An overview of Recurrent Neural Networks

Jeremy Watt

Features and supervised learning

- Some data types have **independent features**

Features and supervised learning

- Some data types have **independent features**
- **Order in which we feed them in doesn’t matter**

Race	Gender	Diabetes	Weight	Readmitted
caucasian	male	No	188	No

Features and supervised learning

- Some data types have **spatially correlated features**

Features and supervised learning

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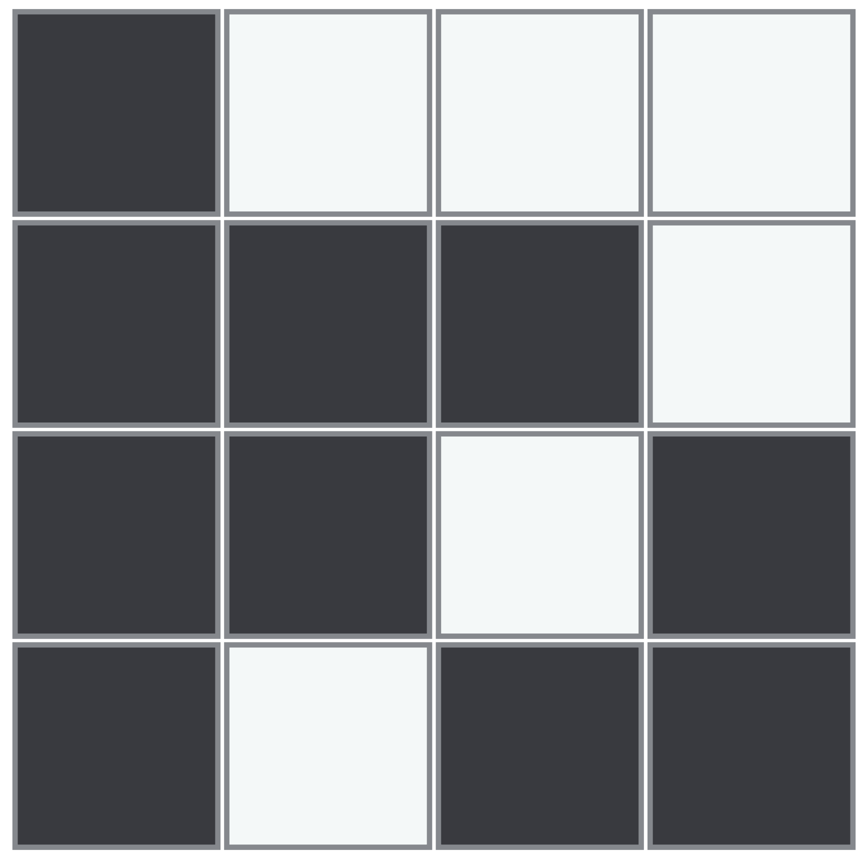
Features and supervised learning

- Some data types have **spatially correlated features**
- **Order in which we feed them in definitely matters**
- Convolutional modeling can leverage this



Features and supervised learning

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Features and supervised learning

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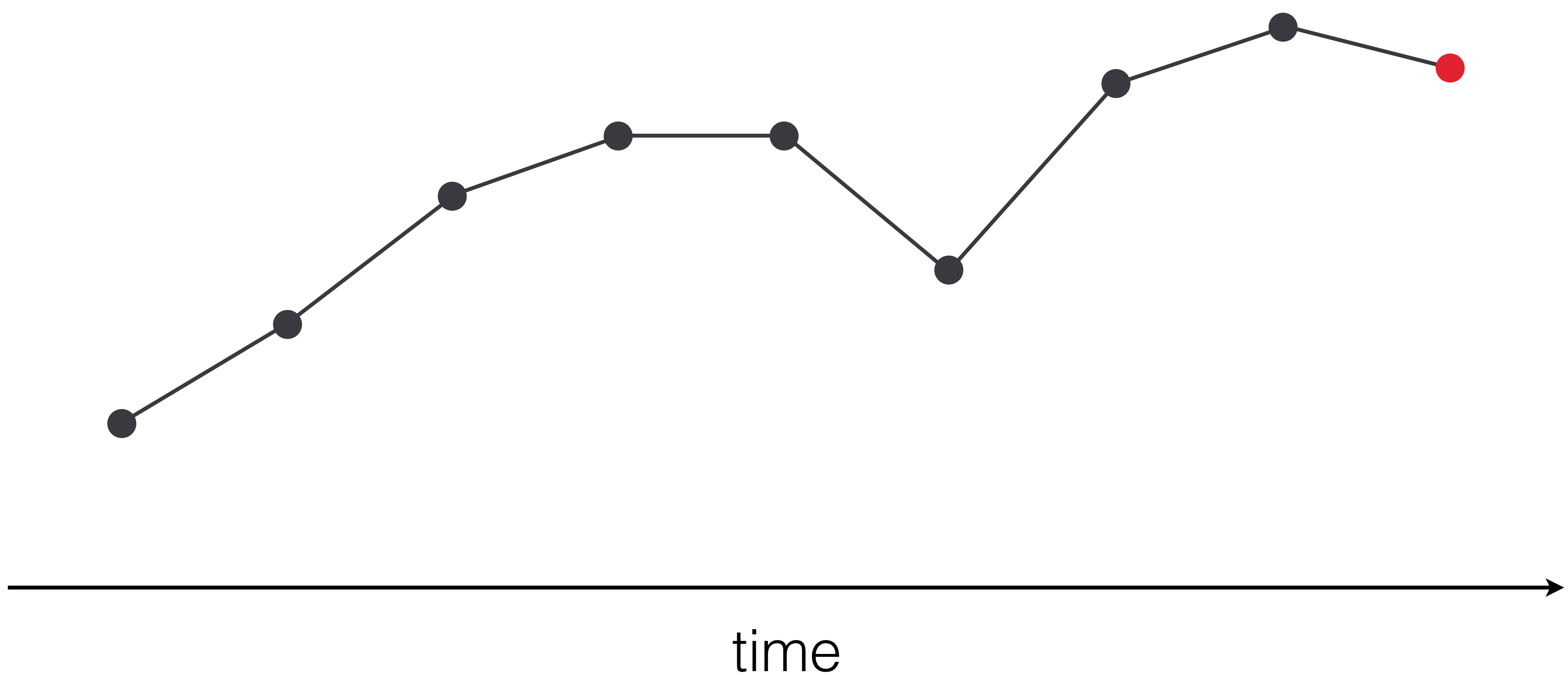
Features and supervised learning

- Some data types have **temporarly ordered features**
- **Order in which we feed them in definitely matters**
- **Recursive modeling can leverage this** (e.g., RNNs)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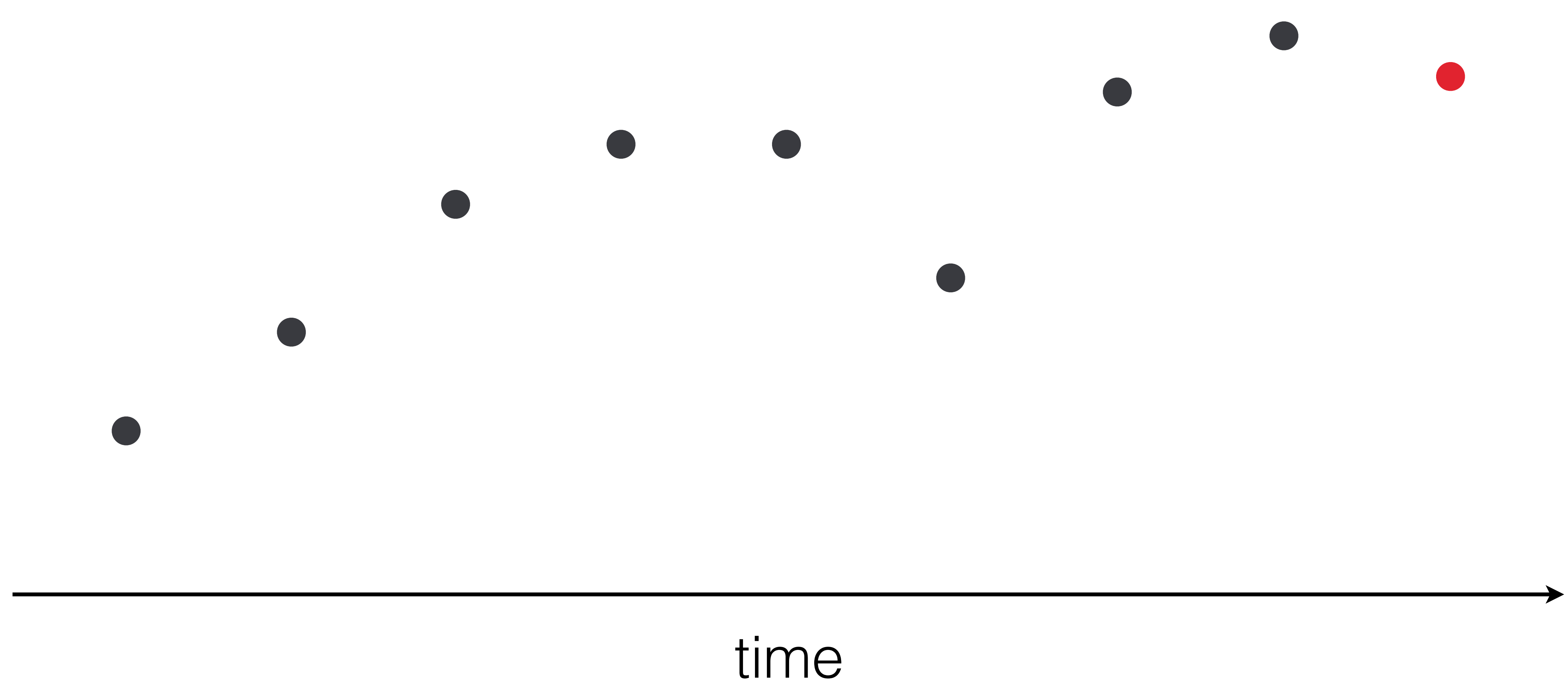
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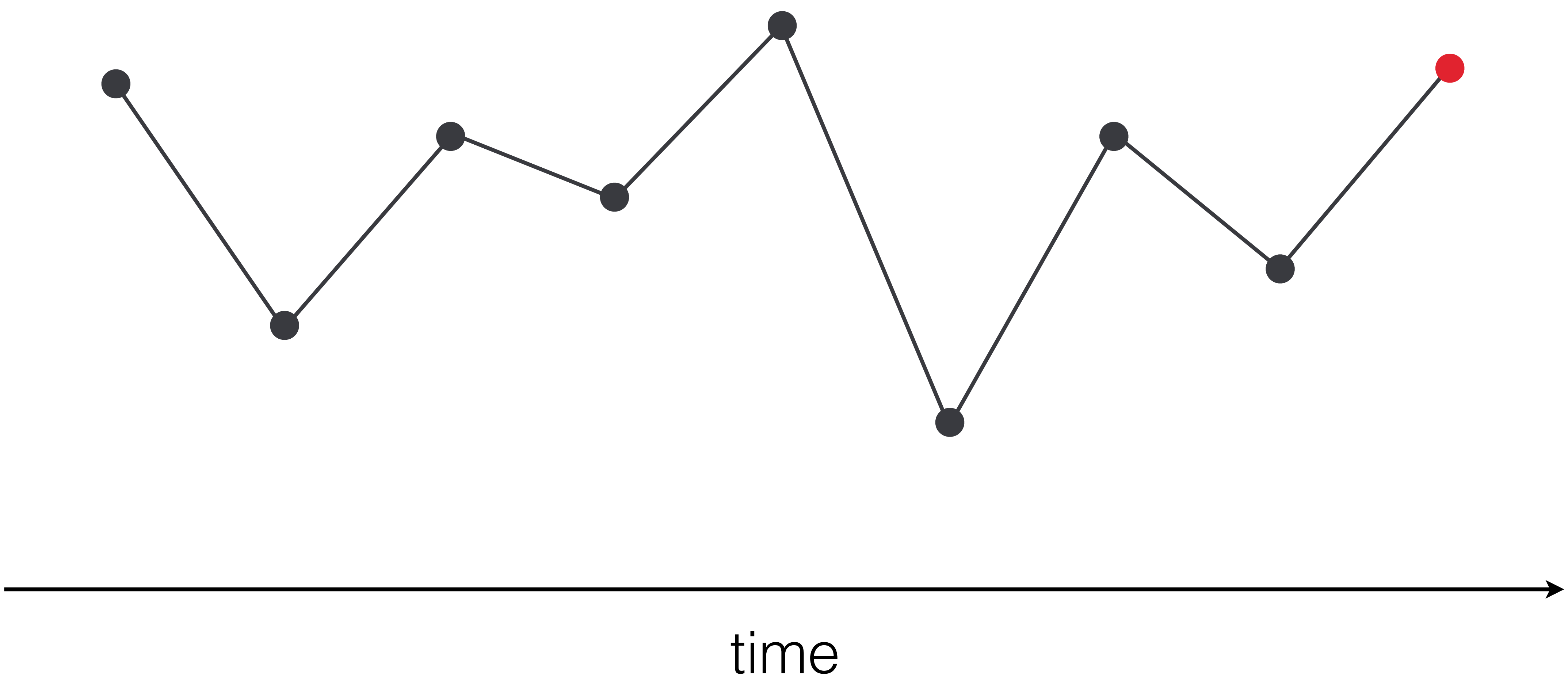
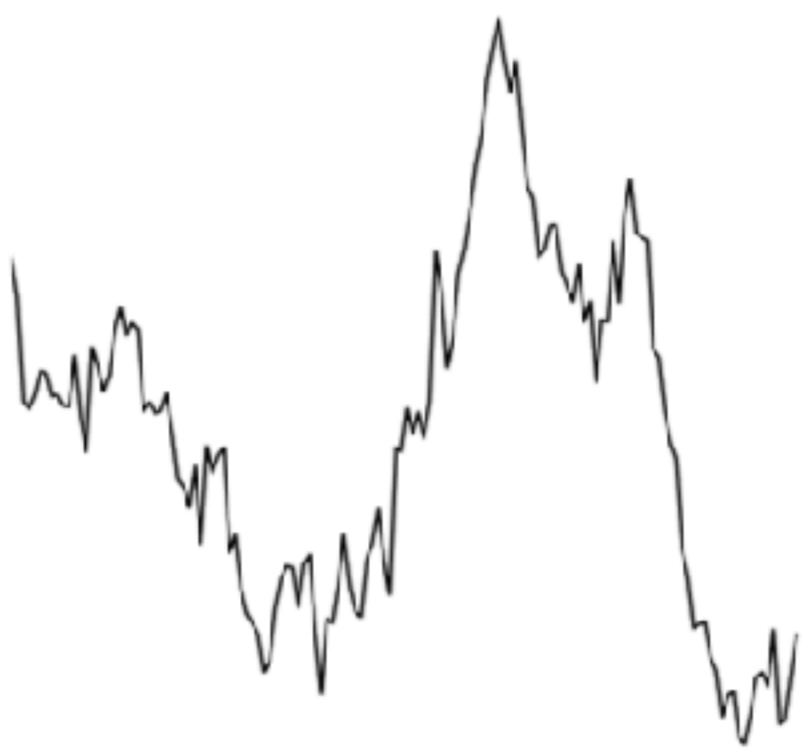

time

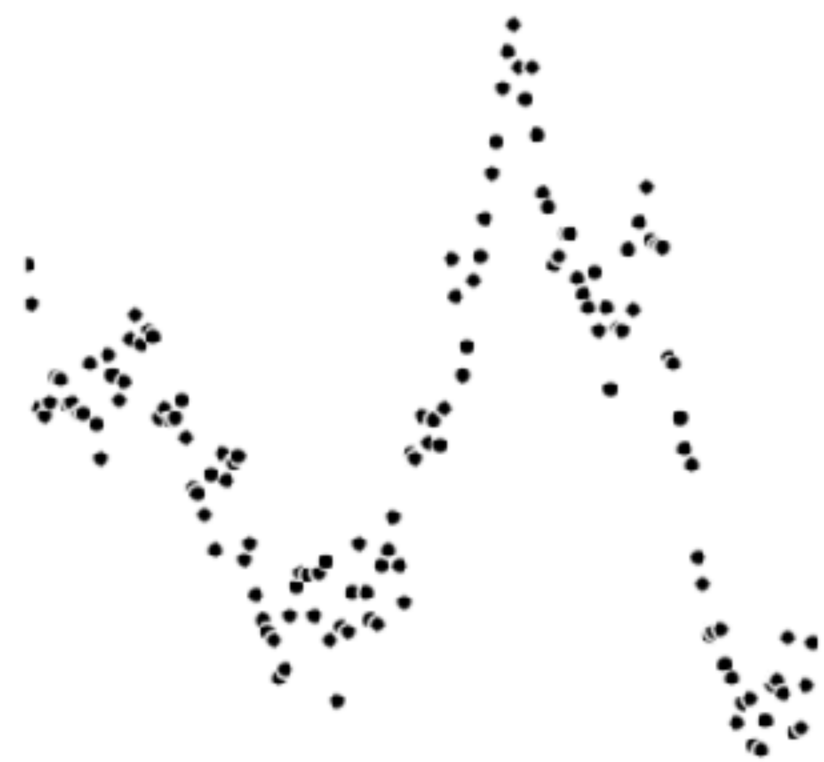
Popular problems with ordered sequential I/O

Time series prediction

- predict future values of a time series
- **input:** ordered sequence of past series values
- **output:** ordered sequence of future series values



series shown interpolated



series really looks like this

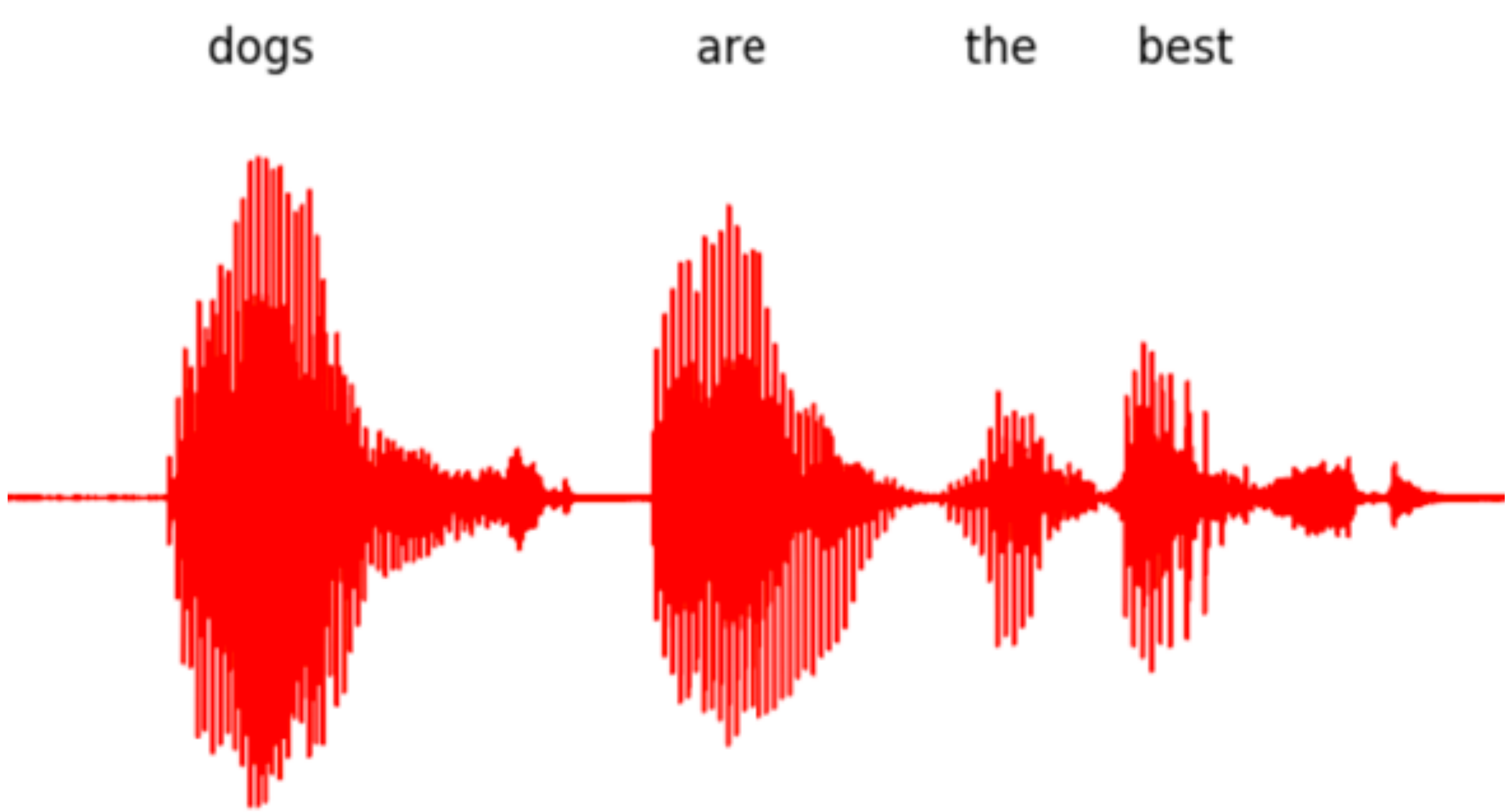
Machine translation

- Translate language X into language Y
- **input:** ordered sequence of words (in X)
- **output:** ordered sequence of words (in Y)

  - “I do not like cats” —> “Los gatos me caen mal”

Speech recognition

- Speech to text
- **input:** ordered sequence of raw audio
- **output:** ordered sequence of words



Text generation

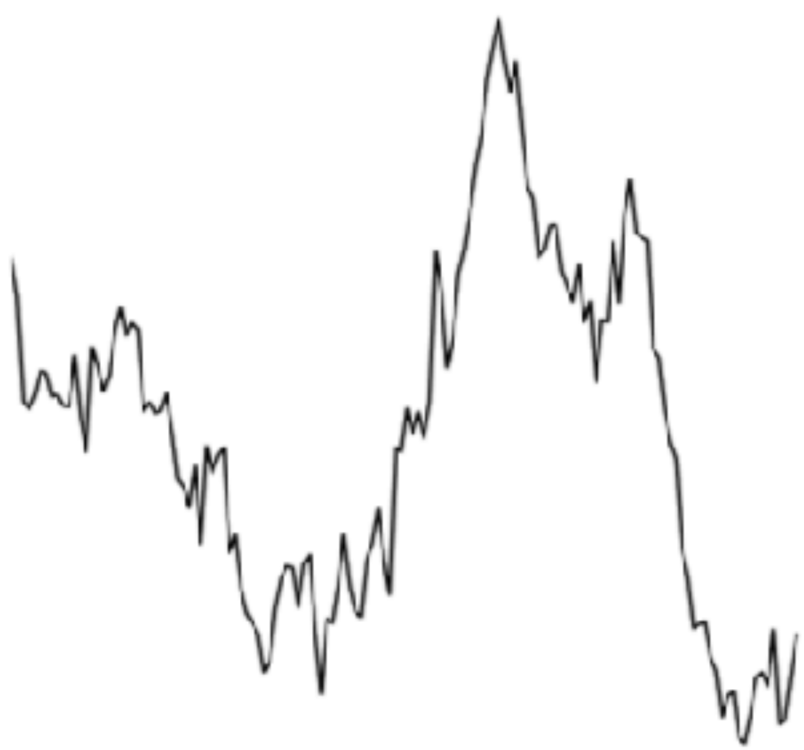
- generate valid but wacky text automatically
- **input:** ordered sequence of characters (training text corpus)
- **output:** ordered sequence of characters

- Generate wacky sentences with this academic RNN text generator
- Various twitter bots that tweet automatically generated text like this one.
- NanoGenMo annual contest to automatically produce a 50,000+ novel automatically
- Robot Shakespear a text generator that automatically produces Shakespear-esk sentences

Ingesting sequential I/O data for supervised learning

Time series prediction

- Sequence of P (floating point) numbers: $\langle s_0, s_1, s_2, \ldots, s_P \rangle$



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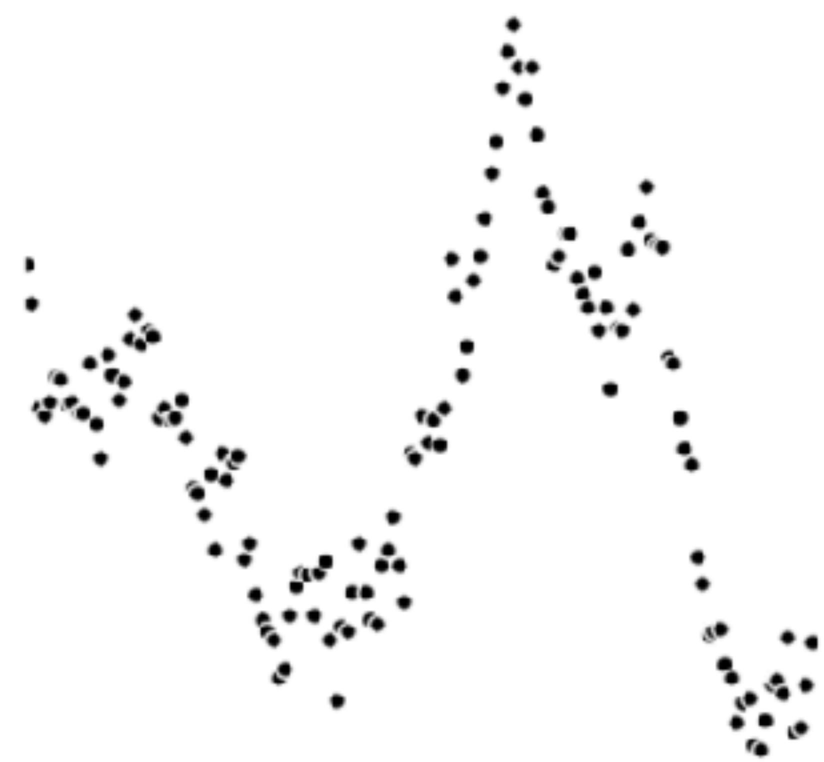

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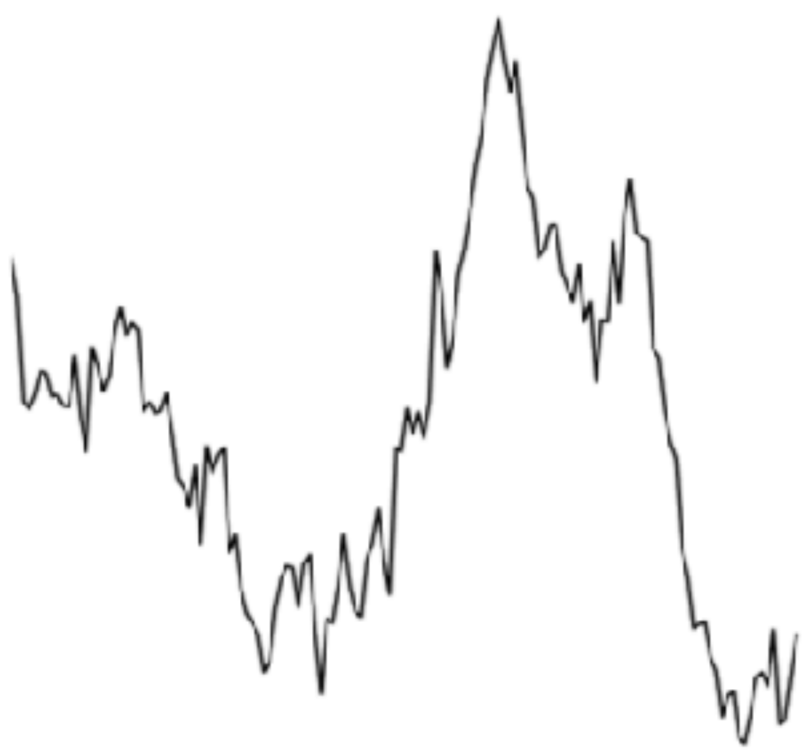
Time series prediction

- Sequence of P (floating point) numbers: $\langle s_0, s_1, s_2, \ldots, s_P \rangle$
- s_p: the pth value



