TensorFlow-Api

快速学习编程语言

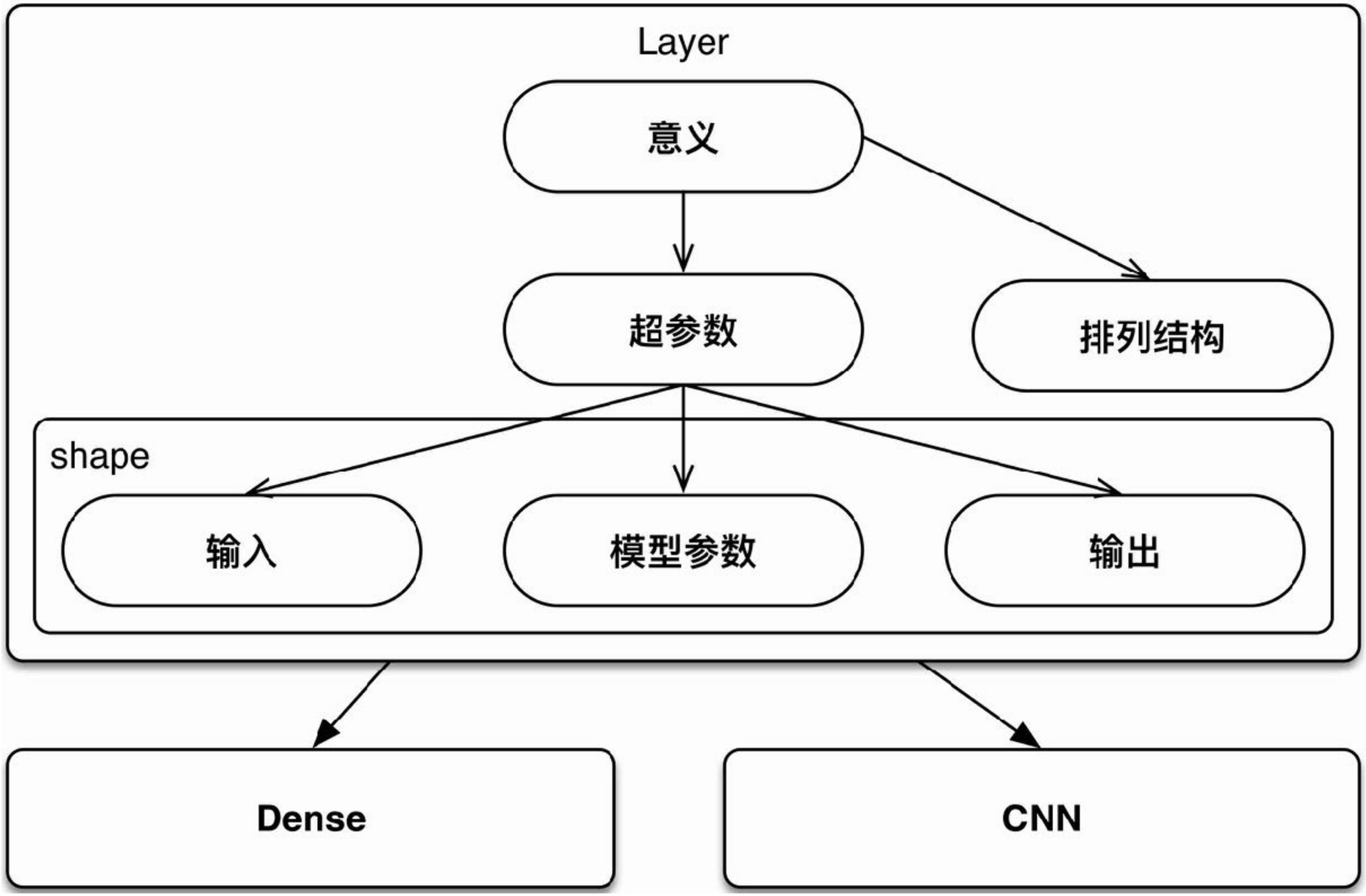
- 把自己当做一个编译器
- 了解语言特性和抽象模型
- 如何查找文档
- 如何debug
- 如何解决奇怪的问题

TensorFlow

- 把自己当做一个编译器
- 计算图, Session, 函数…
- tensorflow.google.cn
- pdb & log
- Google,StackOverflow, 面向关键字编程

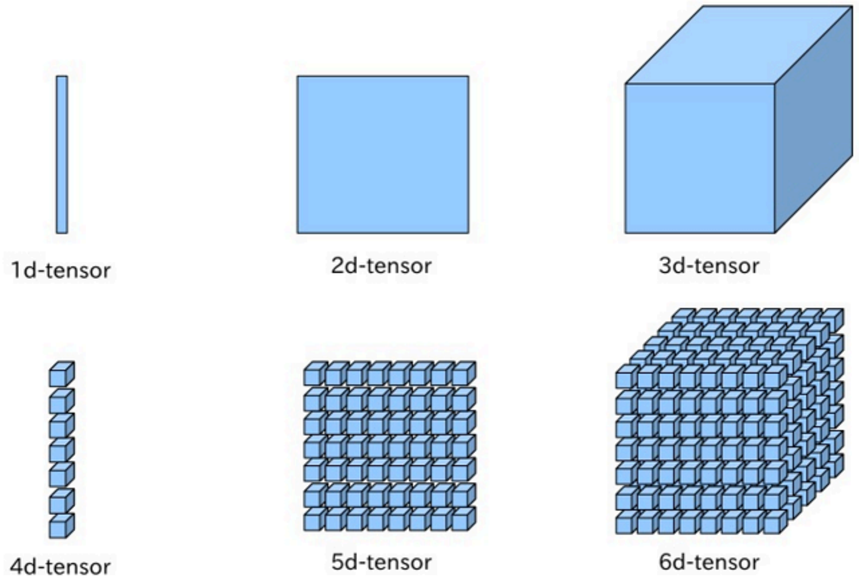
Dense & CNN

学习路线



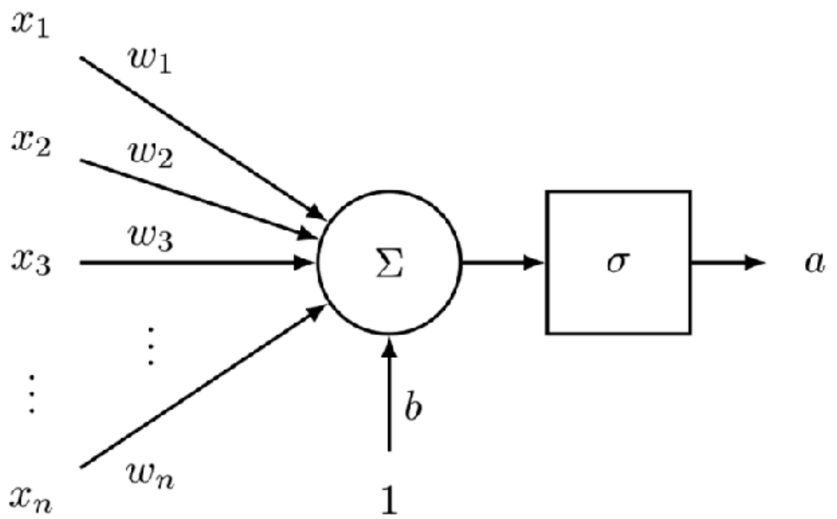
形象化Tensor

- 对于一个4*5*6的Tensor
  - rank : 3d
  - length: 4, 5, 6
  - shape: [4, 5, 6]
  - volume: 4*5*6=120



从Neuron到Layer

- 单个神经元:
  - 输入是1d, 参数是1d, 输出是0d
- 一层神经元构成一个Layer
  - 显然输出的shape和Layer的shape一致.
- batch_size
  - 会影响输出的shape
  - 并不会影响参数的shape



