Deep Learning Explained

Module 5: Recurrence (RNN) and Long-Short Term Memory (LSTM)

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Module outline

Application:

- Time series forecasting with IOT data

Model:

- Recurrence
- Long-short term memory cell

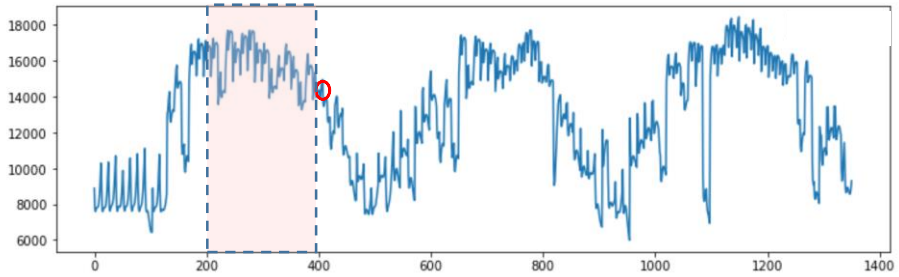
Concepts:

- Recurrence
- LSTM
- Dropout

Train-Test-Predict Workflow

Sequences (many to one)

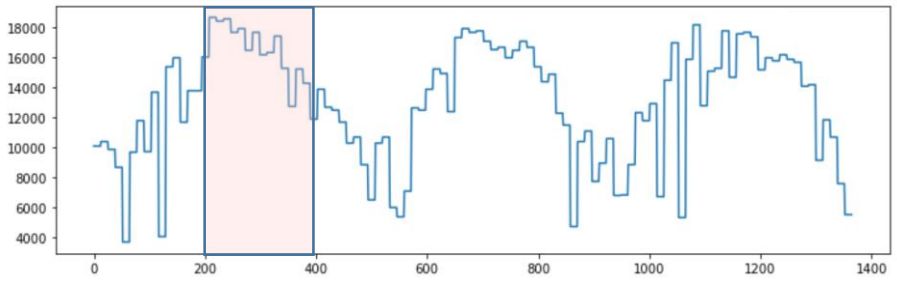
Problem: Time series prediction with IOT data

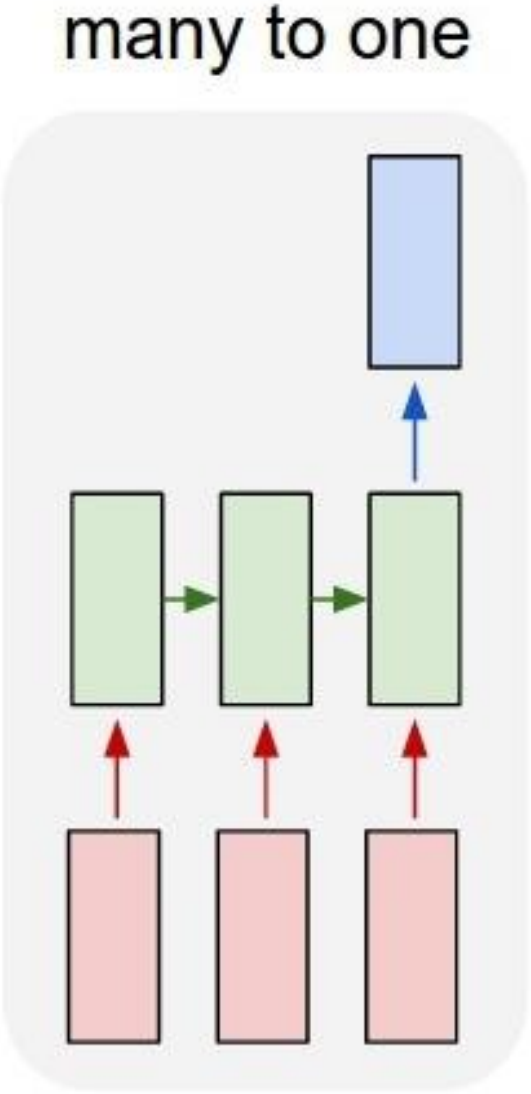


Output
(Y: n x future prediction)

Model
Rec = Recurrence

Input feature
(X: n x 14 data pnts)

