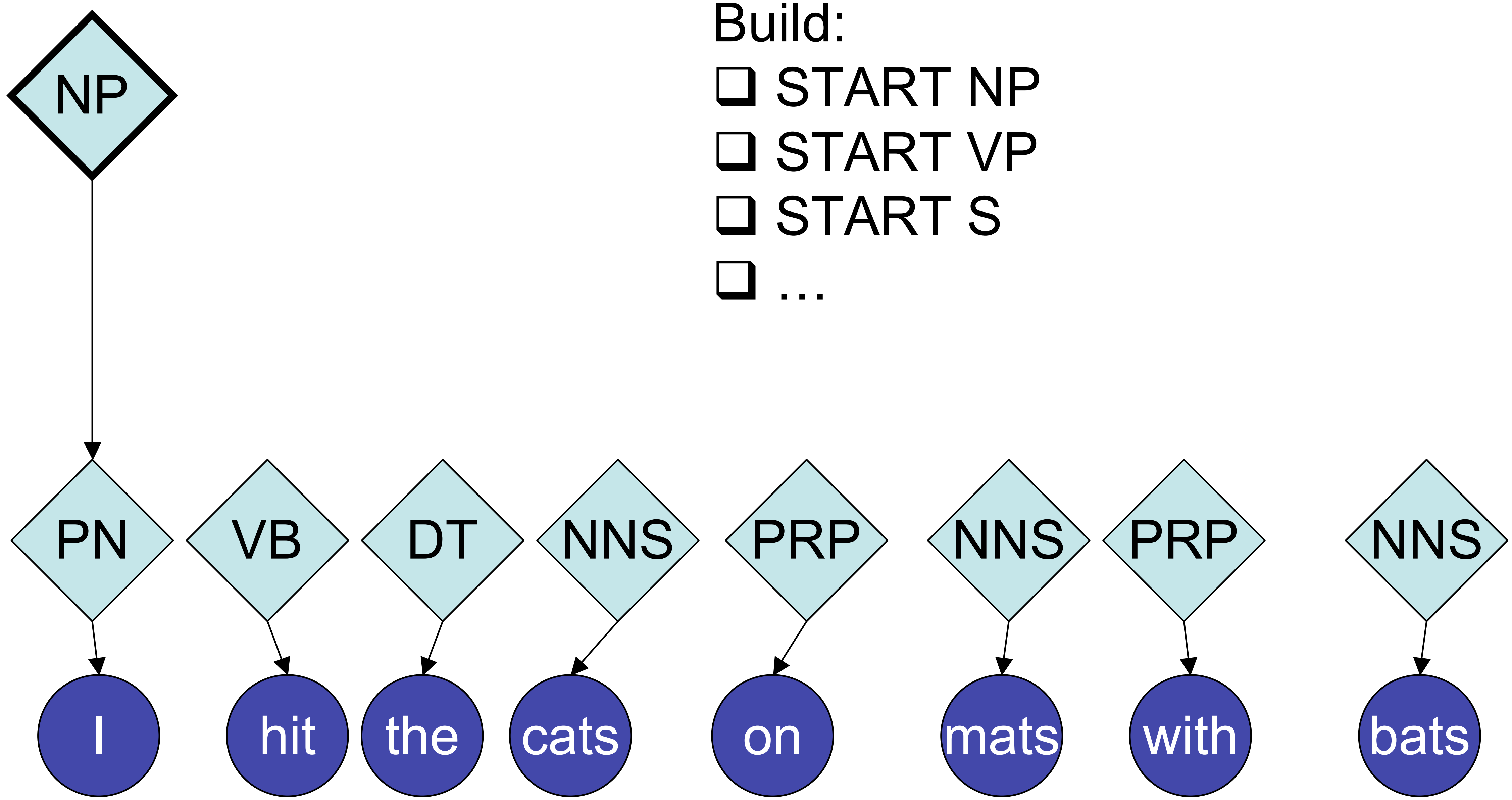

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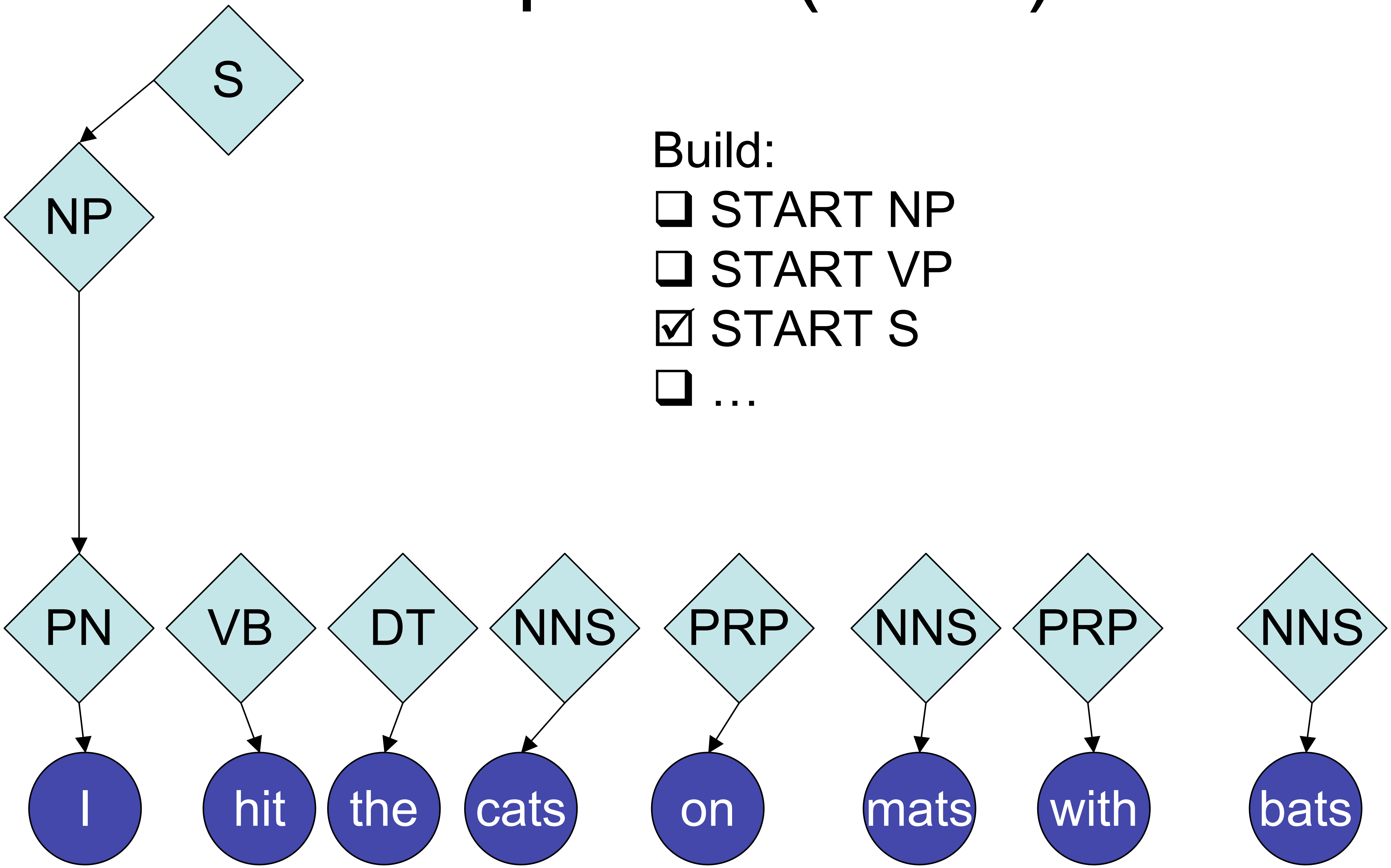

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[Slides: Noah Smith]

