

A Latent Variable Model of Synchronous Parsing for Syntactic and Semantic Dependencies

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Outline

- 1 A Latent Variable Model of Synchronous Parsing
- 2 Probability Model
- 3 Machine Learning Method
- 4 Evaluation

Motivation for synchronous parsing

- Syntax and semantics are **separate structures**, with different generalisations

Sub		Obj
John	broke	the vase.
A0		A1

Sub	
The vase	broke.
A1	

- Syntax and semantics are **highly correlated**, and therefore should be learned jointly
- **Synchronous parsing** provides a single joint model of two separate structures

Motivation for latent variables

- The correlations between syntax and semantics are partly **lexical**, and independence assumptions are **hard to specify** a priori
- The dataset is new, and there was little time for feature engineering
- **Latent variables** provide a powerful mechanism for discovering correlations both within and between the structures

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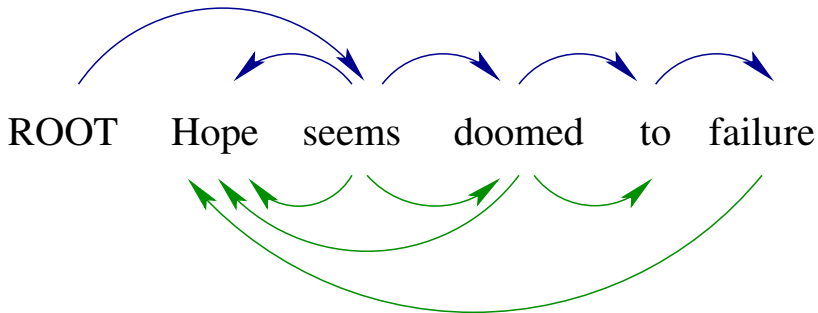
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The Probability Model

- A **generative, history-based** model
- of the **joint probability**
- of syntactic and semantic **synchronous derivations**
- synchronised at **each word**.

Syntactic and semantic dependencies example



$$P(T_d, T_s)$$

Syntactic and semantic derivations

Define **two separate derivations**, one for the syntactic structure and one for the semantic structure.

$$P(T_d, T_s) = P(D_d^1, \dots, D_d^{m_d}, D_s^1, \dots, D_s^{m_s})$$

- Actions of an incremental shift-reduce style parser similar to MALT [Nivre et al., 2006]
- Semantic derivations are less constrained, because their structures are less constrained
- Assumes each dependency structure is **individually planar** (“projective”)

Synchronisation granularity

Use an intermediate synchronisation granularity, between full predications and individual actions.

$$C^t = D_d^{bt_d}, \dots, D_d^{et_d}, \text{shift}_t, D_s^{bt_s}, \dots, D_s^{et_s}, \text{shift}_t$$
$$P(D_d^1, \dots, D_d^{m_d}, D_s^1, \dots, D_s^{m_s}) = P(C^1, \dots, C^n)$$

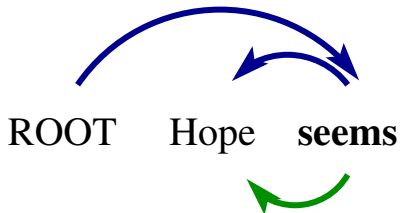
- Synchronisation at **each word** prediction
- Results in **one shared input queue**
- Allows **two separate stacks**

