Coherence Modeling of Asynchronous Conversations: A Neural Entity Grid Approach

Tasnim Mohiuddin[1], Shafiq Joty[1], and Dat Tien Nguyen[2]

[1]Nanyang Technological University, [2]University of Amsterdam

Our Contributions

Extend the existing neural grid model, propose a novel coherence model for written asynchronous conversations (e.g., forums, emails), and show its applications in coherence assessment and thread reconstruction tasks.

Entity Grid and Its Extensions

Barzilay and Lapata (2008)

- Model grammatical role transmission of nouns (heads of NPs) across sentences
- Represent documents as distributions defined over **entity transition** (vectors of 4^k transitions probabilities $\{S, O, X, -\}^k$)
- Assessment of text coherence as a ranking problem in an SVM preference ranking framework

Table: Entity grid representation for a WSJ article.

	INVESTORS	MILLION	FUNDS	EQUIPMENT	CORP.	PAPER	SALE	TELECOMM.	LEASE	PROGRAM	CLEVELAND	RECEIVABLES	LEASES	DATA-PROCESS.	LDI	NON-RECOURSE
s_0	–	O	–	–	S	X	–	–	–	–	X	X	–	–	X	–
s_1	–	–	O	–	–	X	X	–	–	S	–	–	X	–	–	–
s_2	S	–	–	–	X	S	–	–	X	–	–	X	–	–	S	X
s_3	–	–	–	O	–	–	–	X	–	–	–	–	–	X	S	–

Nguyen and Joty (2017)

- A neural version of the grid models
- Transform each grammatical role in grid into distributed representation, then employ 1D convolution to model entity transitions
- Train in end-to-end fashion on target tasks

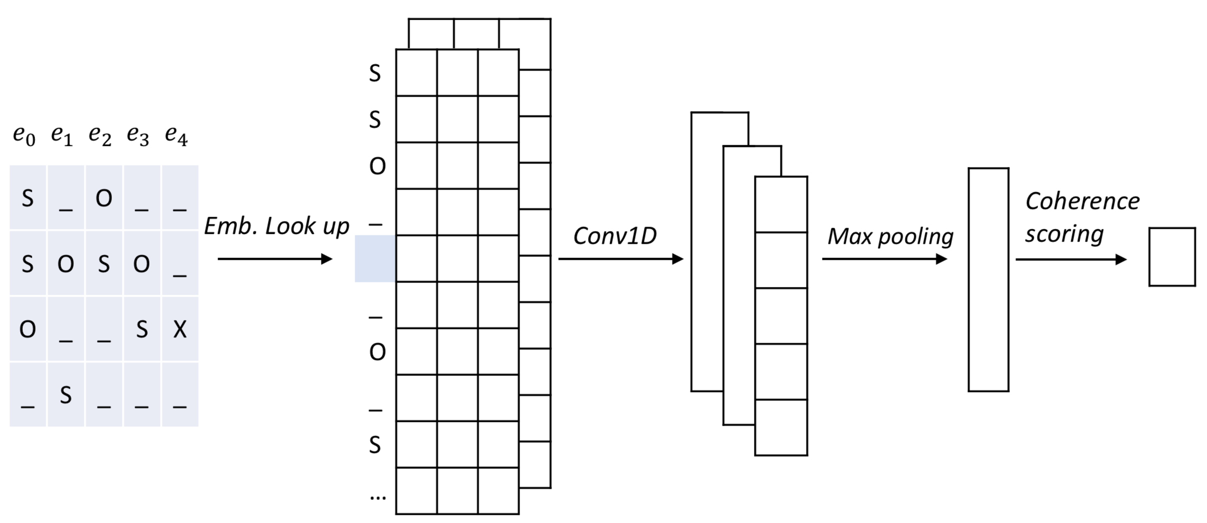


Figure: Neural entity grid model proposed by Nguyen and Joty (2017)

