



# Reading Tea Leaves: How Humans Interpret Topic Models

# Topic Models

- ▷ Used to identify the main themes in a collection of documents.
- ▷ Documents are a collection of topics. Topics are a distribution over words.

TOPIC 1

computer,  
technology,  
system,  
service, site,  
phone,  
internet,  
machine

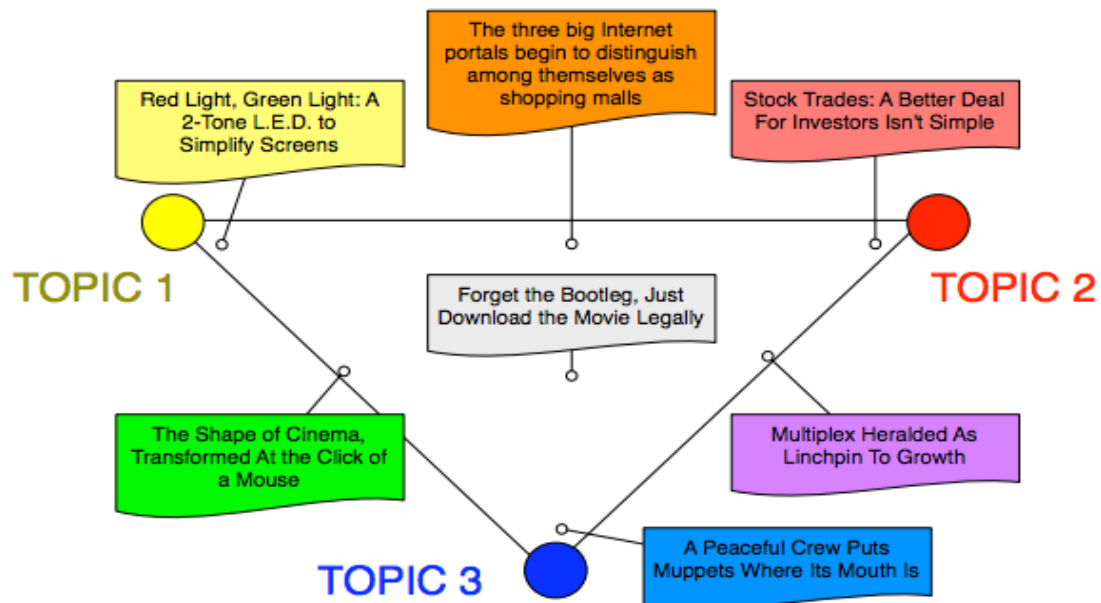
TOPIC 2

sell, sale,  
store, product,  
business,  
advertising,  
market,  
consumer

TOPIC 3

play, film,  
movie, theater,  
production,  
star, director,  
stage

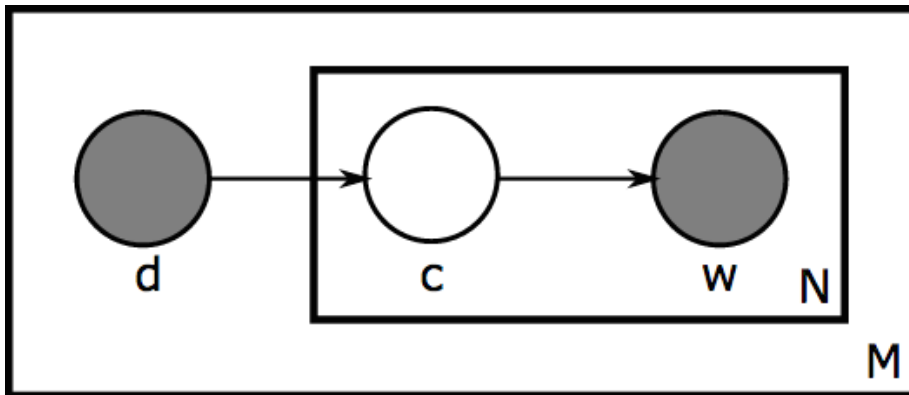
(a) Topics



(b) Document Assignments to Topics

