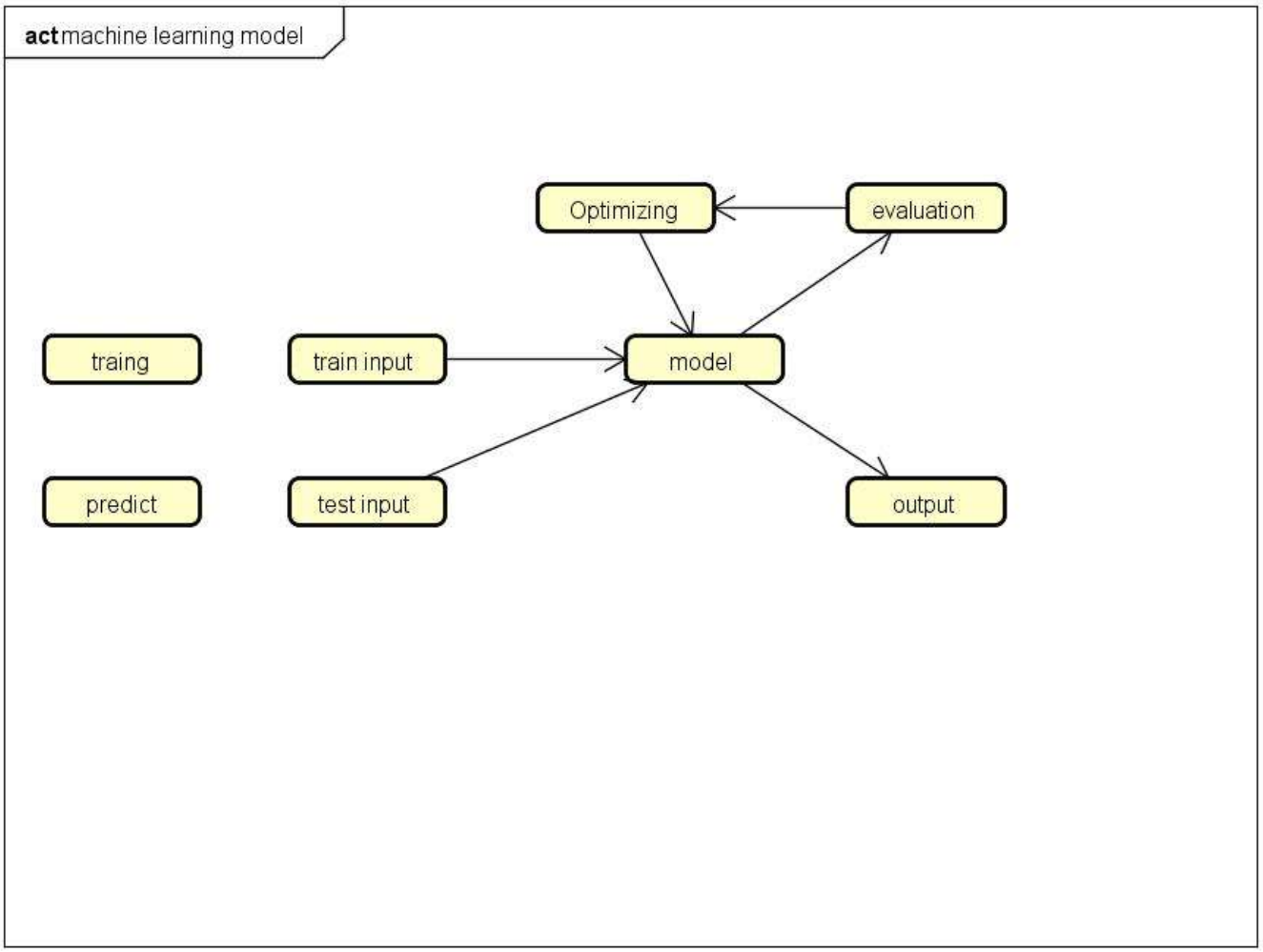
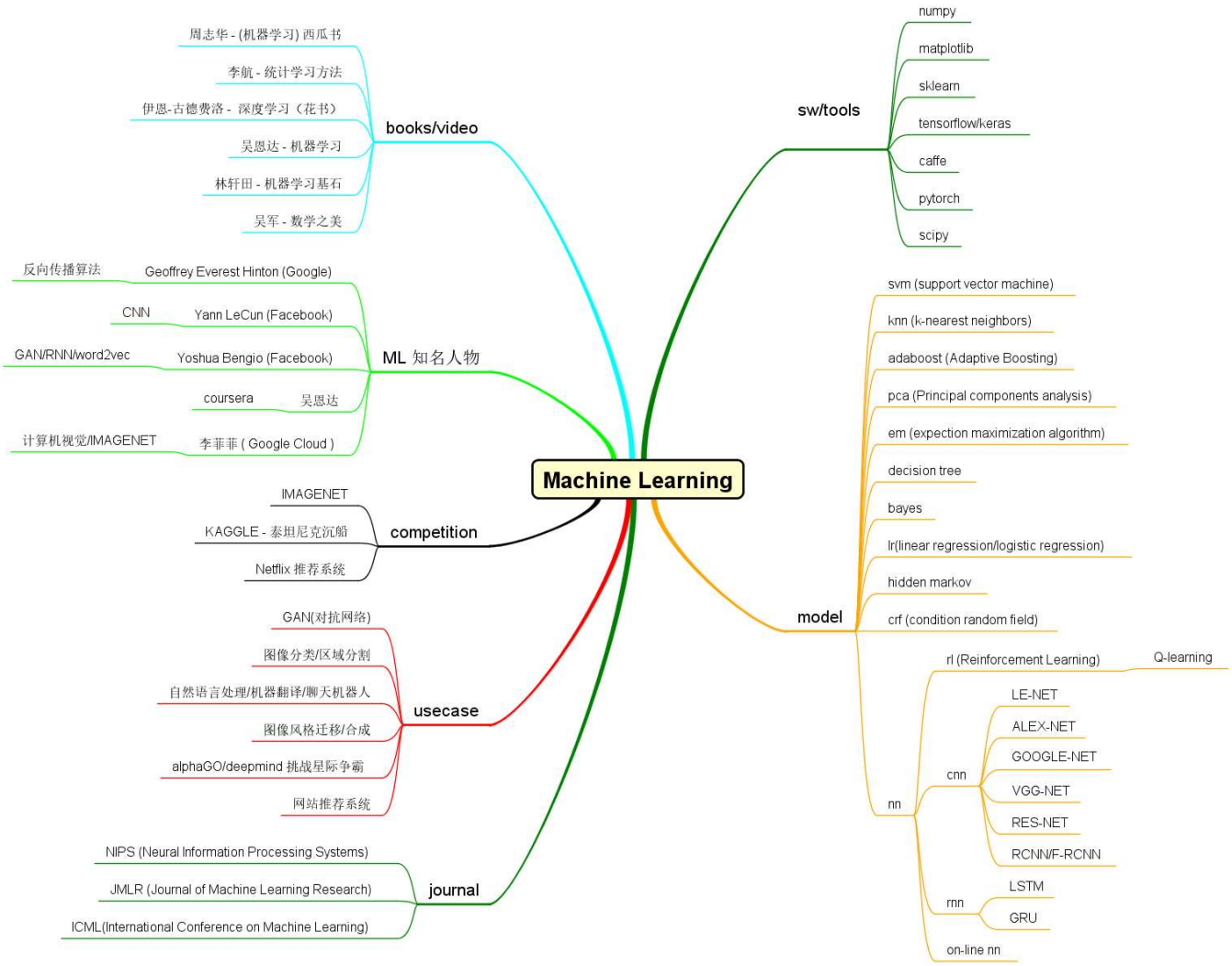
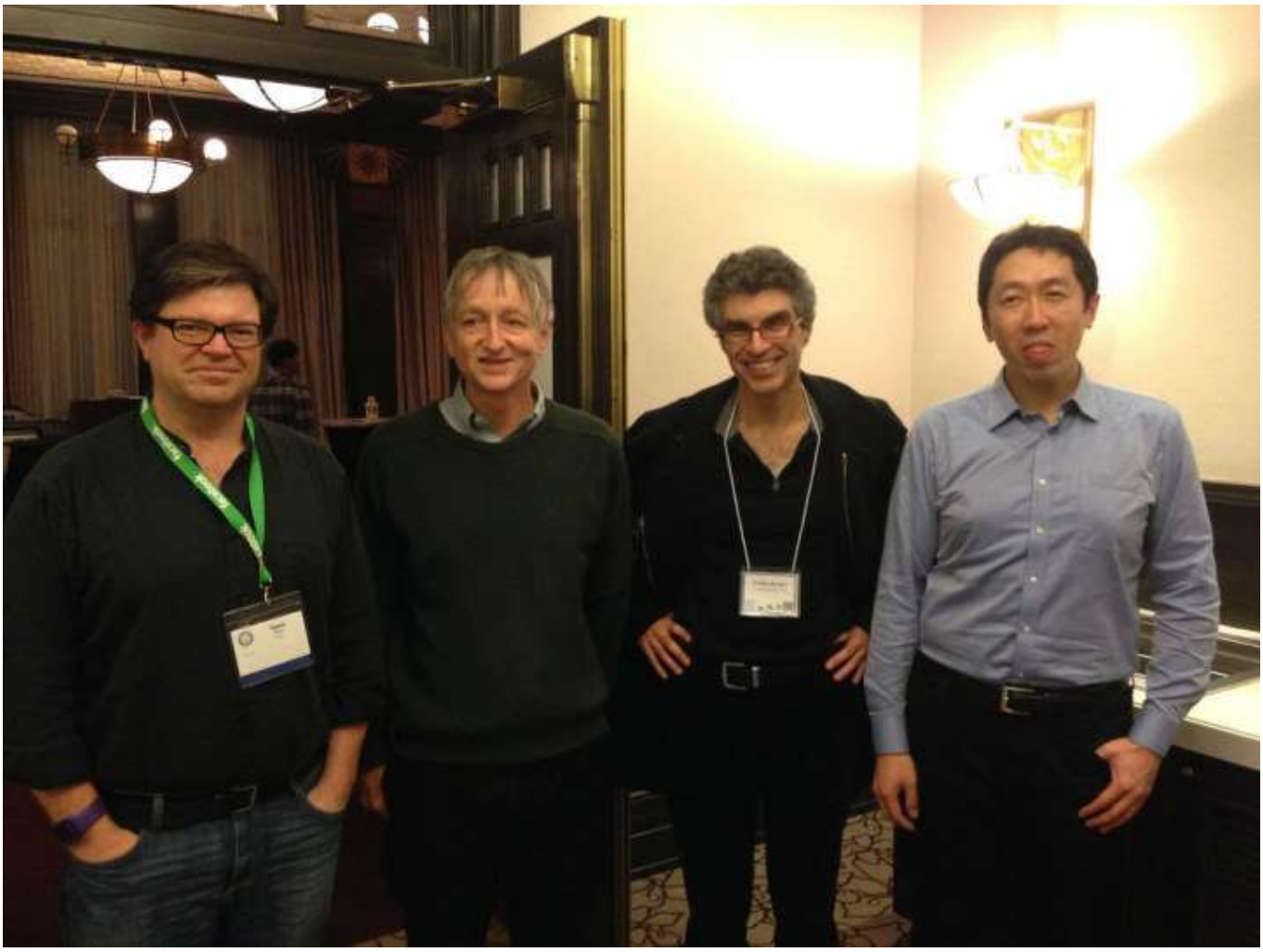
Machine Learning Base introduce

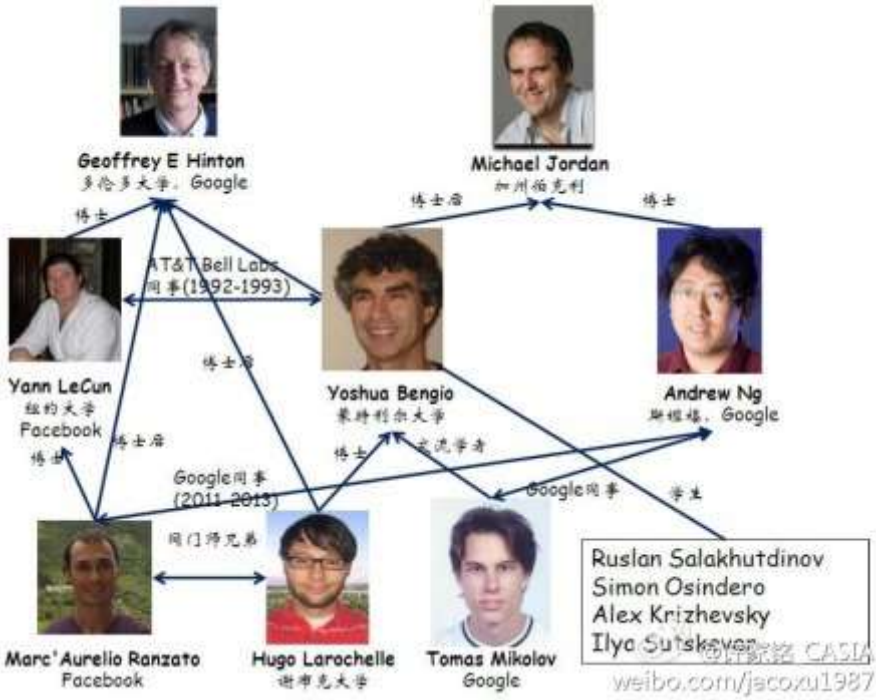
来自 1998 年 Tom Mitchell 的定义，"对于某类任务T和性能度量P，如果一个计算机程序在T上以P衡量的性能随着经验E而自我完善，那么我们称这个计算机程序在从经验E学习。"



by Cloud.yu 2018-3-10


Machine Learning
books/video
周志华 - (机器学习) 西瓜书
李航 - 统计学习方法
伊恩-古德费洛 - 深度学习（花书）
吴恩达 - 机器学习
林轩田 - 机器学习基石
吴军 - 数学之美
ML 知名人物
反向传播算法
Geoffrey Everest Hinton (Google)
CNN
Yann LeCun (Facebook)
GAN/RNN/word2vec
Yoshua Bengio (Facebook)
coursera
吴恩达
计算机视觉/IMAGENET
李菲菲 (Google Cloud)
competition
IMAGENET
KAGGLE - 泰坦尼克沉船
Netflix 推荐系统
usecase
GAN(对抗网络)
图像分类/区域分割
自然语言处理/机器翻译/聊天机器人
图像风格迁移/合成
alphaGO/deepmind 挑战星际争霸
网站推荐系统
journal
NIPS (Neural Information Processing Systems)
JMLR (Journal of Machine Learning Research)
ICML(International Conference on Machine Learning)
sw/tools
numpy
matplotlib
sklearn
tensorflow/keras
caffe
pytorch
scipy
model
svm (support vector machine)
knn (k-nearest neighbors)
adaboost (Adaptive Boosting)
pca (Principal components analysis)
em (expection maximization algorithm)
decision tree
bayes
lr(linear regression/logistic regression)
hidden markov
crf (condition random field)
nn
rl (Reinforcement Learning)
Q-learning
cnn
LE-NET
ALEX-NET
GOOGLE-NET
VGG-NET
RES-NET
RCNN/F-RCNN
rnn
LSTM
GRU
on-line nn




Geoffrey E Hinton
多伦多大学，Google
Michael Jordan
加州伯克利
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博士后
博士
AT&T Bell Labs
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(2011-2013)
Google同事
学生
同门师兄弟
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Simon Osindero
Alex Krizhevsky
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Hugo Larochelle
谢布克大学
Tomas Mikolov
Google
weibo.com/jacoxu1987

Perceptron (感知机)

任务 : 求一条线$wx + b = 0$ 对不同类别的点进行二分类

类型 : 监督学习

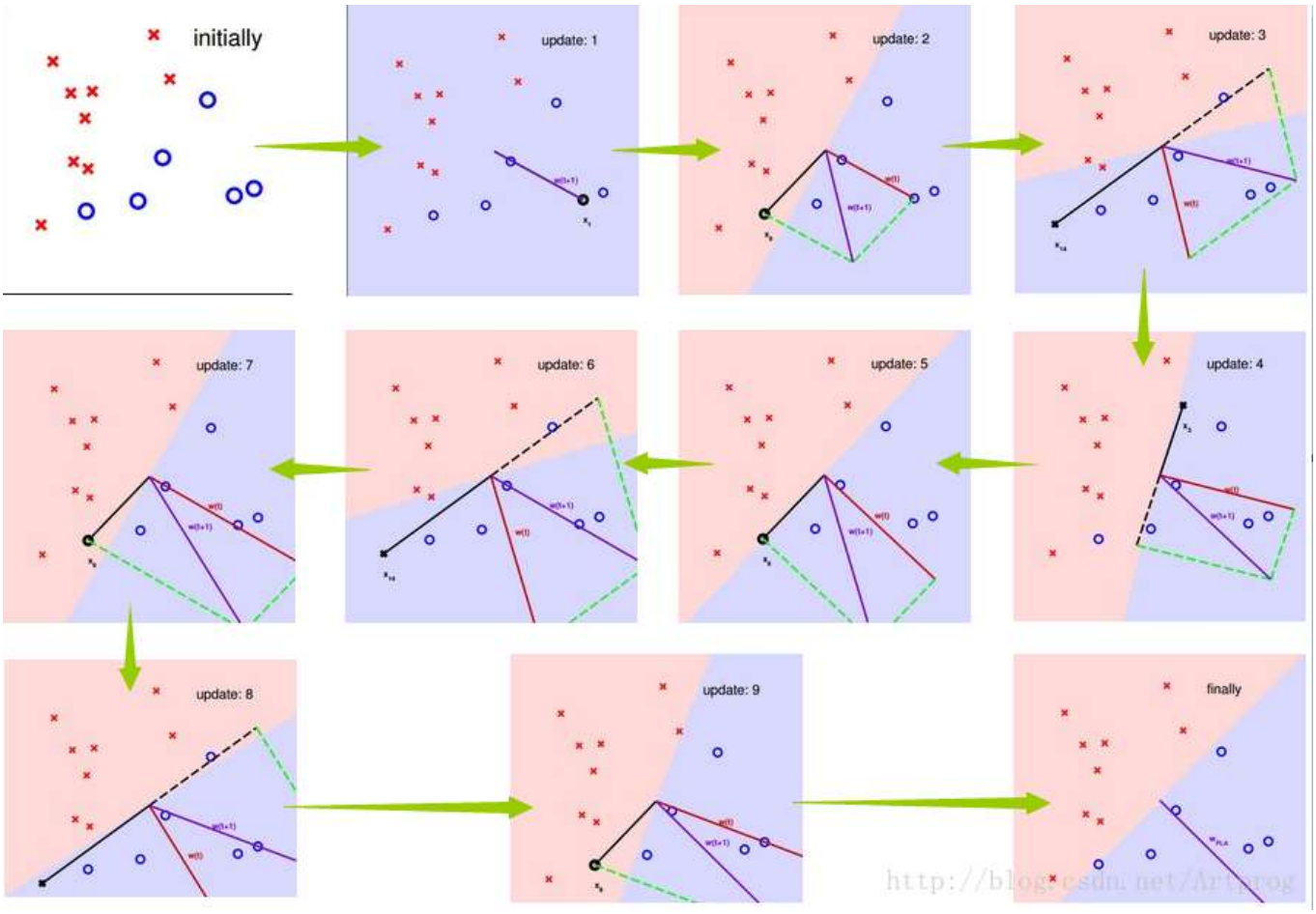
模型 : 感知机 $f(x) = sign(wx + b)$, 其中w叫做权重(weight) ， b叫做偏置(bias)

