

# 自编码器与Neural Transfer

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# 学习目标：

- 优化器
- 自编码器
- 反卷积
- Live Coding - Autoencoder
- Regularization (L1/L2, Dropout, Batch Normalization)
- Neural Transfer

# 讲师介绍：



会coding的科学家，懂数学的工程师，常年提着酱油瓶游走在学术与工程之间，从云计算到DevOps，从微服务到人工智能，不敢止步。

# 回顾

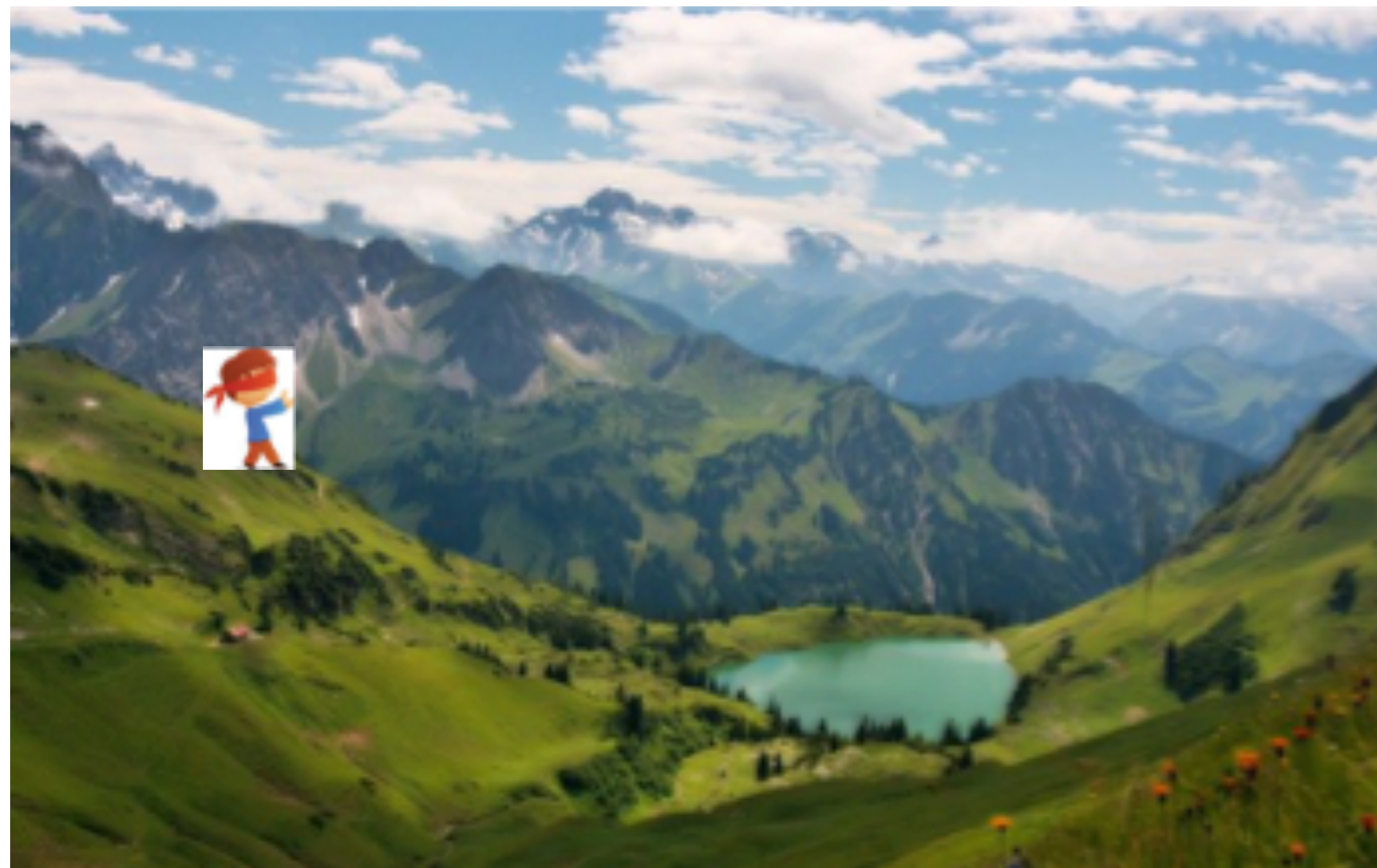


# 卷积神经网络(CNN)

- 解卷积神经网络和相关概念
- 学习如何在 TensorFlow 中创建、训练 CNN 模型

# 优化器 (Optimizer)

# 随机梯度递降 (SGD)



# 随机梯度递降 (SGD)

- 采样一批次 (batch) 数据
- 前向通过计算图，计算Loss
- 反向计算梯度
- 更新参数



# 随机梯度递降 (SGD)

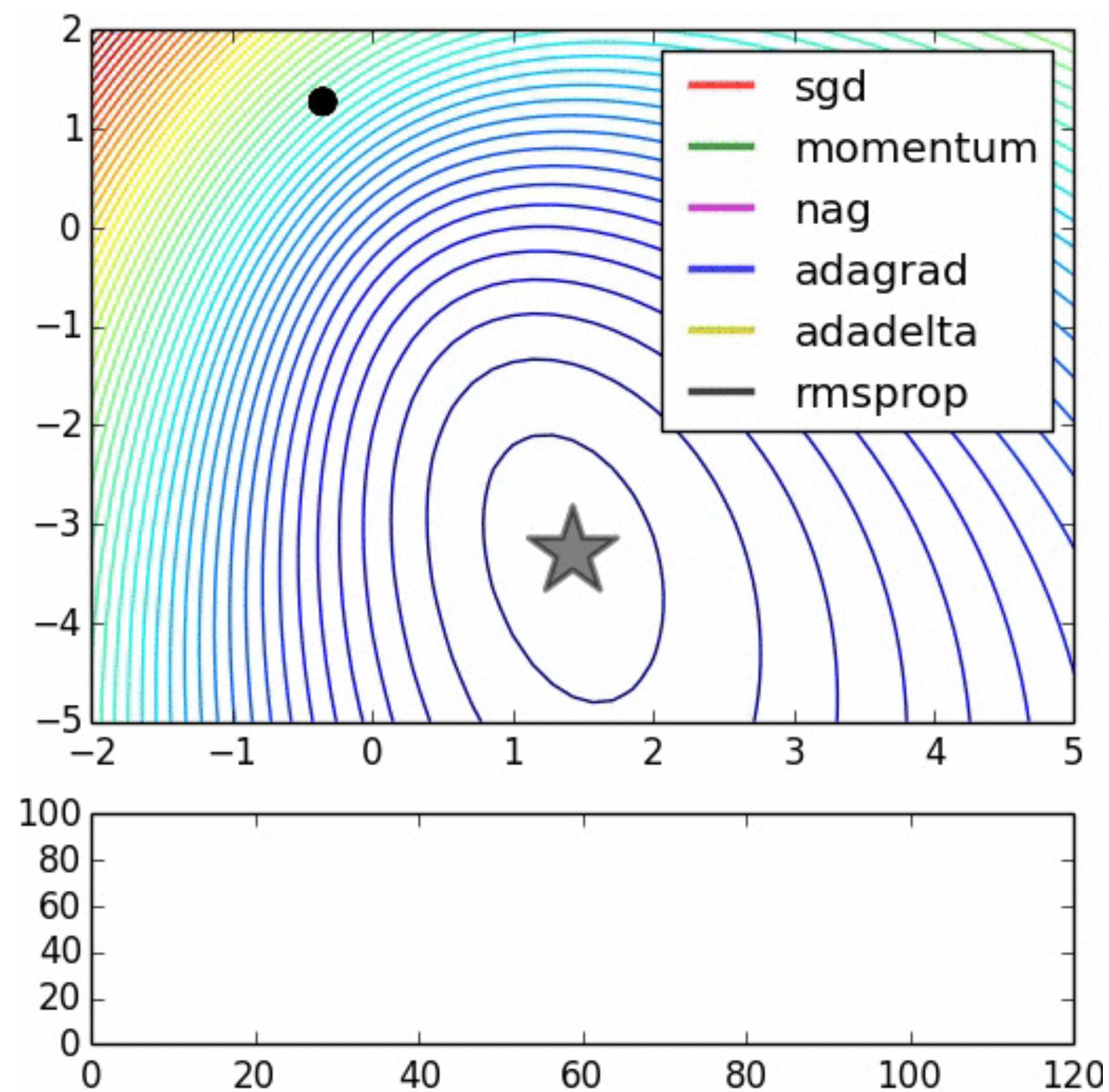
```
while True:
    data_batch = dataset.sample_data_batch()
    loss = network.forward(data_batch)
    dx = network.backward()
    x += - learning_rate * dx
```

