Sequences and Time-Series

MMCi Block 5

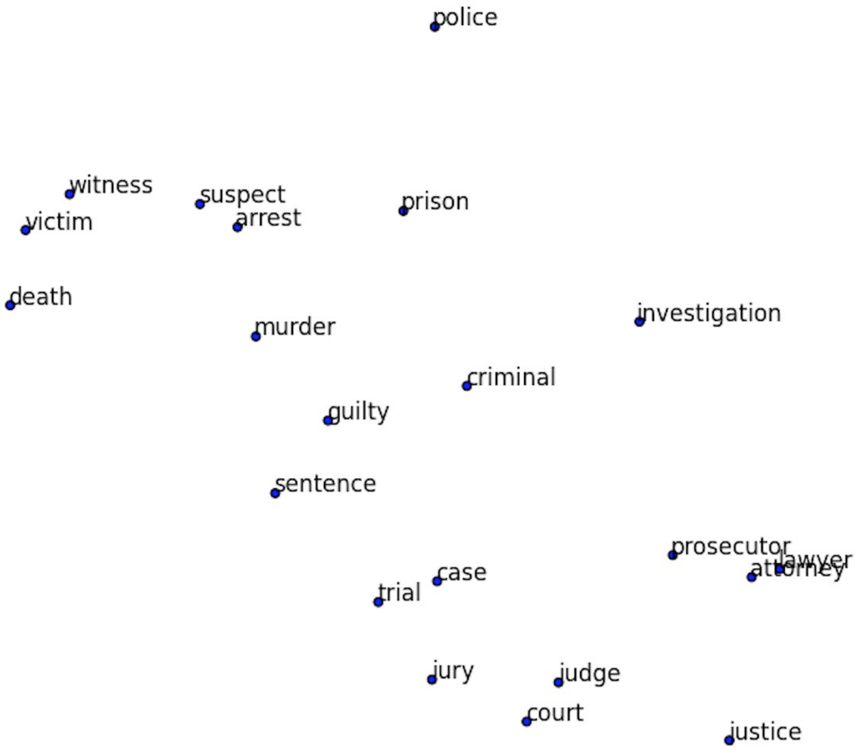
Matthew Engelhard

Recall: Word embeddings allow us to quantify word meaning

If we zoom in on a small region of our word map, it's all related words.

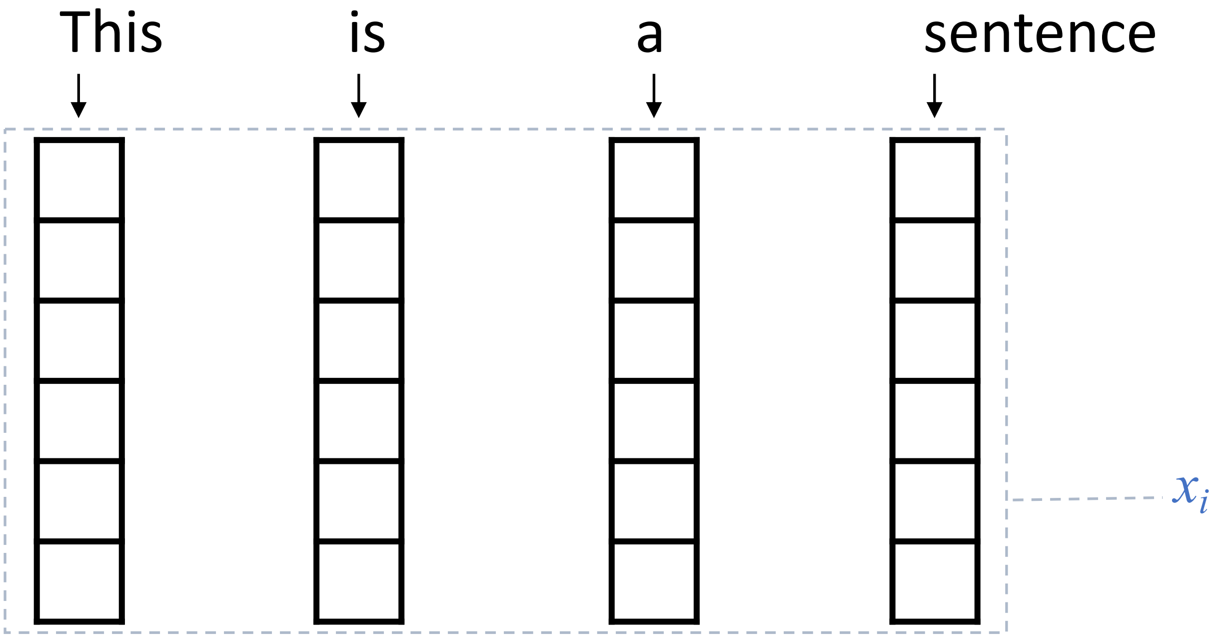
Note the similarity of all the words as a whole, but also of the individual neighbors.

"Lawyer" and "attorney" are nearly identical in space!

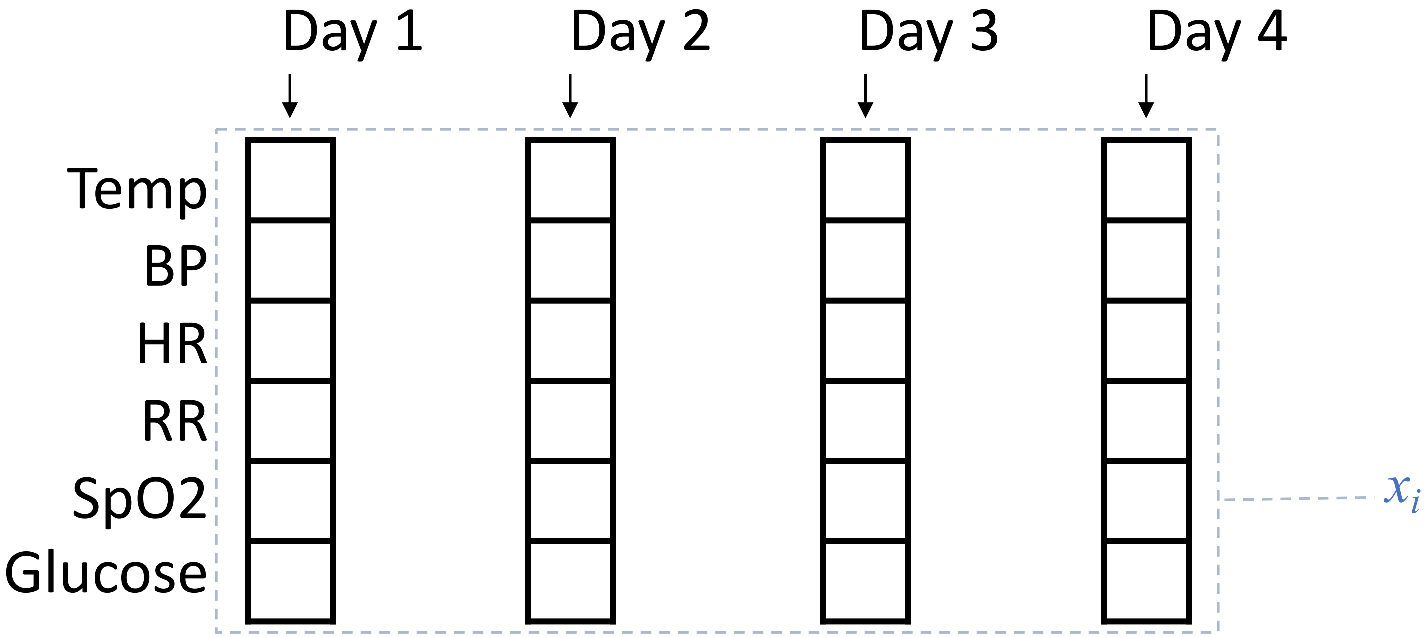


Applying Word Embeddings to a Sentence

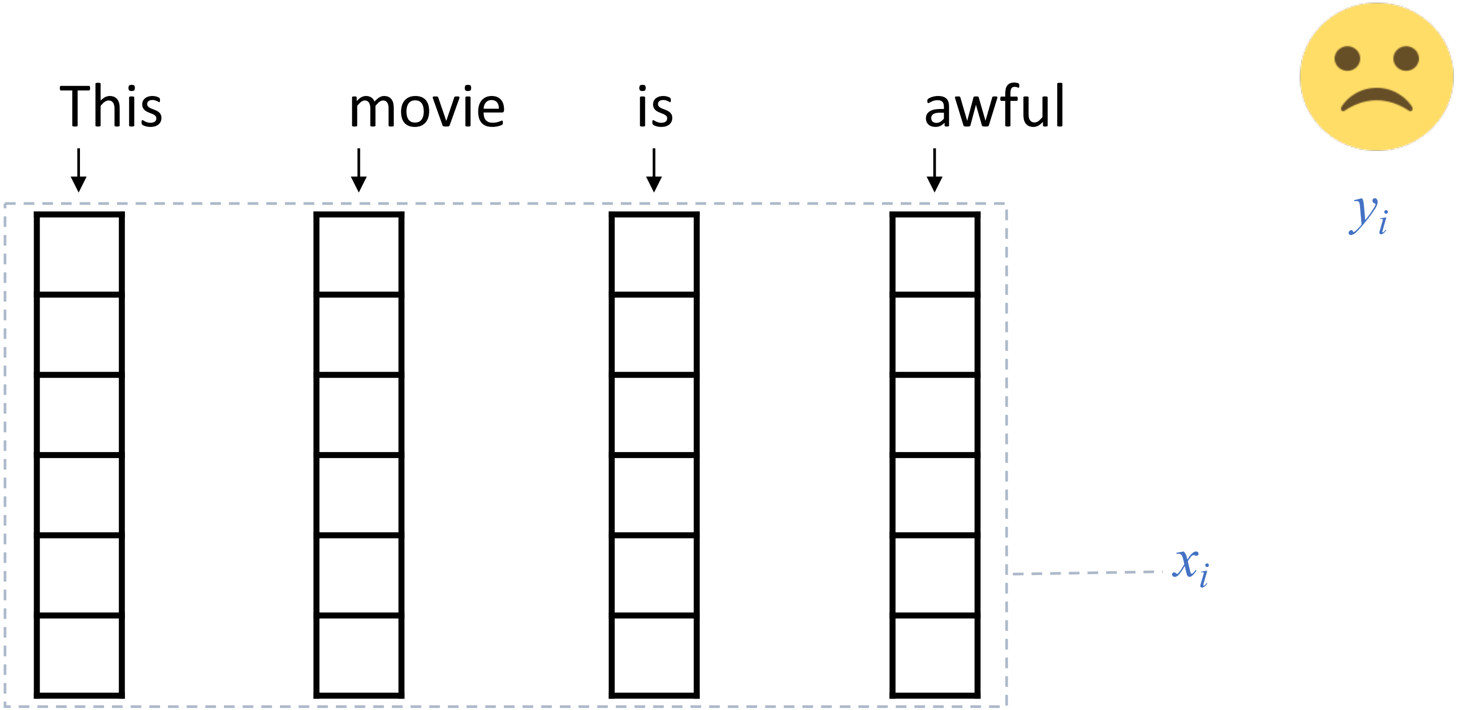
- Look up words individually to obtain their vectors
- Construct a sequence of vectors



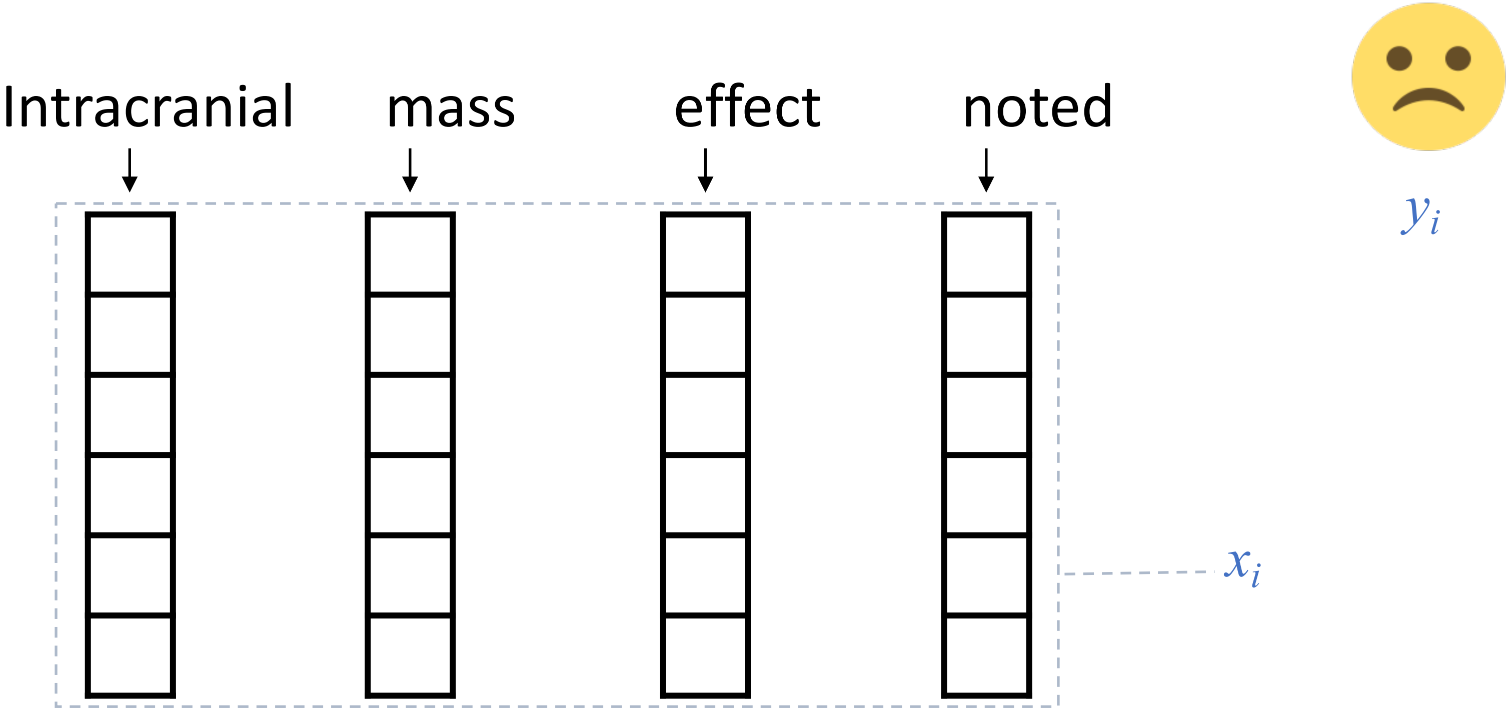
Sequences of measurements: *same structure*



