Brief Introduction to Deep Learning and TensorFlow

Deep Learning in Earth Science Lecture 1 By Xiao Zhuowei



For researchers interested in studying Earth science with deep learning.

All resources in lectures are available at

https://github.com/MrXiaoXiao/DLiES





TensorFlow Basics

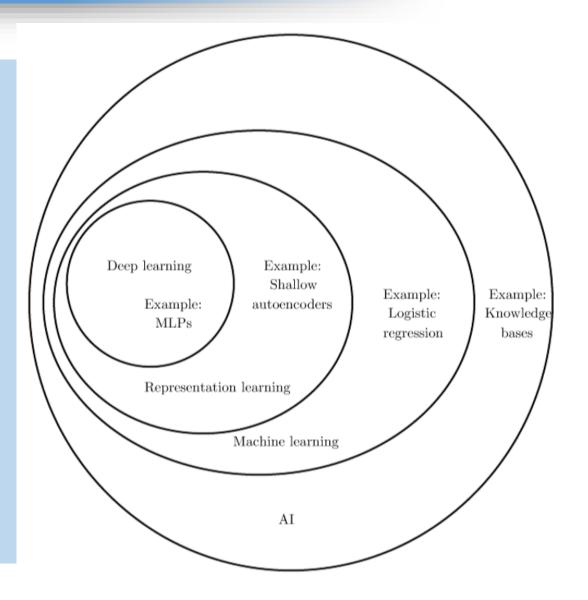


Classifying Stability of Mantle with Neural Networks: An Example



Discussions

Deep Learning is about automatically obtaining representation of input and mapping (from representation) to output with deep neural network architectures.





Obtain the *representation* of input.

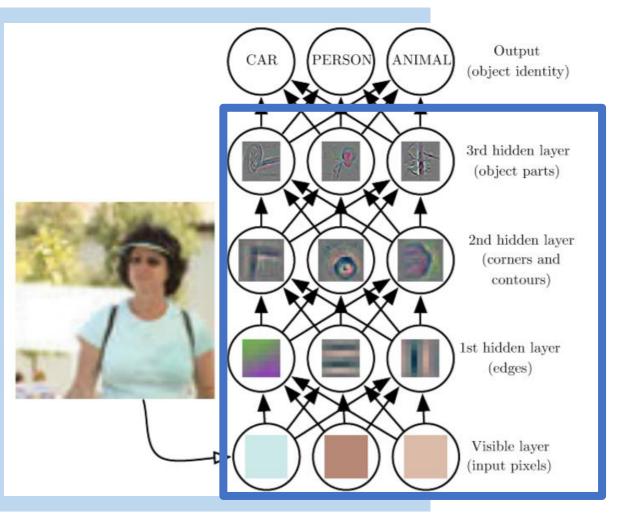


What We See



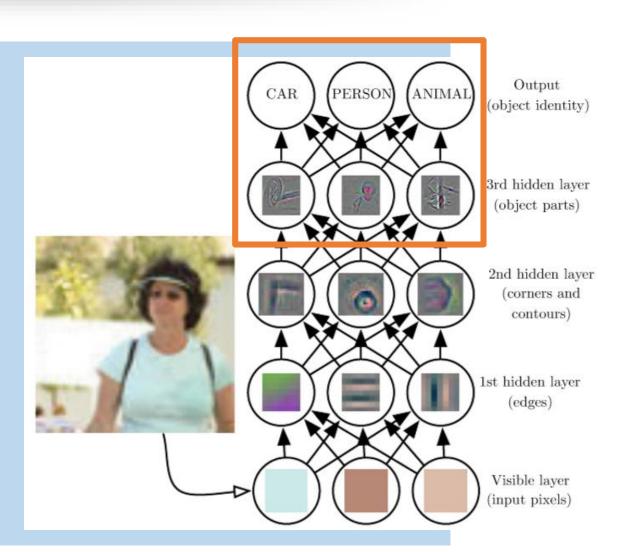
What Computers See

(https://adeshpande3.github.io)



