Topic Modeling

CSCI 1460: Computational Linguistics

Lecture 7

Ellie Pavlick

Fall 2023

Announcements

- Assignment 2 will be out tomorrow (due Sunday Oct 16)
  - Grading will still begin on Monday
- NLP talks in the department!
  - **Oct 7th, 2pm Jennifer Hu** A Targeted Evaluation of Human-like Linguistic Knowledge in Neural Language Models
  - **Oct 13th, 12pm Panel/Discussion** Strong vs. Weak Compositionality in Humans and Machines!

Topics

- Lecture 6 Followup: Word Embeddings from SVD
- What is a topic model
- Latent Semantic Analysis (LSA)
- Latent Dirichelet Allocation (LDA)
  - “Generative Stories”
  - Graphical Model Notation
  - Training and Evaluation

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- **Lecture 6 Followup: Word Embeddings from SVD**
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  - “Generative Stories”
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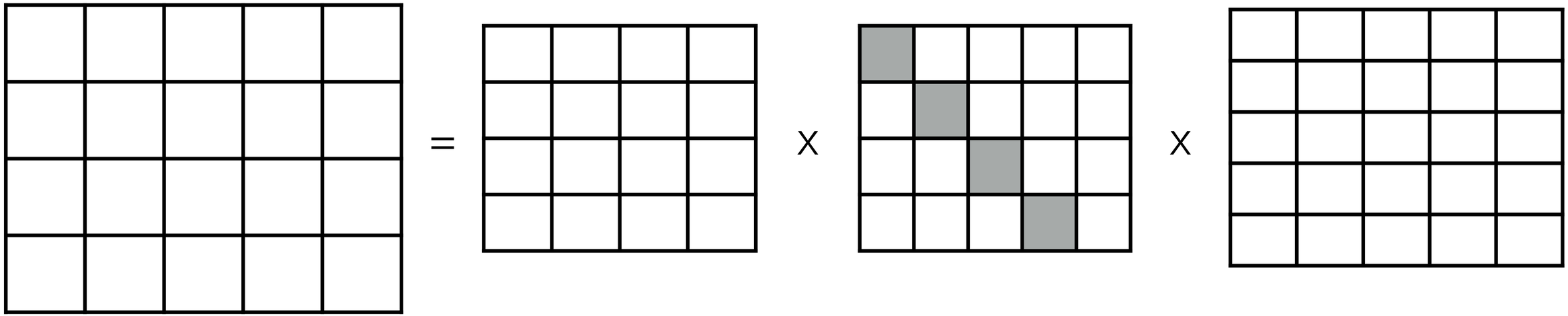
Singular Value Decomposition



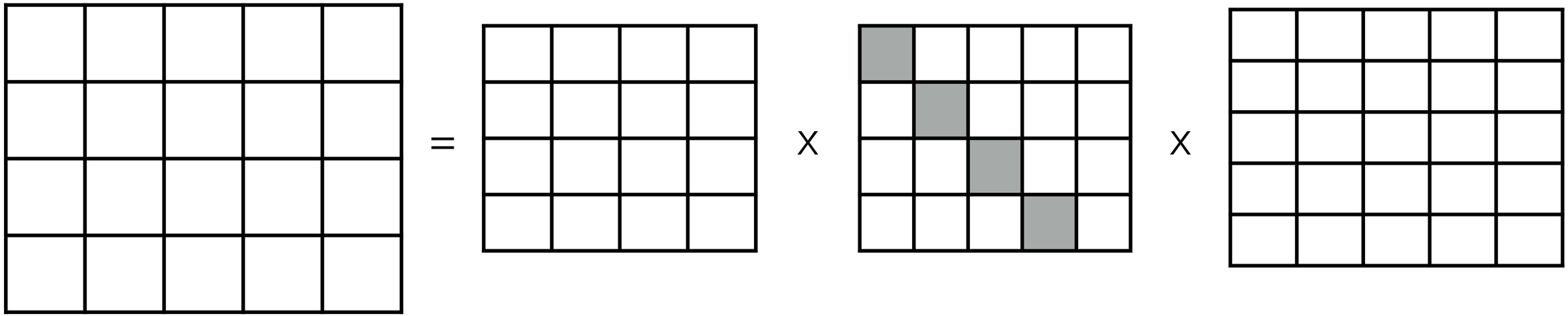
M
m x n

U
m x m

D
m x n

V
n x n

Singular Value Decomposition



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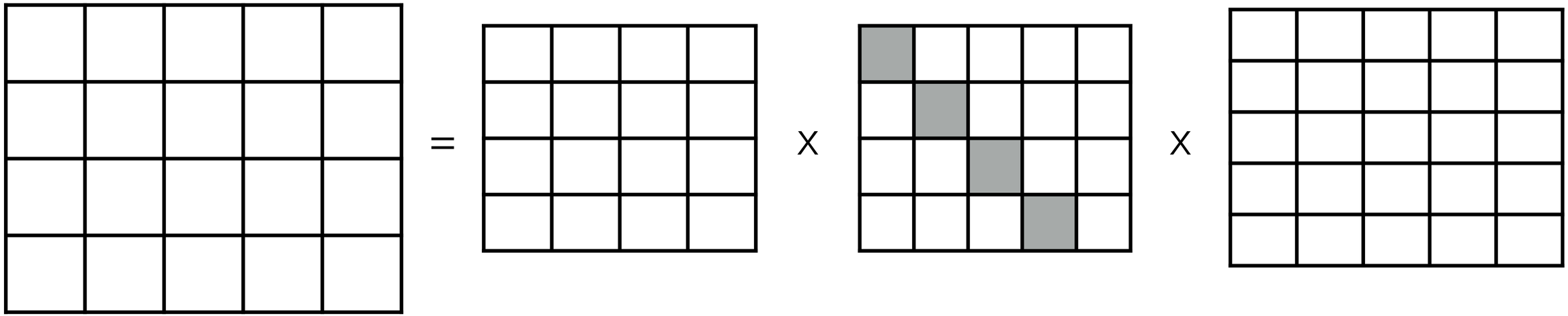
Data Matrix

Singular Value Decomposition



M
m x n

Data Matrix

=

U
m x m

x

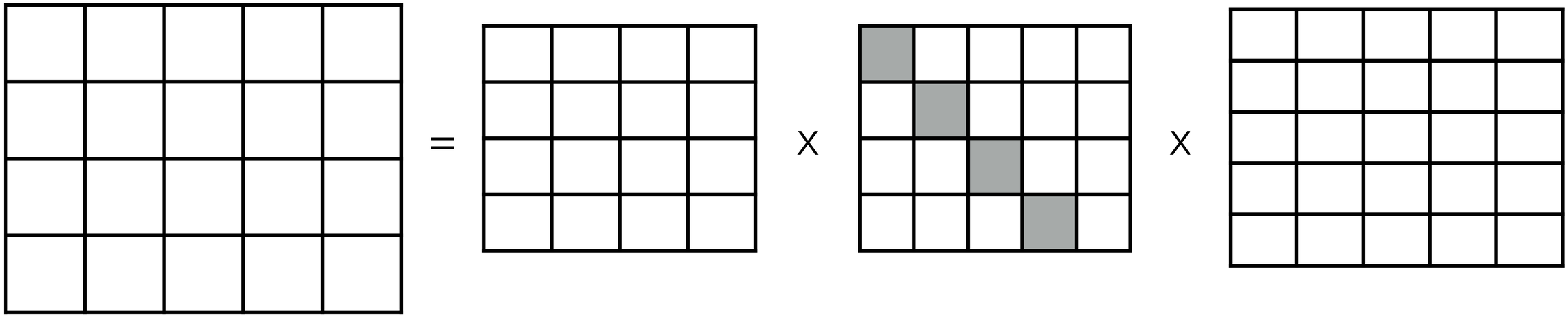
D
m x n

Singular Values of M

x

V
n x n

Singular Value Decomposition



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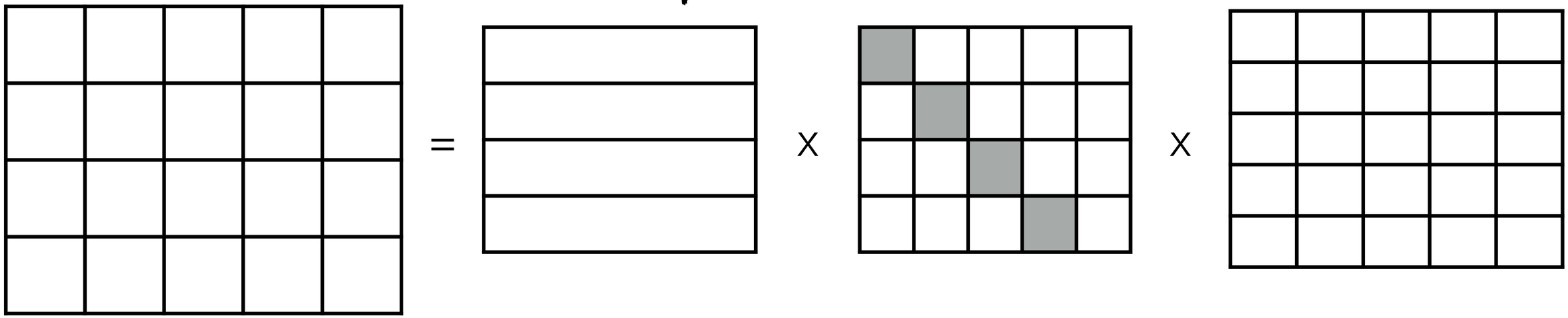
Data Matrix

Singular
Values of M
(#non-zero = rank M)

Singular Value Decomposition

Representation of rows of M in new feature space



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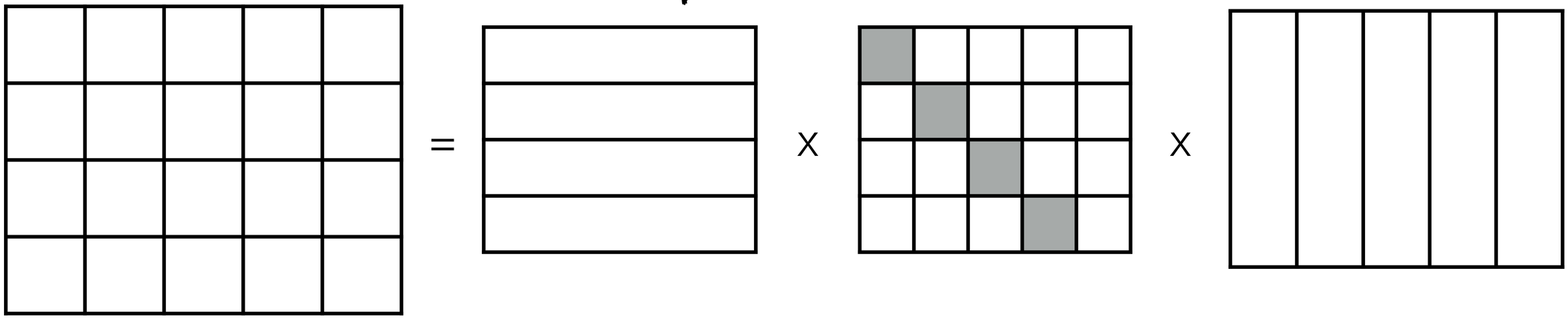
Data Matrix

Singular Values of M (#non-zero = rank M)

Singular Value Decomposition

Representation of rows of M in new feature space

Principle Components (new features)



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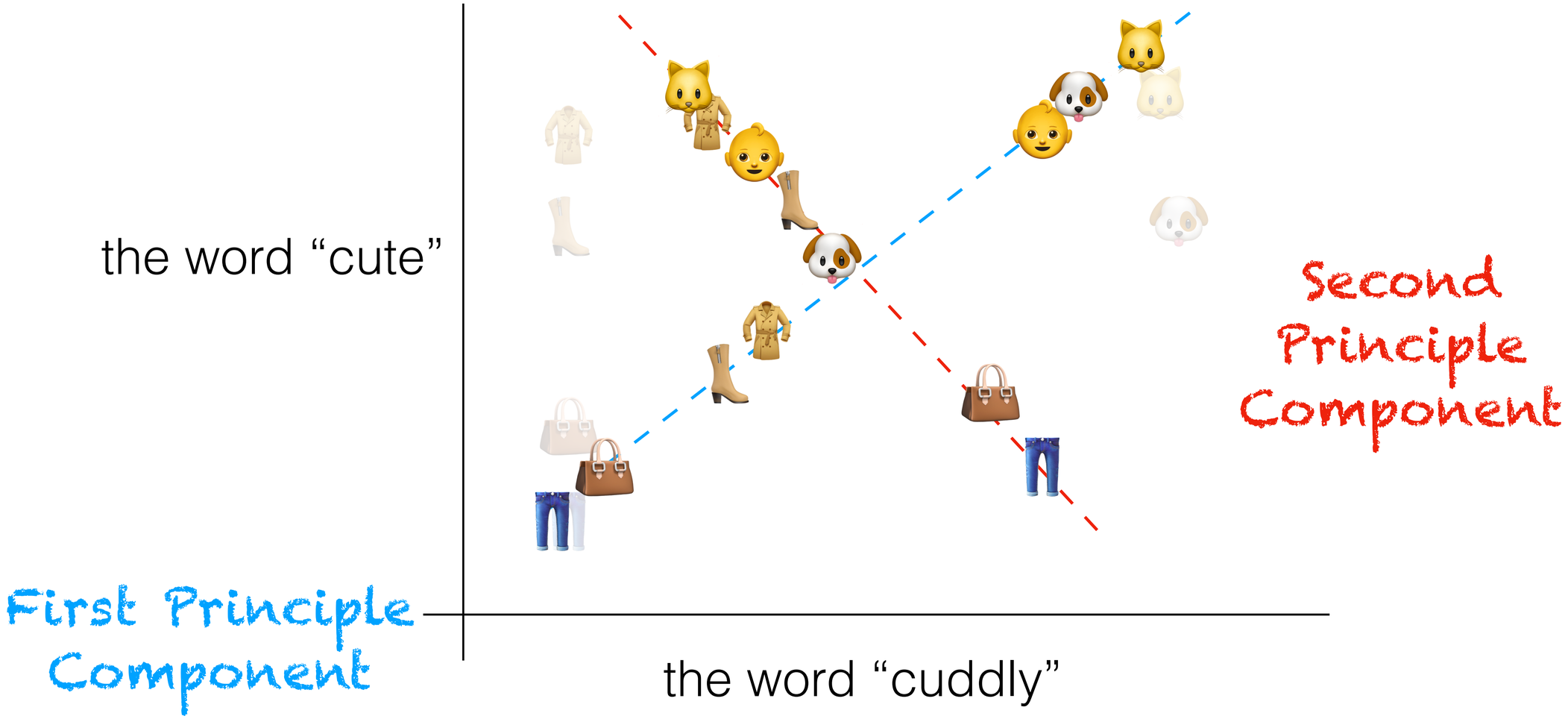
Singular Value Decomposition

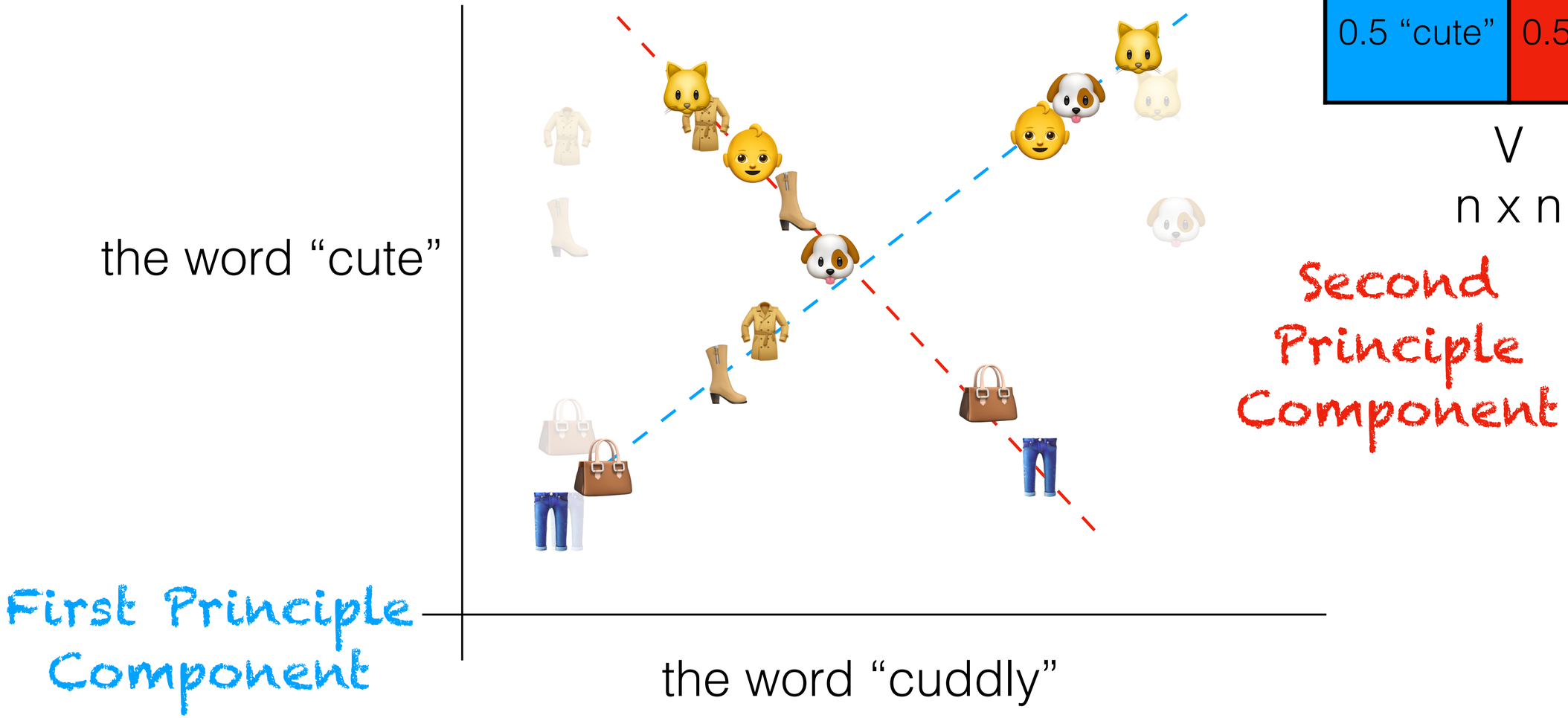


Singular Value Decomposition

0.5 “cuddly”	-0.5 “cuddly”
0.5 “cute”	0.5 “cute”

