Deep Learning MSDS 631

Deep Learning and Text Data

Michael Ruddy

Questions?

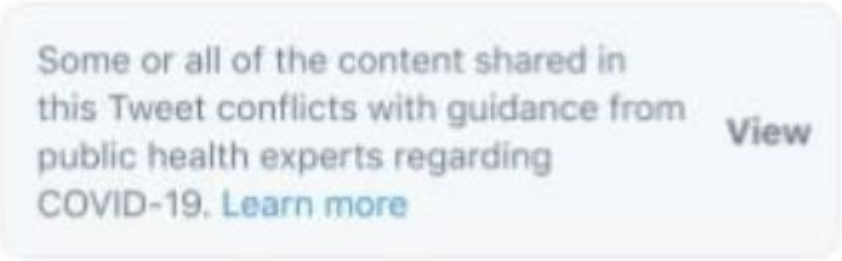
- From last lecture?
- From the lab assignment?

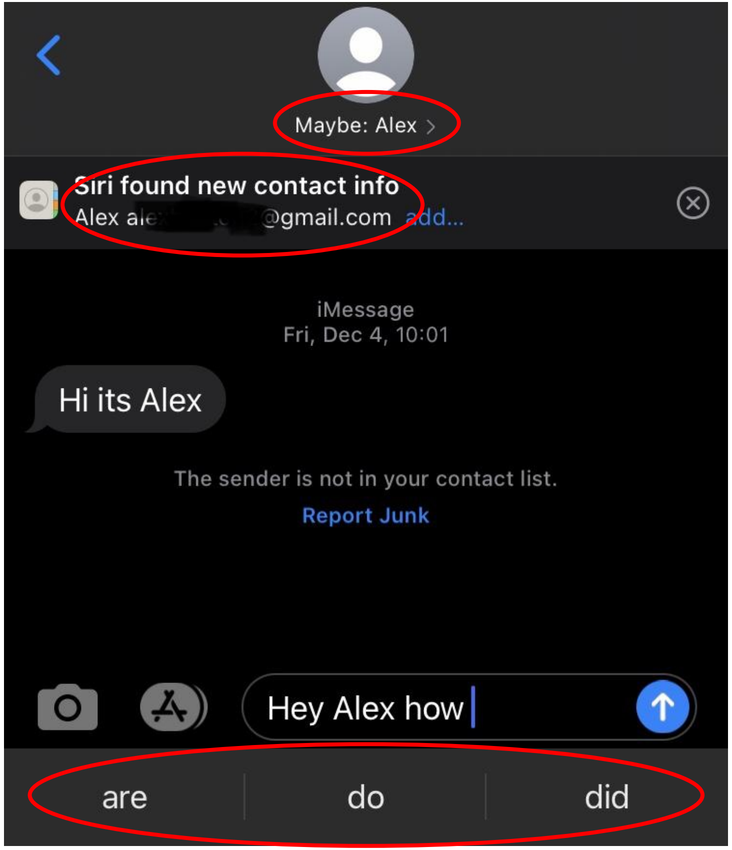
Overview

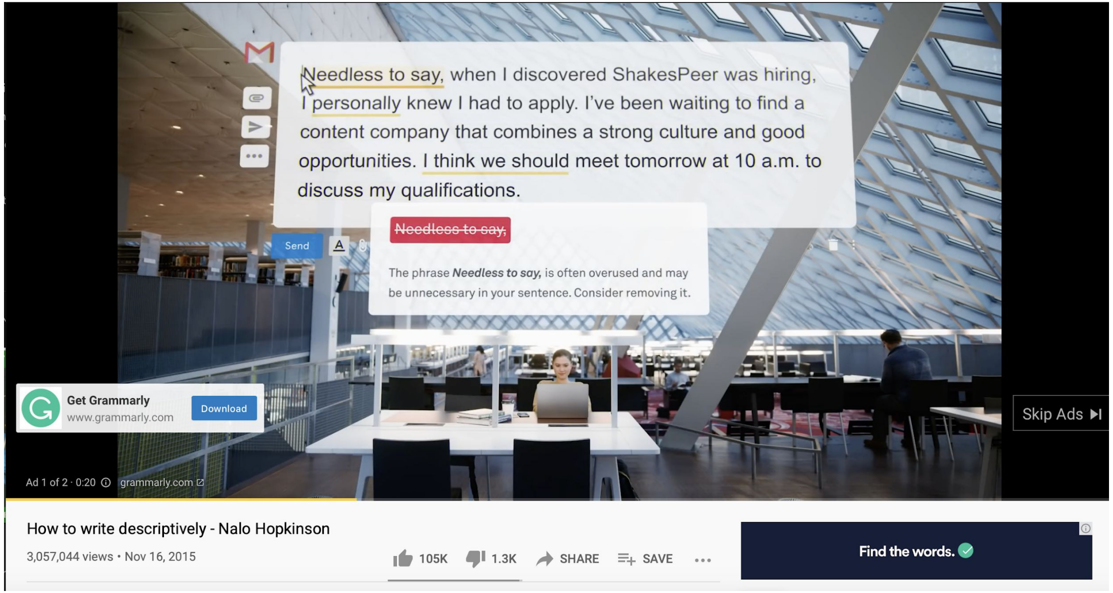
- Why Natural Language Processing (NLP)?
- Tokenization and Cleaning
- Word Embeddings
- Deep Learning and Text

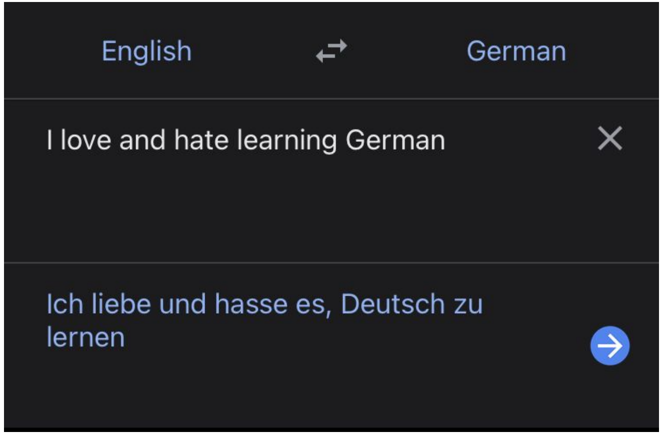
Why Natural Language Processing?

- Understand, analyze, and perform tasks using human language (through text).
- Example Tasks:
    - Sentiment Analysis
    - Auto-complete
    - Translation
    - Question answering
    - Conversation?!






Needless to say, when I discovered ShakesPeer was hiring, I personally knew I had to apply. I've been waiting to find a content company that combines a strong culture and good opportunities. I think we should meet tomorrow at 10 a.m. to discuss my qualifications.
~~Needless to say,~~
The phrase Needless to say, is often overused and may be unnecessary in your sentence. Consider removing it.
Send
Get Grammarly
www.grammarly.com
Download
Skip Ads
Ad 1 of 2 · 0:20
grammarly.com
How to write descriptively - Nalo Hopkinson
3,057,044 views • Nov 16, 2015
105K
1.3K
SHARE
SAVE
Find the words.


English
German
I love and hate learning German
Ich liebe und hasse es, Deutsch zu lernen

NLP is hard!

- How to represent text as data?

$$\begin{bmatrix} 1 & .5 & 1 & 0 \\ 0 & .25 & .5 & 1 \\ 1 & .25 & 0 & 1 \\ .5 & 0 & 1 & 1 \end{bmatrix}$$

NLP is hard!

- How to represent text as data?
- Humans represent text using characters
  - Takes years to learn to read
  - Different peoples do it differently all around the world

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train

brain

head

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train → 20-18-1-9-14

brain → 2-18-1-9-14

head → 8-5-1-4

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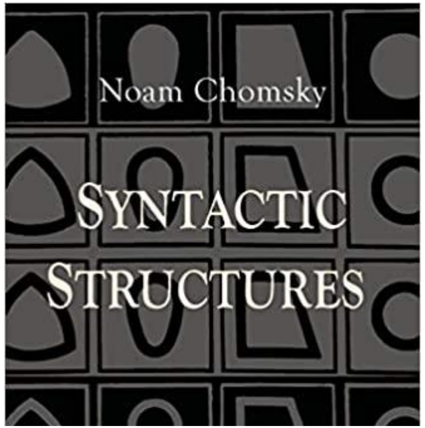

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Tokenization

- Idea: Break up text into pieces (tokens) and treat as categorical variables
  - Often these tokens are words

