TensolFlow

base

constant

Tensorという形式でデータを保持する。

c: Tensor ("Const_2:0", shape=(2, 2), dtype=float32)

In [1]:

```
import tensorflow as tf
import numpy as np

# それぞれ定数を定義
a = tf.constant(1)
b = tf.constant(2, dtype=tf.float32, shape=[3, 2])
c = tf.constant(np.arange(4), dtype=tf.float32, shape=[2, 2])

print('a:', a)
print('b:', b)
print('c:', c)

C:\text{YProgramData\text{Anaconda3\text{Ylib\text{Ysite}-packages\text{Yh5py\text{Y}_init_.py:36: 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
a: Tensor("Const:0", shape=(), dtype=int32)
b: Tensor("Const_1:0", shape=(3, 2), dtype=float32)
```

Session.run(a)すると、runしたノードaに関連するノードをすべて計算し、出力される。

```
In [2]:
```

placeholder

In [3]:

```
# プレースホルダーを定義
x = tf.placeholder(dtype=tf.float32, shape=[None, 3])
print('x:', x)
sess = tf.Session()
X = np.random.rand(2,3)
print('X(numpy):', X)
```

```
x: Tensor("Placeholder:0", shape=(?, 3), dtype=float32)
X(numpy): [[0.83370985 0.4860043 0.98081105]
[0.06851552 0.4632204 0.93428418]]
```

In [4]:

```
# プレースホルダにX[0]を入力
# shapeを(3,)から(1,3)にするためreshape
print('x:', sess.run(x, feed_dict={x:X[0].reshape(1,-1)}))
```

```
x: [[0.83370984 0.4860043 0.98081106]]
```

In [5]:

```
# プレースホルダにX[1]を入力 print('x:', sess.run(x, feed_dict=\{x:X[1].reshape(1,-1)\}))
```

```
x: [[0.06851552 0.4632204 0.9342842 ]]
```

variables

In [6]:

```
# 定数を定義
a = tf. constant (10)
print('a:', a)
# 変数を定義
x = tf. Variable(1)
print('x:', x)
calc_{op} = x * a
print(calc_op)
# xの値を更新
update_x = tf. assign(x, calc_op)
print(update_x)
a: Tensor ("Const_3:0", shape=(), dtype=int32)
WARNING:tensorflow:From C:\(\frac{4}{2}\)ProgramData\(\frac{4}{2}\)Anaconda3\(\frac{4}{1}\)ib\(\frac{4}{2}\)site-packages\(\frac{4}{2}\)tensorflow\(\frac{4}{2}\)pyth
on\forall framework\forall op_def_library.py:263: colocate_with (from tensorflow.python.framewor
k.ops) is deprecated and will be removed in a future version.
Instructions for updating:
Colocations handled automatically by placer.
x: <tf. Variable 'Variable:0' shape=() dtype=int32_ref>
Tensor("mul:0", shape=(), dtype=int32)
Tensor("Assign:0", shape=(), dtype=int32_ref)
In [7]:
sess = tf. Session()
```

```
# 変数の初期化
init = tf.global_variables_initializer()
sess.run(init)
print(sess.run(x))
sess. run (update_x)
print(sess.run(x))
sess.run(update x)
print(sess.run(x))
```

10 100

線形回帰

In [32]:

```
import numpy as np import tensorflow as tf import matplotlib.pyplot as plt iters_num = 300 plot_interval = 10 # データを生成 n = 100 x = np. random. randn (n) #小数の乱数 d = 3 * x + 2 # ノイズを加える noise = 0.3 d = d + noise * np. random. randn (n) print(x)
```

```
\lceil -1.54694948 - 1.51921087 \ 1.57037751 \ 0.44242968 \ 0.93837436 - 1.12738744
-1. 30564086 -1. 15317279 0. 64632078
                              0. 28184709 0. 16976725 -0. 04971216
 1. 94835533 -0. 06157433 0. 21539213 -1. 25684201 0. 4468912
                                                  1.70219375
 0. 21418637 -0. 55039244 -1. 18742887
                              1. 16456899 -0. 61855652
                                                  0. 243373
 1. 7951167 -1. 18503724 -0. 43109097 1. 1094946
                                         0. 45238567 0. 9242078
 0.71382974 1.13459924 -0.70918891 -0.48249614 -1.26960039 0.13389292
 0. 29250417 -0. 11003267 -0. 5317991
                               1.94502461
                                        0.46864993 2.49999654
 1. 19651059 0. 69394048 -0. 39563418 0. 50650395 0. 244284
                                                  1. 91082568
 0. 53858643 -1. 32792827 -0. 74594445 0. 98002203 0. 24095125 -1. 07468647
 1. 42321709 0. 9552136
                     1. 76418517 2. 0902926
                     1. 36217312 -0. 67305506 0. 92075485 1. 55413754
-1.05193381 -0.35954757 -0.84891241 0.91933351 -1.14127111 0.64555559
 0. 05235331 -0. 16250072 -1. 20193001 -1. 37029845
-2. 10189543 1. 0401296
-1.42429152
-0.96081795 -0.49691695 -0.76544498 -0.18550394
```

In [33]:

```
# 入力値(プレースホルダー)
xt = tf.placeholder(tf.float32)
dt = tf.placeholder(tf.float32)

# 最適化の対象の変数を初期化
W = tf.Variable(tf.zeros([1]))
b = tf.Variable(tf.zeros([1]))
y = W * xt + b

print(xt)
print(dt)
```

```
Tensor ("Placeholder_48:0", dtype=float32)
Tensor ("Placeholder_49:0", dtype=float32)
```

In [34]:

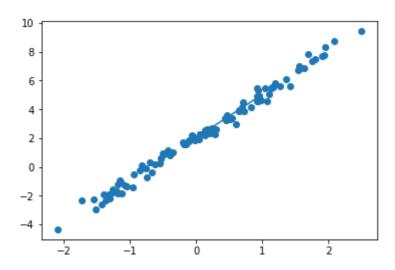
```
# 誤差関数 平均2乗誤差
loss = tf.reduce_mean(tf.square(y - dt))#reduce_meanは平均処理
optimizer = tf.train.GradientDescentOptimizer(0.1)#勾配降下法、学習率0.1、optimizer最適化アルゴリズム
train = optimizer.minimize(loss)#損失関数の最小化

# 初期化
init = tf.global_variables_initializer()
sess = tf.Session()
sess.run(init)
```

In [35]:

```
# 作成したデータをトレーニングデータとして準備
x_{train} = x. reshape(-1, 1)
d_train = d. reshape (-1, 1) #訓練用ラベル
# トレーニング
for i in range(iters_num):#反復回数
    sess.run(train, feed_dict={xt:x_train, dt:d_train})#訓練実行
    if (i+1) % plot_interval == 0:
       loss_val = sess.run(loss, feed_dict={xt:x_train, dt:d_train})
       W_val = sess.run(W)
       b_val = sess. run(b)
       _____rint('Generation: ' + str(i+1) + '. 誤差 = ' + str(loss_val))
print(W_val)
print(b_val)
# 予測関数
def predict(x):
    return W_val * x + b_val
fig = plt. figure()
subplot = fig. add_subplot(1, 1, 1)
plt. scatter(x, d)
linex = np. linspace (0, 1, 2)
liney = predict(linex)
subplot.plot(linex, liney)
plt.show()
```

```
Generation: 10. 誤差 = 0.16891193
Generation: 20. 誤差 = 0.10064526
Generation: 30. 誤差 = 0.10034347
Generation: 40. 誤差 = 0.10034214
Generation: 50. 誤差 = 0.100342125
Generation: 60. 誤差 = 0.10034214
Generation: 70. 誤差 = 0.10034214
Generation: 80. 誤差 = 0.10034214
Generation: 90. 誤差 = 0.10034214
Generation: 100. 誤差 = 0.10034214
Generation: 110. 誤差 = 0.10034214
Generation: 120. 誤差 = 0.10034214
Generation: 130. 誤差 = 0.10034214
Generation: 140. 誤差 = 0.10034214
Generation: 150. 誤差 = 0.10034214
Generation: 160. 誤差 = 0.10034214
Generation: 170. 誤差 = 0.10034214
Generation: 180. 誤差 = 0.10034214
Generation: 190. 誤差 = 0.10034214
Generation: 200. 誤差 = 0.10034214
Generation: 210. 誤差 = 0.10034214
Generation: 220. 誤差 = 0.10034214
Generation: 230. 誤差 = 0.10034214
Generation: 240. 誤差 = 0.10034214
Generation: 250. 誤差 = 0.10034214
Generation: 260. 誤差 = 0.10034214
Generation: 270. 誤差 = 0.10034214
Generation: 280. 誤差 = 0.10034214
Generation: 290. 誤差 = 0.10034214
Generation: 300. 誤差 = 0.10034214
[2.9889605]
[2. 041801]
```

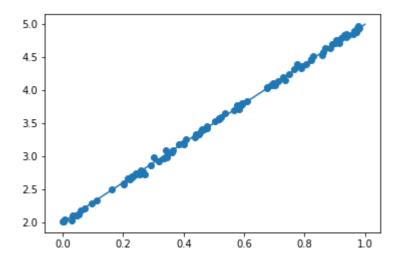


• noiseの値を変更しよう(noise 0.3を0.03に変更)

In [36]:

```
iters num = 300
plot interval = 10
# データを生成
n = 100
x = np. random. rand(n)
d = 3 * x + 2
# ノイズを加える
noise = 0.03
d = d + noise * np. random. randn(n)
# 入力値
xt = tf. placeholder (tf. float32)
dt = tf.placeholder(tf.float32)
# 最適化の対象の変数を初期化
W = tf. Variable(tf. zeros([1]))
b = tf. Variable(tf. zeros([1]))
y = W * xt + b
# 誤差関数 平均2乗誤差
loss = tf. reduce_mean(tf. square(y - dt))
optimizer = tf. train. GradientDescentOptimizer (0.1)
train = optimizer.minimize(loss)
#初期化
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
# 作成したデータをトレーニングデータとして準備
x_{train} = x. reshape(-1, 1)
d_{train} = d. reshape (-1, 1)
# トレーニング
for i in range(iters num):
    sess.run(train, feed_dict={xt:x_train, dt:d_train})
    if (i+1) % plot interval == 0:
        loss_val = sess.run(loss, feed_dict={xt:x_train, dt:d_train})
       W val = sess.run(W)
       b_val = sess. run(b)
       print('Generation: ' + str(i+1) + '. 誤差 = ' + str(loss_val))
print(W val)
print(b val)
# 予測関数
def predict(x):
    return W_val * x + b_val
fig = plt. figure()
subplot = fig. add\_subplot(1, 1, 1)
plt. scatter (x, d)
linex = np. linspace (0, 1, 2)
liney = predict(linex)
subplot.plot(linex, liney)
plt.show()
```

```
Generation: 10. 誤差 = 0.17103556
Generation: 20. 誤差 = 0.10534405
Generation: 30. 誤差 = 0.07941533
Generation: 40. 誤差 = 0.05995369
Generation: 50. 誤差 = 0.045305546
Generation: 60. 誤差 = 0.034280248
Generation: 70. 誤差 = 0.025981836
Generation: 80. 誤差 = 0.019735824
Generation: 90. 誤差 = 0.01503463
Generation: 100. 誤差 = 0.011496145
Generation: 110. 誤差 = 0.008832831
Generation: 120. 誤差 = 0.0068282373
Generation: 130. 誤差 = 0.005319431
Generation: 140. 誤差 = 0.0041837976
Generation: 150. 誤差 = 0.003329029
Generation: 160. 誤差 = 0.0026856798
Generation: 170. 誤差 = 0.002201438
Generation: 180. 誤差 = 0.0018369699
Generation: 190. 誤差 = 0.0015626396
Generation: 200. 誤差 = 0.001356159
Generation: 210. 誤差 = 0.0012007478
Generation: 220. 誤差 = 0.0010837722
Generation: 230. 誤差 = 0.0009957276
Generation: 240. 誤差 = 0.0009294575
Generation: 250. 誤差 = 0.00087957934
Generation: 260. 誤差 = 0.0008420385
Generation: 270. 誤差 = 0.0008137801
Generation: 280. 誤差 = 0.000792513
Generation: 290. 誤差 = 0.00077650486
Generation: 300. 誤差 = 0.0007644552
[2. 9944782]
[1.9983674]
```

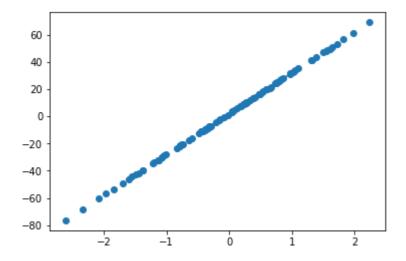


• dの数値を変更しよう (d=3x+2をd=30x+2に変更)

In [13]:

```
iters num = 300
plot interval = 10
# データを生成
n = 100
x = np. random. randn(n)
d = 30 * x + 2
# ノイズを加える
noise = 0.3
d = d + noise * np. random. randn(n)
# 入力値
xt = tf. placeholder (tf. float32)
dt = tf.placeholder(tf.float32)
# 最適化の対象の変数を初期化
W = tf. Variable(tf. zeros([1]))
b = tf. Variable(tf. zeros([1]))
y = W * xt + b
# 誤差関数 平均2乗誤差
loss = tf. reduce_mean(tf. square(y - dt))
optimizer = tf. train. GradientDescentOptimizer (0.1)
train = optimizer.minimize(loss)
#初期化
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
# 作成したデータをトレーニングデータとして準備
x_{train} = x. reshape(-1, 1)
d_{train} = d. reshape (-1, 1)
# トレーニング
for i in range(iters num):
    sess.run(train, feed_dict={xt:x_train, dt:d_train})
    if (i+1) % plot interval == 0:
        loss_val = sess.run(loss, feed_dict={xt:x_train, dt:d_train})
       W val = sess.run(W)
       b val = sess.run(b)
       print('Generation: ' + str(i+1) + '. 誤差 = ' + str(loss_val))
print(W val)
print(b val)
# 予測関数
def predict(x):
    return W_val * x + b_val
fig = plt. figure()
subplot = fig. add\_subplot(1, 1, 1)
plt. scatter (x, d)
linex = np. linspace (0, 1, 2)
liney = predict(linex)
subplot.plot(linex, liney)
plt.show()
```

Generation: 10. 誤差 = 8.645359 Generation: 20. 誤差 = 0.1549129 Generation: 30. 誤差 = 0.0781575 Generation: 40. 誤差 = 0.07746361 Generation: 50. 誤差 = 0.077457316 Generation: 60. 誤差 = 0.077457145 Generation: 70. 誤差 = 0.07745706 Generation: 80. 誤差 = 0.07745706 Generation: 90. 誤差 = 0.07745706 Generation: 100. 誤差 = 0.07745706 Generation: 110. 誤差 = 0.07745706 Generation: 120. 誤差 = 0.07745706 Generation: 130. 誤差 = 0.07745706 Generation: 140. 誤差 = 0.07745706 Generation: 150. 誤差 = 0.07745706 Generation: 160. 誤差 = 0.07745706 Generation: 170. 誤差 = 0.07745706 Generation: 180. 誤差 = 0.07745706 Generation: 190. 誤差 = 0.07745706 Generation: 200. 誤差 = 0.07745706 Generation: 210. 誤差 = 0.07745706 Generation: 220. 誤差 = 0.07745706 Generation: 230. 誤差 = 0.07745706 Generation: 240. 誤差 = 0.07745706 Generation: 250. 誤差 = 0.07745706 Generation: 260. 誤差 = 0.07745706 Generation: 270. 誤差 = 0.07745706 Generation: 280. 誤差 = 0.07745706 Generation: 290. 誤差 = 0.07745706 Generation: 300. 誤差 = 0.07745706 [30.003994] [1, 9790144]



非線形回帰

In [14]:

```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
iters num = 10000
plot_interval = 100
# データを生成
n=100
x = np. random. rand(n). astype(np. float32) * 4 - 2
d = -0.4 * x ** 3 + 1.6 * x ** 2 - 2.8 * x + 1
# ノイズを加える
noise = 0.05
d = d + noise * np. random. randn(n)
# モデル
# bを使っていないことに注意.
xt = tf. placeholder (tf. float32, [None, 4])
dt = tf.placeholder(tf.float32, [None, 1])
W = tf. Variable(tf. random_normal([4, 1], stddev=0.01))
y = tf. matmul(xt, W)
#誤差関数 平均2乗誤差
loss = tf. reduce_mean(tf. square(y - dt))
optimizer = tf. train. AdamOptimizer (0.001)
train = optimizer.minimize(loss)
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
# 作成したデータをトレーニングデータとして準備
d_{train} = d. reshape (-1, 1)
x_{train} = np. zeros([n, 4])
for i in range(n):
   for j in range (4):
       x_{train[i, j]} = x[i]**j
# トレーニング
for i in range(iters num):
    if (i+1) % plot interval == 0:
        loss_val = sess.run(loss, feed_dict={xt:x_train, dt:d_train})
       W val = sess.run(W)
       print('Generation: ' + str(i+1) + '. 誤差 = ' + str(loss_val))
    sess.run(train, feed dict={xt:x train, dt:d train})
print(W_val[::-1])
# 予測関数
def predict(x):
    result = 0.
    for i in range (0, 4):
       result += W val[i, 0] * x ** i
    return result
fig = plt. figure()
subplot = fig. add\_subplot(1, 1, 1)
```

```
plt. scatter(x , d)
linex = np. linspace(-2, 2, 100)
liney = predict(linex)
subplot. plot(linex, liney)
plt. show()
```

