Introduction to
Artificial Intelligence
with Python

Language

Natural Language Processing

Natural Language Processing

- automatic summarization
- information extraction
- machine translation
- question answering
- text classification
- ...

Syntax

"Just before nine o'clock Sherlock Holmes stepped briskly into the room."

"Just before Sherlock Holmes nine o'clock stepped briskly the room."

"I saw the man on the mountain with a telescope."

Semantics

"Just before nine o'clock Sherlock Holmes stepped briskly into the room."

"A few minutes before nine, Sherlock Holmes walked quickly into the room."

"Colorless green ideas sleep furiously."

Natural Language Processing

formal grammar

a system of rules for generating sentences
in a language

Context-Free Grammar

she saw the city

N	V	D	N
she	saw	the	city

N → she | city | car | Harry | ...

D → the | a | an | ...

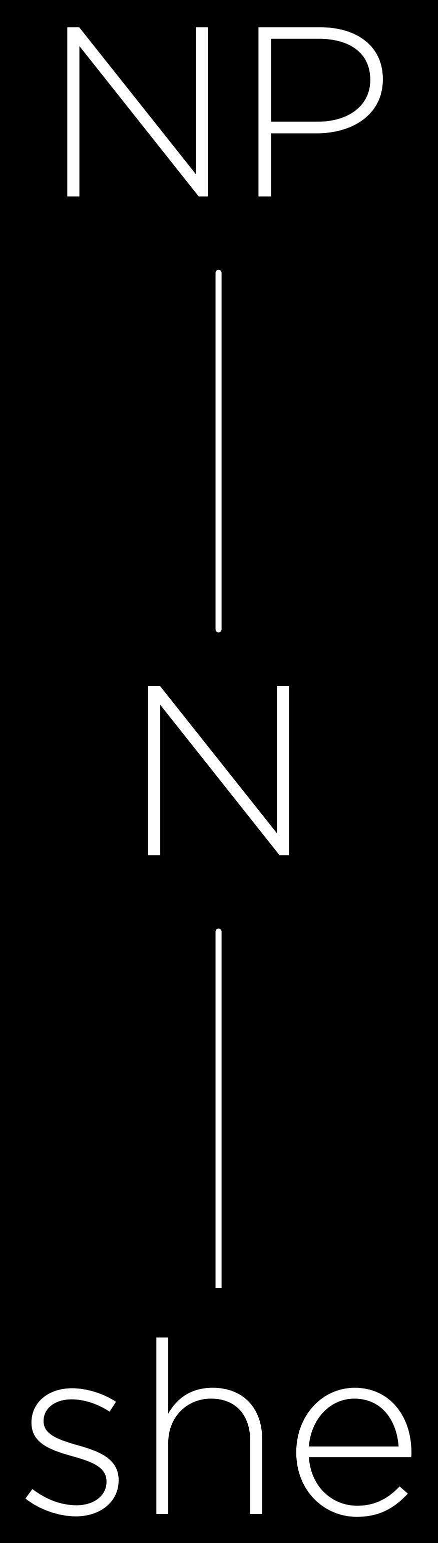
V → saw | ate | walked | ...

P → to | on | over | ...

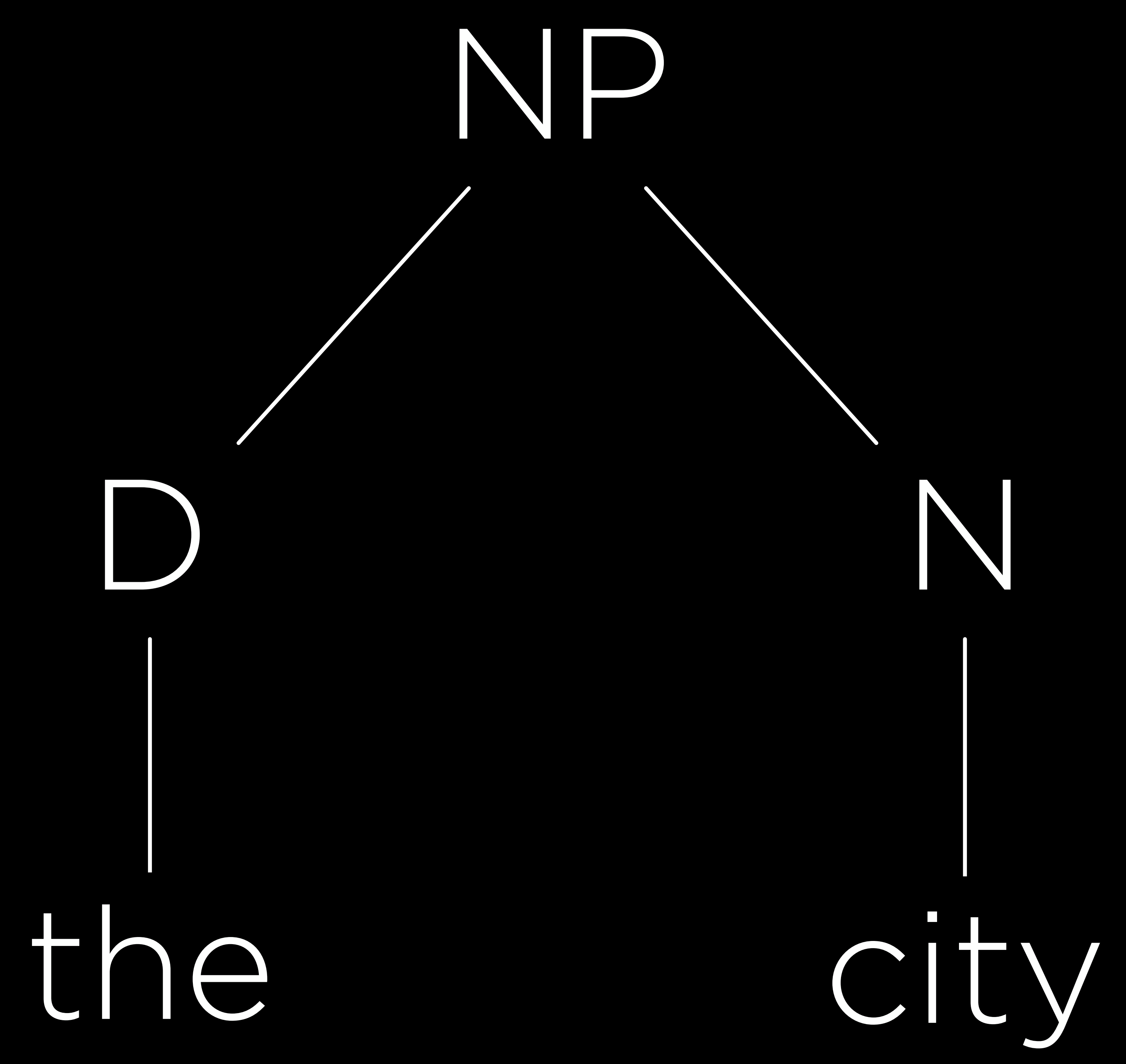
ADJ → blue | busy | old | ...

$$NP \rightarrow N \mid D\ N$$

```
NP → N | D N
```

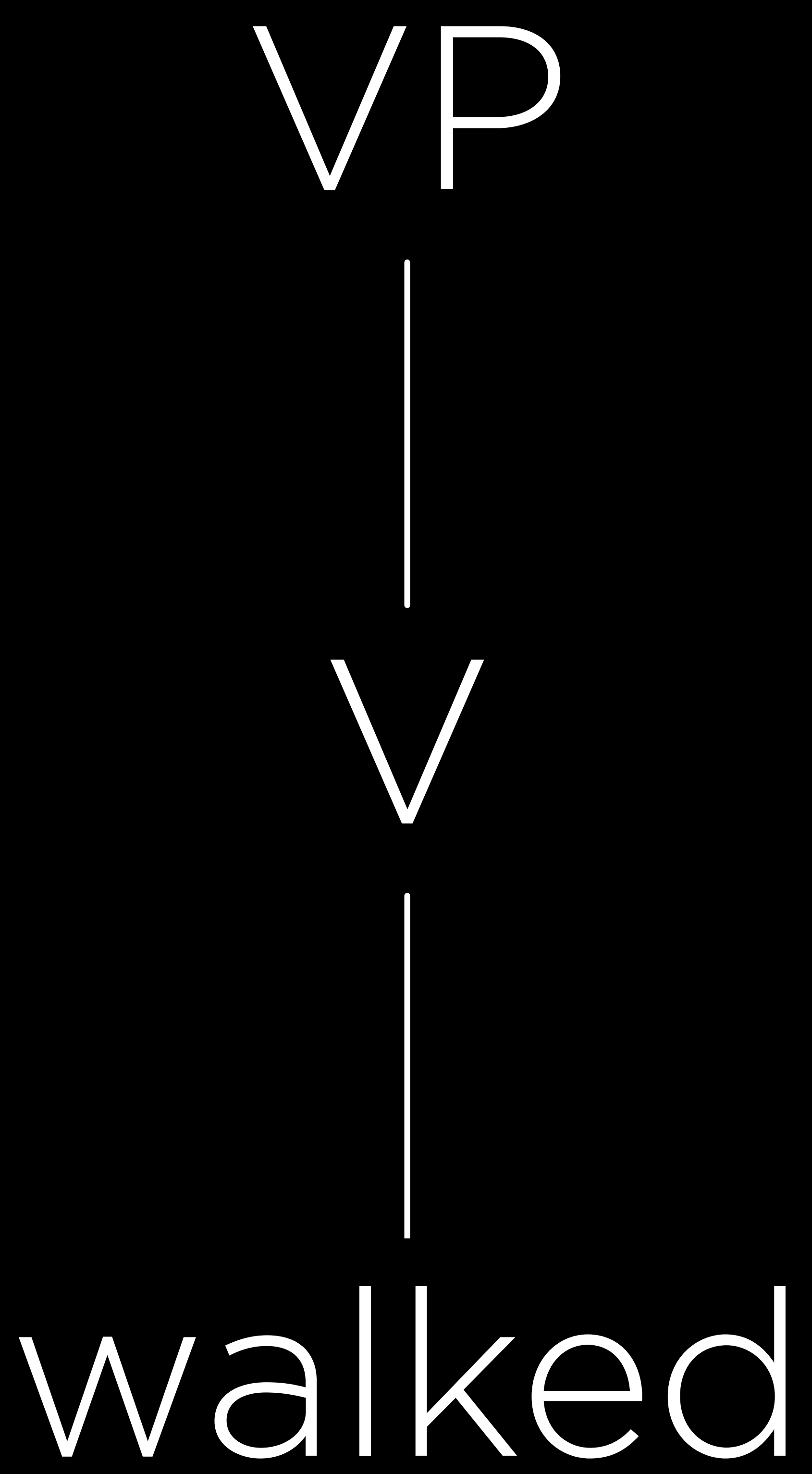


$$NP \rightarrow N \mid D\ N$$

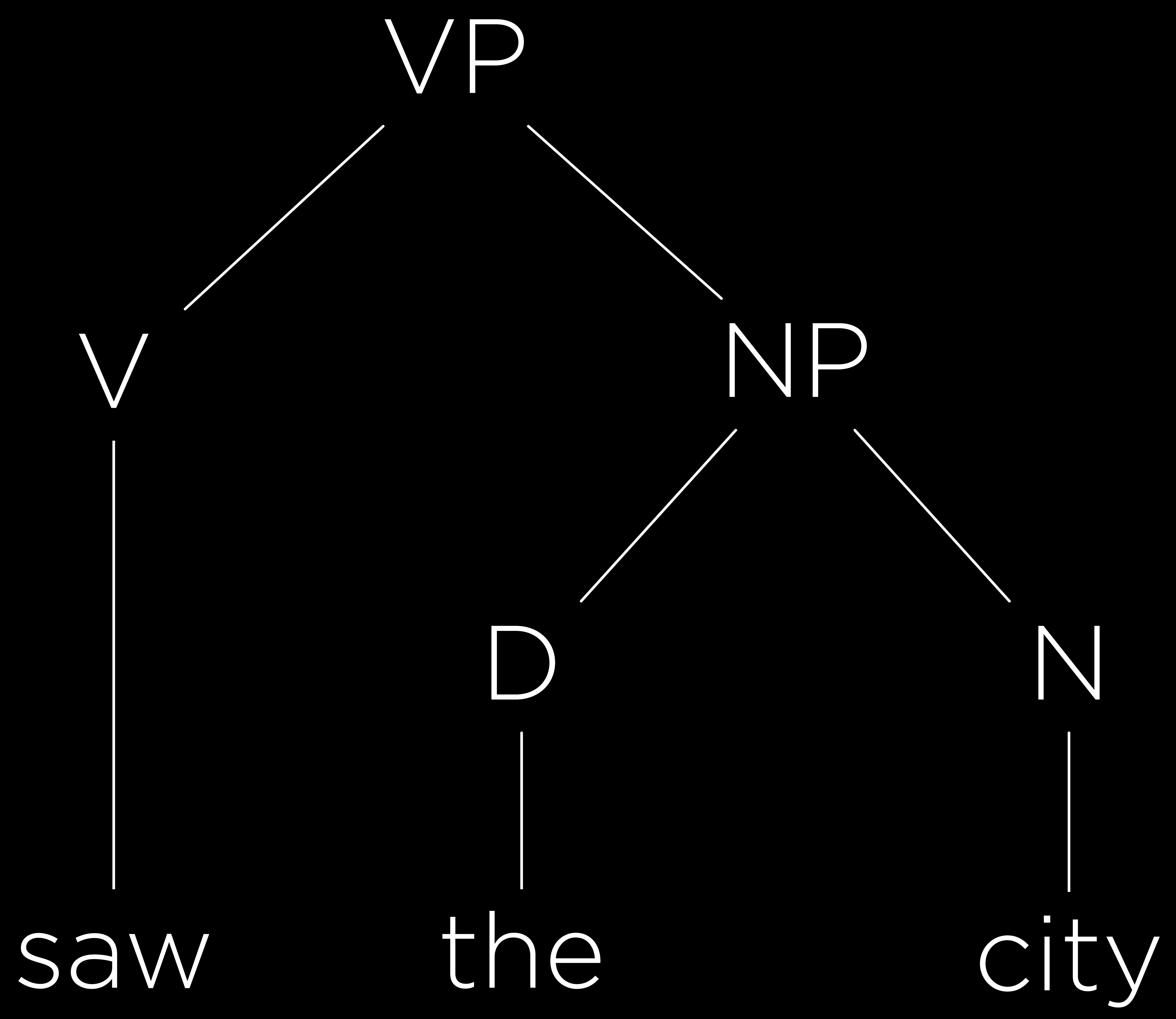


$$VP \rightarrow V \mid V\ NP$$

$$VP \rightarrow V \mid V\ NP$$

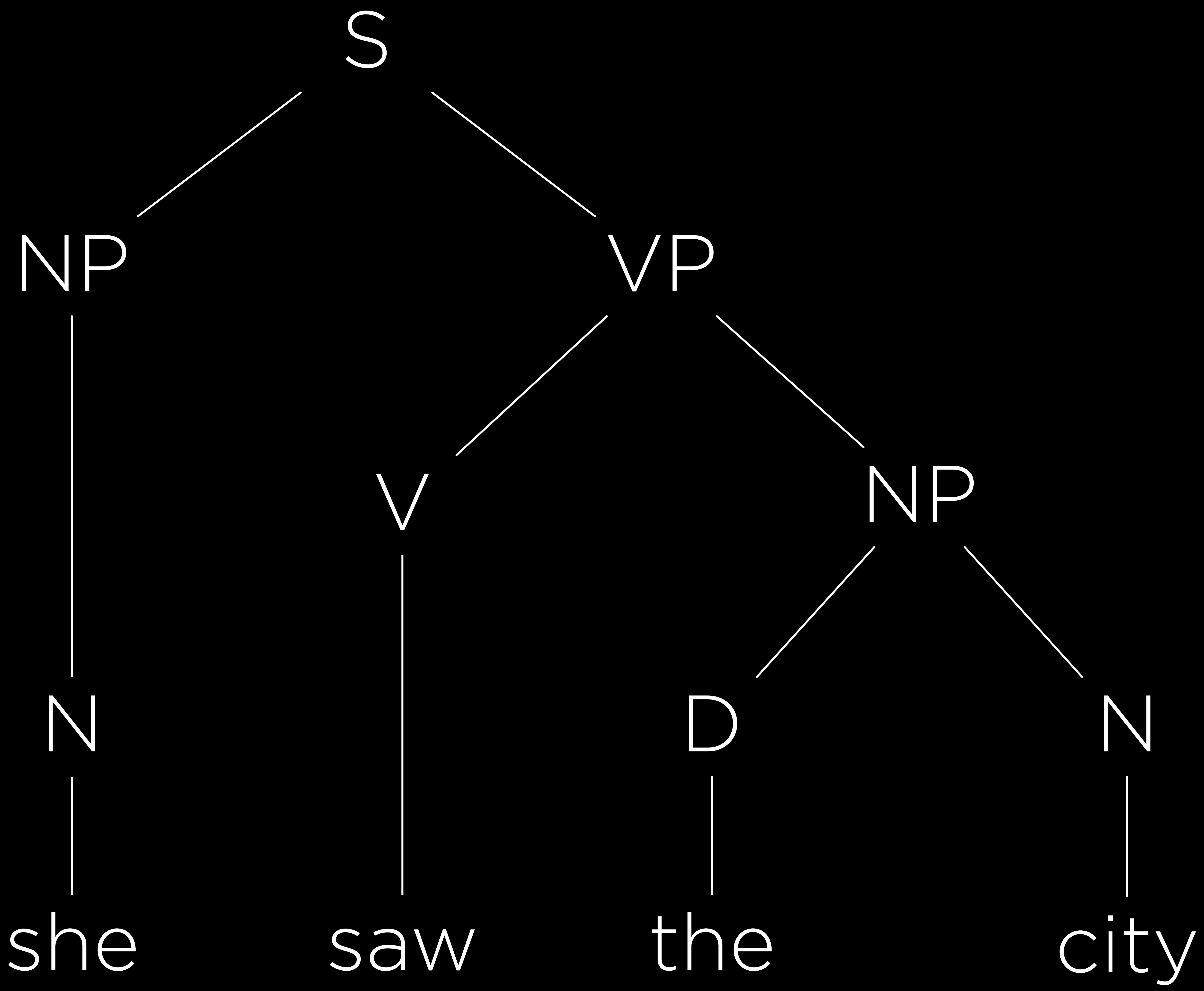


$$VP \rightarrow V \mid V\ NP$$



$S \rightarrow NP\ VP$

S → NP VP



nltk

n-gram

a contiguous sequence of n items
from a sample of text

"How often have I said to you that when you have eliminated the impossible whatever remains, however improbable, must be the truth?"

"**How often have** I said to you that when you have eliminated the impossible whatever remains, however improbable, must be the truth?"

"How **often have I** said to you that when you have eliminated the impossible whatever remains, however improbable, must be the truth?"

"How often **have I said** to you that when you have eliminated the impossible whatever remains, however improbable, must be the truth?"

"How often have **I said to** you that when you have eliminated the impossible whatever remains, however improbable, must be the truth?"

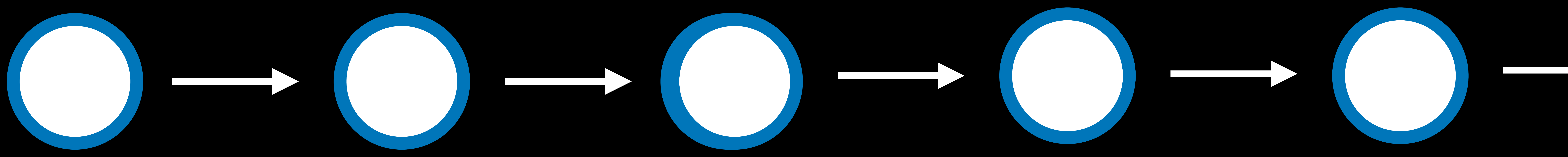
"How often have I **said to you** that when you have eliminated the impossible whatever remains, however improbable, must be the truth?"

"How often have I said **to you that** when you have eliminated the impossible whatever remains, however improbable, must be the truth?"

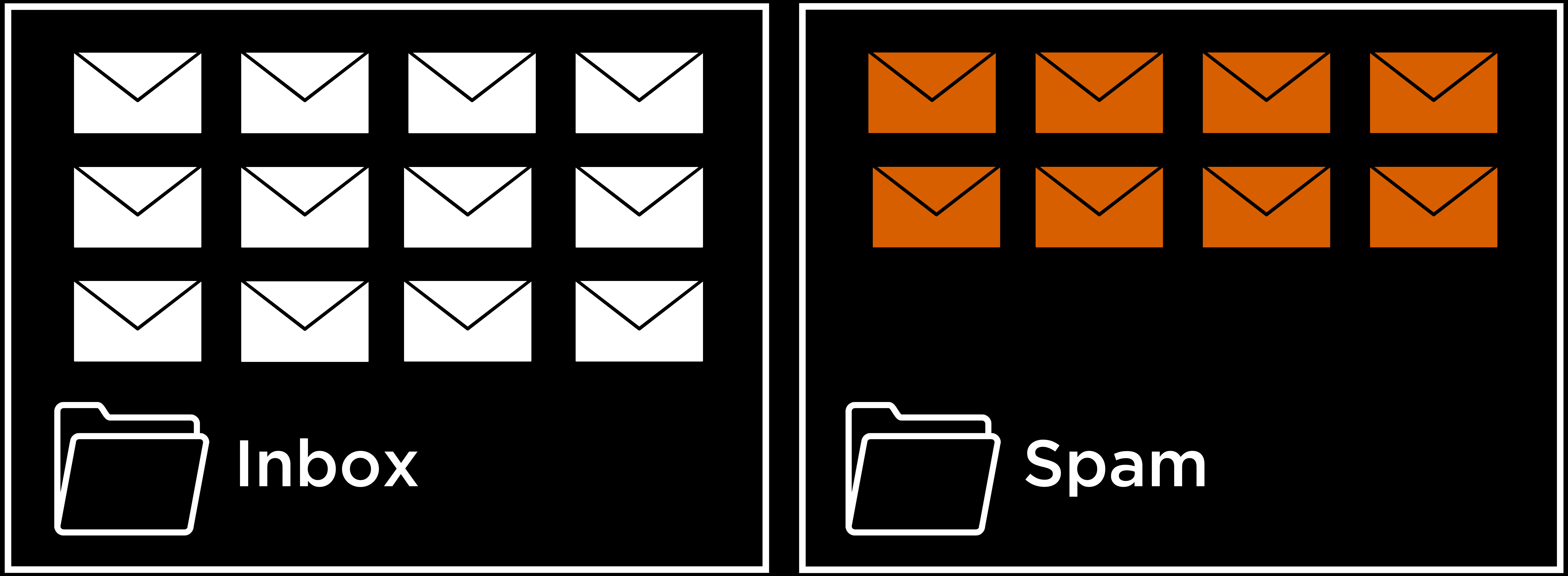
tokenization

the task of splitting a sequence of characters into pieces (tokens)

Markov Chains



Text Categorization


Inbox
Spam

"My grandson loved it! So much fun!"

"Product broke after a few days."

"One of the best games I've played in a long time."

"Kind of cheap and flimsy, not worth it."

