Deciphering Clinical Narratives – Augmented Intelligence for Decision Making in Health Care Sector

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Keynote Talk

Outline of the talk

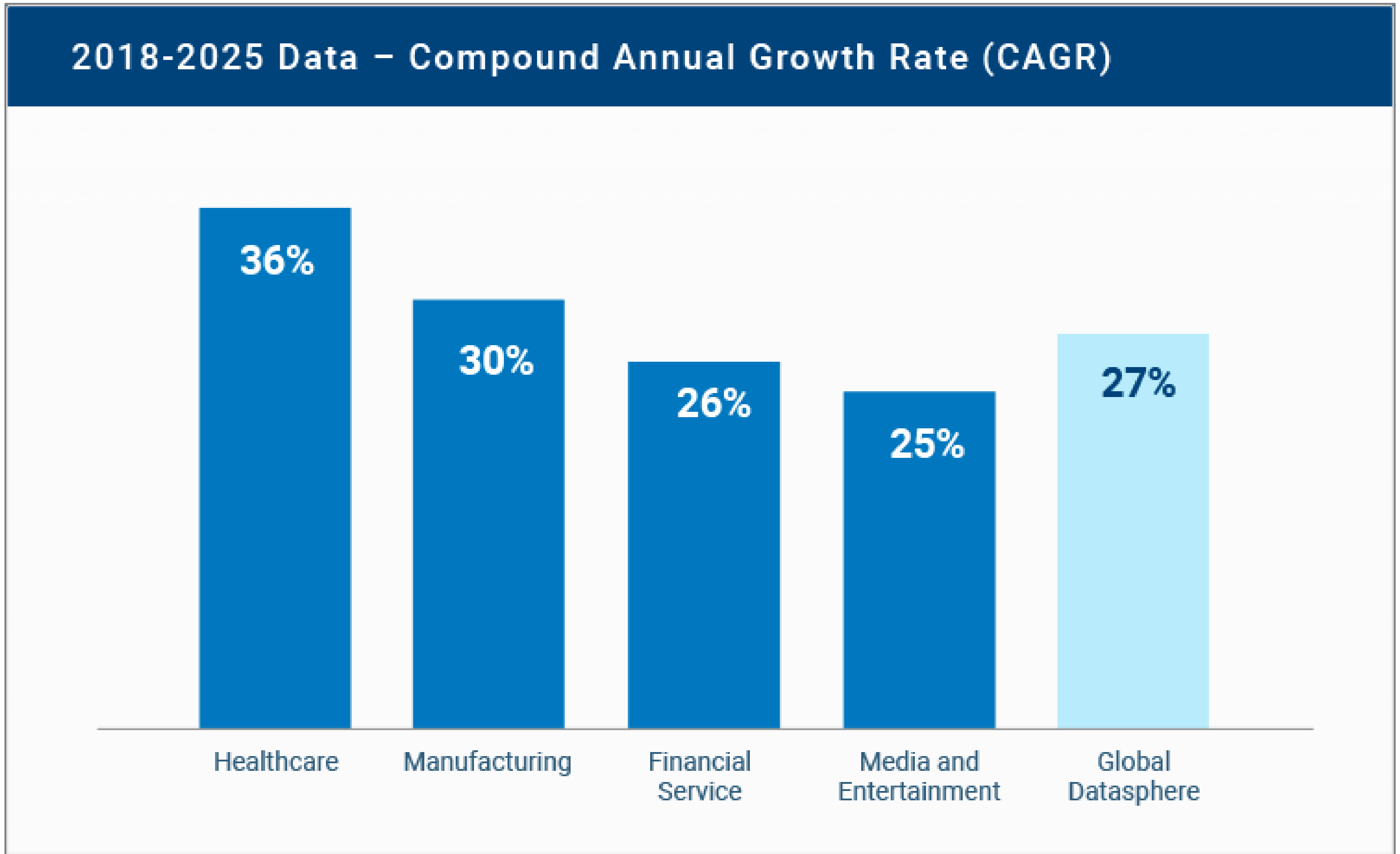
- Clinical texts and Decision-Making problems in Health Care Sector
- Predicting Length of stay in ICU using first day's nursing notes
  - Results and Learnings
- Forming Patient Cohorts
  - Deeper dive into risk factors for each group
- Way forward – some plans

Clinical narratives - Main form of communication within health care

- **Clinical Data**
  - Electronic Medical Records (EMR)/Electronic Health Records (EHR)
  - Physician and Care-giver notes - patient history, assessments and treatments
  - Clinical trials management – trial description, monitoring trial progress
- **Social Media (tweets, Facebook comments, message boards, etc.)**
  - personal accounts of patients – signals for mental health – adverse effects of drugs
  - Health care system feedback
- **Medical Literature**
  - News feeds, Medical journals
- **Insurance Providers (claims from private and government payers)**
  - Underwriter notes

Was estimated to be 25,000 petabytes by the end of 2020 – COVID 19 enhanced it by many orders

Most rapidly rising data repository



Source: Coughlin et al Internal Medicine Journal article "Looking to tomorrow's healthcare today: a participatory health perspective". IDC White Paper, Doc# US44413318, November 2018: The Digitization of the World – From Edge to Core".

https://www.rbccm.com/en/gib/healthcare/episode/the_healthcare_data_explosion

Challenges of working with Clinical Data

Chances of Privacy violation

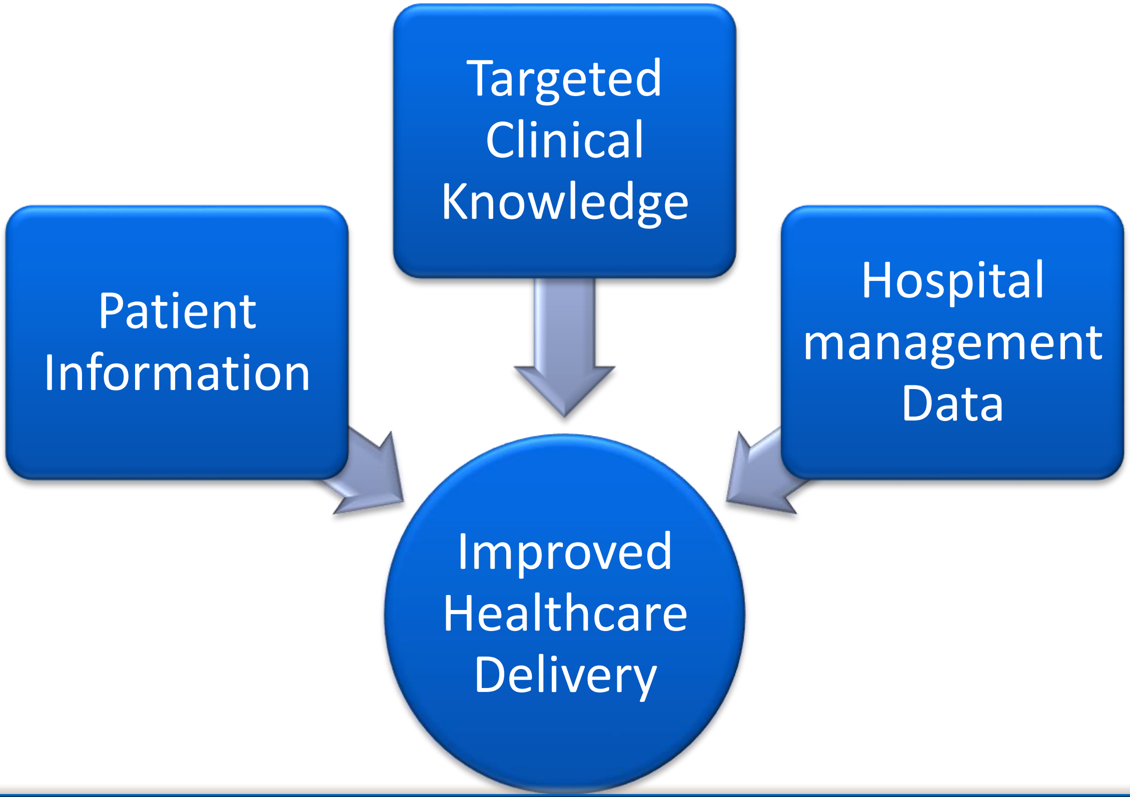
Not available in large quantities for research

Makes training and evaluation of Machine Learning techniques difficult

Non-standard terminologies

Textual narratives are more so

Decision Support Systems in Health Care Sector



- Hospital Logistics Management
- Expectation management for patients and their family
- Personalized Patient Care

Using Clinical Notes

ICU LENGTH OF STAY PREDICTION

About MIMIC-III v1.4 Dataset

- MIMIC-III v1.4 Database contains details of 58976 admission records of 46,520 patients who stayed in critical care units of the Beth Israel Deaconess Medical Center (BIDMC) between 2001 and 2012 - developed by the Laboratory for Computational Physiology, MIT.
- Has pre-existing ***Institutional Review Board (IRB) approval***
- Adheres to ***stringent anonymization protocols*** - meticulously safeguards patient privacy
- Ensures heightened privacy protection by ***obfuscating precise dates and times of events***
- Researchers can access the data ***after successfully completing the training course*** "Data or Specimens Only Research" provided by the Collaborative Institutional Training Initiative (CITI)

ICU Length of Stay (LOS) Prediction – ***why is this important?***

- According to the World Health Organization (WHO) patient Length of Stay (LOS) in hospitals is an important performance measurement and monitoring indicator
- Intensive Care Units (ICU) are premium facilities in a hospital – comprising hospital resources, manpower, and equipment
    - Accurate prediction of patient LOS aids healthcare specialists to take medical decisions and allocate medical team and resources appropriately
- Better logistics planning – ensures ***better resource usage*** for critically ill patients
- Patient and insurance companies may use this prediction to manage their budget