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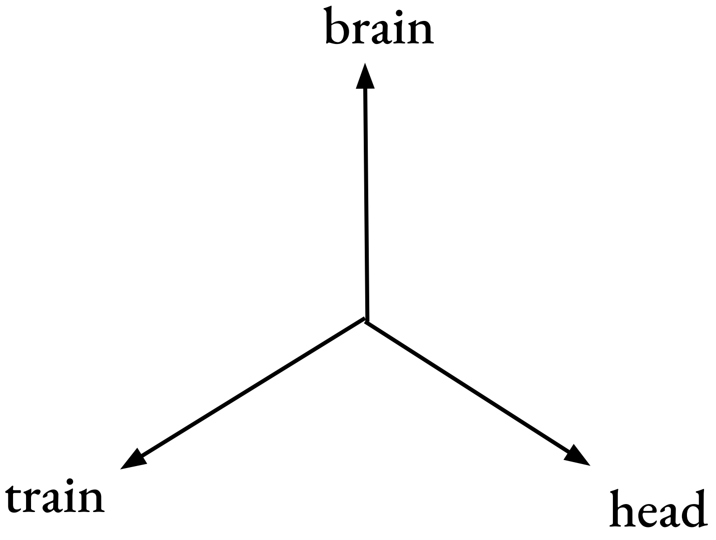
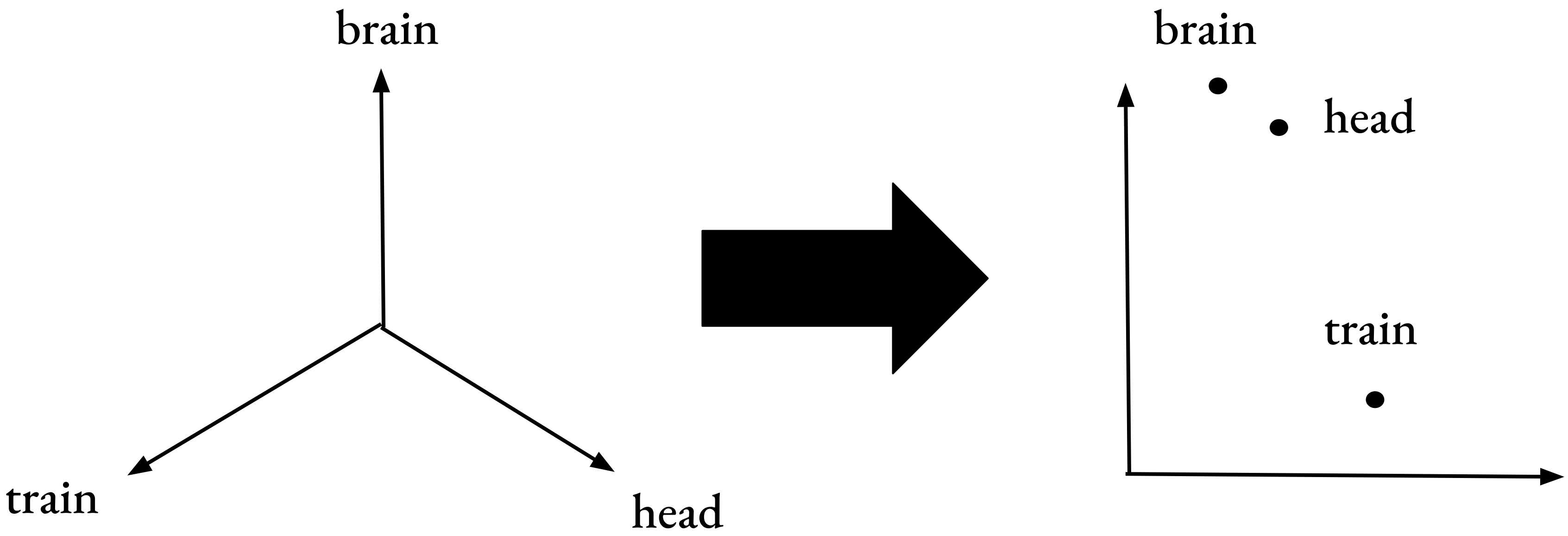
$$\underset{\text{a}}{\begin{bmatrix}1\\0\\0\\\vdots\\0\end{bmatrix}} \quad \underset{\text{aadvark}}{\begin{bmatrix}0\\1\\0\\\vdots\\0\end{bmatrix}} \quad \cdots \quad \underset{\text{zebra}}{\begin{bmatrix}0\\0\\0\\\vdots\\1\end{bmatrix}}$$



Word Embedding



High-dimensional space

Low-dimensional space

Other Types of Tokenization

- Idea: Break up text into pieces (tokens) and treat as categorical variables
- Words -> Tokens

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- Words -> Tokens
  - N-grams: Common phrases as one token instead of separate tokens

data_science vs. data, science

Other Types of Tokenization

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- Characters -> Tokens

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Other Types of Tokenization

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- Words -> Tokens
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- Sub-words -> Tokens
    - Break up words into smaller tokens
    - Smaller dictionary, less total tokens
    - Better at handling unknown, less lemmatization

Unfortunately -> un + fortunate + ly
skiing -> ski + ing

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  - Many Algorithms: BPE, Unigram, WordPiece

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Other Types of Tokenization

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- Words -> Tokens
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- Sentence Segmentation
  - EOS (End of Sentence) and SOS (Start of Sentence) tokens are common

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- Sentence Segmentation
  - EOS (End of Sentence) and SOS (Start of Sentence) tokens are common
  - Non-trivial to find these!
  - Binary Classifier, complicated logic trees

Can’t just rely on periods!

The U.K. exports of goods and services as percent of GDP was 31.6% in 2019.

Other Types of Tokenization

- Idea: Break up text into pieces (tokens) and treat as categorical variables
- Words -> Tokens
- Characters -> Tokens
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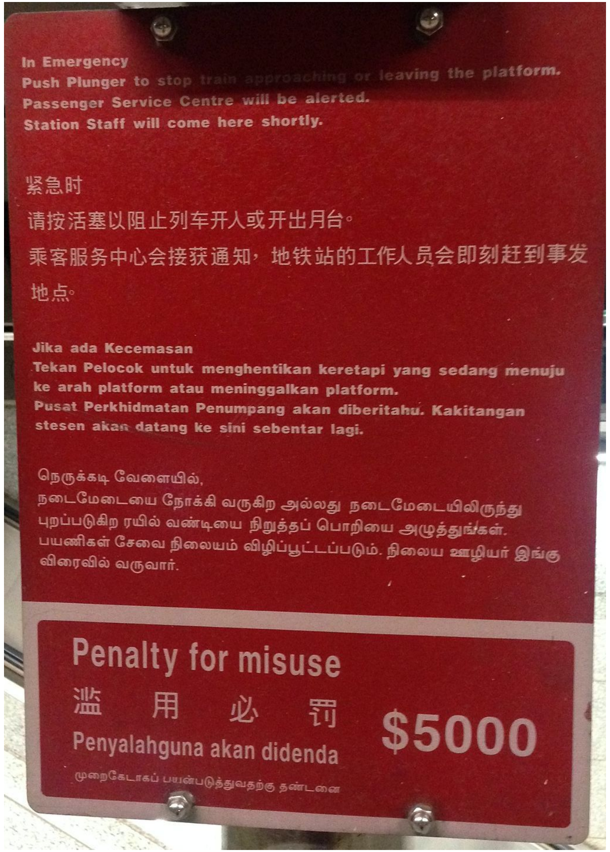
- Sentence Segmentation
- Other languages:
    - Chinese languages, Arabic, French, etc.



Word Tokenization Techniques

- Lemmatization
    - Reduce words to their base
    - Shrink dictionary size

running -> run
mice -> mouse

Word Tokenization Techniques

- Lemmatization
- Infrequent words (misspelled or weird words)
    - Remove from text or encode as single UNK token

Word Tokenization Techniques

- Lemmatization
- Infrequent words (misspelled or weird words)
- Cleaning before tokenization
    - Lower case
    - Remove weird characters/numbers/punctuation
    - Remove stop words

the, to, a, an, etc.

Word Tokenization Techniques

- Lemmatization
- Infrequent words (misspelled or weird words)
- Cleaning before tokenization
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  - Remove stop words
- Named Entity Recognition

Apple vs. apple
Xerox vs. xerox

Word Embeddings

- Word2Vec
- Learn the word embedding by training on a “simple” NLP task.
- Fill in the blank using surrounding context

<u>I</u> <u>am</u> <u>at</u> <u>track</u> <u>five</u>. <u>Here</u> <u>comes</u> <u>the</u> __?__

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- Distributional Semantics: The meaning of a word is given by the words that most often appear in the same context.
- There is a treasure trove of data for this task.
    - Ex. Use Wikipedia as your data.

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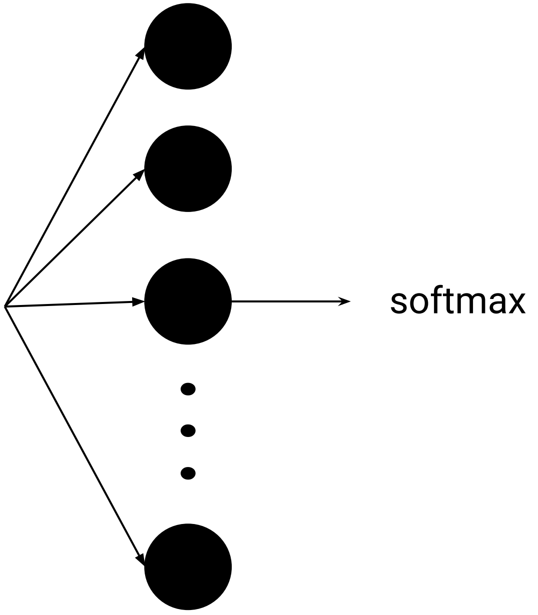

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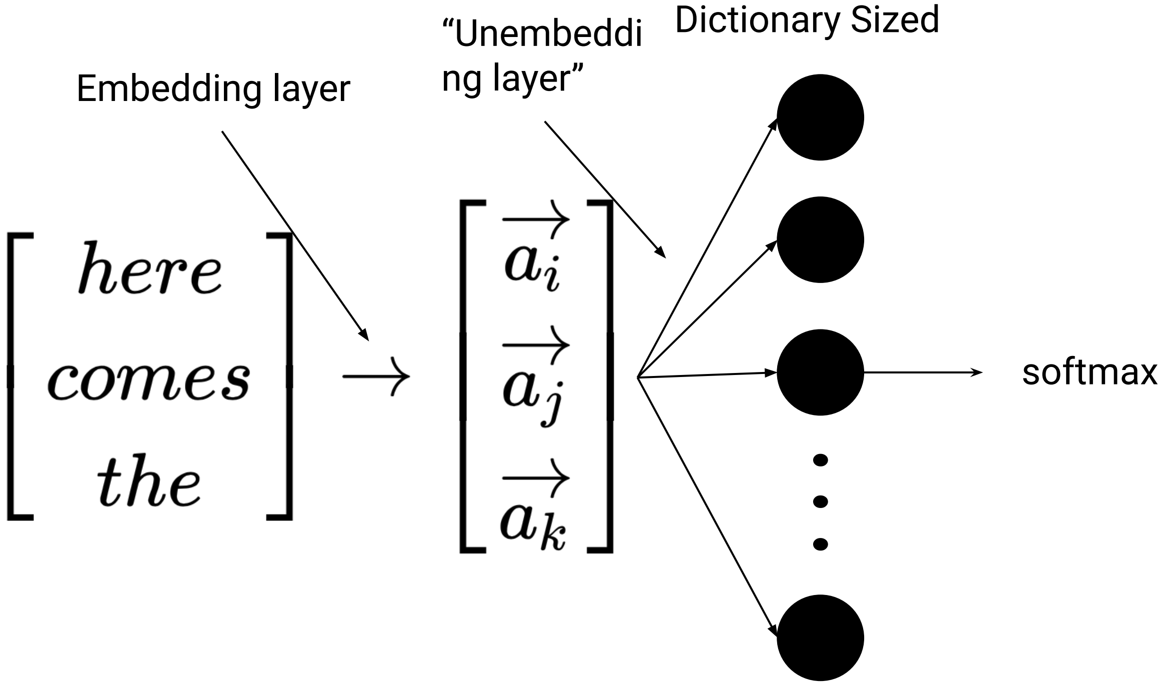

