A Stochastic Memoizer for Sequence Data

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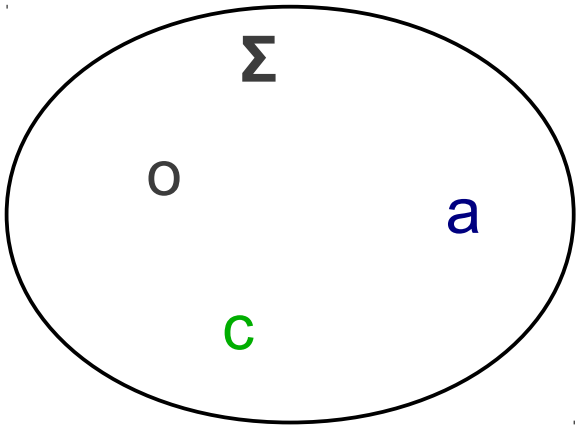
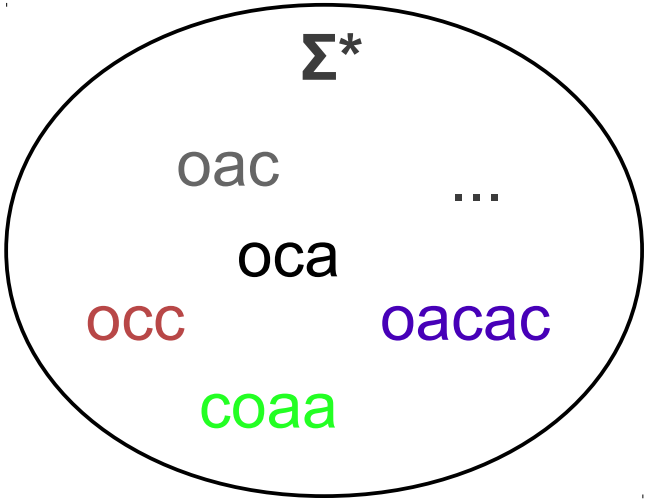
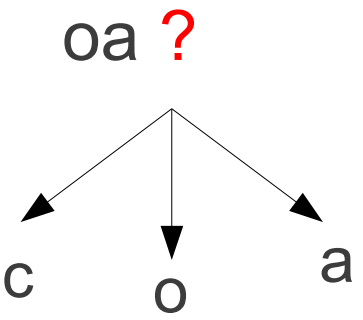
Outline

- Problem Overview
- Existing Techniques
- Proposed Solution
- Contributions
- Model Used
- Inference & Prediction
- Experiments
- Summary & Discussion

Problem Overview







Existing Techniques

- N-grams
  - Markov assumption applies
  - Given n-1 characters, what is the probability vector of the n^{th} character (given our vocabulary)
  - Very good perplexity rates
  - Problems:
    - Determining optimal value of n
    - We need more training data

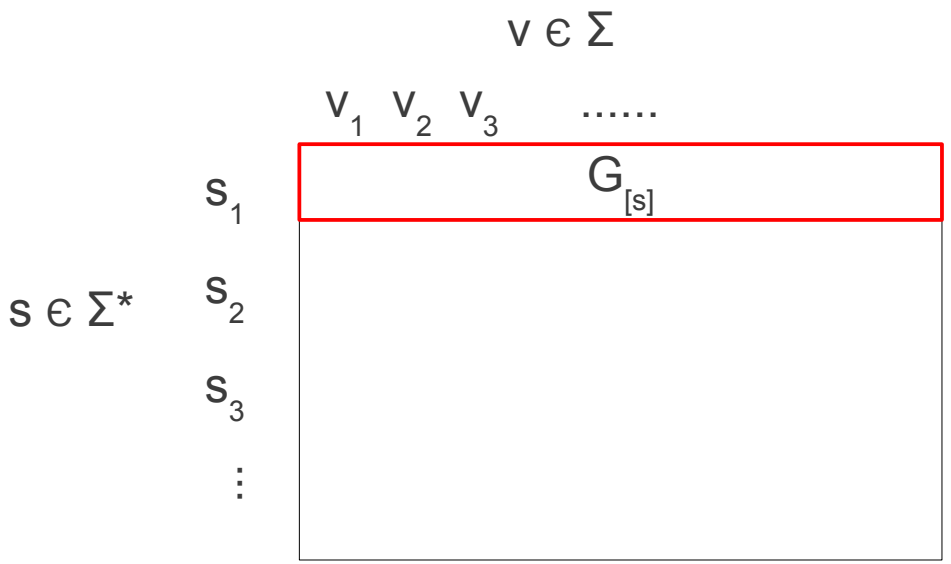
Proposed Solution

- Use a non-Markov model
  - Next value in sequence is conditionally dependent on **all** preceding values → ∞-gram
  - This introduces a large number of latent variables
  - Use Pitman-Yor (PY) process with concentration parameter = 0
  - Use Hierarchial PY Process (HPYP) to allow comparing common suffixes

