Incremental Semantic Judgments

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Abstract

- Goal: Model incrementality AND expectation/prediction.
- Dynamic Syntax provides a formalism for incremental dialogue, making it eligible for a general story about expectation/prediction.
- Distributional semantics: words are not fixed concepts, but points in a vector space, words with similar affordances will be nearby points.
- Dynamic Syntax with distributional semantics gives us incremental, meaning representations.
- The geometric interpretation gives an intuition for prediction and expectation;
- We can test this theory on real data with incremental semantic judgments

People are incremental

- Incremental comprehension and production

People are incremental

- Incremental comprehension and production
- Incremental disambiguation

    The footballer dribbled …

People are incremental

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  The footballer dribbled …

  the ball across the pitch.

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  The footballer dribbled ...

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  The baby dribbled ...

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  The footballer dribbled … the ball across the pitch.

  The baby dribbled … the milk all over the floor.

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  The footballer dribbled …

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- Expectation and prediction

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- Incremental comprehension and production
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  The footballer dribbled …

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  The baby dribbled …

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- Expectation and prediction

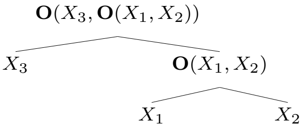
  The baby dribbled …

  the ball across the pitch.
- Cognitive neuroscience e.g. Predictive Processing model [Clark, 2015]
  - Incremental prediction with learning from an error signal

DYNAMIC SYNTAX

Partial tree development

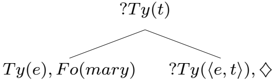
- Trees with (typed) formulas and applications



- ? specifies requirement for further development (type, but no formula)
- $\Diamond$ specifies the node currently under development
- (Links connect trees of arguments, e.g. conjunctives)

Running example DSλ

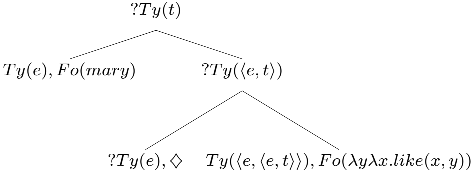
"Mary..."



Requirement: $?Ty(X)$, pointer: $\Diamond$

Running example DSλ

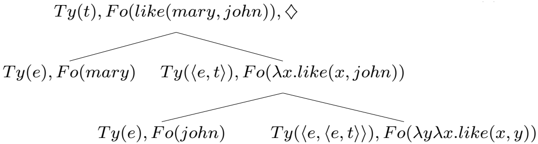
"Mary likes..."



Requirement: $?Ty(X)$, pointer: $\Diamond$

Running example DSλ

“Mary likes John...”



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Is this incremental enough?

- Incremental enough …for predictive processing?
- We'd like to model prediction and expectation

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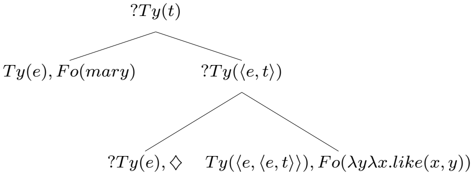
- We'd like to model prediction and expectation
- ...at a "syntactic" level, we can [Eshghi et al., 2013] ...
- ...but at a semantic level?



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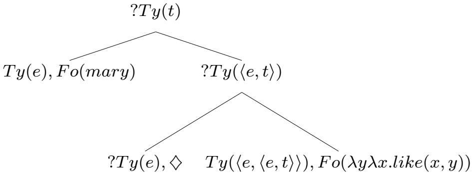
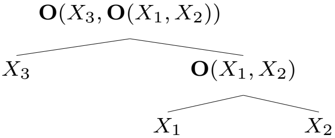


- What's the notion of similarity? The error signal?

