



Statistical Inference for NLP algorithms

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What are the authors trying to solve?

Computer
Science/Linguistics

Statistical
Approaches

- ◎ In NLP, statistical techniques used infrequently
- ◎ Uncertainty quantification is difficult
- ◎ word2vec has strong statistical underpinnings



“History Diabetes high blood pressure”

$C = c$ (Center Word)	$C' = c'$ (Neighbouring Word)	$D = 0/1$ (Boolean neighbour)
diabetes	history	$D = 1$
diabetes	diabetes	$D = 1$
diabetes	high	$D = 1$
diabetes	blood	$D = 1$
diabetes	pressure	$D = 0$
↓	↓	↓
pressure	history	$D = 0$
↓	↓	↓

$PMI > 0$
 – C, C' associated

$PMI < 0$
 – C, C' not associated

$$PMI = \log \frac{P(C = c | C' = c', D = 1)}{P(C = c | D = 1)}$$



*Can **statistical** techniques improve
our understanding of **diabetes**
classification?*

Yes, but we need to do some work first.

- PMI model
- MLE estimation
- Multivariate delta method

$$PMI = \log \frac{P_1(C = c | C' = c', D = 1)}{P_2(C = c | D = 1)}$$

	MLE	MVDM	DM
$P_1(C = c C' = c', D = 1) = \frac{\exp(\beta^T X)}{1 + \exp(\beta^T X)}$	$\rightarrow \hat{\beta}$	$\rightarrow \hat{\sigma}_1^2 = Var(\hat{P}_1)$	\searrow
$P_2(C = c D = 1) = \frac{\exp(\alpha)}{1 + \exp(\alpha)}$	$\rightarrow \hat{\alpha}$	$\rightarrow \hat{\sigma}_2^2 = Var(\hat{P}_2)$	\nearrow

\widehat{PMI}

Building a predictive model from data

- Goal: Identify type-2 diabetes in EHR
- Two summary statistics for two groups
- Word association pairs, words with the 'diabet' stem

$(diabet-, c')$

$$m_k PMI_d^d$$

$$m_k PMI_d^{xd}$$

(c, c')

$$m_k PMI^d$$

$$m_k PMI^{xd}$$

A decorative network diagram in the top-left corner, featuring a complex web of interconnected nodes and lines. The nodes are represented by small circles, some of which are larger and have concentric circles, suggesting different levels of connectivity or importance. The lines are thin and gray, creating a mesh-like structure.

RESULTS



1000 patients

500 Diabetes, 500 non-diabetes

61,489 total words

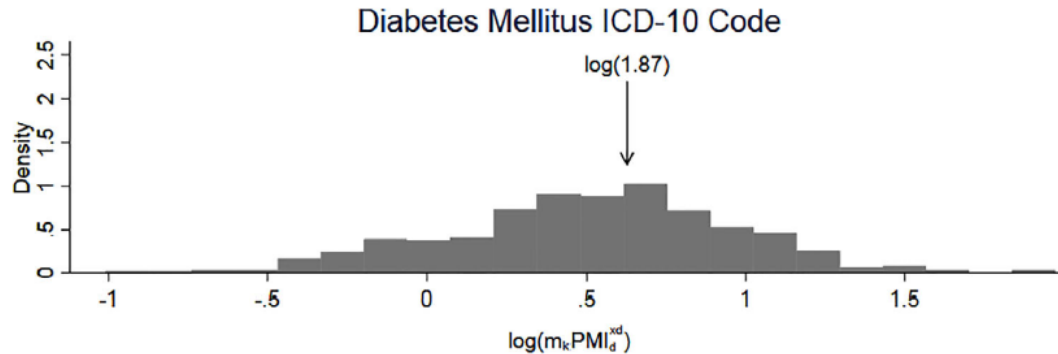
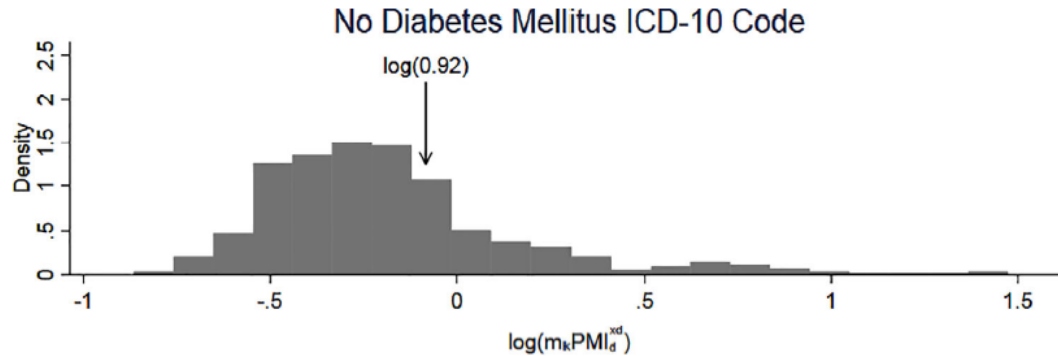
Each patient has many records (notes)

