Psych 253
Advanced Statistical Modeling

Intro to Tensorflow

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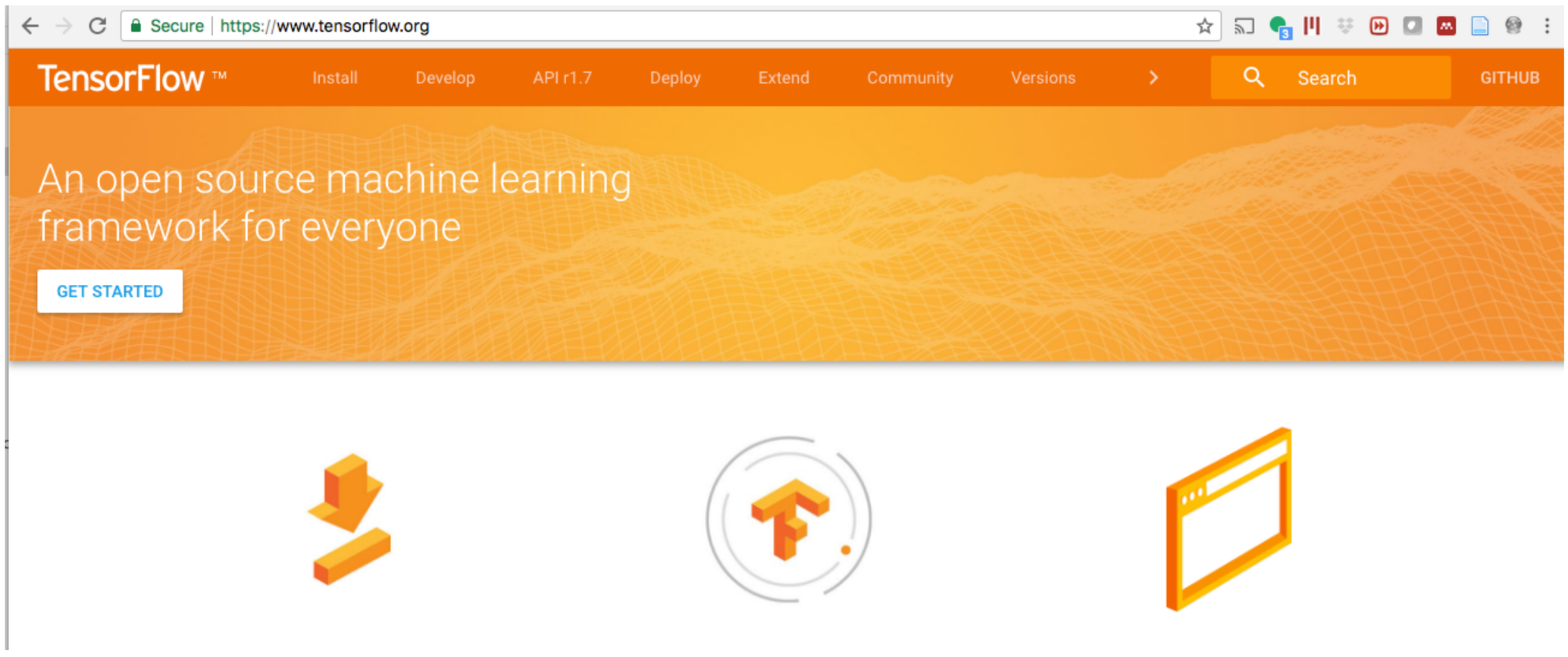
Graph Model of Computation

Tensorflow is a graph computation language.



Graph Model of Computation

$$e=(a+b)*(b+1)$$

Graph Model of Computation

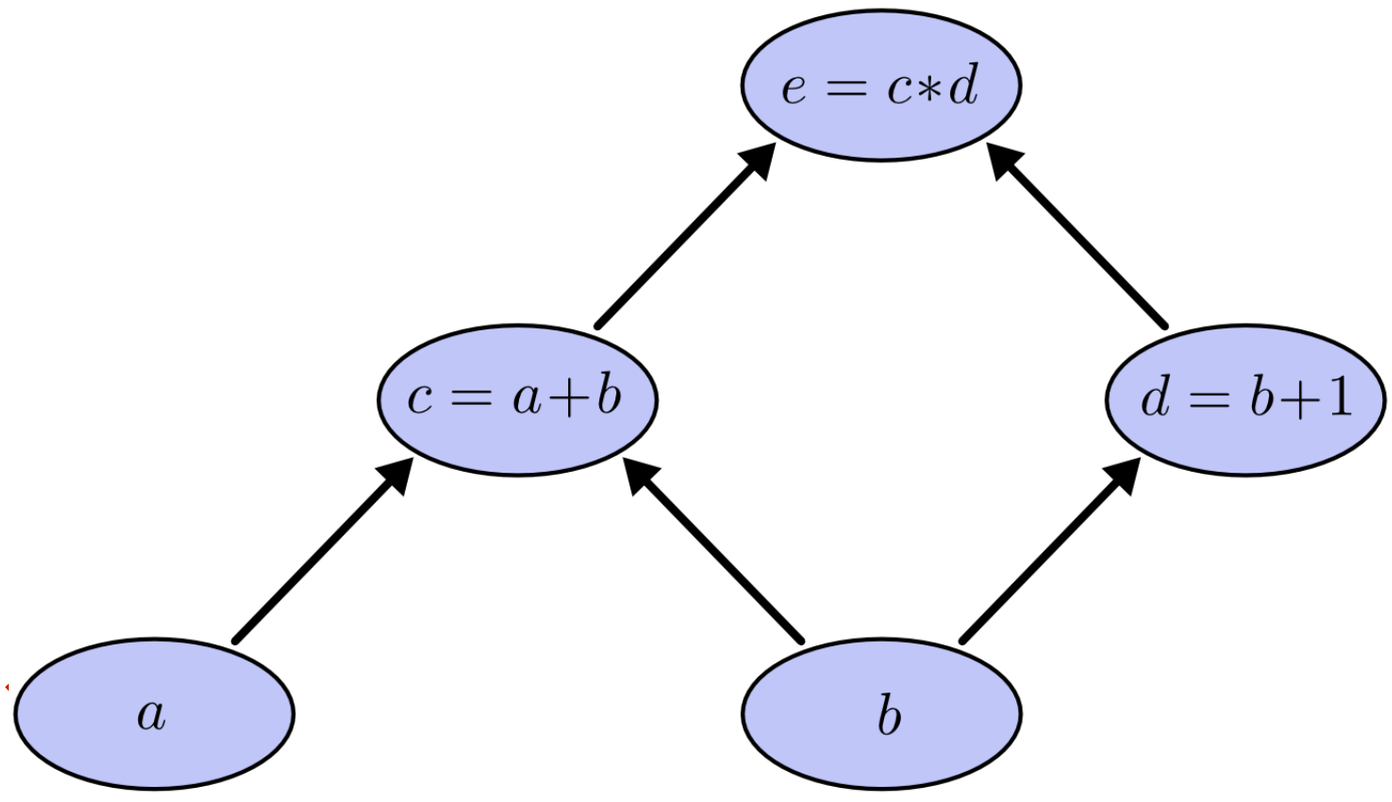
e=(a+b)*(b+1)

decomposes into 5 "nodes":

c=a+b

d=b+1

e=c*d



It's a Directed Acyclic Graph (DAG)

Graph Model of Computation

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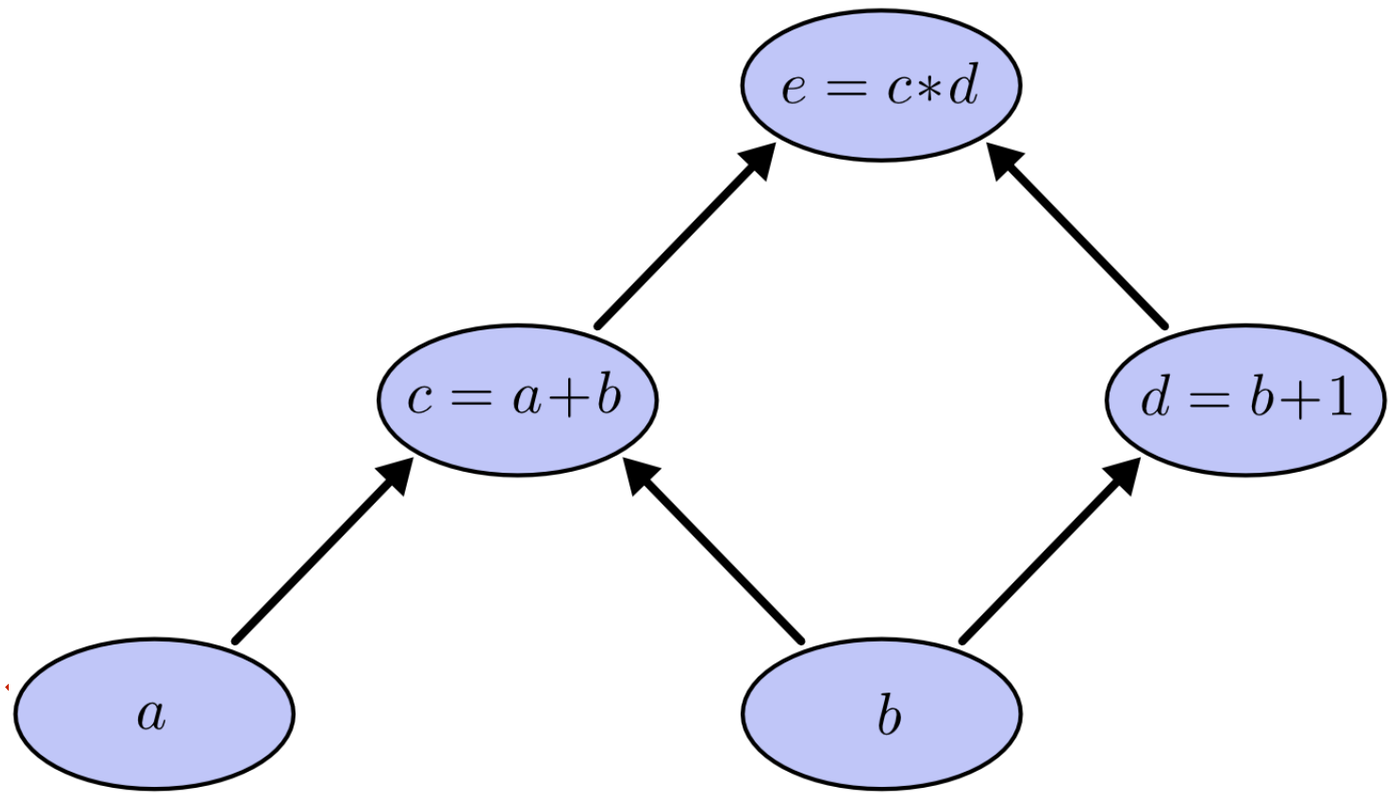

Ok let's see what happens if a=2 and b = 1.

Graph Model of Computation

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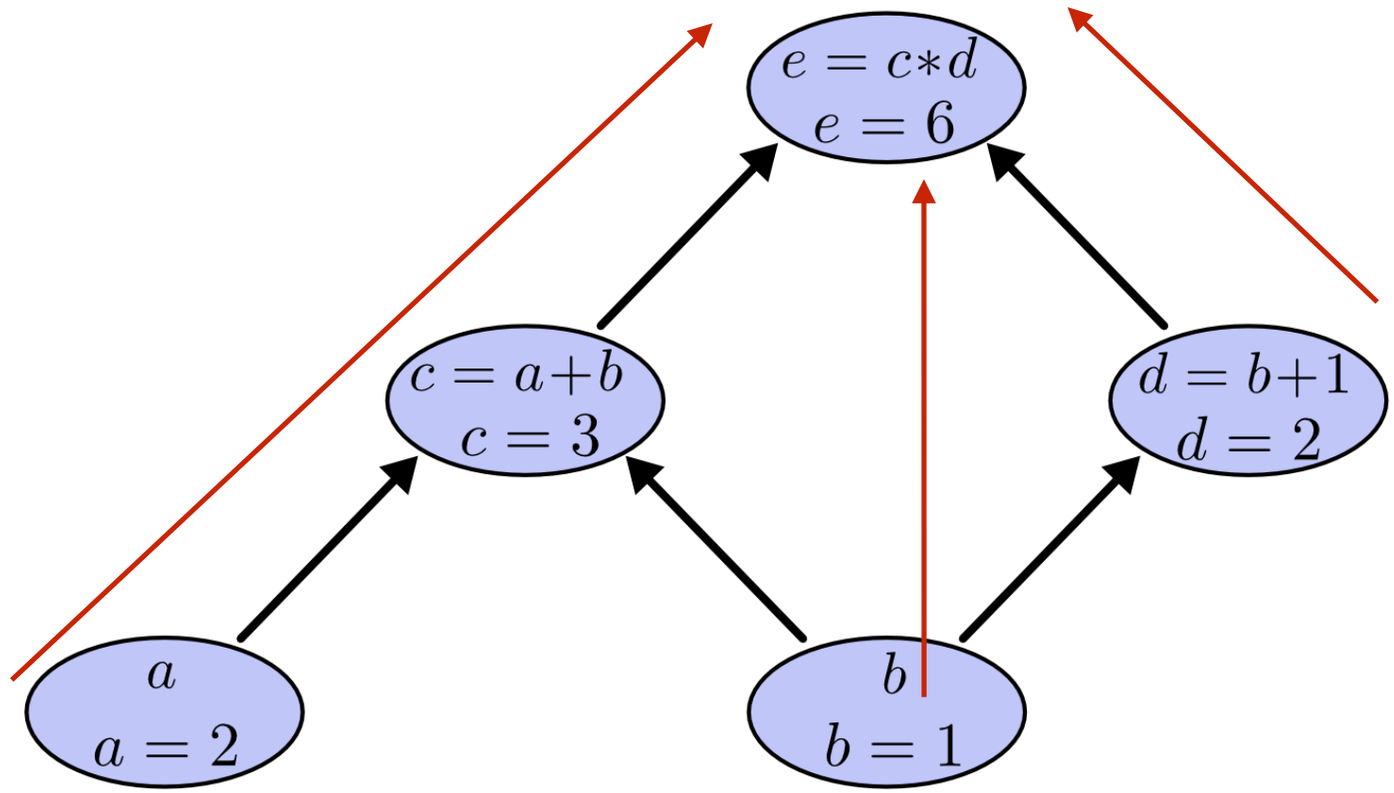


Ok let's see what happens if a=2 and b = 1.

