

Incremental Syntactic Language Models for Phrase-based Translation

Lane Schwartz

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Translation Model vs Language Model

Syntax in the Translation Model

Abeillé *et al.*, 1990; Poutsma, 1998; Poutsma, 2000; Yamada & Knight, 2001; Yamada & Knight, 2002; Eisner, 2003; Gildea, 2003; Hearne & Way, 2003; Poutsma, 2003; Imamura *et al.*, 2004; Galley *et al.*, 2004; Graehl & Knight, 2004; Melamed, 2004; Ding & Palmer, 2005; Hearne, 2005; Quirk *et al.*, 2005; Cowan *et al.*, 2006; Galley *et al.*, 2006; Huang *et al.*, 2006; Liu *et al.*, 2006; Marcu *et al.*, 2006; Zollmann & Venugopal, 2006; Bod, 2007; DeNeefe *et al.*, 2007; Liu *et al.*, 2007; Chiang *et al.*, 2008; Lavie *et al.*, 2008; Mi & Huang, 2008; Mi *et al.*, 2008; Resnik, 2008; Shen *et al.*, 2008; Zhou *et al.*, 2008; Chiang, 2009; Hanneman & Lavie, 2009; Liu *et al.*, 2009; Chiang, 2010; Huang & Mi, 2010; ...



Motivation

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Syntactic LM

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Decoder Integration

○○○○○

Results

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Questions?

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Definition

An **incremental syntactic language model** uses an incremental statistical parser to define a probability model over the dependency or phrase structure of target language strings.

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- Phrase-based decoder produces translation in the target language incrementally from left-to-right
- Phrase-based syntactic LM parser should parse target language hypotheses incrementally from left-to-right
- Related work:
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We use a standard HHMM parser (Schuler *et al.*, 2010)

Engineering simple model, equivalent to PPDA

Engineering linear-time parsing

Algorithmic elegant fit into phrase-based decoder

Cognitive nice psycholinguistic properties

Other parsers Roark (2001), Henderson (2004),
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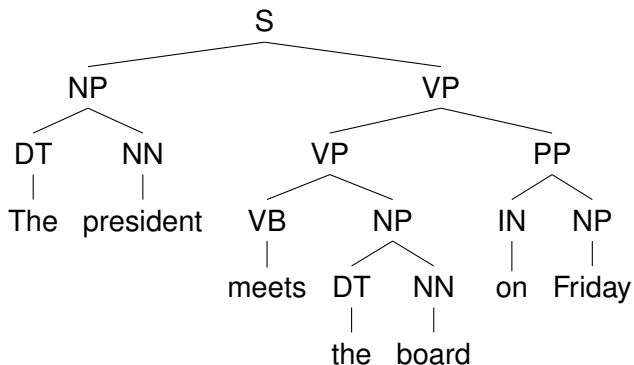
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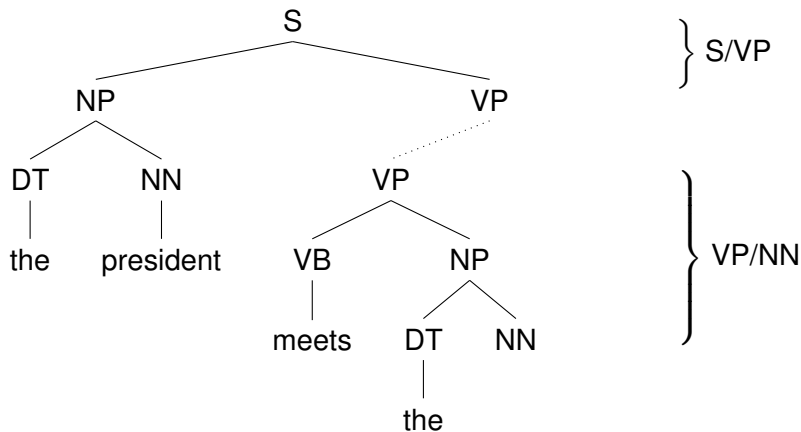
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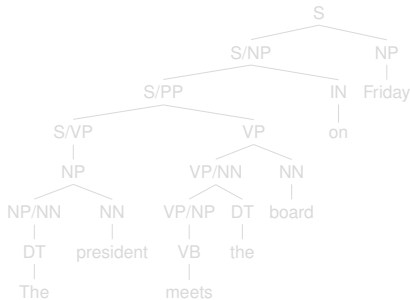
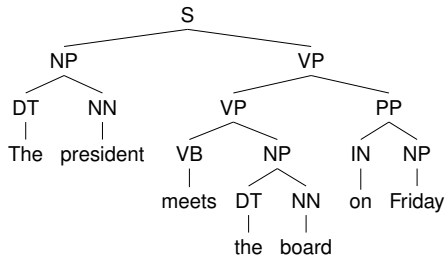
Incremental Parsing



