Final Report: MedMap – The NLP-Driven Healthcare Visualization Tool

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1. Introduction/Problem definition: Throughout a typical workday, physicians dedicate more than half their working time to reviewing, analyzing, and entering data into electronic health records (EHRs). Consequentially, this time competes with their time with patients and working with other clinicians, leading to increased physician dissatisfaction, burnout, and harm to the patient. Seeing an opportunity to alleviate this burden for these workers, our solution aims to use advanced Natural Language Processing (NLP) techniques to transform raw clinical data into interactive visual reports for healthcare professionals and stakeholders, simplifying time-consuming interactions with EHRs and improving clinical productivity. The novelty of this approach considers a wider array of chronic diseases, with filtering features that enable healthcare professionals to quickly access patient information by highlighting key medical phrases such as main diagnosis, comorbidities, procedures, and medications. This NLP-driven interactive healthcare visualization tool, called MedMap, will enable users to draw comparisons among patients with similar conditions, enhancing clinical decision-making and personalized care. Given our team's lack of subject matter expertise, we are treating MedMap as a proof-of-concept expanding upon existing implementations, ensuring we integrate human-in-the-loop design to receive feedback and verification from clinicians.

2. Literature Survey: To highlight the clinical need, physicians spend an average of 16 minutes and 14 seconds in EHRs per patient encounter [1], reducing direct provider-to-patient interaction time and contributing to physician burnout and job dissatisfaction. This culminates in, of the average 11.4 hours worked per day, family medicine physicians spending 5.9 of those hours interacting with a computer [2]. It is documented that the shorter the visit, the greater the likelihood of patient harm with inappropriate prescriptions such as overprescription of antibiotics or harmful drug interactions like the co-prescription of opioids and benzodiazepines [3].

Considering the diverse types and formats of EHRs, such as discharge summaries, procedural notes, lab reports, etc., as well as varying data structures among practices, and hospitals, and clinics, Robertson [4] and Morrison [5] point out the complexity of managing and processing unstructured healthcare data. Ford [6], Abudiyab [7], and Chishtie [8] highlight the importance of preprocessing complex datasets to enable robust data analytics and visualizations downstream for healthcare end-users. Kop [9], Liu [10], Adarsh [11], and Suryanarayanan [12] highlight NLP's role in improving efficiency, accelerating data extraction, and enhancing clinical decisions. Inspired by Benavent's [13] and Grout's [14] research using NLP to identify and understand comorbidities for patients with rheumatoid arthritis and diabetes and by Shah-Mohammadi's and Finkelstein's [15] demonstration of the effectiveness of using NLP to accurately detect Chronic Obstructive Pulmonary Disease within the first 24 hours of hospital admissions for patients, our team is expanding MedMap to encompass a wider array of chronic diseases. As highlighted by Velupillai [16], the adaptation and effective use of NLP for health outcomes research underscores the necessity for advancements in visualization techniques. Tian [17] and Shaikh [18] additionally underscore the importance of developing intuitive designs with data for interacting visualizations. The team will focus on maximizing the user-friendliness of MedMap, considering the unique needs of clinicians.

3. Innovations and Methodologies: MedMap integrates several innovative advancements into the existing landscape of healthcare reporting:

1. **Instant Access to the Latest Doctor Visits:** Providing doctors with quick lookup access to the latest doctor visits enhances the efficiency of healthcare delivery. This feature ensures that doctors have the most up-to-date and pertinent information readily available without digging unnecessarily through a lot of noise. Doctors can then make informed decisions during patient consultations and maximize their time with patients by reducing their EHR review time.
2. **Streamlined Patient Matching for Chronic Diseases:** Implementing a logic system that allows for easy application to multiple chronic diseases enables doctors to efficiently match patients with similar conditions, facilitating targeted treatment strategies. This patient matching feature allows doctors to explore patients with similar characteristics using a similarity index. Specifically, our team focused on the following chronic diseases for the final tool: Heart Disease, Cancer, Chronic Lung Disease, Stroke, Alzheimer's Disease, Diabetes, and Chronic Kidney Disease. These are the deadliest or most prevalent chronic diseases cited by the CDC [19].
3. **Enhanced User Interface (UI):** Consolidating key model outputs, MedMap offers a better UI experience for users seeking to explore key medical identifiers and comparisons across patient profiles. By focusing on data relevance and accessibility, the UI streamlines user interactions, improving overall work satisfaction and productivity for clinicians.

