SI 630

Natural Language Processing: Algorithms and People

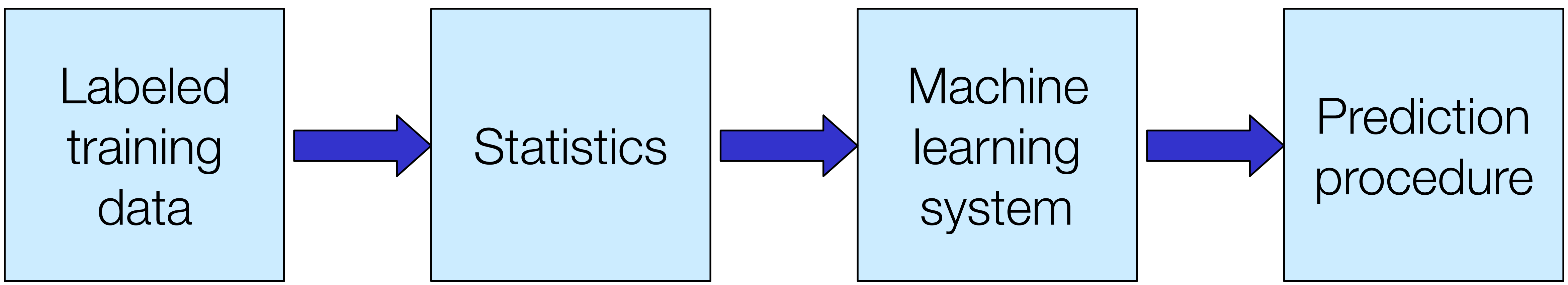
Lecture 7: Unsupervised Learning

Feb. 19, 2020

Some slides adapted from Chris Manning, Dan Jurafsky, Kai-Wei Chang, Roger Levy, Sharon Goldwater, Qiaozhu Mei, V.G. Vinod Vydiswaran, Heng Ji, Jan Wiebe and Kavita Ganesan

Supervised Learning

Training:



- Standard statistical systems use a supervised paradigm.

The real story: Annotating labeled data is labor-intensive!!!

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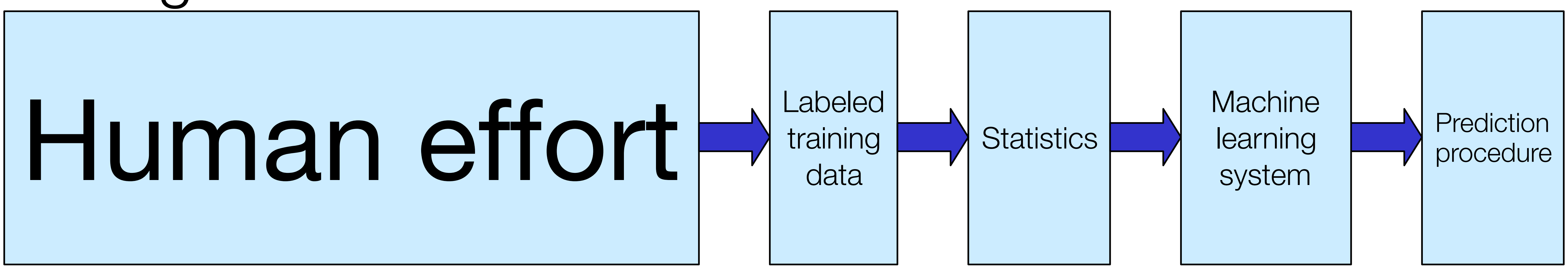

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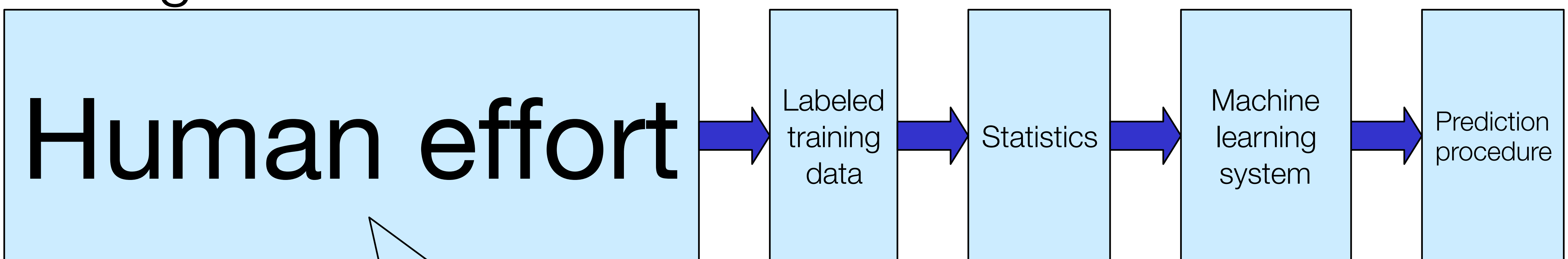

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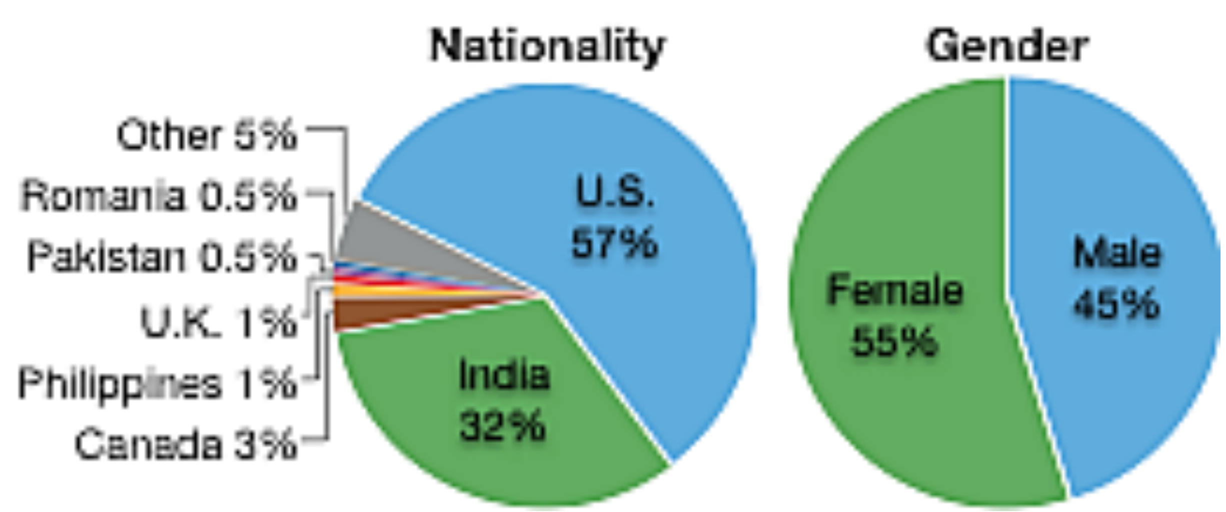
Training:

Human effort → Labeled training data → Statistics → Machine learning system → Prediction procedure



Ross et al. (2011)

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- But unlabeled data is cheap!
- It would be nice to use the unlabeled data directly to learn the labelings you want in your model.
- Today we'll look at methods for doing this, which is called unsupervised learning

Motivating Example

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- JFK Assassination Records - 2017 Additional Documents Release. July 24, 2017: 3,810 documents
    - October 26, 2017: 2,891 documents
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- 337,626 pages of documents!
  How can we make sense of this quickly as a journalist?

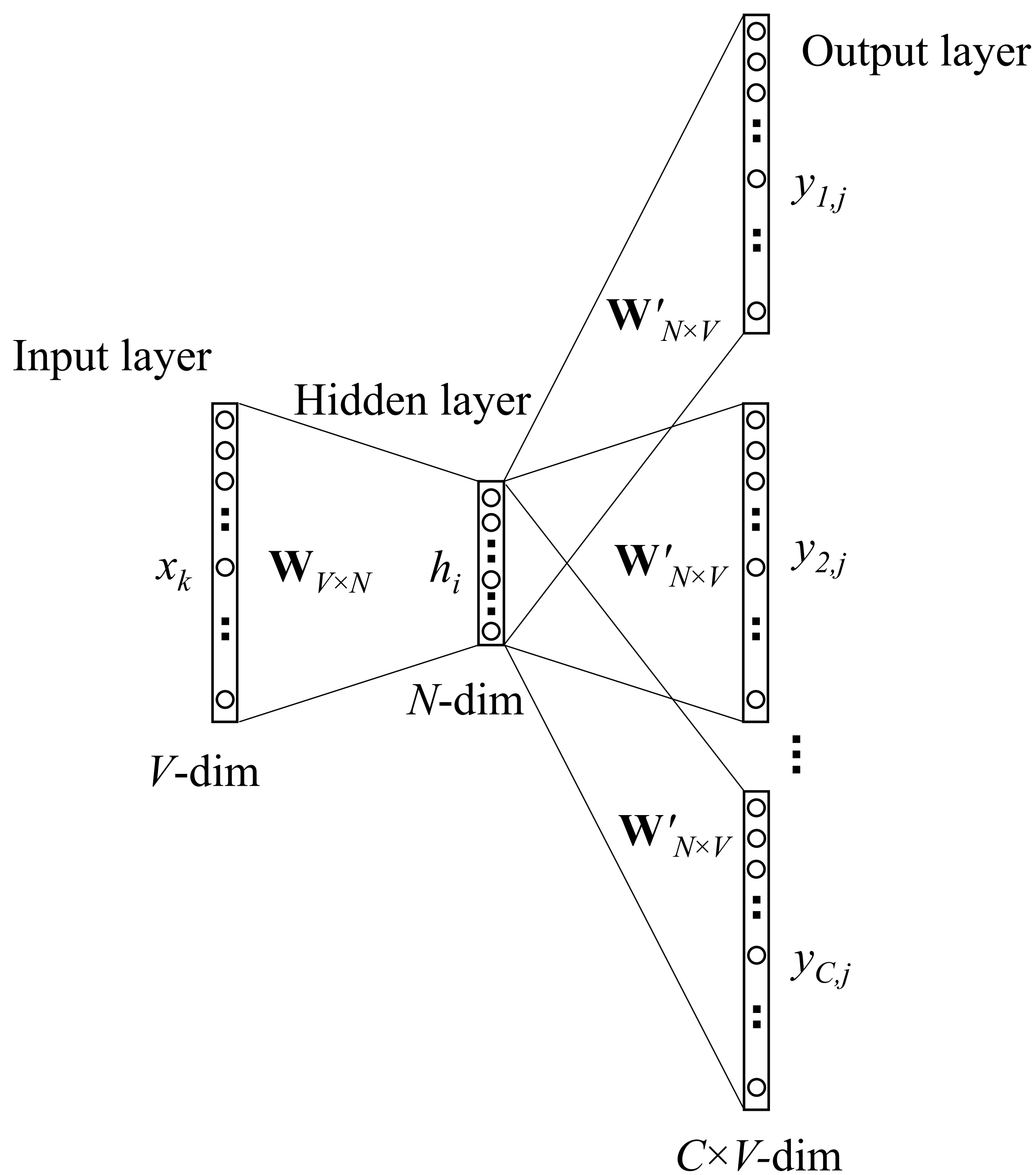
Today's plan

- Look at three kinds of unsupervised learning for NLP
- Start with words and move to documents

https://commons.wikimedia.org/wiki/File:Crayola_1st_No48_a_few_crayons.jpg

Brown Clustering

We know how to learn word meaning



What if we wanted to learn categories of words?

"You shall know a word by the company it keeps"

[Firth 1957]

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a cocktail with	______________	and seltzer

Brown clustering combines the Distributional Hypothesis with Language Modeling!

- An agglomerative clustering algorithm that clusters words based on which words precede or follow them
- These word clusters can be turned into a kind of vector
- We'll give a very brief sketch here.

Brown Clustering

- Similar to a language model but the basic unit is a word cluster

- Intuition is that similar words appear in similar contexts

- Recap: Bigram Language Model:

$$\prod_{i}^{n} P(w_i \mid w_{i-1}) \times P(STOP \mid w_n)$$

Maximum likelihood estimate $\dfrac{c(w_{i-1}, w_i)}{c(w_{i-1})}$

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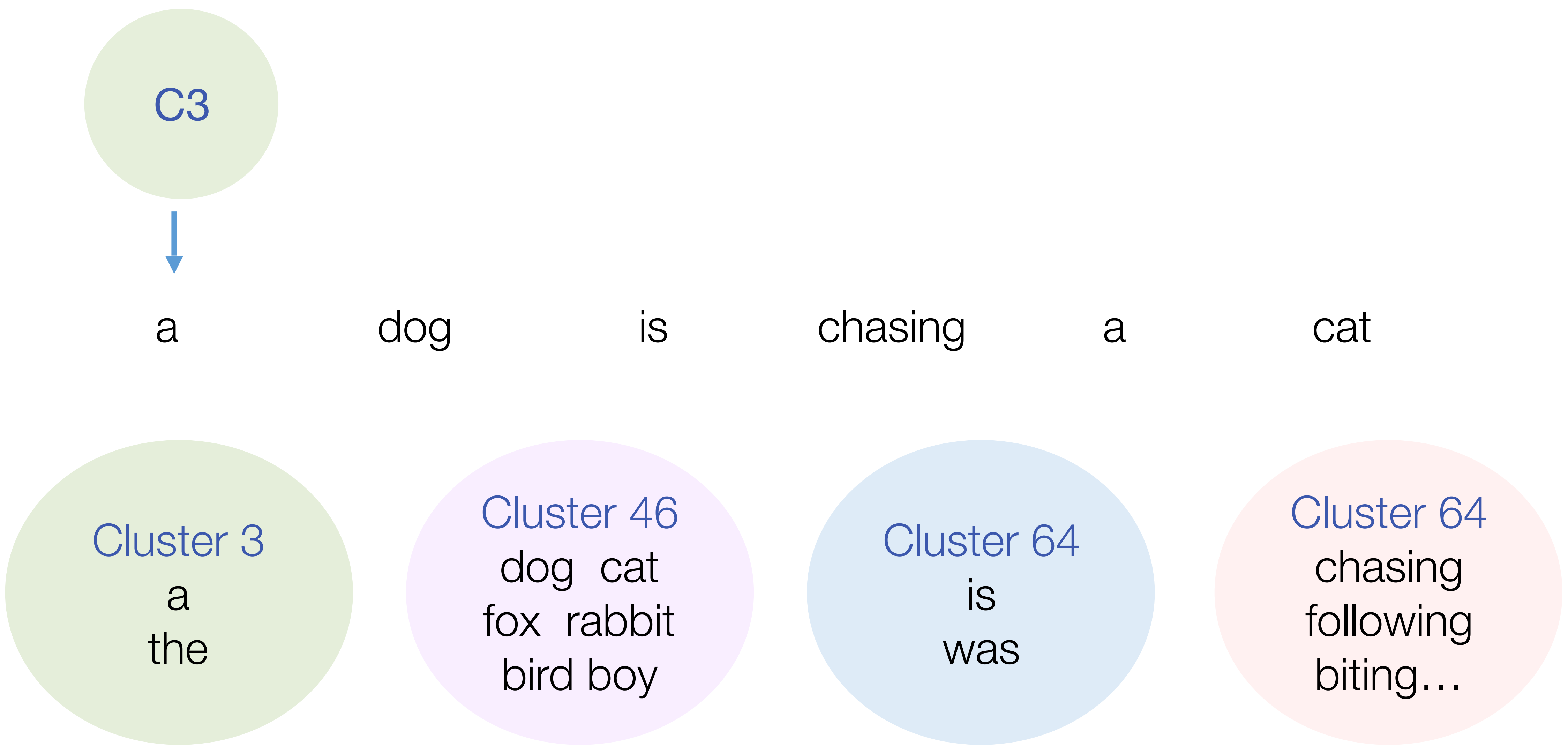

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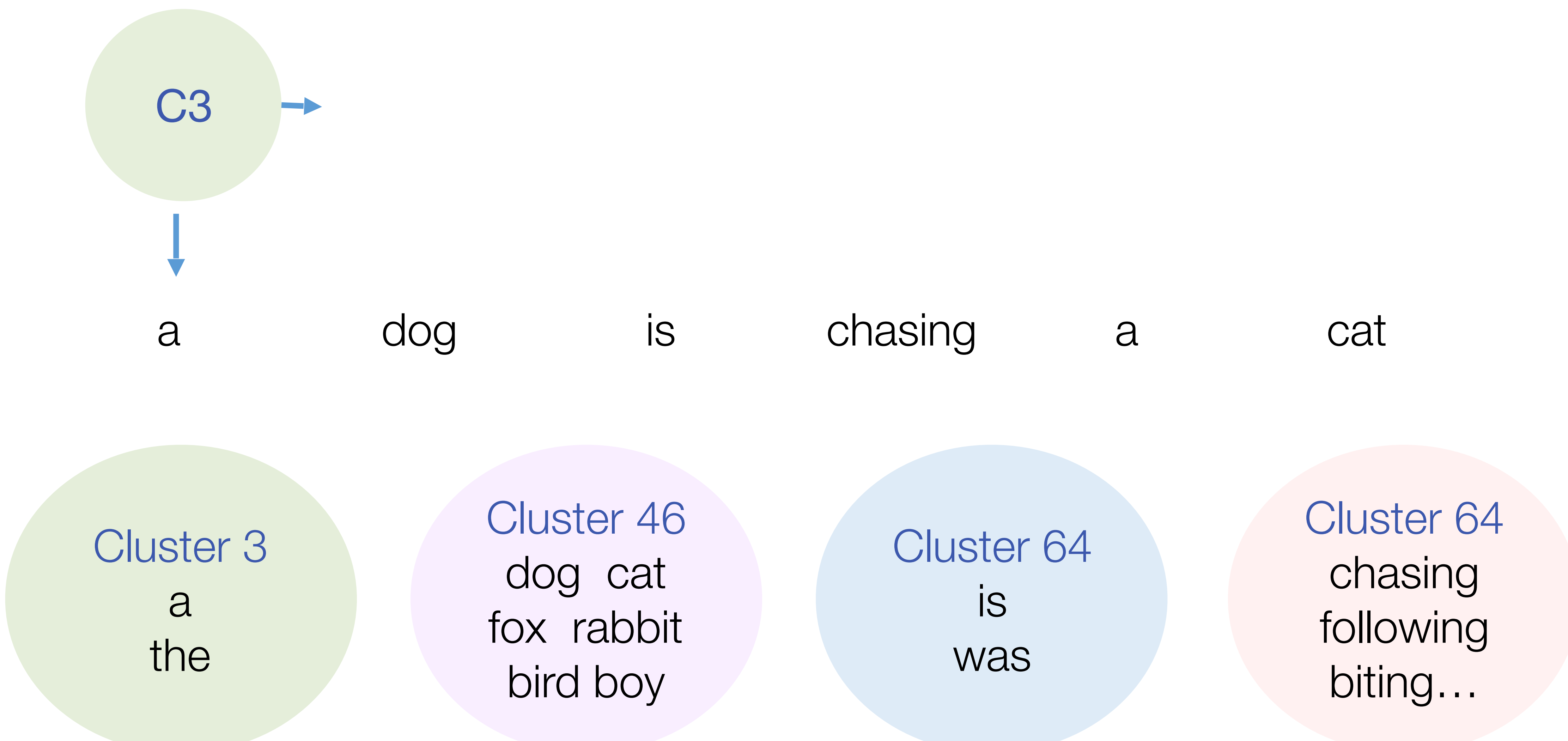

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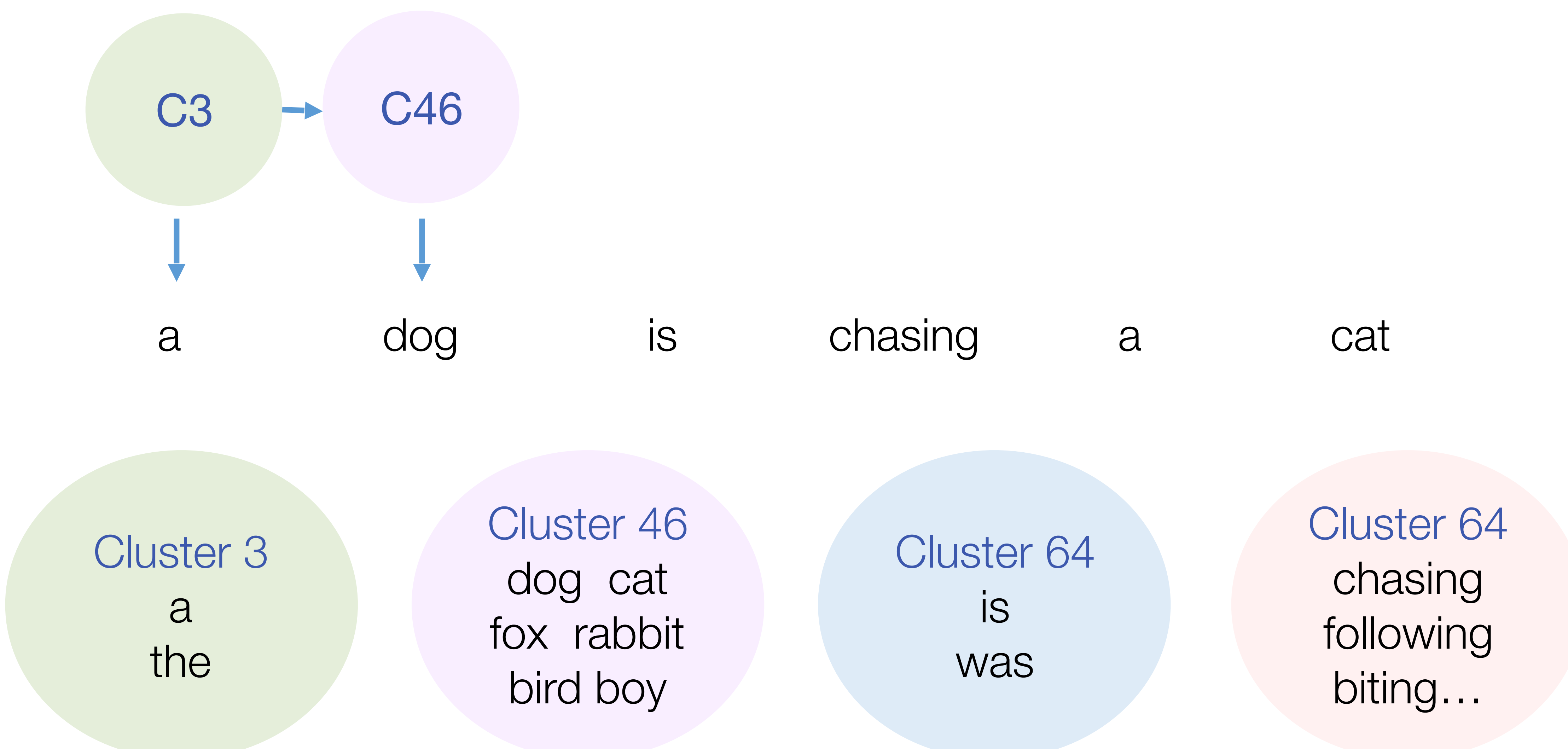

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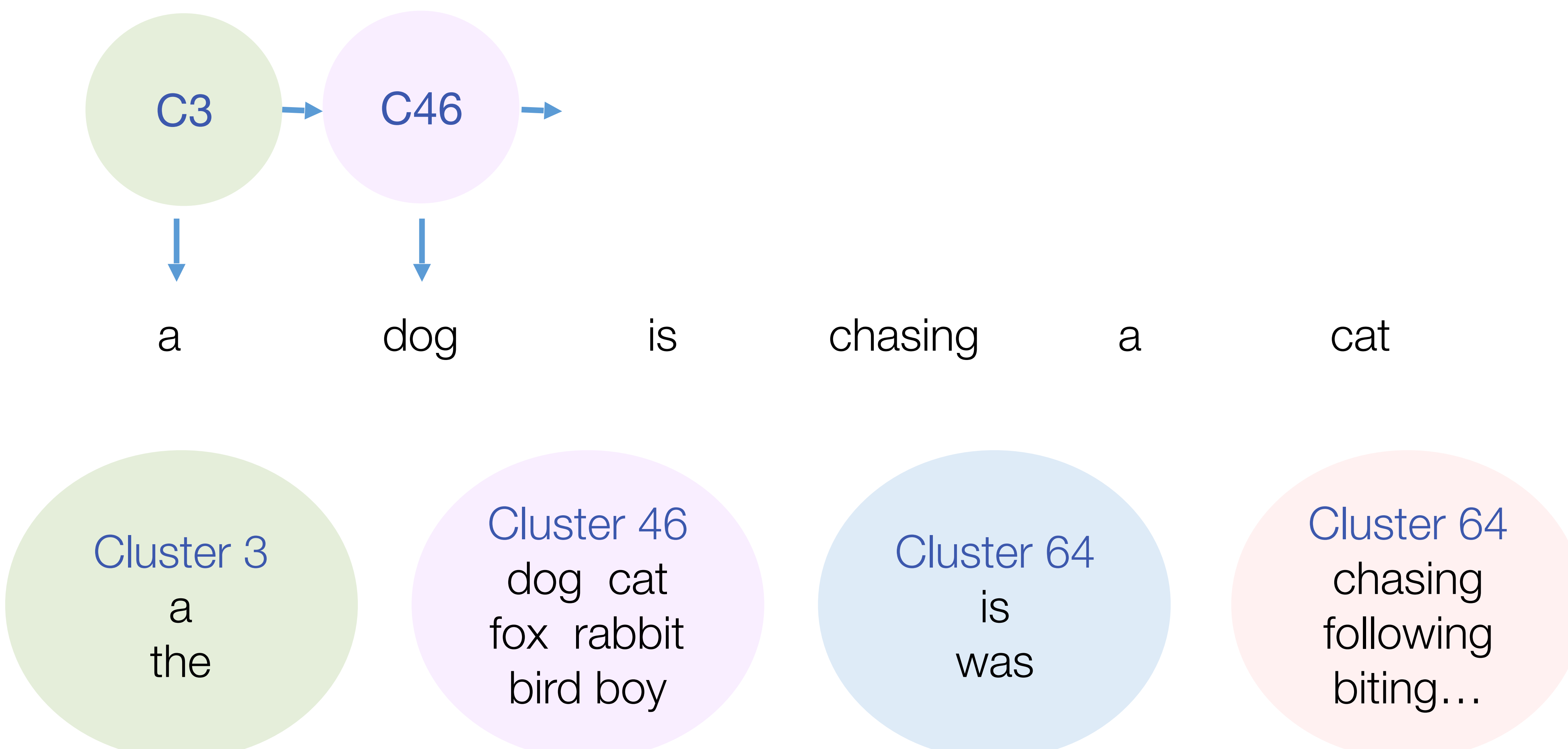

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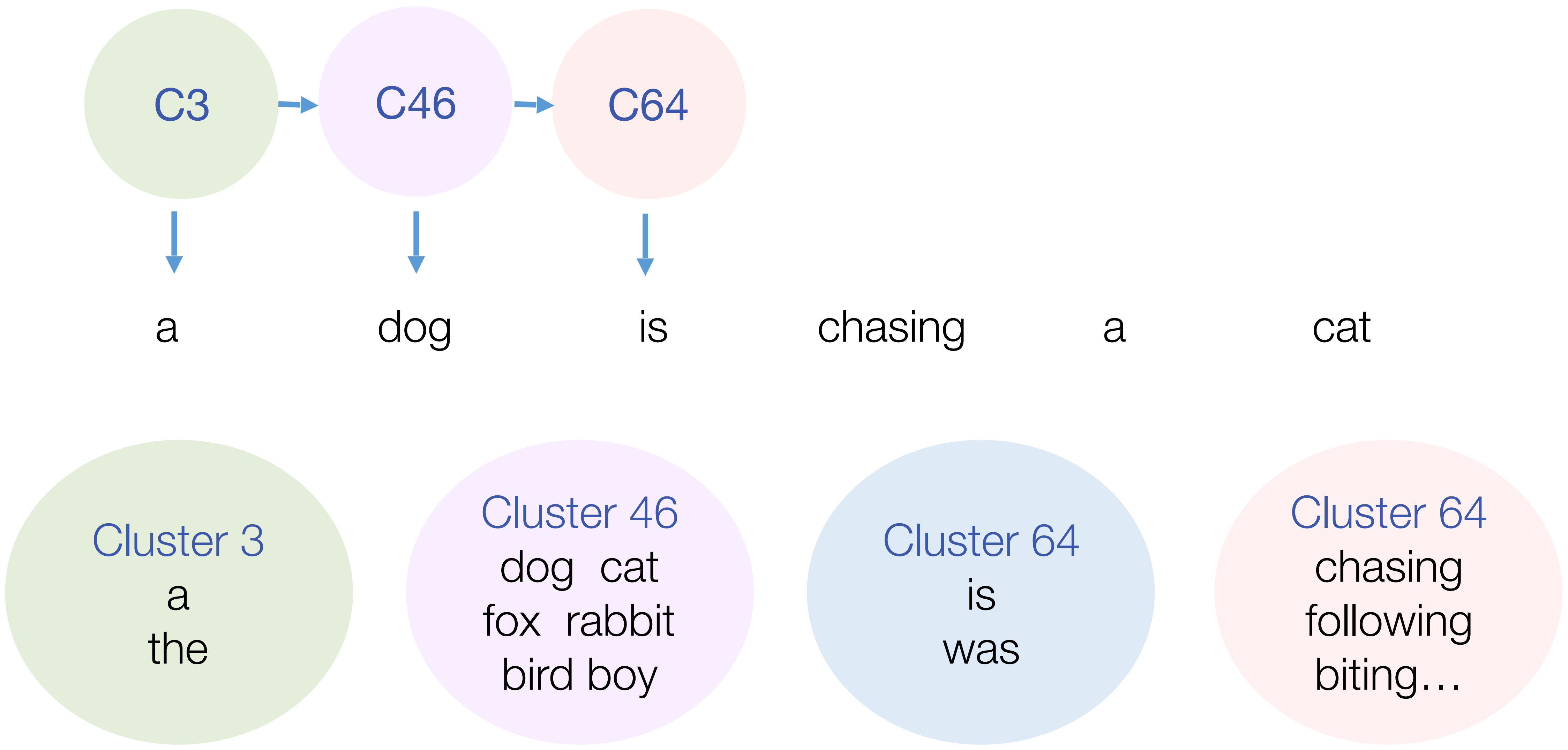

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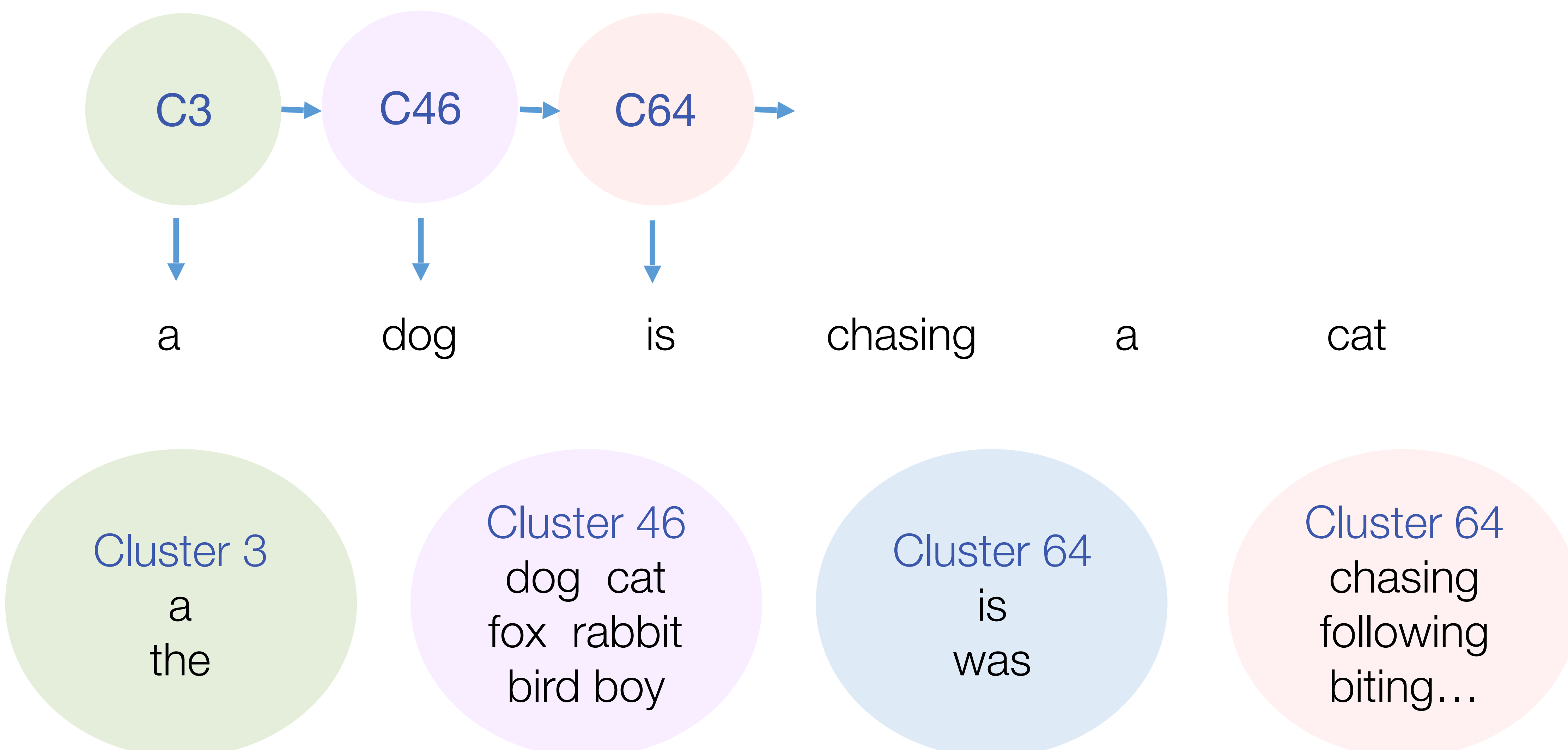

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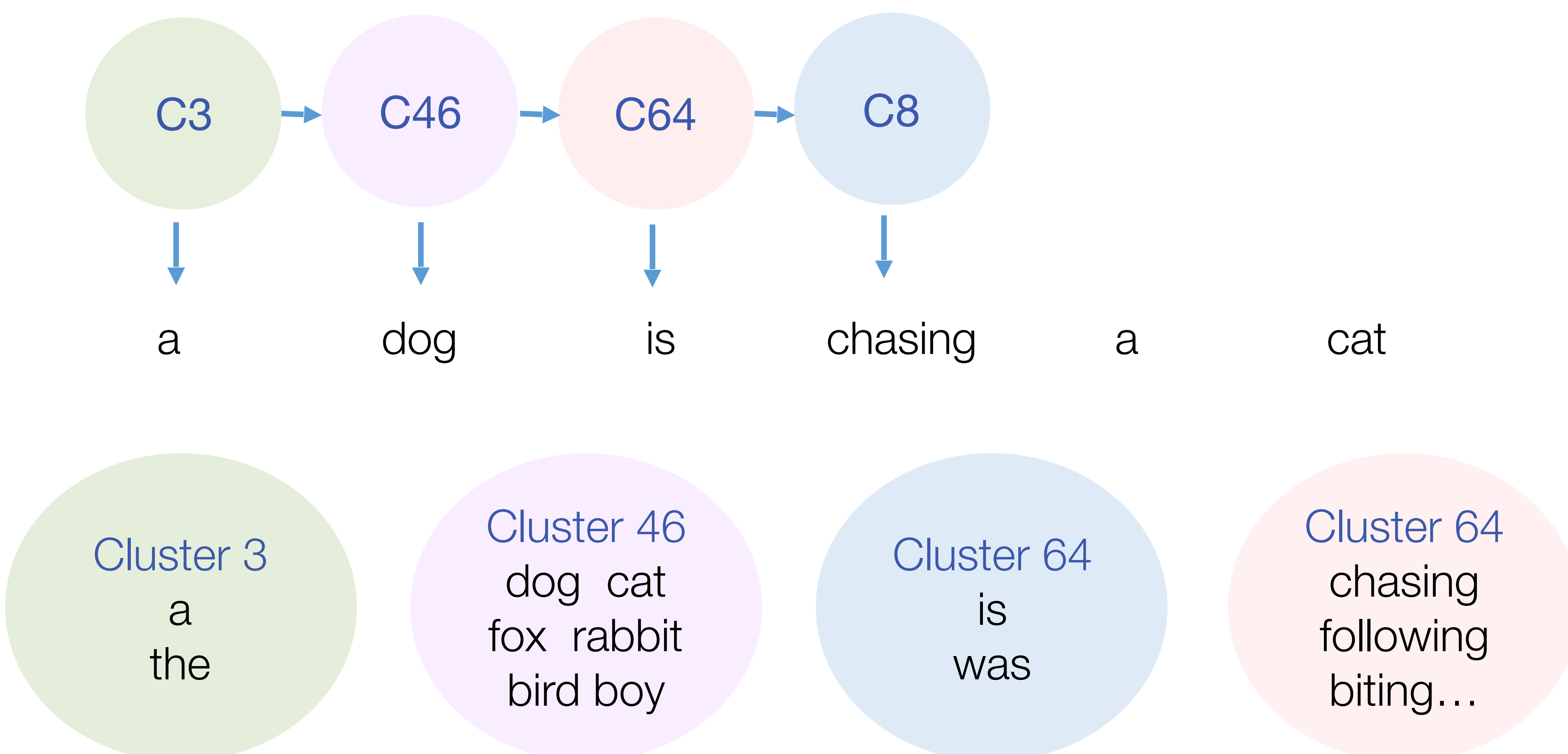

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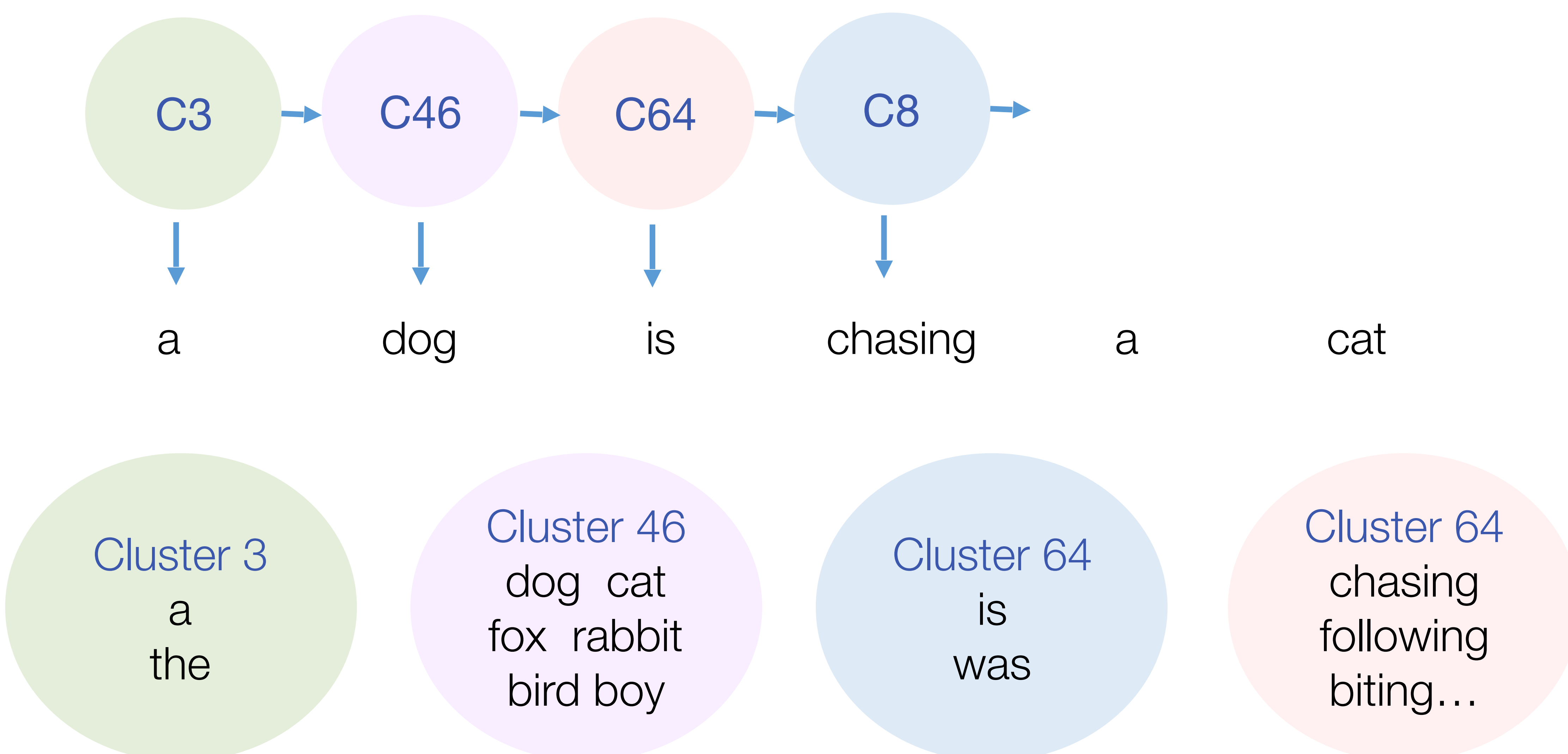

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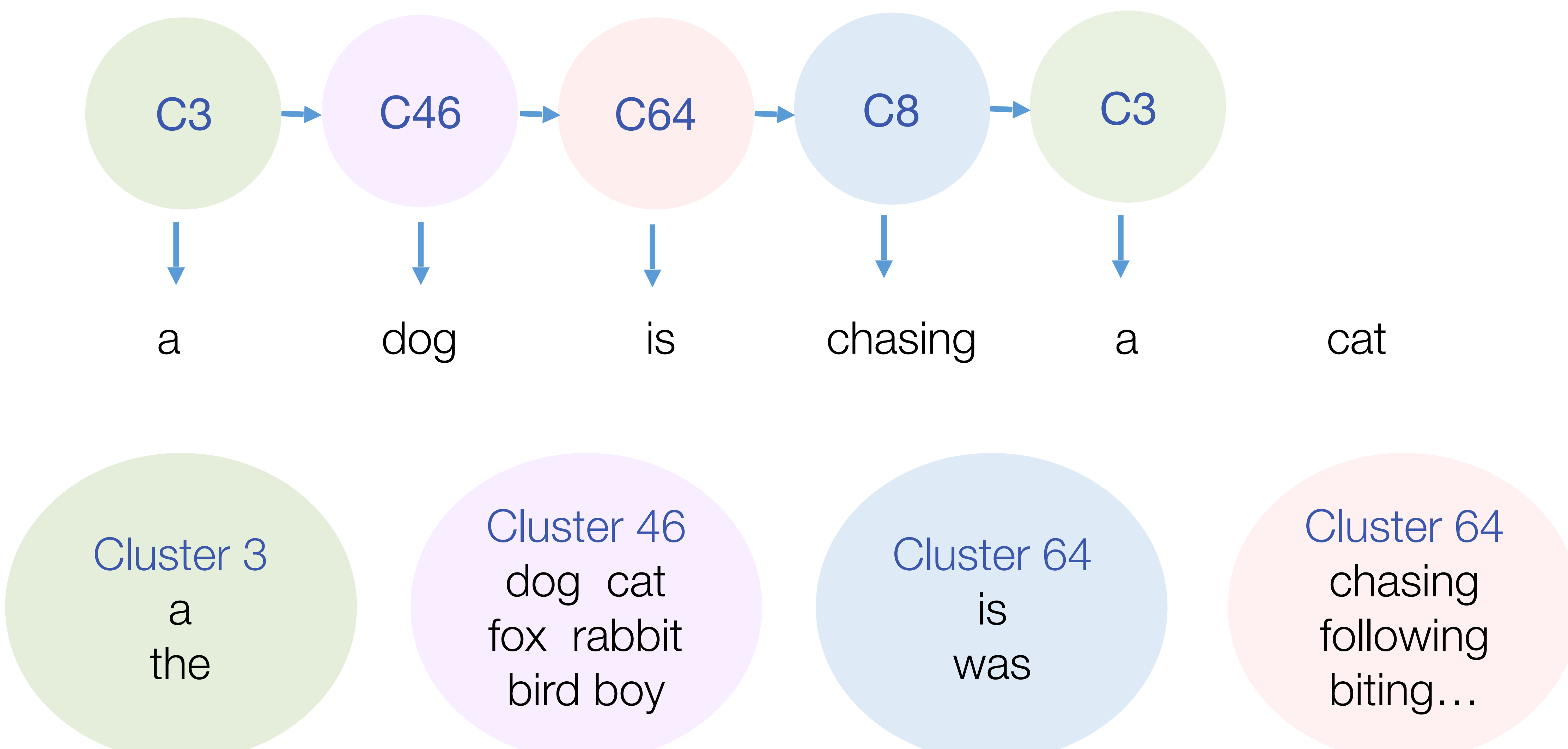

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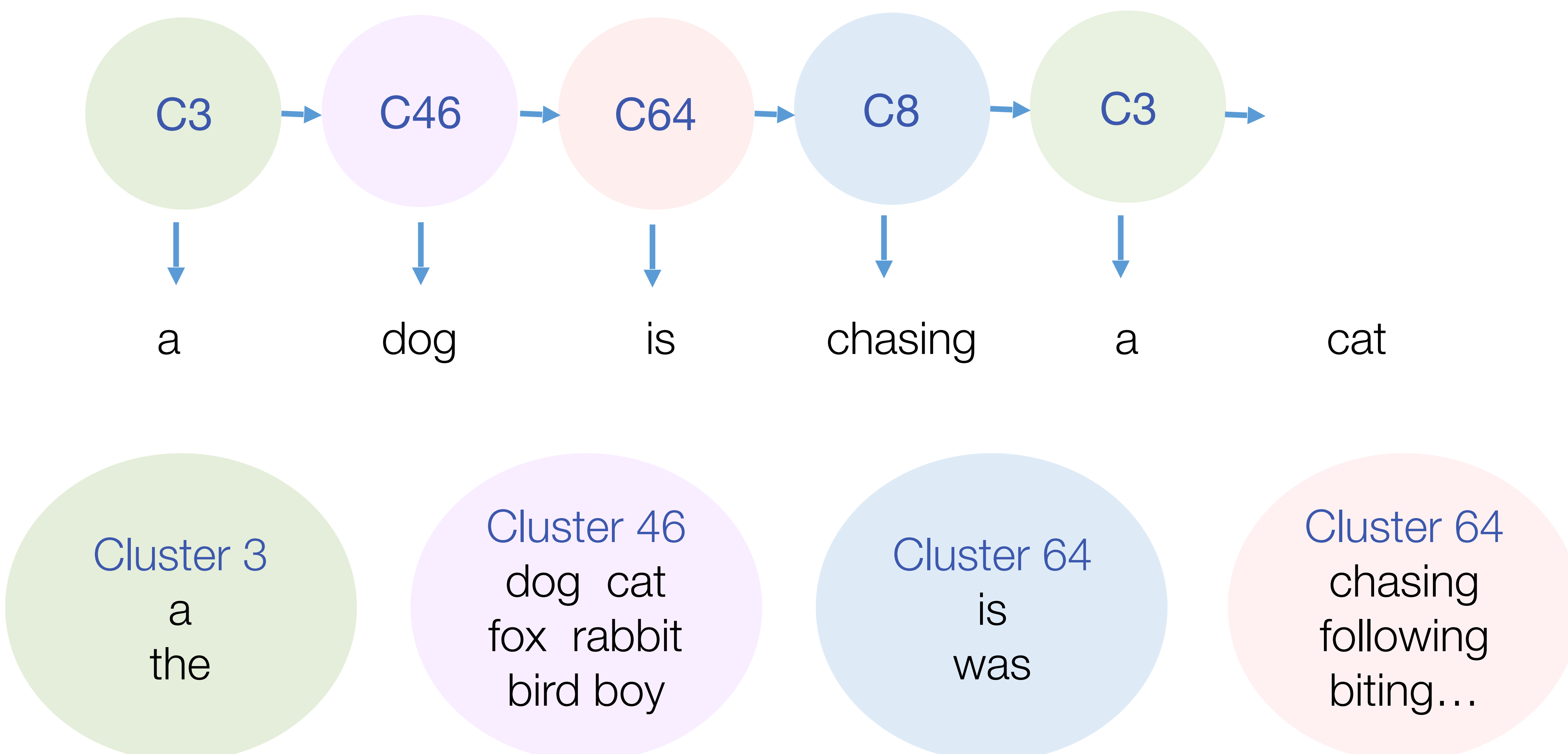

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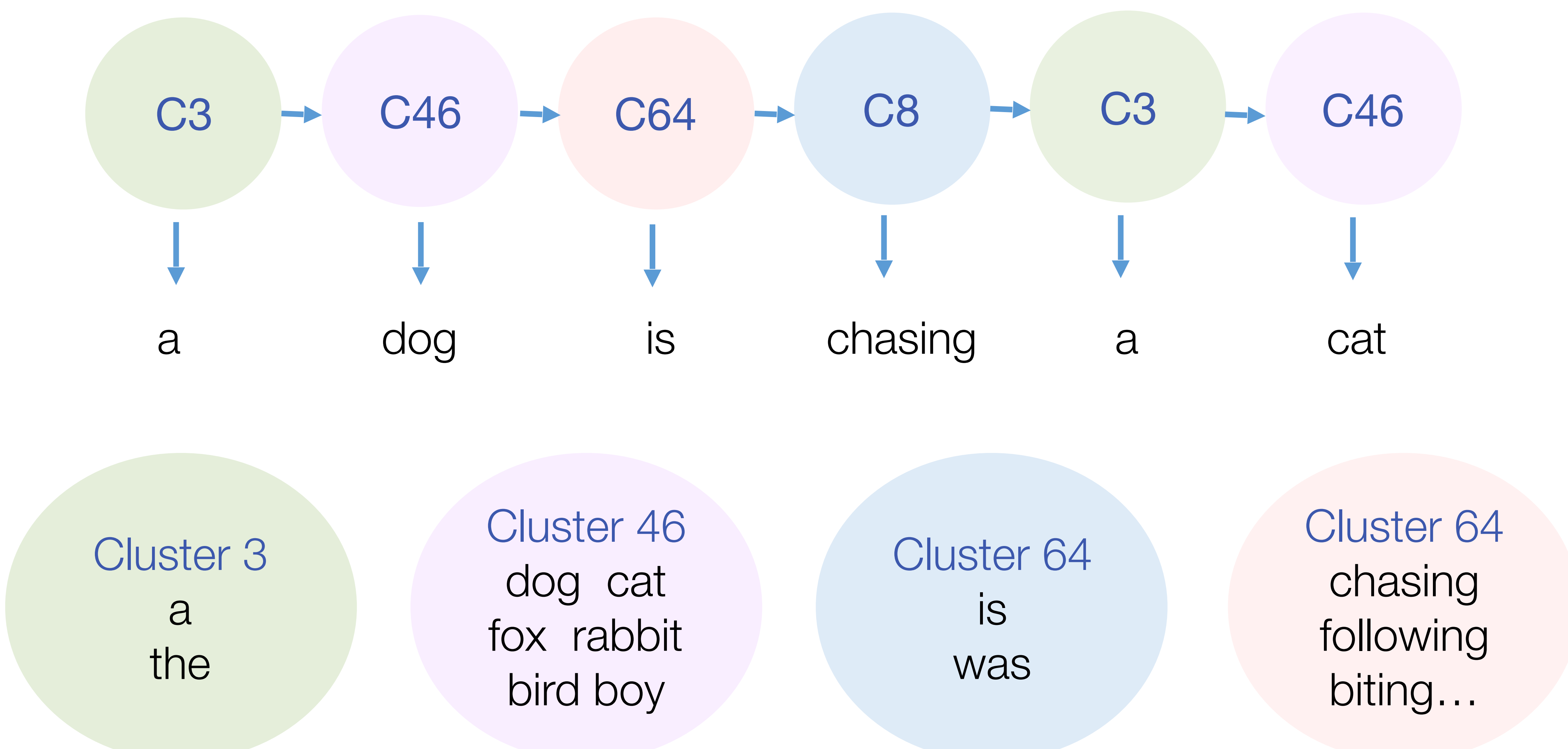