Incremental Parsing



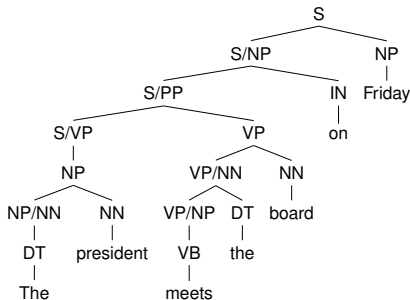
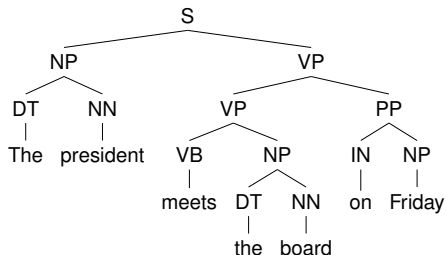
Transform right-expanding sequences of constituents
into left-expanding sequences of incomplete constituents (Johnson 1998)



Incomplete constituents can be processed incrementally using a
Hierarchical Hidden Markov Model parser. (Murphy & Paskin, 2001; Schuler et al. 2010)

Incremental Parsing using HHMM (Schuler et al. 2010)

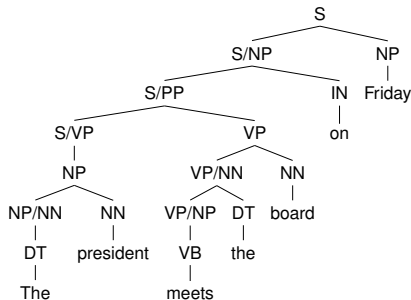
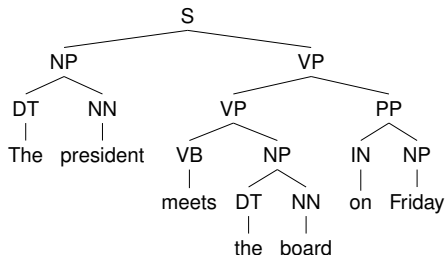
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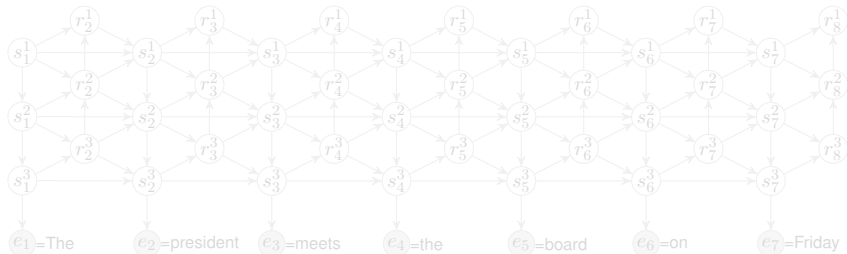
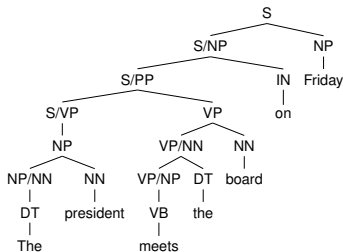


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Hierarchical Hidden Markov Model

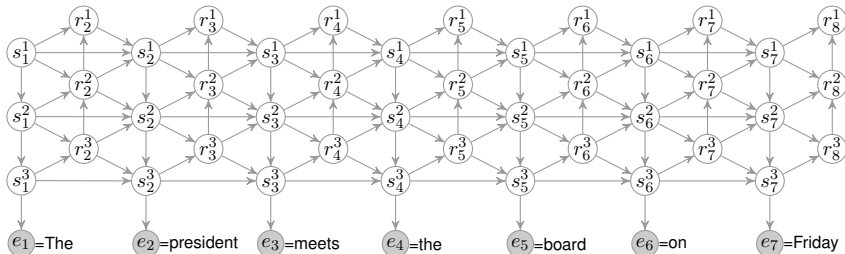
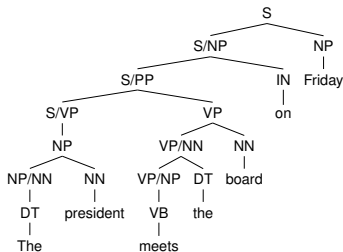
- Circles denote hidden random variables
- Edges denote conditional dependencies
- Shaded circles denote observed values



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Hierarchical Hidden Markov Model

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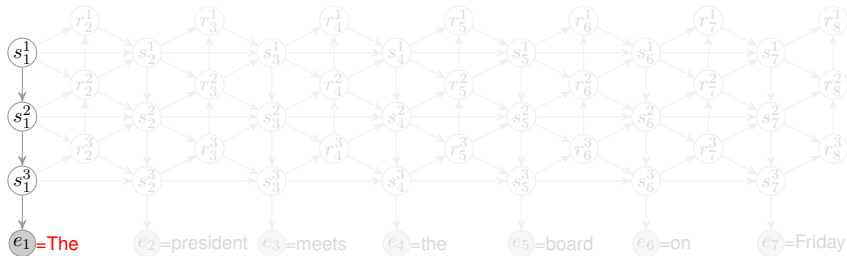
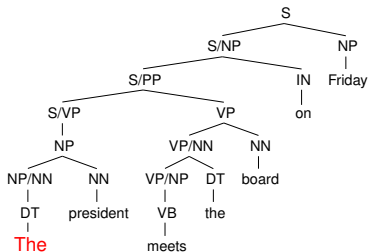