The team focused on analyzing discharge summaries for EHRs due to the variety of treatments, medications, lab results, and procedures captured in this type of record. The data comes from the MIMIC-IV clinical database, with 331,794 deidentified discharge summaries for 145,915 patients. These records are complex, given their differentiating data structures across practices, so the team conducted thorough Exploratory Data Analysis (EDA), resulting in the following findings and solutions:

- Most discharge data was in one long format text column, so key sections (i.e., gender, medications, medical history, discharge condition, etc.) were parsed out into separate columns and unnecessary columns were dropped (i.e., deidentified columns such as name and date/time of service).
- The same medical terms can be referred to by different abbreviations, such as COPD for chronic obstructive pulmonary disease, so the team created a dictionary of common abbreviations to find and replace them with their full form, enabling data standardization and greater entity recognition.
- For patients with multiple office visits, several of the prior office visit rows contained vast redundant amounts of information. For MedMap, the team removed all prior office visits to focus on the latest record, creating a new variable to retain the number. The final dataset is a patient-level table with the latest office visit per patient.

After performing data cleaning and parsing, the final patient-level dataset is split into 70% training and 30% testing. Though not an exhaustive list of the final text data, we are exploring the ingestion of the following key columns into our models:

Feature	Description	Type	Example Value(s)
Service	Category of provided service	Text	i.e., Medicine, Surgery, Neurology
Chief complaint	Primary reason for visit	Text	"Chest pain", "acetaminophen overdose"
Major surgical or invasive procedure	Description of procedure performed for this office visit	Text	"none", "intubation with mechanical ventilation (x2) tracheostomy placement right internal jugular..."

History of present illness	Description of preceding events for current illness	Text	"___ y/o m with pmhx of metastatic melanoma, recently admitted ___ for persistent diarrhea..."
Past medical history	General medical history of the patient	Text	"past medical history: aaa, chronic diastolic heart failure with ejection fraction`40%, chronic kidney disease..."
Medications on admission	Medications the patient is currently taking	Text	"2. thyroid 75 mg by mouth daily 3. hydrochlorothiazide 12.5 mg by mouth daily..."
Discharge medications	Medications the patient is prescribed	Text	"1. metronidazole 500 mg tablet sig: one (1) tablet by mouth q8h (every 8 hours)..."
Discharge diagnosis	All diagnoses upon leaving the office	Text	"primary: chronic obstructive pulmonary disease exacerbation, pneumonia, anxiety"
Discharge condition	Mental status and physical condition of the patient	Text	"mental status: clear and coherent... activity status: ambulatory - requires assistance..."

MedMap advances the application of NLP in healthcare, focusing on a comprehensive approach for identifying and managing chronic diseases and their comorbidities in EHRs. While prior work in the field focused on the identification of singular chronic diseases, the team adapted MedMap to more chronic diseases and comorbidities, facilitating a more holistic and efficient patient care model. In particular, the team used industry standard NLP packages in Python (SpaCy, NLTK, and Scikit-Learn) for entity recognition and extraction of key medical terms, allowing for more accessible annotations and expanding the scope of proactive management of chronic diseases.

The team also implemented a lexical similarity algorithm that forms the foundation of the Patient Matcher feature. First, the text is vectorized using Term Frequency Inverse Document Frequency (TF-IDF), which calculates how important a word is based on its number of occurrences. Then an unsupervised clustering algorithm groups together similar patients based on these word vectors. Finally, cosine similarity is computed between patients within the same cluster. This data substantiates a patient's highlighted information, providing the most similar patients to the selected patient for further interactive exploration.

