

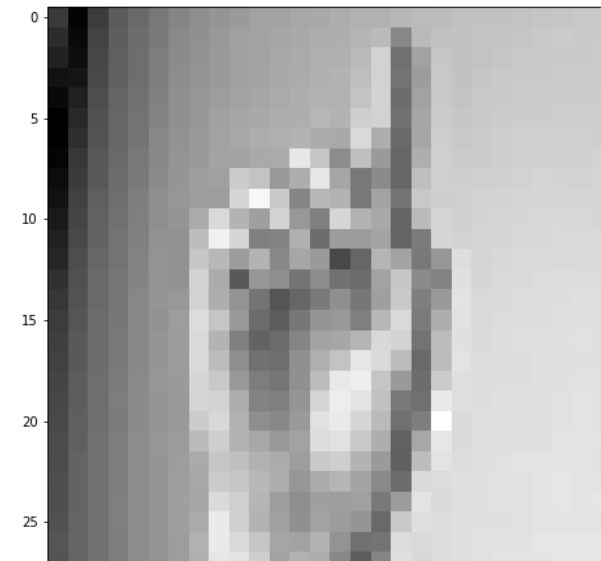
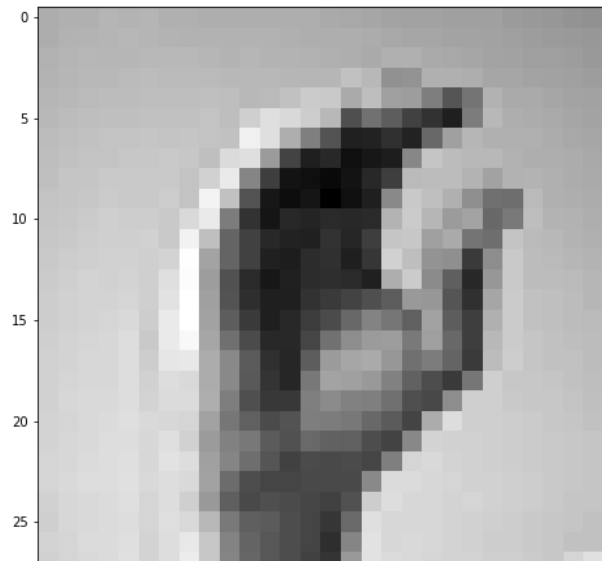
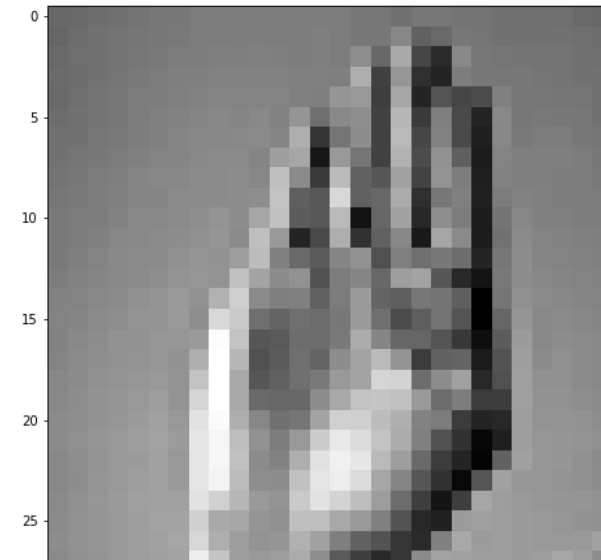
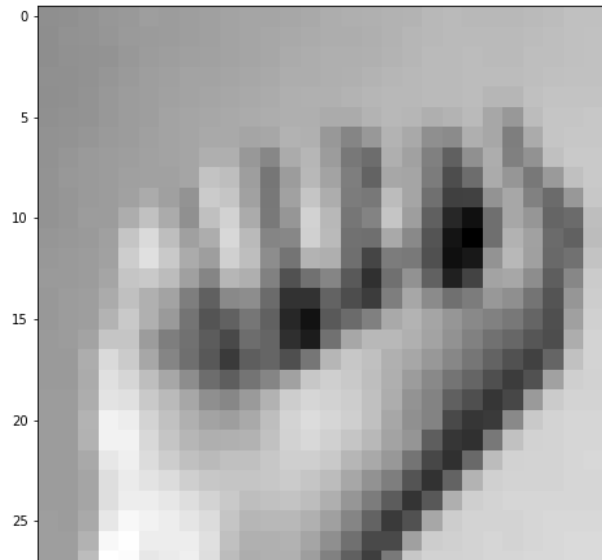
# Defining neural networks with Keras