Synchronous parsing example

ROOT **Hope**

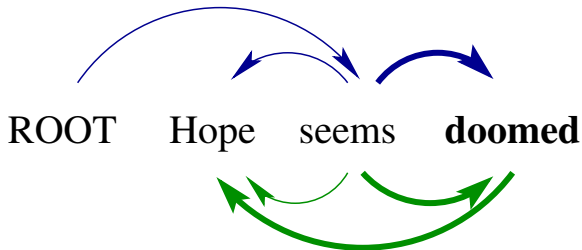
$P(C^1)$

Synchronous parsing example



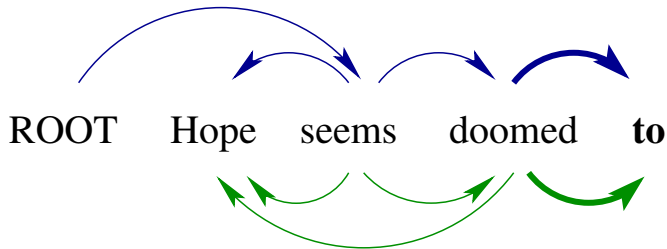
$$P(C^1) \mathbf{P}(C^2|C^1)$$

Synchronous parsing example



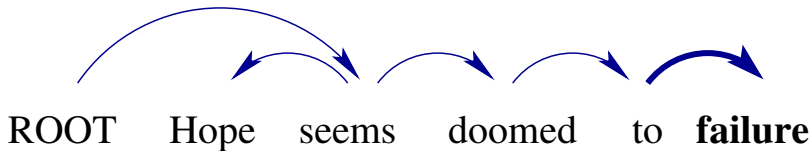
$$P(C^1) P(C^2|C^1) \mathbf{P}(C^3|C^1, C^2)$$

Synchronous parsing example



$$P(C^1) P(C^2|C^1) P(C^3|C^1, C^2) \mathbf{P}(C^4|C^1, C^2, C^3)$$

Synchronous parsing example



$$P(C^1) P(C^2|C^1) P(C^3|C^1, C^2) P(C^4|C^1, C^2, C^3) \mathbf{P(C^5|C^1, C^2, C^3, C^4)}$$

