아티스트를 위한 머신러닝 & 딥러닝

텐서플로를 활용한 딥러닝 #6

서울대학교 & V.DO / 김대식

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Recap

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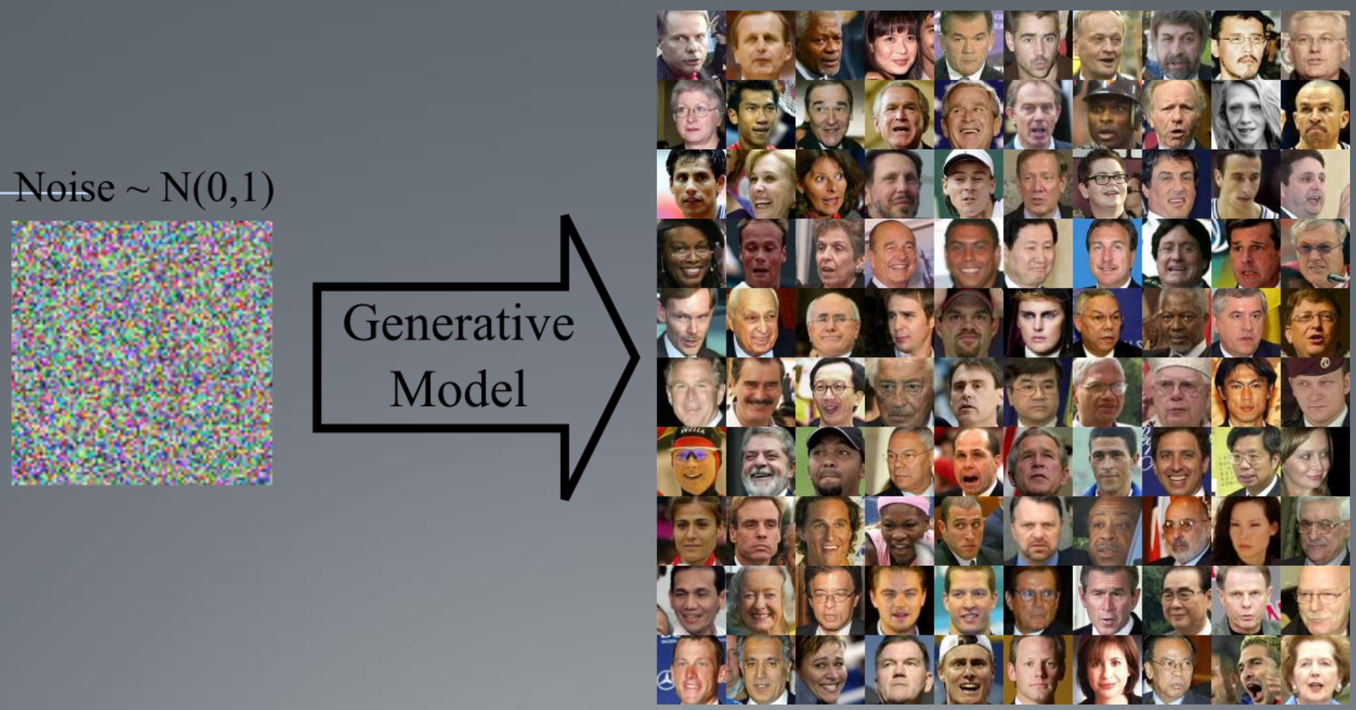
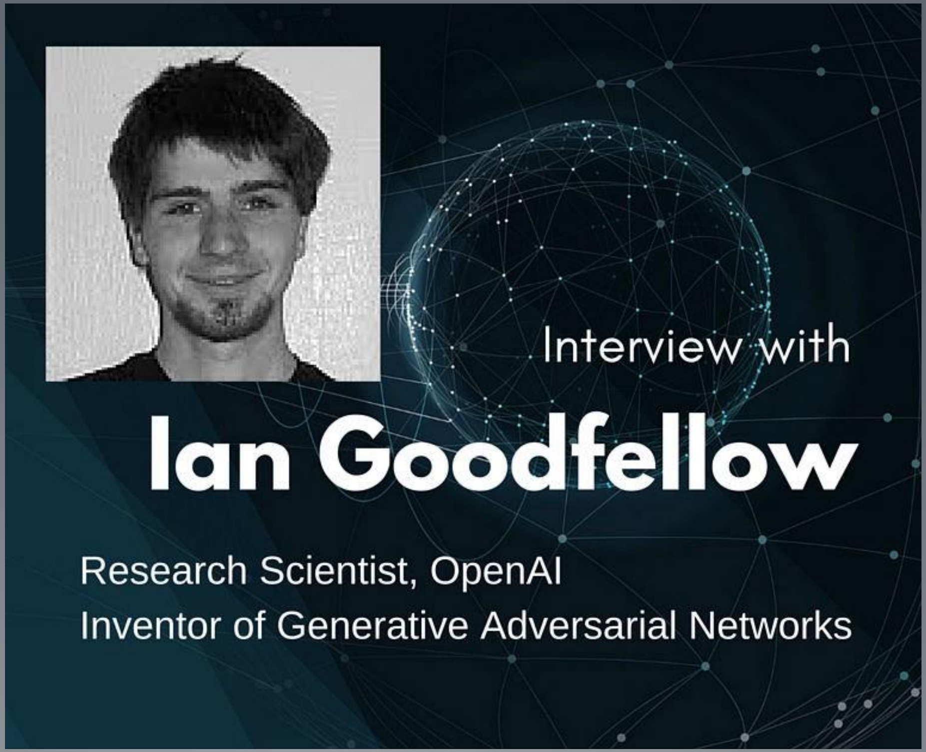
Generative Adversarial network(GAN)



Generative Adversarial network(GAN)



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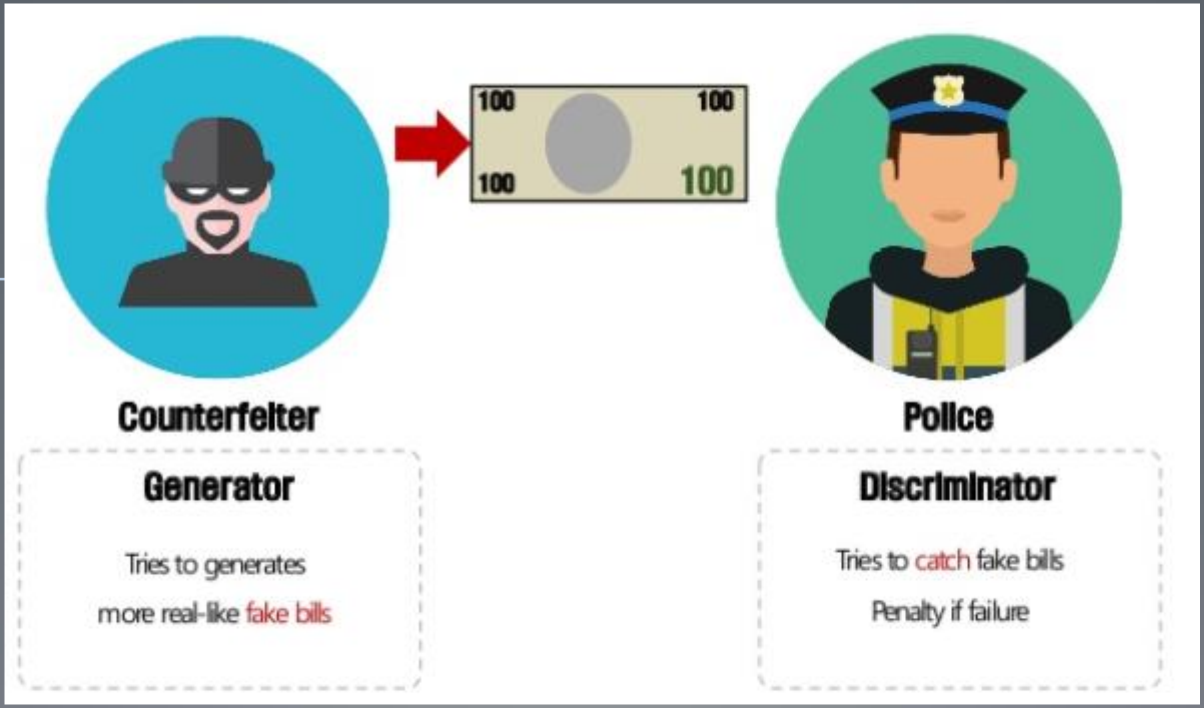
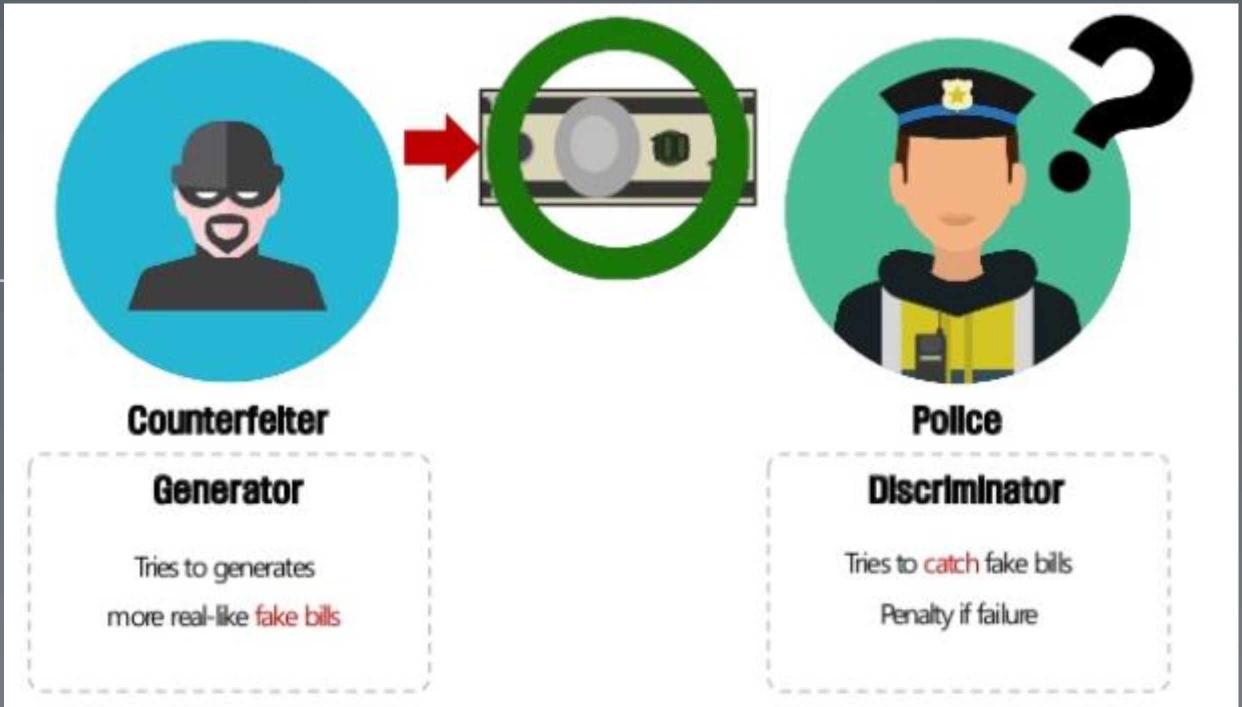
위조지폐범 vs 경찰


