Integration of machine learningand dictionary-based approach for identification of adverse drug reactions in drug labels

#### **Junguk Hur**

#### University of North Dakota School of Medicine and Health Sciences hurlab.med.und.edu



#### Team: CONDL

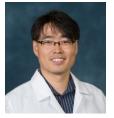
- Centrality- and Ontology-based Network Discovery using Literature data
- Mert Tiftikci<sup>1</sup>, Arzucan Özgür<sup>1</sup>, Yongqun (Oliver) He<sup>2</sup>, and Junguk Hur<sup>3</sup>

<sup>1</sup>Bogazici University, Istanbul, Turkey <sup>2</sup>University of Michigan, Ann Arbor, MI, USA <sup>3</sup>University of North Dakota, Grand Forks, ND, USA













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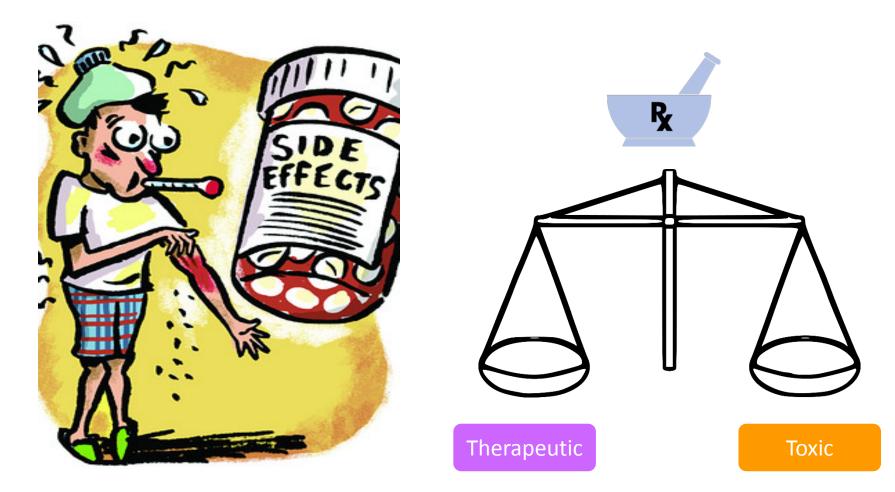
Oliver

### Outline

- Background
  - Adverse drug reactions
- Our approach & results
  - Mention Extraction from drug label (Deep learning / SciMiner)
  - ADR normalization (SciMiner)
- Summary & discussion



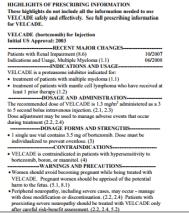
## **Adverse Drug Reaction (ADR)**





### **Resources for ADR**

- Drug labels (prescribing information or package inserts)
  - Drugs@FDA database
  - SIDER4.1 database
- Post-marketing
  - FDA's Adverse Event Reporting System (FAERS)
  - Database of Suspected Adverse Drug Reaction (EDSADR)



 Hypotension can occur. Caution should be used when treating patients receiving antihypertensives, those with a history of syncope, and those who are dehydrated. (5.3)

 Patients with risk factors for, or existing heart disease, should be closely monitored. (5.4)

 Acute diffuse infiltrative pulmonary disease has been reported. (5.5)
 Nausea, diarrhea, constipation, and vomiting have occurred and may require use of antiemetic and antidiarrheal medications or fluid replacement. (5.7)

 Thrombocytopenia or neutropenia can occur; complete blood counts should be regularly monitored throughout treatment. (5.8)
 Tumor Lysis Syndrome (5.9), Reversible Posterior

Leukoencephalopathy Syndrome (5.6), and acute hepatic failure (5.10) have been reported. ADVERSE REACTIONS

Most commonly reported adverse reactions (incidence ≥30%) in clinical studies include asthenic conditions, diarrhea, nausea, constipation, peripheral neuropathy, vomiting pyrexia, thrombocytopenia, purylaji kultopenia and anorexia and decreased appetite, neuropenia, neuralgia, tuckopenia and amenia. Other adverse reactions, including serious adverse reactions, have been recorded. (6.1)

 Women should be advised against breast feeding or becoming pregnant while being treated with VELCADE. (5.1, 8.1, 8.3)
 Patients with diabetes may require close monitoring of blood glucose and adjustment of anti-diabetic medication. (8.8)
 See 17 for PATIENT COUNSELING INFORMATION.

