

# Topic Detection - LDA

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# Background



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BEIJING INSTITUTE OF TECHNOLOGY

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- 1 What is TDT
- 2 why
- 3 Framework



TDT research begins with a constantly arriving stream of text from newswire and from automatic speech-to-text systems that are monitoring selected television, radio, and Web broadcast news shows. Roughly speaking, the goal of TDT is to break the text down into individual news stories, to monitor the stories for events that have not been seen before, and to gather the stories into groups that each discuss a single news topic.

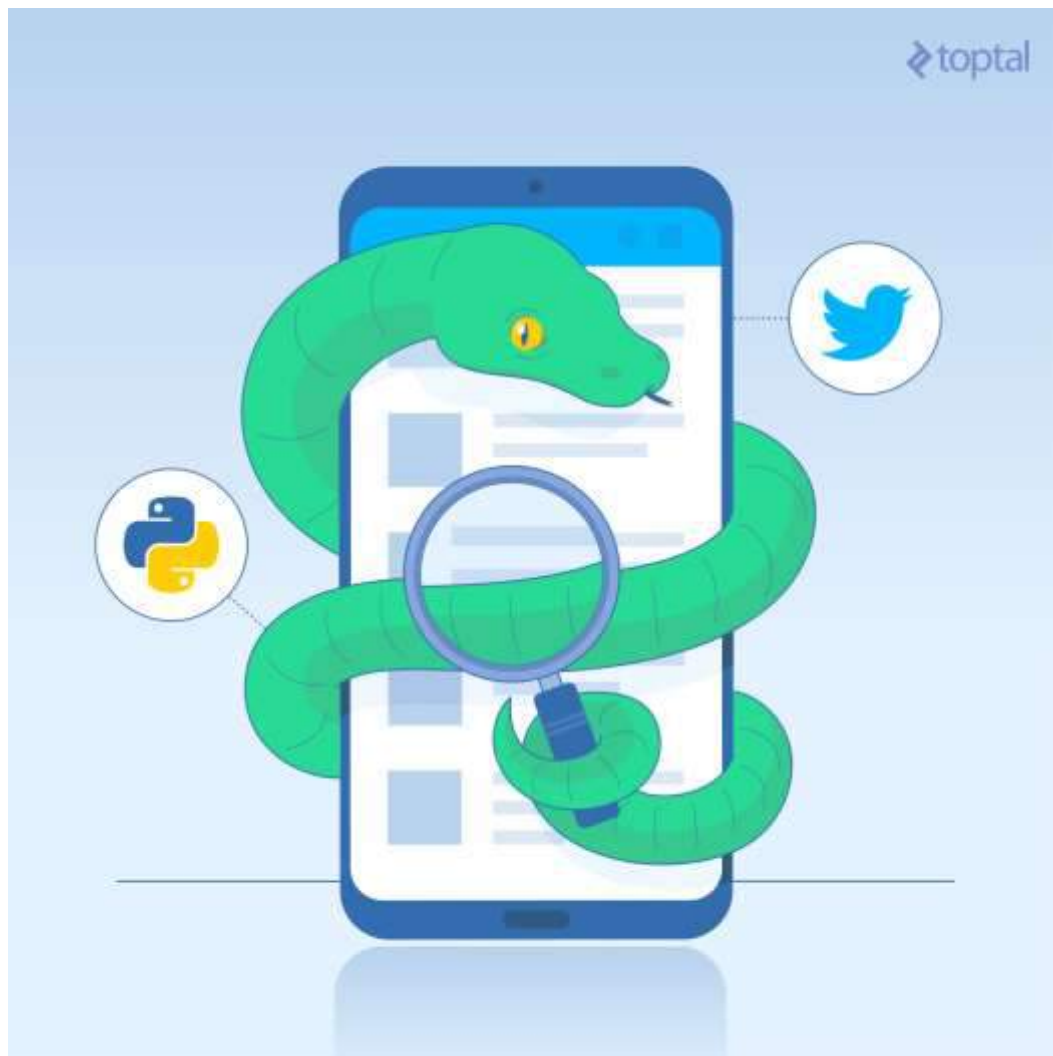
The initial motivation for research in TDT was to provide a core technology for an envisioned system that would monitor broadcast news and alert an analyst to new and interesting events happening in the world. Analysts are very





Suppose you have a huge number of documents(corpus) New York times

Topic detection provide a corpus-level intuition of major themes

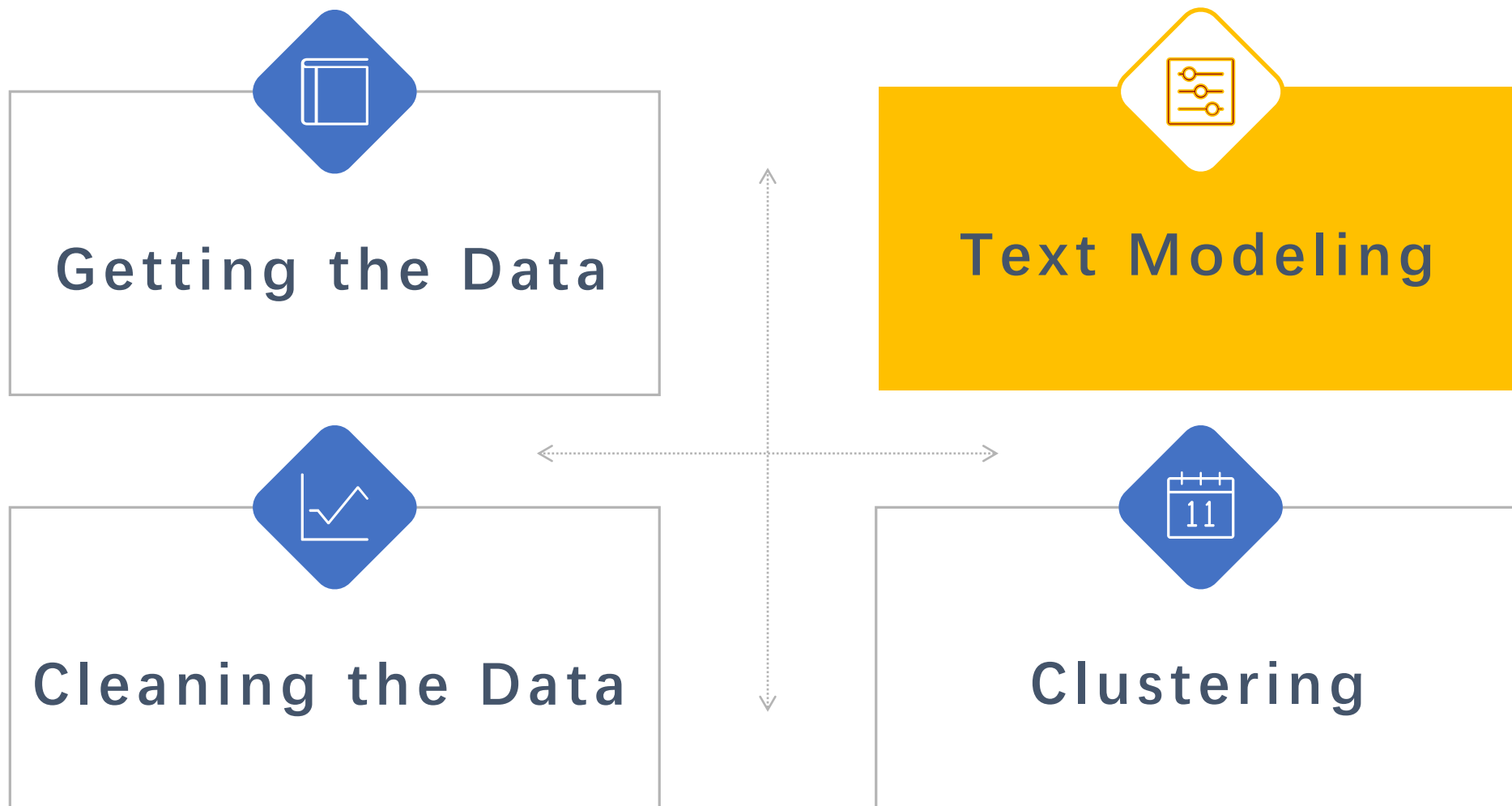


Getting raw

Before we can complete our review of your developer account application, we need some more details about your use case, and who will be using your product.

Please reply to this email with the following information:

- A list of the government or public sector entities that will have access to Twitter content, or information derived from Twitter content, under this use case.
- The specific use cases of your product or service by government or public sector entities.



# Getting the Data



WALLS.IO

topic\_detection\_LDA  
walls.io/b6sdq

Settings Moderation Content Analytics Embed & Display View wall

Posts  
Admins & Moderators  
Language filter  
Spam filter  
Settings  
Export

Notifications are off  
Desktop notifications will notify you about new posts if you have this browser tab open in the background.  
TURN ON

Walls.io Trial  
6 days 14 hours left  
UPGRADE ACCOUNT

Visibility Networks Post Types Search

**Susan Yerkes Cary** | @susanyerkesary  
Twitter · 39 seconds ago · in English

@RudyGiuliani Dude, who is YOUR lawyer? Cuz you're going to need one. **trump** is definitely going to throw you under the **trump** train. And soon. He is only out for himself.

HIDE HIGHLIGHT REPORT SPAM LANGUAGE WHITELIST USER CTA

**Leinhart** | @Leinhartcleric  
Twitter · 39 seconds ago · in English

@kaitlancollins There is no reason to believe anything **Trump** says at this point. I'm not sure he is even capable of the truth under oath.

