CEP course on Deep Learning for Natural Language Processing

Text Mining in Biomedical and Healthcare Domain

Dr. Shweta Yadav
Postdoctoral Research Fellow
Wright State University, USA
http://shwetanlp.github.io/

Overview

1. Introduction: Types of Biomedical Text
2. Patient Data De-Identification (Entity Extraction from EMR)
3. Medical Sentiment Analysis
4. Pharmacovigilance Mining from Social Media

INTRODUCTION:
Types of Biomedical Texts

Types Of Biomedical Text and its Sources

01 Biomedical Literatures (MEDLINE,PubMed, PMC)

02 Electronic Medical Record

03 Social Media (Twitter, Medical Discussion Forums, Blogs)

BIOMEDICAL LITERATURE

MEDLINE

MEDLINE is a bibliographic database of life sciences and biomedical information. It includes bibliographic information for articles from academic journals covering medicine, nursing, pharmacy, dentistry, veterinary medicine, and health care. Wikipedia

History: 1879-present

No. of records: Over 26 million

Record depth: NLM Medical subject headings, abstracts, indexing

Cost: Free

Temporal coverage: 1946-present

Owner: Lister Hill National Center for Biomedical Communications

Producer	U.S. National Library of Medicine (United States)
History	1879-present
Languages	40 languages for current journals, 60 for older journals
	Coverage
Record depth	NLM Medical subject headings, abstracts, indexing,
Format coverage	Mostly academic journals; a small number of newspapers, magazines, and newsletters; over 40% are for cited articles published in the U.S., about 93% are published in English
Temporal coverage	1946-present
No. of records	Over 26 million
Update frequency	Daily; 2,000-4,000 references per update
	Links

- Website

Image credit: Wikipedia

ELECTRONIC MEDICAL RECORDS

John B. Costello, M.D.

2821 North Ballas Rd Ste 165
St Louis, MO 63131

Phone: 314-995-9988
Fax: 314-995-7241

Wednesday, May 05, 2004

Patient
Mr. Steve A Pal
100 Anystreet
Saint Louis, MO 63146
44 year old Male
DOB: 01/01/60

Visit Date
Thursday, April 22, 2004

Chief Complaint
Sore Throat

History of Present Illness
Injection site identified and marked. Sterile pred with alcohol x3 and ethyl chloride.
LOCATION: throat *QUALITY:* scratchy *SEVERITY:* moderate *DURATION:* 2 days

Diagnosis - Major
Classic Heartburn 90901

Medications - Current
ACCUPRIL 20 mg 1 1/d Per Oral
Accolate 20 mg 1 2/d Per Oral
ACTONEL 30 mg 1 1/d Per Oral

Image credit: Wikipedia

SOCIAL MEDIA

ye @kanyewest Follow

I'm loving the new music I've been working on. 6 months off meds I can feel me again. Remember when dark fantasy came out I used to tweet a storm also.

alex joanne @alexvelours · 10h

ignore my greasy eyebrows i just put castor oil on lmao but why is my eyelid like that ong it's swollen and lumpy.. i'm like 60% sure it's an eyelash glue **allergy** but i can't tell HDKDH

lizzie_18070

Hi all,

ive been suffering pretty bad the last few weeks with my anxiety and this week have felt very dizzy ans lightheaded. is this common for anxiety? Or is it possibly something else? does anyone feel this way when their anxiety is up?

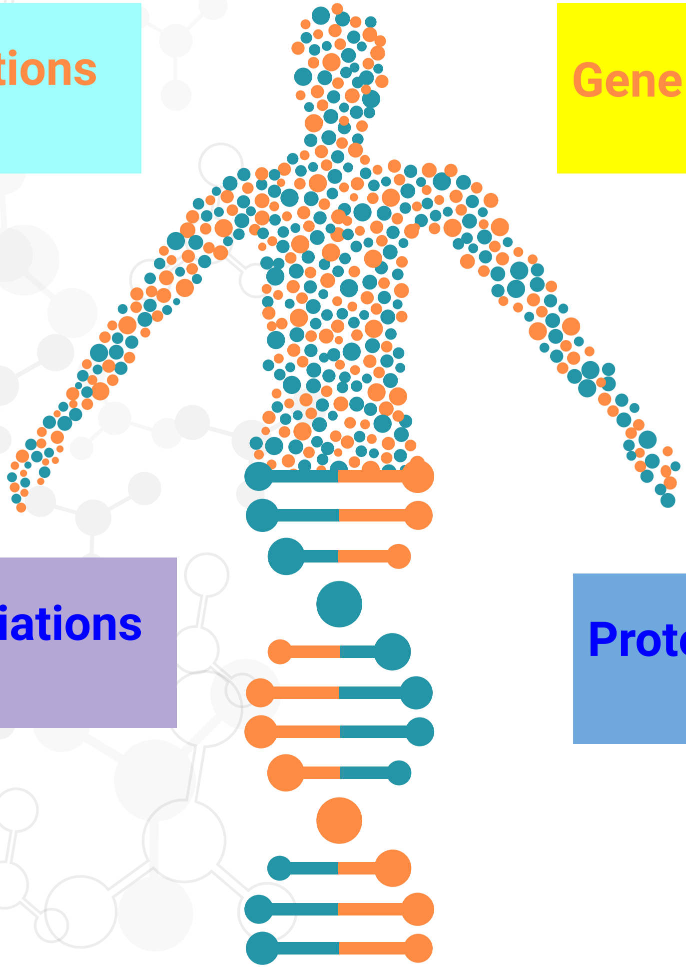
0 likes, 9 replies

APPLICATION

Biomedical Literature

Gene-disease associations

Gene cluster identification



Protein-disease associations

Protein interactions

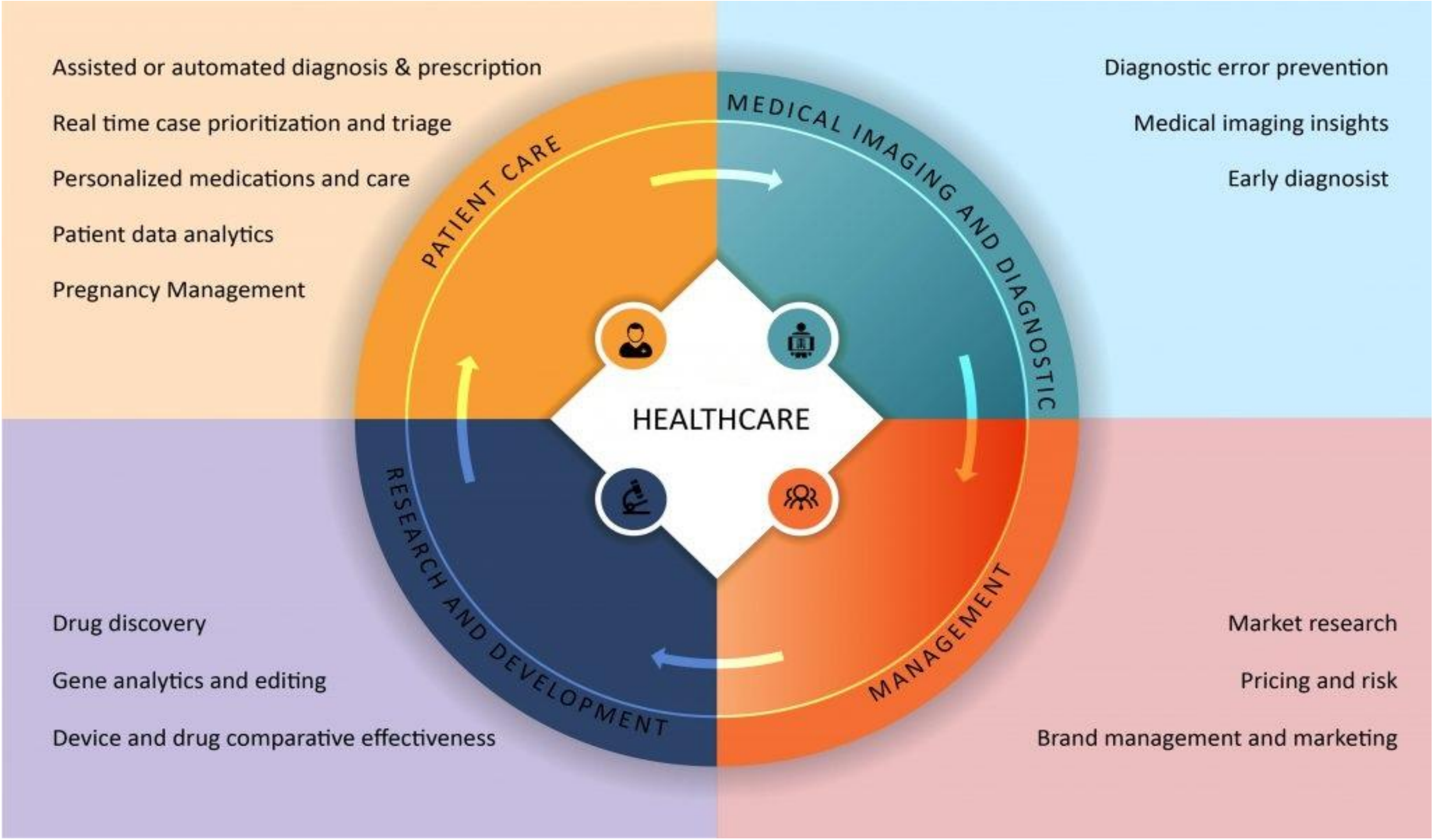


Image credit: [30]

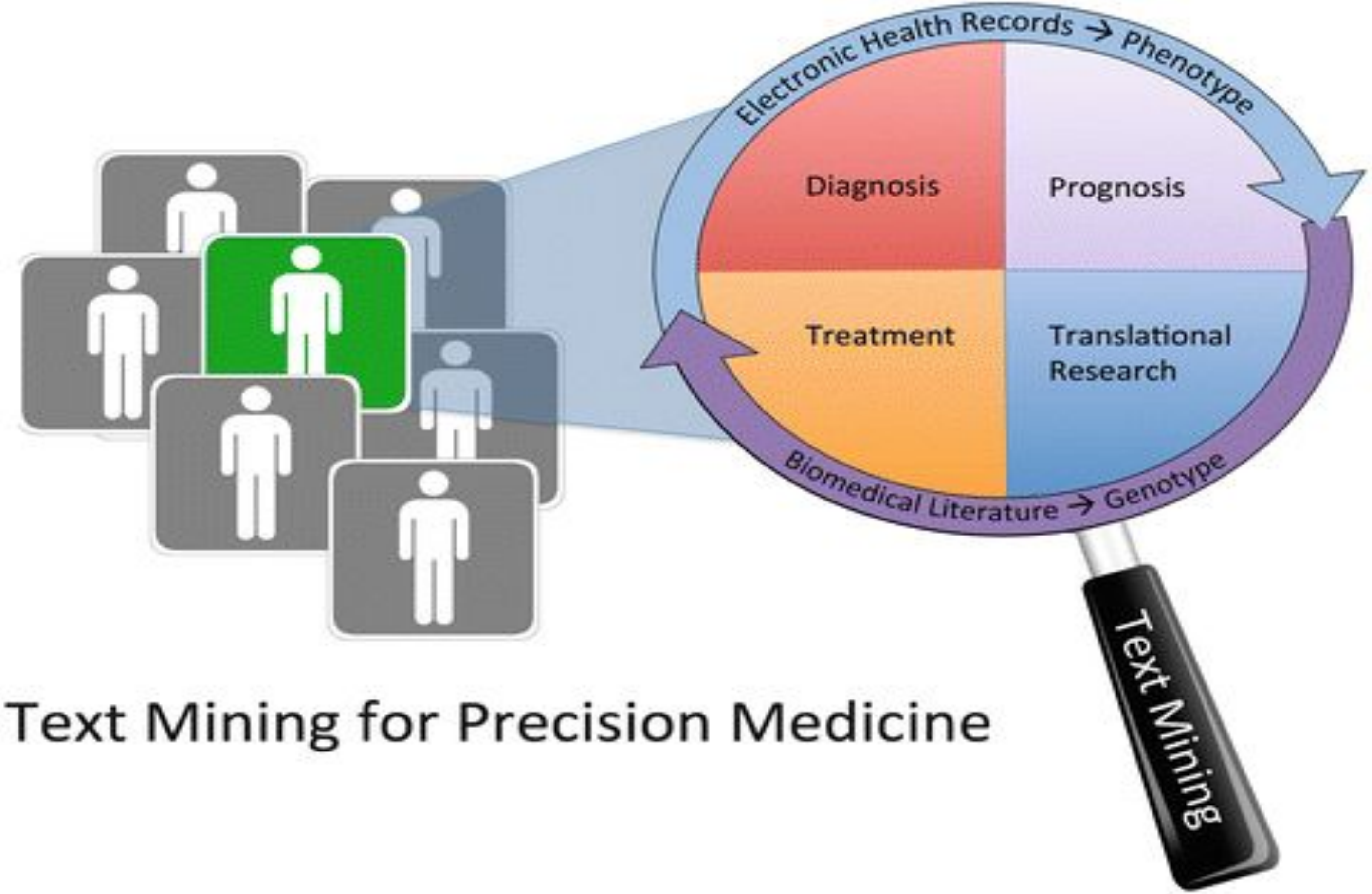


Image credit: [30]

