텍스트마이닝 세미나

ToBig's 9기 신용재

Recurrent Neural Network

a.k.a RNN

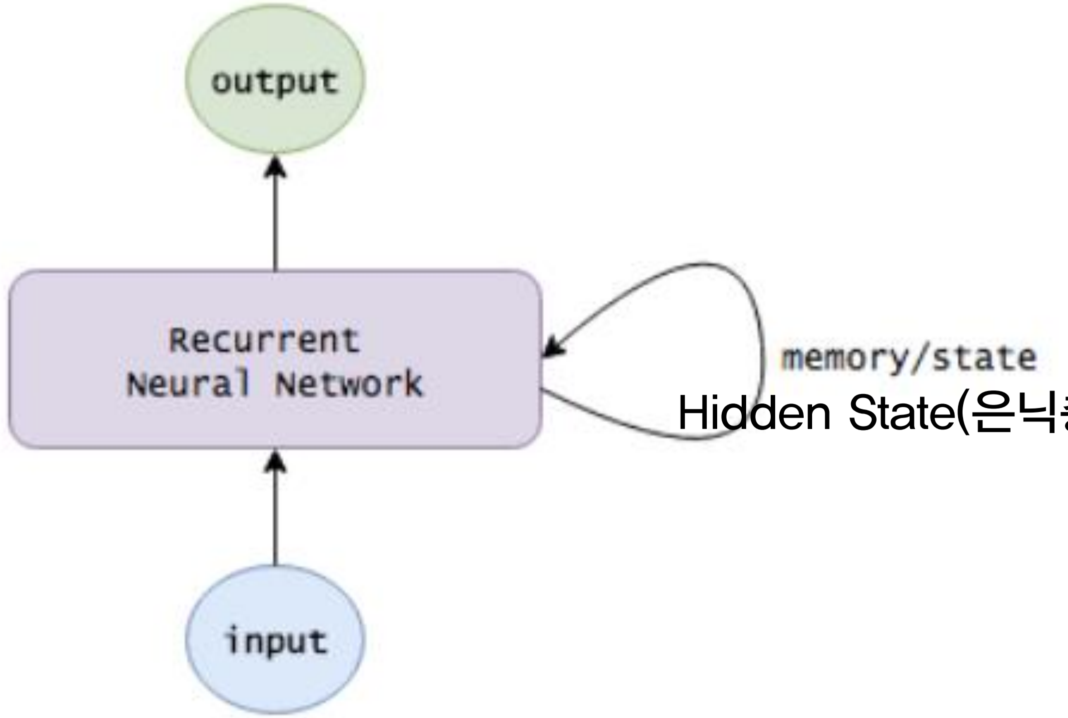
Contents

Recurrent Neural Network
(Recurrent= 되풀이되는, 반복되는)

순차적 데이터의 패턴을 인식하는 인공신경망

쓰임: 텍스트, 유전자, 손글씨, 음성, 동영상, 주가 … 시계열

Unit 01 | RNN이란



Hidden State(은닉층)

Recurrent Neural Network

Recurrent= 되풀이되는, 반복되는

피드백 구조
–과거의 출력이 다시 모델에 입력되는 구조

–〉모든 sequence에서..
같은 함수, 같은 파라미터가 계속해서 적용.

은닉층
–입력 데이터는 은닉층에 저장된다. 기억을
저장하고 있듯이 은닉층에 기억을 저장한다.

–〉 입력과 보유하고 있던 기억으로 다음 행동을 결정.

