Language Modeling

Task

7. Imagine that you are now 25 years old. Write about the life you are leading, your interests, your home life and your work at the age of 25. (You have 30 minutes to do this).

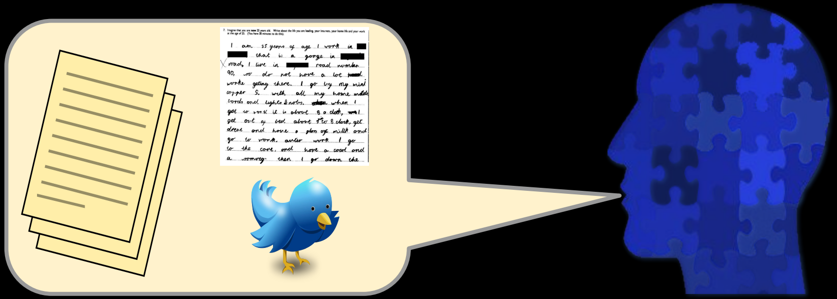
I am 25 yeors of age I work in [redacted]
[redacted] that is a gorge in [redacted]
road, I live in [redacted] road number
90, we do not have a lot
worke geting there. I go by my mini
copper S. with all my home madde
bords and lights & nobs. when I
got to work it is about 8 o clock, I
get out of bed about 5 to 8 clock, get
drese and have a glass of millk and
go to work. after work I go
to the cave, and have a cool and
a somveg. then I go down the

- Language Modeling (i.e. auto-complete)

how? →

- **Probabilistic Modeling**
  - ○ **Probability Theory**
  - ○ **Logistic Regression**
  - ○ **Sequence Modeling**

Task



7. Imagine that you are now 25 years old. Write about the life you are leading, your interests, your home life and your work at the age of 25. (You have 30 minutes to do this).

I am 25 years of age I work in [redacted]
[redacted] that is a gorge in [redacted]
road, I live in [redacted] road number
90, we do not have a lot
worke geting there. I go by my mini
copper S. with all my home madde
lords and lights &nobs. when I
get to work it is about 8 o clock, I
get out of bed about 5 to 8 clock, get
drese and have a glass of millk and
go to work. after work I go
to the cave, and have a cool and
a somveg. then I go down the

- Language Modeling (i.e. auto-complete)

how? →

- Probabilistic Modeling
  - Probability Theory
  - Logistic Regression
  - Sequence Modeling
- **Eventually: Deep Learning**
  - **Recurrent Neural Nets**
  - **Transformer Networks**

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

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

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

$= P(w_n | w_1, w_2, ..., w_{n-1})$

:probability of a next word given history

Language Modeling

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

:probability of a sequence of words

P(He ate the cake with the fork) = ?

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

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

:probability of a next word given history

P(fork | He ate the cake with the) = ?

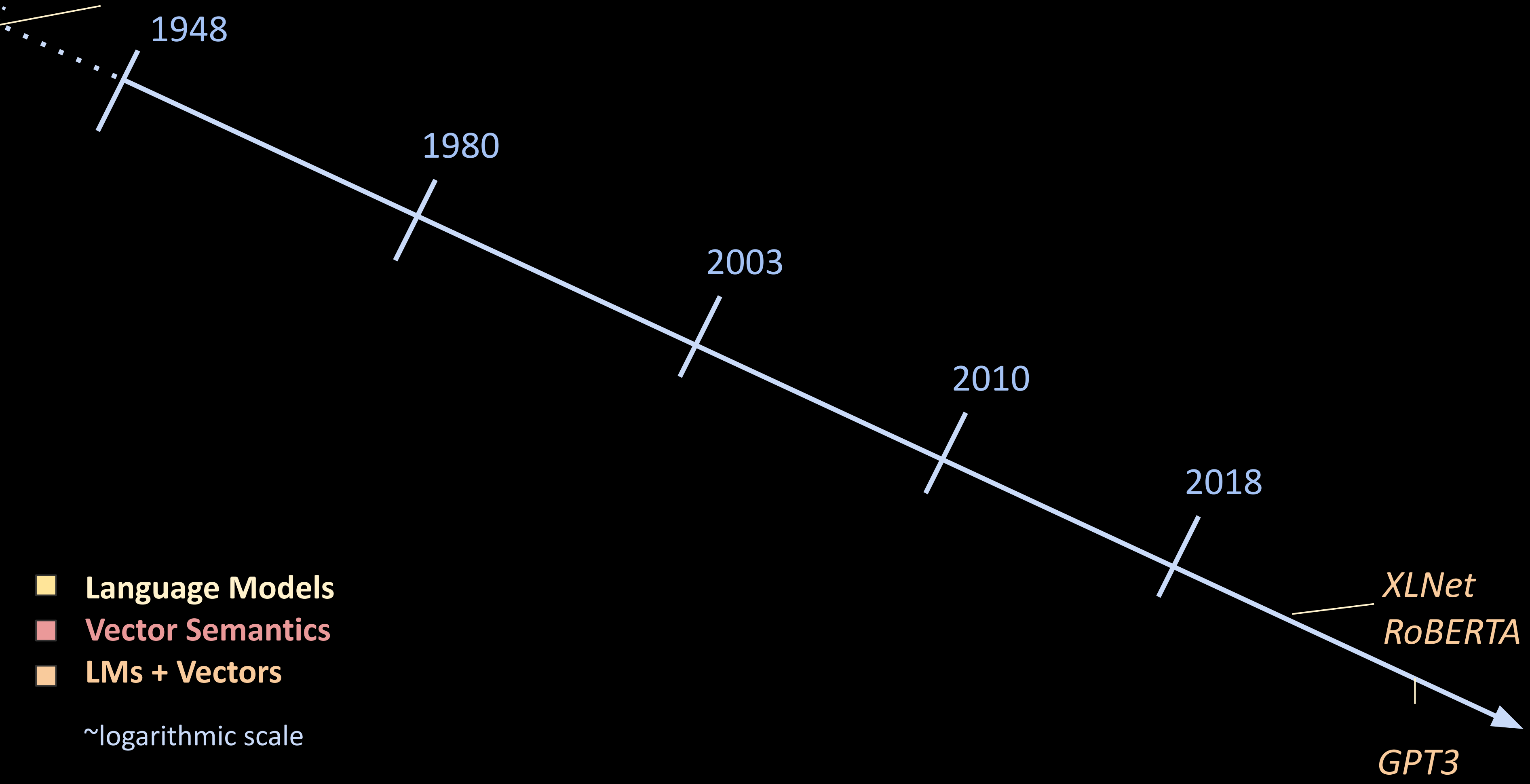
Language Modeling

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; ..did you say "giraffe ski 2,017"?)