The Earlier the better

Earlier Work – using Patient Health Parameters

Comparing with SOTA	Dataset	Feature used	Method	Best Result
Alghatani et al., 2021	44,000 ICU stays from MIMIC	patient’s vital signs like, heart rate, BP, temp., resp. etc	Random Forest	65% accuracy
Su et al., 2021	2224 Sepsis patients PICMISD	Age, P(v-a)CO_2 /C(a-v)O, SO, wbc etc.	XG-Boost model	F1: 0.69, AUC-ROC:0.76
Rocheteau, Liò, et al., 2020	eICU critical care dataset	medical features, Gender, Age, Ethnicity, etc.	Temporal convolution	Kappa score = 0.58
Harutyunyan et al., 2019	42276 ICU stays of 33798 unique patients from mimic database	17 clinical variables like, Capillary refill rate, Diastolic blood pressure etc. from first 24 hours of admission.	LSTM	AUC-ROC : 0.84
van Aken et al., 2021	38013 admission notes from MIMIC III	Created admission notes from ***discharge summaries***	Pretrained CORe + BioBERT	AUC-ROC : 0.72%

Nursing Notes - a complete clinical narrative of hospital admission

The pt is a complicated 62yo man who was transferred from ajh last evening with mrsa bacteremia and pnx. Pt arrived via EMS,intubated, sedated on Propofol 15mcg/kg-min, on Dopa gtt at 5mcg/kg-min. Transferred to Big Boy bed with 6-person assist, MICU-A monitor, and MICU-A IV pumps.**Dopamine** titrated up to max of 6.5mcg/kg-min with SBP 90's-80's, Propfol weaned from 15mcg/kg-min -> 12. Levo-phed started at 0.05mcg/kg-min and dopa weaned to 4.0mcg at time of shift report. Propofol d/c'd, and fentanyl and midazolam started at 25mcg/kg-min and 0.5mg/hr, respectively......Pt turned upon admission; SBP by a-line dropped to 70's with + wave-form, and SpO2 dropped to 80's**.....Skin breakdown noted** over back of neck, sloughed skin with serosanguinous drng OTA on arrival......NaHCO3 3 amps given after 2nd ABG when acidosis was worsening with repsiratory intervention....Daughter in to see pt. Gravity of pt status discussed with daughter.....Patient remains on mechanical ventilation;switched to PCV due to high Paw.PIP improved as well as Pa02,but patient still has significant metabolic acidosis.**Renal insufficiency,patient may need to be dialysised.BS diminished,suctioned for small amount of clear thick tenacious type of secretion. the micu team is concerned that the pt may have mrsa endocarditis and the plan is to obtain a tte later today.** he continued to have a difficult noc with persistent fevers, hypoxia, acidosis, copd/emphysema, asbesteosis, endometriosis with hematuria as well as requiring an increase in pressor support.....

Nursing notes are very detailed, time-stamped account of a patient's stay in a hospital

- Observations made by Doctors about symptoms and diseases
- Prior medical history including drug allergies etc.
- Critical examinations suggested and / or reports
- Treatment plans
  - Medicines prescribed
  - Procedures suggested
- General conditions – appetite, mobility, pain

Predicting ICU stay on the day of admission to ICU

- Most of the earlier work used vital parameters to predict LOS
- Van Aken et al., 2021 used Discharge Summaries - contains entire history of patient during admission
- **Our work**
  - ***Use the first day's Nursing Note prepared after patient's admission to ICU along with vital parameters to predict the LOS***
- Though called LOS –
  - usually prediction is about LONG / SHORT stay
    - SHORT <= MEDIAN, LONG > MEDIAN
  - Exact stay is decided based on multiple other factors like age, availability of facility, patient willingness etc.

Processing Nursing Notes

Patient is a 83 yo female, recently admitted for treatment of severe multilobar pnx.......CXR revealed worsening multifocal pnx and free air under diaphragm.....Currently on 100%NRB with 4l NC. O2 sat 94-97%, rr 14-18, Bp 80-110/40-50, HR 80-105 Hypoactive BS, abdomen soft, distended and tender to touch. No stool thus far....Alert and oriented, pleasant and cooperative...No sob, No abdominal pain...no bs heard....triple antibiotic coverage..also to start amphotericin tonoc....had some oozing from neck line..redressed with gelfoam..no further bleeding noted..no other sites...Family is abroad...back on Wednesday per patient......Plan: Monitor resp status, monitor hemodynamic status, monitor temp, wbc's, follow cultures, continue amphotericin.

Embedding generated using transformer Architectures

Disease Name

scispaCy is a Python package containing spaCy models for processing biomedical, scientific or clinical text.

Disease, Test, Treatment

Cliner based on LSTM for Clinical concept extraction (CCE)

Demography, Health Condition, Lifestyle, Interventions

Inhouse BERT based BioNER

Drugs

Medications from MIMIC Data

Patient is a 83 yo female, recently admitted for treatment of severe multilobar pnx.......CXR revealed worsening multifocal pnx and free air under diaphragm.....Currently on 100%NRB with 4l NC. O2 sat 94-97%, rr 14-18, Bp 80-110/40-50, HR 80-105 Hypoactive BS, abdomen soft, distended and tender to touch. No stool thus far....Alert and oriented, pleasant and cooperative...No sob, No abdominal pain...no bs heard....triple antibiotic coverage..also to start amphotericin tonoc....had some oozing from neck line..redressed with gelfoam..no further bleeding noted..no other sites...Family is abroad...back on Wednesday per patient......Plan: Monitor resp status, monitor hemodynamic status, monitor temp, wbc's, follow cultures, continue amphotericin.

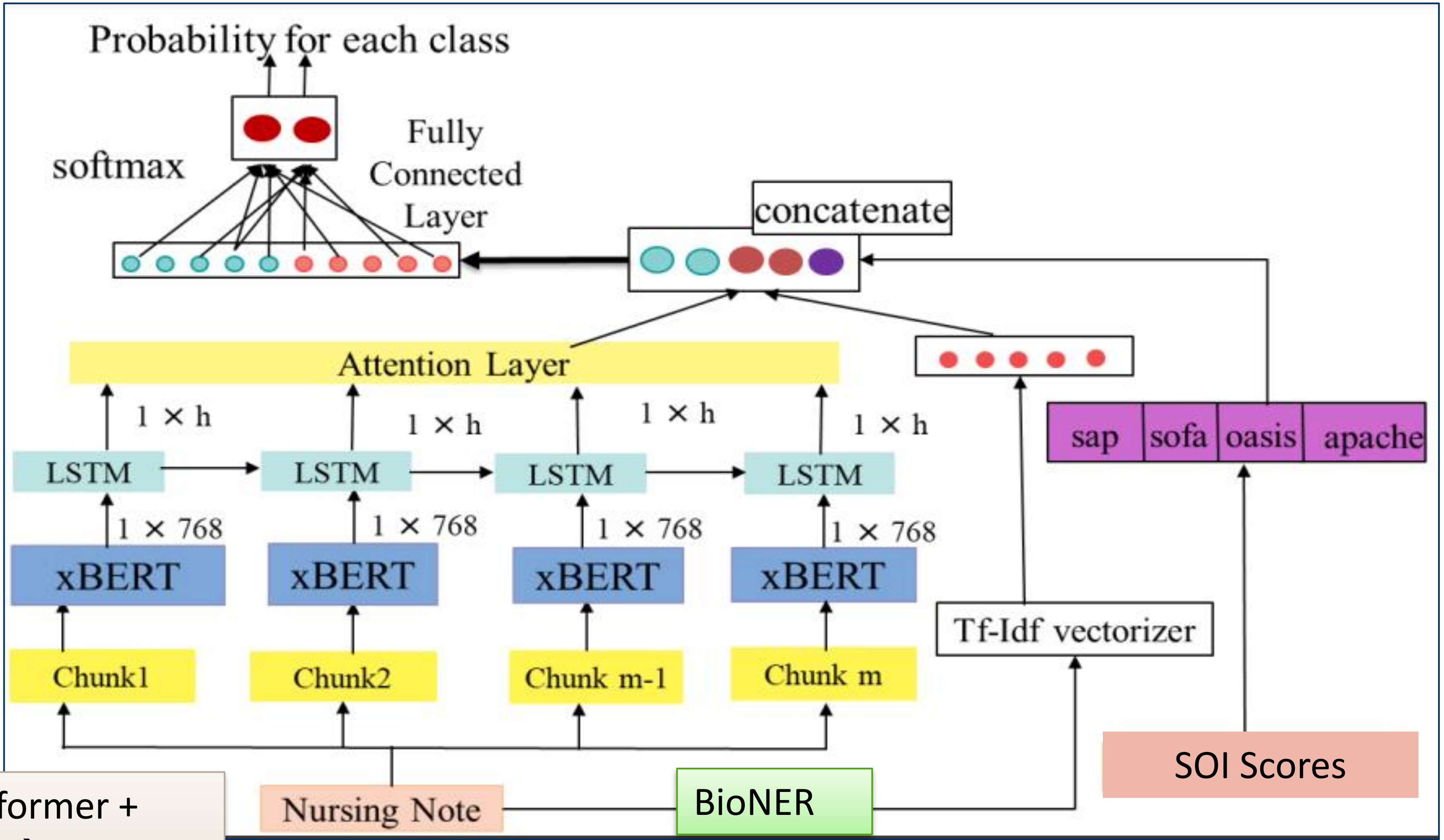
Patient's Demography · Patient's Condition · Treatments/ Medications · Test results · Negative symptoms · Treatment plans