V

n x n

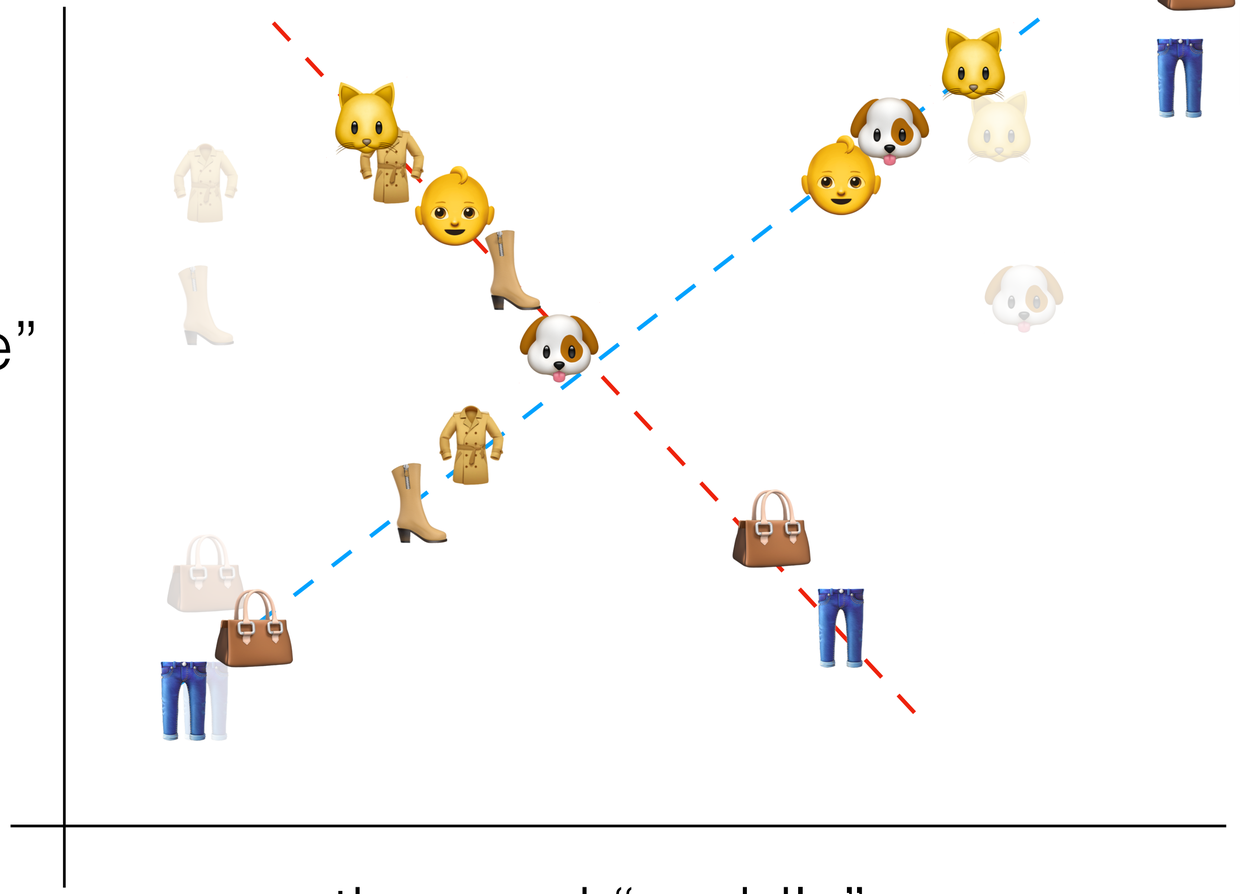


*warning: numbers are made up (not necessarily to scale)

Singular Value Decomposition

🐱	3	-3
🐶	2.5	-0.5
👜	-2	1.5
👖	-2.5	2

U
m x m



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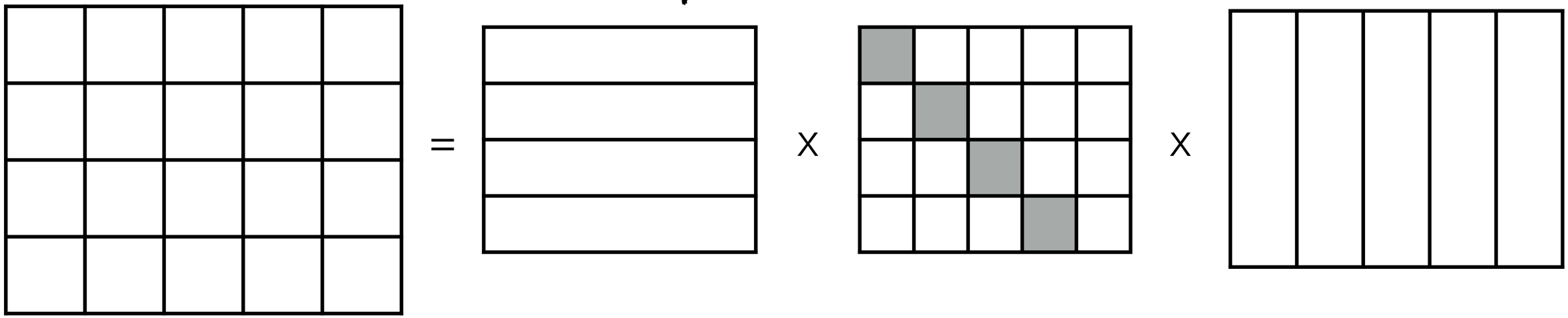
Singular Value Decomposition

Representation of rows of M in new feature space

Principle Components (new features)



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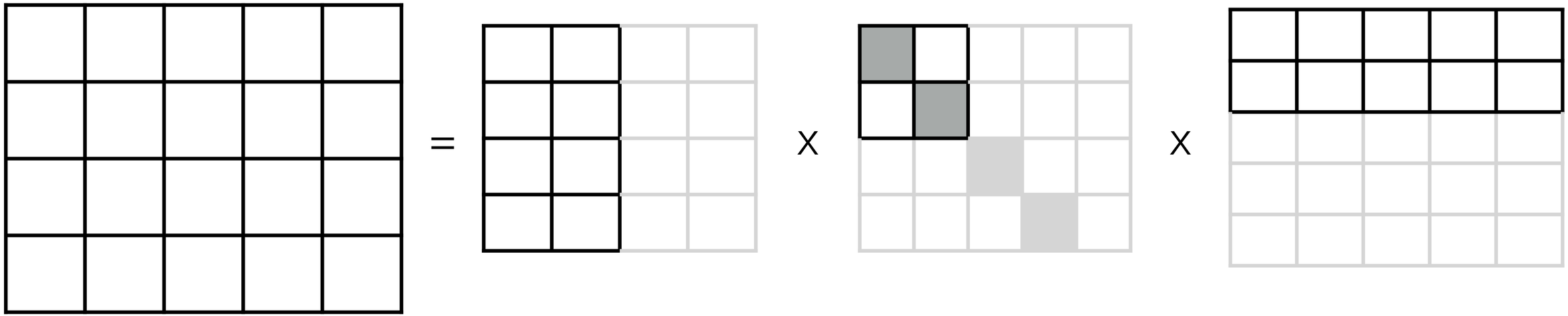
Data Matrix

Singular Values of M (#non-zero = rank M)

Truncated SVD

keep only first l components



M
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U
m x l

D
l x l

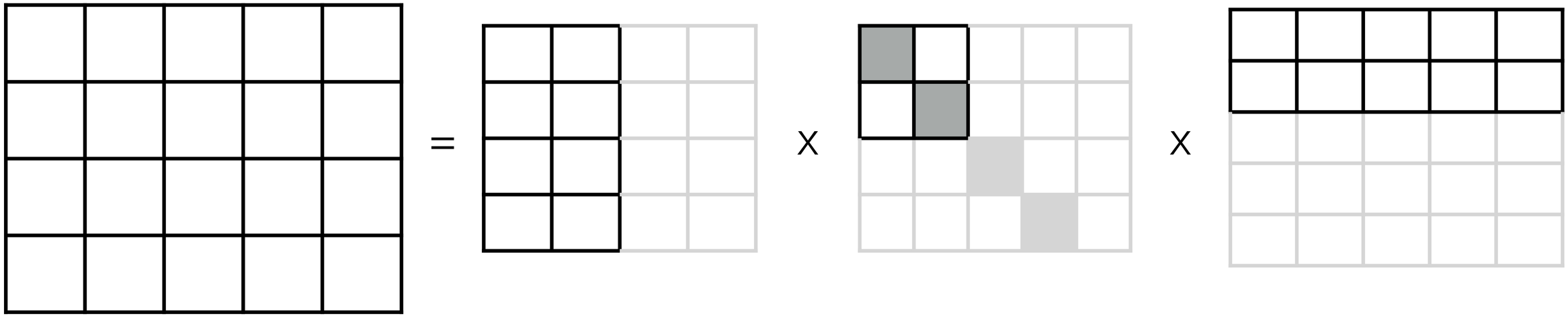
V
l x n

Data Matrix

Truncated SVD

keep only first l components

"best l-rank approximation of M"



M
m x n

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Data Matrix

$||M - UDV||^2$ as small as possible

Truncated SVD

	cat	kitten	cute	adorable
cat	1	1	1	1
kitten	1	0	1	0
cute	1	1	0	1
adorable	1	0	1	1

M

cat	-0.60	-0.39	0.70
kitten	-0.48	0.50	-0.12
cute	-0.43	-0.58	-0.69
adorable	-0.48	0.50	-0.12

U

3.06	0.00	0.00
0.00	1.81	0.00
0.00	0.00	0.57

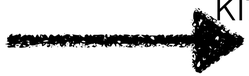
D

cat	kitten	cute	adorable
-0.65	-0.34	-0.51	-0.34
0.02	-0.54	0.34	-0.54
-0.42	0.02	0.79	0.02

V

Truncated SVD

Word-Context Matrix



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V

Truncated SVD

Word-Context Matrix

Word Embeddings

	cat	kitten	cute	adorable
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Truncated SVD

Word-Context Matrix

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adorable	1	0	1	1

M

New Features ("Topics")

Word Embeddings

U

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cute	-0.43	-0.58	-0.69
adorable	-0.48	0.50	-0.12

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0.02	-0.54	0.34	-0.54
-0.42	0.02	0.79	0.02

Word Embeddings

What's the point?

- Computational Reasons
  - Lower dimensional = less computationally intensive
- Better Generalization
  - Lower dimensional forces abstraction: two columns that capture effectively the same information can be combined
  - Lower dimensional removes noise: throw away columns that don't improve predictive power on held-out data
- Representational Richness
  - Dimensionality reduction can capture "second order" effects
  - E.g., w1 occurs with c1, w2 occurs with c2, c1 and c2 are similar. Thus, w1 and w2 are similar.

Word Embeddings

What's the point?

***Don't count, predict!* A systematic comparison of context-counting vs. context-predicting semantic vectors**

Marco Baroni and **Georgiana Dinu** and **Germán Kruszewski**
Center for Mind/Brain Sciences (University of Trento, Italy)
(marco.baroni|georgiana.dinu|german.kruszewski)@unitn.it

Word Embeddings

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ki)@unitn.it

name	task	measure	source	soa
rg	relatedness	Pearson	Rubenstein and Goodenough (1965)	Hassan and Mihalcea (2011)
ws	relatedness	Spearman	Finkelstein et al. (2002)	Halawi et al. (2012)
wss	relatedness	Spearman	Agirre et al. (2009)	Agirre et al. (2009)
wsr	relatedness	Spearman	Agirre et al. (2009)	Agirre et al. (2009)
men	relatedness	Spearman	Bruni et al. (2013)	Bruni et al. (2013)
toefl	synonyms	accuracy	Landauer and Dumais (1997)	Bullinaria and Levy (2012)
ap	categorization	purity	Almuhareb (2006)	Rothenhäusler and Schütze (2009)
esslli	categorization	purity	Baroni et al. (2008)	Katrenko and Adriaans (2008)
battig	categorization	purity	Baroni et al. (2010)	Baroni and Lenci (2010)
up	sel pref	Spearman	Padó (2007)	Herdağdelen and Baroni (2009)
mcrae	sel pref	Spearman	McRae et al. (1998)	Baroni and Lenci (2010)
an	analogy	accuracy	Mikolov et al. (2013a)	Mikolov et al. (2013c)
ansyn	analogy	accuracy	Mikolov et al. (2013a)	Mikolov et al. (2013a)
ansem	analogy	accuracy	Mikolov et al. (2013a)	Mikolov et al. (2013c)

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	rg	ws	wss	wsr	men	toefl	ap	esslli	battig	up	mcrae	an	ansyn	ansem
best setup on each task														
cnt	74	62	70	59	72	76	66	84	98	41	27	49	43	60
pre	84	75	**80**	**70**	**80**	91	75	86	**99**	41	28	**68**	**71**	**66**
best setup across tasks														
cnt	70	62	70	57	72	76	64	84	98	37	27	43	41	44
pre	83	73	78	68	**80**	86	71	77	98	41	26	67	69	64
worst setup across tasks														
cnt	11	16	23	4	21	49	24	43	38	-6	-10	1	0	1
pre	74	60	73	48	68	71	65	82	88	33	20	27	40	10
best setup on rg														
cnt	(74)	59	66	52	71	64	64	84	98	37	20	35	42	26
pre	(84)	71	76	64	79	85	72	84	98	39	25	66	70	61

Word Embeddings

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- **What is a topic model**
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  - “Generative Stories”
  - Graphical Model Notation
  - Training and Evaluation

What is a topic model?

Example

- Imagine building a classifier to recommend articles to readers
  - Option 1: Use BOW models
    - “Since you read an article with the word ‘court-side’, you might also like this article which has the word ‘rebound’”
  - Option 2: Topics!
    - “Since you read an article about basketball, you might also like this other article about basketball”

What is a topic model?

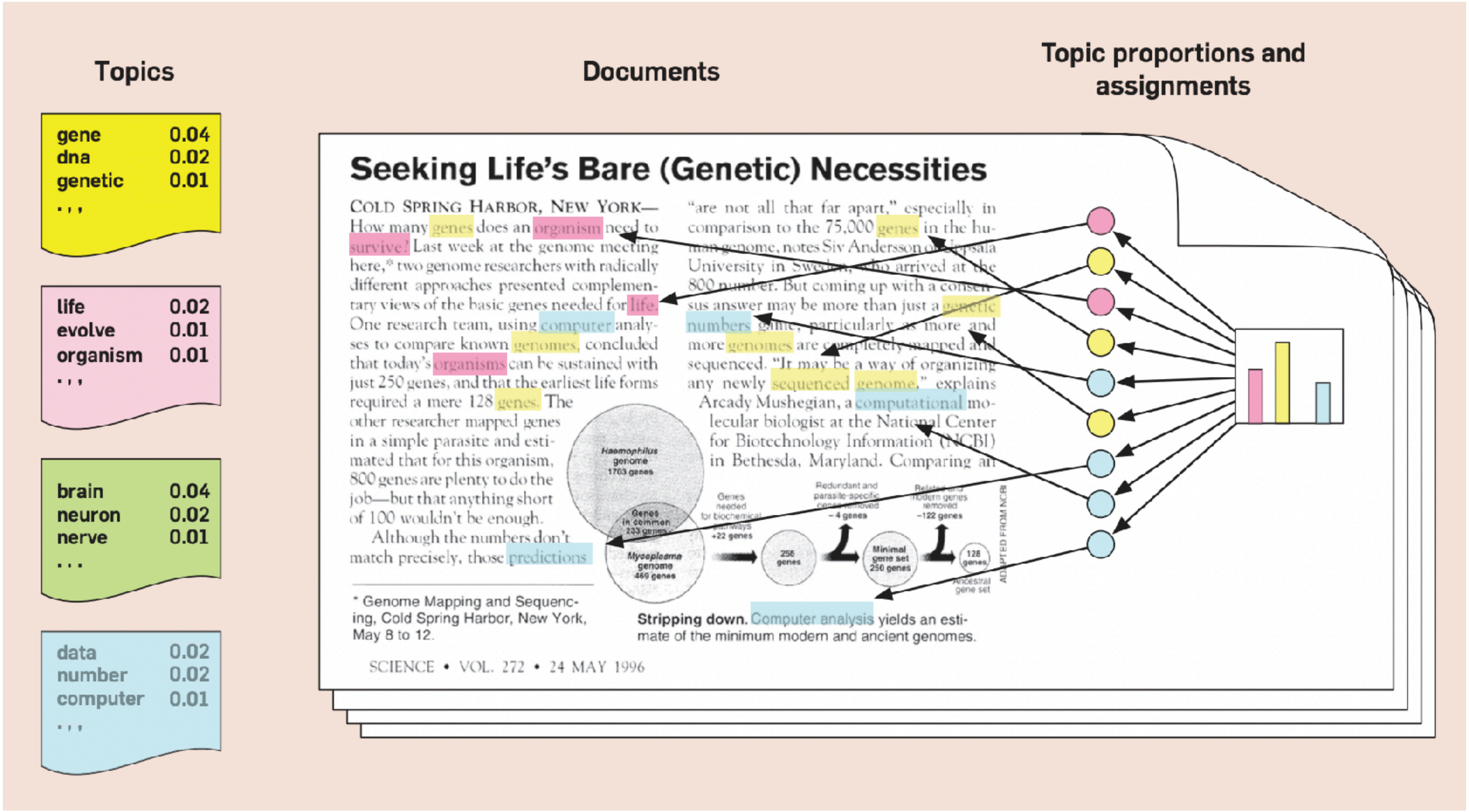
Example

- Imagine working as a campaign strategist and analyzing public opinion in your district
  - Option 1: Use BOW models
    - “In the past year, there has been an increase in the use of the word ‘price’ and a decrease in the word ‘classroom’”
  - Option 2: Topics!
    - “In the past year, people have been talking more about the economy than about schools”

What is a topic model?

- Method for ***automatically*** organizing a collection of text
- Used for ***unlabeled*** document collections

What is a topic model?



What is a topic model?