Unit 01 | RNN이란

RNN의 쓰임.. Unfold 형태

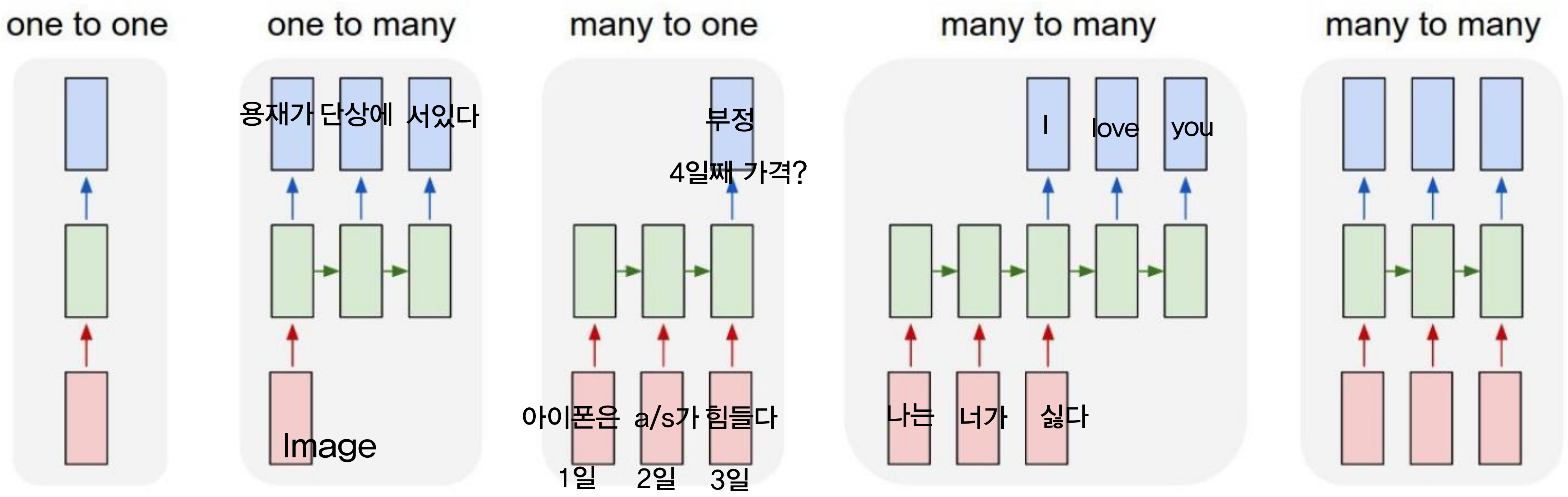


Image Captioning

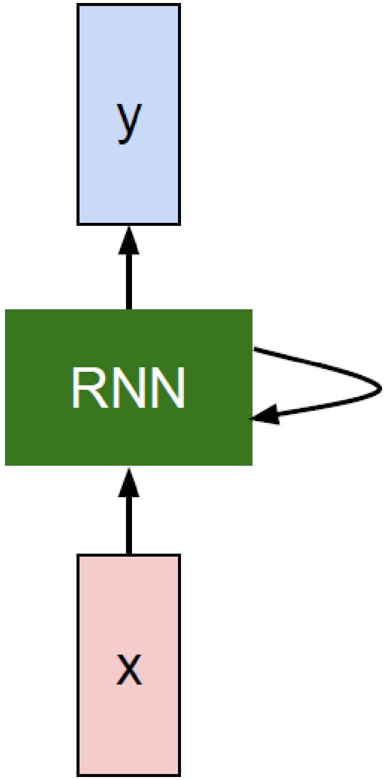
Sentiment Classification
Stock Price

Machine translation

Video Classification

http://cs231n.stanford.edu/slides/2017/

Unit 02 | RNN의 구조



(Vanilla) RNN

$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

some function
with parameters W

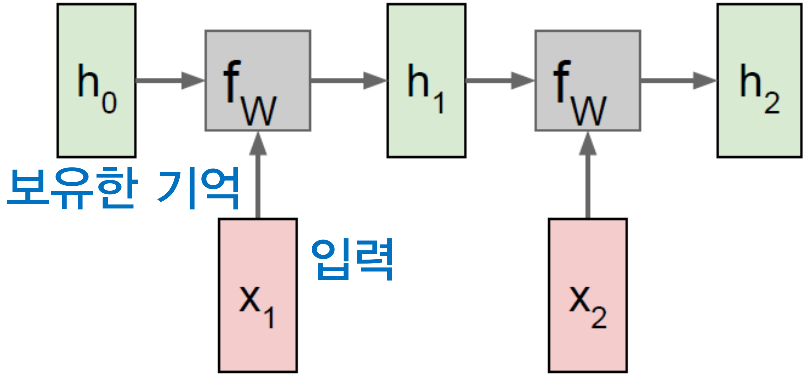
old state

input vector at
some time step

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

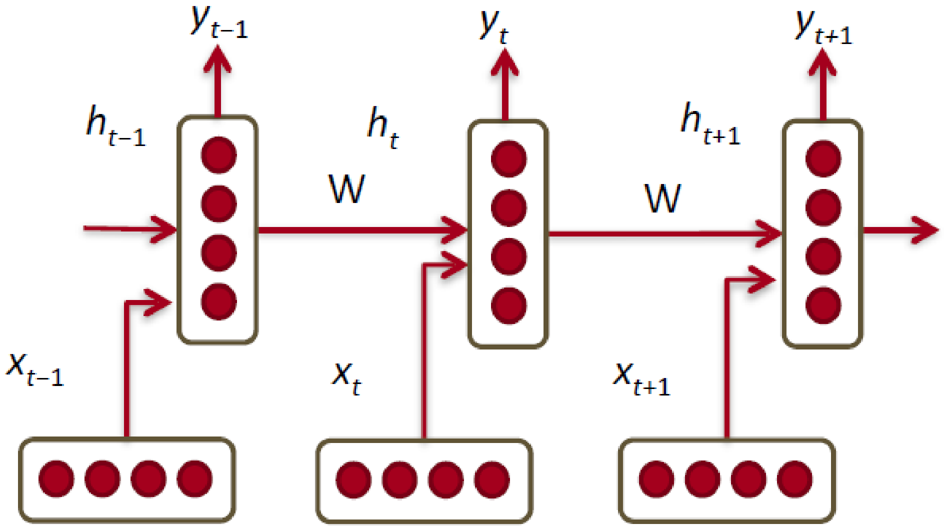
$$y_t = W_{hy}h_t$$

*Neural Net: σ (WX+b)



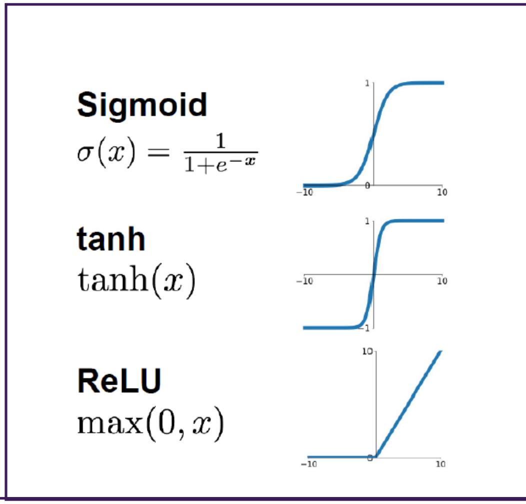
http://cs231n.stanford.edu/slides/2017/

Unit 02 | RNN의 구조



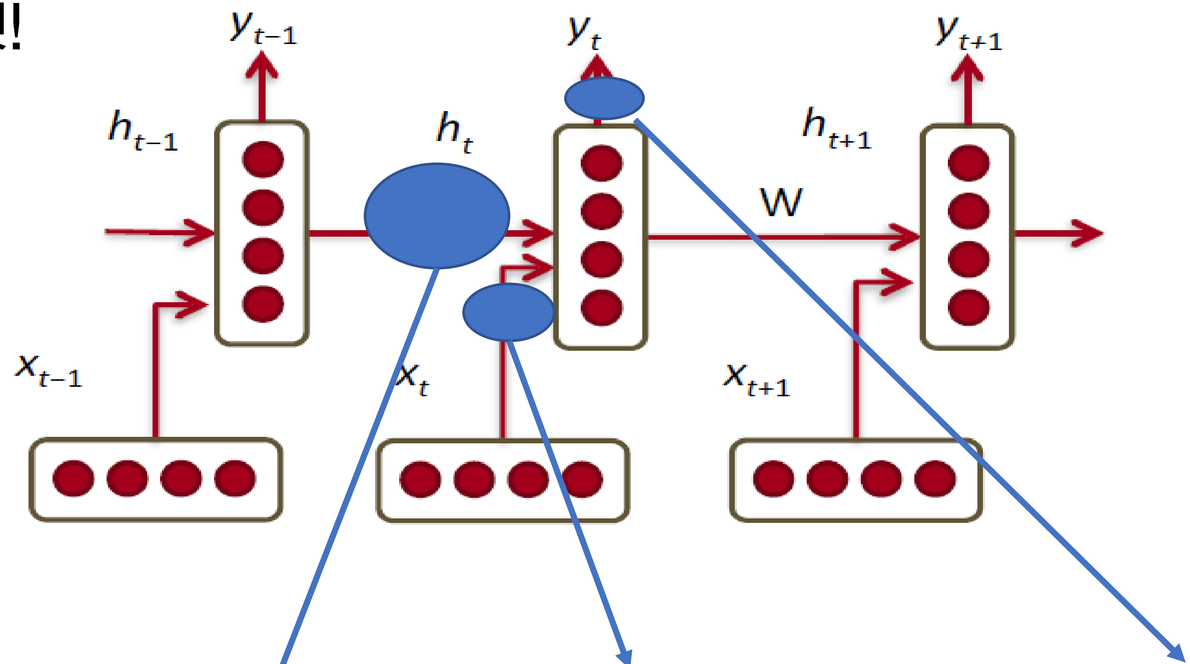
$$h_t = \tanh(\boxed{W_{hh}}\boxed{h_{t-1}} + \boxed{W_{xh}}\boxed{x_t})$$