Incremental Parsing using HHMM (Schuler et al. 2010)

Analogous to “Maximally Incremental”
CCG Parsing

Equivalent to Probabilistic
Push-Down Automata

Isomorphic Tree \rightarrow Path



Motivation
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Syntactic LM
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Decoder Integration
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Results
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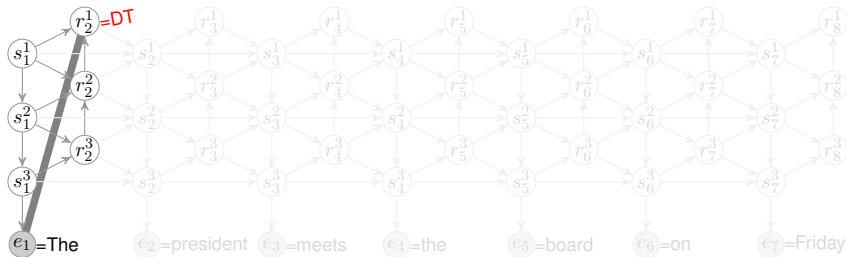
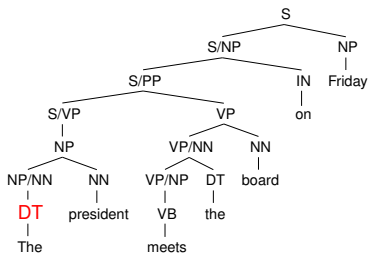
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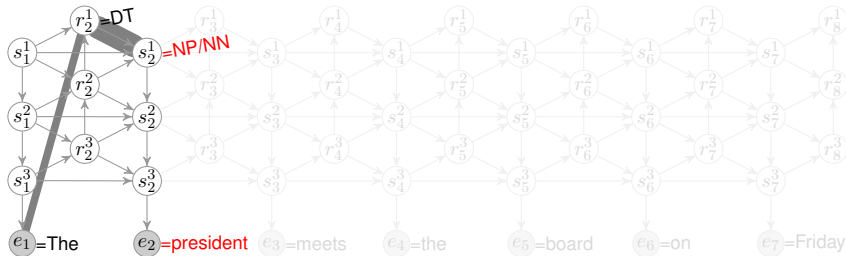
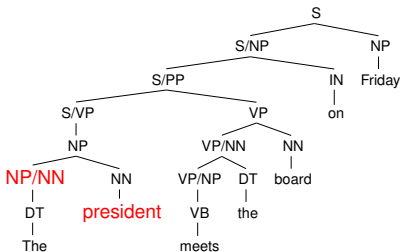
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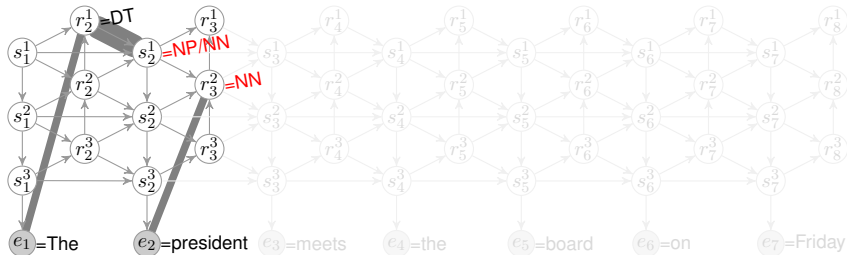
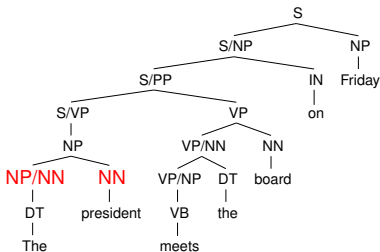
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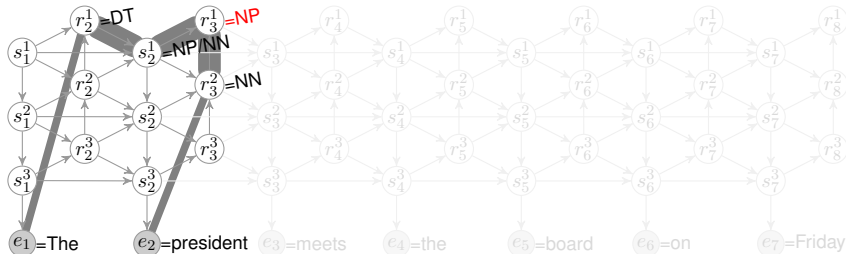
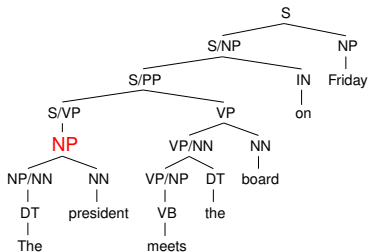
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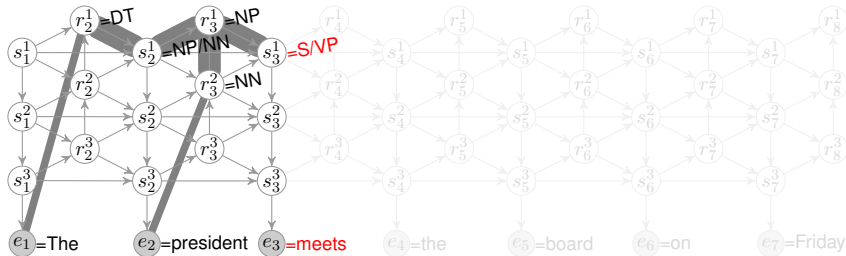
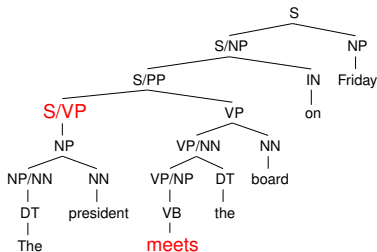
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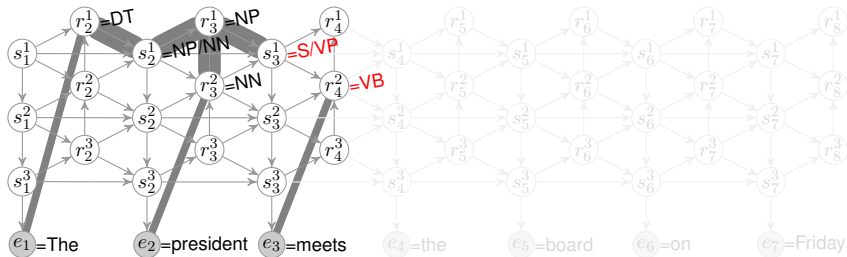
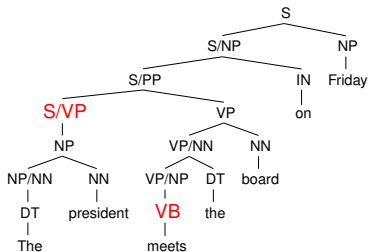


