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

$N \rightarrow$ she | city | car | Harry | ...

$D \rightarrow$ the | a | an | ...

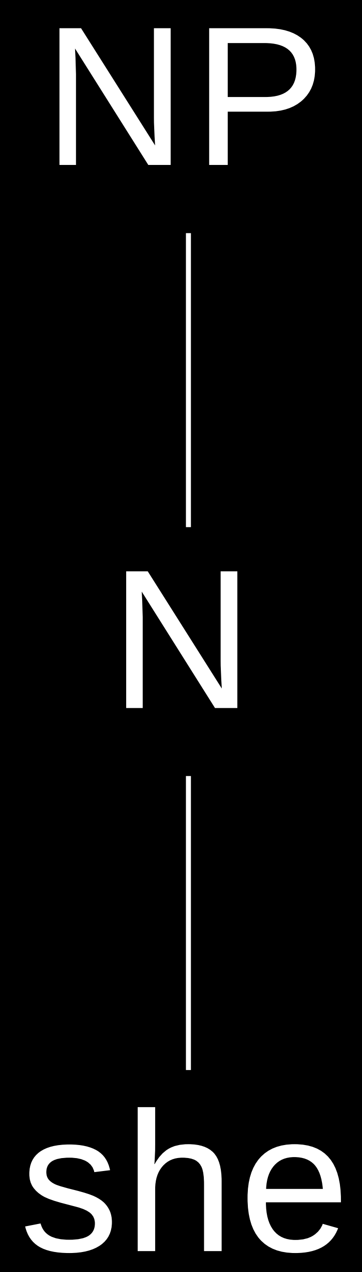
$V \rightarrow$ saw | ate | walked | ...

$P \rightarrow$ to | on | over | ...

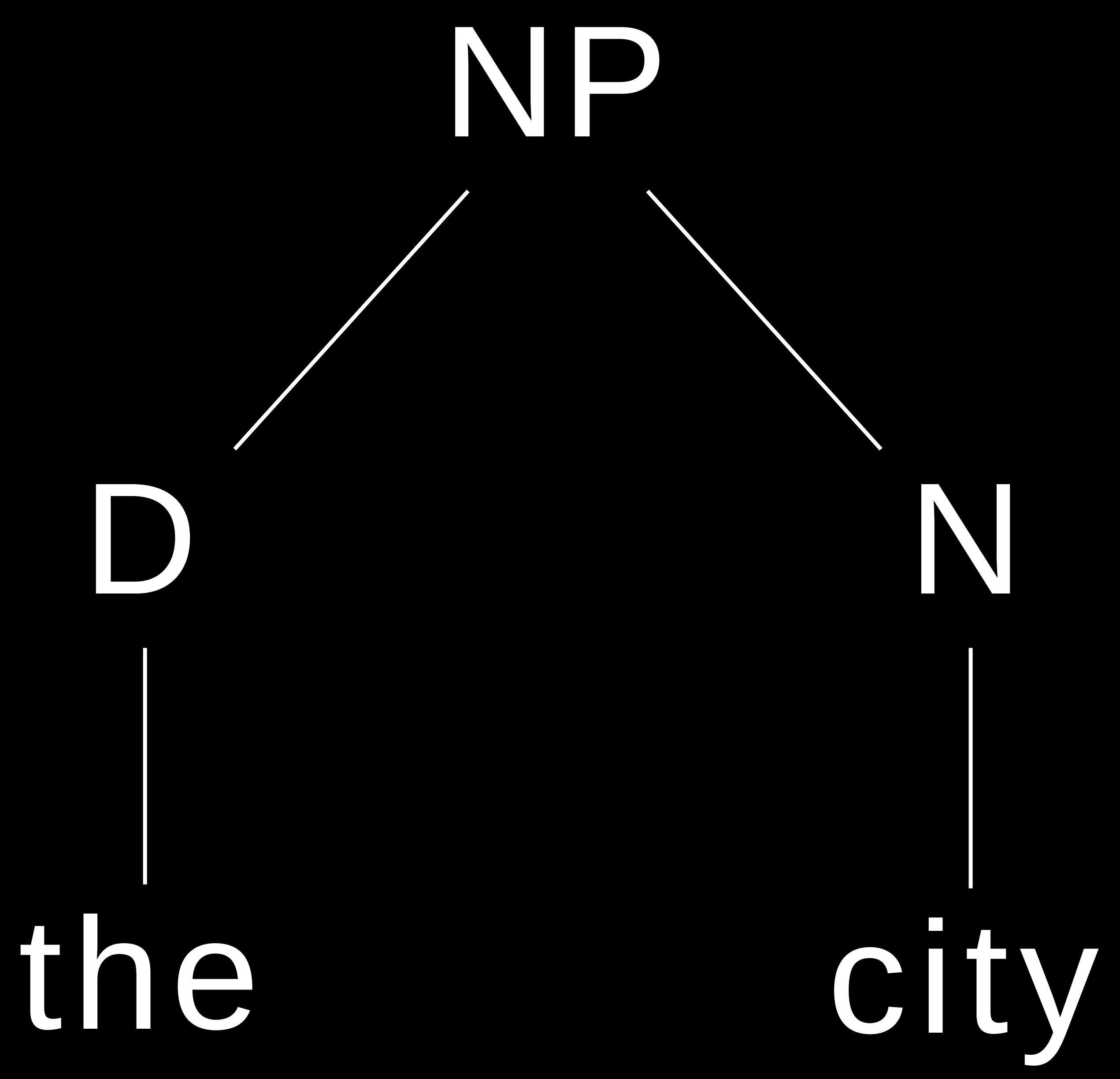
$ADJ \rightarrow$ blue | busy | old | ...

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

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

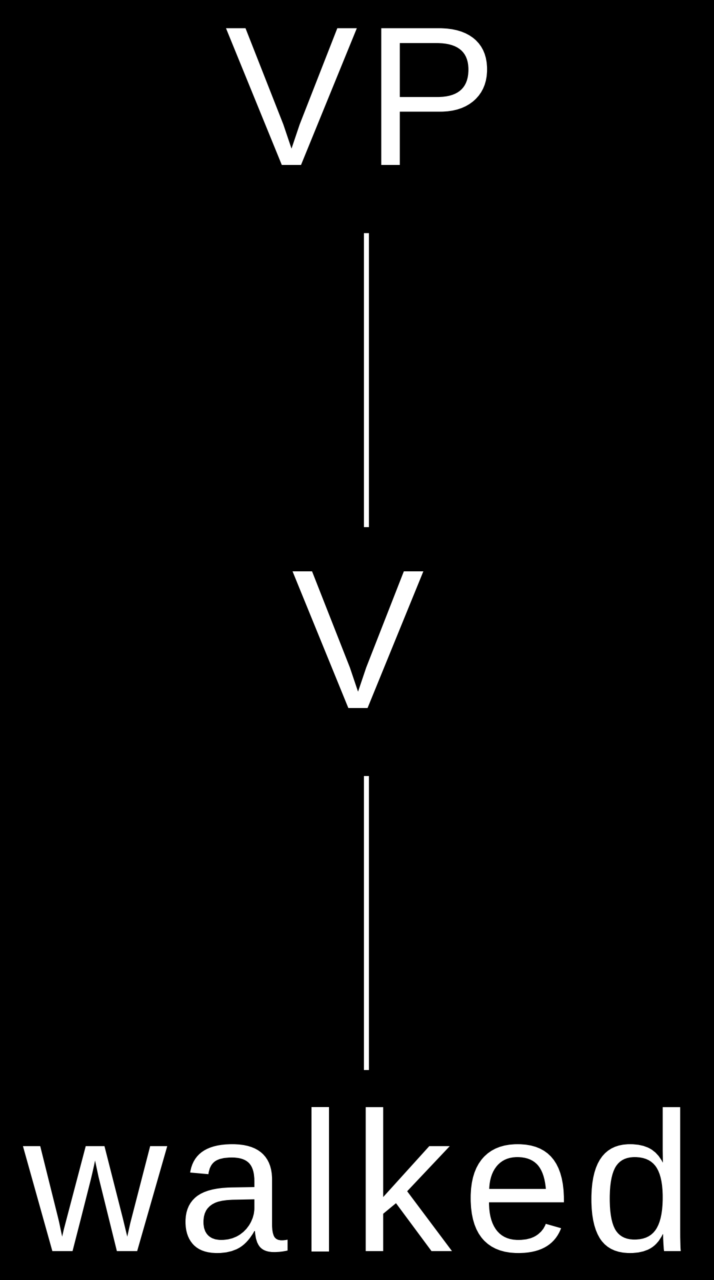


$$\mathrm{NP} \rightarrow \mathrm{N} \mid \mathrm{D}\ \mathrm{N}$$

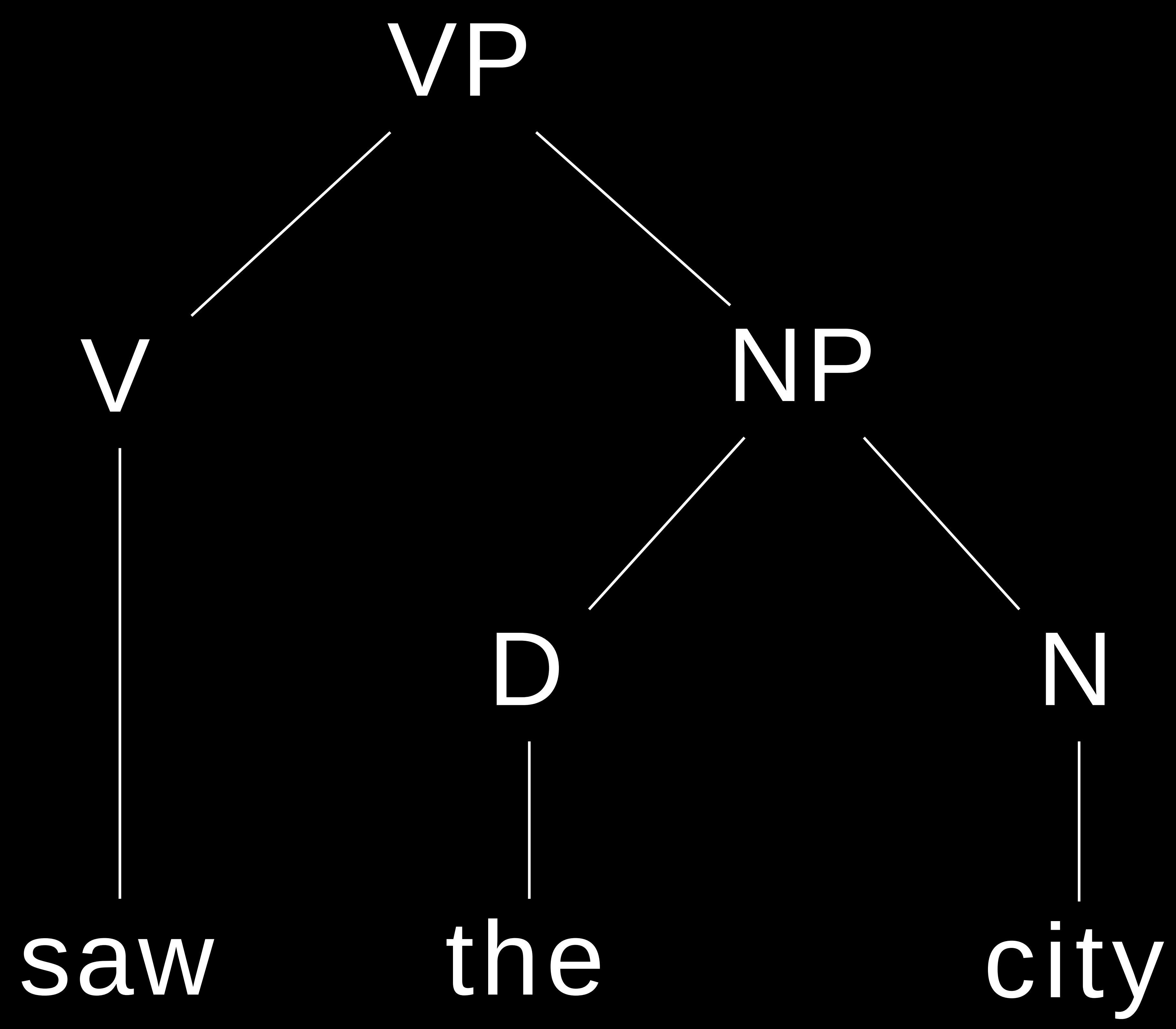


$$VP \rightarrow V \;\; | \;\; V \;\; NP$$

$VP \rightarrow V \mid V\ NP$

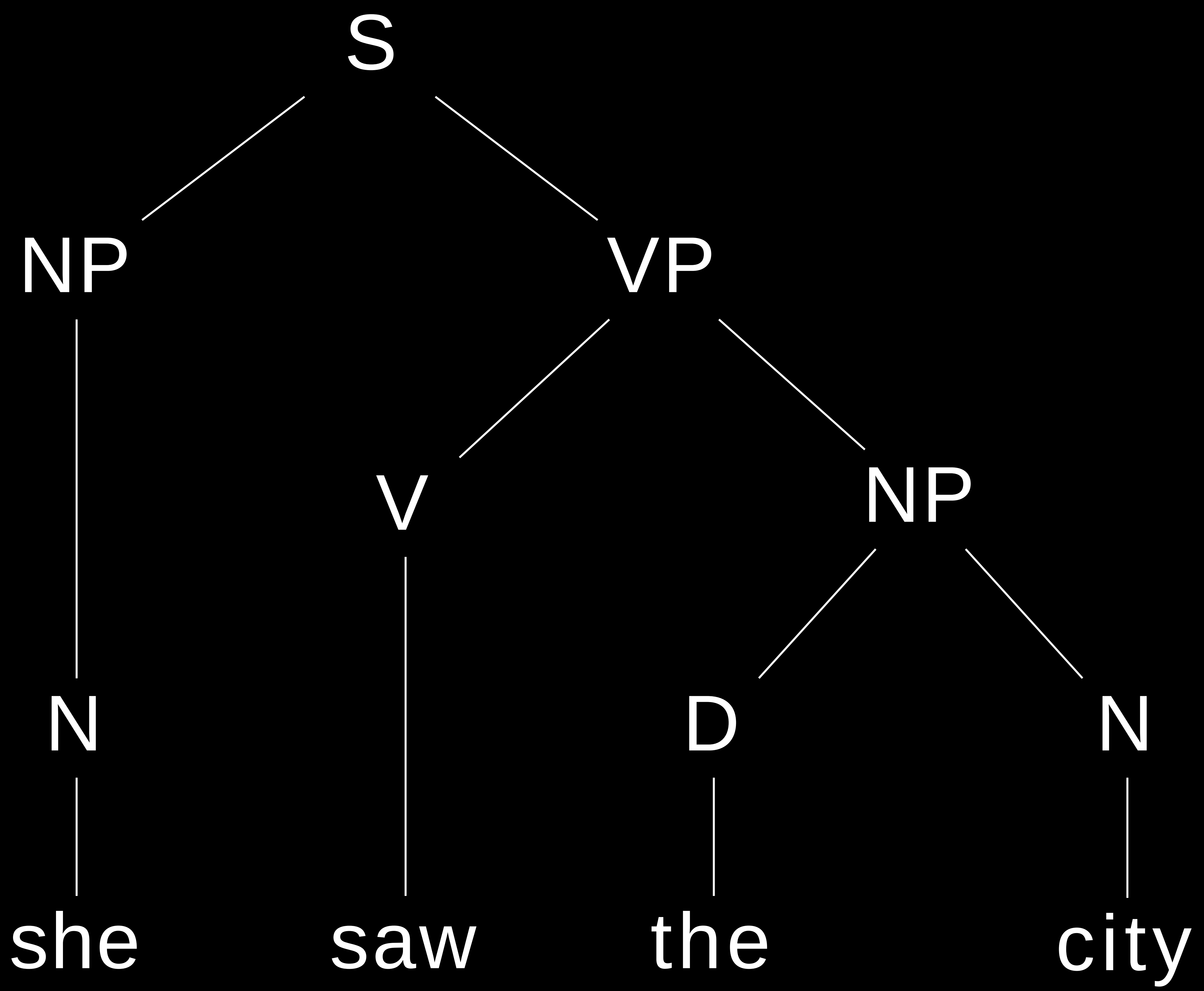


$$VP \rightarrow V \mid V\ NP$$



$$S \rightarrow NP \ \ VP$$

$$S \rightarrow NP\ VP$$



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?"

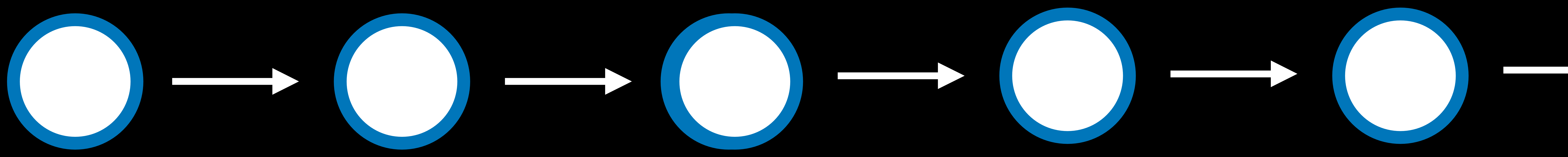
"How often have I **said to you** that when you have eliminated the impossible whatever remains, however improbable, must be the truth?"

