

A Unified Local and Global Model for Discourse Coherence

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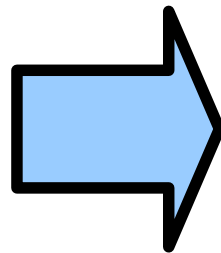
Coherence Ranking

Sentence 4
Sentence 3
Sentence 1
Sentence 2

Sentence 2
Sentence 1
Sentence 4
Sentence 3

Sentence 1
Sentence 2
Sentence 3
Sentence 4

Proposed
Orderings



Sentence 1
Sentence 2
Sentence 3
Sentence 4

Sentence 2
Sentence 1
Sentence 4
Sentence 3

Sentence 4
Sentence 3
Sentence 1
Sentence 2

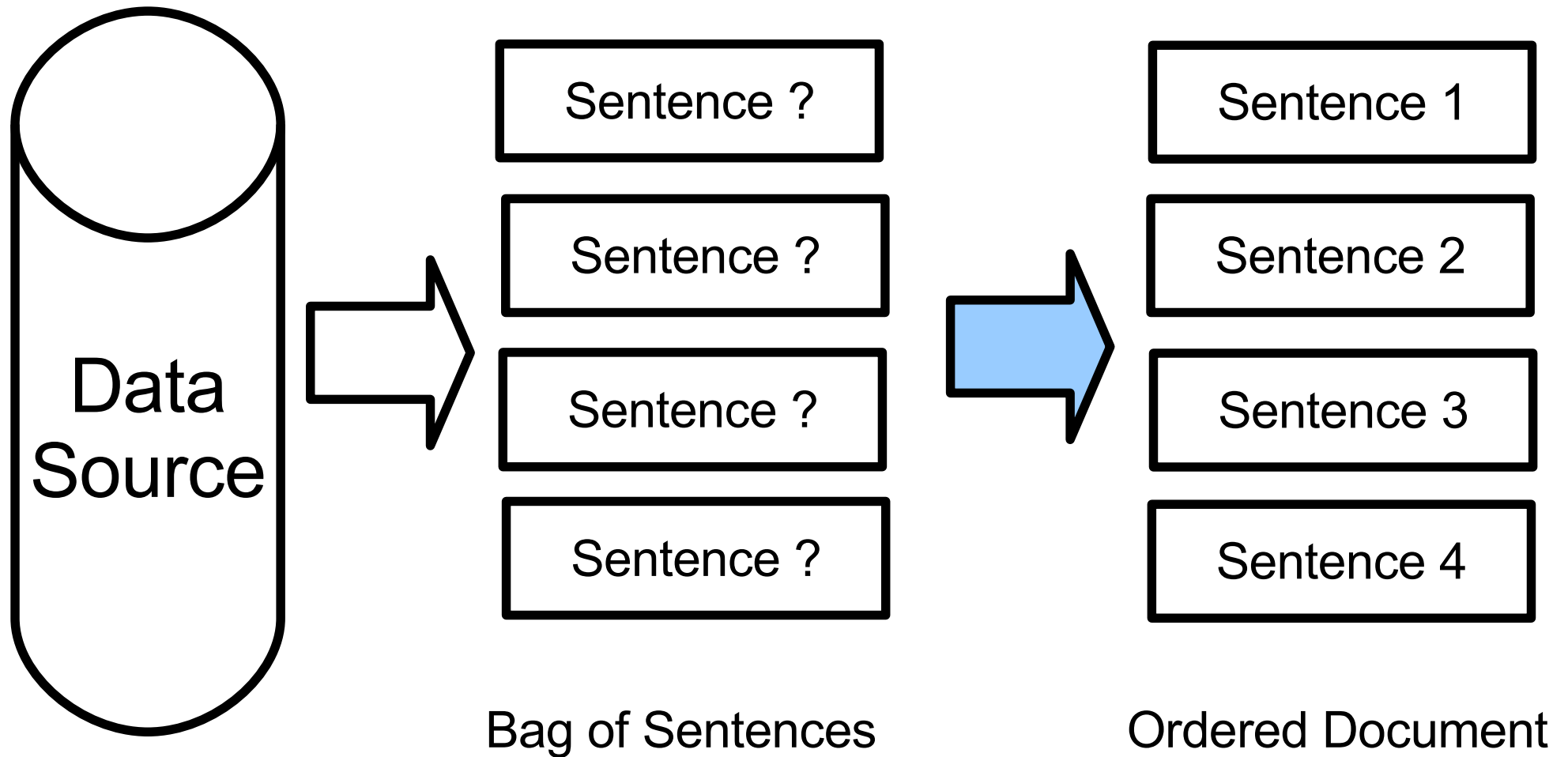
A+!

