CS 6120/CS 4120: Natural Language Processing

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Logistics

- Reminder for late day usage:
  - “Each student has a budget of 5 days throughout the semester before a late penalty is applied.”
  - No need to inform TAs about late submission.
  - For assignments, we will start grading one week after the deadline. Let us know on piazza if you plan to submit later than that.
  - Grace period of one hour is given.
- NO CLASS next Tuesday (instructor out of town for academic meetings). Quiz will be on next **Friday**.
  - See schedule at http://www.ccs.neu.edu/home/luwang/courses/cs6120_sp2019/cs6120_sp2019.html

Brown Clusters

Brown Clusters -- Unsupervised

- Goal
  - To learn about regularities in words
  - By clustering words into groups

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

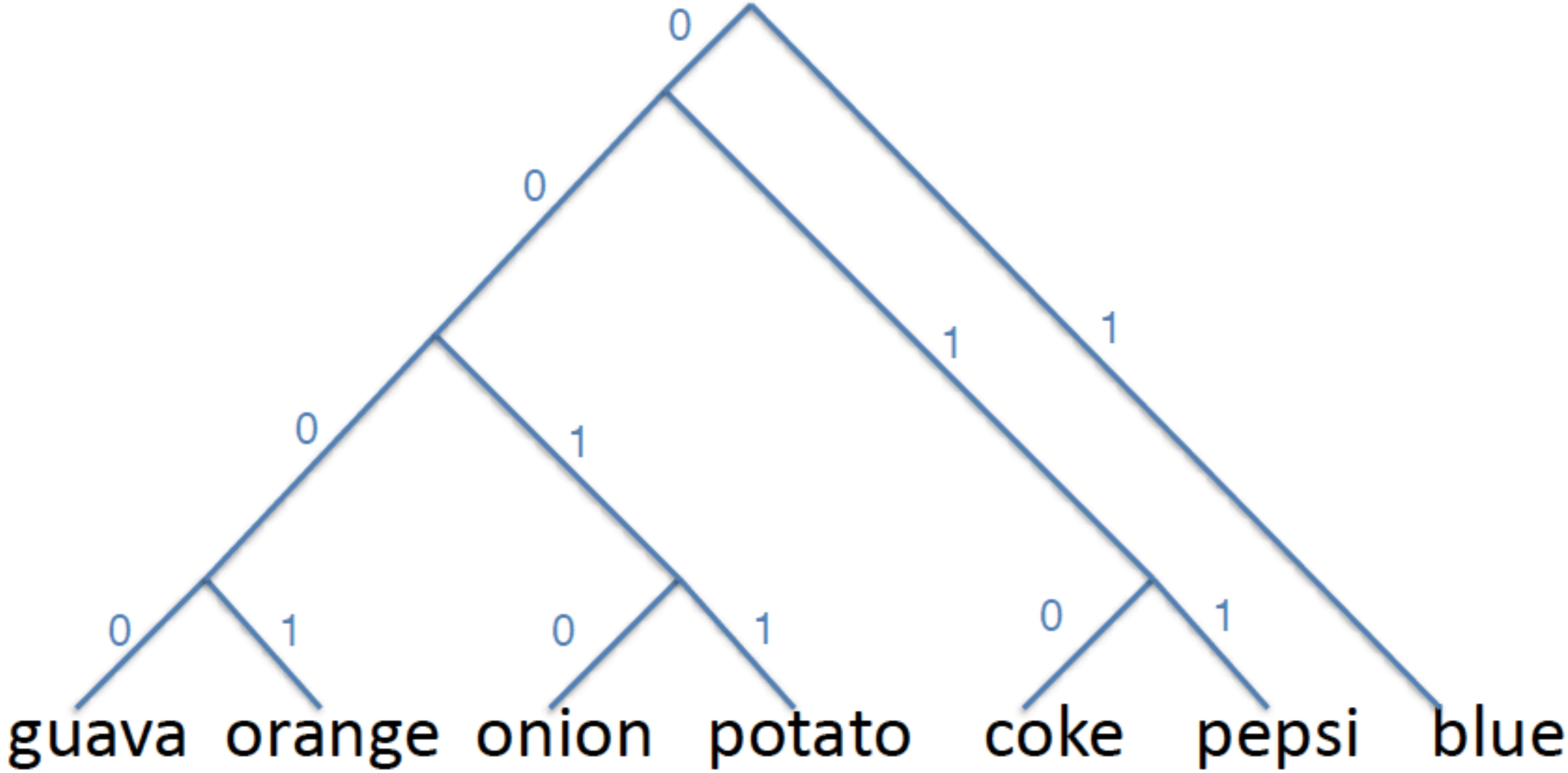
Brown Clustering Algorithm

- Input: a (large) corpus of words
- Output 1: a partition of words into word clusters
- Output 2 (generalization of 1): a hierarchical word clustering

- Assigns each word a binary representation

guava orange onion potato coke pepsi blue

- Assigns each word a binary representation



- onion: 0010

- Different prefix lengths: different abstractions

- *111111110110000* *slapped*
- 111111110110000 shattered
- 111111110110000 commissioned