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

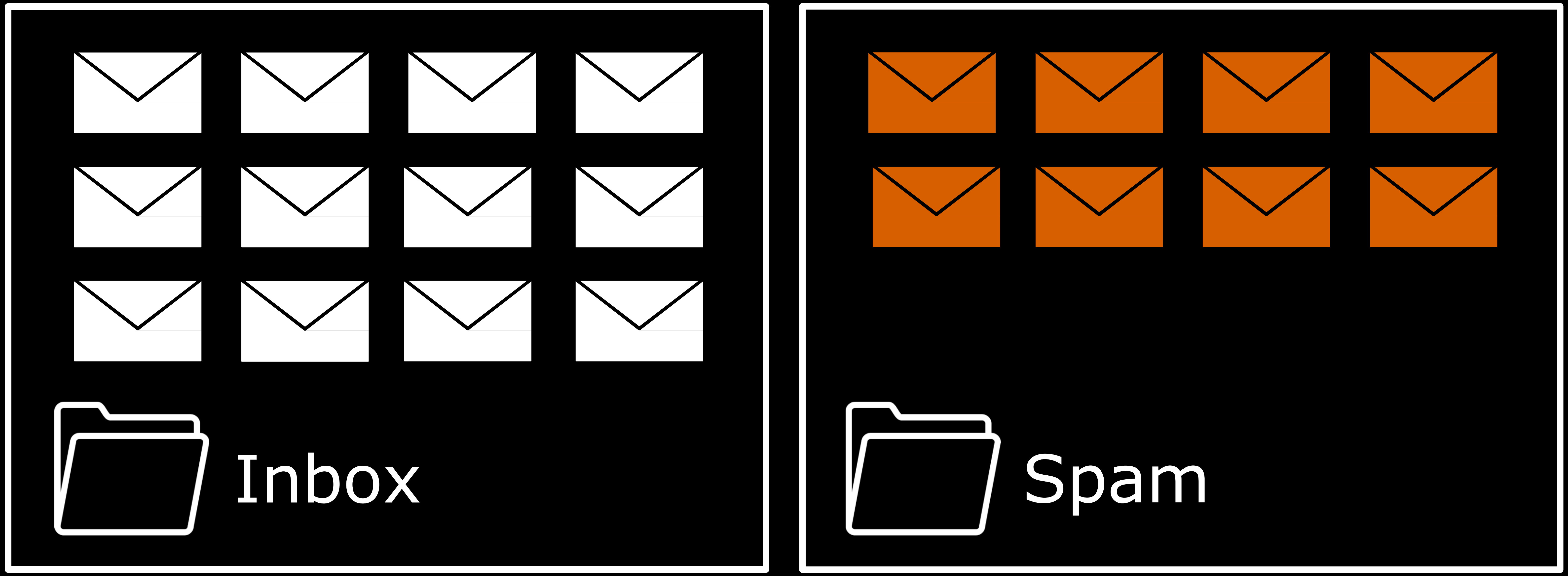
tokenization

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(😀)

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

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

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

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

equal to

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

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

proportional to

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

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

proportional to

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

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

naively proportional to

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

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

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

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

😀	🙁
0.49	0.51

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

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

😀	🙁
0.49	0.51

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

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

😀	🙁
0.49	0.51

😀 0.00014112

	😀	🙁
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

😀 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

	😀	🙁
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

🙁 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

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

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

😀	🙁
0.49	0.51

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

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

😀	🙁
0.49	0.51

	😀	🙁
my	0.30	0.20
grandson	0.00	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

😀 0.00000000

🙁 0.00006528

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

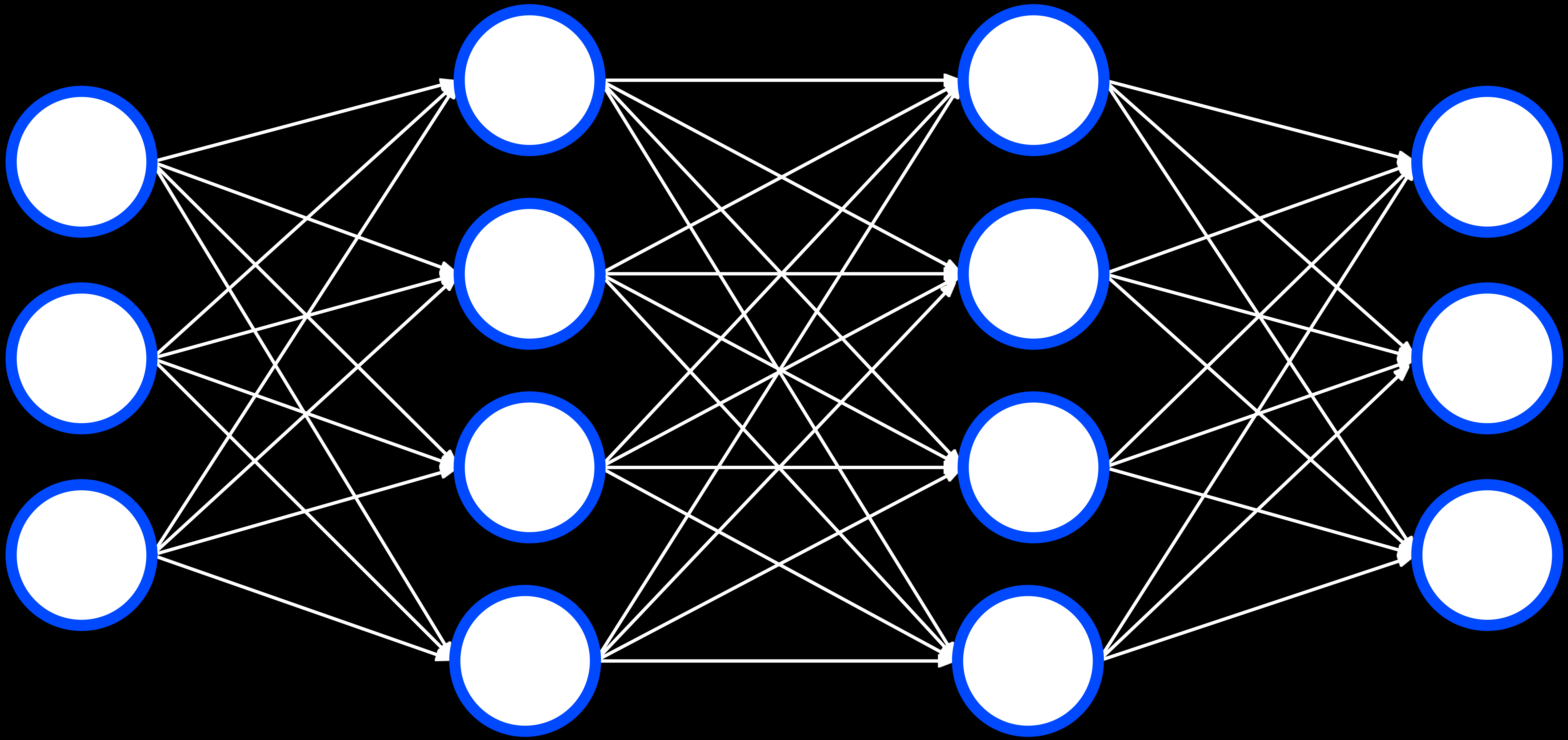
additive smoothing

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

Laplace smoothing

adding 1to 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, ...]

