Notes de cours CADL - session-2

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- The basic components of a neural network
- How to use gradient descent to optimize parameters of a neural network
- How to create a neural network for performing regression

Contents

1 Introduction

1.1 Generalities

- Use data and gradient descent to teach the network what the values of the parameters of the network should be.
- Idea of machine learning : letting the machine learn from the data.
- We are interested in letting the computer figure out what representations it needs in order to better describe the data and some objective we've defined.

1.2 Gradient Descent

- Operation of the network are meant to transform the input data into something meaningful that we want the network to learn about.
- Parameters of the NW are random so output is random as well.
- If we need specific output, we can use "Gradient Descent" : way to optimize set of parameters.

1.3 Defining Cost

- Mesure of the "error"
- Exemple : recognize apple or orange. Random network spit ou random 0s or 1s for apples and oranges. We can define :
  - if the network predicts a 0 for an orange, then the error is 0. If the network predicts a 1 for an orange, then the error is 1.
  - And vice-versa for apples. If it spits out a 1 for an apple, then the error is 0. If it spits out a 0 for an apple, then the error is 1.
- Defining error in terms of our parameters :

$$error = network(image) - true\_label \tag{1}$$

$$network(image) = predicted\_label \tag{2}$$

$$E = f(X) - y \tag{3}$$

1.4 Minimizing Error

- Feed the network many images (100 for e.g) to see what the network is doing on average.
- Changing network's parameters can have effect on the error.
- The error provides a "training signal" or a measure of the "loss" or our network.
- Assumptions in assuming our funtion is continuous and differentiable.
- Gradiant descent in a nutshell : "Error", "Cost", "Loss", or "Training Signal"

1.5 Backpropagation

- The gradient is just saying, how does the error change at the current set of parameters.
- To figure out what is the gradiet we use backpropagation. Whatever differences that output has with the output we wanted it to have, gets *backpropagated* to every single param in our network.
- Backprop is an effective way to find the gradient. Uses the *chain rule* to find the gradian of the error.

- $y = mx + b$ linear function. The slope or gradian is m.
- The process described :

$$\theta = \theta - \eta * \nabla_\theta * J(\theta) \tag{4}$$

  - θ : parameters
  - ∇ : gradient, with repect to parameters θ, ∇_θ
  - J : error
  - η : learning rate describes how far along this gradient we should travel, typically value between 0.01 to 0.00001

1.6 Local Minima/Optima and learning Rate

- Dilemma : find a local or global minima.
- The NW may have million of parameters, so the problem becomes more and more difficult.
- Wize choice of the learning rate :
  - To small we dont get any better cost where we started
  - To big the cost goes up and down

2 Creating a Neural Network

2.1 Exemple with sine wave

- Input X output y
- Here te input is values in an interval instead of images like before.
- The exemple is to create sine wave with uniform noise and create a neural network that is able to discover the sine wave.

```
# Create data : sine wave with random noise in the interval
n_obs = 1000
xs = np.linscape(-n, n, n_obs)
ys = np.sin(xs) + np.random.uniform(-0.5,0.5,n_obs)
plt.scatter(xs, ys)
```

- Train the NW to ginve any value on the x axis and have the value it should be on the y axis. (fundamental idea of regression : predicting some continuous output value given some continuous input value)

2.2 Defining cost

- Use of placeholder to define input and output values. Those variables will filled at the computation of the graph.

```
X = tf.placeholder(tf.float32, name='X')
Y = tf.placeholder(tf.float32, name='Y')
```

- Create session and define the parameters center and close to 0 with *tf.random_normal(nb_values, stddev=).eval()*

```
sess = tf.InteractiveSession()
n = tf.random_normal([1000], stddev=0.1).eval()
```

- Create **varaibles** using *tf.Variable*, it does need an initial value or we can call an initializer.
- Define two *tf.Variable* for weight and bias

```
W = tf.Variable(tf.random_normal([1], dtype=tf.float32, stddev=0.1),
    name='weight')
B = tf.Variable(tf.constant([0], dtype=tf.float32), name='bias')
# Scale input placholder X
Y_pred = X * W + B
```

- Use gradient descent to lean what the best value of W and b.
- Before that we have to know how to measure what the *best* mean for what we try to do.
- Let's define the absolute *distance(val1, val2)* from the predicted value to the assumed sine wave value.

```
cost = distance(Y_pred, tf.sin(X))
```

- We calculate the mean of the cost we have for every observation

```
cost = tf.reduce_mean(distance(Y_pred, tf.sin(X))
```

2.3 Training Parameters

- Use tensorflow optimizer

```
optimizer =
    tf.train.GradientDescentOptimizer(learning_rate=0.01).minimize(cost)
```

- Run the optimizer

```
with tf.Session() as sess:
   #initilization of all the tf.Variable
   sess.run(tf.global_varables_initializer())
   prev_training_cost = 0.0
   for it_i in range(n_iterations):
      sess.run(optimizer, feed_dict={X:xs, Y:ys})
      training_cost = sess.run(cost, feed_dict={X:xs}) #...,session=sess)

      # each 10 iterations
      if it_i % 10 == 0:
         ys_pred = Y_pred.eval(feed_dict={X:xs})
         # print stuff like training_cost and plots

      if np.abs(prev_training_cost - training_cost < 0.000001:
         break # if local minima found

      prev_trianing_cost = training_cost
```

- The output doesn't look like a sine wave at all. Actually it's only a line.
- Training vs Testing : Have to learn more about the different between training and testing networks.