# 随机梯度递降 (SGD)

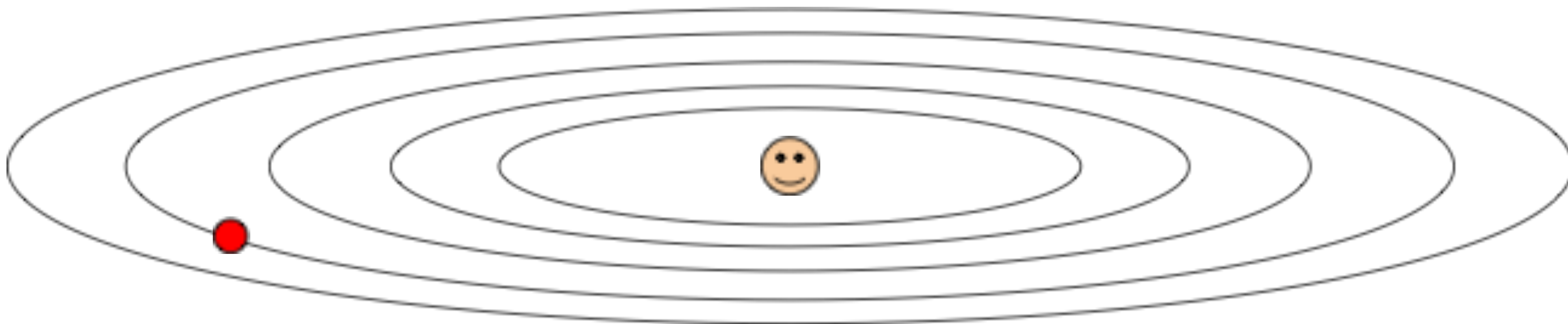
```
while True:
    data_batch = dataset.sample_data_batch()
    loss = network.forward(data_batch)
    dx = network.backward()
    x += - learning_rate * dx
```

更复杂的更新策略

# 随机梯度递降 (SGD)



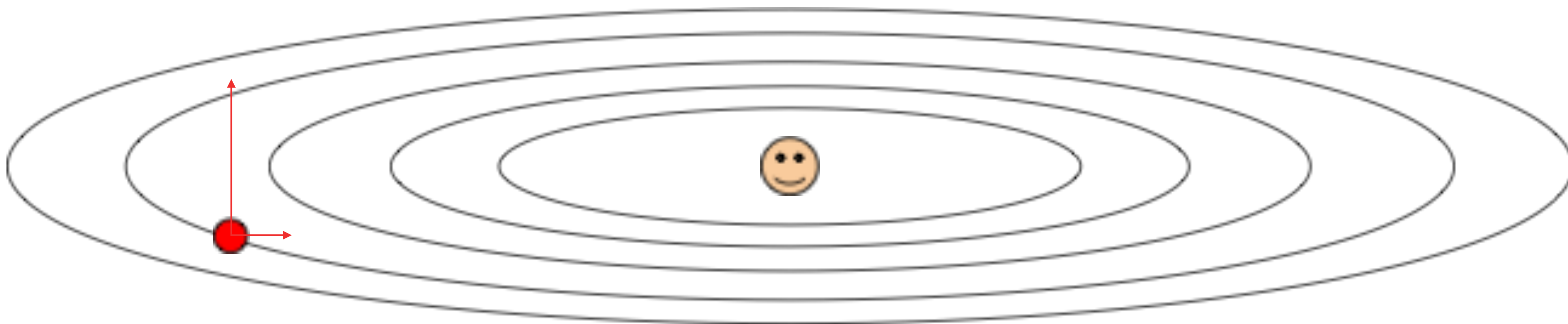
# 随机梯度递降 (SGD)



思考：当前情况下，SGD策略的更新轨迹是什么样的。

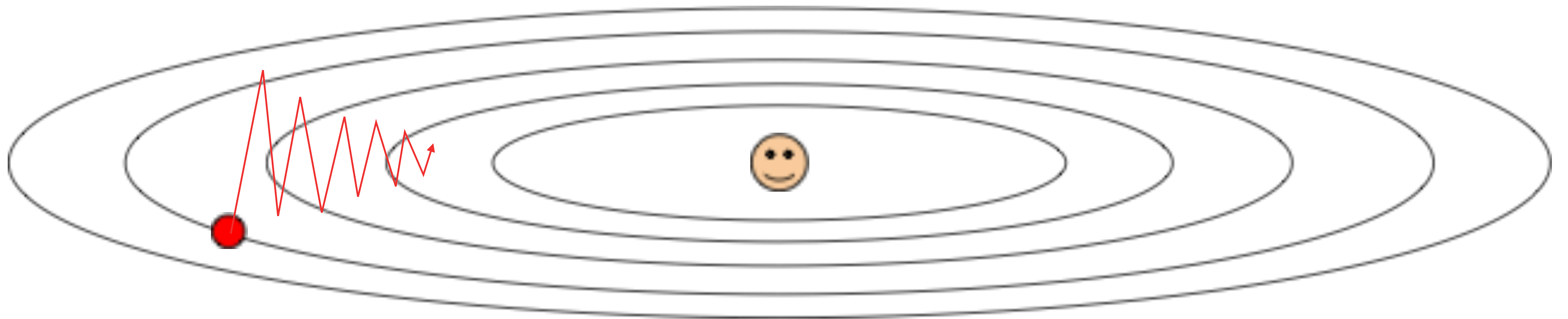


# 随机梯度递降 (SGD)



思考：当前情况下，SGD策略的更新轨迹是什么样的。

# 随机梯度递降 (SGD)




思考：当前情况下，SGD策略的更新轨迹是什么样的。  
在比较陡峭的方向会来回抖动，在平缓的方向缓慢趋向最低点。

# Momentum (动量) Update

```
x += - learning_rate * dx
```

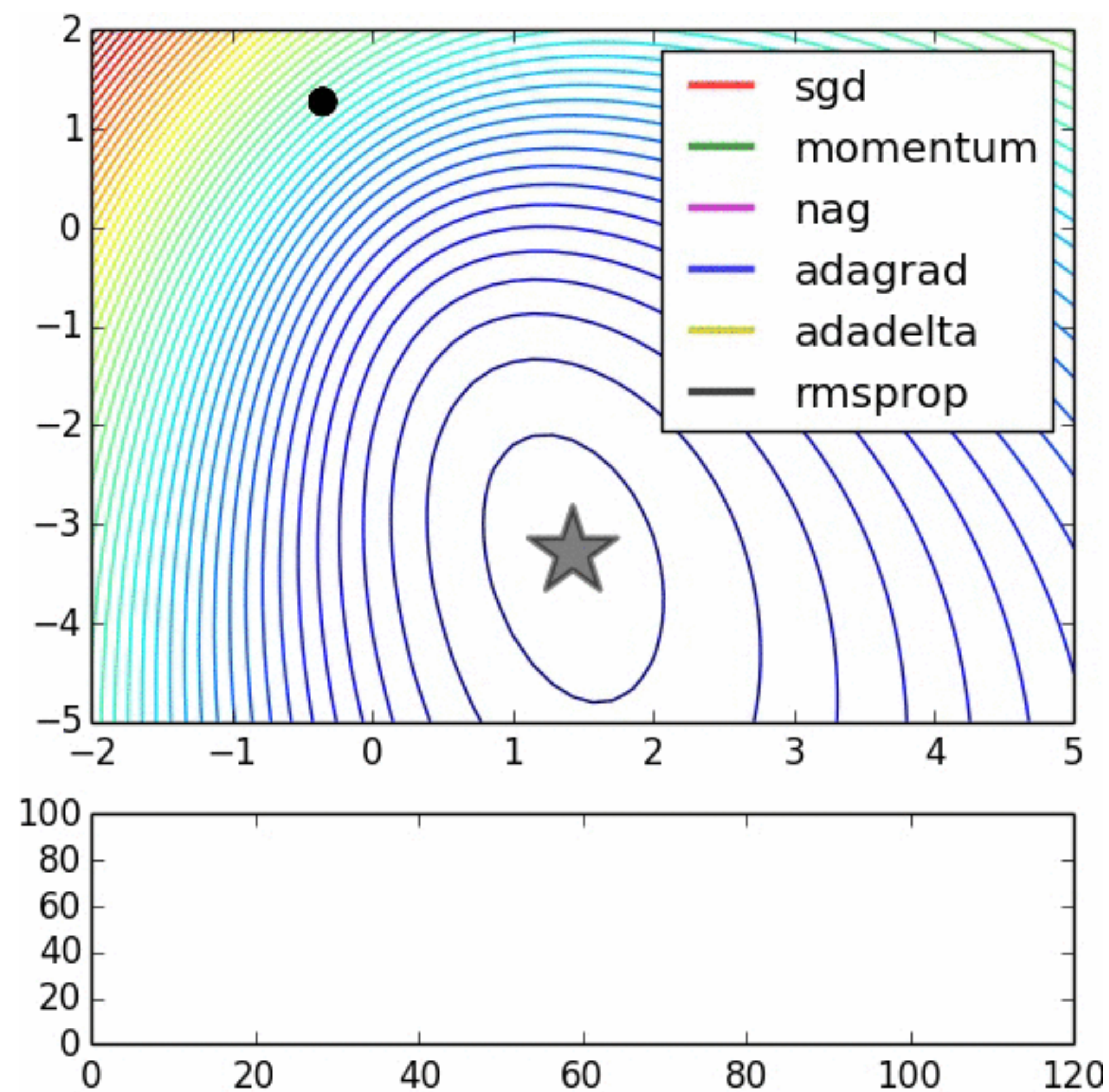
从物理的惯性角度思考  
在平缓的方向上，不断累积速度，  
在陡峭的方向上，由于不断变换符号，速度会被抑制。



```
x = mu * v - learning_rate * dx  
x += v
```