B

C

Ranked
Orderings

Sentence Ordering



Overview

- **Previous Work: Entity Grids**
- Previous Work: Hidden Markov Model
- Relaxed Entity Grid
- Unified Hidden Markov Model
- Corpus and Experiments
- Conclusions and Future Work

An Entity Grid

Barzilay and Lapata '05, Lapata and Barzilay '05.

The commercial **pilot**, sole **occupant** of the **airplane**, was not injured.

The **airplane** was owned and operated by a private **owner**.

Visual meteorological **conditions** prevailed for the personal cross country **flight** for which a VFR flight **plan** was filed.

The **flight** originated at Nuevo **Laredo** , Mexico , at approximately 1300.

Syntactic Role in Sentence										
	Plan	Airplane	Condition	Flight	Pilot	Laredo	Owner	Occupant		
	0	-	X	-	-	O	-	-	X	
	1	-	O	-	-	-	-	X	-	
	2	O	-	S	X	-	-	-	-	
	3	-	-	-	S	-	X	-	-	

Local Coherence: Entity Grids

- Loosely based on Centering Theory.
 - Coherent texts *repeat important nouns*.
- Grid shows most prominent role of each head noun in each sentence.

	Airplane	Condition	Fly
-	X	-	
-	O	-	
O	-	S	
-	-	-	

A **transition** from X to O.
(Here the history size is 1,
but 2 works better.)

Computing with Entity Grids

- Generatively: Lapata and Barzilay.
 - Assume independence between columns.

	Airplane	Condition	Flly
en	-	X	-
-	-	0	-
0	-	-	S
-	-	-	-
Π	Π	Π	Π

Π

- This independence assumption can cause problems for the generative approach.
 - Barzilay and Lapata get better results with SVMs.

Computing with Entity Grids

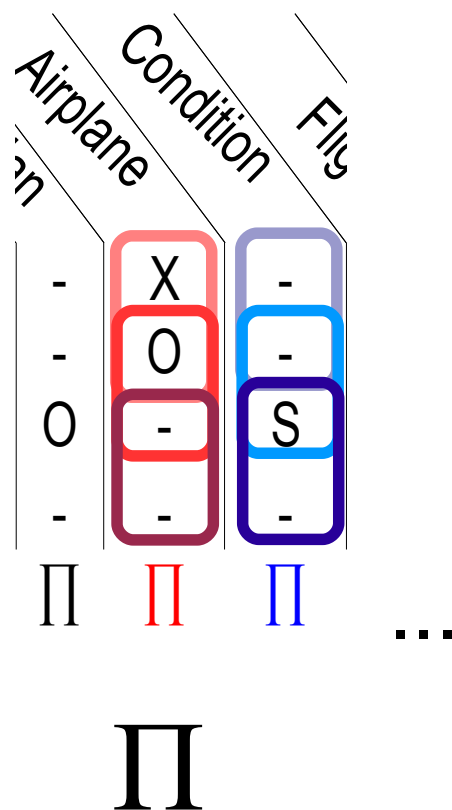
- Generatively: Lapata and Barzilay.
 - Assume independence between columns.