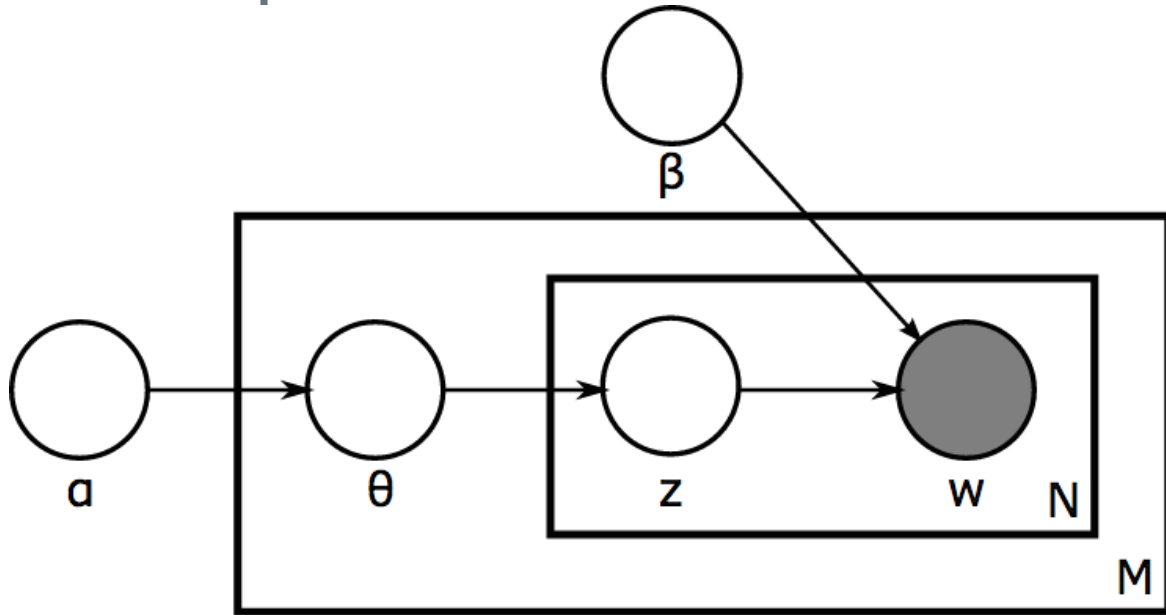
# Probabilistic Latent Semantic Indexing (pLSI)

Probability of each co-occurrence is modelled as a mixture of conditionally independent multinomial distributions



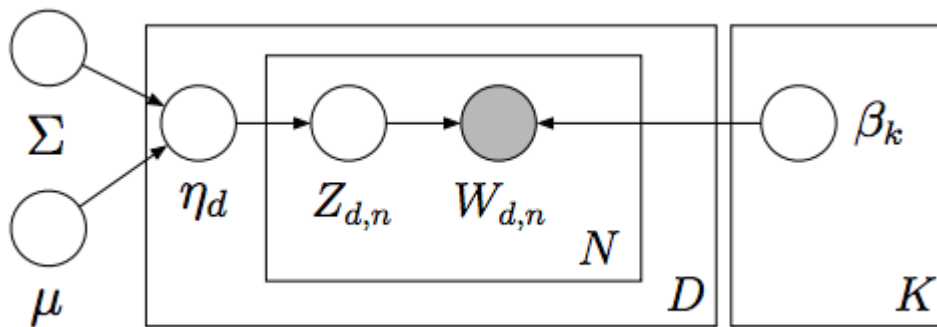
# Latent Dirichlet Analysis (LDA)

Topic distribution assumed to have a Dirichlet prior.



# Correlated Topic Model (CTM)

Allows for richer covariance structure between topic proportions. Uses a logistic normal prior over topic mixture proportions.



TOPIC 1

computer,  
technology,  
system,  
service, site,  
phone,  
internet,  
machine