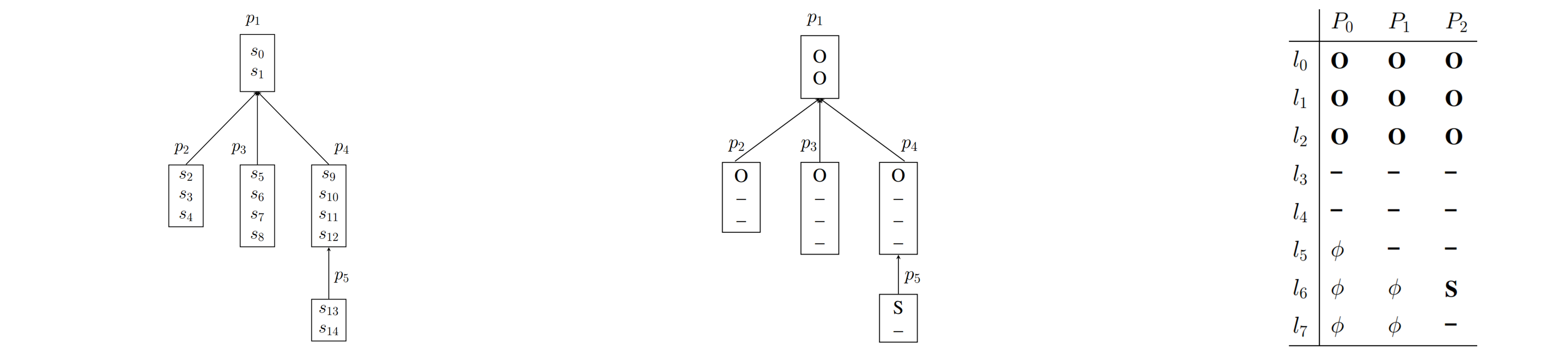
Limitations of entity grid models and their extensions

- Do not consider any lexical information regarding the entities
- Only focus on monologic discourse (e.g., news article)

Lexicalized Neural Entity Grid

- Attach the entity name with the grammatical roles
- Initialize entity-role embeddings randomly, or with pre-trained word embeddings for the entity

Coherence Models for Asynchronous Conversations



(a) Thread structure of a conversation (b) Entity role transition (c) 2D role transition matrix

Our Proposed Tree-level Model

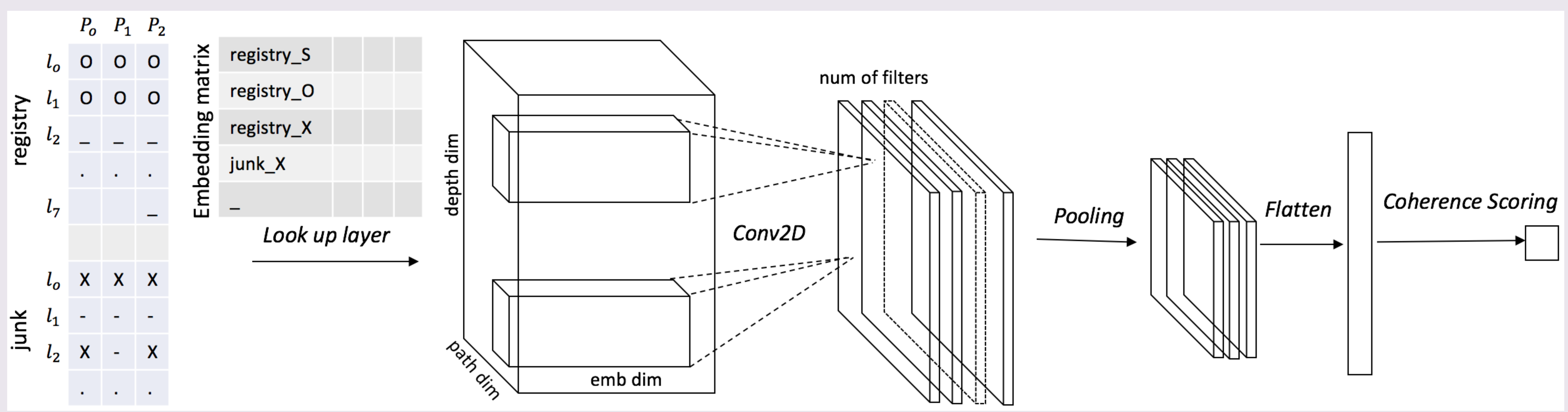


Figure: Conversational Neural Grid model for assessing coherence in asynchronous conversations

