# Automatically Evaluating Text Coherence Using Discourse Relations

Discourse Coherence Theory and Modeling

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#### **Overview**

- ☐ Motivation☐ Background
  - Different discourse frameworks
  - State of the art development
  - How to utilize PDTB in this task?
- ☐ The Refined Approach
  - Discourse Role
  - Discourse Role Transitions and Lexical Chains
  - Discourse Role Matrix (Exercise)
- ☐ Evaluation of Results
- ☐ Conclusion
- ☐ Summary (Exercise)

### **Motivation**

☐ Distinguish a Coherent Text from an Incoherent Text Automatically

☐ Improves state of the art model: Synergistic with the previous approach suggested by Barzilay and Lapata(2005)

☐ Use in Summarization, Text Generation and Essay Scoring.

#### Different discourse frameworks

If I had an alarm clock, I would have broken it every morning.

I could not wake up with my alarm clock, which has been broken since yesterday.

RST
Discourse Relations

Elaboration
Evidence

Satellite +
Nucleus

Nucleus+
Satellite

Different discourse frameworks

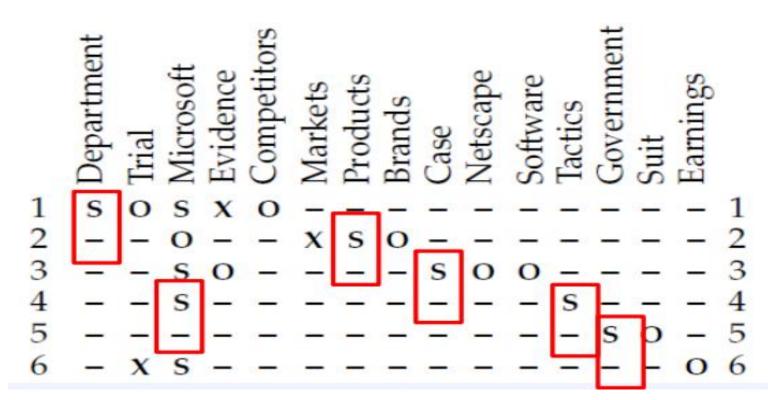
[The constitution does not expressly give the president such power.] $\mathbf{S_1}$  [However the president does have a duty not to violate the constitution.] $\mathbf{S_2}$  [The question is whether his only means of defense is the veto.] $\mathbf{S_3}$ 

Pattern: Contrast-followed-by-Cause

Coherent text exhibits measurable preferences for specific intraand inter-discourse relation ordering.

State of the art related work

Local entity transition model by Barzilay and Lapata (2005)



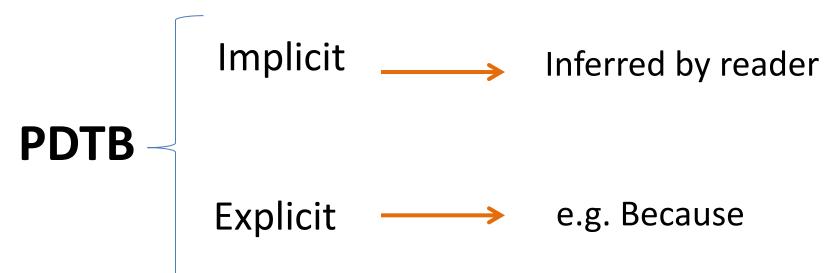
**Use of PDTB** 

You want to model the Discourse Relation Transition



Identify Discourse Relations by some automatic annotators

Discourse Lexicalized Tree Adjoining Grammar (D-LTAG)



**Use of PDTB** 

**D-LTAG** tags relations with two levels of types:

The use of compound subjects help lengthen simple sentences but simple sentences are often short.

Temporal(Temp)
They have not spoken to each other since the huge argument they had last year.

Contingency(Cont)

Since you said you'll not drop by, I left home at 8PM.

Expansion(Exp)

### Approach: Discourse Role

```
[ Japan normally depends heavily on the Highland Valley and Cananea
mines as well as the Bougainville mine in Papua New Guinea. ] S<sub>1</sub>
[ Recently, Japan has been buying copper elsewhere. ] S<sub>2</sub>
[ [ But as Highland Valley and Cananea begin operating, ] C_{3:1} [ they
are expected to resume their roles as Japan's suppliers. ] C_{3\cdot 2} S_3
[ [ According to Fred Demler, metals economist for Drexel Burnham
Lambert, New York, ] C_{4\cdot 1} [ "Highland Valley has already started
operating ] C_{4\cdot 2} [ and <u>Cananea</u> is expected to do so soon." ] C_{4\cdot 3} ] S_4
1.Implicit Comparison < S<sub>1</sub>:Arg1, S<sub>2</sub>:Arg2 >
2.Explicit Comparison < S<sub>2</sub>:Arg1, S<sub>3</sub>:Arg2 >
3.Explicit Temporal < C_3 :Arg1, C_3 :2:Arg2>
4.Implicit Expansion < $\sigma_3:\text{Arg1, $\sigma_4:\text{Arg2}}$
5.Explicit Expansion \langle C_{4\cdot 2} : Arg1, C_{4\cdot 3} : Arg2 \rangle
```