100
100
100
100
Counterfelter
Generator
Tries to generates
more real-like fake bills
Police
Discriminator
Tries to catch fake bills
Penalty if failure

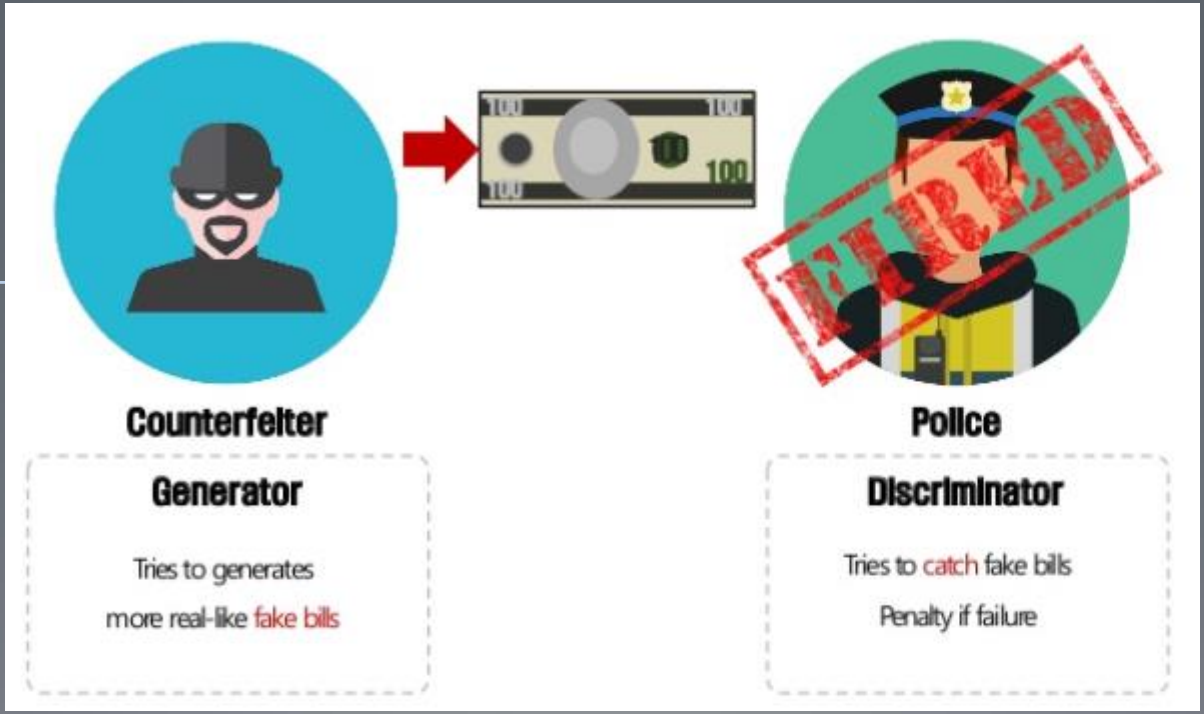
위조지폐범 vs 경찰


100
100
BUSTED!
100
100
Counterfelter
Generator
Tries to generates
more real-like fake bills
Police
Discriminator
Tries to catch fake bills
Penalty if failure

위조지폐범 vs 경찰

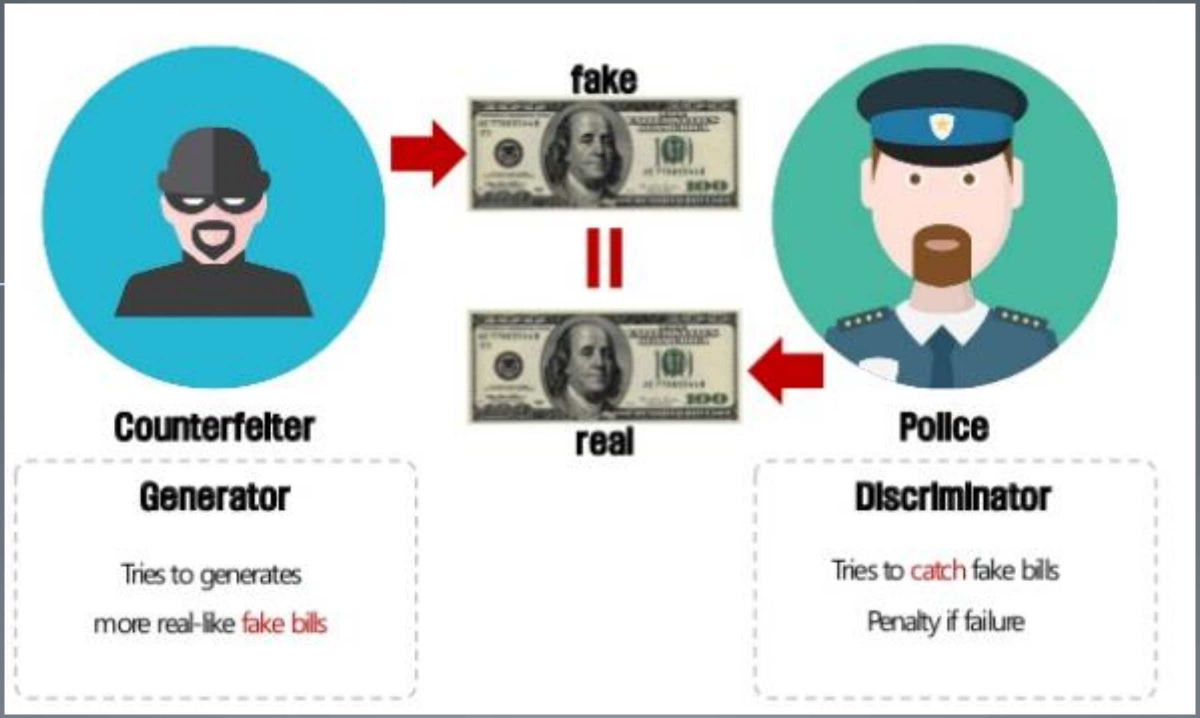

Counterfelter
Generator
Tries to generates
more real-like fake bills
Police
Discriminator
Tries to catch fake bills
Penalty if failure

위조지폐범 vs 경찰

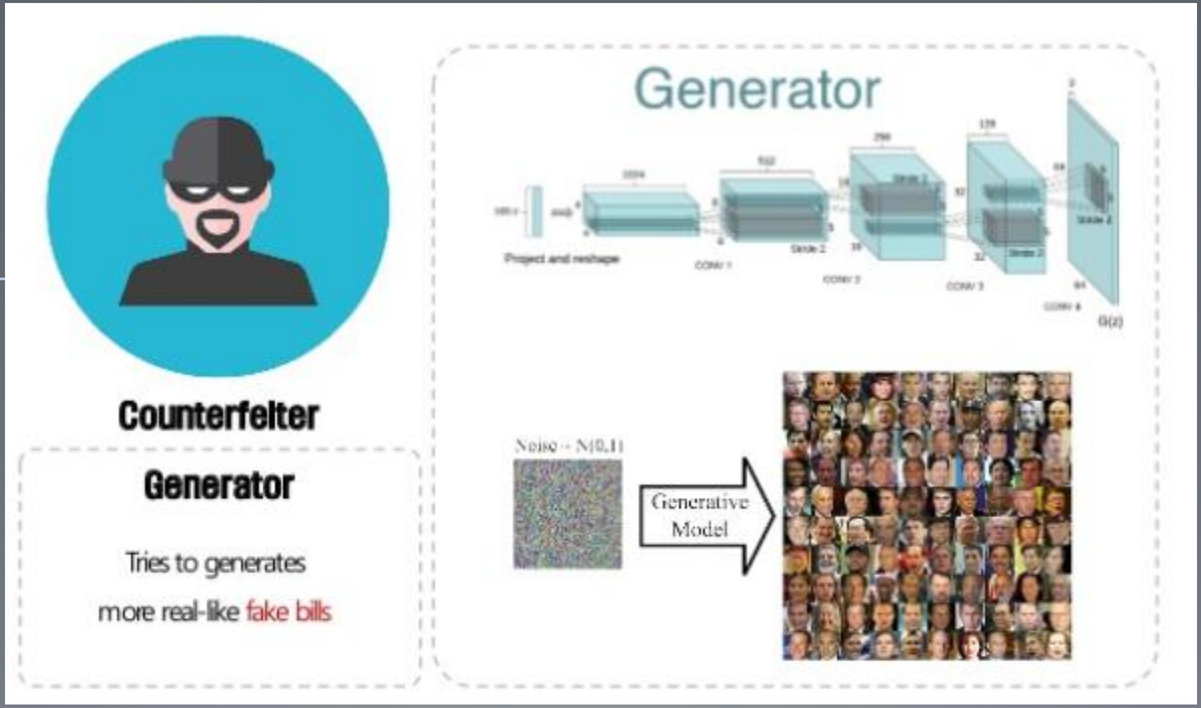


100
Counterfelter
Generator
Tries to generates
more real-like fake bills
FIRED
Police
Discriminator
Tries to catch fake bills
Penalty if failure

위조지폐범 vs 경찰


fake
real
Counterfeiter
Generator
Tries to generates
more real-like fake bills
Police
Discriminator
Tries to catch fake bills
Penalty if failure

