Unsupervised Language Learning

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Outline

- Overview and goals
- Implementation
- Results

Overview / Goals

Goal: Find the best Tree Substitution Grammar (TSG) for the “numerical” data

Procedure:

- Define a simple **CFG** that generates numbers
- Parse the corpus, randomly extract elementary trees and create an initial **TSG**
- Make small changes to the data and check if data likelihood improves in order to find **best TSG**

Overview / Goals

Extract numeral data from the Penn WSJ Treebank.

Procedure:

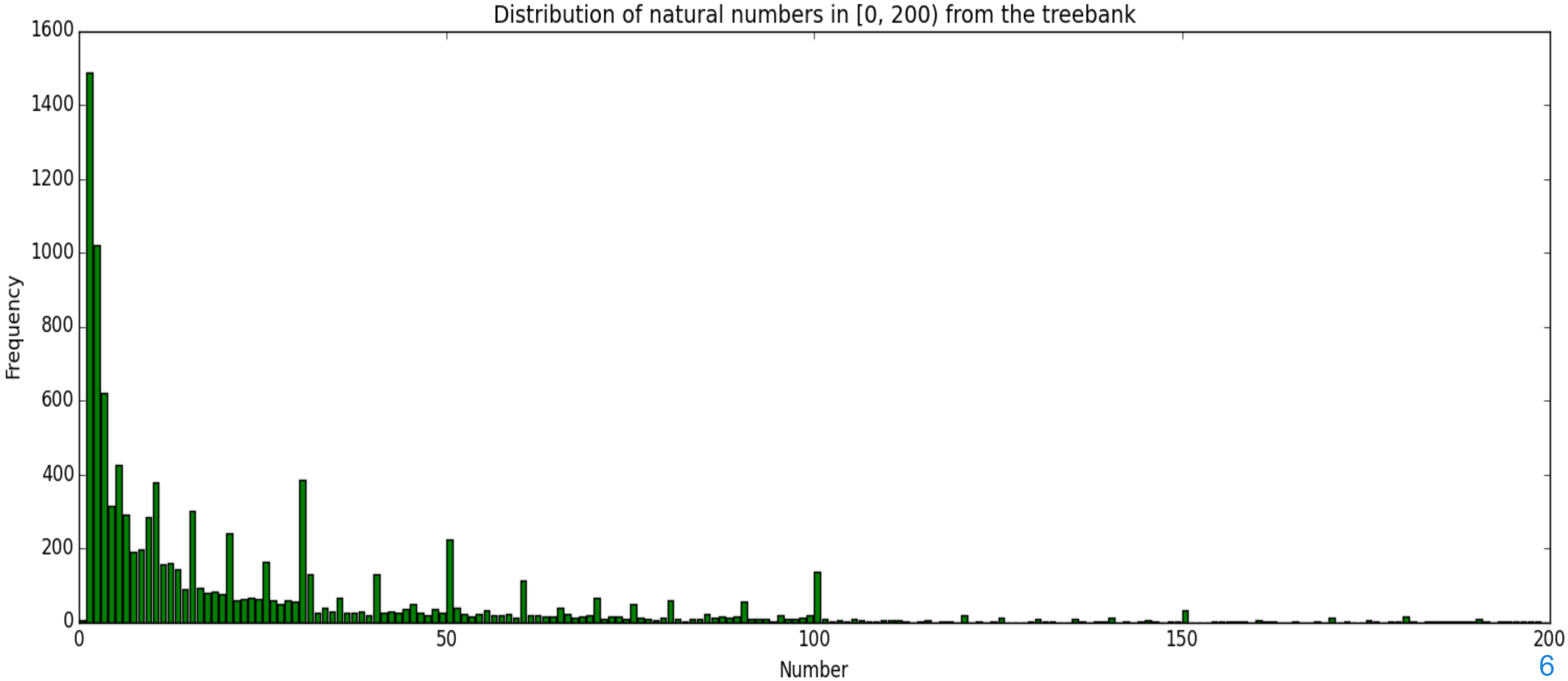
- Look for tags “CD”.
- Extract the values inside this tag.
- If in alphabetic form, translate to number form.

Overview / Goals

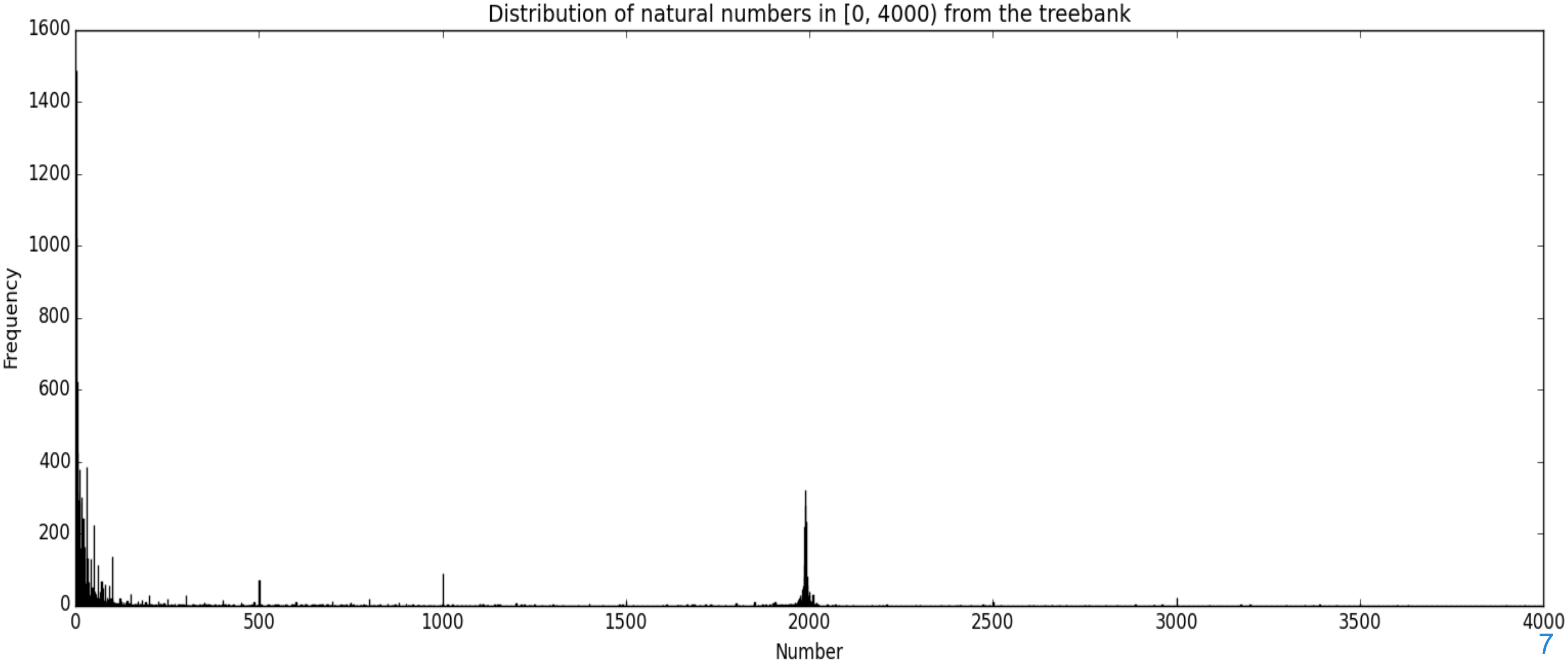
Examples:

- “12” → 12.
- “two hundred” → 200.
- “1.45 million” → 1,450,000.
- “early-1980s” → 1980.
- etc.