(Deep Learning, MIT Press, 2016)

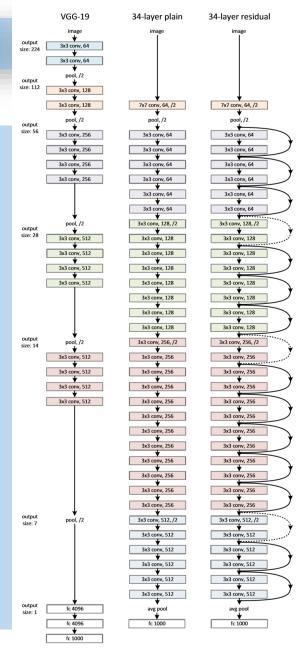
Obtain *mapping* from representation to output.



(Deep Learning, MIT Press, 2016)

Complicated representations are built out of simpler ones.

The graph of deep learning architecture is deep, with many layers.



Brief Introdu

Brief Introduction to Deep Learning

Considering deep learning as algorithm for non-linear function approximation

 $Ideal\ Output = Ideal\ Function(Input + Noise)$

Approximation of Ideal Output = DL Model(Input + Noise)



What can deep learning do in Earth science?

Classification

Denoising

Forward Modeling

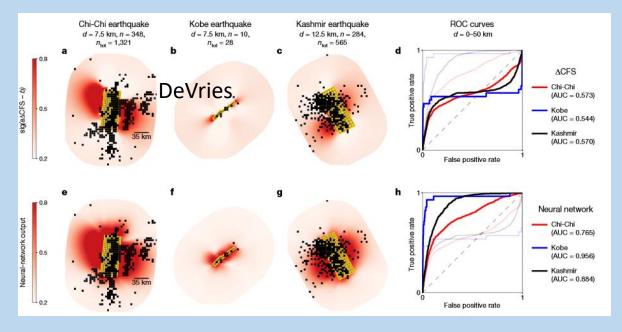
Inversion

• • •

What can deep learning do in Earth science?

Classification

Predicting aftershocks following large earthquakes

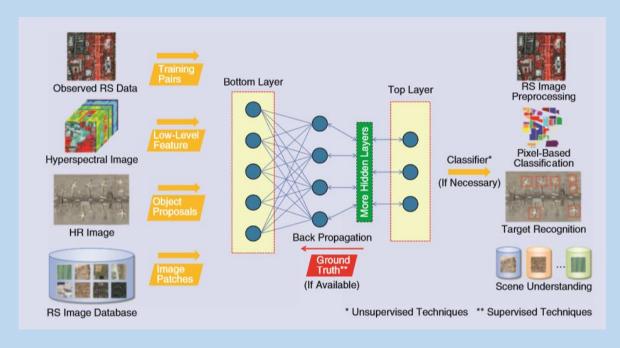


(DeVries et al., 2018)

What can deep learning do in Earth science?

Classification

Processing remote sensing data



(Zhang et al., 2016)

What can deep learning do in Earth science? Denoising Trace number Trace number Noisy input DL output

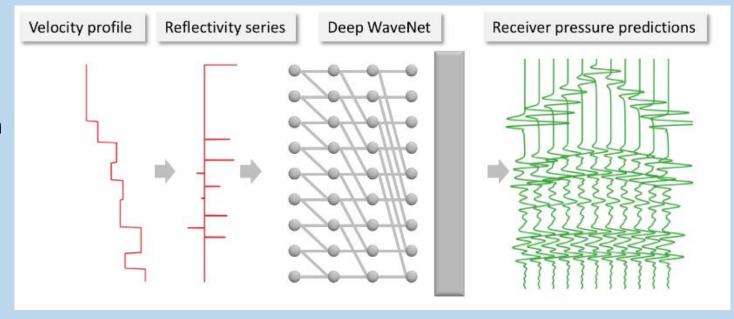
(Beckouche and Ma, 2014)



What can deep learning do in Earth science?