INTRODUCTION TO TENSORFLOW IN PYTHON

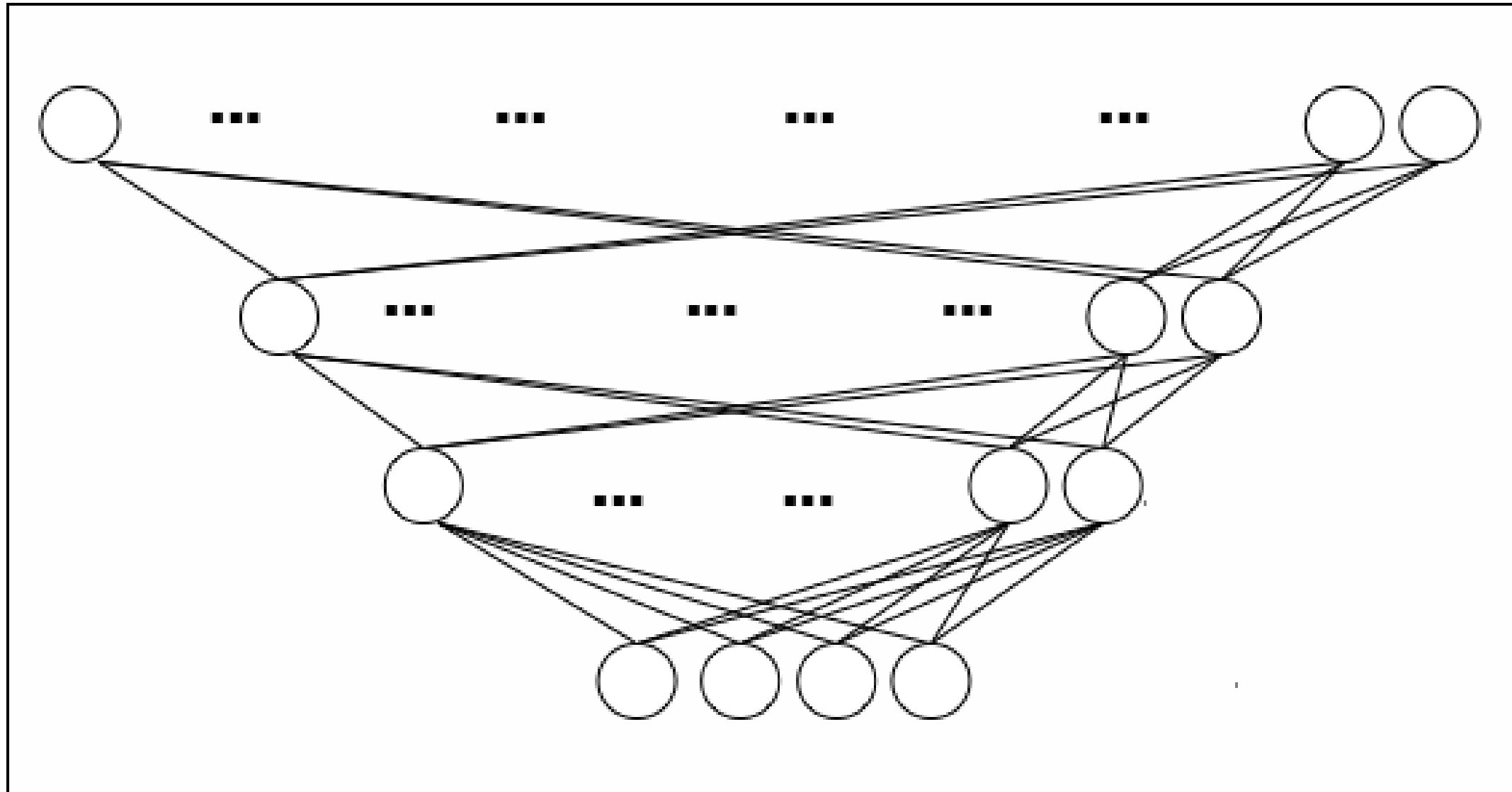


Isaiah Hull  
Economist

# Classifying sign language letters



# The sequential API



# The sequential API

- Input layer
- Hidden layers
- Output layer
- Ordered in sequence

# Building a sequential model

```
# Import tensorflow  
from tensorflow import keras
```

```
# Define a sequential model  
model = keras.Sequential()
```

```
# Define first hidden layer  
model.add(keras.layers.Dense(16, activation='relu', input_shape=(28*28,)))
```

