Predicting readmission risk from doctors’ notes

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Abstract

We develop a model using deep learning techniques and natural language processing on unstructured text from medical records to predict hospital-wide 30-day unplanned readmission, with c-statistic .70. Our model is constructed to allow physicians to interpret the significant features for prediction.

1 Introduction

Hospital readmission is bad for the health of patients and costly to the healthcare system. Cases of unavoidable readmission exist, but the variation of readmission rates across hospitals suggests that some cases are predictable and avoidable. In 2012 the Affordable Care Act enacted the Hospital Readmissions Reduction Program as an incentive for hospitals to reduce readmissions for some conditions. In this study we consider hospital-wide unplanned readmission for acute care within 30 days of discharge. The Centers for Medicare and Medicaid Services (CMS) define an unplanned readmission as a readmission for unscheduled acute care that is not for an organ transplant, chemotherapy, or radiation, or a potentially planned visit that includes acute or complication of care. The definition applies to hospital-wide (“all-cause”) visits. Admissions within 24 hours for the same condition are not considered readmissions by the CMS.

Research on unplanned readmission has sought to identify features of patients that put them at risk. The systematic reviews of Kansagara et al. (2011) and Zhou et al. (2016) show increased interest in predictive models, citing 14 models from 2011 to 2015 that predict 30-day hospital-wide unplanned readmission with c-statistics ranging from .55 to .79.

These models are valuable for two purposes: for use in clinical tools that flag at-risk patients for intervention during their hospital stay to reduce their risk of readmission, and for retrospective analysis of the causes of readmission. Models for early detection use features such as demographics, admission diagnosis and acuity, and prior hospital visits. Models for retrospective analysis use these features as well as administrative data available at the time of billing, such as comorbidities, length of stay, procedures, and prescriptions. The LACE score (length of stay, acuity of admission, comorbidities, prior emergency visits) is used by many models.

Increasingly, models also use clinical information, such as laboratory tests, or patient surveys. Administrative data and clinical information are available as structured entries in the electronic  

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medical record (EMR), and computational methods render that data available sufficiently early for clinical use. However, while structured data contain features that are well-established predictors of readmission, they offer an incomplete picture of the patient. An example is the presence of comorbidities. Patients may have preexisting conditions for which they received no treatment during the index hospitalization. Diabetes and dementia are common examples.

Doctors’ notes hold information about a patient that cannot always be found in administrative data, laboratory reports, or nursing evaluations. Physicians often describe the patient history and ongoing conditions, the treatments and procedures attempted during the index hospitalization together with their success or failure, and discharge instructions that indicate whether the patient is able to resume normal activity. Finally, physicians occasionally write a direct opinion on the patient’s prognosis.

We are interested in extracting information from the unstructured text in medical records using deep learning models and natural language processing (NLP). Often these models have strong predictive power but their predictions resist interpretation. A model is more useful as a clinical tool if the physician understands the features underlying its predictions. In this work we demonstrate that it is feasible to extract meaningful signal from unstructured text using a deep learning model that lends itself to interpretation by physicians. The information derived from our model is informative for detecting and intervening on behalf of patients at risk of unplanned readmission hospital-wide.

We trained a convolutional neural network (CNN) to predict hospital-wide 30-day unplanned readmission using the text of doctors’ discharge notes. We used simple preprocessing to segment the text into sections and lists. We also used standard techniques to convert words of text to vectors for input to the CNN. To overcome the black box nature of neural networks, we structured our model to allow visualization and explanation of its predictions. The c-statistic for our model was .7 on test data, as compared to .65 for a logistic regression on the features used in the LACE score.

NLP has been applied in the medical domain for some time. Research has applied standard machine learning techniques and NLP on unstructured text to predict readmissions for certain conditions and hospital-wide. Recent work has applied deep learning techniques and NLP to characterize patient phenotype for the purpose of individualized patient care. Other recent work has applied deep learning techniques and NLP to predict readmissions for diabetes patients.

2 Methods and Data

Our goal is to predict 30-day, hospital-wide, unplanned hospital readmissions at Sarasota Memorial Hospital. We classify a readmission as planned or unplanned using the planned readmission algorithm developed by CMS. We note that this hospital sets itself apart as one of the 4% of U.S. hospitals with a readmission rate lower than the national readmission rate (13.6% vs 15.3%). Our patient population has ages ranging from 29 to 108 (median: 71, mean: 69), and 91% of patients self-identify as White or Caucasian.