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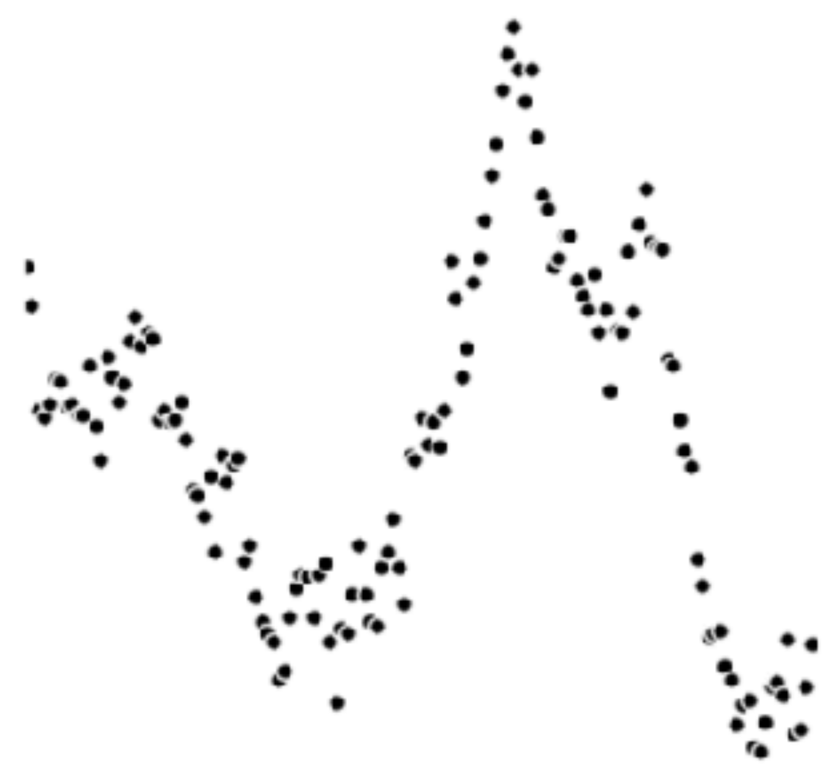

series really looks like this

Time series prediction

- Sequence of P (floating point) numbers: $\langle s_0, s_1, s_2, \ldots, s_P \rangle$
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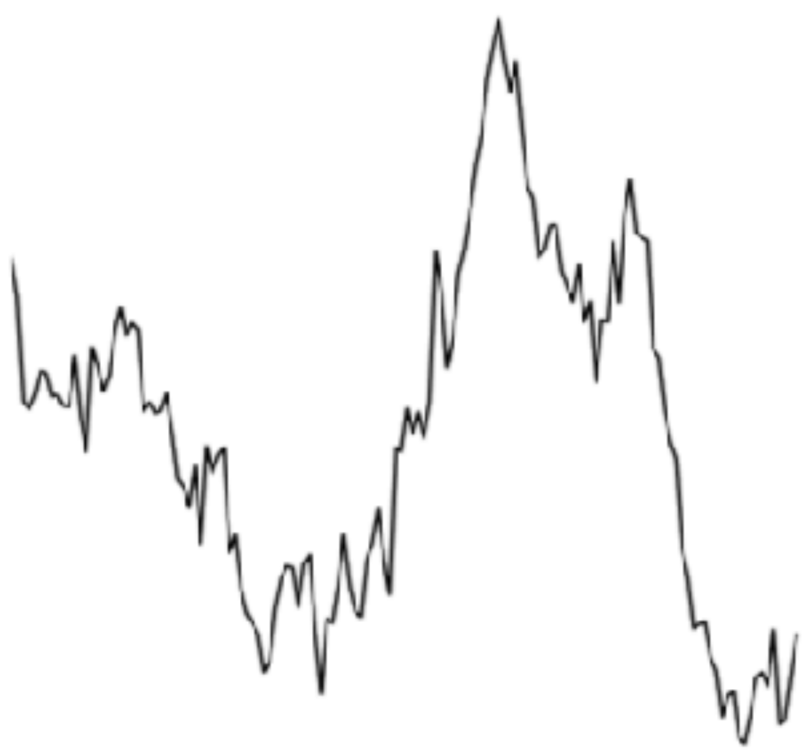
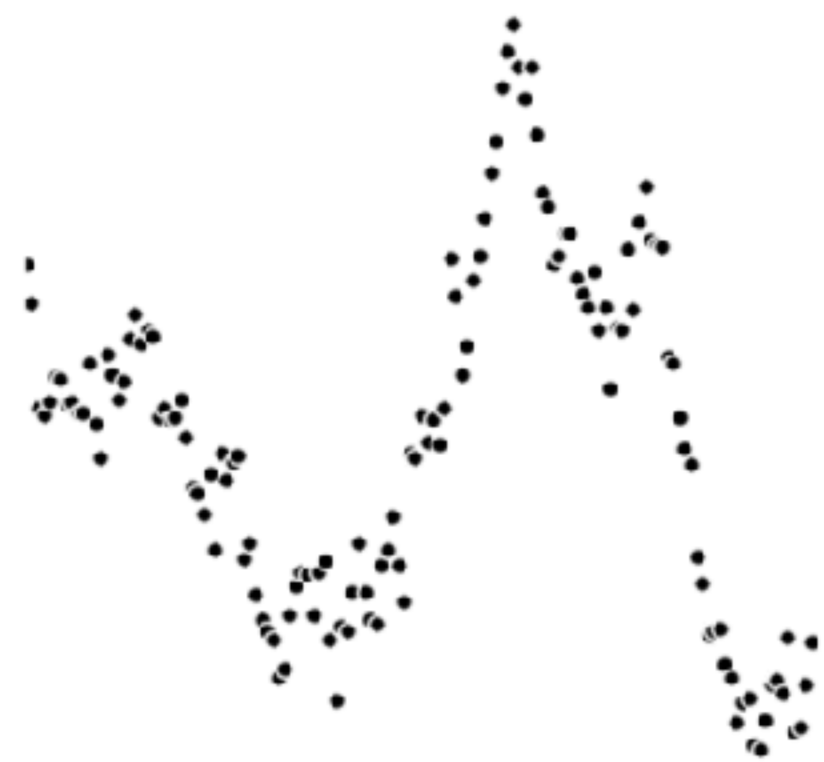
- **regression problem**- I/O are windowed subsequences



series shown interpolated



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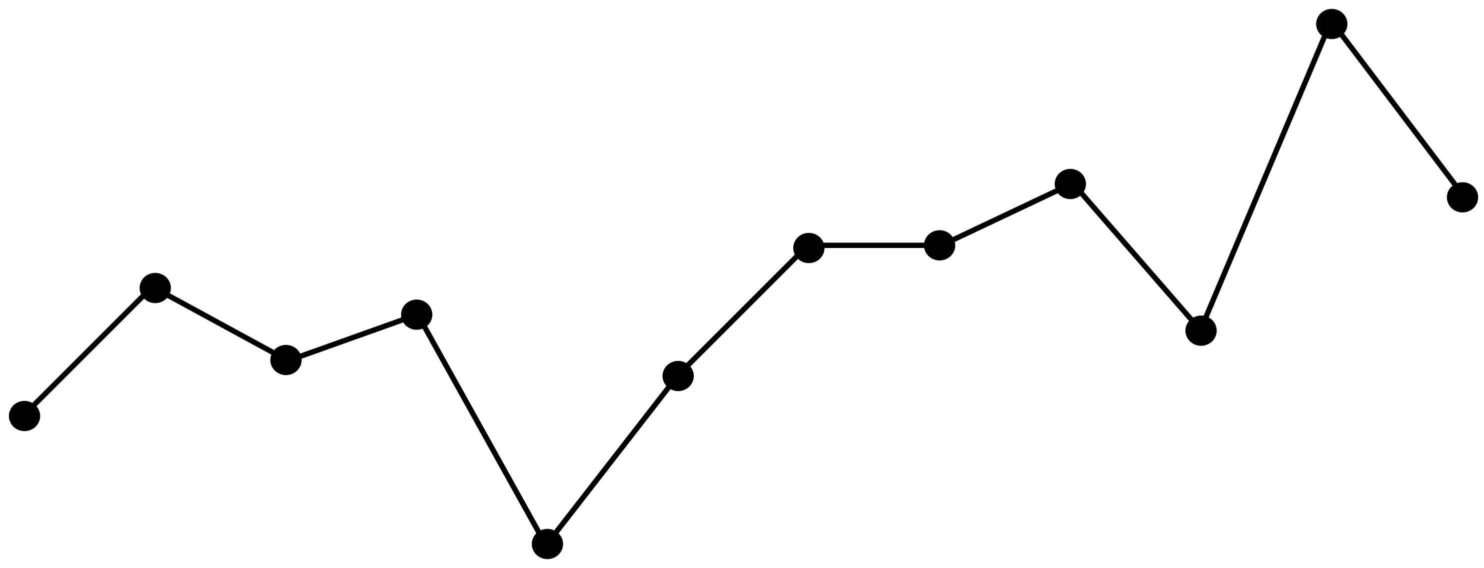
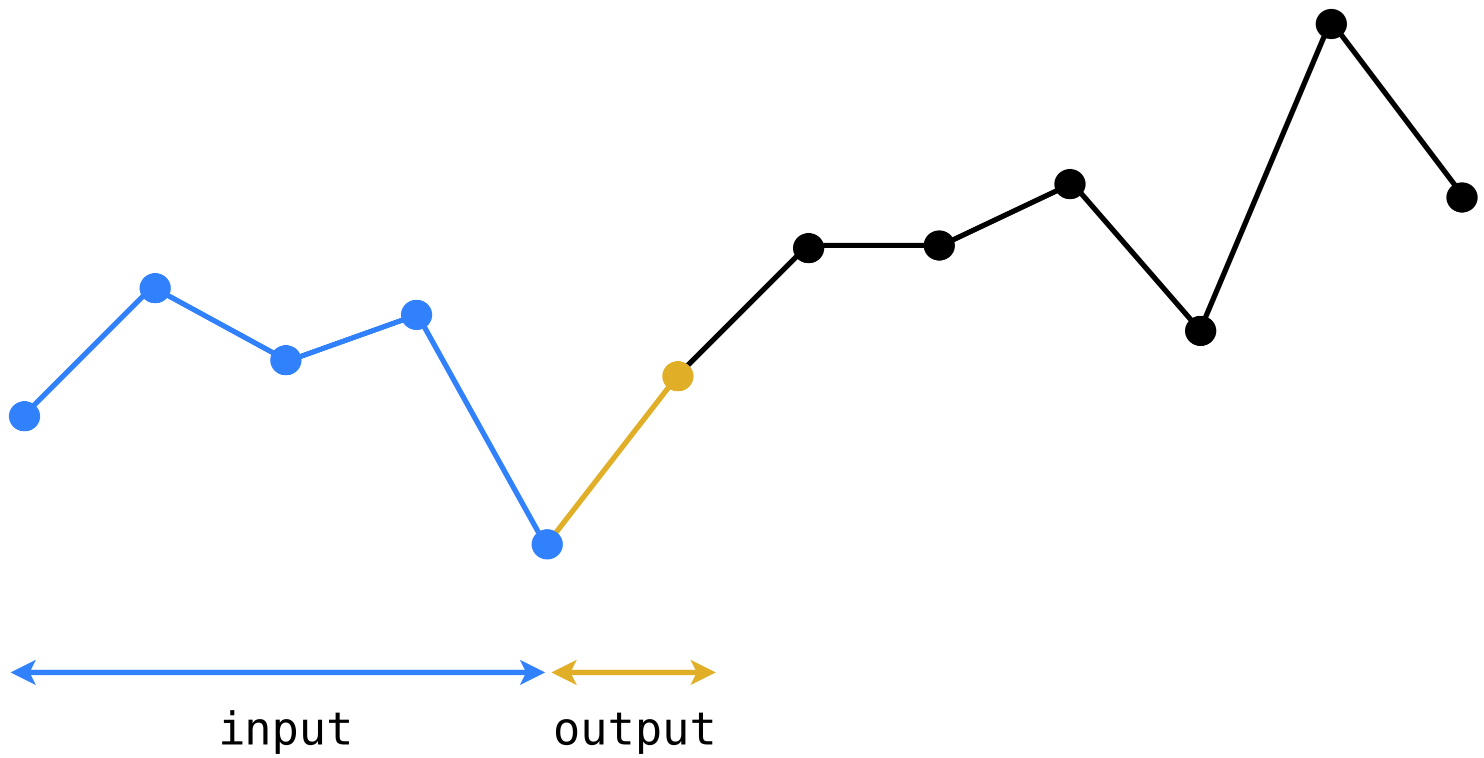
Time series prediction

- Sequence of P (floating point) numbers: $\langle s_0, s_1, s_2, \ldots, s_P \rangle$
- s_p : the pth value
- - **regression problem**- I/O are windowed subsequences