Task 1: Predict a label associated with the sentence

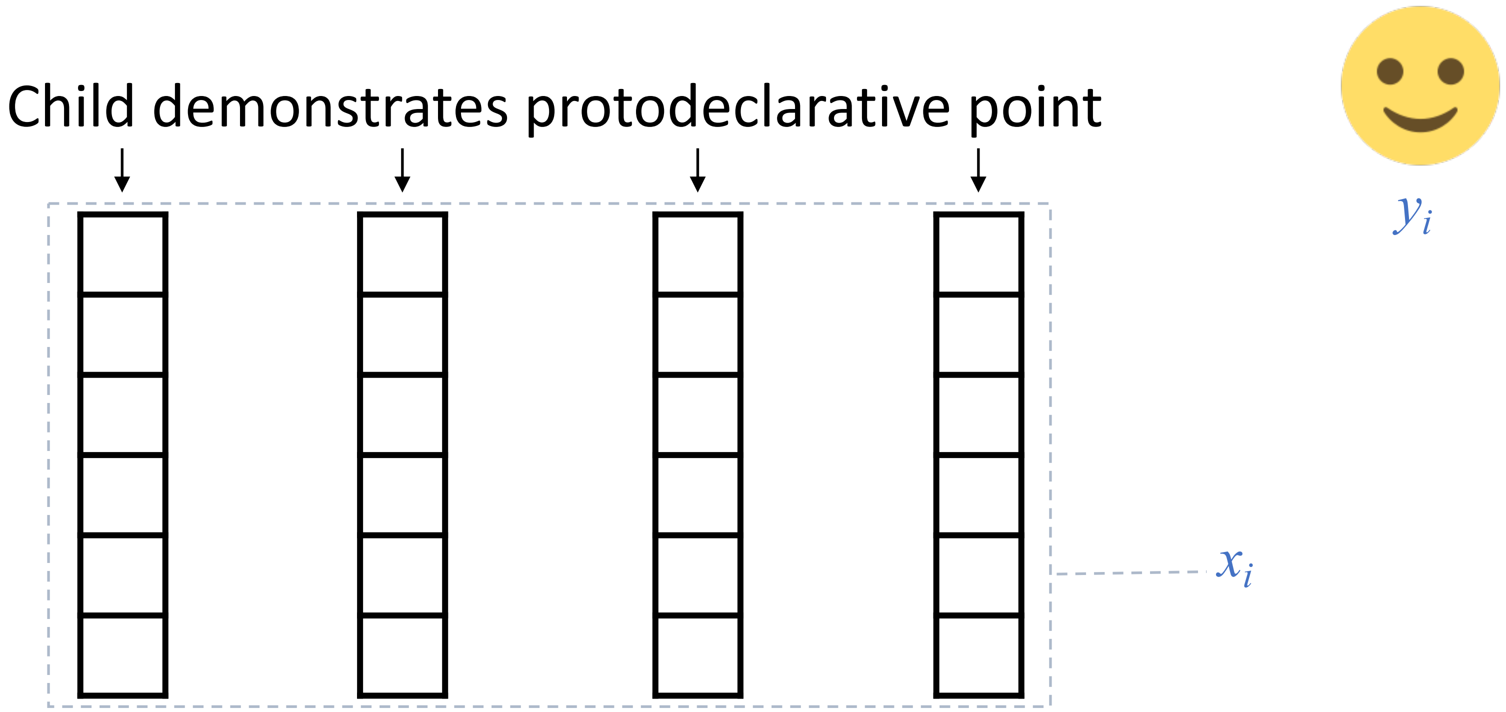


Task 1: Predict a label associated with the report

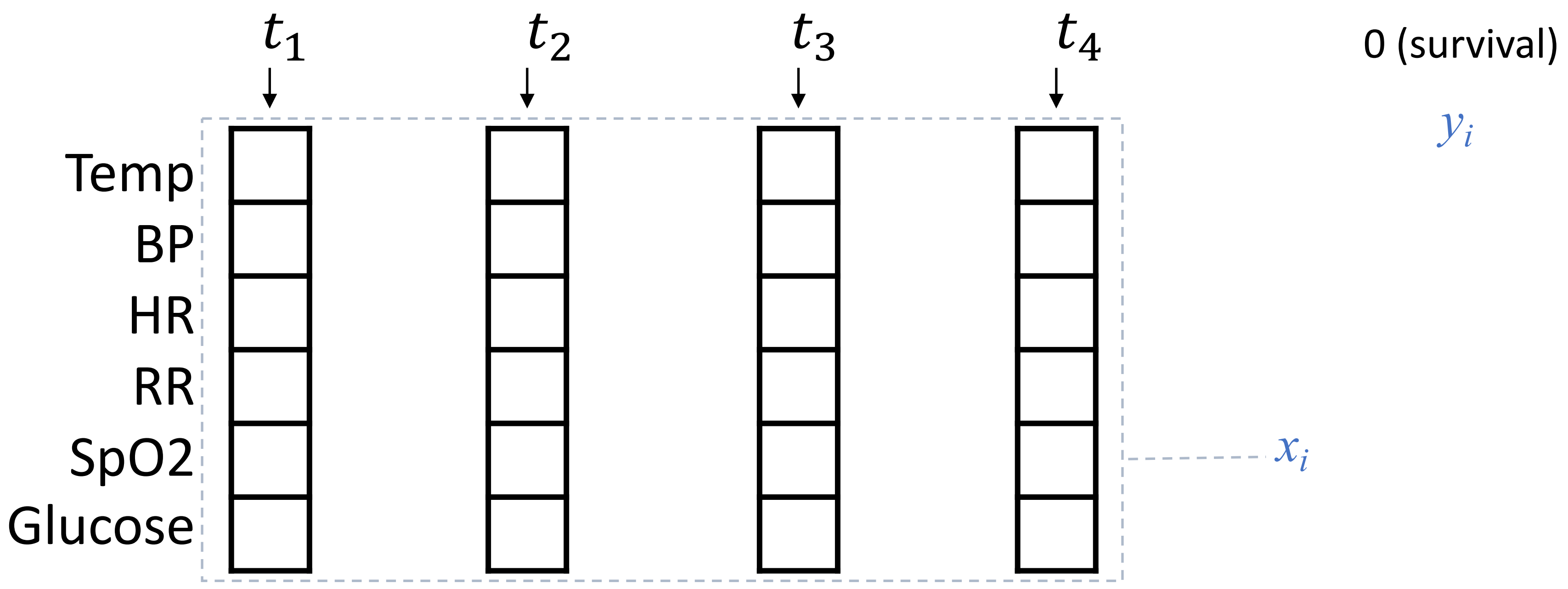


Classification of radiology reports using neural attention models, *IJCNN 2017*

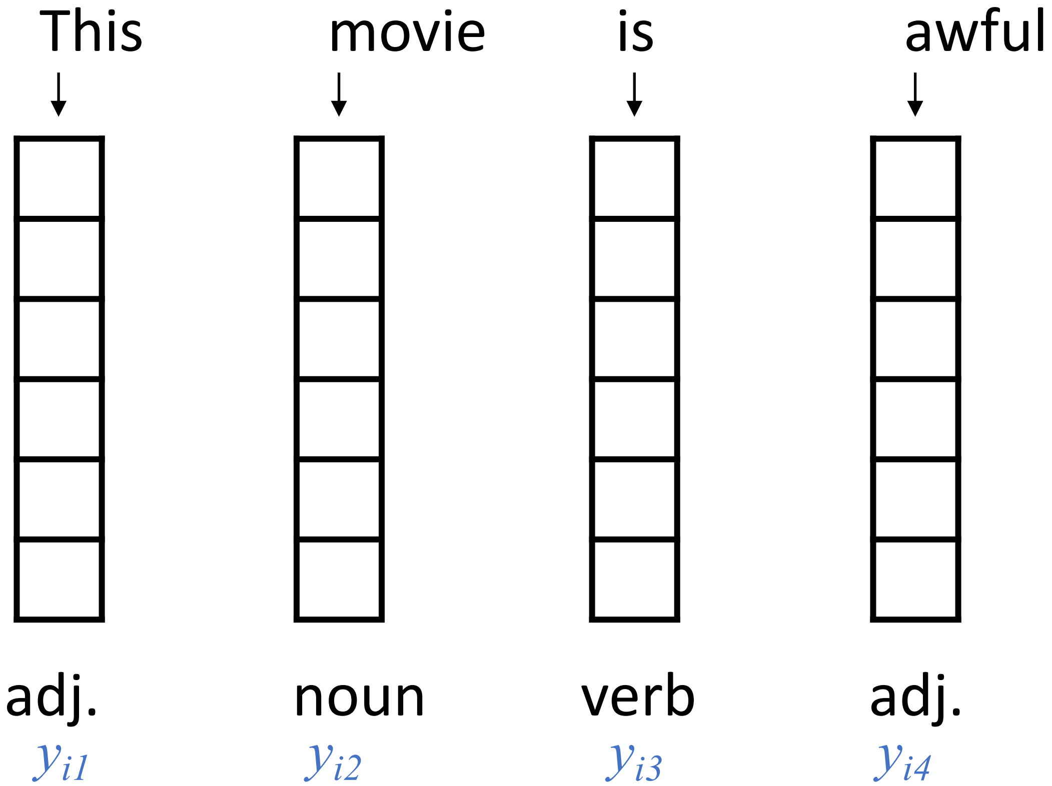
Task 1: Predict a label associated with the note



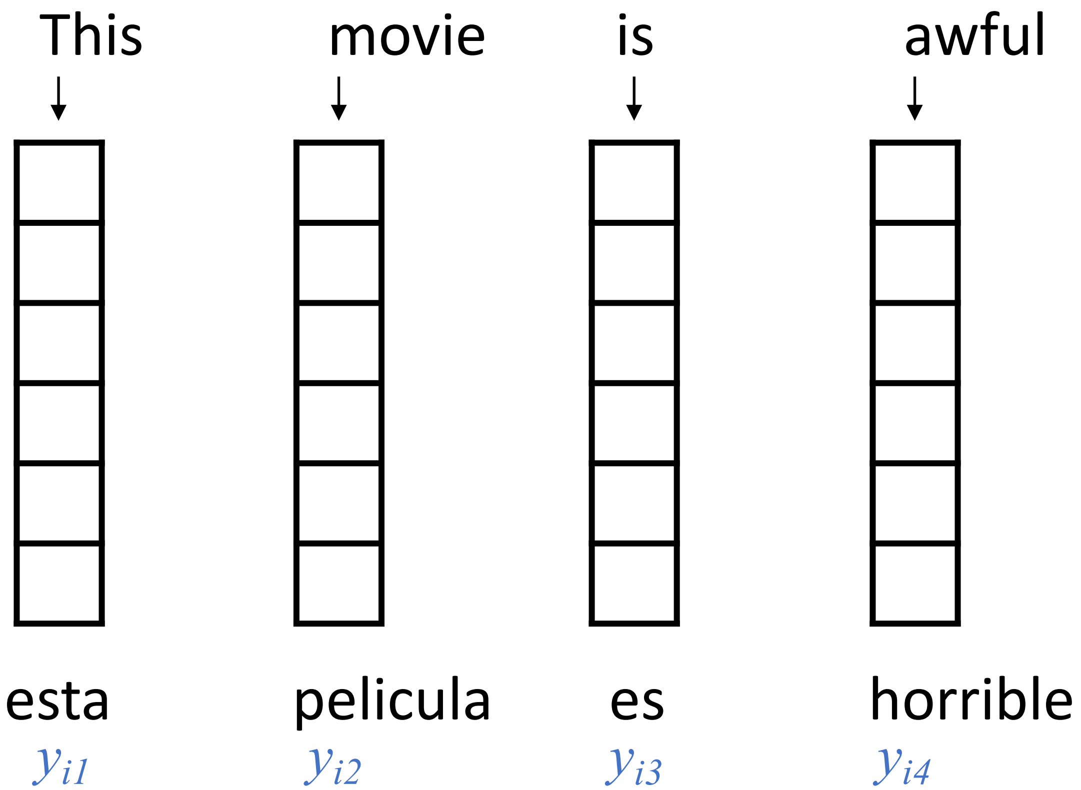
Task 1: Predict label assoc. with all measurements



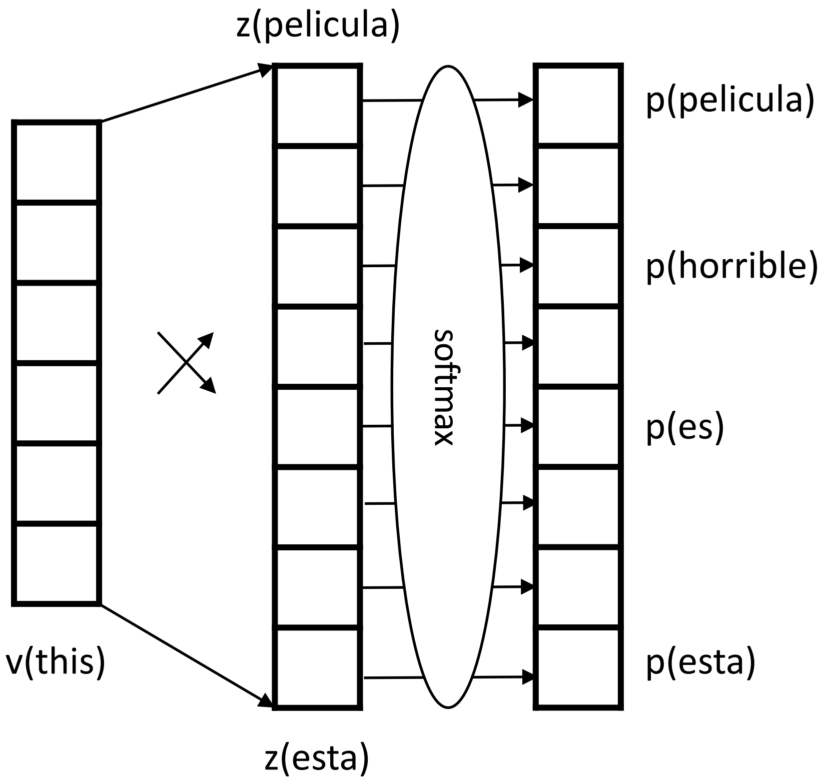
Task 2: Predict a label associated with each word



Task 2: Predict a **label** (?) associated with each word



Multi-Class Logistic Regression (many classes)



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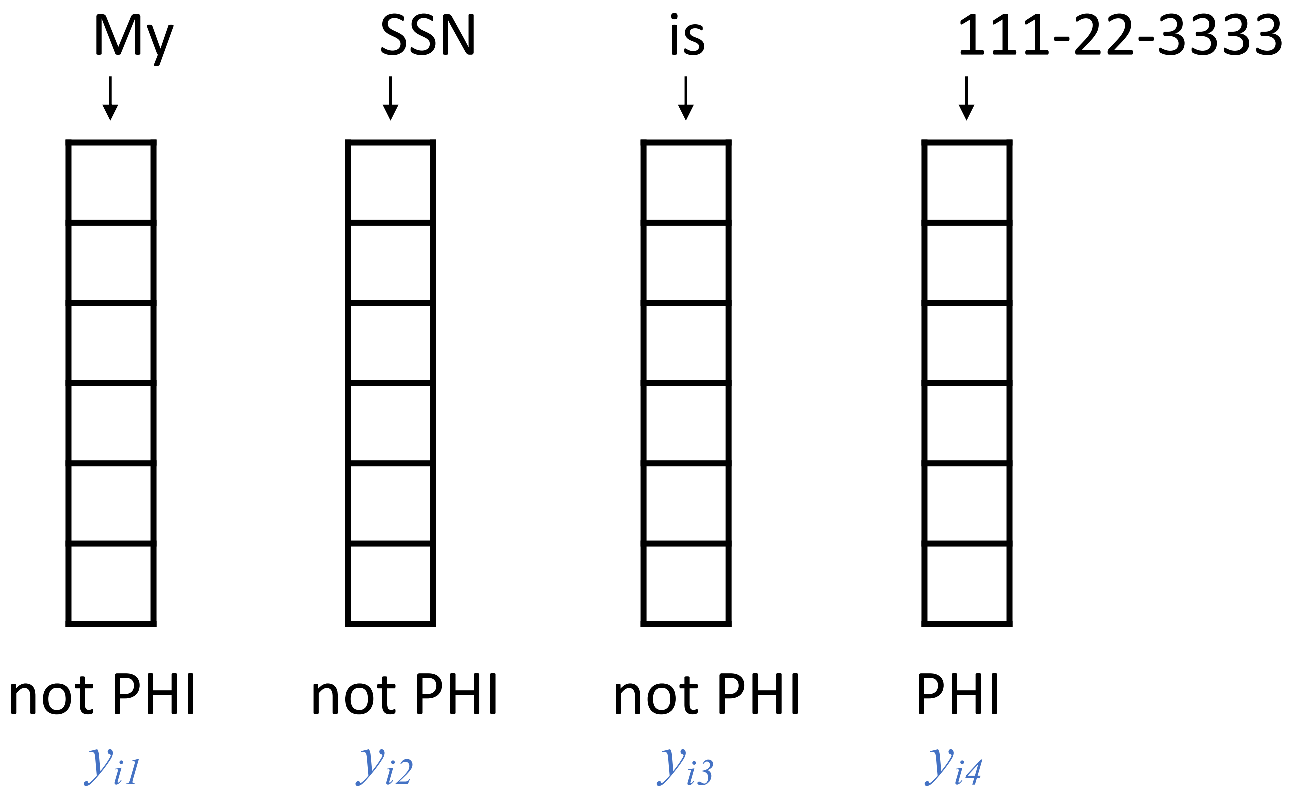

