Natural Language Processing

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Adapted from Info 256 - David Bamman, UC Berkeley

Clustering

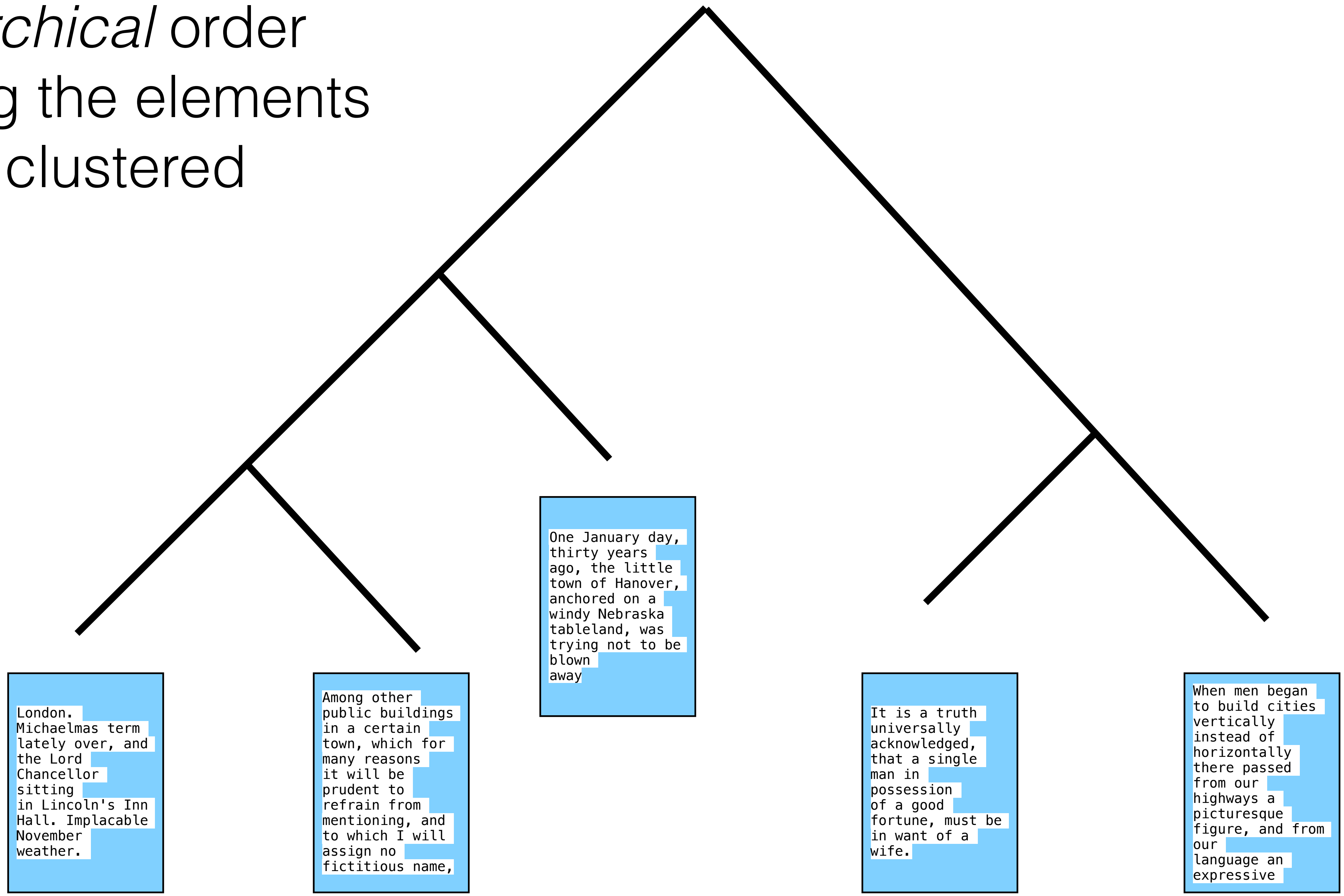
- Document clustering
- Token clustering (topic modeling)

Clustering

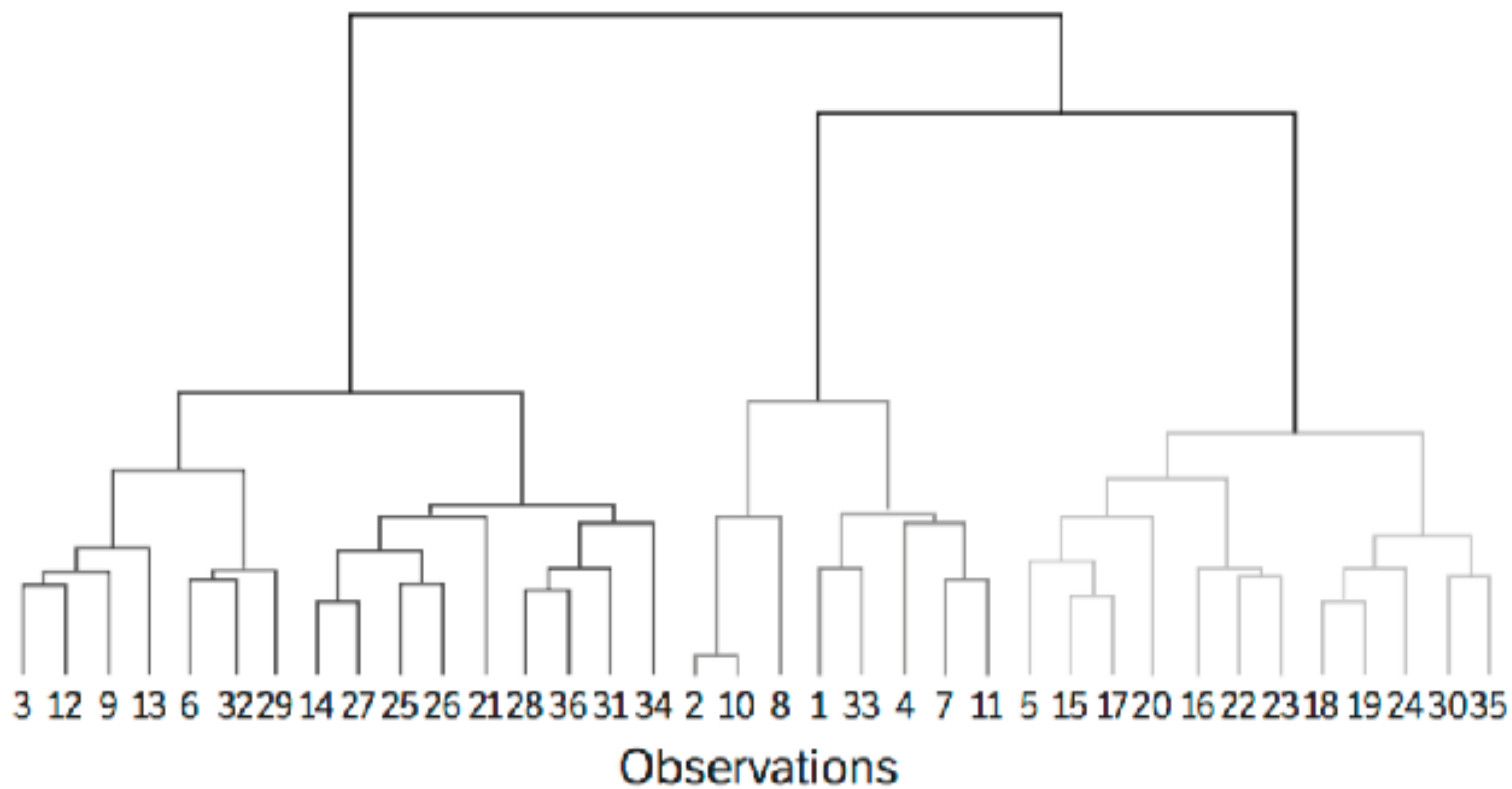
- Clustering is designed to learn structure in the data:
    - Hierarchical structure between data points
    - Natural partitions between data points

Hierarchical Clustering

- *Hierarchical* order among the elements being clustered



Hierarchical clustering



A Midsummer Night's Dream (3)
Twelfth Night (12)
Much Ado About Nothing (9)
Two Gentlemen (13)
Measure for Measure (6)
Othello (32)
Julius Caesar (29)

The Winter's Tale (14)
Cymbeline (27)
Antony and Cleopatra (25)
Coriolanus (26)
Henry VIII (21)
Hamlet (28)
Troilus and Cressida (36)
Macbeth (31)
Timon of Athens (34)

All's Well That Ends Well (2)
Taming of the Shrew (10)
Merry Wives of Windsor (8)
A Midsummer Night's Dream (1)
Romeo and Juliet (33)
Comedy of Errors (4)
Merchant of Venice (7)
The Tempest (11)

Love's Labours' Lost (5)
1 Henry IV (15)
2 Henry IV (17)
Henry V (20)
1 Henry VI (16)
King John (22)
Richard II (23)

2 Henry VI (18)
2 Henry VI (19)
Richard III (24)
King Lear (30)
Titus Andronicus (35)

Allison et al. 2009

Bottom-up clustering

Algorithm 1 Hierarchical agglomerative clustering

```
Data: N training data points x ∈ ℝ^F
Let X denote a set of objects x
Given some linkage function d(X, X') → ℝ
Initialize clusters 𝒞 = {C_1, ..., C_N} to singleton data points
while data points not in one cluster do
    Identify X, Y as clusters with smallest linkage function among clusters in 𝒞
    Create new cluster Z = X ∪ Y
    remove X, Y from 𝒞
    add Z to 𝒞
end while
```

Similarity

$$\mathcal{P}(\mathcal{X}) \times \mathcal{P}(\mathcal{X}) \to \mathbb{R}$$

- What are you comparing?
- How do you quantify the similarity/difference of those things?

Unigram probability

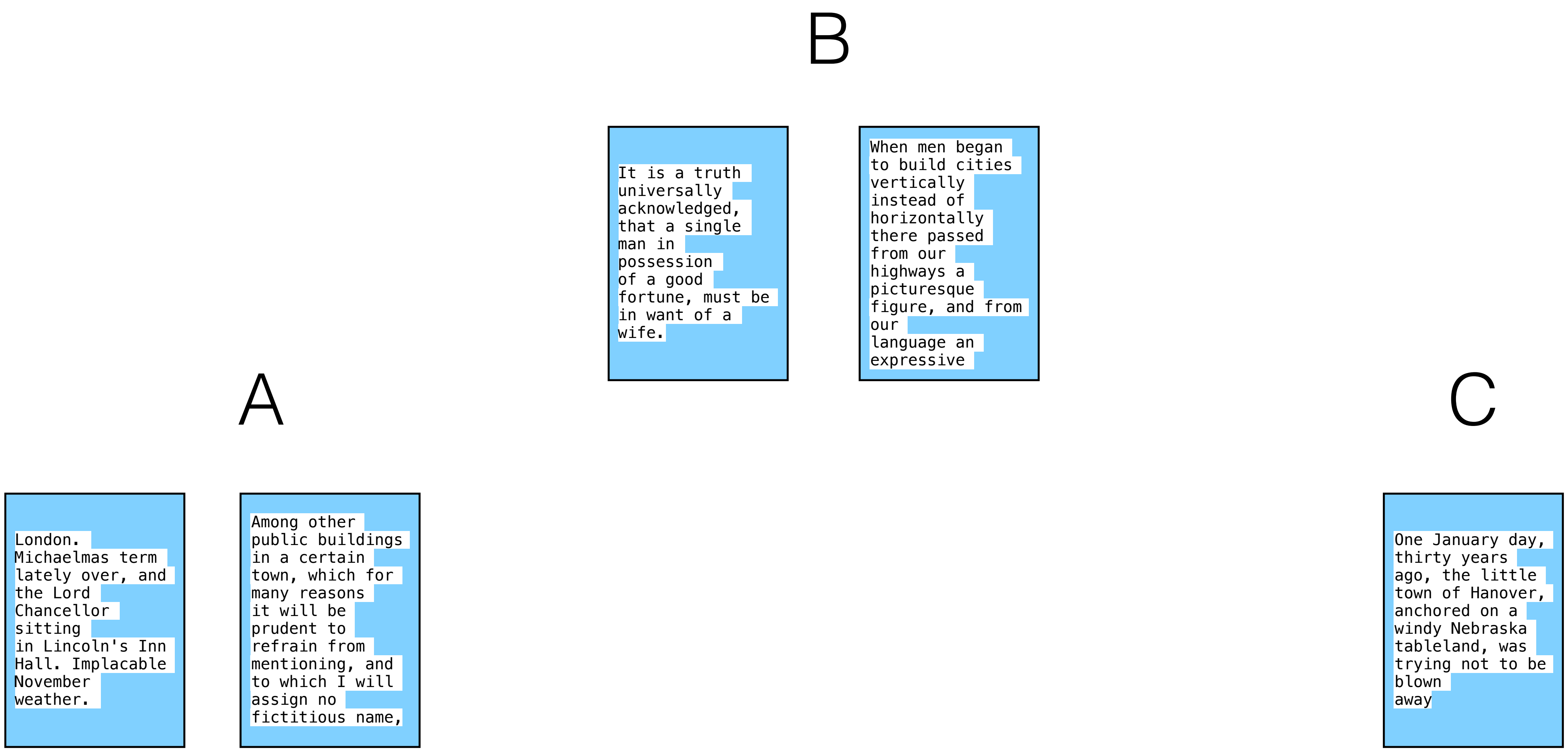
Similarity

$$\text{Euclidean} = \sqrt{\sum_{i}^{vocab} \left(P_i^{\text{Hamlet}} - P_i^{\text{Romeo}}\right)^2}$$

Cosine similarity, Jensen-Shannon divergence…

Flat Clustering

- Partitions the data into a set of *K* clusters

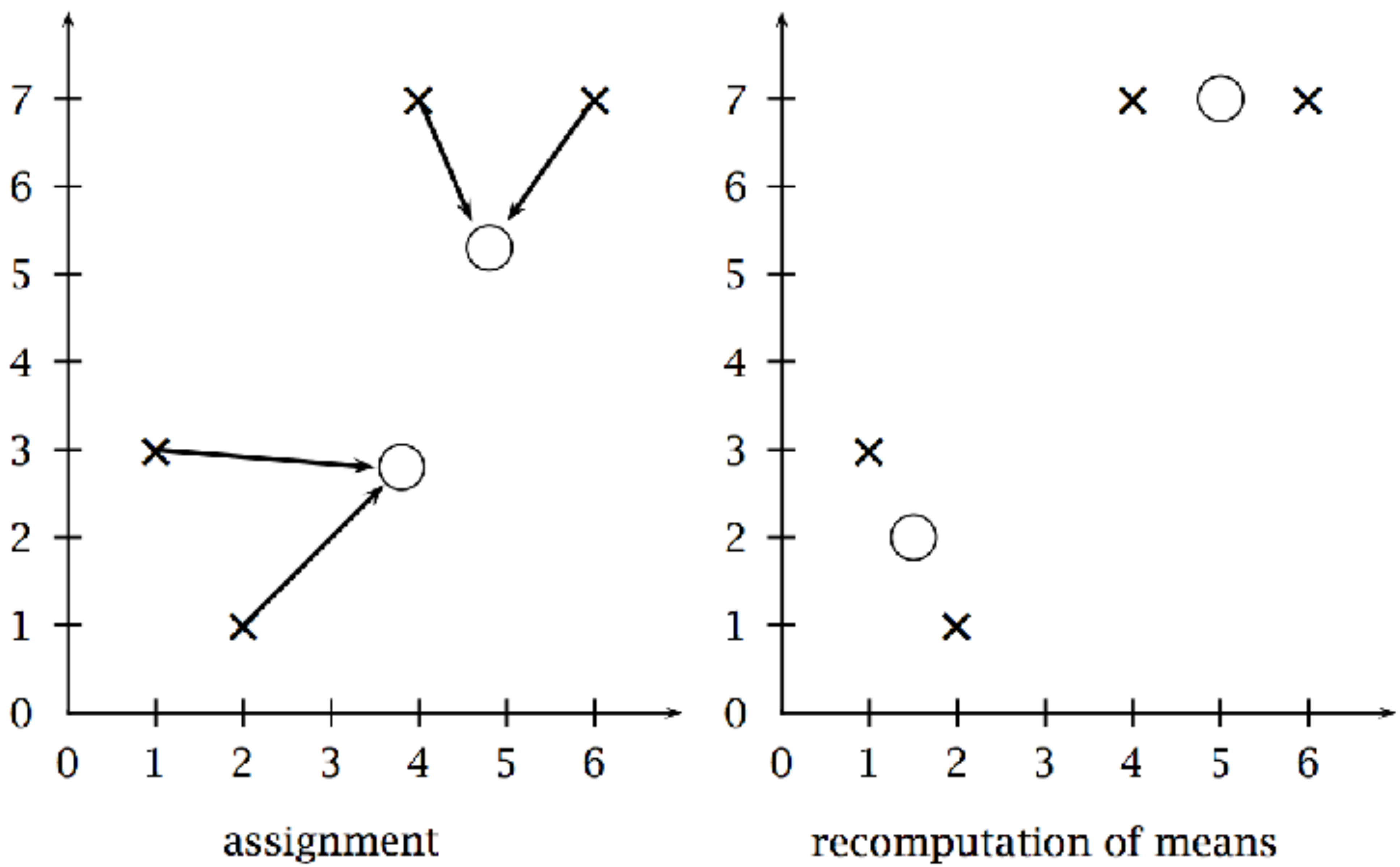


K-means

Algorithm 1 K-means

Data: training data $x \in \mathbb{R}^F$
Given some distance function $d(x, x') \rightarrow \mathbb{R}$
Select k initial centers $\{\mu_1, \ldots, \mu_k\}$
while not converged **do**
    for $i = 1$ to N **do**
        Assign x_i to $\arg\min_c d(x_i, \mu_c)$
    end for
    for $i = 1$ to K **do**
        $\mu_i = \frac{1}{D_i} \sum_{j=1}^{D_i} x_i$
    end for
end while

K-means



Representation

$$x \in \mathbb{R}^F$$

[x is a data point characterized by F real numbers, one for each feature]

- This is a huge decision that impacts what you can learn

Representation

- Books (e.g., to learn genres)
- News articles (e.g., to learn articles about the same event)

```
sklearn.cluster.KMeans

sklearn.cluster.AgglomerativeClustering
```

Topic Models

- A probabilistic model for discovering hidden "topics" or "themes" (groups of terms that tend to occur together) in documents.
- Unsupervised (find *interesting structure* in the data)
- Clustering algorithm:

How to tokens cluster into topics?

Topic Models

- **Input**: set of documents, number of clusters to learn.
- **Output**:
  - topics
  - topic ratio in each document
  - topic distribution for each word in doc

{album, band, music}	{government, party, election}	{game, team, player}
album	government	game
band	party	team
music	election	player
song	state	win
release	political	play
{god, call, give}	**{company, market, business}**	**{math, number, function}**
god	company	math
call	market	number
give	business	function
man	year	code
time	product	set
{city, large, area}	**{math, energy, light}**	**{law, state, case}**
city	math	law
large	energy	state
area	light	case
station	field	court
include	star	legal

topic models cluster tokens into “topics”

… The messenger, however, does not reach Romeo and, instead, Romeo learns of Juliet's apparent death from his servant Balthasar. Heartbroken, Romeo buys poison from an apothecary and goes to the Capulet crypt. He encounters Paris who has come to mourn Juliet privately. Believing Romeo to be a vandal, Paris confronts him and, in the ensuing battle, Romeo kills Paris. Still believing Juliet to be dead, he drinks the poison. Juliet then awakens and, finding Romeo dead, stabs herself with his dagger. The feuding families and the Prince meet at the tomb to find all three dead. Friar Laurence recounts the story of the two "star-cross'd lovers". The families are reconciled by their children's deaths and agree to end their violent feud. The play ends with the Prince's elegy for the lovers: "For never was a story of more woe / Than this of Juliet and her Romeo."