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

J. R. Firth, 1957

for		he	ate

for	breakfast	he	ate

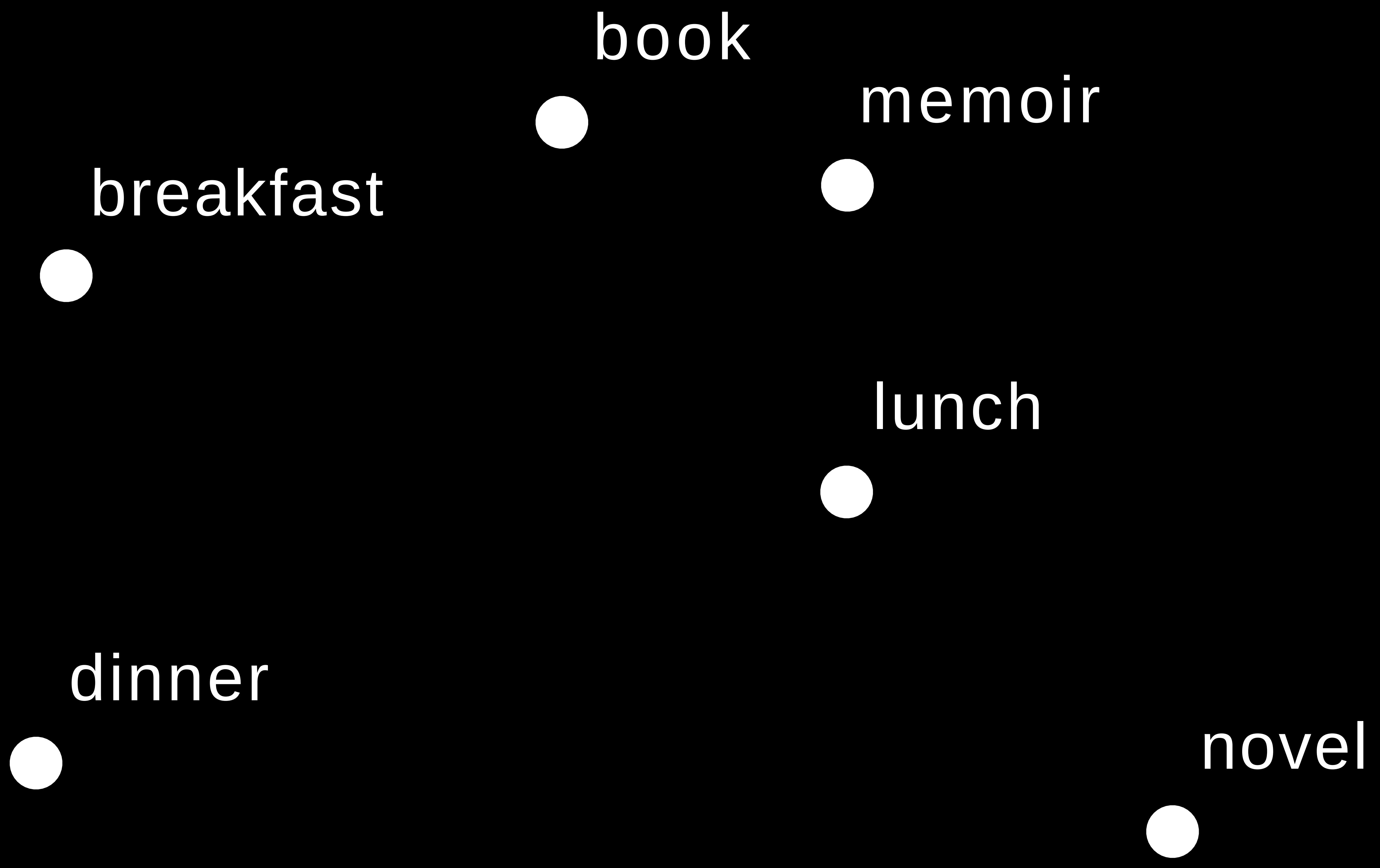
for	lunch	he	ate

for	dinner	he	ate

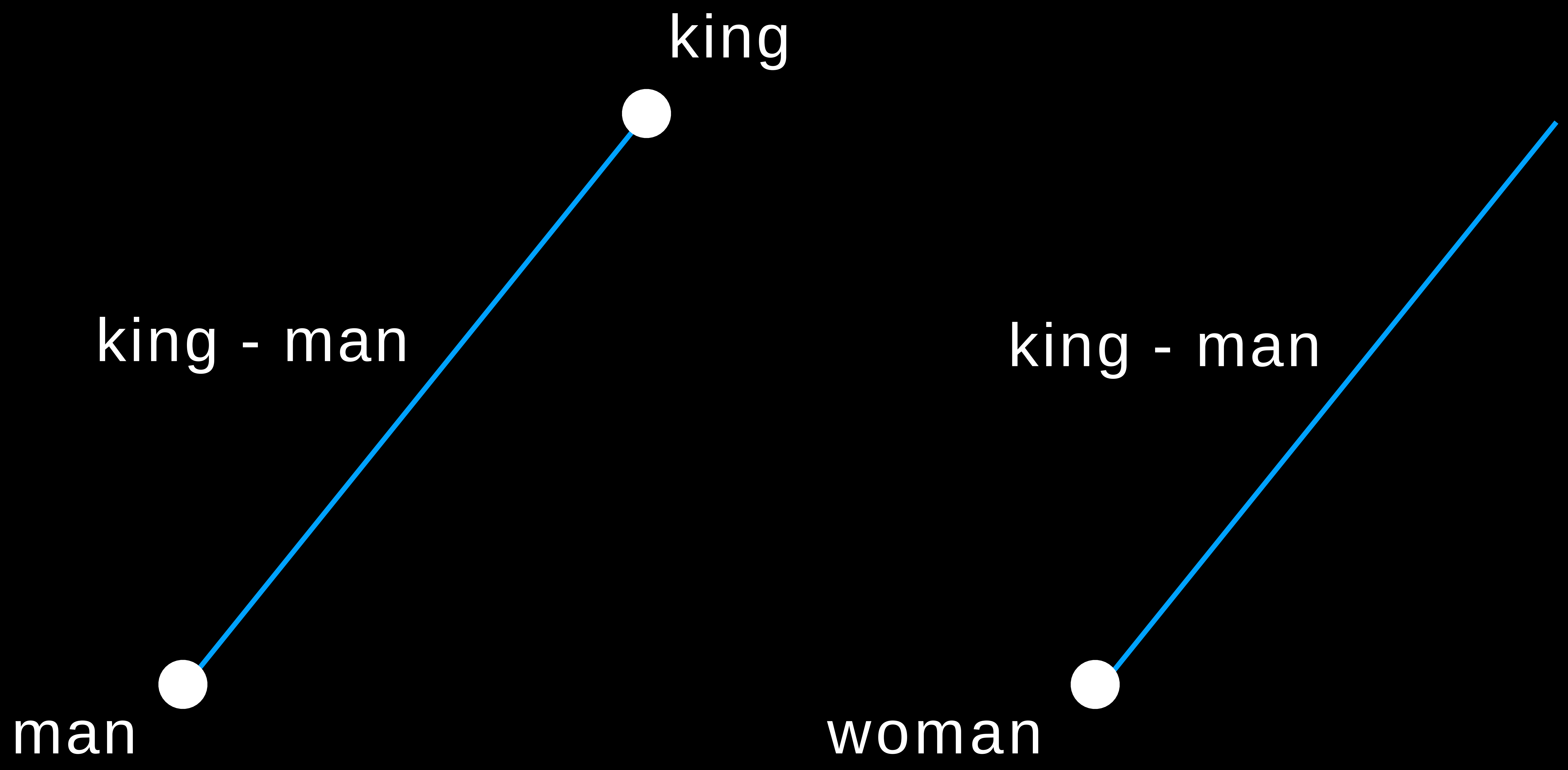
for		he	ate

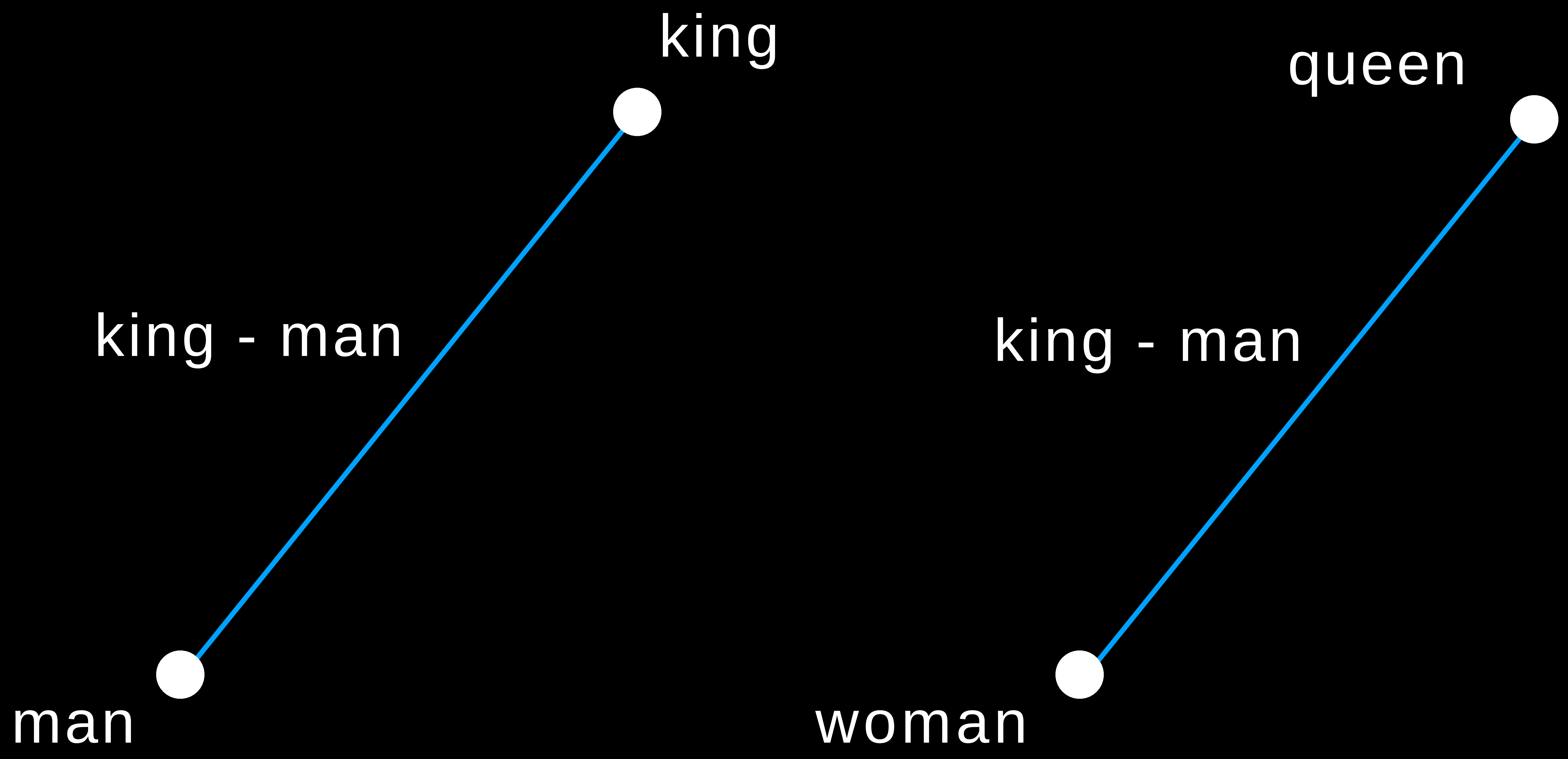
word2vec

model for generating word vectors

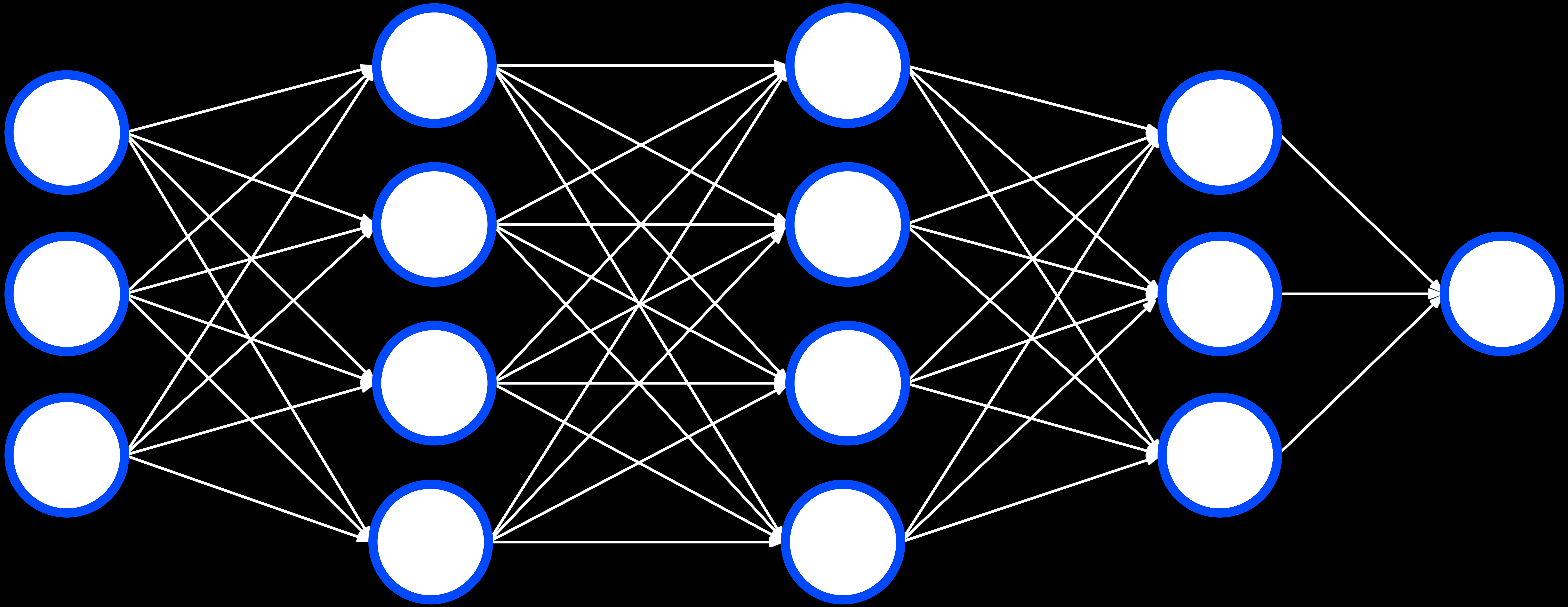

book
memoir
breakfast
lunch
dinner
novel

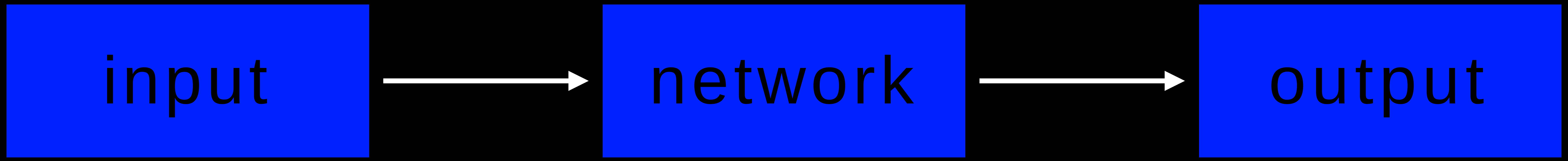

memoir
book
breakfast
novel
lunch
dinner

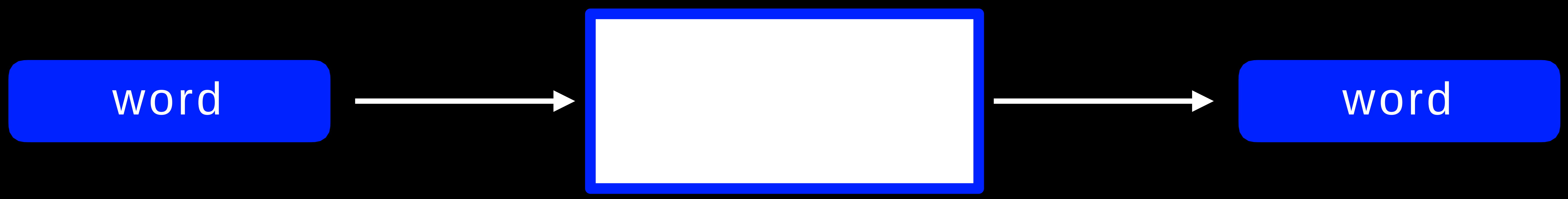

king
king - man
king - man
man
woman

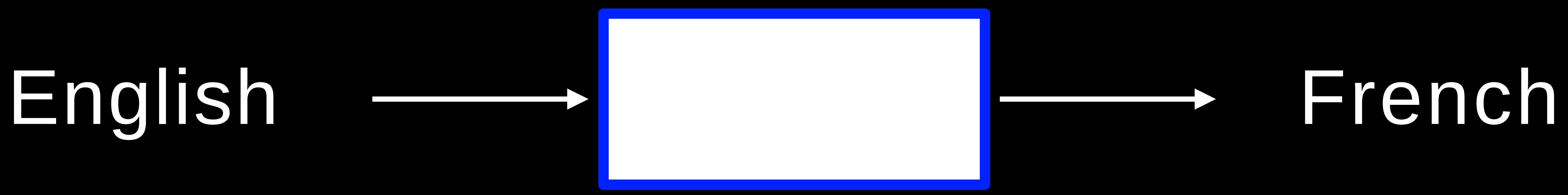

king
queen
king - man
king - man
man
woman

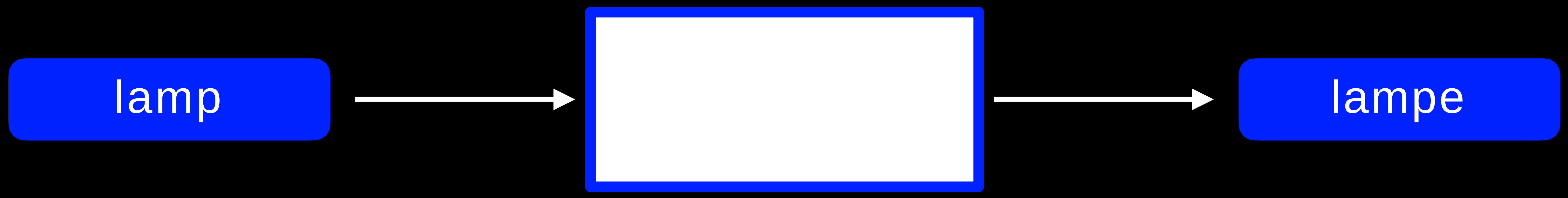
Neural Networks




input
network
output

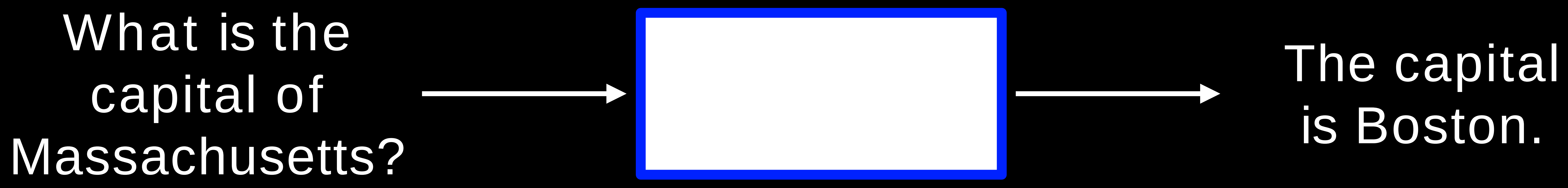

word
word

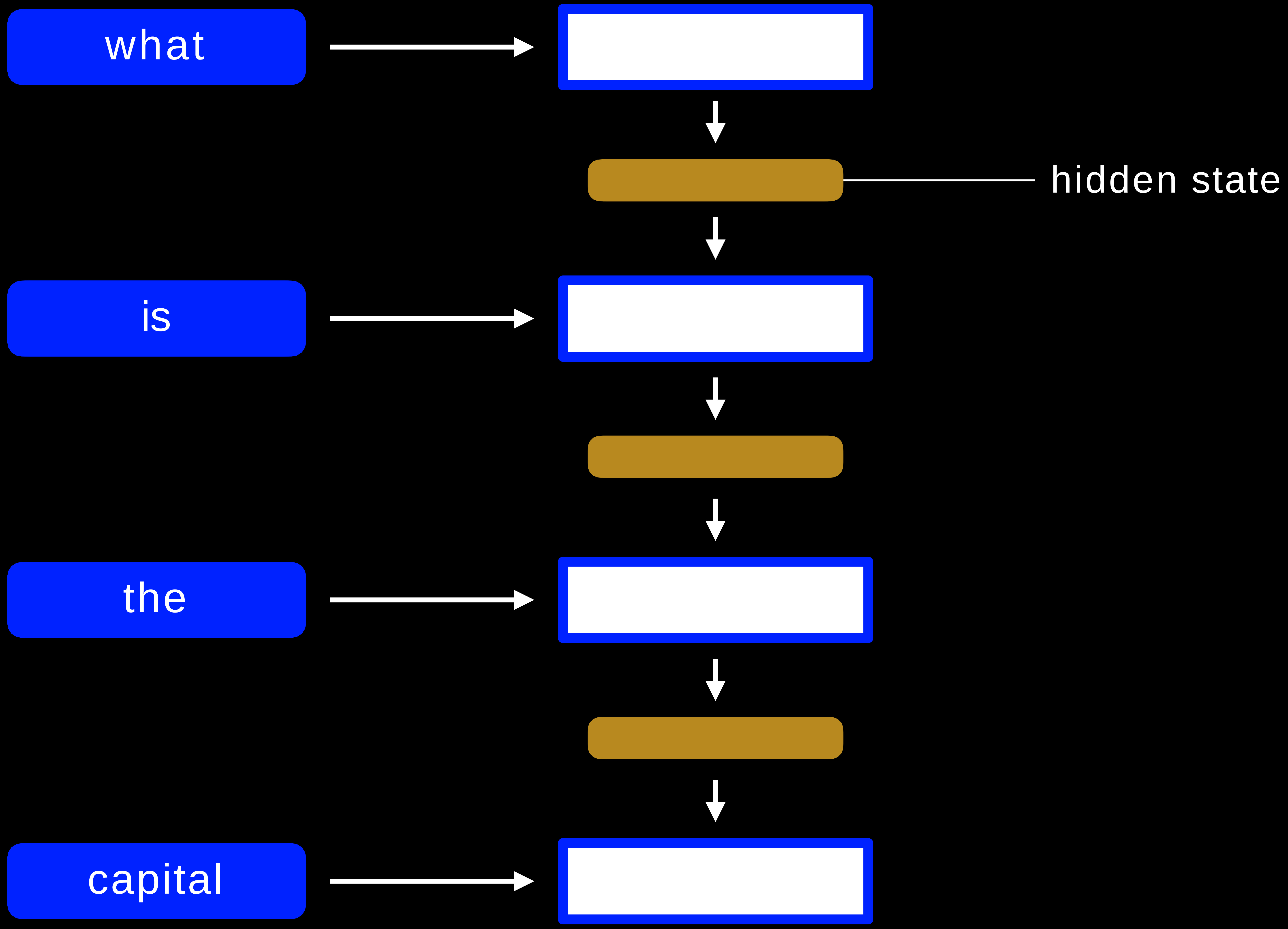

English
French

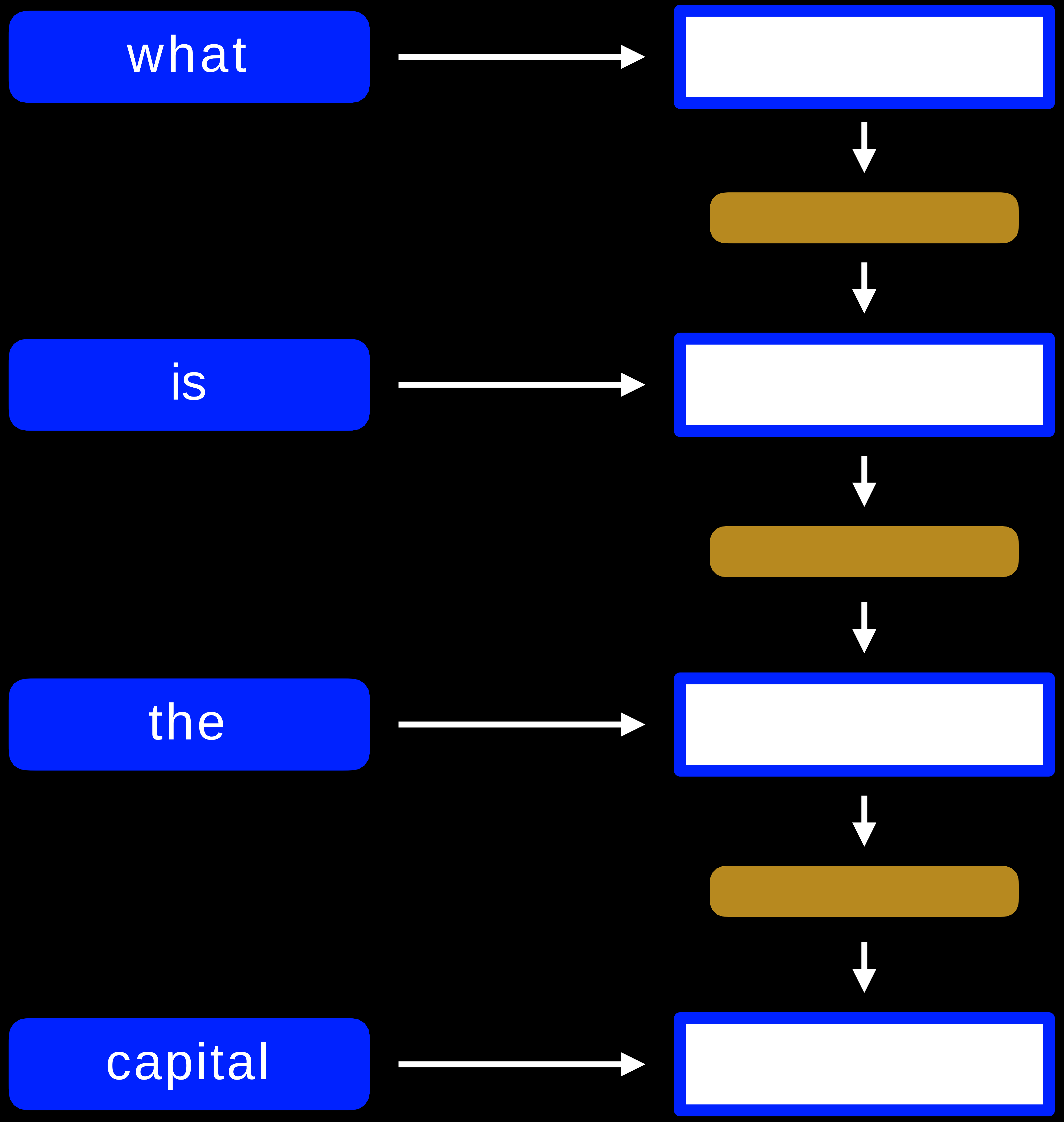

lamp
lampe

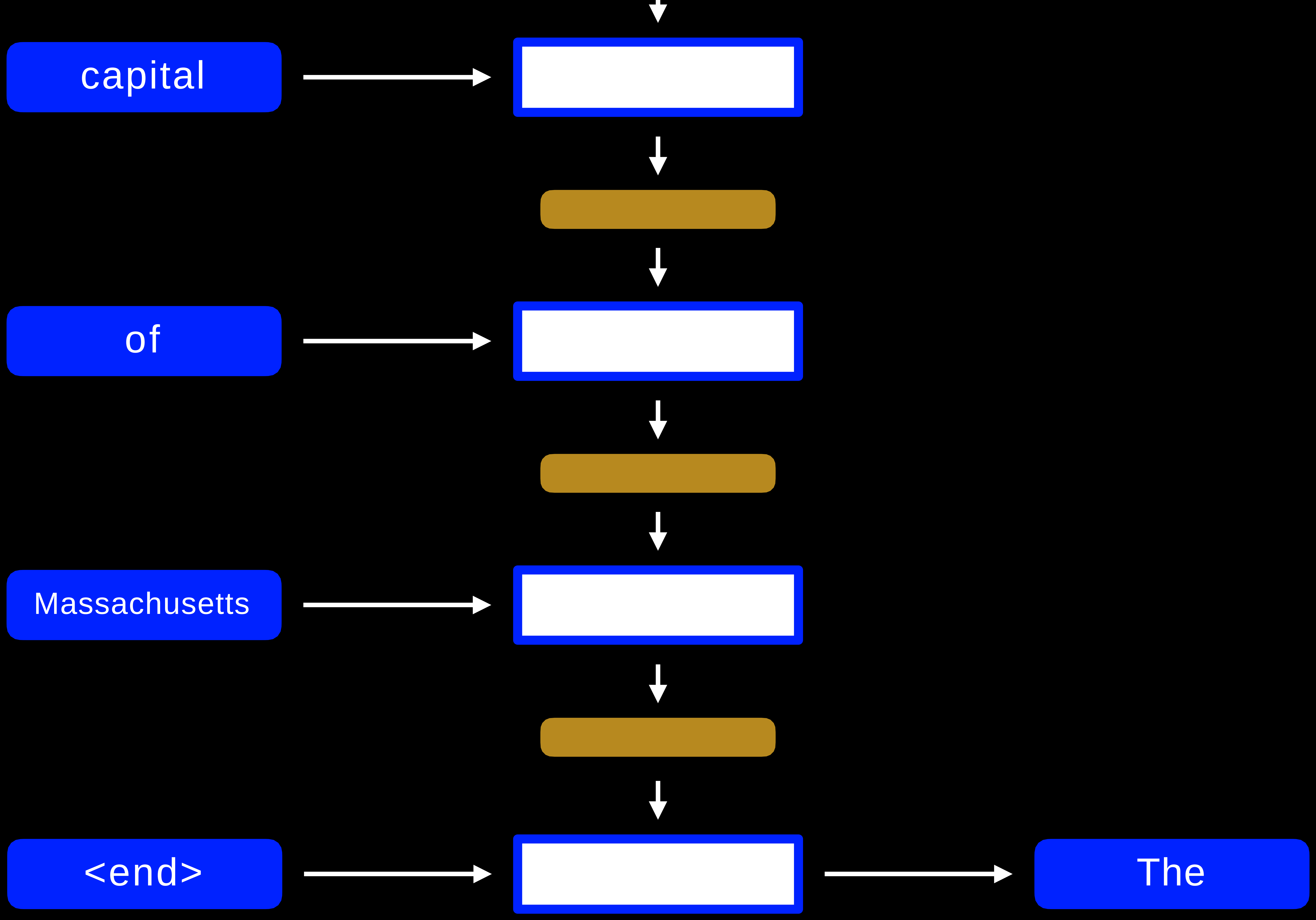
The only light in the room came from the lamp upon the table at which I had been reading.

