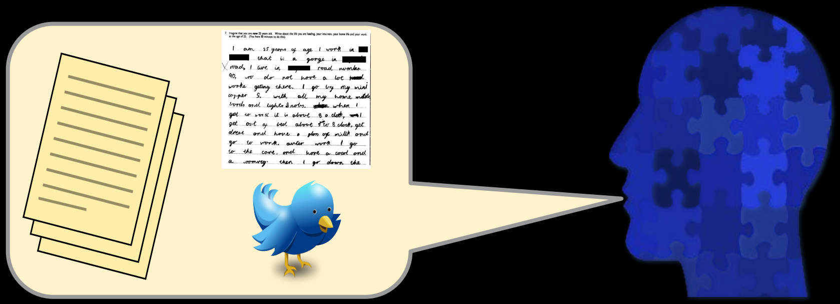
Language Modeling

CSE392 - Spring 2019
Special Topic in CS

Task



- Language Modeling (auto-complete)

how?

- Probabilistic Modeling
  - ML: Logistic Regression
  - Probability Theory

Language Modeling

-- assigning a probability to sequences of words.

Version 1: Compute $P(w1, w2, w3, w4, w5) = P(W)$

:probability of a sequence of words

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Version 2: Compute $P(w5 \mid w1, w2, w3, w4)$

$= P(w_n \mid w_1, w_2, \ldots, w_{n-1})$

:probability of a next word given history

Language Modeling

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$P(\text{He ate the cake with the fork}) = ?$

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Language Modeling

Applications:

- Auto-complete: What word is next?
- Machine Translation: Which translation is most likely?
- Spell Correction: Which word is most likely given error?
- Speech Recognition: What did they just say?
  "eyes aw of an"
  (example from Jurafsky, 2017)

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$P(\text{fork} \mid \text{He ate the cake with the}) = ?$

Simple Solution

Version 1: Compute $P(w1, w2, w3, w4, w5) = P(W)$

:probability of a sequence of words

$$P(\text{He ate the cake with the fork}) = \frac{count(\text{He ate the cake with the fork})}{count(* \quad * \quad * \quad * \quad * \quad * \quad *)}$$

Simple Solution: The Maximum Likelihood Estimate

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total number of observed *7grams*

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Simple Solution: The Maximum Likelihood Estimate

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Example from (Jurafsky, 2017)

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The Chain Rule:

$$P(X_1, X_2..., X_n) = P(X_1)P(X_2|X_1)P(X_3|X_1, X_2)...P(X_n|X_1, ..., X_{n-1})$$

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Markov Assumption:

P(Xn| X

What about Logistic Regression? Y = next word
P(Y|X) = P(Xn | X1, X2, X3, ...)

Not a terrible option, but X1 through Xn-1 would be modeled as independent dimensions. Let's revisit later.

The Chain

P(X1, X2..., Xn) = P((X2|X1)P(X3|X1, X2)...P(Xn|X1, ..., Xn-1)

Markov Assumption: $$P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i | X_{i-k}, X_{i-(k-1)}, ..., X_i)$$

$P(Xn| X1..., Xn\text{-}1) \approx P(Xn| Xn\text{-}k, ..., Xn\text{-}1)$ where $k < n$

Unigram Model: k = 0; $$P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i)$$

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$P(A, B, C) = P(A)P(B|A)P(C| A, B)$

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Markov Assumption: $$P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i | X_{i-k}, X_{i-(k-1)}, ..., X_i)$$

P(Xn| X1..., Xn-1) ≈ P(Xn| Xn-k, ..., Xn-1) where k < n

Bigram Model: k = 1; $$P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i | X_{i-1})$$

Example generated sentence:

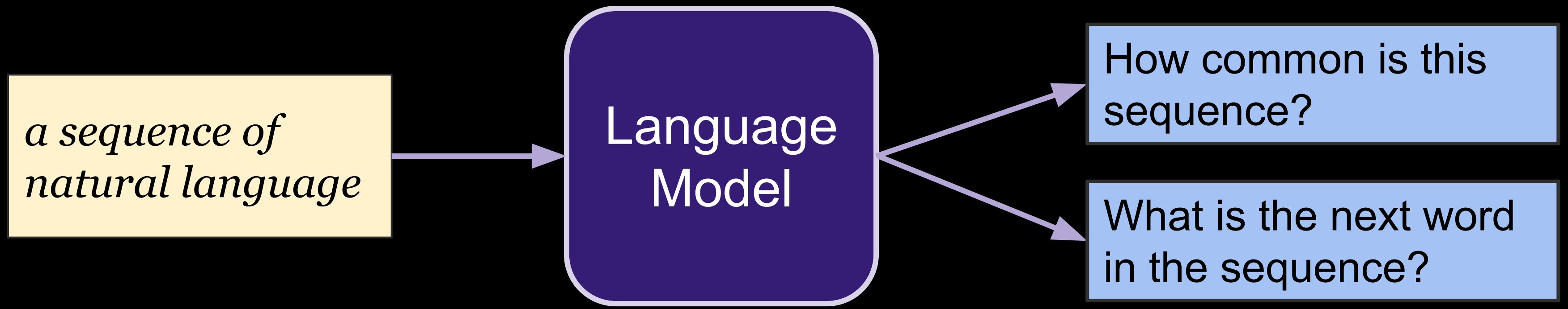
outside, new, car, parking, lot, of, the, agreement, reached

*P(X1 = "outside", X2="new", X3 = "car", ...) ≈ P(X2="new"|X1 = "outside) * P(X3="car" | X2="new") * ...*

Example from (Jurafsky, 2017)

Language Modeling

Building a model (or system / API) that can answer the following:



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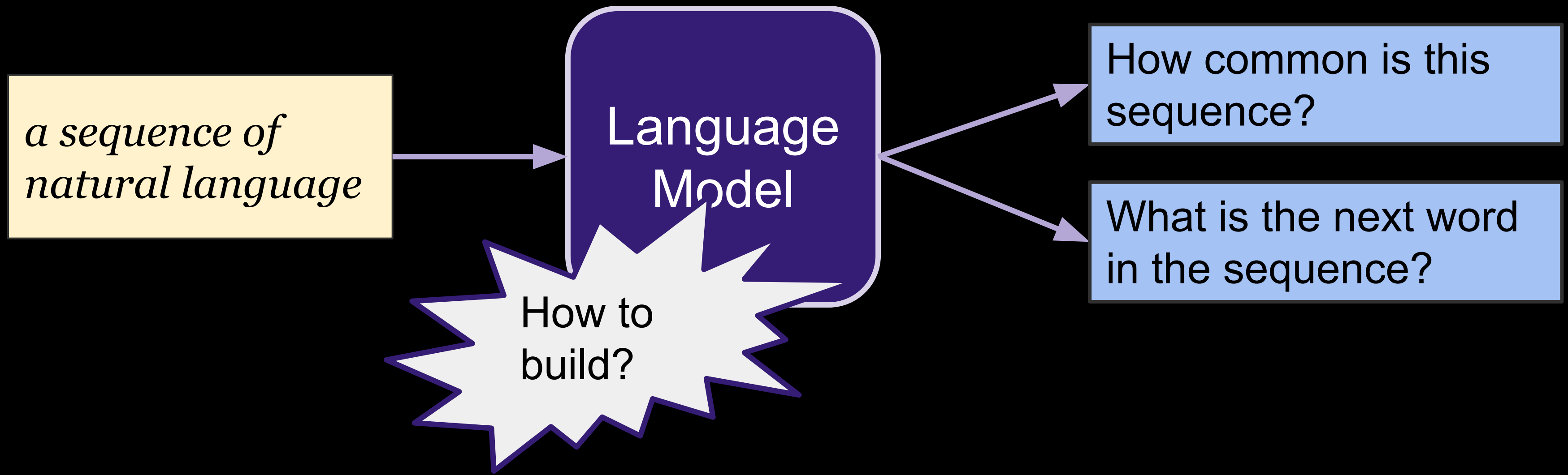