$$y_t = \boxed{W_{hy}} h_t$$



Unit 02 | RNN의 구조

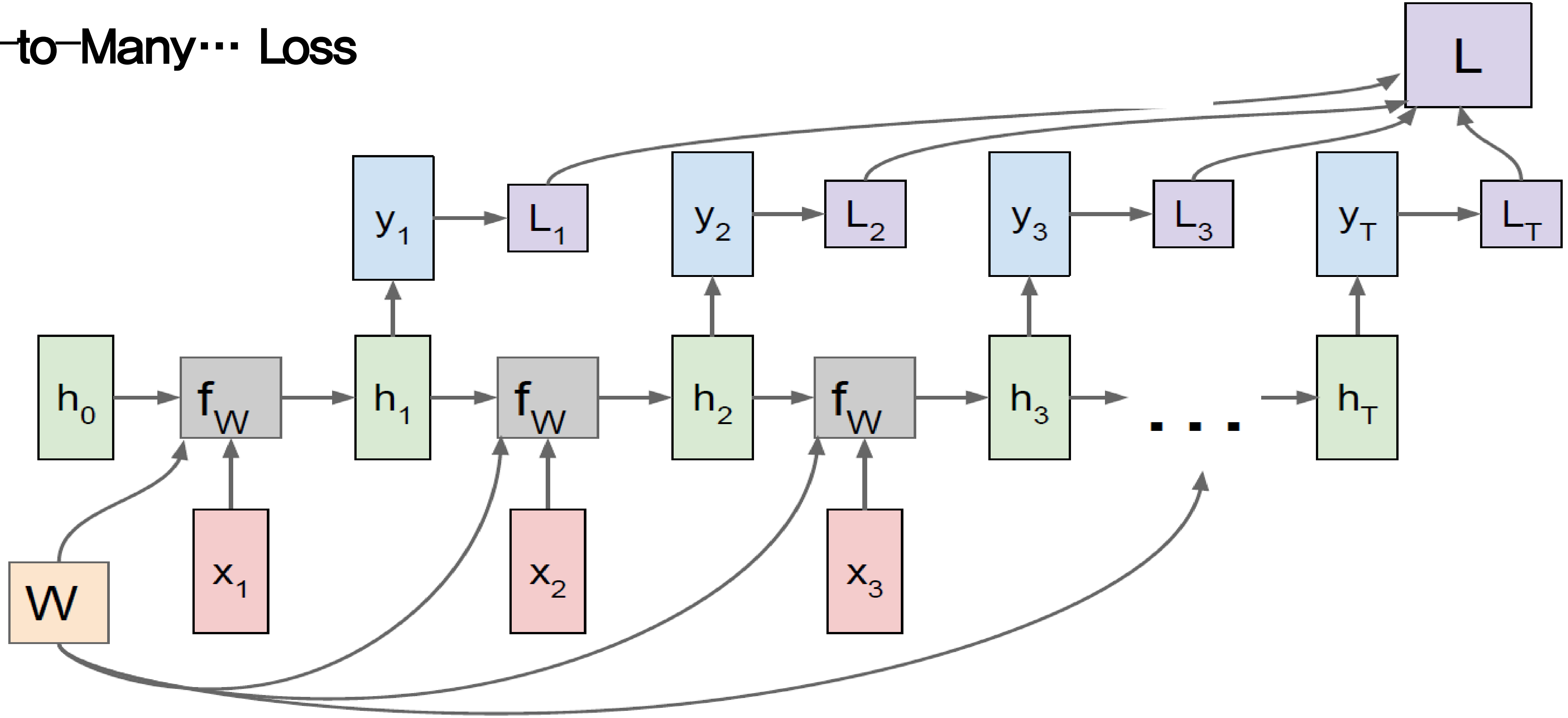
RNN의 목표
파라미터(W) 학습시키는 것!



$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t) \qquad y_t = W_{hy}h_t$$

Unit 02 | RNN의 구조

Many-to-Many… Loss



http://cs231n.stanford.edu/slides/2017/

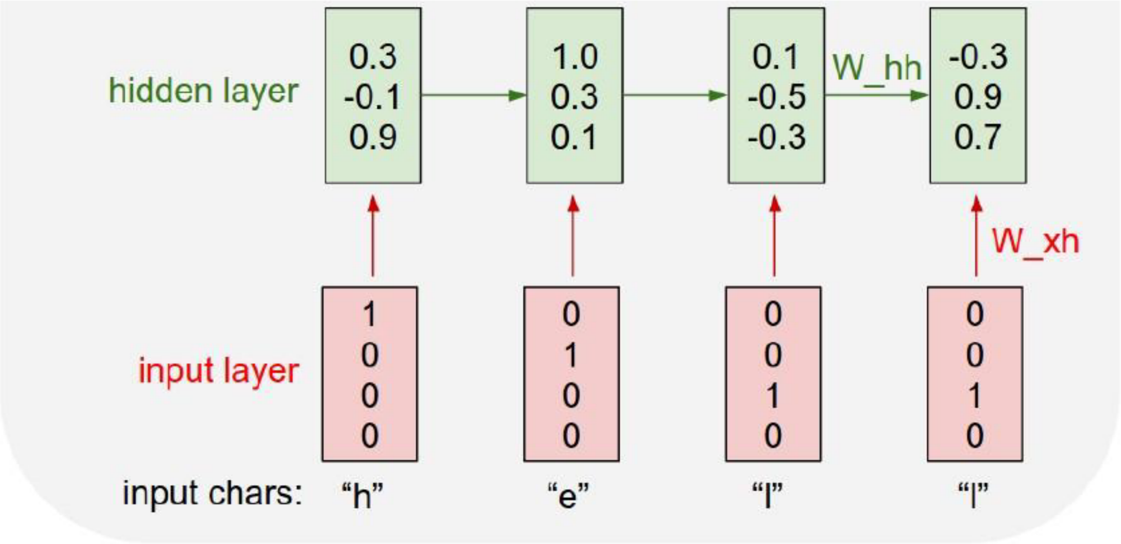
Unit 03 | Character Level Language Model