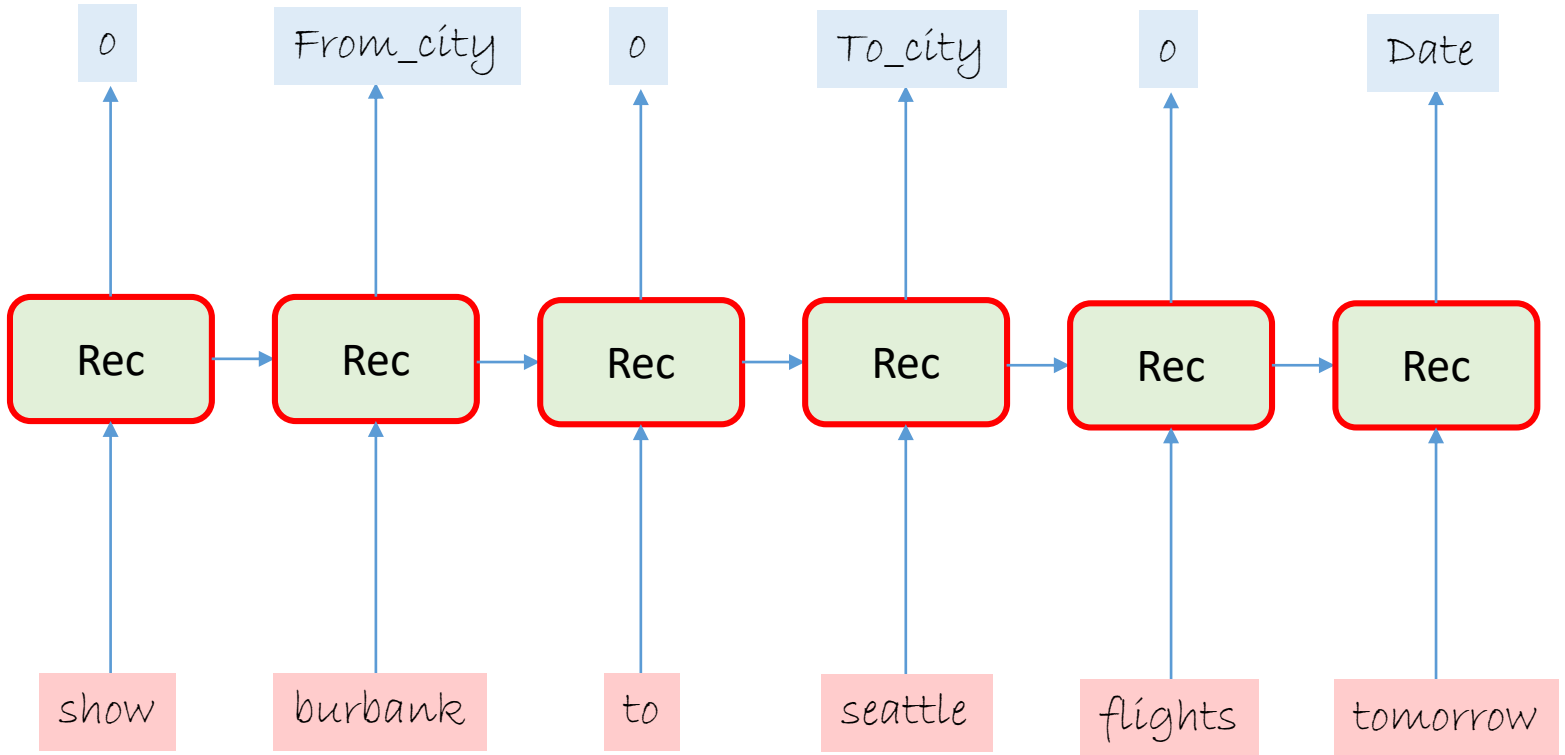


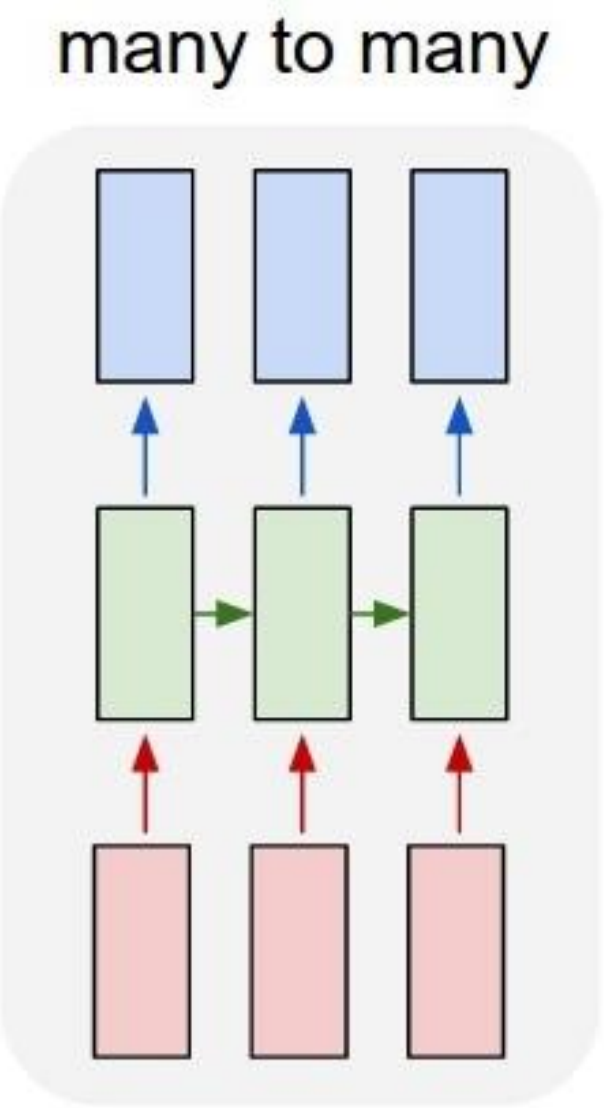


http://karpathy.github.io/2015/05/21/rnn-effectiveness/

Sequences (many to many + 1:1)

Problem: Tagging entities in Air Traffic Controller (ATIS) data





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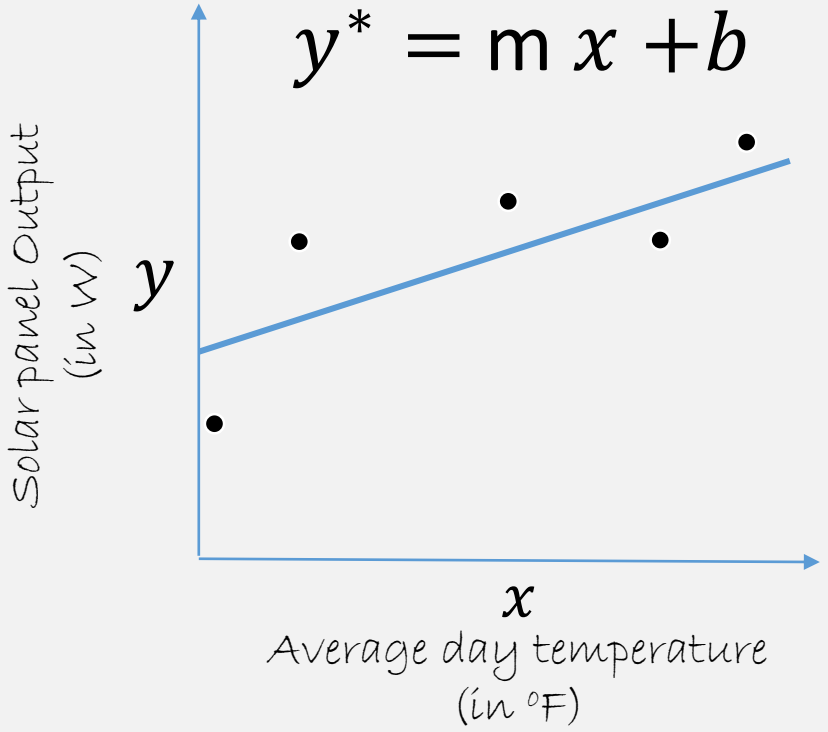
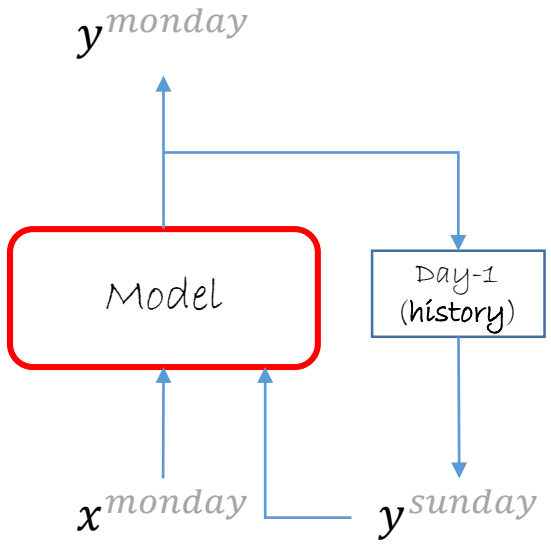
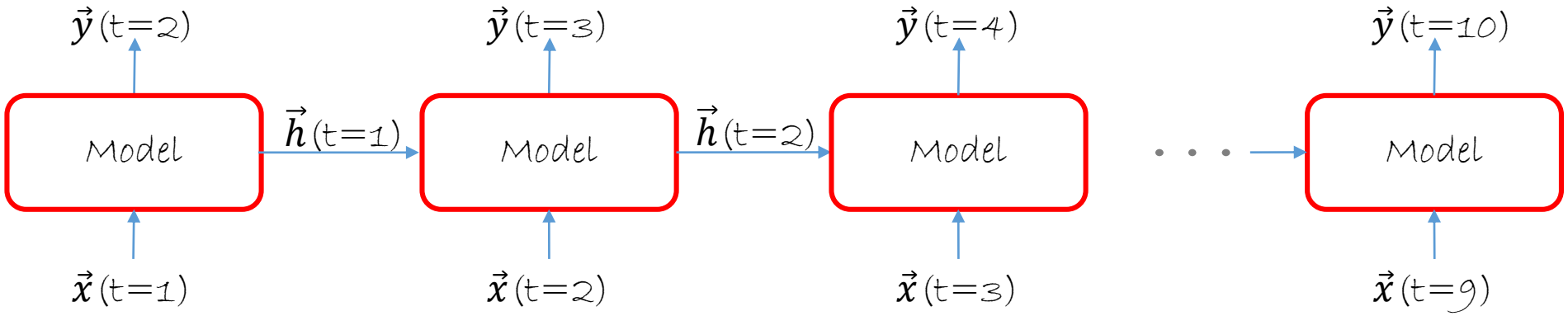
Forecasting





Recurrence

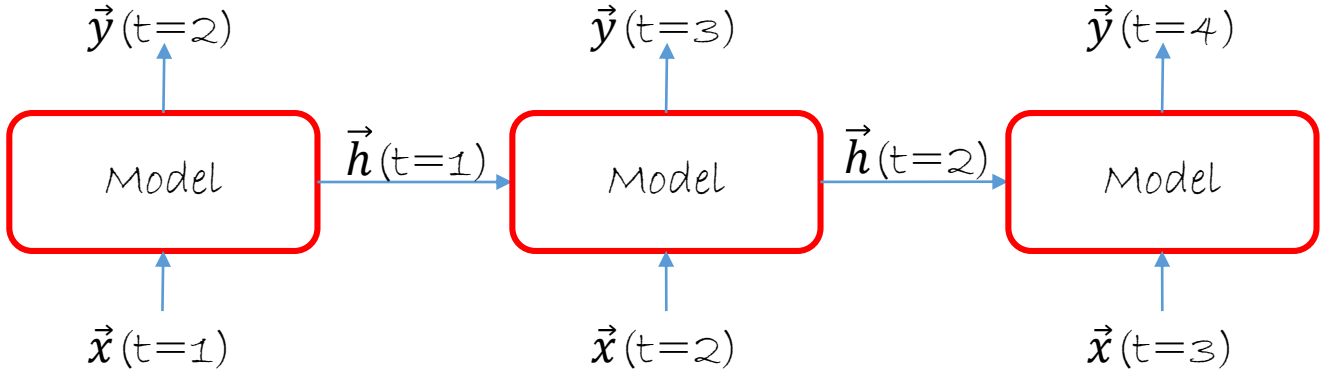


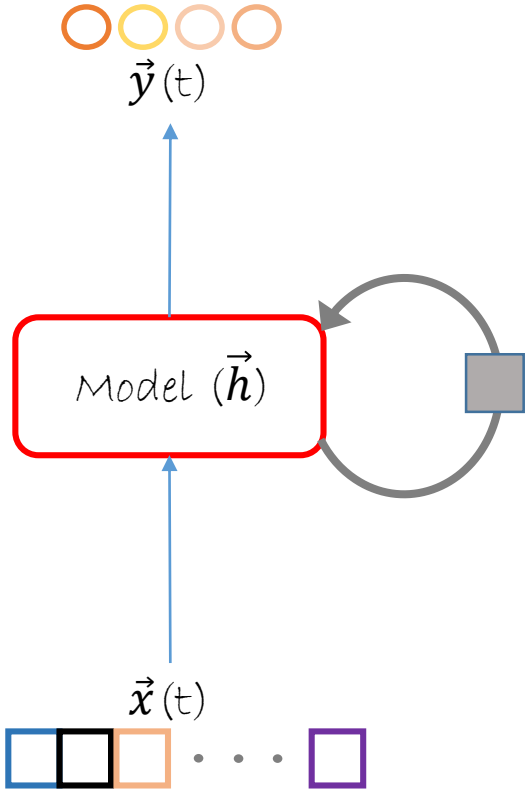
$\vec{x}$(t) : Input (n-dimensional array) at time t
$\vec{y}$(t) : Output (c-dimensional array) at time t
$\vec{h}$(t) : Internal State [m-dimensional array] at time t a.k.a history