Good news! it's a general model

Compatible with any suitable semantic framework [Kempson et al., 2001]



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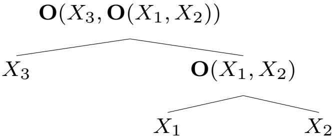

DS-TTR: [Purver et al., 2010]
DS-MTT: Next talk (Stergios)

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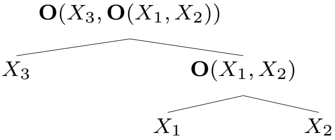

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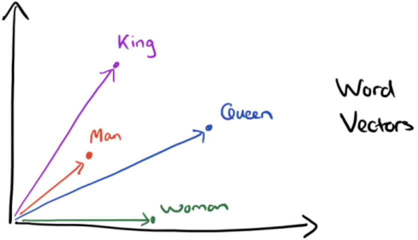
Let's insert vectors and tensors!

Distributional Semantics: Meaning in Context

	army	work	child
king	15	1	3
queen	20	1	1
woman	2	11	5
man	4	10	3



Composing Word Embeddings: A Challenge

Coordination	$\overrightarrow{\text{dancing } \textbf{and} \text{ running}} = ??$
Quantification	$\overrightarrow{\textbf{Every} \text{ student likes } \textbf{some} \text{ teacher}} = ??$
Anaphora	$\overrightarrow{\text{shaves } \textbf{himself}} = ??$
Ellipsis	$\overrightarrow{\text{Ruth went to Malta and Gijs } \textbf{did too}} = ??$

Compositional Vector Semantics

Compositional Vector Semantics

Framework	
Pregroups/Lambek	[Coecke et al., 2010, Coecke et al., 2013]
LF/PLF	[Baroni et al., 2014, Paperno et al., 2014]
CCG	[Maillard et al., 2014]
LG	[Wijnholds, 2014]

Compositional Vector Semantics

SOURCE
Categorial Grammar

→ *Homomorphism* →

TARGET
Vector Spaces

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Specific phenomena	
Coordination	[Kartsaklis, 2016]
Relative Pronouns	[Sadrzadeh et al., 2013, Moortgat and Wijnholds, 2017]
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Ellipsis	[Wijnholds and Sadrzadeh, 2018, Wijnholds and Sadrzadeh, 2019b]

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Ellipsis	[Wijnholds and Sadrzadeh, 2018, Wijnholds and Sadrzadeh, 2019b]
Evaluation	[Grefenstette and Sadrzadeh, 2011, Kartsaklis and Sadrzadeh, 2013]
	[Milajevs et al., 2014, Wijnholds and Sadrzadeh, 2019a]

Compositional Vector Semantics

- Instead of types, we have vector spaces:

$$\begin{array}{rcl} \lfloor e \rfloor & = & W \\ \lfloor t \rfloor & = & S \\ \lfloor e \to t \rfloor & = & W \otimes S \end{array}$$

- Instead of formulas, we have vectors, tensors and contractions:

$$\begin{array}{rcl} mary^{\circ} & = & T_i^{mary} \in W \\ likes(mary, john)^{\circ} & = & T_i^{mary} T_{ijk}^{likes} T_k^{john} \in S \\ \lambda x.likes(mary, x)^{\circ} & = & T_i^{mary} T_{ijk}^{likes} \in W \otimes S \end{array}$$

An example

	infant	nappy	pitch	goal
baby	34	10	0	0
milk	10	1	0	0
footballer	0	0	11	52
ball	0	1	27	49

$$T_i^{word} \in W$$

$$T_i^{baby}, T_i^{milk}, T_i^{footballer}, T_i^{ball} \in W$$

$$T_i^{baby} = (34, 10, 0, 0)$$

Vector learnt from co-occurrence counts

An example

	$\langle$infant, $\top\rangle$	$\langle$infant, $\bot\rangle$	$\langle$nappy, $\top\rangle$	$\langle$nappy, $\bot\rangle$	$\langle$pitch, $\top\rangle$	$\langle$pitch, $\bot\rangle$	$\langle$goal, $\top\rangle$	$\langle$goal, $\bot\rangle$
vomit	10	2	9	3	3	9	0	12
score	1	7	0	8	7	1	8	0
dribble	22	2	21	3	14	10	16	8

$$T_{ij}^{word} \in W \otimes S$$

$$T_{ij}^{vomit}, T_{ij}^{score}, T_{ij}^{dribble} \in W \otimes S$$

$$T_{ij}^{vomit} = \begin{pmatrix} 10 & 2 \\ 9 & 3 \\ 3 & 9 \\ 0 & 12 \end{pmatrix}$$