Severity of Illness Score

- **Acute Physiology and Chronic Health Evaluation (APACHE-II) score** – Uses 12 physiological variables that include mean arterial pressure, temperature, heart rate, respiratory rate, oxygenation, GCS, pH, sodium, potassium, creatinine, hematocrit, and WBC level in the blood
- **Simplified Acute Physiology Score (SAPS-II)** - Uses logistic regression techniques to predict the SOI using 12 physiological variables, age, type of admission such as surgical or medical, and three variables related to acquired immuno-deficiency syndrome, metastatic cancer, and hematologic malignancy
- **Sepsis-related Organ Failure Assessment (SOFA) score** - Used to measure a person's organ function or rate of failure during the stay in an ICU. This score is based on six different values coming from the assessment of the respiratory, cardiovascular, hepatic, coagulation, renal, and neurological systems
- **Oxford Acute Severity of Illness Score (OASIS)** - computed from 10 variables: elective surgery, age, pre-ICU length of stay, and seven physiological measurements

For our model, all four scores are calculated using data from first 24 h of ICU stay only – using libraries

Multimodal DNN for Predicting ICU LOS



Transformer + LSTM → handles long notes

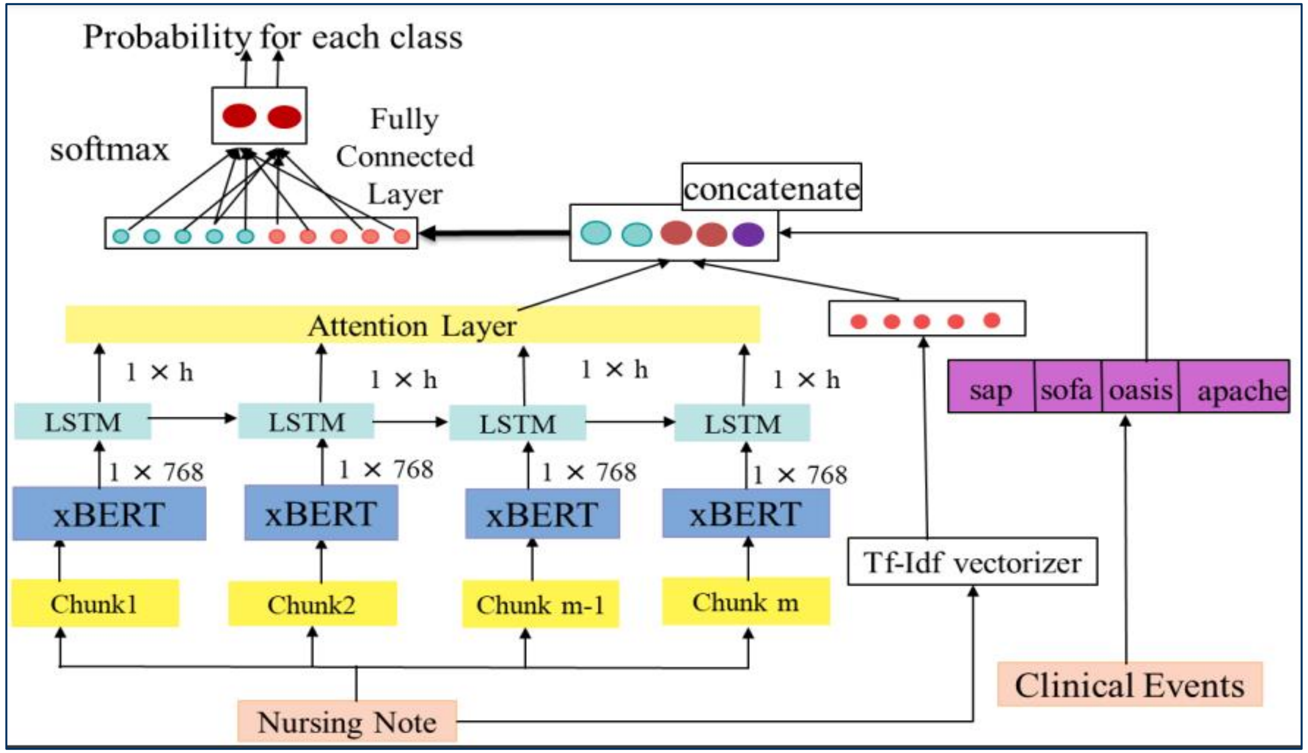
TF-IDF weights of Top 2000 significant Linguistic features fed additionally

X-BERT

Clinical BioBERT - developed by further training the BioBERT (base version; 110 million parameters with 12 layers, 768 hidden units, and 12 attention heads) using clinical text from the MIMIC-III corpus.

BlueBERT - language model trained on Biomedical and Clinical texts – PUBMED abstracts and MIMIC III clinical notes

LIME Framework to add explainability



Local Interpretable Model-agnostic Explanations

Attempts to understand the model by perturbing the input of data samples and observe how the predictions change

- *Weighted average from multi-head attention models*

Output

Long ICU Stays - "HR dropping", "requiring mask ventilation for resp. failure", "couldn't breathe"

Short ICU Stays - "good effect from Ativan", "comfortable breathing", "hemodynamically stable"

Results obtained from 22789 admissions which had Nursing Notes for first day

Model	Accuracy	F1 score Class 'Short'	F1 score Class 'Long'	AUC-ROC
BlueBERT+LSTM+Attn+TF-IDF+SOI	**0.797**	**0.810**	**0.790**	0.872
BlueBERT+LSTM+Attn+TF-IDF	0.792	0.800	**0.790**	**0.873**
BlueBERT+CNN+TF-IDF	0.789	0.800	0.780	0.872
BlueBERT	0.776	0.790	0.760	0.833
Clinical BioBERT+LSTM+TF-IDF+SOI	0.780	0.790	0.770	0.871
Clinical BioBERT+LSTM+TF-IDF	0.778	0.780	0.770	0.857
Clinical BioBERT+CNN+TF-IDF	0.776	0.780	0.770	0.864
Clinical BioBERT	0.741	0.750	0.730	0.818

Studying the Discharge Notes to gain insights about wrong predictions

- Patients developed complications mid-way

- Complications could be about other organs and not related to the disease on admission

- Initial Nursing Notes not always indicative of type of procedures patients underwent later
  - ***Admitted for Pneumonia – underwent Bypass Surgeries***
  - ***Delay in scheduling unplanned procedure***

- Four most common procedures
  - Bypass Surgery
  - Stenting
  - Tracheotomy
  - Cholecystectomy

Reformulated Problem – Predict LOS and Major Procedure requirements

- ***Helps in better planning of resources***
- ***Better expectation management for patient’s family***

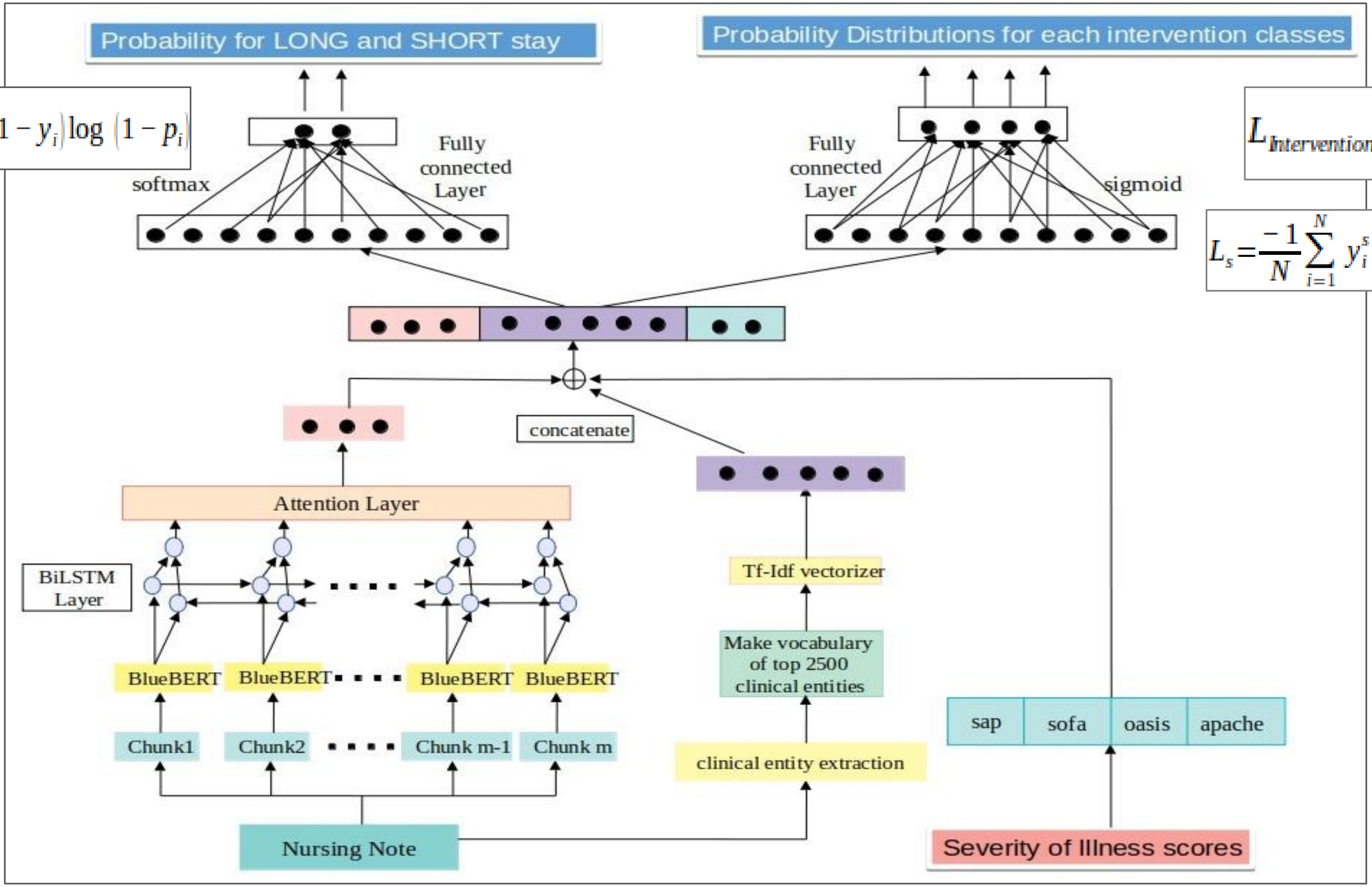
Multitask, Multimodal Architecture for predicting LOS and Major Procedures