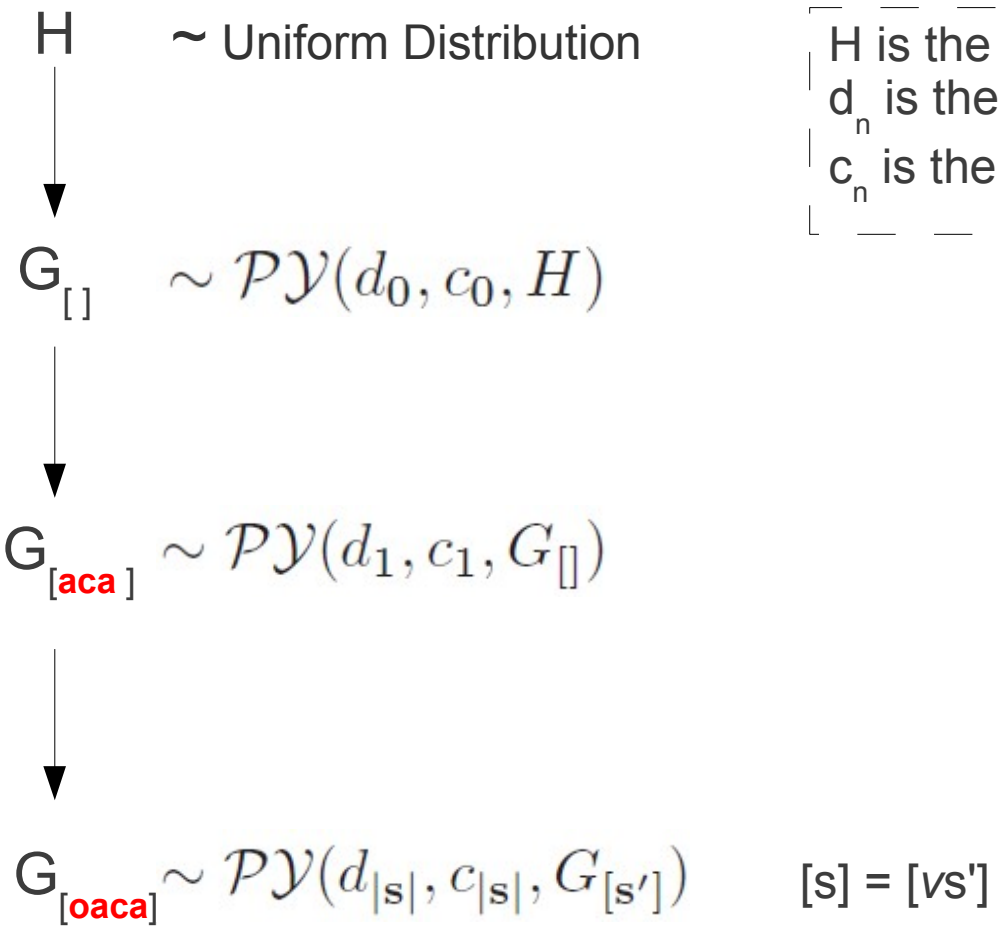
Contribution

- Stochastic Memoizer
  - Probabilistic technique
  - Remembers previously returned values
    - Return previously returned symbols or a new symbol
  - Goals
    - Relate shorter sequences with longer sequences
    - Use a HPYP that is tractable

Hierarchial Formulation



Hierarchial Formulation *Cont'd*



H is the base measure
d_n is the discount parameter
c_n is the precision paramter

Hierarchial Formulation *Cont'd*

H ~ Uniform Distribution

$$G_{[\,]} \sim \mathcal{PY}(d_0, c_0, H)$$

$$G_{[s`\,]} \sim \mathcal{PY}(d_1, c_1, G_{[]})$$

$$G_{[s]} \sim \mathcal{PY}(d_{|\mathbf{s}|}, c_{|\mathbf{s}|}, G_{[\mathbf{s}']})$$

[s] = [*v*s']

H is the base measure
d_n is the discount parameter
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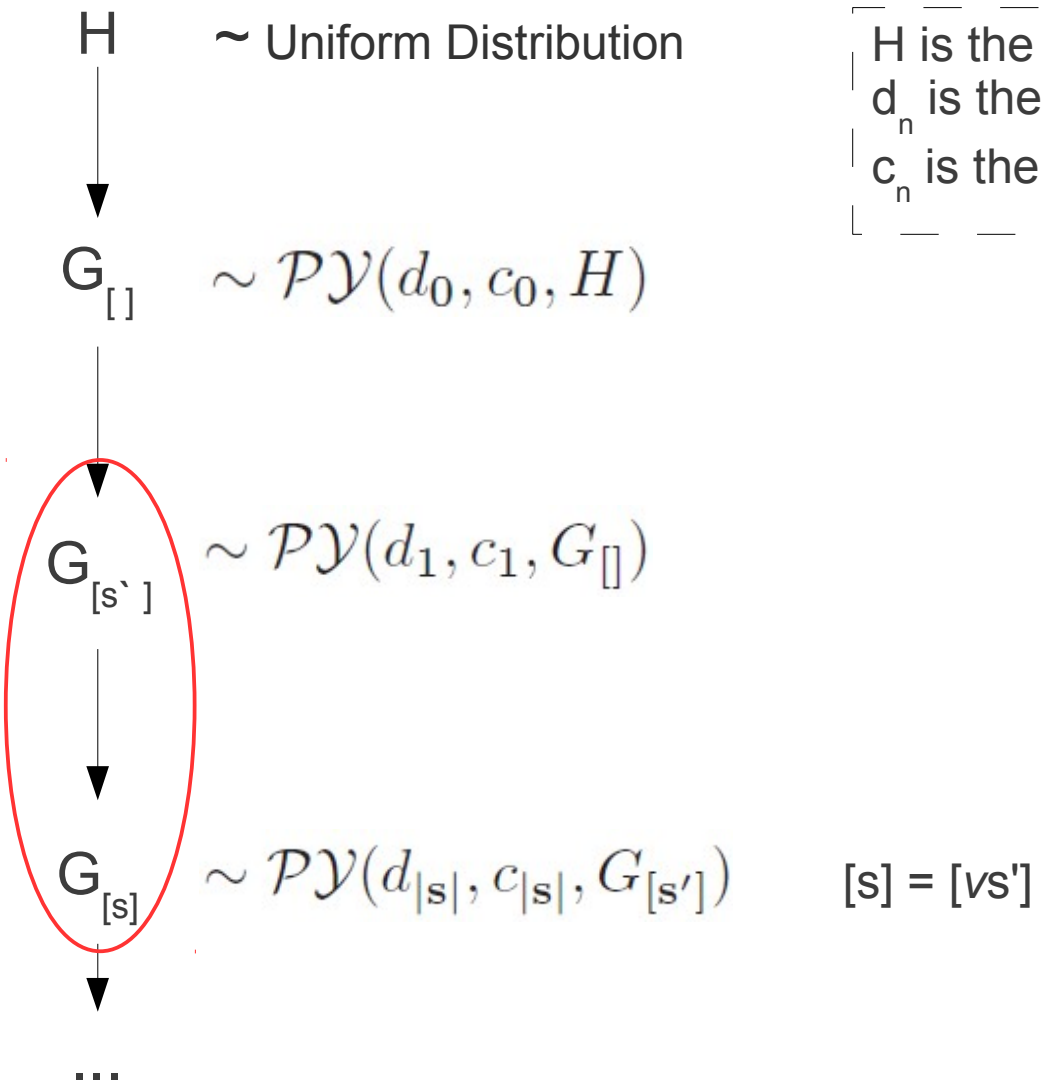
Hierarchial Formulation *Cont'd*