Matrix learnt from plausible (i.e. observed) subject-verb combinations vs. randomly generated implausible combinations. [Polajnar et al., 2014]

An example

$$T_i^{baby} T_{ij}^{vomit} = \begin{pmatrix} 34 \\ 10 \\ 0 \\ 0 \end{pmatrix} \times \begin{pmatrix} 10 & 2 \\ 9 & 3 \\ 3 & 9 \\ 0 & 12 \end{pmatrix}$$

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$$T_i^{baby} T_{ij}^{vomit} = \begin{pmatrix} 34 \\ 10 \\ 0 \\ 0 \end{pmatrix} \times \begin{pmatrix} 10 & 2 \\ 9 & 3 \\ 3 & 9 \\ 0 & 12 \end{pmatrix}$$

$$\begin{aligned} T_i^{babies} T_{ij}^{vomit} = \quad & (C_1^{baby} C_{11}^{vomit} + C_2^{baby} C_{21}^{vomit} + C_3^{baby} C_{31}^{vomit} + C_4^{baby} C_{41}^{vomit})\top + \\ & (C_1^{baby} C_{12}^{vomit} + C_2^{baby} C_{22}^{vomit} + C_3^{baby} C_{32}^{vomit} + C_4^{baby} C_{42}^{vomit})\bot \\ & = (34 \times 10 + 10 \times 9)\top + (34 \times 2 + 10 \times 3)\bot \\ & = 430\top + 98\bot \end{aligned}$$

An example

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$$T^{\text{babies score}} = 34\top + 318\bot$$

$$T^{\text{babies dribble}} = 958\top + 98\bot$$

An example

	⟨infant, ⊤, infant⟩	⟨infant, ⊥, infant⟩	⟨infant, ⊤, nappy⟩	...	⟨goal, ⊤, ball⟩	⟨goal, ⊥, ball⟩
control	0	2	1	...	0	1
dribble	1	4	2	...	6	8

$$T^{word}_{ijk} \in W \otimes S \otimes W$$

$$T^{control}_{ijk}, T^{dribble}_{ijk} \in W \otimes S \otimes W$$

$$T^{control}_{ijk} = (\text{a cube})$$

An example

	⟨infant, ⊤, infant⟩	⟨infant, ⊥, infant⟩	⟨infant, ⊤, nappy⟩	…	⟨goal, ⊤, ball⟩	⟨goal, ⊥, ball⟩
control	0	2	1	…	0	1
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$$T^{control}_{ijk}, T^{dribble}_{ijk} \in W \otimes S \otimes W$$

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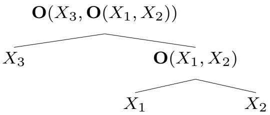
- Note that we're not limited to plausibility: S is arbitrary
- But plausibility may be able to model semantic prediction/expectation/surprise, more on that later

DYNAMIC SYNTAX WITH TENSORS

Tensor Trees

- Abstract Tree



- Mapping objects

$$\begin{array}{lllll} X_1 & \mapsto & T_{i_1 i_2 \cdots i_n} & \in & V_1 \otimes V_2 \otimes \cdots V_n \\ X_2 & \mapsto & T_{i_n i_{n+1} \cdots i_{n+k}} & \in & V_n \otimes V_{n+1} \otimes \cdots V_{n+k} \\ X_3 & \mapsto & T_{i_{n+k} i_{n+k+1} \cdots i_{n+k+m}} & \in & V_{n+k} \otimes V_{n+k+1} \otimes \cdots V_{n+k+m} \end{array}$$