Tensorflow

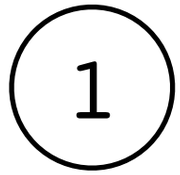
Agenda:

- Tensor constants
- Tensor operations
- Tensor variables
- Automatic Gradients

[ipynb]

Tensor Constants

```
one = tf.constant(1)
```



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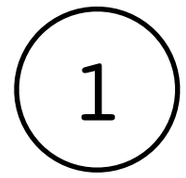
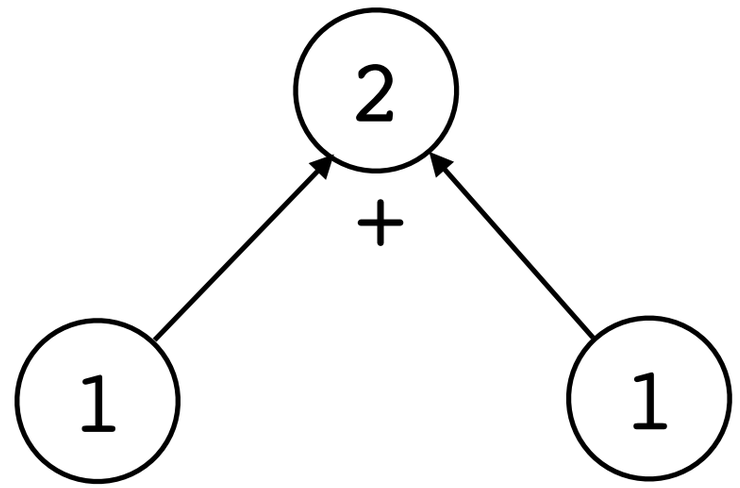



```
two = one + one
```



Tensor Constants

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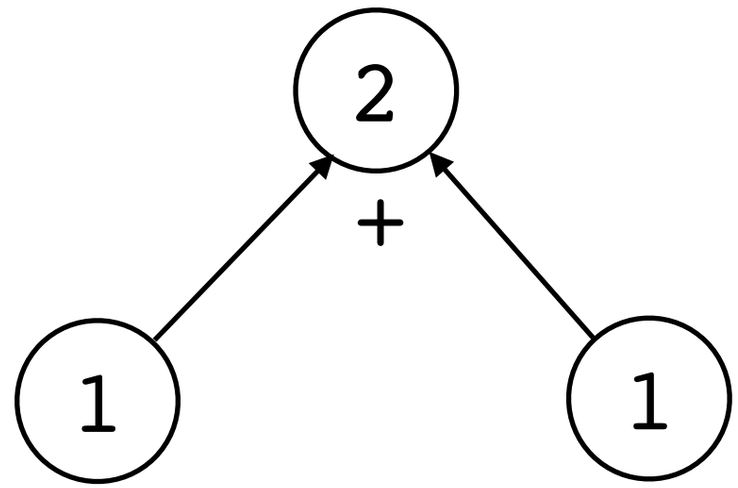
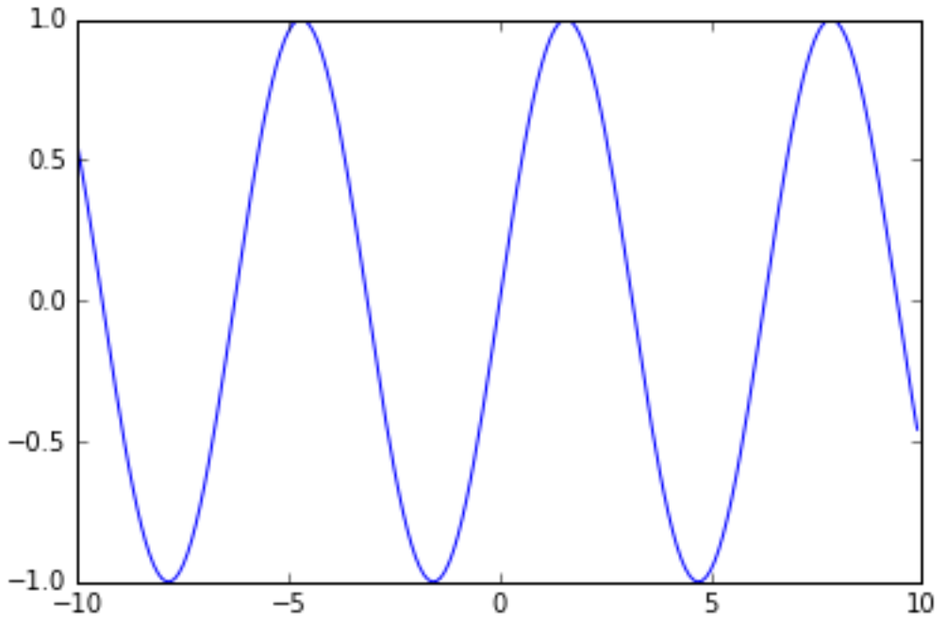


+ matrices and tensors with shapes just like in NumPy.

Tensor Operations

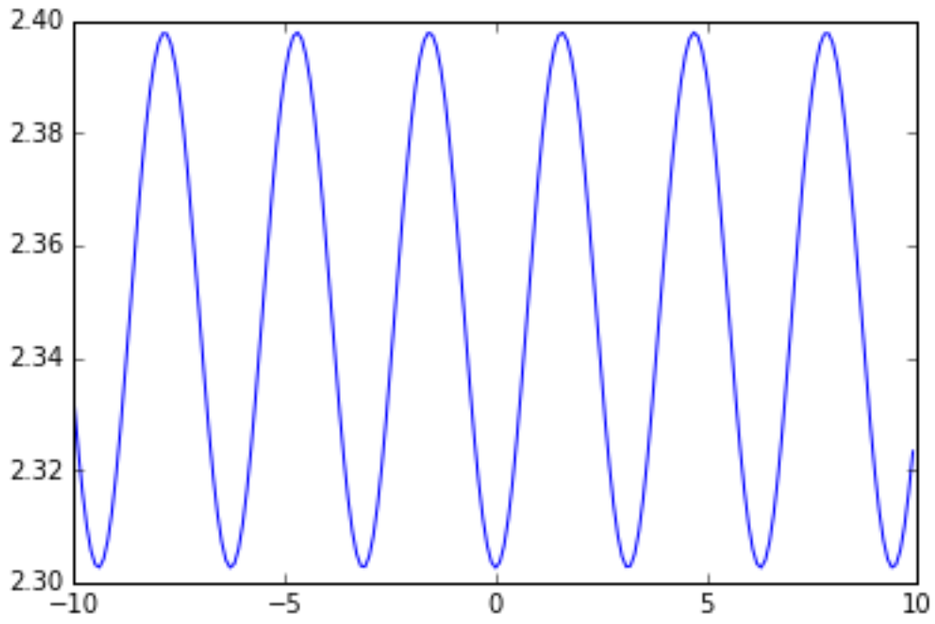
```
x = tf.range(-10, 10, .1)
y = tf.sin(x)

plt.plot(x, y)
```



Tensor Operations

```
x = tf.range(-10, 10, .1)
y = tf.sin(x)
z = y**2 + 10
w = tf.log(z)
```

```
plt.plot(x, y)
```



Tensor Operations

Element-wise multiplication:

```
m1 * m2
```

```
m1.shape == m2.shape
```

(NumPy broadcasting rules apply)

Matrix multiplication:

```
tf.matmul(m1, m2)
```

```
m1.shape[1] == m2.shape[0]
```

Tensor Operations

Convolution:

constant filter

does blurring

```
blurred = tf.nn.conv2d(imtensor, filterarray,
    strides=[1, 1, 1, 1], padding='VALID')
```

Having constructed variables

```
neural_data.shape —> (batch_size, num_neurons)

category_labels.shape —> (batch_size, num_categories)

weights.shape —> (num_neurons, num_categories)

bias.shape -> (num_categories,)
```

We then make hinge loss like so:

```
margins = tf.matmul(neural_data, weights) + bias

hinge_loss = tf.maximum(0., 1. - category_labels * margins)
```

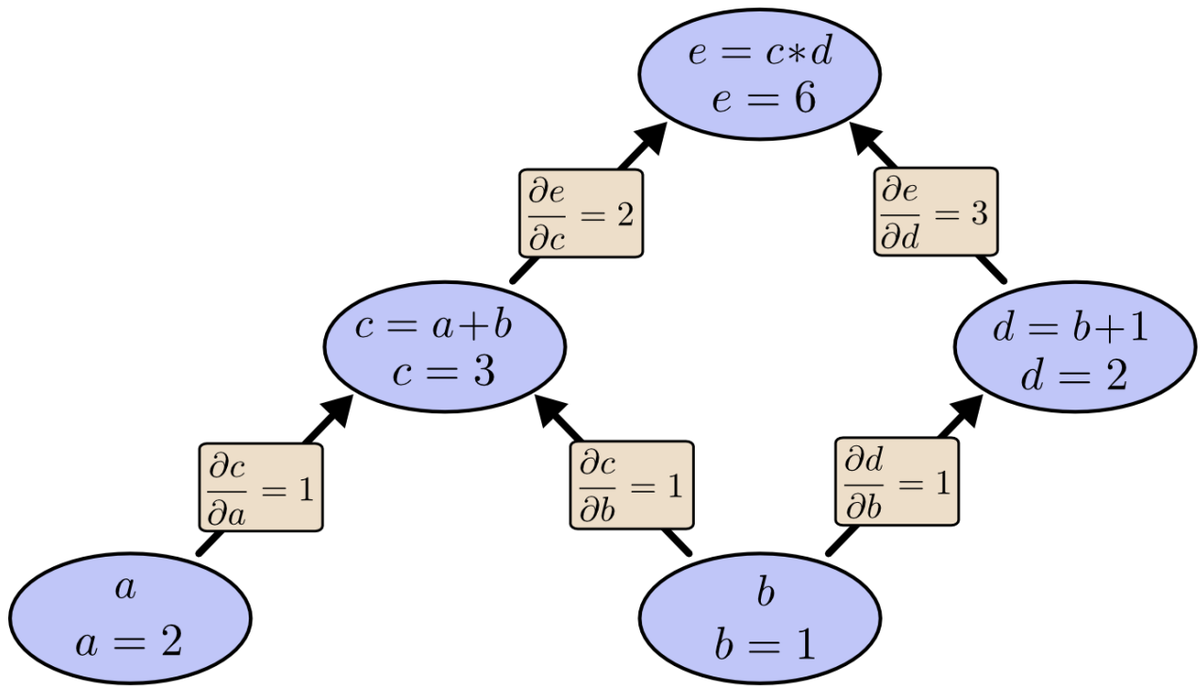
Graph Model of Computation

$$\frac{\partial}{\partial a}(a+b) = \frac{\partial a}{\partial a} + \frac{\partial b}{\partial a}$$

$$\frac{\partial}{\partial u} u \cdot v = u \cdot \frac{\partial v}{\partial u} + \frac{\partial u}{\partial u} \cdot v = v$$