HIDE HIGHLIGHT REPORT SPAM LANGUAGE WHITELIST USER CTA

**paolo López layman** | @radioss  
Twitter · 40 seconds ago · in Spanish · tuxtla gutierrez chiapas

#Últimominuto México va estableció comunicación con EU por dichos de **Trump** movmontes.com/?p=8338 movmontes.com/?





	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Comment	Type	External name	External fulln	External image	External created	Status	Is highligh	Location	Longitude	Latitude	Language	
2	Imagine the Trump/Rocky picture in a history book some day.	twitter	LeahKraus	Leah Kraus	https://pbs.twimg	2019/11/27 20:18	1	0	Memphis, TN	-88.4831	35.76146	en	
3	Personally, I don't put much belief in 'polls', too easy to slant the opinions, bias. If	twitter	pink2yoo	j k miller	https://pbs.twimg	2019/11/27 20:18	1	0	Wi USA	-88.7879	43.78444	en	
4	@KlassLib @Atomreisfleisch Der weitgehend erfolglose Obama hat sicherlich das	twitter	DamasiusPugne	Luke Grumpli	https://pbs.twimg	2019/11/27 20:18	1	0	Grumplor			de	
	@Osiris_Rep_UPR @GuiguiVincenti @CH_Gallois @idrissaberkane c'est tant mieux !												
	Et ce n'est pas pour rien que les USA de Trump ont promis d'aider l'Angleterre lors du Brexit.	twitter	MarcChinal	Marc Chinal	https://pbs.twimg	2019/11/27 20:18	1	0	Lyon	4.828693	45.77007	fr	
	Mais le Brexit n'existe toujours pas... donc s'appuyer sur le fait "qu'il n'y a pas de pb avec le Brexit" reste une escroquerie intellectuelle de certains #UPR.												
5	@LindseyGrahamSC No, you have that wrong @LindseyGrahamSC Trump is invit	twitter	Trumpisaphony	Duncan Scott	https://abs.twimg	2019/11/27 20:18	1	0	USA	-95.7129	37.09024	en	
6	欽樁merica First欽?is another Trump fraud: Watchdog reveals how foreign compa	twitter	BLKROCKET	ROBERT	https://pbs.twimg	2019/11/27 20:18	1	0	Naked Blue Planet			en	
7	17 States Sue Trump Administration to Keep Endangered Species Act Intact https:	twitter	susanLa60	susan Lane	https://pbs.twimg	2019/11/27 20:18	1	0	Australia	-94.5258	39.00882	en	
8	The fact that these idiots can vote is why trump was able to steal an election. @cc	twitter	Arigon52	Greg Butler	https://pbs.twimg	2019/11/27 20:18	1	0	BKNY US	-73.9442	40.67818	en	
9	There is a real danger of us not getting the no deal we require to sell the NHS to tRump	twitter	skybluebint	kathy	https://pbs.twimg	2019/11/27 20:18	1	0	salford.	-2.29013	53.48752	en	
10	I fixed it for you												
11	Trump 2020. Read it and weap "Democrats "	twitter	ChachiButt	Bob Martin	https://abs.twimg	2019/11/27 20:18	1	0				en	
	#Trump's #Bribery Apprentice? How Failed Bribery Plot Put Governor In #Prison For 14 Years   #MSNBC	twitter	Gjallarhornet	Oden	https://pbs.twimg	2019/11/27 20:18	1	0	Helsingborg, S	12.69451	56.04647	en	
12	https://t.co/pMy60q5a9V via @YouTube												
13	Thank #God we have #Leaders like @SpeakerPelosi Protecting #America #Americ	twitter	Ramon36069	Ramon 360	https://pbs.twimg	2019/11/27 20:18	1	0	Metro NY Area	-74.0005	40.71864	en	
14	Boo. Just got a 12 hour ban. My first. I'm so proud. I wonder which trump cried. M	twitter	AI_K_Hall64	Huw Jones	https://pbs.twimg	2019/11/27 20:18	1	0	In Your Dreams	-97.4721	35.21885	en	
15	@ccollao @Silc_nj @Travon There isnt a fucking wall. All a lie like everything else	twitter	reznov194513	why so serious	https://pbs.twimg	2019/11/27 20:18	1	0				en	
16	@Emolclause @WFrance26 @Paula_White Another irrational idiot who Trump sur	twitter	JayKevinJohnso	Jay Kevin Joh	https://pbs.twimg	2019/11/27 20:18	1	0	Palm Springs, C	-116.524	33.82508	en	
17	Reminds me of when I tweeted that I was wondering what Canadians were thinkir	twitter	hsiyinl	Evangeline	https://pbs.twimg	2019/11/27 20:18	1	0	Earth	4.392025	52.14478	en	
18	@thehill Yeah trump has his self surrounded by some real cut throat politicians. t	twitter	c_blabeblabe	james c blade	https://pbs.twimg	2019/11/27 20:17	1	0	Pineville, La	-92.3944	31.34387	en	
19	Trump hates himself. And he hates those that kiss up to him, because he hates hir	twitter	Mindy9469452	Sillybird 1313	https://pbs.twimg	2019/11/27 20:17	1	0				en	
	I'm sure I'm missing a ton of good Twitter content today because I have to speed-scroll past all of those godawful photoshopped trump/Rocky images.	twitter	Resist_Agitate	Really Mom	https://pbs.twimg	2019/11/27 20:17	1	0	Tennessee, US	-86.3172	35.83052	en	
	I bet the WH staff will soon be instructed to make that image their icon on all social media platforms.												
20	Trump Security Adviser Kash Patel sues NY Times over Ukraine story https://t.co/zl	twitter	raybae689	RAY BAEZ	https://pbs.twimg	2019/11/27 20:17	1	0	Queens, NY	-73.7976	40.75009	en	
21	@JamesEI09687611 @piersmorgan Lighten up. Why can't the left meme, or												

2019-11-27-20-18-32-bbsdq.csv = (~\Downloads) - GVIM

文件(F) 编辑(E) 工具(T) 语法(S) 缓冲区(B) 窗口(W) 帮助(H)

3 4 5 6 7 8 9 10 11 12 13 14 15 16 17 18 19 20 21 22 23 24 25 26 27 28 29 30 31 32 33 34 35 36 37 38 39 40 41 42 43 44 45 46 47 48 49 50 51 52 53 54 55 56 57 58 59 60 61 62 63 64 65 66 67 68 69 70 71 72 73 74 75 76 77 78 79 80 81 82 83 84 85 86 87 88 89 90 91 92 93 94 95 96 97 98 99 100 101 102 103 104 105 106 107 108 109 110 111 112 113 114 115 116 117 118 119 120 121 122 123 124 125 126 127 128 129 130 131 132 133 134 135 136 137 138 139 140 141 142 143 144 145 146 147 148 149 150 151 152 153 154 155 156 157 158 159 160 161 162 163 164 165 166 167 168 169 170 171 172 173 174 175 176 177 178 179 180 181 182 183 184 185 186 187 188 189 190 191 192 193 194 195 196 197 198 199 200 201 202 203 204 205 206 207 208 209 210 211 212 213 214 215 216 217 218 219 220 221 222 223 224 225 226 227 228 229 230 231 232 233 234 235 236 237 238 239 240 241 242 243 244 245 246 247 248 249 250 251 252 253 254 255 256 257 258 259 260 261 262 263 264 265 266 267 268 269 270 271 272 273 274 275 276 277 278 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2623 2624 2625 2626 2627 2628 2629 2630 2631 2632 2633 2634 2635 2636 2637 2638 2639 2640 2641

Common data cleaning steps on all text:

1. Split (, . ‘ ‘)
2. Remove stopwords (a, the, or)
3. stemming(ed, ing)

# Text Modeling



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- 2 LDA
- 3 Gibbs Sampling





# Latent Dirichlet Allocation

- Input: **Document-Term Matrix**, **number of topics**, **number of iterations**
- Gensim will go through the process of finding the best word distribution for each topic and best topic distribution for each document.
- Output: **The top words in each topic**. It is your job as a human to interpret this and see if the results makes sense. If not, try altering the parameters - terms in the document-term matrix, number of topics, number of iterations, etc. **Stop when the topics make sense**.



