

NaCTeM at 2018 n2c2 Shared-Task Extracting Adverse Drug Events and Medication in EHRs with Ensembles of Feature-based and Deep Learning Models

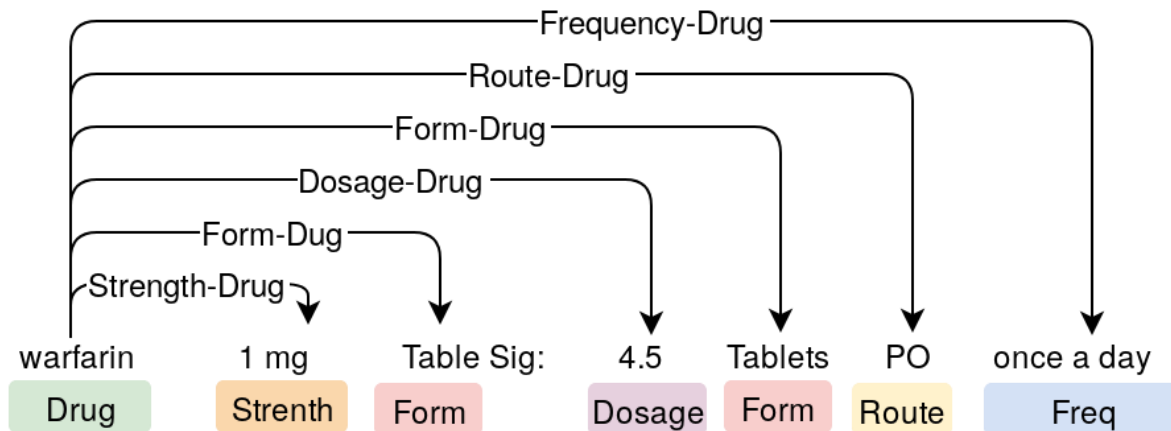


Nhung T.H. Nguyen, Fenia Christopoulou,
Thy Thy Tran, **Meizhi Ju**, Sunil Kumar Sahu,
Makoto Miwa, Sophia Ananiadou

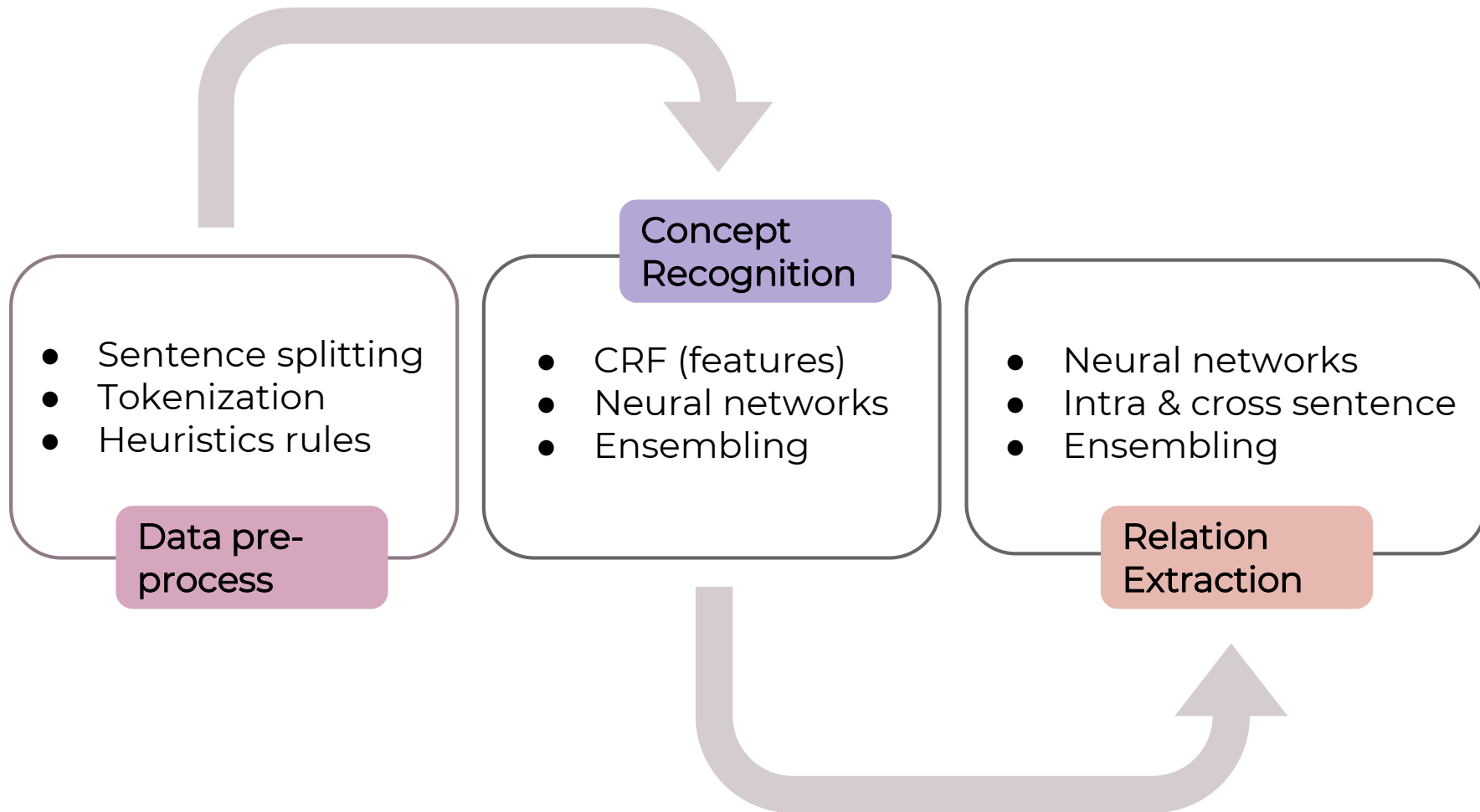
• N2C2 Shared Task: Track 2 •

- Input: discharge summaries from electronic health records
- Tasks:
 1. Concept recognition
 2. Relation extraction: binary relations
 3. End-to-end system: identify concepts and relations from scratch

Entities	Ratio (%)	Relations	Ratio (%)
Duration	1.1	Duration-Drug	1.7
ADE	1.8	ADE-Drug	3.0
Reason	7.5	Reason-Drug	14.2
Dosage	8.28	Dosage-Drug	11.6
Route	10.7	Route-Drug	15.2
Frequency	12.3	Frequency-Drug	17.3
Form	12.9	Form-Drug	18.2
Strength	13.1	Strength-Drug	18.4
Drug	31.8		