a changes at rate 1

=> c changes at rate 1



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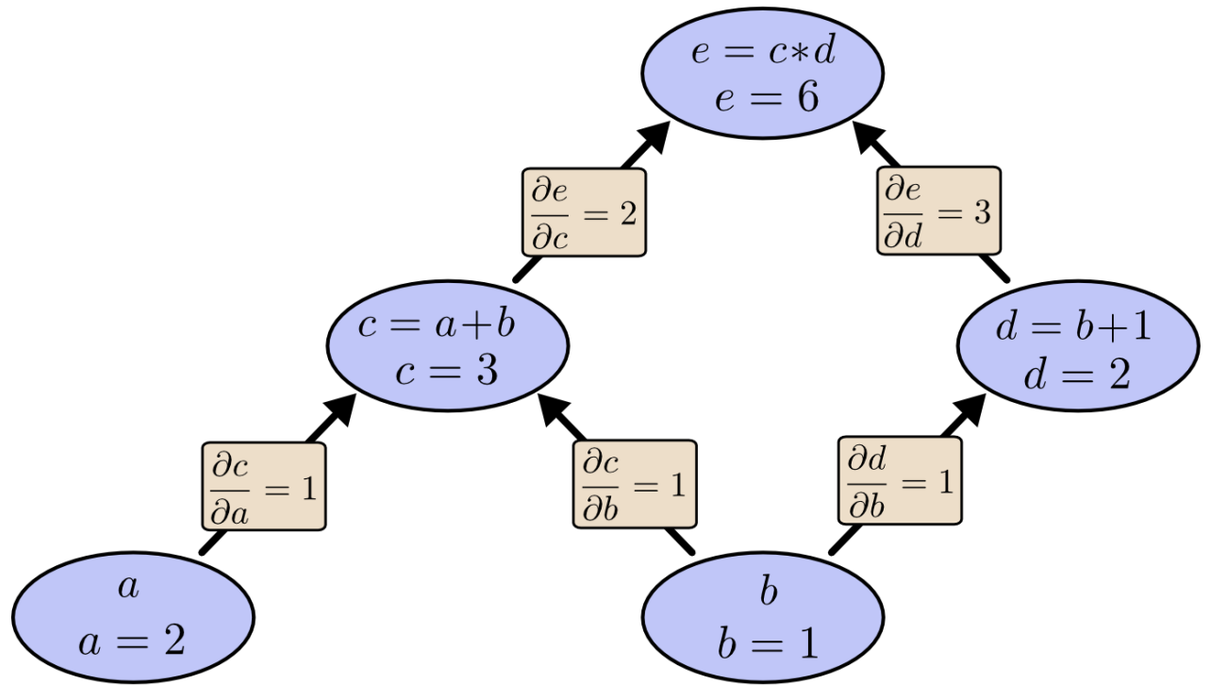
a changes at rate 1
=> c changes at rate 1

c changes at rate 1
=> e changes at rate 2

$$\frac{\partial e}{\partial a} = 1 \cdot 2 = 2$$



Graph Model of Computation

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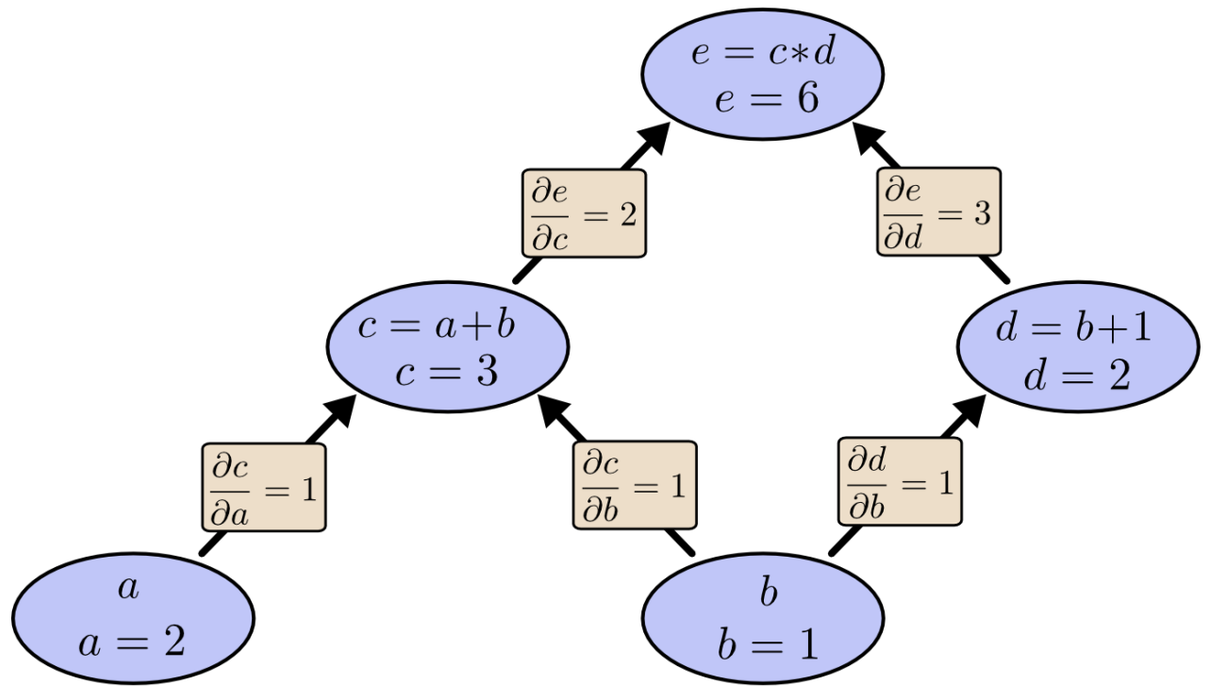
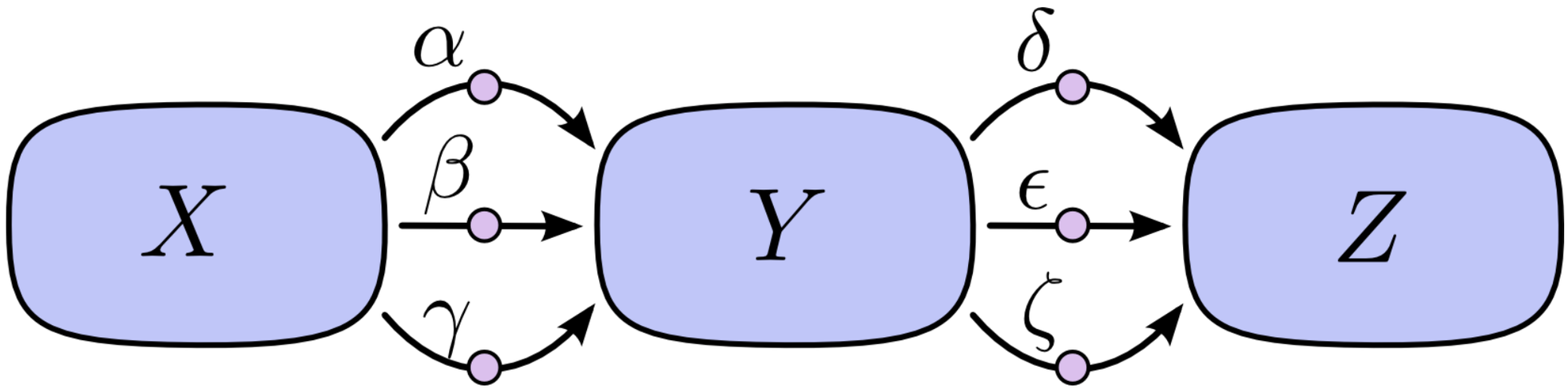


effect of n1 on n2: sum over all paths between n1 and n2, multiply across edges

$$\frac{\partial e}{\partial b} = 1 \cdot 2 + 1 \cdot 3 = 6$$

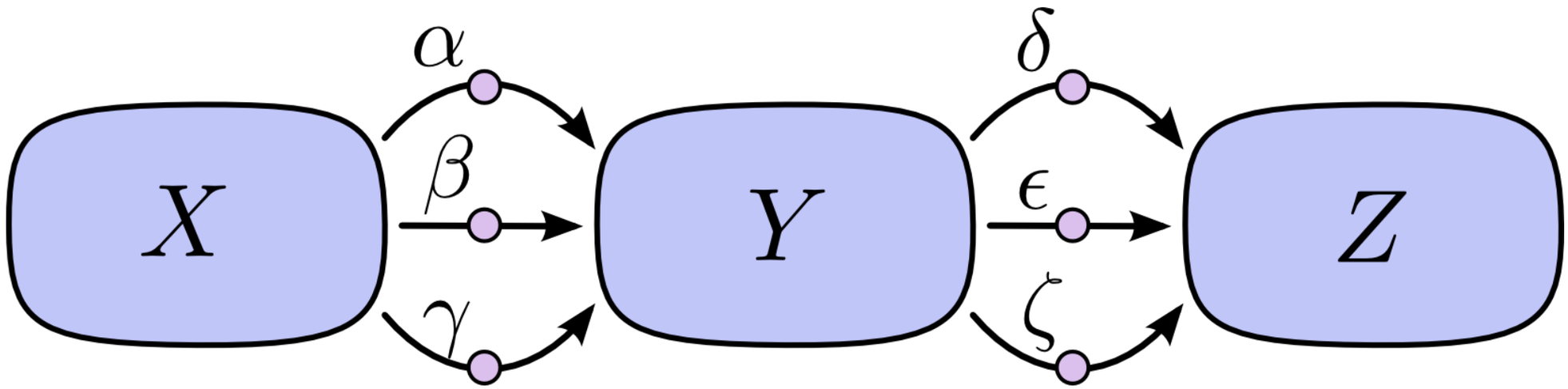
Graph Model of Computation



$$\frac{\partial Z}{\partial X} = \alpha\delta + \alpha\epsilon + \alpha\zeta + \beta\delta + \beta\epsilon + \beta\zeta + \gamma\delta + \gamma\epsilon + \gamma\zeta$$

How to prevent combinatorial explosion?

Graph Model of Computation



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How to prevent combinatorial explosion? **Factor and merge.**

$$\frac{\partial Z}{\partial X} = (\alpha + \beta + \gamma) \cdot (\delta + \epsilon + \zeta)$$

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Method 1: start at an input, move up; sum all paths as you go.

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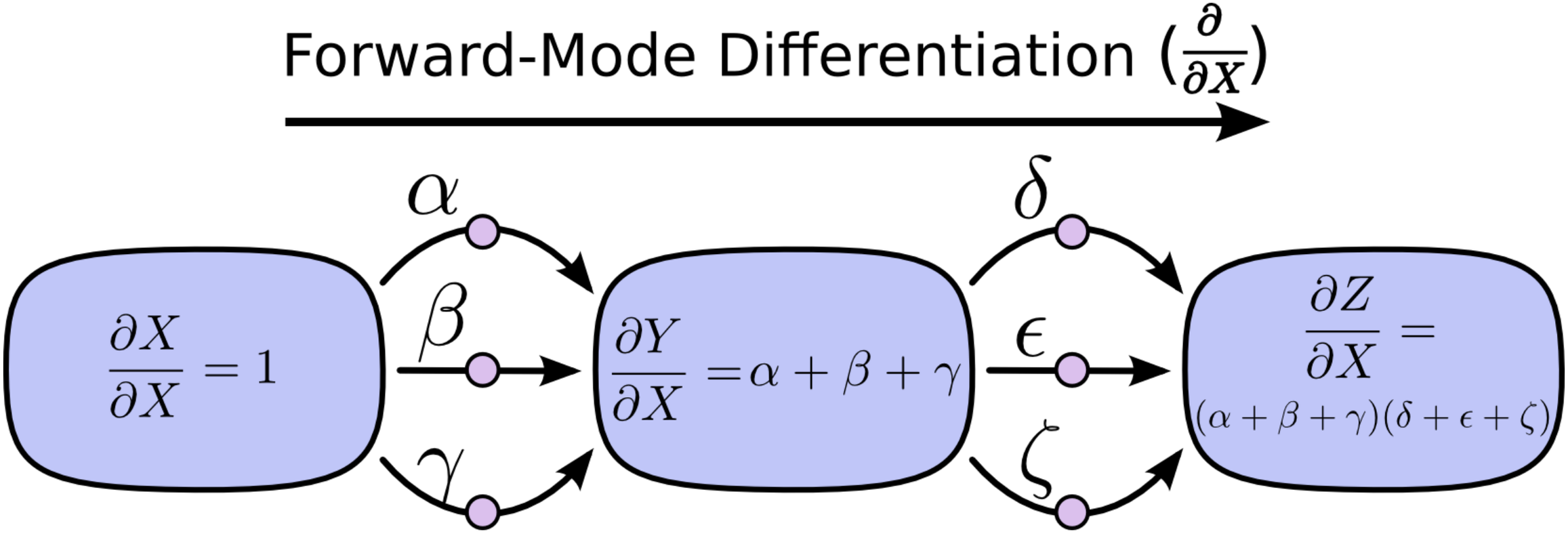