Deidentification of Patient Notes

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PHI category	ANN
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	Results**02/20/2087** NA 135, K 3.2 (L), CL 96 (L), CO2 30.6, BUN 1
	Jose Church, M.D. /ray DD: 01/18/20 DT: **01/19/:0** DV: 01/18/20

De-identification of patient notes with recurrent neural networks
Dernoncourt F, Lee JY, Uzuner O, Szolovits P
JAMIA 24(3), 2017, 596–606

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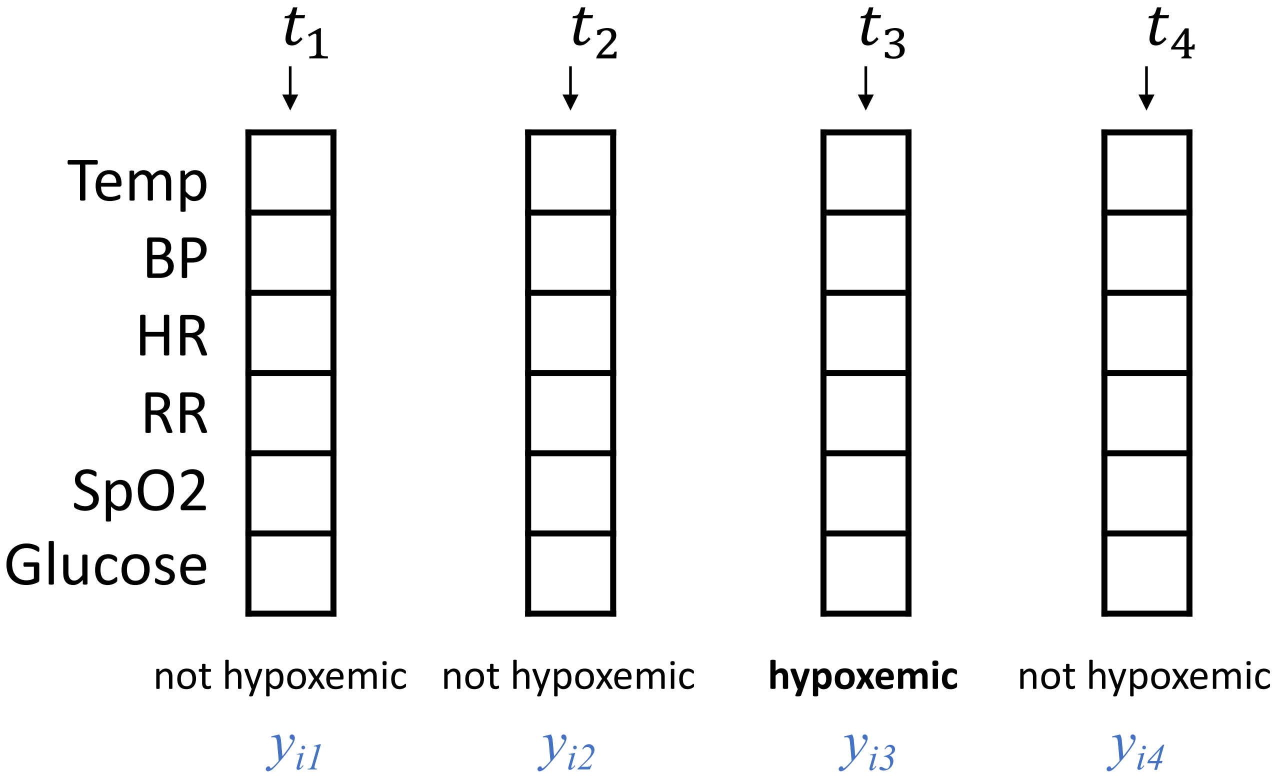
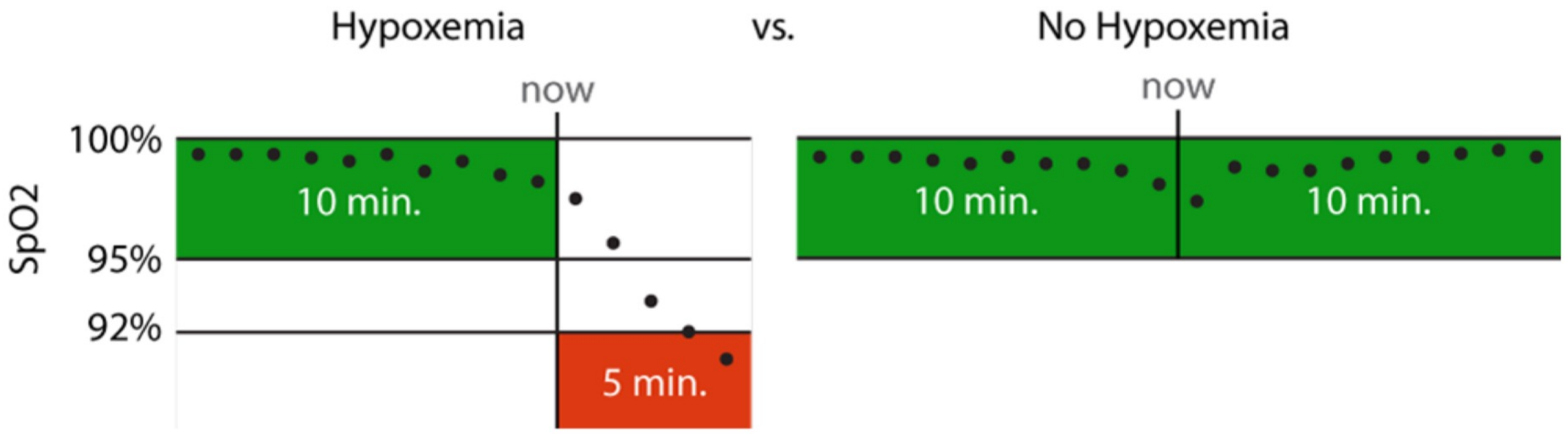


Hypoxemia Prediction during Surgery

Real-time Prediction Task:

- hypoxemia (yes/no) in the next 5 minutes
- based on data from the Anesthesia Information Management System
- static features + real-time features collected up to that time point

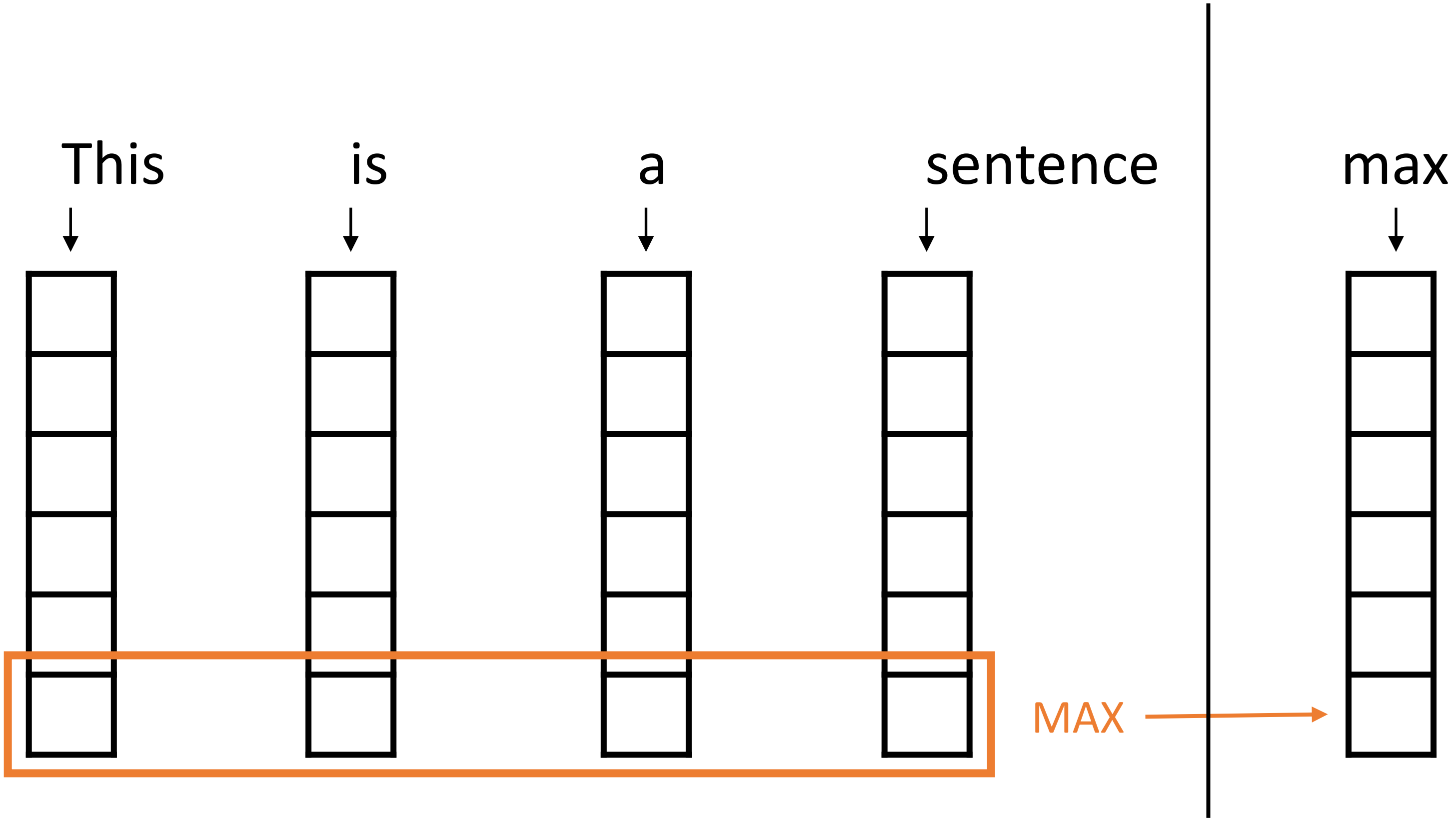


Problem 1: Sequences Vary in Length

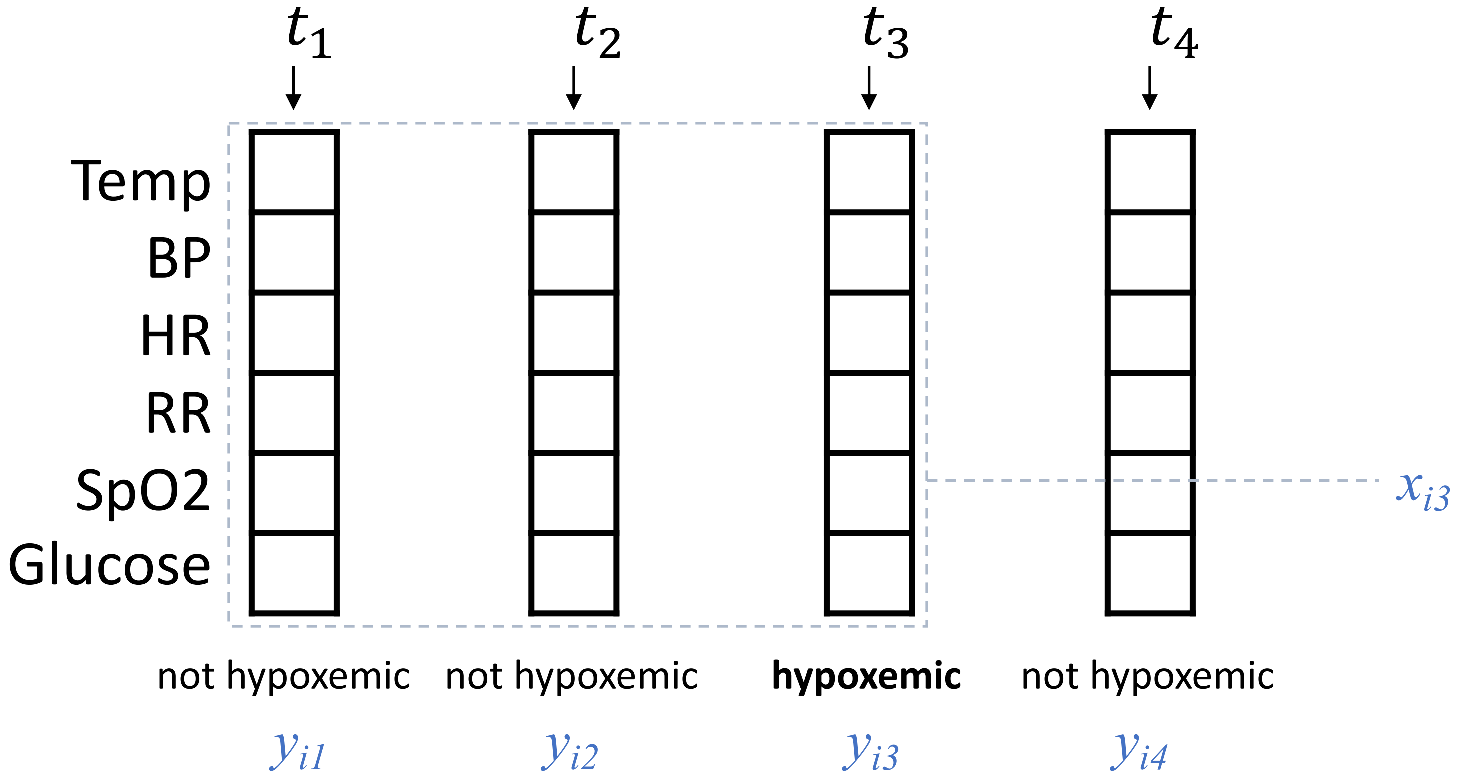
- Sentences/text have different # words
- Time-series have different # measurement times

- <u>Solution 1:</u> aggregate over words/time points

VSWEM allows us to convert a variable-length sentence to a fixed-length feature vector