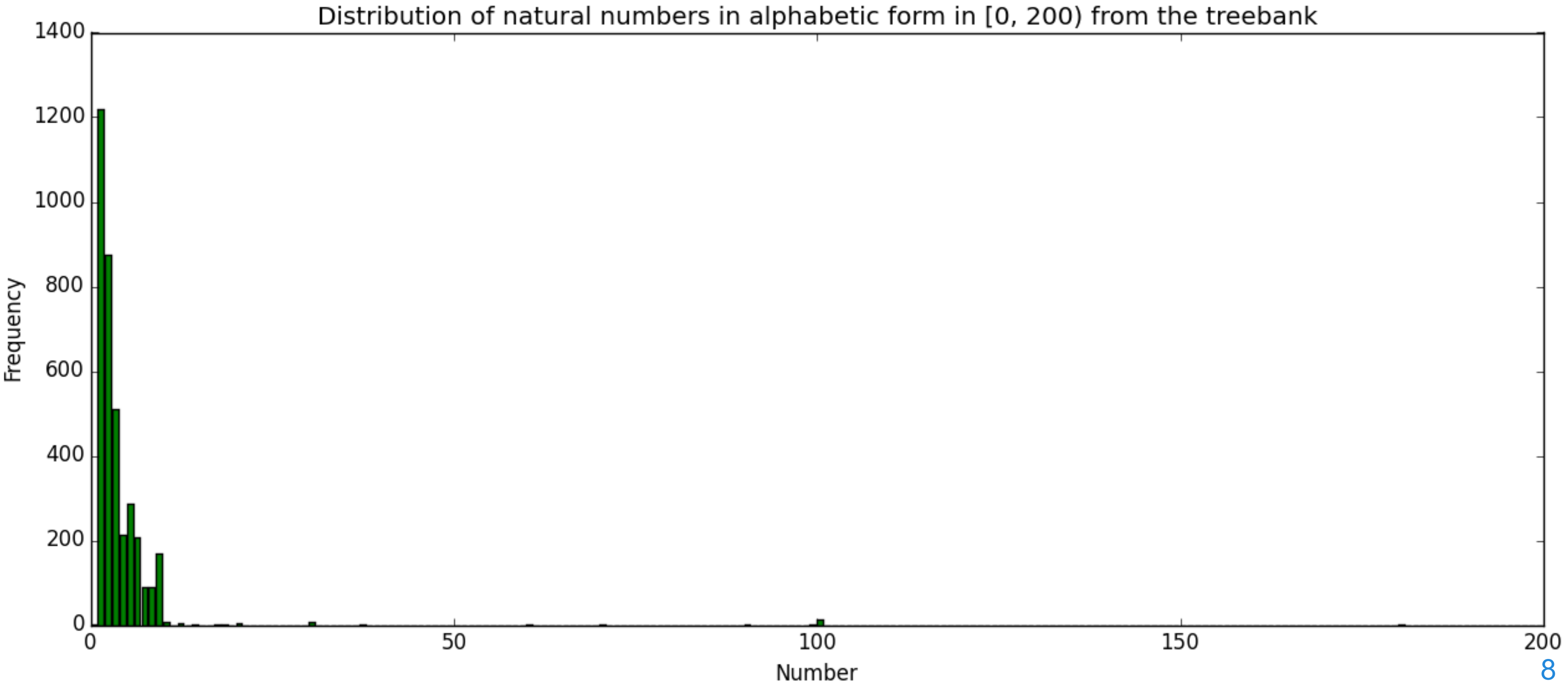
Overview / Goals



Overview / Goals



Overview / Goals



Overview / Goals

Total number of numbers:

- Number form: 9.392
- Alphabetic form: 3.728
- Both forms: 13.120

Overview / Goals

Extension: instead of using the probability of the best derivation of a string, use the **actual likelihood** of a string

p(derivation):

$$\mathrm{P}_G(\psi) = \prod_{r \in R} p(r)^{f_r(\psi)}$$

p(string):

$$\mathrm{P}_G(w) = \sum_{\psi \in \Psi_G(w)} \mathrm{P}_G(\psi)$$

p(best derivation):

$$\max_{\psi \in \Psi_G(w)} \mathrm{P}_G(\psi)$$

Overview / Goals

Expectation: Using the exact data likelihood while sampling leads to a better TSG than using an approximated data likelihood.

Problems:

- Fast implementation is indispensable
- How to measure differences between two approaches

CDEC Decoder

- Cdec is a decoder and aligner used in Machine Translation
- It translates sentences while deriving syntax trees for both the target and source language.
- CFG for source and target required.
- in C++ and Python-wrapper
- provides inside probability of root symbol

Example PCFG

root | Source language | Target language | Probability

```
[S]   ||| [D,1]          ||| [D,1]          ||| LogProb=-0.69314
[S]   ||| [S1,1] [S2,2]  ||| [S1,1] [S2,2]  ||| LogProb=-0.69314
[S1]  ||| [NZ,1] [S2,2]  ||| [NZ,1] [S2,2]  ||| LogProb=-0.69314
[S1]  ||| [NZ,1]         ||| [NZ,1]         ||| LogProb=-0.69314
[S2]  ||| [D,1] [S2,2]   ||| [D,1] [S2,2]   ||| LogProb=-0.69314
[S2]  ||| [D,1]          ||| [D,1]          ||| LogProb=-0.6931
[D]   ||| 1              ||| 1              ||| LogProb=-2.3025850

...
```

Metropolis-Hastings Sampling

- Repeat:
  - Generate a random candidate change
    - Remove or add substitution site marker
  - Compute new likelihood L_{new} of the data with change
  - Accept candidate change in two cases:
    - if $L_{new} > L_{old}$ always accept
    - otherwise accept with probability L_{new} / L_{old}

Grammars for Numerals

Deterministic:

```
[S] → [0]      | [1]      | [2]      | … | [9]
[S] → [1] [P]  | [2] [P]  | [3] [P]  | … | [9] [P]
[P] → [0]      | [1]      | [2]      | … | [9]
[P] → [0] [P]  | [1] [P]  | [2] [P]  | … | [9] [P]
```

Only one derivation is possible

Grammars for Numerals

Half ambiguous:

```
[S]  → [D] [D]       | [S1] [S2]
[S1] → [NZ] [S2]     | [NZ]
[S2] → [D] [S2]      | [D]
[NZ] → [1]           | [2]        | [3] | … | [9]
[D]  → [0]           | [1]        | [2] | … | [9]
```

Not deterministic

Grammars for Numerals

Highly ambiguous:

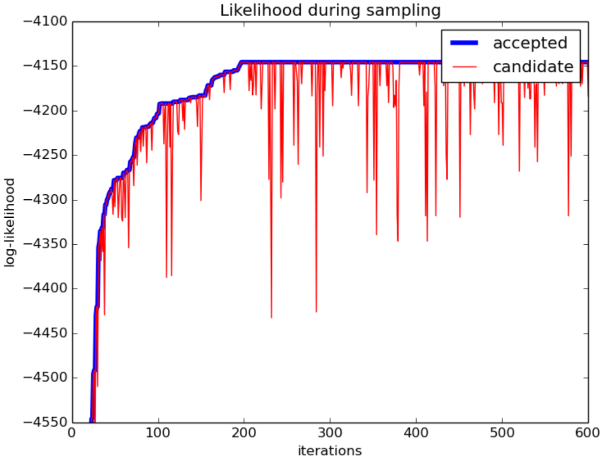
```
[S]  →  [Z]    | [NZ]        | [S1] [S2]
[S1] →  [NZ]   | [NZ] [S2]   | [S1] [S2]
[S2] →  [Z]    | [NZ]        | [Z] [Z]   | [Z] [NZ]  | [NZ] [Z] | [NZ] [NZ]
[NZ] →  [1]    | [2]         | [3]       |   …       | [9]
[Z]  →  [0]
```

Many parses

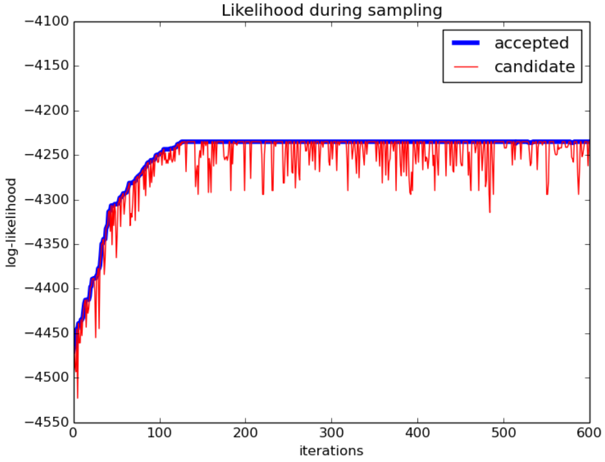
Comparison between grammars

Likelihood

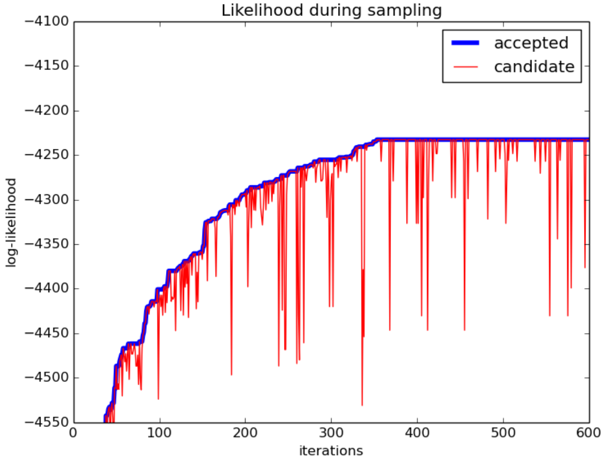
Highly ambiguous



Half ambiguous



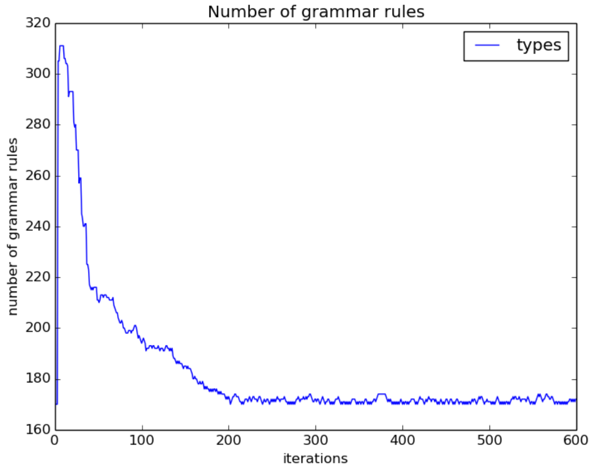
Deterministic



Comparison between grammars

Count of used rules

Highly ambiguous



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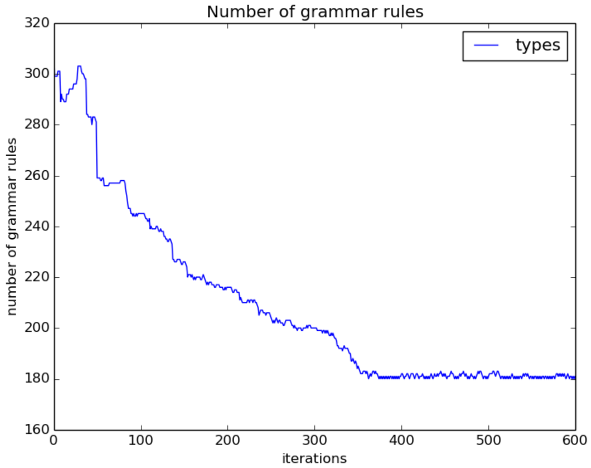
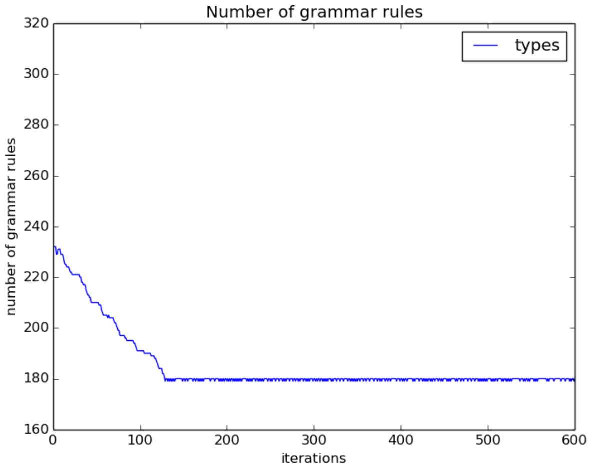