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“Death”

topic models cluster tokens into “topics”

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“Love”

topic models cluster tokens into “topics”

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“Family”

topic models cluster tokens into "topics"

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"Etc."

tokens, not types

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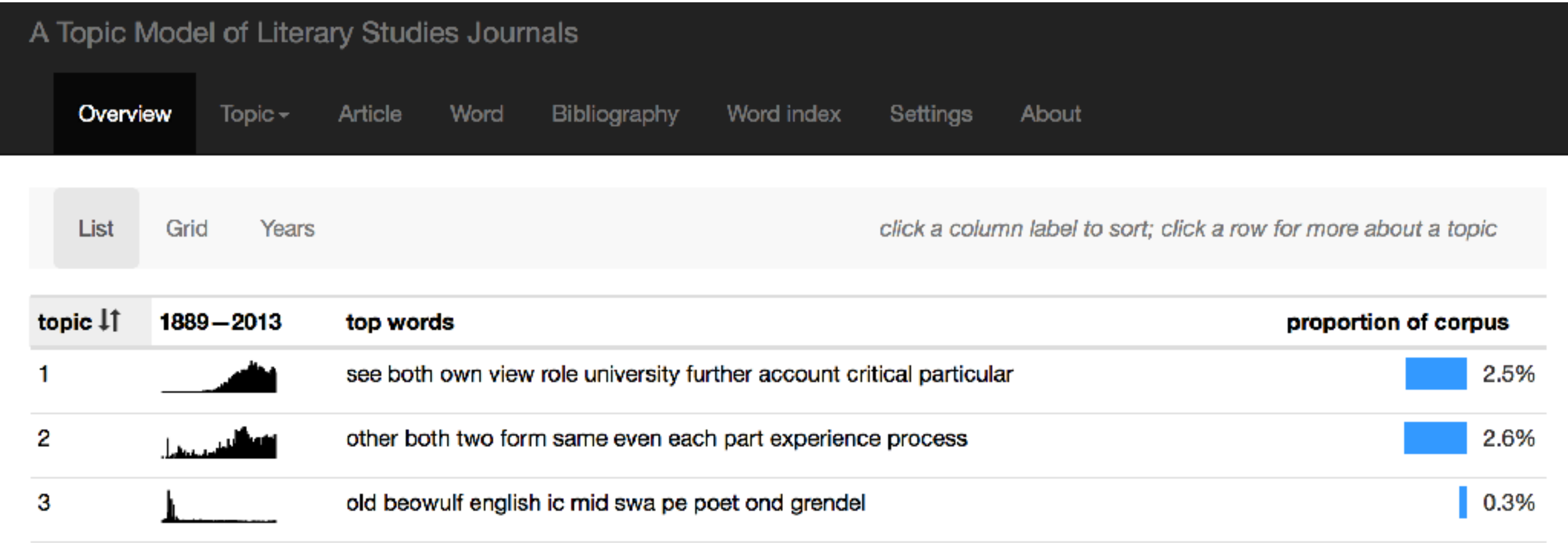
"People"

A different *Paris* token might belong to a "Place" or "French" topic

Applications



A Topic Model of Literary Studies Journals

Overview | Topic | Article | Word | Bibliography | Word index | Settings | About

List | Grid | Years

click a column label to sort; click a row for more about a topic

topic	1889—2013	top words	proportion of corpus
1		see both own view role university further account critical particular	2.5%
2		other both two form same even each part experience process	2.6%
3		old beowulf english ic mid swa pe poet ond grendel	0.3%

http://www.rci.rutgers.edu/~ag978/quiet/

x = feature vector

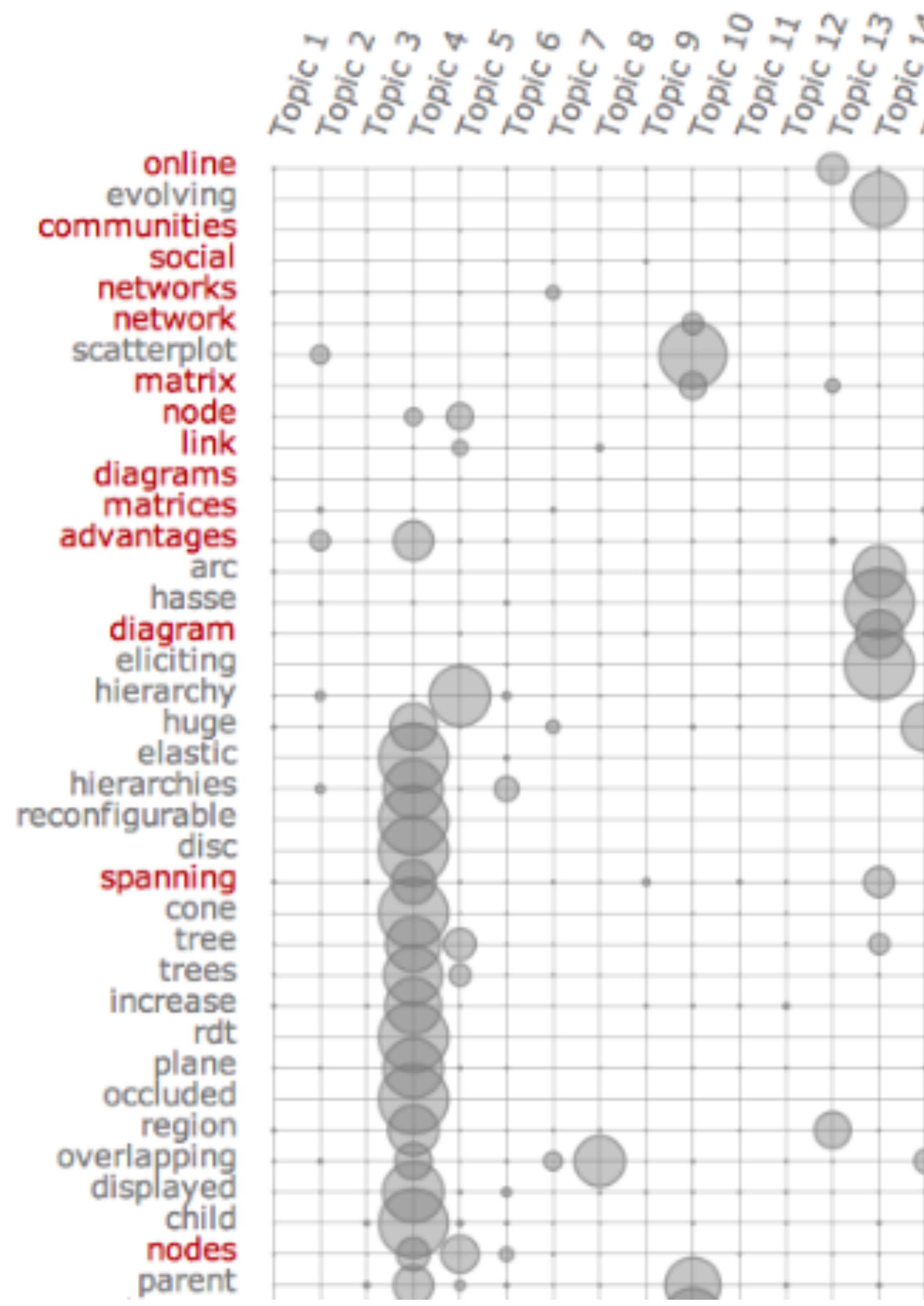
Feature	Value
follow clinton	0
follow trump	0
“republican” in profile	0
“democrat” in profile	0
“benghazi"	1
topic 1	0.55
topic 2	0.32
topic 3	0.13

β = coefficients

Feature	β
follow clinton	-3.1
follow trump	6.8
“republican” in profile	7.9
“democrat” in profile	-3.0
“benghazi"	-1.7
topic 1	0.3
topic 2	-1.2
topic 3	5.7

Software

- Mallet
  http://mallet.cs.umass.edu/
- Gensim (python)
  https://radimrehurek.com/gensim/
- Visualization
  https://github.com/uwdata/termite-visualizations

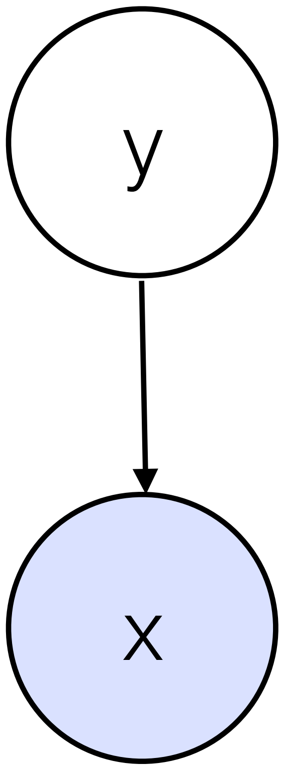


Latent variables

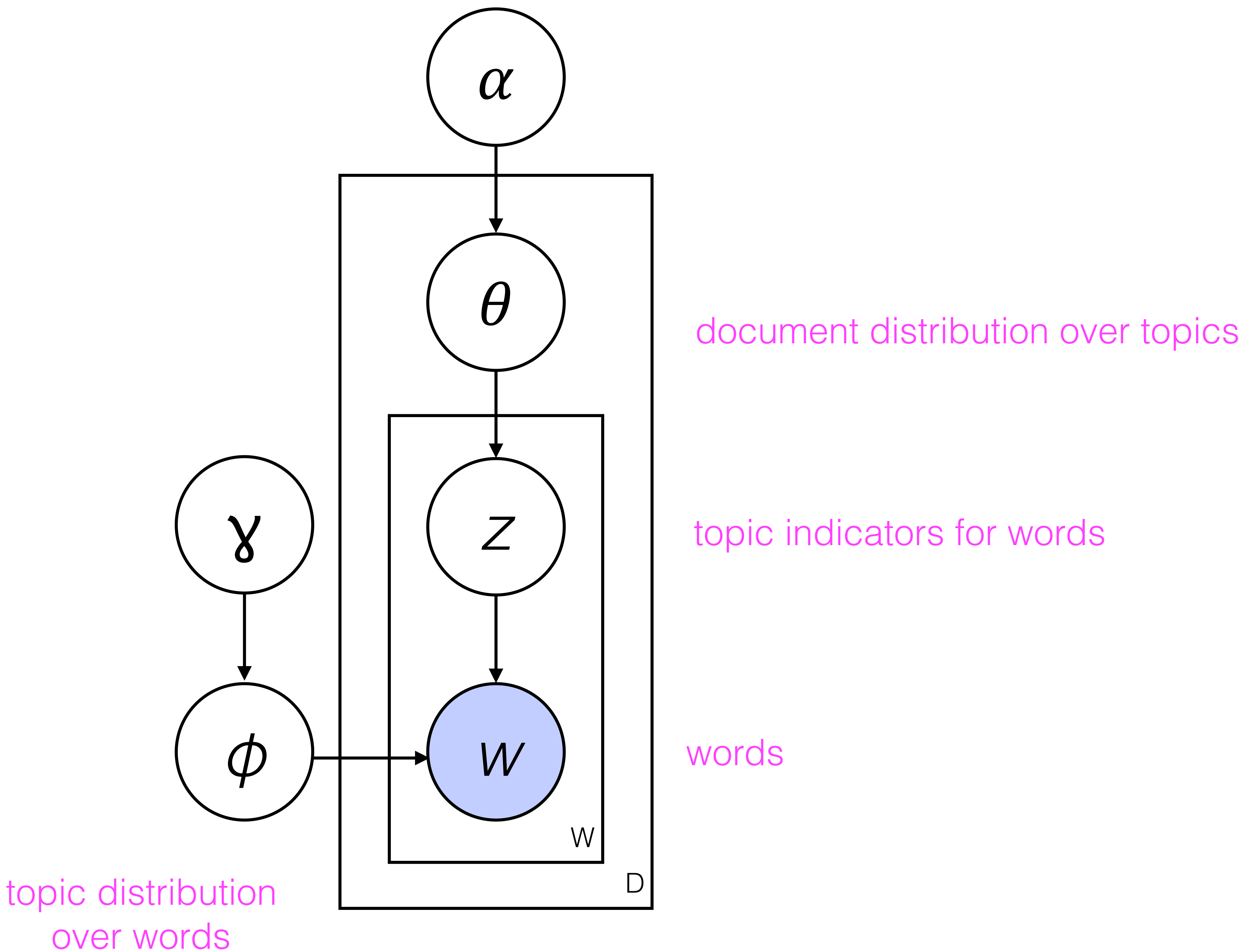
- A latent variable is one that's unobserved, either because:
    - we are predicting it (but have observed that variable for other data points)
    - it is unobservable

Probabilistic graphical models

- Nodes represent variables (shaded = observed, clear = latent)
- Arrows indicate conditional relationships
- The probability of x here is dependent on y
- Simply a visual way of writing the joint probability:



$$P(x, y) = P(y)\, P(x \mid y)$$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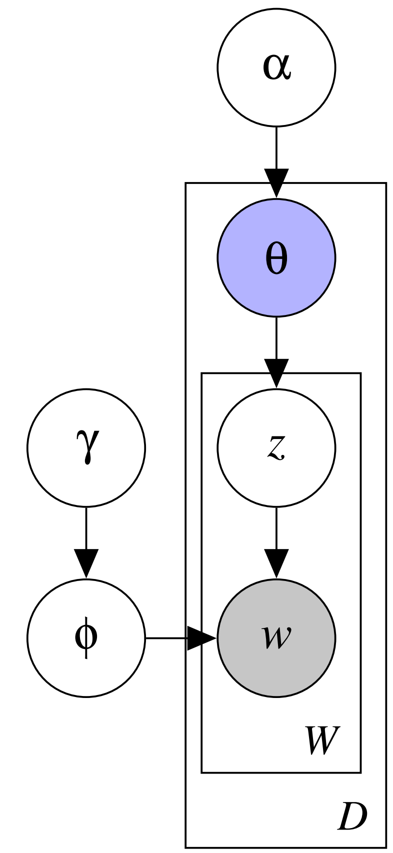
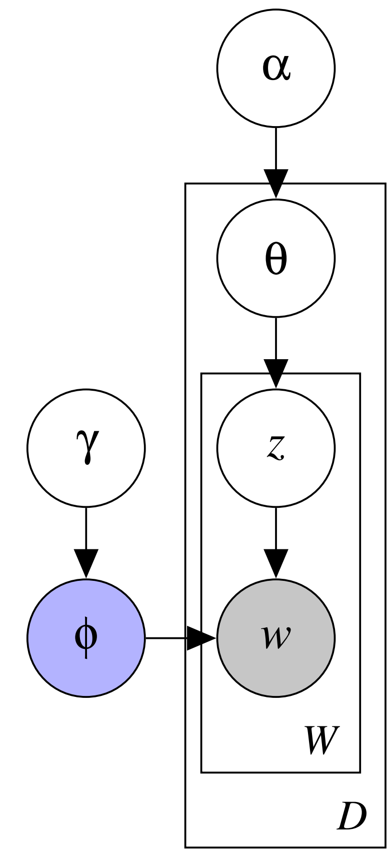
document distribution over topics
topic indicators for words
words
topic distribution
over words