- **Key hypothesis**: In coherent conversations, entities exhibit certain local patterns in the conversation tree in terms of their distribution and syntactic realization
- Model conversational discourse structure using tree representation
- A 3D grid *(entities, tree-depth and paths)* for representing entity roles
- Employ 2D convolution to model two-dimensional spatial entity transitions in a conversation tree

Baselines:

- Temporal: disregarding tree structure, and consider a conversation as a monologue
- Path-level: disregarding left-to-right (*breadth*) structure of a tree
  - Consider each path in a conversation separately
  - Coherence score is computed by averaging scores of its paths

Thread Reconstruction Task

- **Goal:** building a predictive model to uncover the thread structure of a conversation from its posts
  - A model can recover the tree structure in Figure (a) from the sequence of posts $(p1, p2, ..., p5)$
- Training: a *tree-level* coherence model that distinguishes a gold tree (original reply structure) from a set of false candidate trees (respecting chronological order of the comments but false reply structure)
- Inference: selecting the structure with the highest coherence score

Dataset

	Sections	# Doc.	Avg. # Sen.	# Pairs
Train	00-13	1,378	21.5	26,422
Test	14-24	1,053	22.3	20,411

Table: Statistics on the WSJ dataset

	#Thread	Avg Com	Avg Sen	#Pairs (tree)	#Pairs (path)
Train	2,400	6.01	28.76	47,948	106,122
Test	750	5.75	27.79	14,986	33,852
Dev	675	6.27	30.70	13,485	28,897
Total	3,825	5.98	28.77	76,419	168,871

Table: Statistics on the CNET dataset

Experimental Results

Table: Discrimination results on the WSJ dataset.

	Model	Emb.	Std (F_1)	Inv (F_1)
I	Grid (E&C)	-	81.60	75.78
	Ext. Grid (E&C)	-	84.95	80.34
II	Neural Grid (N&J)	Random	84.36	83.94
	Ext. Neural Grid (N&J)	Random	85.93	83.00
III	Lex. Neural Grid	Random	87.03†	86.88†
	Lex. Neural Grid	Google	**88.56**†	**88.23**†

Table: Discrimination results on the CNET dataset

Conv. Rep	Model	Emb.	Std (F_1)	Inv (F_1)
Temporal	Neural Grid (N&J)	random	82.28	70.53
	Lex. Neural Grid	random	86.63	80.40
	Lex. Neural Grid	Google	87.17	80.76
Path-level	Neural Grid (N&J)	random	82.39	75.68†
	Lex. Neural Grid	random	88.13	88.38†
	Lex. Neural Grid	Google	88.44	89.31†
Tree-level	Neural Grid (N&J)	random	83.98†	77.33†
	Lex. Neural Grid	random	89.87†	89.23†
	Lex. Neural Grid	Google	**91.29**†	**90.40**†

Evaluation on Thread Reconstruction

Table: Thread reconstruction results

	Thread-level	Edge-level	
	Acc	F_1	Acc
All-previous	27.00	52.00	61.83
All-first	25.67	48.23	58.19
COS-sim	27.66	50.56	60.30
Conv. Entity Grid	**30.33**†	**53.59**†	**62.81**†

Conclusion

Our contribution

- Extend existing neural grid model by lexicalizing its entity transitions
- Adapt the model to conversational discourse
- Design a 3D grid representation for capturing spatio-temporal entity transitions in a conversation tree
- Yield state-of-the-art results on standard coherence assessment tasks in monologues and conversations

Future work:

- Generate new conversations based on coherence degree

Code and Data

https://ntunlpsg.github.io/demo/project/coherence/n-coh-acl18/

mohi0004@e.ntu.edu.sg, srjoty@ntu.edu.sg, t.d.nguyen@uva.nl