위조지폐범 vs 경찰



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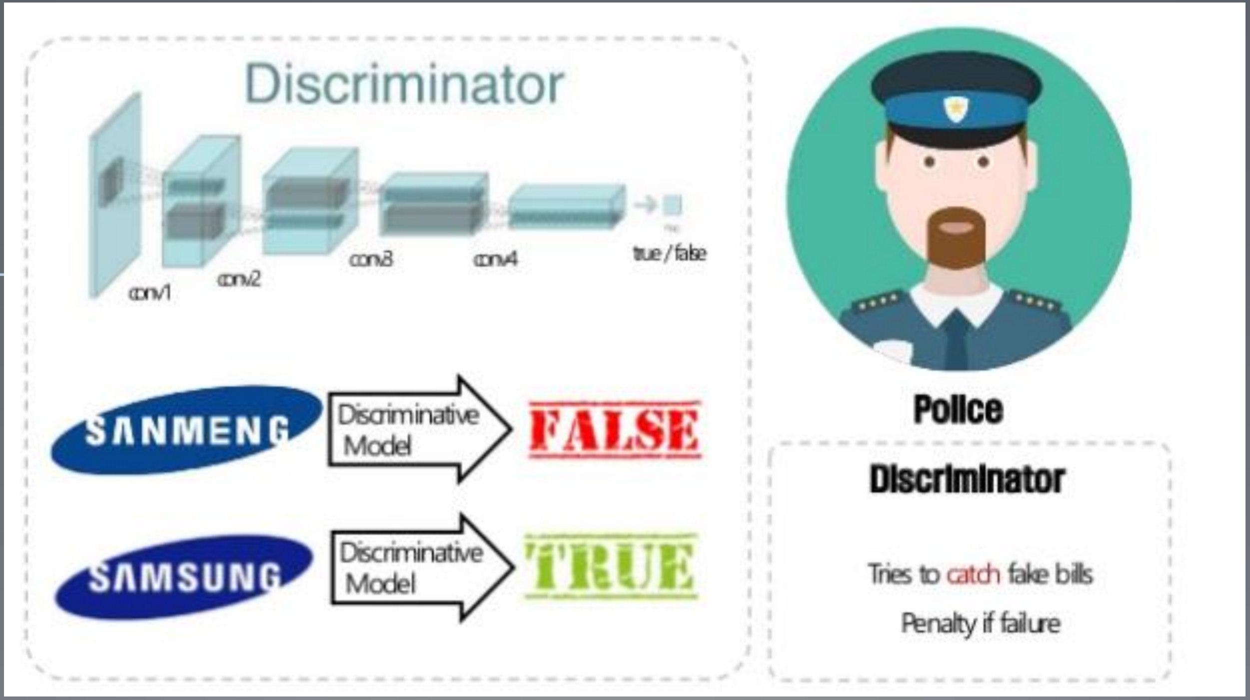
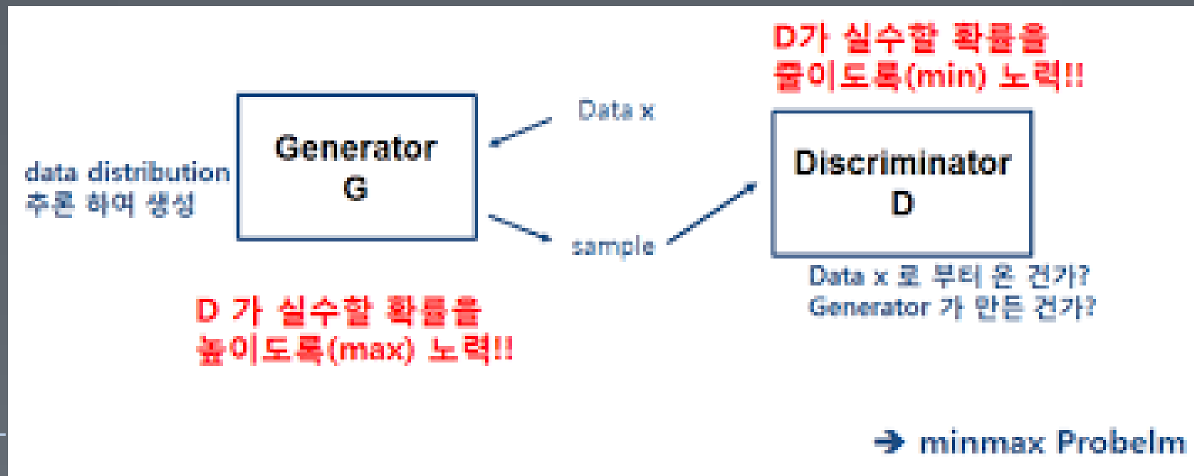
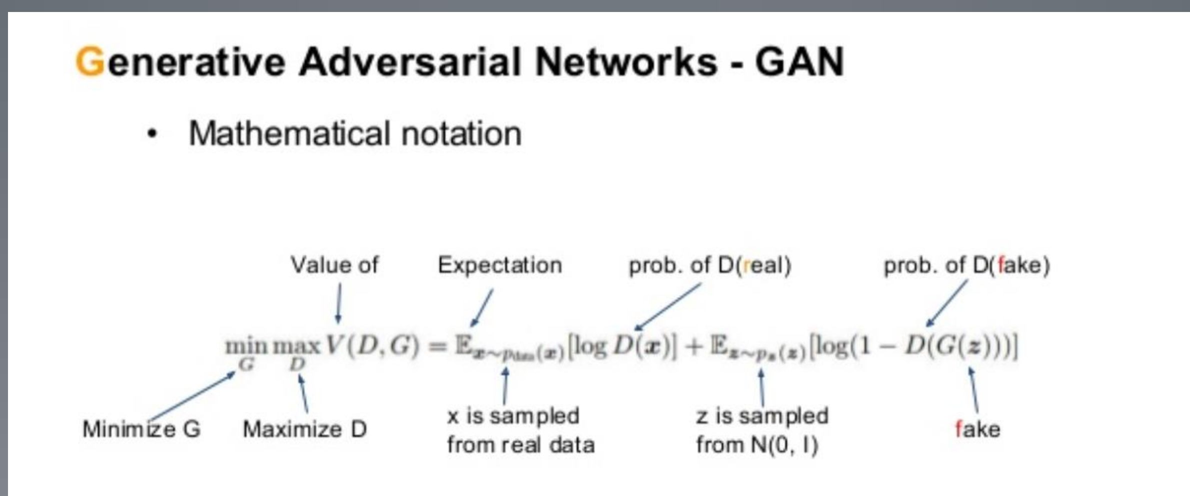
위조지폐범 vs 경찰



Discriminator
conv1
conv2
conv3
conv4
true / false
SANMENG
Discriminative Model
FALSE
SAMSUNG
Discriminative Model
TRUE
Police
Discriminator
Tries to catch fake bills
Penalty if failure

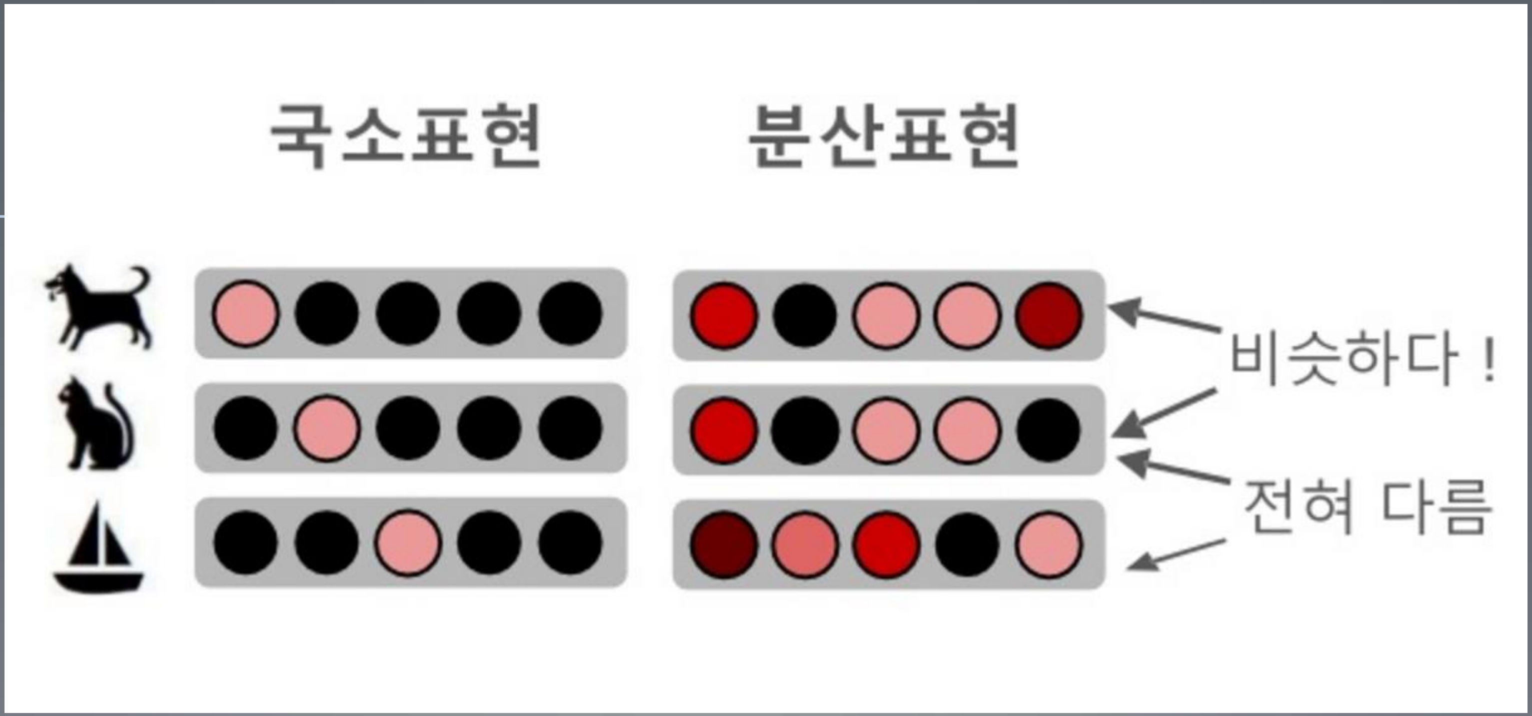
GAN 학습법


D가 실수할 확률을
줄이도록(min) 노력!!
Generator
G
Data x
data distribution
추론 하여 생성
sample
Discriminator
D
Data x 로 부터 온 건가?
Generator 가 만든 건가?
D 가 실수할 확률을
높이도록(max) 노력!!
➔ minmax Probelm


Generative Adversarial Networks - GAN
• Mathematical notation
Value of
Expectation
prob. of D(real)
prob. of D(fake)
$\min_G \max_D V(D,G) = \mathbb{E}_{x \sim p_{data}(x)}[\log D(x)] + \mathbb{E}_{z \sim p_z(z)}[\log(1 - D(G(z)))]$
Minimize G
Maximize D
x is sampled
from real data
z is sampled
from N(0, I)
fake