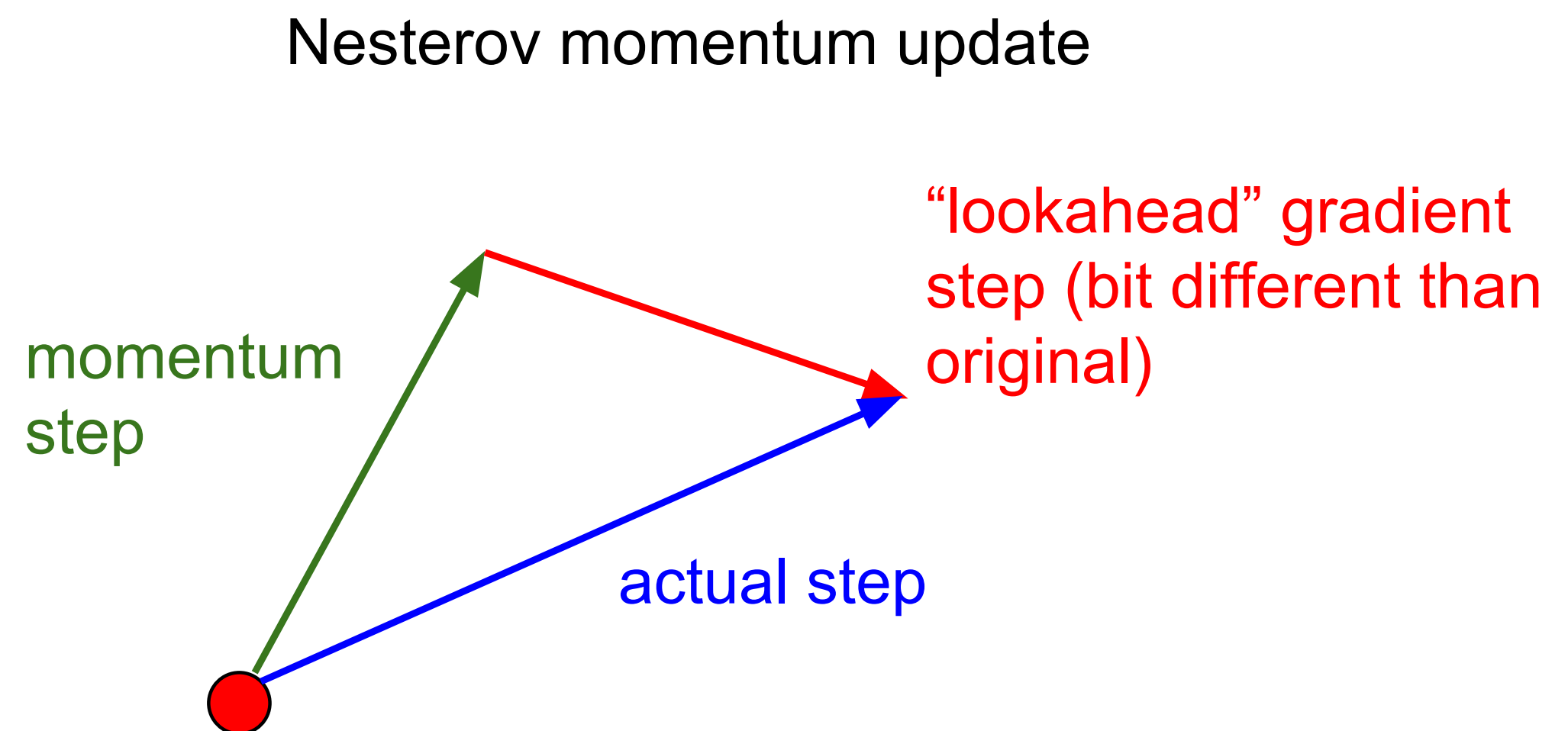
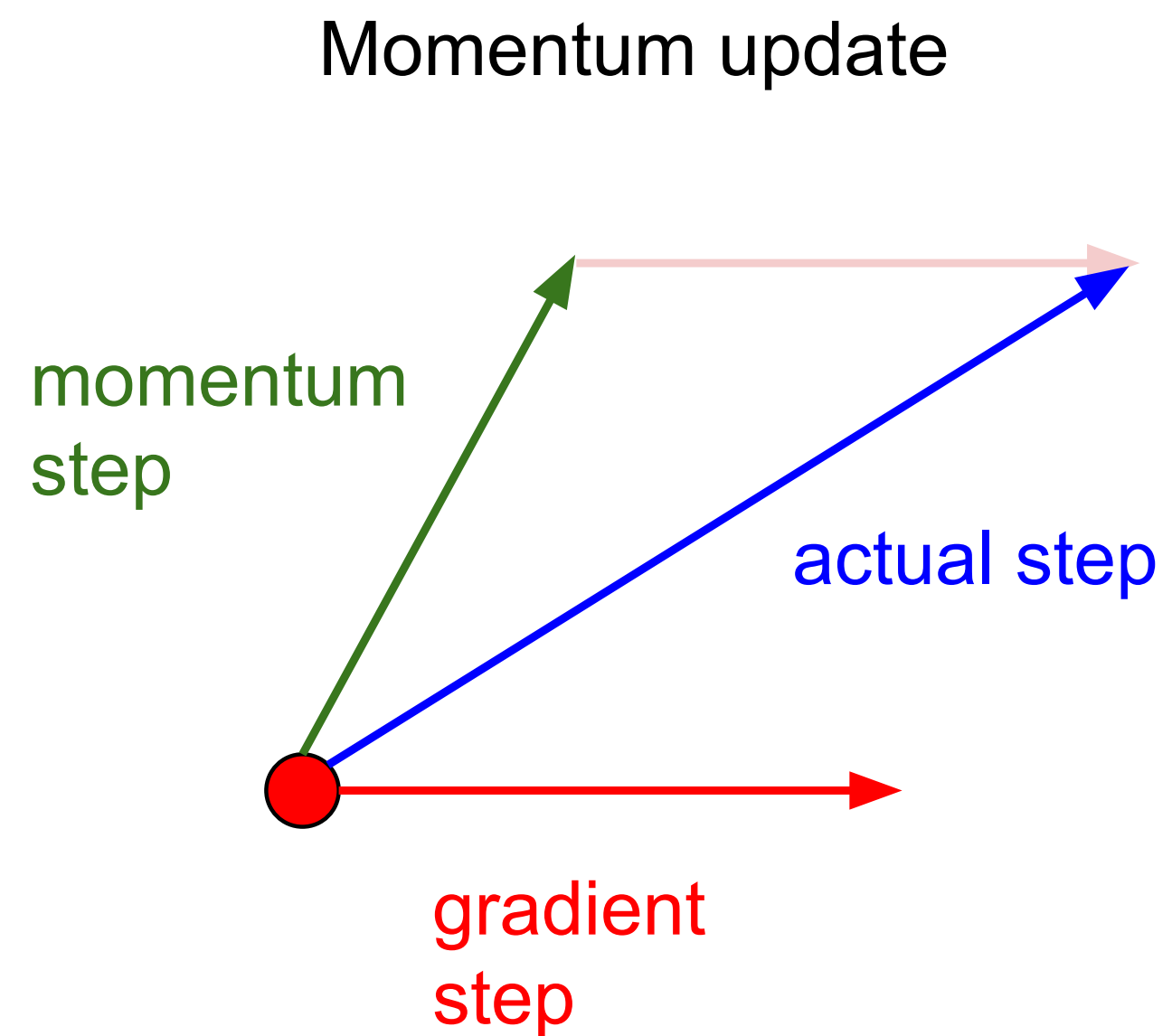
其中， $\mu=0.5, 0.9, 0.99$

