Introduction to Deep Learning with Tensorflow

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Summary

What we will cover...

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- Simple Example: Linear Regression with Tensorflow

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- Intro to Deep Learning

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- OpenAI Gym
- Implement basic DQN

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- Programming interface: Python, C++, C... Python is most well developed and documented.
- Latest version: 1.12 (same time last year 1.5). Commonly used version: ≈1.0. (depend on other dependencies)
- Can be installed via pip. Best supported on mac os and linux.

TensorFlow: A System for Large-Scale Machine Learning

Martín Abadi, Paul Barham, Jianmin Chen, Zhifeng Chen, Andy Davis, Jeffrey Dean, Matthieu Devin, Sanjay Ghemawat, Geoffrey Irving, Michael Isard, Manjunath Kudlur, Josh Levenberg, Rajat Monga, Sherry Moore, Derek G. Murray, Benoit Steiner, Paul Tucker, Vijay Vasudevan, Pete Warden, Martin Wicke, Yuan Yu, and Xiaoqiang Zheng, *Google Brain*

(e) Tensorflow paper

Simple Example: Linear Regression

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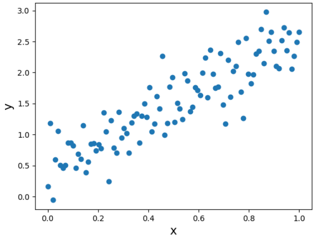
Linear Regression: Data

```
# true parameters
true_theta = 2.
true_theta_0 = .5

# generate data
x = np.linspace(0,1,100)
y = true_theta * x + true_theta_0 + np.random.randn(x.size) * .3
```

(f) True Parameters



(g) Data

Linear Regression with Tensorflow

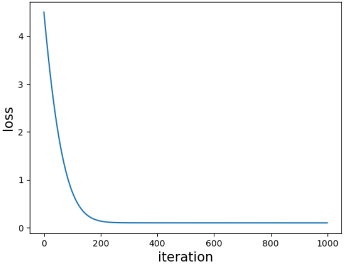
Let us just focus on defining **architecture**...

```
# specify placeholders
X = tf.placeholder(tf.float32,[None])
Y = tf.placeholder(tf.float32,[None])

# specify models
theta = tf.Variable(tf.truncated_normal([1]))
theta_0 = tf.Variable(tf.truncated_normal([1]))
Y_hat = tf.multiply(X,theta) + theta_0

# loss
loss = tf.reduce_mean(tf.square(Y_hat - Y))
```

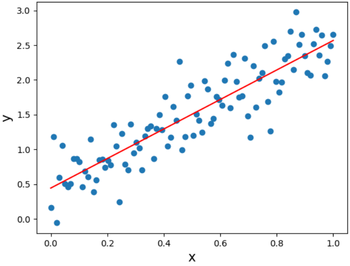
(h) Linear regression tf code

Linear Regression with Tensorflow

We launch the training...



(i) loss



(j) fitted line

Intro to DL

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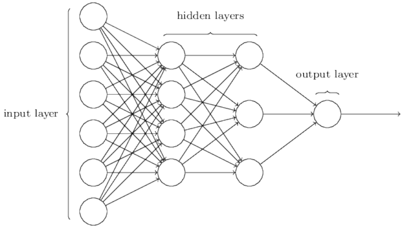
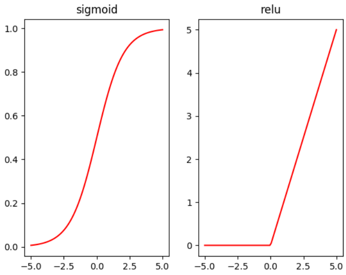
  - second layer has W_2, b_2, transform as $h_2 = \sigma(W_2 h_2 + b_2) \in \mathbb{R}^3$
  - final output $\hat{y} = W_3 \sigma(W_2 \sigma(W_1 x + b_1) + b_2) + b_3 \in \mathbb{R}$



(u) mlp



(v) nonlinear functions

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- Parameters: weights W_1, W_2, W_3 and bias b_1, b_2, b_3.
  - Linear regression: slope θ and bias θ_0

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Algorithm 4 Generic DL regression

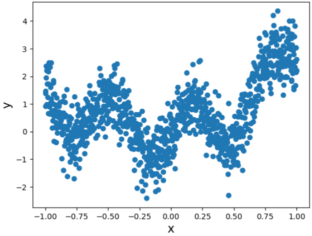
Input: model architecture, data $\{x_i, y_i\}$, learning rate α
Initialize: Model parameters $\theta = \{W_i, b_i\}$
for t=1,2,3...T **do**
    Compute prediction $\hat{y}_i = f_\theta(x_i)$
    Compute loss $J = \frac{1}{N}\sum_i(\hat{y}_i - y_i)^2$
    Gradient update $\theta \leftarrow \theta - \alpha\nabla_\theta J$
end for

DL Regression: Data

Generate data using $y = x^3 + x^2 + \sin(10x) + \textbf{noise}$. Linear regression will fail.

```
# generate data
x = np.linspace(-1,1,1000)
y = x**3 + x**2 * 2 + np.sin(10 * x) + np.random.randn(x.size) * .6
```

(w) data generation



(x) data plots

DL Regression with Tensorflow

Specify the **Architecture, Loss** using Tensorflow syntax just like linear regression.