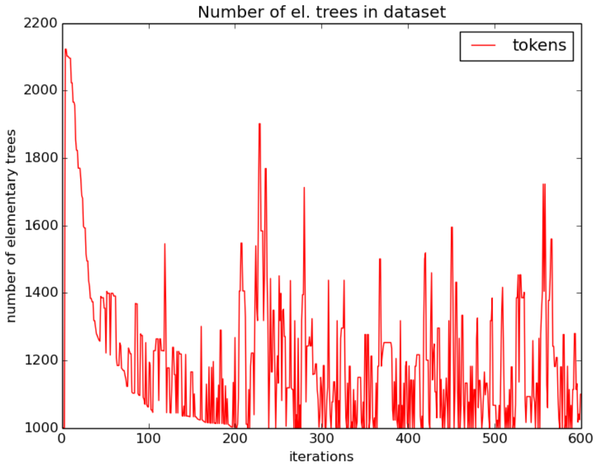
Deterministic



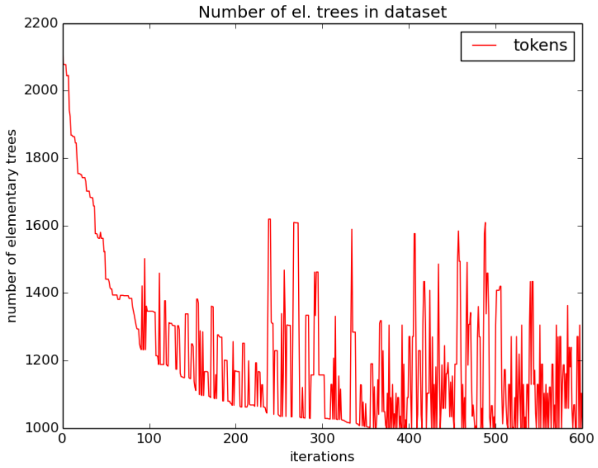
Comparison between grammars

Grammar size

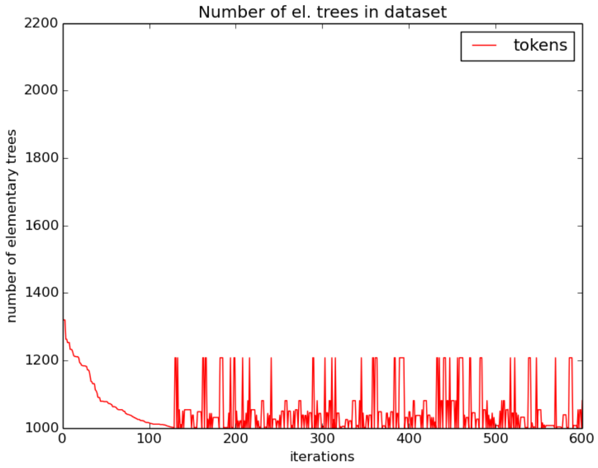
Highly ambiguous



Half ambiguous



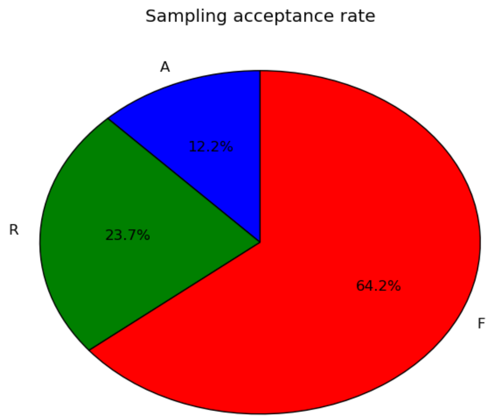
Deterministic



Comparison between grammars

Acceptance rate

Highly ambiguous



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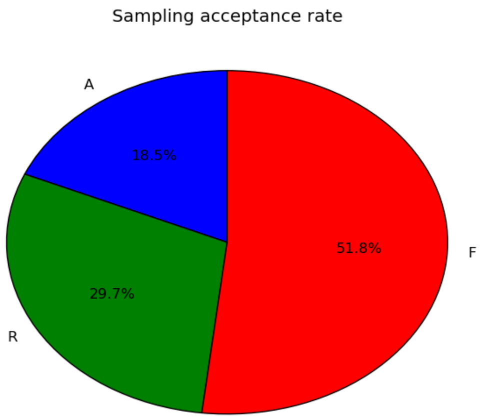
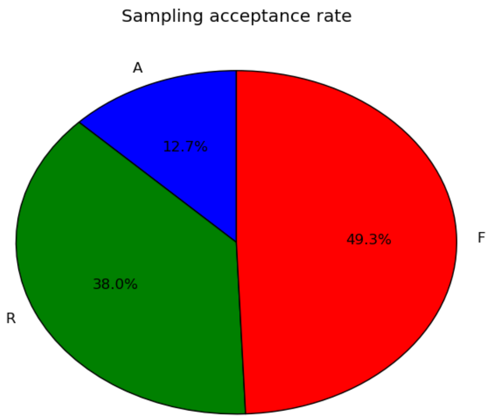


Deterministic



Comparison: viterbi vs inside

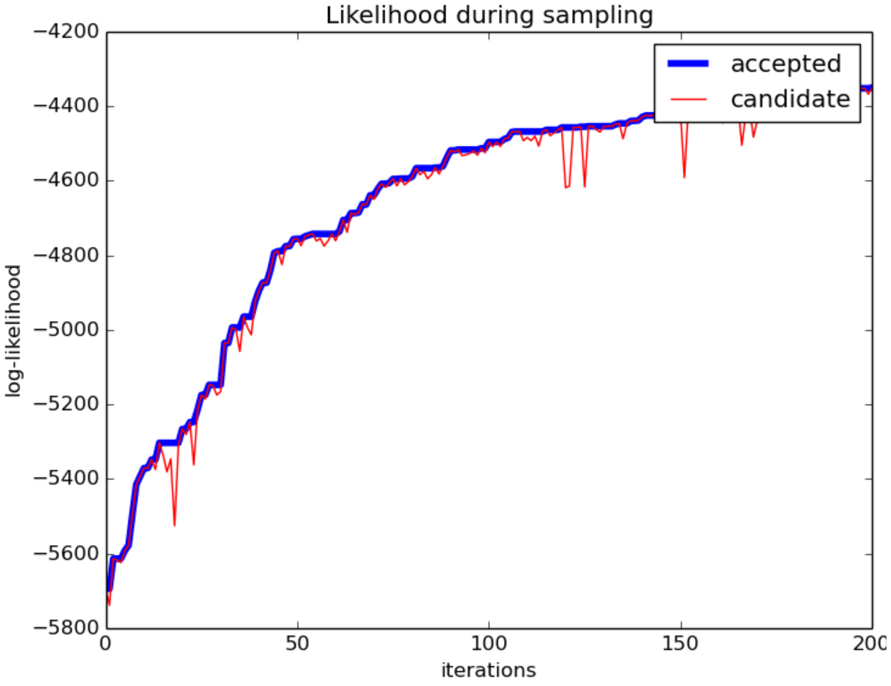
Experiment: use same data set and sample

- using inside probability
- using viterbi probability

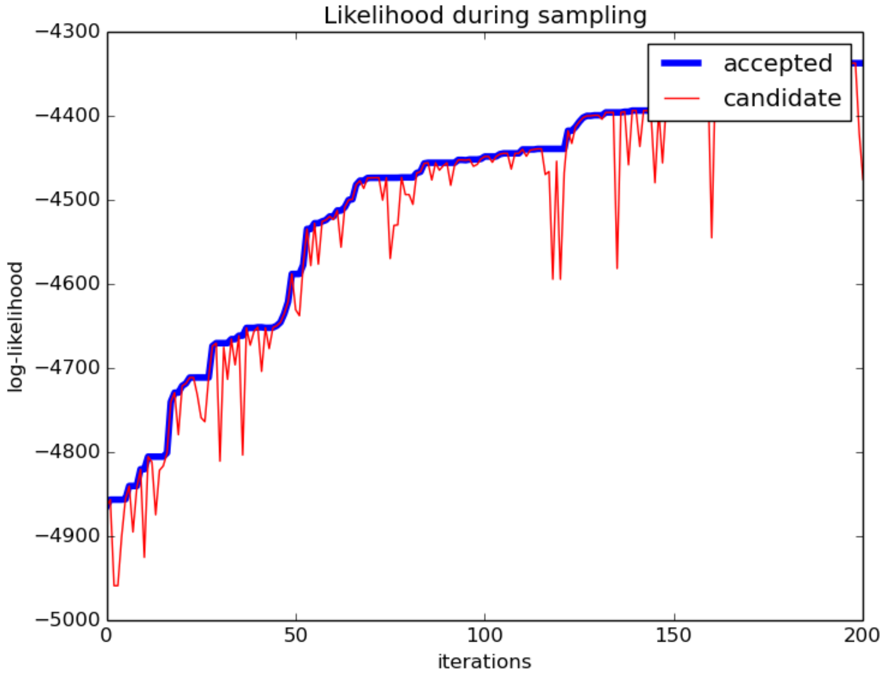
What are the differences?