Example: Character-level Language Model

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t)$$

Vocabulary: [h,e,l,o]

Example training sequence: **“hello”**

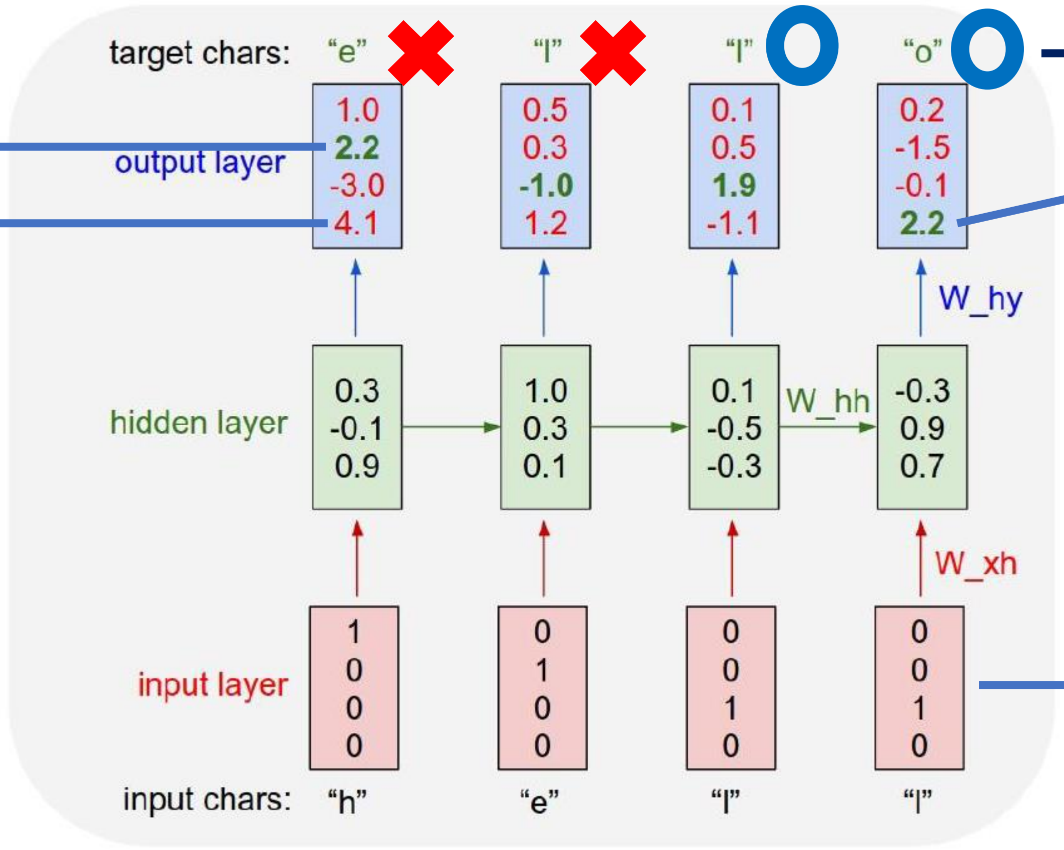


http://cs231n.stanford.edu/slides/2017/

Unit 03 | Character Level Language Model

Answer

Predict



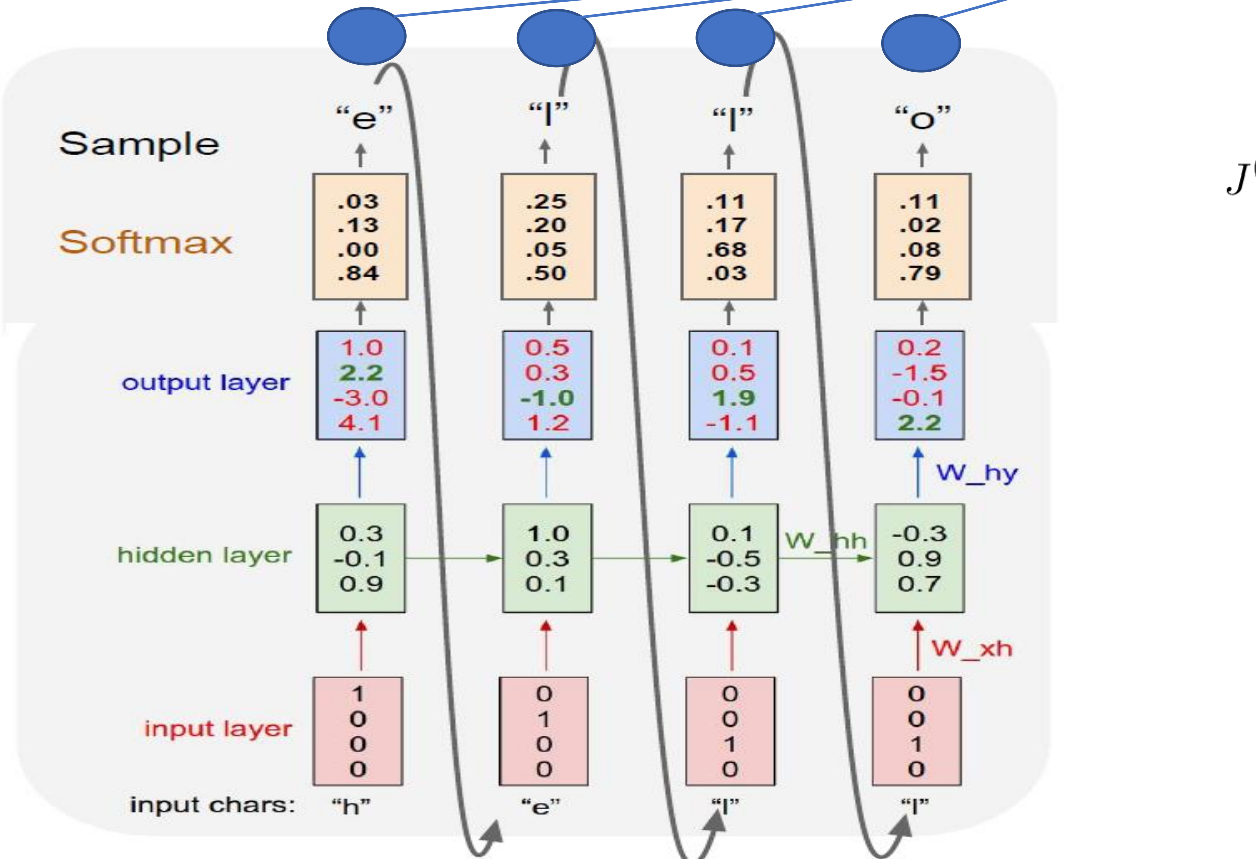
예측에 따른 Loss 발생 → Loss 최소화하도록 갱신

Predict = Answer

Input vector

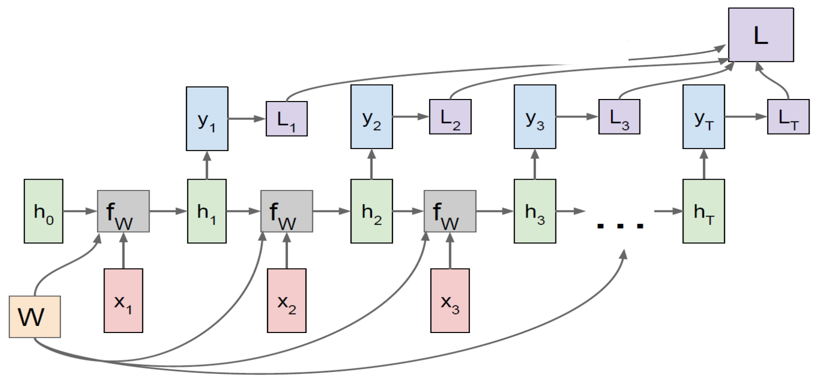
