Lecture 6: Representing Words

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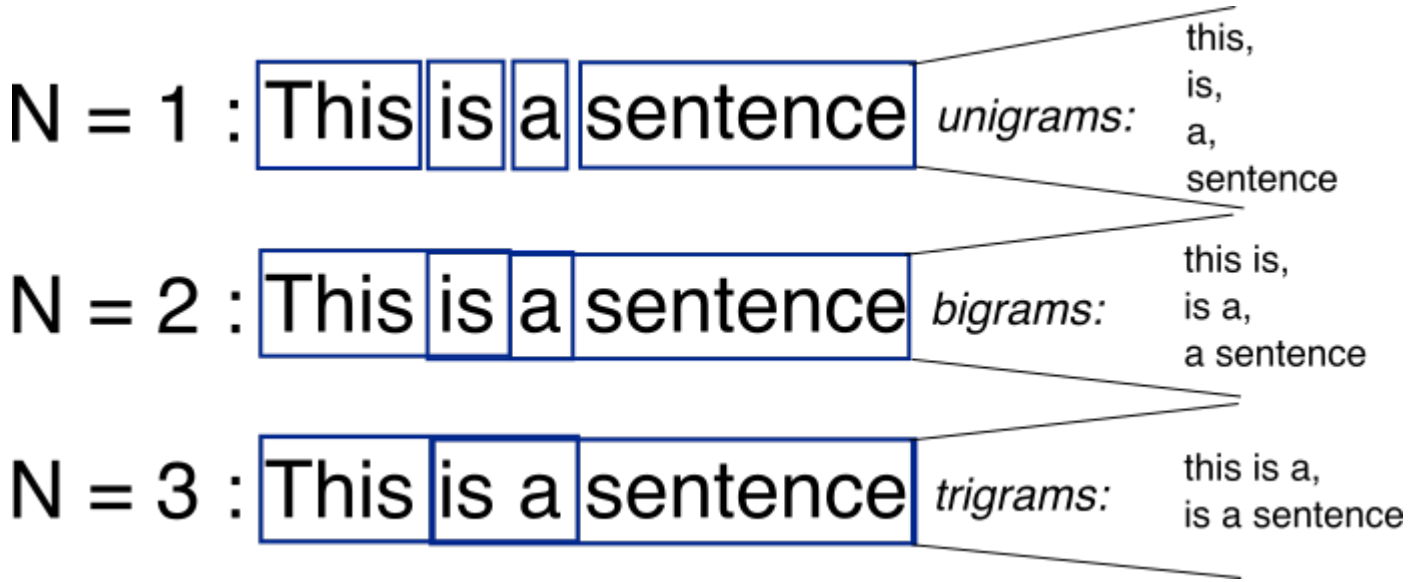
Couse webpage: https://uclanlp.github.io/CS269-17/

Bag-of-Words with N-grams

- N-grams: a contiguous sequence of n tokens from a given piece of text



http://recognize-speech.com/language-model/n-gram-model/comparison

Language model

- Probability distributions over sentences (i.e., word sequences)

  $P(W) = P(w_1 w_2 w_3 w_4 \ldots w_k)$

- Can use them to generate strings

  $P(w_k \mid w_2 w_3 w_4 \ldots w_{k-1})$

- Rank possible sentences
  - P("Today is Tuesday") > P("Tuesday Today is")
  - P("Today is Tuesday") > P("Today is Los Angeles")

N-Gram Models

- Unigram model: $P(w_1)P(w_2)P(w_3) \dots P(w_n)$
- Bigram model:
  $P(w_1)P(w_2|w_1)P(w_3|w_2) \dots P(w_n|w_{n-1})$
- Trigram model:
  $P(w_1)P(w_2|w_1)P(w_3|w_2, w_1) \dots P(w_n|w_{n-1}w_{n-2})$
- N-gram model:
  $P(w_1)P(w_2|w_1) \dots P(w_n|w_{n-1}w_{n-2} \dots w_{n-N})$

