AI from Scratch:
Build your First Neural Network

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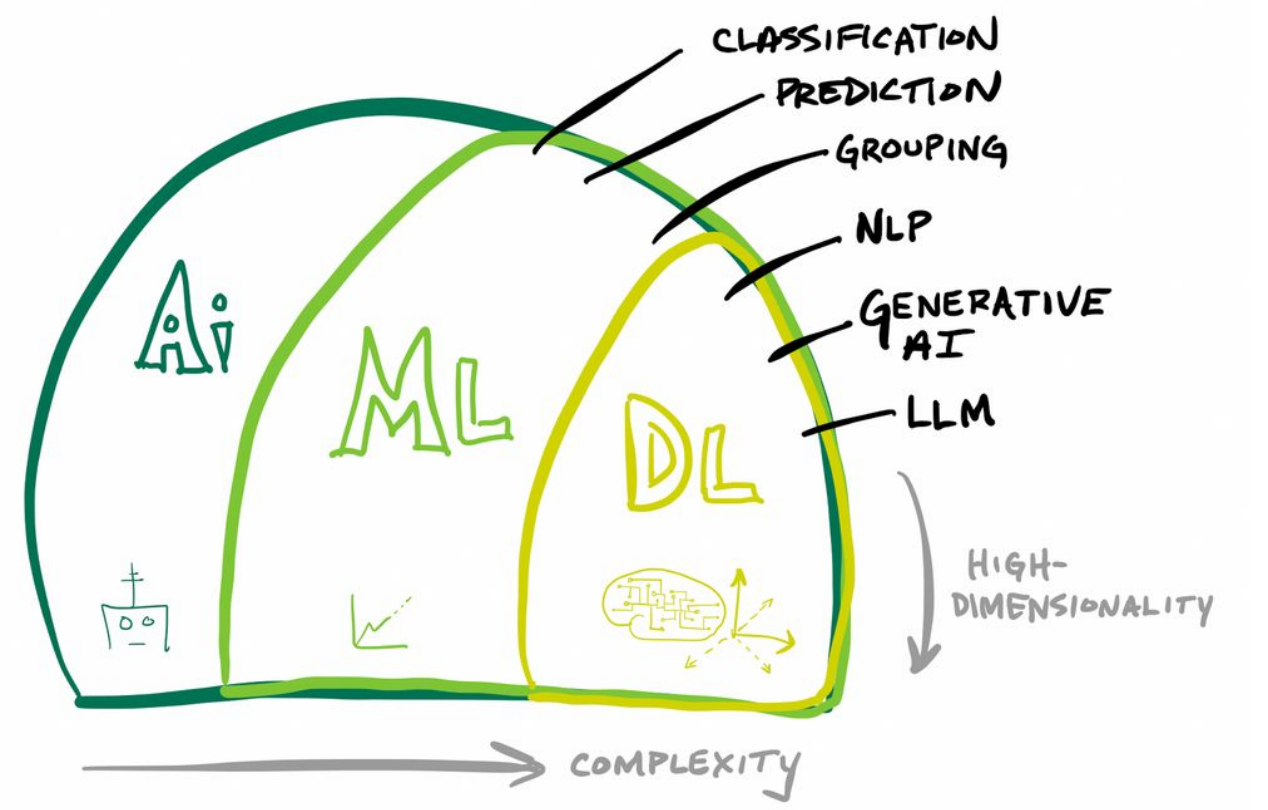
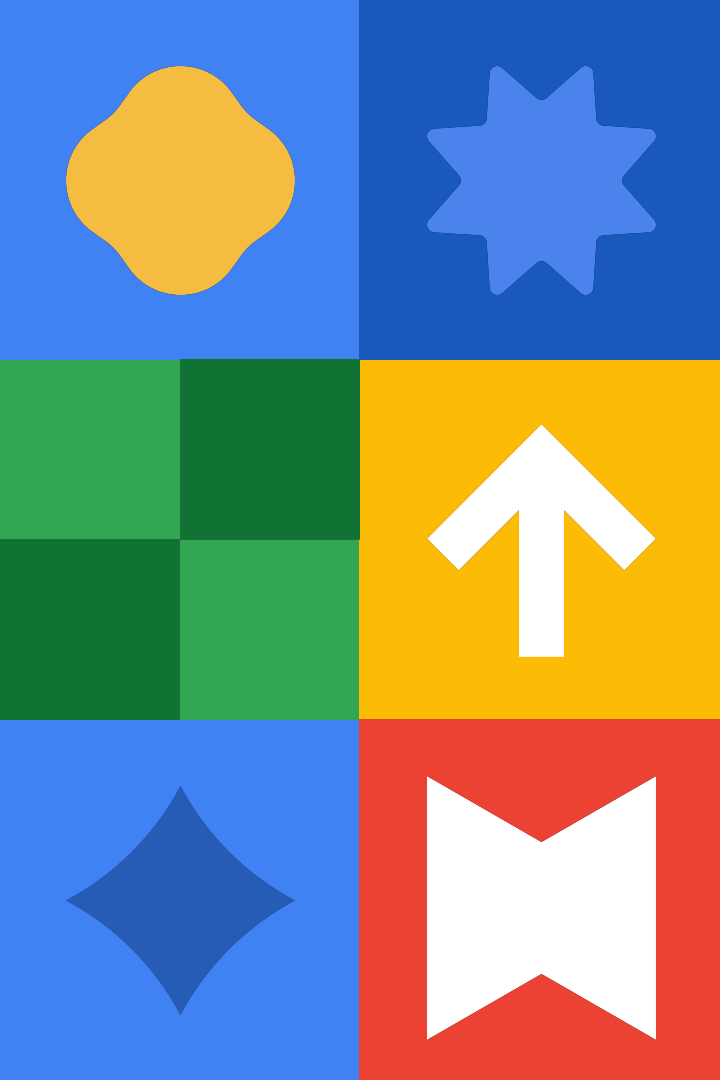
Head of AI/ML, GDGoC RJIT