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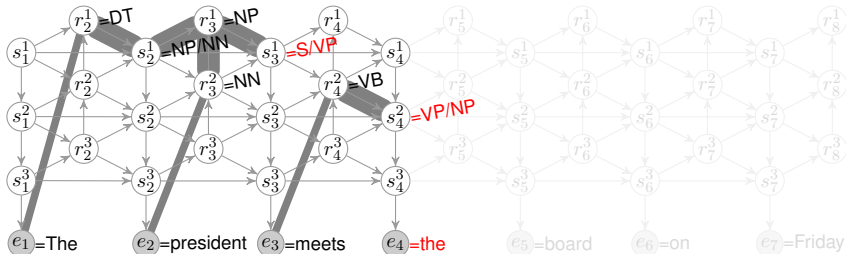
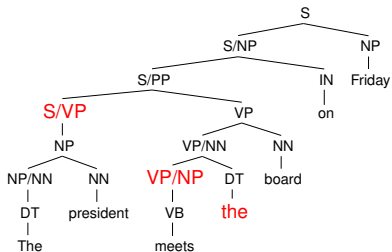
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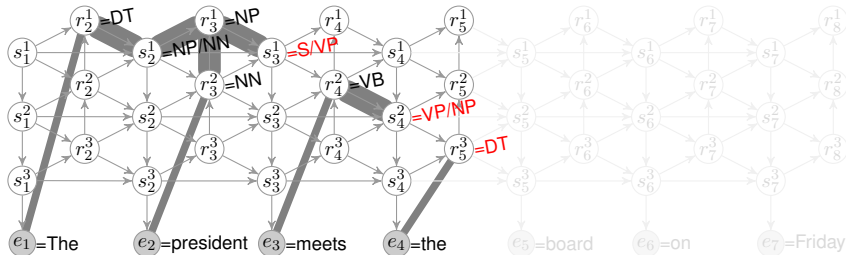
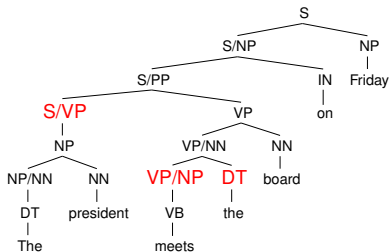