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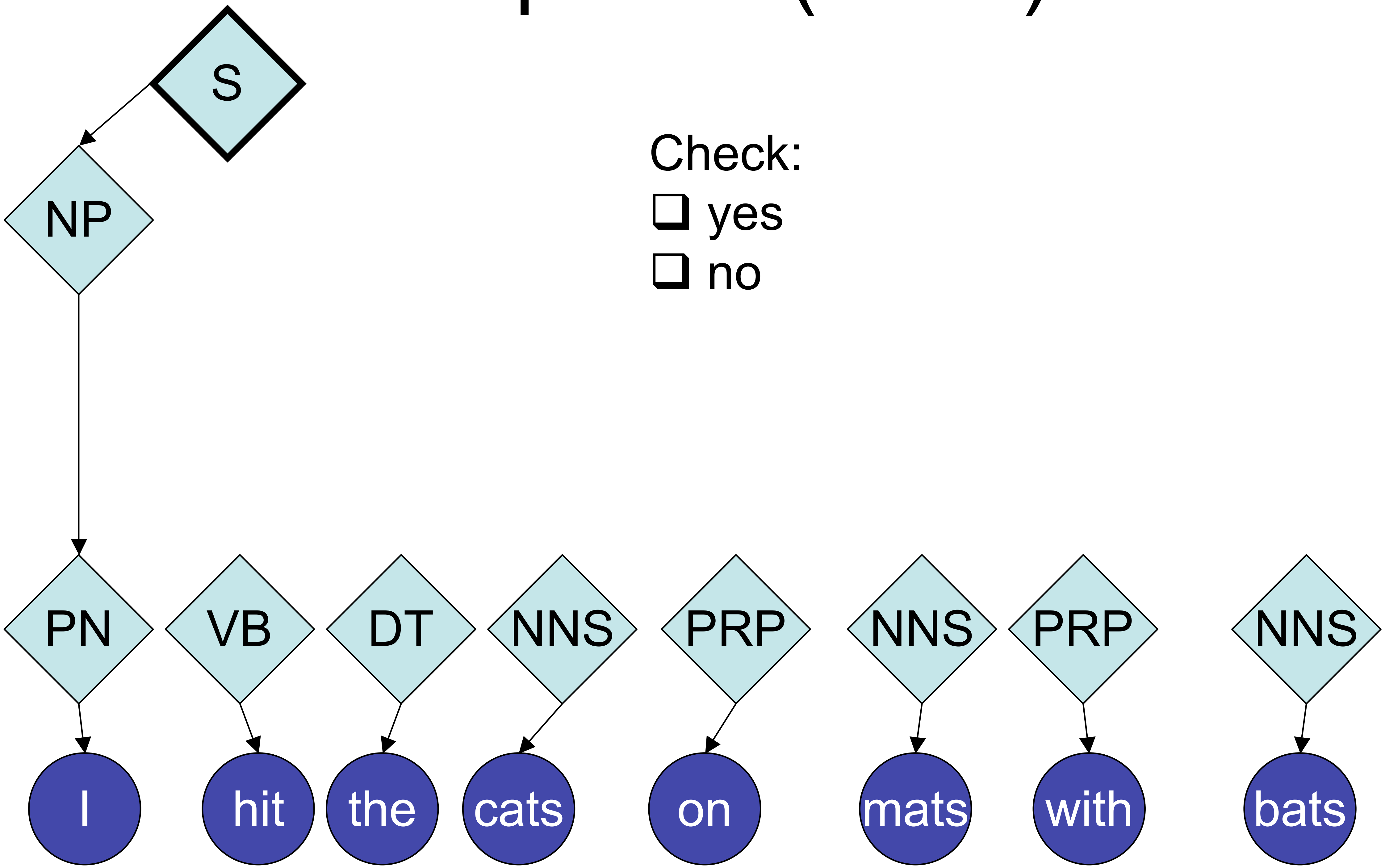

Check:
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[Slides: Noah Smith]

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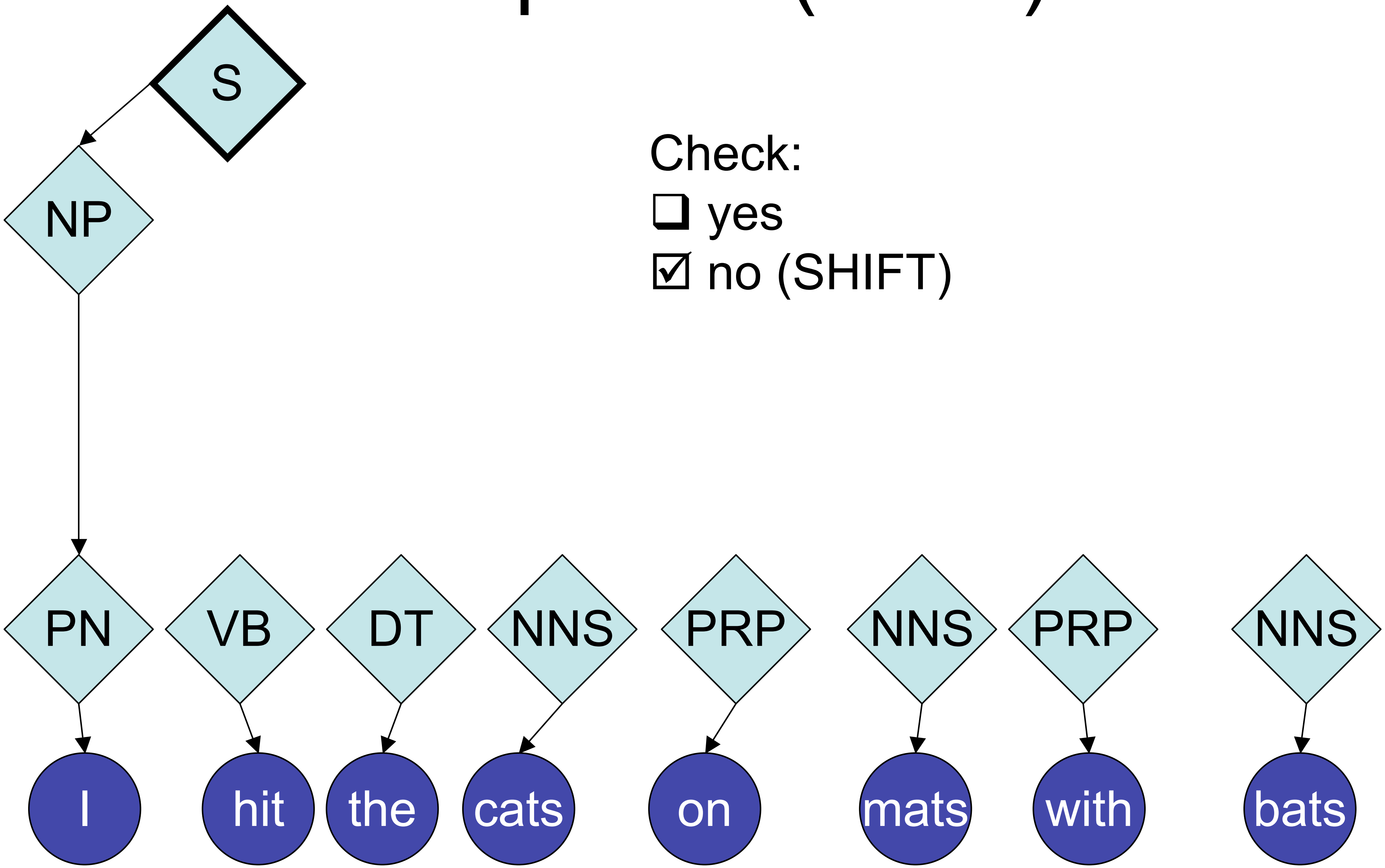
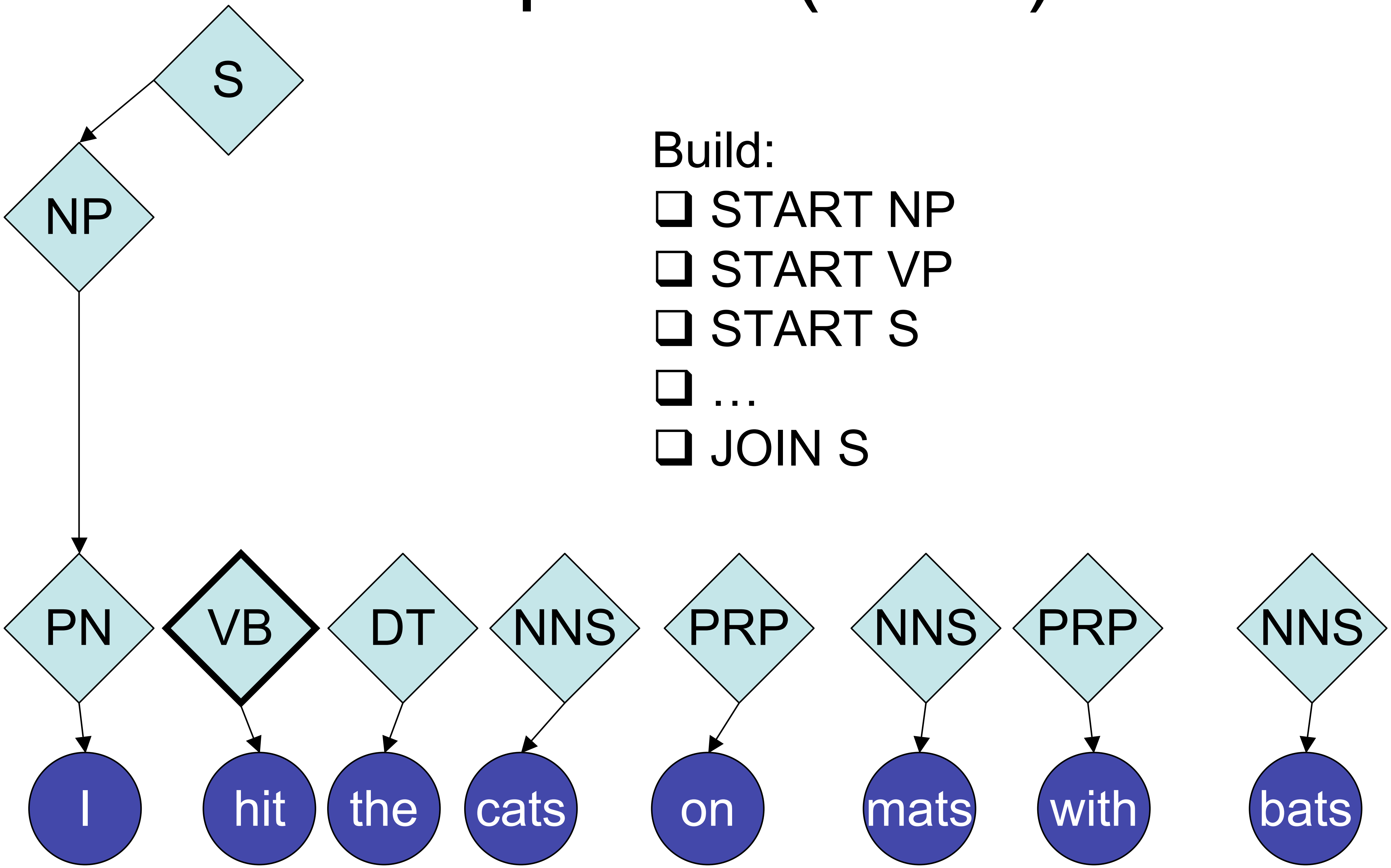