Topic Models

- A document has *distribution over topics*

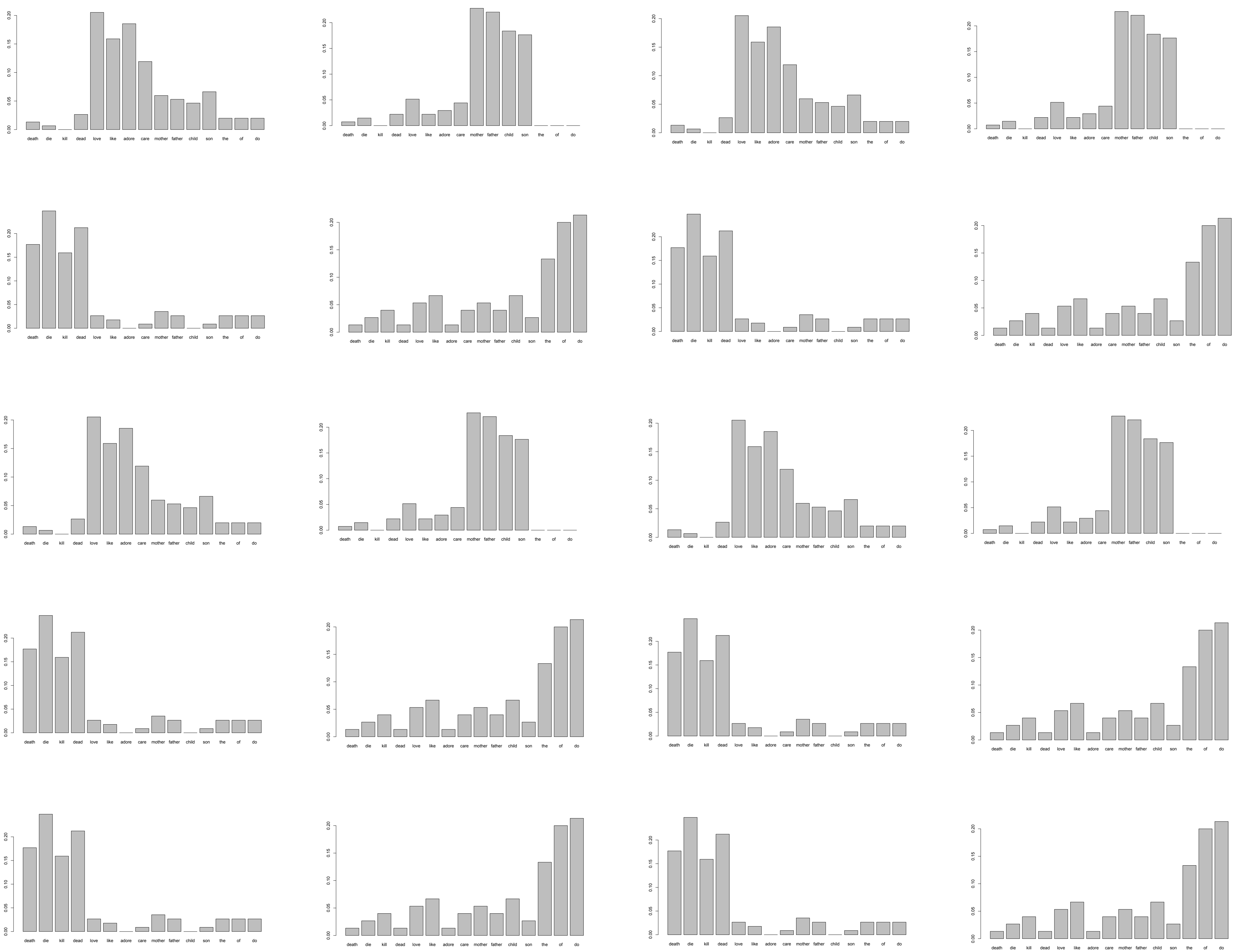


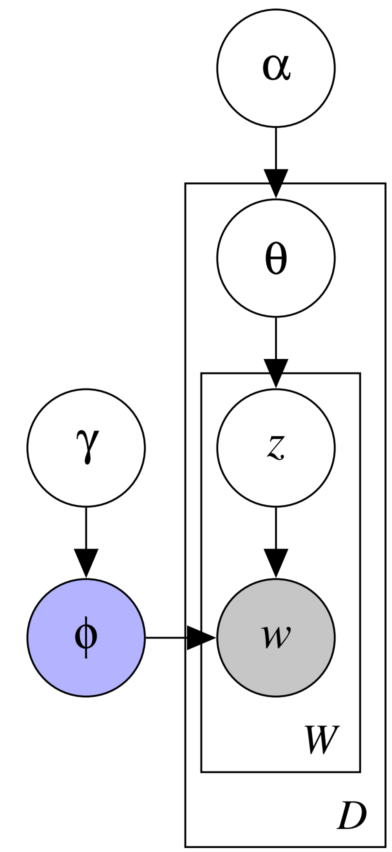
Topic Models



- A topic is a distribution over words

- e.g., P("adore" | topic = love) = .18


death die kill dead love like adore care mother father child son the of do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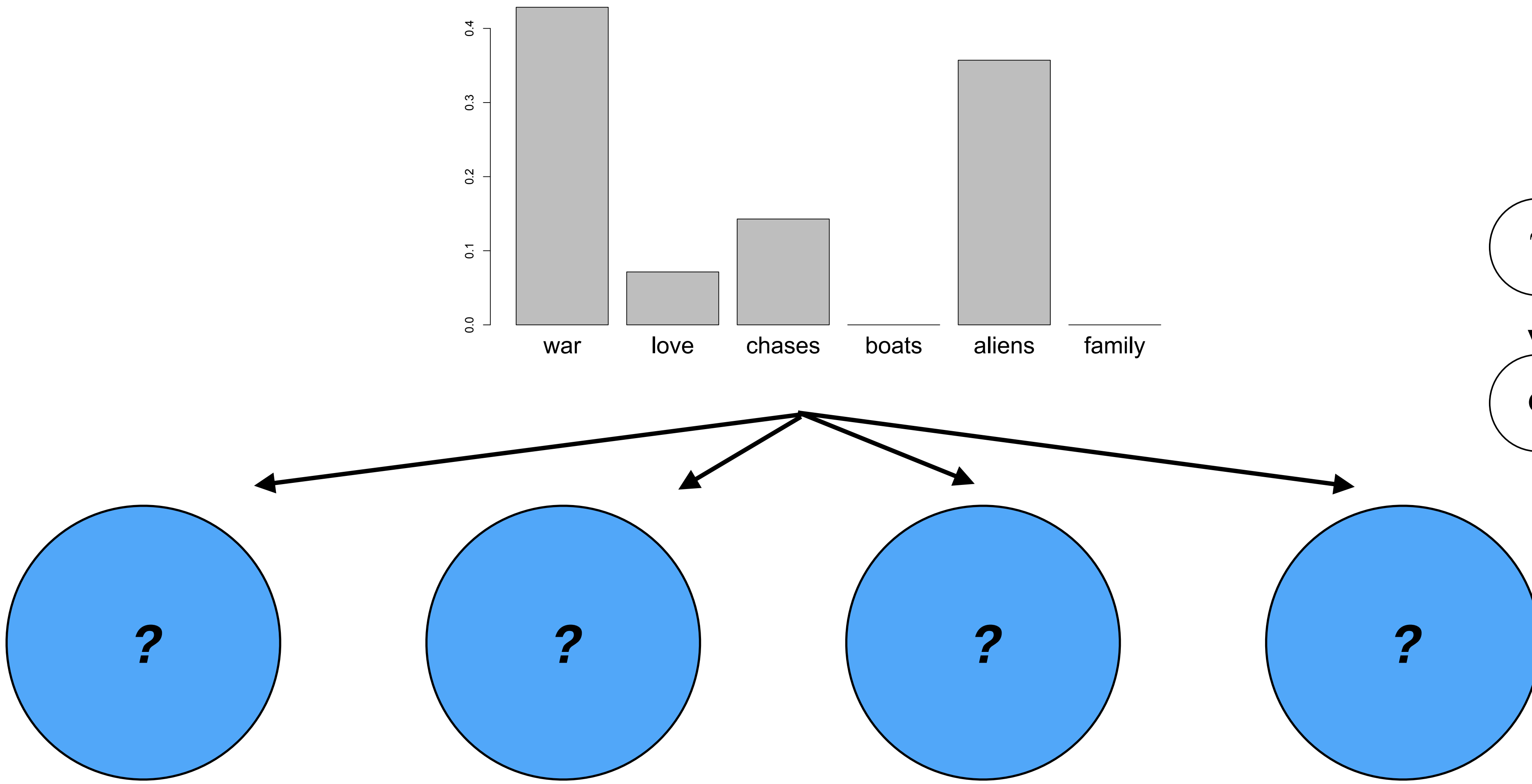
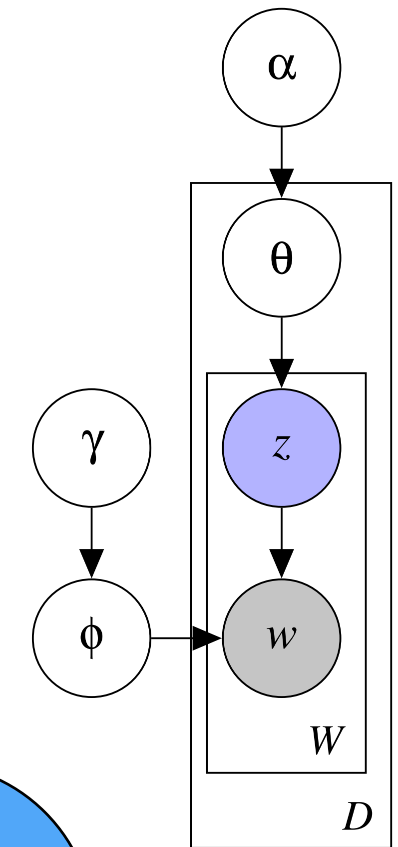
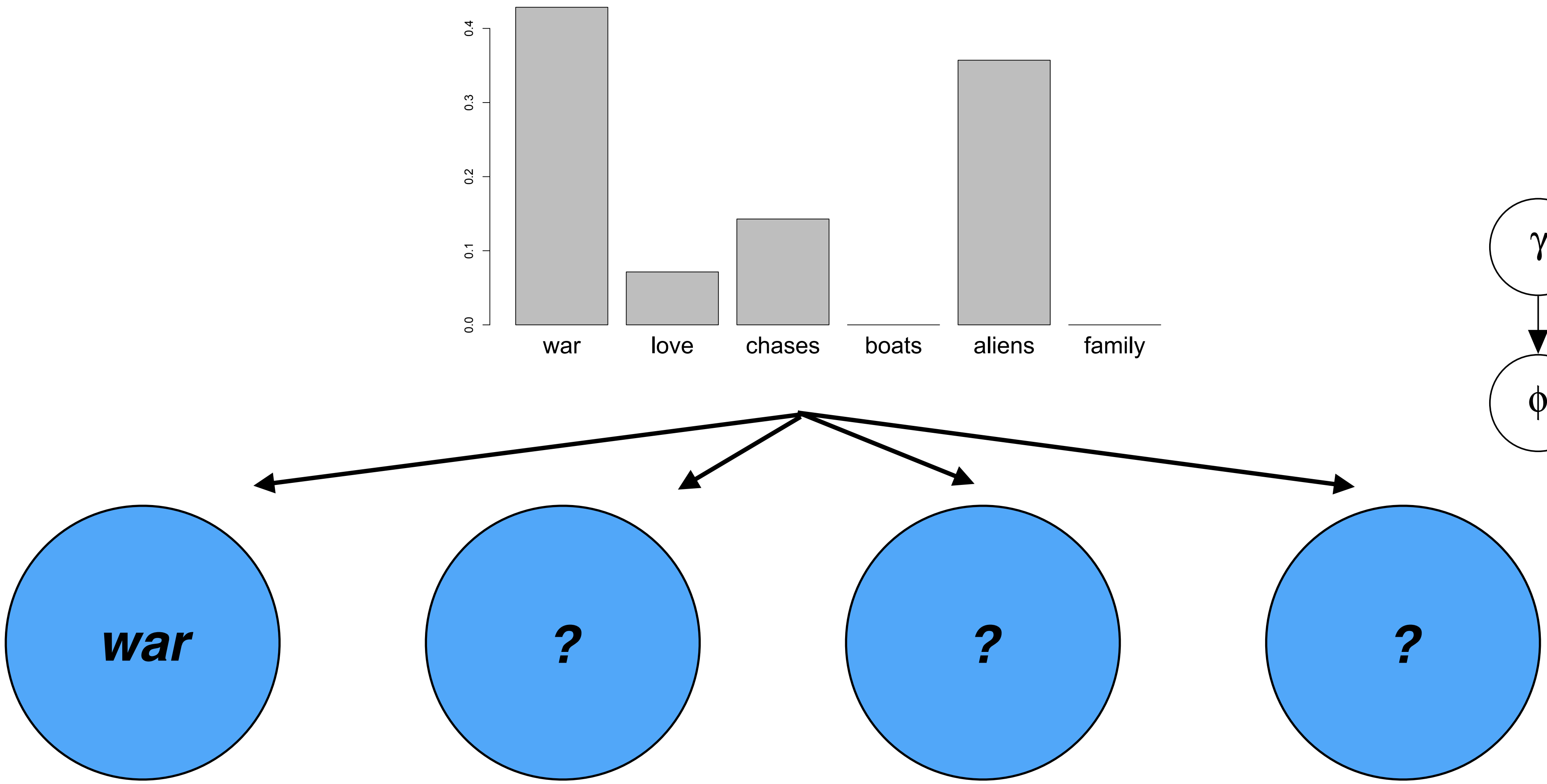
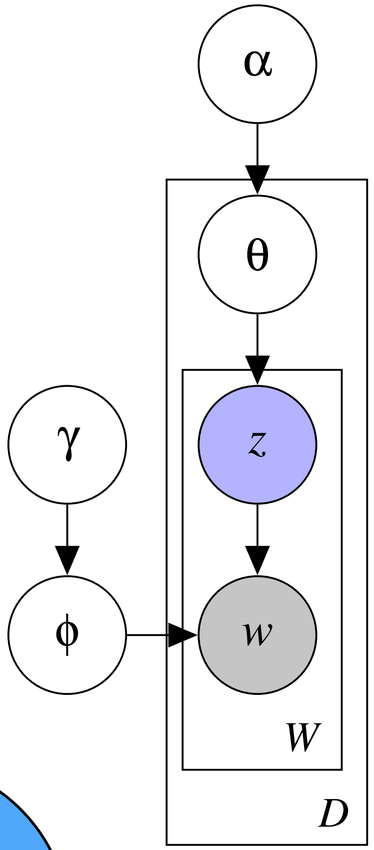




P(topic | topic distribution)





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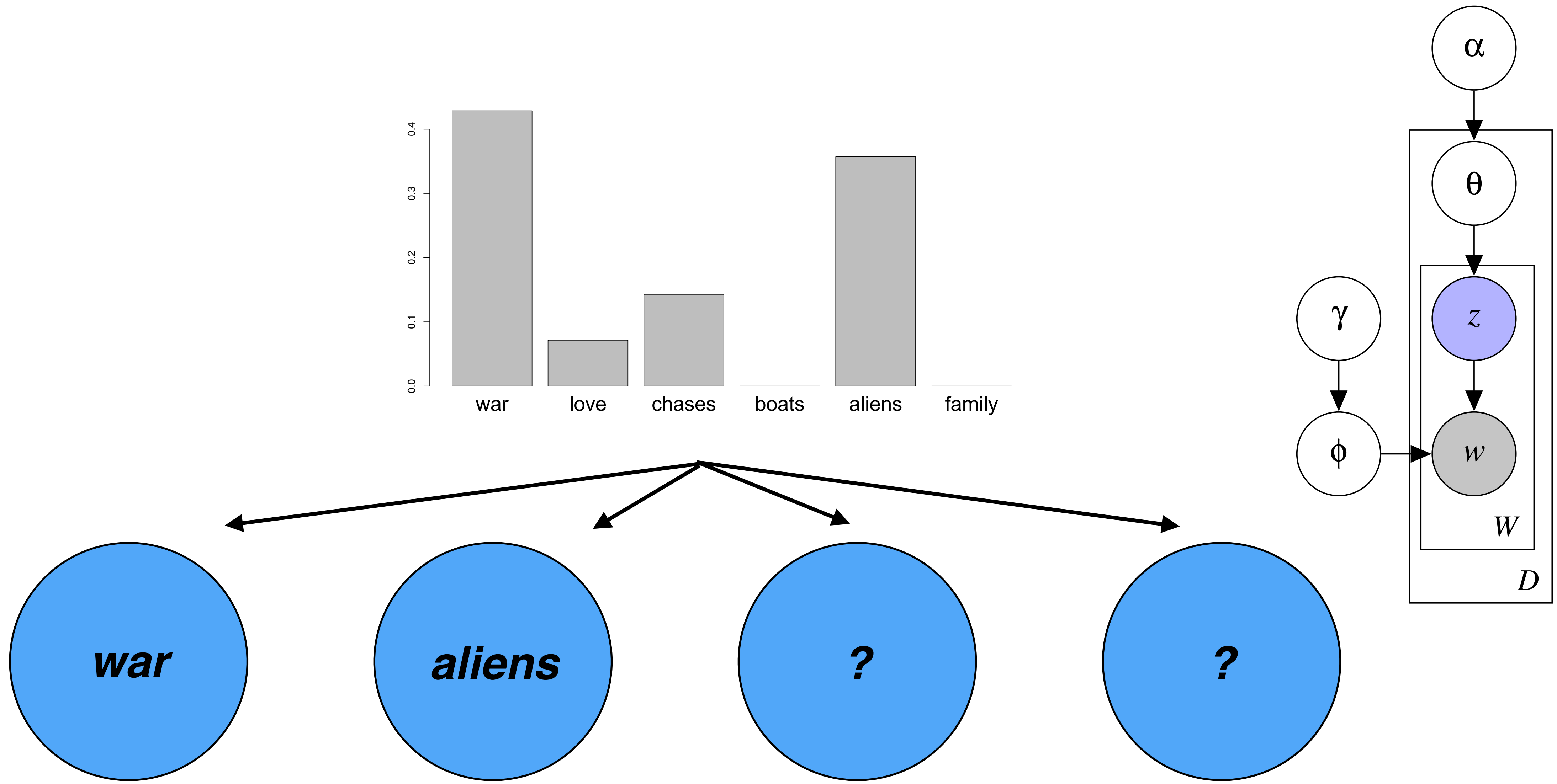

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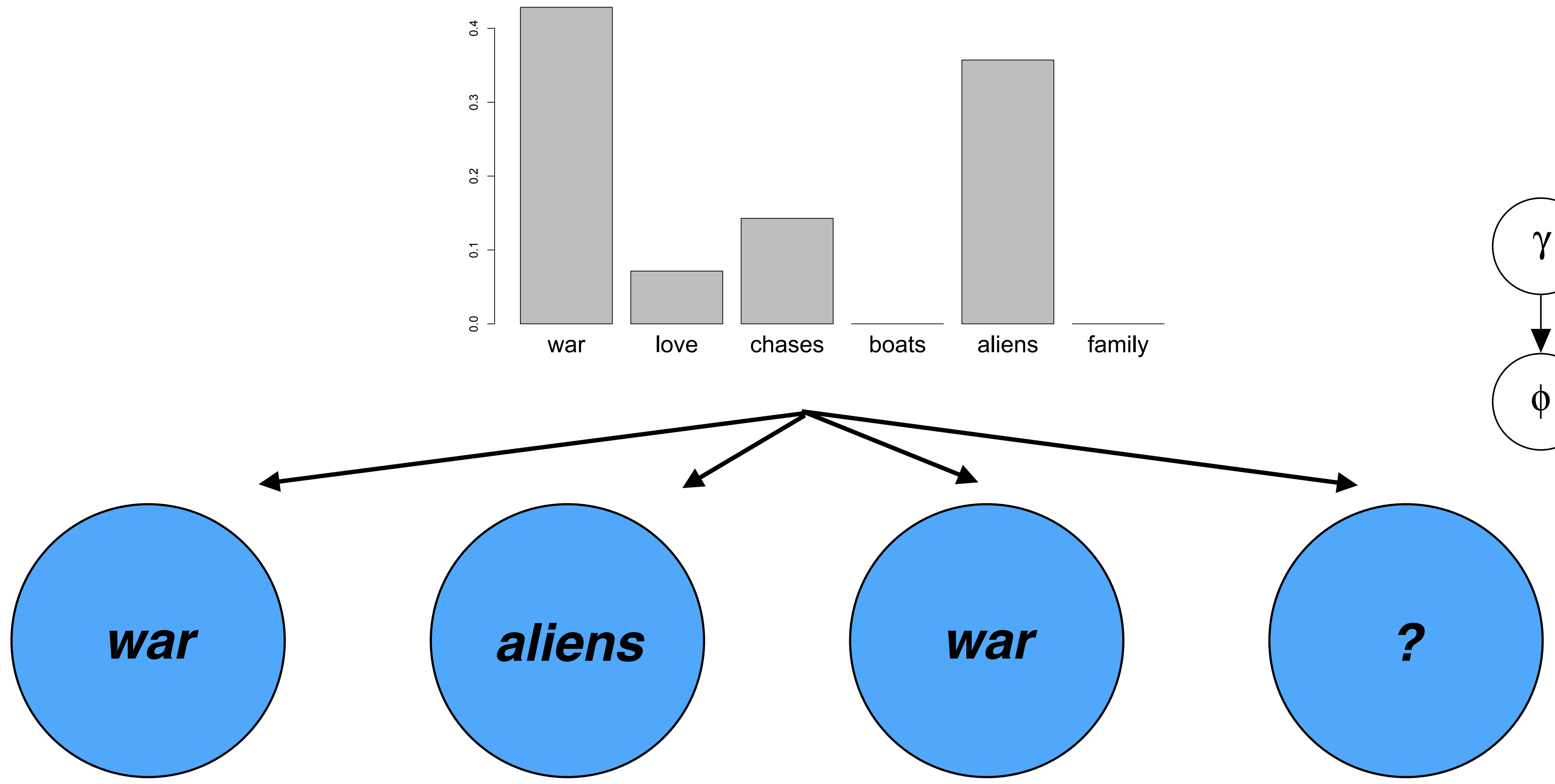

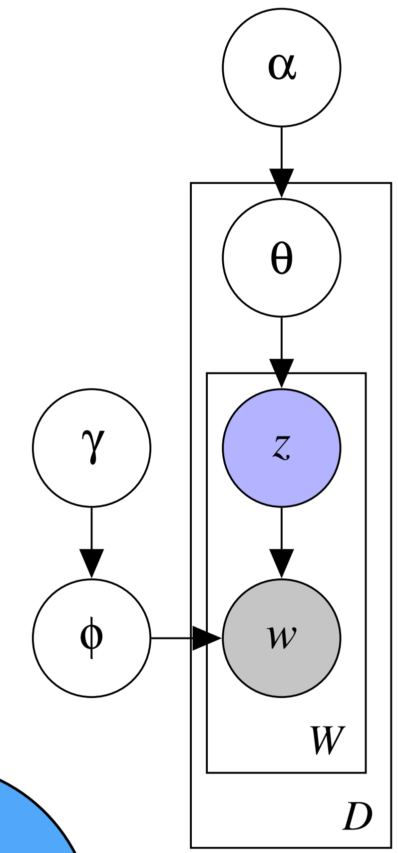

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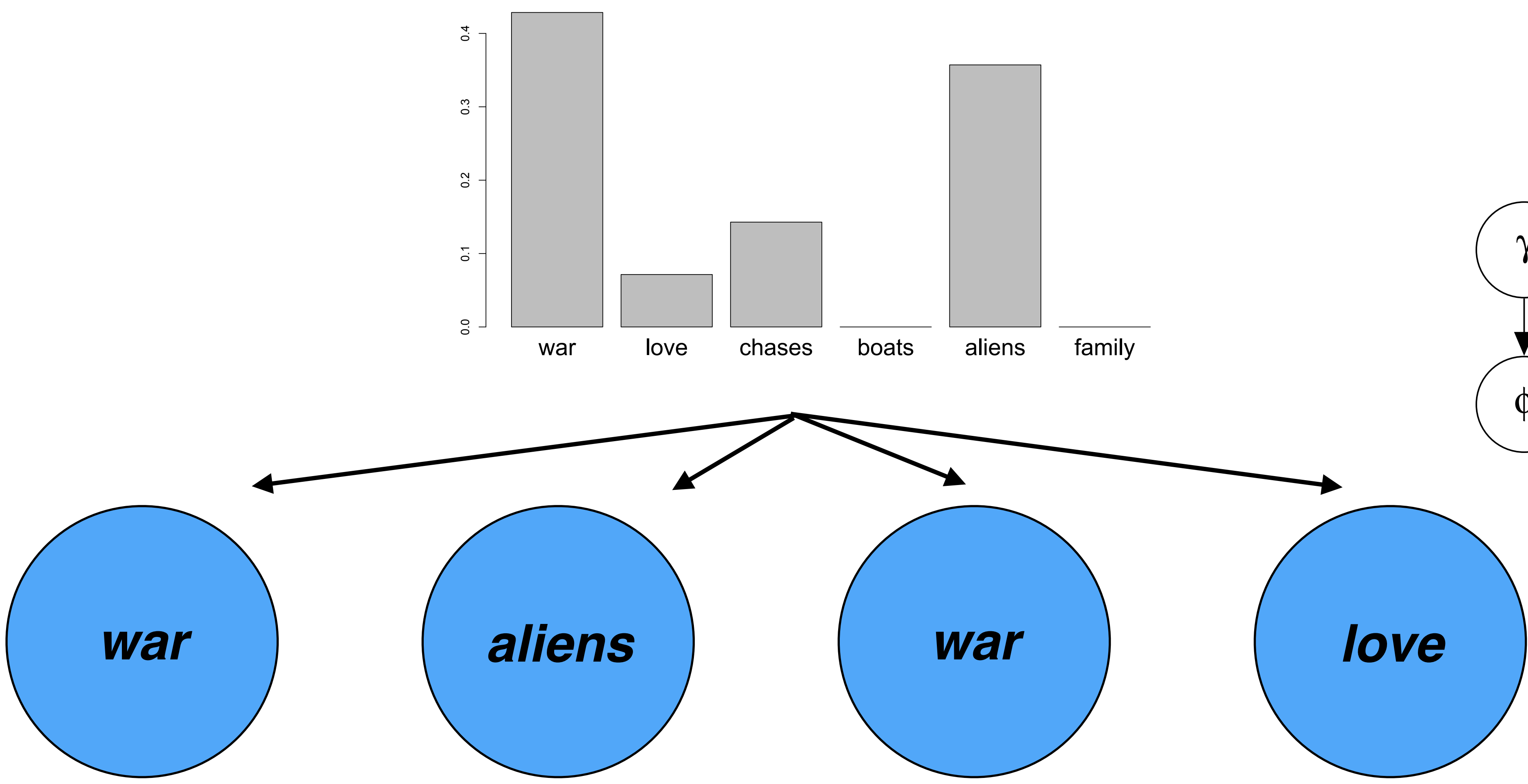