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

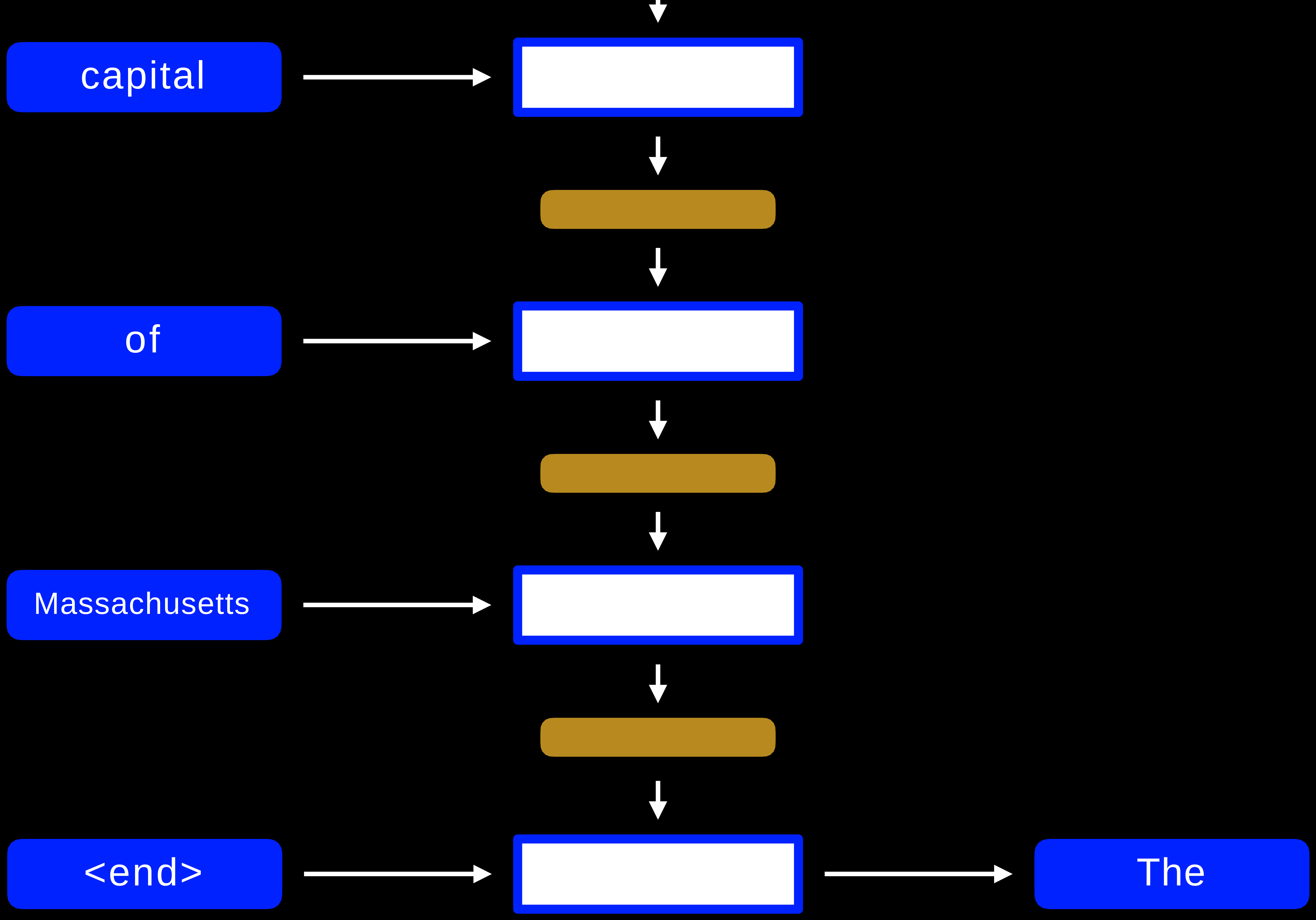

What is the capital of Massachusetts?
The capital is Boston.