Integration of analytical tools into healthcare systems faces many challenges, with one of the most significant being the lack of effective use of visualization when adopting these tools into the healthcare system. To address this, the team built a Python Streamlit application to create a UI with visualizations that highlight medical terms to allow clinicians to analyze patients with chronic diseases and pop-ups of patients with similar profiles to the patient of interest. These visualizations can assist healthcare professionals and stakeholders (hospitals, clinics, and billing departments) to access and interpret patient data effectively.

The MedMap UI consists of the following three interactive visual tabs:
1. **"Report" Tab**: This tab displays a selected patient's highlighted medical data based on the MedSpacy NLP model. Users can choose a patient ID from the dropdown menu and scroll down to explore easily viewable categories and medical terms in that patient's healthcare record.

MedMap ⚕

The NLP-Driven Healthcare Visualization Tool

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Report   Patient Matcher   Visualization   About

The NLP-Driven Healthcare Visualization Tool

Select a subject ID

10245250 ▾

Below are the details about this patient:

10245250-discharge summary-8

subject_id: 10245250

History of present illness

Select entity labels ▾

___ history of alcoholic cirrhosis c/b hepatocellular carcinoma CANCER s/p ddlt (___) with post-op course c/b coagulopathy leading to washout/exploration, and roux en y hepaticojejunostomy, aortic stenosis HEART_DISEASE well aortic stenosis HEART_DISEASE portal vein stenosis s/p ptbd, cytomegalovirus viremia who now presents with one day of cough, congestion and elevated lfts on outpatient ___. patient reports that he has been feeling well except yesterday started to develop

Medications on admission

Select entity labels ▾

the preadmission medication list incentive spirometry LUNG_DISEASE accurate and complete. 1. metformin DIABETES (metformin DIABETES) 500 magnesium by mouth twice a day 2. ferrous sulfate 325 magnesium by mouth daily 3. multivitamins 1 tablet by mouth daily 4. fluticasone propionate 110mcg 2 puff intrahospital twice a day 5. omeprazole 20 magnesium by mouth daily 6. albuterol inhaler ___ puff intrahospital twice a day

Discharge diagnosis

Select entity labels ▾

primary diagnoses ================== cytomegalovirus viremia acute kidney injury CHRONIC_KIDNEY_DISEASE secondary diagnoses ==================== alcoholic cirrhosis status post deceased donor liver transplant transaminitis macrocytic anemia pancytopenia neutropenia hypertension diabete mellitus

2. **"Patient Matcher" Tab**: This tab displays the most similar patients to the selected patient based on the similarity index algorithm. Of these similar patients, users can choose one from a new dropdown box and explore a similar highlighted report for this chosen similar patient, facilitating comparison between the Report and Patient Matcher tabs.

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Report   Patient Matcher   Visualization   About

Patient Matcher

Disclaimer: Calculating patient similarities... May take a minute or two...

Identified similar patients to the provided patient ID based on Semantic/Language Similarities

Using the selected ID, you can look up the most similar patients to enable physicians to quickly identify treatment plans per cohort.

Select a subject ID

10368348 ▾

	similar_patient_id	similarity_score
0	10285646	0.9894
1	10148333	0.9867
2	10423496	0.9863
3	10436504	0.9857