评价方法 : $\min\{\sum (\mathrm{y}(\mathrm{wx} + \mathrm{b}) < 0)\}$

优化方法 : PLA/Pocket

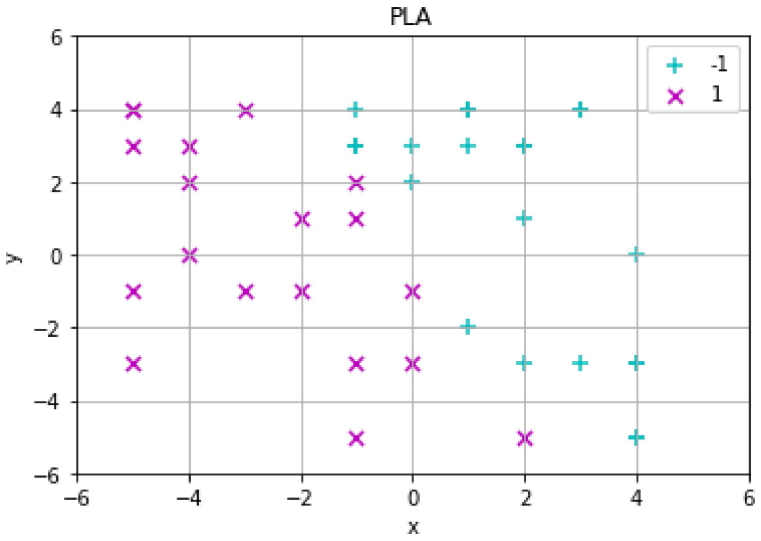
PLA (Percetron Learning Algorithm)

- **Input**: traing data ($T = \{(x_0, y_0), (x_1, y_1), \ldots, (x_i, y_i)\}$)
- **Output**: (w, b)
  - init $(w, b) \rightarrow (0, 0)$, $i \rightarrow 0$
  - while $i! = len(T)$ do
    - if $y_i(wx_i + b) <= 0$ then
      - $(w, b) \rightarrow (w, b) + y_i x_i$
      - $i \rightarrow 0$
    - else
      - $i = i + 1$
    - end if
  - end while


initially
update: 1
update: 2
update: 3
update: 4
update: 5
update: 6
update: 7
update: 8
update: 9
finally

In [3]:

```
import numpy as np
import matplotlib
import matplotlib.pyplot as plt

LEN = 40
x = np.random.randint(-5,5, (LEN,2))
line = np.random.randint(-5,5, (2, 1))
#  2y - 3x
label = np.sign(np.dot(x, line))
label[label == 0] = 1
fig = plt.figure(1)
idx_0 = np.where(label[:, 0] == -1)
p0 = plt.scatter(x[idx_0,1], x[idx_0,0], marker = '+', color = 'c', label='-1', s = 50)
idx_1 = np.where(label[:, 0] == 1)
p1 = plt.scatter(x[idx_1,1], x[idx_1,0], marker = 'x', color = 'm', label='1', s = 50)
plt.title('PLA')
plt.xlabel('x')
plt.ylabel('y')
plt.xlim((-6,6))
plt.ylim((-6,6))
plt.legend()
plt.grid(True)
plt.show()
```



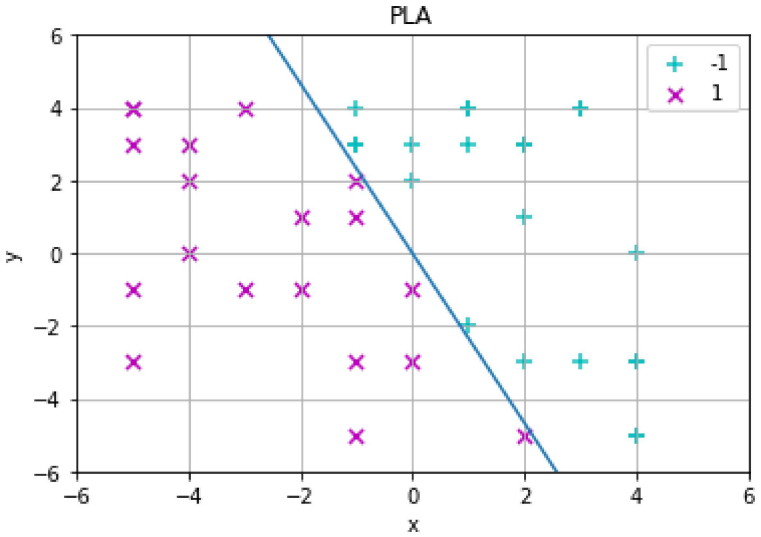
In [4]:

```
cnt = 0
pla = np.zeros((2,1))
_update = 0

while cnt<LEN:
    _update = np.sign(np.dot(x[cnt,:], pla)) * label[cnt, 0]
    if _update <= 0:
        _x = x[cnt, :]
        _x.shape = (1,2)
        _x = np.transpose(_x)
        pla = pla + _x*label[cnt, 0]
        cnt = 0
    else:
        cnt = cnt+1
        continue
print(pla)
```

```
[[-3.]
 [-7.]]
```

In [5]:

```
fig = plt.figure(1)
idx_0 = np.where(label[:, 0] == -1)
p0 = plt.scatter(x[idx_0,1], x[idx_0,0], marker = '+', color = 'c', label='-1', s = 50)
idx_1 = np.where(label[:, 0] == 1)
p1 = plt.scatter(x[idx_1,1], x[idx_1,0], marker = 'x', color = 'm', label='1', s = 50)
plt.title('PLA')
plt.xlabel('x')
plt.ylabel('y')
plt.xlim((-6,6))
plt.ylim((-6,6))
plt.legend()
plt.grid(True)

k = -pla[1,:] / pla[0,:]
line_x = np.linspace(-5,5,50)
line_y = k*line_x
plt.plot(line_x,line_y)
plt.show()
```



POCKET Algorithm

- **Input**: traing data ($T = \{(x_0, y_0), (x_1, y_1), \dots, (x_i, y_i)\}$)
- **Output**: (w, b)
  - init $(w_{best}, b_{best}) \rightarrow random$
  - $loss_{min} \leftarrow sum(sign(w_{best}x + b_{best})! = y)$
  - for $i = 0 \rightarrow 1000$ do
    - init $(w, b) \rightarrow random$ and $j \rightarrow 0$
    - Save error label data to $T_{error} = \{(x_0, y_0), (x_1, y_1), \dots, (x_{err}, y_{err})\}$
    - while $j! = len(T_{error})$ do
      - $(\bar{w}, \bar{b}) \rightarrow (w, b) + y_j x_j$
      - $loss \leftarrow sum(sign(\bar{w}x + \bar{b})! = y)$
      - if $loss < loss_{min}$ then
        - break
      - end if
      - $j = j + 1$
    - end while
    - if $j! = len(y_{err})$
      - $(w_{best}, b_{best}) \leftarrow (\bar{w}, \bar{b})$
      - $loss_{min} \leftarrow loss$
    - end if
    - j = 0
  - end for

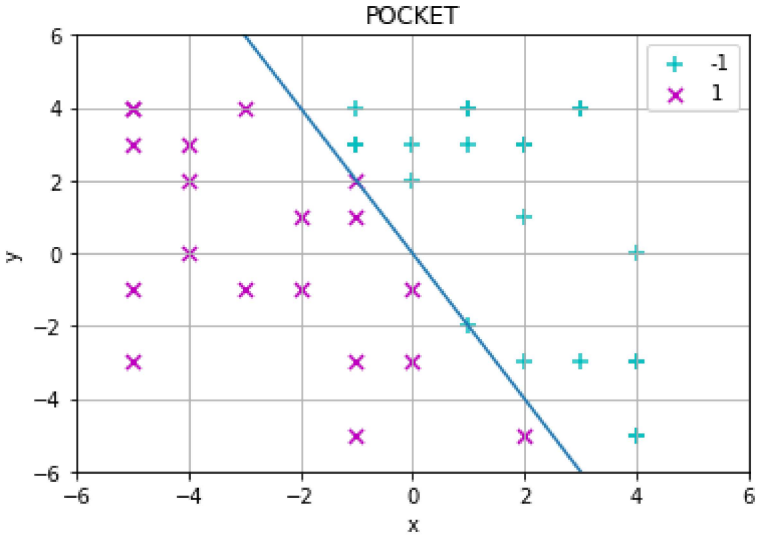
In [6]:

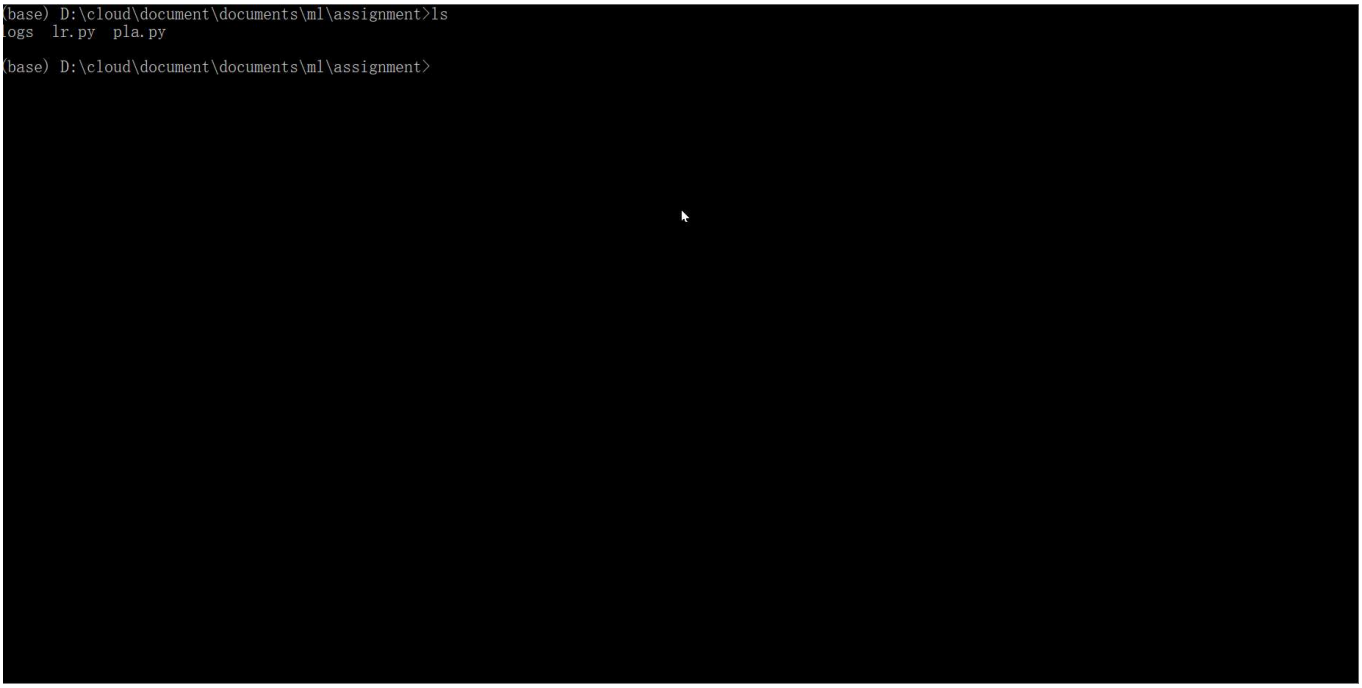
```
def cal_loss(_pocket, _x, _label):
    _cal = np.sign(np.dot(_x, _pocket))
    _cal.shape = (40,1)
    idx = np.where(_cal[:, 0] != _label[:, 0])
    loss = np.sum(_cal[:, 0] != _label[:, 0])
    return list(idx[0]), loss

# random init best pocket and min loss value
pocket_best = np.random.randint(-5,5, (2,1))
_, min_loss = cal_loss(pocket_best, x, label)


for i in range(15):
    # random pocket and cur loss for each period
    pocket = np.random.randint(-5,5, (2,1))
    _pocket = pocket
    idx, cur_loss = cal_loss(pocket, x, label)
    while cnt < len(idx):
        _x = x[idx[cnt], :]
        _x.shape = (2,1)
        _pocket = pocket + _x * label[idx[cnt], 0]
        _, cur_loss = cal_loss(_pocket, x, label)
        # compare cur loss with min loss
        if cur_loss < min_loss:
            break
        else:
            cnt = cnt + 1
    if cnt != len(idx):
        pocket_best = _pocket
        _, min_loss = cal_loss(pocket_best, x, label)
    cnt = 0

pocket = pocket_best
print(pocket)
```

```
[[-2]
 [-4]]
```

In [7]:

```
fig = plt.figure(1)
idx_0 = np.where(label[:, 0] == -1)
p0 = plt.scatter(x[idx_0,1], x[idx_0,0], marker = '+', color = 'c', label='-1', s = 50)
idx_1 = np.where(label[:, 0] == 1)
p1 = plt.scatter(x[idx_1,1], x[idx_1,0], marker = 'x', color = 'm', label='1', s = 50)
plt.title('POCKET')
plt.xlabel('x')
plt.ylabel('y')
plt.xlim((-6,6))
plt.ylim((-6,6))
plt.legend()
plt.grid(True)

k = -pocket[1,:] / pocket[0,:]
line_x = np.linspace(-5,5,50)
line_y = k*line_x
plt.plot(line_x,line_y)
plt.show()
```






ase) D:\cloud\document\documents\ml\assignment>


ase) D:\cloud\document\documents\ml\assignment>ls
A.gif PLA_ERR.gif logs lr.py pla.py pocket.py
ase) D:\cloud\document\documents\ml\assignment>pytho

SVM (Support Vector Machine)

任务 : 对线性/非线性可分不同类别的点进行二分类

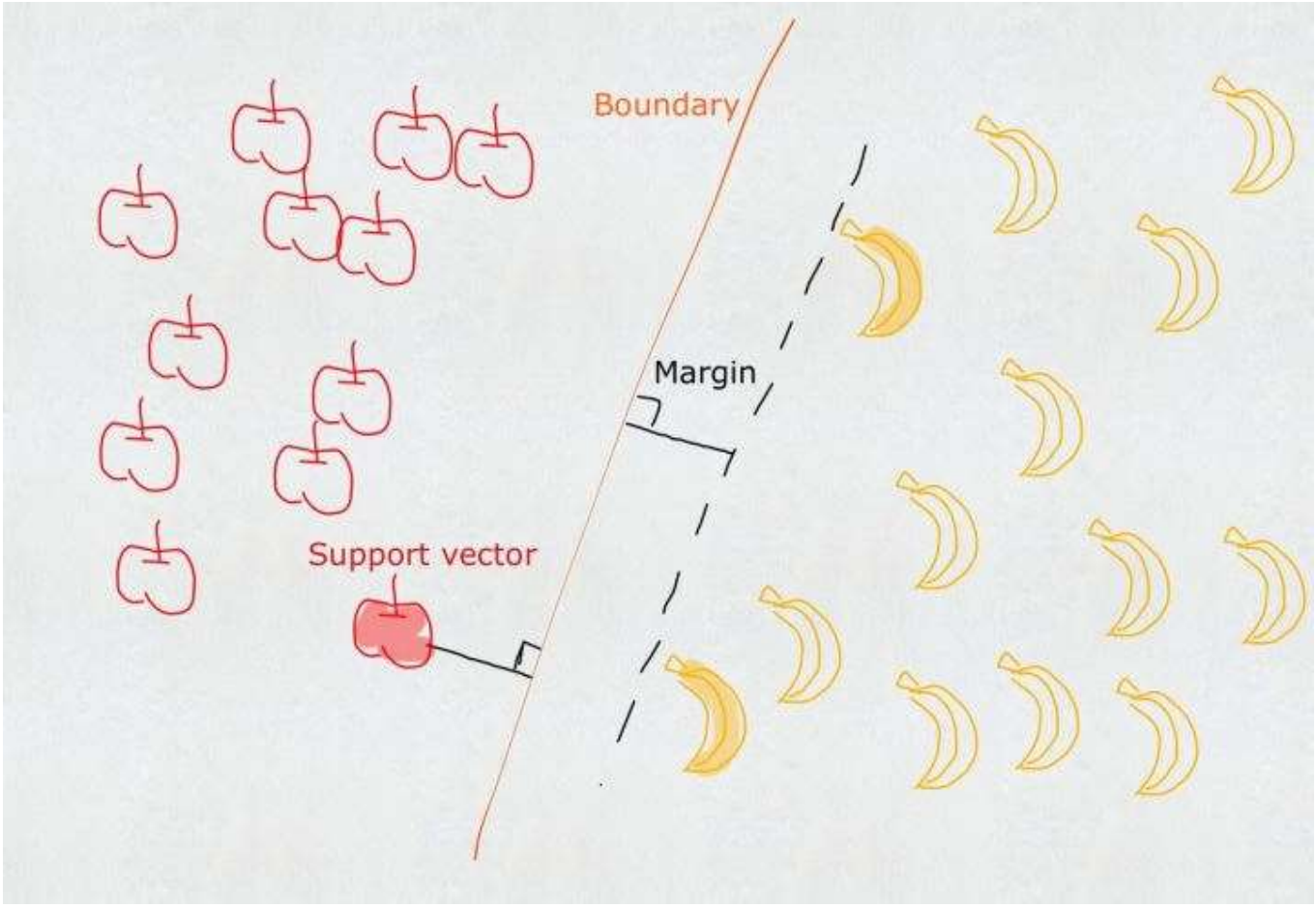
类型 : 监督学习

模型 : $f(x) = sign(wx + b)$

评价方法 : $\min\limits_{w,b}(\frac{1}{2}||w||^2) + C\sum\limits_{i=1}^{m}\max(0, 1 - y_i(w^T x_i + b))$

$$s.t.\ y_i(wx_i + b) - 1 \geq 0, i = 1, 2, \ldots, N$$

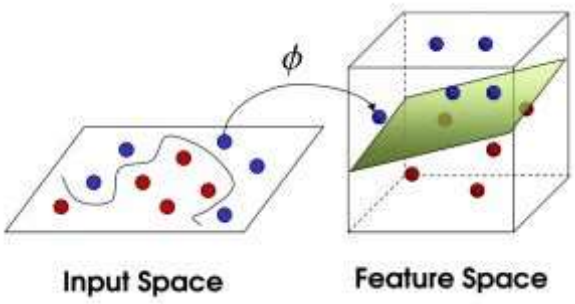
优化方法 : 核技巧/SMO



核技巧

核函数是二元函数，输入是变换之前的两个向量，其输出与两个向量变换之后的内积相等.
$k(x_1, x_2) = f(x_1^T x_2)$

- 定义直线 $y(x) = w^T x + b$
- 任意点x_0到直线的距离为$\frac{1}{||w||}(w^T x_0 + b)$
- 求在误分类最少的情况下的最大间距: $\arg\max_{w,b}\{\frac{1}{||w||}\min_n[y_i(w^T x_i + b)]\}$
- 最大间距对偶形式：$\arg\max_{\alpha}\sum_{i=1}^{N}\alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}y_i y_j \alpha_i \alpha_j \langle x_i, x_j\rangle$



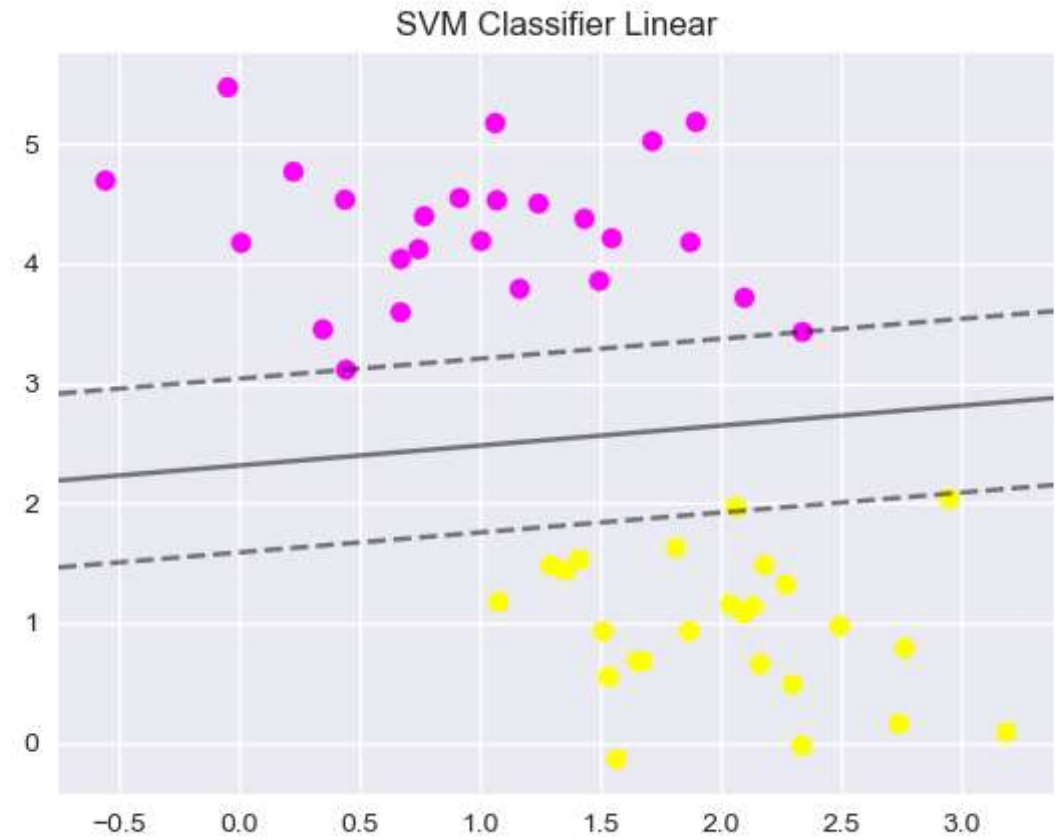
- linear: $K(\mathbf{x}_i, \mathbf{x}_j) = \mathbf{x}_i^T \mathbf{x}_j$.
- polynomial: $K(\mathbf{x}_i, \mathbf{x}_j) = (\gamma {\mathbf{x}_i}^T \mathbf{x}_j + r)^d$, $\gamma > 0$.
- radial basis function (RBF): $K(\mathbf{x}_i, \mathbf{x}_j) = \exp(-\gamma\|\mathbf{x}_i - \mathbf{x}_j\|^2)$, $\gamma > 0$.
- sigmoid: $K(\mathbf{x}_i, \mathbf{x}_j) = \tanh(\gamma {\mathbf{x}_i}^T \mathbf{x}_j + r)$.