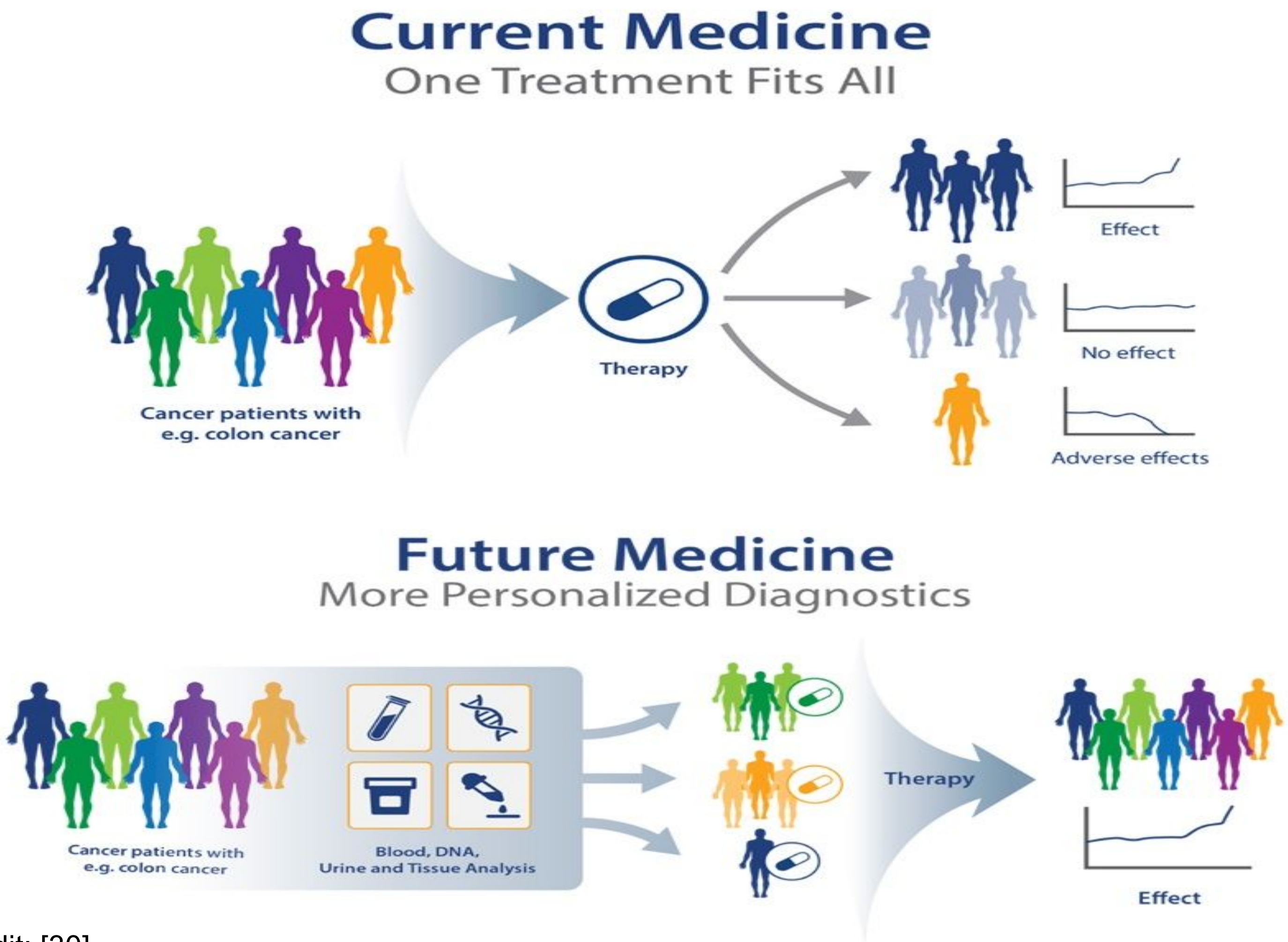


Image credit: [30]

How to maintain the unstructured biomedical and clinical information ??

DOMAIN KNOWLEDGE BASE

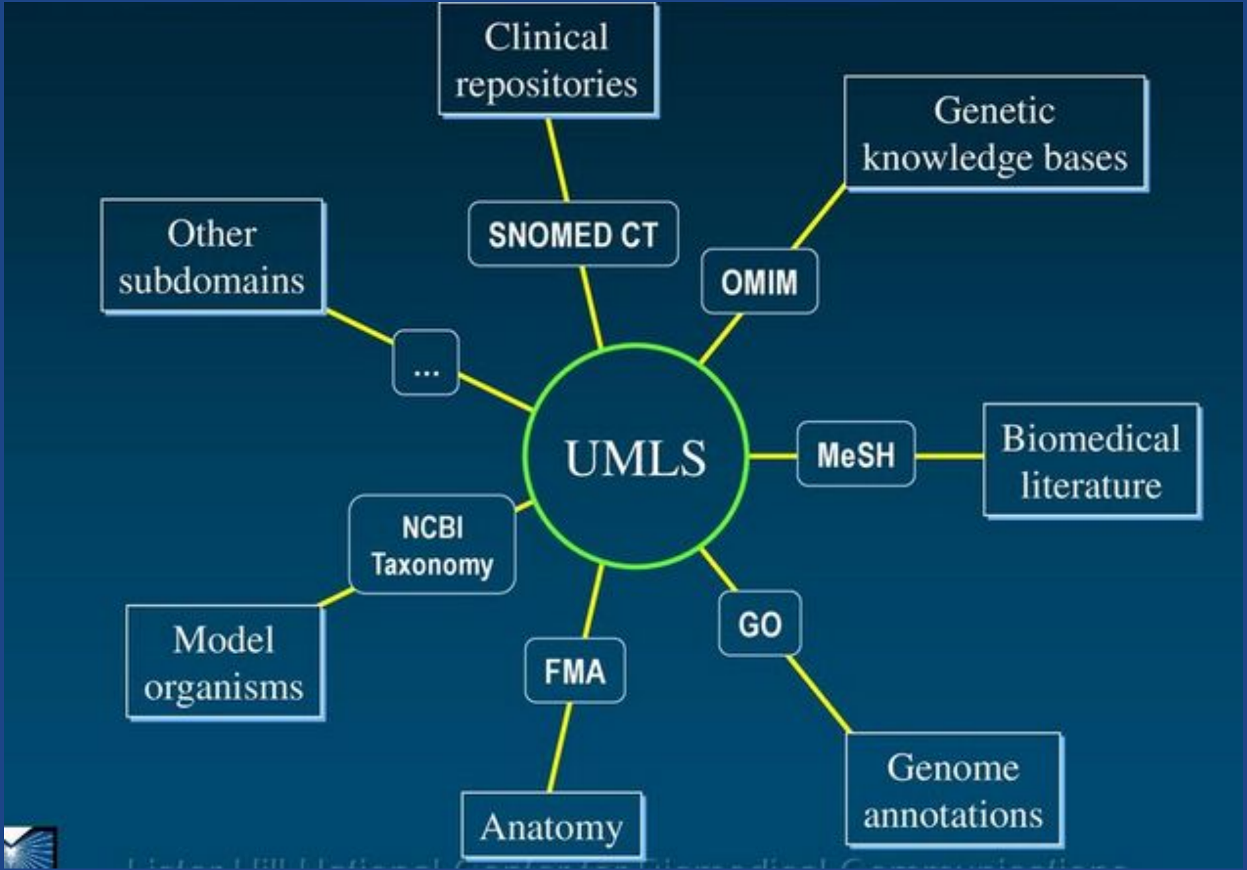
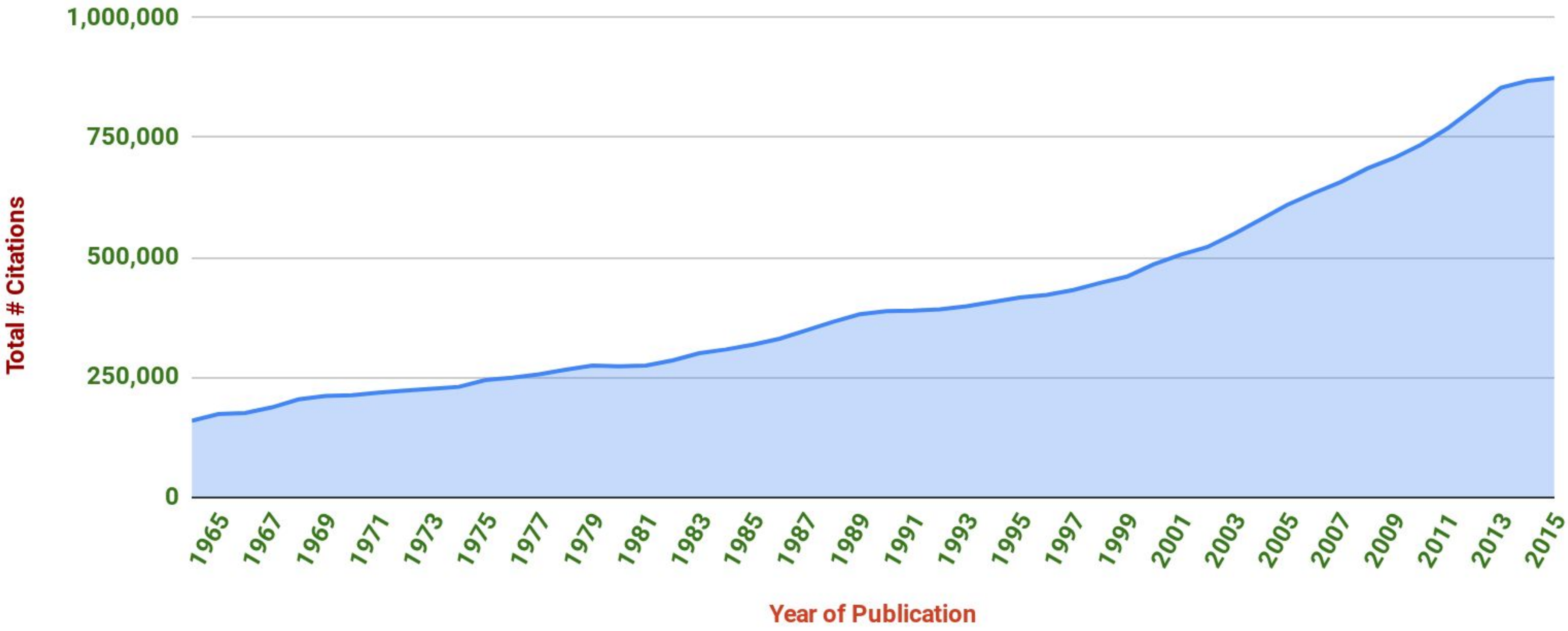
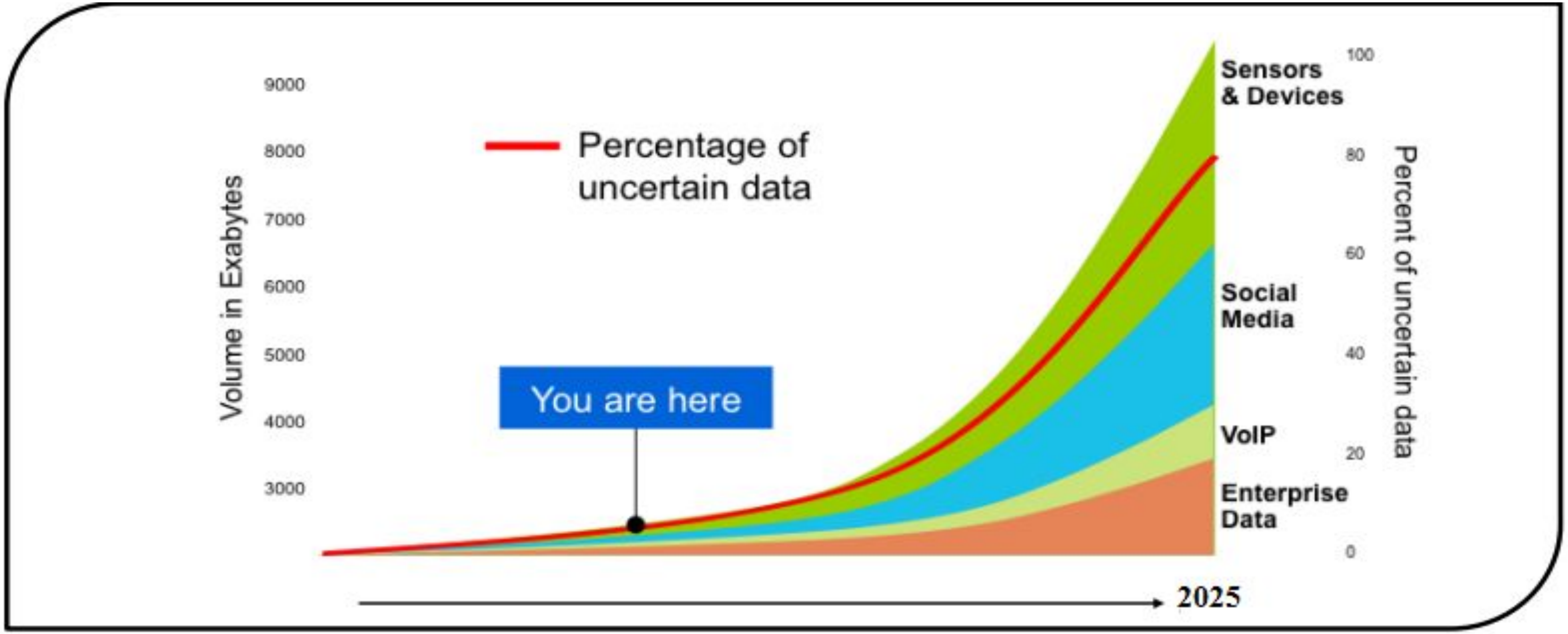


