Big Data Technology

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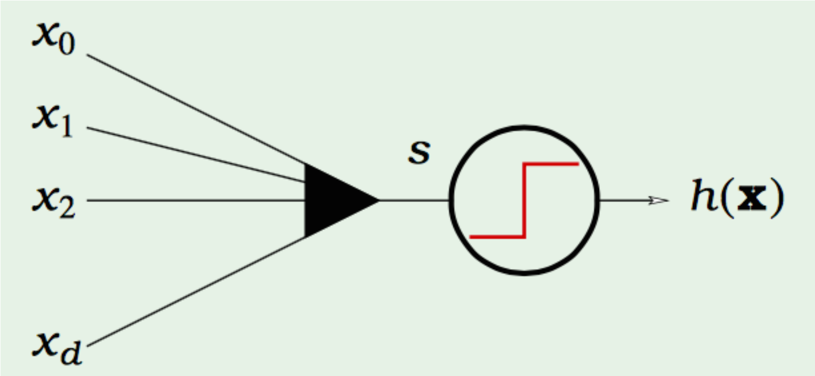
Outline

- **Logistics**
- **Summary and Review Previous Sections**
- **Tensorflow**

Review Models

Linear Classification

h(x) = Sign ($\sum_{i=0}^{n} w_i \, x_i$)



Sign function:

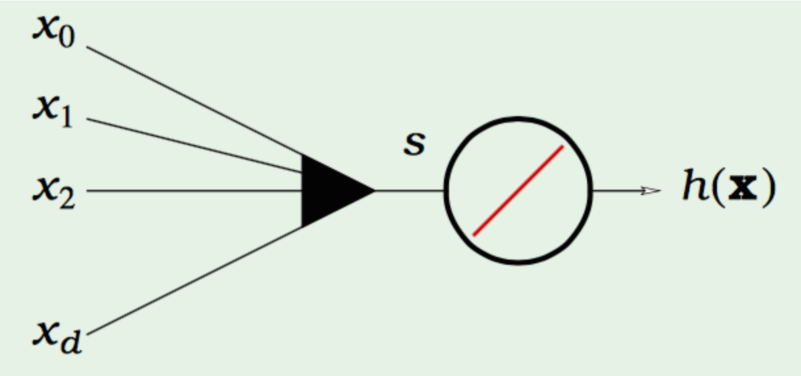
h(s) = 1 s >=0

h(s) = 0 s < 0

Hard Threshold : Certainty

Linear Regression

h(x) = $\sum_{i=0}^{n} w_i \, x_i$

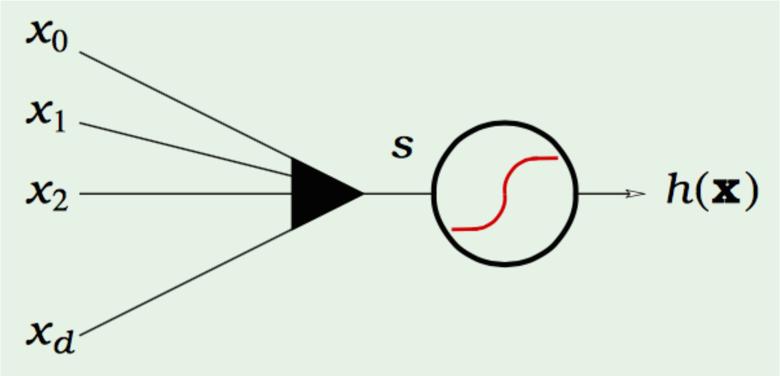


identity function:

h(s) = s

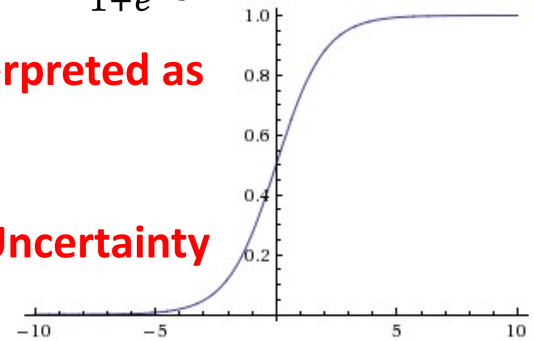
Logistic Regression

h(x) = Sigmoid ($\sum_{i=0}^{n} w_i \, x_i$)



