Representation Learning for Discourse Parsing

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Discourse in natural language

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- an interesting story?
- a good joke?
- a persuasive argument?

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- Individual sentences (e.g., parsing, translation)
- Bag-of-words representations of documents (e.g., topic models, sentiment analysis)

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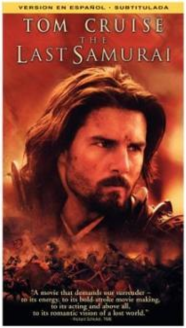
Discourse is the missing link between micro-level and macro-level linguistic phenomena.

Example: discourse and sentiment

It could have been a **great** movie. It could have been **excellent**, and to all the people who have forgotten about the older, **greater** movies before it, will think that as well. It does have **beautiful** scenery, some of the **best** since Lord of the Rings. The acting is **well** done, and I really **liked** the son of the leader of the Samurai. He was a **likeable** chap, and I **hated** to see him die... But, other than all that, this movie is nothing more than hidden **rip-offs**.



Discourse and sentiment

Voll and Taboada [VT07]:

- Annotated discourse structure (RST) improves sentiment analysis...
- ... but automatically-parsed discourse structure makes it worse!

Why is discourse hard?

- Discourse relations are **semantic**:
  - Montreal is a bilingual city
  - (Because) they speak French and English
- Typical solution is bilexical features, e.g., $\langle$speak,bilingual$\rangle$
- Discourse-annotated datasets are way too small for this to work.

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- Discourse-annotated datasets are way too small for this to work.
- **Representation learning can help**, by inducing distributed models of discourse semantics.

This talk

Representation learning for two discourse structures:

- **Rhetorical structure theory**: learn to parse discourse into trees, while jointly learning word representations [JE14b].
- **Penn Discourse Treebank**: learn compositional operators for distributed semantics [JE14a].

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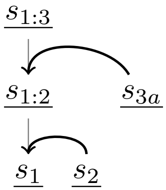
Rhetorical structure theory

In RST, discourse relations compose elementary units into a tree [MT88].

- *s*1: Montreal is a bilingual city.
- *s*2: They speak French and English.
- *s*3*a*: This makes it an interesting place to visit.



Rhetorical structure theory

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- *s*1: Montreal is a bilingual city.
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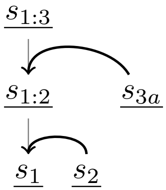

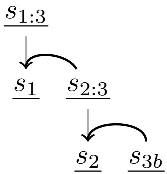

Rhetorical structure theory

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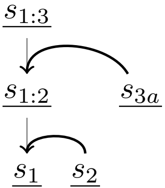
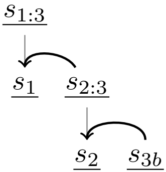
- *s*1: Montreal is a bilingual city.
- *s*2: They speak French and English.
- *s*3*b*: But the French sounds a little funny.
- Elementary discourse units (EDUs) $\approx$ clauses
- Relations include: cause-effect, comparison, temporal order, ...





RST Results

	Span	Nuclearity	Relation
Annotator agreement	88.7	77.7	65.8

Shift-reduce discourse parsing

Incremental (transition-based) parsing

- Keep a stack with elements $s_1, s_2, \ldots, s_N$
- The unread part of the discourse is on a queue, $q_0, \ldots q_M$
- At each step, make a decision whether to **shift** or **reduce**:

$$\hat{a} = \arg\max_{a} \boldsymbol{\theta}^{\top} \mathbf{f}(s_1, s_2, q_0, a)$$

Basic features

Sagae combined shift-reduce and perceptron, using many surface-level features [Sag09]:

- First/last words and POS, e.g., however
- Distance between discourse units
- "Head set": words with dependencies outside the unit (often main verbs)

More recent work

- **Feng and Hirst**: better features [FH12]
- **Joty et al**: more complex algorithm [JCNM13]

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Why should these features work?

Our example:

- s_1: Montreal is a bilingual city.
- s_2: They speak French and English.
- q_0: This makes it interesting to visit.