😀 "My grandson loved it! So much fun!"

🙁 "Product broke after a few days."

😀 "One of the best games I've played in a long time."

🙁 "Kind of cheap and flimsy, not worth it."

😀 "My grandson **loved** it! So much **fun**!"

🙁 "Product **broke** after a few days."

😀 "One of the **best** games I've played in a long time."

🙁 "Kind of **cheap** and **flimsy**, not worth it."

bag-of-words model

model that represents text as an unordered collection of words

Naive Bayes

Bayes' Rule

$$P(b \quad a) = \frac{P(a \quad b)\, P(b)}{P(a)}$$

$$P(\text{Positive})$$

$$P(\text{Negative})$$

$$P(\text{😀})$$

$$P(\text{🙁})$$

"My grandson loved it!"

P(😀)

$P($😀$\mid$ "my grandson loved it"$)$

$$P(\text{😀} \mid \text{"my"}, \text{"grandson"}, \text{"loved"}, \text{"it"})$$

$$P(\text{😀} \mid \text{"my"}, \text{"grandson"}, \text{"loved"}, \text{"it"})$$

$$P(\text{😀} \mid \text{"my"}, \text{"grandson"}, \text{"loved"}, \text{"it"})$$

equal to

$$\frac{P(\text{"my"}, \text{"grandson"}, \text{"loved"}, \text{"it"} \mid \text{😀})\, P(\text{😀})}{P(\text{"my"}, \text{"grandson"}, \text{"loved"}, \text{"it"})}$$

the denominator can be ignored since the probability that all those words appear in the review doesn't depend on whether we are looking at the positive or negative sentiment case

$$P(\text{😀} \mid \text{"my"}, \text{"grandson"}, \text{"loved"}, \text{"it"})$$

proportional to

$$P(\text{"my"}, \text{"grandson"}, \text{"loved"}, \text{"it"} \mid \text{😀})\, P(\text{😀})$$

which will later be normalized

$$P(\text{😀} \mid \text{"my"}, \text{"grandson"}, \text{"loved"}, \text{"it"})$$

proportional to

can be rewritten as joint probability

$$P(\text{😀}, \text{"my"}, \text{"grandson"}, \text{"loved"}, \text{"it"})$$

P(😀 | "my", "grandson", "loved", "it")

naively proportional to

if we assume all words are independent, we can rewrite as

P(😀)*P*("my" | 😀)*P*("grandson" | 😀)
P("loved" | 😀) *P*("it" | 😀)

each word is dependent on sentiment

$$P(\text{😀}) = \frac{\text{number of positive samples}}{\text{number of total samples}}$$

$$P(\text{"loved"} \mid \text{😀}) = \frac{\text{number of positive samples with "loved"}}{\text{number of positive samples}}$$

$P(😀)P(\text{"my"} \mid 😀)P(\text{"grandson"} \mid 😀)$
$P(\text{"loved"} \mid 😀)\ P(\text{"it"} \mid 😀)$

😀	🙁
0.49	0.51

	😀	🙁
my	0.30	0.20
grandson	0.01	0.02
loved	0.32	0.08
it	0.30	0.40

$P(😀)P(\text{"my"} \mid 😀)P(\text{"grandson"} \mid 😀)$
$P(\text{"loved"} \mid 😀)\ P(\text{"it"} \mid 😀)$

😀	🙁
0.49	0.51

	😀	🙁
my	0.30	0.20
grandson	0.01	0.02
loved	0.32	0.08
it	0.30	0.40

$$P(😀)P(\text{"my"} \mid 😀)P(\text{"grandson"} \mid 😀)$$
$$P(\text{"loved"} \mid 😀)\ P(\text{"it"} \mid 😀)$$

😀	🙁
0.49	0.51

😀 0.00014112

	😀	🙁
my	0.30	0.20
grandson	0.01	0.02
loved	0.32	0.08
it	0.30	0.40

$P($😀$)P(\text{"my"} \mid$ 😀$)P(\text{"grandson"} \mid$ 😀$)$
$P(\text{"loved"} \mid$ 😀$)\ P(\text{"it"} \mid$ 😀$)$

😀	🙁
0.49	0.51

😀 0.00014112

	😀	🙁
my	0.30	0.20
grandson	0.01	0.02
loved	0.32	0.08
it	0.30	0.40

P(🙁)*P*("my" | 🙁)*P*("grandson" | 🙁)
P("loved" | 🙁) *P*("it" | 🙁)

😀	🙁
0.49	0.51

	😀	🙁
my	0.30	0.20
grandson	0.01	0.02
loved	0.32	0.08
it	0.30	0.40

😀 0.00014112

P(🙁)P("my" | 🙁)P("grandson" | 🙁)
P("loved" | 🙁) P("it" | 🙁)

😀	🙁
0.49	0.51

😀 0.00014112

	😀	🙁
my	0.30	0.20
grandson	0.01	0.02
loved	0.32	0.08
it	0.30	0.40

P(🙁)*P*("my" | 🙁)*P*("grandson" | 🙁)
P("loved" | 🙁) *P*("it" | 🙁)

😀	🙁
0.49	0.51

😀 0.00014112

🙁 0.00006528

	😀	🙁
my	0.30	0.20
grandson	0.01	0.02
loved	0.32	0.08
it	0.30	0.40

P(🙁)*P*("my" | 🙁)*P*("grandson" | 🙁)
P("loved" | 🙁) *P*("it" | 🙁)

😀	🙁
0.49	0.51

	😀	🙁
my	0.30	0.20
grandson	0.01	0.02
loved	0.32	0.08
it	0.30	0.40

😀 0.00014112

🙁 0.00006528

will normalize to...

P(🙁)*P*("my" | 🙁)*P*("grandson" | 🙁)
P("loved" | 🙁) *P*("it" | 🙁)

😀	🙁
0.49	0.51

😀 0.6837

🙁 0.3163

	😀	🙁
my	0.30	0.20
grandson	0.01	0.02
loved	0.32	0.08
it	0.30	0.40

$$P(\text{🙁})P(\text{"my"} \mid \text{🙁})P(\text{"grandson"} \mid \text{🙁})$$
$$P(\text{"loved"} \mid \text{🙁})\ P(\text{"it"} \mid \text{🙁})$$

😀	🙁
0.49	0.51

	😀	🙁
my	0.30	0.20
grandson	0.01	0.02
loved	0.32	0.08
it	0.30	0.40

P(🙁)*P*("my" | 🙁)*P*("grandson" | 🙁)
P("loved" | 🙁) *P*("it" | 🙁)

😀	🙁
0.49	0.51

	😀	🙁
my	0.30	0.20
grandson	0.00	0.02
loved	0.32	0.08
it	0.30	0.40

P(🙁)*P*("my" | 🙁)*P*("grandson" | 🙁)
P("loved" | 🙁) *P*("it" | 🙁)

😀	🙁
0.49	0.51

😀 0.00000000

🙁 0.00006528

	😀	🙁
my	0.30	0.20
grandson	0.00	0.02
loved	0.32	0.08
it	0.30	0.40

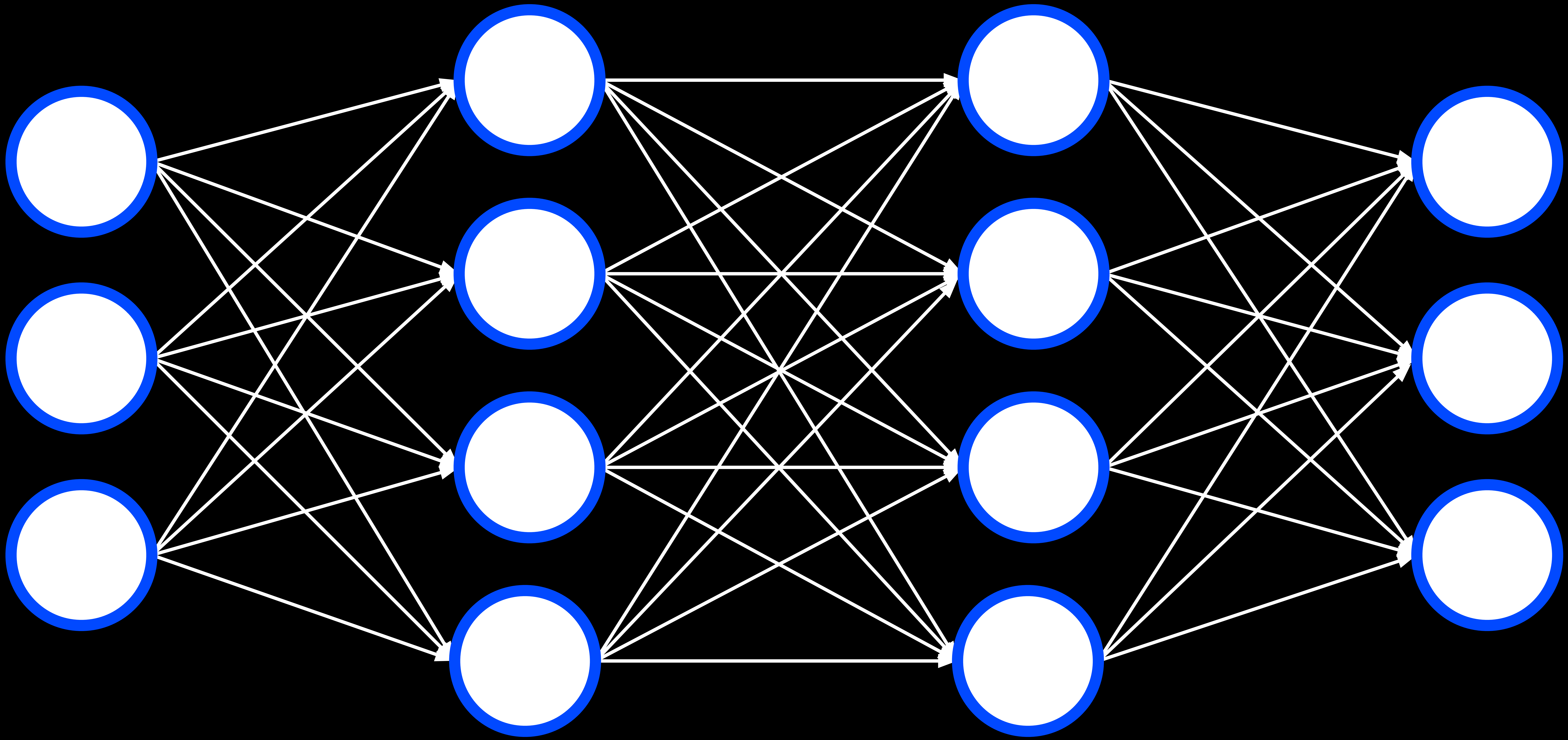
additive smoothing

adding a value α to each value in our distribution to smooth the data

Laplace smoothing

adding 1 to each value in our distribution: pretending we've seen each value one more time than we actually have

Word Representation



"He wrote a book."

```
he    [1, 0, 0, 0]
wrote [0, 1, 0, 0]
a     [0, 0, 1, 0]
book  [0, 0, 0, 1]
```

one-hot representation

representation of meaning as a vector with a single 1, and with other values as 0

"He wrote a book."

```
he    [1, 0, 0, 0]
wrote [0, 1, 0, 0]
a     [0, 0, 1, 0]
book  [0, 0, 0, 1]
```

"He wrote a book."

```
he    [1, 0, 0, 0, 0, 0, 0, ...]
wrote [0, 1, 0, 0, 0, 0, 0, ...]
a     [0, 0, 1, 0, 0, 0, 0, ...]
book  [0, 0, 0, 1, 0, 0, 0, ...]
```

"He wrote a book."

"He authored a novel."

```
wrote     [0, 1, 0, 0, 0, 0, 0, ...]
authored  [0, 0, 0, 0, 1, 0, 0, ...]

book      [0, 0, 0, 1, 0, 0, 0, ...]
novel     [0, 0, 0, 0, 0, 0, 1, ...]
```

distributed representation

representation of meaning distributed across multiple values

"He wrote a book."

```
he    [-0.34, -0.08, 0.02, -0.18, 0.22, ...]
wrote [-0.27, 0.40, 0.00, -0.65, -0.15, ...]
a     [-0.12, -0.25, 0.29, -0.09, 0.40, ...]
book  [-0.23, -0.16, -0.05, -0.57, 0.05, ...]
```

define the meaning of a word by the context words that appear around it

"You shall know a word
by the company it keeps."