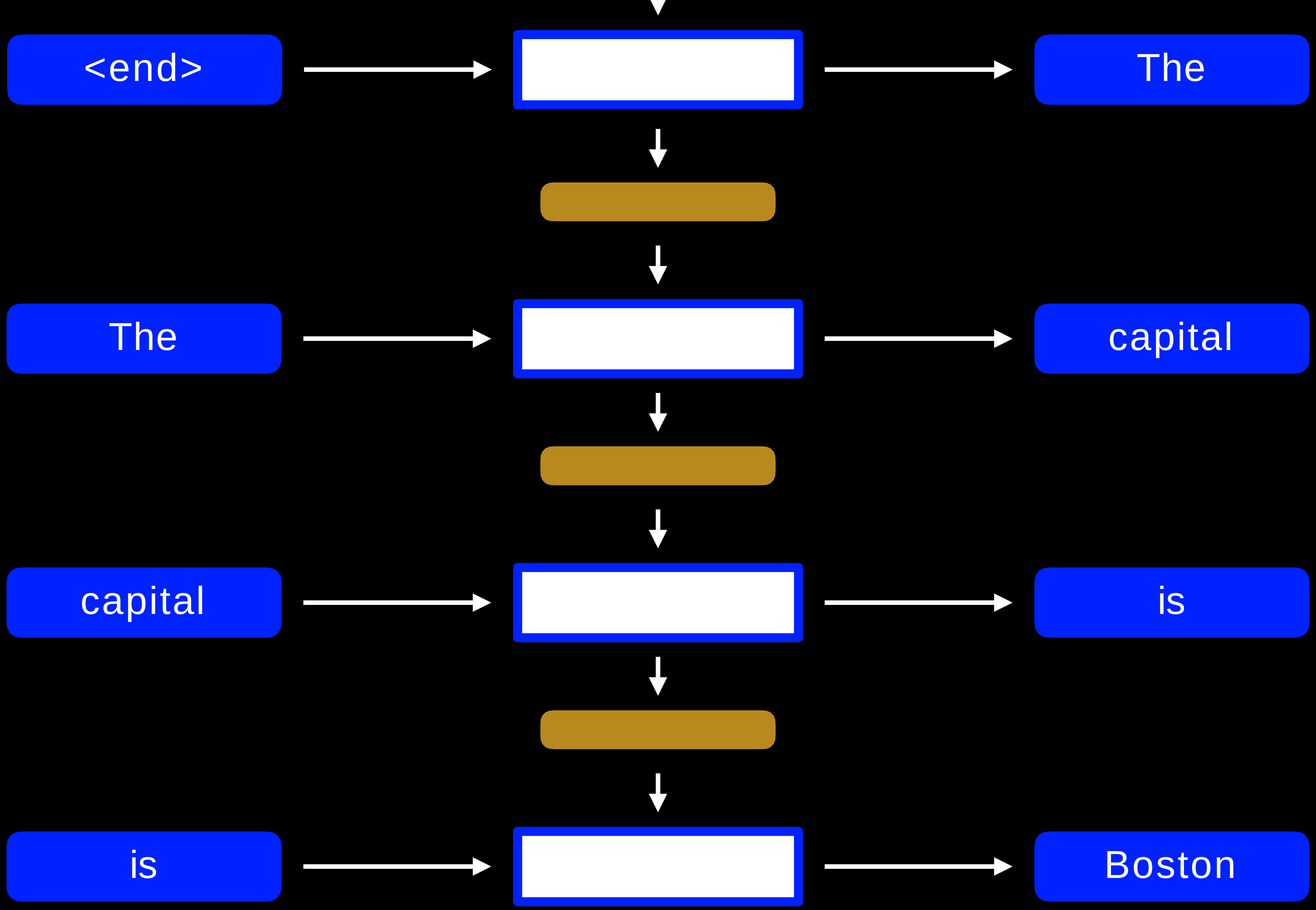

what
hidden state
is
the
capital


what
is
the
capital

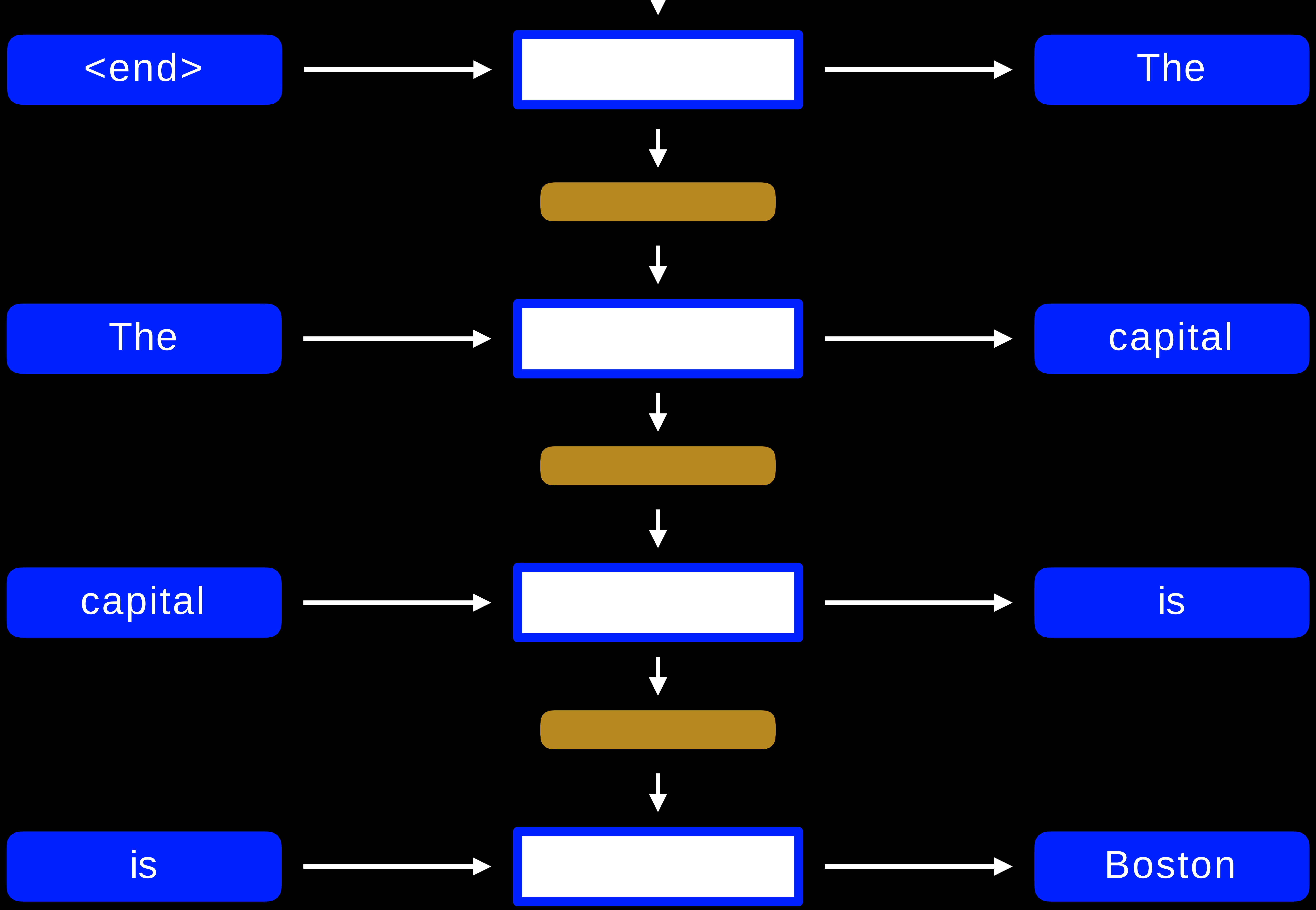


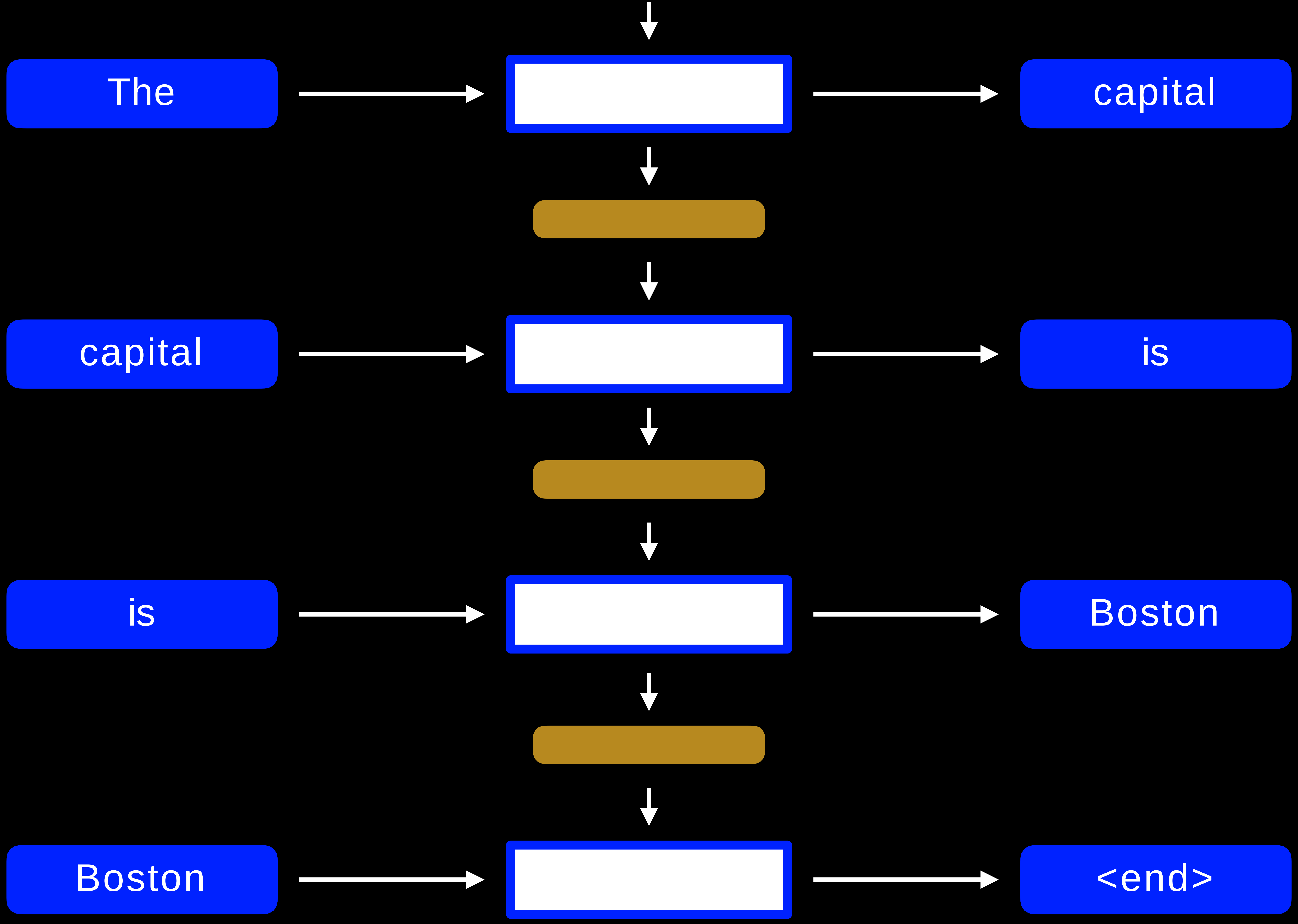
capital
of
Massachusetts
<end>
The

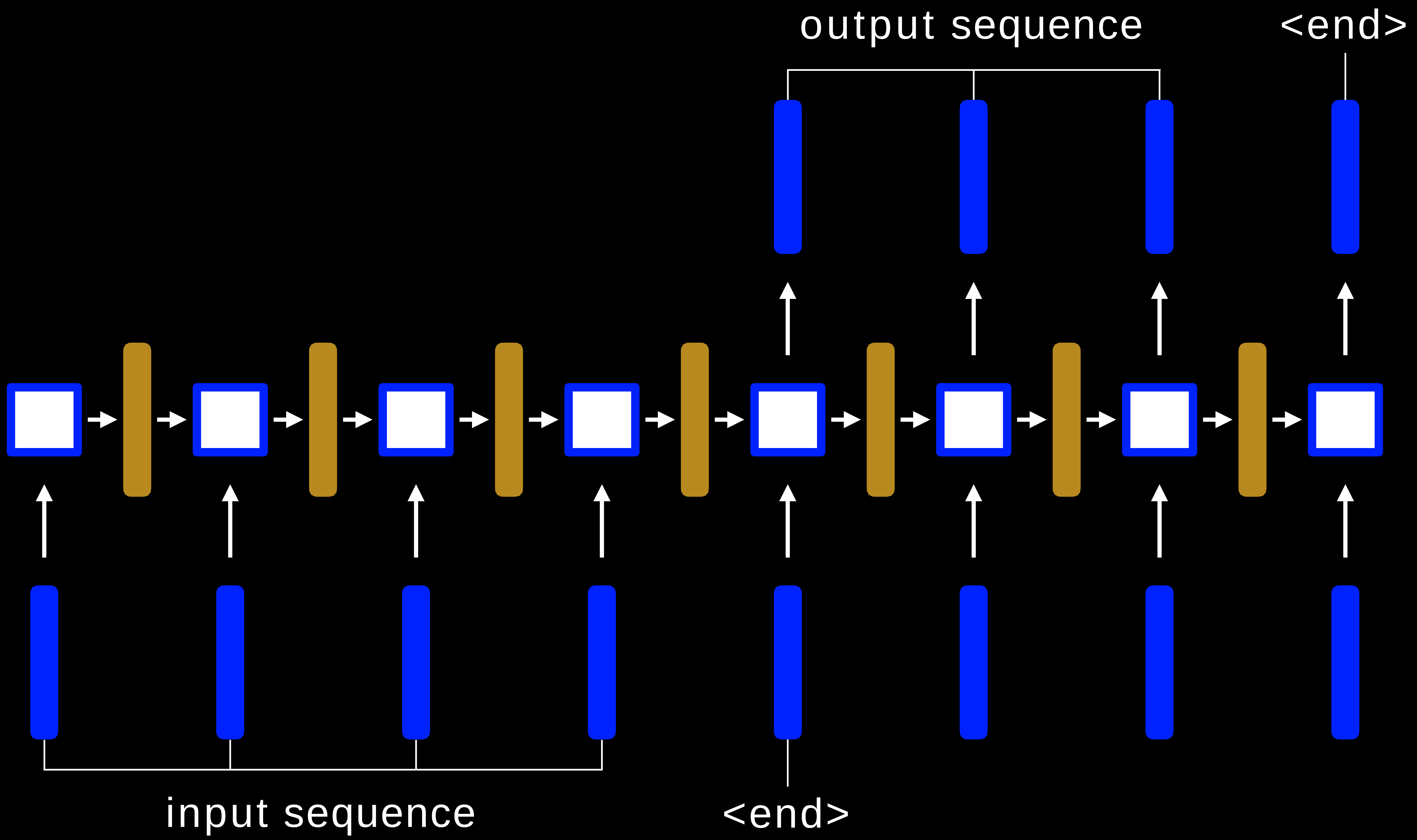

capital
of
Massachusetts
<end>
The



<end>
The
The
capital
capital
is
is
Boston


<end>
The
The
capital
capital
is
is
Boston


The
capital
capital
is
is
Boston
Boston
<end>


output sequence
<end>
input sequence
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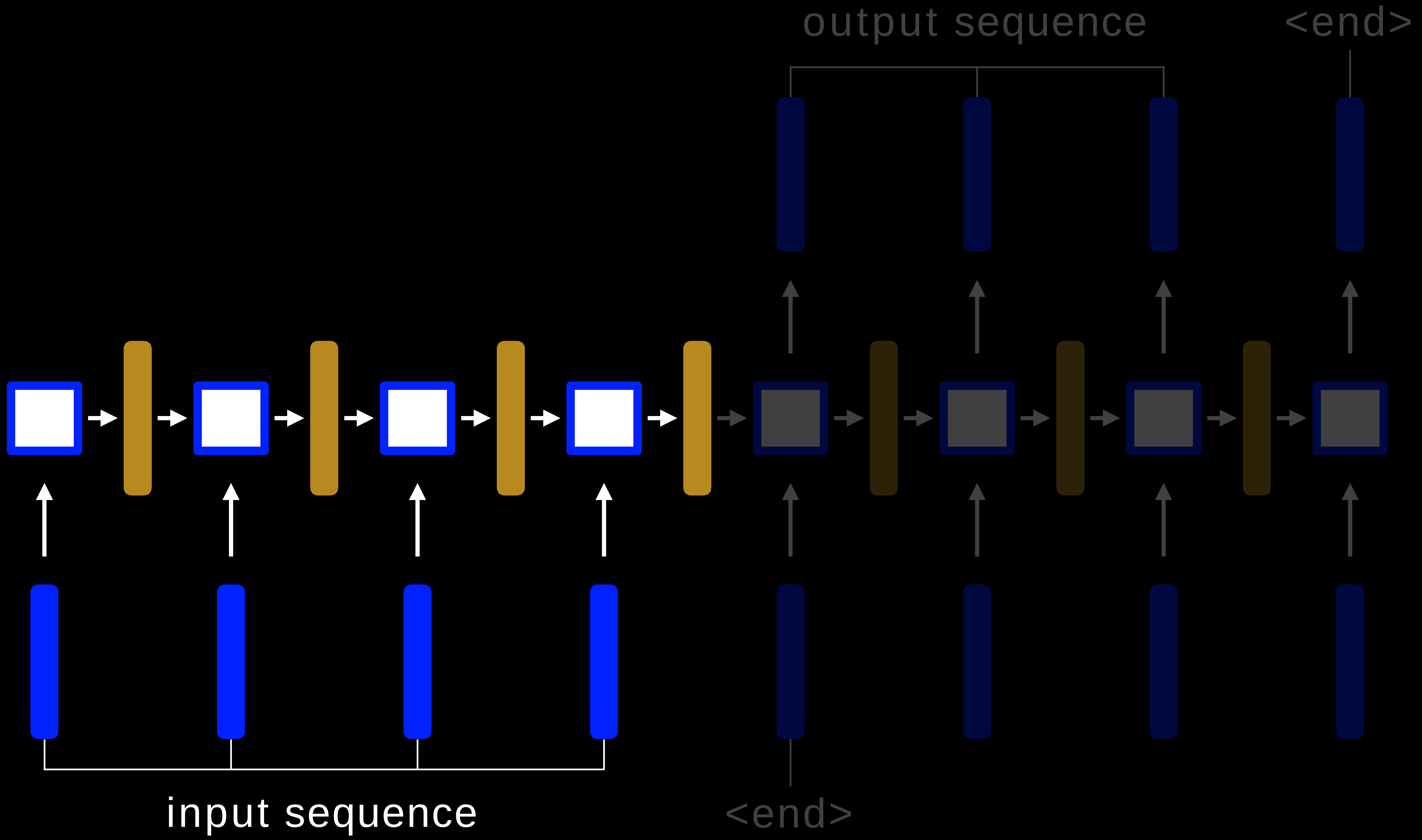
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input sequence
