Neural Networks Language Models

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N-Gram Backoff Language Model

- Previously, we approximated

$$p(W) = p(w_1, w_2, ..., w_n)$$

- ... by applying the chain rule

$$p(W) = \sum_i p(w_i|w_1, ..., w_{i-1})$$

- ... and limiting the history (Markov order)

$$p(w_i|w_1, ..., w_{i-1}) \simeq p(w_i|w_{i-4}, w_{i-3}, w_{i-2}, w_{i-1})$$

- Each $p(w_i|w_{i-4}, w_{i-3}, w_{i-2}, w_{i-1})$ may not have enough statistics to estimate

$\rightarrow$ we back off to $p(w_i|w_{i-3}, w_{i-2}, w_{i-1})$, $p(w_i|w_{i-2}, w_{i-1})$, etc., all the way to $p(w_i)$

– exact details of backing off get complicated — "interpolated Kneser-Ney"

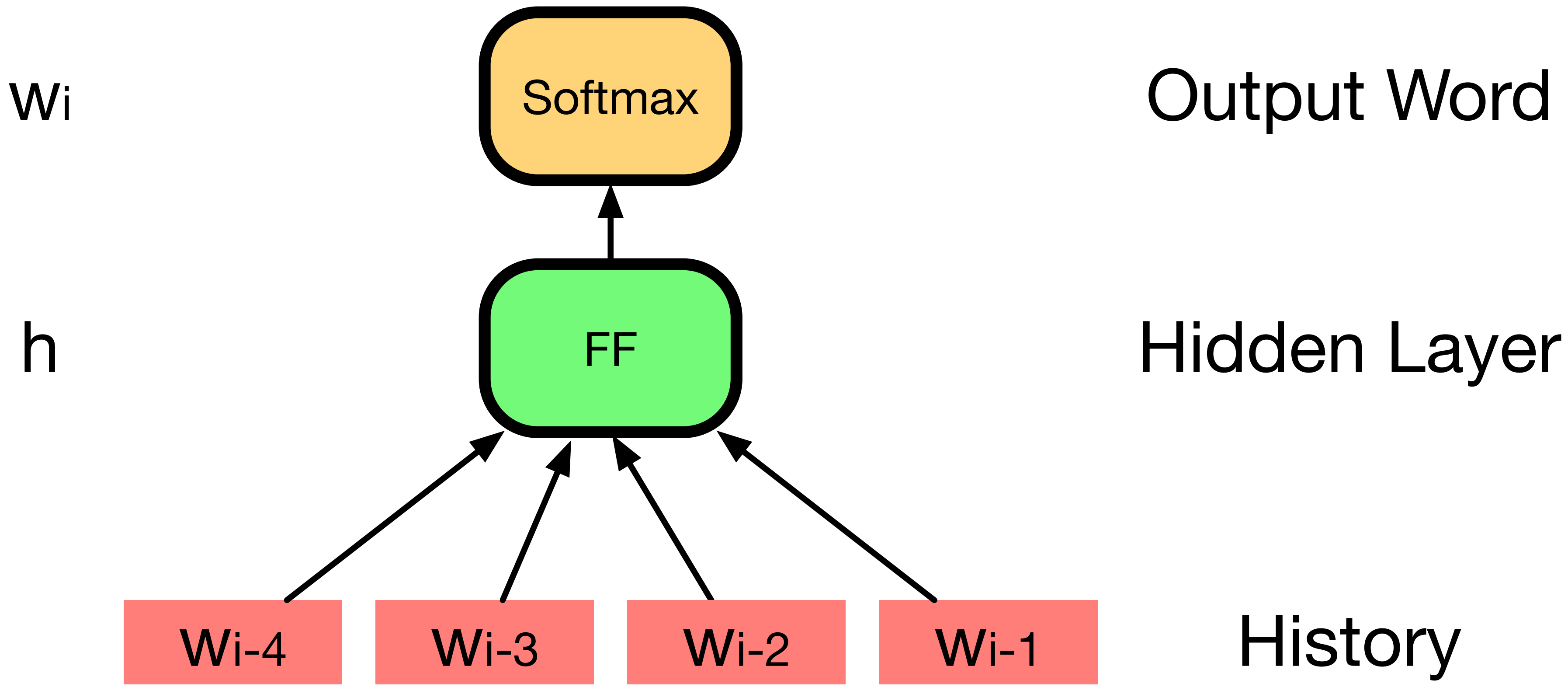
Refinements

- A whole family of back-off schemes
- Skip-n gram models that may back off to $p(w_i|w_{i-2})$
- Class-based models $p(C(w_i)|C(w_{i-4}), C(w_{i-3}), C(w_{i-2}), C(w_{i-1}))$