J. R. Firth, 1957

for		he	ate

for	**breakfast**	he	ate

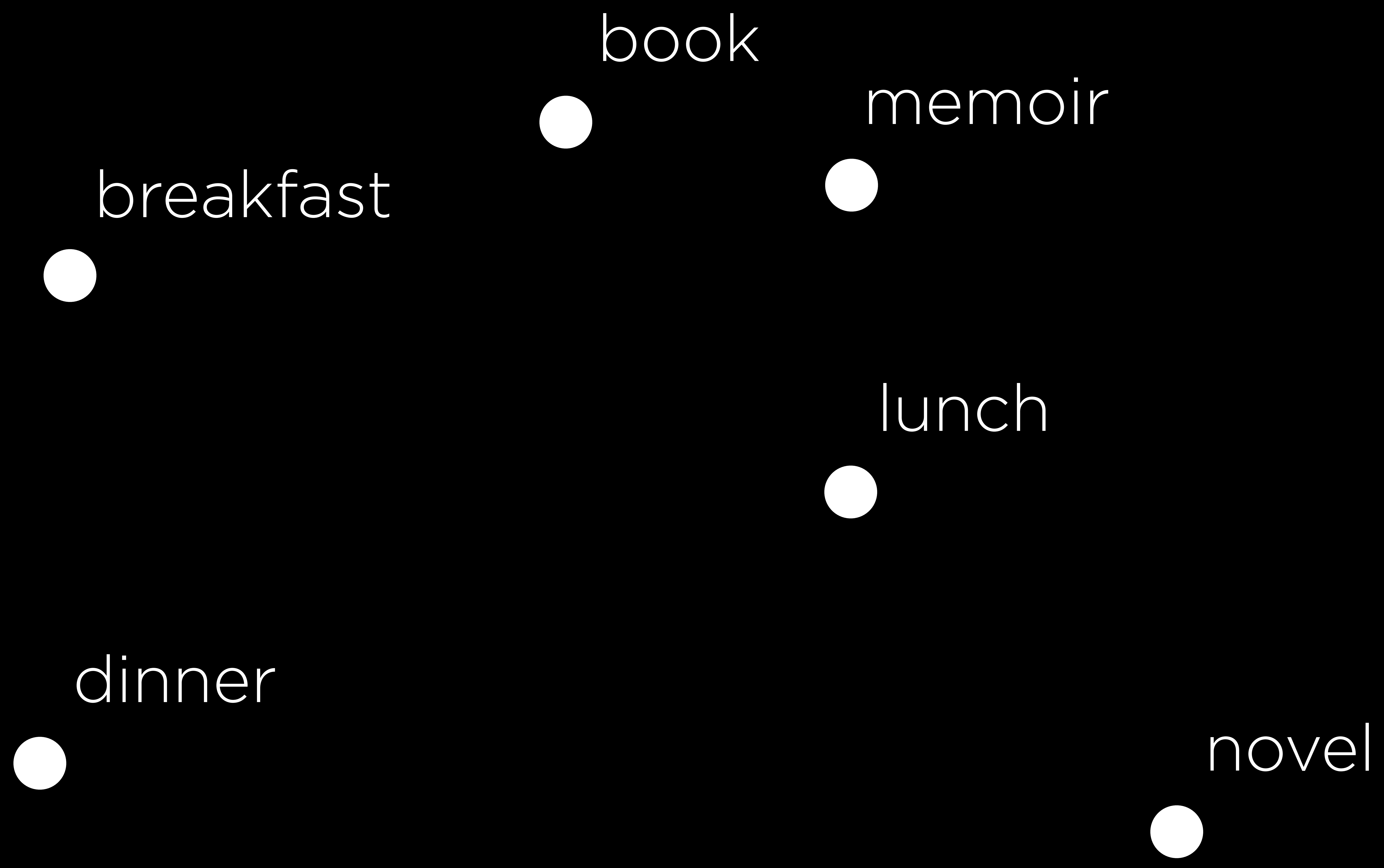
for	**lunch**	he	ate

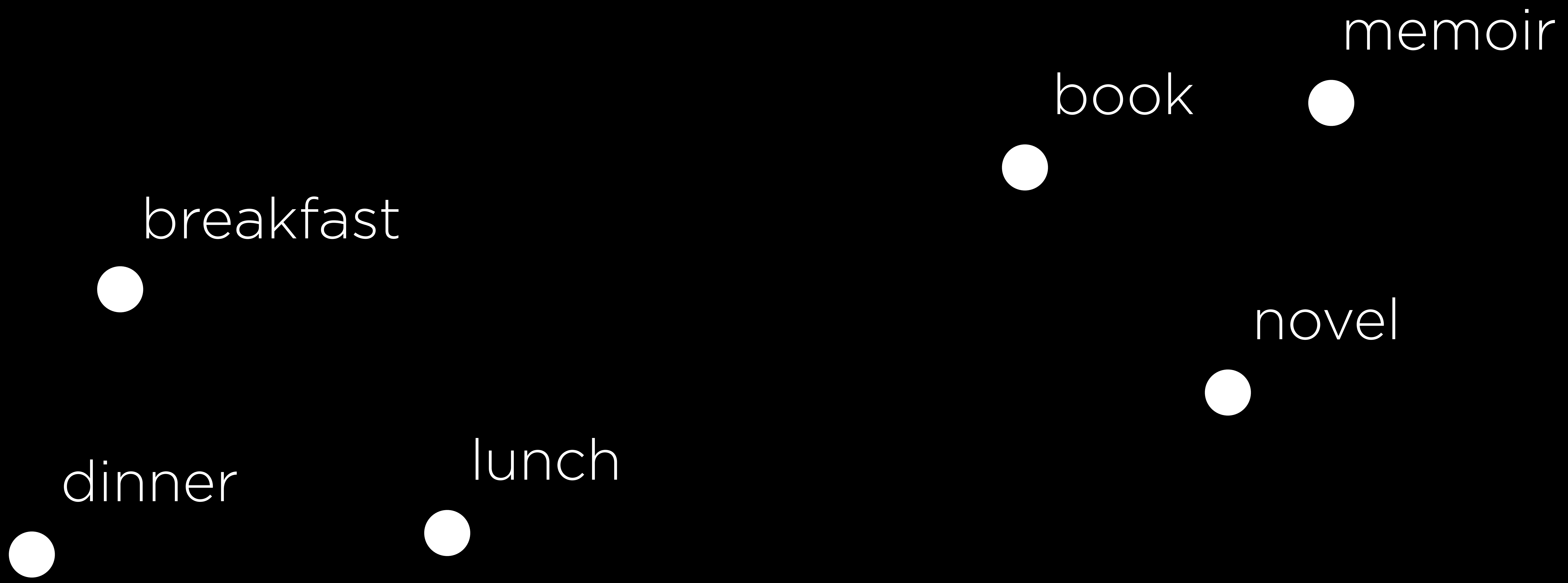
for	**dinner**	he	ate

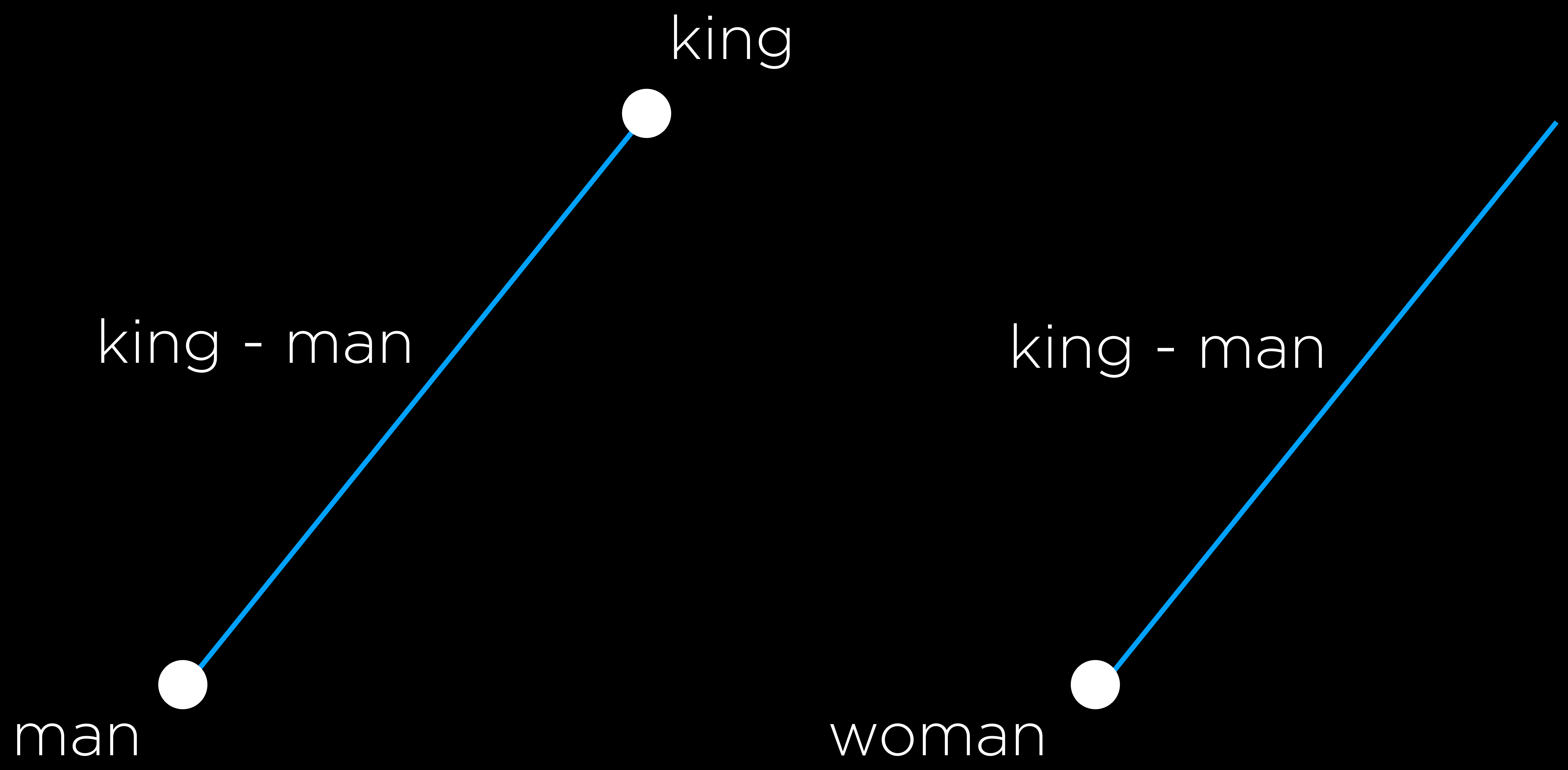
for		he	ate

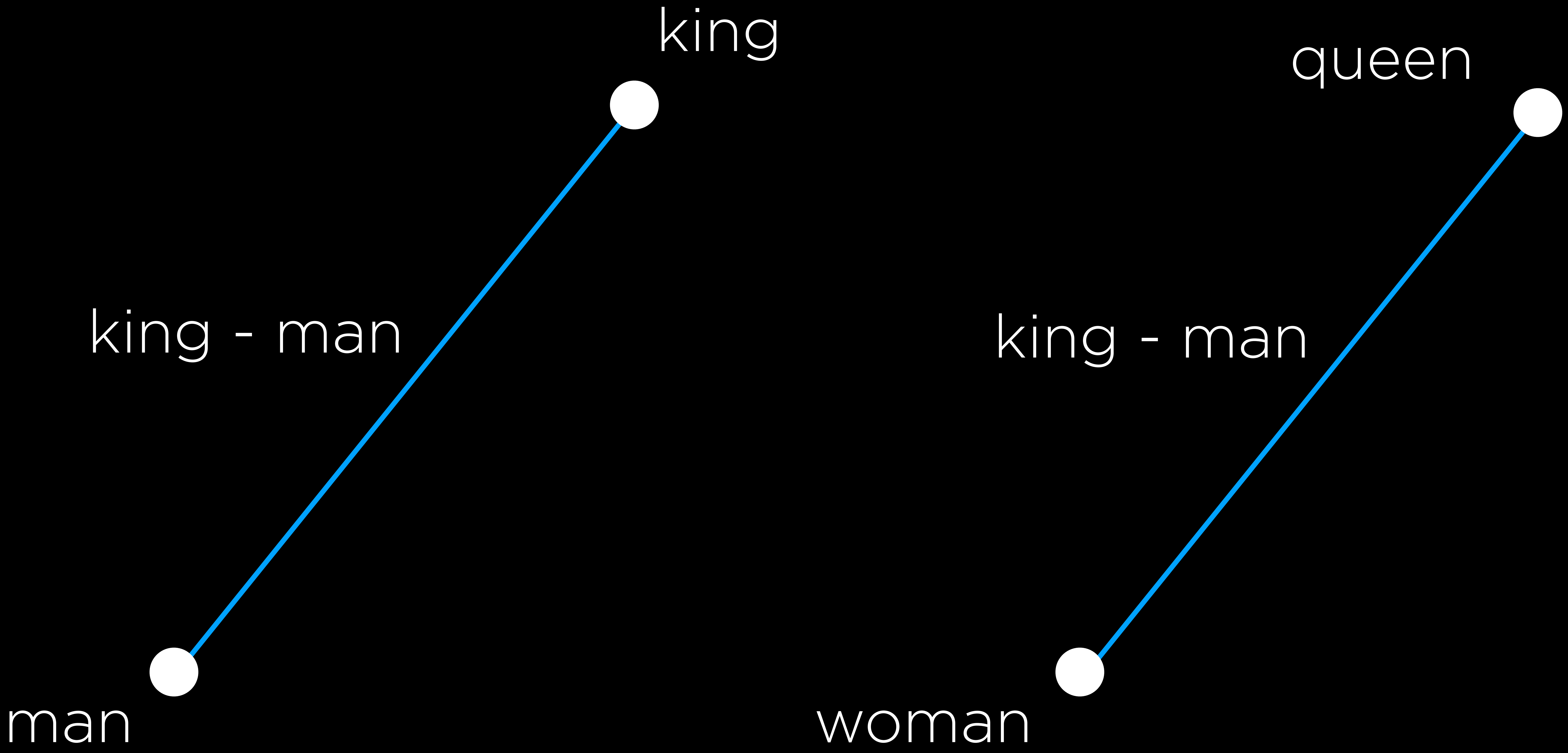
word2vec

model for generating word vectors

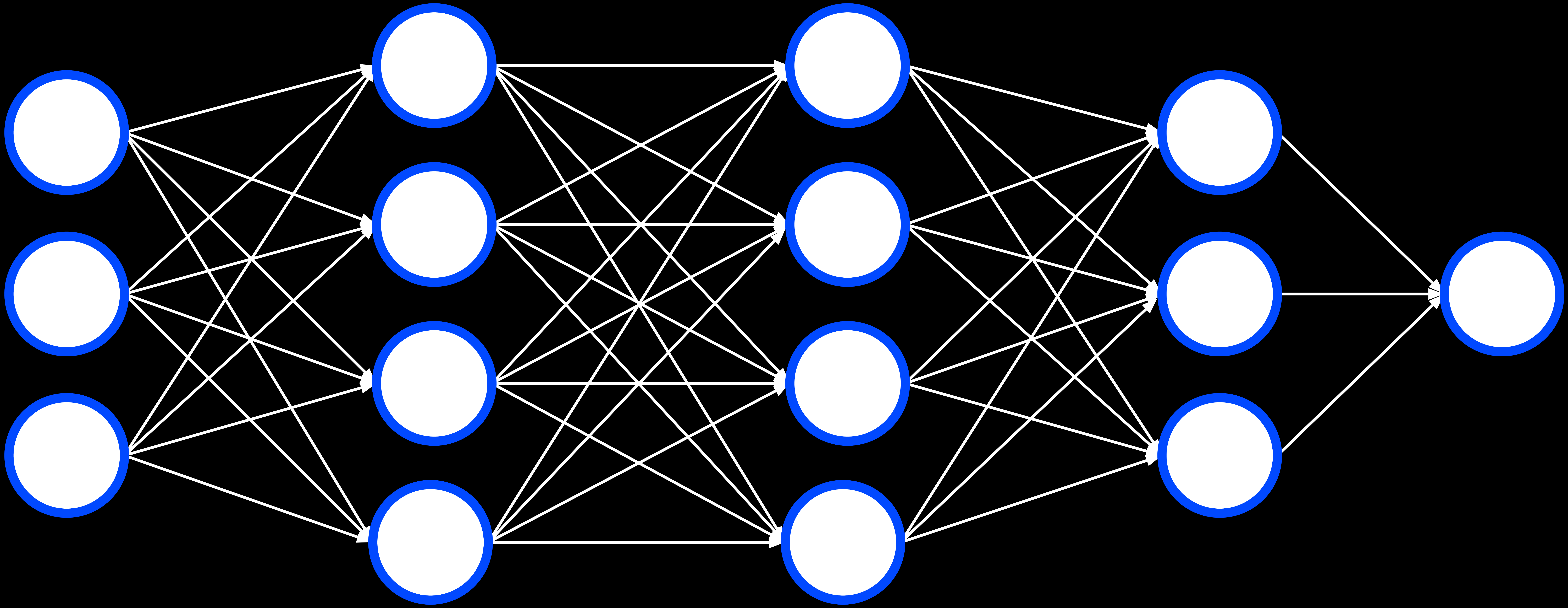

book
memoir
breakfast
lunch
dinner
novel

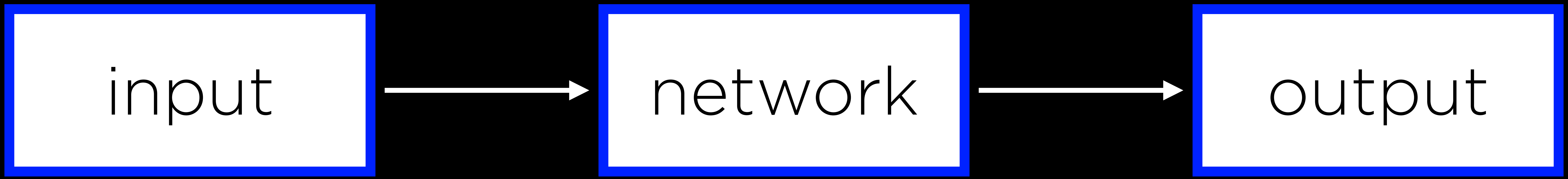

memoir
book
breakfast
novel
lunch
dinner

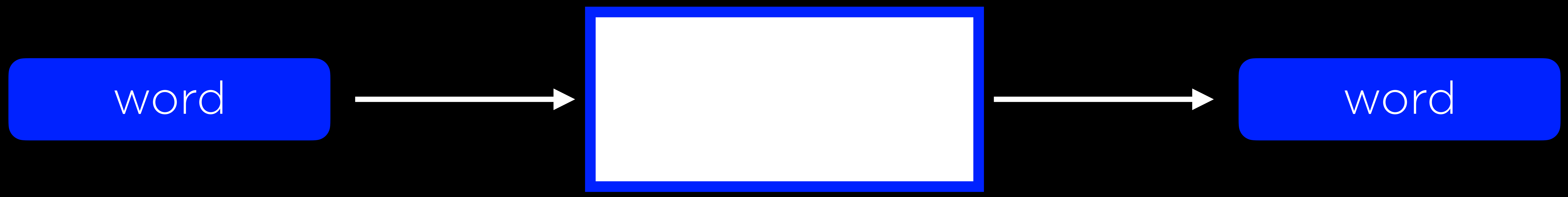

king
king - man
man
king - man
woman

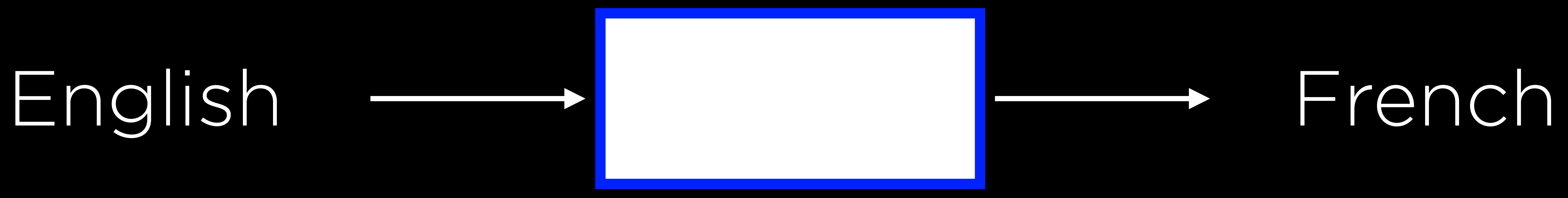

king
queen
king - man
king - man
man
woman

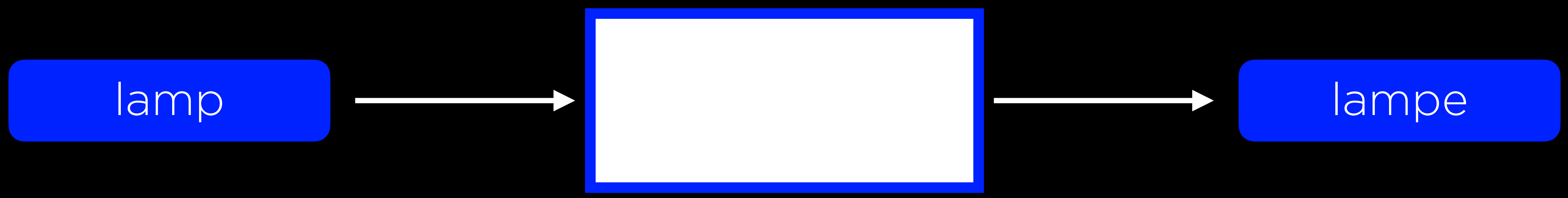
Neural Networks




input
network
output

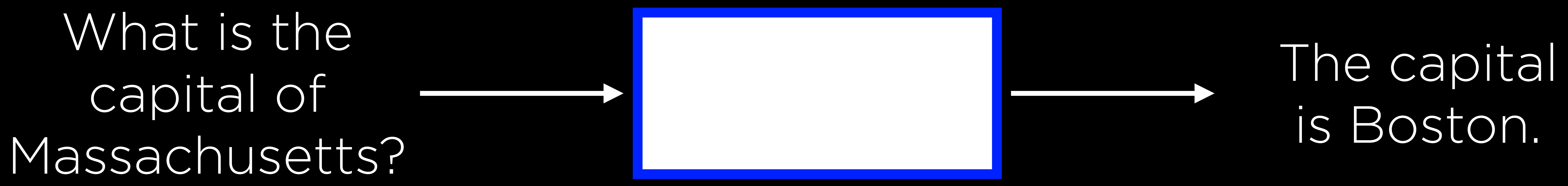

word
word

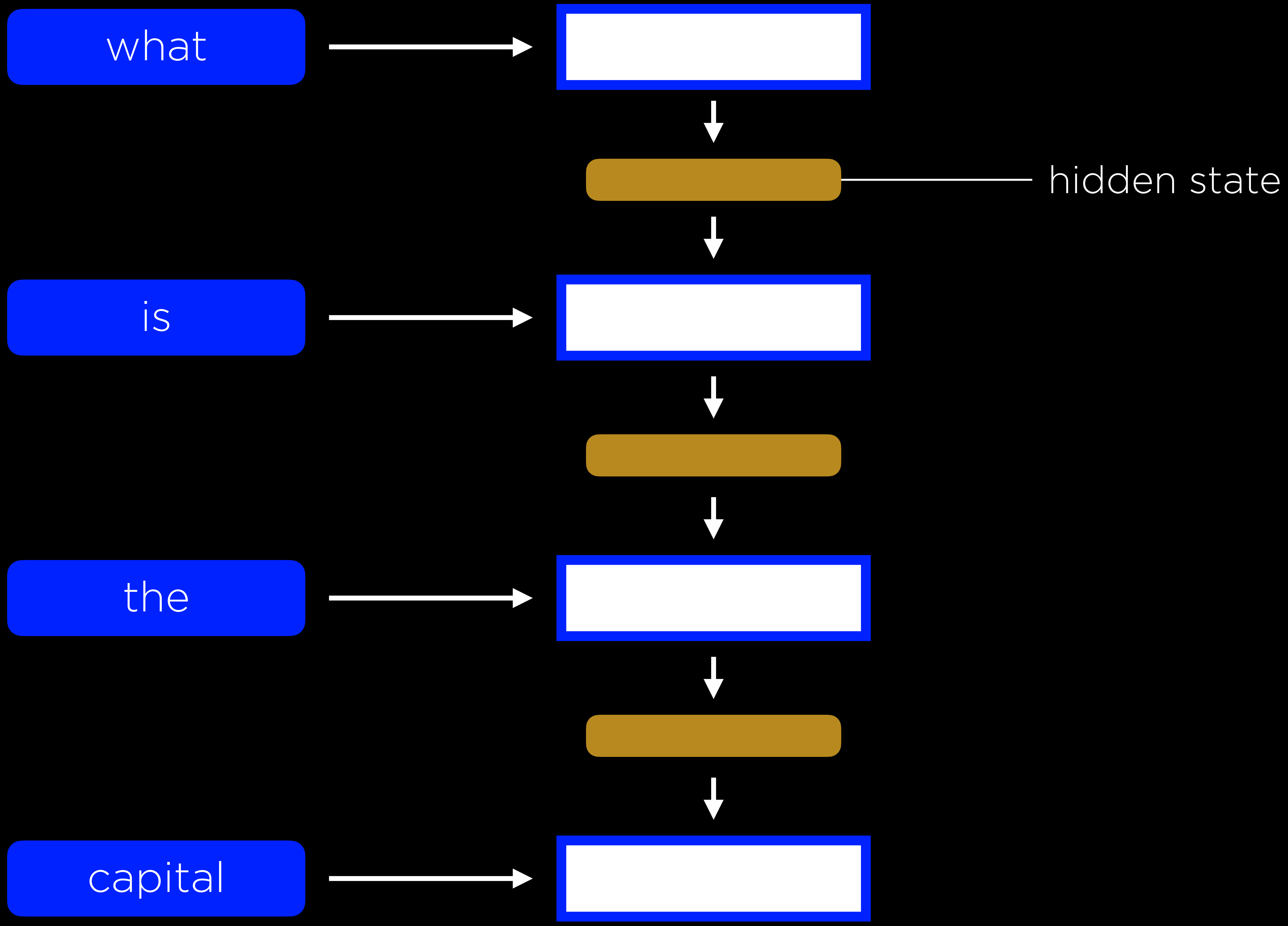

English
French

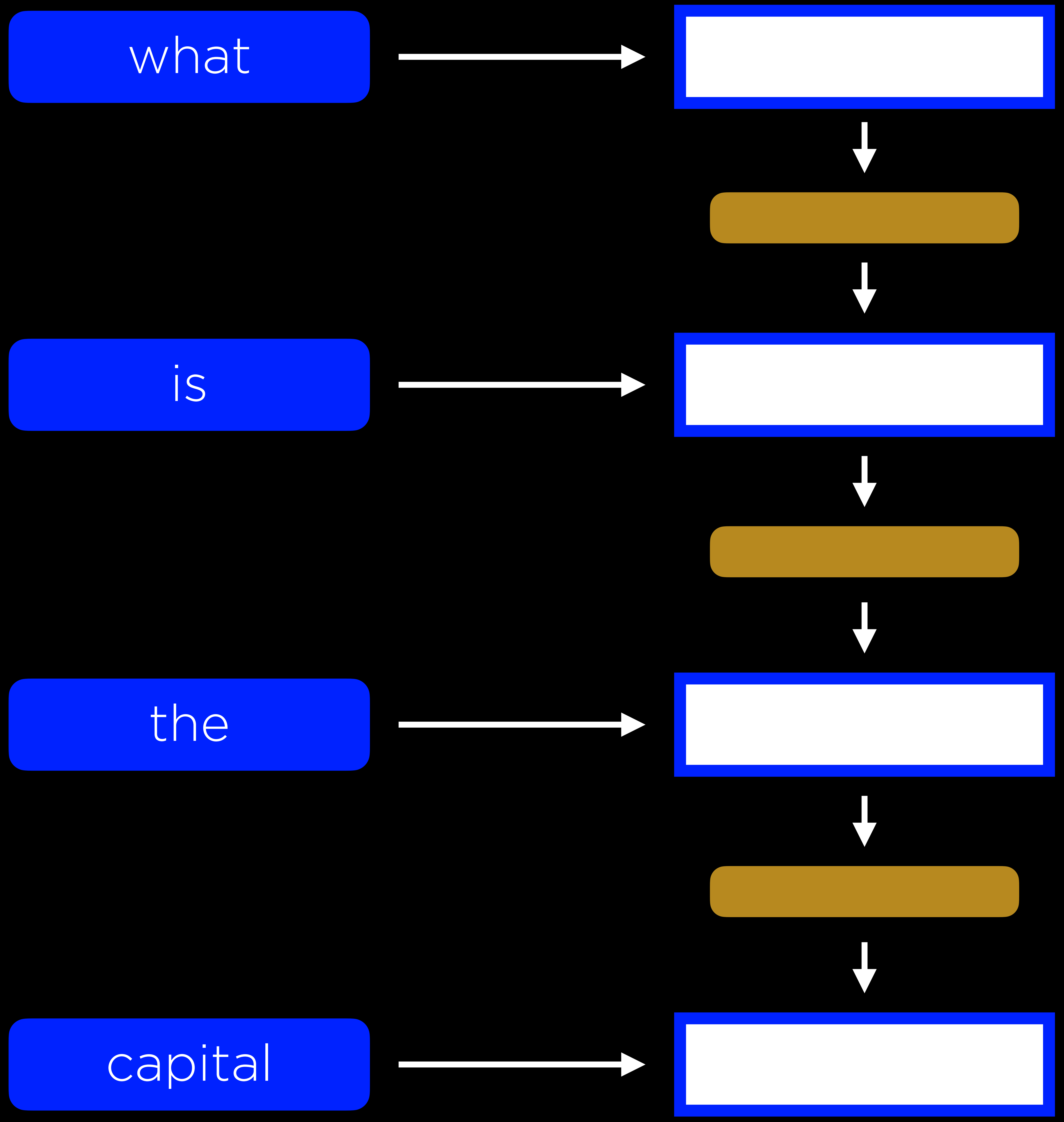

lamp
lampe

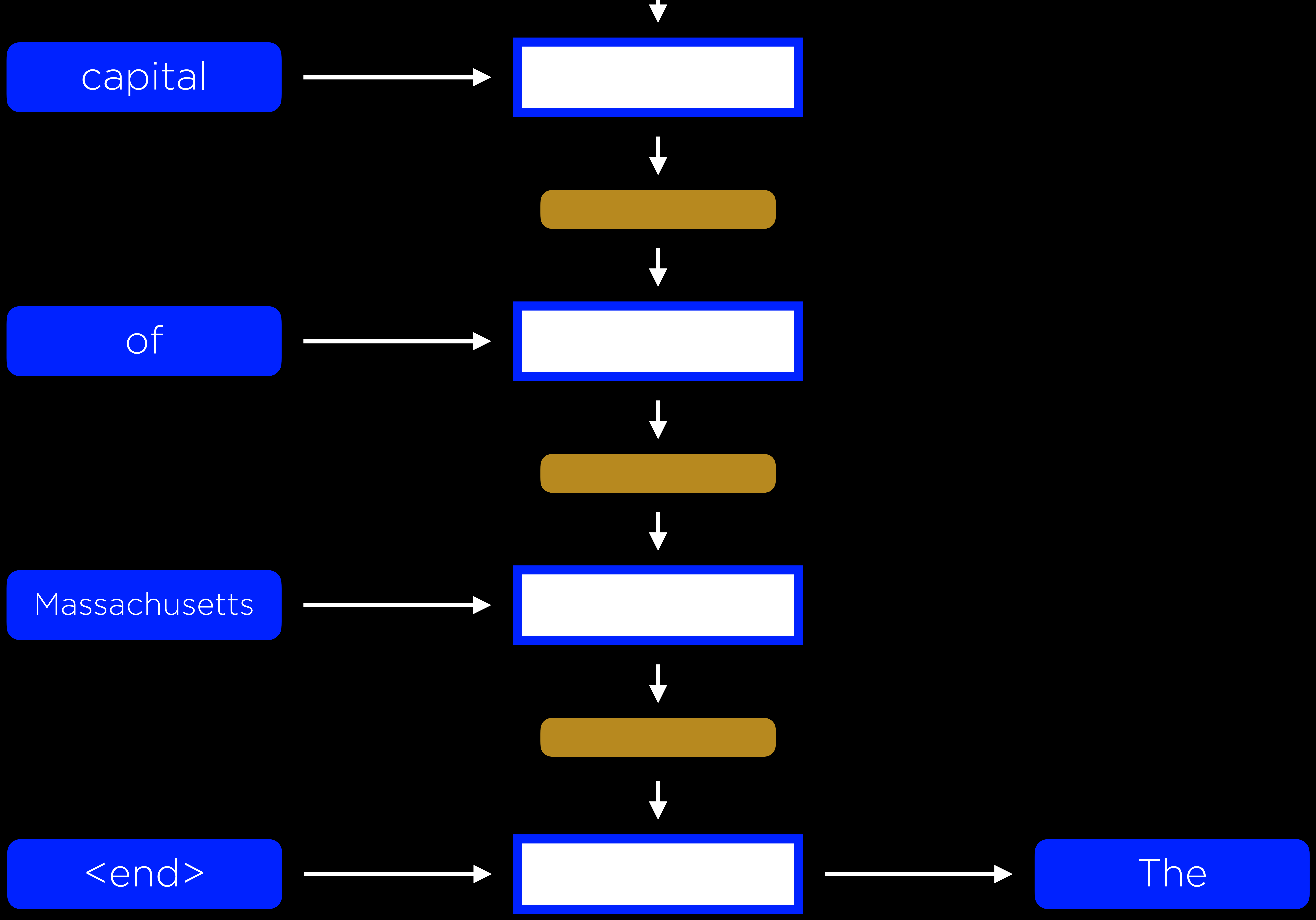
The only light in the room came from the lamp upon the table at which I had been reading.