Forward Modeling

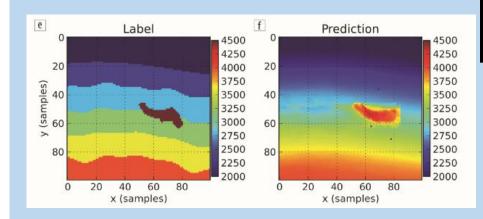
Fast approximate simulation of seismic waves with deep learning



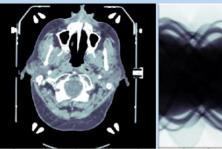
(Moseley et al., 2018)

What can deep learning do in Earth science?

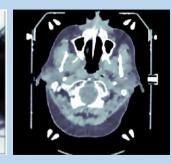
Inversion



(Araya-Polo et al., 2018)



Model Observation



Inversion by DL

(Adler and Öktem, 2017)





TensorFlow Basics



Classifying Stability of Mantle with Neural Networks: An Example



Discussions

TensorFlow™ is an open source software library for high performance numerical computation.

https://www.tensorflow.org/

or

https://tensorflow.google.cn/



Install TensorFlow via Anaconda

Anaconda Distribution is a free, easy-to-install package manager, environment manager and Python distribution with a collection of 1,000+ open source packages with free community support.



Anaconda Download (https://www.anaconda.com/download/)

Tensorflow-in-Anaconda

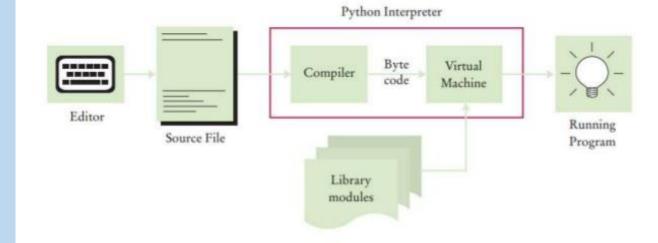
(https://www.anaconda.com/blog/developer-blog/tensorflow-in-anaconda/)

Python is an interpreted high-level programming language for general-purpose programming.



(https://www.python.org/)

How The Python Interpreter Works



(http://opensourceforgeeks.blogspot.com/2015/10/how-python-works.html)

The Jupyter Notebook is an open-source web application that allows you to create and share documents that contain live code, equations, visualizations and narrative text.

https://jupyter.org/



Image Manipulation with skimage

This example builds a simple UI for performing basic image manipulation with scikit-image.

- In [21]: from ipywidgets import interact, interactive, fixed from IPython.display import display
- In [22]: import skimage
 from skimage import data, filter, io
- In [23]: i = data.coffee()
- In [24]: io.Image(i)

Out[24]:



```
In [25]: def edit_image(image, sigma=0.1, r=1.0, g=1.0, b=1.0):
    new_image = filter.gaussian_filter(image, sigma=sigma, multichannel=True)
    new_image[;;;,0] = r*new_image[;;,0]
    new_image[;;;,1] = g*new_image[;;,1]
    new_image[;;;,2] = b*new_image[;;,2]
    new_image = io.Image(new_image)
    display(new_image)
    return new_image
```

In [26]: lims = (0.0,1.0,0.01)
w = interactive(edit_image, image=fixed(i), sigma=(0.0,10.0,0.1), r=lims, g=lims, b=lims)
display(w)



TensorFlow Hello World

TensorFlow Hello World

Modified from https://github.com/aymericdamien/TensorFlow-Examples/blob/master/examples/1_Introduction/helloworld.py

```
In [1]: import tensorflow as tf
In [2]: # Simple hello world using TensorFlow
         # Create a Constant op
         # The op is added as a node to the default graph.
         # The value returned by the constructor represents the output
         # of the Constant op.
         hello = tf.constant('Hello, TensorFlow!')
In [3]: print(hello)
         Tensor("Const:0", shape=(), dtype=string)
In [4]: # Start tf session
         sess = tf. Session()
In [5]: # Run the op
         print(sess.run(hello))
         b'Hello, TensorFlow!'
```