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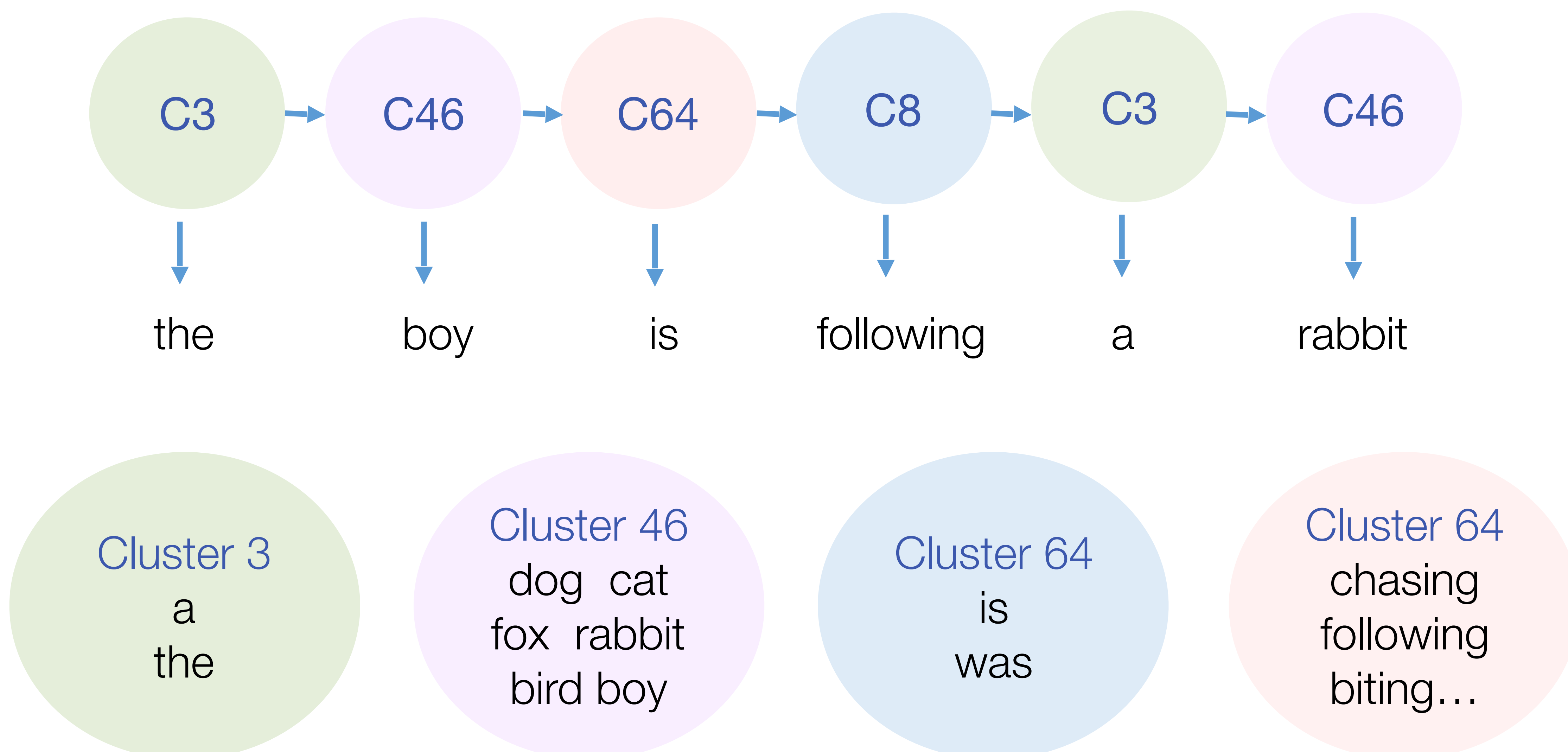

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- Assume every word belongs to a cluster
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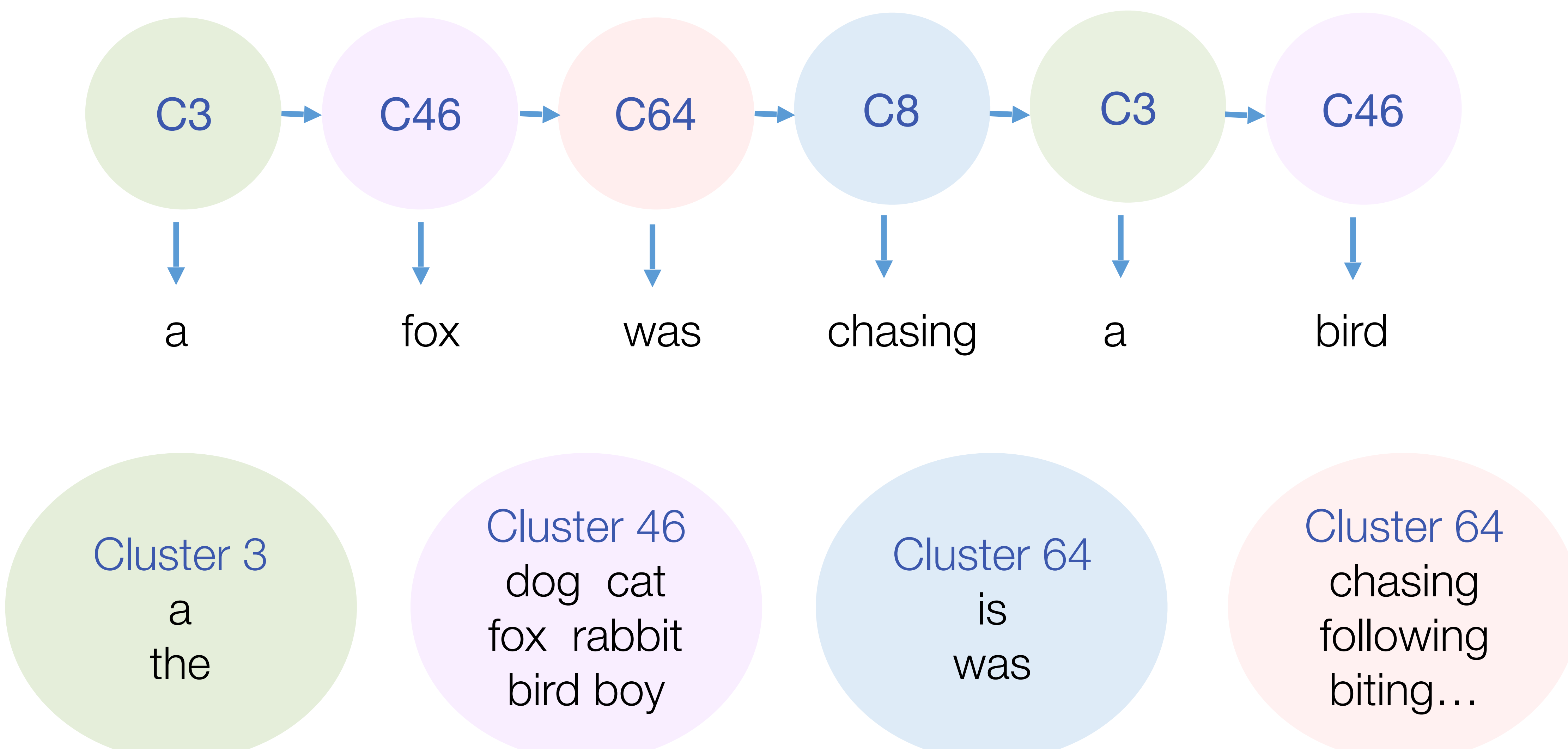

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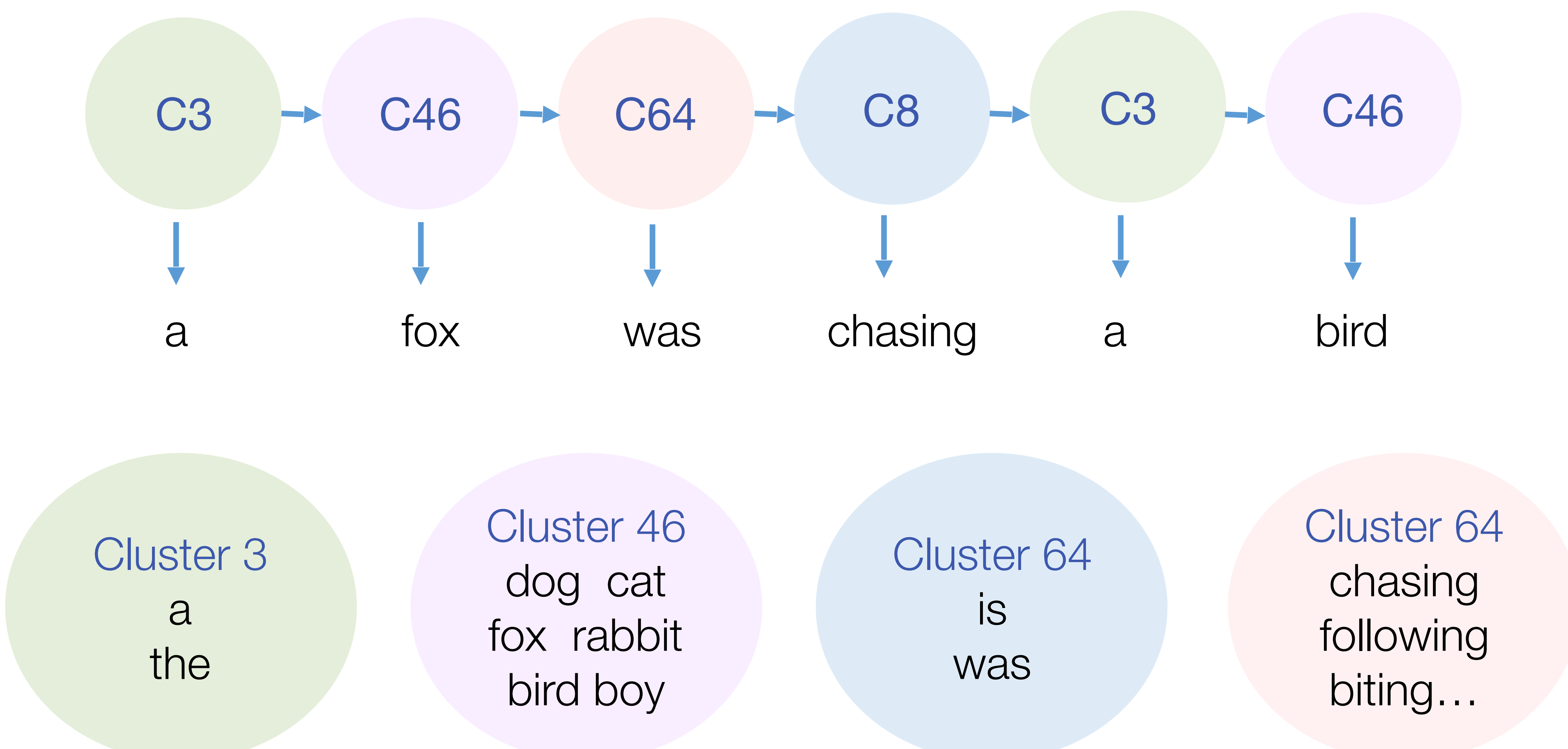

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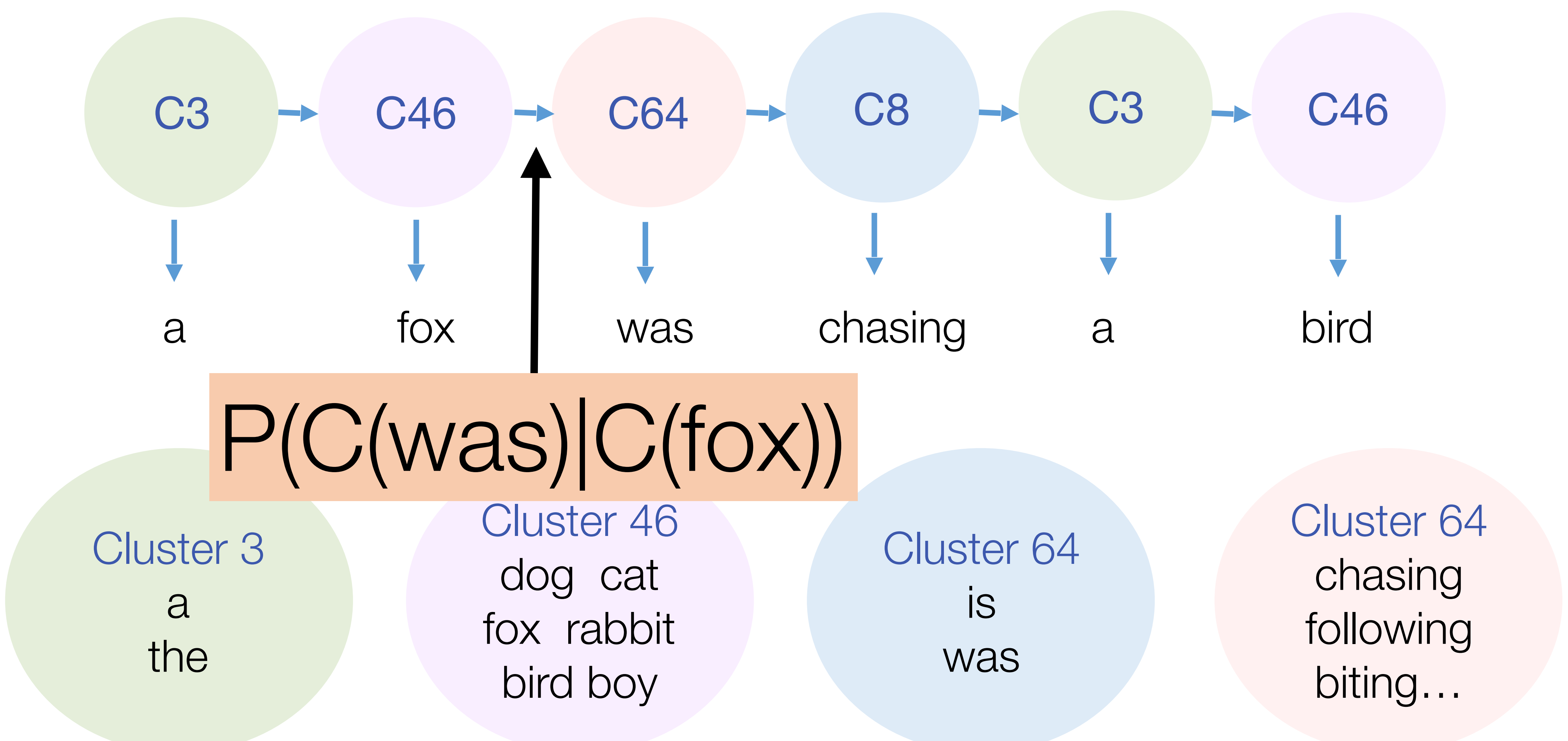

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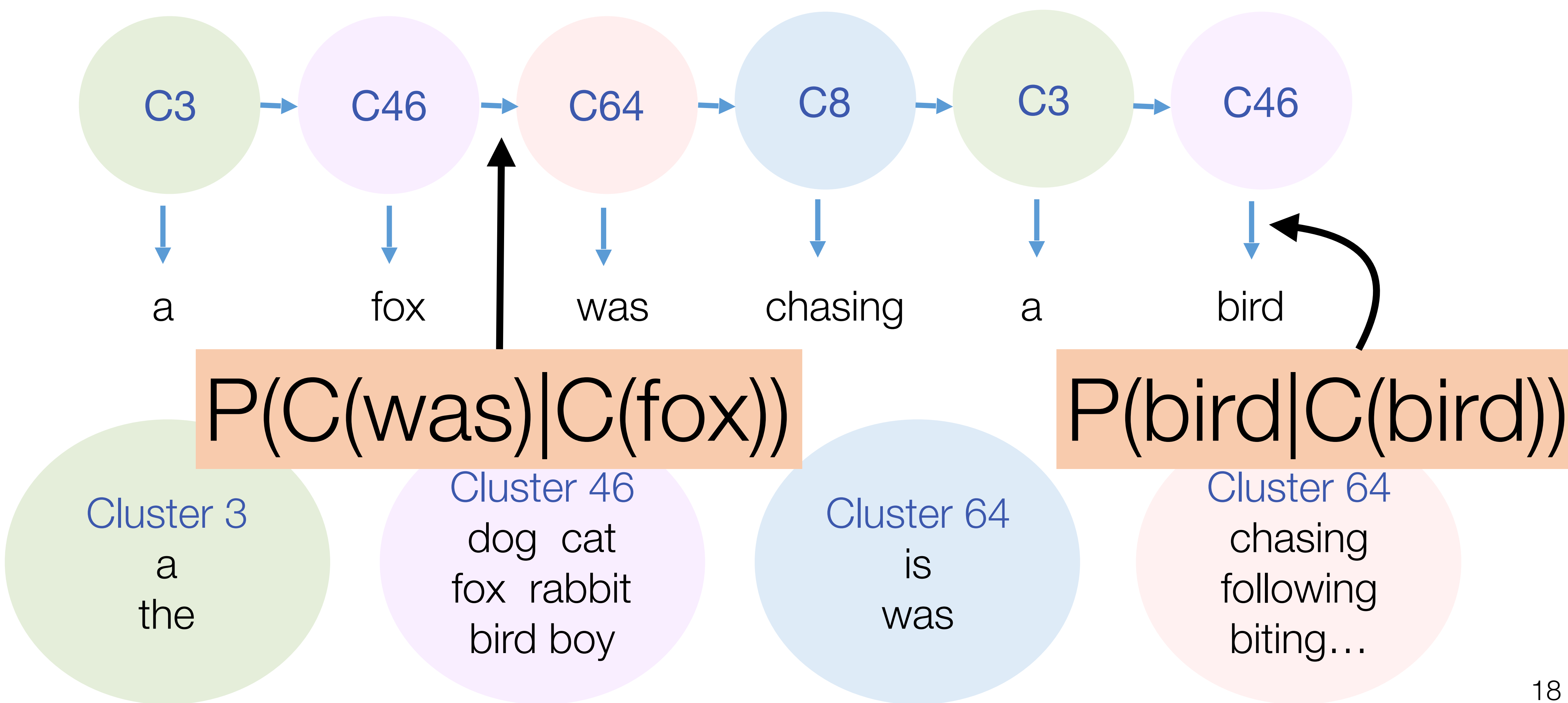
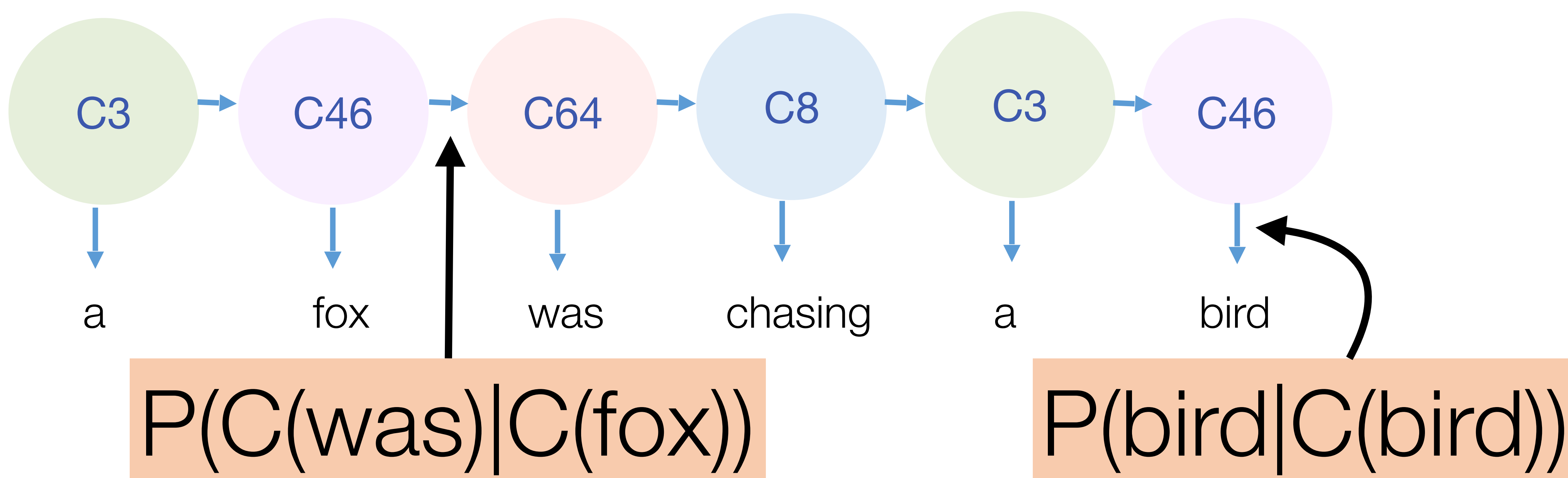


How do we measure the probability of this sequence?

- "a fox was chasing a bird"
- P("a", "dog", …, "cat") =
  - Before: P("a"|START) … P("cat"|"a")
  - Now= P(C3|START) P("a"|C3) P(C46|C3) … P("bird"|C46)



Class-based language model

- Suppose each word was in some class c_i:

$$P(w_i|w_{i-1}) = P(c_i|c_{i-1})P(w_i|c_i)$$

$$P(\text{corpus}|C) = \prod_{i-1}^{n} P(c_i|c_{i-1})P(w_i|c_i)$$

Where do the classes come from?

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- Clustering proceeds until all words are in one big cluster.

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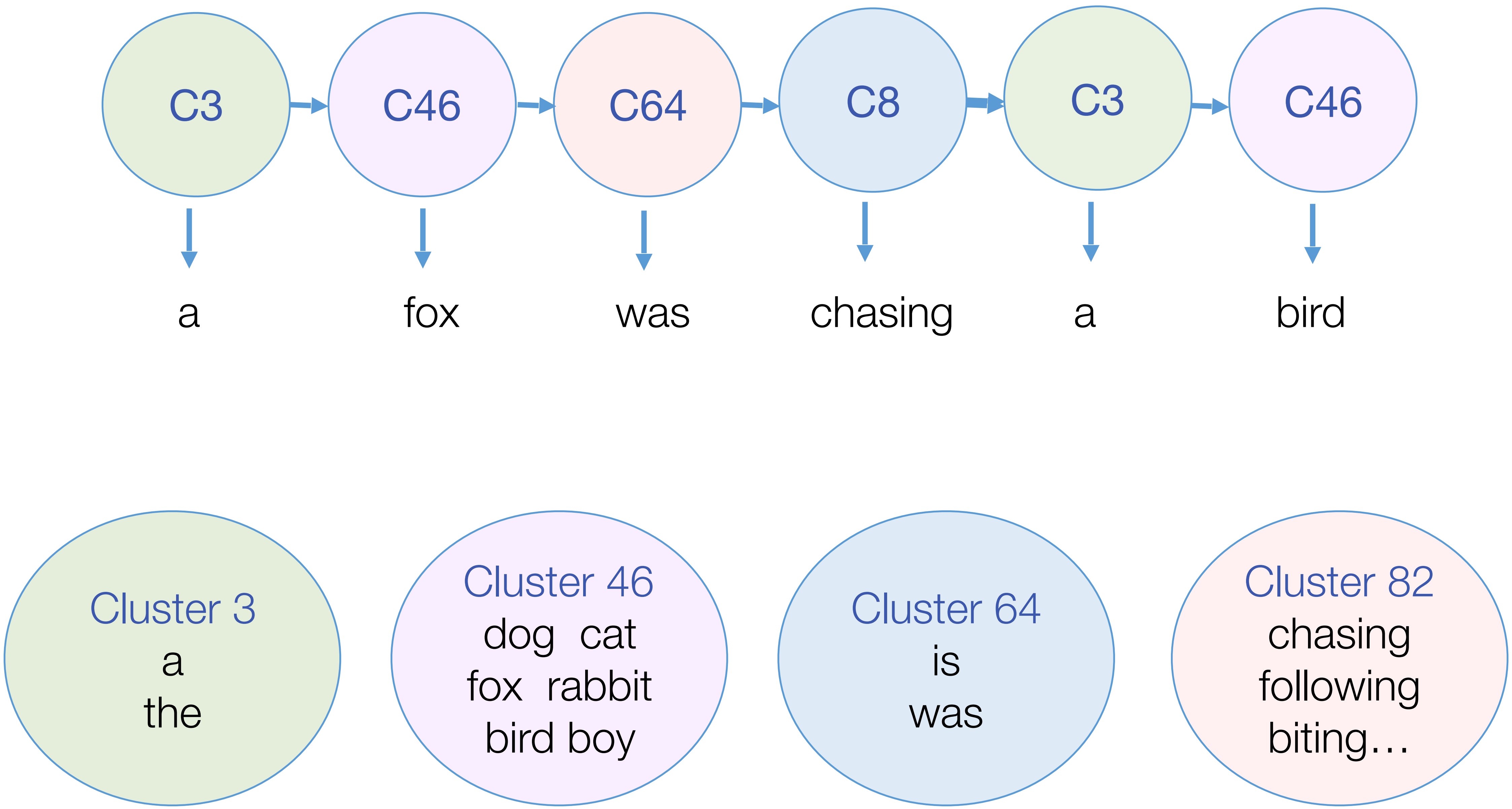

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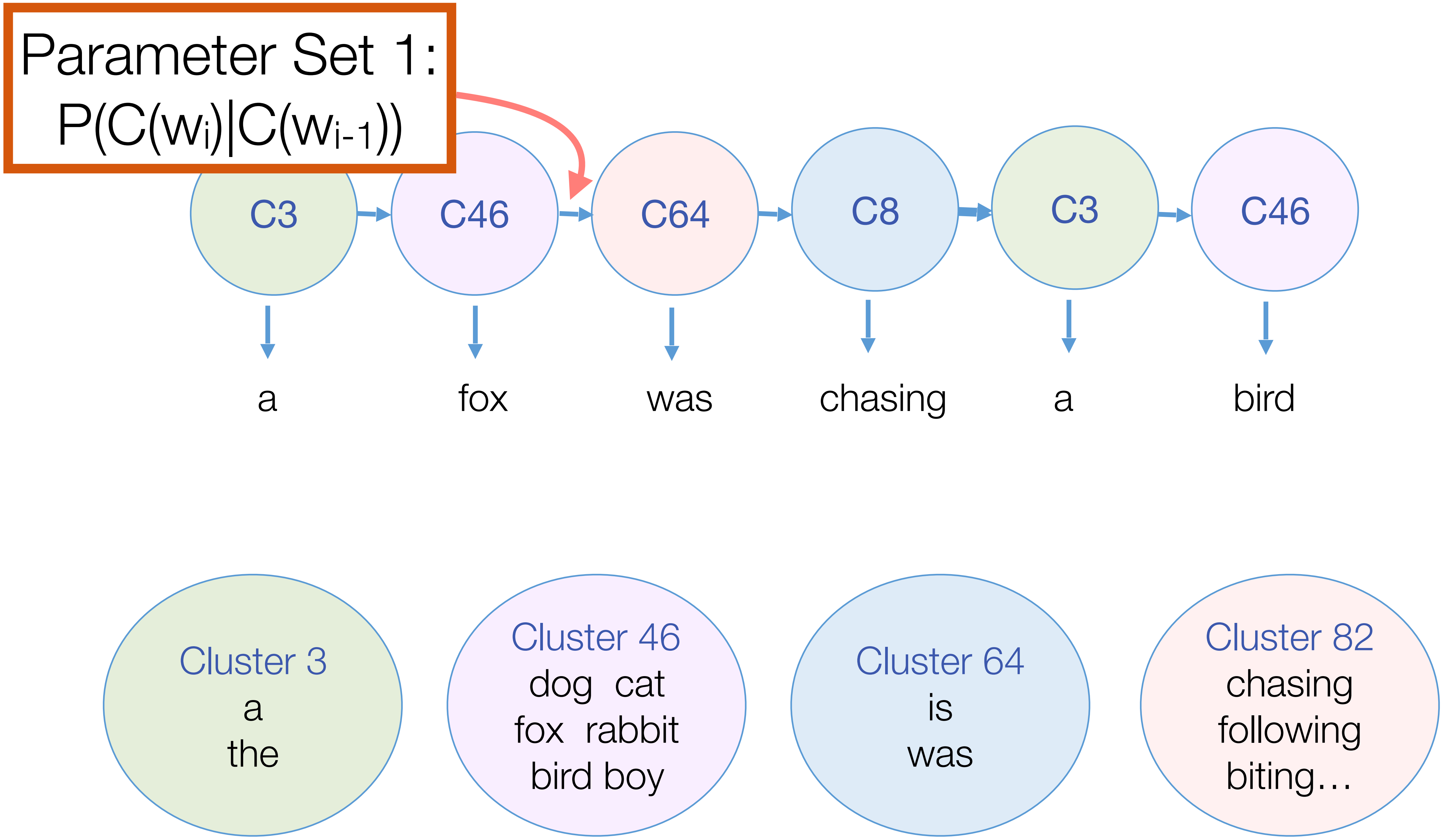

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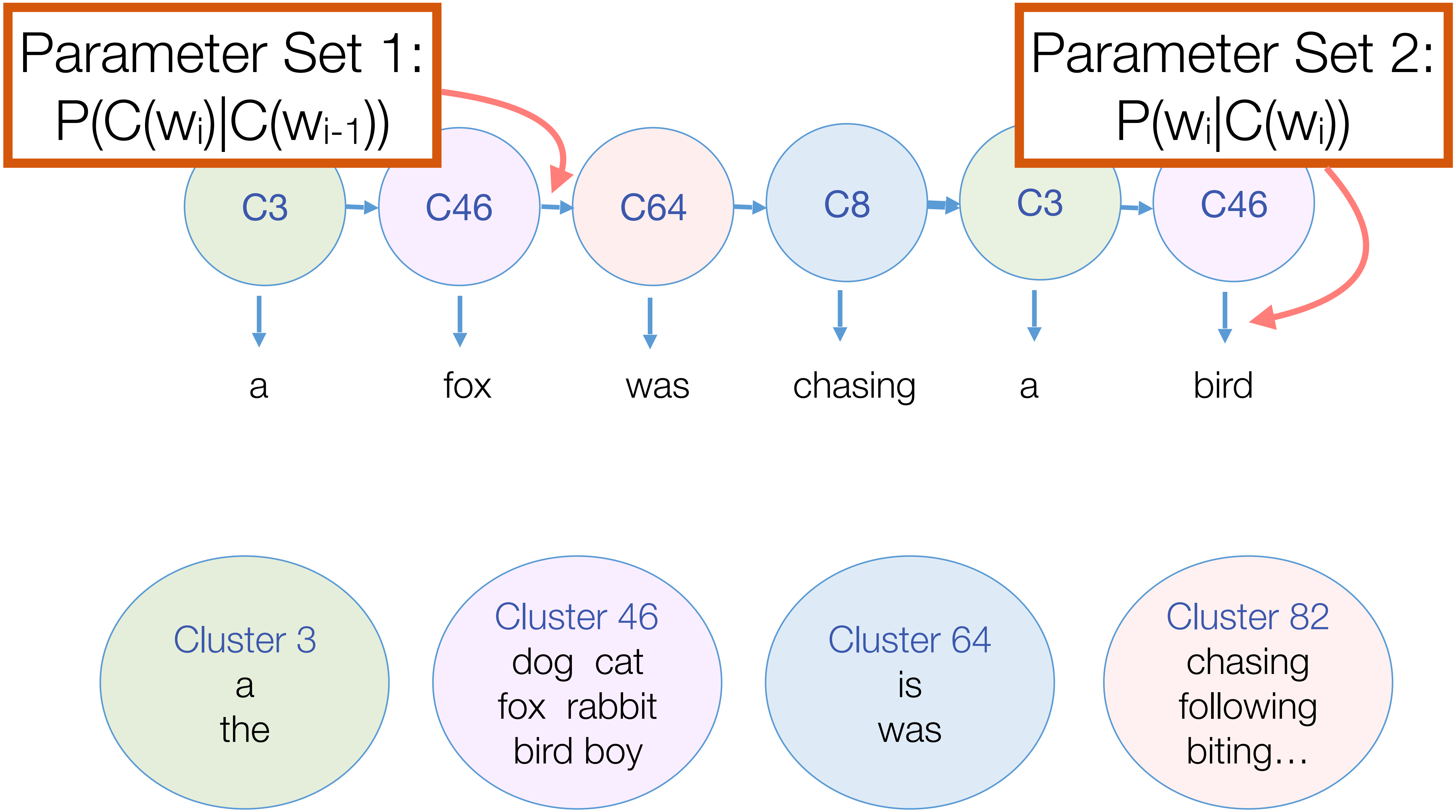

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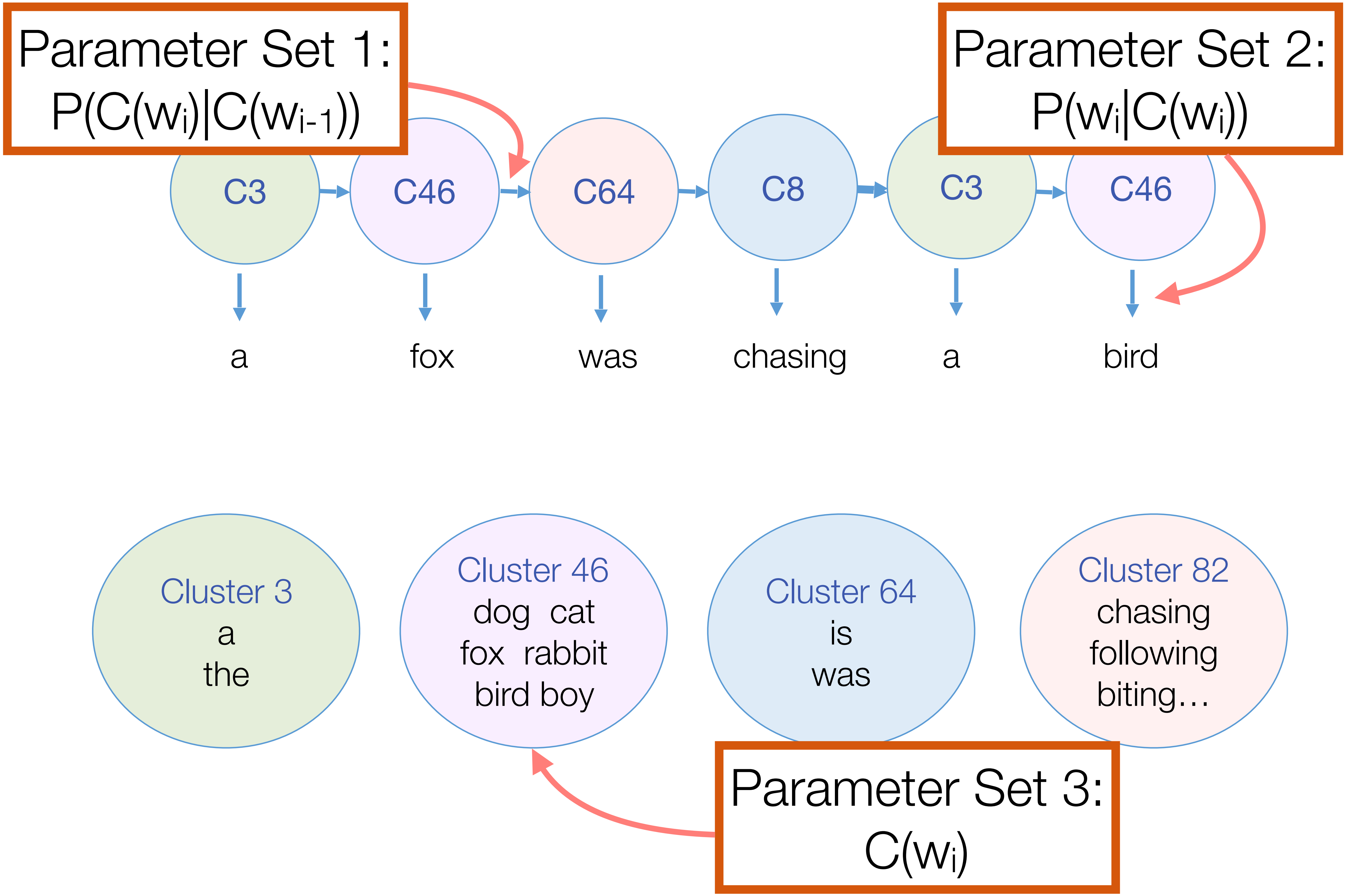

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- Maximizing LL(θ, C) can be done by alternatively updating θ and C
- Maximizing LL(θ, C) is “how much do the current classes and transition probabilities explain the data I see”

Maximizing θ for LL(θ,C)

- Count things!
  - $P(C_i|C_{i-i}) = (\#(C_{i-1},C_i)) / (\#C_i)$
  - $P(w|C) = (\#(w,C)) / (\#C)$

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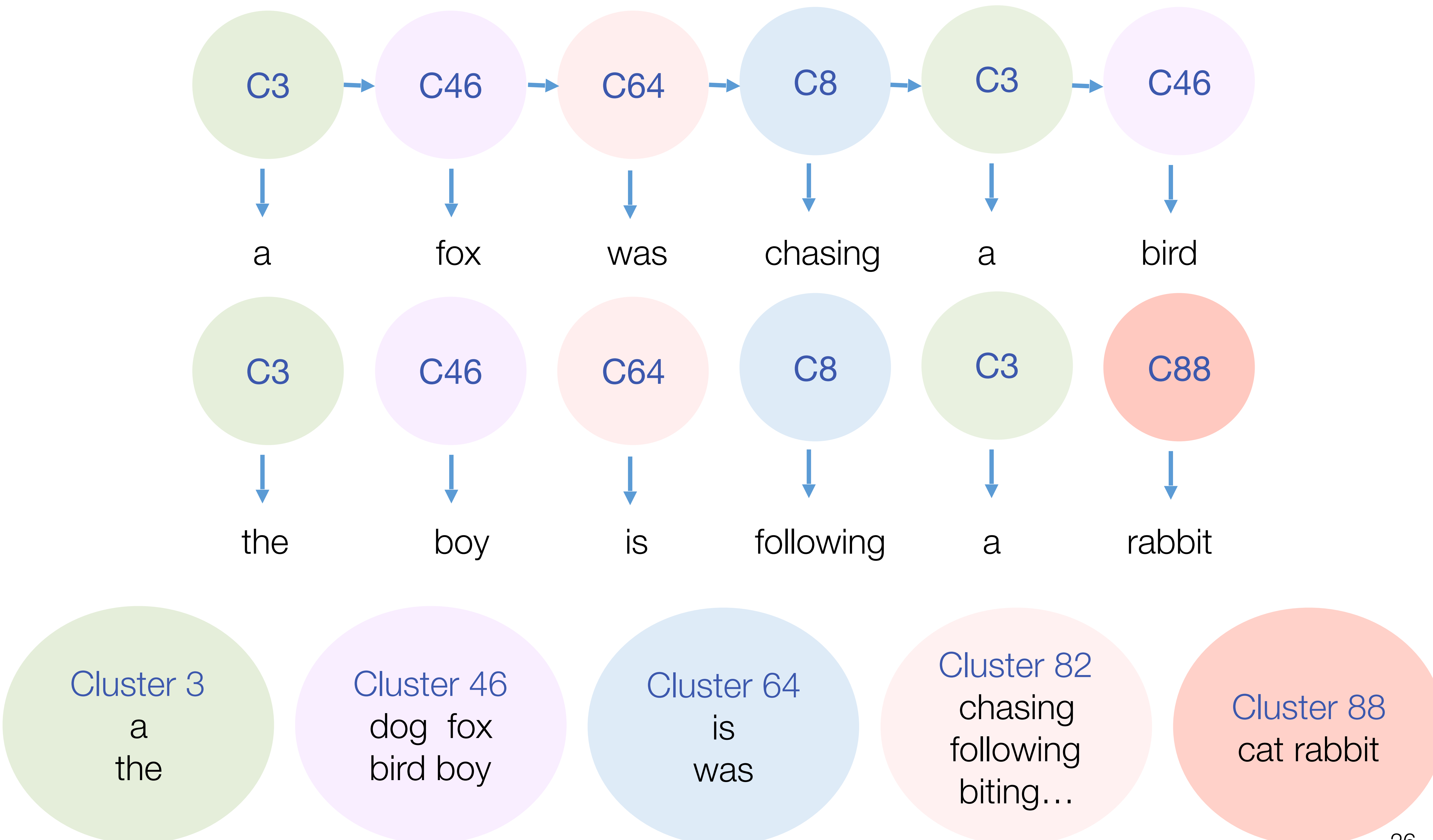

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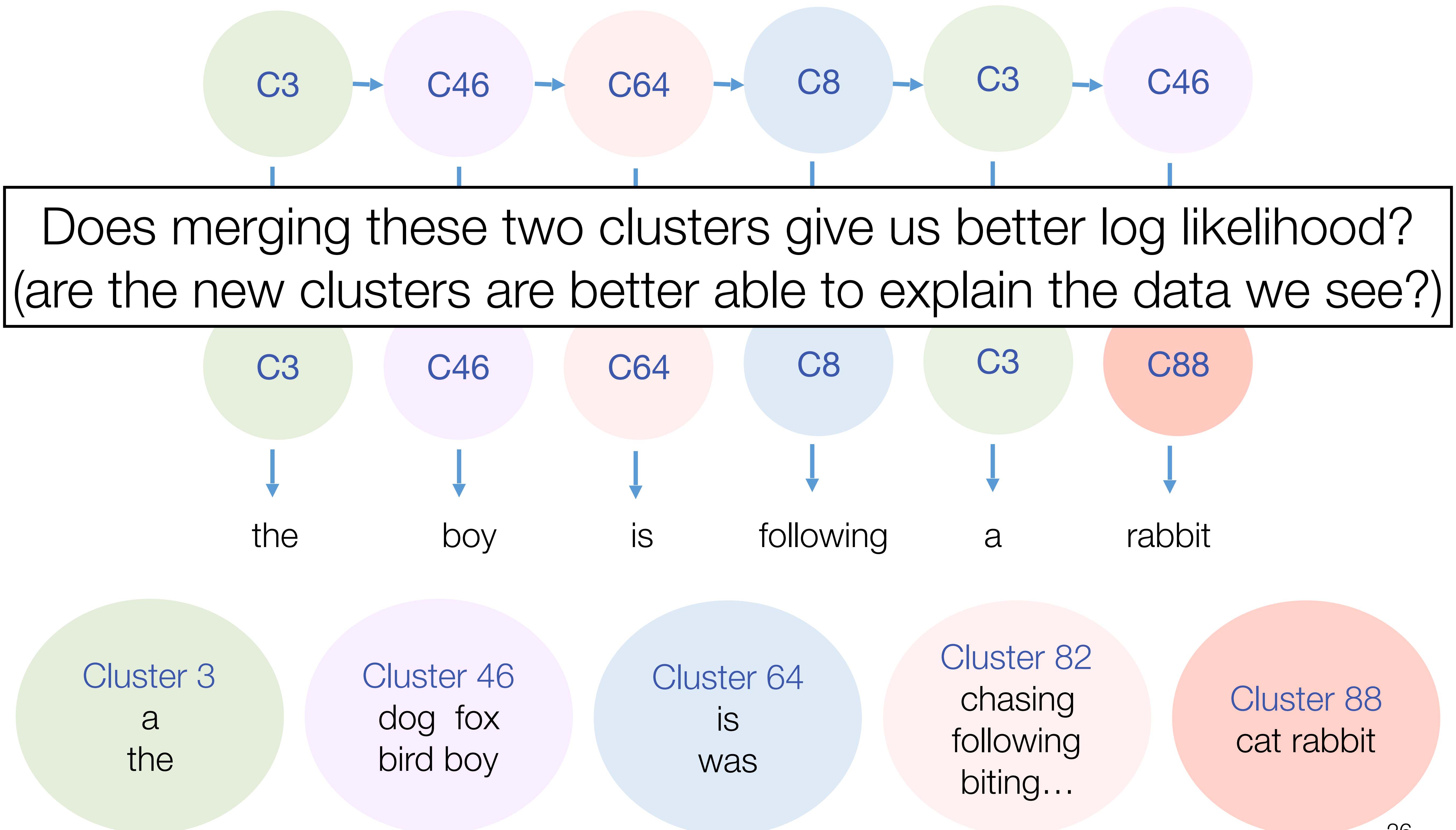

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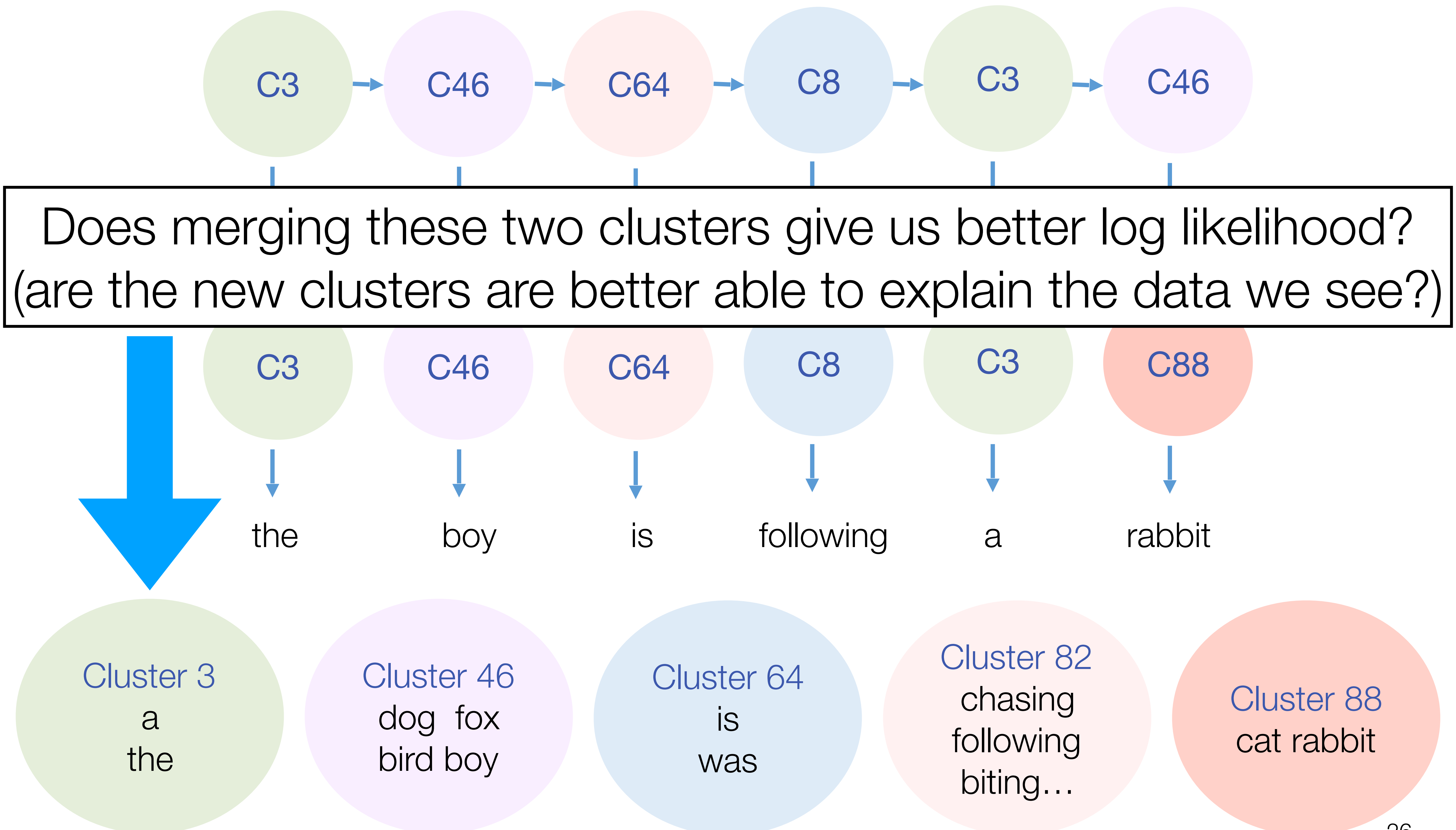

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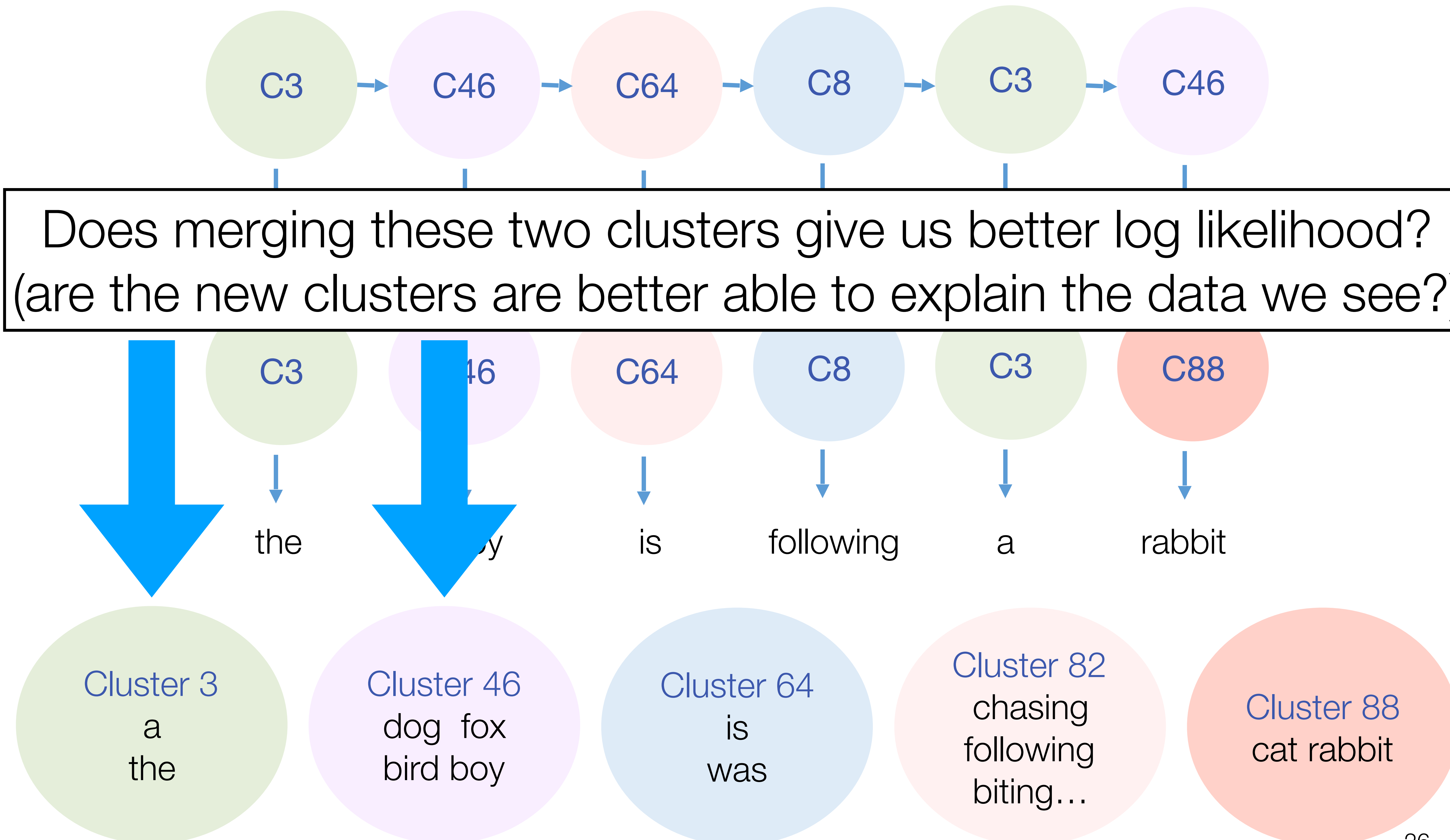

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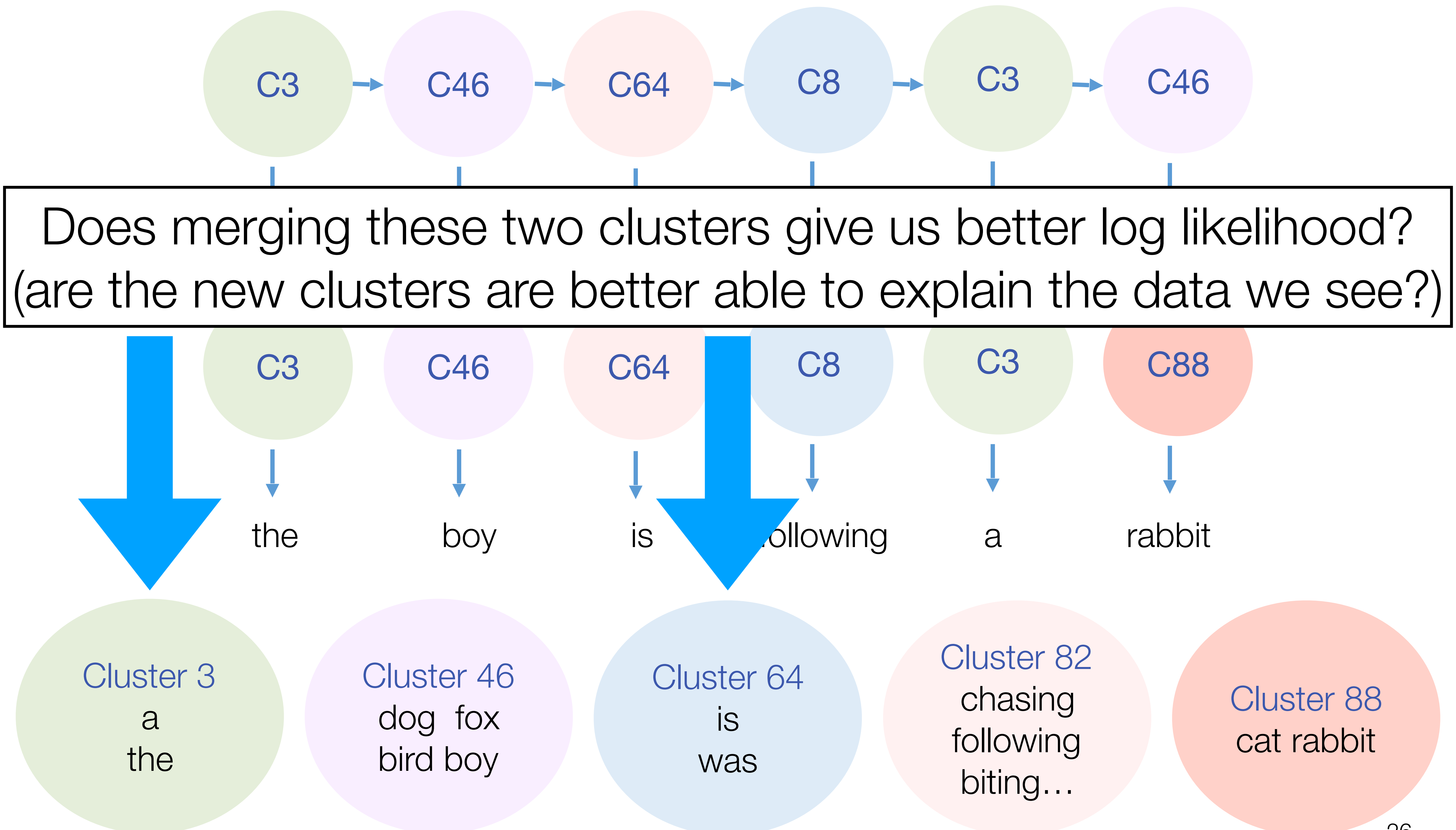