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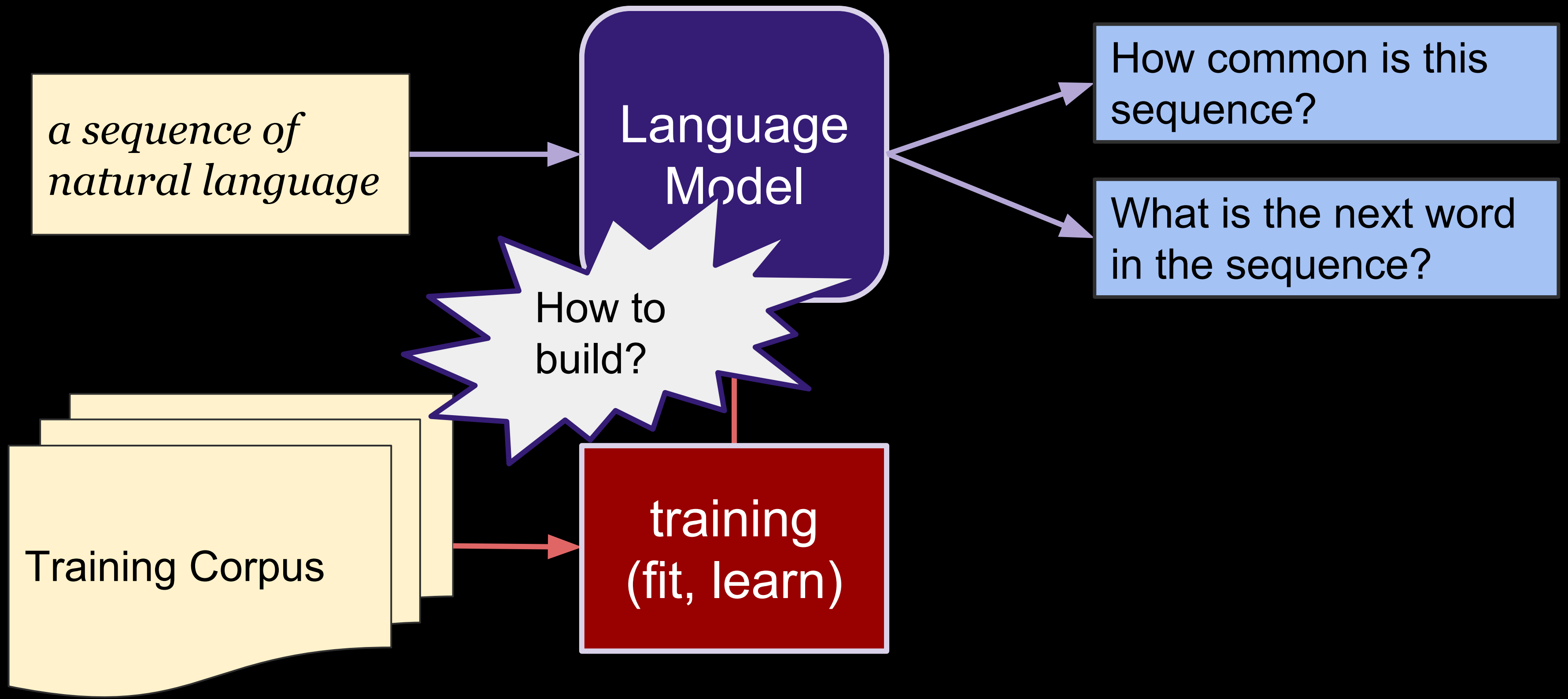

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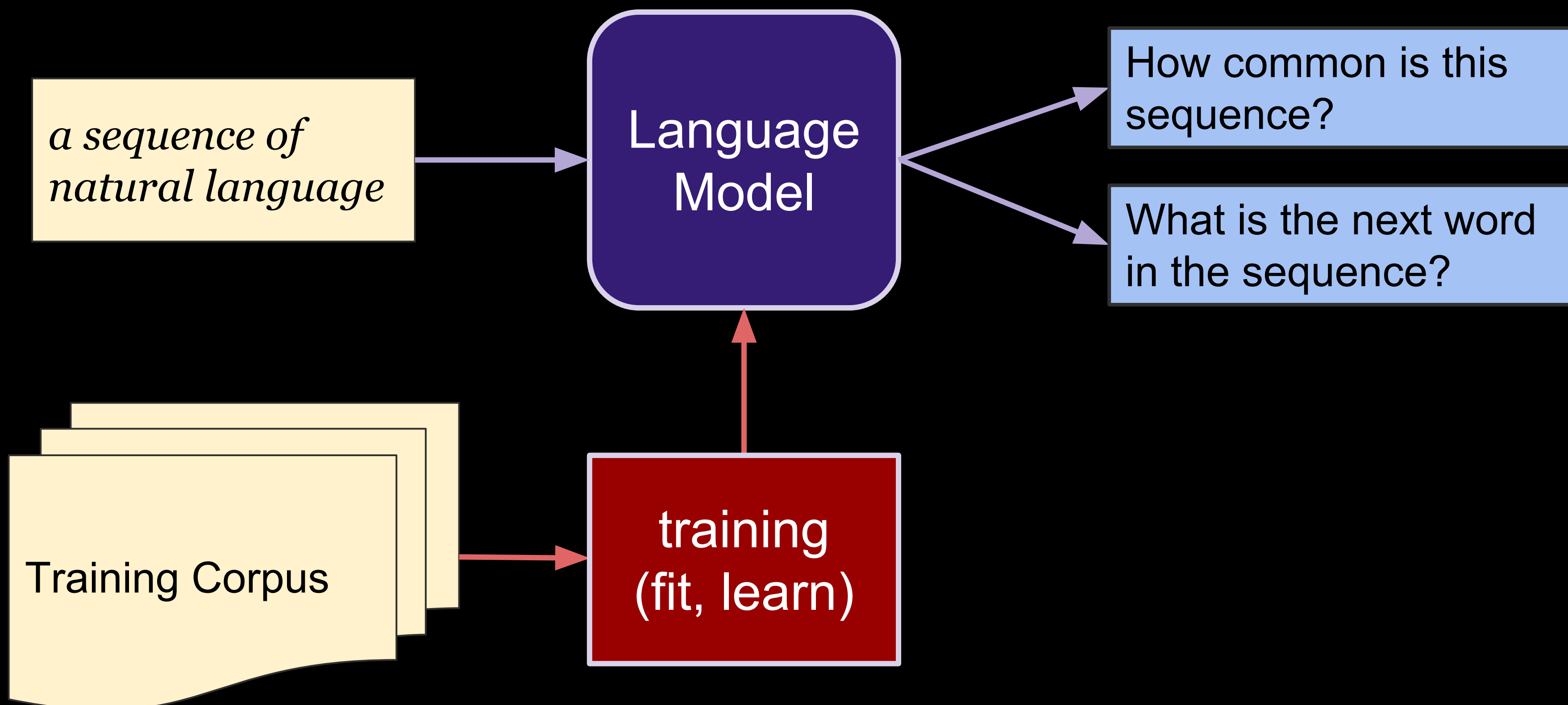
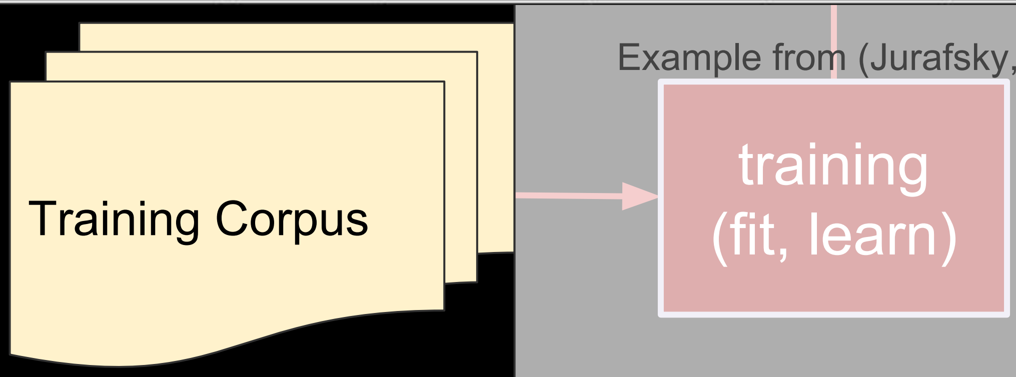