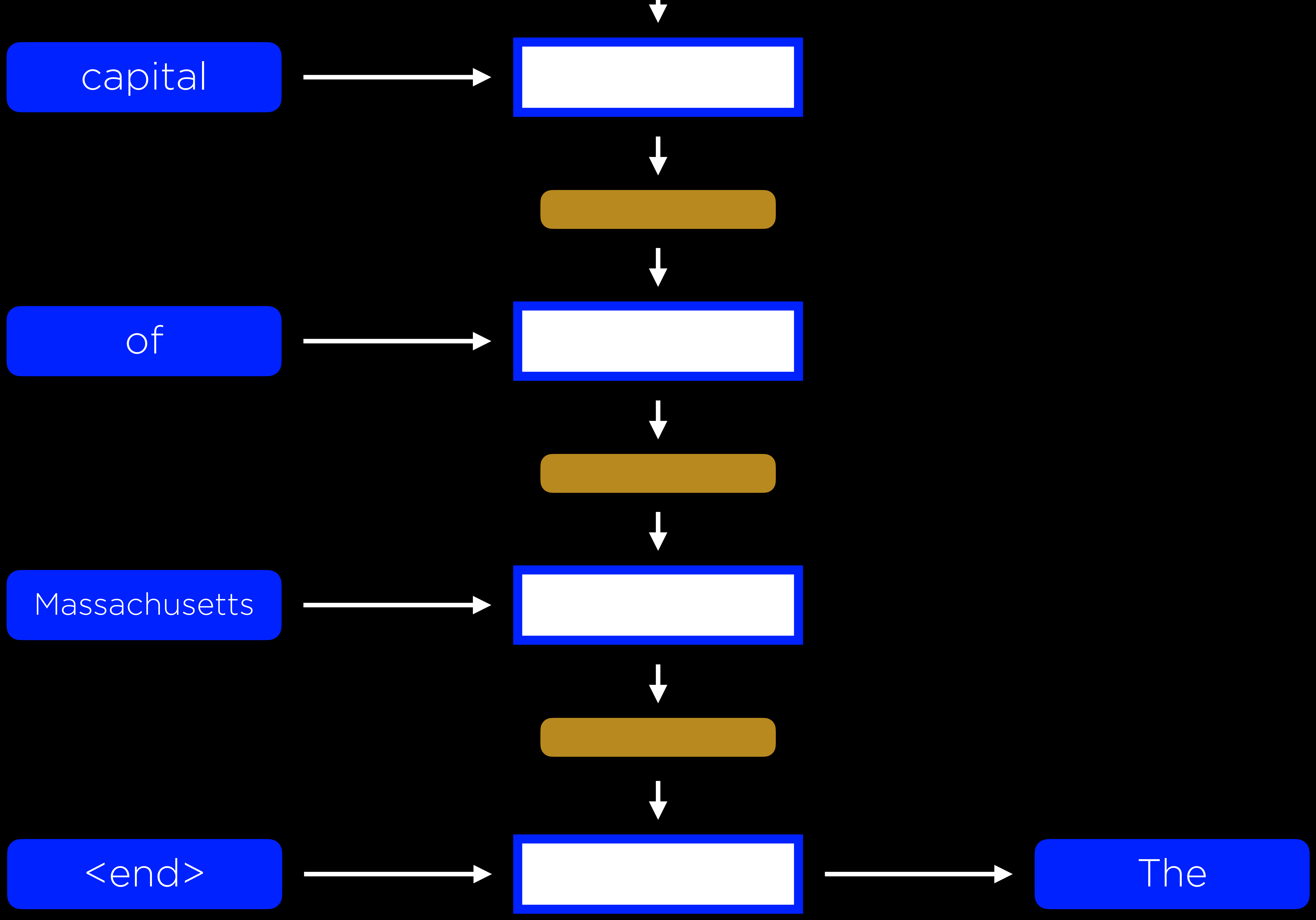
La pièce n'était éclairée que par la lampe placée sur la table où je lisais.

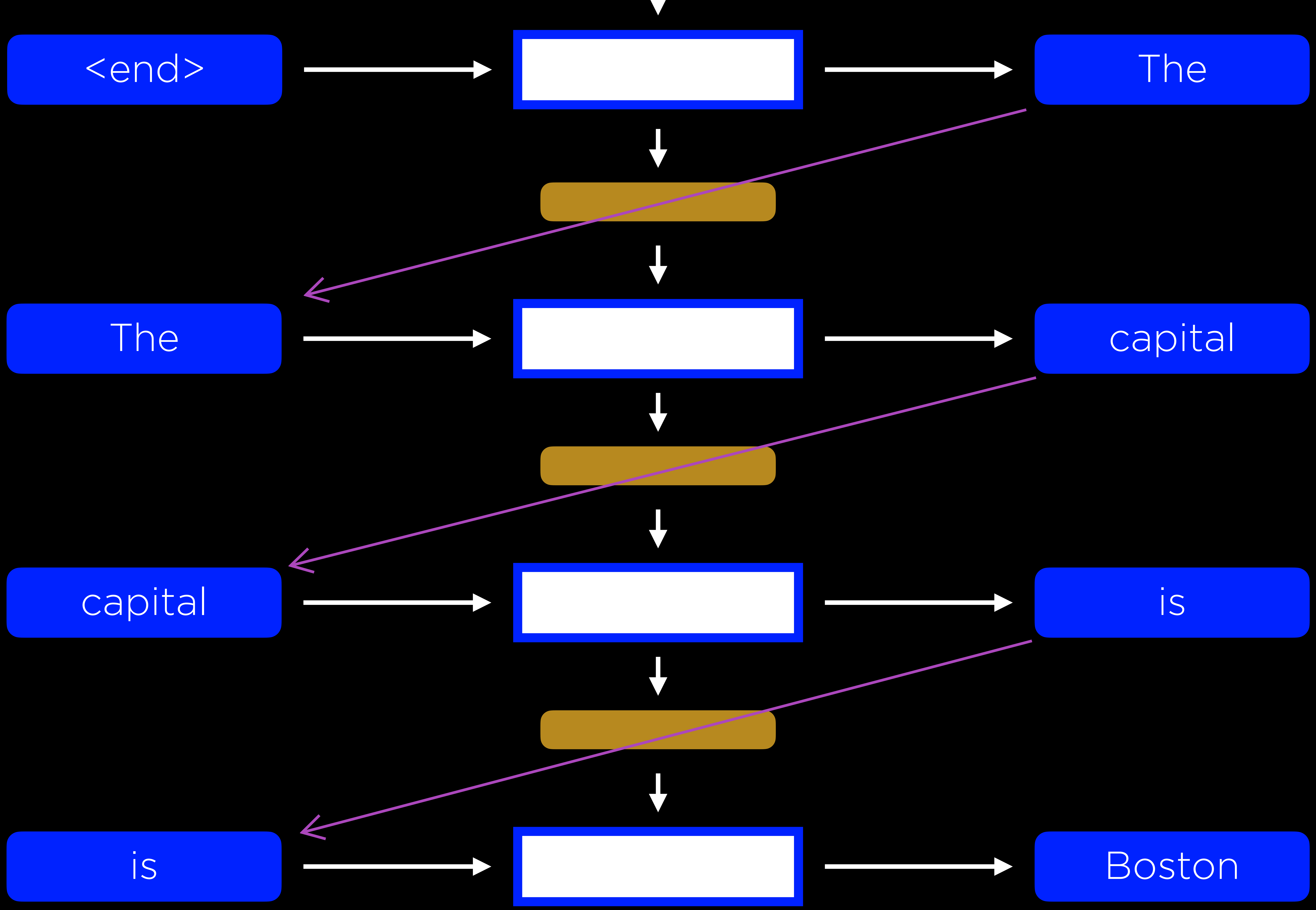

What is the capital of Massachusetts?
The capital is Boston.