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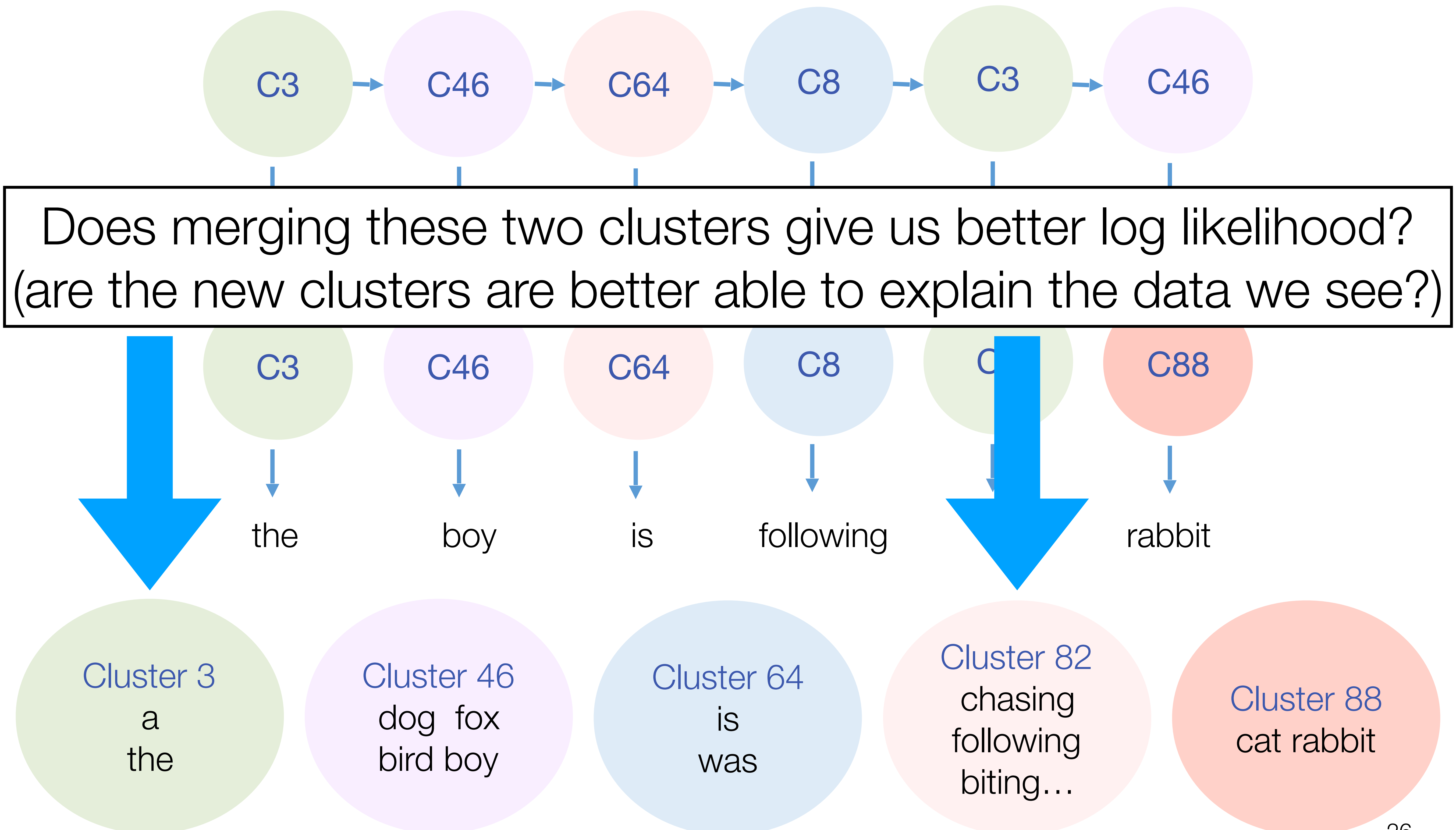

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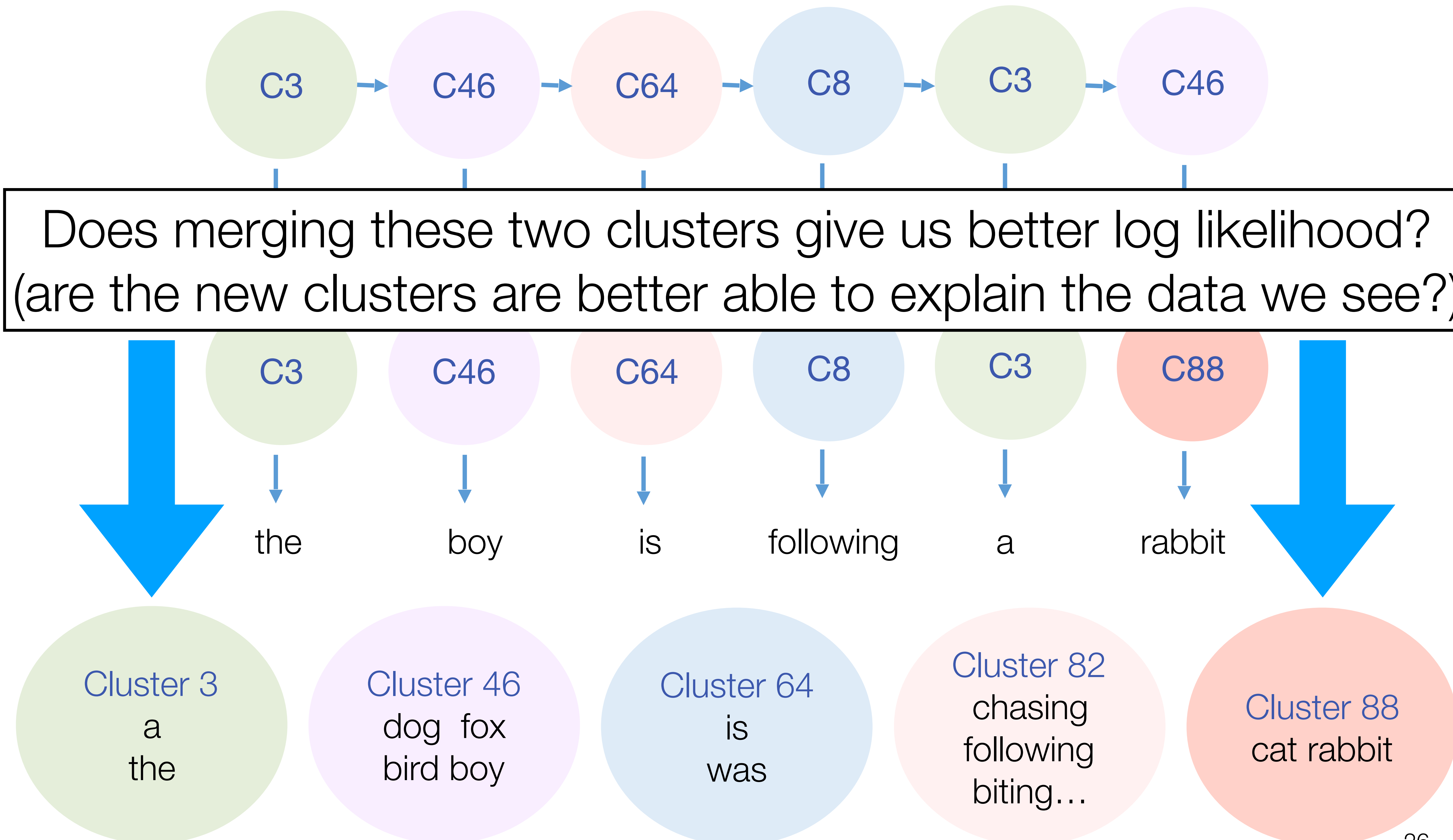

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  - (Can be improved to $O(|V|^3)$)

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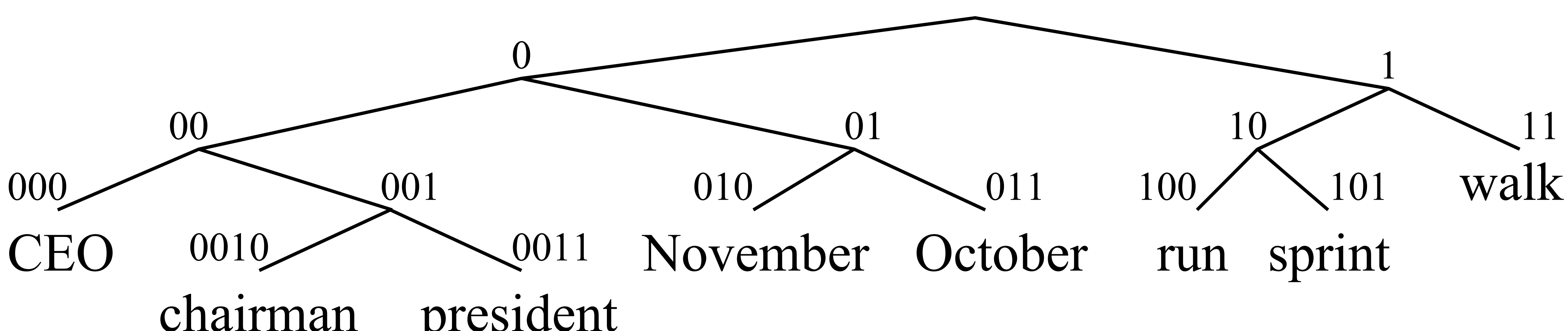
- Carry out *m*-1 final merges to get a full hierarchy
- Cost? $O(|V|m^2 + n)$ where *n* is the # of words in corpus

Brown Clusters as vectors

- By tracing the order in which clusters are merged, the model builds a binary tree from bottom to top.
- Each word represented by binary string = path from root to leaf
- Each intermediate node is a cluster
- Chairman is 0010, “months” = 01, and verbs = 1



Brown cluster examples

Friday Monday Thursday Wednesday Tuesday Saturday Sunday weekends Sundays Saturdays
June March July April January December October November September August
pressure temperature permeability density porosity stress velocity viscosity gravity tension
anyone someone anybody somebody
had hadn't hath would've could've should've must've might've
asking telling wondering instructing informing kidding reminding bothering thanking deposing
mother wife father son husband brother daughter sister boss uncle
great big vast sudden mere sheer gigantic lifelong scant colossal
down backwards ashore sideways southward northward overboard aloft downwards adrift

Example clusters

Friday Monday Thursday Wednesday Tuesday Saturday Sunday weekends Sundays Saturdays
June March July April January December October November September August
people guys folks fellows CEOs chaps doubters commies unfortunates blokes
down backwards ashore sideways southward northward overboard aloft downwards adrift
water gas coal liquid acid sand carbon steam shale iron
great big vast sudden mere sheer gigantic lifelong scant colossal
man woman boy girl lawyer doctor guy farmer teacher citizen
American Indian European Japanese German African Catholic Israeli Italian Arab
pressure temperature permeability density porosity stress velocity viscosity gravity tension
mother wife father son husband brother daughter sister boss uncle
machine device controller processor CPU printer spindle subsystem compiler plotter
John George James Bob Robert Paul William Jim David Mike
anyone someone anybody somebody
feet miles pounds degrees inches barrels tons acres meters bytes
director chief professor commissioner commander treasurer founder superintendent dean custodian
liberal conservative parliamentary royal progressive Tory provisional separatist federalist PQ
had hadn't hath would've could've should've must've might've
asking telling wondering instructing informing kidding reminding bothering thanking deposing
that tha theat
head body hands eyes voice arm seat eye hair mouth

Brown (1992)

Example Hierarchy

lawyer	1000001101000
newspaperman	100000110100100
stewardess	100000110100101
toxicologist	10000011010011
slang	1000001101010
babysitter	100000110101100
conspirator	1000001101011010
womanizer	1000001101011011
mailman	10000011010111
salesman	100000110110000
bookkeeper	1000001101100010
troubleshooter	10000011011000110
bouncer	10000011011000111
technician	1000001101100100
janitor	1000001101100101
saleswoman	1000001101100110
...	
Nike	1011011100100101011100
Maytag	10110111001001010111010
Generali	10110111001001010111011
Gap	1011011100100101011110
Harley-Davidson	10110111001001010111110
Enfield	101101110010010101111110
genus	101101110010010101111111
Microsoft	10110111001001011000
Ventritex	101101110010010110010
Tractebel	1011011100100101100110
Synopsys	1011011100100101100111
WordPerfect	1011011100100101101000
....	
John	10111001000000000
Consuelo	10111001000000001
Jeffrey	10111001000000010
Kenneth	1011100100000001100
Phillip	10111001000000011010
WILLIAM	10111001000000011011
Timothy	1011100100000001110
Terrence	10111001000000011110
Jerald	10111001000000011111
Harold	10111001000000100
Frederic	10111001000000101
Wendell	1011100100000011

from Miller (2004)

Works really well in social people, especially with lots of spelling variation

Cluster ID	Constituent word types
00111001	can cn cann caan cannn ckan shalll ccan caaan cannnn caaaan
001011111001	ii id ion iv ll iii ud wd uma ul idnt provoking hed 1+1 ididnt hast ine 2+2 idw #thingsblackpeopledo iiii #onlywhitepeople dost doan uon apt-get
01111010111110	hoping wishing considering wishin contemplating dreading regretting hopin hopeing considerin suspecting regreting wishn comtemplating hopen

from Derczynski and Chester (2015)

K-Means Clustering

What is Clustering?

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- Cluster: a collection of data objects
  - Similar to one another within the same cluster
  - Dissimilar to the objects in other clusters

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  - no predefined classes

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- Cluster: a collection of data objects
  - Similar to one another within the same cluster
  - Dissimilar to the objects in other clusters

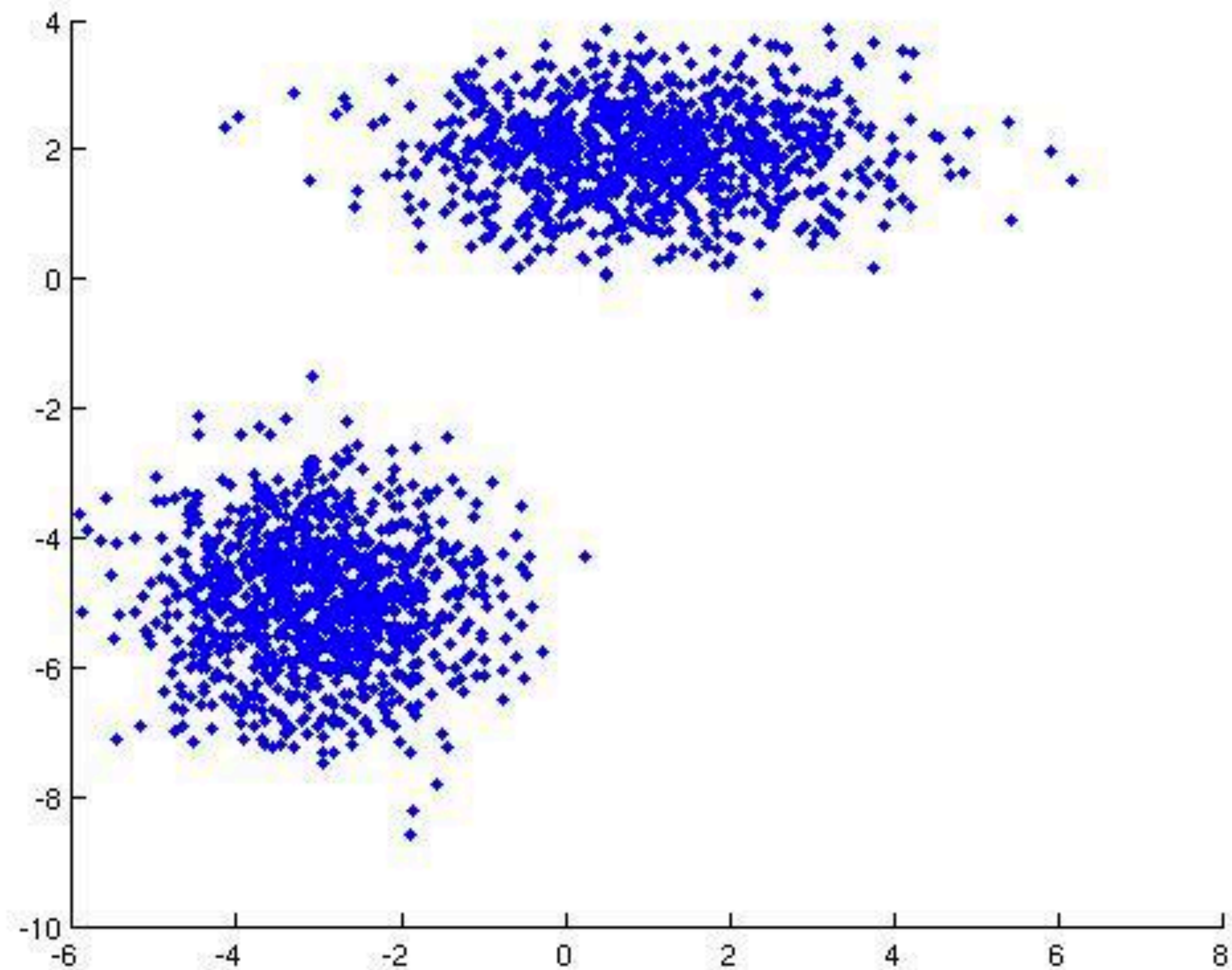
- Clustering is unsupervised classification:
  - no predefined classes

- Typical applications
  - As a stand-alone tool to get insight into data distribution
  - As a preprocessing step for other NLP algorithms

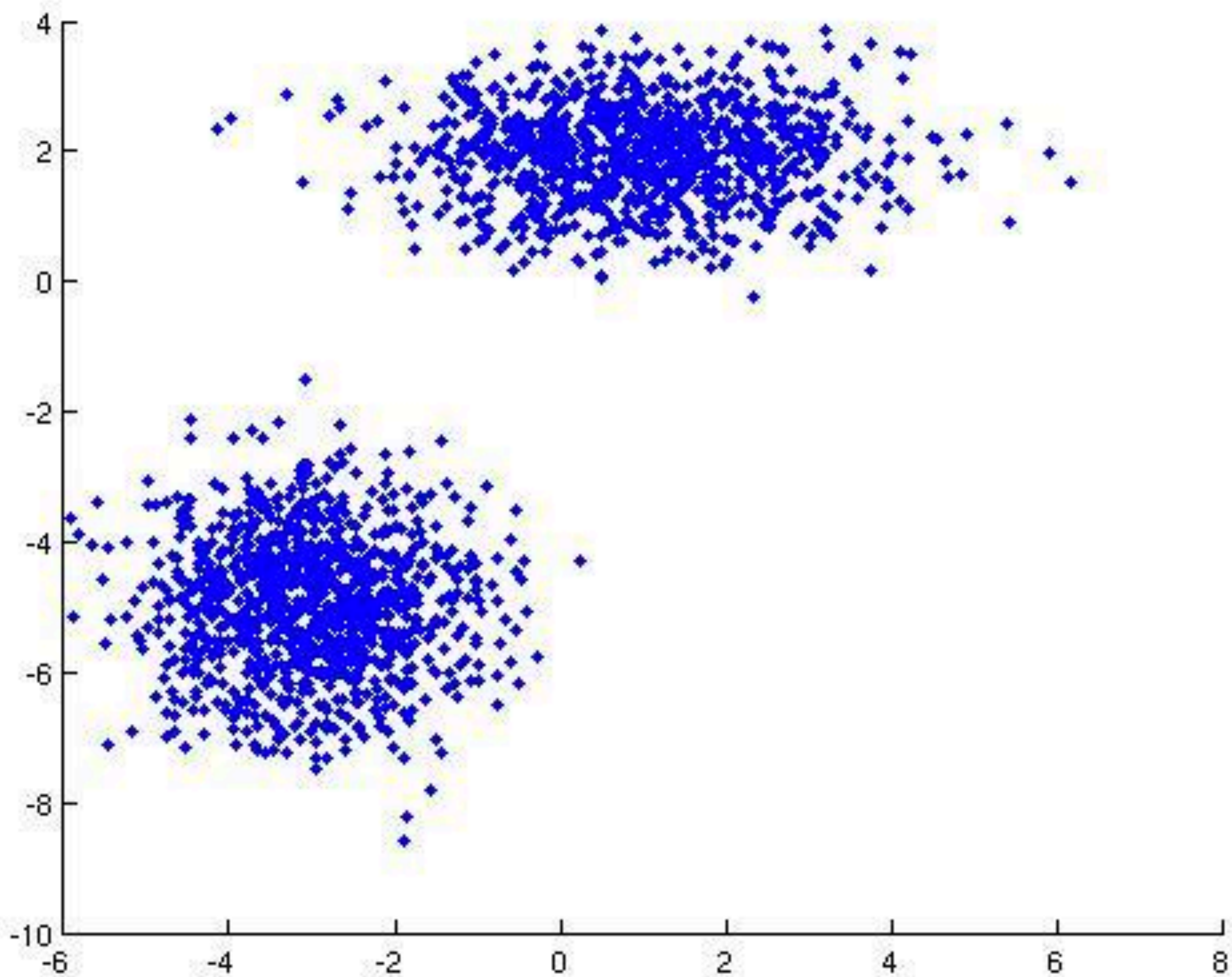
Clustering in NLP

- Most linguistic items can be represented as vectors, e.g., your word2vec vectors
- We compare linguistic items using similarity metrics — often cosine similarity
- This lets us apply standard clustering methods to text
    - but we often visualize algorithms in 2D as points

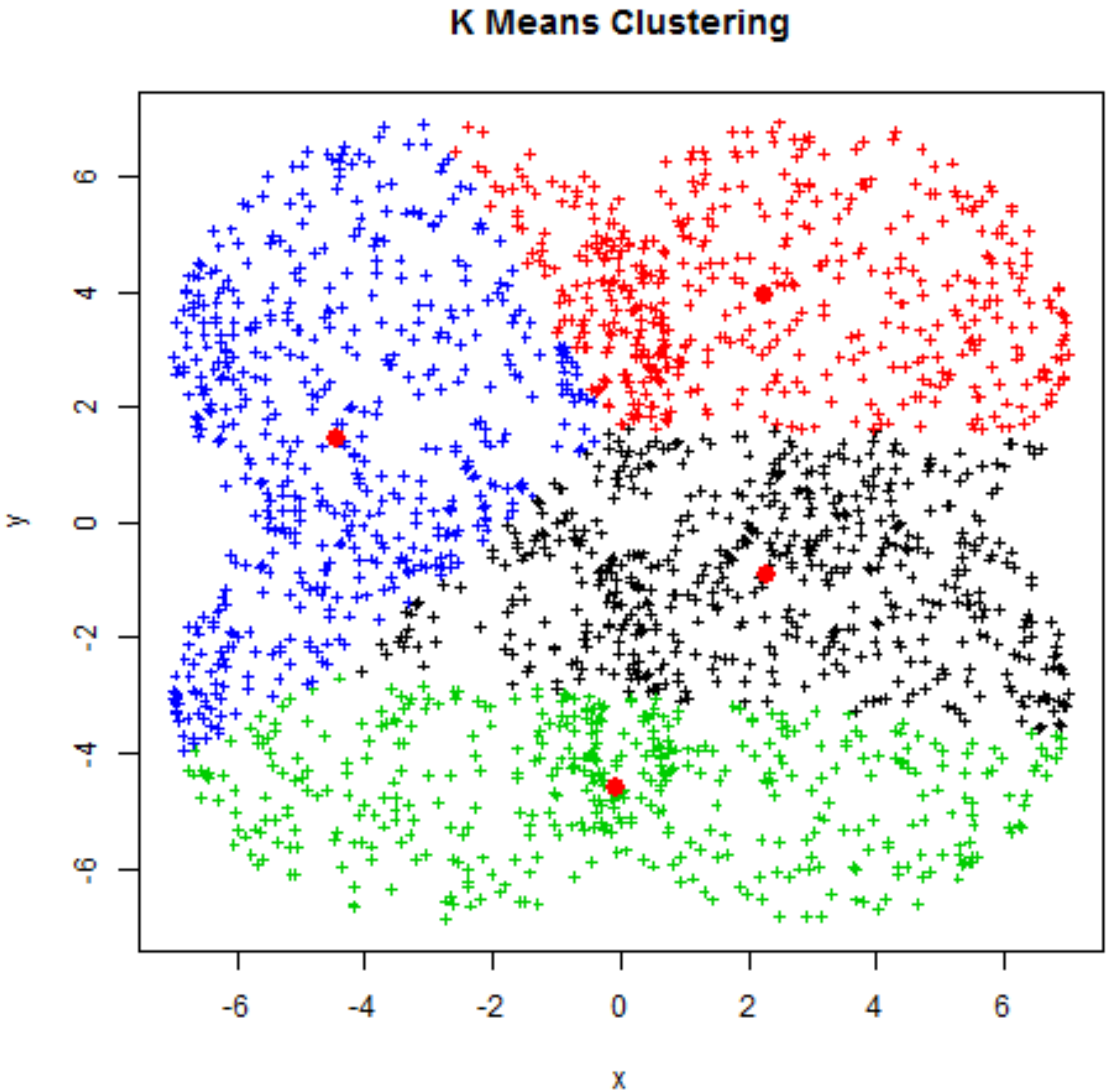
How many clusters are there here?



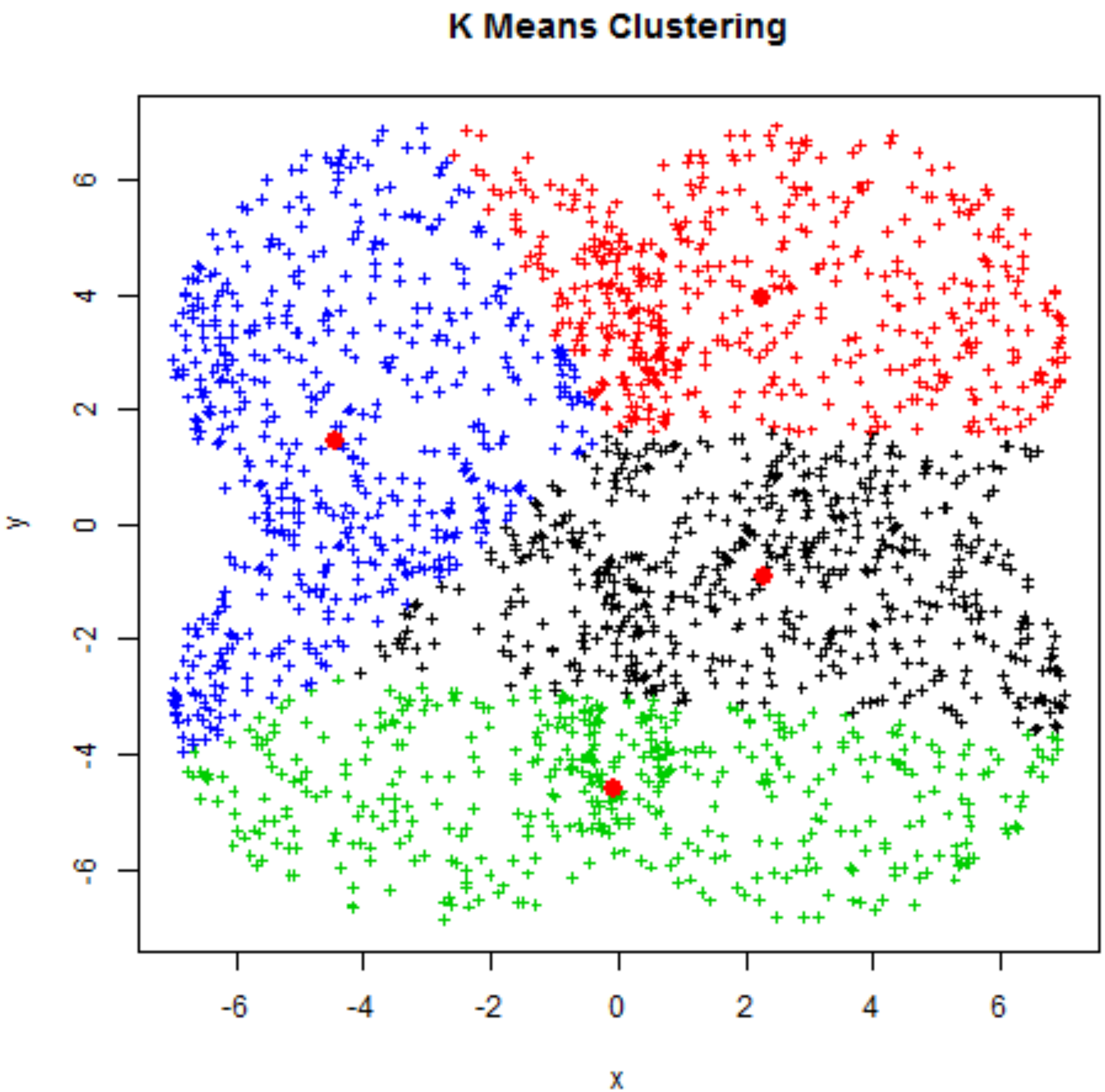
If I told you there were two clusters, how would we find the center?



K-Means



K-Means



K-Means

- Groups data into K clusters and attempts to group data points to minimize the distance to their central mean.

- Algorithm works by iterating between two stages until the data points converge.

Problem Formulation

- Given a data set of $\{\mathbf{x}_1,\ldots,\mathbf{x}_N\}$ which consists of N random instances of a random D-dimensional variable $\mathbf{x}$.

- Introduce a set of K prototype vectors, μ_k where $k=1,\ldots,K$ and μ_k corresponds to the mean of the k^{th} cluster (also know as a centroid).

Problem Formulation

- Goal is to find a grouping of data points and prototype vectors that minimizes the distance of each data point.
  - In spatial cases, we define distance as the sum of squares
  - In text, we often define distance as cosine distance

Problem Formulation (cont.)

- This can be formalized by introducing an indicator variable for each data point:
  - r_{nk} is {0,1}, and k=1,…,K
  - The indicator is 1 if the data point is in the cluster
- Our objective function becomes:

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} ||x_n - \mu_k||^2$$

How K-Means works

- Algorithm initializes the K prototype vectors to K distinct random data points.
- Cycles between two stages until convergence is reached.
- Convergence: since there are only a finite set of possible assignments.

How K-Means works

$$r_{nk} = \begin{cases} 1 & if\ k = argmin_j ||x_n - \mu_k||^2 \\ 0 & otherwise \end{cases}$$

$$\mu_k = \frac{\sum_n r_{nk} x_n}{\sum_n r_{nk}}$$

How K-Means works

$$r_{nk} = \begin{cases} 1 & if\ k = \boxed{argmin_j ||x_n - \mu_k||^2} \\ 0 & otherwise \end{cases}$$

Is this cluster's centroid the closest?

$$\mu_k = \frac{\sum_n r_{nk} x_n}{\sum_n r_{nk}}$$

How K-Means works

- 1. For each data point, determine r_{nk} where:

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- 2. Update μ_k :

$$\mu_k = \frac{\sum_n r_{nk} x_n}{\boxed{\sum_n r_{nk}}}$$

# of items in the cluster

How K-Means works

- 1. For each data point, determine r_{nk} where:

$$r_{nk} = \begin{cases} 1 & if\ k = \boxed{argmin_j ||x_n - \mu_k||^2} \\ 0 & otherwise \end{cases}$$

Is this cluster's centroid the closest?

- 2. Update μ_k :

The sum of all vectors in the cluster

$$\mu_k = \frac{\boxed{\sum_n r_{nk} x_n}}{\boxed{\sum_n r_{nk}}}$$

# of items in the cluster

K-Means

Initialization example

- Pick *K* cluster centers (note the unfortunate choice)

K-Means

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Initialization example

- Pick *K* cluster centers (random choice)

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K-Means++

K-Means with smart initial seeding

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K-Means with smart initial seeding

- Choose one center uniformly at random from among the data points.

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- For each data point x, compute $D(x)$, the distance between x and the nearest center that has already been chosen.

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K-Means with smart initial seeding

- Choose one center uniformly at random from among the data points.
- For each data point x, compute $D(x)$, the distance between x and the nearest center that has already been chosen.
- Choose one new data point at random as a new center, using a weighted probability distribution where a point x is chosen with probability proportional to $D(x)^2$.

K-Means++

K-Means with smart initial seeding

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- Choose one new data point at random as a new center, using a weighted probability distribution where a point x is chosen with probability proportional to $D(x)^2$.
- Repeat Steps 2 and 3 until k centers have been chosen.
- Now that the initial centers have been chosen, proceed using standard k-means.

K-Means++

- This seeding method yields considerable improvement in the final error of ***k***-means
- Takes more time to initialize
- Once initialized, K-Means converges quickly
- Usually faster than K-Means
- 1000 times less prone to error than K-Means

Pros and Cons of K-Means

$$J = \sum_{n=1}^{N} \sum_{k=1}^{K} r_{nk} || x_n - \mu_k ||^2$$

- Convergence: J may converge to a local minima and not the global minimum. May have to repeat algorithm multiple times.
- With a large data set, the distance calculations can be slow.
- K is an input parameter. If K is inappropriately chosen it may yield poor results.

Local Minima

- K-Means might not find the best possible assignments and centers.
- Consider points 0, 20, 32.
  - K-means can converge to centers at 10, 32.
  - Or to centers at 0, 26.
- Heuristic solutions
  - Start with many random starting points and pick the best solution.

https://twitter.com/eminem

EM: Expectation Maximization

Soft Clustering

- Clustering typically assumes that each instance is given a “hard” assignment to exactly one cluster.

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Soft Clustering

- Clustering typically assumes that each instance is given a “hard” assignment to exactly one cluster.
- Does not allow uncertainty in class membership or for an instance to belong to more than one cluster.
- Soft clustering gives probabilities that an instance belongs to each of a set of clusters.
- Each instance is assigned a probability distribution across a set of discovered categories (probabilities of all categories must sum to 1).

EM

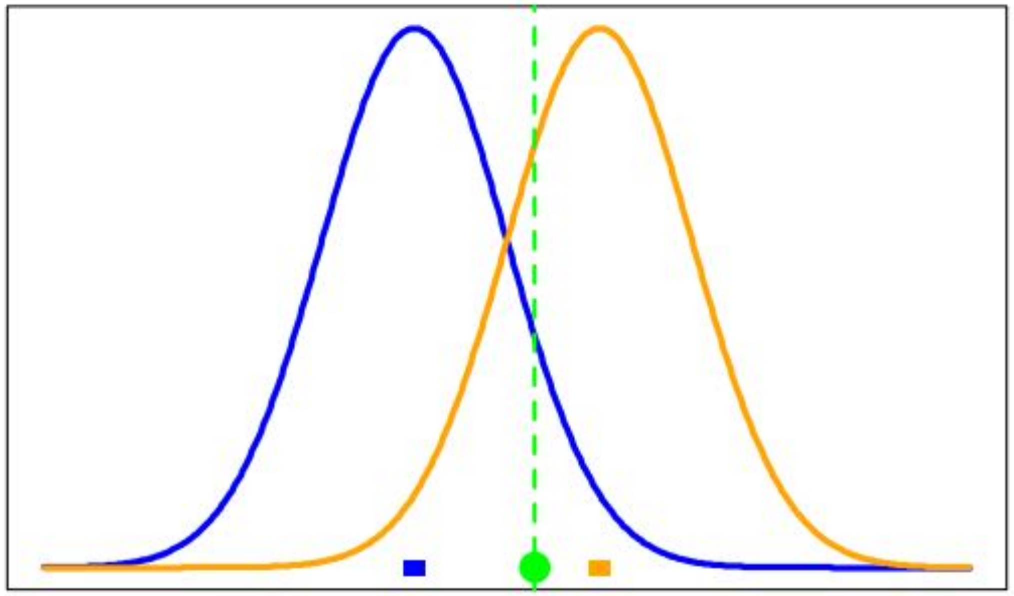
- Soft Assignments
  - A point is partially assigned to all clusters.
- Uses a probabilistic formulation
- Tends to work better than K-Means

Mixture of Gaussians

- A gaussian specifies a distribution over points according to two parameters: mean m and variance σ

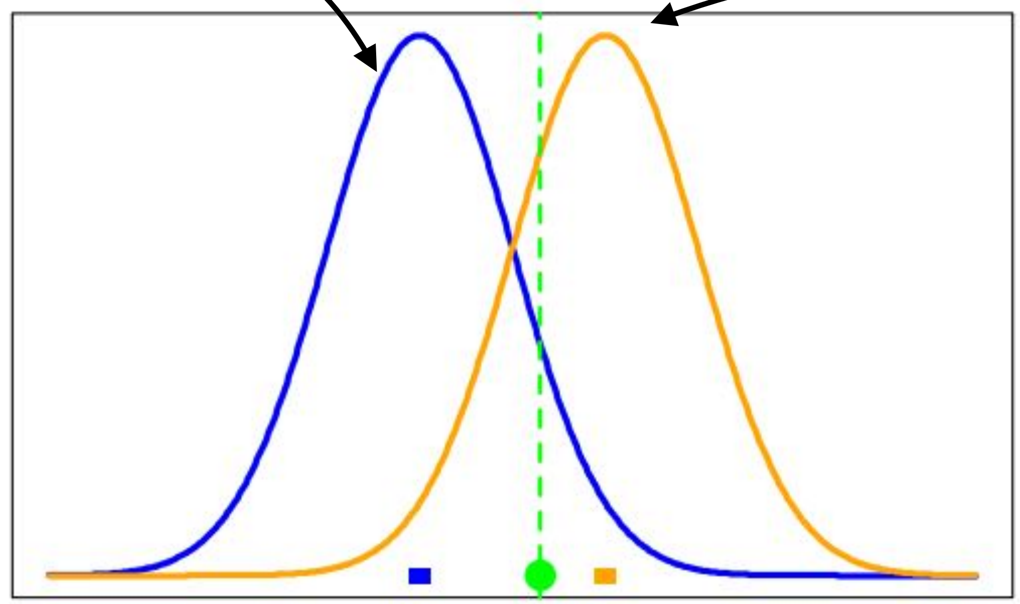
- $g(x; m, \sigma)$ is the probability of a point x based on a Gaussian Distribution with mean m and variance σ

Intuition



Intuition

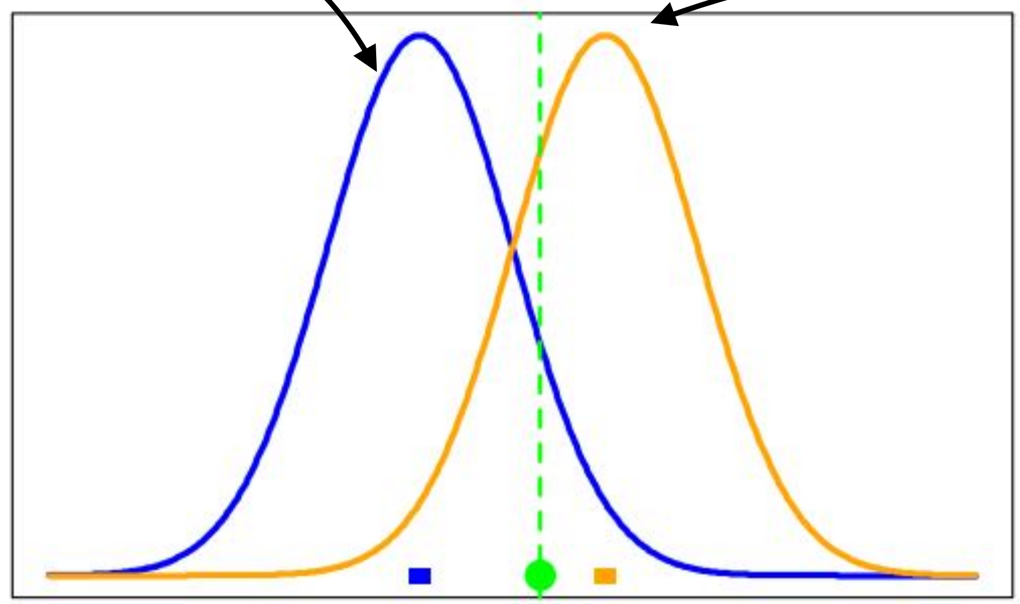
Gaussian
Distribution #1



Gaussian
Distribution #2

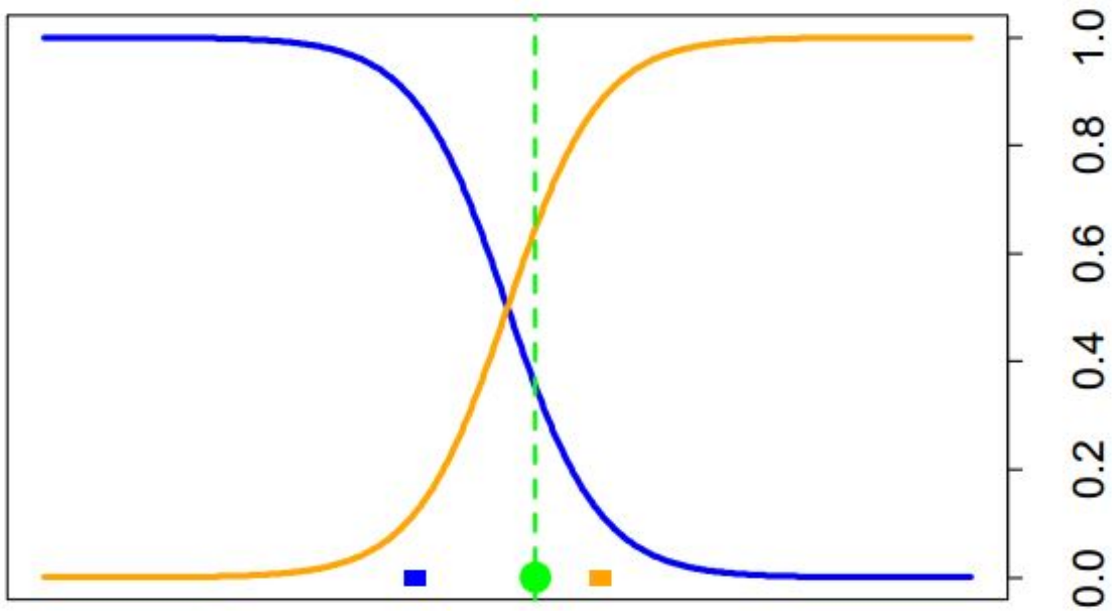
Intuition

Gaussian Distribution #1



Gaussian Distribution #2

Probability of a point being generated by each distribution



EM Intuition Building

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- Suppose we have two coins A and B

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- Assume bias of B is θ_2, e.g., $p(heads|B)$

EM Intuition Building

- Suppose we have two coins A and B
- Assume bias of A is θ_1, e.g., p(heads|A)
- Assume bias of B is θ_2, e.g., p(heads|B)
- We want to find θ_2 and θ_2 by performing a bunch of trials (coin flips)

EM Intuition Building: Experiment #1

- We do 5 trials by picking a coin at random
- Then we flip the chosen coin 10 times

EM Intuition Building: Experiment #1

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- Then we flip the chosen coin 10 times

Trial	Results
A	H T T T H H T H T H

EM Intuition Building: Experiment #1

- We do 5 trials by picking a coin at random
- Then we flip the chosen coin 10 times

Trial	Results
A	H T T T H H T H T H
B	H H H H T H H H H H

EM Intuition Building: Experiment #1

- We do 5 trials by picking a coin at random
- Then we flip the chosen coin 10 times

Trial	Results
A	H T T T H H T H T H
B	H H H H T H H H H H
B	H T H H H H H T H H

EM Intuition Building: Experiment #1

- We do 5 trials by picking a coin at random
- Then we flip the chosen coin 10 times

Trial	Results									
A	H	T	T	T	H	H	T	H	T	H
B	H	H	H	H	T	H	H	H	H	H
B	H	T	H	H	H	H	H	T	H	H
A	H	T	H	T	T	T	H	H	T	T

EM Intuition Building: Experiment #1

- We do 5 trials by picking a coin at random
- Then we flip the chosen coin 10 times

Trial	Results									
A	H	T	T	T	H	H	T	H	T	H
B	H	H	H	H	T	H	H	H	H	H
B	H	T	H	H	H	H	H	T	H	H
A	H	T	H	T	T	T	H	H	T	T
B	T	H	H	H	T	H	H	H	T	H

EM Intuition Building: Experiment #1

- We do 5 trials by picking a coin at random
- Then we flip the chosen coin 10 times

Trial	Results									
A	H	T	T	T	H	H	T	H	T	H
B	H	H	H	H	T	H	H	H	H	H
B	H	T	H	H	H	H	H	T	H	H
A	H	T	H	T	T	T	H	H	T	T
B	T	H	H	H	T	H	H	H	T	H

$\theta_1 =$

$\theta_2 =$

EM Intuition Building: Experiment #1

- We do 5 trials by picking a coin at random
- Then we flip the chosen coin 10 times

Trial	Results
A	H T T T H H T H T H
B	H H H H T H H H H H
B	H T H H H H H T H H
A	H T H T T T H H T T
B	T H H H T H H H T H

$$\theta_1 = \frac{\text{\# A heads}}{\text{total \# of A flips}}$$

$$\theta_2 = \frac{\text{\# B heads}}{\text{total \# of B flips}}$$

EM Intuition Building: Experiment #1

Trial	Results
A	H T T T H H T H T H
B	H H H H T H H H H H
B	H T H H H H H T H H
A	H T H T T T H H T T
B	T H H H T H H H T H

EM Intuition Building: Experiment #1

A	B
5 H, 5 T	
	9 H, 1 T
	8 H, 2 T
4 H, 6 T	
	7 H, 3 T

Trial	Results
A	H T T T H H T H T H
B	H H H H T H H H H H
B	H T H H H H H T H H
A	H T H T T T H H T T
B	T H H H T H H H T H

EM Intuition Building: Experiment #1

Trial	Results
A	H T T T H H T H T H
B	H H H H T H H H H H
B	H T H H H H H T H H
A	H T H T T T H H T T
B	T H H H T H H H T H

A	B
5 H, 5 T	
	9 H, 1 T
	8 H, 2 T
4 H, 6 T	
	7 H, 3 T
24 H, 6 T	9 H, 11 T

EM Intuition Building: Experiment #1

Trial	Results
A	H T T T H H T H T H
B	H H H H T H H H H H
B	H T H H H H H T H H
A	H T H T T T H H T T
B	T H H H T H H H T H

A	B
5 H, 5 T	
	9 H, 1 T
	8 H, 2 T
4 H, 6 T	
	7 H, 3 T
24 H, 6 T	9 H, 11 T

$$\theta_1 = \frac{24}{24+6} = 0.8$$

$$\theta_2 = \frac{9}{9+11} = 0.45$$

EM Intuition Building: Experiment #2

Trial	Results									
?	H	T	T	T	H	H	T	H	T	H
?	H	H	H	H	T	H	H	H	H	H
?	H	T	H	H	H	H	H	T	H	H
?	H	T	H	T	T	T	H	H	T	T
?	T	H	H	H	T	H	H	H	T	H

Challenge: What if we don't know which code was flipped during each trial? (The coin name becomes a hidden variable)

EM Intuition Building: Experiment #2

Trial	Results
?	H T T T H H T H T H
?	H H H H T H H H H H
?	H T H H H H H T H H
?	H T H T T T H H T T
?	T H H H T H H H T H

EM Intuition Building: Experiment #2

Trial	Results
?	H T T T H H T H T H
?	H H H H T H H H H H
?	H T H H H H H T H H
?	H T H T T T H H T T
?	T H H H T H H H T H

Step 1: initialize parameters

$$\hat{\theta}_A^{(0)} = 0.6$$

$$\hat{\theta}_B^{(0)} = 0.5$$

EM Intuition Building: Experiment #2

Trial	Results
?	H T T T H H T H T H
?	H H H H T H H H H H
?	H T H H H H H T H H
?	H T H T T T H H T T
?	T H H H T H H H T H

Step 1: initialize parameters

$$\hat{\theta}_A^{(0)} = 0.6$$

$$\hat{\theta}_B^{(0)} = 0.5$$

EM Intuition Building: Experiment #2

2: **E**-Step

Trial	Results	p(x|A)	p(x|B)
?	H T T T H H T H T H		
?	H H H H T H H H H H		
?	H T H H H H H T H H		
?	H T H T T T H H T T		
?	T H H H T H H H T H		

Step 1: initialize parameters $\hat{\theta}_A^{(0)} = 0.6$ $\hat{\theta}_B^{(0)} = 0.5$

EM Intuition Building: Experiment #2

2: **E**-Step

Trial	Results	p(x|A) p(x|B)
?	H T T T H H T H T H	0.45 × A, 0.55 × B
?	H H H H T H H H H H	
?	H T H H H H H T H H	
?	H T H T T T H H T T	
?	T H H H T H H H T H	

Step 1: initialize parameters $\hat{\theta}_A^{(0)} = 0.6$ $\hat{\theta}_B^{(0)} = 0.5$

EM Intuition Building: Experiment #2

2: **E**-Step

Trial	Results										p(x|A)	p(x|B)
?	H	T	T	T	H	H	T	H	T	H	0.45 × A,	0.55 × B
?	H	H	H	H	T	H	H	H	H	H		
?	H	T	H	H	H	H	H	T	H	H		
?	H	T	H	T	T	T	H	H	T	T		
?	T	H	H	H	T	H	H	H	T	H		

A	**B**
≈ 2.2H, 2.2T	≈ 2.8H, 2.8T

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EM Intuition Building: Experiment #2

2: **E**-Step

Trial	Results	p(x|A) p(x|B)
?	H T T T H H T H T H	0.45 × A, 0.55 × B
?	H H H H T H H H H H	0.80 × A, 0.20 × B
?	H T H H H H H T H H	
?	H T H T T T H H T T	
?	T H H H T H H H T H	

A	B
≈ 2.2H, 2.2T	≈ 2.8H, 2.8T

Step 1: initialize parameters $\hat{\theta}_A^{(0)} = 0.6$ $\hat{\theta}_B^{(0)} = 0.5$

EM Intuition Building: Experiment #2

2: **E**-Step

Trial	Results	p(x|A) p(x|B)
?	H T T T H H T H T H	0.45 × A, 0.55 × B
?	H H H H T H H H H H	0.80 × A, 0.20 × B
?	H T H H H H H T H H	
?	H T H T T T H H T T	
?	T H H H T H H H T H	

A	B
≈ 2.2H, 2.2T	≈ 2.8H, 2.8T
≈ 7.2H, 0.8T	≈ 1.8H, 0.2T

Step 1: initialize parameters $\hat{\theta}_A^{(0)} = 0.6$ $\hat{\theta}_B^{(0)} = 0.5$

EM Intuition Building: Experiment #2

2: **E**-Step

Trial	Results	p(x|A) p(x|B)	A	B
?	H T T T H H T H T H	0.45 × A, 0.55 × B	≈ 2.2H, 2.2T	≈ 2.8H, 2.8T
?	H H H H T H H H H H	0.80 × A, 0.20 × B	≈ 7.2H, 0.8T	≈ 1.8H, 0.2T
?	H T H H H H H T H H	0.73 × A, 0.27 × B	≈ 5.9H, 1.5T	≈ 2.1H, 0.5T
?	H T H T T T H H T T			
?	T H H H T H H H T H			

Step 1: initialize parameters

$$\hat{\theta}_A^{(0)} = 0.6$$

$$\hat{\theta}_B^{(0)} = 0.5$$

EM Intuition Building: Experiment #2

2: **E**-Step

Trial	Results	p(x|A) p(x|B)
?	H T T T H H T H T H	0.45 × A, 0.55 × B
?	H H H H T H H H H H	0.80 × A, 0.20 × B
?	H T H H H H H T H H	0.73 × A, 0.27 × B
?	H T H T T T H H T T	0.35 × A, 0.65 × B
?	T H H H T H H H T H	

A	B
≈ 2.2H, 2.2T	≈ 2.8H, 2.8T
≈ 7.2H, 0.8T	≈ 1.8H, 0.2T
≈ 5.9H, 1.5T	≈ 2.1H, 0.5T
≈ 1.4H, 2.1T	≈ 2.6H, 3.9T

Step 1: initialize parameters $\hat{\theta}_A^{(0)} = 0.6$ $\hat{\theta}_B^{(0)} = 0.5$

EM Intuition Building: Experiment #2

2: **E**-Step

Trial	Results	p(x|A) p(x|B)	A	B
?	H T T T H H T H T H	0.45 × A, 0.55 × B	≈ 2.2H, 2.2T	≈ 2.8H, 2.8T
?	H H H H T H H H H H	0.80 × A, 0.20 × B	≈ 7.2H, 0.8T	≈ 1.8H, 0.2T
?	H T H H H H H T H H	0.73 × A, 0.27 × B	≈ 5.9H, 1.5T	≈ 2.1H, 0.5T
?	H T H T T T H H T T	0.35 × A, 0.65 × B	≈ 1.4H, 2.1T	≈ 2.6H, 3.9T
?	T H H H T H H H T H	0.65 × A, 0.25 × B	≈ 4.5H, 1.9T	≈ 2.5H, 1.1T

Step 1: initialize parameters

$$\hat{\theta}_A^{(0)} = 0.6$$

$$\hat{\theta}_B^{(0)} = 0.5$$

EM Intuition Building: Experiment #2

2: **E**-Step

Trial	Results	p(x|A) p(x|B)	A	B
?	H T T T H H T H T H	0.45 x A, 0.55 x B	≈ 2.2H, 2.2T	≈ 2.8H, 2.8T
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			≈ 21.3H, 8.6T	≈ 11.7H, 8.4T

Step 1: initialize parameters $\hat{\theta}_A^{(0)} = 0.6$ $\hat{\theta}_B^{(0)} = 0.5$

EM Intuition Building: Experiment #2

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Step 1: initialize parameters $\hat{\theta}_A^{(0)} = 0.6$ $\hat{\theta}_B^{(0)} = 0.5$

3: **M**-Step

EM Intuition Building: Experiment #2

2: **E**-Step

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			≈ 21.3H, 8.6T	≈ 11.7H, 8.4T

$$\hat{\theta}_A^{(1)} \approx \frac{21.3}{21.3 + 8.6} \approx$$

$$\hat{\theta}_B^{(1)} \approx \frac{11.7}{11.7 + 8.4} \approx$$

Step 1: initialize parameters

$$\hat{\theta}_A^{(0)} = 0.6$$

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3: **M**-Step

EM Intuition Building: Experiment #2

2: **E**-Step

Trial	Results	p(x|A) p(x|B)	A	B
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			≈ 21.3H, 8.6T	≈ 11.7H, 8.4T

Step 1: initialize parameters

$$\hat{\theta}_A^{(0)} = 0.6$$

$$\hat{\theta}_B^{(0)} = 0.5$$

$$\hat{\theta}_A^{(1)} \approx \frac{21.3}{21.3 + 8.6} \approx 0.71$$

$$\hat{\theta}_B^{(1)} \approx \frac{11.7}{11.7 + 8.4} \approx 0.58$$

3: **M**-Step

EM Intuition Building: Experiment #2

2: **E**-Step

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$$\hat{\theta}_A^{(1)} \approx \frac{21.3}{21.3 + 8.6} \approx 0.71$$

$$\hat{\theta}_B^{(1)} \approx \frac{11.7}{11.7 + 8.4} \approx 0.58$$

4: **Finish**

$$\hat{\theta}_A^{(10)} \approx 0.80$$

$$\hat{\theta}_B^{(10)} \approx 0.52$$

Step 1: initialize parameters $\hat{\theta}_A^{(0)} = 0.6$ $\hat{\theta}_B^{(0)} = 0.5$

3: **M**-Step

What happens if we have more than two coins? A mixture of K Gaussians

- A distribution generated by randomly selecting one of K Gaussians, then randomly draw a point from that distribution.
- Gaussian k with a probability of p_k

$$p(x; m, \sigma) = \sum_{k=1}^{K} p_k g(x; m_k, \sigma_k)$$

- Goal: find p_k, σ_k, m_k that maximize the probability of all our data points x.