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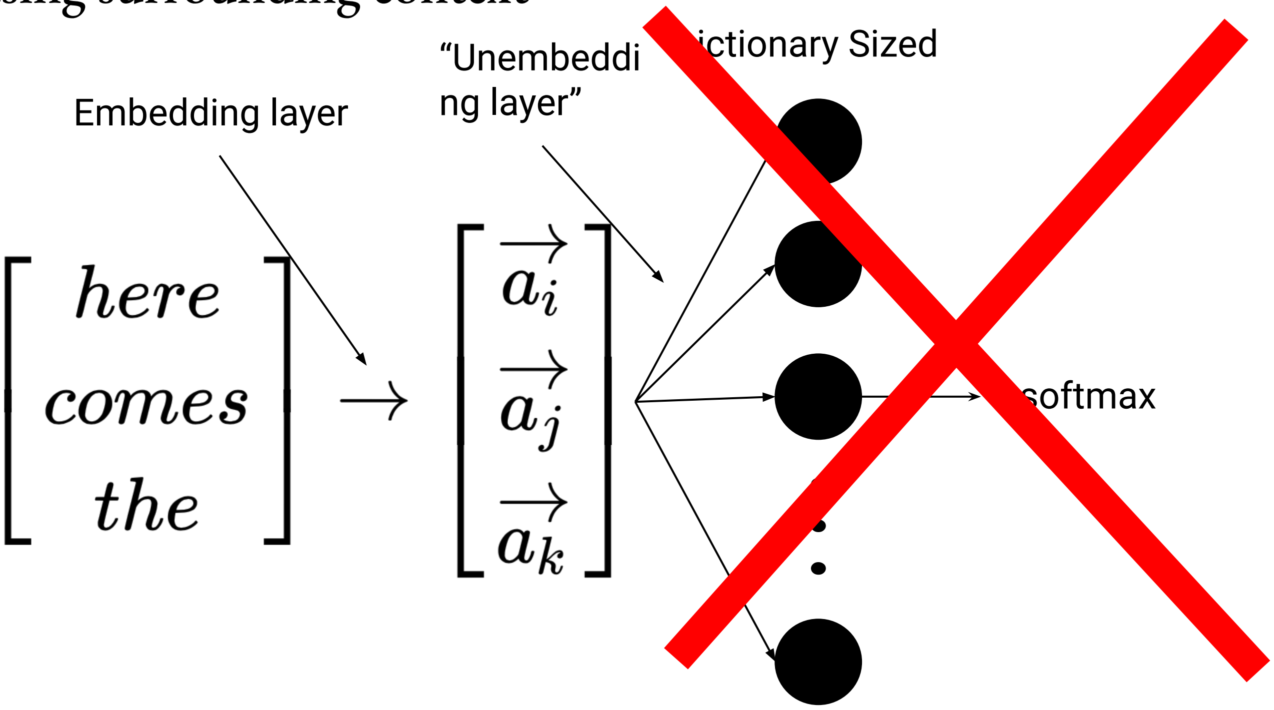

Word Embeddings

- Word2Vec
- GloVe
    - Unsupervised learning using co-occurences of words in your corpus

GloVe: Global Vectors for Word Representation

Jeffrey Pennington, Richard Socher, Christopher D. Manning
Computer Science Department, Stanford University, Stanford, CA 94305
jpennin@stanford.edu, richard@socher.org, manning@stanford.edu

Word Embeddings

- Idea: closeness in feature space <-> similarity in meaning

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- Construct Analogies
  - v(cat) - v(feline) ~ v(dog) - v(canine)

Word Embeddings

- Idea: closeness in feature space <-> similarity in meaning
- Construct Analogies
  - v(cat) - v(feline) ~ v(dog) - v(canine)
- Word embedding only as good as your text!

Man is to Computer Programmer as Woman is to Homemaker? Debiasing Word Embeddings

Tolga Bolukbasi[1], **Kai-Wei Chang**[2], **James Zou**[2], **Venkatesh Saligrama**[1,2], **Adam Kalai**[2]
[1]Boston University, 8 Saint Mary's Street, Boston, MA
[2]Microsoft Research New England, 1 Memorial Drive, Cambridge, MA
tolgab@bu.edu, kw@kwchang.net, jamesyzou@gmail.com, srv@bu.edu, adam.kalai@microsoft.com

Deep Learning and NLP

- Before Deep Learning: Statistics, Handcrafted features for text/words

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- Before Deep Learning: Statistics, Handcrafted features for text/words
- Now: Use Deep Learning to take advantage of tons of text data

Deep Learning and NLP

- Before Deep Learning: Statistics, Handcrafted features for text/words
- Now: Use Deep Learning to take advantage of tons of text data
- NLP Tasks
    - Sequence Classification (Sentiment analysis)
    - Summarization
    - Question Answering
    - Similarity Detection
    - Translations
    - And more!

Deep Learning and NLP

- Sequences
  - Variable length
  - Relationships between elements of sequence

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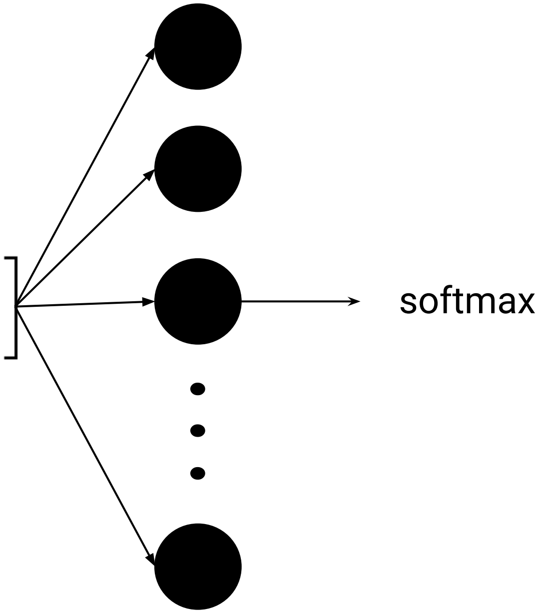
- Continuous Bag of Words (CBOW)-style Model

$$\begin{bmatrix} here \\ comes \\ the \end{bmatrix} \rightarrow \begin{bmatrix} \overrightarrow{a_i} \\ \overrightarrow{a_j} \\ \overrightarrow{a_k} \end{bmatrix} \rightarrow \left[(\overrightarrow{a_i} + \overrightarrow{a_j} + \overrightarrow{a_k})/3 \right]$$



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Deep Learning and NLP

- Sequences
  - Variable length (OVERCOME)
  - Relationships between elements of sequence (LOST)
- Continuous Bag of Words (CBOW)-style Model

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$$\begin{bmatrix} here \\ comes \\ the \end{bmatrix} \rightarrow \begin{bmatrix} \overrightarrow{a_i} \\ \overrightarrow{a_j} \\ \overrightarrow{a_k} \end{bmatrix} \rightarrow \left[(\overrightarrow{a_i} + \overrightarrow{a_j} + \overrightarrow{a_k})/3 \right]$$

Deep Learning and NLP

- Sequences
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- Continuous Bag of Words (CBOW)
- 1D CNN
  - 1-dimensional filter

<u>I</u> <u>am</u> <u>at</u> <u>track</u> <u>five</u>. <u>Here</u> <u>comes</u> <u>the</u> <u>train.</u>

Filter size: 3

Deep Learning and NLP

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$$\begin{bmatrix} f_1 & f_2 & \cdots & f_7 \end{bmatrix}$$

I am at track five. Here comes the train.

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Filter size: 3

Deep Learning and NLP

I am at track five. Here comes the train.

$$\begin{bmatrix} a_I^1 \\ a_I^2 \\ \vdots \\ a_I^{100} \end{bmatrix} \begin{bmatrix} a_{am}^1 \\ a_{am}^2 \\ \vdots \\ a_{am}^{100} \end{bmatrix} \begin{bmatrix} a_{at}^1 \\ a_{at}^2 \\ \vdots \\ a_{at}^{100} \end{bmatrix}$$

100-dim word embedding

Deep Learning and NLP

<u>I</u> <u>am</u> <u>at</u> <u>track</u> <u>five</u>. <u>Here</u> <u>comes</u> <u>the</u> <u>train.</u>

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100-dim word embedding

“Width 3, 100 channels”

Deep Learning and NLP

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$$\begin{bmatrix} a_I^1 \\ a_I^2 \\ \vdots \\ a_I^{100} \end{bmatrix} \begin{bmatrix} a_{am}^1 \\ a_{am}^2 \\ \vdots \\ a_{am}^{100} \end{bmatrix} \begin{bmatrix} a_{at}^1 \\ a_{at}^2 \\ \vdots \\ a_{at}^{100} \end{bmatrix} * \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ \vdots & \vdots & \vdots \\ w_{100,1} & w_{100,2} & w_{100,3} \end{bmatrix}$$

100-dim word embedding

Filter size 3, 100 channels

“Width 3, 100 channels”

$$\begin{bmatrix} f_1 & f_2 & \dots & f_7 \end{bmatrix}$$

Deep Learning and NLP

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$$\begin{bmatrix} a_{am}^{1} \\ a_{am}^{2} \\ \vdots \\ a_{am}^{100} \end{bmatrix} \begin{bmatrix} a_{at}^{1} \\ a_{at}^{2} \\ \vdots \\ a_{at}^{100} \end{bmatrix} \begin{bmatrix} a_{track}^{1} \\ a_{track}^{2} \\ \vdots \\ a_{track}^{100} \end{bmatrix} * \begin{bmatrix} w_{11} & w_{12} & w_{13} \\ w_{21} & w_{22} & w_{23} \\ \vdots & \vdots & \vdots \\ w_{100,1} & w_{100,2} & w_{100,3} \end{bmatrix}$$

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$$\begin{bmatrix} f_1 & f_2 & \dots & f_7 \end{bmatrix}$$

I am at track five. Here comes the train.