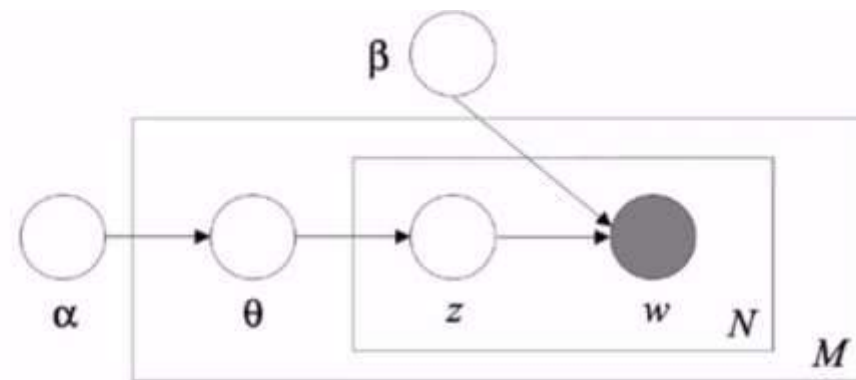
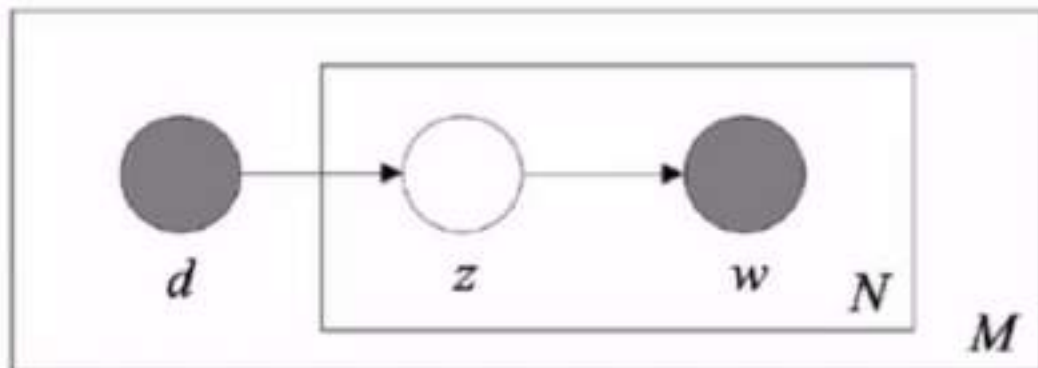
	Supervised	Un_Supervised
Hierachical	PLSA, LDA	HDP
Non-Hierachical	Labeled LDA	HSLDA



All topic models are based on the same basic assumption:

- each **document** consists of a mixture of *topics*, and
- each *topic* consists of a collection of **words**.

# 1 LDA



$$p(\mathbf{w}) = \int_{\theta} \left( \prod_{n=1}^N \sum_{z_n=1}^k p(w_n|z_n; \beta) p(z_n|\theta) \right) p(\theta; \alpha) d\theta,$$

LDA improves PLSA by imposing Dirichlet priors on the model parameters

$\beta_k$ 

Topics

gene 0.04  
dna 0.02  
genetic 0.01  
...

life 0.02  
evolve 0.01  
organism 0.01  
...

brain 0.04  
neuron 0.02  
nerve 0.01  
...

data 0.02  
number 0.02  
computer 0.01  
...

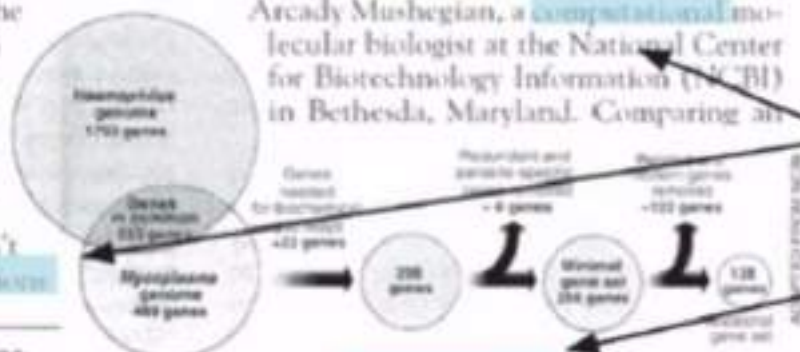
Documents

## Seeking Life's Bare (Genetic) Necessities

COLD SPRING HARBOR, NEW YORK—How many **genes** does an **organism** need to **survive**? Last week at the genome meeting here,\* two genome researchers with radically different approaches presented complementary views of the basic genes needed for **life**. One research team, using **computer** analyses to compare known **activities**, concluded that today's **organisms** can be sustained with just 250 genes, and that the earliest life forms required a mere 128 **genes**. The other researcher mapped genes in a simple parasite and estimated that for this organism, 800 genes are plenty to do the job—but that anything short of 100 wouldn't be enough.

Although the numbers don't match precisely, those **predictions**

"are not all that far apart," especially in comparison to the 75,000 **genes** in the human genome, notes Siv Anderson of Uppsala University in Sweden. She arrived at the 800 number. But coming up with a consensus answer may be more than just a **genetic** numbers game, particularly as more and more **genomes** are completely mapped and sequenced. "It may be a way of organizing any newly **sequenced genome**," explains Arcady Mushegian, a **computational** molecular biologist at the National Center for Biotechnology Information (NCBI) in Bethesda, Maryland. Comparing an

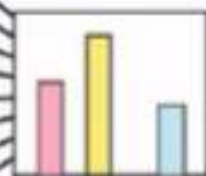


\* Genome Mapping and Sequencing, Cold Spring Harbor, New York, May 8 to 12.

Stripping down. Computer analysis yields an estimate of the minimum modern and ancient genomes.

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Topic proportions and assignments

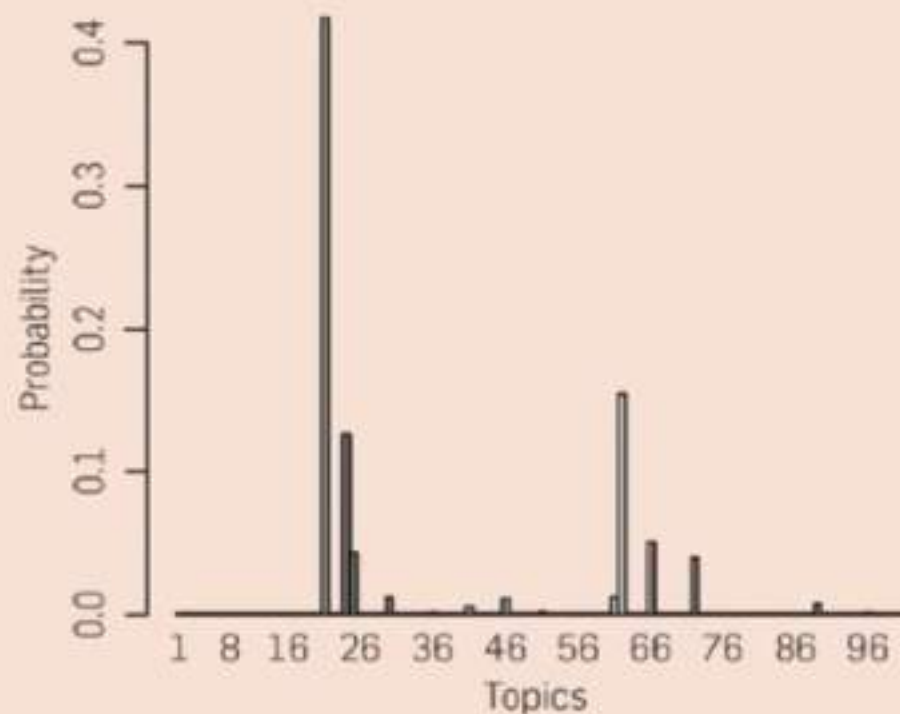
 $z_{d,n}$  $\theta_d$ 





$\beta$ :

Word probabilities for each topic		
Topics		



### “Genetics”

human  
genome  
dna  
genetic  
genes  
sequence  
gene  
molecular  
sequencing  
map  
information  
genetics  
mapping  
project  
sequences

### “Evolution”

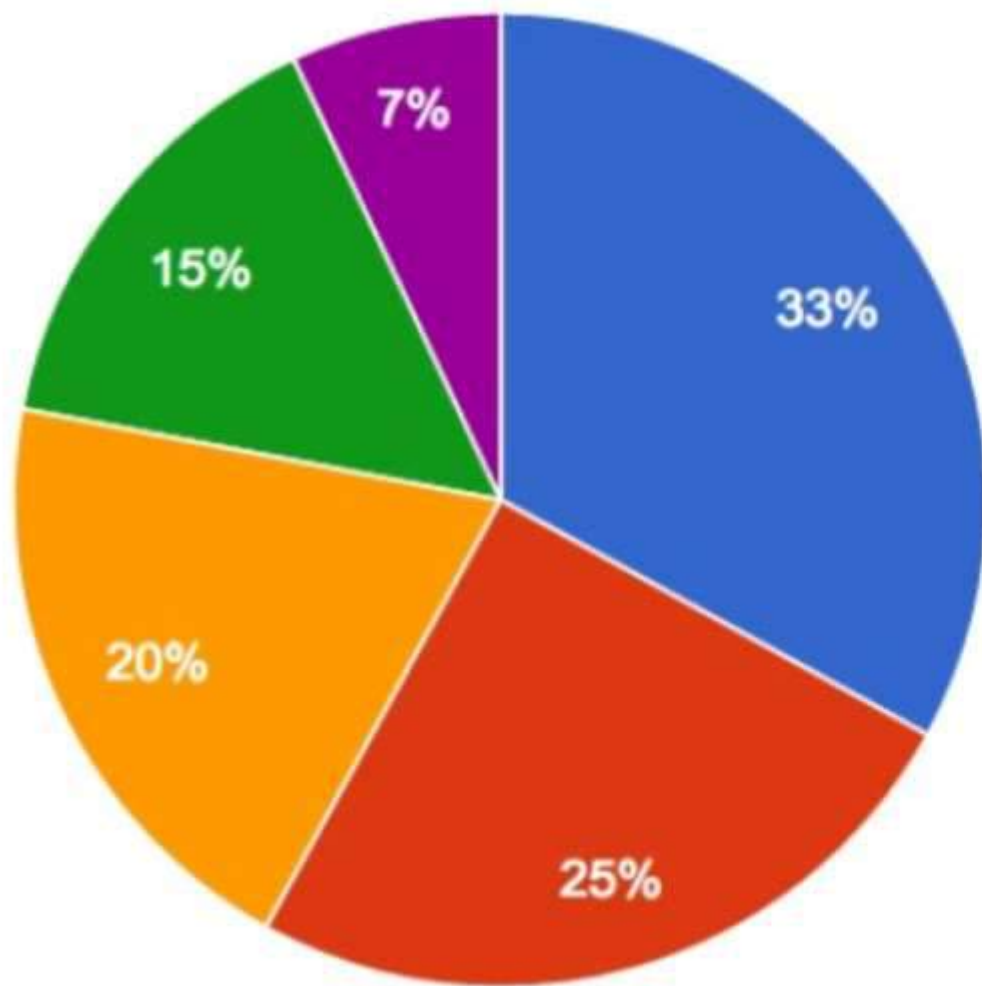
evolution  
evolutionary  
species  
organisms  
life  
origin  
biology  
groups  
phylogenetic  
living  
diversity  
group  
new  
two  
common