What happens if we have more than two coins? A mixture of K Gaussians

- A distribution generated by randomly selecting one of K Gaussians, then randomly draw a point from that distribution.
- Gaussian k with a probability of p_k

probability of a x being generated from a gaussian with mean m and variance σ

$$p(x; m, \sigma) = \sum_{k=1}^{K} p_k \boxed{g(x; m_k, \sigma_k)}$$

- Goal: find p_k, σ_k, m_k that maximize the probability of all our data points x.

Back to EM

- Iterative Algorithm
- Goal: group some primitives together
- Chicken and Egg problem:
  - Items in group -> Description of the group
  - Description of the group -> Items in group

Brace Yourselves..

EM

- Iterative Algorithm: E Step and M Step
- E Step:
- Compute the probability that point n is generated by distribution k

$$p^{(i)}(k|n) = \frac{p_k^{(i)} g(x_n; m_k^{(i)}, \sigma_k^{(i)})}{\sum_{m=1}^{K} p_k^{(i)} g(x_n; m_k^{(i)}, \sigma_k^{(i)})}$$

EM

- M Step:

$$m_k^{(i+1)} = \frac{\sum_{n=1}^{N} p^{(i)}(k|n) x_n}{\sum_{n=1}^{N} p^{(i)}(k|n)}$$

$$\sigma_k^{(i+1)} = \sqrt{\frac{1}{D} \frac{\sum_{n=1}^{N} p^{(i)}(k|n) \, ||x_n - m_k^{(i+1)}||^2}{\sum_{n=1}^{N} p^{(i)}(k|n)}}$$

$$p_k^{(i+1)} = \frac{1}{N} \sum_{n=1}^{N} p^{(i)}(k|n)$$

EM

- Converges to a locally optimal solution
- Each step increases the probability of the points given the distributions.
- Can get stuck in local optima

(less than K-Means)

EM and K-means

EM and K-means

- Notice the similarity between EM for Normal mixtures and K-means.
  - The expectation step is the assignment.
  - The maximization step is the update of centers

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- Notice the similarity between EM for Normal mixtures and K-means.
  - The expectation step is the assignment.
  - The maximization step is the update of centers
- K-means is a simplified EM.
- K-means makes a hard decision while EM makes a soft decision when updating the parameters of the model.

Ethics, Society, and Computing (ESC)

Undergraduate Student Mixer

Free food, games, and conversation.
No previous ESC experience necessary.

Monday, February 24, 2020
4:30–6:30 p.m., drop-ins welcome
South Lounge, Michigan Union

ESC

esc.umich.edu


the CRÈME shop
MY MELODY
HANDY DANDY CREAM
STRAWBERRY CAKE
LIMITED EDITION
Made in Korea
MY MELODY
the CRÈME shop
CREAM
STRAWBERRY CAKE
Hand Cream with Shea Butter
LIMITED EDITION
Made in Korea

Topic Modeling:
Latent Dirichlet Allocation

Why Use Topic Models?

- Often you have a large collection of text
  - Decades of books
  - Newly released gov't docs
  - Wikipedia
- We want to know what happens in it
- But it's infeasible to read it all!
- Topic models provide an automatic way to get high-level themes from a corpus

Topic Modeling at a high level

An input corpus

How many topics? k

Topic Model

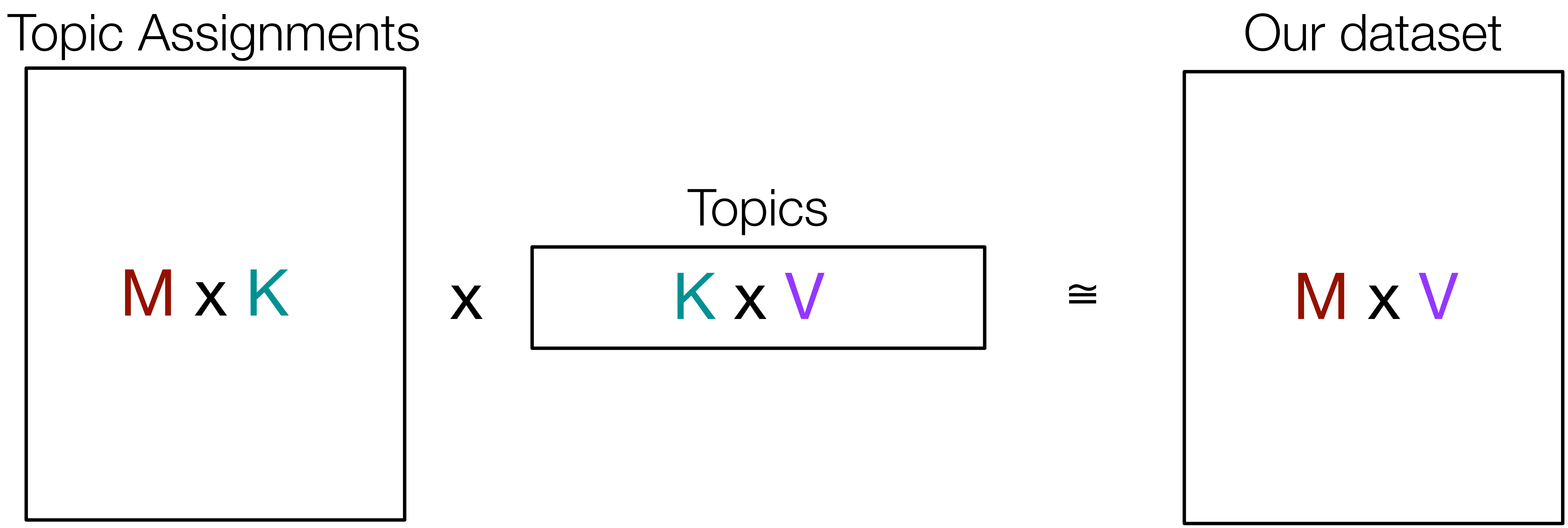
- Each doc's topics
- Each topic's words

Example: Topics

human	evolution	disease	computer
genome	evolutionary	host	models
dna	species	bacteria	information
genetic	organisms	diseases	data
genes	life	resistance	computers
sequence	origin	bacterial	system
gene	biology	new	network
molecular	groups	strains	systems
sequencing	phylogenetic	control	model
map	living	infectious	parallel
information	diversity	malaria	methods
genetics	group	parasite	networks
mapping	new	parasites	software
project	two	united	new
sequences	common	tuberculosis	simulations

- Example from David Blei's slides

Topic Modeling is a kind of Matrix Factorization



M documents
V unique words (vocabulary)
K topics

Demo Time!

https://mimno.infosci.cornell.edu/jsLDA/jslda.html

Consider a unigram model for generating text

$p(w_1) \cdot p(w_2) \cdot p(w_3) \ldots p(w_N)$

We can explicitly show model's parameters β

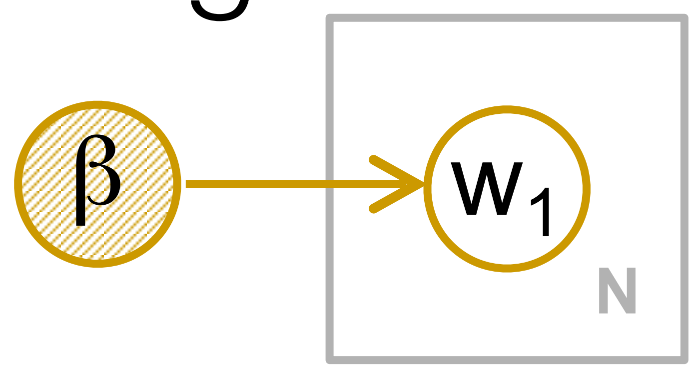
β is a vector that says which unigrams are likely

$p(\beta) \cdot p(w_1 \mid \beta) \cdot p(w_2 \mid \beta) \cdot p(w_3 \mid \beta) \ldots p(w_N \mid \beta)$

The arrows show that each word is generated form the same parameters, β

Plate notation simplifies diagram

β is a vector that says which unigrams are likely



$p(\beta) \cdot p(w_1 \mid \beta) \cdot p(w_2 \mid \beta) \cdot p(w_3 \mid \beta) \ldots$

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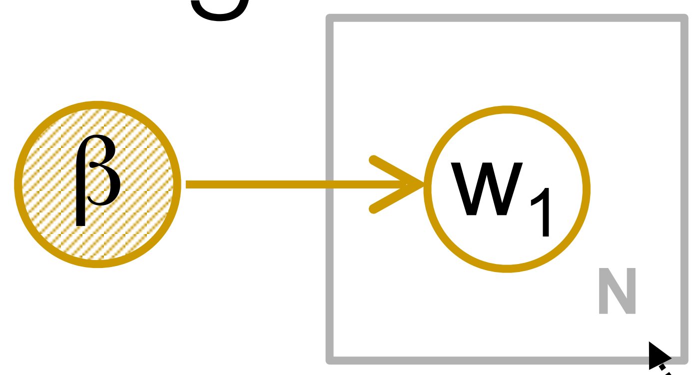


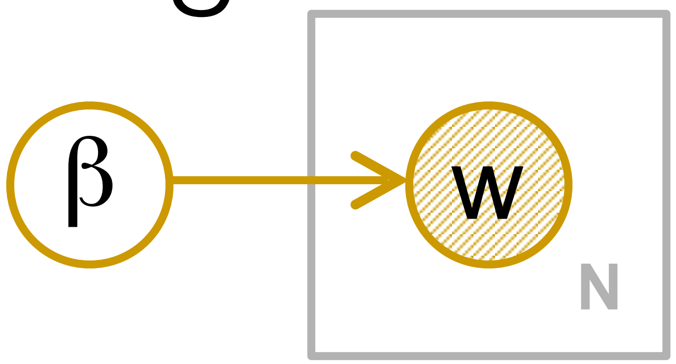
The N says how many things are generated

$$p(\beta) \cdot p(w_1 \mid \beta) \cdot p(w_2 \mid \beta) \cdot p(w_3 \mid \beta) \ldots$$

The arrows show that each word is generated form the same parameters, β

Learn β from observed words

β is a vector that says which unigrams are likely



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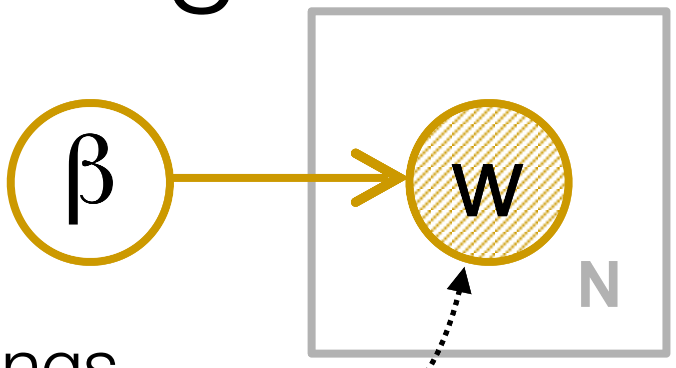

In Plate notation, the things we observe are shaded

The N says how many things are generated

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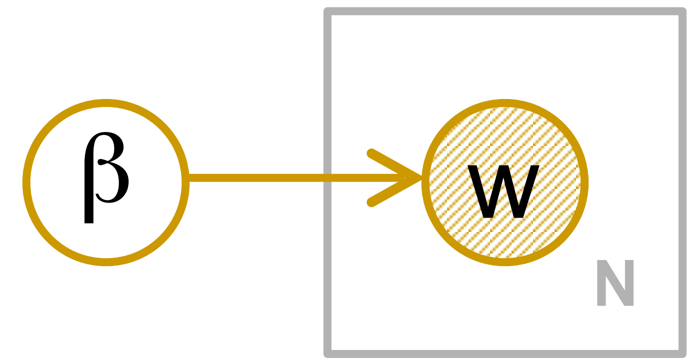
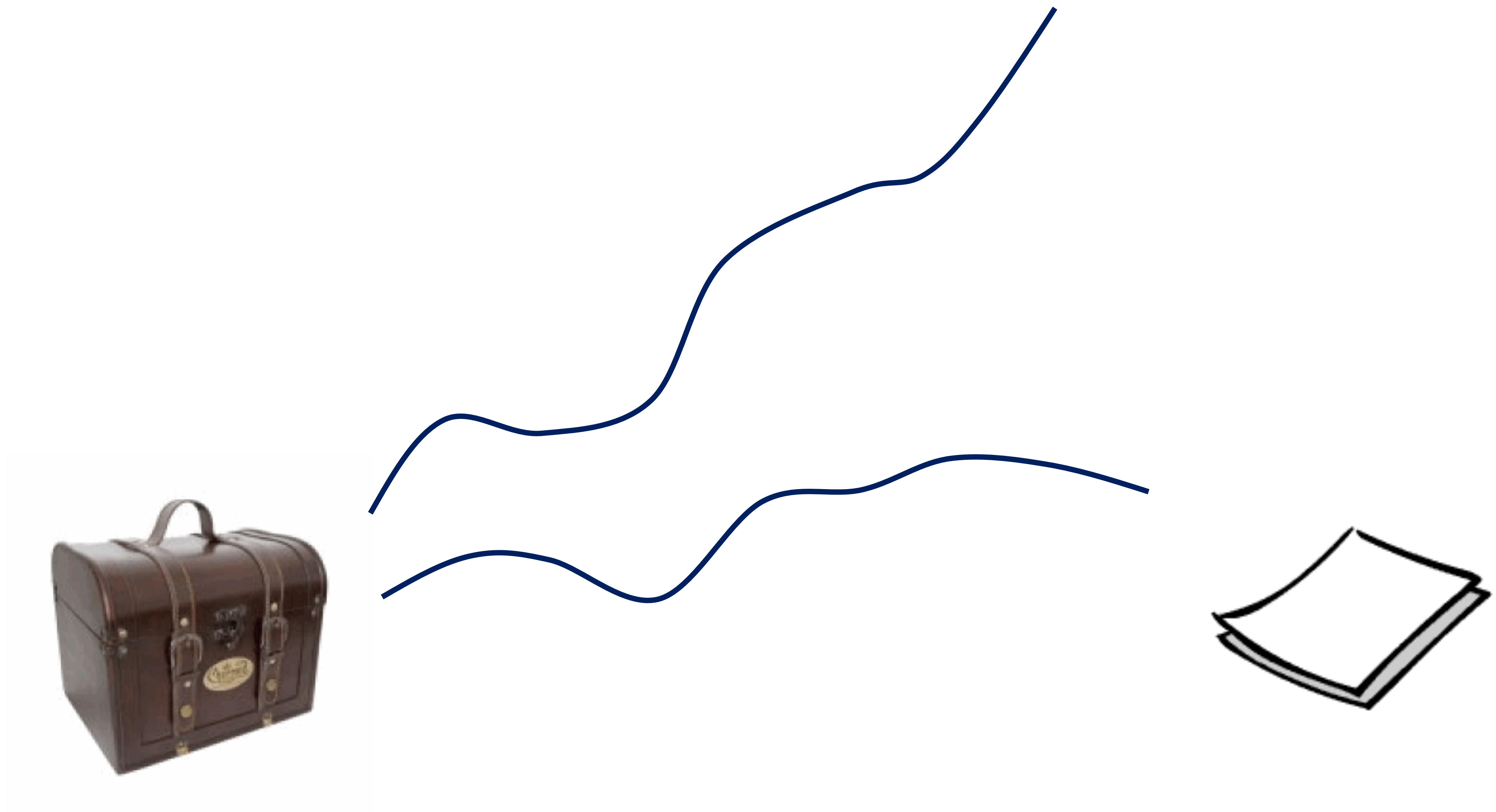
The arrows show that each word is generated form the same parameters, β

Extending this model to topics



- β represents a probability distribution for generating words in all documents
- But many documents are on different topics
- What if we wanted wanted to have different β for different topics?

Generative Model of Text



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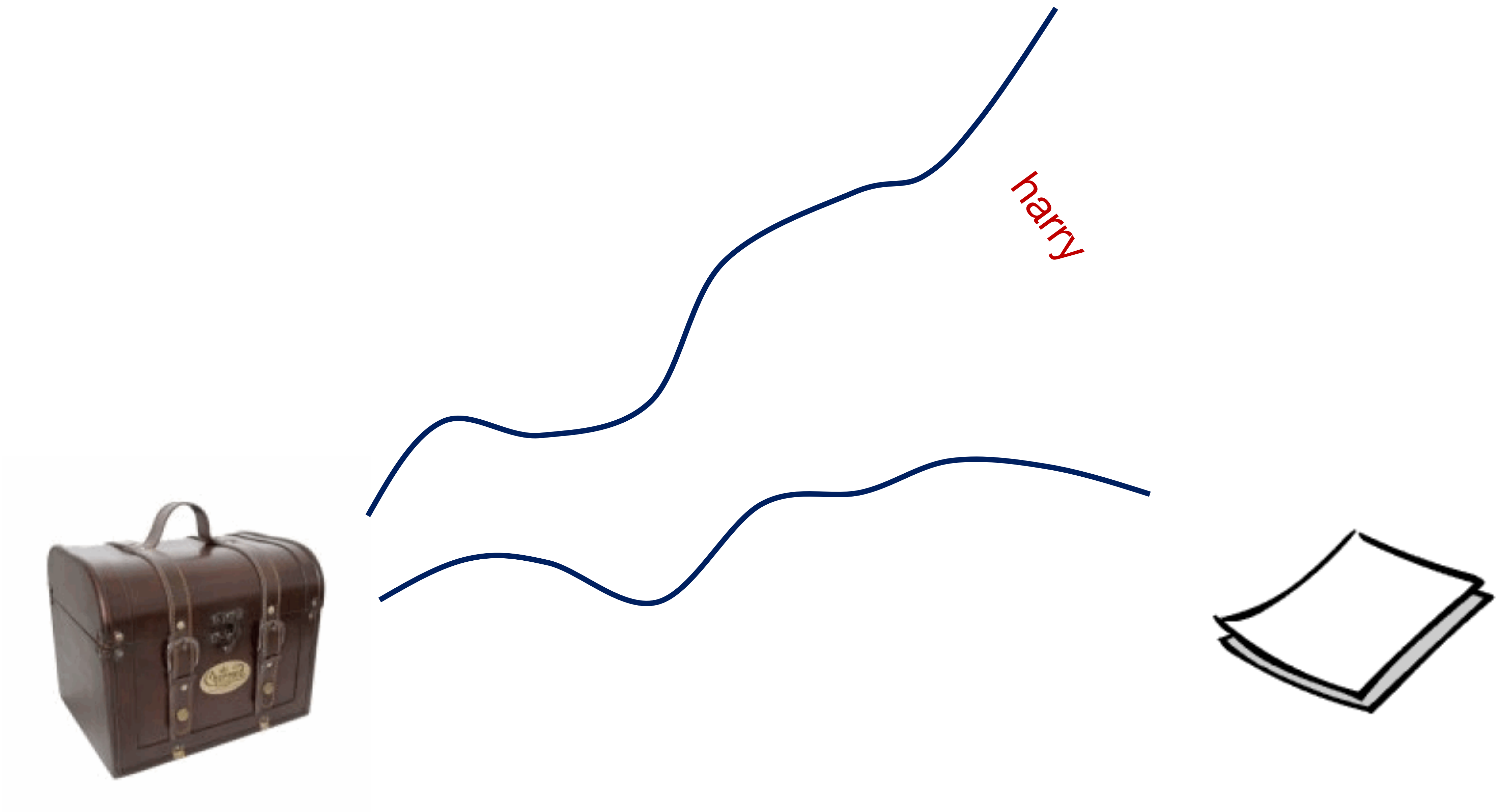

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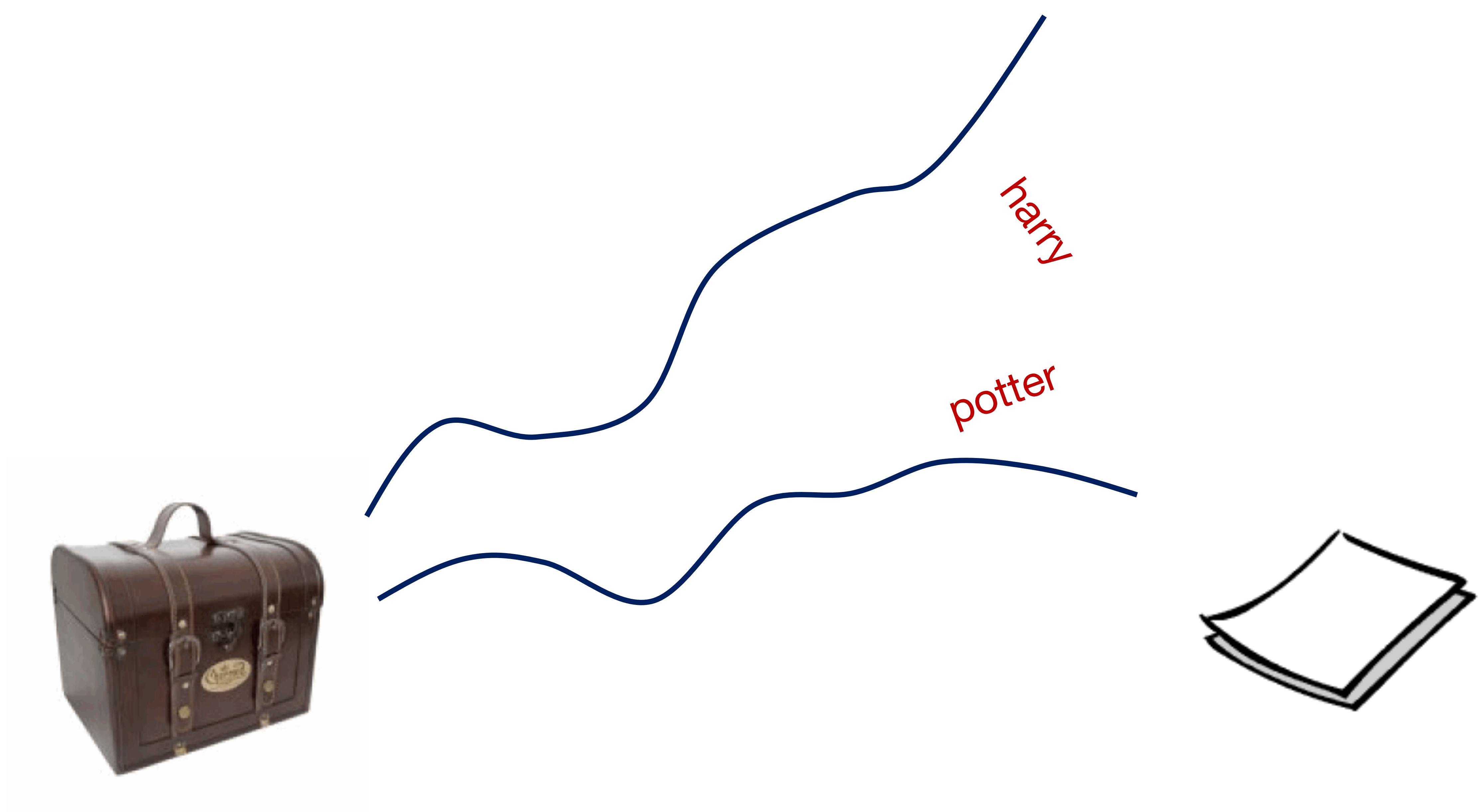

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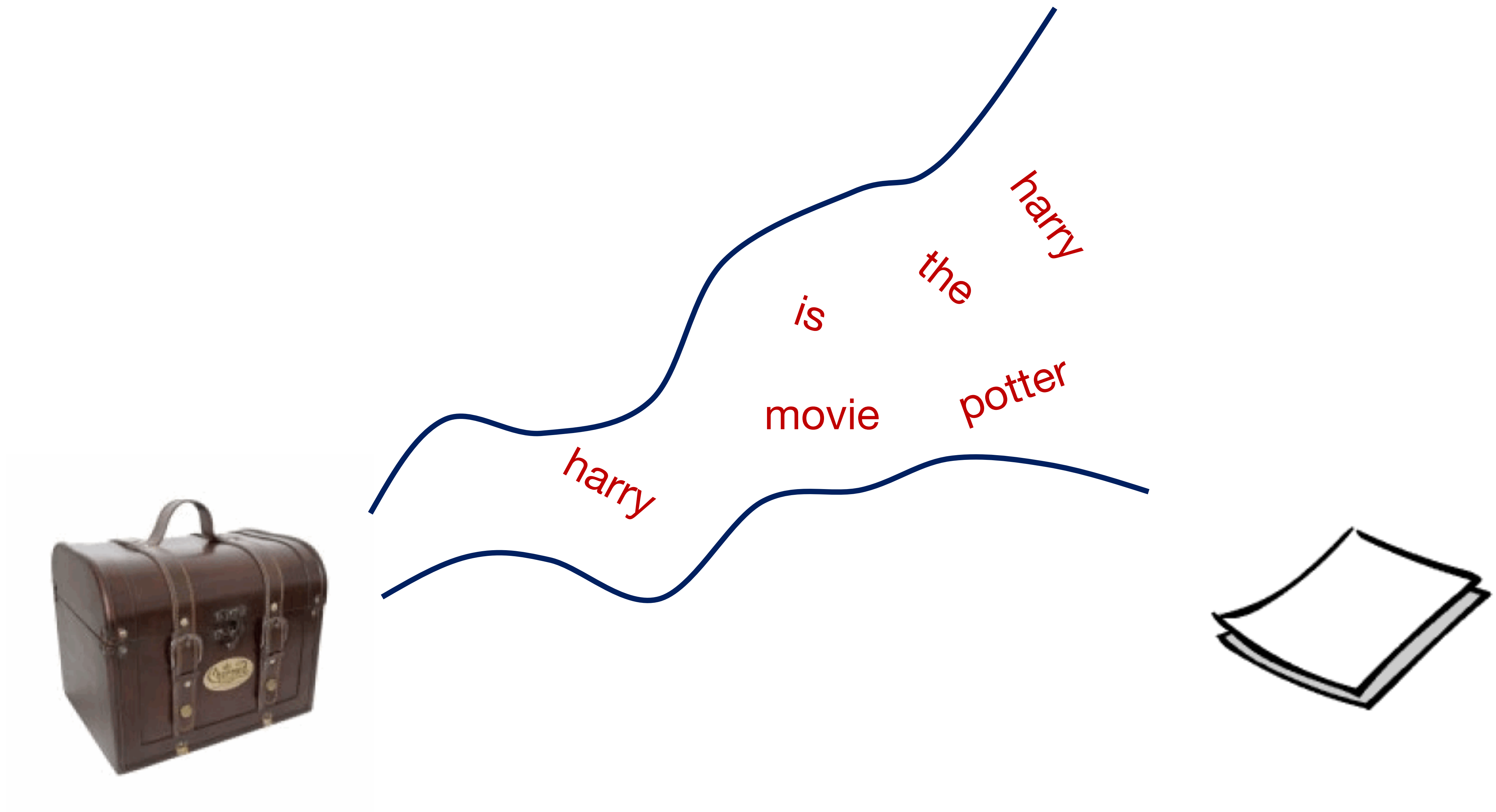

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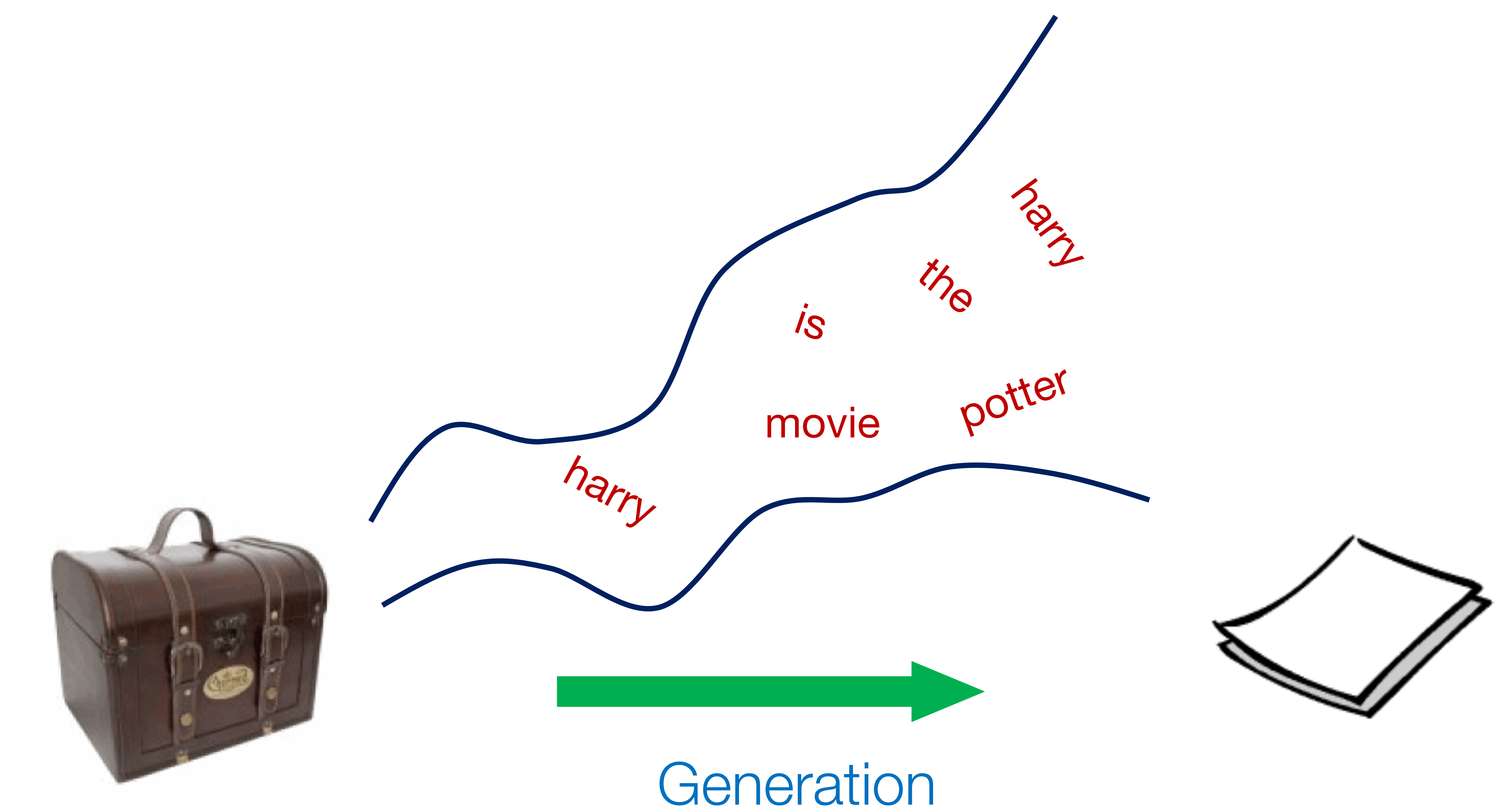

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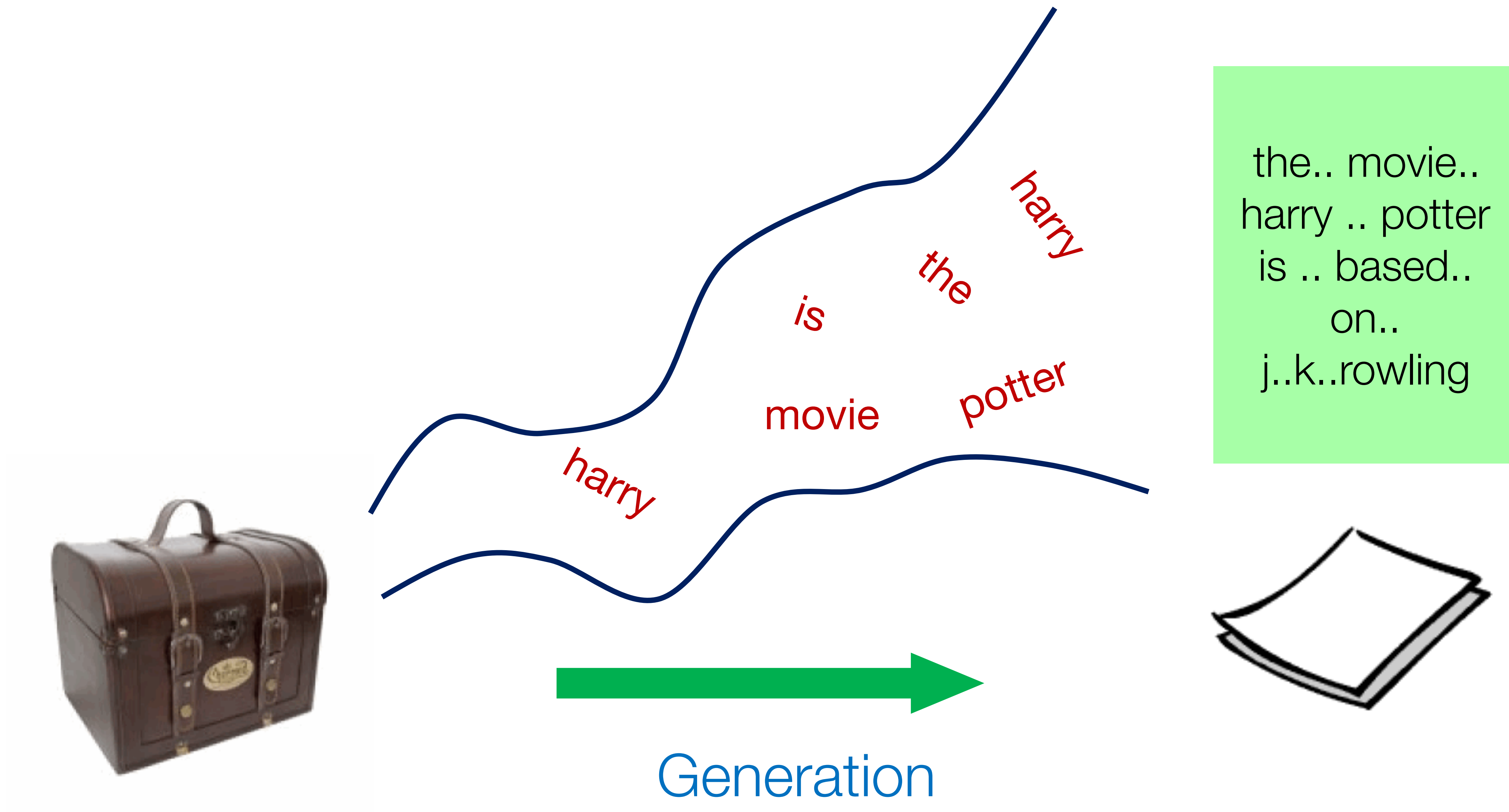

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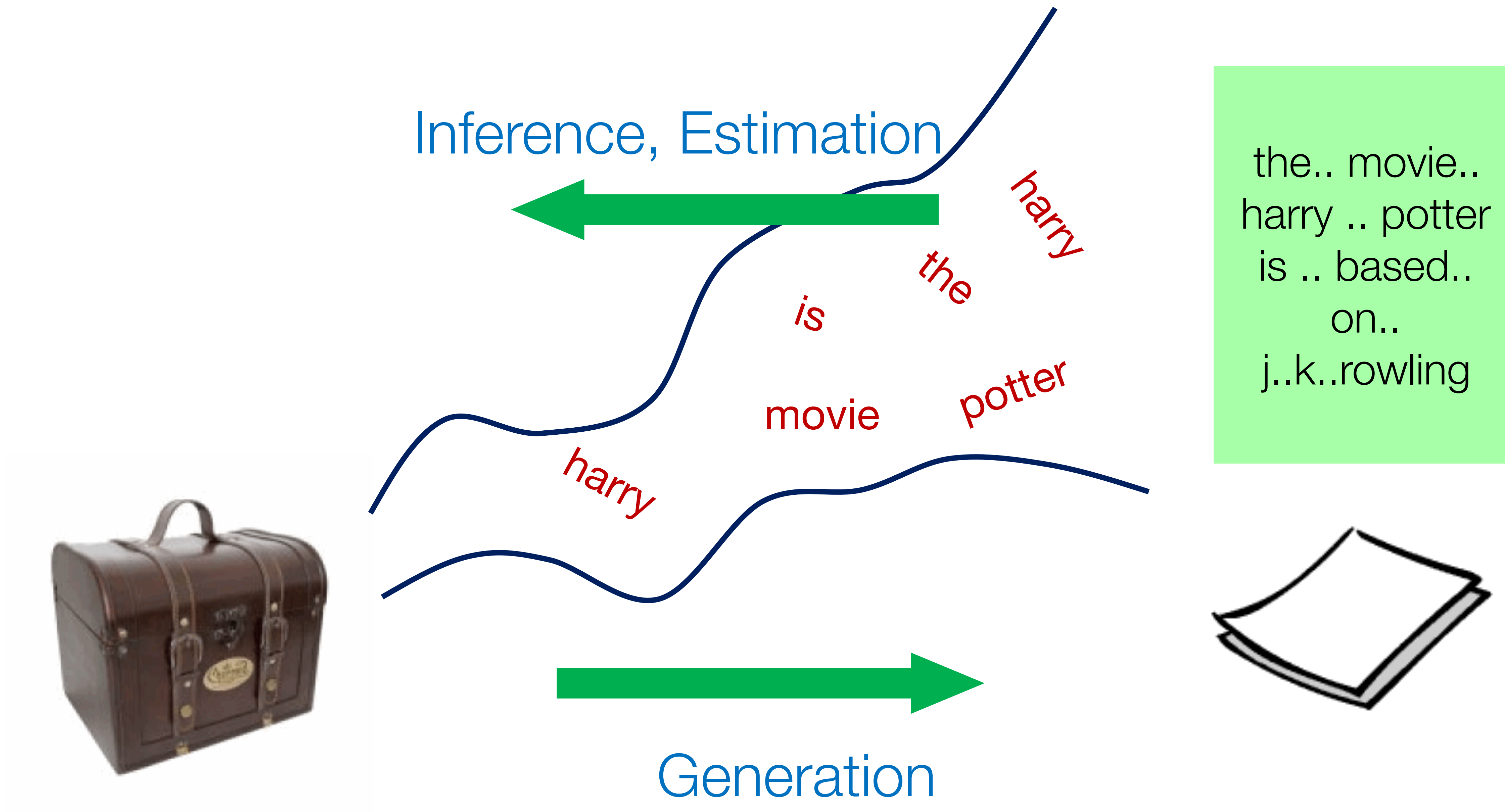

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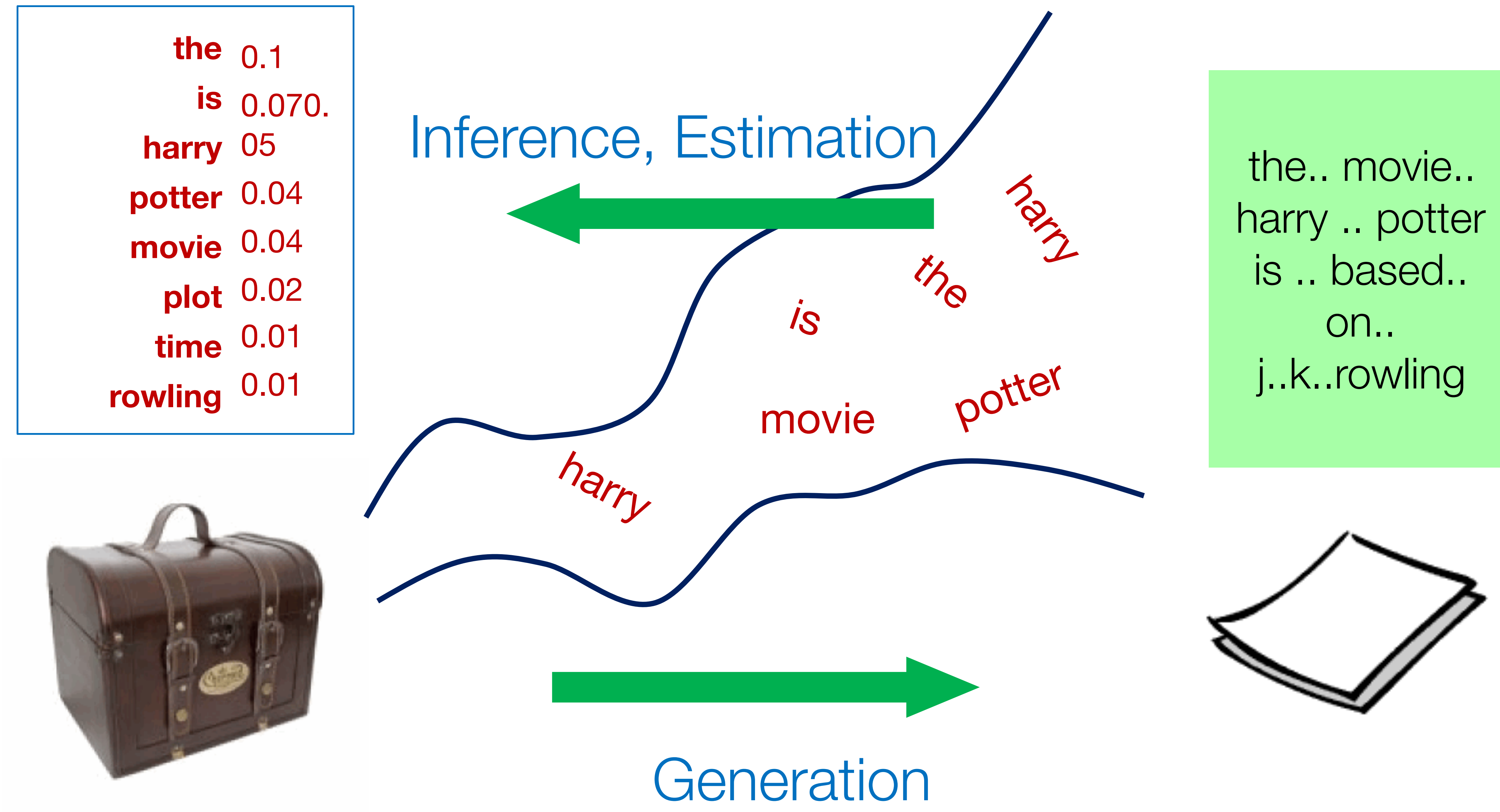
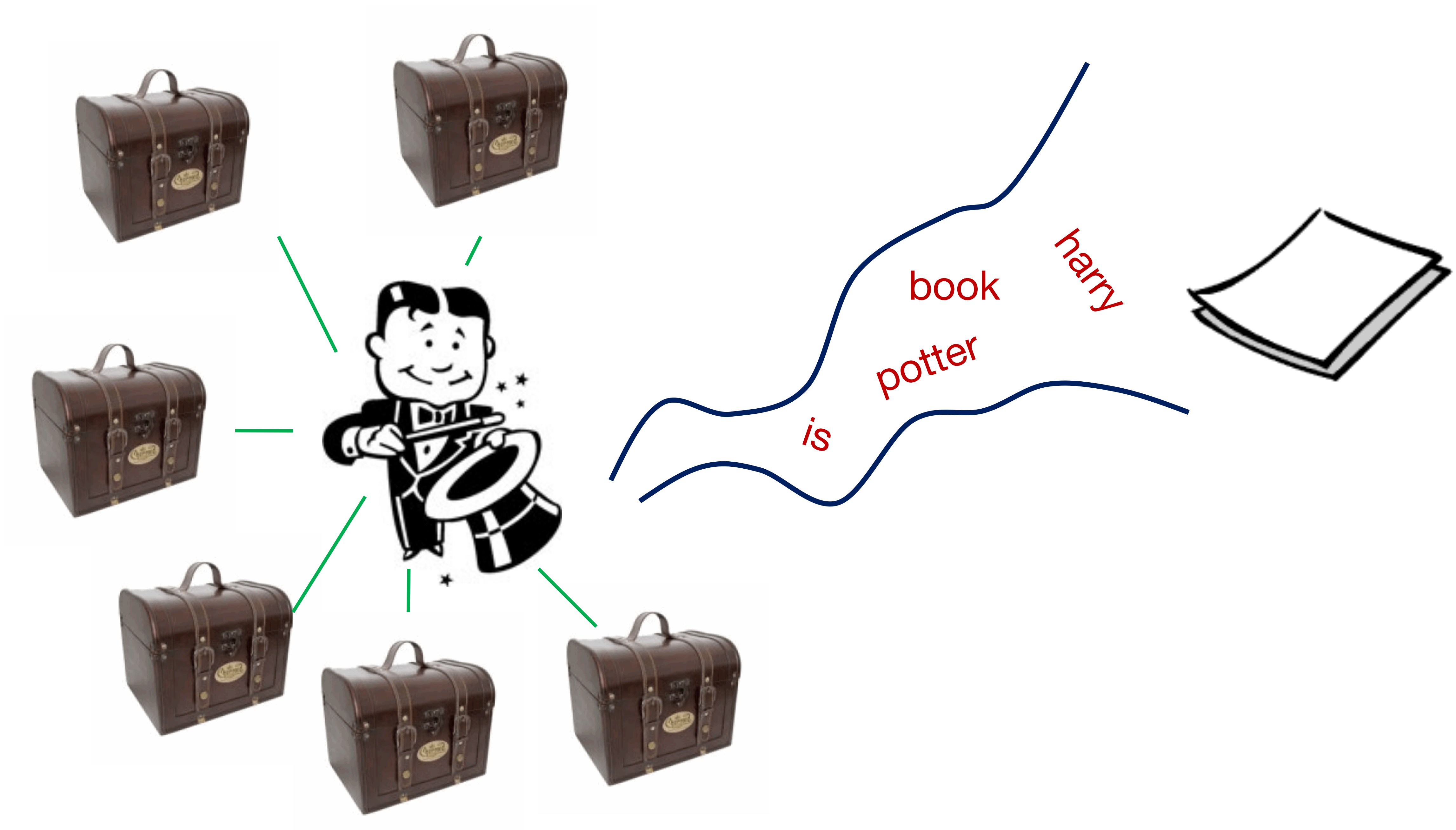


A Generative Model can be Much More Complicated (e.g., a Mixture Model)



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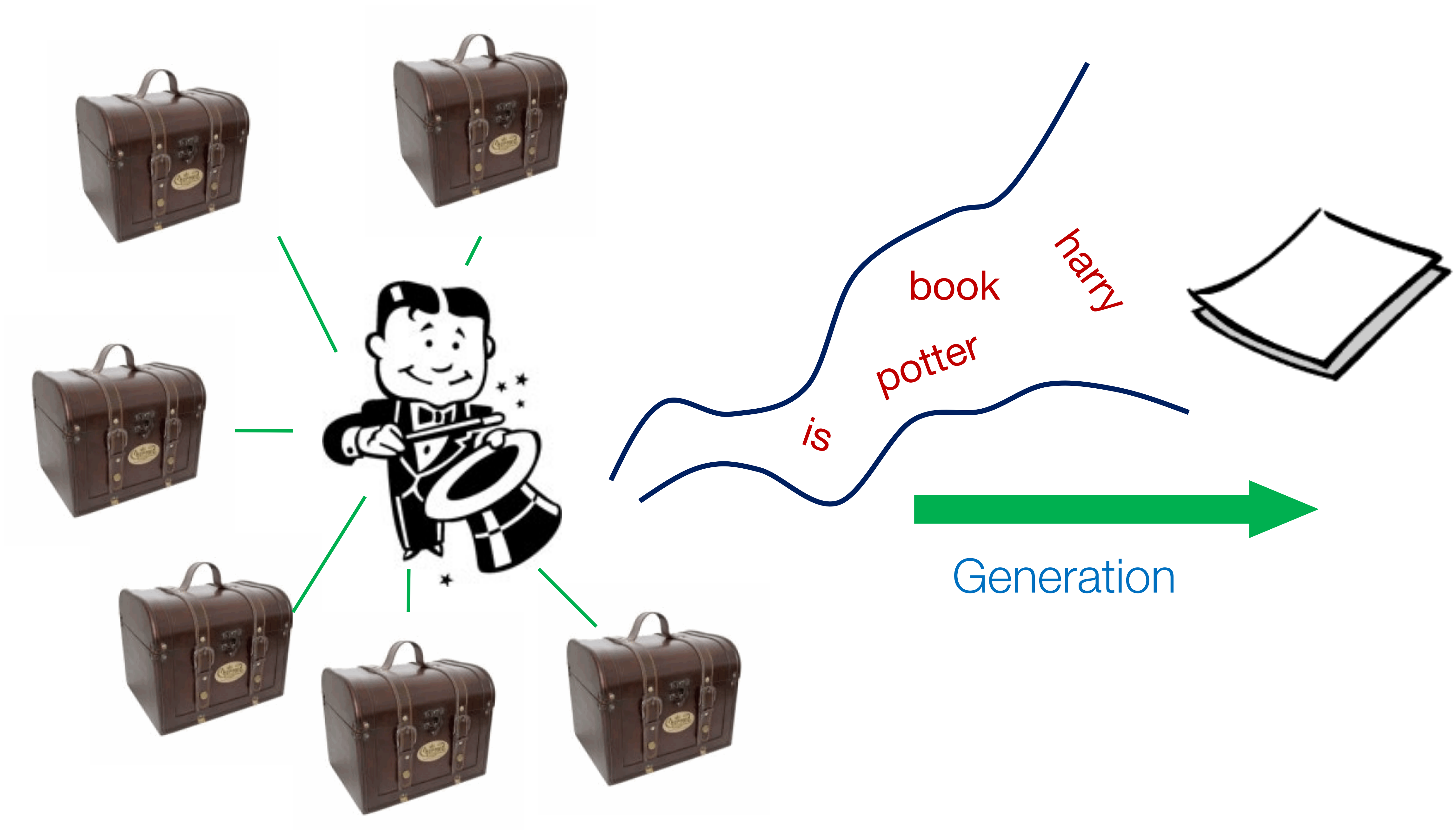