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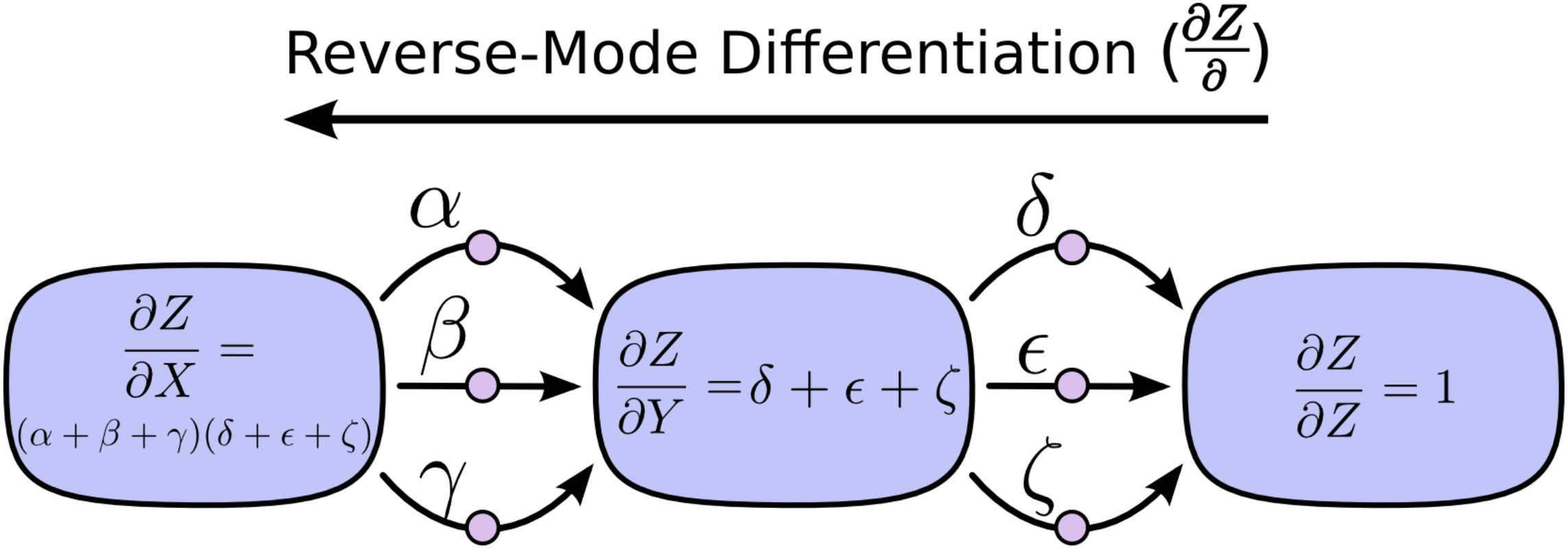
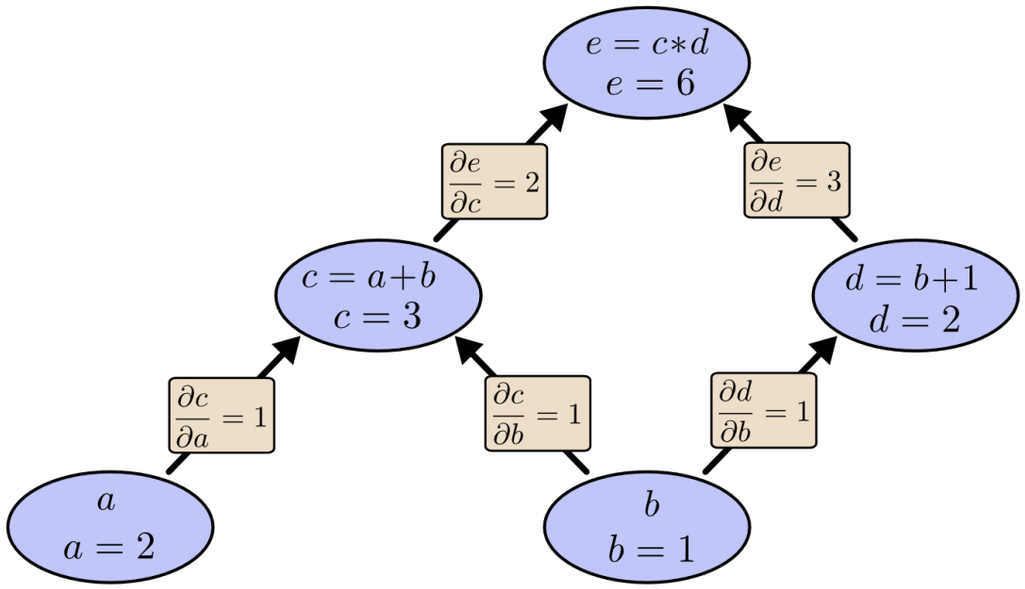


Graph Model of Computation

Goal: calculate $\dfrac{\partial e}{\partial b}$



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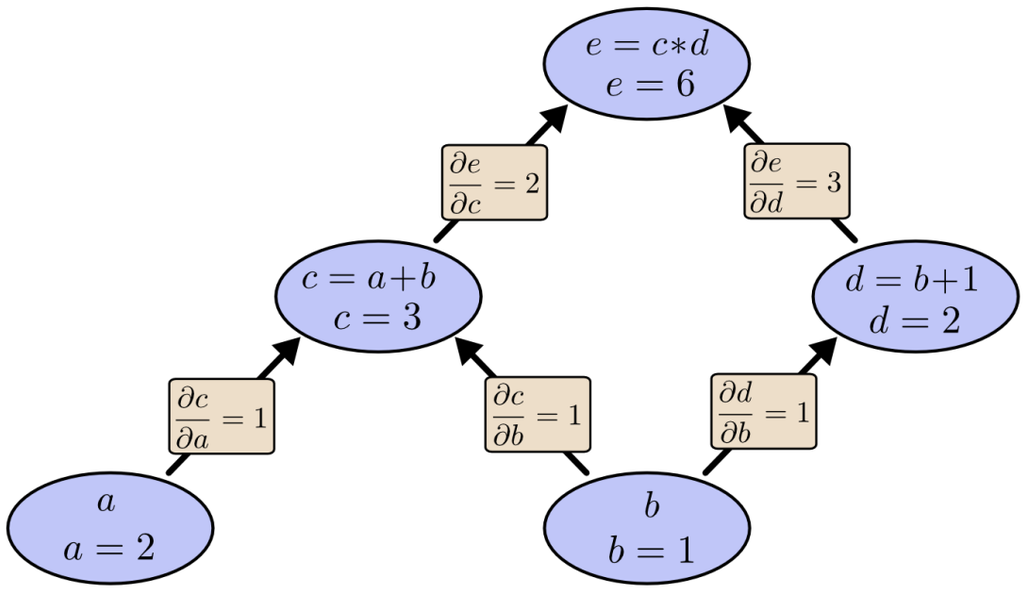
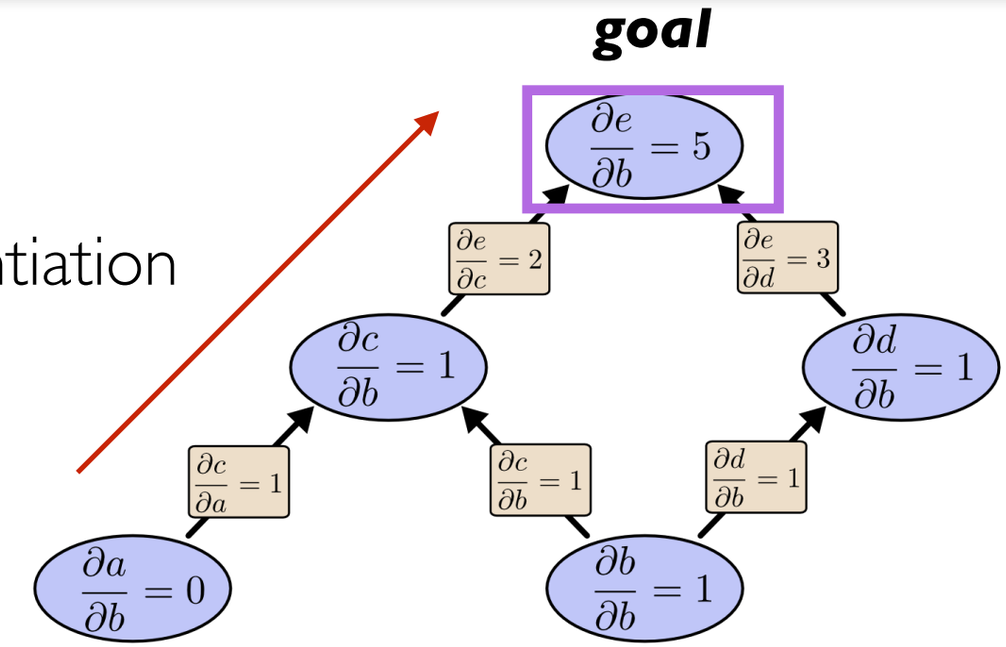
Forward differentiation





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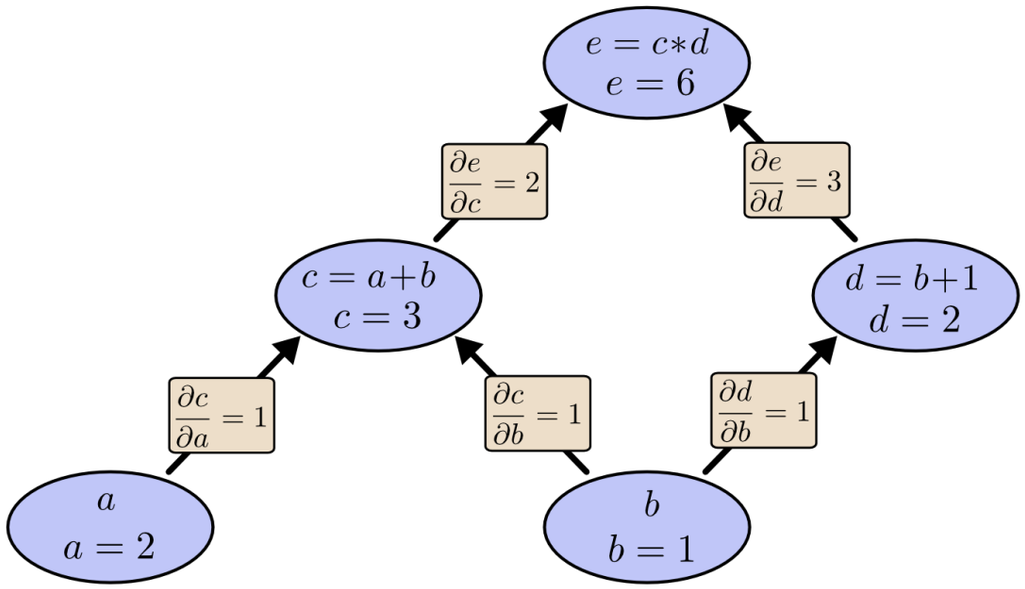

