Discovering Implicit Discourse Relations Through Brown Cluster Pair Representation and Coreference Pattern

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Discourse relations influence interpretation.

(1) I want to go home for the holiday.
<u>So</u> I will book a flight to Boston.

(2) I want to go home for the holiday.
<u>Nonetheless</u>, I will book a flight to Boston.

(3) I want to go home for the holiday.
I will book a flight to Boston.

Applications

- Discourse relation information improves **summarization**. (Louis et al, 2010)

- Discourse relations help assess **text readability**. (Pitler, 2008)

- Discourse relation transitions can evaluate and rerank **coherence**. (Lin, 2011)

Implicit discourse relations in the Penn Discourse Treebank

	Explicit %	Implicit %
Comparison	42.71%	15.11%
Contingency	28.59%	25.68%
Expansion	0.55%	53.48%
Temporal	28.15%	5.73%
Total Count	13086	16569

Implicit discourse relations in the Penn Discourse Treebank

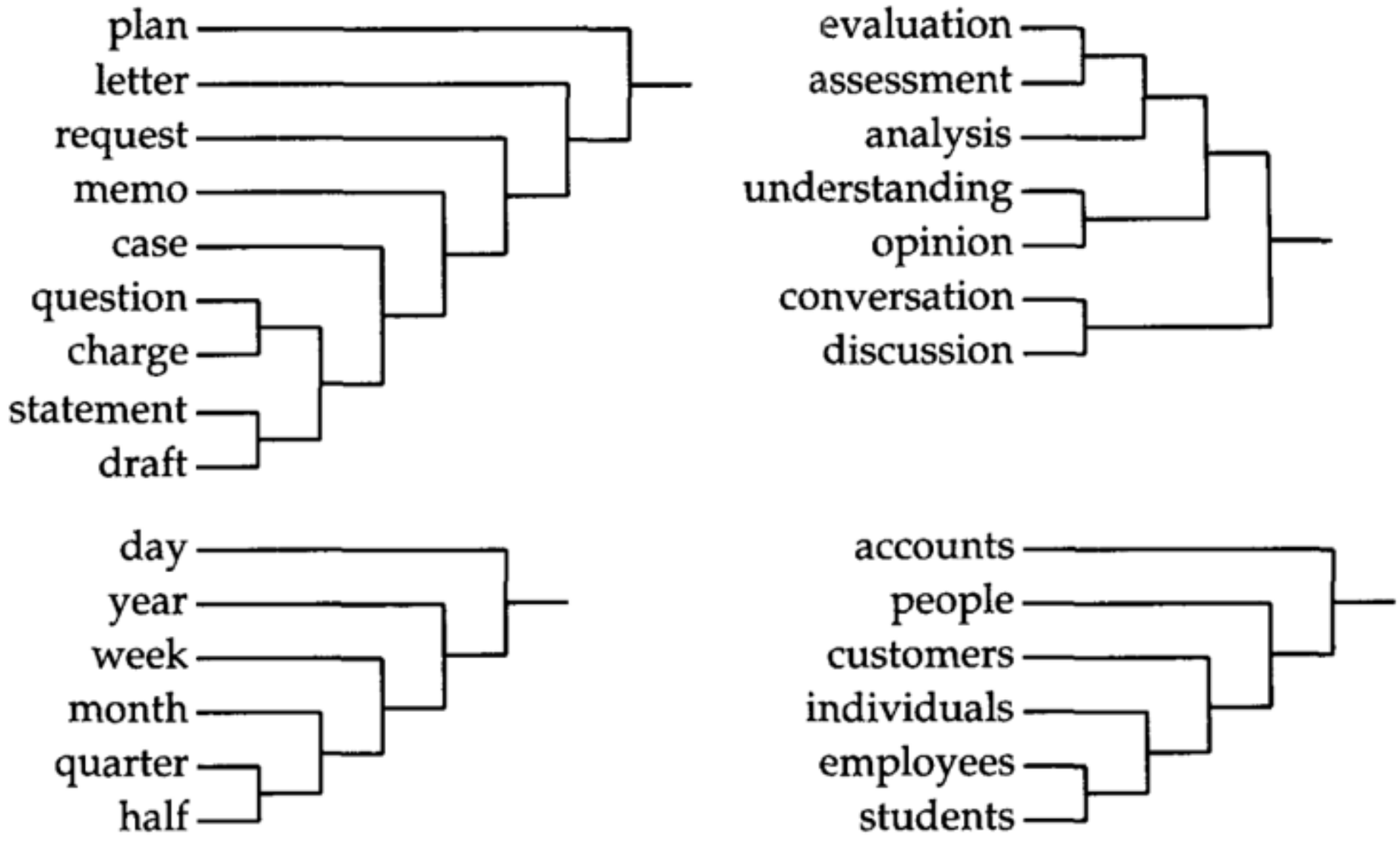
	Explicit %	Implicit %	Explicit F1 (Pitler et al, 2008)	Implicit F1 (Park and Cardie, 2012)
Comparison	42.71%	15.11%	95.44	31.32
Contingency	28.59%	25.68%	83.28	49.82
Expansion	0.55%	53.48%	96.54	79.22
Temporal	28.15%	5.73%	88.50	26.57
Total Count	13086	16569		

