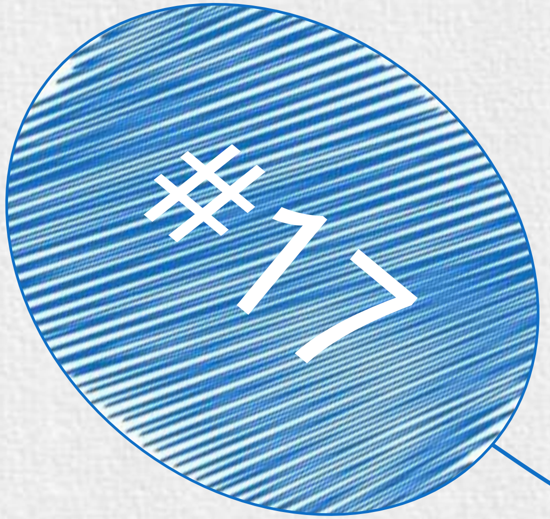
6주차 발표

BOAZ 17기 이소정


CONTENTS



Topics to learn today

1. Review from last lecture
2. Batch/Stochastic Gradient Descent
3. Advanced Gradient Descent Algorithms
4. How to visualize the result

Batch/Stochastic Gradient Descent

#17

Gradient Descent

$$\theta = \theta - \eta \nabla J(\theta)$$

θ: parameter set of the model
η : Learning rate
$J(\theta)$: Loss function

#17

1. Batch Gradient Descent

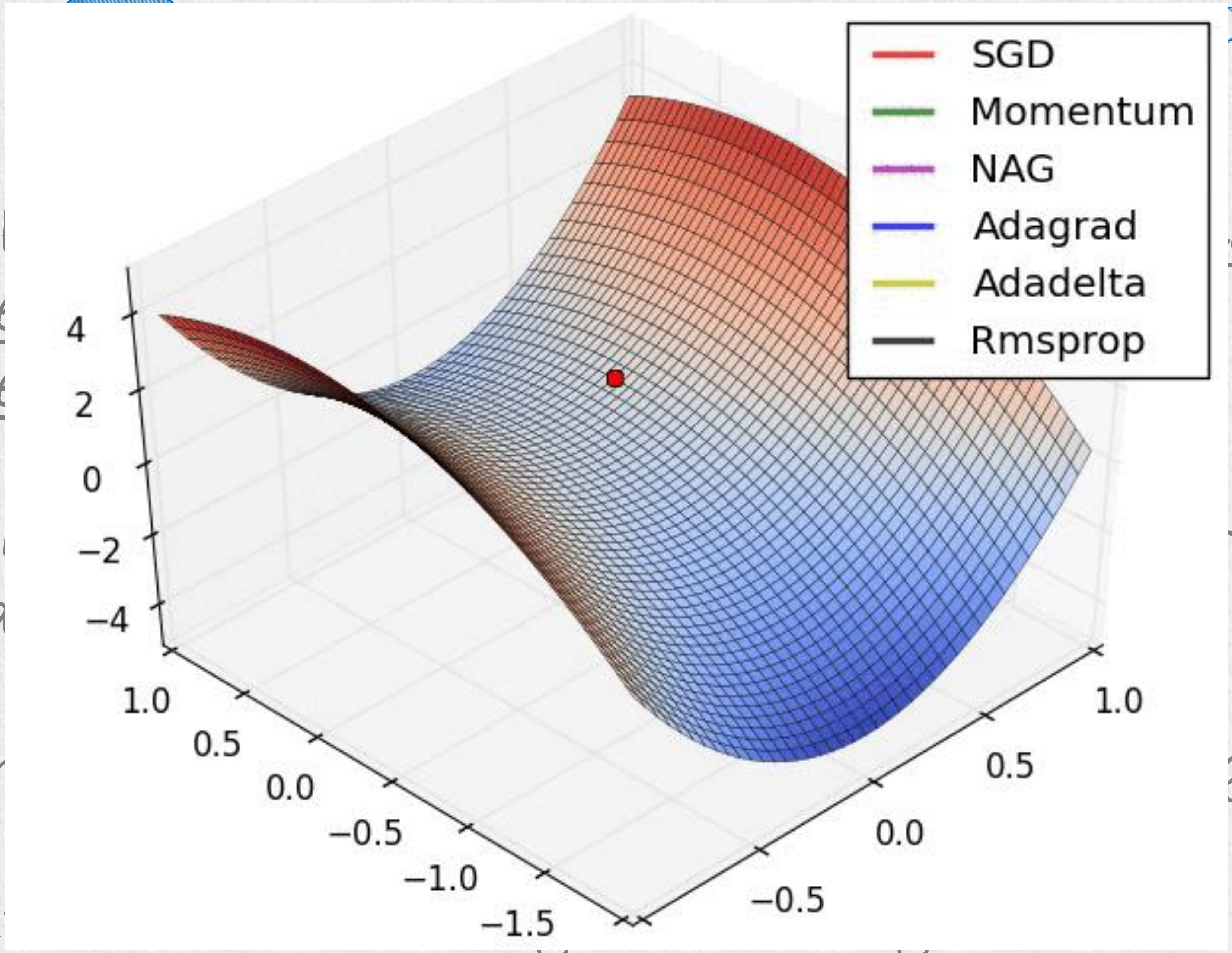
- Calculate gradient of parameters for whole training dataset.
- Need a lot of memory depending on data.
- Calculating gradient is too slow, thus optimization is slow.

#17

2. Stochastic Gradient Descent (SGD)

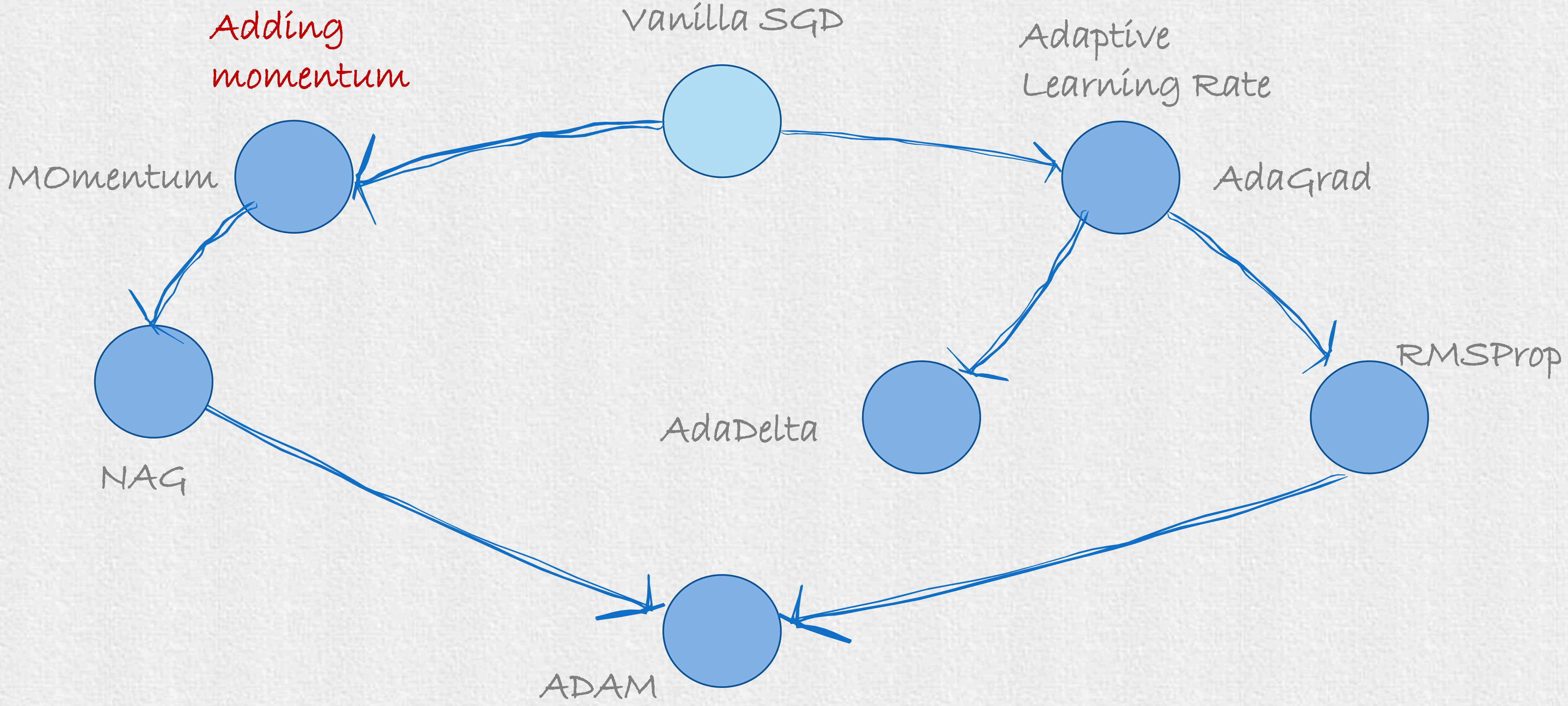
- Calculate gradient for small chunk of whole training dataset (mini-batch) rather than the whole training dataset (batch).
- Stochastic sine the gradient is not deterministic, but stochastic depending on the mini-batch.
- Faster than batch gradient descent, while converging similar.
- Can avoid local minima by stochasticity.