# Building a sequential model

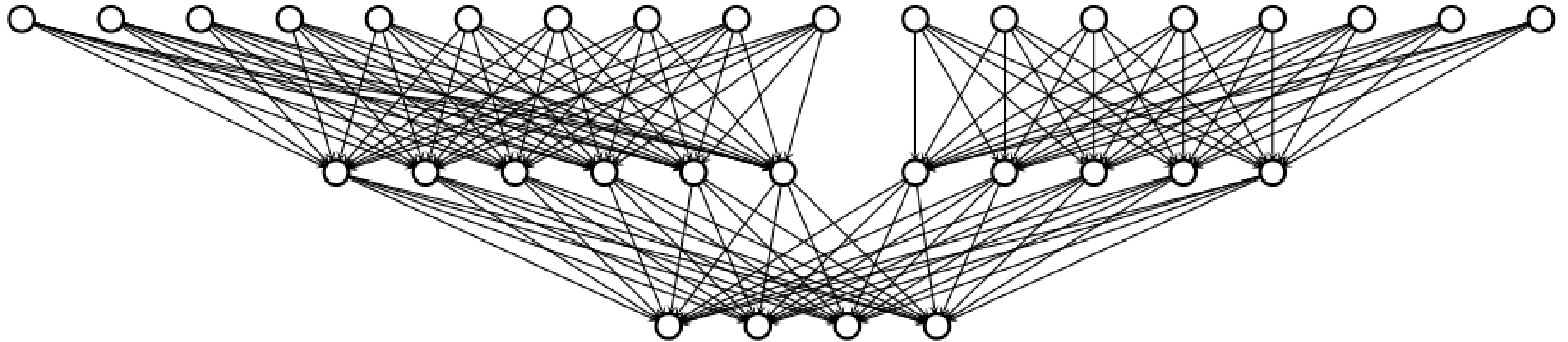
```
# Define second hidden layer
model.add(keras.layers.Dense(8, activation='relu'))
```

```
# Define output layer
model.add(keras.layers.Dense(4, activation='softmax'))
```

```
# Compile the model
model.compile('adam', loss='categorical_crossentropy')
```

```
# Summarize the model
print(model.summary())
```

# The functional API



# Using the functional API

```
# Import tensorflow
import tensorflow as tf

# Define model 1 input layer shape
model1_inputs = tf.keras.Input(shape=(28*28,))

# Define model 2 input layer shape
model2_inputs = tf.keras.Input(shape=(10,))
```

```
# Define layer 1 for model 1
model1_layer1 = tf.keras.layers.Dense(12, activation='relu')(model1_inputs)

# Define layer 2 for model 1
model1_layer2 = tf.keras.layers.Dense(4, activation='softmax')(model1_layer1)
```



# Using the functional API

```
# Define layer 1 for model 2
model2_layer1 = tf.keras.layers.Dense(8, activation='relu')(model2_inputs)

# Define layer 2 for model 2
model2_layer2 = tf.keras.layers.Dense(4, activation='softmax')(model2_layer1)

# Merge model 1 and model 2
merged = tf.keras.layers.add([model1_layer2, model2_layer2])

# Define a functional model
model = tf.keras.Model(inputs=[model1_inputs, model2_inputs], outputs=merged)

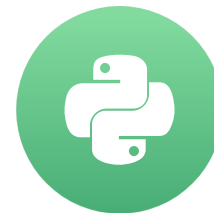
# Compile the model
model.compile('adam', loss='categorical_crossentropy')
```

# Let's practice!

INTRODUCTION TO TENSORFLOW IN PYTHON

# Training and validation with Keras

INTRODUCTION TO TENSORFLOW IN PYTHON



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Economist

# Overview of training and evaluation

1. Load and clean data
2. Define model
3. Train and validate model
4. Evaluate model

# How to train a model

```
# Import tensorflow
import tensorflow as tf

# Define a sequential model
model = tf.keras.Sequential()
```

```
# Define the hidden layer
model.add(tf.keras.layers.Dense(16, activation='relu', input_shape=(784,)))
```

```
# Define the output layer
model.add(tf.keras.layers.Dense(4, activation='softmax'))
```

# How to train a model

```
# Compile model  
model.compile('adam', loss='categorical_crossentropy')
```

```
# Train model  
model.fit(image_features, image_labels)
```