Sigmoid function:

h(s) = $\frac{1}{1+e^{-s}}$



The output is interpreted as probability

Soft Threshold : Uncertainty

Probability Interpretation

h(x) = Sigmoid ($\sum_{i=0}^{n} w_i\, x_i$) = θ (s) is interpreted as a probability

Logistic Regression

h(x) = Sigmoid ($\sum_{i=0}^{n} w_i\, x_i$)

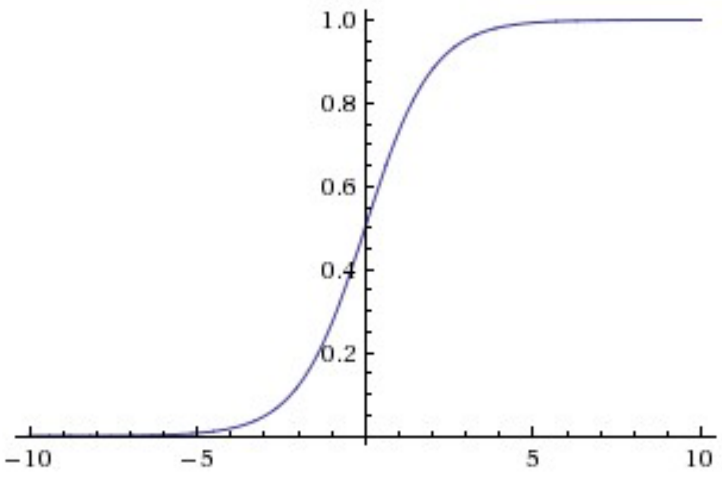
Example: Prediction of heart attacks

Input **X**: x1 =cholesterol level, x2 =patient age, x3 =patient weight, etc.

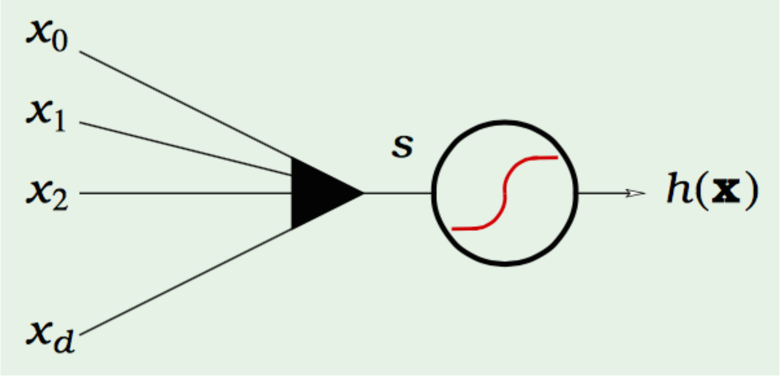
θ (s): probability of a heart attack

S= $\sum_{i=0}^{n} w_i\, x_i$ **"risk score"**

θ(s) = $\frac{1}{1+e^{-s}}$



S



Sigmoid function

Computational Graph – Tensorflow

What does TensorFlow do?

TensorFlow lets us do all our processing in TensorFlow environment, by creating the whole **computational graph first**, then **passing in data and actually computing the result at a later time**

- TensorFlow computations define a computation graph that has no numberical value until evaluated! (Symbolic presentation)
- Computational Graph: Build the graph, then run it later
- Benefits include distributed processing, drastic speedups, focus on algorithm not implementation
- Theano and Torch have done this before, TensorFlow builds on these approaches
- Tensor can be represented as a multidimensional array of numbers

TensorFlow variables

When you train a model you use variables to hold and update parameters. Variables are in-memory buffers containing tensors – TensorFlow Docs.