- Calcul … g
  datase
  datase
- Stoch … t
  stocha
- Faster … g similar.
- Can a



Advanced Gradient Descent Methods

Diagram of Gradient Descent Development

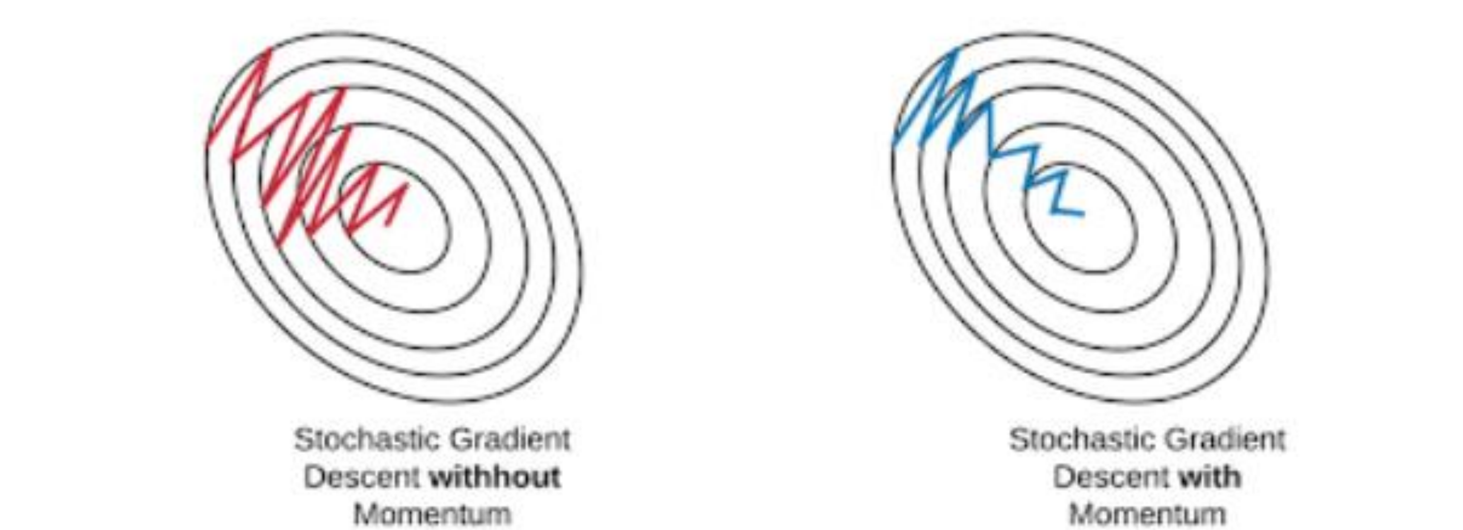


#17

Momentum

$$\theta = \theta - v_t$$

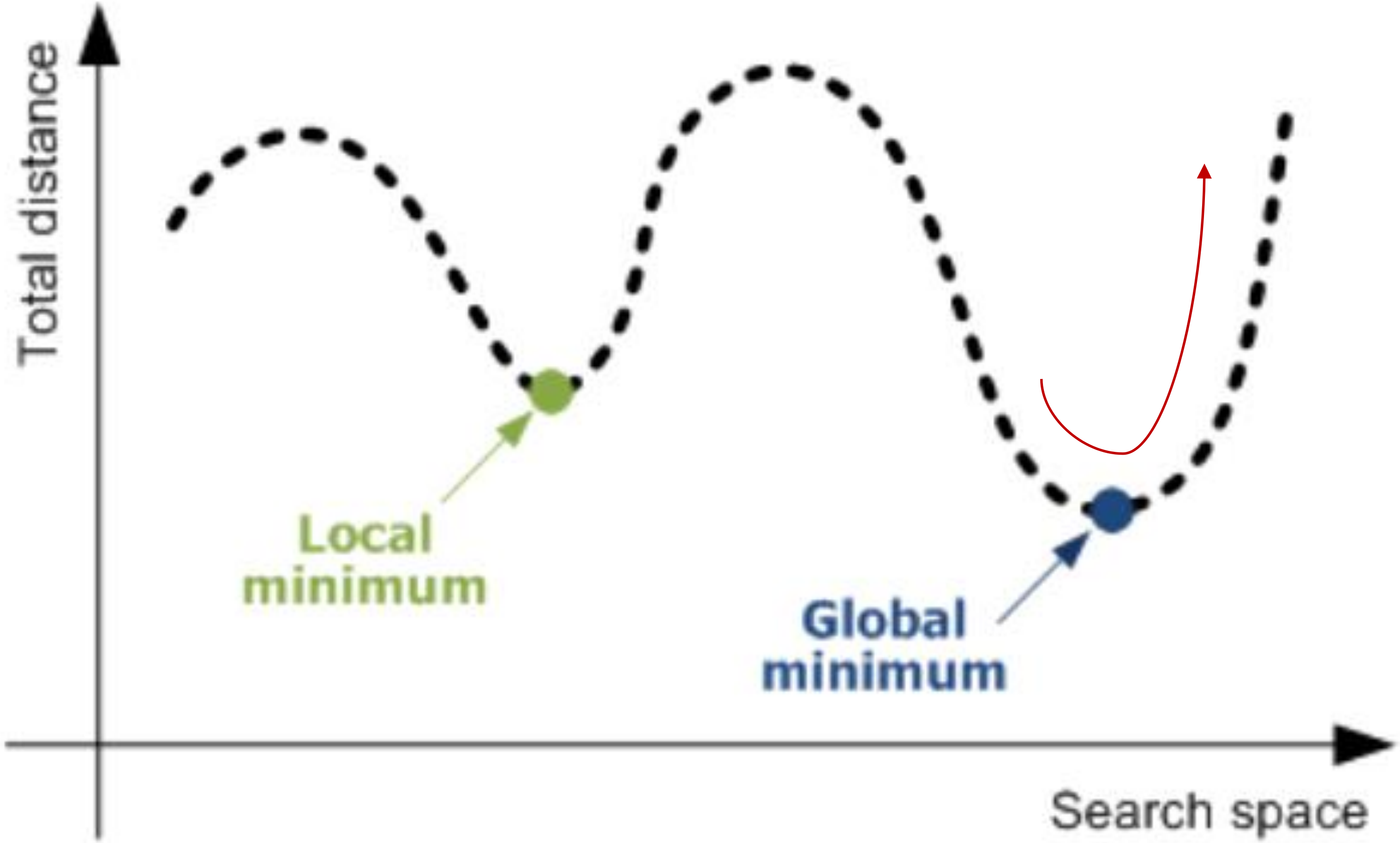
$$v_t = \gamma v_{t-1} + \eta \nabla_\theta J(\theta)$$



#17

Momentum

Can escape local minima, but cannot stop or slow at global minima!!

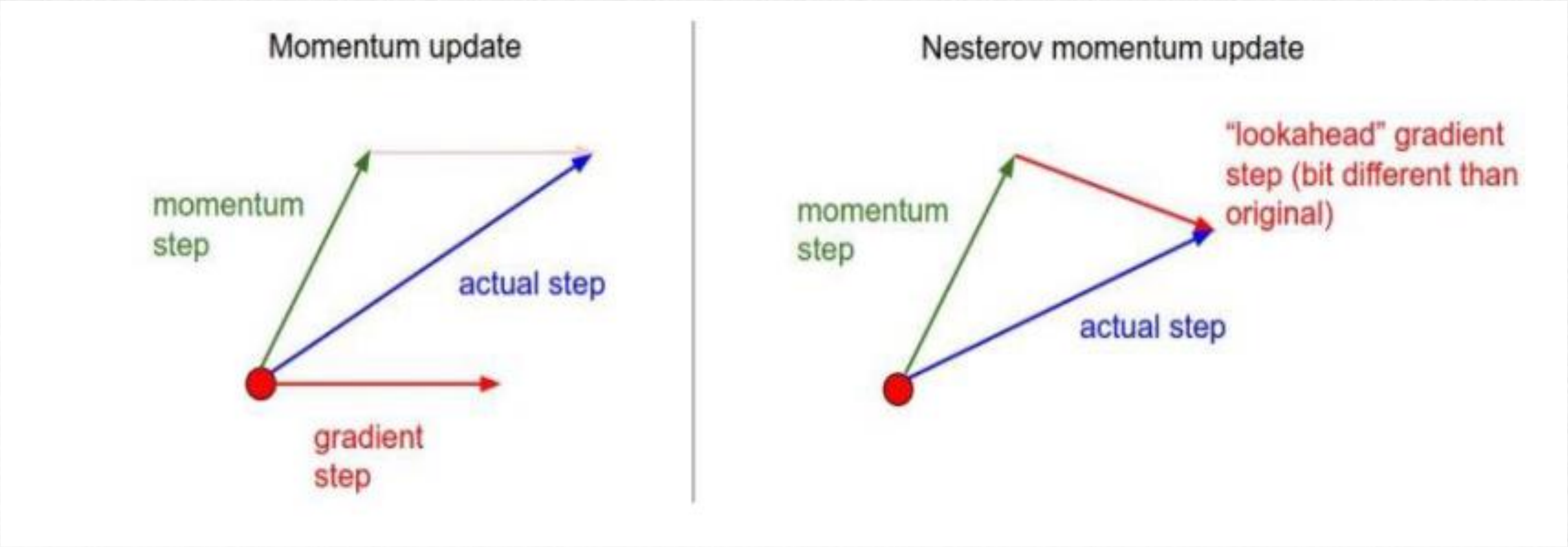


#17

Nesterov Accelerated Gradient (NAG)