Select Similar Patient ID

Select a similar subject ID

10067042 ▾

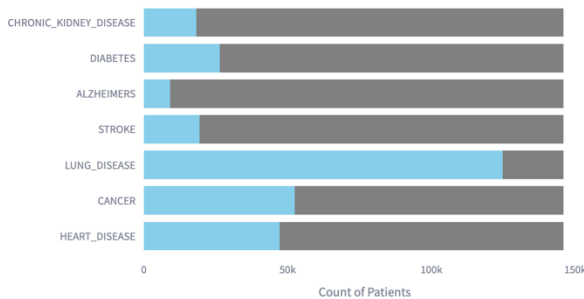achalasia

___ myotomy with partial fundoplication

History of present illness

Select entity labels ▾

medical record. ___ incentive spirometry LUNG_DISEASE a ___ year old patient who presents to discuss surgical intervention due to achalasia. the patient was seen by dr. ___ week atrial tachycardia which time treatment options were outlined to the patient. he states that the achalasia was discovered inch the late ___ when he had a bout of bronchitis. the patient states that he has been suffering from dysphagia for many years. he denies history of reflex symptoms currently. his parents had told him that he would vomit often aortic stenosis HEART_DISEASE a child. he states that he suffers from the events where he feels like his food wants to come back pain up especially atrial tachycardia night. the patient states he has had multiple episodes of bronchitis over the years.

3. **"Visualization" Tab**: This tab provides supplemental visuals for the current EHR data. It includes a bar graph of patients with and without chronic conditions and a histogram of the number of prior office visits broken out by gender with an interactive option for the user to select different Service types.

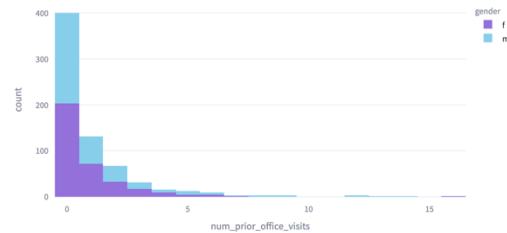Breakdown of Chronic Disease Across All Patient EHRs

Histogram of Prior Office Visits for surgery

4. Experiments and Evaluation: The experiments focused on evaluating the effectiveness of using NLP techniques to accurately identify chronic diseases using NLP. The testbed consisted of a large dataset of de-identified EHRs from MIT's PhysioNet's MIMIC IV (Beth Israel Deaconess Medical Center), ensuring no protected health information (PHI) was included. The key questions the experiments answered were: 1) **Accuracy:** How accurately can NLP models identify chronic diseases? 2) **Model Comparison:** Which pre-trained clinical NLP SpaCy models are most accurate for the reviewing tasks?

The experiments involved using pre-trained SpaCy NLP models and developing custom TargetMatcher rules, patterns used by SpaCy to match specific phrases or entities in text data, to extract relevant clinical information from sections of pre-processed and parsed EHR discharge summaries.

Table 1. Clinical SpaCy Model Performance

Model Name	Average Precision	Average Recall	Average F1 Score
en_core_sci_sm	0.488	0.876	0.573
en_ner_bc5cdr_md	0.483	0.881	0.571
medspacy_md	0.796	0.909	0.783

Table 2. Top Performing Model per Condition

Condition	Model Name	F1 Score
ALZHEIMERS	medspacy_md	0.783
CANCER	medspacy_md	0.948
CHRONIC_KIDNEY_DISEASE	en_core_sci_sm	0.573
DIABETES	medspacy_md	0.898
HEART_DISEASE	medspacy_md	0.961
LUNG_DISEASE	medspacy_md	1.00

Approach: The models were applied to sections such as 'History of present illness', 'Past medical history', 'Discharge medications', and 'Discharge diagnosis'. Our approach enabled comprehensive evaluations of the models' performance in these different sections to accurately identify chronic diseases.

Analysis: The team evaluated these models using recall, precision, and F1 scores. The top performing model was the medspacy_md with an Average F1 Score of 0.783, Average Recall of 0.909, and Average Precision of 0.796, scoring the highest in five out of the six chronic diseases. The ScispaCy en_ner_bc5cdr_md model performed the lowest with an Average F1 Score of 0.571, Average Recall of 0.881, and Average Precision of 0.483. When considering the context of the medical domain, usually medical practitioners require models to score 0.95 or higher in precision, recall, and F1 Scores, meaning the medspacy_md model performed well in identifying heart and lung disease as well as cancer. The model has room for improvement in recognizing chronic kidney disease, diabetes, and Alzheimer's.