$\Rightarrow$ We are wrestling here with

- using as much relevant evidence as possible
- pooling evidence between words

First Sketch

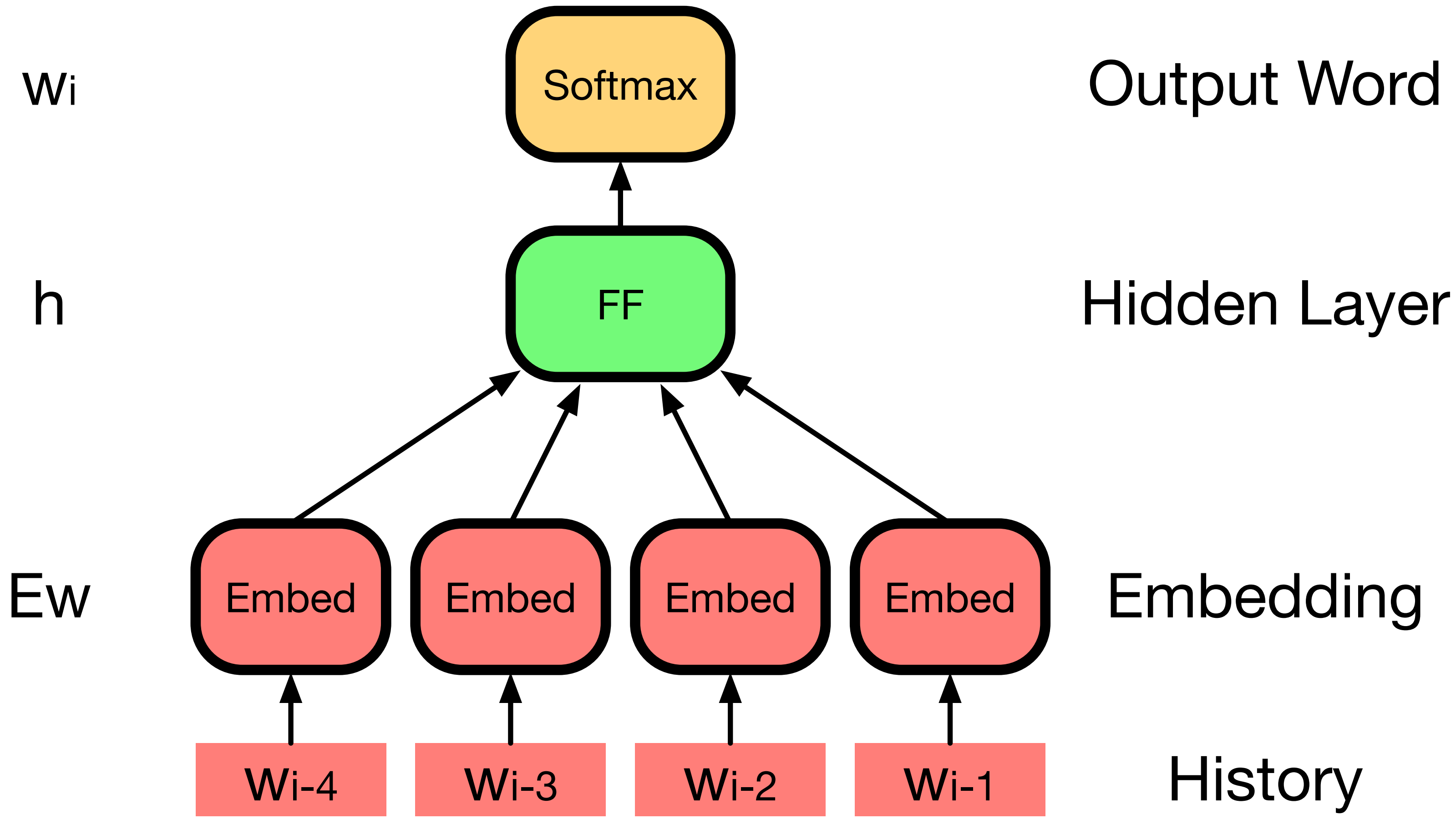


Representing Words

- Words are represented with a one-hot vector, e.g.,
  - dog = (0,0,0,0,1,0,0,0,0,....)
  - cat = (0,0,0,0,0,0,0,1,0,....)
  - eat = (0,1,0,0,0,0,0,0,0,....)
- That's a large vector!
- Remedies
  - limit to, say, 20,000 most frequent words, rest are OTHER
  - place words in $\sqrt{n}$ classes, so each word is represented by
    - 1 class label
    - 1 word in class label
  - splitting rare words into subwords
  - character-based models

word embeddings

Add a Hidden Layer

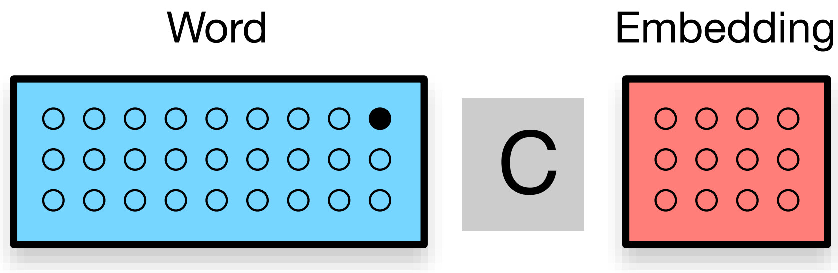


- Map each word first into a lower-dimensional real-valued space
- Shared weight matrix E

Details (Bengio et al., 2003)

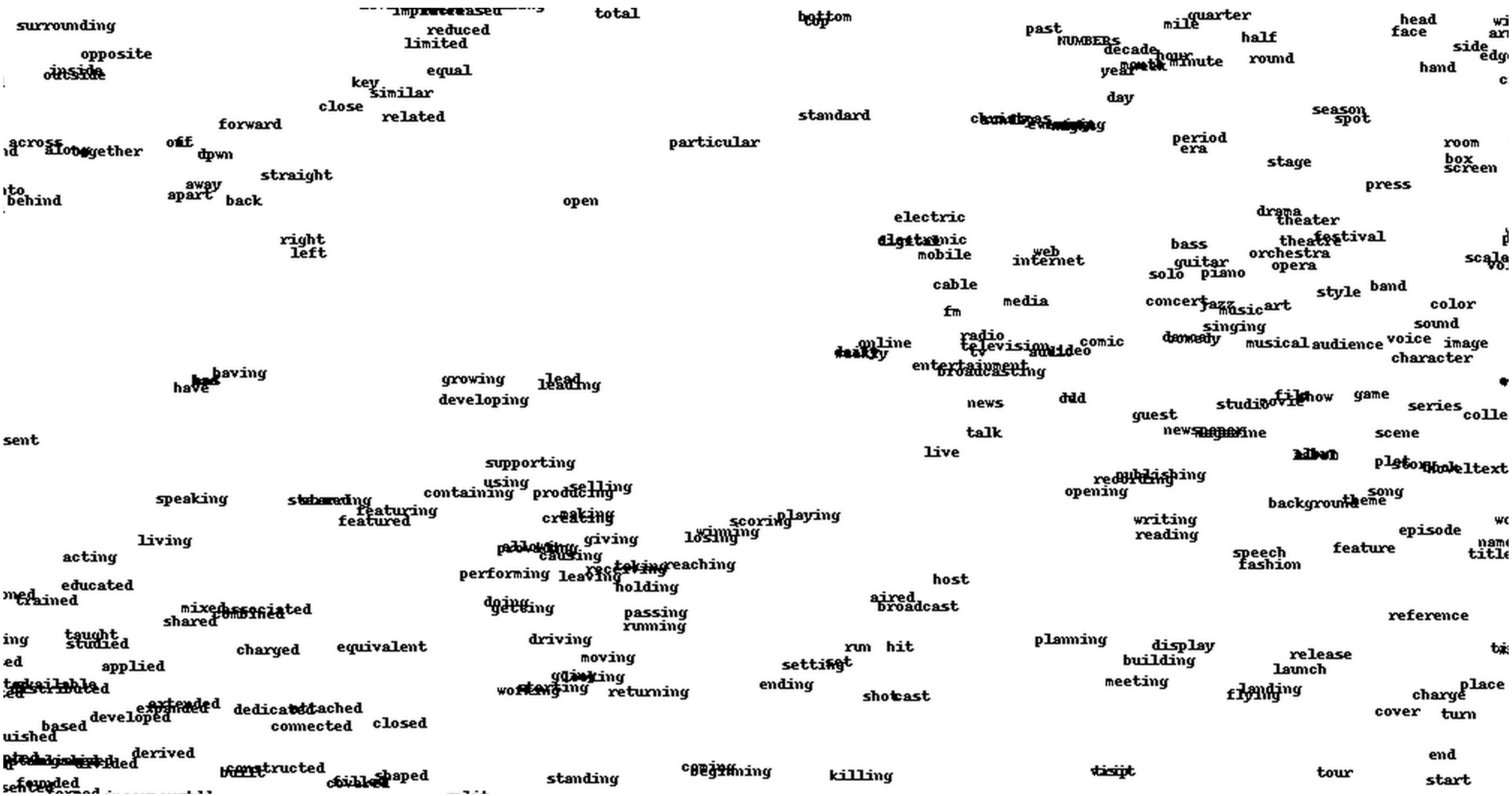
- Add direct connections from embedding layer to output layer
- Activation functions
  - input→embedding: none
  - embedding→hidden: tanh
  - hidden→output: softmax
- Training
  - loop through the entire corpus
  - update between predicted probabilities and 1-hot vector for output word