http://cs231n.stanford.edu/slides/2017/

Unit 03 | Character Level Language Model



$$J = -\frac{1}{T}\sum_{t=1}^{T}\sum_{j=1}^{|V|} y_{t,j}\log \hat{y}_{t,j}$$ –〉 Loss Function

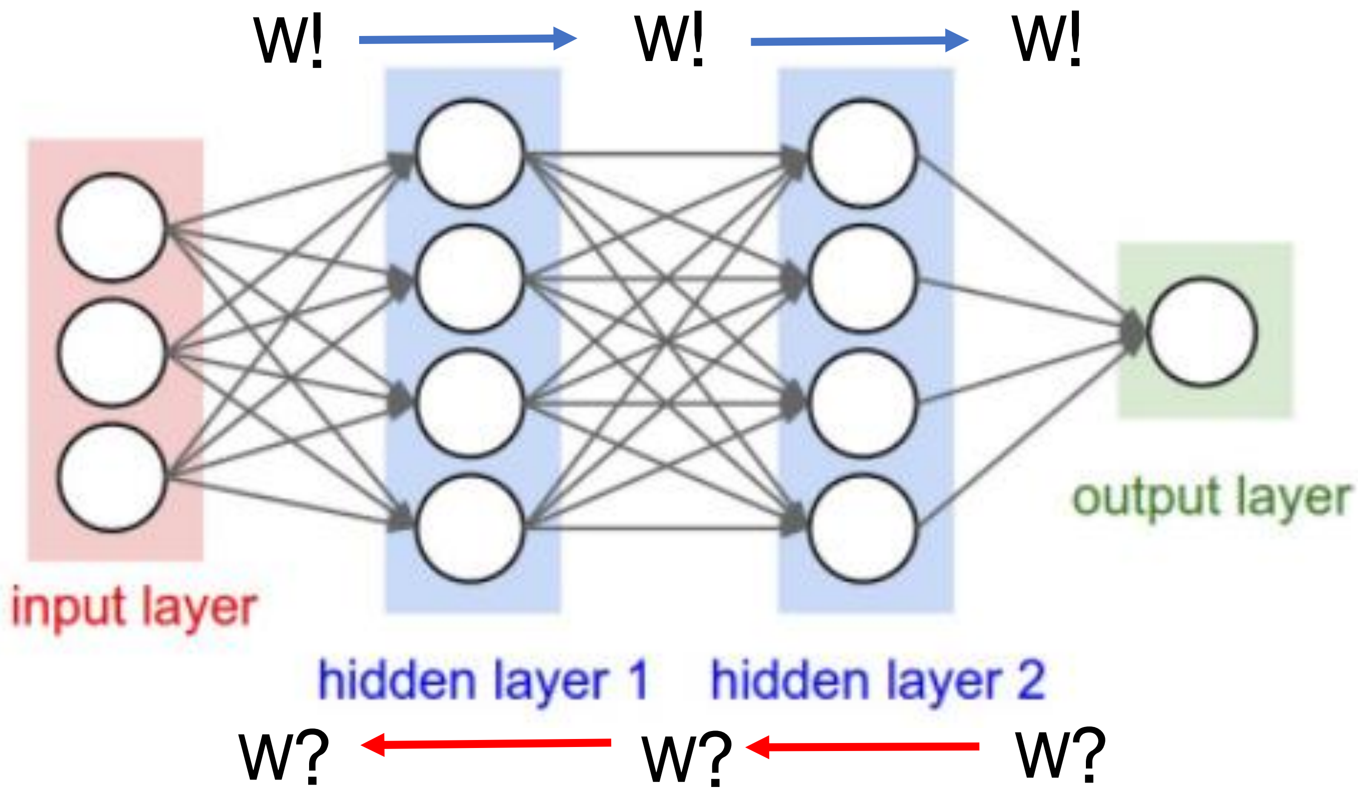
$$J^{(t)}(\theta) = -\sum_{j=1}^{|V|} y_{t,j}\log \hat{y}_{t,j}$$

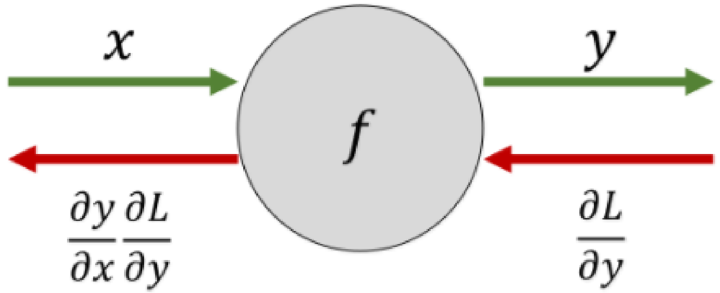


http://cs231n.stanford.edu/slides/2017/
http://web.stanford.edu/class/cs224n/archive/WWW_1617/

Unit 04 | NN Forward, Backward Propagation

Recap!