Check:
❑ yes
☑ no (SHIFT)

[Slides: Noah Smith]

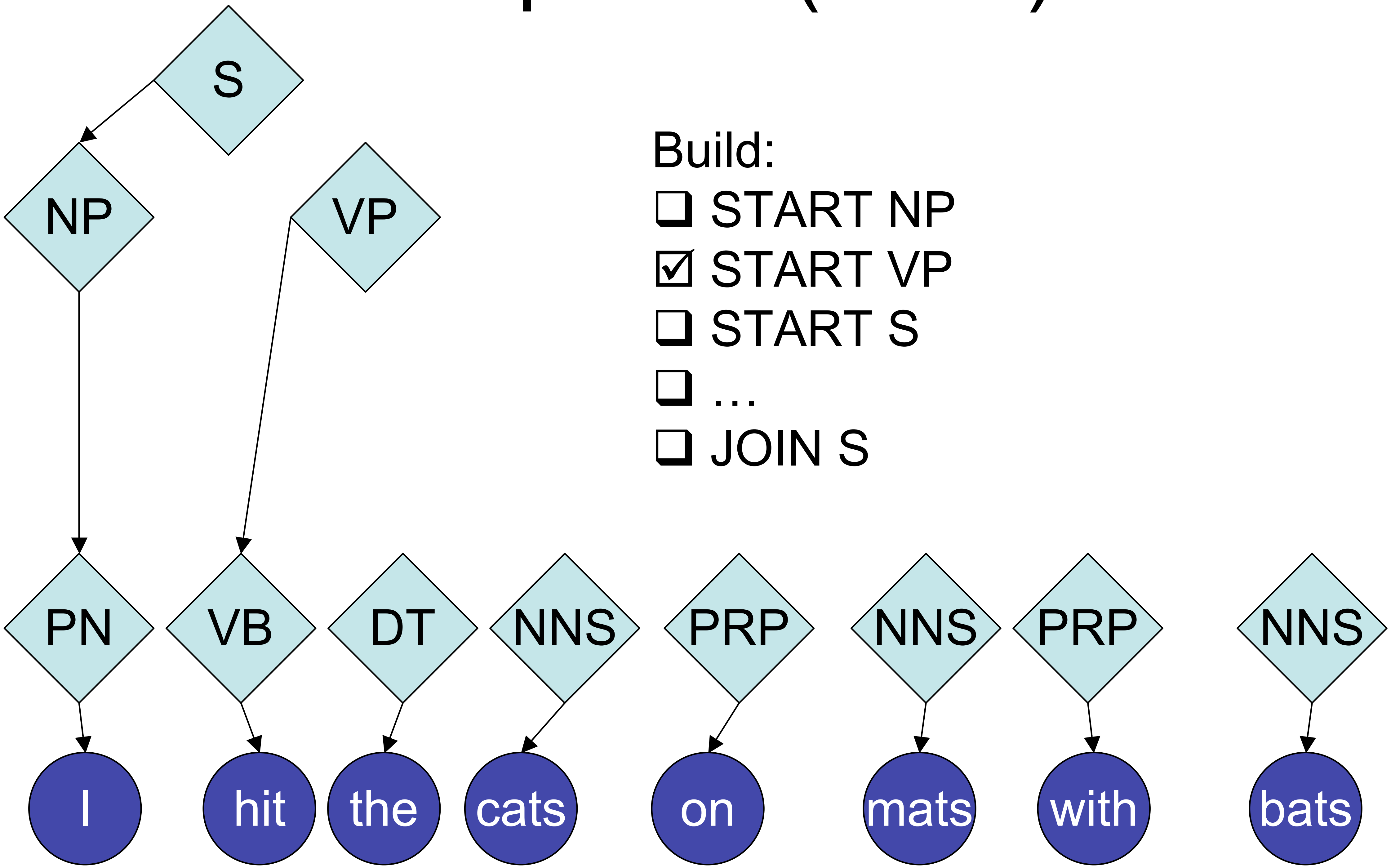
Ratnaparkhi (1998)



Build:
- ❑ START NP
- ❑ START VP
- ❑ START S
- ❑ …
- ❑ JOIN S

[Slides: Noah Smith]

Ratnaparkhi (1998)



