Addition of 2 Numbers

Background

This is a project to build dense networks for perform addtion of 2 numbers between 0-100, by purposely removing certain number(s) from the training data set. For example, 50, or any other number(s).

Certain other notes and considerations:

- This is a classfication problem, not regression.
- Dataset is not given, needs DIY.
- It's obvious that the output needs one-hot encoding, what about input?
- Use model.save & load_model to deal with save and restore

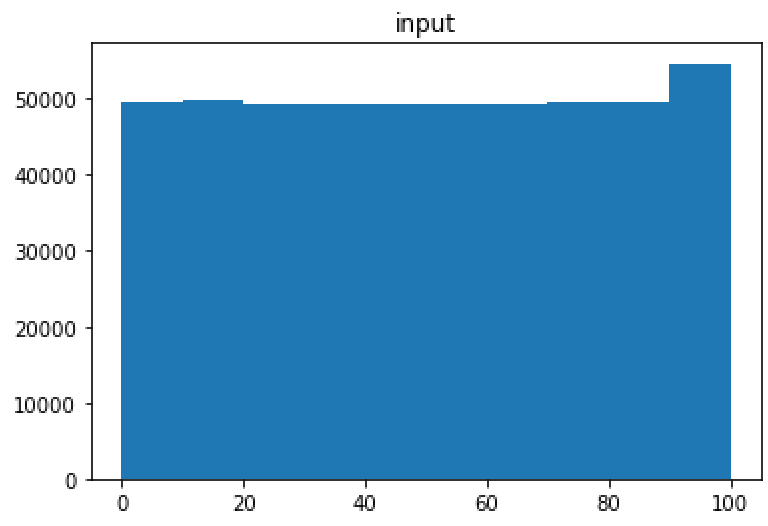
Preparing the Datasets

Using random from numpy module to create training datasets

In [3]:
```
import numpy as np
%matplotlib inline
import matplotlib.pyplot as plt
import keras
import tensorflow as tf

print(keras.__version__)
print(tf.__version__)

# Generate 20000 groups of numbers, value from 0 to 101(exclusive)
np.random.seed(2)
input = np.random.randint(0, 101, size=500000)

# Verify the dimension of the dataset
print(input.shape)
print(input)

# Plot the numbers by visually inspecting it's evenly distributed
plt.hist(input)
plt.title("input")
```

```
Using TensorFlow backend.

2.0.8
1.3.0
(500000,)
[40 15 72 ..., 12 28  3]
```

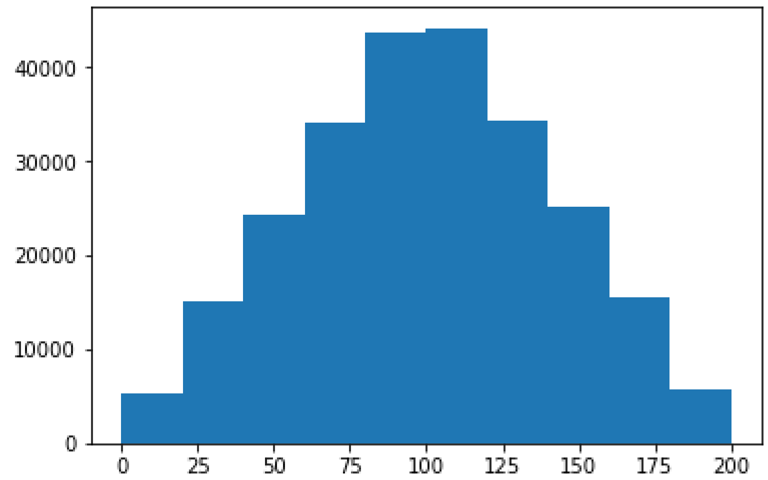
Out[3]: `<matplotlib.text.Text at 0x125f4ffd0>`



In [4]:
```
# Remove the numbers that we want the network to perform the prediction
remove_num = [50]
for i in remove_num:
    input = input[input != i]
    # Another way could be
    #iIndex = np.argwhere(input == i)
    #input = np.delete(input, iIndex)

# Remove the last number if the size of input is odd number
input_train = input if input.size%2==0 else input[:input.size-1]
print(input_train.shape)
print(input_train)

# Reshape to groups of 2 integers
input_train = input_train.reshape(int(input_train.size/2), 2)
print(input_train[0])

# Calculate the output and plot it, the result should be normally distributed
output_train = np.sum(input_train, axis=1)
plt.hist(output_train)
```

```
(494996,)
[40 15 72 ..., 15 12 28]
[40 15]
```