# SGD vs Momentum





# Nesterov Accelerated Gradient



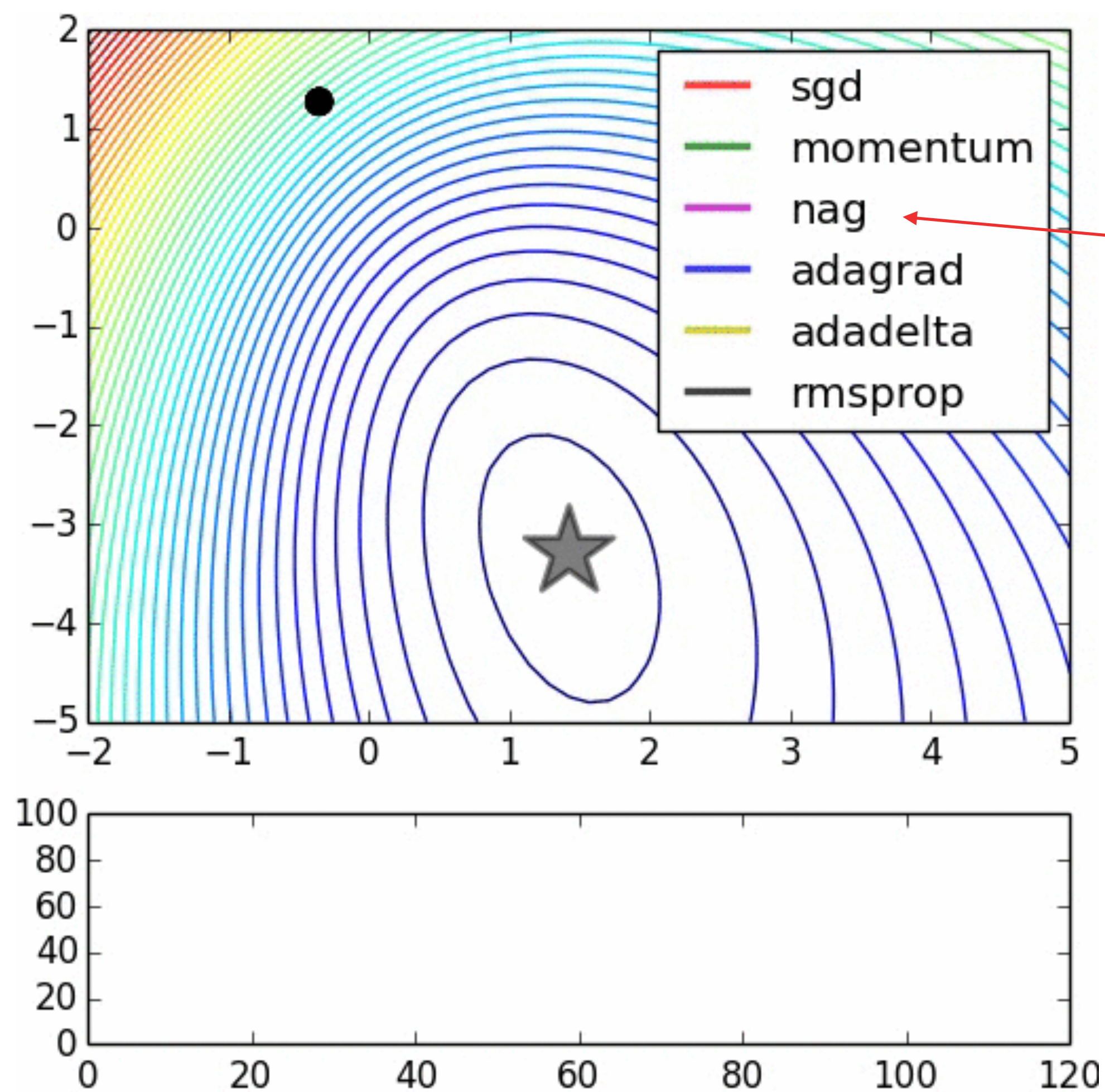
# Nesterov Accelerated Gradient

```
x = mu * v - learning_rate * dx  
x += v
```



```
v_prev = v  
v = mu * v - learning_rate * dx  
x += -mu * v_prev + (1 + mu) * v
```

# NAG



# AdaGrad

```
cache += dx**2  
x += - learning_rate * dx / (np.sqrt(cache) + 1e-7)
```

基于每个维度每一个元素的历史平方和，计算learning\_rate的调整比例



# AdaGrad

```
cache += dx**2  
x += - learning_rate * dx / (np.sqrt(cache) + 1e-7)
```

基于每个维度每一个元素的历史平方和，计算learning\_rate的调整比例  
随着训练时间越来越长，每次更新的步长会越来越小。

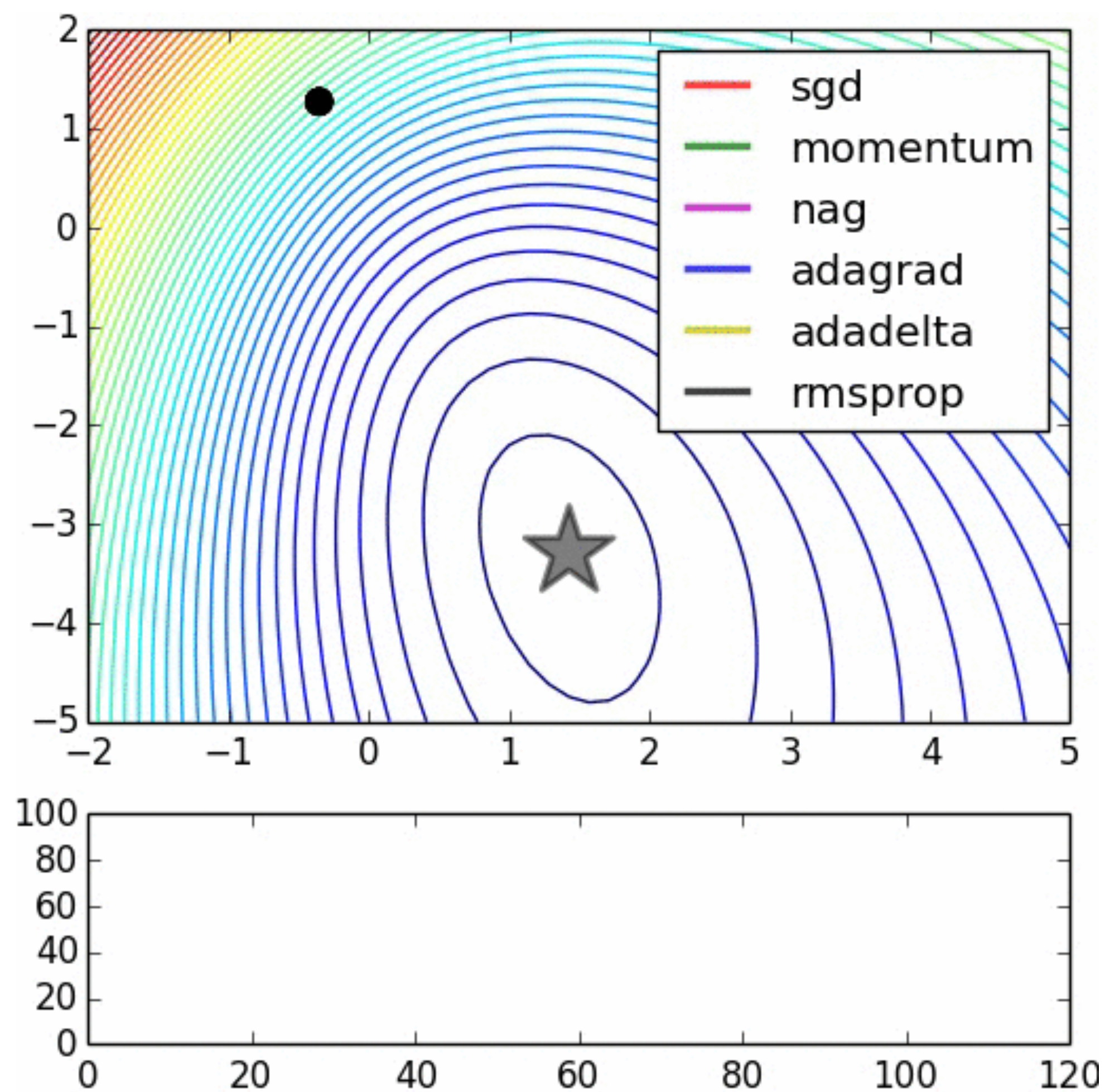
# RMSProp

```
cache += dx**2  
x += - learning_rate * dx / (np.sqrt(cache) + 1e-7)
```



```
cache += decay_rate * cache + (1 - decay_rate) * dx**2  
x += - learning_rate * dx / (np.sqrt(cache) + 1e-7)
```