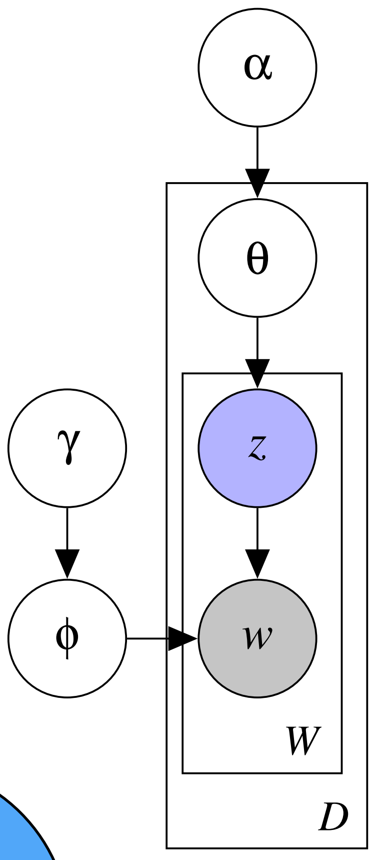

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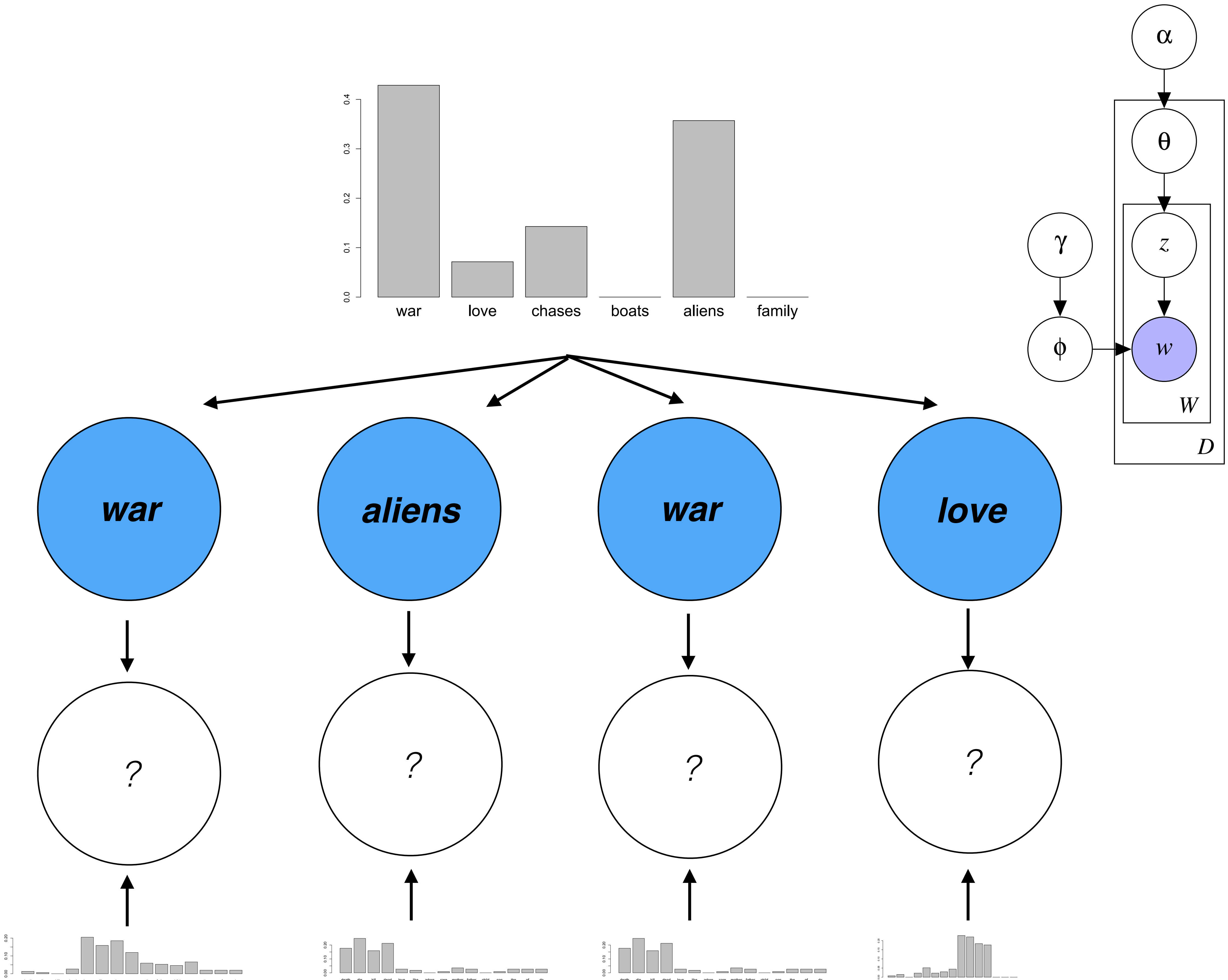

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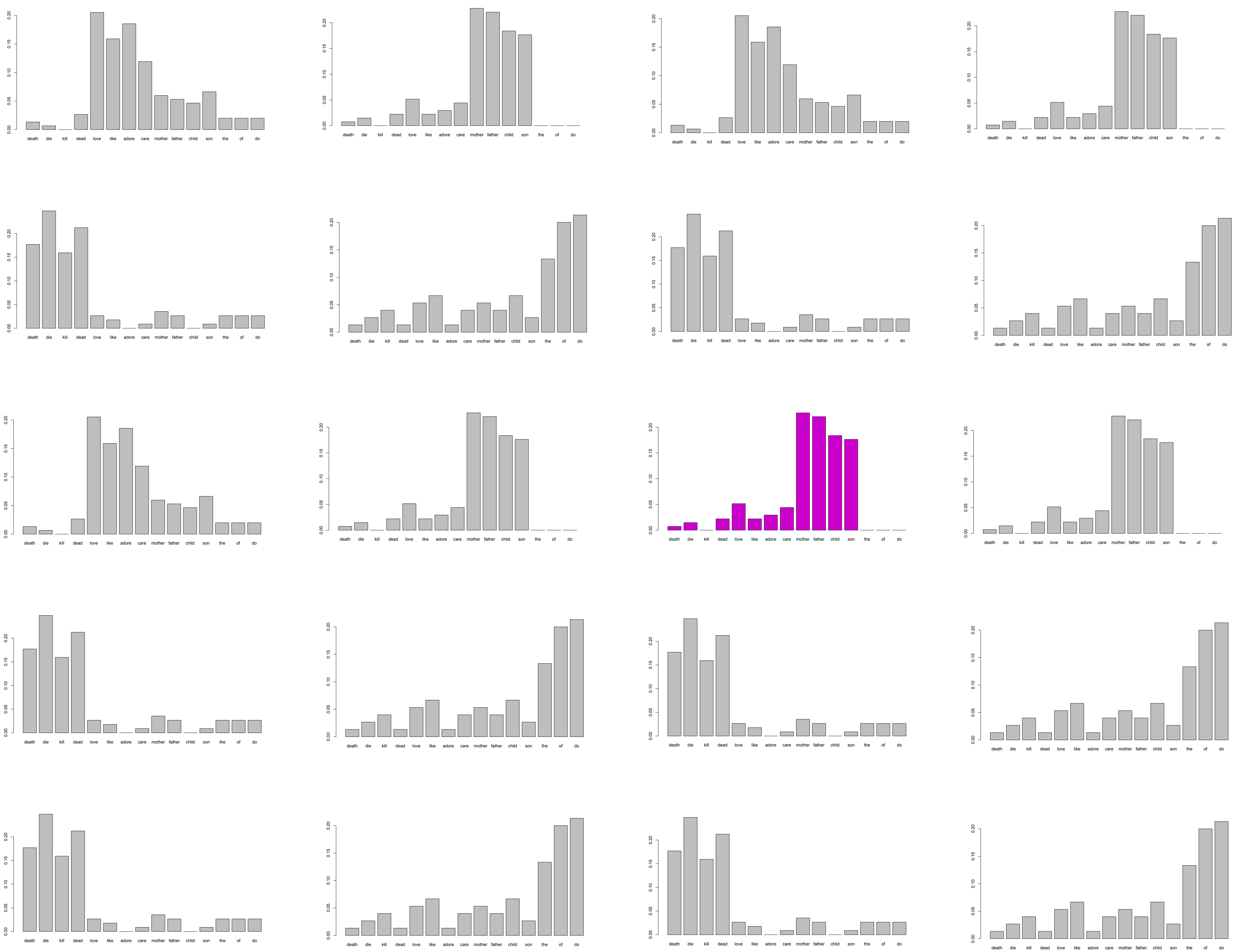
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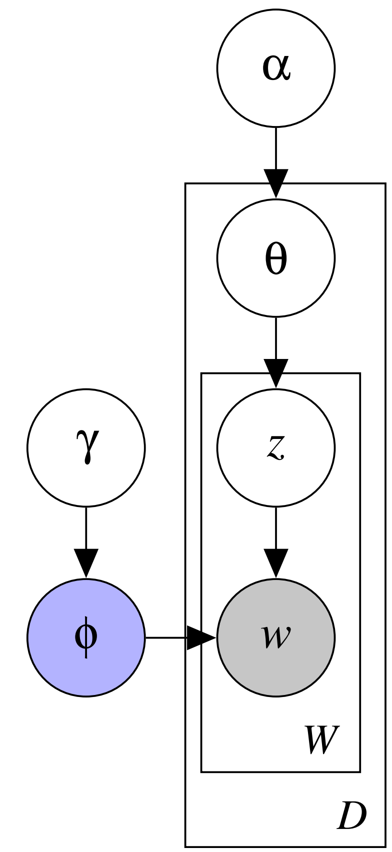
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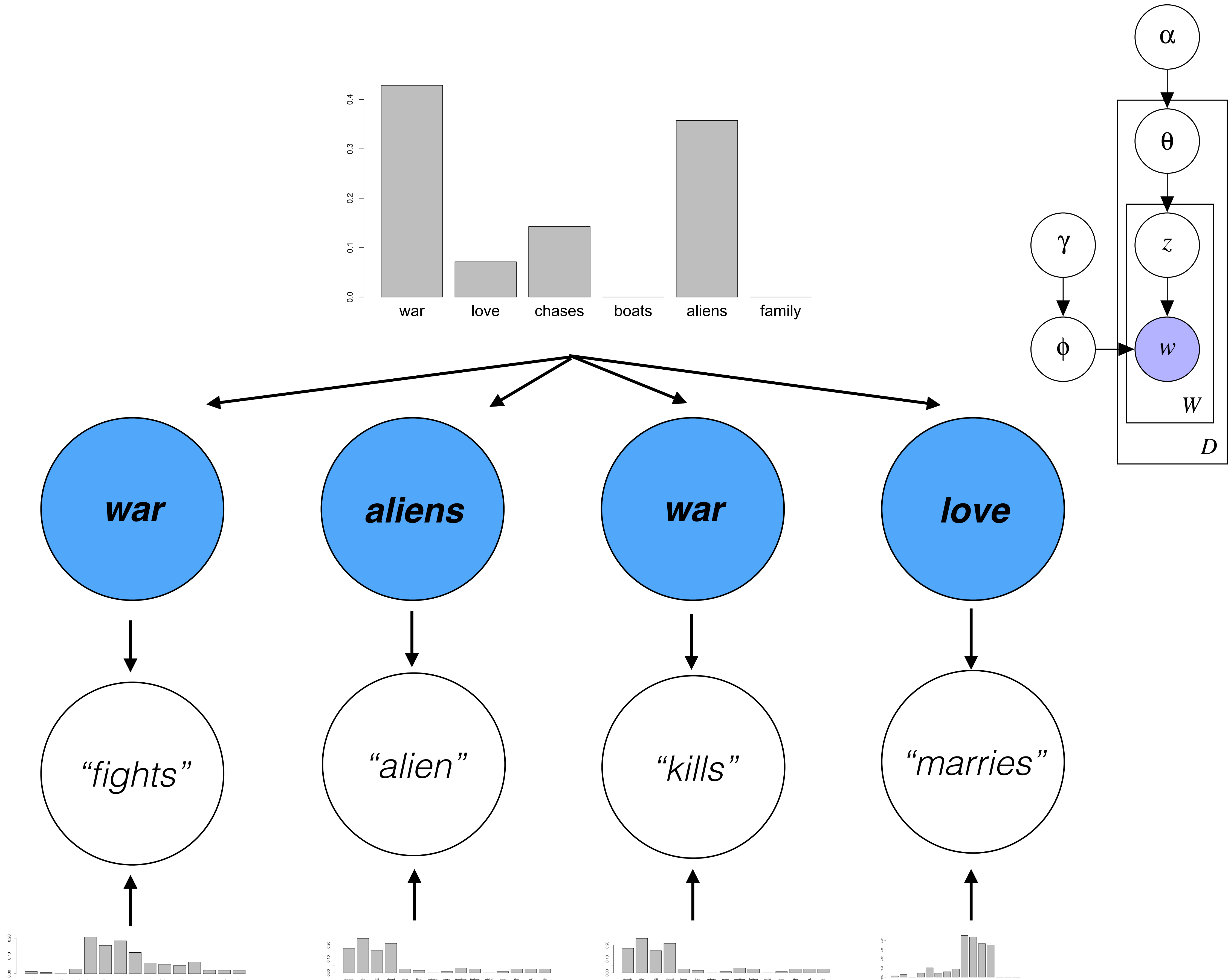
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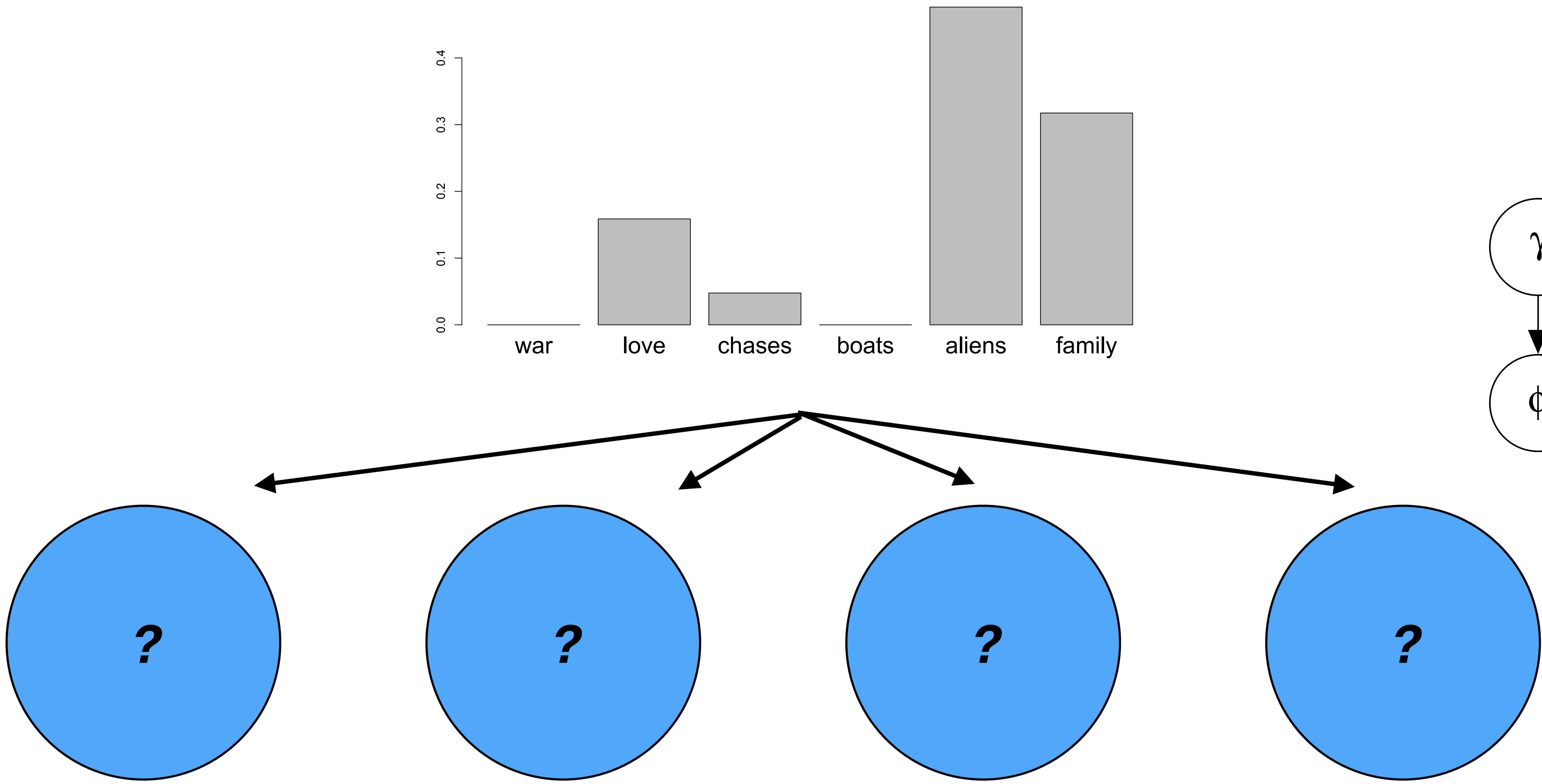

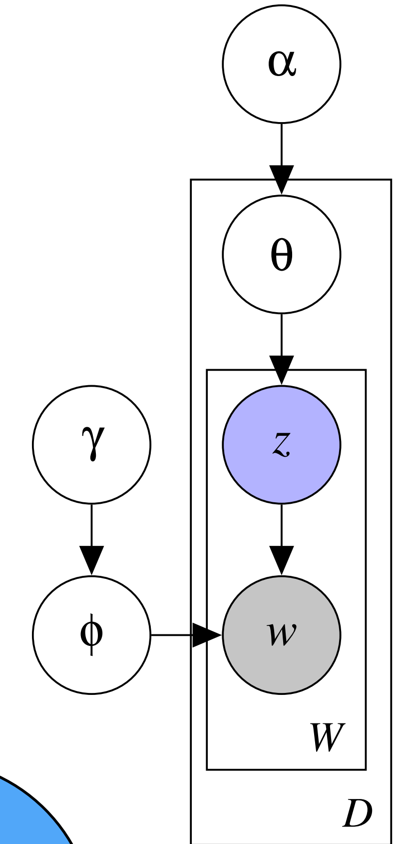

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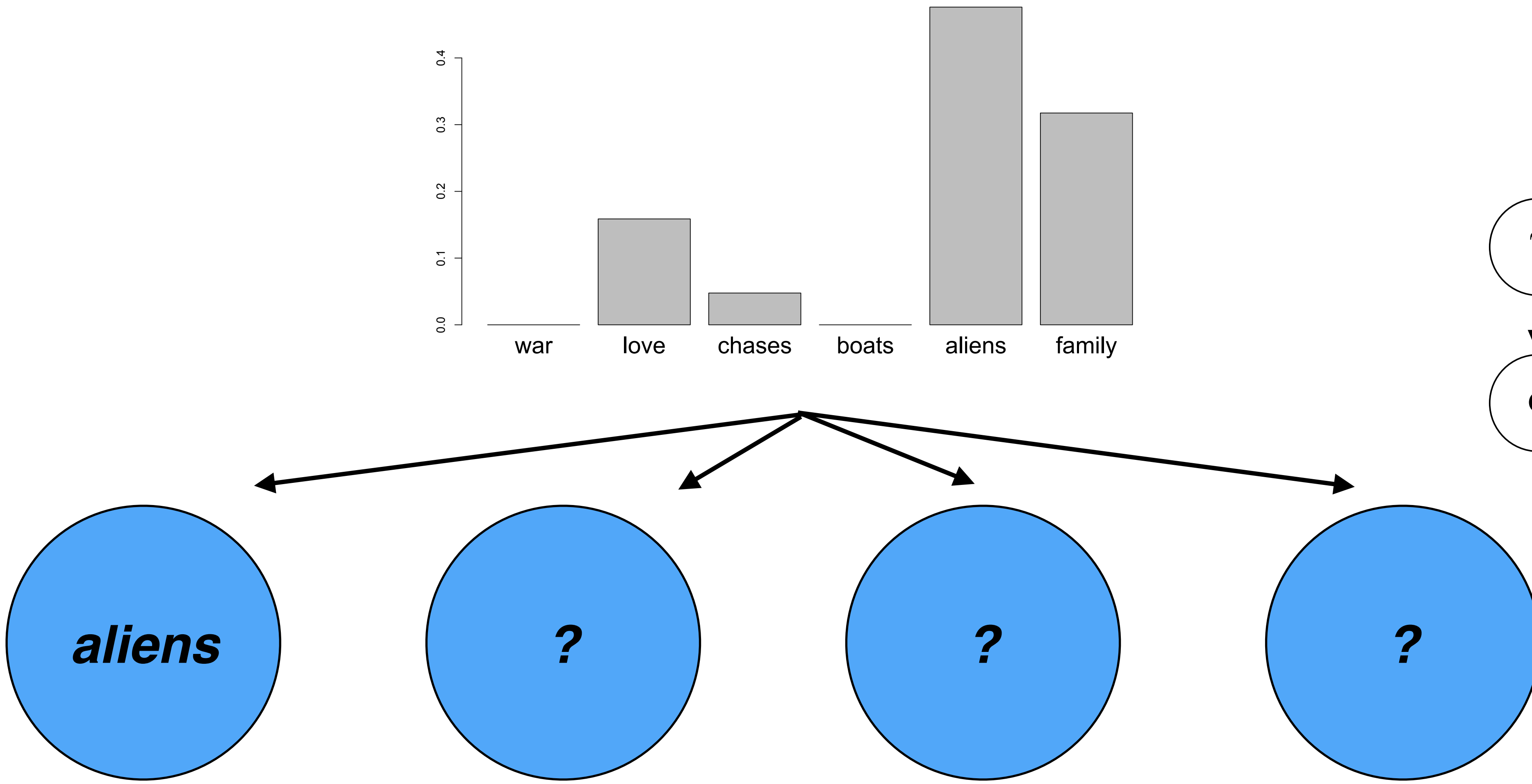

