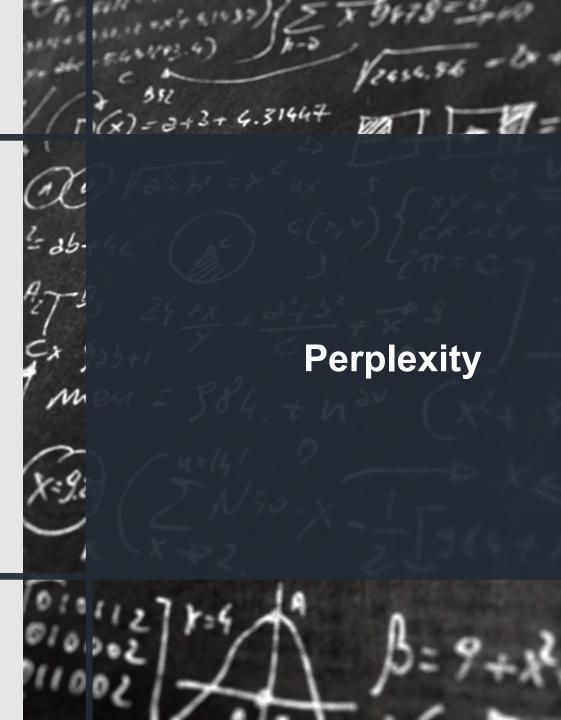
Evaluating Language Models

Natalie Parde UIC CS 421

- Two types of evaluation paradigms:
 - Extrinsic
 - Intrinsic
- Extrinsic evaluation: Embed the language model in an application, and compute changes in task performance
- Intrinsic evaluation: Measure the quality of the model, independent of any application

Evaluating Language Models

- Intrinsic evaluation metric for language models
- Perplexity (PP) of a language model on a test set is the inverse probability of the test set, normalized by the number of words in the test set





More formally....

•
$$PP(W) = \sqrt[n]{\frac{1}{P(w_1 w_2 \dots w_n)}} = \sqrt[n]{\prod_{i=1}^n \frac{1}{P(w_i | w_1 \dots w_{i-1})}}$$

- Where W is a test set containing words $w_1, w_2, ..., w_n$
- History size depends on n-gram size
 - $P(w_i|w_{i-1})$ vs $P(w_i|w_{i-2}w_{i-1})$, etc.
- Higher conditional probability of a word sequence → lower perplexity
 - Minimizing perplexity = maximizing test set probability according to the language model

Training Set

| Word | Frequency |
|-------------|-----------|
| CS | 10 |
| 421 | 10 |
| Statistical | 10 |
| Natural | 10 |
| Language | 10 |
| Processing | 10 |
| University | 10 |
| of | 10 |
| Illinois | 10 |
| Chicago | 10 |

Training Set

| Word | Frequency |
|-------------|-----------|
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| 421 | 10 |
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Test String

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Test String

$$PP(W) = \sqrt[n]{\frac{1}{P(w_1 w_2 \dots w_n)}} = \sqrt[n]{\prod_{i=1}^{n} \frac{1}{P(w_i | w_1 \dots w_{i-1})}}$$

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Training Set

| Word | Frequency | P(Word) |
|-------------|-----------|---------|
| CS | 10 | 0.1 |
| 421 | 10 | 0.1 |
| Statistical | 10 | 0.1 |
| Natural | 10 | 0.1 |
| Language | 10 | 0.1 |
| Processing | 10 | 0.1 |
| University | 10 | 0.1 |
| of | 10 | 0.1 |
| Illinois | 10 | 0.1 |
| Chicago | 10 | 0.1 |

Test String

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| Language | 10 | 0.1 |
| Processing | 10 | 0.1 |
| University | 10 | 0.1 |
| of | 10 | 0.1 |
| Illinois | 10 | 0.1 |
| Chicago | 10 | 0.1 |

Test String

CS 421 Statistical Natural Language Processing University of Illinois Chicago

$$PP(W) = \sqrt[n]{\frac{1}{P(w_1 w_2 \dots w_n)}} = \sqrt[n]{\prod_{i=1}^{n} \frac{1}{P(w_i | w_1 \dots w_{i-1})}}$$

Training Set

| Word | Frequency | P(Word) |
|-------------|-----------|---------|
| CS | 1 | |
| 421 | 1 | |
| Statistical | 1 | |
| Natural | 1 | |
| Language | 1 | |
| Processing | 1 | |
| University | 1 | |
| of | 1 | |
| Illinois | 1 | |
| Chicago | 91 | |

Test String

Illinois Chicago Chicago Chicago Chicago Chicago Chicago Chicago Chicago Chicago Chicago

$$PP(W) = \sqrt[n]{\frac{1}{P(w_1 w_2 \dots w_n)}} = \sqrt[n]{\prod_{i=1}^{n} \frac{1}{P(w_i | w_1 \dots w_{i-1})}}$$