Input:

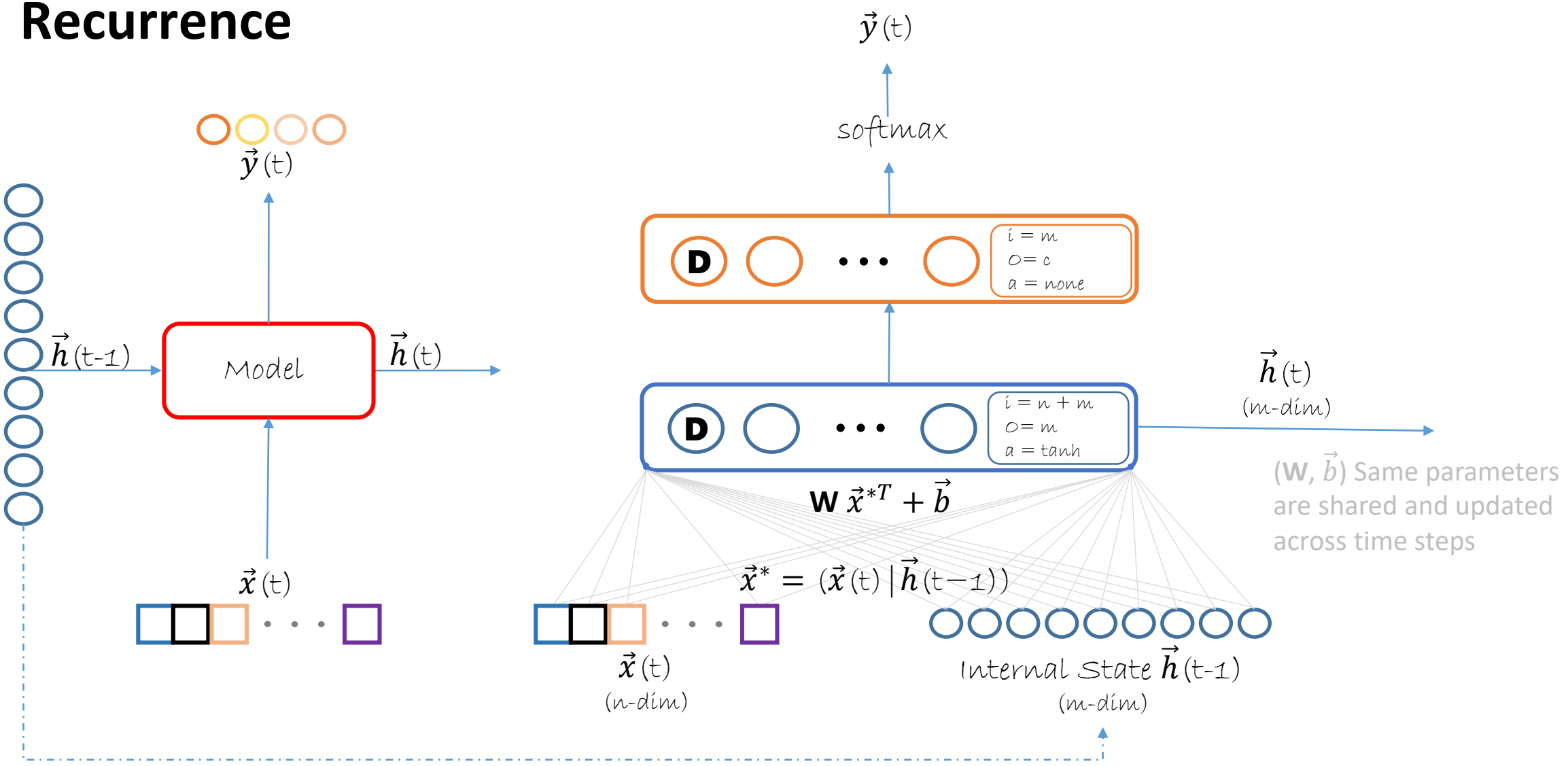
For numeric: Array of numeric values coming from different sensor
For an image: Pixels in an array, Map the image pixels to a compact representation (say n values)
For word in text: Represent words as a numeric vector using embeddings (word2vec or GloVe)

Recurrence

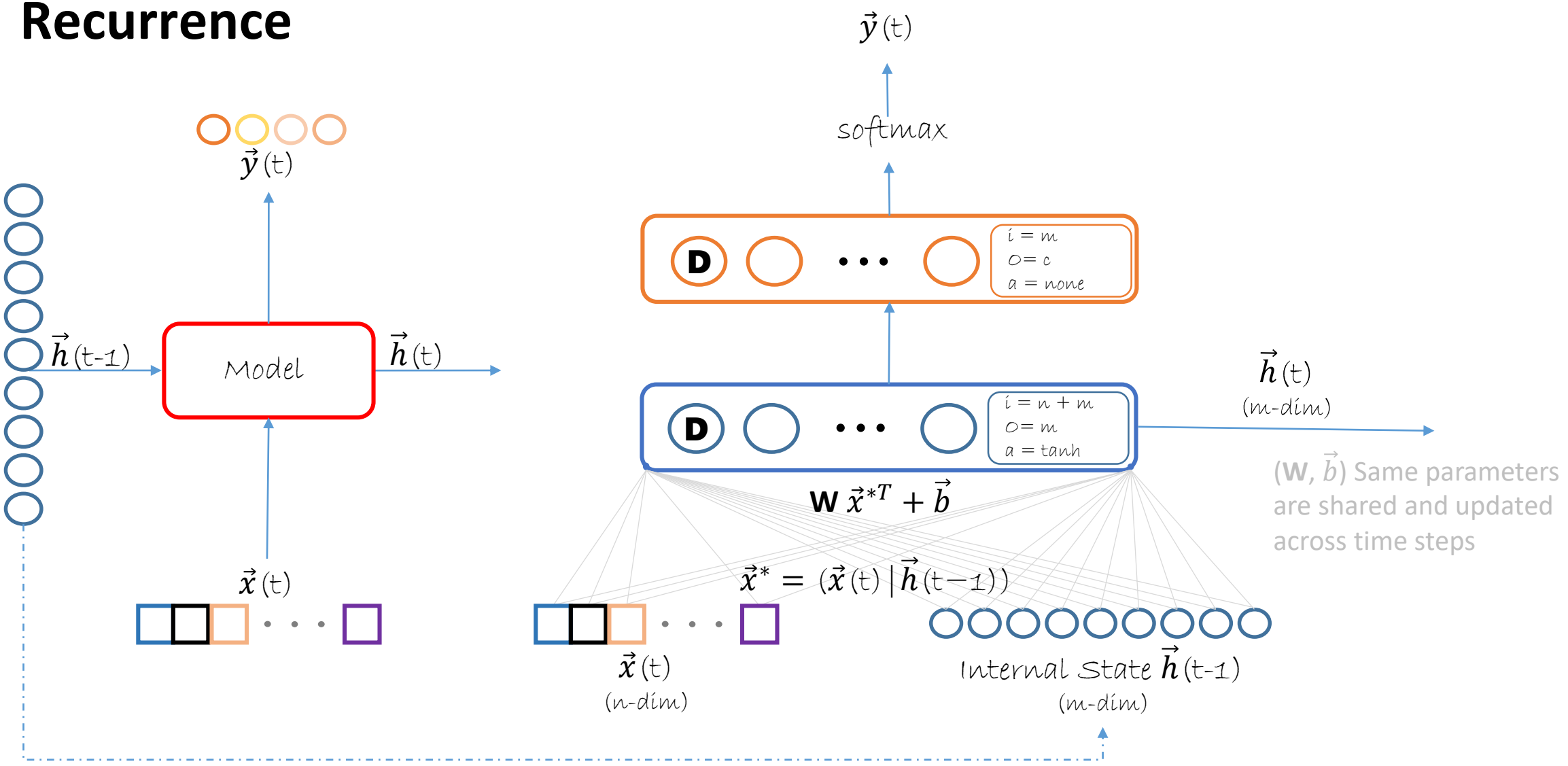

$\vec{y}$(t=2)
$\vec{y}$(t=3)
$\vec{y}$(t=4)
Model
$\vec{h}$(t=1)
Model
$\vec{h}$(t=2)
Model
$\vec{x}$(t=1)
$\vec{x}$(t=2)
$\vec{x}$(t=3)