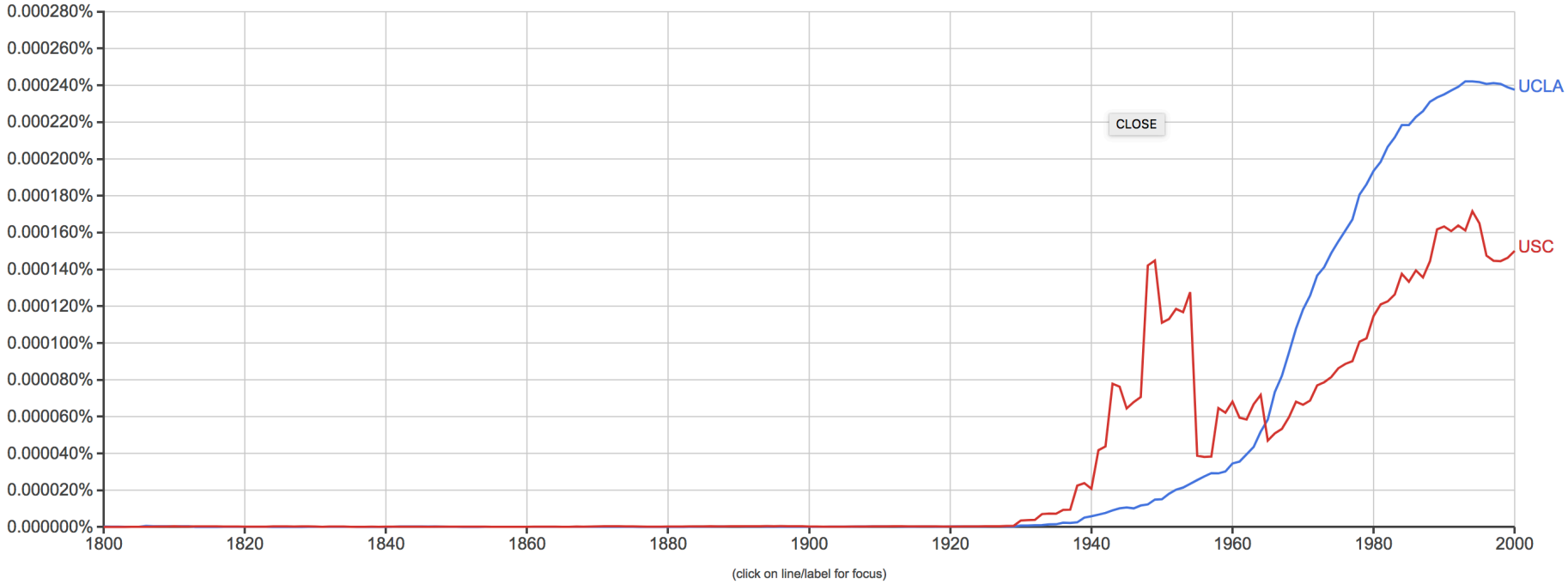
Random language via n-gram

- http://www.cs.jhu.edu/~jason/465/PowerPoint/lect01,3tr-ngram-gen.pdf

Collection of n-gram

- https://research.googleblog.com/2006/08/all-our-n-gram-are-belong-to-you.html

N-Gram Viewer



https://books.google.com/ngrams

How to represent words?

- N-gram -- cannot capture word similarity
- Word clusters
  - Brown Clustering
  - Part-of-speech tagging
- Continuous space representation
  - Word embedding

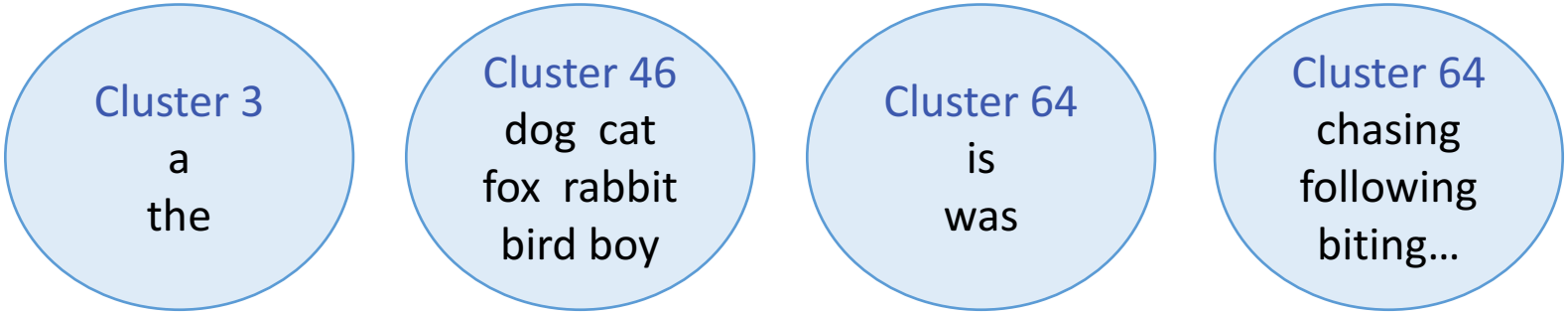
Brown Clustering

- Similar to language model
  But, basic unit is “word clusters”
- Intuition: similar words appear in similar context
- Recap: Bigram Language Models
  - $P(w_0, w_1, w_2, \dots, w_n)$
    $= P(w_1 \mid w_0)P(w_2|w_1) \dots P(w_n \mid w_{n-1})$
    $= \Pi_{i=1}^{n} P(w_i \mid w_{i-1})$

w_0 is a dummy word representing ”begin of a sentence”