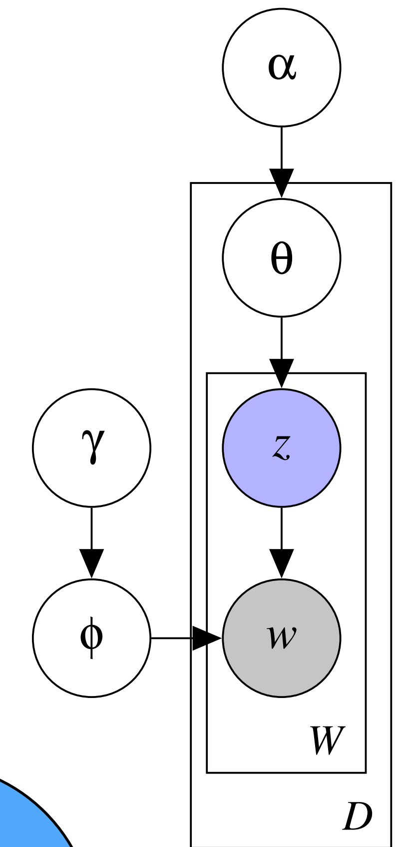

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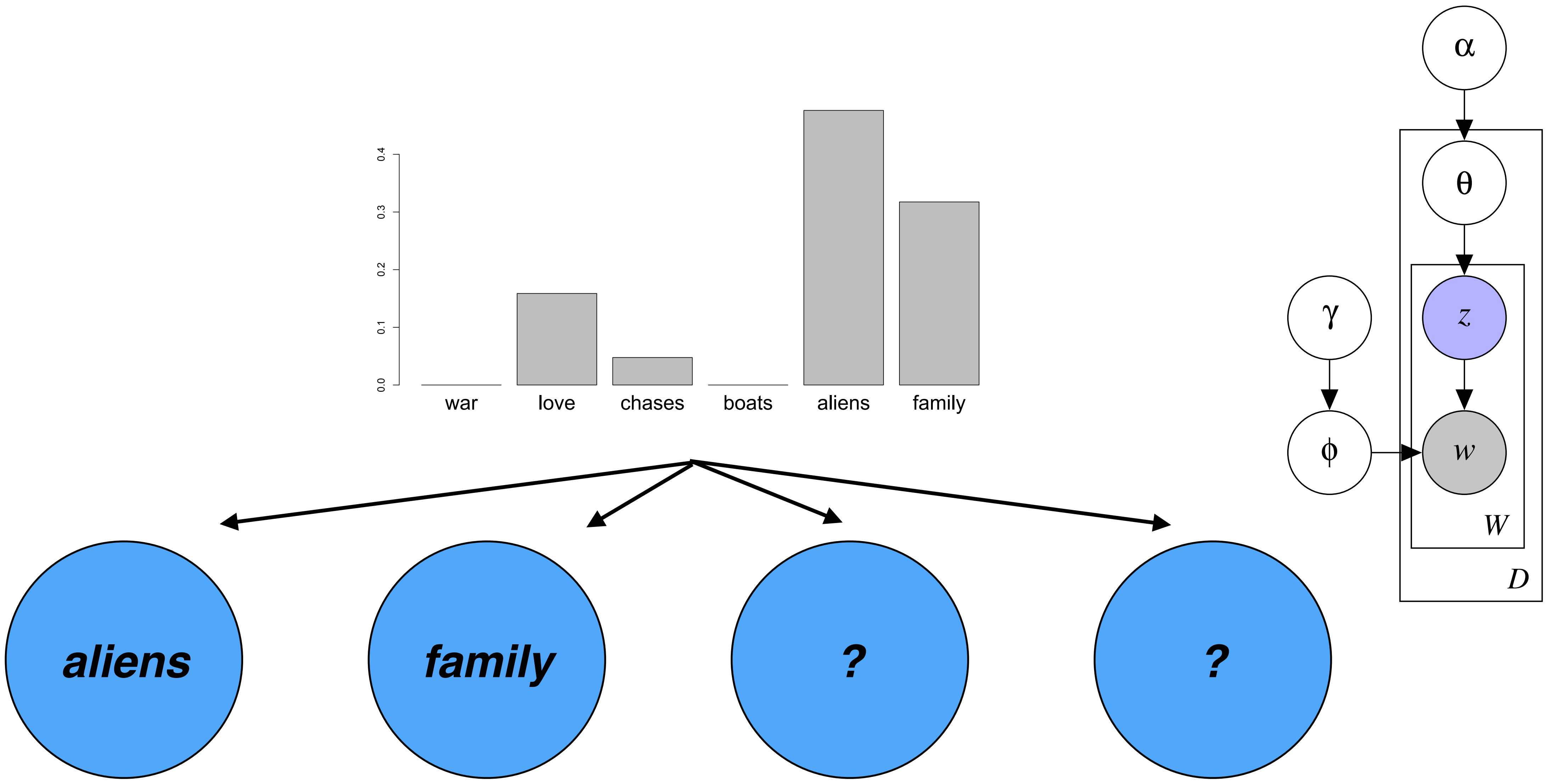

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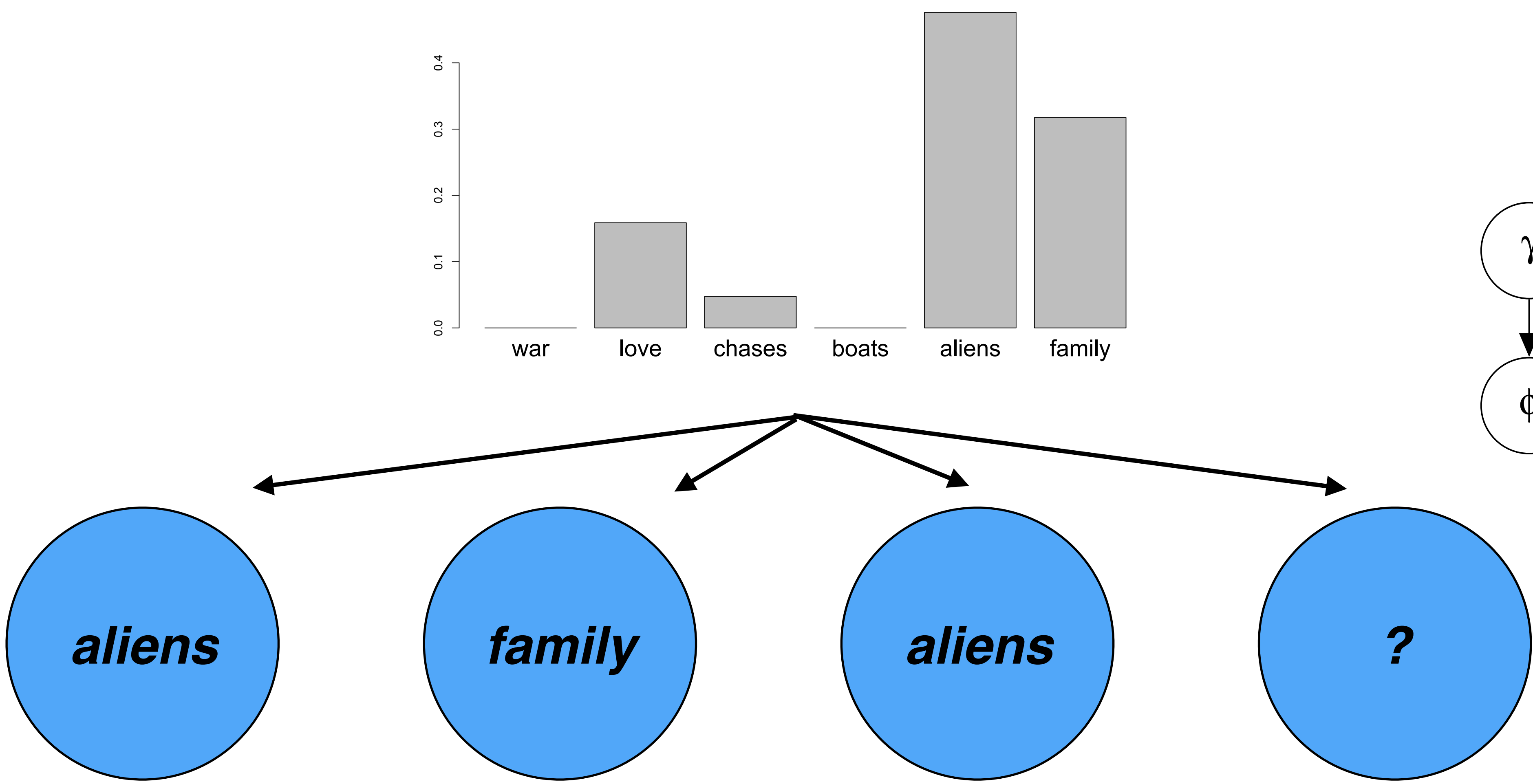

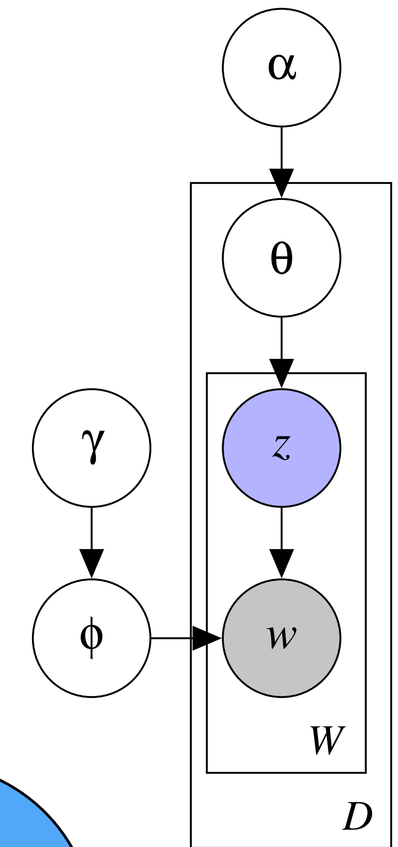

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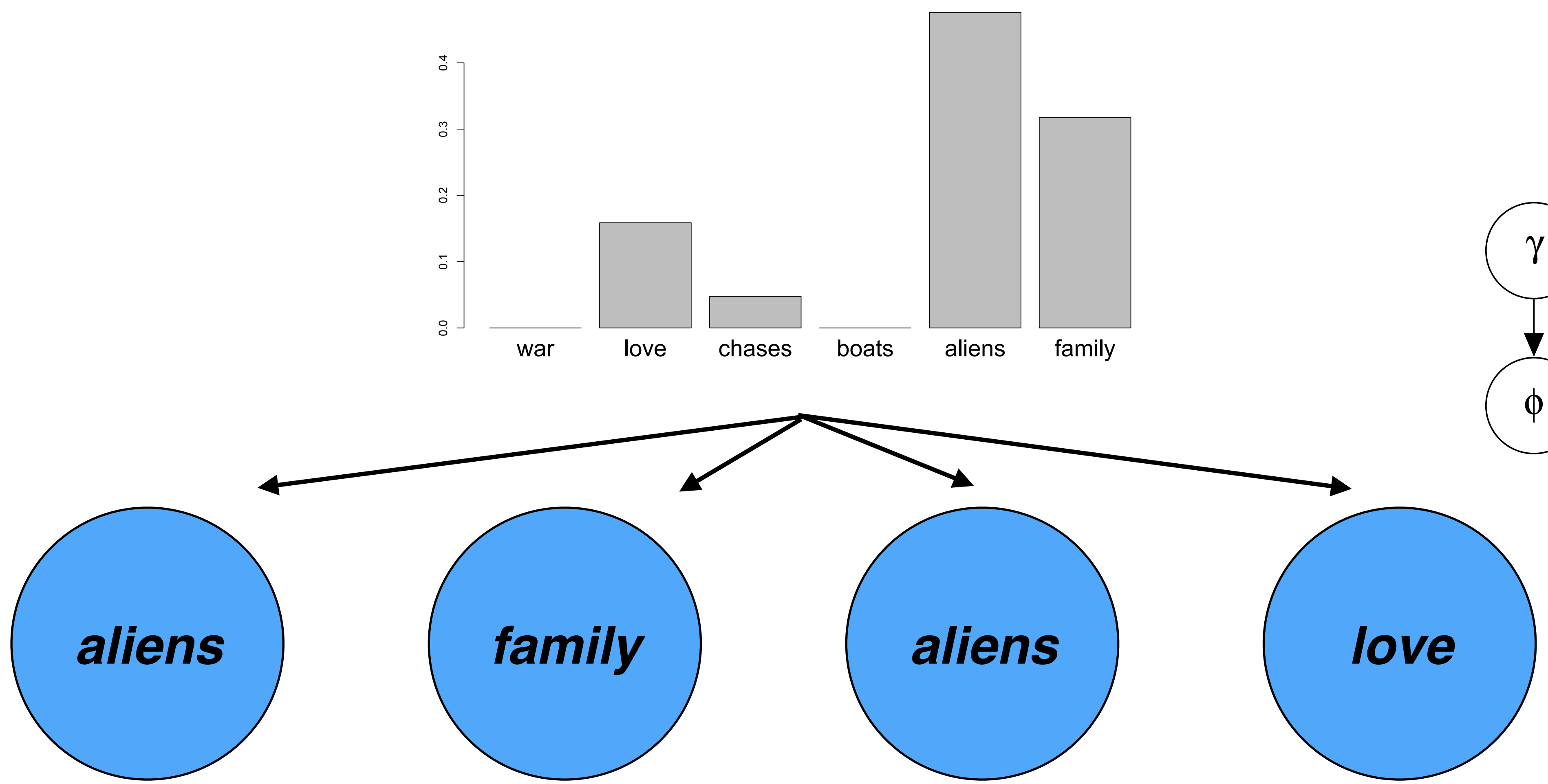

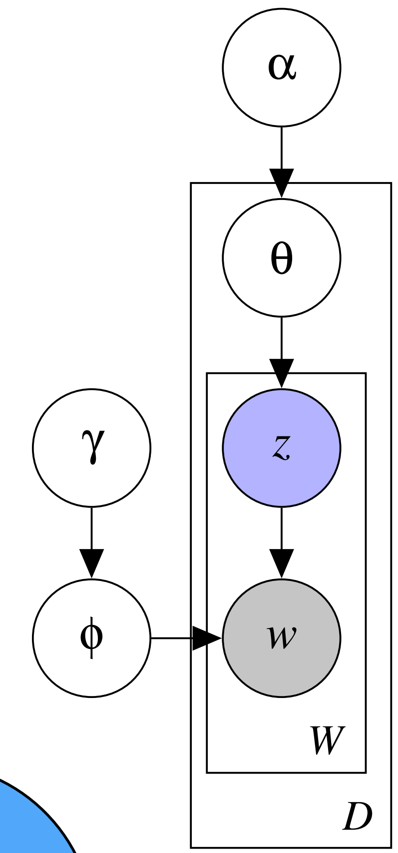

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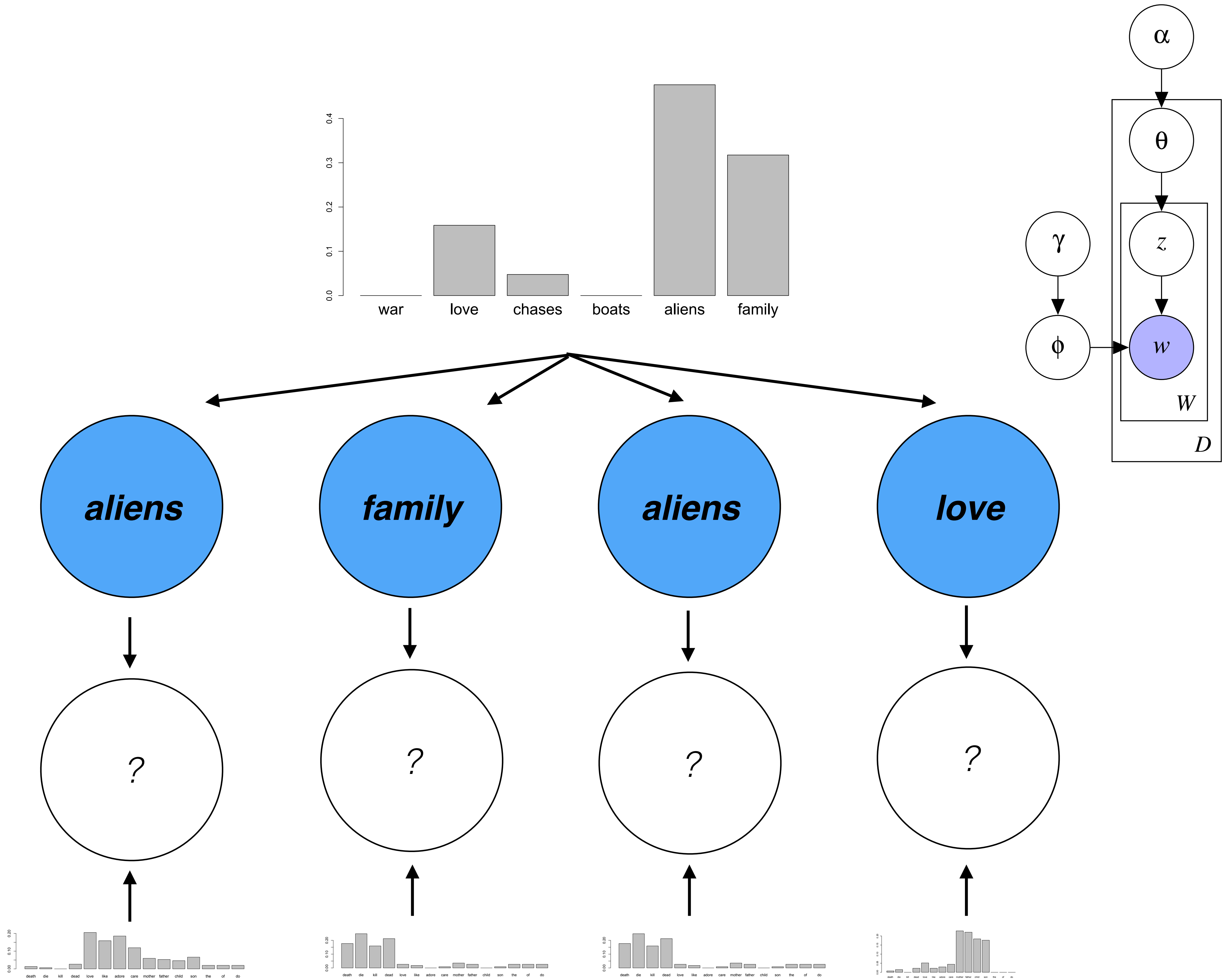