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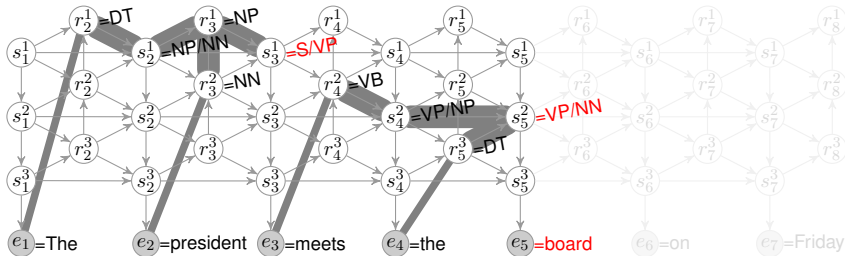
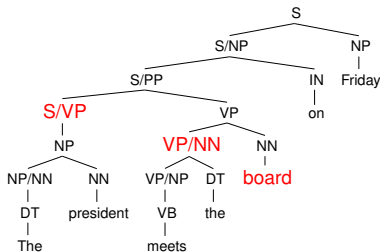
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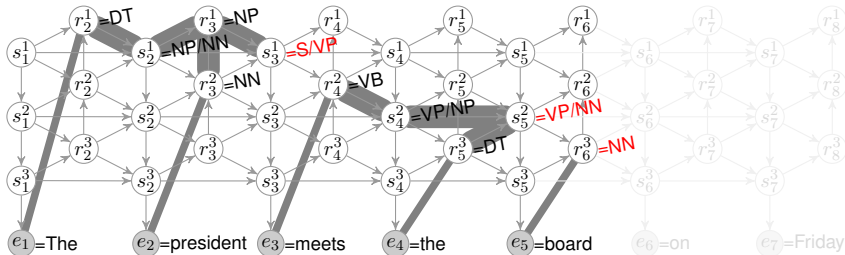
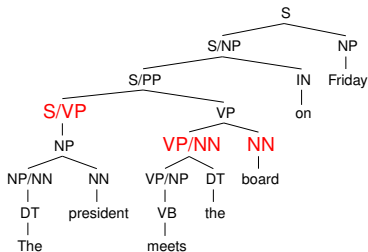
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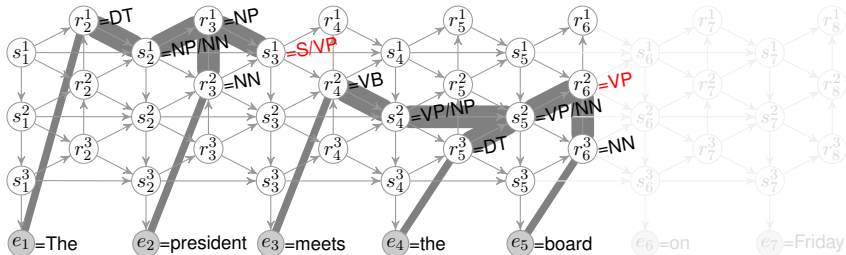
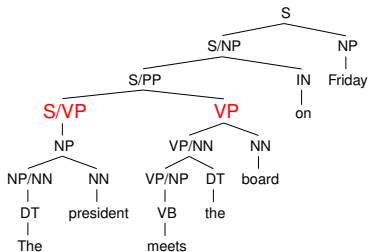
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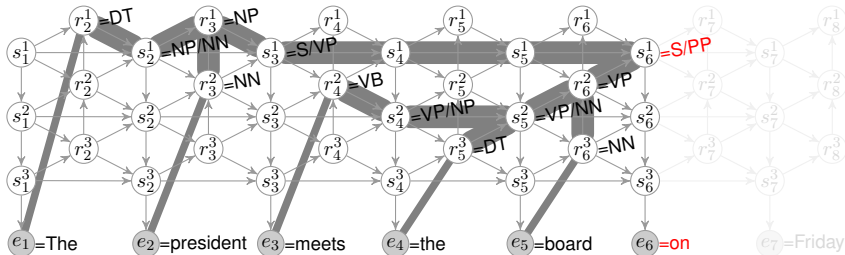
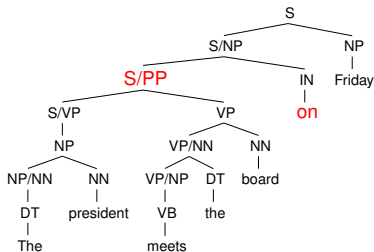
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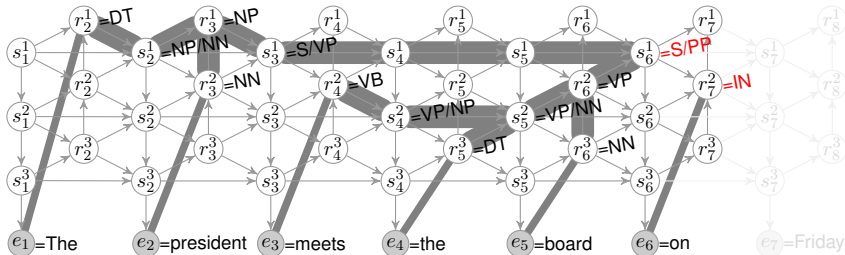
