Learning to Fuse Disparate Sentences

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The problem: text-to-text generation

Input

The bodies showed signs of torture.

They were left on the side of a highway in Chilpancingo, in the southern state of Guerrero, state police said.

Output

The bodies of the men, which showed signs of torture, were left on the side of a highway in Chilpancingo, state police told Reuters.

Motivation

Humans fuse sentences:

- Multidocument summaries (Banko+Vanderwende '04)
- Single document summaries (Jing+McKeown '99)
- **Editing (this study)**

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Previous work: multidocument case:

- Similar sentences (*themes*)
- Goal: summarize common information

(Barzilay+McKeown ‘05), (Krahmer+Marsi ‘05), (Filippova+Strube ‘08)...

Our task setting

Sentences fused by professional editors–
Related by discourse, but...

Content is not usually similar!

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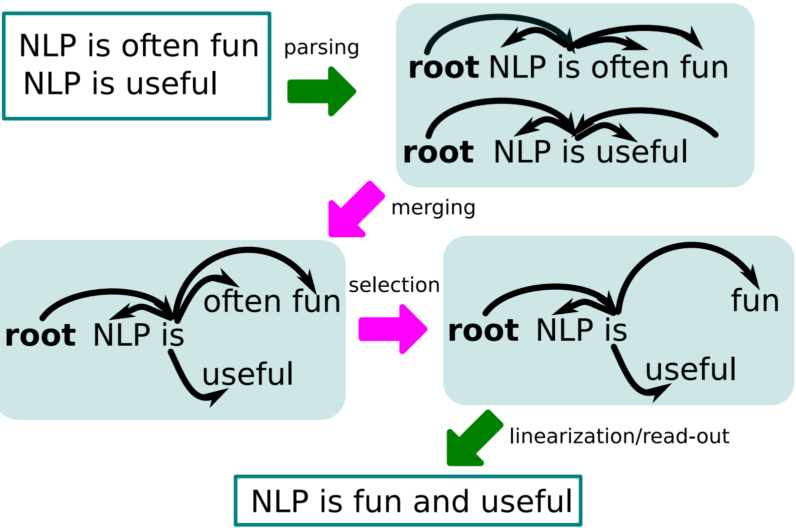
Content is not usually similar!

Editing data:

- Naturally occurring dataset
- Probably more similar to single-document summary
- Poses problems for standard approaches

Generic framework for sentence fusion



Issues with the generic framework

Selection

What content do we keep?

- Convey the editor's desired information
- Remain grammatical

Merging

Which nodes in the graph match?
Dissimilar sentences: correspondences are noisy!

Learning

Can we learn to imitate human performance?

Issues with the generic framework

Selection

What content do we keep?

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  - **Requires discourse; not going to address**
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Can we learn to imitate human performance?

Contribution: Use structured learning

Overview

Motivation

Setting up the problem

Fusion as optimization
- Jointly finding correspondences
- Staying grammatical

Learning to fuse
- Defining an objective
- Structured learning

Evaluation

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The data

500 article pairs processed by professional editors:

Novel dataset courtesy of Thomson Reuters

THOMSON REUTERS

Each article in two versions: **original** and **edited**

We align originals with edited versions to find:

- 175 split sentences
- 132 merged sentences
- ... treat both as fusion examples

The content selection problem

Which content to select:

Many valid choices (Daume+Marcu '04), (Krahmer+al '08)

Input

Uribe appeared unstoppable after the rescue of Betancourt.

His popularity shot to over 90 percent, but since then news has been bad.

The content selection problem

Which content to select:

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Input

Uribe appeared unstoppable **after the rescue of Betancourt**.

His popularity shot to over 90 percent, but since then news has been bad.

Output

Uribe’s popularity shot to over 90 percent after the rescue of Betancourt.

The content selection problem

Which content to select:

Many valid choices (Daume+Marcu ‘04), (Krahmer+al ‘08)

Input

Uribe appeared unstoppable after the rescue of Betancourt.

His popularity shot to over 90 percent, **but since then news has been bad.**

Output

Uribe used to appear unstoppable, but since then news has been bad.

Faking content selection: finding alignments

Use simple dynamic programming to align input with truth...
Provide true alignments to both **system** and **human judges**.