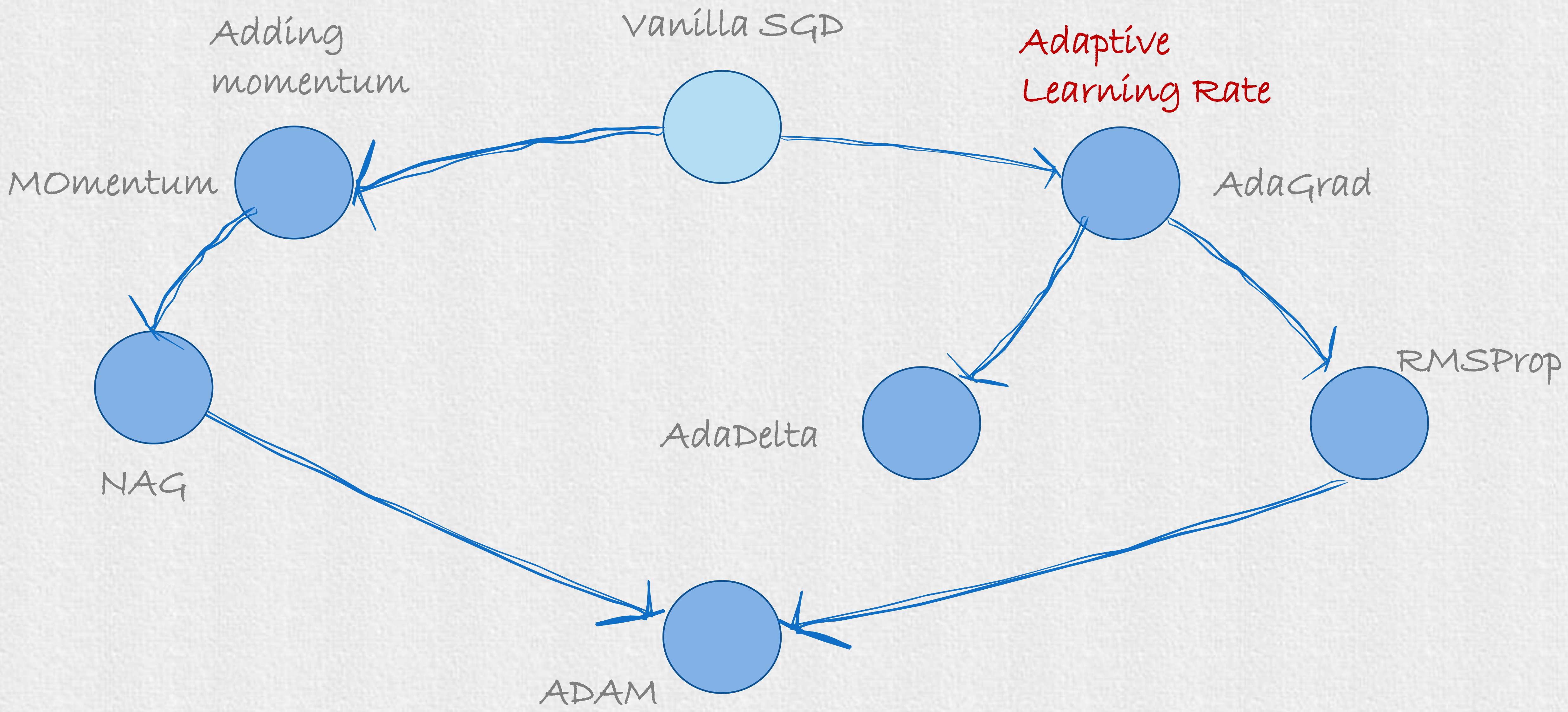
$$\theta = \theta - v_t$$

$$v_t = \gamma v_{t-1} + \eta \nabla_\theta J(\theta - \gamma v_{t-1})$$



#17

Diagram of Gradient Descent Development



#17

Adaptive Gradient (Adagrad)

$$\theta_{t+1} = \theta - \frac{\eta}{\sqrt{G_t + \epsilon}} \cdot \nabla_\theta J(\theta_t)$$

$$G_t = G_{t-1} + (\nabla_\theta J(\theta_t))^2$$

#17

Adaptive Gradient (Adagrad)

G keep increases, thus step size decays to zero !!

$$\theta_{t+1} = \theta - \frac{\eta}{\sqrt{G_t + \epsilon}} \cdot \nabla_\theta J(\theta_t)$$

$$G_t = G_{t-1} + (\nabla_\theta J(\theta_t))^2$$

#17

RMSProp

$$\theta_{t+1} = \theta - \frac{\eta}{\sqrt{G_t + \epsilon}} \cdot \nabla_\theta J(\theta_t)$$

$$G_t = \gamma G_{t-1} + (1 - \gamma)(\nabla_\theta J(\theta_t))^2$$

#17

AdaDelta

$$\theta_{t+1} = \theta_t - \Delta_\theta$$

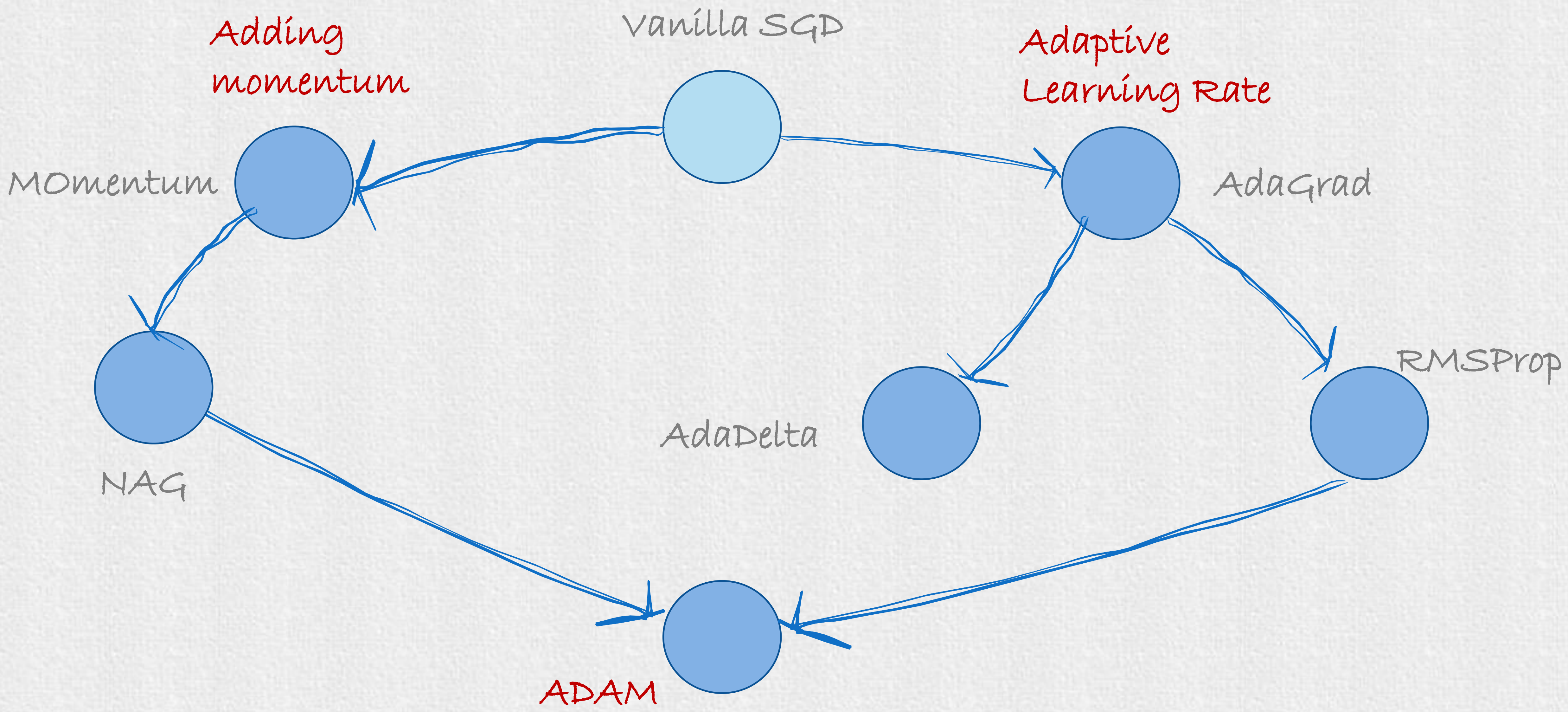
$$\Delta_\theta = \frac{\sqrt{s + \epsilon}}{\sqrt{G + \epsilon}} \cdot \nabla_\theta J(\theta_t)$$