$\vec{y}$(t)
Model ($\vec{h}$)
$\vec{x}$(t)

Recurrence


$\vec{y}(t)$
softmax
D
i = m
o = c
a = none
D
i = n + m
o = m
a = tanh
$\vec{h}(t)$
(m-dim)
$\mathbf{W}\,\vec{x}^{*T} + \vec{b}$
$\vec{x}^* = (\vec{x}(t) \mid \vec{h}(t-1))$
$\vec{y}(t)$
$\vec{h}(t-1)$
Model
$\vec{h}(t)$
$\vec{x}(t)$
$\vec{x}(t)$
(n-dim)
Internal State $\vec{h}(t-1)$
(m-dim)
($\mathbf{W}$, $\vec{b}$) Same parameters are shared and updated across time steps

Recurrence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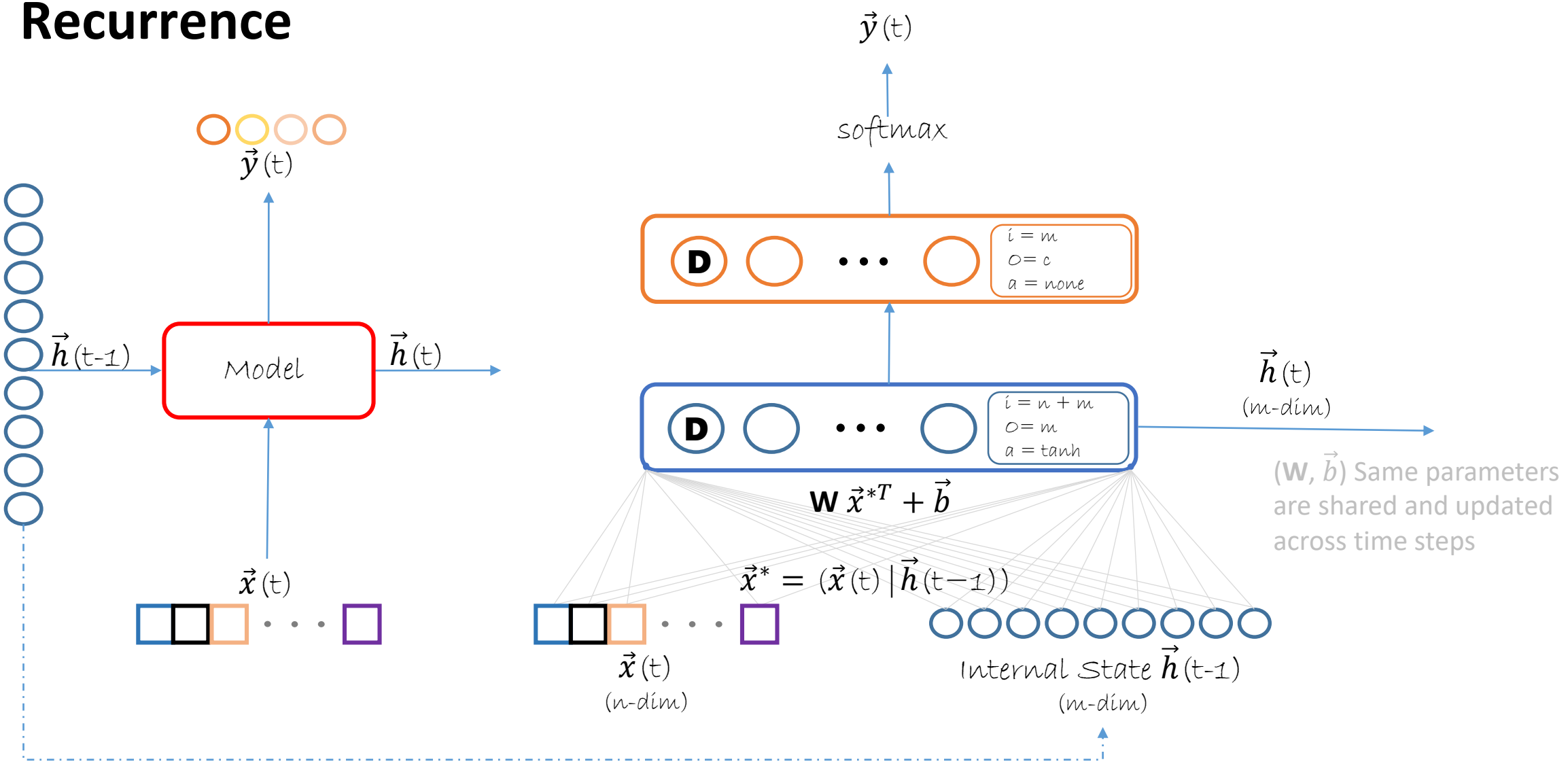
Recurrence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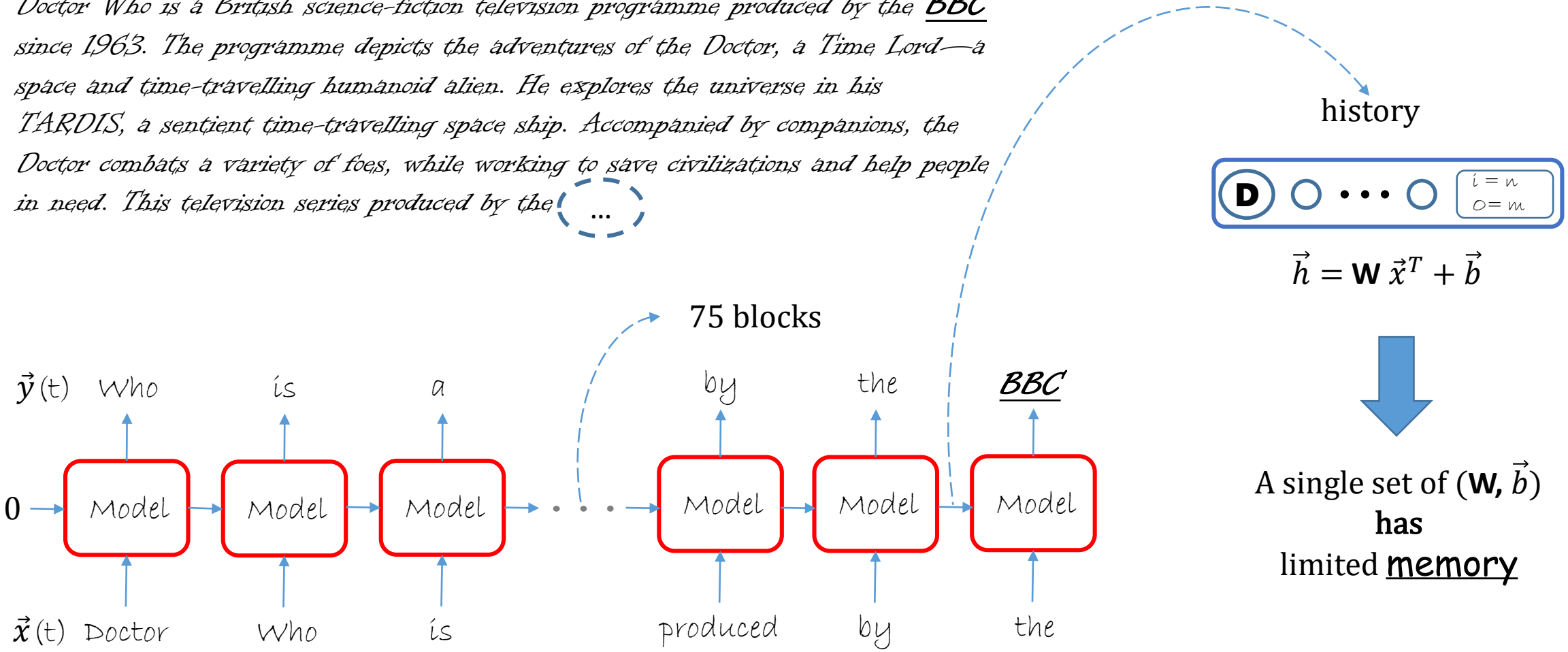
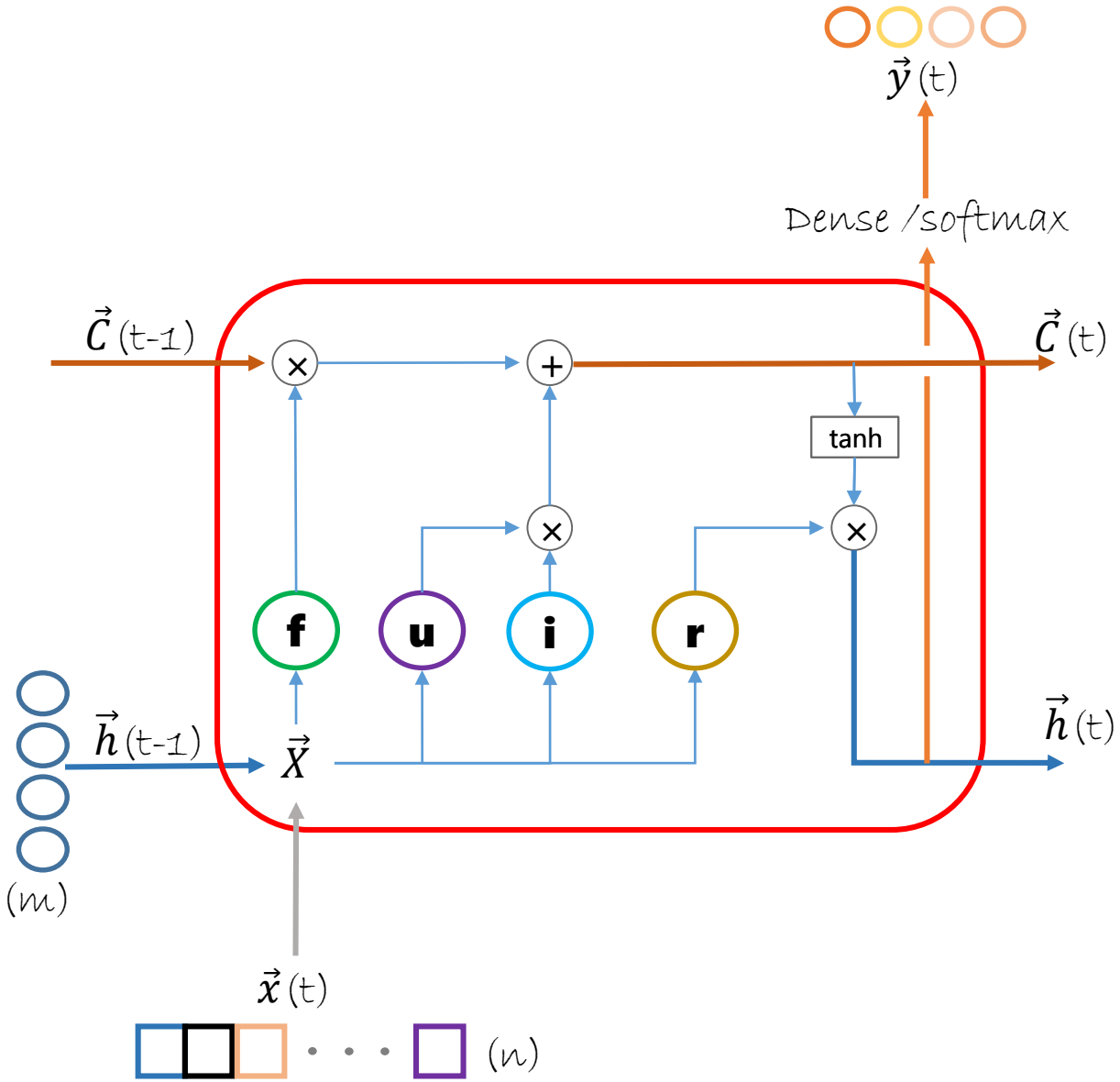
($\mathbf{W}$, $\vec{b}$) Same parameters are shared and updated across time steps