Dense

- 意义: 多层Dense构成MLP, 用于解分类问题.
- 排列结构: Layer的结构是1d
- 超参数: 神经元的个数U
- shape:
  - input = L
  - weights = L* U
  - output = U

```
tf.layers.dense(
    inputs,
    units,
    activation=None,
    use_bias=True,
    kernel_initializer=None,
    bias_initializer=tf.zeros_initializer(),
    kernel_regularizer=None,
    bias_regularizer=None,
    activity_regularizer=None,
    kernel_constraint=None,
    bias_constraint=None,
    trainable=True,
    name=None,
    reuse=None
)
```

CNN常用结构

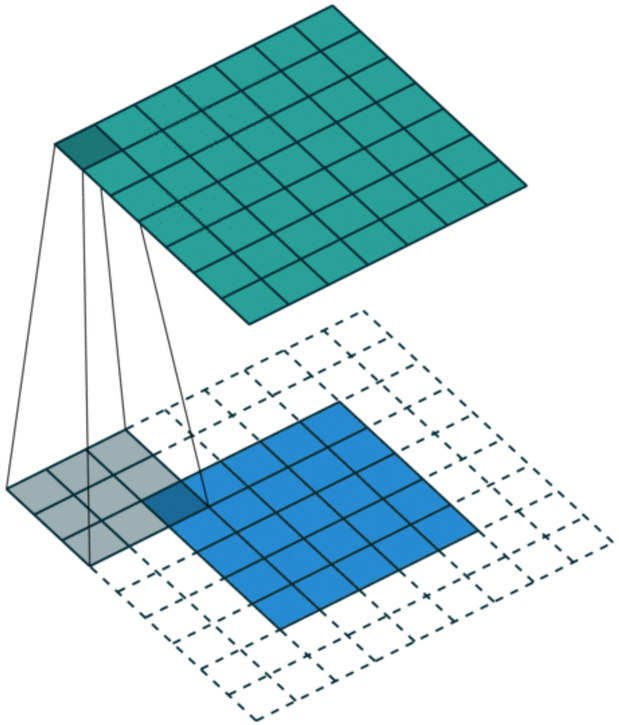
- convolutional layers 卷积层
- pooling layers 采样层
- normalization layers 正则层(dropout)
- MLP 分类器

MLP处理图像

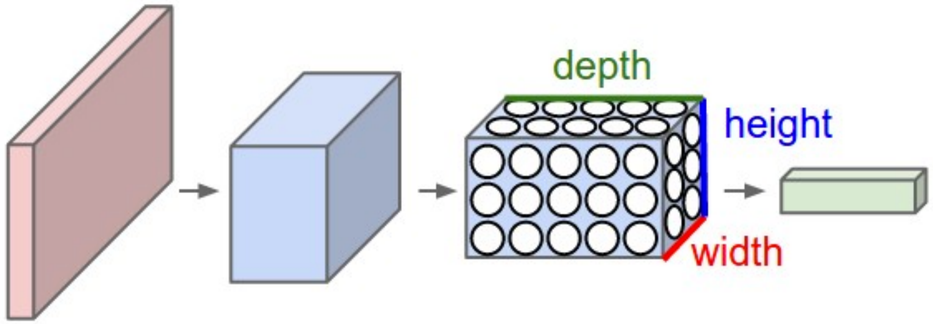
- 考虑用MLP来处理一张图像
  - 图像单个像素点的颜色RGB值表示
  - 一张200x200x3的图片
  - 单个神经元有200*200*3 = 120,000参数!

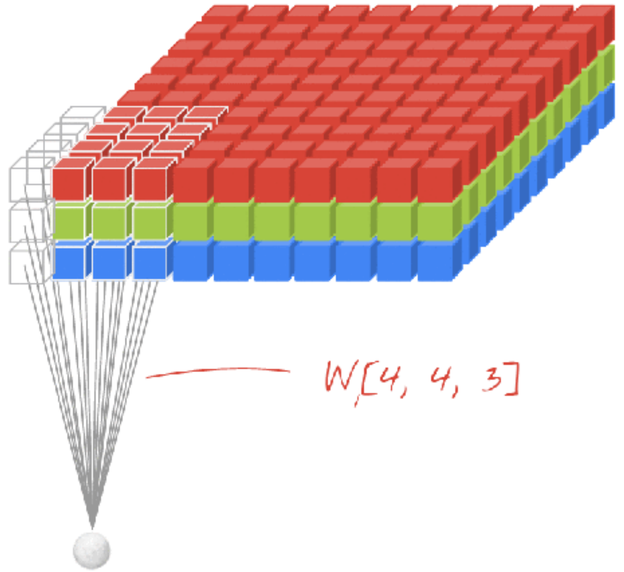
2d卷积核

- 卷积核是一个多维数组，参数由学习算法得到的
- 定义输入的长度(W), 卷积核的大小(F), 核移动的步长stride(S), zero padding(P)
- 输出的长度L = (W-F+2P)/S+1
- 并行化: 做一个和输出一样大小的Layer, Layer里面所有的神经元参数都一样!



3d卷积核





- 输入是3d的
- 有多个卷积核

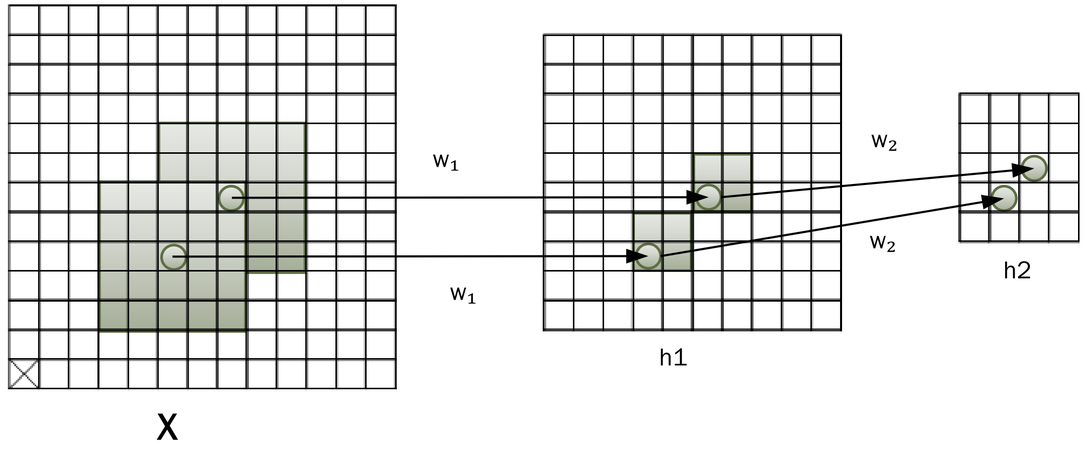
卷积层

- 意义: 用于处理图像.
- 排列结构: Layer的结构是3d
- 超参数: 卷积核个数(D), 核大小(F), padding(P), strides(S)
- shape:
  - Input = W*W*3
  - L = (W-F+2P)/S+1
  - Layer = L*L*D
  - Weights = F*F*D
  - Output = L*L*D

```
tf.layers.conv2d(
    inputs,
    filters,
    kernel_size,
    strides=(1, 1),
    padding='valid',
    data_format='channels_last',
    dilation_rate=(1, 1),
    activation=None,
    use_bias=True,
    kernel_initializer=None,
    bias_initializer=tf.zeros_initializer(),
    kernel_regularizer=None,
    bias_regularizer=None,
    activity_regularizer=None,
    kernel_constraint=None,
    bias_constraint=None,
    trainable=True,
    name=None,
    reuse=None
)
```