1500 words kept

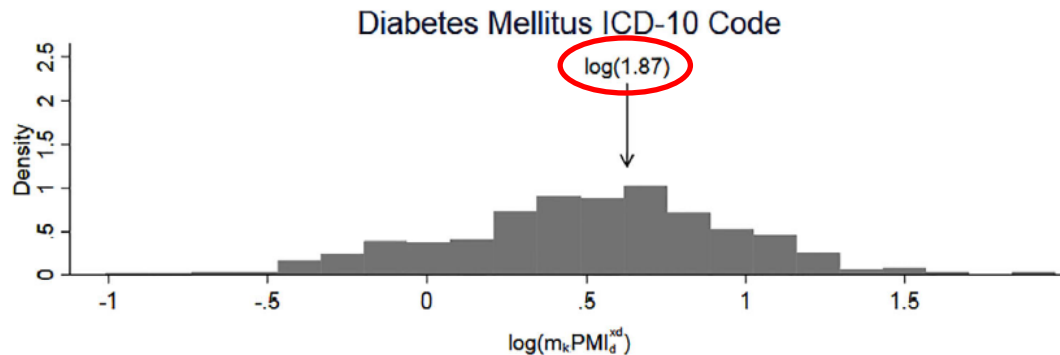
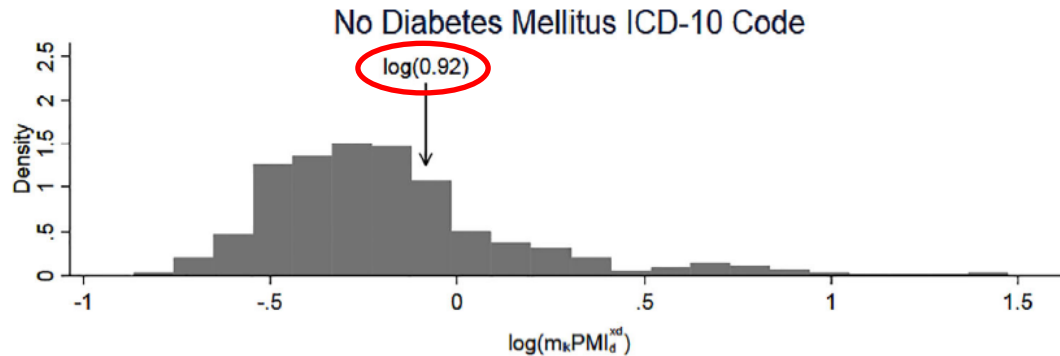
Reduces dimensionality of dataset