Features:

s_1 first word: Montreal, head set: city, ...

s_2 first word: they, head set: speak, ...

q_0 first word: this, head set: makes, ...

Adding learned representations: first try

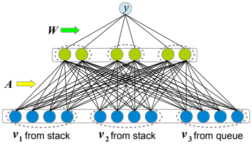
- Let's add a distributed representation for each discourse unit!
- Compositionality (see [LLH14])

inter-unit	"strong compositionality criterion" use the nucleus, ignore the satellite
intra-unit	just add up word representations for each word in the unit. (Blacoe and Lapata show that this is not as crazy as it sounds [BL12].)

- Word representations
  - Collobert and Weston [CW08]
  - Non-negative matrix factorization

Representation schemes

$$\mathbf{f}(\mathbf{v}, \mathbf{A}) = \mathbf{A} \begin{bmatrix} \mathbf{v}_{s_1} \\ \mathbf{v}_{s_2} \\ \mathbf{v}_{q_1} \end{bmatrix}$$



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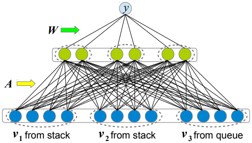

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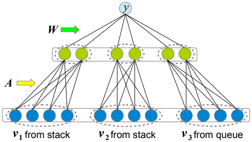

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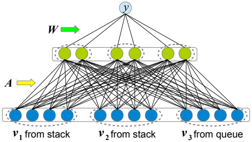

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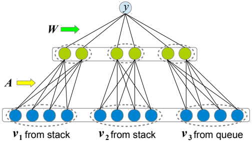

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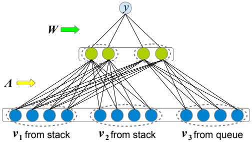

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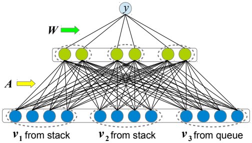

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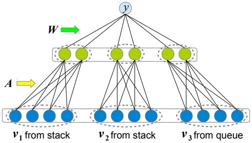

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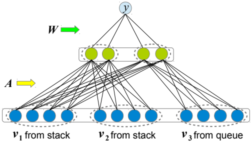

The concatenation form does best in most cases, but see the paper for details.

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Word embeddings	75.3	67.1	53.8
NMF	78.6	67.7	54.8

Adding learned representations: second try

- Let's learn the word representations jointly with the parser!
- Basically, a hidden-variable support vector machine. Iterate:
  - Solve SVM dual objective
  - Perform gradient update to word representations

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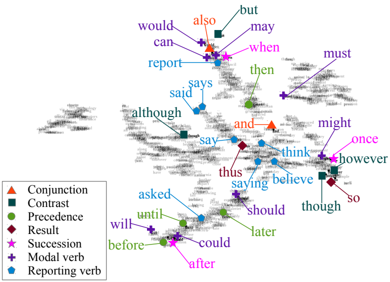
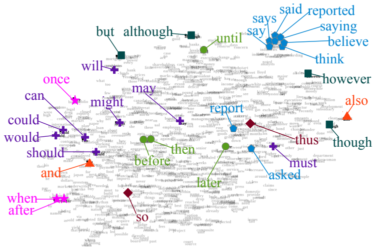
Representation learning	80.9	69.4	59.0
+basic features	82.1	**71.1**	**61.6**

On discourse relations, representation learning cuts the gap between SOTA and inter-annotator agreement by 60%!