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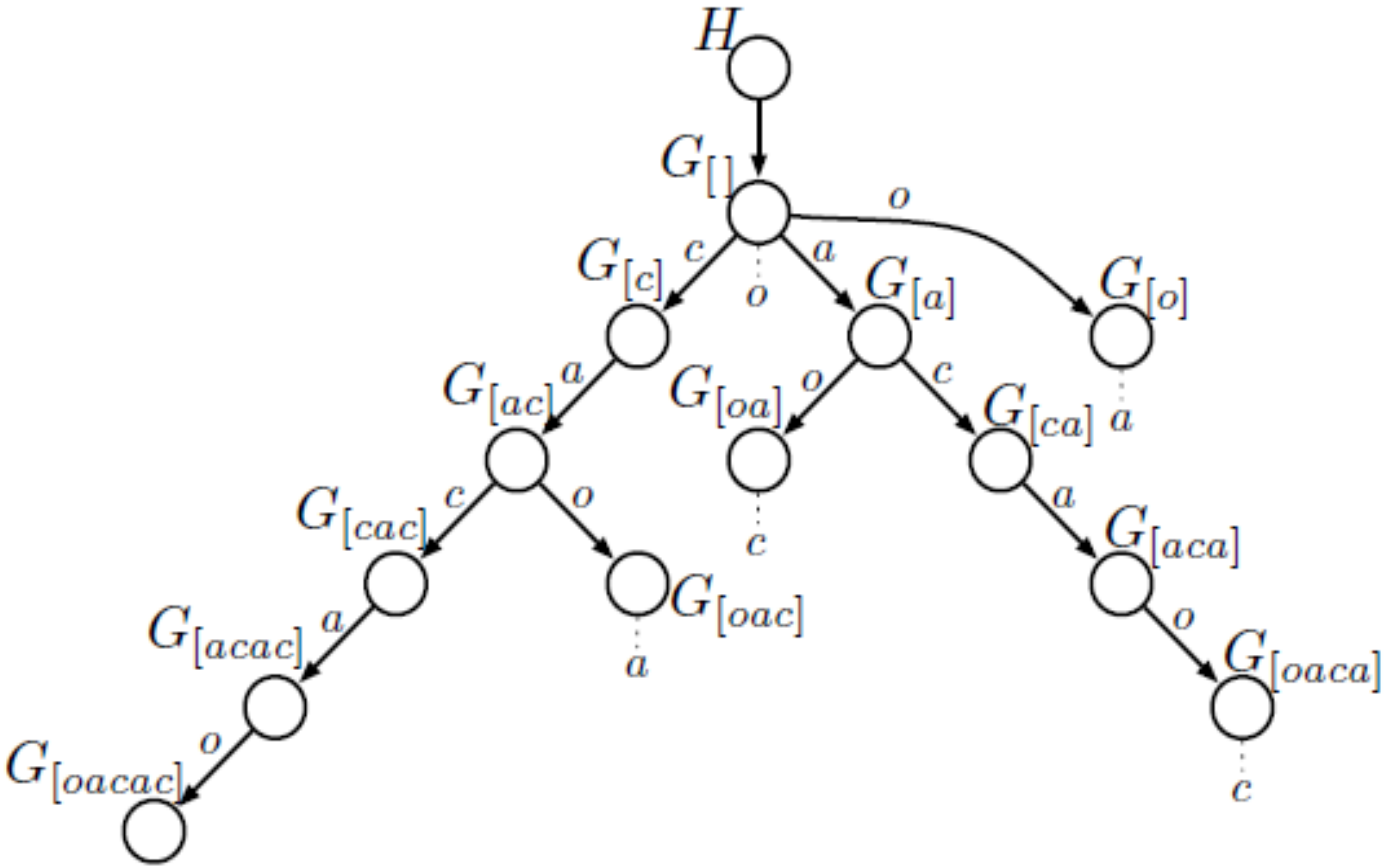
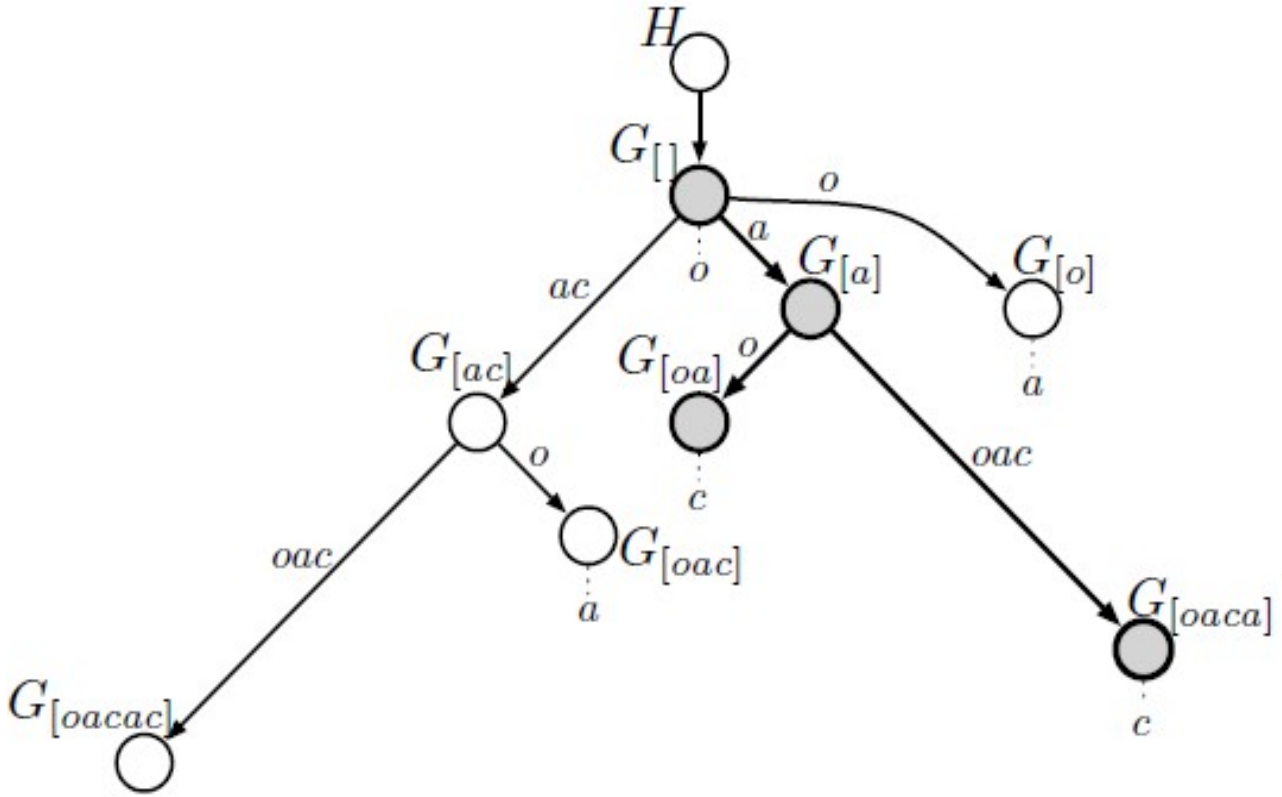
Prefix Tries



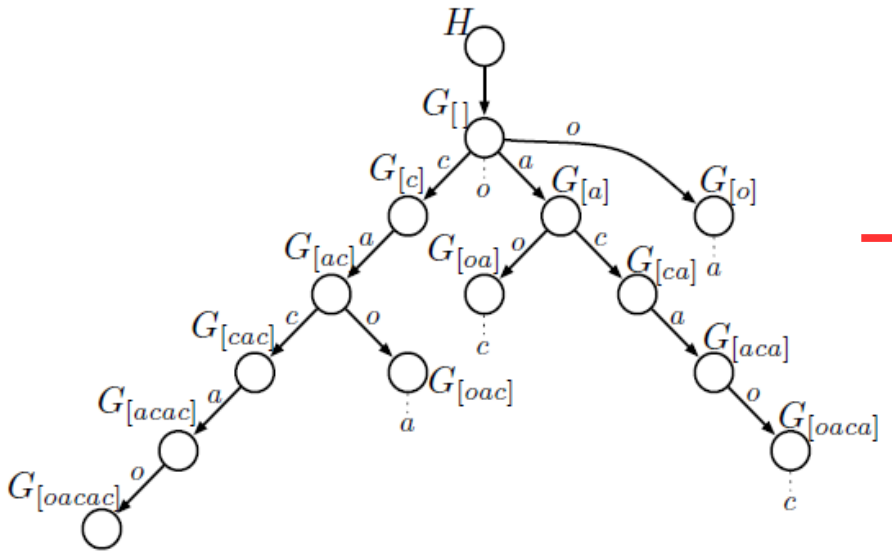
Prefix trie for *oacac*.

