Tensorflow Example: Fizzbuzz

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Fizzbuzz in Tensorflow

• Fizzbuzz:

- Print the numbers from 1 to 100, except that if the number is divisible by 3 print "fizz", if it's divisible by 5 print "buzz", and if it's divisible by 15 print "fizzbuzz"
- We look at implementation of Fizzbuzz in Tensorflow
 - As a simple MLP with one hidden layer
 - See http://joelgrus.com/2016/05/23/fizz-buzzin-tensorflow/

Useful Python syntax

- 1. % operator, e.g., b % a
 - divides left-hand operator by right-hand operator and returns remainder
- 2. == condition, e.g., a==b
 - Condition becomes true if operands are equal
- 3. &, e.g., a&b
 - Bitwise logical AND operator
- 4. Range function, e.g., range(3)=[0,1,2]

Standard Imports

- import numpy as np
- import tensorflow as tf

Input treated as a vector

- Input is a number, output is "fizzbuzz" representation of that number.
- In particular, we need to turn each input into a vector of "activations". One simple way would be to convert it to binary.
 - Define a binary encoder for the input i

```
def binary_encode(i, num_digits):
return np.array([i >> d & 1 for d in range(num_digits)])
```

Mapping input to fizzbuzz

```
def fizz_buzz_encode(i):
    if i % 15 == 0: return np.array([0, 0, 0, 1])
    elif i % 5 == 0: return np.array([0, 0, 1, 0])
    elif i % 3 == 0: return np.array([0, 1, 0, 0])    else
return np.array([1, 0, 0, 0])
```

Generating Training Samples

 It would be cheating to use the numbers 1 to 100 in our training data, so let's train it on all the remaining numbers up to 1024:

```
NUM_DIGITS = 10
trX = np.array([binary_encode(i, NUM_DIGITS)
for i in range(101, 2 ** NUM_DIGITS)])
```

```
trY = np.array([fizz_buzz_encode(i)
for i in range(101, 2 ** NUM_DIGITS)])
```

No. of Hidden Units

Chosen arbitrarily to be 10

NUM HIDDEN =
$$100$$

Input and Output Variables

- We'll need an input variable of with width NUM DIGITS
- Output variable with width 4

```
X = tf.placeholder("float", [None, NUM_DIGITS])
Y = tf.placeholder("float", [None, 4])
```

Randomly initialized weights

One hidden layer and one output layer

ReLU Activation

Ready to define model using ReLU activation

```
def model(X, w_h, w_o):
    h = tf.nn.relu(tf.matmul(X, w_h))
    return tf.matmul(h, w_o)
```

Softmax Cross-Entropy Cost

We try and minimize it

```
py_x = model(X, w_h, w_o)
cost = tf.reduce_mean(tf.nn.softmax_cross_entropy_with_logits(py_x, Y))
train op = tf.train.GradientDescentOptimizer(0.05).minimize(cost)
```

Prediction

Prediction will just be the largest output
 predict_op = tf.argmax(py_x, 1)

 predict_op will output a number from 0 to 3 but we want a fizzbuzz output

```
def fizz_buzz(i, prediction):
return [str(i), "fizz", "buzz", "fizzbuzz"][prediction]
```

Training

 We grab a tensorflow session and initialize the variables

```
with tf.Session() as sess:
    tf.initialize all variables().run()
```

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Training epochs

- 10,000 epochs of training
- Shuffle them for each iteration

for epoch in range(10000):

```
p = np.random.permutation(range(len(trX))) trX,
trY = trX[p], trY[p]
```

Each Training Pass

- Each epoch trained in batches of 128
 BATCH_SIZE=128
- Each training pass looks like

```
for start in range(0, len(trX), BATCH_SIZE):
end = start + BATCH_SIZE sess.run(train_op,
feed dict={X: trX[start:end], Y: trY[start:end]})
```

Printing Accuracy of Training Data

It is helpful see how training accuracy evolves

```
print(epoch, np.mean(np.argmax(trY, axis=1) ==
    sess.run(predict_op, feed_dict={X: trX, Y:
        trY})))
```

Fizzbuzz Testing

 Input is just the binary encoding of numbers 1 to 100

```
numbers = np.arange(1, 101)
teX = np.transpose(binary_encode(numbers,
NUM_DIGITS))
```

Output

 Output is fizzbuzz function applied to model output

```
teY = sess.run(predict_op, feed_dict={X: teX})
output = np.vectorize(fizz_buzz)(numbers, teY)
print(output)
```

Performance

- In [185]: output
- Out[185]:
- array(['1', '2', 'fizz', '4', 'buzz', 'fizz', '7', '8', 'fizz', 'buzz', '11', 'fizz', '13', '14', 'fizzbuzz', '16', '17', 'fizz', '19', 'buzz', '21', '22', '23', 'fizz', 'buzz', '26', 'fizz', '28', '29', 'fizzbuzz', '31', 'fizz', 'fizz', '34', 'buzz', 'fizz', '37', '38', 'fizz', 'buzz', '41', '42', '43', '44', 'fizzbuzz', '46', '47', 'fizz', '49', 'buzz', 'fizz', '52', 'fizz', 'fizz', 'buzz', '56', 'fizz', '58', '59', 'fizzbuzz', '61', '62', 'fizz', '64', 'buzz', 'fizz', '67', '68', '69', 'buzz', '71', 'fizz', '73', '74', 'fizzbuzz', '76', '77', 'fizz', '79', 'buzz', '81', '82', '83', '84', 'buzz', '86', '87', '88', '89', 'fizzbuzz', '91', '92', '93', '94', 'buzz', 'fizz', '97', '98', 'fizz', 'fizz'],
- dtype='<U8')

Conclusion

- Running this code on GitHub got some of the outputs wrong!
 - I count 0.90 fizz-accuracy, and 0.99 buzzaccuracy. So it's clearly harder to teach fizzing than buzzing.
- A deeper network may help