Comparison: viterbi vs inside

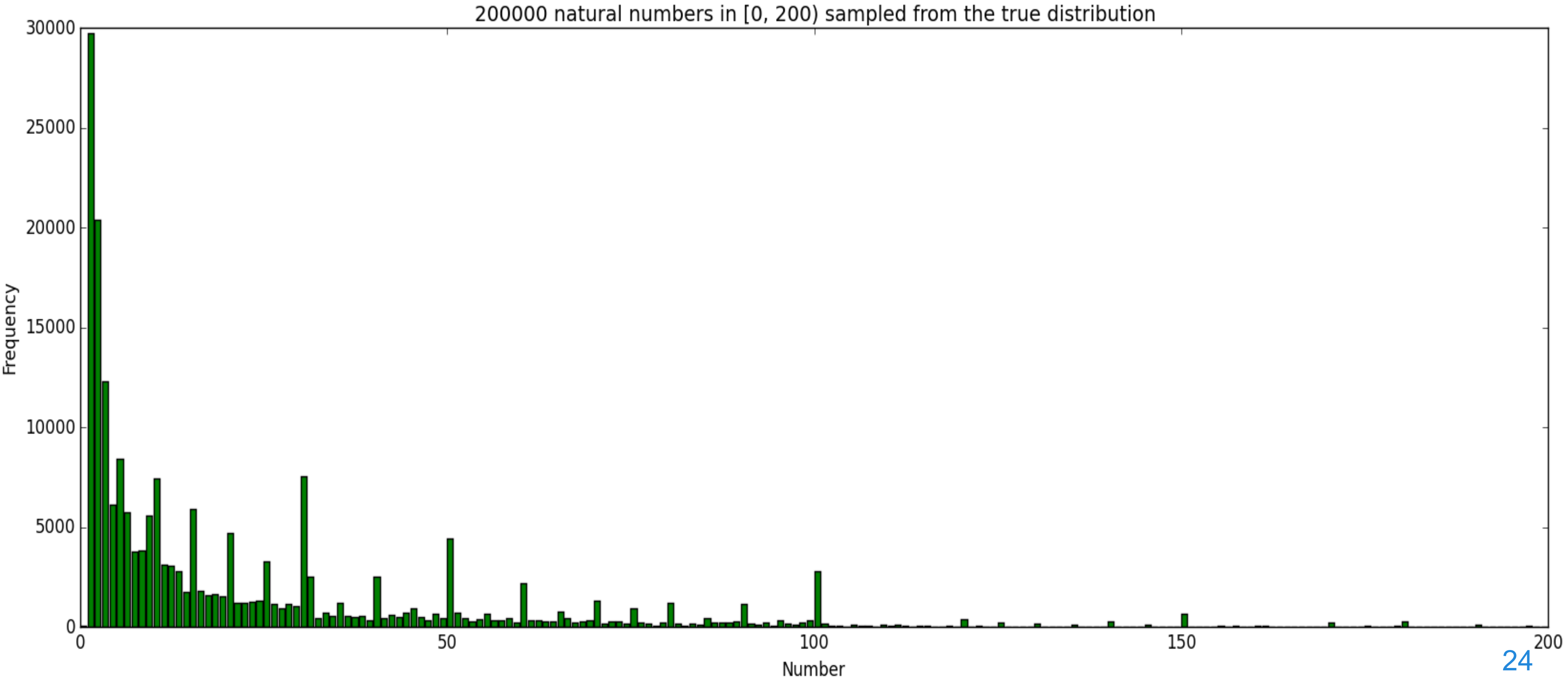
viterbi



inside



Comparison: Sampled distributions



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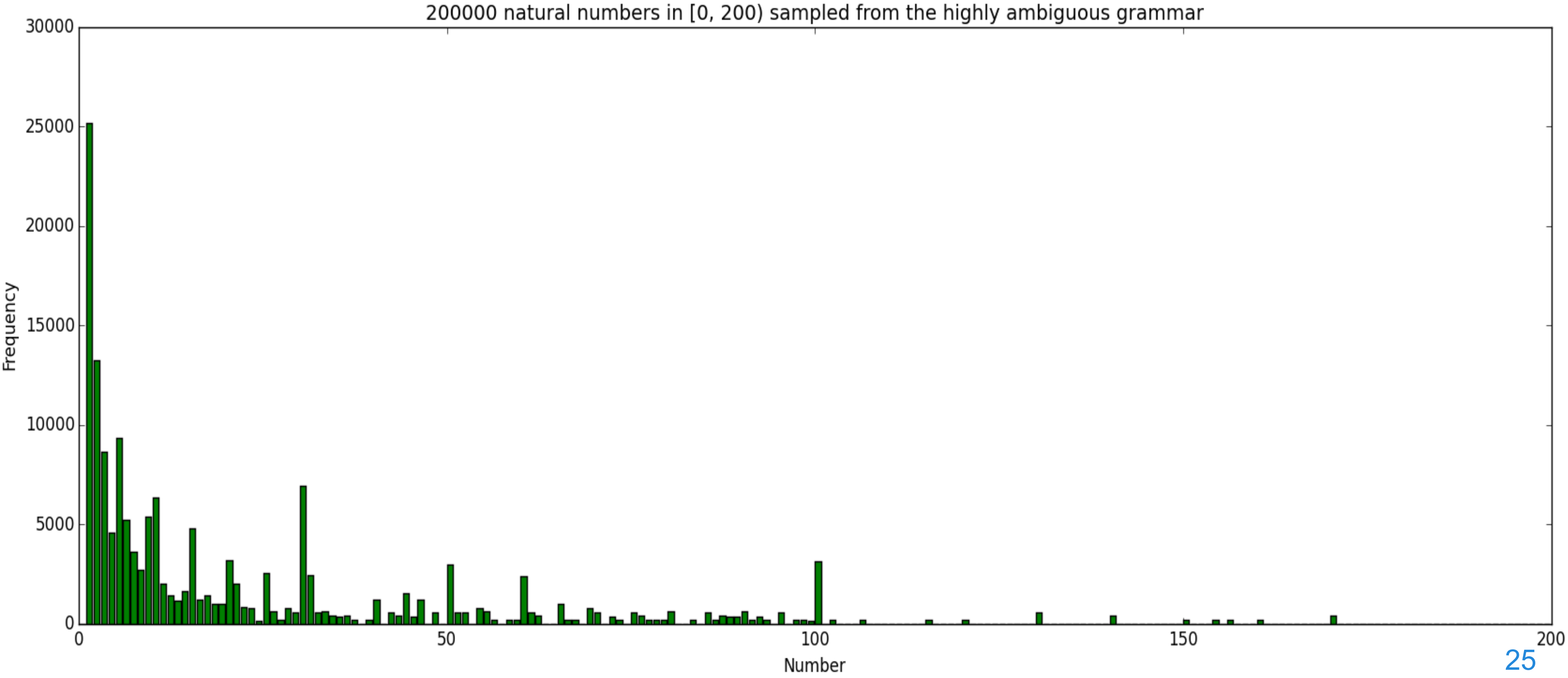