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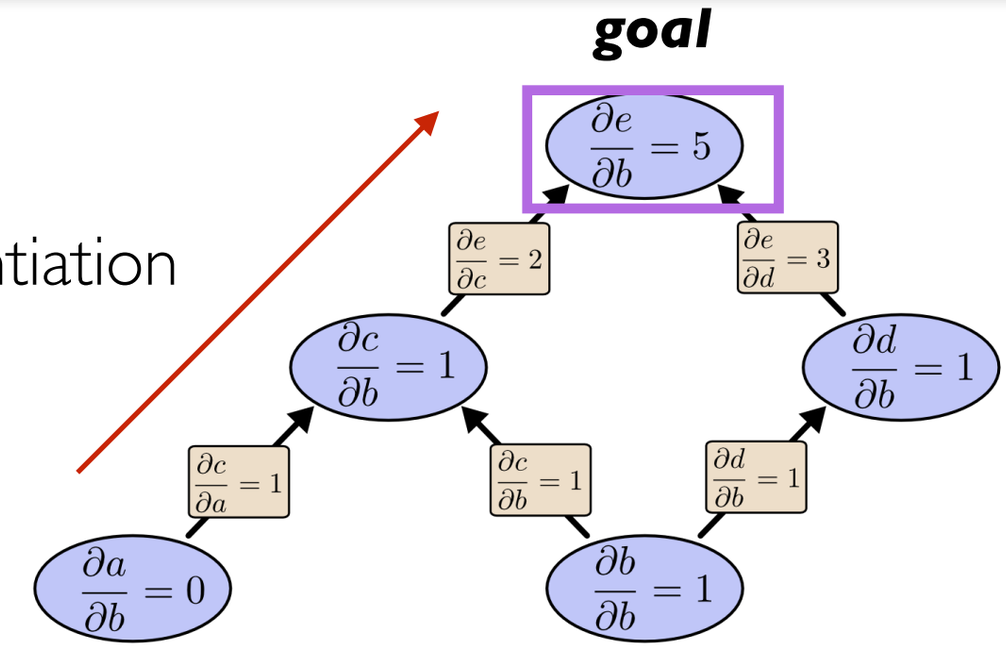
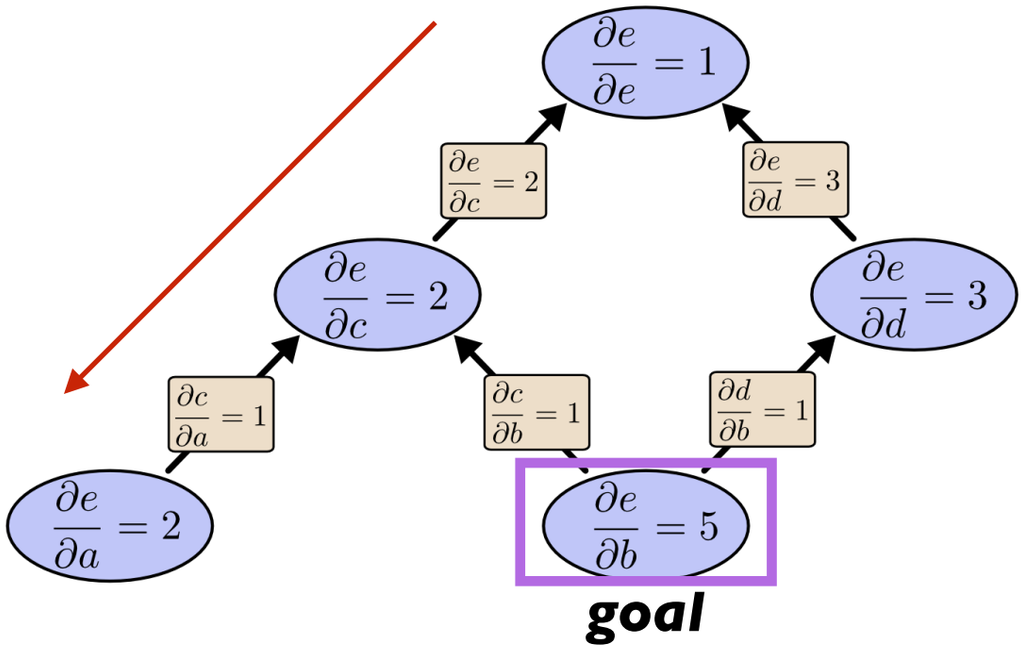
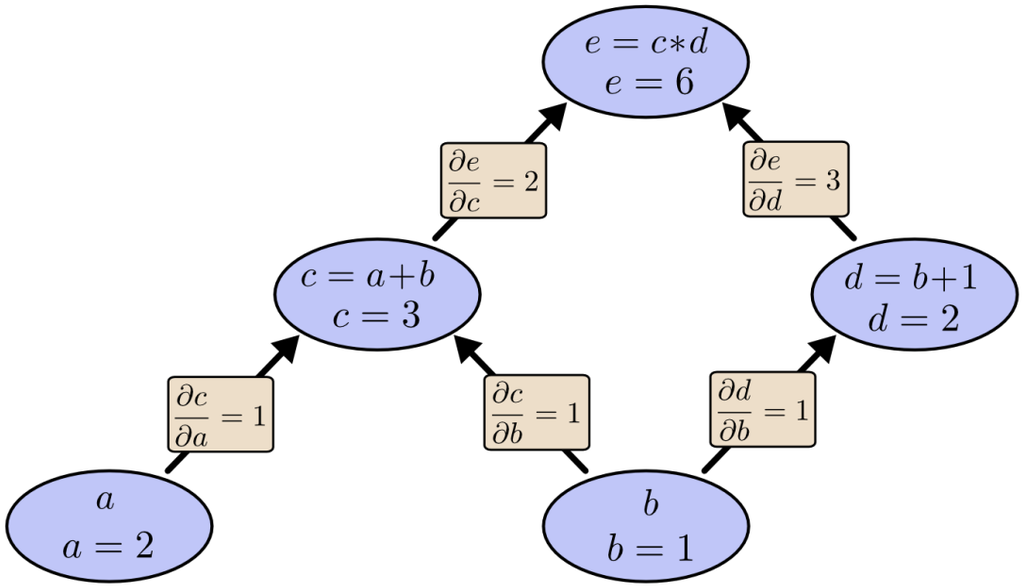




Reverse Differentiation

Graph Model of Computation

Goal: calculate $\frac{\partial e}{\partial b}$



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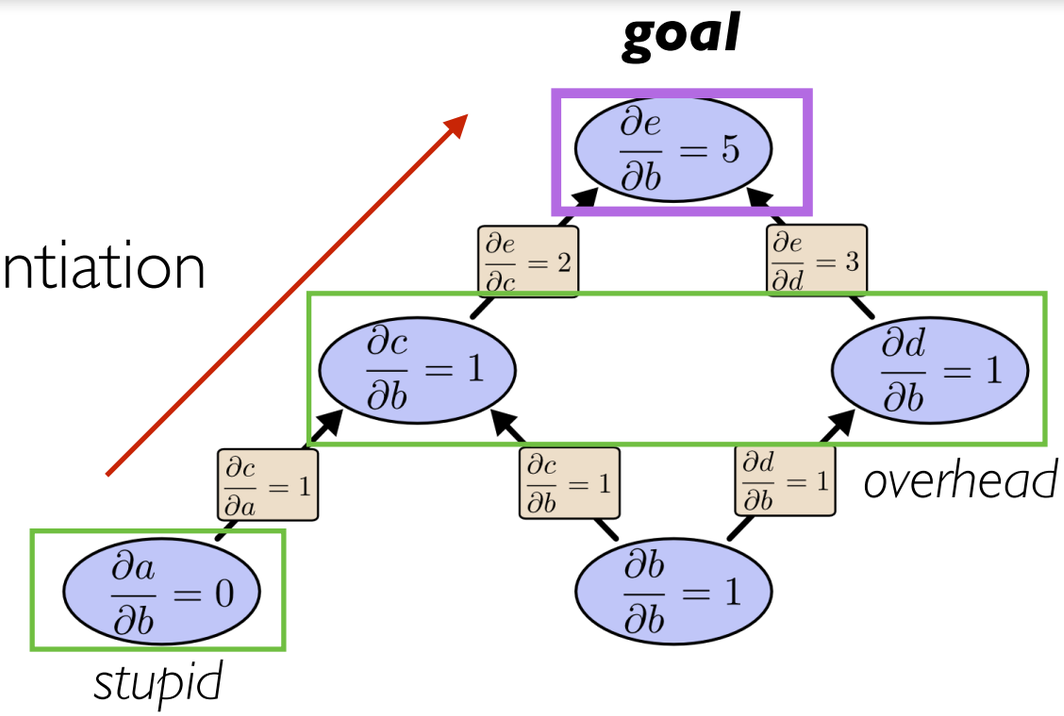
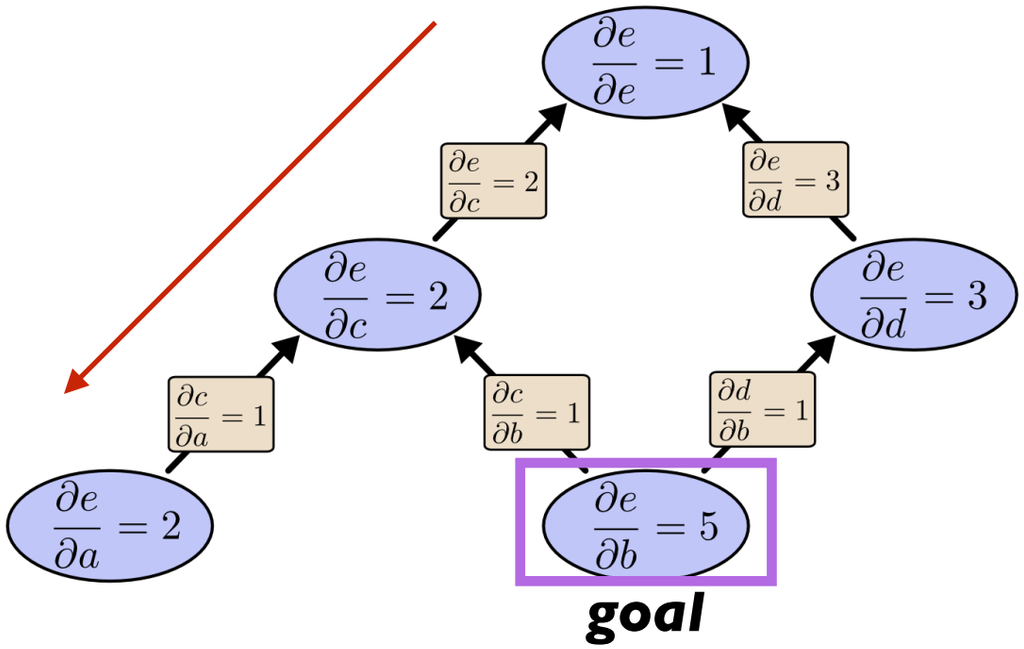


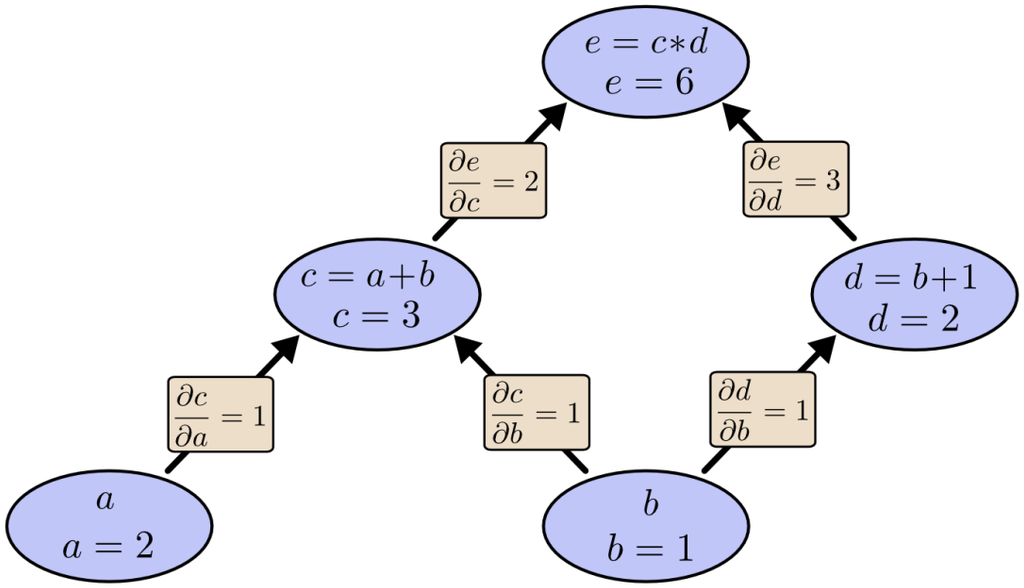


Reverse Differentiation

Graph Model of Computation

Goal: calculate $\frac{\partial e}{\partial b}$

Get: $\frac{\partial e}{\partial b}$ and $\frac{\partial e}{\partial a}$



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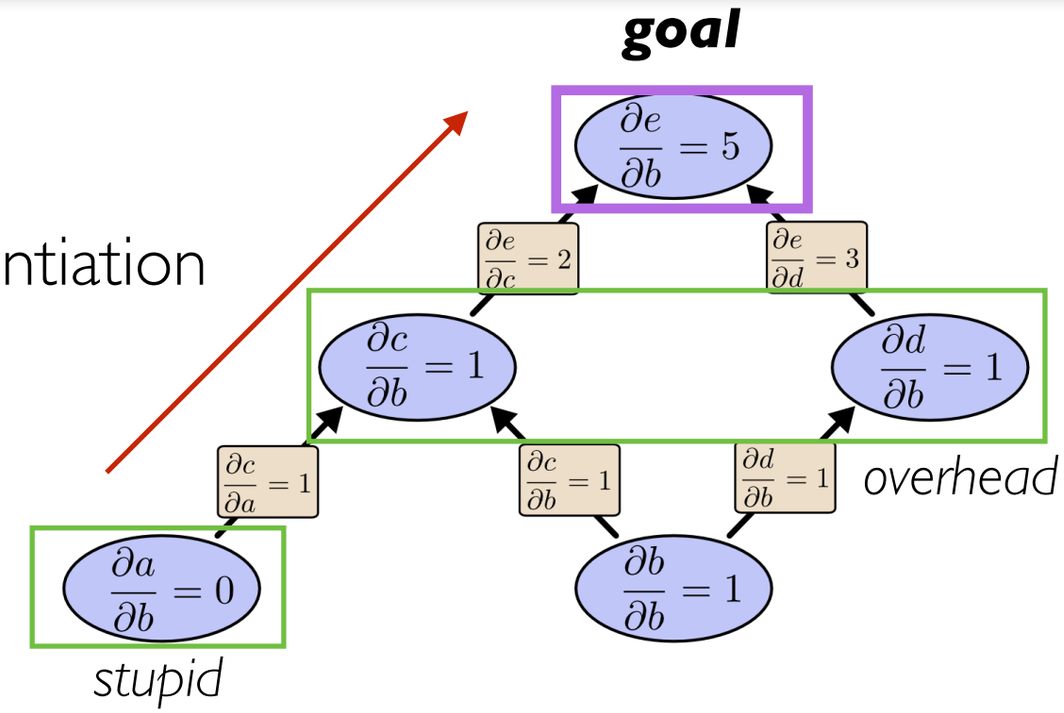

