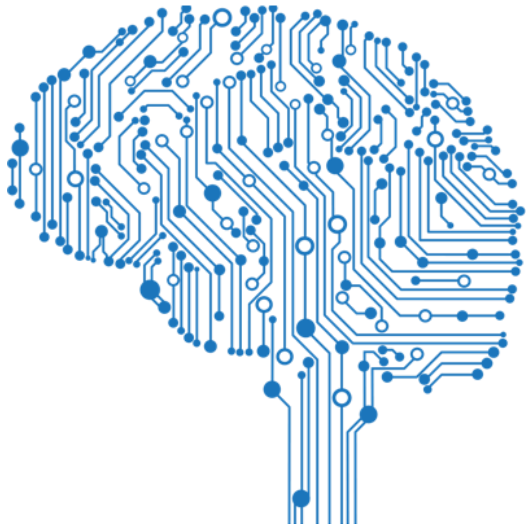
# Introduction to Deep Learning

## Neural networks, computation, optimization



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#DeepLearning

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# Computational Graphs

Performing simple calculations…
just harder

# Installing `tensorflow`

- Use Anaconda
  - It's easier, and arguably much faster
  - Run as administrator
- If possible, try installing the GPU version
  - The installer will tell you whether it's compatible with your graphics card

```
conda install tensorflow-gpu
```

- Otherwise, fall back to the CPU (standard) version

```
conda install tensorflow
```

- There's no difference in the API
  - GPUs perform computations much faster
    - Sometimes $\sim 10^2 - 10^4$ times faster

## Computational Graphs in `tensorflow`

- "Flow of tensors (multidimensional matrices)"
- Computational graph (DAG)
  - A useful representation of computation sequences
  - Contains data and operations
  - Data "flows" through and gets transformed
- A simple example
  - $(2a + 3b)^2$

$$\begin{tikzcd}
a \arrow[r] & 2(\cdot) \arrow[dr] & & & \\
 & & + \arrow[r] & (\cdot)^2 \arrow[r] & \text{result} \\
b \arrow[r] & 3(\cdot) \arrow[ur] & & &
\end{tikzcd}$$

## Computational Graphs in `tensorflow` (2)

- Import the library

```
import tensorflow as tf
```

- Create two constants for $a$ and $b$
  - We will provide their values later to get the result

```
a = tf.constant(2)
b = tf.constant(3)
```

- Create the function
  - Using tensorflow operations

```
def compute(a, b):
    return tf.pow(
                tf.add(
                    tf.multiply(2, a),
                    tf.multiply(3, b)
                ),
            2)
```

## Computational Graphs in `tensorflow` (3)

- However, it can be much, much simpler!

```
def compute(a, b):
    return (2 * a + 3 * b) ** 2
```

- This works in regular Python, numpy, and `tensorflow`
  - Depends on the types of `a` and `b`

```
compute(2, 3)# 169
compute(2.0, 3.0) # 169.0

compute(np.array([2, 3, 4]), np.array([3, 4, 5]))
# array([169, 324, 529], dtype=int32)

compute(tf.constant(2), tf.constant(3))
# <tf.Tensor: id=53, shape=(), dtype=int32, numpy=169>
compute(tf.constant([2, 3, 4]), tf.constant([3, 4, 5]))
# <tf.Tensor: id=62, shape=(3,), dtype=int32,
#    numpy=array([169, 324, 529])>
```

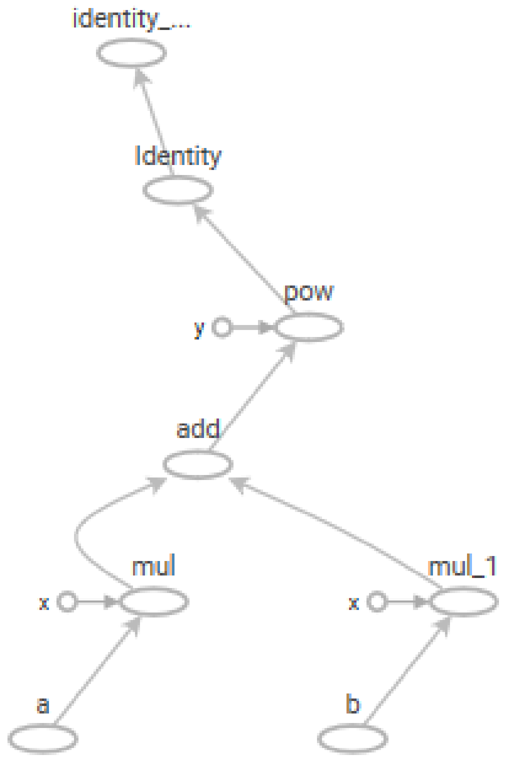
## Visualizing the Graph

- Decorate the function with `@tf.function`
- Trace the execution

```
a, b = tf.constant([2, 3, 4]), tf.constant([3, 4, 5])

tf.summary.trace_on(graph = True, profiler = True)
result = compute(a, b)
print(result.numpy())
with writer.as_default():
    tf.summary.trace_export(
        name = "compute_trace",
        step = 0,
        profiler_outdir = "logs")
```