Pipeline Workflow



- **Data pre-process**

- *Data splitting*
- *Existing tools*
- *Heuristics rules*

Pre-processing

	Subset	Documents	Sentences
Training data	Train (80 %)	242	44932
	Dev (20 %)	61	11063
Testing data	Test	202	37390

Sentence splitting
[Lingpipe]

Tokenization
[OSCAR 4]

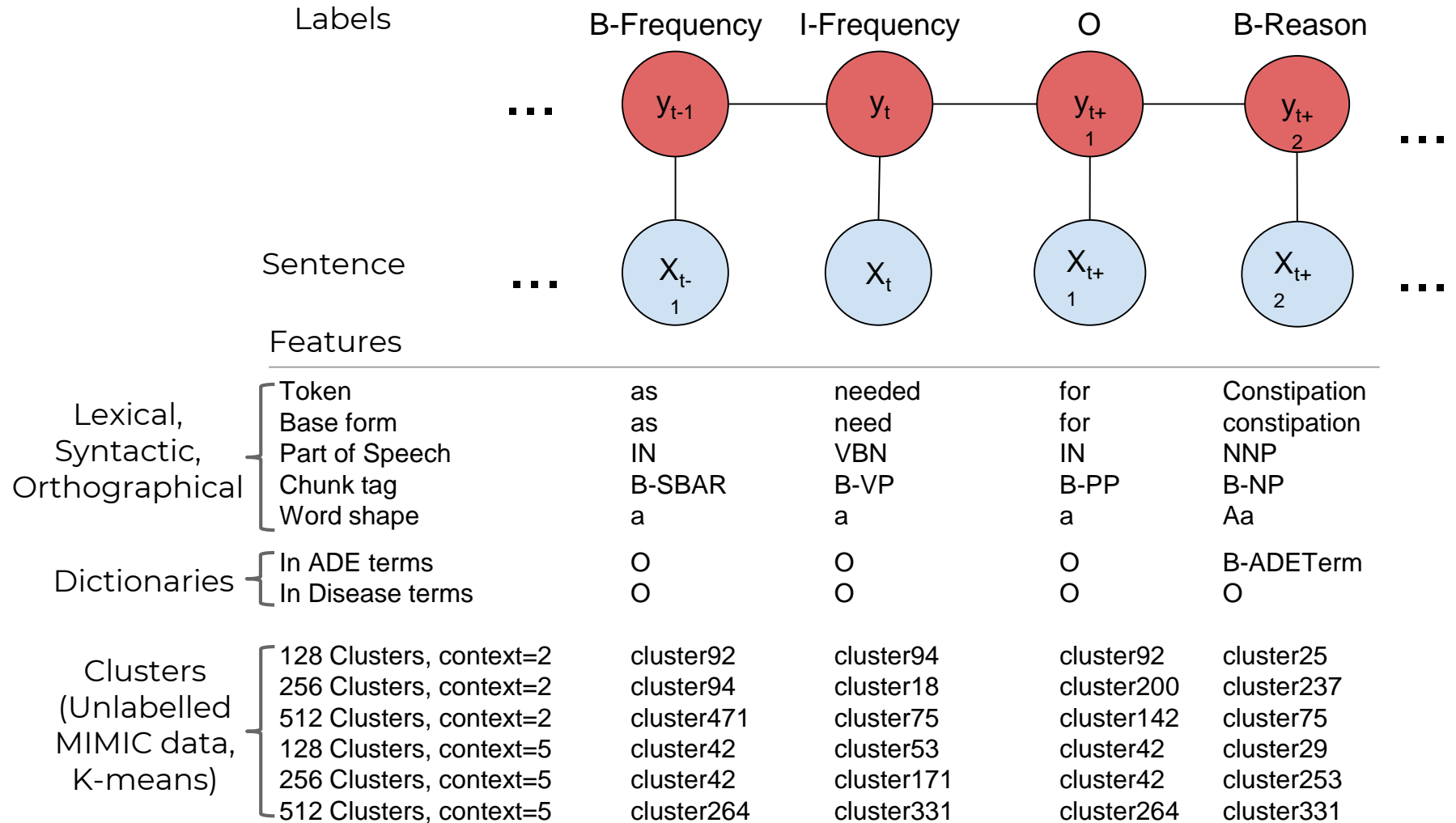
Further process
[Rules]

- **Concept Recognition**

- *CRF Model*
- *Neural Network Model*

Concept Recognition

CRF Model



Use NERSuite (Cho et al., 2013): <http://nersuite.nlplab.org>

Concept Recognition

Neural Network Model

Motivation

- Nested entity: entities embedded in longer entities.

He was assessed ... vincristine toxic polyneuropathy ...

Inner entity

Drug

Outer entity

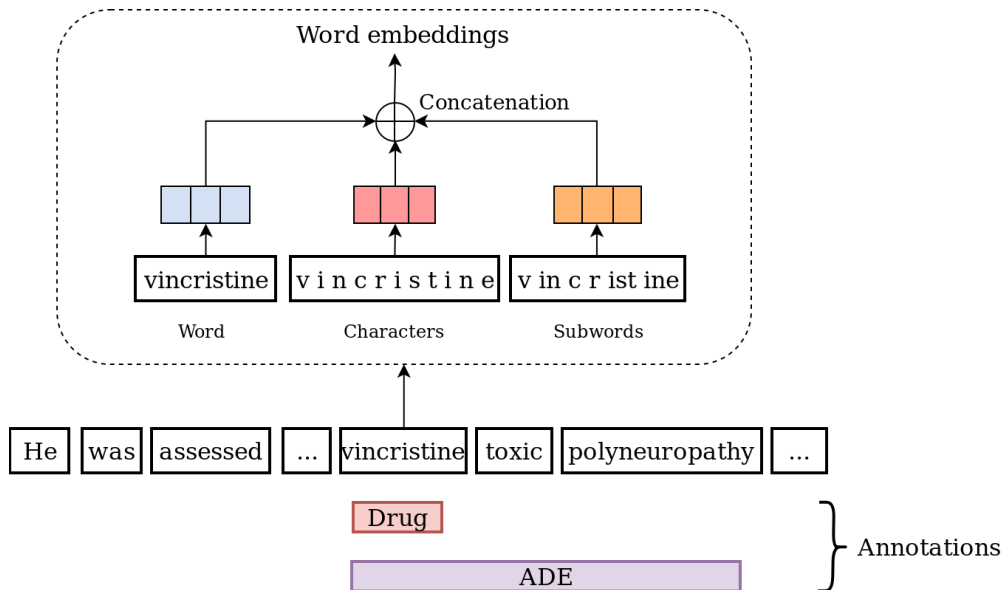
ADE

- Inner entities are informative indicators for outer entities (Ju, et al. 2018).
- Rare and unseen words can be well represented by re-tokenizing sentences into subwords based on frequencies. (Sennrich, et al. 2016).