# AdaGrad vs RMSProp

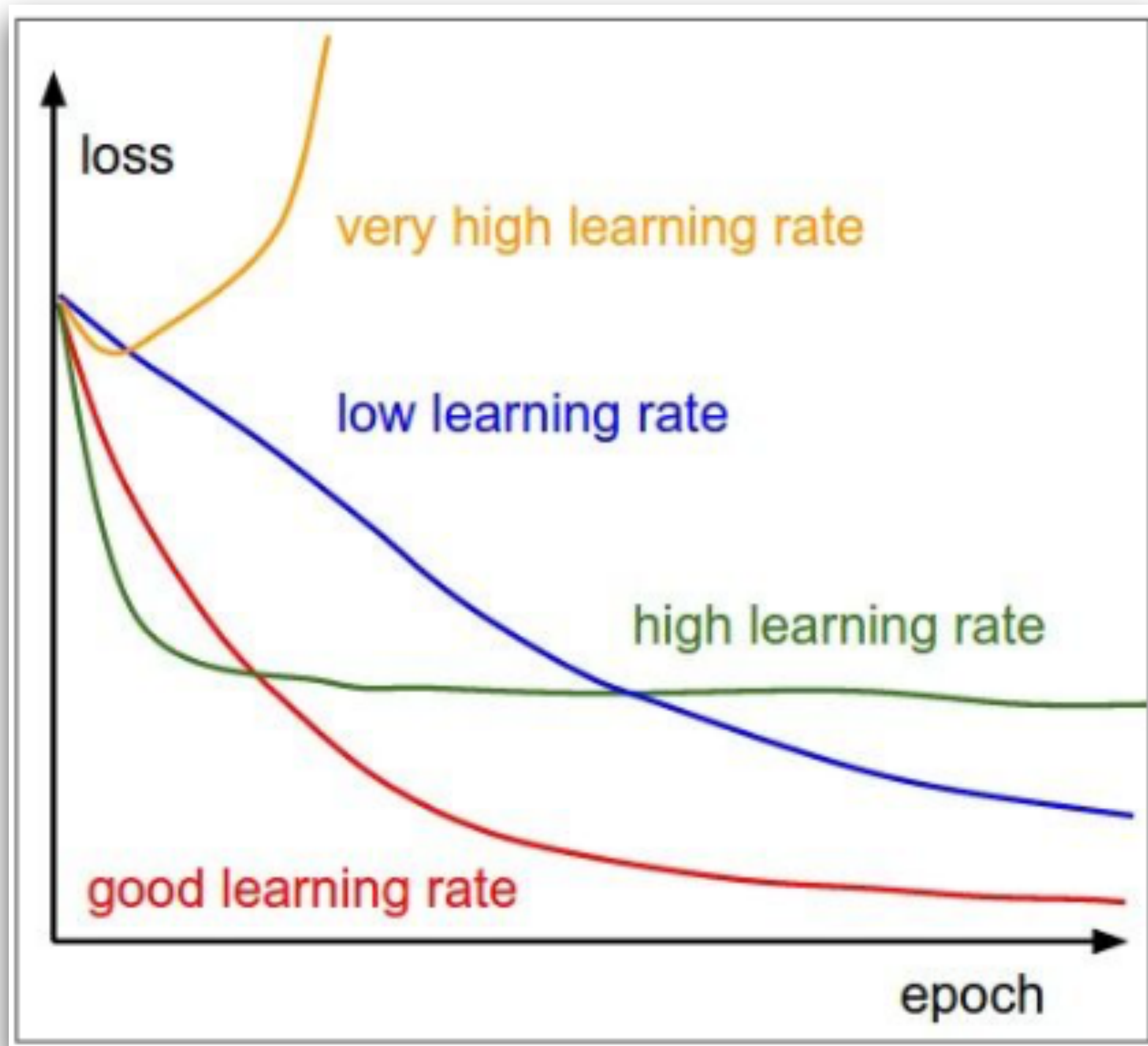


# Adam Update

```
m = beta1 * m + (1 - beta1) * dx
v = beta2*v + (1 - beta2) * (dx**2)
mb = m / (1 - beta1**5)
vb = v / (1 - beta2**t)
x += - learning_rate * mb / (np.sqrt(vb) + 1e-7)
```

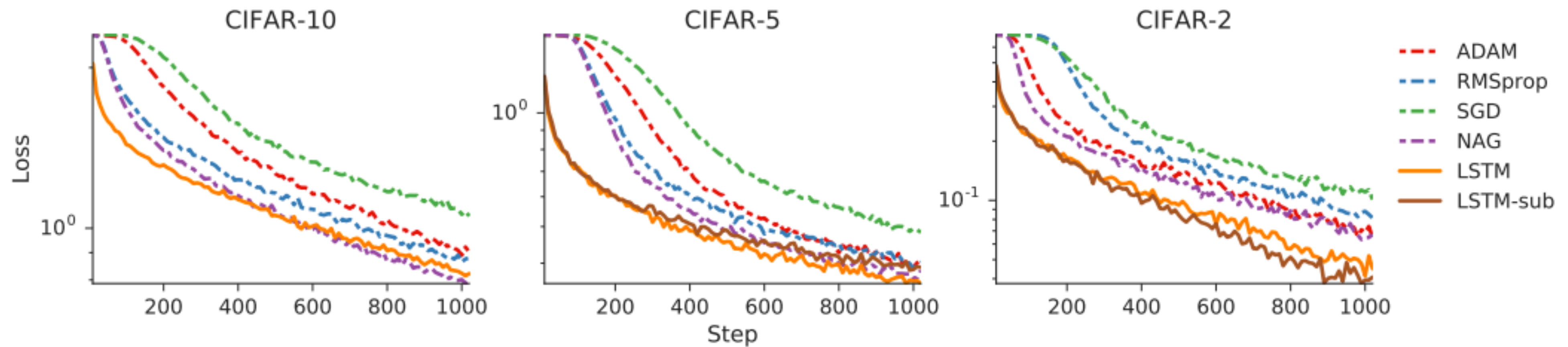
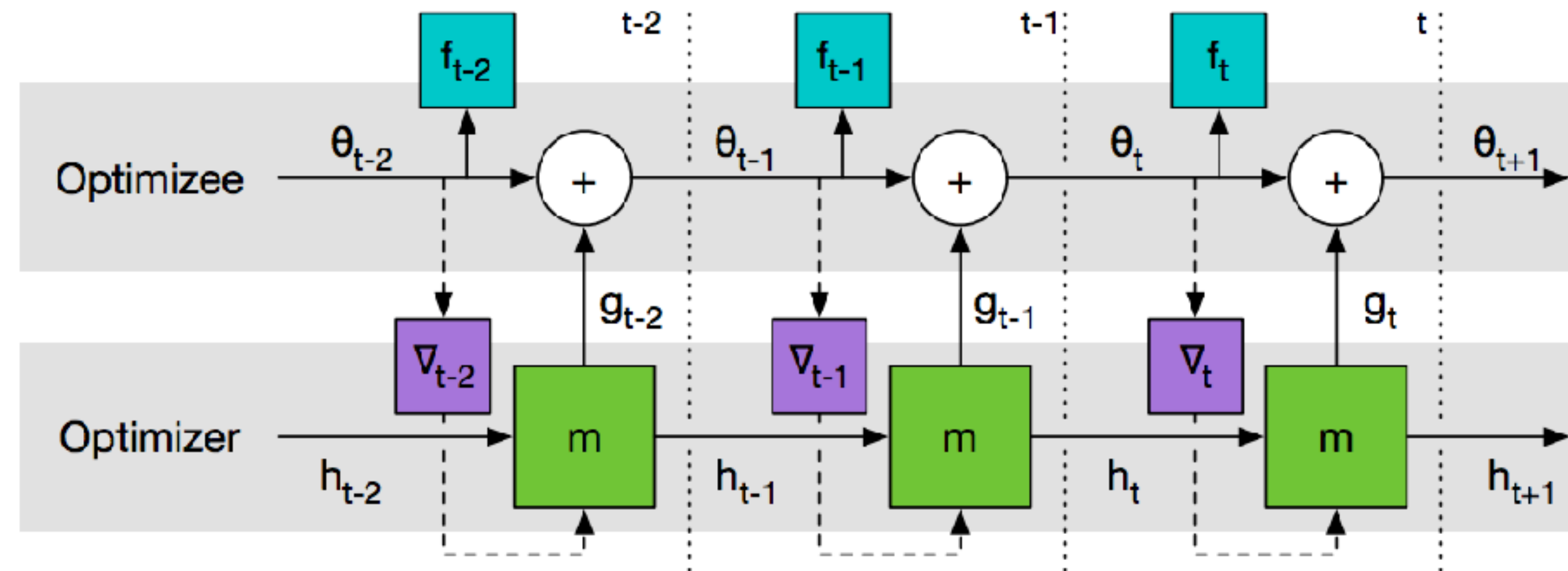