Task formulation and paradigm

- Input : e.g.
  When the deal ran into trouble, the stock tumbled.
  It closed at $ 198 yesterday. (WSJ2057)

- Train 4 classifiers from the same feature set

Brown clustering



Brown et al, 1992

Brown cluster pair representation

When the deal ran into trouble , the stock tumbled.

It closed at $ 198 yesterday.

Brown cluster pair representation

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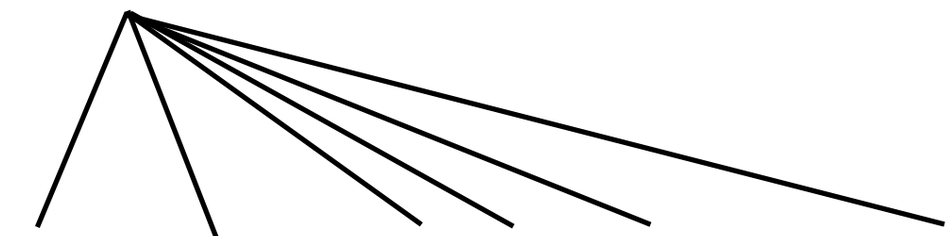
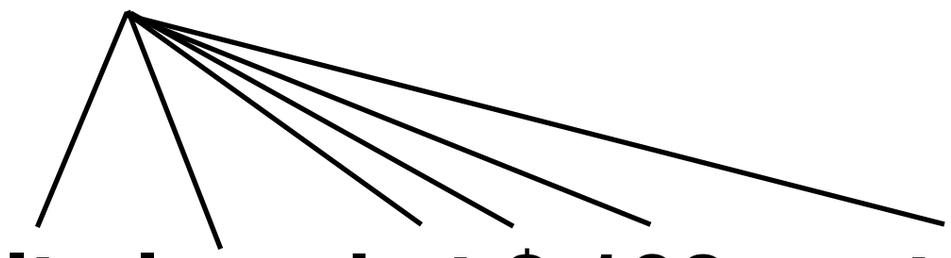


It closed at $ 198 yesterday.

When-It
When-closed
When-at
When-$
When-198
When-yesterday

Brown cluster pair representation

When the deal ran into trouble , the stock tumbled.



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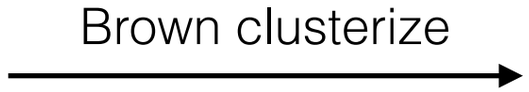


When-It	Cluster12-Cluster3
When-closed	Cluster12-Cluster86
When-at	Cluster12-Cluster41
When-$	Cluster12-Cluster135
When-198	Cluster12-Cluster94
When-yesterday	Cluster12-Cluster23

Coreference features

- Number of coreferential pairs
- Does the coreferential entity or similar nouns have similar predicates?
- Does the argument pair have similar main predicates?
- Does the argument pair have similar subject?