Length 9 sequence embedding, 100 channels

Length 7 sequence of features, 50 channels

$$\begin{bmatrix} a_{11} & a_{12} & \cdots & a_{19} \\ \vdots & & & \vdots \\ a_{100,1} & a_{100,2} & \cdots & a_{100,9} \end{bmatrix} \longrightarrow \begin{bmatrix} f_{11} & f_{12} & \cdots & f_{17} \\ \vdots & & & \vdots \\ f_{50,1} & f_{50,2} & \cdots & f_{50,7} \end{bmatrix}$$

50 filters of width 3 with 100 channels

Deep Learning and NLP

- Sequences
  - Variable length
  - Relationships between elements of sequence
- Continuous Bag of Words (CBOW)
- 1D CNN
- Recurrent Neural Network (RNN)
  - Keep track of a hidden state vector of features as you move along a sequence
  - Sequence length agnostic

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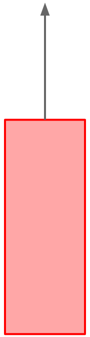
  - Sequence length agnostic
- Diagrams shown without bias term (optional)

Deep Learning and NLP

- Vanilla RNN

Input sequence $(x_1, x_2, \ldots, x_N)$

$$\overrightarrow{a_i} = embedding(x_i)$$



$\overrightarrow{a_i}$

Next feature/embedding vector

Deep Learning and NLP

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Input sequence $(x_1, x_2, \ldots, x_N)$

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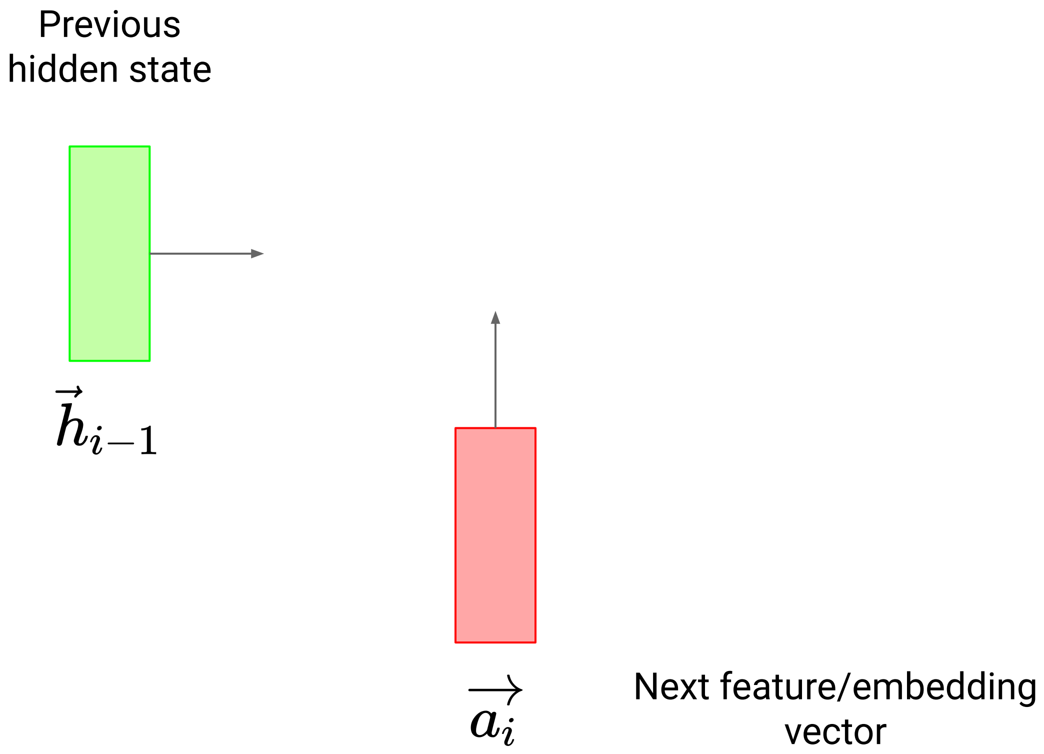

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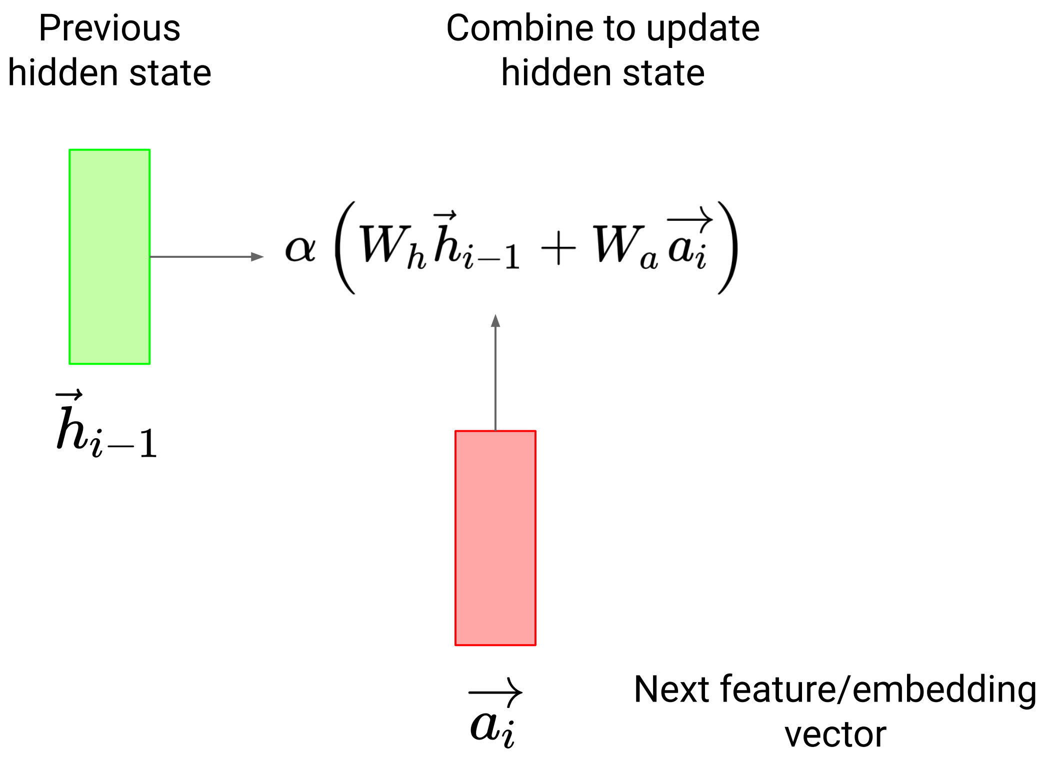

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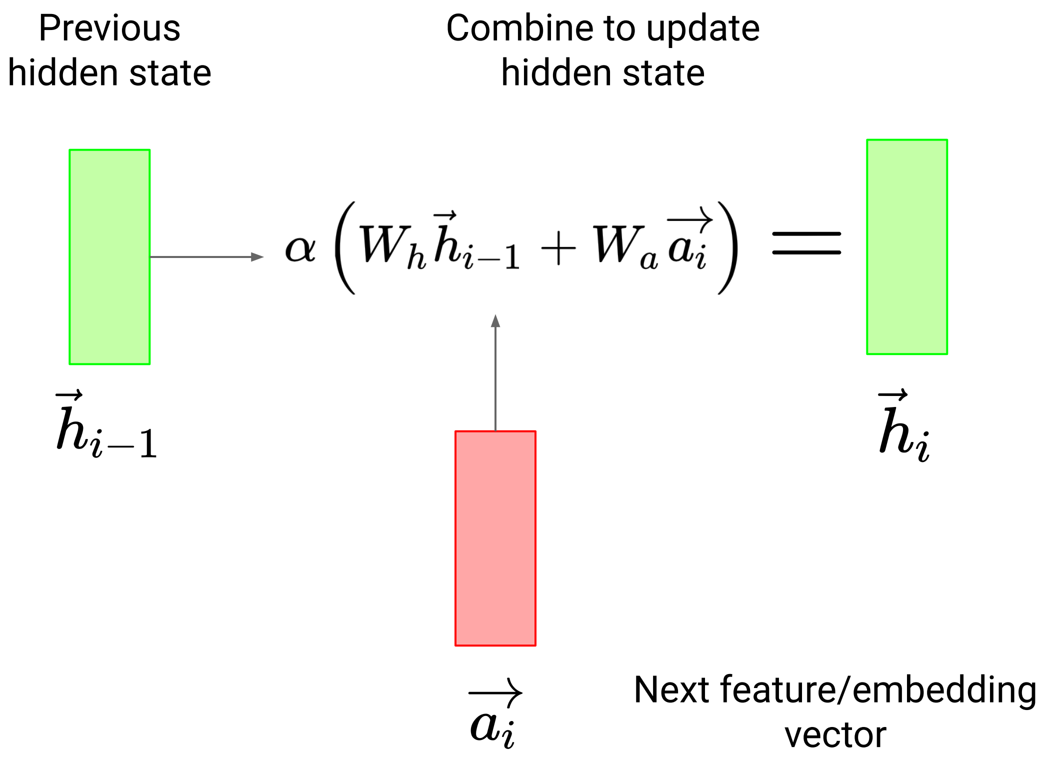

Deep Learning and NLP

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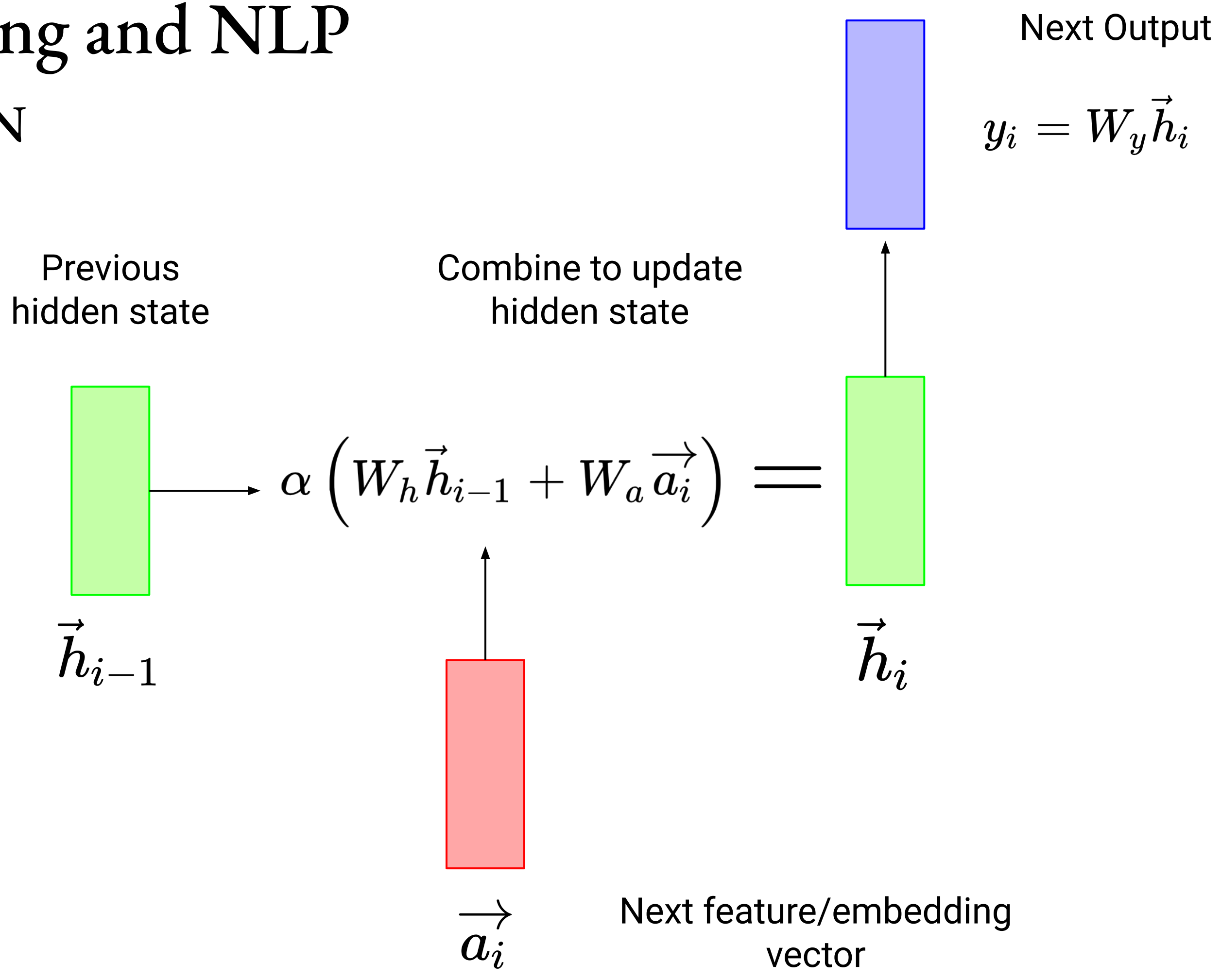