Timeline: *Language Modeling* and *Vector Semantics*

1913 Markov: Probability that next letter would be vowel or consonant.



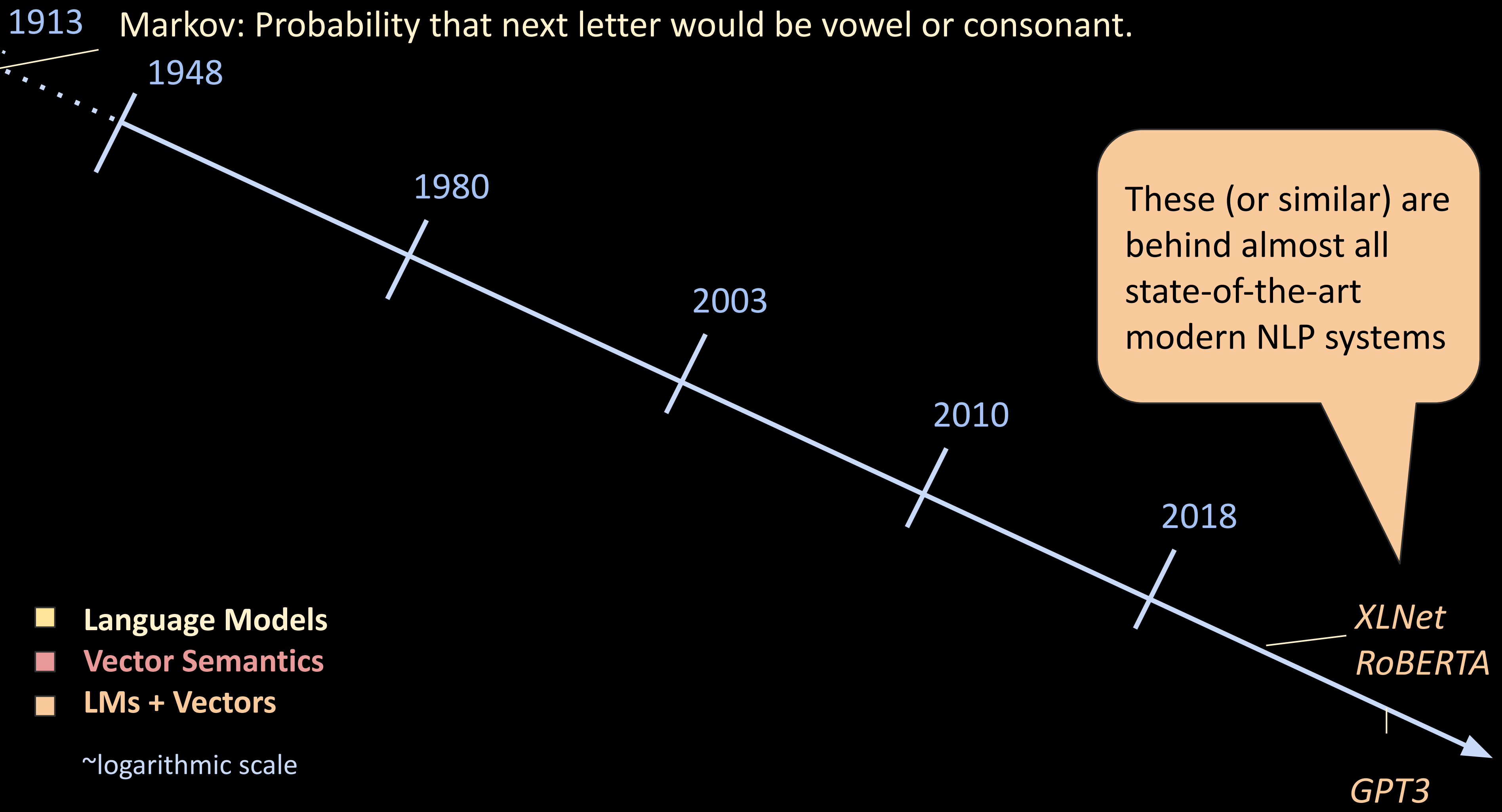
🟨 **Language Models**

🟥 **Vector Semantics**

🟧 **LMs + Vectors**

~logarithmic scale

Timeline: *Language Modeling* and *Vector Semantics*



1913 Markov: Probability that next letter would be vowel or consonant.

These (or similar) are behind almost all state-of-the-art modern NLP systems

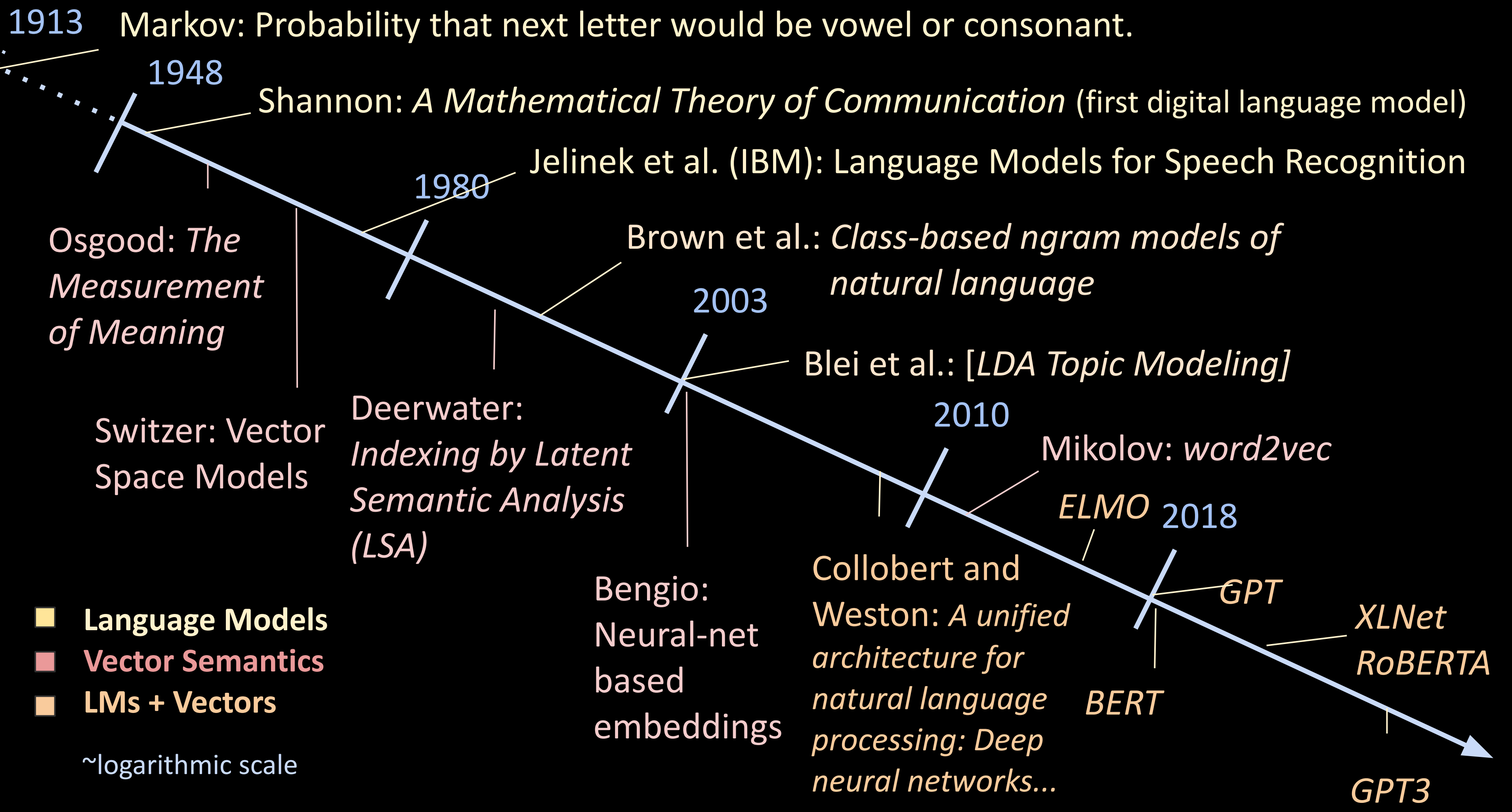
🟨 **Language Models**

🟥 **Vector Semantics**

🟧 **LMs + Vectors**

~logarithmic scale

Timeline: *Language Modeling* and *Vector Semantics*



1913 Markov: Probability that next letter would be vowel or consonant.

1948 Shannon: *A Mathematical Theory of Communication* (first digital language model)

Osgood: *The Measurement of Meaning*

Switzer: Vector Space Models

1980 Jelinek et al. (IBM): Language Models for Speech Recognition

Deerwater: *Indexing by Latent Semantic Analysis (LSA)*

Brown et al.: *Class-based ngram models of natural language*

2003 Blei et al.: [*LDA Topic Modeling]*

Bengio: Neural-net based embeddings

Collobert and Weston: *A unified architecture for natural language processing: Deep neural networks...*

2010 Mikolov: *word2vec*

ELMO

2018 *GPT*

BERT

XLNet

RoBERTA

GPT3

🟨 **Language Models**

🟥 **Vector Semantics**

🟧 **LMs + Vectors**

~logarithmic scale

Language Modeling

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

:probability of a sequence of words

P(He ate the cake with the fork) = ?

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

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

:probability of a next word given history

P(fork | 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

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

:probability of a sequence of words

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

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

total number of observed *7grams*

Simple Solution: The Maximum Likelihood Estimate

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

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

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

$$\frac{\textit{count(He ate the cake with the fork)}}{\textit{count(He ate the cake with the} *)}$$

Simple Solution: The Maximum Likelihood Estimate

Problem: even the Web isn't large enough to enable good estimates of most phrases.

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

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

Problem: even the Web isn’t large enough to enable good estimates of most phrases.

Solution: Estimate from shorter sequences, use more sophisticated probability theory.

Problem: even the Web isn’t large enough to enable good estimates of most phrases.

Solution: Estimate from shorter sequences, use more sophisticated probability theory.

$$P(B|A) = P(B, A) / P(A) \Leftrightarrow P(A)P(B|A) = P(B,A) = P(A,B)$$

Example from (Jurafsky, 2017)

Problem: even the Web isn’t large enough to enable good estimates of most phrases.

Solution: Estimate from shorter sequences, use more sophisticated probability theory.

$$P(B|A) = P(B, A) \,/\, P(A) \Leftrightarrow P(A)P(B|A) = P(B,A) = P(A,B)$$

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

Example from (Jurafsky, 2017)

Problem: even the Web isn't large enough to enable good estimates of most phrases.

Solution: Estimate from shorter sequences, use more sophisticated probability theory.

$$P(B|A) = P(B, A) / P(A) \Leftrightarrow P(A)P(B|A) = P(B,A) = P(A,B)$$

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

The Chain Rule:

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

Example from (Jurafsky, 2017)

Problem: even the Web isn’t large enough to enable good estimates of most phrases.

Solution: Estimate from shorter sequences, use more sophisticated probability theory.

$$P(B|A) = P(B, A) \,/\, P(A) \Leftrightarrow P(A)P(B|A) = P(B,A) = P(A,B)$$

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

The Chain Rule: $P(X_1, X_2, \dots, X_n) = \prod_{i=1}^{n} P(X_i|X_1, X_2, \dots, X_i)$

$$P(X1, X2,\dots, Xn) = P(X1)P(X2|X1)P(X3|X1, X2)\dots P(Xn|X1, \dots, Xn\text{-}1)$$

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

Solution: Estimate from shorter sequences, use more sophisticated probability theory.

$$P(B|A) = P(B, A) \,/\, P(A) \Leftrightarrow P(A)P(B|A) = P(B,A) = P(A,B)$$

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

The Chain Rule: $P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i | X_1, X_2, ..., X_i)$

$$P(X1, X2,..., Xn) = P(X1)P(X2|X1)P(X3|X1, X2)...P(Xn|X1, ..., Xn\text{-}1)$$

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*

Solution: Estimate from shorter sequences, use more sophisticated probability theory.

$P(B|A) = P(B, A) / P(A) \Leftrightarrow P(A)P(B|A) = P(B,A) = P(A,B)$

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

The Chain Rule: $$P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i | X_1, X_2, ..., X_i)$$

$P(X1, X2,..., Xn) = P(X1)P(X2|X1)P(X3|X1, X2)...P(Xn|X1, ..., Xn\text{-}1)$

Markov Assumption: $P(X \ldots X_{\ldots}) \ldots X \ldots _{1}), \ldots, X_i)$

P(Xn| X

What about Logistic Regression? Y = next word
P(Y|X) = P(Xn | Xn-1, Xn-2, Xn-3, ...)

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

$P($

$P($

The Chain $\prod_{i=1} P(X_i|X_1, X_2, \ldots, X_i)$

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

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

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

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

$P(B|A) = P(B, A) / P(A) \Leftrightarrow P(A)P(B|A) = P(B,A) = P(A,B)$

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

The Chain Rule: $$P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i|X_1, X_2, ..., X_i)$$

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

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-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:

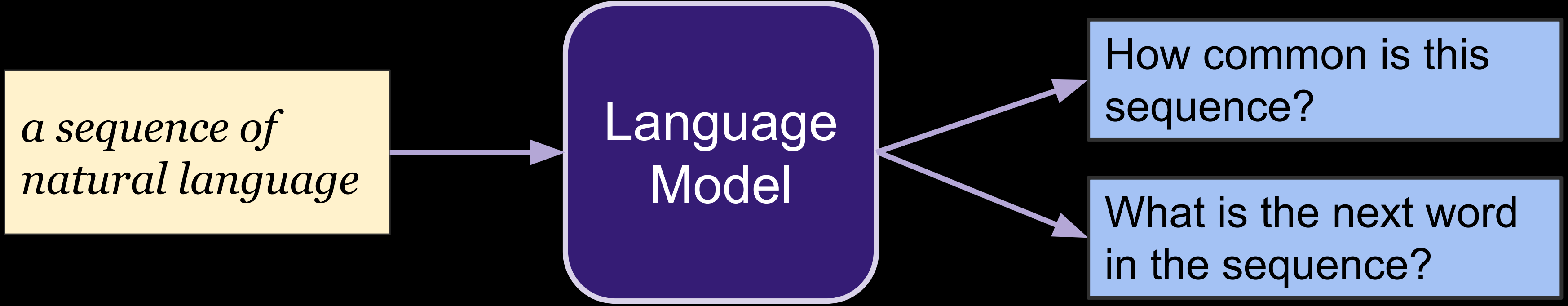
outside, new, car, parking, lot, of, the, agreement, reached

P(X1 = “outside”, X2=”new”, X3 = “car”, ...)
*≈ P(X1=“outside”) * 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:



a sequence of natural language

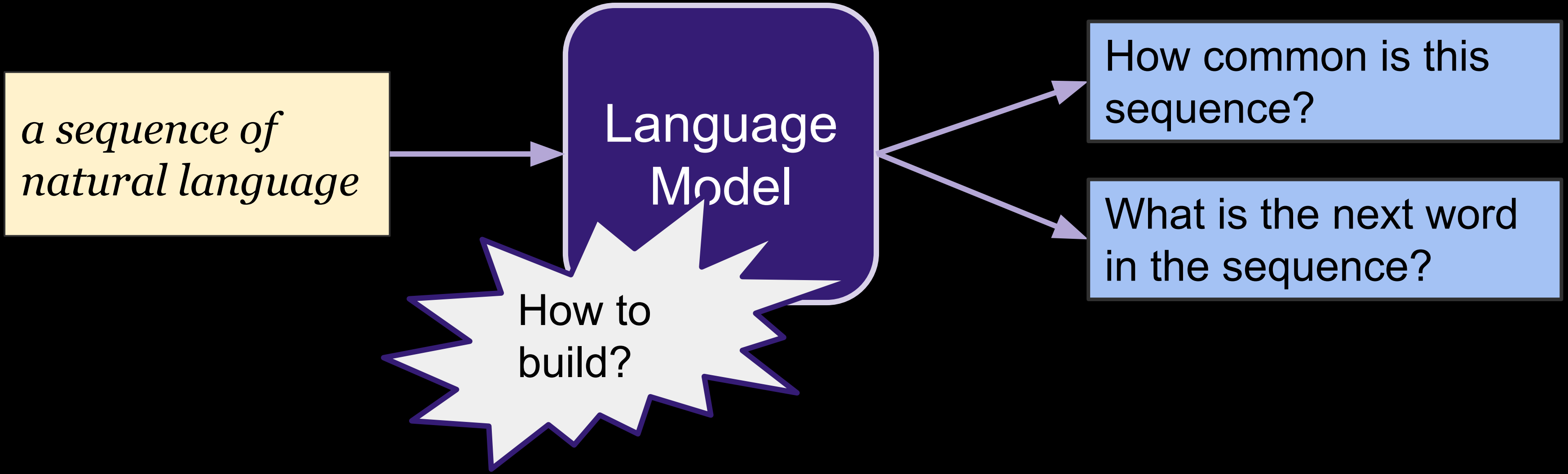
Language Model

How common is this sequence?

What is the next word in the sequence?