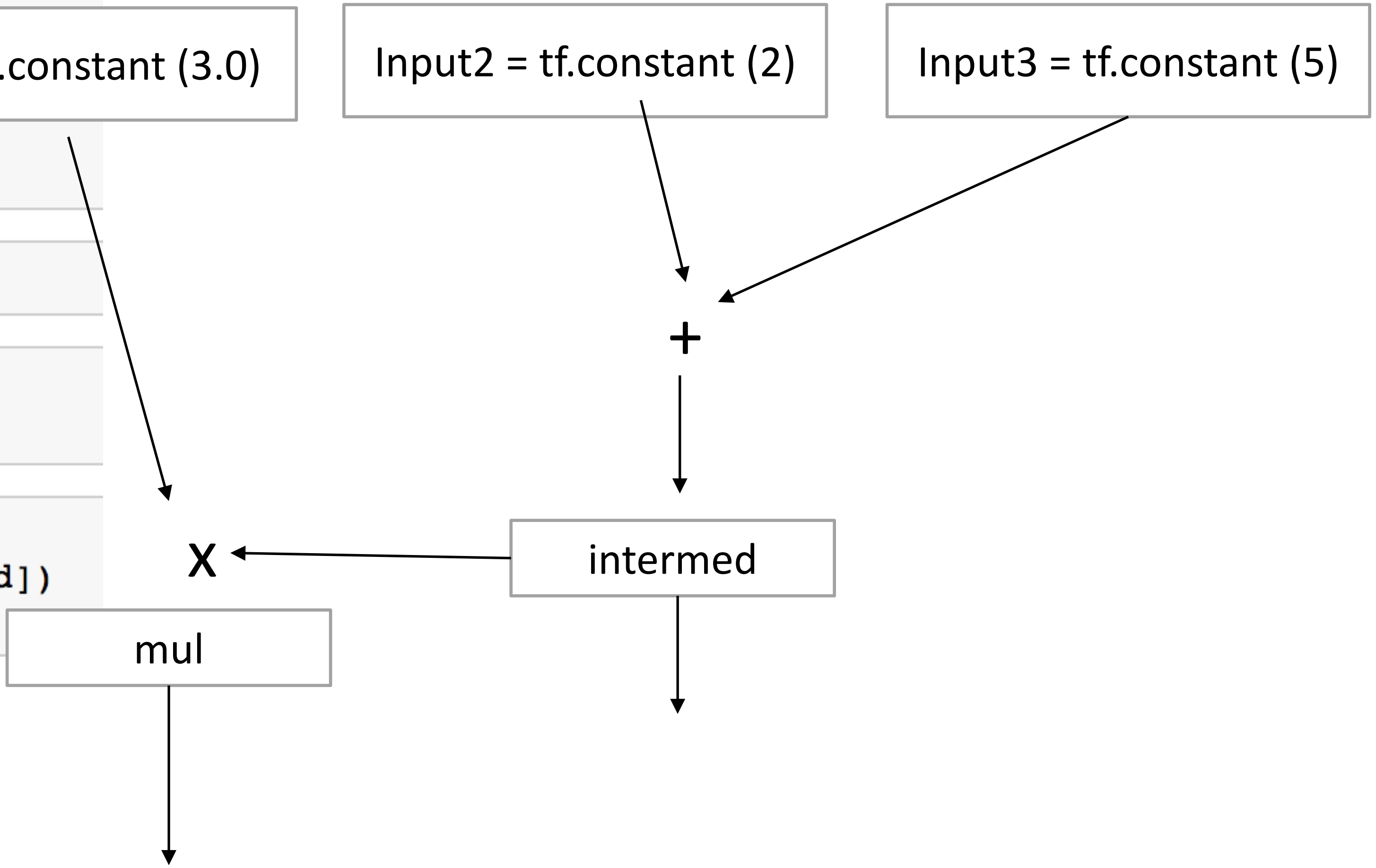
Variable tensor has to be initialized

Numpy vs. Tensorflow

```
In [2]: import numpy as np
        import tensorflow as tf

In [5]: a = np.zeros((2,2))
        print (a)

[[ 0.  0.]
 [ 0.  0.]]

In [6]: ta = tf.zeros((2,2))

In [7]: print (ta)

Tensor("zeros:0", shape=(2, 2), dtype=float32)

In [14]: with tf.Session() as session:
             print (ta.eval())
             print (session.run(ta))

[[ 0.  0.]
 [ 0.  0.]]
[[ 0.  0.]
 [ 0.  0.]]
```