Recurrence (Vanishing Gradients)

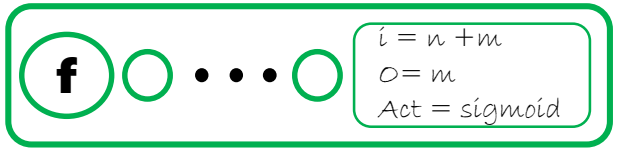
Doctor Who is a British science-fiction television programme produced by the ***BBC*** *since 1963. The programme depicts the adventures of the Doctor, a Time Lord—a space and time-travelling humanoid alien. He explores the universe in his TARDIS, a sentient time-travelling space ship. Accompanied by companions, the Doctor combats a variety of foes, while working to save civilizations and help people in need. This television series produced by the* ...



Long-Short Term Memory (LSTM)

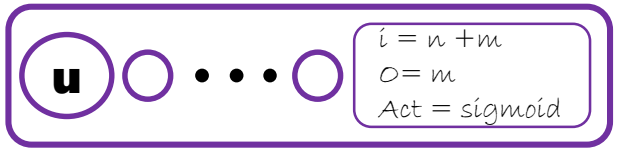


Forget gate



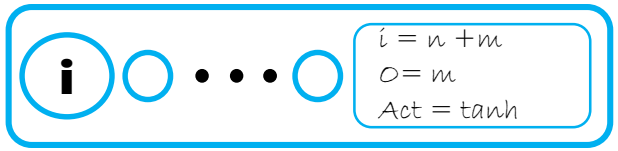
$$\vec{f} = \text{sigmoid}(\mathbf{W}_f \vec{X}^T + \overrightarrow{b_f})$$

Update gate



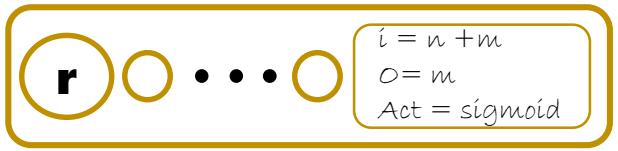
$$\vec{u} = \text{sigmoid}(\mathbf{W}_u \vec{X}^T + \overrightarrow{b_u})$$

Input



$$\vec{X}^* = \tanh(\mathbf{W}_i \vec{X}^T + \overrightarrow{b_i})$$

Result gate



$$\vec{r} = \text{sigmoid}(\mathbf{W}_r \vec{X}^T + \overrightarrow{b_r})$$

New cell memory

$$\vec{C}(t) = \vec{C}(t\text{-}1) \times \mathbf{f} + \mathbf{i} \times \mathbf{u}$$