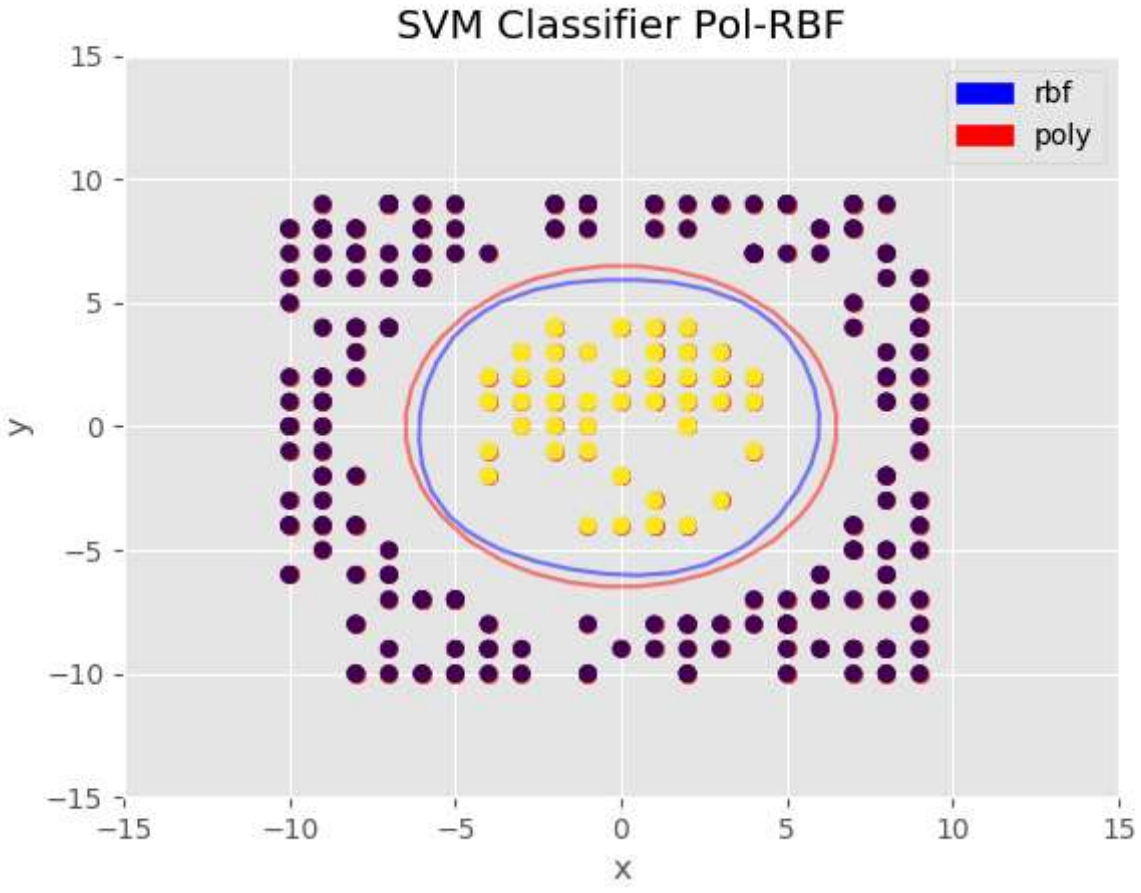
Here, γ, r, and d are kernel parameters.

In [5]:

```
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.patches as mpatches
from matplotlib import style
style.use("ggplot")
from sklearn import svm
from sklearn.datasets.samples_generator import make_blobs

## 测试数据生成
_x = np.random.randint(-10, 10, (400, 2))
_ = np.linalg.norm(_x, axis=1)
circle_in = _x[_<5]
circle_out = _x[_>8]
x = np.vstack((circle_in, circle_out))
y = np.zeros(x.shape[0])
y[0:circle_in.shape[0]] = 1

## 运行SVC核
svc_rbf = svm.SVC(kernel='rbf', C=1e3, gamma=0.1)
svc_poly = svm.SVC(kernel='poly', C=1e3, degree=2)
print(svc_rbf)
print(svc_poly)
```

```
SVC(C=1000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.1, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
SVC(C=1000.0, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=2, gamma='auto', kernel='poly',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```


SVM Classifier Linear
5
4
3
2
1
0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5
3.0


SVM Classifier Pol-RBF
rbf
poly
15
10
5
0
−5
−10
−15
y
−15
−10
−5
0
5
10
15
x

LR (Logisitic Regeression)

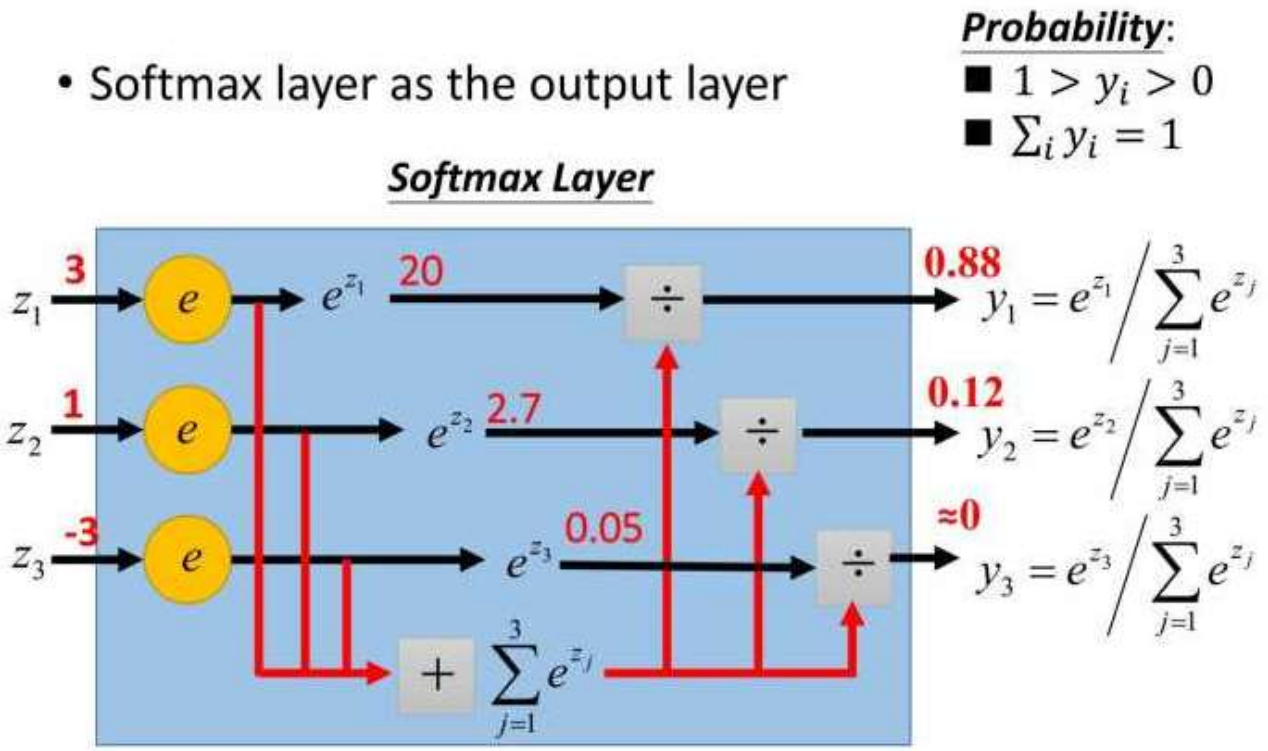
任务 : 对线性/非线性可分不同类别的点进行多分类

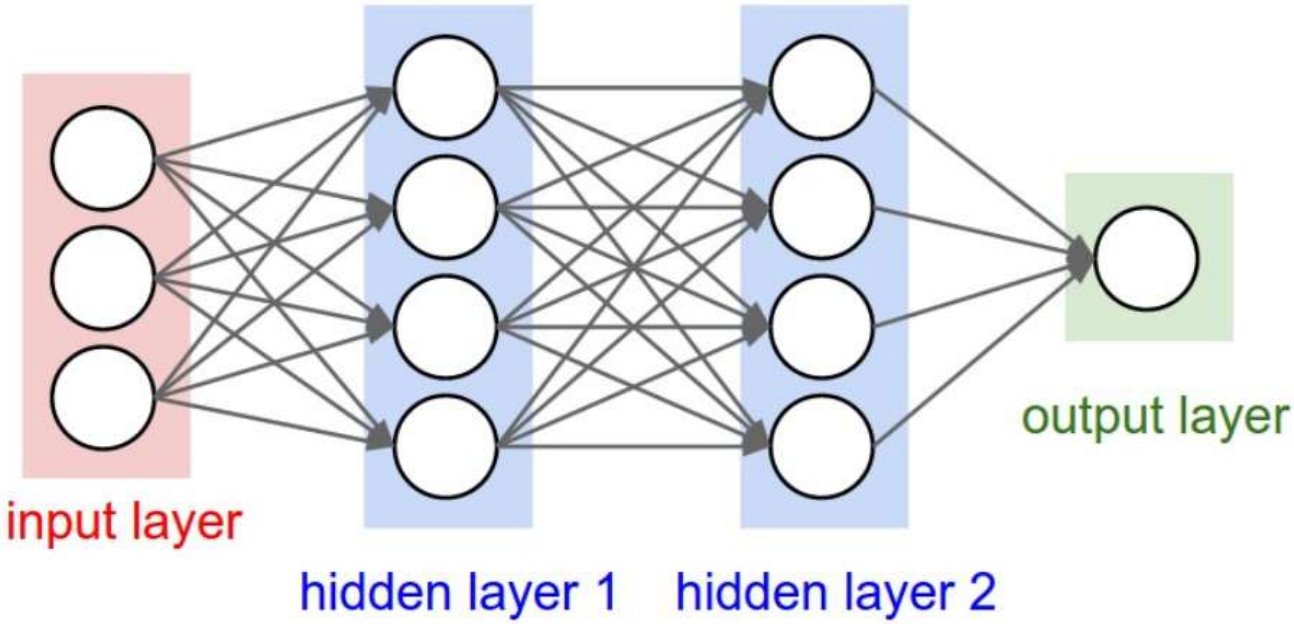
类型 : 监督学习

模型 : 3层fc nn, output layer(softmax) : $y_i = \frac{e^{wx_i+b}}{\sum_{i=1}^{C} e^{wx_i+b}}$

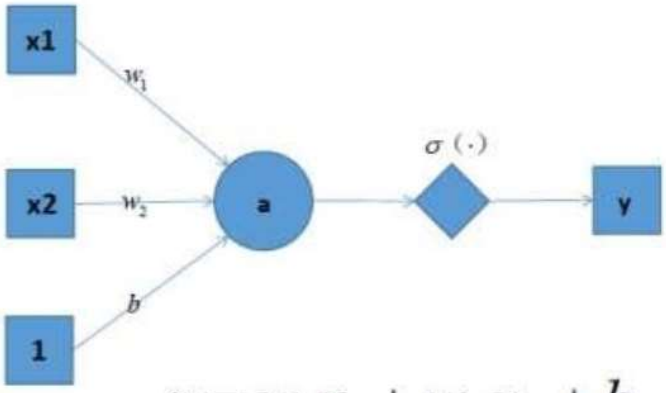
评价方法 : $-\sum_{i=1}^{N} y_i \log \frac{e^{wx_i+b}}{\sum_{j=1}^{C} e^{wx_j+b}}$

优化方法 : Gradient Descent/SGD/ADAM/Adagrad/RMSprop

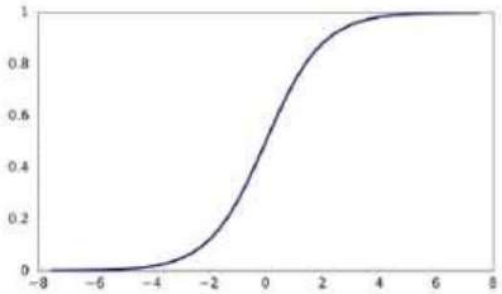




Perceptron with non-linear activation function



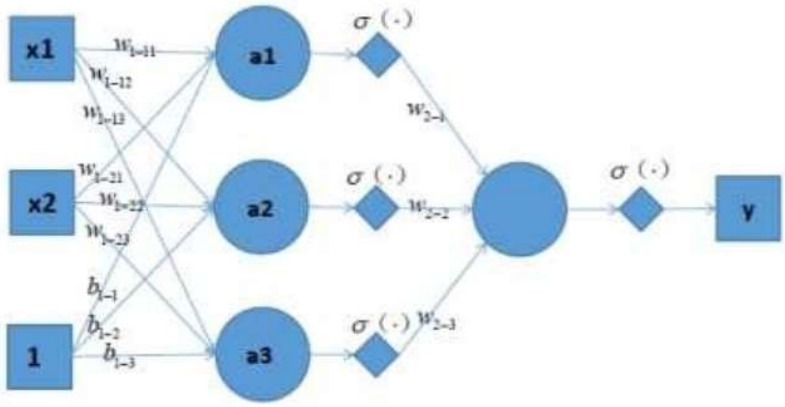
$$a = w_1 x_1 + w_2 x_2 + b$$
$$y = \sigma(a)$$



$\sigma(\cdot)$ is a non-linear activation function, sigmoid was the most popular one,

$$\sigma(y) = \frac{1}{1+e^{-y}}$$

Perceptron with non-linear activation function



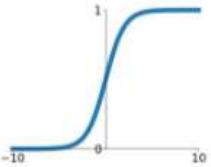
$$a1 = w_{1\text{-}11}x_1 + w_{1\text{-}21}x_2 + b_{1\text{-}1}$$
$$a2 = w_{1\text{-}12}x_1 + w_{1\text{-}22}x_2 + b_{1\text{-}2}$$
$$a3 = w_{1\text{-}13}x_1 + w_{1\text{-}23}x_2 + b_{1\text{-}3}$$

$$y = \sigma(w_{2\text{-}1}\sigma(a1) + w_{2\text{-}2}\sigma(a2) + w_{2\text{-}3}\sigma(a3))$$

Activation functions

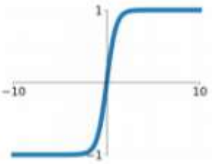
Sigmoid

$$\sigma(x) = \frac{1}{1+e^{-x}}$$



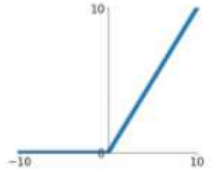
tanh

$$\tanh(x)$$



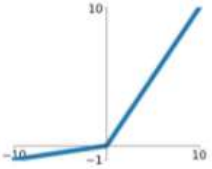
ReLU

$$\max(0, x)$$



Leaky ReLU

$$\max(0.1x, x)$$

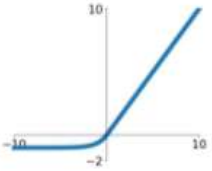


Maxout

$$\max(w_1^T x + b_1, w_2^T x + b_2)$$

ELU

$$\begin{cases} x & x \geq 0 \\ \alpha(e^x - 1) & x < 0 \end{cases}$$



请问人工神经网络中的activation function的作用具体是什么？为...

第一个问题：为什么引入非线性激励函数？

如果不用激励函数（其实相当于激励函数是f(x) = x），在这种情况下你每一层输出都是上层输入的线性函数，很容易验证，无论你神经网络有多少层，输出都是输入的线性组合，与*没有*隐藏层效果相当，这种情况就是*最原始的感知机*（Perceptron）了。

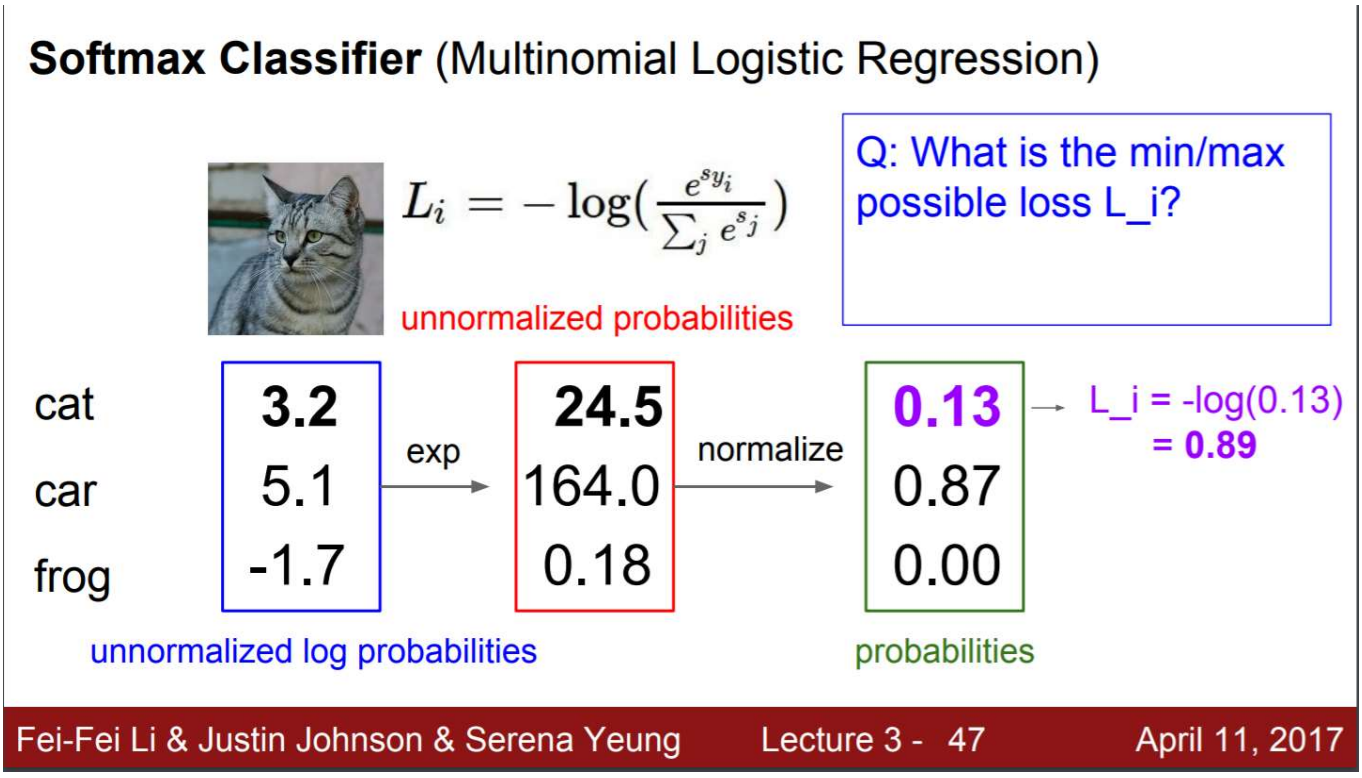
正因为上面的原因，我们决定引入非线性函数作为激励函数，这样深层神经网络就有意义了（不再是输入的线性组合，可以逼近任意函数）。最早的想法是sigmoid函数或者tanh函数，输出有界，很容易充当下一层输入（以及一些人的生物解释balabala）。

第二个问题：为什么引入Relu呢？

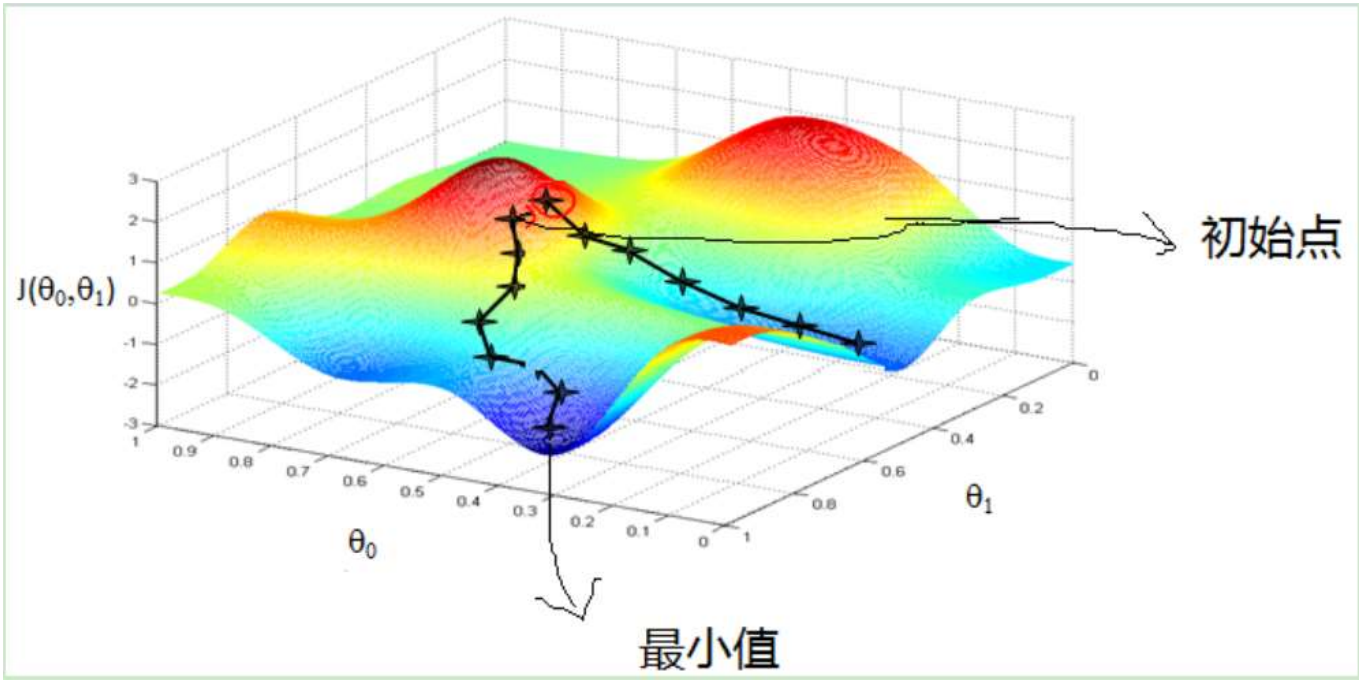
第一，采用sigmoid等函数，*算激活函数时（指数运算），计算量大*，反向传播求误差梯度时，求导涉及除法，计算量相对大，而采用Relu激活函数，整个过程的计算量节省很多。

第二，对于深层网络，sigmoid函数反向传播时，很容易就会出现梯度消失的情况（在sigmoid接近饱和区时，变换太缓慢，导数趋于0，这种情况会造成*信息丢失，参见 @Haofeng Li 答案的第三点*），从而无法完成深层网络的训练。

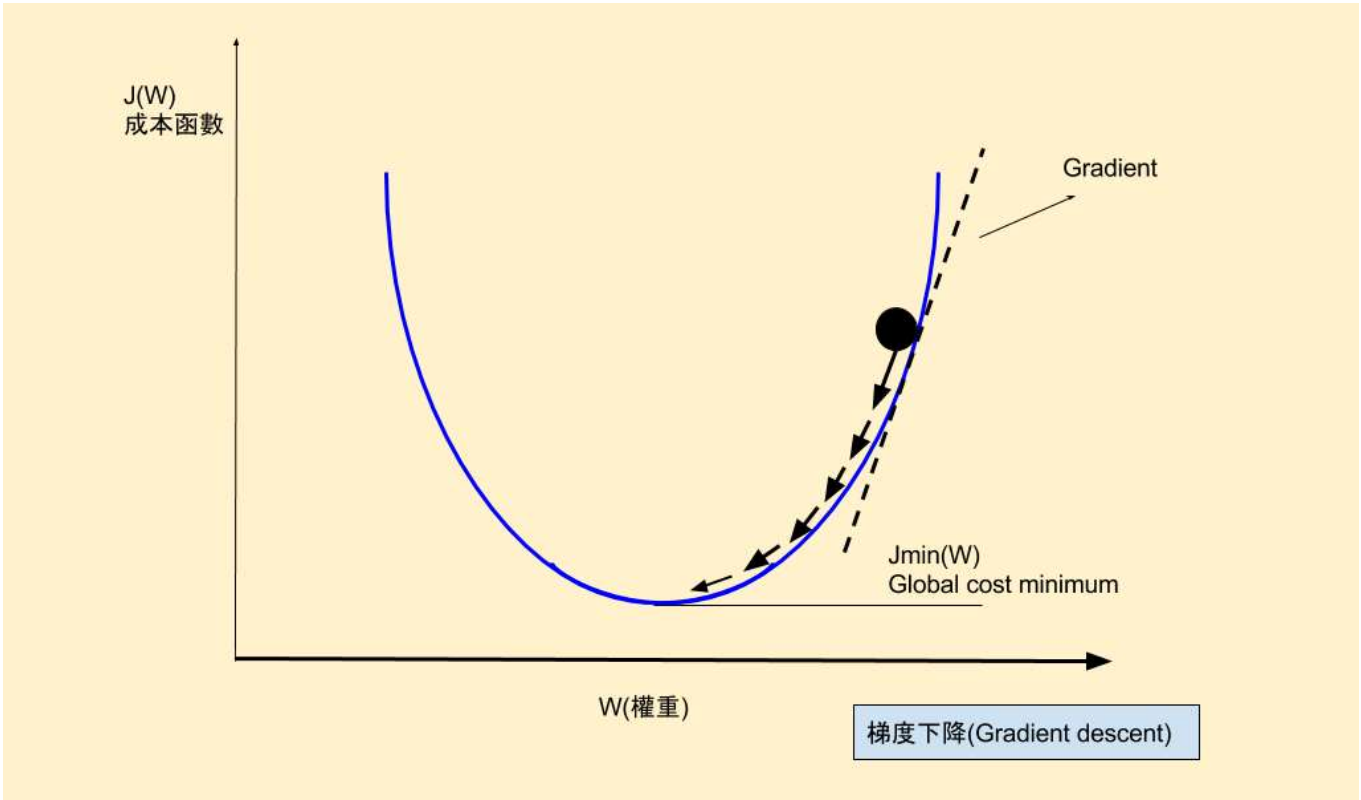
第三，Relu会使一部分神经元的输出为0，这样就造成了网络的稀疏性，并且减少了参数的相互依存关系，缓解了过拟合问题的发生（以及一些人的生物解释balabala）。



Gradient Descent



$$\theta_j = \theta_j - \alpha \frac{\partial}{\partial \theta_j} J(\theta)$$



Backpropagation

Backpropagation: a simple example

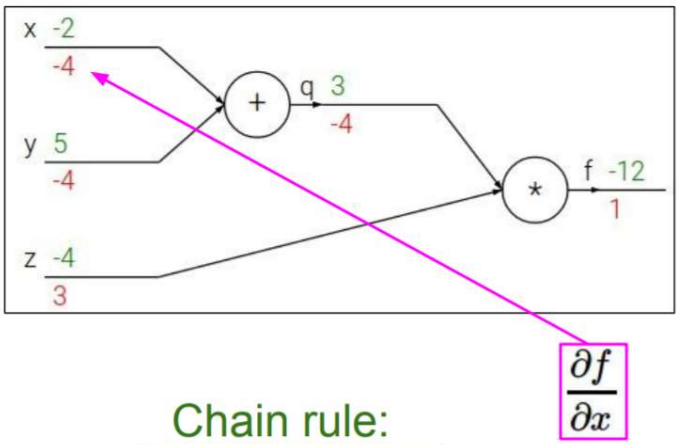
$$f(x,y,z) = (x+y)z$$

e.g. x = -2, y = 5, z = -4

$$q = x + y \qquad \frac{\partial q}{\partial x} = 1, \frac{\partial q}{\partial y} = 1$$

$$f = qz \qquad \frac{\partial f}{\partial q} = z, \frac{\partial f}{\partial z} = q$$

Want: $\frac{\partial f}{\partial x}, \frac{\partial f}{\partial y}, \frac{\partial f}{\partial z}$



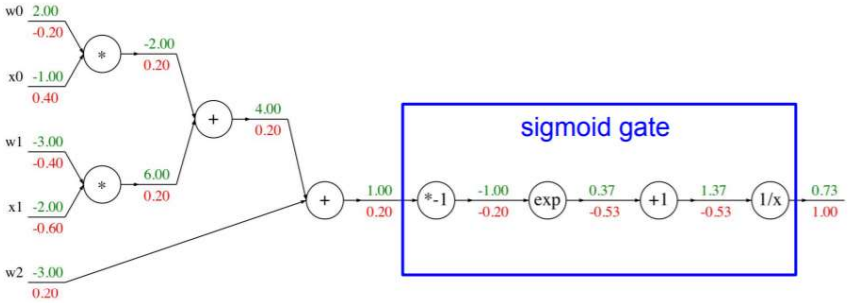
Chain rule:

$$\frac{\partial f}{\partial x} = \frac{\partial f}{\partial q}\frac{\partial q}{\partial x}$$

$$f(w,x) = \frac{1}{1+e^{-(w_0x_0+w_1x_1+w_2)}}$$

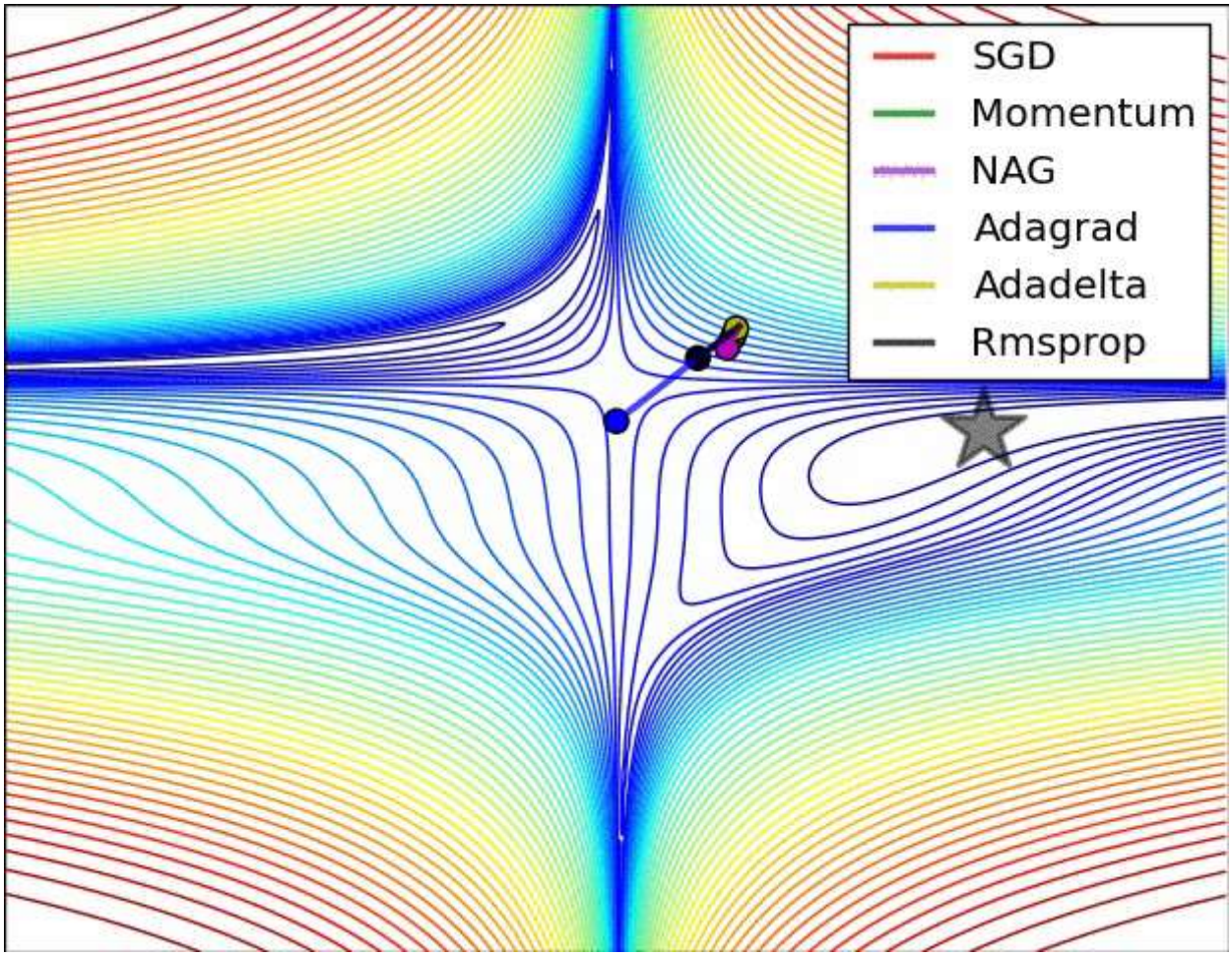
$$\sigma(x) = \frac{1}{1+e^{-x}}$$ sigmoid function

$$\frac{d\sigma(x)}{dx} = \frac{e^{-x}}{(1+e^{-x})^2} = \left(\frac{1+e^{-x}-1}{1+e^{-x}}\right)\left(\frac{1}{1+e^{-x}}\right) = (1-\sigma(x))\,\sigma(x)$$



Gradient Descent各算法对比

https://zhuanlan.zhihu.com/p/32230623 (https://zhuanlan.zhihu.com/p/32230623)



In [1]:

```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
from sklearn.datasets.samples_generator import make_blobs
import time
import os
os.environ['TF_CPP_MIN_LOG_LEVEL']='2'

DIMENSION = 2
KNUM = 4
SAMPLE_CNT = 240

def init_variable(name, shape):
    return(tf.get_variable(name, shape=shape, initializer=tf.contrib.layers.xavier_initializer
()))

# 测试数据生成
x_data, y_data = make_blobs(n_samples=SAMPLE_CNT, n_features=DIMENSION, centers=KNUM, center_box
=(-20, 20), cluster_std=1.5)
x = x_data.tolist()
label=np.zeros((SAMPLE_CNT, KNUM))

label[y_data==0] = [0,0,0,1]
label[y_data==1] = [0,0,1,0]
label[y_data==2] = [0,1,0,0]
label[y_data==3] = [1,0,0,0]

y = label.tolist()
keep_prob = tf.placeholder(tf.float32)
prediction_value = y.copy()

# 生成学习网络
# layer0: input
xs = tf.placeholder("float", [None, 2])
ys = tf.placeholder("float", [None, 4])
keep_prob = tf.placeholder(tf.float32)

# layer1:
W1 = init_variable('W1', [2,20])
bias1 = init_variable('b1', [1,20])
o1 = tf.nn.relu(tf.matmul(xs, W1) + bias1)
o1_drop = tf.nn.dropout(o1, keep_prob)

# layer2:
W2 = init_variable('W2', [20,20])
bias2 = init_variable('b2', [1,20])
o2 = tf.nn.relu(tf.matmul(o1_drop, W2) + bias2)
o2_drop = tf.nn.dropout(o2, keep_prob)

# layer3: output
W3 = init_variable('W3', [20,4])
bias3 = init_variable('b3', [1,4])
#predict = tf.nn.softmax(tf.matmul(o2_drop, W3) + bias3)
o3 = tf.matmul(o2_drop, W3) + bias3
predict = tf.nn.softmax(o3)
```

```
D:\cloud\anaconda\lib\site-packages\h5py\__init__.py:34: FutureWarning: Conversion
of the second argument of issubdtype from `float` to `np.floating` is deprecated.
In future, it will be treated as `np.float64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
```

In [2]:

```
# loss  sum( y*log(predict) )
loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=o3, labels=ys))
#loss = tf.reduce_mean(-tf.reduce_sum(ys*tf.log(predict), reduction_indices=[1]))

# train method
#train = tf.train.GradientDescentOptimizer(0.1).minimize(loss)
train = tf.train.AdamOptimizer(1e-3).minimize(loss)

#init all variables, it will be activated by use sess.run(init)
init = tf.global_variables_initializer()

with tf.Session() as sess:
    sess.run(init)
    for i in range(200):
        sess.run(train, feed_dict={xs:x, ys:y, keep_prob: 0.5})
        if i % 10 == 0:
            prediction_value = sess.run(predict, feed_dict={xs:x, keep_prob: 1})
            print(sess.run(loss, feed_dict={xs:x, ys:y, keep_prob: 1}))
```

```
WARNING:tensorflow:From <ipython-input-2-cd5c0946c093>:2: softmax_cross_entropy_wi
th_logits (from tensorflow.python.ops.nn_ops) is deprecated and will be removed in
a future version.
Instructions for updating:

Future major versions of TensorFlow will allow gradients to flow
into the labels input on backprop by default.

See tf.nn.softmax_cross_entropy_with_logits_v2.