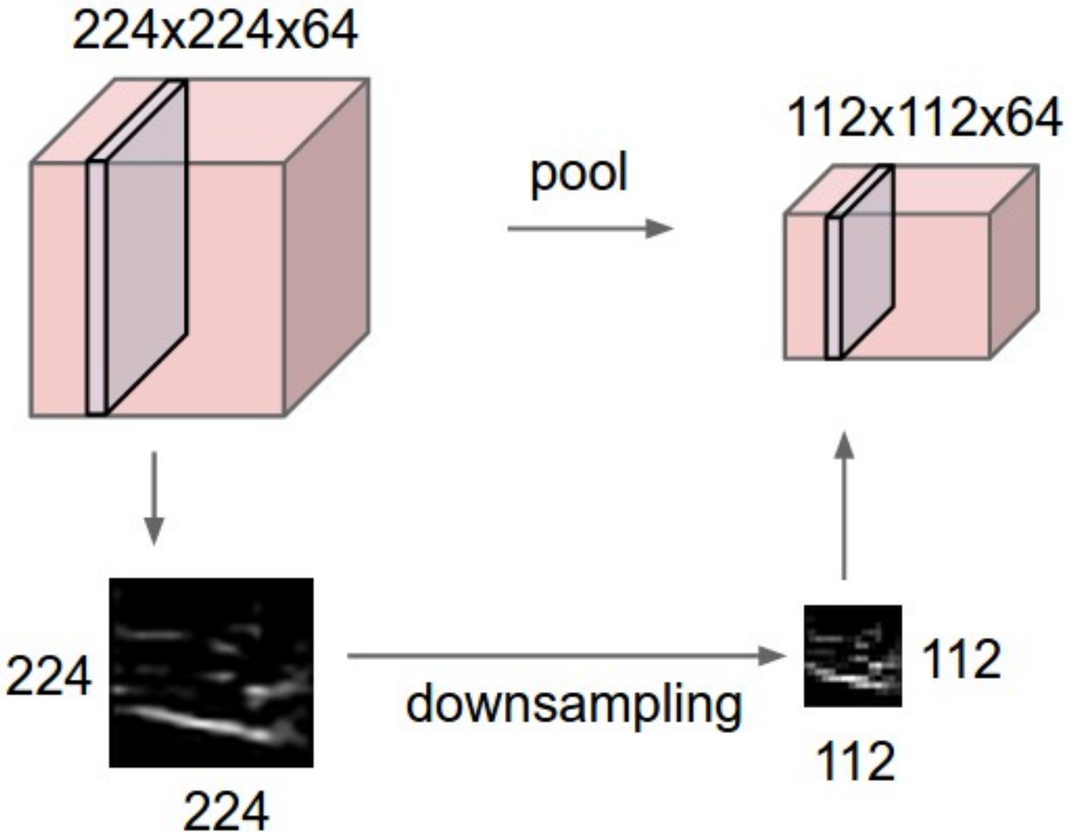
空间权重共享

- 卷积网络（Convolutional neural network，简称CNN）
- 特点：局部区域的权重W共用（weight sharing）（空间维度）
- 每一个卷积层后通常紧跟着一个下采样层subsample，比如采用max-pooling 方法完成下采样。



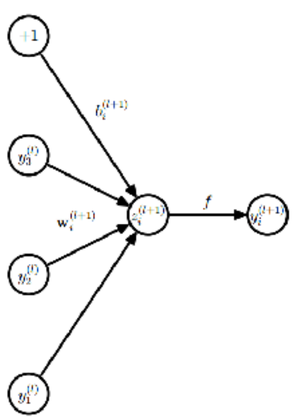
Pooling层

- 意义: 采样,缩小模型大小
- 排列结构: Layer的结构是3d
- 超参数：pooling_type, window_shape, padding, strides
- 一个2*2核, strides=2的pooling层, 等于减少75%的输出
- pooling层并不会改变tensor的深度

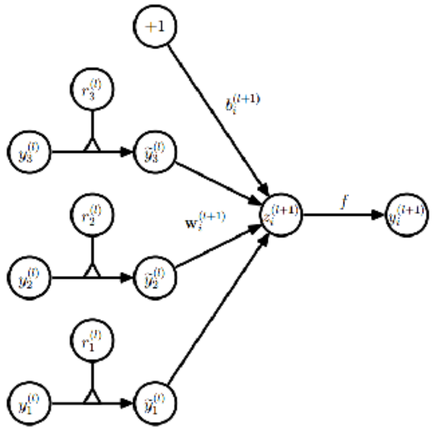


Dropout层

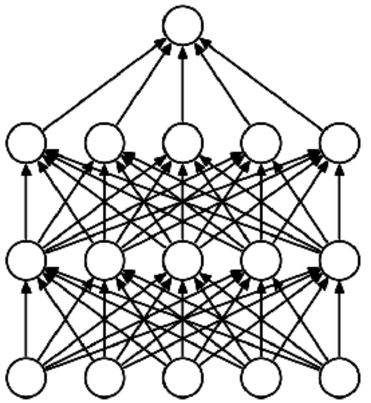
- 意义: 一种正则化方法, 减少CNN过拟合问题
- 超参数: keep_prob 丢弃率
- 对于所有的输入, 有keep_prob概率保留并乘以1/keep_prob, 以保证前后总和大致相等, 否则输出0