### “Disease”

disease  
host  
bacteria  
diseases  
resistance  
bacterial  
new  
strains  
control  
infectious  
malaria  
parasite  
parasites  
united  
tuberculosis

### “Computers”

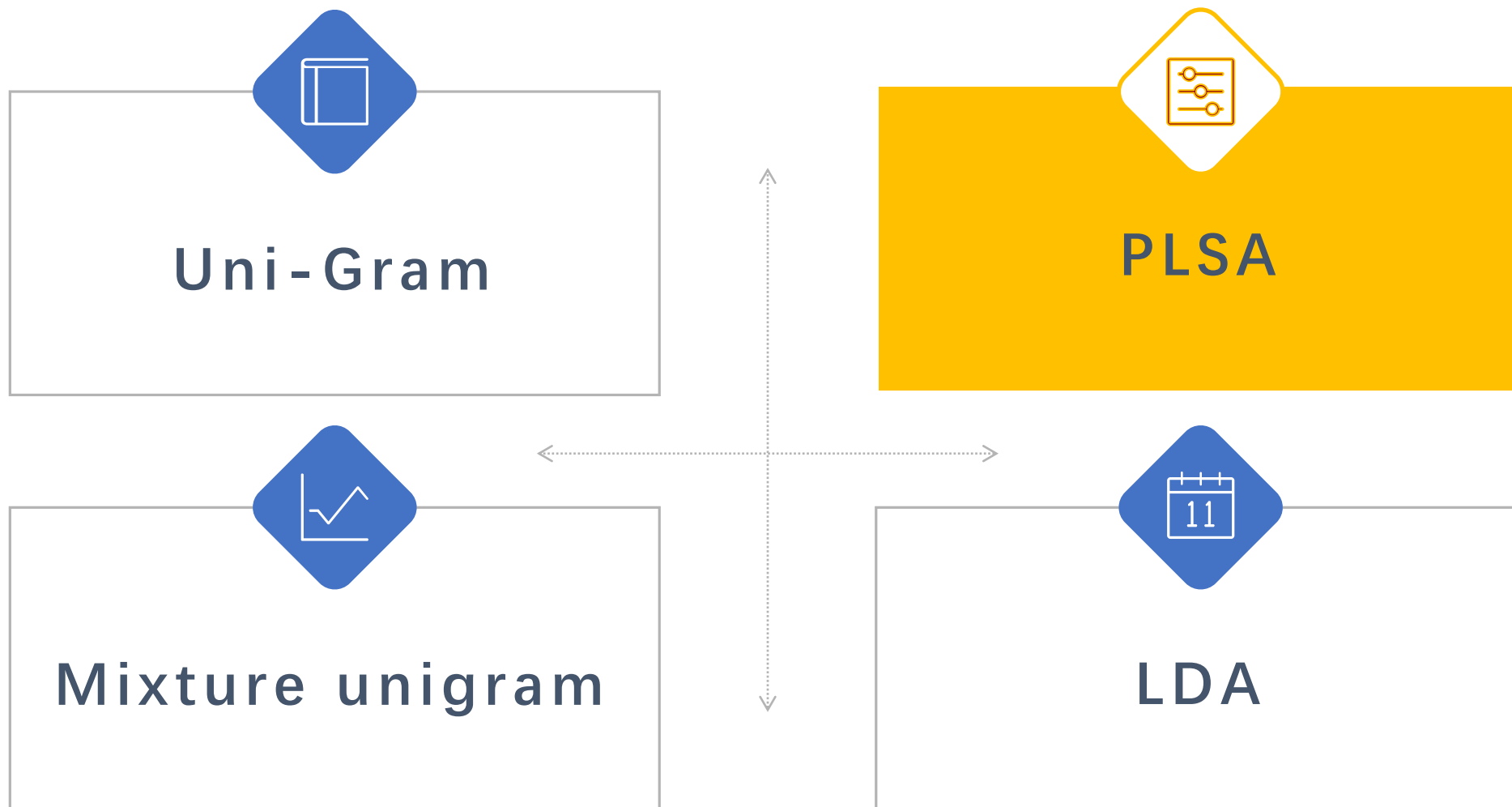
computer  
models  
information  
data  
computers  
system  
network  
systems  
model  
parallel  
methods  
networks  
software  
new  
simulations



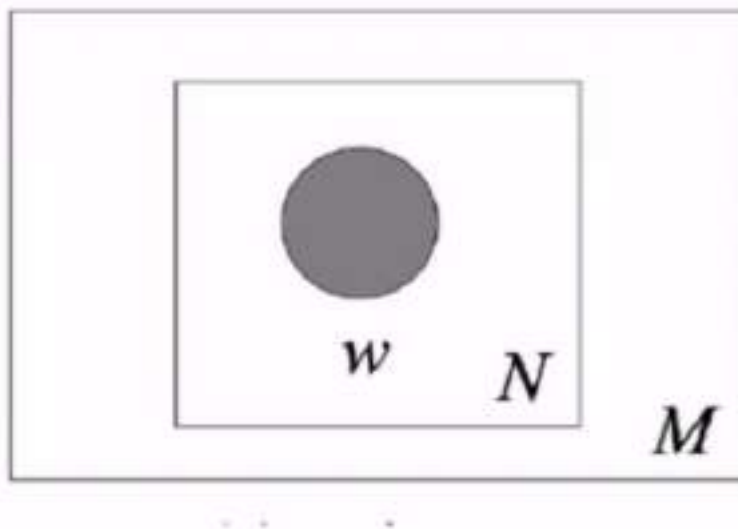
## A Pie Chart!

The multinomial distribution is when there are **multiple** identical independent trials where each trial has  $k$  possible outcomes.

The categorical distribution is when there is **only one** such trial.



# Unigram Model



- the words of every document are drawn independently from a single multinomial distribution

$$p(\mathbf{w}) = \prod_{n=1}^N p(w_n).$$



Chimpanzee seated at a typewriter

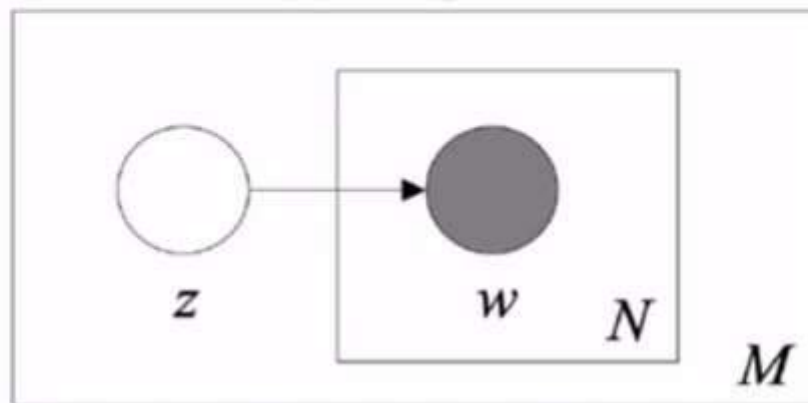
## Infinite monkey theorem

From Wikipedia, the free encyclopedia

The **infinite monkey theorem** states that a monkey hitting keys at **random** on a typewriter keyboard for an **infinite** amount of time will **almost surely** type any given text, such as the complete works of **William Shakespeare**. In fact, the monkey would almost