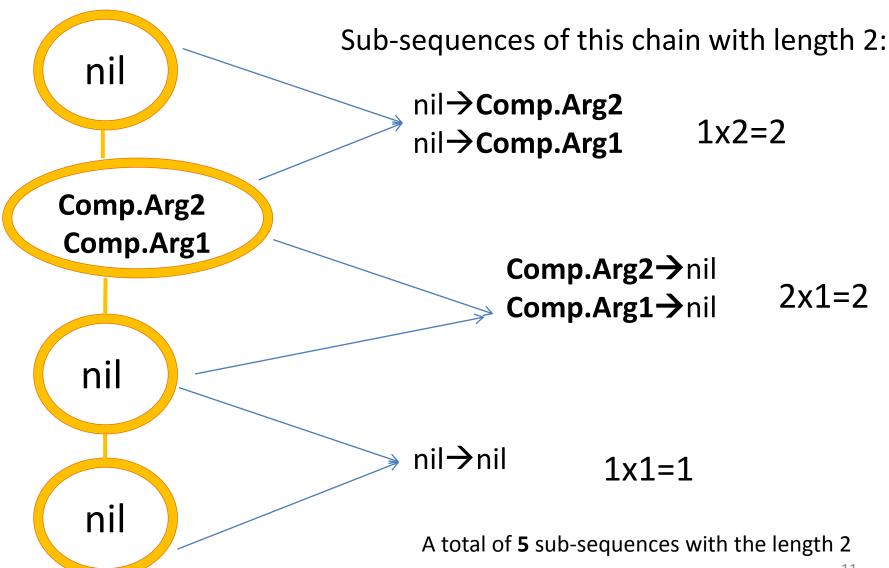
**Discourse Role=Discourse Relation Type + Argument Span Position** 

### **Approach:** Discourse Role Transitions

Sub-sequence of discourse roles for a term in multiple consecutive sentences.

- 1. Find the discourse roles of a word over the text (for each sentence)
- 2. Put the discourse roles of the word for a particular sentence in a node
- Connect the nodes as their associated sentences are connected over the text
- 4. Now you have a **Lexical Chain** with simplified nodes and typed with relations
- 5. Any sub-sequence at any length extracted from this chain is a Discourse Role Transition

### **Approach: Discourse Role Transitions**



### Approach: Discourse Role Matrix

S#	Copper	Cananea	Operate	Depend
S <sub>1</sub>	nil	Comp.Arg1	nil	Comp.Arg1
S <sub>2</sub>	Comp.Arg2 Comp.Arg1	nil	nil	nil
S <sub>3</sub>	nil	Comp.Arg2 Temp.Arg1 Exp.Arg1	Comp.Arg2 Temp.Arg1 Exp.Arg1	nil
S <sub>4</sub>	nil	Exp.Arg2	Exp.Arg2 Exp.Arg1	nil

5 7 1

3

12

S#	Mike	Frank	story
S <sub>1</sub>	Temp.Arg1 Temp.Arg2	nil	Temp.Arg1
S <sub>2</sub>	nil	Comp.Arg2 Con.arg1	nil
S <sub>3</sub>	Temp.Arg2 Temp.Arg1 Con.Arg2	Temp.Arg2 Temp.Arg1 Con.Arg2	nil

5 8 2

# How does the approach model Discourse Relation Transitions?

Imagine The matrices of the whole text:

☐ Identify all the possible sub-sequences of any term(column) with any length.

**Length 2: 25** 

Length 3: ...

Length 4: ...

☐ What is the probability of each of the subsequences? P(Comp.Arg2→Exp.Arg2)?

## Approach: Distribution of Discourse Role

☐ By computing the probabilities of all the possible sub-sequences, we access the "Distribution of Discourse Roles" in the text.

☐ Hypothesis: This distribution is distinguishable between coherent and incoherent texts.