Word Embeddings

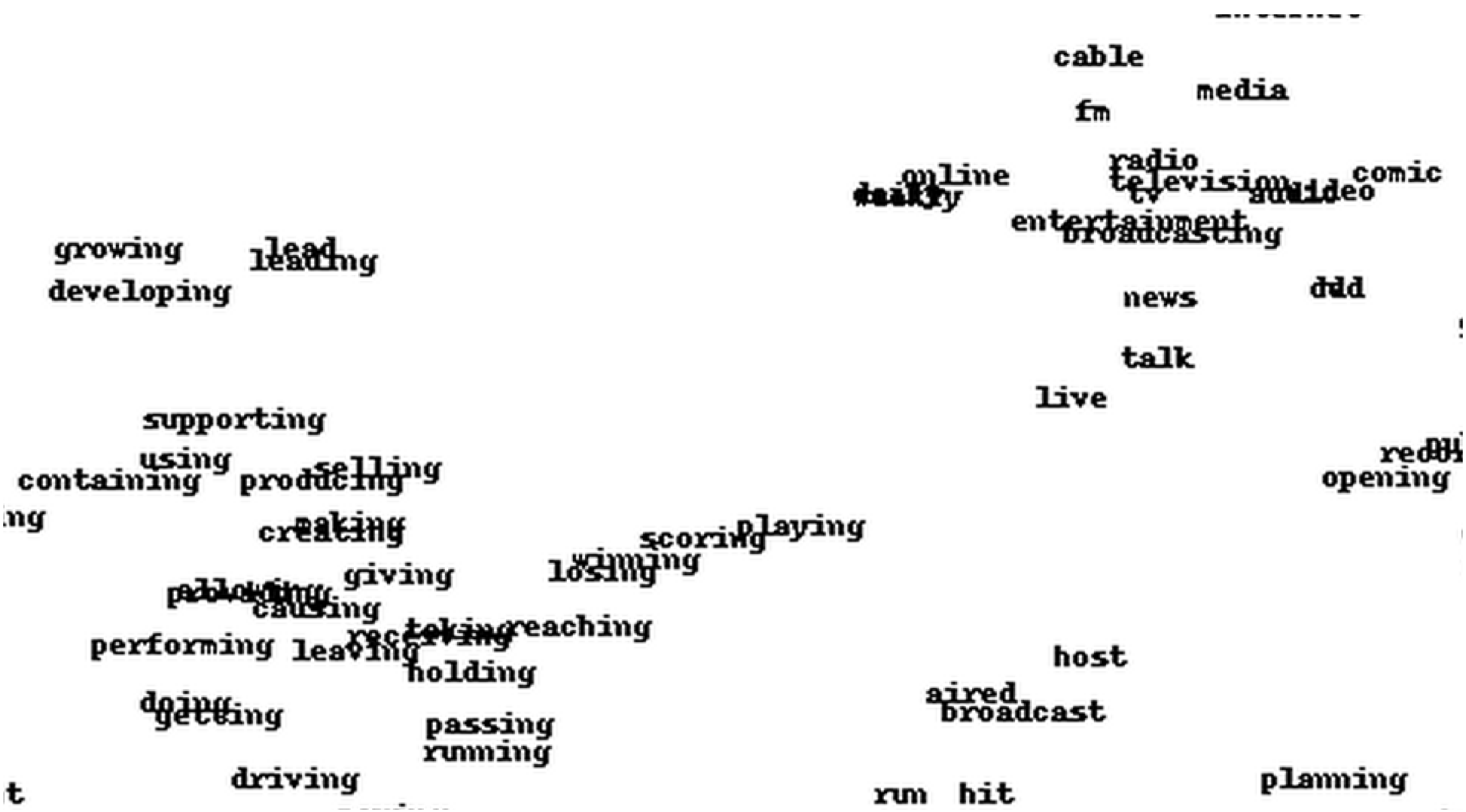


- By-product: embedding of word into continuous space
- Similar contexts $\rightarrow$ similar embedding
- Recall: distributional semantics

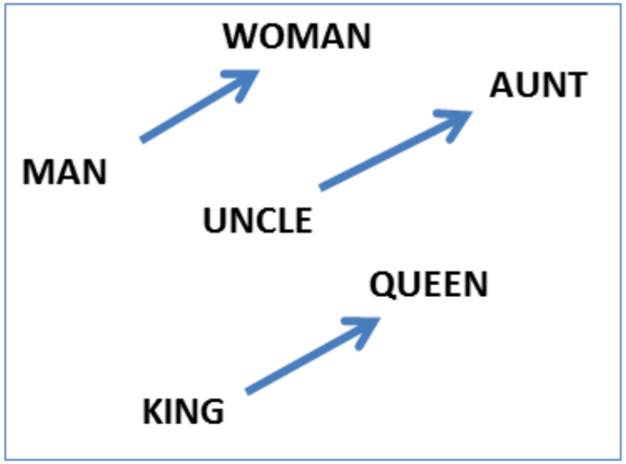
Word Embeddings

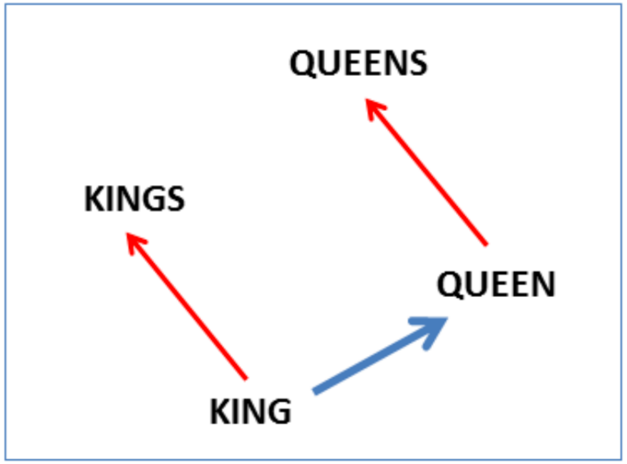


Word Embeddings



Are Word Embeddings Magic?