Language Modeling

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



a sequence of natural language

Language Model

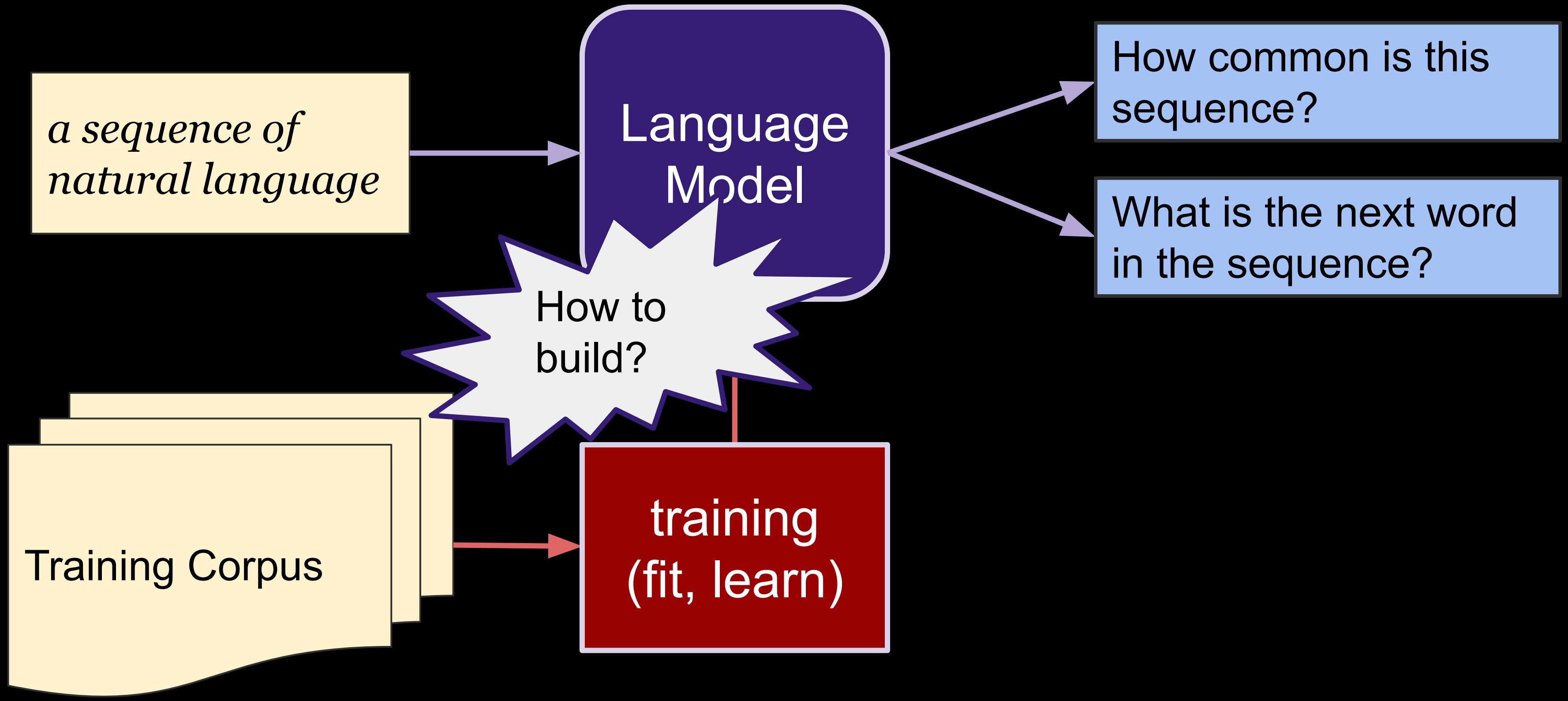
How to build?

How common is this sequence?

What is the next word in the sequence?

Language Modeling

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



a sequence of natural language

Language Model

How common is this sequence?

What is the next word in the sequence?

How to build?

Training Corpus

training (fit, learn)

Language Mo

Building a model (

Food corpus from Jurafsky (2018). Samples:

can you tell me about any good cantonese restaurants close by

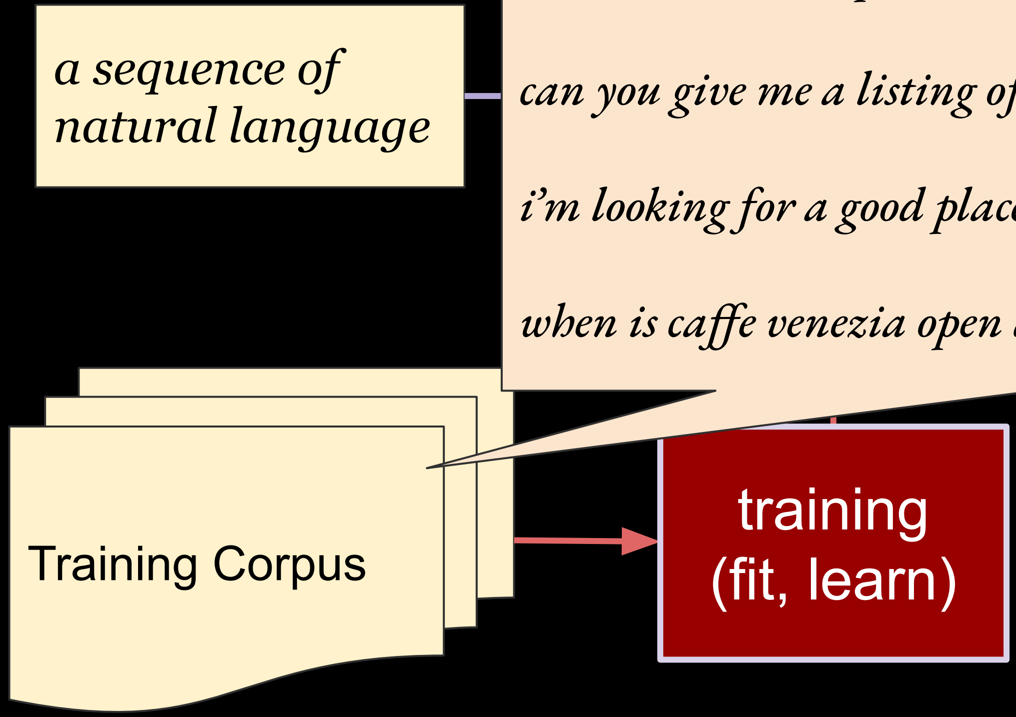
mid priced thai food is what i'm looking for

tell me about chez panisse

can you give me a listing of the kinds of food that are available

i'm looking for a good place to eat breakfast

when is caffe venezia open during the day



a sequence of natural language

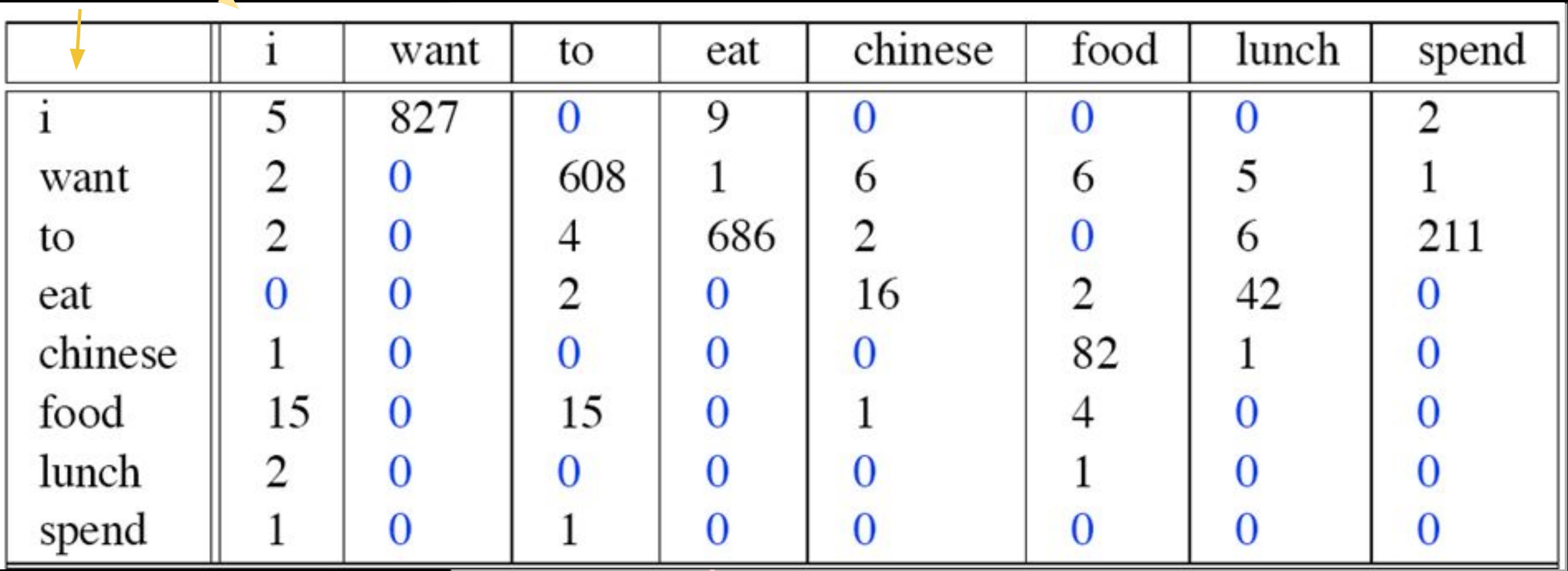
Training Corpus

training (fit, learn)

Bigram Counts

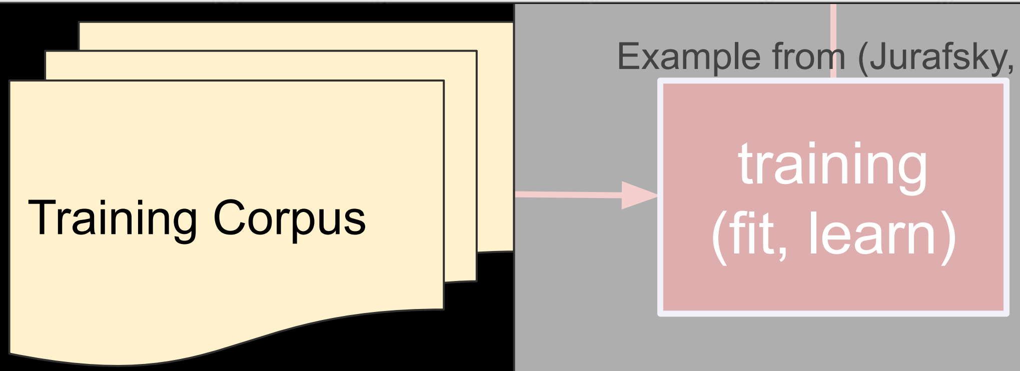
first word

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

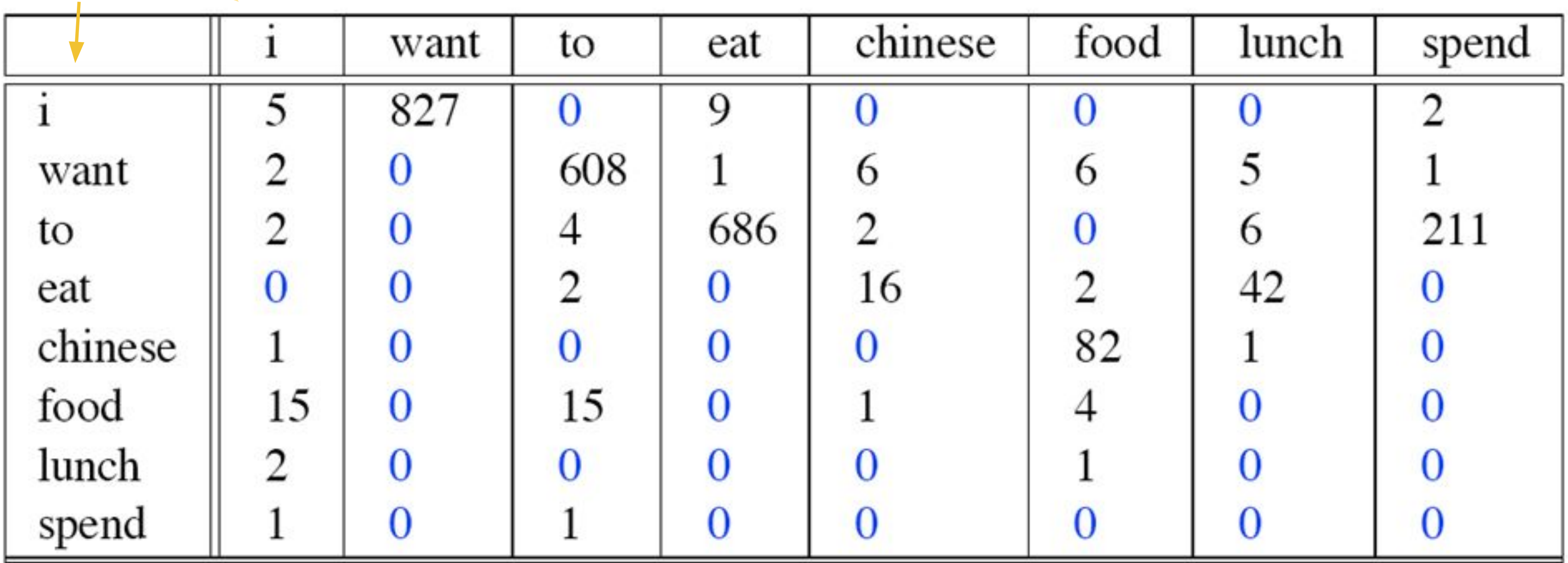
Example from (Jurafsky, 2017)