Previous features

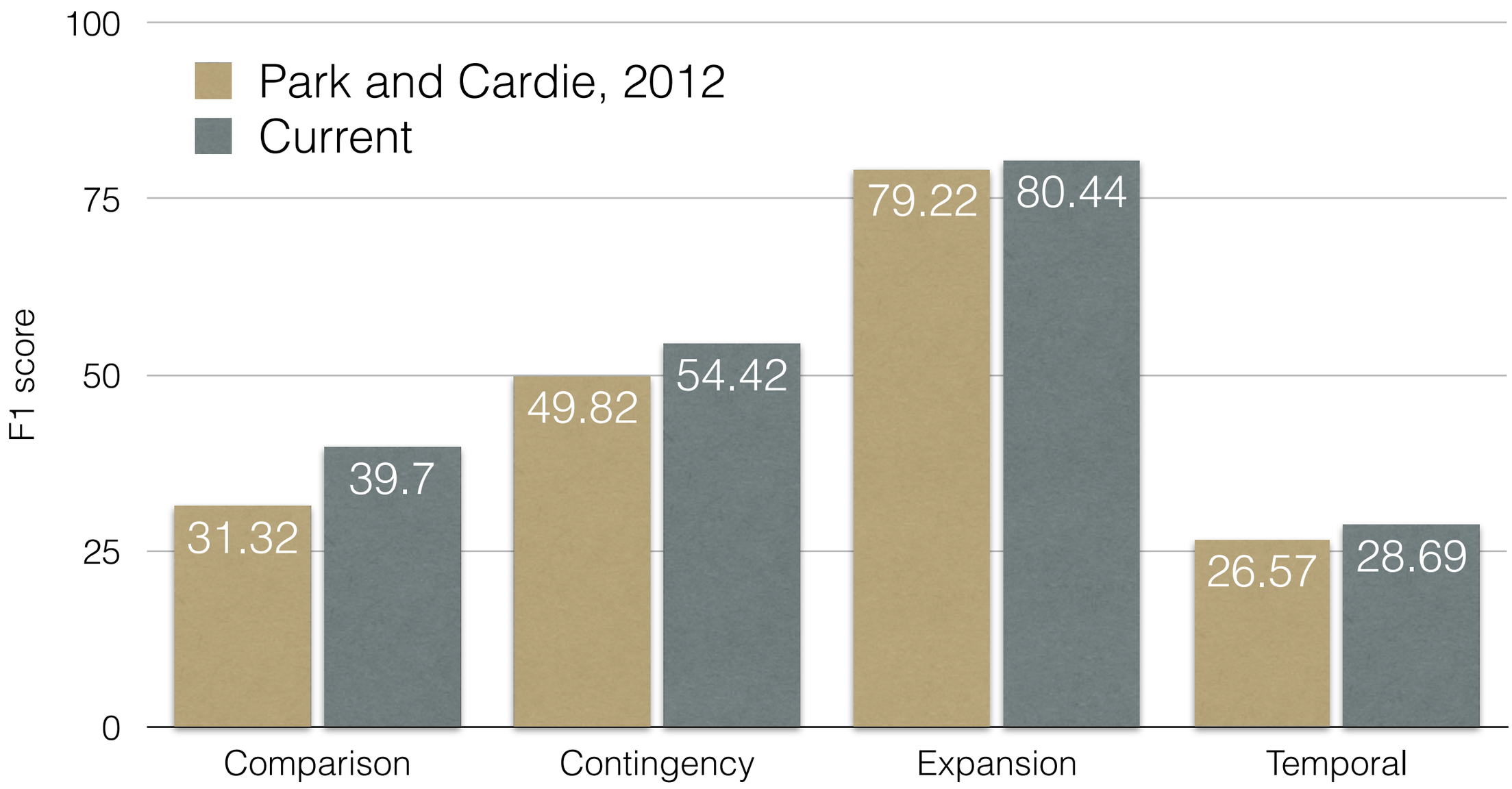
- Numerical, time expressions
- Production rules used by Arg1, Arg2, and both
- General inquirer tags, verb classes, polarity scores
- etc.