Out[4]:
```
(array([  5280.,  15131.,  24304.,  34047.,  43800.,  44194.,  34414.,
         25109.,  15491.,   5728.]),
 array([   0.,   20.,   40.,   60.,   80.,  100.,  120.,  140.,  160.,
         180.,  200.]),
 <a list of 10 Patch objects>)
```



In [5]:
```
# One-hot encode the training output, there are 201 possible values of output
import keras
from keras.models import Model, Sequential
from keras.layers import *
n_classes = 201
print(output_train)

# Normalize the training input
x_train = input_train.astype('float32')
x_train = x_train / 100
y_train = keras.utils.to_categorical(output_train, n_classes)
print(output_train[0], '\n', input_train[0], '\n', x_train[0], '\n', y_train[0], '\n', y_train.shape)
```

```
[ 55  94 125 ..., 121  94  40]
55
 [40 15]
 [ 0.40000001  0.15000001]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  1.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.]
 (247498, 201)
```

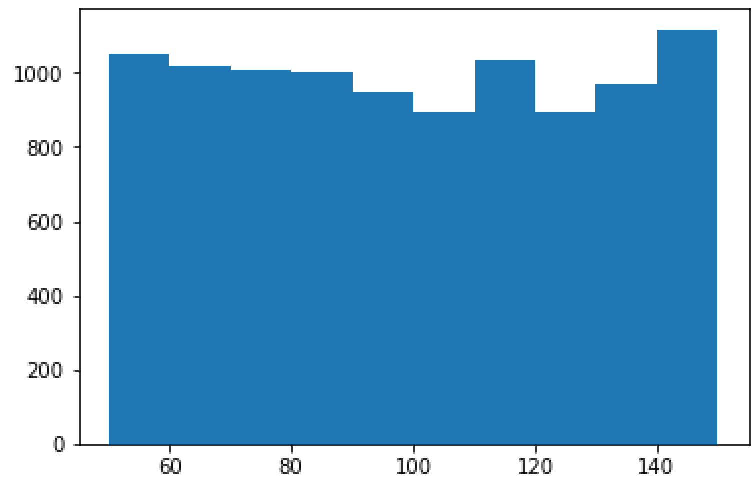
Create testing datasets

The way to create testing datasets will be slightly different from the training dataset. A two dimensional numpy array will be created first, then we only keep those groups contain the number we want to test against to.

In [6]:
```
# Create 100000 pairs of integers
np.random.seed(2)
input_test = np.random.randint(0, 101, size=(500000,2))
print(input_test.shape)

# Create a list to store the valid testing cases, numpy array is immunable
temp_list = []
for i in input_test:
    for m in remove_num:
        if i[0] == m or i[1] == m:
            temp_list.append(i)
            # If found match from either element of the group, continue
            continue

# Conver to numpy array
input_test = np.array(temp_list)
print(input_test.shape)

# Remove the last number if the size of testing dataset is odd number
num_rows = input_test.shape[0]
input_test = input_test if num_rows%2==0 else input_test[:num_rows-1]
print(input_test.shape)

# Visually inspecting output_test, the value should range [50,150]
output_test = np.sum(input_test, axis = 1)
plt.hist(output_test)
```

```
(500000, 2)
(9951, 2)
(9950, 2)
```

Out[6]:
```
(array([ 1052.,  1016.,  1010.,  1004.,   950.,   895.,  1037.,   897.,
          972.,  1117.]),
 array([  50.,   60.,   70.,   80.,   90.,  100.,  110.,  120.,  130.,
         140.,  150.]),
 <a list of 10 Patch objects>)
```



In [7]:
```
# One-hot encode the test output same way as training output, normalize the test input
x_test = input_test.astype('float32')
x_test = x_test/100
y_test = keras.utils.to_categorical(output_test, n_classes)

print(x_test[10], '\n', output_test[10], '\n', y_test[10], '\n', y_test.shape)
```

```
[ 0.5         0.56999999]
 107
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  1.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
  0.  0.  0.]
 (9950, 201)
```