2.0771701
1.4298545
1.2080476
1.062615
0.9569904
0.8710387
0.8117963
0.7671517
0.7361572
0.71022105
0.6842088
0.6632282
0.6432349
0.63005894
0.6273728
0.6227281
0.6168578
0.61016667
0.60824126
0.60349876
```

LR (Linear Regeression)

任务 : 对一组数据进行曲线拟合

类型 : 监督学习

模型 : 2层fc nn, output layer : $y_i = wx_i + b$

评价方法 : $\sum_{i=1}^{N} (\mathrm{y}_i - (wx_i + b))^2$

优化方法 : Gradient Descent/SGD/ADAM/Adagrad/RMSprop

In [6]:

```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
import time
import os
os.environ['TF_CPP_MIN_LOG_LEVEL']='2'

# 测试数据生成
x_data = np.linspace(-1, 1, 300)[:, np.newaxis]
noise = np.random.normal(0, 0.05, x_data.shape)
y_data = np.square(x_data) - 0.5 + noise

# 生成学习网络
# layer0: input
xs = tf.placeholder(tf.float32, [None, 1])
ys = tf.placeholder(tf.float32, [None, 1])

# layer1:
W1 = tf.Variable(tf.random_normal([1,10]))
bias1 = tf.Variable(tf.zeros([1, 10]) + 0.1)
o1 = tf.nn.relu(tf.matmul(xs, W1) + bias1)

# layer2: output
W2 = tf.Variable(tf.random_normal([10,1]))
bias2 = tf.Variable(0.1)
predict = tf.matmul(o1, W2) + bias2

# loss
loss = tf.reduce_mean(tf.reduce_sum(tf.square(ys - predict),
                    reduction_indices=[1]))

# train method
train = tf.train.GradientDescentOptimizer(0.1).minimize(loss)

#init all variables, it will be activated by use sess.run(init)
init = tf.global_variables_initializer()


with tf.Session() as sess:
    sess.run(init)
    for i in range(1000):
        sess.run(train, feed_dict={xs:x_data, ys:y_data})
        if i % 100 == 0:
            prediction_value = sess.run(predict, feed_dict={xs:x_data})
            print(sess.run(loss, feed_dict={xs:x_data, ys:y_data}))
```

```
0.21007633
0.009326225
0.0065052332
0.0041997177
0.0037967209
0.003648324
0.0035490533
0.0034687535
0.003410836
0.0033446297
```

KMEANS

任务 : 对未标记的点进行多分类

类型 : 非监督学习

模型 : $y_j -> \min \sum_{i=1}^{K} (x_j - k_i)^2$

评价方法 : $\sum_{i=1}^{K} \sum_{j=1}^{N} (x_j - k_i)^2$

优化方法 : $k_j -> \frac{1}{N} \sum_{i=1}^{N} x_i \bullet (y_i == j)$

KMEANS Algorithm

- **Input**: data ($T = \{x_0, x_1, \ldots, x_i\}$)
- **Output**: $\{y_0, y_1, \ldots, y_i\}$
  - init $\{k_0, k_1, \ldots, k_K\} \rightarrow x_{random}$ (s.t. kmeans cluster cnt: K)
  - update $y_i \rightarrow minarg\{(x_i - k)^2\}$
  - $loss_{min}, loss_{cur}, loss_{pre} \leftarrow \sum_{i}^{K} \sum_{j}^{y==i} (x_j - k_i)^2$
  - for $i = 0 \rightarrow 1000$ do
    - init $(w, b) \rightarrow random$ and $j \rightarrow 0$
    - Save error label data to $T_{error} = \{(x_0, y_0), (x_1, y_1), \ldots, (x_{err}, y_{err})\}$
    - while $j != len(T_{error})$ do
      - $(\bar{w}, \bar{b}) \rightarrow (w, b) + y_j x_j$
      - $loss \leftarrow sum(sign(\bar{w}x + \bar{b}) != y)$
      - if $loss < loss_{min}$ then
        - break
      - end if
      - $j = j + 1$
    - end while
    - if $j != len(y_{err})$
      - $(w_{best}, b_{best}) \leftarrow (\bar{w}, \bar{b})$
      - $loss_{min} \leftarrow loss$
    - end if
    - j = 0
  - end for

In [12]:

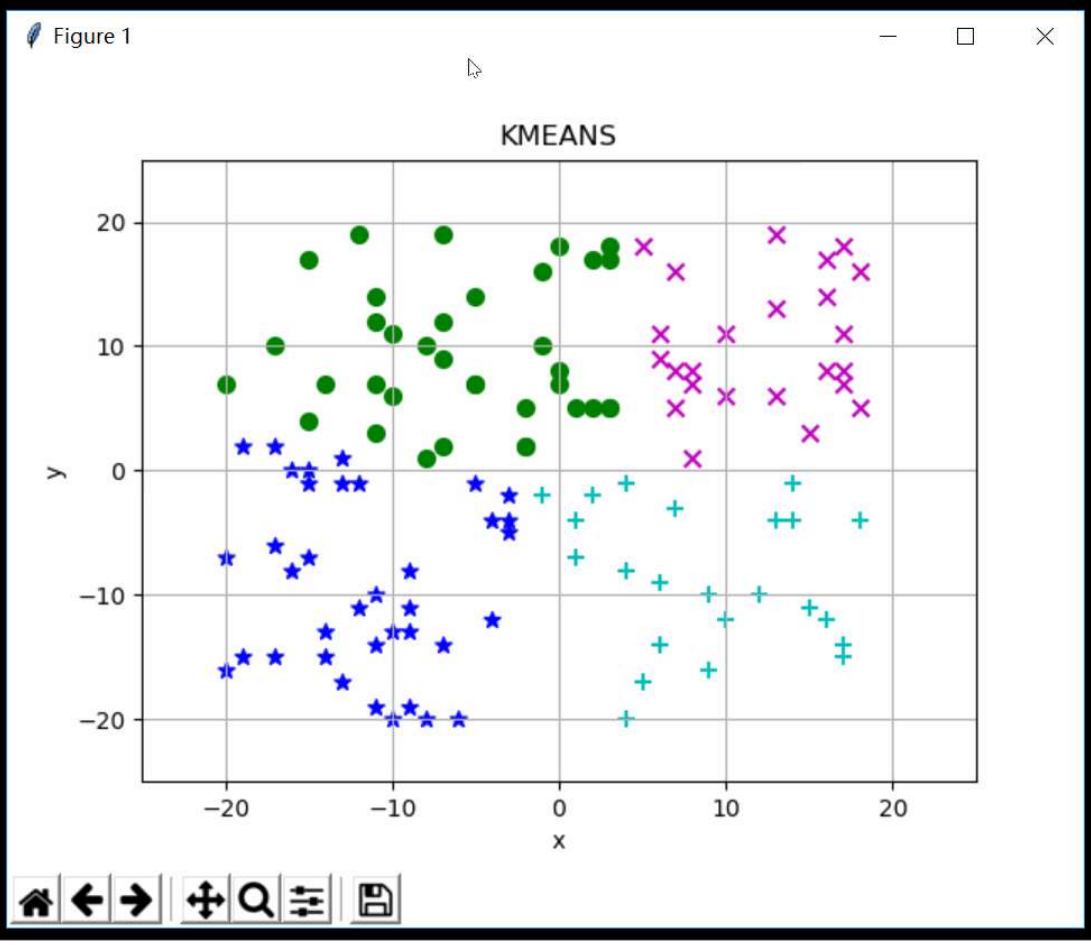
```
import numpy as np
import matplotlib
import matplotlib.pyplot as plt
from sklearn.datasets.samples_generator import make_blobs

DIMENSION = 2
KNUM = 4
SAMPLE_CNT = 240
train_step = 100


def label_reset(x, kpoint):
    _label = np.zeros((x.shape[0], 1))
    for i in range(0, x.shape[0]):
        _ = np.linalg.norm(x[i,:] - kpoint, axis=1)
        _label[i] = np.argmin(_, 0)

    return _label


def kpoint_reset(x, label):
    _kpoint = np.zeros((KNUM, DIMENSION))
    idx = 0
    for i in range(0, KNUM):
        idx = np.where(label[:, 0] == i)
        _kpoint[i] = np.mean(x[idx], axis=0)
    return _kpoint

def cal_total(x, kpoint, label):
    _sum = 0
    for i in range(0, KNUM):
        idx = np.where(label[:, 0] == i)
        _linalg = np.linalg.norm(x[idx] - kpoint[i], axis=1)
        _sum += np.sum(_linalg)
    _sum /= SAMPLE_CNT
    return _sum

'''
# x, y, label
x = np.zeros((SAMPLE_CNT, DIMENSION))
x = np.random.randint(-20, 20, (SAMPLE_CNT, DIMENSION))
'''
x, _ = make_blobs(n_samples=SAMPLE_CNT, n_features=DIMENSION, centers=KNUM, center_box=(-20, 20
), cluster_std=1.5)

label = np.zeros((SAMPLE_CNT, 1))

#kmeans init
kpoint = np.random.randint(-20, 20, (KNUM, DIMENSION))
kpoint_min = kpoint.copy()

label = label_reset(x, kpoint)
label_min = label.copy()

sum = cal_total(x, kpoint, label)
sum_min = sum
delta = sum
```

In [13]:

```
for i in range(train_step):
    kpoint = np.random.randint(-20, 20, (KNUM, DIMENSION))
    label = label_reset(x, kpoint)
    sum = cal_total(x, kpoint, label)
    delta = sum
    while delta > 0.001:
        kpoint = kpoint_reset(x, label)
        label = label_reset(x, kpoint)
        _sum = cal_total(x, kpoint, label)
        delta = sum - _sum
        sum = _sum
        #print("sum: %f" %sum)
    if sum < sum_min:
        print("Update sum_min: %f" %sum)
        sum_min = sum
        kpoint_min = kpoint.copy()
        label_min = label.copy()
print(sum)
```

```
Update sum_min: 1.833920
Update sum_min: 1.833920

D:\cloud\anaconda\lib\site-packages\numpy\core\fromnumeric.py:2957: RuntimeWarnin
g: Mean of empty slice.
  out=out, **kwargs)
D:\cloud\anaconda\lib\site-packages\numpy\core\_methods.py:73: RuntimeWarning: inv
alid value encountered in true_divide
  ret, rcount, out=ret, casting='unsafe', subok=False)

1.8339197144463897
```

```
(base) D:\cloud\document\documents\ml\assignment>python kmeans.py
sum: 8.749348
sum: 8.621762
sum: 8.576851
sum: 8.502088
sum: 8.115657
sum: 7.818776
sum: 7.626627
sum: 7.498779
```



CNN

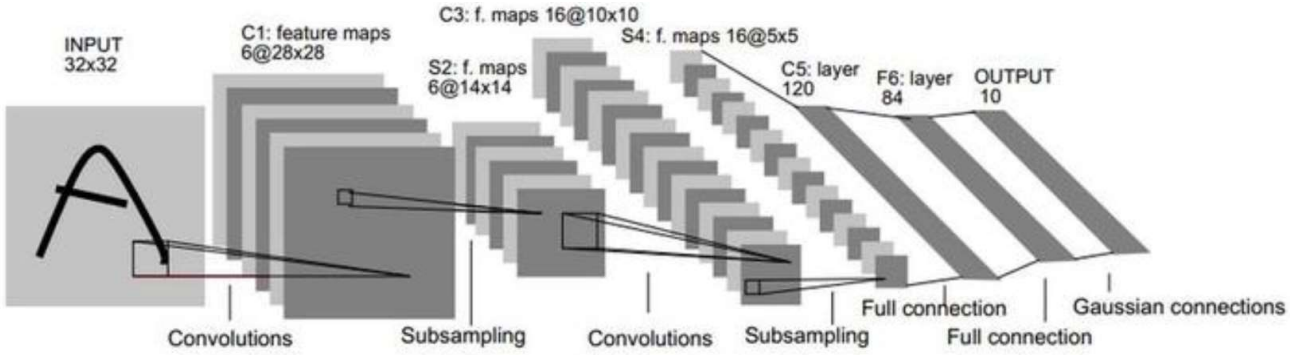
任务 : OCR end-to-end 识别

类型 : 监督学习

模型 : 3层cnn + 3层relu + 2层fc, output layer(softmax) : $y_i = \frac{e^{wxn+b}}{\sum_{i=1}^{C} e^{wx_i+b}}$

评价方法 : $-\sum_{i=1}^{N} y_i \log \frac{e^{wx_i+b}}{\sum_{j=1}^{C} e^{wx_j+b}}$

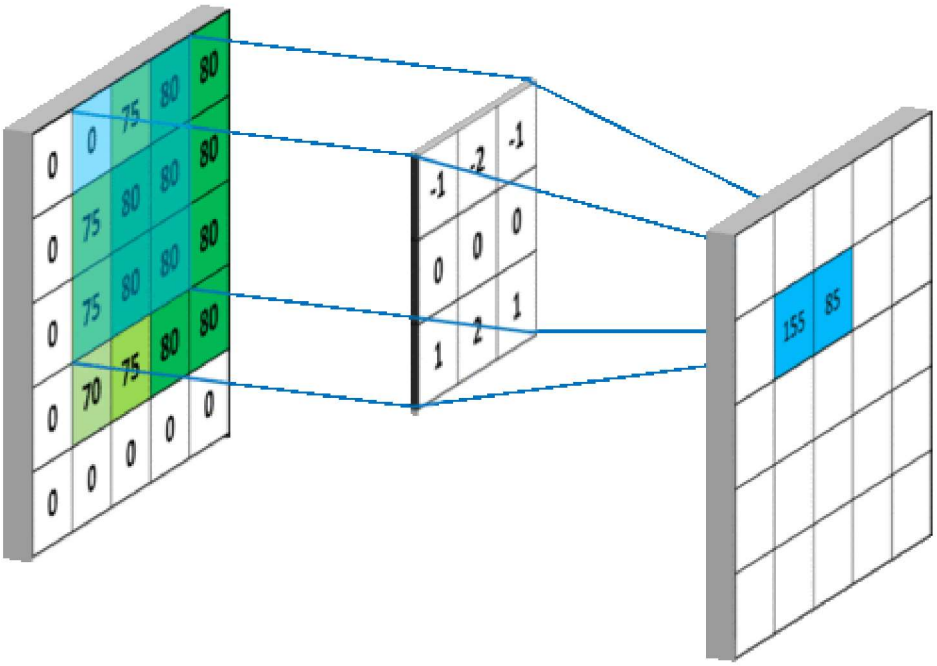
优化方法 : Gradient Descent/SGD/ADAM/Adagrad/RMSprop



Convolution

翻转->移动->乘积->求和

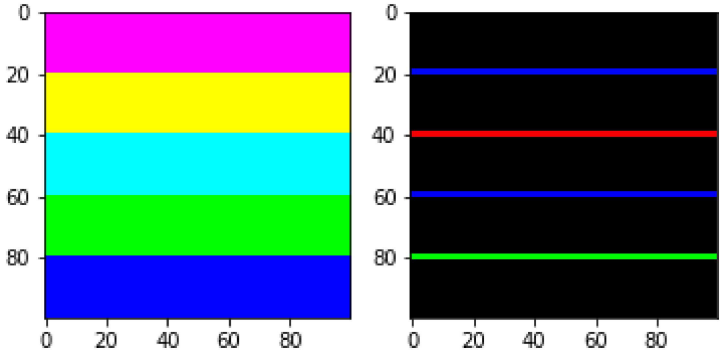
$$f[x,y] * g[x,y] = \sum_{n1=-\infty}^{\infty} \sum_{n2=-\infty}^{\infty} f[n_1,n_2] \bullet g[x-n_1, y-n_2]$$



In [22]:

```
import cv2
import matplotlib.pyplot as plt
import numpy as np
import sys
%matplotlib inline

img = np.ones((100,100,3))
img[0:20,:,1] = 255
img[20:40,:,2] = 255
img[40:100,:,0] = 255
img[60:80,:,2] = 255
img[80:100,:,1] = 255

prewitt = np.array([[-1,-1,-1],
           [0,0,0],
           [1,1,1]])
res = cv2.filter2D(img,-1,prewitt)
regular = np.uint8(res)
print(img[19:22,19:22,1])
print(res[20,20,1])

plt.figure()
plt.subplot(1,2,1)
plt.imshow(img)
plt.subplot(1,2,2)
plt.imshow(regular)
plt.show()
```