Constant

```
In [1]: import tensorflow as tf

In [2]: input1 = tf.constant(3.0)
        input2 = tf.constant(2.0)

In [3]: input3 = tf.constant(5.0)

In [4]: intermed = tf.add(input2, input3)
        mul = tf.mul(input1, intermed)

In [5]: with tf.Session() as session:
            result = session.run([mul, intermed])
            print (result)

[21.0, 7.0]
```



In [1]:
```python
import tensorflow as tf
```

In [2]:
```python
x = tf.constant (35, name='x')
```

In [3]:
```python
y = x + 5
```

In [4]:
```python
print (y)
```

```
Tensor("add:0", shape=(), dtype=int32)
```

so far, we have the graph, how do we work out its value?

In [5]:
```python
with tf.Session() as session:
    print (session.run(y))
```

```
40
```

Exercises

In [11]:
```
import tensorflow as tf
```

In [12]:
```
x = tf.constant([35, 40, 45], name='x')
y = tf.Variable(x + 5, name='y')
```

In [15]:
```
print (y)
```

```
<tensorflow.python.ops.variables.Variable object at 0x1072ee4e0>
```

In [16]:
```
model = tf.initialize_all_variables()
```

In [19]:
```
with tf.Session() as session:
    session.run(model)
    print(session.run(y))
```

```
[40 45 50]
```

Generate a NumPy array of 10,000 random numbers (called x) and create a Variable storing the equation

$$y = 5x^2 - 3x + 15$$

In [1]:
```
import tensorflow as tf
import numpy as np
```

In [2]:
```
data = np.random.randint(1000,size=10000)
print (data)
x = tf.constant(data)
print (x)
```

```
[525 744 559 ..., 245 471   7]
Tensor("Const:0", shape=(10000,), dtype=int64)
```

In [3]:
```
y = 2*(x*x) -3 * x + 15
```

In [4]:
```
model = tf.initialize_all_variables()
```

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

```
Tensor("add:0", shape=(10000,), dtype=int64)
```

so far, we have the graph, how do we work out its value? Nothing will be computed until we create a tensorflow session

In [6]:
```
with tf.Session() as session:
    session.run(model)
    print (session.run(y))
```

```
[ 549690 1104855  623300 ...,  119330  442284      92]
```