Generation: 100. 誤差 = 26.545837 Generation: 200. 誤差 = 22.251637 Generation: 300. 誤差 = 18.533943 Generation: 400. 誤差 = 15.338687 Generation: 500. 誤差 = 12.613826 Generation: 600. 誤差 = 10.309445 Generation: 700. 誤差 = 8.377865 Generation: 800. 誤差 = 6.7738466 Generation: 900. 誤差 = 5.4547877 Generation: 1000. 誤差 = 4.380972 Generation: 1100. 誤差 = 3.515791 Generation: 1200. 誤差 = 2.8259377 Generation: 1300. 誤差 = 2.2815566 Generation: 1400. 誤差 = 1.8563008 Generation: 1500. 誤差 = 1.527305 Generation: 1600. 誤差 = 1.2750434 Generation: 1700. 誤差 = 1.083127 Generation: 1800. 誤差 = 0.9380164 Generation: 1900. 誤差 = 0.8286844 Generation: 2000. 誤差 = 0.7463011 Generation: 2100. 誤差 = 0.6838835 Generation: 2200. 誤差 = 0.6359978 Generation: 2300. 誤差 = 0.59847856 Generation: 2400. 誤差 = 0.5681932 Generation: 2500. 誤差 = 0.54283065 Generation: 2600. 誤差 = 0.52072835 Generation: 2700. 誤差 = 0.5007215 Generation: 2800. 誤差 = 0.4820201 Generation: 2900. 誤差 = 0.46410888 Generation: 3000. 誤差 = 0.4466671 Generation: 3100. 誤差 = 0.42950803 Generation: 3200. 誤差 = 0.41253242 Generation: 3300. 誤差 = 0.3956974 Generation: 3400. 誤差 = 0.3789939 Generation: 3500. 誤差 = 0.3624318 Generation: 3600. 誤差 = 0.3460315 Generation: 3700. 誤差 = 0.32981813 Generation: 3800. 誤差 = 0.3138184 Generation: 3900. 誤差 = 0.29805923 Generation: 4000. 誤差 = 0.2825663 Generation: 4100. 誤差 = 0.26736426 Generation: 4200. 誤差 = 0.2524762 Generation: 4300. 誤差 = 0.2379235 Generation: 4400. 誤差 = 0.223726 Generation: 4500. 誤差 = 0.20990208 Generation: 4600. 誤差 = 0.19646865 Generation: 4700. 誤差 = 0.18344124 Generation: 4800. 誤差 = 0.17083448 Generation: 4900. 誤差 = 0.15866151 Generation: 5000. 誤差 = 0.14693469 Generation: 5100. 誤差 = 0.13566533 Generation: 5200. 誤差 = 0.12486374 Generation: 5300. 誤差 = 0.11453949 Generation: 5400. 誤差 = 0.104701005 Generation: 5500. 誤差 = 0.09535494 Generation: 5600. 誤差 = 0.08650741 Generation: 5700. 誤差 = 0.07816276 Generation: 5800. 誤差 = 0.07032368 Generation: 5900. 誤差 = 0.0629908 Generation: 6000. 誤差 = 0.05616277 Generation: 6100. 誤差 = 0.049835563

```
Generation: 6200. 誤差 = 0.044003095
Generation: 6300. 誤差 = 0.03865607
Generation: 6400. 誤差 = 0.033782884
Generation: 6500. 誤差 = 0.029369364
Generation: 6600. 誤差 = 0.025398478
Generation: 6700. 誤差 = 0.021850767
Generation: 6800. 誤差 = 0.018704606
Generation: 6900. 誤差 = 0.015936418
Generation: 7000. 誤差 = 0.013520882
Generation: 7100. 誤差 = 0.011431473
Generation: 7200. 誤差 = 0.009641048
Generation: 7300. 誤差 = 0.00812167
Generation: 7400. 誤差 = 0.006845699
Generation: 7500. 誤差 = 0.0057857935
Generation: 7600. 誤差 = 0.0049155597
Generation: 7700. 誤差 = 0.004209771
Generation: 7800. 誤差 = 0.0036447167
Generation: 7900. 誤差 = 0.0031985224
Generation: 8000. 誤差 = 0.002851249
Generation: 8100. 誤差 = 0.0025850318
Generation: 8200. 誤差 = 0.0023842803
Generation: 8300. 誤差 = 0.0022354496
Generation: 8400. 誤差 = 0.0021270707
Generation: 8500. 誤差 = 0.002049628
Generation: 8600. 誤差 = 0.0019954022
Generation: 8700. 誤差 = 0.0019582256
Generation: 8800. 誤差 = 0.0019332838
Generation: 8900. 誤差 = 0.0019169616
Generation: 9000. 誤差 = 0.0019065297
Generation: 9100. 誤差 = 0.0019000337
Generation: 9200. 誤差 = 0.001896099
Generation: 9300. 誤差 = 0.0018937829
Generation: 9400. 誤差 = 0.0018924671
Generation: 9500. 誤差 = 0.001891742
Generation: 9600. 誤差 = 0.001891348
Generation: 9700. 誤差 = 0.0018911499
Generation: 9800. 誤差 = 0.001891051
Generation: 9900. 誤差 = 0.0018910011
Generation: 10000. 誤差 = 0.0018909833
[[-0.3999309]
[ 1.5972086]
 [-2. 80164 ]
 [ 1.0043371]]
```

15.0 12.5 10.0 7.5 5.0 2.5 0.0 -1.5 -1.0-0.5 0.0 0.5 1.0 1.5 -2.02.0

• noiseの値を変更しよう(0.05を1に変更)

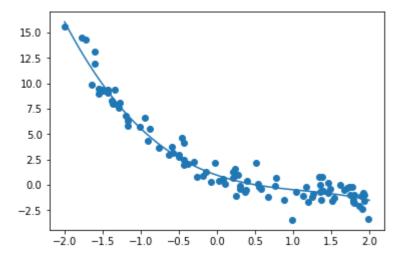
In [15]:

```
iters num = 10000
plot interval = 100
    # データを生成
n=100
x = np. random. rand(n). astype(np. float32) * 4 - 2
d = -0.4 * x ** 3 + 1.6 * x ** 2 - 2.8 * x + 1
# ノイズを加える
noise = 1
d = d + noise * np. random. randn(n)
# モデル
# bを使っていないことに注意.
xt = tf.placeholder(tf.float32, [None, 4])
dt = tf.placeholder(tf.float32, [None, 1])
W = tf. Variable(tf. random_normal([4, 1], stddev=0.01))
v = tf. matmul(xt. W)
# 誤差関数 平均2乗誤差
loss = tf. reduce_mean(tf. square(y - dt))
optimizer = tf. train. AdamOptimizer (0.001)
train = optimizer.minimize(loss)
#初期化
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
# 作成したデータをトレーニングデータとして準備
d_{train} = d. reshape (-1, 1)
x_{train} = np. zeros([n, 4])
for i in range(n):
    for j in range (4):
       x_{train[i, j]} = x[i]**j
# トレーニング
for i in range(iters num):
    if (i+1) % plot_interval == 0:
        loss val = sess.run(loss, feed dict={xt:x train, dt:d train})
       W val = sess.run(W)
       print('Generation: ' + str(i+1) + '. 誤差 = ' + str(loss val))
    sess.run(train, feed_dict={xt:x_train, dt:d_train})
print(W_val[::-1])
# 予測関数
def predict(x):
   result = 0.
    for i in range (0, 4):
       result += W_val[i, 0] * x ** i
    return result
fig = plt. figure()
subplot = fig. add_subplot(1, 1, 1)
plt. scatter (x, d)
linex = np. linspace (-2, 2, 100)
liney = predict(linex)
```

subplot.plot(linex, liney)
plt.show()

Generation: 100. 誤差 = 21.640308 Generation: 200. 誤差 = 18.205376 Generation: 300. 誤差 = 15.24938 Generation: 400. 誤差 = 12.723288 Generation: 500. 誤差 = 10.580398 Generation: 600. 誤差 = 8.776509 Generation: 700. 誤差 = 7.270082 Generation: 800. 誤差 = 6.0224476 Generation: 900. 誤差 = 4.997961 Generation: 1000. 誤差 = 4.1641345 Generation: 1100. 誤差 = 3.4916868 Generation: 1200. 誤差 = 2.9545393 Generation: 1300. 誤差 = 2.5297062 Generation: 1400. 誤差 = 2.1971385 Generation: 1500. 誤差 = 1.939532 Generation: 1600. 誤差 = 1.7420802 Generation: 1700. 誤差 = 1.5922426 Generation: 1800. 誤差 = 1.4795123 Generation: 1900. 誤差 = 1.3951956 Generation: 2000. 誤差 = 1.3322101 Generation: 2100. 誤差 = 1.2848932 Generation: 2200. 誤差 = 1.2488123 Generation: 2300. 誤差 = 1.2205856 Generation: 2400. 誤差 = 1.1976997 Generation: 2500. 誤差 = 1.1783452 Generation: 2600. 誤差 = 1.1612641 Generation: 2700. 誤差 = 1.1456128 Generation: 2800. 誤差 = 1.1308494 Generation: 2900. 誤差 = 1.1166435 Generation: 3000. 誤差 = 1.1028062 Generation: 3100. 誤差 = 1.0892389 Generation: 3200. 誤差 = 1.0758988 Generation: 3300. 誤差 = 1.0627748 Generation: 3400. 誤差 = 1.0498741 Generation: 3500. 誤差 = 1.0372111 Generation: 3600. 誤差 = 1.0248044 Generation: 3700. 誤差 = 1.0126725 Generation: 3800. 誤差 = 1.0008332 Generation: 3900. 誤差 = 0.9893027 Generation: 4000. 誤差 = 0.97809494 Generation: 4100. 誤差 = 0.9672225 Generation: 4200. 誤差 = 0.9566959 Generation: 4300. 誤差 = 0.946524 Generation: 4400. 誤差 = 0.936714 Generation: 4500. 誤差 = 0.9272717 Generation: 4600. 誤差 = 0.9182016 Generation: 4700. 誤差 = 0.9095078 Generation: 4800. 誤差 = 0.9011929 Generation: 4900. 誤差 = 0.89325935 Generation: 5000. 誤差 = 0.8857092 Generation: 5100. 誤差 = 0.87854266 Generation: 5200. 誤差 = 0.8717607 Generation: 5300. 誤差 = 0.8653635 Generation: 5400. 誤差 = 0.85935014 Generation: 5500. 誤差 = 0.85371894 Generation: 5600. 誤差 = 0.8484676 Generation: 5700. 誤差 = 0.84359246 Generation: 5800. 誤差 = 0.8390884 Generation: 5900. 誤差 = 0.83494896 Generation: 6000. 誤差 = 0.8311658 Generation: 6100. 誤差 = 0.8277293

```
Generation: 6200. 誤差 = 0.8246274
Generation: 6300. 誤差 = 0.8218471
Generation: 6400. 誤差 = 0.8193729
Generation: 6500. 誤差 = 0.8171881
Generation: 6600. 誤差 = 0.81527495
Generation: 6700. 誤差 = 0.8136139
Generation: 6800. 誤差 = 0.81218505
Generation: 6900. 誤差 = 0.8109681
Generation: 7000. 誤差 = 0.809942
Generation: 7100. 誤差 = 0.8090862
Generation: 7200. 誤差 = 0.8083809
Generation: 7300. 誤差 = 0.8078063
Generation: 7400. 誤差 = 0.8073444
Generation: 7500. 誤差 = 0.806978
Generation: 7600. 誤差 = 0.8066915
Generation: 7700. 誤差 = 0.80647093
Generation: 7800. 誤差 = 0.8063038
Generation: 7900. 誤差 = 0.80617905
Generation: 8000. 誤差 = 0.80608785
Generation: 8100. 誤差 = 0.80602235
Generation: 8200. 誤差 = 0.8059763
Generation: 8300. 誤差 = 0.8059442
Generation: 8400. 誤差 = 0.80592275
Generation: 8500. 誤差 = 0.8059087
Generation: 8600. 誤差 = 0.8058995
Generation: 8700. 誤差 = 0.8058937
Generation: 8800. 誤差 = 0.8058903
Generation: 8900. 誤差 = 0.80588835
Generation: 9000. 誤差 = 0.805887
Generation: 9100. 誤差 = 0.8058862
Generation: 9200. 誤差 = 0.80588603
Generation: 9300. 誤差 = 0.8058857
Generation: 9400. 誤差 = 0.8058856
Generation: 9500. 誤差 = 0.8058856
Generation: 9600. 誤差 = 0.80588555
Generation: 9700. 誤差 = 0.8058856
Generation: 9800. 誤差 = 0.8058855
Generation: 9900. 誤差 = 0.80588555
Generation: 10000. 誤差 = 0.8058856
[[-0.4597927]
[ 1.578666 ]
 [-2.5477927]
 [ 0.9510553]]
```



• dの数値を変更しよう

(変更前) d = -0.4 x ** 3 + 1.6 x 2 - 2.8 x + 1 (変更後) d = 0.4 x 3 + 1.6 x ** 2 - 2.8 x + 1

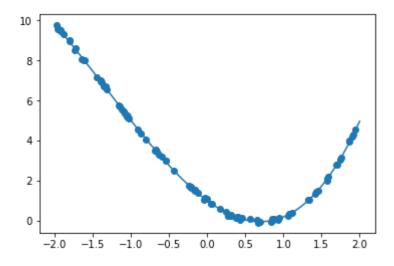
In [16]:

```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
iters num = 10000
plot_interval = 100
# データを生成
n=100
x = np. random. rand(n). astype(np. float32) * 4 - 2
d = 0.4 * x ** 3 + 1.6 * x ** 2 - 2.8 * x + 1
# ノイズを加える
noise = 0.05
d = d + noise * np. random. randn(n)
# モデル
# bを使っていないことに注意.
xt = tf. placeholder (tf. float32, [None, 4])
dt = tf.placeholder(tf.float32, [None, 1])
W = tf. Variable(tf. random_normal([4, 1], stddev=0.01))
y = tf. matmul(xt, W)
#誤差関数 平均2乗誤差
loss = tf. reduce_mean(tf. square(y - dt))
optimizer = tf. train. AdamOptimizer (0.001)
train = optimizer.minimize(loss)
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
# 作成したデータをトレーニングデータとして準備
d_{train} = d. reshape (-1, 1)
x_{train} = np. zeros([n, 4])
for i in range(n):
   for j in range (4):
       x_{train[i, j]} = x[i]**j
# トレーニング
for i in range(iters num):
    if (i+1) % plot interval == 0:
        loss_val = sess.run(loss, feed_dict={xt:x_train, dt:d_train})
       W val = sess.run(W)
       print('Generation: ' + str(i+1) + '. 誤差 = ' + str(loss_val))
    sess.run(train, feed dict={xt:x train, dt:d train})
print(W_val[::-1])
# 予測関数
def predict(x):
    result = 0.
    for i in range (0, 4):
       result += W val[i, 0] * x ** i
    return result
fig = plt. figure()
subplot = fig. add\_subplot(1, 1, 1)
```

```
plt. scatter(x , d)
linex = np. linspace(-2, 2, 100)
liney = predict(linex)
subplot. plot(linex, liney)
plt. show()
```