Build and Train the Neural Network

In [36]:
```
# Set up parameters
learning_rate = 0.1
training_epochs = 200
batch_size = 50

# Network parameters
n_input = 2
n_hidden_1 = 600
n_hidden_2 = 300
n_classes = 201

# Build network
Inp = Input(shape=(2,))
x = Dense(n_hidden_1, activation='relu', name='Dense_1')(Inp)
x = Dense(n_hidden_2, activation='relu', name='Dense_2')(x)
x = Dense(n_hidden_3, activation='relu', name='Dense_3')(x)
output = Dense(n_classes, activation='softmax', name='Output')(x)

model = Model(Inp, output)
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
input_5 (InputLayer)         (None, 2)                 0         
_________________________________________________________________
Dense_1 (Dense)              (None, 600)               1800      
_________________________________________________________________
Dense_2 (Dense)              (None, 300)               180300    
_________________________________________________________________
Dense_3 (Dense)              (None, 200)               60200     
_________________________________________________________________
Output (Dense)               (None, 201)               40401     
=================================================================
Total params: 282,701
Trainable params: 282,701
Non-trainable params: 0
_________________________________________________________________
```

In [37]:
```
model.compile(loss='categorical_crossentropy',
             optimizer='SGD',
             metrics=['accuracy'])
print(x_train[0:3])
print(y_train[0:3])
```

```
[[ 0.40000001  0.15000001]
 [ 0.72000003  0.22      ]
 [ 0.43000001  0.81999999]]
[[ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  1.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  1.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.]
 [ 0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  1.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.  0.
   0.  0.  0.]]
```

In [45]:
```
from keras.callbacks import ModelCheckpoint
from keras.callbacks import ReduceLROnPlateau

checkpointer = ModelCheckpoint(filepath='adding2numbers_mode.h5', verbose=1, save_best_only=True)
reduce_lr = ReduceLROnPlateau(monitor='val_loss', factor=0.9, patience=5, min_lr=0.0001)
history = model.fit(x_train, y_train,
                    batch_size=batch_size,
                    epochs=training_epochs,
                    verbose=1,
                    validation_data=(x_test, y_test),
                    callbacks=[checkpointer, reduce_lr])
```

```
Train on 247498 samples, validate on 9950 samples
Epoch 1/200
247450/247498 [============================>.] - ETA: 0s - loss: 0.3437 - acc: 0.9289Epoch 00000: val_loss im
proved from inf to 0.01625, saving model to adding2numbers_mode.h5
247498/247498 [==============================] - 25s - loss: 0.3436 - acc: 0.9289 - val_loss: 0.0163 - val_ac
c: 1.0000
Epoch 2/200
247250/247498 [============================>.] - ETA: 0s - loss: 0.3580 - acc: 0.9319Epoch 00001: val_loss di
d not improve
247498/247498 [==============================] - 25s - loss: 0.3577 - acc: 0.9319 - val_loss: 0.0170 - val_ac
c: 1.0000
Epoch 3/200
247400/247498 [============================>.] - ETA: 0s - loss: 0.3240 - acc: 0.9353Epoch 00002: val_loss im
proved from 0.01625 to 0.01347, saving model to adding2numbers_mode.h5
247498/247498 [==============================] - 24s - loss: 0.3239 - acc: 0.9354 - val_loss: 0.0135 - val_ac
c: 1.0000
Epoch 4/200
247350/247498 [============================>.] - ETA: 0s - loss: 0.3379 - acc: 0.9311Epoch 00003: val_loss di
d not improve
247498/247498 [==============================] - 24s - loss: 0.3377 - acc: 0.9311 - val_loss: 0.0314 - val_ac
c: 1.0000
Epoch 5/200
247000/247498 [============================>.] - ETA: 0s - loss: 0.3005 - acc: 0.9378Epoch 00004: val_loss di
d not improve
247498/247498 [==============================] - 24s - loss: 0.3000 - acc: 0.9378 - val_loss: 0.0190 - val_ac
c: 1.0000
Epoch 6/200
247250/247498 [============================>.] - ETA: 0s - loss: 0.3026 - acc: 0.9388Epoch 00005: val_loss di
d not improve
247498/247498 [==============================] - 24s - loss: 0.3053 - acc: 0.9383 - val_loss: 2.4661 - val_ac
c: 0.5358
Epoch 7/200
247400/247498 [============================>.] - ETA: 0s - loss: 0.3488 - acc: 0.9293Epoch 00006: val_loss di
d not improve
247498/247498 [==============================] - 24s - loss: 0.3487 - acc: 0.9293 - val_loss: 0.0314 - val_ac
c: 1.0000
Epoch 8/200
247350/247498 [============================>.] - ETA: 0s - loss: 0.2816 - acc: 0.9416Epoch 00007: val_loss im
proved from 0.01347 to 0.01241, saving model to adding2numbers_mode.h5
247498/247498 [==============================] - 25s - loss: 0.2814 - acc: 0.9416 - val_loss: 0.0124 - val_ac
c: 1.0000
Epoch 9/200
247300/247498 [============================>.] - ETA: 0s - loss: 0.3177 - acc: 0.9371Epoch 00008: val_loss di
d not improve
247498/247498 [==============================] - 24s - loss: 0.3176 - acc: 0.9372 - val_loss: 0.0261 - val_ac
c: 1.0000
Epoch 10/200
247100/247498 [============================>.] - ETA: 0s - loss: 0.3180 - acc: 0.9348Epoch 00009: val_loss di
d not improve
247498/247498 [==============================] - 24s - loss: 0.3177 - acc: 0.9348 - val_loss: 0.0200 - val_ac
c: 1.0000
Epoch 11/200
 86700/247498 [=========>....................] - ETA: 15s - loss: 0.3271 - acc: 0.9356
```