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[Slides: Noah Smith]

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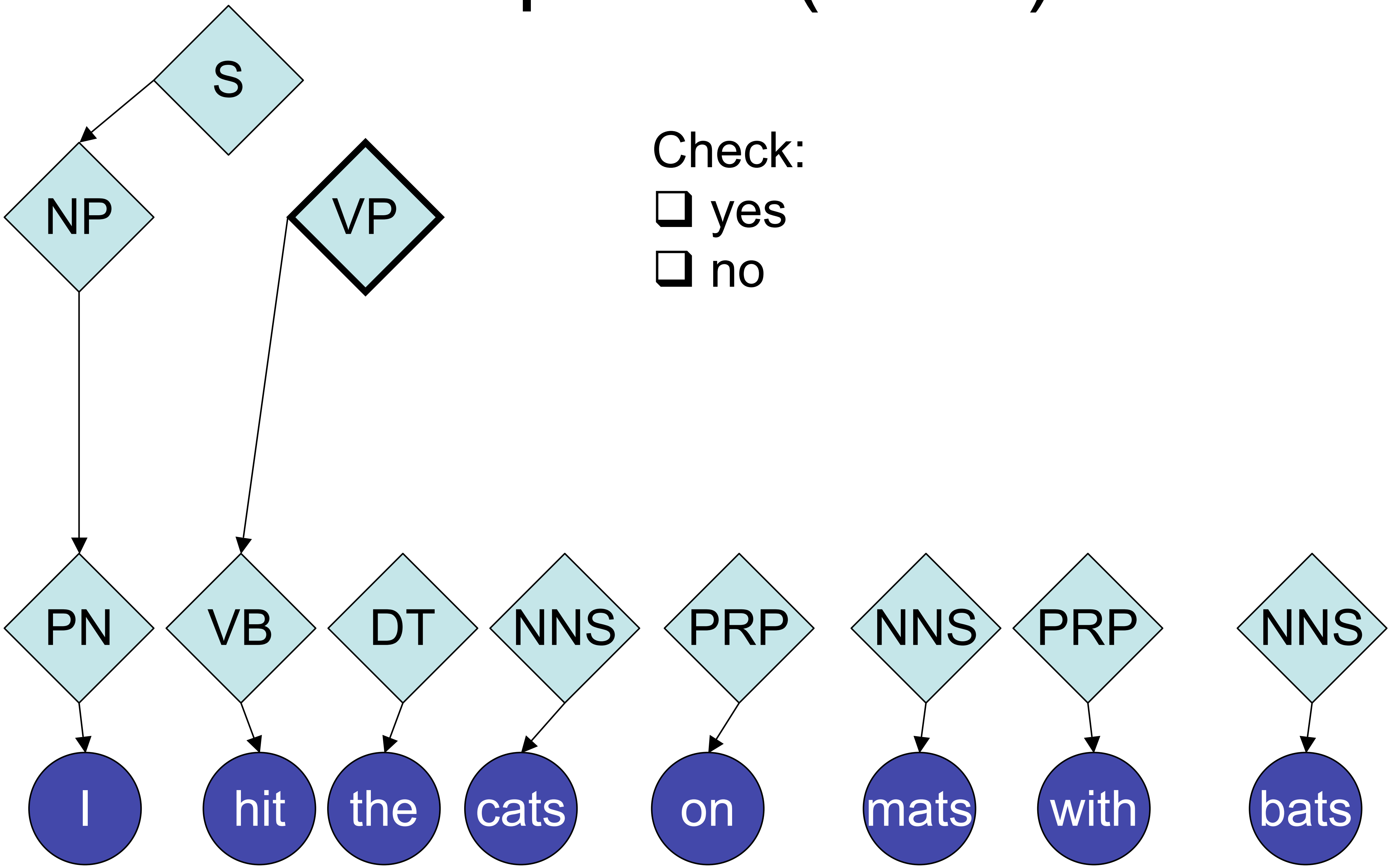

Check:
- ❑ yes
- ❑ no

[Slides: Noah Smith]

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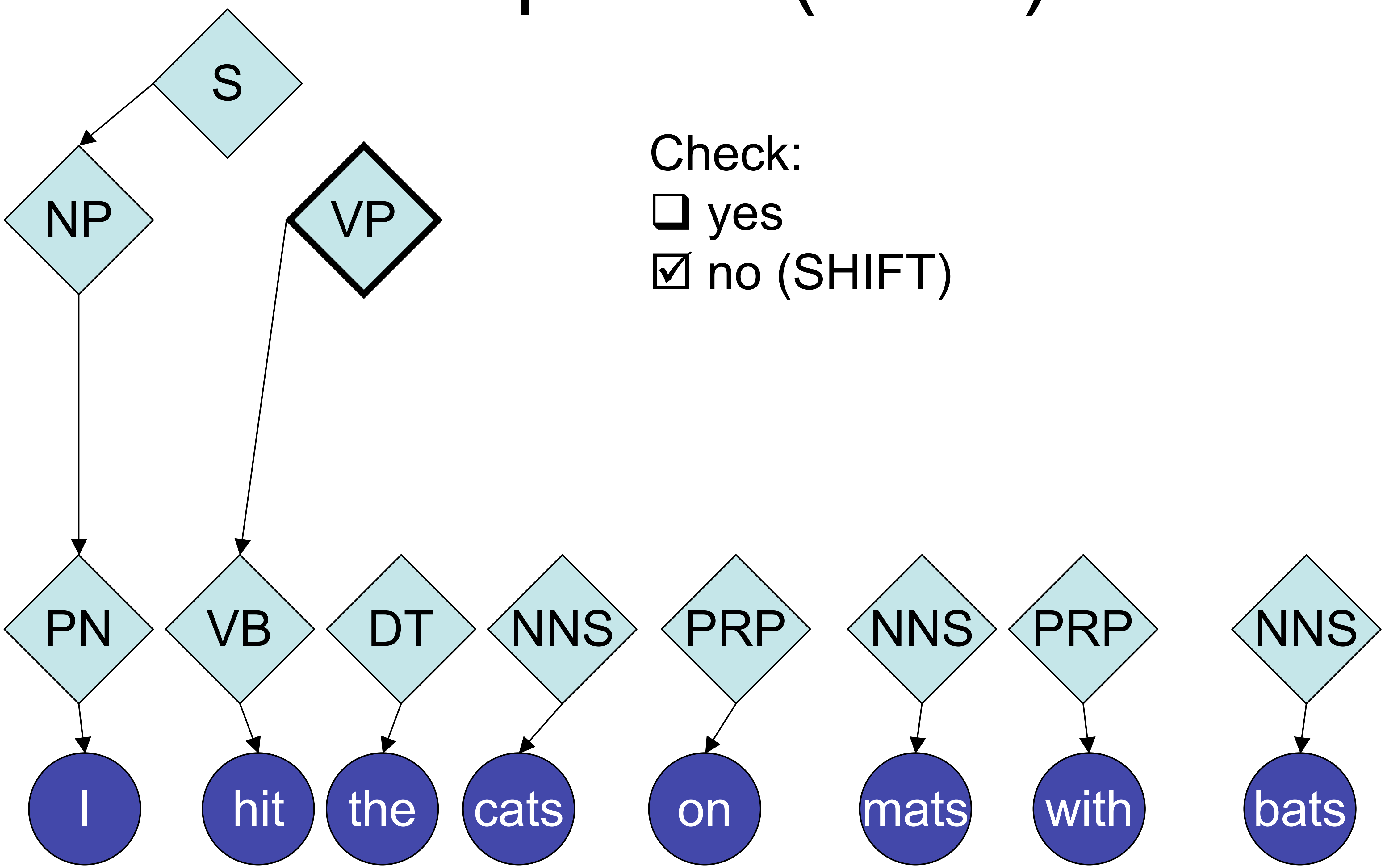