Representation learned



NMF, $K = 20$



Representation learning, $K = 20$

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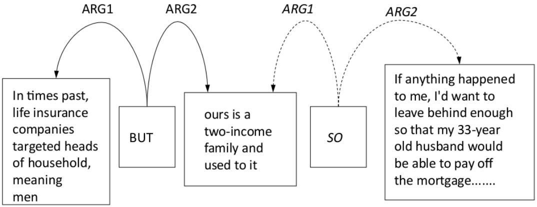
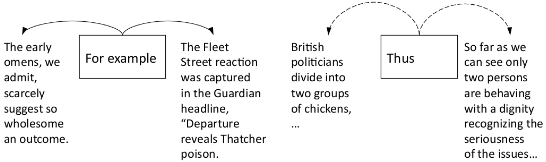
Penn Discourse Treebank

- Spans can participate in multiple relations



- Relations need not link up to cover the text



Implicit relation classification

- Implicit discourse connectives are annotated:
  - Bob gave Tina the burger
  - (Because) she was hungry

  There are 16 classes of level-2 connectives
- Existing approaches again emphasize bilexical features [LKN09].
- Sparsity is again a problem: $\langle$burger, hungry$\rangle$, $\langle$knish, hungry$\rangle$, $\langle$poutine, hungry$\rangle$, ...

A bilinear model

$$\hat{y} = \underset{y \in \mathcal{Y}}{\arg\max} \quad (\mathbf{u}^{(\ell)})^{\mathsf{T}} \mathbf{A}_y \mathbf{u}^{(r)} + b_y$$

- $y \in \mathcal{Y}$ is a relation
- $\mathbf{u}^{(\ell)}$ is the representation of the left argument
- $\mathbf{u}^{(r)}$ is the representation of the right argument
- In practice, we set

$$\mathbf{A}_y = \mathbf{a}_{y,1}\mathbf{a}_{y,2}^{\mathsf{T}} + \mathrm{diag}(\mathbf{a}_{y,3})$$

to avoid overfitting.

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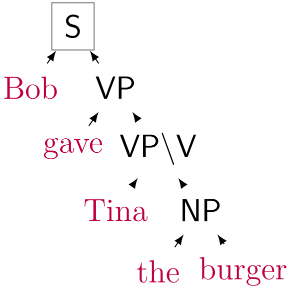
Vector-semantic composition



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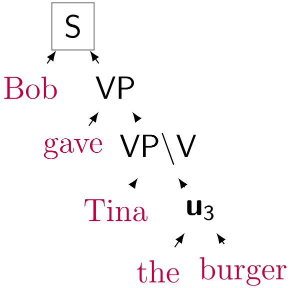

$$\mathbf{u}_3 = \tanh\left(\mathbf{U}\left[\mathbf{u}_{\text{the}}^{\mathsf{T}}\ \mathbf{u}_{\text{burger}}^{\mathsf{T}}\right]^{\mathsf{T}}\right)$$

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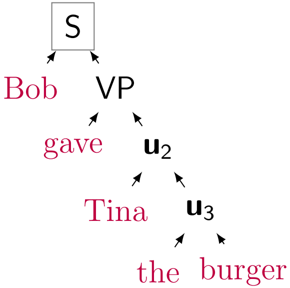

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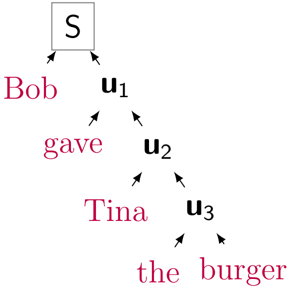

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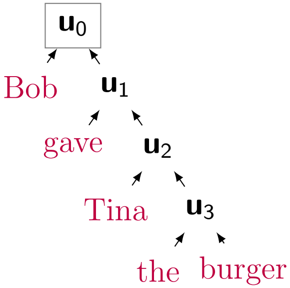

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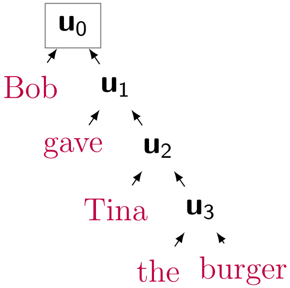

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- DISCO2: **Dis**tributional **co**mpositional semantics for **disco**urse.
- Same architecure as Socher et al [SHP+11].
- The matrix **U** is learned by backpropagating from a hinge loss on relation classification.