Concept Recognition Neural Network Model

Method

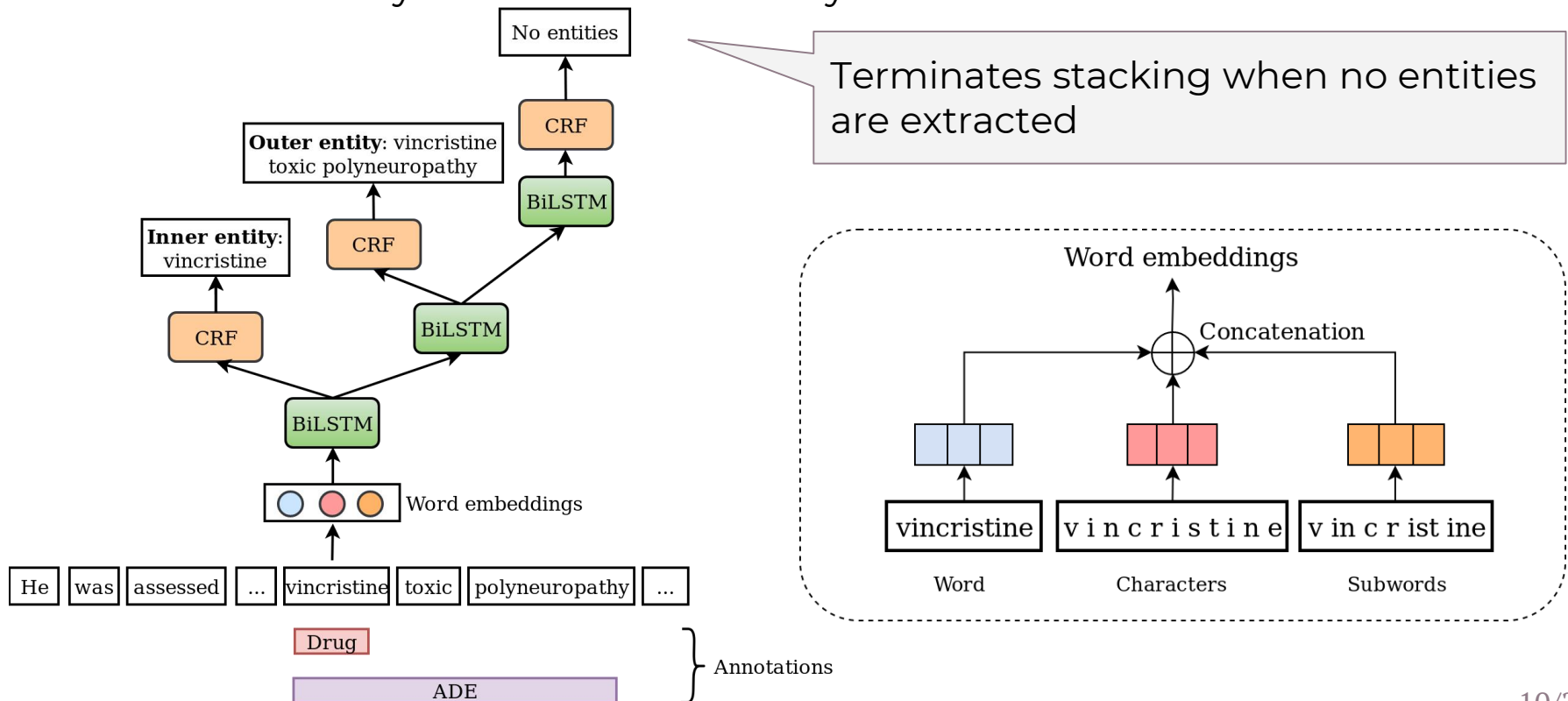
- Extract both nested entities and entities with multiple types
- Independent on linguistic features and external knowledge resources
- Automatically stacks BiLSTM-CRF layers.



Concept Recognition Neural Network Model

Method

- Extract both nested entities and entities with multiple types
- Independent on linguistic features and external knowledge resources
- Automatically stacks BiLSTM-CRF layers.



Experimental Results

Concept

Model	Precision	Recall	F1-score
CRF			
Lexical and syntactic features (Baseline)	0.9525	0.8825	0.9162
Baseline + word shape (ws)	0.9527	0.8815	0.9157
Baseline + dictionary features (df)	0.9511	0.8829	0.9157
Baseline + cluster features (cf)	0.9504	0.8902	0.9193
Baseline + ws + df + cf	0.9486	0.8900	0.9184
Neural network			
Baseline (word + characters)	0.9385	0.9143	0.9262
Baseline (subword + characters)	0.9352	0.9115	0.9232
Baseline (word + subword)	0.9353	0.9224	0.9288
Baseline (word + subword + characters)	0.9507	0.9066	0.9281

- **Relation Extraction**

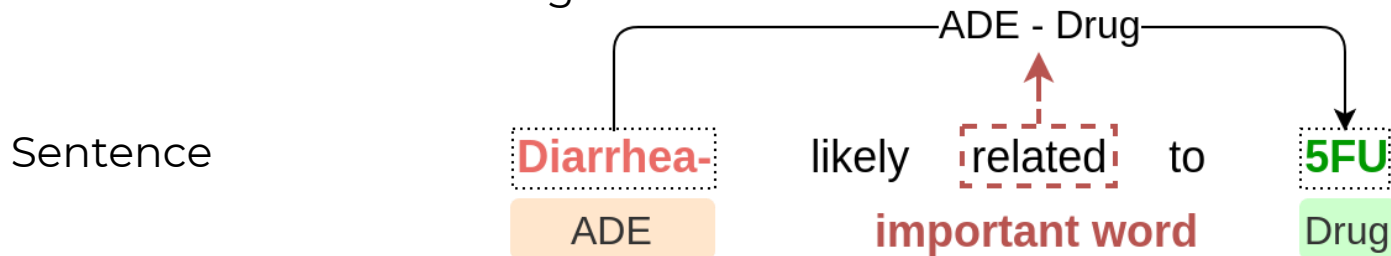
- *Weighted LSTM Model*
- *Walk-based Model*
- *Cross-sentence Model*