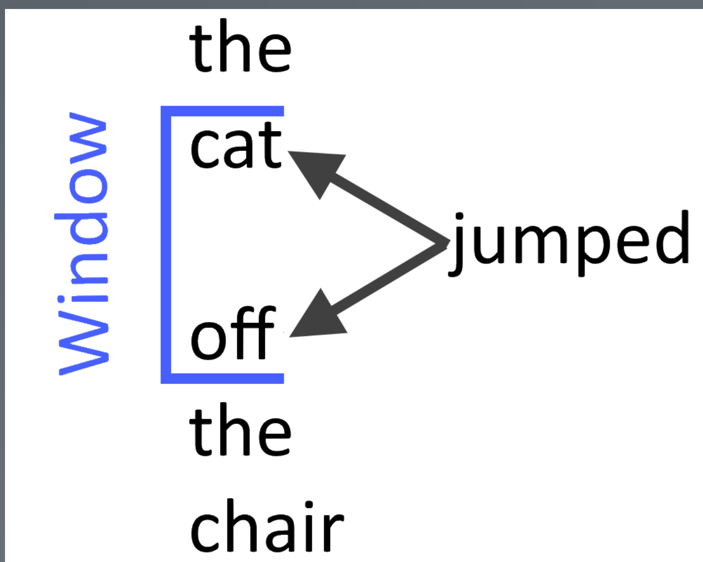
Word Vector

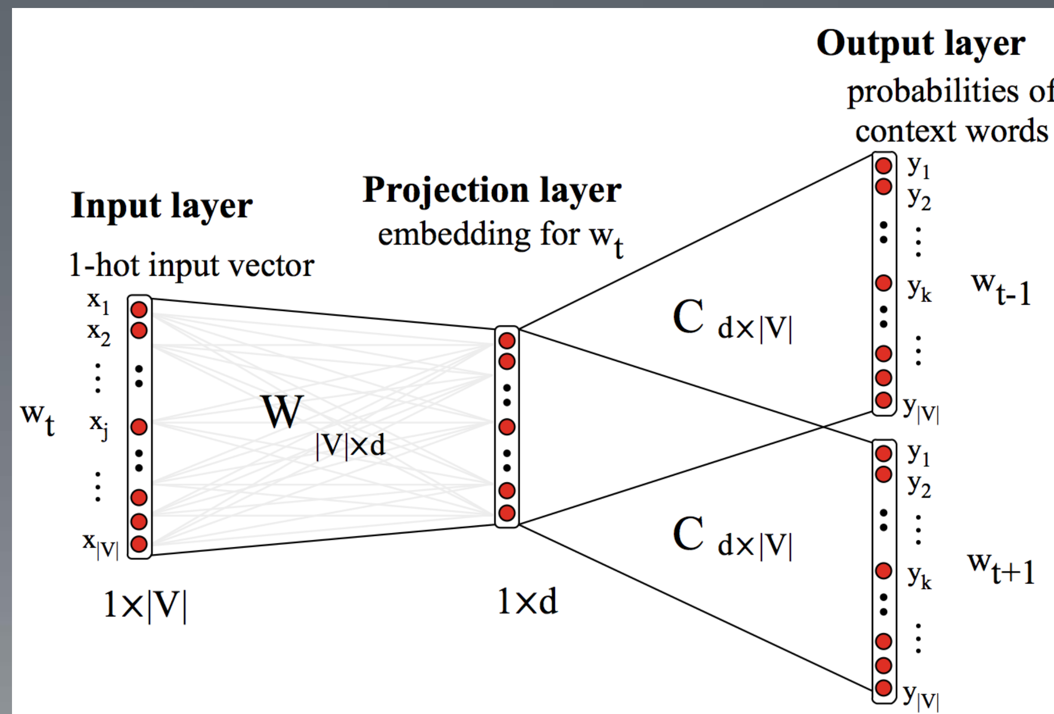
분산 표현 (Distributed Representation)



- CBOW
  - 문맥으로 부터 단어 예측
  - 소규모 데이터 셋에 성능 유리
- Skip-gram
  - 단어로부터 문맥 예측
  - 대규모 데이터셋에 유리

Skip-gram 구조


the
Window
cat
jumped
off
the
chair


Output layer
probabilities of context words
Input layer
1-hot input vector
Projection layer
embedding for w_t
w_t
x_1
x_2
x_j
$x_{|V|}$
W $|V| \times d$
C $d \times |V|$
C $d \times |V|$
y_1
y_2
y_k
$y_{|V|}$
w_{t-1}
w_{t+1}
$1 \times |V|$
$1 \times d$

Word Embedding

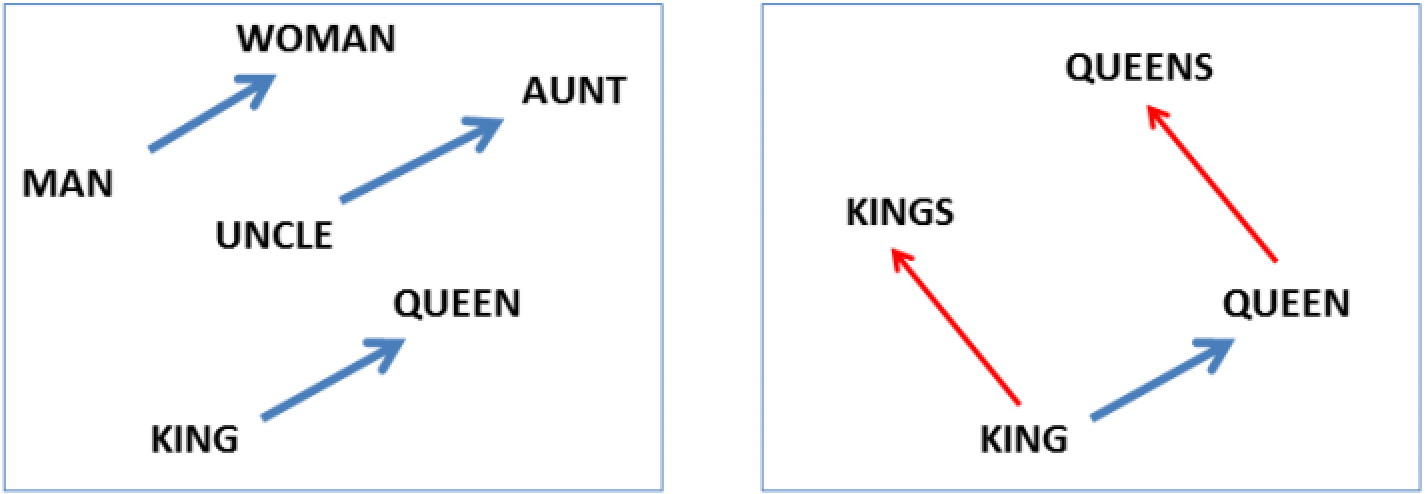
1-hot input

W

Distributed representation

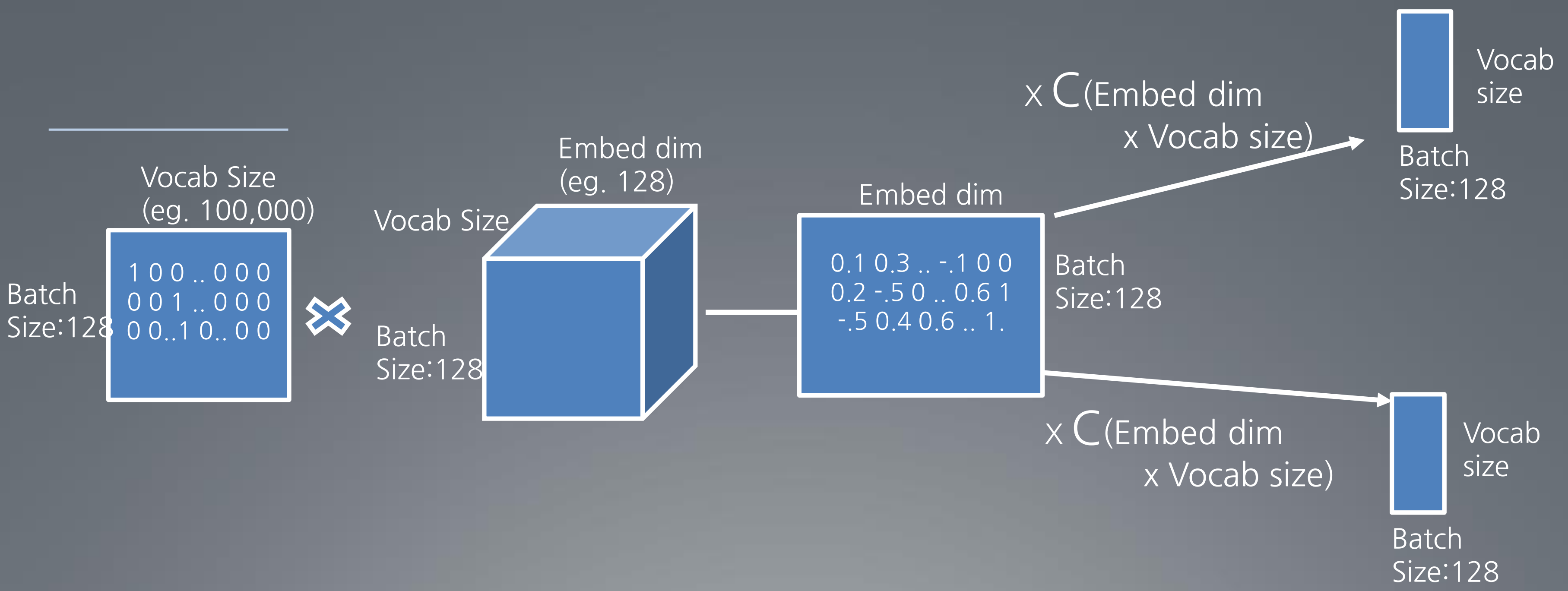
$$[0 \quad 0 \quad 0 \quad \boxed{1} \quad 0] \times \begin{bmatrix} 17 & 24 & 1 \\ 23 & 5 & 7 \\ 4 & 6 & 13 \\ 10 & 12 & 19 \\ 11 & 18 & 25 \end{bmatrix} = [10 \quad 12 \quad 19]$$

Results



(Mikolov et al., NAACL HLT, 2013)

실습 : skip-gram 예제



RNN
(Recurrent Neural Network)

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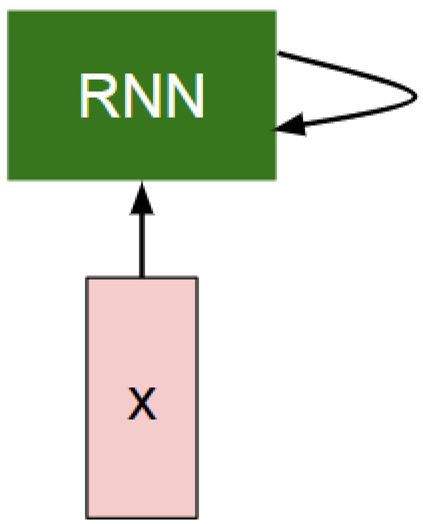
Recurrent Neural Network



Recurrent Neural Network

We can process a sequence of vectors **x** by applying a **recurrence formula** at every time step:

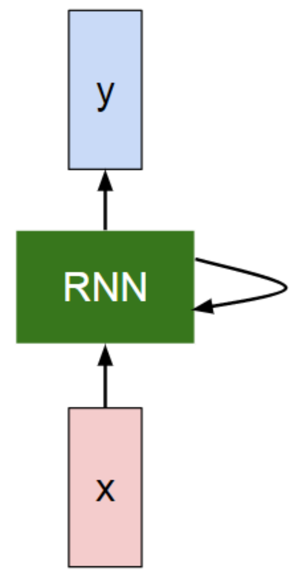
$$\boxed{h_t} = \boxed{f_W}(\boxed{h_{t-1}}, \boxed{x_t})$$

new state

old state

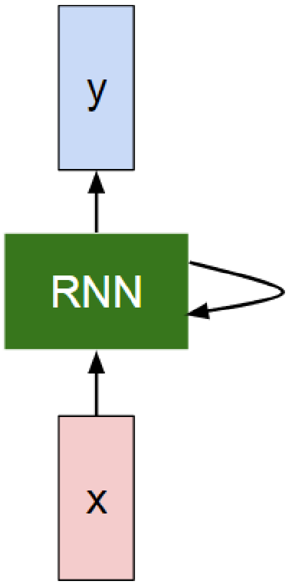
input vector at some time step

some function with parameters W



(Vanilla) Recurrent Neural Network

The state consists of a single *"hidden"* vector **h**:

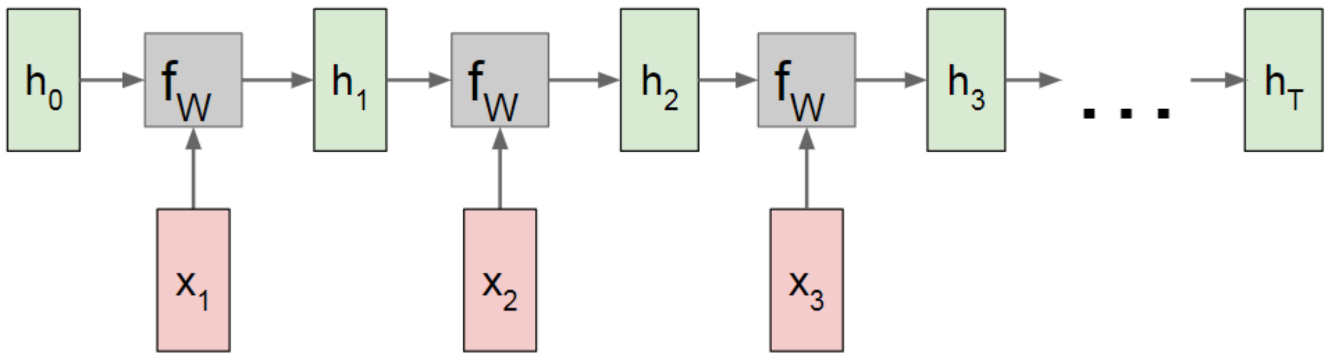


$$h_t = f_W(h_{t-1}, x_t)$$

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

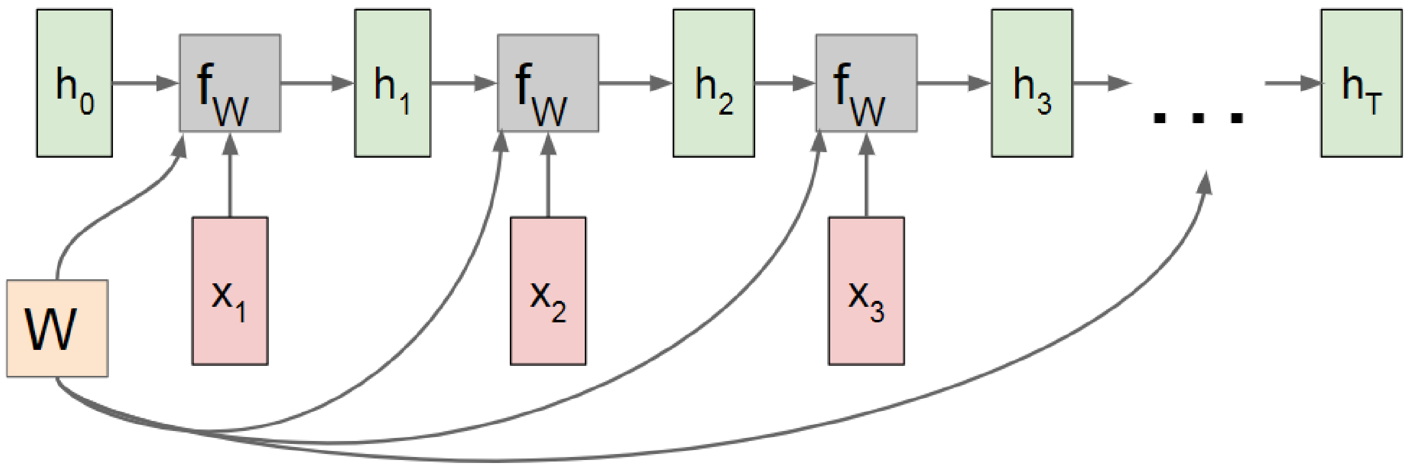
$$y_t = W_{hy}h_t$$

RNN: Computational Graph

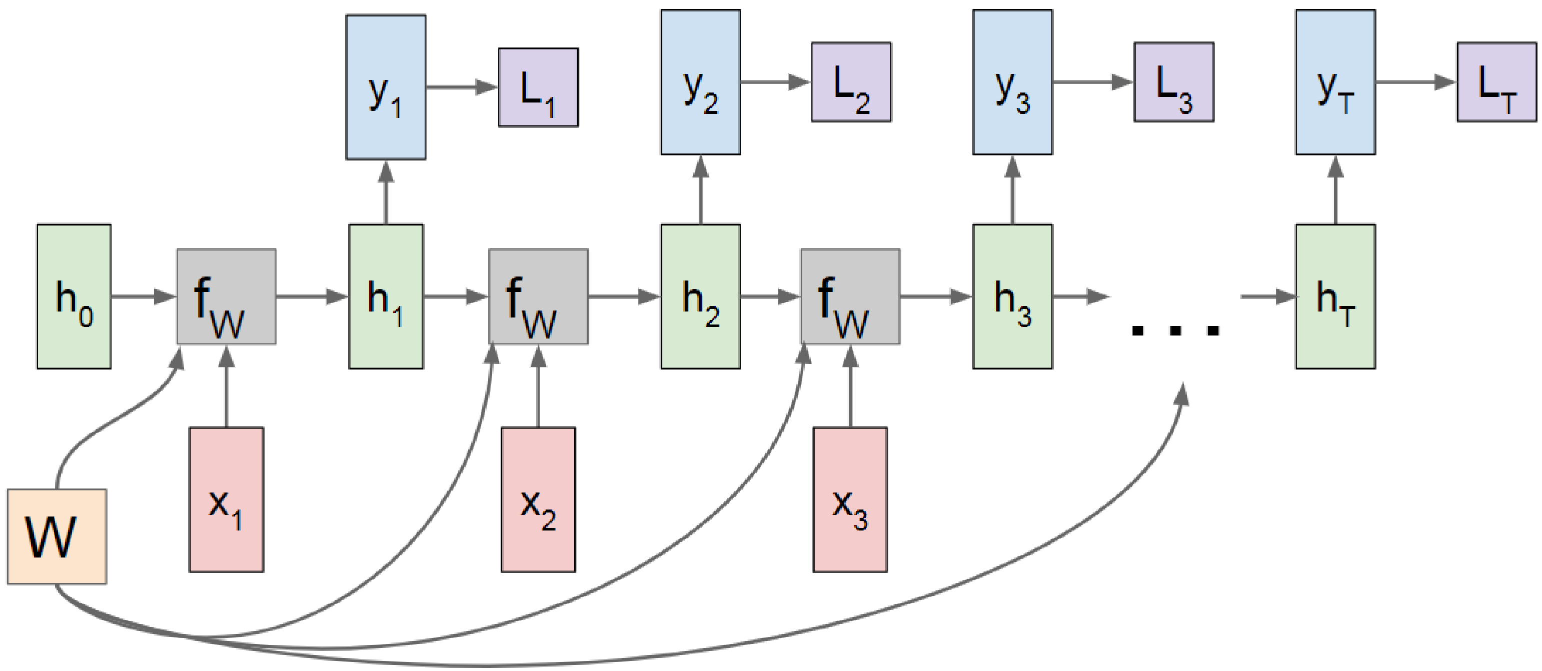


RNN: Computational Graph

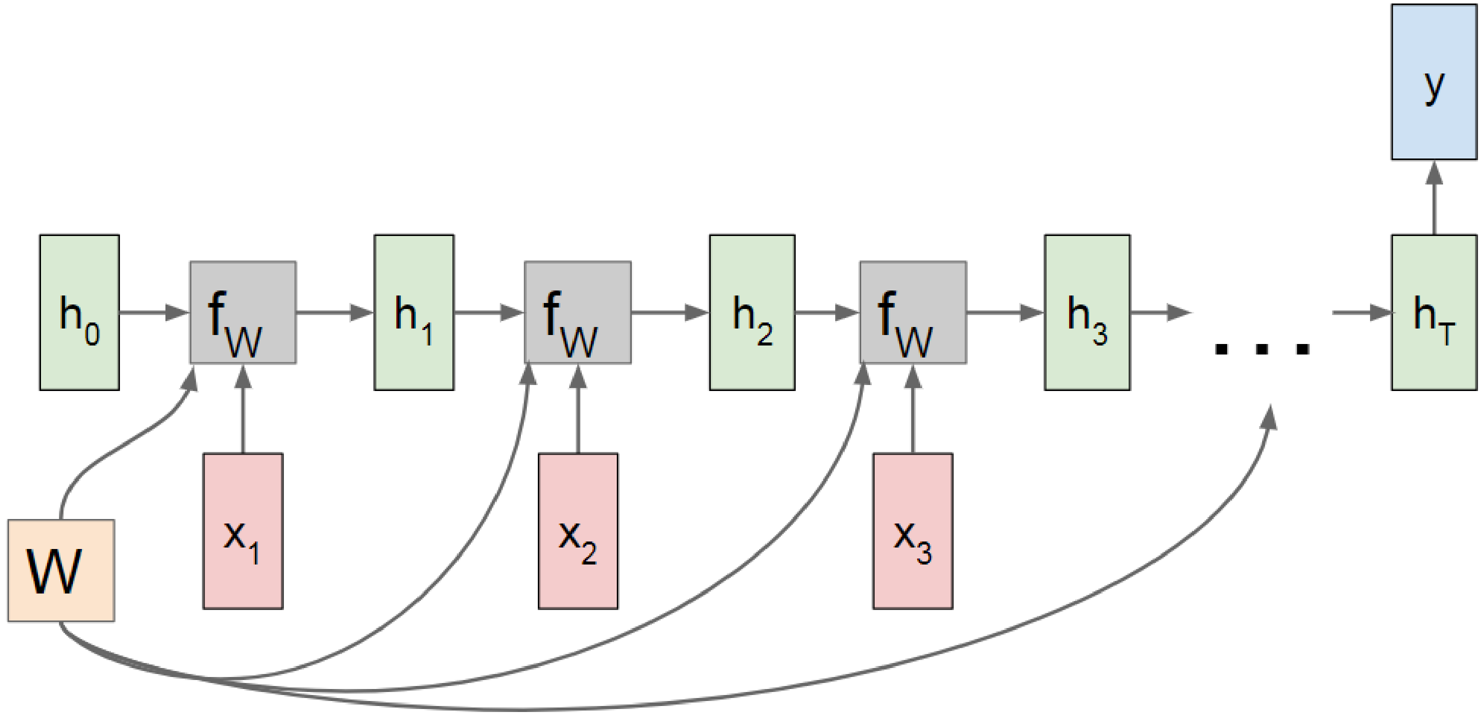
Re-use the same weight matrix at every time-step