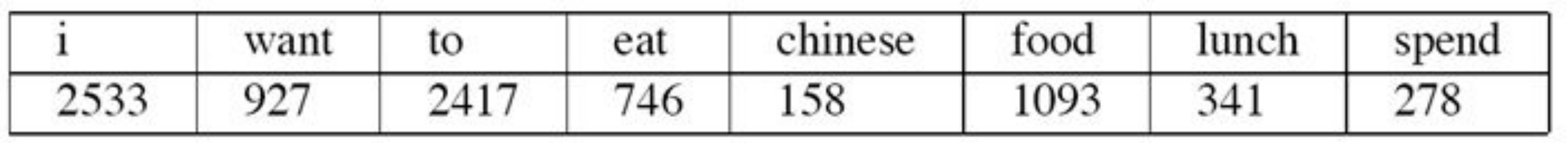
Bigram Counts

second word

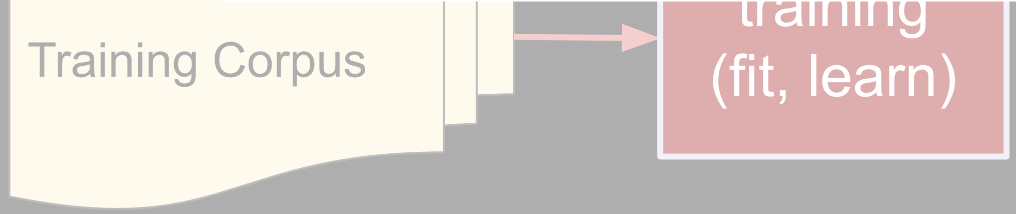
first word



	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



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



first word \ second word

Bigram Counts

	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

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

Training Corpus

training (fit, learn)

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

Need to estimate: *P(Xi | Xi-1)* = count(Xi-1 Xi) / count(Xi-1)

second word: xi

first word: xi-1

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
spend	0.0036	0	0.0036	0	0	0	0	0

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

Training Corpus

training
(fit, learn)

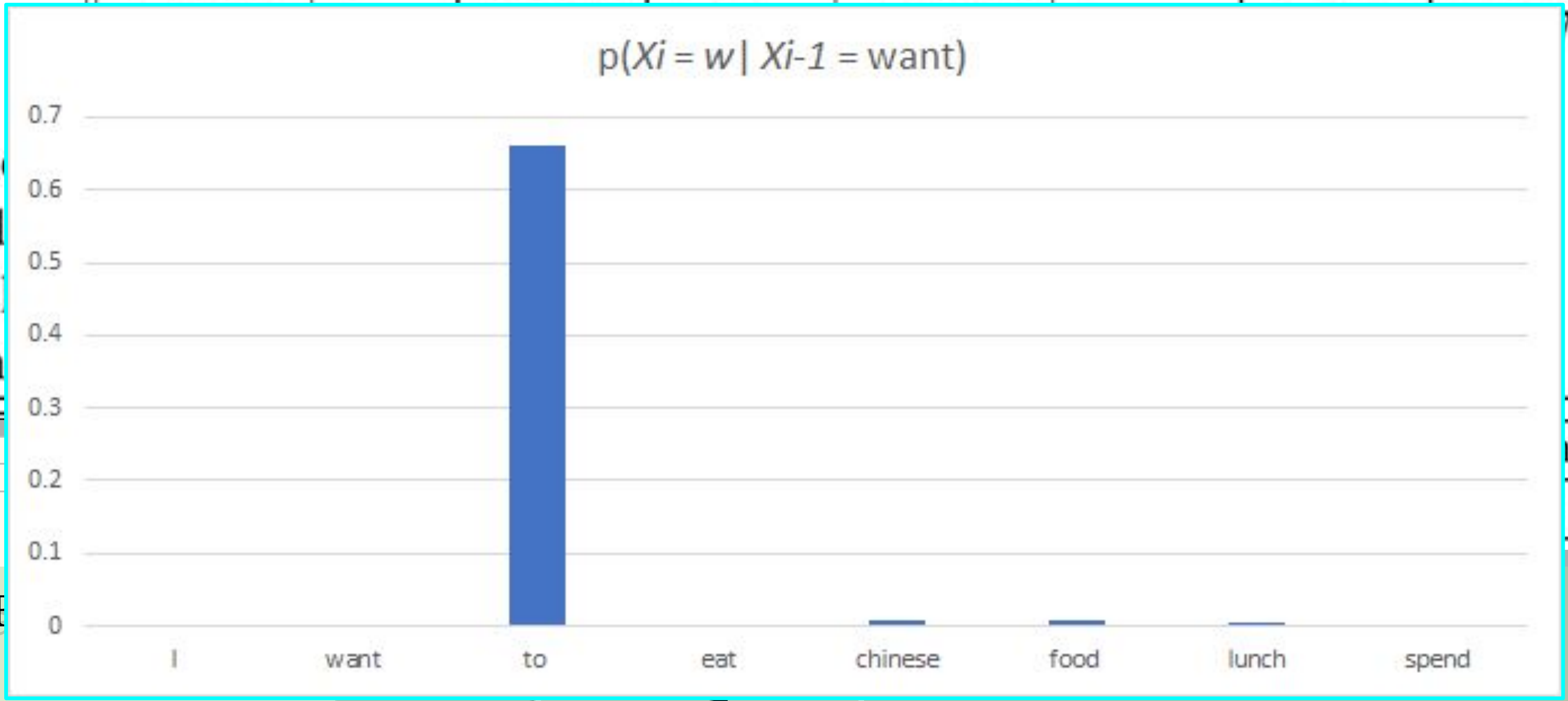
Bigram model: $P(X_1, X_2, ..., X_n) = \prod_{i=1}^{n} P(X_i|X_{i-1})$

Need to estimate: *P(Xi | Xi-1)* = count(Xi-1 Xi) / count(Xi-1)

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

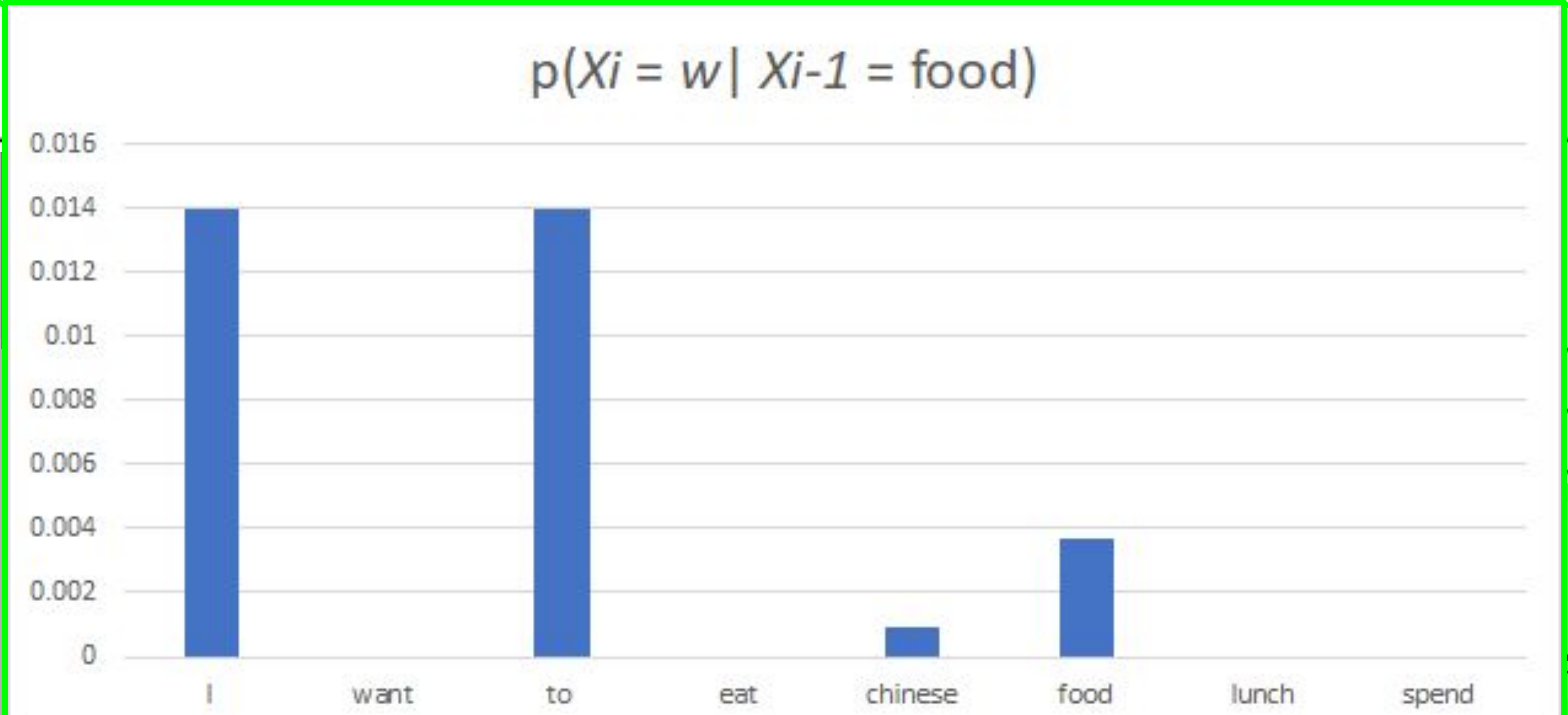
P(Xi | Xi-1)

	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								7
eat								
chin								
food								
lunc								
spen								



Need to estimate: *P(Xi | Xi-1)* = count(Xi-1 Xi) / count(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
								0
								0



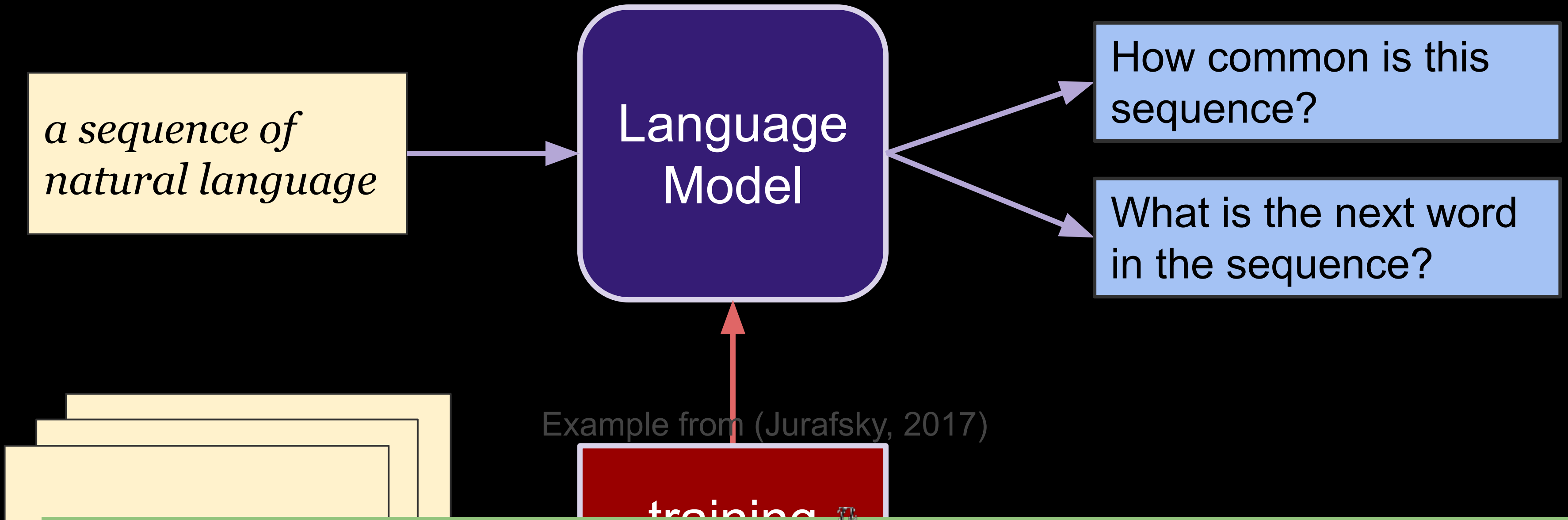
0
0
0

spend
278

:ount(Xi-1)

Language Modeling

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



a sequence of natural language

Language Model

How common is this sequence?