Relation Extraction

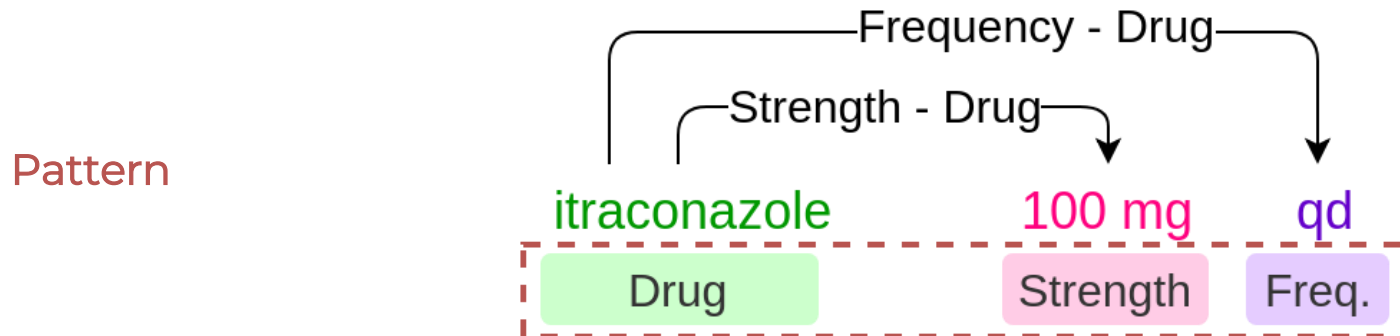
Weighted LSTM

Motivation

- Context-based word meaning



- EHRs contain latent relation patterns e.g. Drug-Form-Frequency

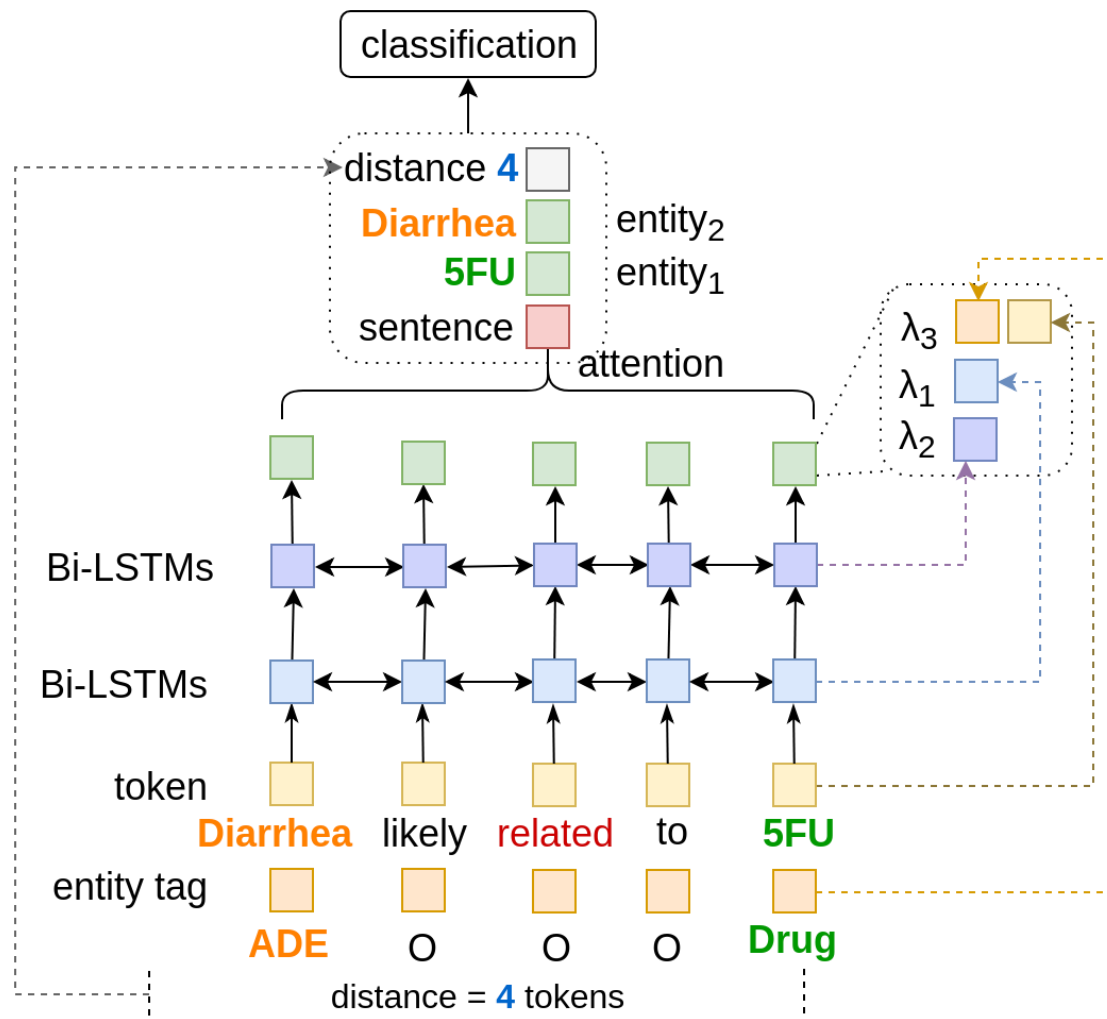


Method

- Attention layer: different emphasis on each word
- Entity tags as input: learn relation patterns

Relation Extraction

Weighted LSTM



(Peters et al. 2018; Christopoulou, et al. 2018)