	Airplane	Condition	Fly	
-	-	X	-	
-	-	0	-	
0	-	-	S	
-	-	-	-	
Π	Π	Π	Π	...
Π				

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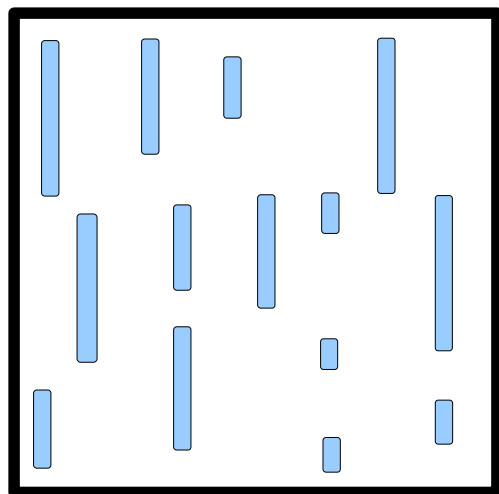
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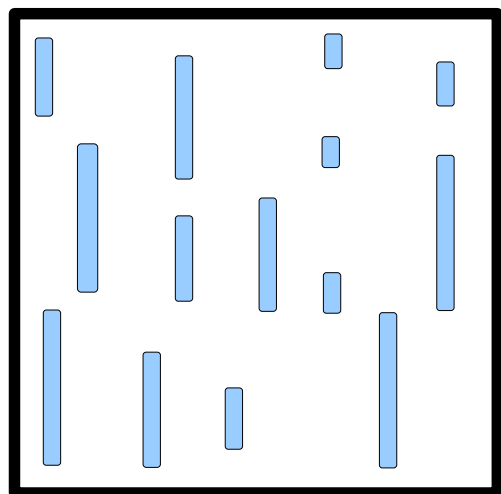
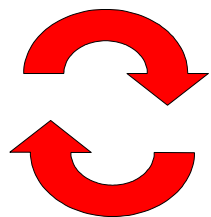
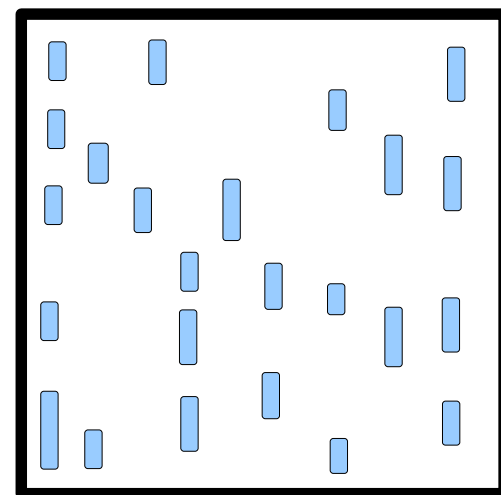
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Entity Grids Model Local Coherence

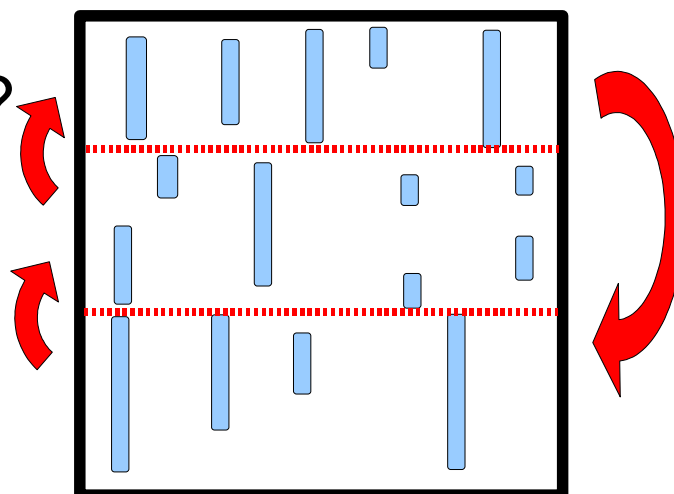


A coherent entity grid at very low zoom:
entities occur in long contiguous columns.

A grid for a randomly
permuted document
tends to look like this.



But what if we flip it?
Or move around
paragraphs?