OFF BEATS


CLASSIFICATION
PREDICTION
GROUPING
NLP
GENERATIVE AI
LLM
AI
ML
DL
HIGH-DIMENSIONALITY
COMPLEXITY

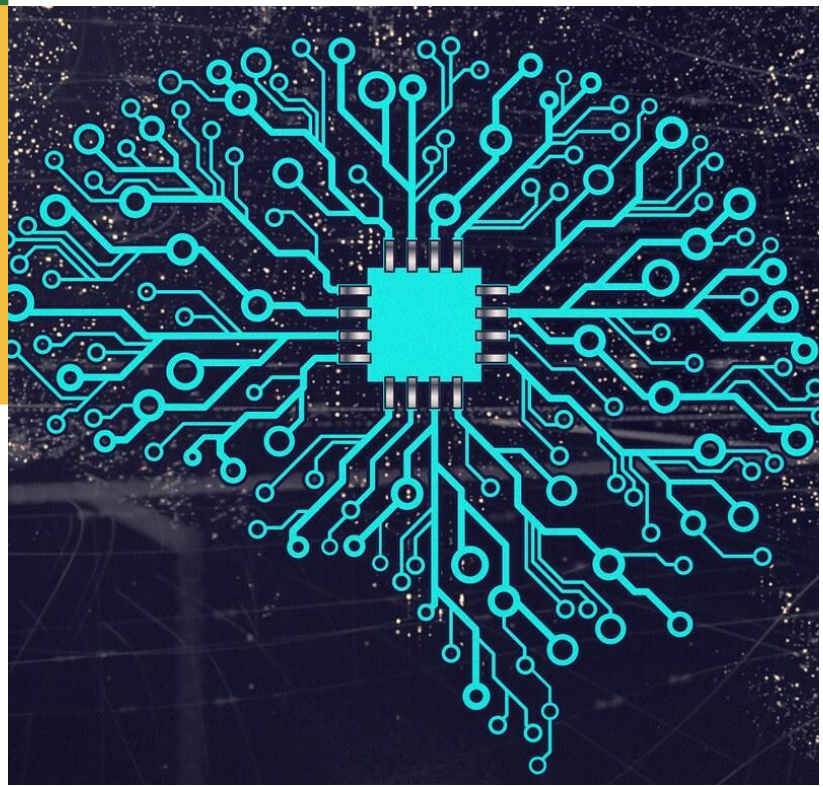


1. From Biology to Mathematics
2. TensorFlow: Your AI Toolkit
3. Hands-On Project
4. Beyond the Basics

POLL

Quick Poll: Your ML Experience

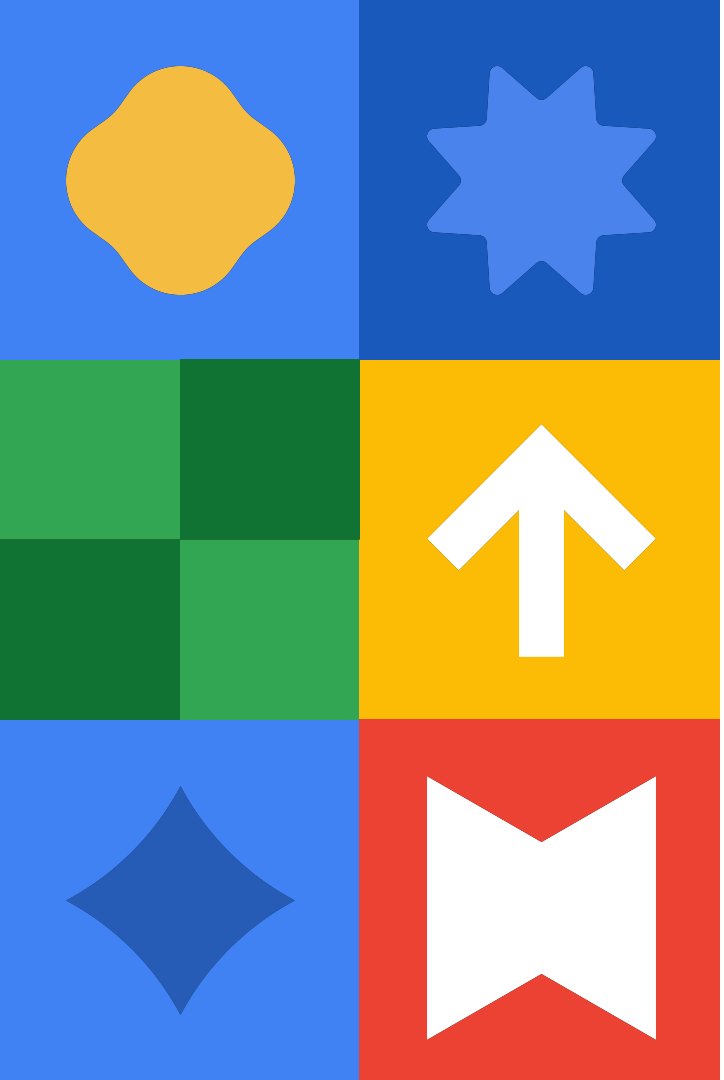
A. ✋ Complete Beginner
B. 🤓 Heard of ML/AI
C. 💻 Some Programming Experience
D. 🔥 Ready to Build Neural Networks!



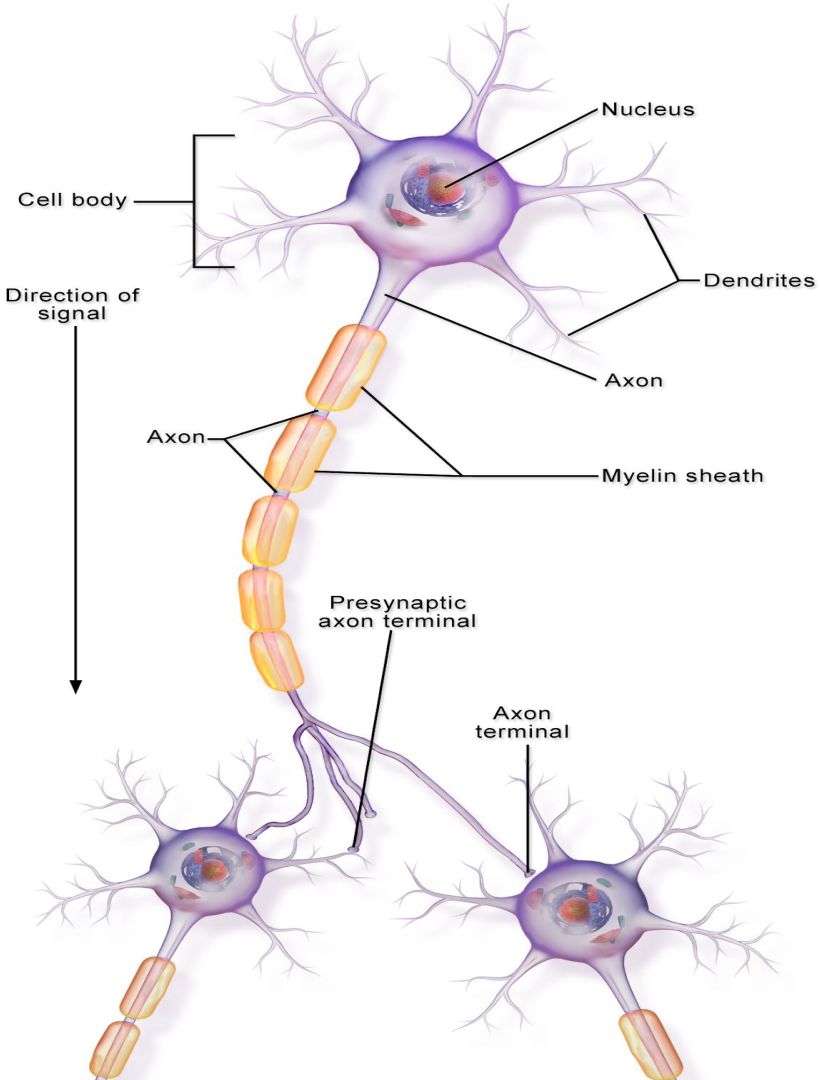
WHY NEURAL NETWORKS MATTER

Neural Networks Are Everywhere

- Your smartphone's camera (image recognition)
- Netflix recommendations
- Google Search & translation
- Self-driving cars
- Medical diagnosis
- Climate prediction