- 111111110110000 drafted
- 111111110110000 authorized
- 111111110110000 authorised
- 111111110110000 imposed
- 111111110110000 established
- 111111110110000 developed

- *111111111100110* *officer*
- 111111111100110 acquaintance
- 111111111100110 policymaker
- 111111111100110 instructor
- 111111111100110 investigator
- 111111111100110 advisor
- 111111111100110 aide
- 111111111100110 expert
- 111111111100110 adviser

- *111110100 Clinton*
- 111110100 Aleman
- 111110100 Zeroual
- 111110100 Sampras
- 111110100 Barzani
- 111110100 Cardoso
- 111110100 Kim
- 111110100 King
- 111110100 Saddam
- 111110100 Netanyahu
- 111110100 Dole

- *111111100 Bill*
- 111111100 Boris
- 111111100 Warren
- 111111100 Fidel
- 111111100 Yasser
- 111111100 Kenneth
- 111111100 Viktor
- 111111100 Benjamin
- 111111100 Jacques
- 111111100 Bob
- 111111100 Alexander

Intuition

- Similar words appear in similar contexts

- Similar words have similar distributions of words to their immediate left and right

eat		juice		eat		juice
grow		seeds		grow		seeds
…		…		…		…
	guava				orange	

Formulation

- V is the set of all words seen in the corpus

- Say C: V → {1, 2,...k} is a partition of the vocabulary into k classes (k ~ 1000)

- The model: (C(w_0) is a special <s> state)

$$\underbrace{p(w_1, w_2, \ldots, w_N)}_{\textit{Corpus}} = \prod_{t=1}^{N} e(w_t \mid C(w_t))\, q(C(w_t) \mid C(w_{t-1}))$$