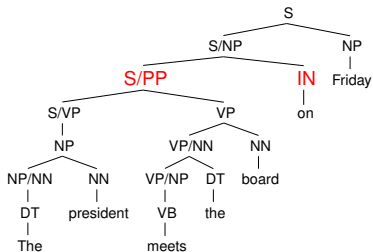
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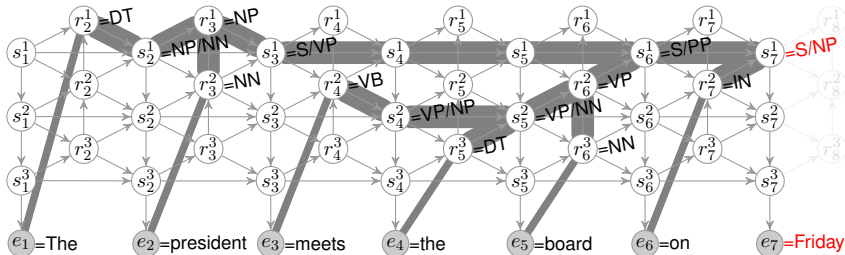
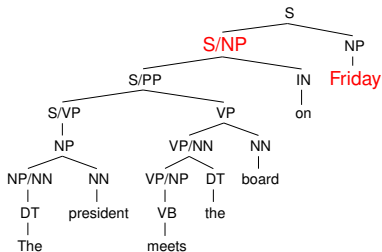
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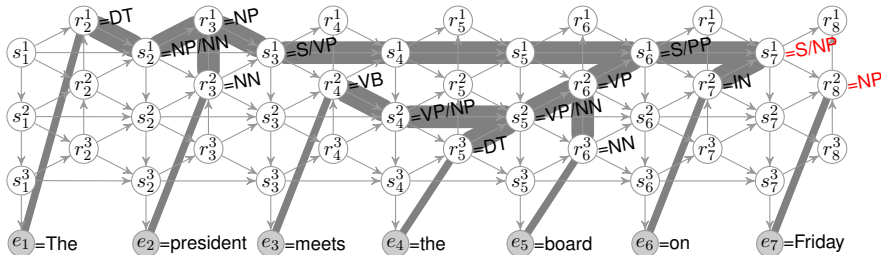
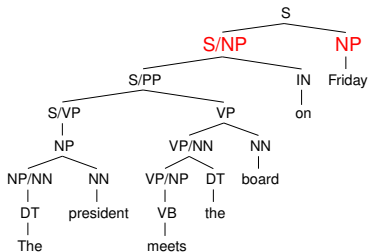
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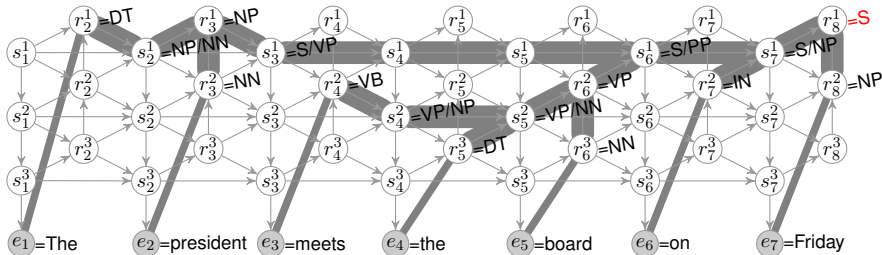
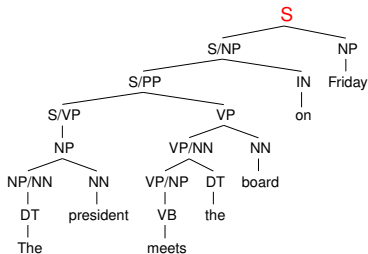
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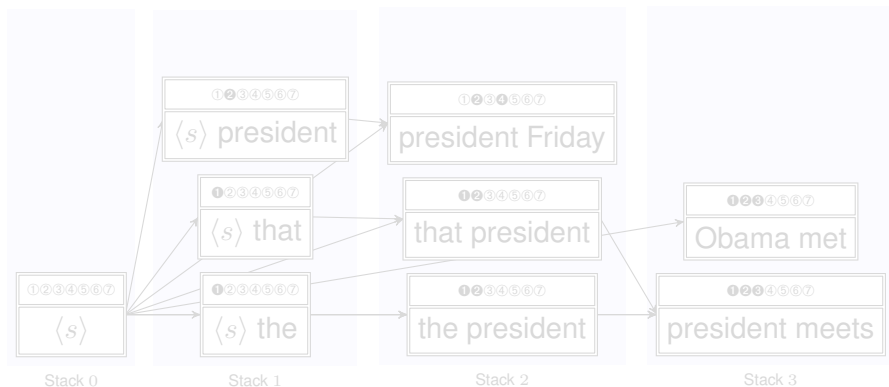
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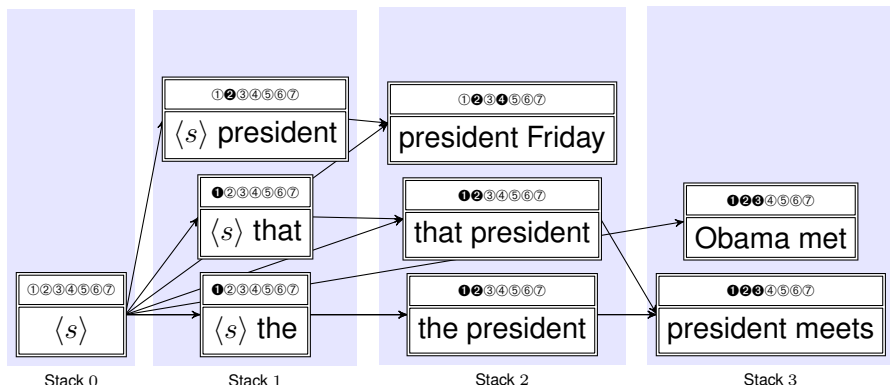
Phrase-Based Translation