$$L_{joint} = \lambda * L_{LOS} + (1-\lambda) * L_{Intervention}$$

$$L_{LOS} = \frac{-1}{N} \sum_{i=1}^{N} y_i \log p_i + (1-y_i) \log (1-p_i)$$

$$L_{Intervention} = \sum_{s \in interventions} L_s$$

$$L_s = \frac{-1}{N} \sum_{i=1}^{N} y_i^s \log p_i^s + (1-y_i^s) \log (1-p_i^s)$$



Results

ICU LOS Prediction

Model	Accuracy	F1 score 'Short'	F1 score 'Long'	AUC
Multitask BiLSTM-blueBERT with tf_idf and SOI	**0.84**	**0.86**	**0.82**	**0.89**
Multitask BiLSTM-blueBERT with tf_idf	0.83	0.84	0.80	0.87
Multitask BiLSTM-blueBERT	0.79	0.79	0.78	0.85
BiLSTM-blueBERT with tf_idf and SOI	0.79	0.81	0.79	0.86
BiLSTM-blueBERT with tf_idf	0.79	0.80	0.78	0.84
BiLSTM-blueBERT	0.77	0.77	0.76	0.83

Procedure Prediction

Model	Accuracy	F1 score "Bypass"	F1 score "Stent"	F1 score "Tracheotomy"	F1 score "Cholecystectomy"	AUC
Multitask BiLSTM-blueBERT with tf_idf and SOI	**0.82**	**0.89**	**0.83**	**0.55**	**0.54**	**0.86**
Multitask BiLSTM-blueBERT with tf_idf	0.81	0.86	0.81	0.53	0.51	0.85
Multitask BiLSTM-blueBERT	0.80	0.85	0.78	0.51	0.48	0.83
BiLSTM-blueBERT with tf_idf and SOI	0.80	0.85	0.79	0.49	0.49	0.83
BiLSTM-blueBERT with tf_idf	0.78	0.81	0.78	0.48	0.46	0.83
BiLSTM-blueBERT	0.77	0.81	0.79	0.47	0.46	0.81

AUC: area under the receiver operating characteristic; SOI: severity of illness.
We report accuracies, AUC scores of the model, and F1 scores of all four classes. Bold values indicate the best performance of our experiments.

Utility of Prediction Model

Procedure Name	Recall	Precision	Gain = (TP-Mentioned_in_firstnote)/total_number)%
Bypass Surgery	0.98	0.82	**47.97**
Stenting	0.75	0.92	**31.92**
Tracheotomy	0.71	0.44	**68.15**
Cholecystectomy	0.41	0.78	**30.93**

Model was able to predict many procedures on first day itself – ***doctors did it much later***

Symptom correlations to procedures were identified by model

Digging Deeper

- We observed that - Though “long” / “short” predictions have improved and are good enough for hospital management – ***actual length prediction of stay is not so good***

- Key observations
  - Two patients with very similar symptoms for major diseases have very different outcomes in terms of Length of Stay
  - Prescriptions / Treatments varied for patients with similar symptoms
  - Actual outcomes may be dependent on comorbidities present

- Individual Outcomes for patients - Risk Assessment

- Patient cohorts - can provide better understanding of diseases when studied in smaller groups

Risk Stratification and Patient Cohorts

- Process to identify individuals who are at different levels of risk for a particular disease
  - in terms of disease progression, complications, or adverse events
- Risk scores are calculated by assigning weights to patient's clinical parameters
- Cohort studies are a way to understand the factors

What is a Patient cohort

It is a term used in medical research to define ***groupings of individuals with common traits, such as social and health factors***

Patient cohorts are integral to researching and developing effective medical interventions

Observational medical studies begin with selecting a patient cohort

Identifying Patient Cohorts using Machine Learning

- Patient Cohorts are selected by clinical researchers
- Studies are rarely reproducible
- ***How do we obtain cohorts and understand risk factors automatically from open research data?***
  - ***Clustering!***

Identifying cohorts within Patient Data

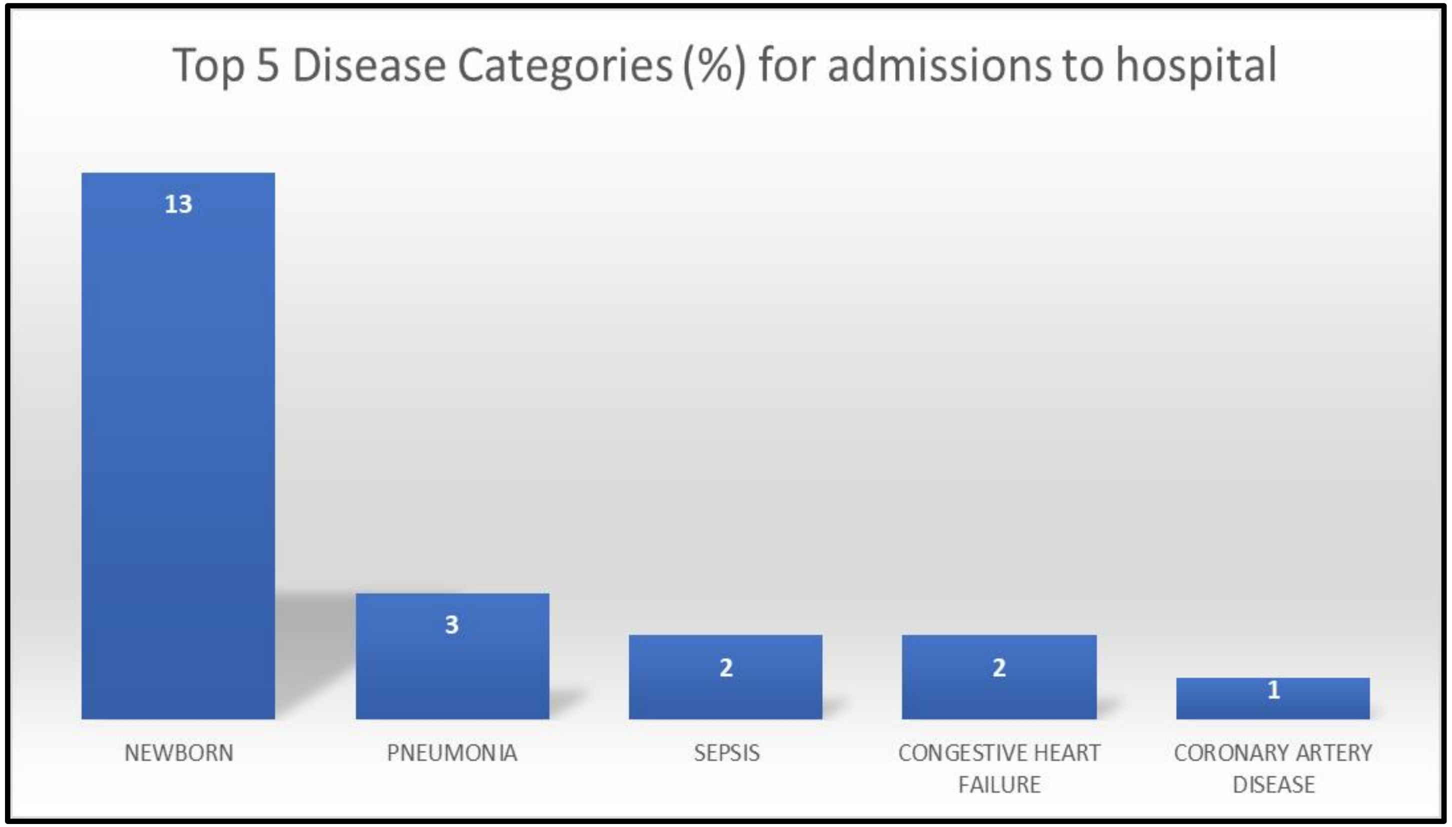
OBJECTIVE:

BETTER RISK ASSESSMENT FOR EACH COHORT

BETTER PREDICTION OF RESOURCES

Choosing the disease to study

- Working with entire dataset for cohort detection did not yield meaningful insights
  - ***Cohort identification is usually done on subsets of patients admitted for a particular disease***
- Nursing Notes of NewBorn is noisy – contains information about mother and neo-natal – ***pneumonia***