Similarly, we can aggregate measurements in a time-series



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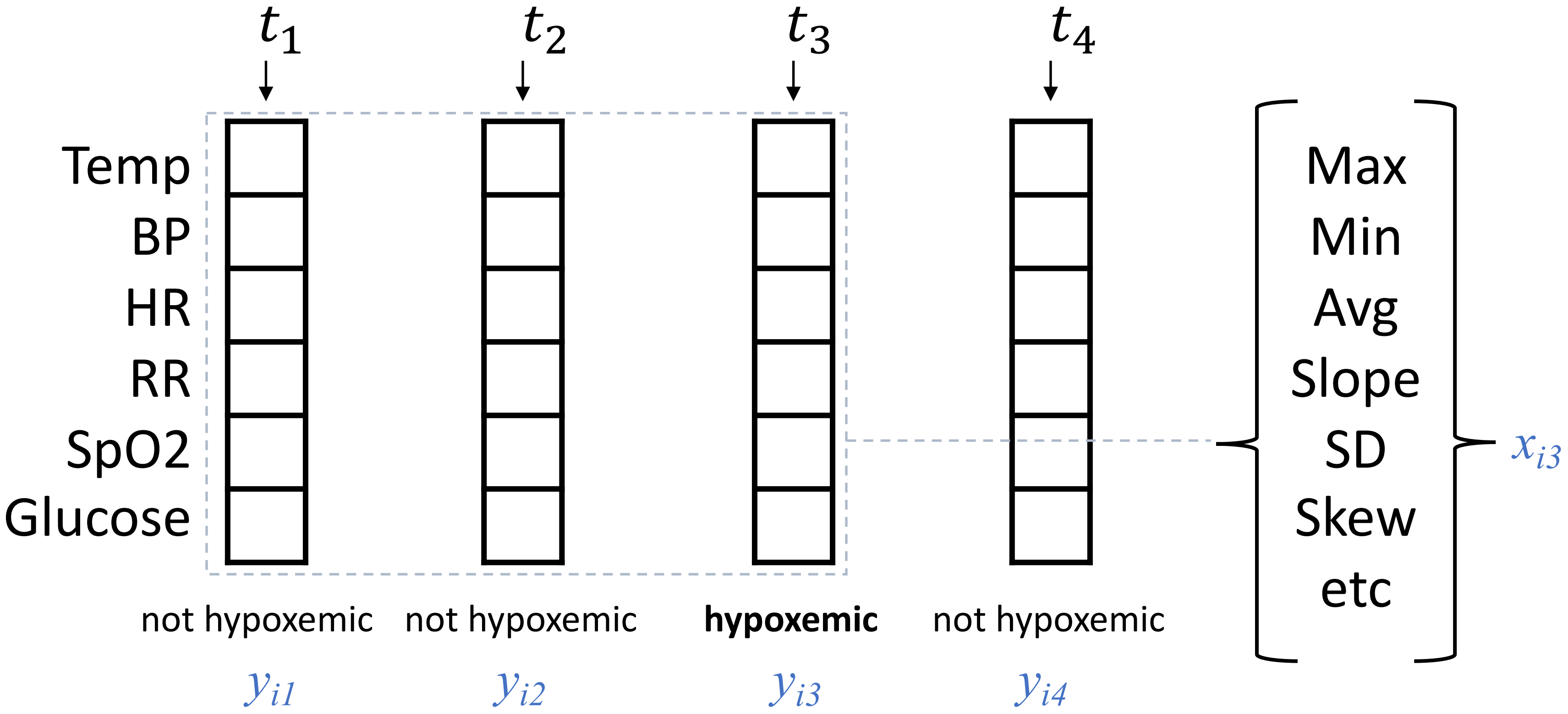
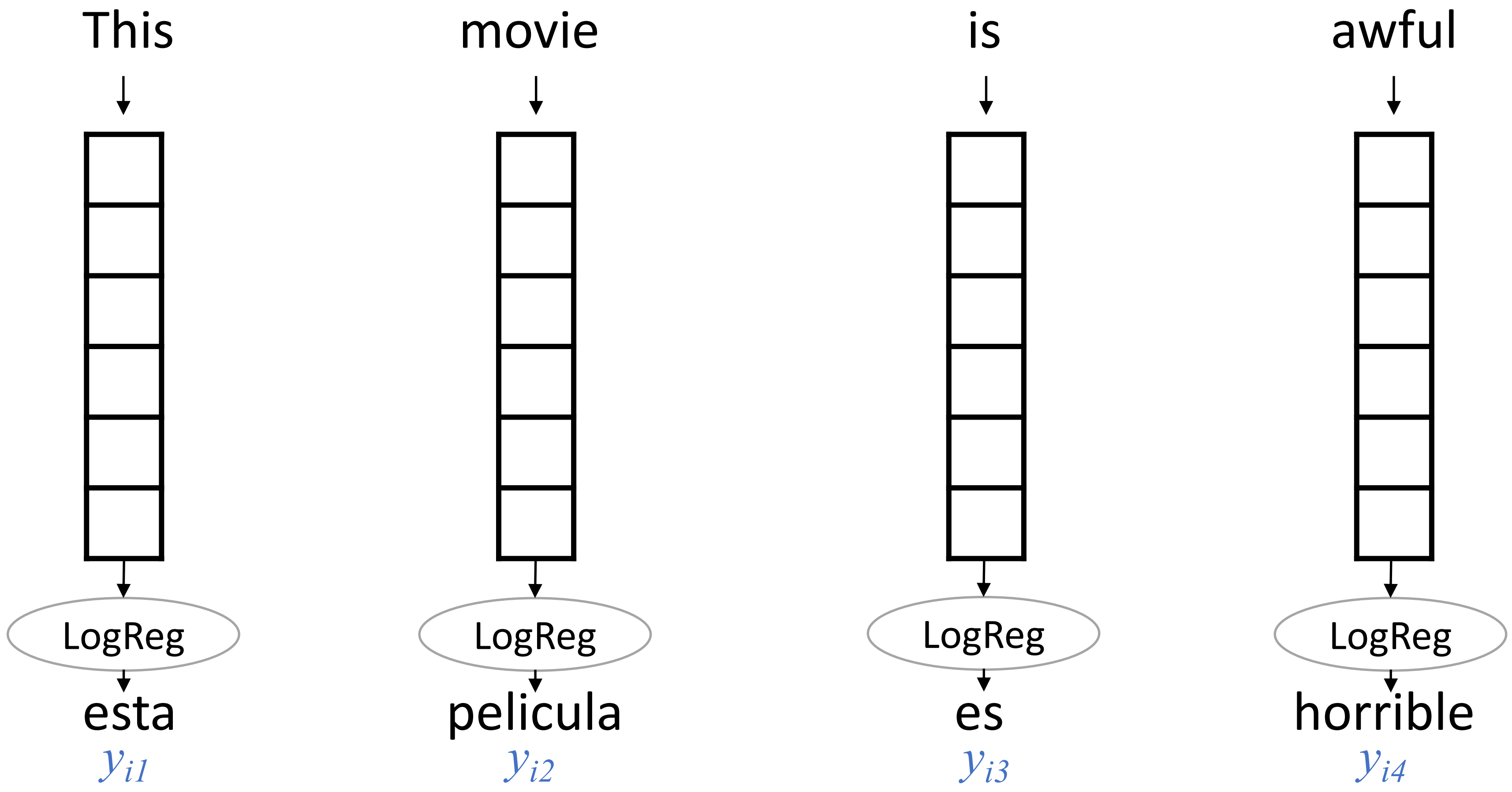


Problem 2: Interpret Words or Measurements *in Context*

- A sentence is more than the average (or max) of its words
- A time-series is more than the average / min / max / SD of individual measurements
- <u>Deep learning</u>: we *learn* what's important about the sequence rather than choosing features or summary stats

Recurrent Neural Networks

Predict a label associated with each word



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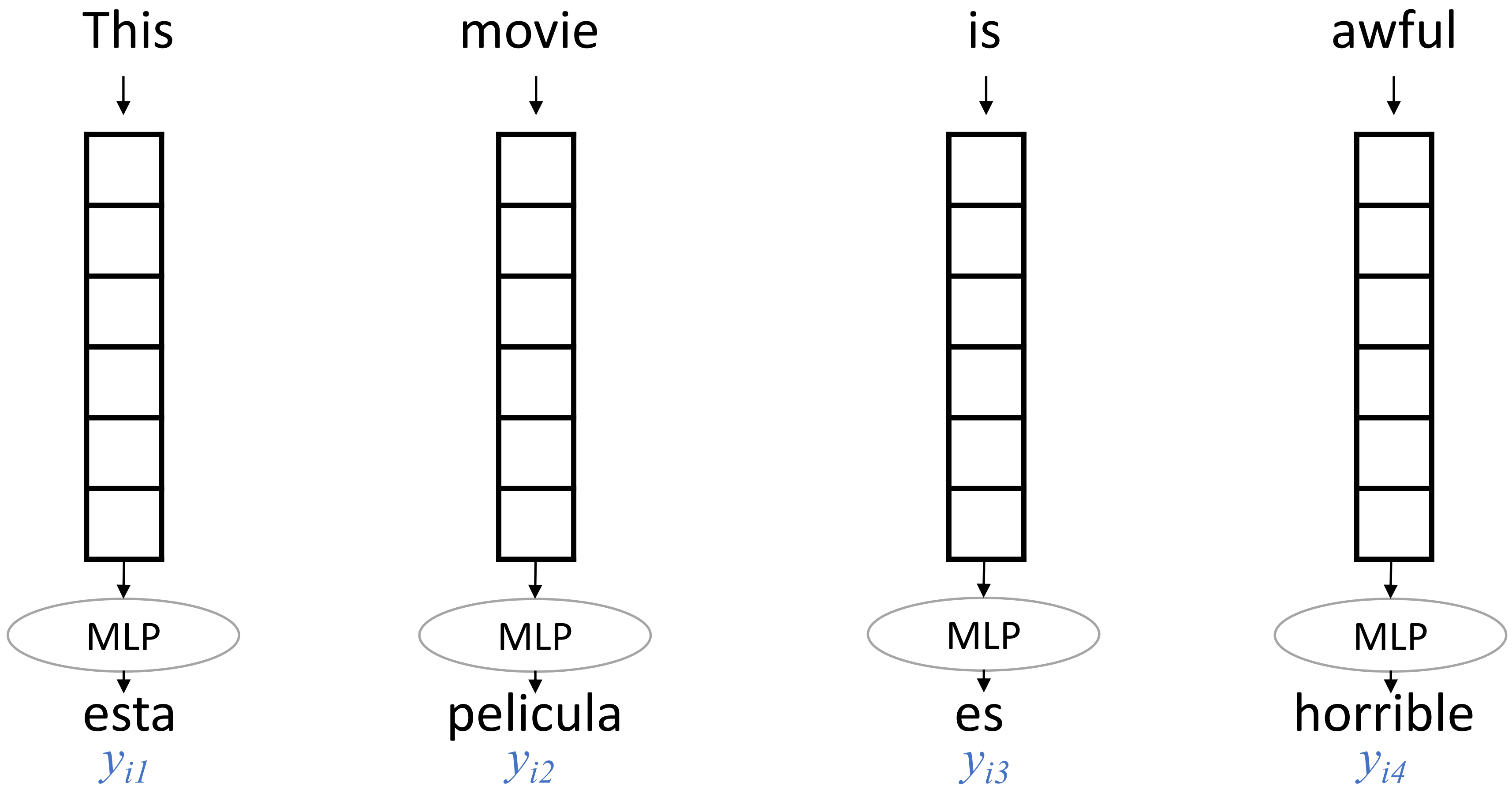
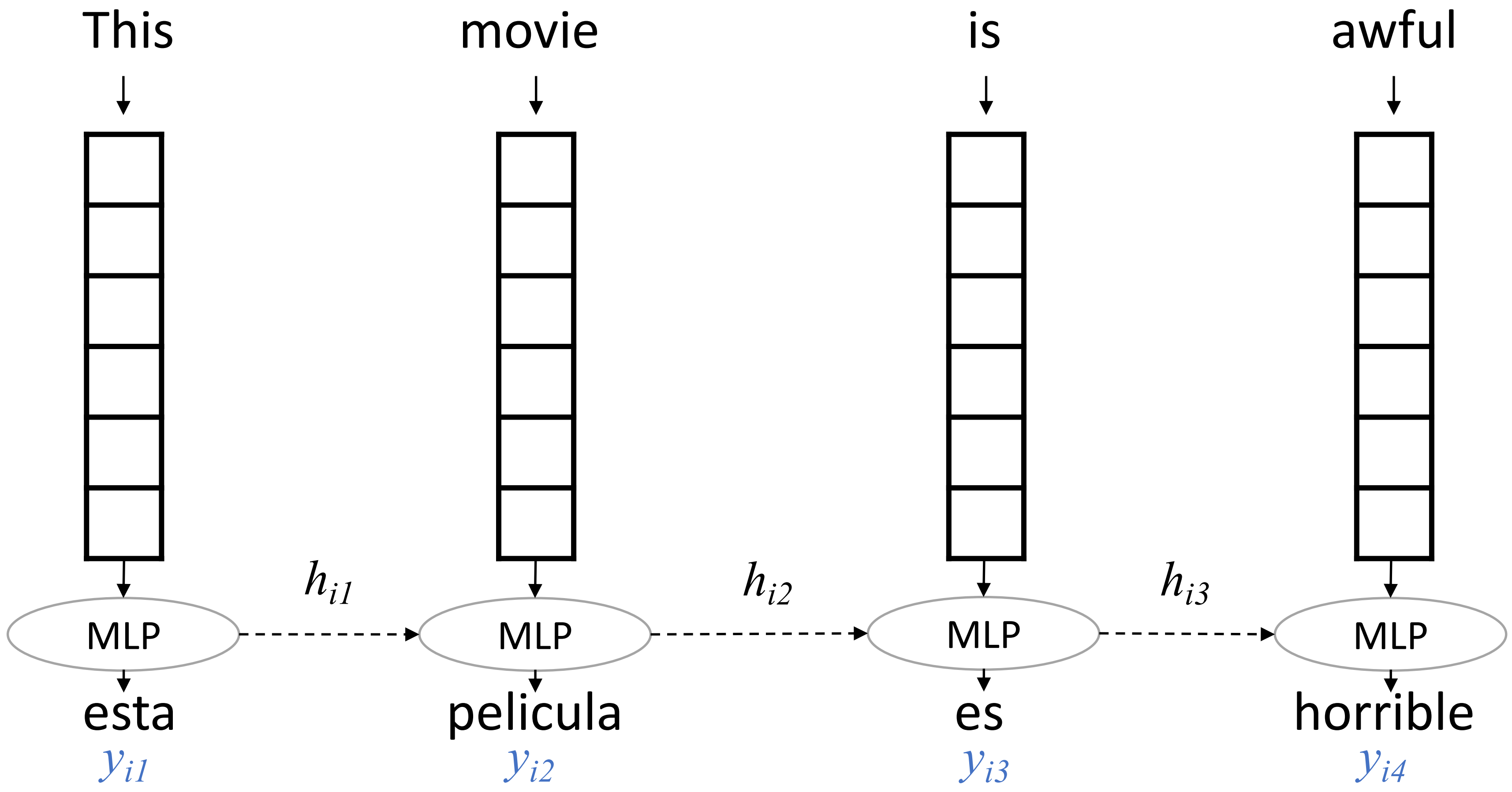
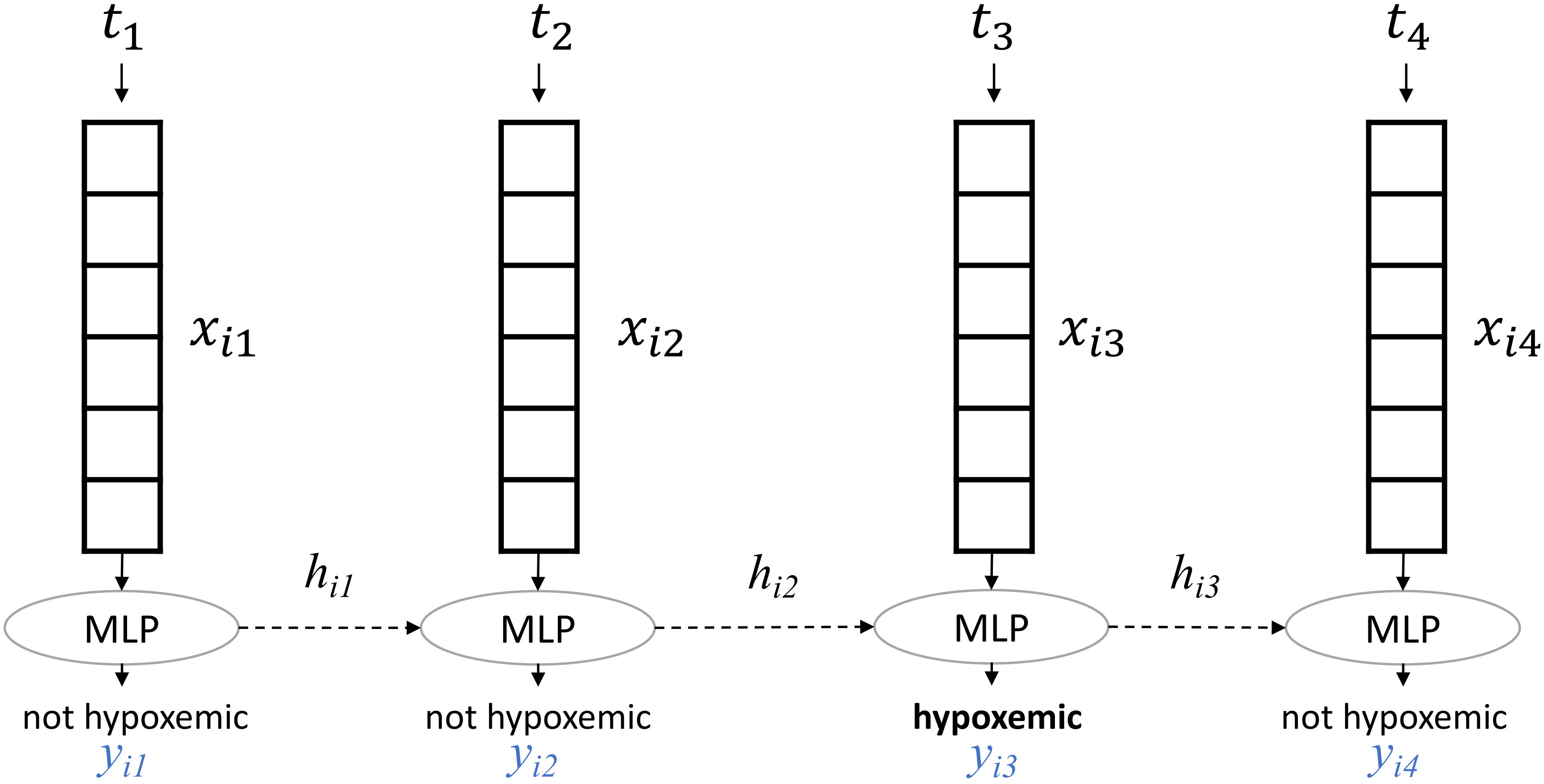