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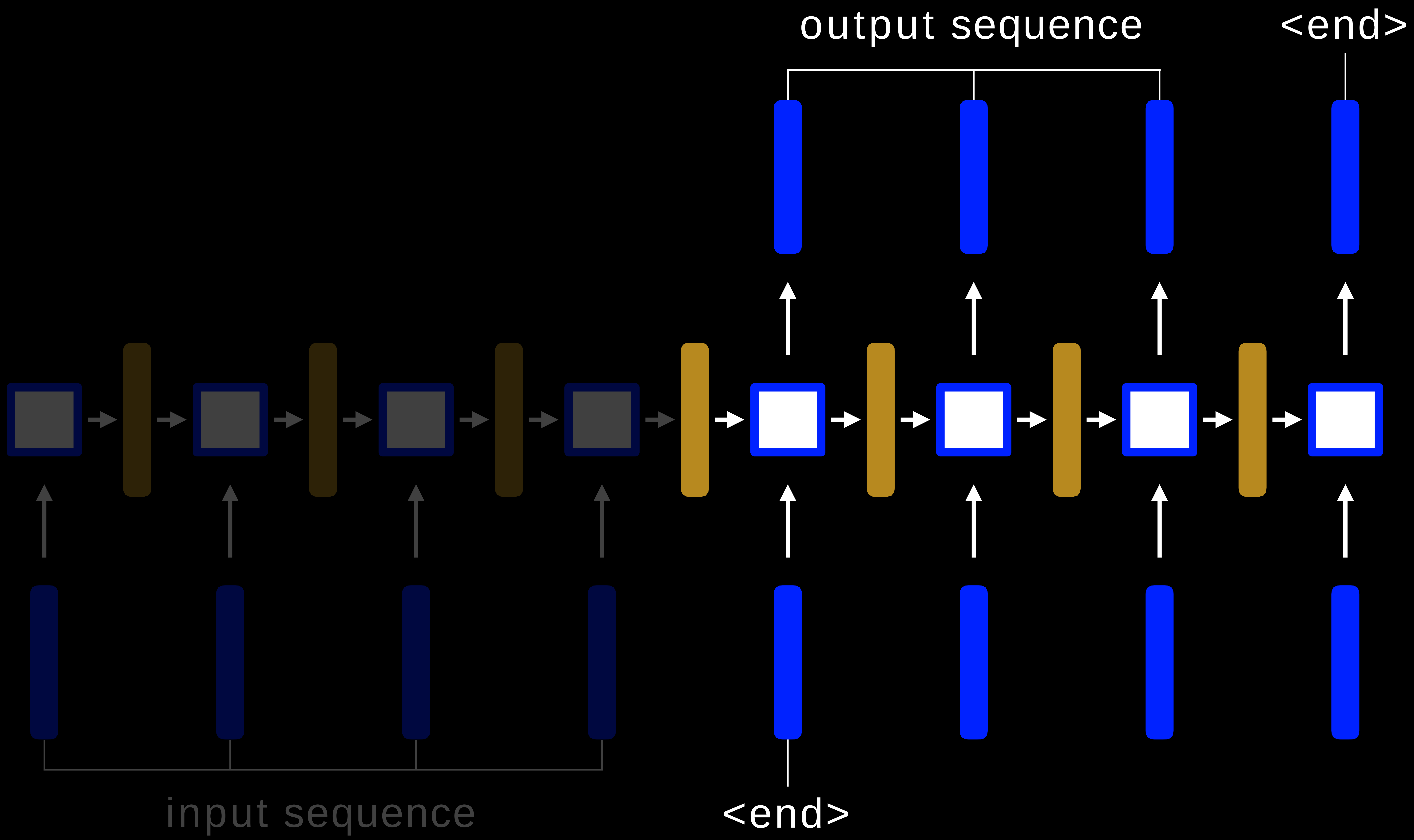
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input sequence
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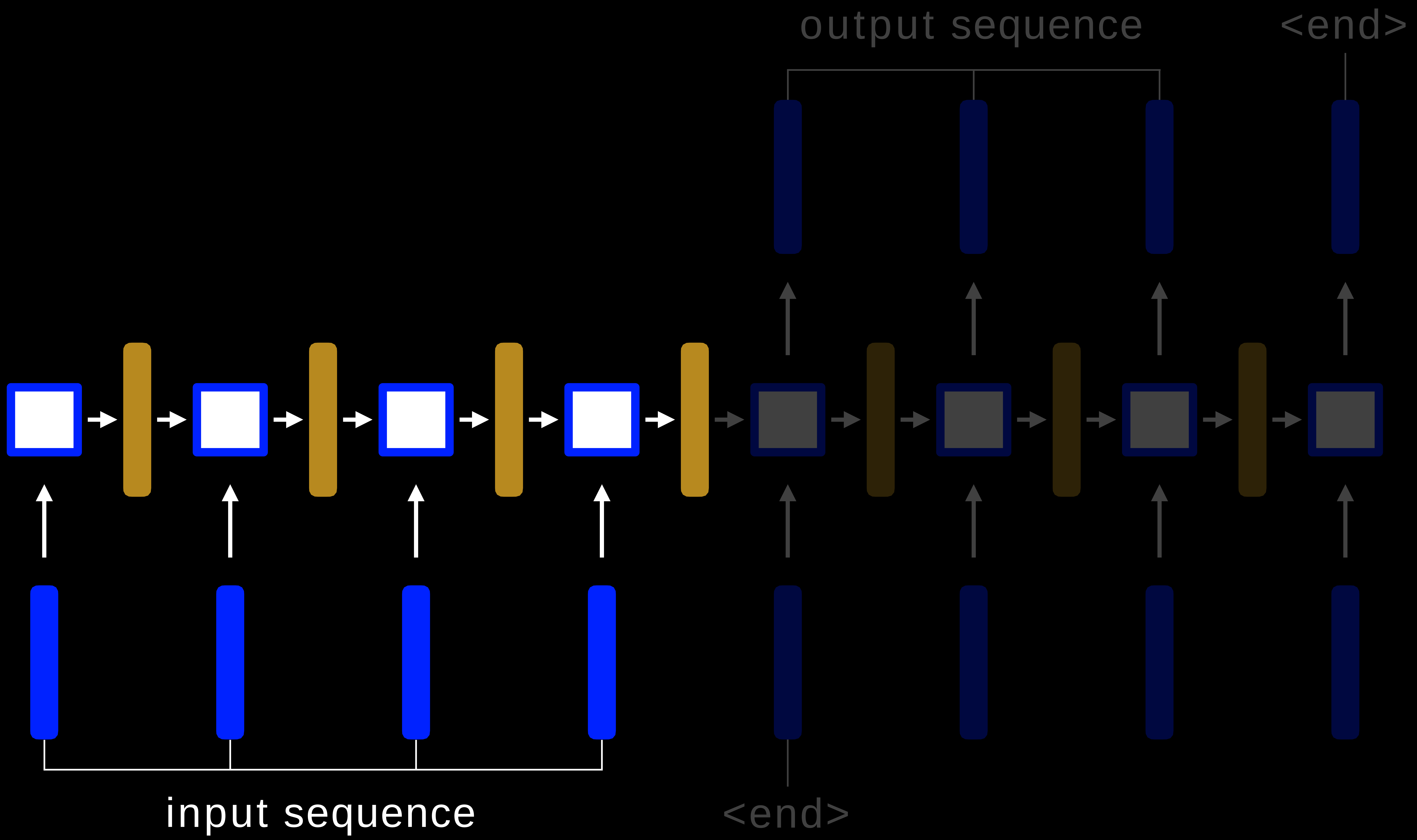
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input sequence
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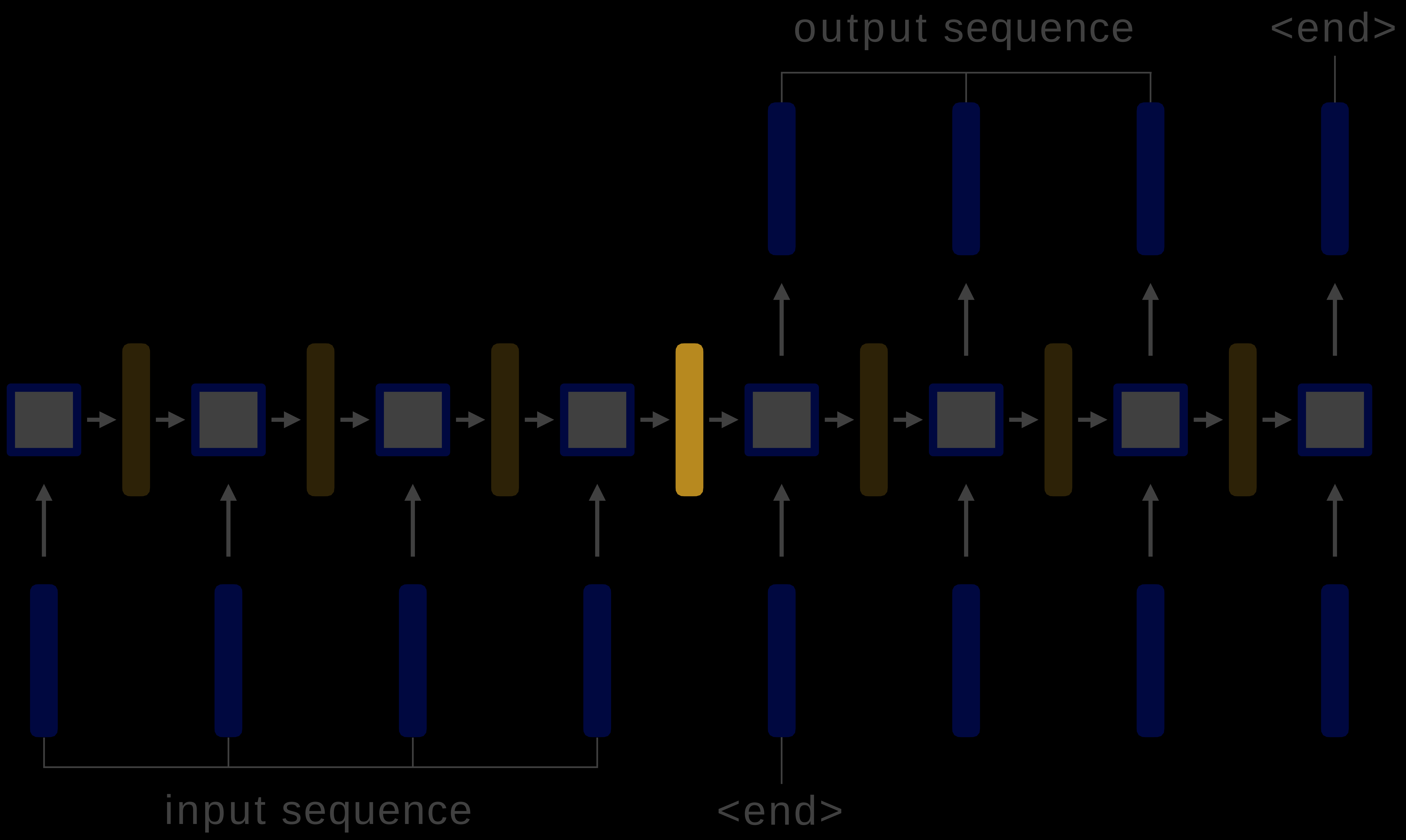
output sequence
<end>
input sequence
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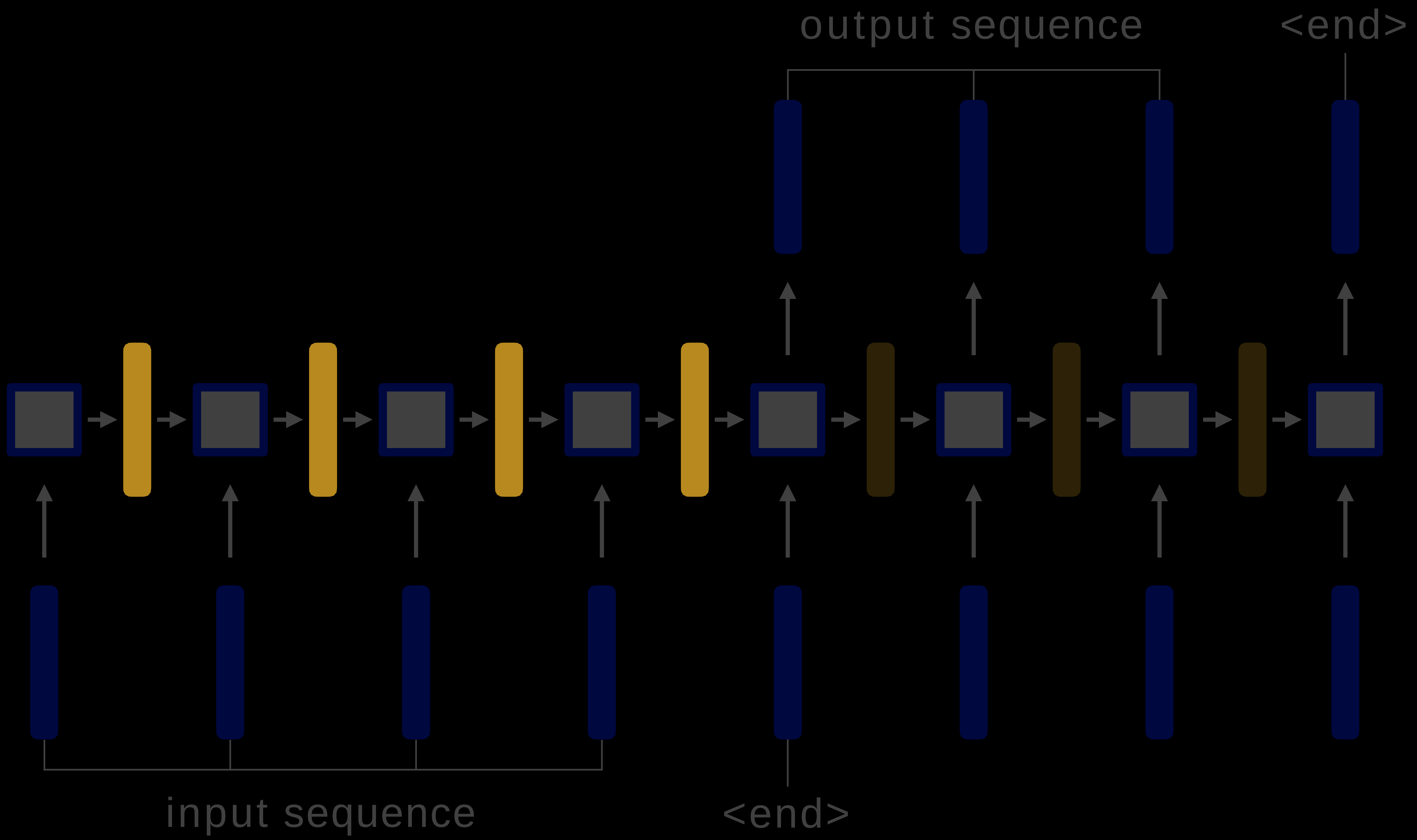
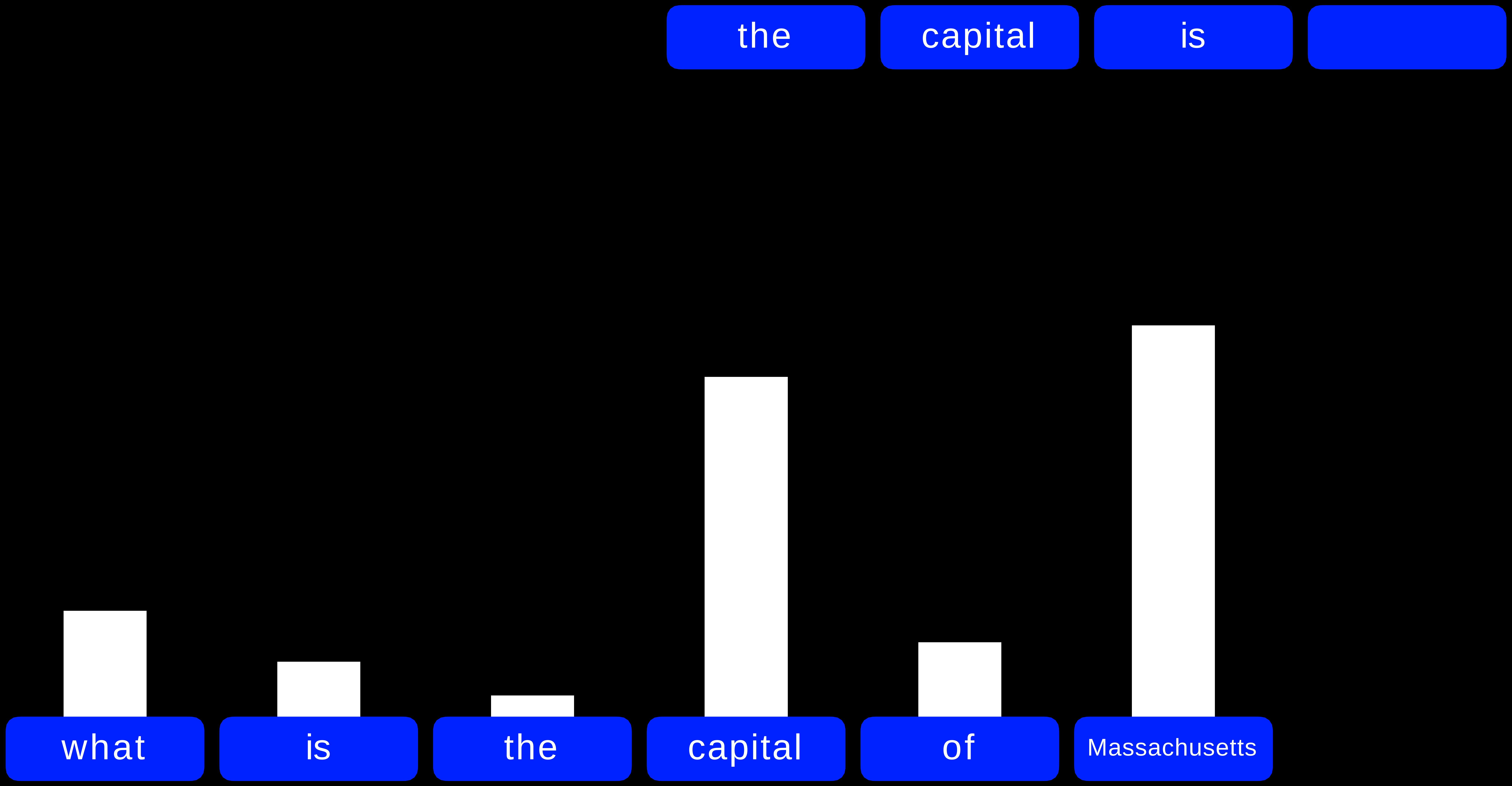
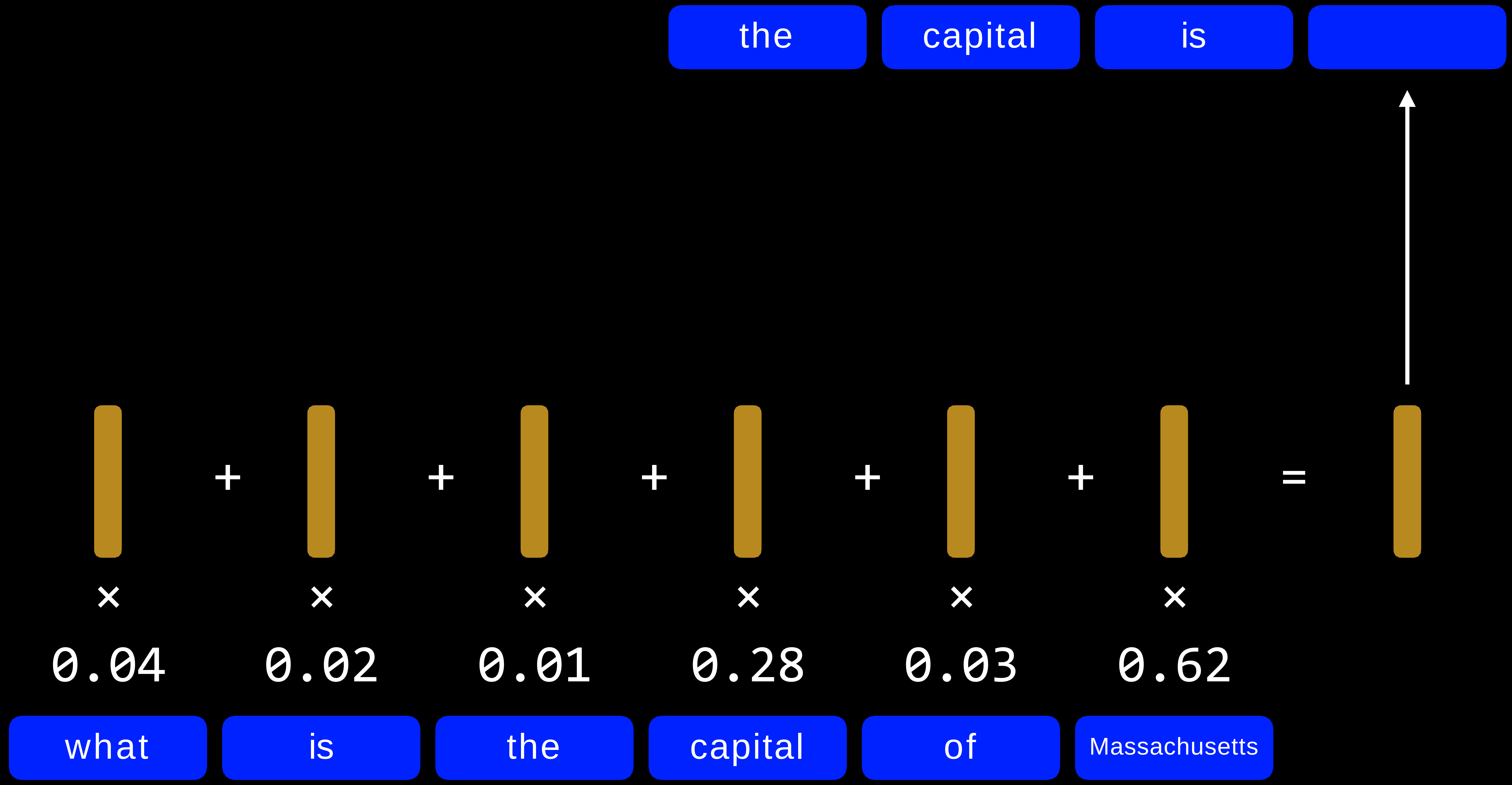