Topics defined as distributions over words

Topics

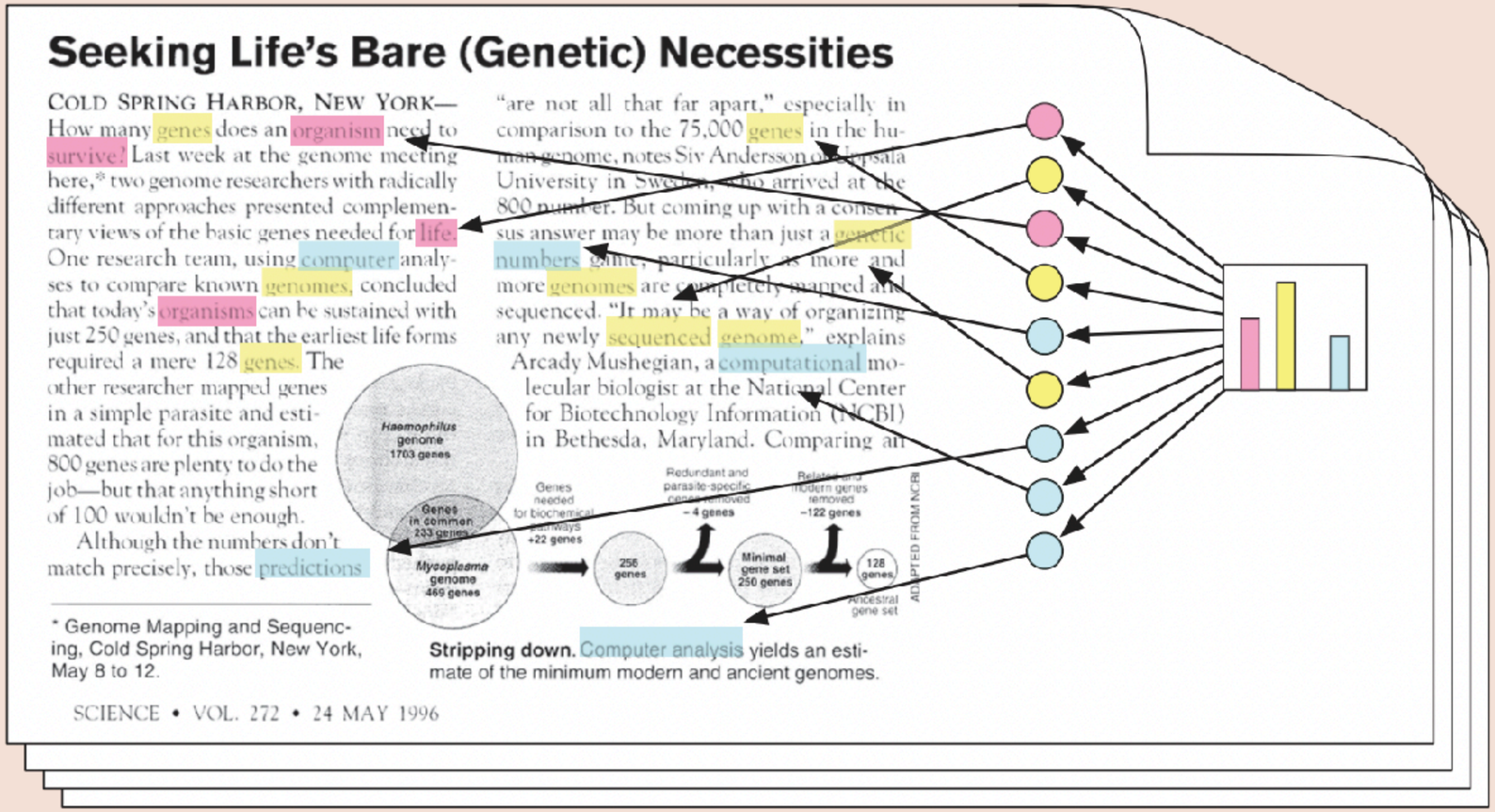
gene	0.04
dna	0.02
genetic	0.01
...	

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
...	

Topic proportions and assignments



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 genomes, 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.

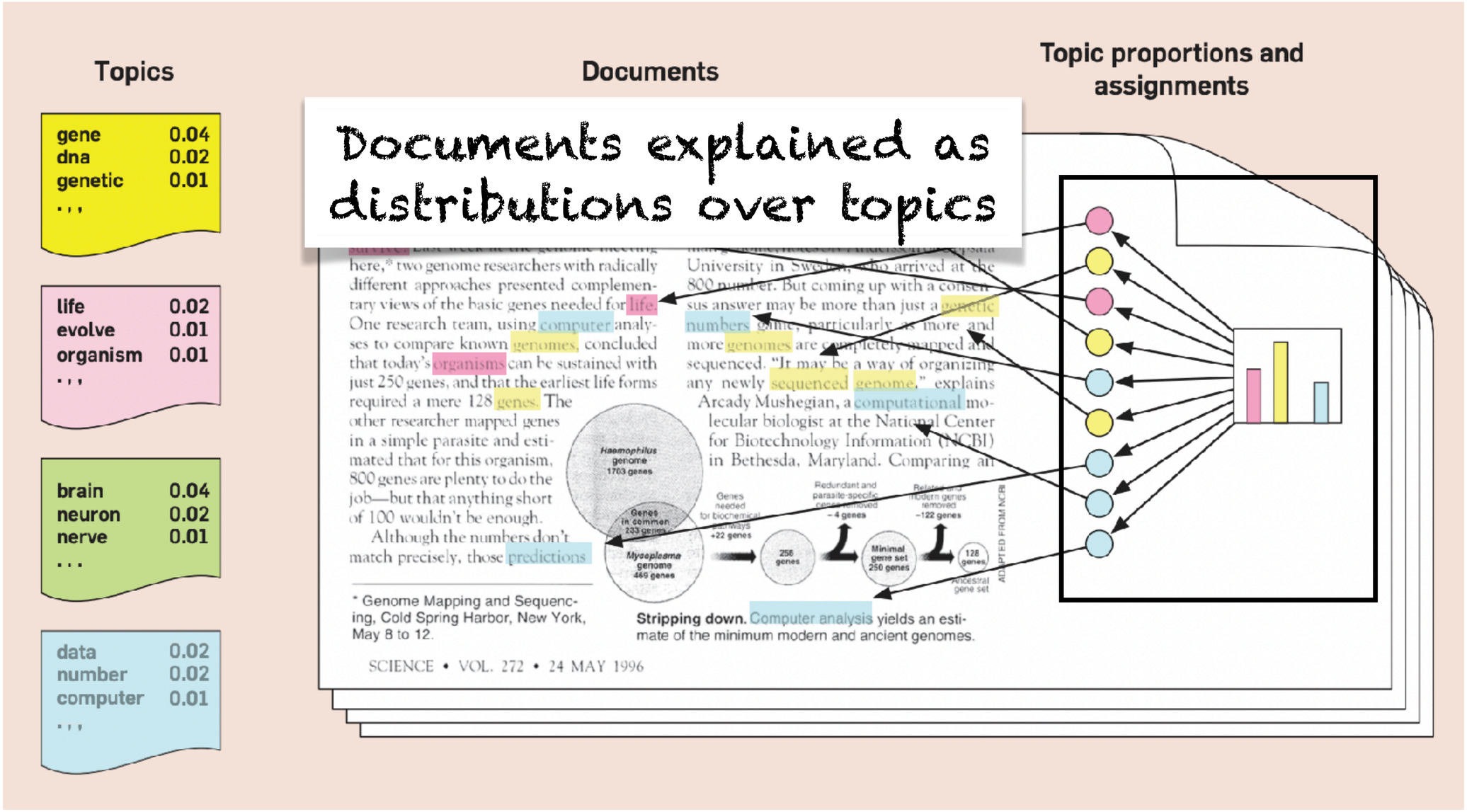
Although the numbers don't match precisely, those predictions "are not all that far apart," especially in comparison to the 75,000 genes in the human genome, notes Siv Andersson of Uppsala University in Sweden, who arrived at the 800 number. But coming up with a consensus answer may be more than just 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.

SCIENCE • VOL. 272 • 24 MAY 1996

What is a topic model?

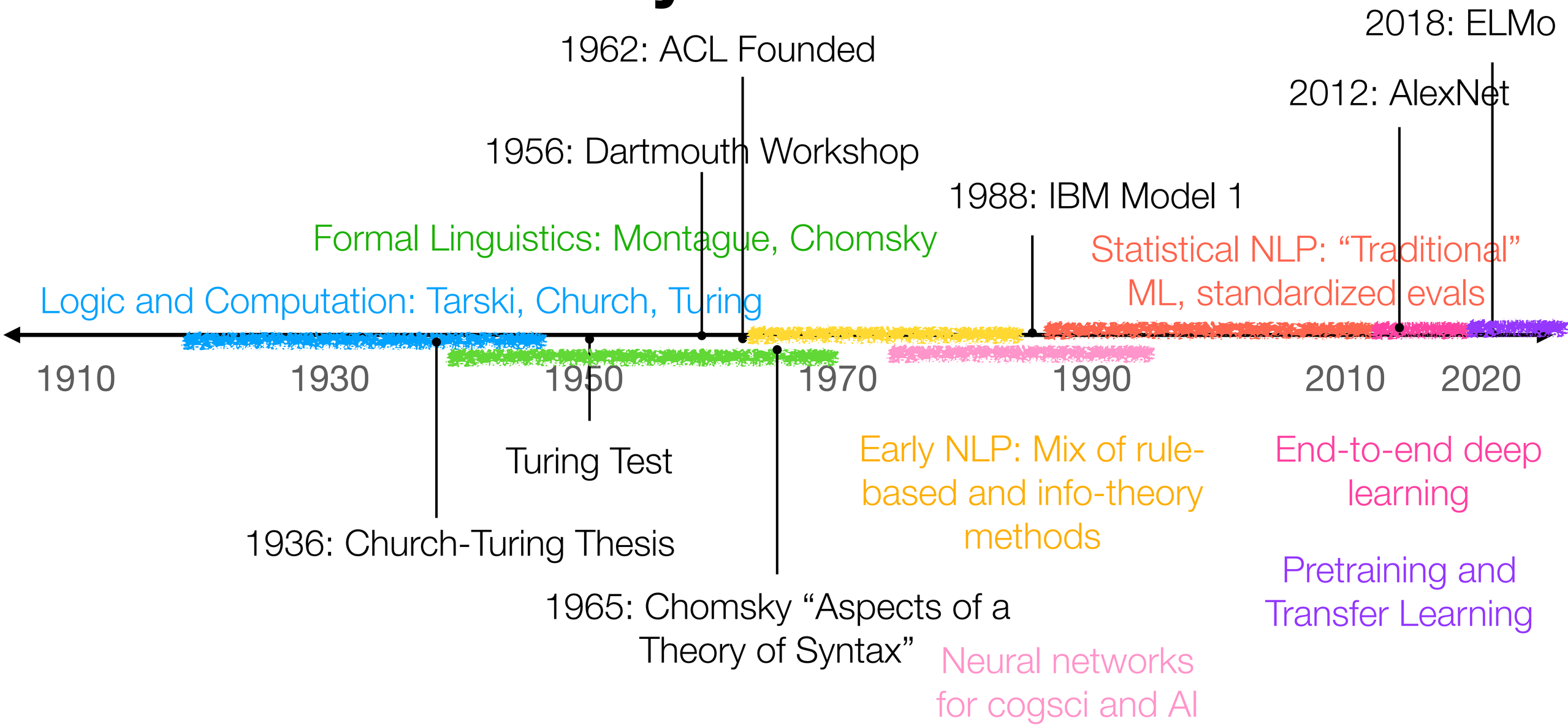


What is a topic model?

LSA vs. LDA

- Two dominant algorithms for producting topic models
  - Latent Semantic Analysis (LSA)
    - Uses dimensionality reduction/linear algebra
  - Latent Dirichelet Allocation (LDA)
    - Uses probability models/graphical models

NLP: A brief history



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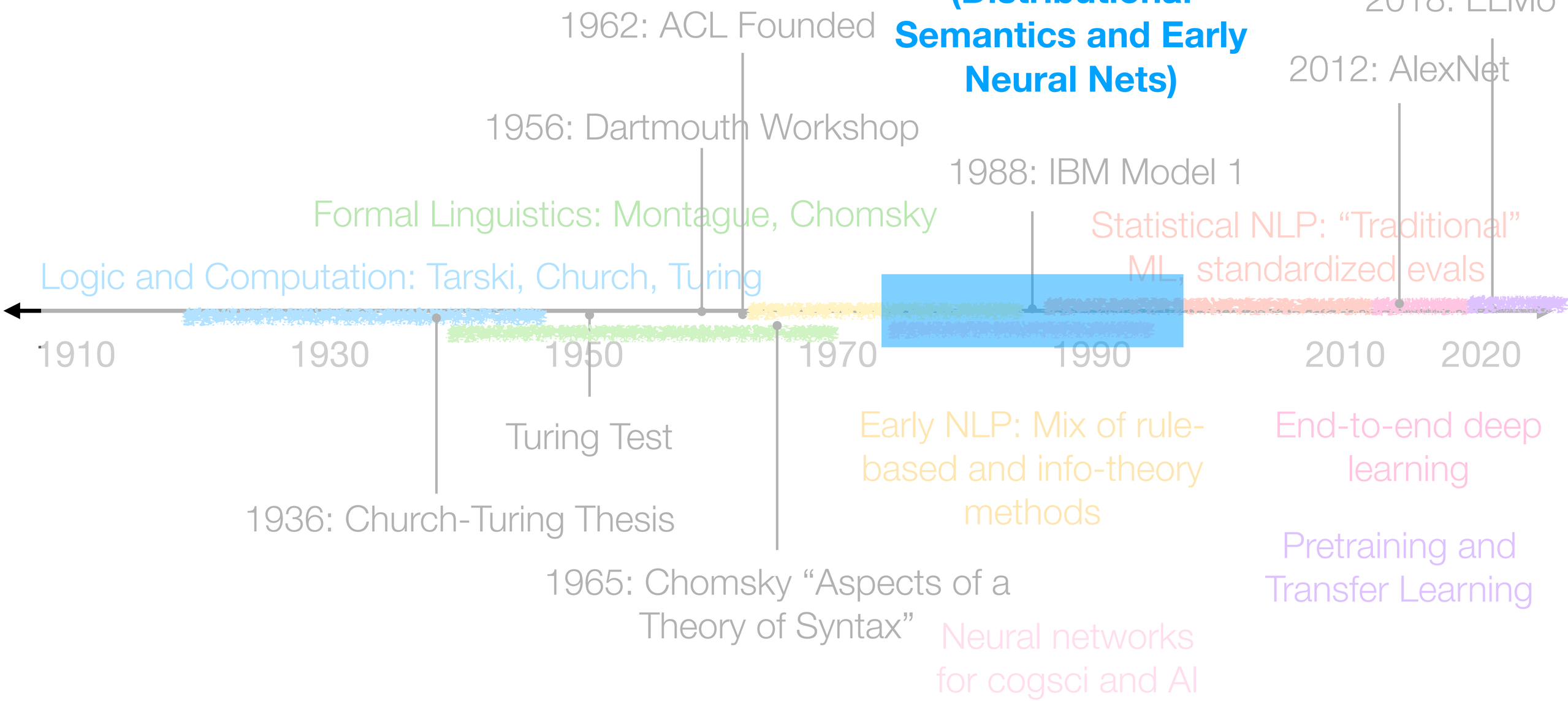

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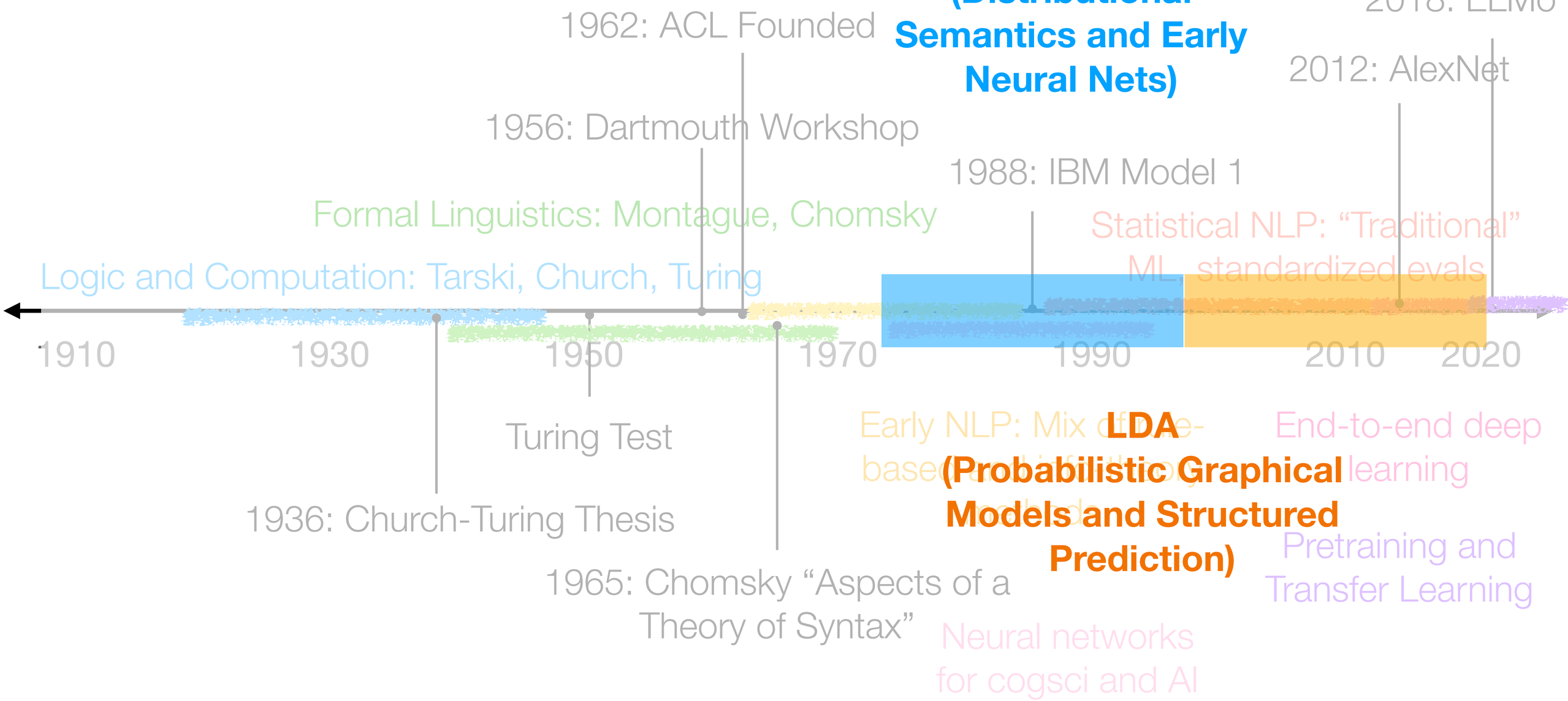

