A Bayesian Topic Model for Human-Evaluated Interpretability

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### SUMMARY

One goal of topic modeling is to produce topics which are interpretable. However, existing methods often produce topics which are difficult for a human evaluator to accurately describe with a single label. This paper aims to improve interpretability in topic modeling by providing a novel, outperforming interpretable topic model. Our approach combines two previously established subdomains in topic modeling: nonparametric and weakly-supervised topic models. Given a nonparametric topic model, we can include weakly-supervised input using novel modifications to the nonparametric generative model. These modifications lay the groundwork for a compelling setting—one in which most corpora, without any previous supervised or weakly-supervised input, can discover interpretable topics. Combining nonparametric topic models with weakly-supervised topic models leads to an exciting discovery—a complete, self-contained and outperforming topic model for interpretability.

## ACKNOLWEDGEMENT

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- The generative model for non-parametric topic modeling (left)
- Weakly-supervised topic modeling is injected into  $\phi_i$
- A distribution is placed over each hyperparameter set

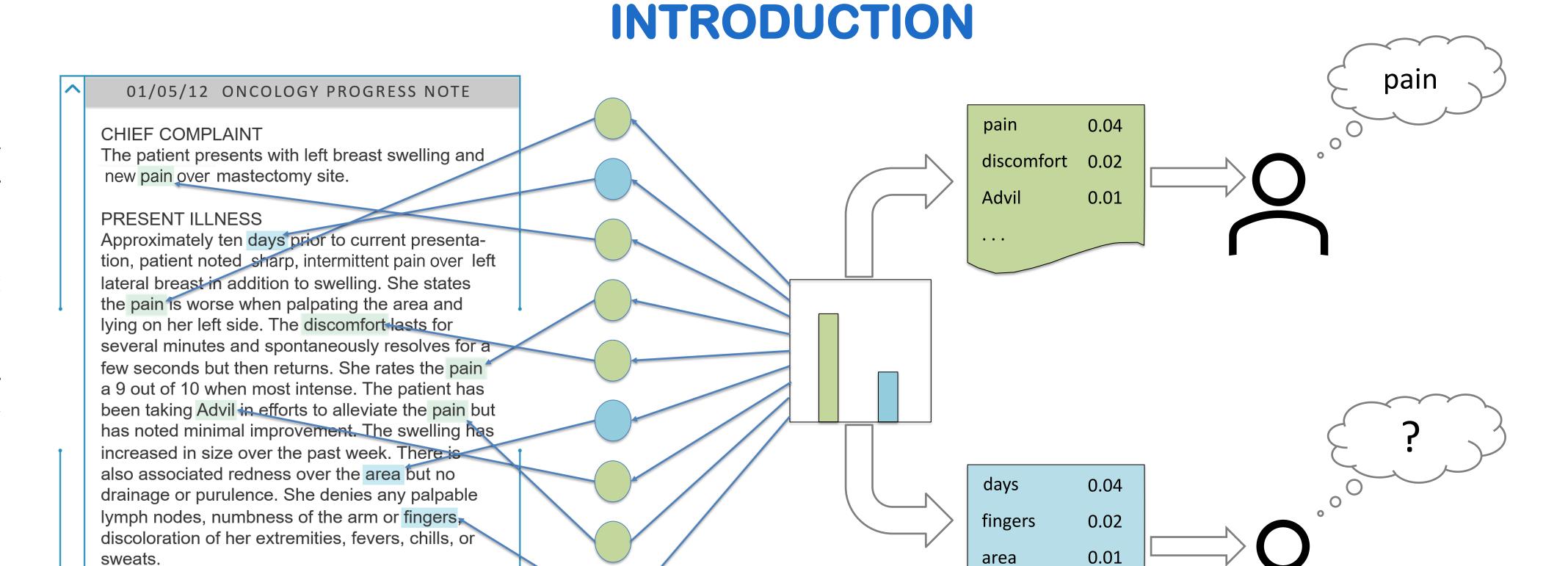
$$\begin{aligned} \theta_{d} &= \sum\nolimits_{i=1}^{\infty} q_{d,i} \cdot \prod\nolimits_{l=1}^{i-1} (1 - q_{d,l}) \, \delta_{\varphi_{d,i}} \\ q_{d,i} &\sim Beta(1,\gamma) \\ \varphi_{d,i} &\sim P \\ P &= \sum\nolimits_{i=1}^{\infty} r_{i} \cdot \prod\nolimits_{l=1}^{i-1} (1 - r_{l}) \, \delta_{\varphi_{i}} \\ r_{i} &\sim Beta(1,\zeta) \\ \varphi_{i} &\sim Dir(\alpha) \end{aligned}$$