Image credit: [31]

Total # Citations vs. Year of Publication





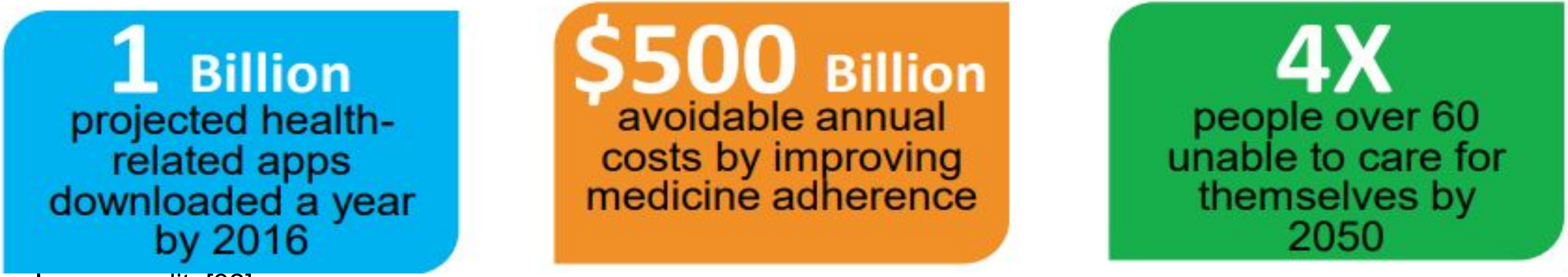


Image credit: [32]

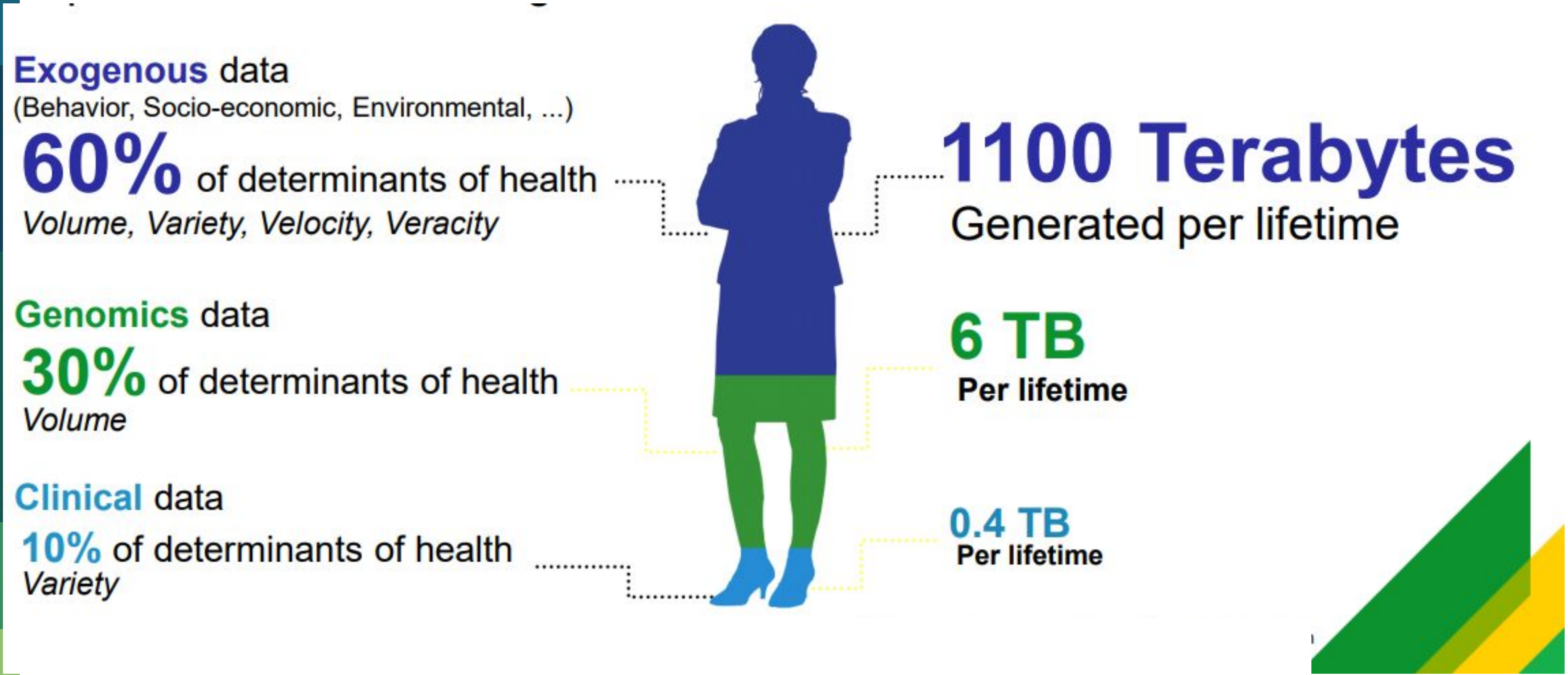


Image credit: [32]

Structured Data

Text Mining

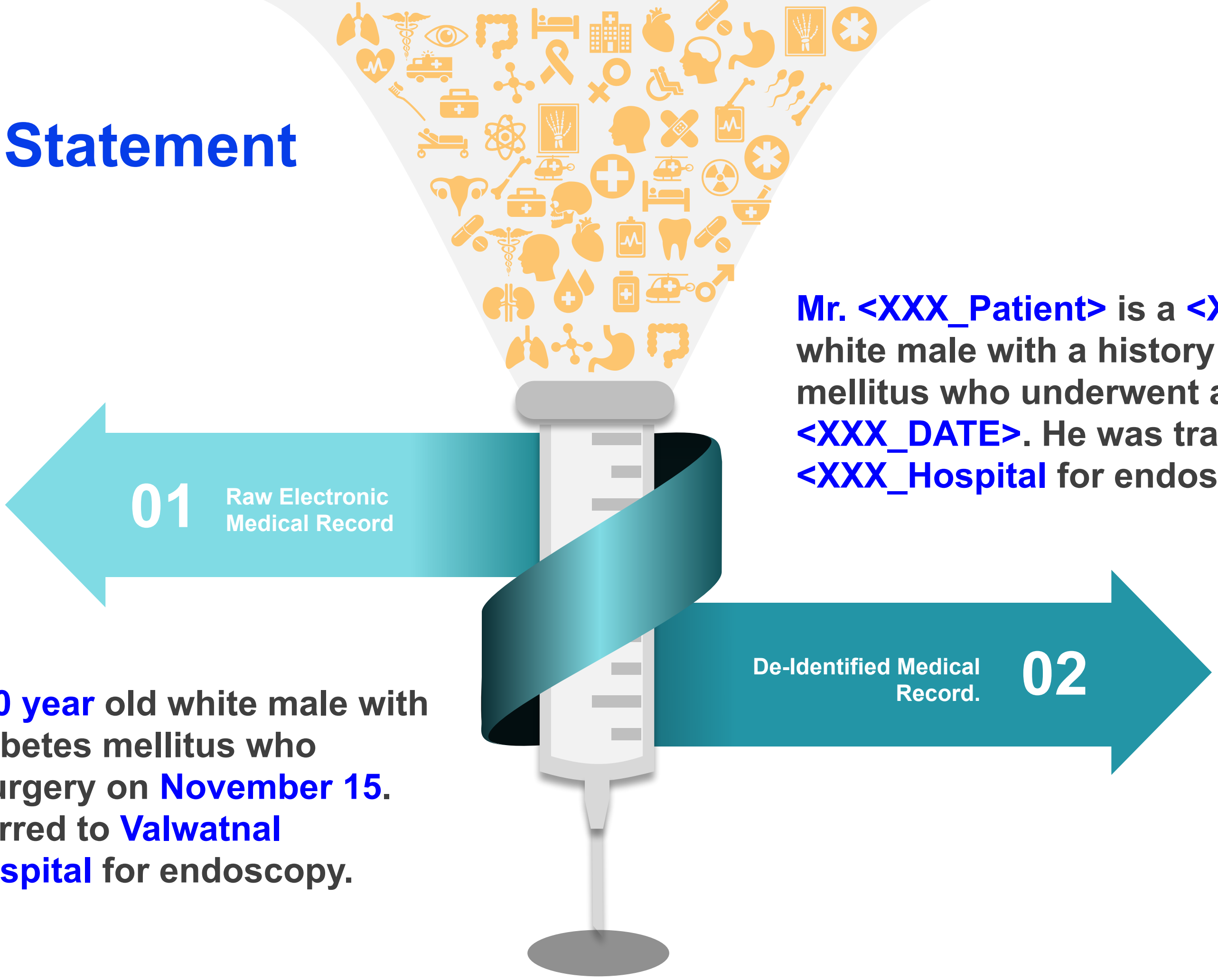
Exponential
Unstructured Data

2

Entity Extraction

Patient Data De-Identification (Electronic Medical Records)

Problem Statement



Mr. <XXX_Patient> is a <XXX_AGE> old white male with a history of diabetes mellitus who underwent a surgery on <XXX_DATE>. He was transferred to <XXX_Hospital for endoscopy.

Mr. John is a 60 year old white male with a history of diabetes mellitus who underwent a surgery on November 15. He was transferred to Valwatnal Community Hospital for endoscopy.

Date

Admission

06/07/1999

Report Status :

Signed

Date

Discharge

06/13/1999

Patient Name

Hospital Name

HISTORY OF PRES

Essentially , Mr. Cornea is a 60 year old male who noted the onset of dark urine during early January .
He underwent CT and ERCP at the Lisonatemi Faylandsburgnic, Community Hospital with a stent placement and resolution of jaundice .
He underwent an ECHO and endoscopy at Ingree and Ot of Weamanshy Medical Center on April 28 .
He was found to have a large , bulging , extrinsic mass in the lesser curvature of his stomach .
Fine needle aspiration showed atypical cells , positively reactive mesothelial cells .

MEDICATIONS PRIOR TO ADMISSION :

Hydrochlorothiazide 25 mg q.d. , Clonidine 0.1 mg p.o. q.d. , baclofen 5 mg p.o.

Physician Name

HOSPITAL COURSE :

Basically , patient underwent a subtotal gastrectomy on the 7th of June by Dr. Kotefooksshuff .

Motivation

- **Automatically augmenting** patient databases
- **Unavailability of clinical records** for research (even for de-identification) without being de-identified

Challenges

- **Inter PHI ambiguity:** PHI terms overlap with the non-PHI terms.

  Brown (Doctor name) vs. brown (non-PHI)

- **Intra PHI ambiguity:** One candidate word seems to belong to two or many different PHI terms.