# The fit() operation

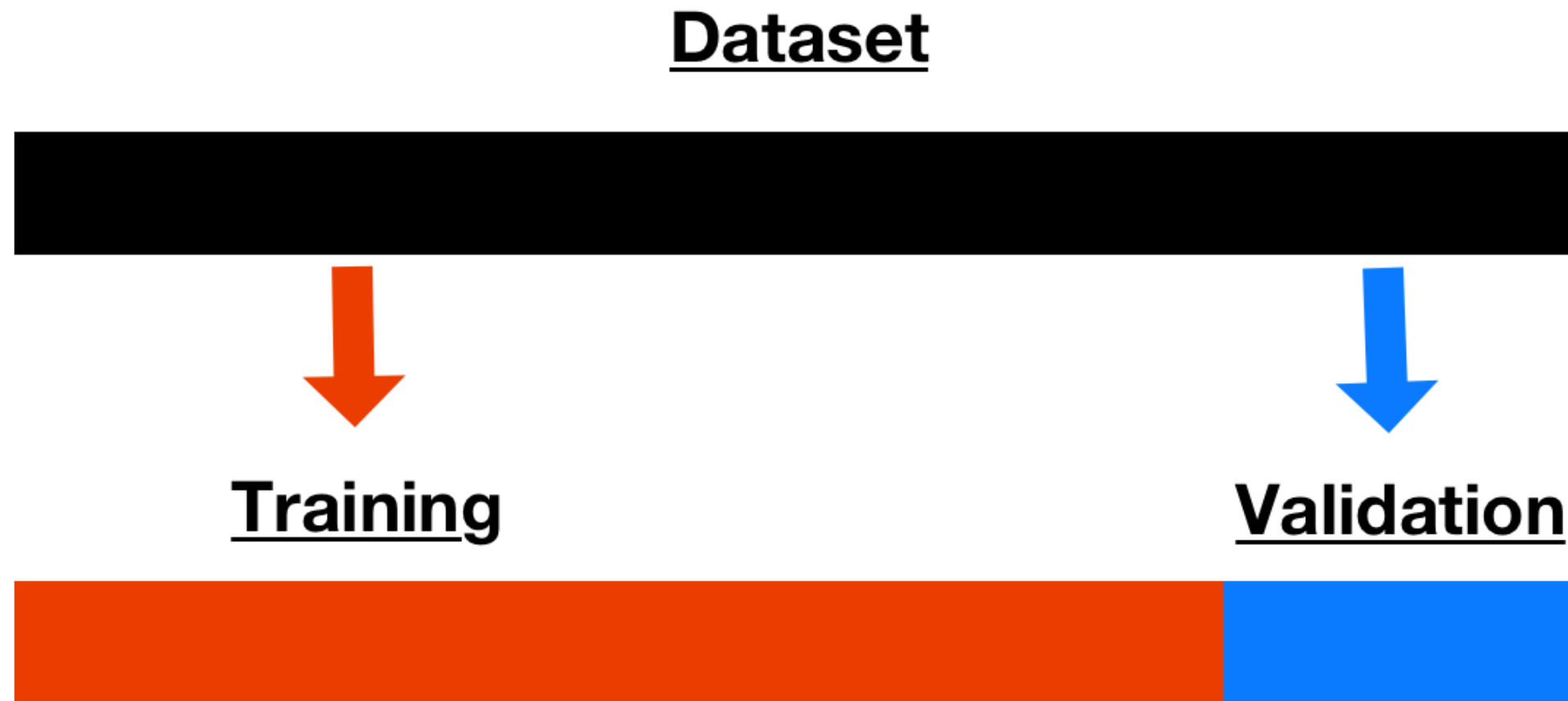
- Required arguments
  - `features`
  - `labels`
- Many optional arguments
  - `batch_size`
  - `epochs`
  - `validation_split`

# Batch size and epochs

		<u>Epochs</u>					
		price	sqft_lot	bedrooms	price	sqft_lot	bedrooms
<u>Batches</u>	Batch 1	221900.0	5650	3	221900.0	5650	3
		538000.0	7212	3	538000.0	7212	3
		180000.0		2	180000.0		2
		604000.0	5000	4	604000.0	5000	4
		510000.0	8080	3	510000.0	8080	3
	Batch 2	1225000.0	101930	4	1225000.0	101930	4
		257500.0	6819	3	257500.0	6819	3
		291850.0		3	291850.0		3
		229500.0	7470	3	229500.0	7470	3
		323000.0	6560	3	323000.0	6560	3
	Batch 3	662500.0	9796	3	662500.0	9796	3
		468000.0	6000	2	468000.0	6000	2
		310000.0		3	310000.0		3
		400000.0	9680	3	400000.0	9680	3
		530000.0	4850	5	530000.0	4850	5