New history

$$\vec{h}(t) = \tanh(\vec{C}(t)) \times \mathbf{r}$$

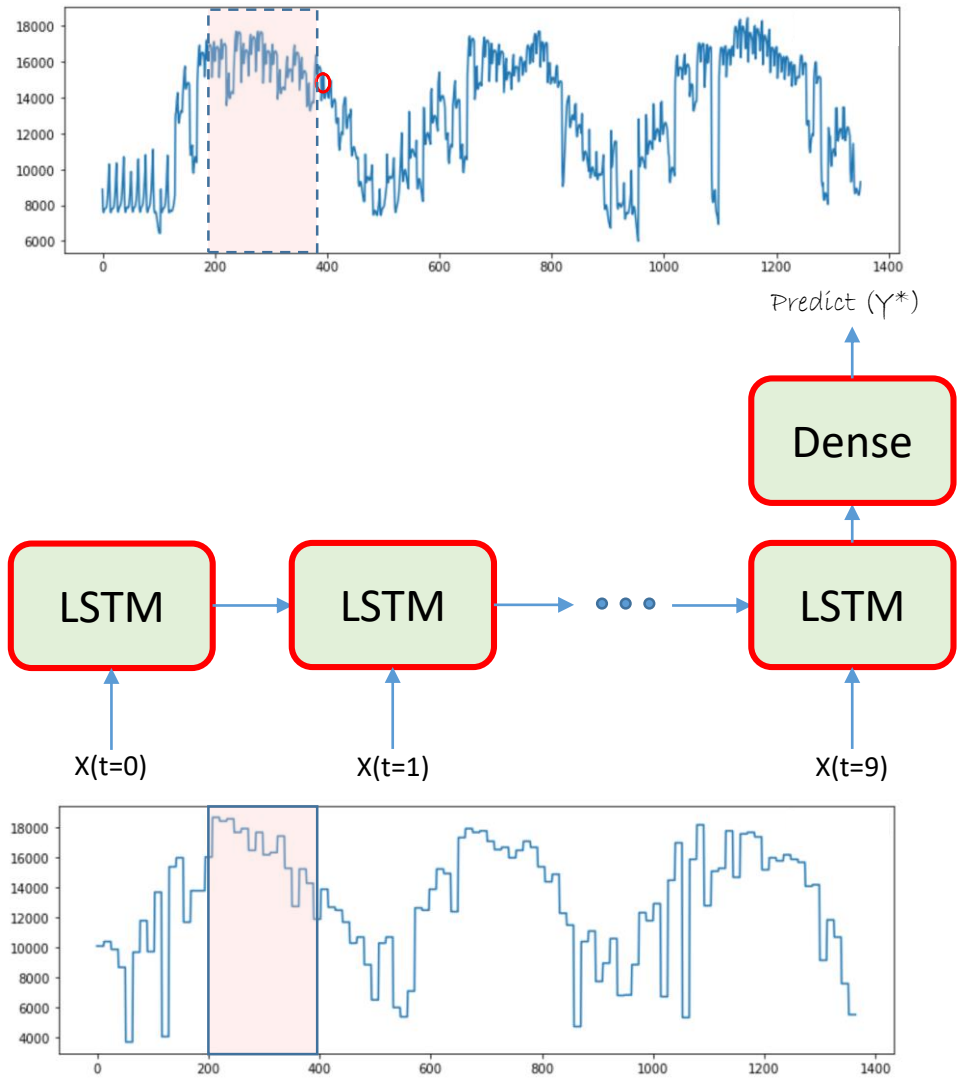
Time-series forecasting

Problem: Time series prediction with IOT data

Output
(Y: n x future prediction)

```
z = create_model(x):
        m = C.layers.Recurrence(C.layers.LSTM(TIMESTEPS))(x)
        m = C.sequence.last(m)
        m = C.layers.Dense(1)(m)
        return m
```

Input feature
(X: n x 14 data pnts)



Dropout

Problem:

Overfitting
Model works great with training data
With new data (unseen during training): high prediction error

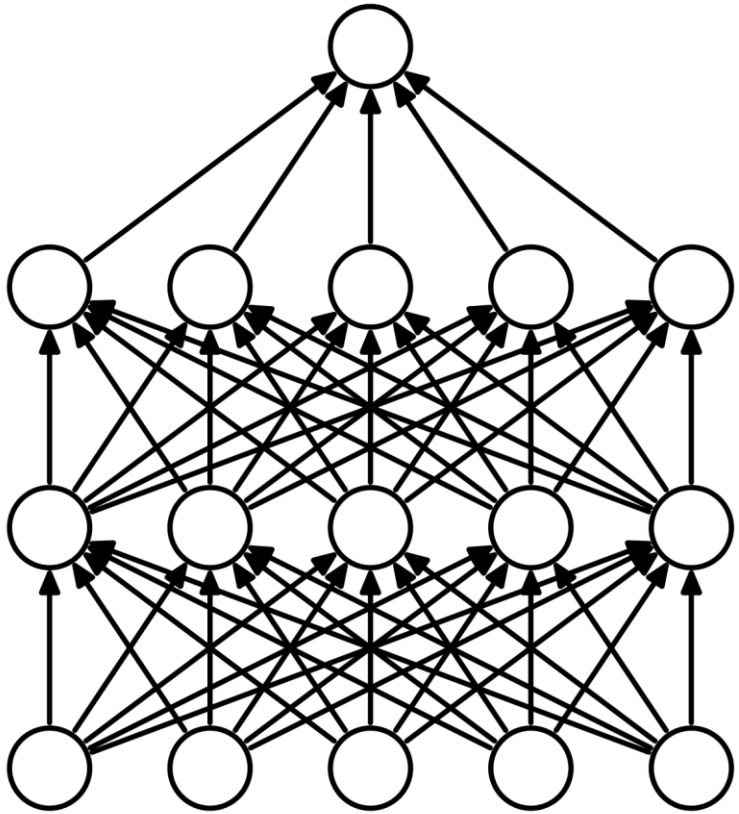
Classical Approach:

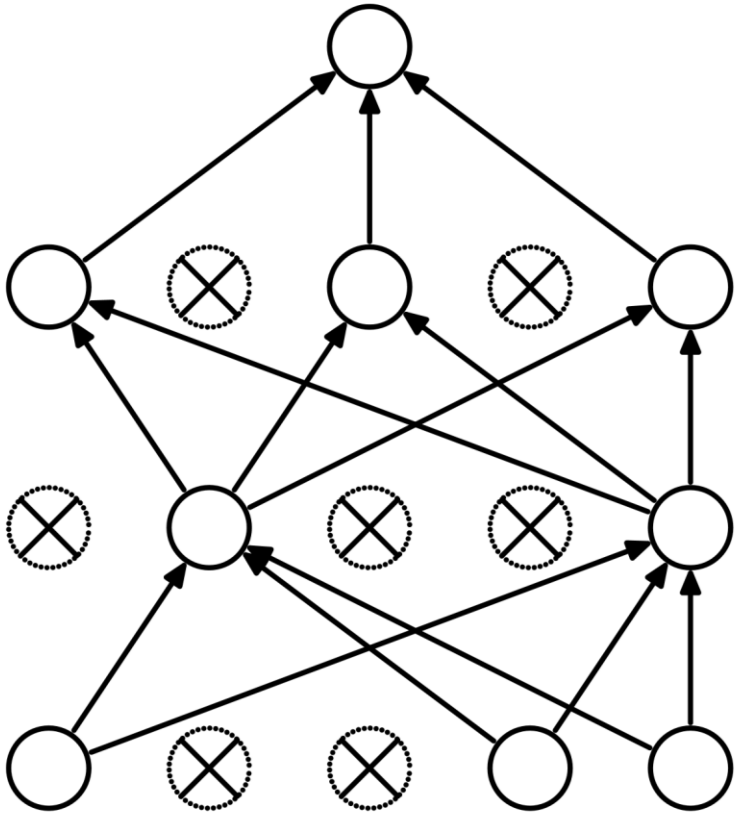
L1 / L2 regularization
Data augmentation / train with noise added
Early stopping

Dropout

Extremely effective technique to tackle overfitting in neural networks

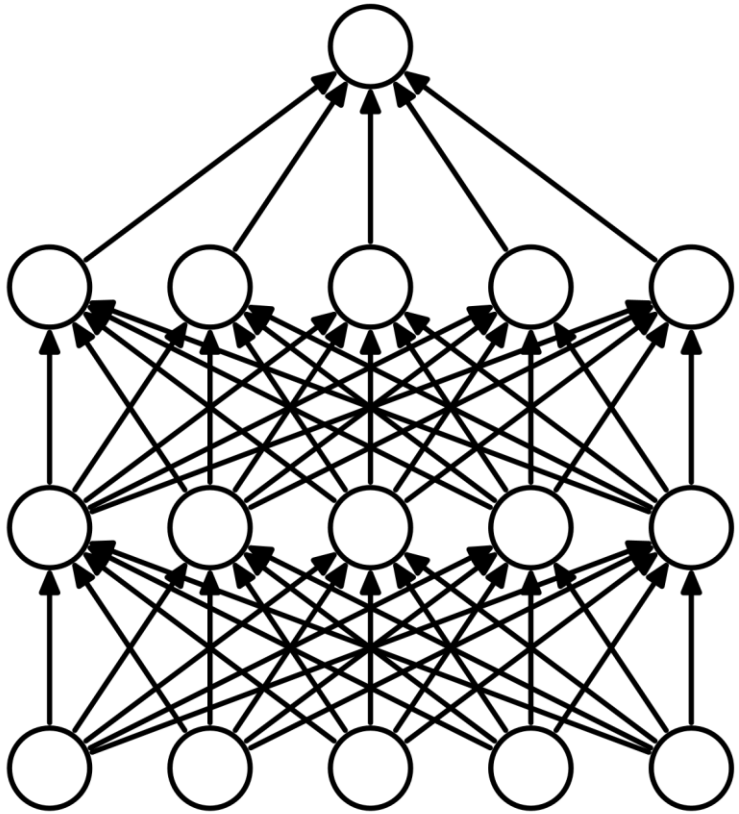
Dropout

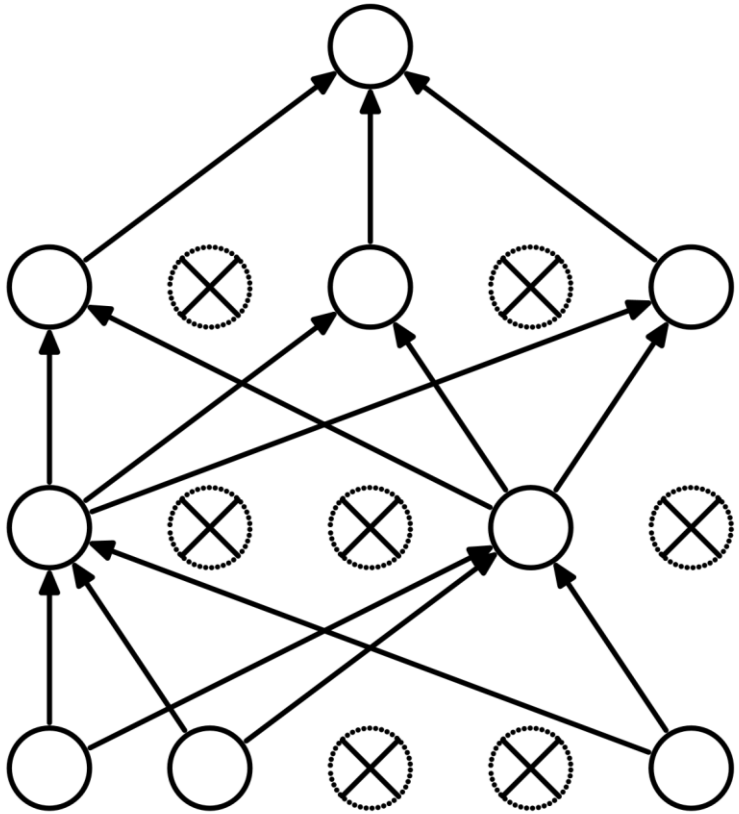




http://www.cs.toronto.edu/~rsalakhu/papers/srivastava14a.pdf

Dropout





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Time-series forecasting

IOT data:

✓ Output of a solar panel, measurements are recorded at every 30 min interval:

- `solar.current`: Current production in Watts
- `solar.total`: Total production for the day so far in Watt/hour

Data Summary:

✓ Starting at a time in the day, two values are recorded

```
time,solar.current,solar.total
7am,6.3,1.7
7:30am,44.3,11.4
...
```

✓ 3 years of data

✓ The input data is not cleansed i.e., errors (panel failed to report) is included

Data pre-processing

Goal:

✓ Compose sequence such that each training instance would be:

- X = [solar.current @ t = 1 – t = 14] (t=1 – 14: corresponds to 1 day)
- Y = Predicted total production for a future day

Pre-processing:

✓ Steps:

- read raw data into a pandas dataframe,
- normalize the data,
- group by day,
- append the columns "solar.current.max" and "solar.total.max", and
- generate the sequences for each day.

✓ Data filtering:

- If X has less than 8 data points – we skip
- If X has more than 14 data points – we truncate

Time-series forecasting

Problem: Time series prediction with IOT data

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(Y: n x future prediction)

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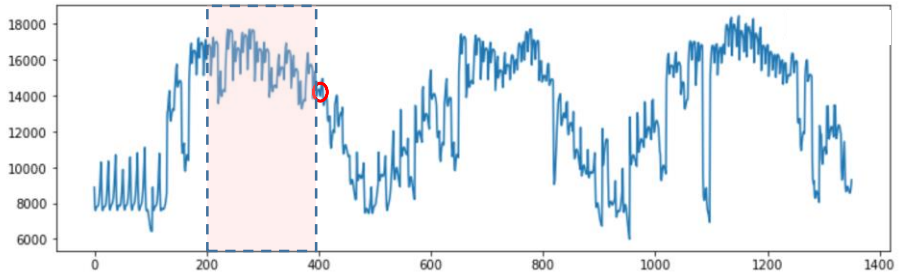
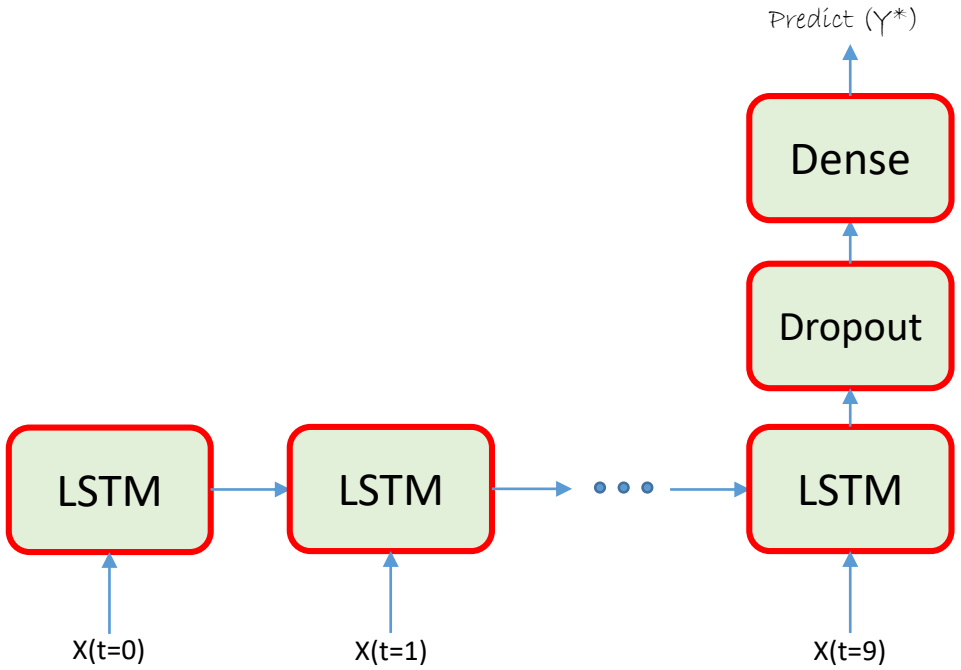
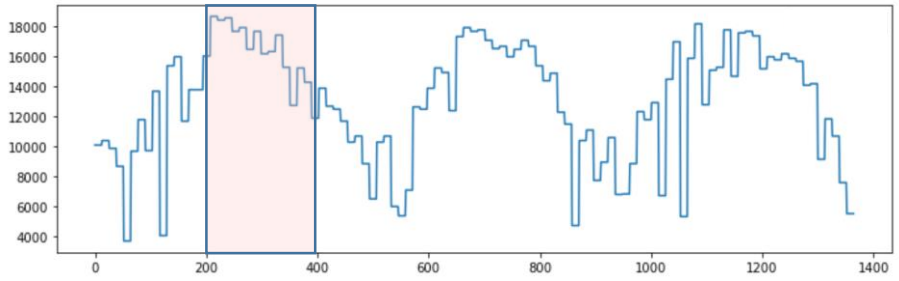
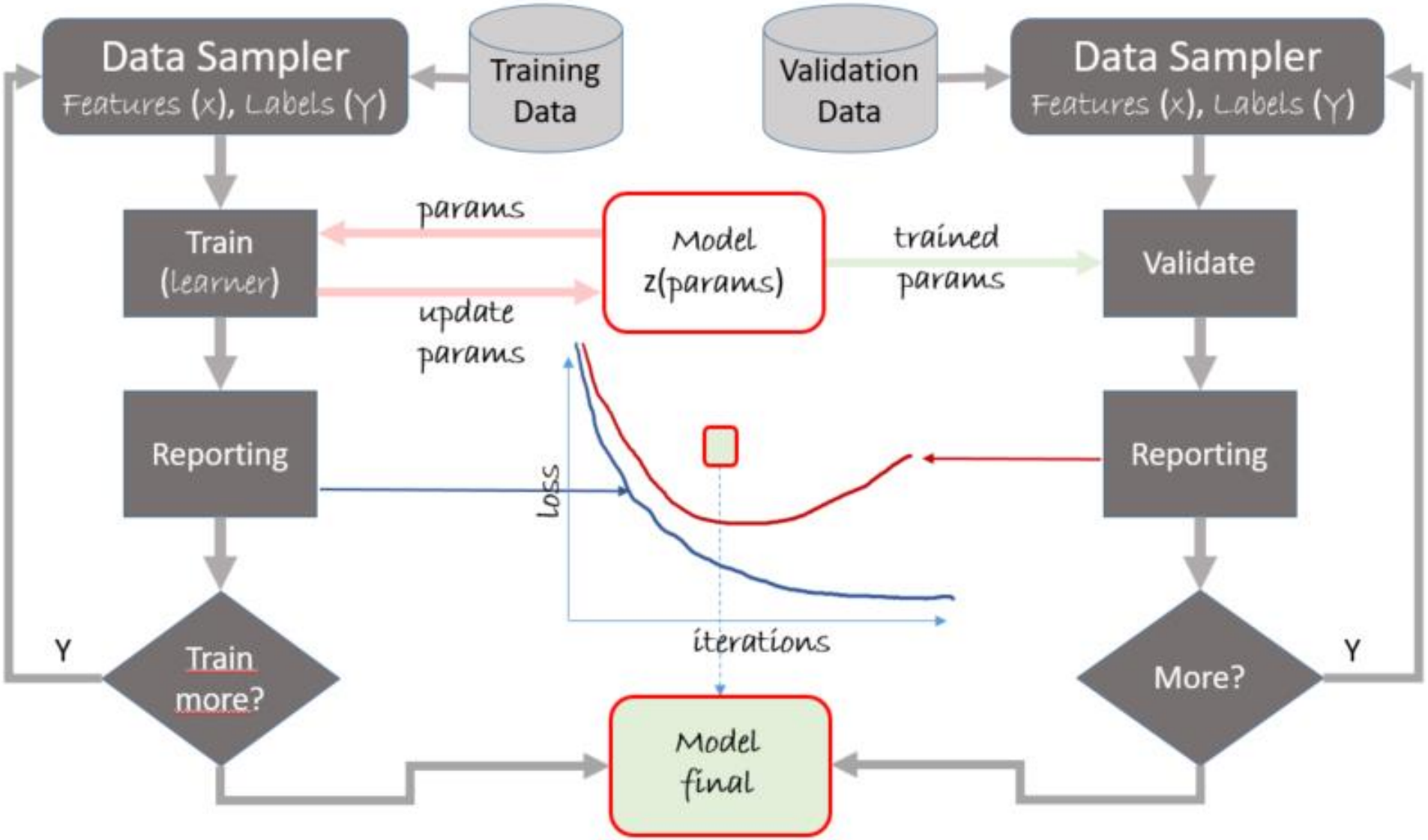