  - so need training and testing sets

  - lets see how both are formed, start with training

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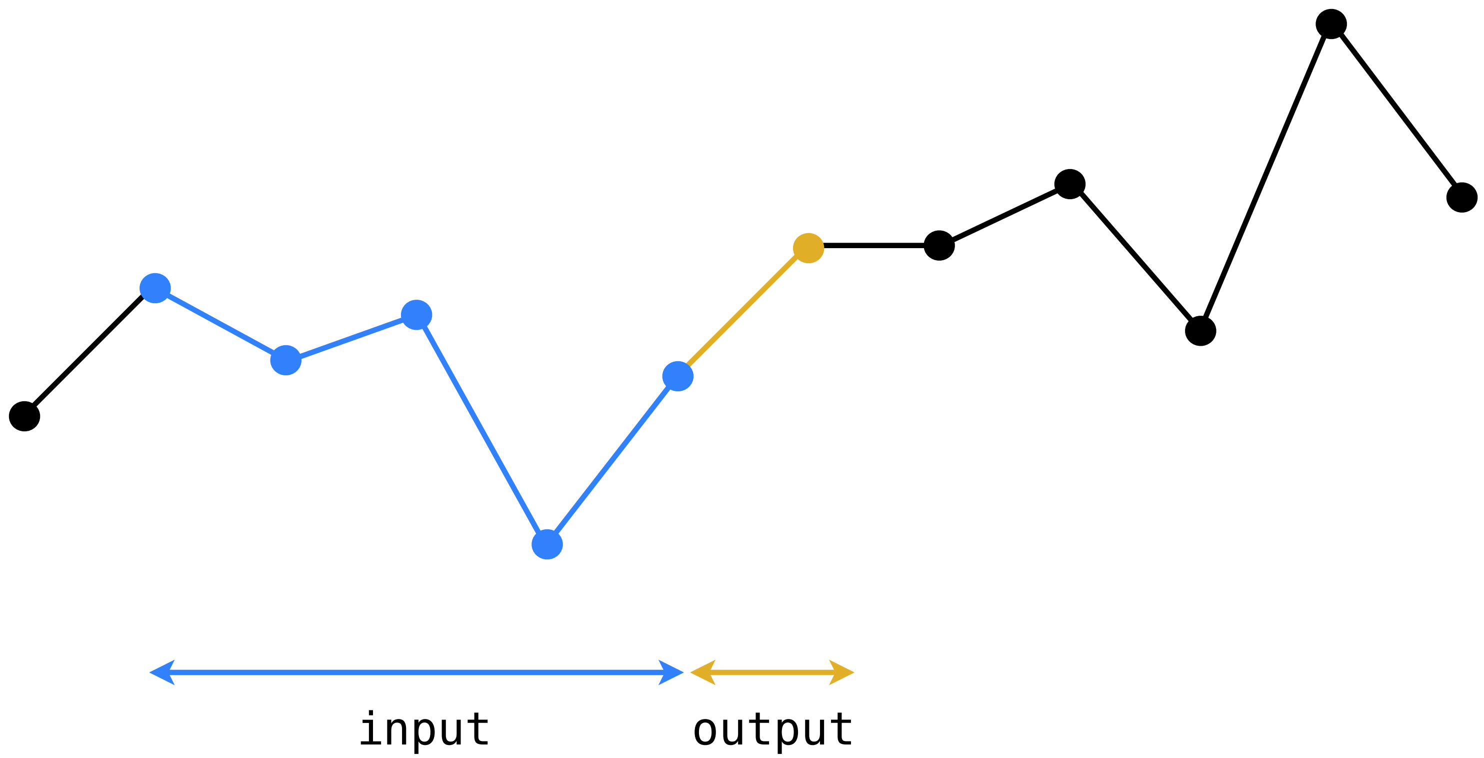
output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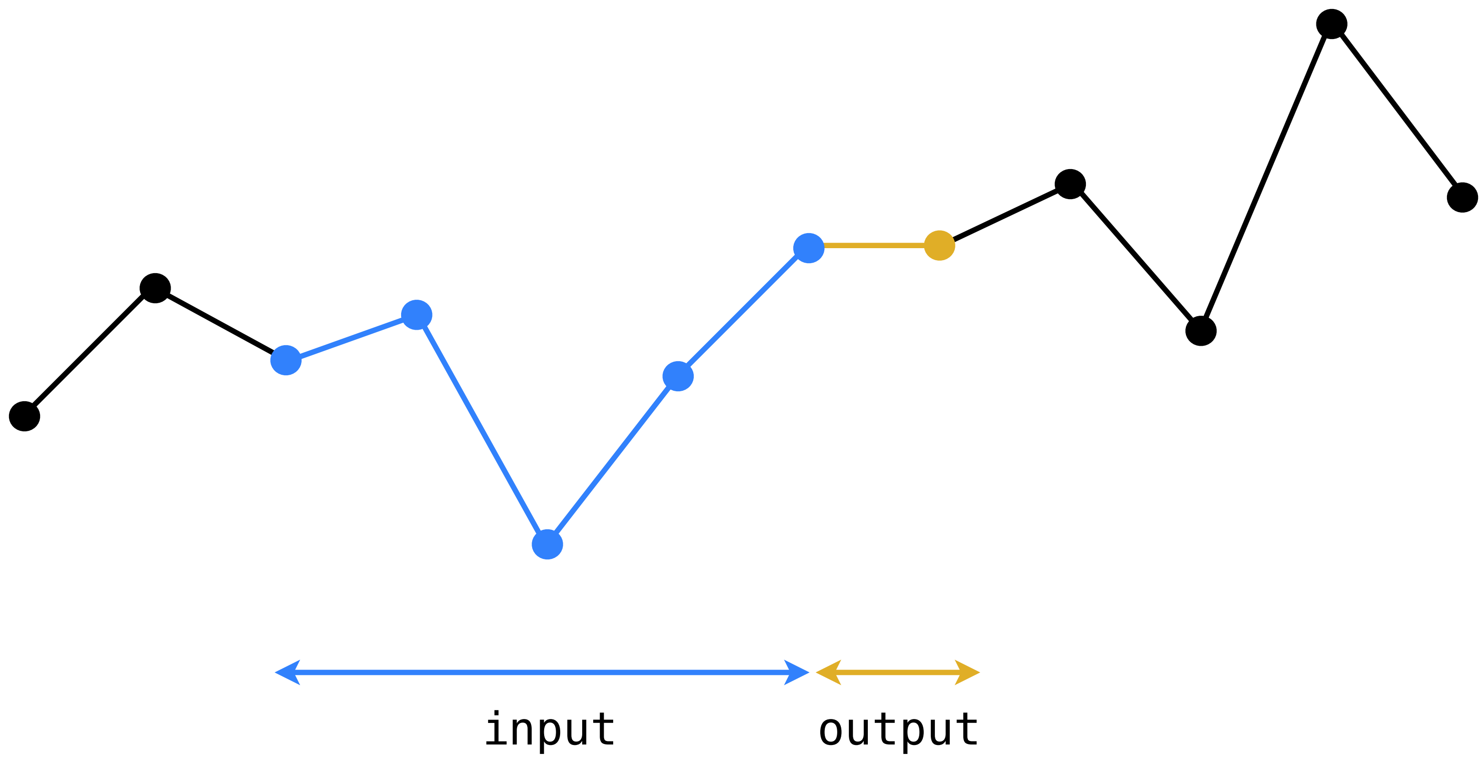
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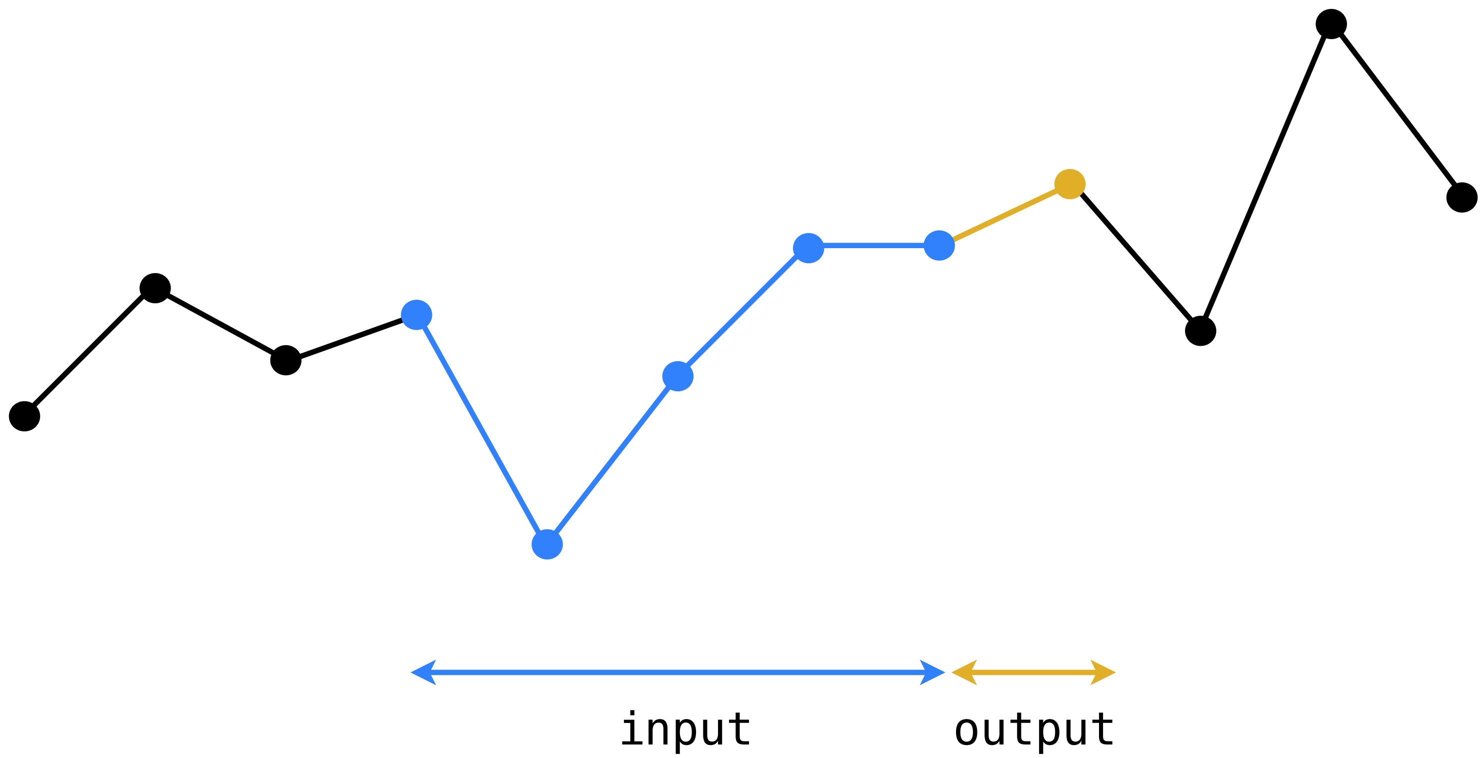
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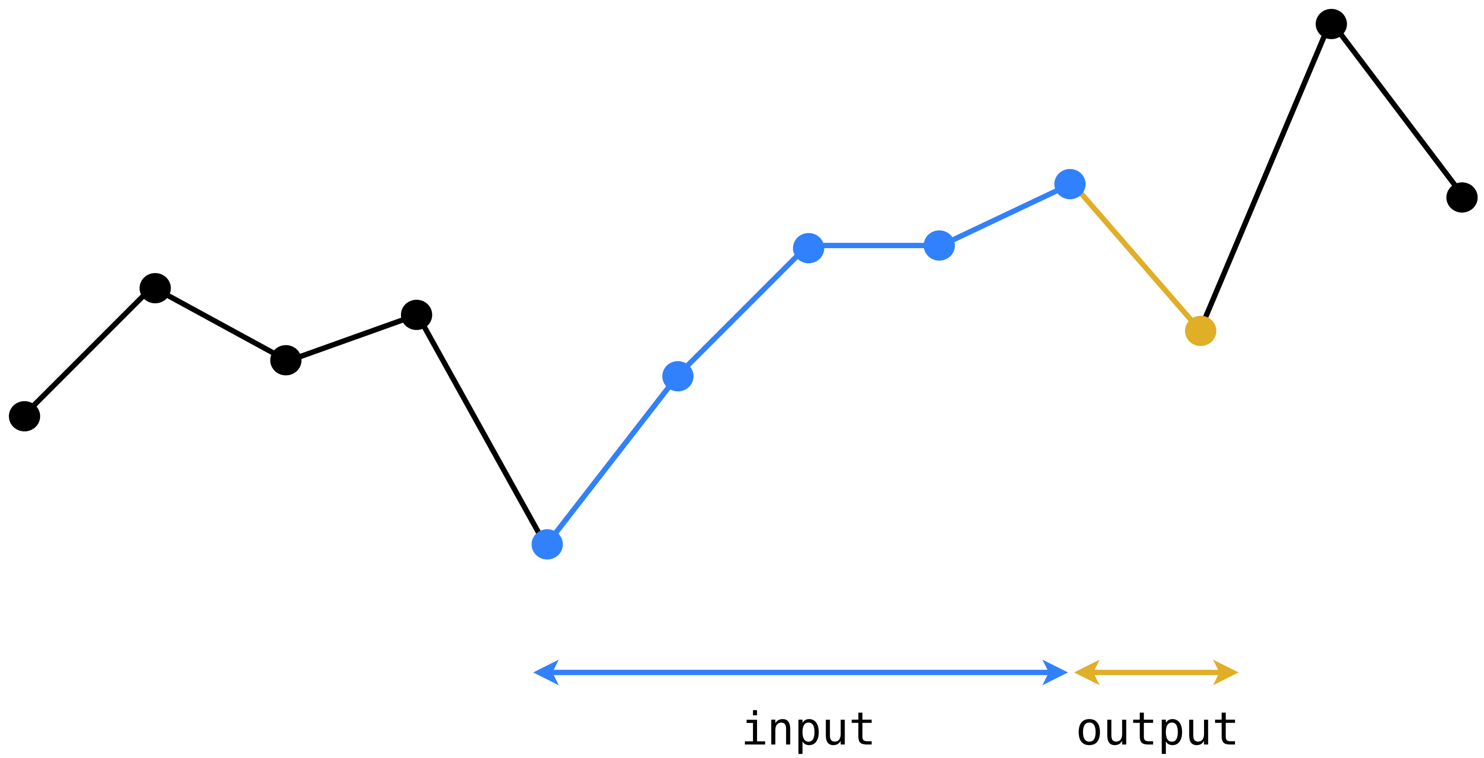
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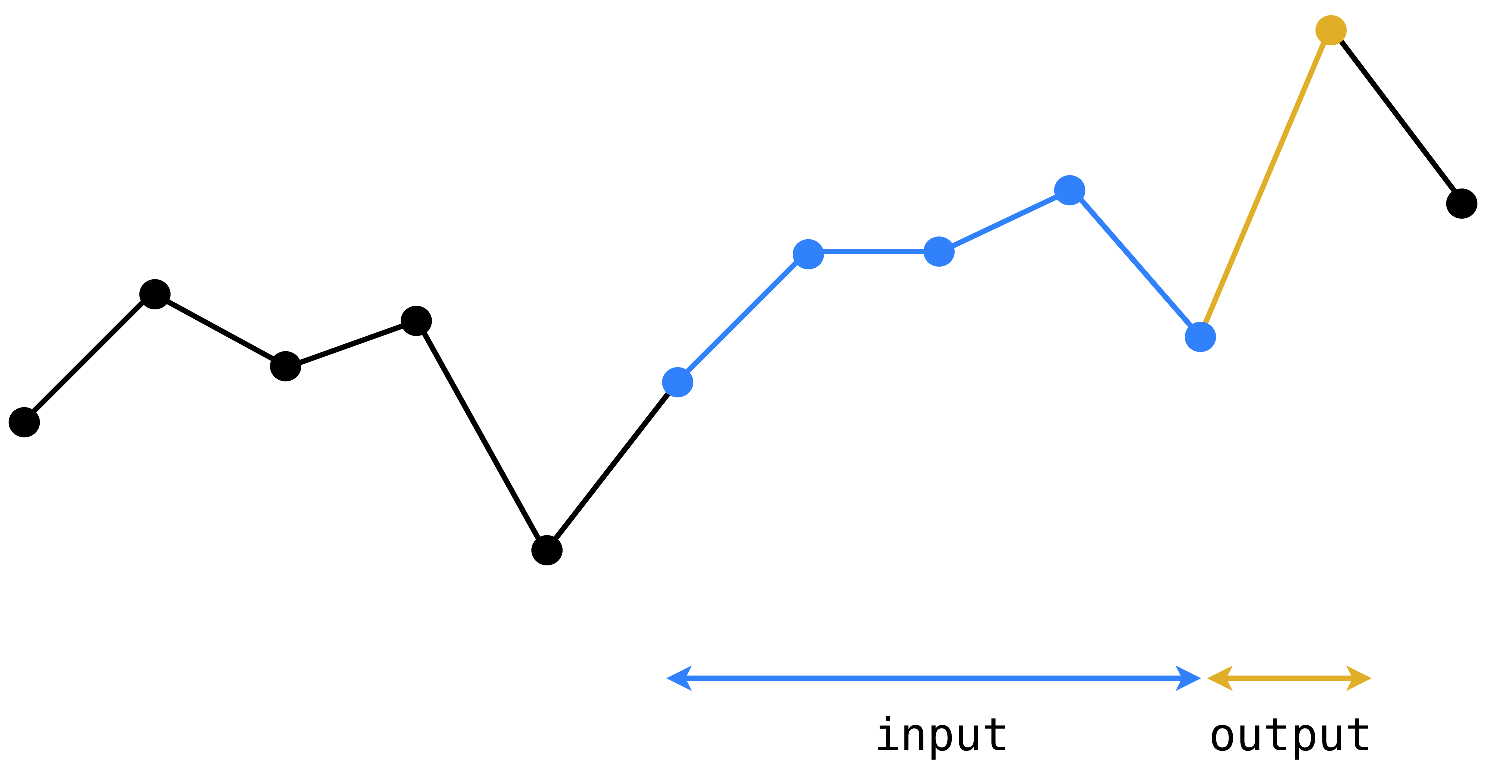
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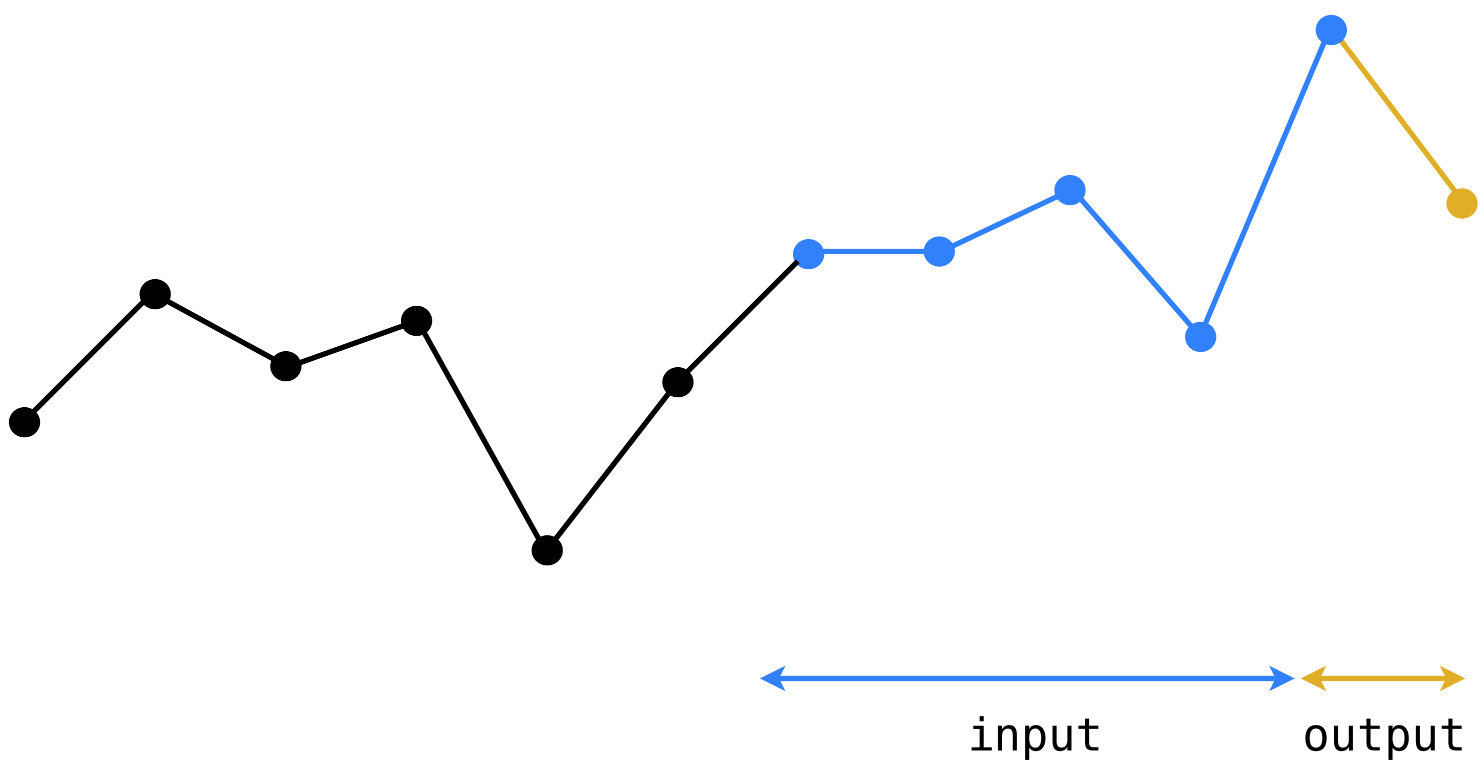
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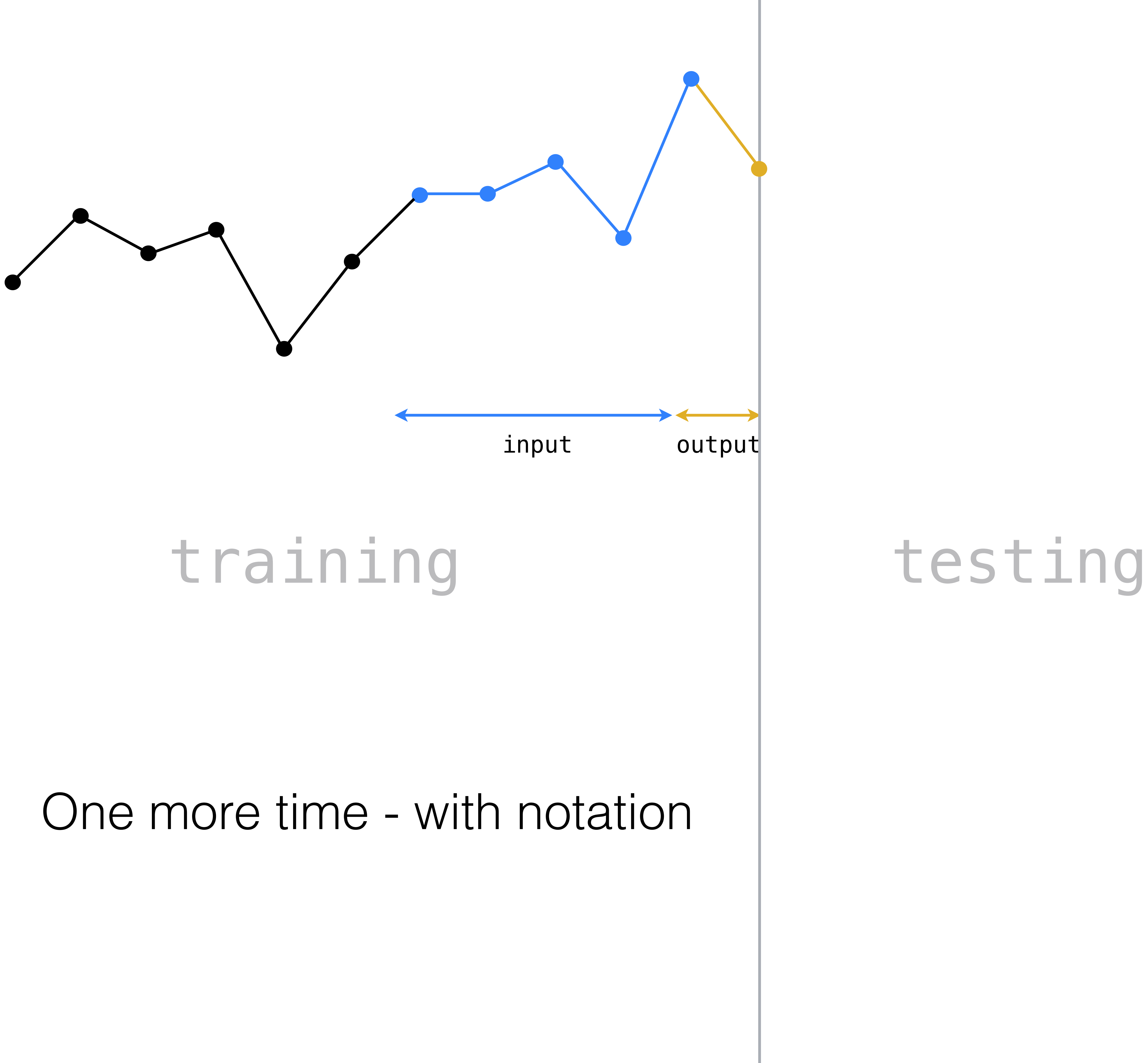
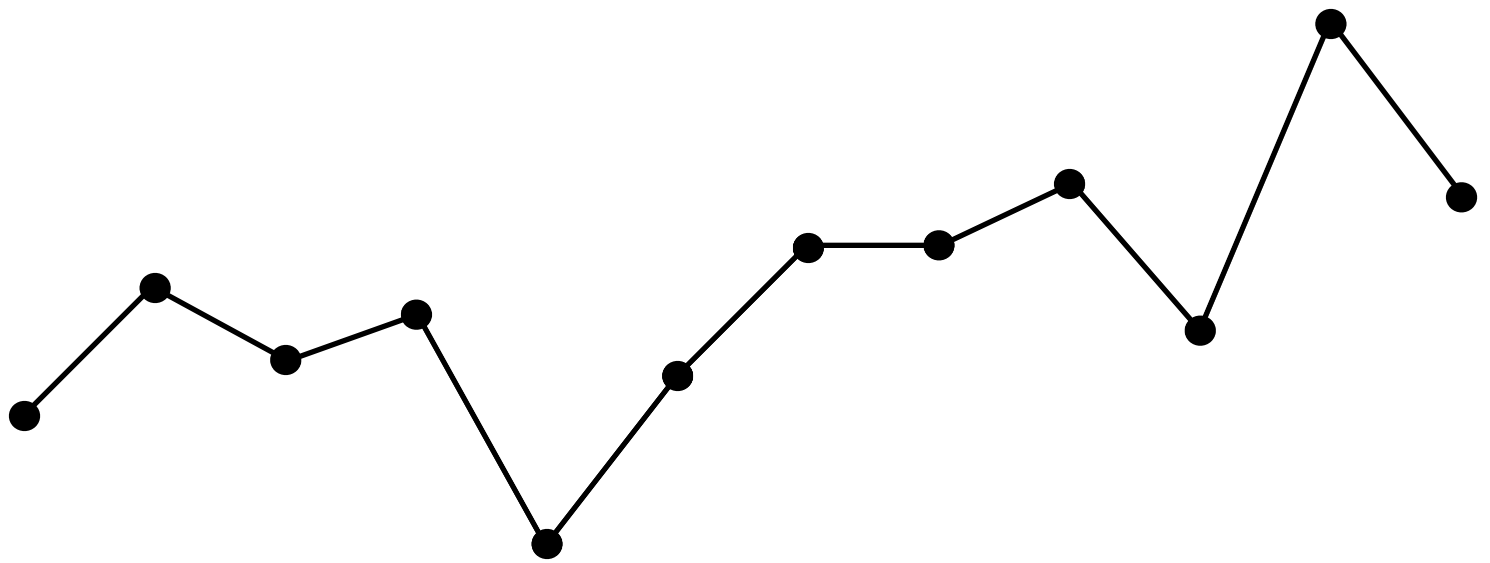
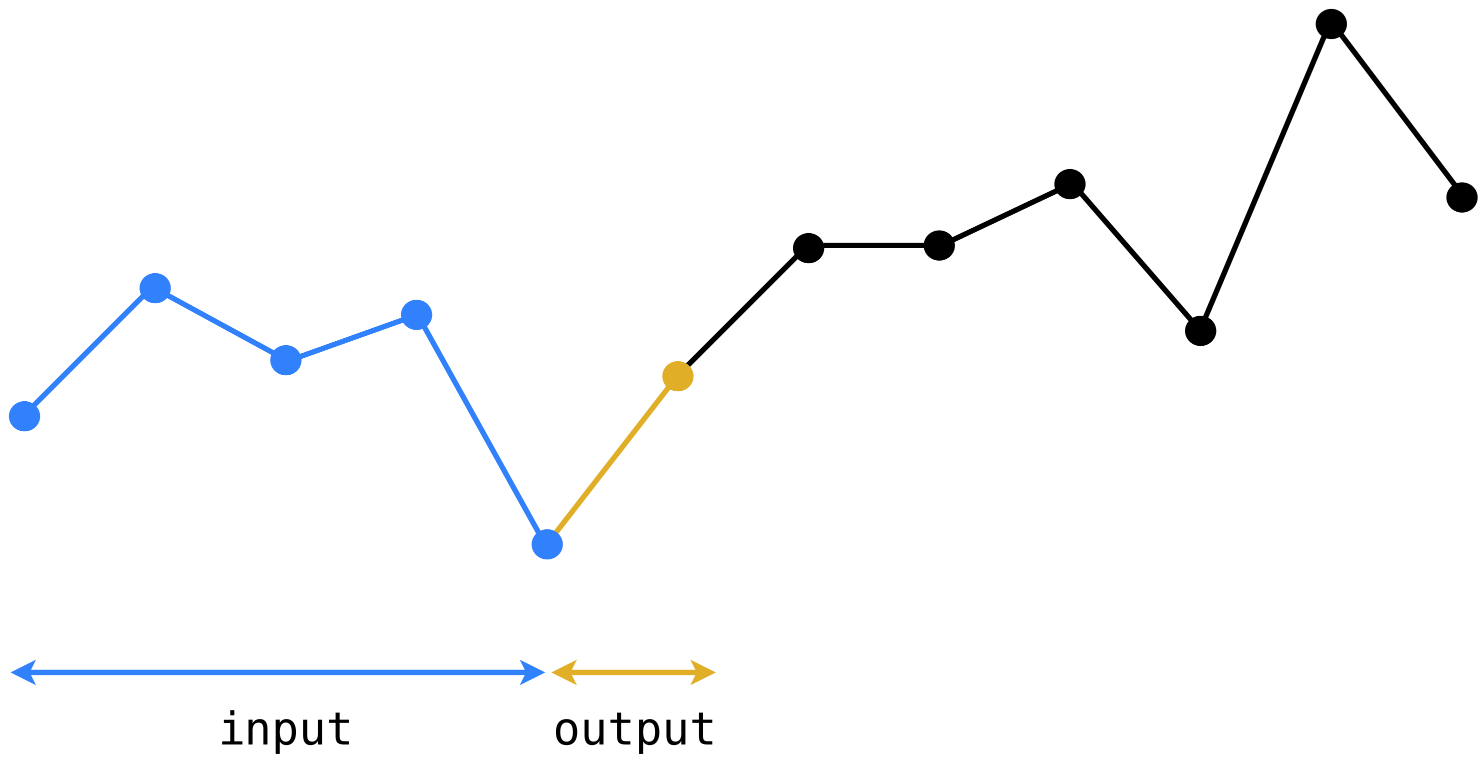


One more time - with notation





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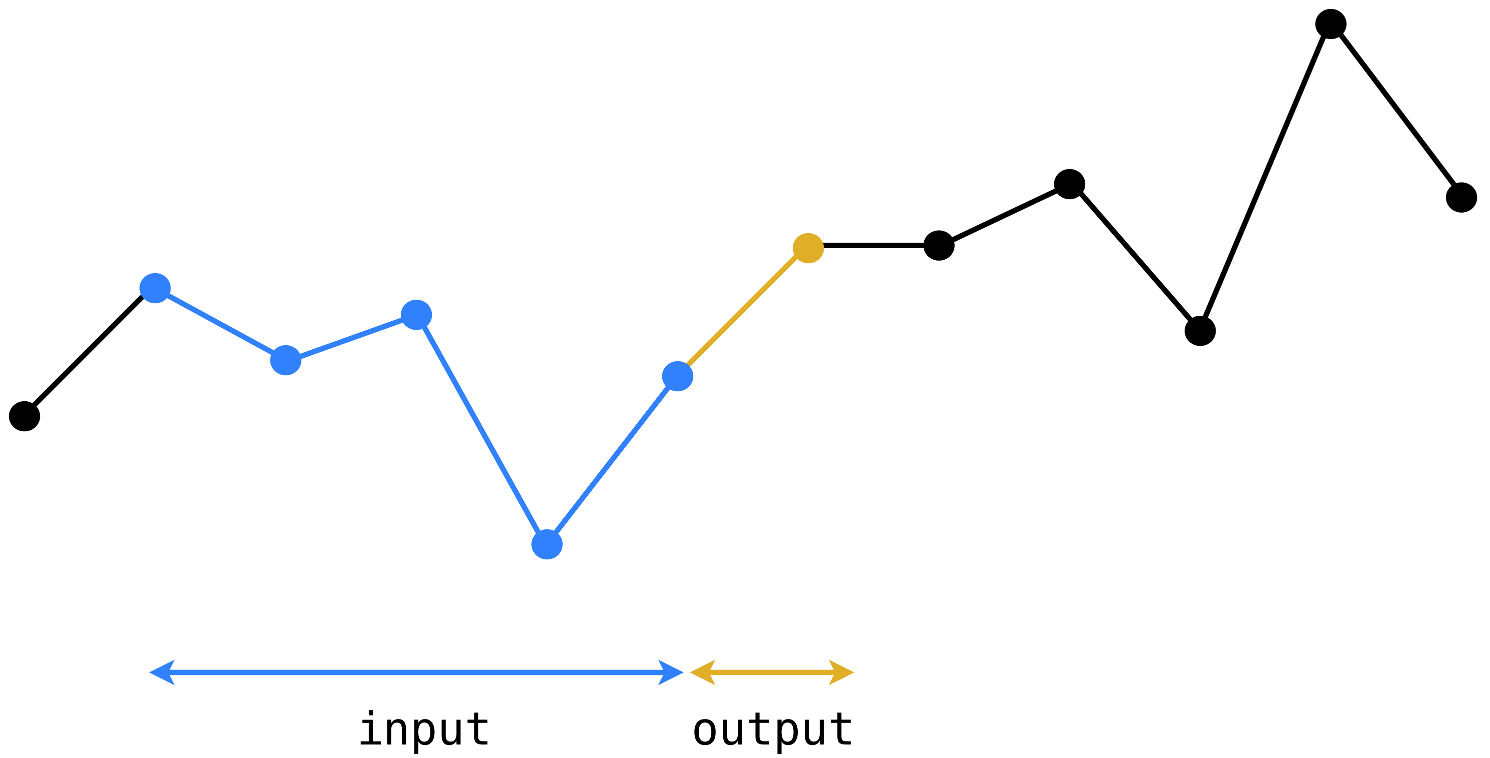
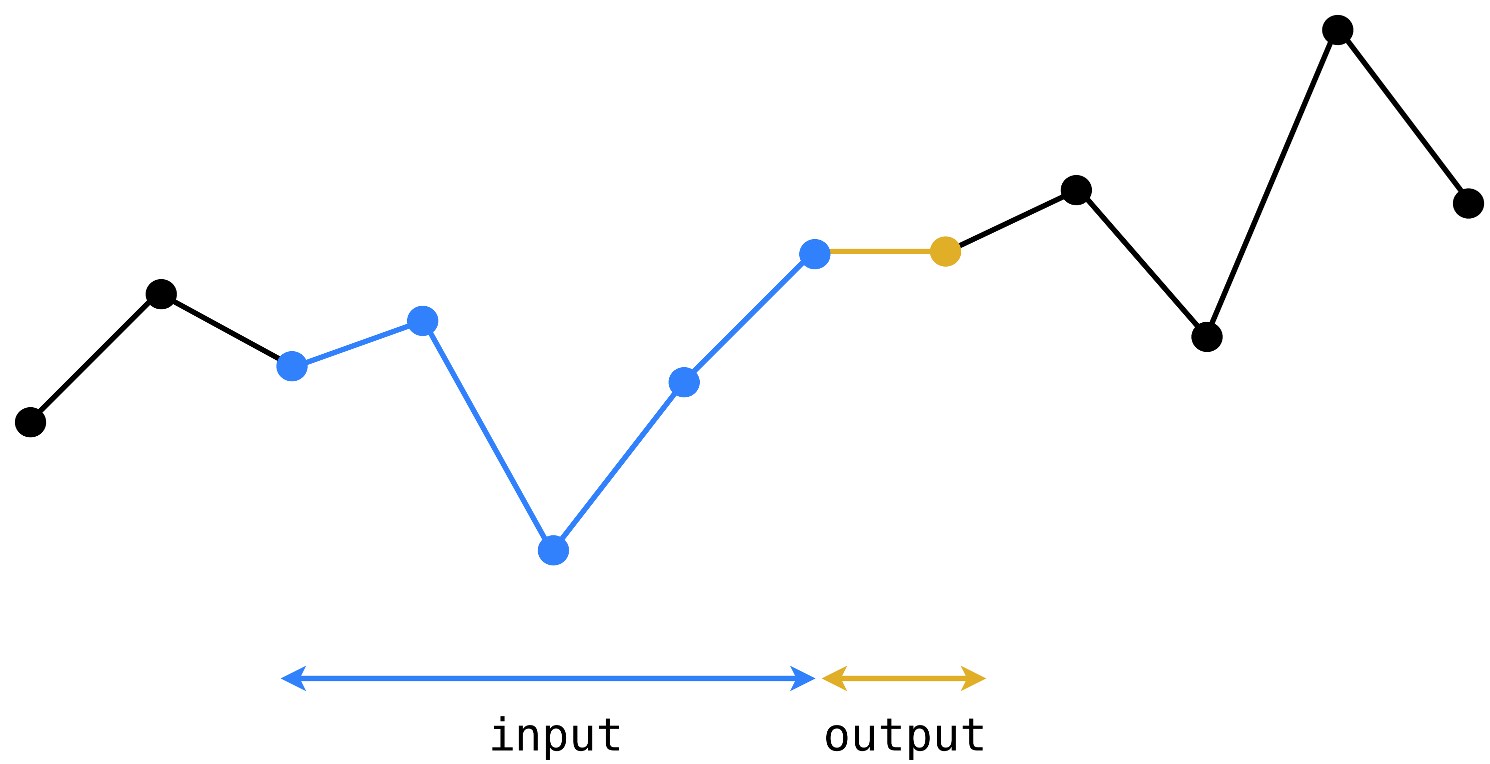
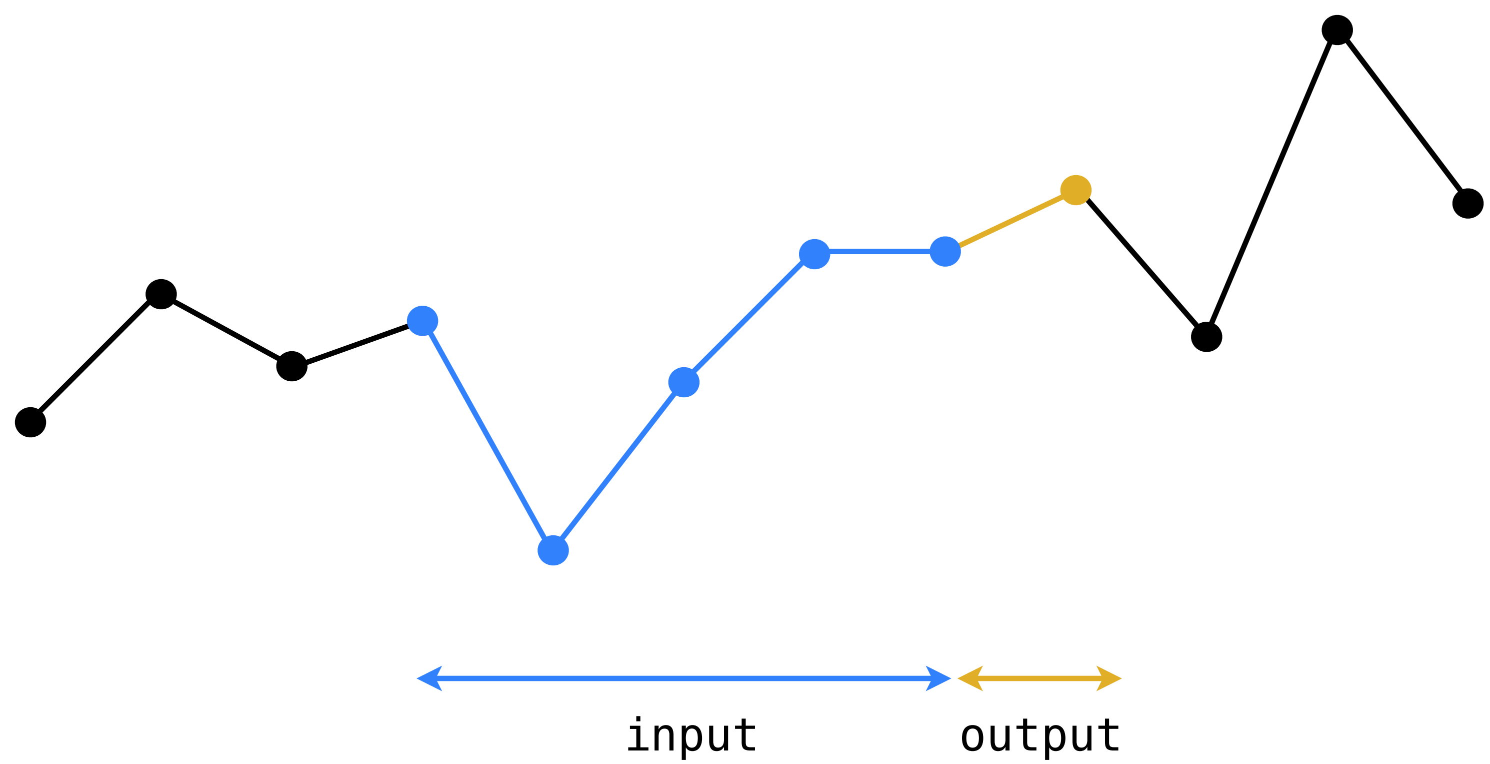


Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4



Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5
$\vdots$	$\vdots$



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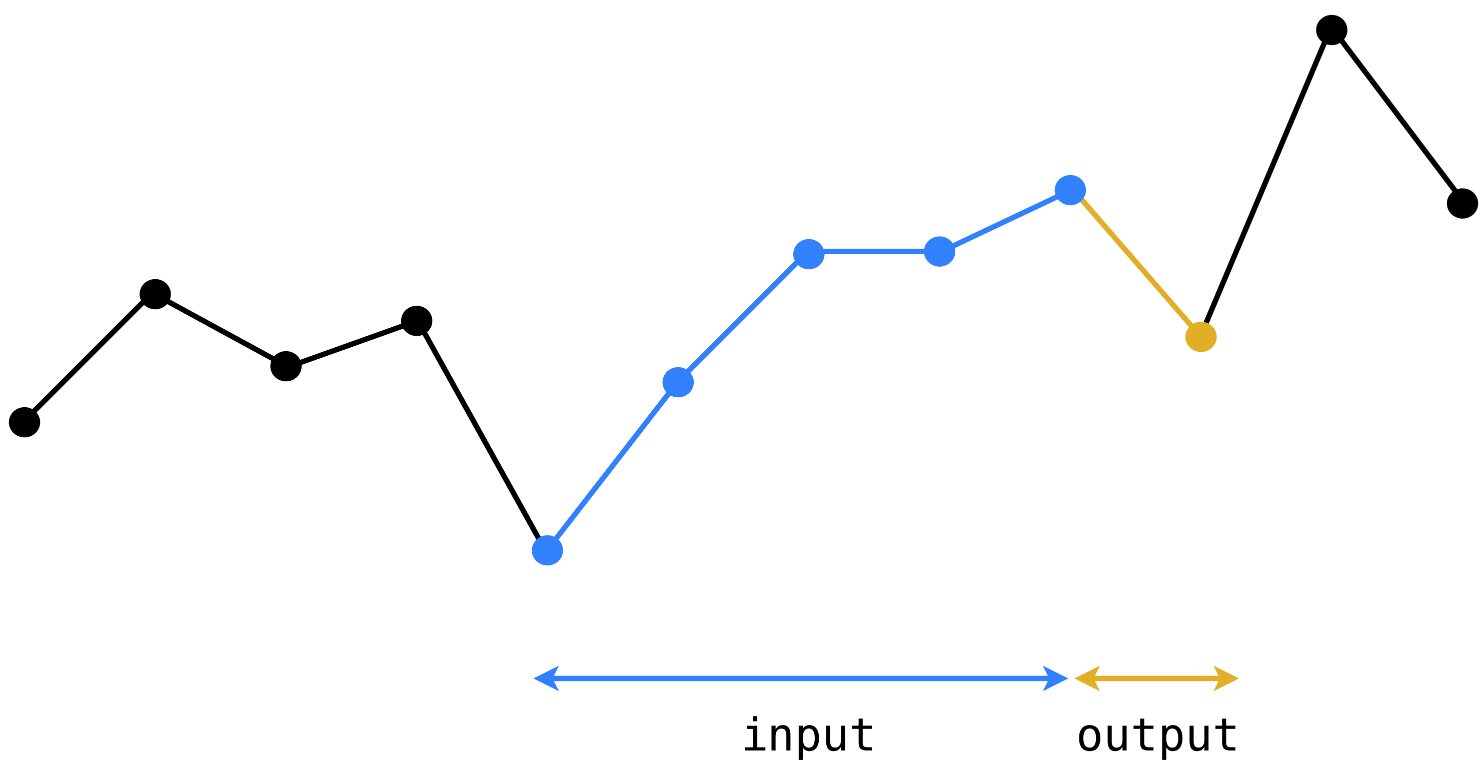
$\vdots$	$\vdots$



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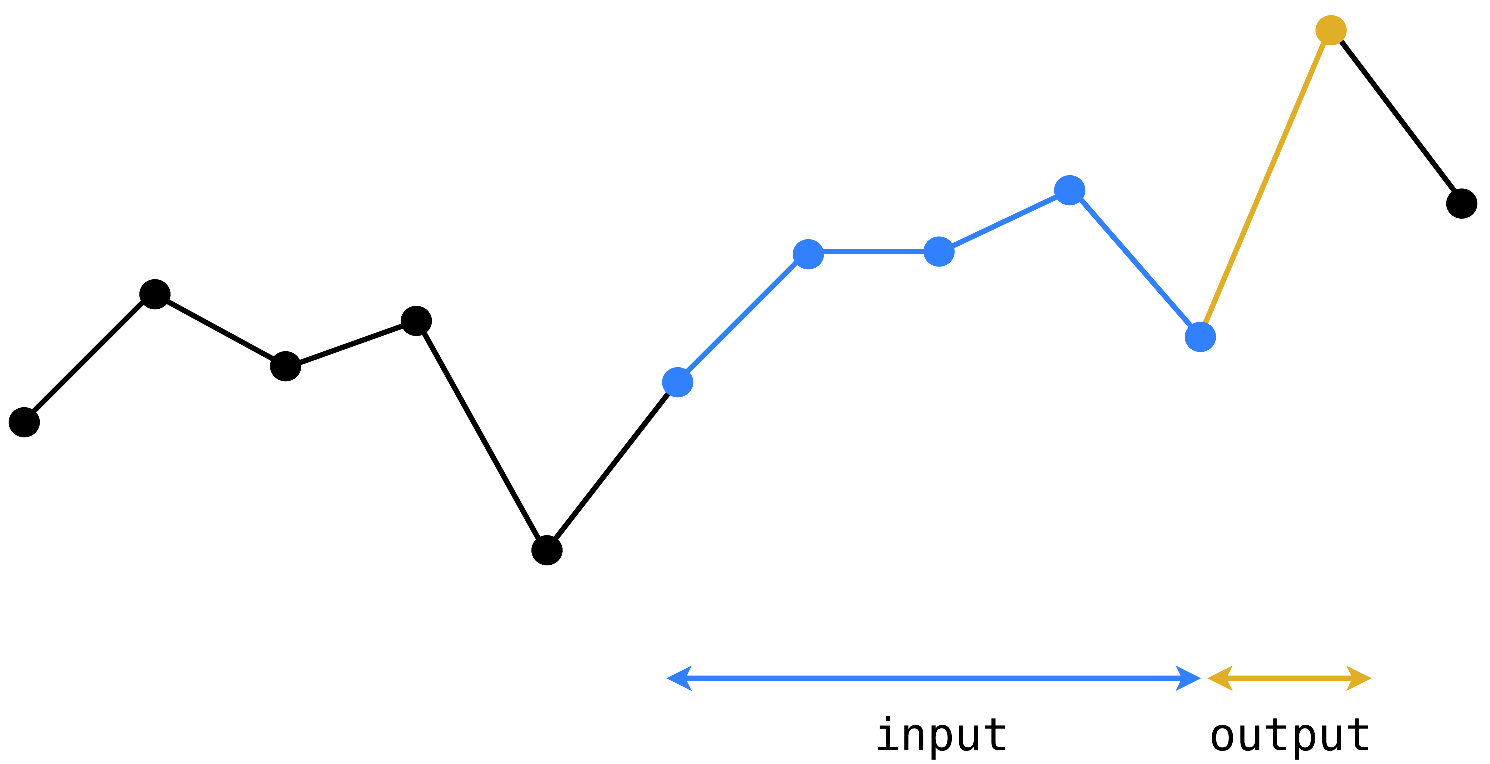

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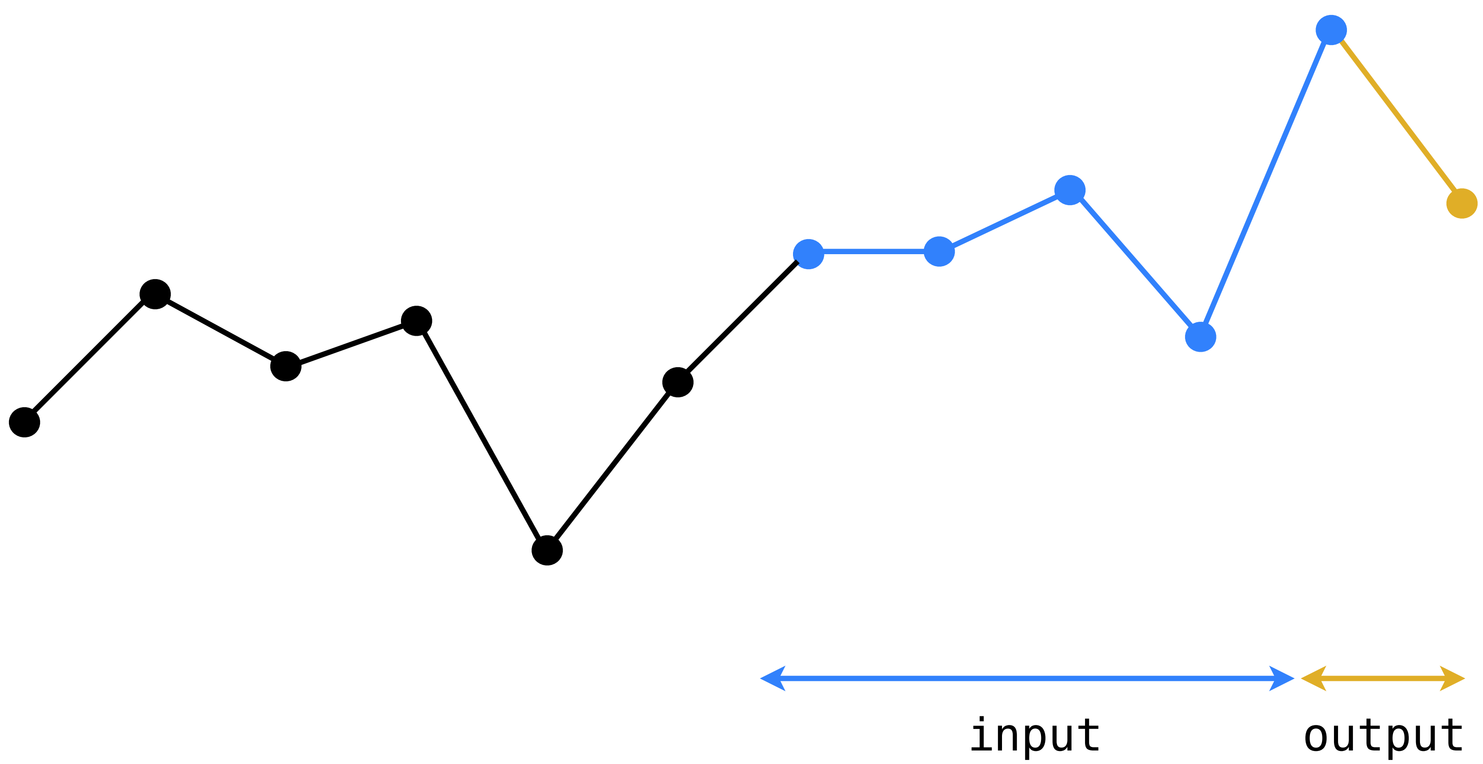

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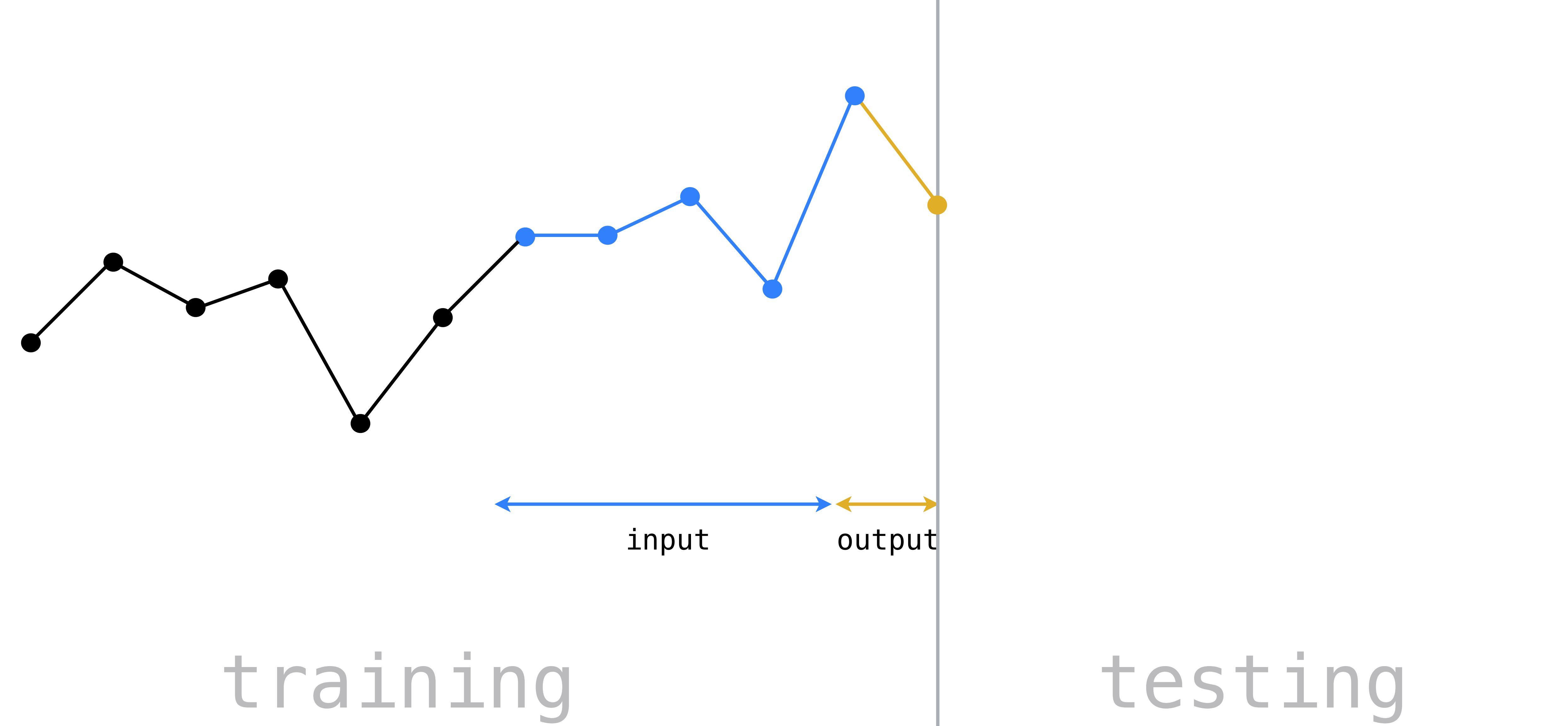
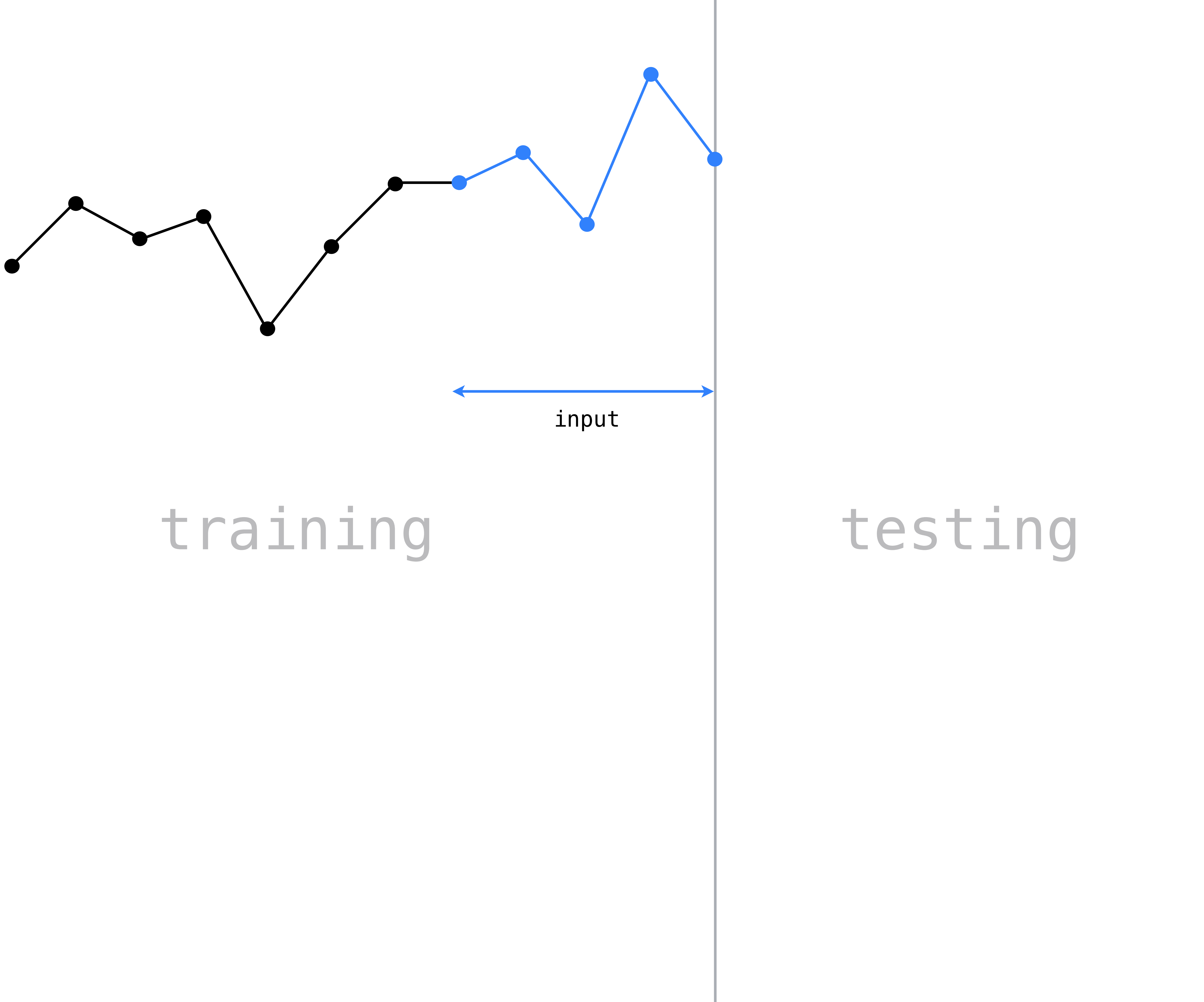
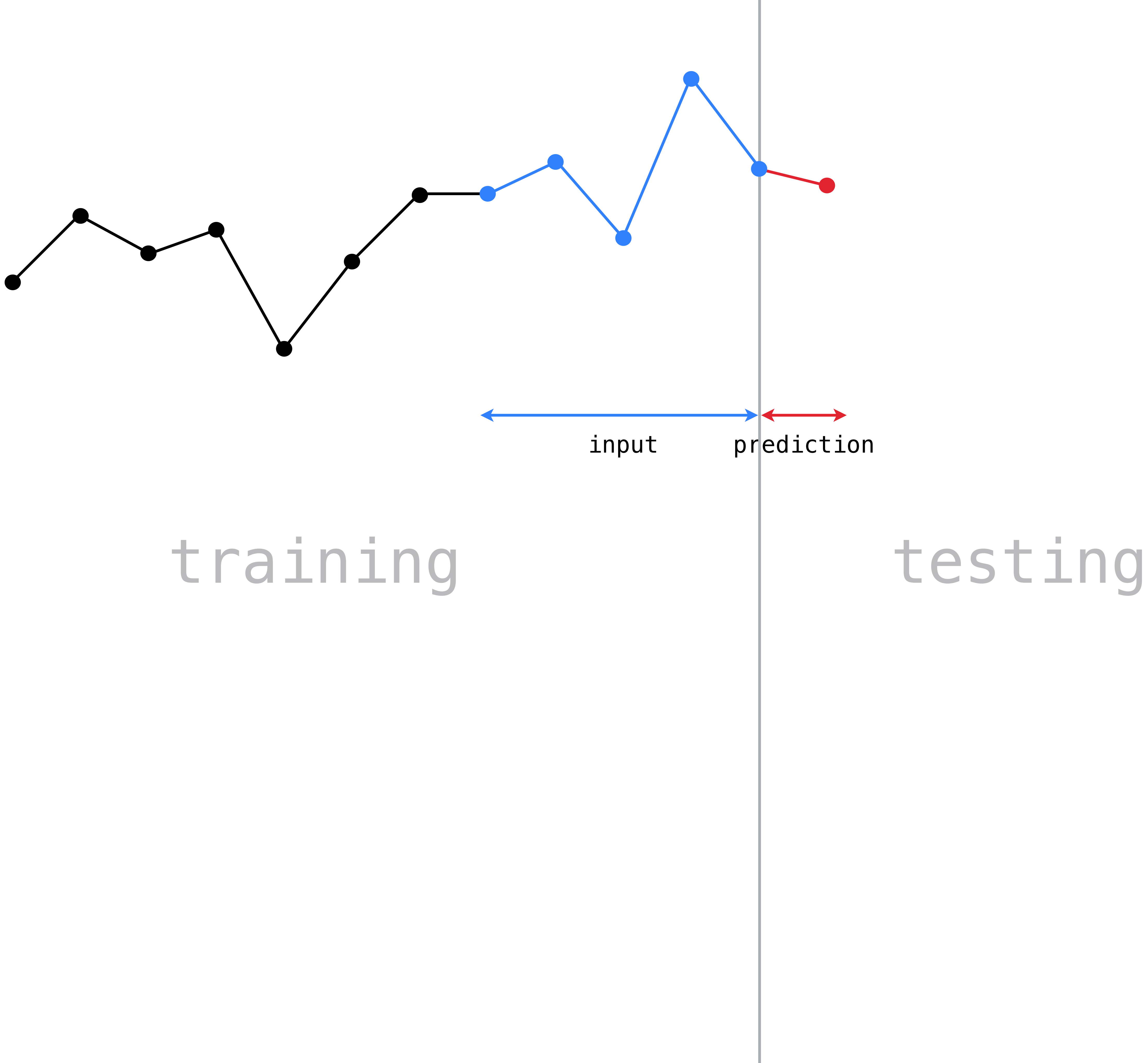
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5
$\vdots$	$\vdots$
$\langle s_{P-4}, s_{P-3}, s_{P-2}, s_{P-1} \rangle$	s_P



Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5
$\vdots$	$\vdots$
$\langle s_{P-4}, s_{P-3}, s_{P-2}, s_{P-1} \rangle$	s_P