# Performing validation



# Performing validation

```
# Train model with validation split  
model.fit(features, labels, epochs=10, validation_split=0.20)
```

# Performing validation

Train on 1599 samples, validate on 400 samples

Epoch 1/10

1599/1599=====] - 0s 159us/sample - loss: 1.2291 - val\_loss: 1.0122

Epoch 2/10

1599/1599=====] - 0s 60us/sample - loss: 0.8873 - val\_loss: 0.7181

Epoch 3/10

1599/1599=====] - 0s 61us/sample - loss: 0.6476 - val\_loss: 0.5414

Epoch 4/10

1599/1599=====] - 0s 58us/sample - loss: 0.4974 - val\_loss: 0.4254

Epoch 5/10

1599/1599=====] - 0s 57us/sample - loss: 0.3958 - val\_loss: 0.3544

Epoch 6/10

1599/1599=====] - 0s 62us/sample - loss: 0.3222 - val\_loss: 0.2936

Epoch 7/10

1599/1599=====] - 0s 58us/sample - loss: 0.2730 - val\_loss: 0.2555

Epoch 8/10

1599/1599=====] - 0s 56us/sample - loss: 0.2320 - val\_loss: 0.2131

Epoch 9/10

1599/1599=====] - 0s 59us/sample - loss: 0.1957 - val\_loss: 0.1843

Epoch 10/10

1599/1599=====] - 0s 55us/sample - loss: 0.1663 - val\_loss: 0.1657

# Changing the metric

```
# Recompile the model with the accuracy metric  
model.compile('adam', loss='categorical_crossentropy', metrics=['accuracy'])
```

```
# Train model with validation split  
model.fit(features, labels, epochs=10, validation_split=0.20)
```

# Changing the metric

Train on 1599 samples, validate on 400 samples

Epoch 1/10

1599/1599=====] - 0s 174us/sample - loss: 1.2956 - acc: 0.4196 - val\_loss: 1.1189 - val\_acc: 0.5075

Epoch 2/10

1599/1599=====] - 0s 59us/sample - loss: 0.9356 - acc: 0.7949 - val\_loss: 0.7843 - val\_acc: 0.8225

Epoch 3/10

1599/1599=====] - 0s 59us/sample - loss: 0.6657 - acc: 0.9037 - val\_loss: 0.5588 - val\_acc: 0.8925

Epoch 4/10

1599/1599=====] - 0s 58us/sample - loss: 0.4898 - acc: 0.9206 - val\_loss: 0.4220 - val\_acc: 0.9175

Epoch 5/10

1599/1599=====] - 0s 59us/sample - loss: 0.3734 - acc: 0.9681 - val\_loss: 0.3319 - val\_acc: 0.9825

Epoch 6/10

1599/1599=====] - 0s 61us/sample - loss: 0.2975 - acc: 0.9762 - val\_loss: 0.2907 - val\_acc: 0.9075

Epoch 7/10

1599/1599=====] - 0s 60us/sample - loss: 0.2414 - acc: 0.9731 - val\_loss: 0.2276 - val\_acc: 0.9550

Epoch 8/10

1599/1599=====] - 0s 61us/sample - loss: 0.1912 - acc: 0.9887 - val\_loss: 0.2026 - val\_acc: 0.9525