Input

Uribe appeared unstoppable after the rescue of Betancourt.

His popularity shot to over 90 percent, but since then news has been bad.

True output

Uribe appeared unstoppable and his popularity shot to over 90 percent.

Faking content selection: finding alignments

Use simple dynamic programming to align input with truth...
Provide true alignments to both **system** and **human judges**.

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Uribe appeared unstoppable after the rescue of Betancourt.

His popularity shot to over 90 percent, but since then news has been bad.

True output

Uribe appeared unstoppable and his popularity shot to over 90 percent.

Still not easy– grammaticality!
Aligned regions often just fragments:

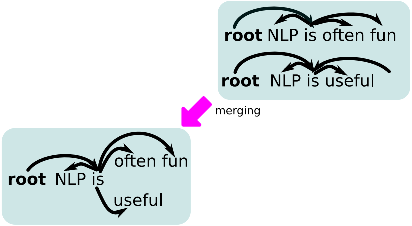
Input

...the **Berlin speech** will be a centerpiece **of the tour**...

Overview

Merging dependency graphs

Previous:



Merge nodes deterministically:

- Lexical similarity
- Local syntax tree similarity

For disparate sentences,
these features are noisy!

Merging dependency graphs

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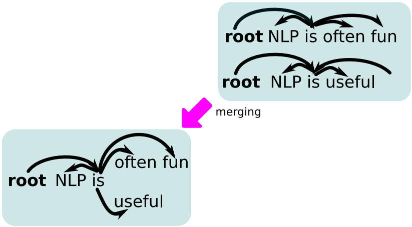

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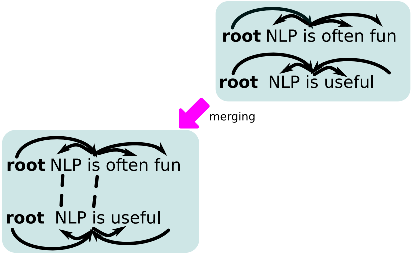
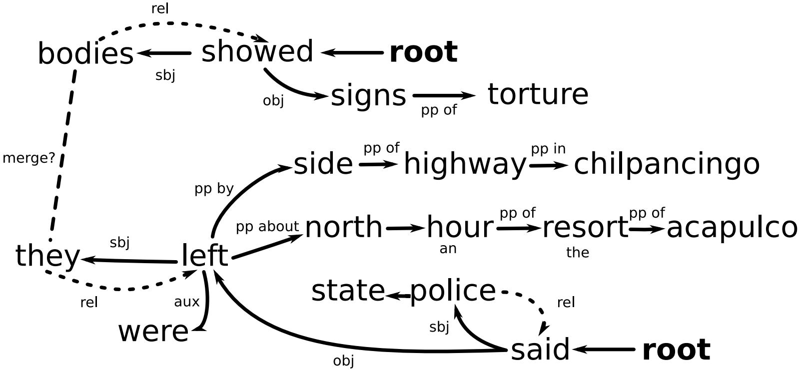
Our work:



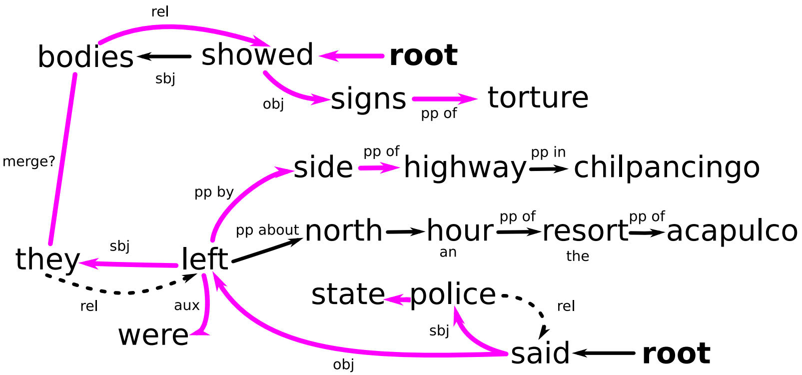
Soft merging: add **merge arcs** to graph
System decides whether to use or not!