# 如何选择?



一个好的学习曲线，应该是一开始可以让Loss快速下降，同时在最低点收敛。

# Learning to Learn



# Optimizer in TensorFlow

## Optimizers

The Optimizer base class provides methods to compute gradients for a loss and apply gradients to variables. A collection of subclasses implement classic optimization algorithms such as GradientDescent and Adagrad.

You never instantiate the Optimizer class itself, but instead instantiate one of the subclasses.

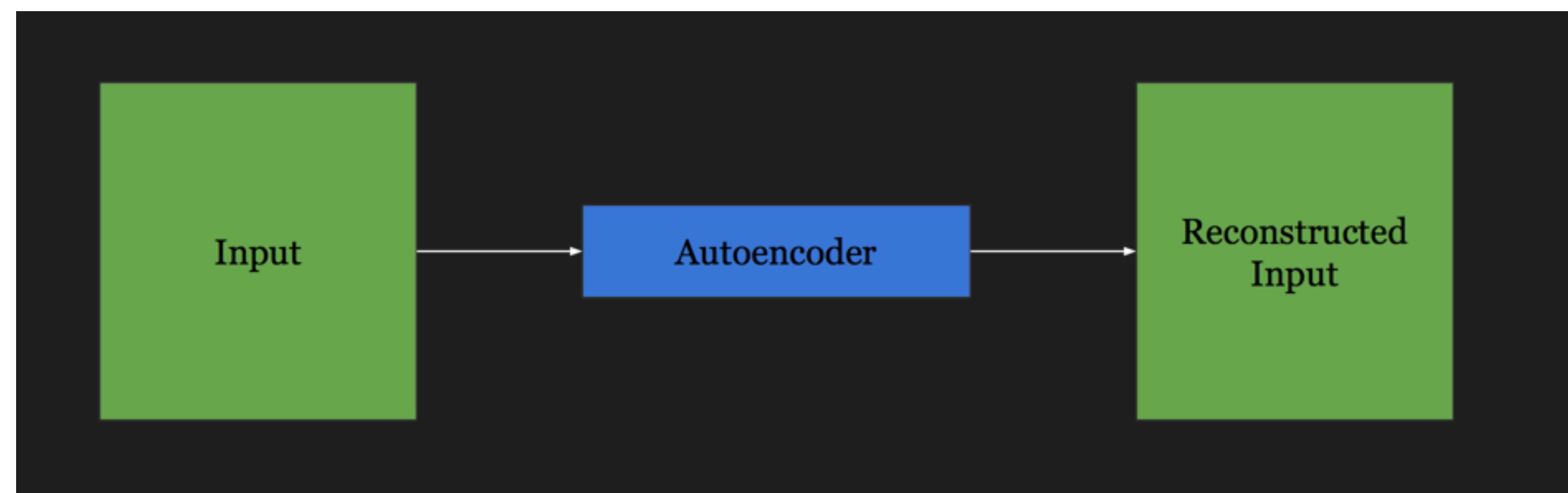
- `tf.train.Optimizer`
- `tf.train.GradientDescentOptimizer`
- `tf.train.AdadeltaOptimizer`
- `tf.train.AdagradOptimizer`
- `tf.train.AdagradDAOptimizer`
- `tf.train.MomentumOptimizer`
- `tf.train.AdamOptimizer`
- `tf.train.FtrlOptimizer`
- `tf.train.ProximalGradientDescentOptimizer`
- `tf.train.ProximalAdagradOptimizer`
- `tf.train.RMSPropOptimizer`

```
optimizer = tf.train.XXOptimizer(learning_rate=0.1).minimize(loss)
```

# 自编码器 (Autoencoder)



# 什么是AUTOENCODER



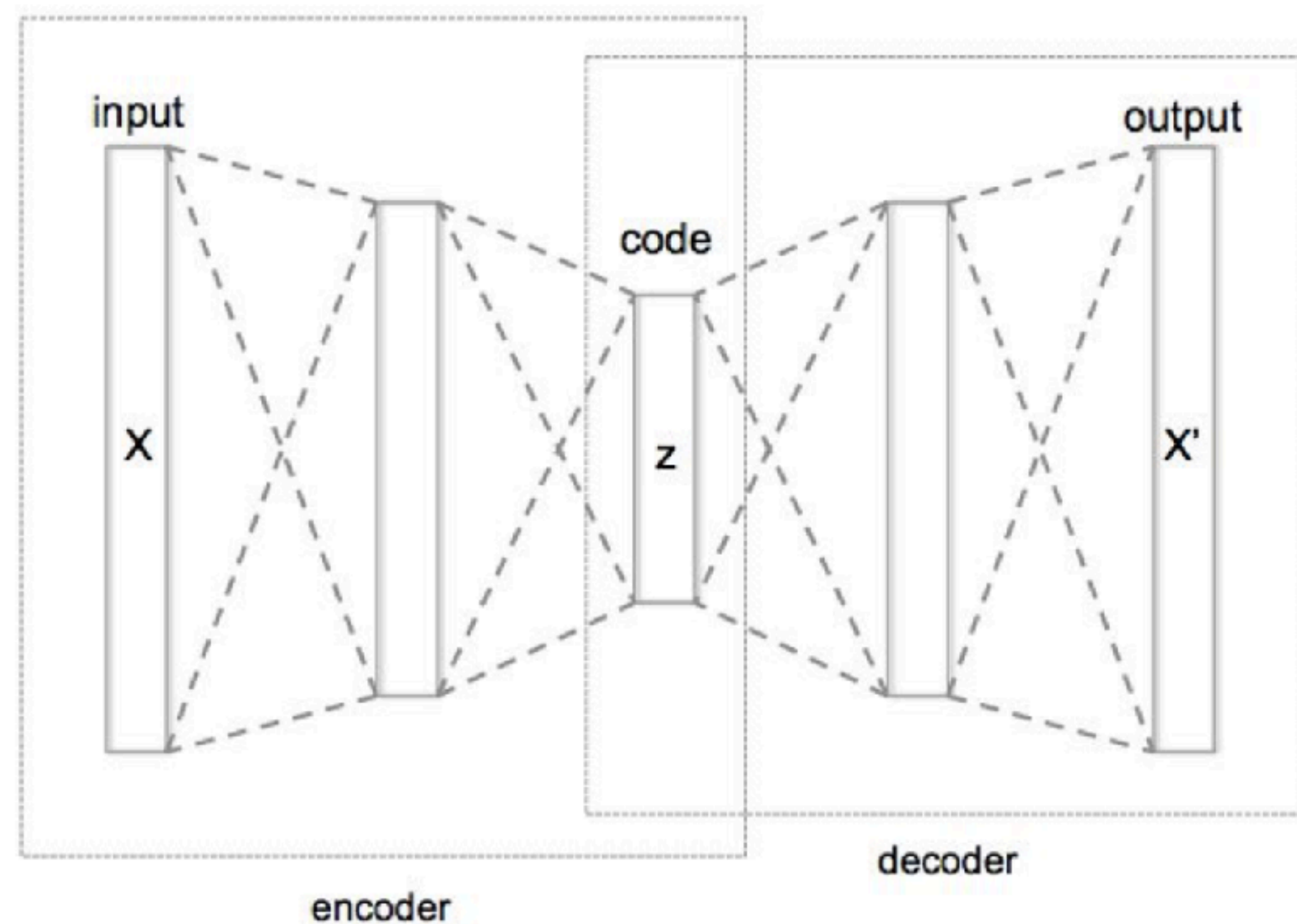
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# AUTOENCODER