Bigram Counts

first word \ second word

	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

Example from (Jurafsky, 2017)



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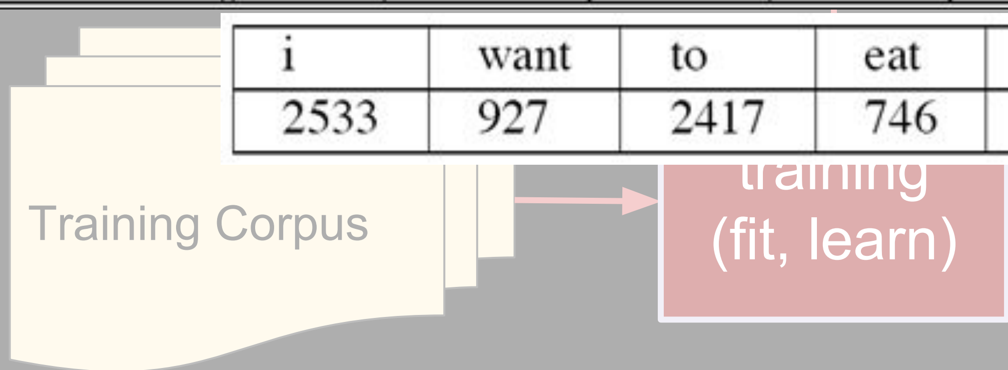
i	want	to	eat	chinese	food	lunch	spend
2533	927	2417	746	158	1093	341	278



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Training Corpus

training (fit, learn)

Bigram model: $P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | X_{i-1})$

Need to estimate: *P(Xi | Xi-1)* = count(Xi-1 Xi) / count(Xi-1) first word(Xi-1) \ second word (Xi)

P(Xi | Xi-1)

	i	want	to	eat	chinese	food	lunch	spend
i	0.002	0.33	0	0.0036	0	0	0	0.00079
want	0.0022	0	0.66	0.0011	0.0065	0.0065	0.0054	0.0011
to	0.00083	0	0.0017	0.28	0.00083	0	0.0025	0.087
eat	0	0	0.0027	0	0.021	0.0027	0.056	0
chinese	0.0063	0	0	0	0	0.52	0.0063	0
food	0.014	0	0.014	0	0.00092	0.0037	0	0
lunch	0.0059	0	0	0	0	0.0029	0	0
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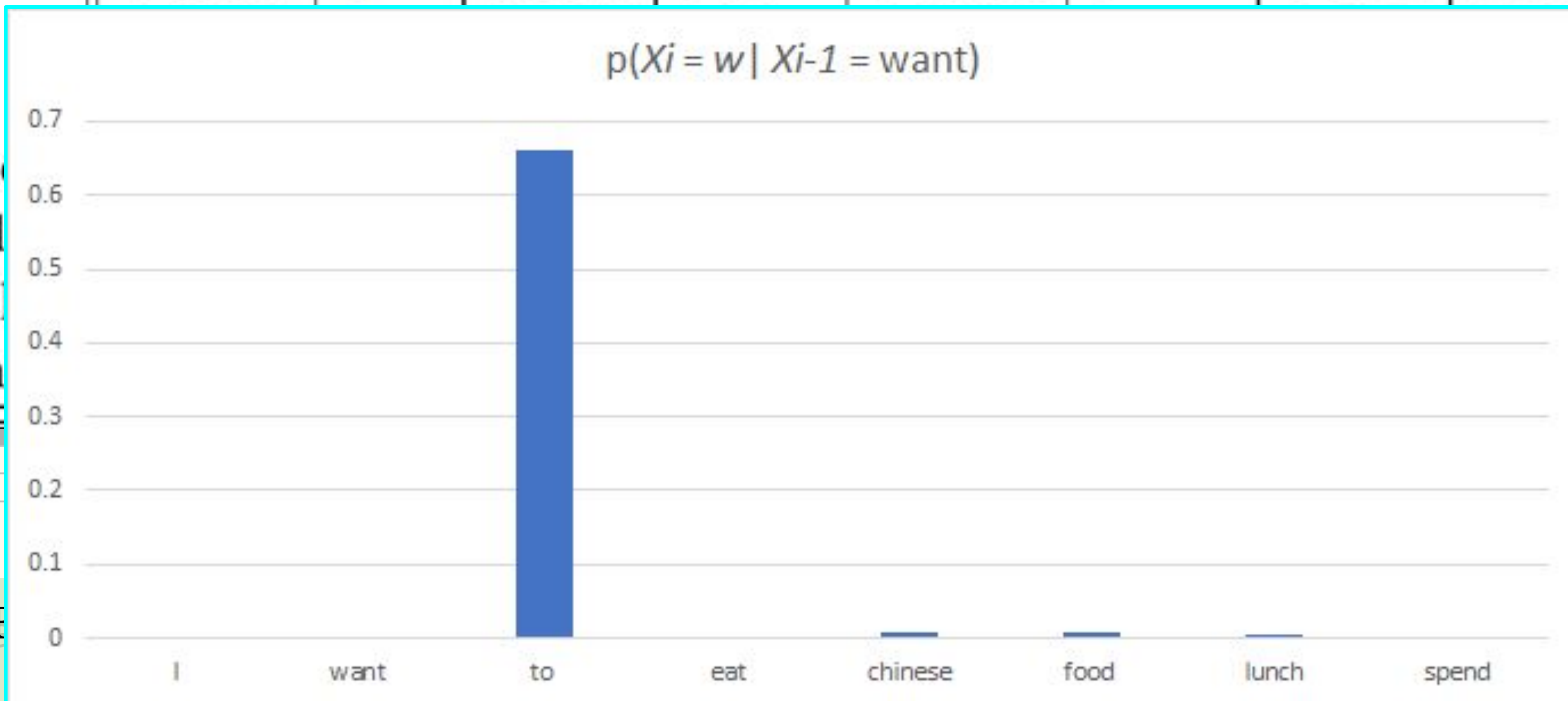