input
training
testing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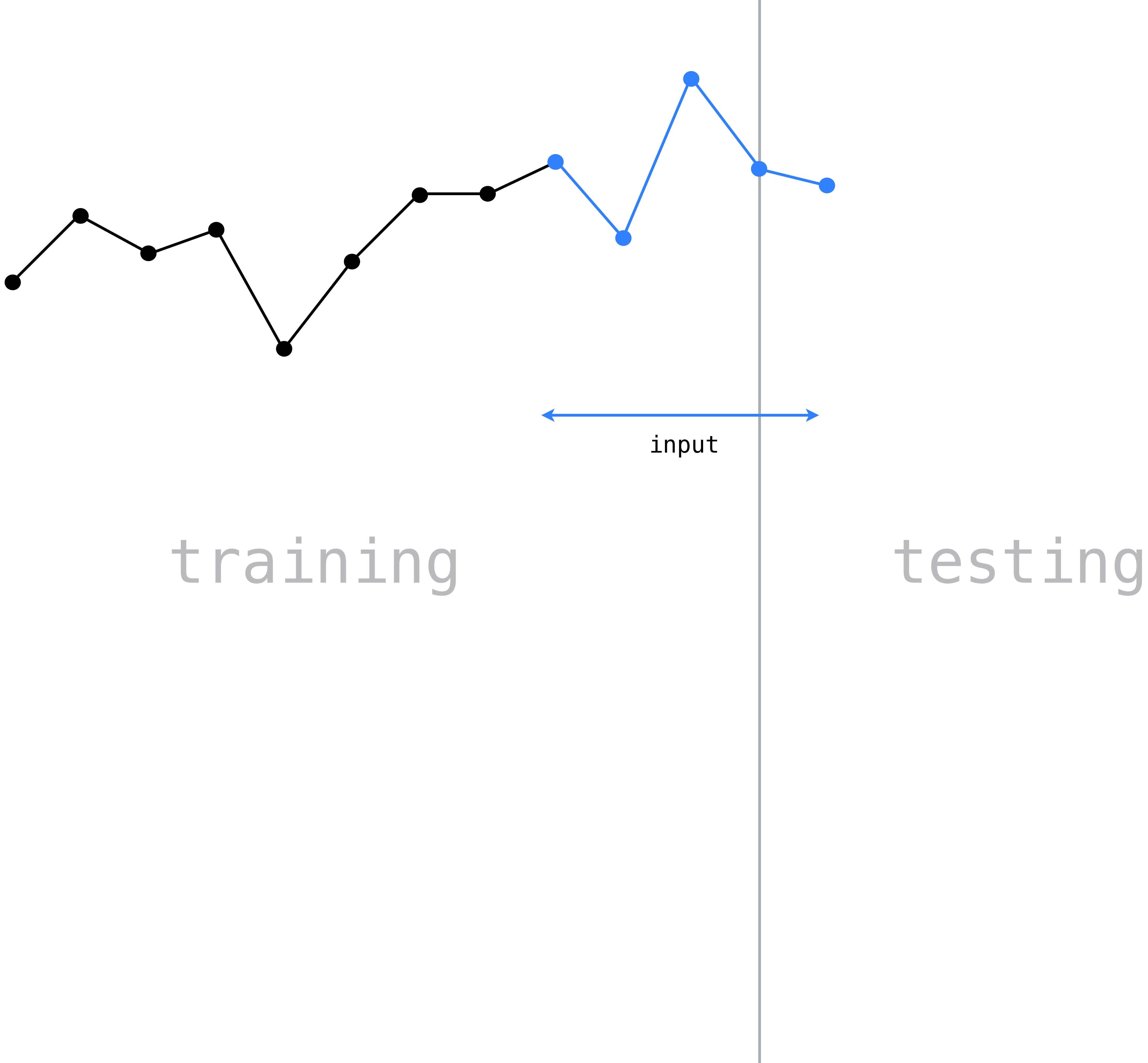
training
testing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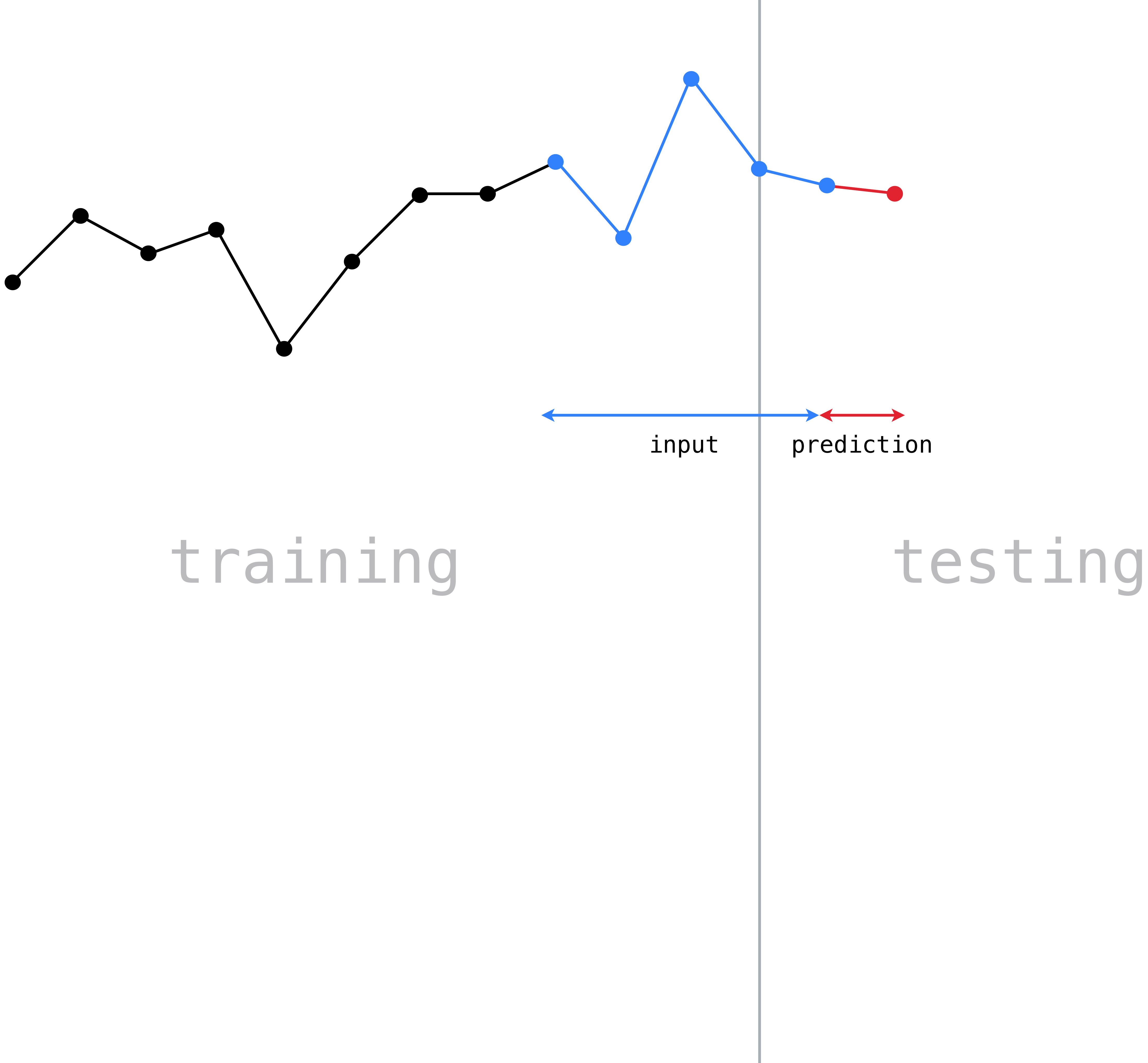
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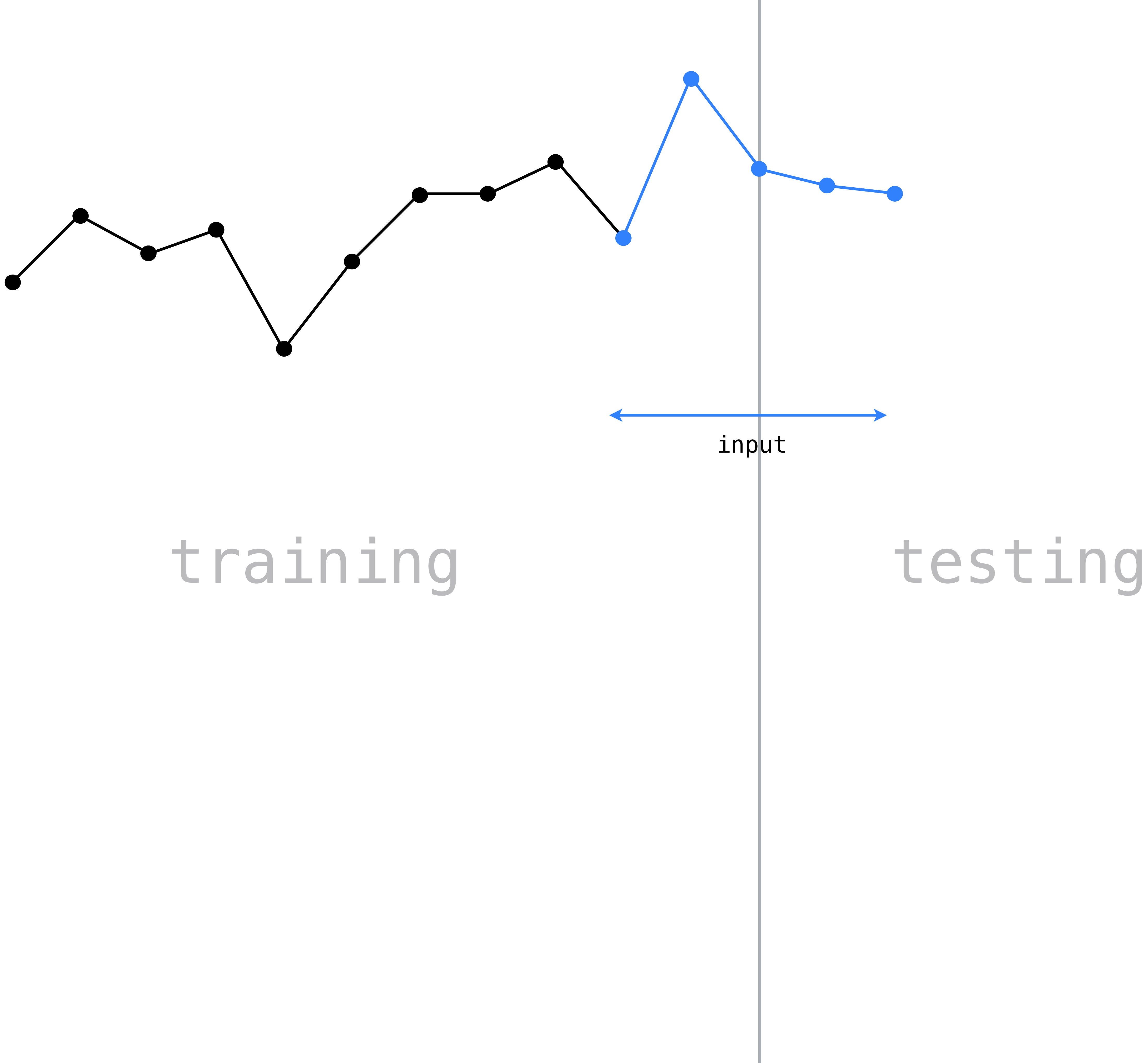
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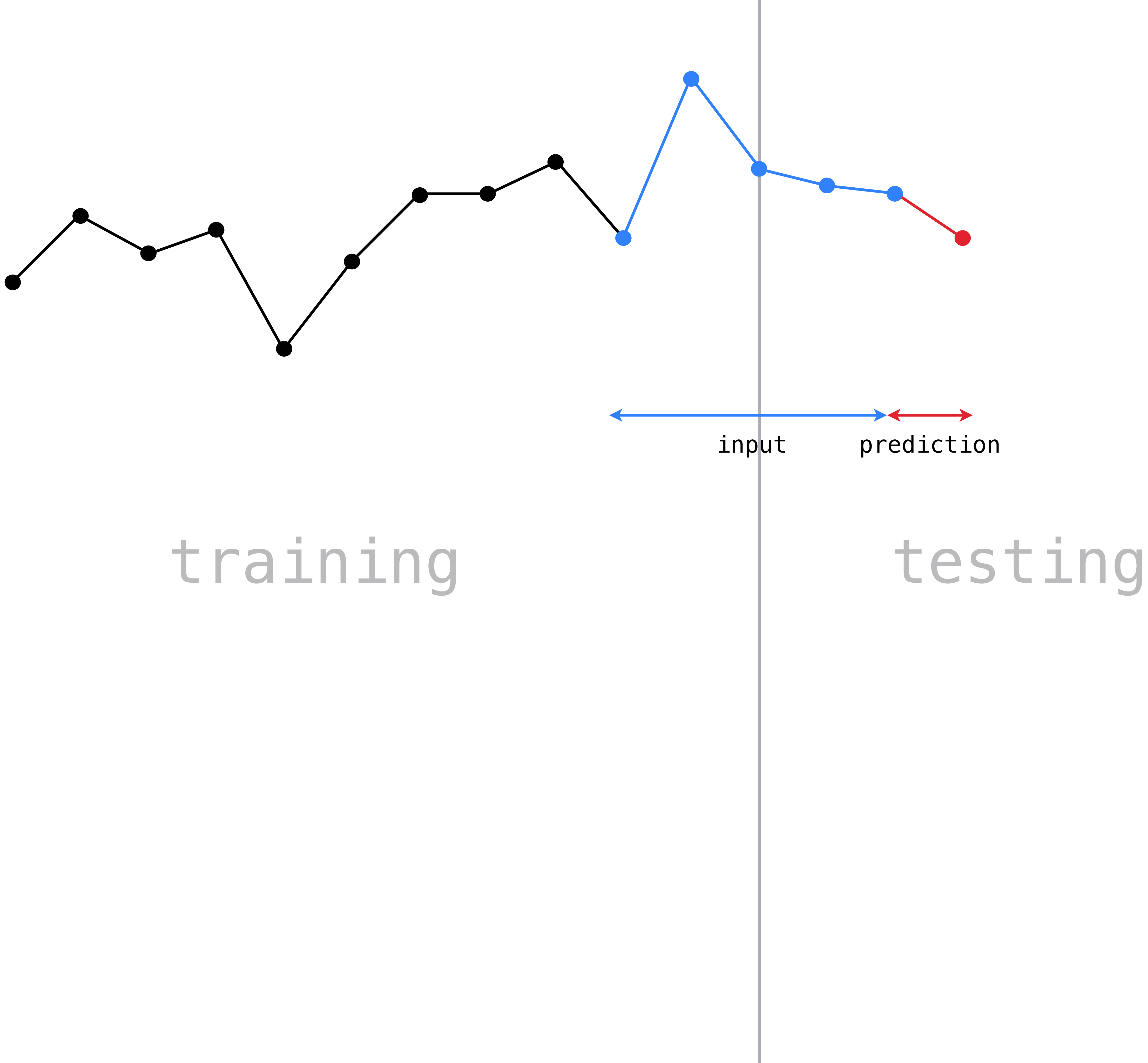
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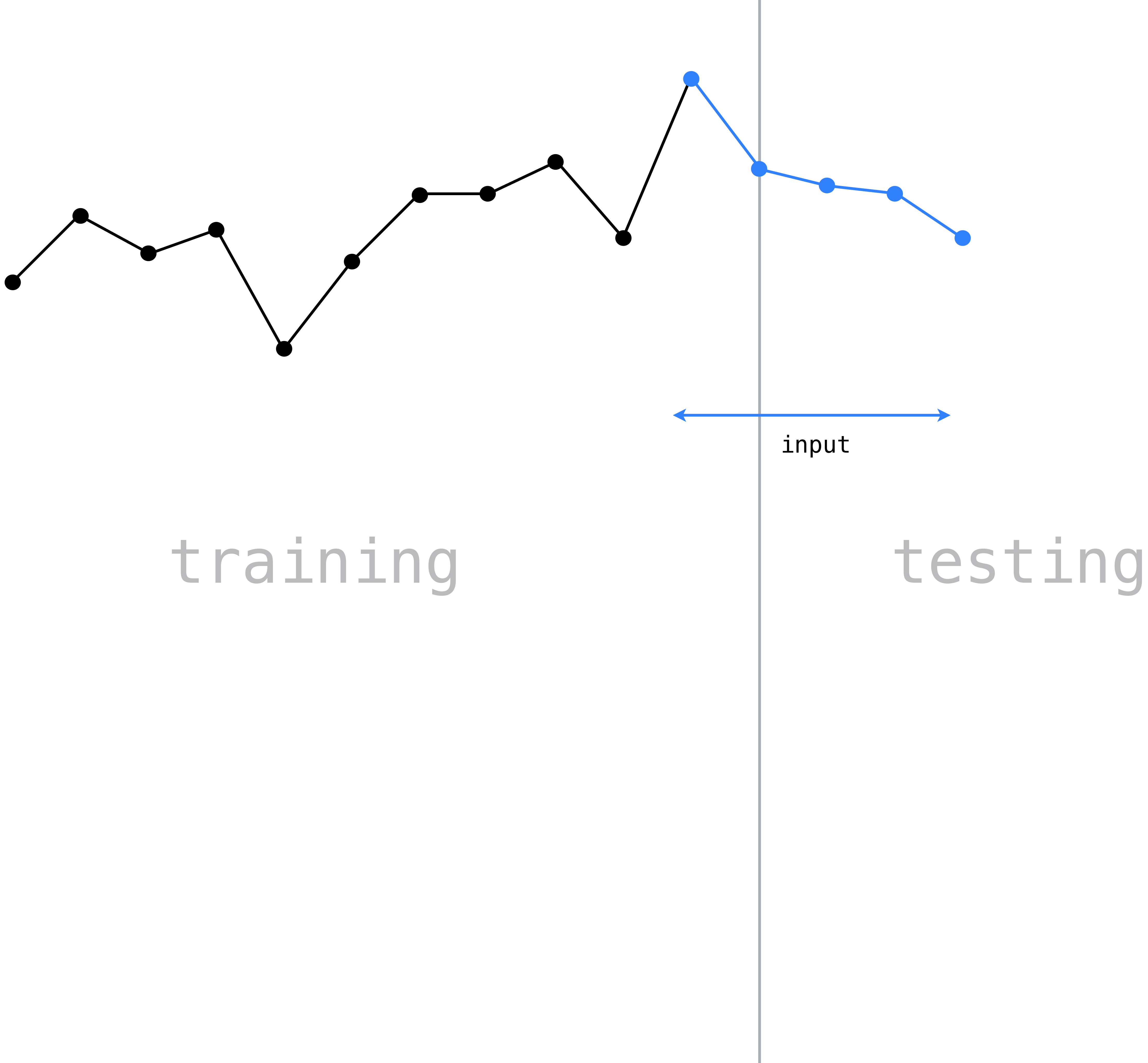
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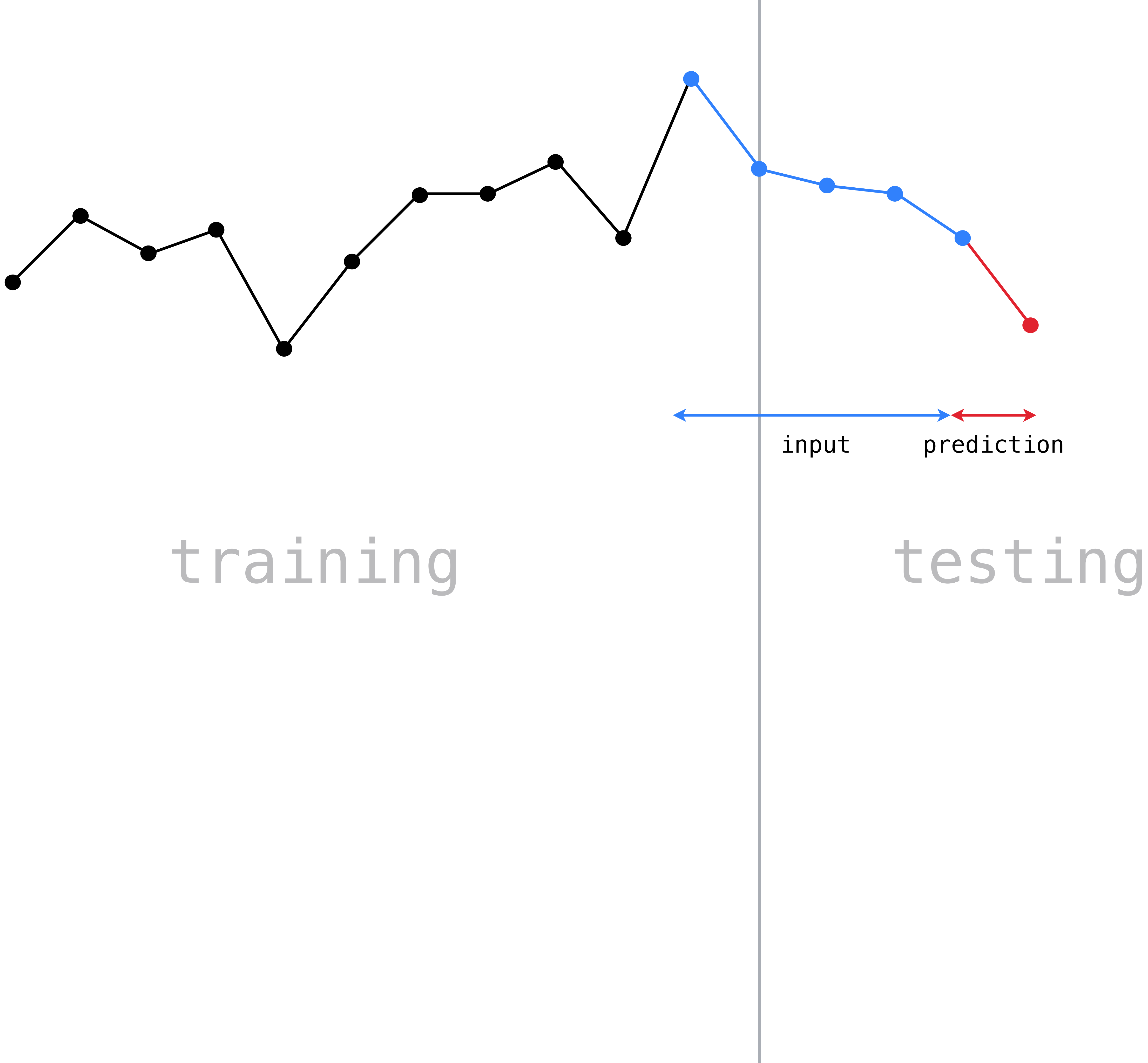
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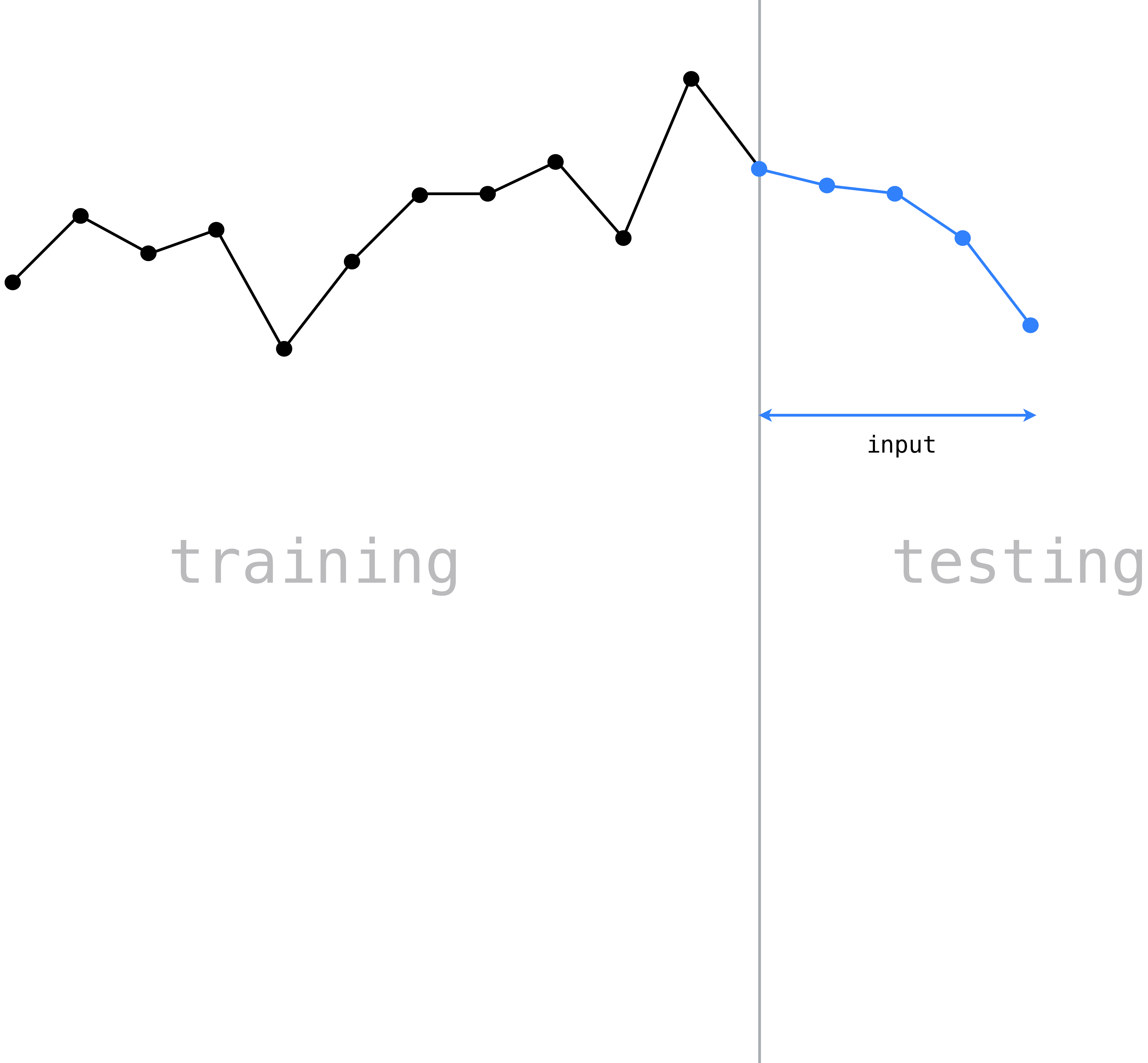
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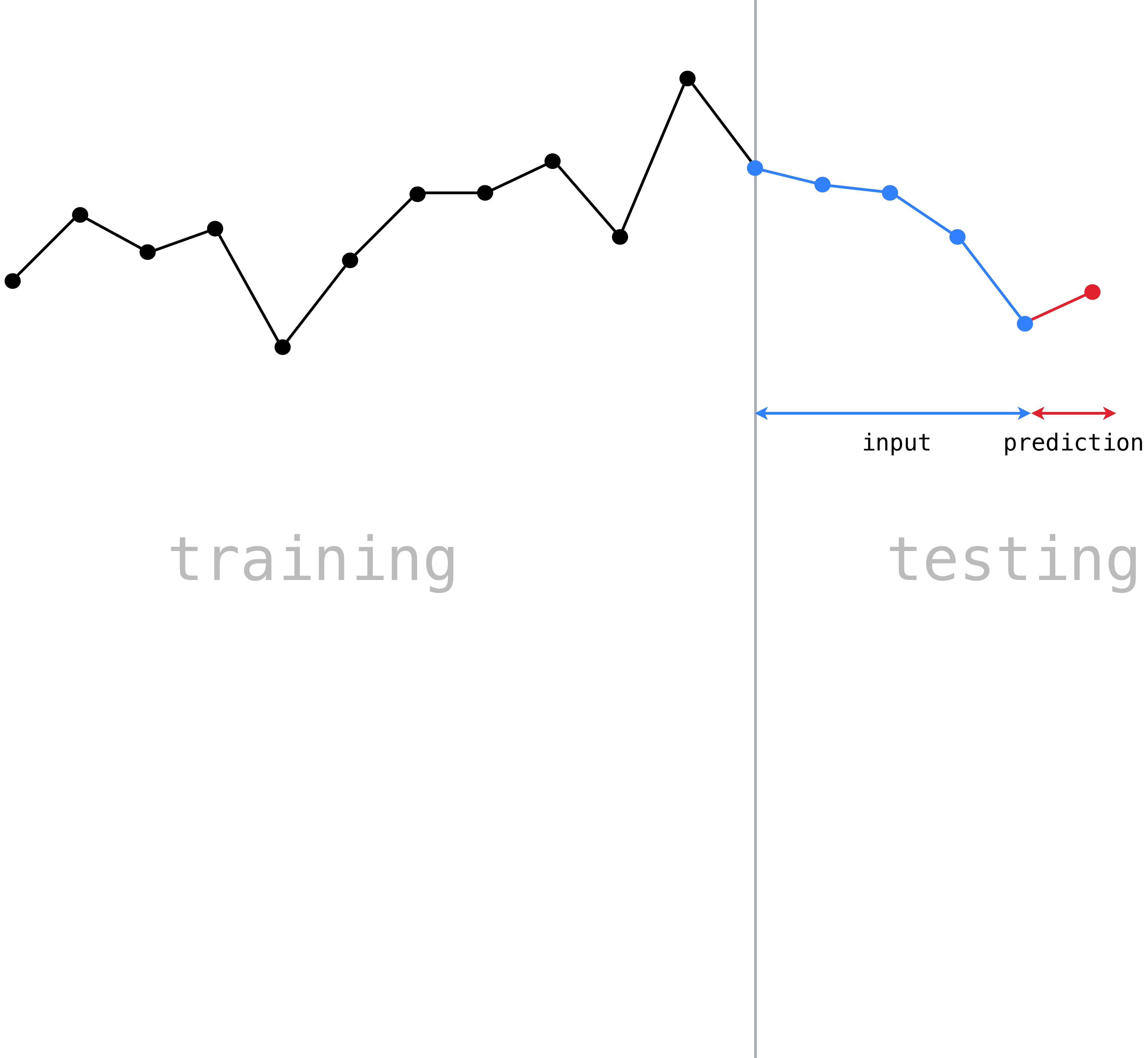
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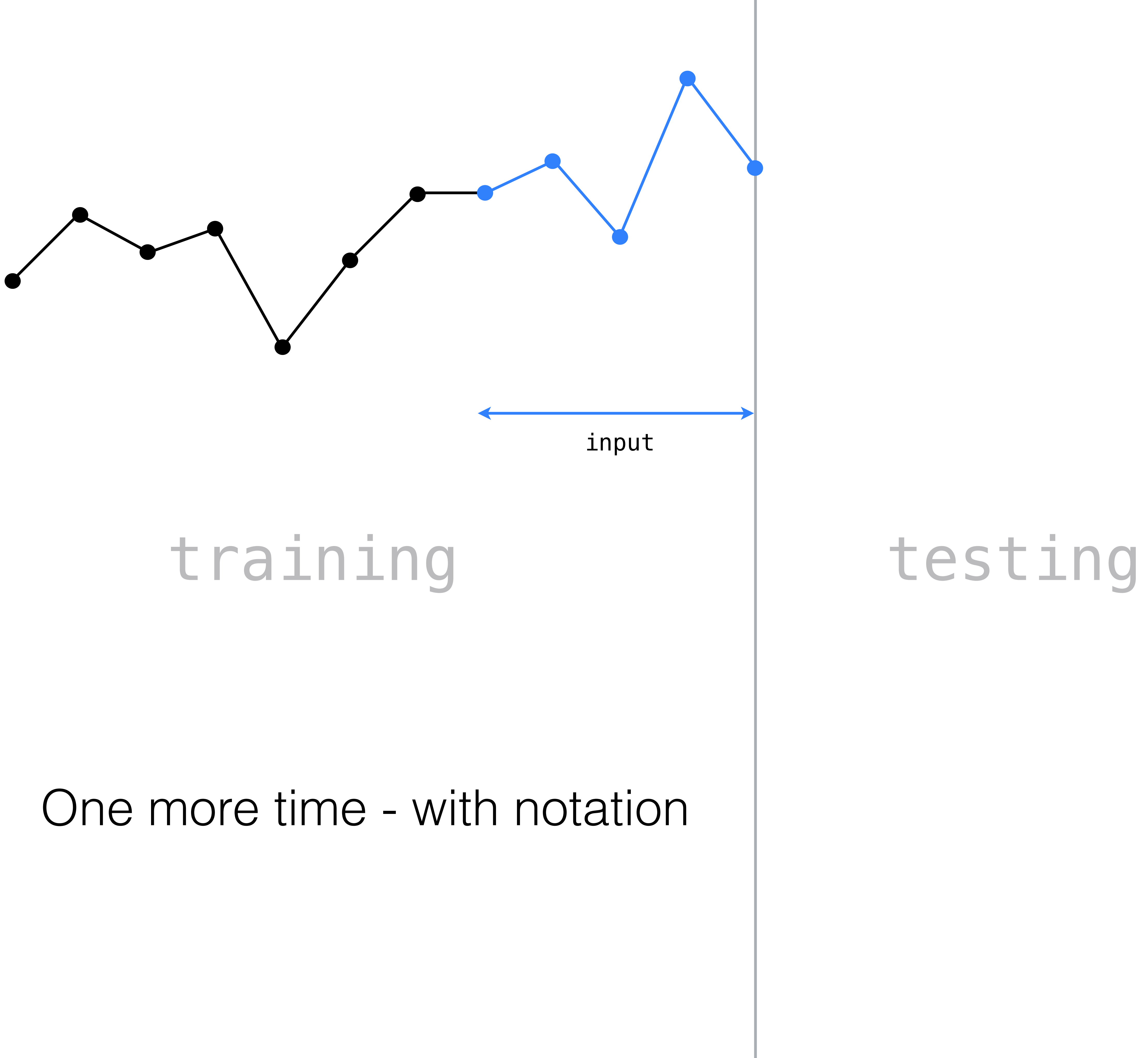