Chose Pneumonia as a subset for experimentation

Processing Nursing Notes

Clustering Nursing Notes directly did not yield good results

Use of Bio-medical Resources can help

Using SciSpacy and Metamap

Detect Negation and its argument using Negex

Standardization using Unified Medical Language System (UMLS) - Entity Resolution

Union of all entities used as Basis for representation

Scispacy detects Disease names Metamap detects

- Disease or Syndrome
- Acquired Abnormality
- Congenital Abnormality
- Mental or Behavioral Dysfunction
- Injury or Poisoning
- Mental process
- Anatomical Abnormality
- Sign or Symptom

Example

patient denied chest pain → neg (chest pain)

Example - Hypertension, High Blood pressure, Hypertensive Disorder, Arterial Hypertension

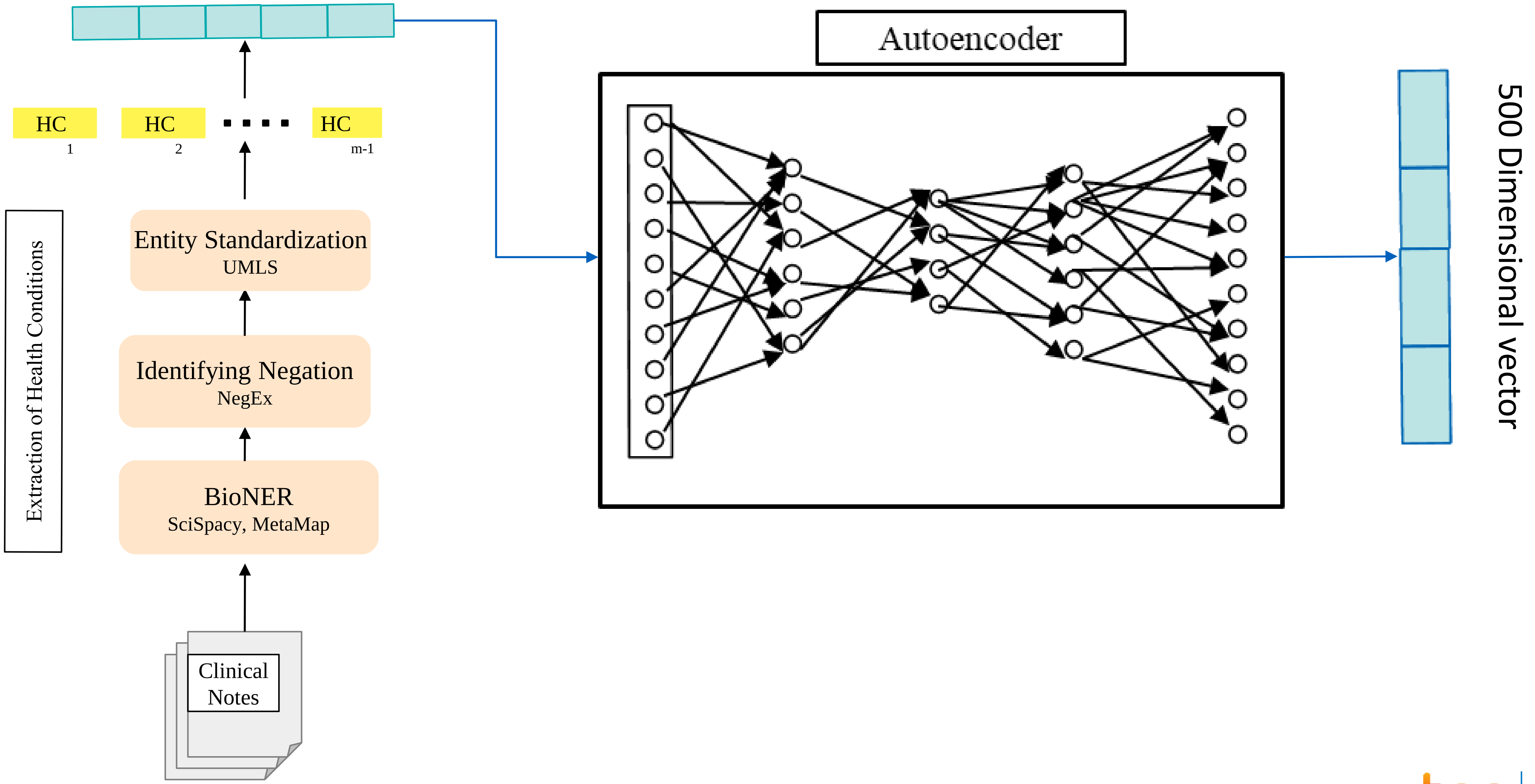
4000+ unique entities

UMLS - A set of files and software that brings together many health and biomedical vocabularies and standards to enable interoperability between computer systems.

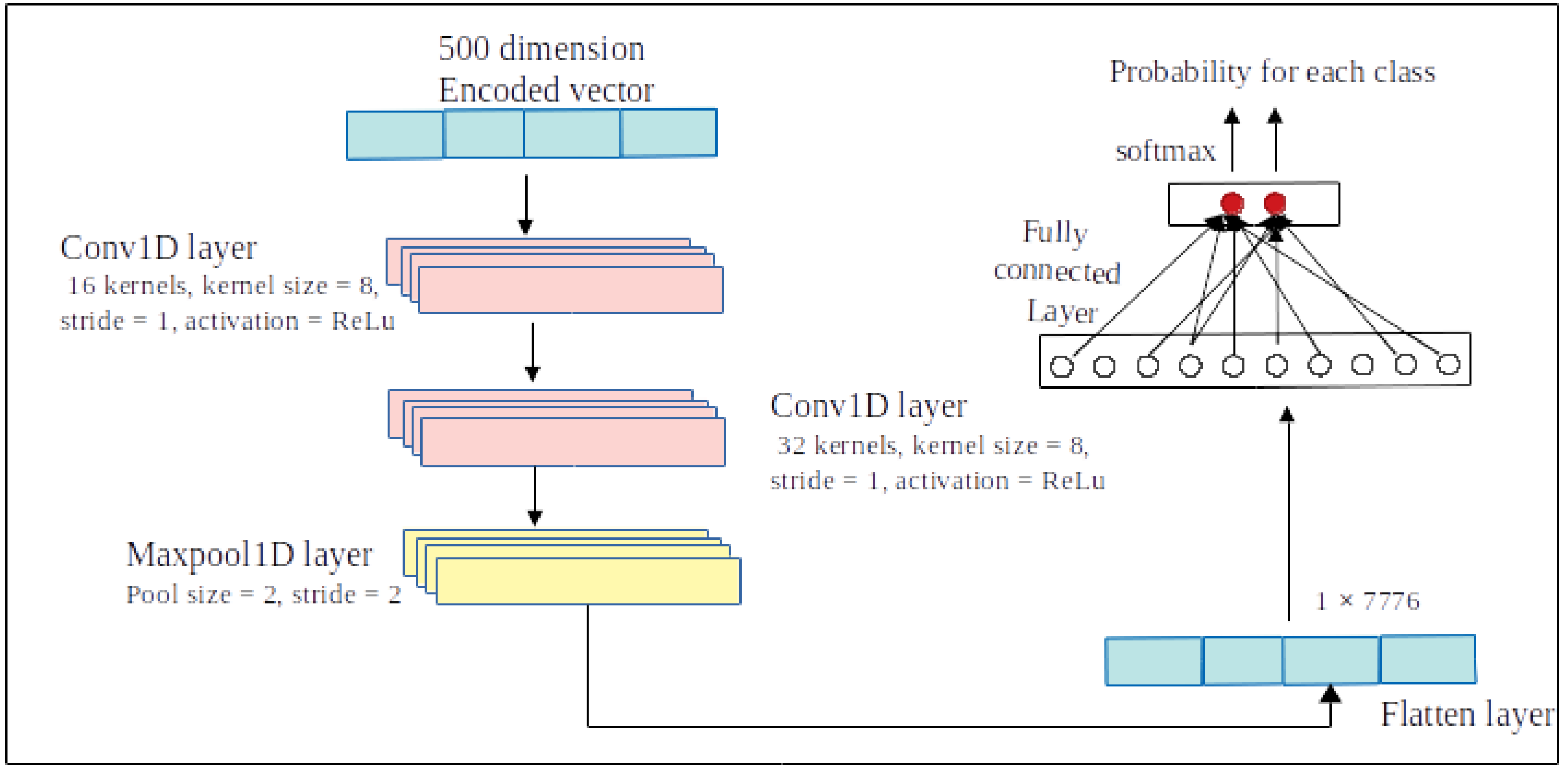
The Metathesaurus is the biggest component of the UMLS. It is a large biomedical thesaurus that is organized by concept, or meaning, and it links similar names for the same concept from nearly 200 different vocabularies

Autoencoders for representation of Nursing Notes

Binary vector of 4541 health conditions – Large and Sparse



LOS Prediction for Pneumonia Patients using Autoencoders and CNN



Observation

Though accuracy improved - actual values predicted were still way off

Shorter stays were more difficult to predict

Varied combination of comorbidities led to different outcomes

Hospital Stay	Recall	Precision	F1-score
Short	0.64	0.94	**0.76**
Long	0.97	0.80	**0.88**