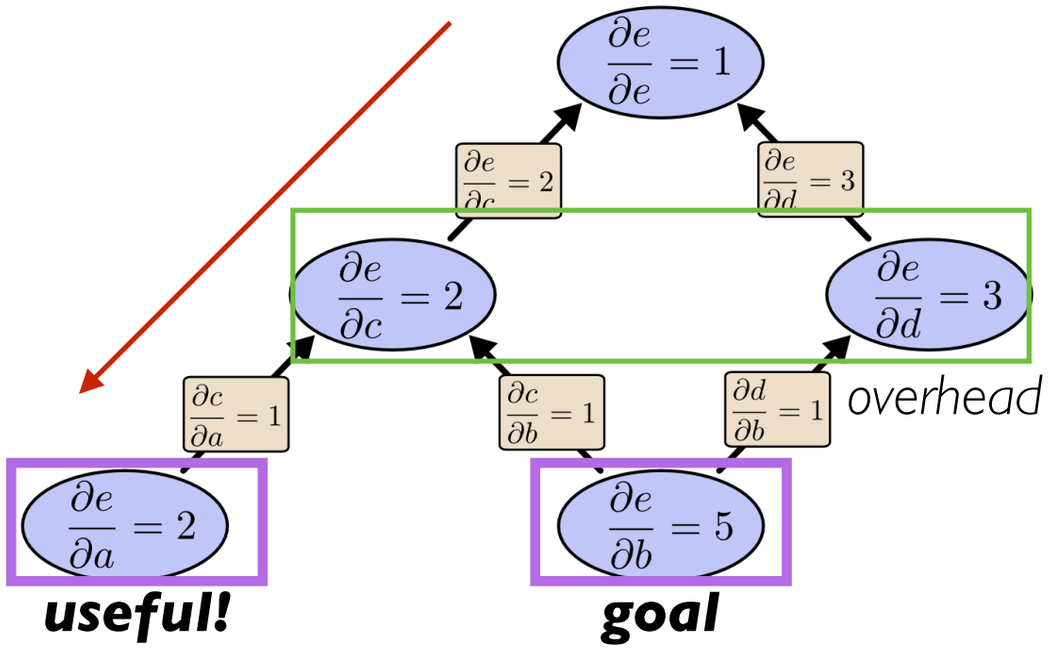

Reverse Differentiation

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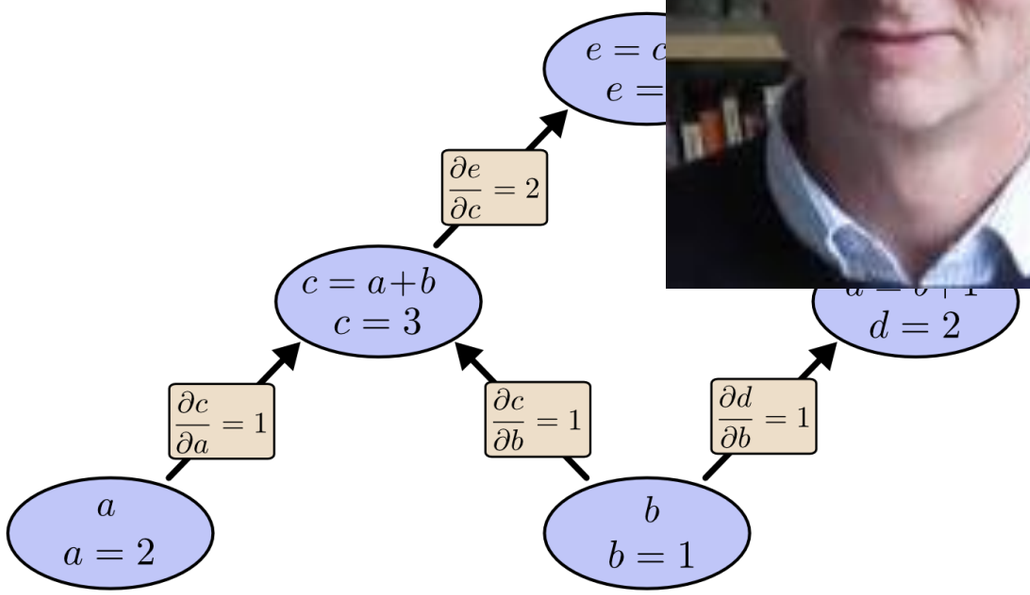
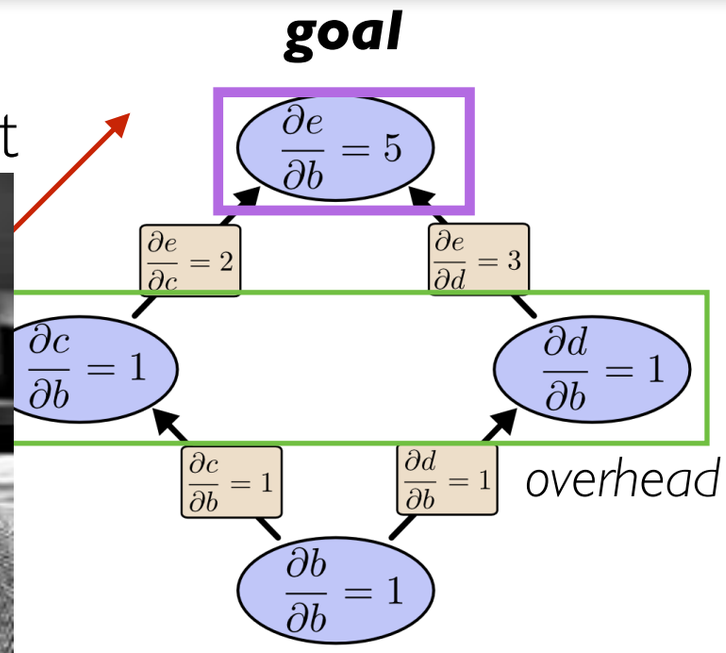
Geoff Hinton

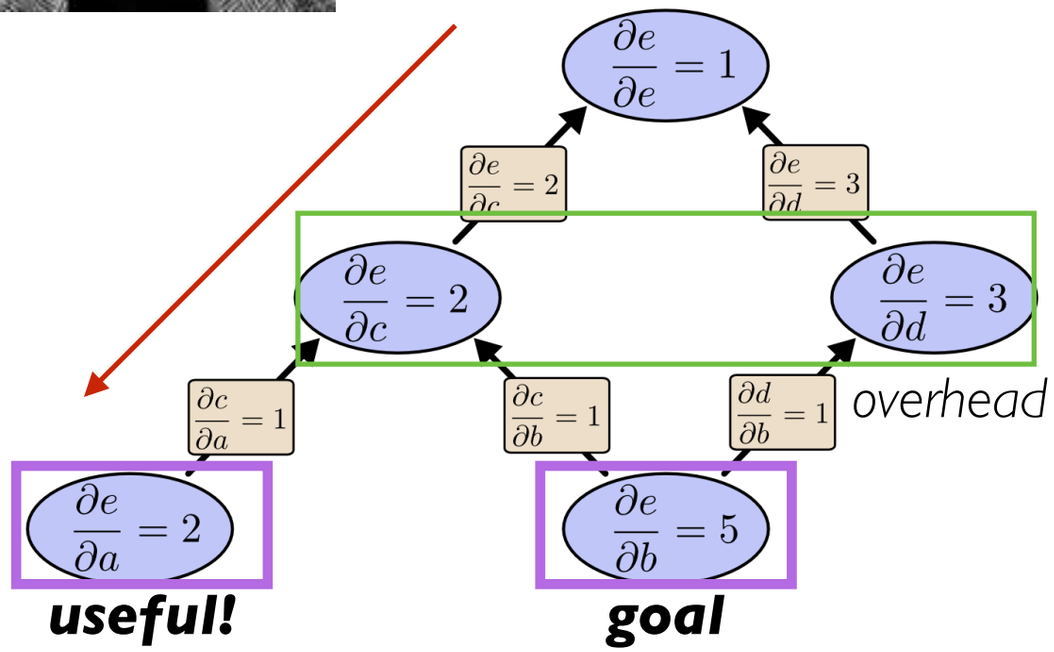
David Rumelhart

dif





The utility of *backpropagation*.

