Predicting Severe Sepsis Using Text from the Electronic Health Record

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Abstract

Employing a machine learning approach we predict, up to 24 hours prior, a diagnosis of severe sepsis. Strongly predictive models are possible that use only text reports from the Electronic Health Record (EHR), and omit structured numerical data. Unstructured text alone gives slightly better performance than structured data alone, and the combination further improves performance. We also discuss advantages of using unstructured EHR text for modeling, as compared to structured EHR data.

1 Introduction

Sepsis, a kind of generalized infection leading to organ failure, is a major concern for health providers. Sepsis causes 20%-30% of deaths in hospitals and consumes $15.4 billion annually in healthcare costs [Henry 2015]. If severe sepsis progresses to septic shock, mortality can run as high as 50% [Bhattacharjee 2017], with delay in diagnosis and treatment increasing mortality by 7.6% for every hour of delay.

1.1 Goals

Although the clinical definition of severe sepsis involves only structured data measurements, the Electronic Health Record also contains potentially useful unstructured text: patient history, progress notes, lab reports, etc. We would like to use machine learning to automate the understanding of these text notes to make decisions from them, such as “Is this patient likely to satisfy the definition for severe sepsis within the next 24 hours?” However, in general, it is difficult for computer software to learn to make decisions from text. The result is that unstructured notes in the EHR are severely under-utilized for computational purposes [Ohno-Machado 2011].

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Working with data from Baystate Health as part of a QI initiative, we performed a retrospective study using Electronic Health Record information for adult inpatients from 2012-2016. We sought to answer three questions:

1. Can we predict, directly from the EHR, which patients will satisfy a clinical definition of severe sepsis at various future times?
2. Can we use only unstructured text notes in the EHR for predictions?
3. How does prediction accuracy compare when using only unstructured data, only structured data, or both types of data from the EHR?

1.2 Previous Research

Researchers use “predict” in two different contexts. Most are screening applications to determine whether patients currently have sepsis, typically as judged by a gold standard team of physicians. Others look at predicting ahead in time, where sufficient structured data is not yet available to fulfill clinical criteria for severe sepsis. Our focus here is using currently available data to predict a future severe sepsis diagnosis, which is made using additional data available at that future time.

Bhattacharjee et al. [2017] describes 10 automated tools using structured data to predict patients with sepsis, severe sepsis, or septic shock. None make significant usage of free text notes, and most of these models are screening models.

A more recent paper by Horng et al. [2017] built Emergency Department triage screening models for sepsis (including severe sepsis and septic shock). They make significant use of text notes and show about 25% improvement when notes are added to structured data. Text modeling involved term frequencies, bi-grams, and topic models, resulting in vectors with 15,000 dimensions. (Reported results did not include using unstructured data alone.)

An earlier use of text notes to predict hospital mortality [Lehman 2012] employed Hierarchical Dirichlet Processes on UMLS clinical concepts extracted from the text. Their mortality predictions showed text-based analysis was better than using structured data alone, and the combination of both produced best results (paralleling our results with severe sepsis).

In other work predicting sepsis, Desautels et al. [2016] reported on a machine learning approach using structured variables that showed improved predictive performance over a number of other methods for predicting sepsis, up to 4 hours in advance. They use a recent definition of sepsis [Singer 2016] that differs from the traditional classifications of sepsis/severe sepsis/septic shock. Paxton et al. [2013] built models to detect septic shock using 1011 structured data features. They also discussed issues around using the Electronic Health Record for modeling in situations where some treatments have already started.

2 Methods

We analyzed 203,000 adult inpatient admissions (encounters) within Baystate hospitals over 5 years from 2012 through 2016. Severe sepsis patients were identified using a modified version of Baystate’s clinical definition for severe sepsis, involving 8 structured variables. Additionally, encounters were marked as severe sepsis if they had corresponding ICD codes. (Simply using severe sepsis ICD codes was not sufficiently reliable, as was previously found by Rhee et al. [2017].) For each patient who satisfied this definition of severe sepsis, we used time stamps for the individual structured variables (or ICD codes) to compute the earliest time the severe sepsis definition was satisfied, which we term the Severe Sepsis Definition Time.