```
[[255. 255. 255.]
 [  1.   1.   1.]
 [  1.   1.   1.]]
-762.0
```

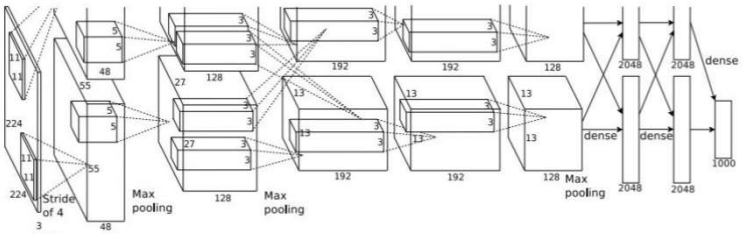


LeNet、AlexNet、GoogLeNet、VGG、ResNet

模型名	AlexNet	VGG	GoogLeNet	ResNet
初入江湖	2012	2014	2014	2015
层数	8	19	22	152
Top-5错误	16.4%	7.3%	6.7%	3.57%
Data Augmentation	+	+	+	+
Inception(NIN)	-	-	+	-
卷积层数	5	16	21	151
卷积核大小	11,5,3	3	7,1,3,5	7,1,3,5
全连接层数	3	3	1	1
全连接层大小	4096,4096,1000	4096,4096,1000	1000	1000
Dropout	+	+	+	+
Local Response Normalization	+	-	+	-
Batch Normalization	-	-	-	+

Case Study: AlexNet

[Krizhevsky et al. 2012]

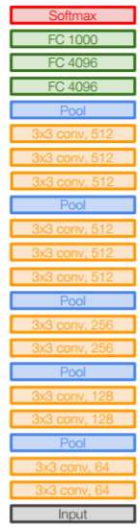


Full (simplified) AlexNet architecture:
[227x227x3] INPUT
[55x55x96] CONV1: 96 11x11 filters at stride 4, pad 0
[27x27x96] MAX POOL1: 3x3 filters at stride 2
[27x27x96] NORM1: Normalization layer
[27x27x256] CONV2: 256 5x5 filters at stride 1, pad 2
[13x13x256] MAX POOL2: 3x3 filters at stride 2
[13x13x256] NORM2: Normalization layer
[13x13x384] CONV3: 384 3x3 filters at stride 1, pad 1
[13x13x384] CONV4: 384 3x3 filters at stride 1, pad 1
[13x13x256] CONV5: 256 3x3 filters at stride 1, pad 1
[6x6x256] MAX POOL3: 3x3 filters at stride 2
[4096] FC6: 4096 neurons
[4096] FC7: 4096 neurons
[1000] FC8: 1000 neurons (class scores)

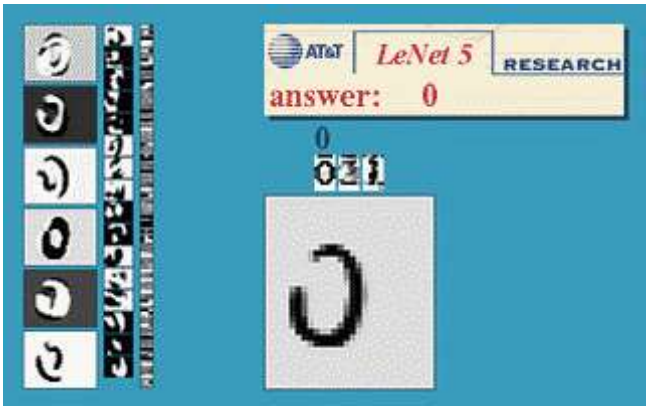
Details/Retrospectives:
- first use of ReLU
- used Norm layers (not common anymore)
- heavy data augmentation
- dropout 0.5
- batch size 128
- SGD Momentum 0.9
- Learning rate 1e-2, reduced by 10 manually when val accuracy plateaus
- L2 weight decay 5e-4
- 7 CNN ensemble: 18.2% -> 15.4%

INPUT: [224x224x3] memory: 224*224*3=150K params: 0 (not counting biases)
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*3)*64 = 1,728
CONV3-64: [224x224x64] memory: 224*224*64=3.2M params: (3*3*64)*64 = 36,864
POOL2: [112x112x64] memory: 112*112*64=800K params: 0
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*64)*128 = 73,728
CONV3-128: [112x112x128] memory: 112*112*128=1.6M params: (3*3*128)*128 = 147,456
POOL2: [56x56x128] memory: 56*56*128=400K params: 0
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*128)*256 = 294,912
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
CONV3-256: [56x56x256] memory: 56*56*256=800K params: (3*3*256)*256 = 589,824
POOL2: [28x28x256] memory: 28*28*256=200K params: 0
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*256)*512 = 1,179,648
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
CONV3-512: [28x28x512] memory: 28*28*512=400K params: (3*3*512)*512 = 2,359,296
POOL2: [14x14x512] memory: 14*14*512=100K params: 0
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
CONV3-512: [14x14x512] memory: 14*14*512=100K params: (3*3*512)*512 = 2,359,296
POOL2: [7x7x512] memory: 7*7*512=25K params: 0
FC: [1x1x4096] memory: 4096 params: 7*7*512*4096 = 102,760,448
FC: [1x1x4096] memory: 4096 params: 4096*4096 = 16,777,216
FC: [1x1x1000] memory: 1000 params: 4096*1000 = 4,096,000

TOTAL memory: 24M * 4 bytes ~= 96MB / image (only forward! ~*2 for bwd)
TOTAL params: 138M parameters

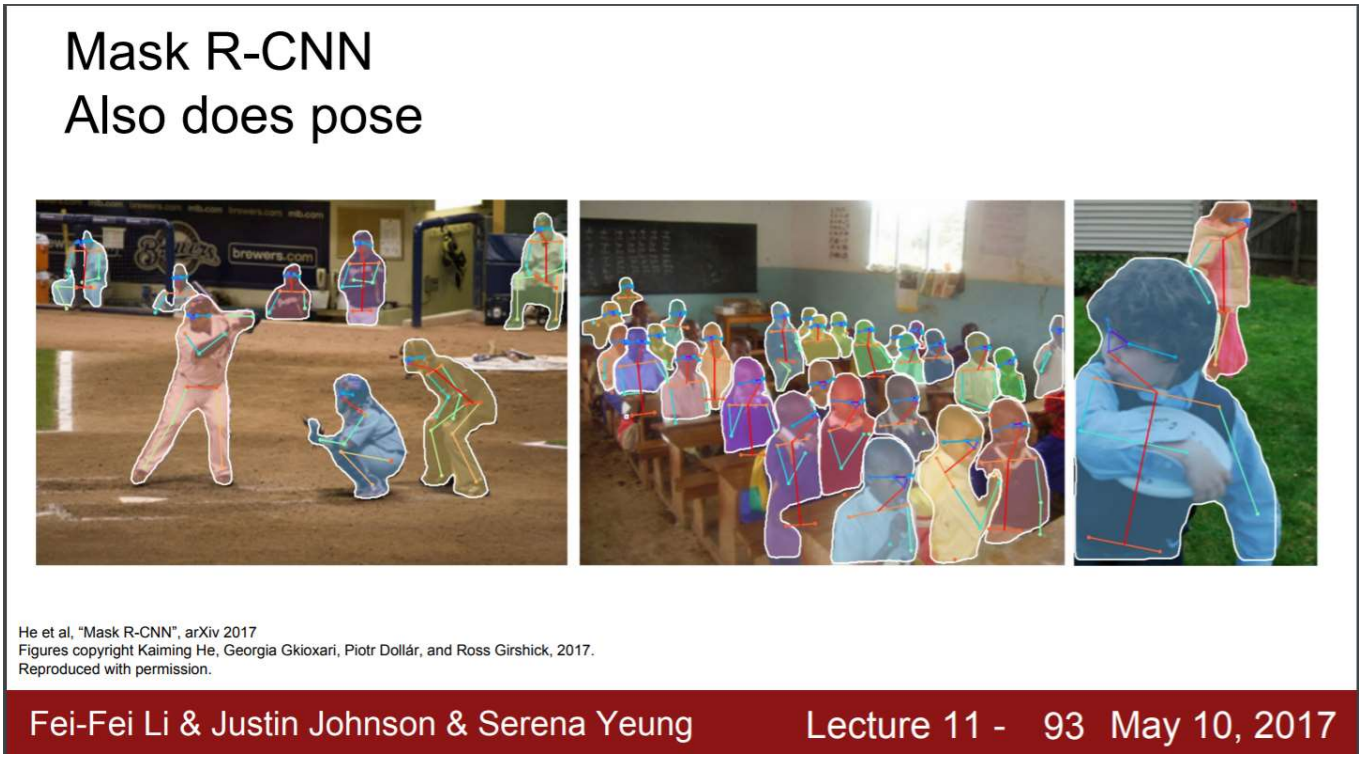


VGG16

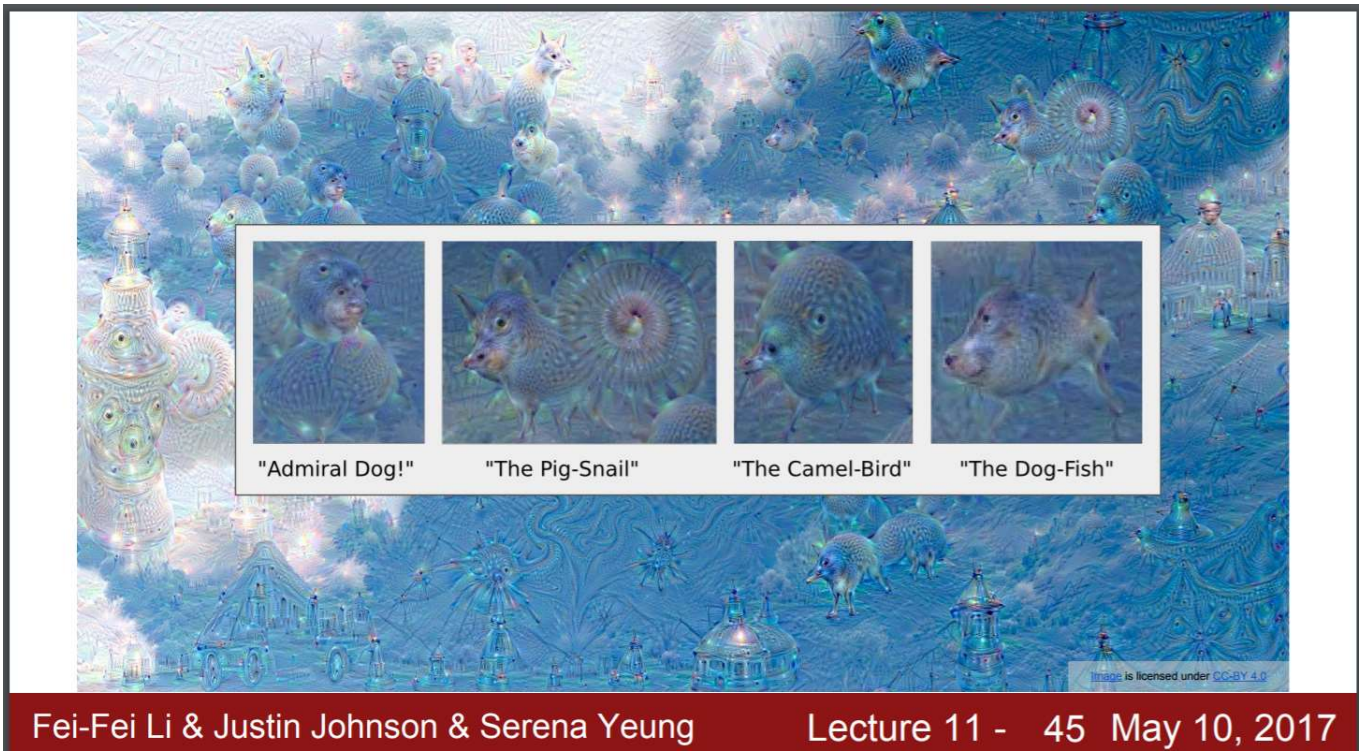


Mask R-CNN Segment

Mask R-CNN Post



DeepDream



Style-transfer

Gramian 矩陣

設 A 為一個 $m \times n$ 階實矩陣，n 階方陣 $G = [g_{ij}] = A^T A$ 稱為 Gramian 或 Gram 矩陣，也有人稱之為交互乘積 (cross-product) 矩陣。考慮 A 的行向量表達式 $A = [\,\mathbf{a}_1 \quad \mathbf{a}_2 \quad \cdots \quad \mathbf{a}_n\,]$，$\mathbf{a}_i \in \mathbb{R}^m$，則:

$$G = A^T A = \begin{bmatrix} \mathbf{a}_1^T \\ \mathbf{a}_2^T \\ \vdots \\ \mathbf{a}_n^T \end{bmatrix} [\,\mathbf{a}_1 \quad \mathbf{a}_2 \quad \cdots \quad \mathbf{a}_n\,] = \begin{bmatrix} \mathbf{a}_1^T\mathbf{a}_1 & \mathbf{a}_1^T\mathbf{a}_2 & \cdots & \mathbf{a}_1^T\mathbf{a}_n \\ \mathbf{a}_2^T\mathbf{a}_1 & \mathbf{a}_2^T\mathbf{a}_2 & \cdots & \mathbf{a}_2^T\mathbf{a}_n \\ & & & \\ \mathbf{a}_n^T\mathbf{a}_1 & \mathbf{a}_n^T\mathbf{a}_2 & \cdots & \mathbf{a}_n^T\mathbf{a}_n \end{bmatrix}$$

In [23]:

```
import numpy as np

A = np.random.randint(0,5, (2,2))

B = np.dot(A.T, A)
print(A)
print(B)
```

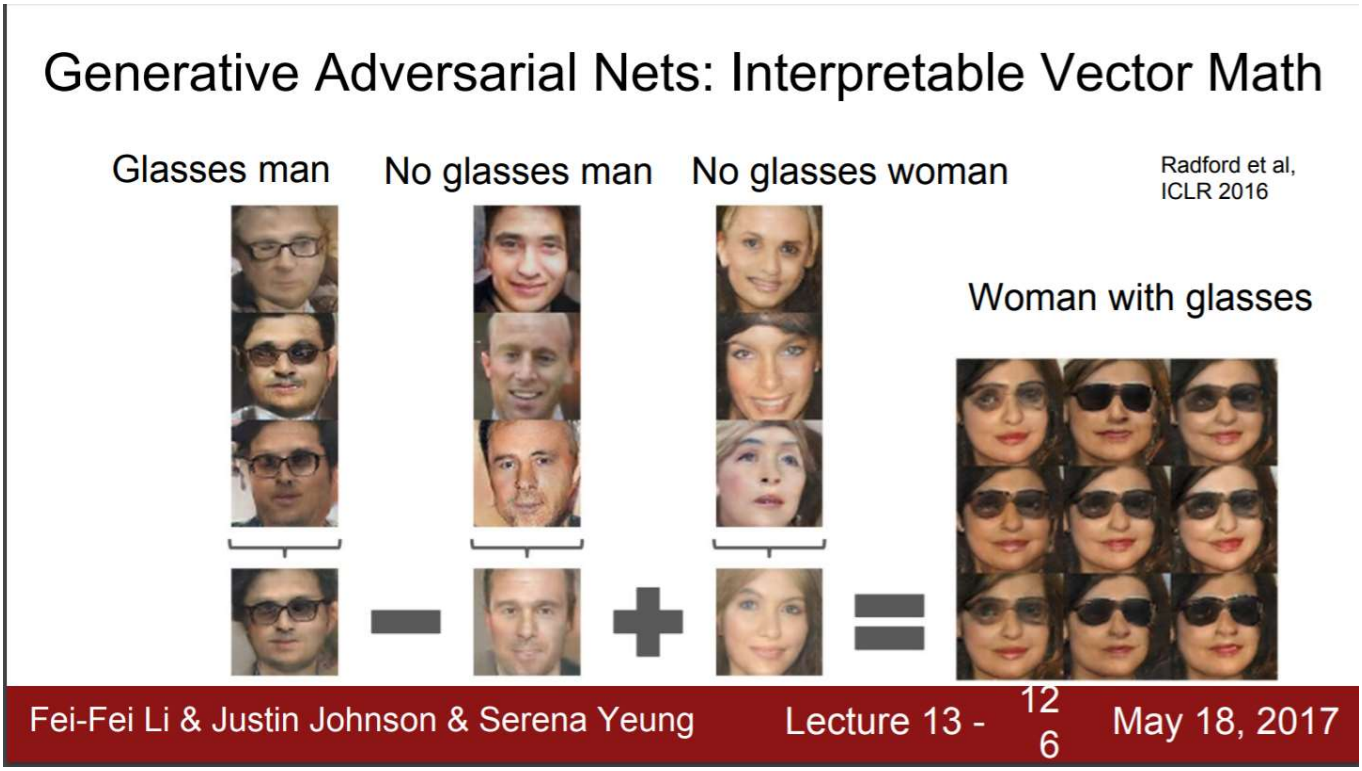
```
[[1 1]
 [3 4]]
[[10 13]
 [13 17]]
```

In [2]:

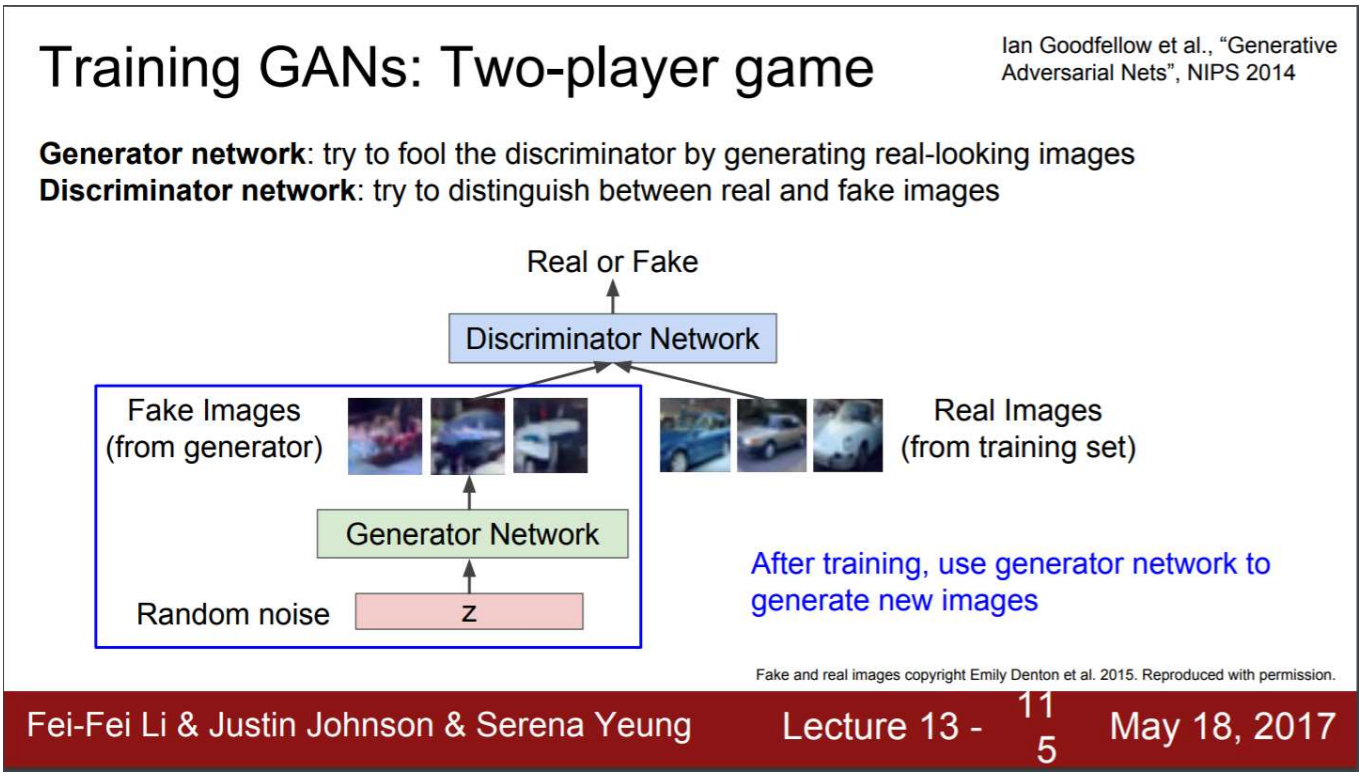
```
        parser.add_argument('--content_layers', nargs='+', type=str, default=['conv4_2'], help=
'VGG19 layers used for content loss')
        parser.add_argument('--style_layers', nargs='+', type=str, default=['relu1_1', 'relu2_1'
, 'relu3_1', 'relu4_1', 'relu5_1'],
                            help='VGG19 layers used for style loss')

        """https://github.com/hwalsuklee/tensorflow-style-transfer/blob/master/style_transfer.p
y"""
        """ compute loss """
        L_content = 0
        L_style = 0
        for id in self.Fs:
            if id in self.CONTENT_LAYERS:
                ## content loss ##

                F = self.Fs[id]            # content feature of x
                P = self.Ps[id]            # content feature of p

                _, h, w, d = F.get_shape() # first return value is batch size (must be one)
                N = h.value*w.value        # product of width and height
                M = d.value                # number of filters

                w = self.CONTENT_LAYERS[id]# weight for this layer

                # You may choose different normalization constant
                if self.content_loss_norm_type==1:
                    L_content += w * tf.reduce_sum(tf.pow((F-P), 2)) / 2 # original paper
                elif self.content_loss_norm_type == 2:
                    L_content += w * tf.reduce_sum(tf.pow((F-P), 2)) / (N*M) #artistic style tra
nsfer for videos
                elif self.content_loss_norm_type == 3: # this is from https://github.com/cysmit
h/neural-style-tf/blob/master/neural_style.py
                    L_content += w * (1. / (2. * np.sqrt(M) * np.sqrt(N))) * tf.reduce_sum(tf.po
w((F - P), 2))

            elif id in self.STYLE_LAYERS:
                ## style loss ##

                F = self.Fs[id]

                _, h, w, d = F.get_shape()  # first return value is batch size (must be one)
                N = h.value * w.value       # product of width and height
                M = d.value                 # number of filters

                w = self.STYLE_LAYERS[id]   # weight for this layer

                G = self._gram_matrix(F)    # style feature of x
                A = self.As[id]             # style feature of a

                L_style += w * (1. / (4 * N ** 2 * M ** 2)) * tf.reduce_sum(tf.pow((G-A), 2))
```