$$\phi_i \sim M$$

$$M = (1 - \xi) \cdot \delta_{A} + \frac{\xi}{B} \cdot \sum_{i=1}^{B} \delta_{\Omega_{i}}$$

$$A \sim Dir(\alpha)$$

$$\Omega_i \sim \text{Dir}(\omega_i)$$

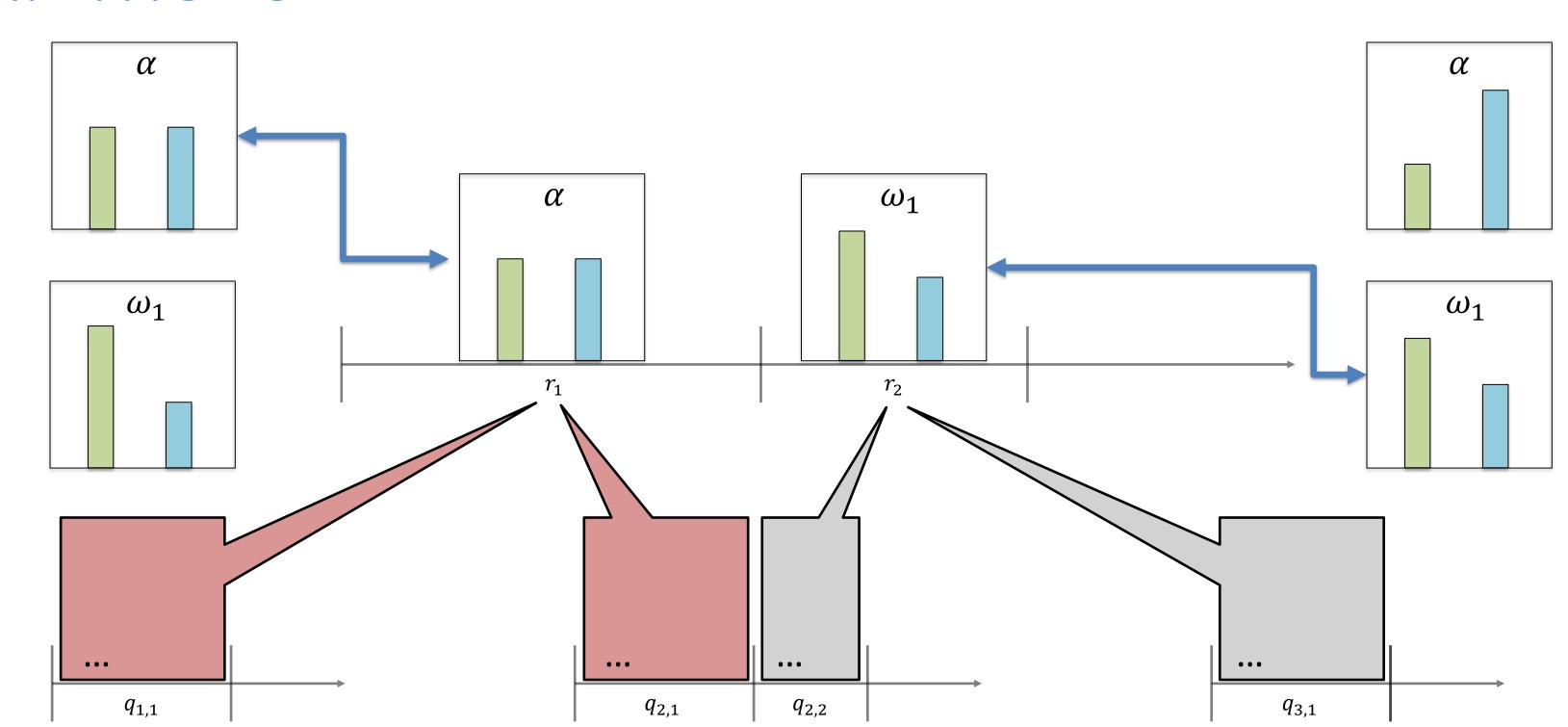


## **METHODS**

**REVIEW OF SYMPTOMS** 

sweats, +fatigue

Constitutional: Abnormal - No fevers, chills, night

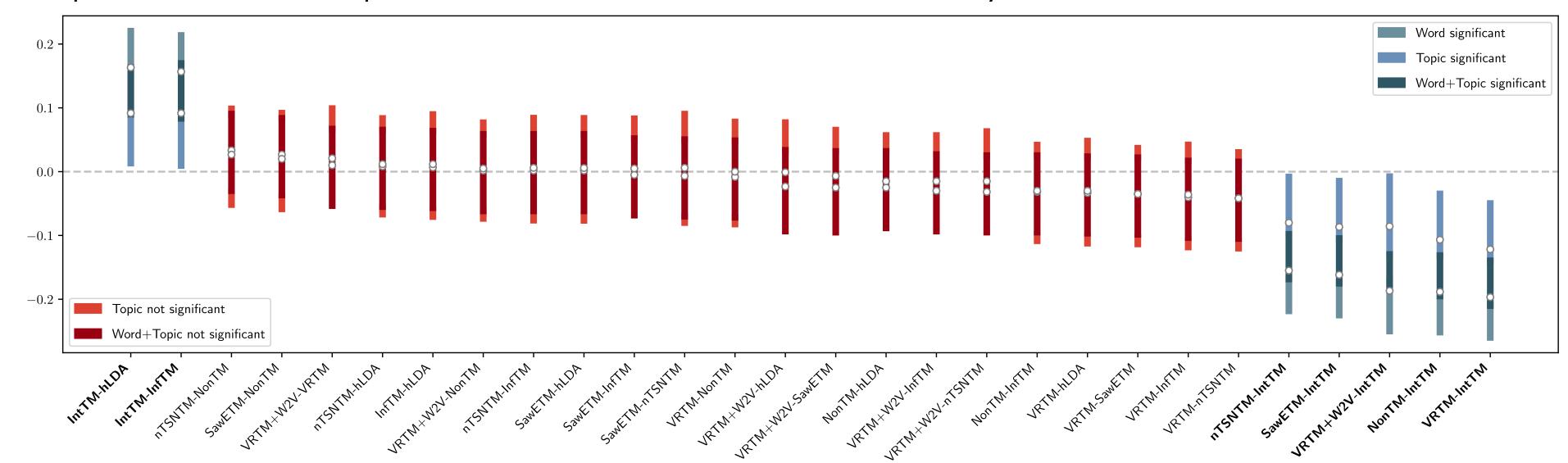


- A visual example of the generative model for three documents.
- The words of each document are portioned into bias from distributions in a stick break.