Pitler et al, 2009

Experimental setup

- Stanford CoreNLP for parsing and coreference
- Brown clusters from Turian et al., 2010
- Data split is the same as Park and Cardie, 2012

Results


100
75
50
25
0
F1 score
Park and Cardie, 2012
Current
31.32
39.7
49.82
54.42
79.22
80.44
26.57
28.69
Comparison
Contingency
Expansion
Temporal

Ablation study

COMPARISON

Feature set	F1	% change
All features	39.70	
Ablated Brown cluster pairs	**35.71**	**-10.05%**
Ablated Production rules	37.27	-6.80%
Ablated First, last, and First 3	39.18	-1.40%
Ablated Polarity	39.39	-0.79%

EXPANSION

Feature set	F1	% change
All features	70.23	
Ablated Brown cluster pairs	**67.48**	**-3.92%**
Ablated First, last, and First 3	69.43	-1.14%
Ablated Inquirer tags	69.73	-0.71%
Ablated Polarity	69.92	-0.44%

CONTINGENCY

Feature set	F1	% change
All features	54.42	
Ablated Brown cluster pairs	**51.50**	**-5.37%**
Ablated First, last, and First 3	53.56	-1.58%
Ablated Polarity	53.82	-1.10%
Ablated Coreference	**53.92**	**-0.92%**

TEMPORAL

Feature set	F1	% change
All features	28.69	
Ablated Brown cluster pairs	**24.53**	**-14.50%**
Ablated Production rules	26.51	-7.60%
Ablated First, last, and First 3	26.56	-7.42%
Ablated Polarity	27.42	-4.43%

Finding useful pairs

- Mutual information $$I(X_i, Y) = \sum_{y} \sum_{x=0,1} \hat{p}(x, y) \log \frac{\hat{p}(x, y)}{\hat{p}(x)\hat{p}(y)}$$
- Brown cluster bipartite graph

cluster5-cluster9
cluster5-cluster4
cluster5-cluster3
cluster7-cluster4
cluster2-cluster10