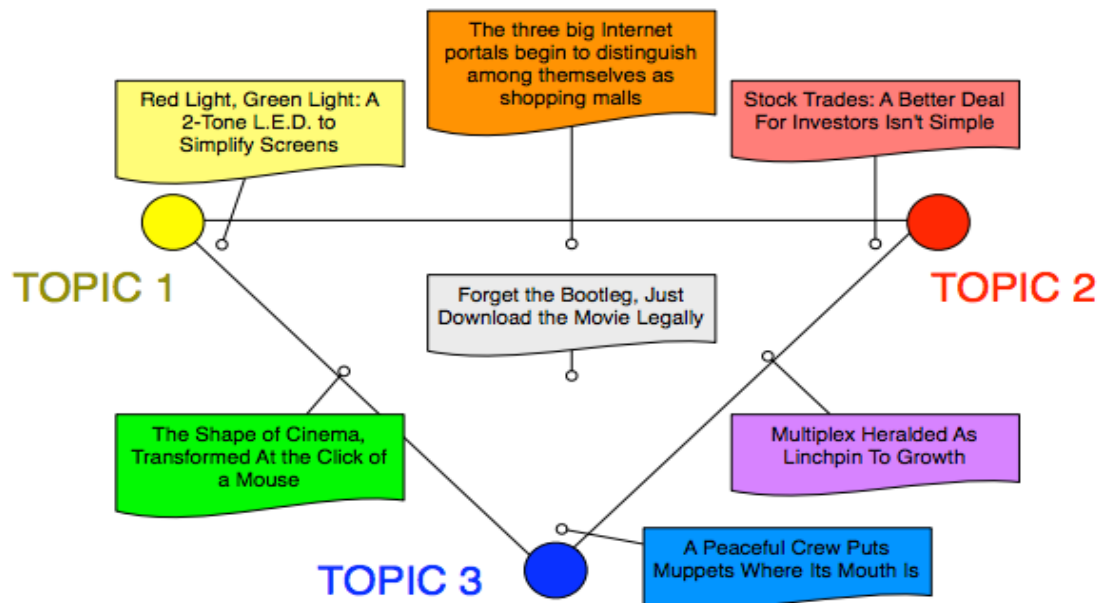
TOPIC 2

sell, sale,  
store, product,  
business,  
advertising,  
market,  
consumer

TOPIC 3

play, film,  
movie, theater,  
production,  
star, director,  
stage

(a) Topics



(b) Document Assignments to Topics

# Goals & Motivation

- ▷ Previously, no measure of interpretability of this latent space.
- ▷ Present a method for measuring interpretability of topic models using human evaluation tasks.



# Word Intrusion

**1 / 10**

floppy alphabet computer processor memory disk

**2 / 10**

molecule education study university school student

**3 / 10**

linguistics actor film comedy director movie

**4 / 10**

islands island bird coast portuguese mainland

# Topic Intrusion

6 / 10

## DOUGLAS\_HOFSTADTER

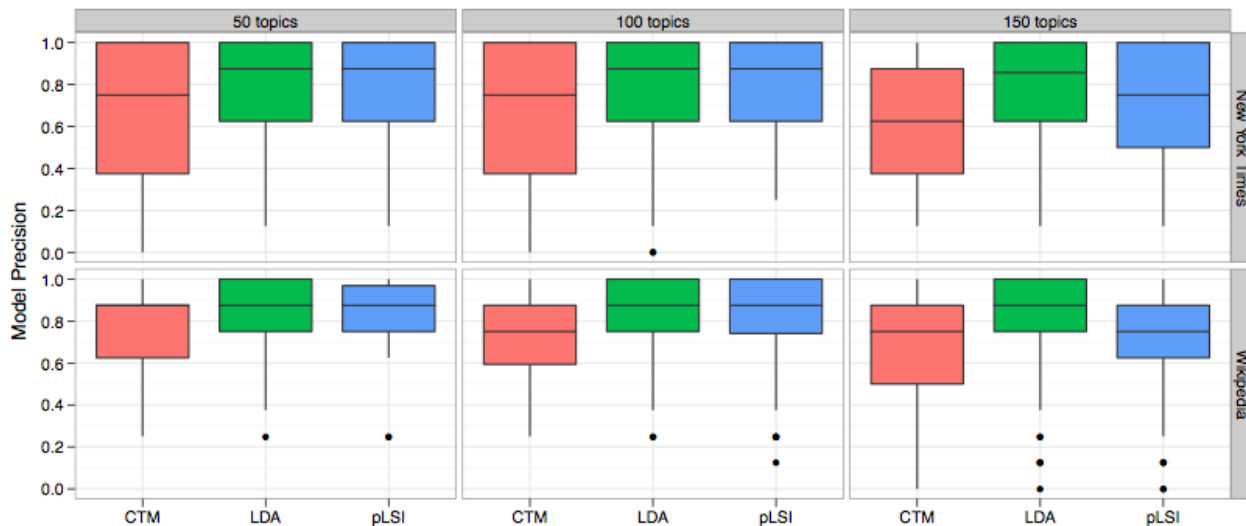
Douglas Richard Hofstadter (born February 15, 1945 in New York, New York) is an American academic whose research focuses on consciousness, thinking and creativity. He is best known for ", first published in

[Show entire excerpt](#)