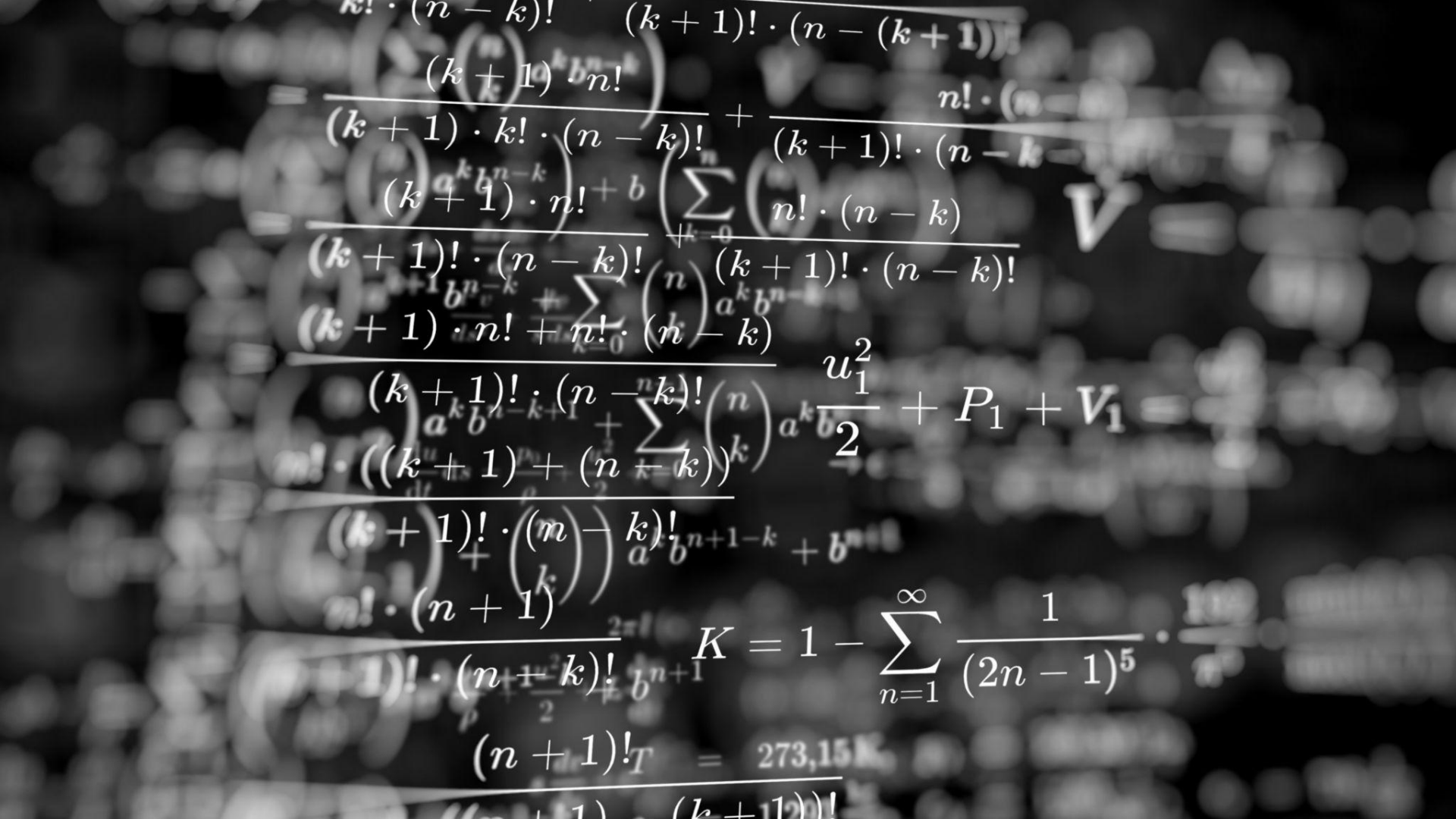
From Biology to Mathematics *Understanding the Foundation*



BIOLOGICAL INSPIRATION

The Human Brain: Nature's Computer

- 86 billion neurons
- Each neuron connects to ~7,000 others
- Processes information in parallel
- Learns through experience
- Inspired artificial neural networks

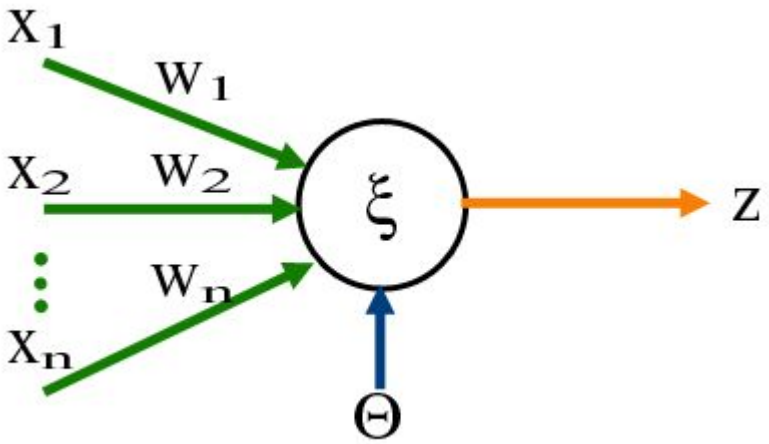

$$\frac{k! \cdot (n-k)!}{(k+1)! \cdot (n-(k+1))!}$$
$$\frac{(k+1) \cdot n!}{(k+1) \cdot k! \cdot (n-k)!} + \frac{n! \cdot (n-k)}{(k+1)! \cdot (n-k)!}$$
$$\frac{(k+1) \cdot n!}{(k+1)! \cdot (n-k)!} + \frac{n! \cdot (n-k)}{(k+1)! \cdot (n-k)!}$$
$$V =$$
$$\frac{(k+1) \cdot n! + n! \cdot (n-k)}{(k+1)! \cdot (n-k)!}$$
$$\frac{n! \cdot ((k+1) + (n-k))}{(k+1)! \cdot (n-k)!}$$
$$\frac{u_1^2}{2} + P_1 + V_1 =$$
$$\frac{n! \cdot (n+1)}{(k+1)! \cdot (n-k)!}$$
$$K = 1 - \sum_{n=1}^{\infty} \frac{1}{(2n-1)^5}$$
$$\frac{(n+1)!}{((k+1)+(n-(k+1)))!}$$
$$T = 273{,}15$$

```python
# Biological Neuron → Mathematical Model
def artificial_neuron(inputs, weights, bias):
    # Weighted sum (like dendrites collecting signals)
    weighted_sum = sum(x * w for x, w in zip(inputs, weights))

    # Add bias (neuron's threshold)
    z = weighted_sum + bias

    # Activation function (neuron fires or not)
    output = sigmoid(z)
    return output

def sigmoid(z):
    return 1 / (1 + math.exp(-z))
```



THE PERCEPTRON

The Simplest Neural Network

Input Layer ⟶ Weights ⟶ Activation ⟶ Output

Mathematical Formula:

$\hat{y} = \sigma(wx + b)$

Where:

- x = input features
- w = learned weights
- b = bias term

NEURAL NETWORK ARCHITECTURE

Building Blocks of Intelligence

Input Layer ➜ Hidden Layer(s) ➜ Output Layer

NEURAL NETWORK ARCHITECTURE

Building Blocks of Intelligence
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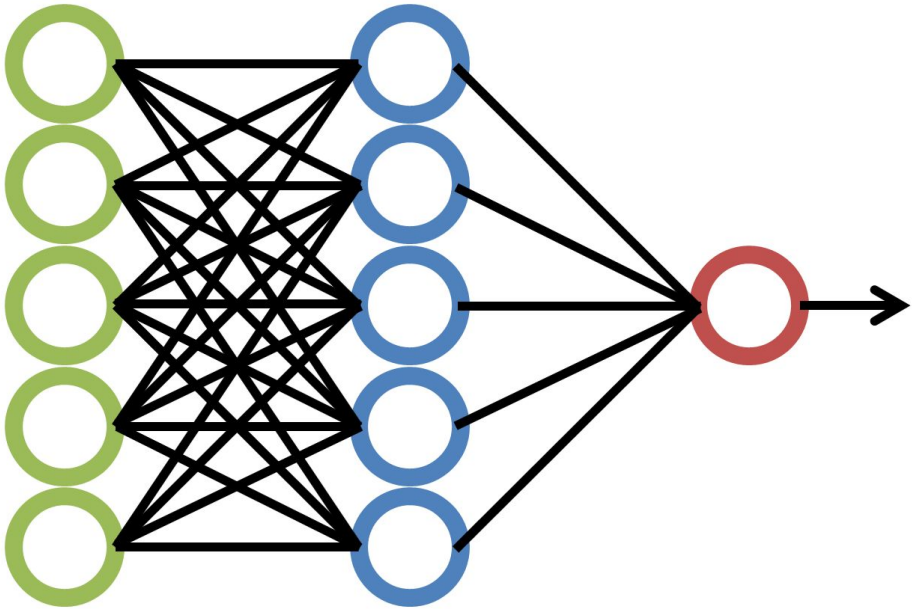


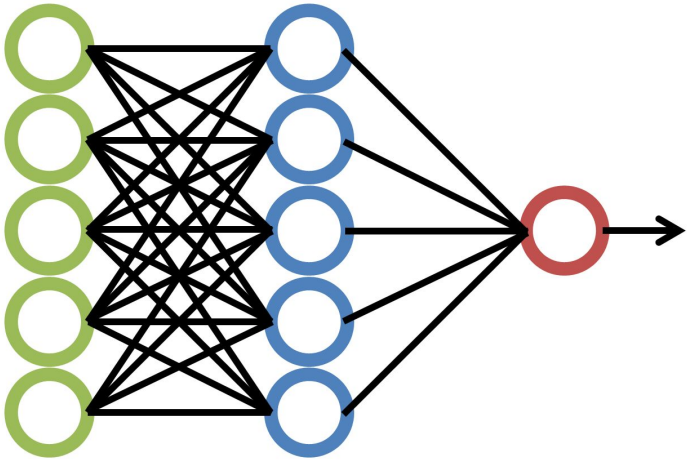
WHY DEEP NETWORKS?

Power of Depth: Learning Hierarchical Features

Layer 1: Edges & Lines

WHY DEEP NETWORKS?

Power of Depth: Learning Hierarchical Features

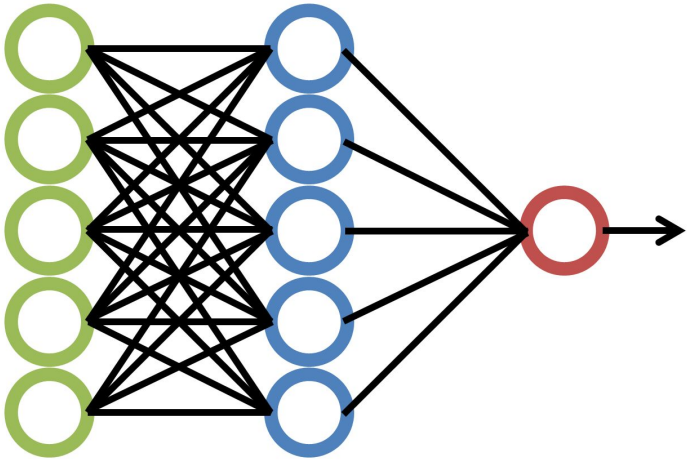


Layer 1: Edges & Lines

Layer 2: Shapes & Textures

WHY DEEP NETWORKS?

Power of Depth: Learning Hierarchical Features



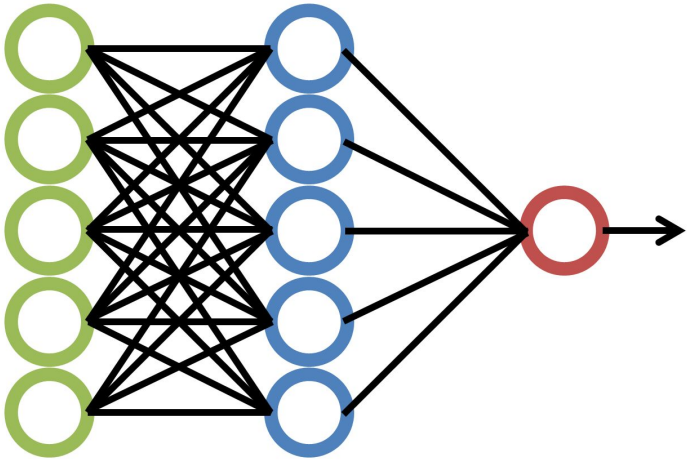
Layer 1: Edges & Lines

Layer 2: Shapes & Textures

Layer 3: Objects & Parts

WHY DEEP NETWORKS?

Power of Depth: Learning Hierarchical Features



Layer 1: Edges & Lines

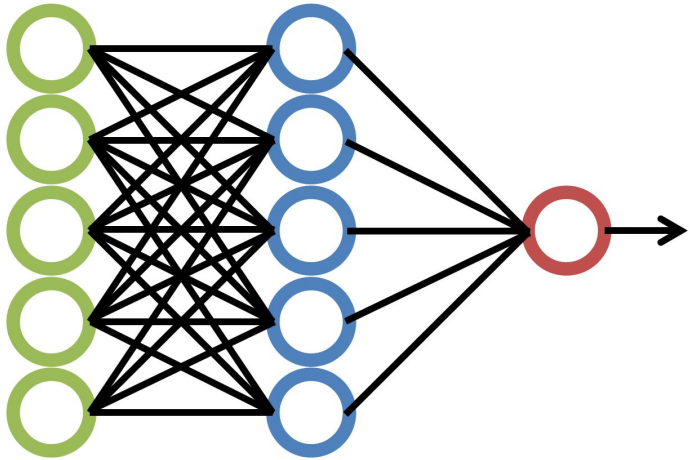
Layer 2: Shapes & Textures

Layer 3: Objects & Parts

Layer 4: Complete Objects

WHY DEEP NETWORKS?