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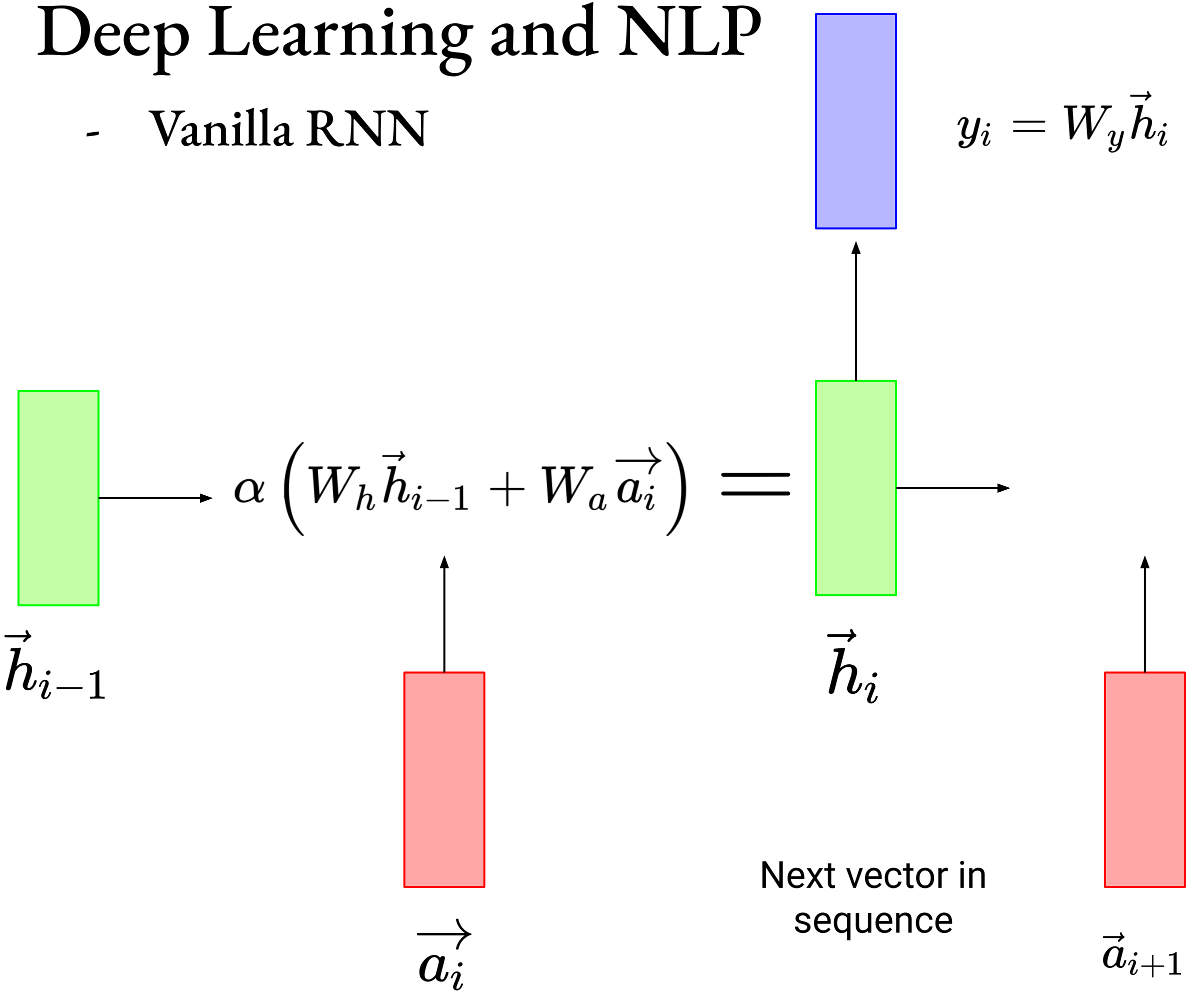

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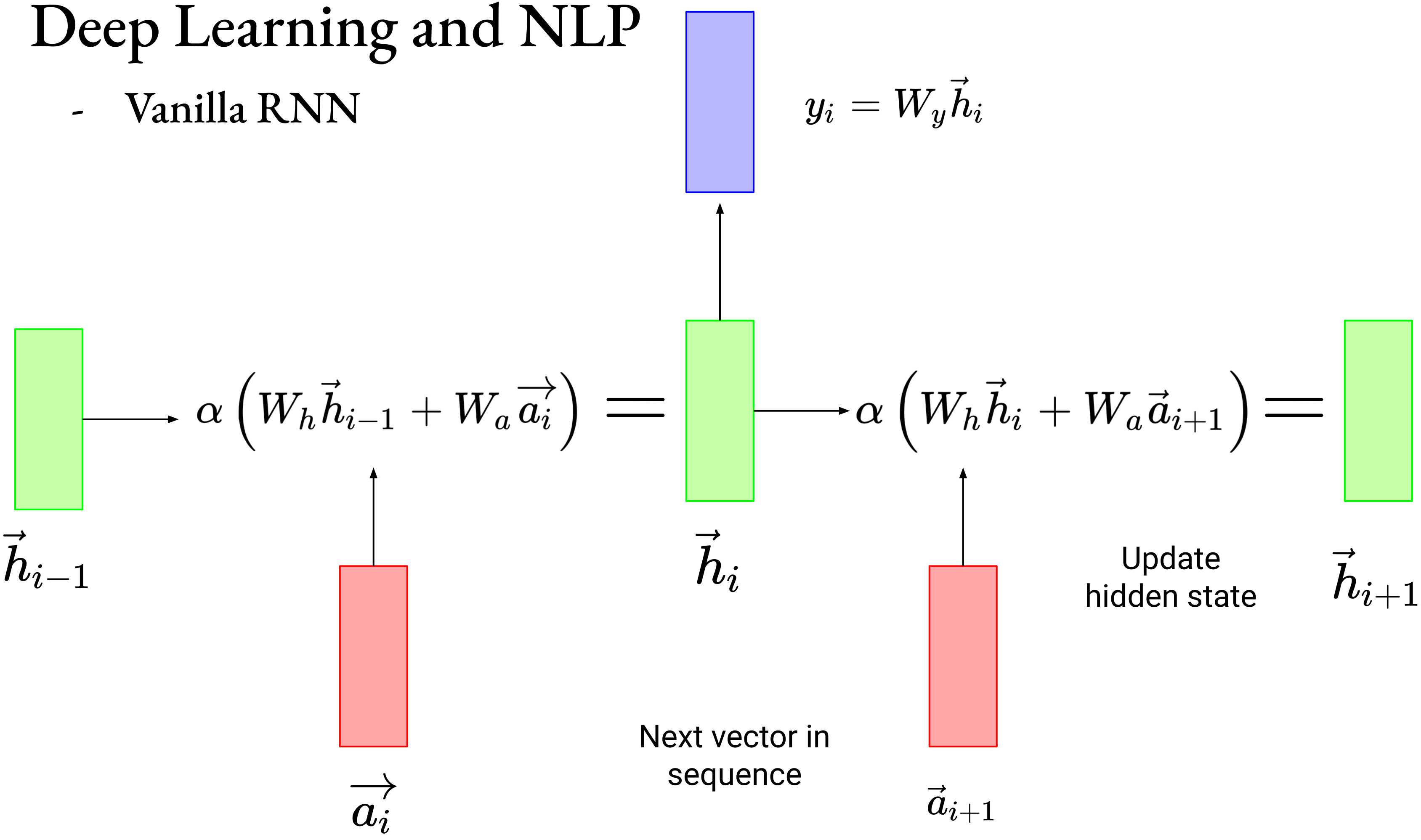

