Classifying Physician Needed Response Questions on Online Health Forums

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Background

In a 2001 research study, **~40%** of respondents with Internet access reported **using the Internet to look for health/health care advice**, with ⅓ of those respondents reporting that information found **affected a health/healthcare decision**.[1]

Online health forums (also called web medical forums) provide a **knowledge-sharing platform** for discussions between patients, patients loved ones/caregivers, and physicians for medical consultations.[2]

Patient communities serve as a **social network**[2] & **support mechanism** for patients and loved ones to receive **informational and emotional support**.[3]

The **natural-language content** allows the users to fully express their information needs without knowing medical lingo.[4]

Problem

With ⅓ of respondents reporting that using the Internet **affected a health/healthcare decision**[1], it is vital that those individuals do not receive potentially **harmful, incorrect, incomplete or bias information**.[5]

In general, **physicians feel obliged** to provide online consultations, but feel the new responsibility comes with **increased burden** (i.e. time, responsibility, lack of background knowledge on a given case).[6]

In a 2015 study (n=6,880), **54.4%** (3,680) of physicians reported at least 1 symptom of **burnout**, representing a **10% increase** since 2011 (45.5%,3,310).[7]

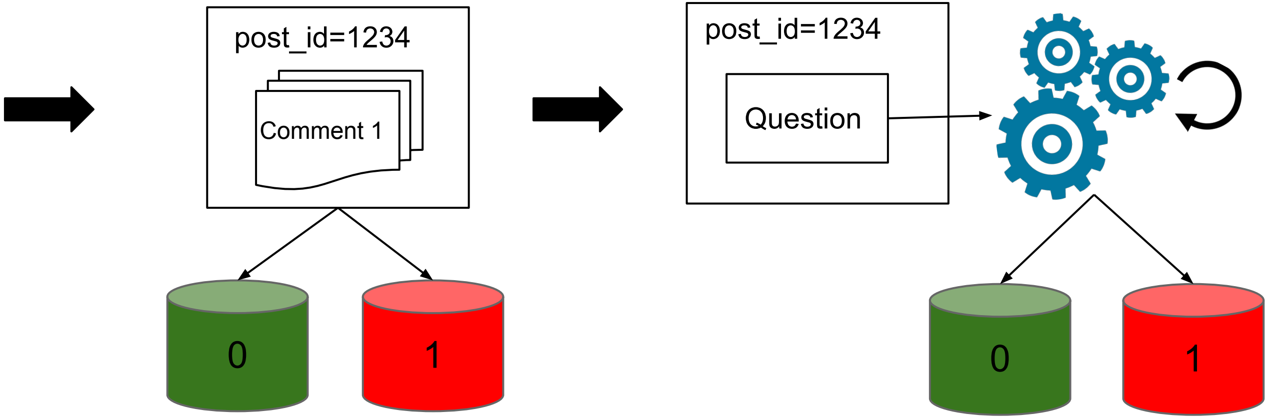
With physician burnout at an all time high, and with increased demand for physician responses on online health forums, how do patients receive reliable medical advice online?

Methods

Data:
1,403,220 questions
2,366,387 follow-up comments

Task 1:
Question Labeling Task based on Comments

Task 2:
Question Classification Task

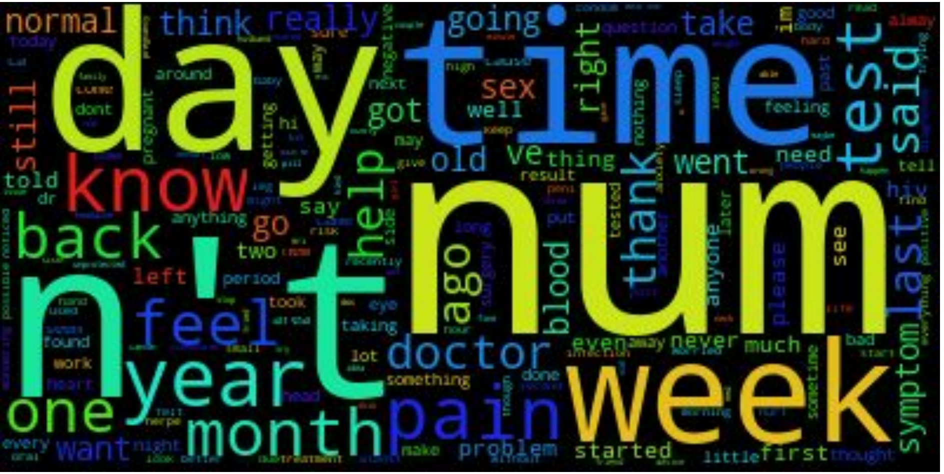


Task 1: Question Labeling based on Comments

Initial Regex	Random 200 comments		
Labeled 1’s and 0’s	Cohen’s Kappa = 0.73		
Patterns & Errors	Finalized Regex		
	Prec	Recall	F1
	0.76	0.91	0.83
Labeled comments → questions	~23% labeled as 1’s		