PDTB Results

Most common class	26.0
Additive word representations	**28.7**
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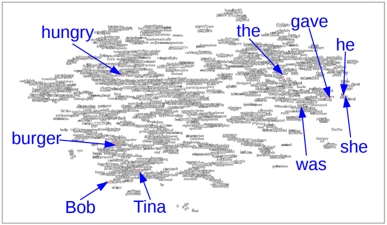
Disco2 + [LKN09] features	42.5

Are we done?

- Bob gave Tina the burger.
- **She** was hungry.

- Bob gave Tina the burger.
- **He** was hungry.

The discourse relations are completely different.
The distributed representations are nearly identical.



One vector is not enough.

If we insist on representing each discourse argument as a single vector, we lose the ability to track references across the discourse.

Or to put it another way...

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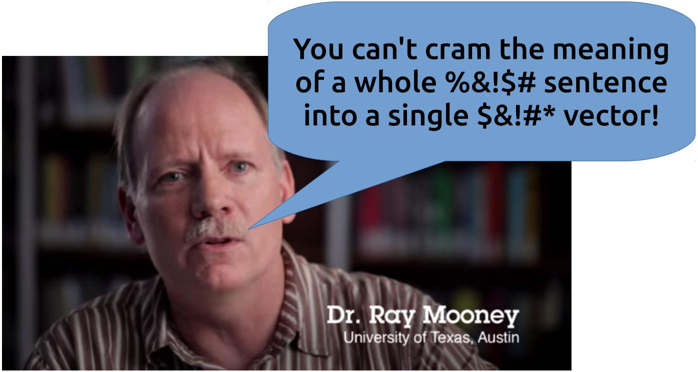


Entity-augmented distributed semantics

Look at things from Tina's perspective:

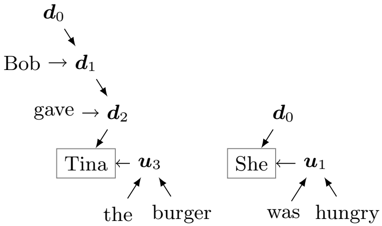
- $s1$: She got the burger from Bob
- $s2$: She was hungry

Let's represent these Tina-centric meanings with more vectors!

The downward pass

A **downward pass** computes a downward vector for each node in the parse.

$$\mathbf{d}_i = \tanh\left(\mathbf{V}\begin{bmatrix}\mathbf{d}_{\rho(i)}\\ \mathbf{u}_{s(i)}\end{bmatrix}\right)$$



This computation preserves the feedforward architecture.

A new bilinear model

$$\hat{y} = \arg\max_{y \in \mathcal{Y}} (\mathbf{u}^{(\ell)})^\top \mathbf{A}_y \mathbf{u}^{(r)} + \sum_{\langle i,j \rangle \in \mathcal{A}} (\mathbf{d}_i^{(\ell)})^\top \mathbf{B}_y \mathbf{d}_j^{(r)} + b_y$$

We now sum over coreferent mention pairs $\langle i, j \rangle \in \mathcal{A}$, obtained from the Berkeley coreference system.

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Disco2	37.0
Disco2 + [LKN09] features	42.5
Disco2 + [LKN09] features + entity semantics	**43.6**

- Only 30% of PDTB relation pairs have coreferent mentions (according to Berkeley coref).
- On these examples, the improvement is 2.7%.

Between vectors and lambdas

- Pure vector semantics are insufficiently expressive for discourse analysis.
- But broad-coverage formal semantic parsing is (currently) too brittle.
- What's in between?
  - Lewis and Steedman: make formal semantics a little more distributional [LS13].
  - Entity-augmented distributed semantics: make distributed semantics a little more formal.

Summary: a call to arms

- Discourse relations are all about **meaning**, and black-box machine learning won't work.
  - Simple surface features are insufficiently expressive to capture semantics.
  - More complex surface features cause overfitting.
- Discourse also connects with a huge number of NLP applications.
- Machine learning researchers: **join the fight!**

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