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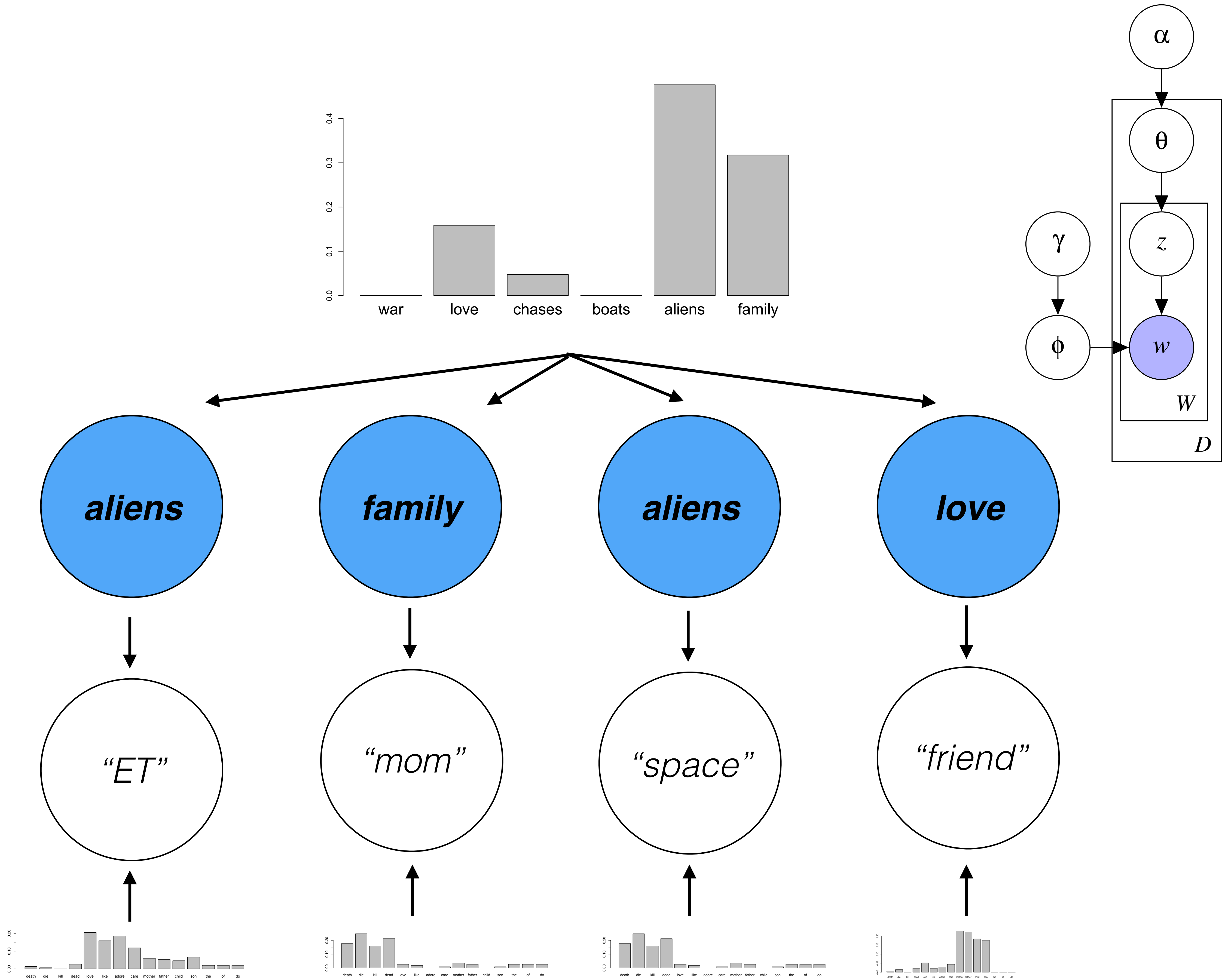
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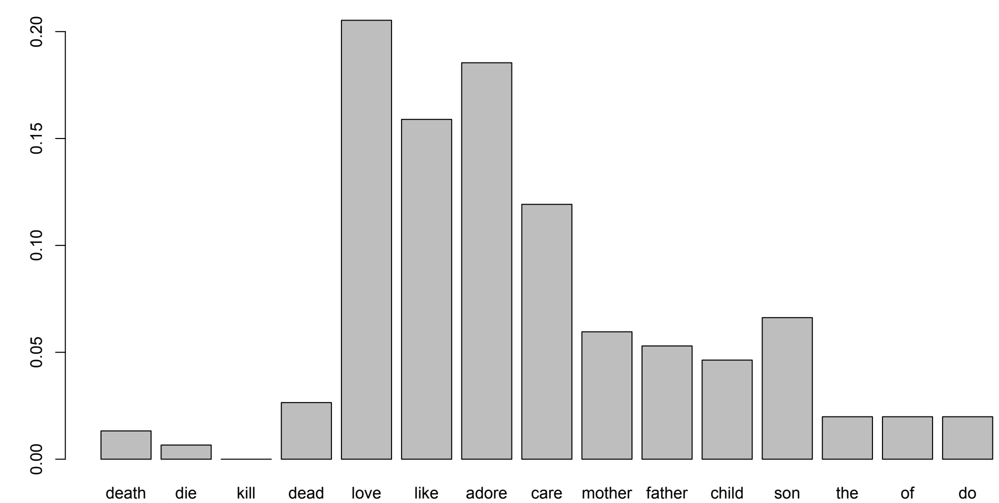
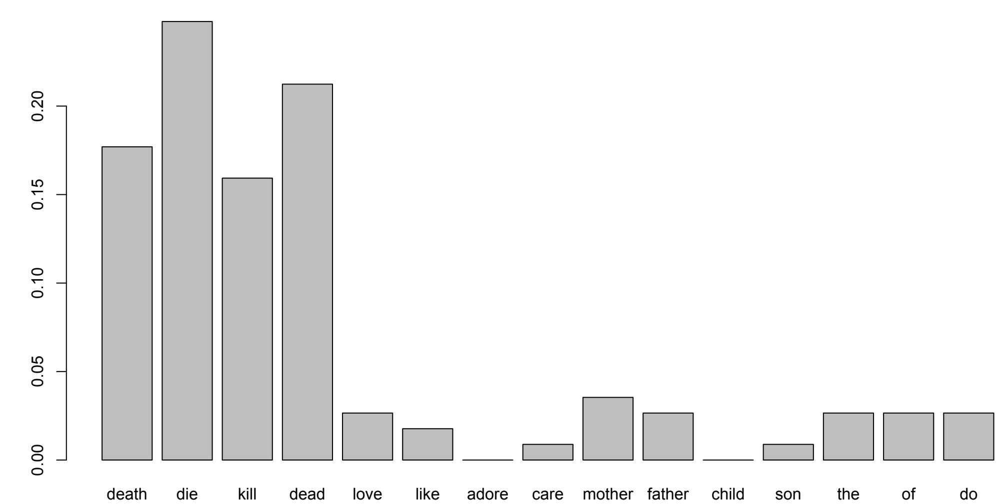
Inferred Topics

{album, band, music}	{government, party, election}	{game, team, player}
album	government	game
band	party	team
music	election	player
song	state	win
release	political	play

{god, call, give}	{company, market, business}	{math, number, function}
god	company	math
call	market	number
give	business	function
man	year	code
time	product	set

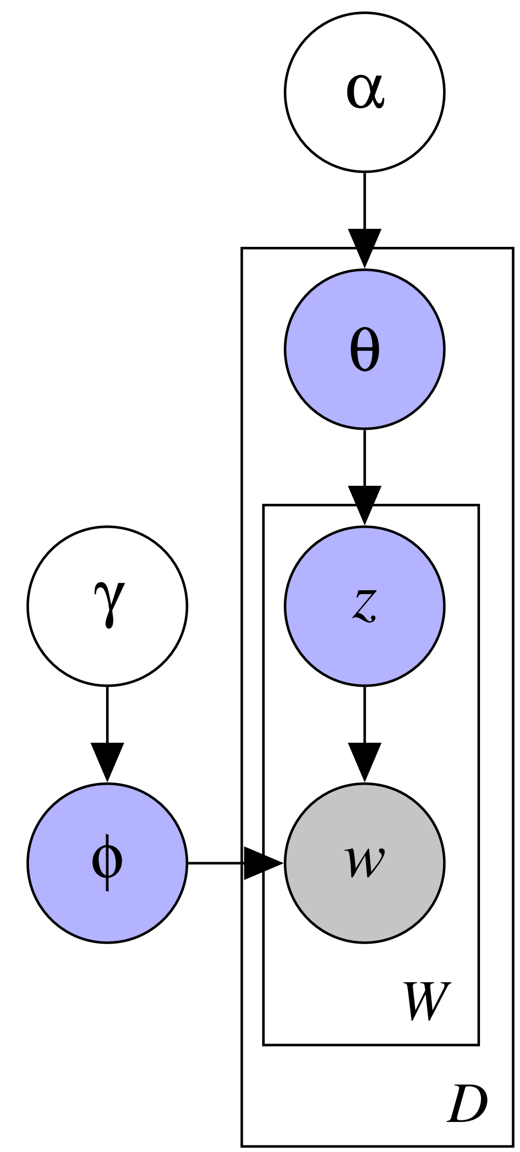
{city, large, area}	{math, energy, light}	{law, state, case}
city	math	law
large	energy	state
area	light	case
station	field	court
include	star	legal





Inference

- What are the topic distributions for each document?
- What are the topic assignments for each word in a document?
- What are the word distributions for each topic?



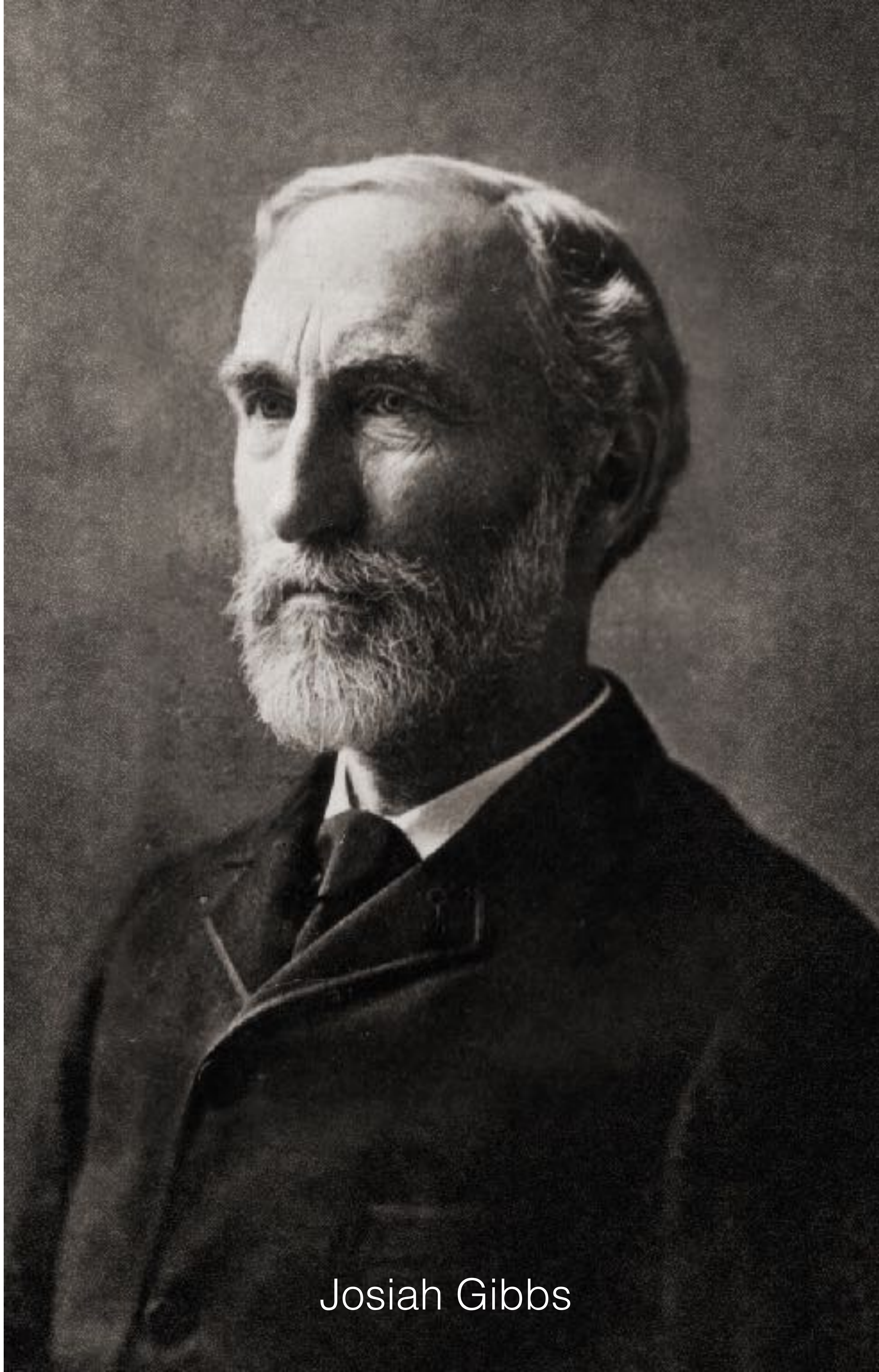
Find the parameters that maximize the likelihood of the data!

Inference

- Markov chain Monte Carlo (Gibbs sampling, Metropolis Hastings, etc.)
- Variational methods
- Spectral methods (Anandkumar et al. 2012, Arora et al. 2013)

Gibbs Sampling

- Markov chain Monte Carlo method for approximating the joint distribution of a set of variables (Geman and Geman 1984; Metropolis et al. 1953; Hastings et al. 1970)

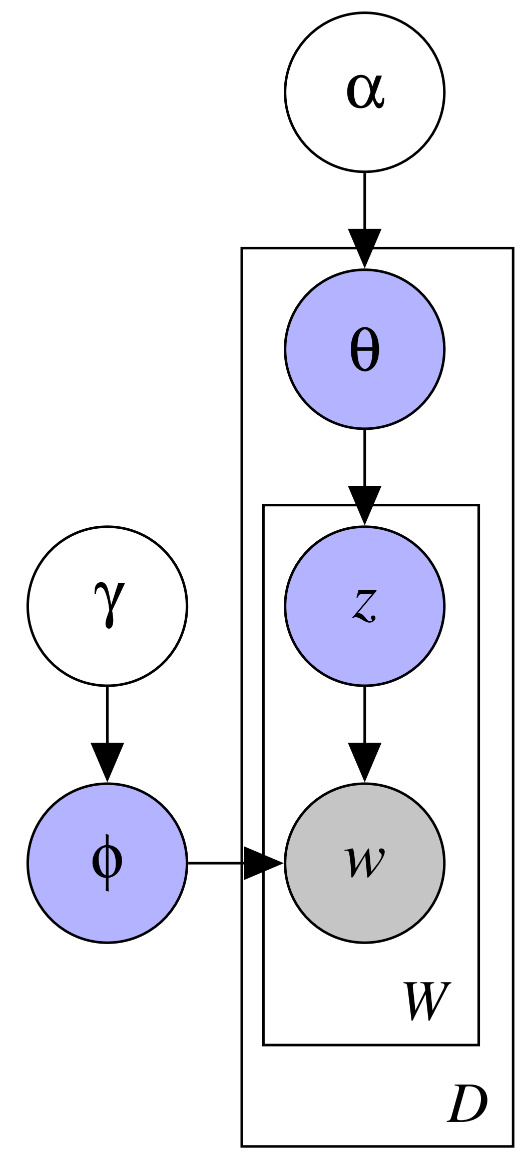


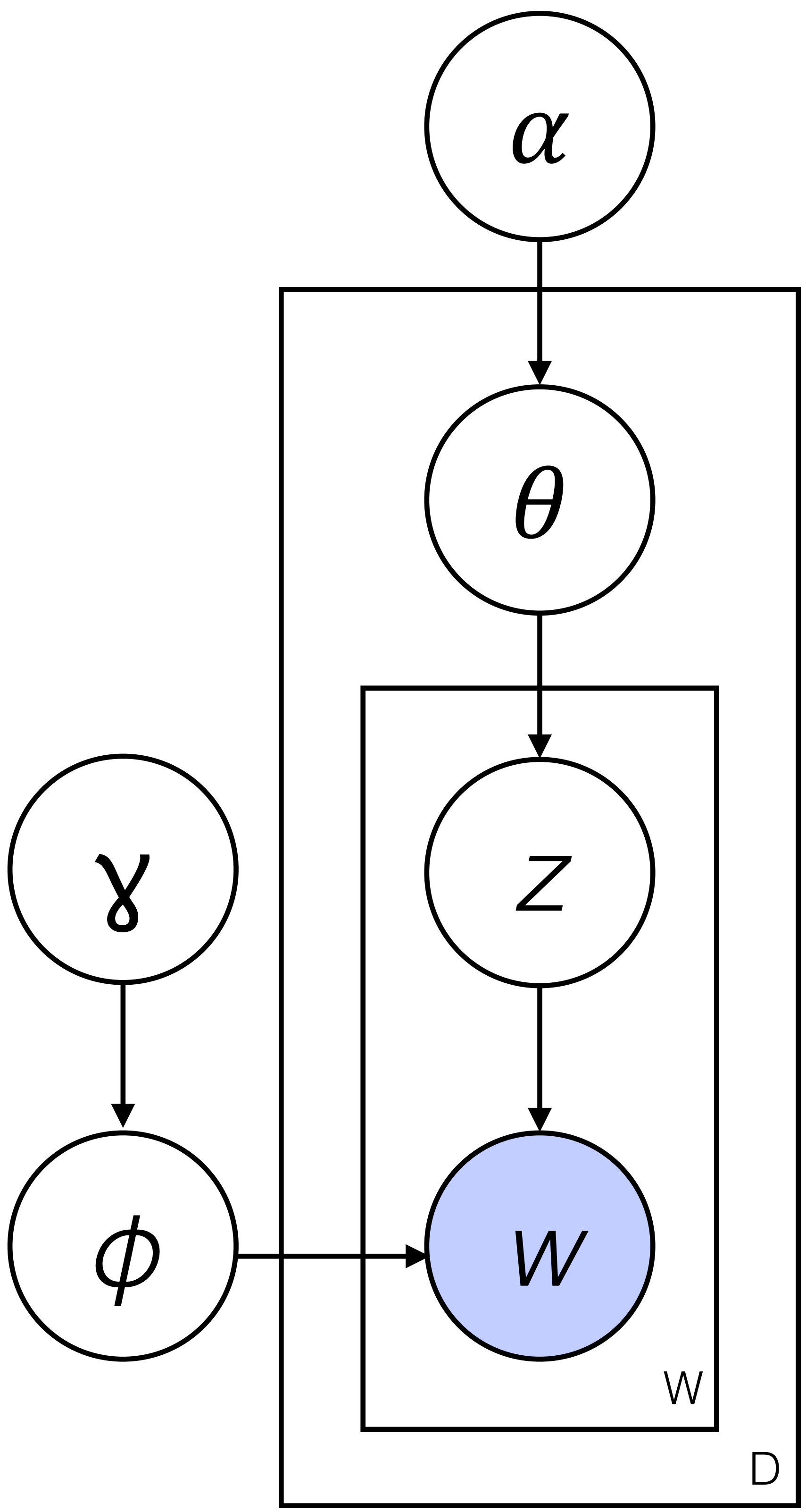
Gibbs Sampling

1. Start with some initial value for all the variables

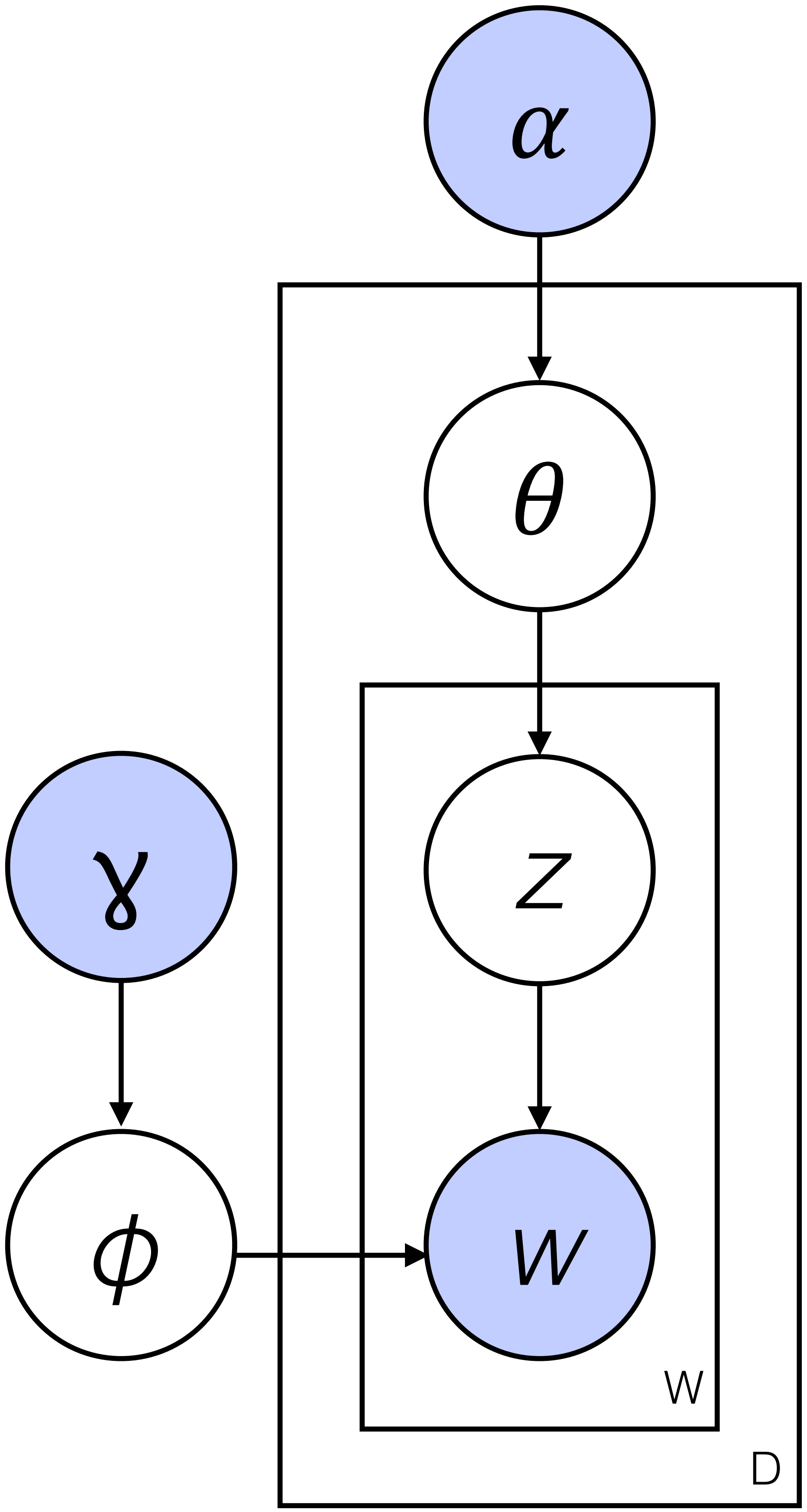
2. Sample a value for a variable conditioned on all of the other variables around it (using Bayes' theorem)