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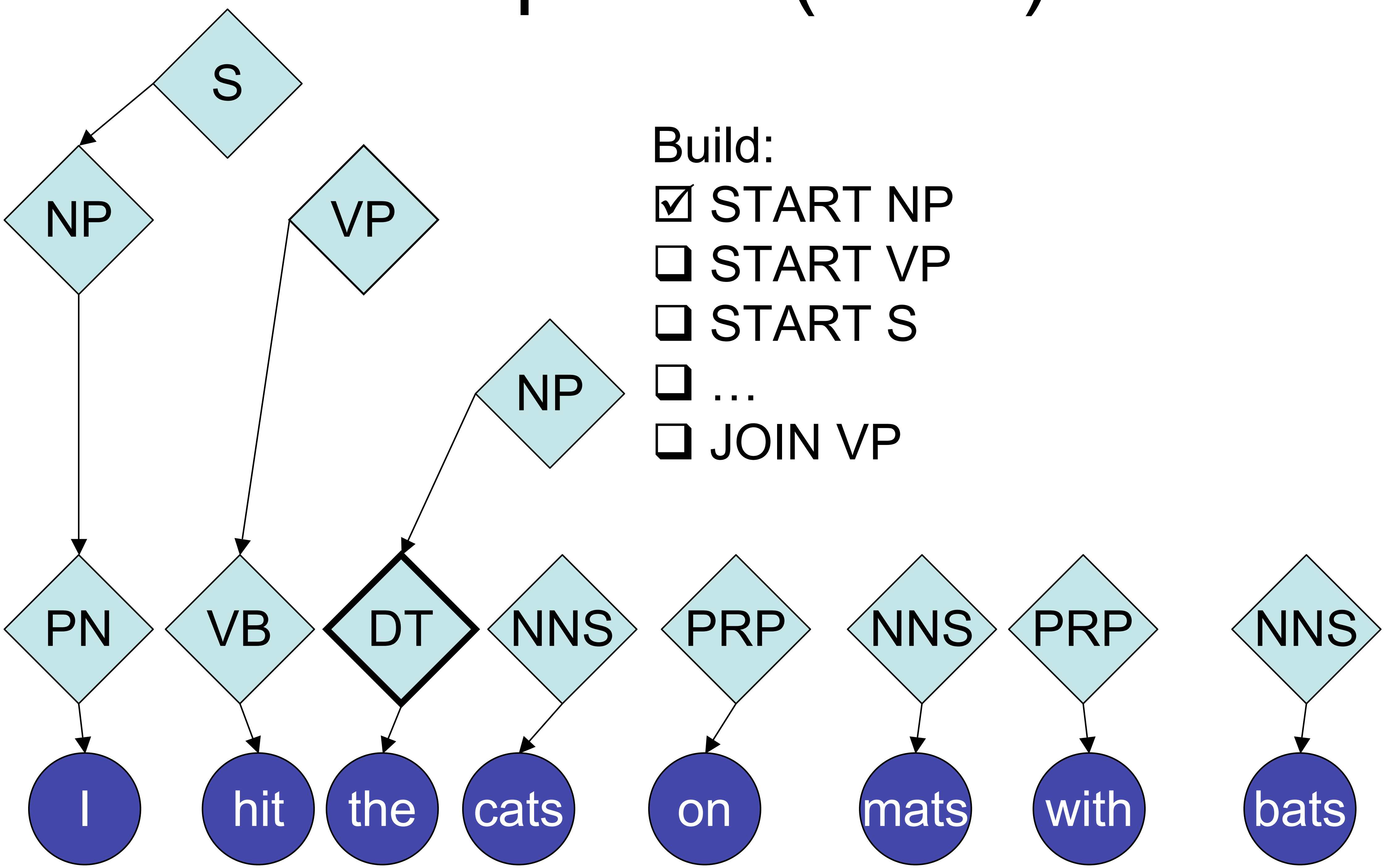

Build:

- ☑ START NP
- ☐ START VP
- ☐ START S
- ☐ …
- ☐ JOIN VP

[Slides: Noah Smith]

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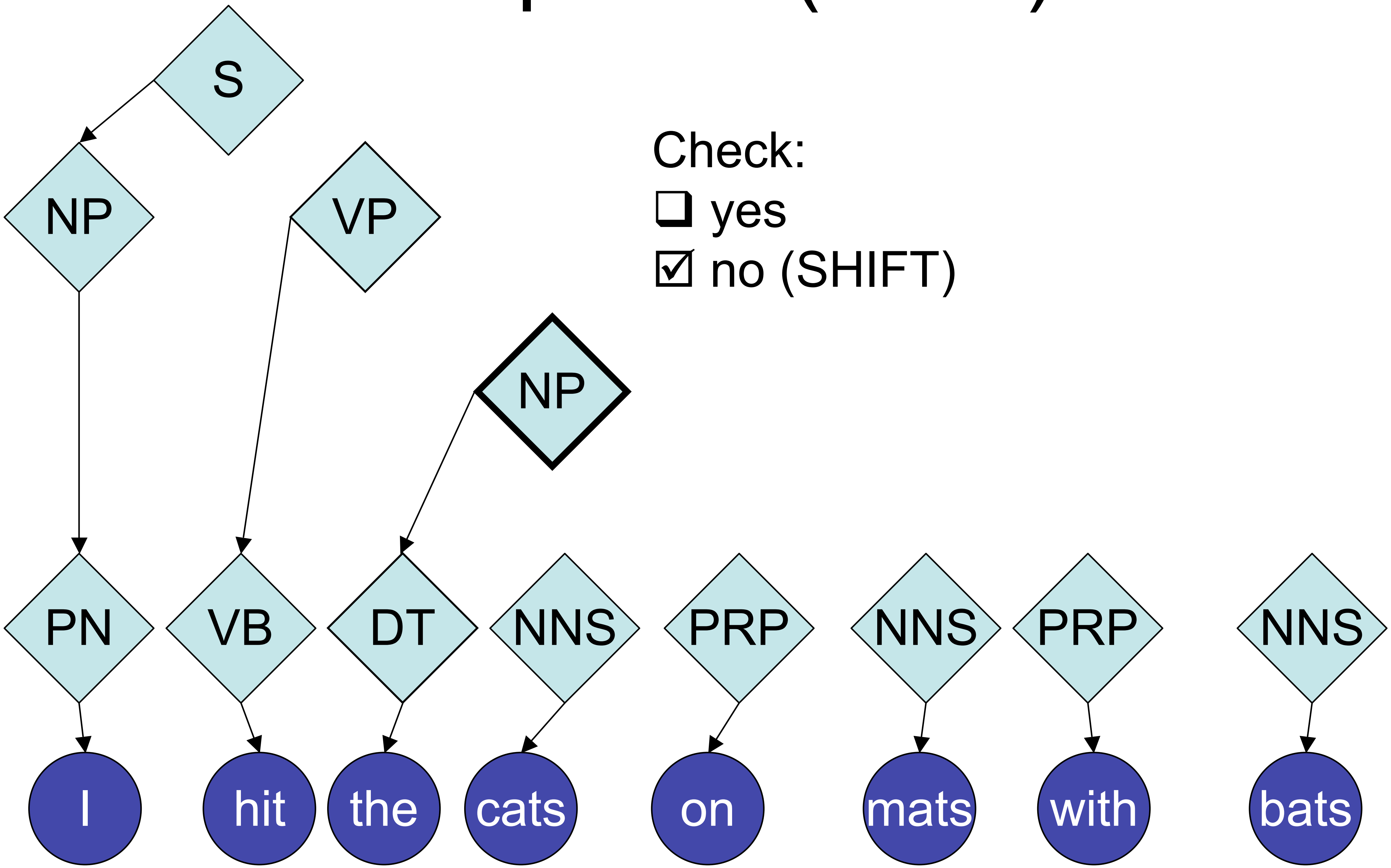