Generation: 100. 誤差 = 16.858486 Generation: 200. 誤差 = 13.833863 Generation: 300. 誤差 = 11.420864 Generation: 400. 誤差 = 9.5036955 Generation: 500. 誤差 = 7.976492 Generation: 600. 誤差 = 6.7478223 Generation: 700. 誤差 = 5.7439466 Generation: 800. 誤差 = 4.9096203 Generation: 900. 誤差 = 4.206179 Generation: 1000. 誤差 = 3.6077561 Generation: 1100. 誤差 = 3.0970533 Generation: 1200. 誤差 = 2.6618237 Generation: 1300. 誤差 = 2.292502 Generation: 1400. 誤差 = 1.9808923 Generation: 1500. 誤差 = 1.719563 Generation: 1600. 誤差 = 1.5016239 Generation: 1700. 誤差 = 1.3206865 Generation: 1800. 誤差 = 1.1708791 Generation: 1900. 誤差 = 1.0468887 Generation: 2000. 誤差 = 0.94398165 Generation: 2100. 誤差 = 0.8580217 Generation: 2200. 誤差 = 0.78546834 Generation: 2300. 誤差 = 0.7233559 Generation: 2400. 誤差 = 0.6692601 Generation: 2500. 誤差 = 0.6212512 Generation: 2600. 誤差 = 0.57783854 Generation: 2700. 誤差 = 0.537905 Generation: 2800. 誤差 = 0.50064397 Generation: 2900. 誤差 = 0.4654965 Generation: 3000. 誤差 = 0.4320932 Generation: 3100. 誤差 = 0.40020633 Generation: 3200. 誤差 = 0.36970666 Generation: 3300. 誤差 = 0.340531 Generation: 3400. 誤差 = 0.31265804 Generation: 3500. 誤差 = 0.28609 Generation: 3600. 誤差 = 0.26083988 Generation: 3700. 誤差 = 0.23692356 Generation: 3800. 誤差 = 0.21435456 Generation: 3900. 誤差 = 0.19314188 Generation: 4000. 誤差 = 0.17328703 Generation: 4100. 誤差 = 0.15478437 Generation: 4200. 誤差 = 0.13762054 Generation: 4300. 誤差 = 0.12177444 Generation: 4400. 誤差 = 0.10721764 Generation: 4500. 誤差 = 0.09391472 Generation: 4600. 誤差 = 0.08182403 Generation: 4700. 誤差 = 0.07089843 Generation: 4800. 誤差 = 0.061084695 Generation: 4900. 誤差 = 0.05232543 Generation: 5000. 誤差 = 0.04455975 Generation: 5100. 誤差 = 0.037723497 Generation: 5200. 誤差 = 0.0317501 Generation: 5300. 誤差 = 0.026572032 Generation: 5400. 誤差 = 0.022120733 Generation: 5500. 誤差 = 0.018328058 Generation: 5600. 誤差 = 0.015126827 Generation: 5700. 誤差 = 0.012451649 Generation: 5800. 誤差 = 0.010239606 Generation: 5900. 誤差 = 0.008431014 Generation: 6000. 誤差 = 0.0069697965 Generation: 6100. 誤差 = 0.0058040507

```
Generation: 6200. 誤差 = 0.0048864726
Generation: 6300. 誤差 = 0.004174379
Generation: 6400. 誤差 = 0.003630045
Generation: 6500. 誤差 = 0.0032205302
Generation: 6600. 誤差 = 0.0029176122
Generation: 6700. 誤差 = 0.0026974913
Generation: 6800. 誤差 = 0.0025405593
Generation: 6900. 誤差 = 0.0024308737
Generation: 7000. 誤差 = 0.0023558019
Generation: 7100. 誤差 = 0.0023055633
Generation: 7200. 誤差 = 0.0022727223
Generation: 7300. 誤差 = 0.0022517713
Generation: 7400. 誤差 = 0.0022387647
Generation: 7500. 誤差 = 0.0022308992
Generation: 7600. 誤差 = 0.0022262812
Generation: 7700. 誤差 = 0.0022236563
Generation: 7800. 誤差 = 0.002222209
Generation: 7900. 誤差 = 0.0022214376
Generation: 8000. 誤差 = 0.002221041
Generation: 8100. 誤差 = 0.002220846
Generation: 8200. 誤差 = 0.002220753
Generation: 8300. 誤差 = 0.002220709
Generation: 8400. 誤差 = 0.002220692
Generation: 8500. 誤差 = 0.0022206828
Generation: 8600. 誤差 = 0.0022206793
Generation: 8700. 誤差 = 0.0022206819
Generation: 8800. 誤差 = 0.0022206807
Generation: 8900. 誤差 = 0.0022206793
Generation: 9000. 誤差 = 0.0022206774
Generation: 9100. 誤差 = 0.00222068
Generation: 9200. 誤差 = 0.002220675
Generation: 9300. 誤差 = 0.0022206767
Generation: 9400. 誤差 = 0.0022206784
Generation: 9500. 誤差 = 0.0022206828
Generation: 9600. 誤差 = 0.0022206819
Generation: 9700. 誤差 = 0.0022206805
Generation: 9800. 誤差 = 0.002220678
Generation: 9900. 誤差 = 0.002220681
Generation: 10000. 誤差 = 0.0022206795
[[ 0. 4005766]
[ 1.5947251]
 [-2.8117151]
 [ 1.0070072]]
```



• 次の式をモデルとして回帰を行おう

$$y = 30x^2 + 0.5x + 0.2$$

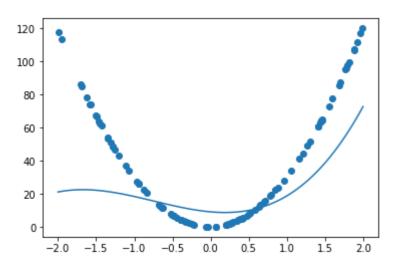
In [17]:

```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
iters num = 10000
plot_interval = 100
# データを生成
n=100
x = np. random. rand(n). astype(np. float32) * 4 - 2
d = 30 * x ** 2 + 0.5 * x + 0.2
# ノイズを加える
noise = 0.05
d = d + noise * np. random. randn(n)
# モデル
# bを使っていないことに注意.
xt = tf. placeholder (tf. float32, [None, 4])
dt = tf.placeholder(tf.float32, [None, 1])
W = tf. Variable(tf. random_normal([4, 1], stddev=0.01))
y = tf. matmul(xt, W)
#誤差関数 平均2乗誤差
loss = tf. reduce_mean(tf. square(y - dt))
optimizer = tf. train. AdamOptimizer (0.001)
train = optimizer.minimize(loss)
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
# 作成したデータをトレーニングデータとして準備
d_{train} = d. reshape (-1, 1)
x_{train} = np. zeros([n, 4])
for i in range(n):
   for j in range (4):
       x_{train[i, j]} = x[i]**j
# トレーニング
for i in range(iters num):
    if (i+1) % plot interval == 0:
        loss_val = sess.run(loss, feed_dict={xt:x_train, dt:d_train})
       W val = sess.run(W)
       print('Generation: ' + str(i+1) + '. 誤差 = ' + str(loss_val))
    sess.run(train, feed dict={xt:x train, dt:d train})
print(W_val[::-1])
# 予測関数
def predict(x):
    result = 0.
   for i in range (0, 4):
       result += W val[i, 0] * x ** i
    return result
fig = plt. figure()
subplot = fig. add\_subplot(1, 1, 1)
```

```
plt. scatter(x , d)
linex = np. linspace(-2, 2, 100)
liney = predict(linex)
subplot. plot(linex, liney)
plt. show()
```

Generation: 100. 誤差 = 2658.9 Generation: 200. 誤差 = 2624.853 Generation: 300. 誤差 = 2591.5386 Generation: 400. 誤差 = 2558.9316 Generation: 500. 誤差 = 2527.011 Generation: 600. 誤差 = 2495.7532 Generation: 700. 誤差 = 2465.1367 Generation: 800. 誤差 = 2435.1409 Generation: 900. 誤差 = 2405.7466 Generation: 1000. 誤差 = 2376.9329 Generation: 1100. 誤差 = 2348.682 Generation: 1200. 誤差 = 2320.975 Generation: 1300. 誤差 = 2293.794 Generation: 1400. 誤差 = 2267.1218 Generation: 1500. 誤差 = 2240.9407 Generation: 1600. 誤差 = 2215.235 Generation: 1700. 誤差 = 2189.9873 Generation: 1800. 誤差 = 2165.182 Generation: 1900. 誤差 = 2140.8025 Generation: 2000. 誤差 = 2116.8337 Generation: 2100. 誤差 = 2093.2593 Generation: 2200. 誤差 = 2070.064 Generation: 2300. 誤差 = 2047.2323 Generation: 2400. 誤差 = 2024.7489 Generation: 2500. 誤差 = 2002.5984 Generation: 2600. 誤差 = 1980.765 Generation: 2700. 誤差 = 1959.2339 Generation: 2800. 誤差 = 1937.9894 Generation: 2900. 誤差 = 1917.0167 Generation: 3000. 誤差 = 1896.3007 Generation: 3100. 誤差 = 1875.8263 Generation: 3200. 誤差 = 1855.5793 Generation: 3300. 誤差 = 1835.5457 Generation: 3400. 誤差 = 1815.7119 Generation: 3500. 誤差 = 1796.0654 Generation: 3600. 誤差 = 1776.5948 Generation: 3700. 誤差 = 1757.2894 Generation: 3800. 誤差 = 1738.1394 Generation: 3900. 誤差 = 1719.1375 Generation: 4000. 誤差 = 1700.2762 Generation: 4100. 誤差 = 1681.5513 Generation: 4200. 誤差 = 1662.9575 Generation: 4300. 誤差 = 1644.4926 Generation: 4400. 誤差 = 1626.1547 Generation: 4500. 誤差 = 1607.9418 Generation: 4600. 誤差 = 1589.8544 Generation: 4700. 誤差 = 1571.8894 Generation: 4800. 誤差 = 1554.0518 Generation: 4900. 誤差 = 1536.3359 Generation: 5000. 誤差 = 1518.7477 Generation: 5100. 誤差 = 1501.2825 Generation: 5200. 誤差 = 1483.9448 Generation: 5300. 誤差 = 1466.7319 Generation: 5400. 誤差 = 1449.6462 Generation: 5500. 誤差 = 1432.6859 Generation: 5600. 誤差 = 1415.8538 Generation: 5700. 誤差 = 1399.1469 Generation: 5800. 誤差 = 1382.5685 Generation: 5900. 誤差 = 1366.115 Generation: 6000. 誤差 = 1349.7905 Generation: 6100. 誤差 = 1333.5906

```
Generation: 6200. 誤差 = 1317.5192
Generation: 6300. 誤差 = 1301.5728
Generation: 6400. 誤差 = 1285.7533
Generation: 6500. 誤差 = 1270.0598
Generation: 6600. 誤差 = 1254.4907
Generation: 6700. 誤差 = 1239.0492
Generation: 6800. 誤差 = 1223.731
Generation: 6900. 誤差 = 1208.5386
Generation: 7000. 誤差 = 1193.471
Generation: 7100. 誤差 = 1178.5264
Generation: 7200. 誤差 = 1163.7075
Generation: 7300. 誤差 = 1149.0118
Generation: 7400. 誤差 = 1134.439
Generation: 7500. 誤差 = 1119.9907
Generation: 7600. 誤差 = 1105.665
Generation: 7700. 誤差 = 1091.4614
Generation: 7800. 誤差 = 1077.3811
Generation: 7900. 誤差 = 1063.4231
Generation: 8000. 誤差 = 1049.5868
Generation: 8100. 誤差 = 1035.8721
Generation: 8200. 誤差 = 1022.28
Generation: 8300. 誤差 = 1008.8091
Generation: 8400. 誤差 = 995.45917
Generation: 8500. 誤差 = 982.23193
Generation: 8600. 誤差 = 969.12335
Generation: 8700. 誤差 = 956.1356
Generation: 8800. 誤差 = 943.27026
Generation: 8900. 誤差 = 930.5217
Generation: 9000. 誤差 = 917.8977
Generation: 9100. 誤差 = 905.38947
Generation: 9200. 誤差 = 893.00476
Generation: 9300. 誤差 = 880.7364
Generation: 9400. 誤差 = 868.5899
Generation: 9500. 誤差 = 856.5608
Generation: 9600. 誤差 = 844.6525
Generation: 9700. 誤差 = 832.86127
Generation: 9800. 誤差 = 821.1902
Generation: 9900. 誤差 = 809.63617
Generation: 10000. 誤差 = 798.2025
[[ 4. 237667 ]
[ 9.442325 ]
[-4. 06645 ]
 [ 9. 2579775]]
```



• 誤差が収束するようlearning_rateを調整しよう(0.001を0.1に変更。)

In [18]:

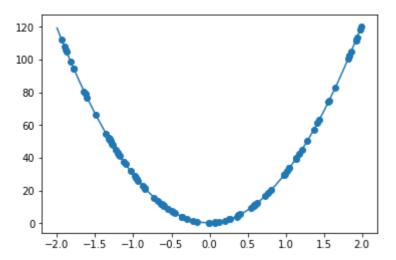
```
import numpy as np
import tensorflow as tf
import matplotlib.pyplot as plt
iters num = 10000
plot_interval = 100
# データを生成
n=100
x = np. random. rand(n). astype(np. float32) * 4 - 2
d = 30 * x ** 2 + 0.5 * x + 0.2
# ノイズを加える
noise = 0.05
d = d + noise * np. random. randn(n)
# モデル
# bを使っていないことに注意.
xt = tf. placeholder (tf. float32, [None, 4])
dt = tf.placeholder(tf.float32, [None, 1])
W = tf. Variable(tf. random_normal([4, 1], stddev=0.01))
y = tf. matmul(xt, W)
#誤差関数 平均2乗誤差
loss = tf.reduce_mean(tf.square(y - dt))
optimizer = tf. train. AdamOptimizer (0.1)
train = optimizer.minimize(loss)
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
# 作成したデータをトレーニングデータとして準備
d_{train} = d. reshape (-1, 1)
x_{train} = np. zeros([n, 4])
for i in range(n):
   for j in range (4):
       x_{train[i, j]} = x[i]**j
# トレーニング
for i in range(iters num):
    if (i+1) % plot_interval == 0:
        loss_val = sess.run(loss, feed_dict={xt:x_train, dt:d_train})
       W val = sess.run(W)
       print('Generation: ' + str(i+1) + '. 誤差 = ' + str(loss_val))
    sess.run(train, feed dict={xt:x train, dt:d train})
print(W_val[::-1])
# 予測関数
def predict(x):
    result = 0.
    for i in range (0, 4):
       result += W_val[i, 0] * x ** i
    return result
fig = plt. figure()
subplot = fig. add_subplot(1, 1, 1)
```

```
plt. scatter(x , d)
linex = np. linspace(-2, 2, 100)
liney = predict(linex)
subplot. plot(linex, liney)
plt. show()
```

```
Generation: 100. 誤差 = 1000.7947
Generation: 200. 誤差 = 338.7539
Generation: 300. 誤差 = 159.625
Generation: 400. 誤差 = 102.543076
Generation: 500. 誤差 = 69.70407
Generation: 600. 誤差 = 45.770912
Generation: 700. 誤差 = 28.660395
Generation: 800. 誤差 = 17.090307
Generation: 900. 誤差 = 9.697431
Generation: 1000. 誤差 = 5.2305775
Generation: 1100. 誤差 = 2.6783893
Generation: 1200. 誤差 = 1.3003355
Generation: 1300. 誤差 = 0.5978639
Generation: 1400. 誤差 = 0.2602947
Generation: 1500. 誤差 = 0.10762539
Generation: 1600. 誤差 = 0.042778827
Generation: 1700. 誤差 = 0.016966928
Generation: 1800. 誤差 = 0.007366726
Generation: 1900. 誤差 = 0.0040382203
Generation: 2000. 誤差 = 0.0029663749
Generation: 2100. 誤差 = 0.0026466073
Generation: 2200. 誤差 = 0.002558667
Generation: 2300. 誤差 = 0.0025364738
Generation: 2400. 誤差 = 0.002531321
Generation: 2500. 誤差 = 0.0025302577
Generation: 2600. 誤差 = 0.0025300742
Generation: 2700. 誤差 = 0.0025300109
Generation: 2800. 誤差 = 0.002530031
Generation: 2900. 誤差 = 0.0025300079
Generation: 3000. 誤差 = 0.002529989
Generation: 3100. 誤差 = 0.0025300074
Generation: 3200. 誤差 = 0.0025300079
Generation: 3300. 誤差 = 0.0025300067
Generation: 3400. 誤差 = 0.0025300083
Generation: 3500. 誤差 = 0.0025300118
Generation: 3600. 誤差 = 0.0025300253
Generation: 3700. 誤差 = 0.0025300323
Generation: 3800. 誤差 = 0.0025300318
Generation: 3900. 誤差 = 0.0025300167
Generation: 4000. 誤差 = 0.0025299883
Generation: 4100. 誤差 = 0.002530022
Generation: 4200. 誤差 = 0.0025300074
Generation: 4300. 誤差 = 0.002529998
Generation: 4400. 誤差 = 0.0025300132
Generation: 4500. 誤差 = 0.0025300127
Generation: 4600. 誤差 = 0.0025300076
Generation: 4700. 誤差 = 0.0025300381
Generation: 4800. 誤差 = 0.0025300256
Generation: 4900. 誤差 = 0.0025300088
Generation: 5000. 誤差 = 0.0025300253
Generation: 5100. 誤差 = 0.0025300246
Generation: 5200. 誤差 = 0.0025300172
Generation: 5300. 誤差 = 0.002530029
Generation: 5400. 誤差 = 0.0025300141
Generation: 5500. 誤差 = 0.002530029
Generation: 5600. 誤差 = 0.002530029
Generation: 5700. 誤差 = 0.0025300365
Generation: 5800. 誤差 = 0.0025300365
Generation: 5900. 誤差 = 0.0025300318
Generation: 6000. 誤差 = 0.0025300353
Generation: 6100. 誤差 = 0.0025300318
```