Revised: [06/2008]

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	Prednisone				lan and Pro	daisone		VELCADE, Melphalan and Perdaisante			Melphalan and Prednisone		
		(N=346)			(N=337)				(N=346)			(N=337)	
ModDRA System Organ Class	Total	Tenkity C	irade, ± (%)		Tenkety Gr		ModDRA System Organ Class.	Total		leade, ± (%)	Total	Tenkity G	
Psefered Term	a(%)	3	- 24	a.06	3	24	Parkend Jarm	a (%)	3	24	. n 17-0	3	24.
Blood and Lymphatic System Disorders							Illoed and Lymphatic System Disorders						
Thrombocytopenia	178 ( 57)	68 ( 20)	99(17)	159(47)	55(36)	47(14)	Throubocytopenia	178 ( 57)	68 ( 20)	59 (17)	159(47)	55(36)	47 ( 14)
Neutropenia	163 ( 49)	102 ( 30)	35 ( 10)	155 ( 45)	294 235	49 ( 12)	Neutropenia	163 ( 49)	102 ( 30)	35 ( 10)	155 ( 45)	29 ( 23 )	49 ( 15)
Anoma	147(43)	53 ( 16)	94 3)	187 ( 55)	66 ( 20)	26 ( 10	Ancinia	147 ( 43)	53 ( 16)	9( 3)	187 ( 55)	66 ( 20)	26 ( 10
Lockopenia	113 (33)	67 (20)	19 ( 3)	100 ( 50)	35 (16)	13 ( 4)	Leukopenia	113 (33)	67 (20)	19 ( 3)	200 ( 50)	35 (16)	13 ( 4)
Lymphoponas	10 ( 24)	49 ( 14)	184 59	58(17)	304 71	76 21	Lymphoponas	10 ( 24)	49 ( 14)	184 53	58(17)	301.71	76 21
<b>Castrolatestinal Disorders</b>							<b>Gastrolatestinal Disorders</b>						
Neusoa	164 (48)	14(-4)	0	941.20	1140	0	Namora	164 ( 48)	14(-4)	0	941.20	11403	0
Diaritea	157(-46)	23(7)	24.15	58(17)	26.0	0	Dearthea	157(-46)	23(7)	24.15	58(17)	200	0
Constipation	125 (37)	2(1)	0	54(16)	0	0	Constignation	125 ( 37)	2(1)	0	54(16)	0	0
Vositing	112 (33)	14(-4)	0	55(16)	20.0	0	Vositing	112 (33)	14(-4)	0	55(16)	20.0	0
Abduminal Pain	49 (14)	7(2)	0	22(7)	1(<1)	0	Abdominal Pain	49 ( 14)	7(2)	0	22( 7)	1(<1)	0
Abdoninal Pain Upper	40 ( 12)	1(<1)	0	291.55	0	0	Abdominal Pain Upper	40 ( 12)	1(<0)	0	291.92	0	0
Dyspepsia	39(11)	0	0	23 ( 7)	0	0	Dyspepsia	39(21)	0	0	23 ( 7)	0	0
Nervous System Disorders							Nervous System Disorders						
Peripheral Neuroscutty	159(47)	43 (13)	24.19	18(.5)	6	0	Peripheral Neuropathy	159(47)	43(13)	26.18	18(.5)	6	0
Neuralgia	121(36)	28 ( 8)	2(1)	51.40	1(<1)	0	Neuralgia	121(36)	28(8)	2(1)	51 10	1(<1)	0
Dargingen	56(16)	7 ( 2)	0	37(11)	1(41)	0	Distances	56(16)	7 ( 2)	0	37(11)	1(41)	0
Hendache	49(14)	2(1)	0	35(10)	44,13	0	Headache	49 ( 24)	2(3)	6	35(10)	44(1)	0
Parothesia	45(13)	6(2)	0	15(4)	0	0	Paresthesia	45 (13)	6(2)	0	15(4)	0	0
General Disorders and Administration Sile Conditions							General Disorders and Administration Sile Conditions						
Pyrchie	99 (29)	8(2)	26.10	64(19)	6 ( 2)	24.13	Pyrene	99 (20)	8(2)	2(1)	64(19)	6(2)	26.1)
Tatigat	98 ( 29)	23 (7)	24.13	86(26)	7(2)	0	Facigae	58 ( 29)	23(7)	24.19	86(26)	7(2)	0
Arthenia	75 ( 21)	20(6)	1(<1)	601100	94.31	0	Arthenia	73 ( 21)	20(6)	1(*1)	(61)0#	96.31	0
Edona Peripheral	6K ( 20)	24 1)	0	34(10)	0	0	Edona Peripheral	68 ( 20)	2(1)	0	34(10)	0	0
Infections and Infectations							Infections and Infectations						
Paramenta	56(16)	16 ( 5)	13(-4)	36(11)	12(-4)	94 33	Parametia	56(16)	16 ( 5)	13(-4)	36(11)	12(-4)	94 33
Herpes Zostar	45 (17)	14 (3)	0	141.40	6 ( 2)	0	Herpes Zestat	45 (17)	11(3)	0	14(-4)	6 ( 2)	0
Branchitis	44 (13)	4(1)	0	27 ( 8)	40.13	0	Brouchitis	44 (13)	4(1)	0	27 ( 8)	40.13	0
Nosopharyngitis	39(11)	1(<1)	0	27(8)	0	0	Nosopharyngitis	39(11)	1(<1)		27(8)	0	0