- Run tensorboard to visualize the graph and function trace

```
tensorboard --logdir logs
```



## Linear Models

Logistic regression using `tensorflow`

# Logistic Regression

- Data: Iris dataset

```
from sklearn.datasets import load_iris
iris = load_iris()
attributes, labels = iris.data, iris.target
```

- Prepare the output – one-hot encoding

```
labels_onehot = tf.one_hot(labels, depth = 3).numpy()
```

- Define the model
  - I'm doing the 3 LRs at once (with the same inputs)
    - Equivalent results to `scikit-learn`'s one-vs-rest strategy
  - We can inspect it after that

```
model = tf.keras.models.Sequential([
    tf.keras.layers.Input(shape = (4,)),  # Not required
    tf.keras.layers.Dense(3, activation = "sigmoid")
])
```

## Logistic Regression (2)

- Compile the model
  - Specify the loss function

```
model.compile(optimizer = "adam", loss = "categorical_crossentropy")
```

- Fit the model
  - Of course, you can use train / test splits, etc.

```
model.fit(attributes, labels_onehot, epochs = 50)
```

- View the results and see some metrics

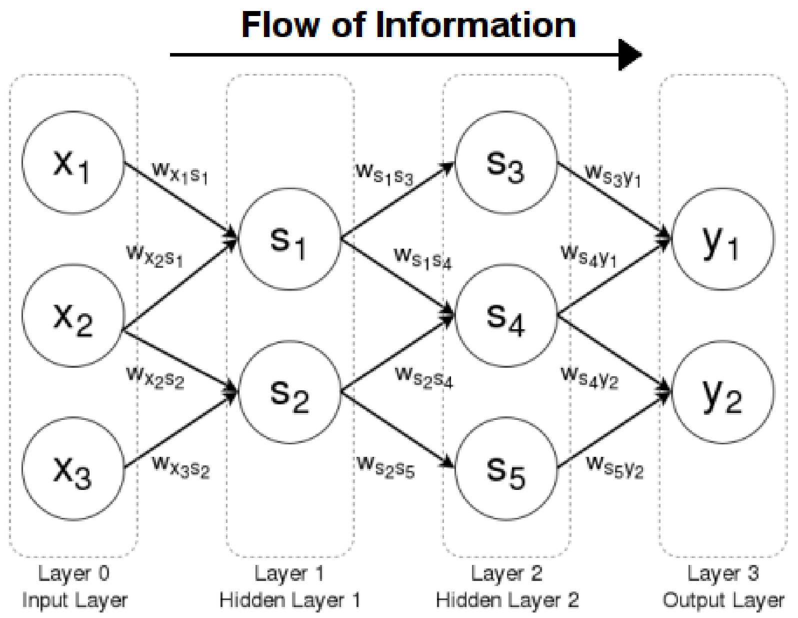
```
predictions = model.predict(attributes)

acc = tf.metrics.categorical_accuracy(
    labels_onehot,
    model.predict(attributes))
print(tf.math.reduce_mean(acc).numpy())
# or add, metrics = ["categorical_accuracy"] to model.compile()
```

## Neural Networks

Going deeper

# Deep Feed-Forward Neural Network

- Many perceptrons arranged in layers
  - **Input** layer
  - **Hidden** layers
  - **Output** layer



- Computing output: forward propagation
- Training: backpropagation
- We can do this using the low-level API
  - If you want to implement this, don't forget
    - Bias term for each layer
    - Activation function
    - Random weight initialization (small numbers with $\mu = 0$)

## Example: MNIST

- Load and normalize the data

```
mnist = tf.keras.datasets.mnist

(x_train, y_train), (x_test, y_test) = mnist.load_data()
x_train, x_test = x_train / 255.0, x_test / 255.0
```

- Create and evaluate the model

```
model = Sequential([
    Flatten(),
    Dense(512, activation = "relu"),
    Dropout(0.2),
    Dense(10, activation = "softmax")])
model.compile(
    optimizer = "adam",
    loss = "sparse_categorical_crossentropy",
    metrics = ["accuracy"])
```

```
model.fit(x_train, y_train, epochs = 5)
model.evaluate(x_test, y_test)
# or add validation_data = (x_test, y_test) to model.fit()
```

## Summary

- Computational graphs
- Simple models with `tensorflow`
  - Low-level API
- Building neural networks
- Regularization

Questions?