# Further Refine the approach Salience

Divide the Matrix into two parts

#### Salient

Term Frequency in the column is greater than a threshold

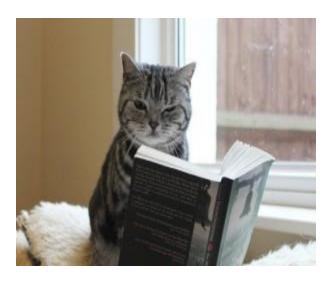
**Non-Salient** 

A low frequency

### **Approach:** Preference Ranking

Coherence of a text (or the level to which we comfortably read) is relative







### **Experiment**

■ Task: Which of two texts is more coherent? A source text or its permutations?

■ Data collections: Wall Street Journal articles and AP articles about earthquakes also articles about accidents(NTSB)

■ Parameters: Term Frequency as threshold for salience(TF>=2) and length of sub-sequences as features(<=3)</p>

### Results

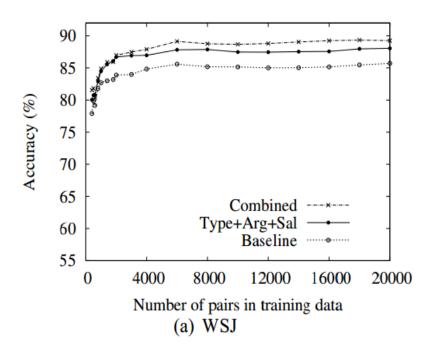
- ☐ This model outperforms the baseline(Local Entity Transition Model)
- ☐ Eliminating each of the information sources: Argument tags and salience play more important roles than relations.
- ☐ The combination of baseline and this approach outperforms both of the approaches: As it collects features from different aspects of coherence.

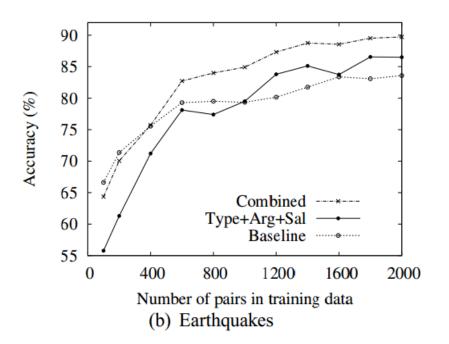
## Test Set Ranking Accuracy

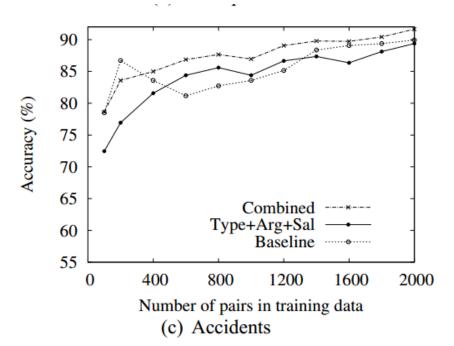
	WSJ	Earthquakes	accidents
Baseline	85.71	83.59	89.93
Type+Arg+Sal	88.06	86.50	89.38
Arg+Sal	88.28	85.89	87.06
Type+Sal	87.06	82.98	86.05
Type+Arg	85.98	82.67	87.87
Baseline & Type+Arg+Sal	89.25	89.72	91.64

### Conclusion

- ☐ The combined model performs better than each of its constituents .
- ☐ The full model outperforms the baseline in the mid-segment of the curve:
  - —It fails in some permutations.
  - —PDTB doesn't work with implicit relations as it works with explicit ones.
- ☐ Relation/length ratio determines why the accuracy is better in accidents







### Summary

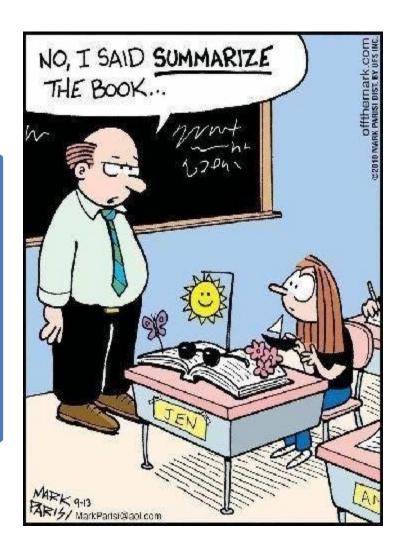
**Distribution of Discourse role** 

**Discourse Role Matrix** 

Salience

**Baseline: Barzilay & Lapata(2005)** 

**Preference Ranking** 





### References

Ziheng Lin, Hwee Tou Ng and Min-Yen Kan. 2011. Automatically Evaluating Text Coherence Using Discourse Relations. *ACL*: 997-1006

Regina Barzilay and Mirella Lapata. 2008. Modeling local coherence: An entity-based approach. Computational Linguistics, 34(1), 1-34.



Thank you!