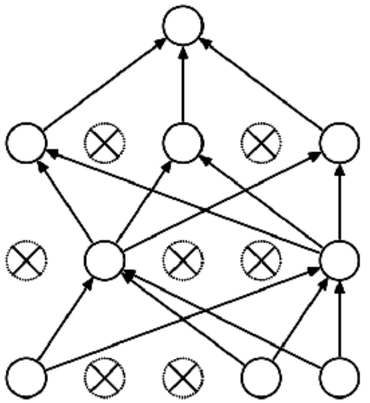
(a) Standard network



(b) Dropout network

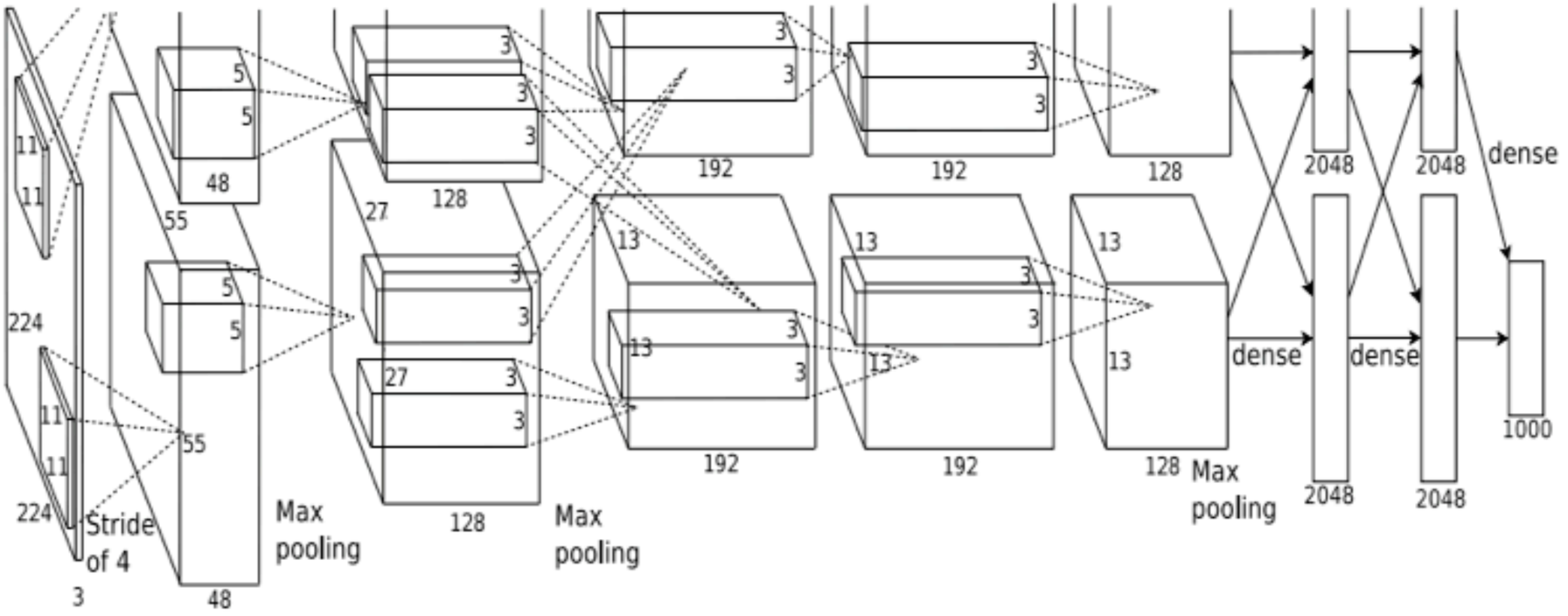


(a) Standard Neural Net



(b) After applying dropout.

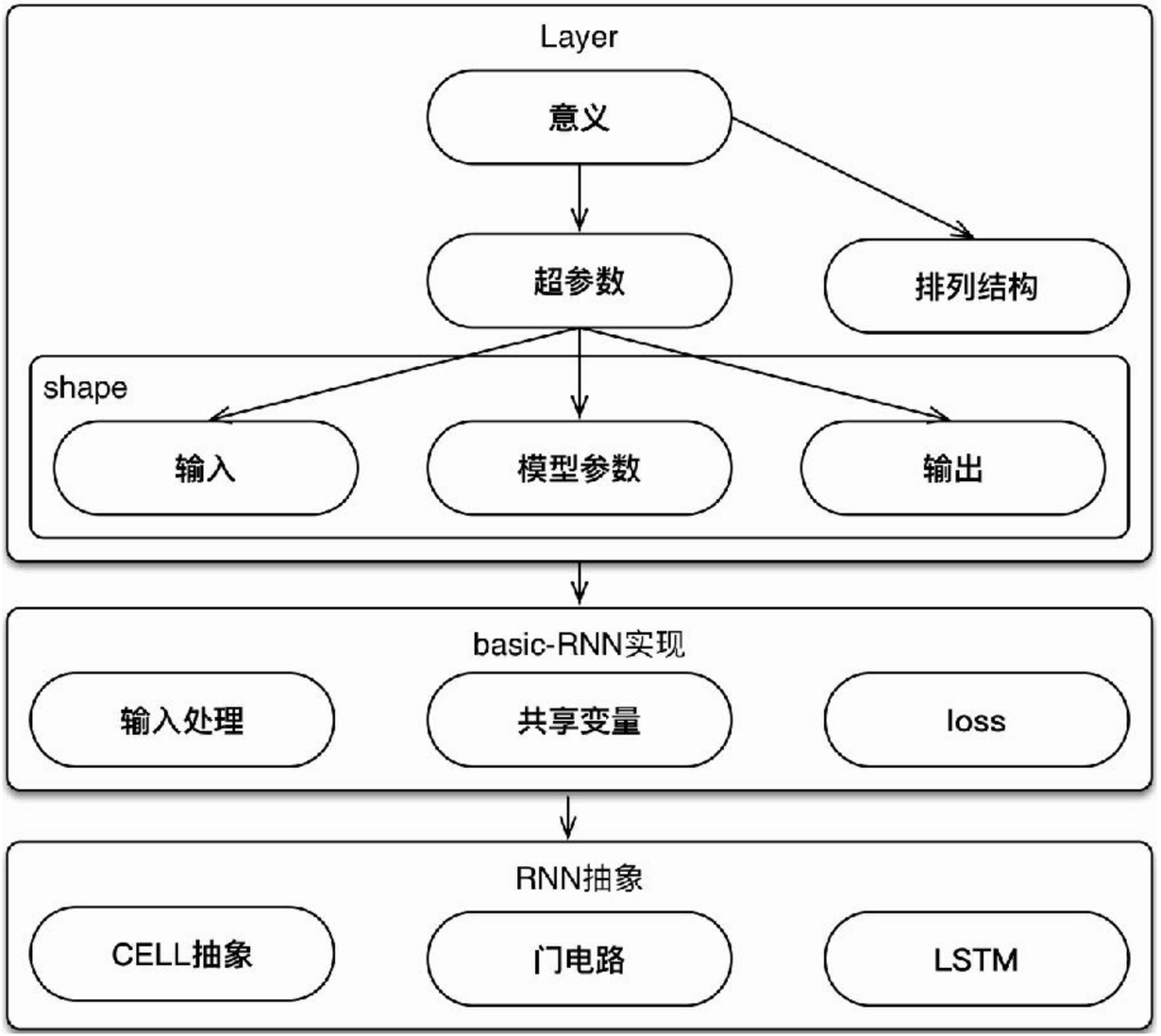
课后作业



阅读 Alex Krizhevsky, Ilya Sutskever and Geoffrey E. Hinton. "ImageNet classification with deep convolutional neural networks." NIPS 2012.