노드(원): 함수 및 연산
엣지(선): 값

∂L/∂y: y에 대한 Loss의 변화량
∂L/∂x: 현재 입력값에 대한 현재 연산결과의 변화량(로컬 그래디언트)

https://ratsgo.github.io/deep%20learning/2017/05/14/backprop

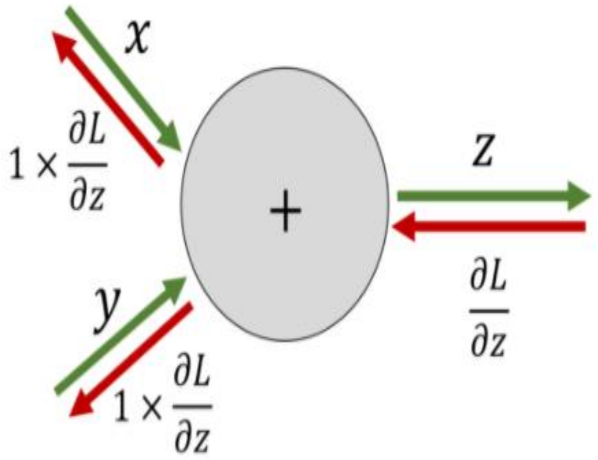
Unit 04 | NN Forward, Backward Propagation

덧셈 노드

$$z = f(x, y) = x + y$$

$$\frac{\partial z}{\partial x} = \frac{\partial (x+y)}{\partial x} = 1$$

$$\frac{\partial z}{\partial y} = \frac{\partial (x+y)}{\partial y} = 1$$



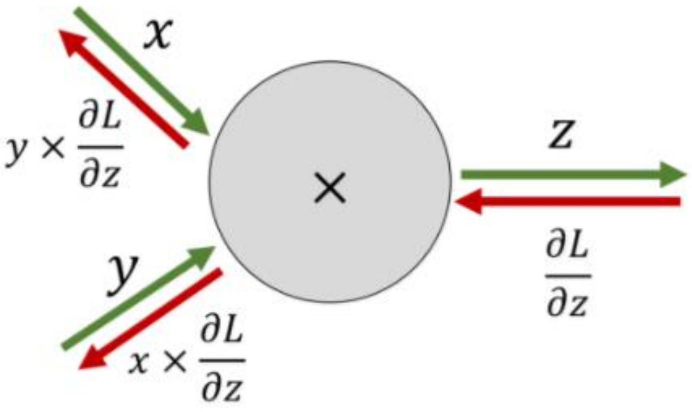
덧셈 노드의 역전파는
흘러들어온 그래디언트를 그대로 흘려보낸다.

곱셈 노드

$$z = f(x, y) = xy$$

$$\frac{\partial z}{\partial x} = \frac{\partial (xy)}{\partial x} = y$$

$$\frac{\partial z}{\partial y} = \frac{\partial (xy)}{\partial y} = x$$

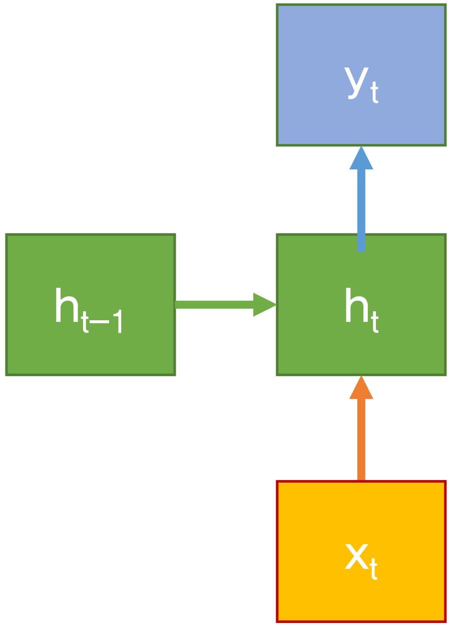


곱셈 노드의 역전파는
입력 신호들을 서로 바꾼 값을 곱해서 흘려보낸다.

$$y = tanh(x). \quad \frac{\partial y}{\partial x} = 1 - y^2$$

https://ratsgo.github.io/deep%20learning/2017/05/14/backprop

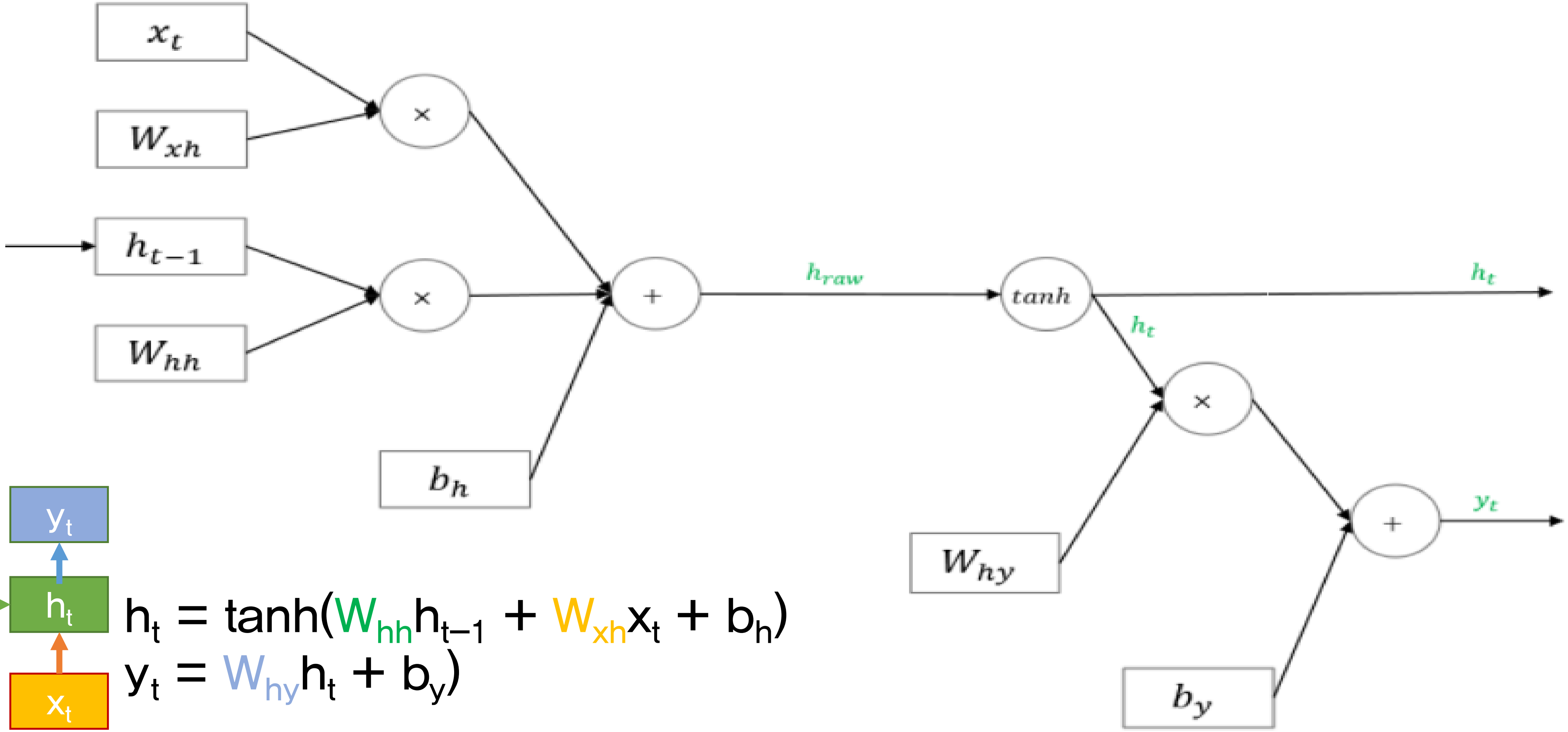
Unit 05 | RNN Forward, Backward Propagation