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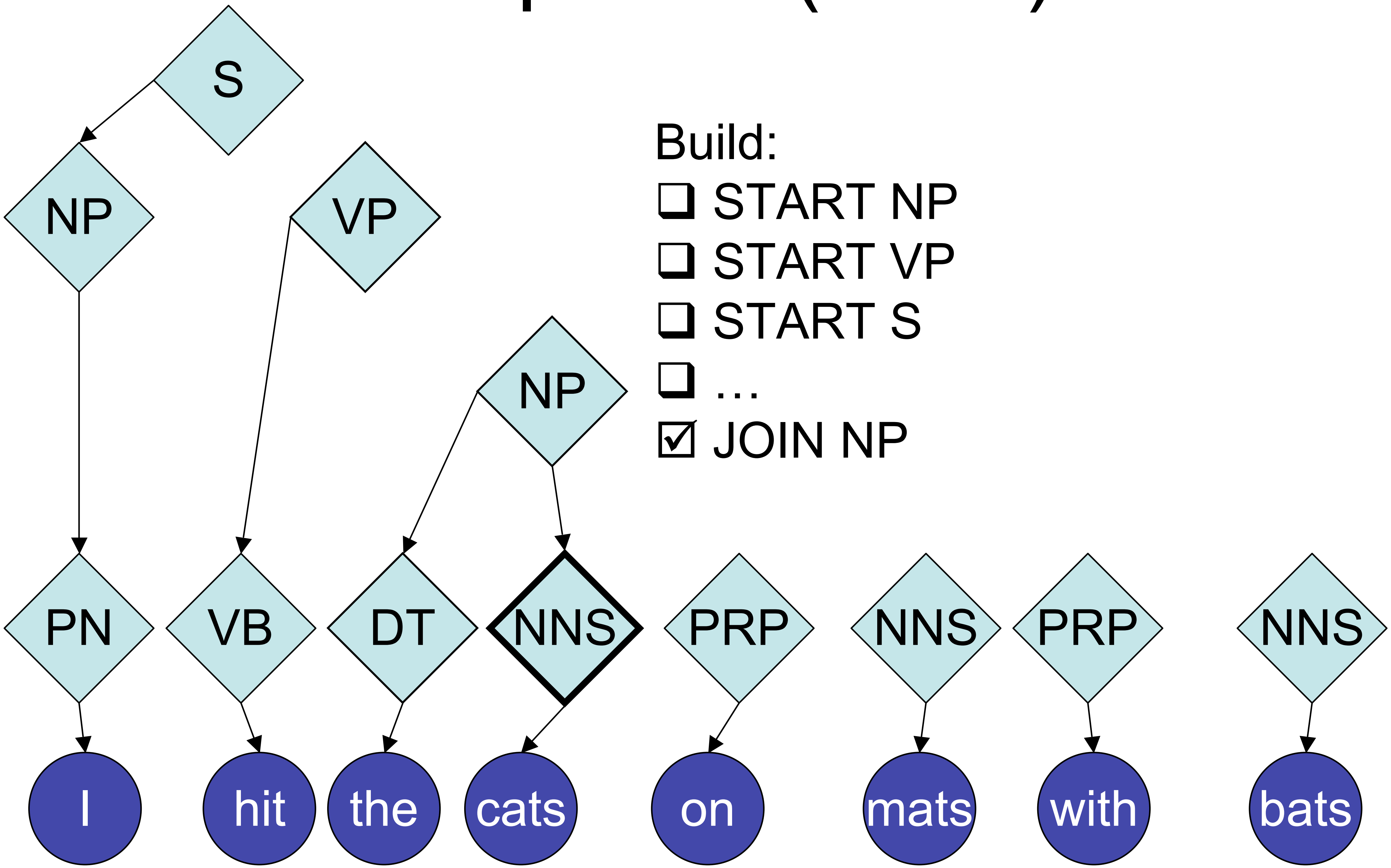

Build:

- ❑ START NP
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- ❑ START S
- ❑ …
- ☑ JOIN NP

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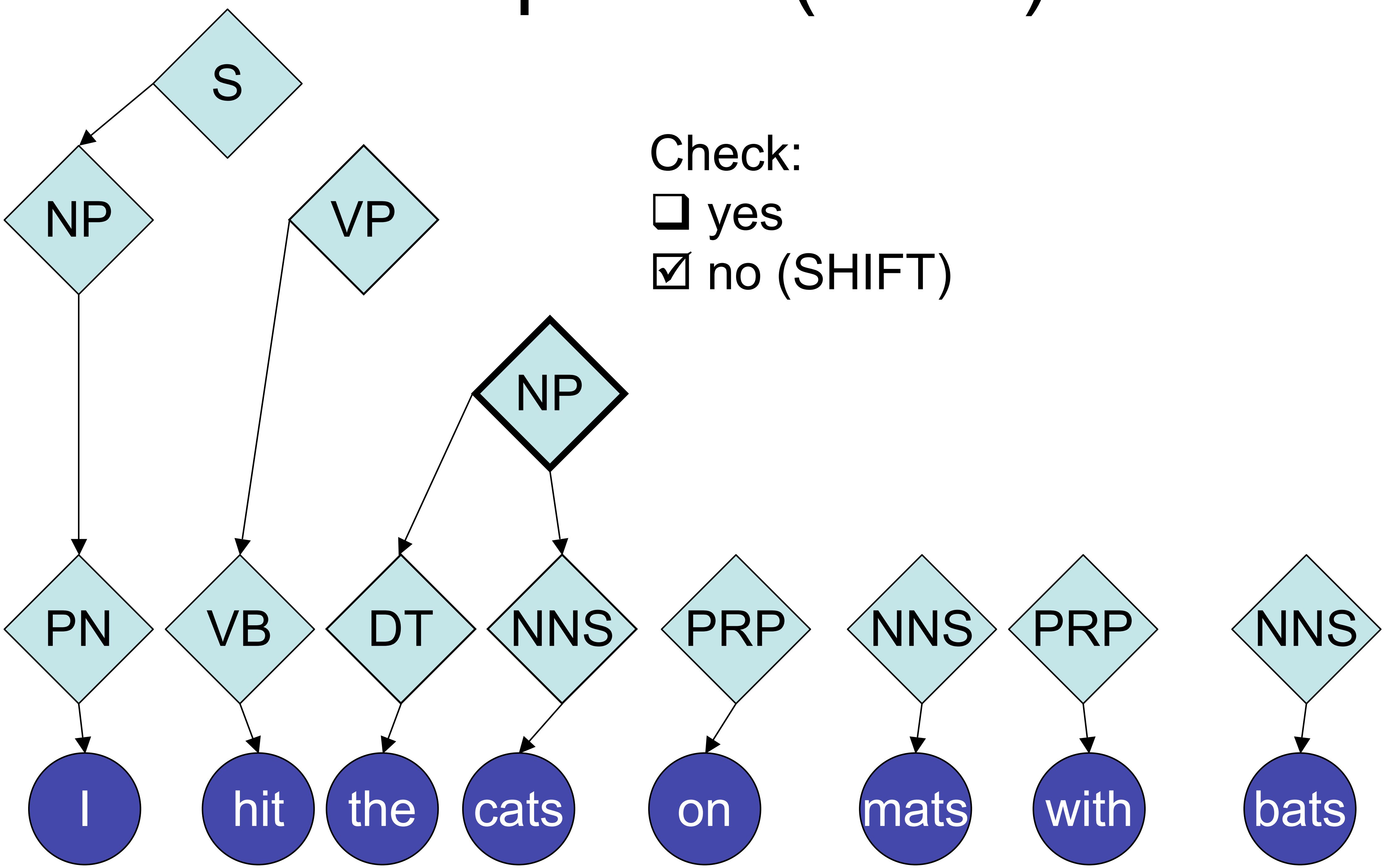