Prefix Trees



Prefix tree for *oacac*.

Trie to Tree Conversion



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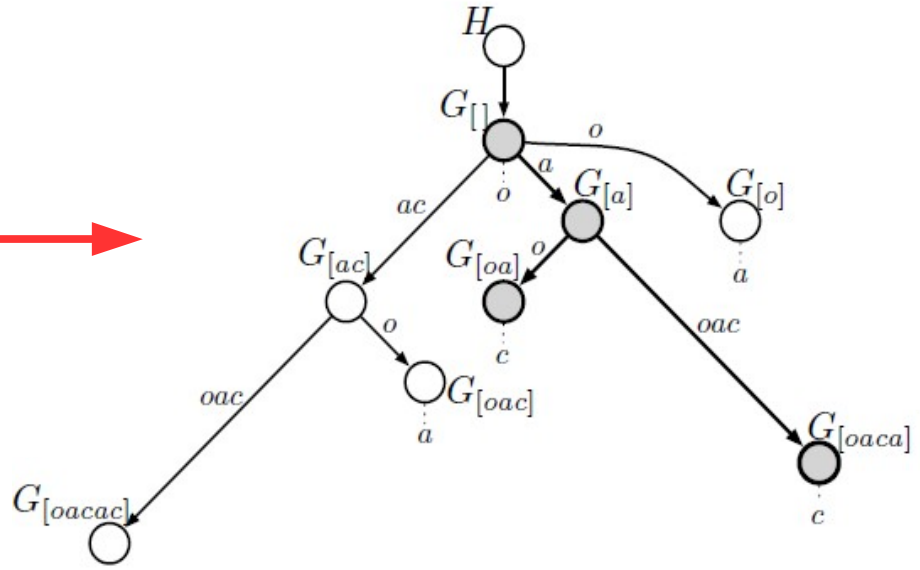
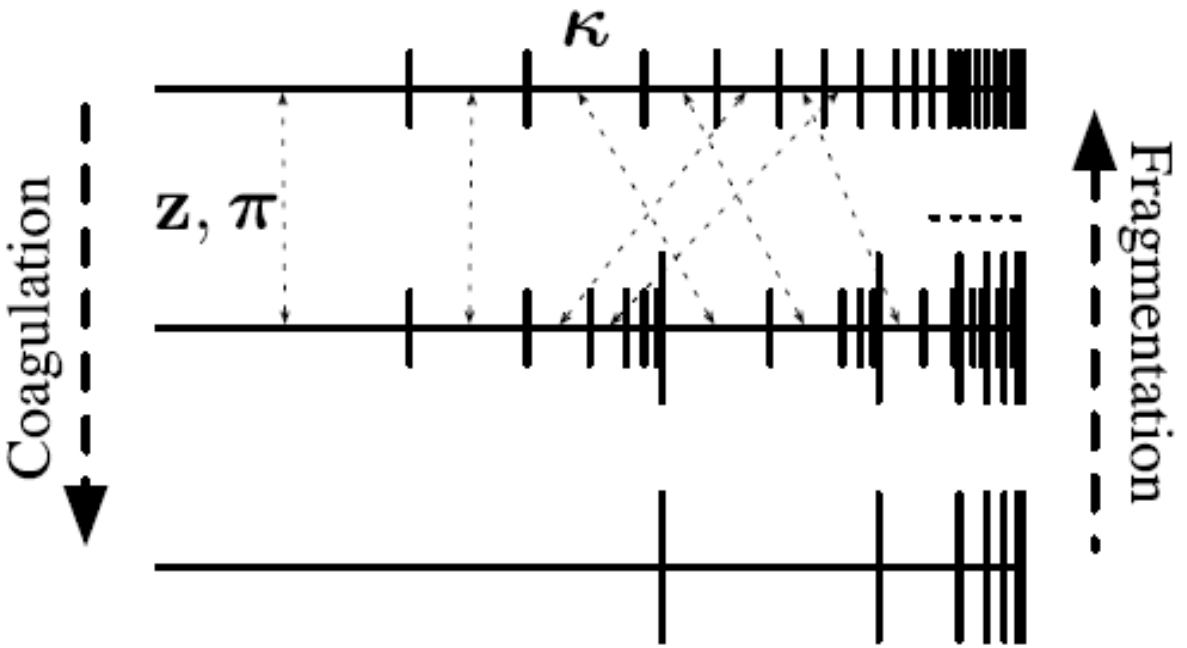


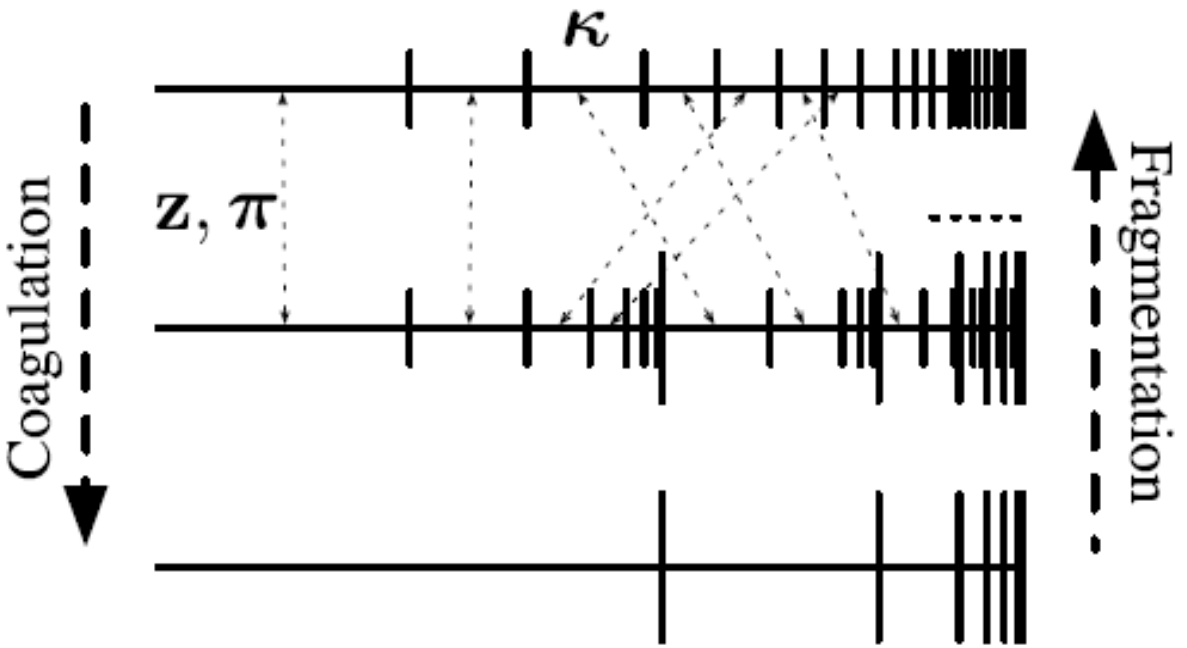
Prefix tree for *oacac*.