TensorFlow Multiply Matrices

TensorFlow Multiply Matrices Example

```
Modified from https://github.com/vahidk/EffectiveTensorflow

In [1]: import tensorflow as tf

In [2]: x = tf.random_normal([3,3])
    y = tf.random_normal([3,3])
    z = tf.matmul(x,y)

In [3]: print('{}\n{}\n{}\n{}\)'.format(x,y,z))

    Tensor("random_normal:0", shape=(3, 3), dtype=float32)
    Tensor("random_normal_1:0", shape=(3, 3), dtype=float32)
    Tensor("MatMul:0", shape=(3, 3), dtype=float32)

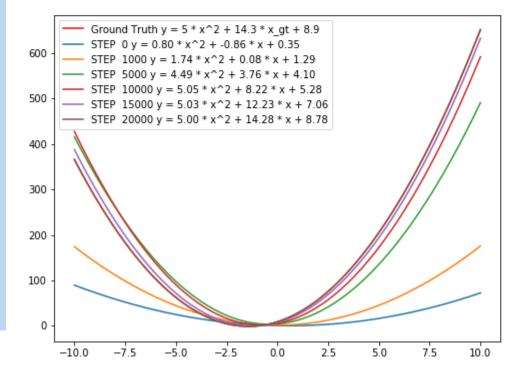
In [4]: sess = tf.Session()
    z_val = sess.run(z)

In [5]: print(z_val)
```

```
In [5]: print(z_val)

[[-1.8857789    0.02845232    2.23009  ]
    [ 0.20160252    0.49441913    0.37605742]
    [ 3.5984905    1.7590961    -0.84973013]]
```

Approximate Quadratic Function With TensorFlow



Recommended TensorFlow tutorials

Effective TensorFlow

https://github.com/vahidk/EffectiveTensorflow

TensorFlow Official Tutorial

https://www.tensorflow.org/tutorials/

Simple and ready-to-use tutorials for TensorFlow

https://github.com/astorfi/TensorFlow-World





TensorFlow Basics



Classifying Stability of Mantle with Neural Networks: An Example

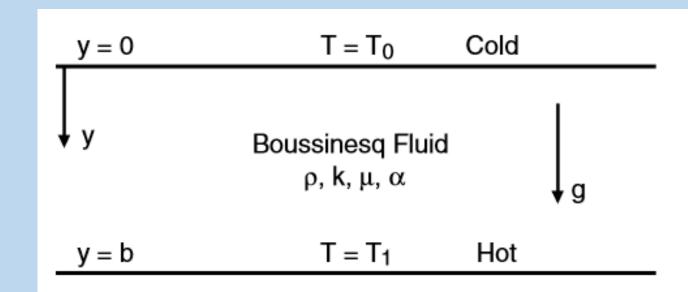


Discussions



Classifying Stability of Mantle with Neural Networks: An Example

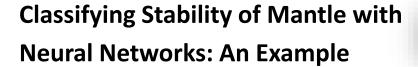
Plane Layer Heated from Below



(Schuber et al., 2001)