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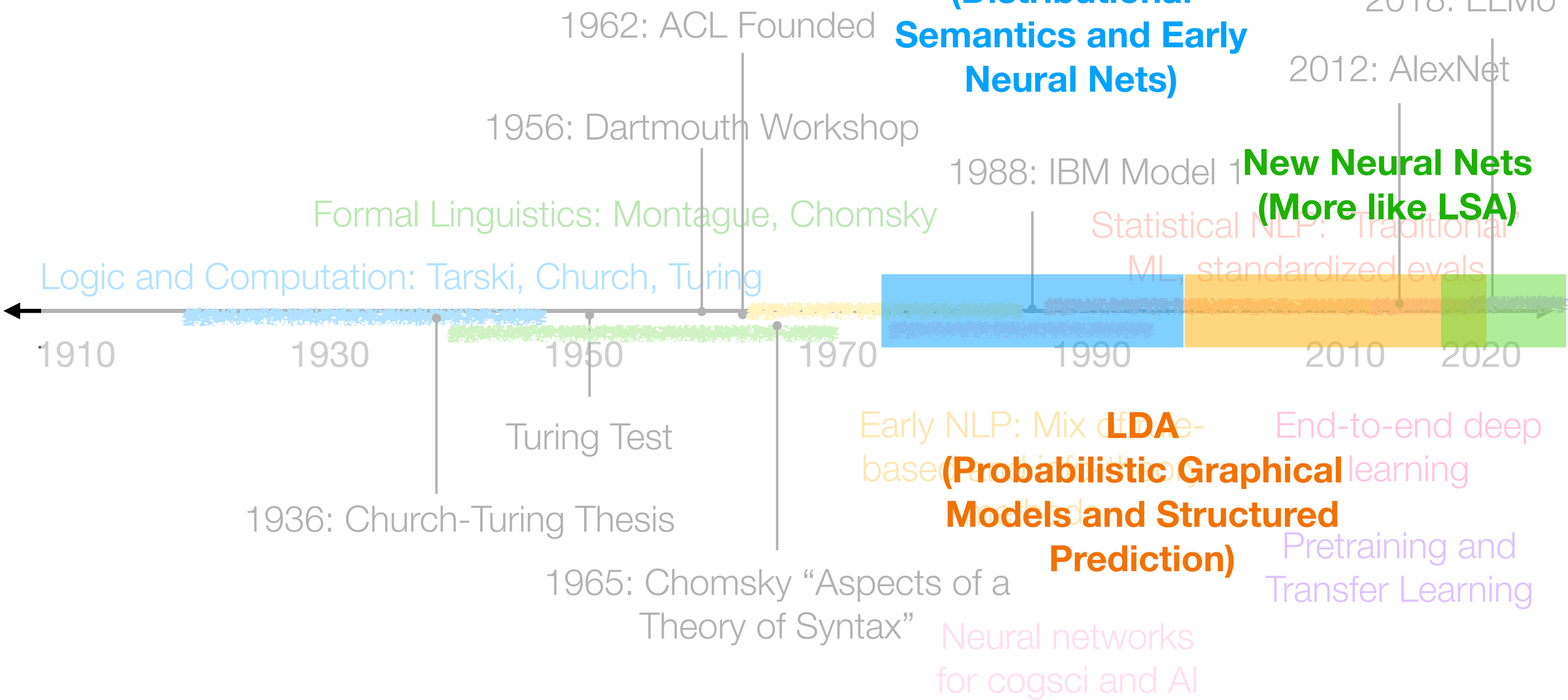

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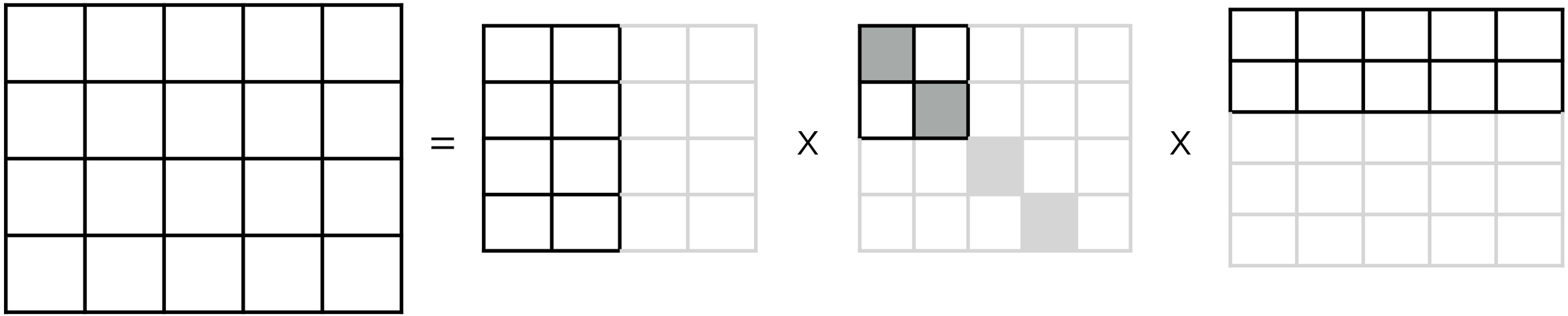
Latent Semantic Analysis (LSA)

Overview

- For a topic model, we want to find:
  - Topics = combinations of words
  - Documents = combinations of topics
- Dimensionality reduction gives us this via the V and U matrix, respectively

*warning: these numbers are purely made up. they may not be "to scale"

Latent Semantic Analysis (LSA)



M
m x n

U
m x l

D
l x l

V
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Data Matrix

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Latent Semantic Analysis (LSA)

	cat	kitten	adorable	cute
doc1	1	1	1	1
doc2	1	0	1	0
doc3	1	1	0	1
doc4	1	0	1	1

M

doc1	0.6	0.39
doc2	0.48	0.50
doc3	0.43	0.58
doc4	0.48	0.50

U

3.06	0.00
0.00	1.81

D

2.5	0.3
3.4	0.1
0.6	1.5
0.9	4.4

V

*warning: these numbers are purely made up. they may not be "to scale"

Latent Semantic Analysis (LSA)

	cat	kitten	adorable	cute
doc1	1	1	1	1
doc2	1	0	1	0
doc3	1	1	0	1
doc4	1	0	1	1

M

new features, i.e., "topics", i.e., weighting of words

doc1	0.6	0.39
doc2	0.48	0.50
doc3	0.43	0.58
doc4	0.48	0.50

U

3.06	0.00
0.00	1.81

D

2.5	0.3
3.4	0.1
0.6	1.5
0.9	4.4

V

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Latent Semantic Analysis (LSA)

	cat	kitten	adorable	cute
doc1	1	1	1	1
doc2	1	0	1	0
doc3	1	1	0	1
doc4	1	0	1	1

M

new features, i.e., "topics", i.e., weighting of words

doc1 in new feature space (i.e., weighting of topics)

doc1	0.6	0.39
doc2	0.48	0.50
doc3	0.43	0.58
doc4	0.48	0.50

U

3.06	0.00
0.00	1.81

D

2.5	0.3
3.4	0.1
0.6	1.5
0.9	4.4

V

*warning: these numbers are purely made up. they may not be "to scale"

Latent Semantic Analysis (LSA)

	cat	kitten	adorable	cute
doc1	1	1	1	1
doc2	1	0	1	0
doc3	1	1	0	1
doc4	1	0	1	1

M

weight of topic1 for doc1

doc1	0.6	0.39
doc2	0.48	0.50
doc3	0.43	0.58
doc4	0.48	0.50

U

3.06	0.00
0.00	1.81

D

2.5	0.3
3.4	0.1
0.6	1.5
0.9	4.4

V

*warning: these numbers are purely made up. they may not be "to scale"

Latent Semantic Analysis (LSA)

	cat	kitten	adorable	cute
doc1	1	1	1	1
doc2	1	0	1	0
doc3	1	1	0	1
doc4	1	0	1	1

M

weight of topic1 for doc1

weight of word "cat" in topic1

doc1	0.6	0.39
doc2	0.48	0.50
doc3	0.43	0.58
doc4	0.48	0.50

U

3.06	0.00
0.00	1.81

D

2.5	0.3
3.4	0.1
0.6	1.5
0.9	4.4

V

Latent Semantic Analysis (LSA)

Example

- Imagine building a classifier to recommend articles to readers
  - ~~Option 1: Use BOW models~~
    - ~~“Since you read an article with the word ‘court-side’, you might also like this article which has the word ‘rebound’”~~
  - Option 2: Topics!
    - “Since you read an article about basketball, you might also like this other article about basketball”

doc1	0.6	0.39
doc2	0.48	0.50
doc3	0.43	0.58
doc4	0.48	0.50

U

2.5	0.3
3.4	0.1
0.6	1.5
0.9	4.4

V

Latent Semantic Analysis (LSA)

Example

- Imagine building a classifier to recommend articles to readers
  - ~~Option 1: Use BOW m~~
    - ~~"Since you read an a~~ ~~'court-side', you mig~~ ~~article which has the word 'rebound'"~~
  - Option 2: Topics!
    - "Since you read an article about basketball, you might also like this other article about basketball"

Use embeddings as input to your classifier.

doc1	0.6	0.39
doc2	0.48	0.50
doc3	0.43	0.58
doc4	0.48	0.50

U

2.5	0.3
3.4	0.1
0.6	1.5
0.9	4.4

V

Latent Semantic Analysis (LSA)

Example

- Imagine building a classifier to recommend articles to readers
  - ~~Option 1: Use BOW m~~
    - ~~"Since you read an a~~ ~~'court-side', you mig~~ ~~article which has the word 'rebound'"~~
  - Option 2: Topics!
    - "Since you read an article about basketball, you might also like this other article about basketball"

Refer to topics to understand/ explain predictions

doc1	0.6	0.39
doc2	0.48	0.50
doc3	0.43	0.58
doc4	0.48	0.50

U

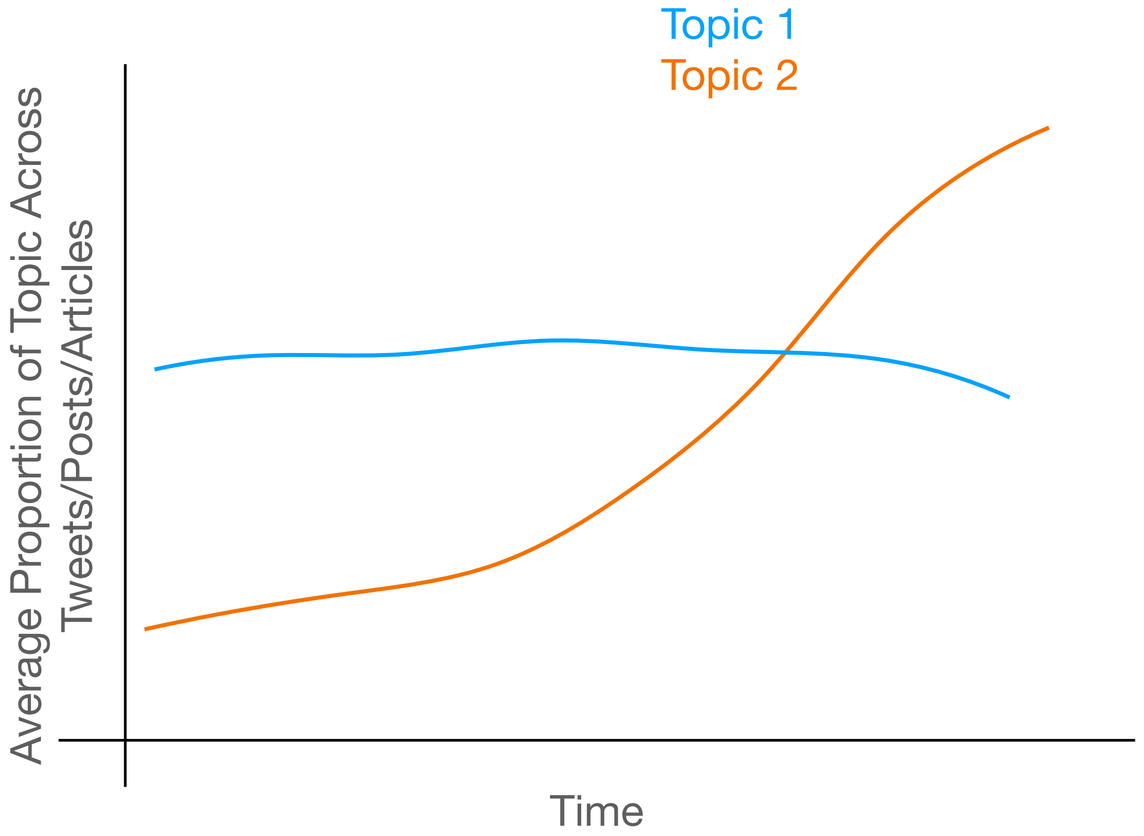
2.5	0.3
3.4	0.1
0.6	1.5
0.9	4.4

V

What is a topic model?

Example

- Imagine working as a campaign strategist and analyzing public opinion in your district
  - ~~Option 1: Use BOW models~~
    - ~~"In the past year, there has been an increase in the use of the word 'price' and a decrease in the word 'classroom'"~~
  - Option 2: Topics!
    - "In the past year, people have been talking more about the economy than about schools"



Topics

- Lecture 6 Followup: Word Embeddings from SVD
- What is a topic model
- Latent Semantic Analysis (LSA)
- **Latent Dirichelet Allocation (LDA)**
  - “Generative Stories”
  - Graphical Model Notation
  - Training and Evaluation

Latent Dirichlet Allocation (LDA)

Overview

- Probabilistic model for finding topic models (in contrast to LSA has no notion of probability)
- We are covering LDA today because:
  - Its a good, popular method for training topic models!
  - It introduces important ideas about **generative models** which are used elsewhere in NLP
  - It introduces the notion of **“graphical models”** which are used elsewhere in NLP

Latent Dirichlet Allocation (LDA)

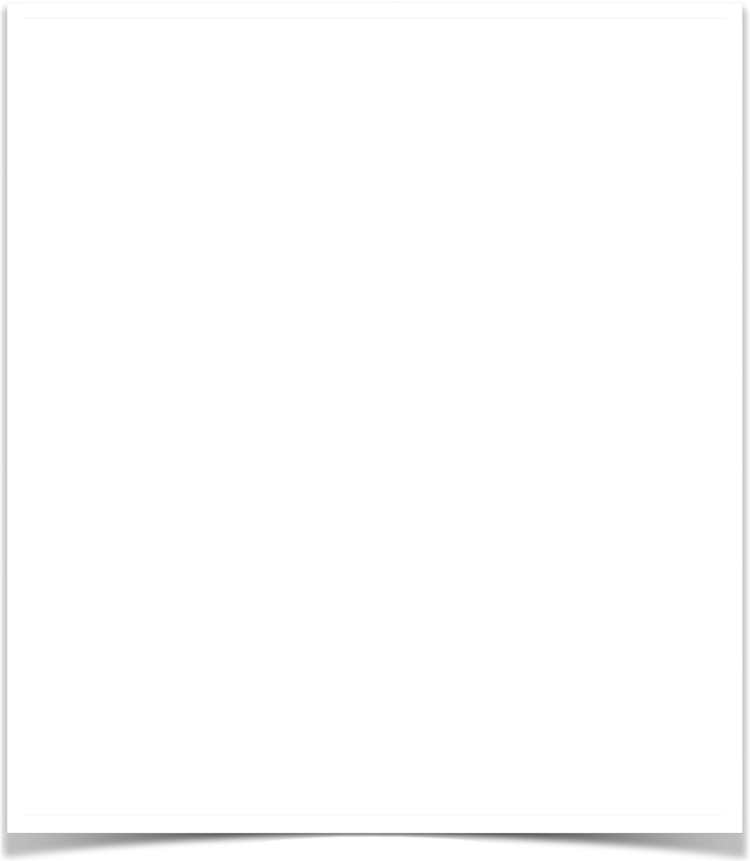
Generative Story

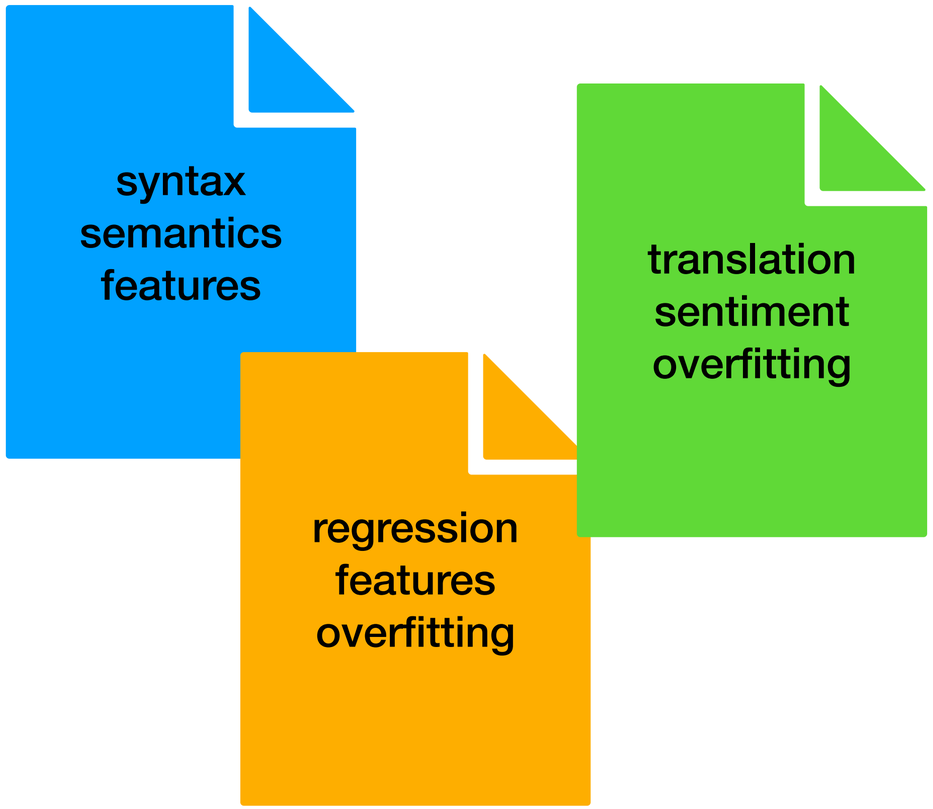
- Step 1 of building models is to make assumptions about the structure of the data/problem
- In many* NLP models, these assumptions are given by the “generative story”
- Story for how the observed data came to be; provides intuition behind the set of assumptions that are then encoded in the model
- We will return to this concept (Machine Translation, Sequence Tagging, …)

*Specifically, probabilistic generative models

Latent Dirichlet Allocation (LDA)