Training Set

| Word | Frequency | P(Word) |
|-------------|-----------|---------|
| CS | 1 | 0.01 |
| 421 | 1 | 0.01 |
| Statistical | 1 | 0.01 |
| Natural | 1 | 0.01 |
| Language | 1 | 0.01 |
| Processing | 1 | 0.01 |
| University | 1 | 0.01 |
| of | 1 | 0.01 |
| Illinois | 1 | 0.01 |
| Chicago | 91 | 0.91 |

Test String

Illinois Chicago Chicago Chicago Chicago Chicago Chicago Chicago Chicago Chicago Chicago

$$PP(W) = \sqrt[n]{\frac{1}{P(w_1 w_2 \dots w_n)}} = \sqrt[n]{\prod_{i=1}^{n} \frac{1}{P(w_i | w_1 \dots w_{i-1})}}$$

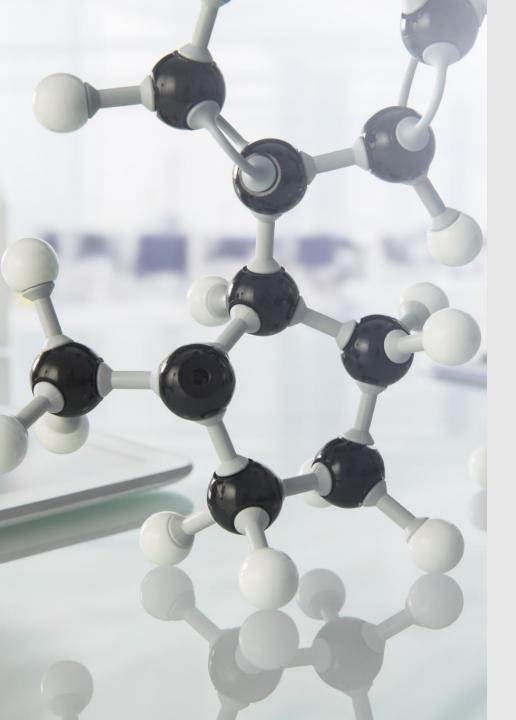
Training Set

| Word | Frequency | P(Word) |
|-------------|-----------|---------|
| CS | 1 | 0.01 |
| 421 | 1 | 0.01 |
| Statistical | 1 | 0.01 |
| Natural | 1 | 0.01 |
| Language | 1 | 0.01 |
| Processing | 1 | 0.01 |
| University | 1 | 0.01 |
| of | 1 | 0.01 |
| Illinois | 1 | 0.01 |
| Chicago | 91 | 0.91 |

Test String

Illinois Chicago Chicago Chicago Chicago Chicago Chicago Chicago Chicago Chicago Chicago

$$PP(W) = \sqrt[n]{\frac{1}{P(w_1 w_2 \dots w_n)}} = \sqrt[n]{\prod_{i=1}^{n} \frac{1}{P(w_i | w_1 \dots w_{i-1})}}$$



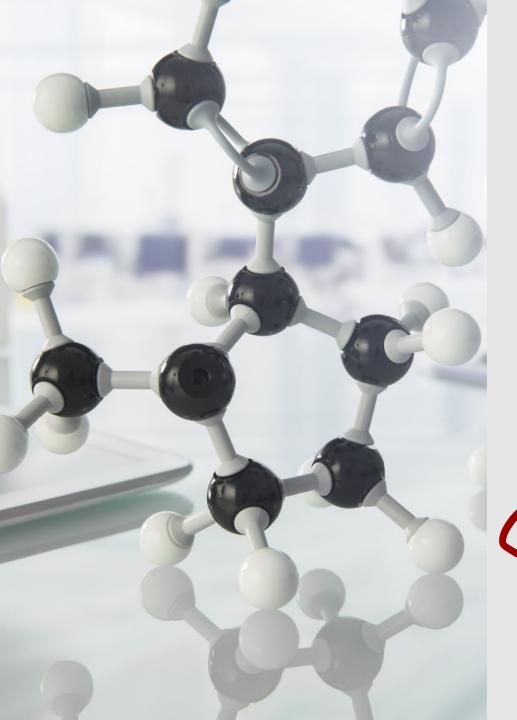
Perplexity can be used to compare different language models.

Which language model is best?

• Model A: Perplexity = 962

• Model B: Perplexity = 170

• Model C: Perplexity = 109



Perplexity can be used to compare different language models.

Which language model is best?

• Model A: Perplexity = 962

Model B: Perplexity = 170

Model C: Perplexity = 109

A cautionary note....

- Improvements in perplexity do not guarantee improvements in task performance!
- However, the two are often correlated (and perplexity is quicker and easier to check)
- Strong language model evaluations also include an extrinsic evaluation component