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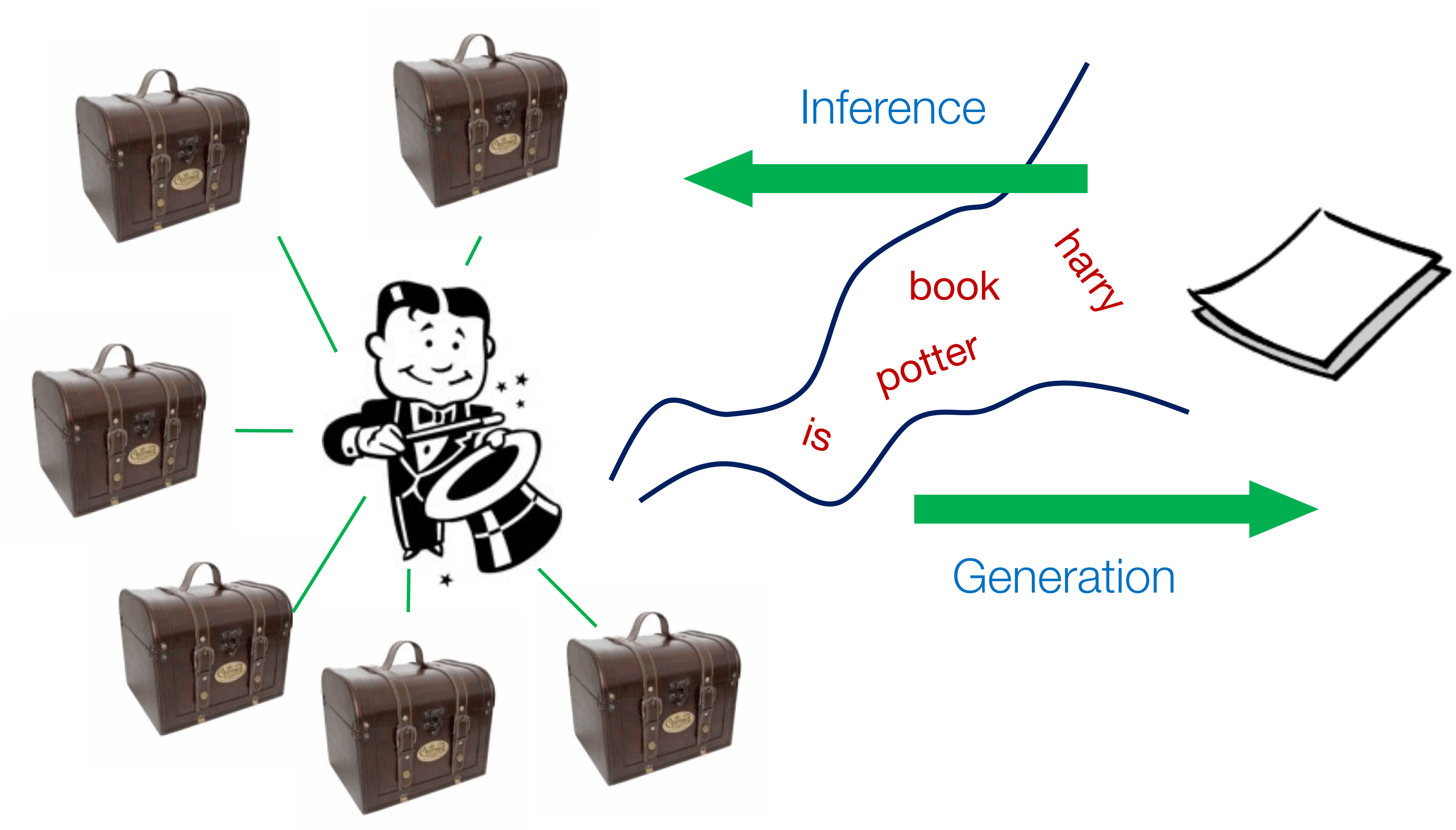

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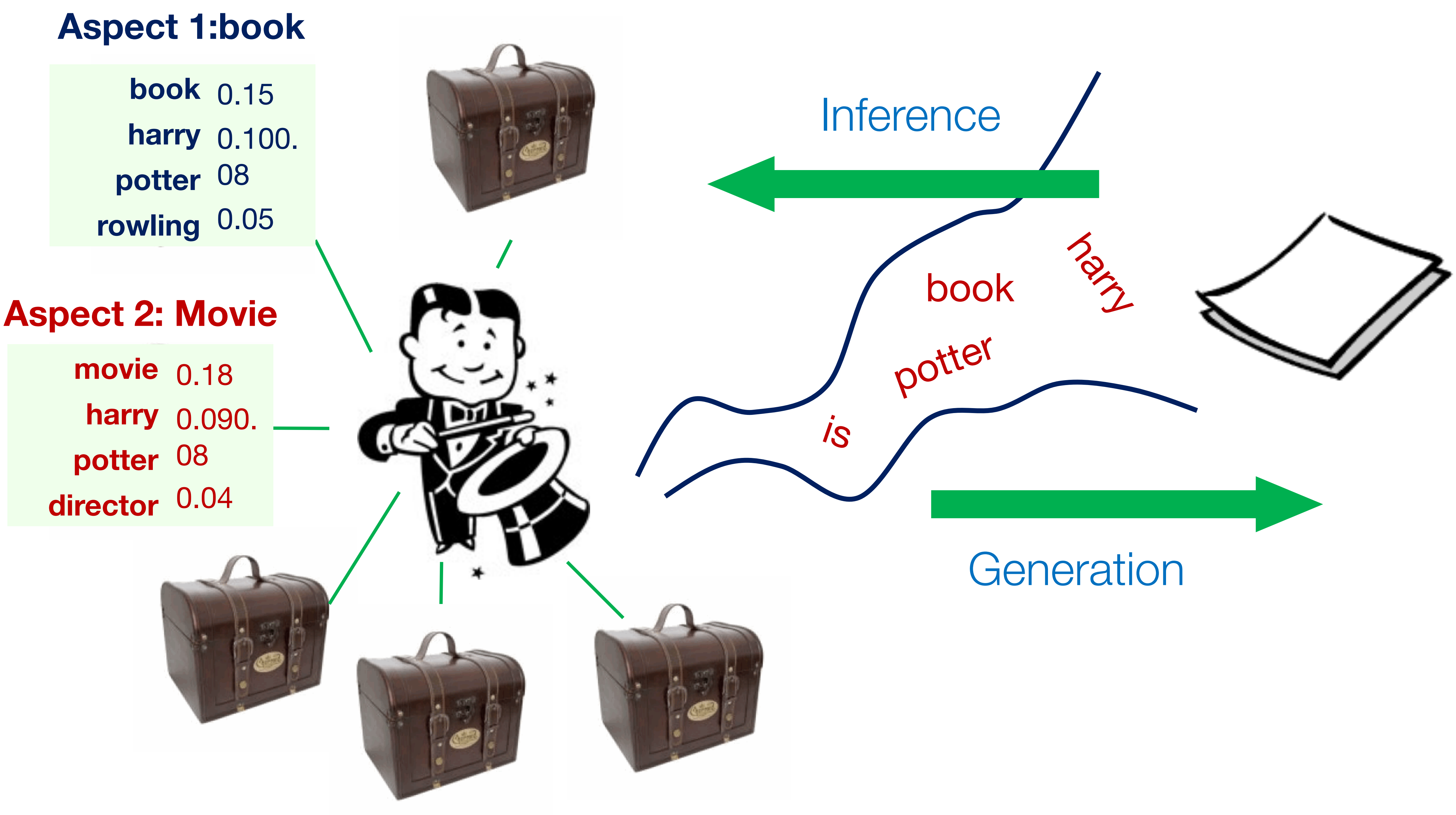


The Simplest Generative Model: Unigram Model

- Only one topic in the entire corpus, or one topic in each document
- Generative process:
- For each document d:
  - For each word token w_n in d:
  - Choose a word w according to the multinomial distribution P(w).

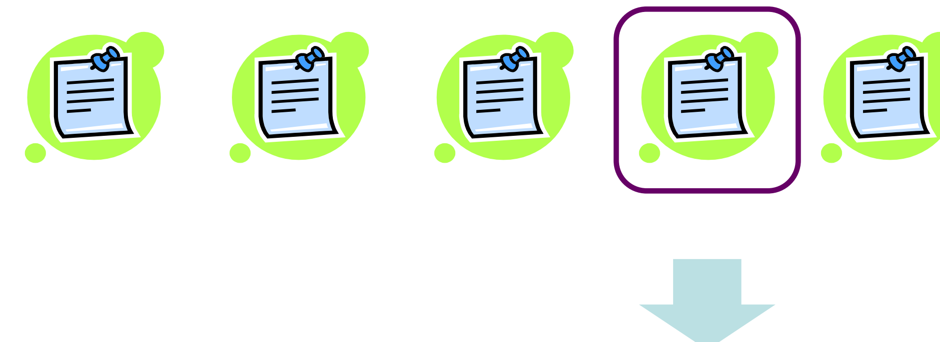
Simple Unigram – Generative Process

$$P(d) = \prod_{w \in d} P(w)$$

movie	*0.100*
harry	*.090.*
potter	*05*
ipod	*0.01*
music	*0.02*

I [redacted]
the music of
the [redacted]
[redacted] potter to
my [redacted] nano

Simple Unigram – Generative Process



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I **downloaded**
the music of
the **movie**
harry potter to
my **ipod** nano

Graphical Structure of Unigram Models

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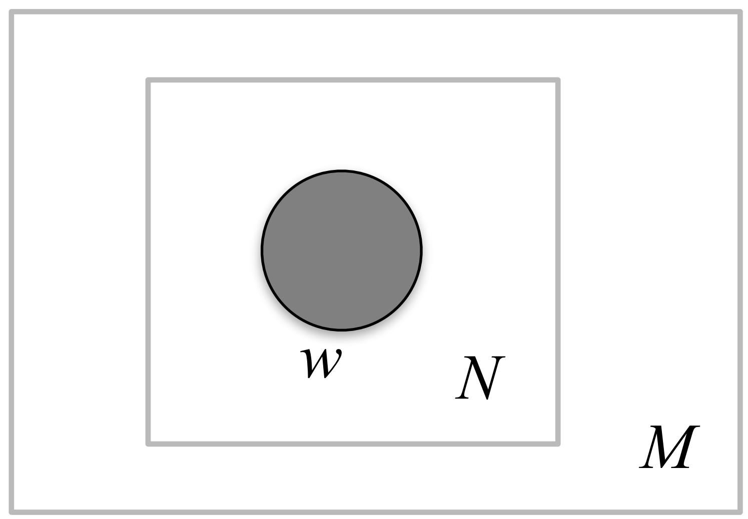
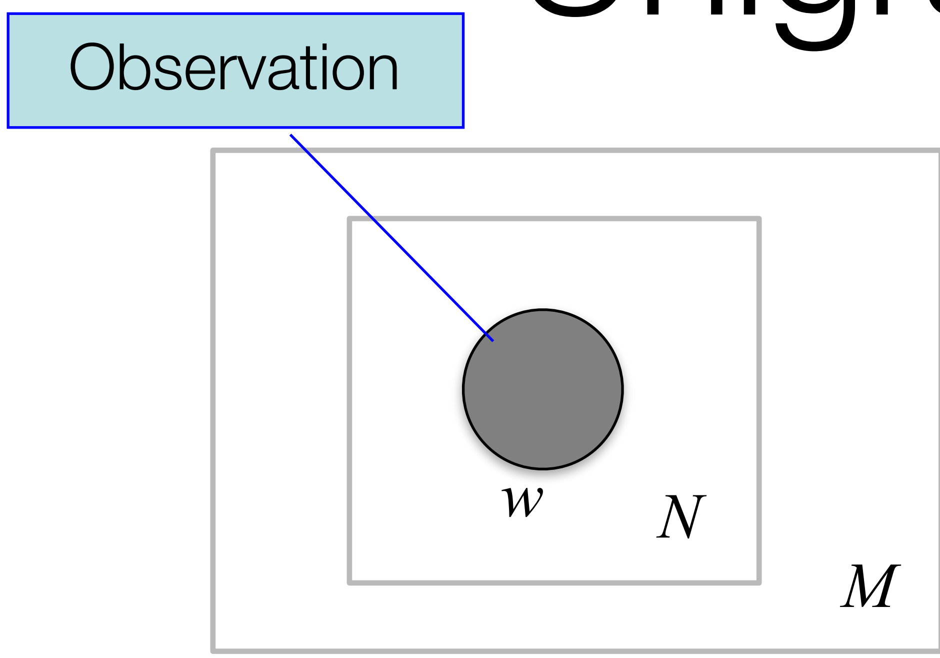


Graphical Structure of Unigram Models



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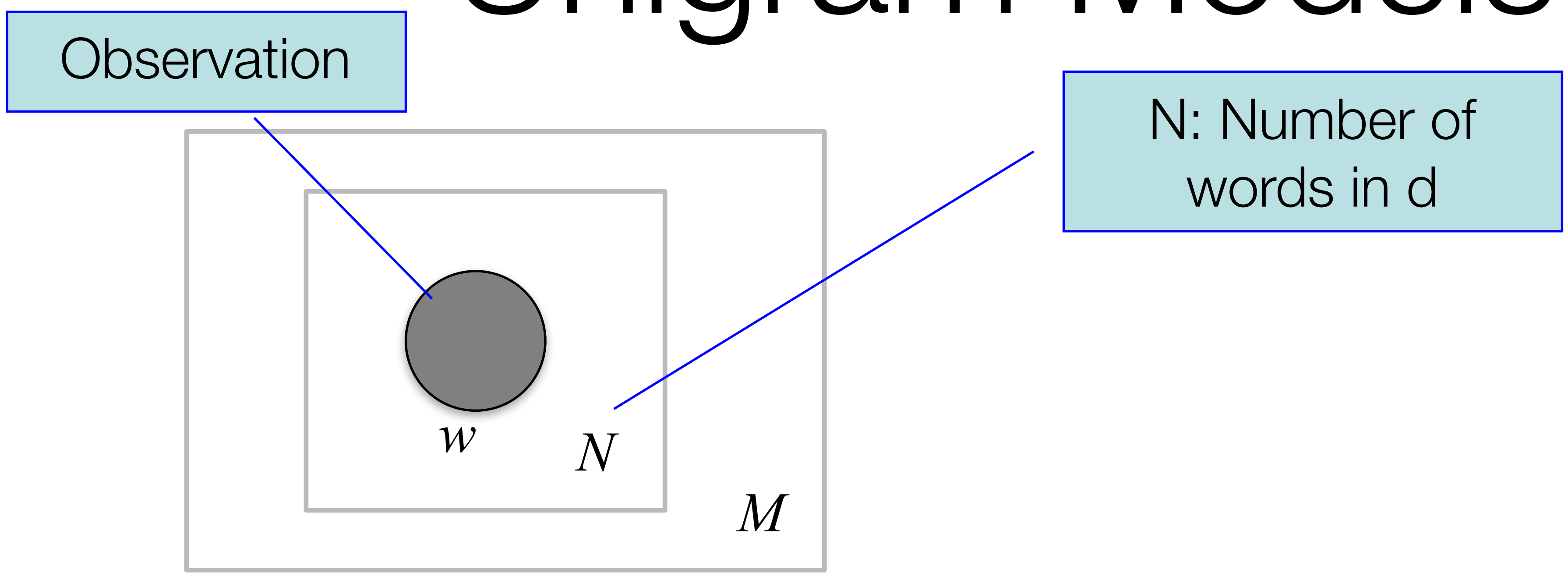

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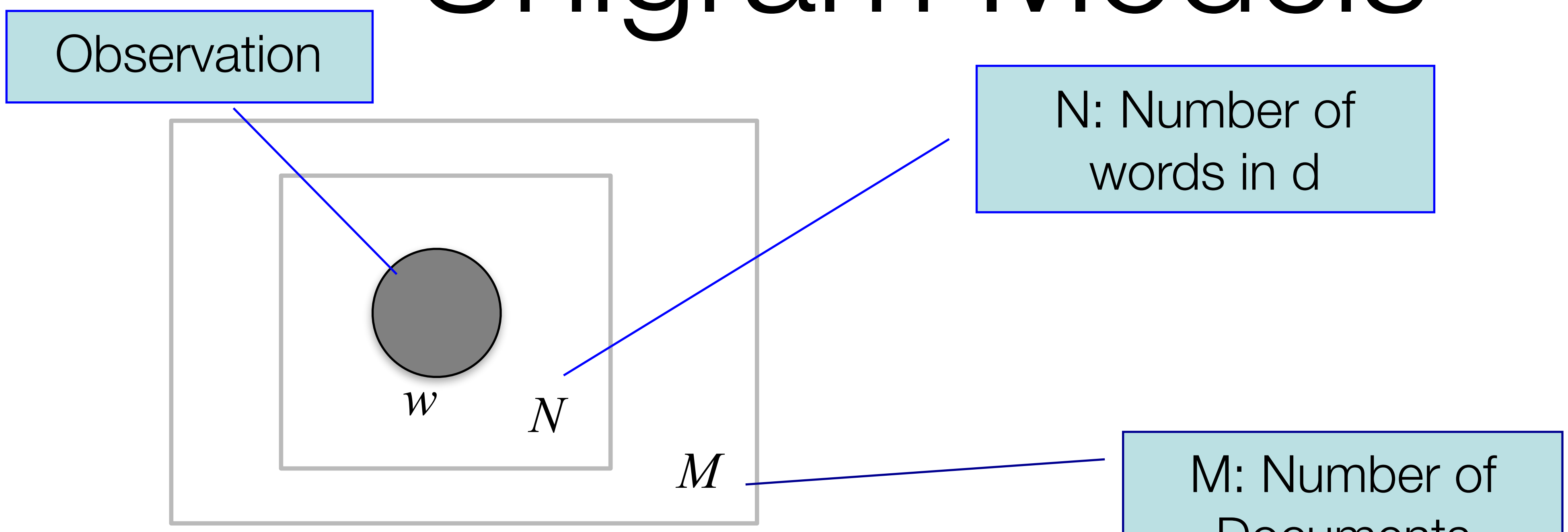

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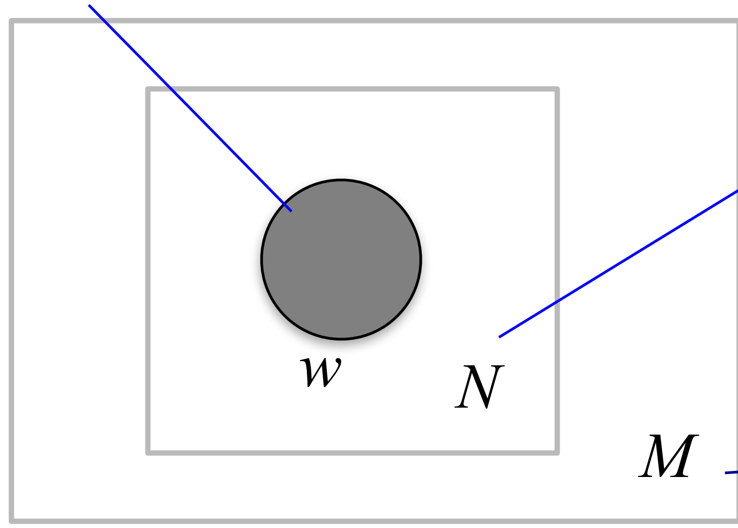
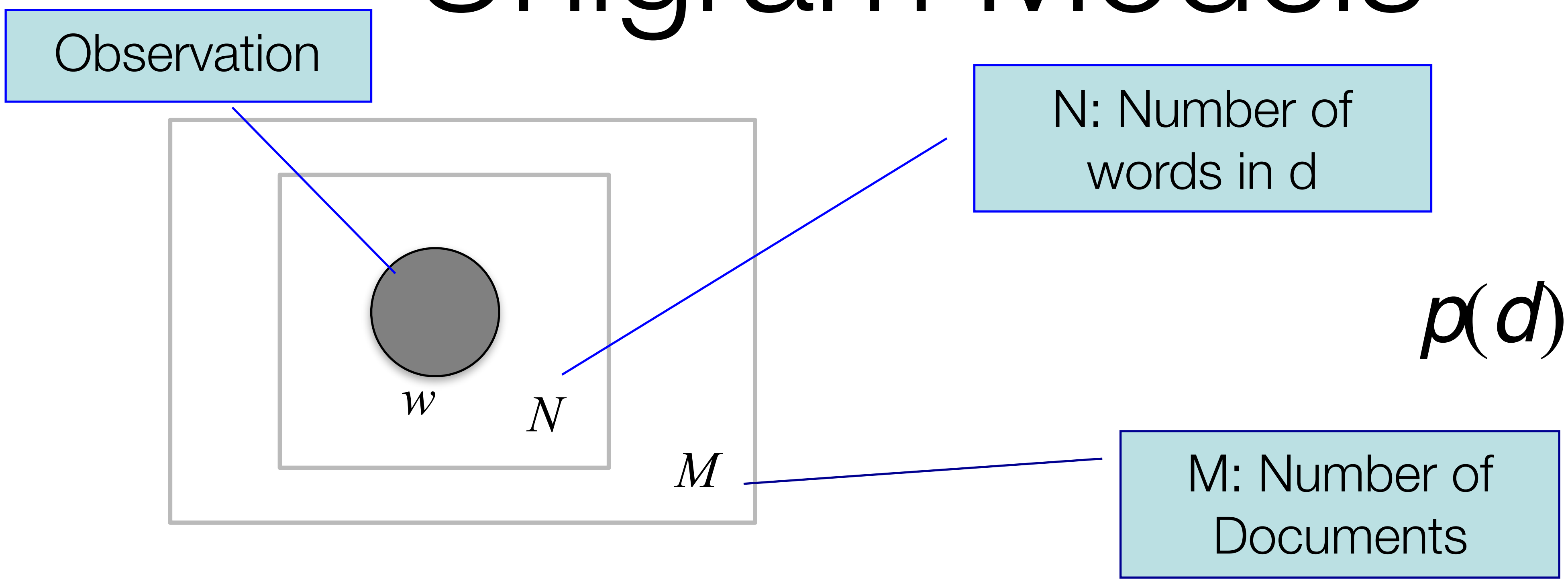


$$p(d) = \prod_{n=1}^{N} p(w_n)$$

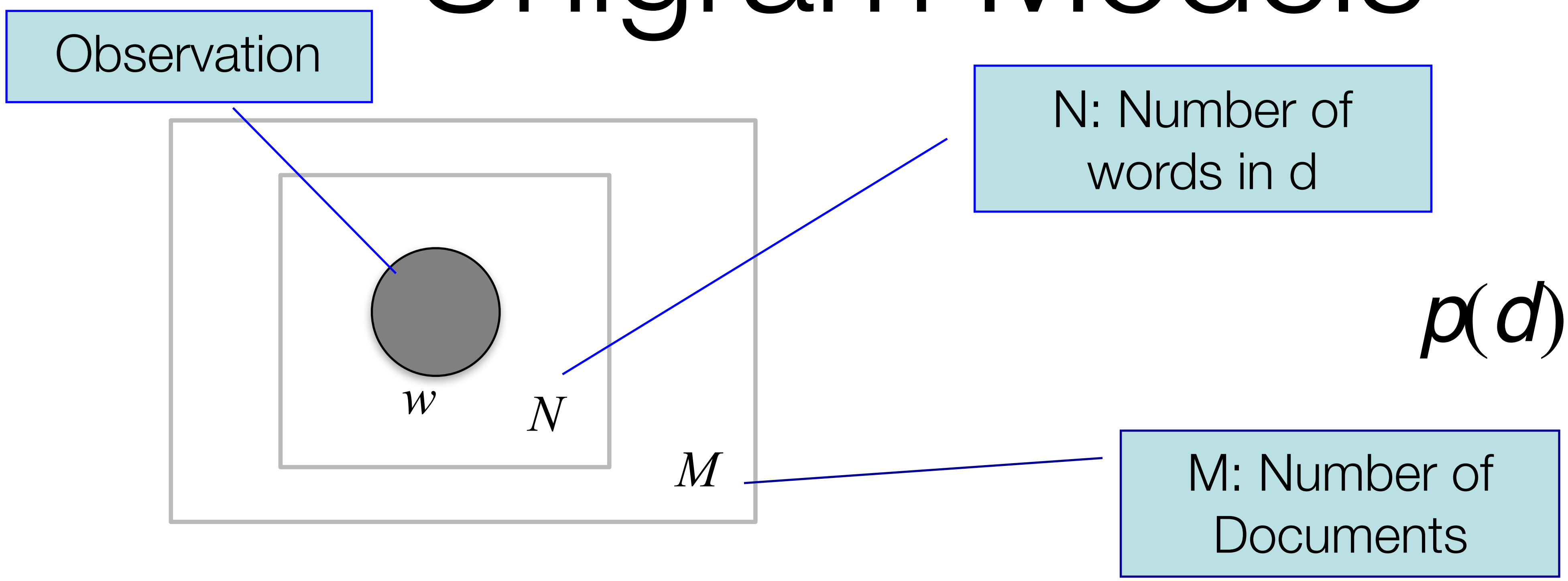
Graphical Structure of Unigram Models



$$p(d) = \prod_{n=1}^{N} p(w_n)$$

- No dependency among variables

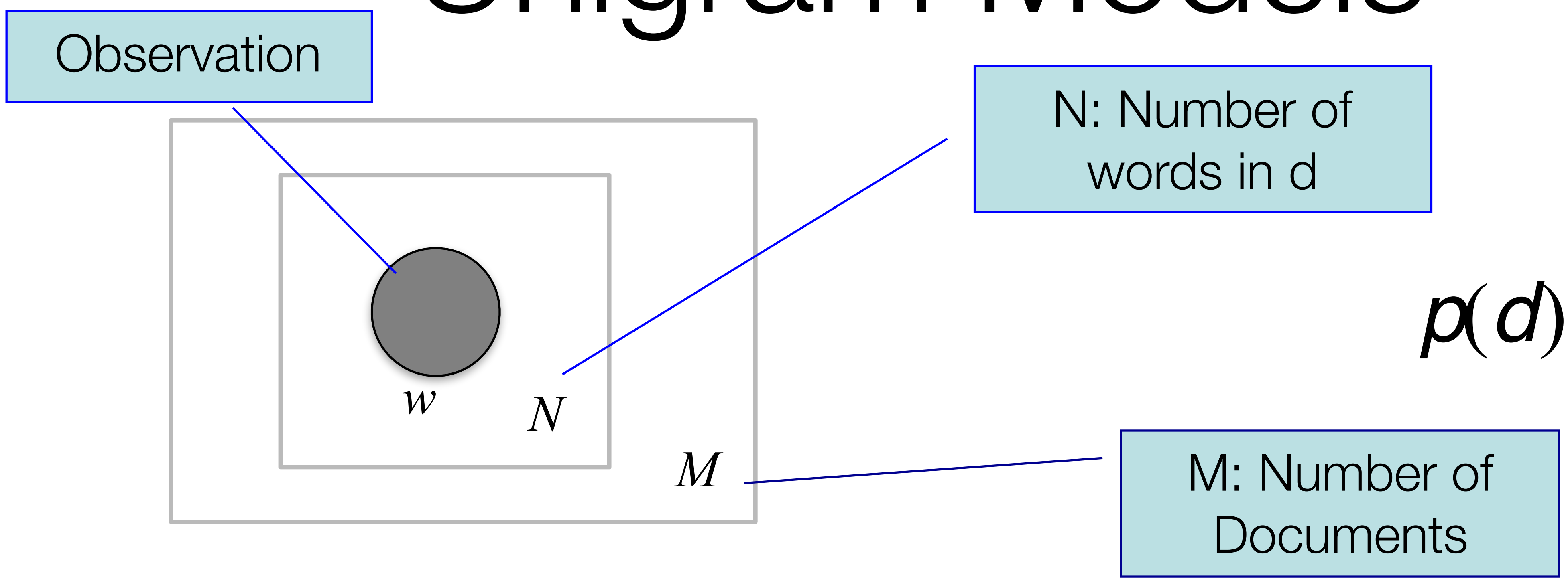
Graphical Structure of Unigram Models



$$p(d) = \prod_{n=1}^{N} p(w_n)$$

- No dependency among variables
- Parameter: p(w)

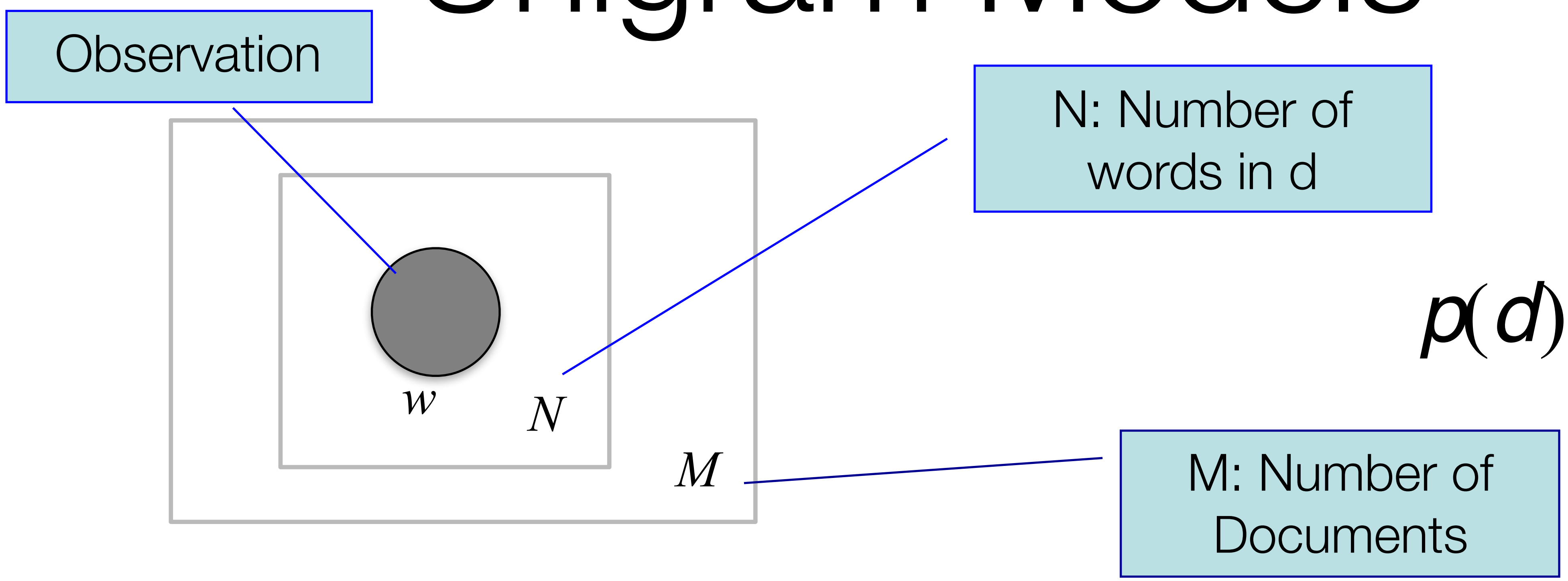
Graphical Structure of Unigram Models



$$p(d) = \prod_{n=1}^{N} p(w_n)$$

- No dependency among variables
- Parameter: p(w)
- Parameter estimation:
  - Maximum likelihood estimation (MLE)

Graphical Structure of Unigram Models



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- Parameter: p(w)
- Parameter estimation:
  - Maximum likelihood estimation (MLE)
- Applications:
  - language modeling based information retrieval

Mixture of Unigrams

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Mixture of Unigrams – Generative Process

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nano	0.080
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download	0.02
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movie	*0.100*
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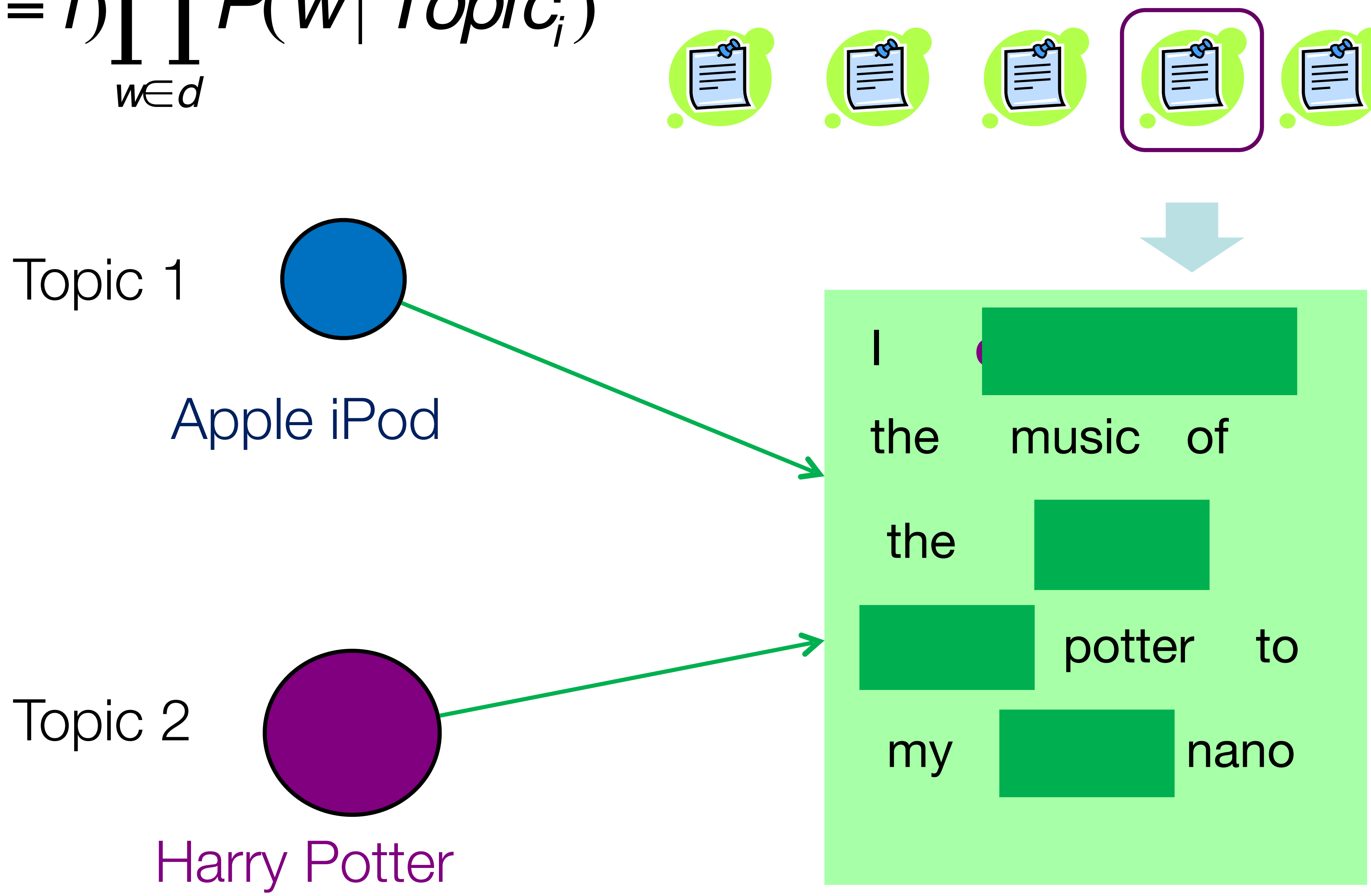

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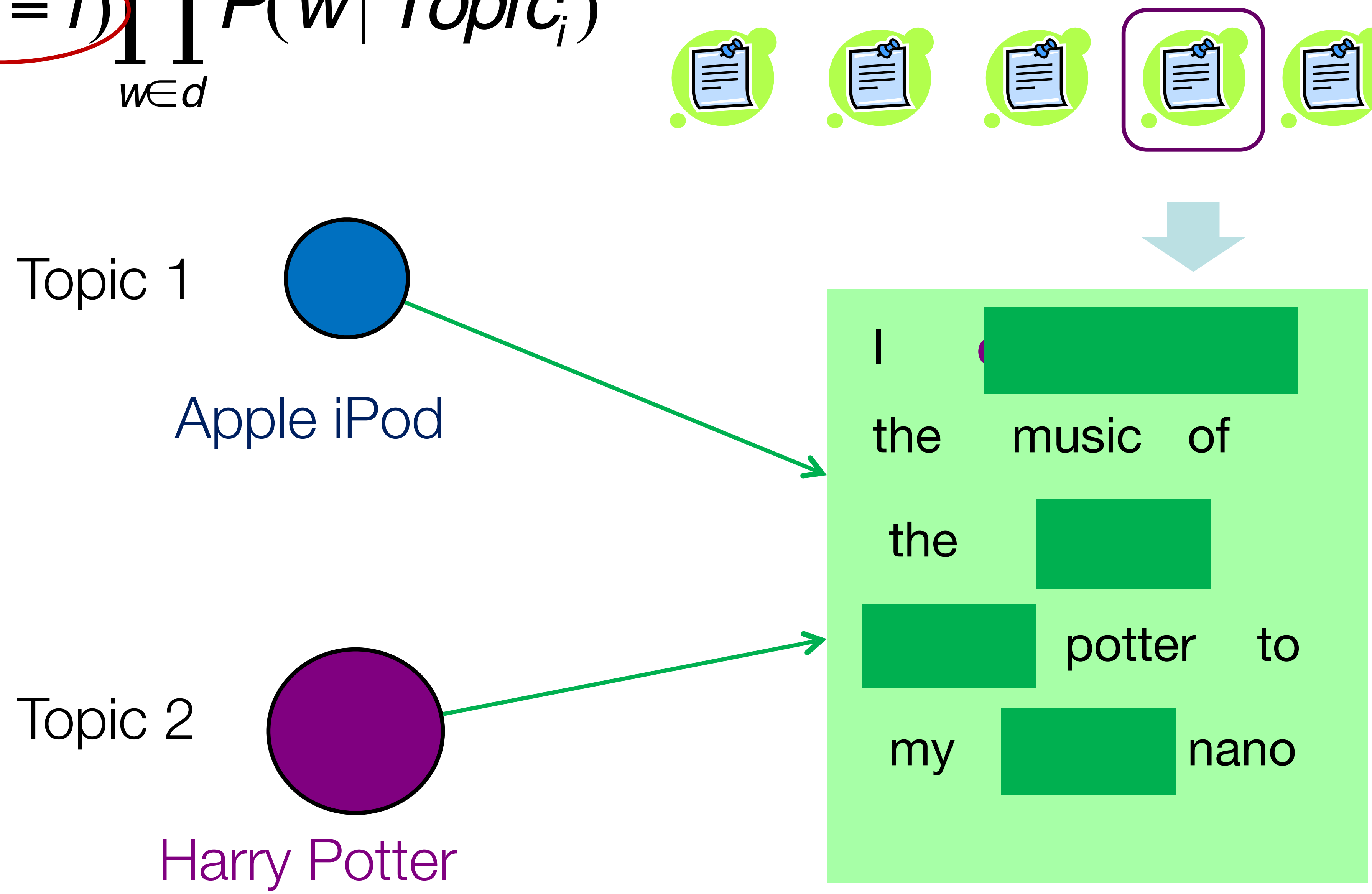

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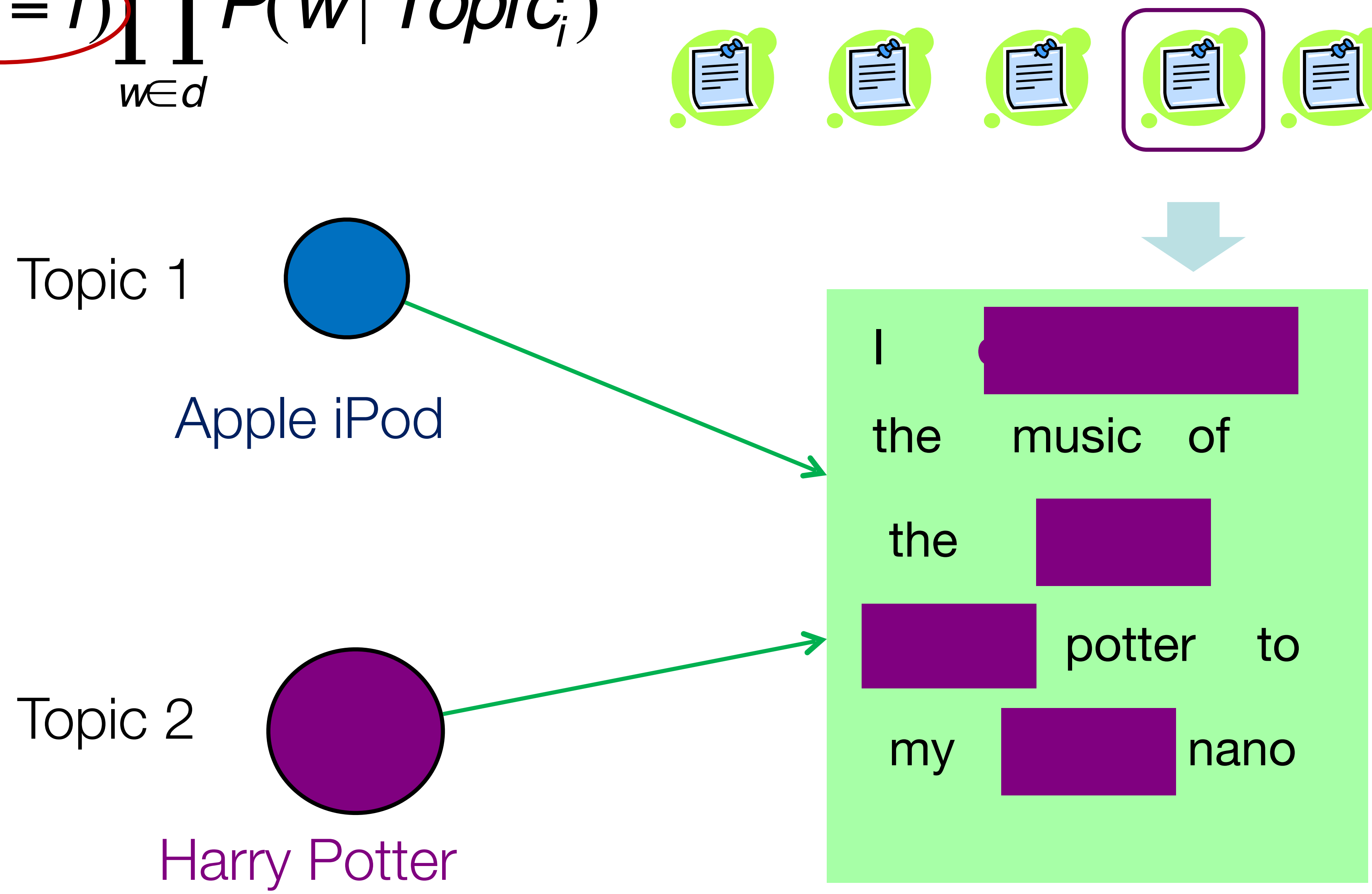

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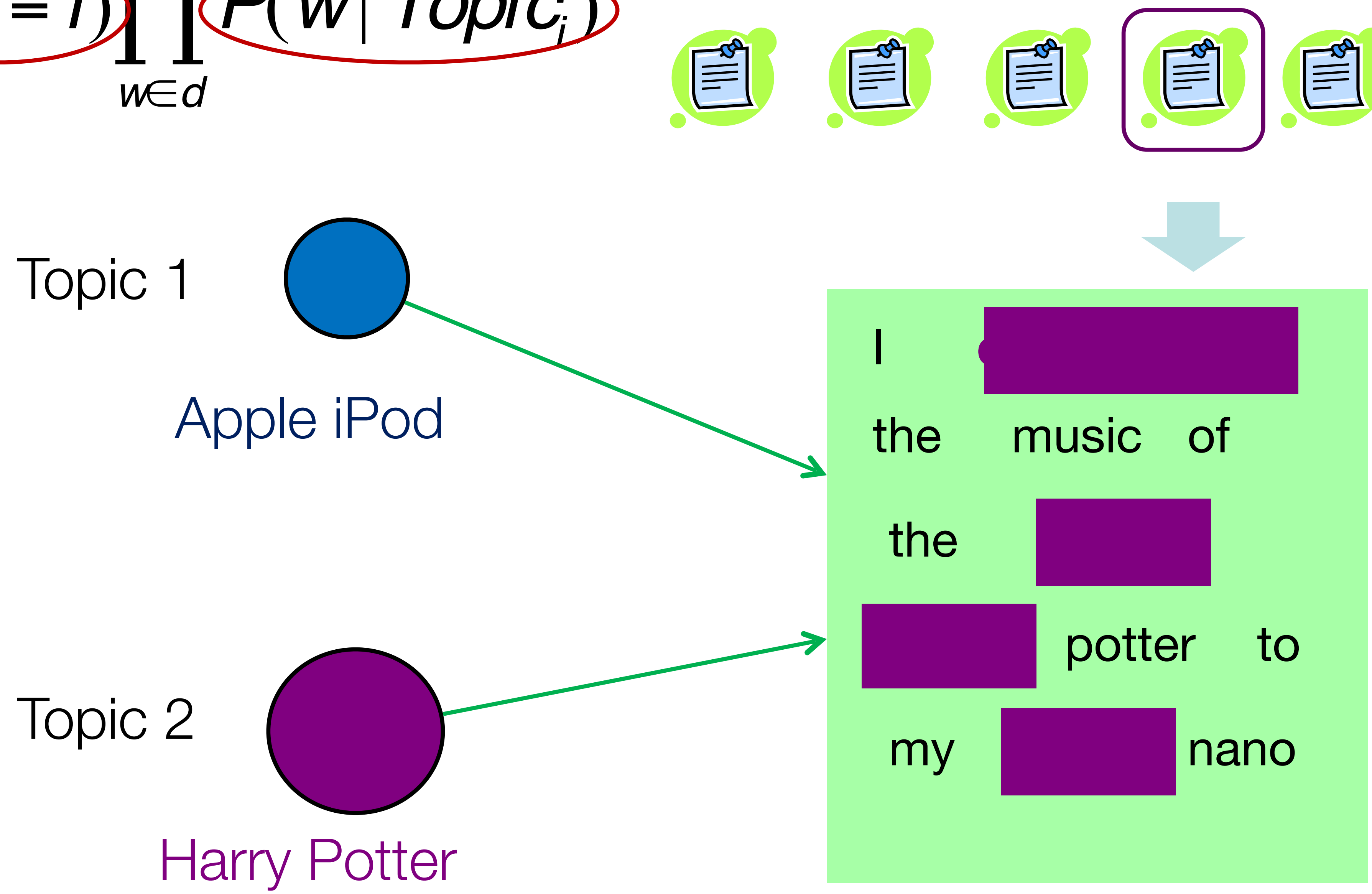

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Topic 1

Apple iPod

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Topic 2

Harry Potter

I [redacted]
the music of
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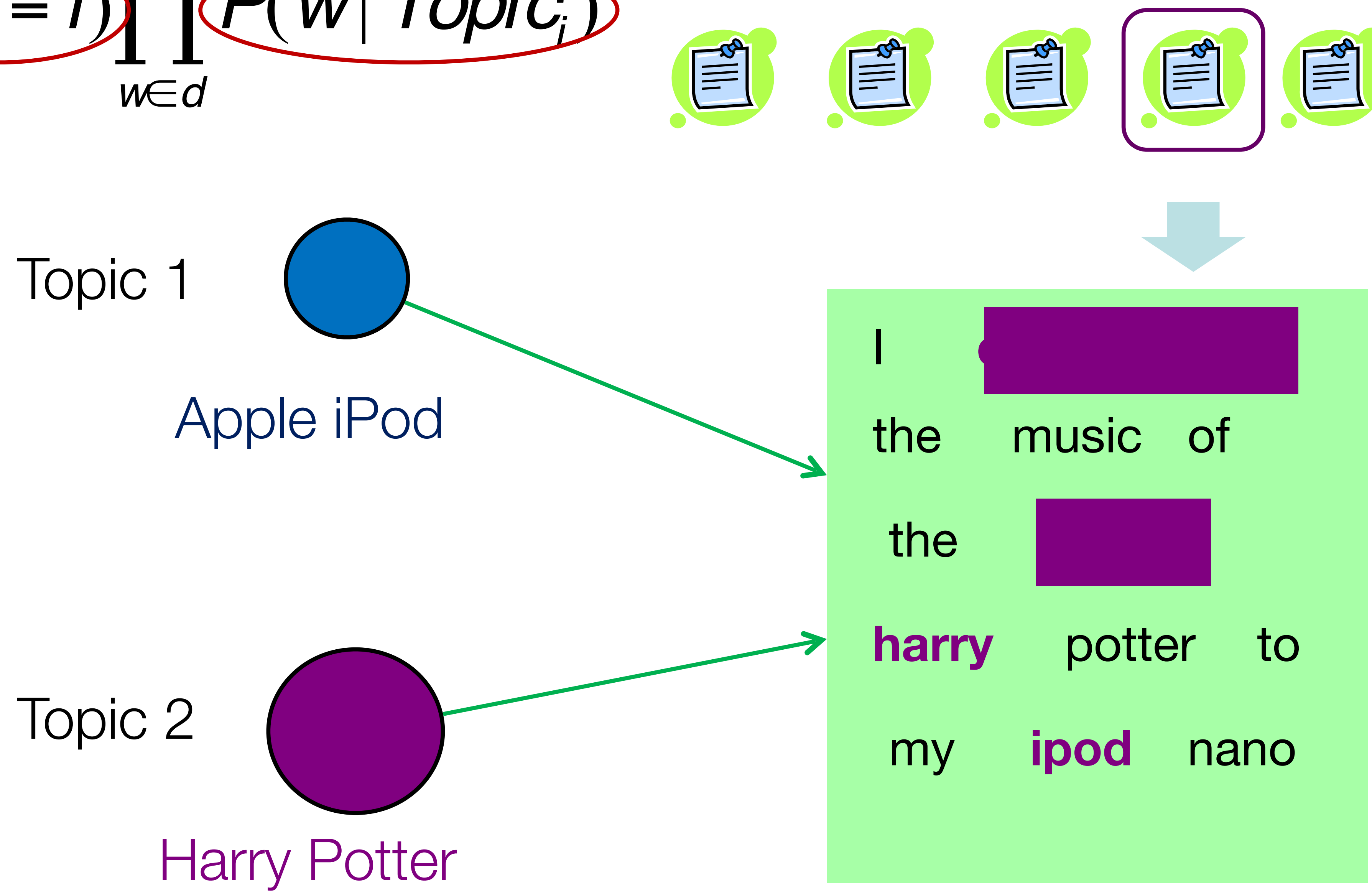

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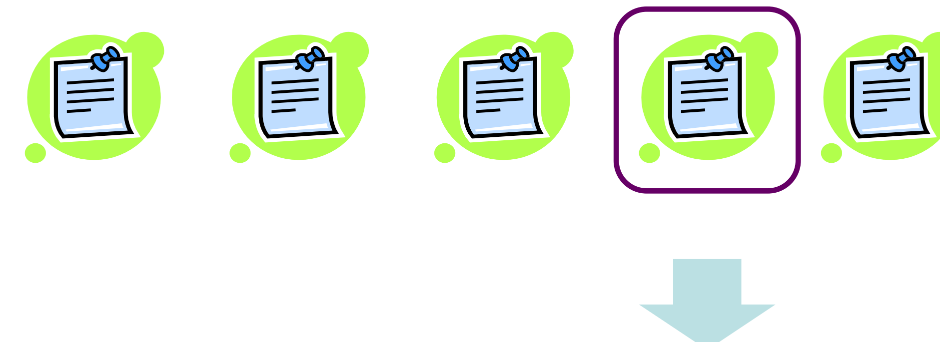

