



# Developing computational models for predicting diagnoses of depression

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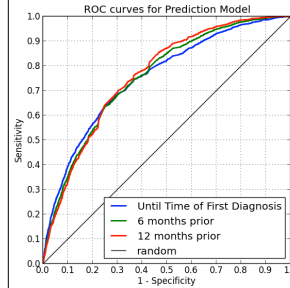
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## Introduction

- About 14% of individuals worldwide have major depression. Despite its prevalence, diagnosing depression is a challenge: primary care physicians identify ~50% of depression cases.<sup>1</sup>
- Mining of electronic health records (EHR) data has proven useful in predicting diagnoses of other disorders.
- We present a model that predicts the risk of a patient becoming diagnosed with depression, using both structured and unstructured EHR data.

## Preliminary Results

*time of first diagnosis*: our estimate of when the doctor first diagnoses the patient with depression; calculated as the first point in the patient's medical history at which both a depression ICD-9 code and drug term have occurred



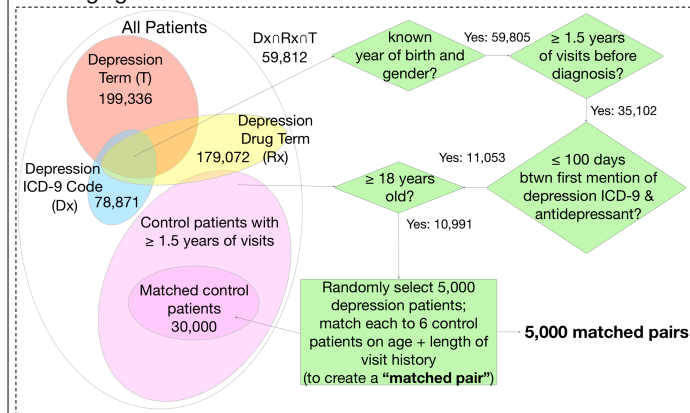
Top features, based on information gain, when training the model:

Cutoff Point	AUC
time of first diagnosis	0.754
6-month cutoff	0.756
12-month cutoff	0.762

Feature	Description	IG	% Dep	% Control
ICD-9 V72.3	Gynecological examination	0.009	15.1%	4.7%
Drug ingredient	Acellular pertussis vaccine	0.008	8.9%	22.5%
Drug ingredient	Tetanus toxoid vaccine	0.008	9.6%	23.3%
ICD-9 V06.1	Vaccination of DTP-DTaP	0.006	6.9%	17.9%
ICD-9 V04.8	Need for prophylactic vaccination	0.005	10.0%	3.3%
ICD-9 780.79	Other malaise and fatigue	0.005	20.7%	10.7%
Drug ingredient	Vitamin d	0.005	9.3%	19.4%
ICD-9 300.00	Anxiety state, unspecified	0.004	11.5%	4.7%
ICD-9 780.52	Insomnia, unspecified	0.004	13.0%	5.9%

## Methods and Workflow

### Creating "gold standard"



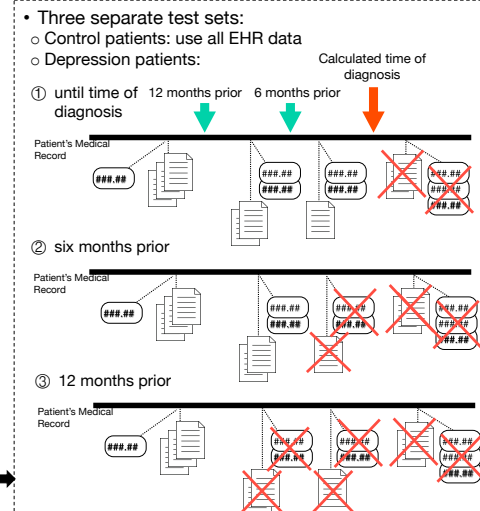
### Gather features

- gender
- billing codes (ICD-9 codes)
- visit history density (# visits/year)
- disease and drug ingredient note terms

### Training phase

Naive Bayes model, with feature selection based on information gain

### Test phase



## Conclusions

- Our results suggest the use of EHR can improve the timely diagnosis of depression. Even a year before being diagnosed, patients show patterns in their medical history that our model can detect.
- The accuracy of our predictive model rivals that of primary care physicians, who have a sensitivity of 50% and a specificity of 80% in diagnosing depression.<sup>1</sup>
- Our model has the potential to:
  - serve as a screening tool in identifying high-risk patients for closer examination, and
  - enable better cohort building for clinical studies on depression.

## Ongoing Work

- Evaluate the portability of the model by testing it on an external dataset of approximately 17,000 patients, treated for depression and scored using the Patient Health Questionnaire (PHQ-9).
- Develop models to predict severity of depression and treatment outcomes, using this new dataset. Early results are promising; we achieve an average AUC of 0.73 for predicting severity and 0.70 for predicting treatment effectiveness.

## Literature Cited

- Mitchell AJ, Vaze A, Rao S. Clinical diagnosis of depression in primary care: a meta-analysis. *Lancet* 2009;374:609-19.

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