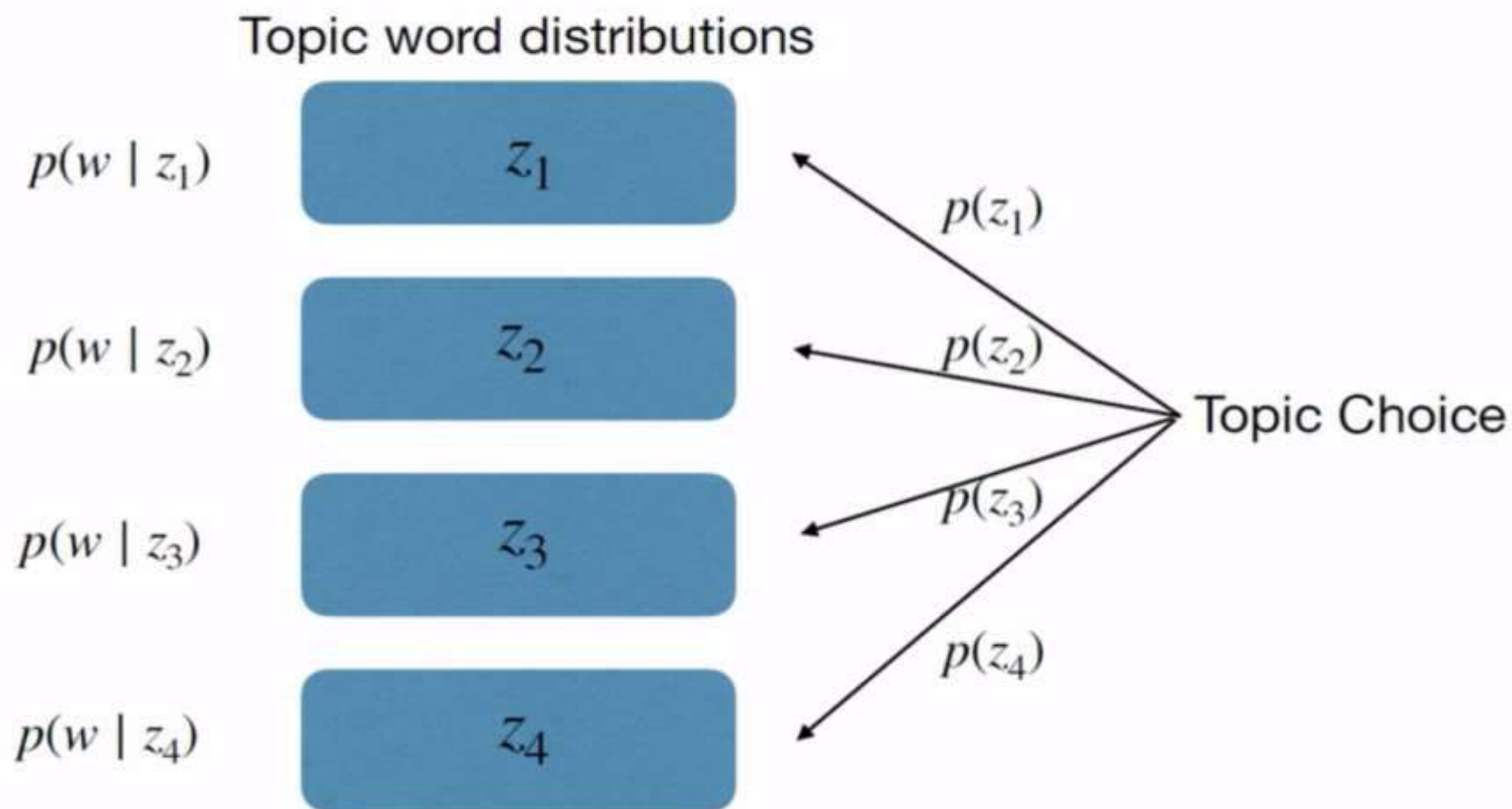
# Mixture of Unigrams Model

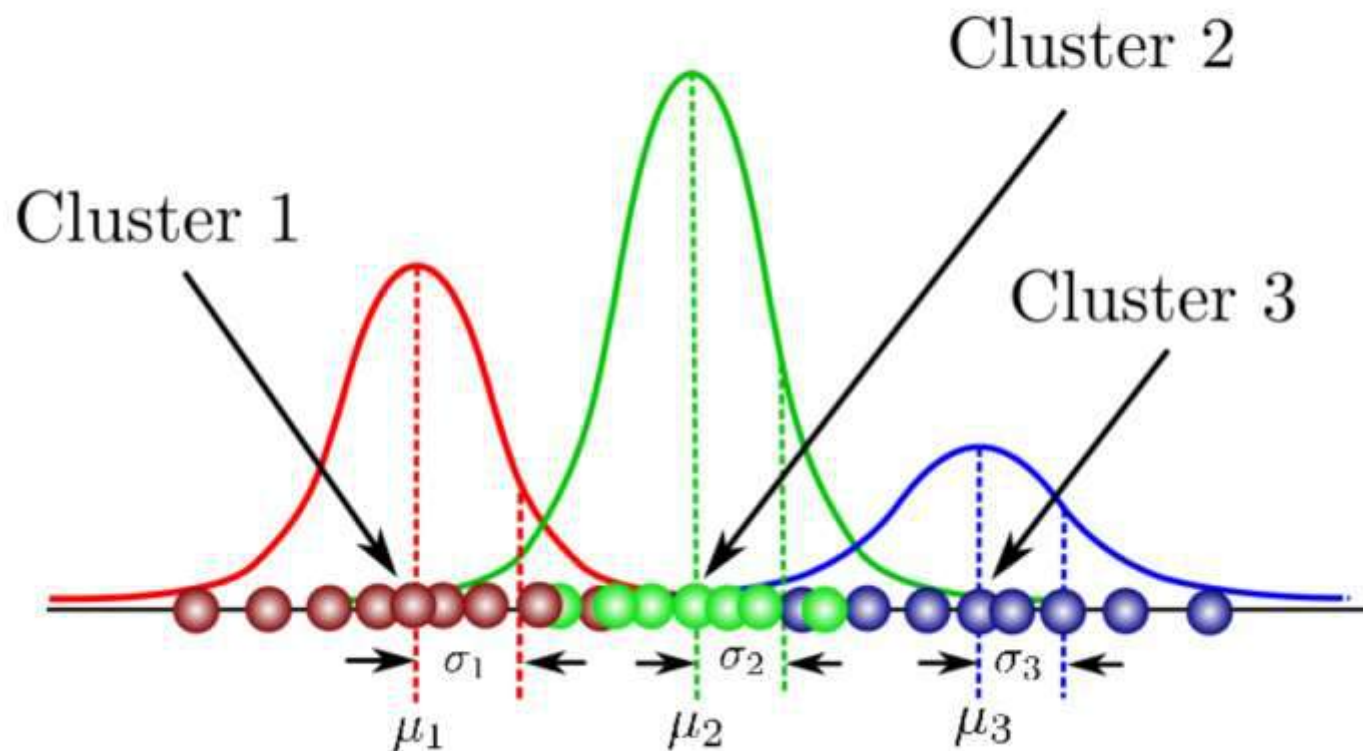


- Argument the unigram model with a discrete random topic variables  $z$  and obtain a mixture of unigrams model.
- Each document is generated by first choosing a topic  $z$  and then generating words independently from the conditional multinomial

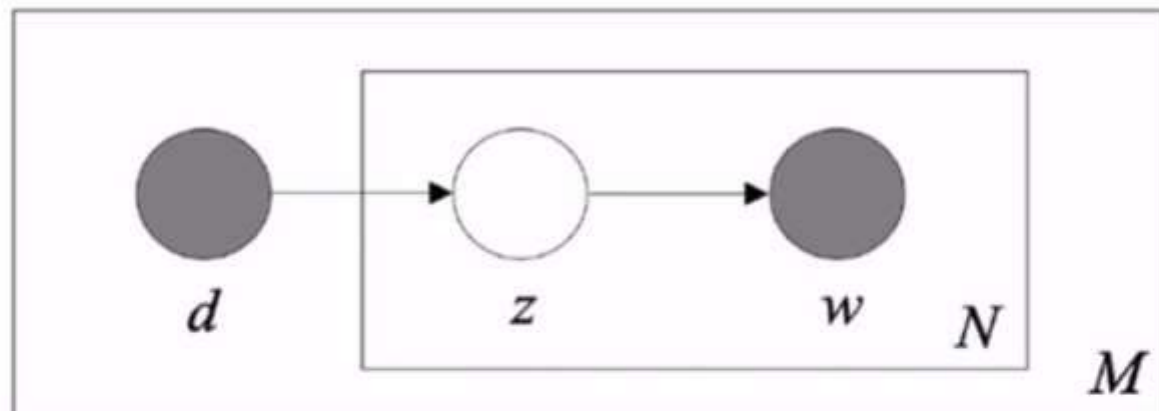
$$p(\mathbf{w}) = \sum_z p(z) \prod_{n=1}^N p(w_n | z).$$