Parts of drug label for Velcade (bortezomib)



# Importance of label mining

- All about safety
- From unpredictable to predictable events
- Personalized medicine
- Automatic extraction of ADRs from drug labels
  - comparing the ADRs present in labels from different manufacturers for the same drug
  - performing post-marketing safety analysis (pharmacovigilance) by identifying new ADRs not currently present in the labels
  - to improve the efficiency of this process, the extraction of the ADRs from the drug labels needs to be automated



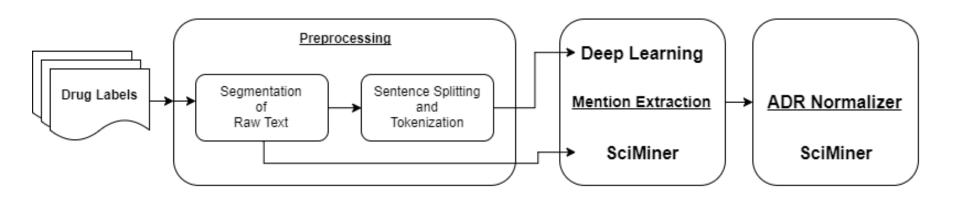
# <u>Goals</u>

#### (1) To develop text mining system of mentions (ADR, drug class, animal, severity, factor, and negation) from drug labels (Task#1)

#### (2) To normalize extracted ADRs onto MedDRA Preferred Terms (PTs) (Task#4)



#### **Our Workflow**



- **Deep Learning (DL) model** works on vector representation of tokens of sentences
  - Rule-base text segmentation applied on raw text
  - Text segments split to sentences & Sentences tokenized<sup>1</sup>
- **Dictionary- and Rule-based SciMiner** for mention extraction and normalizing detected ADRs



<sup>1)</sup>NLTK package for sentence splitting and tokenization

## **DL - Preprocessing**

#### **Raw Text from label APTIOM**

\* Suicidal Behavior and Ideation [see Warnings and Precautions (5.1)]

Mentions (Overlapping and non-contiguous example)

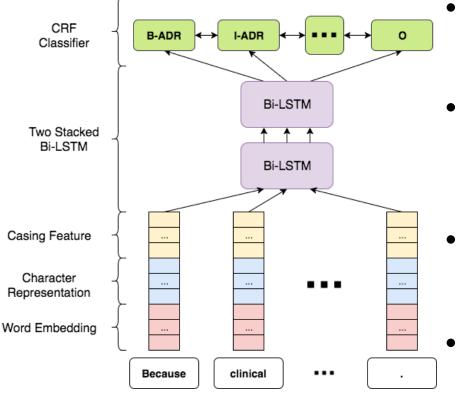
<Mention id="M1" section="S1" type="AdverseReaction" start="151" len="17" str="Suicidal Behavior" /> <Mention id="M2" section="S1" type="AdverseReaction" start="151,173" len="8,8" str="Suicidal Ideation" />