Accuracy Score : 0.83

K-means Clustering of Auto encoded Nursing Notes

- Input Auto-encoder vectors
- Distance Metric - Euclidean distance
- Set ***k = 2***
- Iterate to find right value of ***k*** by optimizing the Silhouette Score
  - Measure Silhouette score of each point ***i*** belonging to C_I as

$$s'(i) = \frac{b'(i) - a'(i)}{\max\{a'(i), b'(i)\}}$$

  - where

$$a'(i) = d(i, \mu_{C_I}) \qquad b'(i) = \min_{C_J \neq C_I} d(i, \mu_{C_J})$$

  - Compute Silhouette Coefficient as

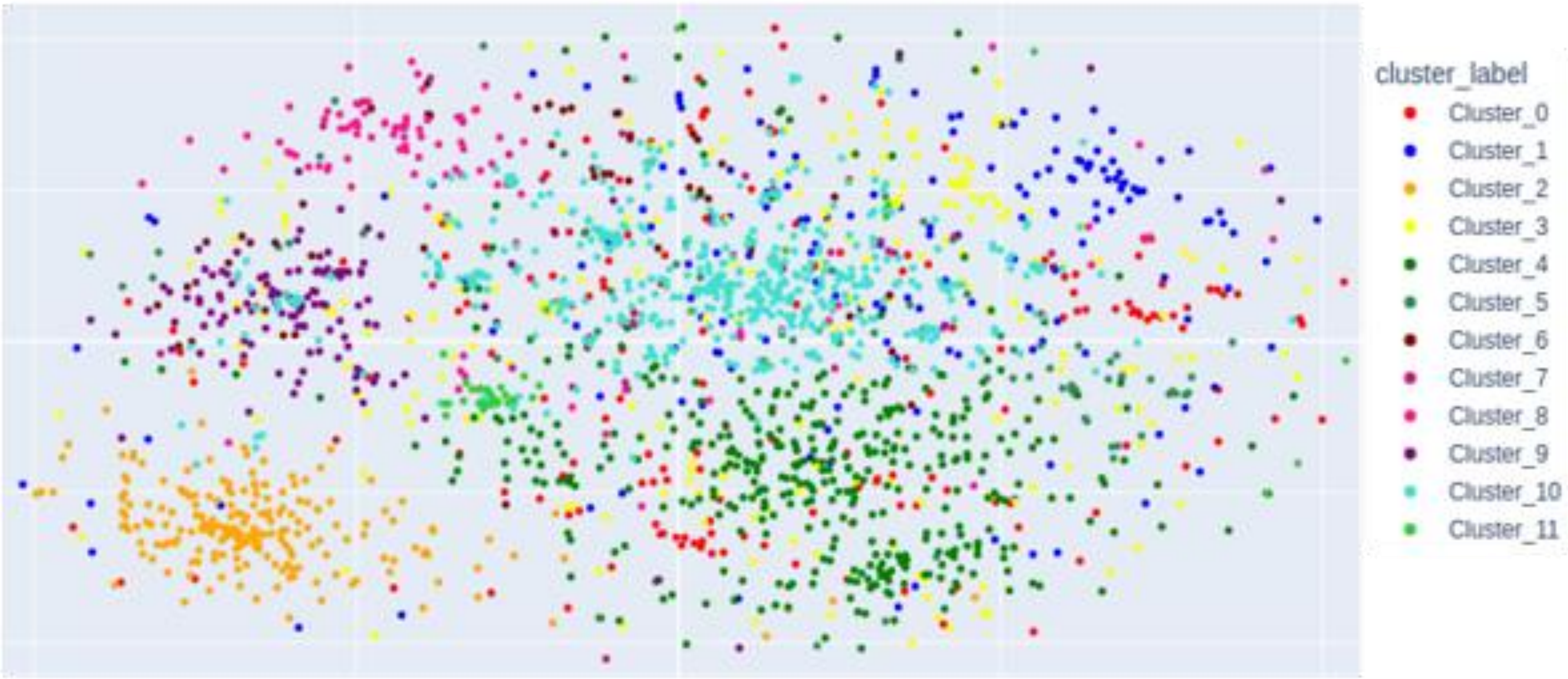
$$SC' = \max_k \frac{1}{N} \sum_i s'(i)$$

- Find ***k which minimizes*** Silhouette Coefficient

Silhouette coefficient of each point measures its relative distance from its own cluster center and other centers - ***cohesiveness versus distinctiveness***

Silhouette coefficient measures the maximum value of the mean of all scores

Clustering 2106 Pneumonia Patients – 2D visualization using tSNE



How to interpret the clusters?

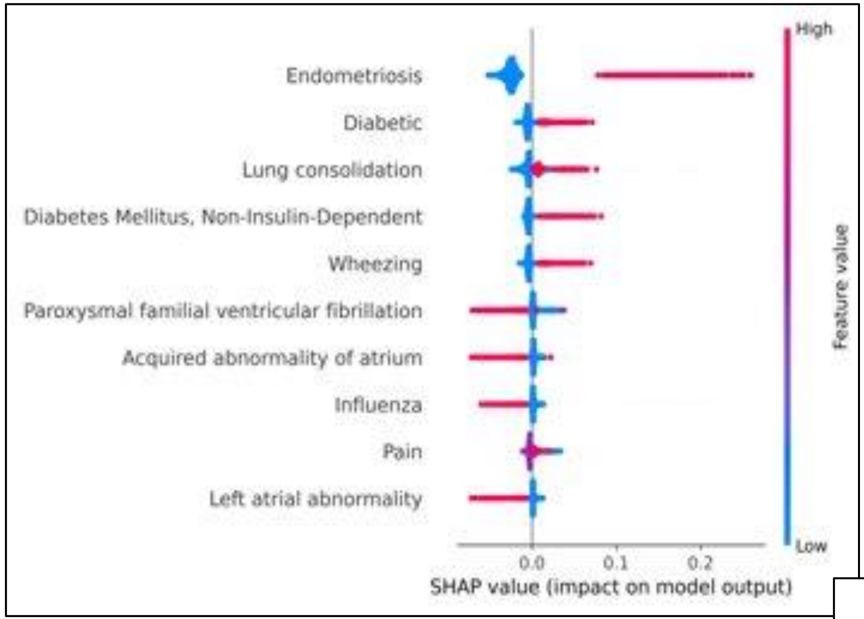
SHAP Values for interpreting clusters

- SHAP values are based on game theory
  - Determines the importance of each feature towards label assignment
- Features with positive SHAP values positively impact the prediction, while those with negative values have a negative impact
- Magnitude measures the strength of impact

- Using the Cluster IDs as label
- The original 4541 entity vector was used as input to a Random Forest Classifier
- Models were fed to SHAP tree explainer
- Obtained the SHAP values for each feature towards determination of the labels

SHAP Explainability for a few clusters

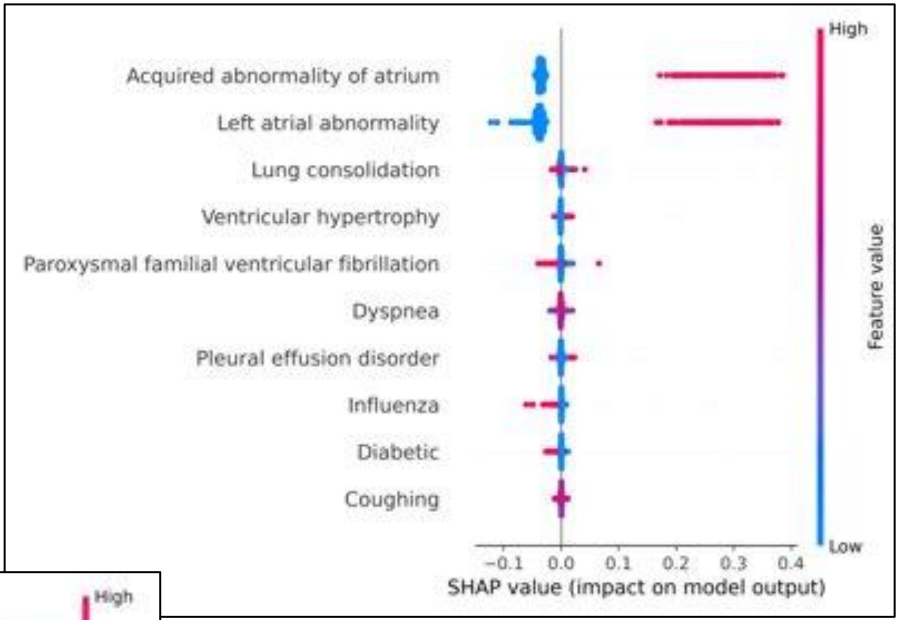
Cluster 2 – Acquired Abnormality of Atrium, Left Atrial Abnormality

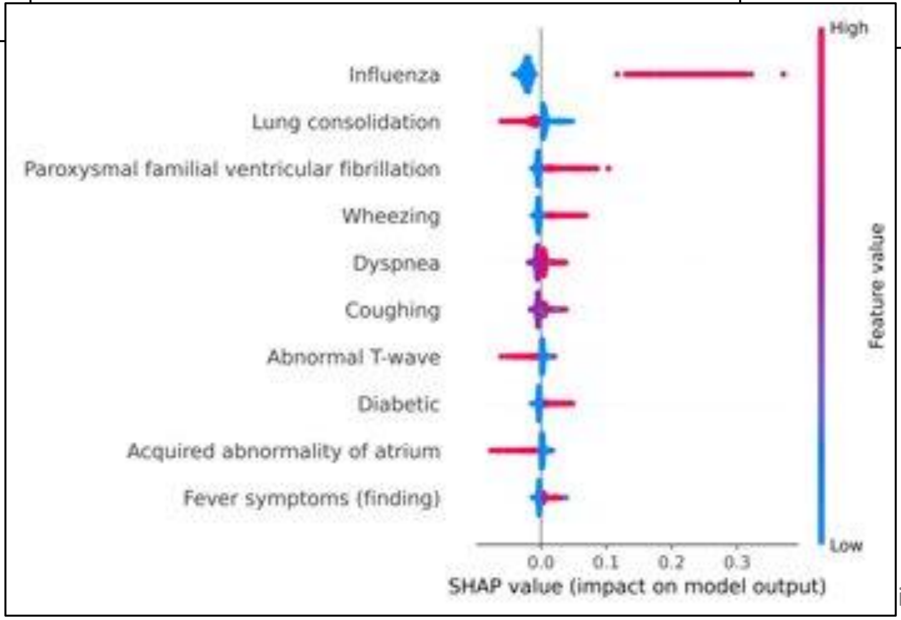


Cluster 0 – Diabetic Patients with Endometriosis

Each cluster could be described uniquely using top three disease / symptom as attributes (present / absent)