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b1 = tf.Variable(tf.truncated_normal([10]))
W2 = tf.Variable(tf.truncated_normal([10,10]))  # layer 2
b2 = tf.Variable(tf.truncated_normal([10]))
W3 = tf.Variable(tf.truncated_normal([10,1]))  # layer 3
b3 = tf.Variable(tf.truncated_normal([1]))

h1 = tf.nn.relu(tf.matmul(X,W1) + b1)
h2 = tf.nn.relu(tf.matmul(h1,W2) + b2)
Y_hat = tf.matmul(h2,W3) + b3

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- train the model just like linear regression

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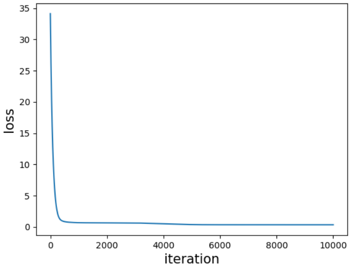

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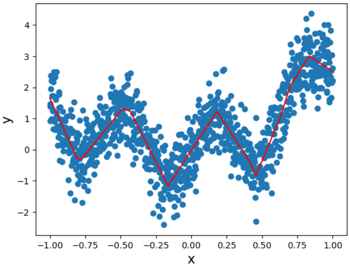

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Batch training

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- Sample a batch of data $\rightarrow$ Compute gradient on the batch $\rightarrow$ Update parameters.
- **Batch size:** too small: high variance in data stream, unstable training; too large: too costly to compute gradients.

Auto-differentiation

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- Taking gradients in linear model is easy.
- Question: how to take gradients for MLP? $\nabla_{W_1} J$ is not straightforward as in linear regression.

$$J = \frac{1}{N}\sum_i (y_i - \hat{y}_i)^2, \hat{y}_i = W_3\sigma(W_2\sigma(W_1 x_i + b_1) + b_2) + b_3$$

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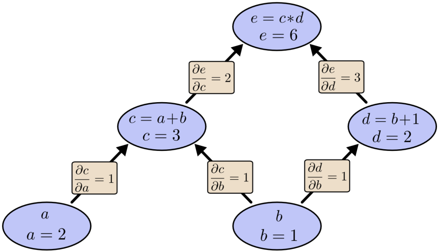
- Example: start with a, b, compute e: $c = a + b, d = b + 1, e = c \cdot d$. Consider

$$\frac{\partial e}{\partial a} = \frac{\partial e}{\partial d}\frac{\partial d}{\partial a} + \frac{\partial e}{\partial c}\frac{\partial c}{\partial a}$$



() computation graph

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- forward computation $\rightarrow$ local forward ops $\rightarrow$ local gradient $\rightarrow$ long range gradients.
- Just like error back-propagating from output to inputs and params, **back-propagation**.
- Useful link: http://deeplearning.stanford.edu/wiki/index.php/UFLDL_Tutorial

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- **Variable:** tf objects that represent parameters that can be updated through autodiff. Embedded inside the graph.
- All expressions computed from primitive variables and placeholders are vertices in the graph.

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- And many more...

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- Define **session** to launch the training
- Initialize variables
- Feed data into the computation graph

```
# define loss
loss = tf.reduce_mean(tf.square(Y_hat - Y))

# use optimizers to define update operations
optimizer = tf.train.AdamOptimizer(1e-2)
opt = optimizer.minimize(loss)

# initialize sessiont to run update
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())  # initialize all variables
    ldict = []  # a list that records loss
    for _ in range(1000):
        l,_ = sess.run([loss,opt],feed_dict={X:x,Y:y})  # one step gradient update
        ldict.append(l)  # record loss
```

() launch the training

Training: whole landscape

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# define models
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h2 = tf.nn.relu(tf.matmul(h1,W2) + b2)
Y_hat = tf.matmul(h2,W3) + b3

# loss
loss = tf.reduce_mean(tf.square(Y_hat - Y))

# gradients
optimizer = tf.train.AdamOptimizer(1e-3)
opt = optimizer.minimize(loss)

# ========
# launch training
# ========
with tf.Session() as sess:
    sess.run(tf.global_variables_initializer())
    ldict = []
    x = np.expand_dims(x,1)
    y = np.expand_dims(y,1)
    for _ in range(10000):
        l,_ = sess.run([loss,opt],feed_dict={X:x,Y:y})
        ldict.append(l)
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Beyond Regression

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- **Structured Prediction:** regression on high dimensional objects (autoencoders)
- **Reinforcement Learning:** DQN, policy gradients...
    - DQN is an analogy to regression
    - PG is an analogy to classification

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- Need hand tuning or cross validation to select good hyper-parameters.