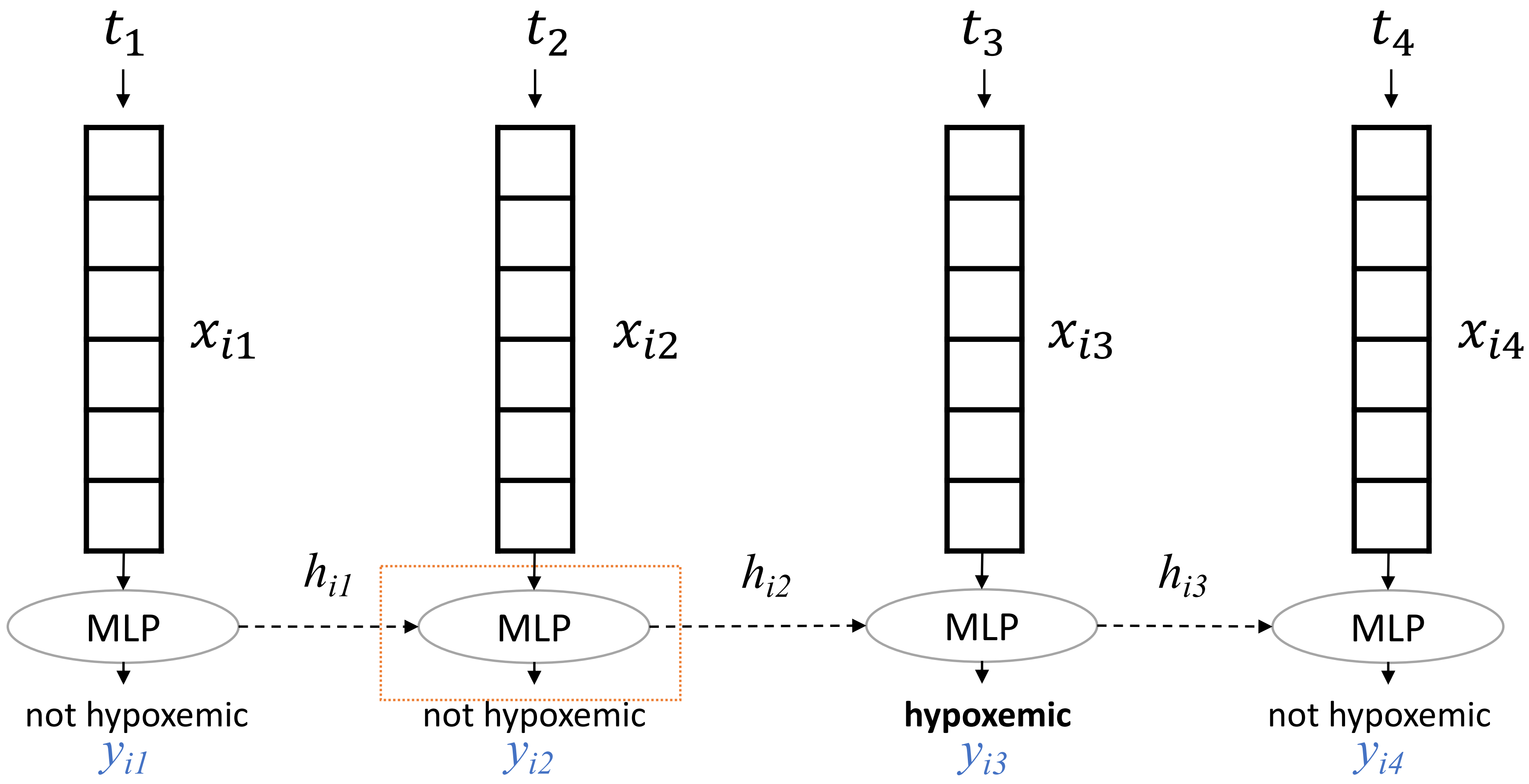
Transfer *relevant* information about earlier words



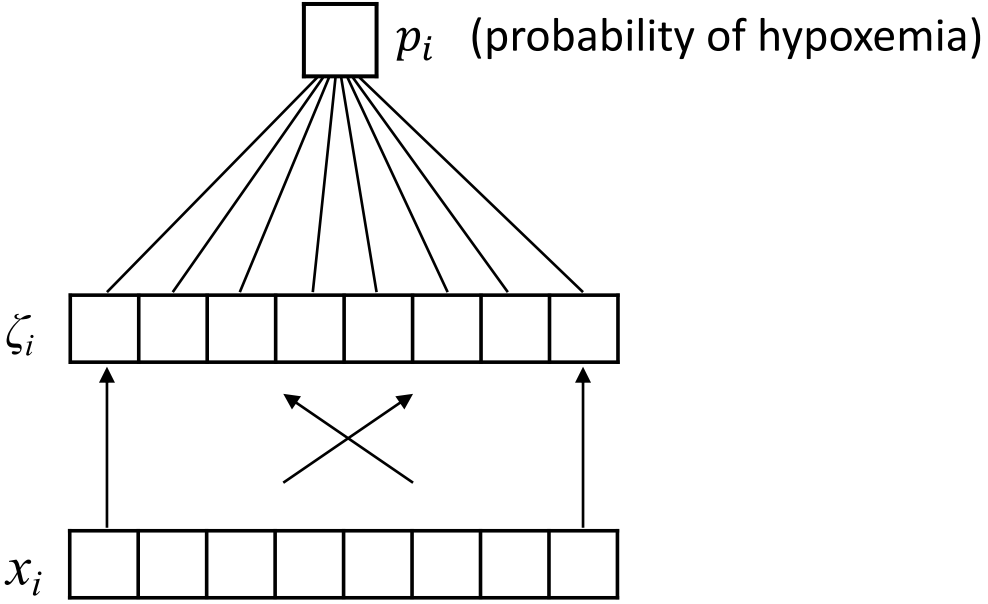
Transfer *relevant* information about earlier values



Transfer *relevant* information about earlier values



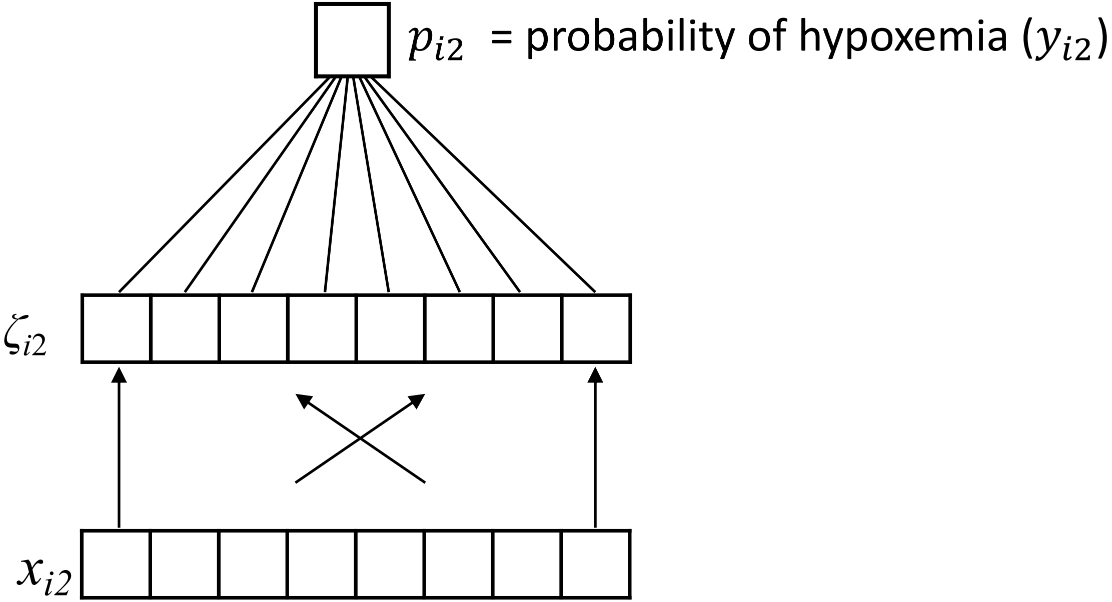
Back to Lecture 1…



Since they are neither an input nor an output, the features ζ are said to be a "hidden" layer

- Instead of predicting p_i directly from our feature vector x, introduce a vector of **"latent" features** ζ (zeta) that we will use to predict p_i

- Think of ζ as a <u>learned representation</u> that is useful for predicting *p*