  August (Patient name) vs. August (Date)

- **Lexical Variation:** For example, variation of the entities such as the **'50 yo m', '50 yo M', '55 YO MALE'**
- **Terminological variation and irregularities:** For example '**3041023MARY'** is the combination of two different PHI categories **'3041023'** which represents the **MEDICALRECORD** and **'MARY'** which is another PHI category

System	Algorithm	Lexical	Syntactic	Semantics
Guo et al.[7]	SVM	Word , Capitalization, Prefixes/Suffixes, Word Length, Numbers, Regular Expression	POS(Word)	Entity Extract by ANNIE(Doc, Hosp, Loc)
Szarvas et al.[8]	Decision Tree	Word Length, Capitalization, Numbers, Regular Expression, Token Frequency	None	Dictionary Terms (Names , US Loc, Counties, cities, Diseases, Non PHI), Section Headings
Uzuner et al. [9]	SVM	Word , Lexical Bigrams, Capitalization, Punctuation, Numbers, Word Length	POS(Word+2 surrounding)	MeSH ID, dictionary Terms(Names, US and word locations, hospital name)
Wellner et al. [10]	CRF	Word Unigram/Bigram, Surroundings word, Prefixes/Suffixes, capitalization, Numbers, Regular Expression	None	Dictionary Terms (US states, months, General English Terms)
Aramaki et al. [11]	CRF	Word, Surroundings words, capitalization, Word Length, Regular Exp, Sentence Position & Length	POS(Word+2 surroundings word)	Dictionary Terms (Names and Loc)

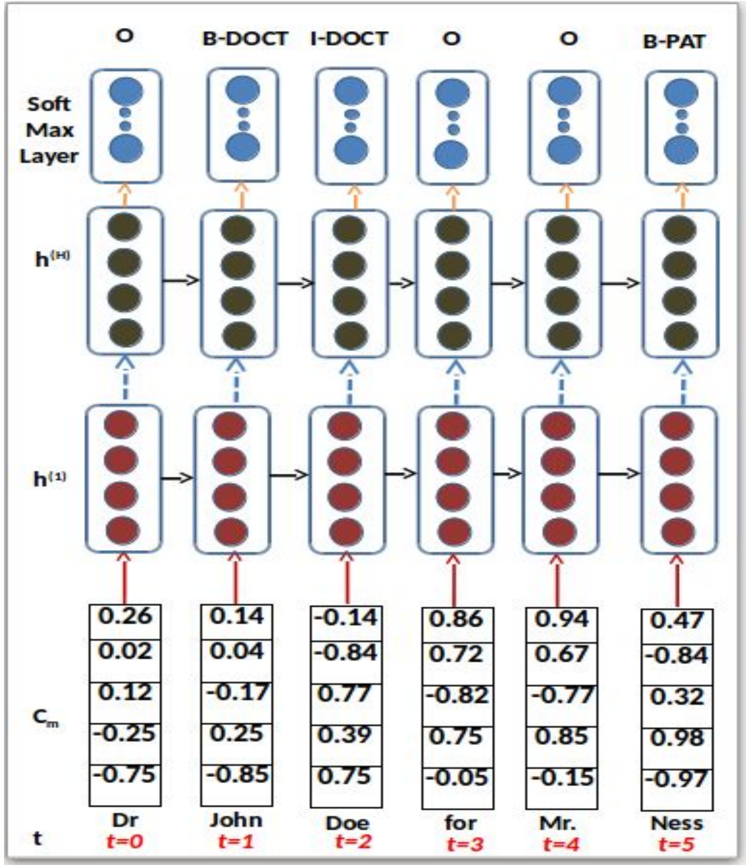
Feature Engineering

- Bag-of-words
- Part-of-speech (POS) tags
- POS tag of current and surrounding token
- Contextual features
- Sentence information
- Affixes
- Orthographic features
- Word shapes
- Section information
- Task specific features

Dataset (i2b2 2014)

PHI Category	Train	Validation	Test
DOCTOR	2262	183	236
PATIENT	707	28	59
HOSPITAL	1342	141	164
DATE	4154	377	498
LOCATION	93	14	19
PHONE	153	12	13
ID	3200	233	264

PROPOSED APPROACH (Elman RNN)



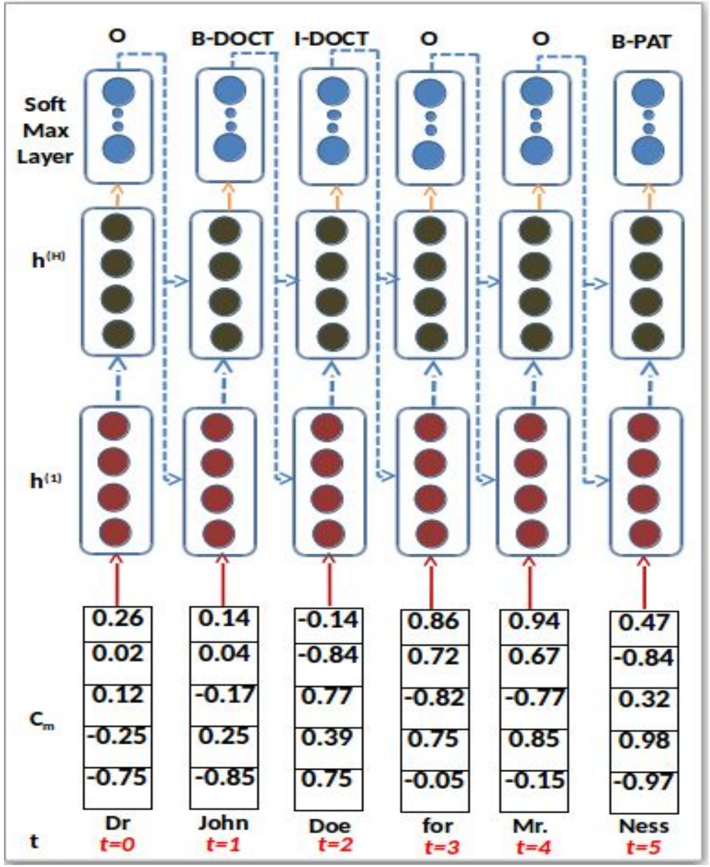
$$P(y(t) = i | C_m(x_{t-m}^{t+m})) = g(Uh^{(H)}(t) + c)$$

$$g(z_m) = \frac{e^{z_m}}{\sum_{j=1}^{j=k} e^{z_j}}$$

$$h^{(1)}(t) = f(W^{(1)} C_m(x_{t-m}^{t+m}) + V^{(1)} h^{(1)}(t-1) + b)$$
$$h^{(H)}(t) = f(W^{(H)} h^{(H-1)}(t) + V^{(H)} h^{(H)}(t-1) + b)$$

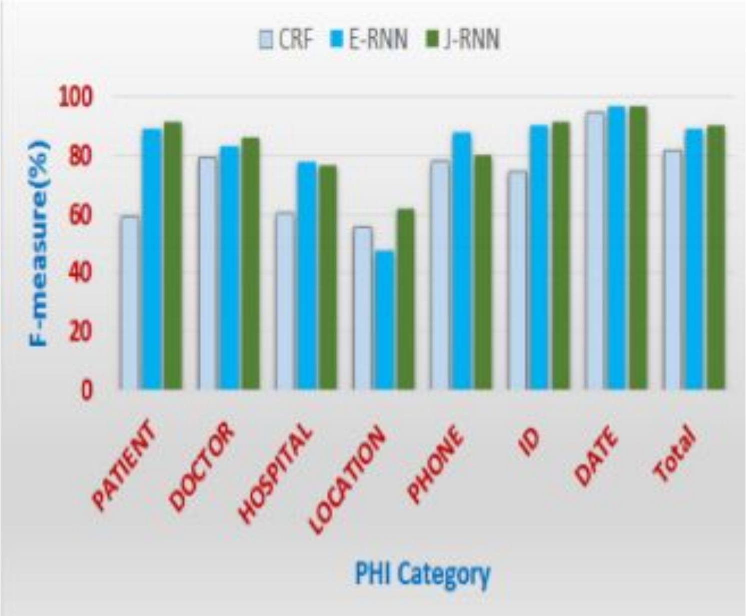
$$C_m(x_{i-m}^{i+m}) = v_{i-m} \oplus \ldots v_i \ldots \oplus v_{i+m}$$

PROPOSED APPROACH (Jordan RNN)



$$h(t) = f(WC_m(x_{t-m}^{t+m}) + VP(y(t-1)) + b)$$

PHI Category	CRF Baseline	Elman RNN	Jordan RNN
PATIENT	58.95	88.89	91.30
DOCTOR	79.08	83.26	85.84
HOSPITAL	60.39	78.03	76.41
LOCATION	55.56	47.83	61.90
PHONE	78.26	88.00	80.00
ID	74.44	90.31	91.68
DATE	94.69	96.74	96.83
Overall	81.39	89.22	90.18



Results with PSO

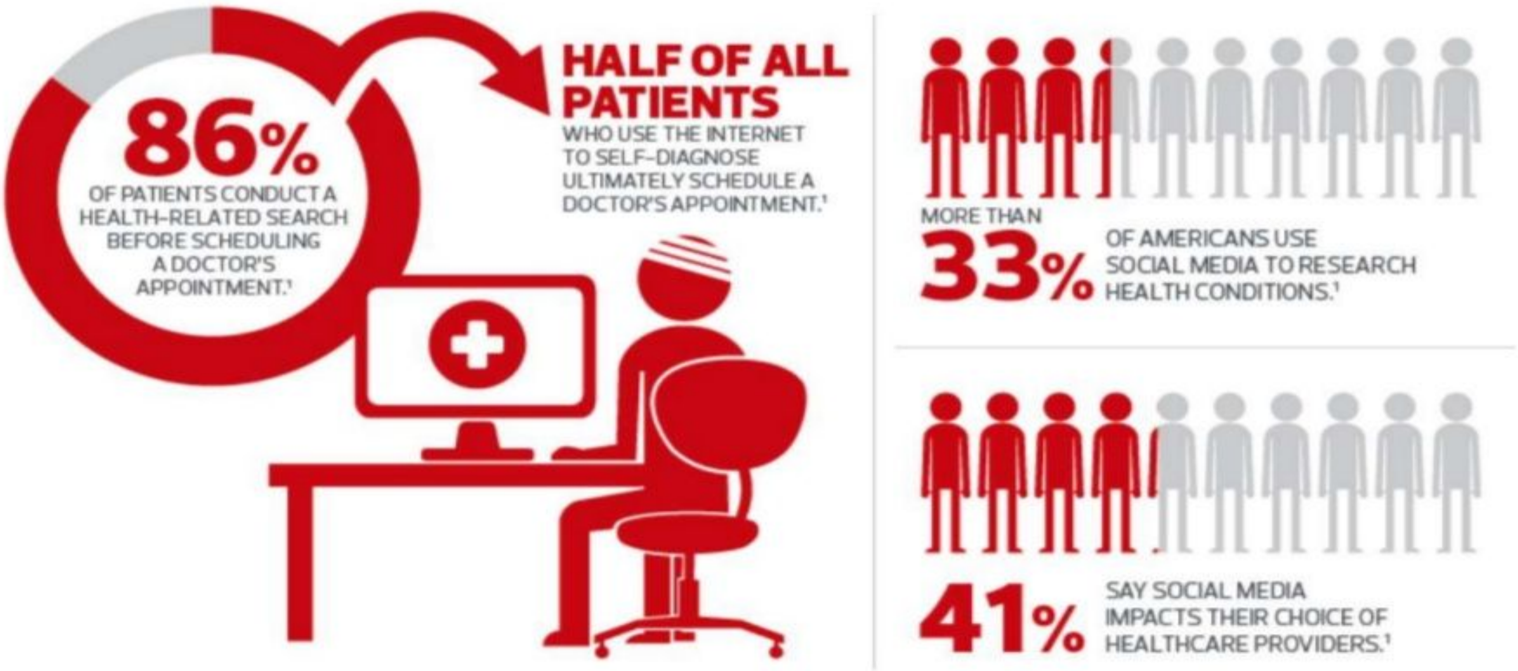
PHI Category	CRF	CRF+PSO	Elman	Jordan
PATIENT	58.95	59.26	88.89	91.30
DOCTOR	79.08	81.02	83.26	85.84
HOSPITAL	60.39	62.51	78.03	76.41
LOCATION	55.56	55.13	47.83	61.90
PHONE	78.26	78.89	88.00	80.00
ID	74.44	75.41	90.31	91.66
DATE	94.69	95.14	96.74	96.83
OVERALL	81.39	82.58	89.22	90.18

3

Medical Sentiment Analysis

Social-media Texts (Medical Blogs)

The Digital Patient



Ref. Pew Internet Research. Social Media Usage: 2005-2015. Pew Research Center, October 2015.; http://www.cdwcommunit.com/perspectives/expert-perspectives/todays-digital-patient/

Sample Medical Blog-post

I feel tired

Posted by: Miracle37 Last Reply: muskrattiger 03/19/2019

5 0

I want to give up on life. I'll just be an observer.