- Morphosyntactic regularities (Mikolov et al., 2013)
  - adjectives base form vs. comparative, e.g., good, better
  - nouns singular vs. plural, e.g., year, years
  - verbs present tense vs. past tense, e.g., see, saw

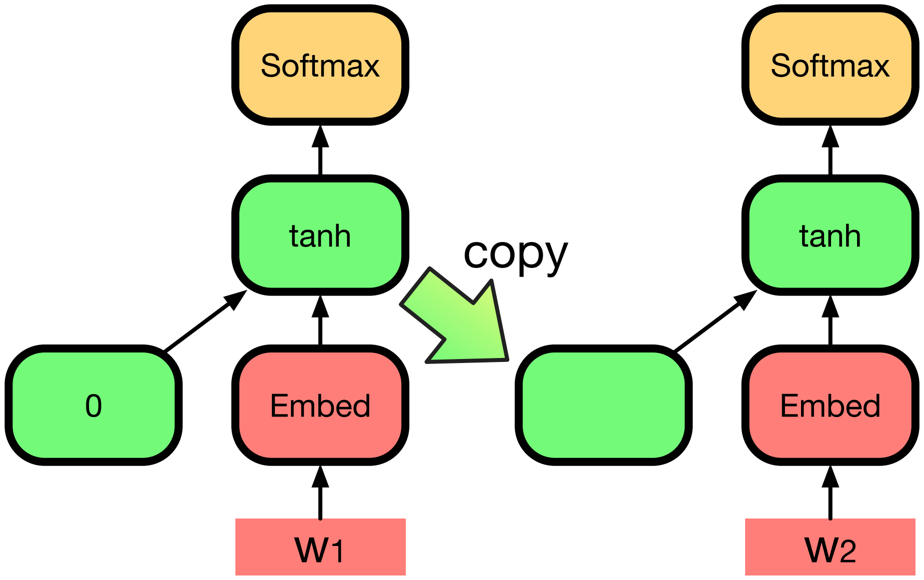
- Semantic regularities
  - clothing is to shirt as dish is to bowl
  - evaluated on human judgment data of semantic similarities

recurrent neural networks

Recurrent Neural Networks

- Start: predict second word from first
- Mystery layer with nodes all with value 1