Relation Extraction

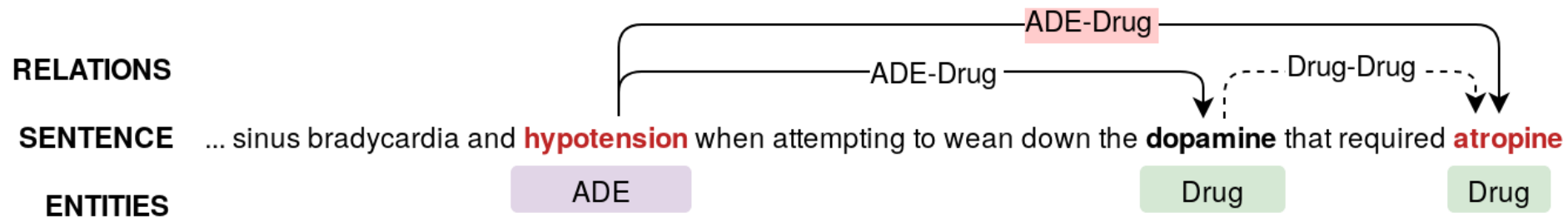
Walk-based Neural Network

Motivation

A potentially related entity pair can be supported by co-existing related pairs in the same sentence (Christopoulou, et al. 2018)

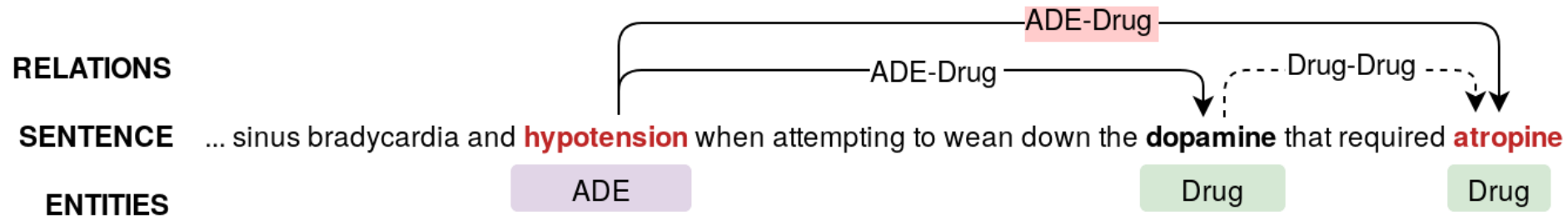
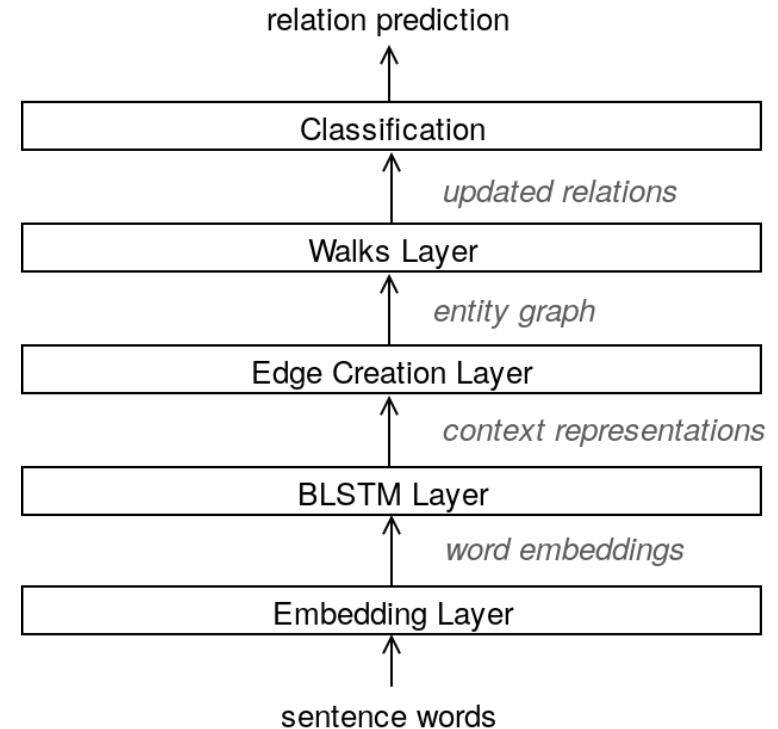
Method

- Map a sentence into a directed graph structure
- Nodes = Entities
- Edges { representation of the relation between them
building block for 1-to- l length walks between the pair entities
- Consider only X-Drug pairs
- Keep Drug-Drug pairs, even without annotation