output sequence
<end>
input sequence
<end>

Attention

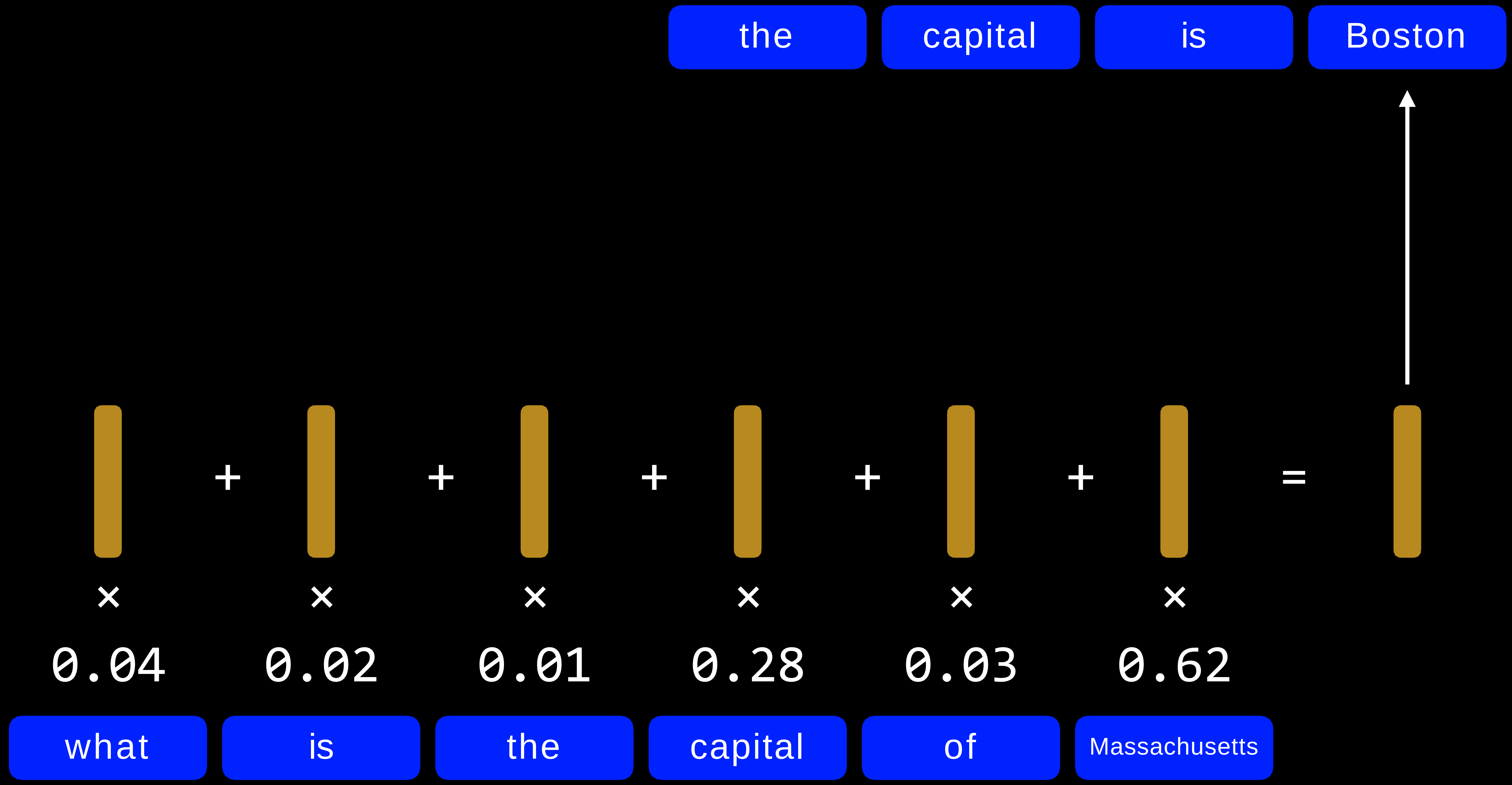
the capital is

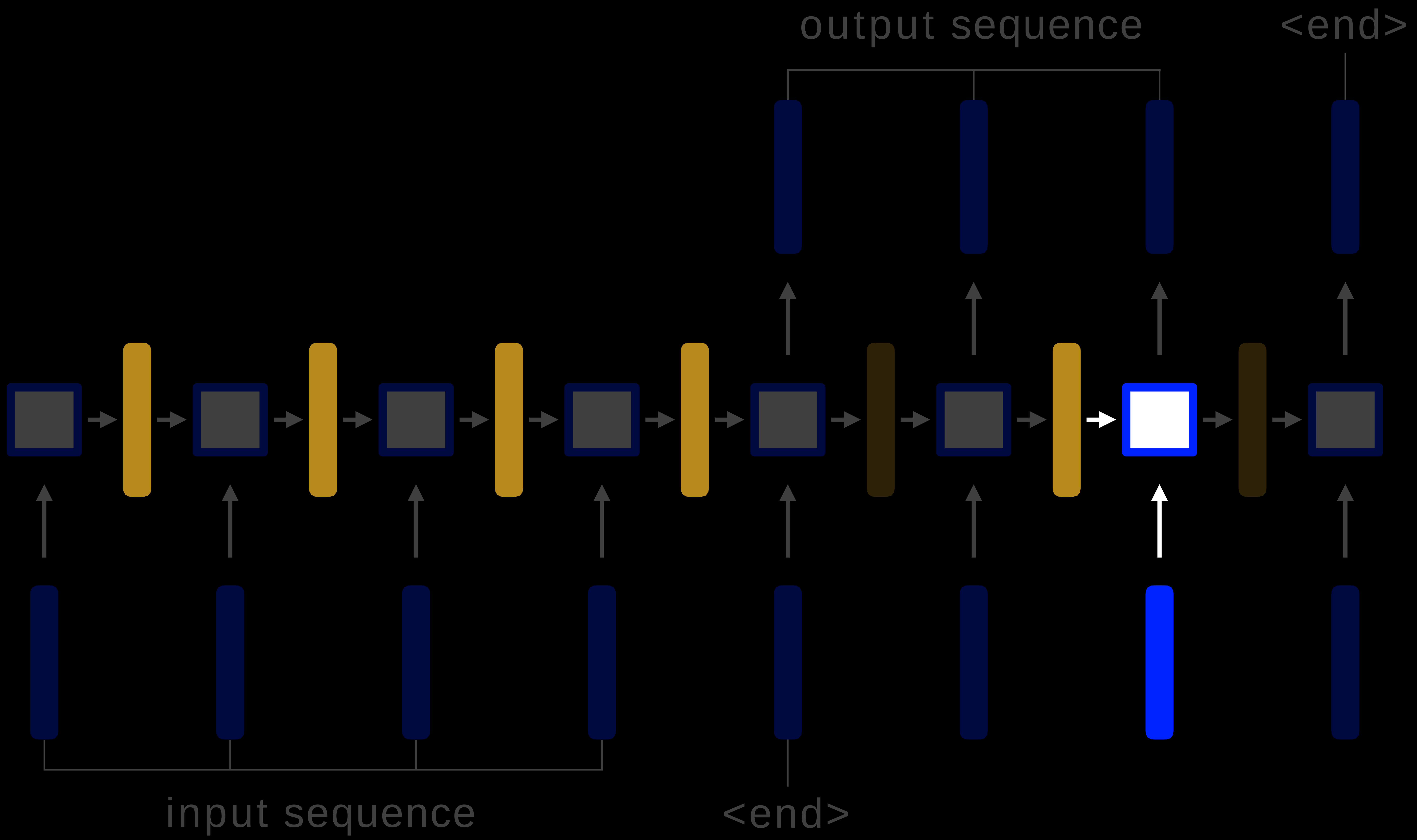
what is the capital of Massachusetts


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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input sequence
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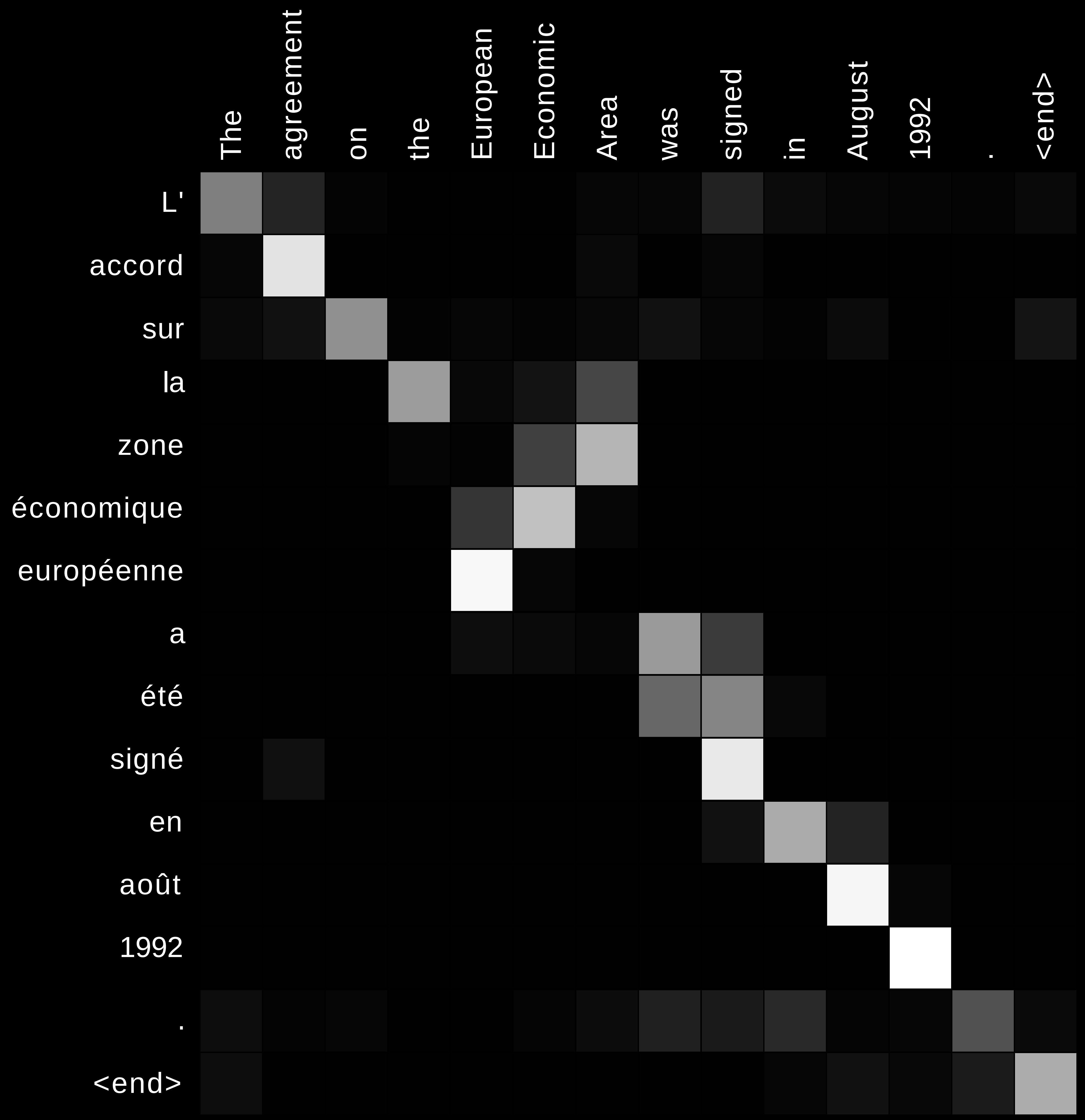
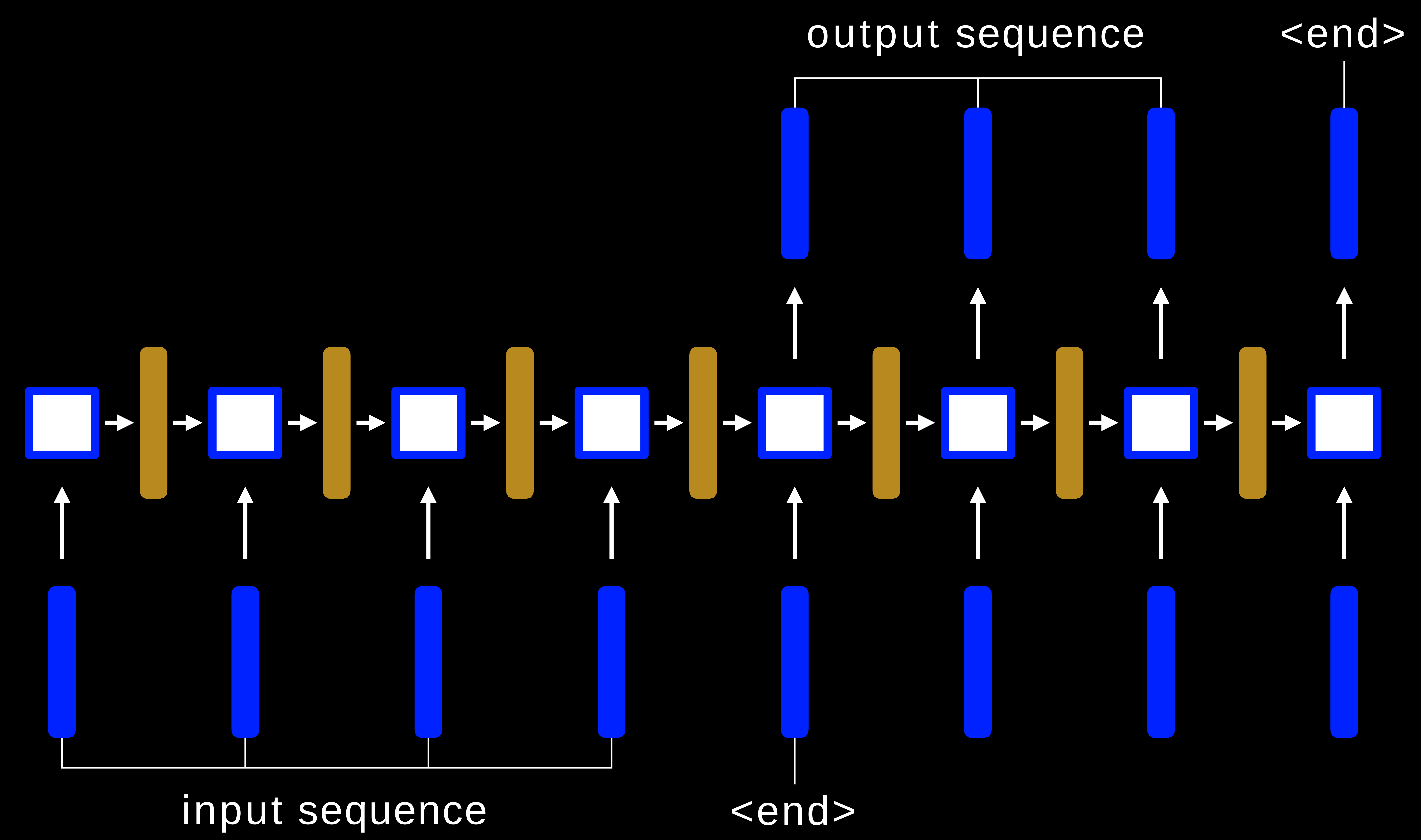
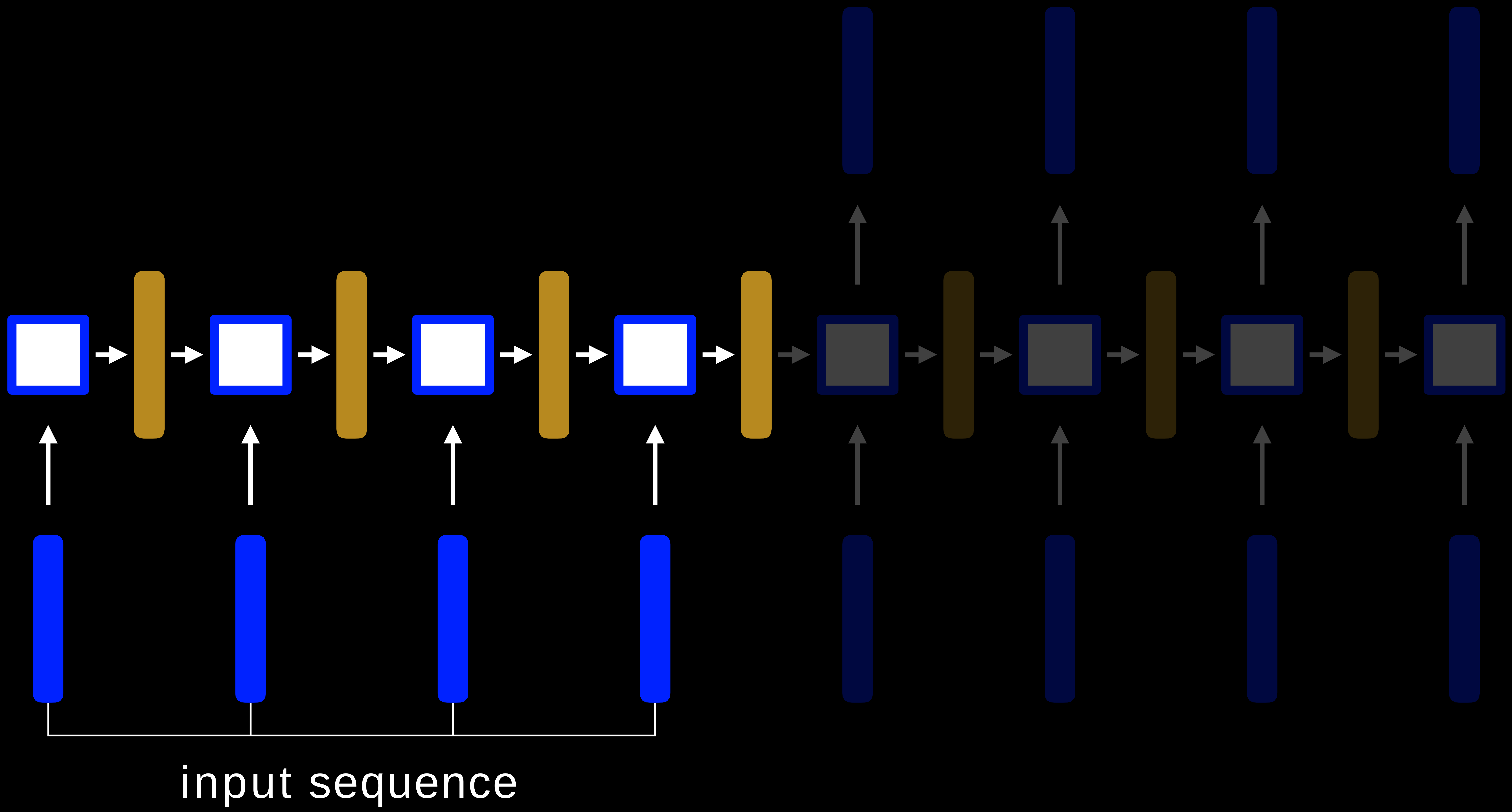
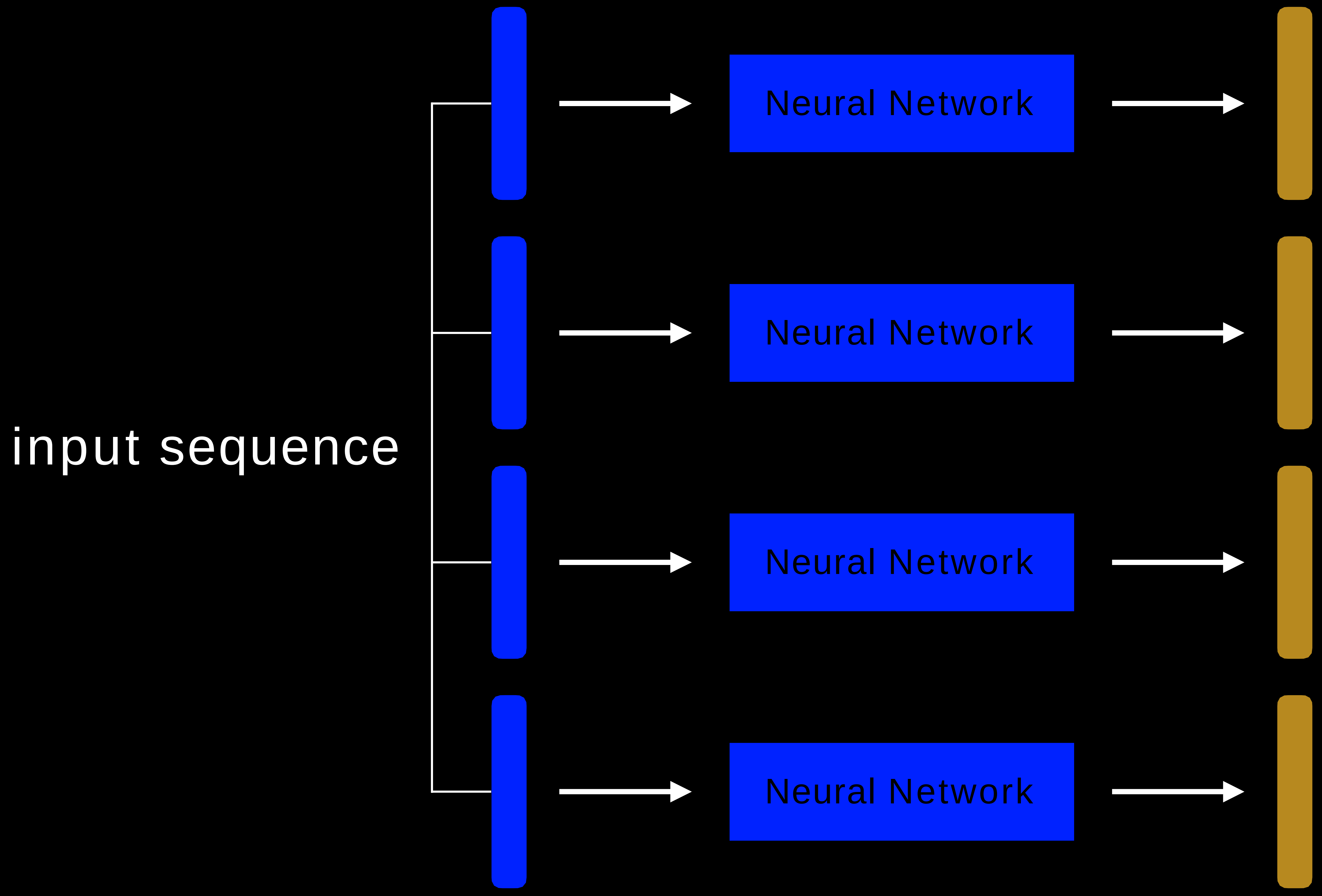


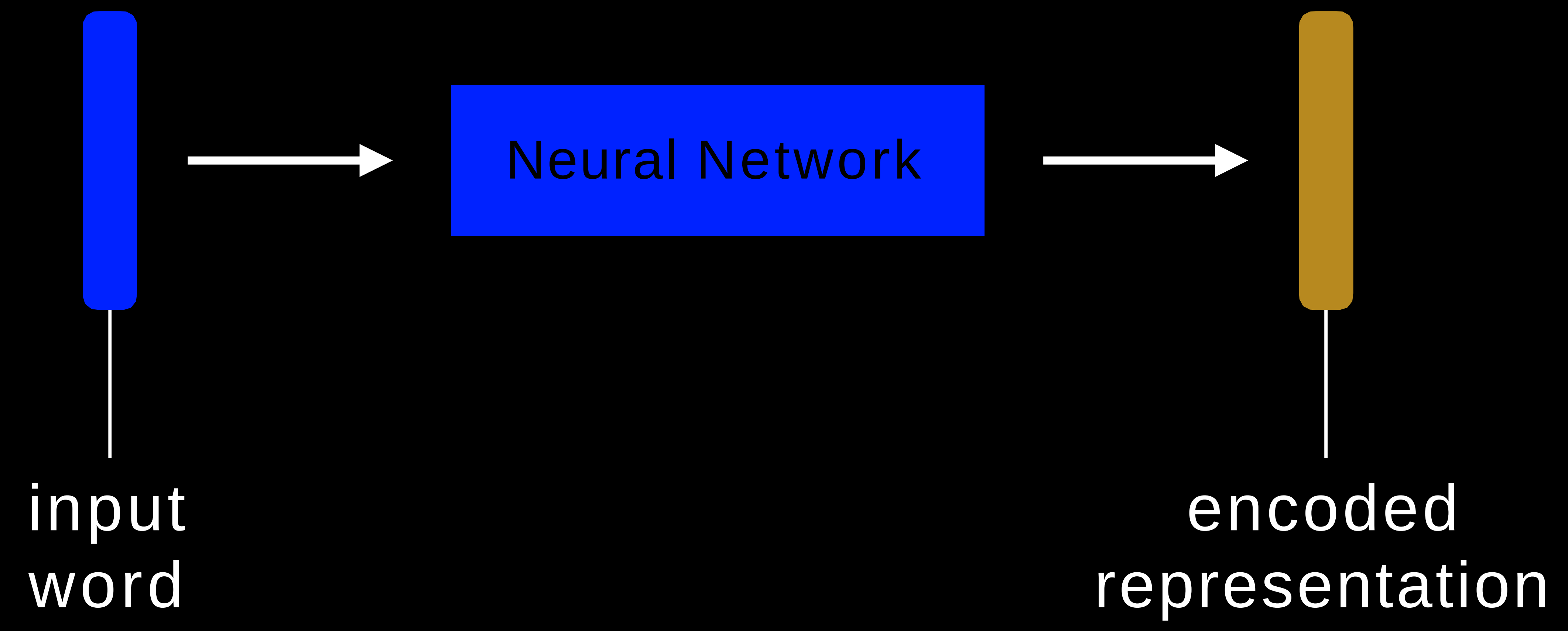
Adapted from Bahdanau et al. 2015.
Neural machine translation by jointly
learning to align and translate