Power of Depth: Learning Hierarchical Features



```python
import numpy as np

def forward_pass(X, W1, b1, W2, b2):
    # Layer 1: Input to Hidden
    z1 = np.dot(X, W1) + b1
    a1 = sigmoid(z1)  # Activation

    # Layer 2: Hidden to Output
    z2 = np.dot(a1, W2) + b2
    a2 = sigmoid(z2)  # Final output

    return a2, a1  # Return outputs and hidden activations
```

FORWARD PROPAGATION

```python
import numpy as np

def forward_pass(X, W1, b1, W2, b2):
    # Layer 1: Input to Hidden
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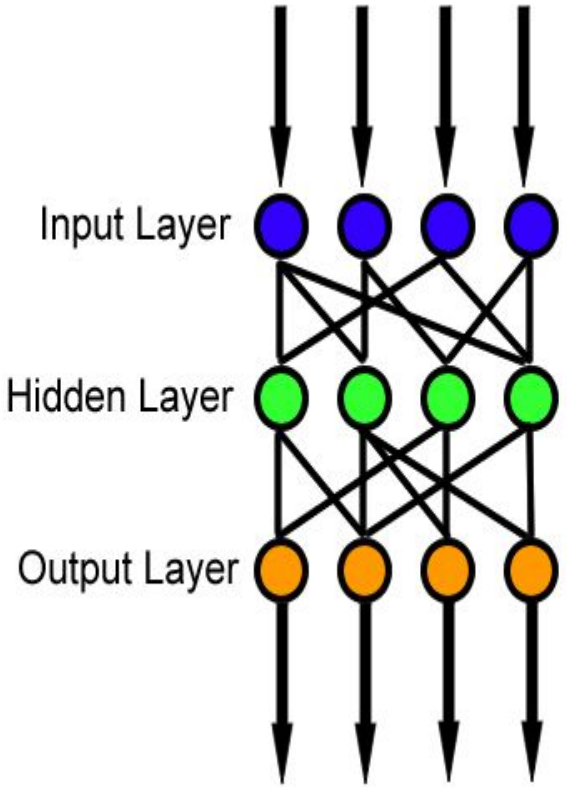
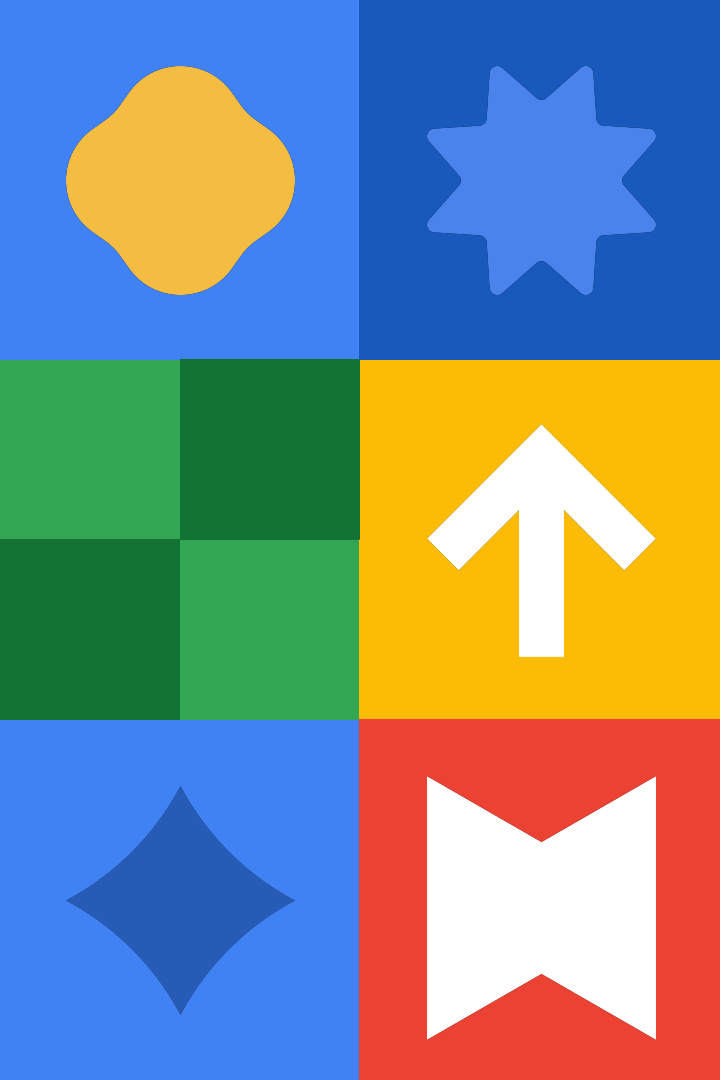
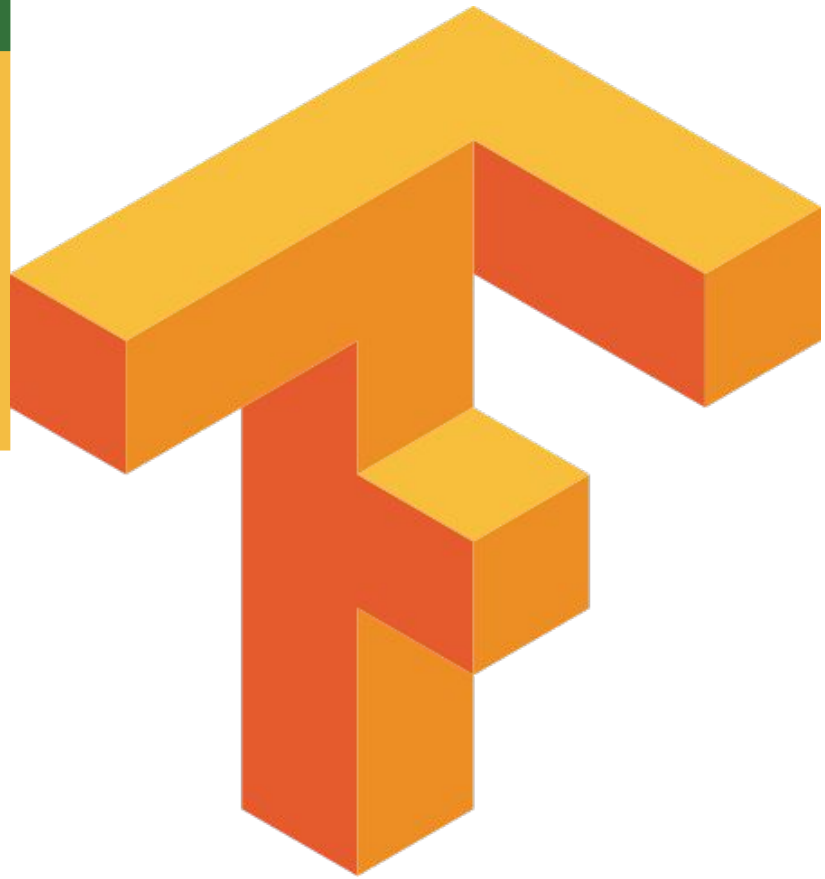
FORWARD PROPAGATION





TensorFlow: Your AI Toolkit *From Theory to Implementation*



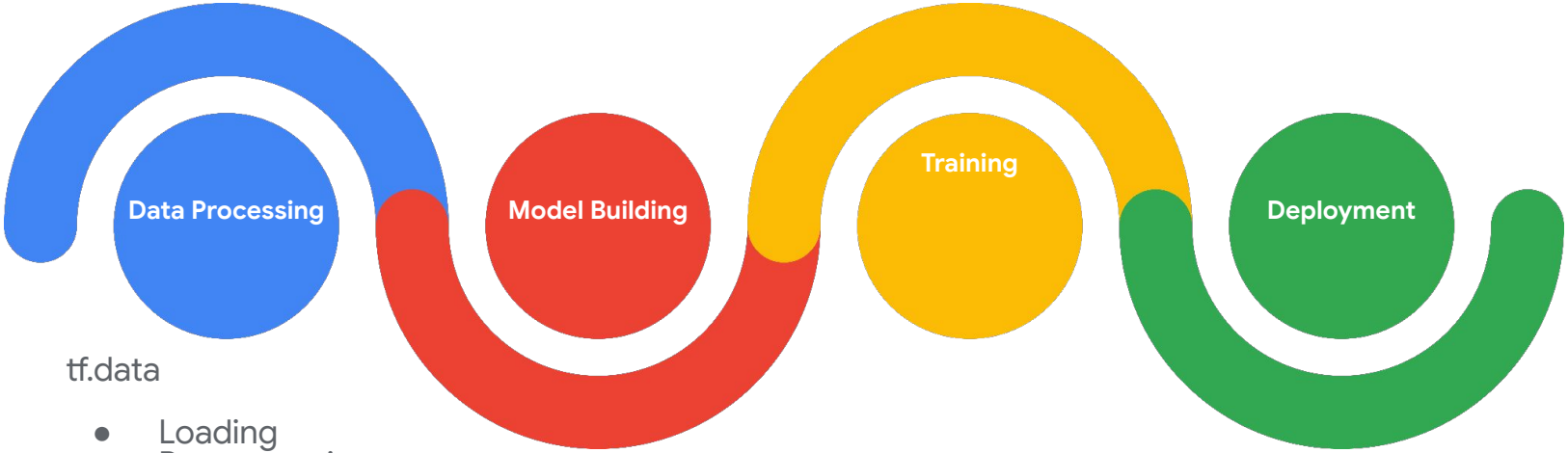
WHAT IS TENSORFLOW?

TensorFlow: Google's Open-Source AI Library

- ✓ Developed by Google Brain team
- ✓ Powers Google Search, Gmail, Photos
- ✓ Supports CPUs, GPUs, and TPUs