Derivation example

ROOT Hope

Derivation example

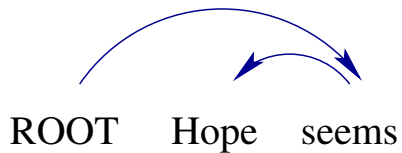
ROOT Hope seems

Derivation example

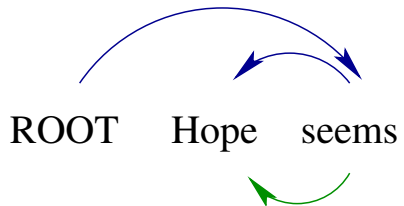
ROOT Hope seems



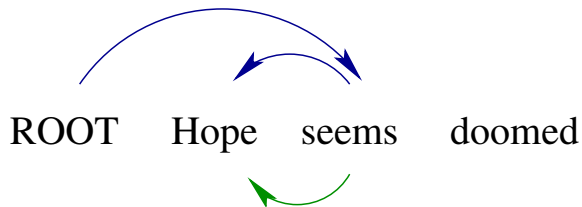
Derivation example



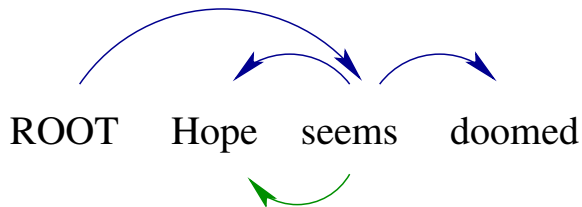
Derivation example



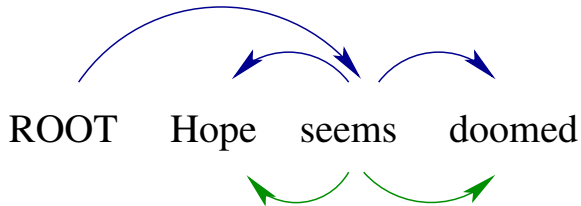
Derivation example



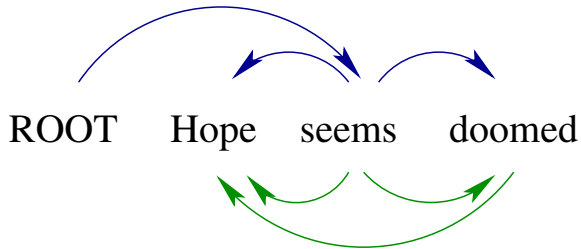
Derivation example



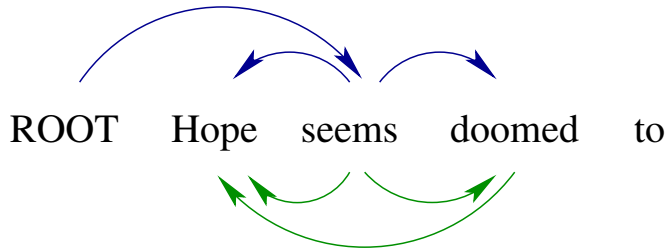
Derivation example



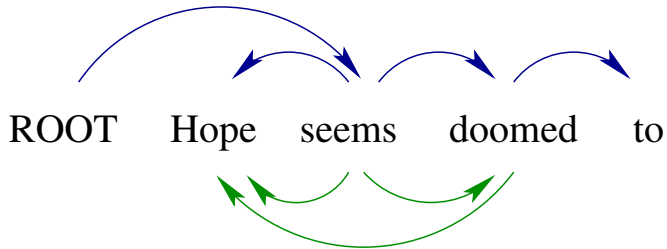
Derivation example



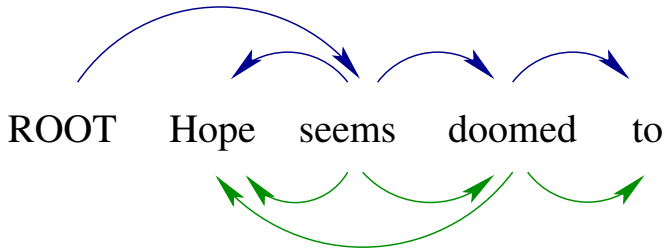
Derivation example



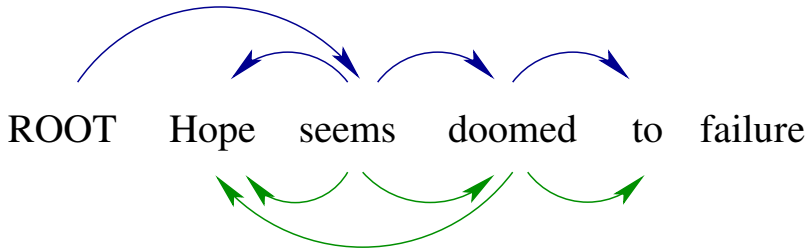
Derivation example



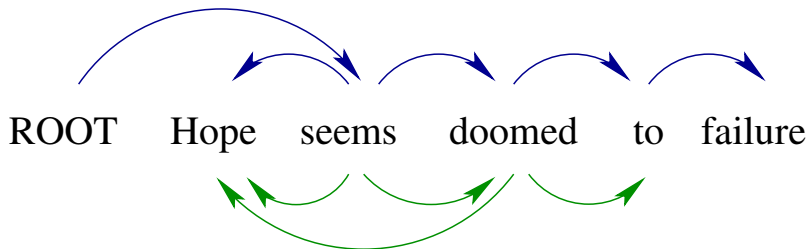
Derivation example



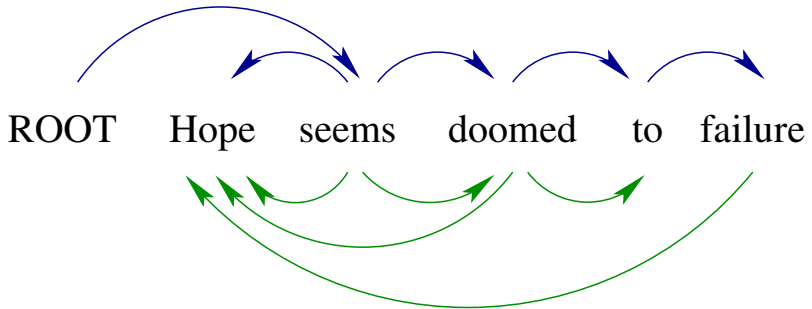
Derivation example



Derivation example



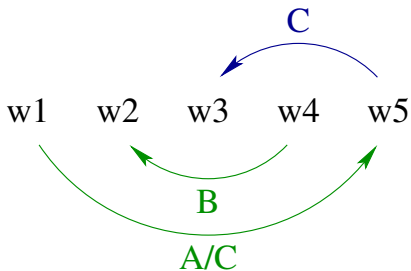
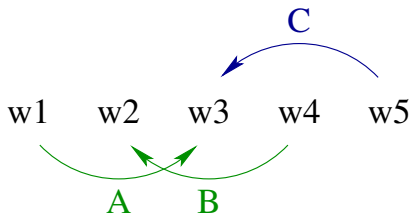
Derivation example



Projectivisation

- Allows crossing links **between syntax and semantics**
- Use the HEAD method [Nivre et al., 2006] to projectivise syntax
- Use syntactic dependencies to projectivise semantic dependencies

Projectivising semantic dependencies



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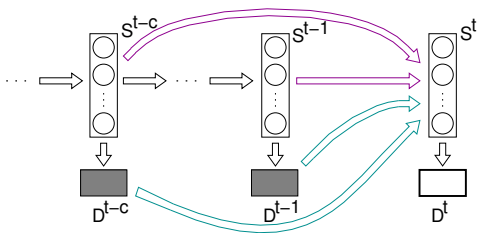
The Machine Learning Method

Synchronous derivations are modeled with an Incremental Sigmoid Belief Network (**ISBN**).