Coagulation & Fragmentation



Coagulation & Fragmentation

Construct collapsed model



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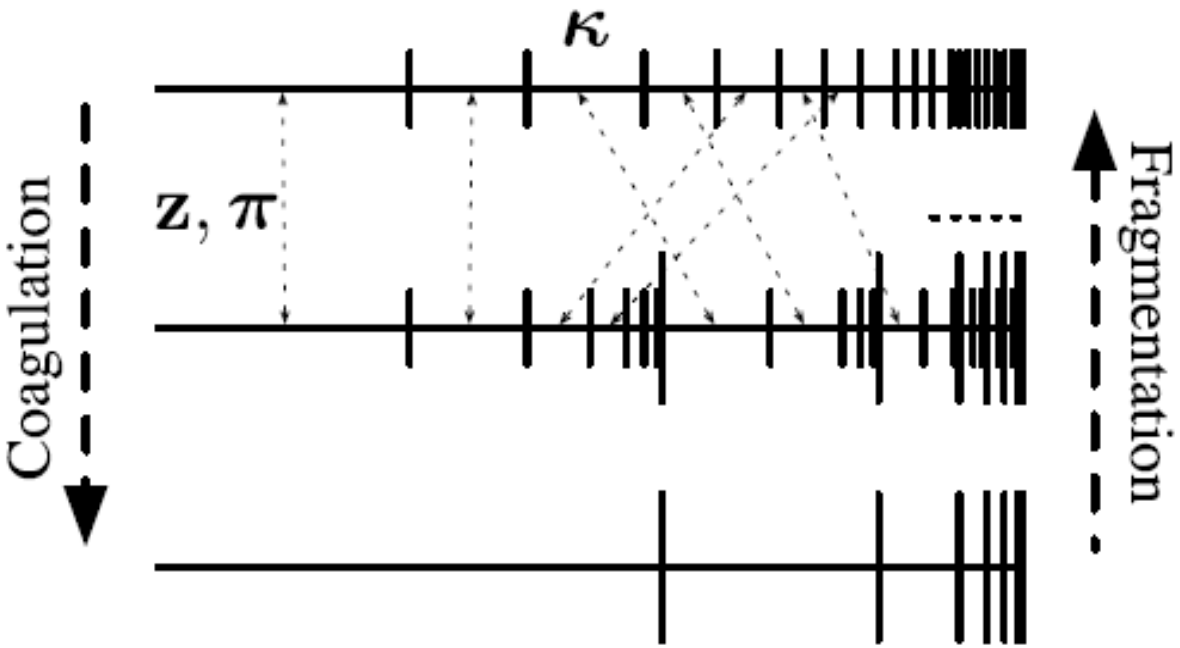


