
Application of Clinical Concept Embeddings for Heart Failure Prediction in UK EHR data

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Abstract

Electronic health records (EHR) are increasingly being used for constructing disease risk prediction models. Feature engineering in EHR data however is challenging due to their highly dimensional and heterogeneous nature. Low-dimensional representations of EHR data can potentially mitigate these challenges. In this paper, we use global vectors (*GloVe*) to learn word embeddings for diagnoses and procedures recorded using 13 million ontology terms across 2.7 million hospitalisations in national UK EHR. We demonstrate the utility of these embeddings by evaluating their performance in identifying patients which are at higher risk of being hospitalized for congestive heart failure. Our findings indicate that embeddings can enable the creation of robust EHR-derived disease risk prediction models and address some the limitations associated with manual clinical feature engineering.

1 Introduction

Risk prediction models are statistical tools which are used to predict the probability that an individual with a given set of characteristics (e.g. smoking, blood pressure, family history of cancer) will experience a health outcome (e.g. heart attack, type 2 diabetes, death). They are a cornerstone of modern clinical medicine [1] as they enable clinicians to intervene earlier or chose the optimal therapeutic strategy for a patient. Electronic health records (EHR), data generated during routine patient interactions with healthcare providers [2, 3], offer the opportunity to create risk prediction models in larger sample populations and higher clinical resolution [4] than previously available. Utilizing EHR data however is challenging [5, 6, 7, 8] and a recent review [9] illustrated that EHR-derived predictive models used a median of only 27 clinical features, mostly engineered in a cross-sectional fashion.

Clinical concept embeddings, i.e. multi-dimensional vector representations of medical concepts, can potentially enable the creation of risk prediction models that make use of a patient's entire EHR (e.g. diagnoses, procedures) and reduce the need for manual feature engineering. Contemporary approaches for learning word embeddings are influenced by the neural language model developed by Bengio et al. [10]. Word embeddings are a very popular way of representing high-dimensional and high-sparsity data in the field of natural language processing and have demonstrated a significant improvement in classification accuracy when combined with existing labelled data [11]. Popular approaches include *word2vec*[12], which includes the continuous bag of words and skip-gram

models, and *GloVe* [13], which produces word embeddings by fitting a weighted log-linear model to aggregated global word-word co-occurrence statistics.

1.1 Previous research and contribution

Word embedding approaches have been previously used to create low-dimensional representations of heterogeneous clinical concepts (e.g. diagnoses, prescriptions, procedures, laboratory findings) from raw EHR data for various supervised and unsupervised learning tasks [14, 15]. Previous research has evaluated the use of clinical concept embeddings in US data for predicting the risk of developing heart failure using recurrent [16, 17] or convolutional [17] neural network architectures. In other disease areas, embeddings have been evaluated for predicting events in critical care patients [18, 19], length of stay and associated costs [20], suicide in mental health patients [21] and hierarchical regularities in dependencies between health states [22].

A cornerstone of building risk prediction tools is external replication of findings [23]. Here, we attempt to replicate and compare, to a certain degree, findings obtained using US data from single hospital care providers [16] using UK EHR from multiple providers, and illustrate the application of embeddings for risk prediction. This is the first study, to our knowledge, to utilize UK EHR data in this context. The UK and US healthcare systems are significantly different in terms of planning, delivery and reimbursement. This in turn directly influences what data are recorded in a patient’s electronic health record. Additionally, in contrast with previous research, we evaluate the predictive performance of different clinical information (e.g. diagnoses, procedures) independently as well since including *all* available data might potentially be counterproductive given the noisy and heterogeneous nature of EHR data.

2 Methods

2.1 Data sources and population

We used secondary care EHR from the UK Biobank [24], a population-based research study comprising 502,629 individuals in the UK. The study contains extensive phenotypic and genotypic information and longitudinal follow-up for health-related outcomes is through linkages to national EHR from hospital care and mortality registers. Diagnoses and procedures were recorded using controlled clinical terminologies, i.e. hierarchical ontologies enables clinicians to systematically record information about a patient’s health and treatment and enable the subsequent use of data for reimbursement [25, 26] and research [27, 28]. Diagnoses were recorded using ICD-9 and ICD-10 [29] and procedures using OPCS-4 [30]. Admitted patients are assigned a primary and up to 15 secondary causes of admission.