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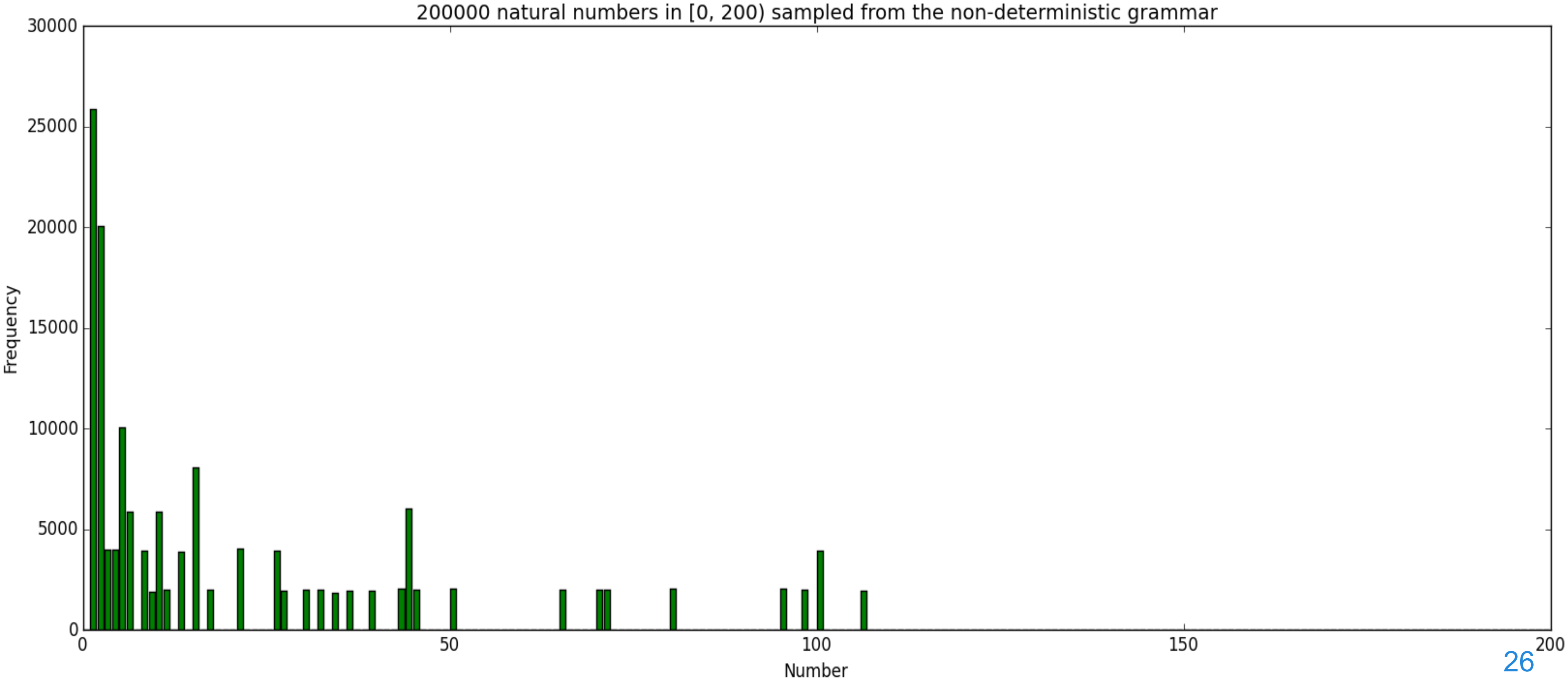

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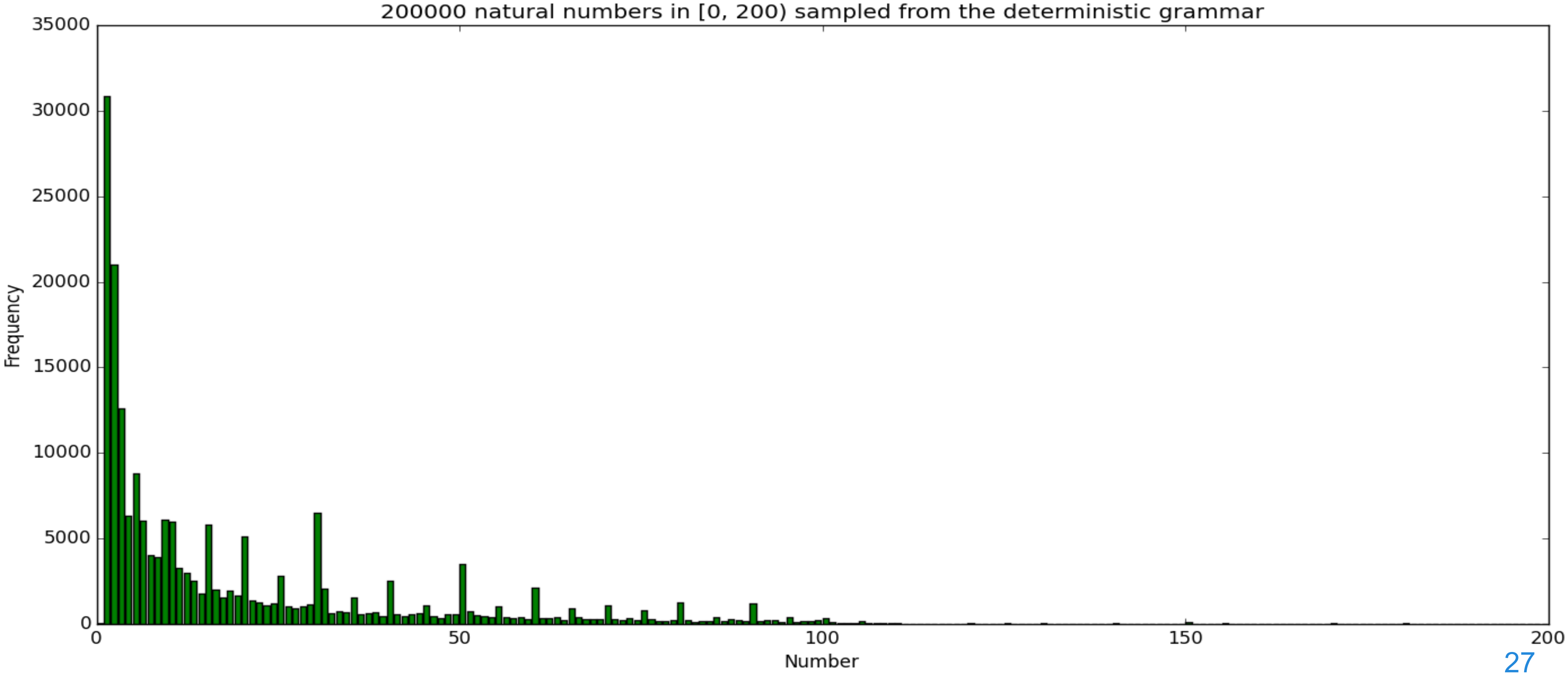