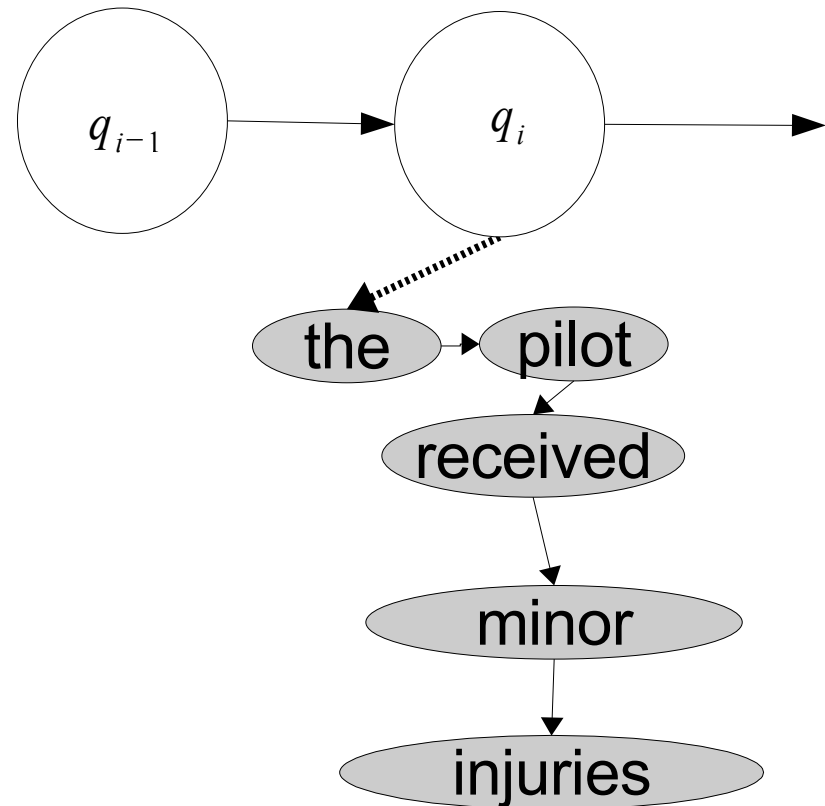


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- **Previous Work: Hidden Markov Model**
- Relaxed Entity Grid
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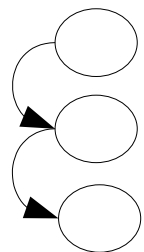
Markov Model

- Barzilay and Lee 2004, “Catching the Drift”
- Hidden Markov Model for document structure.
- Each state generates sentences from another HMM.



Global Coherence

- The HMM is good at learning overall document structure:
 - Finding the start, end and boundaries.
- But **all** local information has to be stored in the state variable.
 - Creates problems with sparsity.



A **wombat** escaped from the cargo bay.

Finally the **wombat** was captured.

The last major **wombat** incident was in 1987.

- Is there a state q-wombat?

Creating a Unified Model

- What we want: an HMM with entity-grid features.
 - We need a quick estimator for transition probabilities in the entity grid.
 - In the past, entity grids have worked better as conditional models...

Overview

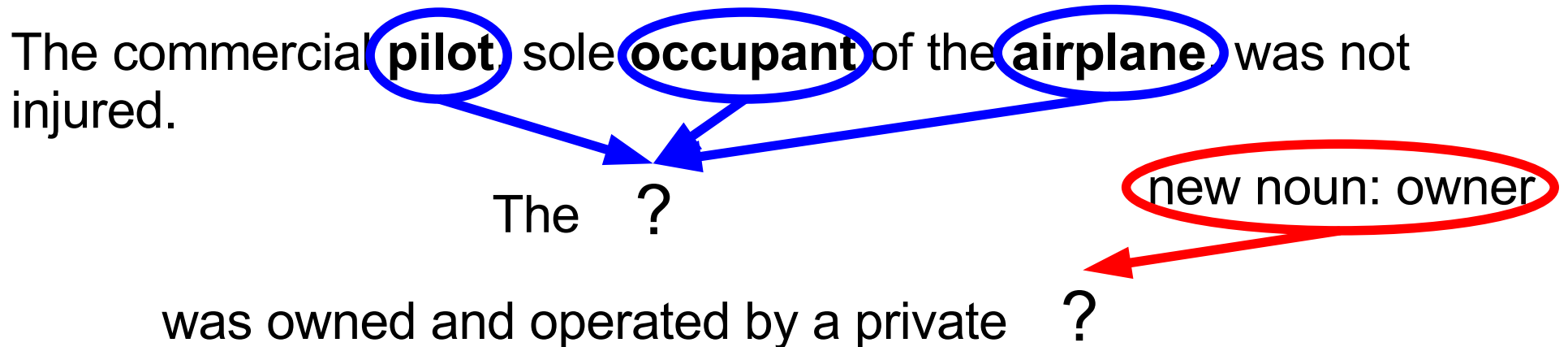
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Relaxing the Entity Grid

- The most common transition is from – to –.
 - The maximum likelihood document has no entities at all!
- Entities don't occur independently.
 - There may not be room for them all.
 - They 'compete' with one another.