---

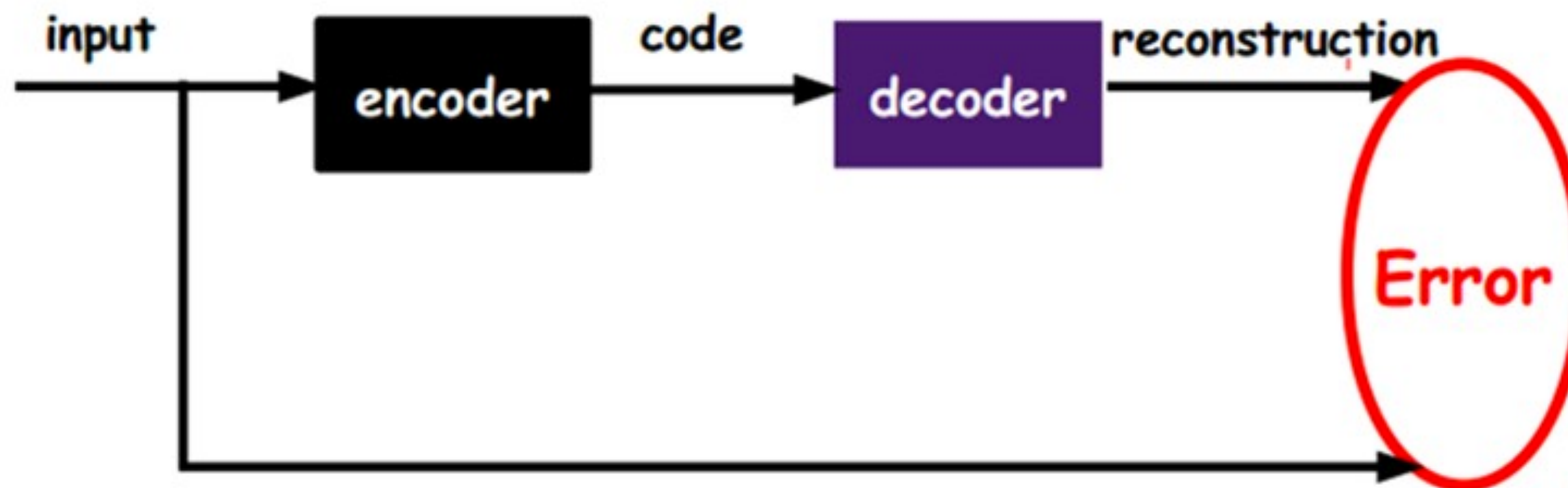
autoencoder就是一种尽可能复现输入信号的神经网络,  
autoencoder是无监督学习