What is the next word in the sequence?

training

T

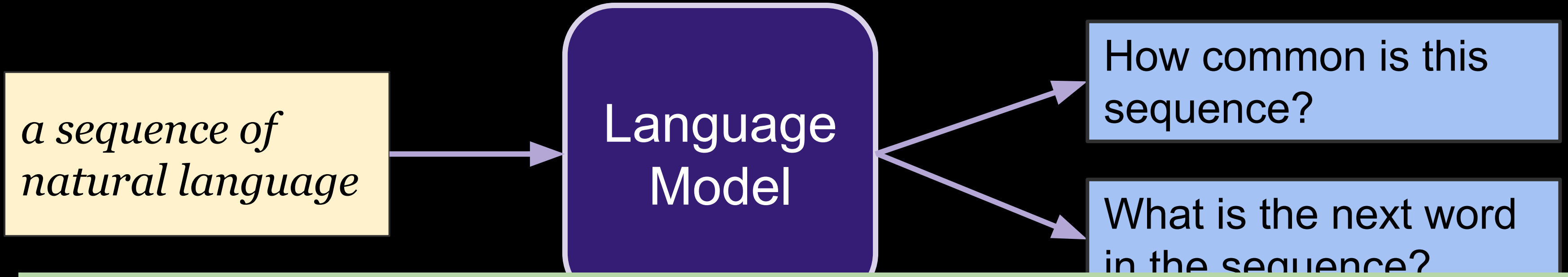
Example from (Jurafsky, 2017)

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

Need to estimate: *P(Xi | Xi-1)* = count(Xi-1 Xi) / count(Xi-1)

Language Modeling

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


a sequence of natural language
Language Model
How common is this sequence?
What is the next word in the sequence?

Trigram model: $P(X_1, X_2, \ldots, X_n) = \prod_{i=1}^{n} P(X_i | X_{i-2}, X_{i-1})$

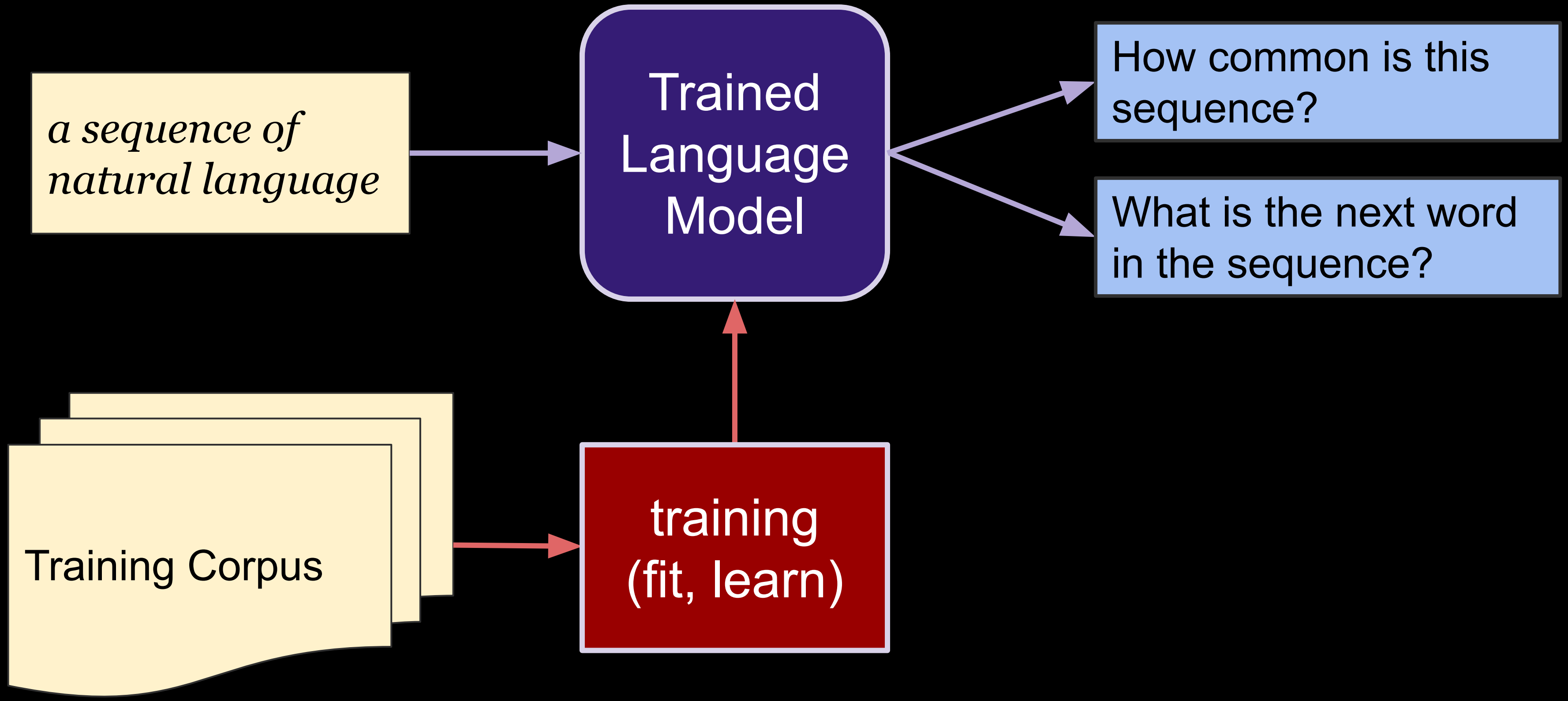
Need to estimate: *P(Xi | Xi-1, Xi-2)* = count(Xi-2 Xi-1 Xi) / count(Xi-2 Xi-1)

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)

Language Modeling

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



a sequence of natural language

Trained Language Model

How common is this sequence?

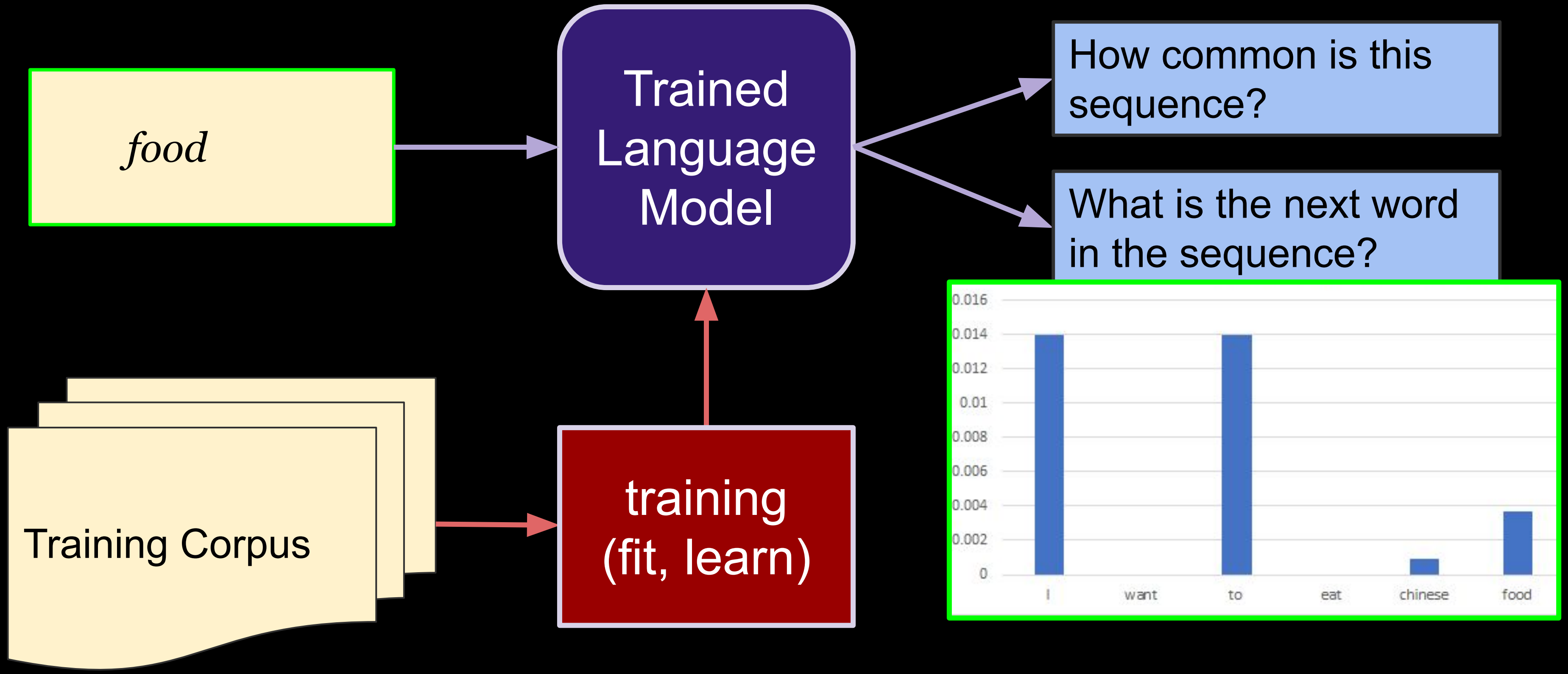
What is the next word in the sequence?

Training Corpus

training (fit, learn)

Language Modeling

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



food

Trained Language Model

How common is this sequence?

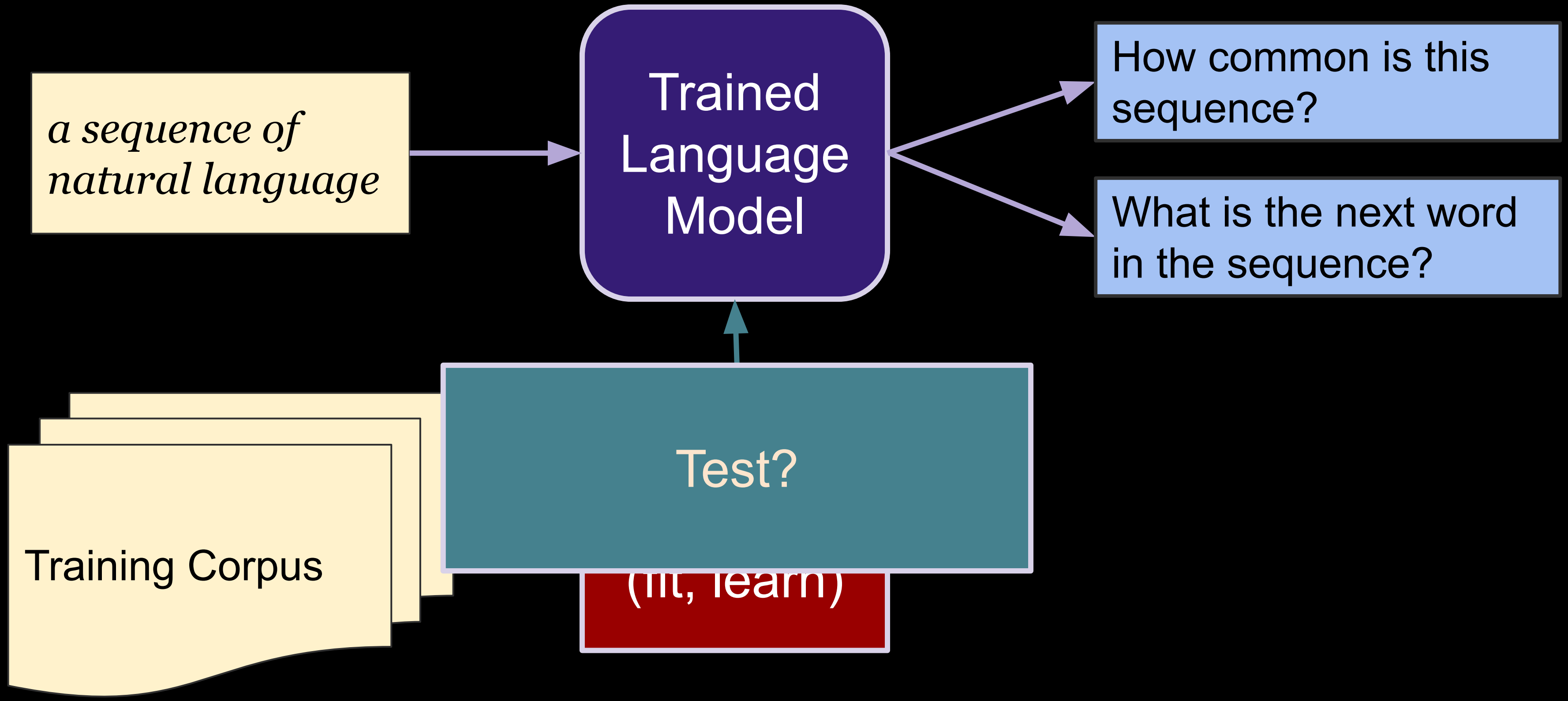
What is the next word in the sequence?