Relation Extraction

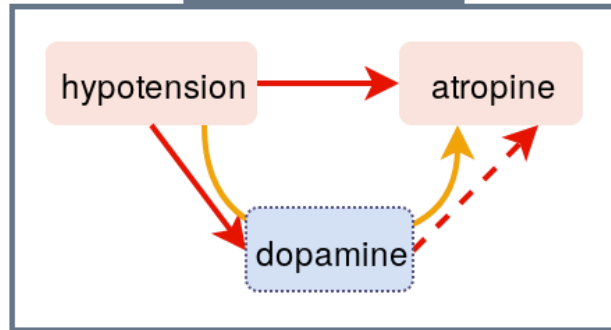
Walk-based Neural Network



Relation Extraction

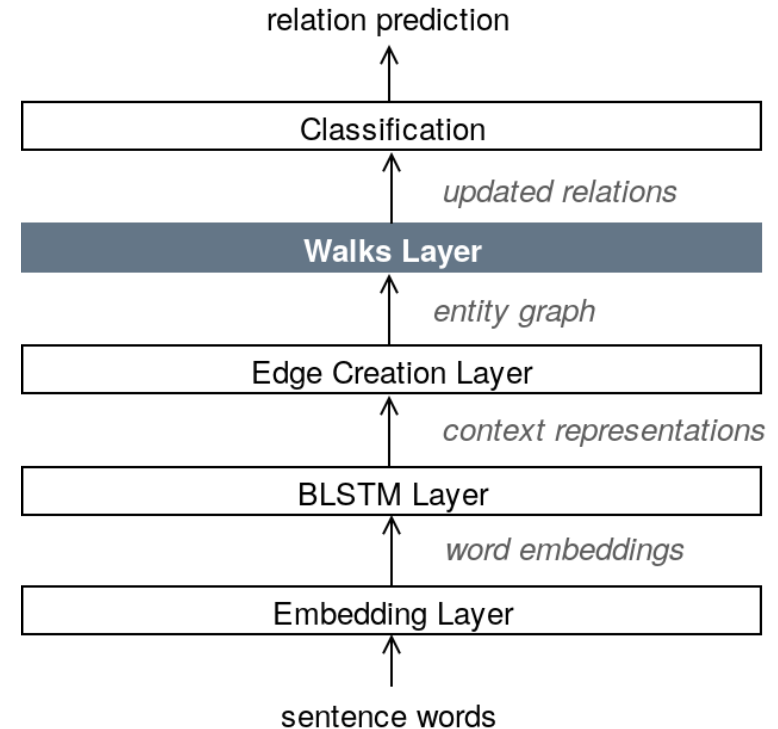
Walk-based Neural Network

Walk Generation



→ direct representation

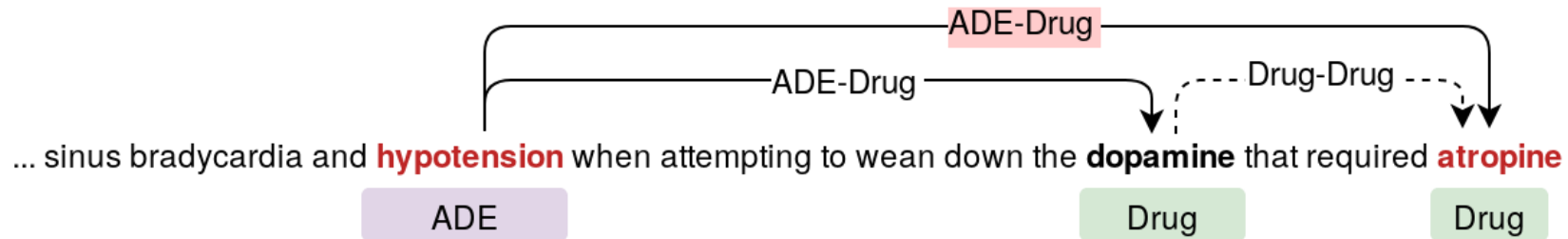
→ indirect representation



RELATIONS

SENTENCE

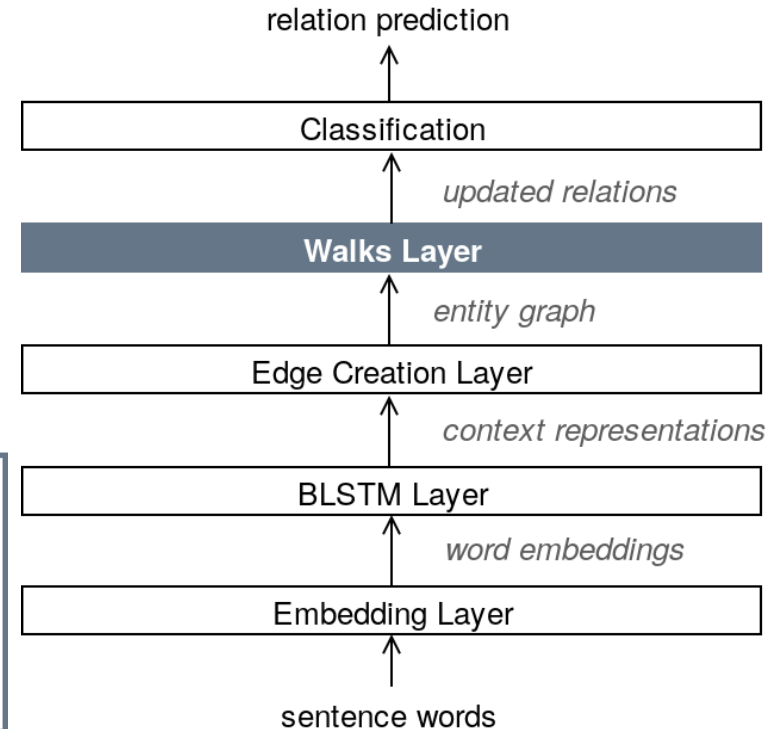
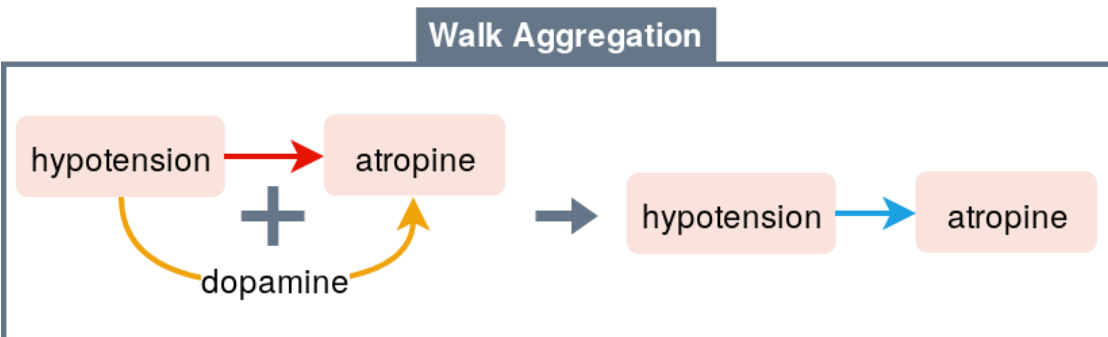
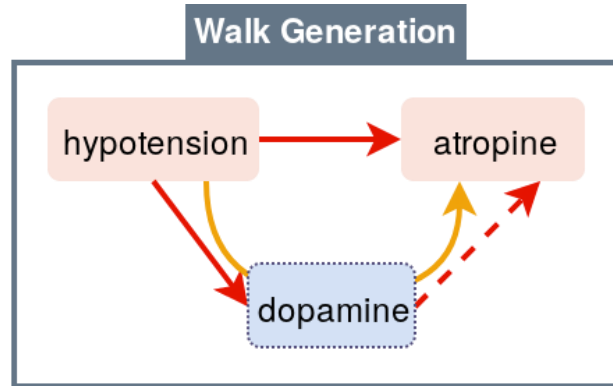
ENTITIES



Relation Extraction

Walk-based Neural Network

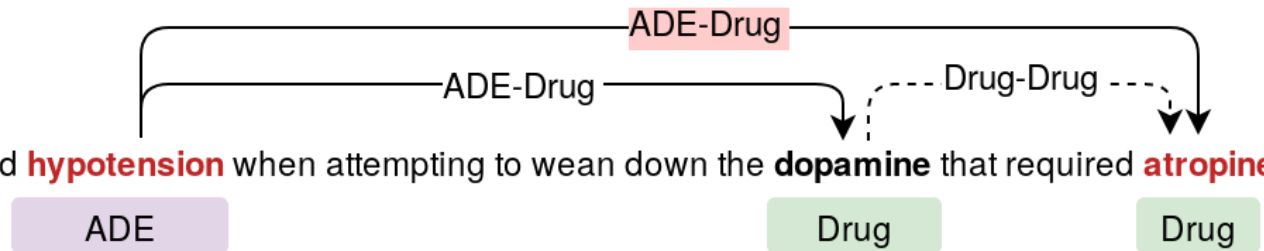
- direct representation
- indirect representation
- **updated** representation