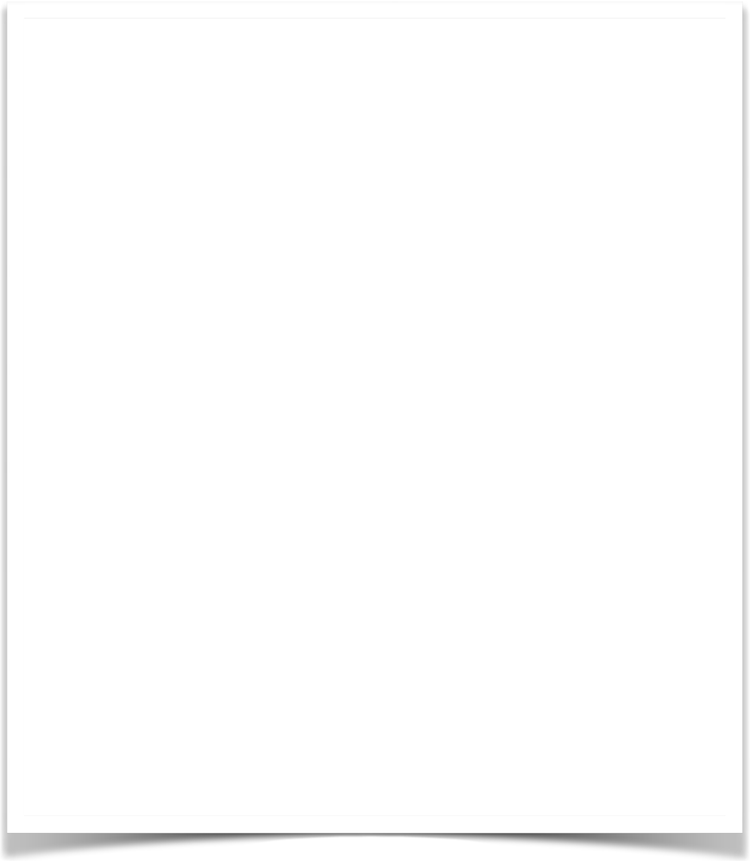
Generative Story

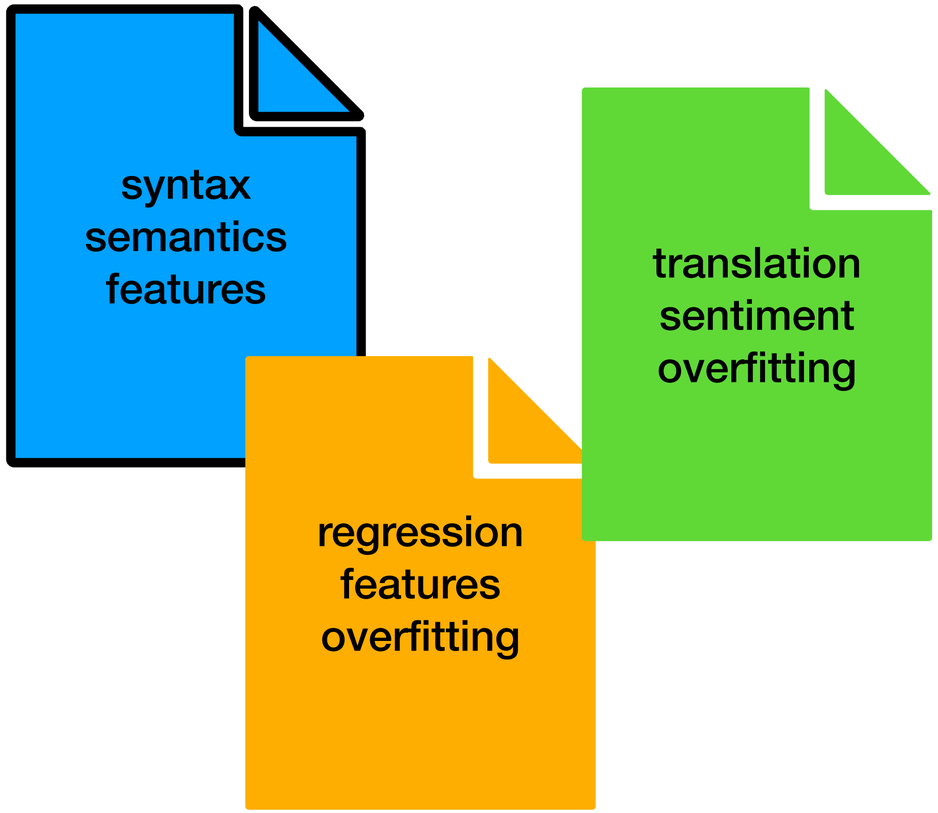




Latent Dirichlet Allocation (LDA)

Generative Story



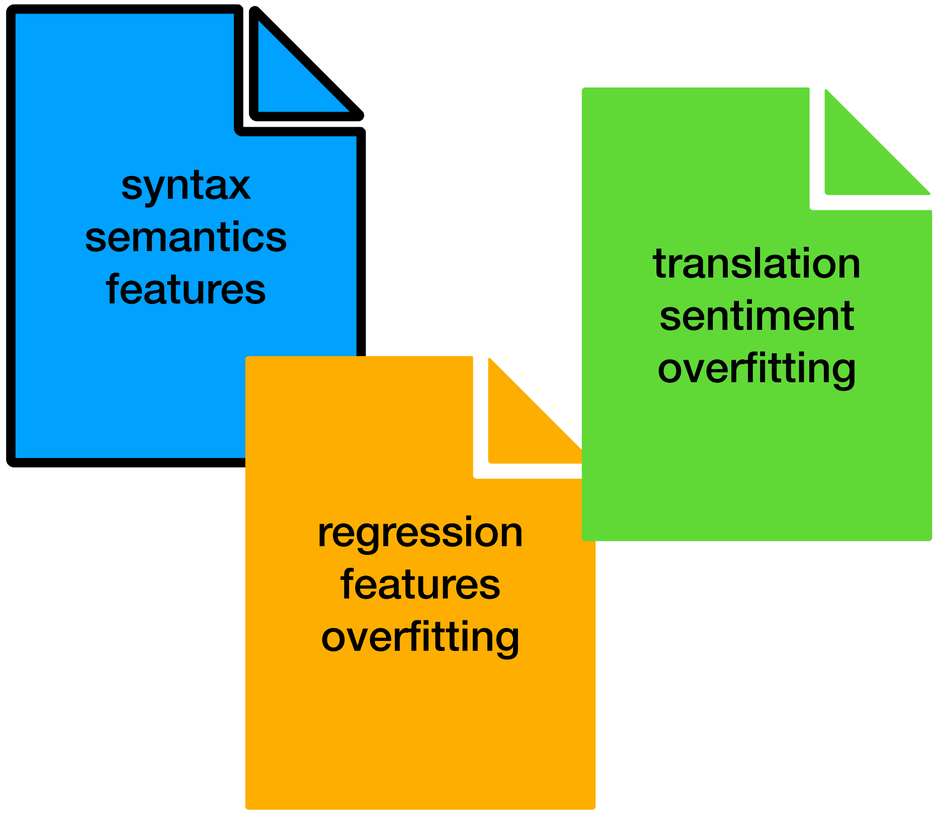


1. Sample a topic

Latent Dirichlet Allocation (LDA)

Generative Story

Semantics

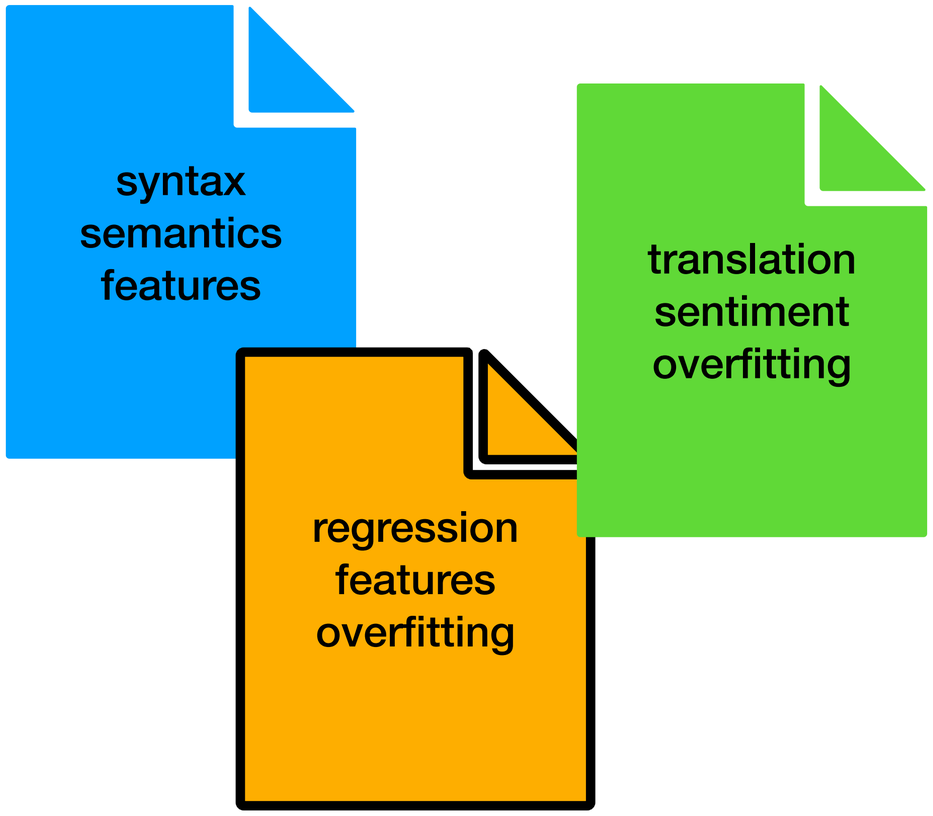


2. Sample a word from that topic

Latent Dirichlet Allocation (LDA)

Generative Story

Semantics

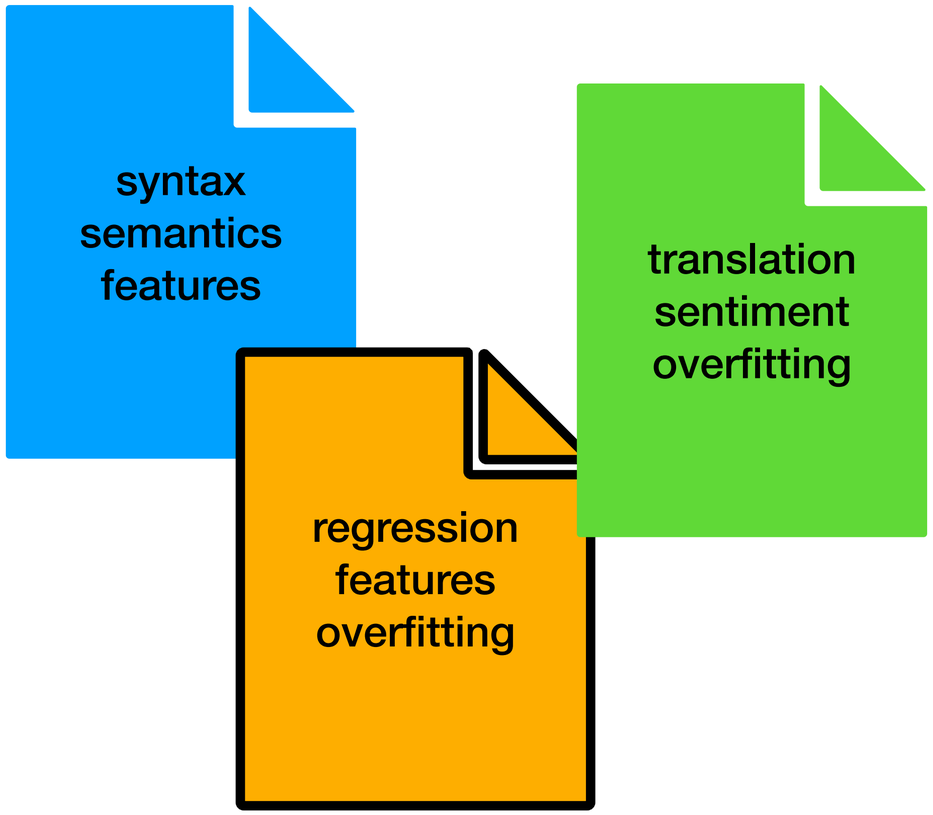


1. Sample a topic

Latent Dirichlet Allocation (LDA)

Generative Story

Semantics regression



2. Sample a word from that topic

Latent Dirichlet Allocation (LDA)

Generative Story

Semantics regression

models features

evaluation difficult

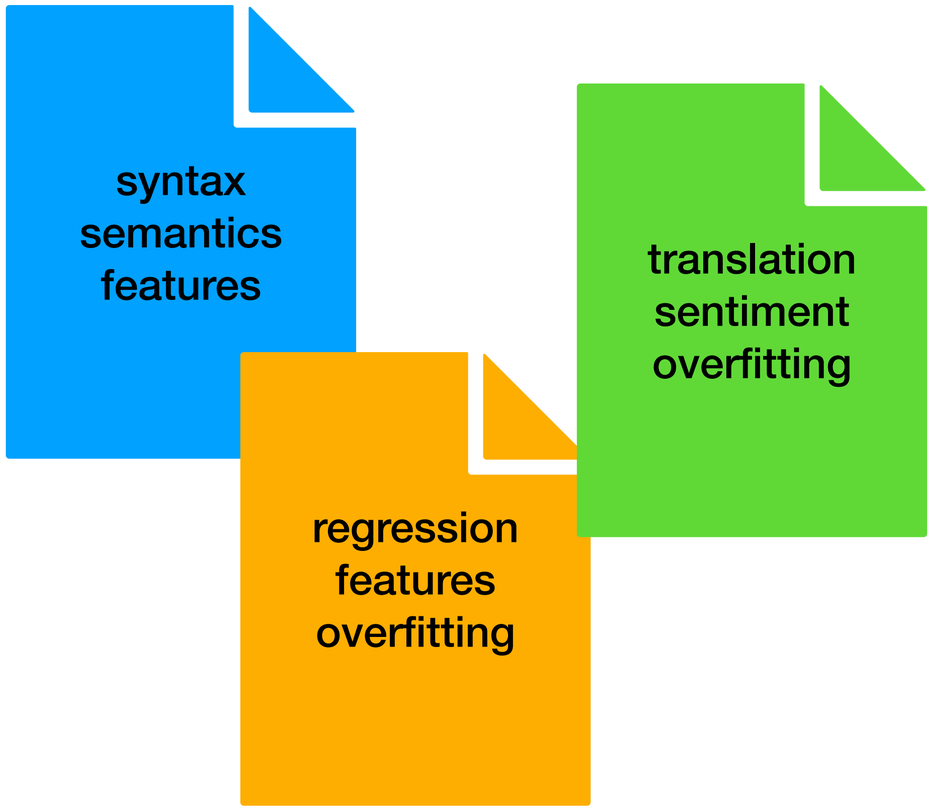
overfitting parameters

loss prediction

errors multilingual

morphology

Repeat



Latent Dirichlet Allocation (LDA)

Generative Story

Still like BOW. Ignores issues of syntax/ word order, semantics, discourse, etc...

Semantics regression

models features

evaluation difficult

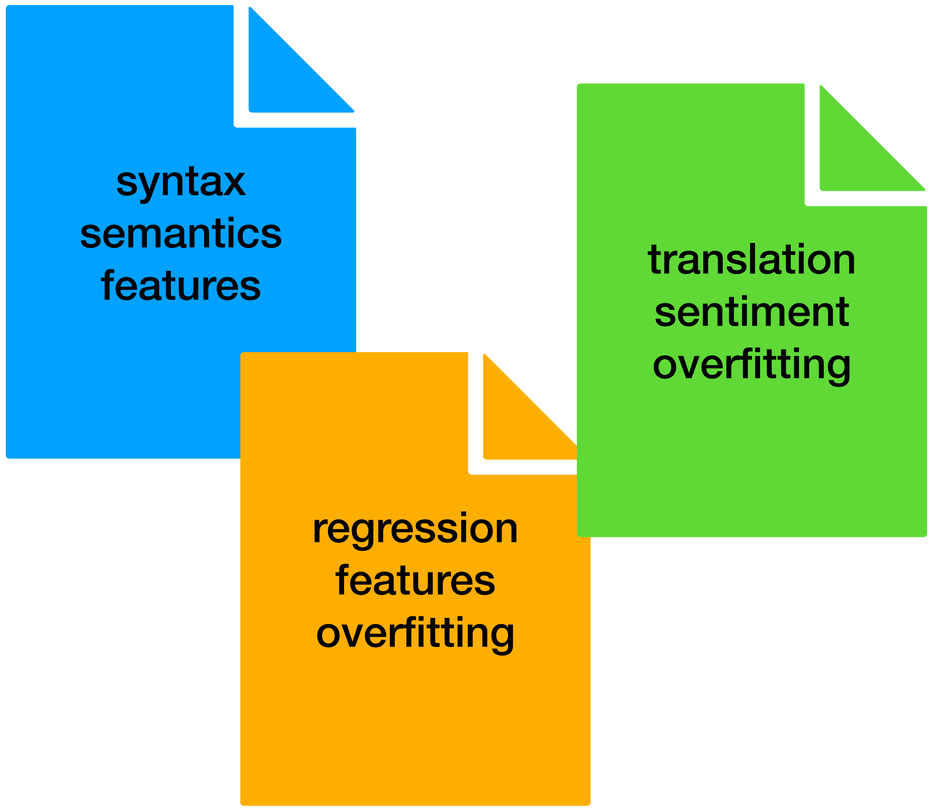
overfitting parameters

loss prediction

errors multilingual

morphology

Repeat



Latent Dirichlet Allocation (LDA)