2.1 Unstructured Data Models

We collected textual notes for patient encounters. There were over 100 types of notes, with most being progress notes or history-and-physical notes. When predicting severe sepsis 24 hours ahead for positive targets (severe sepsis patients), we removed all of the notes that occurred later than 24 hours prior to the Severe Sepsis Definition Time. Remaining data is referred to as the Modeling Data Window, MDW. These encounters constituted positive examples for our modeling.
For non-severe-sepsis patients, we chose a random time during their hospital stay and removed all notes that occurred later than 24 hours before that time. These patients are negative examples. Our intent was to simulate regular application of our models in a clinical setting, to suggest patients for further attention who are in danger of severe sepsis in the next 24 hours.

We eliminated encounters having no unstructured notes remaining in the MDW, because it makes no sense to try to predict with no information at all. This left 68,482 total encounters, of which 1,427 (2.1%) satisfied the definition of severe sepsis during their stay.

We then concatenated all text information for an encounter into a single text block which, along with the severe sepsis target flag, comprised our unstructured data. Encounters were randomly divided into 3 groups of patients, stratifying them to maintain the global ratio of severe sepsis targets within each sample set. For modeling and testing we used 3-fold cross validation, modeling on each set of 2 groups and using the remaining group to measure performance. Final performance was computed over all 3 holdout sets. We also built models using 2012–2015 data for model construction, and 2016 data for testing.

Models to predict 4 and 8 hours ahead used corresponding data preprocessing, with revised Modeling Data Windows. Note that models for 24-hour-ahead predictions had fewer encounters than 4 or 8 hour predictions, because the former had fewer non-empty Modeling Data Windows. In particular, patients admitted with pre-existing severe sepsis were usually eliminated from modeling data for 24-hour models, because their diagnosis occurred in the first 24 hours of their encounter, leaving an empty MDW.

We represented unstructured data using 300-dimensional GloVe vector embeddings for terms [Pennington 2014], and then summing the vectors for terms in the text. Training was by ridge regression.

2.2 Structured Data Models

For models using only structured data, we selected 12 variables thought to be helpful for predicting Severe Sepsis and gathered their data, with timestamps, from the EHR. Values were computed for mean and standard deviation, plus counts of abnormal high, abnormal low, and normal readings, resulting in 29 modeling variables. Once again, we discarded encounters that lacked data for all 29 variables, leaving no data in the Modeling Data Window.

For combination models using both unstructured and structured data, we required that both types of data be non-empty in the MDW.

3 Results

Table 1 gives summary results across all 3 cross-validation folds of the data using only unstructured EHR text. To emphasize actionable results where there is a practical need to avoid over-alarming, we focused upon the most likely predicted 1%, 5%, and 10% encounters for severe sepsis among hold-out data.

Surprisingly, predicting ahead 24 hours gives better results than predicting ahead 4 or 8 hours. This is a consequence of the former set of encounters being smaller in number, and having a higher percentage of longer-term patients who have more information available in their modeling windows. This explanation was supported by building 4, 8, and 24 hour predictive models using the same 24-hour structured data, which showed improved performance for 4 and 8-hour predictions vs. 24-hour predictions.

We manually verified that unstructured text in the MDW did not already have sufficient information to diagnose severe sepsis 24 hours prior to the Severe Sepsis Definition Time. Looking at the top 1% predicted encounters, we found very few (1%-3%) where narratives were sufficient for a prior diagnosis. We judged this to be an acceptable rate. We similarly checked that Vasopressor drugs (an indication of septic shock) were not yet administered during the Modeling Data Window.

Table 2 gives comparisons with unstructured, structured, or combination data when predicting 24 hours into the future. Here we built severe sepsis models using encounters from 2012–2015, and testing with encounters from 2016. Only encounters that have non-empty modeling windows for

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2Not all types of text were used.
Table 1: Predicting Severe Sepsis Using Only Text from the EHR

| Predict Ahead | Usable Data in Modeling Window | Top 1% Predicted | Top 5% Predicted | Top 10% Predicted |
|---------------|--------------------------------|------------------|------------------|-------------------|
| 4 hours       |                                |                  |                  |                   |
| Sample Size   | 129,421                        | 1,294            | 6,471            | 12,942            |
| Targets found | 2,527                          | 521              | 801              | 952               |
| % of Sample   | 40%                            | 12%              | 7%               |                   |
| % of All Targets | 21%                         | 32%              | 38%              |                   |
| AUC           |                                | 0.636            |                  |                   |
| 8 hours       |                                |                  |                  |                   |
| Sample Size   | 117,768                        | 1,178            | 5,888            | 11,777            |
| Targets found | 2,158                          | 503              | 769              | 916               |
| % of Sample   | 43%                            | 13%              | 8%               |                   |
| % of All Targets | 23%                         | 36%              | 42%              |                   |
| AUC           |                                | 0.660            |                  |                   |
| 24 hours      |                                |                  |                  |                   |
| Sample Size   | 68,482                         | 685              | 3,424            | 6,848             |
| Targets found | 1,427                          | 412              | 707              | 829               |
| % of Sample   | 60%                            | 21%              | 12%              |                   |
| % of All Targets | 29%                         | 50%              | 58%              |                   |
| AUC           |                                | 0.727            |                  |                   |