Formulation

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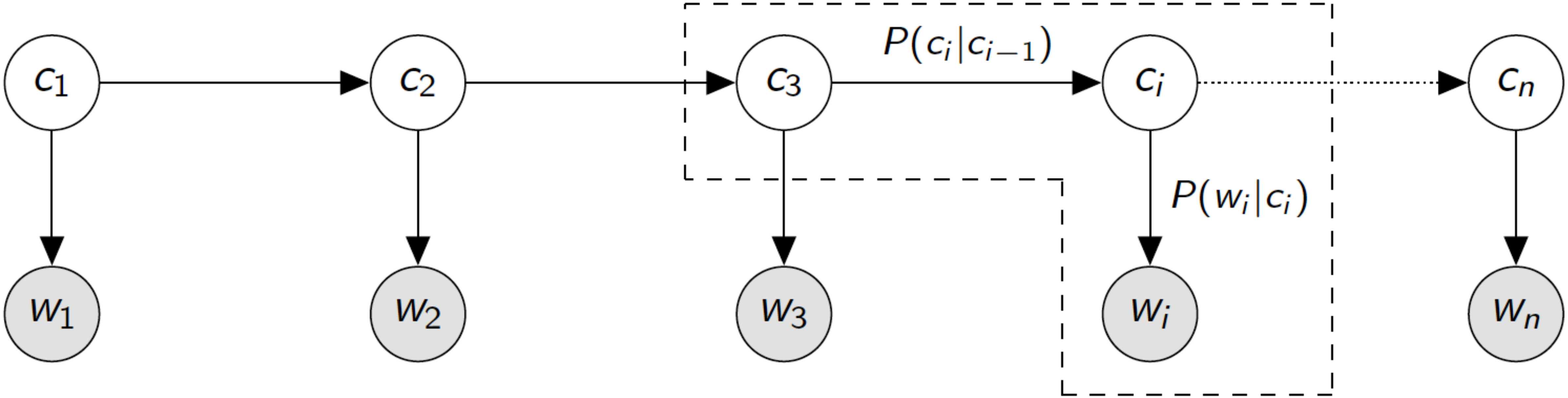
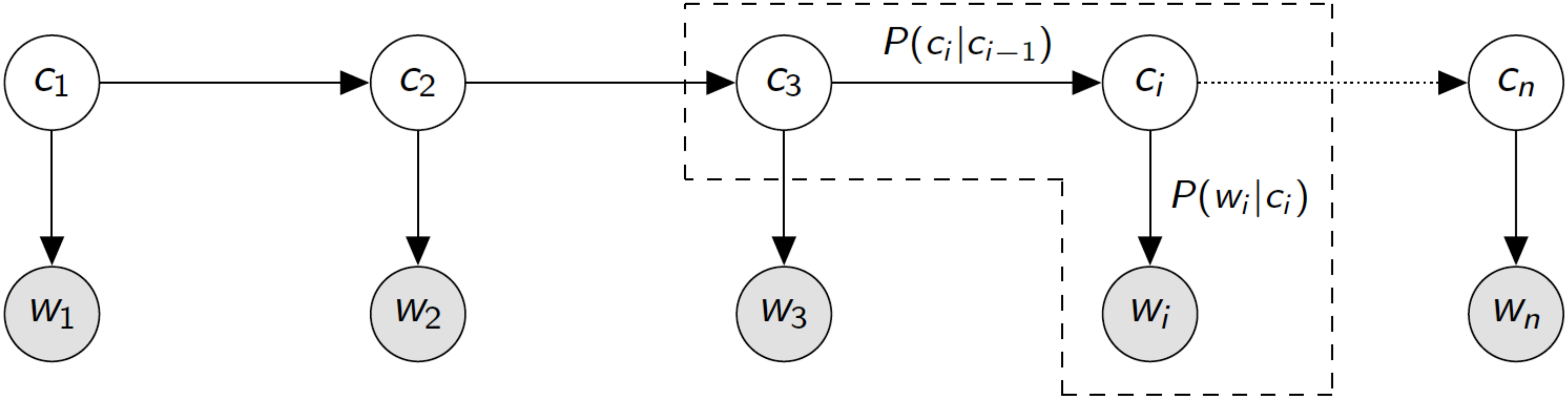
$$\underbrace{p(w_1, w_2, \ldots, w_N)}_{\textit{Corpus}} = \prod_{t=1}^{N} \overbrace{e(w_t \mid C(w_t))}^{\textit{Emission Probability!}} \overbrace{q(C(w_t) \mid C(w_{t-1}))}^{\textit{Transition Probability!}}$$



c_1
c_2
c_3
$P(c_i|c_{i-1})$
c_i
c_n
$P(w_i|c_i)$
w_1
w_2
w_3
w_i
w_n



Difference from HMM: each word can be labeled as *only* one class!