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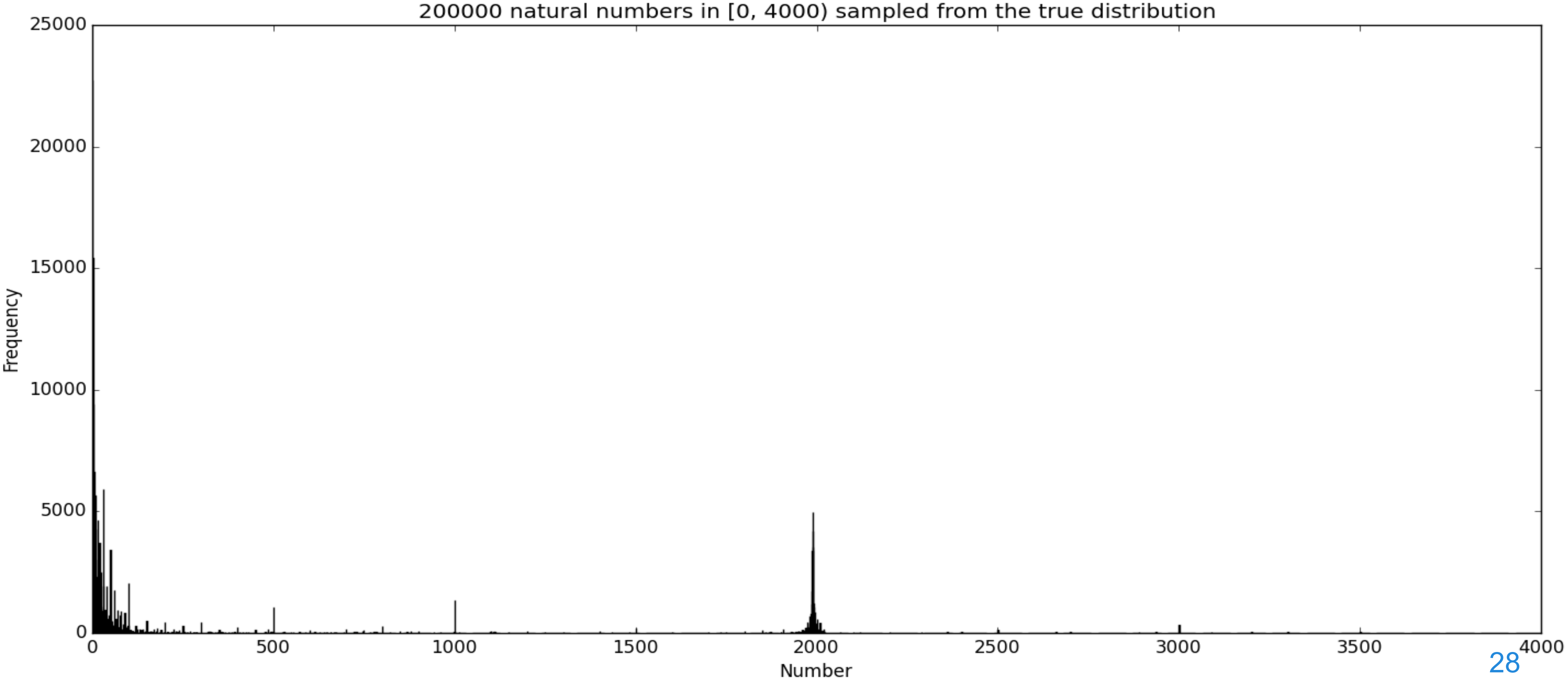

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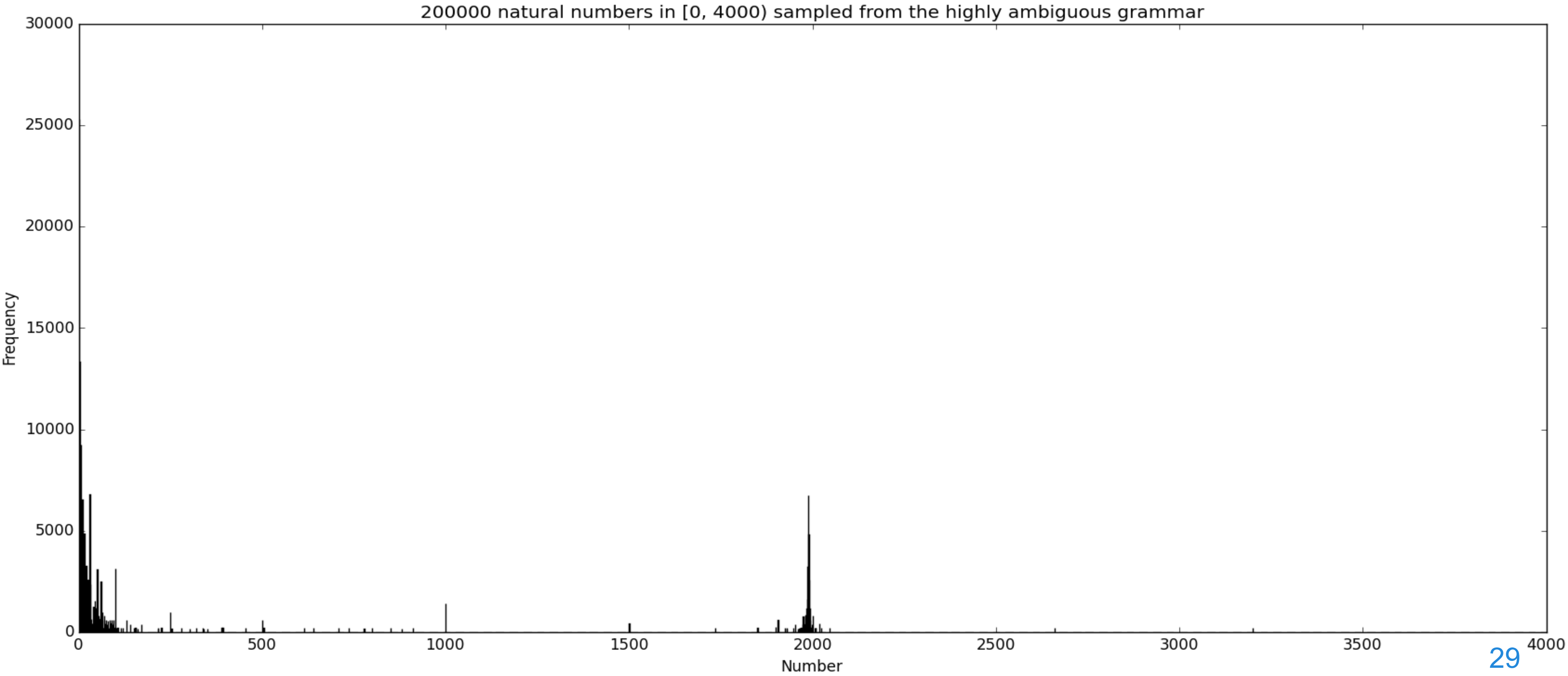