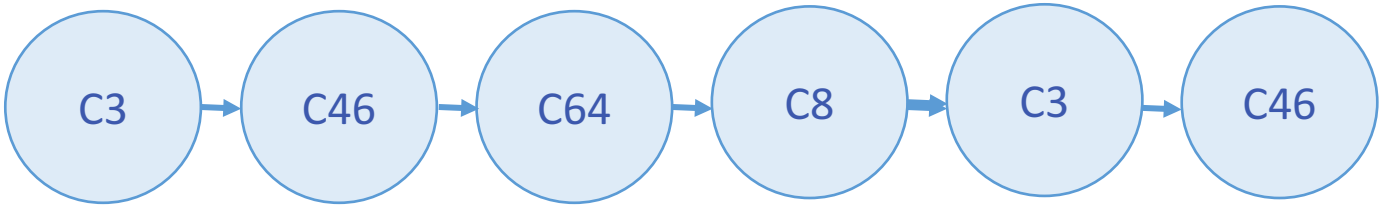
Motivation example

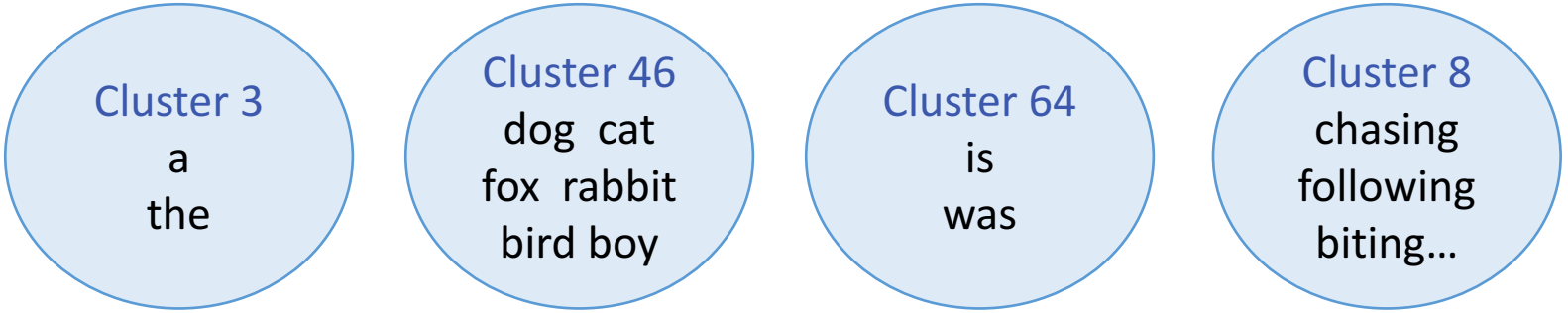
- ”a dog is chasing a cat”
  - $P(w_0, \text{“}a\text{”}, \text{”}dog\text{”}, \ldots, \text{“}cat\text{”})$
    $= P(\text{”}a\text{”} \mid w_0) P(\text{”}dog\text{”} \mid \text{”}a\text{”}) \ldots P(\text{”}cat\text{”} \mid \text{”}a\text{”})$
- Assume Every word belongs to a cluster



Motivation example

- Assume every word belongs to a cluster
  - "a dog is chasing a cat"