Anxiety controlling my life

Posted by: luvpto8 Last Reply: luvpto8 03/18/2019

5 0

I have had ongoing family drama for the past 2+ years. I have an aunt who is mentally ill and cares for my elderly... **READ MORE**

Im a just a "good kid"??/

Posted by: REALMUSIC24 Last Reply: arfie 03/18/2019

2 0

I went o my youth group last night just like any other sunday night. This time there was a new guy. by the end of the... **READ MORE**

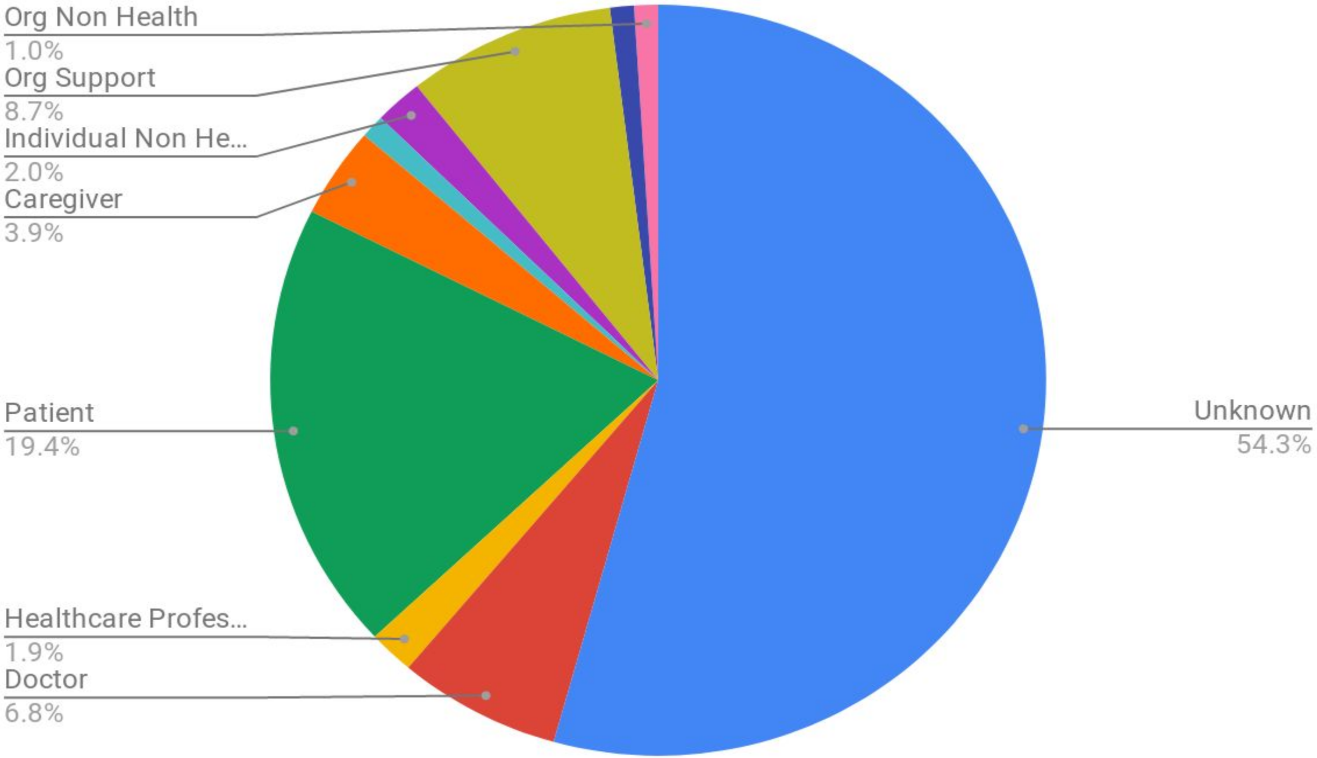
Health Anxiety

Posted by: stlake Last Reply: stlake 03/18/2019

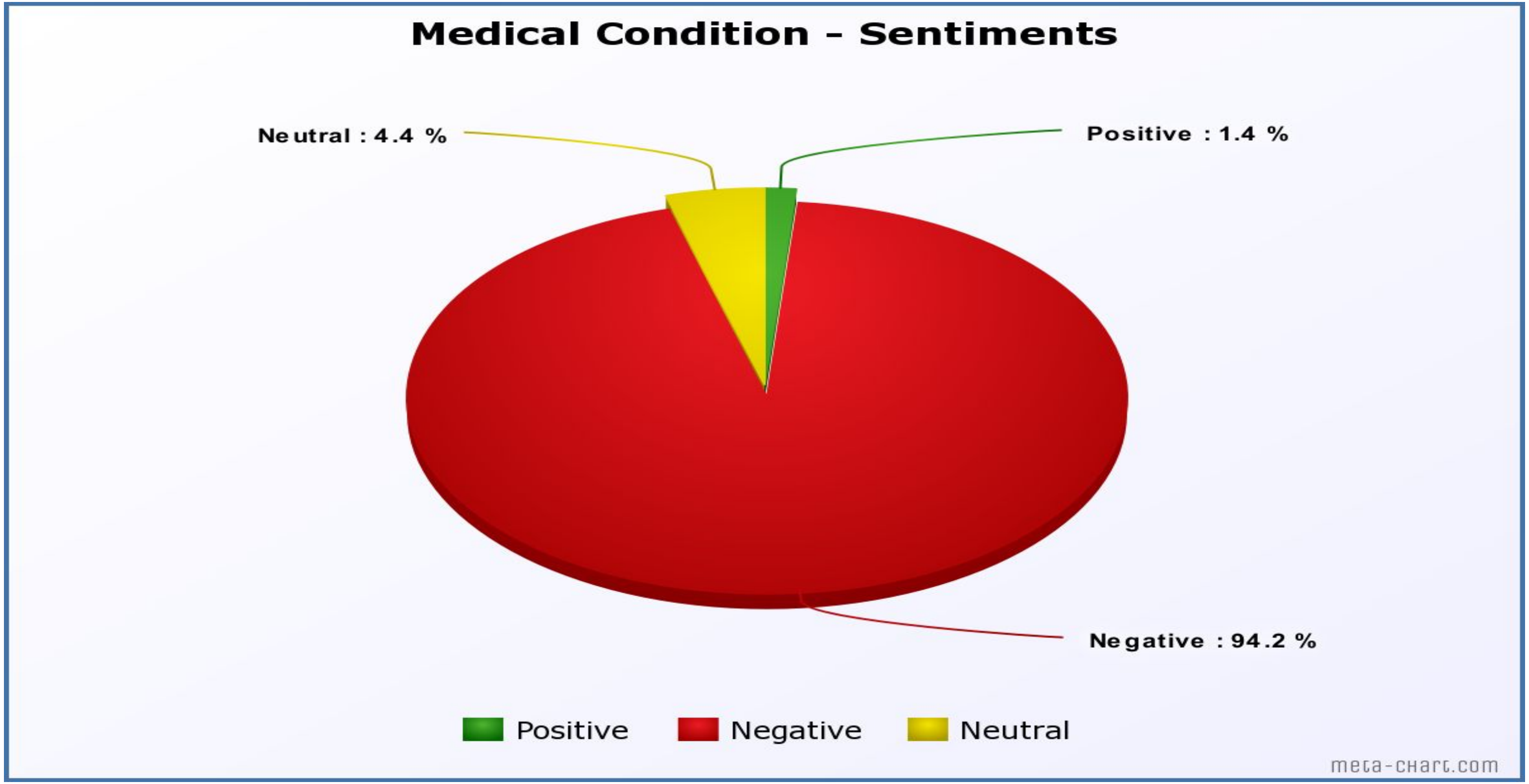
7 0

My wife has been battling cancer for 7 years.Yesteray, we learned that her disease had progressed.I feel so bad for her... **READ MORE**

Who is Talking?



Why Not??? Sentiment Analysis

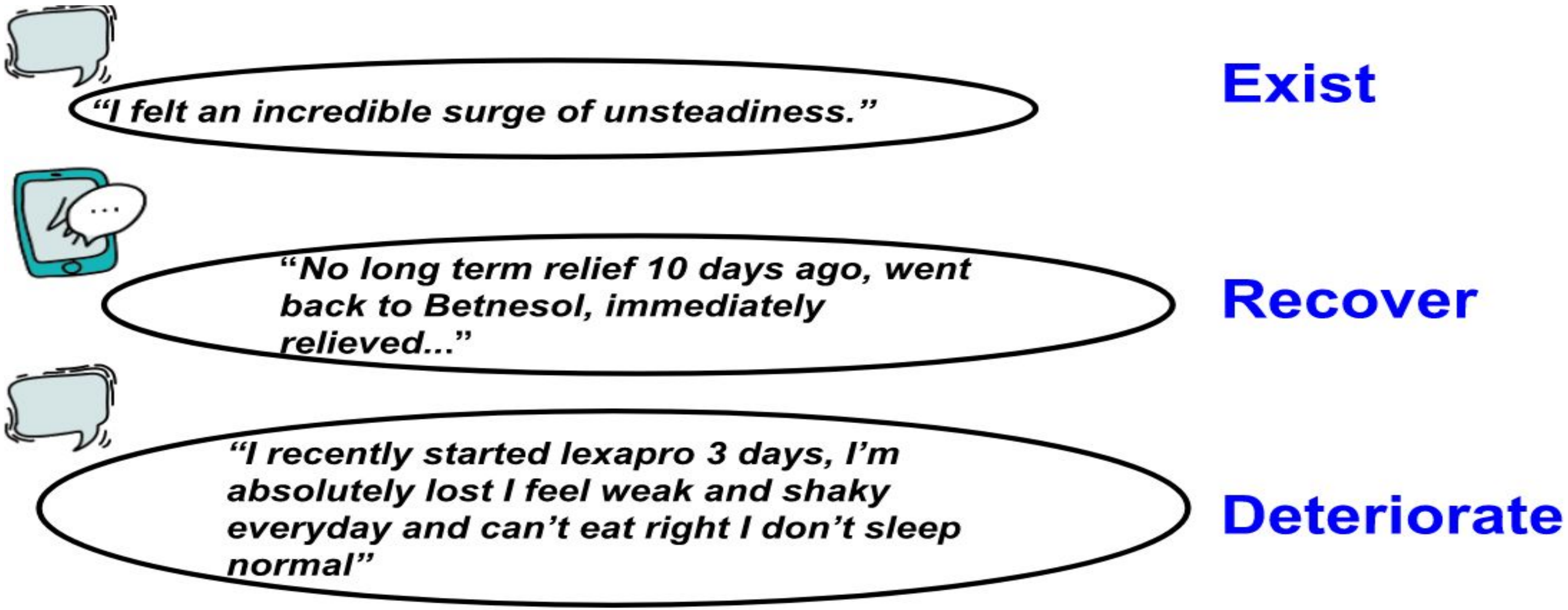


Problem Statement

- To prioritize user blog post over two medical sentiment aspects:

    1. **Status of health condition**
    2. **Outcome of treatment**

Medical Condition



Medication

"I started on 25mg and now been on 50 for around 2 or 3 weeks. My mood has definitely improved"

Effective

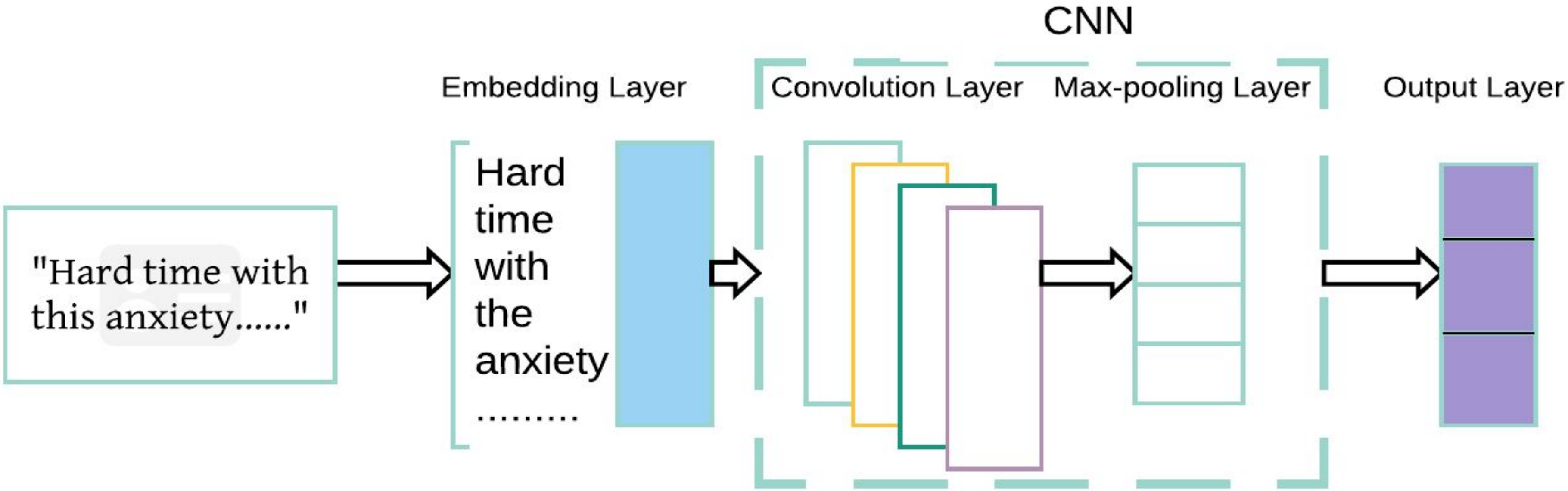
"Nothing seems to help been in bed for two days can't sleep"

Ineffective

"I haven't taken my citalopram. Anxiety is down, but now I'm starting to feel more and more off.."