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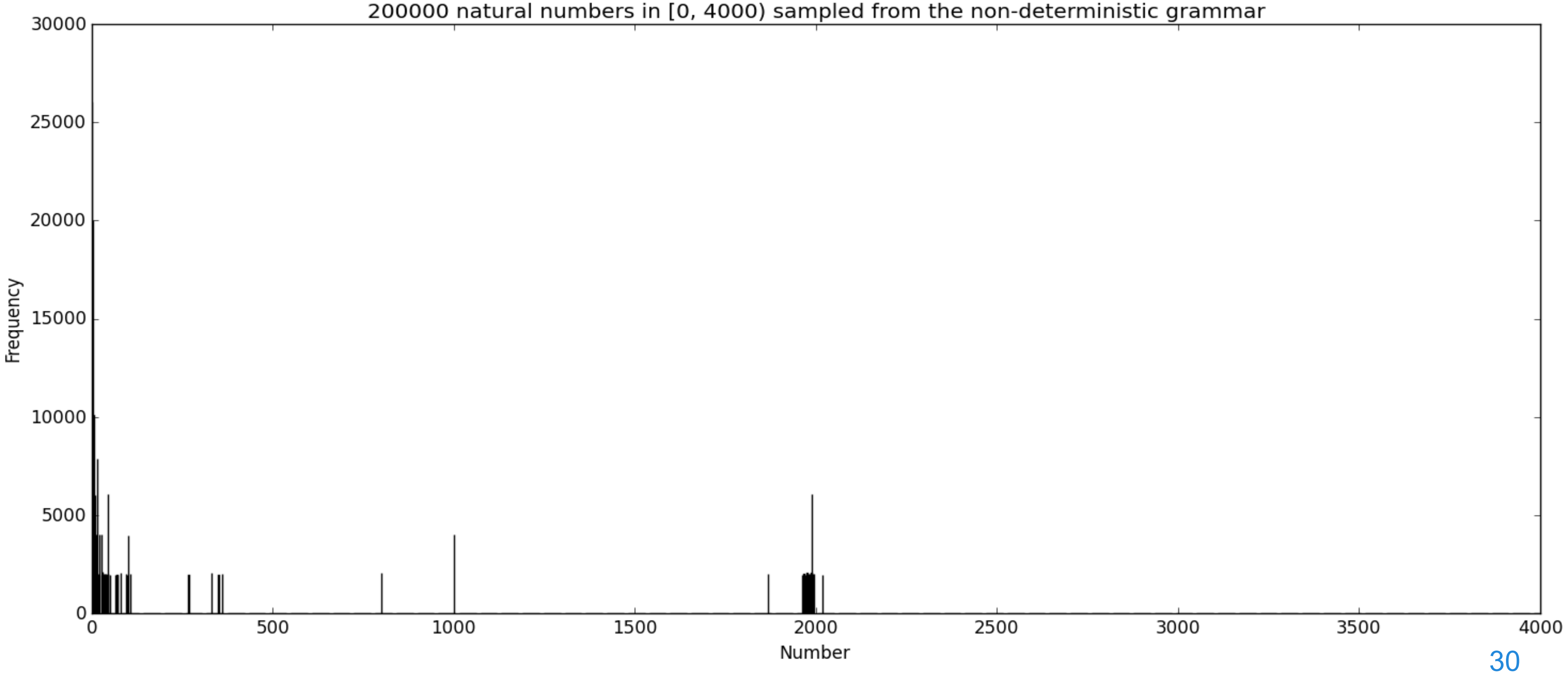

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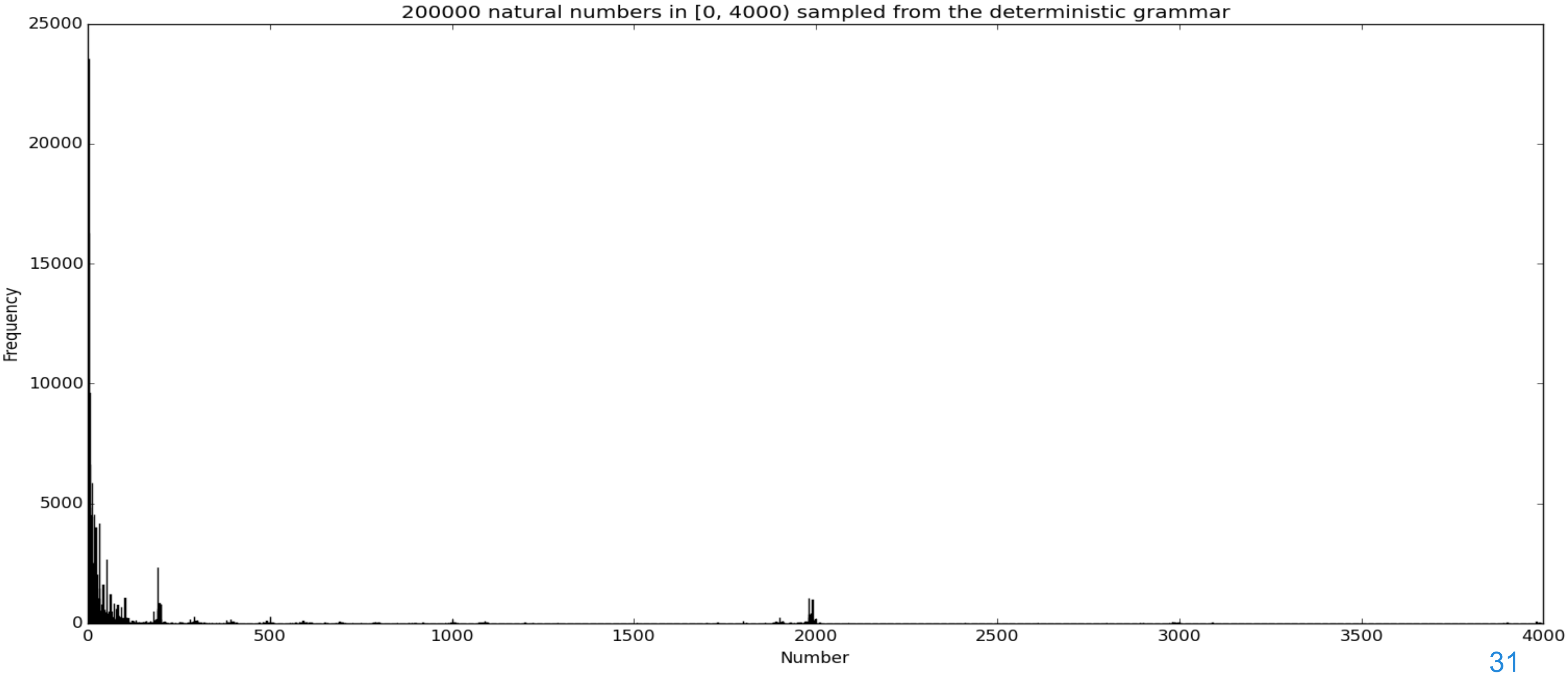

Questions & Answers

Thank you for your attention