Cluster 1 – Influenza, Lung Consolidation absent

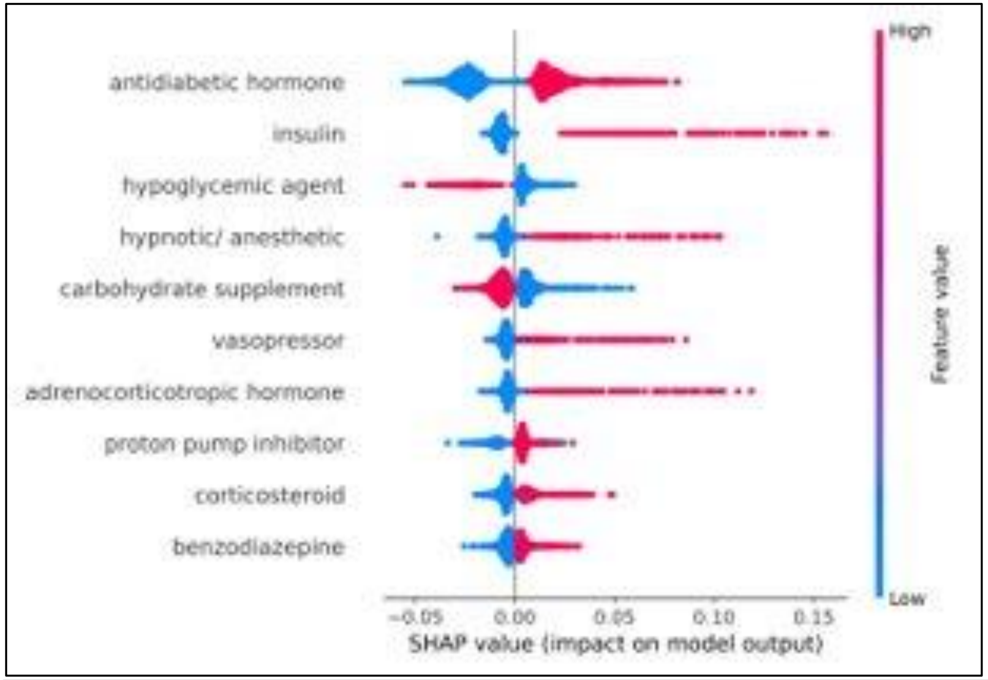




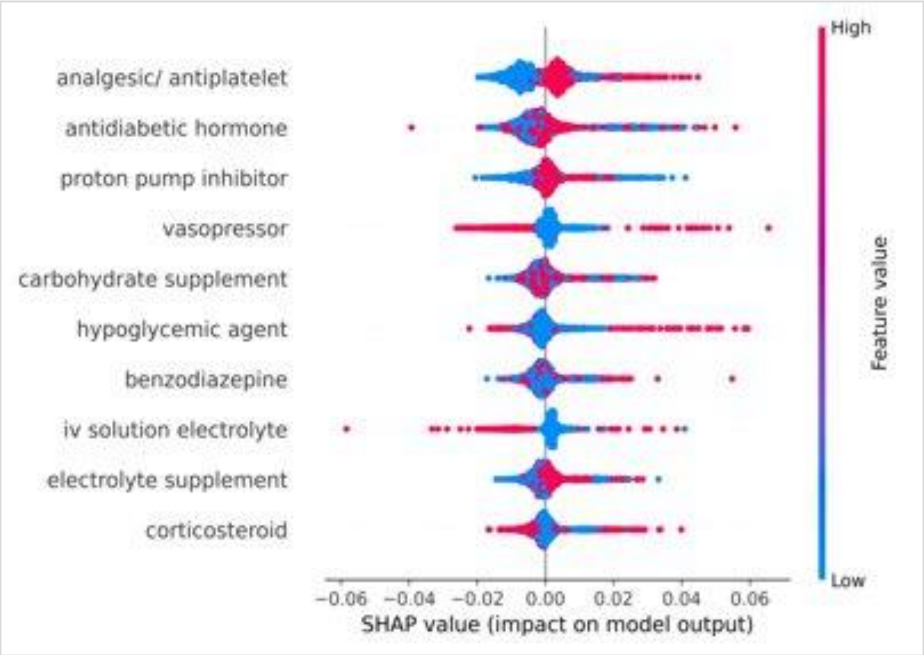
Cluster Overview

Clusters	Number of patient	key diseases present	key disease absence	Key drug category administrated	Key drug category not administrated	Mode LOS	Most patients in the age group
Cluster 0	175	Endometriosis (86%), Diabetes (74%)	Paroxysmal familial ventricular fibrillation, Acquired abnormality of atrium, Influenza	antidiabetic hormone, insulin, hypnotic/anesthetic	hypoglycemic agent	7 days	60-80 years
Cluster 1	174	Influenza(70%)	Lung Consolidation, Acquired abnormality of atrium	antiviral medication for influenza	hypoglycemic agent	7 days	60-80 years
Cluster 2	205	Acquired abnormality of atrium(99%), Left atrial abnormality(98%)	Paroxysmal familial ventricular fibrillation	analgesic/ antiplatelet, proton pump inhibitor	vasopressor	4 days	60-80 years
Cluster 3	228	Paroxysmal familial ventricular fibrillation(91%)	Influenza, Acquired abnormality of atrium, Left atrial abnormality	antidiabetic hormone, vasopressor	hypoglycemic agent, corticosteroid	9 days	60-80 years
Cluster 4	405	Lung Consolidation(93%)	Paroxysmal familial ventricular fibrillation, Acquired abnormality of atrium, Left atrial abnormality, Endometriosis	carbohydrate supplement, hypoglycemic agent, proton pump inhibitor	antidiabetic hormone, insulin, analgesic/ antiplatelet	6 days	60-80 years
Cluster 5	65	Pleural effusion disorder(92%), Bilateral pleural effusion(78%)	Lung Consolidation, Paroxysmal familial ventricular fibrillation	hypoglycemic agent, diuretic, analgesic/ antiplatelet	antidiabetic hormone	5 days	Above 80 years
Cluster 6	51	Atrial Premature Complexes(84%)	Lung Consolidation, Paroxysmal familial ventricular fibrillation	Vasopressor, antidiabetic hormone, proton pump inhibitor, beta-blocker, anticonvulsant/ neuropathic pain agent	Insulin	8 days	Above 80 years
Cluster 7	31	Pneumonia (71%), Edema(50%)	Lung Consolidation, Paroxysmal familial ventricular fibrillation	Corticosteroid, Vasopressor	antidiabetic hormone, proton pump inhibitor, hypoglycemic agent, hypnotic/anesthetic, diuretic	9 days	60-80 years
Cluster 8	101	Left anterior fascicular block(81%), Left axis deviation(60%)	Lung Consolidation, Pleural effusion disorder	hypoglycemic agent, beta-blocker	antidiabetic hormone, proton pump inhibitor, opioid analgesic	7 days	Above 80 years
Cluster 9	120	Abnormal T-wave (95%)	Lung Consolidation, Acquired abnormality of atrium, Left atrial abnormality	carbohydrate supplement, analgesic/ antiplatelet, beta-blocker	proton pump inhibitor, antidiabetic hormone, benzodiazepine	5 days	60-80 years
Cluster 10	516	No diseases predominantly occurred	Lung Consolidation, Paroxysmal familial ventricular fibrillation, Pleural effusion disorder, Acquired abnormality of atrium	hypoglycemic agent	antidiabetic hormone, Vasopressor, proton pump inhibitor	6 days	60-80 years
Cluster 11	35	Ventricular hypertrophy(89%)	Lung Consolidation, Paroxysmal familial ventricular fibrillation, Abnormal T-wave	hypoglycemic agent, analgesic/ antiplatelet	antidiabetic hormone, Vasopressor	6 days	Above 80 years

SHAP values for Drug Associations with each cluster



Cluster 0 – Anti diabetic hormone, Insulin, vasopressor



Cluster 2 – Analgesic, proton pump inhibitor

Drug – Cluster Associations were not significantly unique

More or less same drugs were administered to patients of all clusters

Causality Analysis of Drugs - DoWHY

Disease and Symptoms of each patient were given as attributes – LOS was target variable – drugs as interventions