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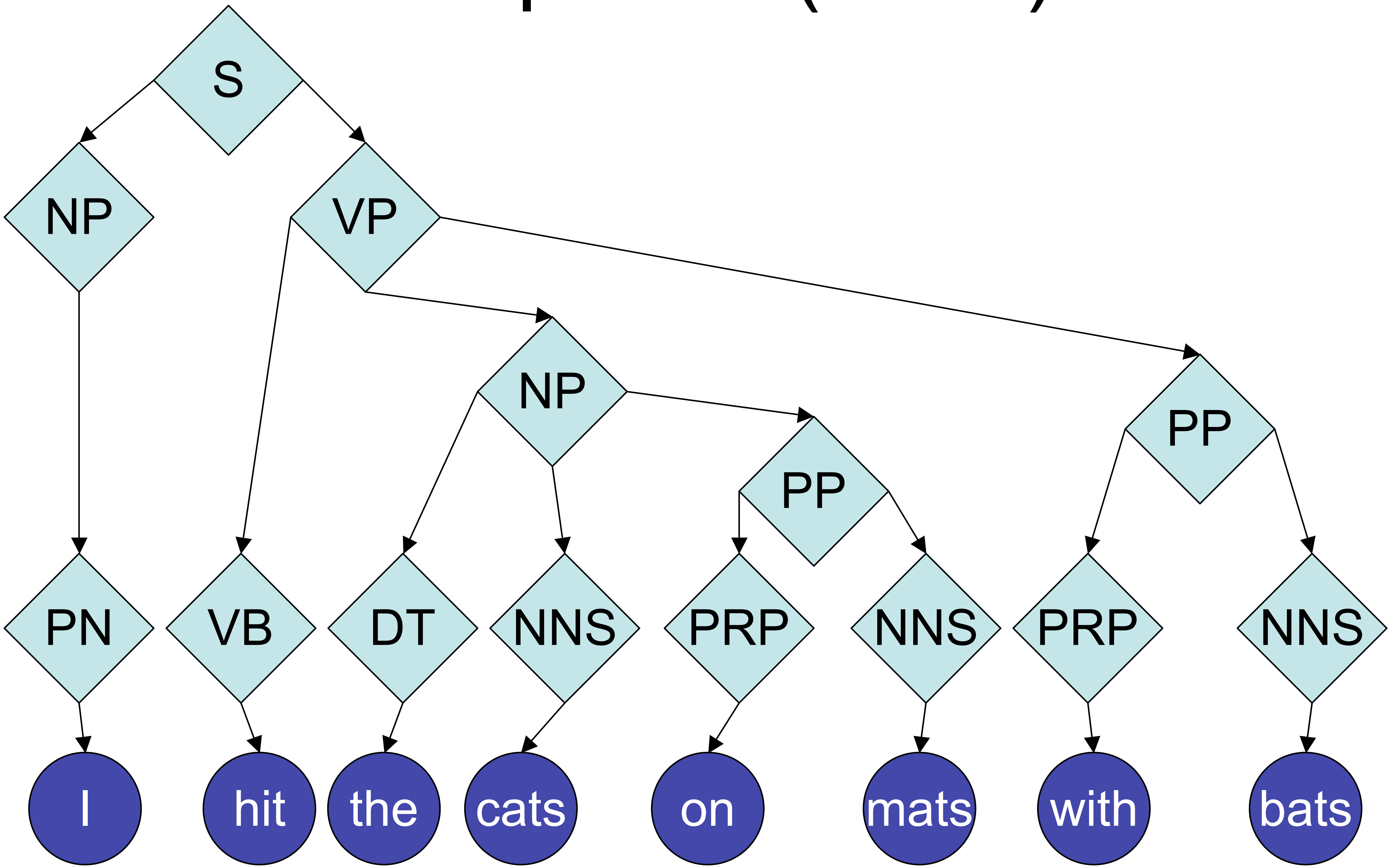


[Slides: Noah Smith]

- Shift-reduce / incremental parsers have powerful features: can look at currently built-up structure so far, and current automaton state.
  - Also called a "history-based model"
- Contrast to global inference approaches. Have to choose between
  - local features + fast dynamic prog. inference (PCFG)
  - global features + slow inference (whole-tree loglinear)

How accurate are these things?

- These constit. parsers all get low 90's% labeled span F-score
    - Dependency parses get low 90's% arc accuracy.
- Which ambiguities or errors matter for what types of tasks?

```
S-----------------------------------------------------------------
               VP-------------------------------------------------
                     NP-------------------------------------------
NP--------------                               PP-----------------
NP---------          NP--------------     NP----------------------
NNP   POS   NNP   VBZ    JJ    NN   NN    IN   DT   NN    NN         .
Doc   's    Place offers cheap bar  food  in   a    chill atmosphere .
```

How accurate are these things?

(Numbers taken from Collins (2003))

- Subject-verb pairs: over 95% recall and precision
- Object-verb pairs: over 92% recall and precision
- Other arguments to verbs: $\approx$ 93% recall and precision
- Non-recursive NP boundaries: $\approx$ 93% recall and precision
- PP attachments: $\approx$ 82% recall and precision
- Coordination ambiguities: $\approx$ 61% recall and precision

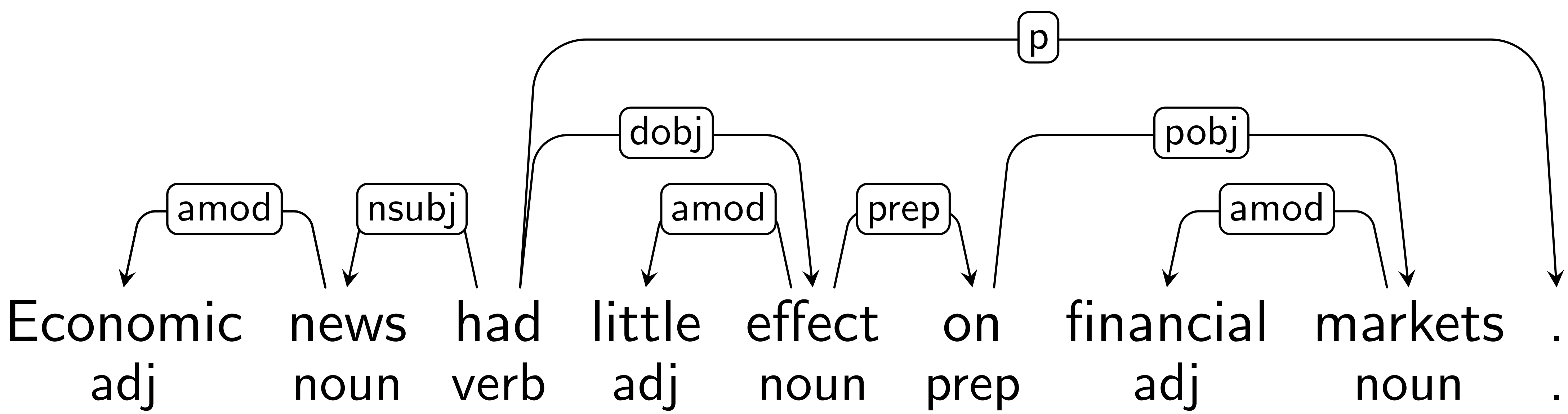
Dependencies

Dependency Syntax

- The basic idea:
  - Syntactic structure consists of lexical items, linked by binary asymmetric relations called dependencies.
- In the words of Lucien Tesnière [Tesnière 1959]:
  - The sentence is an *organized whole*, the constituent elements of which are *words*. [1.2] Every word that belongs to a sentence ceases by itself to be isolated as in the dictionary. Between the word and its neighbors, the mind perceives *connections*, the totality of which forms the structure of the sentence. [1.3] The structural connections establish *dependency* relations between the words. Each connection in principle unites a *superior* term and an *inferior* term. [2.1] The superior term receives the name *governor*. The inferior term receives the name *subordinate*. Thus, in the sentence *Alfred parle* [. . .], *parle* is the governor and *Alfred* the subordinate. [2.2]