# AUTOENCODER



输入和输出的维度应该相同  
输入和输出的范围应该相同

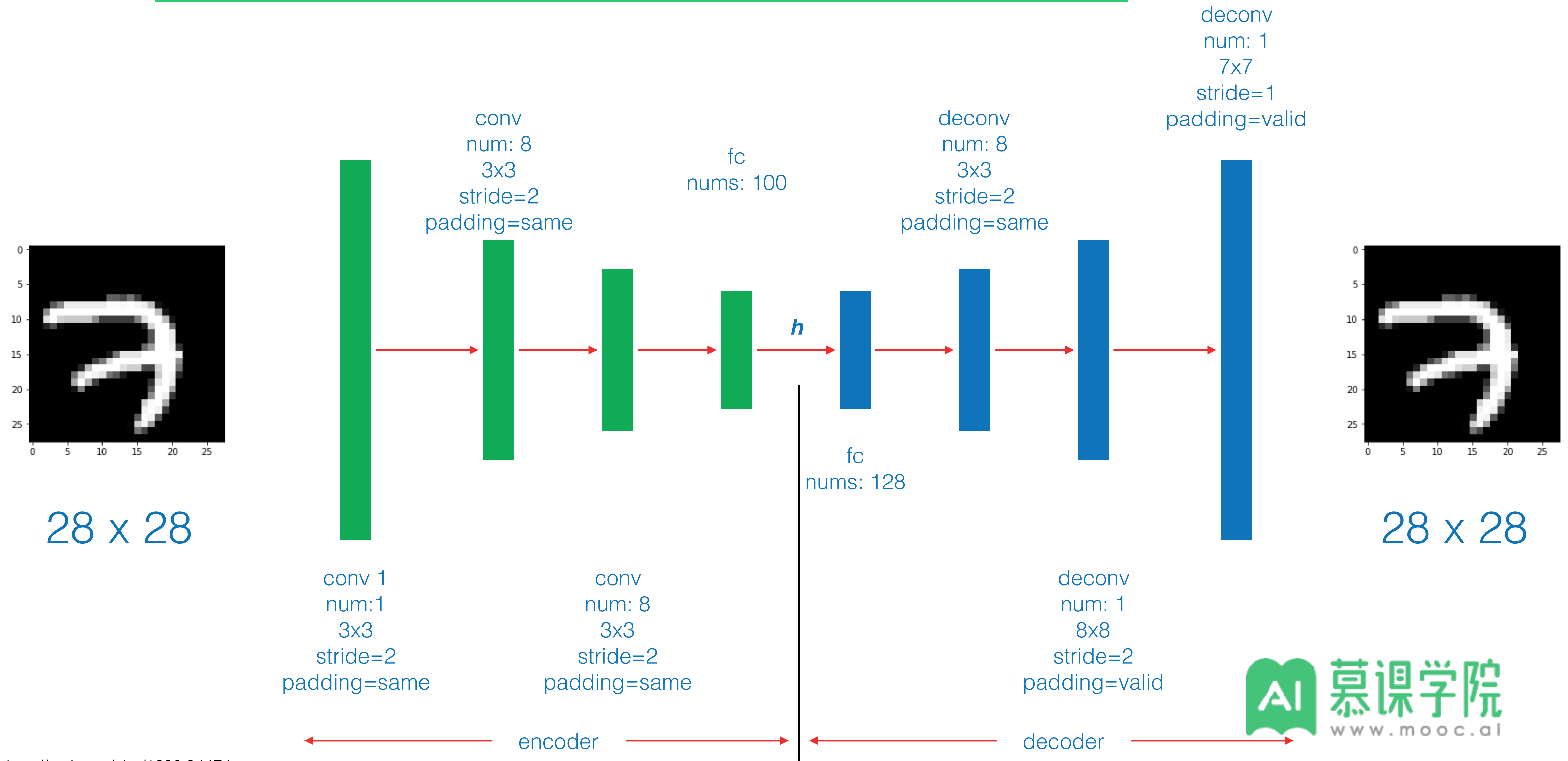
# AUTOENCODER怎么求误差



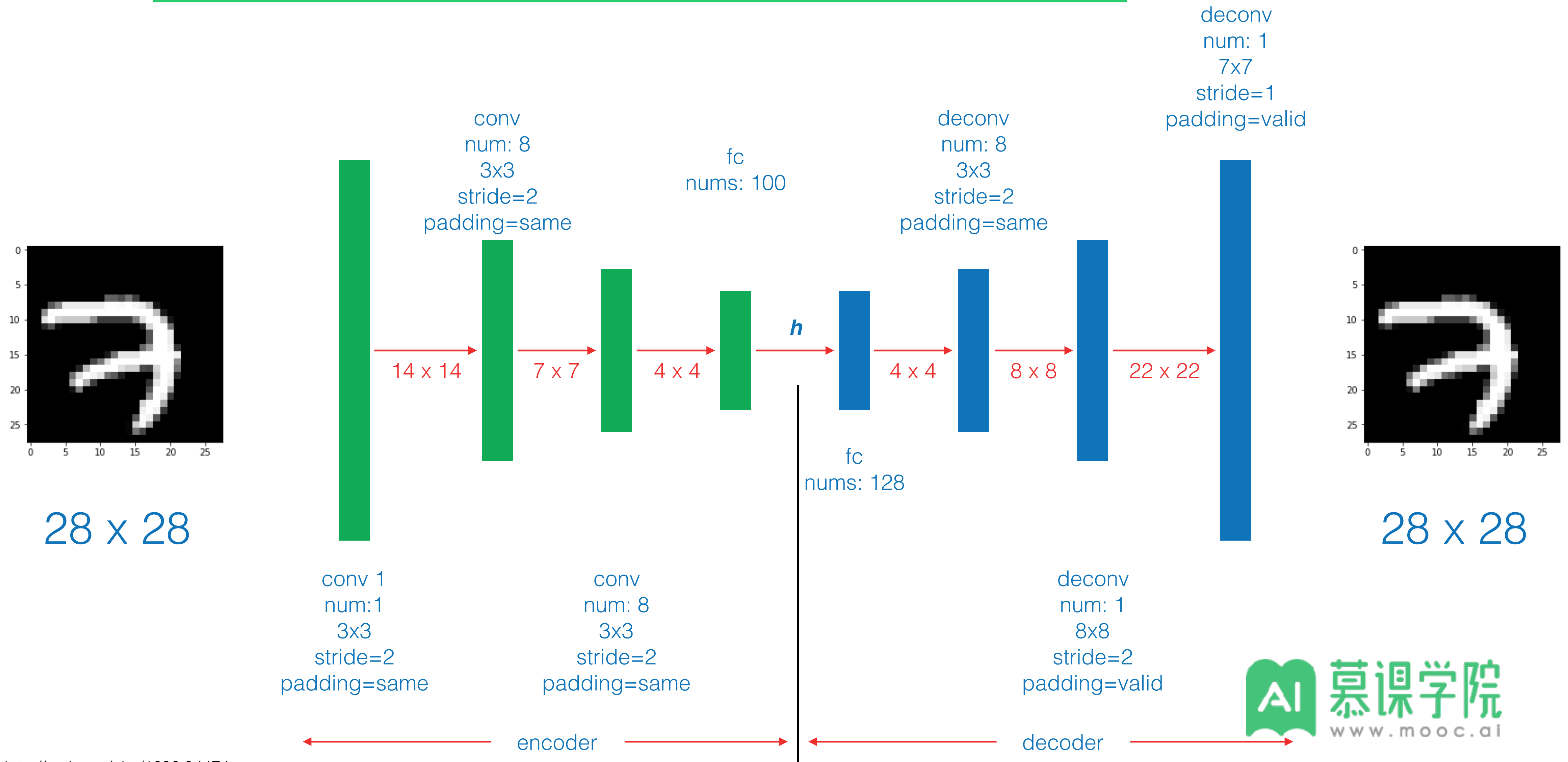
将input输入一个encoder编码器，就会得到一个code，code表示输入，加一个decoder解码器，decoder得到输出，通过通过调整encoder和decoder的参数，使得输入和输出的。



# Autoencoder

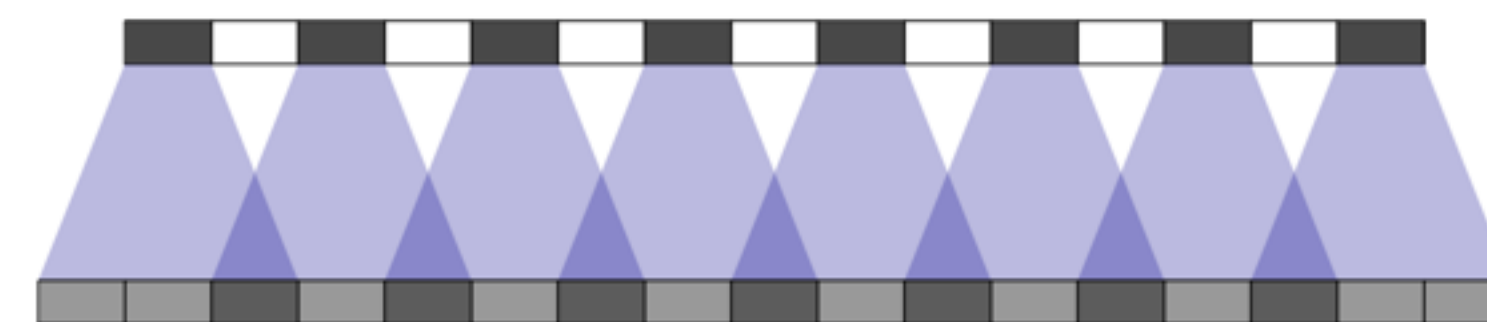
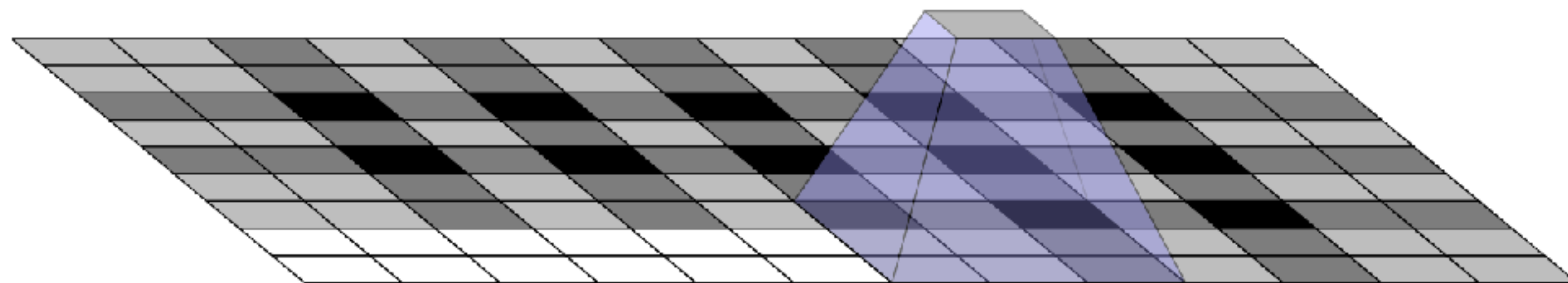


# Autoencoder



# 反卷积 (Deconvolution)

# 反卷积





# 反卷积

```
tf.nn.conv2d_transpose(value, filter, output_shape, strides, padding='SAME',  
data_format='NHWC', name=None)
```

The transpose of `conv2d`.

This operation is sometimes called "deconvolution" after [Deconvolutional Networks](#), but is actually the transpose (gradient) of `conv2d` rather than an actual deconvolution.

## Args:

- `value`: A 4-D Tensor of type `float` and shape `[batch, height, width, in_channels]` for `NHWC` data format or `[batch, in_channels, height, width]` for `NCHW` data format.
- `filter`: A 4-D Tensor with the same type as `value` and shape `[height, width, output_channels, in_channels]`. `filter`'s `in_channels` dimension must match that of `value`.
- `output_shape`: A 1-D Tensor representing the output shape of the deconvolution op.
- `strides`: A list of ints. The stride of the sliding window for each dimension of the input tensor.
- `padding`: A string, either `'VALID'` or `'SAME'`. The padding algorithm. See the [comment here](#)
- `data_format`: A string. `'NHWC'` and `'NCHW'` are supported.
- `name`: Optional name for the returned tensor.

```
def get_deconv2d_output_dims(input_dims, filter_dims, stride_dims, padding):  
    # Returns the height and width of the output of a deconvolution layer.  
    batch_size, input_h, input_w, num_channels_in = input_dims  
    filter_h, filter_w, num_channels_out = filter_dims  
    stride_h, stride_w = stride_dims  
  
    # Compute the height in the output, based on the padding.  
    if padding == 'SAME':  
        out_h = input_h * stride_h  
    elif padding == 'VALID':  
        out_h = (input_h - 1) * stride_h + filter_h  
  
    # Compute the width in the output, based on the padding.  
    if padding == 'SAME':  
        out_w = input_w * stride_w  
    elif padding == 'VALID':  
        out_w = (input_w - 1) * stride_w + filter_w  
  
    return [batch_size, out_h, out_w, num_channels_out]
```

# Live Coding

# Q&A

[https://github.com/tongda/leifeng\\_tf\\_course](https://github.com/tongda/leifeng_tf_course)

# 谢谢

如果您有任何问题和建议

请联系

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