Placeholders

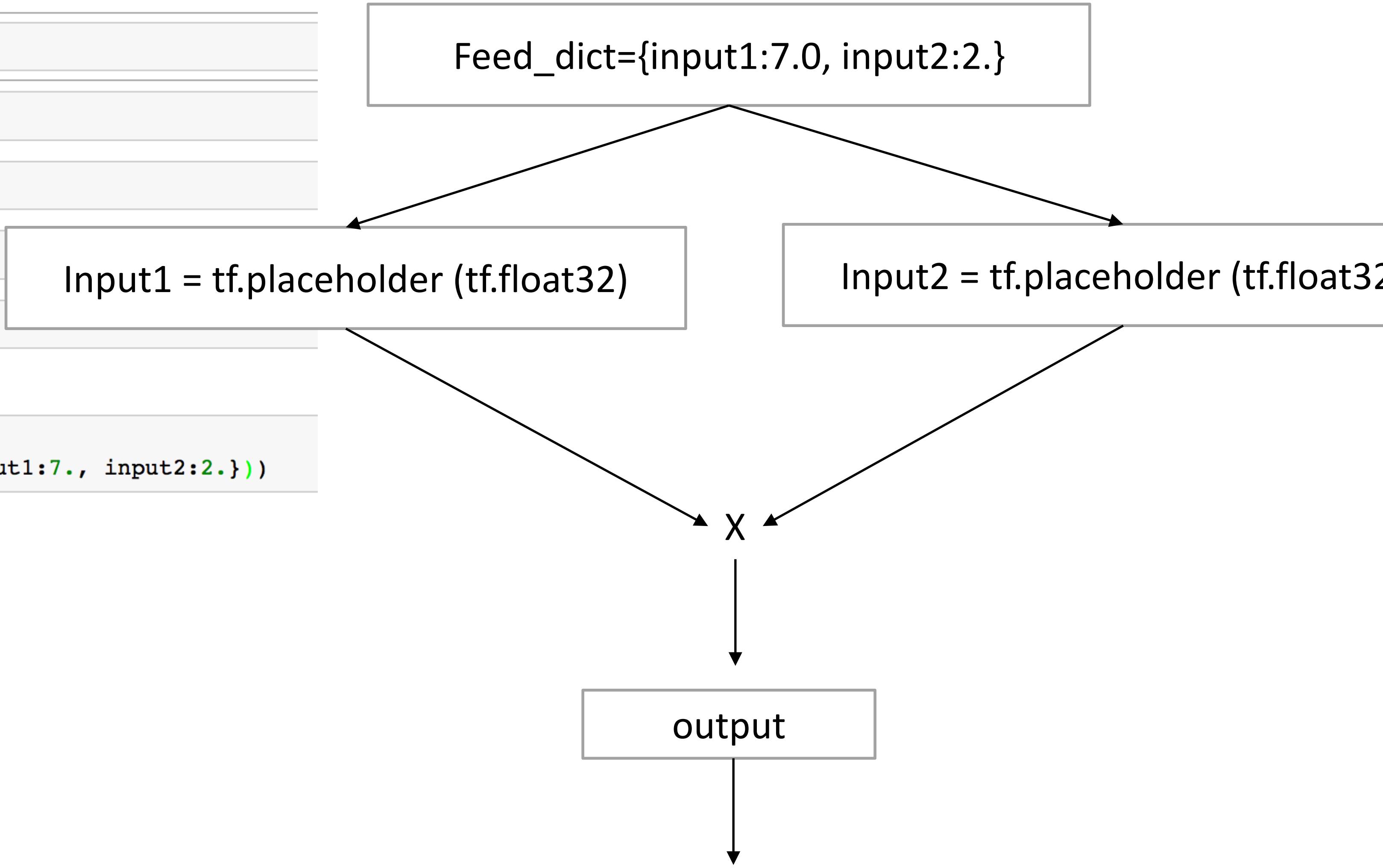
A placeholder is simply a variable (dummy variable) that we will assign data to at a later date.

It allows us to create our operations and build our computation graph, without needing the data.

In TensorFlow terminology, we then *feed* data into the graph through these placeholders.

Placeholder

```
In [2]: import tensorflow as tf

In [6]: input1 = tf.placeholder (tf.float32)

In [7]: input2 = tf.placeholder (tf.float32)

In [8]: output = tf.mul(input1, input2)

In [9]: print (output)

Tensor("Mul:0", dtype=float32)

In [13]: with tf.Session() as session:
             print (session.run(output, feed_dict={input1:7., input2:2.}))

14.0
```



```
In [2]: import tensorflow as tf

In [3]: x = tf.placeholder("float", 3)

In [4]: y = x * 2

In [5]: with tf.Session() as session:
            result = session.run(y, feed_dict={x: [1, 2, 3]})
            print(result)

[ 2.  4.  6.]
```

Placeholders do not need to be statically sized.

```
In [5]: import tensorflow as tf
```

```
In [6]: x = tf.placeholder("float", [None, 3])
```

```
In [7]: y = x * 2
```

```
In [8]: with tf.Session() as session:
            x_data = [[1, 2, 3],
                      [4, 5, 6],]
            result = session.run(y, feed_dict={x: x_data})
            print(result)

        [[  2.   4.   6.]
         [  8.  10.  12.]]
```