- Each stick break contains a distribution that was built from either lpha or  $\omega_i$  hyperparameters.
- The hypermeters are drawn from a discrete distribution over the set  $\{\alpha, \omega_i\}$ .

#### Interpretability

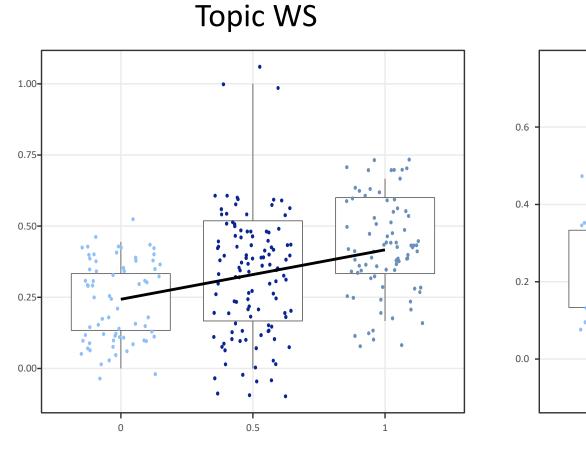
We examine the interpretability of our method against state-of-the-art neural topic models and competing Bayesian models. For a robust set of data, we run each topic model and create word intrusion and topic intrusion tasks from the output. The tasks are then placed on Amazon Mechanical Turk to be scored by human-evaluators.