Generative Story

When training a model we get only this

Semantics regression

models features

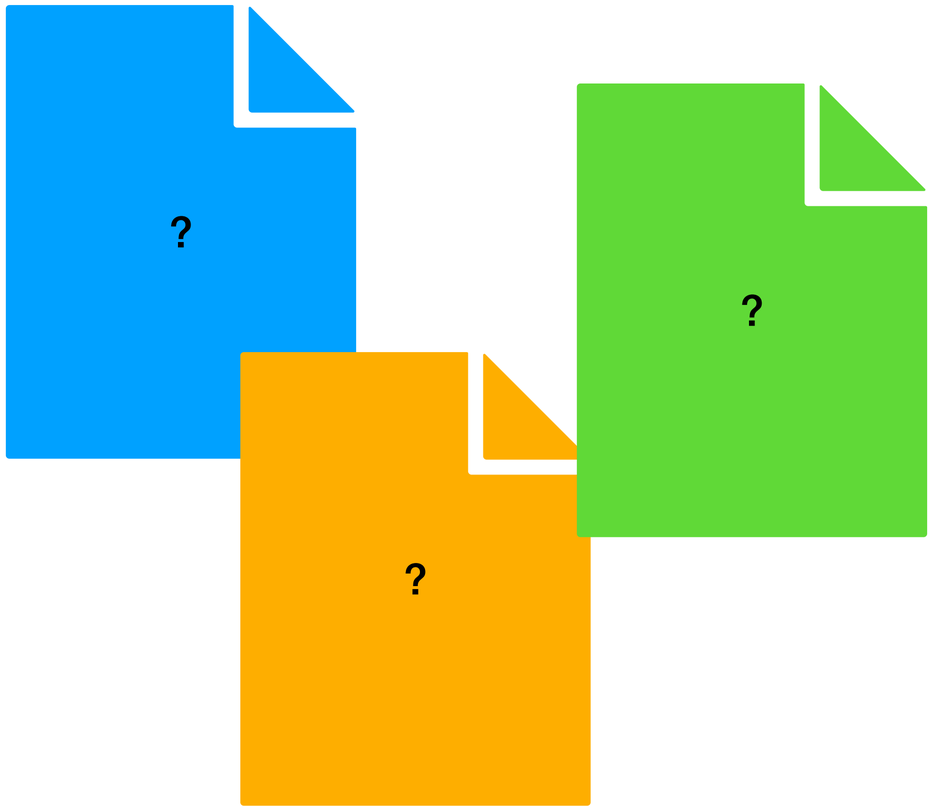
evaluation difficult

overfitting parameters

loss prediction

errors multilingual

morphology



Latent Dirichlet Allocation (LDA)

Generative Story

Semantics regression

models features

evaluation difficult

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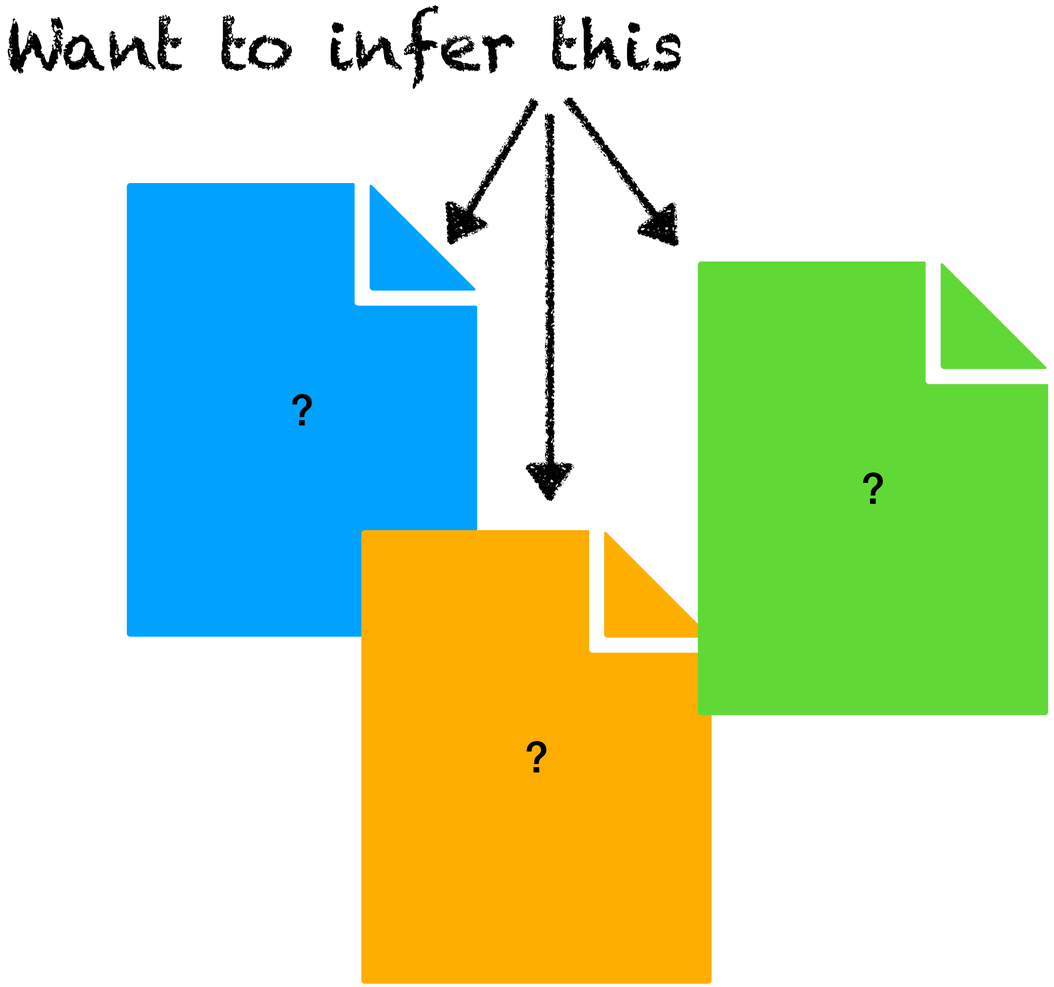


Latent Dirichlet Allocation (LDA)

Generative Story

$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation (LDA)

Generative Story

Probability of the data
(a given word appearing)

$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation (LDA)

Generative Story

Probability of that word for a given topic

$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation (LDA)

Generative Story

Overall probability of that topic

$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation (LDA)

Generative Story

Marginalized over all topics

$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation (LDA)

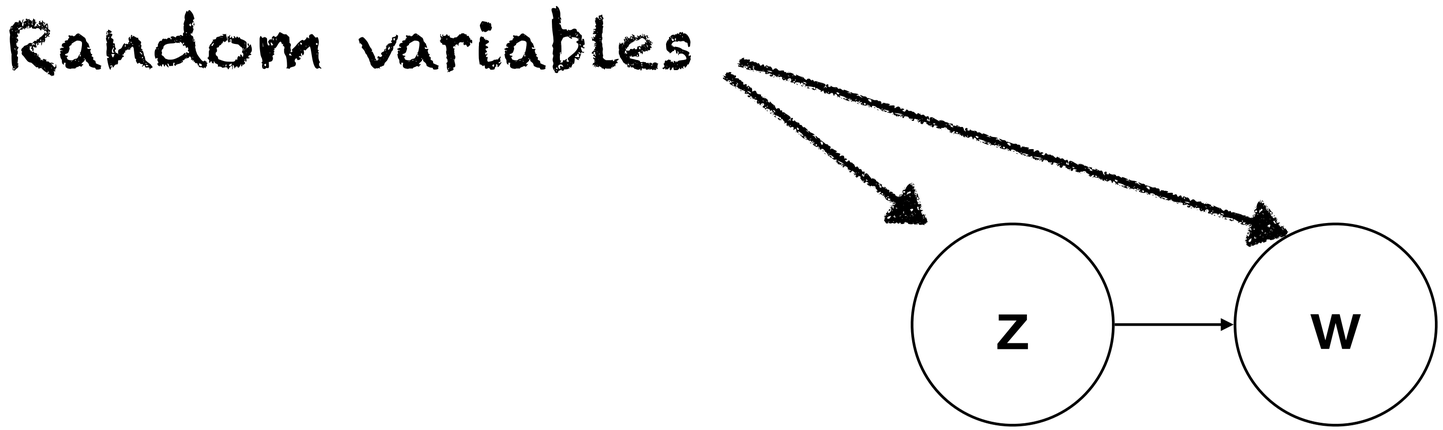
Generative Story

$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Given the observed ws,
find the P(z)s and P(w|z)s that
make the observed ws most likely

Latent Dirichlet Allocation (LDA)

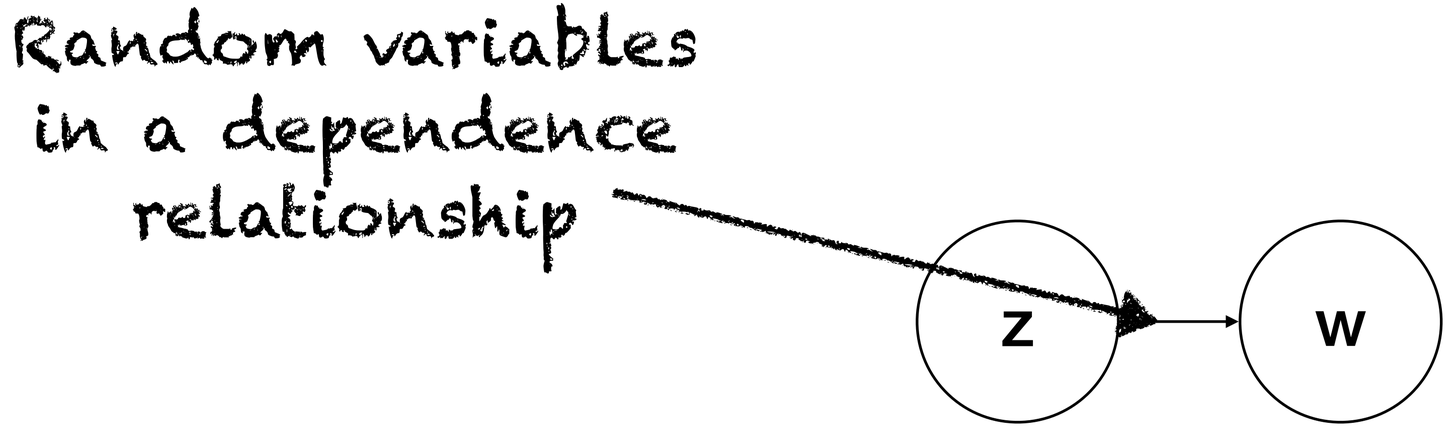
Graphical Model Notation



$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation (LDA)

Graphical Model Notation

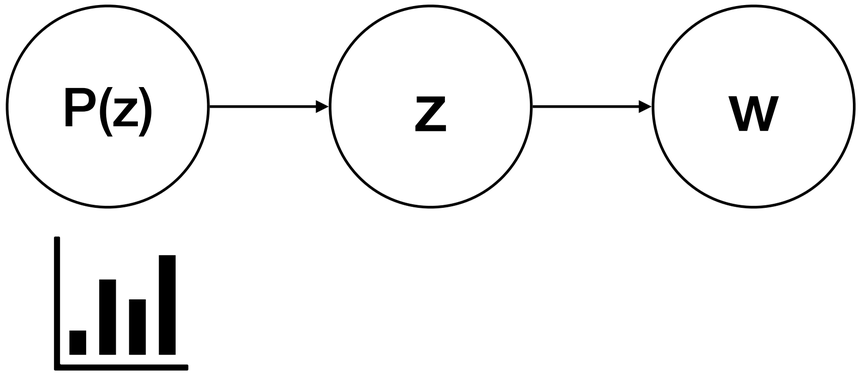


$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation (LDA)

Graphical Model Notation

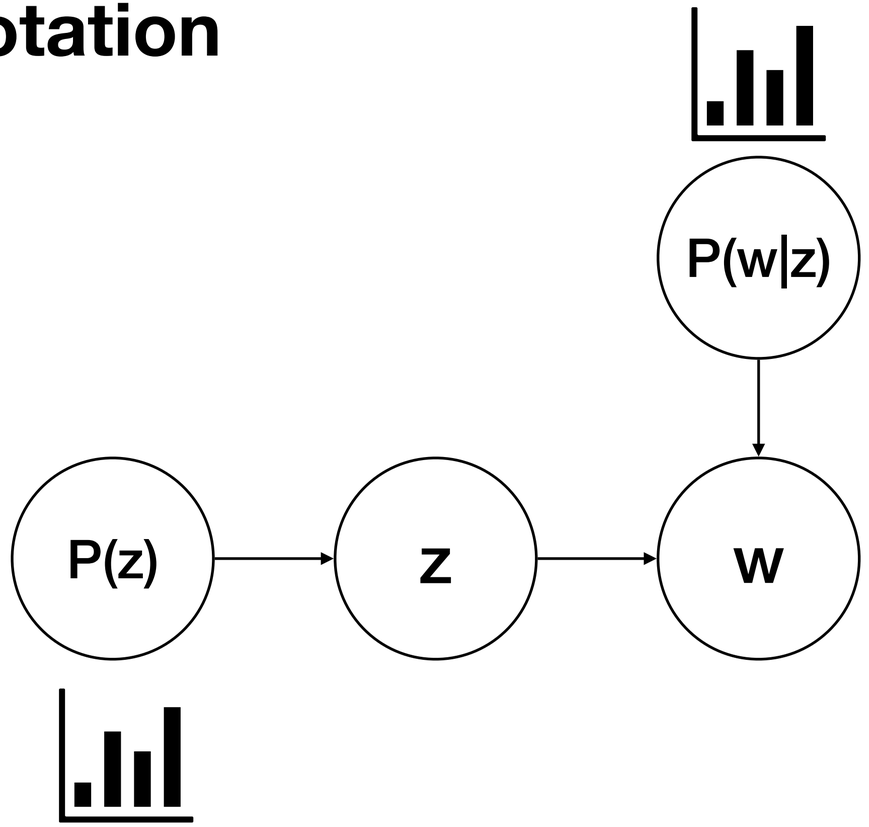
z depends on a multinomial distribution P(z)



$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation (LDA)

Graphical Model Notation

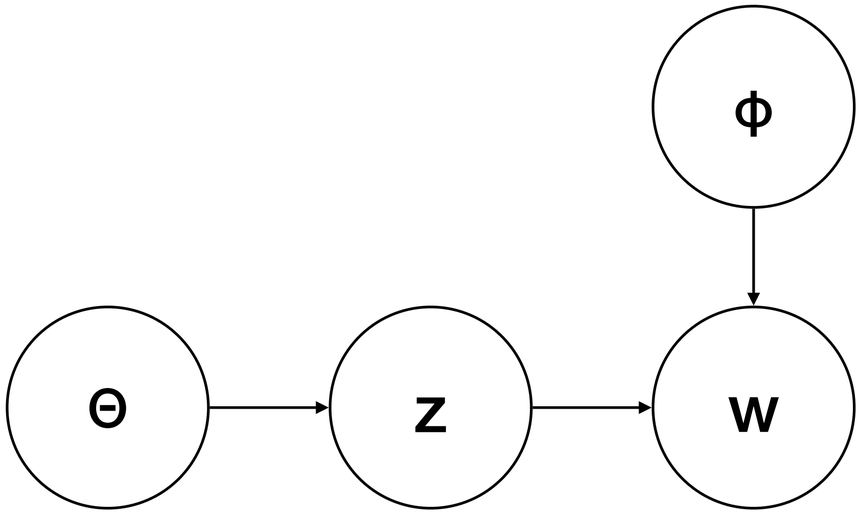


w depends on a multinomial distribution P(w|z)

$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation (LDA)

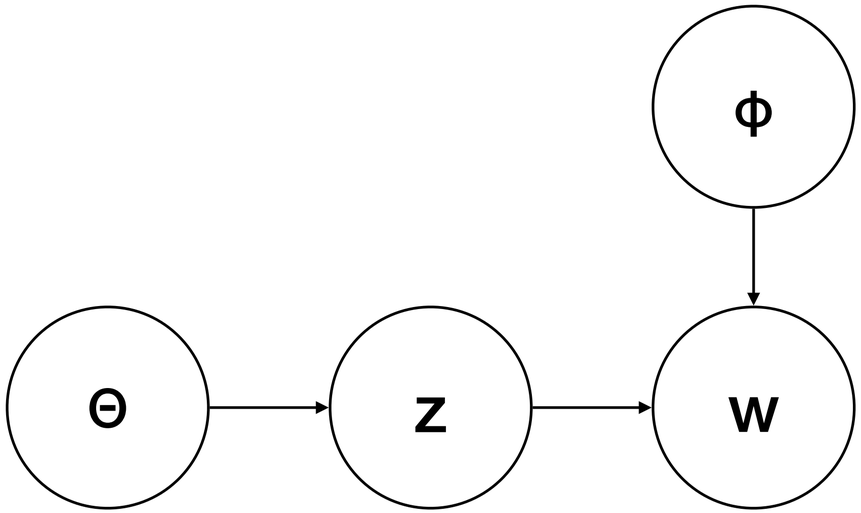
Graphical Model Notation



$$P(w_i) = \sum_{j=1}^{T} P(w_i \mid z_i = j) P(z_i = j)$$

Latent Dirichlet Allocation (LDA)

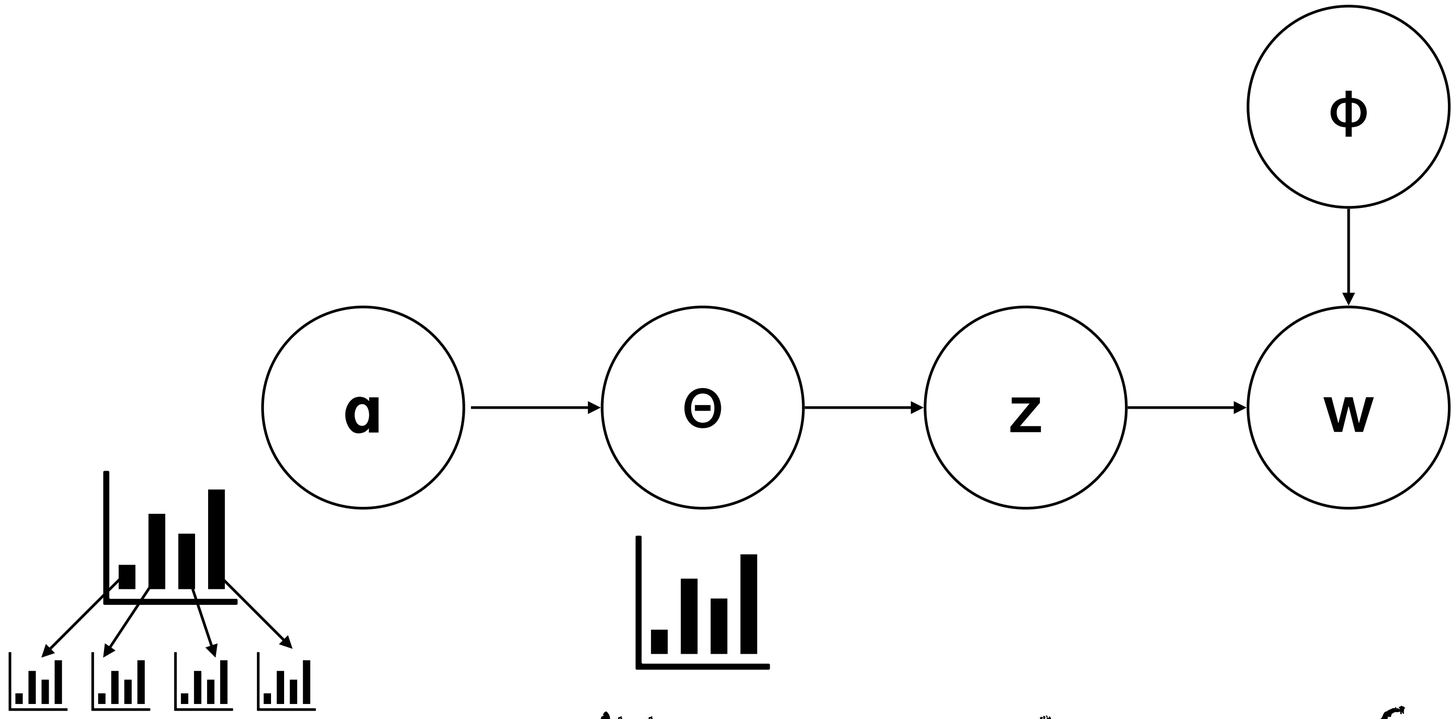
Graphical Model Notation



Θ needs to come from somewhere!