We defined incident and prevalent HF cases using a previously-validated phenotyping algorithm from the CALIBER resource [31, 32, 33]. HF cases were identified using ICD-9 and ICD-10 terms occurring at any position during a patient admission (i.e. primary or otherwise) in patients aged 40-85 years old at the time of admission. For patients with multiple HF diagnoses, the date of onset was defined as the earliest date of admission. HF cases were matched with four eligible controls on assessment centre, year of recruitment, sex and year of birth. Controls were assigned an index date, which was the date of HF diagnosis of the matched case. We excluded prevalent HF cases from our analyses.

2.2 Learning concept and patient embeddings

We created four corpuses (Table 1) using: a) primary diagnosis terms (PRIMDX), b) primary diagnosis terms and procedure terms (PRIMDX-PROC), c) using primary and secondary diagnosis terms (PRIMDX-SECDX) and, d) primary and secondary diagnosis terms and procedure terms (PRIMDX-SECDX-PROC). We learned *concept-level embeddings* using the *GLoVe* model on the four corpuses and evaluated combinations of embedding dimension (50, 100, 150, 250, 500, 1000) and window sizes (50, 10, 20). Models were trained using Adagrad [34] and 150 epochs. We created *patient-level embeddings* (Figure 1.) by: a) extracting all terms from a patients EHR record from the start of follow up to six months (to exclude features very strongly correlated with a subsequent diagnosis [35]) prior to date of HF diagnoses for cases or the index date for matched controls, b) looking up the vector representations for each embedding, c) creating a vector composed of the mean,

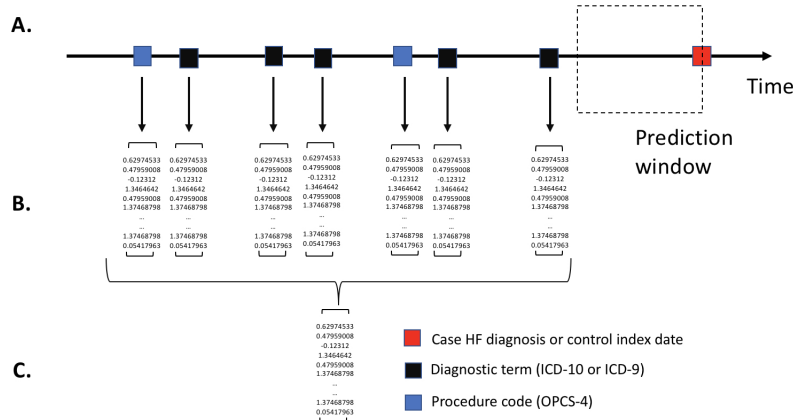


Figure 1: (A) Patient EHR timeline. Concept-level representations of diagnoses and procedures in (B) are transformed into patient-level vector representations. (C) Patients are represented by a vector which is used as input in the supervised risk prediction experiment.

Corpus	Tokens (total)	Tokens (unique)	Tokens (median)	Vocabulary size
PRIMDX	2,766,487	10,606	4	5,581
PRIMDX-SECDX	7,699,930	13,883	7	7,797
PRIMDX-PROC	7,904,942	18,608	11	10,949
PRIMDX-SECDX-PROC	12,838,385	21,885	15	13,165

Table 1: Information on the corpuses used as sources for training the clinical concept embeddings.

max and min of all concept vector representations and, d) normalizing to zero mean and unit variance. For comparisons purposes, we additionally created one-hot representations of EHR data where the feature vector had the same size as the entire vocabulary and only one dimension is on.

2.3 Risk prediction

We evaluated each set embeddings by applying a linear support vector machine (SVM) classifier to predict HF onset as a supervised binary classification task using the normalized patient-level embeddings as input. We split the data into a training dataset and a test dataset (ratio 3:1) and performed six-fold cross-validation in all modeling iterations on the training data to find the optimal hyper-parameters. We evaluated predictive performance using the area under the weighted receiver operating characteristic curve (AUROC) and the weighted F1 score computed on the test dataset which was unseen.

2.4 Implementation

The SVM was implemented using scikit-learn [36]. *GloVe* embeddings were trained using binaries from pennington2014glove. The documented source code using sample synthetic data for our experiments is available at <https://github.com/spiros>. EHR data used in our experiments are available by applying to the UK Biobank [24]. UK Biobank ethical approval ref. 9922.