$$P(\theta|X) = \frac{P(\theta)P(X|\theta)}{\sum_\theta P(\theta)P(X|\theta)}$$





Inference

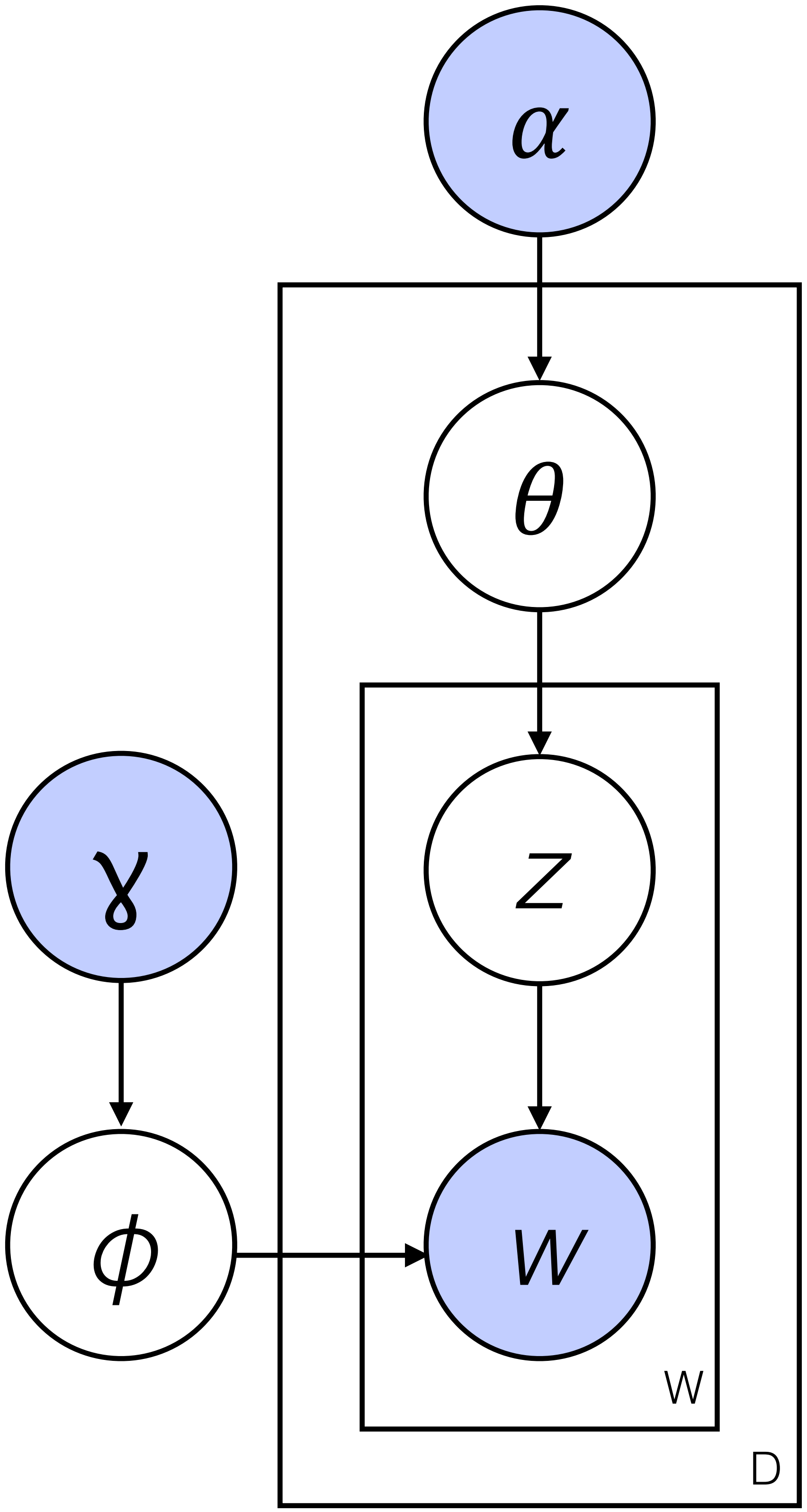


Inference

$$P(\theta_d \mid \alpha, \mathbf{z_d})$$

$$\propto P(\theta_d \mid \alpha) \prod_i P(z_i \mid \theta_d)$$

$$\propto \mathrm{Dir}(\theta \mid \alpha) \prod_i \mathrm{Cat}(z_i \mid \theta)$$



Inference

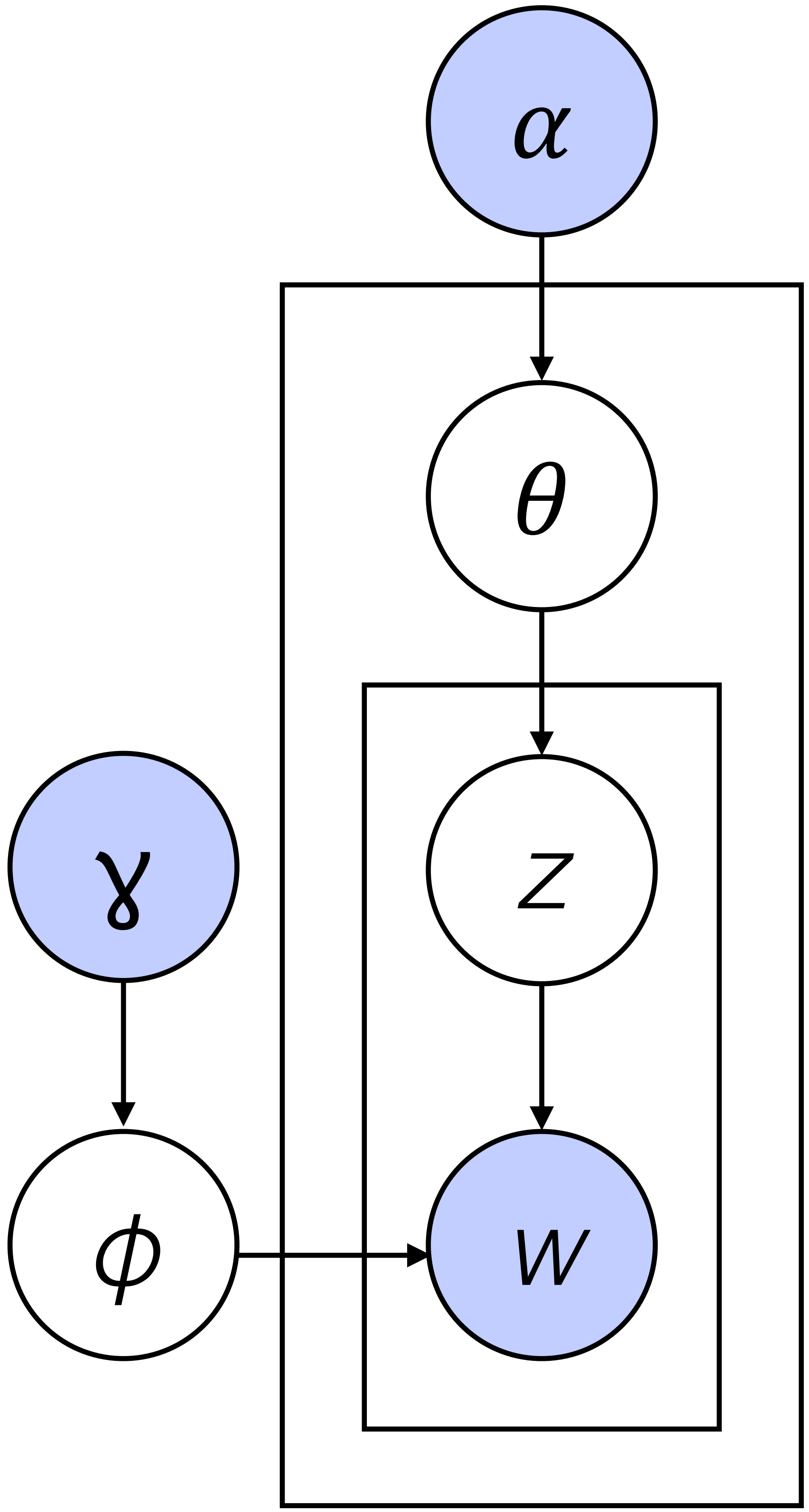
$$P(z \mid \theta_d, w, \phi)$$

$$\propto P(z \mid \theta_d) P(w \mid z, \phi)$$

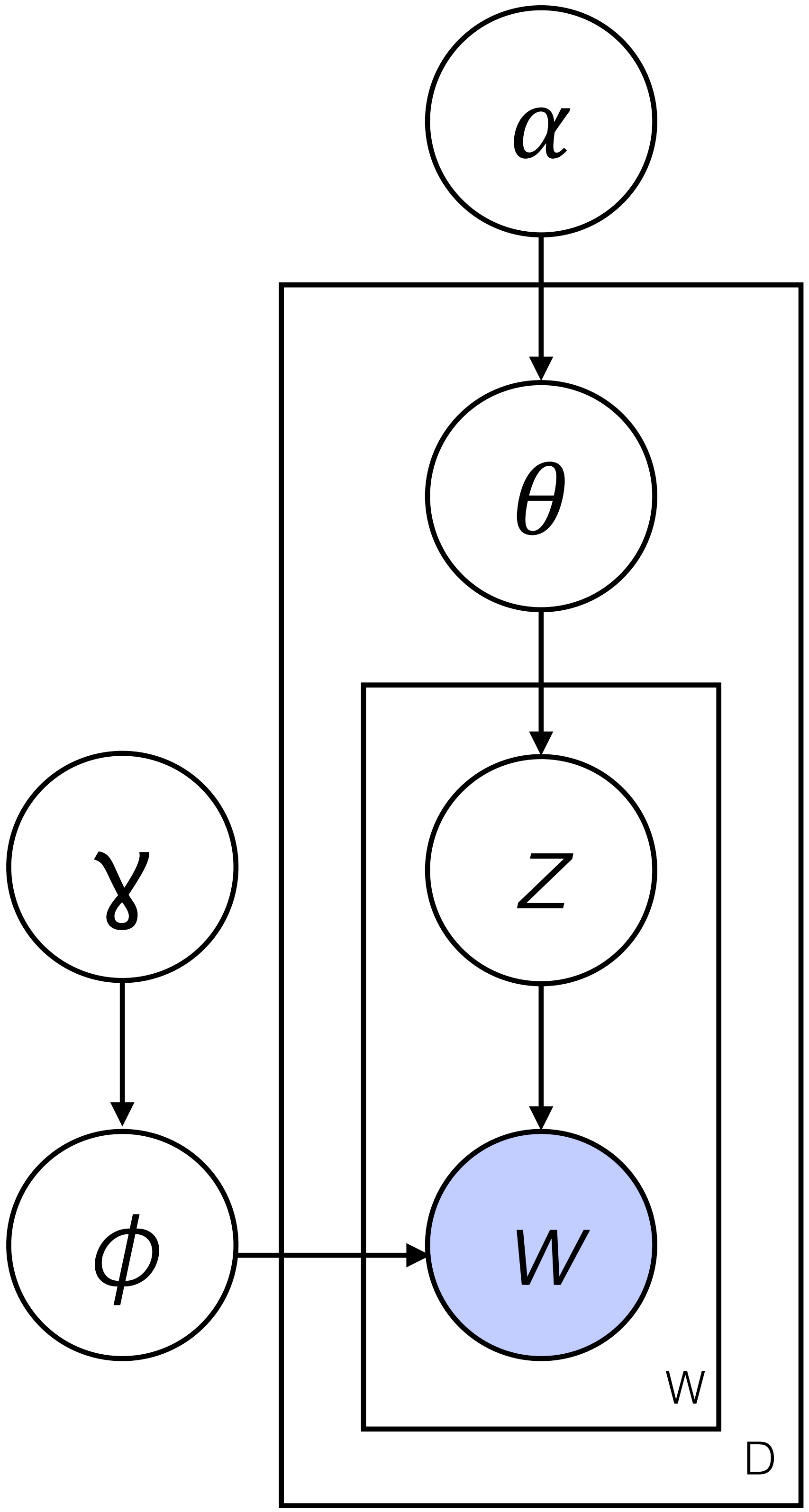
$$\propto \mathrm{Cat}(z \mid \theta_d) \mathrm{Cat}(w \mid z, \phi)$$

$$\propto \theta_d^z \times \phi_z^w$$

Sampling



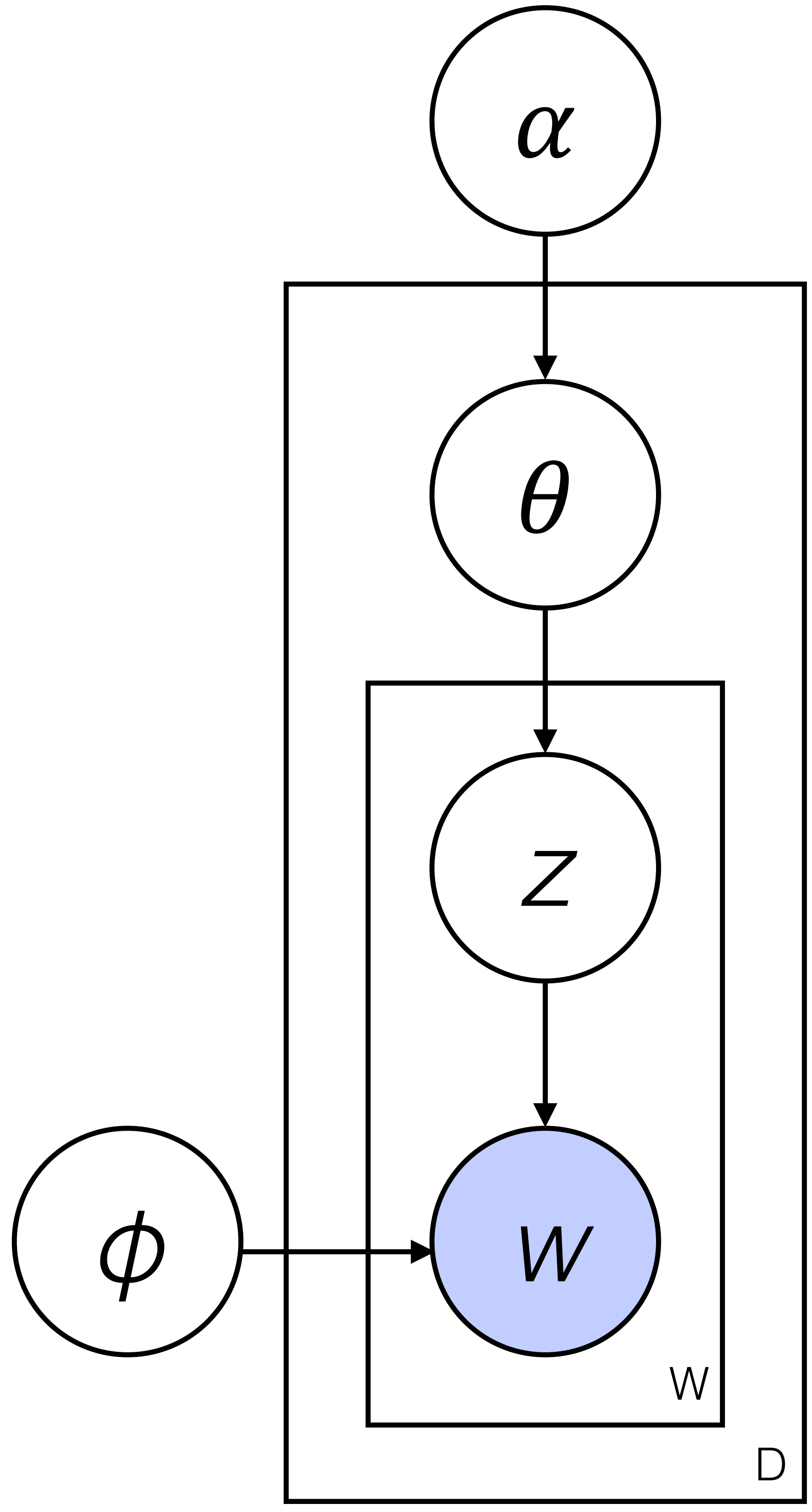
	$P(z\|\theta)$	$P(w\|z)$	$P(z\|\theta)$ $P(w\|z)$	norm
z=1	0.100	0.010	0.001	0.019
z=2	0.200	0.030	0.006	0.112
z=3	0.070	0.020	0.001	0.026
z=4	0.130	0.080	0.010	0.193
z=5	0.500	0.070	0.035	0.651



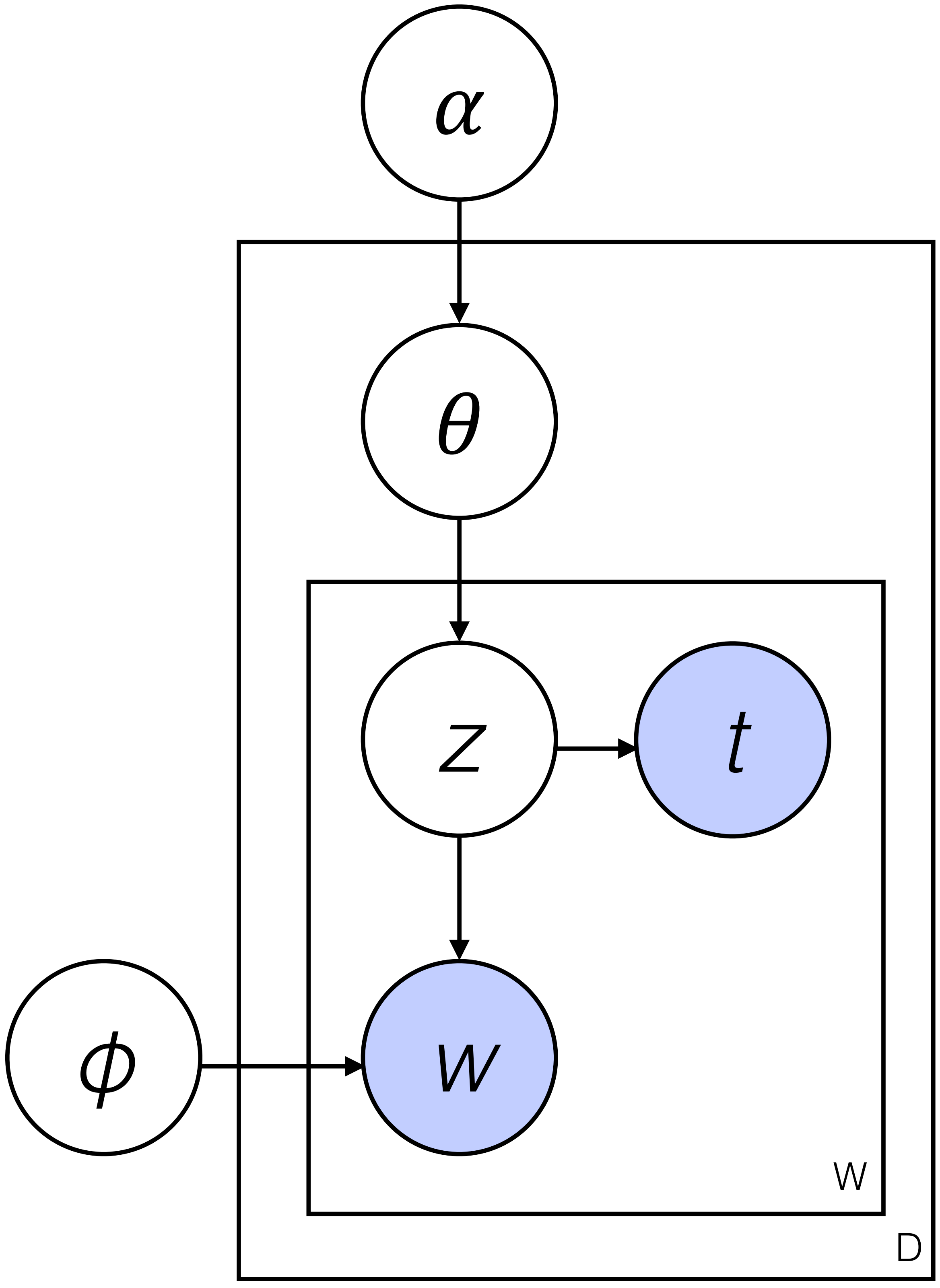
Assumptions

- Every word has one topic
- Every document has one topic distribution
- No sequential information (topics for words are independent of each other given the set of topics for a document)
- Topics don't have arbitrary correlations (Dirichlet prior)
- Words don't have arbitrary correlations (Dirichlet prior)
- The only information you learn from are the identities of **words** and how they are divided into **documents**.