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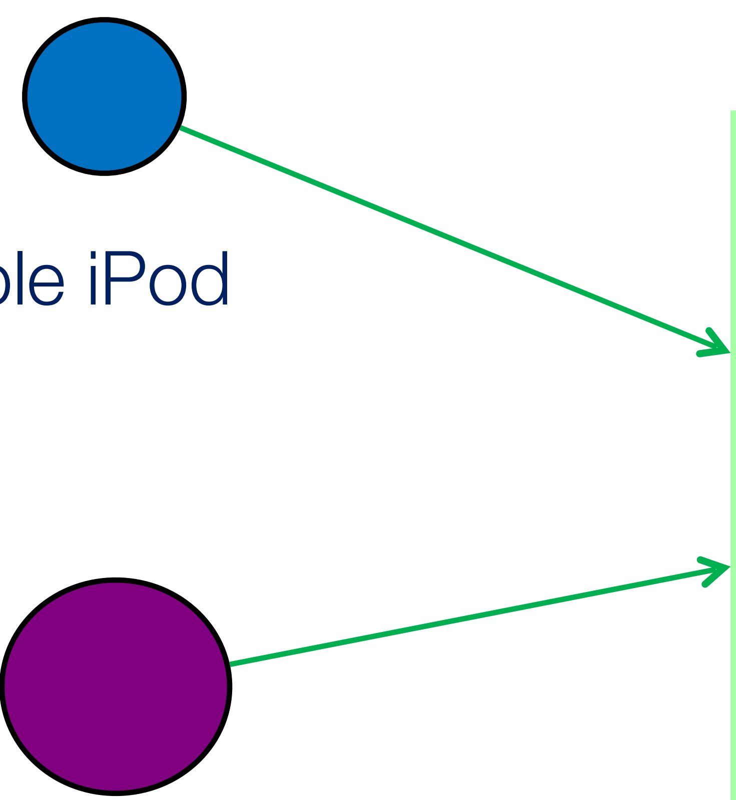

I downloaded the music of the movie harry potter to my ipod nano

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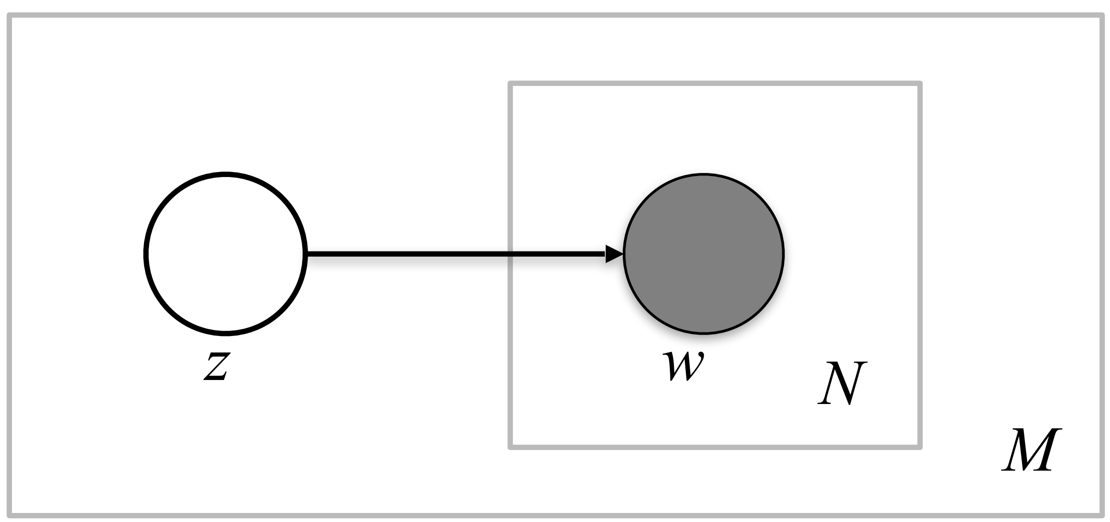

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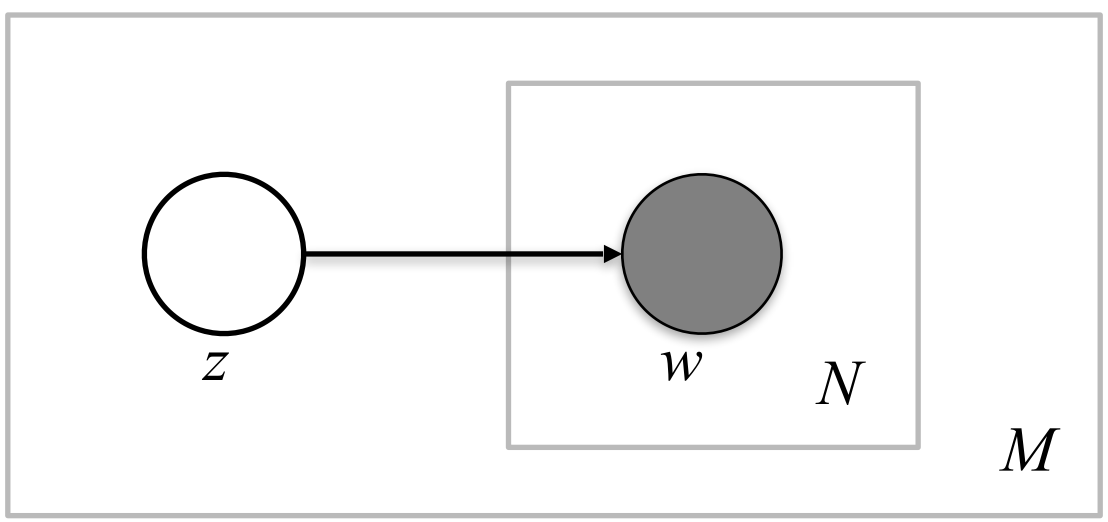

$$p(d) = \sum_{z} p(z) \prod_{n=1}^{N} p(w_n \mid z)$$

- Estimation: MLE and EM Algorithm
- Application: simple document clustering

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- Cons:
  - Usually different parts of a document present different topics
  - Desirable: words in a document to take different identities

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(Hofmann, 1999)

- Also known as probabilistic latent semantic indexing (PLSI)
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  - Both P(z|d) and P(w|z) are fixed but unknown parameters – to be estimated

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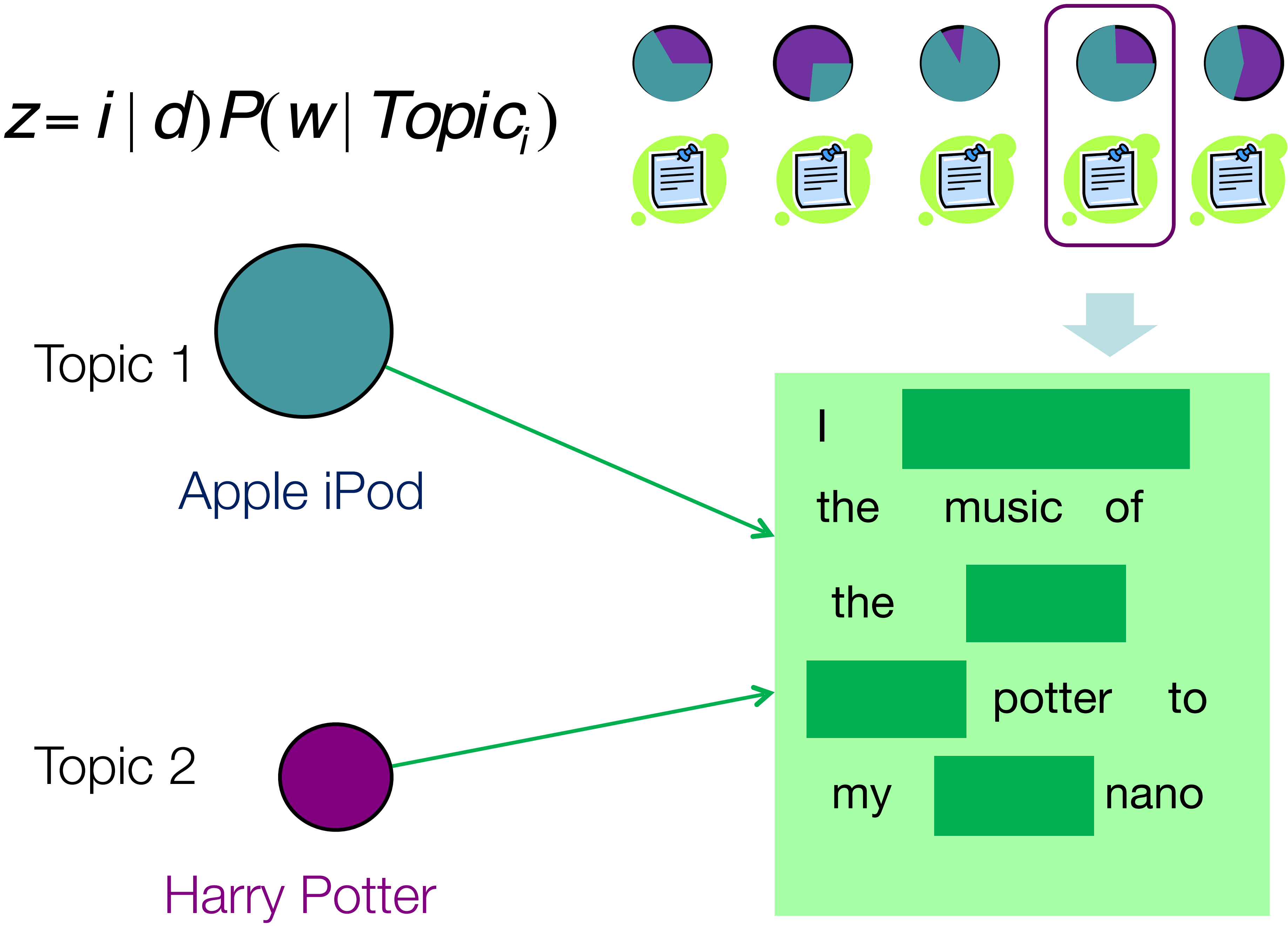

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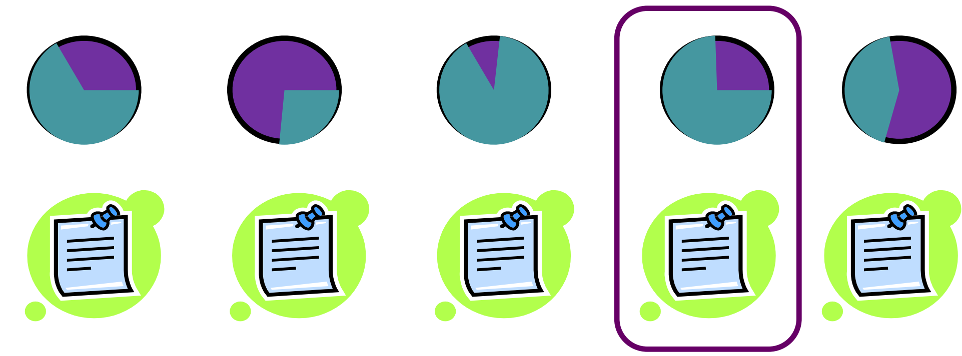

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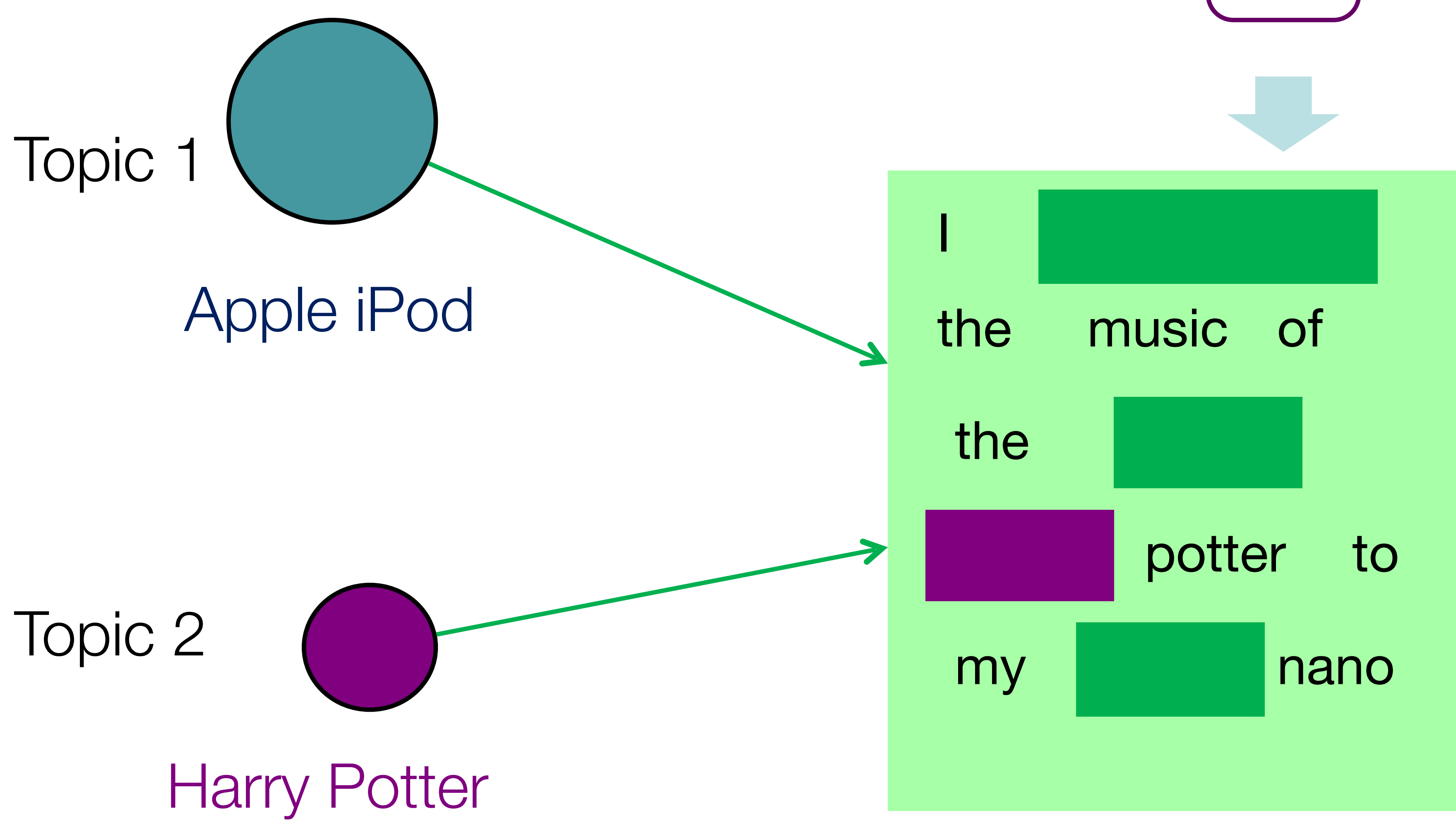

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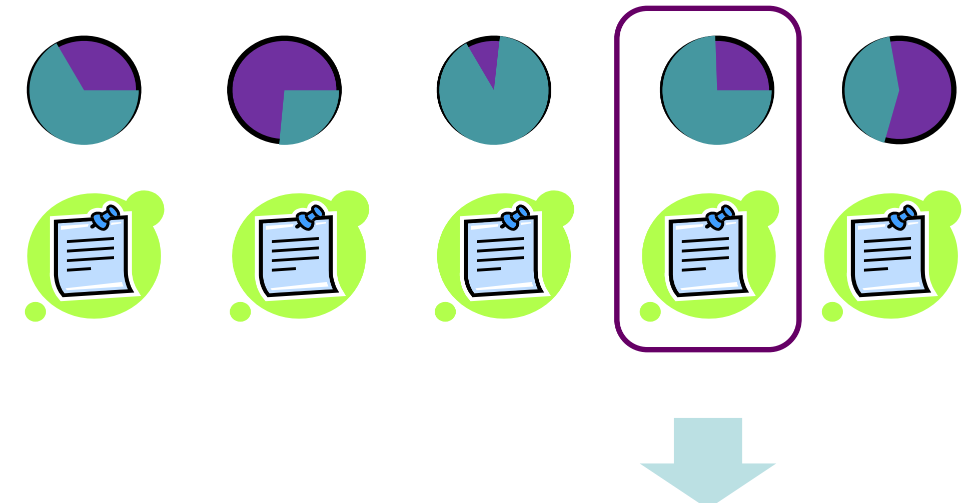

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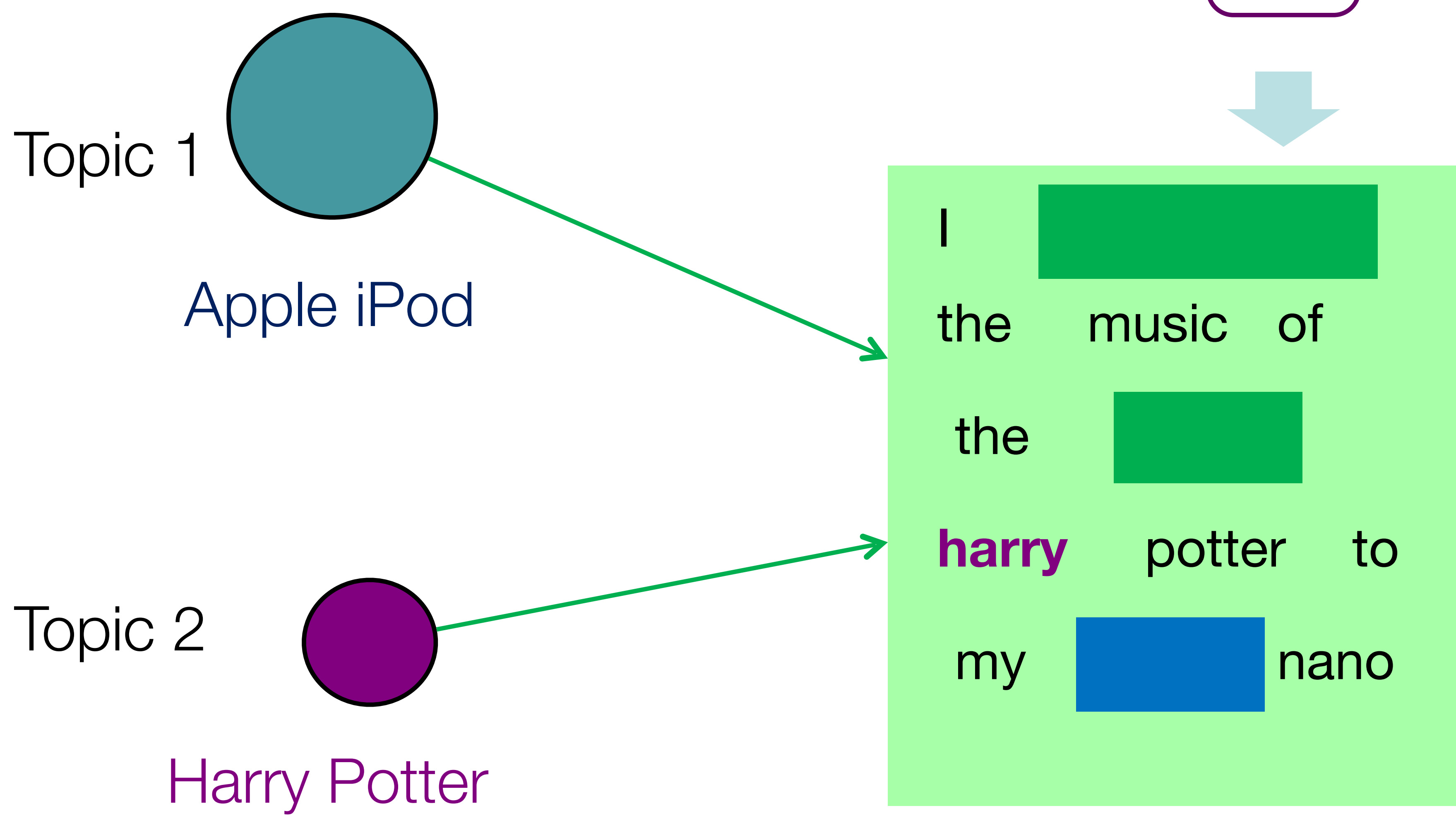

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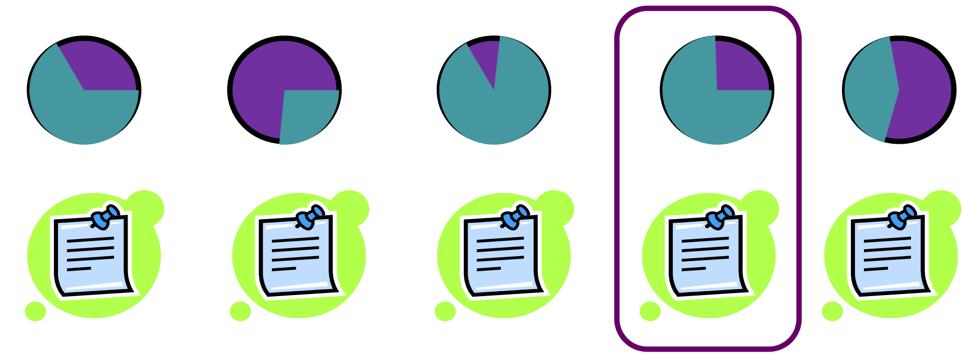

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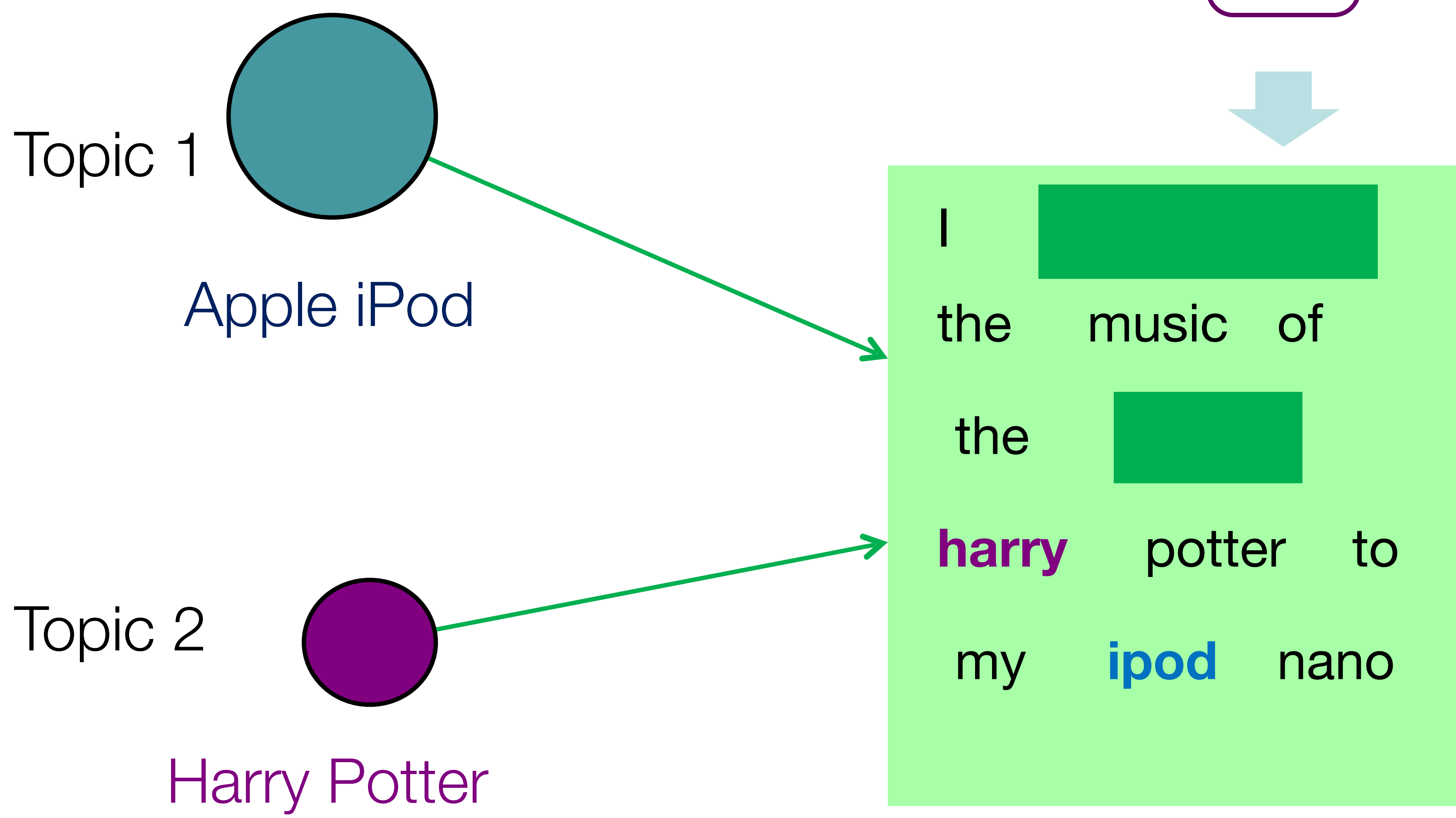

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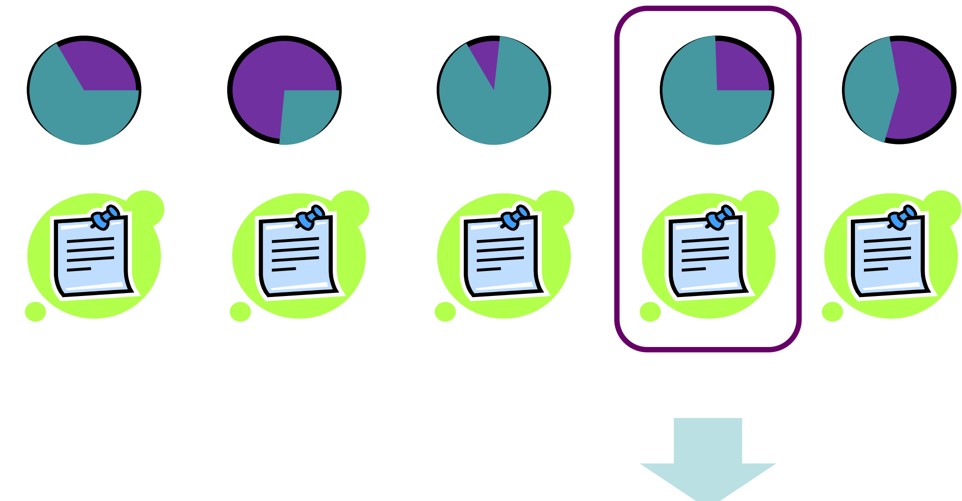

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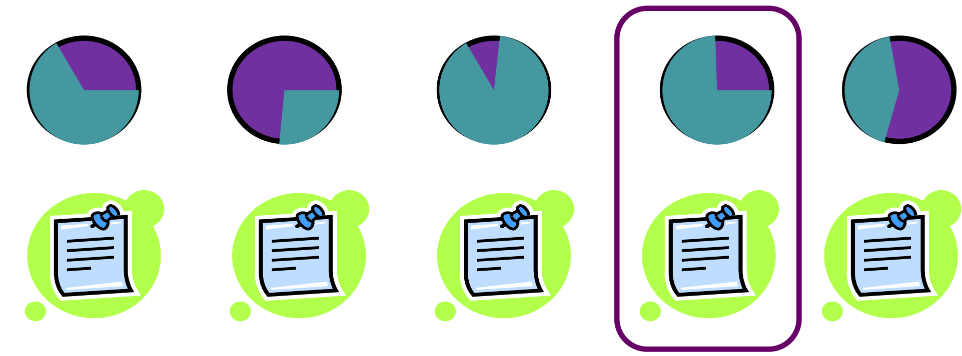

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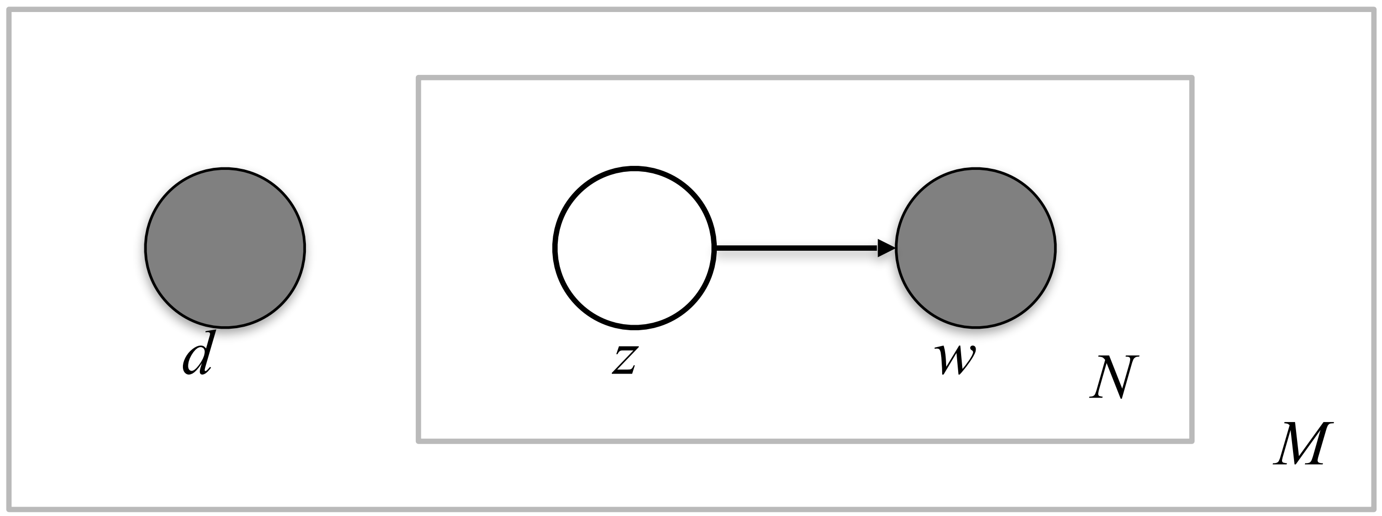

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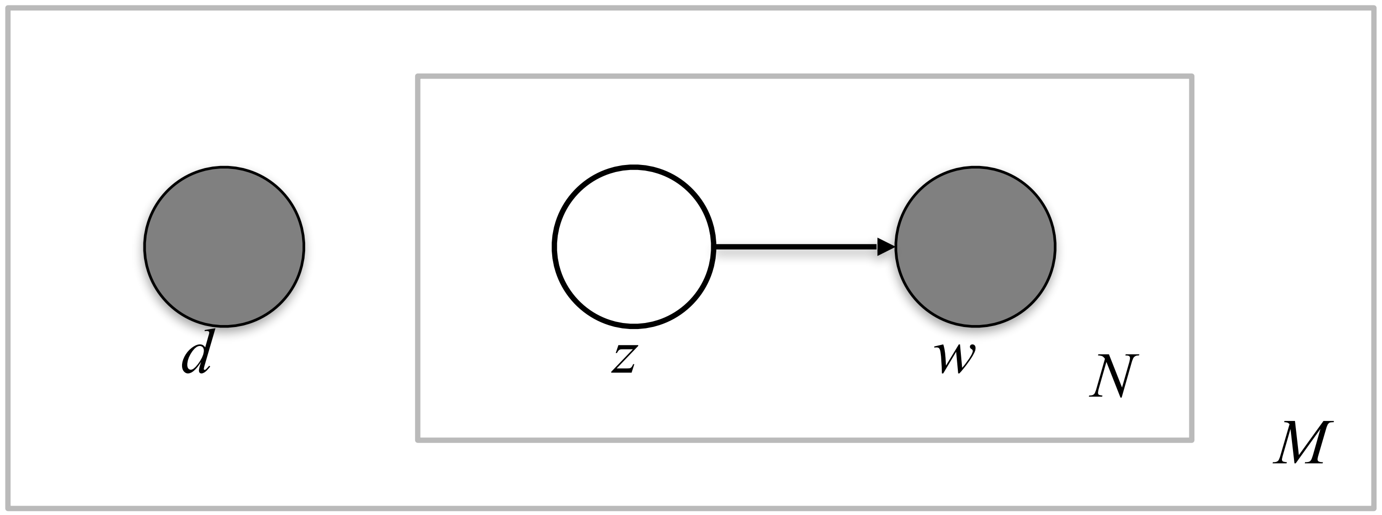

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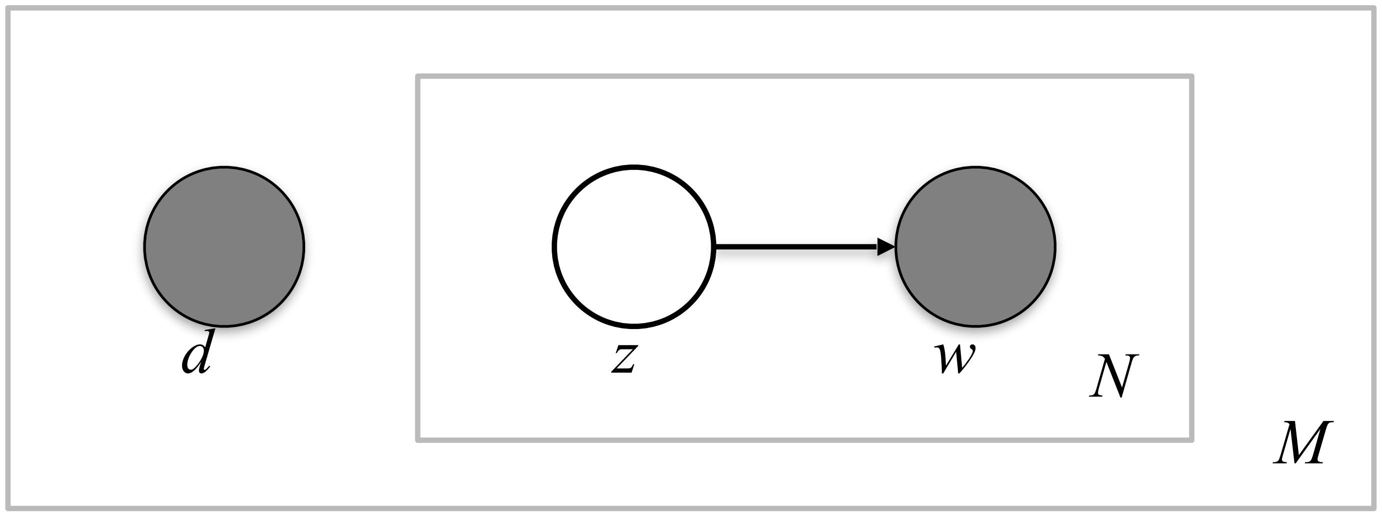

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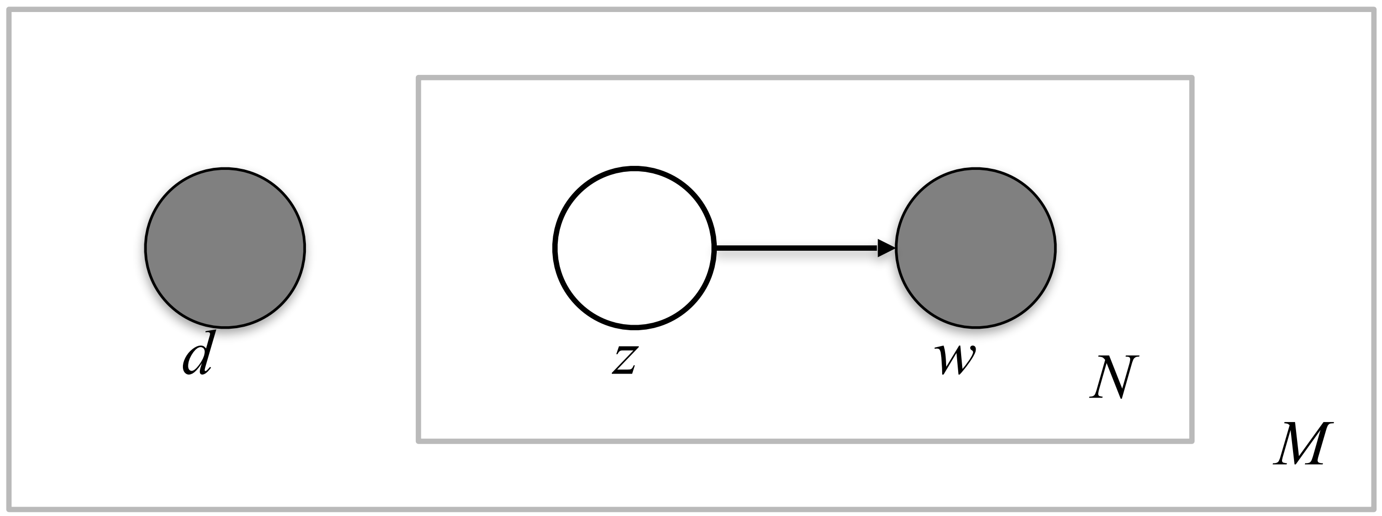

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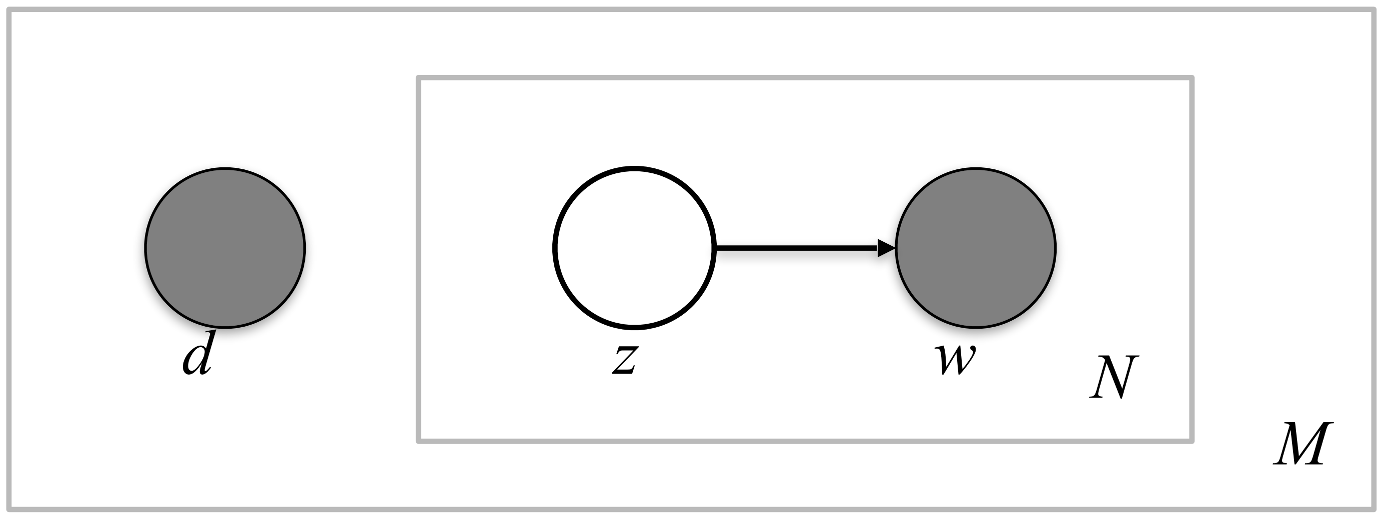

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- Cons:
  - Not a complete Bayesian model: hard to interpret unseen documents
  - Overfits the data (because number of parameters grows linearly with the number of documents).

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(Blei&Ng&Jordan, 2003)

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- For a fuller Bayesian approach, can place a Dirichlet prior to these word multinomial distributions to smooth the probabilities.

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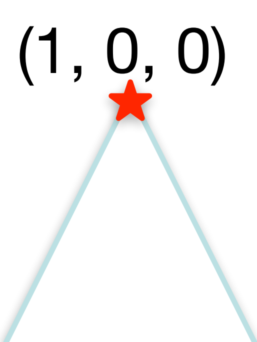

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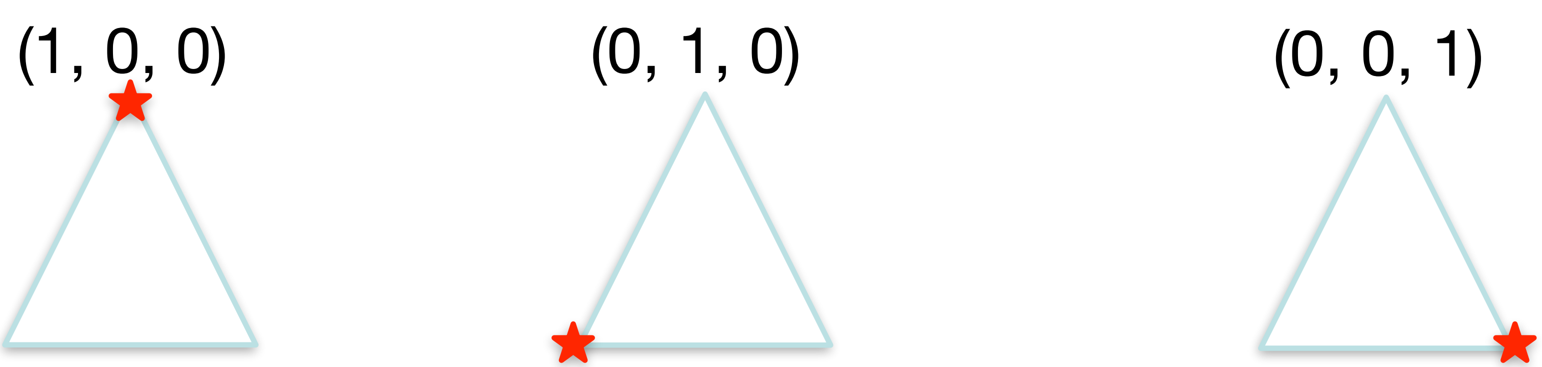

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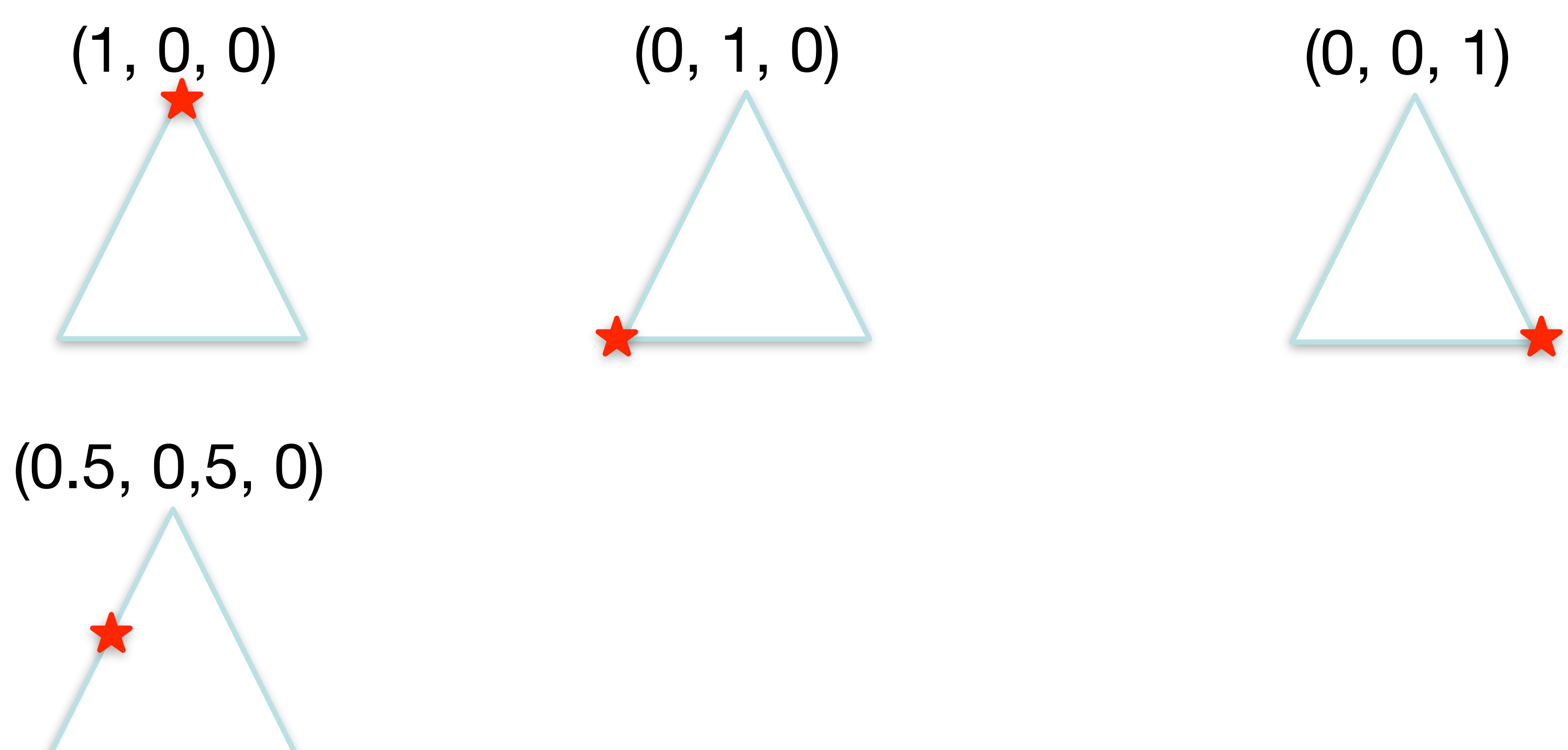

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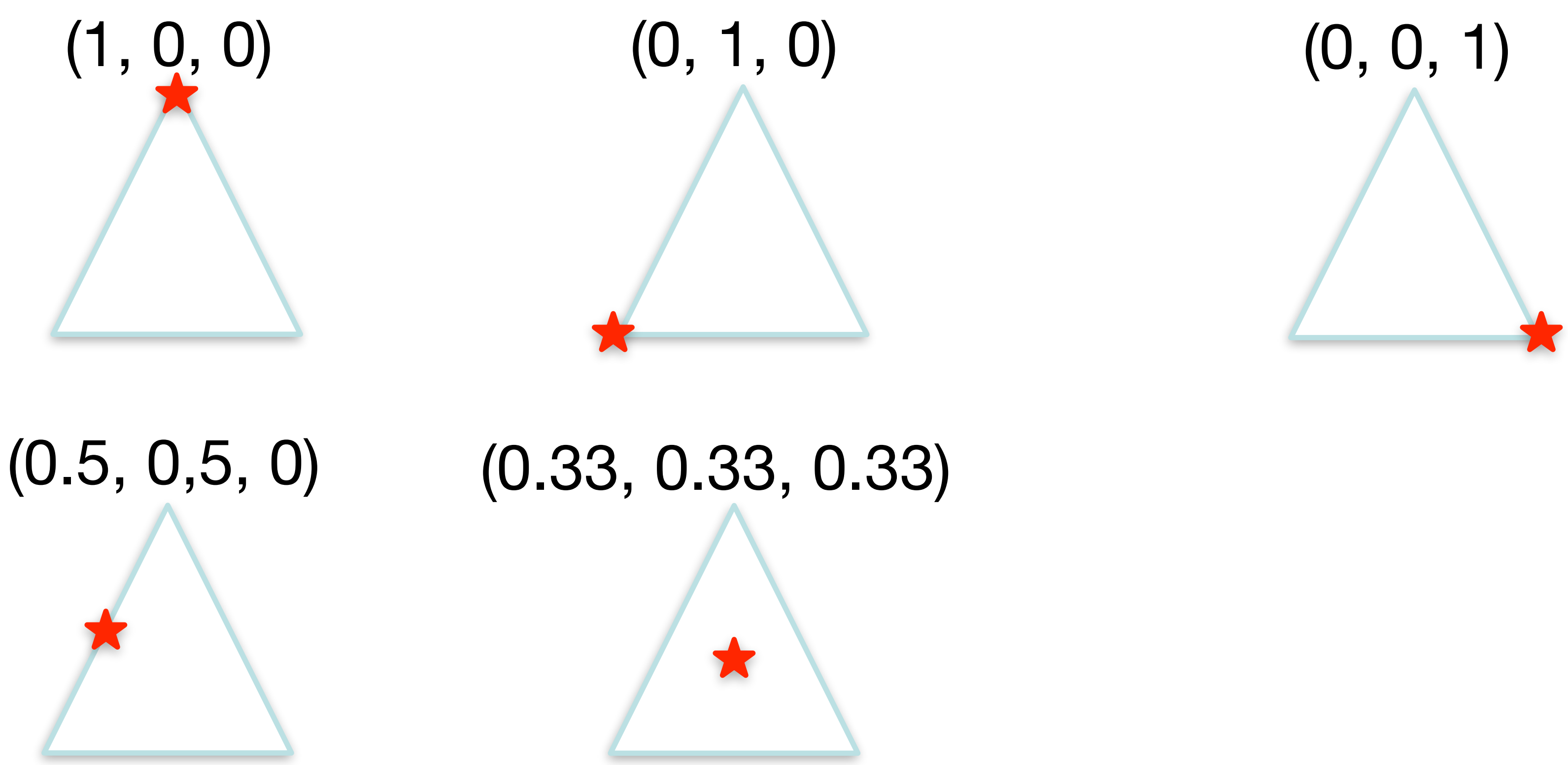

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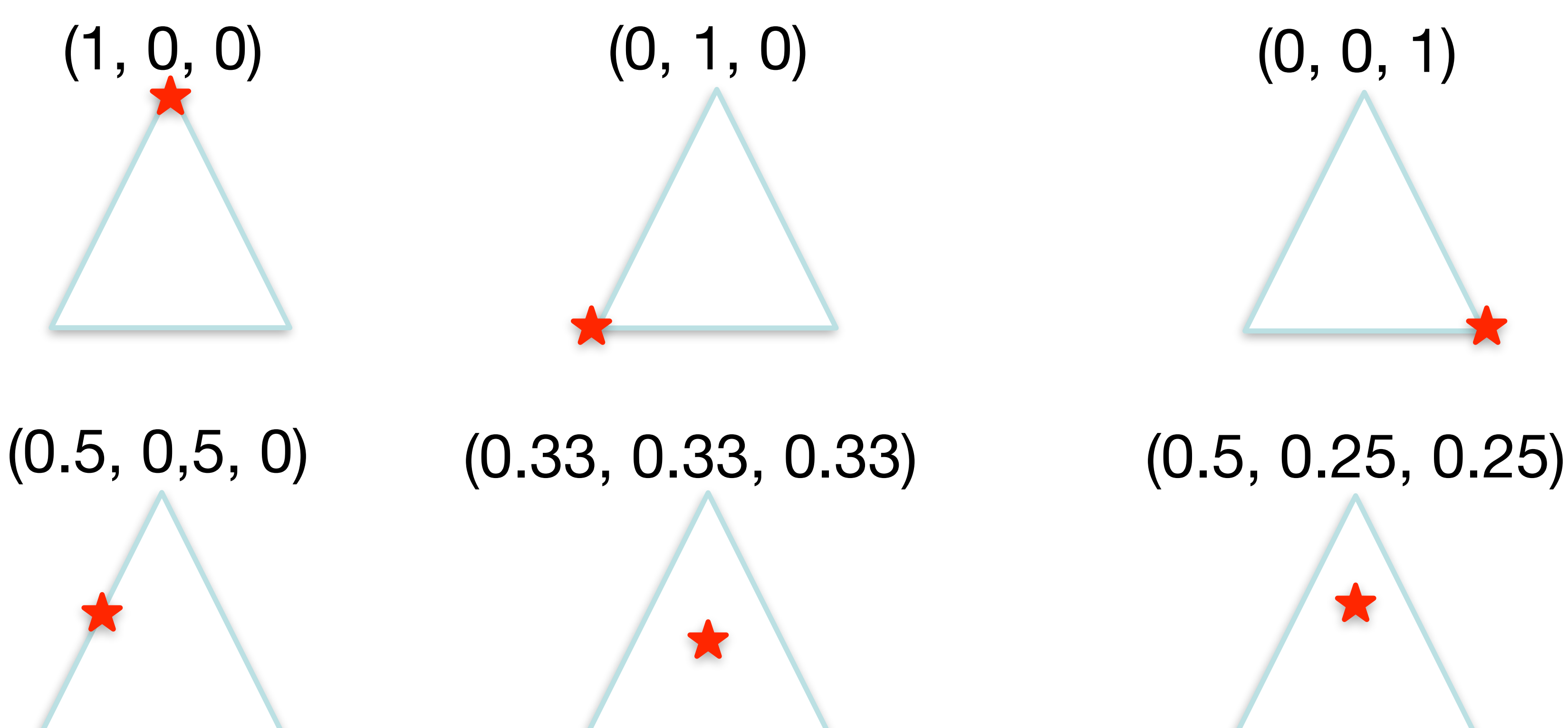