Motivation example

- Assume every word belongs to a cluster
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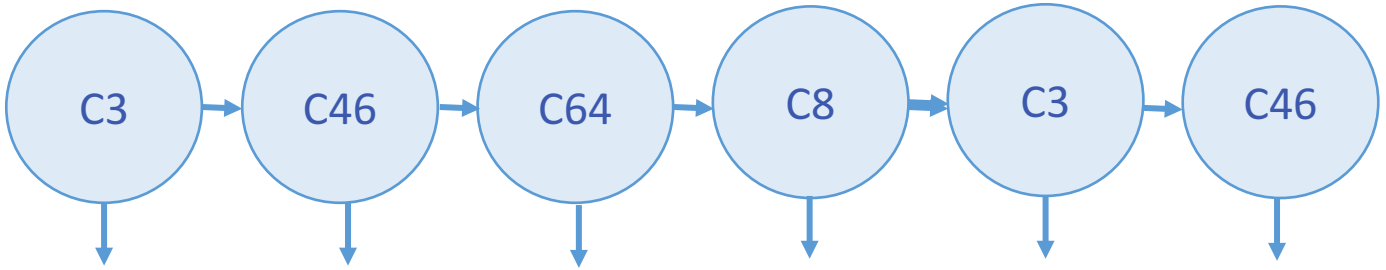
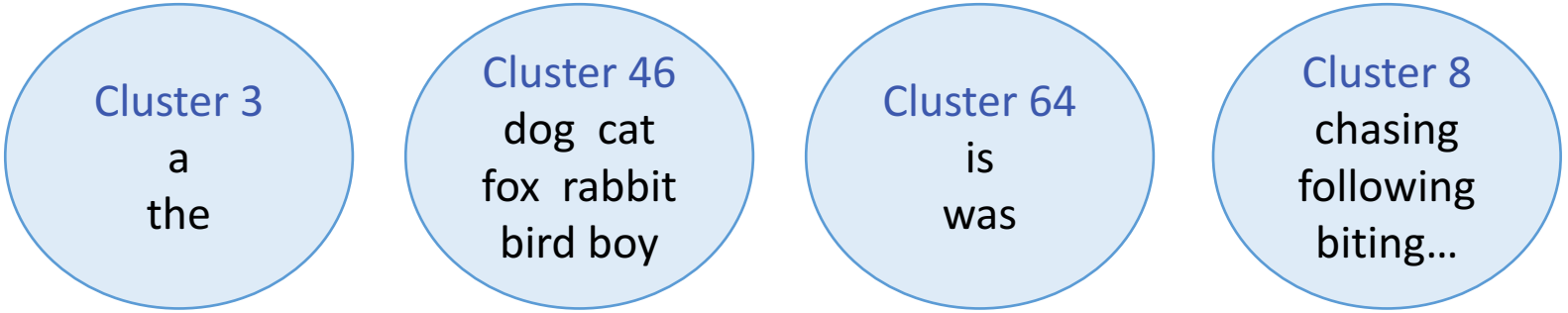
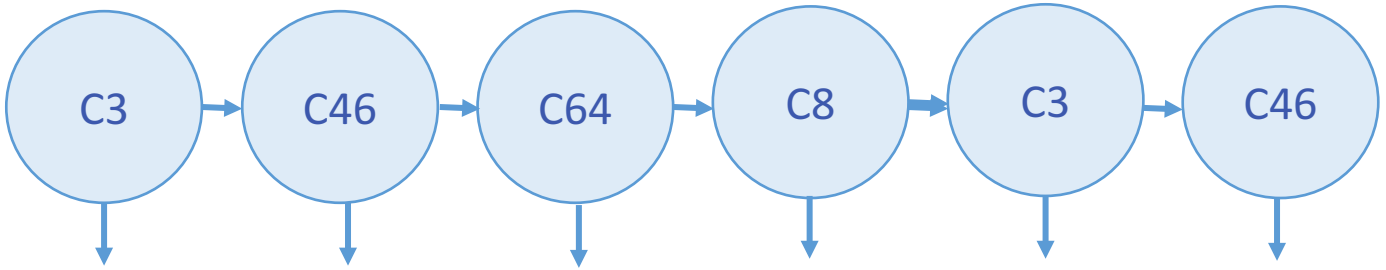
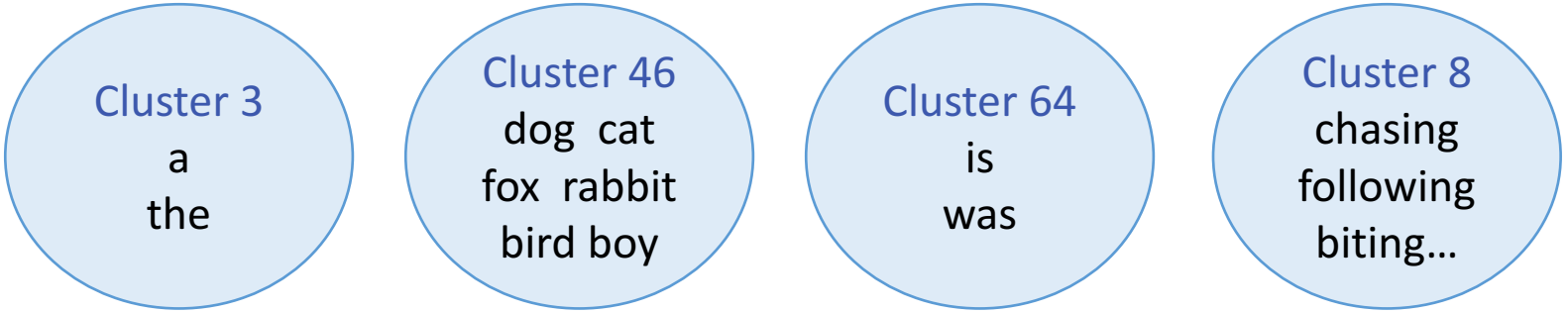