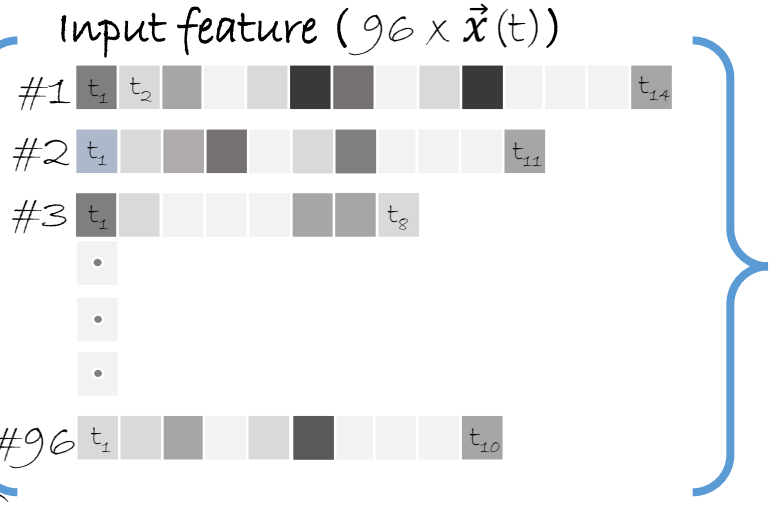




Train / Validation Workflow



Train workflow

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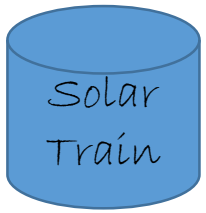


96 samples (mini-batch)

Output feature (96 x 1)
(Y)

Solar panel output for the day

Loss `squared_error(z, Y)`

Error `squared_error(z, Y)`

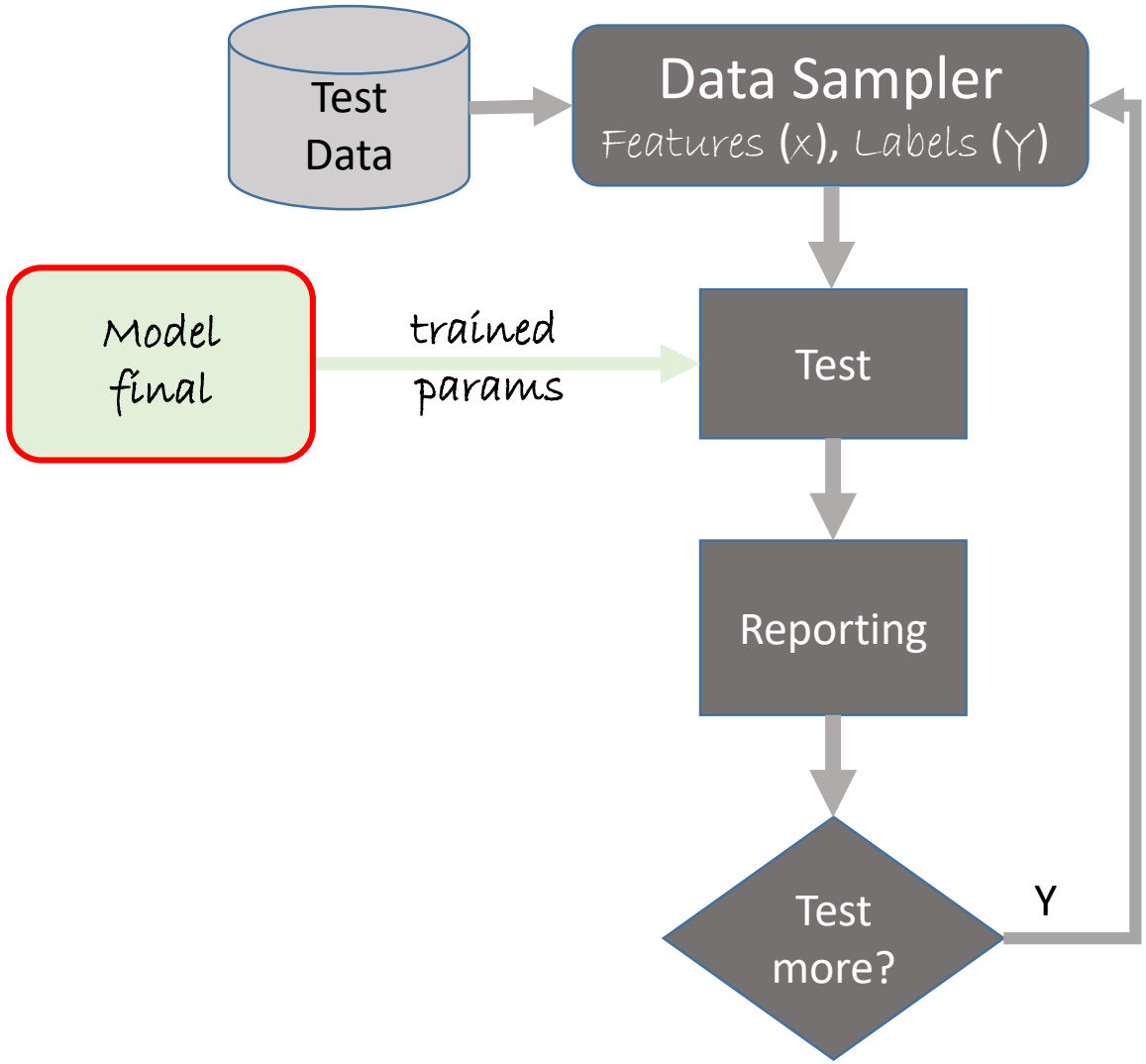
`Trainer(model, (loss, error), learner)`

`Trainer.train_minibatch({X, Y})`

Learner

sgd, adagrad etc, are solvers to estimate

Test workflow



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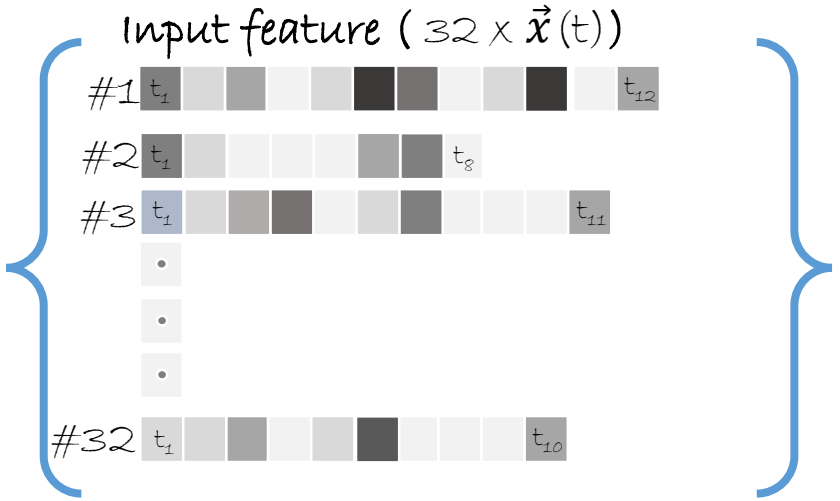


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```

Solar Test

32 samples (mini-batch)

Output feature (32 x 1)
(Y)

Solar panel output for the day

```
Trainer.test_minibatch({X, Y})
```

Returns the squared error between the observed and predicted output from the solar panel

Prediction workflow

Input feature
(new X: $1 \times \vec{x}(t)$)

Model
(w, b)

Model.eval(new X)

Predicted value of the solar panel output(predicted_label)

[y watts]