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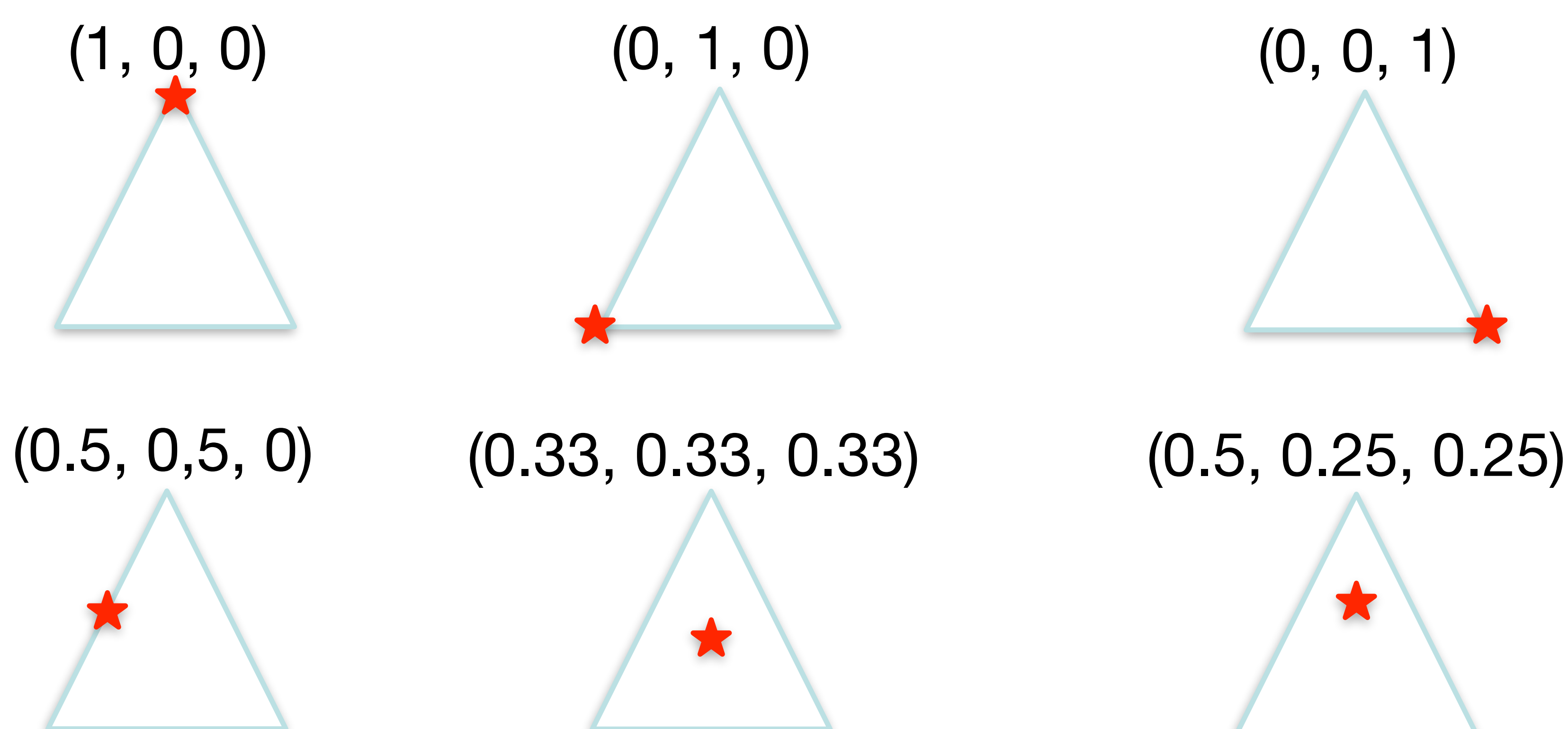

The Dirichlet distribution will give us a distribution over where a multinomial can be placed

Dirichlet Distribution as Priors over Multinomials

Think of α as a scale and *m* as a center

$$P(p|\alpha\mathbf{m}) = \frac{\Gamma(\sum_k \alpha m_k)}{\prod_k \gamma(\alpha m_k)} \prod \rho_k^{\alpha m_k - 1}$$

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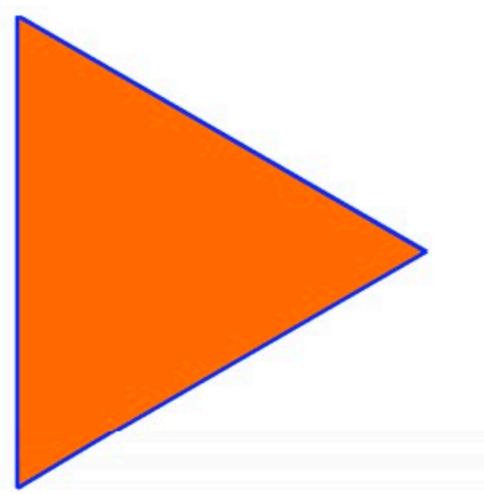

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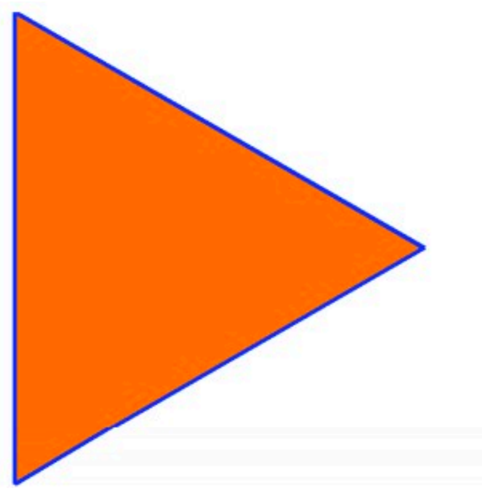

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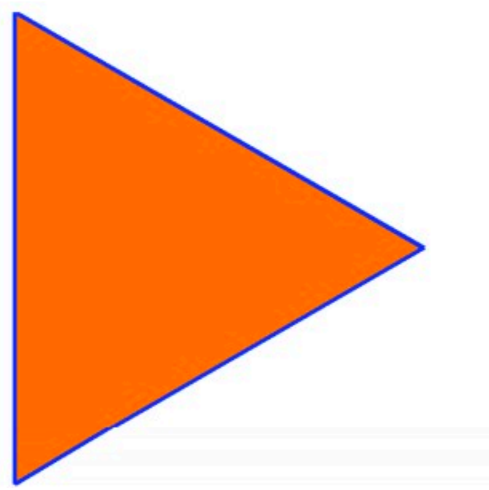
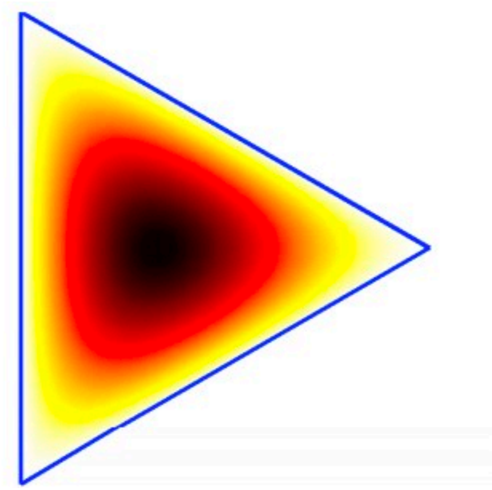
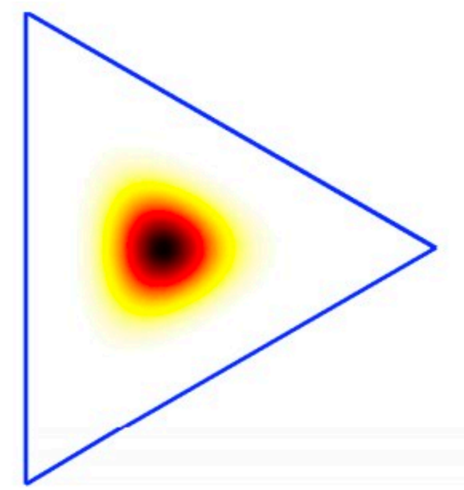


α=6, **m**=(0.3,0.3,0.3)



α=30, **m**=(0.3,0.3,0.3)



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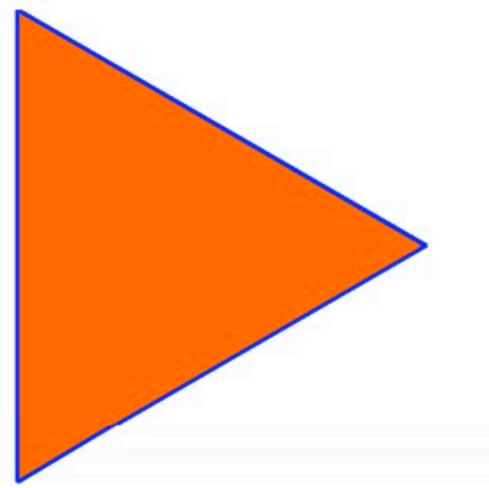

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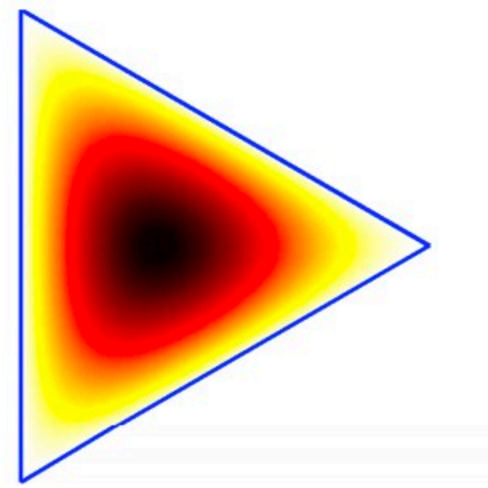

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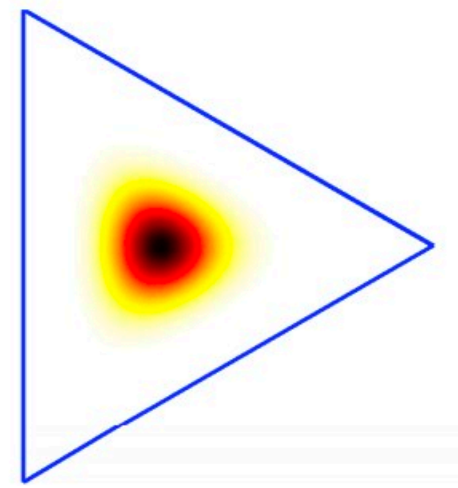

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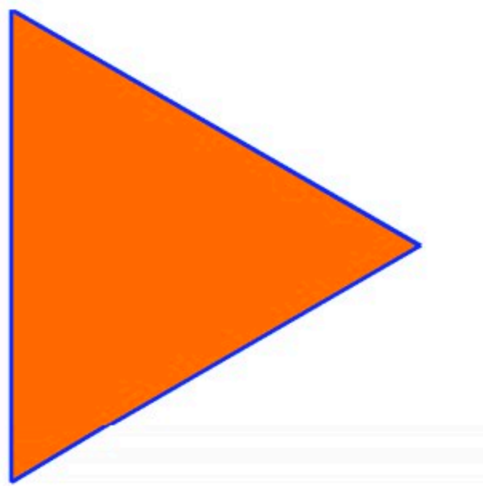

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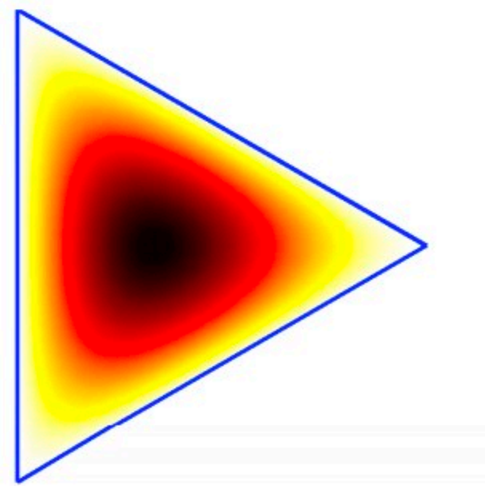

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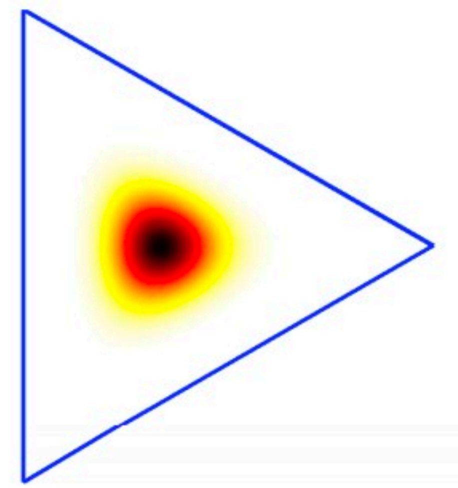

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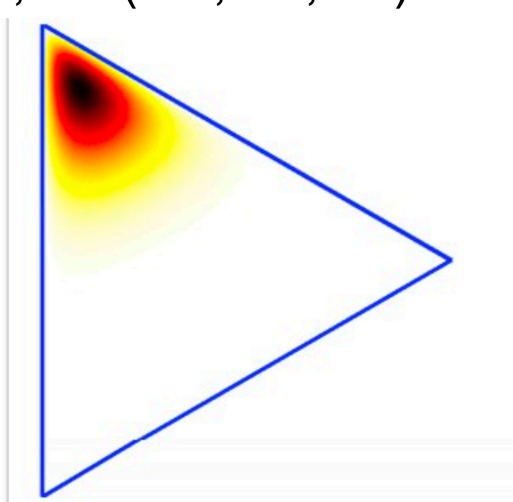

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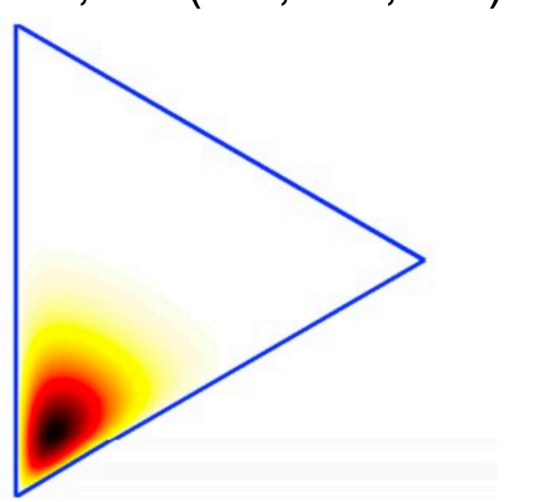

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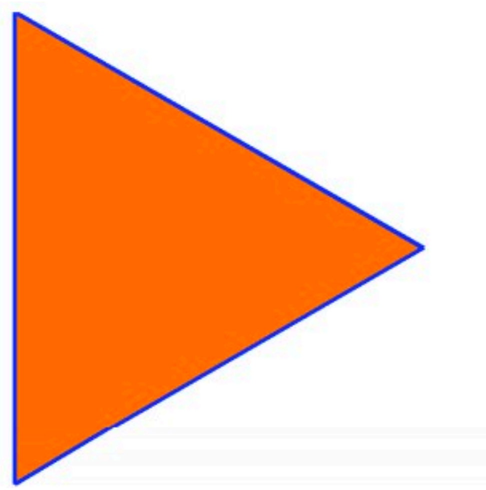

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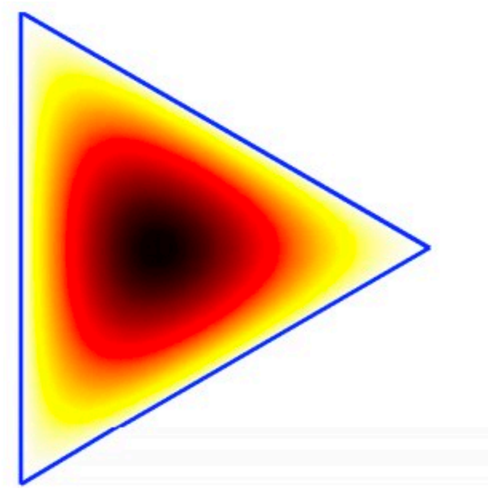

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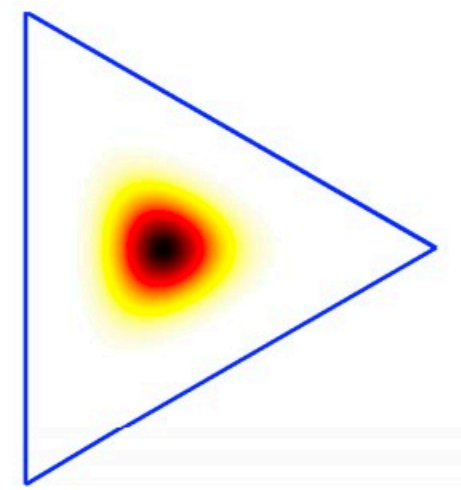

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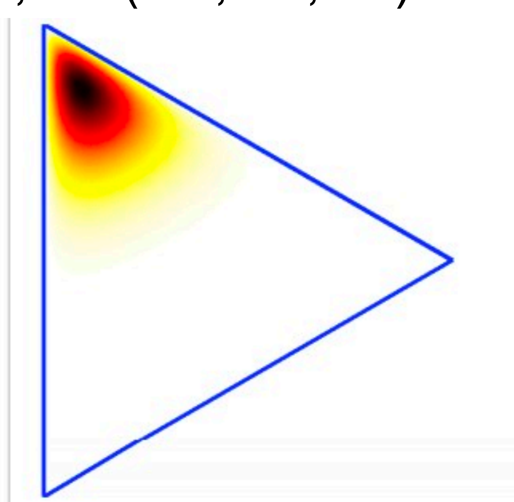

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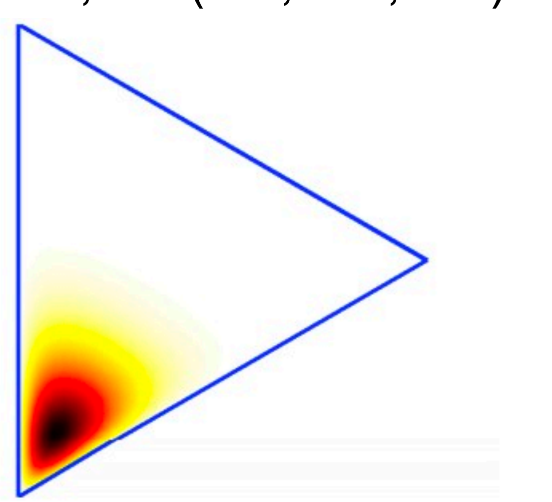

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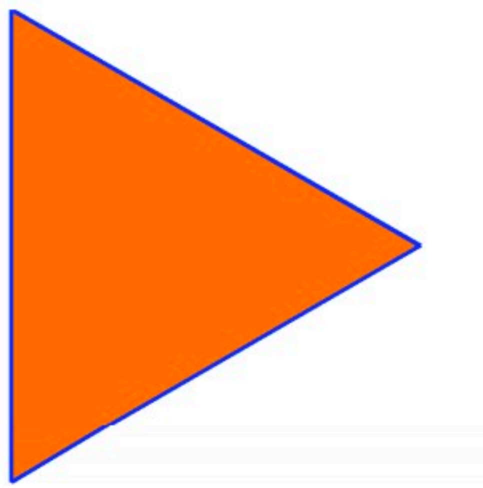

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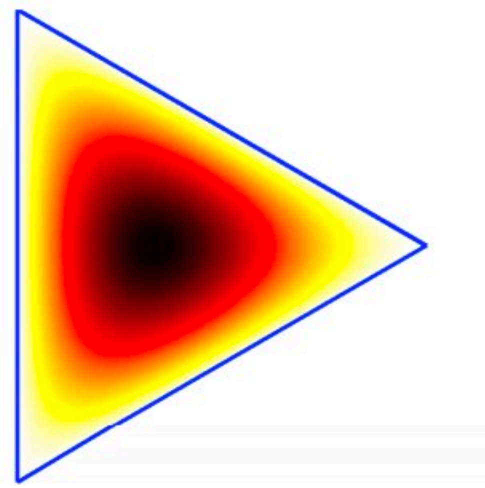

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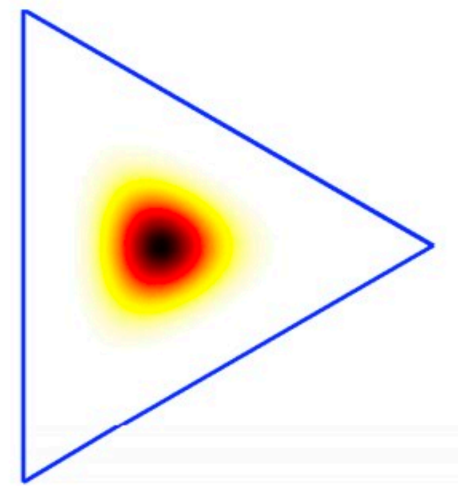

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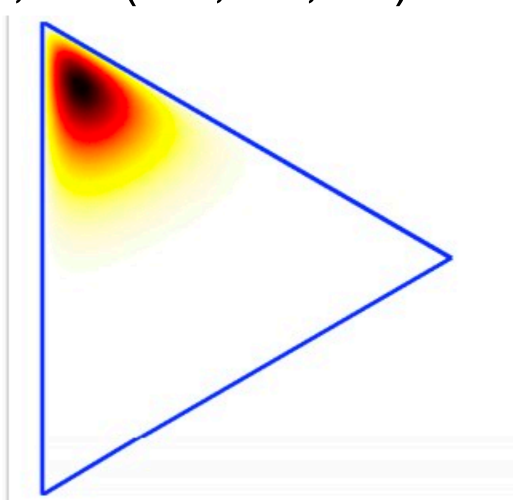
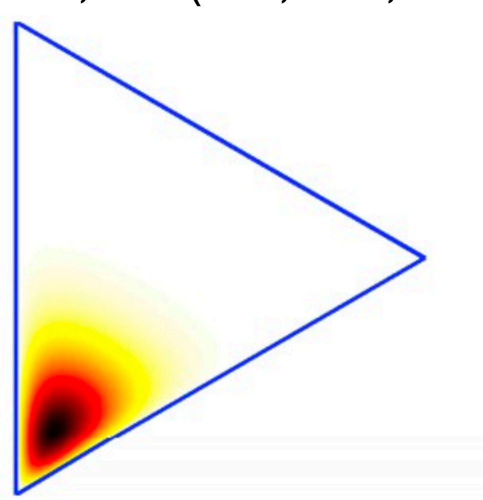
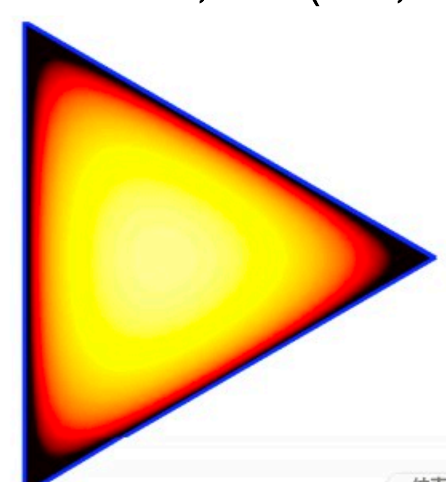


α=14, **m**=(1/7, 1/7, 5/7)

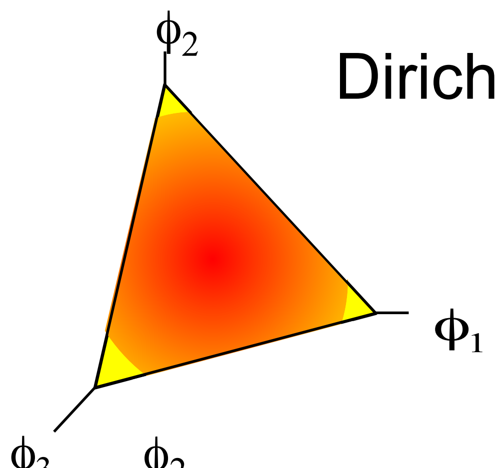


α=.2, **m**=(0.3,0.3,0.3)

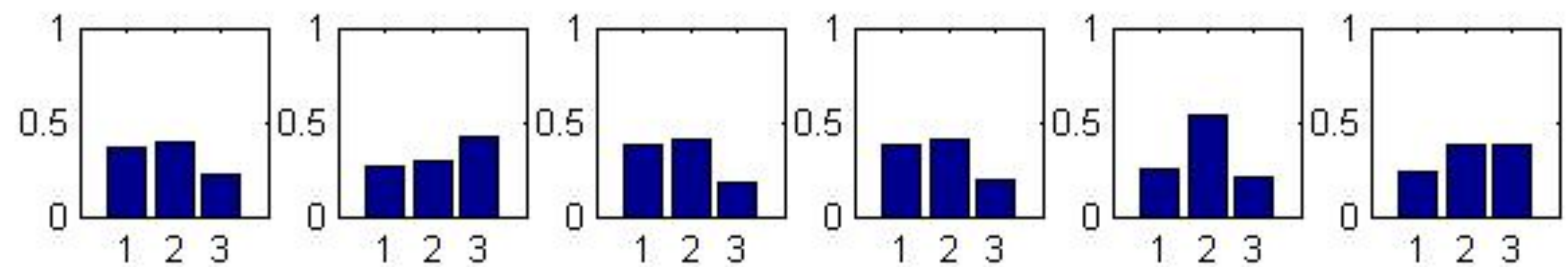


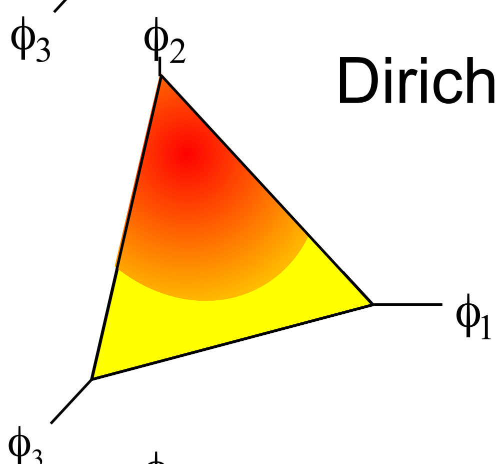
Dirichlet Distribution

- Example draws from a Dirichlet Distribution over the 3-simplex:

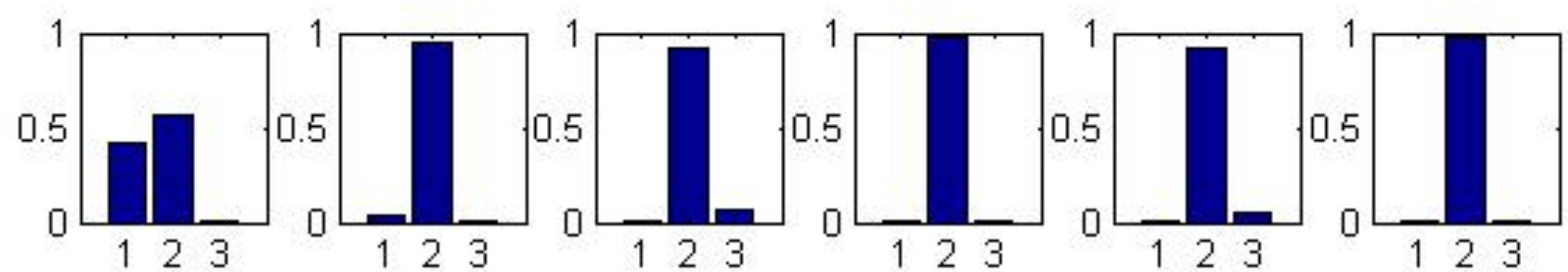


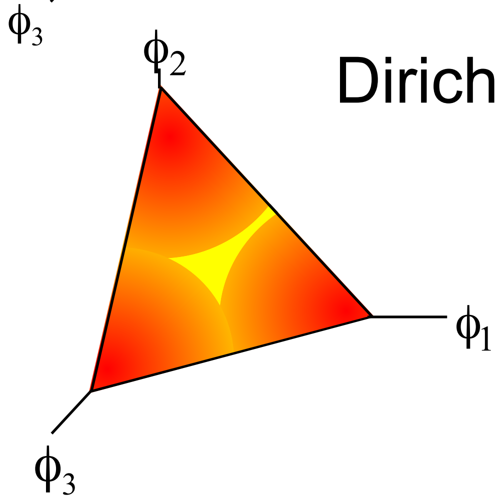
Dirichlet(5,5,5)



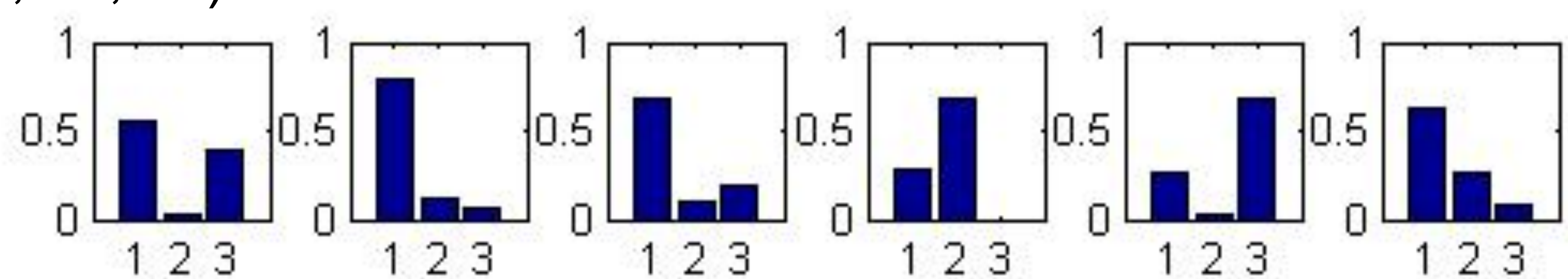


Dirichlet(0.2, 5, 0.2)





Dirichlet(0.5,0.5,0.5)



slide thanks to Nigel Crook

LDA – Generative Process

- For each document d:

LDA – Generative Process

- For each document d:
  - Choose document length

LDA – Generative Process

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$$[\beta]_{k \times V} \quad \beta_{ij} = p(w_j \mid z = i)$$

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$$P(d) = \prod_{w \in d} \sum_{i=1..K} P(z=i \mid d) P(w \mid Topic_i)$$

ipod	0.15
nano	0.080
music	.05
download	0.02
apple	0.01

movie	*0.100*
harry	*.090.*
potter	*05*
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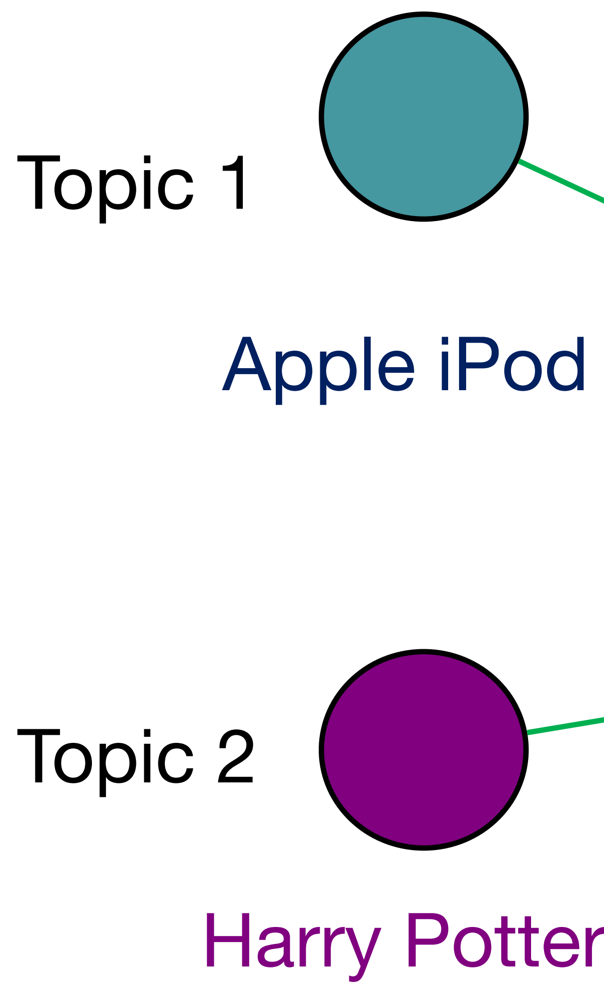

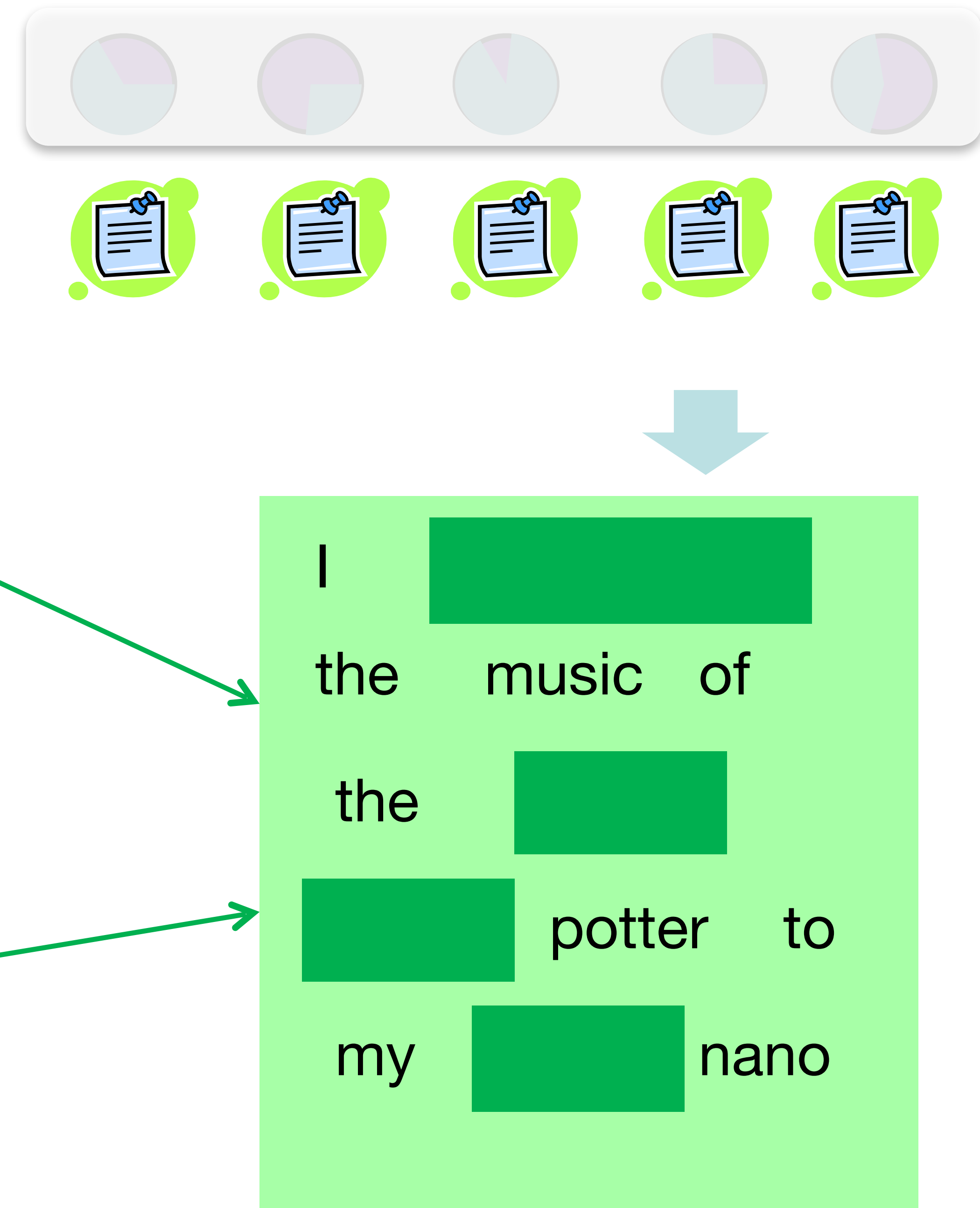

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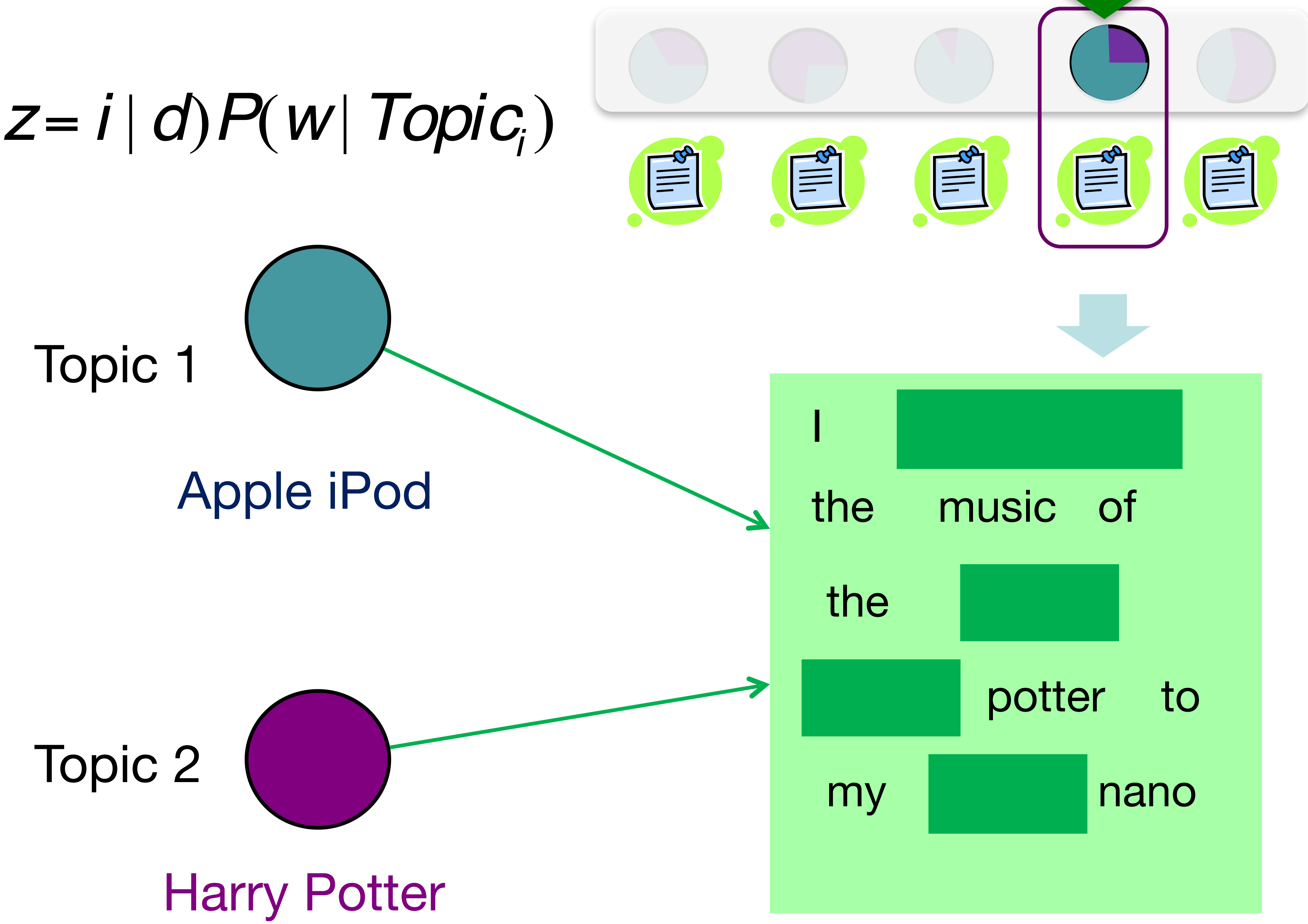

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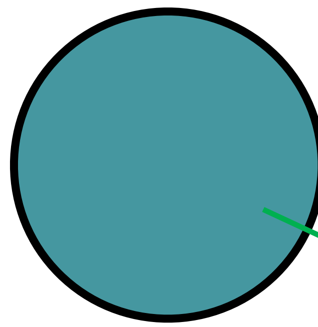

Apple iPod

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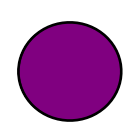
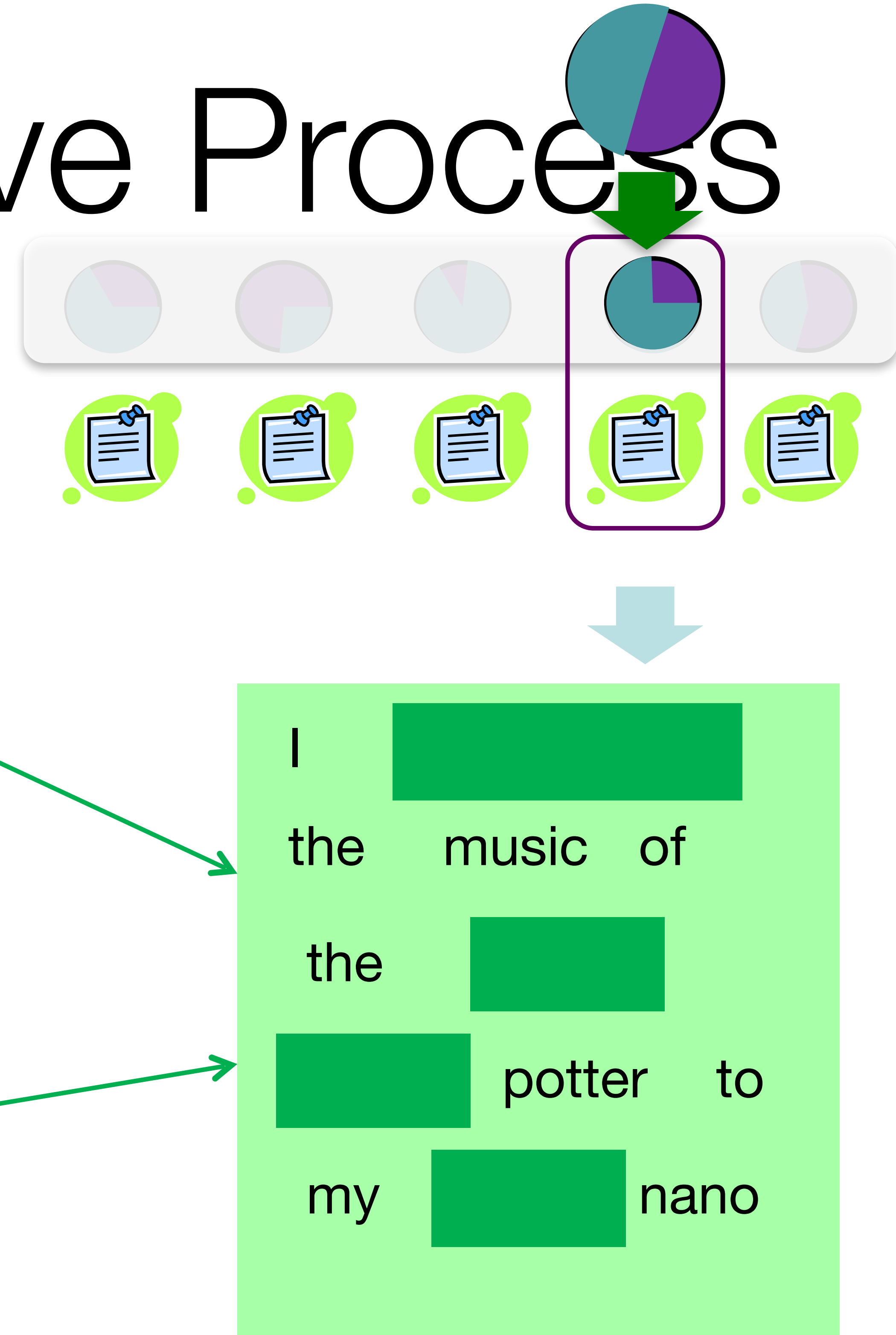
Topic 2



Harry Potter



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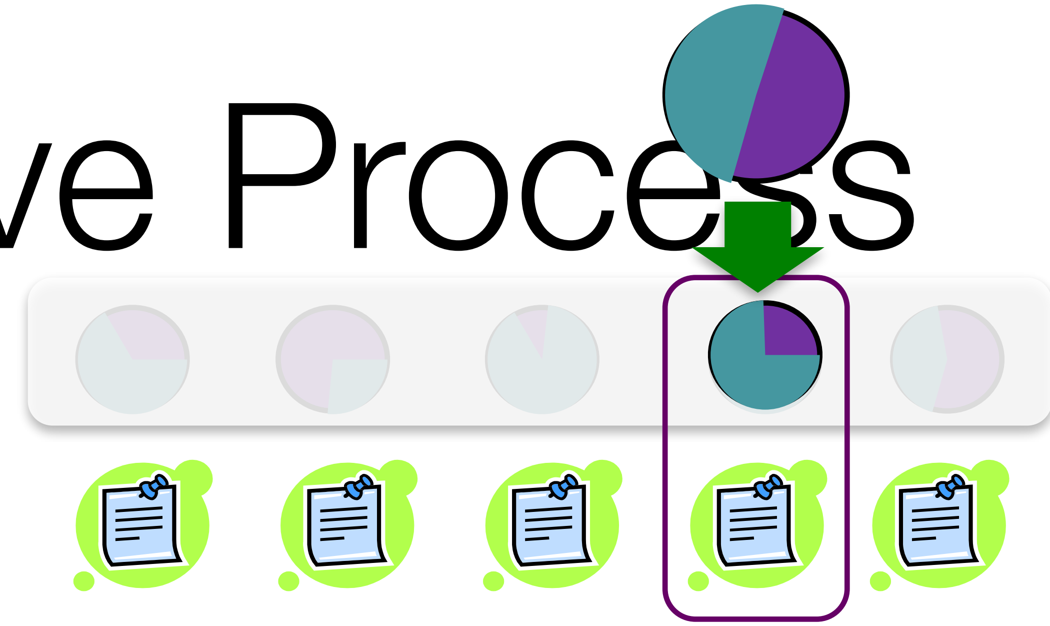

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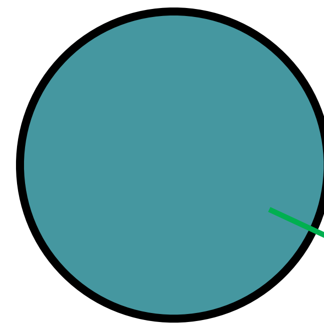
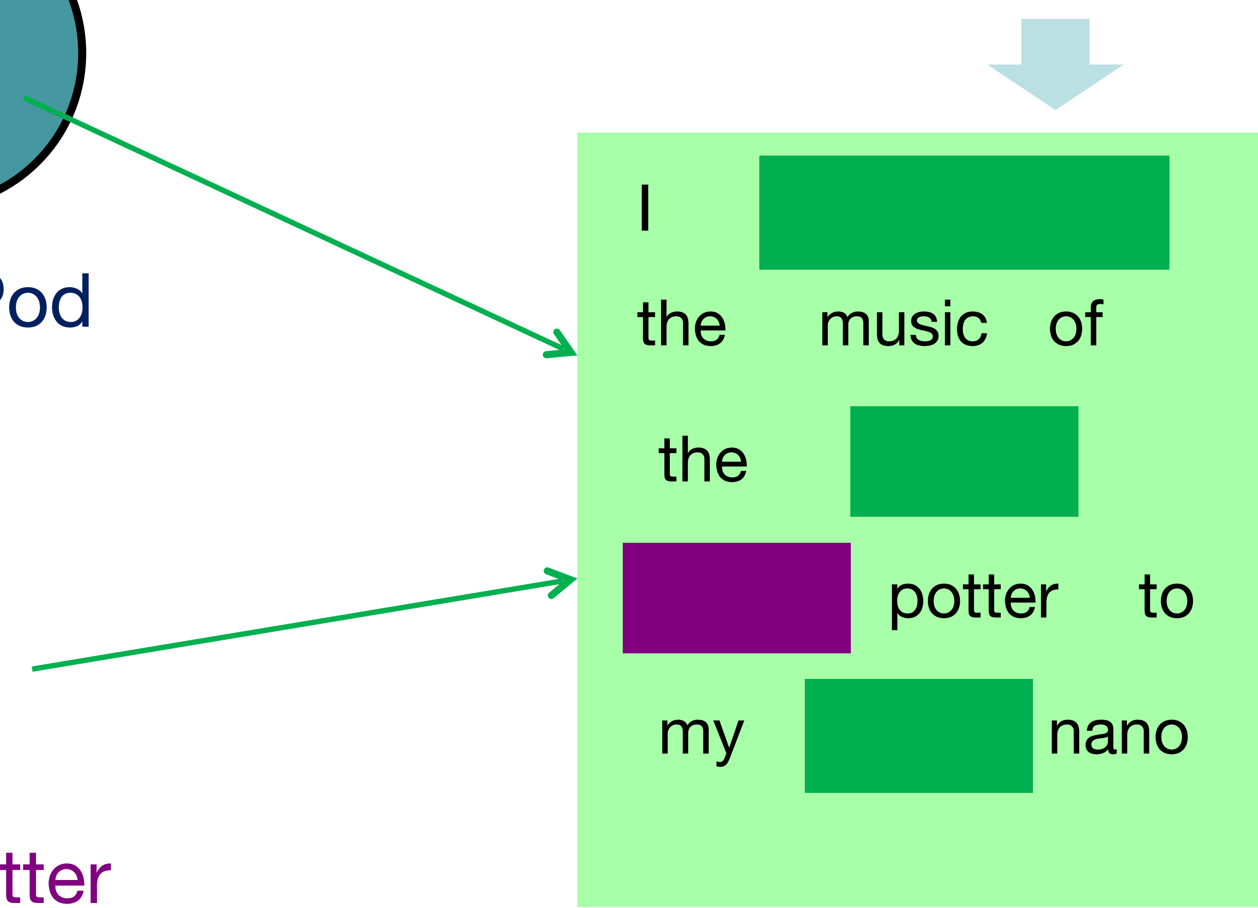


Apple iPod



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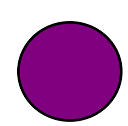
Topic 2



Harry Potter

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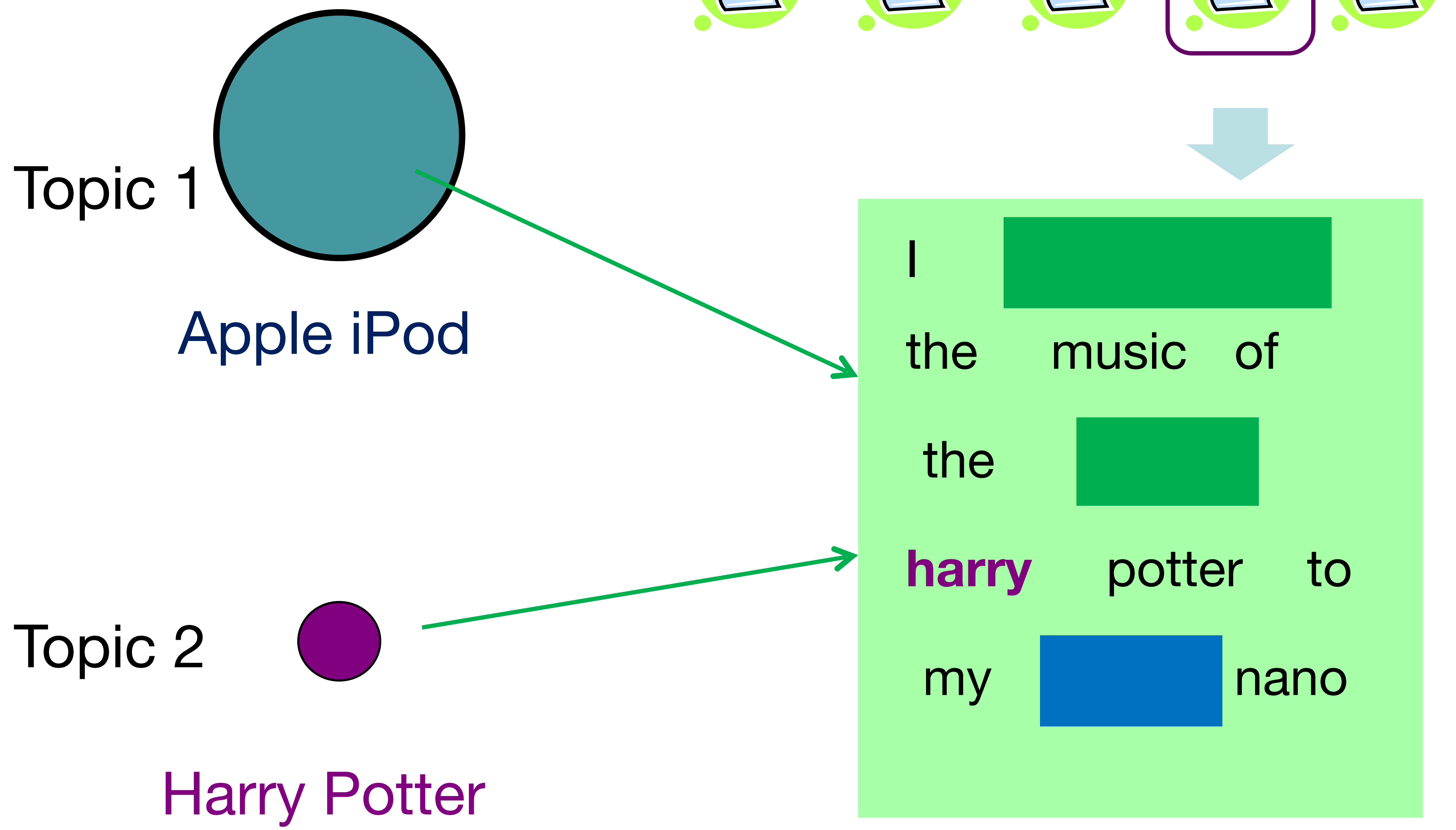