___ yo woman with alzheimer `dementia ALZHEIMERS` , hypertension, `aortic stenosis HEART_DISEASE` with a recent history of substernal chest pain, gastroesophageal reflux disease, recent subdural hematoma and r displaced superior and inferio pubic rami fx s/p a fall, presents to the ___ `aortic stenosis HEART_DISEASE` a transfer from ___ with a l femur periprosthetic spiral fracture. she `incentive spirometry LUNG_DISEASE` a nursing ___ resident, and this fall was a witnessed fall inch the bathroom. her assistant caught her mid-fall; she twisted and was able to sit on the ground. noted immediate thigh pain and inability to bear weight. no headstrike operating room loc.

multiple sclerosis. ___ `incentive spirometry LUNG_DISEASE` a ___ yo woman with history of laryngeal `cancer CANCER` and l temporal lesion `aortic stenosis HEART_DISEASE` well `aortic stenosis HEART_DISEASE` history of multiple lacunar infarcts and microvascular disease `aortic stenosis HEART_DISEASE` well `aortic stenosis HEART_DISEASE` recent admission for hypertensive emergency and headache during which she was found to have small l cerebellar infarct who presents to the emergency department with headache and dizziness. multiple sclerosis. ___ was recently admitted from ___ through ___ to the medicine service after presenting with

Additional Features: The Patient Matcher feature required a unique solution, as performing matrix operations in high dimensional space is quite a computational dilemma. Given that the EHR training data contained over 100,000 patients, this would result in approximately 5 billion unique patient-patient similarity measures! MedMap needed an efficient way to reduce storage and calculate similarities in real-time. To simplify the problem, in the preprocessing stage, TF-IDF vectorization and unsupervised clustering using Sklearn is performed to identify similar subgroups of patients. The team settled on 50 clusters for the full data, resulting in 200 to 6,000 patients per cluster with the goal of reducing computational complexity and runtime. This way, only the similarity indexes of the patients within the same cluster as the provided patient are calculated in real-time.

5. Conclusions and discussion: MedMap represents a promising approach to address the pervasive issue of physician burnout and shortened patient interaction time caused by extensive EHR documentation requirements. Leveraging advanced NLP techniques and interactive visualization tools, MedMap streamlines the process of extracting, analyzing, and presenting key information from EHRs, thereby improving clinical productivity and facilitating more informed decision-making. Key innovations of MedMap include instant access to the latest clinical data, patient matching for informed decision-making, and an enhanced user interface focused on data relevance and accessibility. By integrating these features into a cohesive platform, MedMap empowers healthcare professionals to use their time more efficiently.

MedMap's functionality is broken into three interactive visual tabs. The first tab, Report, allows users to select a patient and instantly access NLP-extracted key information, with essential health terms highlighted for easy review. The second tab, Patient Matcher, identifies the top 10 patients with similar characteristics to the selected individual, enabling clinicians to compare critical health information across similar cases. The third tab provides two visualizations to healthcare professionals summarizing chronic diseases and patient profiles across all EHRs. This comprehensive approach positions MedMap as a valuable tool in alleviating workload for healthcare workers and fostering better patient care.

Future innovations include ongoing refinement and enhancement of MedMap with feedback from clinicians and stakeholders to ensure its usability and effectiveness. Additionally, the integration of MedMap's patient similarity and NLP highlighting algorithms into existing healthcare system workflows can be optimized. This would include incorporating functionality for live EHR database updates and implementing monitoring and reporting standards that account for data drift. MedMap is a significant step forward in leveraging NLP-driven healthcare visualization tools to alleviate the burdens associated with EHR documentation, ultimately improving the well-being of healthcare professionals and their patients.

All team members have contributed equal effort to this project.

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