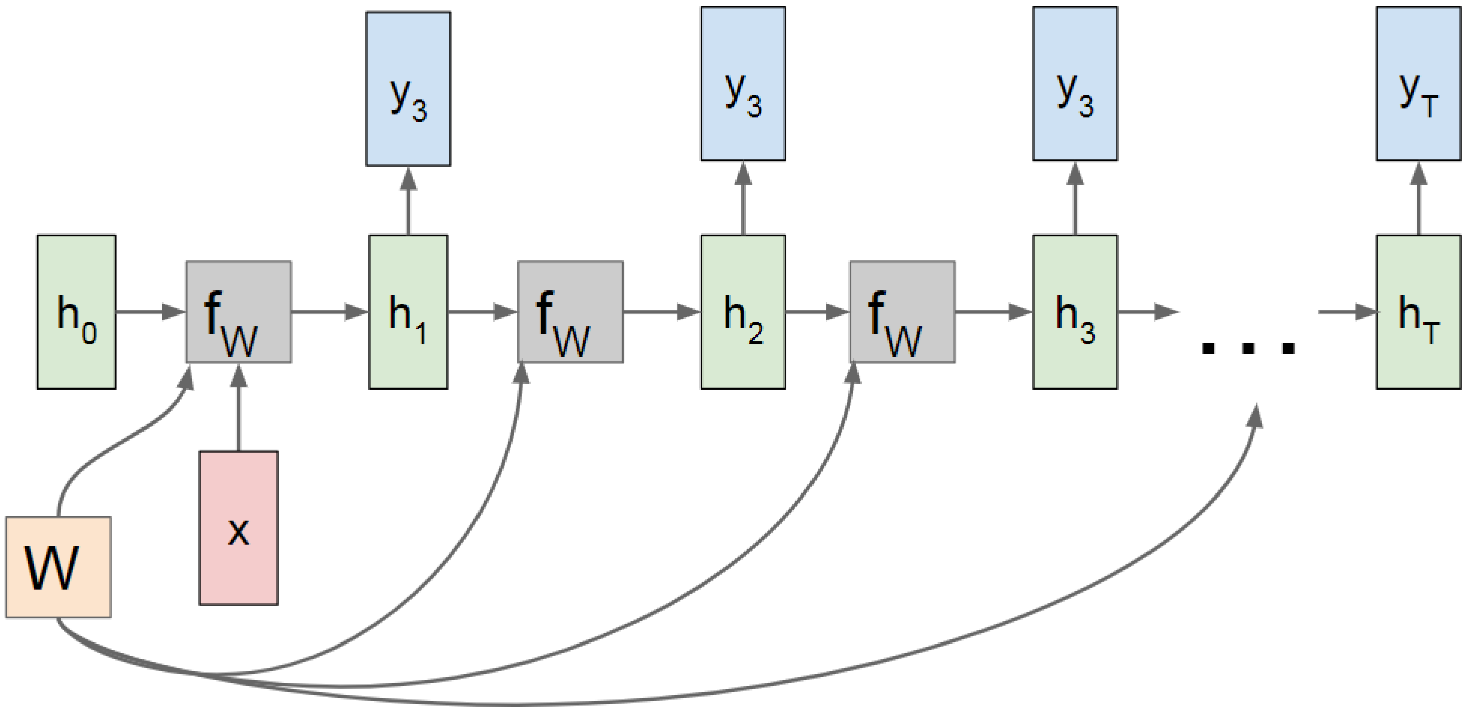
RNN: Computational Graph: Many to Many



RNN: Computational Graph: Many to One



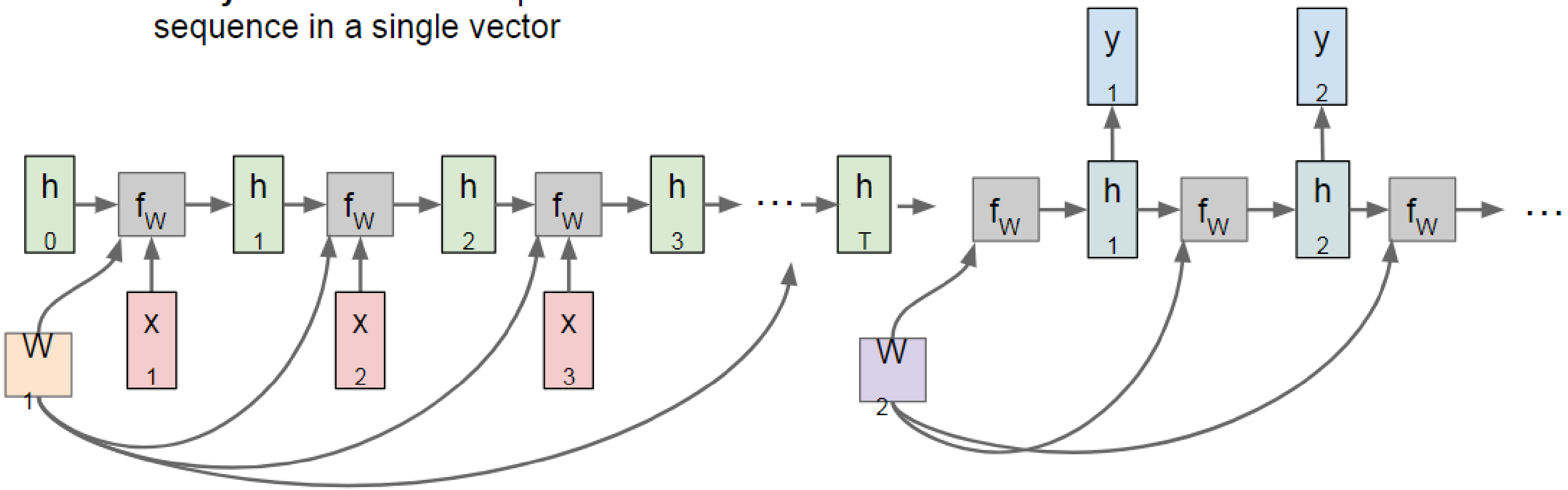
RNN: Computational Graph: One to Many



Sequence to Sequence: Many-to-one + one-to-many

One to many: Produce output sequence from single input vector

Many to one: Encode input sequence in a single vector



Long Short Term Memory (LSTM)

Vanilla RNN

$$h_t = \tanh\left(W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}\right)$$

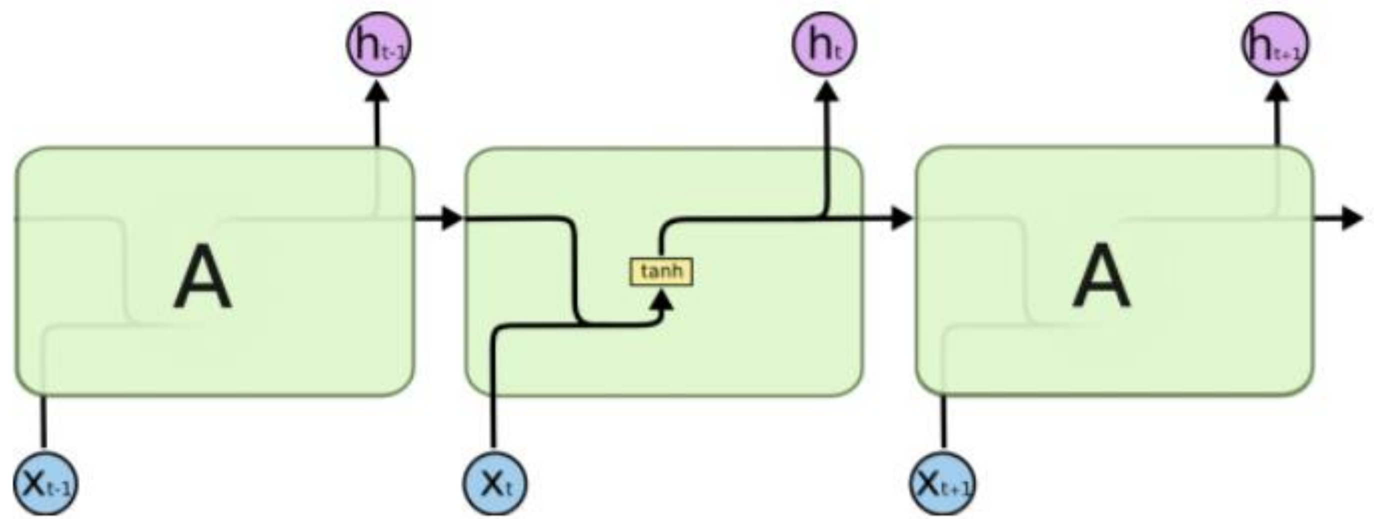
LSTM

$$\begin{pmatrix} i \\ f \\ o \\ g \end{pmatrix} = \begin{pmatrix} \sigma \\ \sigma \\ \sigma \\ \tanh \end{pmatrix} W \begin{pmatrix} h_{t-1} \\ x_t \end{pmatrix}$$

$$c_t = f \odot c_{t-1} + i \odot g$$

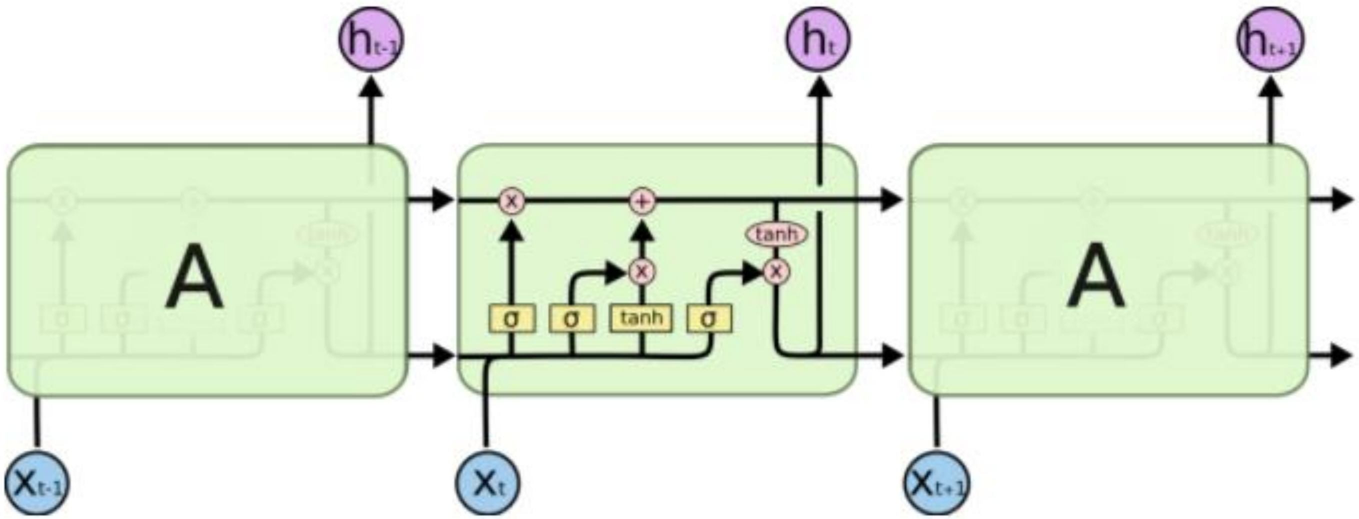
$$h_t = o \odot \tanh(c_t)$$

RNN Cell



The repeating module in a standard RNN contains a single layer.

LSTM Cell



The repeating module in an LSTM contains four interacting layers.