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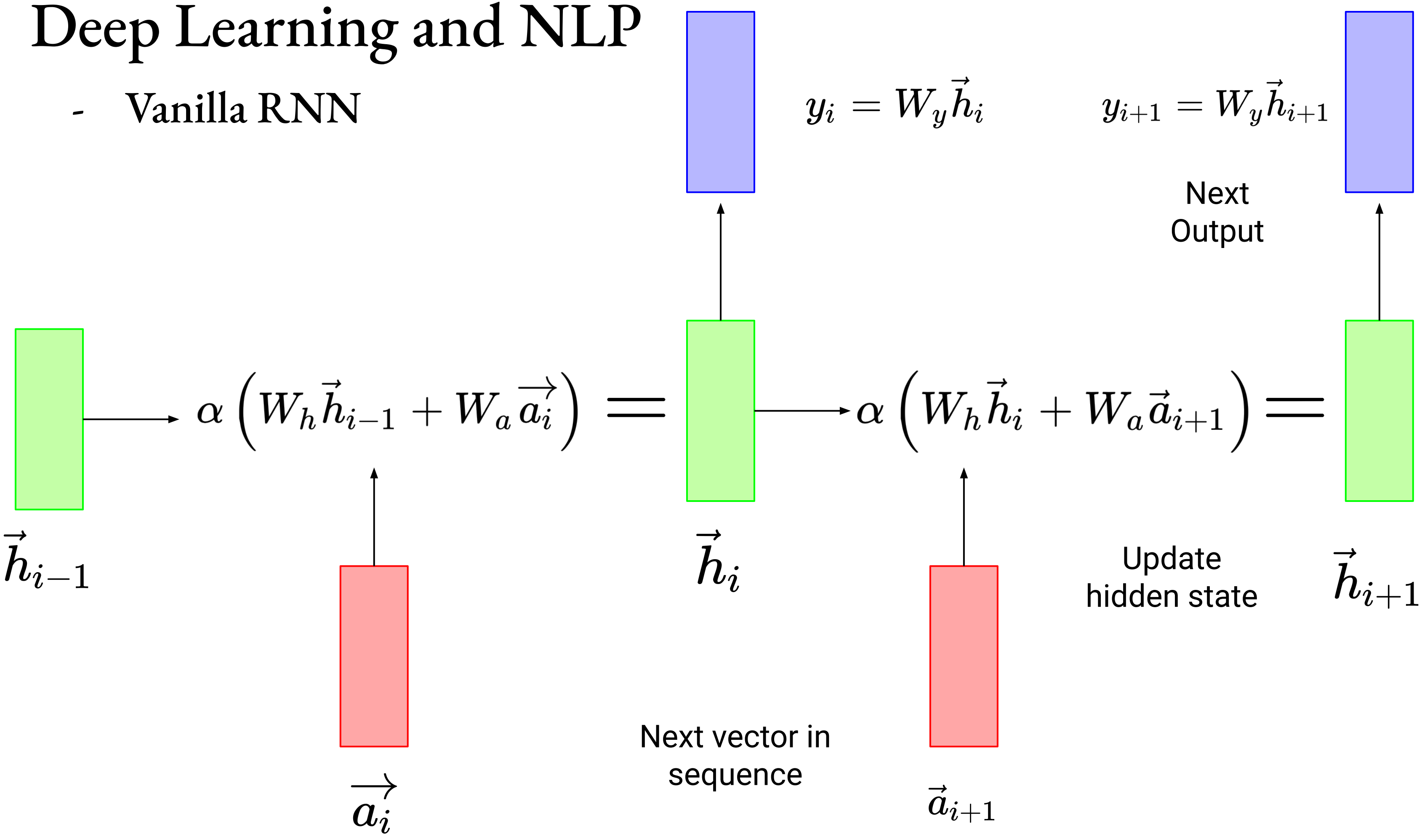

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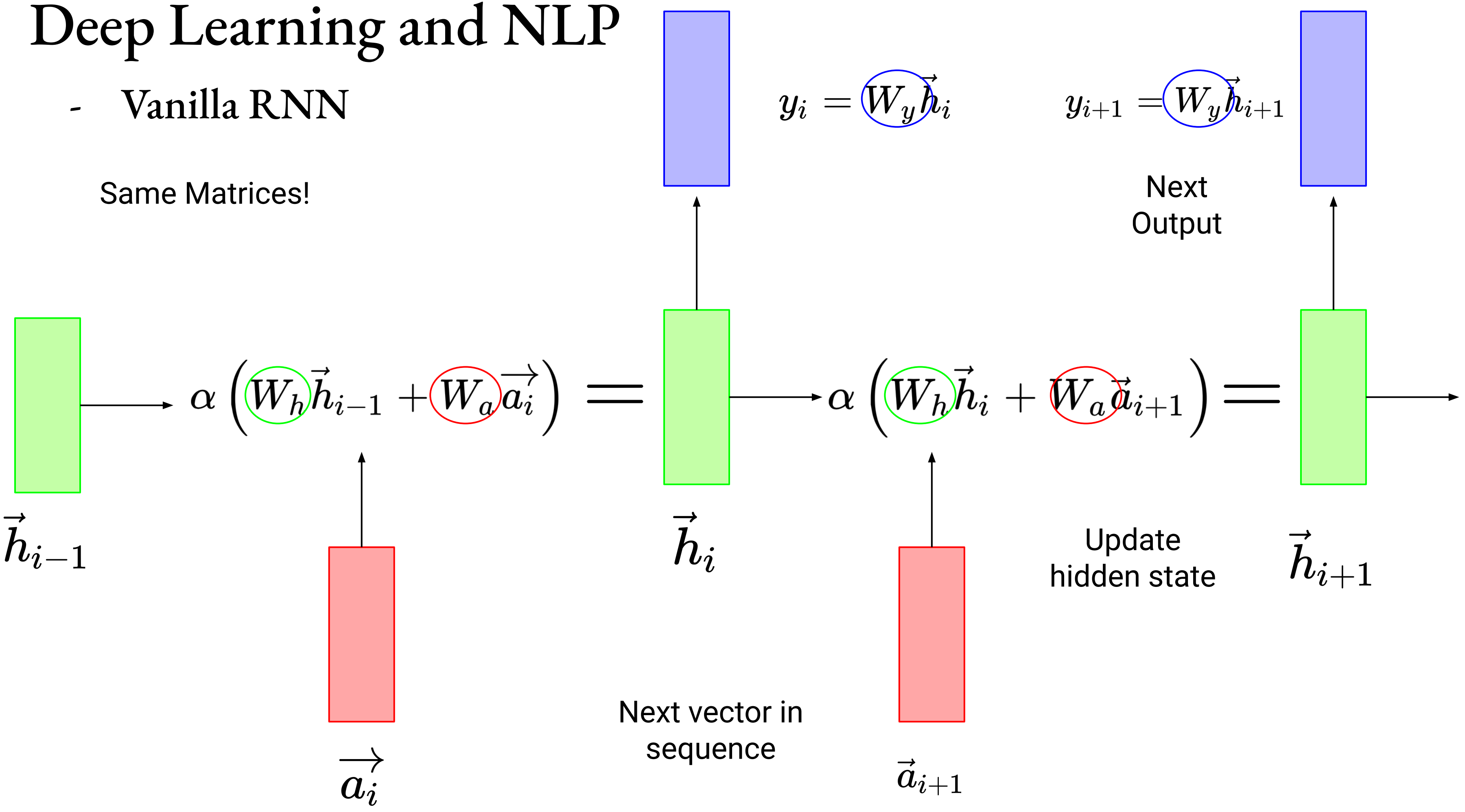