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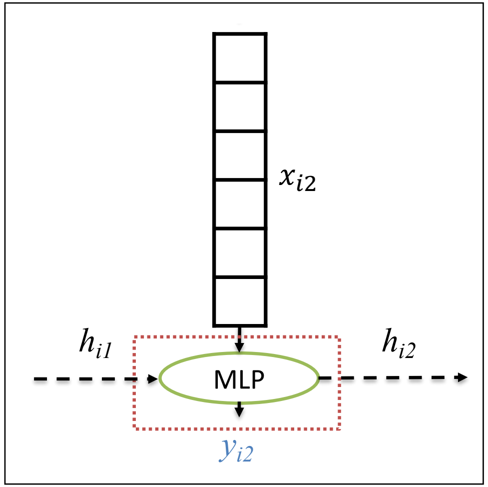
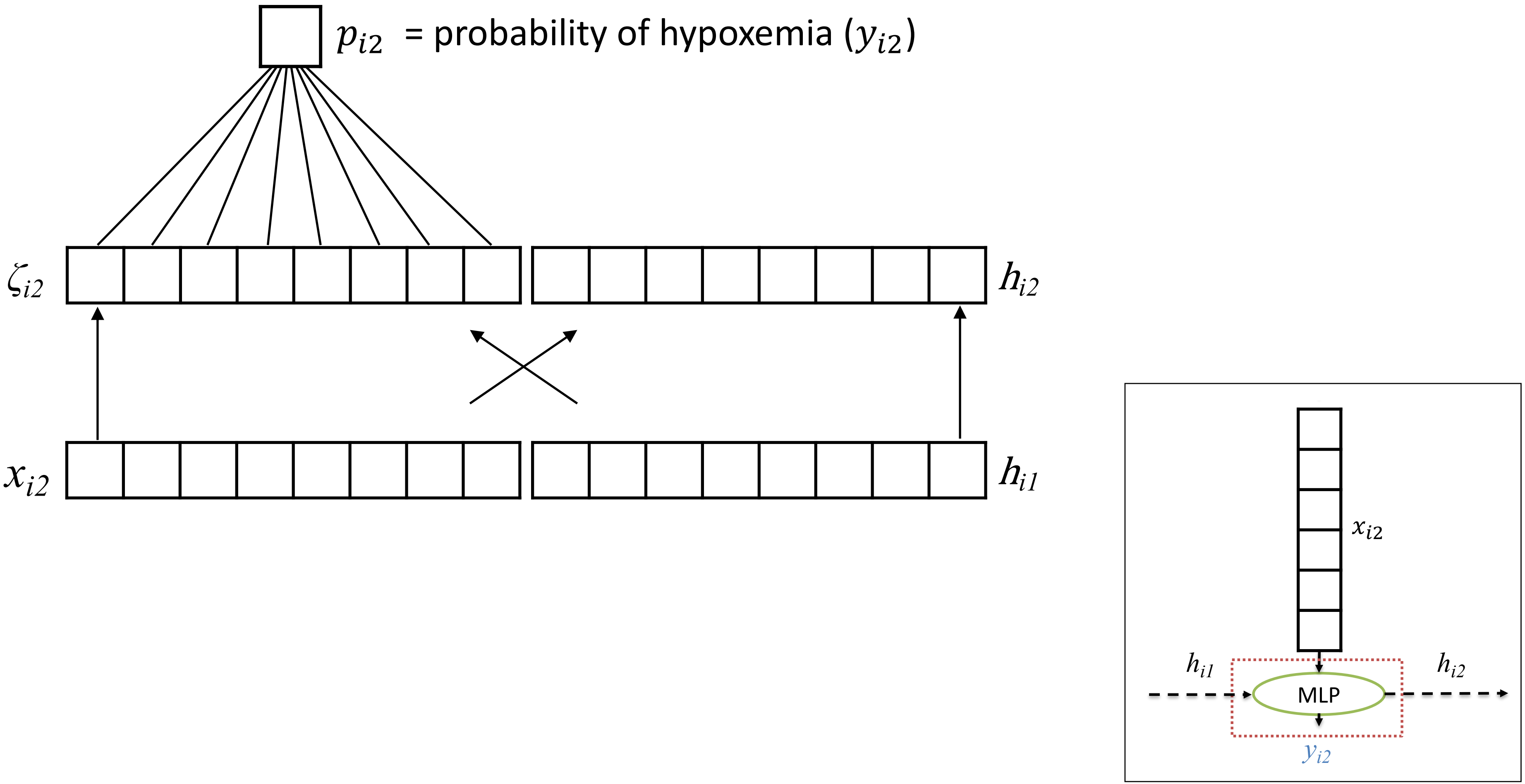
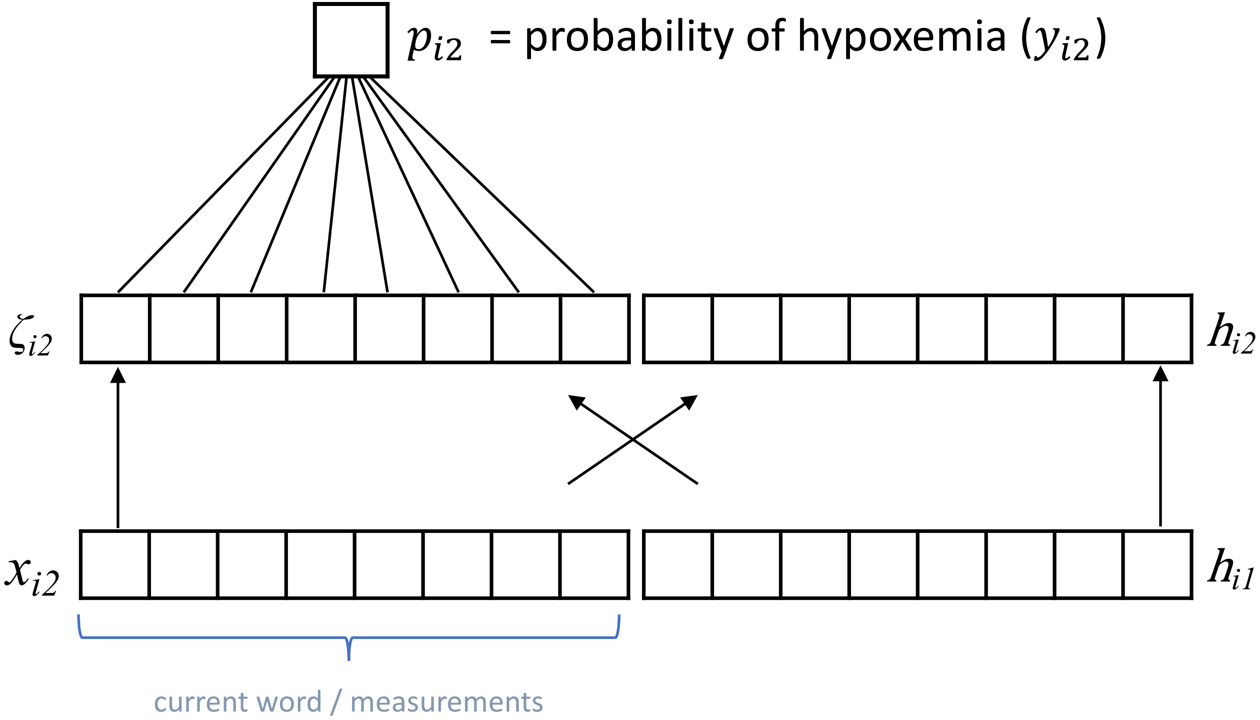
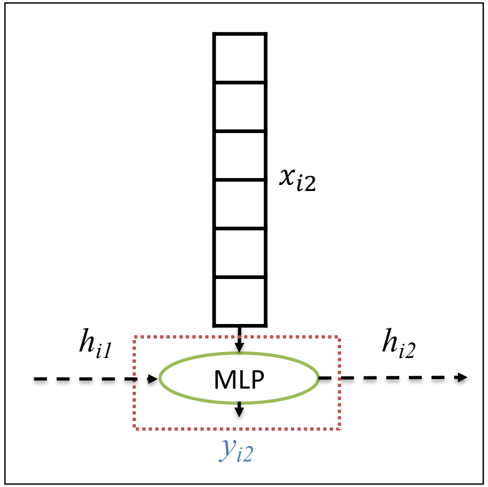
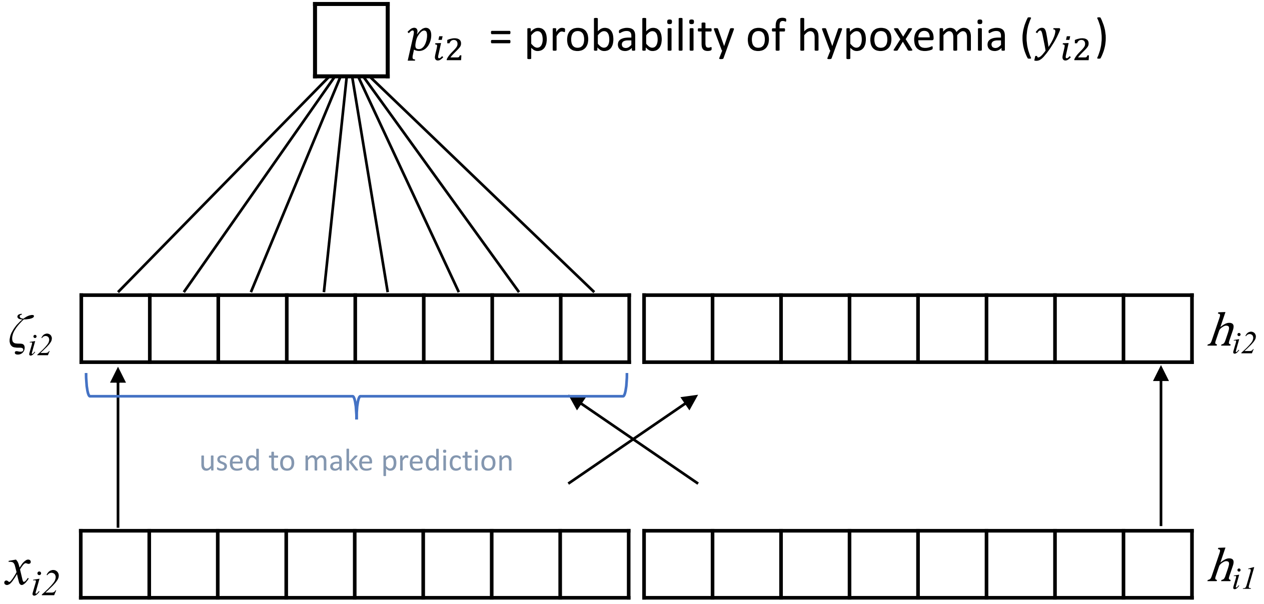




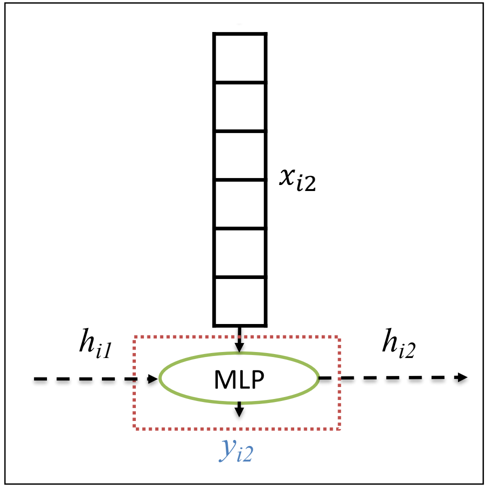
p_{i2} = probability of hypoxemia (y_{i2})
ζ_{i2}
h_{i2}
x_{i2}
h_{i1}
x_{i2}
h_{i1}
MLP
h_{i2}
y_{i2}


p_{i2} = probability of hypoxemia (y_{i2})
ζ_{i2}
h_{i2}
x_{i2}
h_{i1}
current word / measurements

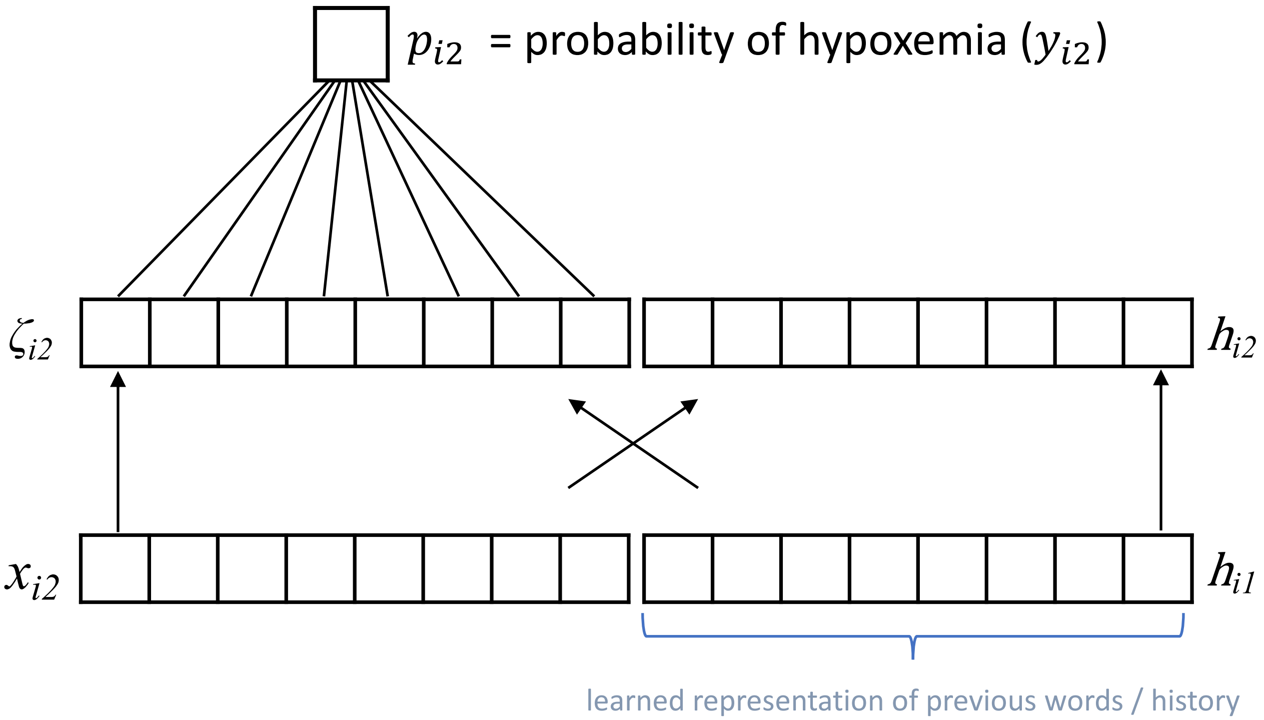

x_{i2}
h_{i1}
MLP
h_{i2}
y_{i2}

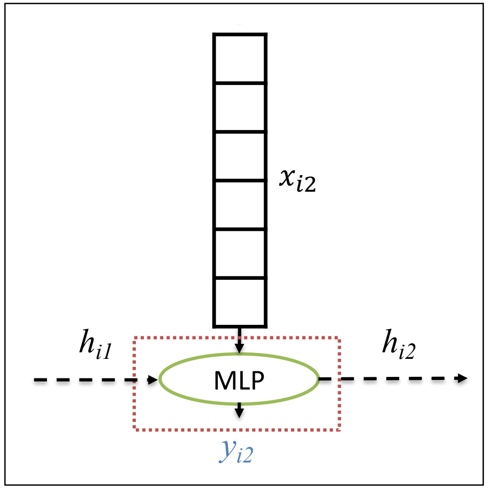


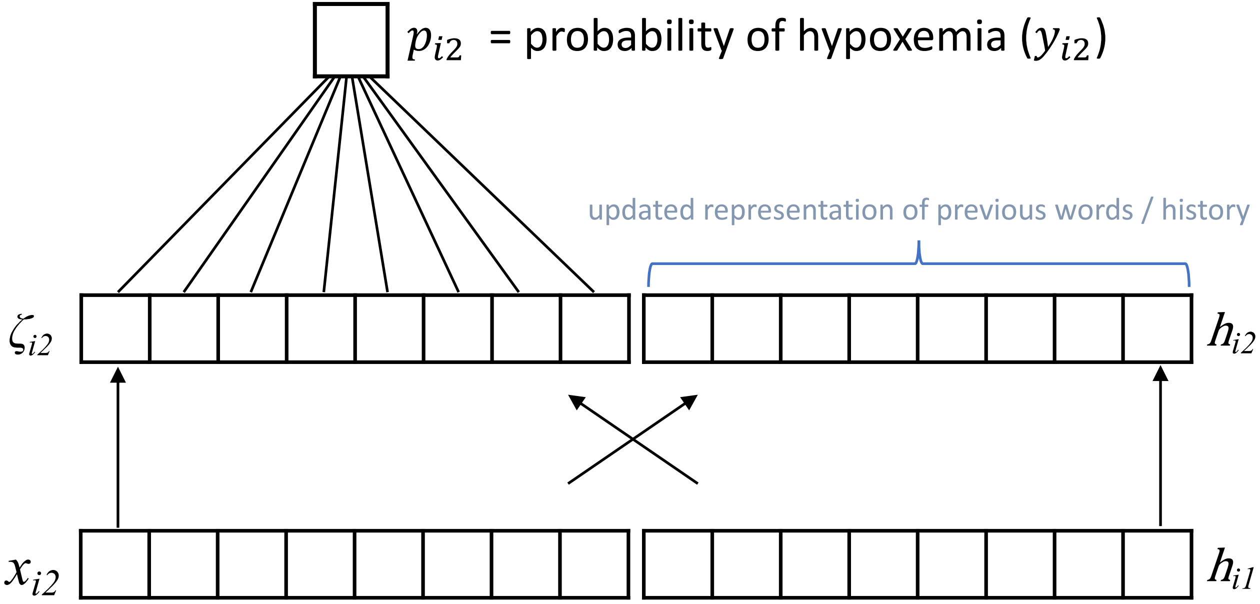
p_{i2} = probability of hypoxemia (y_{i2})
ζ_{i2}
h_{i2}
used to make prediction
x_{i2}
h_{i1}