- ISBNs are Dynamic Bayesian Networks **for modeling structures**,
- with **vectors of latent variables** annotating derivation states
- that represent **features of the derivation history**.
- Use the neural network approximation of ISBNs [Titov and Henderson, ACL 2007] (“Simple Synchrony Networks”)

Statistical dependencies in the ISBN

- **Connections between latent states** reflect locality in the syntactic or semantic **structure**,
- thereby specifying the **domain of locality** for conditioning decisions
- **Explicit conditioning features** of the history are also specified



Connections between latent states

- Distinguish between syntactic states and semantic states of the derivation
- Connections both within and between types of states

Recent	Current	Syn-Syn	Srl-Srl	Syn-Srl	Srl-Syn
Next	Next	+	+	+	(+)
Top	Top	+	+	+	(+)
RgtDepTop	Top	+	+		
LftDepTop	Top	+	+		
HeadTop	Top	+	+		
LftDepNext	Top	+	+		
Next	Top	+			

Explicit conditioning features

State	Syntax			State	Semantics			
	LEX	POS	DEP		LEX	POS	DEP	SENSE
				Next	+	+		+
Next	+	+		SemTop	+	+		+
SynTop	+	+		SemTop - 1	+	+		
SynTop - 1		+		Head SemTop	+		+	
Head SynTop	+			RgtD SemTop			+	
RgtD SynTop			+	LftD SemTop			+	
LftD SynTop			+	LftD Next			+	
LftD Next			+	A0-A5 SemTop		+		
				A0-A5 Next		+		

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The Evaluation

- Two models reported
- Submitted model:
 - vocabulary of 1083 words
 - latent vector of 60 features
 - no semantics-to-syntax latent state connections
 - a form of Minimum Bayes Risk (MBR) decoding for syntax
- Larger model:
 - vocabulary of 4392 words
 - latent vector of 80 features
 - includes semantics-to-syntax latent state connections
 - decoding optimises joint probability

Results

	Syntactic LAS	Semantic			Overall
		P	R	F1	F1
Submitted					
WSJ	87.8	79.6	66.2	72.3	80.2
Brn	80.0	66.6	55.3	60.4	70.3
WSJ+Brn	86.9	78.2	65.0	71.0	79.1
Large					
WSJ	88.5	80.4	69.2	74.4	81.5
Brn	81.0	68.3	57.7	62.6	71.9
WSJ+Brn	87.6	79.1	67.9	73.1	80.5

- Larger model does better (1.5%) than smaller submitted model
- Large model would be **fifth** overall

MBR versus joint inference

	Syntactic LAS
Submitted	
Dev	86.1
Joint optimisation	
Dev	85.5
Large (joint optimisation)	
Dev	86.5

- MBR for syntax helps a bit (0.6%)
- but not as much as the large model (1.0%)

Additional experiments

- Removing latent connections **between syntax and semantics** reduced semantic performance by **3.5%**, indicating the **importance of the latent variables** for finding the correlations between these structures
- When evaluated only on **syntactic dependencies**, the submitted model performs slightly (0.2%) **better** than a model trained **only on syntactic dependencies**, indicating that training a joint model does not harm performance of the syntax component, and may help

Conclusions

- Synchronous derivations are an effective way to build joint models of separate structures
- The latent features of ISBNs help find correlations between structures
- ISBNs extend well to more complex automata than push-down automata

Current Work

- Derivations which **projectivise on-line** (81.8% overall F-measure, 1.3% improvement)
- Better feature engineering, particularly for semantic parse decisions

Acknowledgements

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Projectivising semantic dependencies

- An arc is un-crossed by replacing its argument a with a 's syntactic head and noting this change in the arc label.
- This change is repeated as necessary using a heuristic greedy search.

Decoding

- Beam search used to search for the most probable derivation
- For submitted model, chose syntactic structure by summing over beam of semantic structures