Full Connection and Back Propagation



```
#Define a function to generate data set
def generate_data_set(instance_num = 10000, split_rate = 0.6):
    #instance[0] Gravitational acceleration
    #instance[1] Volume expansion coefficient
    #instance[2] Kinematic viscosity coefficient
    #instance[3] Thermal diffusivity
    #instance[4] Depth
    #instance[5] b
    #instance[6] \(\lambda\)
    #instance[7] (TO - T1)/1000
    #instance[8] stability 0 is unstable and 1 is stable
    data_set = np. zeros([instance_num, 9])
    #simulate gravitational accelerations
    data set[:, 0] = np. random. uniform (8, 10, size=instance num)
    #simulate Volume expansion coefficient
    data_set[:, 1] = np. random. uniform(1e-4, 1e-2, size=instance_num)
    #simulate Kinematic viscosity coefficient
    data set[:, 2] = np. random. uniform(1e-6, 1e-2, size=instance num)
    #simulate Thermal diffusivity
    data_set[:, 3] = np.random.uniform(1.0, 10.0, size=instance_num)
    #simulate Depth 1000km
   data set[:, 4] = np. random. uniform(0, 3.5, size=instance_num)
    for idx in range (instance num):
        #simulate b 1000km
        data set[idx, 5] = np. random. uniform(max([2.5, data set[idx, 4]]), 3.5)
    #simulate \lambda
    data_set[:, 6] = np. random. uniform(0.0, 6.0, size=instance_num)
    #simulate TO - T1
   data_set[:, 7] = np.random.uniform(0.0, 5.0, size=instance_num)
    #simulate stability
    for idx in range(instance_num):
        Ra = (data_set[idx, 0]*data_set[idx, 1]* data_set[idx, 7]*1000
              *(data_set[idx, 4]) **3) / (data_set[idx, 2] *data_set[idx, 3])
        Racr = (((np. pi**4)*((4.0+(data set[idx, 6]/data set[idx, 5])**2)**3))
                /(4*((data_set[idx, 6]/data_set[idx, 5])**4)))
        if Ra > Racr:
            data_set[idx, 8] = 0
        else:
            data_set[idx, 8] = 1
    split_index = int(instance_num*split_rate)
    train set = data set[0:split index,:]
    test set = data set[1:split index,:]
    return train_set, test_set
```



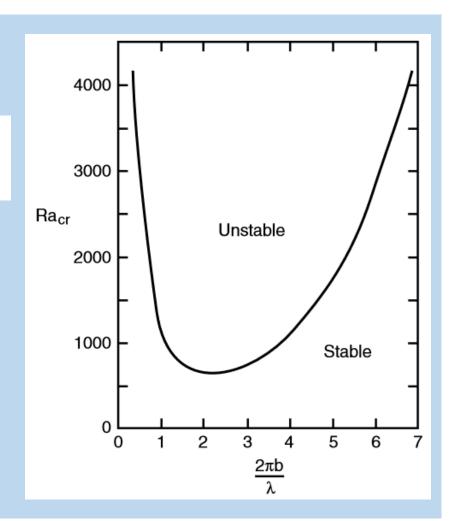
```
In [4]: data_set_size = 1000000
           split_rate = 0.5
          train_set, test_set = generate_data_set(instance_num = data_set_size, split_rate = split_rate)
          Stable:574480 UnStable:425520
 In [5]: #define full connection laver
           def full_connection_layer(input_tensor, n_out,
                                     w_init=tf.truncated_normal_initializer(stddev=0.1),
                                     b_init=tf.constant_initializer(0.1),
                                     activation=tf.nn.sigmoid, name=None):
               n_in = input_tensor.get_shape().as_list()[1]
               with tf.variable_scope(name):
                   weight = tf.get_variable('weight', [n_in, n_out], initializer=w_init)
                  bias = tf.get_variable('bias', [n_out], initializer=b_init)
               output_tensor = activation(tf.matmul(input_tensor, weight)+bias, name=name+'_output')
              return output_tensor
 In [6]: def inference(input_tensor):
              hidden_layer_1 = full_connection_layer(input_tensor=input_tensor, n_out=4, name='fc_layer_1')
              hidden_layer_2 = full_connection_layer(input_tensor=hidden_layer_1, n_out=4, name='fc_layer_2')
              hidden_layer_3 = full_connection_layer(input_tensor=hidden_layer_2, n_out=4, name='fc_layer_3')
              pred = full_connection_layer(input_tensor=hidden_layer_3, n_out=2, name='pred')
 In [7]: #set param for training
           step num = 20001
          batch_size = 1000
          data_length = 8
          learning_rate = 0.01
          #setup training
          input_tensor = tf.placeholder(tf.float32, [None, data_length], name='input')
          label = tf.placeholder(tf.float32, [None, 2], name='label')
          pred = inference(input_tensor=input_tensor)
          loss = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(logits=pred, labels=label))
          train_op = tf. train. AdamOptimizer(learning_rate = learning_rate). minimize(loss)
 In [8]: def get_traning_batch(train_set, batch_size, data_length):
              batch_ids = np. random. choice(len(train_set['input']), batch_size)
               input_batch = np. zeros([batch_size, data_length])
               label_batch = np. zeros([batch_size, 2])
              for idx in range(batch_size):
                  input_batch[idx][:] = train_set['input'][batch_ids[idx]][:]
label_batch[idx][:] = train_set['label'][batch_ids[idx]][:]
              return input_batch, label_batch
 In [9]: sess = tf. Session()
          sess.run(tf.global_variables_initializer())
In [10]: #start traning
          for idx in range(step_num):
              input_batch, label_batch = get_traning_batch(train_set, batch_size, data_length)
               _, loss_val = sess.run([train_op, loss], {input_tensor: input_batch, label: label_batch})
              if idx%2000 == 0:
                  print(loss_val)
          0.6934938
          0.39525732
          0.3629702
          0.3573489
          0.35604522
          0.34598345
          0.34709588
          0.34188947
          0.354488
          0.3468753
          0.3486143
In [11]: correct_pred = tf.equal(tf.argmax(pred, 1), tf.argmax(label, 1))
           accuracy = tf.reduce_mean(tf.cast(correct_pred, tf.float32))
          print('Accuracy: {}'.format(sess.run(accuracy, {input_tensor: test_set['input'], label: test_set['label']})))
          Accuracy: 0.9649959802627563
```