Serious Adverse Effect

Proposed Approach (Single Task Learning)



Results

	Task 1: Medical Condition			Task 2: Medication		
Models	**Precision**	**Recall**	**F-Score**	**Precision**	**Recall**	**F-Score**
Baseline 1: SVM	0.42	0.49	0.43	0.74	0.76	0.75
Baseline 2: Random Forest	0.45	0.48	0.46	0.72	0.73	0.73
Baseline 3: MLP	0.41	0.43	0.46	0.74	0.75	0.74
Proposed Approach (CNN)	0.68	0.60	0.63	0.86	0.77	0.82

Method 2: Multi-task Learning

Multi-tasking in NLP

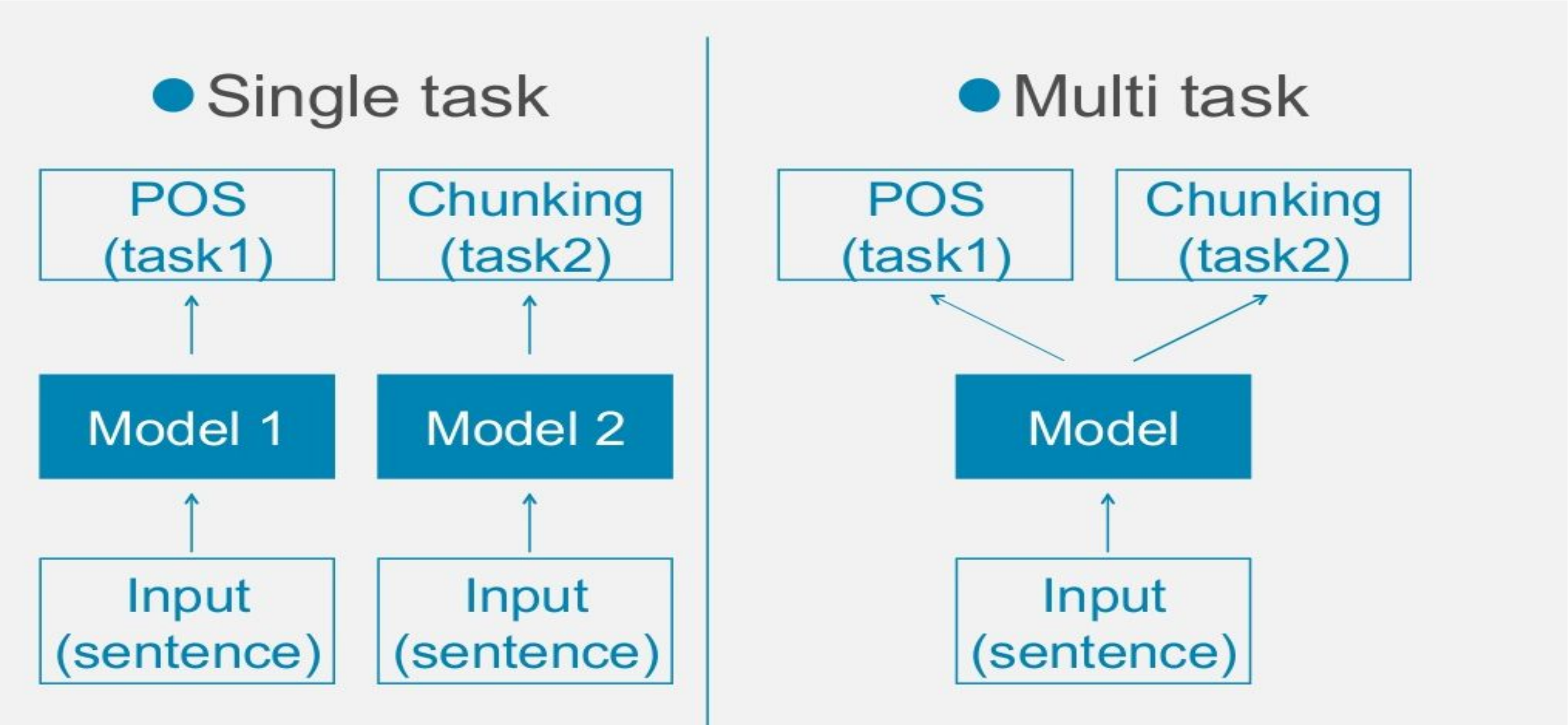
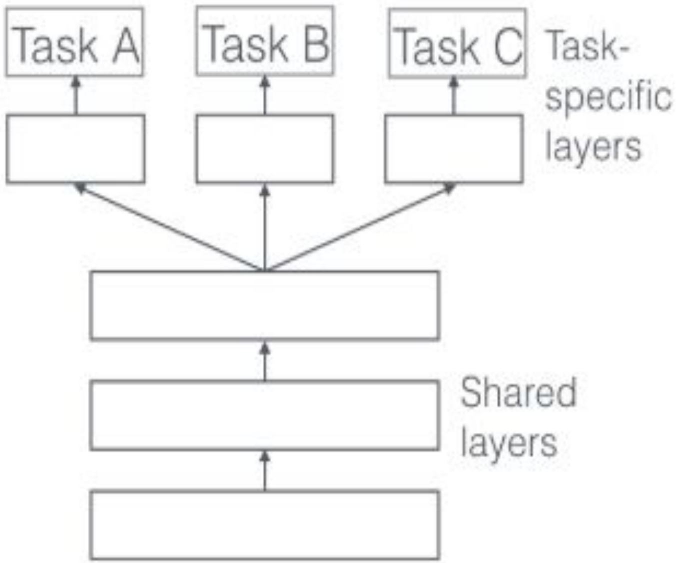


Image Credit:[35]

MTL methods for Deep Learning

Hard parameter sharing



Soft parameter sharing

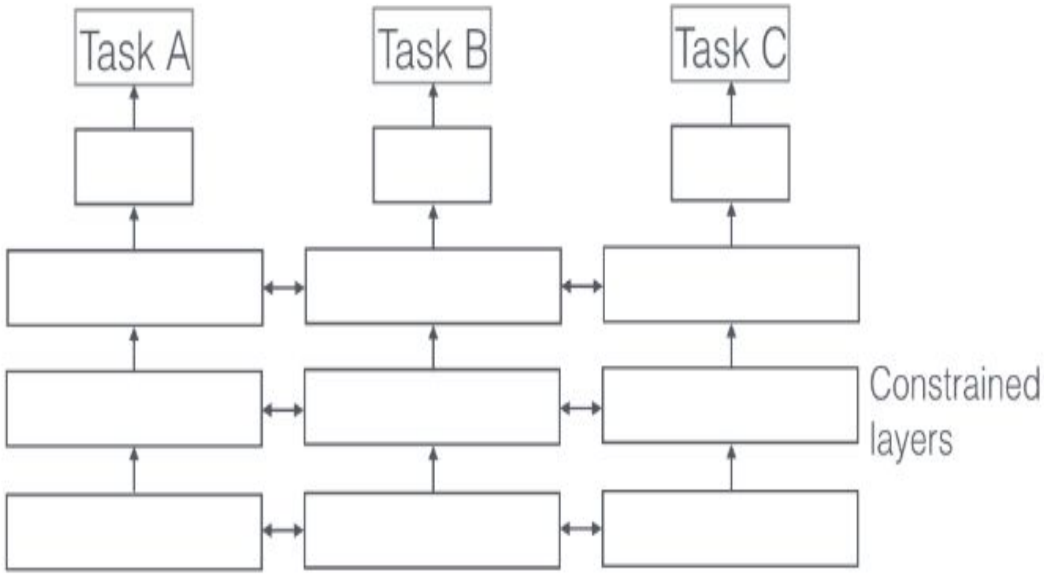


Image Credit:[36]

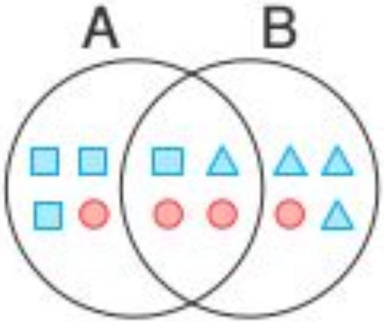
Benefits of MTL

- **Regularization:** it reduces the risk of overfitting as well as the Rademacher complexity of the model

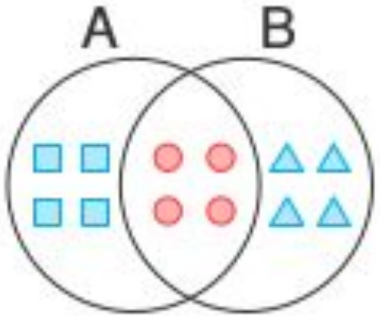
- **Representation bias:** prefer representations that other tasks also prefer. This will also help the model to generalize to new tasks in the future

- **Attention focusing:** focus its attention on those features that actually matter as other tasks will provide additional evidence for the relevance or irrelevance of those features.

Feature Space



Shared Private Model



Goal

Adversarial Learning

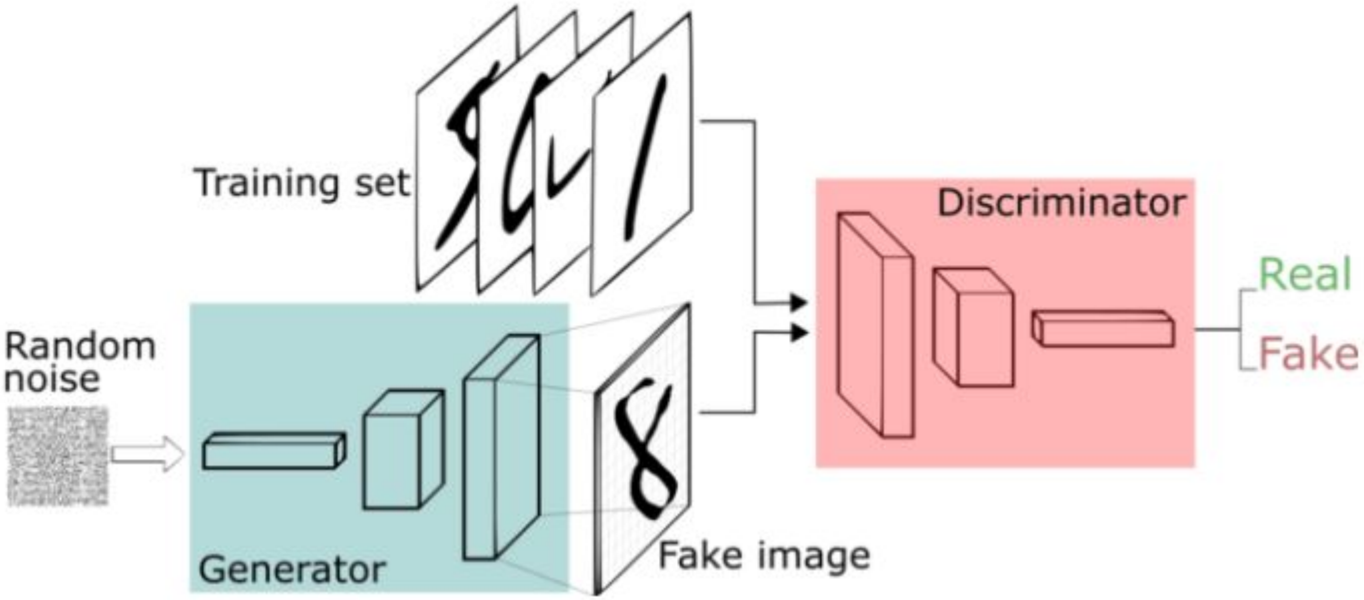


Image Credit: [37]