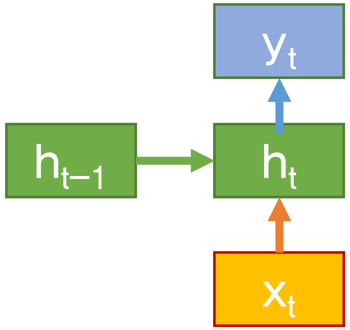


$$y_t = W_{hy}h_t + b_y)$$

$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_h)$$

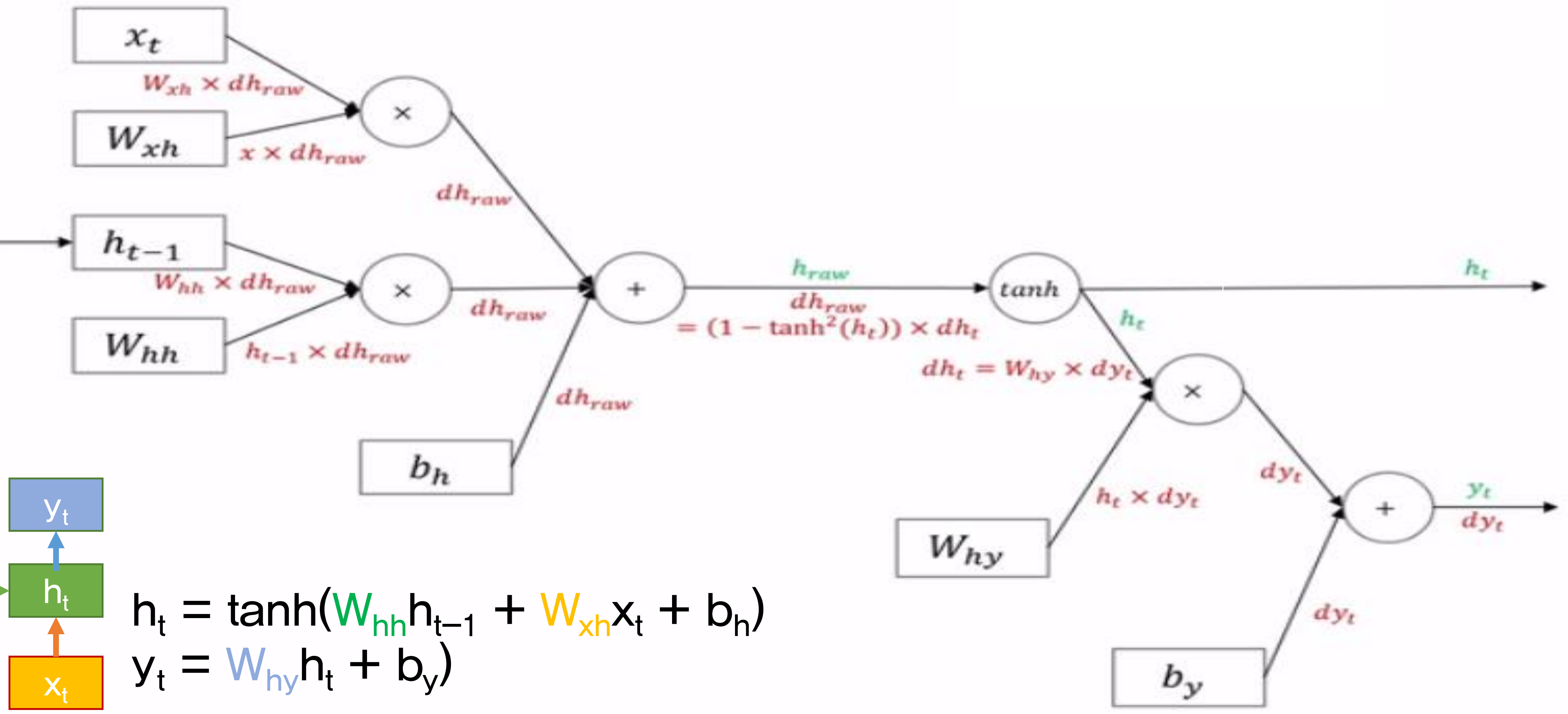
Unit 05 | RNN Forward, Backward Propagation

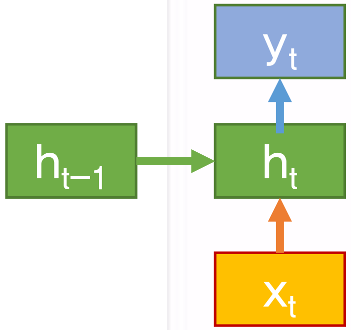




$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_h)$$
$$y_t = W_{hy}h_t + b_y)$$