$$p(\mathbf{w}) = \sum_z p(z) \prod_{n=1}^N p(w_n | z).$$





# pLSI



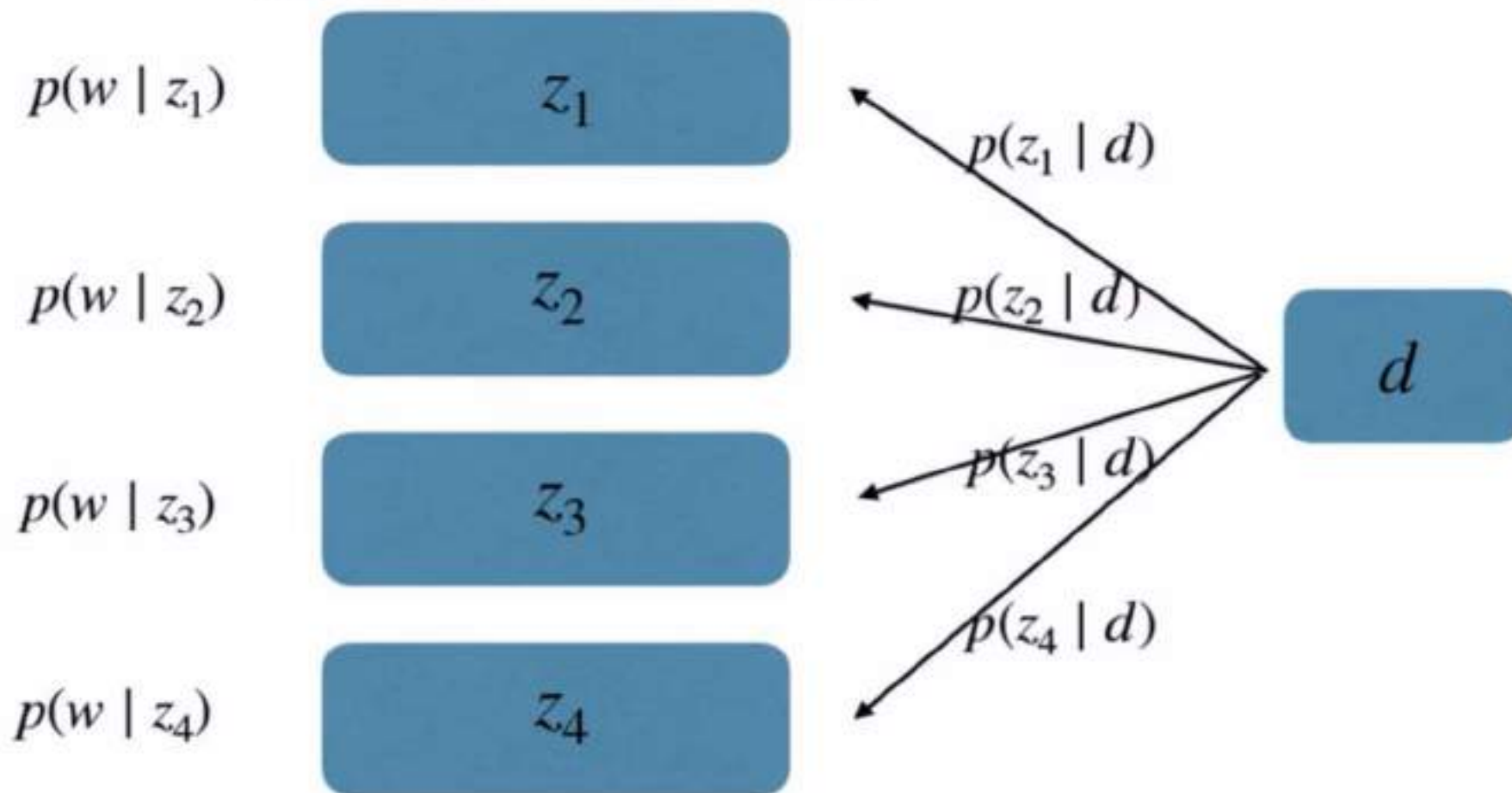
- The pLSI model attempts to relax the simplifying assumption made in the mixture of unigrams model that each document is generated from only one topic.
- Given all parameters, we want to infer the distribution  $z$  a word is from

$$p(d, w_n) = p(d) \sum_z p(w_n | z) p(z | d).$$

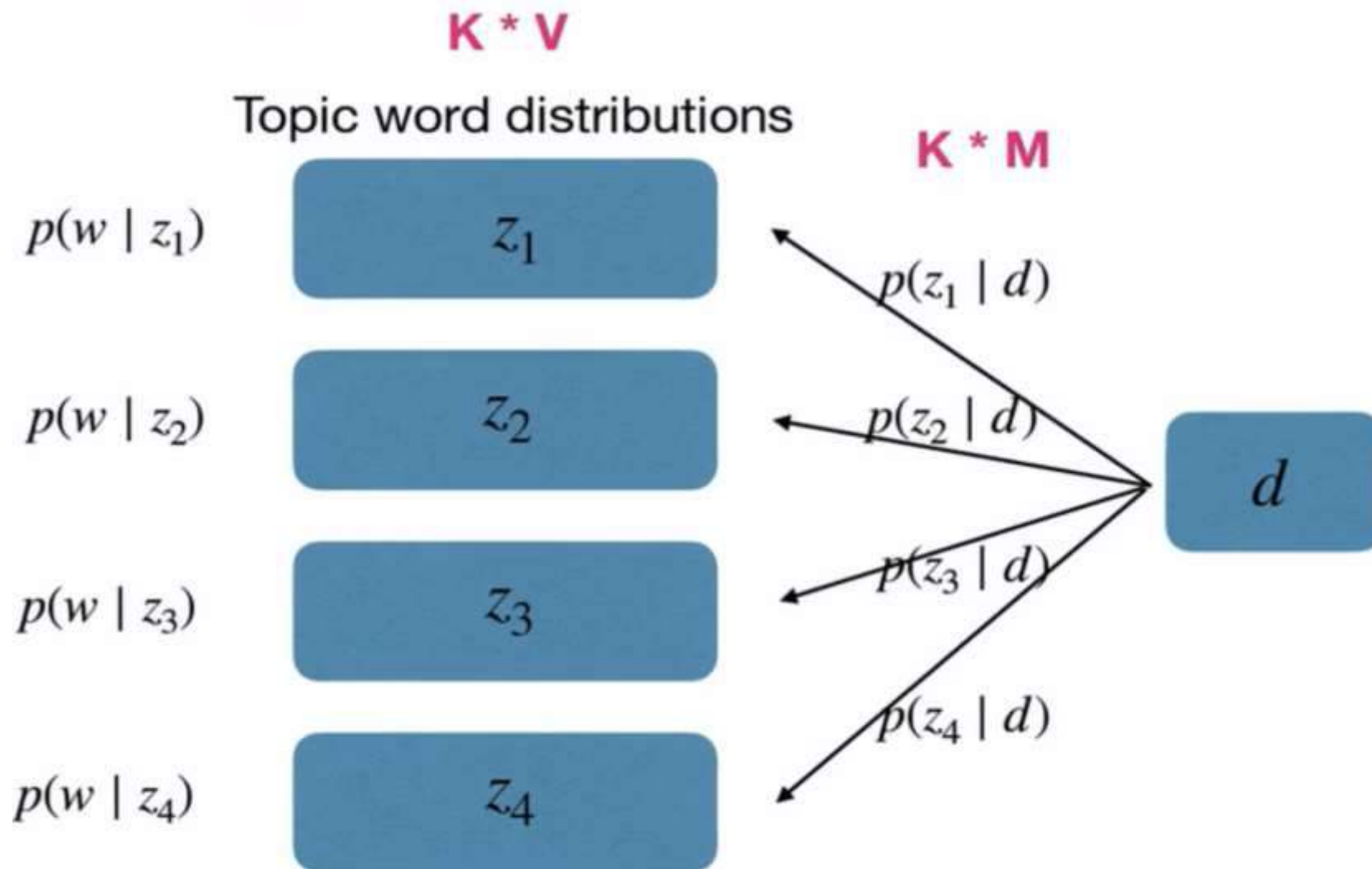


$$p(d, w_n) = p(d) \sum_z p(w_n | z) p(z | d).$$

Topic word distributions







$$p(d, w_n) = p(d) \sum_z p(w_n | z) p(z | d).$$



for a particular document  $d$ . However, it is important to note that  $d$  is a dummy index into the list of documents in the *training set*. Thus,  $d$  is a multinomial random variable with as many possible values as there are training documents and the model learns the topic mixtures  $p(z|d)$  only for those documents on which it is trained. For this reason, pLSI is not a well-defined generative model of

documents on which it is trained. For this reason, pLSI is not a well-defined generative model of documents; there is no natural way to use it to assign probability to a previously unseen document.

number of training documents. The parameters for a  $k$ -topic pLSI model are  $k$  multinomial distributions of size  $V$  and  $M$  mixtures over the  $k$  hidden topics. This gives  $kV + kM$  parameters and



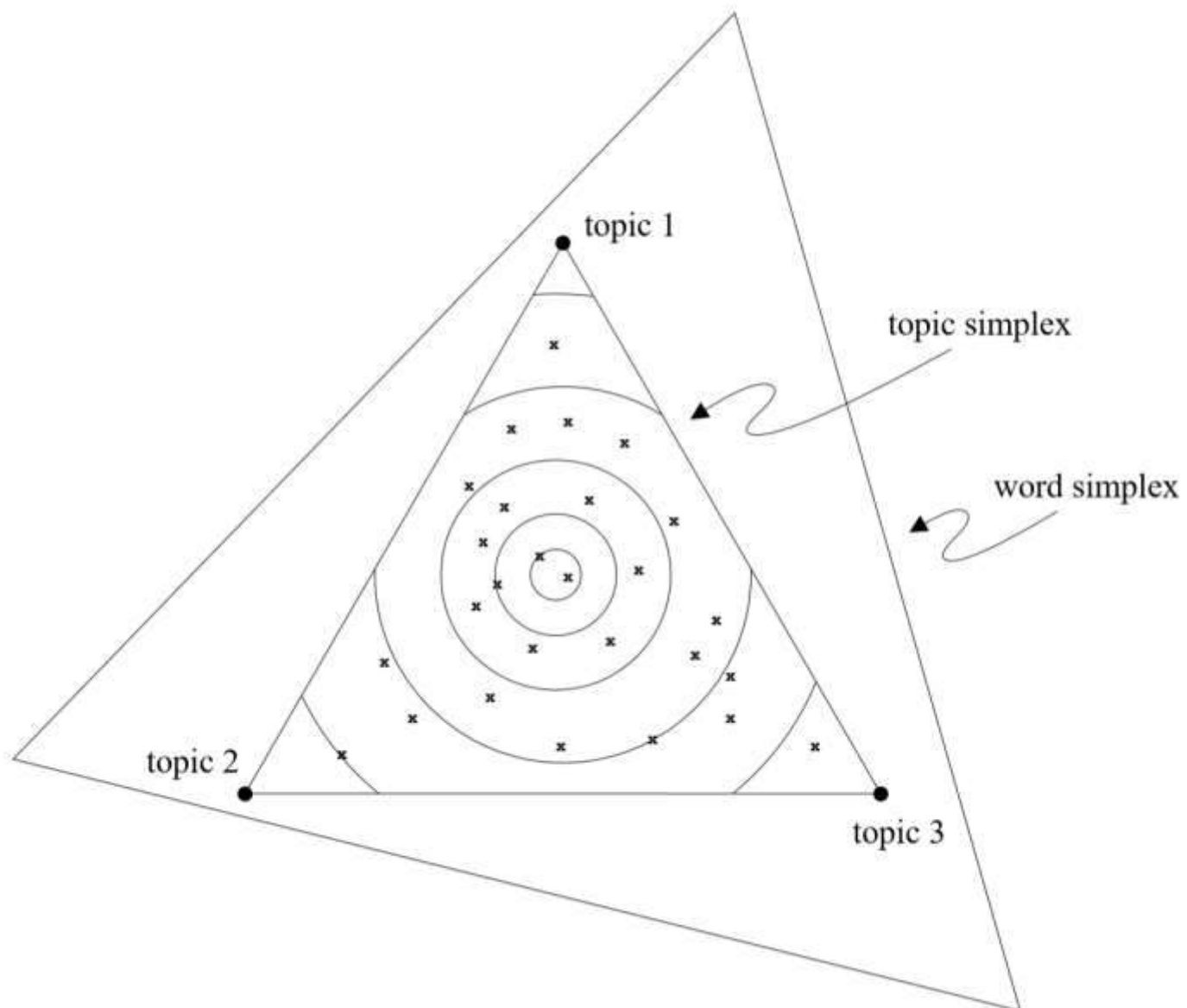
$$f(\mathbf{x}) = \frac{\prod_{k=1}^K \Gamma(\alpha_k)}{\Gamma(\sum_{k=1}^K \alpha_k)} \prod_{k=1}^K x_k^{\alpha_k-1}$$