both unstructured and structured data were used. The 2016 test set contained 13,603 usable encounters, for which 425 patients (3.1%) satisfied the severe sepsis criteria in the next 24 hours. Using out-of-time test data further supported results from Table 1 which used cross-validation. To briefly summarize the comparison: unstructured-only models performed comparably or slightly better than structured-only models, and the combination of unstructured and structured data gave a 5%-10% improvement over unstructured-only models.

Table 2: Predicting Severe Sepsis 24 Hours in the Future Using Unstructured, Structured, or Combination EHR Data

| Type of EHR Data               | AUC  | Predicted Top 1% | Predicted Top 5% | Predicted Top 10% |
|-------------------------------|------|------------------|------------------|-------------------|
|                               |      | Number | Severe Sepsis | Number | Severe Sepsis | Number | Severe Sepsis |
| Unstructured Text only        | 0.81 | 136    | 115          | 680    | 217          | 1,360  | 247          |
| Structured Data only          | 0.80 | 136    | 112          | 680    | 206          | 1,360  | 248          |
| Both Unstructured Text And Structured Data | 0.85 | 136    | 125          | 680    | 239          | 1,360  | 272          |

4 Discussion

Our results indicate that we can construct models, directly from the Electronic Health Record, that are highly predictive for severe sepsis diagnoses over the next 4, 8, and 24 hours, and using only text notes. This is the first result using text to predict ahead in time a sepsis diagnosis, as well as the first sepsis predictions using only unstructured data.

These severe sepsis models appear practically actionable and valuable. For example when predicting ahead 24 hours, if we have 1,000 patients and take the model’s top-scoring 10 patients (top 1%), then we expect 6 of them to satisfy the severe sepsis definition in the next 24 hours.

It was somewhat surprising that such results were possible using merely our baseline “bag of words” distributed representation for the text. Future work will explore more advanced representations that
explicitly represent negation [Gallant 2013], which is helpful in different modeling contexts (such as computer assisted coding of ICD-10 medical codes).

A possible source of noise in our data are the timestamps associated with both unstructured and structured items. A planned prospective study will address this issue.

4.1 The Case for Using Unstructured Text

There are several advantages with using text notes for modeling, as compared with structured values. The medical notes tend to repeat lab results and structured variables, but only the important ones, as judged by skilled clinicians. This expert judgment constitutes a quite valuable resource, and it appears only in the unstructured data.

Surprisingly, unstructured text requires less manual preprocessing effort than using structured data. For example, with structured data there is not a single value for “blood pressure” to be extracted from the EHR; there are multiple blood pressure readings, and these need to be rolled up using max, min, mean, deltas, etc. Also, structured data presents more of a problem with missing data.

Another consideration is that we want to be able to predict many additional health-related targets, such as re-admission risk, over sedation, CHF, etc. Yet we cannot practically include all structured data from the EHR — a huge task — so a separate subset of relevant structured variables needs to be manually defined and extracted for each different prediction target. By contrast, we can reuse the same set of unstructured data for multiple prediction models.

Sepsis may be an especially good candidate for using text notes because it has a complex definition involving many structured data values. Structured data may work comparatively better for simpler targets that are defined by only a few structured data numbers.

4.2 Concluding Remarks

We will report additional details elsewhere, including results using a different prediction target (Over-Sedation), as well as results predicting severe sepsis using the MIMIC dataset [Johnson 2016].

Our findings strongly support the inclusion of unstructured notes when building predictive models. Findings also support an implementation in a clinical setting to prospectively confirm accuracy and usefulness of model predictions.

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3 An exception is that notes on patient history may be useful for targets like re-admission risk, but need to be excluded for targets such as ICD-10 coding for current conditions.
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