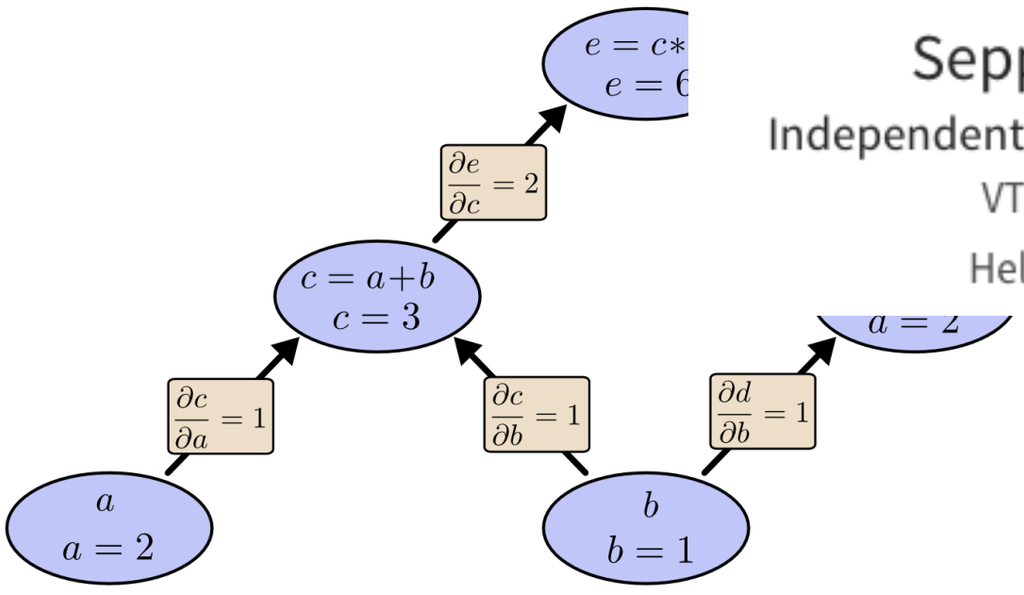


Reverse Differentiation

Graph Model of Computation

Goal: calculate $\frac{\partial e}{\partial b}$

Get: $\frac{\partial e}{\partial b}$ and $\frac{\partial e}{\partial a}$



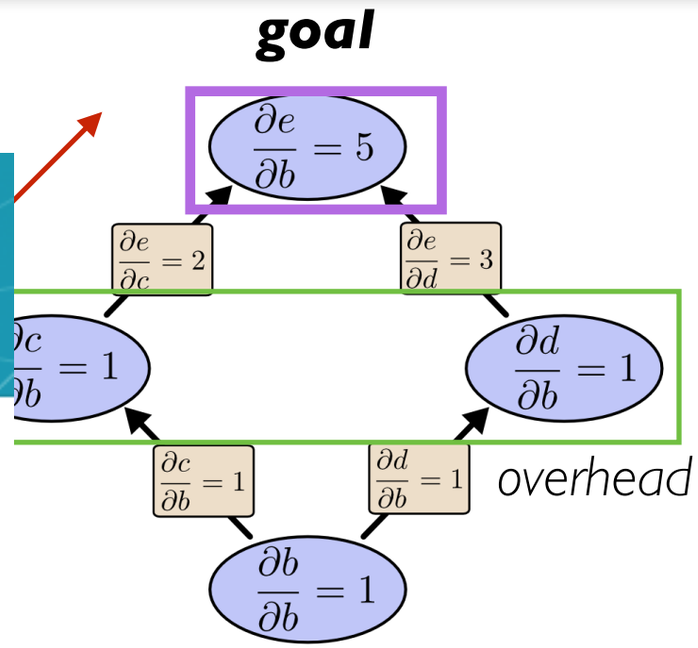
Reverse Mode AD in 1970 MA thesis

Seppo Linnainmaa • 3rd

Independent Computer Software Professional

VTT • University of Helsinki

Helsinki Area, Finland • 72



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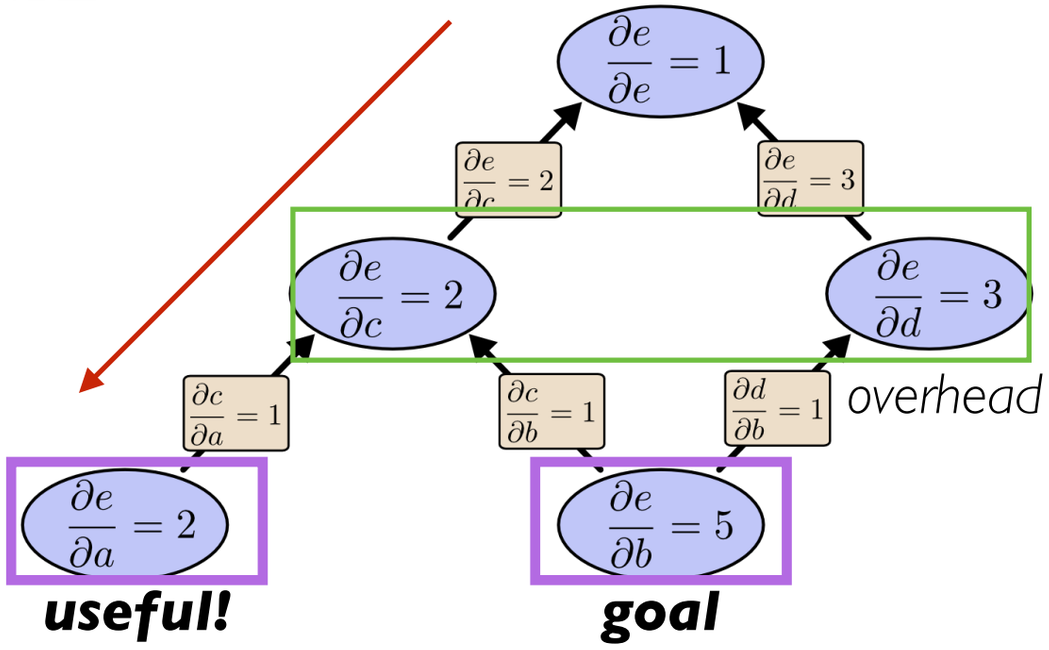


Reverse Differentiation

Graph Model of Computation

tf.Graph

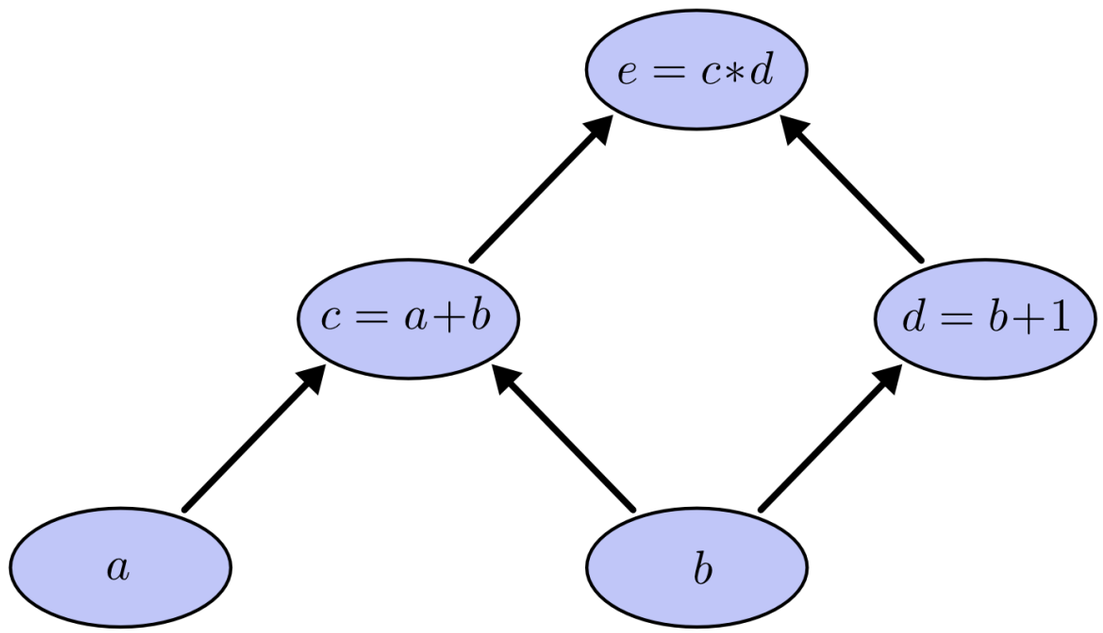
Class **Graph**

Defined in `tensorflow/python/framework/ops.py`.

See the guide: Building Graphs > Core graph data structures

A TensorFlow computation, represented as a dataflow graph.

A `Graph` contains a set of `tf.Operation` objects, which represent units of computation; and `tf.Tensor` objects, which represent the units of data that flow between operations.



Graph Model of Computation

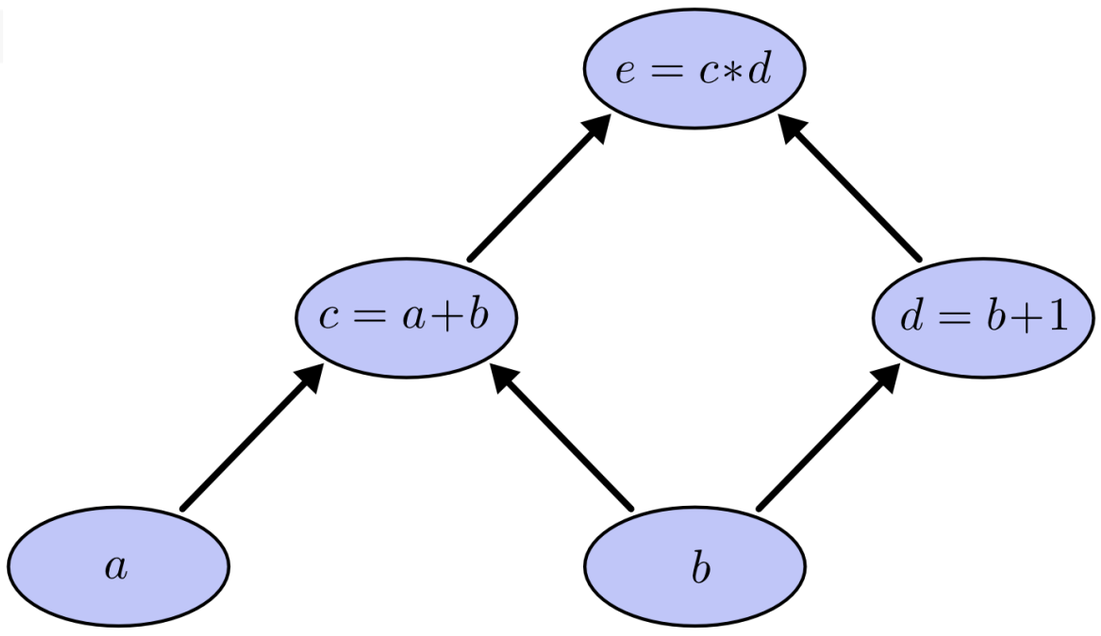
tf.gradients

```
gradients(
    ys,
    xs,
    grad_ys=None,
    name='gradients',
    colocate_gradients_with_ops=False,
    gate_gradients=False,
    aggregation_method=None
)
```

Defined in `tensorflow/python/ops/gradients_impl.py`.

See the guide: Training > Gradient Computation

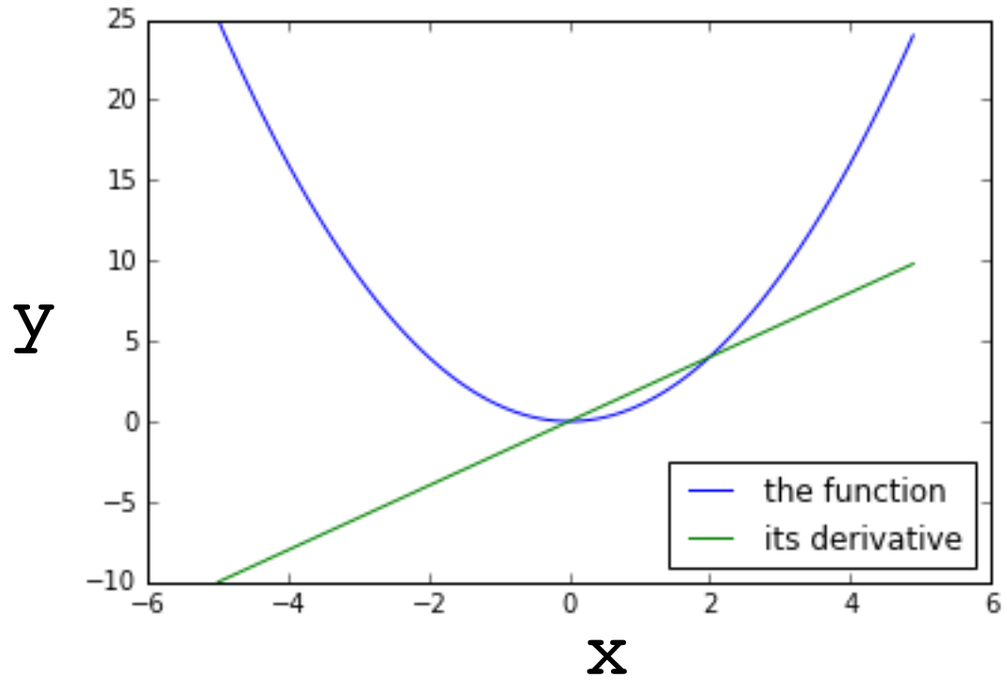
Constructs symbolic partial derivatives of sum of `ys` w.r.t. x in `xs`