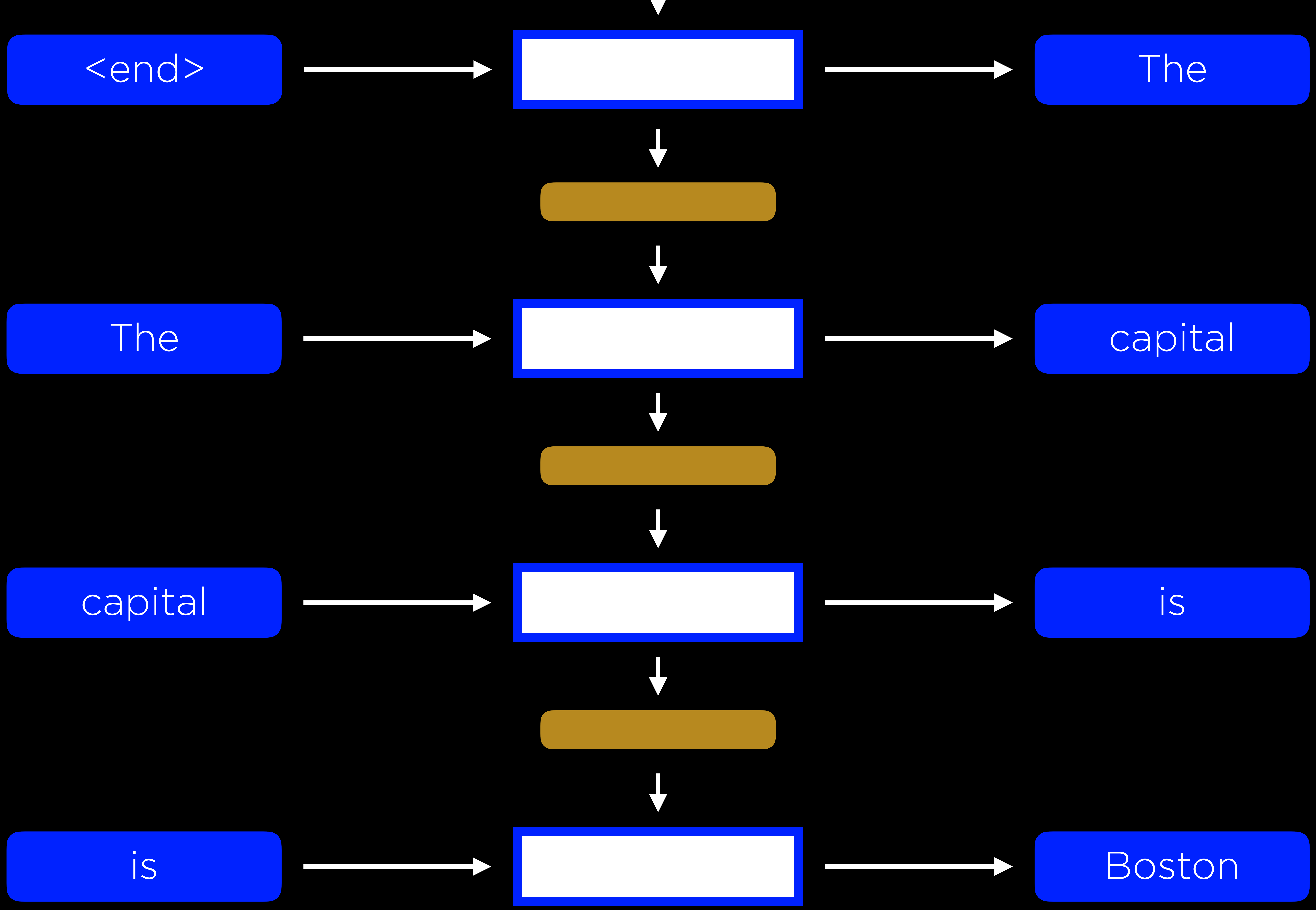

what
hidden state
is
the
capital


what
is
the
capital

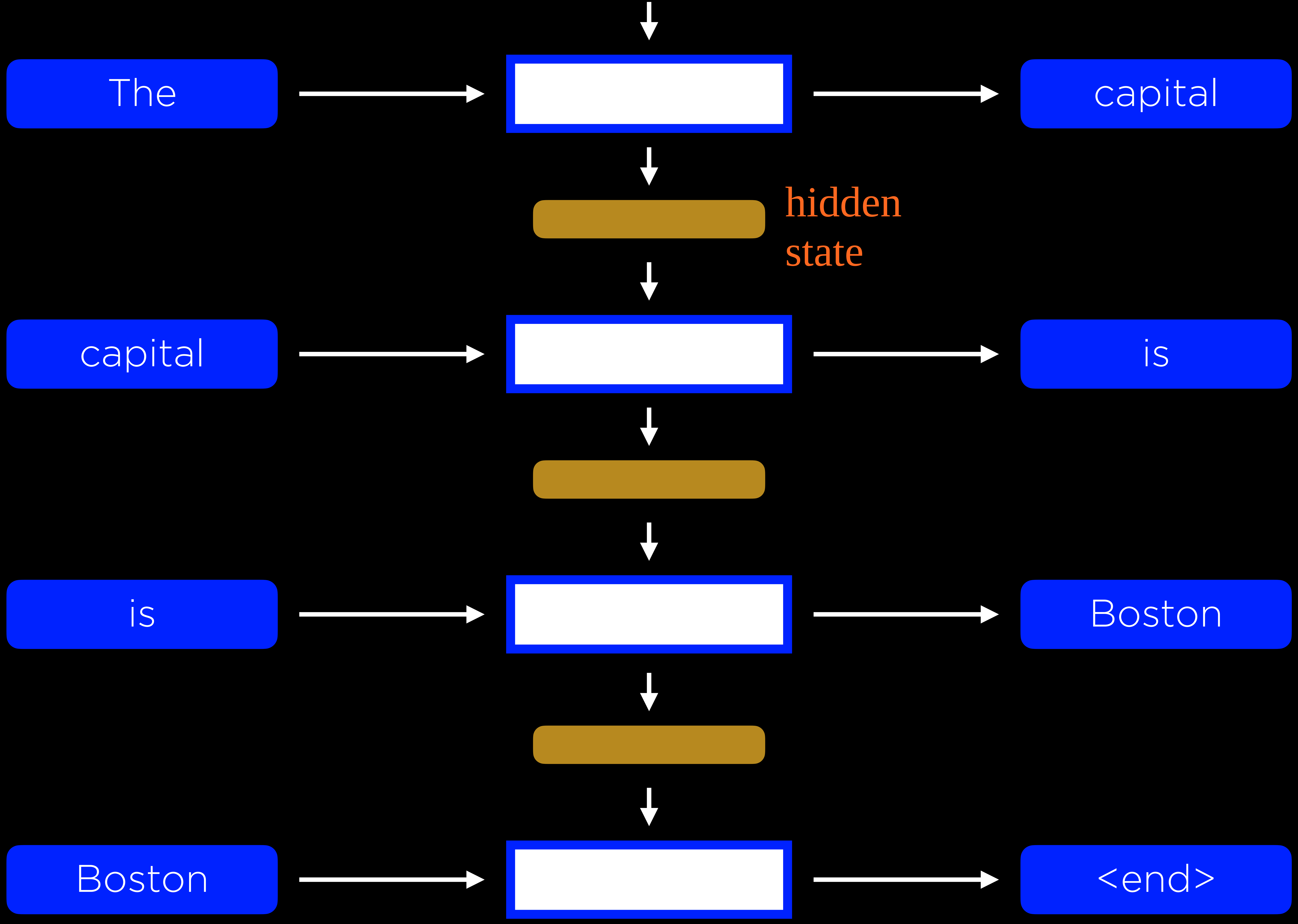

capital
of
Massachusetts
<end>
The

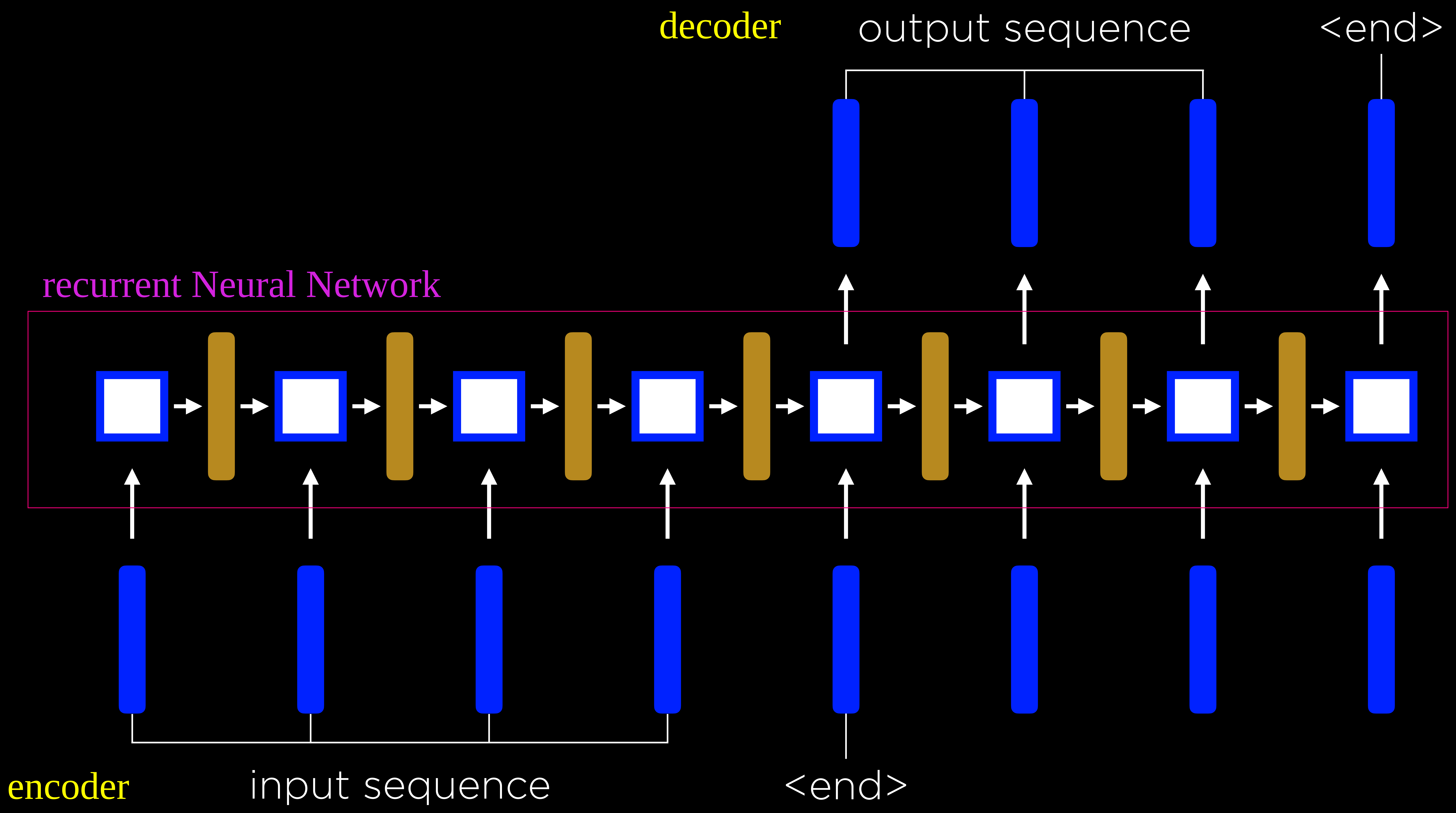

capital
of
Massachusetts
<end>
The

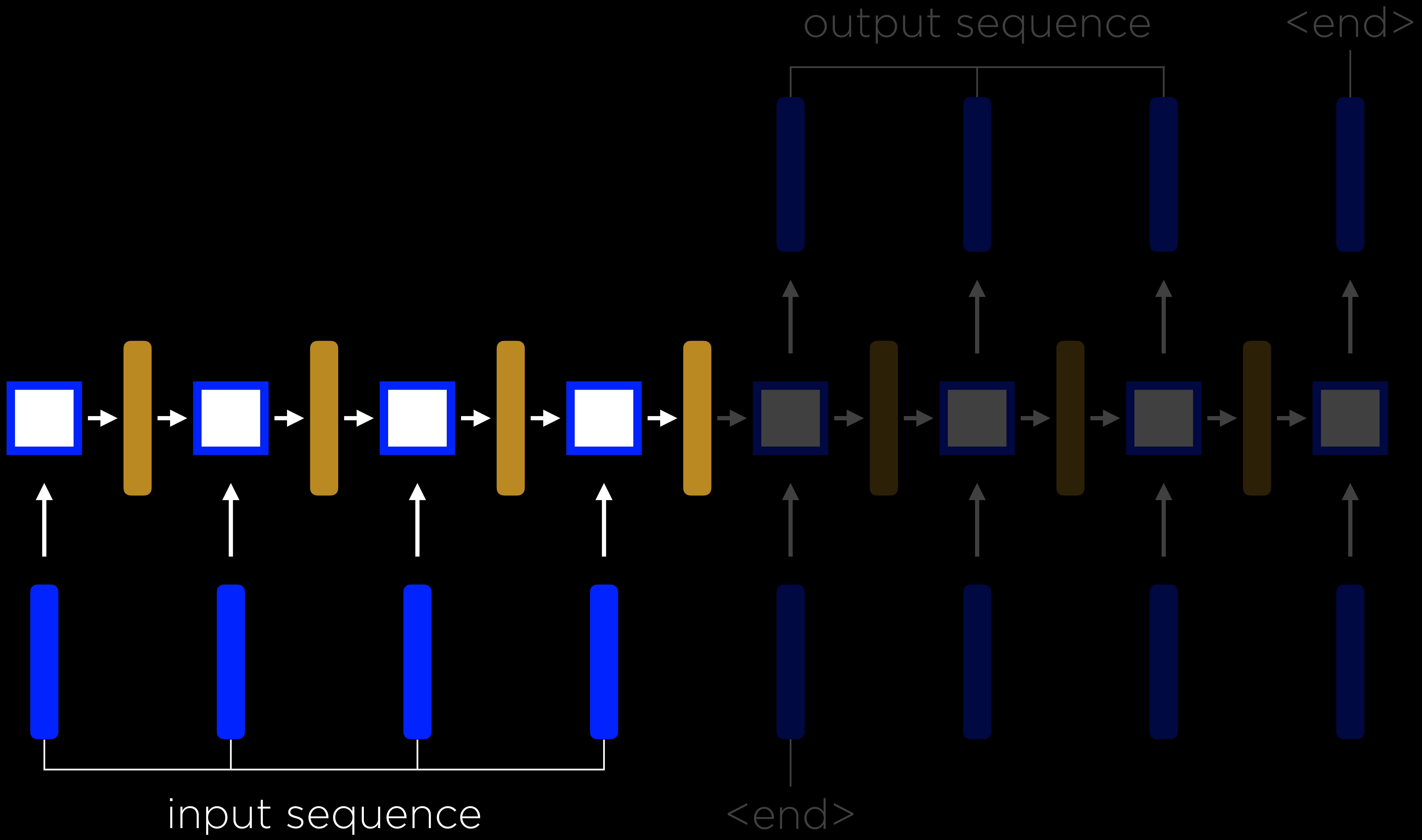

<end>
The
The
capital
capital
is
is
Boston

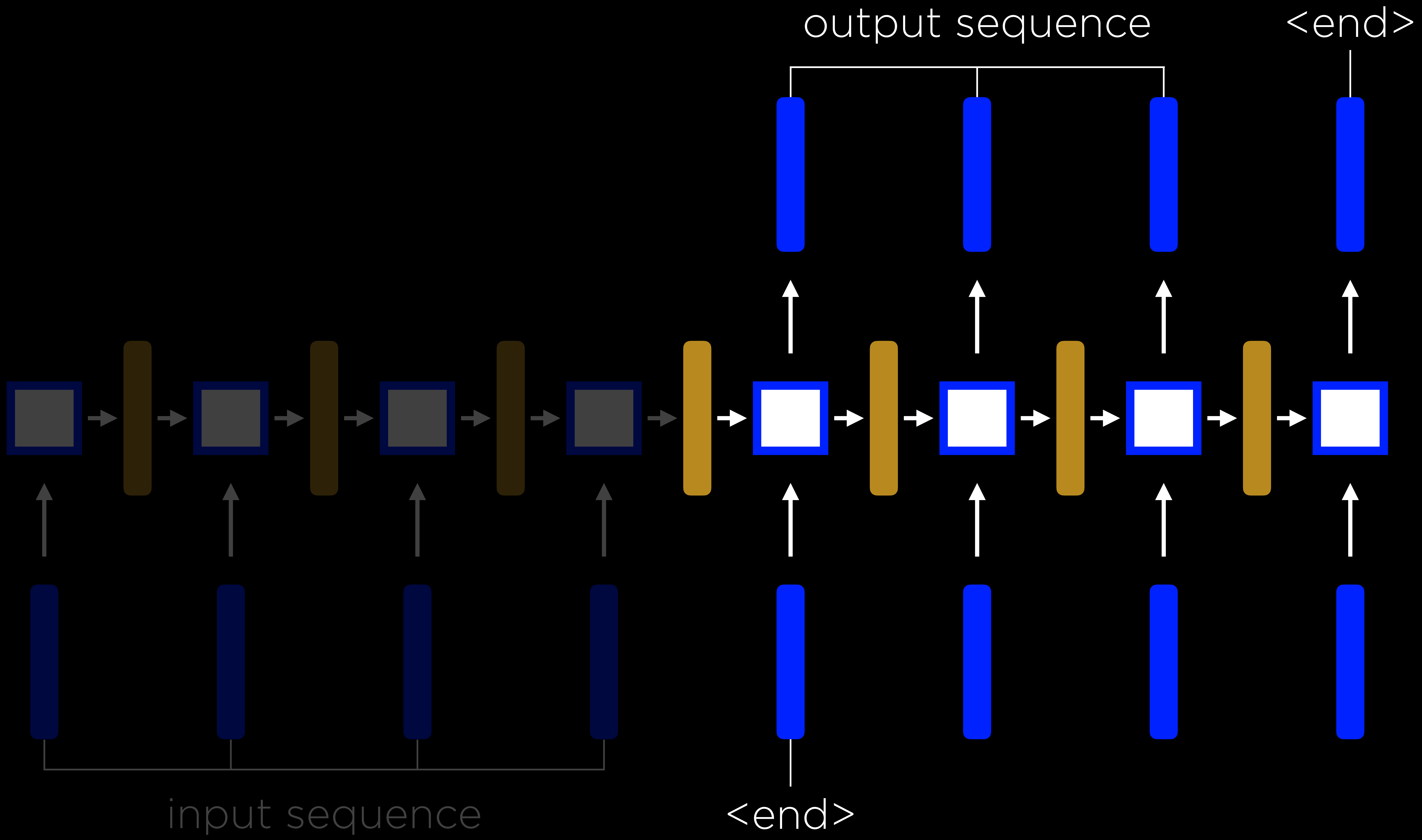


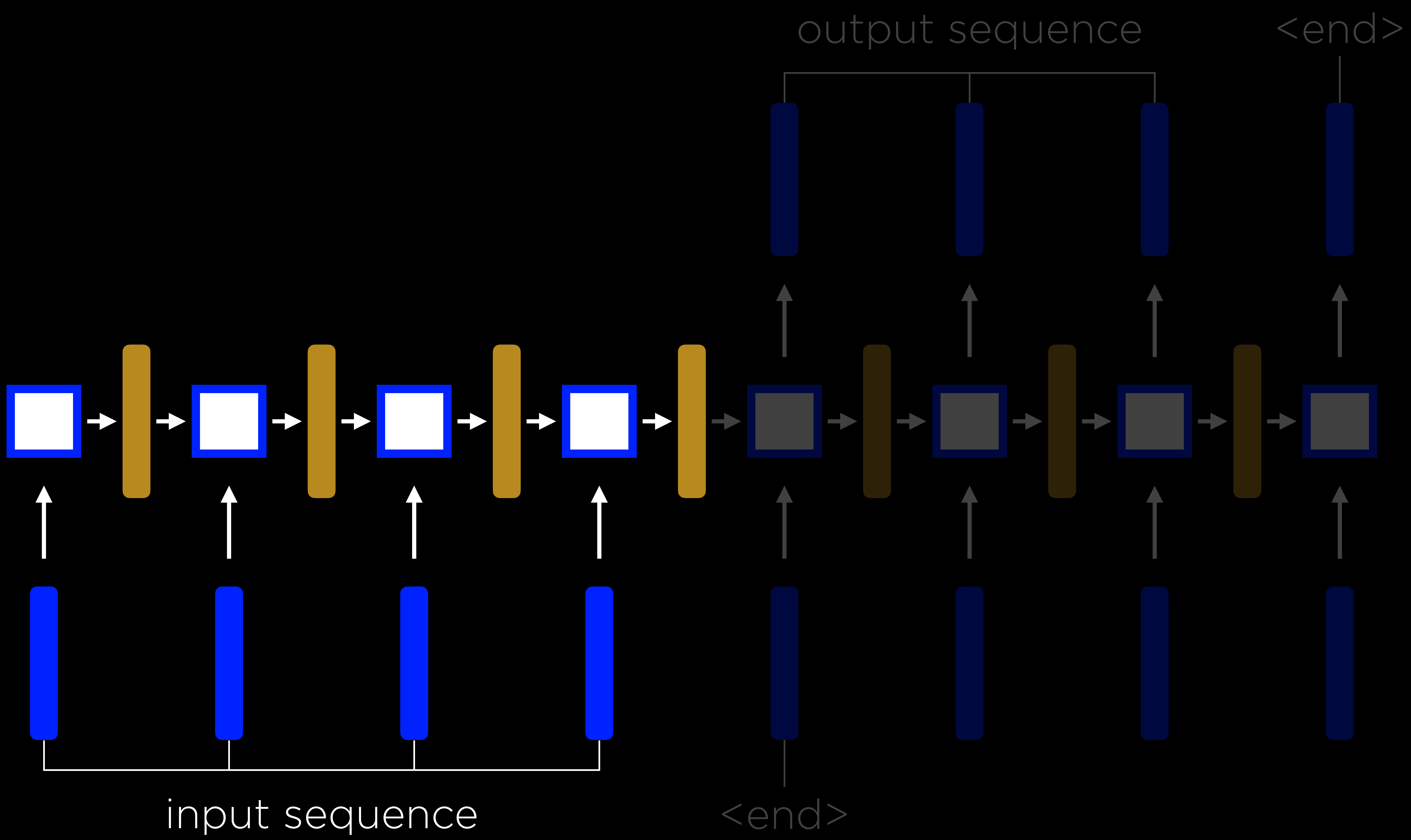
<end>
The
The
capital
capital
is
is
Boston

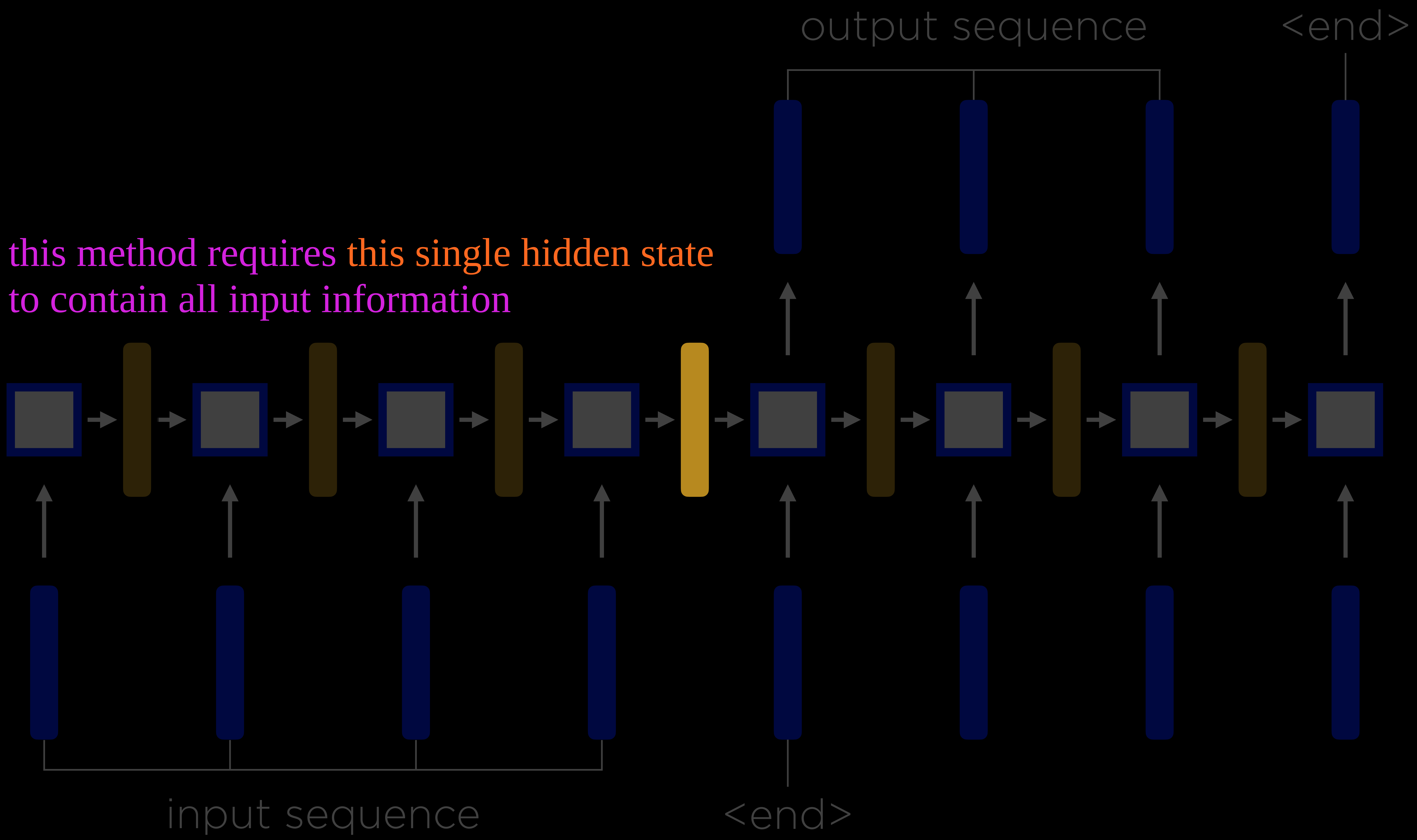

The
capital
hidden
state
capital
is
is
Boston
Boston
<end>

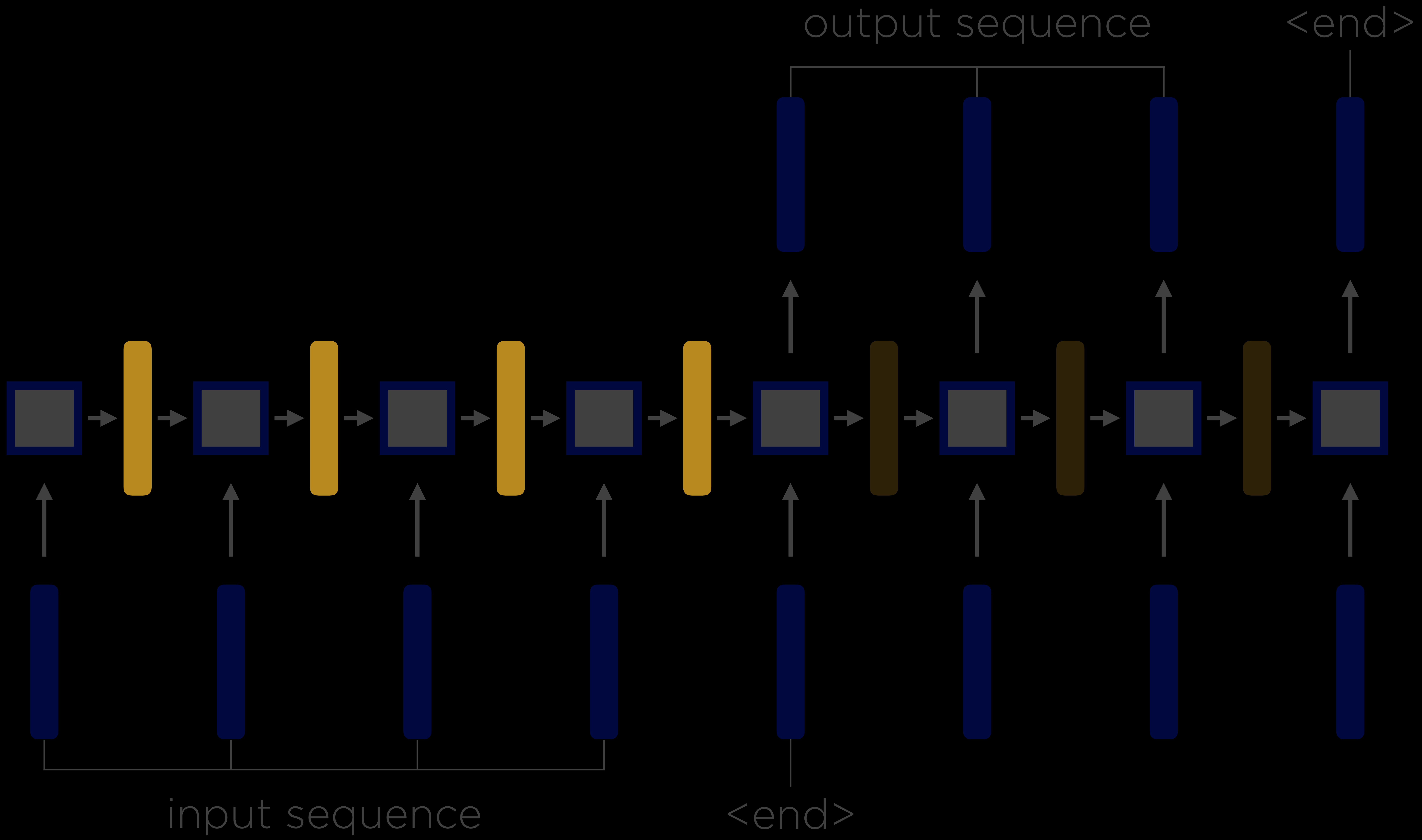

decoder
output sequence
<end>
recurrent Neural Network
encoder
input sequence
<end>


output sequence
<end>
input sequence
<end>


output sequence
<end>
input sequence
<end>


output sequence
<end>
input sequence
<end>


output sequence
<end>
this method requires this single hidden state
to contain all input information
input sequence
<end>

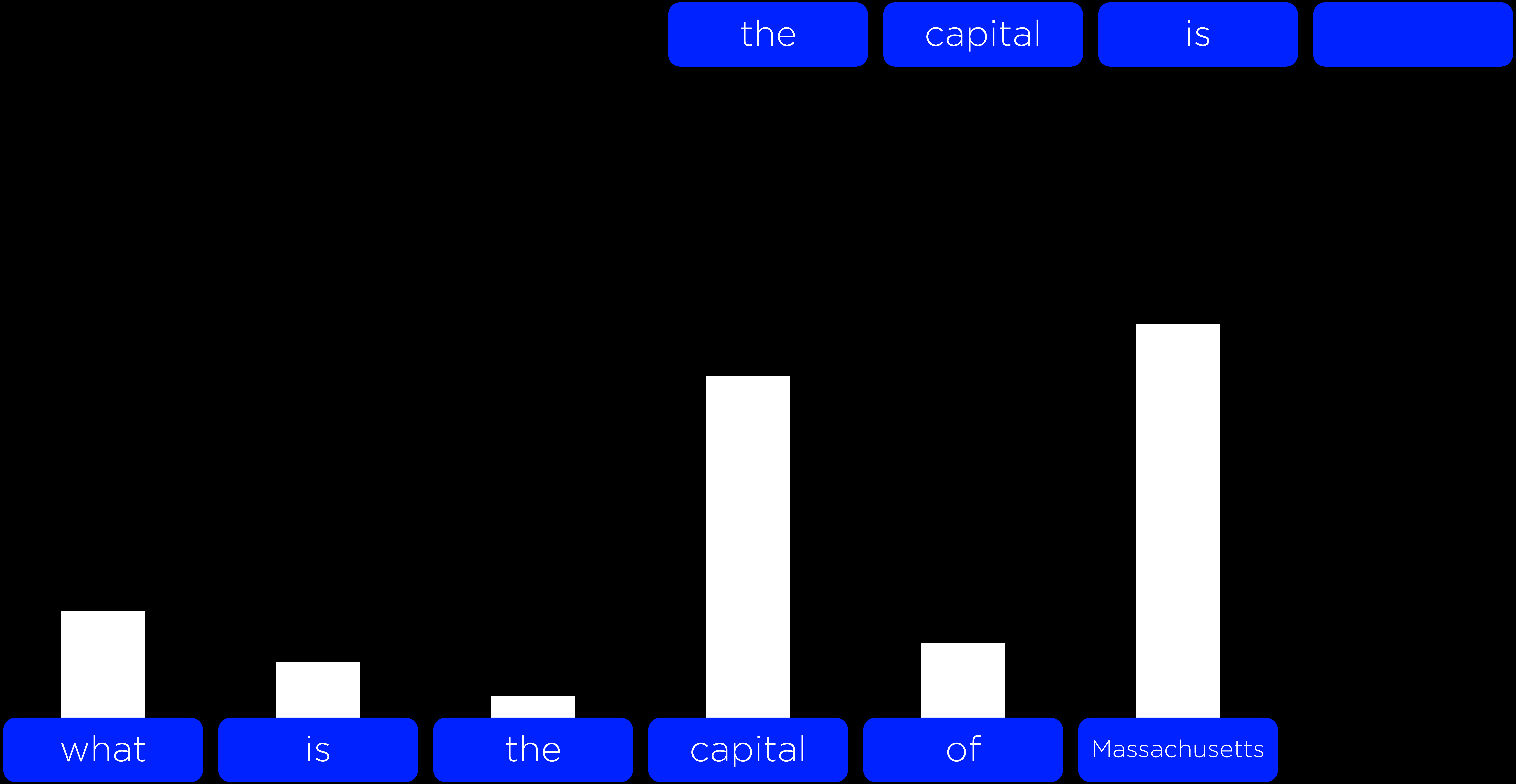

output sequence
<end>
input sequence
<end>

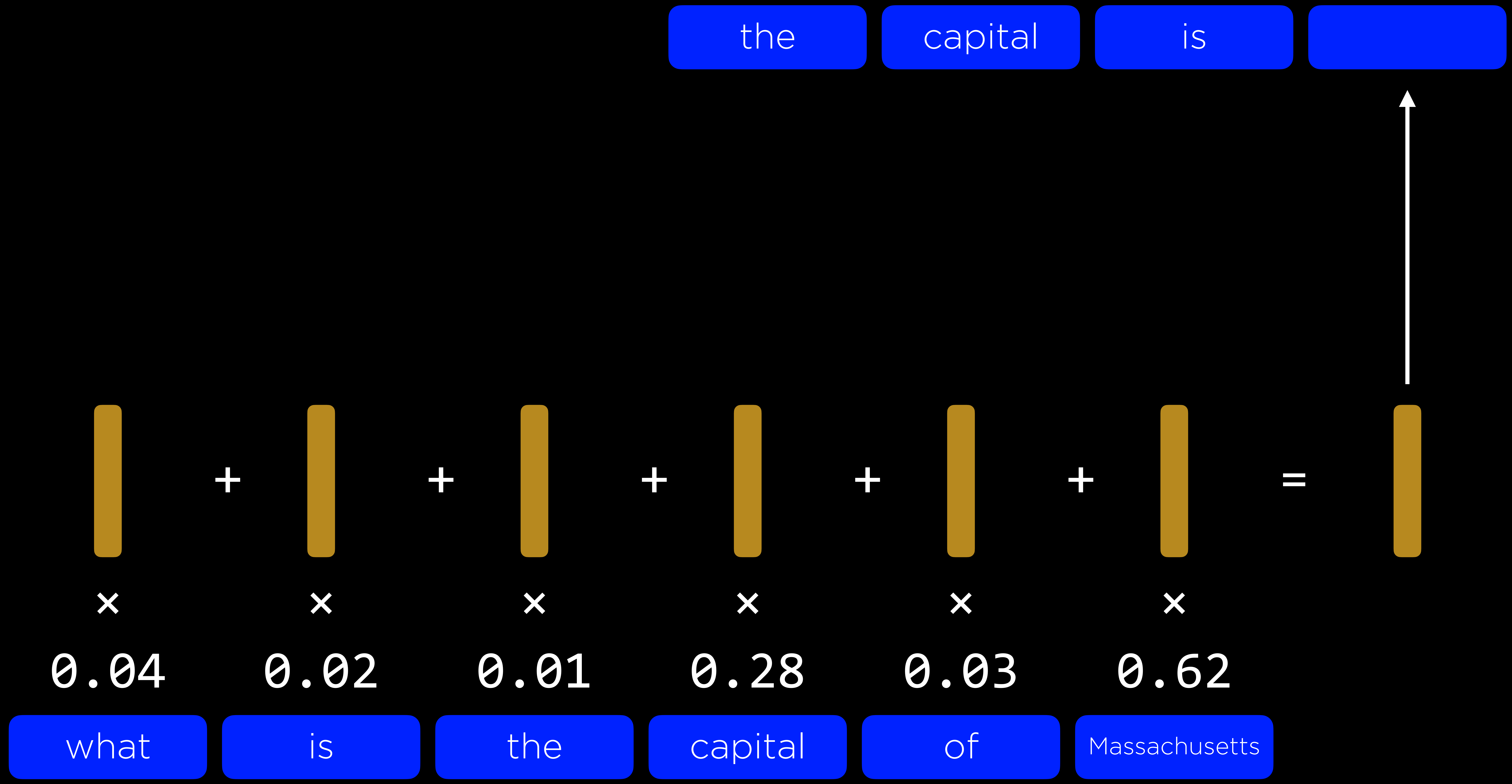
not all words of input sequence are equally important