Motivation example

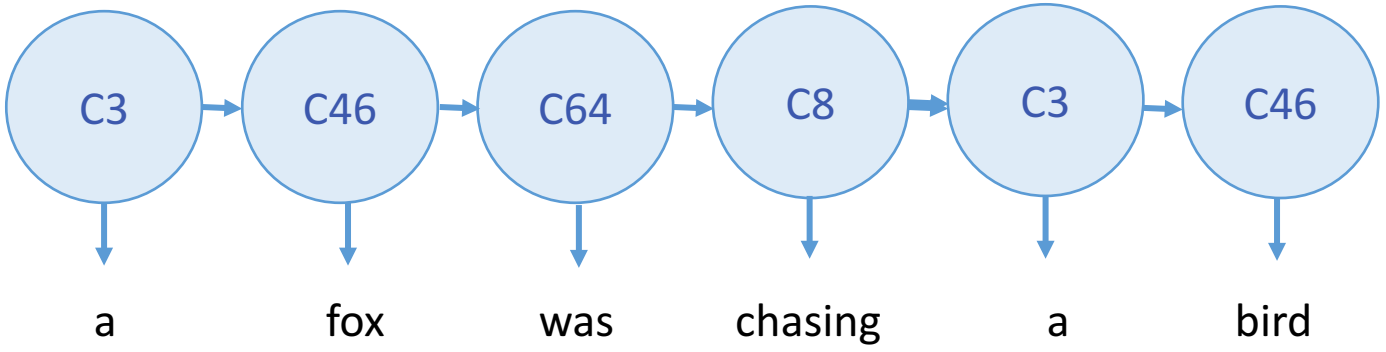
- Assume every word belongs to a cluster
  - "the boy is following a rabbit"