2.4 Stochastic and Mini Batch Gradient Descent

- Tricks to find the best local minima : using *mini-batches* of size *batch_size*.

```
idxs = np.arrange(100) # it will be changed to make it random
batch_size = 10
n_batches = idxs // batch_size
```

- Look some random subset of the datase because neural networks love order and would use it to its advantage. But order is irrelevant to our problem.

```
idxs = np.random.permutation(idxs)
```

- Generalise the entire dataset. We modify the code which runs the optomizer to include the mini-batches program.

```
idxs = np.random.permutation(range(len(xs)))
n_batches = len(idxs) // batch_size
for batch_i in range(n_batches):
   idxs_i = idxs[batch_i * batch_size: (batch_i+1) * batch_size]
   sess.run(optimizer, feed_dict={X:xs[idxs_i], Y:ys[idxs_i]})
training_cost = sess.run(cost, feed_dict={X:xs, Y:ys})
```

  We get a better result : the line has a curve but it doesn't look like a sine wave.

- This method is :

  - Mini-batches : small pieces of data where we perform gradient descent
  - Stochastic : the order of the data is dandomized

- Use a function of training

```
def train(X, Y, Y_pred, n_iterations=100, batch_size=200,
    learning_rate=0.02):
```

- To get better result we can have a bigger set of parameters.
- We are going to multiply our input by 100 values, creating an "inner layer" of 100 neurons.
  - Define *tf.Variables* : Weights (multiplication) and biais (addition)

```
n_neurons = 100
W = tf.Variable(tf.random_normal([1,n_neurons], stddev=0.1))
b = tf.Variable(tf.constant(0, dtype=tf.float32, shape=[n_neurons])
```

  - Operation with matrix and add every neuron's output

```
h = tf.matmul(tf.expand_dims(X, 1), W) + b)
Y_pred = tf.reduce_sum(h, 1)
```

  - Retrain with new Y_pred

```
train(X, Y, Y_pred)
```

- It takes longer to compute and the result is not better. Our function is still linear but the cost is going up and down : good signe = we can reduce the learning rate
- Input's Representation : important to consider the kind of input we are working on. We don't treate the types of data in the same way like :
  - sound using discrete fourier transform
  - text using word histograms

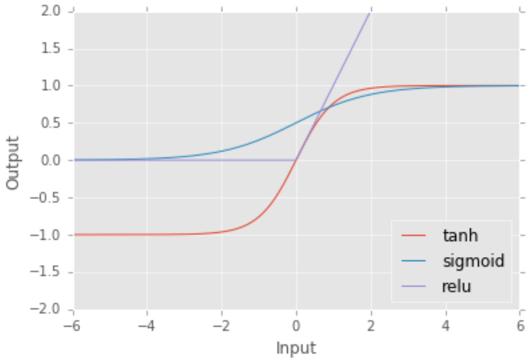
2.5 Over vs. Underfitting

- To approximate curve function we use polynomial function. We will try to learn the influence of each degree of this function

```
Y_pred = tf.Variable(tf.random_normal([1]), name='bias')
for pow_i in range(1,4):
   W = tf.Variable(
      tf.random_normal([1], stddev=0.1, name='weight_%d' % pow_i)
   Y_pred = tf.add(tf.multiply(tf.pow(X, pow_i), W, Y_pred)
```

2.6 Introducing Nonlinearities / Activation Function

- Use of non-linear functions also called activation functions. In every compex DL algorithm there are series of linear, followed by nonlinear operations.
- There are 3 functions used the most : *tanh(), sigmoid(), relu()*



- We modify the matrix multiplication by adding the non-linearity

```
h = tf.nn.tanh(tf.multiply(tf.expland_dims(X,1), W) + b, name='h')
```

- **Fully-connected network** : every neuron is multiplied by every single input value. We multiply our input by a matrix, add a bias, and then apply a non-linearity.

2.7 Going Deeper

- Give useful name within *scopes*. Otherwise the names of the operations are not helpful.

```
W = tf.get_variable( name='W', xhape=[n_input, n_output],
    initializer=tf.random_normal_initializer(mean=0.0, stddev=0.1))
```

- This new initializer will create new random value when *sess.run(tf.global_variables_initializer())* is called
- Possible to visualize the network using **Tensorboard**.

3 Image Inpainting

3.1 Description

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