Add relative clause arcs between subjects and verbs

(Alternates "police said" / "police, who said")



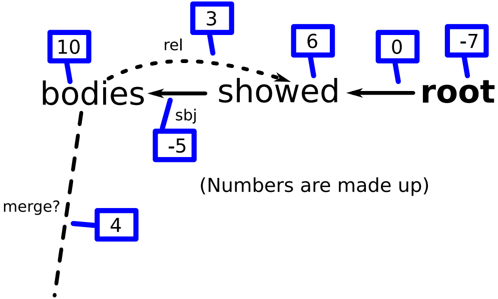
A fused tree: a set of arcs to keep/exclude



"The bodies, which showed signs of torture, were left by the side of a highway"

Finding a good fusion

Put weights on all words and arcs, then maximize the sum for selected items



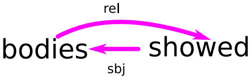
(Numbers are made up)

Weights determine the solution– we will learn them!

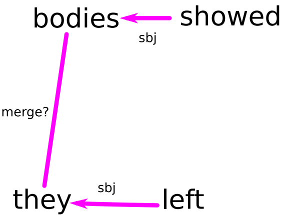
Constraints

Not every set of selected arcs is valid...

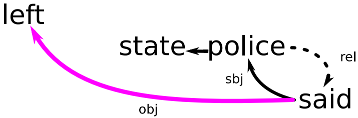
Unconnected fragment



Cycle



Merged node with two heads



Missing argument (subject)

Solving with ILP

Integer Linear Programming (ILP)

Maximize a linear function
subject to:
linear constraints
integrality constraints

NP-hard, but well-studied practical solutions (Ilog CPLEX)

Our ILP based on (Filippova+Strube '08), generalized for soft merging...
Similar setup for sentence compression (Clarke+Lapata '08)

Very efficient for this size problem

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Evaluation

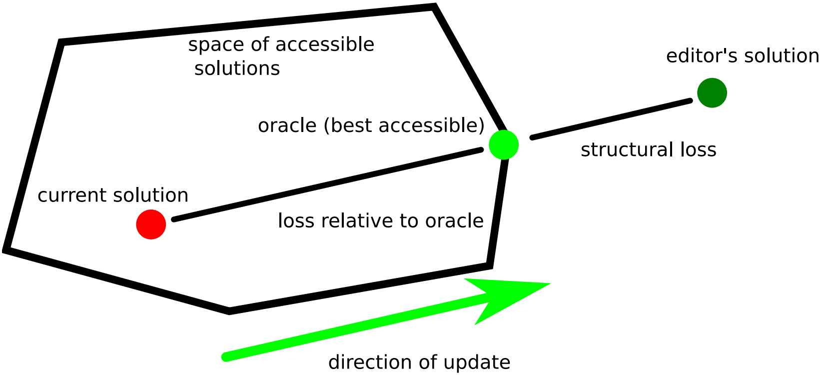
How to fuse?

ILP tells us what fusions are allowed...
  The weights tell us which ones are good.

Recipe for structured learning, (Collins '02),others:

- Define a feature representation
- Define a loss function
- For each datapoint:
  - Compute current solution
  - Compute best possible solution
  - Update weights to push away from current, proportionally to loss

Same thing, with picture



Features

Features for dependencies

Keep this arc?

- Parent/child POS tags
- Dependency label
- Parent/child word retained by editor?
- Dependency is inserted relative clause

Features for words

Keep this word?

- POS tag
- Word retained by editor?

Features 2

Features for merge arcs

Do these two words correspond?

- Same POS tag
- Same word
- Same arc type to parent
- WordNet similarity (Resnik '95),(Pedersen+al '04)
- Thesaurus similarity (Jarmasz+Szpakowicz '03)
- Hand-annotated pronoun coreference

Loss function

Measure similarity to the editor's sentence...

- Not just lexically (the editor can paraphrase, we can't!)

Look at **connections between** the retained content

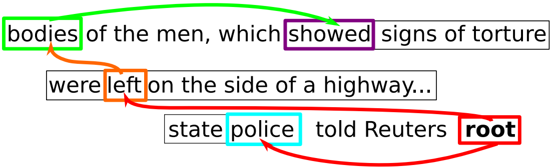
bodies of the men, which showed signs of torture

were left on the side of a highway...