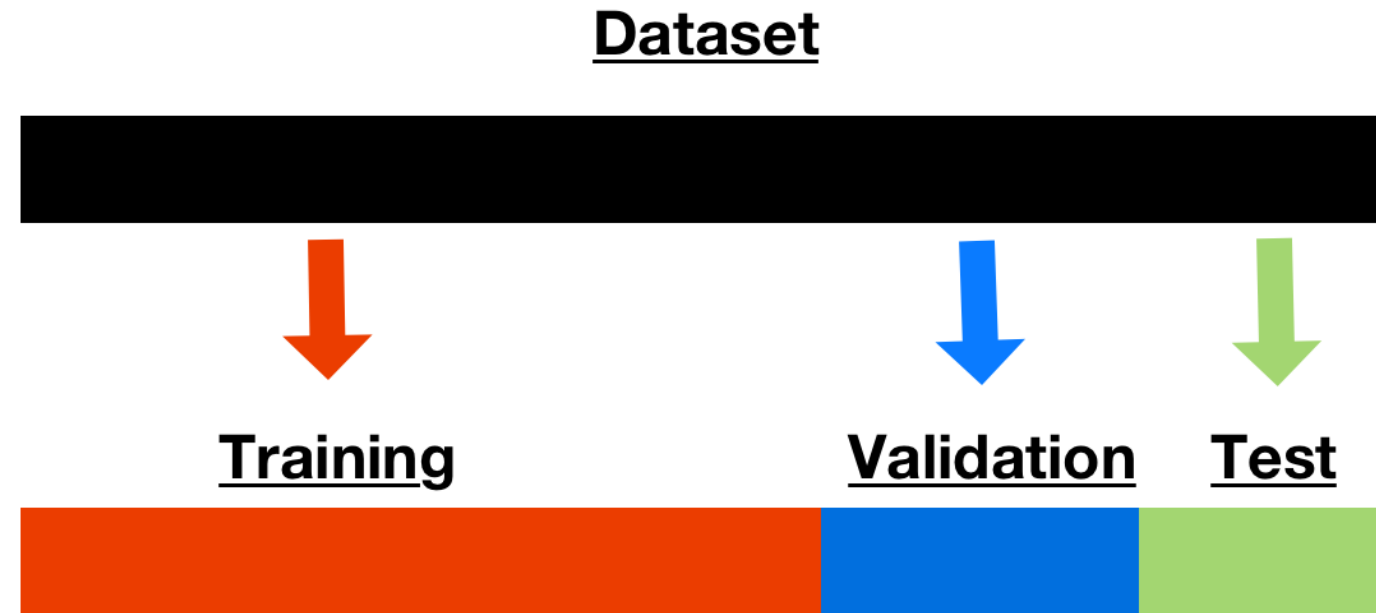
Epoch 9/10

1599/1599=====] - 0s 59us/sample - loss: 0.1649 - acc: 0.9862 - val\_loss: 0.1684 - val\_acc: 0.9675

Epoch 10/10

1599/1599=====] - 0s 58us/sample - loss: 0.1390 - acc: 0.9912 - val\_loss: 0.1374 - val\_acc: 0.9825

# The evaluation() operation



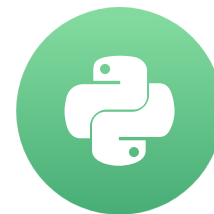
```
# Evaluate the test set  
model.evaluate(test)
```

# Let's practice!

INTRODUCTION TO TENSORFLOW IN PYTHON

# Training models with the Estimators API

INTRODUCTION TO TENSORFLOW IN PYTHON



Isaiah Hull  
Economist



# What is the Estimators API?

- High level submodule
- Less flexible
- Enforces best practices
- Faster deployment
- Many premade models

High-Level  
TensorFlow APIs

Mid-Level  
TensorFlow APIs

Low-level  
TensorFlow APIs

Estimators

Layers

Datasets

Metrics

Python

<sup>1</sup> Image taken from [https://www.tensorflow.org/guide/premade\\_estimators](https://www.tensorflow.org/guide/premade_estimators)

# Model specification and training

1. Define feature columns
2. Load and transform data
3. Define an estimator
4. Apply train operation

# Defining feature columns

```
# Import tensorflow under its standard alias
import tensorflow as tf

# Define a numeric feature column
size = tf.feature_column.numeric_column("size")
```

```
# Define a categorical feature column
rooms = tf.feature_column.categorical_column_with_vocabulary_list("rooms", \
["1", "2", "3", "4", "5"])
```

# Defining feature columns

```
# Create feature column list  
features_list = [size, rooms]
```

```
# Define a matrix feature column  
features_list = [tf.feature_column.numeric_column('image', shape=(784,))]
```

# Loading and transforming data

```
# Define input data function
def input_fn():
    # Define feature dictionary
    features = {"size": [1340, 1690, 2720], "rooms": [1, 3, 4]}
    # Define labels
    labels = [221900, 538000, 180000]
    return features, labels
```

# Define and train a regression estimator

```
# Define a deep neural network regression
model0 = tf.estimator.DNNRegressor(feature_columns=feature_list,\
    hidden_units=[10, 6, 6, 3])

# Train the regression model
model0.train(input_fn, steps=20)
```

# Define and train a deep neural network

```
# Define a deep neural network classifier
model1 = tf.estimator.DNNClassifier(feature_columns=feature_list, \
    hidden_units=[32, 16, 8], n_classes=4)

# Train the classifier
model1.train(input_fn, steps=20)
```

- <https://www.tensorflow.org/guide/estimators>

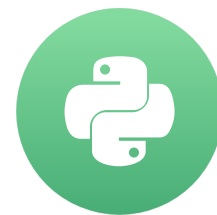
# Let's practice!