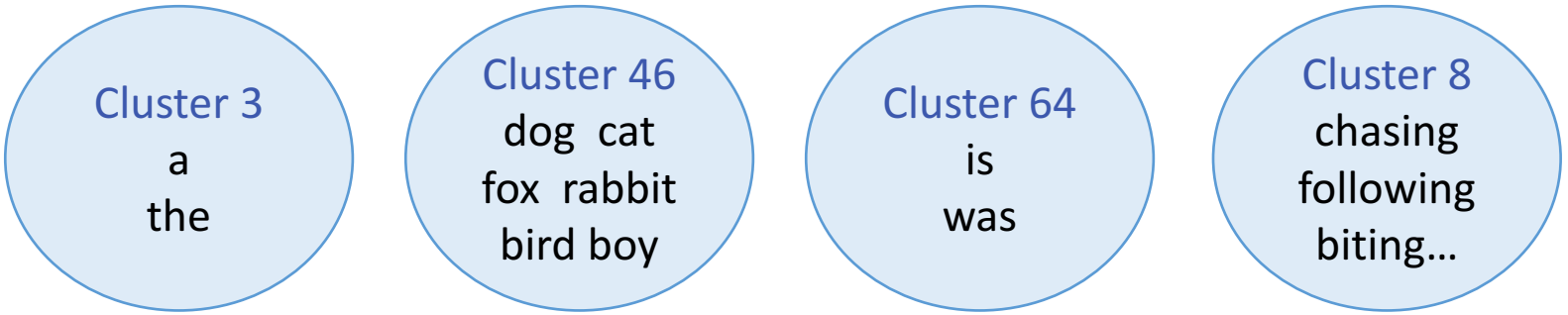




Motivation example

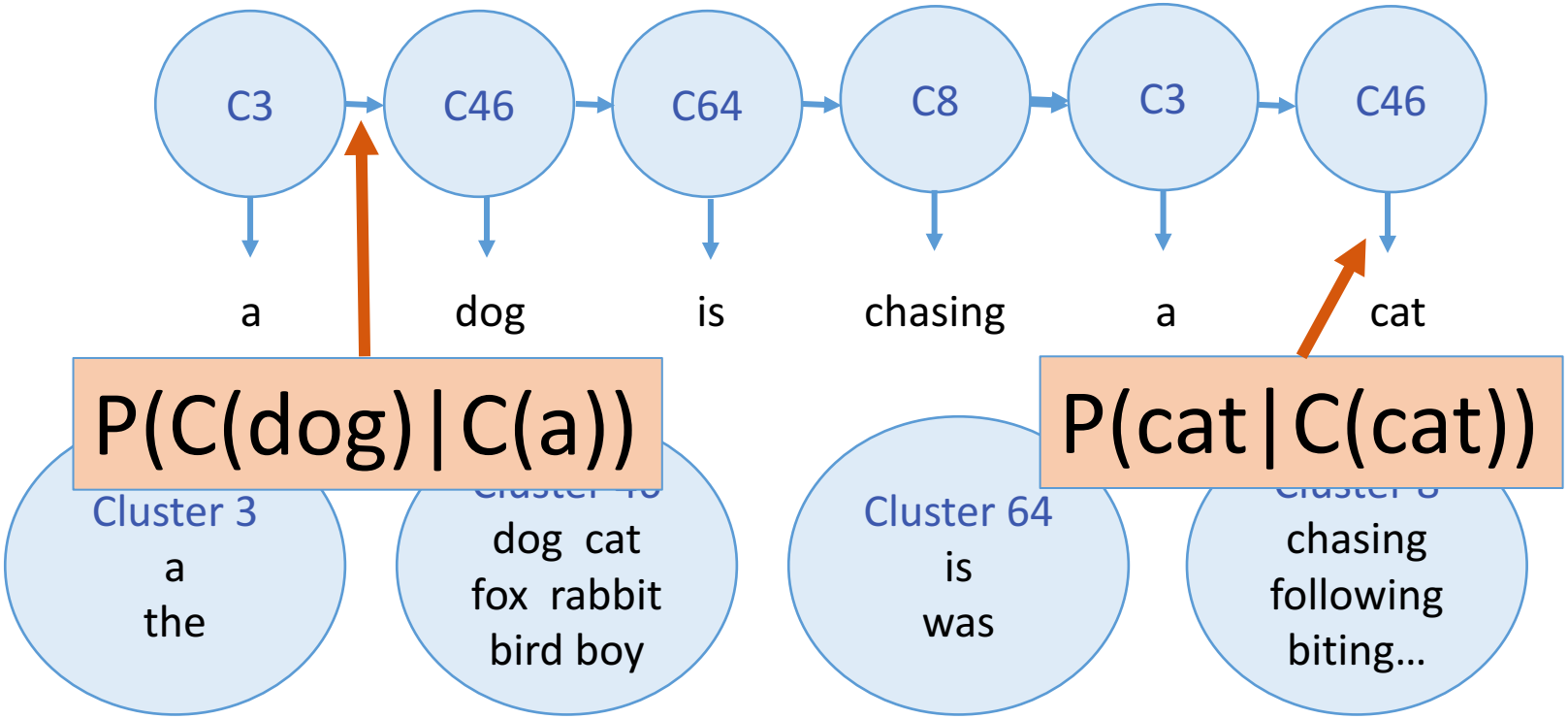
- Assume every word belongs to a cluster
  - "a fox was chasing a bird"





Brown Clustering

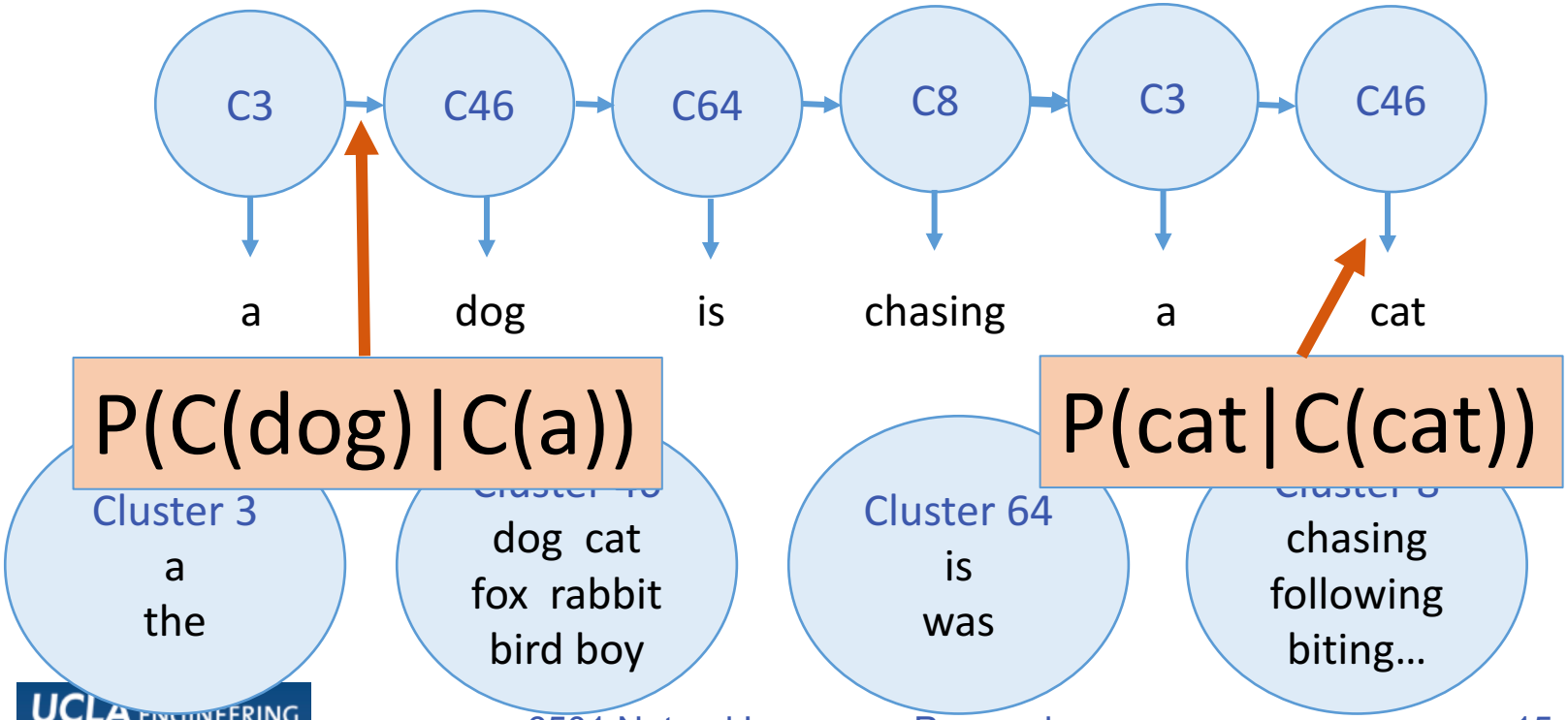
- Let $C(w)$ denote the cluster that w belongs to
  - "a dog is chasing a cat"