Recurrent Neural Networks



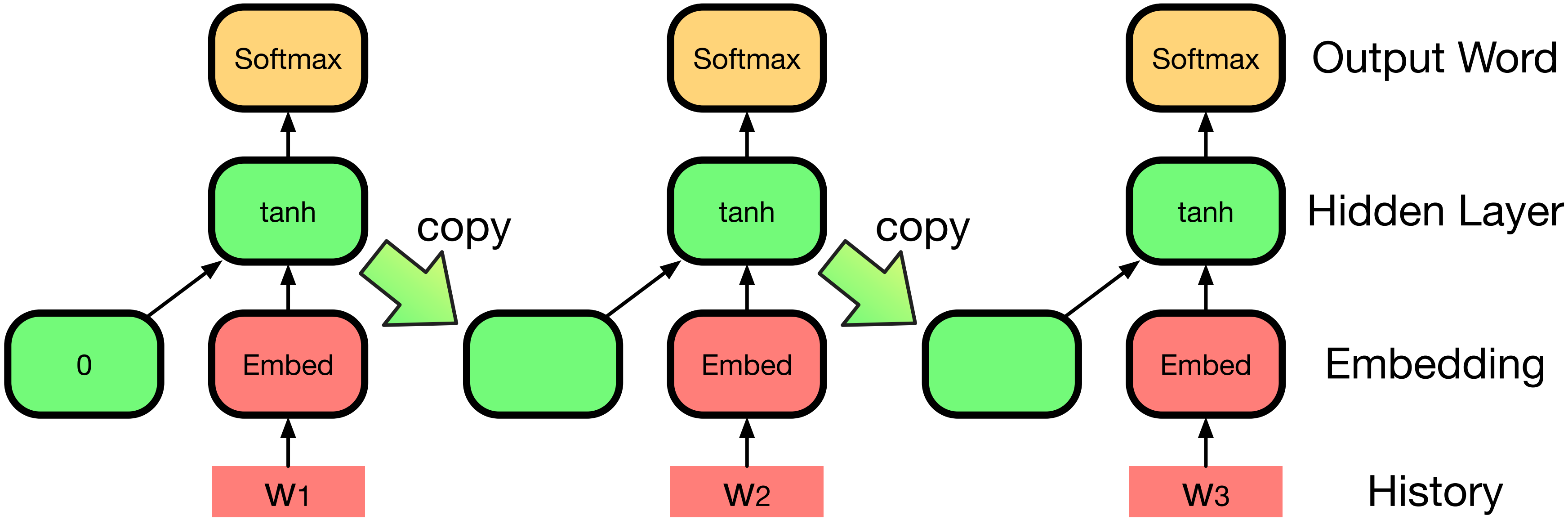
Output Word

Hidden Layer

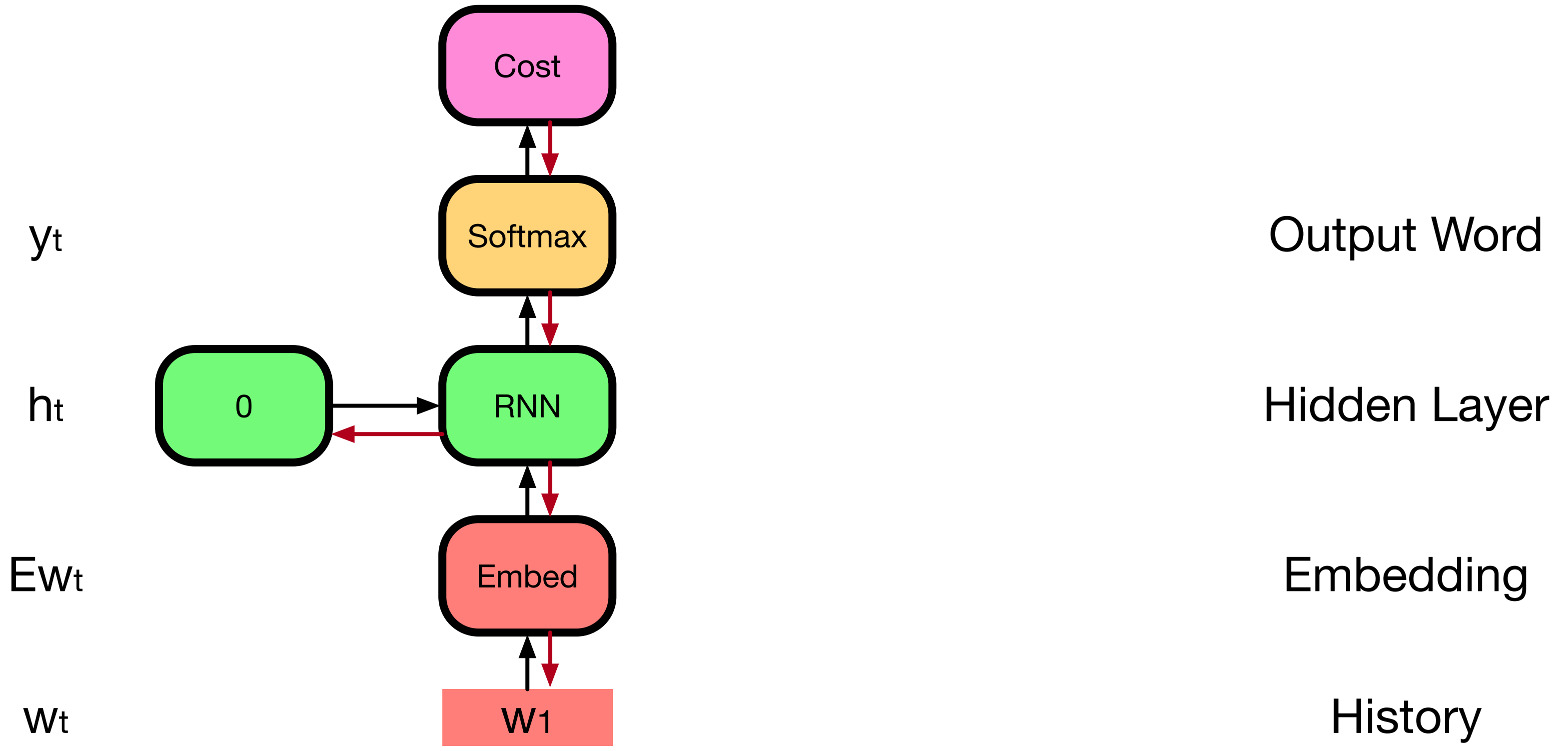
Embedding

History

Recurrent Neural Networks

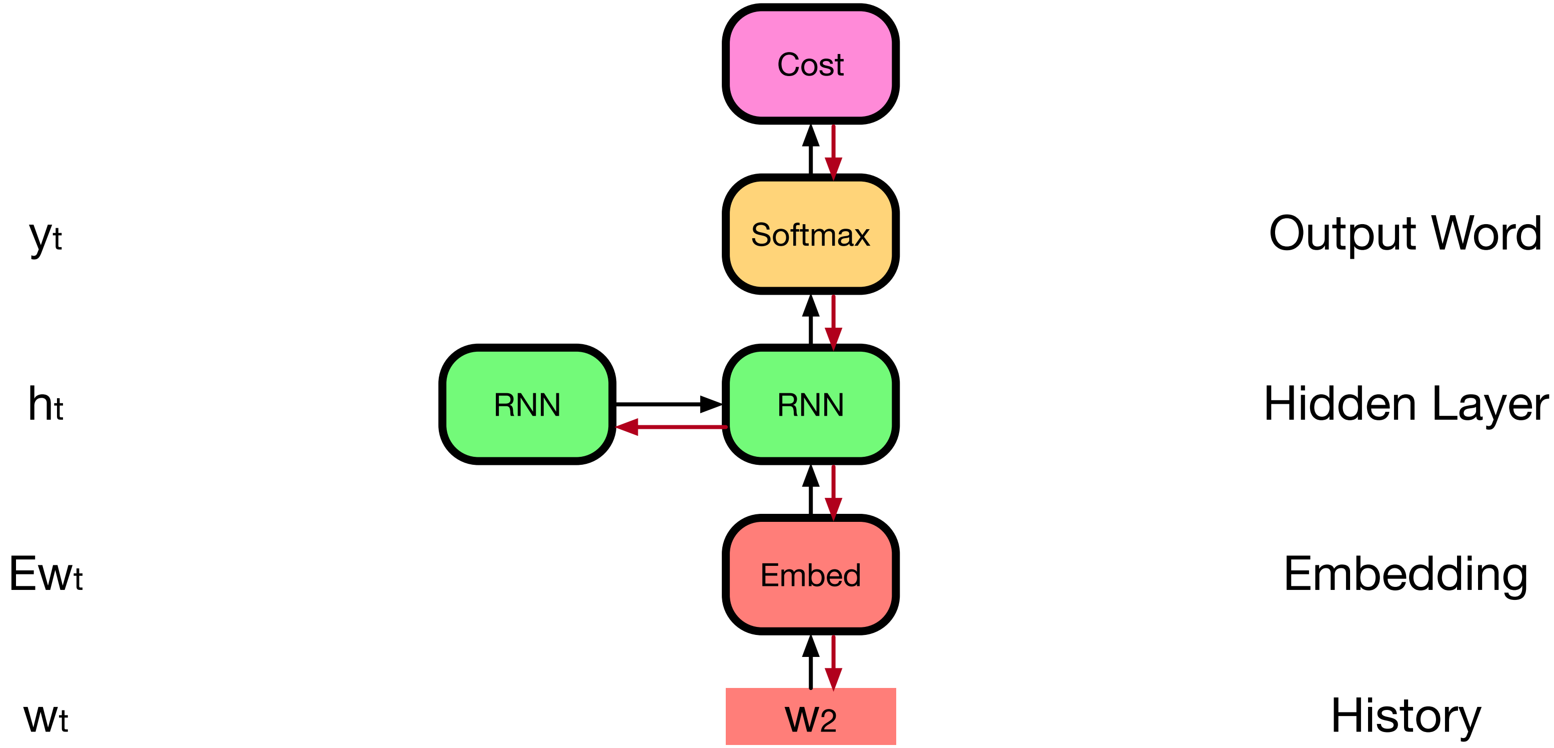


Training



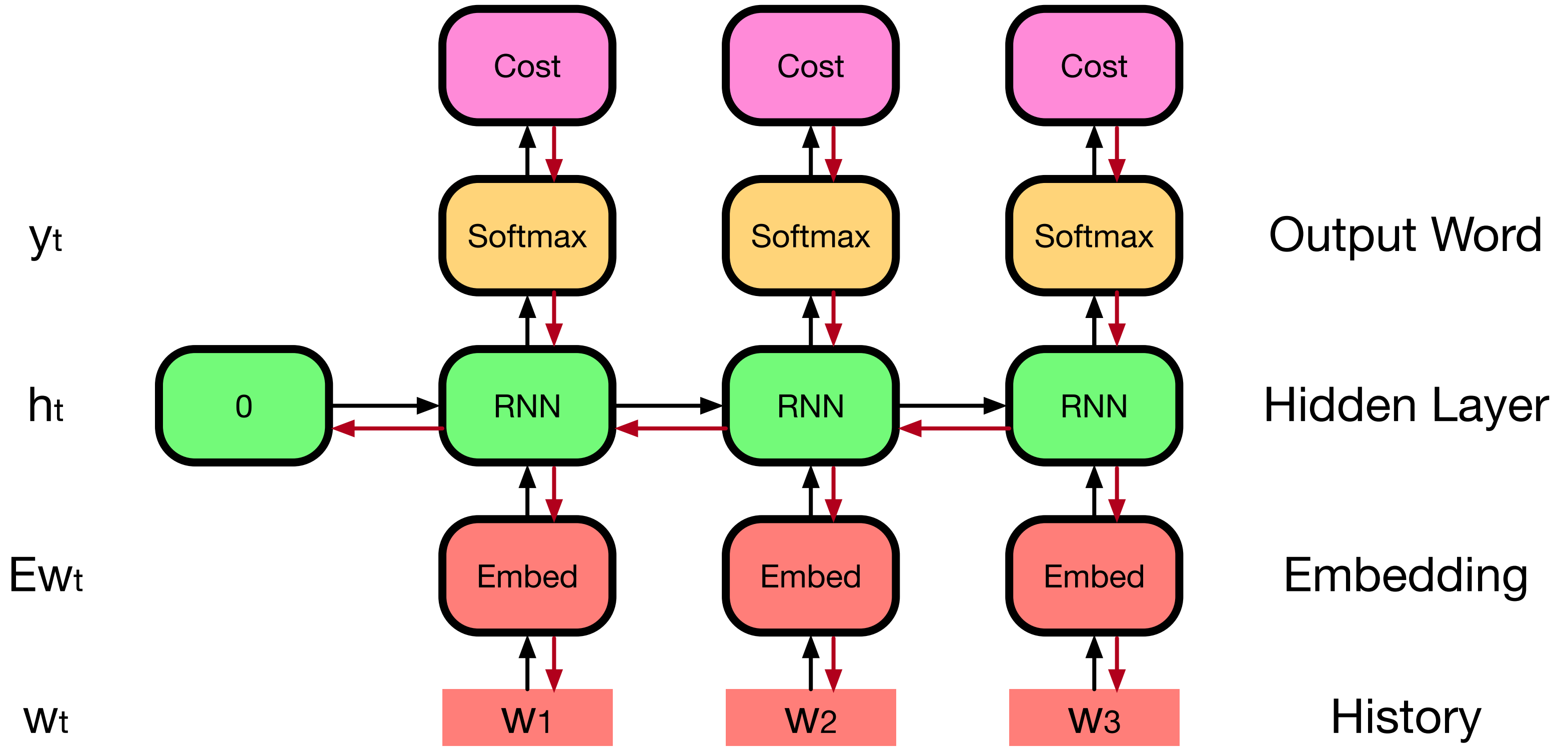
- Process first training example
- Update weights with back-propagation

Training



- Process second training example
- Update weights with back-propagation
- And so on...
- But: no feedback to previous history

Back-Propagation Through Time



- After processing a few training examples,
  update through the unfolded recurrent neural network

Back-Propagation Through Time

- Carry out back-propagation though time (BPTT) after each training example
  - 5 time steps seems to be sufficient
  - network learns to store information for more than 5 time steps

- Or: update in mini-batches
  - process 10-20 training examples