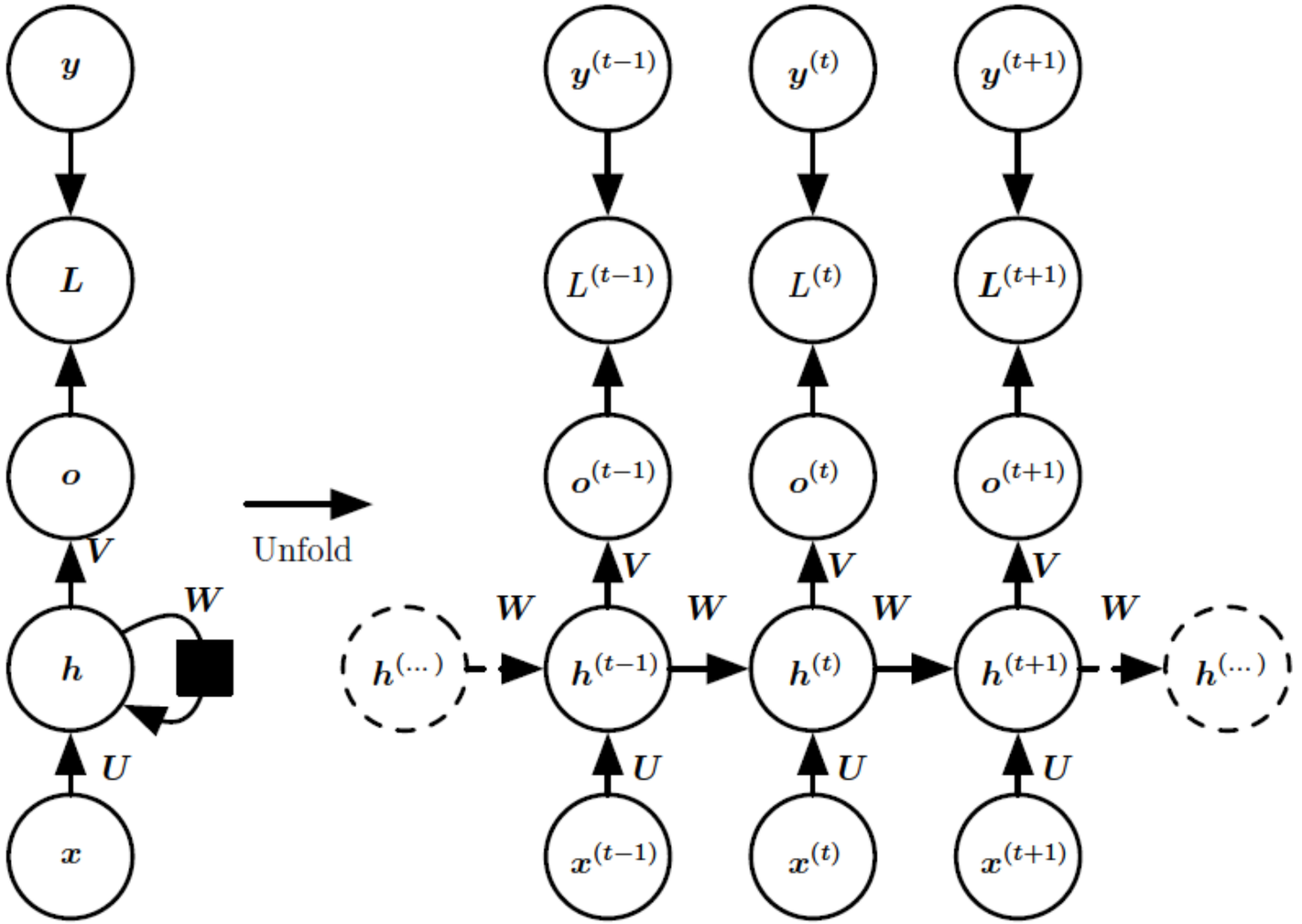
RNN & LSTM

学习路线


Layer
意义
超参数
排列结构
shape
输入
模型参数
输出
basic-RNN实现
输入处理
共享变量
loss
RNN抽象
CELL抽象
门电路
LSTM

RNN

- 循环网络结构
  - y是训练目标
  - L是损失函数
  - o是网络输出
  - h是状态（隐藏单元）
  - x是网络输入
- 计算图的时间步上展开
- 举例：天气预测



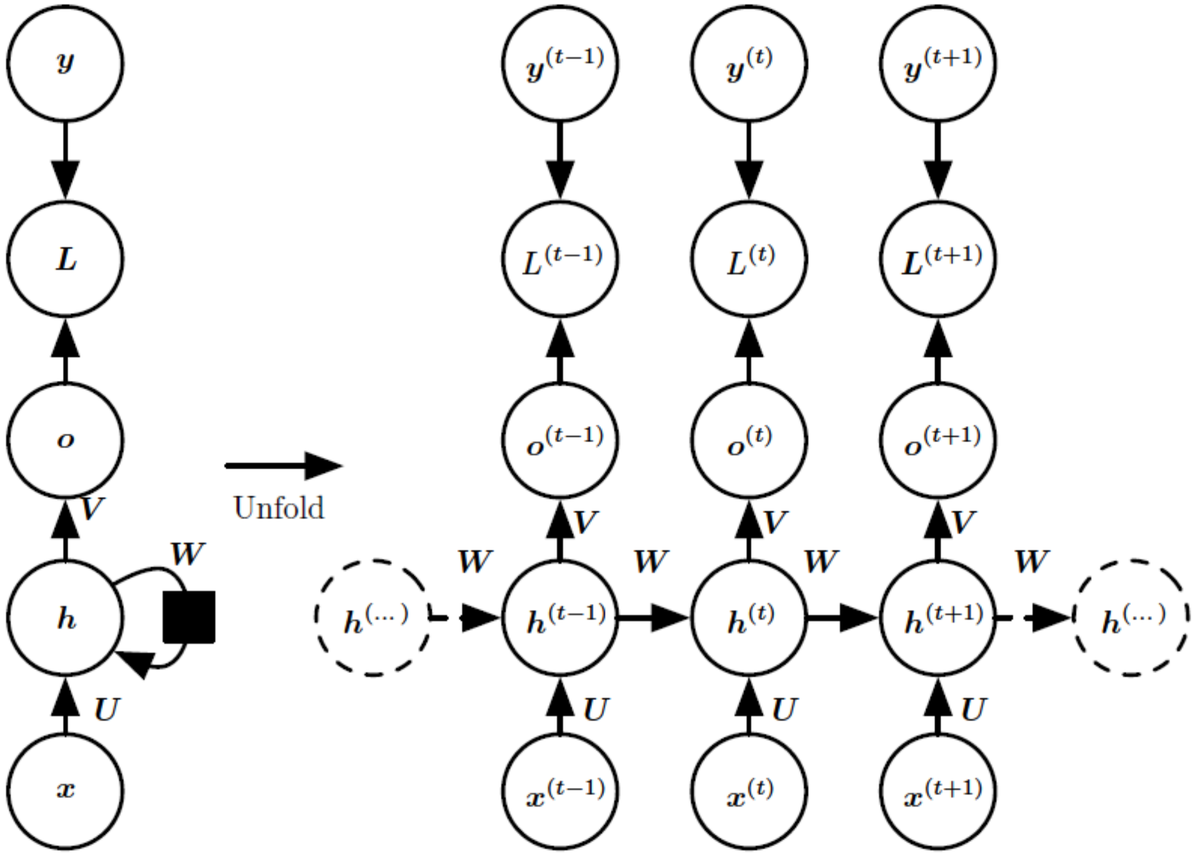
计算图

$$\boldsymbol{a}^{(t)} = \boldsymbol{b} + \boldsymbol{W}\boldsymbol{h}^{(t-1)} + \boldsymbol{U}\boldsymbol{x}^{(t)},$$