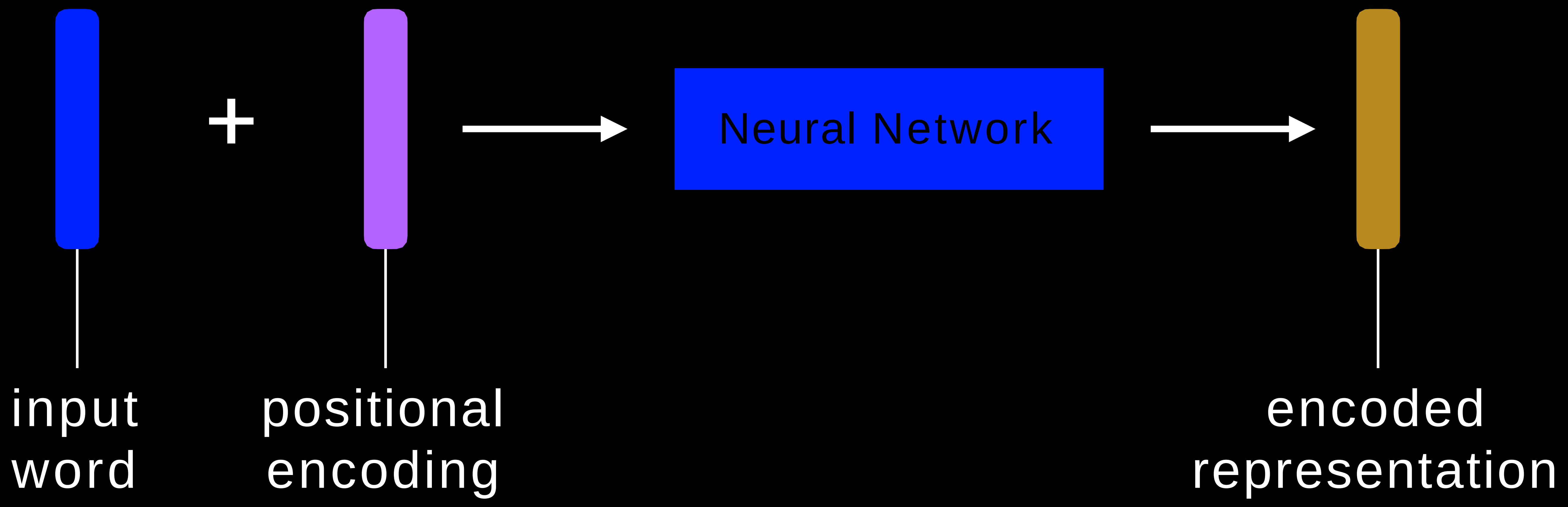

output sequence
<end>
input sequence
<end>

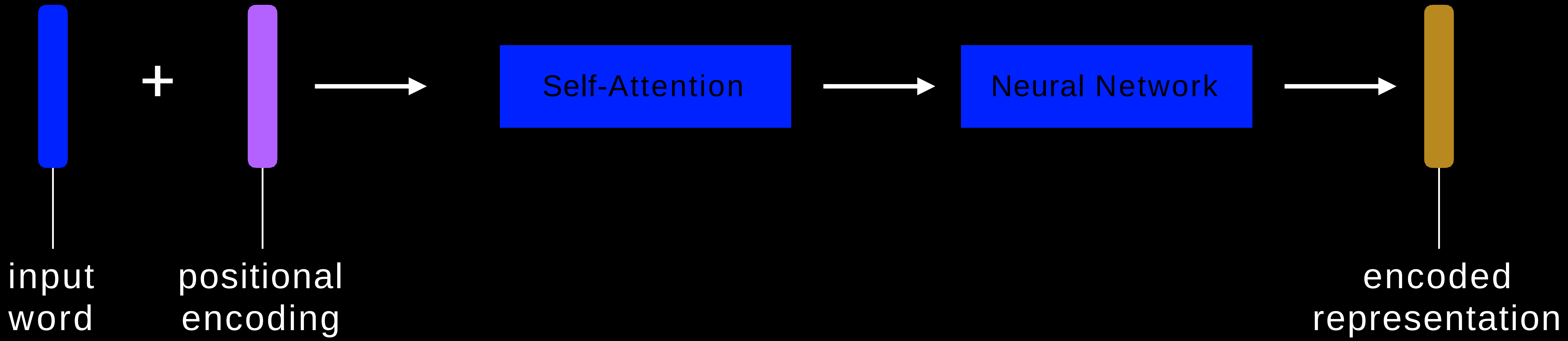
Transformers


input sequence

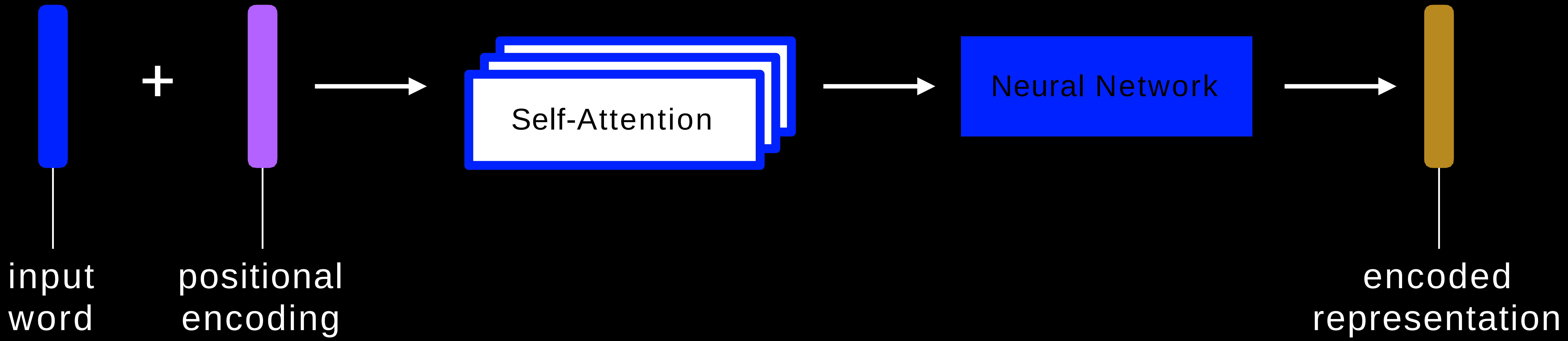

input sequence
Neural Network
Neural Network
Neural Network
Neural Network


Neural Network
input
word
encoded
representation

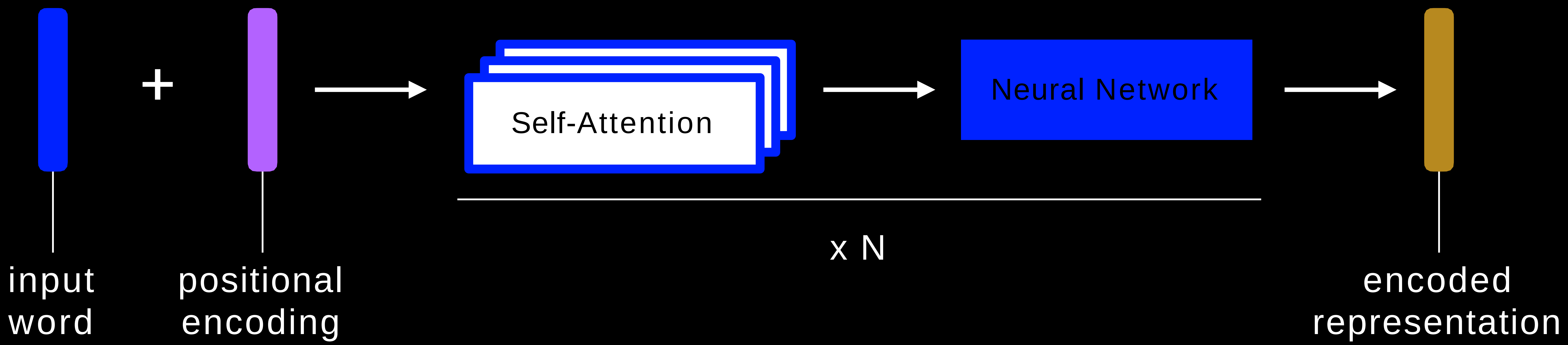

+
Neural Network
input
word
positional
encoding
encoded
representation



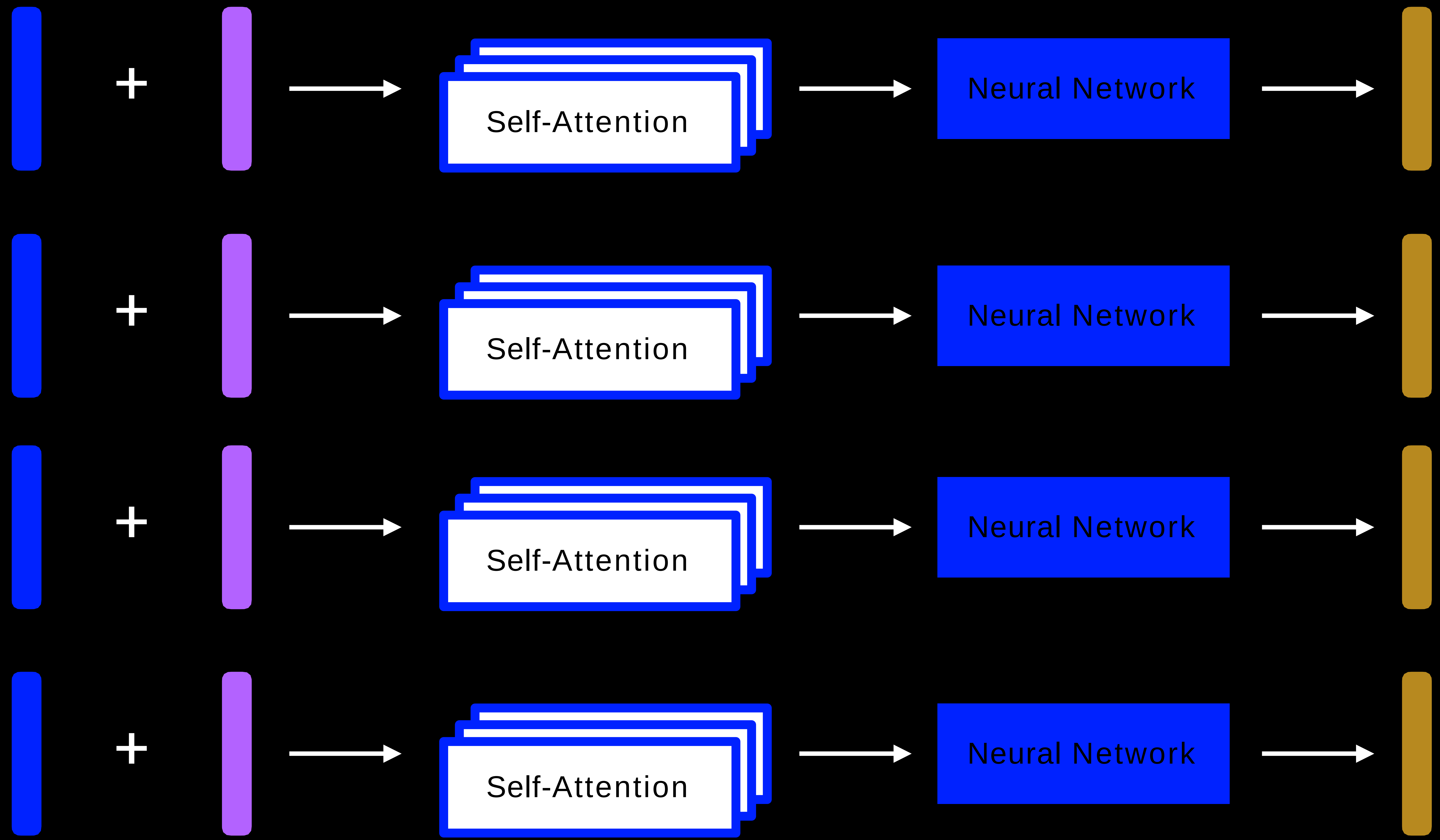
input word
+
positional encoding
Self-Attention
Neural Network
encoded representation

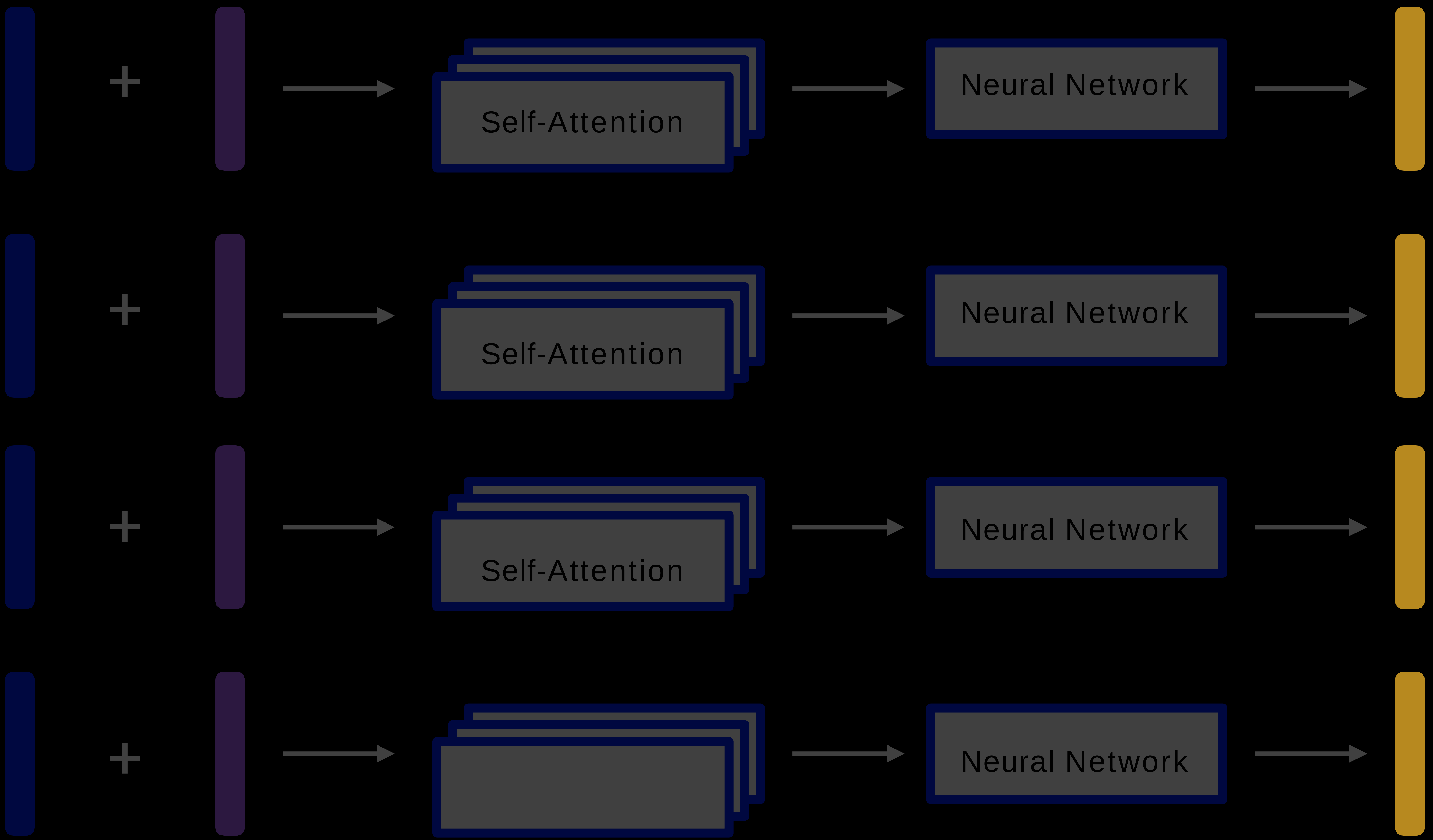


Self-Attention
Neural Network
input
word
positional
encoding
encoded
representation

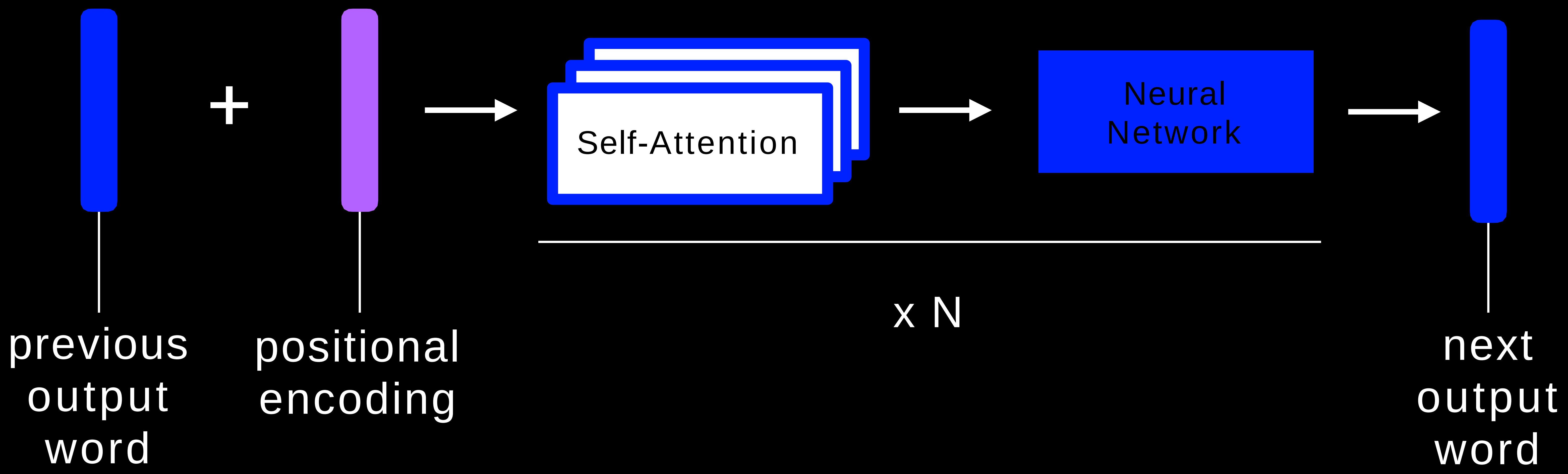


+
Self-Attention
Neural Network
x N
input
word
positional
encoding
encoded
representation

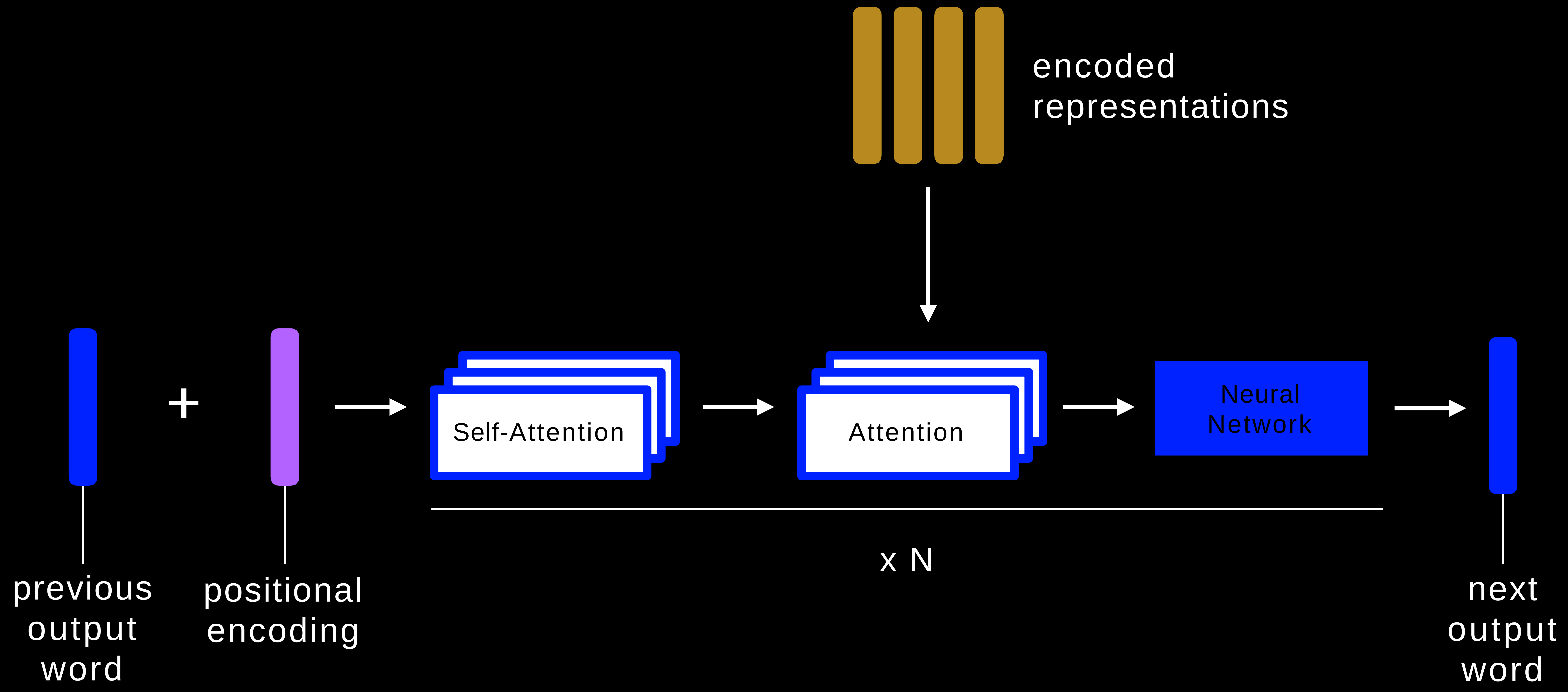

Self-Attention
Neural Network
Self-Attention
Neural Network
Self-Attention
Neural Network
Self-Attention
Neural Network

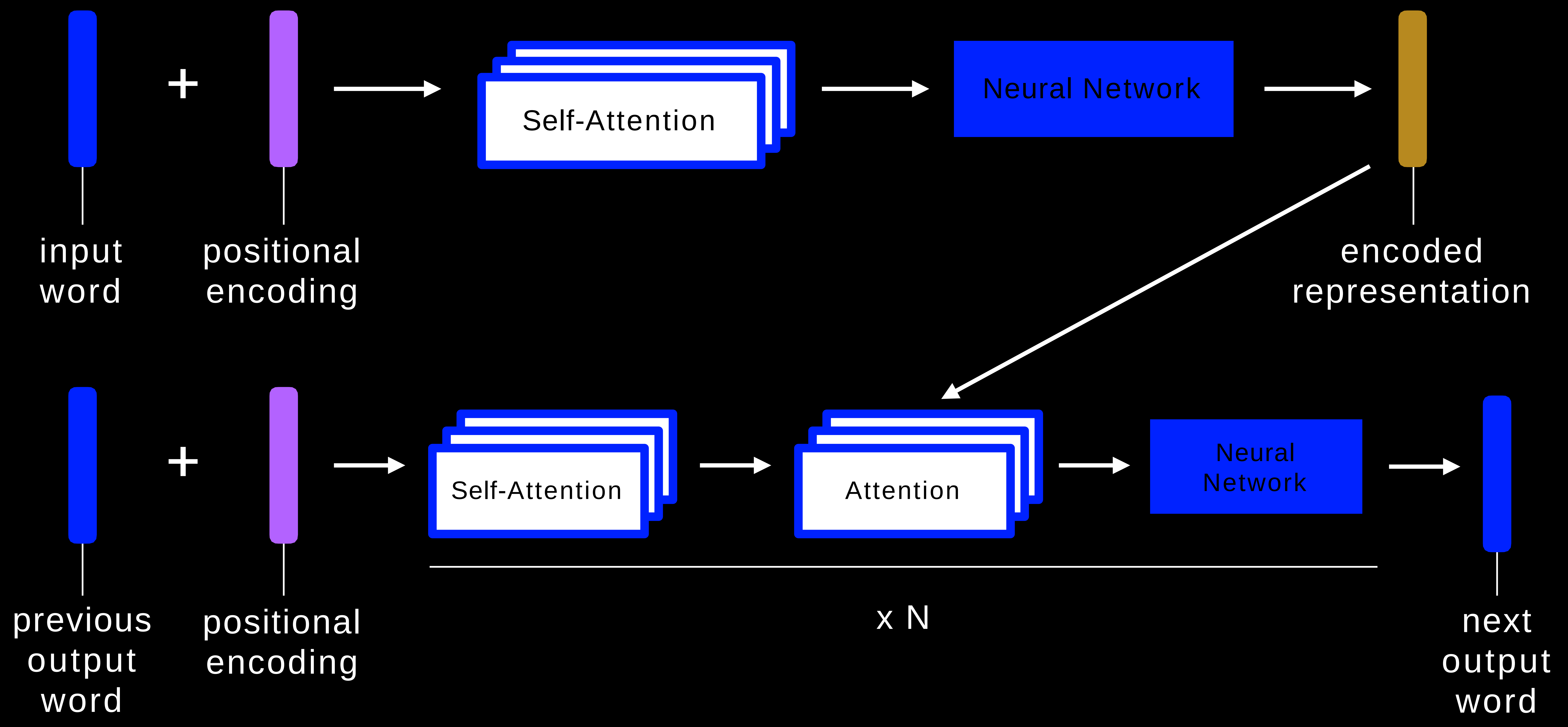


encoded representations



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


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