Derivatives

```
y = x**2

d = tf.gradients(y, x)
```



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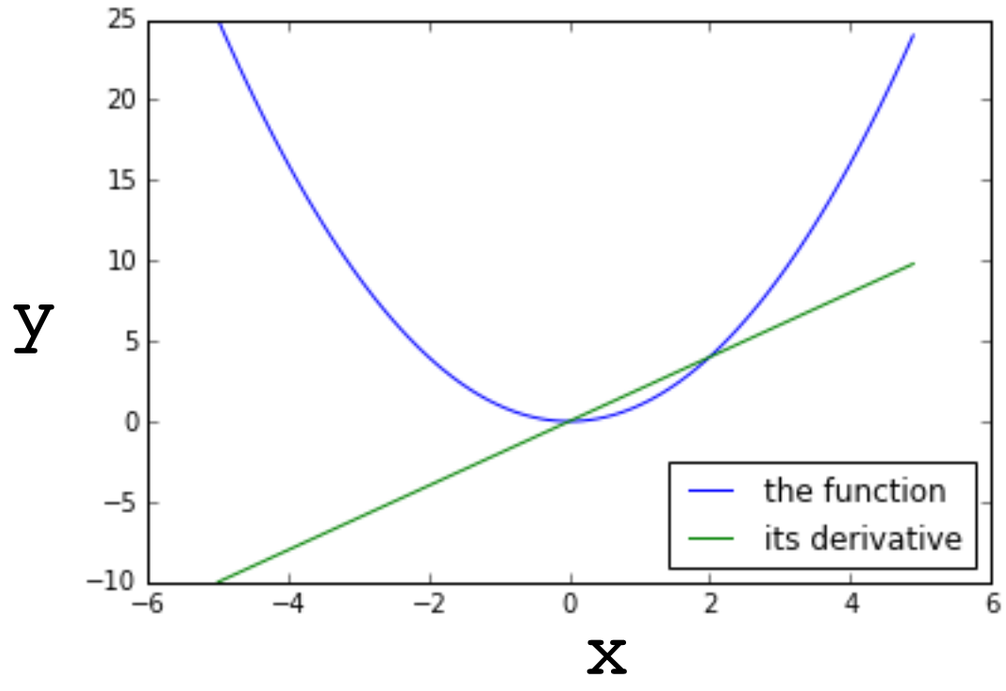
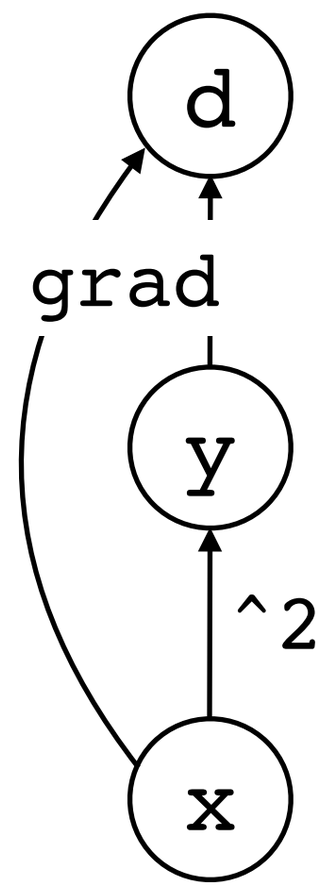
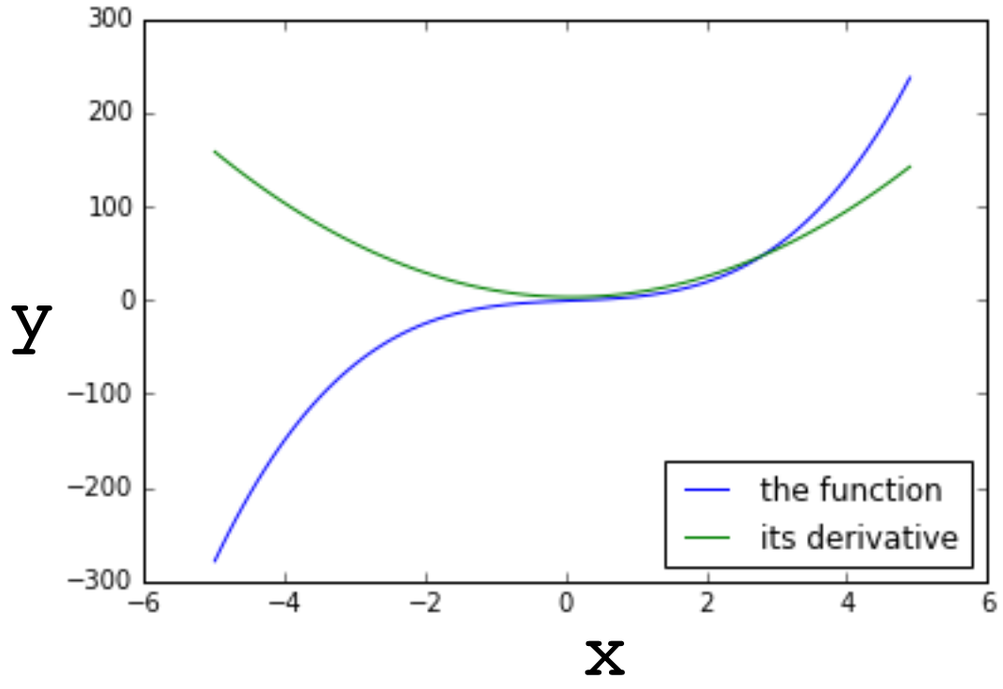


computation graph:



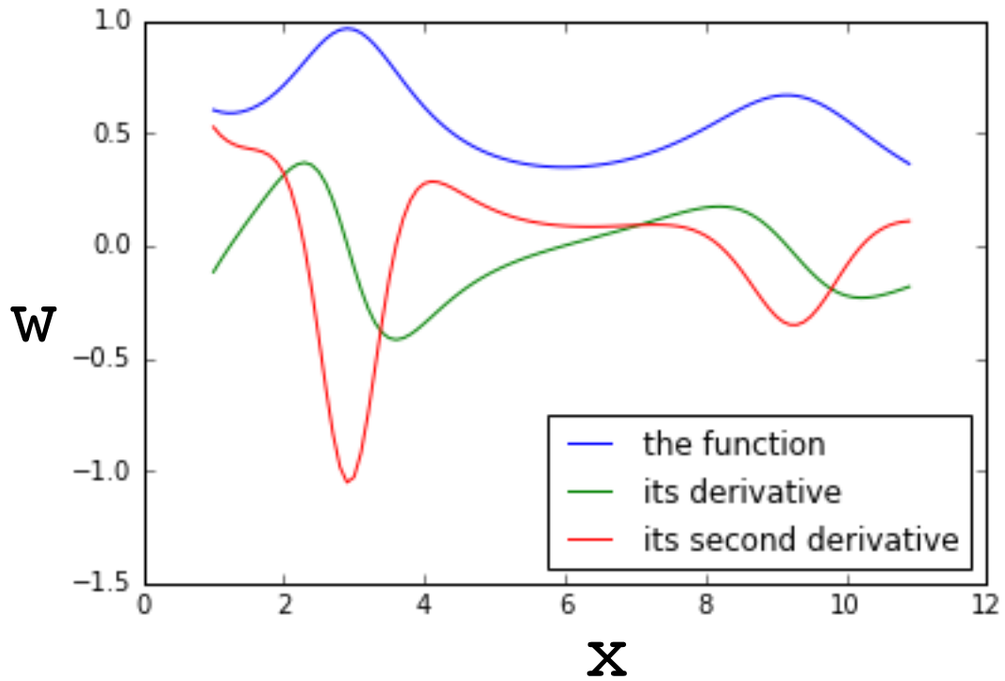
Derivatives

```
y = 2*x**3 - 5*x**2 + 3*x - 1
```



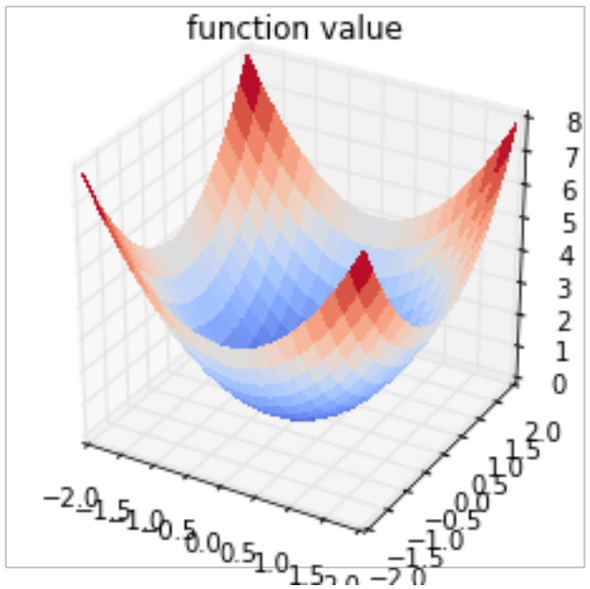
Derivatives

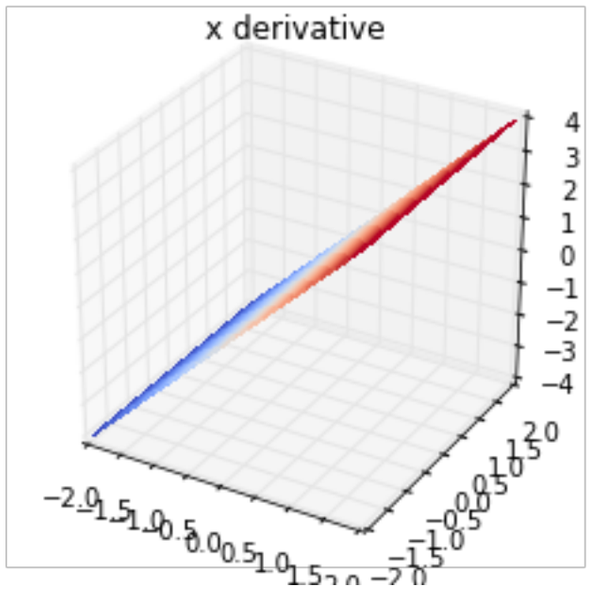
```
y = x**.5
z = tf.log(tf.exp(tf.sin(y) + tf.cos(2*y)) + 1)
w = z / (y + tf.cos(x_arr))
```

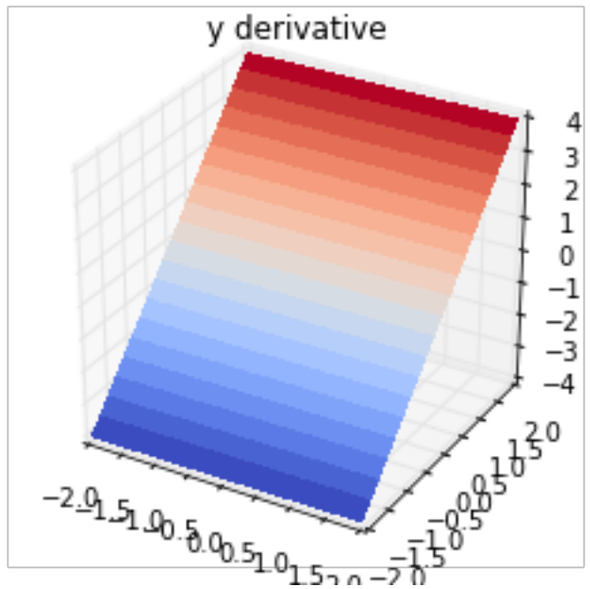


Derivatives

```
z = x**2 + y**2
```

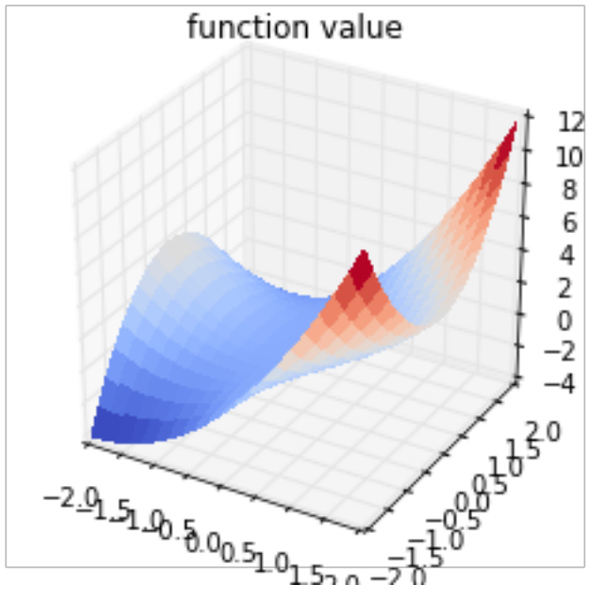


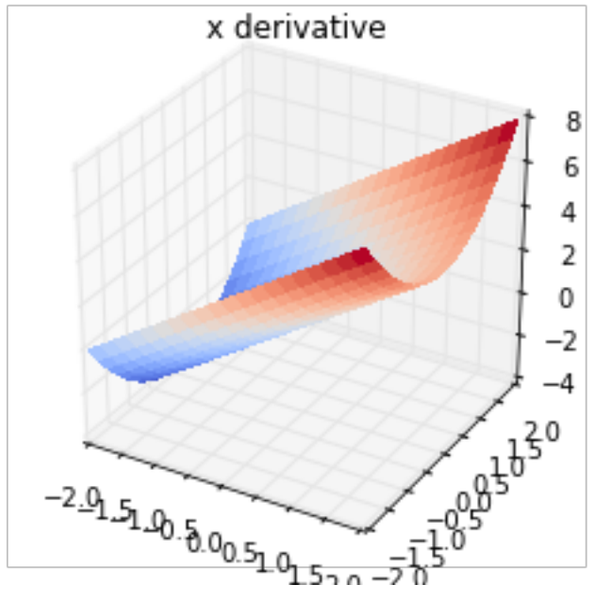


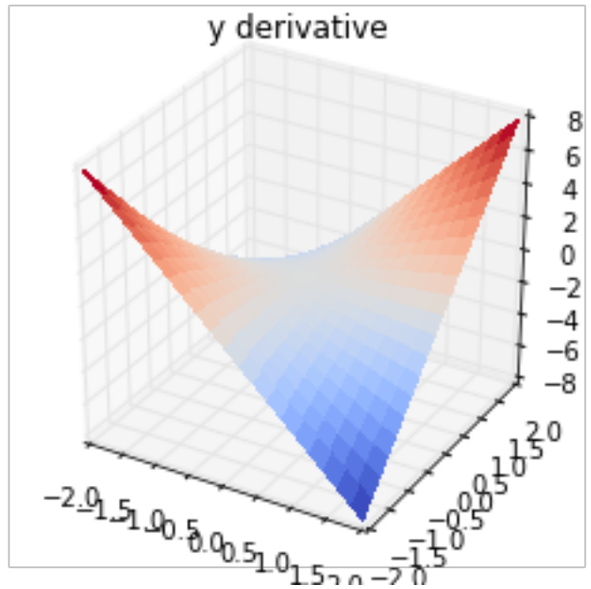


Derivatives

```
z = x**2 + y**2 * x
```







Derivatives

```
z = tf.cosh((3 + tf.cos(x+2*y)**3)**.5 * tf.sin(y-x))
```