Finding useful pairs

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cluster2
cluster5
cluster7

cluster3
cluster4
cluster9
cluster10

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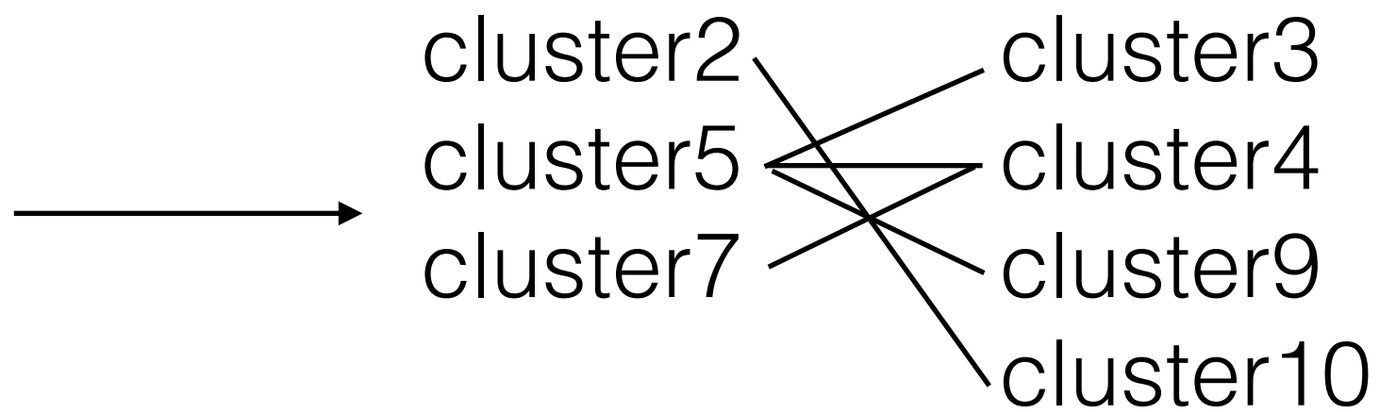
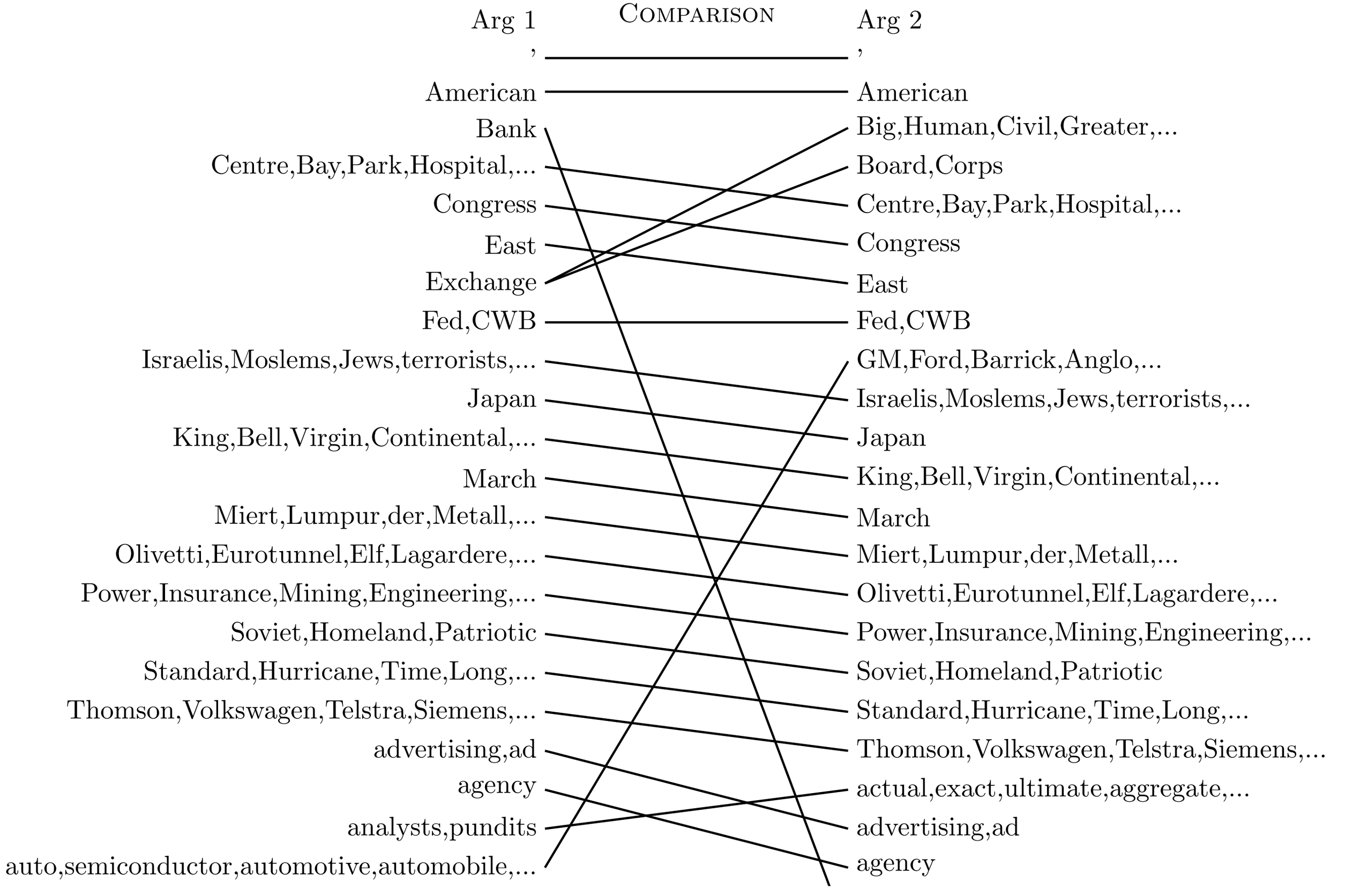
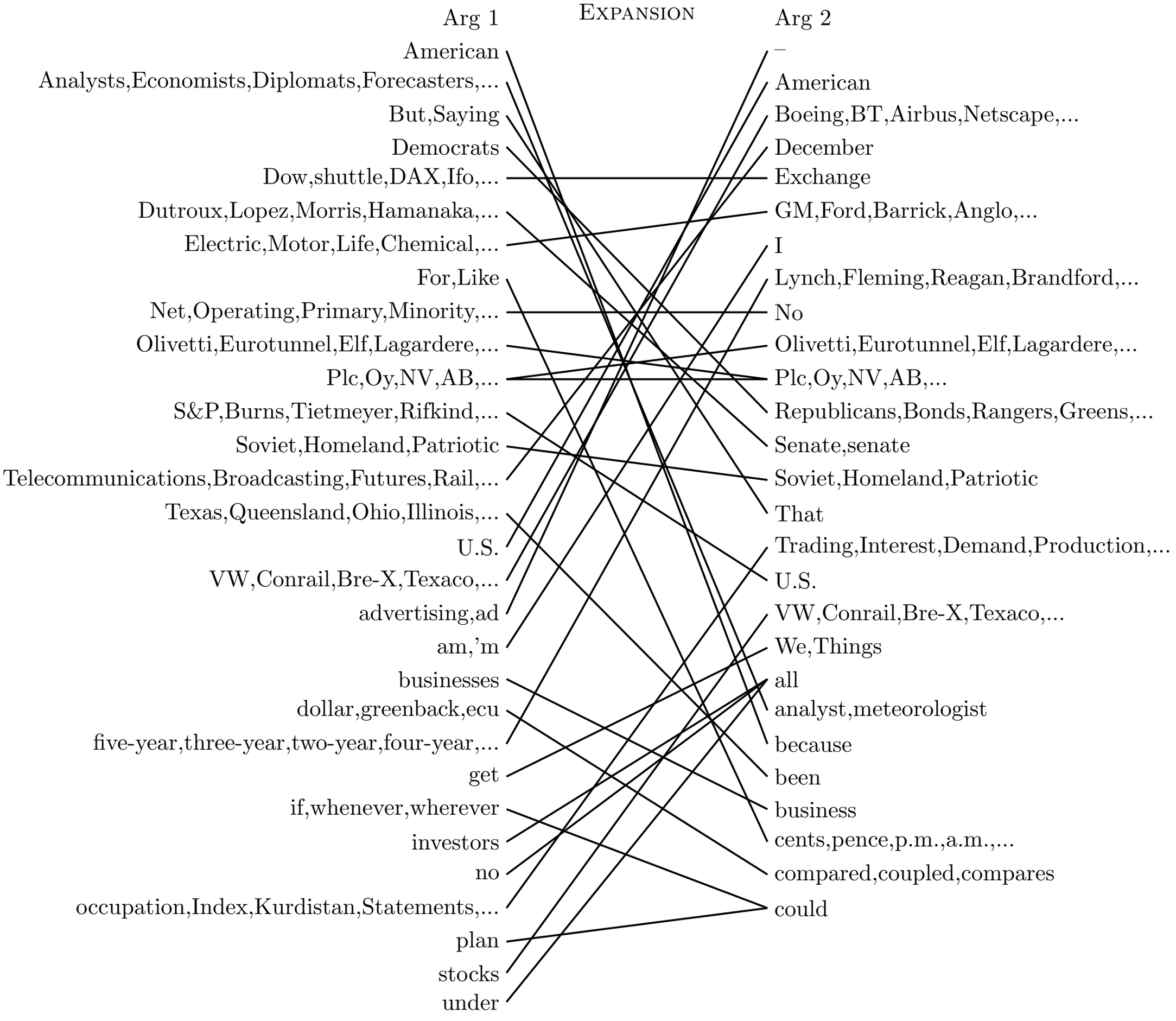