Der Präsident trifft am Freitag den Vorstand
The president meets the board on Friday



Phrase-Based Translation

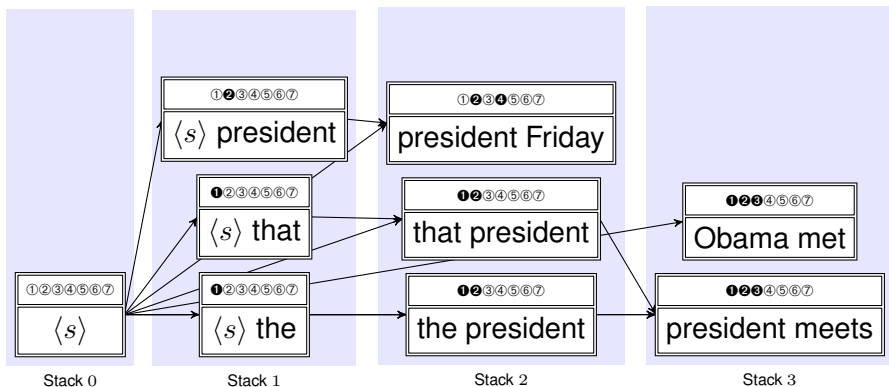
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Phrase-Based Translation with Syntactic LM

Definition

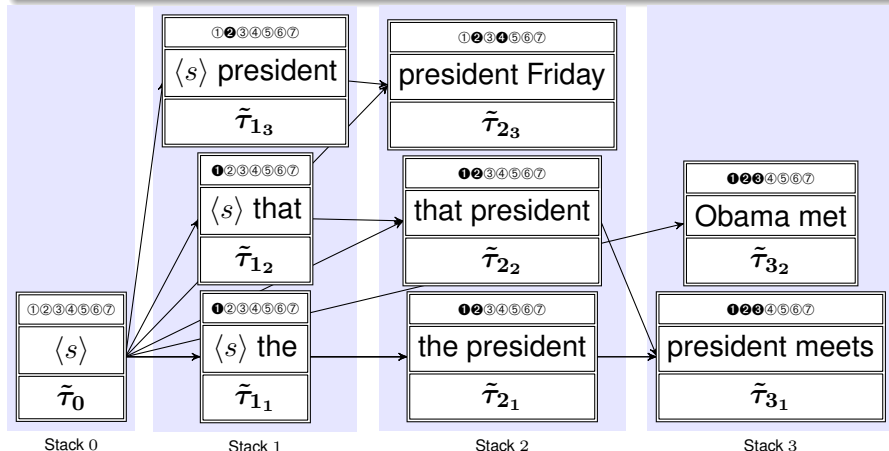
$\tilde{\tau}_{t_h}$ represents parses of the partial translation at node h in stack t



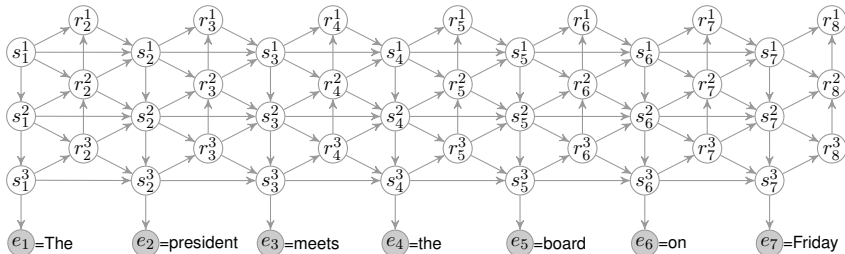
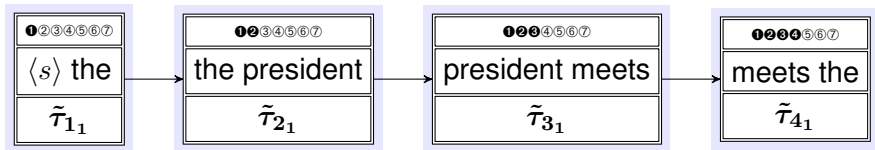
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Integrate Parser into Phrase-based Decoder