3 Experimental Results

We used raw EHR data from 502,639 participants and identified 4,581 HF cases (30.52% female) and matched them as previously described to 13,740 controls. The mean age at HF diagnosis was 63.397 (95% CI 63.174-63.619). We trained the clinical concept embeddings from 2,447 ICD-9, 10,527 ICD-10 and 6,887 OPCS-4 terms across 2,779,598 hospitalizations. We observed that similarly with previous research studies using clinical concept embeddings, diseases which are biologically

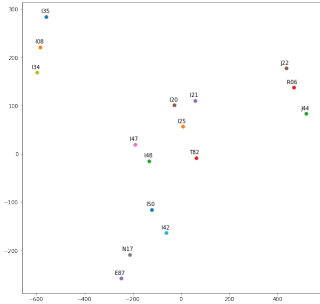


Figure 2: Ten closest neighbours of the ICD-10 term *I50 Heart Failure* in 2D using t-SNE [37].

ICD-10 Term	Similarity
I25 Chronic Ishaemic Heart Disease	0.521853
I48 Atrial Fibrillation and Flutter	0.519000
R06 Abnormalities in Breathing	0.479213
I20 Angina Pectoris	0.468975
I21 Acute Myocardial Infarction	0.460850
I47 Paroxysmal tachycardia	0.441402
N17 Acute renal failure	0.422741
I34 Nonrheumatic mitral valve disorders	0.417978
I08 Multiple valve disease	0.412447
J44 Other COPD	0.387752

or contextually closely related across the entire corpus are located close to each other in the vector space (Figure 2).

We observed similar predictive performance across both one-hot and clinical concept embedding prediction experiments. Clinical concept embeddings performed marginally better than one-hot encoded data. The highest performing models were the ones using information combining all diagnoses and surgical procedures (Table 2), obtained with a vector size of 250 and a context window size of five with embeddings. For models using the less extensive corpuses, the best performing results were observed with vectors of smaller size (50 dimensions) and larger context windows (ranging from 10-20). Although, counter-intuitively, the PRIMDX best embedding outperformed PRIMDX-PROC (using procedures and primary diagnoses), PRIMDX-PROC performed better than PRIMDX on average across all vector size and context window combinations. This suggests that clinical concept vectors could be beneficial for risk prediction in absence of a domain ontology or in a semi-supervised fashion combined with labelled data to boost performance [38].

Embedding	One-hot		Embeddings	
	AUROC	F1	AUROC	F1
PRIMDX	0.6543	0.7558	0.6720	0.7390
PRIMDX-PROC	0.6445	0.7362	0.6662	0.7341
PRIMDX-SECDX	0.6697	0.7527	0.6878	0.7568
PRIMDX-SECDX-PROC	0.6815	0.7664	0.6965	0.7500

Table 2: Best performing embeddings in test dataset with optimal hyper-parameters.

Direct comparison with previous studies is challenging due to the use of different underlying populations, study designs and incomplete definitions of cohorts and outcomes [39, 40]. When comparing our results with previous studies which used clinical concept embeddings to predict HF onset in a similar experimental setup, our approach achieved broadly similar (but slightly worse) overall performance and followed similar patterns: Choi [16] et al. utilized clinical concept vectors trained using *word2vec* skip-gram and reported an AUROC of 0.711 with one-hot encoded input and AUROC of 0.743 using embeddings with a SVM classifier. Interestingly, the fact that we observed similar (albeit slightly worse) results when using data from multiple hospitals compared to a study sourcing data from a single hospital indicates that embedding approaches can potentially be a very useful tool for scaling analyses across large heterogeneous data source and are insensitive to source variations.

4 Conclusion

Our work evaluated the use of word embeddings trained using *GloVe* for creating low-dimensionality representations of heterogeneous clinical concepts in UK EHR data. The use of clinical embeddings produced marginally improved predictive performance compared to conventional one-hot models and thus potentially has numerous applications in healthcare settings where complex, heterogeneous information requires succinct representation or a domain ontology is not fit for purpose. Further research is required to evaluate performance across different prediction windows and increase model interpretability to enable their rapid translation into clinical care.

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