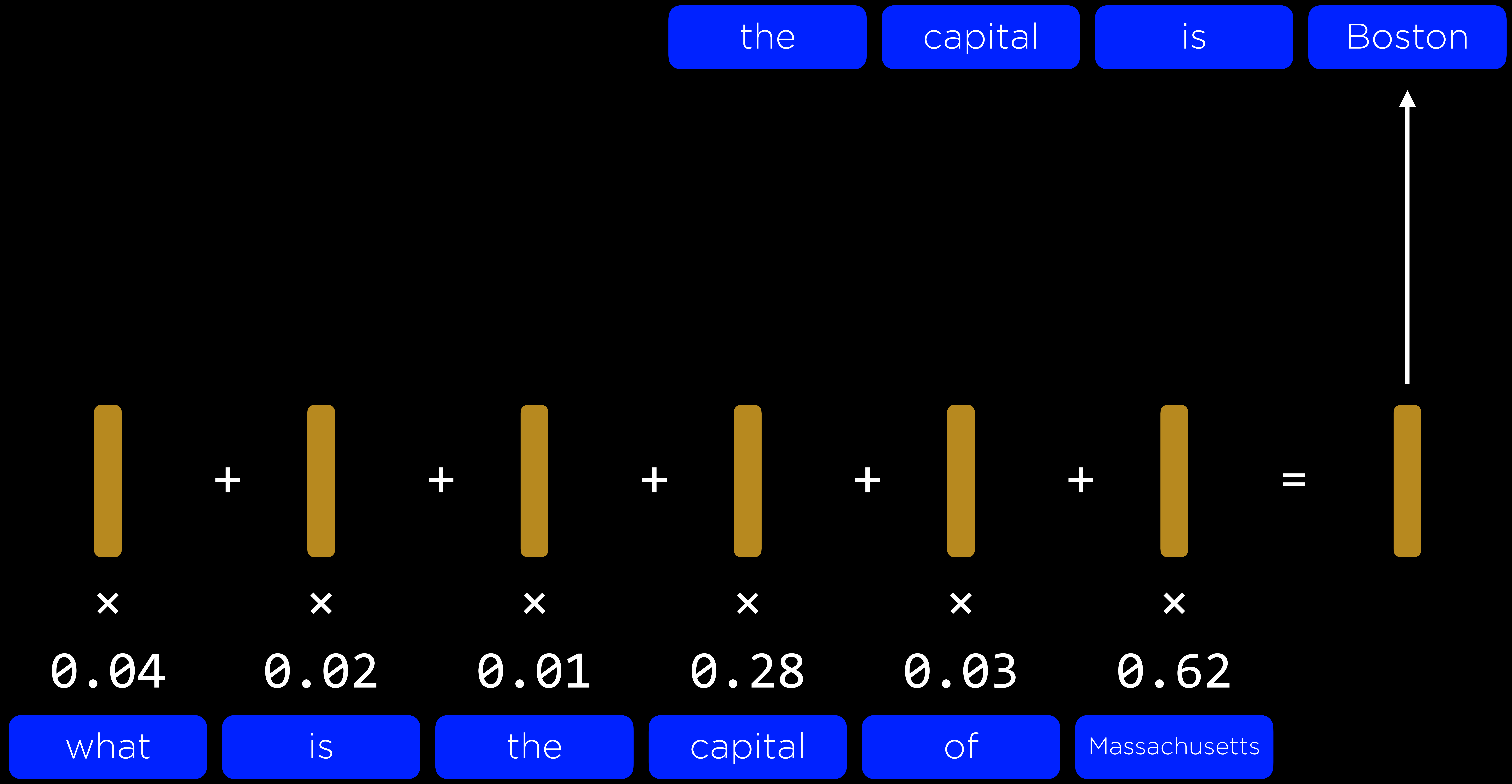
Attention

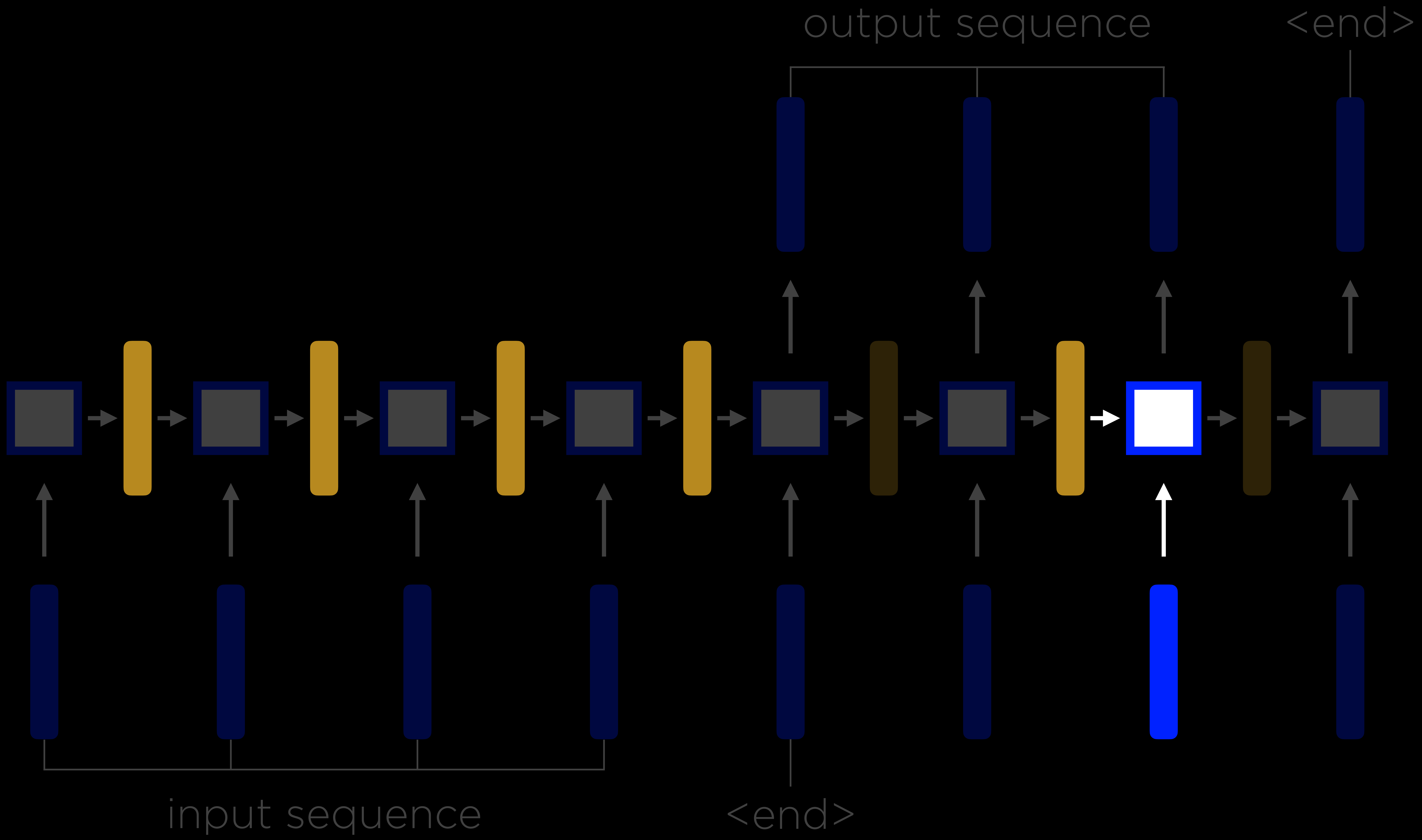
the capital is

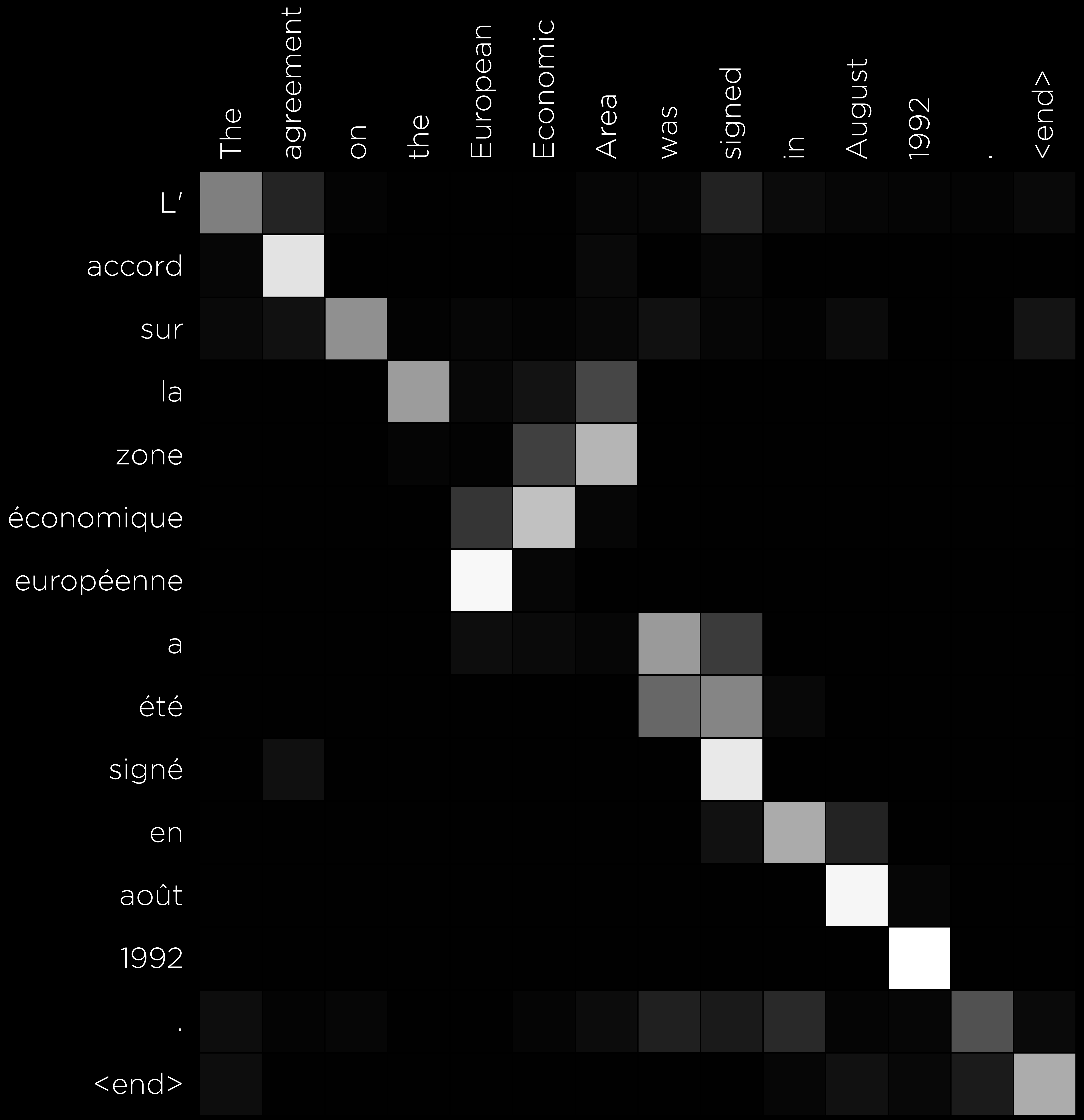
what is the capital of Massachusetts


the
capital
is
what
is
the
capital
of
Massachusetts


the
capital
is
+
+
+
+
+
=
×
×
×
×
×
×
0.04
0.02
0.01
0.28
0.03
0.62
what
is
the
capital
of
Massachusetts


the
capital
is
Boston
+
+
+
+
+
=
×
×
×
×
×
×
0.04
0.02
0.01
0.28
0.03
0.62
what
is
the
capital
of
Massachusetts

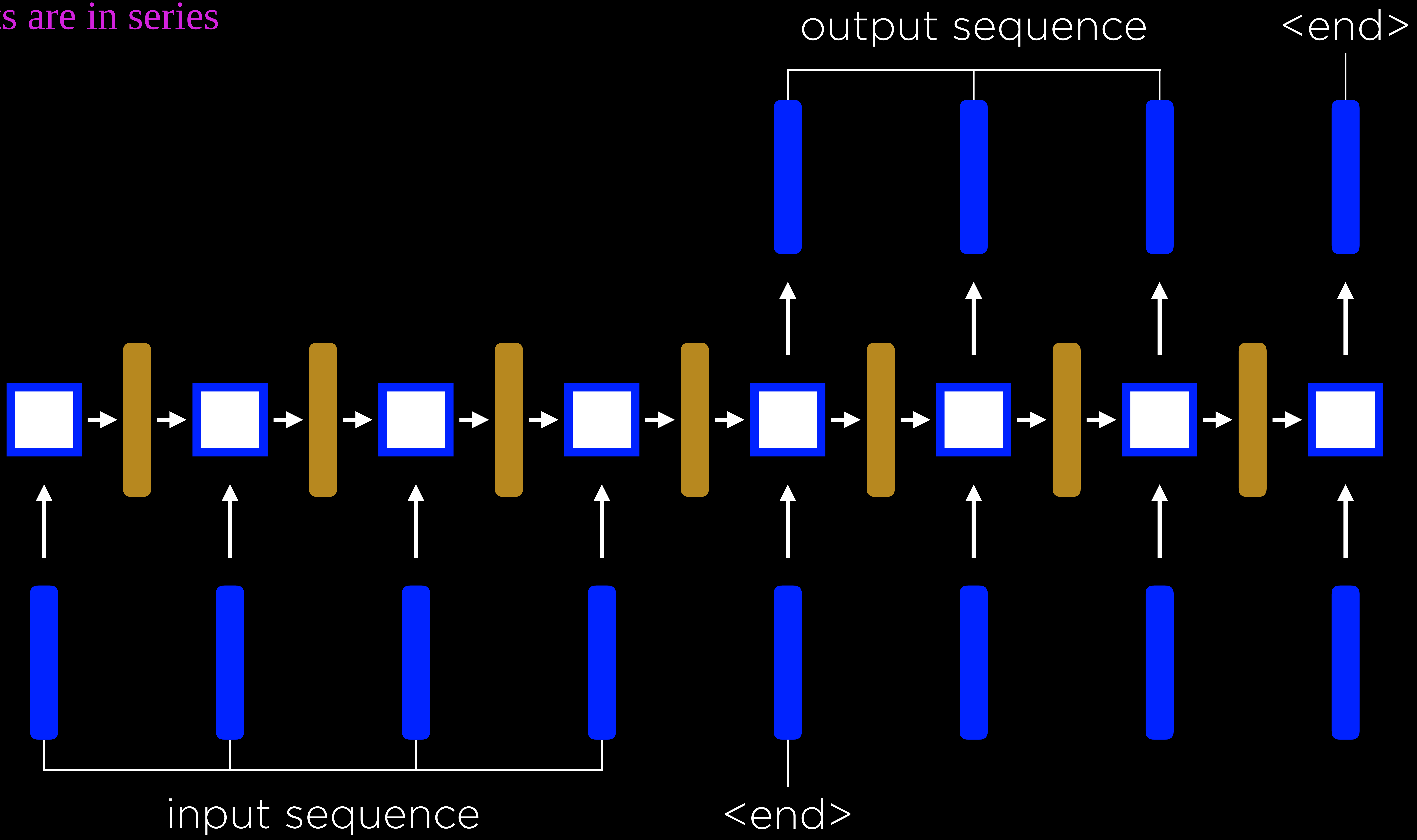

output sequence
<end>
input sequence
<end>



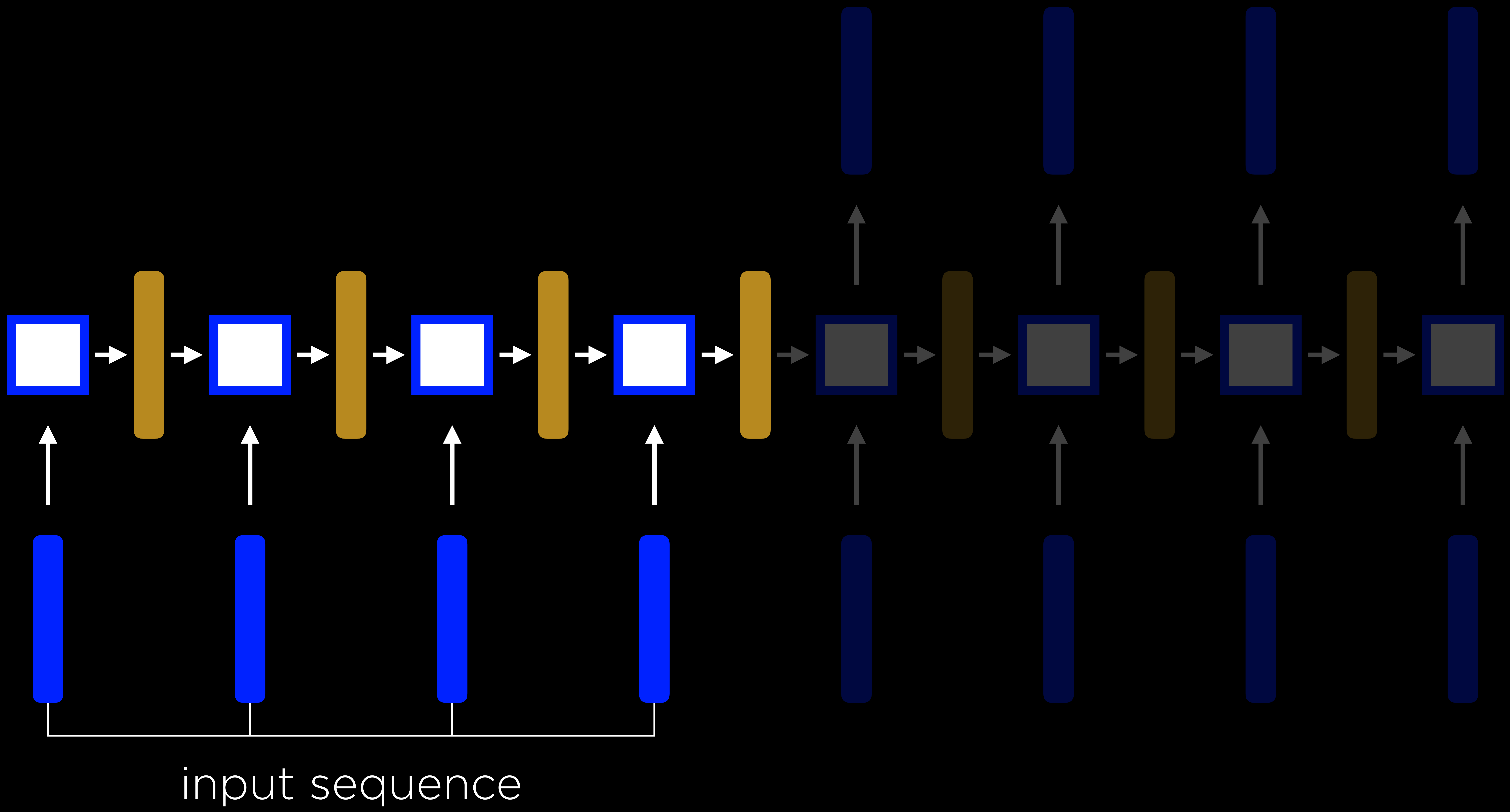
lighter squares indicate
higher attention score

Adapted from Bahdanau et al. 2015.
Neural machine translation by jointly
learning to align and translate