```
  File "<ipython-input-2-e8223f7ccc10>", line 2
    L_content = 0
    ^
IndentationError: unexpected indent
```

CNN GAN



GAN Training



Sequential Model

- Sequence of words in an English sentence
- Acoustic features at successive time frames in speech recognition
- Successive frames in video classification
- Rainfall measurements on successive days in Hong Kong
- Daily values of current exchange rate
- Nucleotide base pairs in a strand of DNA
- **Instead of making independent predictions on samples, assume the dependency among samples and make a sequence of decisions for sequential samples**

Modeling sequential data

- Use the chain rule to express the joint distribution for a sequence of observations

$$p(\mathbf{x}_1, \ldots, \mathbf{x}_T) = \prod_{t=1}^{T} p(\mathbf{x}_t | \mathbf{x}_1, \ldots, \mathbf{x}_{t-1})$$

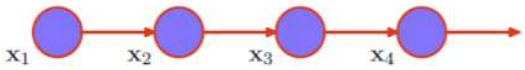
- Impractical to consider general dependence of future dependence on all previous observations $p(\mathbf{x}_t | \mathbf{x}_{t-1}, \ldots, \mathbf{x}_0)$
  - Complexity would grow without limit as the number of observations increases
- It is expected that recent observations are more informative than more historical observations in predicting future values

Markov model

Markov models

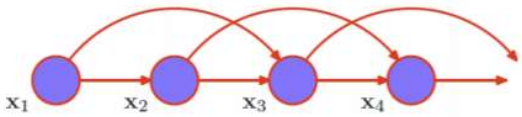
- Markov models assume dependence on most recent observations
- First-order Markov model

$$p(\mathbf{x}_1, \ldots, \mathbf{x}_T) = \prod_{t=1}^{T} p(\mathbf{x}_t|\mathbf{x}_{t-1})$$

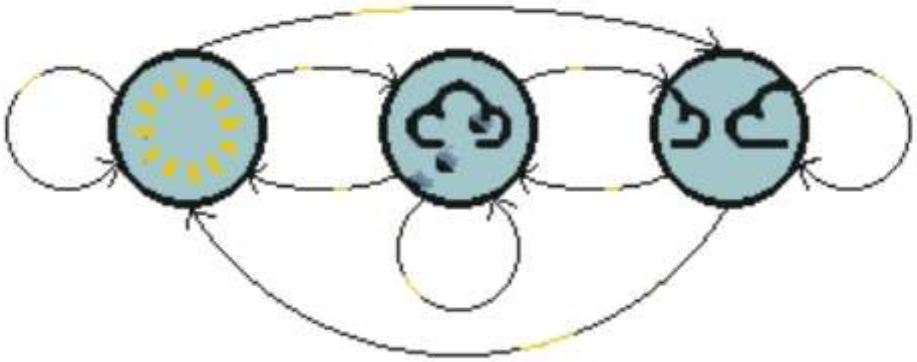


- Second-order Markov model

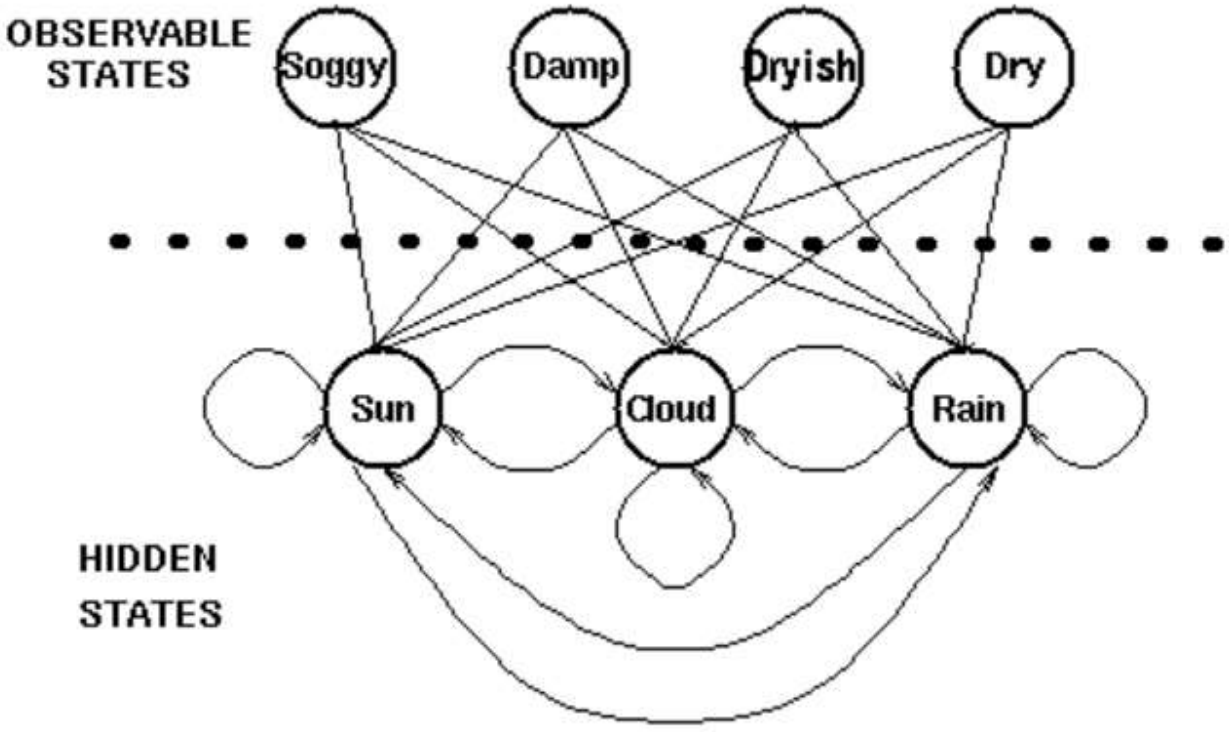
$$p(\mathbf{x}_1, \ldots, \mathbf{x}_T) = \prod_{t=1}^{T} p(\mathbf{x}_t|\mathbf{x}_{t-1}, \mathbf{x}_{t-2})$$



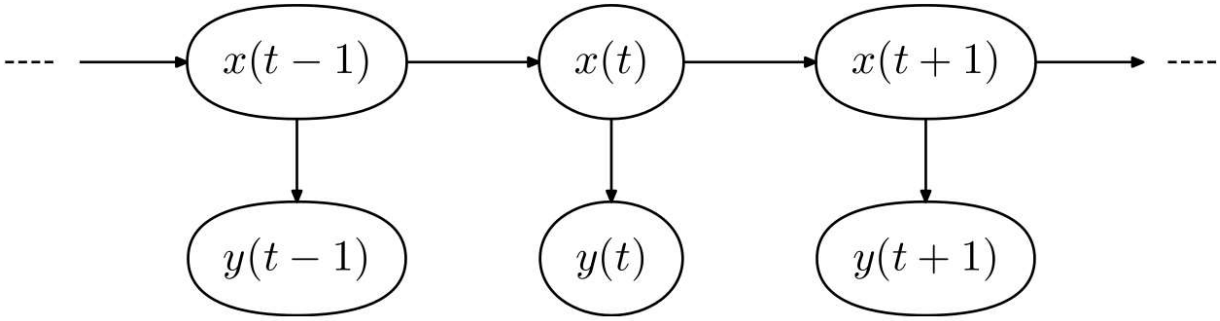
Markov model



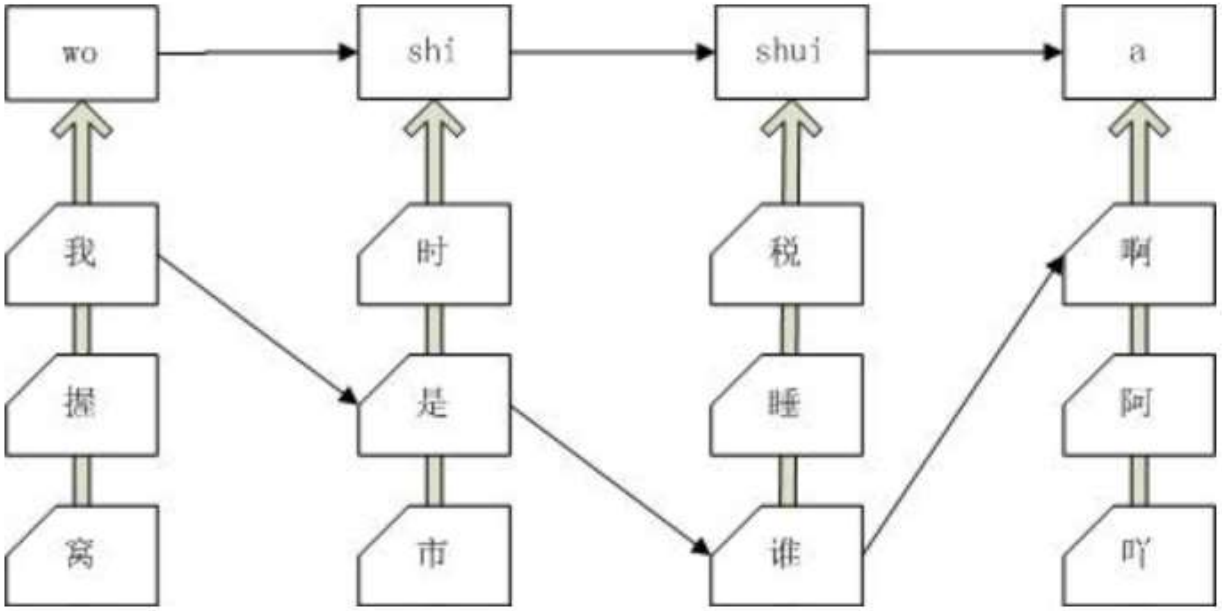
Hidden Markov model



Hidden Markov model

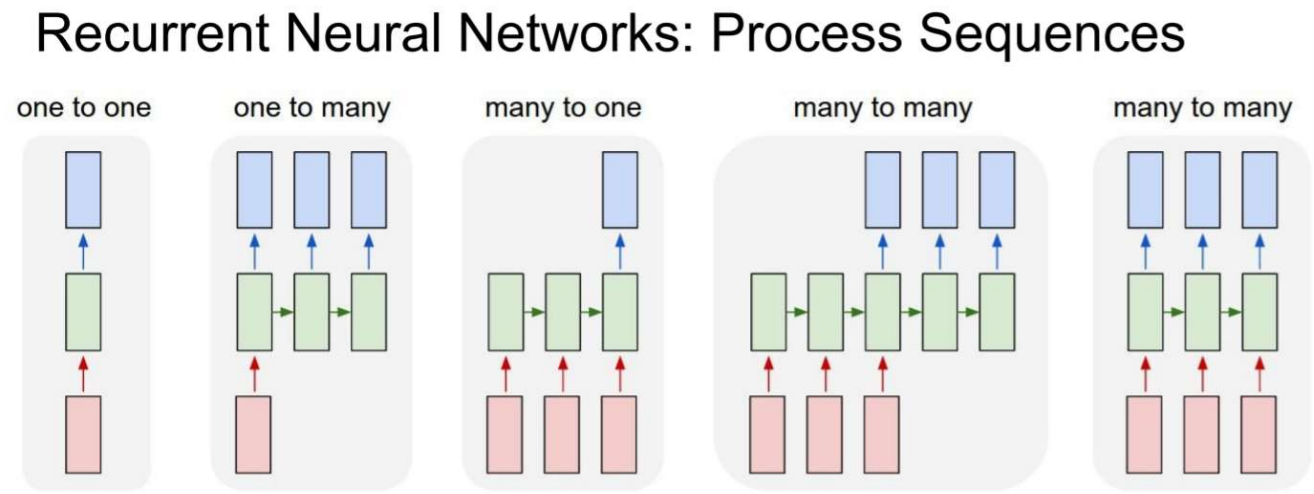


HMM 输入法应用



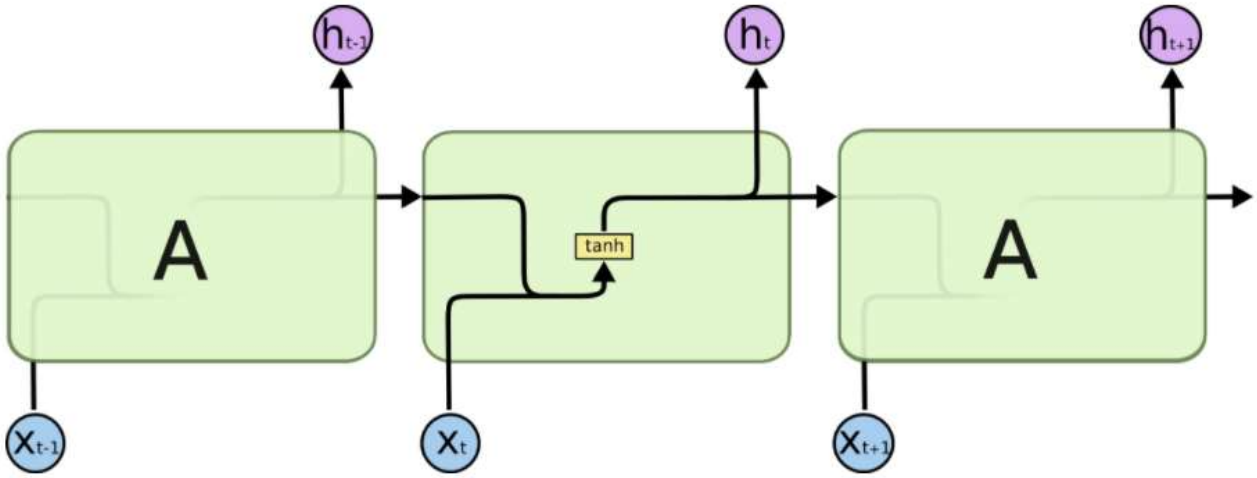
RNN

- image captioning
- sentiment classification
- machine translation
- video classification on frame level



RNN

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



LSTM

Colah LSTM：http://colah.github.io/posts/2015-08-Understanding-LSTMs/ (http://colah.github.io/posts/2015-08-Understanding-LSTMs/)

Colah中文版: https://www.yunaitong.cn/understanding-lstm-networks.html (https://www.yunaitong.cn/understanding-lstm-networks.html)

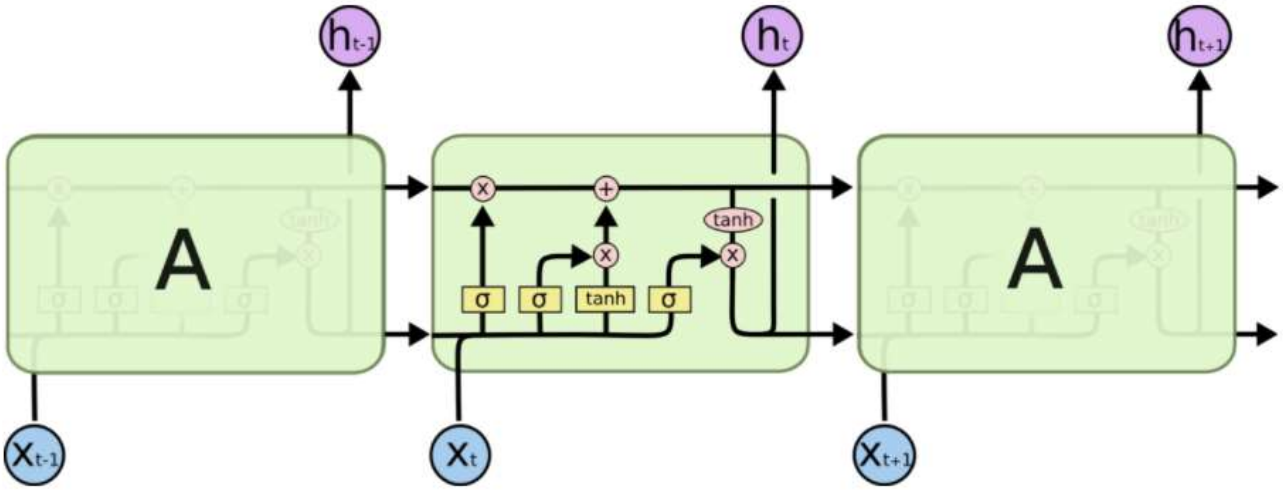


Image Captioning

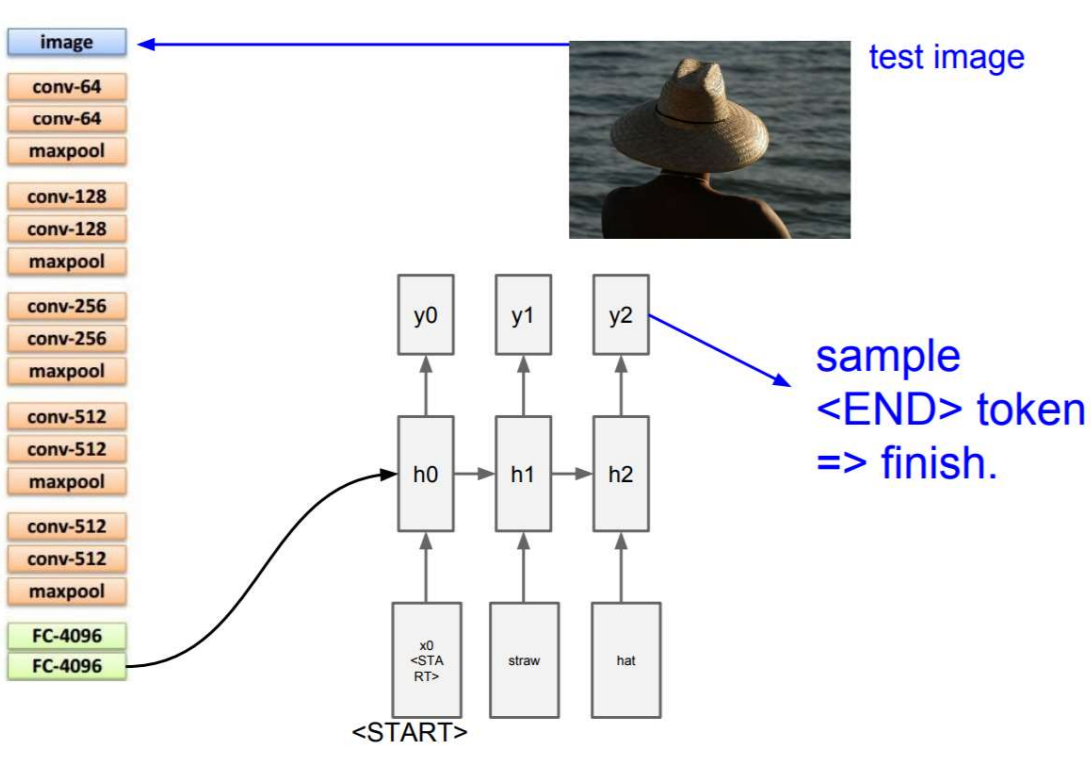


Image Captioning: Example Results

Captions generated using neuraltalk2
All images are CC0 Public domain:
cat suitcase, cat tree, dog, bear,
surfers, tennis, giraffe, motorcycle

A cat sitting on a suitcase on the floor

A cat is sitting on a tree branch

A dog is running in the grass with a frisbee

A white teddy bear sitting in the grass

Two people walking on the beach with surfboards

A tennis player in action on the court

Two giraffes standing in a grassy field

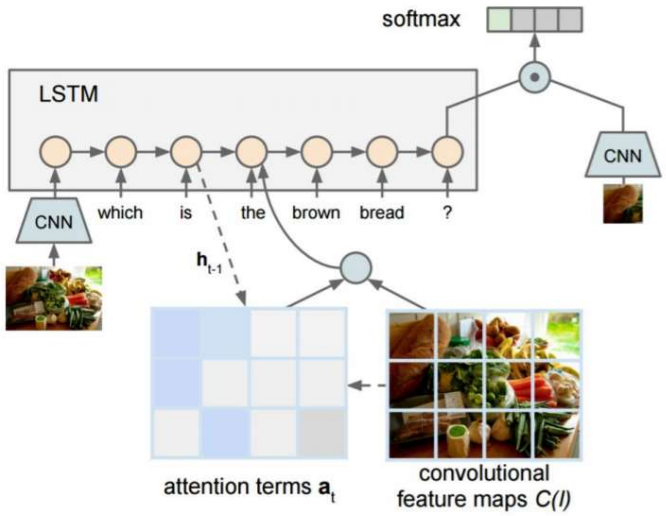
A man riding a dirt bike on a dirt track

Fei-Fei Li & Justin Johnson & Serena Yeung Lecture 10 - 75 May 4, 2017

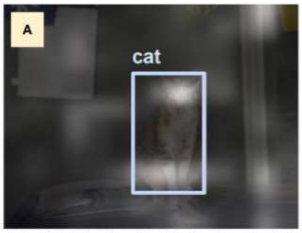
```c
static void do_command(struct seq_file *m, void *v)
{
  int column = 32 << (cmd[2] & 0x80);
  if (state)
    cmd = (int)(int_state ^ (in_8(&ch->ch_flags) & Cmd) ? 2 : 1);
  else
    seq = 1;
  for (i = 0; i < 16; i++) {
    if (k & (1 << 1))
      pipe = (in_use & UMXTHREAD_UNCCA) +
        ((count & 0x00000000fffffff8) & 0x000000f) << 8;
    if (count == 0)
      sub(pid, ppc_md.kexec_handle, 0x20000000);
    pipe_set_bytes(i, 0);
  }
  /* Free our user pages pointer to place camera if all dash */
  subsystem_info = &of_changes[PAGE_SIZE];
  rek_controls(offset, idx, &soffset);
  /* Now we want to deliberately put it to device */
  control_check_polarity(&context, val, 0);
  for (i = 0; i < COUNTER; i++)
    seq_puts(s, "policy ");
}
```

Generated C code

Visual Question Answering: RNNs with Attention



Zhu et al, "Visual 7W: Grounded Question Answering in Images", CVPR 2016
Figures from Zhu et al, copyright IEEE 2016. Reproduced for educational purposes.



What kind of animal is in the photo?
A cat.

Why is the person holding a knife?
To cut the cake with.

RNN中为什么要采用tanh而不是ReLu作为激活函数？

明确的提到的：

Recent research on deep feedforward networks has also produced some impressive results [19, 3] and there is now a consensus that for deep networks, rectified linear units (ReLUs) are easier to train than the logistic or tanh units that were used for many years [27, 40]. At first sight, ReLUs seem inappropriate for RNNs because they can have very large outputs so they might be expected to be far more likely to explode than units that have bounded values. A second aim of this paper is to explore whether ReLUs can be made to work well in RNNs and whether the ease of optimizing them in feedforward nets transfers to RNNs.

也就是说在RNN中直接把激活函数换成ReLU会导致非常大的输出值。为了讲清楚这一点，我们先用同上面相似的符号把原始的RNN表示出来：

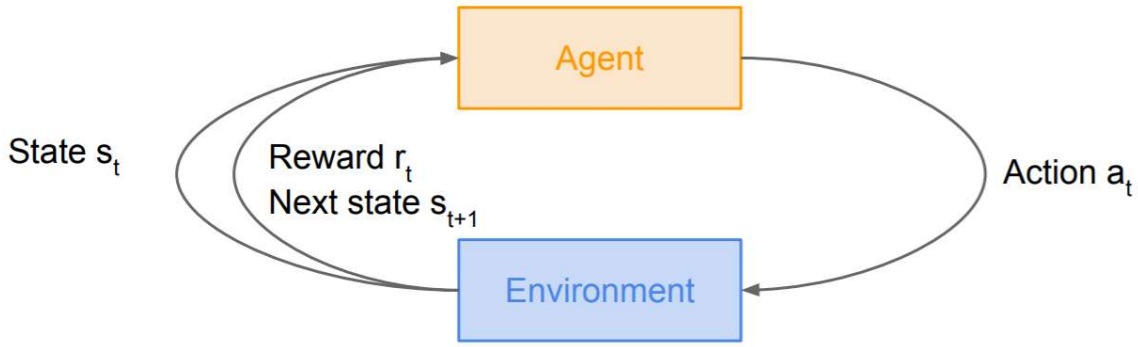
$$a_i = W f_{i-1} + U x_i + b_i \ ,$$

$$f_i = f[a_i]$$

在这个表示中，RNN每个阶段的输入是 x_i ，**和CNN每一层使用独立的参数 W_i 不同，原始的RNN在每个阶段都共享一个参数 W** 。如果我们假设从某一层开始输入 x_i 和偏置 b_i 都为0，那么最后得到的输出就是 $f[W \ldots [W f[W f[W f_i]]]]$ ，**这在某种程度上相当于对参数矩阵 W 作连乘**，很显然，只要 W 有一个大于1的特征值，在经过若干次连乘后都会导致结果是一个数值非常庞大的矩阵。

Reinforcement Learning

Reinforcement Learning



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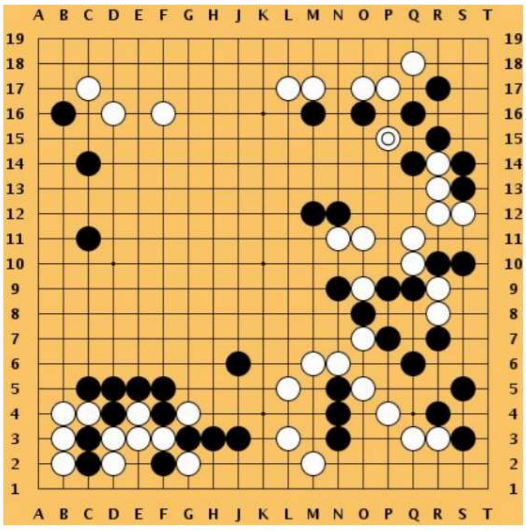
Go



Objective: Win the game!

State: Position of all pieces
Action: Where to put the next piece down
Reward: 1 if win at the end of the game, 0 otherwise

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Q-learning

Q-learning demo 英文版：http://mnemstudio.org/path-finding-q-learning-tutorial.htm (http://mnemstudio.org/path-finding-q-learning-tutorial.htm)

Q-learning demo 中文版: http://www.cnblogs.com/stevenbush/p/3359603.html (http://www.cnblogs.com/stevenbush/p/3359603.html)

算法 1.1 *(Q-learning 算法)*

Step 1 给定参数 γ 和 *reward* 矩阵 R.

Step 2 令 $Q := \mathbf{0}$.

Step 3 *For each episode:*

3.1 随机选择一个初始的状态 s.

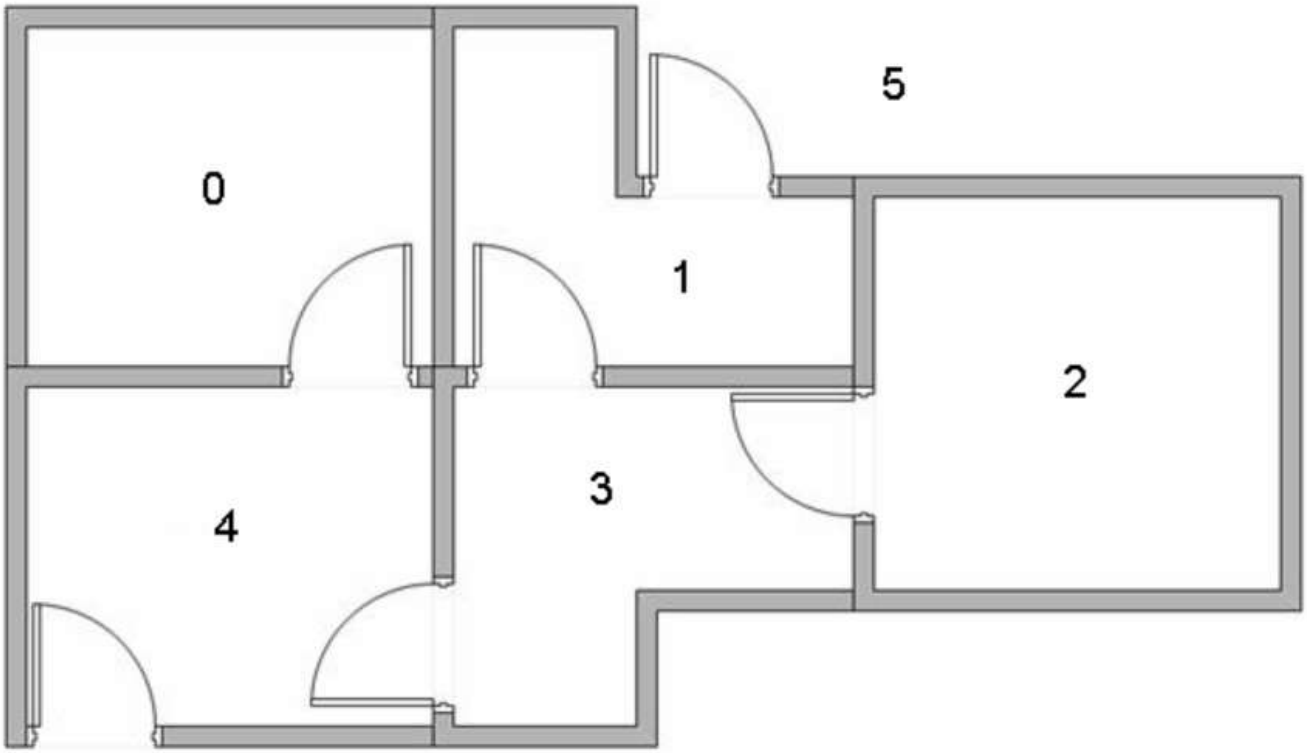
3.2 若未达到目标状态, 则执行以下几步

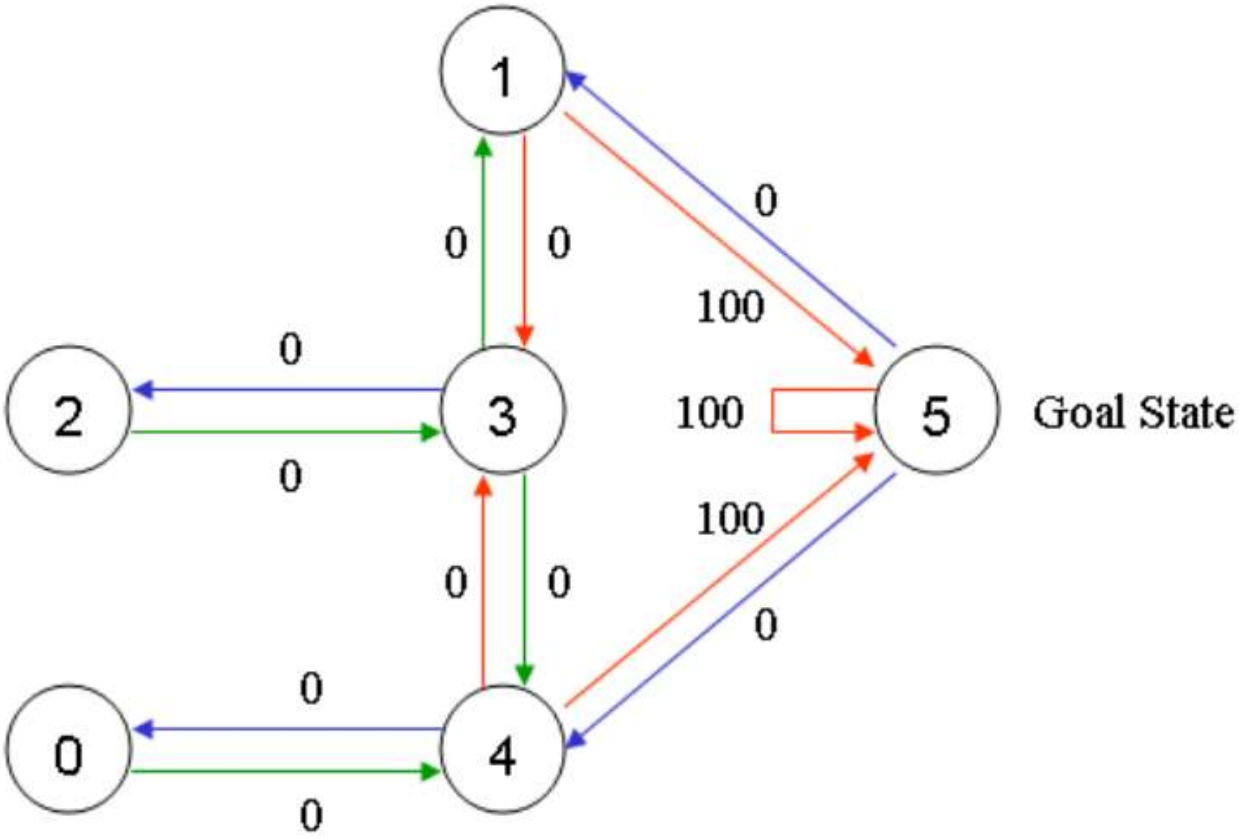
(1) 在当前状态 s 的所有可能行为中选取一个行为 a.

(2) 利用选定的行为 a, 得到下一个状态 $\widetilde{s}$.

(3) 按照 *(1.1)* 计算 $Q(s, a)$.

(4) 令 $s := \widetilde{s}$.


0
1
2
3
4
5

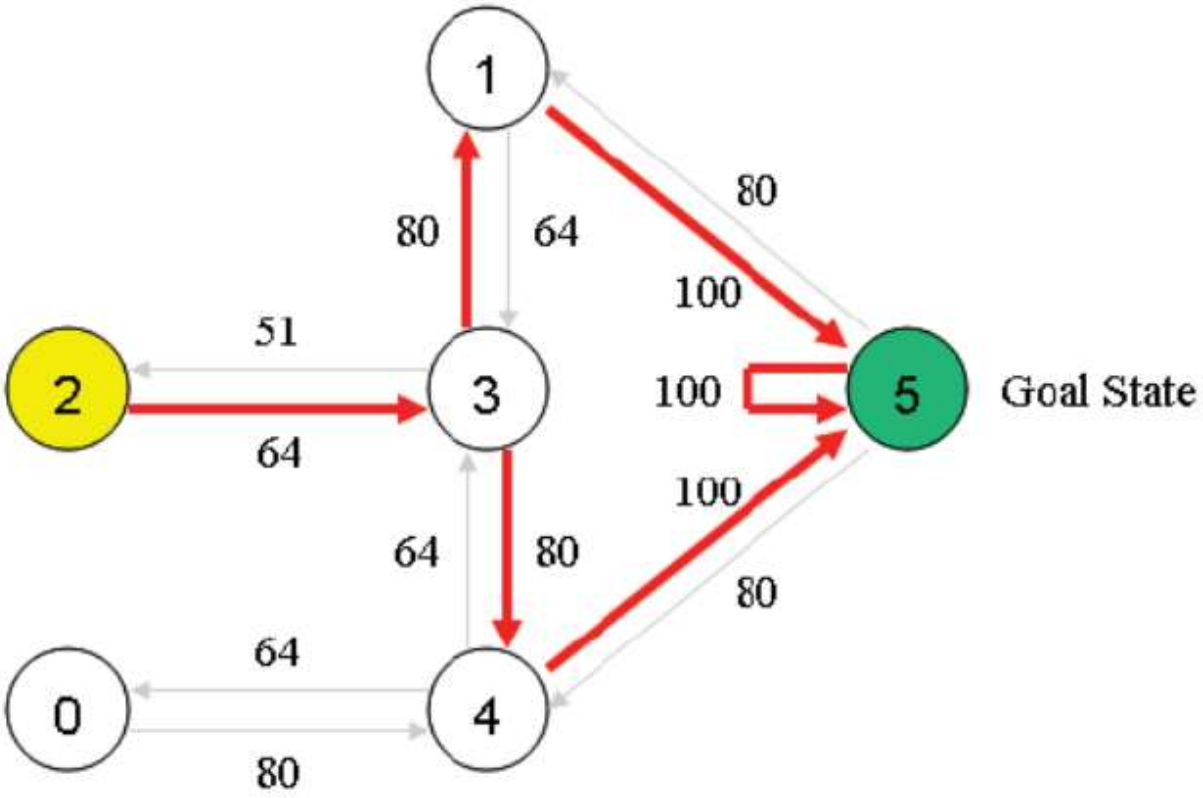

1
2
3
4
5
0
Goal State
0
0
0
100
0
0
100
100
0
0
0
0
0
0

$$R = \begin{array}{c} \\ \text{State} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{cccccc} \multicolumn{6}{c}{\text{Action}} \\ 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{bmatrix} -1 & -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & -1 & 0 & -1 & 100 \\ -1 & -1 & -1 & 0 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 100 \\ -1 & 0 & -1 & -1 & 0 & 100 \end{bmatrix} \end{array}$$

$$Q(1,5) = R(1,5) + 0.8 * \max\{Q(5,1), Q(5,4), Q(5,5)\} = 100 + 0.8 * \max\{0,0,0\} = 100$$

$$Q = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 100 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array}$$

$$Q = \begin{array}{c} \\ 0 \\ 1 \\ 2 \\ 3 \\ 4 \\ 5 \end{array} \begin{array}{c} \begin{array}{cccccc} 0 & 1 & 2 & 3 & 4 & 5 \end{array} \\ \begin{bmatrix} 0 & 0 & 0 & 0 & 400 & 0 \\ 0 & 0 & 0 & 320 & 0 & 500 \\ 0 & 0 & 0 & 320 & 0 & 0 \\ 0 & 400 & 256 & 0 & 400 & 0 \\ 320 & 0 & 0 & 320 & 0 & 500 \\ 0 & 400 & 0 & 0 & 400 & 500 \end{bmatrix} \end{array}$$



2. $Q(S,A) \leftarrow (1-\alpha) * Q(S,A) + \alpha * [R + \gamma * max_a Q(S',a)]$

这个就是Q-learning的训练公式了。其中**α**为**学习速率**（learning rate），**γ**为**折扣因子**（discount factor）。根据公式可以看出，**学习速率α越大，保留之前训练的效果就越少**。折扣因子γ越大，$max_a Q(S',a)$ 所起到的作用就越大。但 $max_a Q(S',a)$ 指什么呢？

小鸟在对状态进行更新时，会考虑到**眼前利益**（R），和**记忆中的利益**（ $max_a Q(S',a)$ ）。

$max_a Q(S',a)$ 指的便是**记忆中的利益**。它是指小鸟记忆里下一个状态 S' 的动作中效用值的最大值。如果小鸟之前在下一个状态 S' 的某个动作上吃过甜头（选择了某个动作之后获得了50的奖赏），那么它就更希望提早地得知这个消息，以便下回在状态 S 可以通过选择正确的动作继续进入这个吃甜头的状态 S' 。

可以看出，γ越大，小鸟就会越重视以往经验，越小，小鸟只重视眼前利益（R）。

In [2]:

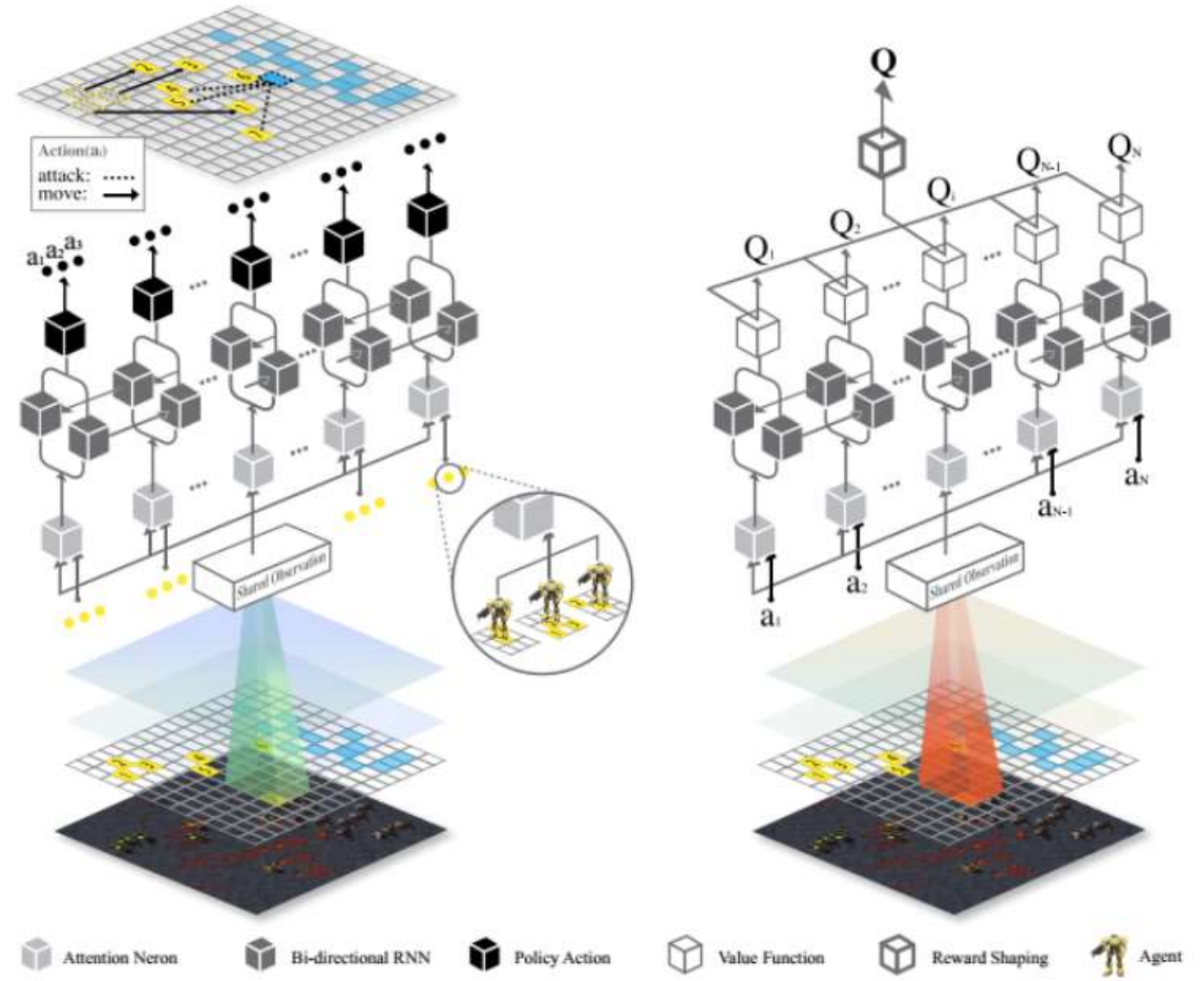
```
from IPython.display import HTML