- ✓ Used by 50+ million developers
- ✓ Keras: High-level API for easy development

TENSORFLOW ECOSYSTEM

Complete ML Pipeline

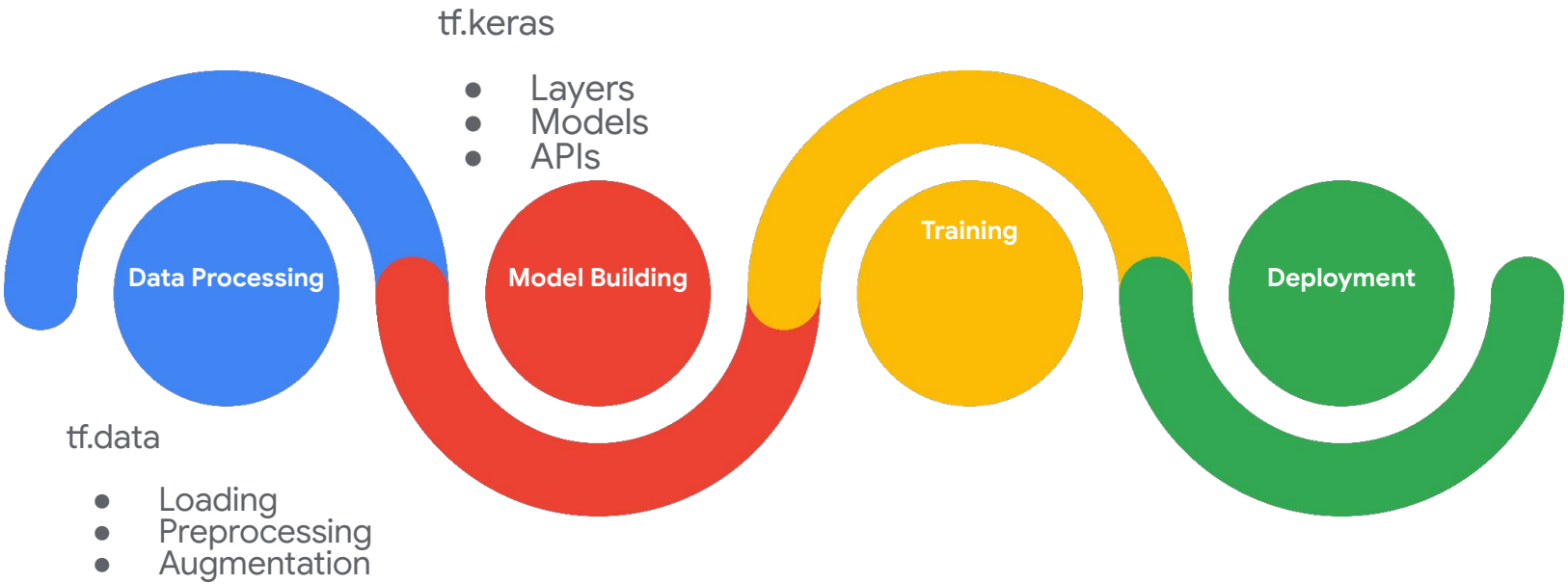


tf.data

- Loading
- Preprocessing
- Augmentation

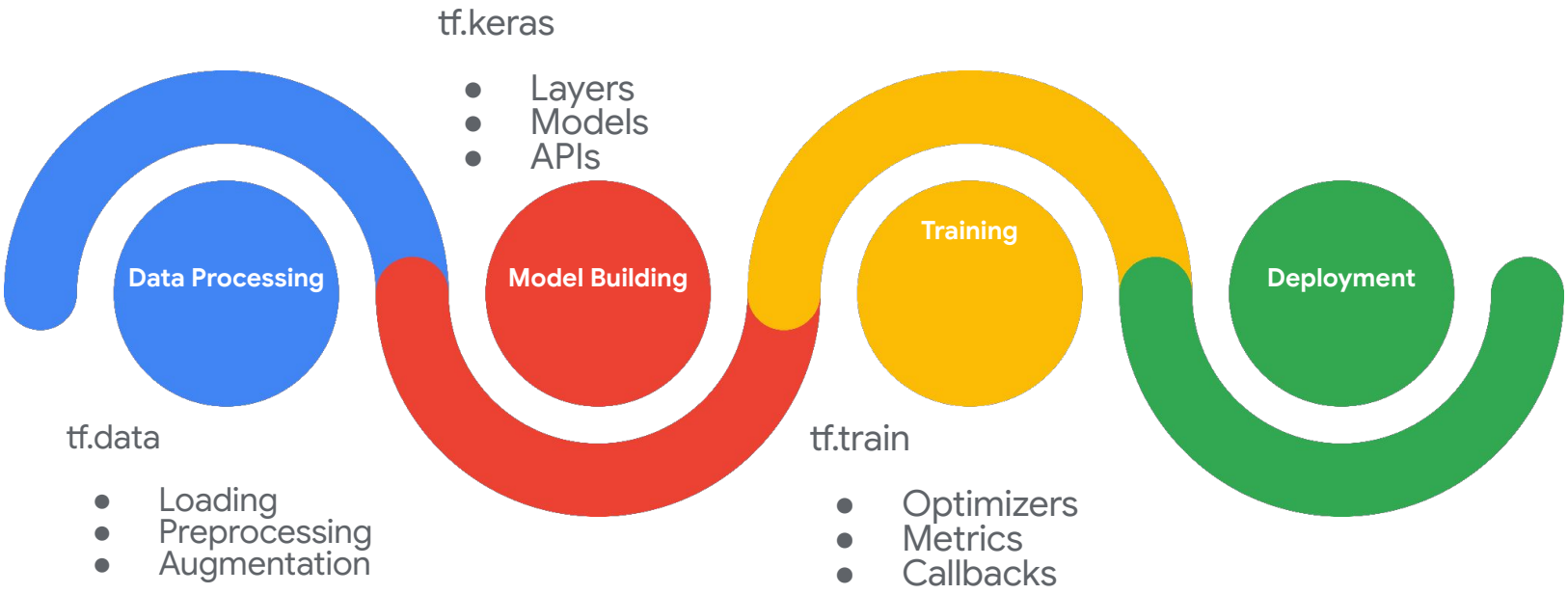
TENSORFLOW ECOSYSTEM

Complete ML Pipeline



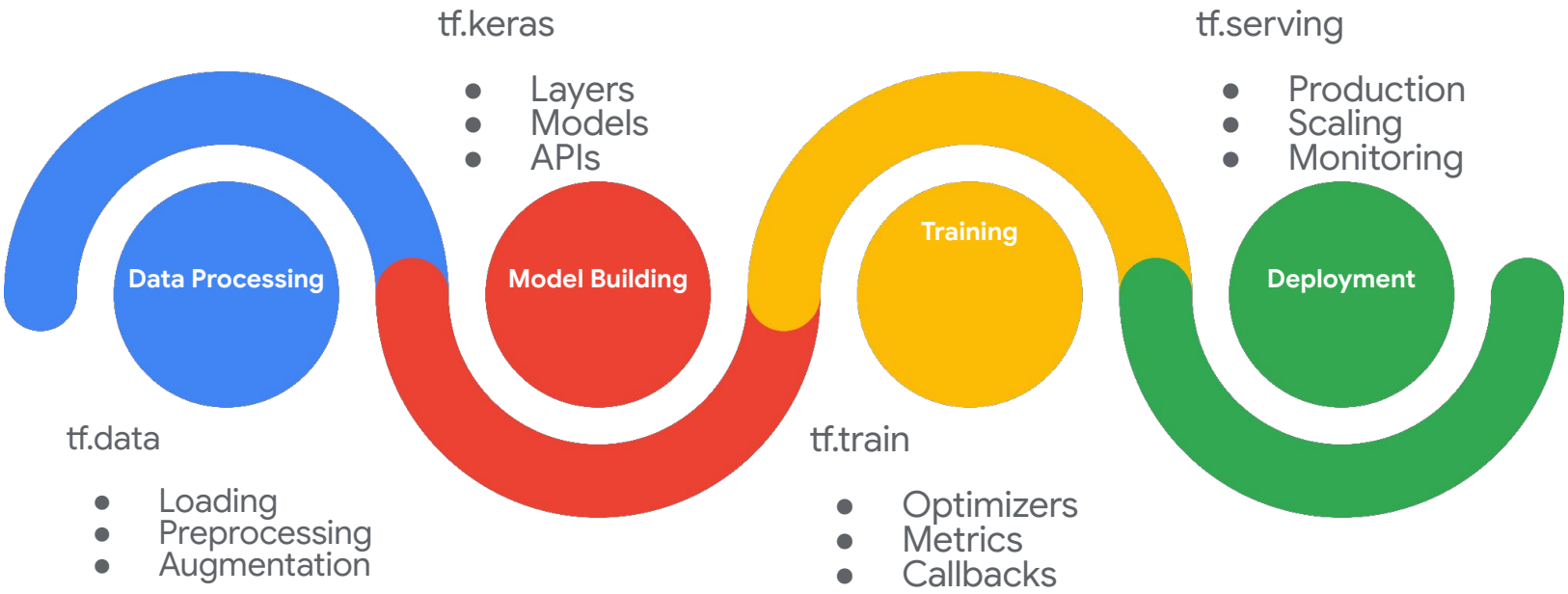
TENSORFLOW ECOSYSTEM

Complete ML Pipeline



TENSORFLOW ECOSYSTEM

Complete ML Pipeline



YOUR FIRST NEURAL NETWORK