Training Corpus

training (fit, learn)

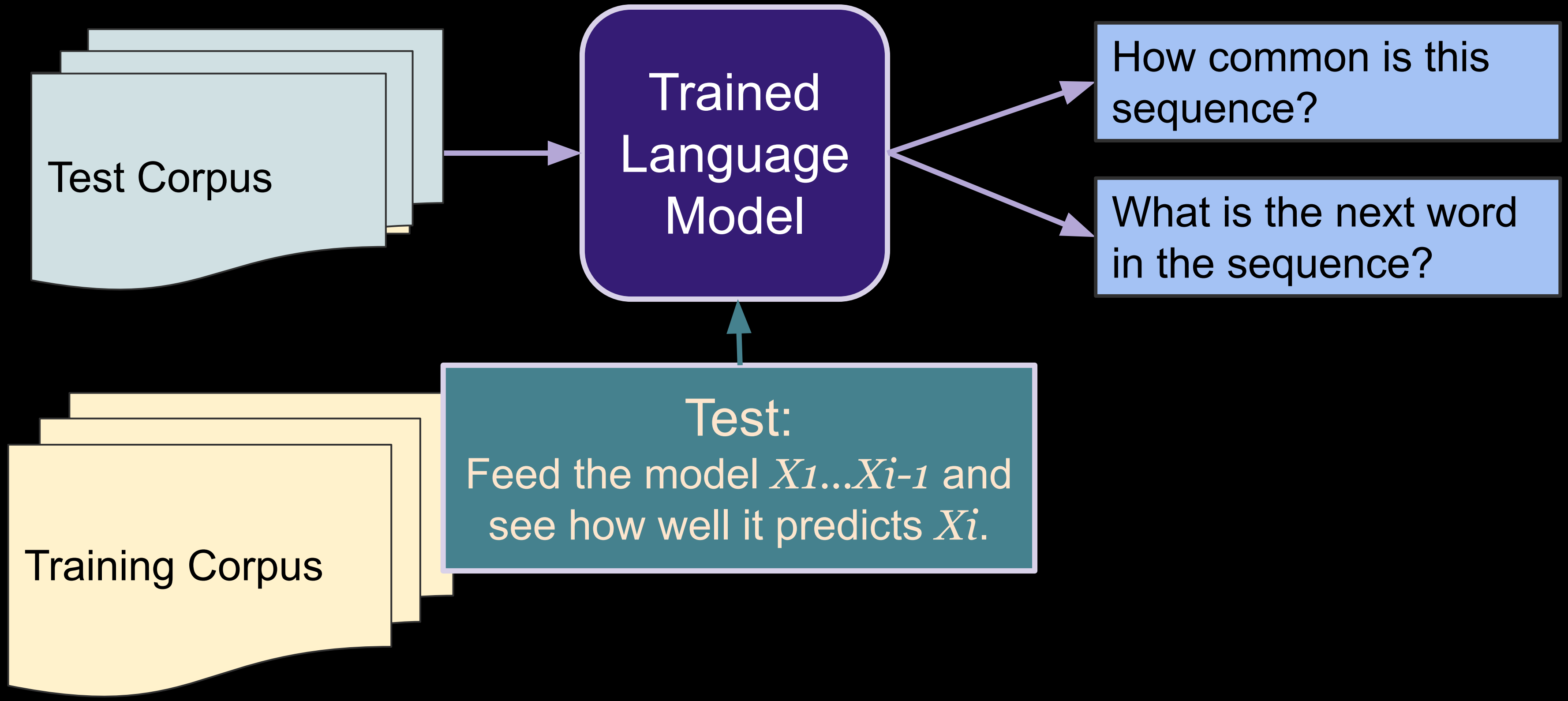
Language Modeling

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


a sequence of natural language
Trained Language Model
How common is this sequence?
What is the next word in the sequence?
Training Corpus
Test?
(fit, learn)

Language Modeling

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



Test Corpus

Trained Language Model

How common is this sequence?

What is the next word in the sequence?

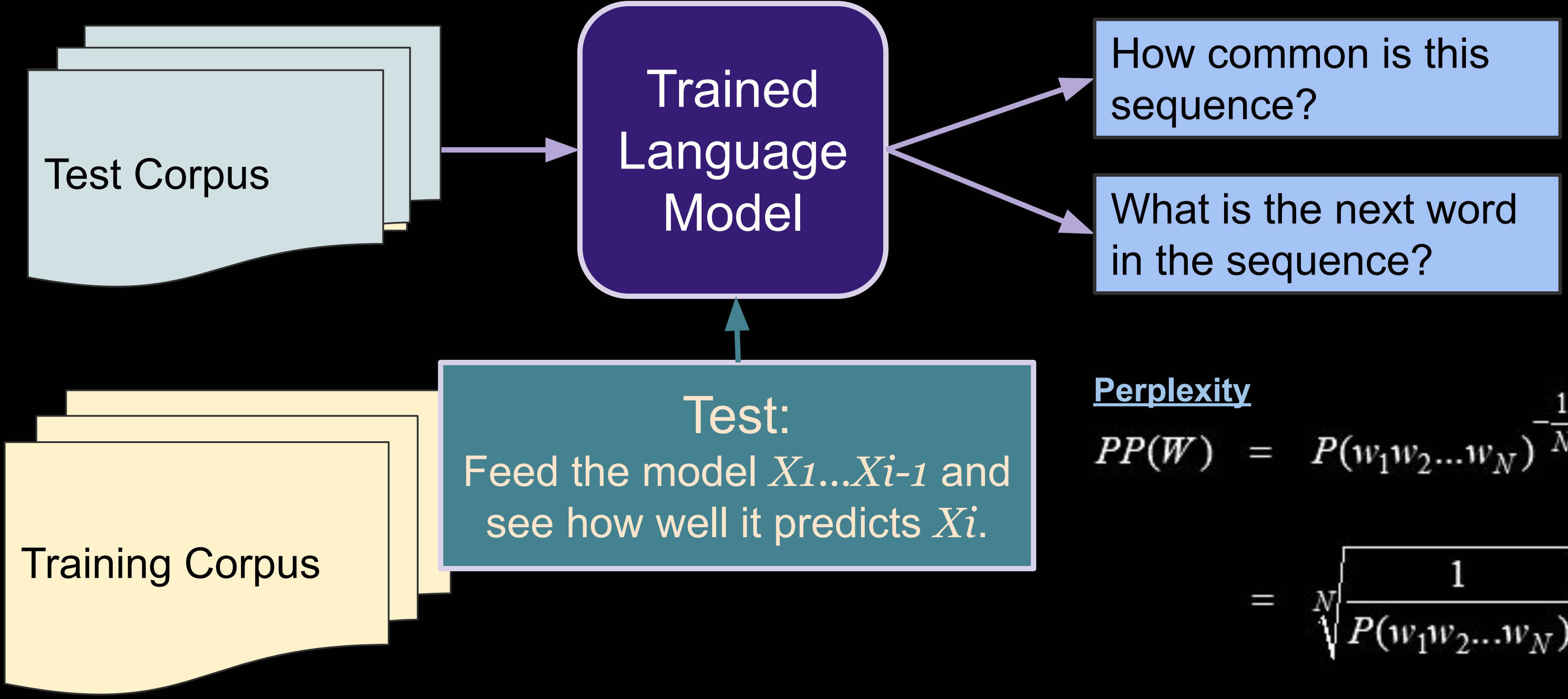
Training Corpus

Test:

Feed the model $X_1 \ldots X_{i-1}$ and see how well it predicts X_i.

Language Modeling

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



Test Corpus

Trained Language Model

How common is this sequence?

What is the next word in the sequence?

Training Corpus

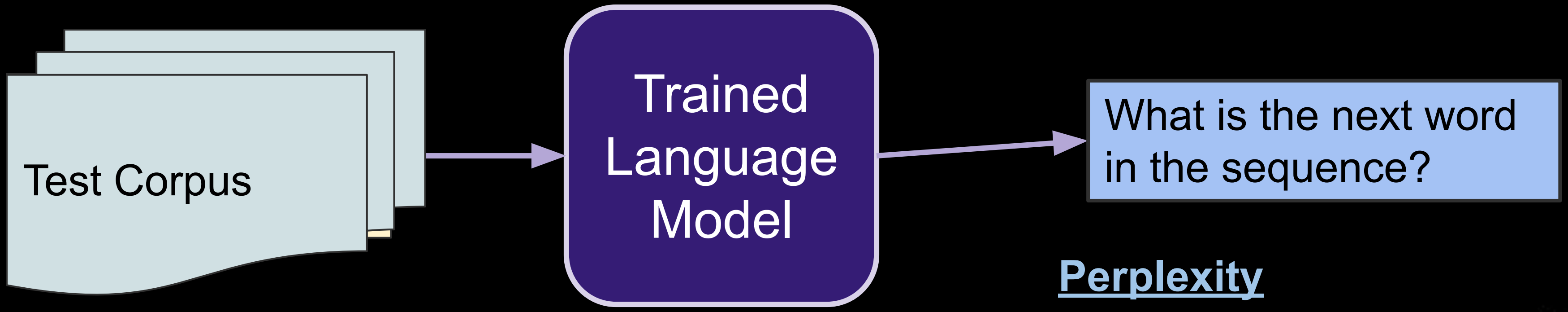
Test:
Feed the model *X1...Xi-1* and see how well it predicts *Xi*.

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

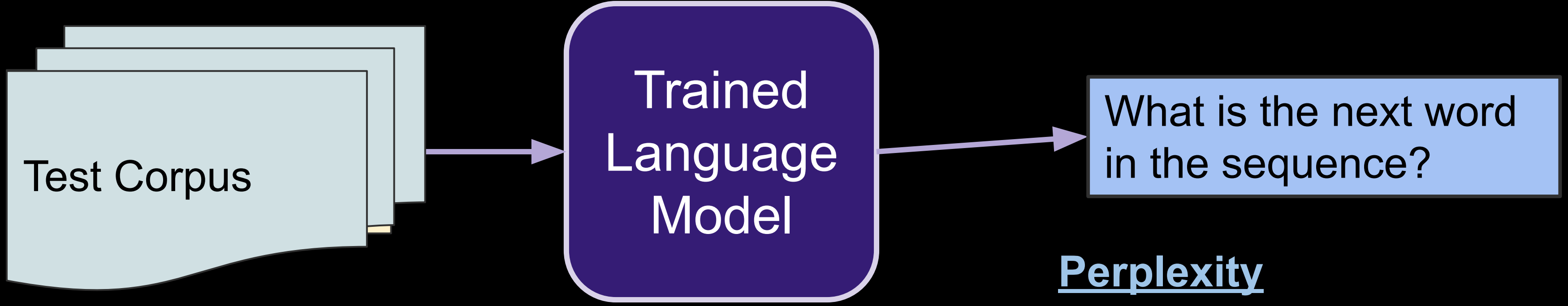


Perplexity

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

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

Evaluation



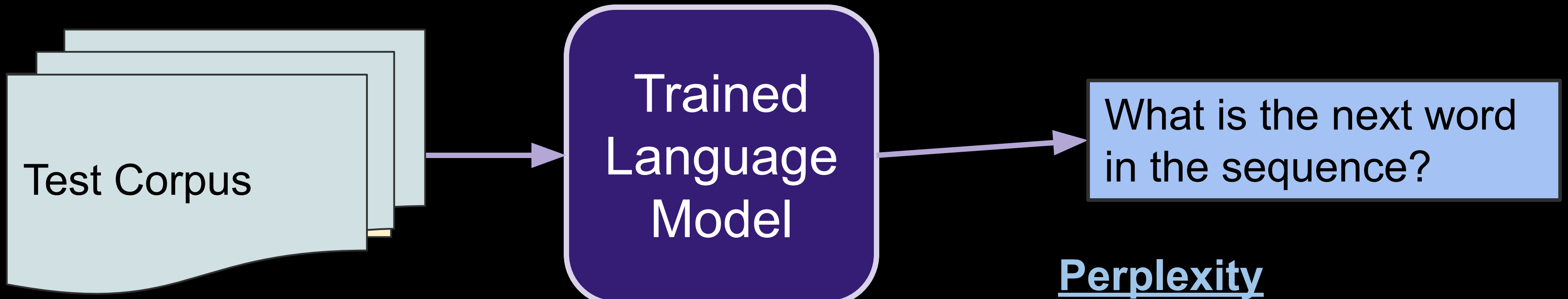
Perplexity

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

$$PP(W) = P(w1w2w3...wN)^{1/N}$$

$$= \sqrt[N]{\frac{1}{P(w1w2w3...wN)}}$$

Evaluation



Test Corpus

Trained Language Model

What is the next word in the sequence?