# Youtube
HTML('<iframe width="720" height="480" src="Bidirectionally-Coordinated Nets (BiCNet) for Playing StarCraft Combats.mp4?rel=0&amp;controls=0&amp;showinfo=0" frameborder="0" allowfullscreen></iframe>')
```

Out[2]:

Mastering StarCraft with AI

Researchers from Alibaba and University College London developed a deep learning-based system that learned how to execute a number of strategies for the popular real-time strategy game StarCraft.



(a) Multiagent policy networks with grouping (b) Multiagent Q networks with reward shaping

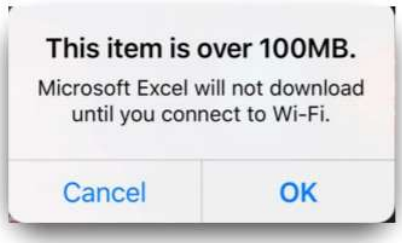
Figure 1: Bidirectionally-Coordinated Net (BiCNet).

ML问题点

- size
- time
- energy

The first Challenge: Model Size

Hard to distribute large models through over-the-air update



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The Second Challenge: Speed

	Error rate	Training time
ResNet18:	10.76%	2.5 days
ResNet50:	7.02%	5 days
ResNet101:	6.21%	1 week
ResNet152:	6.16%	1.5 weeks

Such long training time limits ML researcher's productivity

The Third Challenge: Energy Efficiency

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AlphaGo: 1920 CPUs and 280 GPUs,
$3000 electric bill per game

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on mobile: drains battery
on data-center: increases TCO

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