$C(I)=1$, $C(ate)=C(drank)=2$
$C(guava)=C(pepsi)=3$, $C(and)=4$

$e(I|1)=1$, $e(ate|2)= e(drank|2)= 0.3$
$e(guava|3)=e(pepsi|3)=0.1$, $e(and|4)=1$
$q(1|0)=0.2$, $q(2|1)=0.4$, $q(3|2)=0.3$, $q(4|3)=0.1$, $q(2|4)=0.2$

C(I)=1, C(ate)=C(drank)=2
C(guava)=C(pepsi)=3, C(and)=4

e(I|1)=1, e(ate|2)= e(drank|2)= 0.3
e(guava|3)=e(pepsi|3)=0.1, e(and|4)=1
q(1|0)=0.2, q(2|1)=0.4, q(3|2)=0.3, q(4|3)=0.1, q(2|4)=0.2

P(I ate guava and drank pepsi) =

0.2*1*0.4*0.3*0.3*0.1*0.1*1*0.2*0.3*0.3*0.1

The Model

- Vocabulary *V*
- A function C: *V* → {1..k}
  - partitioning of vocabulary into k classes
- Emission probabilities e(w|C(w))
- Transition probability q(c'|c)

Scoring a Partition: **Quality (C)**

N is the number of words in the corpus

$$\frac{1}{N}\sum_{t=1}^{N}\log\left(e(w_t \mid C(w_t))q(C(w_t) \mid C(w_{t-1}))\right)$$

c and c' are in {1, 2, …, k}

$$=\sum_{c,c'} p(c,c')\log\left(\frac{p(c,c')}{p(c)p(c')}\right)+\sum_{w} p(w)\log p(w)$$

n(c): #occurences of c in corpus under function C

n(c,c'): #occurences of (c,c') in corpus under function C

$$p(c,c')=\frac{n(c,c')}{N} \qquad p(c)=\frac{n(c)}{N}$$

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N is the number of words in the corpus

Mutual information (MI)

constant

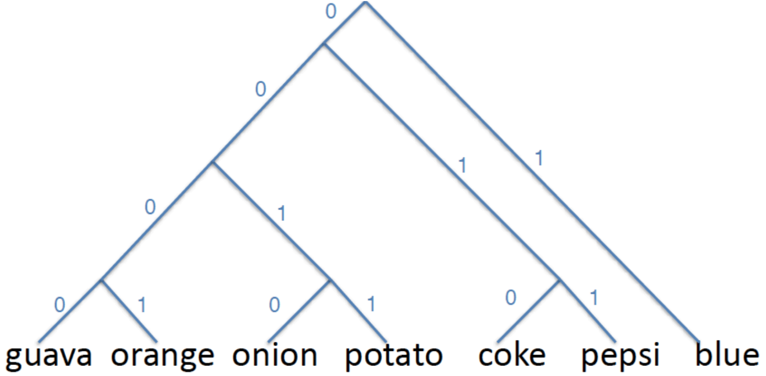
n(c): #occurences of c in corpus under function C
n(c,c’): #occurences of (c,c’) in corpus under function C

$$p(c,c')=\frac{n(c,c')}{N} \qquad p(c)=\frac{n(c)}{N}$$

Proof (not required)

$$\begin{aligned}
\text{Quality}(C) &= \frac{1}{n}\sum_{i=1}^{n} \log P(C(w_i)|C(w_{i-1}))P(w_i|C(w_i)) \\
&= \sum_{w,w'} \frac{n(w,w')}{n} \log P(C(w')|C(w))P(w'|C(w')) \\
&= \sum_{w,w'} \frac{n(w,w')}{n} \log \frac{n(C(w),C(w'))}{n(C(w))} \frac{n(w')}{n(C(w'))} \\
&= \sum_{w,w'} \frac{n(w,w')}{n} \log \frac{n(C(w),C(w'))n}{n(C(w))n(C(w'))} + \sum_{w,w'} \frac{n(w,w')}{n} \log \frac{n(w')}{n} \\
&= \sum_{c,c'} \frac{n(c,c')}{n} \log \frac{n(c,c')n}{n(c)n(c')} + \sum_{w'} \frac{n(w')}{n} \log \frac{n(w')}{n}
\end{aligned}$$

A First (Naïve) Algorithm



- Start with |*V*| clusters: each word gets its own cluster
- Our aim is to find k final clusters
- We run |*V*| - k merge steps:
  - At each merge step we pick two clusters c_i and c_j, and merge them into a single cluster
  - We greedily pick merges such that Quality(C) for the clustering C after the merge step is maximized at each stage