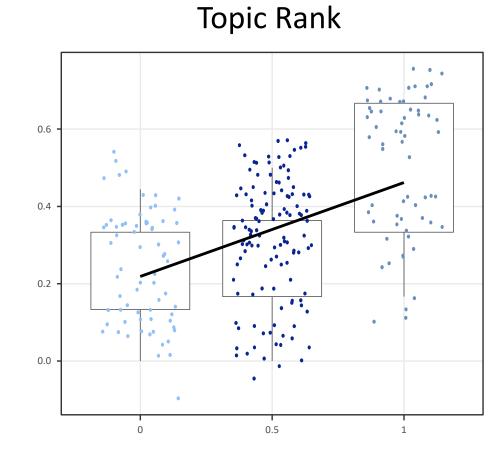
RESULTS

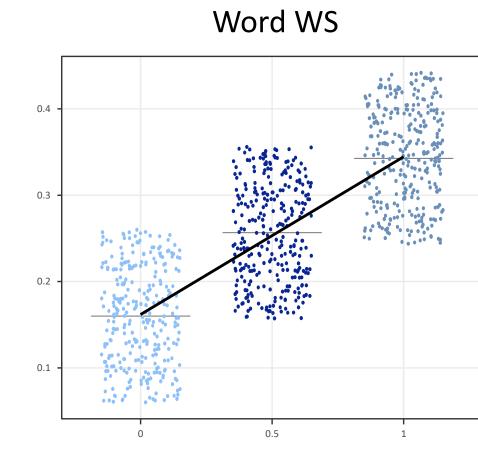


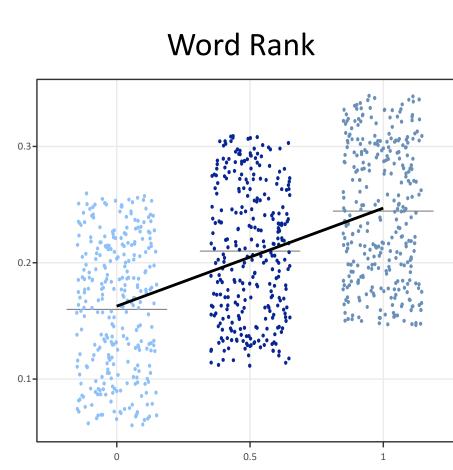
#### $\Leftrightarrow$ Effect of $\xi$

To determine the effect that the  $\xi$  parameter has on interpretability we design an experiment that asks human evaluators to determine word and topic intrusions under different values of  $\xi$ . We also seek to determine the interpretability effect when discovering a knowledge source (Rank) and using a provided knowledge source (WS). All models show that as  $\xi$  increases, so does interpretability.









# RESULTS

#### ♦ Human-evaluated task analysis

We show the statistical analysis of our interpretability experiment which demonstrates for all datasets our interpretable topic modeling approach results in better interpretability than baseline methods.

	Word Intrusion				
	N	$\mu_1$	M D	p-value	
hLDA	600	$0.15 \pm 0.03$	$-0.02 \pm 0.04$	0.83	
InfTM	600	$0.15 \pm 0.03$	$-0.01 \pm 0.04$	0.736	
IntTM	600	$0.31 \pm 0.04$	$0.14 \pm 0.05$	2.20e-09	
NonTM	600	$0.12 \pm 0.03$	$-0.04 \pm 0.04$	0.987	
nTSNTM	600	$0.15 \pm 0.03$	$-0.01 \pm 0.04$	0.709	
SawETM	600	$0.15 \pm 0.03$	$-0.02 \pm 0.04$	0.808	
VRTM	600	$0.11 \pm 0.03$	$-0.05 \pm 0.04$	0.996	
VRTM+W2V	600	$0.12 \pm 0.03$	$-0.04 \pm 0.04$	0.984	

Topic Intrusion			
N	$\mu_1$	M D	p-value
500	$0.27 \pm 0.04$	$0.02 \pm 0.05$	0.236
600	$0.27 \pm 0.04$	$0.02 \pm 0.05$	0.215
600	$0.36 \pm 0.04$	$0.11 \pm 0.05$	1.30e-05
600	$0.26 \pm 0.03$	$0.01 \pm 0.05$	0.421
500	$0.28 \pm 0.04$	$0.03 \pm 0.05$	0.175
600	$0.28 \pm 0.04$	$0.03 \pm 0.05$	0.107
600	$0.28 \pm 0.04$	$0.03 \pm 0.05$	0.163
600	$0.24 \pm 0.03$	$-0.01 \pm 0.05$	0.656
	500 600 600 600 500 600 600	N $\mu_1$ 500 $0.27 \pm 0.04$ 600 $0.27 \pm 0.04$ 600 $0.36 \pm 0.04$ 600 $0.26 \pm 0.03$ 500 $0.28 \pm 0.04$ 600 $0.28 \pm 0.04$ 600 $0.28 \pm 0.04$	N $\mu_1$ MD500 $0.27 \pm 0.04$ $0.02 \pm 0.05$ 600 $0.27 \pm 0.04$ $0.02 \pm 0.05$ 600 $0.36 \pm 0.04$ $0.11 \pm 0.05$ 600 $0.26 \pm 0.03$ $0.01 \pm 0.05$ 500 $0.28 \pm 0.04$ $0.03 \pm 0.05$ 600 $0.28 \pm 0.04$ $0.03 \pm 0.05$ 600 $0.28 \pm 0.04$ $0.03 \pm 0.05$

All models show that as  $\xi$  increases, so does interpretability. This demonstrates that the  $\xi$  acts as a parameter that controls the amount of interpretability into the topic model.