Test sequences not in training data

Coagulation & Fragmentation *Cont'd*

G_1

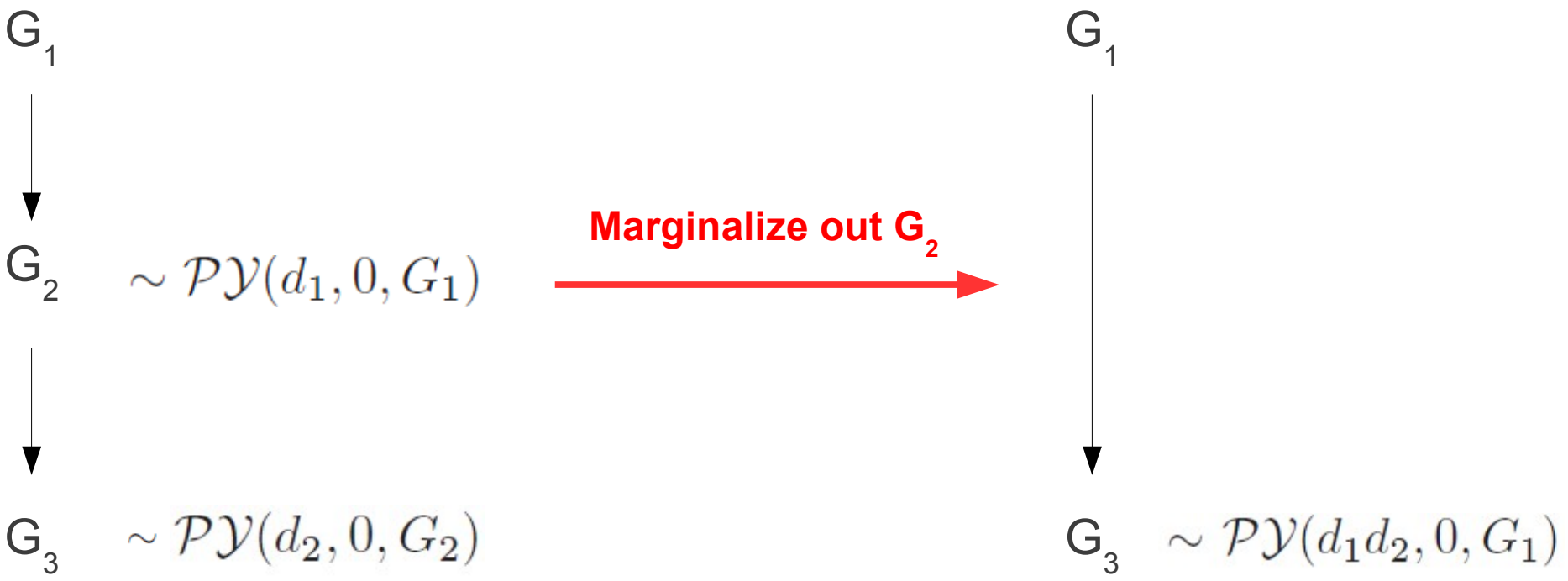
↓

$G_2 \quad \sim \mathcal{PY}(d_1, 0, G_1)$

↓

$G_3 \quad \sim \mathcal{PY}(d_2, 0, G_2)$

Coagulation & Fragmentation *Cont'd*

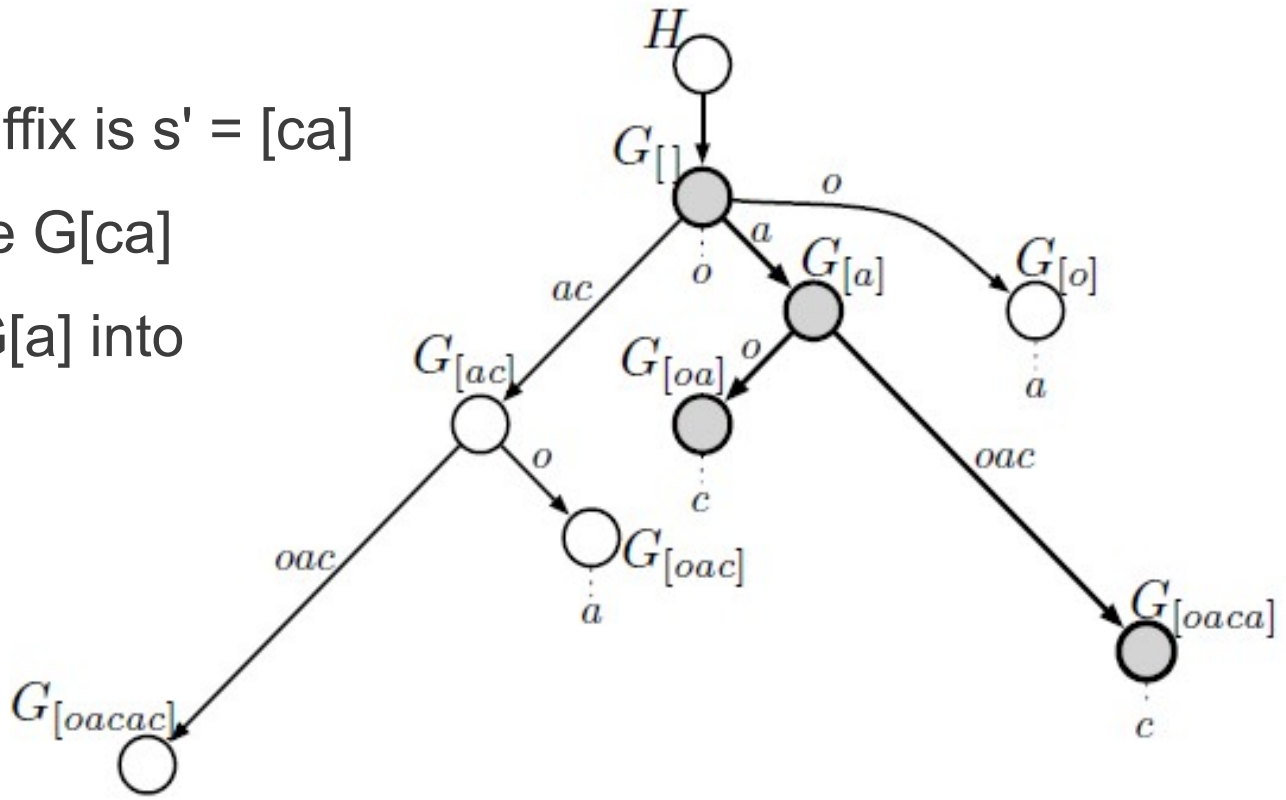


Inference & Prediction

- Same as HPYP
- Use Gibbs sampling in the Chinese Restaurant Franchise (CRF) representation
- $E(G_{[s]}(v)) = E(G_{[s']}(v))$ where s' is the longest common suffix of s
- Need to be able to compute the probability of a symbol ***v*** given a sequence ***s*** that is not in the training data

Unseen Sequences

- Consider s = [oca]
- Longest common suffix is s' = [ca]
- Need to reinstantiate G[ca]
- Fragment G[oaca]|G[a] into **(G[ca] | G[a])** and **(G[oaca] | G[ca])**



Prefix tree for *oacac*.

Experiments

Evaluation Questions

- Do prefix trees provide computational savings?
- Does the sequence memoizer's (∞-gram) performance compare to that of an n-gram model?

Data Sets

- Associated Press (AP) corpus
  - *Vocabulary:* 1 million words
  - *Training:* 15 million words
  - *Testing:* 1 million words
  - *Preprocessing:* Replace low frequency words with a single ”unknown word” symbol
- New York Times (NYT) corpus
  - *Vocabulary:* 150,000 words
  - *Training: 13* million words
  - *Testing:* 200,000 words
  - *Preprocessing:* none

1) Computational Savings

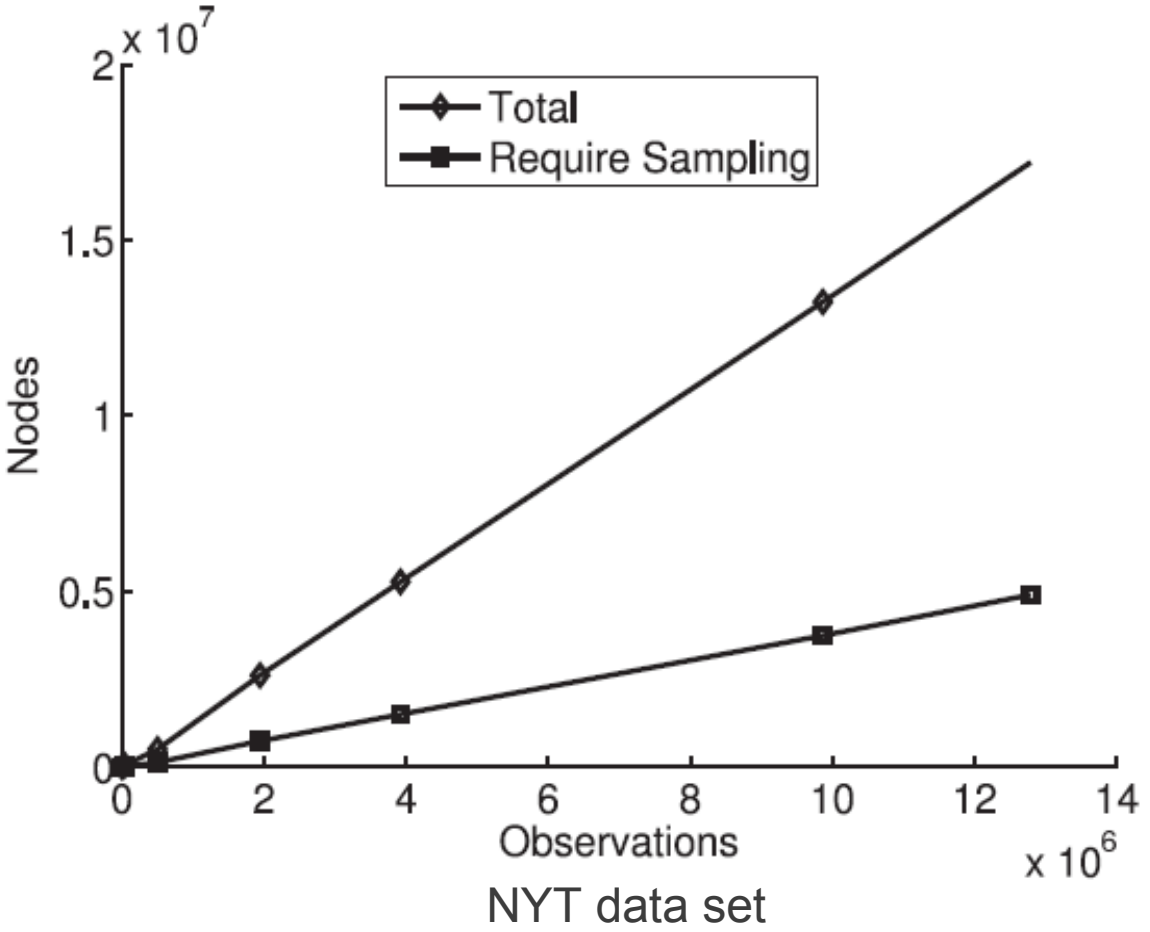
- Use the NYT data set & compare with n-gram model
- Metropolis-Hastings updates used for discount parameters
- Use distinct discount parameters for each of the first 4 levels of the trie, while levels below use a single shared discount parameter