Relaxed Entity Grid

- Assume we have already generated the set of roles we need to fill with known entities.
 - New entities come from somewhere else.



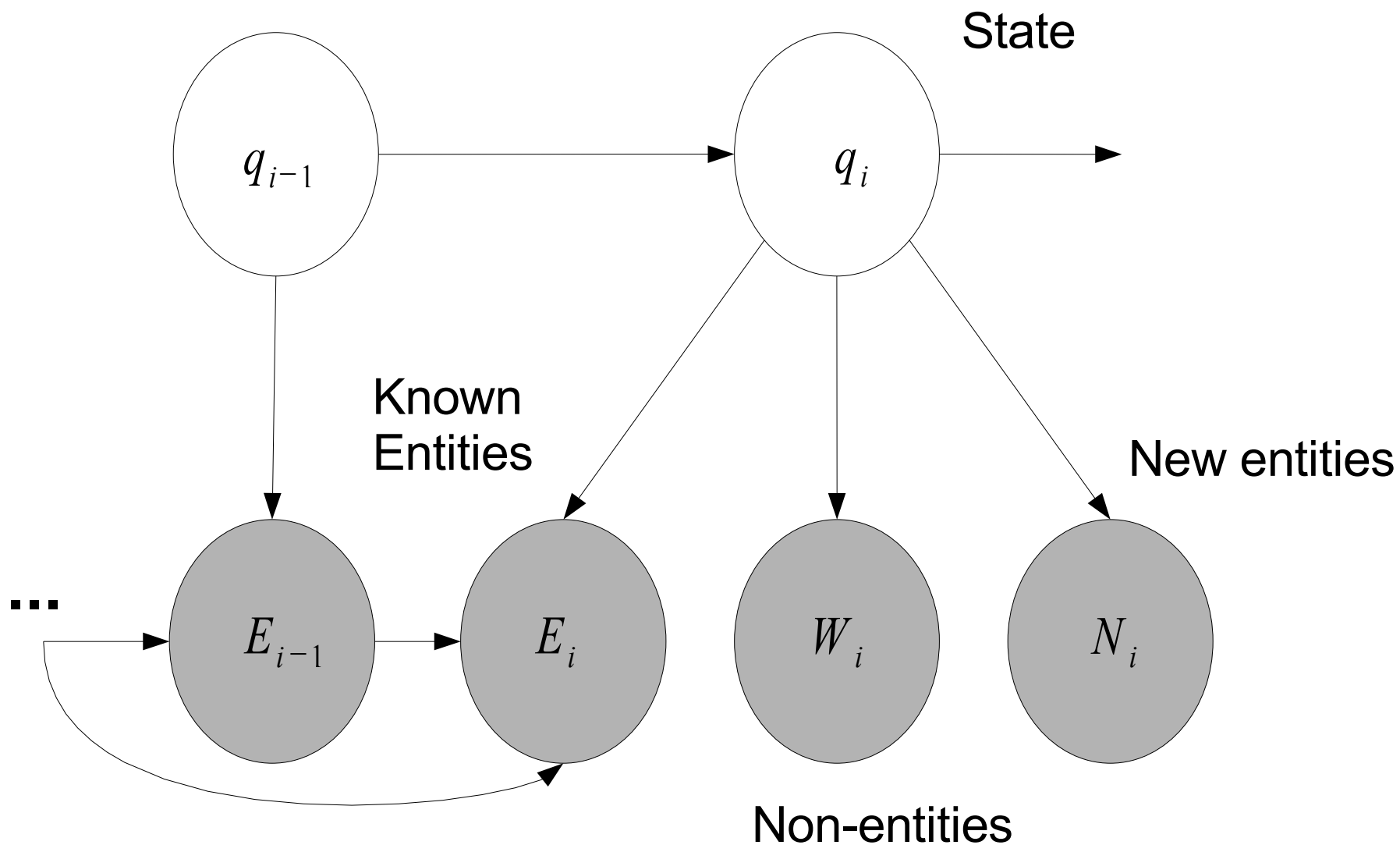
Filling Roles with Known Entities

- $P(\text{entity } e \text{ fills role } j \mid j, \text{ histories of known entities})$
 - history: roles in previous sentences
 - known entity: has occurred before in document
- Still hard to estimate because of sparsity.
 - Too many combinations of histories.
- Normalize:
 $P(\text{entity } e \text{ fills role } j \mid j, \text{ history of entity } e)$
- Much easier to estimate!

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Graphical Model



Hidden Markov Model

- Need to lexicalize the entity grid.
 - States describe common words, not simply transitions.
- Back off to the unlexicalized version.
- Also generate the other words of the sentence (unigram language models):
 - Words that aren't entities.
 - First occurrences of entities.

Learning the HMM

- We used Gibbs sampling to fit:
 - Transition probabilities.
 - Number of states.
- Number of states heavily dependent on the backoff constants.
- We aimed for about 40-50 states.
 - As in Barzilay and Lee.

Has This Been Done Before?

- Soricut and Marcu '06:
 - Mixture model with HMM, entity grid and word-to-word (IBM) components.
 - Results are as good as ours.
- Didn't do joint learning, just fit mixture weights.
 - Less explanatory power.
- Uses more information (ngrams and IBM).
 - Might be improved by adding our model.

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Airplane (NTSB) Corpus

- Traditional for this task.
 - 100 test, 100 train.
- Short (avg. 11.5 sents) press releases on airplane emergencies.
- A bit artificial:
 - 40% begin: “This is preliminary information, subject to change, and may contain errors. Any errors in this report will be corrected when the final report has been completed.”