What if you want to encode other assumptions or reason over other observations?



α
θ
z
ϕ
w
W
D



α
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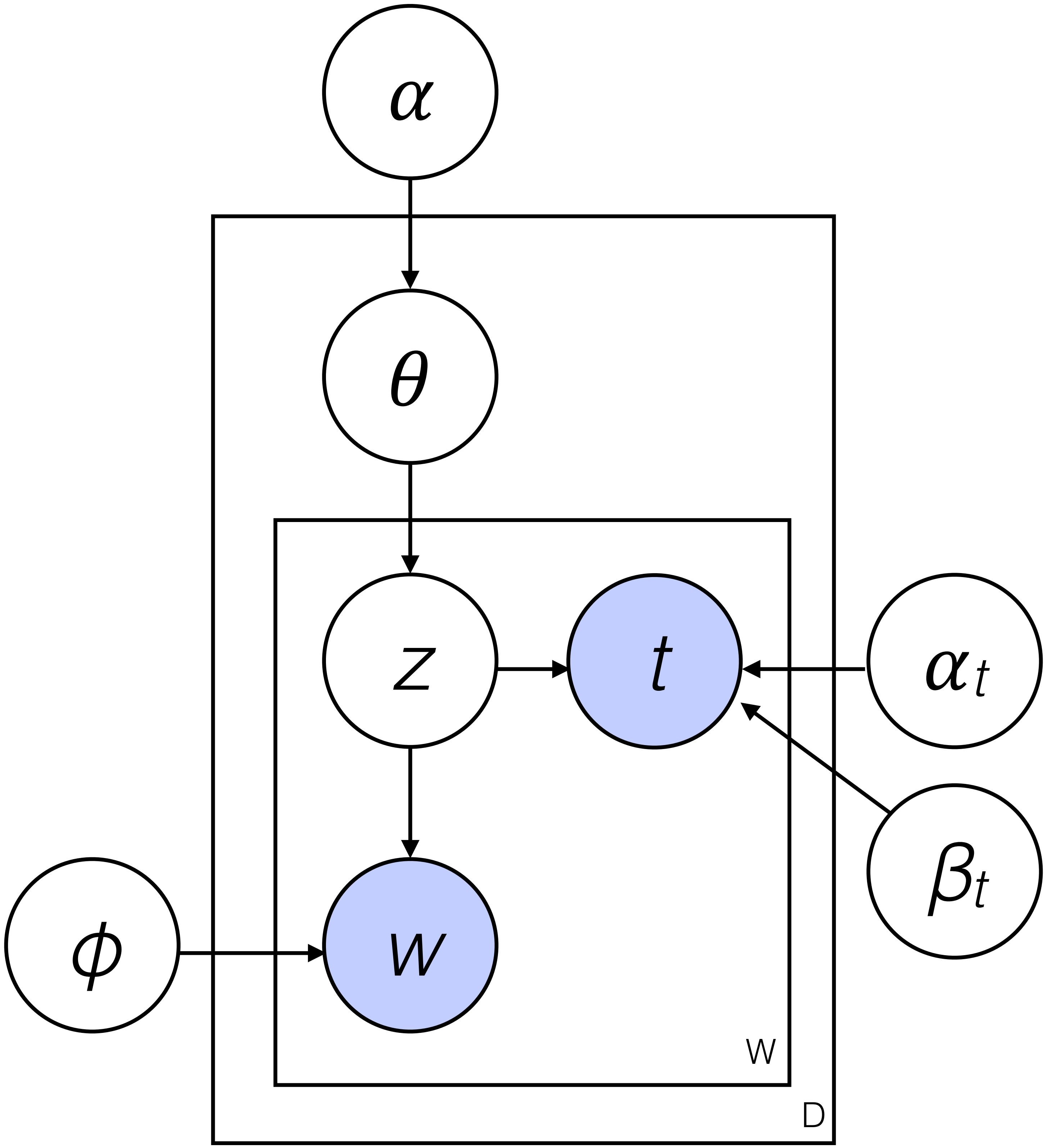
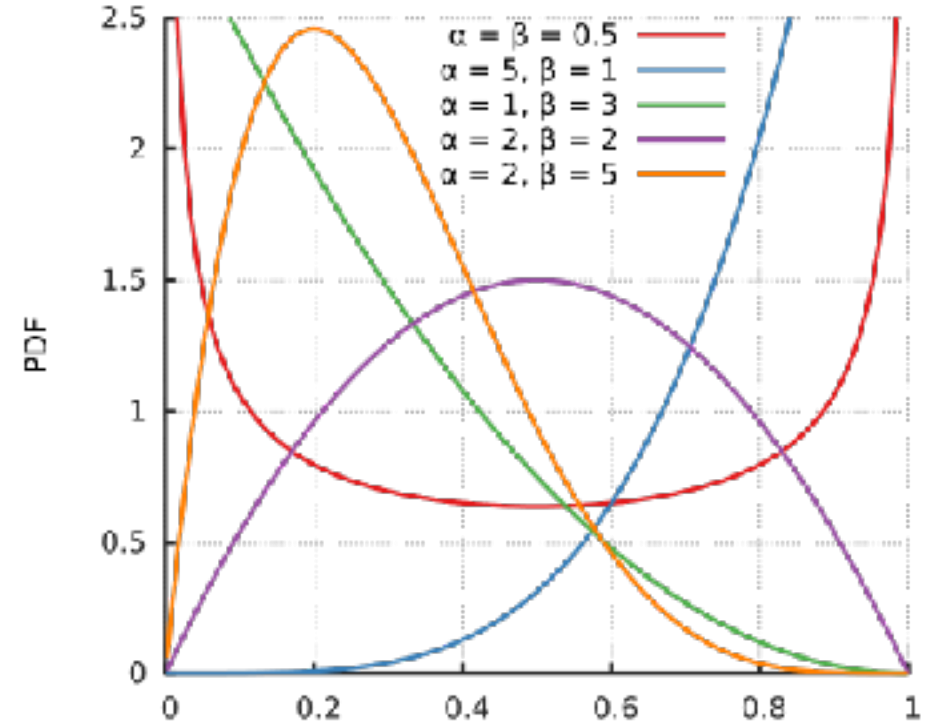
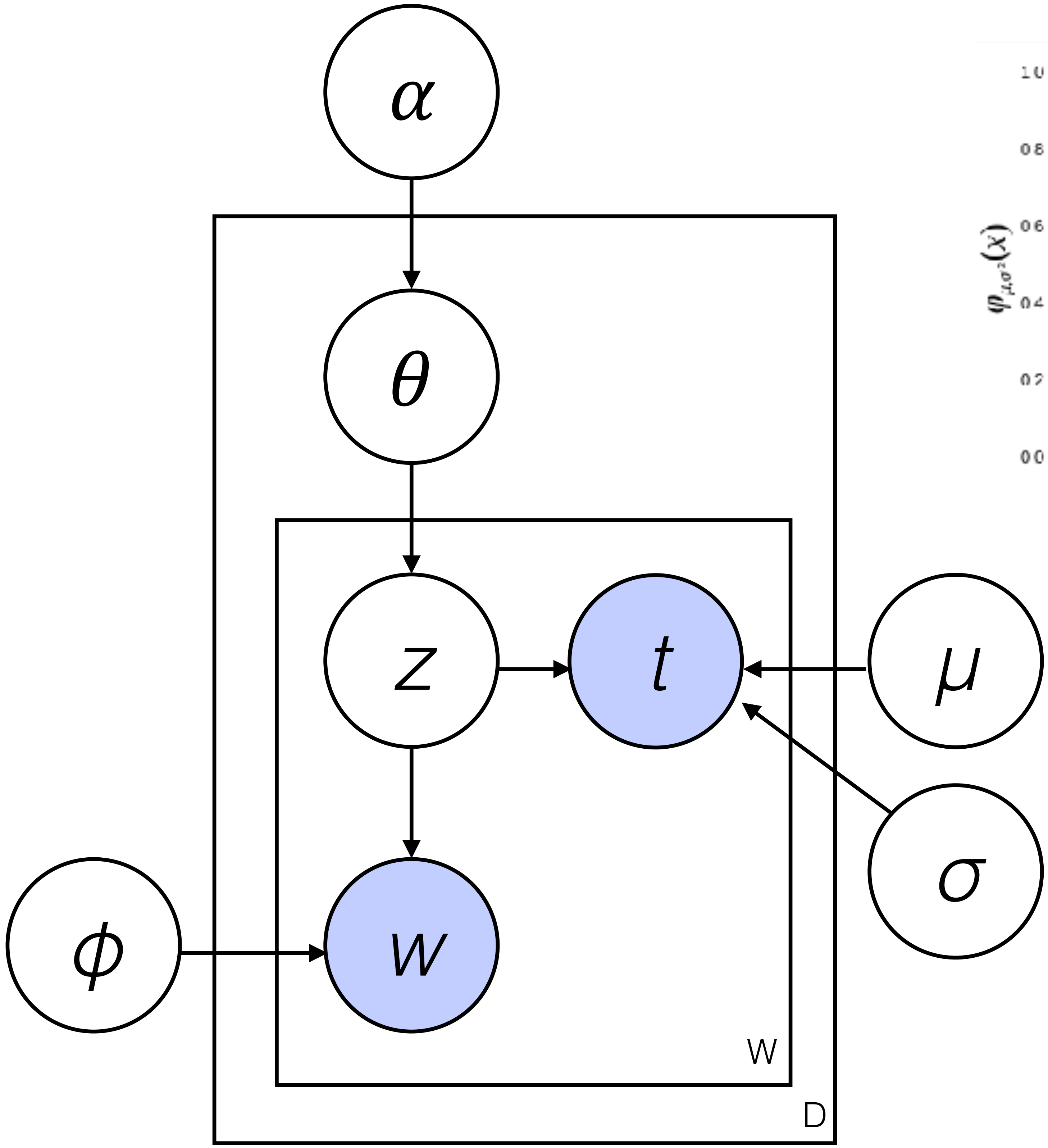


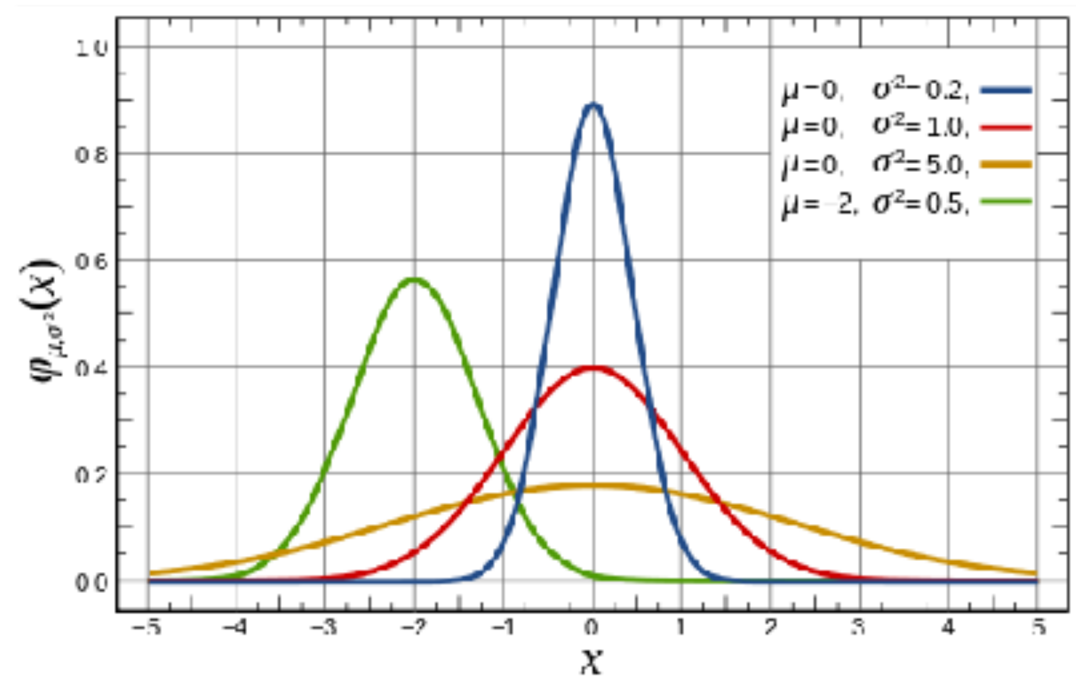


Time is drawn from a Beta distribution

[0,1]

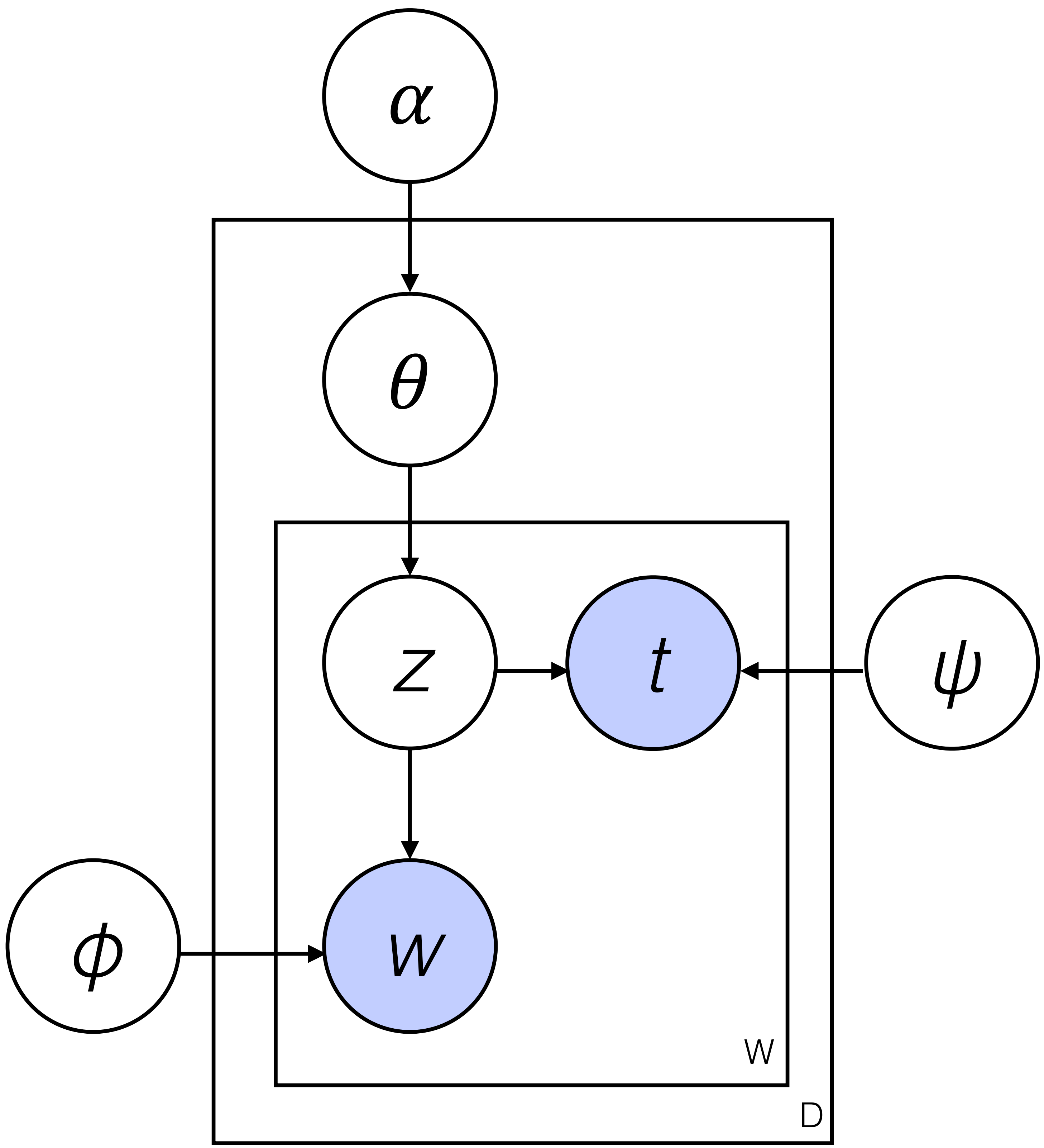
(Wang and McCallum 2006)

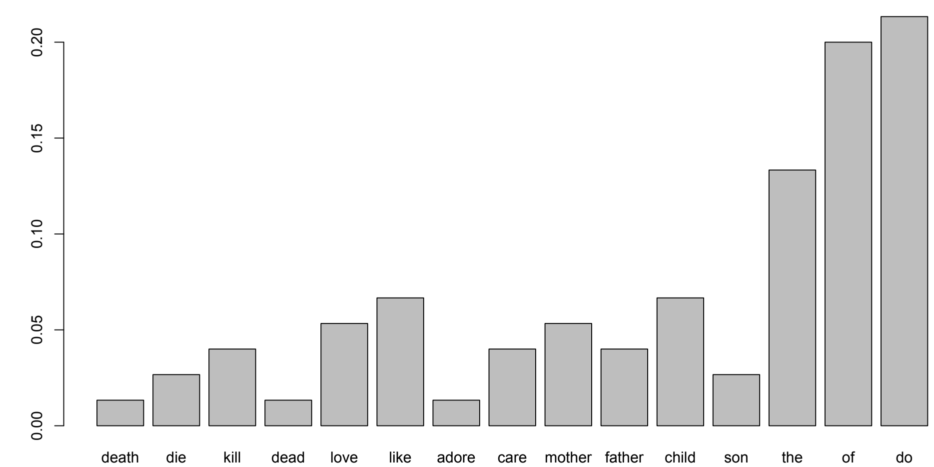




Time is drawn from a Normal distribution

[-∞, ∞]





Time is drawn from a Multinomial distribution

[1, … , K]