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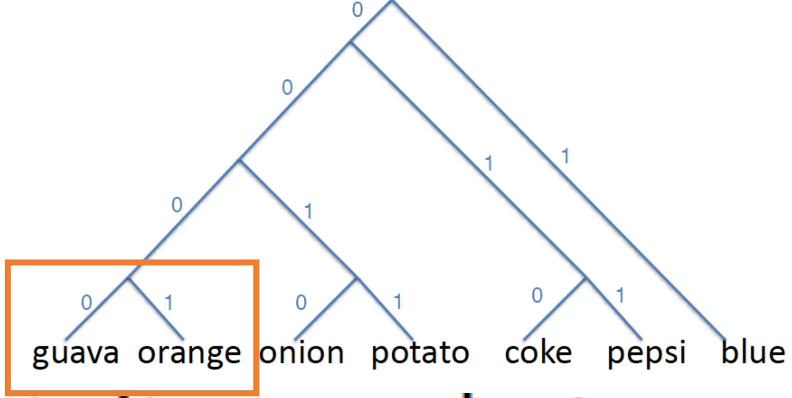

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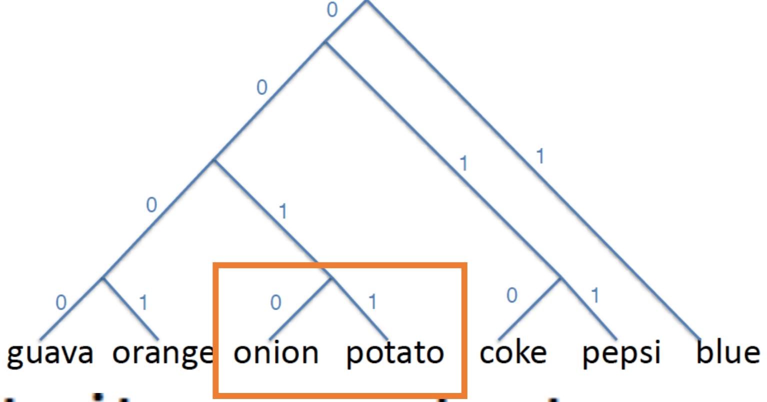

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A First (Naïve) Algorithm

- Cost?
  - Naive = O($|V|^5$). *Calculate everything on-the-fly!*
  - Improved algorithm gives O($|V|^3$) *Store word transitions!*

A First (Naïve) Algorithm

- Cost?
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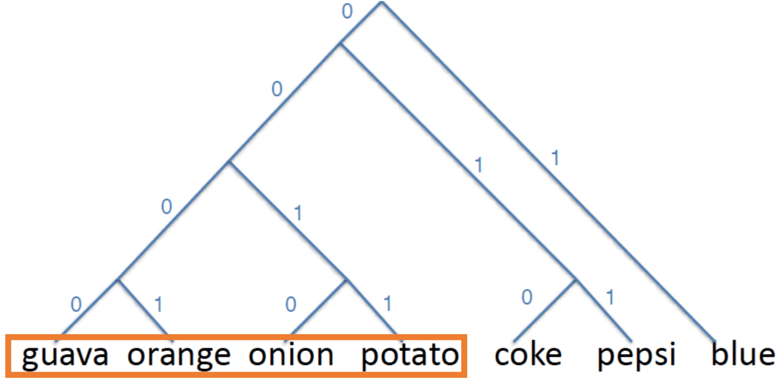
Too slow!