Interactive Sessions

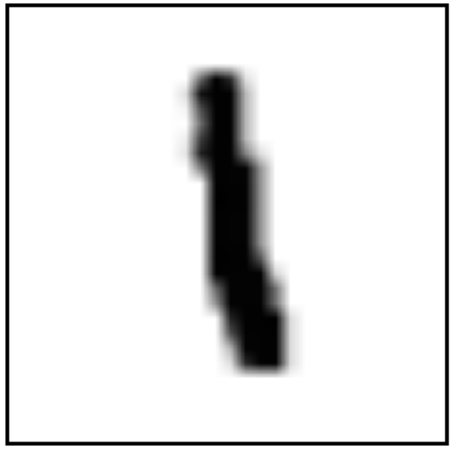
TensorFlow allows us to create a *graph* of operations and variables.

These variables are called Tensors, and represent data, whether that is a single number, a string, a matrix, or something else.

Tensors are combined through operations, and this whole process is modelled in a graph.

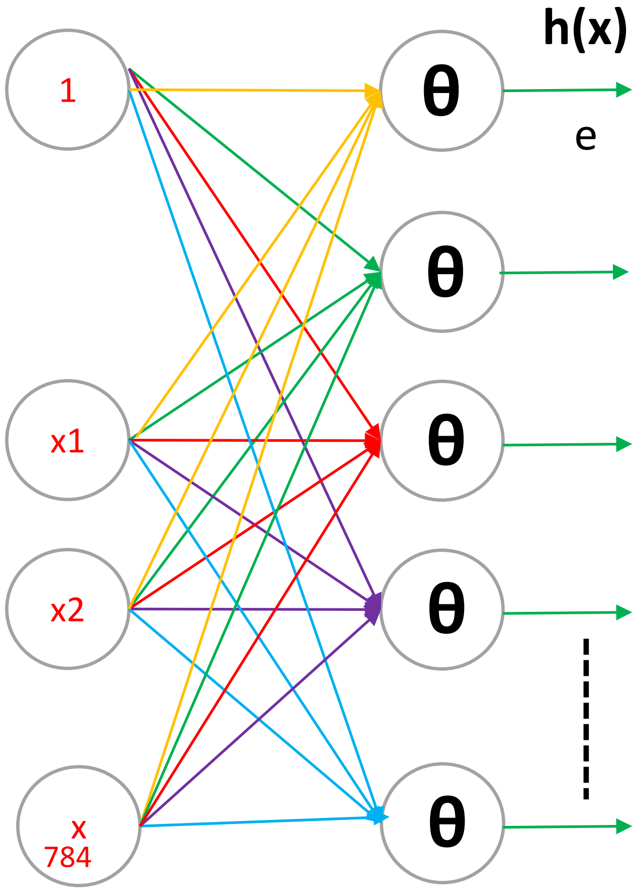
One major change is the use of an InteractiveSession, which allows us to run variables without needing to constantly refer to the session object (less typing!)

MNIST Number Detection Problem



28 X 28 = 784

$$
\begin{bmatrix}
0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&.6&.8&0&0&0&0&0&0\\
0&0&0&0&0&0&.7&1&0&0&0&0&0&0\\
0&0&0&0&0&0&.7&1&0&0&0&0&0&0\\
0&0&0&0&0&0&.5&1&.4&0&0&0&0&0\\
0&0&0&0&0&0&0&1&.4&0&0&0&0&0\\
0&0&0&0&0&0&0&1&.4&0&0&0&0&0\\
0&0&0&0&0&0&0&1&.7&0&0&0&0&0\\
0&0&0&0&0&0&0&1&1&0&0&0&0&0\\
0&0&0&0&0&0&0&.9&1&.1&0&0&0&0\\
0&0&0&0&0&0&0&.3&1&.1&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0\\
0&0&0&0&0&0&0&0&0&0&0&0&0&0
\end{bmatrix}
$$



$$
\begin{pmatrix}1\\0\\0\\0\\0\\0\\0\\0\\0\\0\end{pmatrix}
$$

$$
h(x) = \begin{pmatrix}0\\1\\0\\0\\0\\0\\0\\0\\0\\0\end{pmatrix}
$$