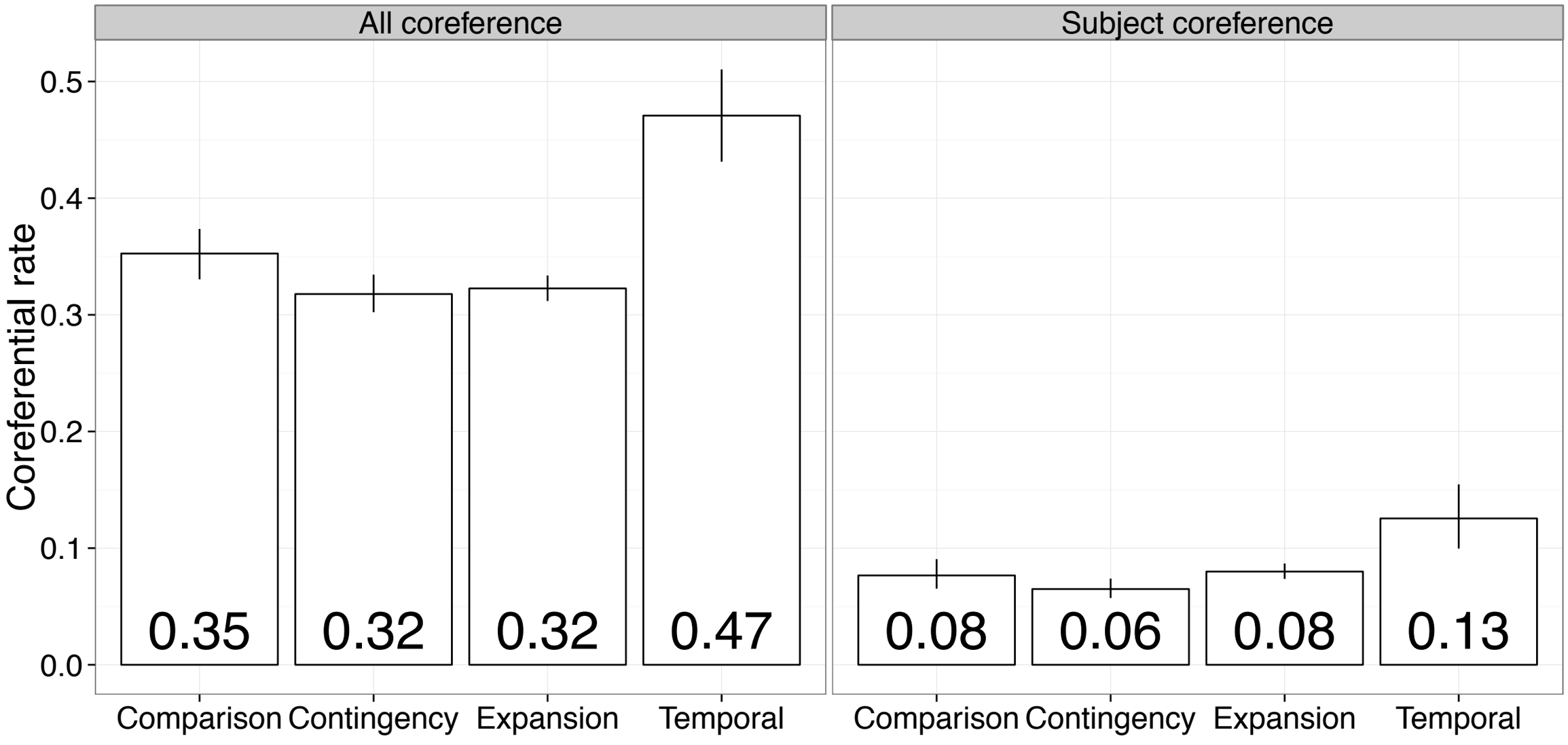

Arg 1
Comparison
Arg 2
,
,
American
American
Bank
Big,Human,Civil,Greater,...
Centre,Bay,Park,Hospital,...
Board,Corps
Congress
Centre,Bay,Park,Hospital,...
East
Congress
Exchange
East
Fed,CWB
Fed,CWB
Israelis,Moslems,Jews,terrorists,...
GM,Ford,Barrick,Anglo,...
Japan
Israelis,Moslems,Jews,terrorists,...
King,Bell,Virgin,Continental,...
Japan
March
King,Bell,Virgin,Continental,...
Miert,Lumpur,der,Metall,...
March
Olivetti,Eurotunnel,Elf,Lagardere,...
Miert,Lumpur,der,Metall,...
Power,Insurance,Mining,Engineering,...
Olivetti,Eurotunnel,Elf,Lagardere,...
Soviet,Homeland,Patriotic
Power,Insurance,Mining,Engineering,...
Standard,Hurricane,Time,Long,...
Soviet,Homeland,Patriotic
Thomson,Volkswagen,Telstra,Siemens,...
Standard,Hurricane,Time,Long,...
advertising,ad
Thomson,Volkswagen,Telstra,Siemens,...
agency
actual,exact,ultimate,aggregate,...
analysts,pundits
advertising,ad
auto,semiconductor,automotive,automobile,...
agency


Arg 1
Expansion
Arg 2
American
Analysts,Economists,Diplomats,Forecasters,...
But,Saying
Democrats
Dow,shuttle,DAX,Ifo,...
Dutroux,Lopez,Morris,Hamanaka,...
Electric,Motor,Life,Chemical,...
For,Like
Net,Operating,Primary,Minority,...
Olivetti,Eurotunnel,Elf,Lagardere,...
Plc,Oy,NV,AB,...
S&P,Burns,Tietmeyer,Rifkind,...
Soviet,Homeland,Patriotic
Telecommunications,Broadcasting,Futures,Rail,...
Texas,Queensland,Ohio,Illinois,...
U.S.
VW,Conrail,Bre-X,Texaco,...
advertising,ad
am,'m
businesses
dollar,greenback,ecu
five-year,three-year,two-year,four-year,...
get
if,whenever,wherever