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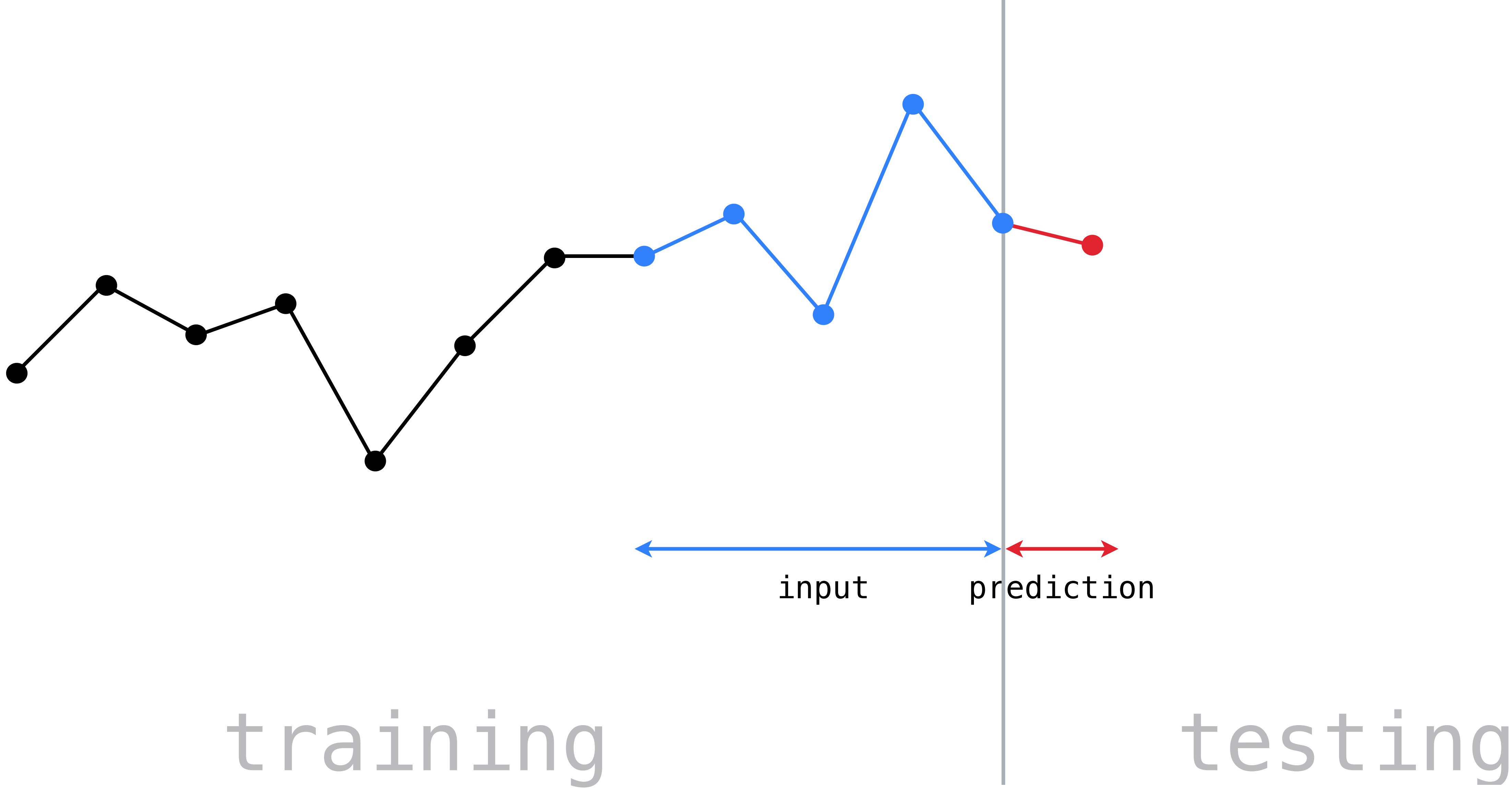
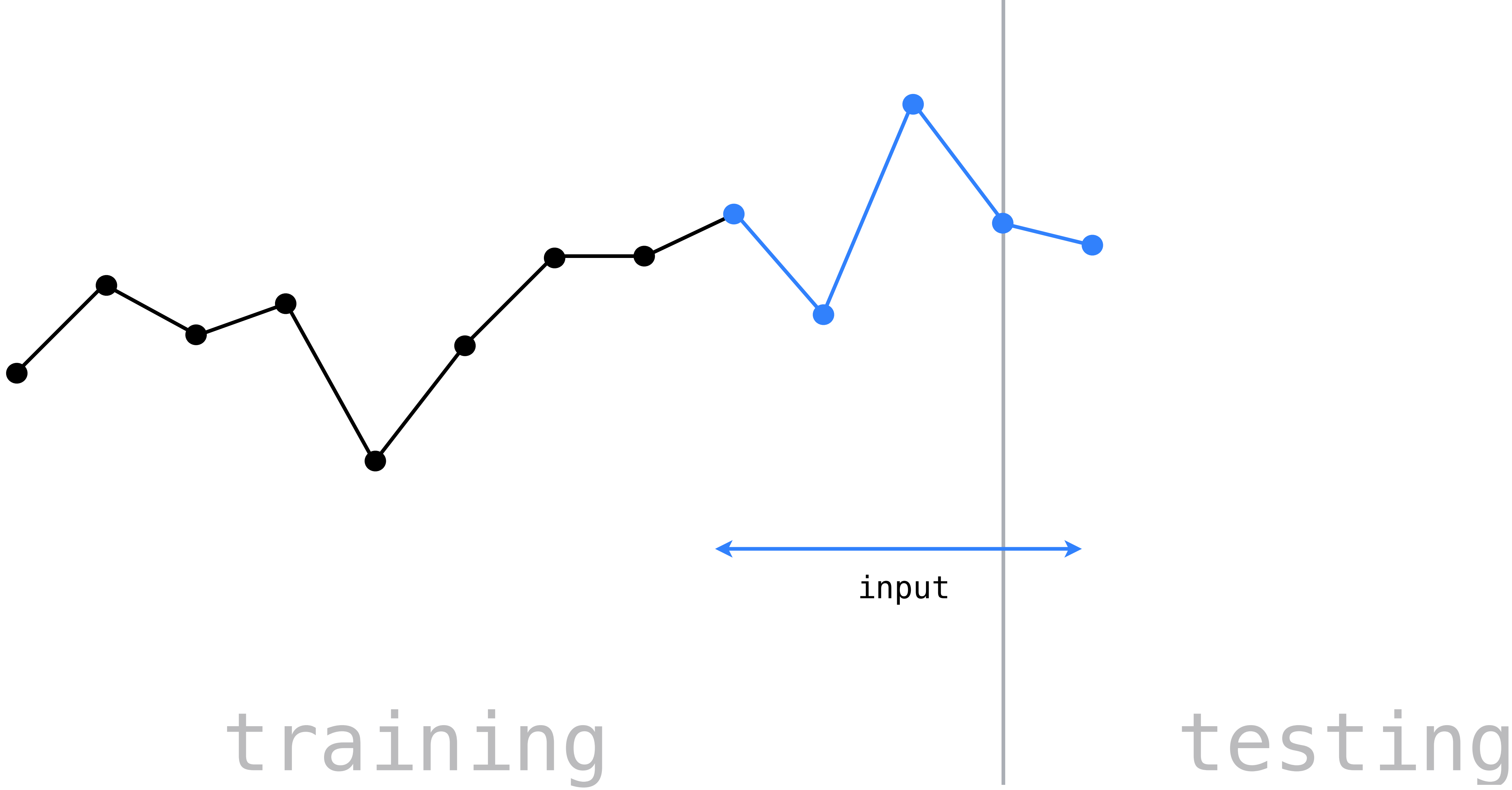


Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$



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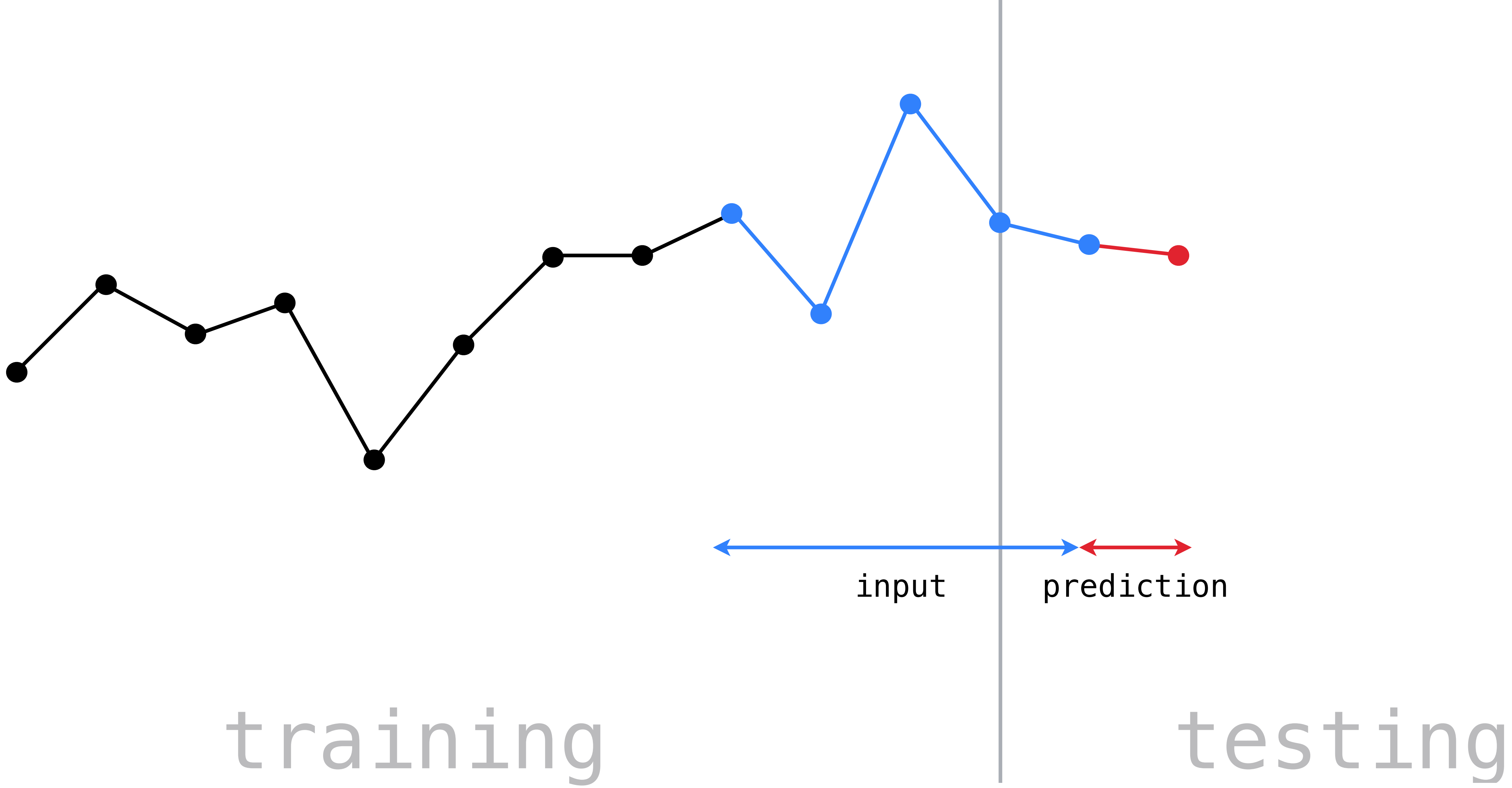
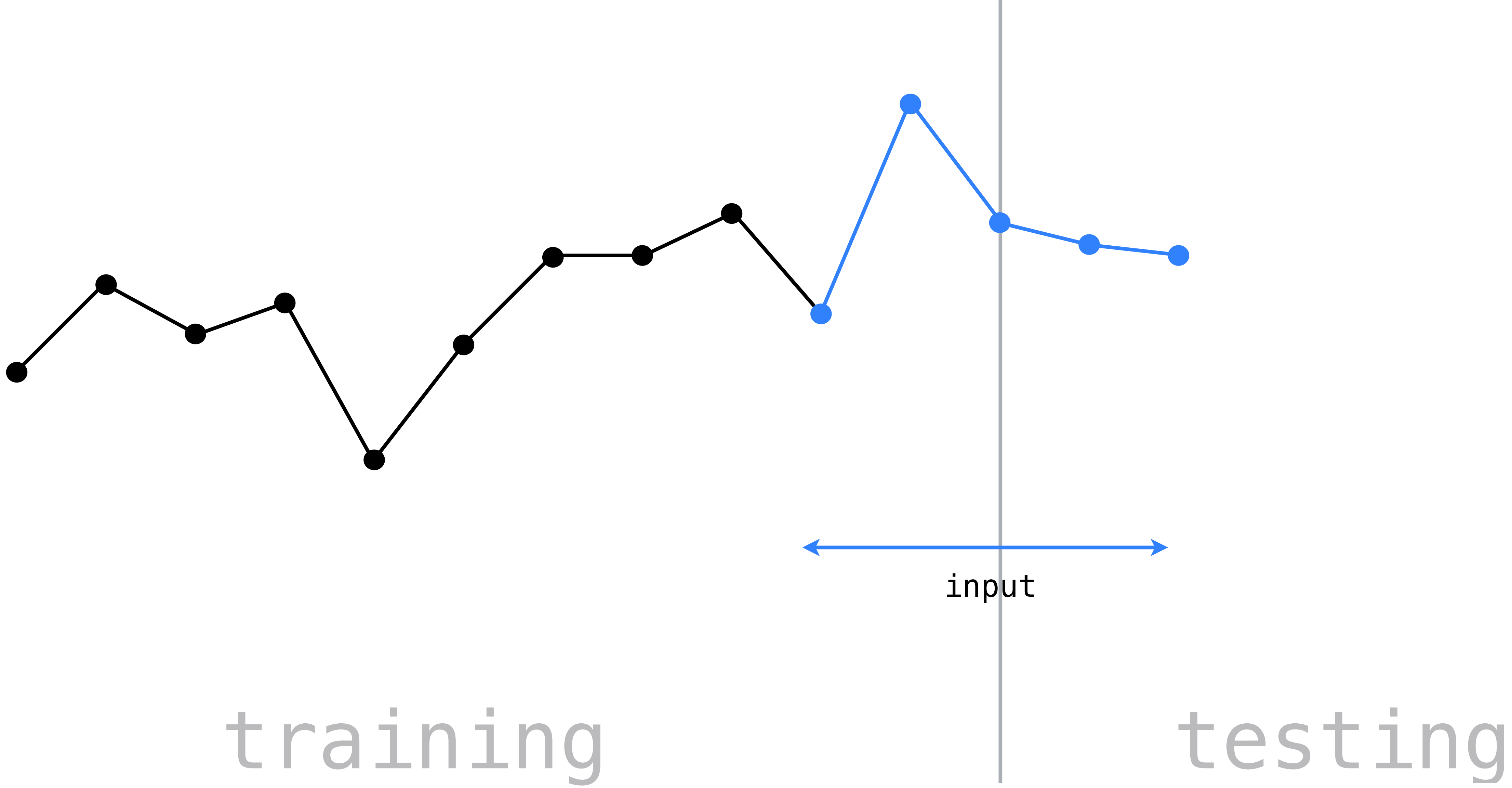
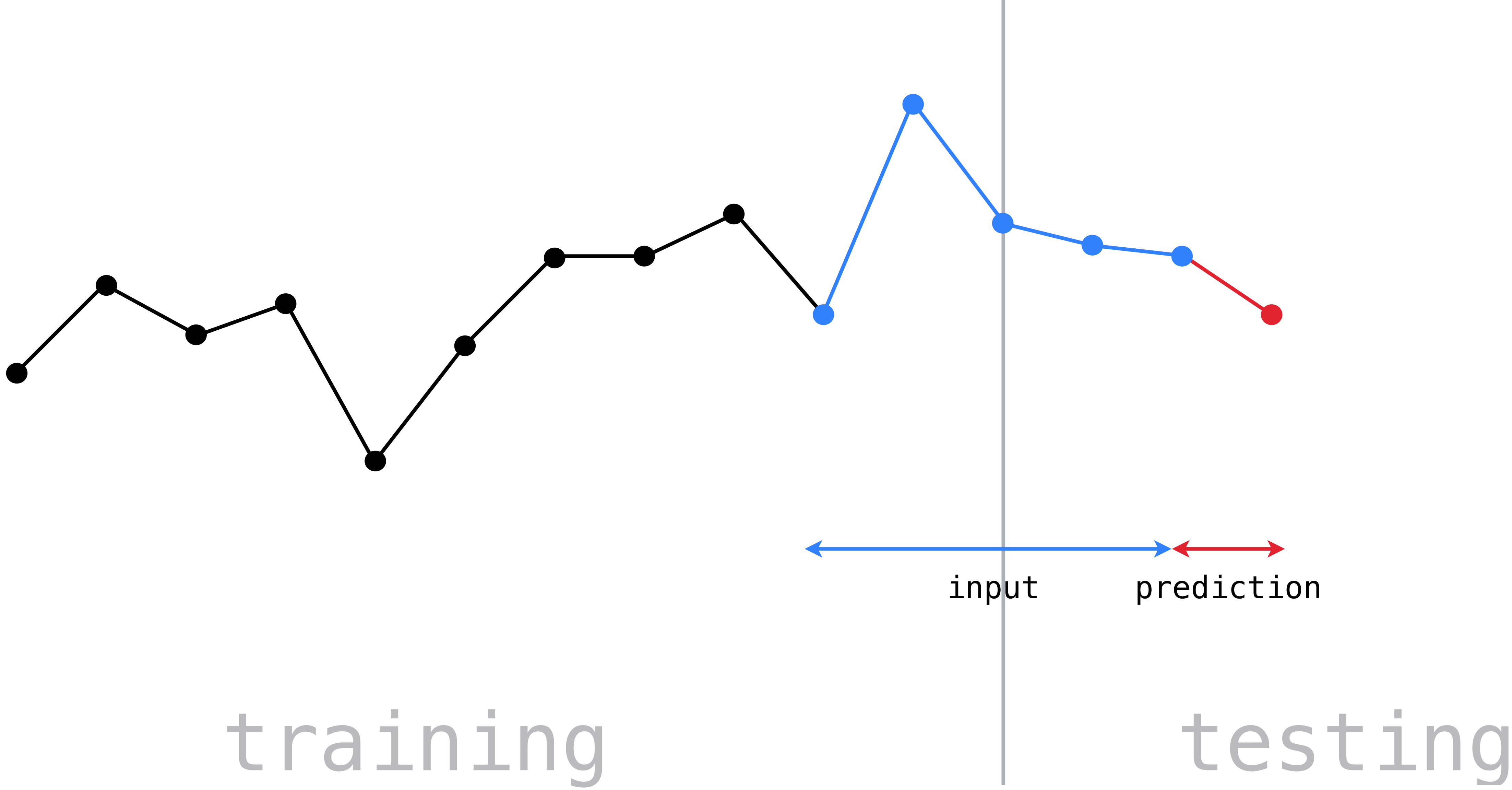


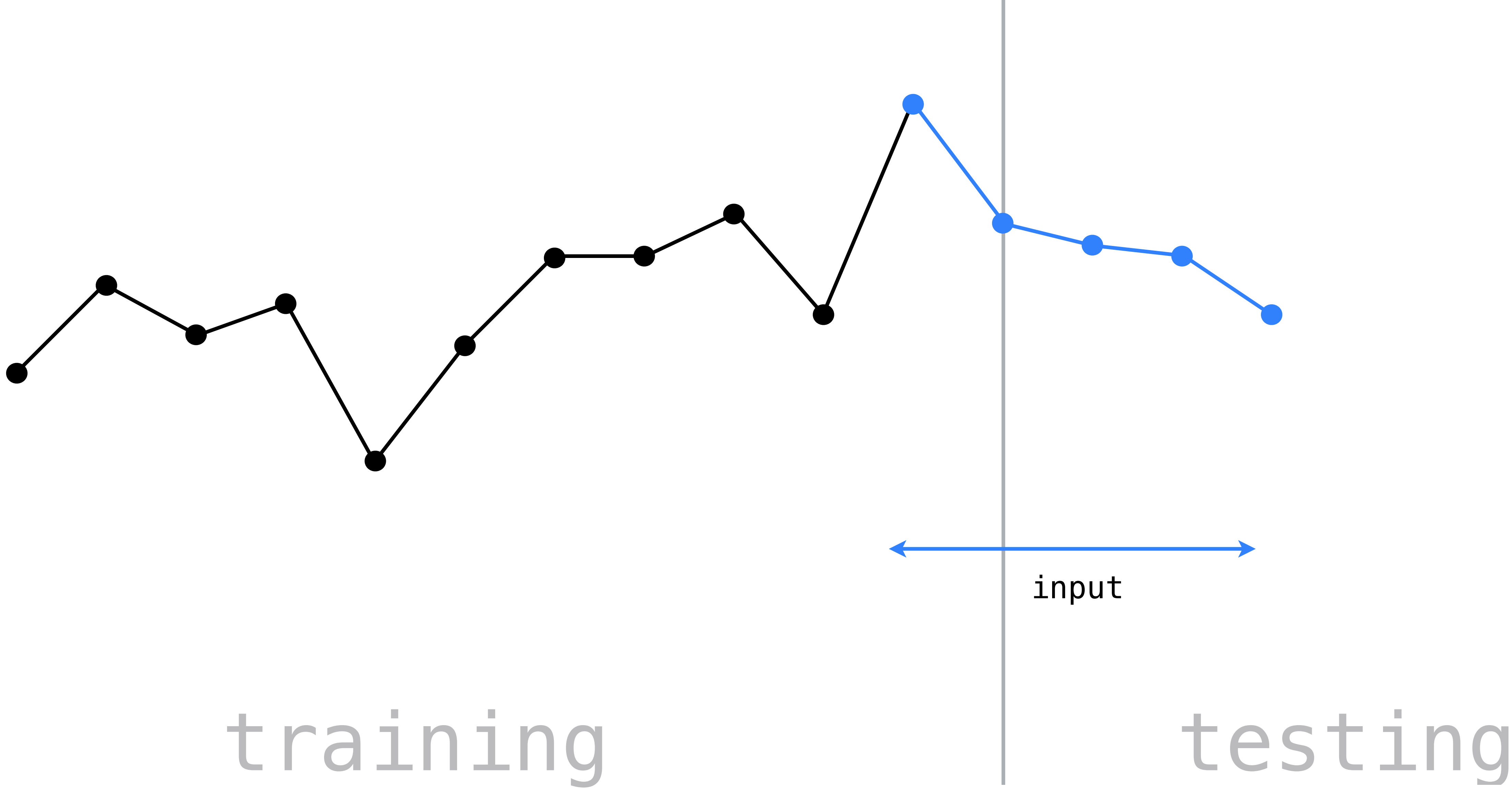
Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$



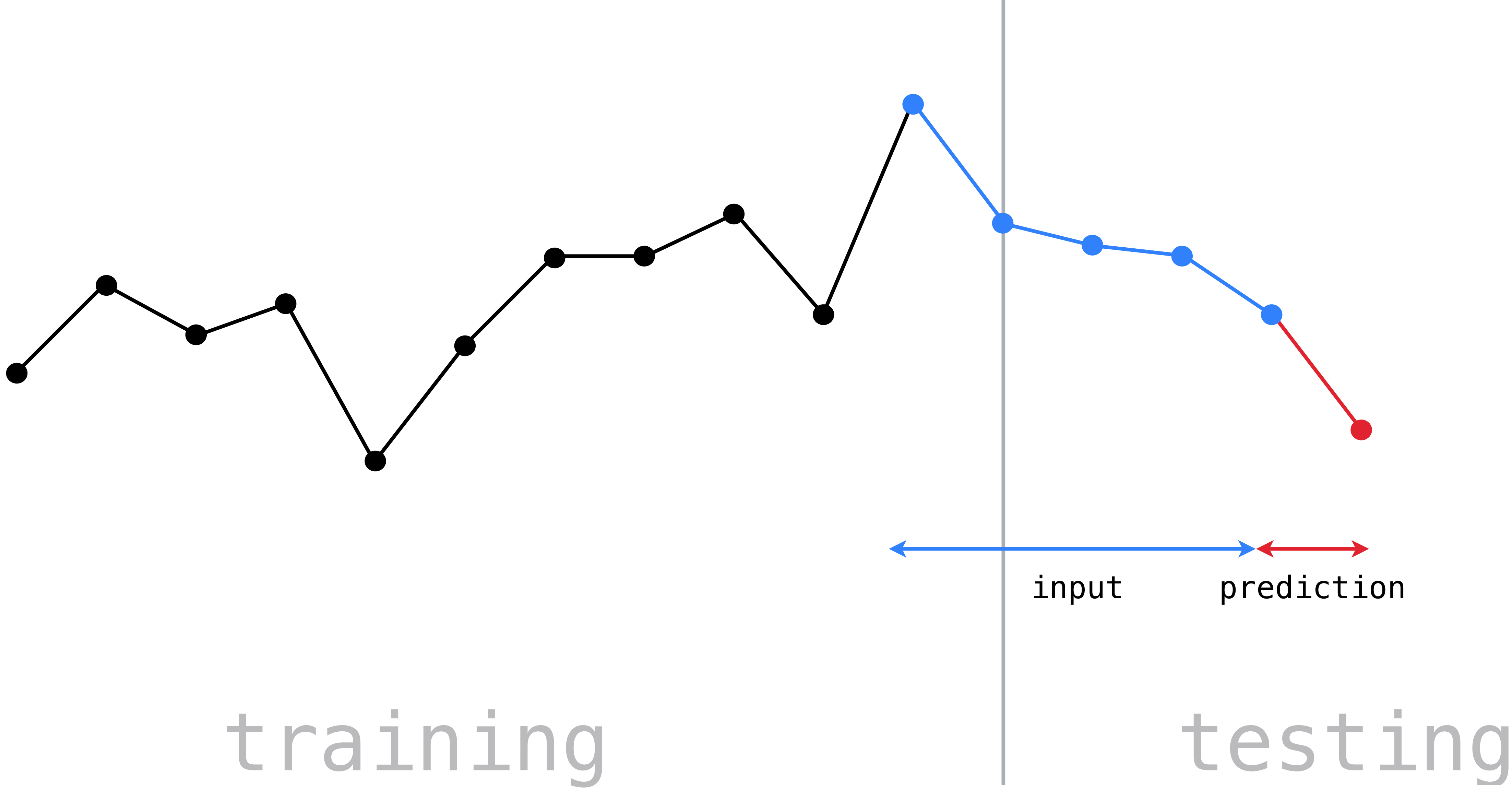
Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$