#### **CoNLL Format**

*	0	NN	<b>S</b> 1	148	1	Warnings	0	NNP	S1	187	8
Suicidal	<b>B-ADR</b>	NNP	<b>S1</b>	151	17	and	0	CCP	S1	196	3
Behavior	I-ADR	NNP	S1	160	8	Precautions	0	NNP	<b>S1</b>	200	11
and	0	CC	<b>S1</b>	169	3	(	0	(	S1	212	1
Ideation	I-ADR	NNP	<b>S1</b>	173	8	5.1	0	CD	S1	215	3
][	0	NNP	S1	182	1	)	0	)	S1	220	1
see	0	VBP	S1	183	3	]	0	NN	<b>S</b> 1	221	1



### Deep Learning Architecture Bi-directional LSTM-CNNs-CRF

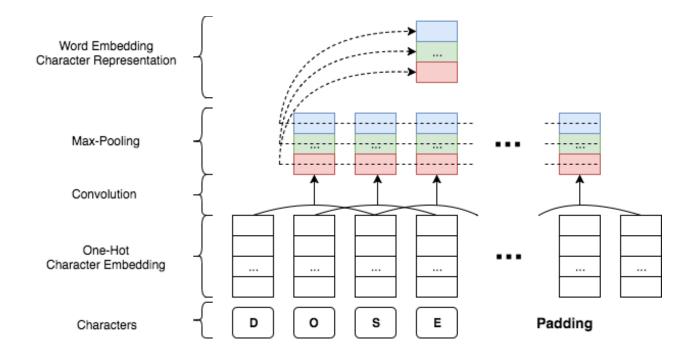


Neural Network Architecture

- Combined Word Embeddings (CWE) are generated for each token of a given sentence
- First Bi-directional long short-term memory LSTM runs on CWEs and second LSTM runs on the output of the first one.
- Conditional Random Fields (CRF) classifier jointly decodes as mention predictions for each token.
- Keras2 library was used in our work. No early stopping was used in our work.

- NORTH DAKOTA School of Medicine and Health Sciences
- This model is an adaptation of implementation for paper [Nils Reimers, and Iryna Gurevych. "Reporting score distributions makes a difference: Performance study of Istm-networks for sequence tagging." *arXiv preprint arXiv:1707.09861* (2017)]

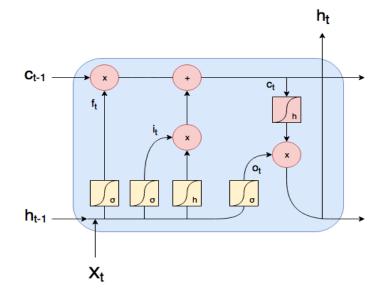
### **Combined Word Embeddings**



- CWEs are created from the concatenation
  - Character Embedding (Generated by CNN)
  - Word Embedding (Generated by Word2Vec) based on PubMed (200D)
  - Casing Embedding (one-hot encoded)



#### LSTM component



$$i_{t} = \alpha(W_{i}[h_{t-1}, x_{t}] + b_{i})$$

$$f_{t} = \alpha(W_{f}[h_{t-1}, x_{t}] + b_{f})$$

$$\tilde{c}_{t} = tanh(W_{c}[h_{t-1}, x_{t}] + b_{c})$$

$$c_{t} = f_{t} * c_{t-1} + i_{t} * \tilde{c}_{t}$$

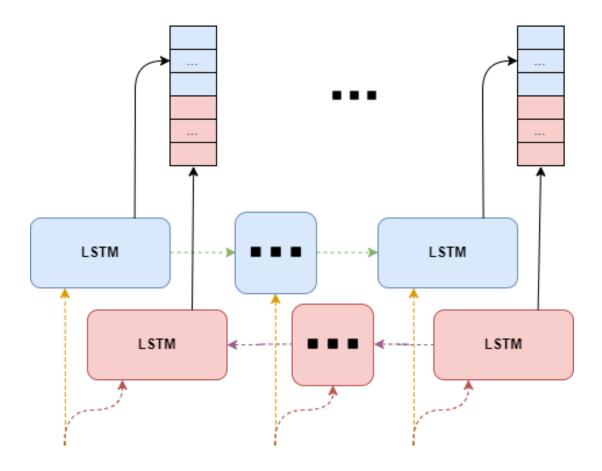
$$o_{t} = \alpha(W_{o}[h_{t-1}, x_{t}] + b_{o})$$