$$d_{[0,1,2,\ldots]} = (.62, .69, .74, .80, .95, .95, \ldots)$$

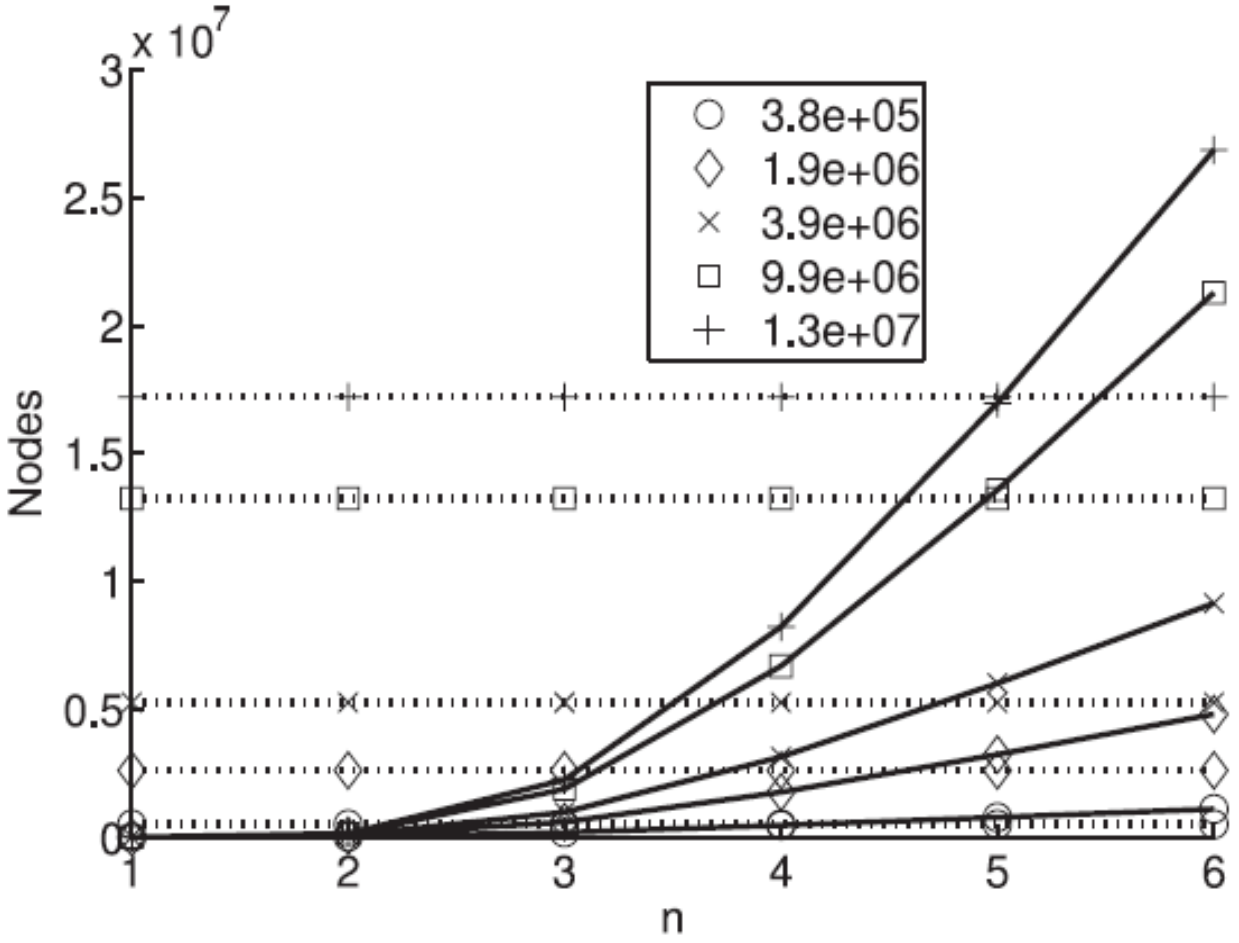
Computational Savings Results

- An ∞-gram with 10 burn-in iterations & 5 samples produced same perplexity scores as a 3-gram model with 125 burn-in iterations & 175 samples