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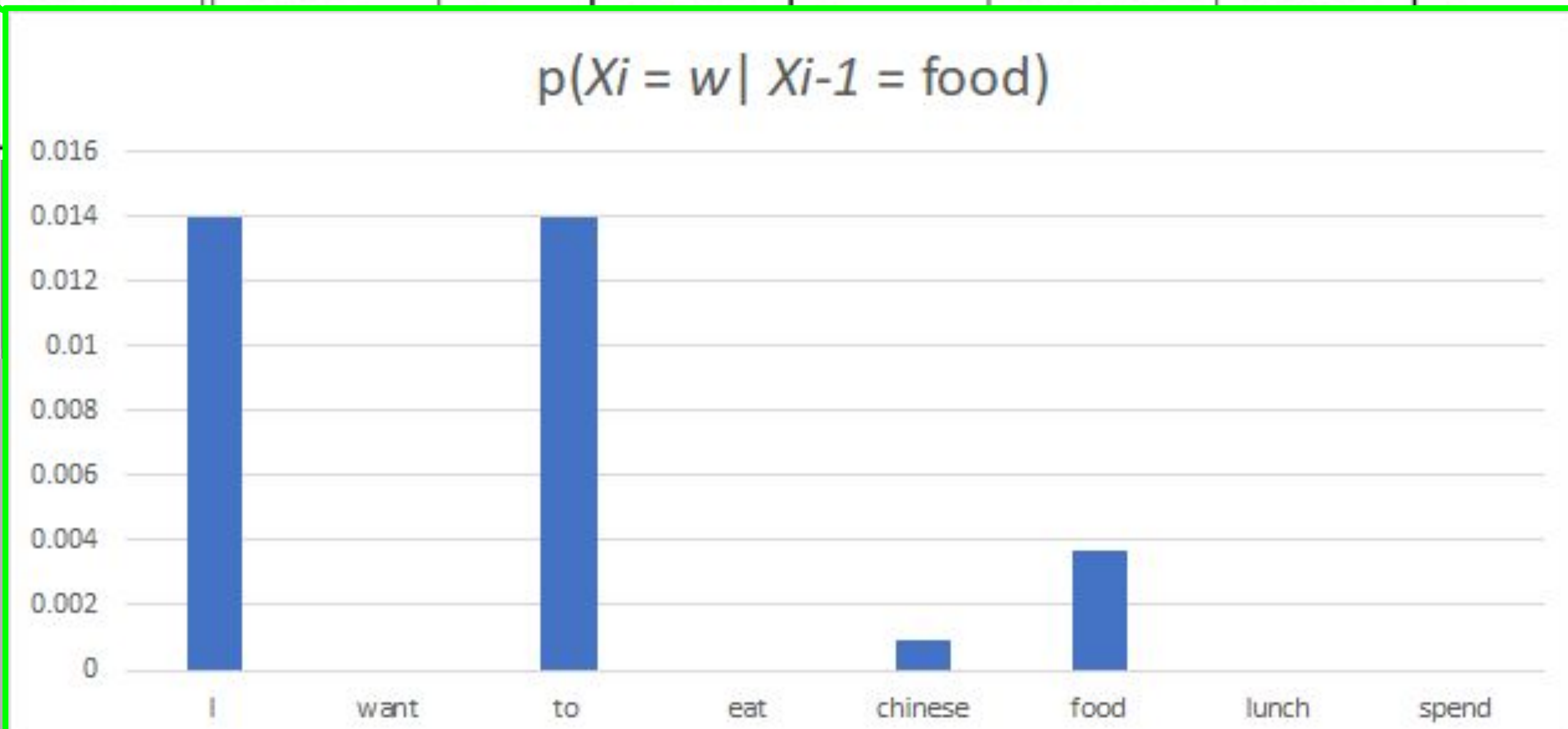
								0
								0

0
0
0

spend
278



/ count(Xi)

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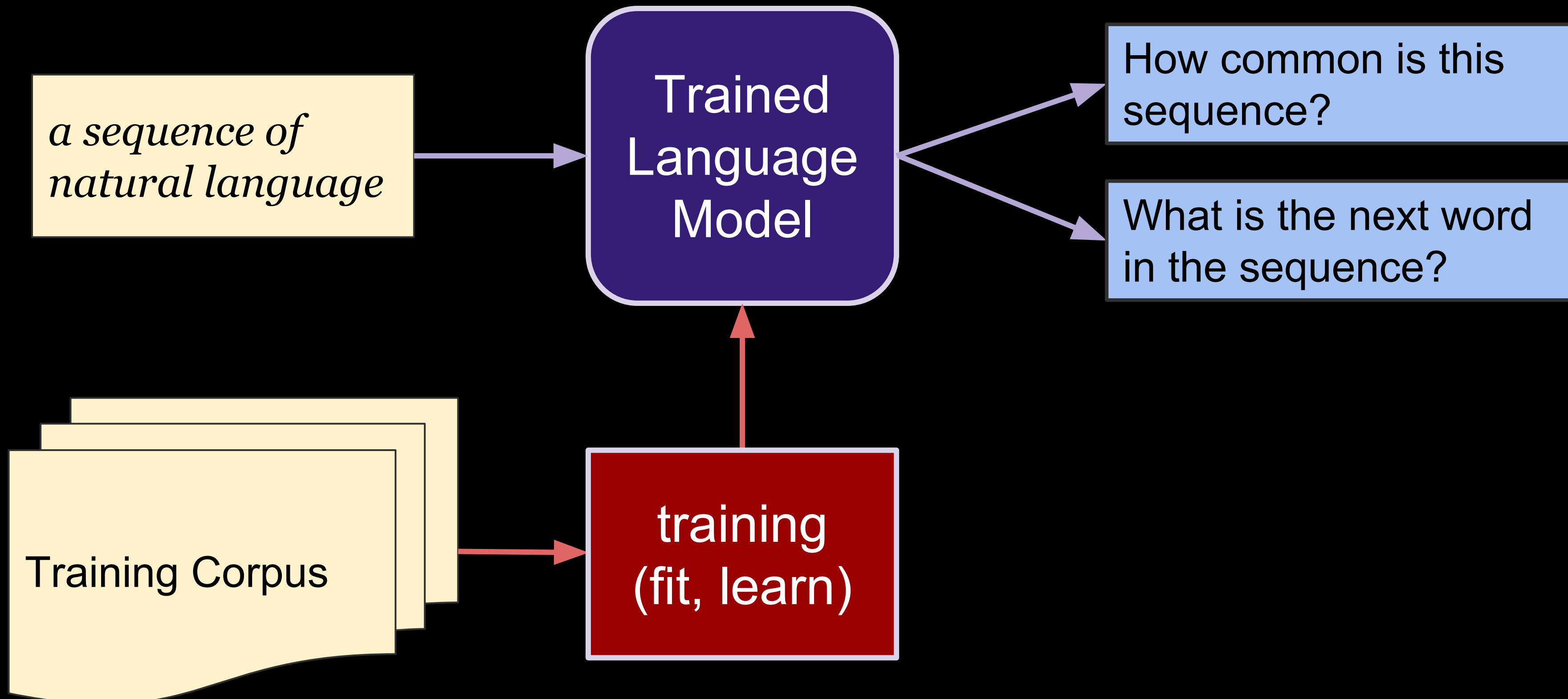