$$s_{t+1} = \gamma s_t + (1 - \gamma)\Delta_\theta$$

$$G_{t+1} = \gamma G_t + (1 - \gamma)(\nabla_\theta J(\theta_t))^2$$

#17

Diagram of Gradient Descent Development



#17

Adam

$$m_t = \beta_1 m_{t-1} + (1 - \beta_1) g_t$$

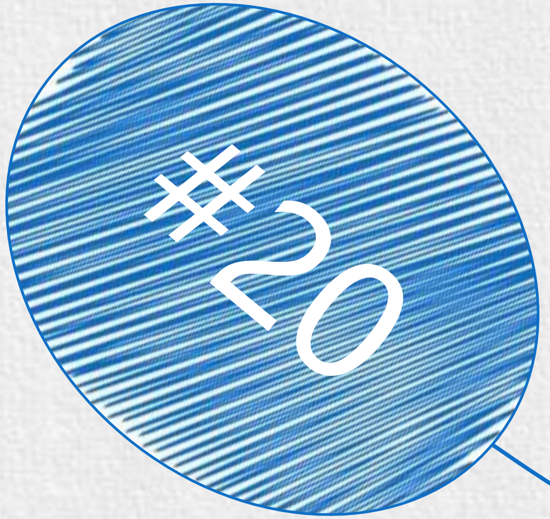
$$v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$$

$$\hat{m}_t = \frac{m_t}{1 - \beta_1^t} \qquad \hat{v}_t = \frac{v_t}{1 - \beta_2^t}$$