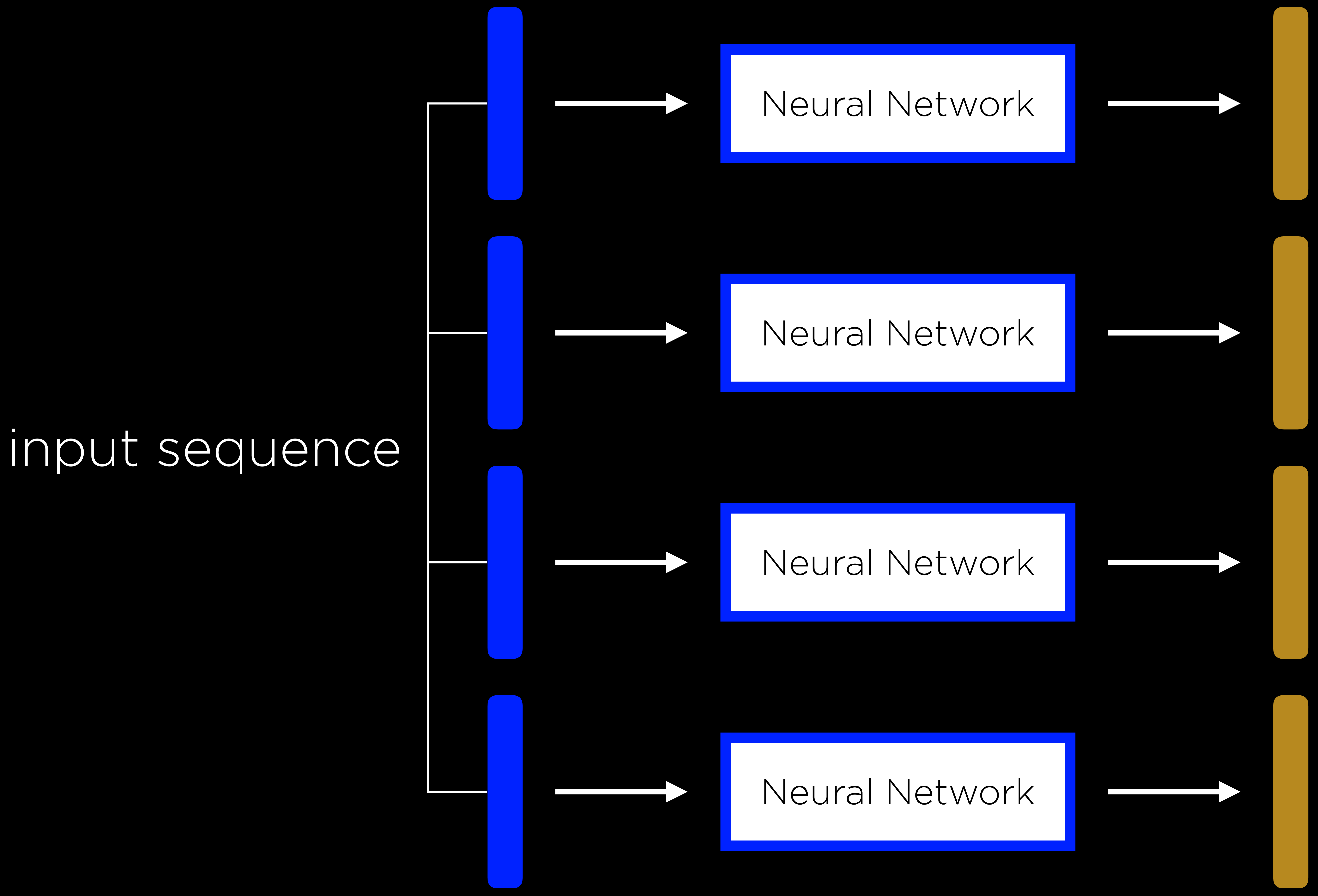
inputs are in series

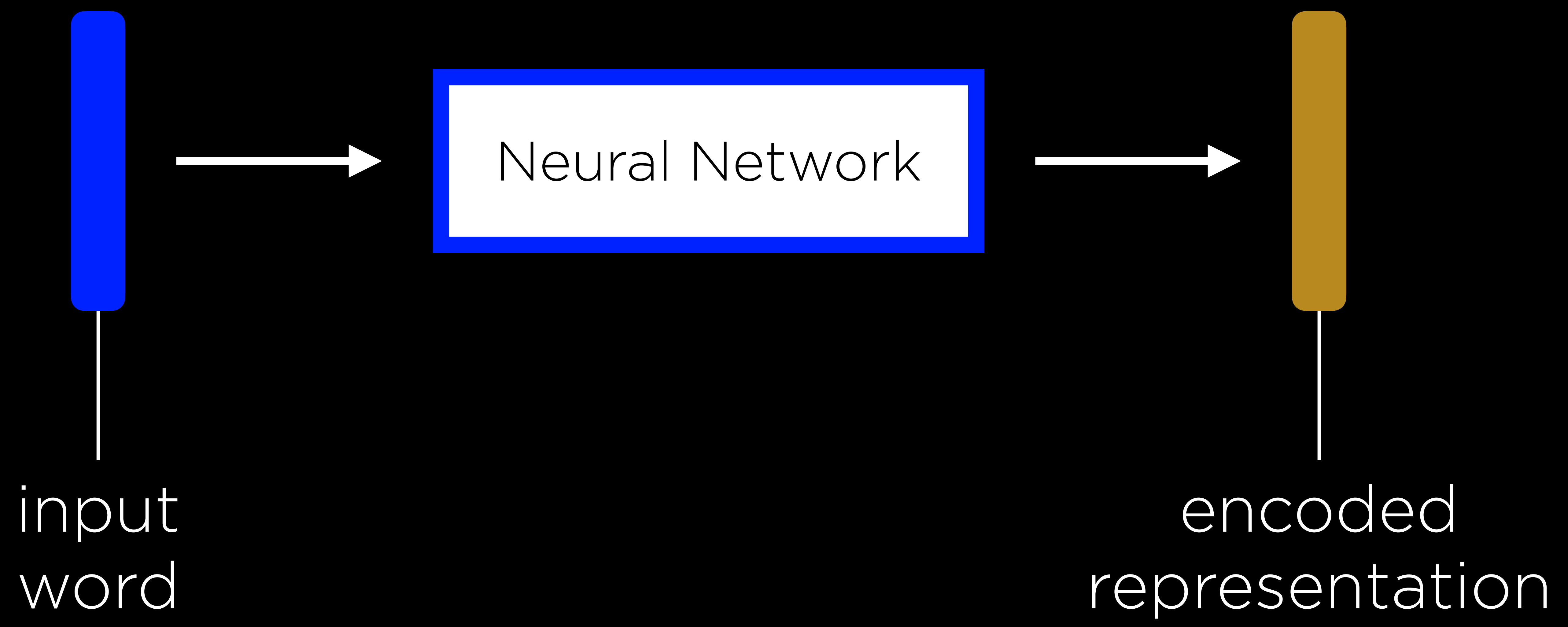


Transformers


input sequence

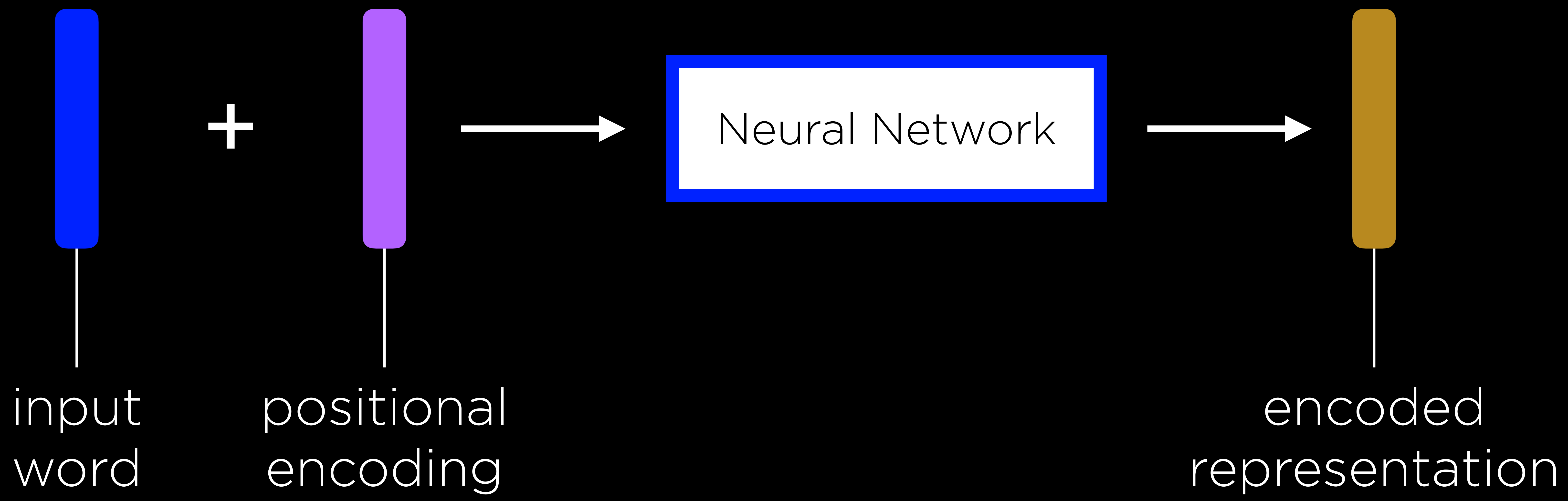
each input word will go through the same neural network





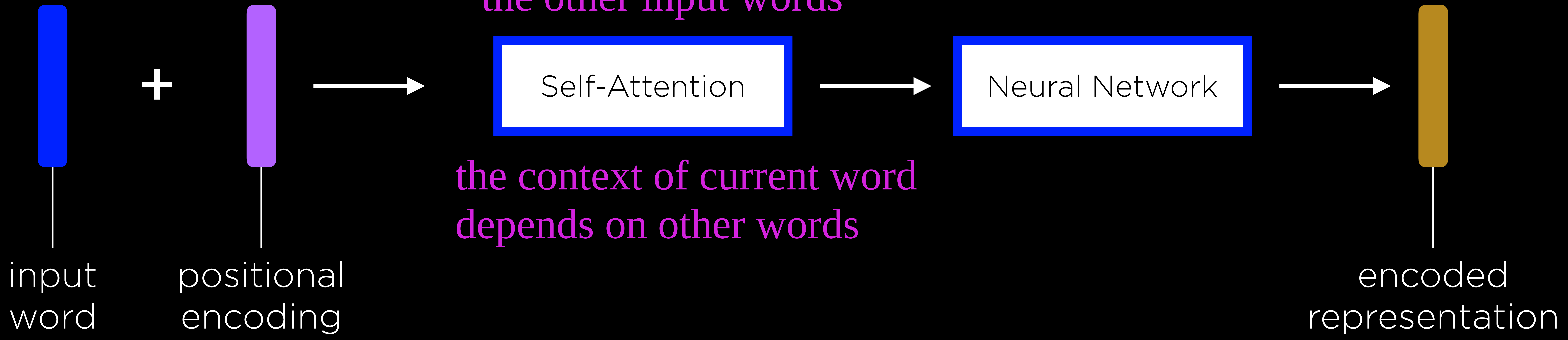
this single example is happening to every word

Jack likes Jill
has different meaning than
Jill likes Jack
so we need to track word's position



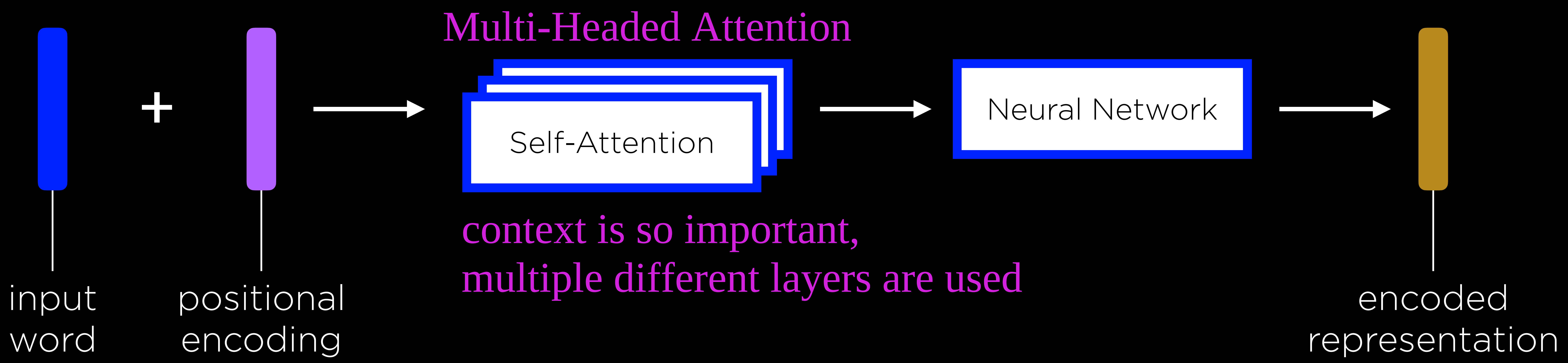
this single example is happening to every word

pay weighted attention to
the other input words

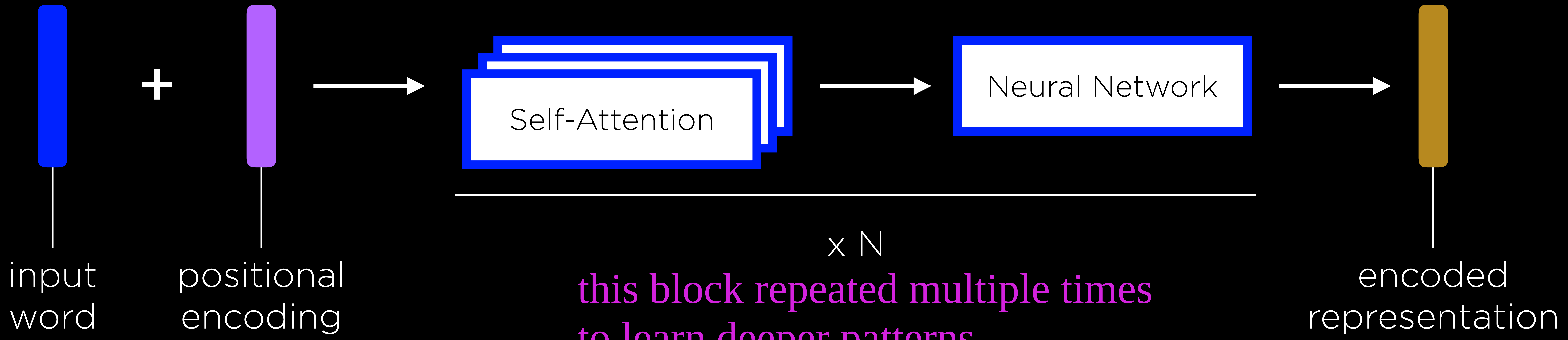


the context of current word
depends on other words

this single example is happening to every word

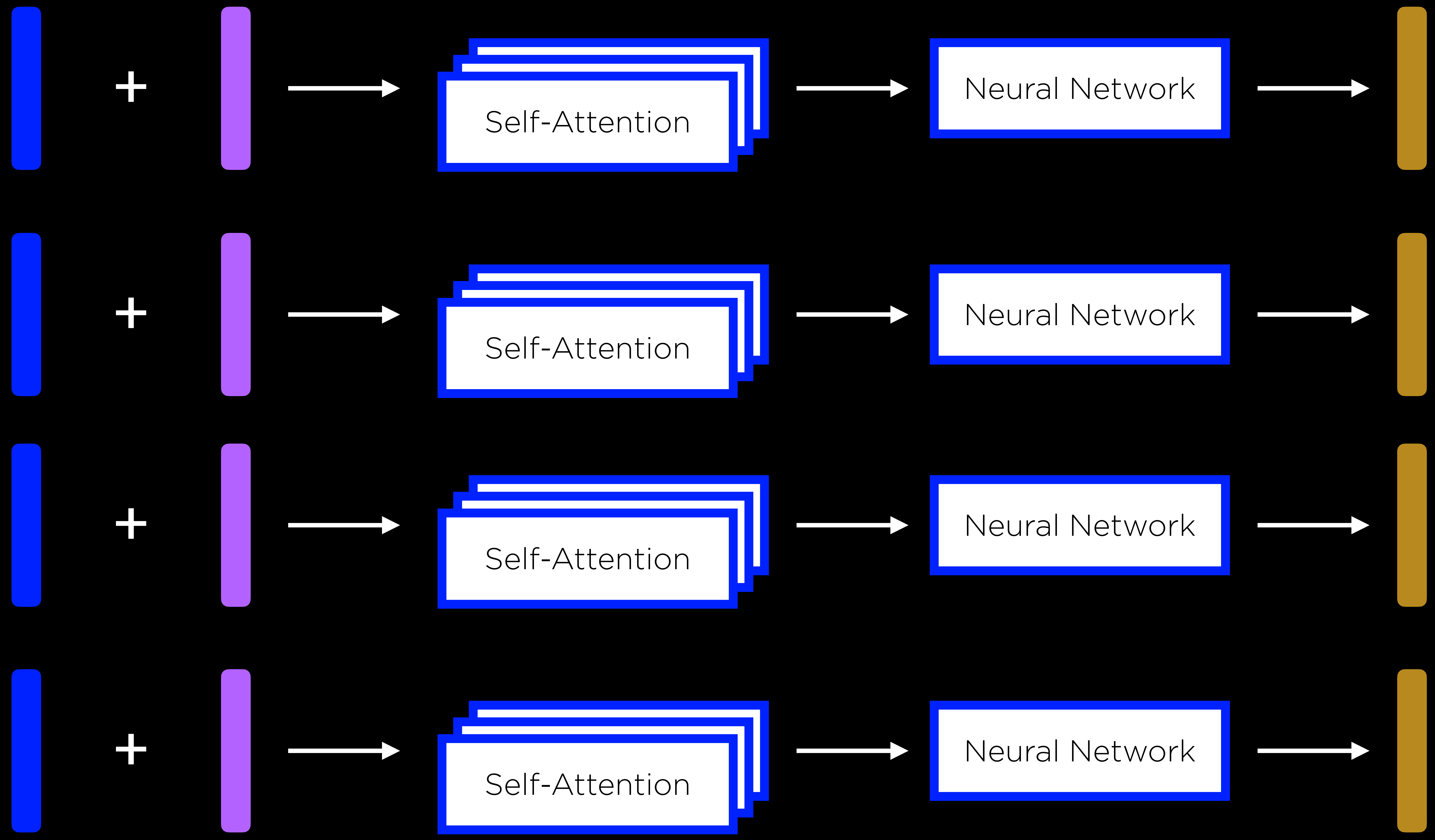


this single example is happening to every word

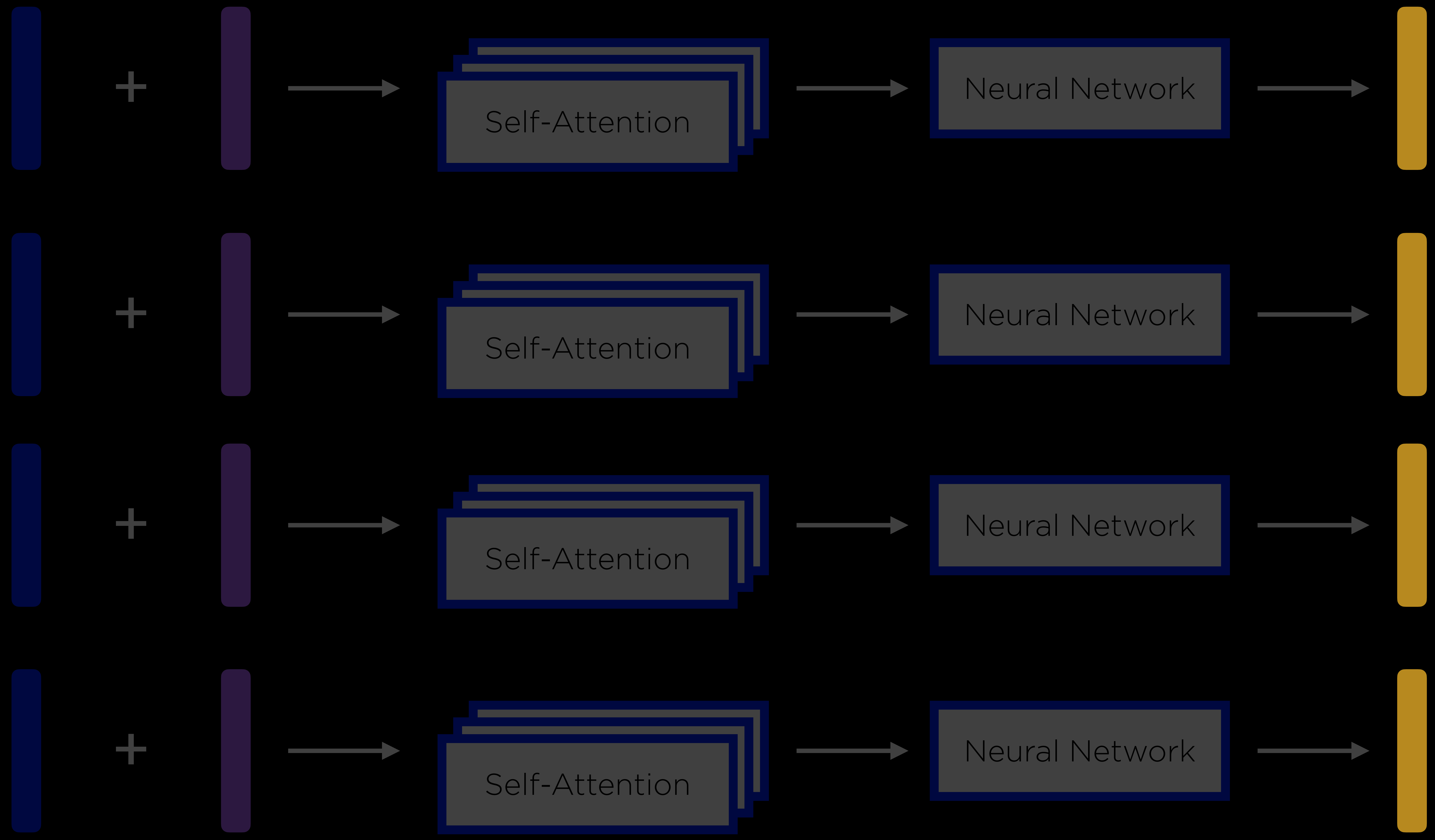


this block repeated multiple times to learn deeper patterns

this single example is happening to every word



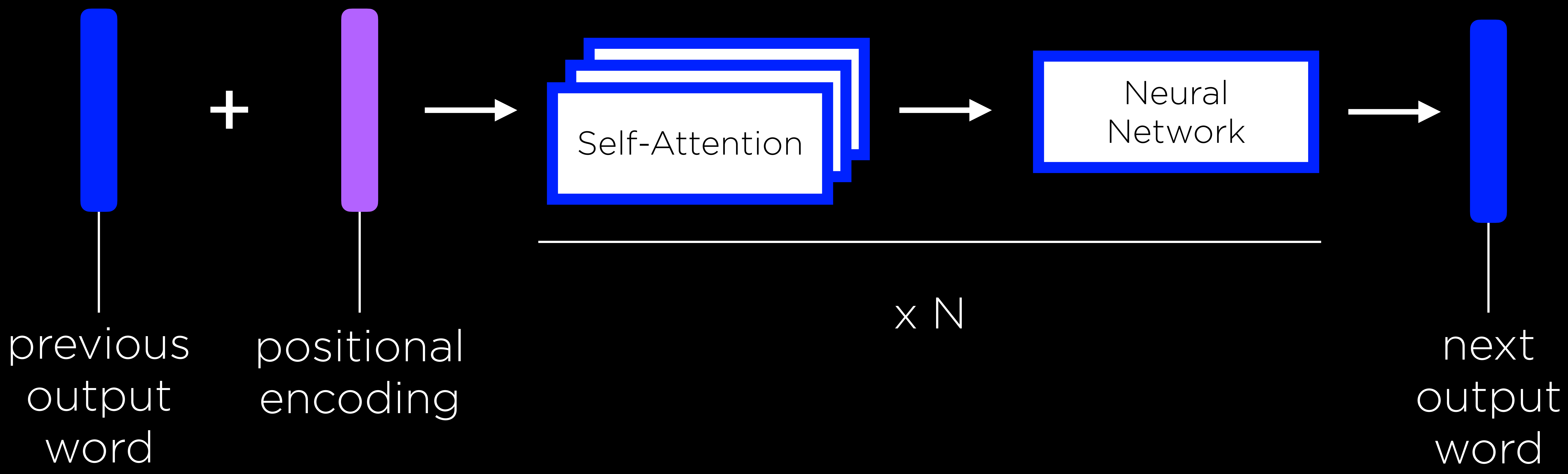
this single example is happening to every word



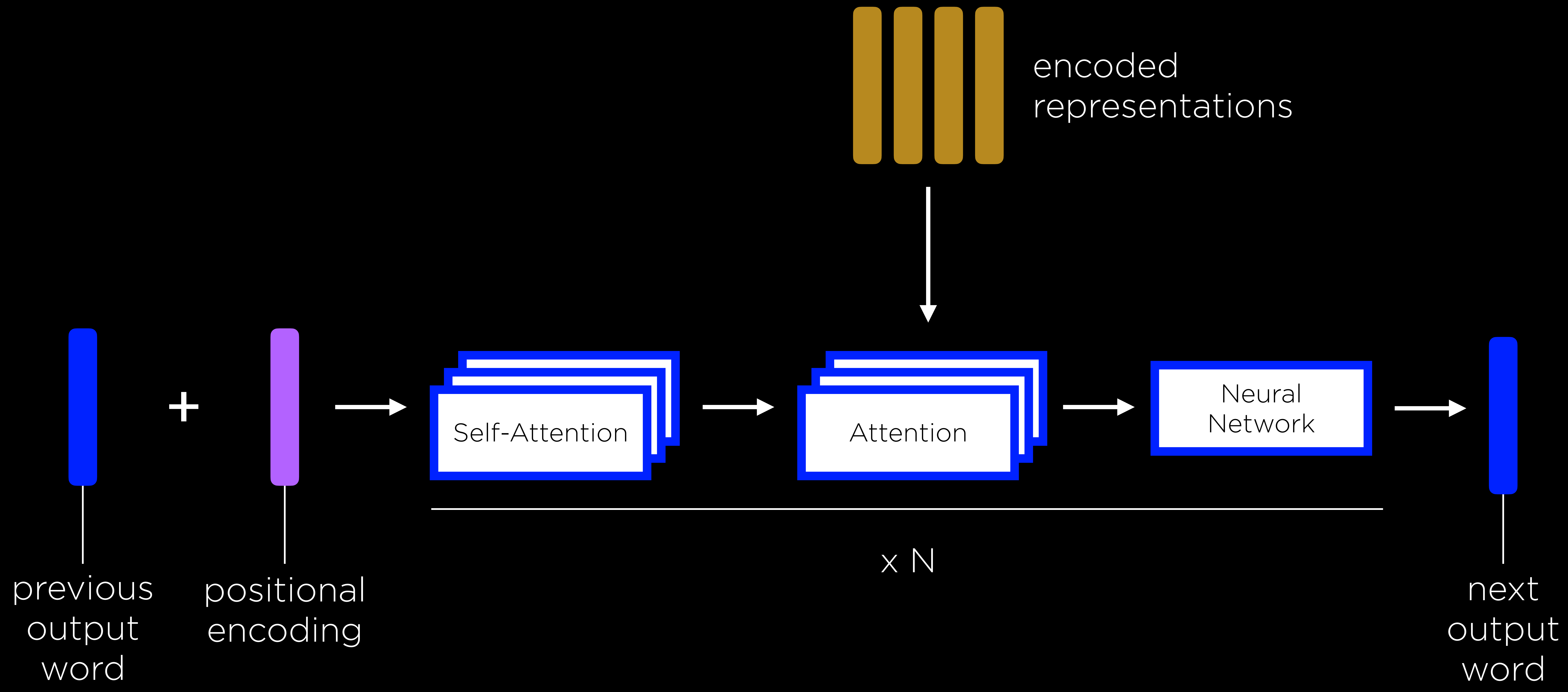
this single example is happening to every word