Adversarial Net Framework

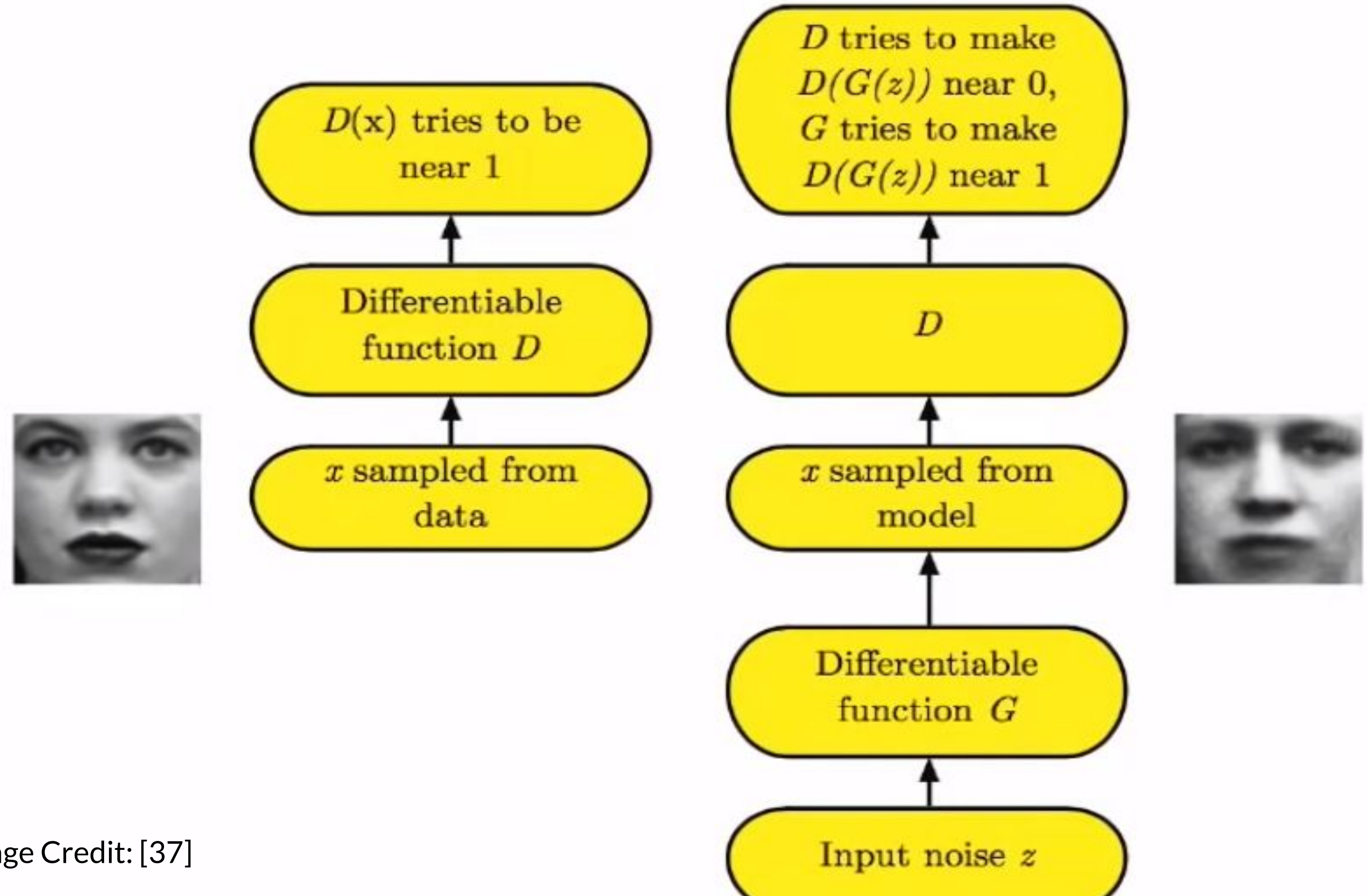
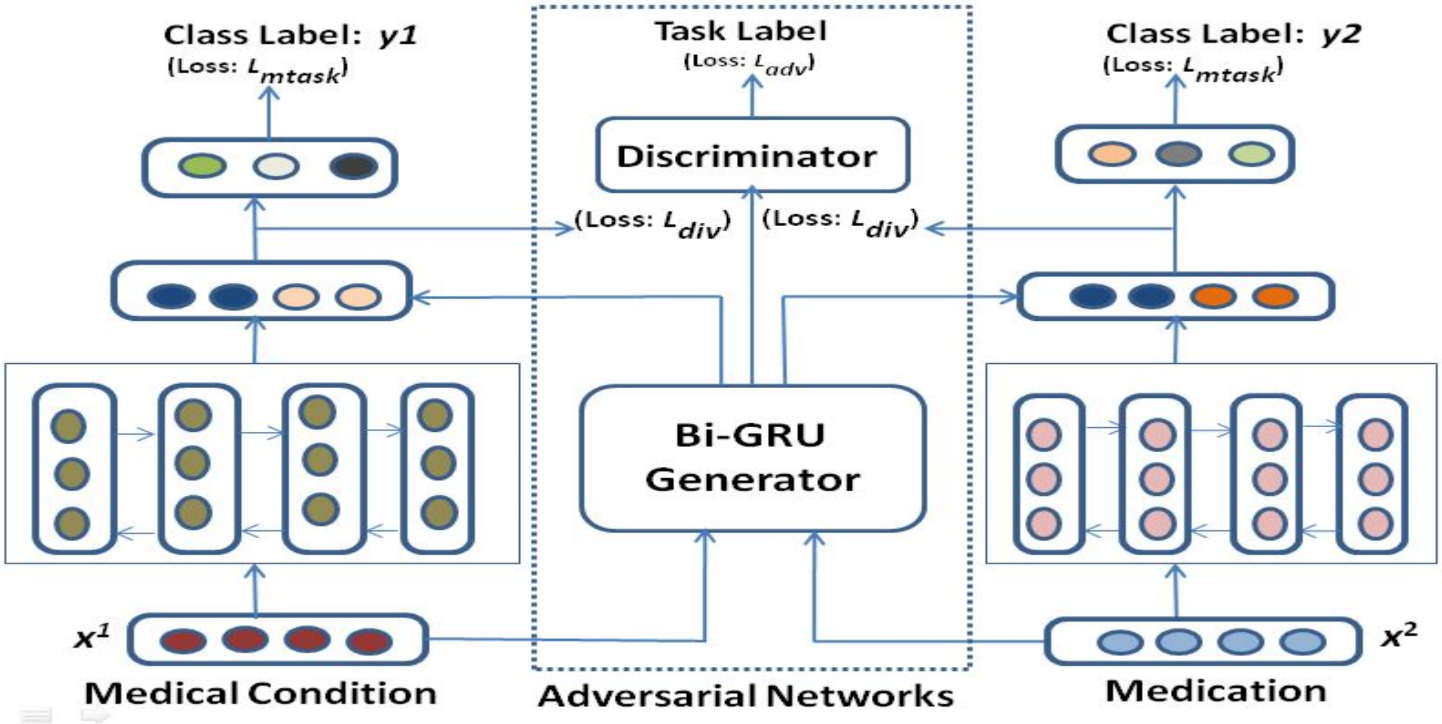


Image Credit: [37]

Proposed Approach (Multi Task Learning)



Results

	Task 1: Medical Condition			Task 2: Medication		
Models	**Precision**	**Recall**	**F-Score**	**Precision**	**Recall**	**F-Score**
Baseline 1: MT-LSTM	63.40	61.38	62.37	88.23	77.38	82.45
Baseline 2: ST-LSTM	63.19	62.47	62.83	85.94	77.46	81.48
Proposed Approach	66.82	63.61	65.18	85.83	81.79	83.76

Error Analysis

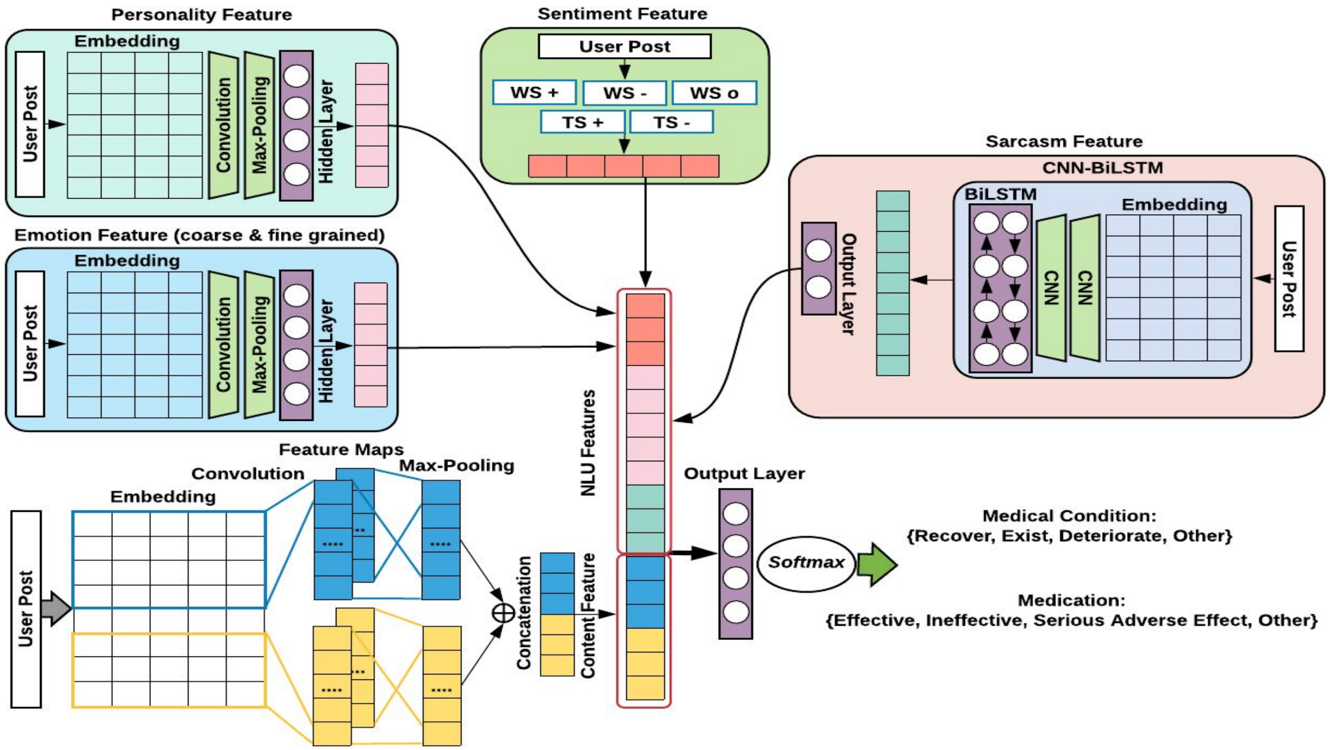
Implicit Sentiment — "what if life comes after death, grab my knife find out myself"

"Love being alone... its great" — **Sarcasm**

Metaphor — "My skin is the paper and the razor is the pen.!"

"I swear i mean well, I'm still goin to hell" — **Implicit Sentiment**

Approach-3

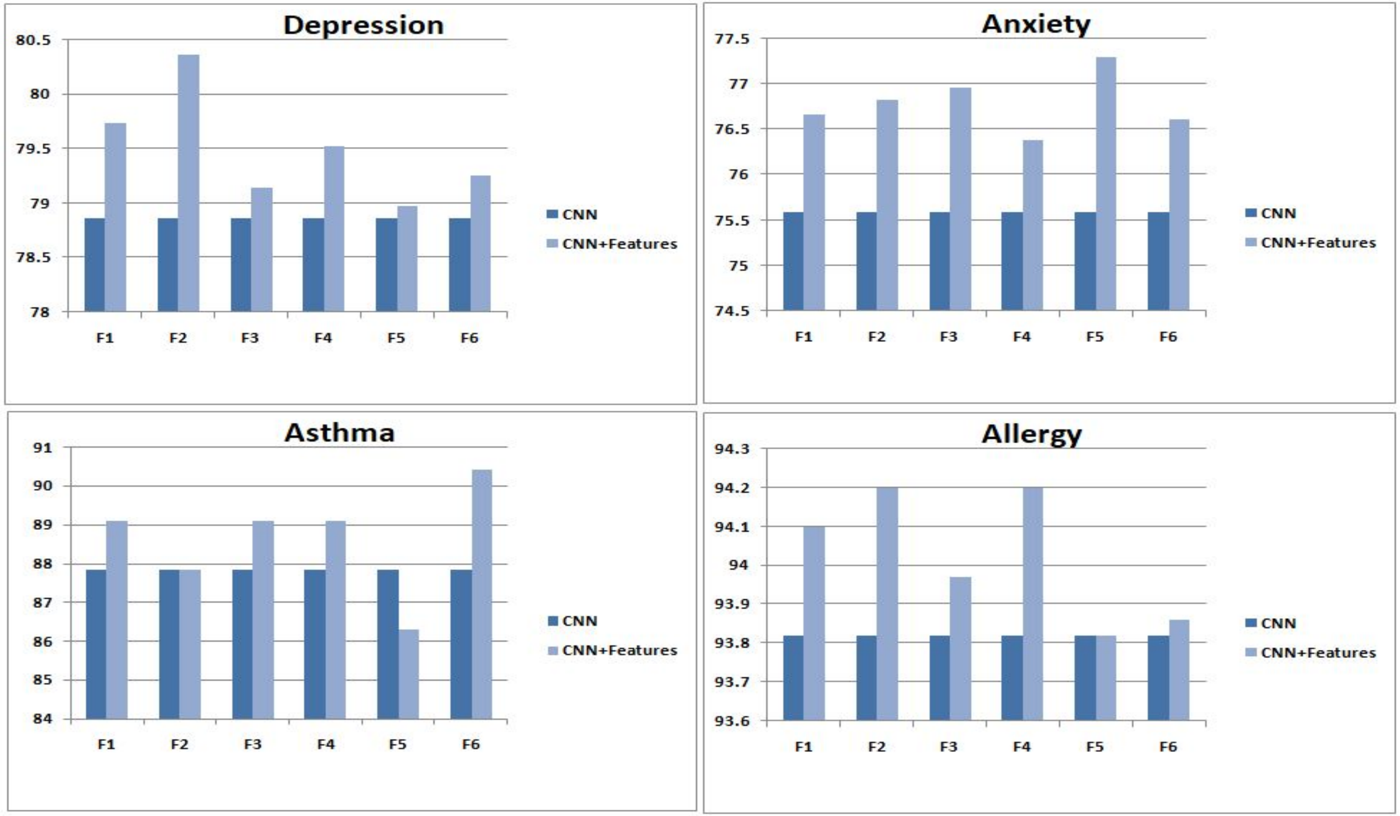


Personality Feature
Embedding
User Post
Convolution
Max-Pooling
Hidden Layer
Emotion Feature (coarse & fine grained)
Embedding
User Post
Convolution
Max-Pooling
Hidden Layer
Sentiment Feature
User Post
WS +
WS -
WS o
TS +
TS -
Sarcasm Feature
CNN-BiLSTM
BiLSTM
Embedding
CNN
CNN
User Post
Output Layer
NLU Features
Feature Maps
Convolution
Max-Pooling
Embedding
User Post
Concatenation
Content Feature
Output Layer
Softmax
Medical Condition:
{Recover, Exist, Deteriorate, Other}
Medication:
{Effective, Ineffective, Serious Adverse Effect, Other}