A Second Algorithm

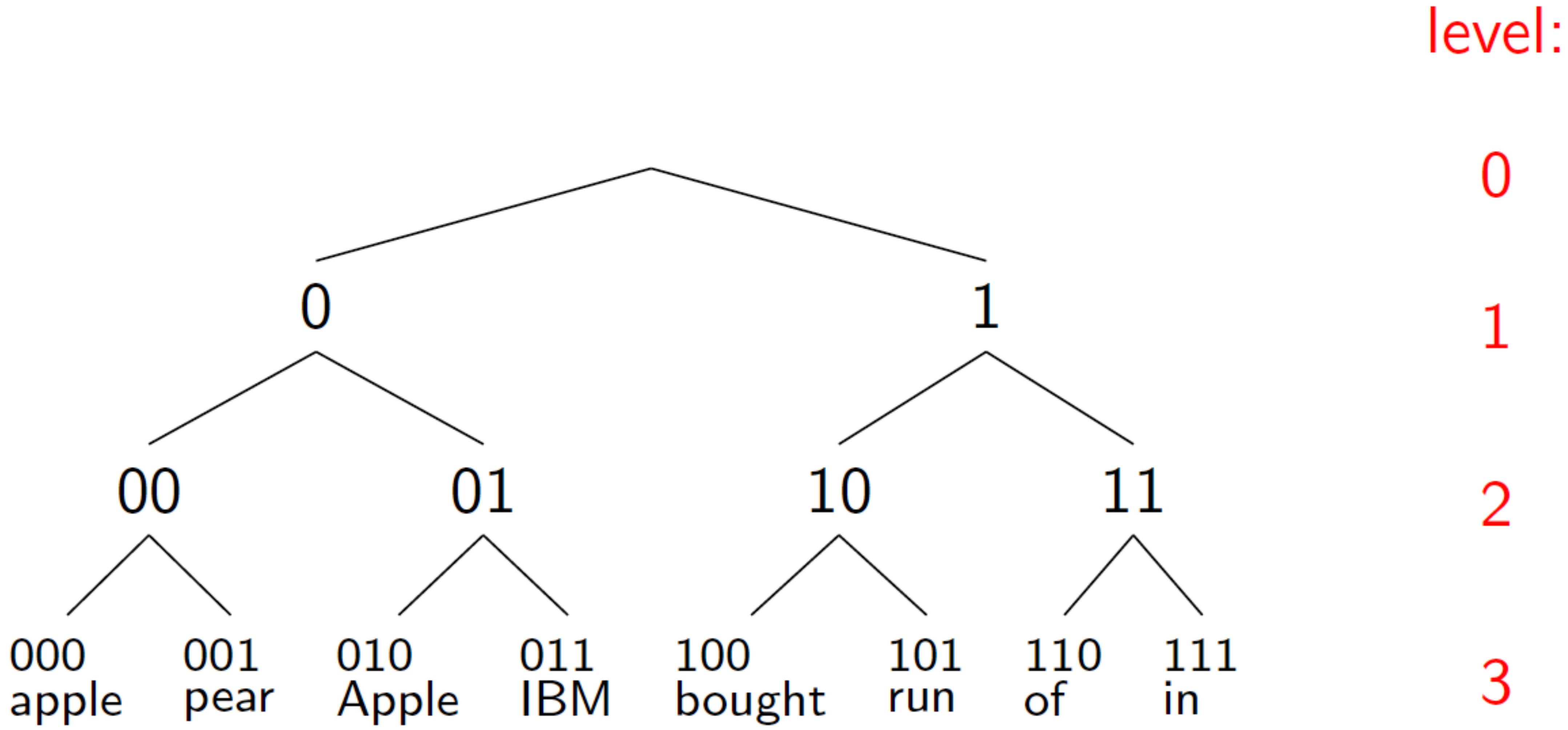


- New parameter: m (e.g., m = 1000)
- Take the top m most frequent words, put each into its own cluster, $c_1, c_2, \ldots c_m$
- For i = (m + 1) … |V|
  - Create a new cluster, c_{m+1} , for the i'th most frequent word. We now have m + 1 clusters
- Choose two clusters from $c_1 \ldots c_{m+1}$ to be merged:
  - pick the merge that gives a maximum value for Quality(C).
  - We're now back to m clusters
- Carry out (m - 1) final merges, to create a full hierarchy