Classifying Stability of Mantle with Neural Networks: An Example

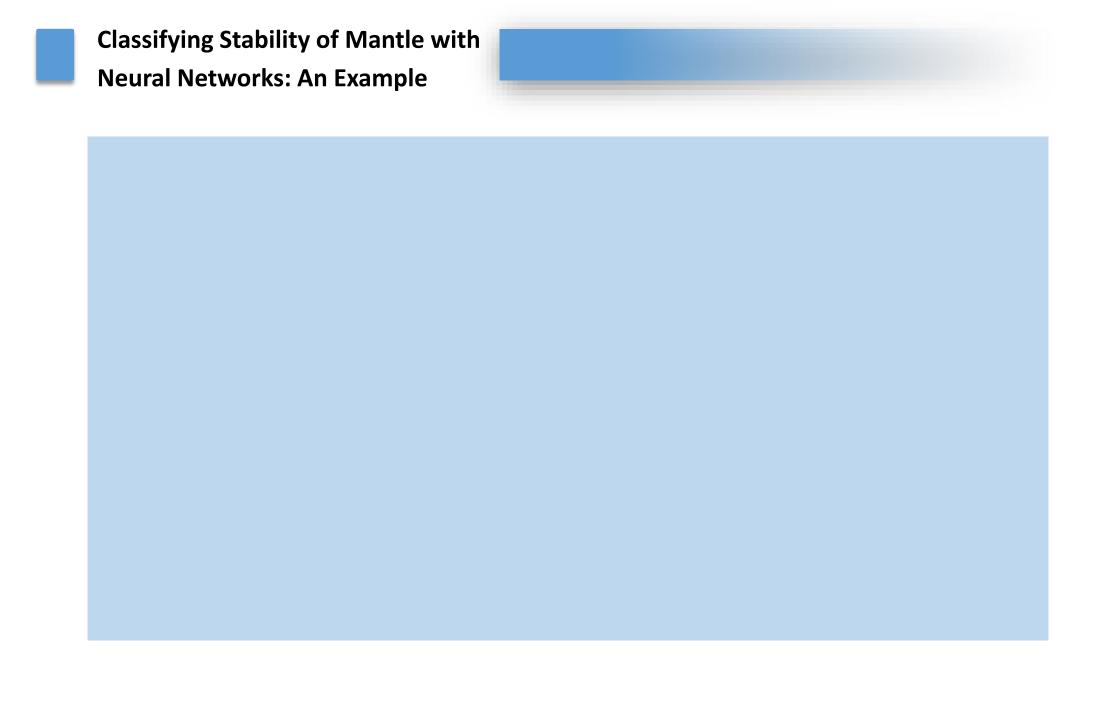
$$Ra = Ra_{cr} = \frac{\left(\pi^2 + 4\pi^2/\lambda^{*2}\right)^3}{4\pi^2/\lambda^{*2}} = \frac{\pi^4}{4\lambda^{*4}} \left(4 + \lambda^{*2}\right)^3$$