$$\theta_{t+1} = \theta_t - \frac{\eta}{\sqrt{\hat{v}_t + \epsilon}} \hat{m}_t$$

#19

Assignment #3 Review



Topics to learn today

1. Review from last lecture
2. Problem of MLP
3. What is Convolutional Neural Network?
4. Implementing CNN with Pytorch

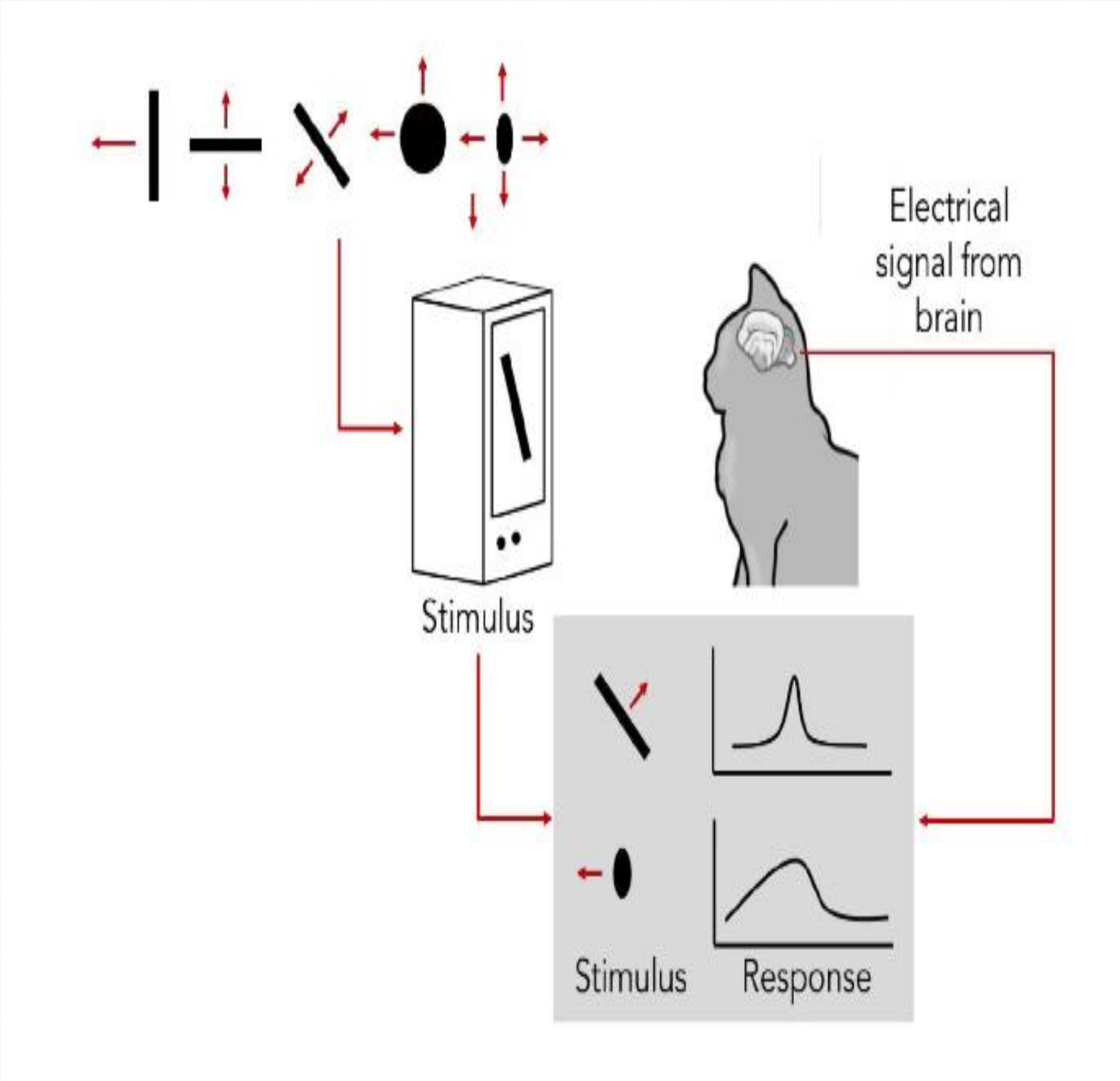
Problems of MLP

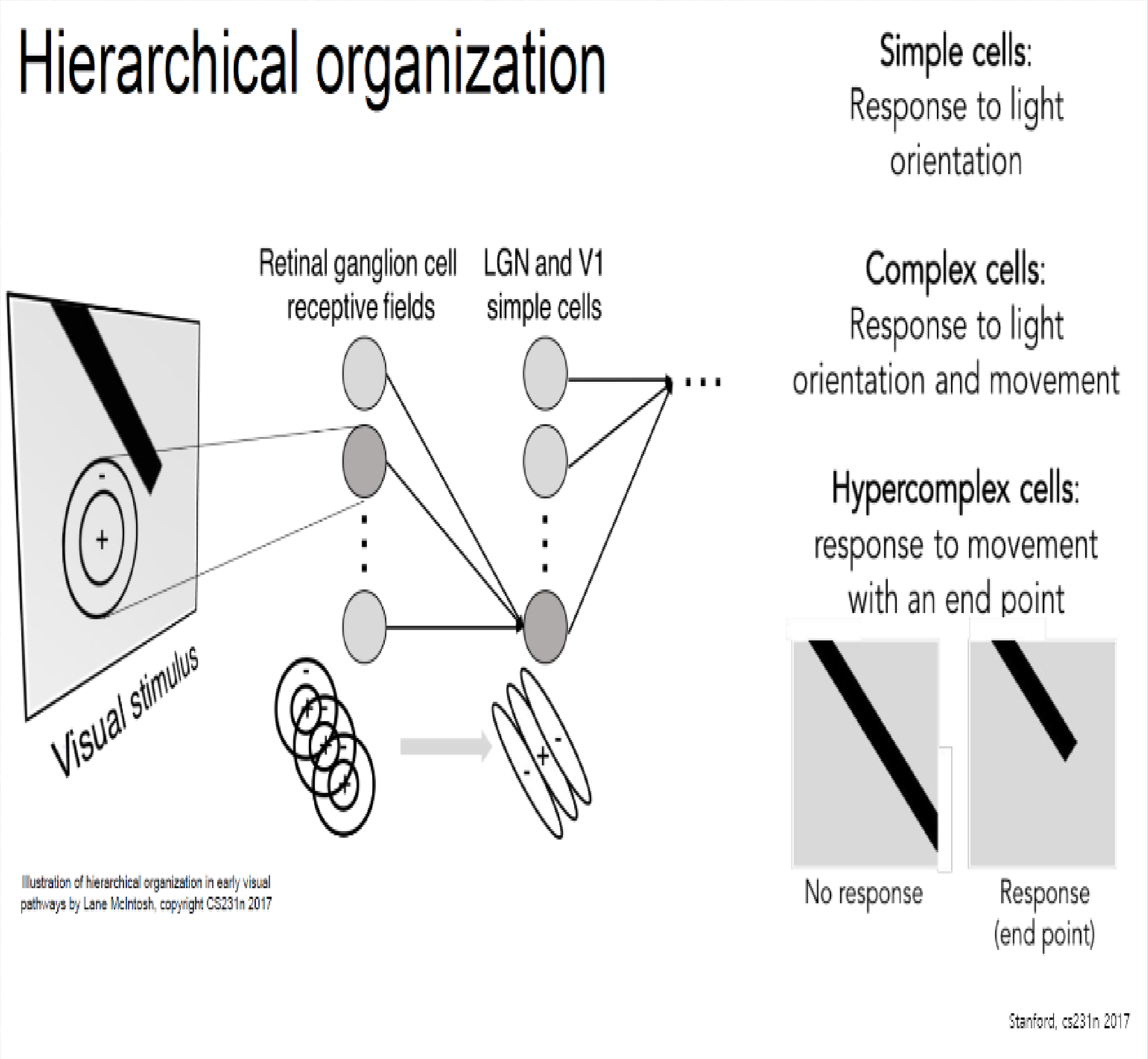
#20

Number of parameters

- Since a neuron is connected with every neurons in preceding layer, number of parameters explodes as model gets deeper.
- Some of the parameters are meaningless.

How human recognize an image?





#20

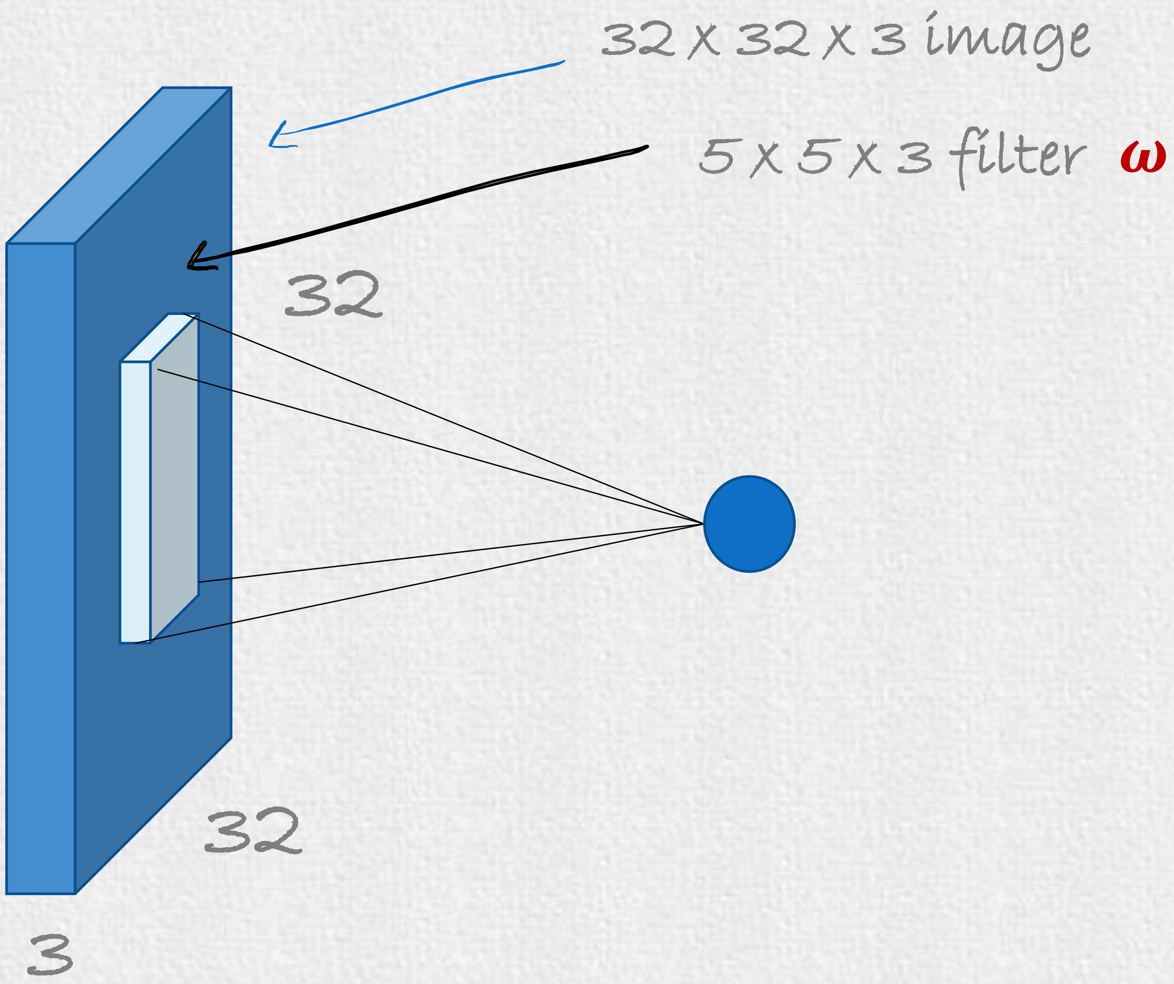
MLP / Fully Connected Layer

32 x 32 x 3 image → stretch to 3072 x 1

What is Convolutional Neural Network?