Latent Dirichlet Allocation (LDA)

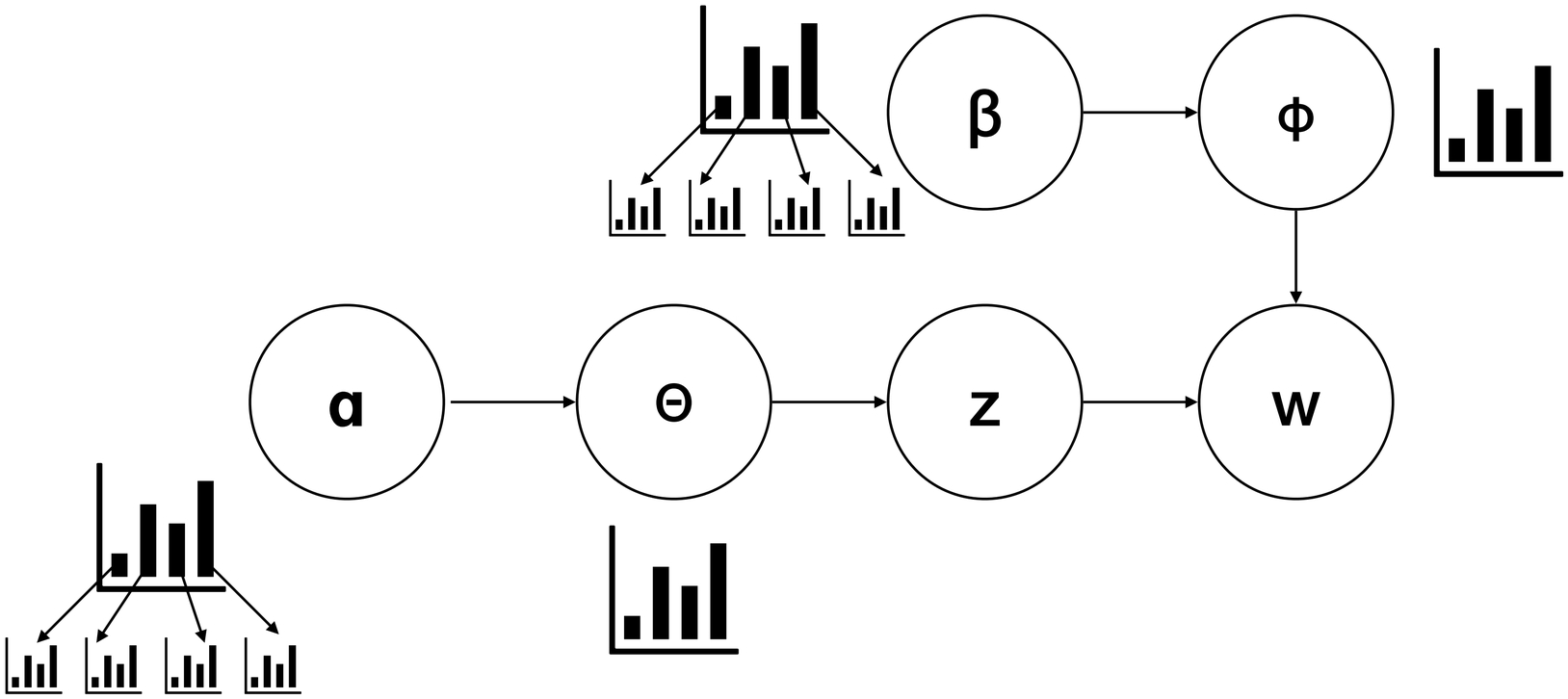
Graphical Model Notation



we'll assume it comes from a Dirichlet distribution α

Latent Dirichlet Allocation (LDA)

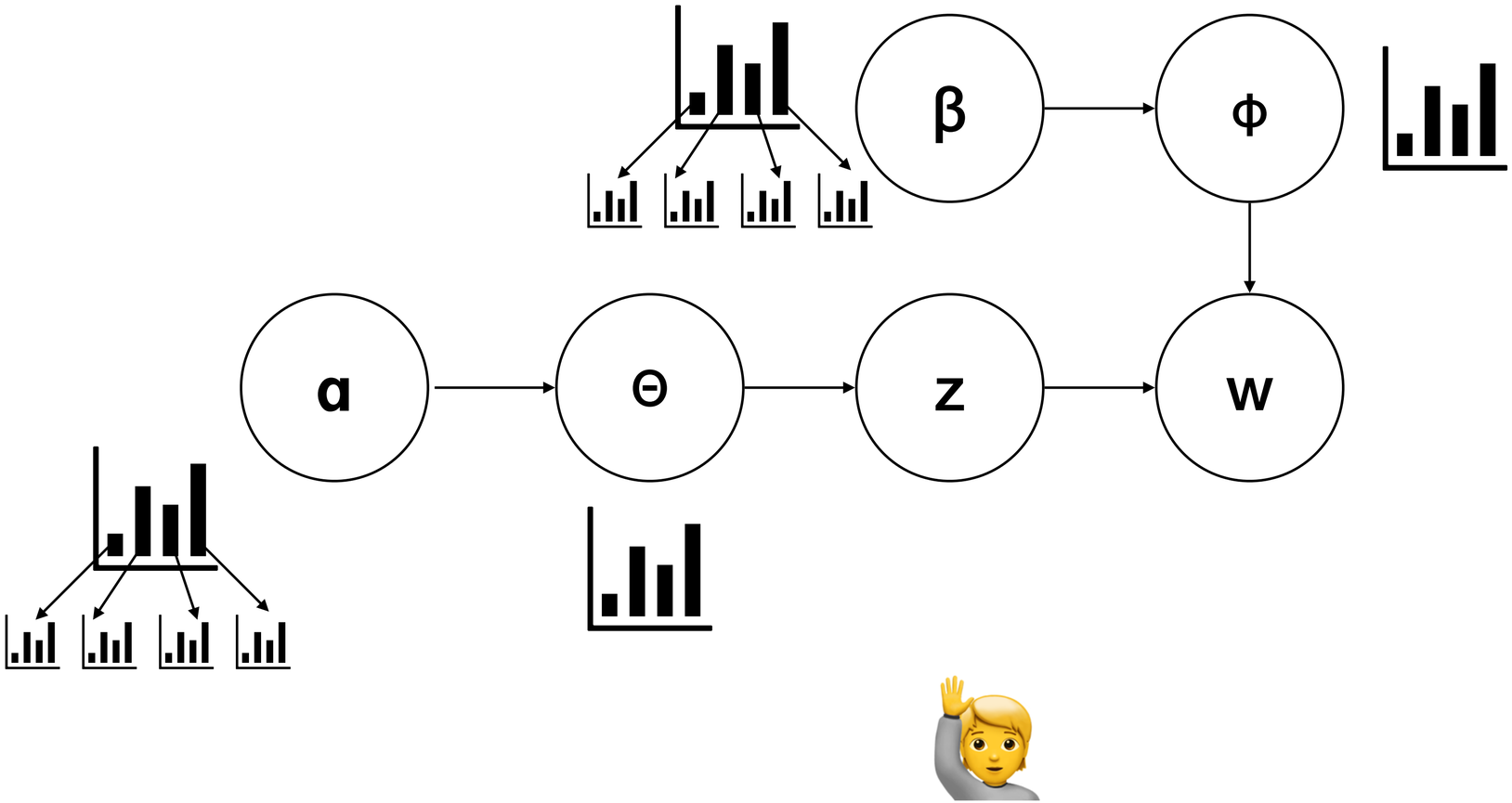
Graphical Model Notation



ϕ too!

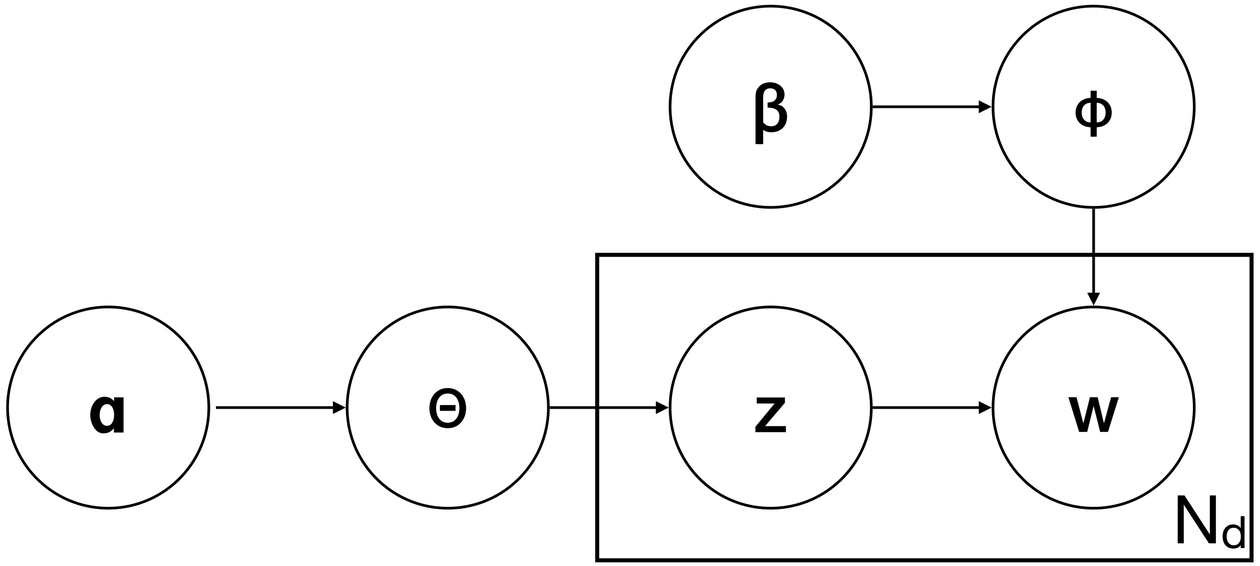
Latent Dirichlet Allocation (LDA)

Graphical Model Notation



Latent Dirichlet Allocation (LDA)

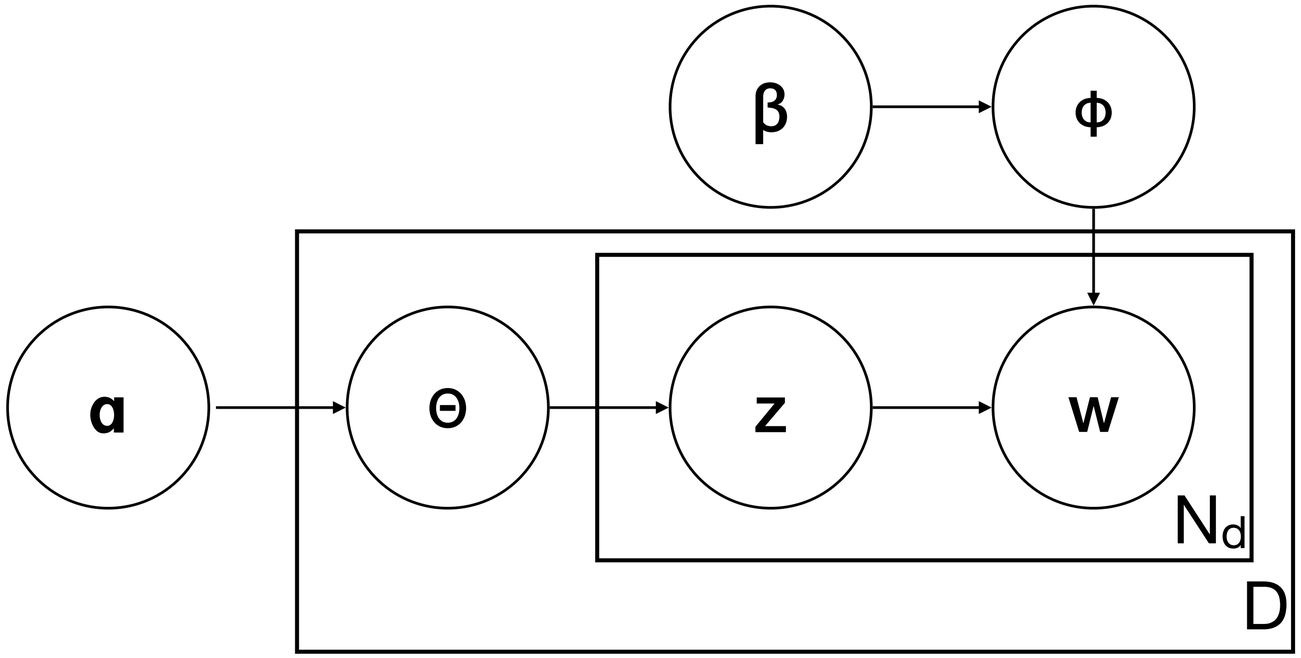
Graphical Model Notation



this step happens N_d times, once for each of N_d words in a document d

Latent Dirichlet Allocation (LDA)

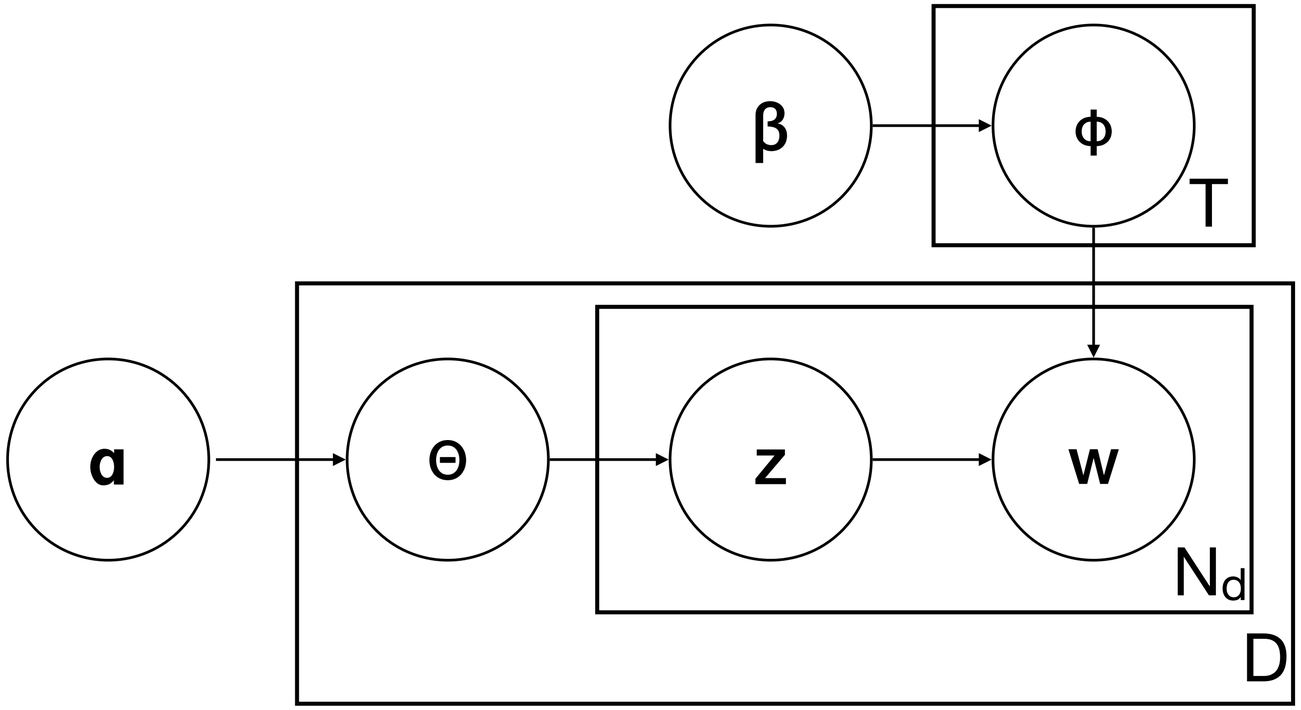
Graphical Model Notation



this step happens D times, once for each of D documents

Latent Dirichlet Allocation (LDA)

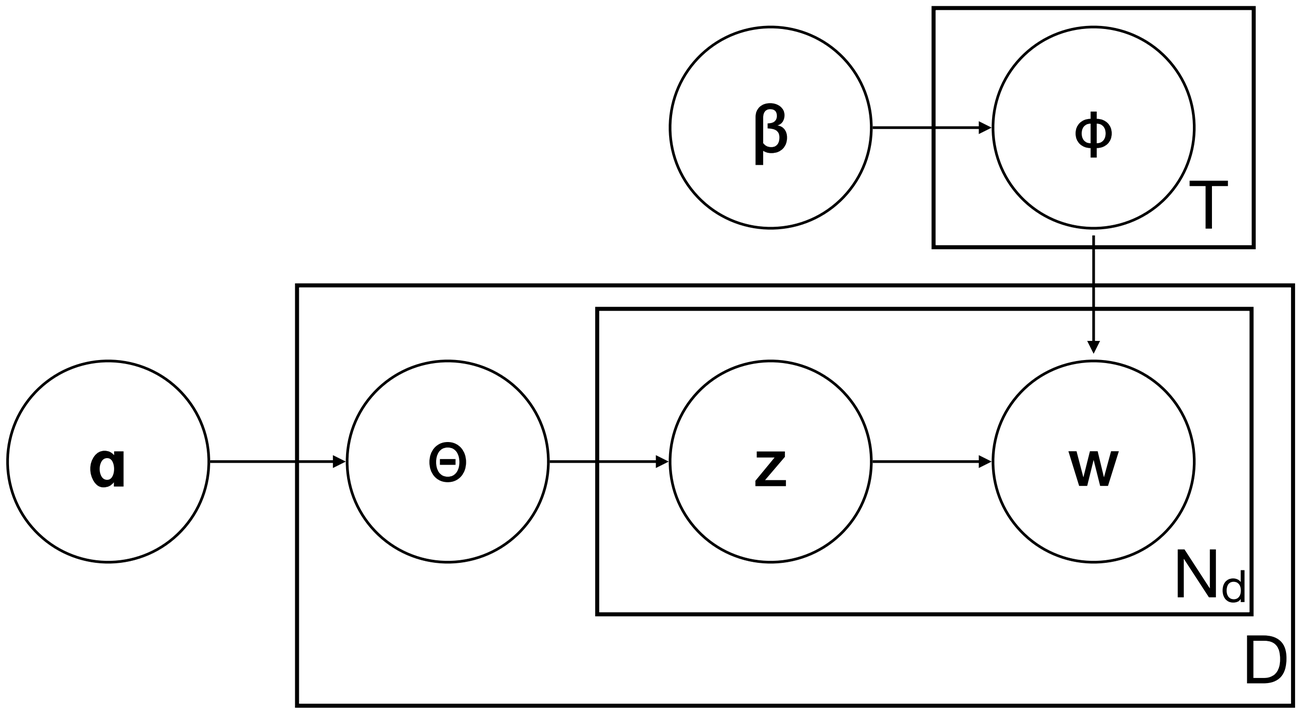
Graphical Model Notation



this step happens T times, once for each of T topics

Latent Dirichlet Allocation (LDA)