Task 2 Question Classification

- Pre-processing
  - removed stop-words
  - replaced numeric values with “num”
- Word frequency analysis



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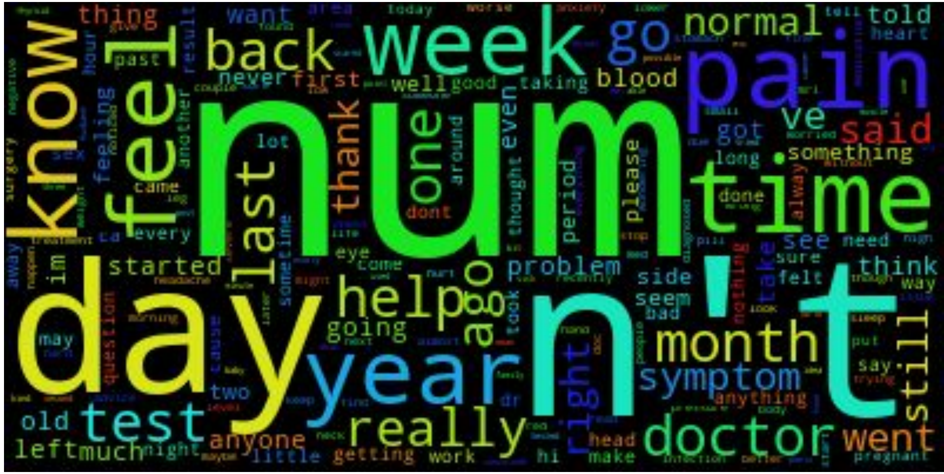
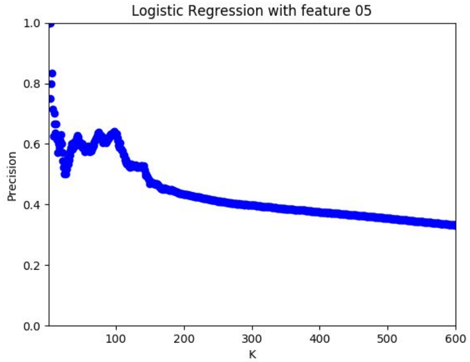


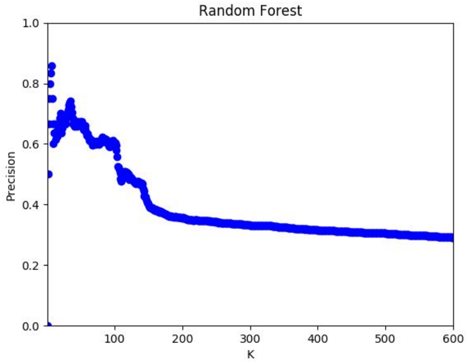
Label = 1

Standard Models

For our initial approach, we used a supervised learning technique with bag of words & TF-IDF (optional).
Below are the top 2 performing models.

Top Models	**acc**	**roc/auc**	**prec**	**recall**	**f1**
Logistic Regression	0.75	0.66	0.68	0.75	0.66
Random Forest	0.74	0.60	0.66	0.74	0.67





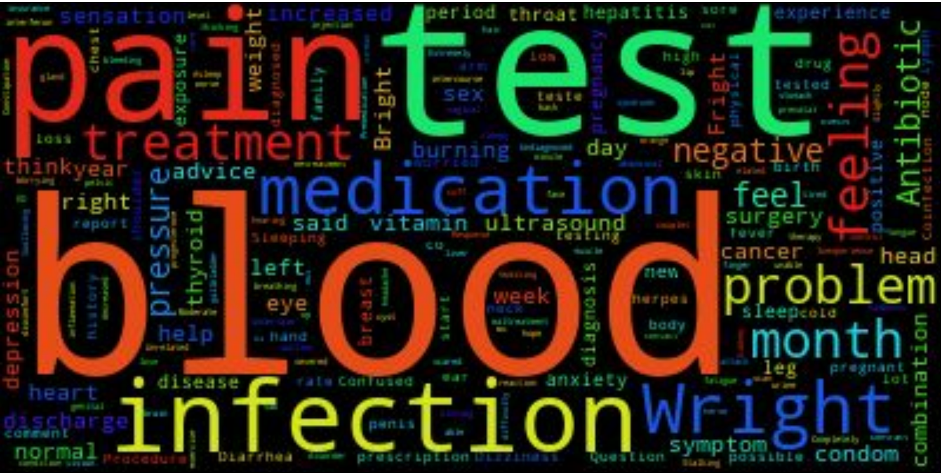
Standard Feature Analysis

- Beginning: **571,045 features**
- Feature Selection (chi-squared):
  - p-value < 0.05: 29,821 features
  - p-value < 0.01: 14,628 features
  - [no difference in model performance]