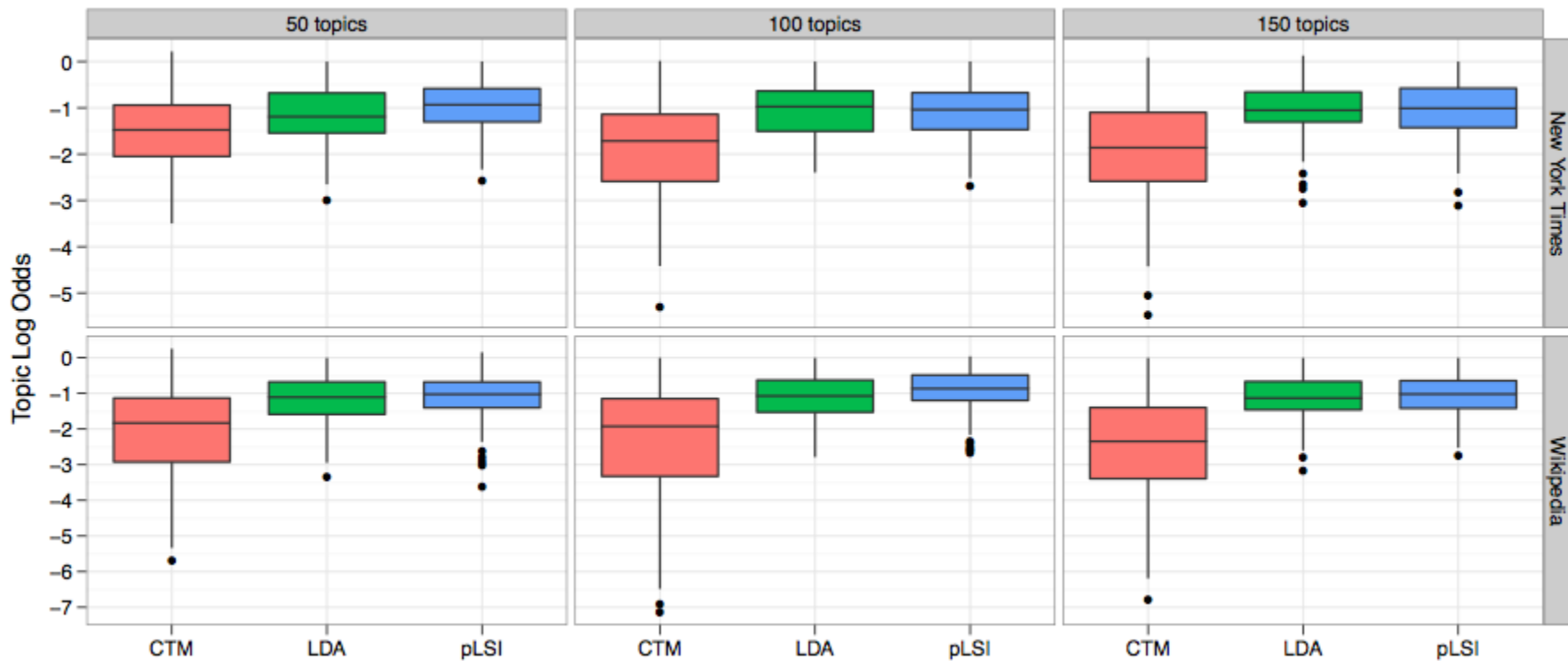
student	school	study	education	research	university	science	learn
human	life	scientific	science	scientist	experiment	work	idea
play	role	good	actor	star	career	show	performance
write	work	book	publish	life	friend	influence	father

# Results - Word Intrusion

CORPUS	TOPICS	LDA	CTM	PLSI
NEW YORK TIMES	50	<b>-7.3214 / 784.38</b>	-7.3335 / 788.58	-7.3384 / 796.43
	100	-7.2761 / 778.24	<b>-7.2647 / 762.16</b>	-7.2834 / 785.05
	150	-7.2477 / 777.32	-7.2467 / <b>755.55</b>	<b>-7.2382 / 770.36</b>
WIKIPEDIA	50	<b>-7.5257 / 961.86</b>	-7.5332 / <b>936.58</b>	-7.5378 / 975.88
	100	-7.4629 / 935.53	<b>-7.4385 / 880.30</b>	-7.4748 / 951.78
	150	-7.4266 / 929.76	<b>-7.3872 / 852.46</b>	-7.4355 / 945.29



# Results - Topic Intrusion



# Conclusion

- ▶ Traditional metrics of evaluation do not capture whether topics are coherent.
- ▶ When developing topic models we should now focus on evaluations which depend on real-world task performance.

# References

Blei, D., & Lafferty, J. (2006). Correlated topic models. *Advances in neural information processing systems*, 18, 147. (CTM Figure)

Blei, D. M., Ng, A. Y., & Jordan, M. I. (2003). Latent dirichlet allocation. *the Journal of machine Learning research*, 3, 993-1022. (LDA Figure)

Chang, J., Gerrish, S., Wang, C., Boyd-graber, J. L., & Blei, D. M. (2009). Reading tea leaves: How humans interpret topic models. In *Advances in neural information processing systems* (pp. 288-296).

"Plsi 1" by Bkkbrad, EduardoValle - <http://en.wikipedia.org/wiki/File:Plsi.svg>. Licensed under CC BY-SA 3.0 via Wikimedia Commons

# Further Reading

Blei, D. M. (2012). Probabilistic topic models. *Communications of the ACM*, 55(4), 77-84.