- The Dirichlet distribution is a generalization of the Beta distribution for multiple random variables
- The Dirichlet distribution is over vectors whose values are all in the interval  $[0, 1]$  and the sum of values in the vector is 1.

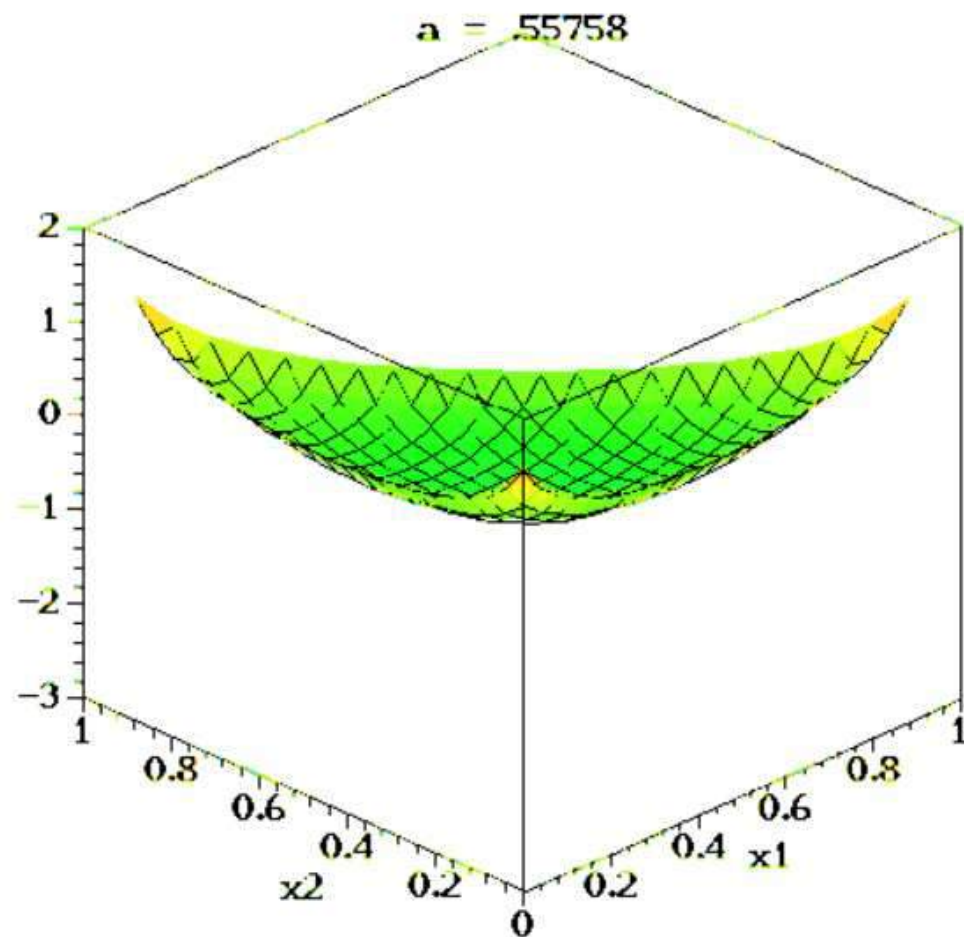




Dirichlet distributions are just a convenient family for representing distributions over the simplex (the set of  $N$ -vectors whose components sum to 1), so it's a useful prior distribution on discrete probability distributions over categorical variables -- in fact it is the conjugate prior to the categorical and multinomial distributions (meaning that multiplying a Dirichlet prior by a multinomial or categorical likelihood will yield another Dirichlet distribution of a certain form). Whether the concentration parameter is below or above 1 controls whether sparse categorical distributions are preferred. The assumptions made are fairly weak, and similar to those of any continuous density; it mostly depends on the shape and concentration parameters selected.







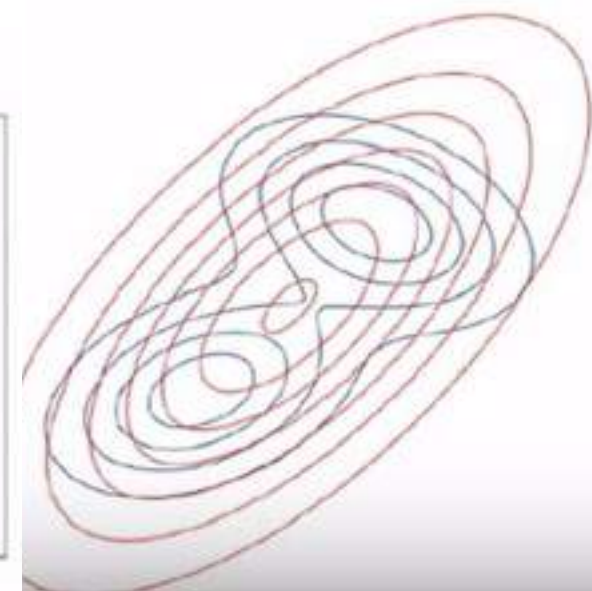
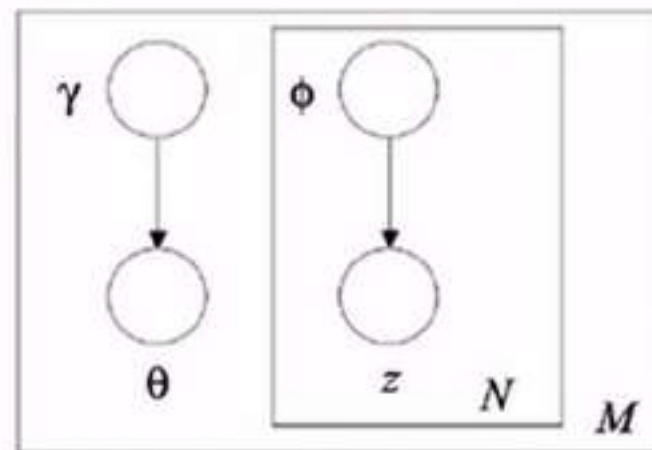
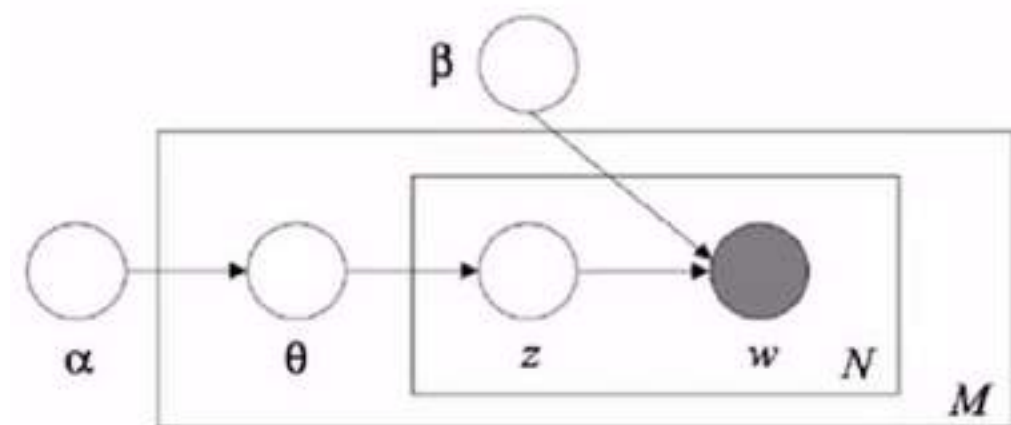