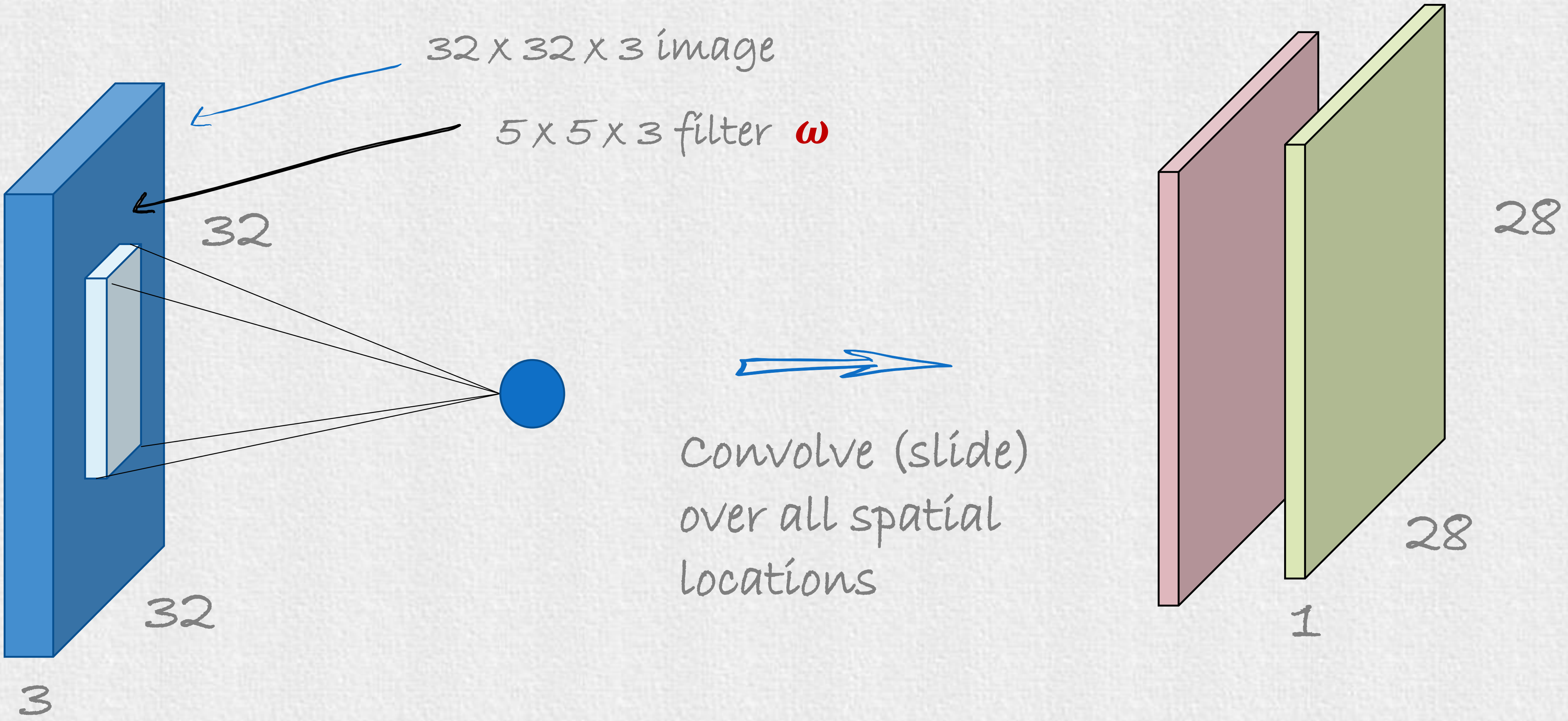
#20

Convolution Layer



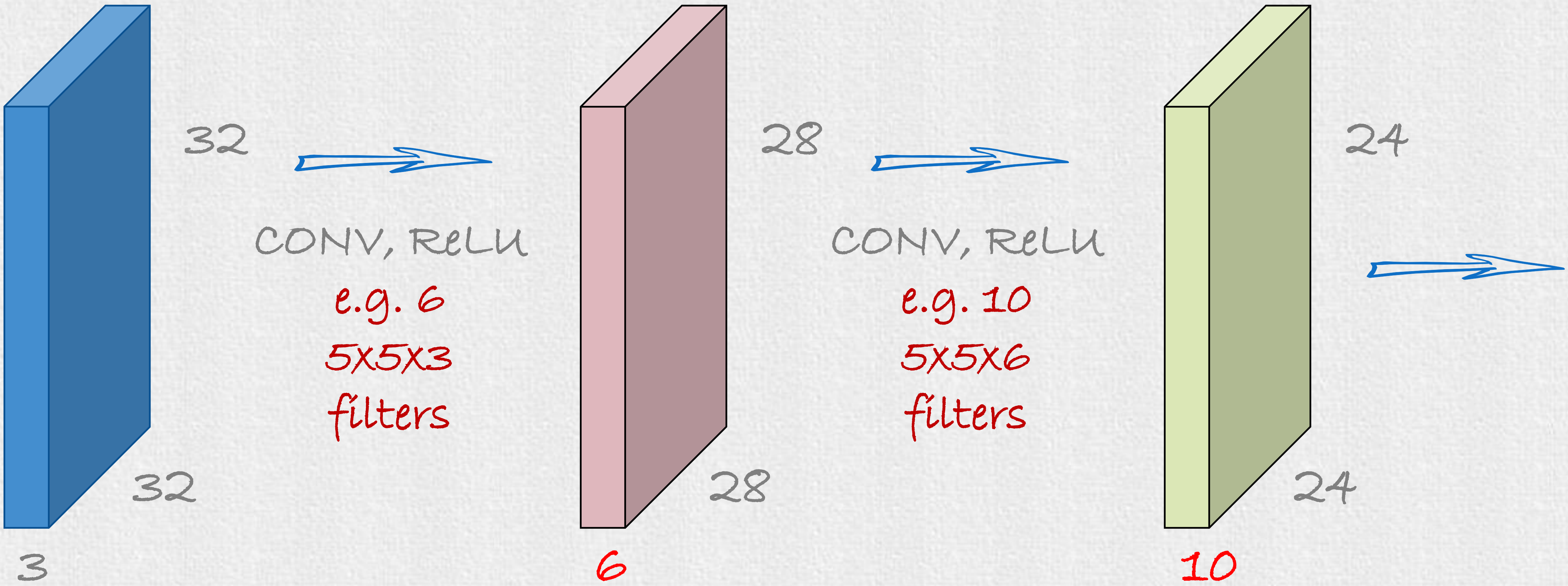
#20

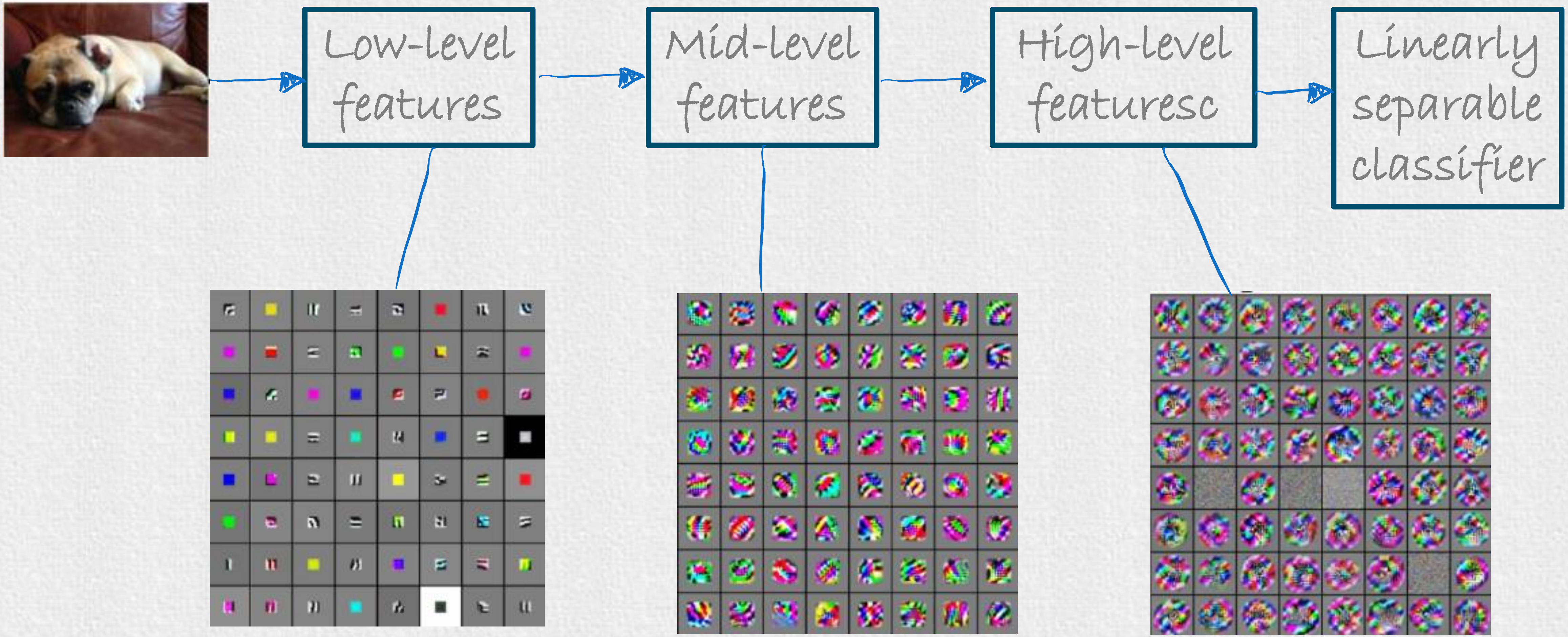
Convolution Layer



#20

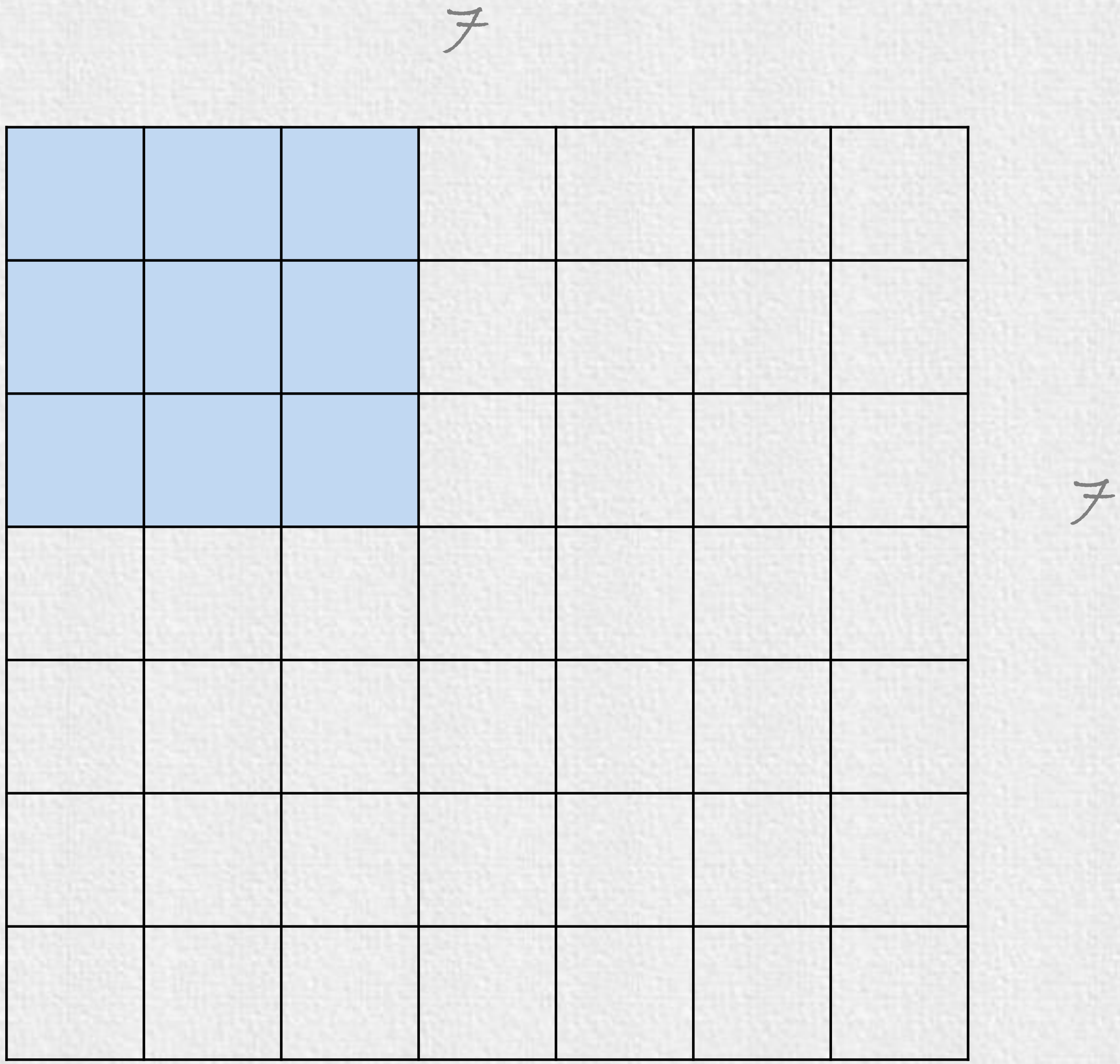
Convolution Net




Low-level features
Mid-level features
High-level featuresc
Linearly separable classifier

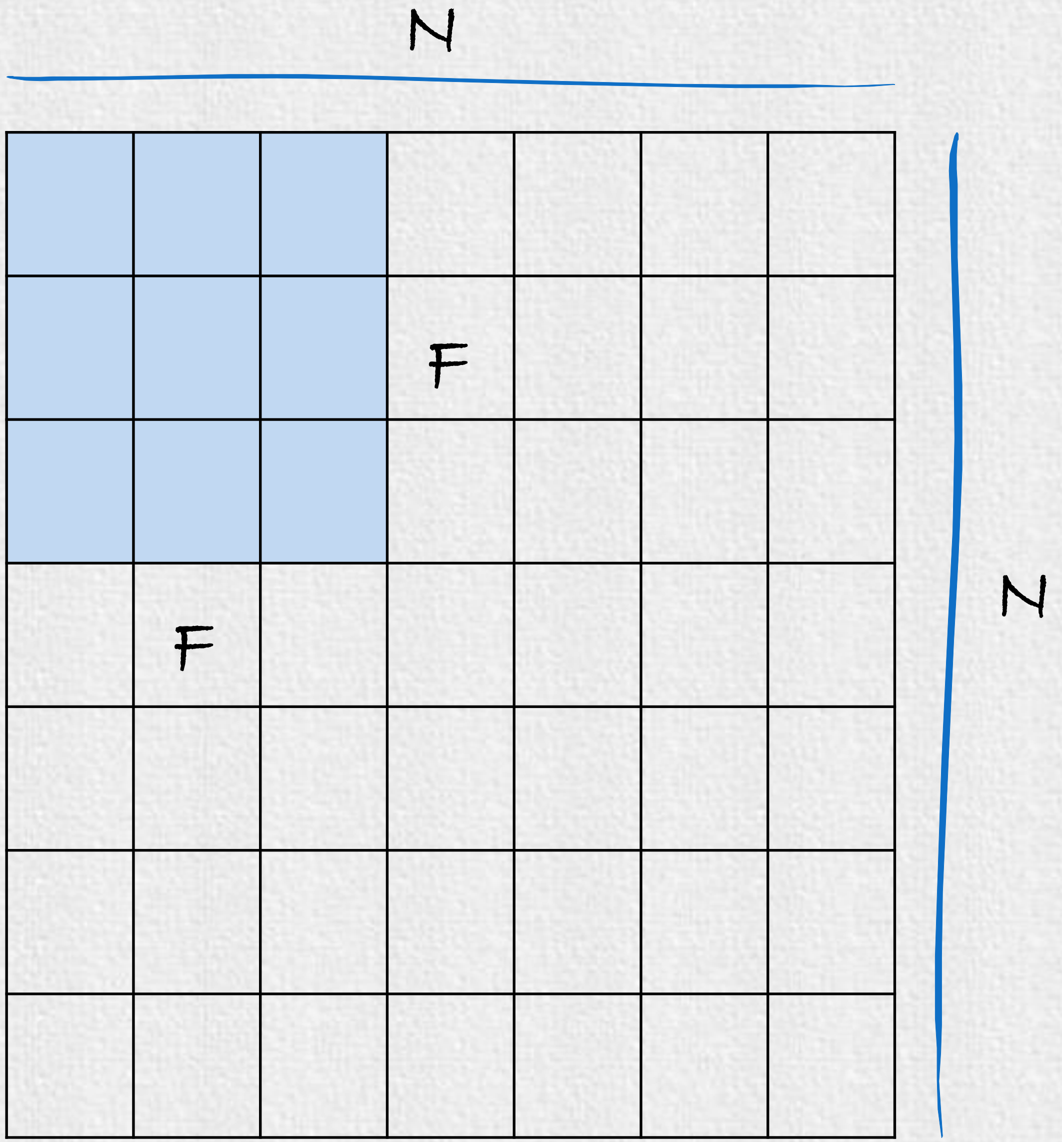
#20