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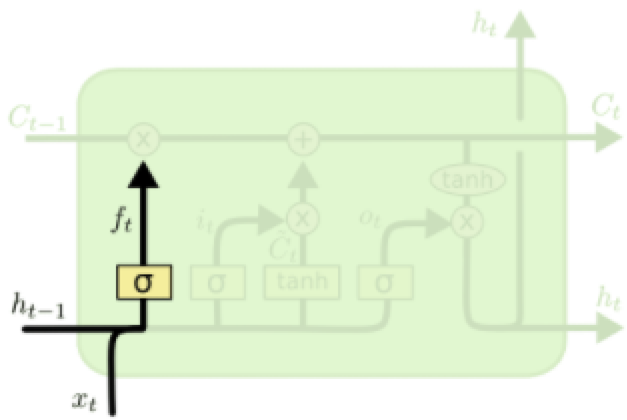
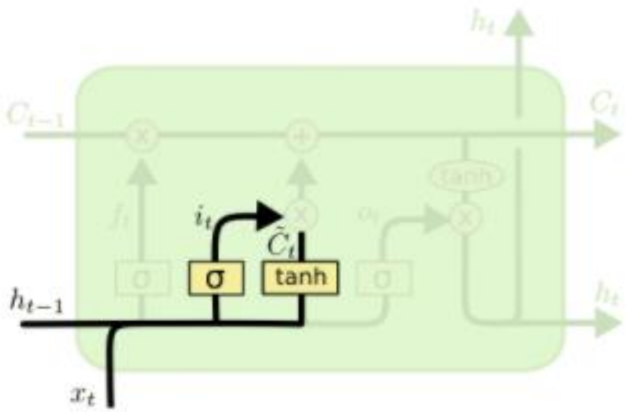
LSTM Cell



$$f_t = \sigma\left(W_f \cdot [h_{t-1}, x_t] \; + \; b_f\right)$$

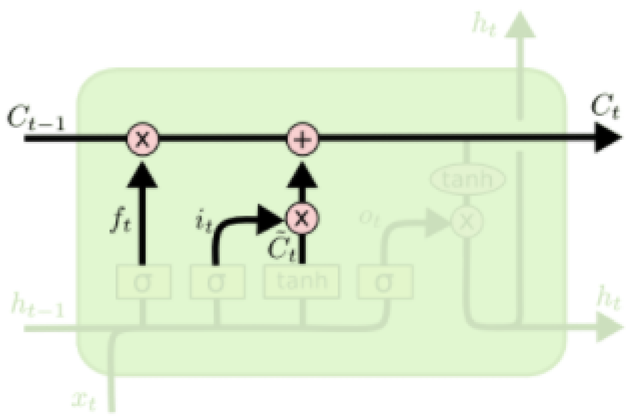
LSTM Cell



$$i_t = \sigma\left(W_i \cdot [h_{t-1}, x_t] \ + \ b_i\right)$$

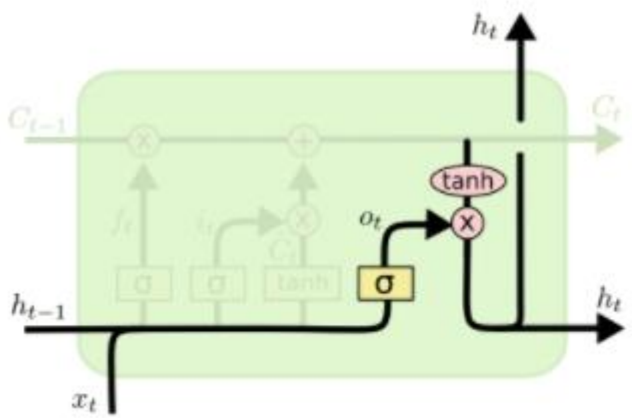
$$\tilde{C}_t = \tanh(W_C \cdot [h_{t-1}, x_t] \ + \ b_C)$$

LSTM Cell



$$C_t = f_t * C_{t-1} + i_t * \tilde{C}_t$$

LSTM Cell



$$o_t = \sigma\left(W_o\ [h_{t-1}, x_t]\ +\ b_o\right)$$
$$h_t = o_t * \tanh\left(C_t\right)$$

Default RNN Cells in Tensorflow

- RNNCELL, GRUCELL, LSTMCELL

Base interface for all RNN Cells

- `tf.contrib.rnn.RNNCell`

Core RNN Cells for use with TensorFlow's core RNN methods

- `tf.contrib.rnn.BasicRNNCell`
- `tf.contrib.rnn.BasicLSTMCell`
- `tf.contrib.rnn.GRUCell`
- `tf.contrib.rnn.LSTMCell`
- `tf.contrib.rnn.LayerNormBasicLSTMCell`

- https://www.tensorflow.org/api_guides/python/contrib.rnn

RNN Cell

- Tf.contrib.rnn.RNNCell
  - Rnn cell, Lstm cell, GRU cell들의 부모 클래스

Properties

`output_size`

Integer or TensorShape: size of outputs produced by this cell.

RNN cell의 hidden node의 수

`state_size`

size(s) of state(s) used by this cell.

It can be represented by an Integer, a TensorShape or a tuple of Integers or TensorShapes.

Methods

`zero_state(batch_size, dtype)`

RNN cell의 hidden node의 초기값(0으로 초기화)

Return zero-filled state tensor(s).

Args:

- `batch_size` : int, float, or unit Tensor representing the batch size.
- `dtype` : the data type to use for the state.

Returns:

If `state_size` is an int or TensorShape, then the return value is a `N-D` tensor of shape `[batch_size x state_size]` filled with zeros.

BasicRNNCell

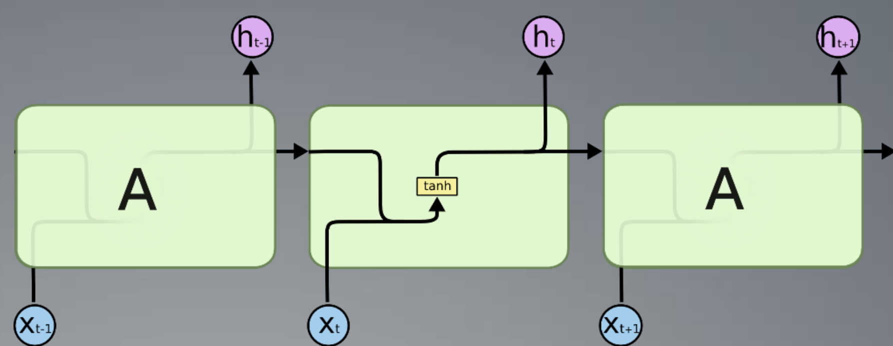
- Tensorflow.contrib.rnn.BasicRNNCell
  - 기본적인 RNN Cell : hidden node로만 이루어져 있음
  -

Deprecated and unused

```
tf.nn.rnn_cell.BasicRNNCell.__init__(num_units, input_size=None,
activation=tanh)
```

RNN cell의 hidden node의 수

Activation function 설정



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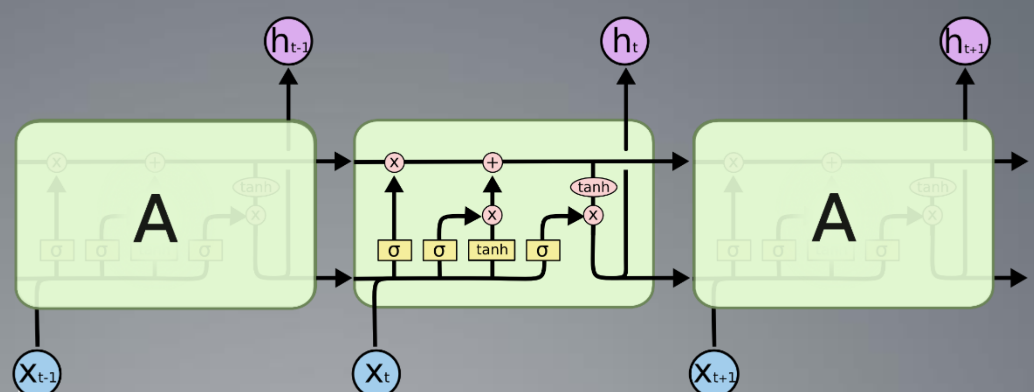
BasicLSTMCell

- Tensorflow.contrib.rnn.BasicLSTMCell
  – LSTM 셀로 4개의 게이트로 이루어짐
  –

Forget gate의 bias 초기값

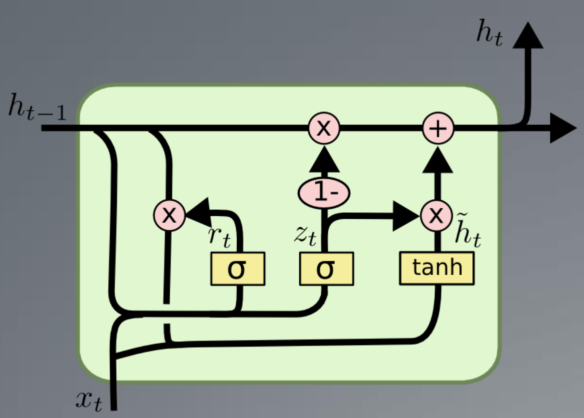
```
tf.nn.rnn_cell.BasicLSTMCell.__init__(num_units, forget_bias=1.0,
input_size=None, state_is_tuple=False, activation=tanh)
```



GRUCell

- Tensorflow.contrib.rnn.GRUCell
  - GRU 셀로 LSTM보다 간단한 구조

```
tf.nn.rnn_cell.GRUCell.__init__(num_units, input_size=None,
activation=tanh)
```



$$z_t = \sigma\left(W_z \cdot [h_{t-1}, x_t]\right)$$

$$r_t = \sigma\left(W_r \cdot [h_{t-1}, x_t]\right)$$

$$\tilde{h}_t = \tanh\left(W \cdot [r_t * h_{t-1}, x_t]\right)$$

$$h_t = (1 - z_t) * h_{t-1} + z_t * \tilde{h}_t$$

RNN Cell wrappers

- Tensorflow.contrib.rnn.MultiRNNCell

```
tf.nn.rnn_cell.MultiRNNCell.__init__(cells, state_is_tuple=False)
```

- Tensorflow.contrib.rnn.DropoutWrapper

```
tf.nn.rnn_cell.DropoutWrapper.__init__(cell, input_keep_prob=1.0,
output_keep_prob=1.0, seed=None)
```

Dropout 비율

RNN Constructing Module

- Tensorflow.nn.dynamic_rnn

```
tf.nn.rnn(cell, inputs, initial_state=None,
dtype=None, sequence_length=None, scope=None)
```

Args:

- `cell`: An instance of RNNCell. RNN cell
- `inputs`: A length T list of inputs, each a `Tensor` of shape `[batch_size, input_size]`, or a nested tuple of such elements. Input data
- `initial_state`: (optional) An initial state for the RNN. If `cell.state_size` is an integer, this must be a `Tensor` of appropriate type and shape `[batch_size, cell.state_size]`. If `cell.state_size` is a tuple, this should be a tuple of tensors having shapes `[batch_size, s] for s in cell.state_size`. State의 초기값
- `dtype`: (optional) The data type for the initial state and expected output. Required if initial_state is not provided or RNN state has a heterogeneous dtype.
- `sequence_length`: Specifies the length of each sequence in inputs. An int32 or int64 vector (tensor) size `[batch_size]`, values in `[0, T)`.
- `scope`: VariableScope for the created subgraph; defaults to "RNN".