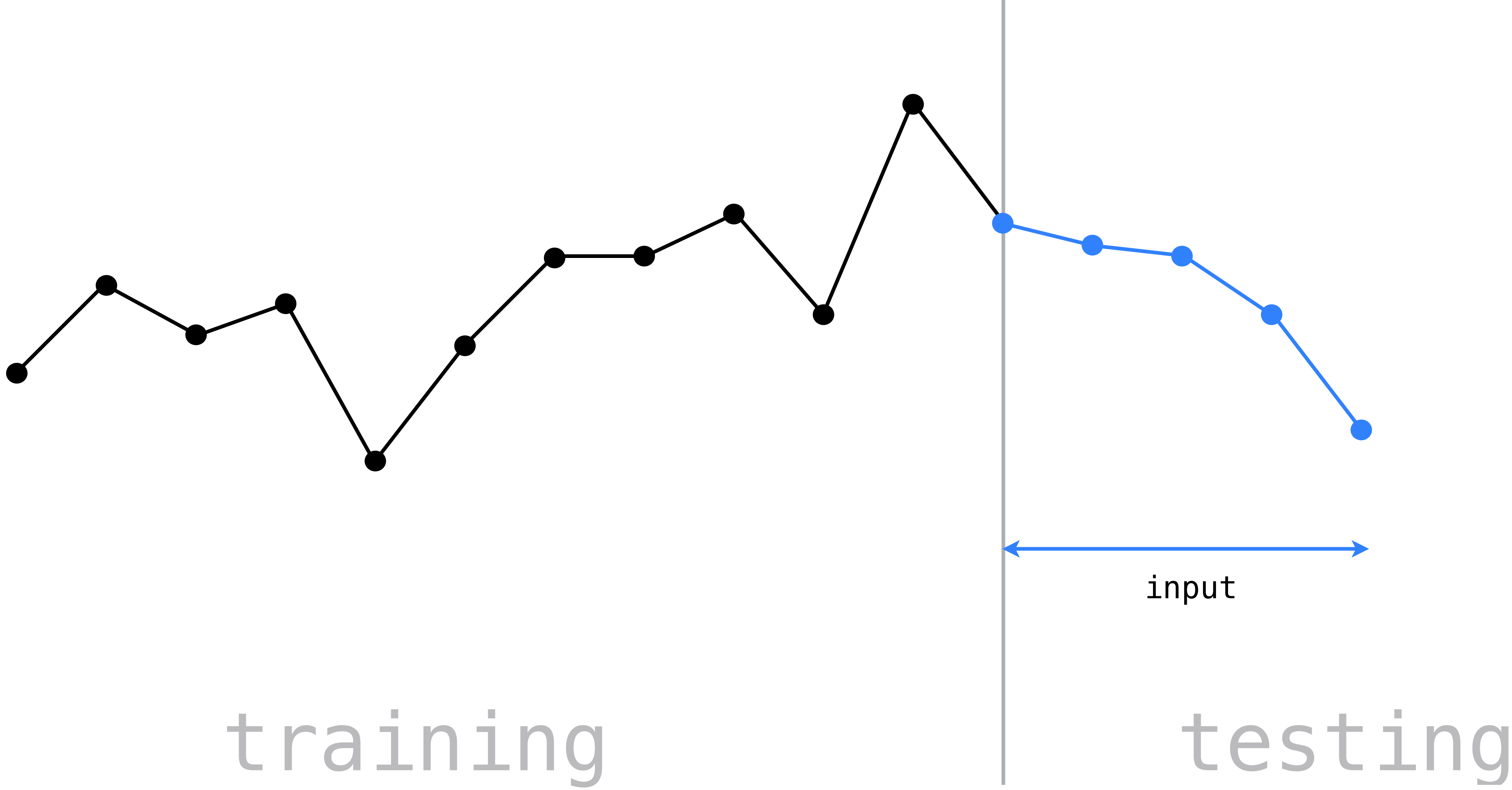
Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$



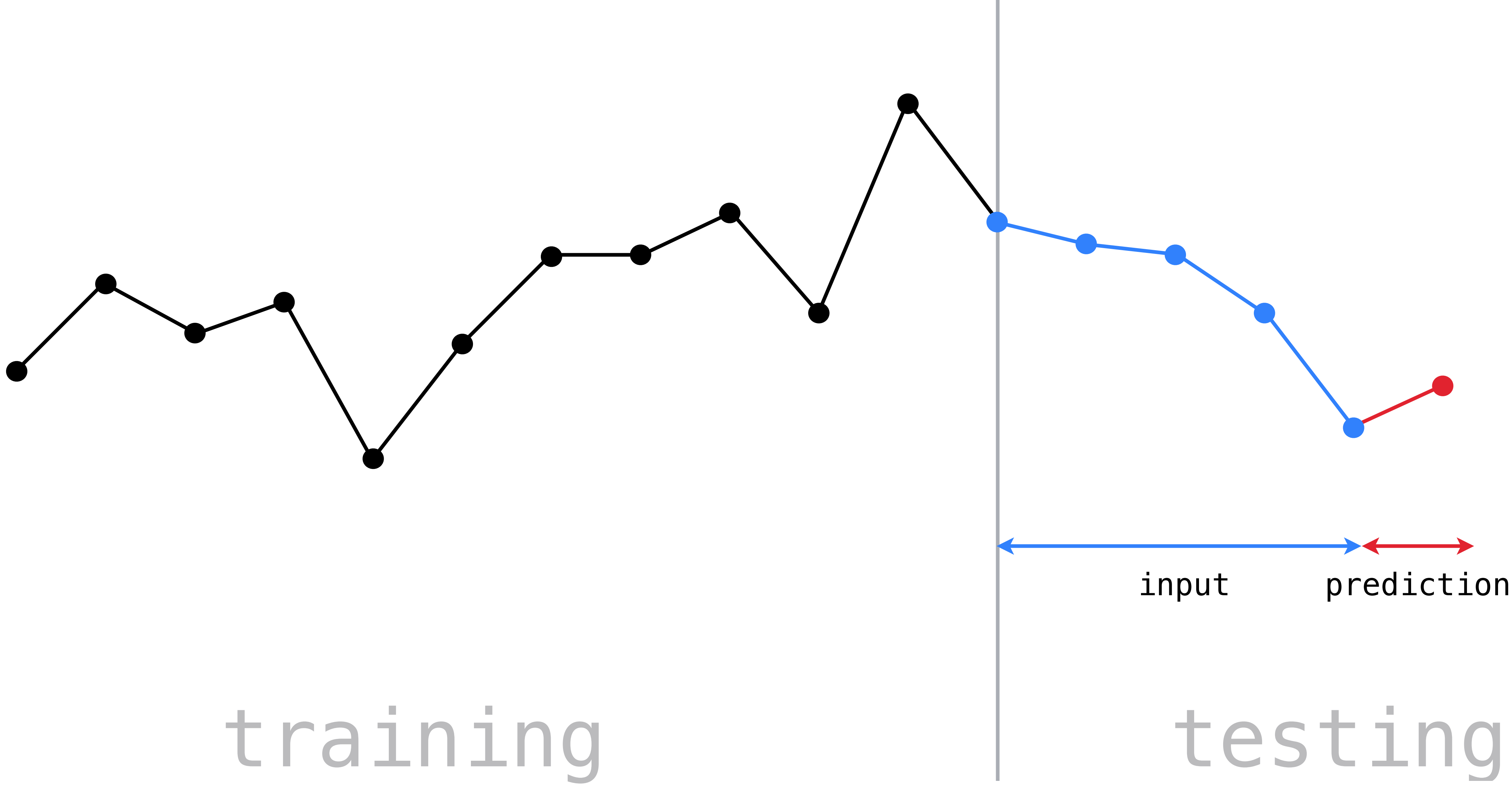
Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$



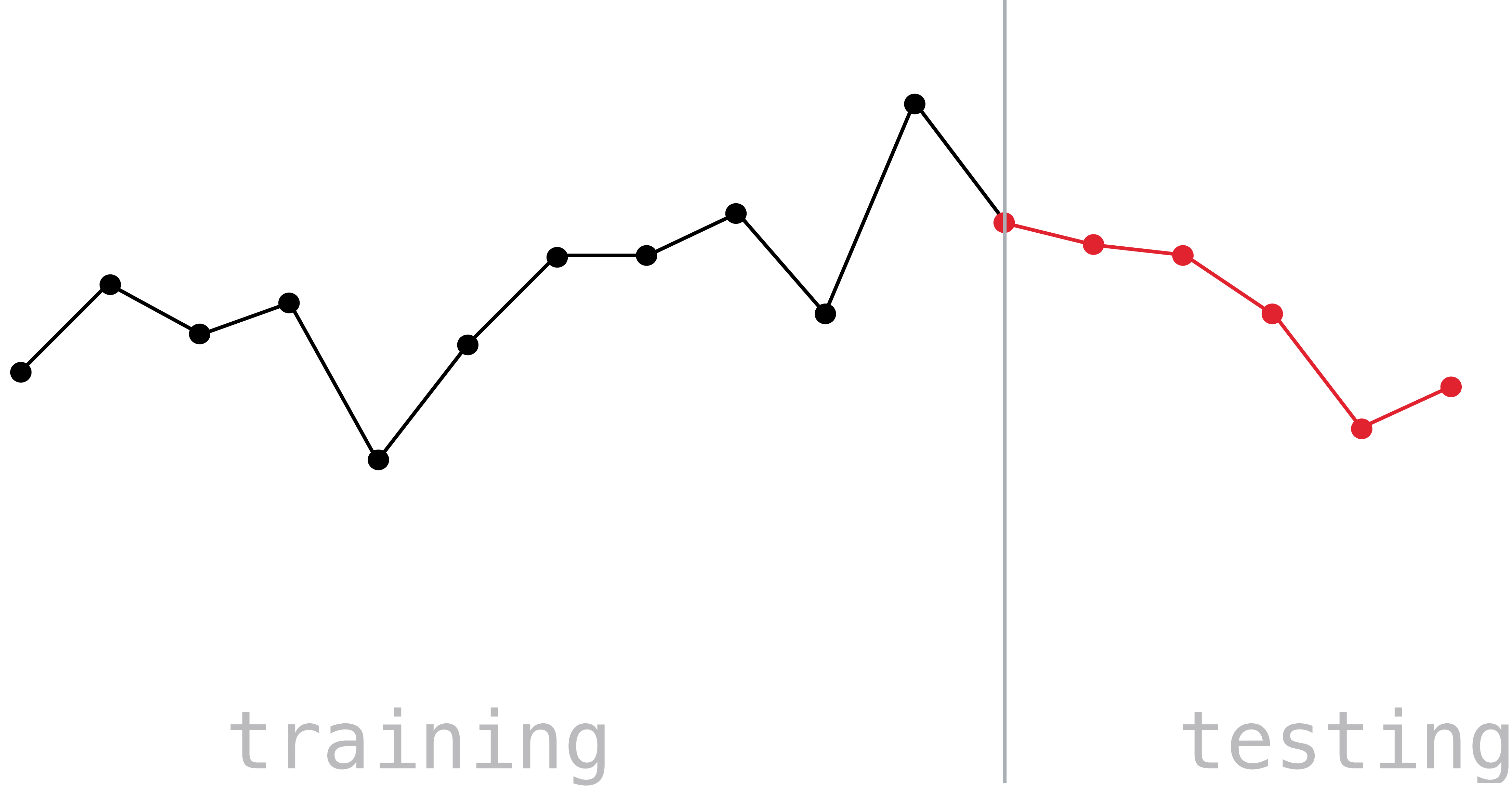
Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$
$\langle s_P, \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3} \rangle$	$\hat{s}_{P+4}$



Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$
$\langle s_P, \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3} \rangle$	$\hat{s}_{P+4}$



Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$
$\langle s_P, \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3} \rangle$	$\hat{s}_{P+4}$
$\langle \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3}, \hat{s}_{P+4} \rangle$	$\hat{s}_{P+5}$



Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$
$\langle s_P, \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3} \rangle$	$\hat{s}_{P+4}$
$\langle \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3}, \hat{s}_{P+4} \rangle$	$\hat{s}_{P+5}$
$\vdots$	$\vdots$

here we illustratred with
window size T = 4

Ingesting sequential I/O data

Text generation

- Sequence of P characters: $\langle s_0, s_1, s_2, \ldots, s_P \rangle$
- s_p: the pth character

Text generation

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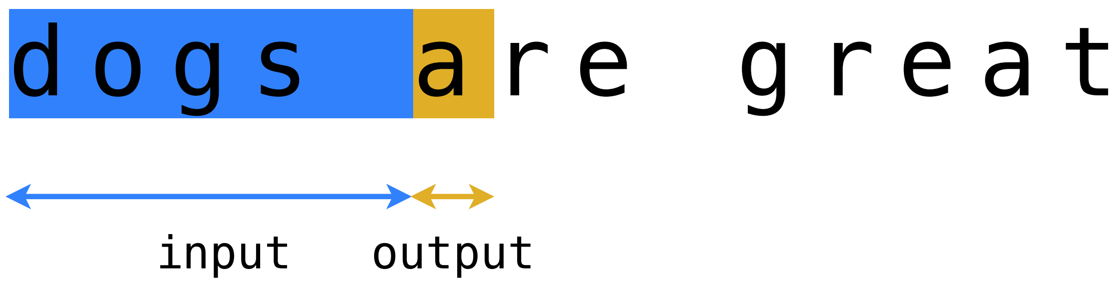
- - **classification problem**- I/O are windowed subsequences

Text generation

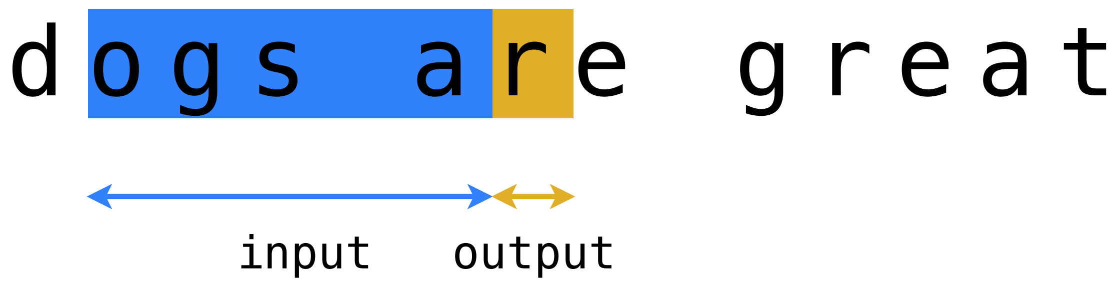
- Sequence of P characters: $\langle s_0, s_1, s_2, \ldots, s_P \rangle$
- s_p: the pth character
- **classification problem**- I/O are windowed subsequences

  - so need training and testing sets

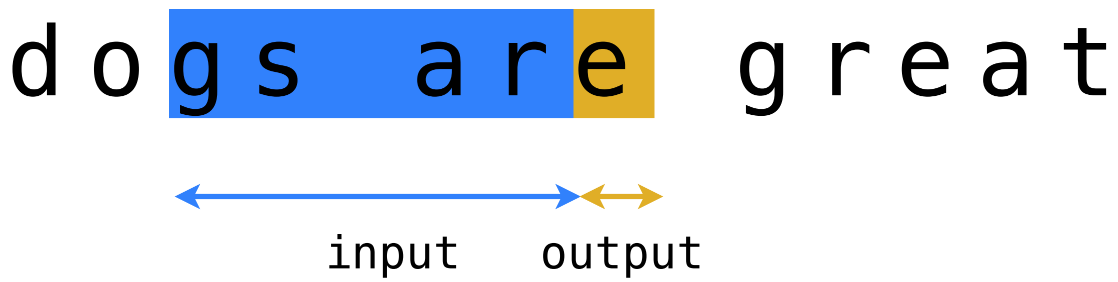
  - lets see how both are formed, start with training dogs are great

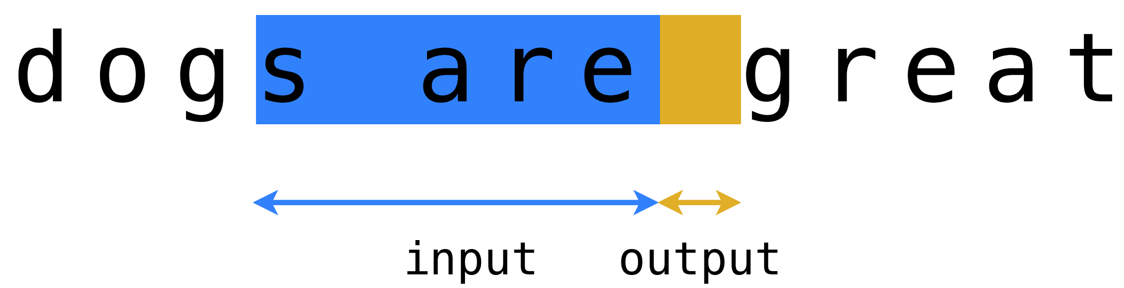


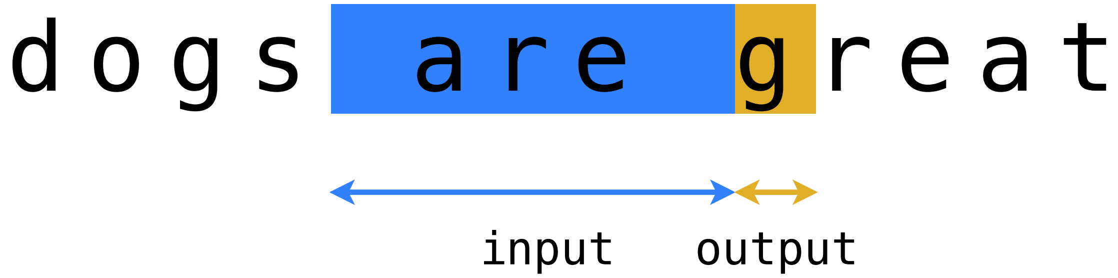
dogs are great
input
output



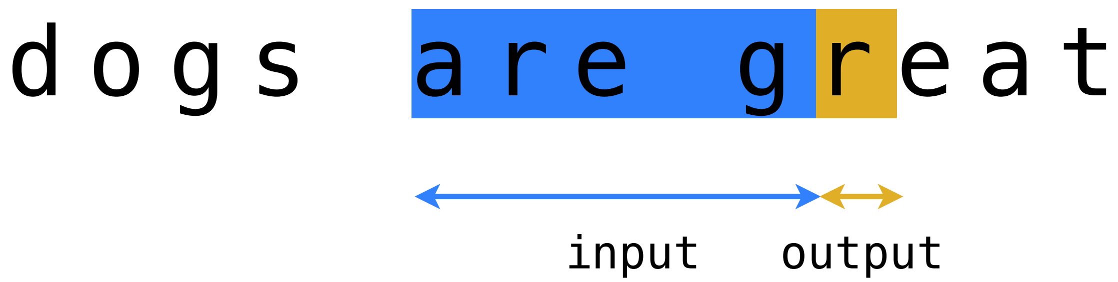
d o g s   a r e   g r e a t
input
output

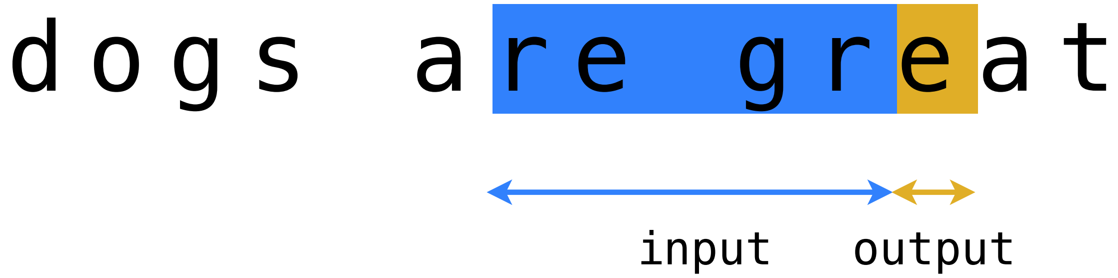

d o g s a r e g r e a t
input
output

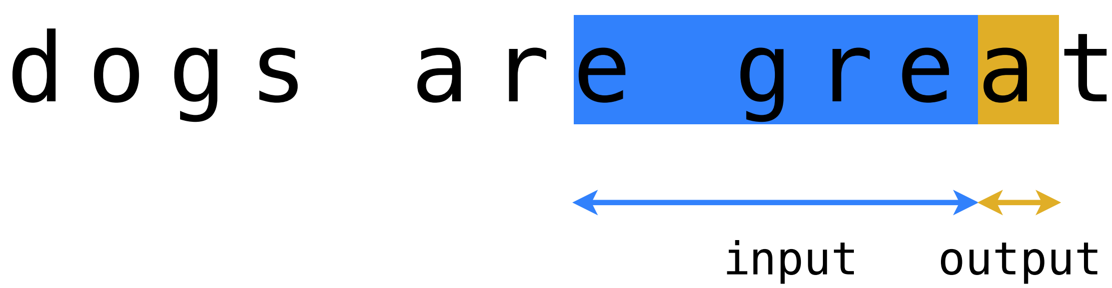

dogs are great
input
output

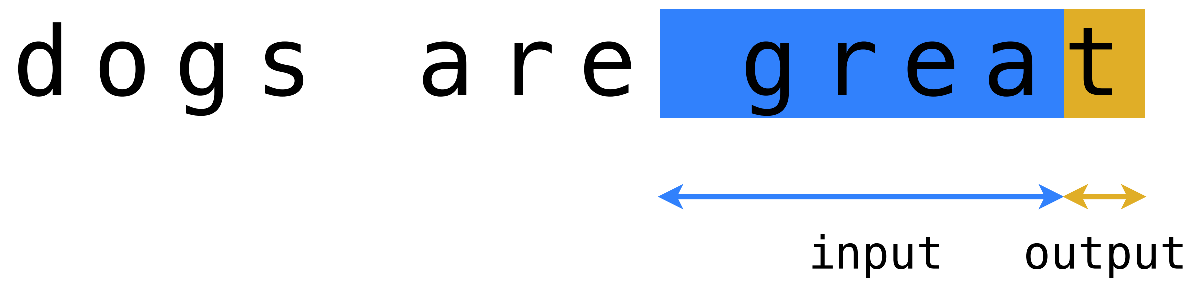


d o g s   a r e   g r e a t
input
output

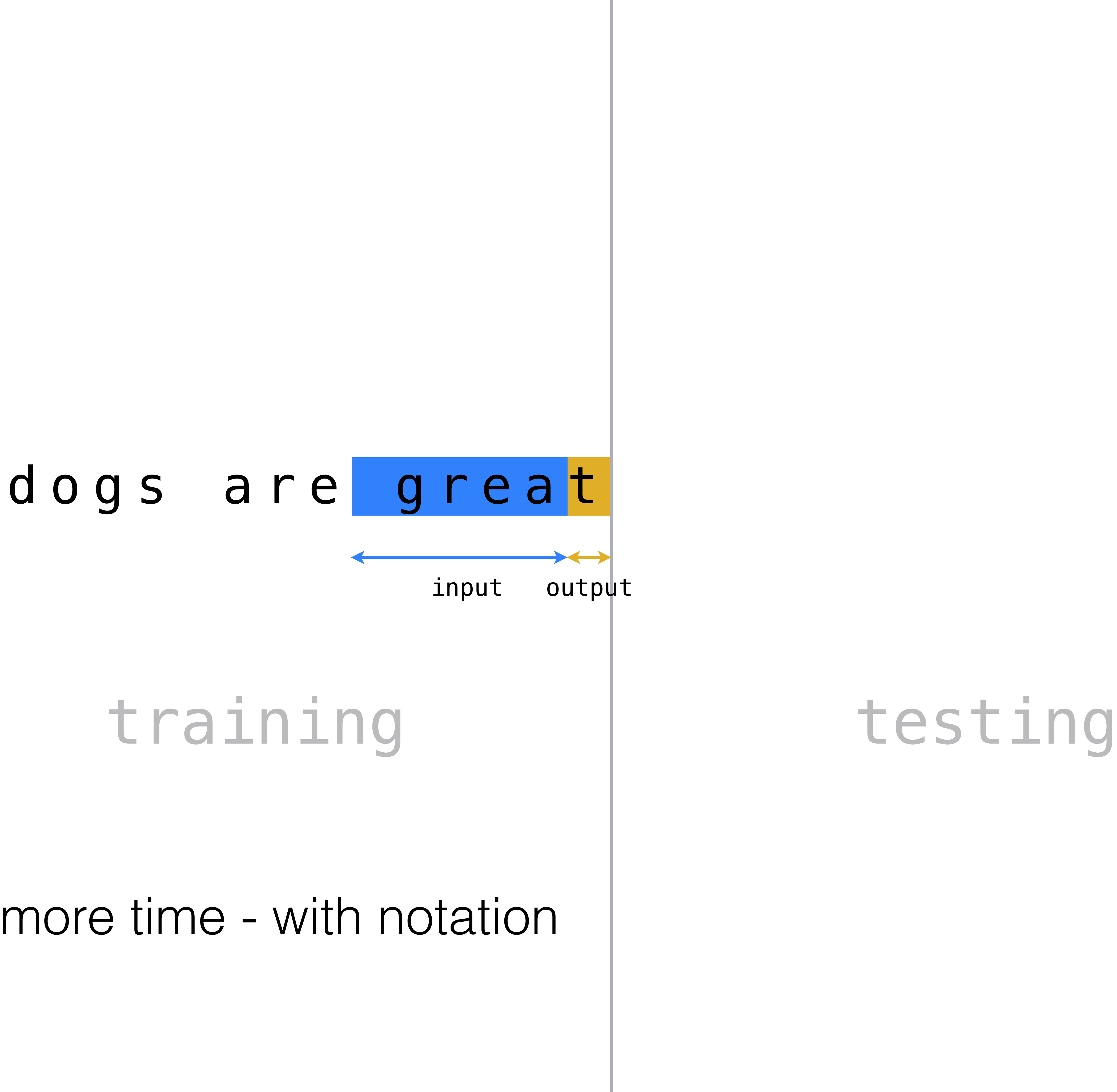

d o g s a r e g r e a t
input
output


dogs are great
input
output

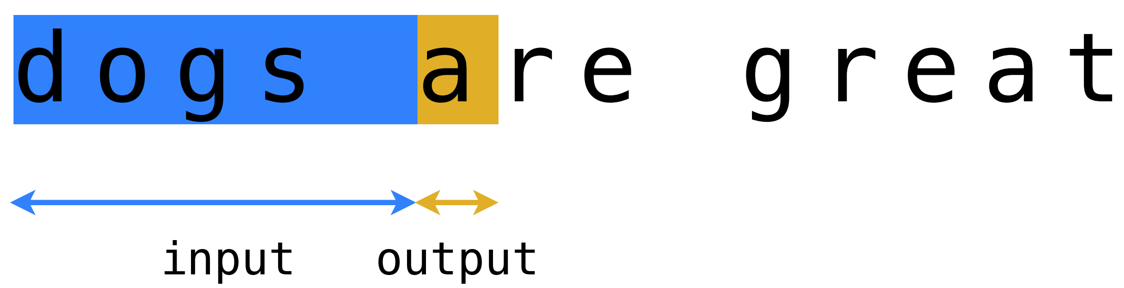

dogs are great
input
output



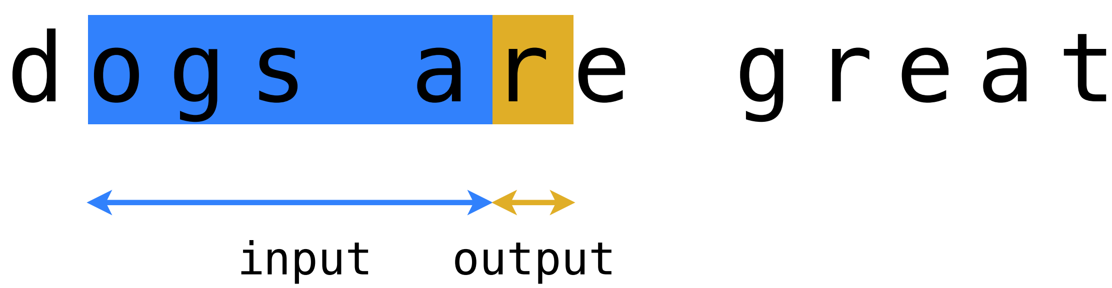
d o g s a r e g r e a t
input
output



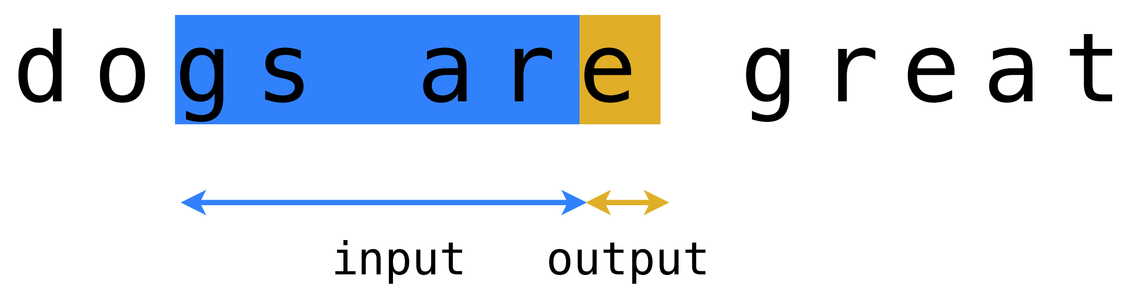
One more time - with notation



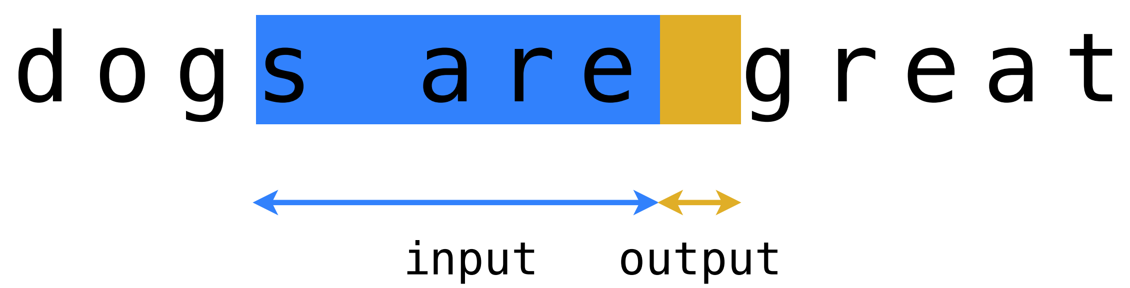
Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4