Our model uses physician’s discharge notes from 141, 226 inpatient visits during the years 2004 to 2014. We omitted visits where the patient was discharged to hospice or passed away within 30 days of discharge. We also omitted visits where the discharge note had fewer than 20 words. This study was approved by the hospital’s Institutional Review Board.

To develop and test our model, we split the data into three groups: a training set (113, 077 visits), a validation set (12, 566 rows) and a test set (15, 583 visits).

2.1 Data preparation

We preprocessed the discharge notes before passing them into our neural network. We removed names, numbers, dates, and punctuation to minimize overfitting and bias. To give all notes the same structure, we labeled and reordered sections (e.g. allergies, prognosis, discharge condition). This was done by manually inspecting notes for consistent section headers, and using pattern matching to extract the sections. Finally, we imposed a length of 700 words on each discharge note by removing words from the end of longer notes, and right-padding shorter notes with the string PADDING.
2.2 Model

After trying several architectures, we found that a one-dimensional convolutional neural network achieved the highest c-statistic. Our model consisted of a word embedding layer (initialized with a pre-trained word embedding from word2vec skip-gram with negative sampling), a convolutional layer, a max pooling layer and a dense layer (figure 1). Training was done using the Keras framework running TensorFlow as the backend, with RMSprop as the optimizer. For full details and model hyperparameters, we refer to our code.

![Figure 1: Model architecture](image)

2.3 Interpretability

To retain model interpretability, we devised a shallow model. The output layer acts on the max pooling layer, and each node in the max pooling layer corresponds directly to a single trigram from the discharge note. As a result of this structure, it is possible to identify the phrases in the text that most influenced the model.

![Figure 2: Predicted readmission, true positive.](image)

For more example discharge notes, refer to figures 4 through 9. These examples represent the extremes in our data: they include patients who were readmitted on the same day as well as patients who were never readmitted, and they show model predictions ranging from .04 to .68.

3 Results

On test data, our model achieved a c-statistic of .70; see Table 1 for comparison with other models.

| Model                        | Data                        | C-statistic |
|-----------------------------|-----------------------------|-------------|
| 1-D convolutional neural network | Discharge note              | .70         |
| 1-D convolutional neural network | Discharge note, LACE features | .70         |
| Random forest               | Discharge note (TF-IDF matrix) | .67         |
| 2-layer feed forward neural network | LACE features, LACE score | .66         |
| Logistic regression         | LACE features, LACE score | .66         |

[https://github.com/farinstitute/ReadmissionRiskDoctorNotes](https://github.com/farinstitute/ReadmissionRiskDoctorNotes)
4 Discussion

While our model does not improve upon the predictive performance of all of the published models, it compares favorably with most. More importantly, it demonstrates that unstructured text in the electronic medical record contains a meaningful signal that is accessible through a neural network model that is shallow enough to remain interpretable.

We passed our training data through the model and recorded the values at each node in the max pooling layer, multiplied by the corresponding weight for the following dense layer. We consider these distributions to be the "contribution" of each node to the final sum and sigmoid that computes the probability of readmission. We sampled a subset of nodes for further study: we looked at those with the largest absolute values and the largest standard deviations. Then, given a single node, we identified the words corresponding to its most extreme contributions; these are the words (and topics) that "light up" this node. From this cursory study, we found that our model's learned features identified clinician opinions (figure 3), procedures performed (figure 10), categories of drugs (figure 11) and ongoing conditions (figure 12). Some of these features are redundant with other medical data; for example, a procedure performed will appear in a patient's clinical orders and billing data. However, the model also identified features unique to clinical text, including ongoing conditions and clinical opinions.

![Figure 3: Learned feature identifying clinician opinion of a poor prognosis.](image)

We note that our study has limitations. Our data originates from a single hospital, so patients who were readmitted within 30 days to another hospital are incorrectly labeled. Another limitation of our data is that 40% of discharge notes are written after discharge, thereby impeding our model's ability to provide timely decision support for all patients.

We envision further research that could improve our model's utility. Our model's predictive power might improve through the incorporation of quantitative data from the electronic medical record, or through restriction to patients with particular conditions and procedures. It may also benefit from the application of further NLP techniques to make the text's signal more readily available to the neural network.

This model also offers opportunity for new administrative and clinical insights through a thorough study of its learned features.