Discriminative Task

- 20 random permutations per document: 2000 tests.

Sentence 2

Sentence 1

Sentence 4

Sentence 3

vs

Sentence 1

Sentence 2

Sentence 3

Sentence 4

- Binary judgement between random permutation and original document.
- Local models do well.

Results

Airplane Test	Discriminative (%)
Barzilay and Lapata (SVM EGrid)	90
Barzilay and Lee (HMM)	74
Soricut and Marcu (Mixture)	-
Unified (Relaxed EGrid/HMM)	94

Ordering Task

- Used simulated annealing to find optimal orderings.
- Score: similarity to original ordering.

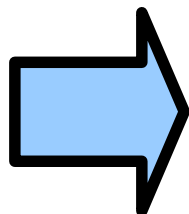
$$\tau = 1$$

Sentence ?

Sentence ?

Sentence ?

Sentence ?



Sentence 1

Sentence 2

Sentence 3

Sentence 4

Kendall's τ metric:
-1 (worst) to 1 (best).
~ # of pairwise swaps.

Results

Airplane Test	Kendall's τ
Barzilay and Lapata (SVM EGrid)	-
Barzilay and Lee (HMM)	0.44
Soricut and Marcu (Mixture)	0.50
Unified (Relaxed EGrid/HMM)	0.50

Relaxed Entity Grid

Airplane Development	τ	Discr. (%)
Generative EGrid	0.17	81
Relaxed EGrid	0.02	87
Unified (Generative EGrid/HMM)	0.39	85
Unified (Relaxed EGrid/HMM)	0.54	96

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What We Did

- Explained strengths of local and global models.
- Proposed a new generative entity grid model.
- Built a unified model with joint local and global features.
 - Improves on purely local or global approaches.
 - Comparable to state-of-the-art.

What To Do Next

- Escape from the airplane corpus!
 - Too constrained and artificial.
 - Real documents have more complex syntax and lexical choices.
- Longer documents pose challenges:
 - Current algorithms aren't scalable.
 - Neither are evaluation metrics.

Acknowledgements

Couldn't have done it without:

- Regina Barzilay (code, data, advice & support)
- Mirella Lapata (code, advice)
- BLLIP (comments & criticism)
- Tom Griffiths & Sharon Goldwater (Bayes)
- DARPA GALE (\$\$)
- Karen T. Romer Foundation (\$\$)