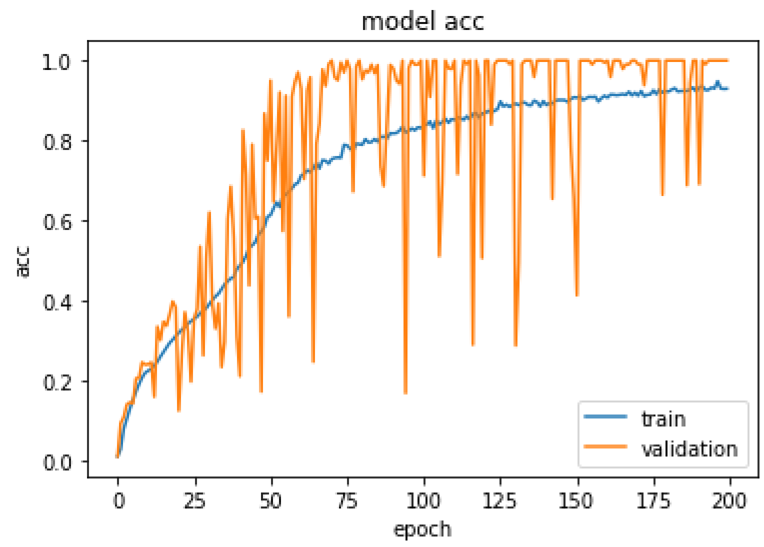
Evaluate the Model

The model was trained against the medium EC2 GPU instance, in total 210 epochs was went through, with 1.5 hours.

Let's plot the training and cross validation history. The training accuracy converged to about 94%. The cross validation accuracy is almost 100%, but sometimes with fluctuations.

In [41]:
```
def plot_train(hist):
    h = hist.history
    if 'acc' in h:
        meas='acc'
        loc='lower right'
    else:
        meas='loss'
        loc='upper right'
    plt.plot(hist.history[meas])
    plt.plot(hist.history['val_'+meas])
    plt.title('model '+meas)
    plt.ylabel(meas)
    plt.xlabel('epoch')
    plt.legend(['train', 'validation'], loc=loc)
```

In [42]:
```
plot_train(history)
```



In [43]:
```
score = model.evaluate(x_test, y_test, verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1])
```

```
Test loss: 0.0196664450673
Test accuracy: 1.0
```

Make prediction with the model and check the result with naked eyes

In [12]:
```
# Use model.predict() to make prediction, use argmax to reverse the 'to_categorical'
print(x_test[0:4])
print(np.argmax(model.predict(x_test[0:4]), axis=1))
print(model.predict(x_test[0:4]))

# Save the model
#model.save('adding2numbers_model.h5')
#model = keras.models.load_model('adding2numbers_model.h5')
```

```
[[ 0.5         0.04      ]
 [ 0.08        0.5       ]
 [ 0.5         0.73000002]
 [ 0.34999999  0.5       ]]
[ 54  58 123  85]
[[  0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   0.00000000e+00   0.00000000e+00   0.00000000e+00
    0.00000000e+00   1.51610160e-26   4.43424767e-18   1.19528012e-17
    2.99959640e-10   3.95751046e-03   9.84461367e-01   1.15811201e-02
```