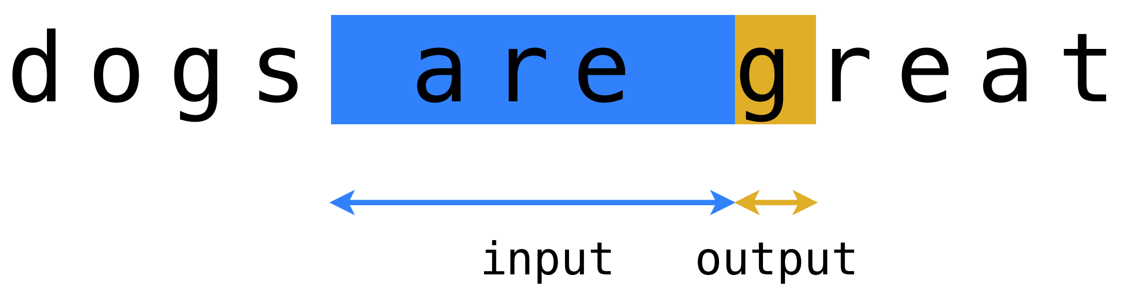
Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5



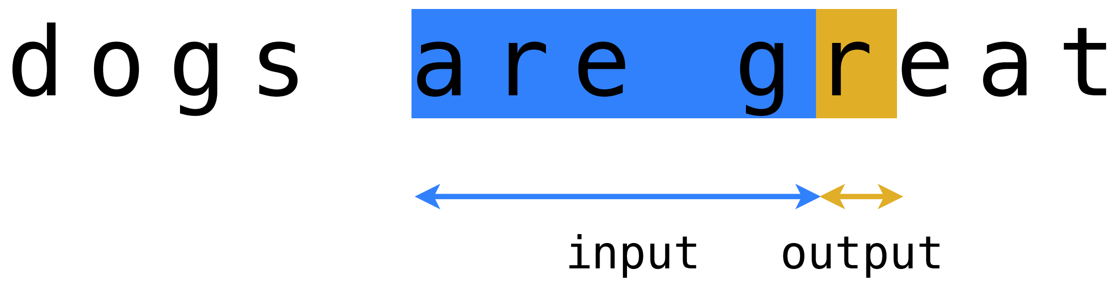
Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5
$\vdots$	$\vdots$



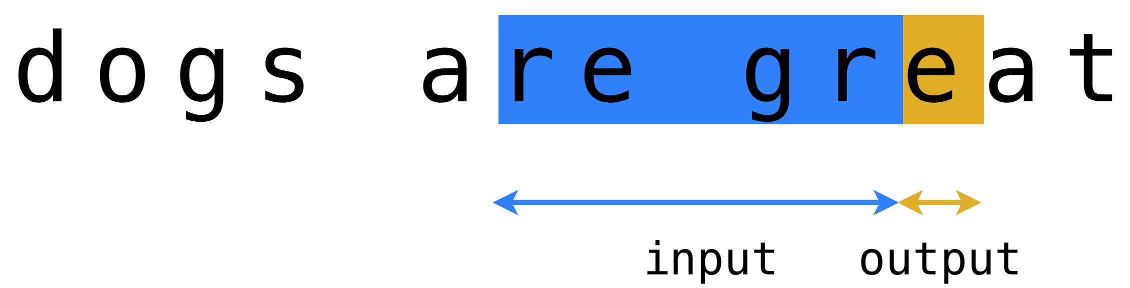
Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5
$\vdots$	$\vdots$



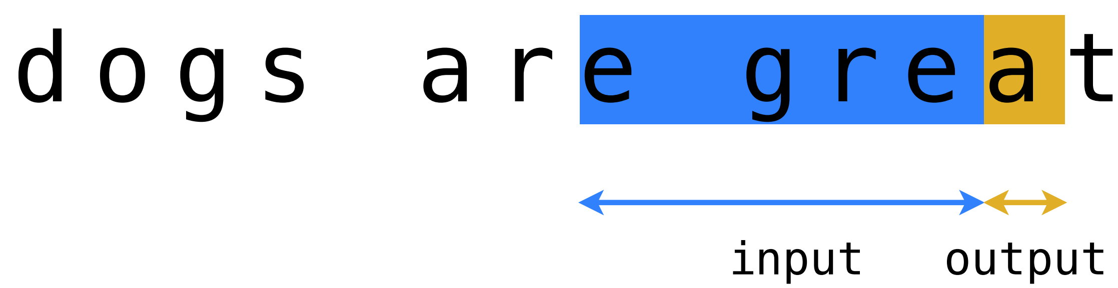
Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5
$\vdots$	$\vdots$



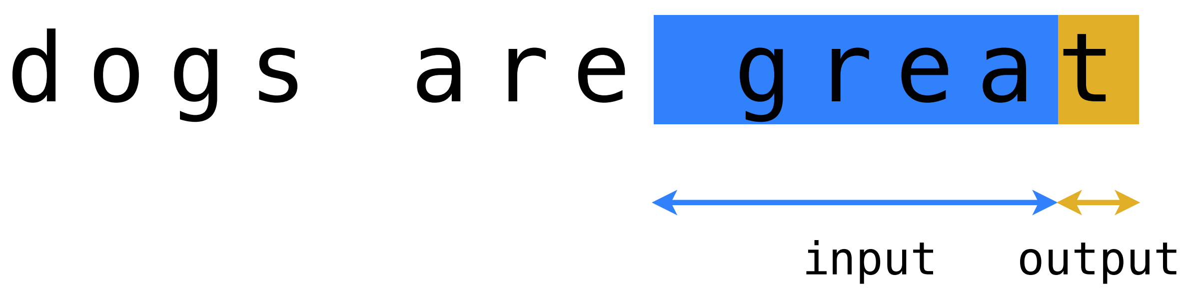
Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5
$\vdots$	$\vdots$



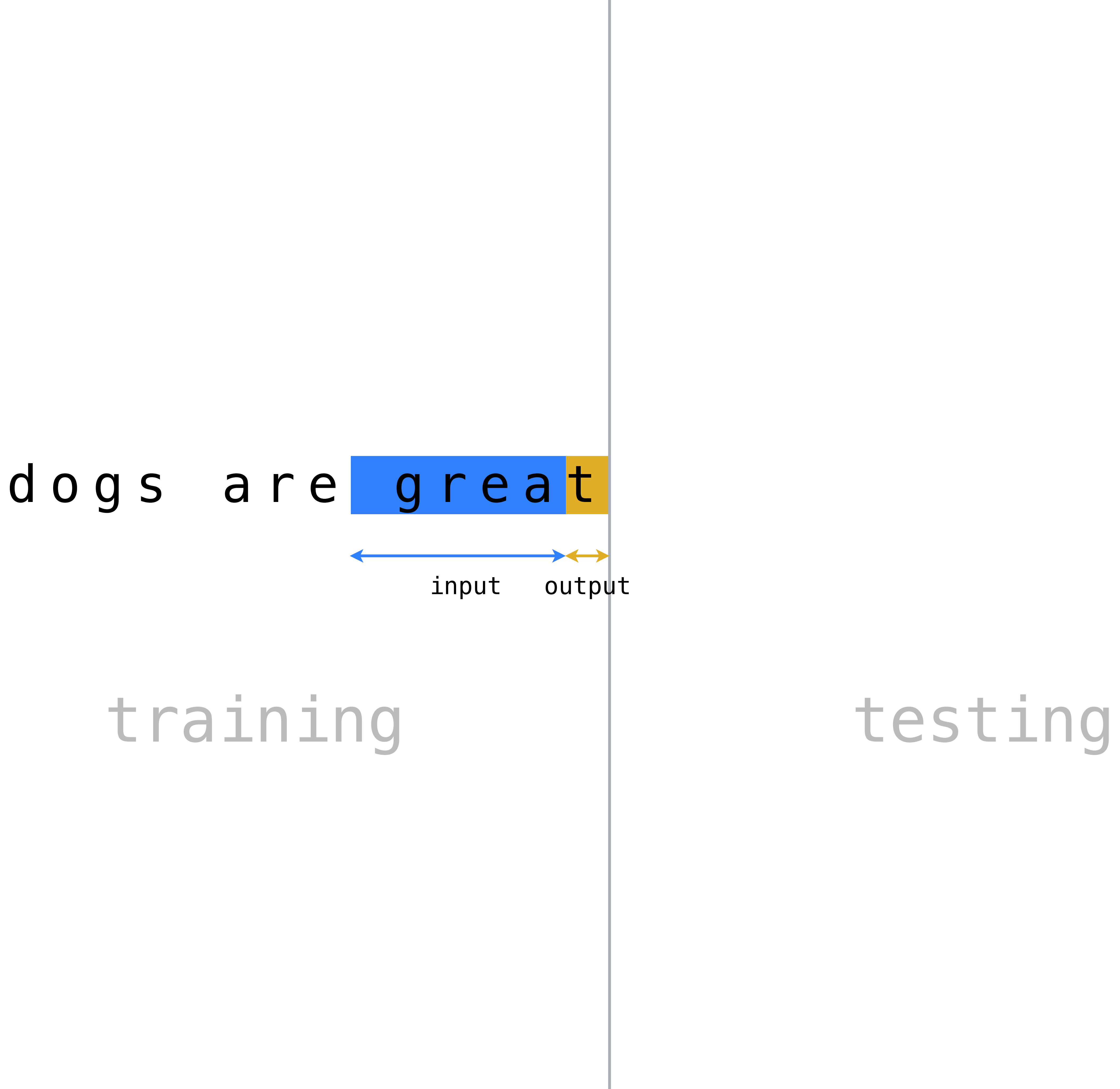
Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5
$\vdots$	$\vdots$



Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5
$\vdots$	$\vdots$



Input	Output
$\langle s_0, s_1, s_2, s_3 \rangle$	s_4
$\langle s_1, s_2, s_3, s_4 \rangle$	s_5
$\vdots$	$\vdots$
$\langle s_{P-4}, s_{P-3}, s_{P-2}, s_{P-1} \rangle$	s_P



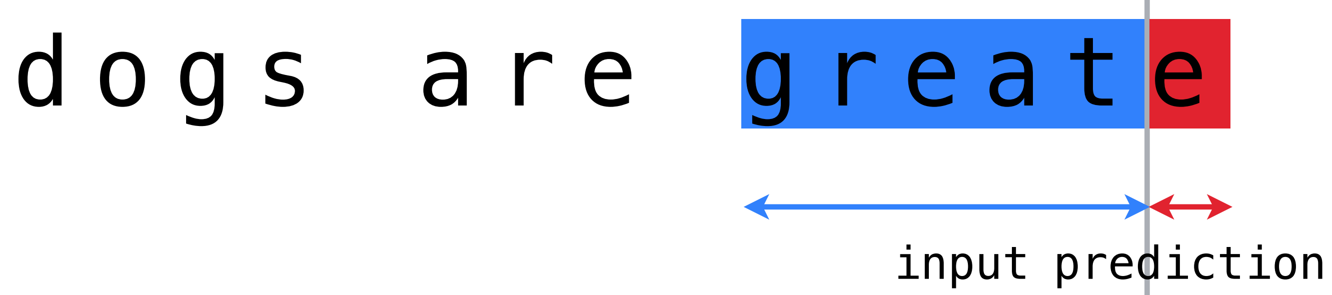
dogs are great
input
output
training
testing

d o g s   a r e   g r e a t

input

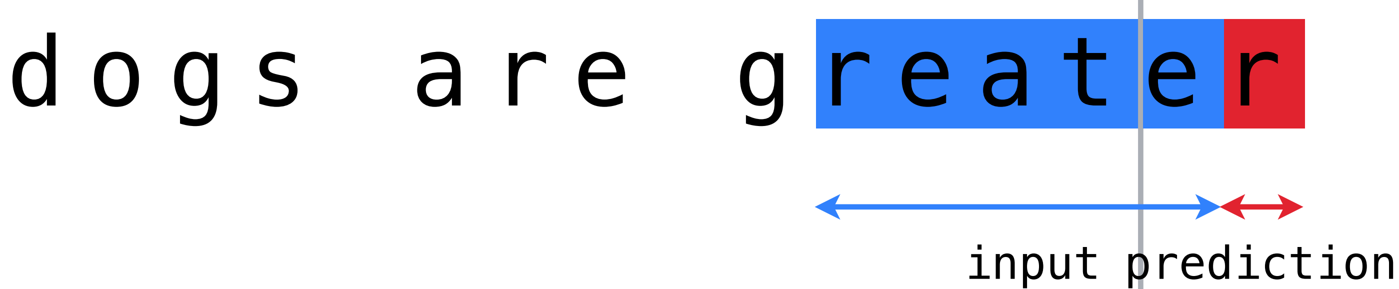
training

testing

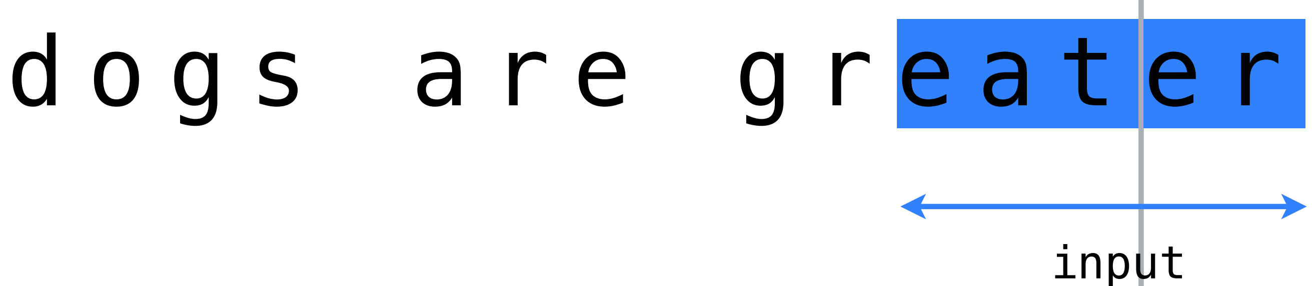


Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$

Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$

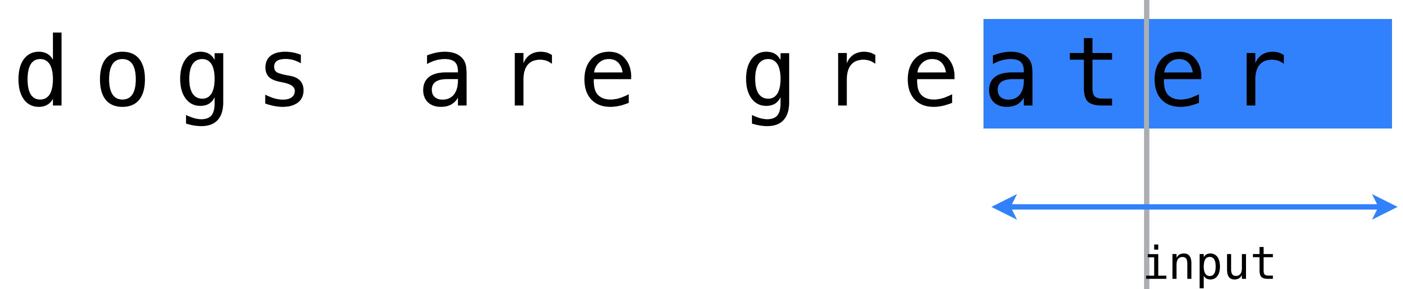


Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$



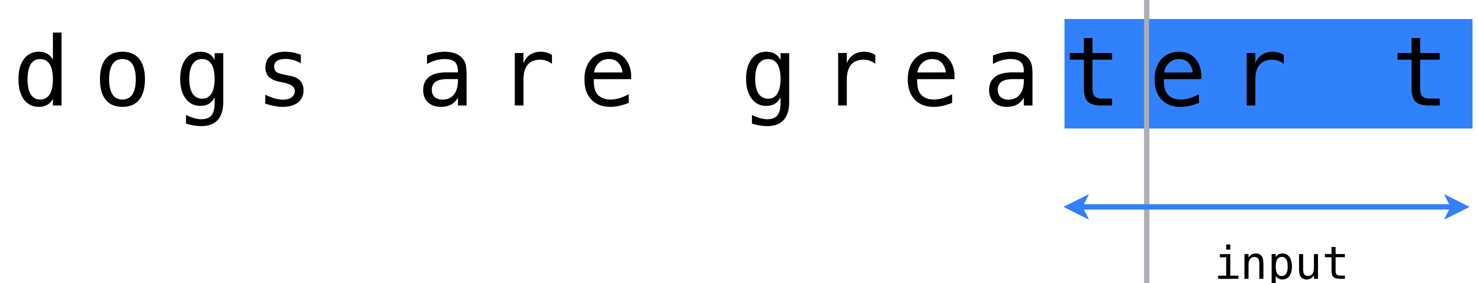
Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$

Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$



Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$

Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$
$\langle s_P, \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3} \rangle$	$\hat{s}_{P+4}$



Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$
$\langle s_P, \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3} \rangle$	$\hat{s}_{P+4}$

Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$
$\langle s_P, \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3} \rangle$	$\hat{s}_{P+4}$
$\langle \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3}, \hat{s}_{P+4} \rangle$	$\hat{s}_{P+5}$

Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$
$\langle s_P, \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3} \rangle$	$\hat{s}_{P+4}$
$\langle \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3}, \hat{s}_{P+4} \rangle$	$\hat{s}_{P+5}$

Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$
$\langle s_P, \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3} \rangle$	$\hat{s}_{P+4}$
$\langle \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3}, \hat{s}_{P+4} \rangle$	$\hat{s}_{P+5}$
$\vdots$	$\vdots$

here we illustratred with
window size T = 4

Input	Output
$\langle s_{P-3}, s_{P-2}, s_{P-1}, s_P \rangle$	$\hat{s}_{P+1}$
$\langle s_{P-2}, s_{P-1}, s_P, \hat{s}_{P+1} \rangle$	$\hat{s}_{P+2}$
$\langle s_{P-1}, s_P, \hat{s}_{P+1}, \hat{s}_{P+2} \rangle$	$\hat{s}_{P+3}$
$\langle s_P, \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3} \rangle$	$\hat{s}_{P+4}$
$\langle \hat{s}_{P+1}, \hat{s}_{P+2}, \hat{s}_{P+3}, \hat{s}_{P+4} \rangle$	$\hat{s}_{P+5}$
$\vdots$	$\vdots$

dogs are greater than

(character pre-processing)

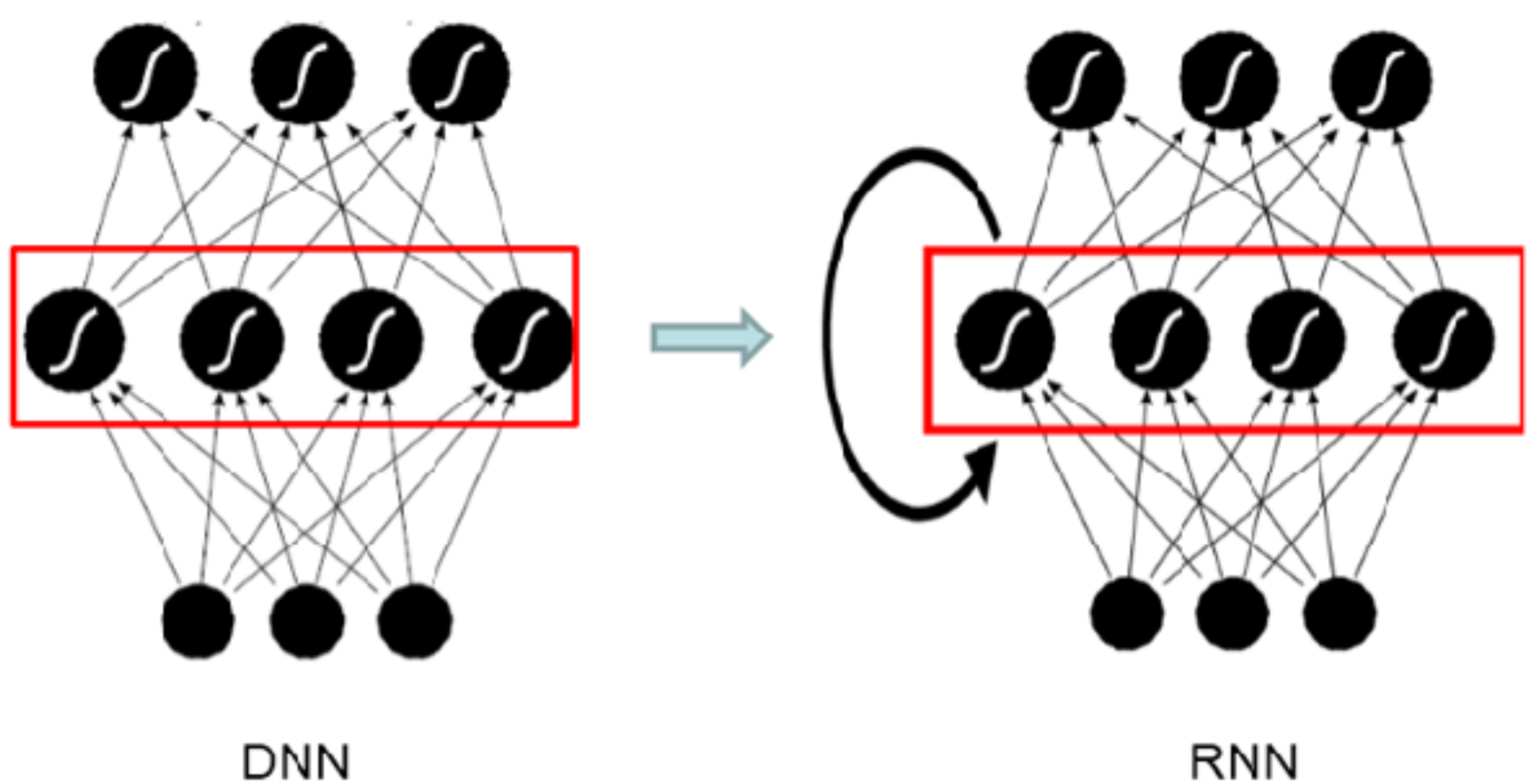
- characters —> numbers for supervised models
- use one-hot encoding scheme

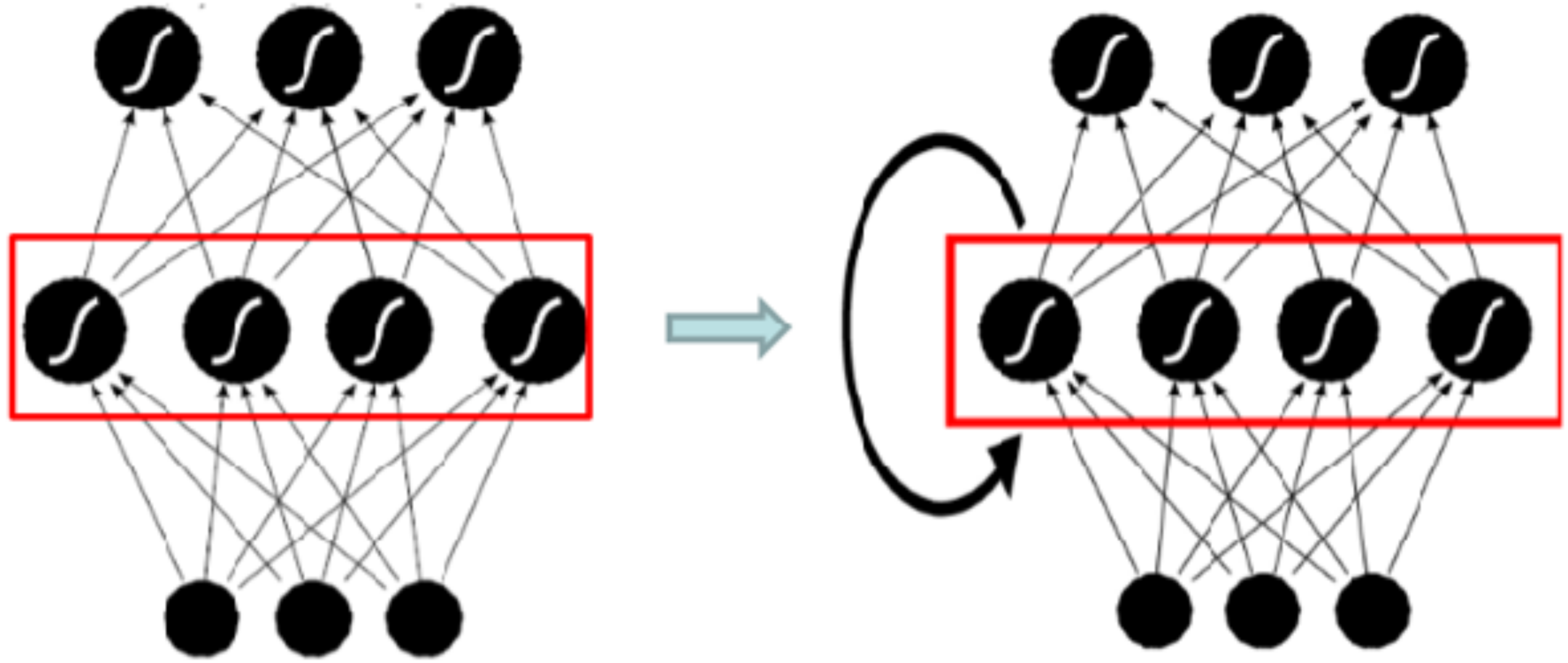
$$a \longleftarrow \begin{bmatrix} 1 \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix} \quad b \longleftarrow \begin{bmatrix} 0 \\ 1 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix} \quad c \longleftarrow \begin{bmatrix} 0 \\ 0 \\ 1 \\ \vdots \\ 0 \\ 0 \end{bmatrix} \cdots$$

RNN architecture

RNN architecture

- **Want:** parameterized supervised learning model that enforces ordered sequential-ness on I/O
- So: extend feedforward nets to ingest sequences





DNN RNN

NN

feed input in **as vector**

$$h = \tanh\left(v_0 + \sum_{t=1}^{T} v_t s_t\right)$$

$$\hat{y} = b + wh$$

$$(y - \hat{y})^2$$

$$h_0 = \tanh\left(v_0 + v s_0\right)$$

$$h_t = \tanh\left(v_0 + v s_t + u h_{t-1}\right)$$

$$\hat{y} = b + w h_T$$

$$(y - \hat{y})^2$$

RNN technical issues

- RNN still trained via gradient descent (a.k.a. backprop)
- Similar 'vanishing gradient' problem as with feedforward nets
- Using different activation (relu) helps, but additional unit architecture helps a lot (<u>Long Term Short Memory</u> module)

SUMMARY

Supervised learning

+

structured data

Beyond vanilla

- Vanilla models don’t exploit ordered sequential I/O
- Include I/O structure in learning framework —> better results
    - Engineer into fixed feature extraction
    - Iimbed parameterized feature extractor in model (e.g., convnets, RNNs)
- RNNs one parameterized way to exploit sequential I/O
- RNNs are natural extension of feedforward nets, and inherit similar technical issues