Beta distribution gives us a single probability,

The Dirichlet distribution gives us  $K$  probabilities that  
Define a probability distribution over  $K$ -d vector that sum  
To one

The key inferential problem that we need to solve in order to use LDA is that of computing the posterior distribution of the hidden variables given a document

Unfortunately, this distribution is intractable to compute in general





## Algorithm

1. For each iteration  $i$ :

1.1 For each document  $d$  and word  $n$  currently assigned to  $z_{old}$ :

1.1.1 Decrement  $n_{d,z_{old}}$  and  $v_{z_{old},w_{d,n}}$

1.1.2 Sample  $z_{new} = k$  with probability proportional to  $\frac{n_{d,k} + \alpha_k}{\sum_i^K n_{d,i} + \alpha_i} \frac{v_{k,w_{d,n}} + \lambda_{w_{d,n}}}{\sum_i v_{k,i} + \lambda_i}$

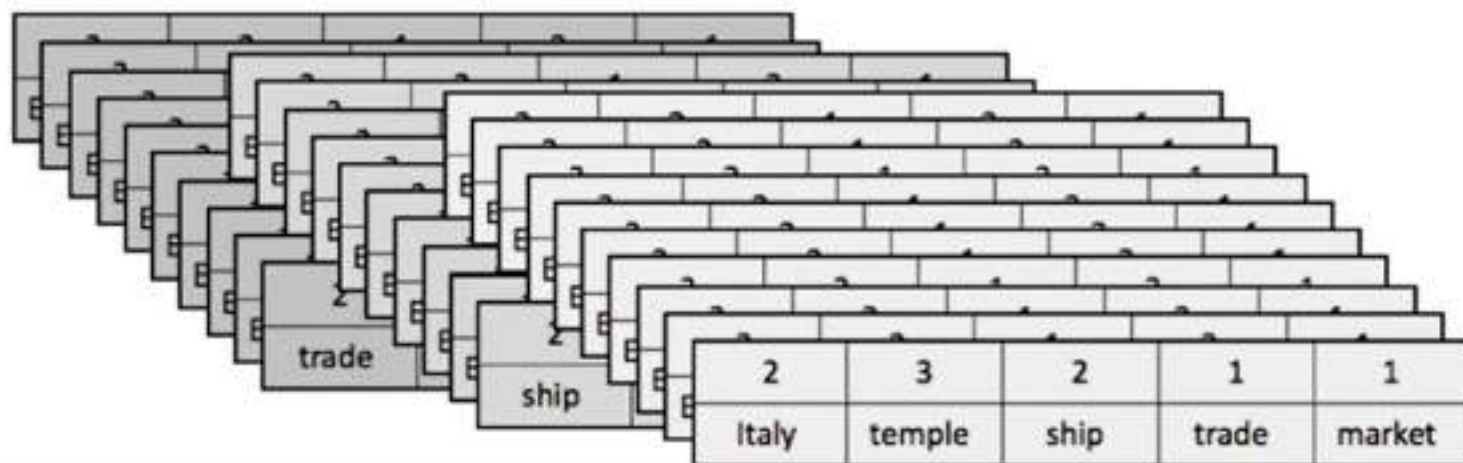
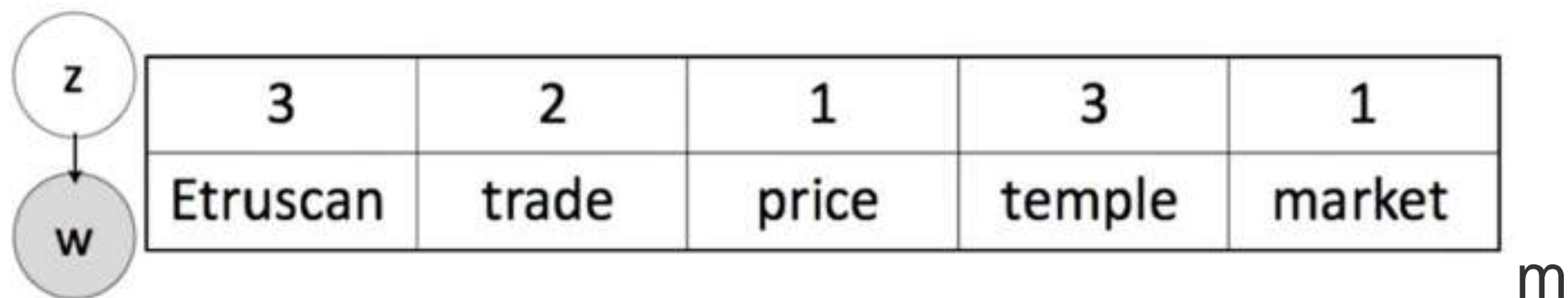
1.1.3 Increment  $n_{d,z_{new}}$  and  $v_{z_{new},w_{d,n}}$



$$p(z_{d,n} = k | \vec{z}_{-d,n}, \vec{w}, \alpha, \lambda) = \frac{n_{d,k} + \alpha_k}{\sum_i^K n_{d,i} + \alpha_i} \frac{v_{k,w_{d,n}} + \lambda_{w_{d,n}}}{\sum_i v_{k,i} + \lambda_i}$$

- Number of times document  $d$  uses topic  $k$
- Number of times topic  $k$  uses word type  $w_{d,n}$
- Dirichlet parameter for document to topic distribution
- Dirichlet parameter for topic to word distribution
- How much this document likes topic  $k$
- How much this topic likes word  $w_{d,n}$





# 1 Total topic counts

3	2	1	3	1
Etruscan	trade	price	temple	market

Total  
counts  
from **all**  
docs



	1	2	3
Etruscan	1	0	35
market	50	0	1
price	42	1	0
temple	0	0	20
trade	10	8	1
...			



3	2	1	3	1
Etruscan	trade	price	temple	market

	1	2	3
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temple	0	0	20
trade	10	8	1
...			



3	?	1	3	1
Etruscan	trade	price	temple	market

	1	2	3
Etruscan	1	0	35
market	50	0	1
price	42	1	0
temple	0	0	20
trade	10	7	1
...			

# How much does this document like each topic

3	?	1	3	1
Etruscan	trade	price	temple	market

Topic 1

Topic 2

Topic 3

$$\frac{n_{d,k} + \alpha_k}{\sum_i^K n_{d,i} + \alpha_i} \frac{v_{k,w_{d,n}} + \lambda_{w_{d,n}}}{\sum_i v_{k,i} + \lambda_i}$$





3	2	1	3	1
Etruscan	trade	price	temple	market

Total  
counts  
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docs



	1	2	3
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market	50	0	1
price	42	1	0
temple	0	0	20
trade	10	8	1
...			

# 1 How much each topic like the word

	1	2	3
trade	10	7	1

$$\frac{n_{d,k} + \alpha_k}{\sum_i^K n_{d,i} + \alpha_i} \frac{v_{k,w_{d,n}} + \lambda_{w_{d,n}}}{\sum_i v_{k,i} + \lambda_i}$$



Topic 1



Topic 2



Topic 3





3	1	1	3	1
Etruscan	trade	price	temple	market

	1	2	3
Etruscan	1	0	35
market	50	0	1
price	42	1	0
temple	0	0	20
trade	11	7	1
...			



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1.1.3 Increment  $n_{d,z_{new}}$  and  $v_{z_{new},w_{d,n}}$





```
# Create a new document-term matrix using only nouns and adjectives, also remove common words with max_df
cvna = CountVectorizer(stop_words=stop_words, max_df=.8)
data_cvna = cvna.fit_transform(data_nouns_adj.transcript)
data_dtmna = pd.DataFrame(data_cvna.toarray(), columns=cvna.get_feature_names())
data_dtmna.index = data_nouns_adj.index
data_dtmna
```

```
# Create the gensim corpus
corpusna = matutils.Sparse2Corpus(scipy.sparse.csr_matrix(data_dtmna.transpose()))

# Create the vocabulary dictionary
id2wordna = dict((v, k) for k, v in cvna.vocabulary_.items())
```

```
# Let's start with 2 topics
ldana = models.LdaModel(corpus=corpusna, num_topics=2, id2word=id2wordna, passes=10)
ldana.print_topics()
```



```
[ (0,
  '0.009*joke" + 0.005*mom" + 0.005*parents" + 0.004*hasan" + 0.004*jokes" + 0.004*anthony" + 0.003*nuts" + 0.003*dead" + 0.003*tit" + 0.003*twitter"),
  (1,
  '0.005*mom" + 0.005*jenny" + 0.005*clinton" + 0.004*friend" + 0.004*parents" + 0.003*husband" + 0.003*cow" + 0.003*ok" + 0.003*wife" + 0.003*john"),
  (2,
  '0.005*bo" + 0.005*gun" + 0.005*guns" + 0.005*repeat" + 0.004*um" + 0.004*ass" + 0.004*eye" + 0.004*contact" + 0.003*son" + 0.003*class"),
  (3,
  '0.006*ahah" + 0.004*nigga" + 0.004*gay" + 0.003*dick" + 0.003*door" + 0.003*young" + 0.003*motherfucker" + 0.003*stupid" + 0.003*bitch" + 0.003*mad" ) ]
```

These four topics look pretty decent. Let's settle on these for now.

- Topic 0: mom, parents
- Topic 1: husband, wife
- Topic 2: guns
- Topic 3: profanity

K-means

Decision Tree

Naïve Bayes

SVM



北京理工大学  
BEIJING INSTITUTE OF TECHNOLOGY

# THANKS

德以明理 学以精工