Brown clustering model

- P("a dog is chasing a cat")

  = P(C("a")|C_0) P(C("dog")|C("a")) P(C("dog")|C("a"))…
  P("a"|C("a"))P("dog"|C("dog"))...



Brown clustering model

- P("a dog is chasing a cat")

  = P(C("a")|C_0) P(C("dog")|C("a")) P(C("dog")|C("a"))…
  P("a"|C("a"))P("dog"|C("dog"))...

- In general

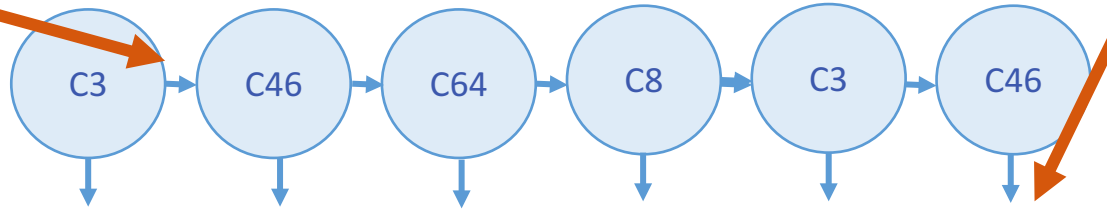
$$P(w_0, w_1, w_2, \dots, w_n)$$
$$= P(C(w_1) \mid C(w_0))P(C(w_2)|C(w_1)) \dots P(C(w_n) \mid C(w_{n-1}))$$
$$P(w_1|C(w_1)P(w_2|C(w_2)) \dots P(w_n|C(w_n))$$
$$= \Pi_{i=1}^{n} \mathrm{P}(C(w_i) \mid C(w_{i-1}))P(w_i \mid C(w_i))$$

Model parameters

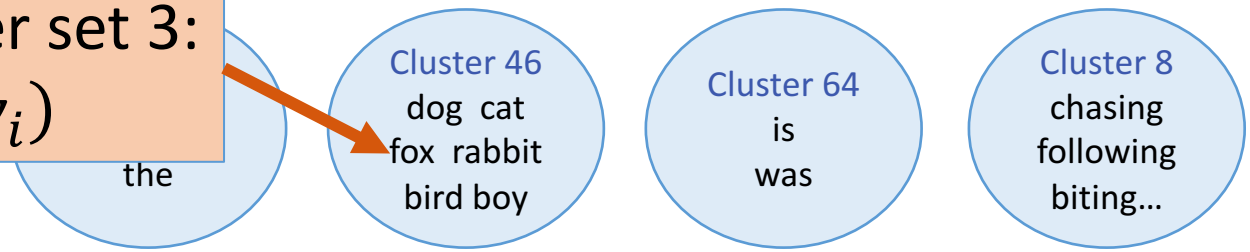
$$P(w_0, w_1, w_2, \ldots, w_n) = \Pi_{i=1}^{n} P(C(w_i) \mid C(w_{i-1}))P(w_i \mid C(w_i))$$