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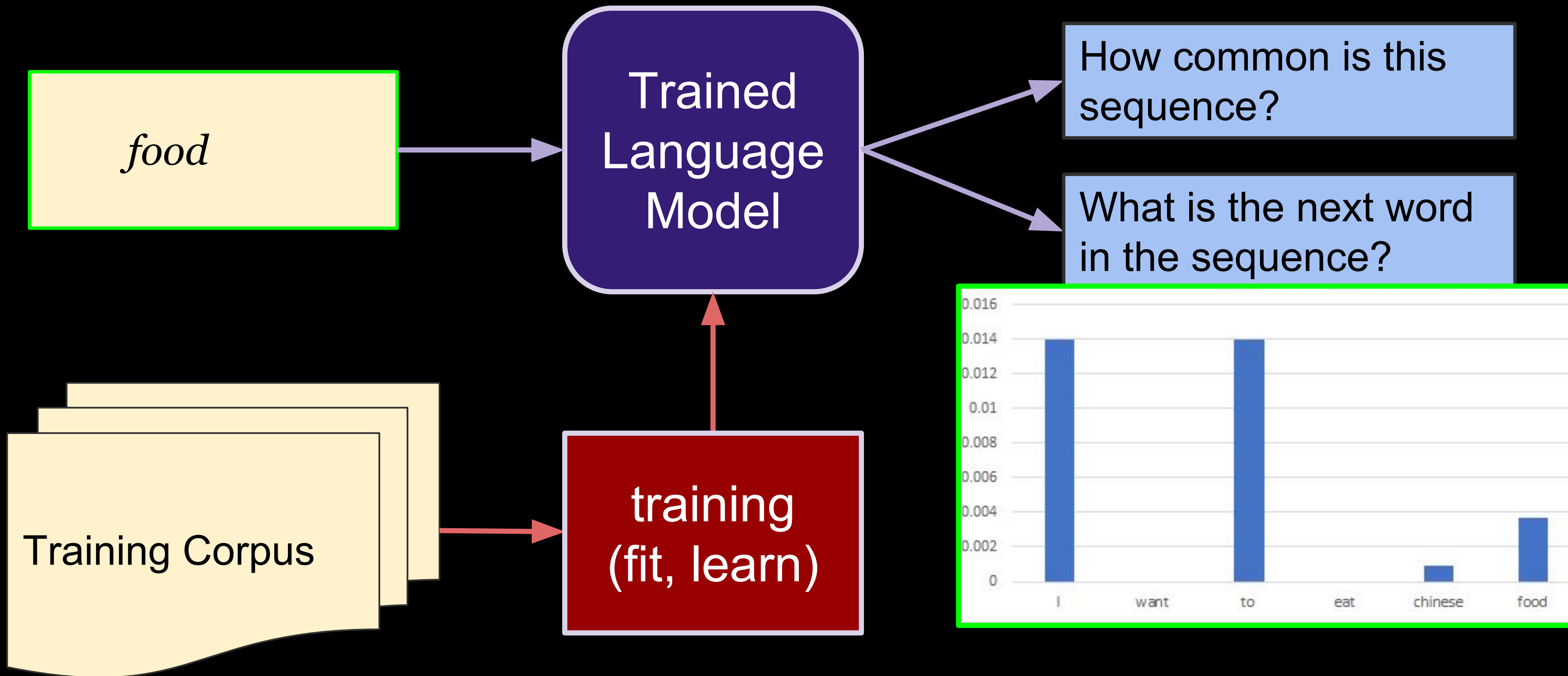

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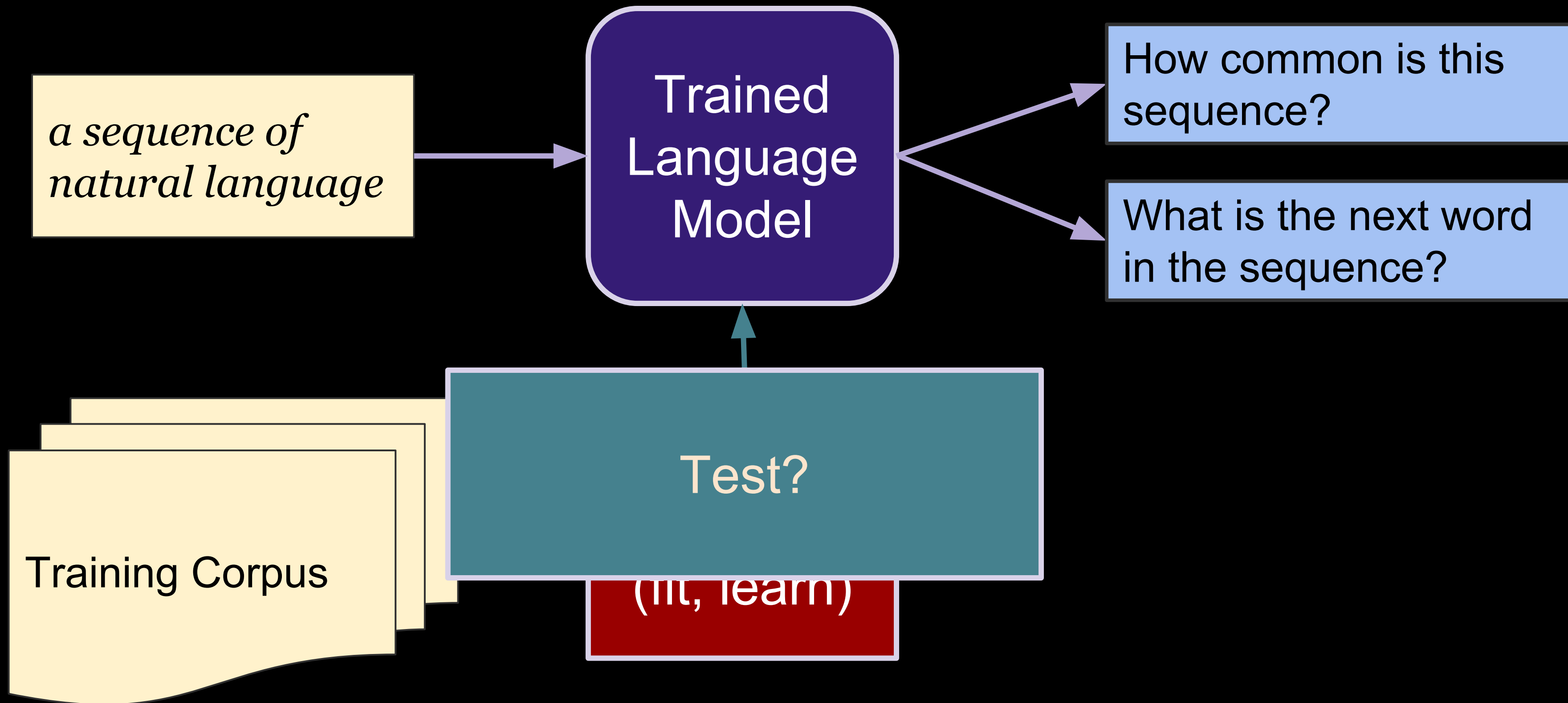