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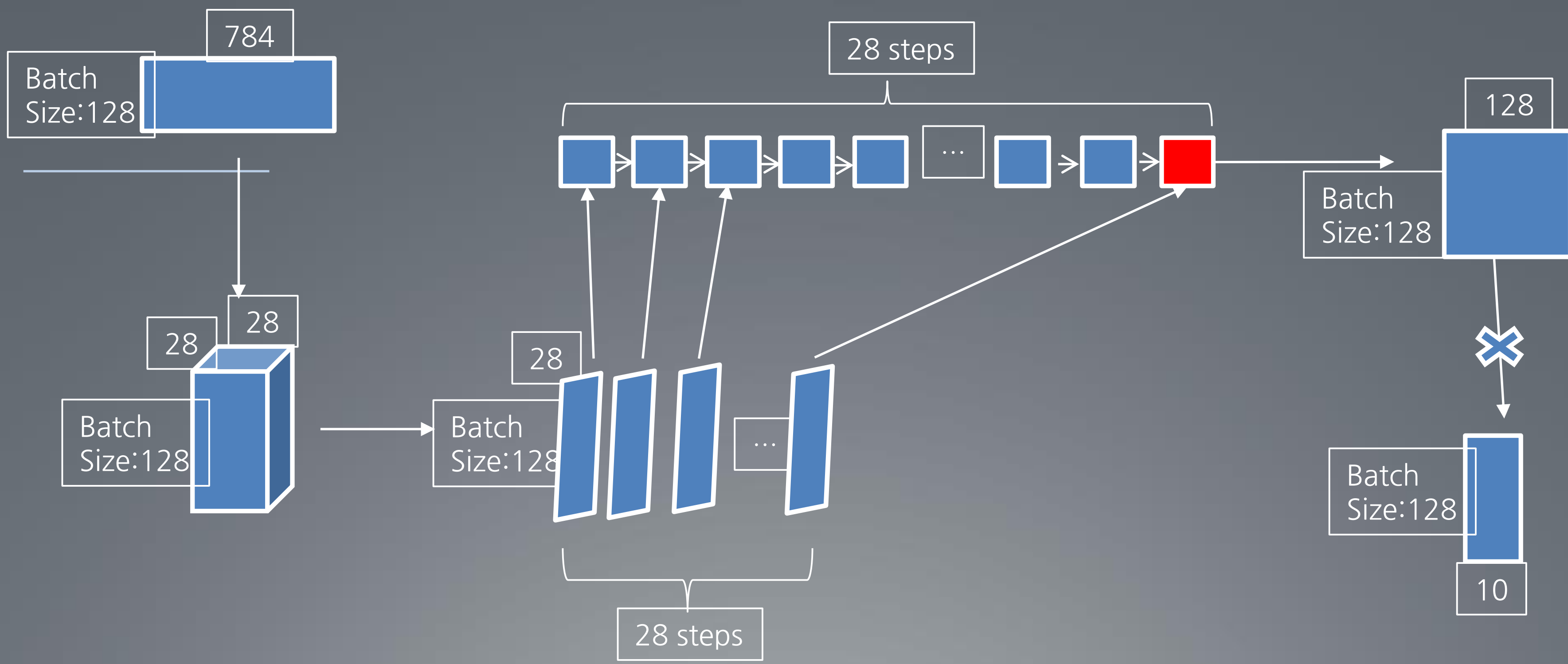
실습 : MNIST 예제



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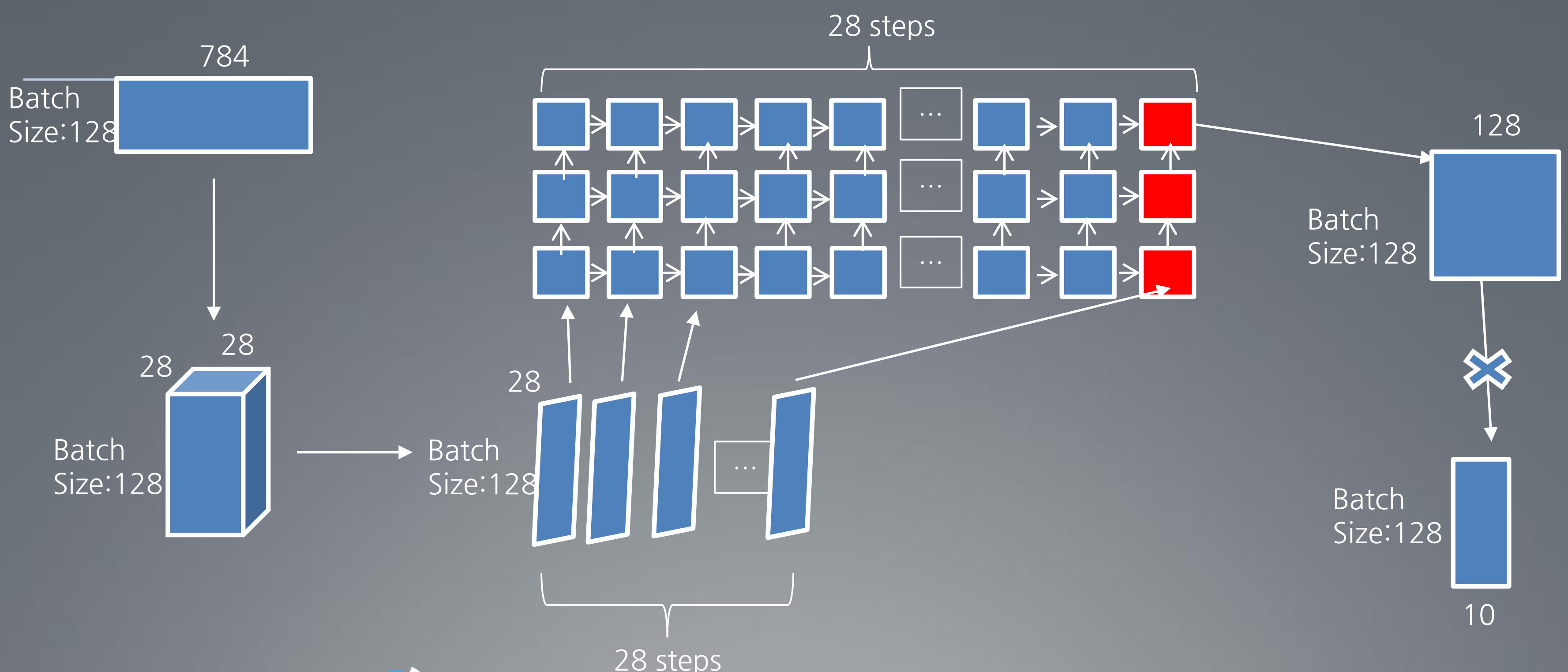
Multi RNN

```
cell = tf.contrib.rnn.BasicRNNCell(n_hidden)
cell = tf.contrib.rnn.DropoutWrapper(cell, output_keep_prob=0.5)
cell = tf.contrib.rnn.MultiRNNCell([cell] * num_layers)
outputs, states = tf.nn.dynamic_rnn(cell, x_t, dtype=tf.float32)
```

- RNN Cell의 List를 MultiRNNCell의 initial argument로 입력
- DropoutWrapper를 이용하여 layer간에 dropout적용

실습 : MNIST 예제


784
Batch
Size:128
28
28
Batch
Size:128
Batch
Size:128
28
28 steps
…
28 steps
…
…
…
128
Batch
Size:128
Batch
Size:128
10

실습: Text Generation(1/5)

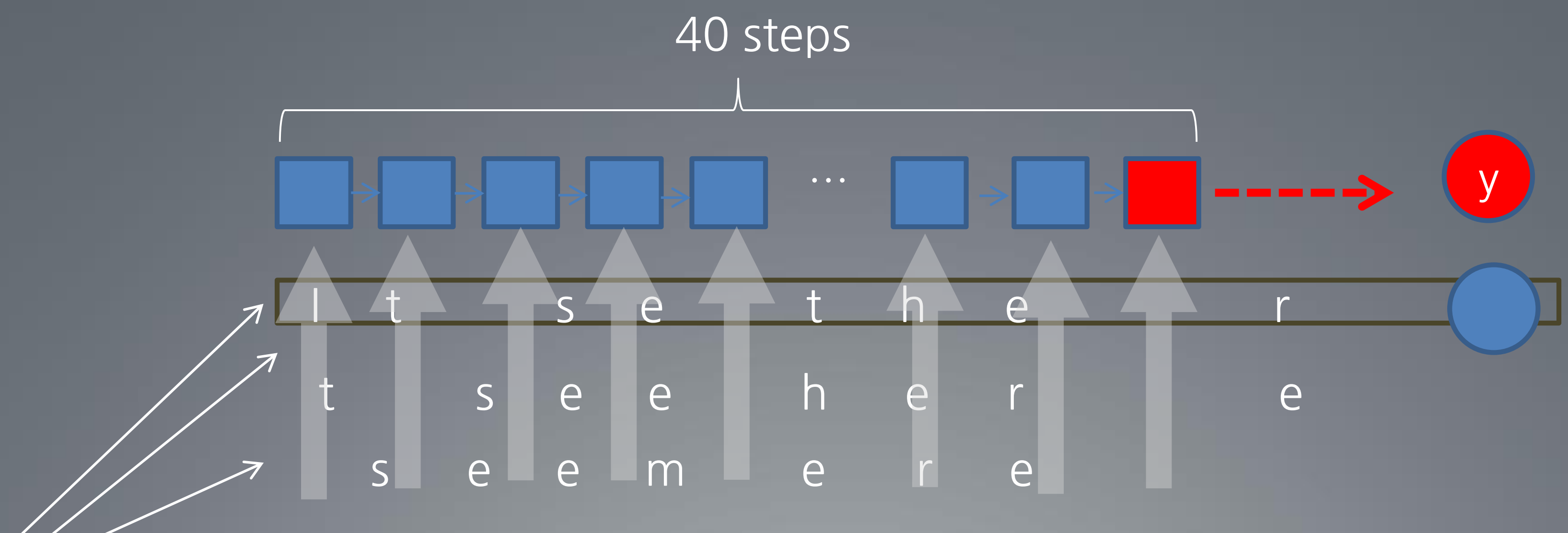
- RNN이 가장 많이 이용되는 분야인 NLP 예제
- 그 중 word단위가 아닌 character단위로 텍스트 분석 및 예측
- 알파벳 character 전후 관계와 문장 전체의 information을 이용

Text Generation (2/5)

- Dataset : nietzsche의 선악의 저편 text (OSIA/data)
- 40 steps의 LSTM 1 layer를 이용하여 다음 character 예측

Text Generation (3/5)

- 데이터 전처리
  - Character 59개를 모두 index화
  - 1 character씩 움직이면서 sentence와 예측할 다음 character를 target으



It seems to me that there is everywhere an attempt at present to divert attention

Text Generation (4/5)

- Training Detail
  - Adam optimizer 사용
  - Learning rate = 0.01
  - Batch size = 128
  - LSTM Hidden cell의 수 = 128

Text Generation (5/5)

- Character Sampling
  - 1000 iteration마다 200 characters 연속 생성
  - 생성되는 character를 다시 input으로 사용
  - 트레이닝이 진행될수록 문장을 이루는 character 생성

감사합니다