- Mapping maps

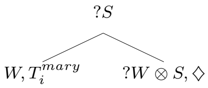
$$\begin{array}{rll} \mathbf{O}(X_1, X_2) & \mapsto & T_{i_1 i_2 \cdots i_n} T_{i_n i_{n+1} \cdots i_{n+k}} \\ & \in & V_1 \otimes V_2 \otimes \cdots \otimes V_{n-1} \otimes V_{n+1} \otimes \cdots \otimes V_{n+k} \\ \mathbf{O}(X_3, \mathbf{O}(X_1, X_2)) & \mapsto & T_{i_1 i_2 \cdots i_n} T_{i_n i_{n+1} \cdots i_{n+k}} T_{i_{n+k} i_{n+k+1} \cdots i_{n+k+m}} \\ & \in & V_1 \otimes V_2 \otimes \cdots \otimes V_{n-1} \otimes V_{n+1} \otimes \cdots \otimes V_{n+k-1} \otimes V_{n+k+1} \otimes \cdots \otimes V_{n+k+m} \end{array}$$

Incremental DS-Tensor: Requirements

- Several possible approaches
- Identity I: no information
- Sum T^{+}: sum of vectors/tensors inhabiting W, $W \otimes S$
  - (average expectation)
- Direct sum $T^{\oplus}$: tuple of vectors/tensors
  - (all possibilities, to be reduced as parsing proceeds)

Running example DS-Tensor

"Mary..."



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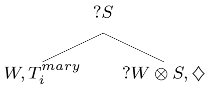
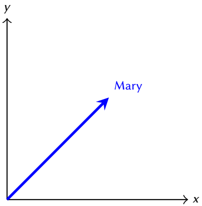
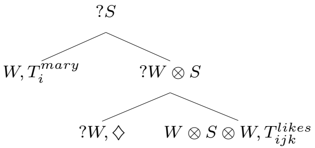


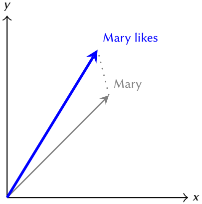


Requirements: The active node is decorated with the identity in that space.

Running example DS-Tensor

"Mary likes..."





Requirements: The active node is decorated with the identity in that space.

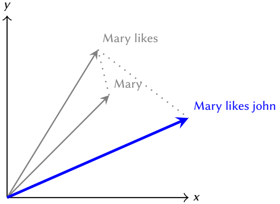
Running example DS-Tensor

"Mary likes John..."

$$S, T_i^{mary} T_{ijk}^{like} T_k^{john}, \Diamond$$

$$W, T_i^{mary} \qquad W \otimes S, T_{ijk}^{like} T_k^{john}$$

$$W, T_k^{john} \qquad W \otimes S \otimes W, T_{ijk}^{like}$$



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Extends to general DS trees

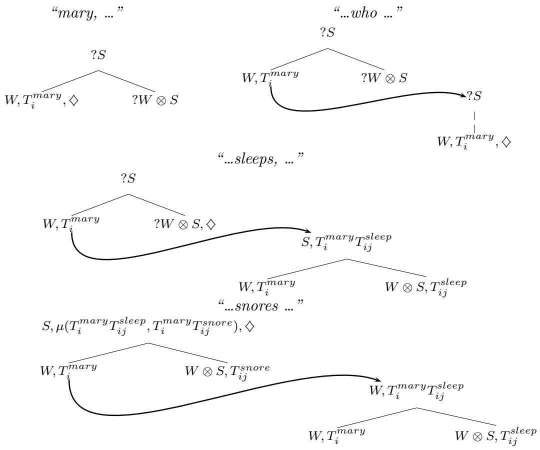

Figure 4: A DS with Vector Space Semantics parse of *"Mary, who sleeps, snores'*'.