Parameter set 1: $P(C(w_i)|C(w_{i-1}))$

Parameter set 2: $P(w_i|C(w_i))$



Parameter set 3: $C(w_i)$



Model parameters

$P(w_0, w_1, w_2, \dots, w_n)$

$= \Pi_{i=1}^{n} P(C(w_i) \mid C(w_{i-1}))P(w_i \mid C(w_i))$

- A vocabulary set W
- A function $C: W \rightarrow \{1, 2, 3, \dots k\}$
  - A partition of vocabulary into k classes
- Conditional probability $P(c' \mid c)$ for $c, c' \in \{1, \dots, k\}$
- Conditional probability $P(w \mid c)$ for $c, c' \in \{1, \dots, k\}, w \in c$

θ represents the set of conditional probability parameters

C represents the clustering

Log likelihood

$$\mathrm{LL}(\theta, C) = \log P(w_0, w_1, w_2, \ldots, w_n \mid \theta, C)$$
$$= \log \Pi_{i=1}^{n} \mathrm{P}(C(w_i) \mid C(w_{i-1}))P(w_i \mid C(w_i))$$
$$= \sum_{i=1}^{n} [\log \mathrm{P}(C(w_i) \mid C(w_{i-1})) + \log P(w_i \mid C(w_i))]$$

- Maximizing $\mathrm{LL}(\theta, C)$ can be done by alternatively update θ and C
  1. $\max_{\theta \in \Theta} LL(\theta, C)$
  2. $\max_{C} LL(\theta, C)$

$$\max_{\theta \in \Theta} LL(\theta, C)$$

$$LL(\theta, C) = \log P(w_0, w_1, w_2, \ldots, w_n \mid \theta, C)$$
$$= \log \Pi_{i=1}^{n} P(C(w_i) \mid C(w_{i-1}))P(w_i \mid C(w_i))$$
$$= \sum_{i=1}^{n} [\log P(C(w_i) \mid C(w_{i-1})) + \log P(w_i \mid C(w_i))]$$

- $P(c' \mid c) = \frac{\#(c', c)}{\#c}$
- $P(w \mid c) = \frac{\#(w, c)}{\#c}$

This part is the same as training a POS tagging model

See section 9.2:
http://ciml.info/dl/v0_99/ciml-v0_99-ch09.pdf

$$\max_C LL(\theta, C)$$

$$\max_C \sum_{i=1}^{n} [\log P(C(w_i) \mid C(w_{i-1})) + \log P(w_i \mid C(w_i))]$$

$$= n \sum_{c=1}^{k} \sum_{c'=1}^{k} p(c, c') \log \frac{p(c,c')}{p(c)p(c')} + G$$

where G is a constant

See classnote here: http://web.cs.ucla.edu/~kwchang/teaching/NLP16/slides/classnote.pdf

- Here,

$$p(c, c') = \frac{\#(c,c')}{\sum_{c,c'} \#(c,c')} \quad , \quad p(c) = \frac{\#(c)}{\sum_c \#(c)}$$

- c: cluster of w_i, c':cluster of w_{i-1}
- $\frac{p(c,c')}{p(c)p(c')} = \frac{p(c|c')}{p(c)}$ (mutual information)

Algorithm 1

- Start with |V| clusters
  each word is in its own cluster
- The goal is to get k clusters
- We run |V|-k merge steps:
  - Pick 2 clusters and merge them
  - Each step pick the merge maximizing $LL(\theta, C)$
- Cost? (can be improved to $O(|V|^3)$)
  O(|V|-k) $O(|V|^2)$ $O(|V|^2) = O(|V|^5)$
  #Iters #pairs compute LL

Algorithm 2

- m : a hyper-parameter, sort words by frequency
- Take the top m most frequent words, put each of them in its own cluster $c_1, c_2, c_3, \ldots c_m$
- For $i = (m+1) \ldots |V|$
  - Create a new cluster c_{m+1} (we have m+1 clusters)
  - Choose two cluster from m+1 clusters based on $LL(\theta, C)$ and merge ⇒ back to m clusters
- Carry out (m-1) final merges ⇒ full hierarchy
- Running time $O(|V|m^2 + n)$, n=#words in corpus

Example clusters (Brown+1992)

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

Example Hierarchy (Miller+2004)

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	10110111001001011100
Maytag	101101110010010111010
Generali	101101110010010111011
Gap	10110111001001011110
Harley-Davidson	101101110010010111110
Enfield	1011011100100101111110
genus	1011011100100101111111
Microsoft	101101110010011000
Ventritex	101101110010010110010
Tractebel	1011011100100101100110
Synopsys	101101110010010110011
WordPerfect	1011011100100101101000
....	
John	10111001000000000
Consuelo	10111001000000001
Jeffrey	10111001000000010
Kenneth	1011100100000001100
Phillip	1011100100000011010