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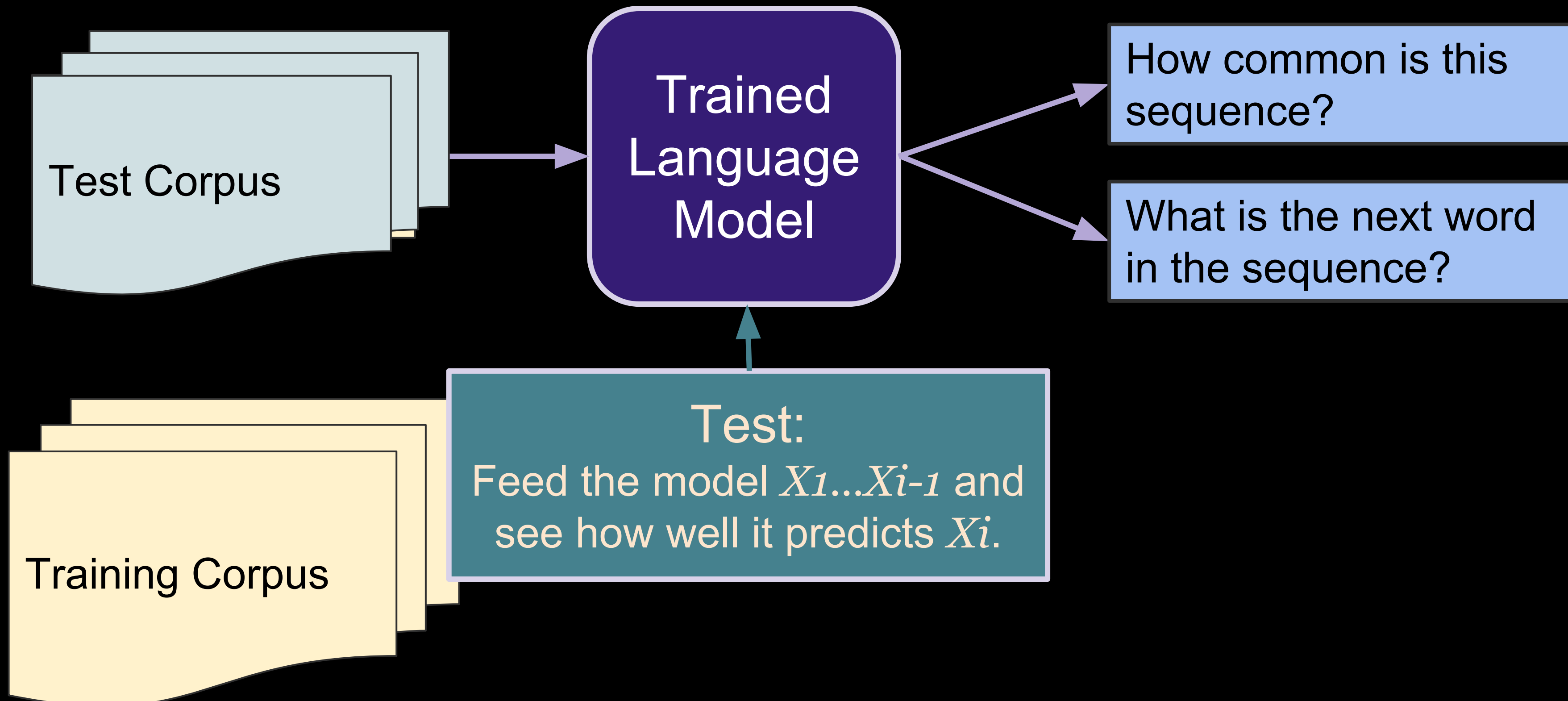