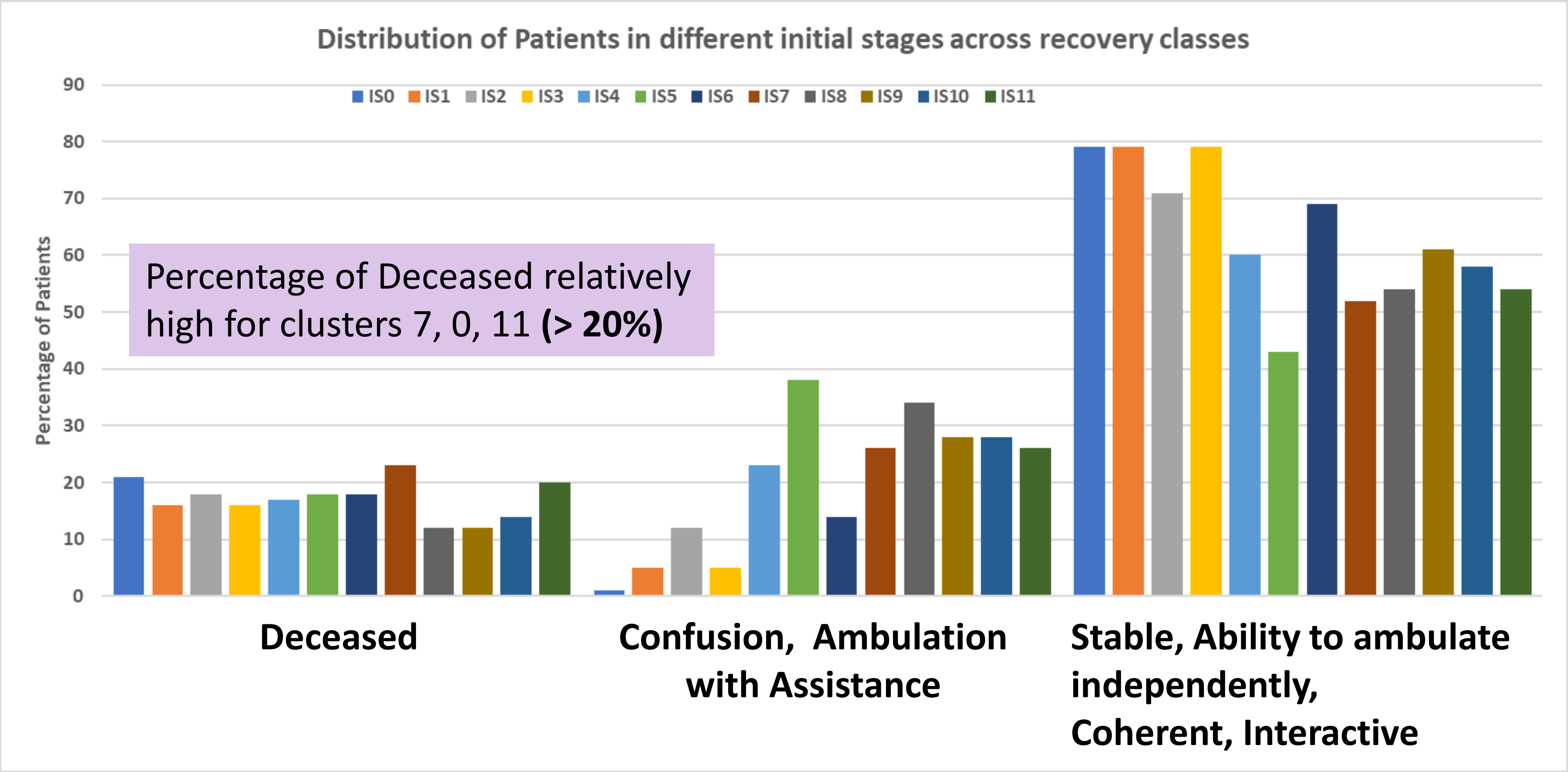
Example Observations

Adrenocorticotropic Hormone → seriously ill patients Suffering from Endometriosis

For patients suffering from ***arterial premature complexes in cluster 6*** - drugs effective in reducing stay were *Corticosteroid* (-3.17), *Anticonvulsant/ neuropathic pain agent* (-3.02), *Opioid analgesic* (-2.4), *Vasopressor* (-1.02)

	Cluster 0	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6	Cluster 7	Cluster 8	Cluster 9	Cluster 10	Cluster 11
adrenocorticotropic hormone	3.34	-	-	-	-	-	-	-	-	-	-	-
analgesic/ antiplatelet	-0.06	0.93	-0.31	-0.96	-2.02	0.50	1.43	-4.69	1.66	-0.36	-1.06	0.86
analgesic/ antipyretic	-	-	-	-	-0.44	-	-	-	-	0.19	-	-
antibiotic/antiprotozoal	-	-	-	0.88	-	-	-	-	-	-	-	-
anticonvulsant/ neuropathic pain	-	-	-	-	-	-	-3.03	-	-	-	-	-
antidepressant	-	-	-	-	-	-	-	-	-	-	-	-1.30
antidiabetic hormone	-0.46	1.41	1.59	1.28	1.41	-0.88	2.09	6.70	-0.17	1.37	-0.86	2.70
antiplatelet	-	-	-	-	-	-	-	-	-	0.81	-	-
antiseptic	0.24	3.49	-0.02	0.60	1.44	0.16	0.88	3.34	2.08	-	0.83	-2.70
antiviral medication for influenza	-	4.12	-	-	-	-	-	-	-	-	-	-
benzodiazepine	4.74	-	1.66	-	0.94	2.31	0.77	4.03	2.10	0.30	1.19	-2.46
beta-blocker	-	1.88	-1.36	-	-2.74	1.02	0.25	-3.98	-0.25	1.76	-	0.42
bronchodilator	3.00	-	0.59	-0.57	-1.51	0.64	-	-	-2.77	-	-	-
carbohydrate supplement	1.62	0.47	-0.14	-0.20	0.24	-2.39	1.51	-6.27	1.77	2.37	-1.71	2.19
corticosteroid	0.06	2.53	2.47	-0.86	-	-	-3.18	5.32	-	0.00	-	-2.92
diuretic	-	-	-	-1.89	-	0.96	-	-	-	-	-	-
electrolyte supplement	2.96	1.34	0.01	1.12	0.75	0.86	-5.05	-7.54	1.57	1.53	-0.30	-1.30
h2 blocker	-	-	-	-1.08	-	-	-	-	-	-	-0.26	-
hypnotic/ anesthetic	6.07	-	-	-	-	-	-	0.00	-	-	1.60	-
hypoglycemic agent	0.64	-0.46	-1.12	1.98	1.10	-2.75	-	1.26	-0.17	0.68	-2.43	4.11
insulin	1.49	-	3.57	-	0.41	-	-	-	-	-	1.21	-
iron supplement	-	-	-	-	-	-	-	-	-	-	-	1.27
iv solution electrolyte	-	-2.77	-2.60	-	-	-	-	-	-	-	-	-
iv solution electrolyte/ carbohydra	-	1.64	-	-1.19	-	-	-	-	0.08	-0.45	-1.81	-
laxative	-	-	-	-	-	2.08	0.92	4.72	-	-1.34	-	-
multivitamin supplement	-	-	-	-	-	-	-	-	-	-	-	-3.03
opioid analgesic	3.33	-	1.11	1.45	2.11	1.57	-2.42	2.33	0.64	-0.29	0.19	1.91
proton pump inhibitor	2.75	0.40	0.51	0.60	1.23	-0.67	1.00	2.45	-0.08	1.03	0.90	0.19
statin	-	-	-	-	-	-	-	-	2.14	-	-	-
stool softener	-	1.10	-	-	-	1.69	-	1.47	-	-	-	-
thyroid hormone	-	-	-	-	-	-	-0.47	-	1.10	-	-	-
vaccine	-	-	-	-	0.58	-	-	-	-	-	-	-
vasopressor	2.42	3.35	5.52	1.30	1.72	-0.45	-1.02	-2.68	1.47	1.53	0.94	6.77
vitamin supplement	-	1.72	-	-	-	-	-2.45	-	-	-	-1.17	-

Cluster-wise Recovery Status (identified from Discharge Notes)



High Risk Pneumonia Patient cohorts identified as those with Risk of Death > 20%

Cluster 7 – *Edema, Hypotensive, Left axis deviation;*

Cluster 0 – *Endometriosis and Diabetes;*

Cluster 11 – *Ventricular hypertrophy*

Risk calculation – Probability of Discharge State given Initial Symptoms

P(Discharge State/Symptom) - computed cluster-wise and over whole dataset

End-state is mostly dependent on Comorbidities rather than majority symptoms – rare events and combinations are more informative

- Initial Comorbidites that have high probability of State Deceased
  - Chronic multifocal osteomyelitis → Deceased (0.85)
  - Portal Vein Thrombosis → Deceased (0.6)
  - Renal Osteodystrophy → Deceased (0.6)
  - Diverticulosis of sigmoid colon→ Confusion, Ambulation with Assistance (0.7)
  - ***Most of the above symptoms are rare (0.01% each) and distributed across clusters***

Learnings from Patient Cohorts

- Clustering and Classification models mostly learn majority features and feature-class associations
  - ***Actual risk factors may be the rare symptoms***

- Each patient belonging to a cluster may share majority features but differ in certain unique aspects which determine the true value of risk and also actual hospital stay
  - ***Not aptly captured by models***

- A lot depends on correct encoding of observations
  - ***discovery of "Chronic multifocal osteomyelitis" after 7 days – is it a new disease or existing disease discovered?***
  - ***If this was present in first day - would prediction be better?***
  - ***Would it help if these factors are known a priori? Would hospitals test for these?***

To Conclude

- Predictive power of Nursing notes are relatively less explored
  - Can improve prediction of Hospital stay and procedure requirements effectively
  - Accuracy of LOS prediction improves when patients of a single disease are considered
  - Explainable mechanisms can provide insights about predictions
- Better insights are possible to obtain from Patient Cohorts

  - Combination of auto-encoders and SHAP explainability offers rich insights about Risks associated

<u>Work in Progress</u>

- Modeling mid-stage records
  - Tracking progression of symptoms – old and new
  - Reconstruction of Recovery Pathways with probabilities
    - Modeling path to recovery as a set of transitions and onset of new knowledge
    - Explainable Risk assessment framework
  - Using other modes of data from MIMIC Database

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Thank You