Prediction of opioid continuation following lumbar fusion using administrative health data

Chloe O'Connell, Felipe Kettlun, Thomas A. Petersen
{chloeo, fkettlun, tap22} @ stanford.edu
Guidance by Eric Sun, MD, Anand Veeravagu, MD and Dr. John K. Ratliff, MD

Background: Given the addictive properties of opioid medications, they are not recommended after the immediate recovery period following surgery. However, approximately 20% of patients undergoing lumbar fusion meet criteria for **"chronic opioid use"** more than 3 months after surgery [1]. Despite growing awareness about the opioid epidemic sweeping the US, we do not have any way to predict which patients will continue taking opioids for prolonged periods of time following surgery. In this project, we attempted to **predict which patients were at risk for continued opioid usage** more than 3 months after lumbar fusion using administrative healthcare data.

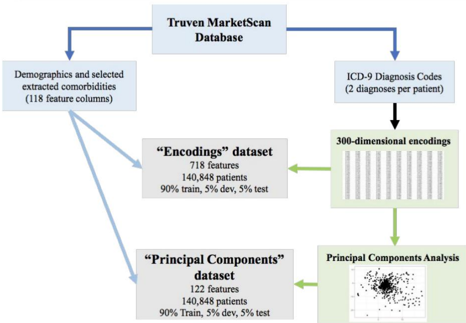

Figure 1: Dataset generation

Dataset: Our dataset includes **140,848 patients** from the Truven MarketScan database, who underwent lumbar fusion between 2007 and 2013. Geographic categories were converted into latitude and longitude estimates to better capture geographic hotspots of opioid use.

Features: In addition to the 67 features above, we also converted each patient's primary and secondary ICD-9 codes (13,000 possible codes) associated with their surgical visit to the 300-dimensional encodings trained by Choi et al. [2]. To reduce feature space, we then used **principal components analysis** to reduce each ICD-9 code encoding from 300 dimensions to the two dimensions capturing the most variation of our dataset. The encodings and principal components were added to create two final datasets consisting of **718 features** (encodings) and **122 features** (principal components only).

Model: We chose an MLP for our network architecture given that our primary goal is binary classification (predicting continued opioid use past 6 months or not). After tuning learning rate, dropout rate, number of layers, L2 regularization, and number of nodes, our best network is a **3 hidden layer** with **500, 1000, and 1000 nodes** respectively. **Dropout rates** on each hidden layer was implemented to reduce overfitting. Dev set accuracy was maximized by the same set of hyperparameters independent of input dataset. The optimal hyperparameters can be seen in Table 1.

Optimal Parameters	
Layers	3
Nodes per layer	{500; 1,000; 1,000}
Learning Rate	0.001
Dropout Rate	0.5
Batch Size	8,192

Table 1

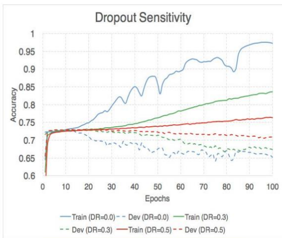

Figure 4: Optimal Dropout rate is 0.5.

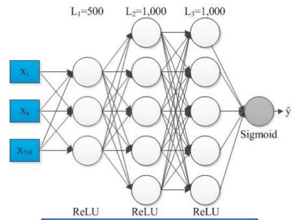

Figure 2: Optimal Architecture

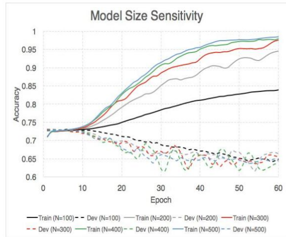

Figure 3: Finding a size that overfits the training set

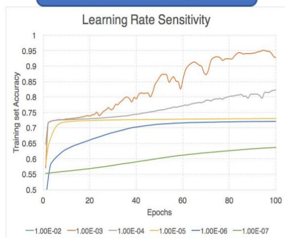

Figure 5: Optimal learning rate is around 0.001.

Results

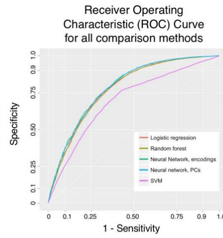

Figure 6: ROC Curves for all methods. NNs do slightly better.

Model*	Accuracy	AUC	Precision (aka PPV)	Recall (aka NPV)
Logistic regression	0.721	0.778	0.740	0.711
Random Forest	0.724	0.775	0.737	0.717
SVM	0.602	0.699	0.670	0.590
Neural network (PCs)	0.728	0.786	0.759	0.841
Neural network (Encodings)	0.725	0.787	0.751	0.833

Test set metrics

PPV = positive predictive value, NPV = negative predictive value

*Comparison methods were conducted with the principal components dataset

Table 2

Conclusions and future work: In our data, 46% of patients continued opioid use beyond 6 months after surgery, and our best model was able to accurately **predict 72.8%** of these. Although it did not significantly outperform existing statistical methods, this may be due to the structured nature of the data (despite feature engineering). There was little difference between the accuracy of models trained on raw encodings versus principal components datasets. Interesting future work would analyze which input features are most predictive.

References
1. O'Connell C, Azad TD, Mittal V, et al. Preoperative depression, lumbar fusion, and opioid use: an assessment of postoperative prescription, quality, and economic outcomes. Neurosurg Focus. 2018;44(1):E5.
2. Choi Y, Yi-I Chiu CM, Sontag D. Learning Low-Dimensional Representations of Medical Concepts. http://people.csail.mit.edu/dsontag/papers/ChoiChiuSontag_AMIA_CRI16.pdf. Accessed May 18, 2018.