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6 Appendix

Figure 4: Predicted readmission, true positive.
Sections predictive by their absence:
- Other
- Abdomen
- Chest
- Complications
- Nec
- Neur
go
- Physical examination
- Present illness

Discharge note:
- Consultations

STARTLIST of urology of of pulmonary medicine of cardiology

Course
problems STARTLIST myocardial infection with congestive heart failure patient presented in congestive heart failure and ruled in for myocardial infection patient was seen by cardiology who actually did admission patient was medically managed and stabilized and subsequently had cardiac catheterization patient was found to have advanced coronary disease there were no lesions that were accessible to percutaneous treatment patient therefore be medically managed and optimized with respiratory insufficiency patient was felt to have component of bronchitis on admission and was started on leviquin and nebulizer treatments patient continued to stabilize he did however have respiratory failure cardiac catheterization which was likely secondary to anasthesia and congestive failure patient was found to have markedly elevated wedge pressure during catheterization patient was intubated and kept in intensive care unit briefly he was easily extubated his respiratory status continued to stabilize patient was followed by pulmonary medicine he continues to have some shortness of breath although this is more cardiac in etiology repeat chest in clear patient has completed course of antibiotics acute on chronic renal failure patient with chronic renal insufficiency with baseline creatinine in he did have clog in creatinine up to following cardiac catheterization likely secondary to component of contrast nephropathy patient renal function stabilized his current creatinine is he is followed by continue patient on his current hematuria patient was thought to have some traumatic hematuria he was seen by urology cather has now been discontinued and he appears to be doing well from urologic standpoint patient multiple medical problems that are chronic remained stable during patient is subsequently thought stable for transfer include STARTLIST all apoptotic peptic zoor flomax cellex tetral insulin units periclist colace plaix nurofen guainessen mirax amiloride aspirin ibuprofen coreg loratian nebulizers with albuterol and atrovent

Discharge diagnoses
STARTLIST acute myocardial infection congestive heart failure secondary to above ischemic cardiomyopathy acute bronchitis respiratory failure following cardiac catheterization requiring intubation and mechanical ventilation acute on chronic renal failure morbid obesity hypertension insulin dependent diabetes melitus hematuria

Procedures
STARTLIST cardiac catheterization which revealed advanced coronary artery disease with recommendations for medical management intubation with mechanical ventilation of respiratory failure following cardiac catheterization renal ultrasound which was negative

Figure 5: Predicted readmission, true positive.

Sections predictive by their absence:
- Other
- Abdomen
- Allergies
- Chest
- Complications
- Consultations
- Core measures
- Course
- Heart
- Heent
- Neck
- Neur
- Physical examination
- Present illness

Discharge note:
- Admission diagnoses
- pelvic bilateral ovarian masses postoperative

Diagnosis
STARTLIST left ovarian cyst uterine leiomyoma adenomyosis

Disposition
home instructions to heavy lifting for pelvic rest for call for signs and symptoms of infection call for intractable nausea vomiting constipation or diarrhea follow up appointment week in office prescriptions percoct take every hours pain emp for

Procedures
total abdominal hysterectomy bilateral salpingo oophorectomy final pathology revealed no evidence of malignancy endometrium mild chronic cervicitis and focal squamous metaplasia leiomyoma of uterine fundus with mitotic rate to high powered right ovary with cystic dermoid cyst opposite ovary shows physiologic change benign fallopian tubes pelvic washings with no malignant cells please chart for complete details briefly this is pleasant year old female who reported pain with menses she was taken to surgery for above mentioned procedure she did well on postop was able to be

Figure 6: Predicted no readmission, true negative.
Sections predictive by their absence:
- Abdomen
- Chest
- Complications
- Consultations
- Core measures
- Course
- Discharge condition
- Head
- Heel
- Neck
- Neurologic
- Physical examination
- Present illness
- Procedures

Discharge note:
- Other

Figure 7: Predicted no readmission, true negative.

Sections predictive by their absence:
- Abdomen
- Chest
- Complications
- Consultations
- Core measures
- Course
- Discharge condition
- Head
- Heel
- Neck
- Neurologic
- Physical examination
- Present illness
- Procedures

Discharge note:
- Other

Figure 8: Predicted readmission, false positive.

Sections predictive by their absence:
- Abdomen
- Chest
- Complications
- Consultations
- Core measures
- Course
- Discharge condition
- Head
- Heel
- Neck
- Neurologic
- Physical examination
- Present illness
- Procedures

Discharge note:
- Other

Figure 9: Predicted no readmission, false negative.
Figure 10: Learned feature identifying a biopsy or heart surgery.

Figure 11: Learned feature identifying presence of steroids in a patient’s chart.

Figure 12: Learned feature identifying ongoing diabetes.