$$\boldsymbol{h}^{(t)} = \tanh(\boldsymbol{a}^{(t)}),$$

$$\boldsymbol{o}^{(t)} = \boldsymbol{c} + \boldsymbol{V}\boldsymbol{h}^{(t)},$$

$$\hat{\boldsymbol{y}}^{(t)} = \mathrm{softmax}(\boldsymbol{o}^{(t)}),$$

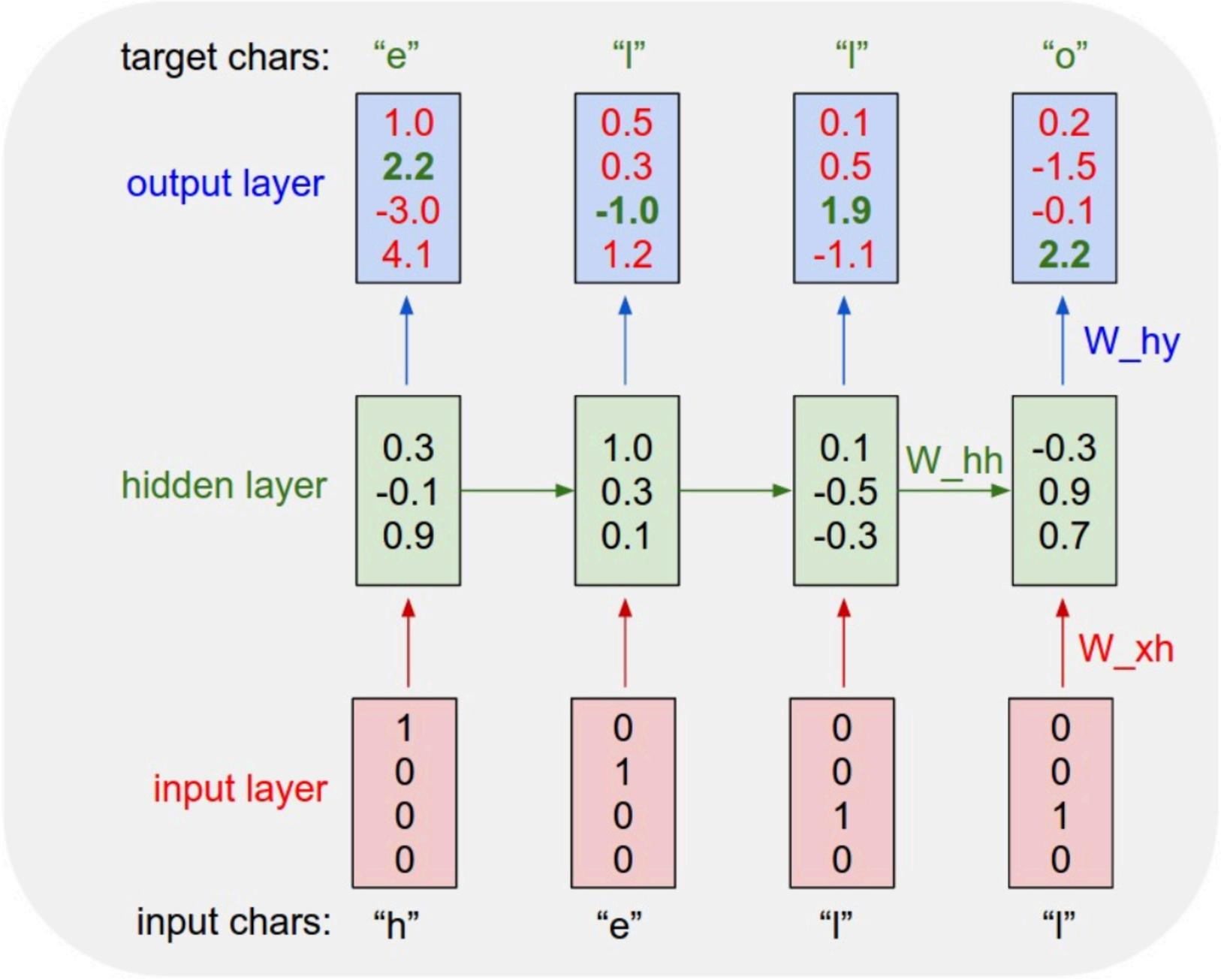


- 循环网络将一个输入序列映射到相同长度的输出序列。
- 信息流动路径：信息在时间上向前（计算输出和损失）和向后（计算梯度）的思想。
- U、V 和W分别对应于输入到隐藏、隐藏到输出和隐藏到隐藏的连接的权重矩阵。
- b 和c 是偏置向量。

basic-rnn 实现

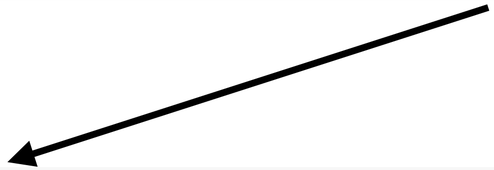
```
iter: 646500, p: 1300, loss: 0.019042
----
 y = tf.get_variable("by", [vocab_size], initializer=initializer)
        by  = tf.get_variable("by", [vocab_size], dtype=tf.float32, name="state:
 hprev_val = np.zeros([1, hidden_size])

while True:
```

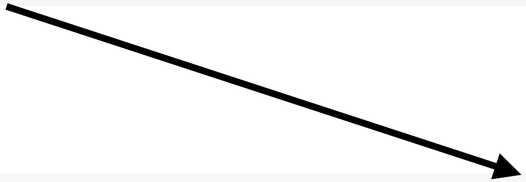
- 3_NeuralNetworks/min-char-rnn-tensorflow.py
- Andrej Karpathy的min-char-rnn tf版本实现
- 实现了一个自动写代码的程序, 输入程序就是本身


target chars:
“e”
“l”
“l”
“o”
output layer
1.0
2.2
-3.0
4.1
0.5
0.3
-1.0
1.2
0.1
0.5
1.9
-1.1
0.2
-1.5
-0.1
2.2
W_hy
hidden layer
0.3
-0.1
0.9
1.0
0.3
0.1
0.1
-0.5
-0.3
W_hh
-0.3
0.9
0.7
W_xh
input layer
1
0
0
0
0
1
0
0
0
0
1
0
0
0
1
0
input chars:
“h”
“e”
“l”
“l”

共享Variable

```python
def my_image_filter(input_images):
    with tf.variable_scope("conv1"):
        # Variables created here will be named "conv1/weights", "conv1/biases".
        relu1 = conv_relu(input_images, [5, 5, 32, 32], [32])
    with tf.variable_scope("conv2"):
        # Variables created here will be named "conv2/weights", "conv2/biases".
        return conv_relu(relu1, [5, 5, 32, 32], [32])
```





```python
with tf.variable_scope("model") as scope:
  output1 = my_image_filter(input1)
  scope.reuse_variables()
  output2 = my_image_filter(input2)
```

生成两套参数

```python
with tf.variable_scope("model") as scope:
  output1 = my_image_filter(input1)
  scope.reuse_variables()
  output2 = my_image_filter(input2)
```