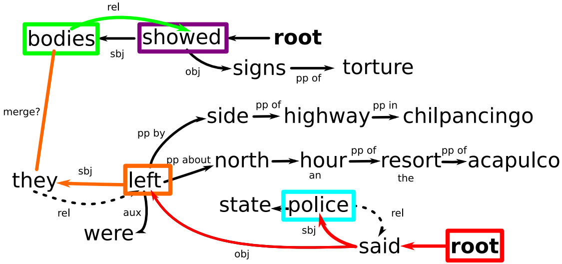
state police told Reuters **root**

Finding the oracle

Match this structure:



On this graph:



Loss, part 2

Our loss function

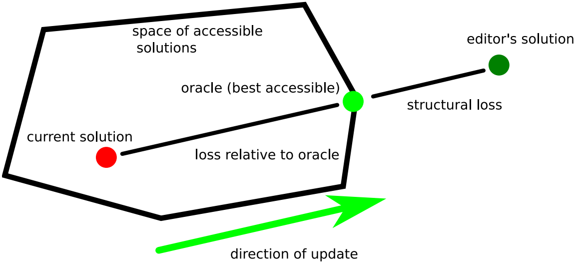
Penalty for:

- Bad/missing connections
- Leaving out words the editor used
- Words the editor didn't use

Can actually find the oracle (minimize loss) with ILP...
Using polynomial number of auxiliary variables.

Optimizing

We have **features**, the **loss** and the **oracle**...
So we can learn...
Just need to choose an update rule:



Use the **perceptron** update with averaging (Freund+Schapire '99) and committee (Elsas+al '08)

Overview

Human evaluation

Evaluated for **readability** and **content** by human judges:

92 test sentences; 12 judges, 1062 observations

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Our parsing and linearization on the editor's sentence

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"and"-splice

All input sentences, spliced with the word "and"

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"and"-splice

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System

Our system output
Only abstractive system we tested

Readability

System	**Avg**
Editor	4.6
Readability UB	4.0
“And”-splice	3.7
System	3.1

- Poor linearization: gap of .6
- System: additional loss of .9
- Average system score still 3, “fair”

Content

System	Avg
Editor	4.6
Readability UB	4.3
“And”-splice	3.8
System	3.8

- Score close to 4, “good”

Comparison with “and”-splice

“and”-splice content scores comparable to ours, but...

- Spliced sentences too long
  - 49 words vs human 34, system 33
- Our system has more extreme scores

	1	2	3	4	5	Total
“And”-splice	**3**	43	60	57	**103**	266
System	**24**	24	39	58	**115**	260

Good

Input

The bodies showed signs of torture.

They **were left on the side of a highway in Chilpancingo**, in the southern state of Guerrero, **state police** said.

Our output

The bodies who showed signs of torture were left on the side of a highway in Chilpancingo state police said.

Good

Input

The suit **claims** the company **helped fly terrorism suspects abroad to secret prisons.**

Holder's **review was disclosed the same day as Justice Department lawyers repeated a Bush administration** state-secret **claim in a lawsuit against a Boeing Co unit.**

Our output

Review was disclosed the same day as Justice Department lawyers repeated a Bush administration claim in a lawsuit against a Boeing Co unit that helped fly terrorism suspects abroad to secret prisons.

Not very good

Our system

Biden a veteran Democratic senator from Delaware that Vice president-elect and Joe had contacted to lobby was quoted by the Huffington Post as saying Obama had made a mistake by not consulting Feinstein on the Panetta choice.

Better parsing/linearization

Vice President-elect Joe Biden, a veteran Democratic senator from Delaware who had contacted...

Not very good

Our system

The White House that took when Israel invaded Lebanon in 2006 showed no signs of preparing to call for restraint by Israel and the stance echoed of the position.

Missing arguments

took, *position*

Conclusion

- Naturally occurring data
- Find correspondences jointly with selection
- Supervised structured learning

Future work

New data:

- Classic similar-sentence fusion (McKeown '10 corpus)
- Single-document summary

Better techniques:

- Automatic coreference
- Paraphrasing rules

Acknowledgements

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