INCREMENTAL SEMANTIC JUDGMENTS

Disambiguation dataset: KS2013

- Kartsaklis D., Sadrzadeh M., and Pulman S. Separating disambiguation from composition in compositional distributional semantics.
- Chose ambiguous verbs and two landmark meanings from [Pickering and Frisson, 2001].
- Picked subjects and objects using most frequently occurring ones in the British National Corpus (ca. 100M words).
- Asked humans to judge similarity in order to assess disambiguation by subjects/objects.
- Example:

Amb. sentence	**Landmark**	
	control	transmit
nerve conduct signal	3.35	5.19
staff conduct research	4.05	2.7

Incremental Disambiguation

- Using a retrained 300-dimensional word2vec space $W = N$
- Following [Grefenstette and Sadrzadeh, 2011]:
  - Transitive S-V-O sentences
  - Take $S = N \otimes N$
  - Build tensors from S-V-O occurrences in dependency-parsed corpus

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- Full sentences:
  - Cos(baby dribble milk, baby drip milk) $= 0.6532$
    $< Cos$(baby dribble milk, baby control milk) $= 0.6709$
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  - $Cos(\text{footballer dribble ball}, \text{footballer control ball}) = 0.6336$
    $< Cos(\text{footballer dribble ball}, \text{footballer drip ball}) = 0.7740$
- Partial sentences:
  - $Cos(\text{baby dribble} \ldots, \text{baby drip} \ldots) = 0.6731$
    $< Cos(\text{baby dribble} \ldots, \text{baby control} \ldots) = 0.6761$
  - $Cos(\text{footballer dribble} \ldots, \text{footballer control} \ldots) = 0.6608$
    $< Cos(\text{footballer dribble} \ldots, \text{footballer drip} \ldots) = 0.7594$

Incremental Disambiguation

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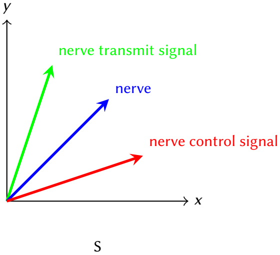

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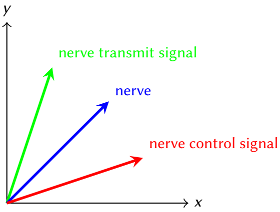
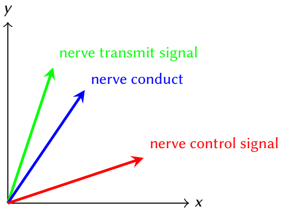


S



SV

Incremental Disambiguation

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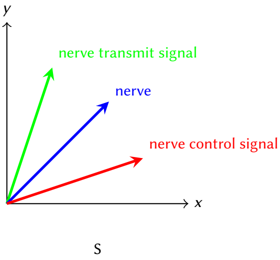
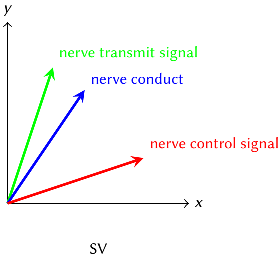
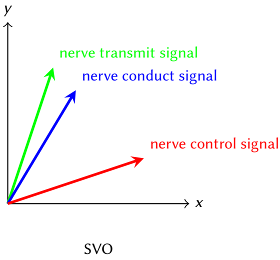






Incremental Disambiguation: models

- Additive:

$$\overrightarrow{subj} + \overrightarrow{obj} + \overrightarrow{verb}$$

- Relational [Grefenstette and Sadrzadeh, 2011]:

$$(\overrightarrow{subj} \otimes \overrightarrow{obj}) \odot \overline{verb}$$

- Copy-Subject:

$$\overrightarrow{subj} \odot (\overline{verb} \times \overrightarrow{obj})$$

- Copy-Object:

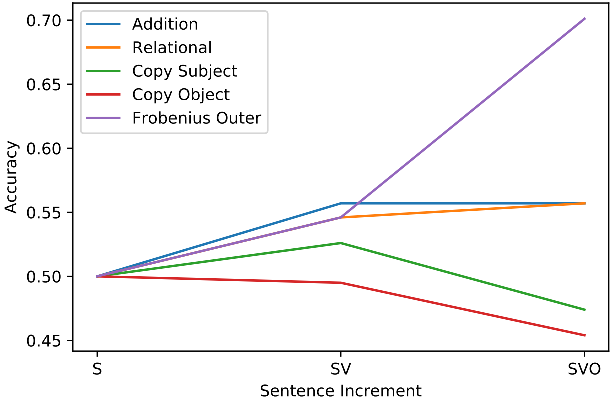
$$(\overrightarrow{subj}^T \times \overline{verb}) \odot \overrightarrow{obj}$$

- Frobenius Outer:

$$(\overrightarrow{subj} \odot (\overline{verb} \times \overrightarrow{obj})) \otimes ((\overrightarrow{subj}^T \times \overline{verb}) \odot \overrightarrow{obj})$$

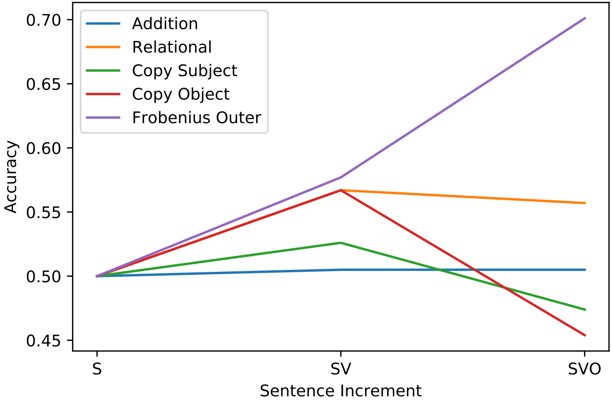
Incremental Disambiguation: Results I
Comparing partial sentences to partial sentences

Verb tensors learnt using plausibility (log. regression between observed SVO triples and random SVO triples).



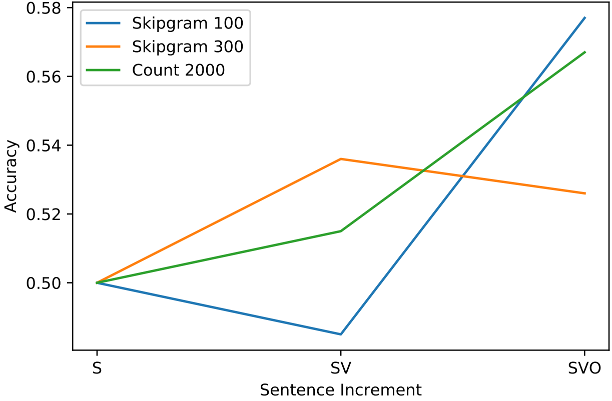
Incremental Disambiguation: Results II
Comparing partial sentences to full sentences

Verb tensors learnt using plausibility (log. regression between observed SVO triples and random SVO triples).



Incremental Disambiguation: Results III

Instead of comparing current vector to ideal vector, we look at the plausibility of the two landmark sentences.



Conclusion I

- We've developed a vector semantics for Dynamic Syntax
- This allows us to model fluid meaning for DS;
- Or it allows us to model incremental vector semantics;
- We can run experiments with incrementality on real data;
- Expanding this to more datasets/models is work in progress...

On the horizon..

- Evaluation on real data needs to compare a (incremental) sentence with its interpretations..
- Plausibility on the other hand models a single representation, but now can't be used on the datasets that intuitively anymore..
- But it's not just the semantic content that is subject to expectations...
  $\rightarrow$ can represent the uncertainty of DS tree building with probabilistic Directed Acyclic Graphs $\rightarrow$ work in progress also!

Thank

Thank you!

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