  - update backwards through all examples
  - removes need for multiple steps for each training example

long short term memory

Vanishing Gradients

- Error is propagated to previous steps

- Updates consider
  - prediction at that time step
  - impact on future time steps

- Vanishing gradient: propagated error disappears

Recent vs. Early History

- Hidden layer plays double duty
  - memory of the network
  - continuous space representation used to predict output words

- Sometimes only recent context important

  After much economic progress over the years, the **country** $\rightarrow$ *has*

- Sometimes much earlier context important

The **country** *which has made much economic progress over the years still* $\rightarrow$ *has*

Long Short Term Memory (LSTM)

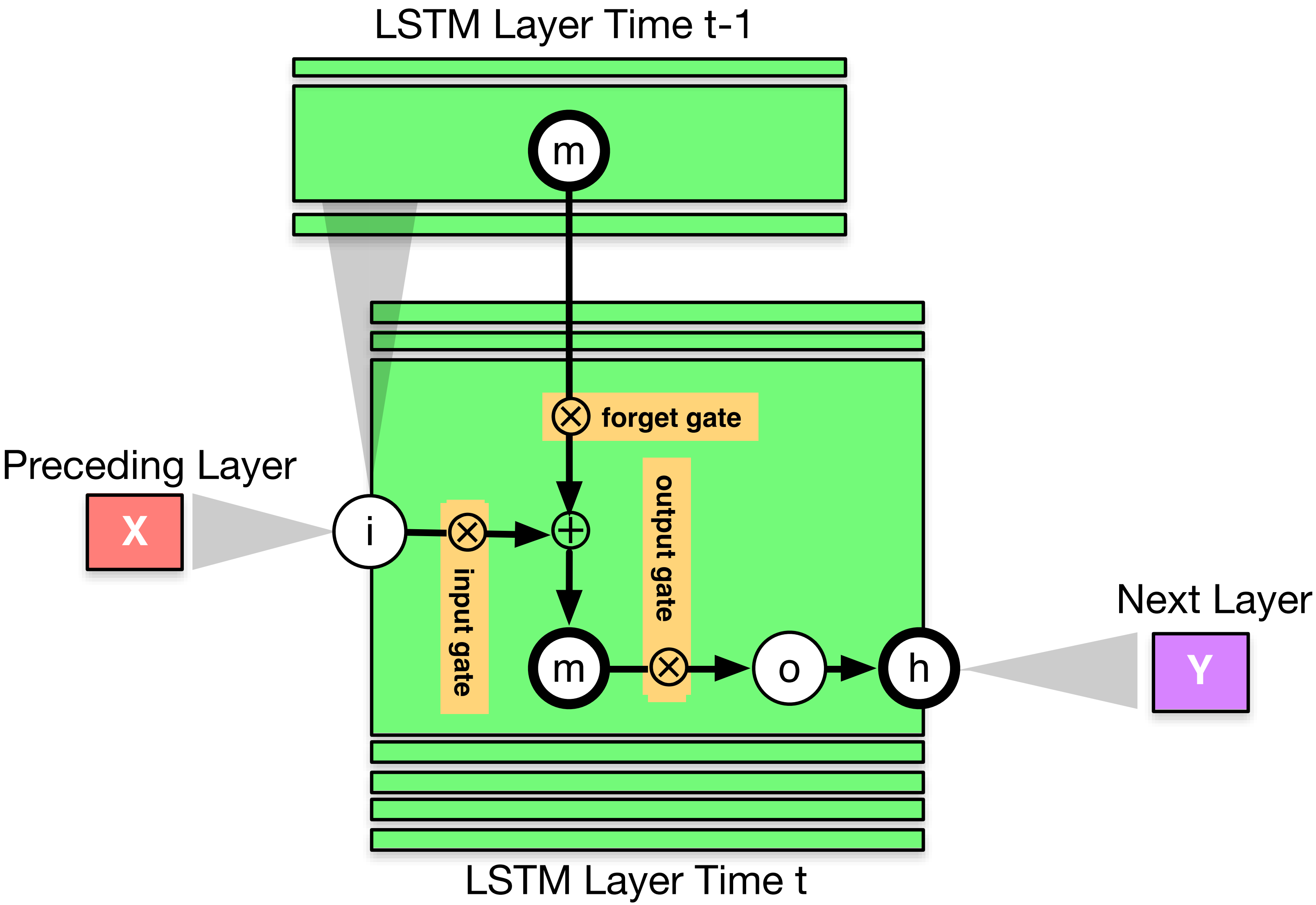
- Design quite elaborate, although not very complicated to use