Result

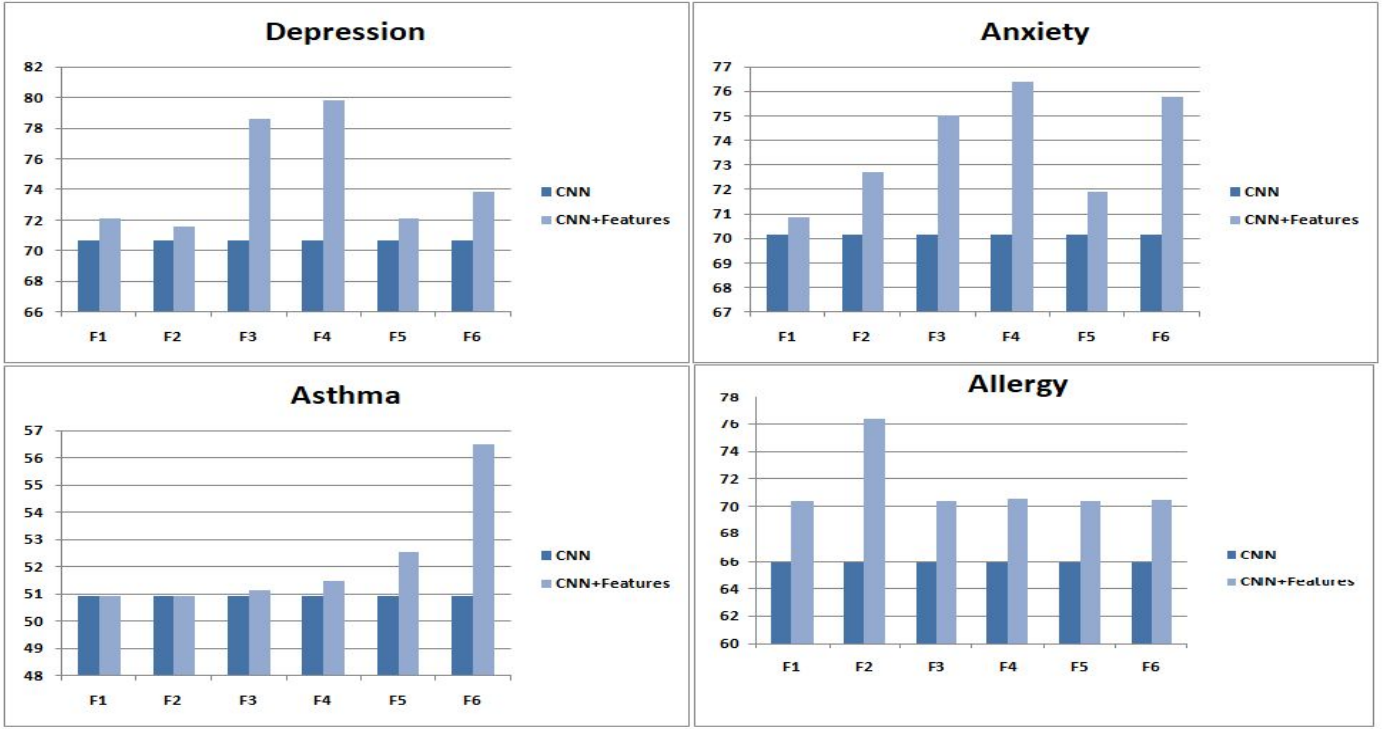
Models	Techniques Used	Medical Condition			Medications		
		Precision	Recall	F-Score	Precision	Recall	F-Score
Baseline 1	LSTM	65.59	61.23	63.33	85.82	76.19	80.71
Baseline 2	CNN	66.29	61.79	63.96	86.61	76.95	81.49
Baseline 3	MT-LSTM	66.71	64.33	65.5	85.33	81.90	83.58
Proposed Approach	CNN + NLU Features	71.57	67.61	69.53	89.57	86.94	88.23

Disease wise Analysis (Medical Condition)



F1: ‘CNN+Emotion (coarse) ’, F2: ‘CNN+Emotion (fine)’, F3: ‘CNN+Sentiment word feature’, F4: ‘CNN+Textual Content Feature’, F5: ‘Personality’, F6: ‘Sarcasm’

Disease wise Analysis (Medication)



F1: 'CNN+Emotion (coarse) ', F2: 'CNN+Emotion (fine)', F3: 'CNN+Sentiment word feature', F4: 'CNN+Textual Content Feature', F5: 'Personality', F6: 'Sarcasm'

4

Pharmacovigilance Mining

Social-media Texts (Medical Blogs)

Introduction

- **Medicines**: is the applied science or practice of the diagnosis, treatment, and prevention of disease.
- Most medicines have both **good** and **bad effects.**
- **Bad effects** called Adverse Drug Reactions (**ADRs**) , it differs from side effects.
- **Side effects** whether therapeutic or adverse

ADRs cause over 700,000 emergency department visits each year in the United States

Slide credit: [33]

Example of ADRs and side effects

- Desired and undesired effects of an aspirin therapy

reduce your headache or fever

reduce the ability of your blood to clot

× bleeding of intestine

Slide credit: [33]

Pharmacovigilance (PhV)

- **Pharmacovigilance** (PhV) is the science that concerns with the detection, assessment, understanding and prevention of ADRs

WIKIPEDIA
The Free Encyclopedia

- Pharmacovigilance (PhV)=drug safety surveillance
- Surveillance for **premarketing** (i.e. Data from preclinical & clinical trials) and **post-marketing** (i.e. throughout a drug's market life)

- Phv trend to **link** the Preclinical human safety with information from post marketing.

Slide credit: [33]

How it Begin??

"Secrets of Seroxat"

BBC Documentary: Panorama broadcasted in 2001

50-minute programme about paroxetine

Crowd Opinion

The programme attracted a record response, including some

65,000 : telephone calls

124,000 : website hits

1,374: emails

FIRST STUDY EXPLORING CROWD INTELLIGENCE

Paroxetine, Panorama and user reporting of ADRs: Consumer intelligence matters in clinical practice and post-marketing drug surveillance

Medawar, C., Herxheimer, A., Bell, A., & Jofre, S. (2002). Paroxetine, Panorama and user reporting of ADRs: Consumer intelligence matters in clinical practice and post-marketing drug surveillance. *International Journal of Risk & Safety in Medicine*, *15*(3, 4), 161-169.

Crowd Intelligence Matters !!

- “Dr Healy confirmed what I already knew. **My husband shot himself after 4 days on Seroxat never having been suicidal in his life. . .**”

- “I took Seroxat 2 years ago because I have a breathing condition called ‘chronic hyperventilation syndrome’ which is exacerbated by stress and anxiety. I have never been depressed or had suicidal feelings. However I was prescribed Seroxat to reduce stress & anxiety. **A day or two after taking the pills I (went) into a severe state of mental turmoil. I felt really suicidal. It was so severe that all I did was stay in bed for two or three days.** Fortunately I recognised Seroxat and stopped taking it immediately.”

The rise of social media provides a **new online avenue** for information related to patient's Adverse Drug Reactions.

Image credit: [33]

Problem Statement

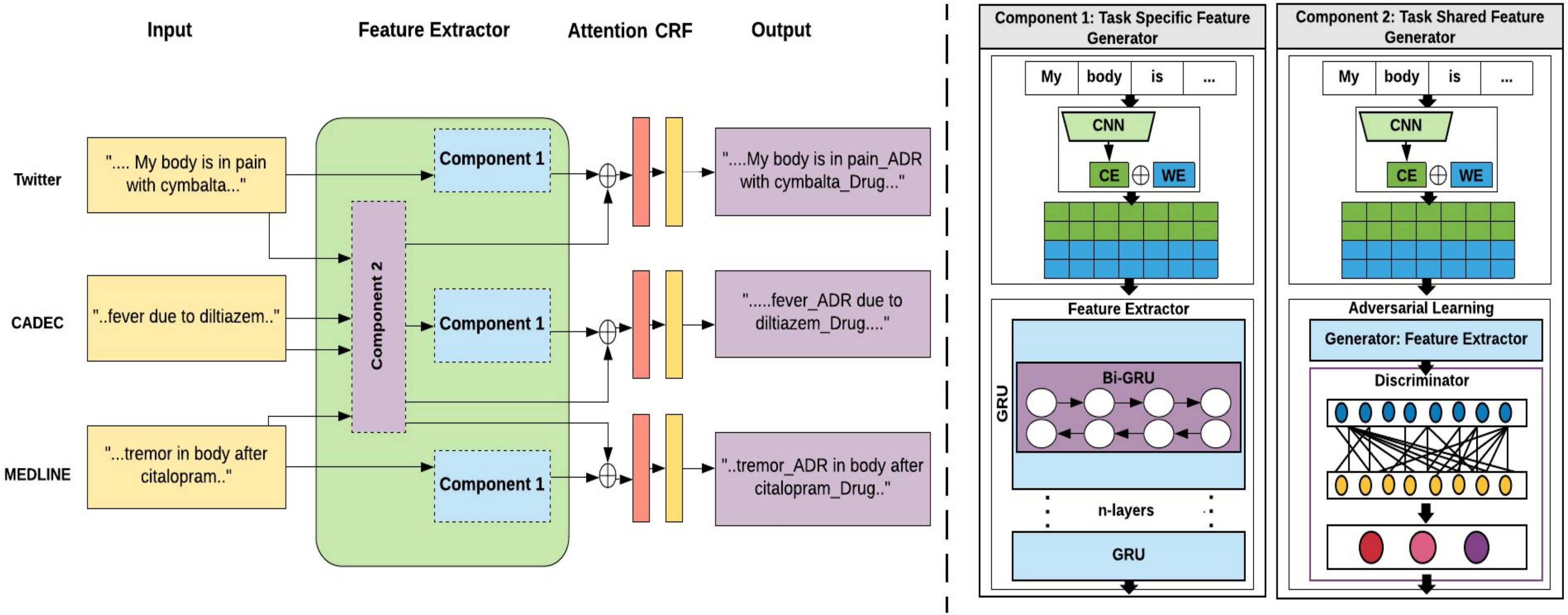
Text 1: took one pill and 20 minute later had **intense pelvic and back pain** felt like a **miscarriage** (i had 3 of them) this intense , **horrid pain** lasted 1.5 hour then i had **spotting** and **terrible bloating and nausea**

Text 2: a 14-year-old girl with newly diagnosed sle developed a **pruritic bullous eruption** while on **prednisone**

Text 3: **cymbalta** , you're **driving me insane**

Text 4: i have got to stop taking my **vyvanse** so late ! ! **nosleep** **add** problems

Proposed Approach



Model	Twitter	CADEC	MEDLINE
ST-BLSTM	57.3	51.1	71.91
ST-CNN	67.1	42.0	70.17
CRNN (Huynh et al.,2016)	64.9	48.2	75.5
RCNN (Huynh et al.,2016)	63.6	43.6	74.0
MT-BLSTM (Chowdhury et al.,2016)	63.19	57.62	74.0
MT-BLSTM-Attention (Chowdhury et al.,2016)	65.73	58.27	77.95
Proposed Approach	69.69	65.58	82.18

Conclusion

- Explored the various unstructured form of biomedical text and its application in solving real-world problem.
- Explored deep learning solution based on Elman and Jordan Deep Learning framework for solving patient data de-identification task.
- Exploited the sentiment analysis in medical domain and neural network approach to address the task.
- Explored the unified multi-task learning framework for pharmacovigilance mining that is generic and easily adaptable to extract the pharmacovigilance information from any form of text.

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THANK YOU!