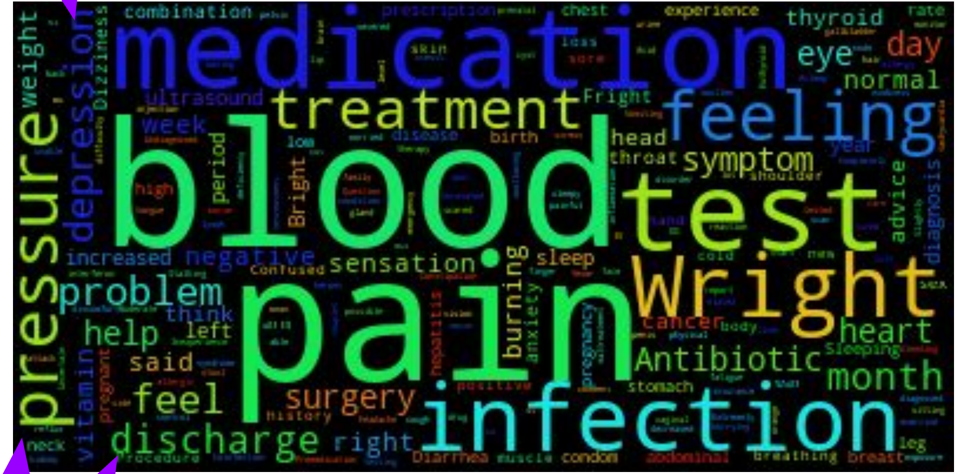
- Top 20 features
  - Back, **chest**, condom, doctor, feel, feeling, go, **heart**, **hiv**, like, normal, **pain**, risk, sex, side, sometimes, started, stomach, symptoms, **worse**

UMLS Word Frequency Analysis (no collocation)

Label = 0



Label = 1

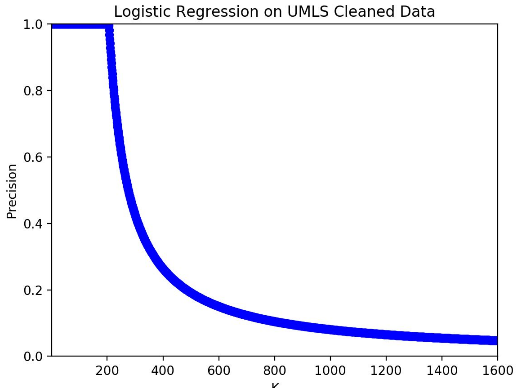


Incorporated QuickUMLS to identify medical concepts for each question

UMLS Models

We used a supervised learning technique with bag of words & TF-IDF. Below are the top 2 performing models.

Logistic regression has higher precision, but random forest has a better precision at k curve.



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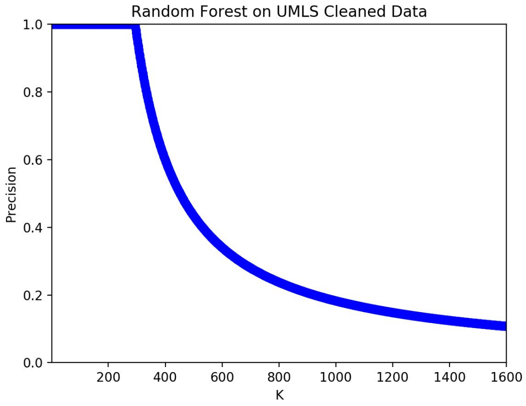

UMLS Feature Analysis

- Beginning: 29,134 features
- Feature Selection (chi-squared, p-value < 0.05): 7,801 features
  - Decreasing p-value → no difference in model performance
    - p-value < 0.01: 5,616 features
    - p-value < 0.001: 4,201 features
- Top 20 features
  - abdominal, **breathing**, **chest**, condom, condoms, constipation, **depression**, discharge, dizziness, dizzy, **dog**, exposure, feeling, **heart**, **medication**, medications, **pain**, pressure, sex, stomach

Top 20 UMLS Features: Dog?

- Bivariate Relations
  - Dog run
  - Dog allergy
  - Dog bite
  - Dog companion
  - Dog day
- Dog community group
  - Questions for vets

Conclusions, Lessons & Future Work

Conclusions

1. UMLS models performs better than standards models
   a. Random Forest with UMLS performs the best
2. But, precision still has room for improvement

Lessons Learned

1. "Occam’s Razor"
   a. Sometimes the simplest model works the best
2. When working with big data, runtime is the bottleneck

Future Work

1. Continue training models to achieve higher support
2. Implement the neural network models (LSTM, CNN)

Thank you

References

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