- Basic building block: **LSTM cell**
  - similar to a node in a hidden layer
  - but: has a explicit memory state

- Output and memory state change depends on gates
  - **input gate**: how much new input changes memory state
  - **forget gate**: how much of prior memory state is retained
  - **output gate**: how strongly memory state is passed on to next layer.

- Gates can be not just be open (1) and closed (0), but slightly ajar (e.g., 0.2)

LSTM Cell


LSTM Layer Time t-1
m
forget gate
Preceding Layer
X
i
input gate
output gate
m
o
h
Next Layer
Y
LSTM Layer Time t

LSTM Cell (Math)

- Memory and output values at time step t

$$\text{memory}^t = \text{gate}_{\text{input}} \times \text{input}^t + \text{gate}_{\text{forget}} \times \text{memory}^{t-1}$$
$$\text{output}^t = \text{gate}_{\text{output}} \times \text{memory}^t$$

- Hidden node value h^t passed on to next layer applies activation function f

$$h^t = f(\text{output}^t)$$

- Input computed as input to recurrent neural network node
  - given node values for prior layer $\vec{x}^t = (x_1^t, ..., x_X^t)$
  - given values for hidden layer from previous time step $\vec{h}^{t-1} = (h_1^{t-1}, ..., h_H^{t-1})$
  - input value is combination of matrix multiplication with weights w^x and w^h and activation function g

$$\text{input}^t = g\left(\sum_{i=1}^{X} w_i^x x_i^t + \sum_{i=1}^{H} w_i^h h_i^{t-1}\right)$$

Values for Gates

- Gates are very important

- How do we compute their value?

  $\rightarrow$ with a neural network layer!

- For each gate $a \in (\text{input}, \text{forget}, \text{output})$
  - weight matrix W^{xa} to consider node values in previous layer $\vec{x}^t$
  - weight matrix W^{ha} to consider hidden layer $\vec{h}^{t-1}$ at previous time step
  - weight matrix W^{ma} to consider memory at previous time step $\vec{\text{memory}}^{t-1}$
  - activation function h

$$\text{gate}_a = h\left(\sum_{i=1}^{X} w_i^{xa} x_i^t + \sum_{i=1}^{H} w_i^{ha} h_i^{t-1} + \sum_{i=1}^{H} w_i^{ma} \text{memory}_i^{t-1}\right)$$

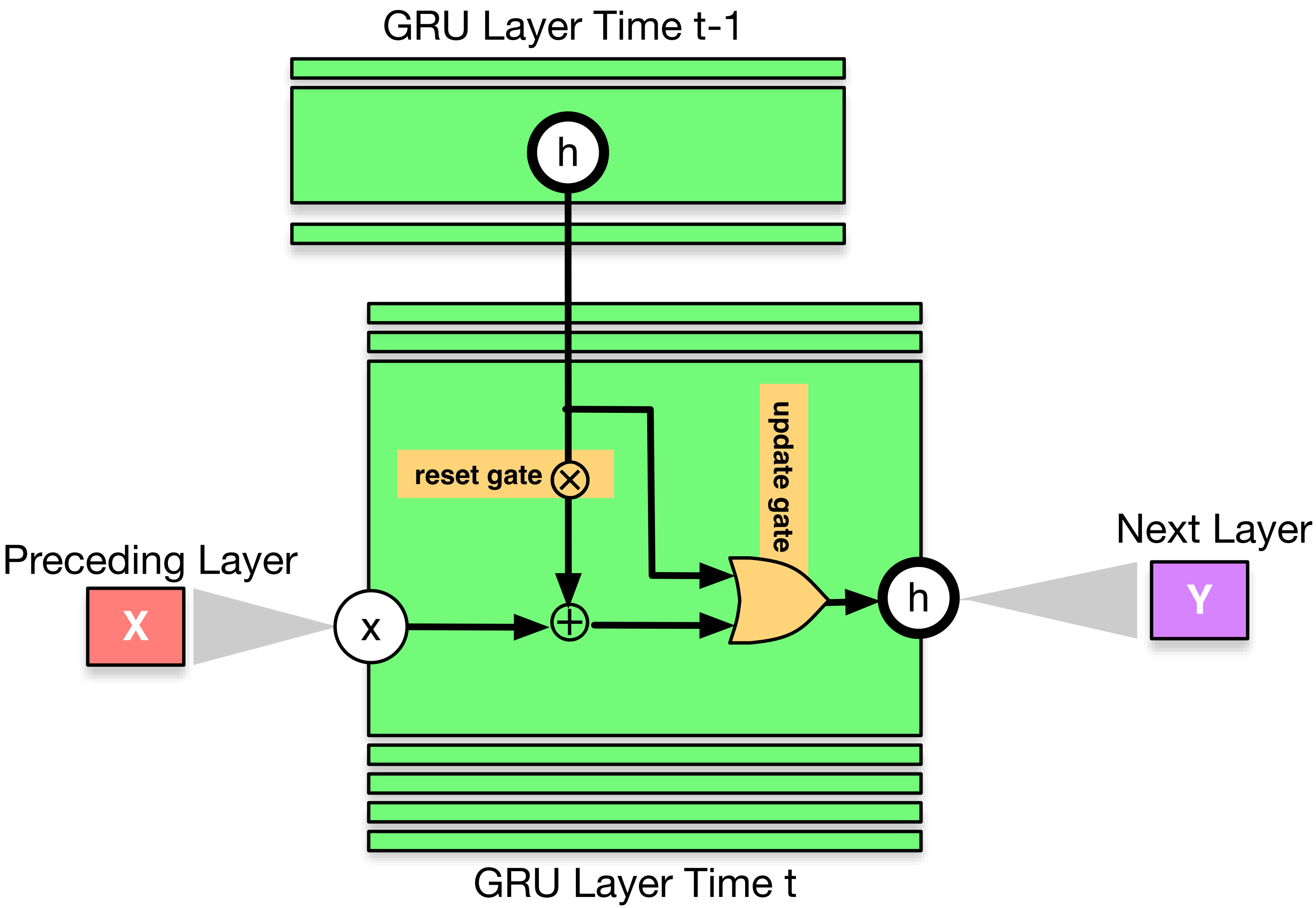
Training

- LSTM are trained the same way as recurrent neural networks
- Back-propagation through time
- This looks all very complex, but:
  - all the operations are still based on
    * matrix multiplications
    * differentiable activation functions