Generation: 6200. 誤差 = 0.002530033 Generation: 6300. 誤差 = 0.0025300265 Generation: 6400. 誤差 = 0.002530027 Generation: 6500. 誤差 = 0.00253003 Generation: 6600. 誤差 = 0.0025300365 Generation: 6700. 誤差 = 0.002530017 Generation: 6800. 誤差 = 0.0025300223 Generation: 6900. 誤差 = 0.0025300207 Generation: 7000. 誤差 = 0.002530033 Generation: 7100. 誤差 = 0.0029303504 Generation: 7200. 誤差 = 0.002530018 Generation: 7300. 誤差 = 0.0025299925 Generation: 7400. 誤差 = 0.0025781246 Generation: 7500. 誤差 = 0.0025300414 Generation: 7600. 誤差 = 0.002529984 Generation: 7700. 誤差 = 0.0027396241 Generation: 7800. 誤差 = 0.0025300141 Generation: 7900. 誤差 = 0.0025347432 Generation: 8000. 誤差 = 0.0025301247 Generation: 8100. 誤差 = 0.0025299871 Generation: 8200. 誤差 = 0.0025302928 Generation: 8300. 誤差 = 0.002531091 Generation: 8400. 誤差 = 0.002530015 Generation: 8500. 誤差 = 0.0025299971 Generation: 8600. 誤差 = 0.0025300093 Generation: 8700. 誤差 = 0.002536235 Generation: 8800. 誤差 = 0.0025299948 Generation: 8900. 誤差 = 0.002529994 Generation: 9000. 誤差 = 0.002533938 Generation: 9100. 誤差 = 0.002530016 Generation: 9200. 誤差 = 0.0025300095 Generation: 9300. 誤差 = 0.0025318987 Generation: 9400. 誤差 = 0.0025299897 Generation: 9500. 誤差 = 0.0066457605 Generation: 9600. 誤差 = 0.0025300877 Generation: 9700. 誤差 = 0.0025299944 Generation: 9800. 誤差 = 0.00280275 Generation: 9900. 誤差 = 0.0025299934 Generation: 10000. 誤差 = 0.0025299964 [[4.5494391e-03] [2.9994068e+01] [4.8868811e-01] [2.0332426e-01]]

file:///C:/Users/克拡/Desktop/upload/後半/4 1 tensorflow codes-ensyu.html



• 誤差が収束するようiters_numを調整しよう

In [19]:

```
iters num = 50000
plot interval = 100
# データを生成
n=100
x = np. random. rand(n). astype(np. float32) * 4 - 2
d = 30 * x ** 2 + 0.5 * x + 0.2
# ノイズを加える
noise = 0.05
d = d + noise * np. random. randn(n)
# モデル
# bを使っていないことに注意.
xt = tf.placeholder(tf.float32, [None, 4])
dt = tf.placeholder(tf.float32, [None, 1])
W = tf. Variable(tf. random_normal([4, 1], stddev=0.01))
v = tf. matmul(xt. W)
# 誤差関数 平均2乗誤差
loss = tf. reduce_mean(tf. square(y - dt))
optimizer = tf. train. AdamOptimizer (0.001)
train = optimizer.minimize(loss)
#初期化
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
# 作成したデータをトレーニングデータとして準備
d_{train} = d. reshape (-1, 1)
x_{train} = np. zeros([n, 4])
for i in range(n):
    for j in range (4):
       x_{train[i, j]} = x[i]**j
# トレーニング
for i in range(iters num):
    if (i+1) % plot_interval == 0:
        loss val = sess.run(loss, feed dict={xt:x train, dt:d train})
       W val = sess.run(W)
       print('Generation: ' + str(i+1) + '. 誤差 = ' + str(loss val))
    sess.run(train, feed_dict={xt:x_train, dt:d_train})
print(W_val[::-1])
# 予測関数
def predict(x):
   result = 0.
    for i in range (0, 4):
       result += W_val[i, 0] * x ** i
    return result
fig = plt. figure()
subplot = fig. add\_subplot(1, 1, 1)
plt. scatter (x, d)
linex = np. linspace (-2, 2, 100)
liney = predict(linex)
```

subplot.plot(linex, liney)
plt.show()

Generation: 100. 誤差 = 2443.1685 Generation: 200. 誤差 = 2408.7278 Generation: 300. 誤差 = 2375.0154 Generation: 400. 誤差 = 2342.0115 Generation: 500. 誤差 = 2309.6956 Generation: 600. 誤差 = 2278.051 Generation: 700. 誤差 = 2247.0579 Generation: 800. 誤差 = 2216.6995 Generation: 900. 誤差 = 2186.9592 Generation: 1000. 誤差 = 2157.8208 Generation: 1100. 誤差 = 2129.2686 Generation: 1200. 誤差 = 2101.2876 Generation: 1300. 誤差 = 2073.863 Generation: 1400. 誤差 = 2046.9812 Generation: 1500. 誤差 = 2020.6282 Generation: 1600. 誤差 = 1994.7908 Generation: 1700. 誤差 = 1969.4558 Generation: 1800. 誤差 = 1944.6111 Generation: 1900. 誤差 = 1920.2444 Generation: 2000. 誤差 = 1896.3434 Generation: 2100. 誤差 = 1872.8969 Generation: 2200. 誤差 = 1849.8934 Generation: 2300. 誤差 = 1827.3213 Generation: 2400. 誤差 = 1805.17 Generation: 2500. 誤差 = 1783.4285 Generation: 2600. 誤差 = 1762.0853 Generation: 2700. 誤差 = 1741.1306 Generation: 2800. 誤差 = 1720.5535 Generation: 2900. 誤差 = 1700.3433 Generation: 3000. 誤差 = 1680.4893 Generation: 3100. 誤差 = 1660.9811 Generation: 3200. 誤差 = 1641.8081 Generation: 3300. 誤差 = 1622.9594 Generation: 3400. 誤差 = 1604.425 Generation: 3500. 誤差 = 1586.1935 Generation: 3600. 誤差 = 1568.2543 Generation: 3700. 誤差 = 1550.5962 Generation: 3800. 誤差 = 1533.2086 Generation: 3900. 誤差 = 1516.0803 Generation: 4000. 誤差 = 1499.1997 Generation: 4100. 誤差 = 1482.5564 Generation: 4200. 誤差 = 1466.1384 Generation: 4300. 誤差 = 1449.9346 Generation: 4400. 誤差 = 1433.9353 Generation: 4500. 誤差 = 1418.1272 Generation: 4600. 誤差 = 1402.5005 Generation: 4700. 誤差 = 1387.047 Generation: 4800. 誤差 = 1371.7535 Generation: 4900. 誤差 = 1356.611 Generation: 5000. 誤差 = 1341.6106 Generation: 5100. 誤差 = 1326.744 Generation: 5200. 誤差 = 1312.0038 Generation: 5300. 誤差 = 1297.3817 Generation: 5400. 誤差 = 1282.87 Generation: 5500. 誤差 = 1268.4669 Generation: 5600. 誤差 = 1254.1656 Generation: 5700. 誤差 = 1239.9626 Generation: 5800. 誤差 = 1225.8561 Generation: 5900. 誤差 = 1211.8422 Generation: 6000. 誤差 = 1197.9213 Generation: 6100. 誤差 = 1184.0906

```
Generation: 6200. 誤差 = 1170.3516
Generation: 6300. 誤差 = 1156.7024
Generation: 6400. 誤差 = 1143.1459
Generation: 6500. 誤差 = 1129.6786
Generation: 6600. 誤差 = 1116.305
Generation: 6700. 誤差 = 1103.0255
Generation: 6800. 誤差 = 1089.8367
Generation: 6900. 誤差 = 1076.7432
Generation: 7000. 誤差 = 1063.7455
Generation: 7100. 誤差 = 1050.8438
Generation: 7200. 誤差 = 1038.0387
Generation: 7300. 誤差 = 1025.3303
Generation: 7400. 誤差 = 1012.71906
Generation: 7500. 誤差 = 1000.20685
Generation: 7600. 誤差 = 987.79443
Generation: 7700. 誤差 = 975.47974
Generation: 7800. 誤差 = 963.2643
Generation: 7900. 誤差 = 951.14905
Generation: 8000. 誤差 = 939.13306
Generation: 8100. 誤差 = 927.21735
Generation: 8200. 誤差 = 915.40186
Generation: 8300. 誤差 = 903.6861
Generation: 8400. 誤差 = 892.072
Generation: 8500. 誤差 = 880.5577
Generation: 8600. 誤差 = 869.1467
Generation: 8700. 誤差 = 857.83417
Generation: 8800. 誤差 = 846.622
Generation: 8900. 誤差 = 835.5128
Generation: 9000. 誤差 = 824.5012
Generation: 9100. 誤差 = 813.59485
Generation: 9200. 誤差 = 802.78674
Generation: 9300. 誤差 = 792.0814
Generation: 9400. 誤差 = 781.47565
Generation: 9500. 誤差 = 770.97186
Generation: 9600. 誤差 = 760.5686
Generation: 9700. 誤差 = 750.2664
Generation: 9800. 誤差 = 740.06506
Generation: 9900. 誤差 = 729.96466
Generation: 10000. 誤差 = 719.96466
Generation: 10100. 誤差 = 710.0661
Generation: 10200. 誤差 = 700.2668
Generation: 10300. 誤差 = 690.5697
Generation: 10400. 誤差 = 680.97064
Generation: 10500. 誤差 = 671.475
Generation: 10600. 誤差 = 662.0767
Generation: 10700. 誤差 = 652.7803
Generation: 10800. 誤差 = 643.58307
Generation: 10900. 誤差 = 634.4849
Generation: 11000. 誤差 = 625.4879
Generation: 11100. 誤差 = 616.58844
Generation: 11200. 誤差 = 607.7898
Generation: 11300. 誤差 = 599.0898
Generation: 11400. 誤差 = 590.4875
Generation: 11500. 誤差 = 581.98615
Generation: 11600. 誤差 = 573.5819
Generation: 11700. 誤差 = 565.27576
Generation: 11800. 誤差 = 557.06915
Generation: 11900. 誤差 = 548.95935
Generation: 12000. 誤差 = 540.9467
Generation: 12100. 誤差 = 533.0332
Generation: 12200. 誤差 = 525.216
```

```
Generation: 12300. 誤差 = 517.4951
Generation: 12400. 誤差 = 509.8721
Generation: 12500. 誤差 = 502.34552
Generation: 12600. 誤差 = 494.9146
Generation: 12700. 誤差 = 487.57907
Generation: 12800. 誤差 = 480.3408
Generation: 12900. 誤差 = 473.19736
Generation: 13000. 誤差 = 466.14874
Generation: 13100. 誤差 = 459.1947
Generation: 13200. 誤差 = 452.33548
Generation: 13300. 誤差 = 445.5711
Generation: 13400. 誤差 = 438.9003
Generation: 13500. 誤差 = 432.32297
Generation: 13600. 誤差 = 425.83878
Generation: 13700. 誤差 = 419.4475
Generation: 13800. 誤差 = 413.14905
Generation: 13900. 誤差 = 406.94333
Generation: 14000. 誤差 = 400.82938
Generation: 14100. 誤差 = 394.8069
Generation: 14200. 誤差 = 388.87558
Generation: 14300. 誤差 = 383.035
Generation: 14400. 誤差 = 377.28485
Generation: 14500. 誤差 = 371.62463
Generation: 14600. 誤差 = 366.05408
Generation: 14700. 誤差 = 360.57266
Generation: 14800. 誤差 = 355.17996
Generation: 14900. 誤差 = 349.87555
Generation: 15000. 誤差 = 344.6589
Generation: 15100. 誤差 = 339.52945
Generation: 15200. 誤差 = 334.48676
Generation: 15300. 誤差 = 329.53024
Generation: 15400. 誤差 = 324.65927
Generation: 15500. 誤差 = 319.87332
Generation: 15600. 誤差 = 315.1716
Generation: 15700. 誤差 = 310.5535
Generation: 15800. 誤差 = 306.01834
Generation: 15900. 誤差 = 301.56534
Generation: 16000. 誤差 = 297.19385
Generation: 16100. 誤差 = 292.90286
Generation: 16200. 誤差 = 288.6916
Generation: 16300. 誤差 = 284.55917
Generation: 16400. 誤差 = 280.50452
Generation: 16500. 誤差 = 276.52673
Generation: 16600. 誤差 = 272.6246
Generation: 16700. 誤差 = 268.79712
Generation: 16800. 誤差 = 265.04294
Generation: 16900. 誤差 = 261.36087
Generation: 17000. 誤差 = 257.74948
Generation: 17100. 誤差 = 254.20726
Generation: 17200. 誤差 = 250.7327
Generation: 17300. 誤差 = 247.32413
Generation: 17400. 誤差 = 243.97993
Generation: 17500. 誤差 = 240.6963
Generation: 17600. 誤差 = 237.47523
Generation: 17700. 誤差 = 234.31157
Generation: 17800. 誤差 = 231.20143
Generation: 17900. 誤差 = 228.14793
Generation: 18000. 誤差 = 225.14484
Generation: 18100. 誤差 = 222.18848
Generation: 18200. 誤差 = 219.27625
Generation: 18300. 誤差 = 216.40564
```

```
Generation: 18400. 誤差 = 213.57399
Generation: 18500. 誤差 = 210.77853
Generation: 18600. 誤差 = 208.01653
Generation: 18700. 誤差 = 205.28517
Generation: 18800. 誤差 = 202.58177
Generation: 18900. 誤差 = 199.90059
Generation: 19000. 誤差 = 197.23967
Generation: 19100. 誤差 = 194.59744
Generation: 19200. 誤差 = 191.97047
Generation: 19300. 誤差 = 189.35664
Generation: 19400. 誤差 = 186.75536
Generation: 19500. 誤差 = 184.16496
Generation: 19600. 誤差 = 181.58414
Generation: 19700. 誤差 = 179.01228
Generation: 19800. 誤差 = 176.44969
Generation: 19900. 誤差 = 173.89644
Generation: 20000. 誤差 = 171.35281
Generation: 20100. 誤差 = 168.81927
Generation: 20200. 誤差 = 166.29646
Generation: 20300. 誤差 = 163.7851
Generation: 20400. 誤差 = 161.28607
Generation: 20500. 誤差 = 158.79922
Generation: 20600. 誤差 = 156.32567
Generation: 20700. 誤差 = 153.86703
Generation: 20800. 誤差 = 151.42311
Generation: 20900. 誤差 = 148.9942
Generation: 21000. 誤差 = 146.58229
Generation: 21100. 誤差 = 144.18611
Generation: 21200. 誤差 = 141.8073
Generation: 21300. 誤差 = 139.44766
Generation: 21400. 誤差 = 137.10352
Generation: 21500. 誤差 = 134.77814
Generation: 21600. 誤差 = 132.47232
Generation: 21700. 誤差 = 130.18622
Generation: 21800. 誤差 = 127.91986
Generation: 21900. 誤差 = 125.673294
Generation: 22000. 誤差 = 123.4466
Generation: 22100. 誤差 = 121.23981
Generation: 22200. 誤差 = 119.05292
Generation: 22300. 誤差 = 116.88598
Generation: 22400. 誤差 = 114.73908
Generation: 22500. 誤差 = 112.61207
Generation: 22600. 誤差 = 110.50637
Generation: 22700. 誤差 = 108.423485
Generation: 22800. 誤差 = 106.36059
Generation: 22900. 誤差 = 104.31766
Generation: 23000. 誤差 = 102.29709
Generation: 23100. 誤差 = 100.297966
Generation: 23200. 誤差 = 98.31873
Generation: 23300. 誤差 = 96.36215
Generation: 23400. 誤差 = 94.426575
Generation: 23500. 誤差 = 92.511696
Generation: 23600. 誤差 = 90.61939
Generation: 23700. 誤差 = 88.74693
Generation: 23800. 誤差 = 86.89777
Generation: 23900. 誤差 = 85.06828
Generation: 24000. 誤差 = 83.26183
Generation: 24100. 誤差 = 81.47521
Generation: 24200. 誤差 = 79.71163
Generation: 24300. 誤差 = 77.96812
Generation: 24400. 誤差 = 76.24706
```

```
Generation: 24500. 誤差 = 74.54671
Generation: 24600. 誤差 = 72.86782
Generation: 24700. 誤差 = 71.210655
Generation: 24800. 誤差 = 69.57411
Generation: 24900. 誤差 = 67.95959
Generation: 25000. 誤差 = 66.36611
Generation: 25100. 誤差 = 64.793396
Generation: 25200. 誤差 = 63.242535
Generation: 25300. 誤差 = 61.712753
Generation: 25400. 誤差 = 60.20375
Generation: 25500. 誤差 = 58.715824
Generation: 25600. 誤差 = 57.249493
Generation: 25700. 誤差 = 55.80395
Generation: 25800. 誤差 = 54.37918
Generation: 25900. 誤差 = 52.975235
Generation: 26000. 誤差 = 51.592354
Generation: 26100. 誤差 = 50.230515
Generation: 26200. 誤差 = 48.88937
Generation: 26300. 誤差 = 47.568897
Generation: 26400. 誤差 = 46.269066
Generation: 26500. 誤差 = 44.989845
Generation: 26600. 誤差 = 43.7312
Generation: 26700. 誤差 = 42.493065
Generation: 26800. 誤差 = 41.275414
Generation: 26900. 誤差 = 40.078175
Generation: 27000. 誤差 = 38.901276
Generation: 27100. 誤差 = 37.74463
Generation: 27200. 誤差 = 36.608173
Generation: 27300. 誤差 = 35.491837
Generation: 27400. 誤差 = 34.39554
Generation: 27500. 誤差 = 33.31921
Generation: 27600. 誤差 = 32.26283
Generation: 27700. 誤差 = 31.22644
Generation: 27800. 誤差 = 30.209742
Generation: 27900. 誤差 = 29.212646
Generation: 28000. 誤差 = 28.235235
Generation: 28100. 誤差 = 27.277424
Generation: 28200. 誤差 = 26.338882
Generation: 28300. 誤差 = 25.419872
Generation: 28400. 誤差 = 24.520031
Generation: 28500. 誤差 = 23.639399
Generation: 28600. 誤差 = 22.77783
Generation: 28700. 誤差 = 21.935253
Generation: 28800. 誤差 = 21.11151
Generation: 28900. 誤差 = 20.306704
Generation: 29000. 誤差 = 19.520472
Generation: 29100. 誤差 = 18.752733
Generation: 29200. 誤差 = 18.003635
Generation: 29300. 誤差 = 17.272812
Generation: 29400. 誤差 = 16.560204
Generation: 29500. 誤差 = 15.865724
Generation: 29600. 誤差 = 15.18923
Generation: 29700. 誤差 = 14.530587
Generation: 29800. 誤差 = 13.889705
Generation: 29900. 誤差 = 13.266402
Generation: 30000. 誤差 = 12.660532
Generation: 30100. 誤差 = 12.072055
Generation: 30200. 誤差 = 11.500737
Generation: 30300. 誤差 = 10.946376
Generation: 30400. 誤差 = 10.408994
Generation: 30500. 誤差 = 9.88823
```

```
Generation: 30600. 誤差 = 9.384121
Generation: 30700. 誤差 = 8.896343
Generation: 30800. 誤差 = 8.42477
Generation: 30900. 誤差 = 7.96923
Generation: 31000. 誤差 = 7.5295577
Generation: 31100. 誤差 = 7.105573
Generation: 31200. 誤差 = 6.6970787
Generation: 31300. 誤差 = 6.303854
Generation: 31400. 誤差 = 5.9256935
Generation: 31500. 誤差 = 5.562395
Generation: 31600. 誤差 = 5.2137513
Generation: 31700. 誤差 = 4.87954
Generation: 31800. 誤差 = 4.559515
Generation: 31900. 誤差 = 4.2534647
Generation: 32000. 誤差 = 3.961162
Generation: 32100. 誤差 = 3.6823394
Generation: 32200. 誤差 = 3.4167526
Generation: 32300. 誤差 = 3.1641228
Generation: 32400. 誤差 = 2.9241996
Generation: 32500. 誤差 = 2.6967065
Generation: 32600. 誤差 = 2.481377
Generation: 32700. 誤差 = 2.2778962
Generation: 32800. 誤差 = 2.0859842
Generation: 32900. 誤差 = 1.9053346
Generation: 33000. 誤差 = 1.7356573
Generation: 33100. 誤差 = 1.5766104
Generation: 33200. 誤差 = 1.4278903
Generation: 33300. 誤差 = 1.2891583
Generation: 33400. 誤差 = 1.1600832
Generation: 33500. 誤差 = 1.040321
Generation: 33600. 誤差 = 0.92952347
Generation: 33700. 誤差 = 0.82733667
Generation: 33800. 誤差 = 0.7334047
Generation: 33900. 誤差 = 0.6473639
Generation: 34000. 誤差 = 0.568844
Generation: 34100. 誤差 = 0.49747458
Generation: 34200. 誤差 = 0.4328746
Generation: 34300. 誤差 = 0.3746727
Generation: 34400. 誤差 = 0.32248497
Generation: 34500. 誤差 = 0.2759327
Generation: 34600. 誤差 = 0.23463911
Generation: 34700. 誤差 = 0.19822556
Generation: 34800. 誤差 = 0.1663171
Generation: 34900. 誤差 = 0.13854635
Generation: 35000. 誤差 = 0.114553906
Generation: 35100. 誤差 = 0.09398413
Generation: 35200. 誤差 = 0.07649599
Generation: 35300. 誤差 = 0.06175964
Generation: 35400. 誤差 = 0.04946148
Generation: 35500. 誤差 = 0.039301928
Generation: 35600. 誤差 = 0.030999407
Generation: 35700. 誤差 = 0.024293266
Generation: 35800. 誤差 = 0.01894249
Generation: 35900. 誤差 = 0.014729746
Generation: 36000. 誤差 = 0.011458495
Generation: 36100. 誤差 = 0.008956441
Generation: 36200. 誤差 = 0.0070726504
Generation: 36300. 誤差 = 0.0056772875
Generation: 36400. 誤差 = 0.0046627778
Generation: 36500. 誤差 = 0.003938858
Generation: 36600. 誤差 = 0.003432084
```