Motivation
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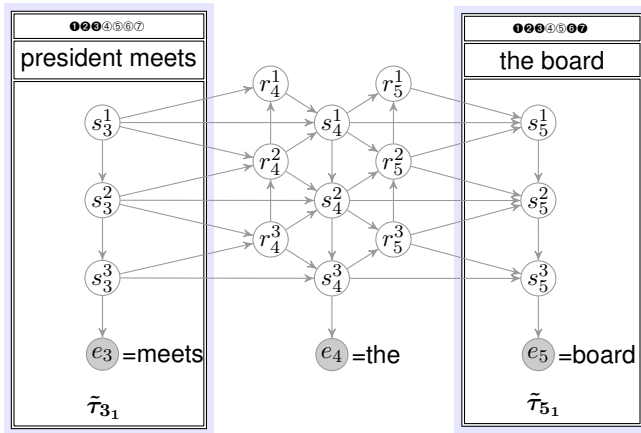
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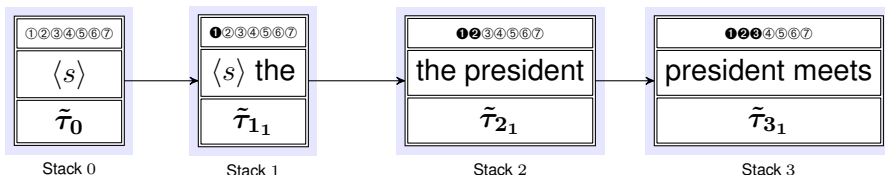


Direct Maximum Entropy Model of Translation

$$\hat{e} = \operatorname{argmax}_e \exp \sum_j \lambda_j h_j(e, \mathbf{f})$$

λ = Set of j feature weights

h = {
Phrase-based translation model
 n -gram LM
Distortion model
⋮
Syntactic LM $P(\tilde{\tau}_{t_h})$



Does an Incremental Syntactic LM Help Translation?

That's nice...

but will it make my BLEU score go up?

Perplexity Results

Language models trained on WSJ Treebank corpus

LM	In-domain Perplexity	Out-of-domain Perplexity
WSJ 5-gram LM	232	1262
WSJ Syntactic LM	385	529

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Perplexity Results

Language models trained on WSJ Treebank corpus
...and n -gram model for larger English Gigaword corpus.

LM	In-domain Perplexity	Out-of-domain Perplexity
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WSJ Syntactic LM	385	529
Interpolated WSJ 5-gram + WSJ SynLM	209	225
Gigaword 5-gram	258	312
Interpolated Gigaword 5-gram + WSJ SynLM	222	123

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Does an Incremental Syntactic LM Help Translation?

Moses with LM(s)	BLEU
Using n -gram LM only	18.78
Using n -gram LM + Syntactic LM	19.78

Experiment

- NIST OpenMT 2008 Urdu-English data set
- Moses with standard phrase-based translation model
- Tuning and testing restricted to sentences ≤ 20 words long
- Results reported on devtest set
- n -gram LM is WSJ 5-gram LM

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Experiment

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- n -gram LM is WSJ 5-gram LM

- Straightforward general framework for incorporating any Incremental Syntactic LM into Phrase-based Translation
- We used an Incremental HHMM Parser as Syntactic LM
 - Syntactic LM shows substantial decrease in perplexity on out-of-domain data over n -gram LM when trained on same data
 - Syntactic LM interpolated with n -gram LM shows even greater decrease in perplexity on both in-domain and out-of-domain data, even when n -gram LM is trained on substantially larger corpus
 - +1 BLEU on Urdu-English task with Syntactic LM
- All code is open source and integrated into Moses

Incremental Syntactic Language Models for Phrase-based Translation

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This looks a lot like CCG

Our parser performs some CCG-style operations:

- Forward function application
 - $NP/NN \ NN \Rightarrow NP$
- Type raising
 - $NP \Rightarrow S/VP$
- Type raising in conjunction with forward function composition
 - $DT \Rightarrow NP/NN$
 - $VP/NP \ NP/NN \Rightarrow VP/NN$

Why not just use CCG?

- No probabilistic version of incremental CCG
- Our parser is constrained
(we don't have backward composition)
- We *do* use those components of CCG (forward function application and forward function composition) which are useful for probabilistic incremental parsing

Mean per-sentence decoding time

Sentence length	Moses	+SynLM beam=50	+SynLM beam=2000
10	0.2 sec	9 min	19 min
20	0.5 sec	20 min	43 min
30	0.9 sec	29 min	62 min
40	1.1 sec	35 min	76 min

- Parser beam sizes are indicated for the syntactic LM
- Parser runs in linear time, but we're **parsing all paths through the Moses lattice** as they are generated by the decoder
- More informed pruning, but slower decoding

Phrase-Based Translation with Syntactic LM

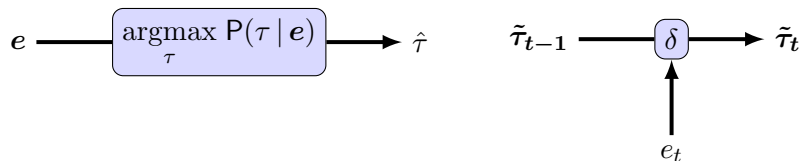
Definition

$e \stackrel{\text{def}}{=} \text{string of } n \text{ target language words } e_1 \dots e_n$

$e_t \stackrel{\text{def}}{=} \text{the first } t \text{ words in } e, \text{ where } t \leq n$

$\tau_t \stackrel{\text{def}}{=} \text{set of all incremental parses of } e_t$

$\tilde{\tau}_t \stackrel{\text{def}}{=} \text{subset of parses } \tau_t \text{ that remain after parser pruning}$



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