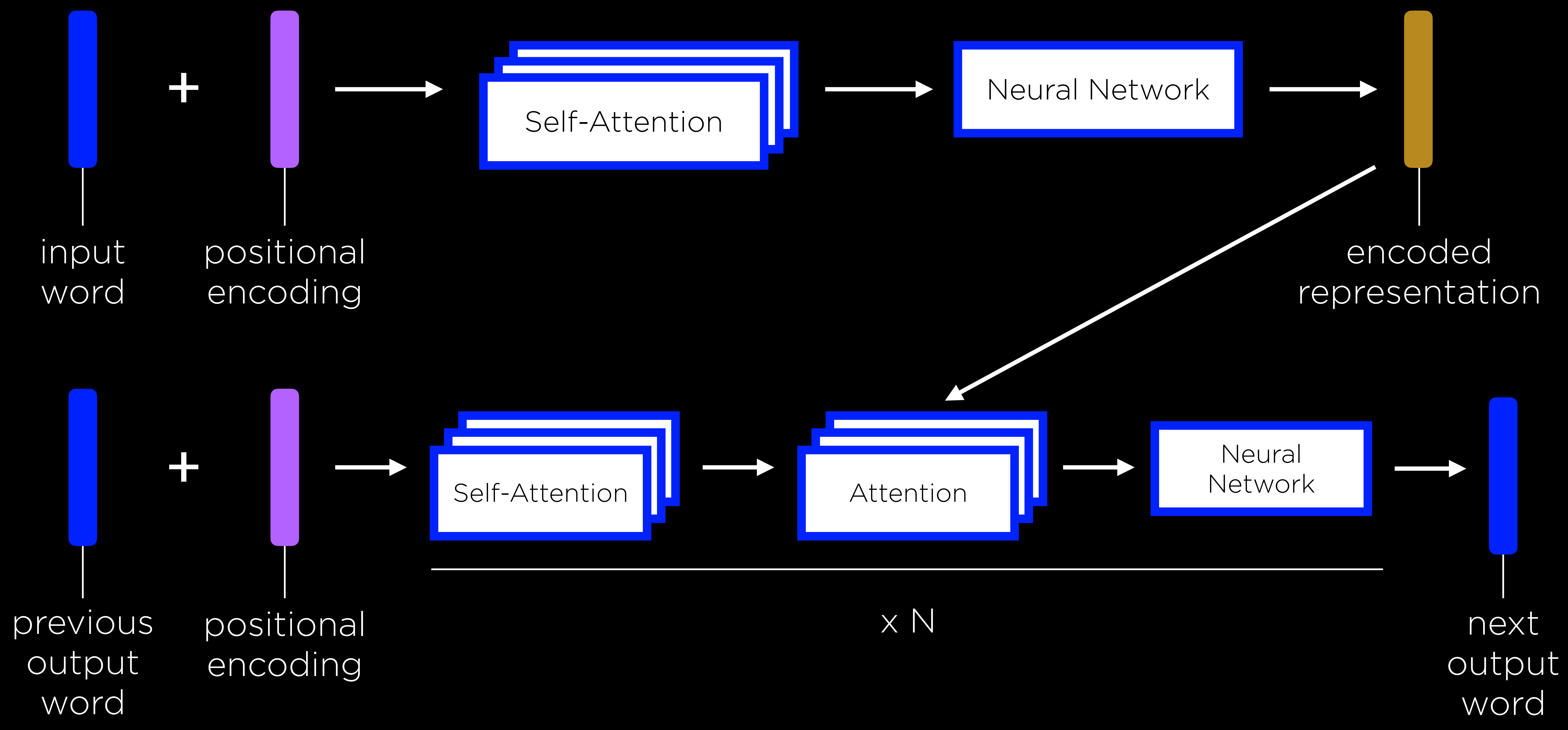
encoded representations

output uses similar structure to input: using the context of other output words
and we also want it to also pay attention to input words



decoder


encoded
representations
Self-Attention
Attention
Neural
Network
x N
previous
output
word
positional
encoding
next
output
word

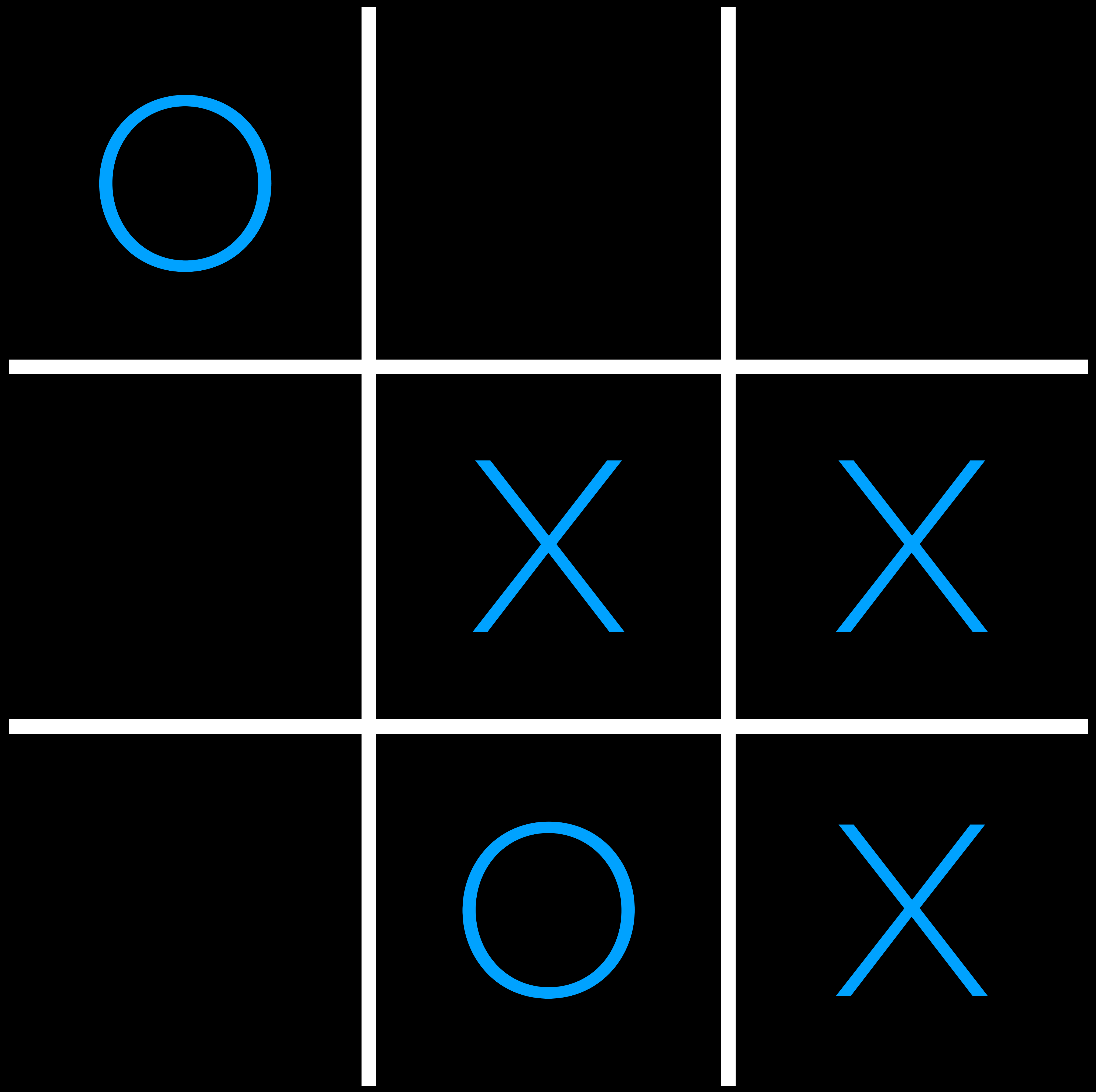


input
word
+
positional
encoding
Self-Attention
Neural Network
encoded
representation
previous
output
word
+
positional
encoding
Self-Attention
Attention
Neural
Network
next
output
word
x N

Language

Artificial Intelligence

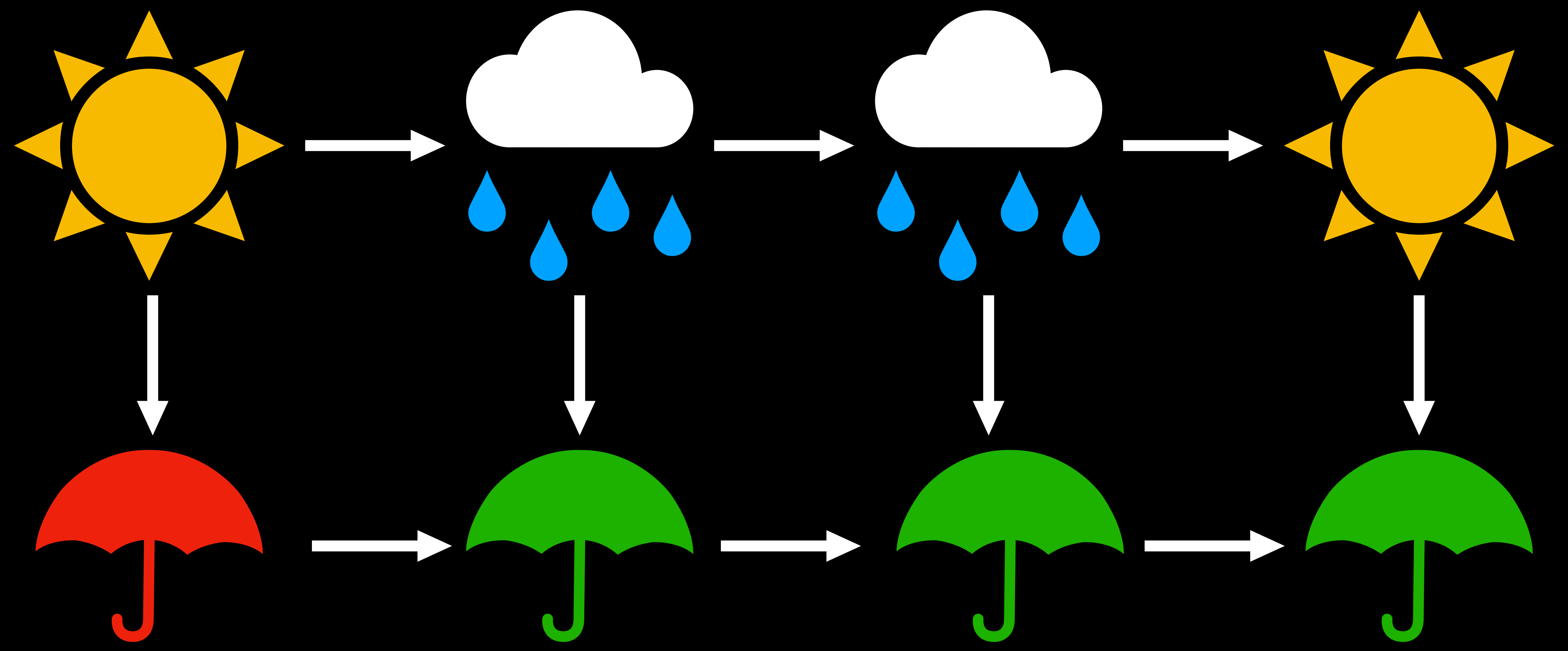
Search



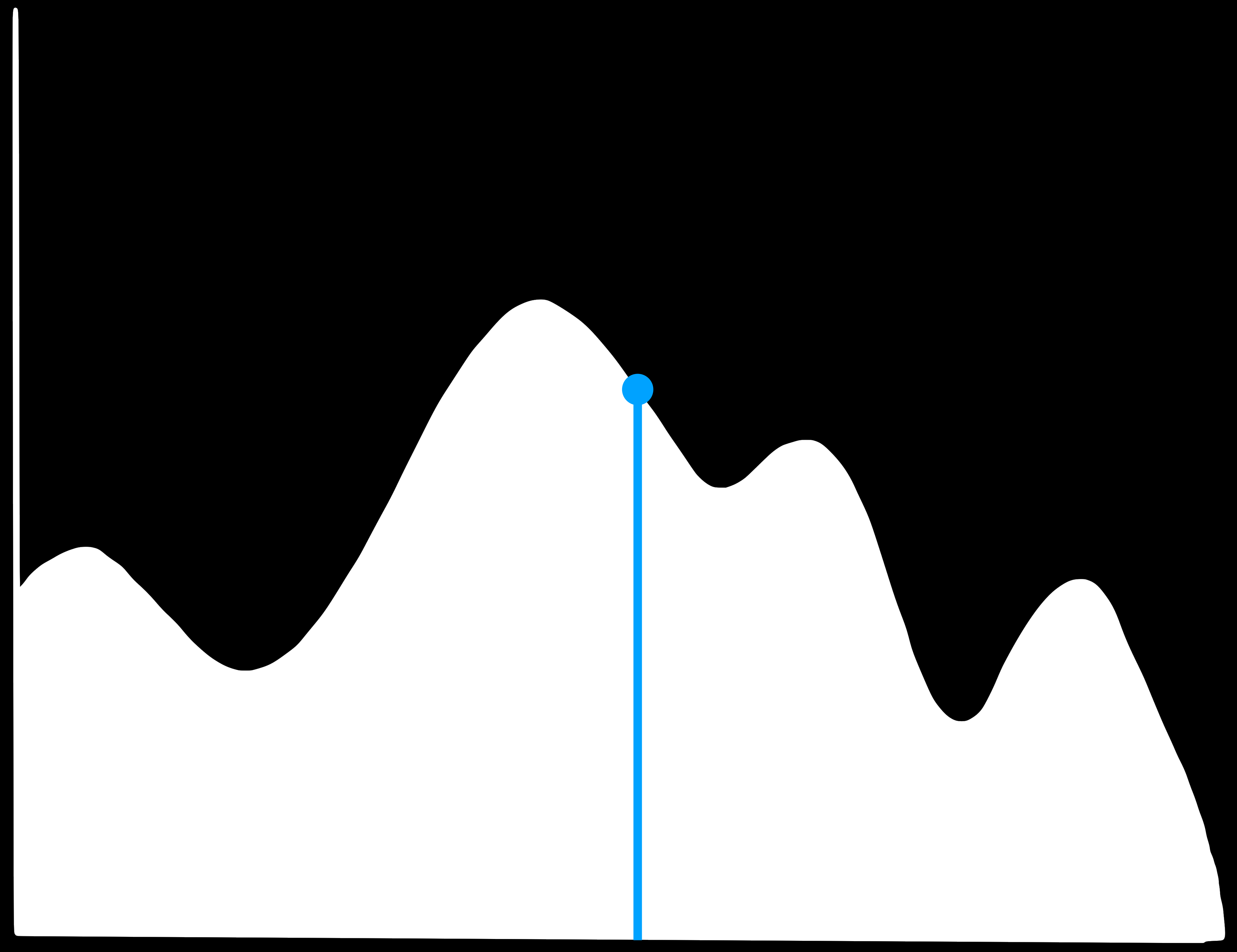
Knowledge

$$\frac{P \to Q \qquad P}{Q}$$

Uncertainty

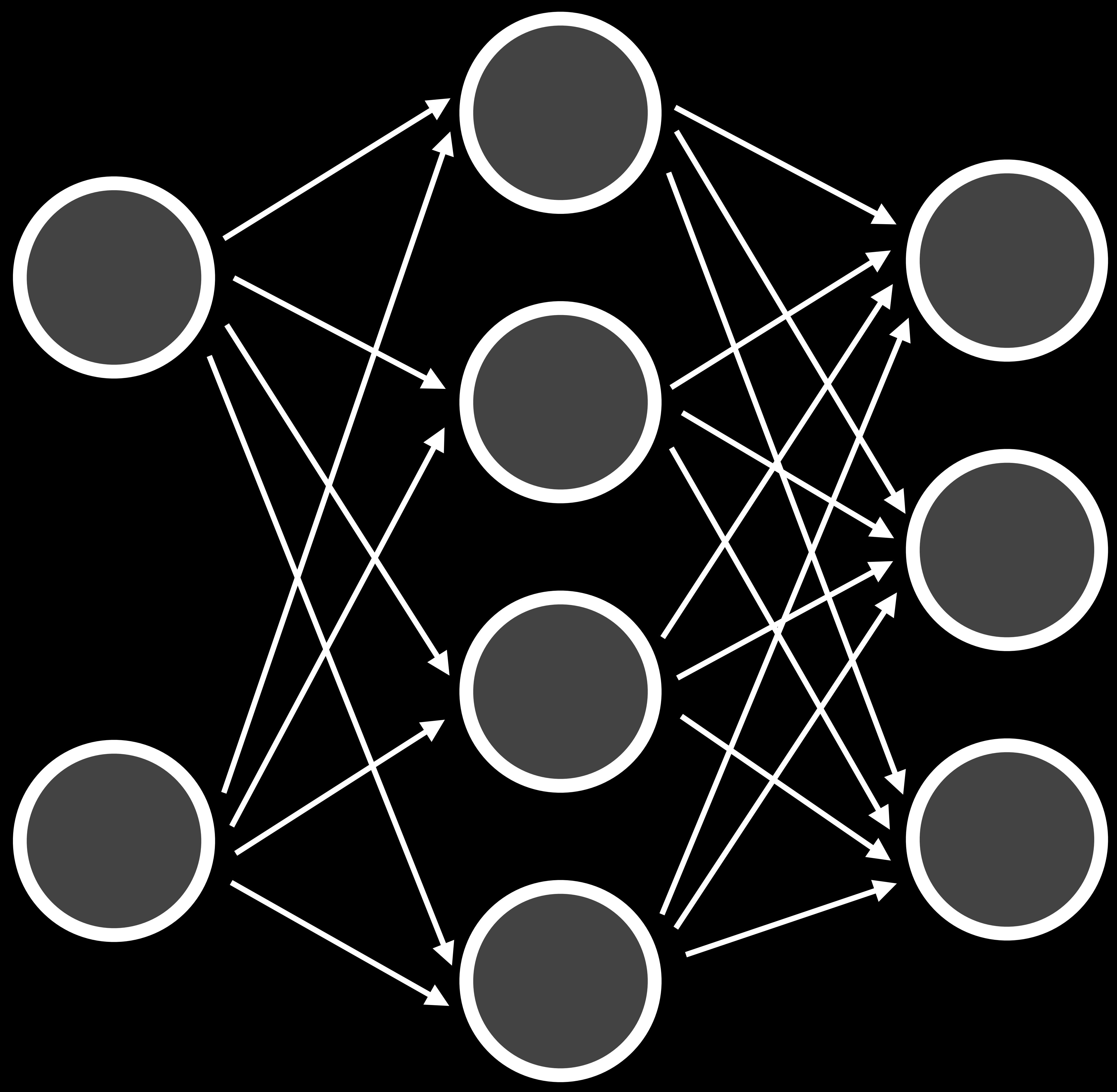


Optimization

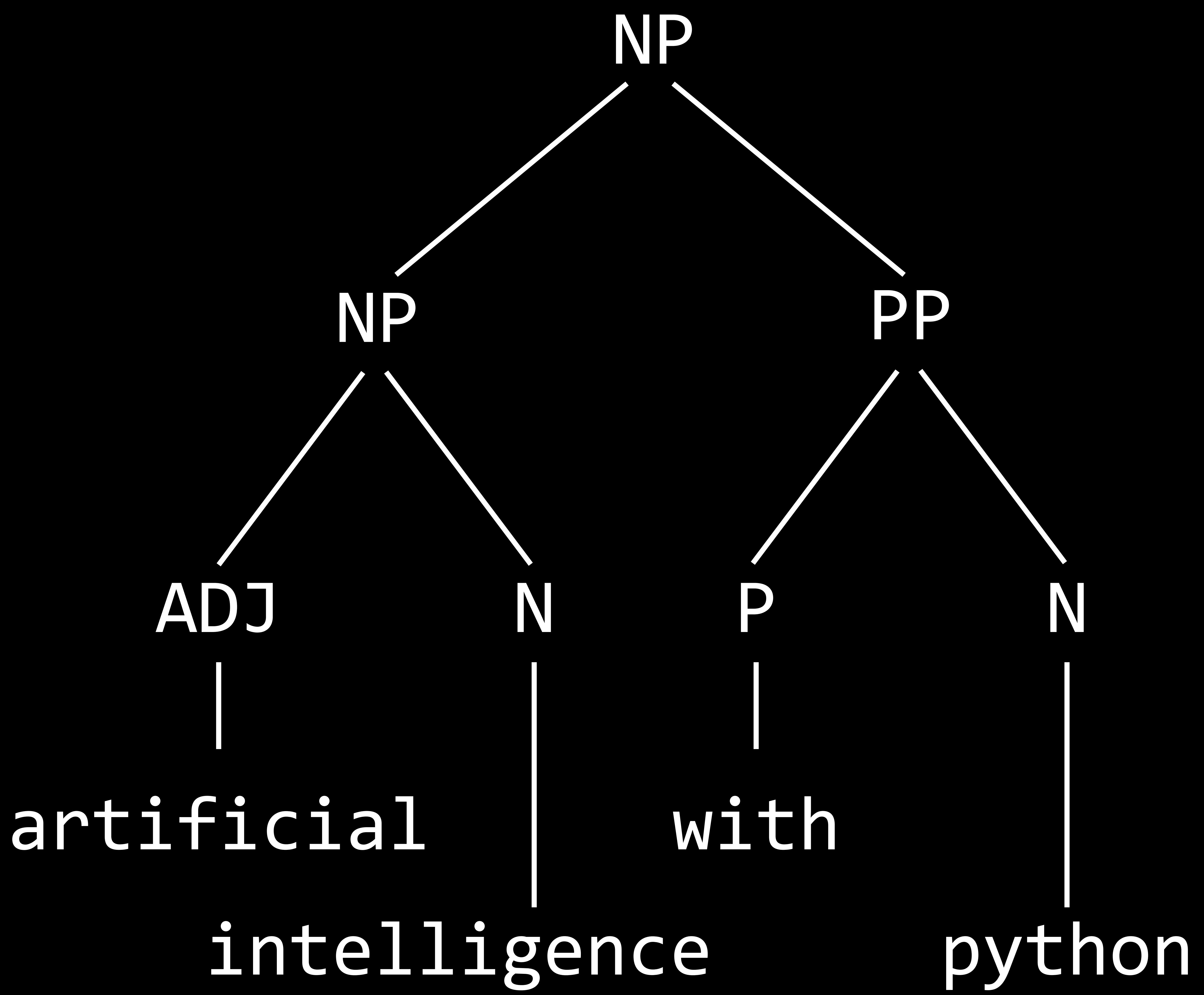


Learning

Neural Networks



Language



Introduction to

Artificial Intelligence

with Python