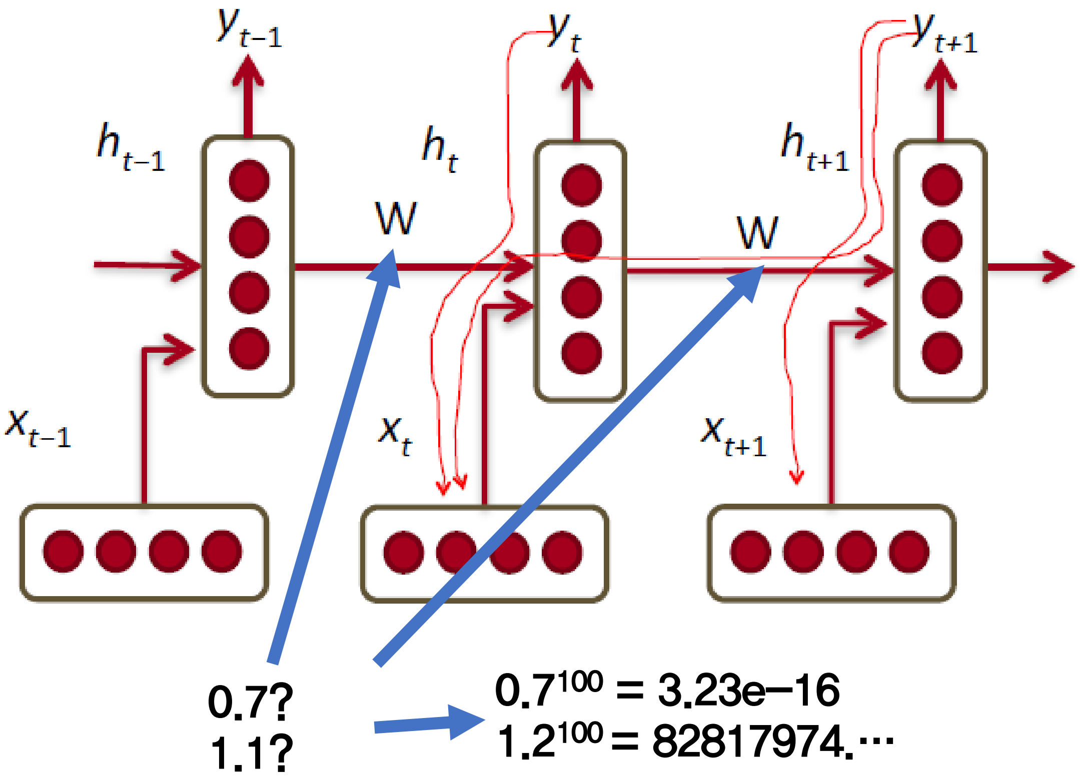
Unit 05 | RNN Forward, Backward Propagation





$$h_t = \tanh(W_{hh}h_{t-1} + W_{xh}x_t + b_h)$$
$$y_t = W_{hy}h_t + b_y)$$

Unit 05 | RNN Forward, Backward Propagation



$0.7^{100} = 3.23e{-16}$
$1.2^{100} = 82817974.\cdots$

–〉 Vanishing or Exploding Gradient

$$h_t = W f(h_{t-1}) + W^{(hx)} x_{[t]}$$
$$\hat{y}_t = W^{(S)} f(h_t)$$

$$\frac{\partial E}{\partial W} = \sum_{t=1}^{T} \frac{\partial E_t}{\partial W}$$

$$\frac{\partial E_t}{\partial W} = \sum_{k=1}^{t} \frac{\partial E_t}{\partial y_t} \frac{\partial y_t}{\partial h_t} \boxed{\frac{\partial h_t}{\partial h_k}} \frac{\partial h_k}{\partial W}$$

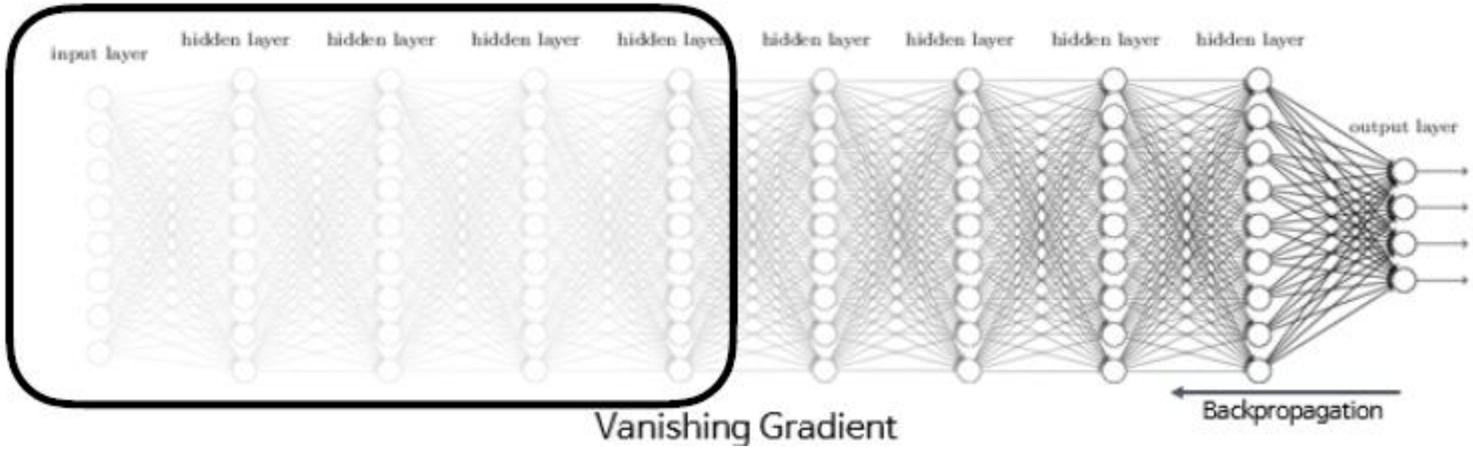
$$\frac{\partial h_t}{\partial h_k} = \prod_{j=k+1}^{t} \frac{\partial h_j}{\partial h_{j-1}}$$

http://web.stanford.edu/class/cs224n/archive/WWW_1617/

Unit 05 | RNN Forward, Backward Propagation

Vanishing and Exploding Gradient Problem-〉 Long Short Term Memory

관련 정보와 그 정보를 사용하는 지점 사이가 멀 경우
역전파시 그래디언트가 점차 줄어 학습능력이 크게 저하된다.



Q & A

들어주셔서 감사합니다.