INTRODUCTION TO TENSORFLOW IN PYTHON



# Congratulations!

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# What you learned

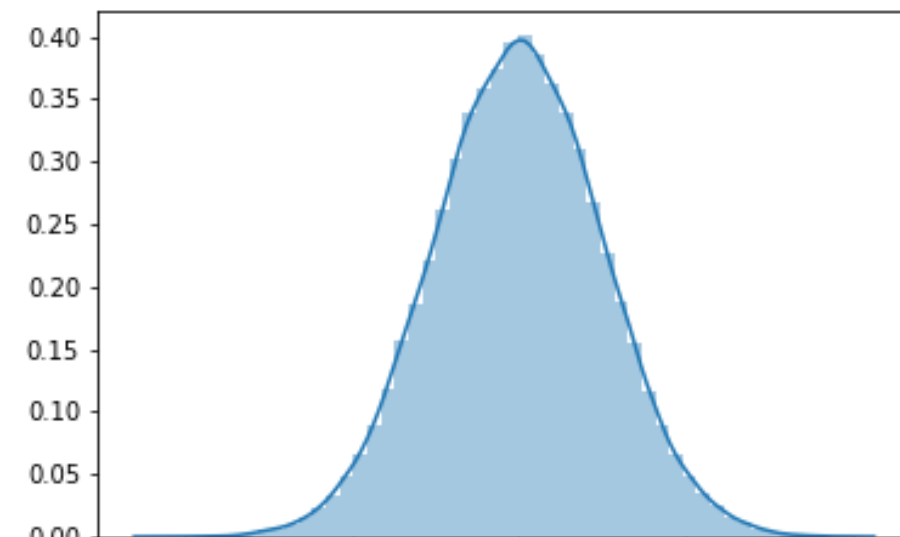
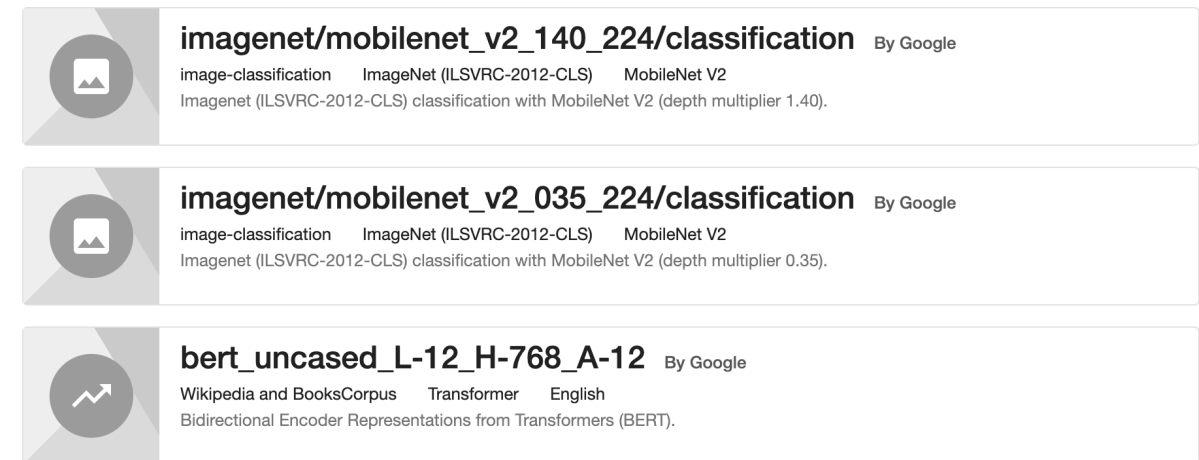
- **Chapter 1**
  - Low-level, basic, and advanced operations
  - Graph-based computation
  - Gradient computation and optimization
- **Chapter 2**
  - Data loading and transformation
  - Predefined and custom loss functions
  - Linear models and batch training