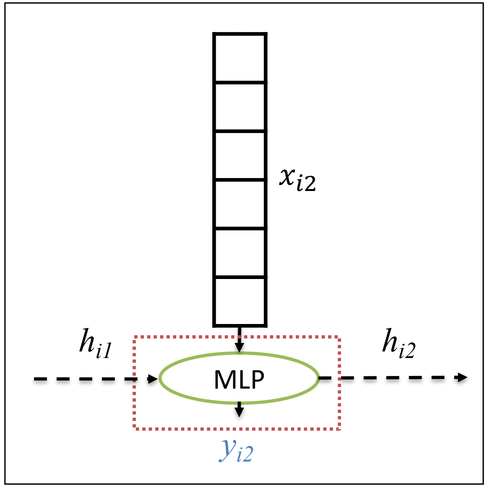


x_{i2}
h_{i1}
h_{i2}
MLP
y_{i2}

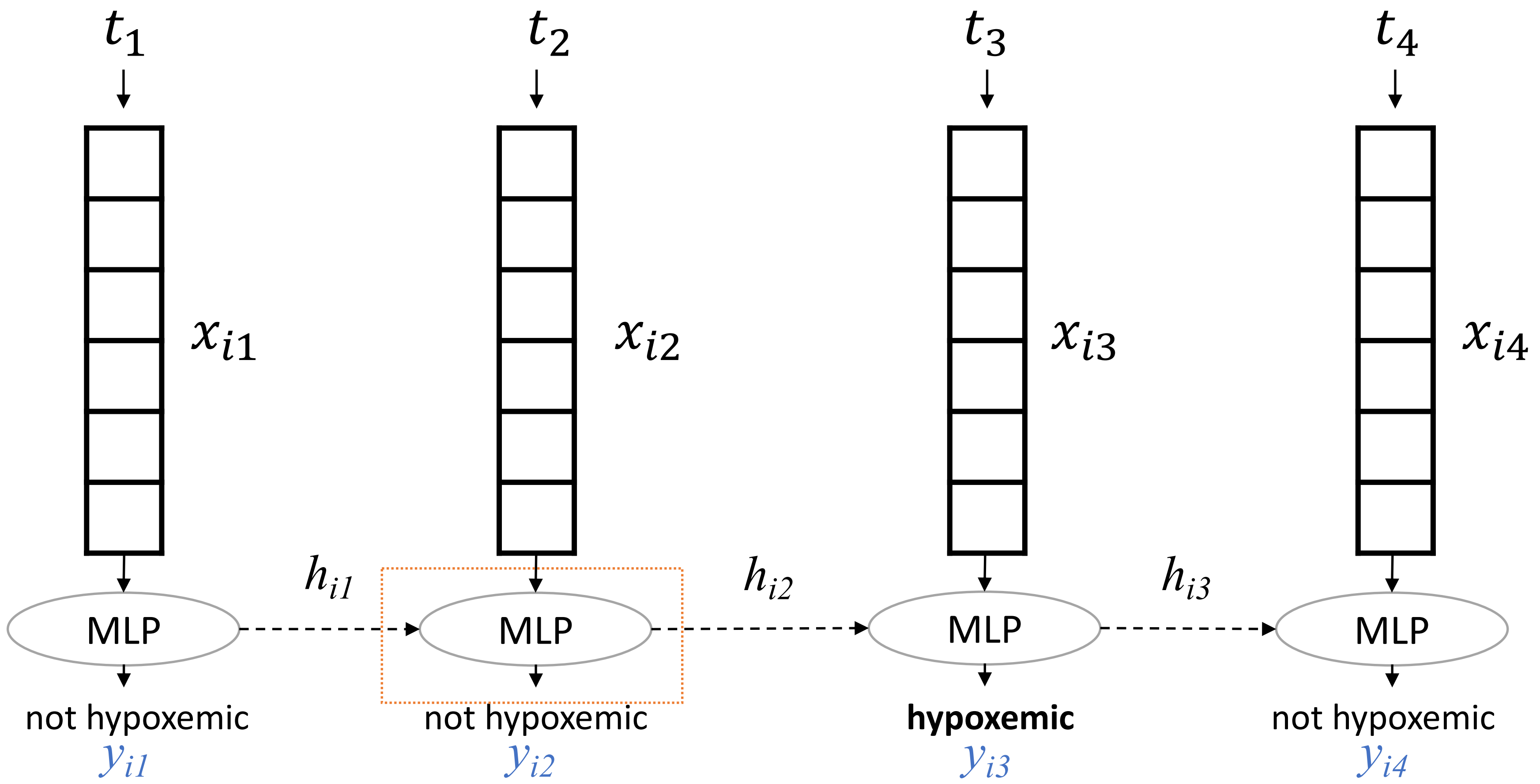

p_{i2} = probability of hypoxemia (y_{i2})
ζ_{i2}
h_{i2}
x_{i2}
h_{i1}
learned representation of previous words / history


x_{i2}
h_{i1}
MLP
h_{i2}
y_{i2}

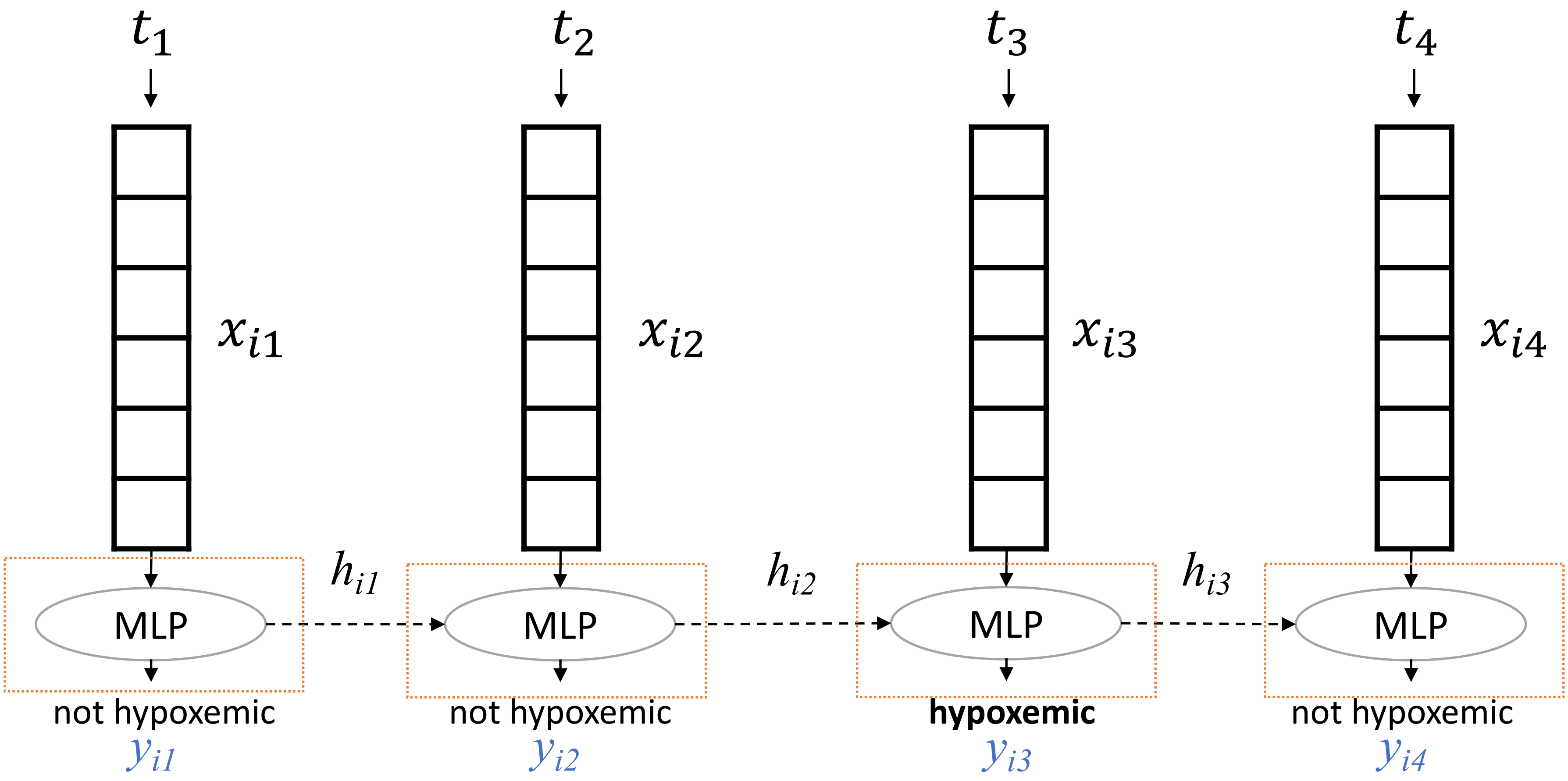

p_{i2} = probability of hypoxemia (y_{i2})
updated representation of previous words / history
ζ_{i2}
h_{i2}
x_{i2}
h_{i1}


x_{i2}
h_{i1}
h_{i2}
MLP
y_{i2}

We *learn* what's important about previous values



Recurrent MLP (NN): these are all the same / have same weights



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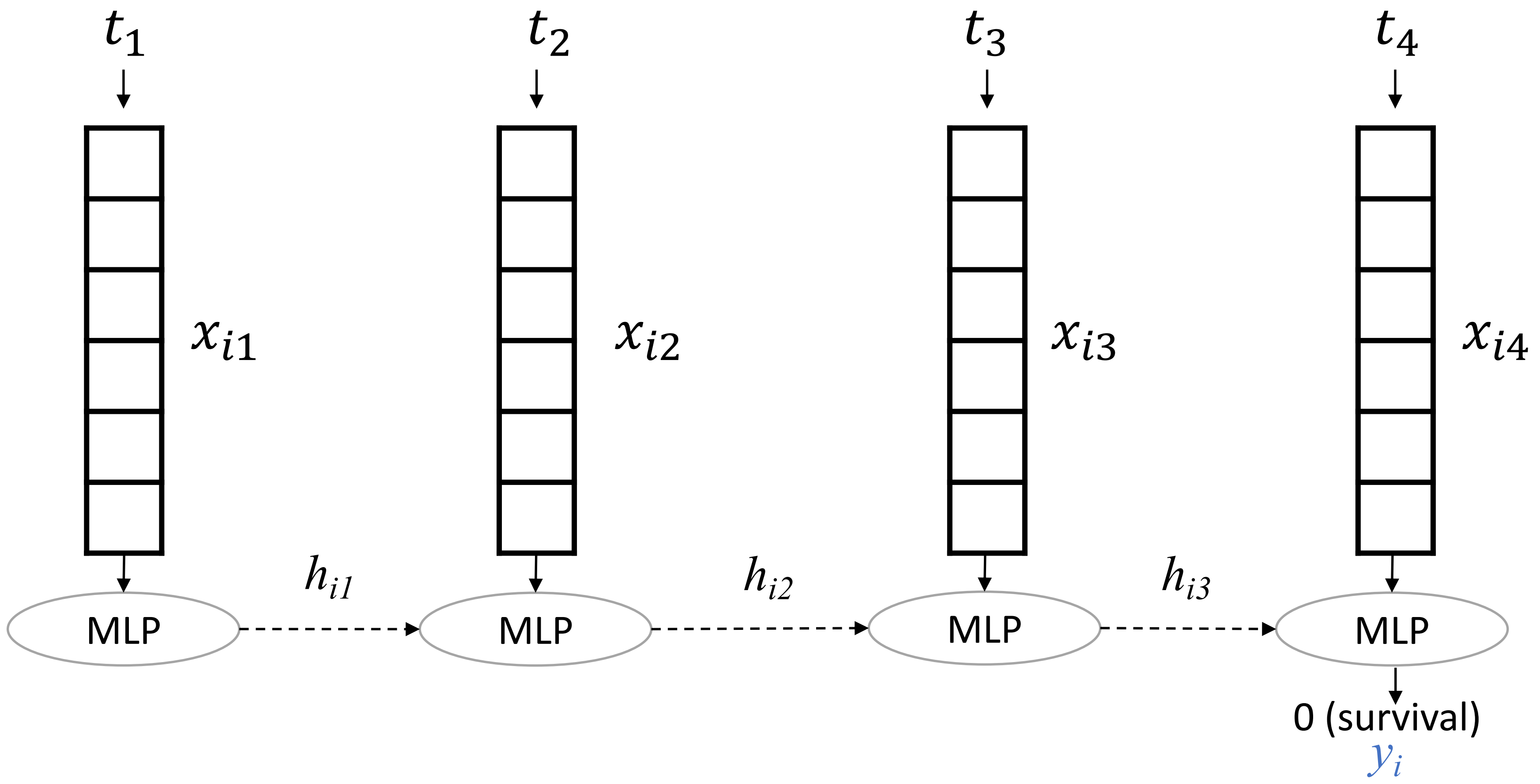

Hypoxemia Prediction: Use learned representation of previous measurements

Real-time Prediction Task:
- hypoxemia (yes/no) in the next 5 minutes
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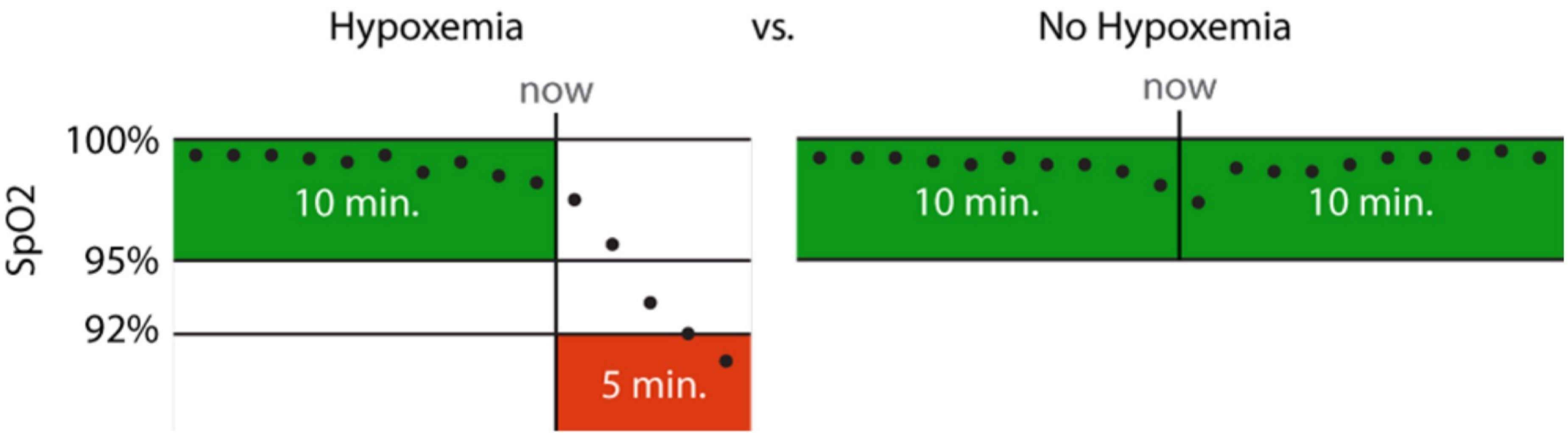

Common RNN Variants

- Gated Recurrent Unit (GRU)
- Long Short Term Memory (LSTM)
- Bidirectional RNNs
  - Look at previous words and upcoming words
  - Usually not appropriate for time-series

Deidentification of Patient Notes

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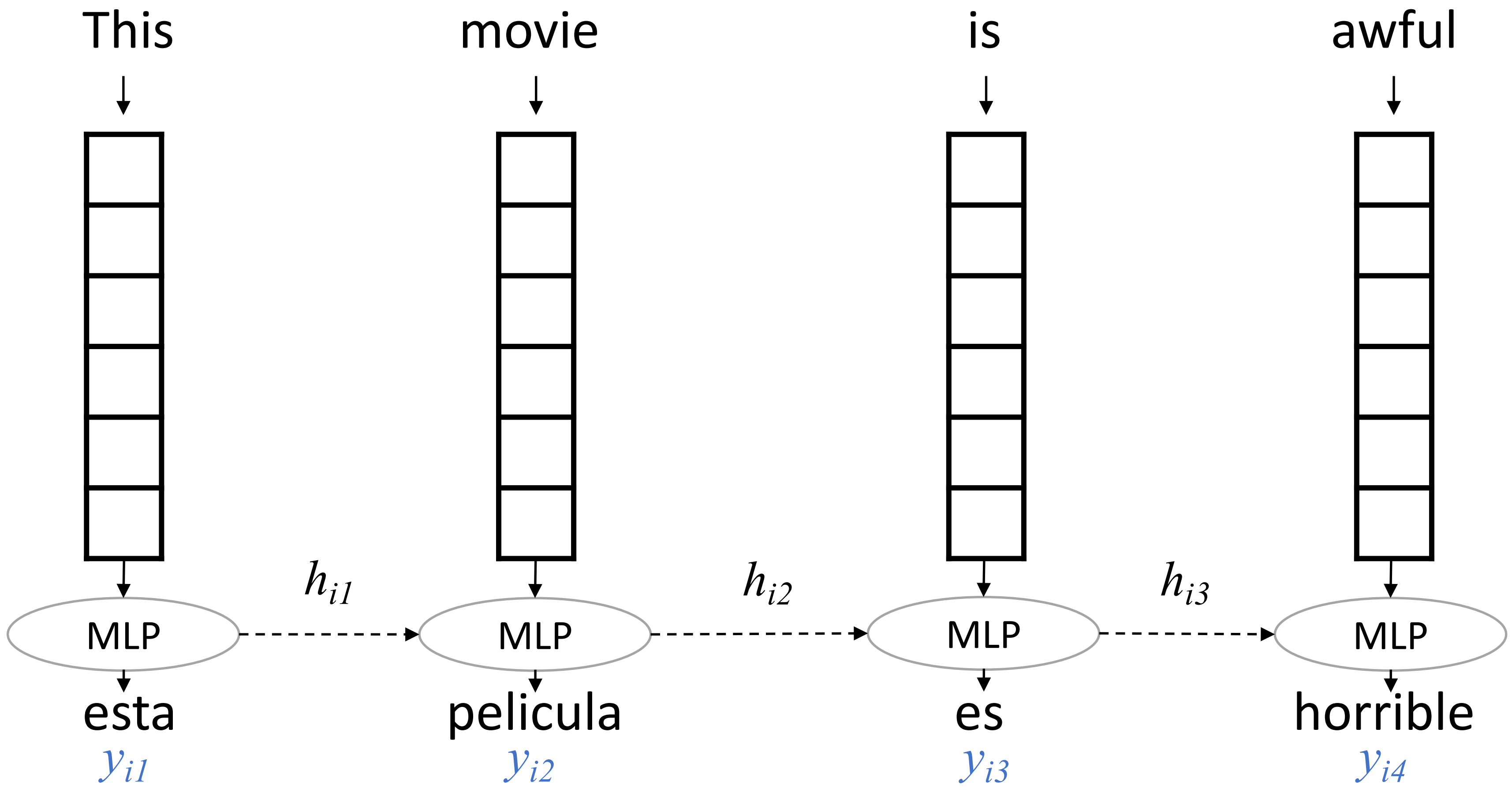