$$h_{t} = o_{t} * tanh(c_{t})$$



S. Hochreiter and J. Schmidhuber

#### Bi-LSTM component with Variational Dropout

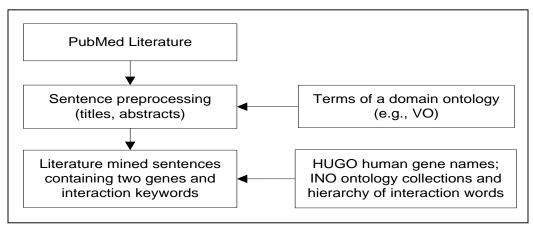




Variational dropout (0.25) depicted by colored & dashed lines

#### SciMiner

- SciMiner: A web-based literature mining tool for (<u>http://hurlab.med.und.edu/SciMiner/</u>)
- Dictionary- and Rule-based mining
- Optimized for identifying genes/proteins and VO/INO/EColi ontology terms



#### **References:**

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- Hur J, Xiang Z, Feldman EL, He Y. Ontology-based *Brucella* vaccine literature indexing and systematic analysis of gene-vaccine association network. *BMC Immunology*. 12(1):49 2011 Aug 26. PMID: 21871085.
- Hur J, Ozgur A, and He Y: Ontology-based literature mining of E. coli vaccine-associated gene interaction networks. J Biomed Semantics, vol. 8, p. 12,

#### **ADR-SciMiner**

- Expanded SciMiner for ADRs identification
- Dictionaries compiled from MedDRA (v20.0 English)
- Term expansion rules for improved coverage
  - Lingua::EN Perl library
  - Token order
  - Casing information (eg. all vs ALL leukaemia)
  - Alternative terms: (eg. increase -> elevation)
- Some exclusions criteria
  - Disease/syndrome names and etc
  - Section titles

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#### • Currently, only for ADR terms

#### **Our submissions**

Set	Mentions (Task 1)	ADR Normalization (Task 4)
CONDL1	DL	ADR-SciMiner
CONDL2	ADR-SciMiner (ADR)	ADR-SciMiner
CONDL3	ADR-SciMiner (ADR) + non-ADRs from DL	ADR-SciMiner



#### Results

		CONDL1	CONDL2	CONDL3				
Task 1		Deep Learning	SciMiner	SciMiner + non-ADRs from DL				
+type	Precision	76.5	65.5	65.2				
/1	Recall	77.5	61.4	69.8				
	F1	77.0	63.4	67.4				
-type	Precision	76.5	65.5	65.2				
	Recall	77.5	61.4	69.8				
	F1	77.0	63.4	67.4				
Tas	k 4	SciMiner	SciMiner	SciMiner				
micro	Precision	88.8	74.6	74.6				
	Recall	77.2	81.0	81.0				
	F1	82.6	77.6	77.6				
macro	Precision	88.2	73.1	73.1				
	Recall	75.8	79.9	79.9				
	F1	80.5	75.6	75.6				

Our results on the TAC ADR testing data (99 drug labels)

CONDL1 (DL+SciMiner): Precision (88.8 / 88.2)  $-1^{st}$  place among 12 submissions in Task#4 F1 (82.6 / 80.5)  $-4^{th}$  place



#### Summary

- Deep learning adaptation (Bi-directional LSTM-CNNs-CRF)
- Dictionary- and Rule-based ADR-SciMiner for ADR extraction and normalization
- Combined system
- Still, much room for improvement



#### **Future Work**

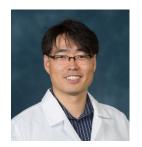
- Performance improvement of DL
  - Better representation for overlapping & noncontiguous chunks
- Performance improvement of ADR-SciMiner
  - Severity of ADR
  - Improved rules
  - Additional dictionary including SNOMED CT
- Better integration



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# Thank you