investors
no
occupation,Index,Kurdistan,Statements,...
plan
stocks
under
–
American
Boeing,BT,Airbus,Netscape,...
December
Exchange
GM,Ford,Barrick,Anglo,...
I
Lynch,Fleming,Reagan,Brandford,...
No
Olivetti,Eurotunnel,Elf,Lagardere,...
Plc,Oy,NV,AB,...
Republicans,Bonds,Rangers,Greens,...
Senate,senate
Soviet,Homeland,Patriotic
That
Trading,Interest,Demand,Production,...
U.S.
VW,Conrail,Bre-X,Texaco,...
We,Things
all
analyst,meteorologist
because
been
business
cents,pence,p.m.,a.m.,...
compared,coupled,compares
could

Other useful pairs

- semantic similarity between the two arguments are indicative of Contingency relations e.g.
  - {analysts, pundits} - {actual, exact, aggregate}
- generality-specific shift is indicative of Expansion relations e.g.
  - {Life, Chemical, Automotive} - {GM, Ford, Barrick}

Coreferential rate comparison



Coreference influences discourse relations

(1) **He** also asserted that exact questions weren't replicated.
When referred to the questions that match, **he** said it was coincidental. (WSJ0045)

(2) **He** also asserted that exact questions weren't replicated.
When referred to the questions that match, **she** said it was coincidental

Conclusion

- State-of-the-art implicit discourse relation identification (online demo soon available)

- Features for this task have to go beyond words.

Results

	Current			Park and Cardie (2012)
	Precision	Recall	F1	F1
Comparison	27.34	72.41	**39.70**	31.32
Contingency	44.52	69.96	**54.42**	49.82
Expansion	69.26	95.92	**80.44**	79.22
Temporal	18.52	63.64	**28.69**	26.57