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earth's h such big	earth's history , we never had such big greenhouse gas			• warm								
concenti methane other ga	concentrations — of co2 , of methane , and of a lot of other gases , " he said .			exaggerate								



Model	Precision	Recall	F-Score				
Balanced Training Data (6926 Conversations)							
Decision Tree (5 features): 10-fold c.v.	0.77	0.69	0.73				
Decision Tree (13 features): 10-fold c.v.	0.79	0.68	0.73				
Random Forest (5 features): 10-fold c.v.	0.71	0.67	0.69				
Random Forest (13 features): 10-fold c.v.	0.74	0.70	0.72				
Imbalanced Real-World Data (40 Conversations)							
Decision Tree–5 (top 1 parent cand.)	0.14	0.14	0.14				
Decision Tree–5 (top 10 parent cand.)	0.06	0.45	0.11				
Decision Tree–13 (top 1 parent cand.)	0.16	0.16	0.16				
Decision Tree–13 (top 10 parent cand.)	0.07	0.46	0.12				
Random Forest–5 (top 1 parent cand.)	0.12	0.12	0.12				
Random Forest–5 (top 10 parent cand.)	0.07	0.32	0.11				
Random Forest–13 (top 1 parent cand.)	0.16	0.16	0.16				
Random Forest–13 (top 10 parent cand.)	0.06	0.45	0.10				
Precision Query (top 1 parent cand.)	0.87	0.04	0.08				
Precision Query (top 10 parent cand.)	0.81	0.05	0.08				
Recall Query (top 1 parent cand.)	0.27	0.28	0.28				
Recall Query (top 10 parent cand.)	0.12	0.38	0.18				
Content Query	0.36	0.29	0.32				
Content Query (threads with 30 msgs)	0.56	0.48	0.51				
Content Query (threads with 10 msgs)	0.70	0.66	0.68				

Model Results

Table 2: Summary of different model results.

Ref.	U/S*	Algorithm	Prec.	Rec.	F-sc.	Acc.	Characteristics
[9]	U	graph-based	-	-	0.7	-	long messages (avg > 60 words) educational discussions
[4]	U	SMSS	0.524	0.524	0.524	-	long messages (avg > 70 words) manually annotated data
[10]	U	similarity matching	-	0.8739	-	-	reliable feature (quotes) e-mails short threads (avg three e-mails)
[6]	S	Decision Tree	0.8307	0.6638	0.7379	-	reliable feature (only one feature: reference to author's name) manually annotated data short threads (4-comment threads)
[1]	S	Decision Tree	0.939	0.918	0.928	-	reliable feature (79.7% of the replies have a <i>distance</i> of 1) balanced training dataset 3-40 posts per thread
[7]	S	Ranking SVM	-	0.9617	-	-	reliable feature (quotes as one of the main features) e-mails short threads (at least three e-mails)
[2]	S	SORTS: Ranking SVM + candidate filtering	0.5264	0.5264	0.5264	-	long messages (avg 63.4 words)
[3]	S	PPC + Ranking SVM	-	-	-	0.970	e-mails short threads (avg 6-12 e-mails)
[5]	S	threadCRF	-	-	-	0.635	reliable feature (reference to author's name, person resolution)
[8]	S	threadCRF	-	-	-	-	uses own set of metrics short threads (avg 6 messages)

Overview of the Related Work

Table 1: Summary of algorithms which are used to reconstruct the reply-relation structure. Listed are the **best evaluation results** of each paper, and the reasons, why these results could be achieved. The best performance for forum data is reached by [1], using Decision Tree algorithm. (* U-unsupervised, S-supervised, Prec.-precision, Rec.-recall, F-sc.-F-score, Acc.-accuracy)

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