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Generation: 36700. 誤差 = 0.0030848074
Generation: 36800. 誤差 = 0.0028521293
Generation: 36900. 誤差 = 0.002699988
Generation: 37000. 誤差 = 0.00260277
Generation: 37100. 誤差 = 0.0025423407
Generation: 37200. 誤差 = 0.0025057143
Generation: 37300. 誤差 = 0.002484363
Generation: 37400. 誤差 = 0.0024719175
Generation: 37500. 誤差 = 0.0024651638
Generation: 37600. 誤差 = 0.002461565
Generation: 37700. 誤差 = 0.002459694
Generation: 37800. 誤差 = 0.0024587428
Generation: 37900. 誤差 = 0.0024583607
Generation: 38000. 誤差 = 0.0024580867
Generation: 38100. 誤差 = 0.0024580199
Generation: 38200. 誤差 = 0.0024579843
Generation: 38300. 誤差 = 0.0024579633
Generation: 38400. 誤差 = 0.0024579847
Generation: 38500. 誤差 = 0.0024579437
Generation: 38600. 誤差 = 0.0024579517
Generation: 38700. 誤差 = 0.0024579898
Generation: 38800. 誤差 = 0.0024579486
Generation: 38900. 誤差 = 0.0024579982
Generation: 39000. 誤差 = 0.0024579559
Generation: 39100. 誤差 = 0.0024579654
Generation: 39200. 誤差 = 0.0024579626
Generation: 39300. 誤差 = 0.0024579617
Generation: 39400. 誤差 = 0.0024579328
Generation: 39500. 誤差 = 0.002457936
Generation: 39600. 誤差 = 0.0024579624
Generation: 39700. 誤差 = 0.0024579621
Generation: 39800. 誤差 = 0.0024579572
Generation: 39900. 誤差 = 0.0024579554
Generation: 40000. 誤差 = 0.0024579538
Generation: 40100. 誤差 = 0.0024579538
Generation: 40200. 誤差 = 0.0024579377
Generation: 40300. 誤差 = 0.0024579442
Generation: 40400. 誤差 = 0.0024579389
Generation: 40500. 誤差 = 0.002457958
Generation: 40600. 誤差 = 0.002457952
Generation: 40700. 誤差 = 0.0024579398
Generation: 40800. 誤差 = 0.0024579628
Generation: 40900. 誤差 = 0.0024579493
Generation: 41000. 誤差 = 0.0024579612
Generation: 41100. 誤差 = 0.0024580075
Generation: 41200. 誤差 = 0.002458107
Generation: 41300. 誤差 = 0.0024579808
Generation: 41400. 誤差 = 0.0024579598
Generation: 41500. 誤差 = 0.0024579451
Generation: 41600. 誤差 = 0.0024579547
Generation: 41700. 誤差 = 0.002457933
Generation: 41800. 誤差 = 0.0024579526
Generation: 41900. 誤差 = 0.0024579512
Generation: 42000. 誤差 = 0.0024579612
Generation: 42100. 誤差 = 0.0024579437
Generation: 42200. 誤差 = 0.002457954
Generation: 42300. 誤差 = 0.002457948
Generation: 42400. 誤差 = 0.0024579582
Generation: 42500. 誤差 = 0.0024579335
Generation: 42600. 誤差 = 0.0024579319
Generation: 42700. 誤差 = 0.00245794
```

```
Generation: 42800. 誤差 = 0.0024579703
Generation: 42900. 誤差 = 0.0024580285
Generation: 43000. 誤差 = 0.0024579596
Generation: 43100. 誤差 = 0.0024580148
Generation: 43200. 誤差 = 0.002457944
Generation: 43300. 誤差 = 0.0024580196
Generation: 43400. 誤差 = 0.002457973
Generation: 43500. 誤差 = 0.0024579638
Generation: 43600. 誤差 = 0.0024579796
Generation: 43700. 誤差 = 0.0024579584
Generation: 43800. 誤差 = 0.0024579742
Generation: 43900. 誤差 = 0.0024579822
Generation: 44000. 誤差 = 0.0024579614
Generation: 44100. 誤差 = 0.0024579496
Generation: 44200. 誤差 = 0.0024579642
Generation: 44300. 誤差 = 0.0024579847
Generation: 44400. 誤差 = 0.0024579626
Generation: 44500. 誤差 = 0.002457951
Generation: 44600. 誤差 = 0.0024579756
Generation: 44700. 誤差 = 0.002457956
Generation: 44800. 誤差 = 0.002457976
Generation: 44900. 誤差 = 0.00245796
Generation: 45000. 誤差 = 0.0024579586
Generation: 45100. 誤差 = 0.002457968
Generation: 45200. 誤差 = 0.0024579586
Generation: 45300. 誤差 = 0.002457959
Generation: 45400. 誤差 = 0.0024579605
Generation: 45500. 誤差 = 0.002457961
Generation: 45600. 誤差 = 0.0024579624
Generation: 45700. 誤差 = 0.0024579575
Generation: 45800. 誤差 = 0.002457974
Generation: 45900. 誤差 = 0.0024581521
Generation: 46000. 誤差 = 0.002457973
Generation: 46100. 誤差 = 0.0024579512
Generation: 46200. 誤差 = 0.002457959
Generation: 46300. 誤差 = 0.0024579891
Generation: 46400. 誤差 = 0.0024579533
Generation: 46500. 誤差 = 0.0024579572
Generation: 46600. 誤差 = 0.0024579745
Generation: 46700. 誤差 = 0.0024579552
Generation: 46800. 誤差 = 0.002457975
Generation: 46900. 誤差 = 0.0024579566
Generation: 47000. 誤差 = 0.0024579605
Generation: 47100. 誤差 = 0.0024579784
Generation: 47200. 誤差 = 0.0024579582
Generation: 47300. 誤差 = 0.0024579489
Generation: 47400. 誤差 = 0.002457965
Generation: 47500. 誤差 = 0.002457955
Generation: 47600. 誤差 = 0.0024579782
Generation: 47700. 誤差 = 0.0024579596
Generation: 47800. 誤差 = 0.0024579559
Generation: 47900. 誤差 = 0.0024579593
Generation: 48000. 誤差 = 0.0024579593
Generation: 48100. 誤差 = 0.0024579563
Generation: 48200. 誤差 = 0.0024579687
Generation: 48300. 誤差 = 0.0024579628
Generation: 48400. 誤差 = 0.002458017
Generation: 48500. 誤差 = 0.0024579645
Generation: 48600. 誤差 = 0.0024579398
Generation: 48700. 誤差 = 0.0024579705
Generation: 48800. 誤差 = 0.002457972
```

```
Generation: 48900. 誤差 = 0.0024579815

Generation: 49000. 誤差 = 0.00245797

Generation: 49100. 誤差 = 0.0024579754

Generation: 49200. 誤差 = 0.0024579745

Generation: 49300. 誤差 = 0.0024579745

Generation: 49400. 誤差 = 0.0024579493

Generation: 49500. 誤差 = 0.0024579572

Generation: 49600. 誤差 = 0.0024579572

Generation: 49700. 誤差 = 0.0024579575

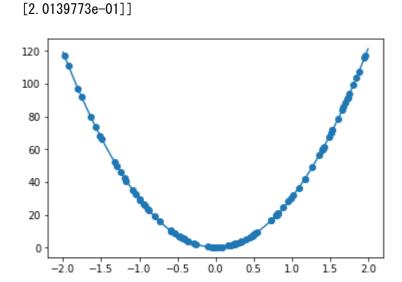
Generation: 49800. 誤差 = 0.0024580092

Generation: 49900. 誤差 = 0.0024580394

[[2.3939405e-03]

[2.9999142e+01]

[4.9005434e-01]
```



分類1層 (mnist) (入力層→出力層)

[try]

- x:入力値, d:教師データ, W:重み, b:バイアス をそれぞれ定義 しよう

In [20]:

```
import tensorflow as tf
import matplotlib.pyplot as plt
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
iters_num = 100
batch\_size = 100
plot_interval = 1
# ----- ここを補填 --
x = tf. placeholder(tf. float32, [None, 784])
d = tf.placeholder(tf.float32, [None, 10])
W = tf. Variable(tf. random_normal([784, 10], stddev=0.01))
b = tf. Variable(tf. zeros([10]))
y = tf. nn. softmax(tf. matmul(x, W) + b)
# 交差エントロピー
cross_entropy = -tf.reduce_sum(d * tf.log(y), reduction_indices=[1])
loss = tf.reduce_mean(cross_entropy)
train = tf. train. GradientDescentOptimizer (0.1). minimize (loss)
# 正誤を保存
correct = tf. equal(tf. argmax(y, 1), tf. argmax(d, 1))
# 正解率
accuracy = tf. reduce_mean(tf. cast(correct, tf. float32))
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
accuracies = []
for i in range(iters_num):
    x_batch, d_batch = mnist.train.next_batch(batch_size)
    sess.run(train, feed_dict={x: x_batch, d: d_batch})
    if (i+1) % plot_interval == 0:
        print(sess.run(correct, feed_dict={x: mnist.test.images, d: mnist.test.labels}))
        accuracy_val = sess.run(accuracy, feed_dict={x: mnist.test.images, d: mnist.test.labels
})
        accuracies. append (accuracy_val)
        print('Generation: ' + str(i+1) + '. 正解率 = ' + str(accuracy_val))
lists = range(0, iters_num, plot_interval)
plt.plot(lists, accuracies)
plt.title("accuracy")
plt. ylim(0, 1.0)
plt.show()
```

WARNING:tensorflow:From <ipython-input-20-77bf5b52a1ed>:4: read_data_sets (from tensorflow.contrib.learn.python.learn.datasets.mnist) is deprecated and will be removed in a future version.

Instructions for updating:

Please use alternatives such as official/mnist/dataset.py from tensorflow/models. WARNING:tensorflow:From C:\programData\parayAnaconda3\parayIb\parayIbarayI

rib¥learn¥python¥learn¥datasets¥mnist.py:260: maybe_download (from tensorflow.cont rib.learn.python.learn.datasets.base) is deprecated and will be removed in a futur e version.

Instructions for updating:

Please write your own downloading logic.

WARNING:tensorflow:From C:\(\)ProgramData\(\)Anaconda3\(\)Iib\(\)site-packages\(\)\tensorflow\(\)Cont rib\(\)Iearn\(\)python\(\)Iearn\(\)datasets\(\)\tensorflow\(\). cont rib. Iearn. python. Iearn. datasets. mnist) is deprecated and will be removed in a futu re version.

Instructions for updating:

Please use tf. data to implement this functionality.

Extracting MNIST_data/train-images-idx3-ubyte.gz

WARNING:tensorflow:From C:\(\)ProgramData\(\)Anaconda3\(\)Iib\(\)site-packages\(\)\tensorflow\(\)Contrib\(\)Iearn\(\)Python\(\)Iearn\(\)Adatasets\(\)\tensorflow\(\). contrib\(\)Iearn\(\) python\(\). Iearn\(\) datasets\(\). mnist\(\) is deprecated and will be removed in a future version.

Instructions for updating:

Please use tf. data to implement this functionality.

Extracting MNIST_data/train-labels-idx1-ubyte.gz

WARNING:tensorflow:From C:\[\text{ProgramData} \] Anaconda3\[\text{lib} \] site-packages\[\tensorflow \] tensorflow \] contrib\[\text{learn} \] tearn\[\text{dense} \] tensorflow. contrib. learn. python. learn. datasets. mnist) is deprecated and will be removed in a future version.

Instructions for updating:

Please use tf. one_hot on tensors.

Extracting MNIST data/t10k-images-idx3-ubvte.gz

Extracting MNIST_data/t10k-labels-idx1-ubyte.gz

WARNING:tensorflow:From C:\[\) ProgramData\[\) Anaconda3\[\] lib\[\) site\[-packages\[\) tensorflow\[\) contrib\[\] learn\[\) python\[\] learn\[\) datasets\[\) mnist\[\] by\[\) 290: Data\[\] Data\[\] be removed in a future version.

Instructions for updating:

Please use alternatives such as official/mnist/dataset.py from tensorflow/models.

[False False False ... False False False]

Generation: 1. 正解率 = 0.3164

[True False True ... False False True]

Generation: 2. 正解率 = 0.3979

[True False True ... False True True]

Generation: 3. 正解率 = 0.5153

[True False True ... False True True]

Generation: 4. 正解率 = 0.5601

[True False True ... False False True]

Generation: 5. 正解率 = 0.5844

[True False True ... False True True]

Generation: 6. 正解率 = 0.6493

[True True True ... False False True]

Generation: 7. 正解率 = 0.649

[True False True ... False False True]

Generation: 8. 正解率 = 0.6325

[True True True ... False False True]

Generation: 9. 正解率 = 0.653

[True True True ... False False True]

Generation: 10. 正解率 = 0.6624

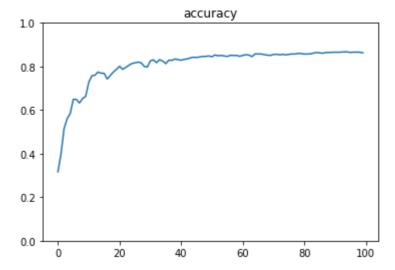
[True True True ... False False True]

Generation: 11. 正解率 = 0.7268

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[True True True False False Generation: 12. 正解率 = 0.7573	True]
[True False True False False	True]
Generation: 13. 正解率 = 0.7597 [True False True False False	Truel
Generation: 14. 正解率 = 0.7744	
[True True True False False Generation: 15. 正解率 = 0.7692	[rue]
[True False True True False	True]
Generation: 16. 正解率 = 0.7687 [True False True True False	True]
Generation: 17. 正解率 = 0.7425 [True False True True False	Truel
Generation: 18. 正解率 = 0.7586	
[True False True False False Generation: 19. 正解率 = 0.7744	[rue]
[True True True True False Generation: 20. 正解率 = 0.7867	True]
[True True True True False	True]
Generation: 21. 正解率 = 0.801 [True True True True False	Truel
Generation: 22. 正解率 = 0.787	
[True True True True False Generation: 23. 正解率 = 0.7957	iruej
[True True True True False Generation: 24. 正解率 = 0.805	True]
[True True True True False	True]
Generation: 25. 正解率 = 0.8135 [True True True True False	True]
Generation: 26. 正解率 = 0.8167 [True True True True False	Truel
Generation: 27. 正解率 = 0.82	
[True True True True False Generation: 28. 正解率 = 0.8172	True
[True True True True False Generation: 29. 正解率 = 0.8008	True]
[True True True True False	True]
Generation: 30. 正解率 = 0.7973 [True True True True False	Truel
Generation: 31. 正解率 = 0.8253	
[True True True True False Generation: 32. 正解率 = 0.8305	[rue]
[True True True False False Generation: 33. 正解率 = 0.8175	True]
[True True True True False	True]
Generation: 34. 正解率 = 0.831 [True True True False False	True]
Generation: 35. 正解率 = 0.8253	
[True True True False False Generation: 36. 正解率 = 0.8129	
[True True True True False Generation: 37. 正解率 = 0.8293	True]
[True True True True False	True]
Generation: 38. 正解率 = 0.8282 [True True True True False	True]
Generation: 39. 正解率 = 0.8344 [True True True True False	Truel
Generation: 40. 正解率 = 0.8317	
[True True True False False Generation: 41. 正解率 = 0.8286	rue
[True True True True False	True]

•	5/1/21		
	Generation: 42. 正解率	= 0.8328	
	[True True True		True]
	Generation: 43. 正解率	= 0.8346	- -
	[True True True	Irue False	[rue]
	Generation: 44. 正解率	= 0.8396	Trucl
	[True True True Generation: 45. 正解率		True]
	[True True True		True]
	Generation: 46. 正解率		ii uoj
	[True True True		True]
	Generation: 47. 正解率		_
	[True True True	True False	True]
	Generation: 48. 正解率		
	[True True True		True]
	Generation: 49. 正解率		T
	[True True True Generation: 50. 正解率		True]
	[True True True		True]
	Generation: 51. 正解率		ii ue
	[True True True	True False	True]
	Generation: 52. 正解率	= 0.8526	
	[True True True		True]
	Generation: 53. 正解率	= 0.8493	
	[True True True		True]
	Generation: 54. 正解率		
	[True True True		True]
	Generation: 55. 正解率		Twucl
	[True True True Generation: 56. 正解率		True]
	[True True True		True]
	Generation: 57. 正解率		ii uoj
	[True True True		True]
	Generation: 58. 正解率		-
	[True True True		True]
	Generation: 59. 正解率	= 0.8509	
	[True True True Generation: 60. 正解率	True True	True]
	Generation: 60. 止解率	= 0.846/	т
	[True True True	- 0 0500	irue」
	Generation: 61. 正解率 [True True True		Trual
	Generation: 62. 正解率		muej
	[True True True		Truel
	Generation: 63. 正解率	= 0.8525	
	[True True True	True True	True]
	Generation: 64. 正解率	= 0.8452	
	[True True True		True]
	Generation: 65. 正解率		
	[True True True		True」
	Generation: 66. 正解率		Truol
	[True True True Generation: 67. 正解率		rruej
	[True True True	True True	Truel
	Generation: 68. 正解率		ii uoj
	[True True True	True True	True]
	Generation: 69. 正解率	= 0.8523	_
	[True True True	True False	True]
	Generation: 70. 正解率		_
	[True True True	True True	True]
	Generation: 71. 正解率		т ¬
	[True True True	Irue False	ırue]
	Generation: 72. 正解率	- U. 8301	

19/1/21	
[True True True True False Generation: 73. 正解率 = 0.8535	True]
[True True True True False	True]
Generation: 74. 正解率 = 0.8558 [True True True True False	Truel
Generation: 75. 正解率 = 0.8533	
[True True True True False Generation: 76. 正解率 = 0.8556	True]
[True True True True False	True]
Generation: 77. 正解率 = 0.8576 [True True True True False	Truol
Generation: 78. 正解率 = 0.8571	ITue
[True True True True False	True]
Generation: 79. 正解率 = 0.8604 [True True True True True	True]
Generation: 80. 正解率 = 0.8589	
[True True True True True Generation: 81. 正解率 = 0.8569	True]
[True True True True False	True]
Generation: 82. 正解率 = 0.8573	
[True True True True False Generation: 83. 正解率 = 0.8579	True]
[True True True True False	True]
Generation: 84. 正解率 = 0.8616	T
[True True True True True Generation: 85. 正解率 = 0.864	iruej
[True True True True False	True]
Generation: 86. 正解率 = 0.8623 [True True True True False	True]
Generation: 87. 正解率 = 0.8609	ii uej
[True True True True False	True]
Generation: 88. 正解率 = 0.8638 [True True True True False	Truel
Generation: 89. 正解率 = 0.8644	
[True True True True False Generation: 90. 正解率 = 0.8652	True]
[True True True True False	True]
Generation: 91. 正解率 = 0.8653	
[True True True True False Generation: 92. 正解率 = 0.8653	iruej
[True True True True False	True]
Generation: 93. 正解率 = 0.866	True]
[True True True True False Generation: 94. 正解率 = 0.8671	ITue
[True True True True False	True]
Generation: 95. 正解率 = 0.8668 [True True True True False	Truel
Generation: 96. 正解率 = 0.8643	
[True True True True False Generation: 97. 正解率 = 0.8659	True]
[True True True True False	True]
Generation: 98. 正解率 = 0.8656	
[True True True True False Generation: 99. 正解率 = 0.8657	ırue]
[True True True True False	True]
Generation: 100. 正解率 = 0.8624	



分類3層 (mnist) (入力層→中間層→中間層→出力層)

```
tf.train.GradientDescentOptimizer
__init__(
    learning_rate,
    use_locking=False,
    name='GradientDescent'
)
tf.train.MomentumOptimizer
__init__(
    learning_rate,
    momentum,
    use_locking=False,
    name=' Momentum',
    use_nesterov=False
)
tf.train.AdagradOptimizer
__init__(
    learning_rate,
    initial_accumulator_value=0.1,
    use_locking=False,
    name='Adagrad'
)
tf.train.RMSPropOptimizer
__init__(
    learning_rate,
    decay=0.9,
    momentum=0.0,
    epsilon=1e-10,
    use_locking=False,
    centered=False.
    name='RMSProp'
)
tf.train.AdamOptimizer
__init__(
    learning rate=0.001.
    beta1=0.9,
    beta2=0.999,
    epsilon=1e-08.
    use_locking=False,
    name=' Adam'
)
```

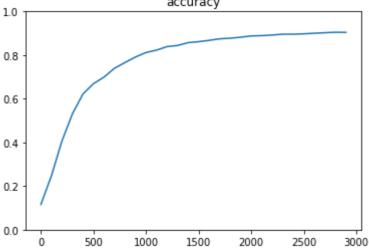
In [21]:

```
import tensorflow as tf
import numpy as np
from tensorflow. examples. tutorials. mnist import input_data
import matplotlib.pyplot as plt
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
iters_num = 3000
batch_size = 100
plot_interval = 100
hidden_layer_size_1 = 600
hidden_layer_size_2 = 300
dropout_rate = 0.5
x = tf. placeholder(tf. float32, [None, 784])
d = tf. placeholder (tf. float32, [None, 10])
W1 = tf. Variable(tf.random_normal([784, hidden_layer_size_1], stddev=0.01))
W2 = tf.Variable(tf.random_normal([hidden_layer_size_1, hidden_layer_size_2], stddev=0.01))
W3 = tf. Variable(tf.random_normal([hidden_layer_size_2, 10], stddev=0.01))
b1 = tf. Variable(tf. zeros([hidden_layer_size_1]))
b2 = tf. Variable(tf. zeros([hidden_layer_size_2]))
b3 = tf. Variable(tf. zeros([10]))
z1 = tf. sigmoid(tf. matmul(x, W1) + b1)
z2 = tf. sigmoid(tf. matmul(z1, W2) + b2)
keep_prob = tf. placeholder (tf. float32)
drop = tf. nn. dropout(z2, keep_prob)
y = tf. nn. softmax(tf. matmul(drop, W3) + b3)
loss = tf.reduce_mean(-tf.reduce_sum(d * tf.log(y), reduction_indices=[1]))
optimizer = tf. train. AdamOptimizer (1e-4)
train = optimizer.minimize(loss)
correct = tf. equal(tf. argmax(y, 1), tf. argmax(d, 1))
accuracy = tf.reduce mean(tf.cast(correct, tf.float32))
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
accuracies = []
for i in range(iters num):
    x batch, d batch = mnist.train.next batch(batch size)
    sess.run(train, feed_dict={x:x_batch, d:d_batch, keep_prob:(1 - dropout_rate)})
    if (i+1) % plot_interval == 0:
        accuracy val = sess.run(accuracy, feed dict={x:mnist.test.images, d:mnist.test.labels, k
eep_prob:1.0})
        accuracies. append (accuracy_val)
        print('Generation: ' + str(i+1) + '. 正解率 = ' + str(accuracy_val))
lists = range(0, iters_num, plot_interval)
plt.plot(lists, accuracies)
plt.title("accuracy")
```

```
plt.ylim(0, 1.0)
plt.show()
```

Extracting MNIST data/train-images-idx3-ubyte.gz

```
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Extracting MNIST data/t10k-images-idx3-ubvte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
WARNING:tensorflow:From <ipython-input-21-7595c106b6f4>:31: calling dropout (from
tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in
a future version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_p
rob`.
Generation: 100. 正解率 = 0.116
Generation: 200. 正解率 = 0.2471
Generation: 300. 正解率 = 0.4066
Generation: 400. 正解率 = 0.5313
Generation: 500. 正解率 = 0.6221
Generation: 600. 正解率 = 0.6691
Generation: 700. 正解率 = 0.6994
Generation: 800. 正解率 = 0.7396
Generation: 900. 正解率 = 0.7661
Generation: 1000. 正解率 = 0.7913
Generation: 1100. 正解率 = 0.8118
Generation: 1200. 正解率 = 0.8228
Generation: 1300. 正解率 = 0.839
Generation: 1400. 正解率 = 0.8441
Generation: 1500. 正解率 = 0.857
Generation: 1600. 正解率 = 0.8615
Generation: 1700. 正解率 = 0.8675
Generation: 1800. 正解率 = 0.8746
Generation: 1900. 正解率 = 0.8773
Generation: 2000. 正解率 = 0.882
Generation: 2100. 正解率 = 0.8878
Generation: 2200. 正解率 = 0.8892
Generation: 2300. 正解率 = 0.8919
Generation: 2400. 正解率 = 0.8958
Generation: 2500. 正解率 = 0.8958
Generation: 2600. 正解率 = 0.8975
Generation: 2700. 正解率 = 0.9001
Generation: 2800. 正解率 = 0.9025
Generation: 2900. 正解率 = 0.9045
Generation: 3000. 正解率 = 0.9041
                       accuracy
 1.0
```



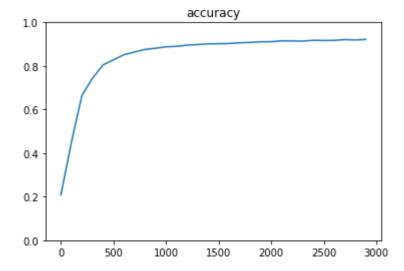
• 隠れ層のサイズを変更してみよう

In [22]:

```
import tensorflow as tf
import numpy as np
from tensorflow. examples. tutorials. mnist import input_data
import matplotlib.pyplot as plt
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
iters_num = 3000
batch_size = 100
plot_interval = 100
hidden_layer_size_1 = 1500
hidden_layer_size_2 = 1000
dropout_rate = 0.5
x = tf. placeholder(tf. float32, [None, 784])
d = tf. placeholder (tf. float32, [None, 10])
W1 = tf. Variable(tf.random_normal([784, hidden_layer_size_1], stddev=0.01))
W2 = tf.Variable(tf.random_normal([hidden_layer_size_1, hidden_layer_size_2], stddev=0.01))
W3 = tf. Variable(tf.random_normal([hidden_layer_size_2, 10], stddev=0.01))
b1 = tf. Variable(tf. zeros([hidden_layer_size_1]))
b2 = tf. Variable(tf. zeros([hidden_layer_size_2]))
b3 = tf. Variable(tf. zeros([10]))
z1 = tf. sigmoid(tf. matmul(x, W1) + b1)
z2 = tf. sigmoid(tf. matmul(z1, W2) + b2)
keep_prob = tf. placeholder (tf. float32)
drop = tf. nn. dropout(z2, keep_prob)
y = tf. nn. softmax(tf. matmul(drop, W3) + b3)
loss = tf.reduce_mean(-tf.reduce_sum(d * tf.log(y), reduction_indices=[1]))
optimizer = tf. train. AdamOptimizer (1e-4)
train = optimizer.minimize(loss)
correct = tf. equal(tf. argmax(y, 1), tf. argmax(d, 1))
accuracy = tf.reduce mean(tf.cast(correct, tf.float32))
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
accuracies = []
for i in range(iters num):
    x batch, d batch = mnist.train.next batch(batch size)
    sess.run(train, feed_dict={x:x_batch, d:d_batch, keep_prob:(1 - dropout_rate)})
    if (i+1) % plot_interval == 0:
        accuracy val = sess.run(accuracy, feed dict={x:mnist.test.images, d:mnist.test.labels, k
eep_prob:1.0})
        accuracies. append (accuracy_val)
        print('Generation: ' + str(i+1) + '. 正解率 = ' + str(accuracy_val))
lists = range(0, iters_num, plot_interval)
plt.plot(lists, accuracies)
plt.title("accuracy")
```