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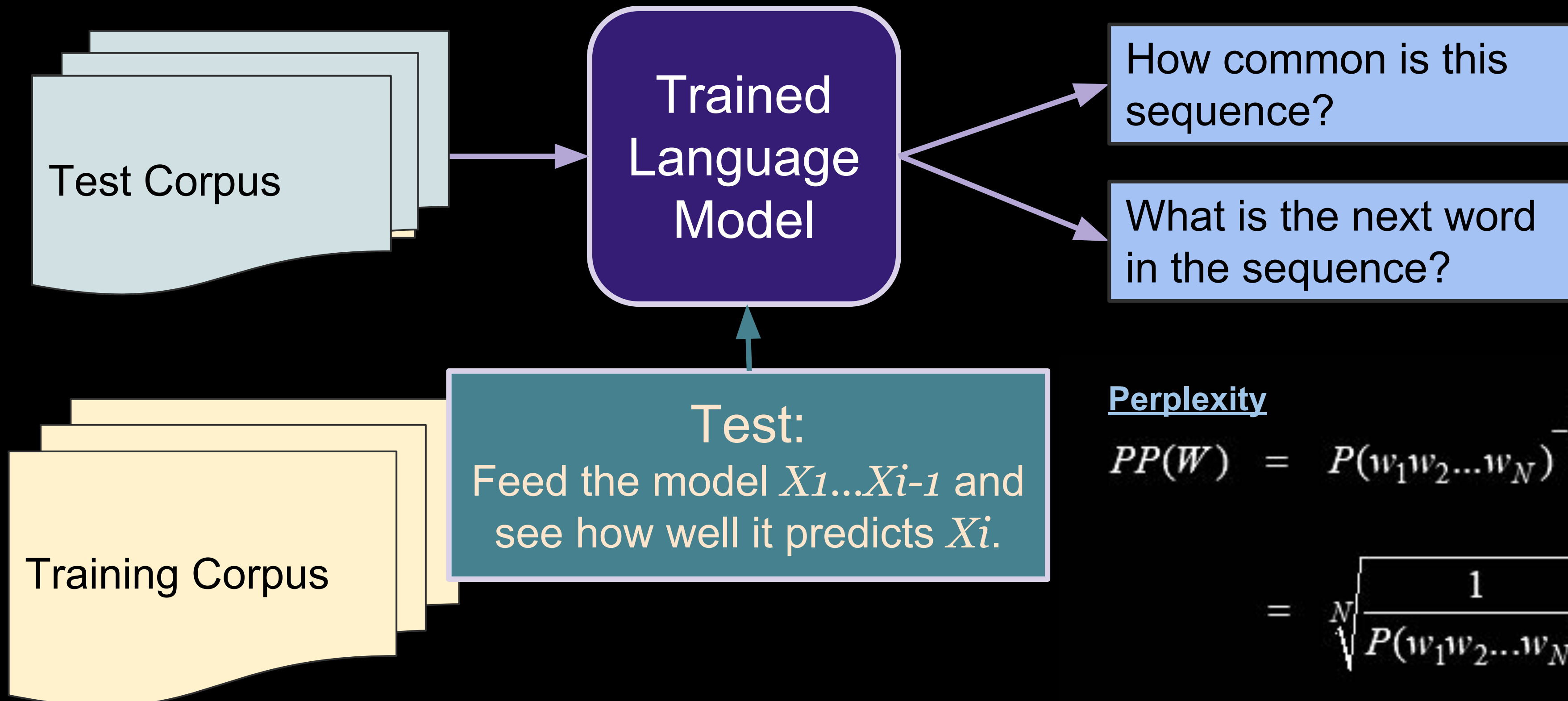
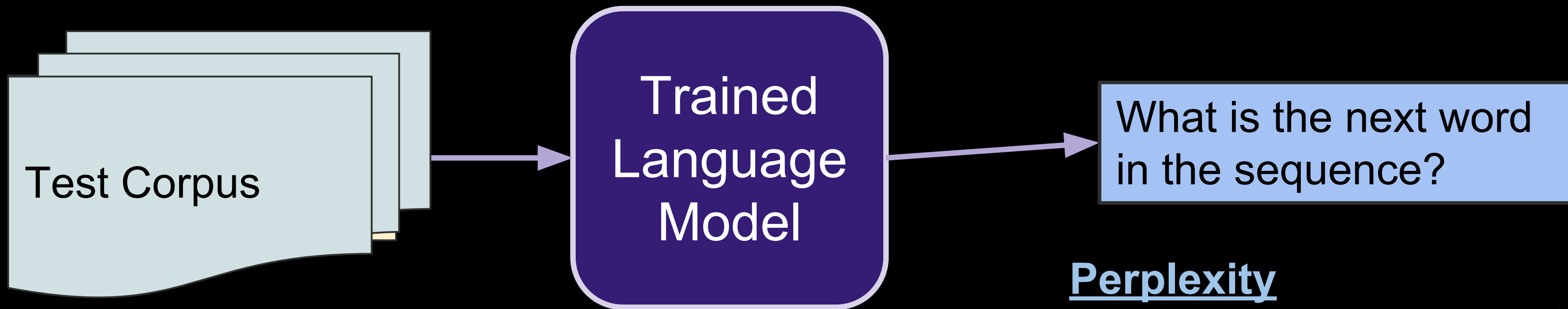


Perplexity

$$PP(W) = P(w_1 w_2 \ldots w_N)^{-\frac{1}{N}} = \sqrt[N]{\frac{1}{P(w_1 w_2 \ldots w_N)}}$$

Evaluation



Perplexity

$$
\begin{aligned}
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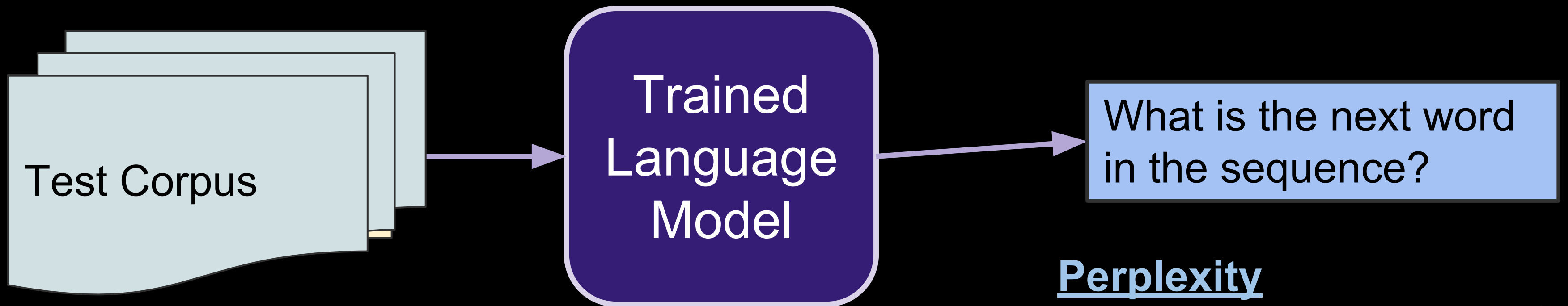

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Apply Chain Rule: $\mathrm{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_1 \ldots w_{i-1})}}$

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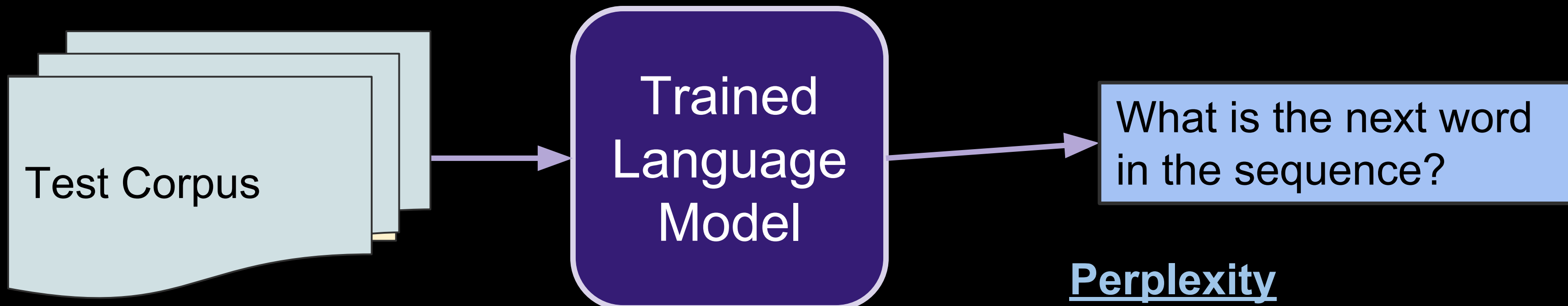

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Thus,
PP for Bigrams: $\mathrm{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_{i-1})}}$

Coding Example: Modeling Tweets from POS data

1. Count unigrams, bigrams, and trigrams
2. Train probabilities for unigram, bigram, and trigram models (over training)
3. Generate language

Trigram model when good evidence (high counts)

Backing off to bigram or even unigram

Coding Example: Modeling Tweets from POS data

Practical Considerations:

- Use log probability to keep numbers reasonable and save computation.
  (uses addition rather than multiplication)

- Out-of-vocabulary (OOV)
  Choose minimum frequency and mark as <OOV>

- Sentence start and end: *<s> this is a sentence </s>*

Zeros and Smoothing

first word(Xi-1) \ second word (Xi)

$P(Xi \mid Xi\text{-}1)$

	i	want	to	eat	chinese	food	lunch	spend
i	0.002	0.33	0	0.0036	0	0	0	0.00079
want	0.0022	0	0.66	0.0011	0.0065	0.0065	0.0054	0.0011
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Example from (Jurafsky, 2017)

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Laplace (“Add one”) smoothing: add 1 to all counts