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  - beyond simple sgd, there are rmsprop, adam, adagrad... adam is popular.
  - learning rate
- **Architectures:** number of layers, hidden units per layers
- **Nonlinear function:** sigmoid, relu, tanh...
- **Initialization:** initialization of variables W, b.
  - arbitrary initializations will fail.
  - xavier initialization, truncated normal...
- Need hand tuning or cross validation to select good hyper-parameters.
- Other topics: batch-normalization, dropout, stochastic layers...

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  - tensorflow.contrib

Beyond Tensorflow

```
import tensorflow as tf

x = tf.placeholder(tf.float32, [None,10])

# build layer
W1 = tf.Variable(tf.truncated_normal([3,10]))
b1 = tf.Variable(tf.truncated_normal([3]))

# compute output
y = tf.nn.relu(tf.matmul(X,W1) + b1)

# ======
# high level definition
# ======
import tensorflow.contrib as tc

# z is the new output
z = tf.layers.dense(x, 3, # 3 is the output dimension
    kernel_initializer=tf.random_uniform_initializer(minval=-3e-3, maxval=3e-3)
```

() low level vs. high level

Additional Resources

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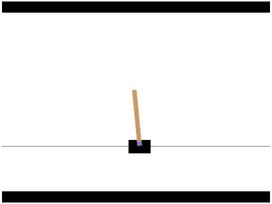
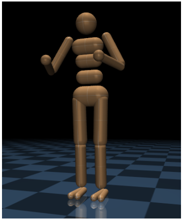
OpenAI Gym - very brief intro



() classic control



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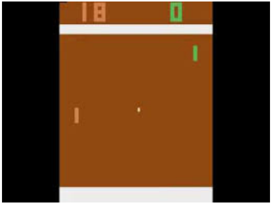

() atari game - pong

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- **display state:** env.render(). Only display current state, need to render in a loop to display consecutive states.

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- Cooler video game: DeepMind StarCraft II Learning Environment

Or build your own environments...

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- Bellman error is zero iff optimal policy $Q^*(s,a)$

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- WIll converge under mild conditions. Converge to the fixed point

$$Q = TQ$$

which gives zero bellman error.

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- Sample based, given tuples $\{(s_i,a_i,r_i,s_i')\}_{i=1}^N$

$$\min_\theta \sum_{i=1}^N \frac{1}{N}(Q_\theta(s_i,a_i) - r_i - \max_a Q_\theta(s_i',a))^2$$

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- **Target Network:** the training target $r_i + \max_a Q_\theta(s_i', a)$ is non-stationary. Make it stationary by introducing a slowly updated target net θ^- and compute target as $r_i + \max_a Q_{\theta^-}(s_i', a)$

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- More advanced exploration: noisy net, parameter space noise, bayesian updates...
- Learning rate: constant $\alpha = .001$ for example, not RM scheme.

Basic DQN

Algorithm 1 DQN

INPUT: target network update period τ, total number of episodes E, initial time steps before update init, learning rate α, exploration prob ϵ, batchsize for training N

INITIALIZE: DQN principal network $Q_\theta(s, a)$ with parameters θ, target network $Q_{\theta^-}(s, a)$ with parameters θ^-, time steps counter $counter \leftarrow 0$, empty buffer $R \leftarrow \{\}$

for $e = 1, 2, 3 ... E$ **do**
  while episode not terminated **do**
    Execute actions
    $counter \leftarrow counter + 1$
    Given state s_t, for prob ϵ, take action uniformly random; otherwise, take action by being greedy $a_t \leftarrow \arg\max_a Q_\theta(s_t, a)$
    Save experience tuple $\{s_t, a_t, r_t, s_{t+1}\}$ to buffer R
    Training θ by gradients
    Sample N tuples $\{s_i, a_i, r_i, s_i'\}$ from replay buffer R (uniformly)
    Compute target $d_j = r_j + \max_{a'} Q_{\theta_j^-}(s_j', a')$ for $1 \leq j \leq N$
    Compute empirical loss

$$L = \frac{1}{N} \sum_{j=1}^{N} (Q_\theta(s_j, a_j) - d_j)^2$$

    Update $\theta \leftarrow \theta - \alpha \nabla_\theta L$
    Update target network θ^-
    if $counter \bmod \tau = 0$ **then**
      Update target parameter $\theta^- \leftarrow \theta$

() dqn pseudocode

End

Thanks!