```
plt.ylim(0, 1.0)
plt.show()
```

```
Extracting MNIST_data/train-images-idx3-ubyte.gz
Extracting MNIST data/train-labels-idx1-ubyte.gz
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
Generation: 100. 正解率 = 0.209
Generation: 200. 正解率 = 0.4502
Generation: 300. 正解率 = 0.6653
Generation: 400. 正解率 = 0.7434
Generation: 500. 正解率 = 0.8048
Generation: 600. 正解率 = 0.8284
Generation: 700. 正解率 = 0.8517
Generation: 800. 正解率 = 0.8642
Generation: 900. 正解率 = 0.8759
Generation: 1000. 正解率 = 0.8814
Generation: 1100. 正解率 = 0.888
Generation: 1200. 正解率 = 0.8901
Generation: 1300. 正解率 = 0.8956
Generation: 1400. 正解率 = 0.8981
Generation: 1500. 正解率 = 0.9018
Generation: 1600. 正解率 = 0.9021
Generation: 1700. 正解率 = 0.9032
Generation: 1800. 正解率 = 0.9066
Generation: 1900. 正解率 = 0.9081
Generation: 2000. 正解率 = 0.9111
Generation: 2100. 正解率 = 0.9114
Generation: 2200. 正解率 = 0.9154
Generation: 2300. 正解率 = 0.915
Generation: 2400. 正解率 = 0.9143
Generation: 2500. 正解率 = 0.9178
Generation: 2600. 正解率 = 0.917
Generation: 2700. 正解率 = 0.9174
Generation: 2800. 正解率 = 0.9213
Generation: 2900. 正解率 = 0.9193
Generation: 3000. 正解率 = 0.9218
```



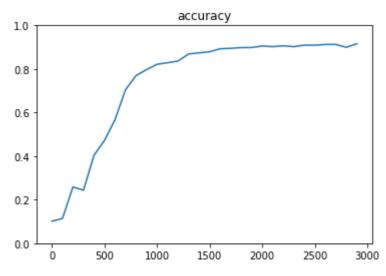
optimizerを変更しよう (AdamをGDに変更)

In [23]:

```
import tensorflow as tf
import numpy as np
from tensorflow. examples. tutorials. mnist import input_data
import matplotlib.pyplot as plt
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
iters_num = 3000
batch_size = 100
plot_interval = 100
hidden_layer_size_1 = 600
hidden_layer_size_2 = 300
dropout rate = 0.5
x = tf. placeholder(tf. float32, [None, 784])
d = tf.placeholder(tf.float32, [None, 10])
W1 = tf. Variable(tf.random_normal([784, hidden_layer_size_1], stddev=0.01))
W2 = tf. Variable(tf.random_normal([hidden_layer_size_1, hidden_layer_size_2], stddev=0.01))
W3 = tf. Variable(tf.random_normal([hidden_layer_size_2, 10], stddev=0.01))
b1 = tf. Variable(tf.zeros([hidden_layer_size_1]))
b2 = tf. Variable(tf. zeros([hidden_layer_size_2]))
b3 = tf. Variable(tf. zeros([10]))
z1 = tf. sigmoid(tf. matmul(x, W1) + b1)
z2 = tf. sigmoid(tf. matmul(z1. W2) + b2)
keep_prob = tf.placeholder(tf.float32)
drop = tf. nn. dropout(z2, keep_prob)
y = tf. nn. softmax(tf. matmul(drop, W3) + b3)
loss = tf.reduce_mean(-tf.reduce_sum(d * tf.log(y), reduction_indices=[1]))
optimizer = tf. train. GradientDescentOptimizer (0.5)
train = optimizer.minimize(loss)
correct = tf. equal(tf. argmax(y, 1), tf. argmax(d, 1))
accuracy = tf.reduce_mean(tf.cast(correct, tf.float32))
init = tf.global variables initializer()
sess = tf. Session()
sess.run(init)
accuracies = []
for i in range(iters_num):
    x batch, d batch = mnist.train.next batch(batch size)
    sess.run(train, feed dict={x:x batch, d:d batch, keep prob:(1 - dropout rate)})
    if (i+1) % plot_interval == 0:
        accuracy_val = sess.run(accuracy, feed_dict={x:mnist.test.images, d:mnist.test.labels, k
eep_prob:1.0})
        accuracies. append (accuracy_val)
        print('Generation: ' + str(i+1) + '. 正解率 = ' + str(accuracy val))
lists = range(0, iters_num, plot_interval)
```

```
plt.plot(lists, accuracies)
plt.title("accuracy")
plt.ylim(0, 1.0)
plt.show()
```

```
Extracting MNIST_data/train-images-idx3-ubyte.gz
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Extracting MNIST data/t10k-labels-idx1-ubvte.gz
Generation: 100. 正解率 = 0.1009
Generation: 200. 正解率 = 0.1135
Generation: 300. 正解率 = 0.2584
Generation: 400. 正解率 = 0.2434
Generation: 500. 正解率 = 0.4038
Generation: 600. 正解率 = 0.4722
Generation: 700. 正解率 = 0.5675
Generation: 800. 正解率 = 0.705
Generation: 900. 正解率 = 0.7695
Generation: 1000. 正解率 = 0.797
Generation: 1100. 正解率 = 0.8216
Generation: 1200. 正解率 = 0.8287
Generation: 1300. 正解率 = 0.8364
Generation: 1400. 正解率 = 0.8689
Generation: 1500. 正解率 = 0.8741
Generation: 1600. 正解率 = 0.8792
Generation: 1700. 正解率 = 0.8927
Generation: 1800. 正解率 = 0.8947
Generation: 1900. 正解率 = 0.8982
Generation: 2000. 正解率 = 0.8985
Generation: 2100. 正解率 = 0.9055
Generation: 2200. 正解率 = 0.9025
Generation: 2300. 正解率 = 0.9063
Generation: 2400. 正解率 = 0.9025
Generation: 2500. 正解率 = 0.9094
Generation: 2600. 正解率 = 0.9092
Generation: 2700. 正解率 = 0.9124
Generation: 2800. 正解率 = 0.9127
Generation: 2900. 正解率 = 0.8995
Generation: 3000. 正解率 = 0.9159
```



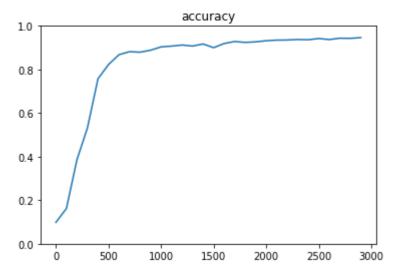
optimizerを変更しよう (AdamをMomentumに変更)

In [24]:

```
import tensorflow as tf
import numpy as np
from tensorflow. examples. tutorials. mnist import input_data
import matplotlib.pyplot as plt
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
iters_num = 3000
batch_size = 100
plot_interval = 100
hidden_layer_size_1 = 600
hidden_layer_size_2 = 300
dropout_rate = 0.5
x = tf. placeholder(tf. float32, [None, 784])
d = tf. placeholder (tf. float32, [None, 10])
W1 = tf. Variable(tf.random_normal([784, hidden_layer_size_1], stddev=0.01))
W2 = tf.Variable(tf.random_normal([hidden_layer_size_1, hidden_layer_size_2], stddev=0.01))
W3 = tf. Variable(tf.random_normal([hidden_layer_size_2, 10], stddev=0.01))
b1 = tf. Variable(tf. zeros([hidden_layer_size_1]))
b2 = tf. Variable(tf. zeros([hidden_layer_size_2]))
b3 = tf. Variable(tf. zeros([10]))
z1 = tf. sigmoid(tf. matmul(x, W1) + b1)
z2 = tf. sigmoid(tf. matmul(z1, W2) + b2)
keep_prob = tf. placeholder (tf. float32)
drop = tf. nn. dropout(z2, keep_prob)
y = tf. nn. softmax(tf. matmul(drop, W3) + b3)
loss = tf.reduce_mean(-tf.reduce_sum(d * tf.log(y), reduction_indices=[1]))
optimizer = tf. train. MomentumOptimizer (0.1. 0.9)
train = optimizer.minimize(loss)
correct = tf. equal(tf. argmax(y, 1), tf. argmax(d, 1))
accuracy = tf. reduce mean(tf. cast(correct, tf. float32))
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
accuracies = \Pi
for i in range(iters num):
    x_batch, d_batch = mnist.train.next_batch(batch_size)
    sess.run(train, feed_dict={x:x_batch, d:d_batch, keep_prob:(1 - dropout_rate)})
    if (i+1) % plot interval == 0:
        accuracy val = sess.run(accuracy, feed dict={x:mnist.test.images, d:mnist.test.labels, k
eep_prob:1.0})
        accuracies. append (accuracy_val)
        print('Generation: ' + str(i+1) + '. 正解率 = ' + str(accuracy_val))
lists = range(0, iters num, plot interval)
plt.plot(lists, accuracies)
```

plt.title("accuracy")
plt.ylim(0, 1.0)
plt.show()

```
Extracting MNIST data/train-images-idx3-ubyte.gz
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Extracting MNIST data/t10k-images-idx3-ubyte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
Generation: 100. 正解率 = 0.0982
Generation: 200. 正解率 = 0.1619
Generation: 300. 正解率 = 0.3859
Generation: 400. 正解率 = 0.532
Generation: 500. 正解率 = 0.7573
Generation: 600. 正解率 = 0.8224
Generation: 700. 正解率 = 0.868
Generation: 800. 正解率 = 0.8817
Generation: 900. 正解率 = 0.8794
Generation: 1000. 正解率 = 0.8884
Generation: 1100. 正解率 = 0.9036
Generation: 1200. 正解率 = 0.9073
Generation: 1300. 正解率 = 0.9122
Generation: 1400. 正解率 = 0.9075
Generation: 1500. 正解率 = 0.917
Generation: 1600. 正解率 = 0.9
Generation: 1700. 正解率 = 0.9192
Generation: 1800. 正解率 = 0.9283
Generation: 1900. 正解率 = 0.9243
Generation: 2000. 正解率 = 0.9268
Generation: 2100. 正解率 = 0.9319
Generation: 2200. 正解率 = 0.9348
Generation: 2300. 正解率 = 0.9353
Generation: 2400. 正解率 = 0.9376
Generation: 2500. 正解率 = 0.9365
Generation: 2600. 正解率 = 0.9421
Generation: 2700. 正解率 = 0.9373
Generation: 2800. 正解率 = 0.9436
Generation: 2900. 正解率 = 0.9429
Generation: 3000. 正解率 = 0.9461
```



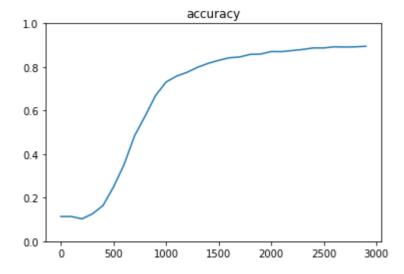
optimizerを変更しよう (AdamをAdagradに変更)

In [25]:

```
import tensorflow as tf
import numpy as np
from tensorflow. examples. tutorials. mnist import input_data
import matplotlib.pyplot as plt
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
iters_num = 3000
batch_size = 100
plot_interval = 100
hidden_layer_size_1 = 600
hidden_layer_size_2 = 300
dropout_rate = 0.5
x = tf. placeholder(tf. float32, [None, 784])
d = tf.placeholder(tf.float32, [None, 10])
W1 = tf. Variable(tf.random_normal([784, hidden_layer_size_1], stddev=0.01))
W2 = tf.Variable(tf.random_normal([hidden_layer_size_1, hidden_layer_size_2], stddev=0.01))
W3 = tf. Variable(tf.random_normal([hidden_layer_size_2, 10], stddev=0.01))
b1 = tf. Variable(tf. zeros([hidden_layer_size_1]))
b2 = tf. Variable(tf. zeros([hidden_layer_size_2]))
b3 = tf. Variable(tf. zeros([10]))
z1 = tf. sigmoid(tf. matmul(x, W1) + b1)
z2 = tf. sigmoid(tf. matmul(z1, W2) + b2)
keep_prob = tf. placeholder (tf. float32)
drop = tf. nn. dropout(z2, keep_prob)
y = tf. nn. softmax(tf. matmul(drop, W3) + b3)
loss = tf.reduce_mean(-tf.reduce_sum(d * tf.log(y), reduction_indices=[1]))
optimizer = tf. train. AdagradOptimizer (0.1)
train = optimizer.minimize(loss)
correct = tf. equal(tf. argmax(y, 1), tf. argmax(d, 1))
accuracy = tf. reduce mean(tf. cast(correct, tf. float32))
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
accuracies = \Pi
for i in range(iters num):
    x_batch, d_batch = mnist.train.next_batch(batch_size)
    sess.run(train, feed_dict={x:x_batch, d:d_batch, keep_prob:(1 - dropout_rate)})
    if (i+1) % plot interval == 0:
        accuracy val = sess.run(accuracy, feed dict={x:mnist.test.images, d:mnist.test.labels, k
eep_prob:1.0})
        accuracies, append (accuracy val)
        print('Generation: ' + str(i+1) + '. 正解率 = ' + str(accuracy_val))
lists = range(0, iters num, plot interval)
plt.plot(lists, accuracies)
```

```
plt.title("accuracy")
plt.ylim(0, 1.0)
plt.show()
```

```
Extracting MNIST_data/train-images-idx3-ubyte.gz
Extracting MNIST data/train-labels-idx1-ubvte.gz
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
Generation: 100. 正解率 = 0.1135
Generation: 200. 正解率 = 0.1135
Generation: 300. 正解率 = 0.1028
Generation: 400. 正解率 = 0.1259
Generation: 500. 正解率 = 0.1637
Generation: 600. 正解率 = 0.2493
Generation: 700. 正解率 = 0.3515
Generation: 800. 正解率 = 0.4838
Generation: 900. 正解率 = 0.5739
Generation: 1000. 正解率 = 0.669
Generation: 1100. 正解率 = 0.731
Generation: 1200. 正解率 = 0.7581
Generation: 1300. 正解率 = 0.7756
Generation: 1400. 正解率 = 0.7986
Generation: 1500. 正解率 = 0.8166
Generation: 1600. 正解率 = 0.8304
Generation: 1700. 正解率 = 0.842
Generation: 1800. 正解率 = 0.8459
Generation: 1900. 正解率 = 0.8577
Generation: 2000. 正解率 = 0.8592
Generation: 2100. 正解率 = 0.8709
Generation: 2200. 正解率 = 0.8705
Generation: 2300. 正解率 = 0.8755
Generation: 2400. 正解率 = 0.8805
Generation: 2500. 正解率 = 0.8874
Generation: 2600. 正解率 = 0.8874
Generation: 2700. 正解率 = 0.8925
Generation: 2800. 正解率 = 0.8916
Generation: 2900. 正解率 = 0.8925
Generation: 3000. 正解率 = 0.8949
```



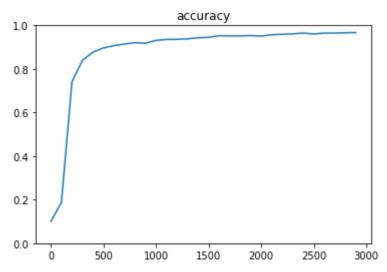
optimizerを変更しよう (AdamをRMSPropに変更)

In [26]:

```
import tensorflow as tf
import numpy as np
from tensorflow. examples. tutorials. mnist import input_data
import matplotlib.pyplot as plt
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
iters_num = 3000
batch_size = 100
plot_interval = 100
hidden_layer_size_1 = 600
hidden_layer_size_2 = 300
dropout_rate = 0.5
x = tf. placeholder(tf. float32, [None, 784])
d = tf.placeholder(tf.float32, [None, 10])
W1 = tf. Variable(tf.random_normal([784, hidden_layer_size_1], stddev=0.01))
W2 = tf.Variable(tf.random_normal([hidden_layer_size_1, hidden_layer_size_2], stddev=0.01))
W3 = tf. Variable(tf.random_normal([hidden_layer_size_2, 10], stddev=0.01))
b1 = tf. Variable(tf. zeros([hidden_layer_size_1]))
b2 = tf. Variable(tf. zeros([hidden_layer_size_2]))
b3 = tf. Variable(tf. zeros([10]))
z1 = tf. sigmoid(tf. matmul(x, W1) + b1)
z2 = tf. sigmoid(tf. matmul(z1, W2) + b2)
keep_prob = tf. placeholder (tf. float32)
drop = tf. nn. dropout(z2, keep_prob)
y = tf. nn. softmax(tf. matmul(drop, W3) + b3)
loss = tf.reduce_mean(-tf.reduce_sum(d * tf.log(y), reduction_indices=[1]))
optimizer = tf. train. RMSPropOptimizer (0.001)
train = optimizer.minimize(loss)
correct = tf. equal(tf. argmax(y, 1), tf. argmax(d, 1))
accuracy = tf. reduce mean(tf. cast(correct, tf. float32))
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
accuracies = \Pi
for i in range(iters num):
    x_batch, d_batch = mnist.train.next_batch(batch_size)
    sess.run(train, feed_dict={x:x_batch, d:d_batch, keep_prob:(1 - dropout_rate)})
    if (i+1) % plot interval == 0:
        accuracy val = sess.run(accuracy, feed dict={x:mnist.test.images, d:mnist.test.labels, k
eep_prob:1.0})
        accuracies, append (accuracy val)
        print('Generation: ' + str(i+1) + '. 正解率 = ' + str(accuracy_val))
lists = range(0, iters num, plot interval)
plt.plot(lists, accuracies)
```