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eat	1	1	3	1	17	3	43	1
chinese	2	1	1	1	1	83	2	1
food	16	1	16	1	2	5	1	1
lunch	3	1	1	1	1	2	1	1
spend	2	1	2	1	1	1	1	1

Laplace ("Add one") smoothing: add 1 to all counts

Unsmoothed probs

first word(Xi-1) \ second word (Xi)

P(Xi | Xi-1)

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Example from (Jurafsky, 2017)

Smoothed

$$P_{Add-1}(w_i \mid w_{i-1}) = \frac{c(w_{i-1}, w_i)+1}{c(w_{i-1})+V}$$

(vocabulary size)

first word(Xi-1) \ second word (Xi)

P(Xi | Xi-1)

	i	want	to	eat	chinese	food	lunch	spend
i	0.0015	0.21	0.00025	0.0025	0.00025	0.00025	0.00025	0.00075
want	0.0013	0.00042	0.26	0.00084	0.0029	0.0029	0.0025	0.00084
to	0.00078	0.00026	0.0013	0.18	0.00078	0.00026	0.0018	0.055
eat	0.00046	0.00046	0.0014	0.00046	0.0078	0.0014	0.02	0.00046
chinese	0.0012	0.00062	0.00062	0.00062	0.00062	0.052	0.0012	0.00062
food	0.0063	0.00039	0.0063	0.00039	0.00079	0.002	0.00039	0.00039
lunch	0.0017	0.00056	0.00056	0.00056	0.00056	0.0011	0.00056	0.00056
spend	0.0012	0.00058	0.0012	0.00058	0.00058	0.00058	0.00058	0.00058

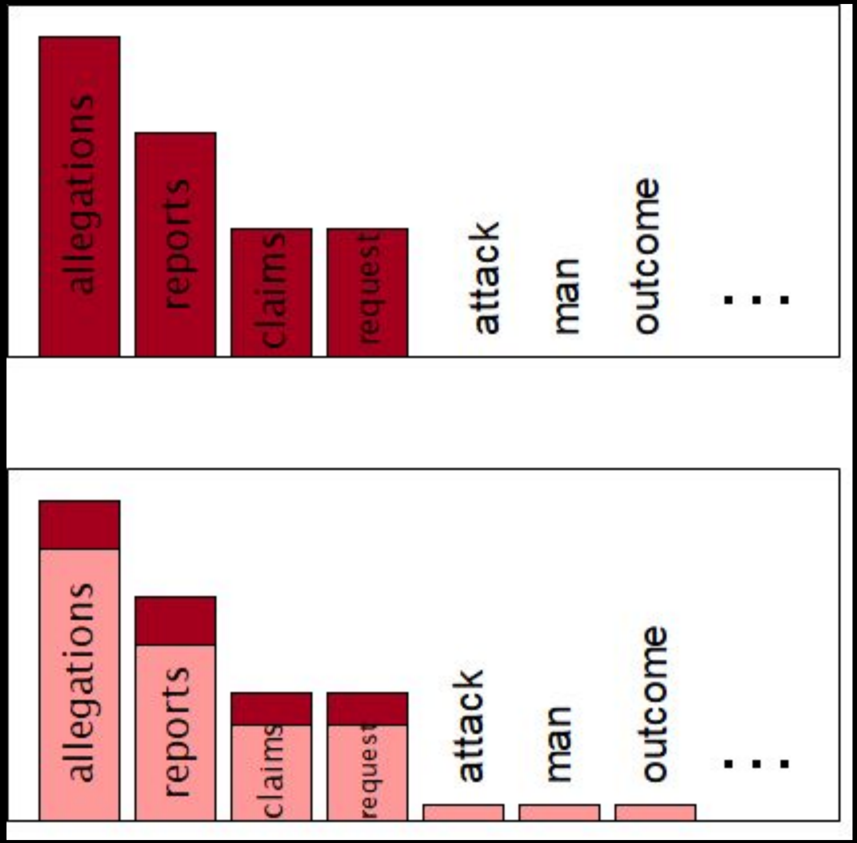
Example from (Jurafsky, 2017)

Why Smoothing? Generalizes

Original

With Smoothing

(Example from Jurafsky / Originally Dan Klein)



Why Smoothing? Generalizes

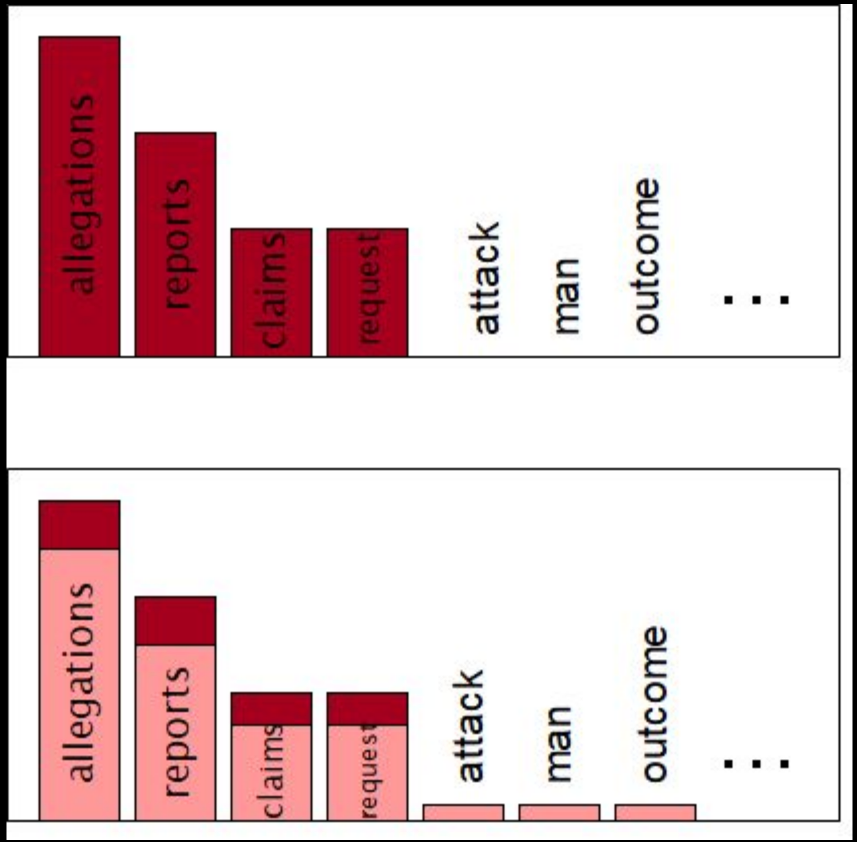
Add-one is blunt:
can lead to very large changes.

Better Smoothing:

- Good-Turing

- Kneser-Nay

These are outside scope of course because we will eventually cover, even stronger, deep learning based models.



Language Modeling Summary

- Two versions of assigning probability to sequence of words
- Applications
- The Chain Rule, The Markov Assumption: $P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i | X_{i-k}, X_{i-(k-1)}, ..., X_i)$
- Training a unigram, bigram, trigram model based on counts
- Evaluation: Perplexity
- Zeros, Low Counts, and Generalizability
- Add-one smoothing