共享一套参数

https://www.tensorflow.org/programmers_guide/variables#sharing_variables

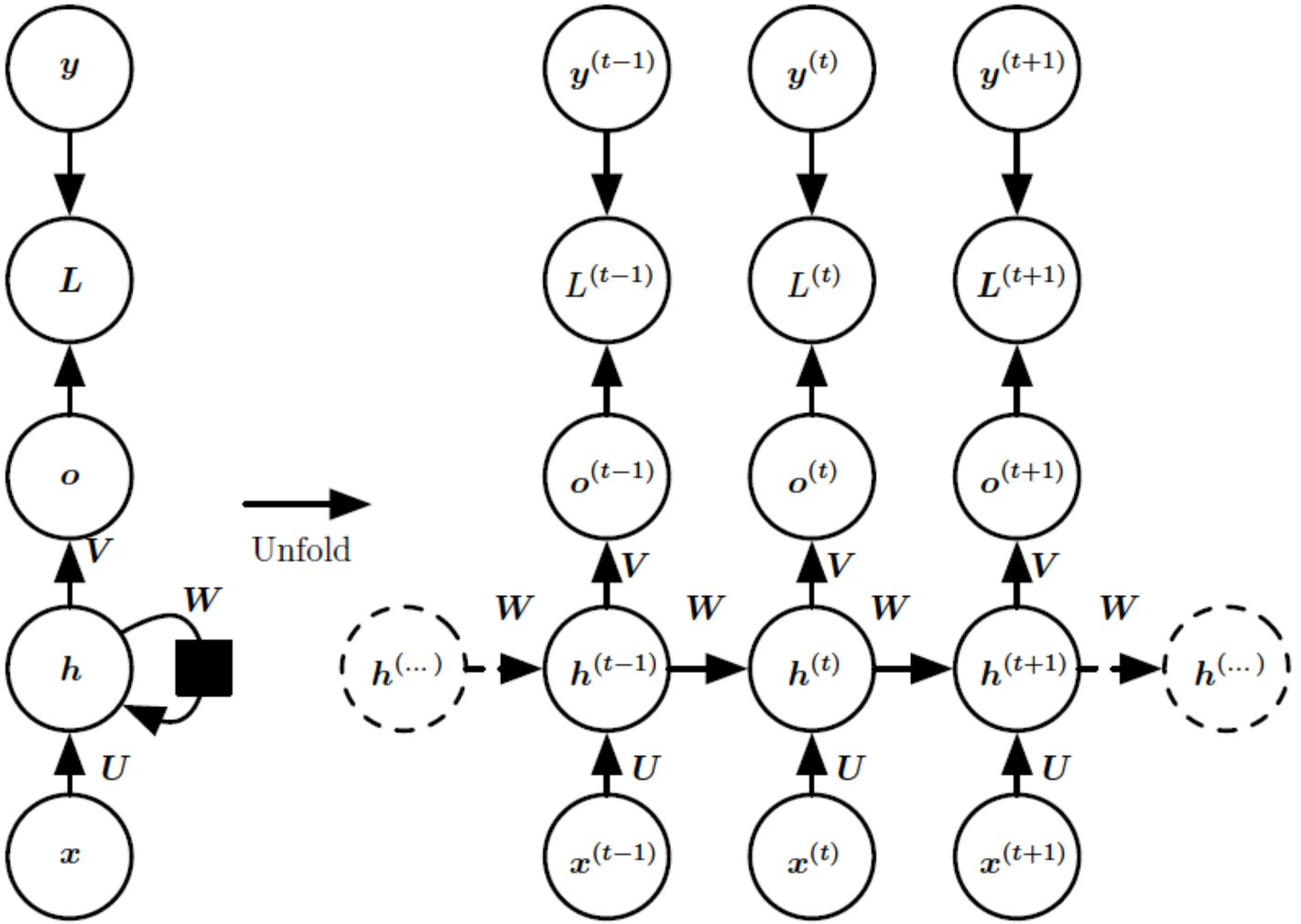
输入和loss处理

- 给定序列长度(模型超参数), 把输入序列化
- one-hot 离散化处理
- hst在变, U, V, W 共享权重
- 收集所有时刻的输出,计算的loss
- 梯度截取预防梯度爆炸

$$
\begin{aligned}
&L\left(\{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(\tau)}\}, \{\boldsymbol{y}^{(1)}, \ldots, \boldsymbol{y}^{(\tau)}\}\right) \\
&= \sum_t L^{(t)} \\
&= -\sum_t \log p_{\text{model}}\left(y^{(t)} \mid \{\boldsymbol{x}^{(1)}, \ldots, \boldsymbol{x}^{(t)}\}\right)
\end{aligned}
$$

时间权重共享

- 循环神经网络在不同的时间步上采用相同的U、V、W参数
- 输入到隐藏的连接由权重矩阵U 参数化
- 隐藏到输出的连接由权重矩阵V 参数化
- 隐藏到隐藏的循环连接由权重矩阵W 参数化



rnn-cell抽象

```
__init__(
    num_units,
    activation=None,
    reuse=None,
    name=None
)
```

Cell超参数: num_units

```
__call__(
    inputs,
    state,
    scope=None,
    *args,
    **kwargs
)
```

调用时刻要输入state

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

static-rnn抽象

```
  state = cell.zero_state(...)
  outputs = []
  for input_ in inputs:
    output, state = cell(input_, state)
    outputs.append(output)
  return (outputs, state)
```

rnn-example

https://www.tensorflow.org/api_docs/python/tf/contrib/rnn/BasicRNNCell

rnn-cell抽象

- hidden-units：模型的容量大小
- I(input) + S(state) -> O(output) + S(new_state)
- inputs: 输入
- state: 隐含了之前所有的输出信息
- 当前的输出完全取决于state和当前的输入

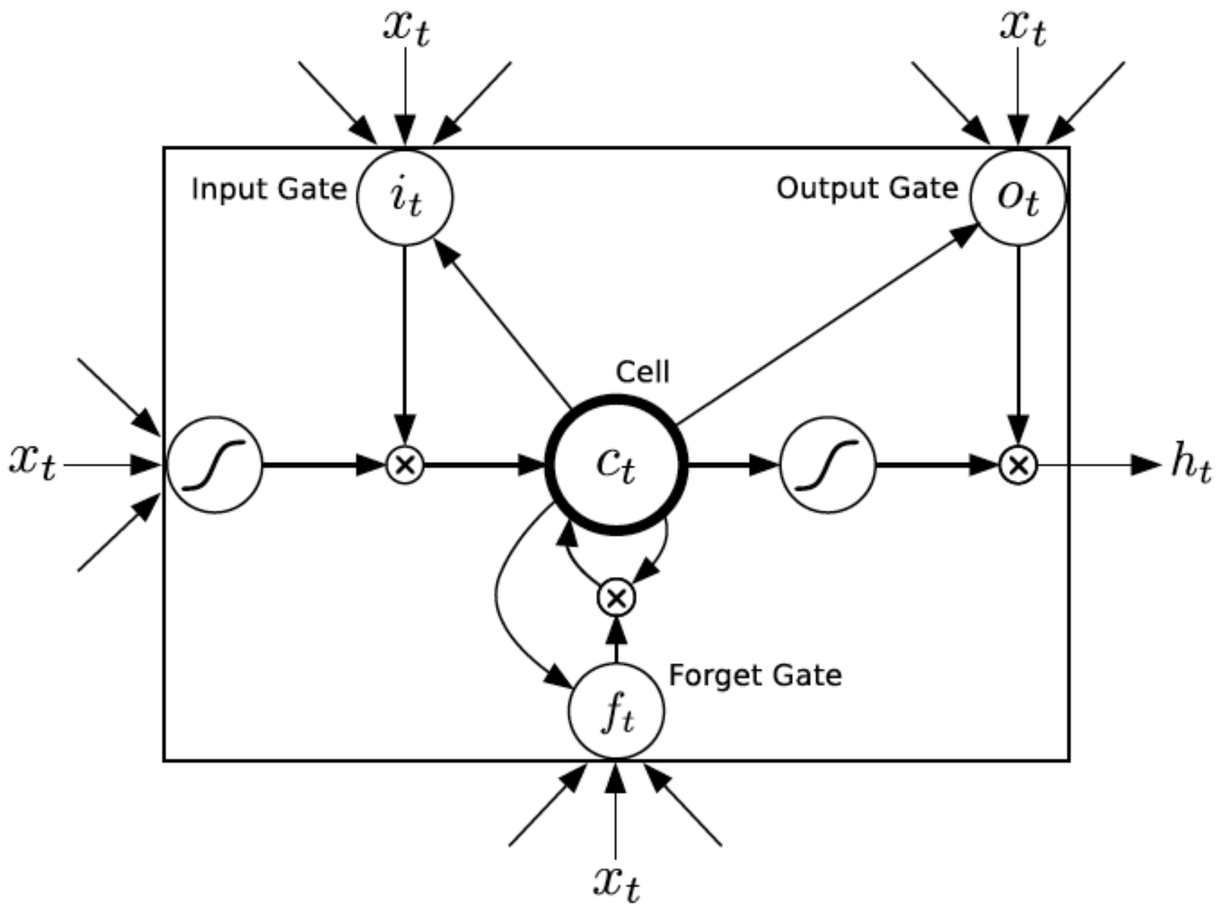
dynamic-rnn

- 3_NeuralNetworks/dynamic_rnn.py
- 动态生成计算图
- 不需要固定序列长度

```
tf.nn.dynamic_rnn(
    cell,
    inputs,
    sequence_length=None,
    initial_state=None,
    dtype=None,
    parallel_iterations=None,
    swap_memory=False,
    time_major=False,
    scope=None
)
```