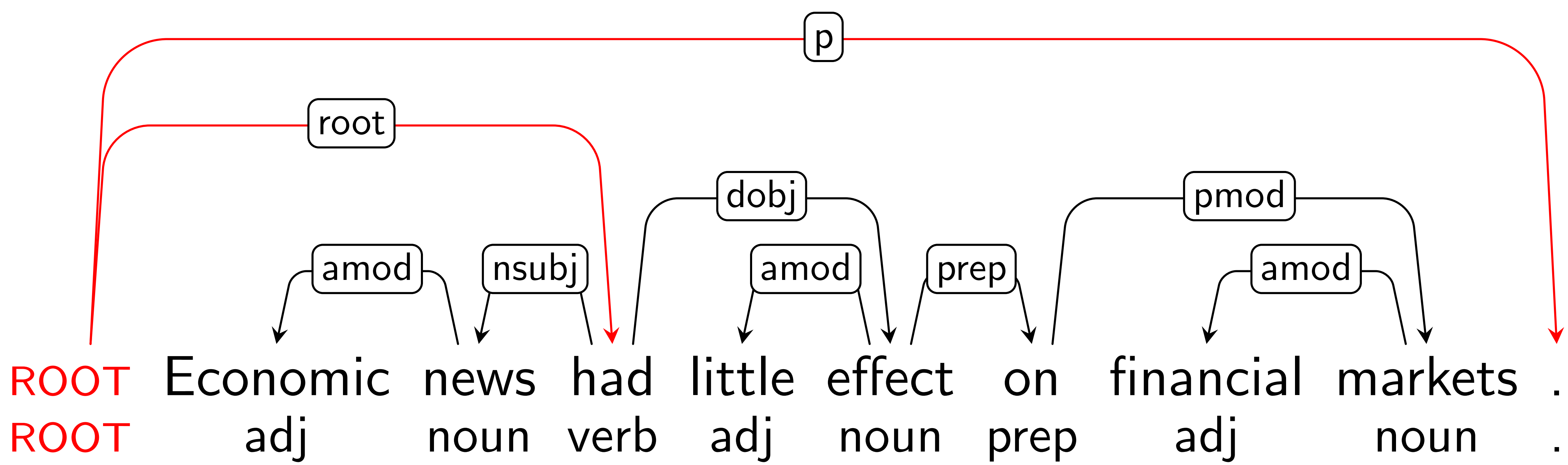
[Slides: Nivre and McDonald, EACL 2014 tutorial]

Dependency Structure



Connectedness, Acyclicity and Single-Head

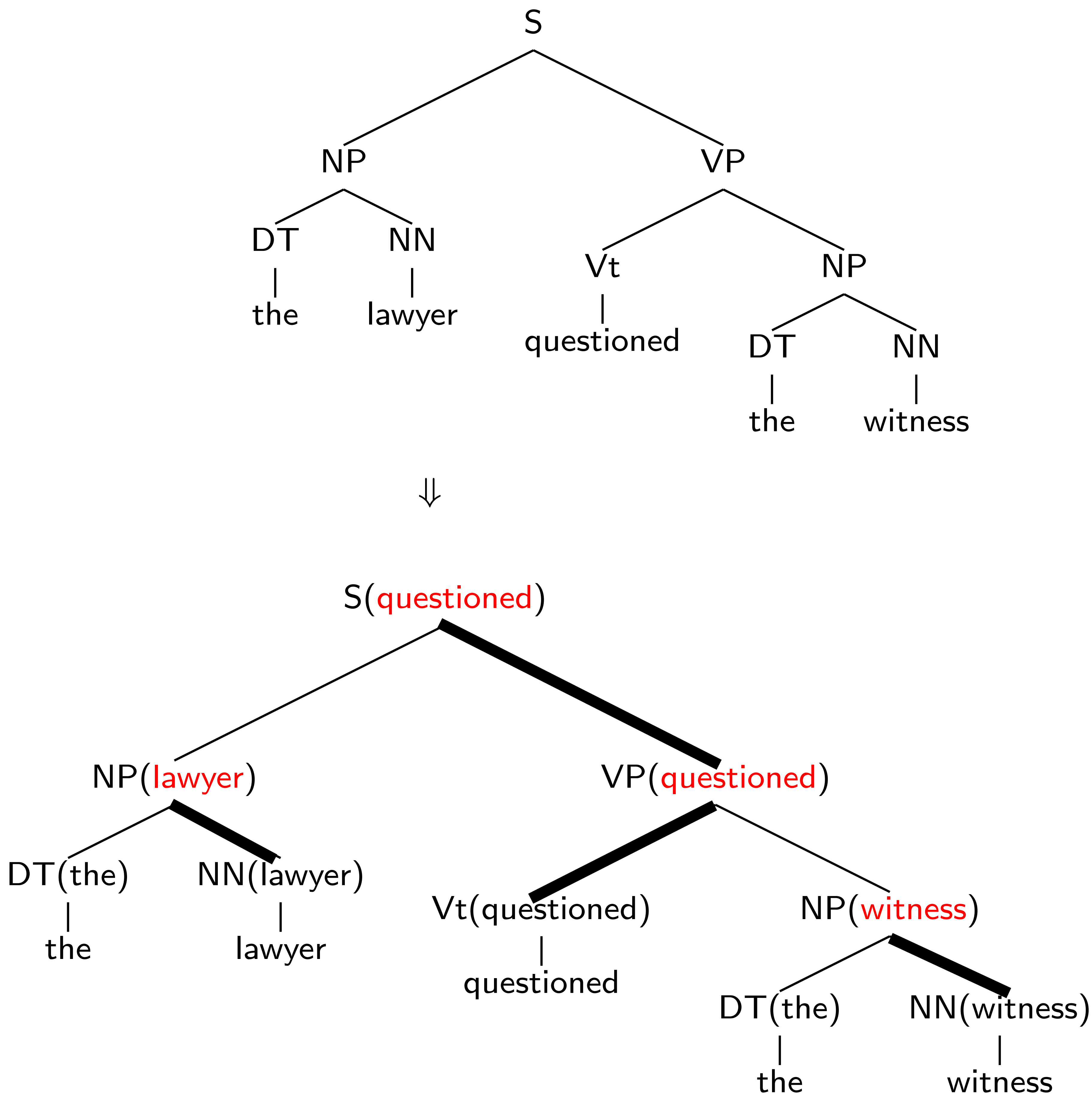
- Intuitions:
  - Syntactic structure is complete (Connectedness).
  - Syntactic structure is hierarchical (Acyclicity).
  - Every word has at most one syntactic head (Single-Head).
- Connectedness can be enforced by adding a special root node.



Constits -> Deps

- Every phrase has a head word. It dominates all other words of that phrase in the dep. graph.
- Head rules: for every nonterminal in tree, choose one of its children to be its "head". This will define head words.
- Every nonterminal type has a different head rule; e.g. from Collins (1997):

- If parent is NP,
  - Search from right-to-left for first child that's NN, NNP, NNPS, NNS, NX, JJR
  - Else: search left-to-right for first child which is NP


S
NP
VP
DT
NN
the
lawyer
Vt
NP
questioned
DT
NN
the
witness
⇓
S(questioned)
NP(lawyer)
VP(questioned)
DT(the)
NN(lawyer)
the
lawyer
Vt(questioned)
NP(witness)
questioned
DT(the)
NN(witness)
the
witness

Constits -> Deps

- Head rules were first used to add words into PCFG nonterminals (“lexicalized PCFGs”)
- But you can also extract dependency graphs from them!
- Two ways to parse to dependencies:
  - Run a constit parser, then run your favorite constit->deps converter
  - Direct dependency parsing
- Dependencies useful for many applications
- Dependency annotations are available for more languages ... perhaps easier to annotate