Computational Savings Results *Cont'd*

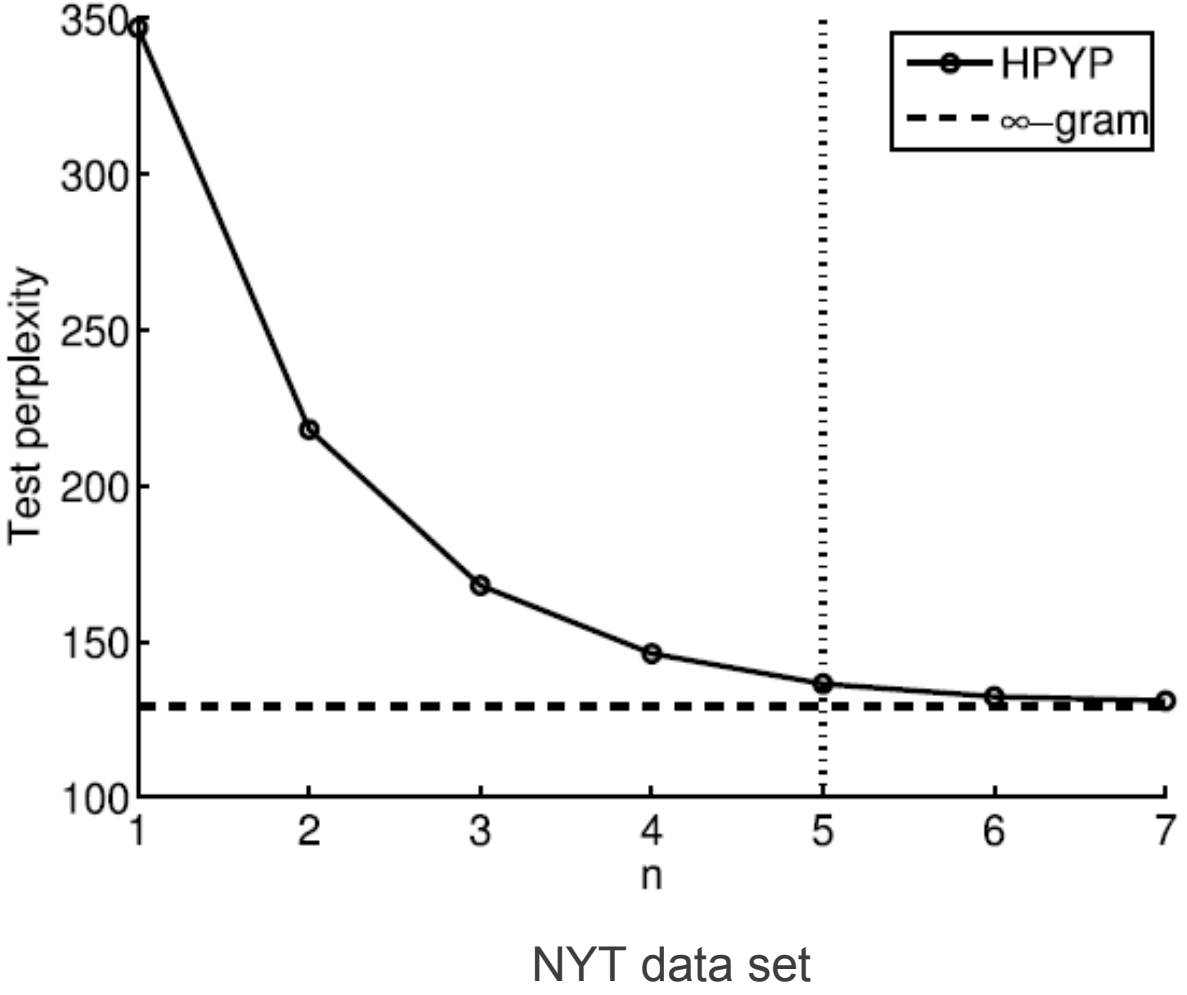


Computational Savings Results *Cont'd*

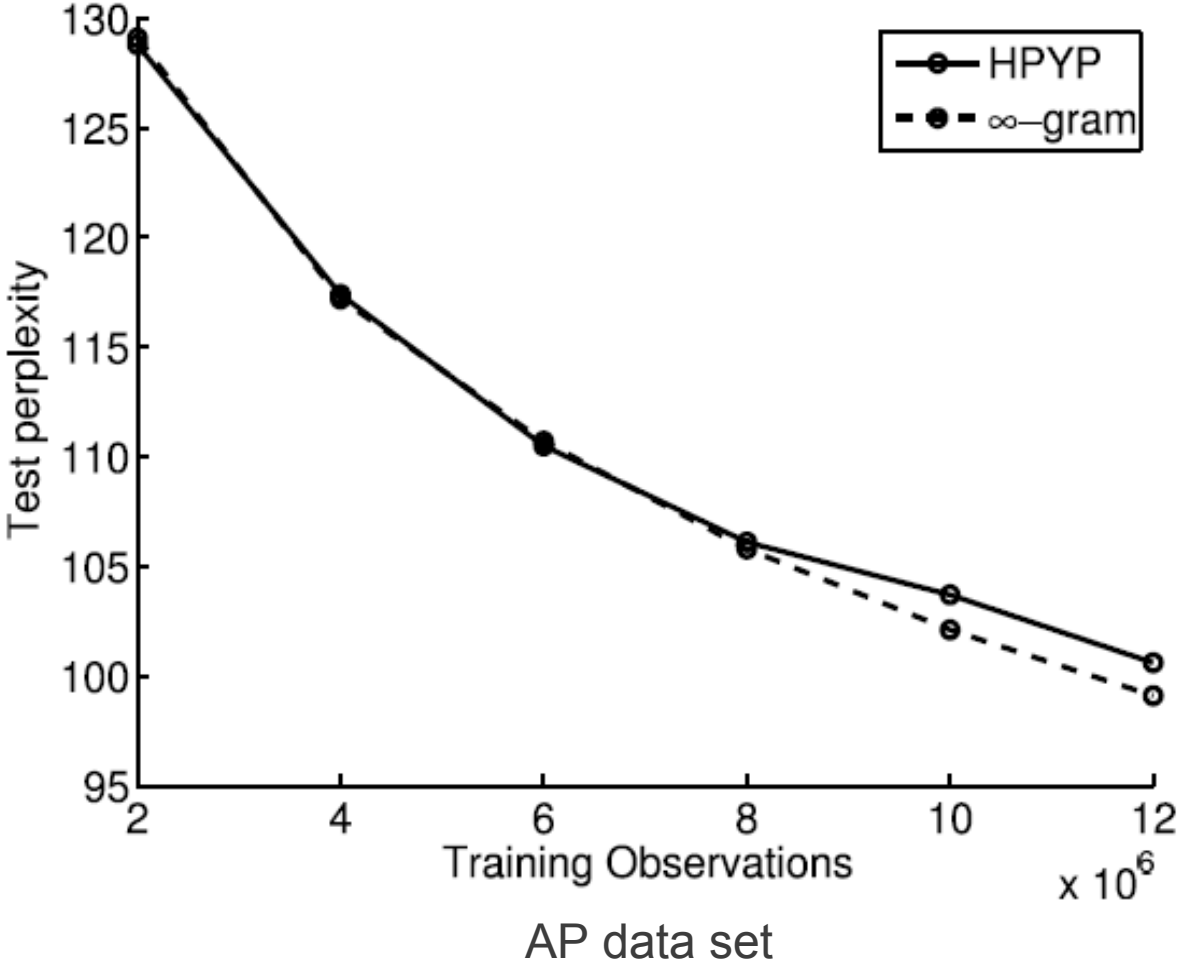


NYT data set

2) Performance Results



Performance Results *Cont'd*



Take Home Message

- N-gram models perform based on the choice of n
- An ∞-gram model relieves this constraint
  - Common suffixes used to collapse prefix trie
  - Achieves **at least** same perplexity as n-gram
  - In most cases, saves computation & storage

Discussion

- Complexity of coagulation & fragmentation processes
- Frequency of fragmentation during experiments
- Intuition of setting concentration parameters to 0
- Computational savings on AP corpus
- Did not mention which n-gram sampler had 125 burn-in & 175 samples
- Different values for discount parameters in lower levels

Thank You
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Reinstantiating G[ca]|G[c] ”restaurant”