$$Ra = \frac{\alpha g (T_1 - T_0) b^3}{\nu \kappa}$$

$$\lambda^* = \lambda/b$$

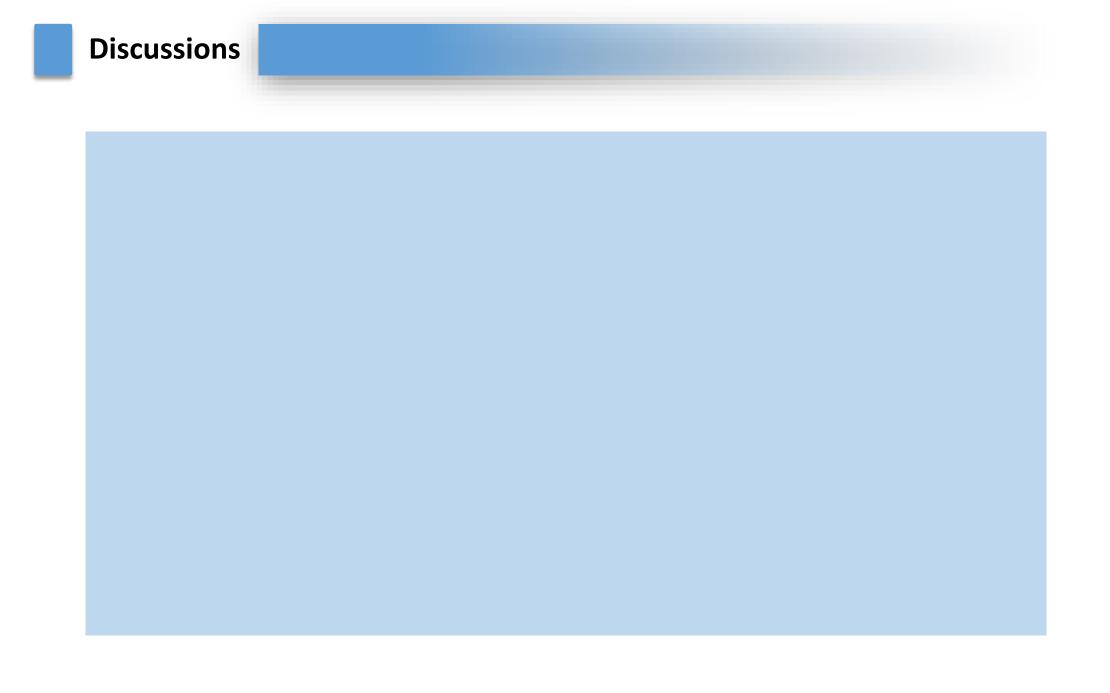


(Schuber et al., 2001)





- **TensorFlow Basics**
- Classifying Stability of Mantle with Neural Networks: An Example
- 4 Discussions



TensorFlow Installation via Anaconda

Step 1. Install Anaconda from (https://www.anaconda.com/download/)



Anaconda

Prompt

Step 2. Create a new conda environment containing TensorFlow.

Open Anaconda Prompt and run

'conda create -n tensorflow_env tensorflow python=3.6'

or

'conda create -n tensorflow_gpuenv tensorflow-gpu python=3.6'

for GPU version

Congratulations...