Perplexity

$$PP(W) = P(w1w2w3...wN)^{1/N}$$

$$= \sqrt[N]{\frac{1}{P(w1w2w3...wN)}}$$

Apply Chain Rule:

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

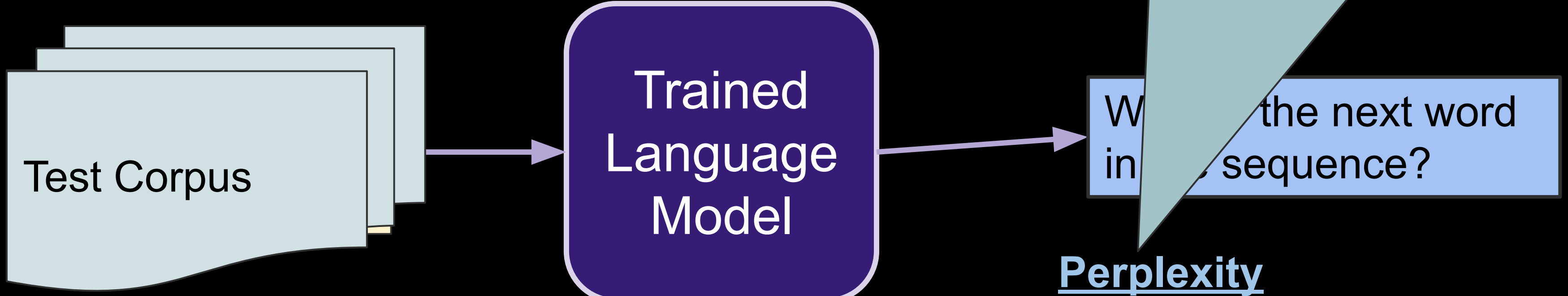
Thus,
PP for Bigrams:

$$\text{PP}(W) = \sqrt[N]{\prod_{i=1}^{N} \frac{1}{P(w_i|w_{i-1})}}$$

Evaluation

Reasoning:

1) Inverse of probability
(i.e. minimize perplexity = maximize likelihood)
2) (weighted) average branching factor



Test Corpus

Trained Language Model

W the next word
in sequence?

Perplexity

$$PP(W) = P(w1w2w3...wN)^{1/N}$$

$$= \sqrt[N]{\frac{1}{P(w1w2w3...wN)}}$$

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

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

Practical Considerations:

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

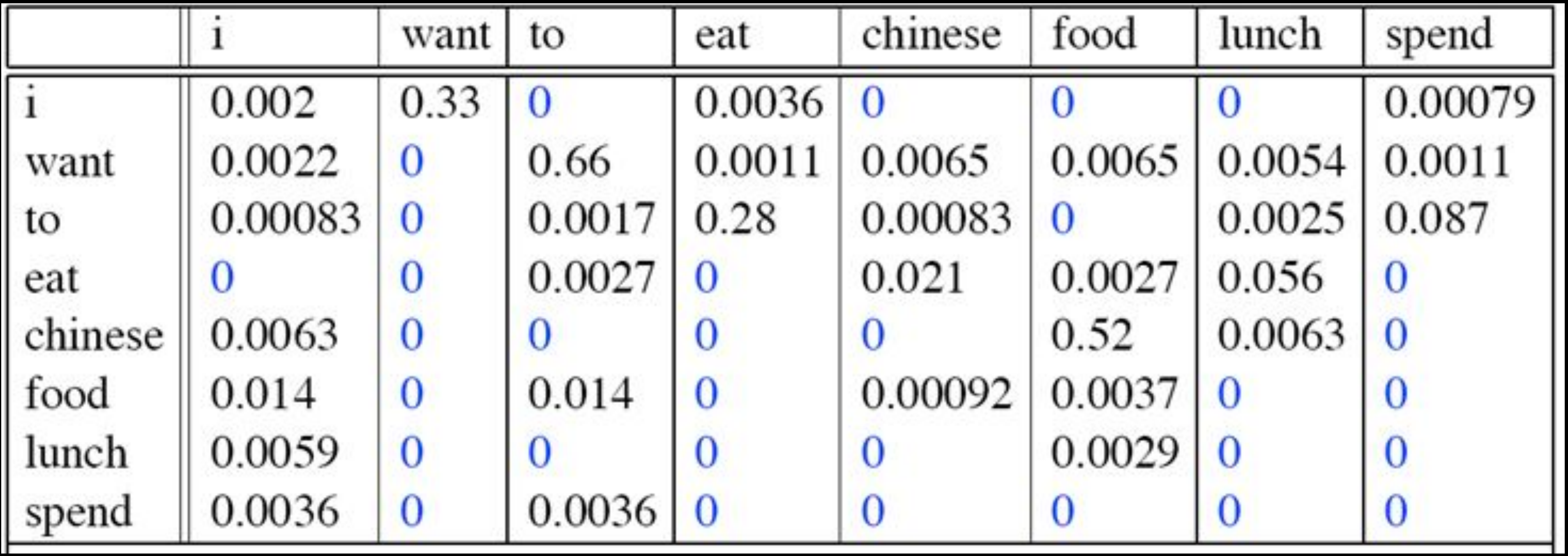
- Out-of-vocabulary (OOV)
  Choose minimum frequency and mark as <OOV>

- Sentence start and end: *<s> this is a sentence </s>*
  Advantage: models word probability at beginning or end.

Zeros and Smoothing

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

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



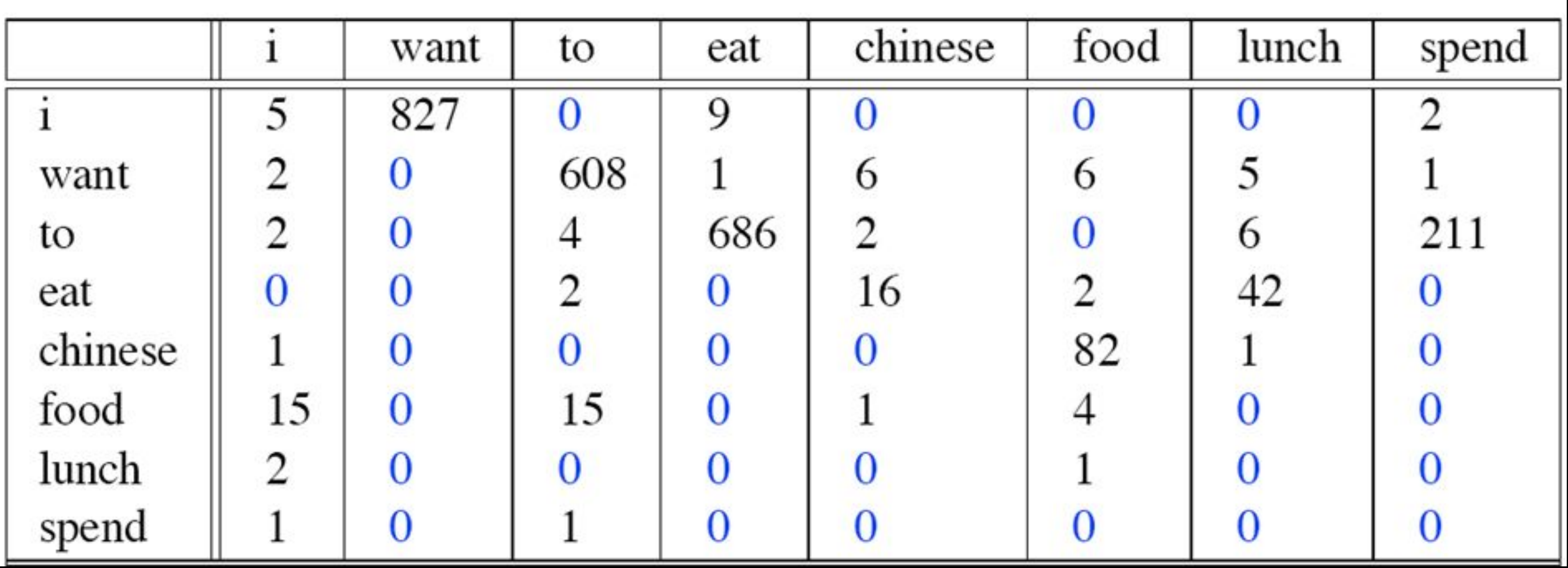
	i	want	to	eat	chinese	food	lunch	spend
i	0.002	0.33	0	0.0036	0	0	0	0.00079
want	0.0022	0	0.66	0.0011	0.0065	0.0065	0.0054	0.0011
to	0.00083	0	0.0017	0.28	0.00083	0	0.0025	0.087
eat	0	0	0.0027	0	0.021	0.0027	0.056	0
chinese	0.0063	0	0	0	0	0.52	0.0063	0
food	0.014	0	0.014	0	0.00092	0.0037	0	0
lunch	0.0059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

Example from (Jurafsky, 2017)

Zeros and Smoothing

first word \ second word

Bigram Counts



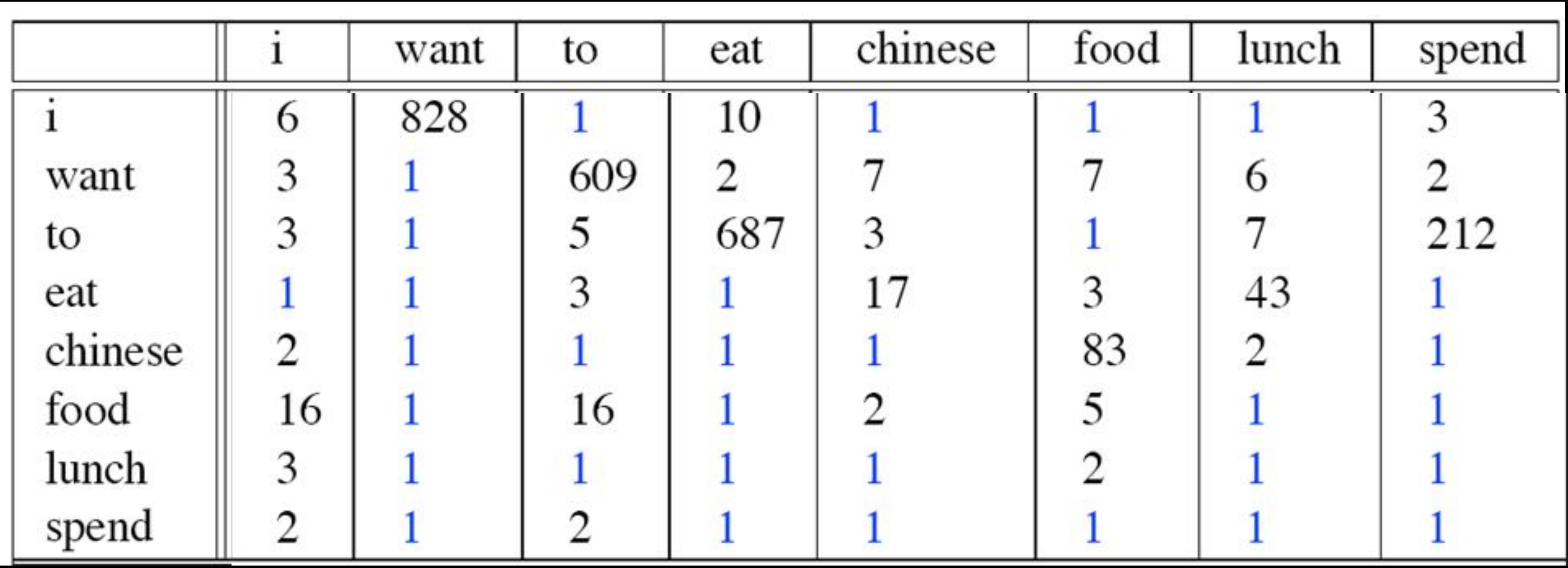
	i	want	to	eat	chinese	food	lunch	spend
i	5	827	0	9	0	0	0	2
want	2	0	608	1	6	6	5	1
to	2	0	4	686	2	0	6	211
eat	0	0	2	0	16	2	42	0
chinese	1	0	0	0	0	82	1	0
food	15	0	15	0	1	4	0	0
lunch	2	0	0	0	0	1	0	0
spend	1	0	1	0	0	0	0	0