RELATIONS

SENTENCE ... sinus bradycardia and **hypotension** when attempting to wean down the **dopamine** that required **atropine**

ENTITIES



Relation Extraction

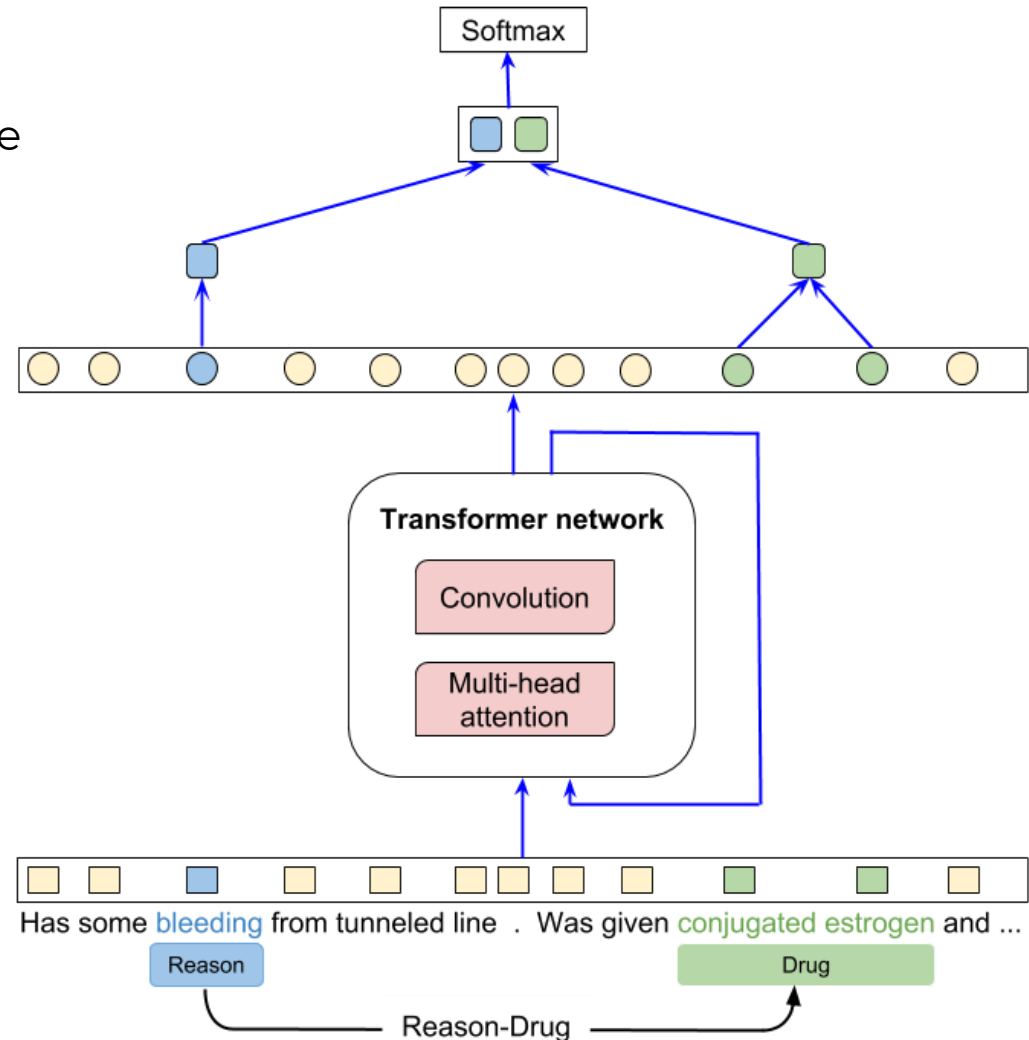
Cross-sentence Model

Motivation

- In the dataset, approx. 8 % of the relations are cross-sentence.

Method

- Only drug, non-drug pairs
- Only consider up to two span of sentences
- Employ transformer network (Vaswani et al, 2017)
 - RNN: low time efficient in longer sequence computation



Experimental Results

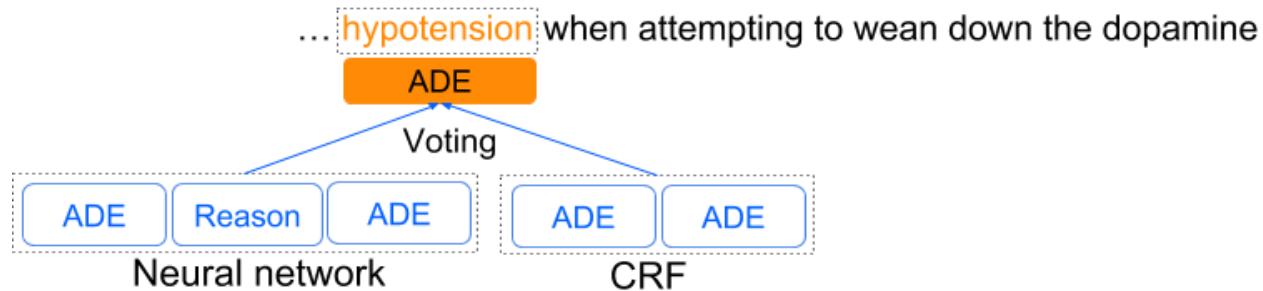
Relation

Model	Precision	Recall	F1-score
Weighted LSTM			
Weighted-one-BLSTM	0.9729	0.9108	0.9408
Weighted-stack-BLSTM-hyperparam-set1	0.9751	0.9102	0.9416
Weighted-stack-BLSTM-hyperparam-set2	0.9693	0.9146	0.9411
Walk-based Model			
Walks-L2-random_embeddings	0.9792	0.9041	0.9402
Walks-L4-pubmed_embeddings	0.9723	0.9112	0.9408
Walks-L8-pubmed_embeddings	0.9782	0.9086	0.9421
Walks-L8-random_embeddings	0.9721	0.9208	0.9457
Cross-sentence Model			
Transformer-span-1	0.9663	0.9077	0.9361
Cross-sentence-transformer-span-2	0.9538	0.9423	0.9480
Cross-sentence-transformer-span-3	0.9115	0.9536	0.9321