Calculating spatial dimension



7 x 7 input (spatially)
assume 3 x 3 filter

Calculating spatial dimension

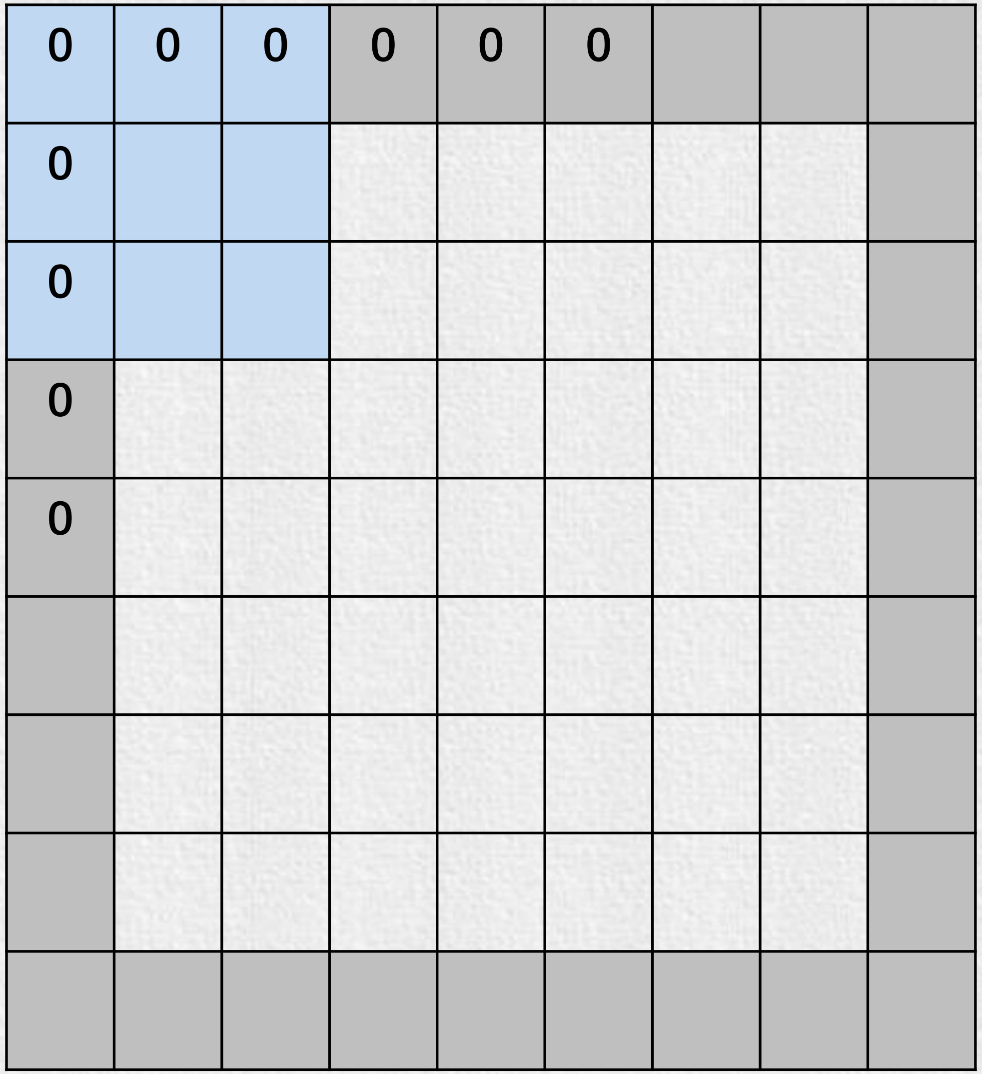


Output size:
(N-F) / stride + 1

e.g. N=7, F=3:
Stride 1 => (7-3)/1+1=5
Stride 2 => (7-3)/2+1=3
Stride 3 => (7-3)/3+1=2.33

#20

Zero padding



e.g input 7 x7

3 x 3 filter, applied with stride 1

Pad with 1 pixcel border => what is output?