```
plt.title("accuracy")
plt.ylim(0, 1.0)
plt.show()
```

```
Extracting MNIST_data/train-images-idx3-ubyte.gz
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
Generation: 100. 正解率 = 0.1009
Generation: 200. 正解率 = 0.1876
Generation: 300. 正解率 = 0.7408
Generation: 400. 正解率 = 0.8401
Generation: 500. 正解率 = 0.8773
Generation: 600. 正解率 = 0.8965
Generation: 700. 正解率 = 0.9069
Generation: 800. 正解率 = 0.9147
Generation: 900. 正解率 = 0.9203
Generation: 1000. 正解率 = 0.9183
Generation: 1100. 正解率 = 0.931
Generation: 1200. 正解率 = 0.9356
Generation: 1300. 正解率 = 0.936
Generation: 1400. 正解率 = 0.9384
Generation: 1500. 正解率 = 0.9432
Generation: 1600. 正解率 = 0.9454
Generation: 1700. 正解率 = 0.9527
Generation: 1800. 正解率 = 0.9521
Generation: 1900. 正解率 = 0.9516
Generation: 2000. 正解率 = 0.9532
Generation: 2100. 正解率 = 0.951
Generation: 2200. 正解率 = 0.9571
Generation: 2300. 正解率 = 0.9593
Generation: 2400. 正解率 = 0.9609
Generation: 2500. 正解率 = 0.9648
Generation: 2600. 正解率 = 0.9605
Generation: 2700. 正解率 = 0.9646
Generation: 2800. 正解率 = 0.9648
Generation: 2900. 正解率 = 0.9664
Generation: 3000. 正解率 = 0.9671
```



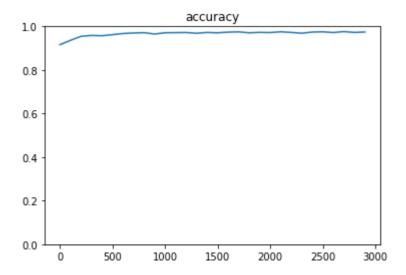
optimizerを変更しよう (Adamをに変更)

In [28]:

```
import tensorflow as tf
import numpy as np
from tensorflow. examples. tutorials. mnist import input_data
import matplotlib.pyplot as plt
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
iters_num = 3000
batch_size = 100
plot_interval = 100
hidden_layer_size_1 = 600
hidden_layer_size_2 = 300
dropout_rate = 0.5
x = tf. placeholder(tf. float32, [None, 784])
d = tf. placeholder (tf. float32, [None, 10])
W1 = tf. Variable(tf.random_normal([784, hidden_layer_size_1], stddev=0.01))
W2 = tf.Variable(tf.random_normal([hidden_layer_size_1, hidden_layer_size_2], stddev=0.01))
W3 = tf. Variable(tf.random_normal([hidden_layer_size_2, 10], stddev=0.01))
b1 = tf. Variable(tf. zeros([hidden_layer_size_1]))
b2 = tf. Variable(tf. zeros([hidden_layer_size_2]))
b3 = tf. Variable(tf. zeros([10]))
z1 = tf. sigmoid(tf. matmul(x, W1) + b1)
z2 = tf. sigmoid(tf. matmul(z1, W2) + b2)
keep_prob = tf. placeholder (tf. float32)
drop = tf. nn. dropout(z2, keep_prob)
y = tf. nn. softmax(tf. matmul(drop, W3) + b3)
loss = tf.reduce_mean(-tf.reduce_sum(d * tf.log(y), reduction_indices=[1]))
optimizer = tf. train. AdamOptimizer (1e-2)
train = optimizer.minimize(loss)
correct = tf. equal(tf. argmax(y, 1), tf. argmax(d, 1))
accuracy = tf.reduce mean(tf.cast(correct, tf.float32))
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
accuracies = []
for i in range(iters num):
    x batch, d batch = mnist.train.next batch(batch size)
    sess.run(train, feed_dict={x:x_batch, d:d_batch, keep_prob:(1 - dropout_rate)})
    if (i+1) % plot_interval == 0:
        accuracy val = sess.run(accuracy, feed dict={x:mnist.test.images, d:mnist.test.labels, k
eep_prob:1.0})
        accuracies. append (accuracy_val)
        print('Generation: ' + str(i+1) + '. 正解率 = ' + str(accuracy_val))
lists = range(0, iters_num, plot_interval)
plt.plot(lists, accuracies)
plt.title("accuracy")
```

```
plt.ylim(0, 1.0)
plt.show()
```

```
Extracting MNIST_data/train-images-idx3-ubyte.gz
Extracting MNIST_data/train-labels-idx1-ubyte.gz
Extracting MNIST_data/t10k-images-idx3-ubyte.gz
Extracting MNIST_data/t10k-labels-idx1-ubyte.gz
Generation: 100. 正解率 = 0.9161
Generation: 200. 正解率 = 0.9359
Generation: 300. 正解率 = 0.9544
Generation: 400. 正解率 = 0.9585
Generation: 500. 正解率 = 0.9572
Generation: 600. 正解率 = 0.9621
Generation: 700. 正解率 = 0.9673
Generation: 800. 正解率 = 0.9698
Generation: 900. 正解率 = 0.9712
Generation: 1000. 正解率 = 0.965
Generation: 1100. 正解率 = 0.9708
Generation: 1200. 正解率 = 0.9714
Generation: 1300. 正解率 = 0.972
Generation: 1400. 正解率 = 0.9686
Generation: 1500. 正解率 = 0.9723
Generation: 1600. 正解率 = 0.9706
Generation: 1700. 正解率 = 0.9737
Generation: 1800. 正解率 = 0.975
Generation: 1900. 正解率 = 0.9706
Generation: 2000. 正解率 = 0.9726
Generation: 2100. 正解率 = 0.9718
Generation: 2200. 正解率 = 0.9753
Generation: 2300. 正解率 = 0.9723
Generation: 2400. 正解率 = 0.9688
Generation: 2500. 正解率 = 0.974
Generation: 2600. 正解率 = 0.9752
Generation: 2700. 正解率 = 0.9718
Generation: 2800. 正解率 = 0.9763
Generation: 2900. 正解率 = 0.9723
Generation: 3000. 正解率 = 0.9742
```



分類CNN (mnist)

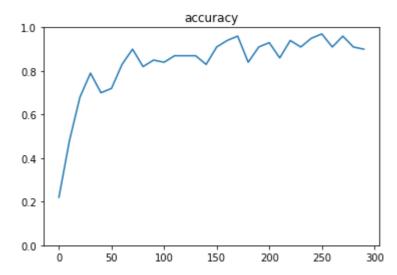
conv - relu - pool - conv - relu - pool affin - relu - dropout - affin - softmax

In [29]:

```
import tensorflow as tf
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
import matplotlib.pyplot as plt
iters_num = 300
batch size = 100
plot_interval = 10
dropout rate = 0.5
# placeholder
x = tf. placeholder(tf. float32, shape=[None, 784])
d = tf.placeholder(tf.float32, shape=[None, 10])
# 画像を784の一次元から28x28の二次元に変換する
# 画像を28x28にreshape
x_image = tf.reshape(x, [-1, 28, 28, 1]) #画像n個、28行、28列、1チャンネル
# 第一層のweightsとbiasのvariable
W_conv1 = tf. Variable(tf. truncated_normal([5, 5, 1, 32], stddev=0.1)) #5行5列のフィルタ、1チャン
ネルを32チャンネルに拡張、標準偏差0.01
b conv1 = tf. Variable(tf. constant(0.1. shape=[32]))
# 第一層のconvolutionalとpool
# strides[0] = strides[3] = 1固定
h_{conv1} = tf. nn. relu(tf. nn. conv2d(x_image, W_conv1, strides=[1, 1, 1, 1], padding='SAME') + b_conv1
nv1)
# プーリングサイズ n*n にしたい場合 ksize=[1, n, n, 1]
h_pool1 = tf.nn.max_pool(h_conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')
#第二層
W_{conv2} = tf. Variable(tf. truncated_normal([5, 5, 32, 64], stddev=0.1))
b_conv2 = tf. Variable(tf. constant(0.1, shape=[64]))
h conv2 = tf.nn.relu(tf.nn.conv2d(h_pool1, W_conv2, strides=[1, 1, 1, 1], padding='SAME') + b_co
h_pool2 = tf.nn.max_pool(h_conv2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')
# 第一層と第二層でreduceされてできた特徴に対してrelu
W fc1 = tf. Variable(tf. truncated normal([7 * 7 * 64, 1024], stddev=0.1))
b fc1 = tf. Variable(tf. constant(0.1, shape=[1024]))
h pool2 flat = tf. reshape(h pool2, [-1, 7*7*64])
h_fc1 = tf. nn. relu(tf. matmul(h_pool2_flat, W_fc1) + b_fc1)
# Dropout
keep prob = tf. placeholder (tf. float32)
h fc1 drop = tf. nn. dropout(h fc1, keep prob)
# 出来上がったものに対してSoftmax
W_fc2 = tf. Variable(tf. truncated_normal([1024, 10], stddev=0.1))
b fc2 = tf. Variable(tf. constant(0.1, shape=[10]))
y conv=tf. nn. softmax (tf. matmul (h fc1 drop, W fc2) + b fc2)
# 交差エントロピー
loss = -tf. reduce_sum(d * tf. log(y_conv))
train = tf. train. AdamOptimizer (1e-4). minimize (loss)
correct = tf. equal (tf. argmax (y_conv, 1), tf. argmax (d, 1))
```

```
accuracy = tf. reduce_mean(tf. cast(correct, tf. float32))
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
accuracies = []
for i in range(iters_num):
    x_batch, d_batch = mnist.train.next_batch(batch_size)
    sess.run(train, feed_dict={x: x_batch, d: d_batch, keep_prob: 1-dropout_rate})
    if (i+1) % plot_interval == 0:
        accuracy_val = sess.run(accuracy, feed_dict=\{x:x_batch, d: d_batch, keep_prob: 1.0\})
        accuracies. append (accuracy_val)
        print('Generation: ' + str(i+1) + '. 正解率 = ' + str(accuracy_val))
lists = range(0, iters_num, plot_interval)
plt.plot(lists, accuracies)
plt. title("accuracy")
plt. ylim(0, 1.0)
plt.show()
```

Extracting MNIST data/train-images-idx3-ubyte.gz Extracting MNIST_data/train-labels-idx1-ubyte.gz Extracting MNIST data/t10k-images-idx3-ubyte.gz Extracting MNIST_data/t10k-labels-idx1-ubyte.gz Generation: 10. 正解率 = 0.22 Generation: 20. 正解率 = 0.48 Generation: 30. 正解率 = 0.68 Generation: 40. 正解率 = 0.79 Generation: 50. 正解率 = 0.7 Generation: 60. 正解率 = 0.72 Generation: 70. 正解率 = 0.83 Generation: 80. 正解率 = 0.9 Generation: 90. 正解率 = 0.82 Generation: 100. 正解率 = 0.85 Generation: 110. 正解率 = 0.84 Generation: 120. 正解率 = 0.87 Generation: 130. 正解率 = 0.87 Generation: 140. 正解率 = 0.87 Generation: 150. 正解率 = 0.83 Generation: 160. 正解率 = 0.91 Generation: 170. 正解率 = 0.94 Generation: 180. 正解率 = 0.96 Generation: 190. 正解率 = 0.84 Generation: 200. 正解率 = 0.91 Generation: 210. 正解率 = 0.93 Generation: 220. 正解率 = 0.86 Generation: 230. 正解率 = 0.94 Generation: 240. 正解率 = 0.91 Generation: 250. 正解率 = 0.95 Generation: 260. 正解率 = 0.97 Generation: 270. 正解率 = 0.91 Generation: 280. 正解率 = 0.96 Generation: 290. 正解率 = 0.91 Generation: 300. 正解率 = 0.9



[try]

• ドロップアウト率を0に変更しよう

In [30]:

```
import tensorflow as tf
from tensorflow.examples.tutorials.mnist import input_data
mnist = input_data.read_data_sets("MNIST_data/", one_hot=True)
import matplotlib.pyplot as plt
iters_num = 300
batch size = 100
plot_interval = 10
dropout_rate = 0
# placeholder
x = tf. placeholder(tf. float32, shape=[None, 784])
d = tf.placeholder(tf.float32, shape=[None, 10])
# 画像を784の一次元から28x28の二次元に変換する
# 画像を28x28にreshape
x_{image} = tf. reshape(x, [-1, 28, 28, 1])
# 第一層のweightsとbiasのvariable
W_{conv1} = tf. Variable(tf. truncated_normal([5, 5, 1, 32], stddev=0.1))
b_conv1 = tf. Variable(tf. constant(0.1, shape=[32]))
# 第一層のconvolutionalとpool
# strides[0] = strides[3] = 1固定
h_{conv1} = tf. nn. relu(tf. nn. conv2d(x_image, W_conv1, strides=[1, 1, 1, 1], padding='SAME') + b_conv1
nv1)
# プーリングサイズ n*n にしたい場合 ksize=[1, n, n, 1]
h_pool1 = tf.nn.max_pool(h_conv1, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')
#第二層
W_{conv2} = tf. Variable(tf. truncated_normal([5, 5, 32, 64], stddev=0.1))
b_conv2 = tf. Variable(tf. constant(0.1, shape=[64]))
h_conv2 = tf. nn. relu(tf. nn. conv2d(h_pool1, W_conv2, strides=[1, 1, 1, 1], padding='SAME') + b_co
nv2)
h_pool2 = tf.nn.max_pool(h_conv2, ksize=[1, 2, 2, 1], strides=[1, 2, 2, 1], padding='SAME')
# 第一層と第二層でreduceされてできた特徴に対してrelu
W_fc1 = tf. Variable(tf. truncated_normal([7 * 7 * 64, 1024], stddev=0.1))
b fc1 = tf. Variable(tf. constant(0.1, shape=[1024]))
h pool2 flat = tf. reshape(h pool2, [-1, 7*7*64])
h fc1 = tf. nn. relu(tf. matmul(h pool2 flat, W fc1) + b fc1)
# Dropout
keep_prob = tf. placeholder (tf. float32)
h fc1 drop = tf. nn. dropout(h fc1, keep prob)
# 出来上がったものに対してSoftmax
W fc2 = tf. Variable(tf. truncated normal([1024, 10], stddev=0.1))
b_fc2 = tf. Variable(tf. constant(0.1, shape=[10]))
y_conv=tf. nn. softmax (tf. matmul (h_fc1_drop, W_fc2) + b_fc2)
# 交差エントロピー
loss = -tf.reduce_sum(d * tf.log(y_conv))
train = tf. train. AdamOptimizer (1e-4). minimize (loss)
correct = tf. equal(tf. argmax(y conv. 1), tf. argmax(d, 1))
accuracy = tf. reduce mean(tf. cast(correct, tf. float32))
```

```
init = tf.global_variables_initializer()
sess = tf. Session()
sess.run(init)
accuracies = []
for i in range(iters_num):
   x_batch, d_batch = mnist. train. next_batch(batch_size)
    sess.run(train, feed_dict={x: x_batch, d: d_batch, keep_prob: 1-dropout_rate})
    if (i+1) % plot_interval == 0:
        accuracy_val = sess.run(accuracy, feed_dict={x:x_batch, d: d_batch, keep_prob: 1.0})
        accuracies. append (accuracy_val)
        print('Generation: ' + str(i+1) + '. 正解率 = ' + str(accuracy_val))
lists = range(0, iters_num, plot_interval)
plt.plot(lists, accuracies)
plt.title("accuracy")
plt. ylim(0, 1.0)
plt.show()
```

Extracting MNIST data/train-images-idx3-ubyte.gz Extracting MNIST_data/train-labels-idx1-ubyte.gz Extracting MNIST data/t10k-images-idx3-ubyte.gz Extracting MNIST_data/t10k-labels-idx1-ubyte.gz Generation: 10. 正解率 = 0.21 Generation: 20. 正解率 = 0.47 Generation: 30. 正解率 = 0.65 Generation: 40. 正解率 = 0.75 Generation: 50. 正解率 = 0.73 Generation: 60. 正解率 = 0.78 Generation: 70. 正解率 = 0.91 Generation: 80. 正解率 = 0.83 Generation: 90. 正解率 = 0.85 Generation: 100. 正解率 = 0.91 Generation: 110. 正解率 = 0.9 Generation: 120. 正解率 = 0.89 Generation: 130. 正解率 = 0.84 Generation: 140. 正解率 = 0.87 Generation: 150. 正解率 = 0.87 Generation: 160. 正解率 = 0.9 Generation: 170. 正解率 = 0.92 Generation: 180. 正解率 = 0.93 Generation: 190. 正解率 = 0.94 Generation: 200. 正解率 = 0.92 Generation: 210. 正解率 = 0.96 Generation: 220. 正解率 = 0.92 Generation: 230. 正解率 = 0.94 Generation: 240. 正解率 = 0.93 Generation: 250. 正解率 = 0.97 Generation: 260. 正解率 = 0.93 Generation: 270. 正解率 = 0.95 Generation: 280. 正解率 = 0.93 Generation: 290. 正解率 = 0.94 Generation: 300. 正解率 = 0.94

