

# Assignment 1 + Language Properties

## (SNLP tutorial 2)

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# Organisational Issues

- Teammates
- Assignment submissions
  - ▶ Naming your assignment folder: Name1\_id1\_Name1\_id2.zip
  - ▶ Your Notebooks and files should be directly inside the main folder (no unnecessary nesting)
  - ▶ Do not submit the following files:
    - o \_\_pycache\_\_*
    - o .ipynb\_checkpoints*
    - o data/\**
    - o any other pdf or information file accompanying the assignment*
  - ▶ Only submit: Notebook + Python files. Otherwise points can be deducted.

# Part 1: Discussion of Assignment 1

- Exercise 1: Instructions for setup
- Exercise 2: Mandelbrot distribution + Stick breaking
- Exercise 3: Zipf's Law at word level
- Bonus: Zipf's Law at character level

## Part 2: Overview of current topics

- Basics of Probability Theory
- Perplexity
- Maximum Likelihood Estimation
- Smoothing

# Probability Theory for Language Models

## Predict

$P(w_1, w_2 \dots w_N)$  which can be decomposed as  $\prod P(w_i | h_i)$

## Bonus question

Compare for uniform, unigram, bigram, trigram... ngram models.

- Where do we assume statistical independence?
- What is this kind of assumption called?

# Probability Theory for Language Models

## Entropy as Expectation value

$$E[f(V)] = \sum_{w_i \in V} p(w_i) f(w_i)$$

Entropy is a property of any distribution, e.g. that of a unigram language model.

$$H = E[-\log(p(V))] = - \sum_{w_i \in V} p(w_i) \log(p(w_i))$$

What does this mean? What are we capturing by the entropy of the LM distribution?

Consider a bigram model where

$$E[-\log P('in', w)] = 10.42 \text{ \{e.g. ('in', 'fact'), ('in', 'that'), ('in', 'my')\}}$$

$$E[-\log P('the', w)] = 15.11 \text{ \{e.g. ('the', 'day'), ('the', 'most'), ('the', 'end')\}}$$

What do the expectation values indicate here?

## Bonus Questions

- 1 What is the entropy of a fair die  $p = (\frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6})$ ?
- 2 What is the entropy of a loaded die  $q = (\frac{1}{12}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{1}{6}, \frac{2}{6})$ ?
- 3 What is the cross-entropy of the same distribution?  $H(p, p)$
- 4 What is the cross-entropy of the loaded die  $q$  if we assume a fair die  $p$   $H(q, p)$ ?

# Perplexity

## Formulae

$$PP = 2^{-\frac{1}{n} \sum_1^n \log p(w_i | w_{i-1})}$$

$$PP = 2^{-\sum_{w,h} f(w,h) \log_2 P(w|h)}$$

How do these two formulae relate to each other?



# Maximum Likelihood Estimation

- A way to estimate language model (distribution) parameters
- Trying to maximize probability of the training data
- NOTE: Separate the text itself from the language model
- LMs exist independent of the text and MLE only maximizes their performance on the text

# LM Smoothing

- Q: What happens if an unknown token is encountered and the LM assigns it 0 probability?
- Q: What are some quick solutions to this issue?

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- Q: How are LMs useful in downstream tasks?

# Homework

- Exercise 1: Perplexity calculation by hand
- Exercise 2: Plotting n-gram distributions
- Exercise 3: MLE language models, Perplexity calculation
- Bonus: Custom alternative to perplexity

# Resources

1 TODO