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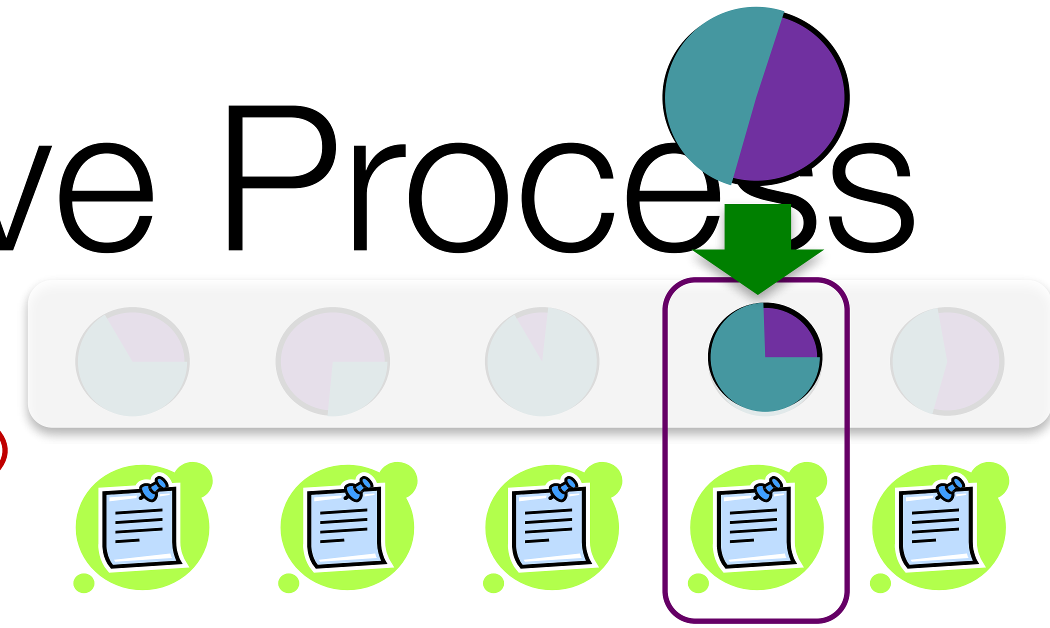

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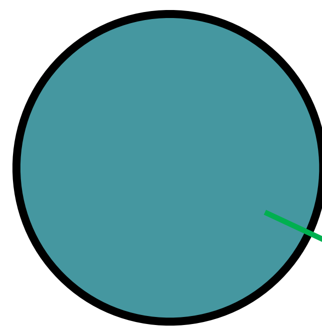

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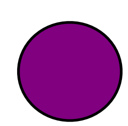

Harry Potter

I

the music of

the

harry potter to

my **ipod** nano

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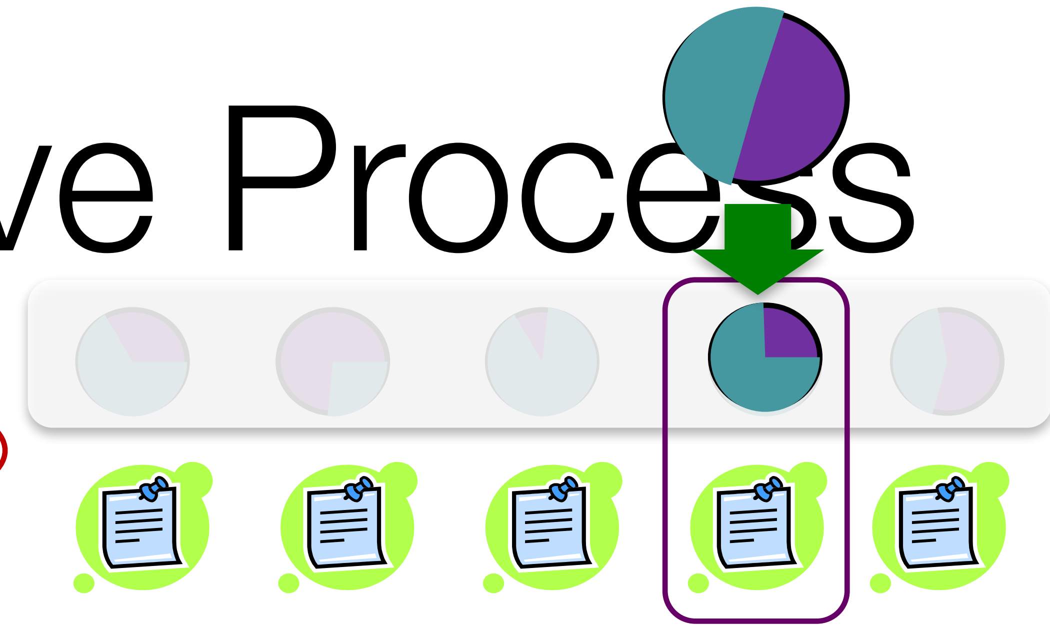

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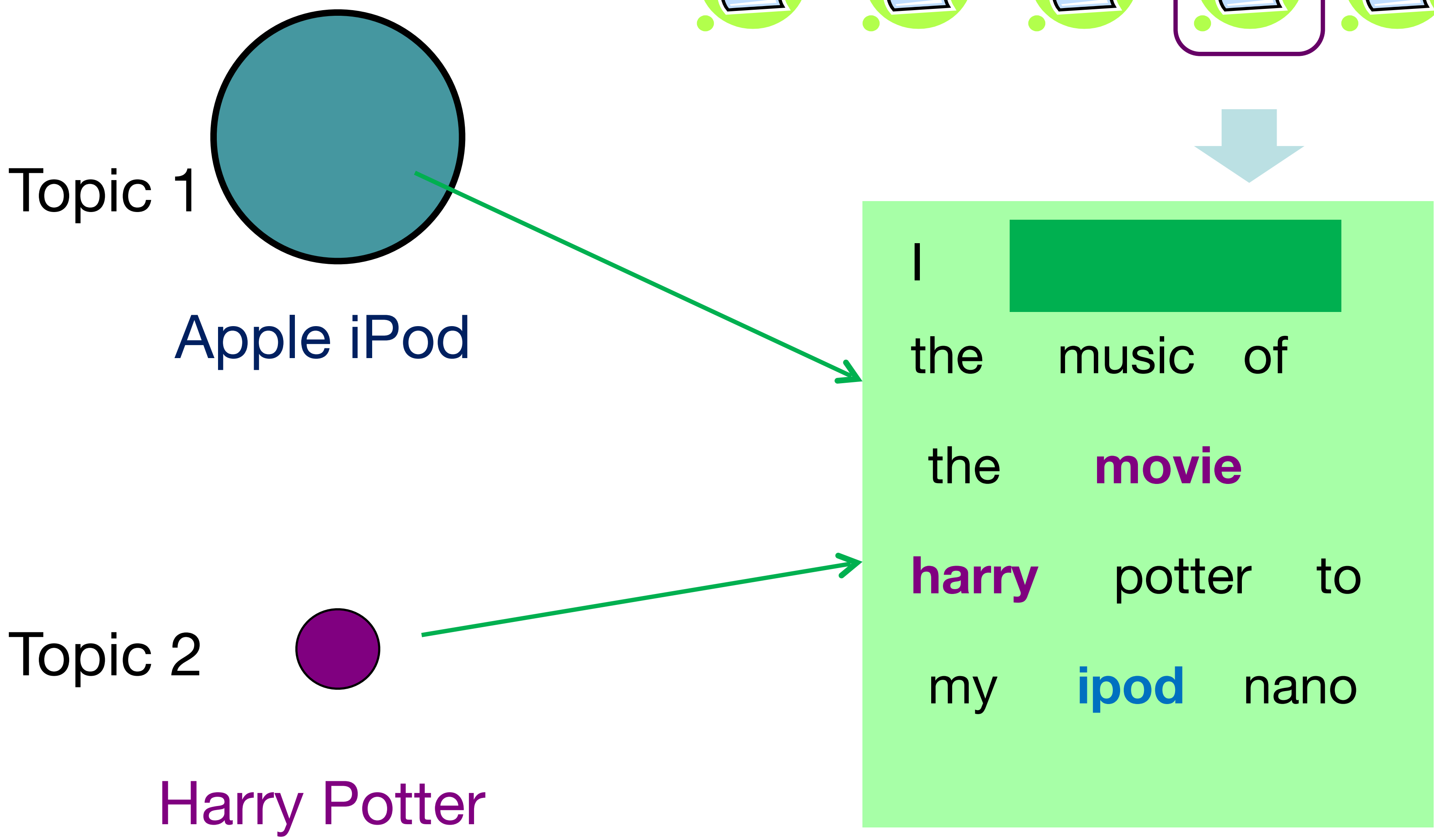

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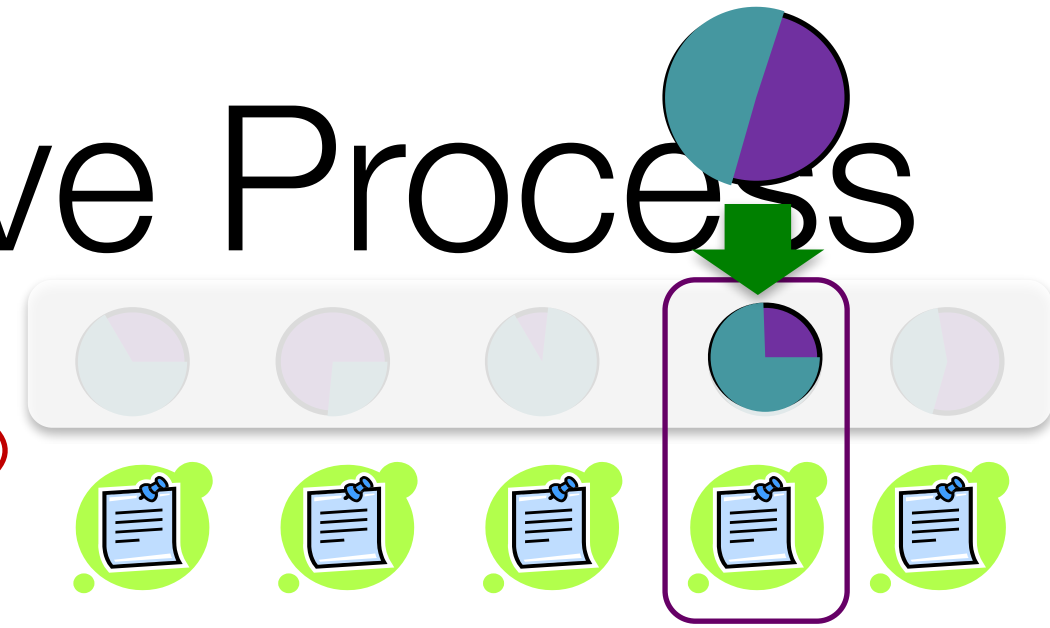

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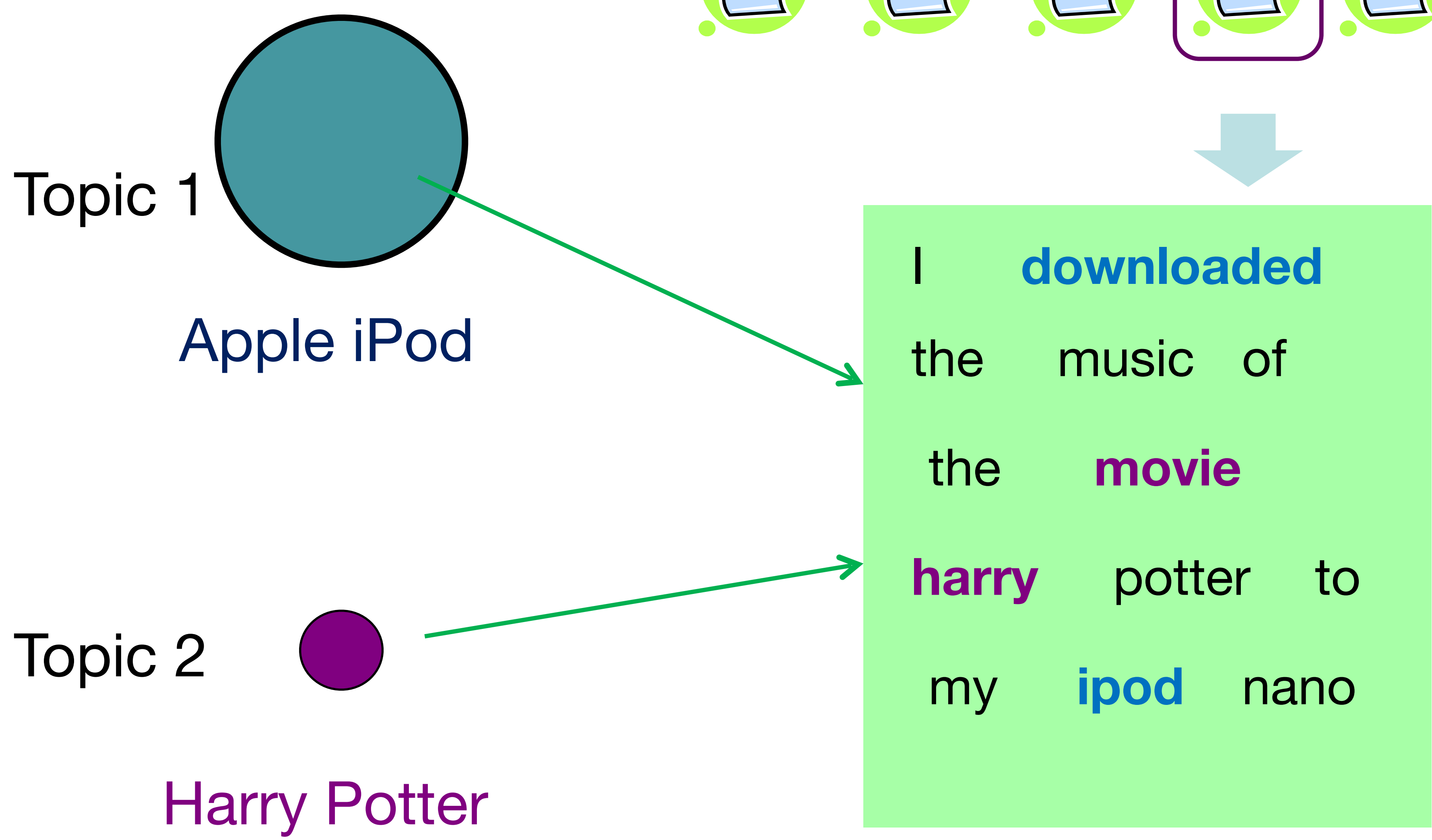

Graphical Model of LDA

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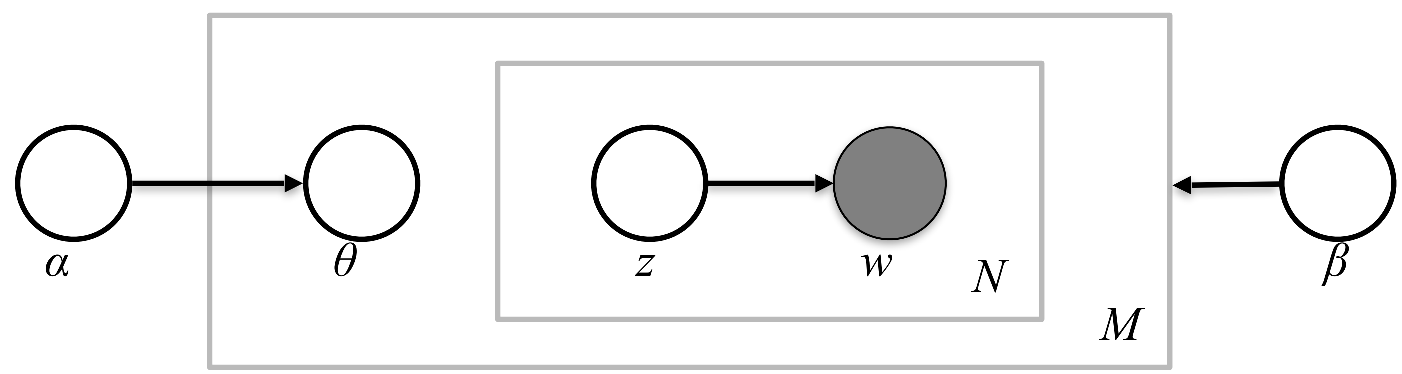
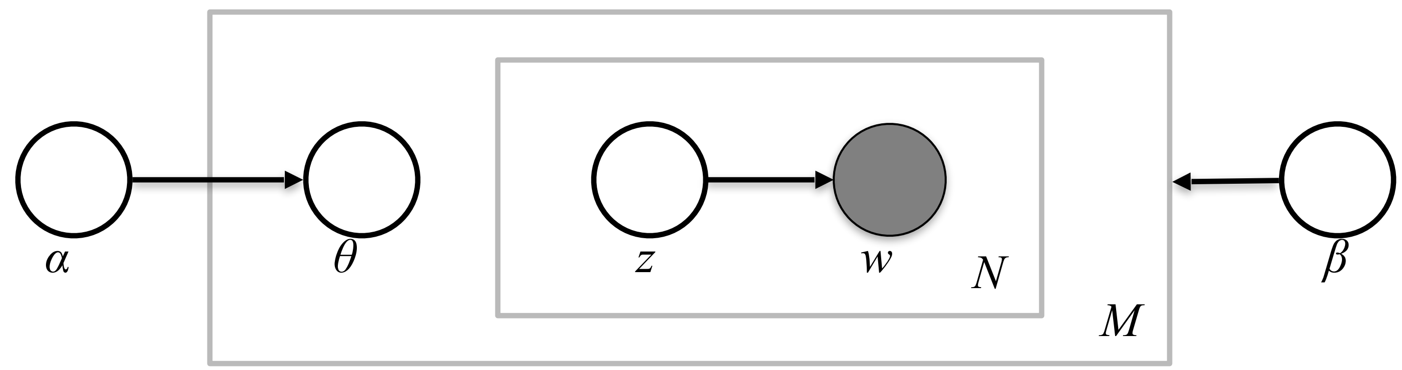


Graphical Model of LDA



Complete likelihood:
(if we observe all latent variables)

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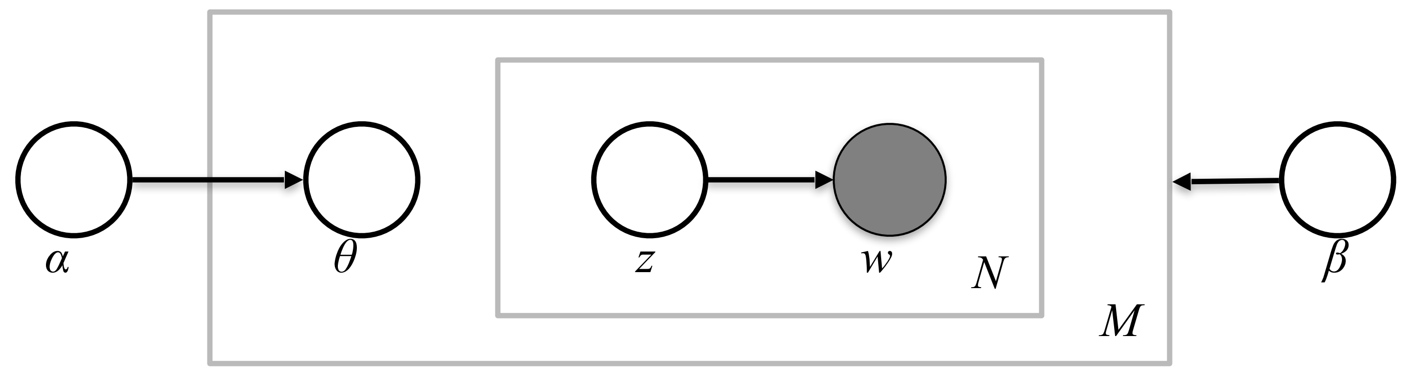

Complete likelihood: $p(\theta, \mathbf{z}, \mathbf{w} | \alpha, \beta) =$
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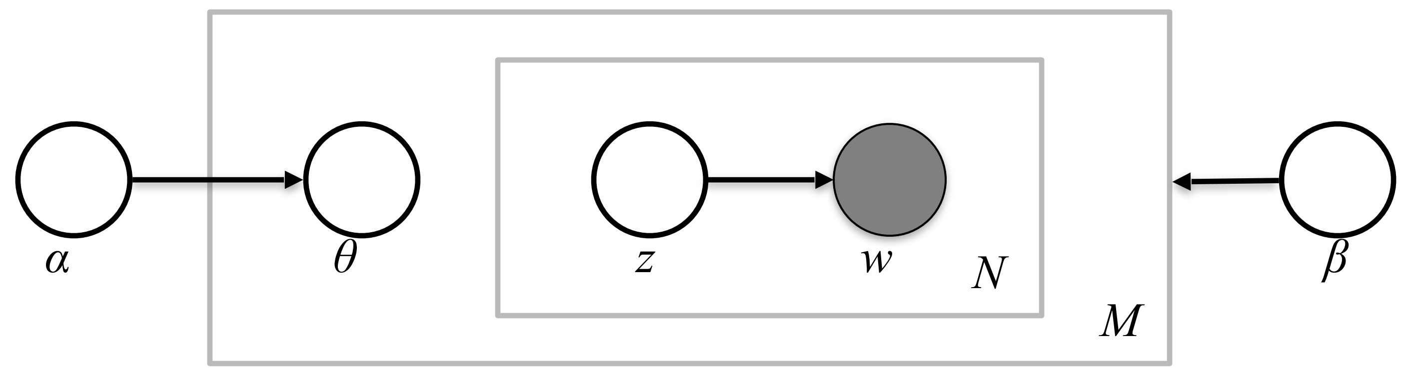
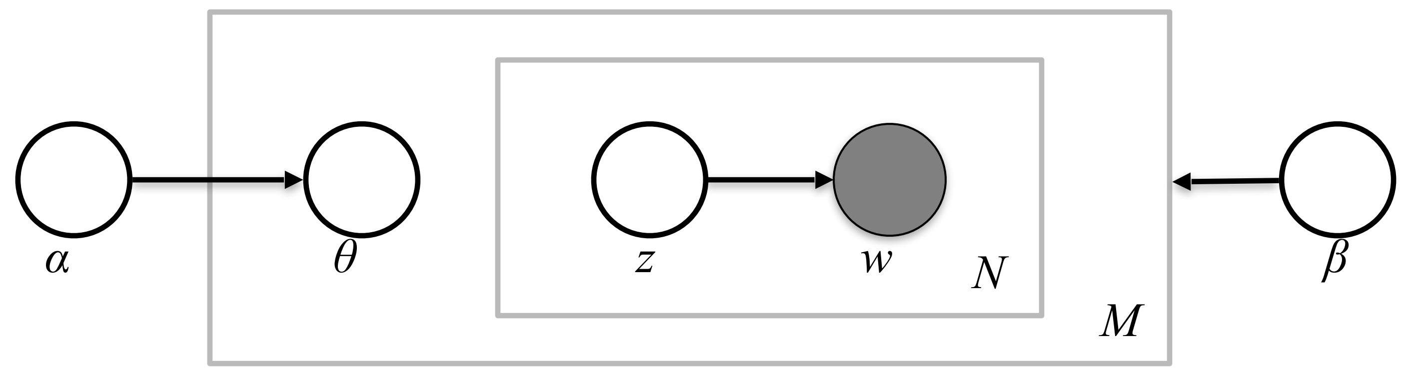
Graphical Model of LDA



Complete likelihood: $p(\theta, \mathbf{z}, \mathbf{w} | \alpha, \beta) = p(\theta | \alpha) \prod_{n=1}^{N} p(z_n | \theta) p(w_n | z_n, \beta)$

(if we observe all latent variables)

Graphical Model of LDA



Complete likelihood: $p(\theta, \mathbf{z}, \mathbf{w} | \alpha, \beta) = p(\theta|\alpha) \prod_{n=1}^{N} p(z_n|\theta) p(w_n | z_n, \beta)$
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Data likelihood:

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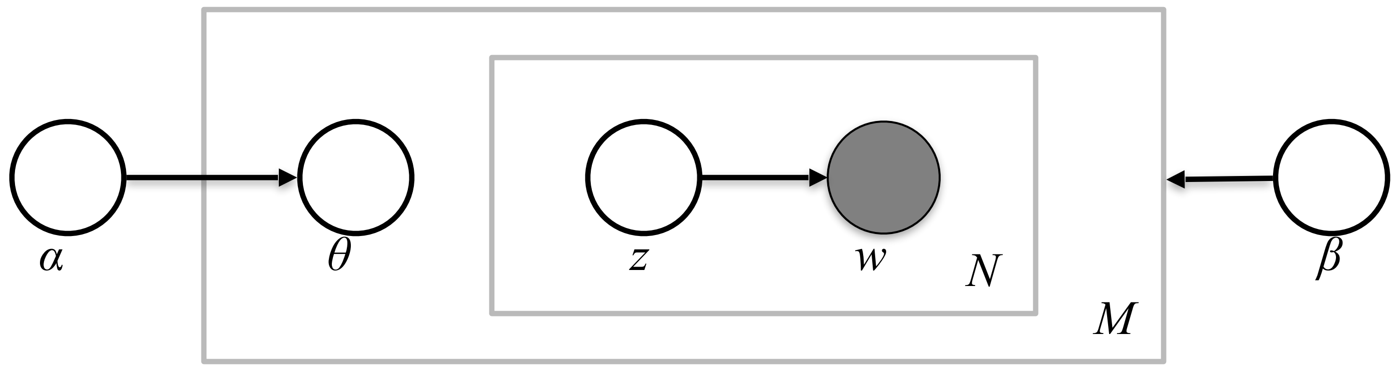

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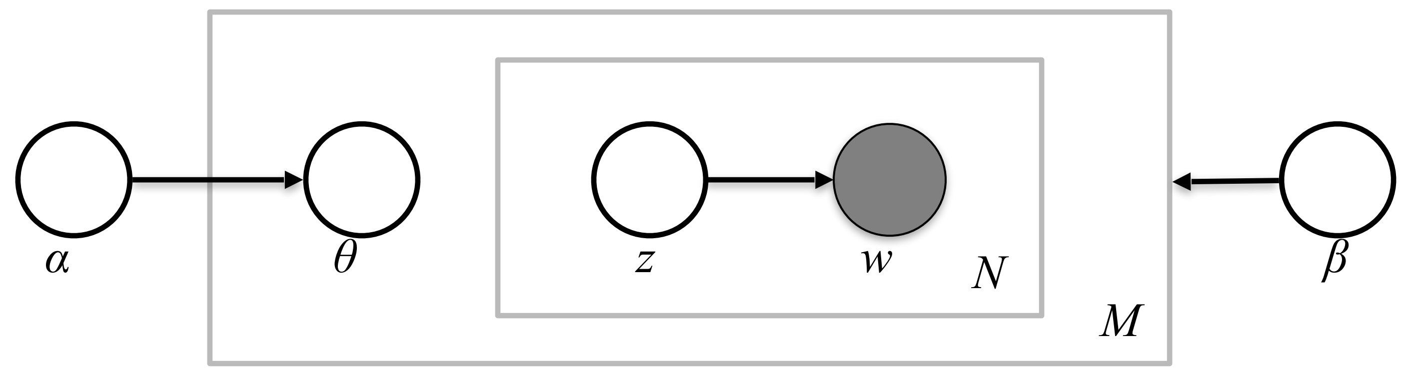

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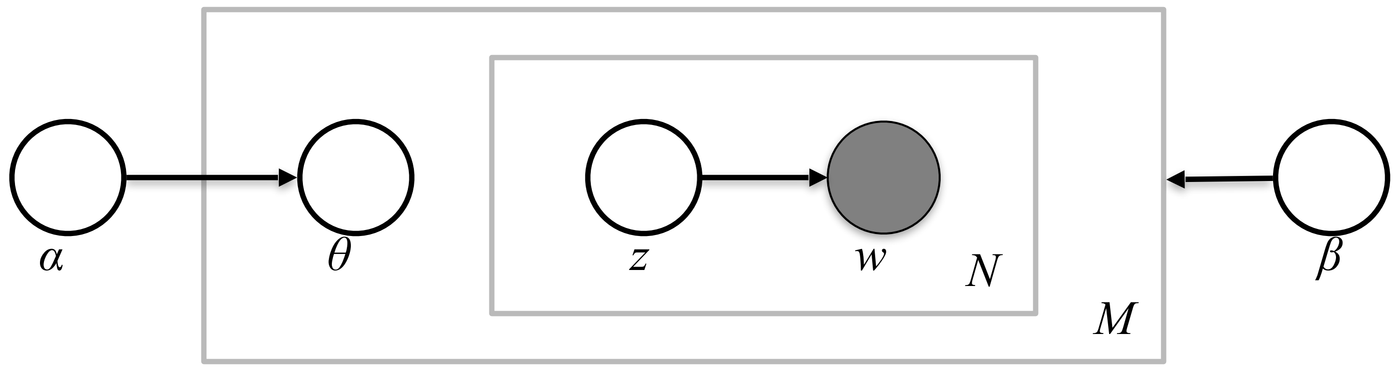

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- But inference becomes much more complicated

Putting all the pieces together

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- PLSA is also proved to be equivalent to non-negative matrix factorization (with a specific loss function)

Application to corpus data

- TASA corpus: text from first grade to college
- 26414 word types, over 37000 documents, used approximately 6 million word tokens
- Run Gibbs for models with $T = 300, 500, \ldots, 1700$ topics

A selection from 500 topics $\left[P(w|z=j)\right]$

THEORY	SPACE	ART	STUDENTS	BRAIN	CURRENT
SCIENTISTS	EARTH	PAINT	TEACHER	NERVE	ELECTRICITY
EXPERIMENT	MOON	ARTIST	STUDENT	SENSE	ELECTRIC
OBSERVATIONS	PLANET	PAINTING	TEACHERS	SENSES	CIRCUIT
SCIENTIFIC	ROCKET	PAINTED	TEACHING	ARE	IS
EXPERIMENTS	MARS	ARTISTS	CLASS	NERVOUS	ELECTRICAL
HYPOTHESIS	ORBIT	MUSEUM	CLASSROOM	NERVES	VOLTAGE
EXPLAIN	ASTRONAUTS	WORK	SCHOOL	BODY	FLOW
SCIENTIST	FIRST	PAINTINGS	LEARNING	SMELL	BATTERY
OBSERVED	SPACECRAFT	STYLE	PUPILS	TASTE	WIRE
EXPLANATION	JUPITER	PICTURES	CONTENT	TOUCH	WIRES
BASED	SATELLITE	WORKS	INSTRUCTION	MESSAGES	SWITCH
OBSERVATION	SATELLITES	OWN	TAUGHT	IMPULSES	CONNECTED
IDEA	ATMOSPHERE	SCULPTURE	GROUP	CORD	ELECTRONS
EVIDENCE	SPACESHIP	PAINTER	GRADE	ORGANS	RESISTANCE
THEORIES	SURFACE	ARTS	SHOULD	SPINAL	POWER
BELIEVED	SCIENTISTS	BEAUTIFUL	GRADES	FIBERS	CONDUCTORS
DISCOVERED	ASTRONAUT	DESIGNS	CLASSES	SENSORY	CIRCUITS
OBSERVE	SATURN	PORTRAIT	PUPIL	PAIN	TUBE
FACTS	MILES	PAINTERS	GIVEN	IS	NEGATIVE

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WORLD	STORIES	MAGNETIC	STUDY	GAME	WORK
DREAM	TELL	MAGNET	SCIENTISTS	TEAM	JOBS
DREAMS	CHARACTER	WIRE	SCIENTIFIC	FOOTBALL	CAREER
THOUGHT	CHARACTERS	NEEDLE	KNOWLEDGE	BASEBALL	EXPERIENCE
IMAGINATION	AUTHOR	CURRENT	WORK	PLAYERS	EMPLOYMENT
MOMENT	READ	COIL	RESEARCH	PLAY	OPPORTUNITIES
THOUGHTS	TOLD	POLES	CHEMISTRY	FIELD	WORKING
OWN	SETTING	IRON	TECHNOLOGY	PLAYER	TRAINING
REAL	TALES	COMPASS	MANY	BASKETBALL	SKILLS
LIFE	PLOT	LINES	MATHEMATICS	COACH	CAREERS
IMAGINE	TELLING	CORE	BIOLOGY	PLAYED	POSITIONS
SENSE	SHORT	ELECTRIC	FIELD	PLAYING	FIND
CONSCIOUSNESS	FICTION	DIRECTION	PHYSICS	HIT	POSITION
STRANGE	ACTION	FORCE	LABORATORY	TENNIS	FIELD
FEELING	TRUE	MAGNETS	STUDIES	TEAMS	OCCUPATIONS
WHOLE	EVENTS	BE	WORLD	GAMES	REQUIRE
BEING	TELLS	MAGNETISM	SCIENTIST	SPORTS	OPPORTUNITY
MIGHT	TALE	POLE	STUDYING	BAT	EARN
HOPE	NOVEL	INDUCED	SCIENCES	TERRY	ABLE

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- Dynamic topic model: We also observe a year for each document. The k topics β used in 2011 have evolved slightly from their counterparts in 2010.

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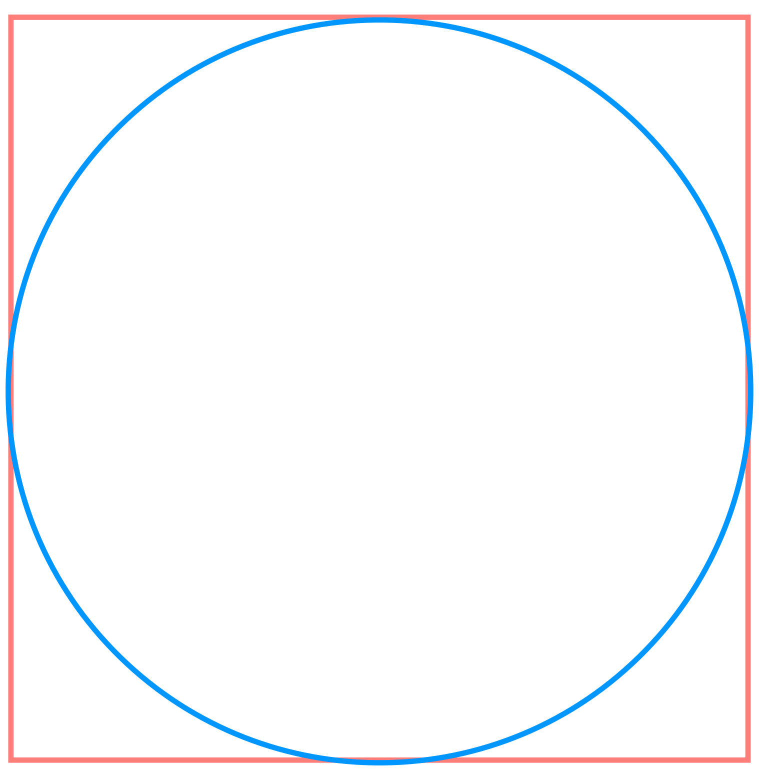

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Pretend we never saw the topic assignment for the n^{th} word in the d^{th} document

What Gibbs Sampling is doing at an abstract level

Topic 1	Topic 2	Topic 3	Topic 4
wizard	movie	Harry	school
magic	book	Hermoine	teacher
wand	novel	Ron	class
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(In the real version, all words are assigned a topic!)

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Gibbs Sampling Equation

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

Gibbs Sampling Equation

$$\underbrace{\frac{n_{d,k} + \alpha_k}{\sum_i^K n_{d,i} + \alpha_i}}_{\text{How much this document likes topic k}} \frac{v_{k,w_{d,n}} + \lambda_{w_{d,n}}}{\sum_i v_{k,i} + \lambda_i}$$

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How much this document likes topic k

How much this topic likes word $w_{d,n}$

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Number of times document d uses topic k

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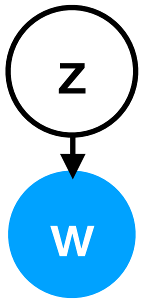

Etrustcan	trade	price	temple	market

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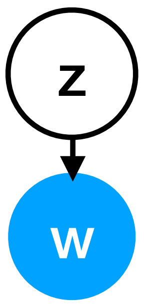

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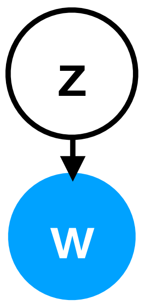

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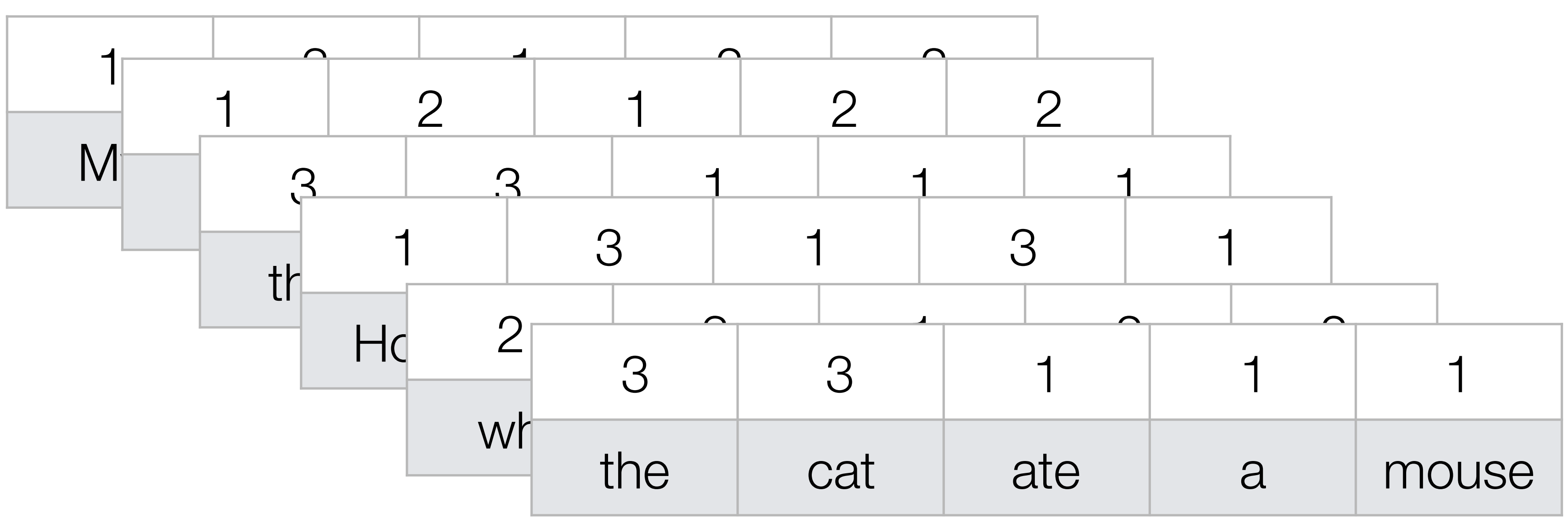

Total Topic Counts

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Total counts from
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We want to sample this word

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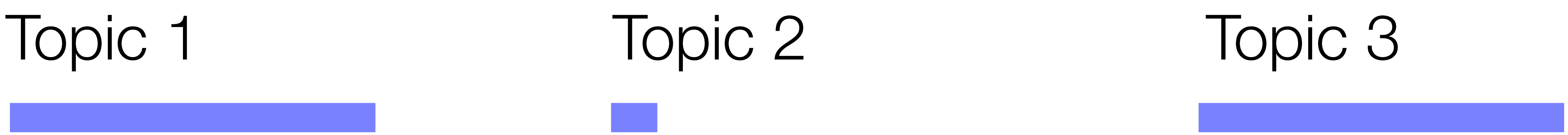

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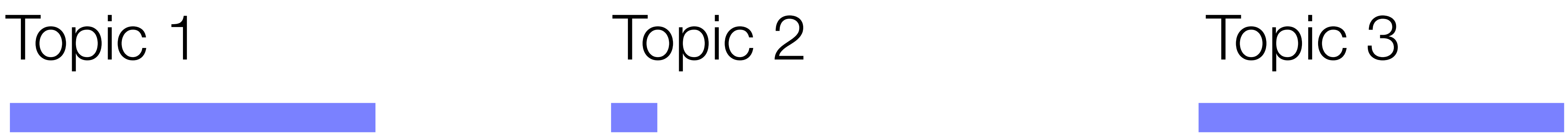

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Topic 1 Topic 2 Topic 3

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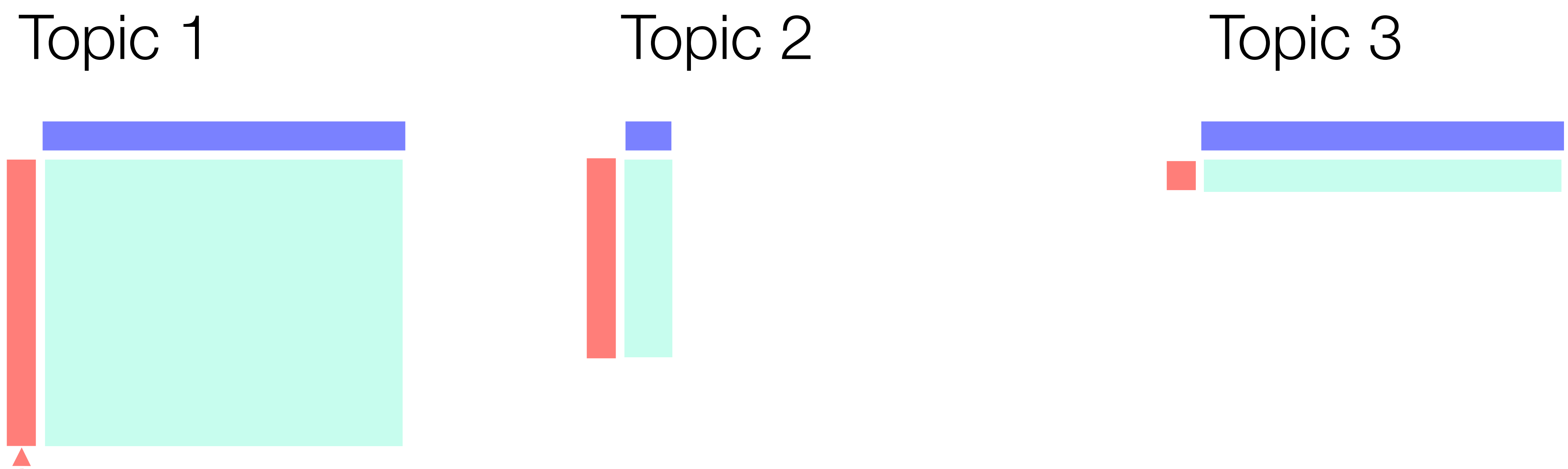

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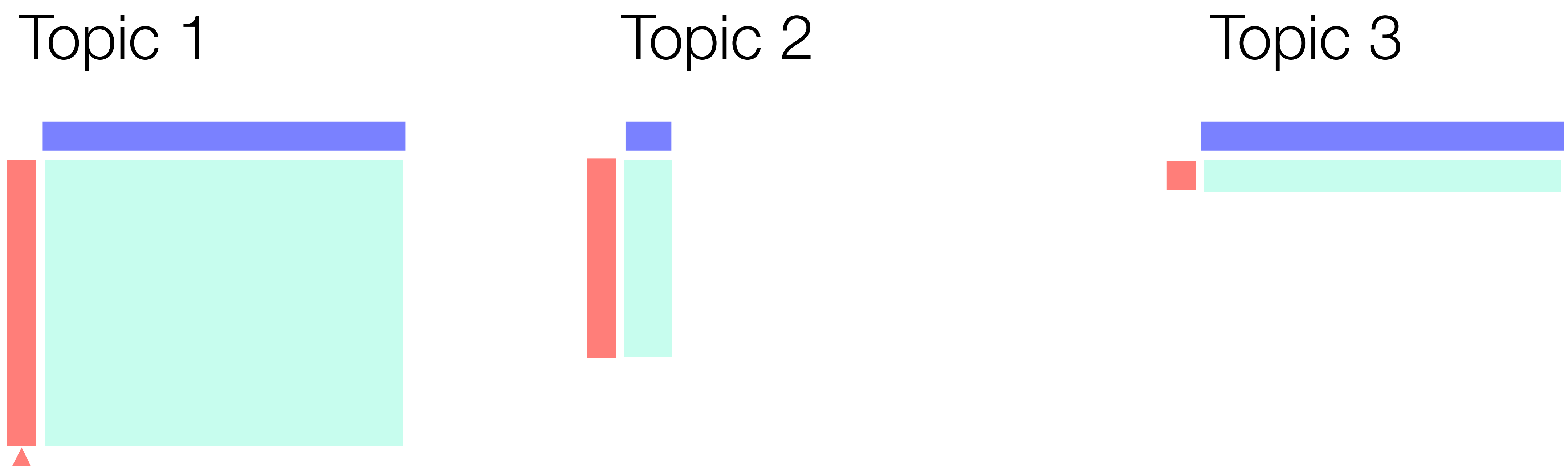

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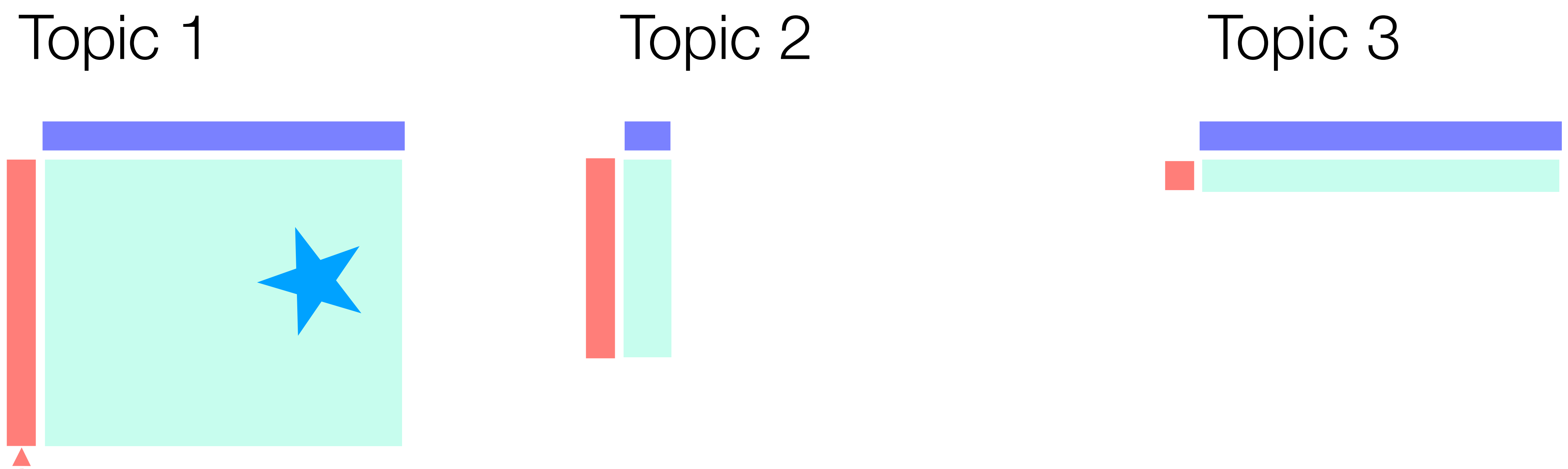

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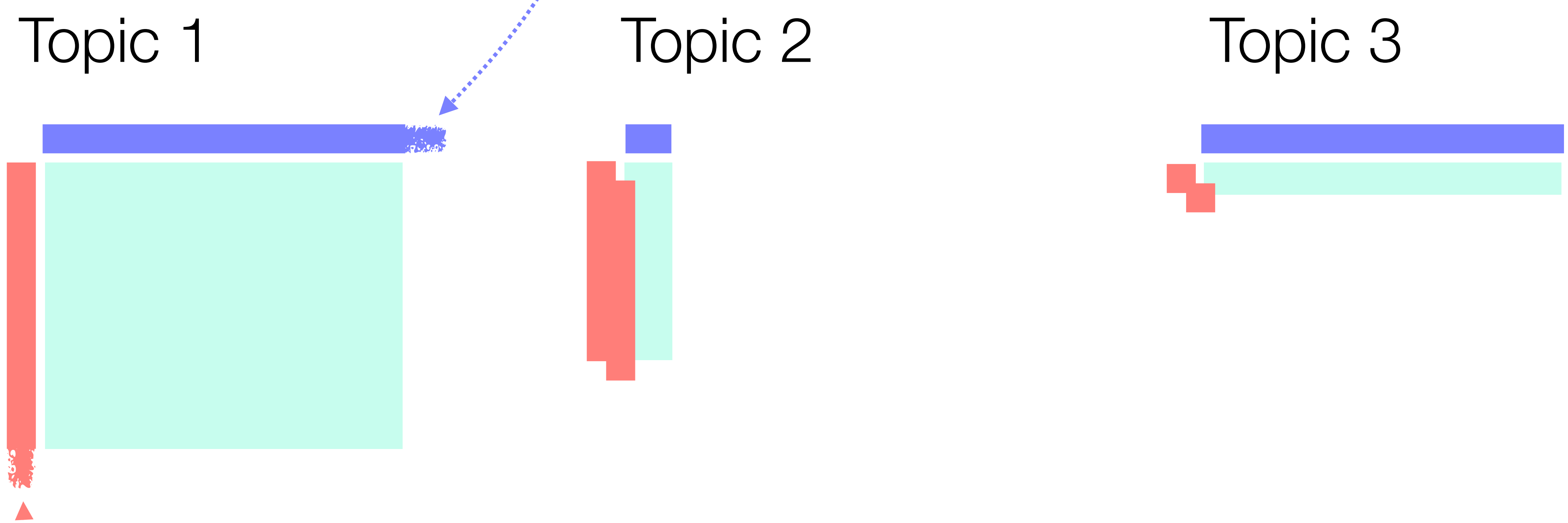

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Homework 4

- You'll be implementing the Gibbs Sampling updates part of LDA!
- We've given you a bunch of skeleton code; your part is ~10 lines, very similar to what we covered today
- 90% thinking; 10% coding

Gibbs Sampling for the Uninitiated

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Abstract

This document is intended for computer scientists who would like to try out a Markov Chain Monte Carlo (MCMC) technique, particularly in order to do inference with Bayesian models on problems related to text processing. We try to keep theory to the absolute minimum needed, though we work through the details much more explicitly than you usually see even in "introductory" explanations. That means we've attempted to be ridiculously explicit in our exposition and notation.

After providing the reasons and reasoning behind Gibbs sampling (and at least nodding our heads in the direction of theory), we work through an example application in detail—the derivation of a Gibbs sampler for a Naïve Bayes model. Along with the example, we discuss some practical implementation issues, including the integrating out of continuous parameters when possible. We conclude with some pointers to literature that we've found to be somewhat more friendly to uninitiated readers.

1 Introduction

Markov Chain Monte Carlo (MCMC) techniques like Gibbs sampling provide a principled way to approximate the value of an integral.

How do we know if the topics we learned are good?

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- Bad:
  - Chang (2009) show that likelihood is not correlated with human judgements of goodness

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- Good: Correlates with human judgements!
- Bad: Can't be done automatically

Many other metrics

- Qualitative
  - Expert judgements
  - Word Clouds
  - Visualizing word-topic assignments
- Quantitative
  - Topic Coherence: Better models have words that are highly related according to some external source (Newman, 2010; Mimno et al., 2011)

Fancier metrics are also possible

8. CONCLUSION

We proposed a unifying framework that span the space of all known coherence measures and allows to combine all main ideas in the context of coherence quantification. We evaluated 237 912 coherence measures on six different benchmarks for topic coherence—to the best of our knowledge, this is the largest number of benchmarks used for topic coherences so far. We introduced coherence measures from

Röder et al. (2015)

Summarizing what we learned about topic models

Image credit: Ted Underwood

Topic Modeling in Practice

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- Number of topics have to be predetermined
  - Finding the right number of topics can be hard
  - Bayesian model selection – enumerate all K
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  - Methods to generate labels for topics (Mei et al., 2007)
- Evaluation is subjective
  - Likelihood of held-out data, quality of topics, quality of document clusters, human judgments, …

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- But can provide "deep" features for those tasks
- Works well when few training examples are available
- Extremely powerful when contextual variables are observed and concerned with
  - Very easy to extend, by adding variables into the Bayesian network (graphical structure)

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  - The co-occurrence assumption doesn't hold in your data
- Try to leverage meta-data or context information to improve the performance of topic modeling
  - Authorship
  - Time, geographic location
  - Networks of documents and words
  - User-guidance, …

Resources of Topic Modeling

- Topic Modeling Bibliography
  - Collected by David Mimno: https://mimno.infosci.cornell.edu/topics.html
- Toolkits:
  - LDA-C: command-line version from David Blei
  - LDA++: Easy-to-use C++ implementation
  - MALLET: Java package, with good support of text mining in general
  - Gensim: Python package for on-line topic modeling (not so good) and wraps MALLET in a python interface (good!)
  - Mahout: Machine learning toolkit adaptable on Hadoop
- Topic modeling in digital humanities
  - http://mith.umd.edu/topic-modeling-in-the-humanities-an-overview/
  - http://journalofdigitalhumanities.org/2-1/words-alone-by-benjamin-m-schmidt/

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- Brown clustering can help you learn categories of words —and the brown vectors are useful representations
- Topic modeling is ~~magic~~ a powerful technique for learning broad themes in text
  - But is difficult to evaluate—don't trust the output without looking at it and using it for somethign!