LSTM

- RNN训练有以下问题
  - RNN梯度爆炸
  - RNN梯度消失
- LSTM解决以上问题

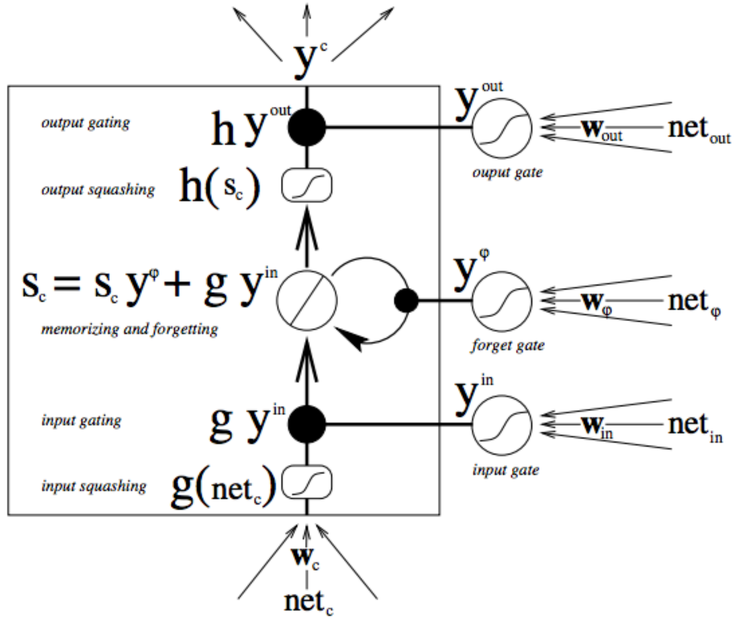


- LSTM是RNN的一个改进，LSTM增加了一个主输入单元和其他三个辅助的门限输入单元：

- 输入门（Input gate）控制是否输入，遗忘门（Forget gate）控制是否存储，输出门（Output gate）控制是否输出。

- 辅助单元可以寄存时间序列的输入，在训练过程中会利用后向传播的方式进行。

- 记忆单元和这些门单元的组合，大大提升了RNN处理远距离依赖问题的能力，解决RNN网络收敛慢的问题。



- RNN

$$h_t = \mathcal{H}\left(W_{xh}x_t + W_{hh}h_{t-1} + b_h\right) \quad (1)$$

$$y_t = W_{hy}h_t + b_y \quad (2)$$

- LSTM

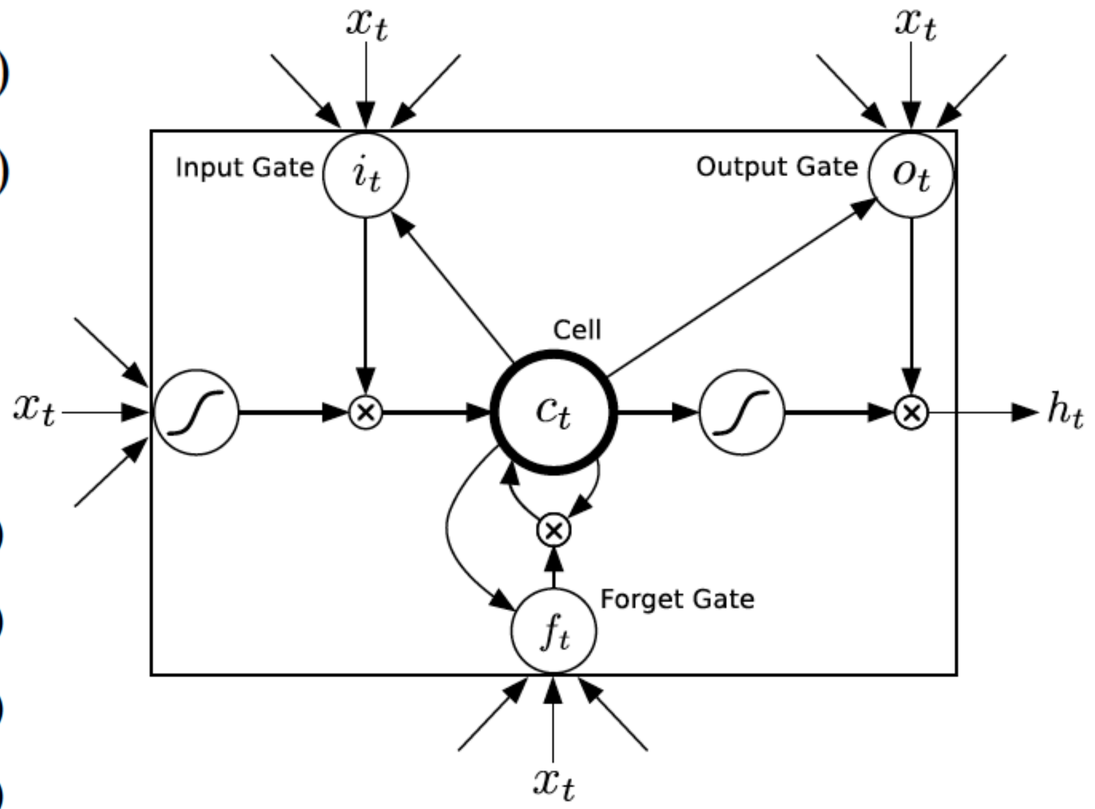
$$i_t = \sigma\left(W_{xi}x_t + W_{hi}h_{t-1} + W_{ci}c_{t-1} + b_i\right) \quad (3)$$

$$f_t = \sigma\left(W_{xf}x_t + W_{hf}h_{t-1} + W_{cf}c_{t-1} + b_f\right) \quad (4)$$

$$c_t = f_t c_{t-1} + i_t \tanh\left(W_{xc}x_t + W_{hc}h_{t-1} + b_c\right) \quad (5)$$

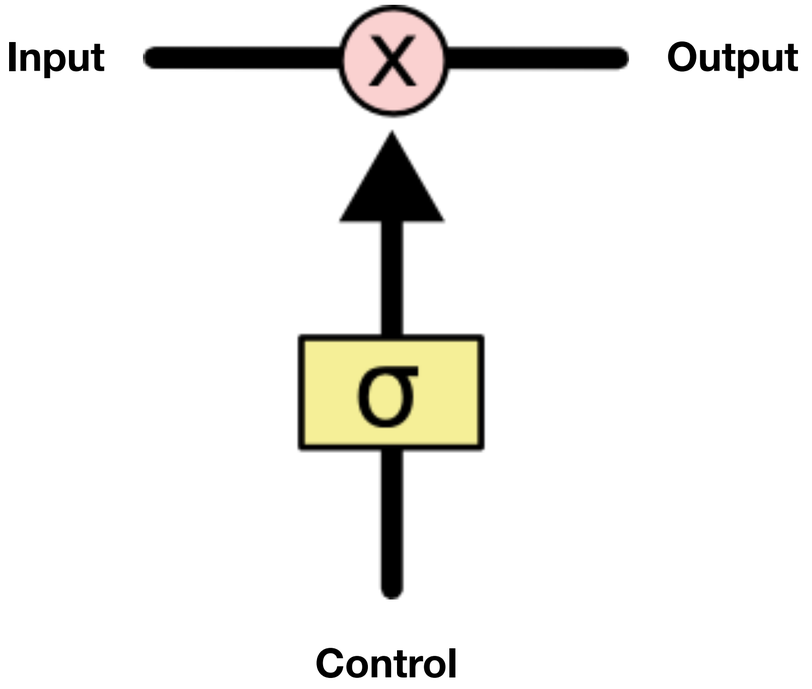
$$o_t = \sigma\left(W_{xo}x_t + W_{ho}h_{t-1} + W_{co}c_t + b_o\right) \quad (6)$$

$$h_t = o_t \tanh(c_t) \quad (7)$$



门电路

- Input和Control形状一致
- Control经过Sigmoid函数后, 变成一个范围在0-1之间的一个同形状的Tensor
- Input和σ(Control) 元素相乘等到一个同形的Output



推荐阅读

- The Unreasonable Effectiveness of Recurrent Neural Networks
- Understanding-LSTMs

练习作业

- 用RNN解决一个实际问题
- 每组不超过4人
- 在Gitlab上建立一个private仓库, 加入组员为master
- Deadline : 两周时间
- 仓库要求
  - README.md 说明文件
  - main.py 文件可直接训练执行.
  - 每个人都得有commit

谢谢!