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

Zeros and Smoothing

first word \ second word

Bigram Counts



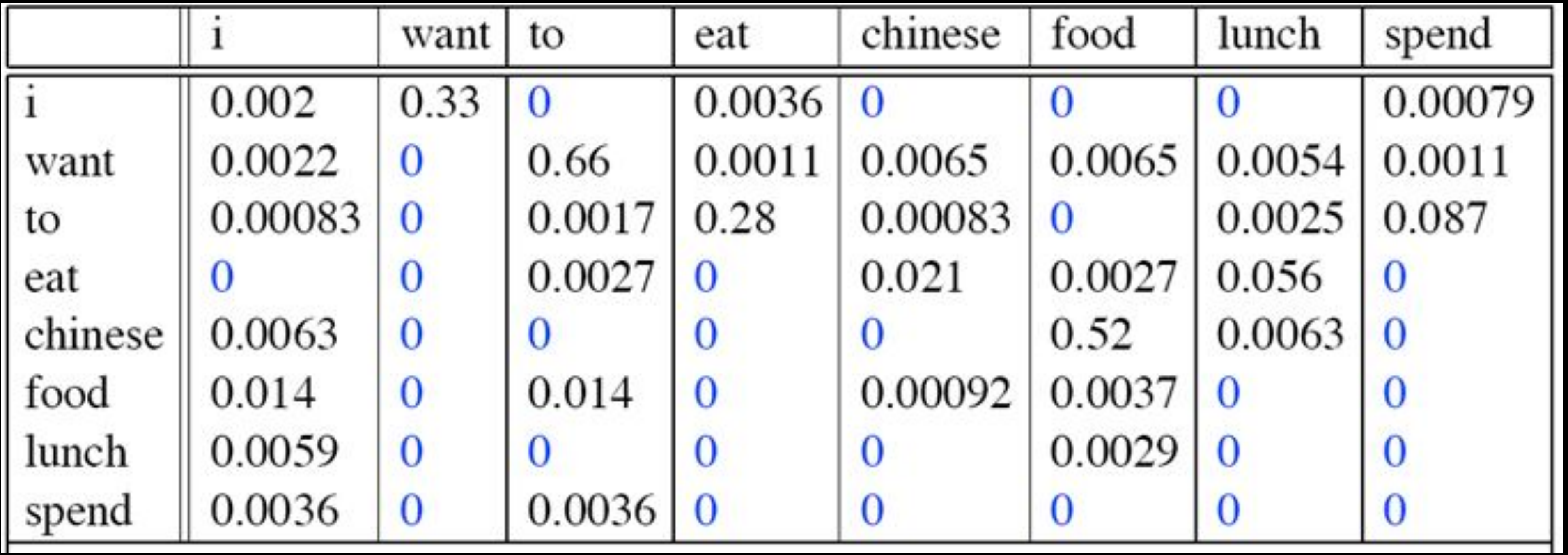
	i	want	to	eat	chinese	food	lunch	spend
i	6	828	1	10	1	1	1	3
want	3	1	609	2	7	7	6	2
to	3	1	5	687	3	1	7	212
eat	1	1	3	1	17	3	43	1
chinese	2	1	1	1	1	83	2	1
food	16	1	16	1	2	5	1	1
lunch	3	1	1	1	1	2	1	1
spend	2	1	2	1	1	1	1	1

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

Unsmoothed probs

first word(X_{i-1}) \ second word (X_i)

$P(X_i \mid X_{i-1})$



	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
spend	0.0036	0	0.0036	0	0	0	0	0

Example from (Jurafsky, 2017)

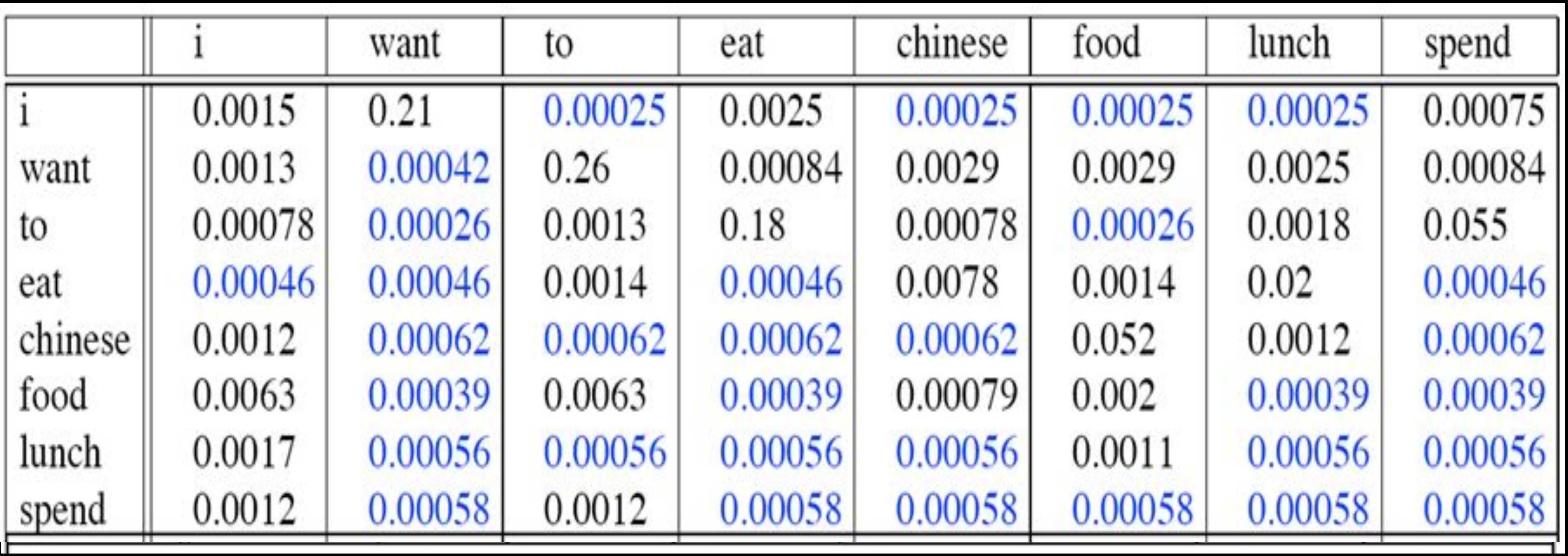
Smoothed

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

(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

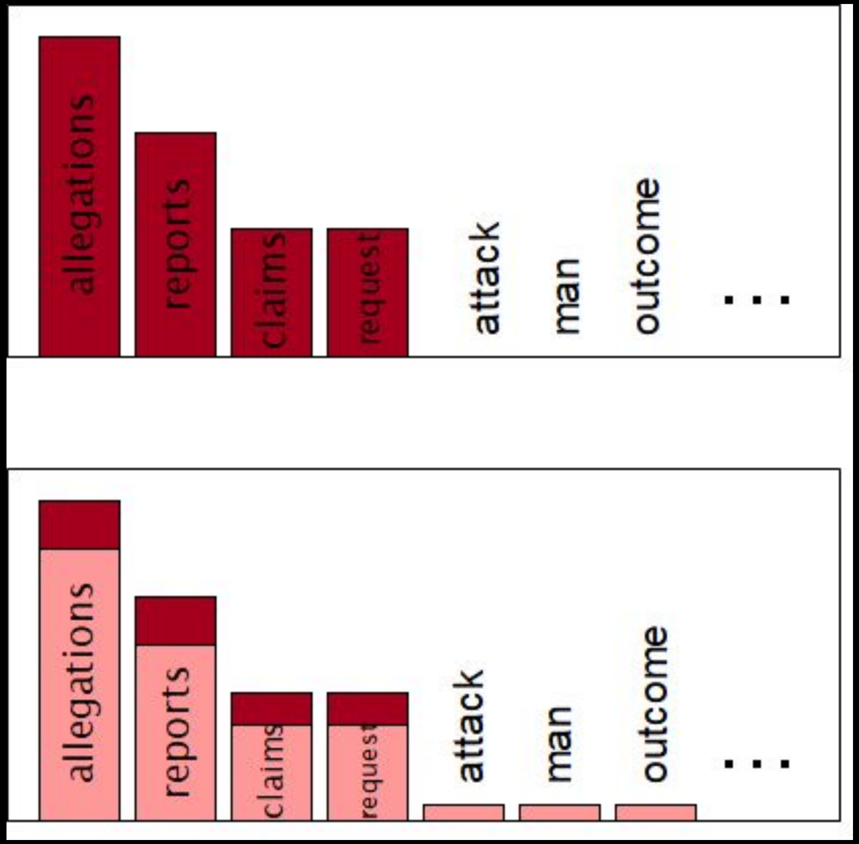
Example from (Jurafsky, 2017)

Why Smoothing? Generalizes

Original

With Smoothing

(Example from Jurafsky / Originally Dan Klein)



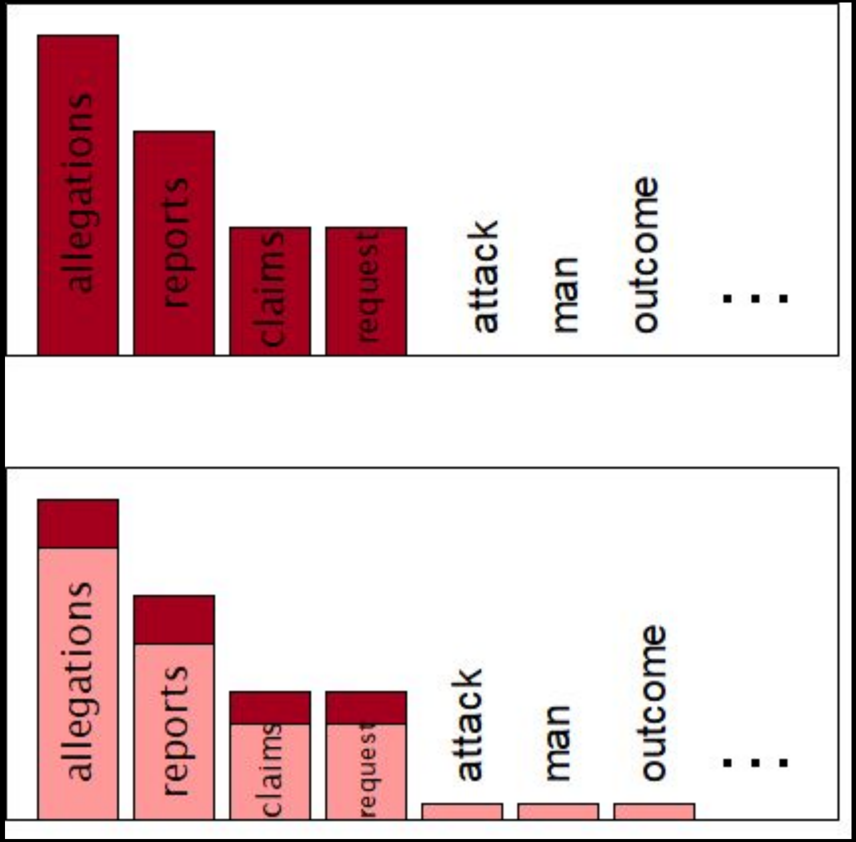
Why Smoothing? Generalizes

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

More Advanced:

Good-Turing Smoothing
Kneser-Nay Smoothing

These are outside scope for now.
We will eventually cover, even stronger, deep learning based models.



Why Smoothing?

What about Logistic Regression? Y = next word

P(Y|X) = P(Xn | Xn-1, Xn-2, Xn-3, ...)

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

Why Smoothing?

What about Logistic Regression? Y = next word

P(Y|X) = P(Xn | Xn-1, Xn-2, Xn-3, ...)

Not a terrible option, but Xn-1 through Xn-k would be modeled as independent dimensions. Let’s revisit later. Could use:

P(Xn | Xn-1, [Xn-1 Xn-2], [Xn-1 Xn-2 Xn-3], ...)

Example how to produce language generator

1. Count unigrams, bigrams, and trigrams
2. Train probabilities for unigram, bigram, and trigram models (over training)
    a. with smoothing
    b. without smoothing
3. Generate language: Given previous word or previous 2 words, take a random draw from what words are most likely to be next.

Trigram model when good evidence (high counts)

Backing off to bigram or even unigram

Limitation: Long distance dependencies

The horse which was raced past the barn tripped .

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