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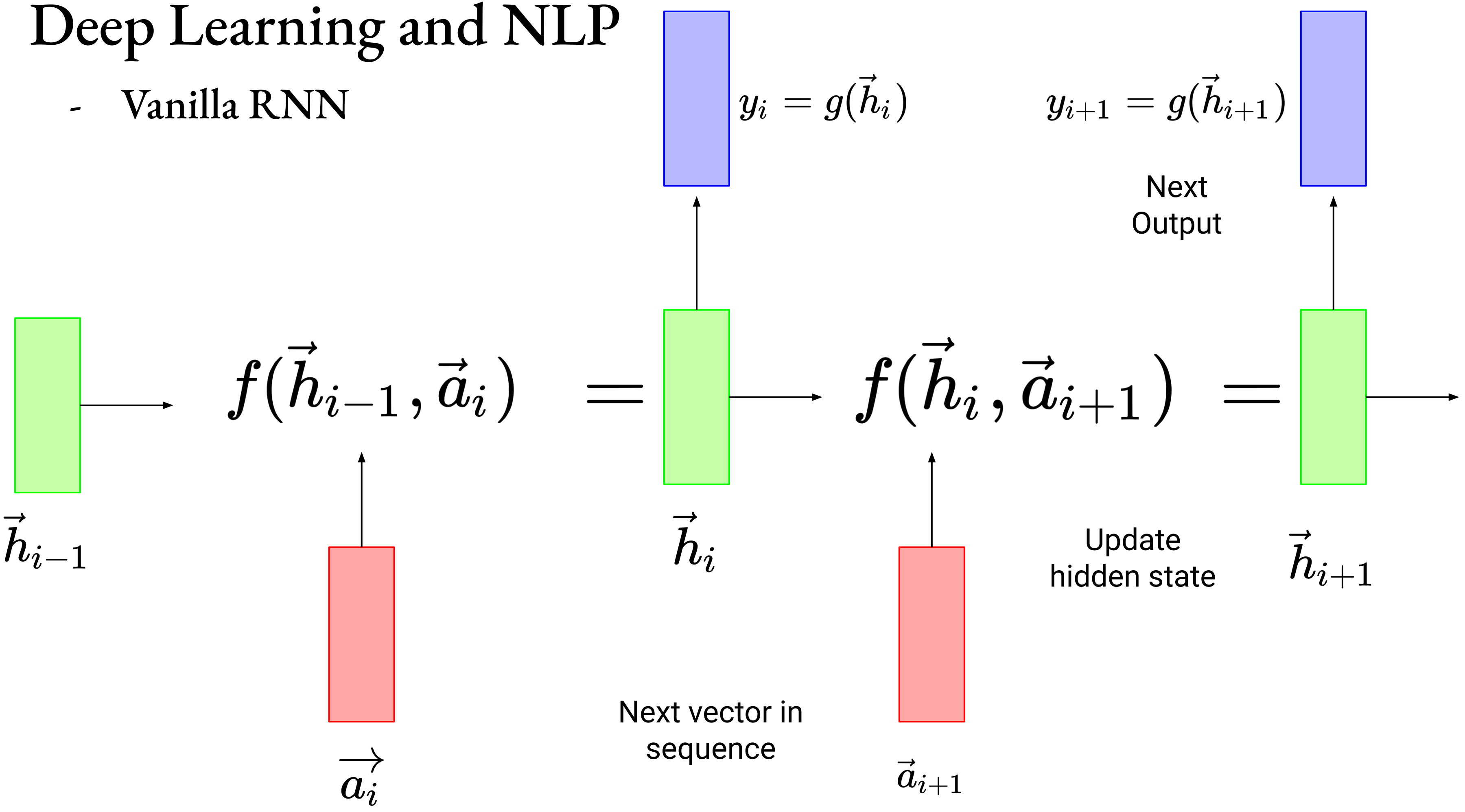
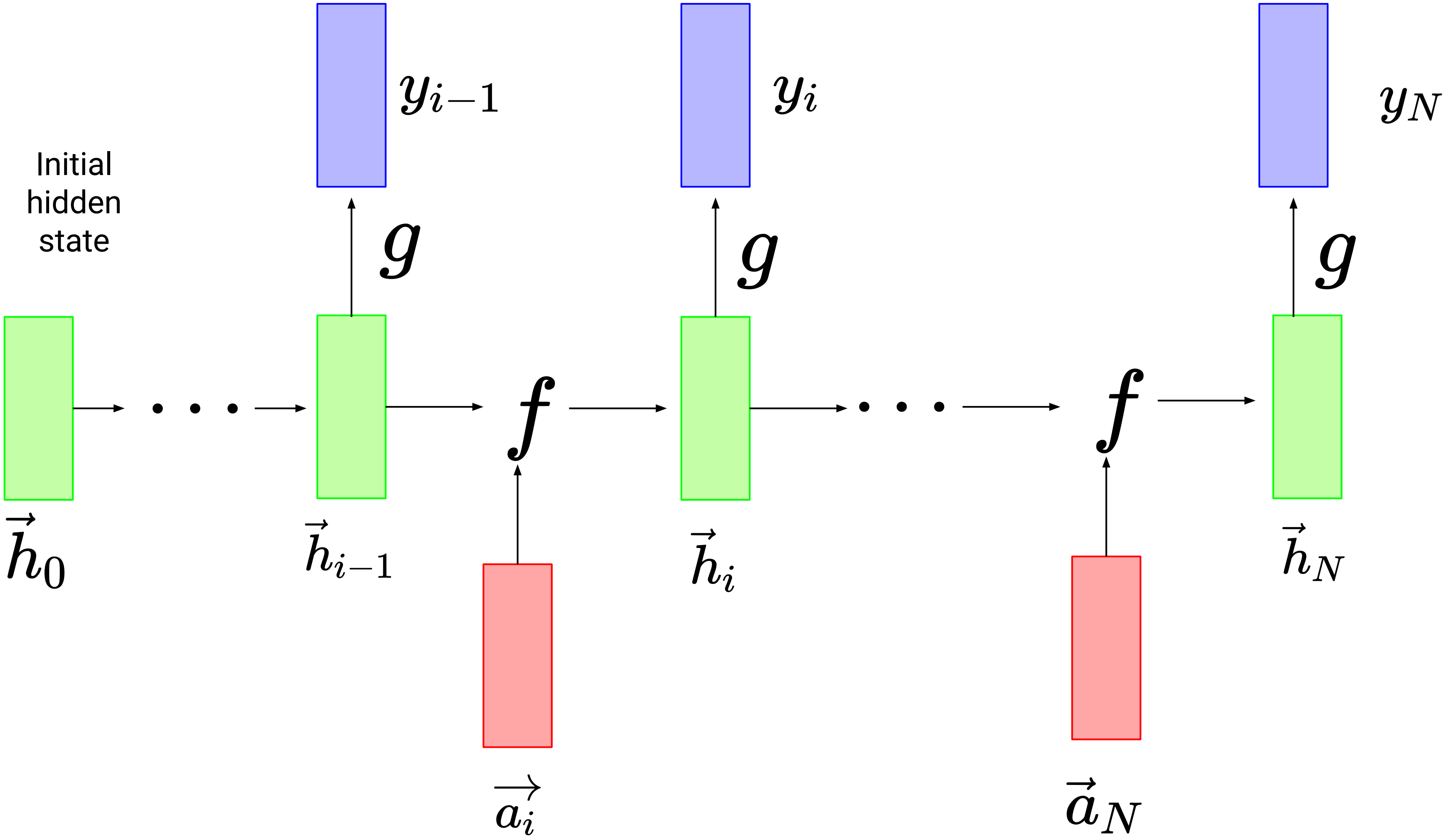
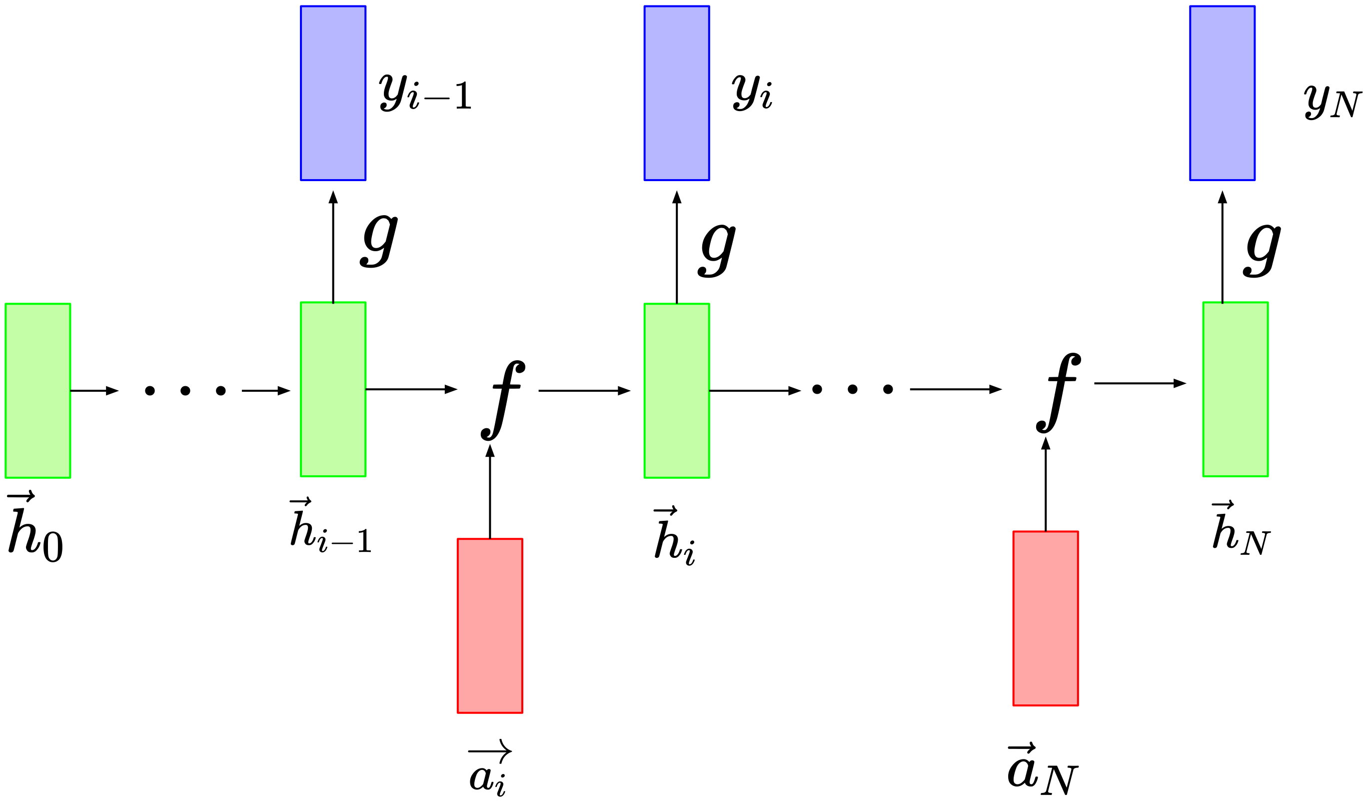
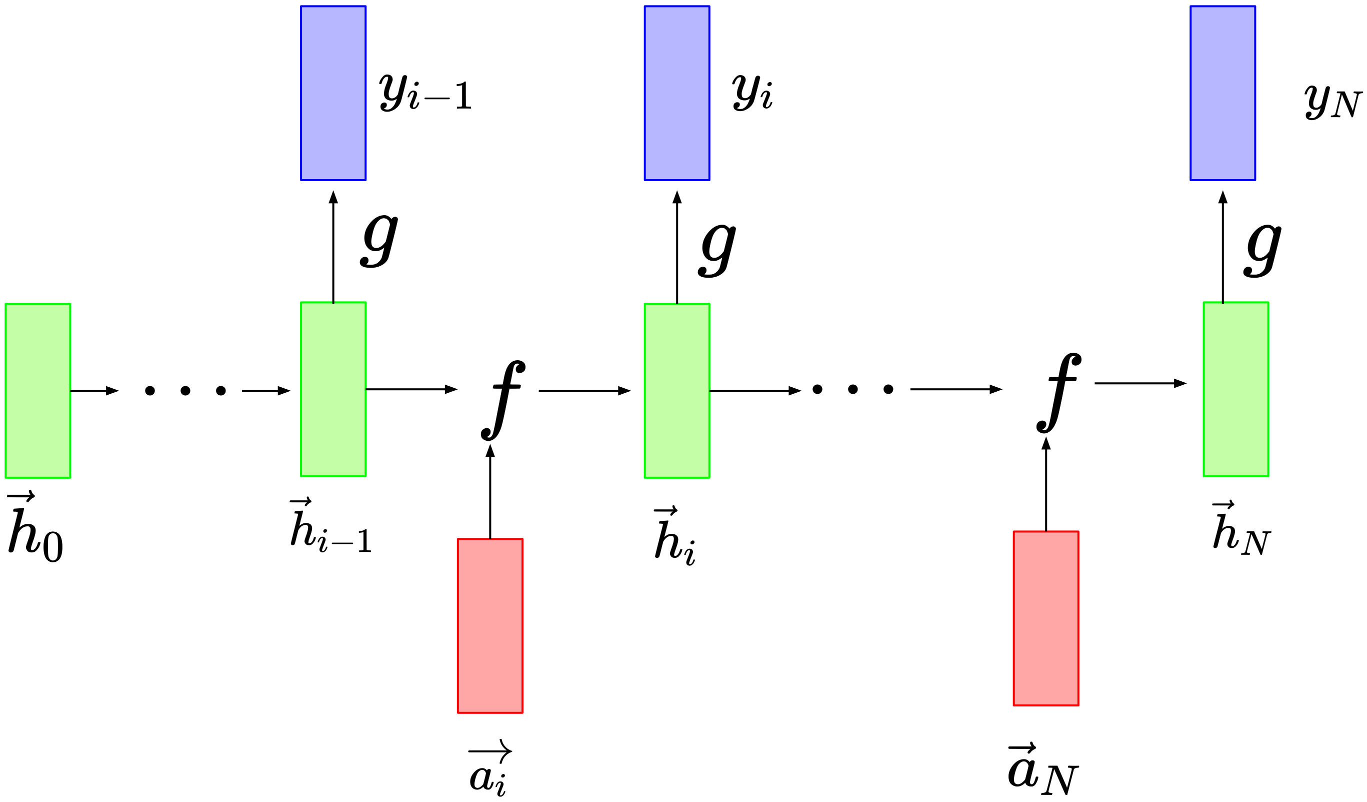



Initial hidden state
y_{i-1}
y_i
y_N
g
g
g
f
f
$\vec{h}_0$
$\vec{h}_{i-1}$
$\vec{h}_i$
$\vec{h}_N$
$\overrightarrow{a_i}$
$\vec{a}_N$