# What you learned

- **Chapter 3**
  - Dense neural network layers
  - Activation functions
  - Optimization algorithms
  - Training neural networks
- **Chapter 4**
  - Neural networks in Keras
  - Training and validation
  - The Estimators API

# TensorFlow extensions

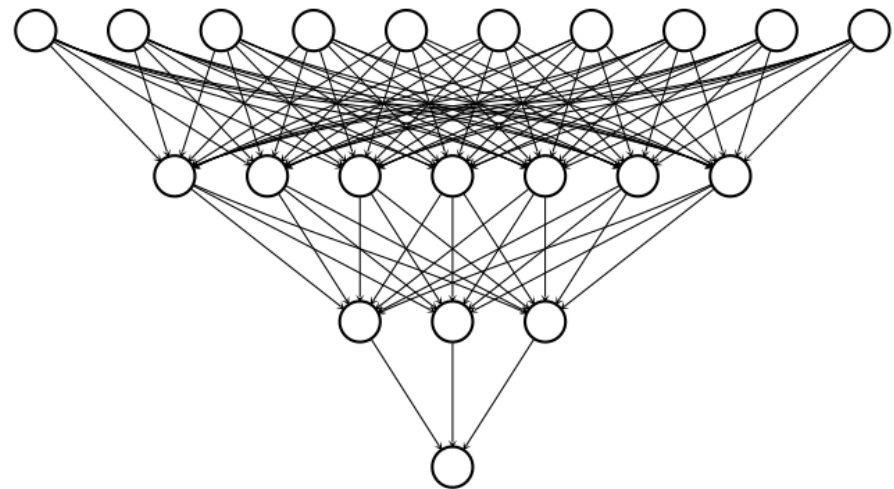
- TensorFlow Hub
  - Pretrained models
  - Transfer learning
- TensorFlow Probability
  - More statistical distributions
  - Trainable distributions
  - Extended set of optimizers



<sup>1</sup> Screenshot from <https://tfhub.dev>.

# TensorFlow 2.0

- TensorFlow 2.0
  - `eager_execution()`
  - Tighter `keras` integration
  - `Estimators`
  - `function()`



High-Level  
TensorFlow APIs

Estimators

Mid-Level  
TensorFlow APIs

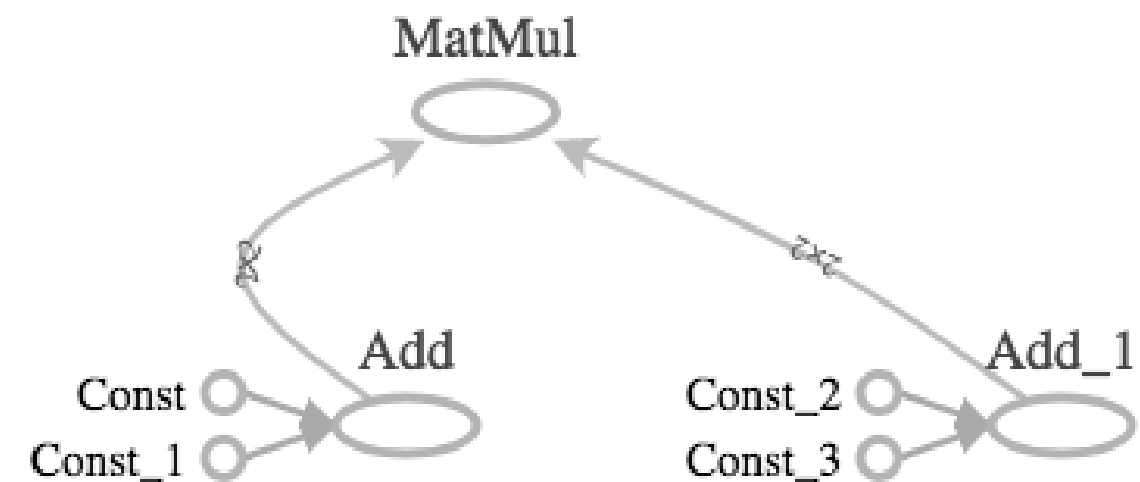
Layers

Datasets

Metrics

Low-level  
TensorFlow APIs

Python



<sup>1</sup> Screenshot taken from [https://www.tensorflow.org/guide/premade\\_estimators](https://www.tensorflow.org/guide/premade_estimators)

# Congratulations!

INTRODUCTION TO TENSORFLOW IN PYTHON