PREDICTIVE MODEL

Mean PMI over non-diabetics where $C' = \text{'diabet'}$



PREDICTIVE MODEL



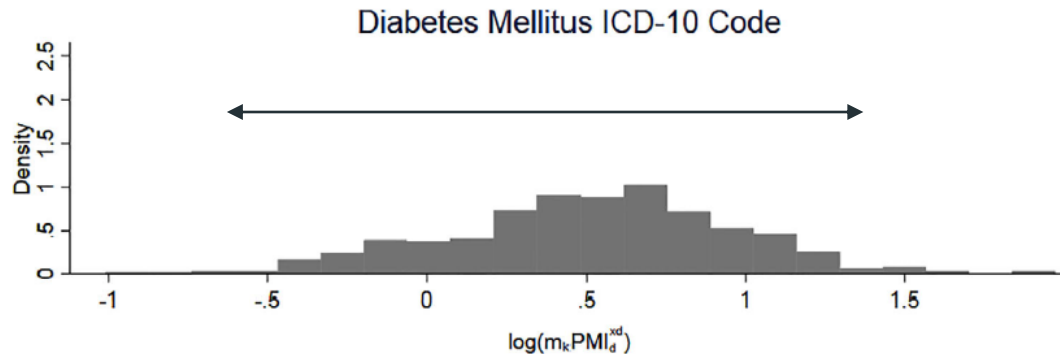
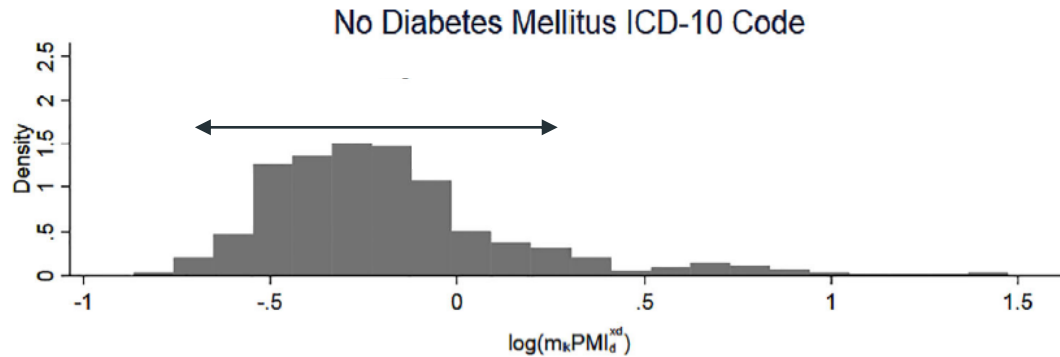
Mean PMI over non-diabetics where $C' = \text{'diabet'}$

Key Takeaway:

Less words associated with 'diabet' in non-diabetics

More words associated with 'diabet' in diabetics

PREDICTIVE MODEL



Mean PMI over non-diabetics where $C' = \text{'diabetes'}$

Key Takeaway:

Non-diabetics have tighter distribution

PMI's in non-diabetes group are better at predicting who doesn't have diabetes



**So understanding the
distribution of the PMI
can tell us a lot!**



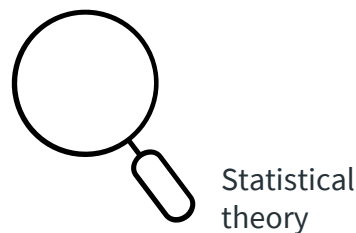
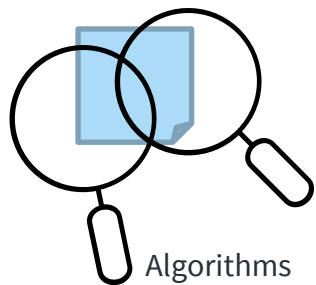
In summary,

- ◎ Novel framework to calculate SEs for PMI

$$PMI = \log \frac{P(C = c | C' = c', D = 1)}{P(C = c | D = 1)}$$

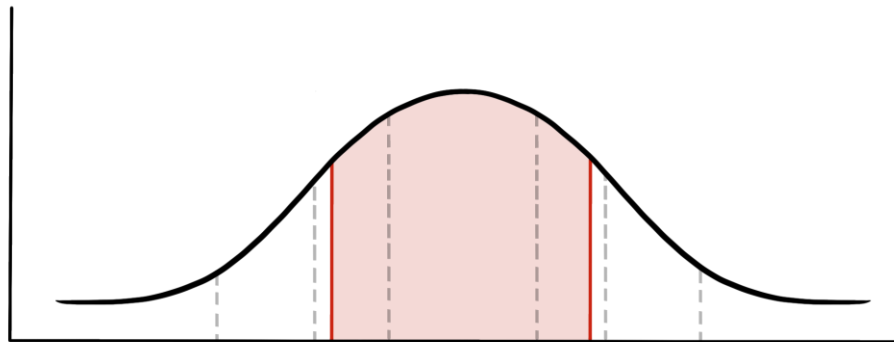
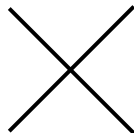
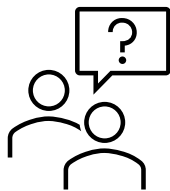
$$\rightarrow \frac{\widehat{PMI}}{Var(\widehat{PMI})}$$

- ◎ Importance of statistical analysis in NLP and data science



In summary,

- ◎ High relevance contribution in a sparse literature space





**Thank you
for listening**