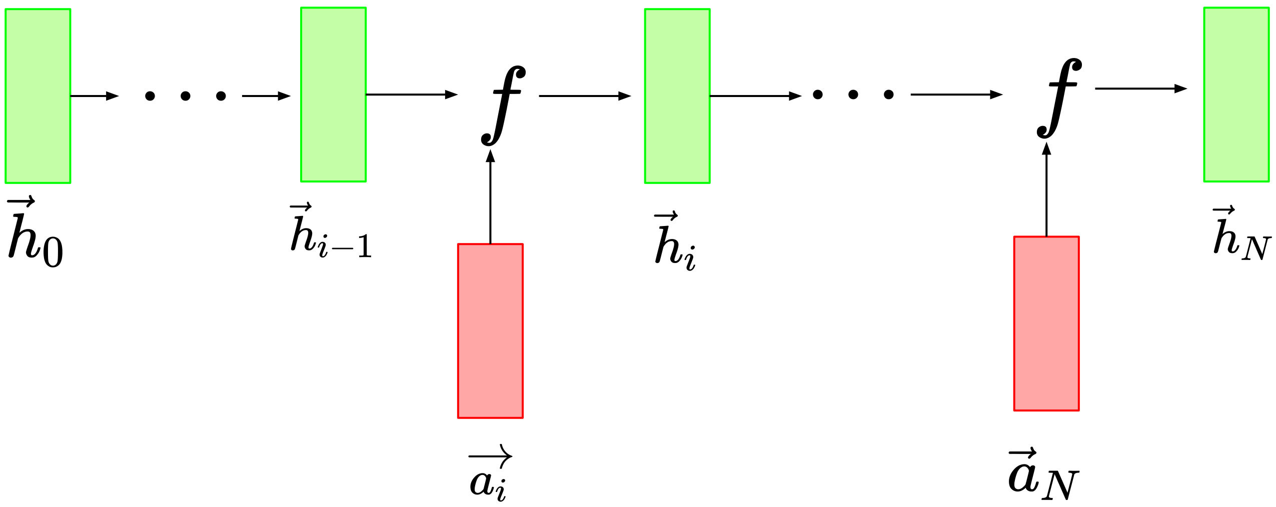
- Can either train on output sequence or discard



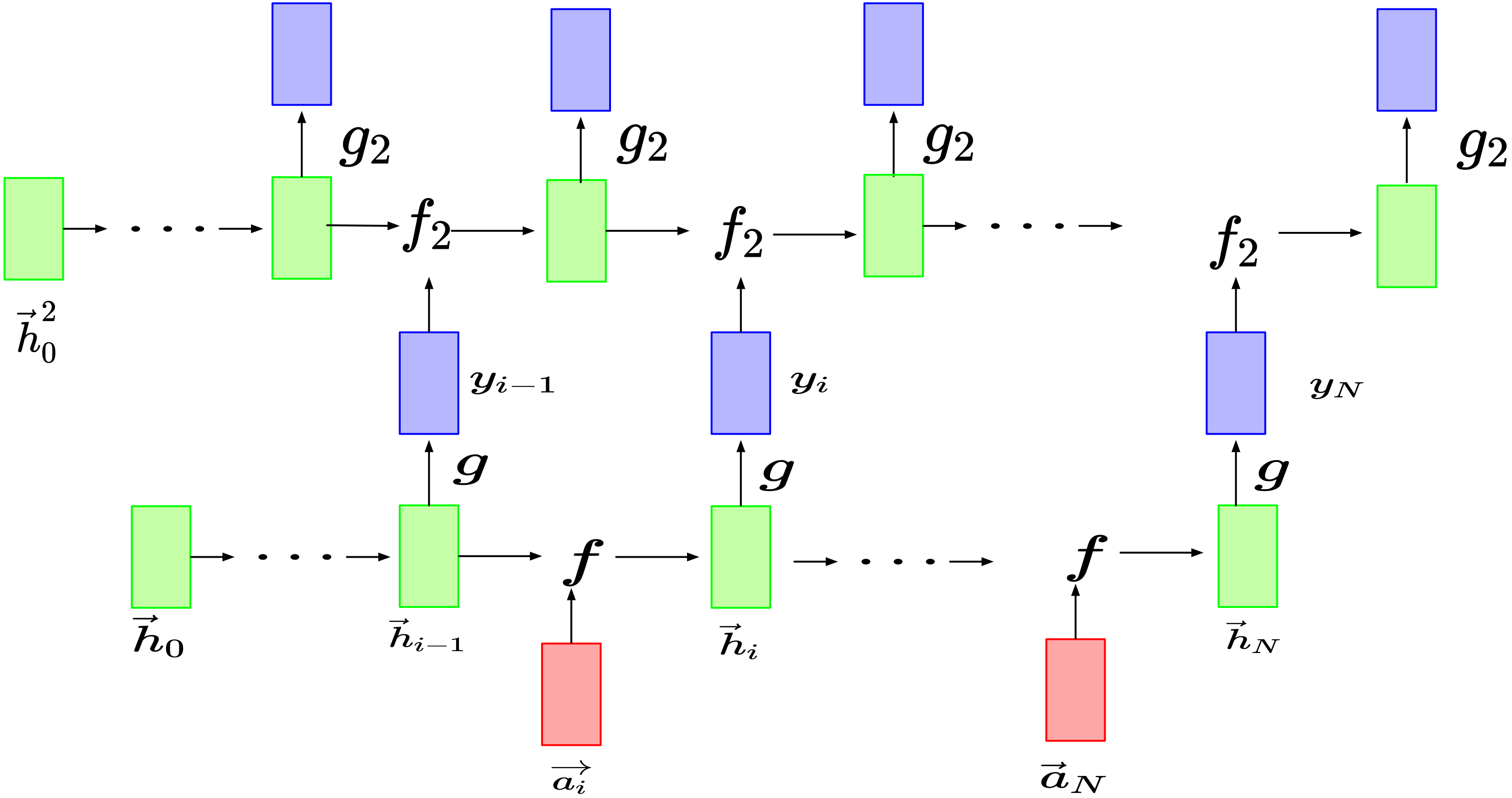
- Can either train on output sequence or discard



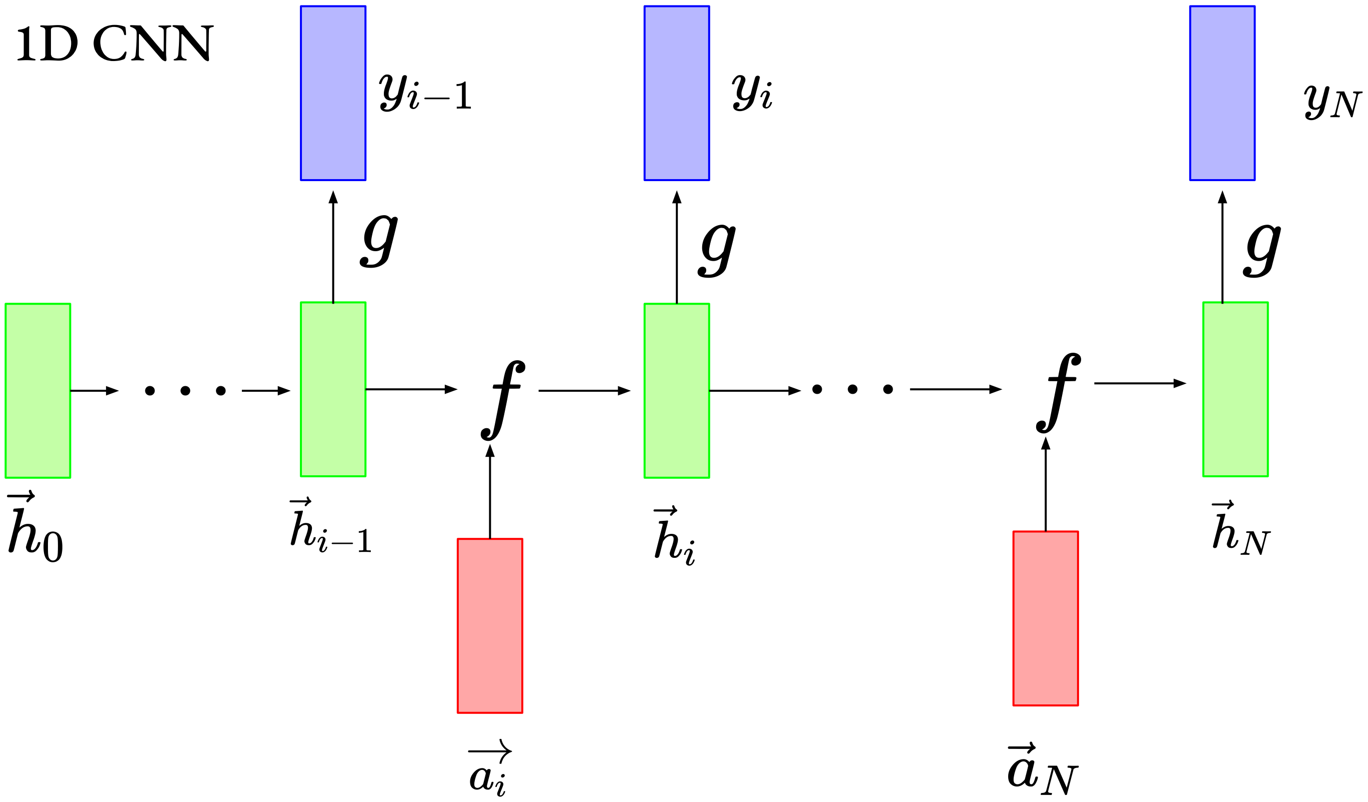
- Can either train on output sequence or discard



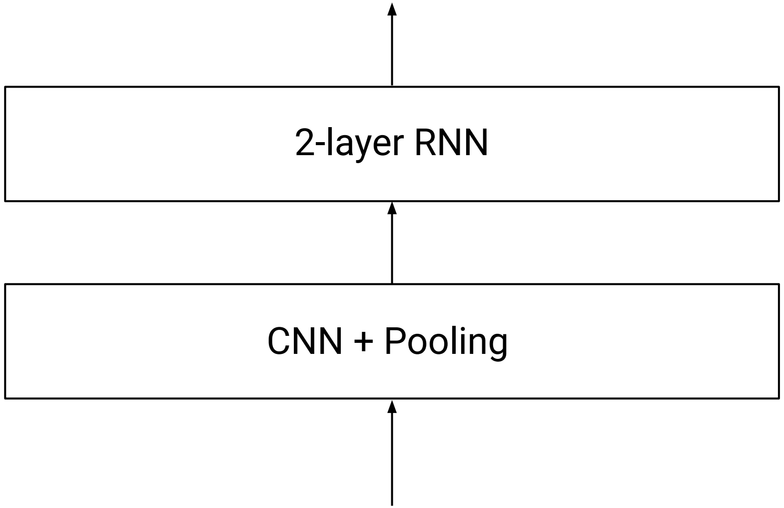
- Can either train on output sequence or discard
- Stack RNNs



- Can either train on output sequence or discard
- Stack RNNs
- Input can be from 1D CNN



- Can either train on output sequence or discard
- Stack RNNs
- Input can be from 1D CNN



$$(x_1, x_2, \ldots, x_N)$$