7 x 7 output!

In general, common to see CONV layers with stride 1, filters of size F x F, and zero-padding with (F-1)/2. (will preserve size spatially)

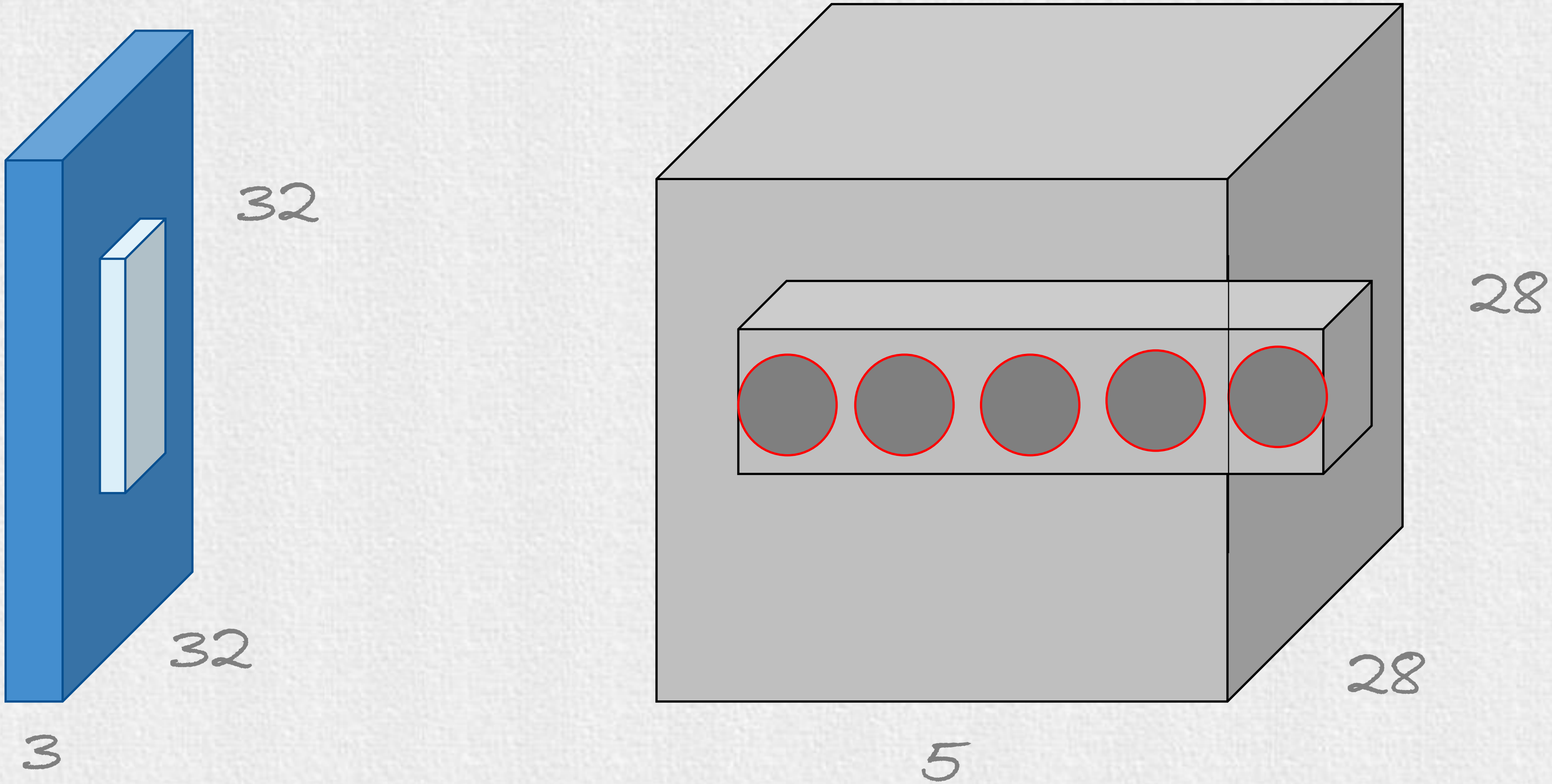
e.g. F = 3 => zero pad with 1

F = 5 => zero pad with 2

F = 7 => zero pad with 3

#20

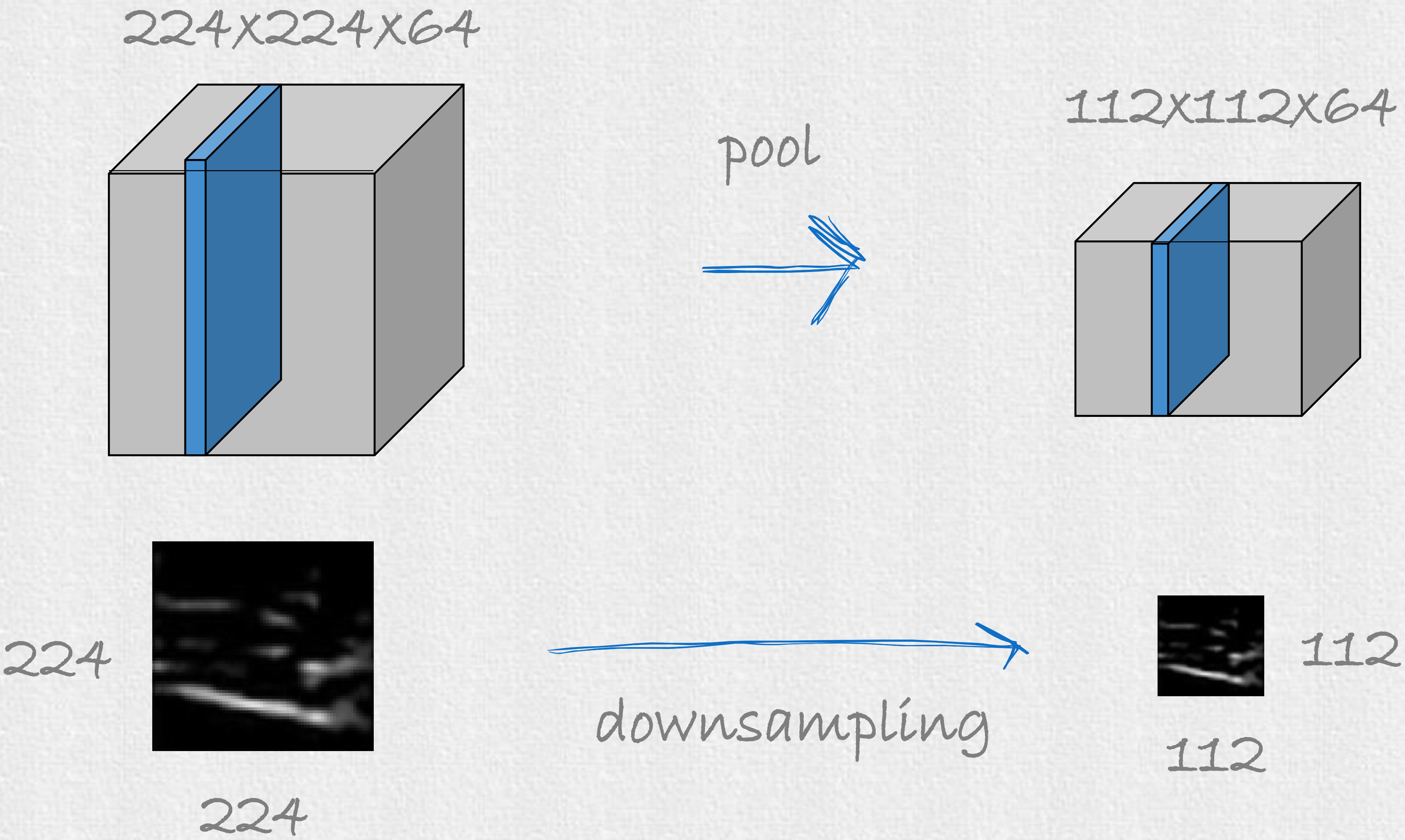
Neuron view of Convolutional Layer



Pooling and FC Layer

#20

Pooling layer



#20

MAX POOLING

Single depth slice

x

1	1	2	4
5	6	7	8
3	2	1	0
1	2	3	4

y

Max pool with 2x2 filters and stride 2

6	8
3	4

#20

Fully Connected Layer (FC)

MLP

#20

Convolution Net