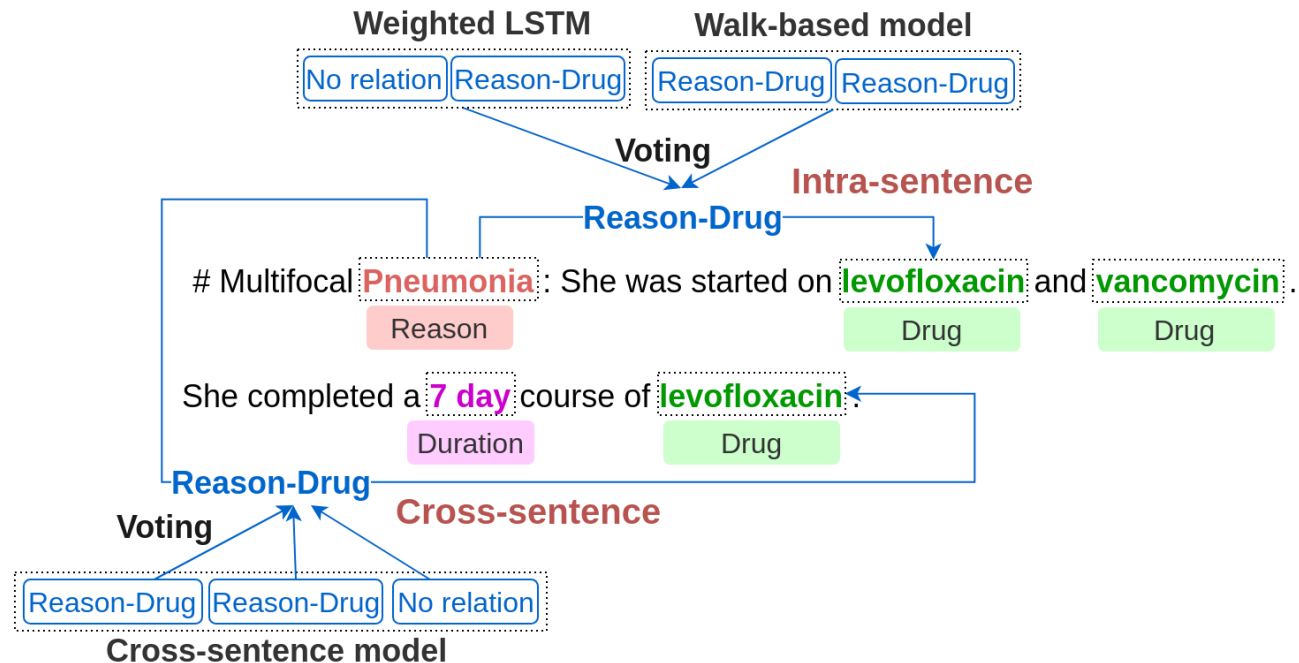
Ensemble Methods

Majority Voting

Concept



Relation



Submission Results

Track 2

Task	System	P	R	F1
Concept	(1) NN ensemble	0.9664	0.8875	0.9253
	(2) CRF ensemble	0.9532	0.8797	0.9150
	(3) Ensemble of NN and CRF	0.9444	0.9073	0.9255
Relation	(1) Walked-based (BEST) + Cross sentence	0.9420	0.9517	0.9468
	(2) Ensemble: Walked-based + Cross sentence	0.9463	0.9467	0.9465
	(3) Ensemble: Weighted LSTM + Walked-based + Cross sentence	0.9463	0.9480	0.9472
End-to-end	Concept (1) + Relation (1)	0.9463	0.8091	0.8723
	Concept (3) + Weighted LSTM + Cross sentence	0.9264	0.8318	0.8765
	Concept (3) + Relation (3)	0.9284	0.8289	0.8759

Submission Results

Best Concept Ensemble

Category	P	R	F
Drug	0.9567	0.9533	0.9550
Strength	0.9815	0.9804	0.9810
Duration	0.8875	0.7513	0.8138
Route	0.9662	0.9445	0.9552
Form	0.9653	0.9436	0.9543
ADE	0.4697	0.1984	0.2790
Dosage	0.9356	0.9433	0.9395
Reason	0.7254	0.5470	0.6237
Frequency	0.9788	0.9666	0.9727
Overall (micro)	0.9444	0.9073	0.9255
Overall (macro)	0.9397	0.8932	0.9144

Submission Results

Best Relation Ensemble

Category	P	R	F
Strength -> Drug	0.9879	0.984	0.986
Dosage -> Drug	0.9814	0.9777	0.9796
Duration -> Drug	0.8968	0.9178	0.9072
Frequency -> Drug	0.9772	0.9655	0.9713
Form -> Drug	0.9921	0.9792	0.9856
Route -> Drug	0.9804	0.9729	0.9766
Reason -> Drug	0.8080	0.8182	0.8131
ADE -> Drug	0.7029	0.8458	0.7678
Overall (micro)	0.9462	0.9479	0.9472
Overall (macro)	0.9408	0.9449	0.9420

Submission Results

Best End2End Ensemble

Category	P	R	F
Strength -> Drug	0.974	0.9621	0.968
Dosage -> Drug	0.9311	0.9124	0.9217
Duration -> Drug	0.7983	0.6784	0.7335
Frequency -> Drug	0.9672	0.9286	0.9475
Form -> Drug	0.9588	0.9264	0.9423
Route -> Drug	0.9516	0.9140	0.9324
Reason -> Drug	0.7179	0.4463	0.5505
ADE -> Drug	0.502	0.1678	0.2515
Overall (micro)	0.9264	0.8318	0.8765
Overall (macro)	0.9072	0.7954	0.8423

Conclusions

Concept Recognition

- Detect nested and multi-label entities
- NN-based model does not depend on any external knowledge resources and hand-crafted features

Relation Extraction

- Independence of external syntactic tools and dictionaries
- Detect both intra and cross-sentence relations

A light gray outline map of the world serves as the background for the slide. Two dark gray callout boxes are positioned over the map: one over Europe labeled 'NaCTeM' and another over East Asia labeled 'AIST-AIRC TTI'.

NaCTeM

AIST-AIRC
TTI

THANK YOU FOR YOUR ATTENTION!

Questions?