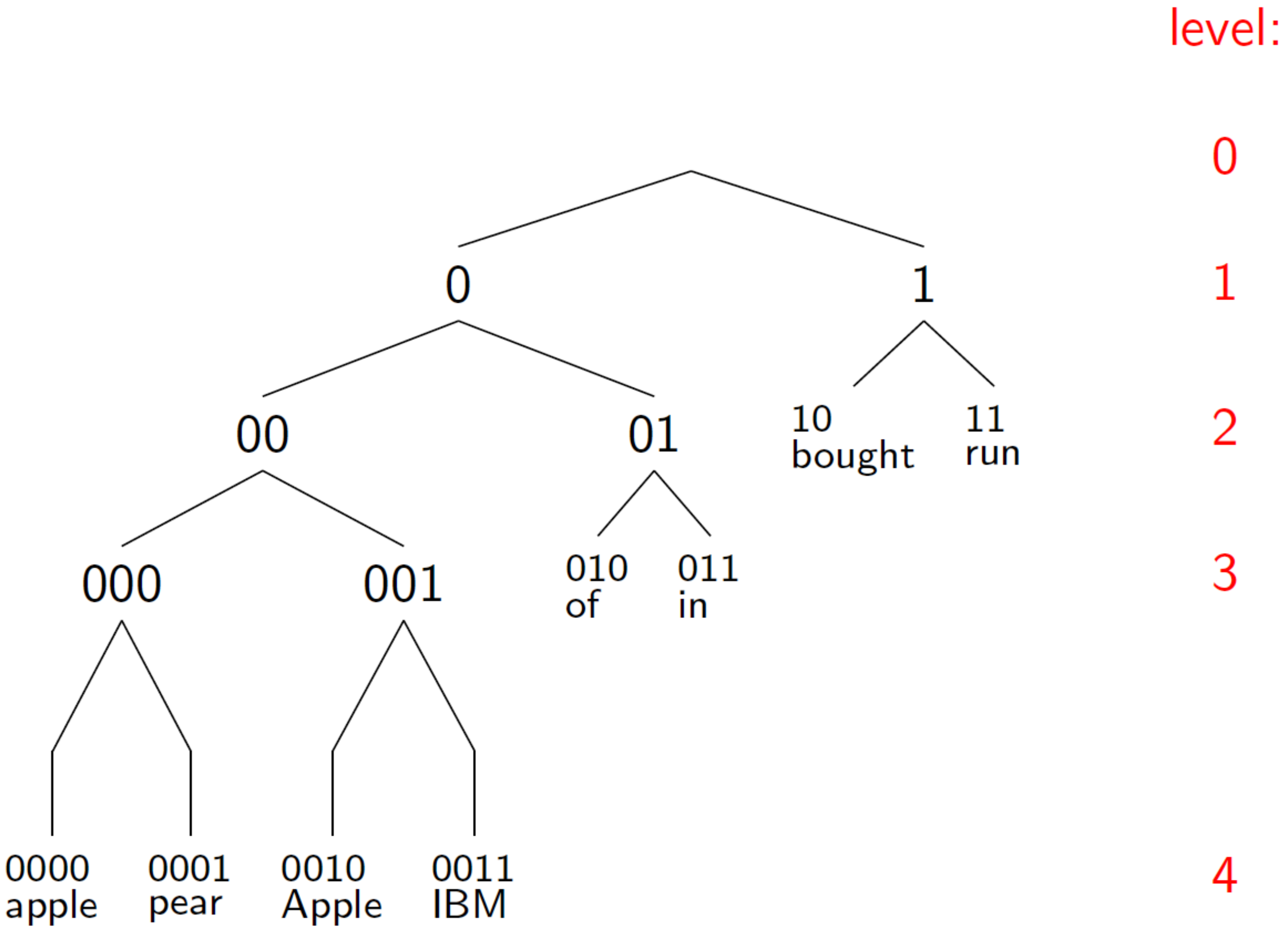
A Second Algorithm

- Running time: $O(|V|m^2 + n)$ where n is corpus length

A perfect balanced binary tree



In reality:



level:
0
1
2
3
4
0
1
00
01
10
bought
11
run
000
001
010
of
011
in
0000
apple
0001
pear
0010
Apple
0011
IBM