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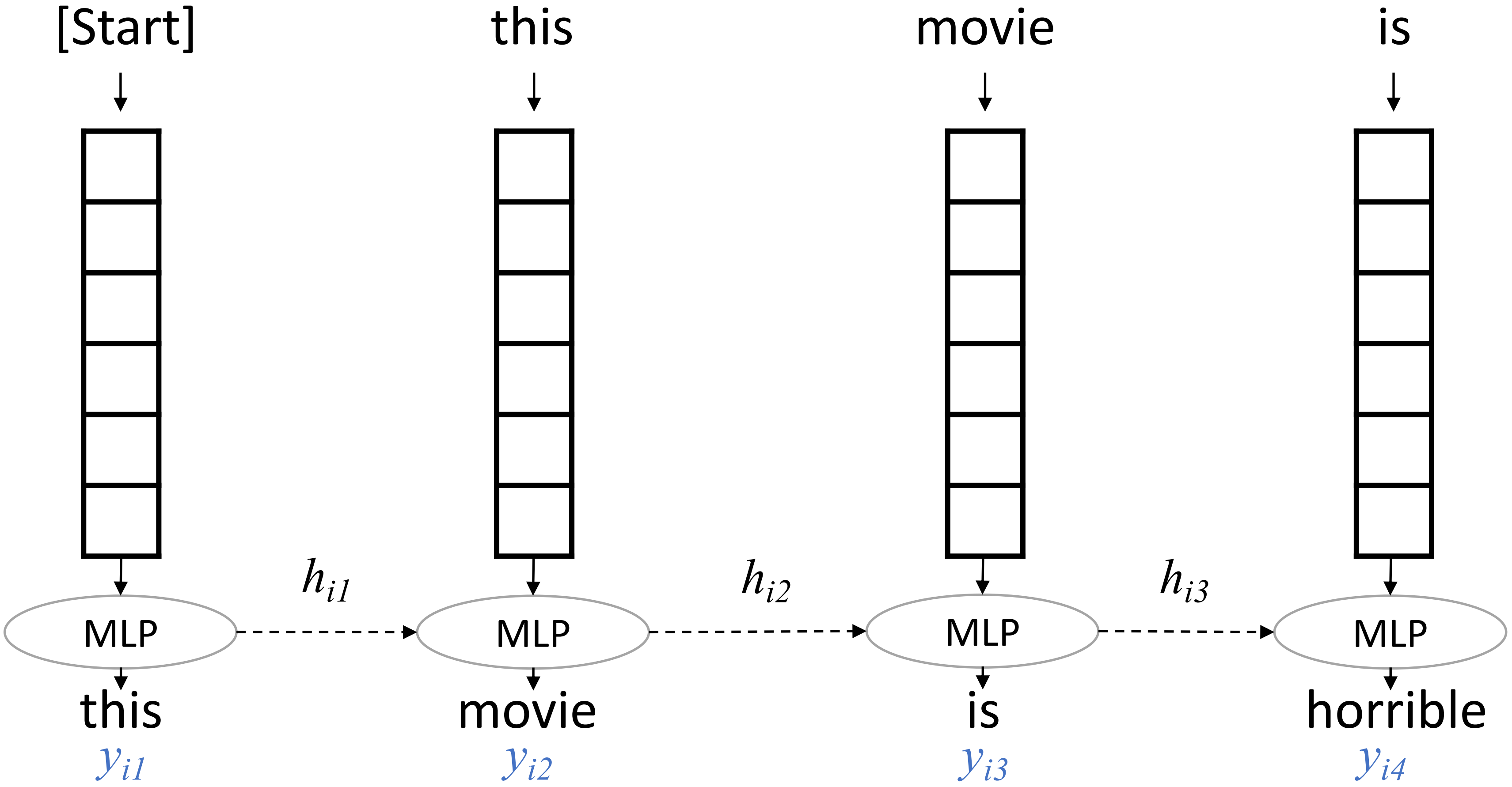
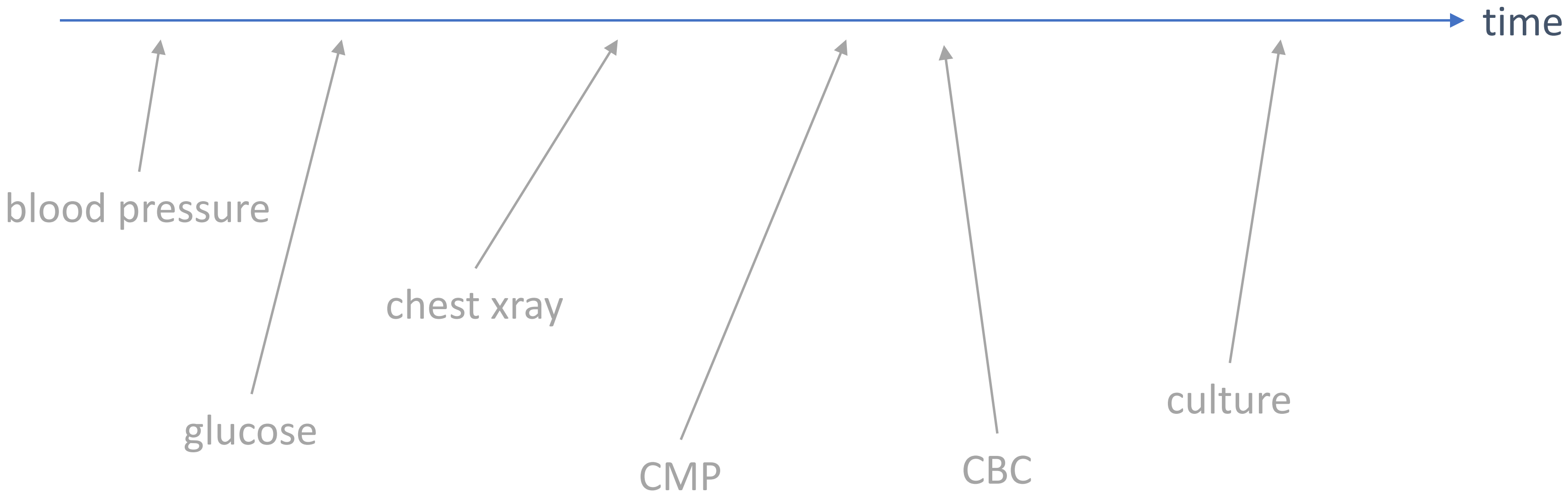


Working with irregularly spaced measurements

Still Another Problem…

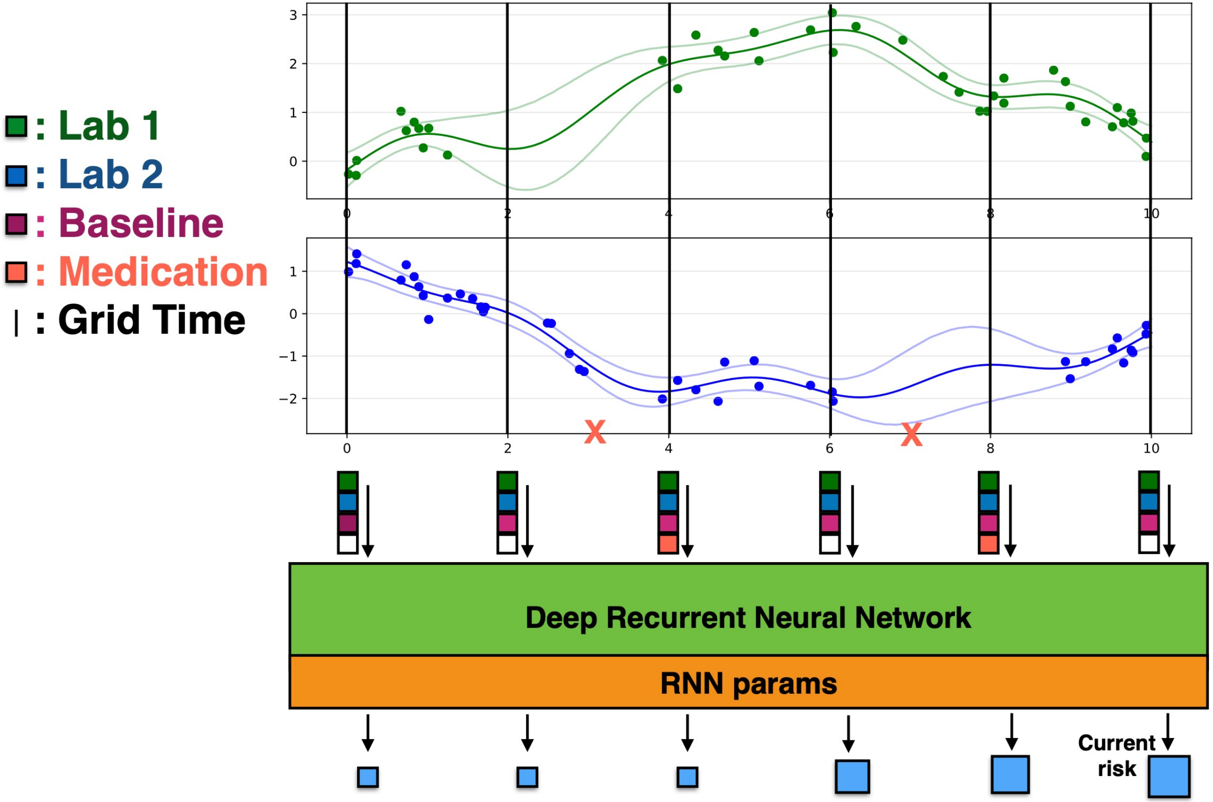
- All of this supposes we have a nice grid of complete measurements
- For text, we do have this.
- But in real-world time-series data – and particularly in healthcare – we usually have incomplete sets of measurements at irregular intervals
- How do we use an RNN?

Measurements on the Wards…



This is a major difficulty!

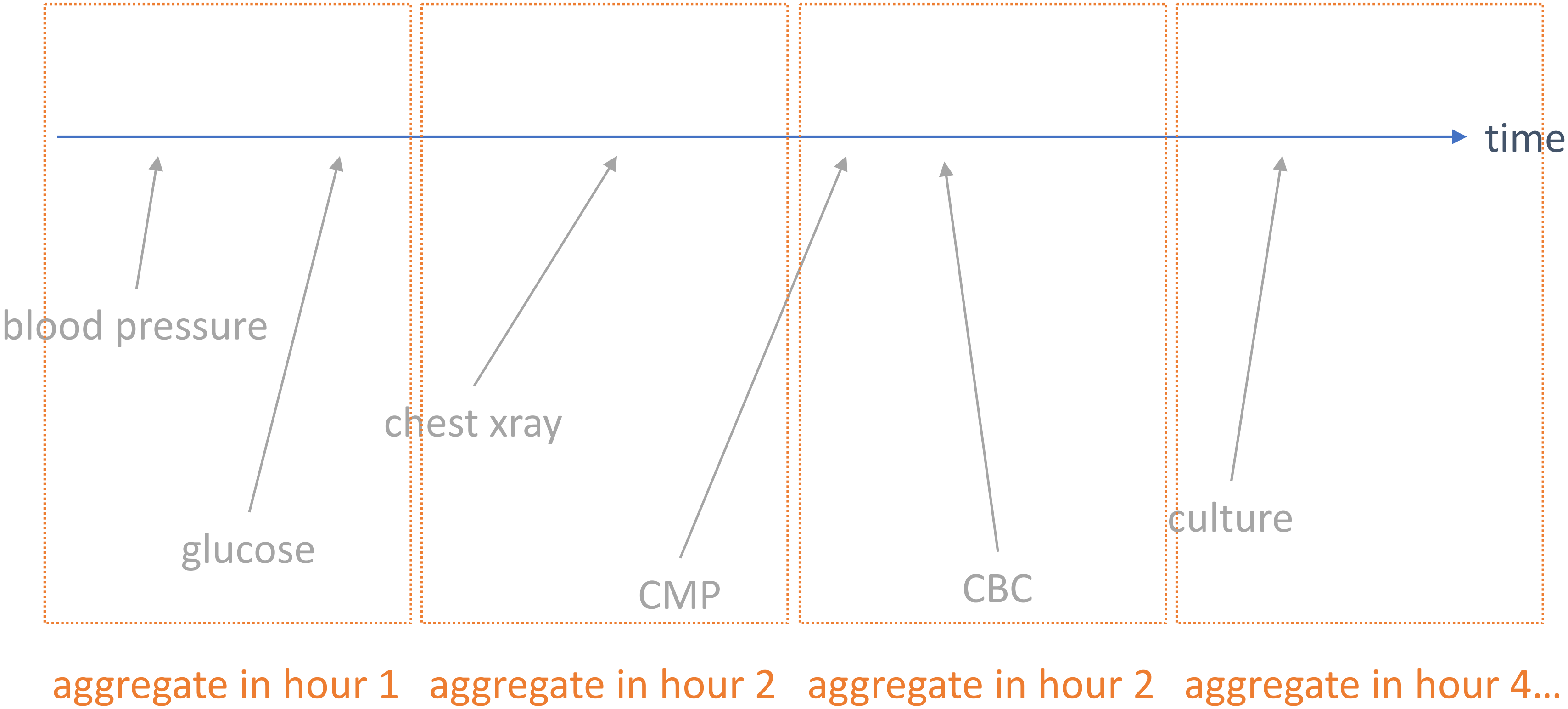
DIHI Sepsis Watch



<- Use GP regression to predict measurements at regular intervals

<- Predict sepsis risk using an RNN

Simplest Method...



In the EHR, measurements are highly “sparse”

- Many more missing measurements than non-missing
- Consider diagnosis codes, procedure codes, uncommon labs, etc
- We want to learn from these measurements, but most patients don’t have them

Conclusions

- Often, aggregating measurements/features is sufficient
- RNNs allow us to learn a representation of earlier measurements (or words) that helps us make predictions. But, in can be time and memory intensive to train.
- The RNN is just that: a recurrent / repeating MLP block
- Sparse data (most values are missing) is common in health applications and remains very challenging