$\rightarrow$ we can compute gradients for objective function with respect to all parameters

$\rightarrow$ we can compute update functions

Gated Recurrent Unit (GRU)



Gated Recurrent Unit (Math)

- Two Gates

$$\text{update}_t = g(W_{\text{update}}\ \text{input}_t + U_{\text{update}}\ \text{state}_{t-1} + \text{bias}_{\text{update}})$$
$$\text{reset}_t = g(W_{\text{reset}}\ \ \text{input}_t + U_{\text{reset}}\ \ \ \text{state}_{t-1} + \text{bias}_{\text{reset}})$$

- Combination of input and previous state
(similar to traditional recurrent neural network)

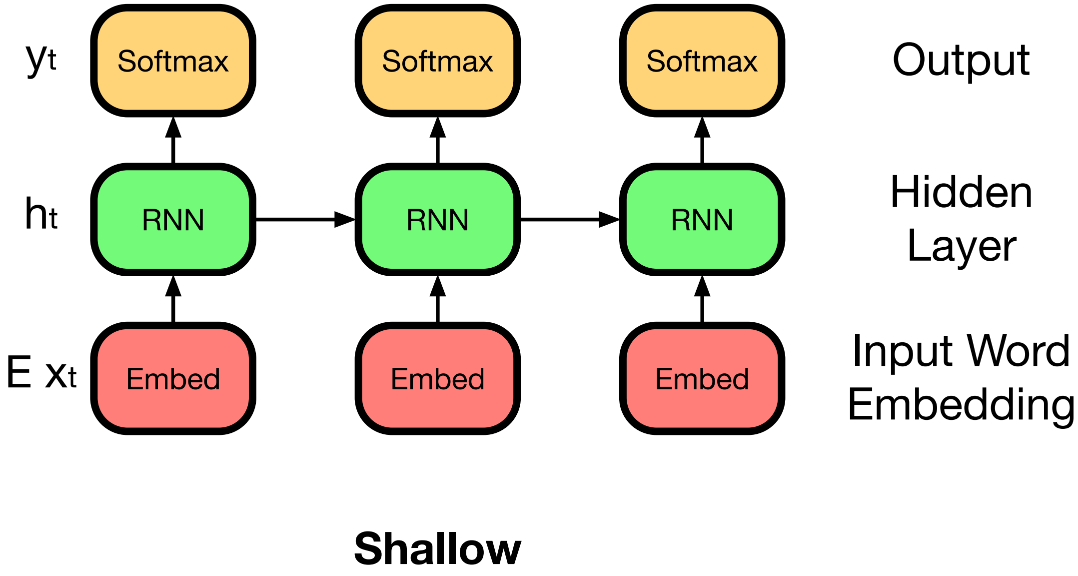
$$\text{combination}_t = f(W\ \text{input}_t + U(\text{reset}_t \circ \text{state}_{t-1}))$$

- Interpolation with previous state

$$\begin{aligned}\text{state}_t =&(1 - \text{update}_t) \circ \text{state}_{t-1} + \\ &\text{update}_t \qquad\quad \circ \text{combination}_t) + \text{bias}\end{aligned}$$

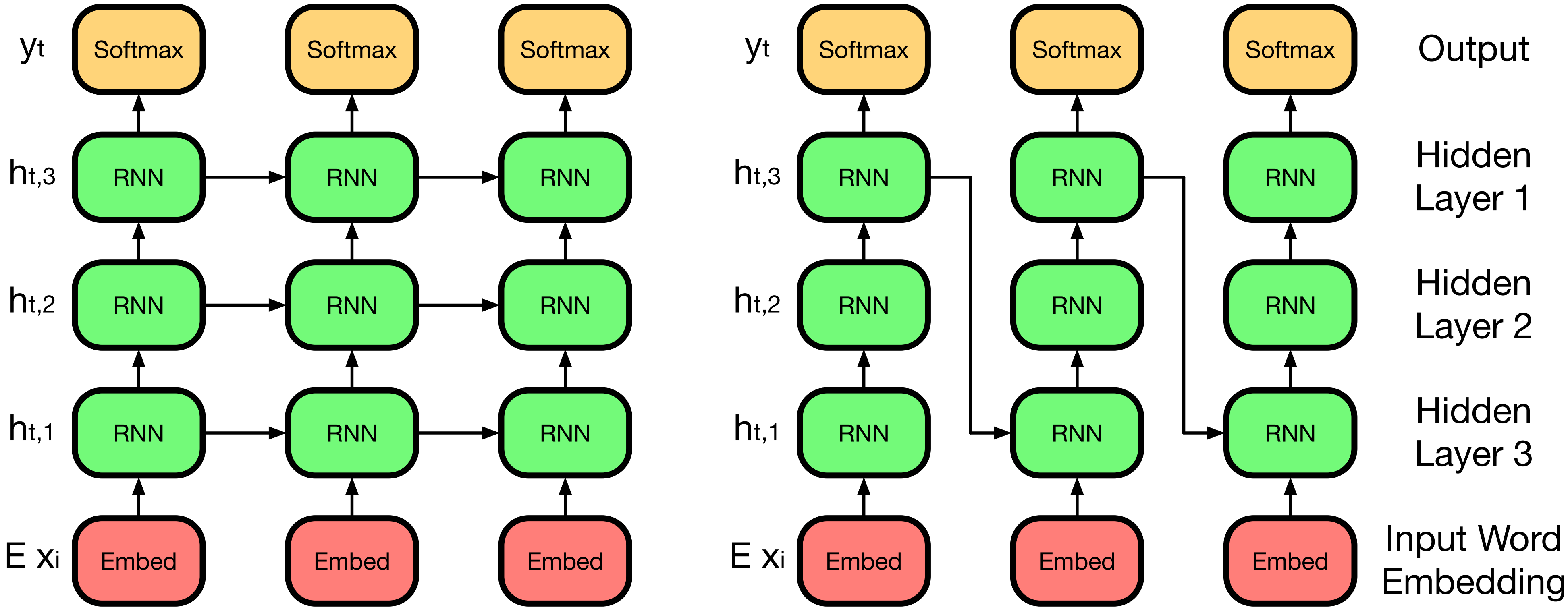
deeper models

Deep Learning?



- Not much **deep** learning so far
- Between prediction from input to output: only 1 hidden layer
- How about more hidden layers?

Deep Models



Deep Stacked **Deep Transitional**

questions?