Graphical Model Notation



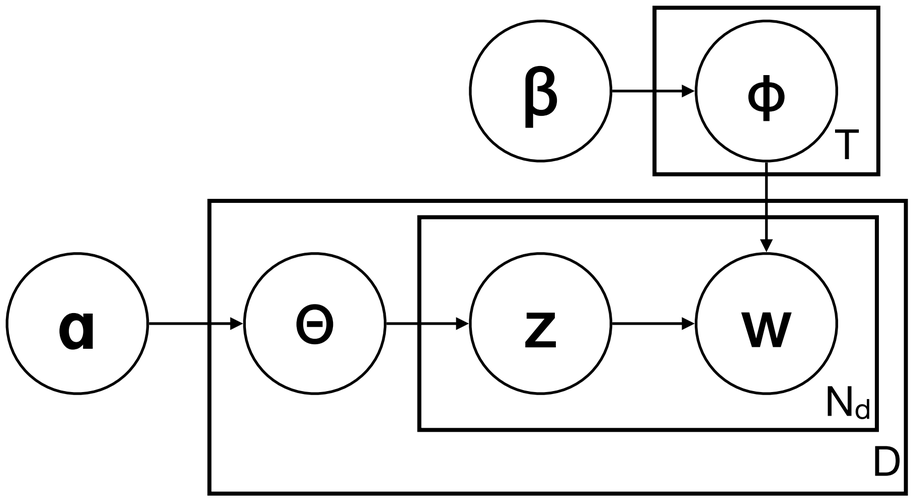
this step happens T times, once for each of T topics

Latent Dirichlet Allocation (LDA)

Graphical Model Notation <-> Generative Story

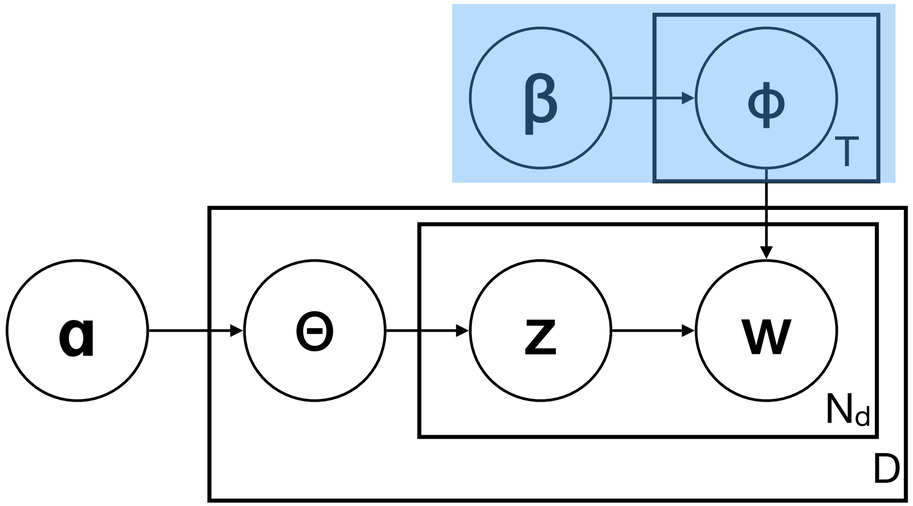
Latent Dirichlet Allocation (LDA)

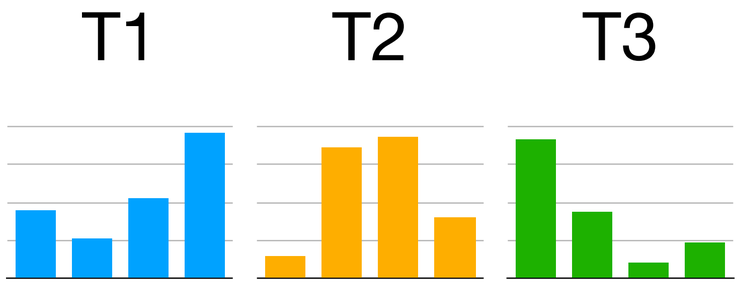
Graphical Model Notation <-> Generative Story



Latent Dirichlet Allocation (LDA)

Graphical Model Notation <-> Generative Story

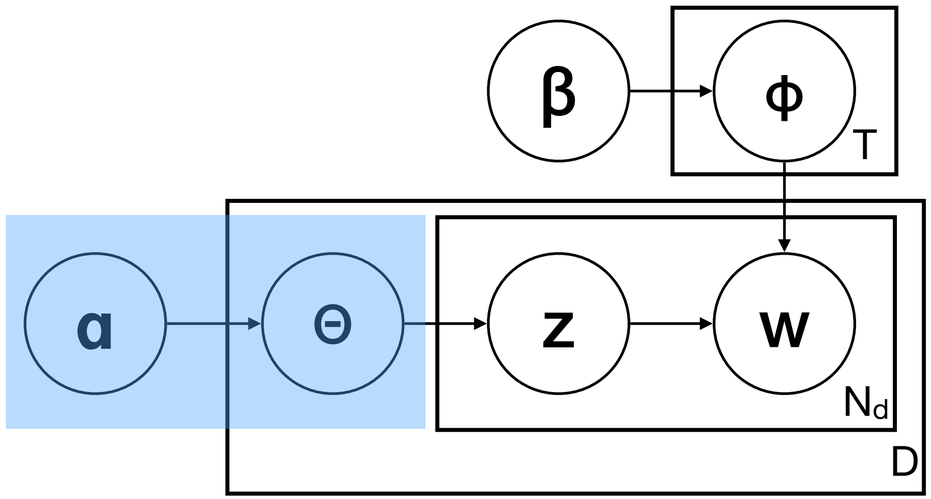


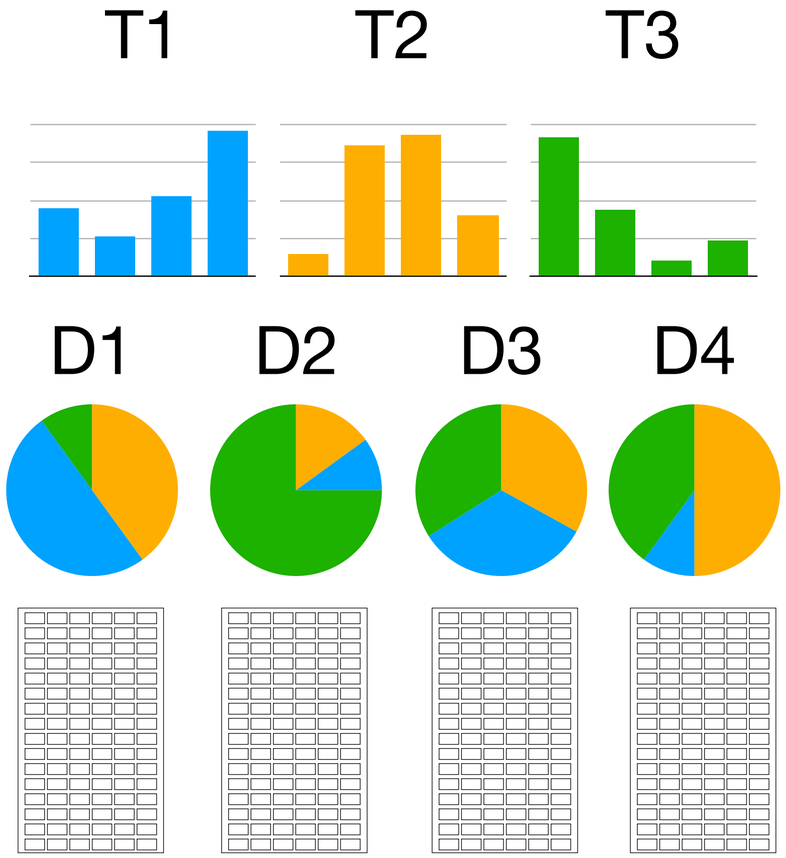


For each topic, sample a multinomial distribution over words

Latent Dirichlet Allocation (LDA)

Graphical Model Notation <-> Generative Story





For each document,
sample a multinomial
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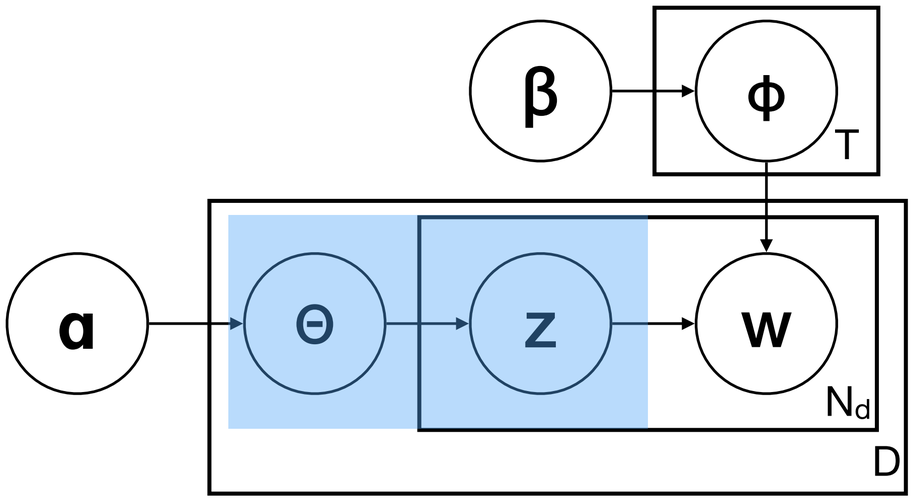
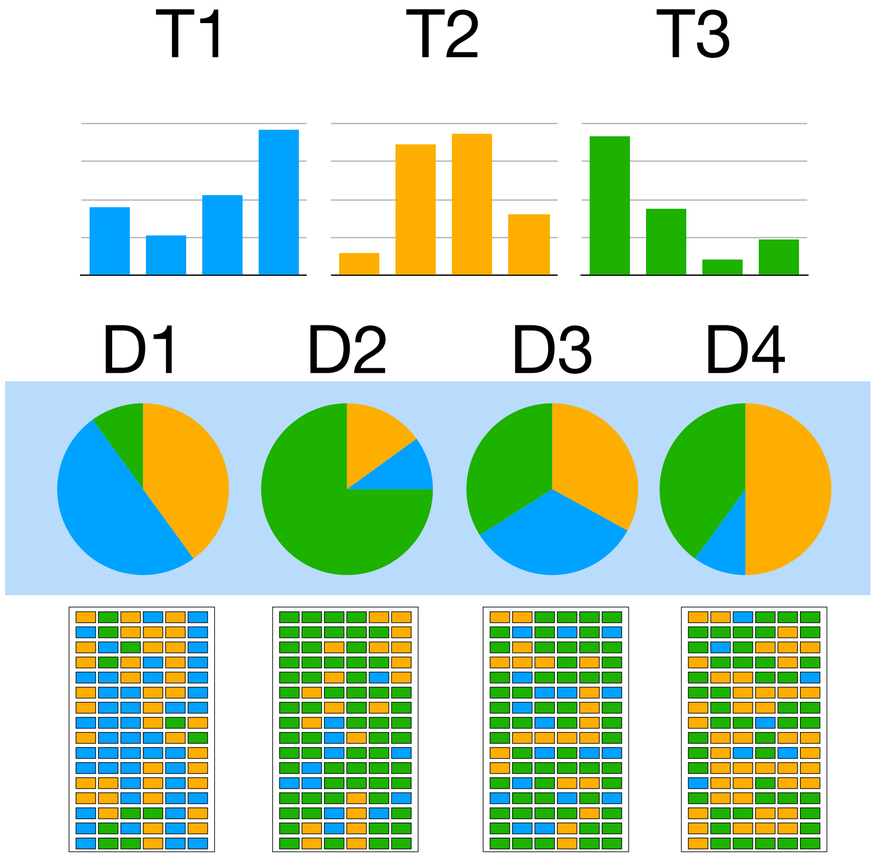
Latent Dirichlet Allocation (LDA)

Graphical Model Notation <-> Generative Story

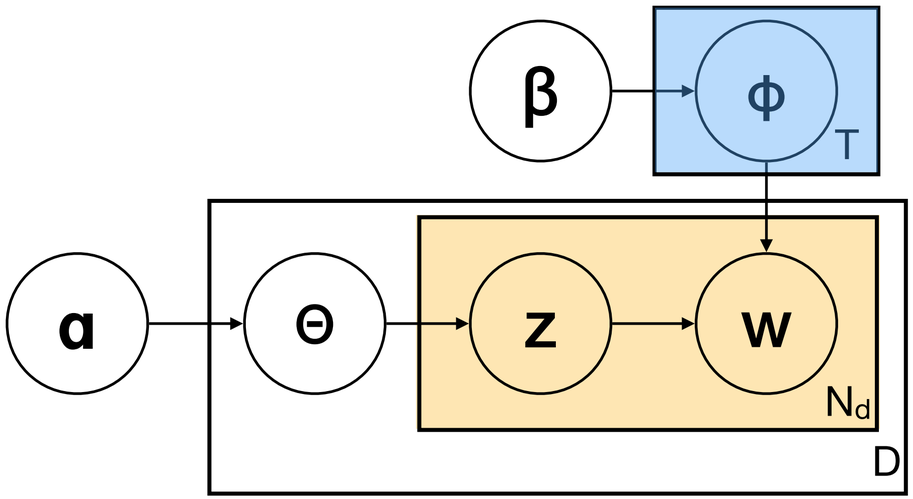


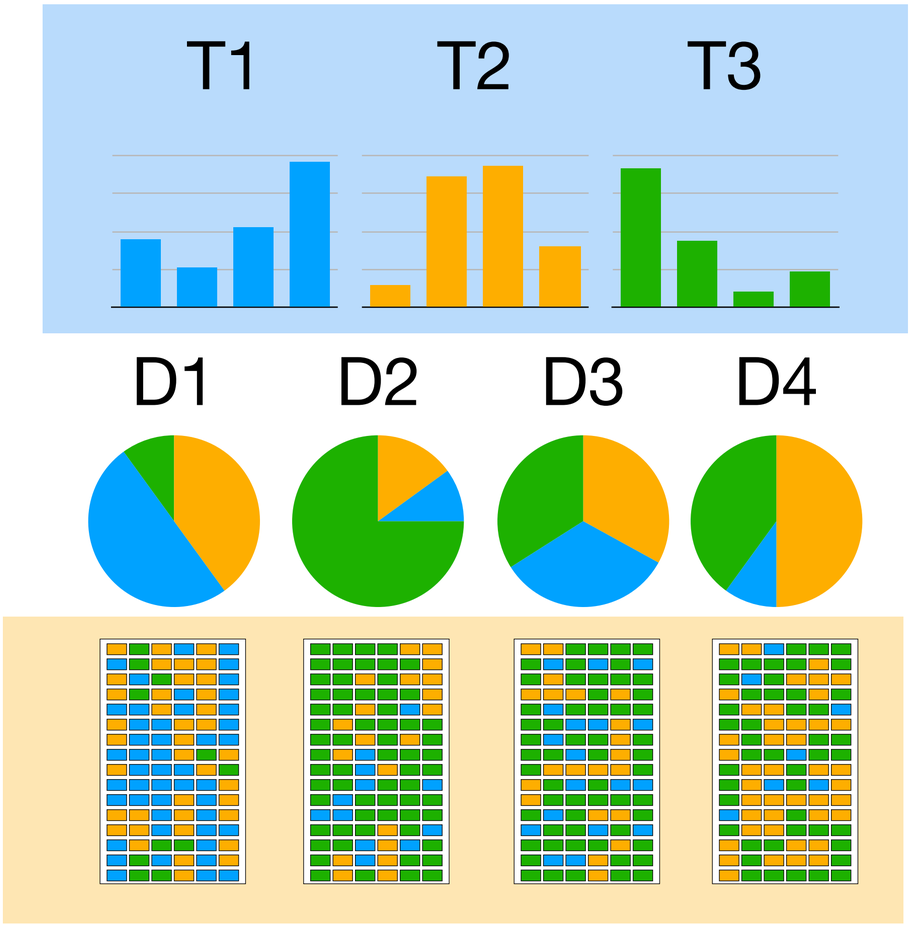


For each document, for each word, sample a topic

Latent Dirichlet Allocation (LDA)

Graphical Model Notation <-> Generative Story





For document, for each word, given the sampled topic, sample a word

Latent Dirichlet Allocation (LDA)

Posterior Estimation

- We set up a probability model, but how do we set the parameters of the model?
  - I.e., how do we decide the actual probabilities of words for a given topic, probabilities of topics, etc?
- Recall:
  - We are trying to $P(z|w) = P(z,w)/P(w)$
  - $P(w)$ is intractable to estimate in general
    - (Same issue we dealt with in Naive Bayes! In NB, we made aggressive independence assumptions, but we don't want to do that here)

Latent Dirichlet Allocation (LDA)

Posterior Estimation

- Resort to approximate methods for **posterior estimation**
  - Details beyond the scope of this course (see, maybe, APMA 1740)
- Broadly, two types of approaches:
  - Sampling Methods (MCMC, Gibbs Sampling)
  - Variational Inference

Latent Dirichlet Allocation (LDA)

Posterior Estimation: Basic Ideas

- Gibbs Sampling
  - Start by randomly assigning words to topics
  - Iteratively make small updates until your underlying model begins to mirror the observed posterior
  - https://www.youtube.com/watch?v=u7l5hhmdc0M
- Variational Inference
  - Posit some simpler probability distribution parameterized by some parameters Θ
  - Use optimization algorithms to optimize Θ until the result is close to the true, observed posterior