```
import tensorflow as tf
from tensorflow import keras

# 1. Create the model
model = keras.Sequential([
    keras.layers.Dense(128, activation='relu', input_shape=(784,)),
    keras.layers.Dense(64, activation='relu'),
    keras.layers.Dense(10, activation='softmax')
])

# 2. Compile the model
model.compile(optimizer='adam',
              loss='sparse_categorical_crossentropy',
              metrics=['accuracy'])

# 3. Train the model
model.fit(train_images, train_labels, epochs=5)
```

YOUR FIRST NEURAL NETWORK

UNDERSTANDING LAYERS

Neural Network Layers Explained

Dense Layer: Fully connected neurons

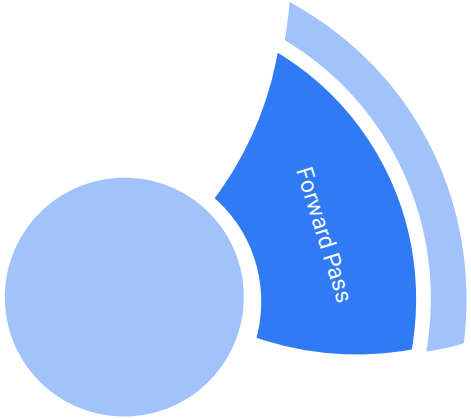
- Every input connected to every output
- Most common layer type
- Great for general problems

Activation Functions:

- ReLU: f(x) = max(0, x) - Most popular
- Sigmoid: f(x) = 1/(1+e^-x) - Output probability
- Softmax: Converts to probability distribution

TRAINING PROCESS

How Neural Networks Learn



TRAINING PROCESS

How Neural Networks Learn

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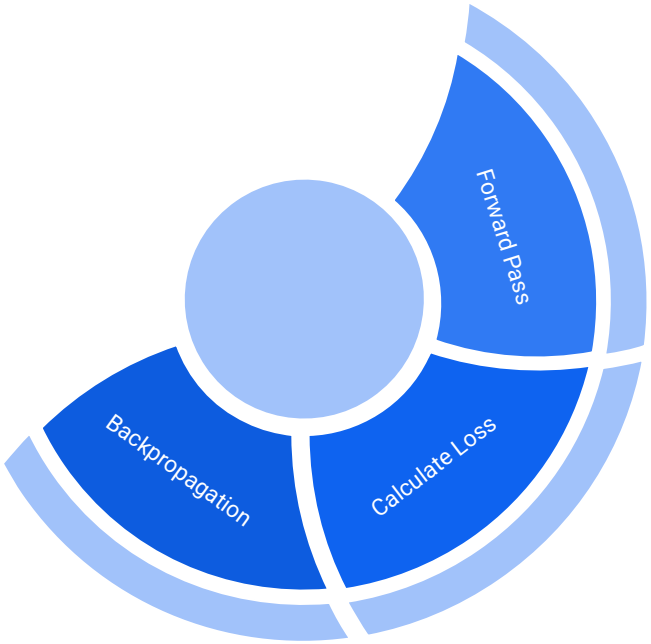
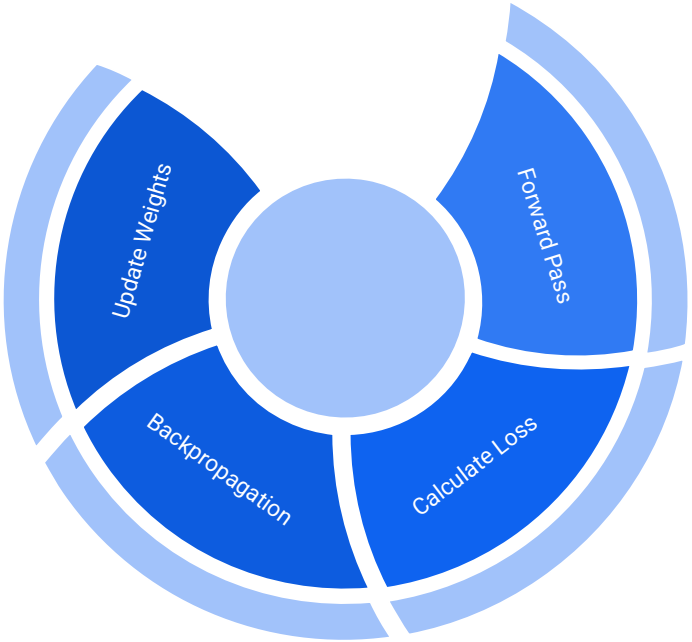
How Neural Networks Learn



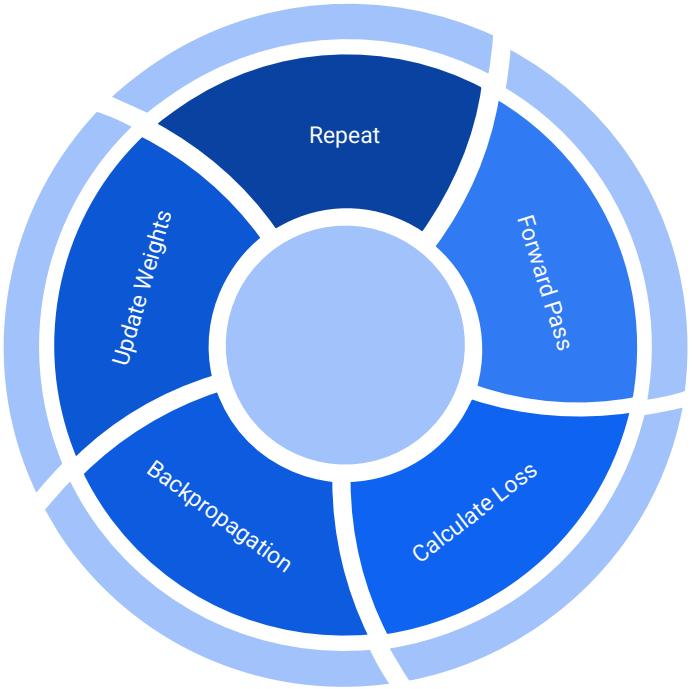
TRAINING PROCESS

How Neural Networks Learn



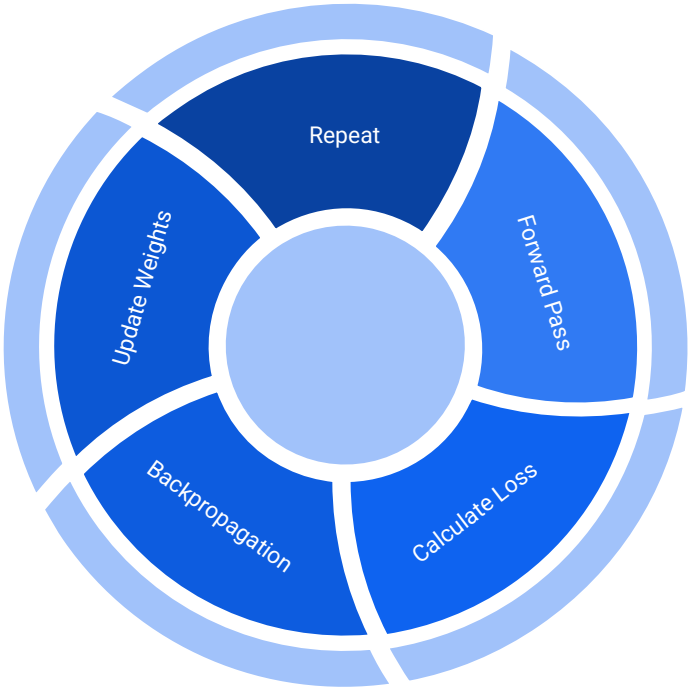
TRAINING PROCESS

How Neural Networks Learn



TRAINING PROCESS

How Neural Networks Learn



TRAINING PROCESS

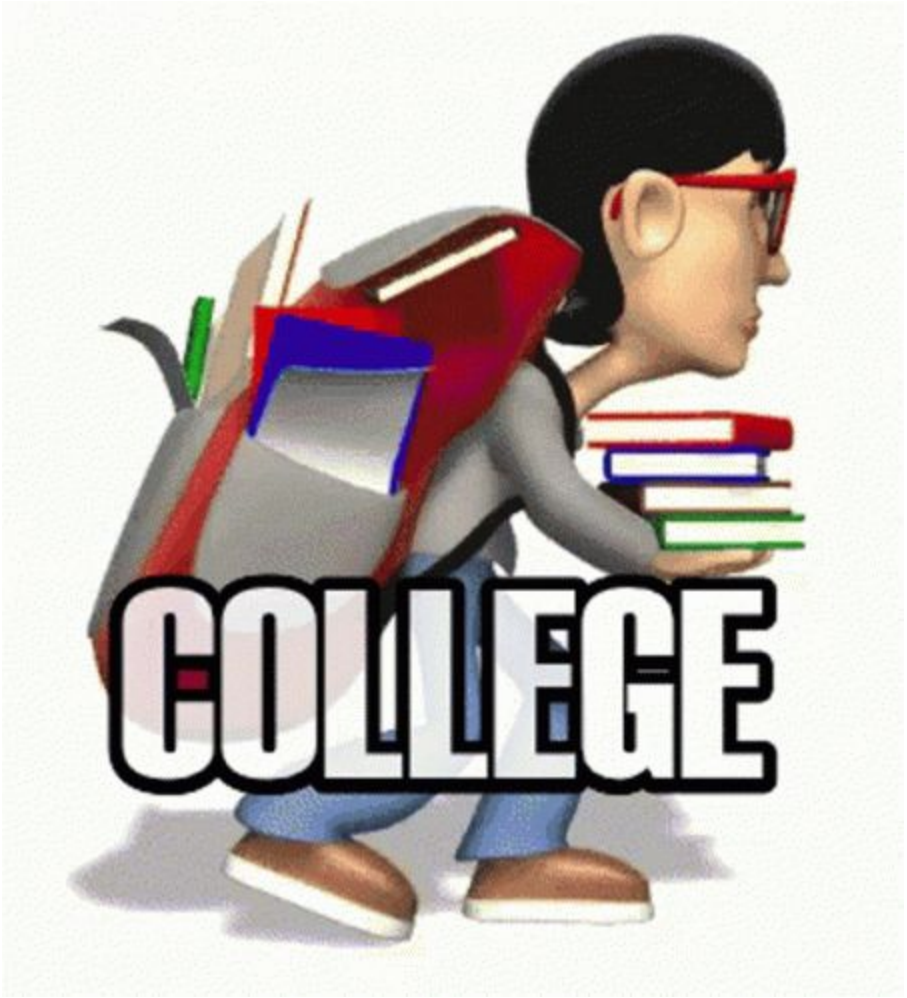
How Neural Networks Learn

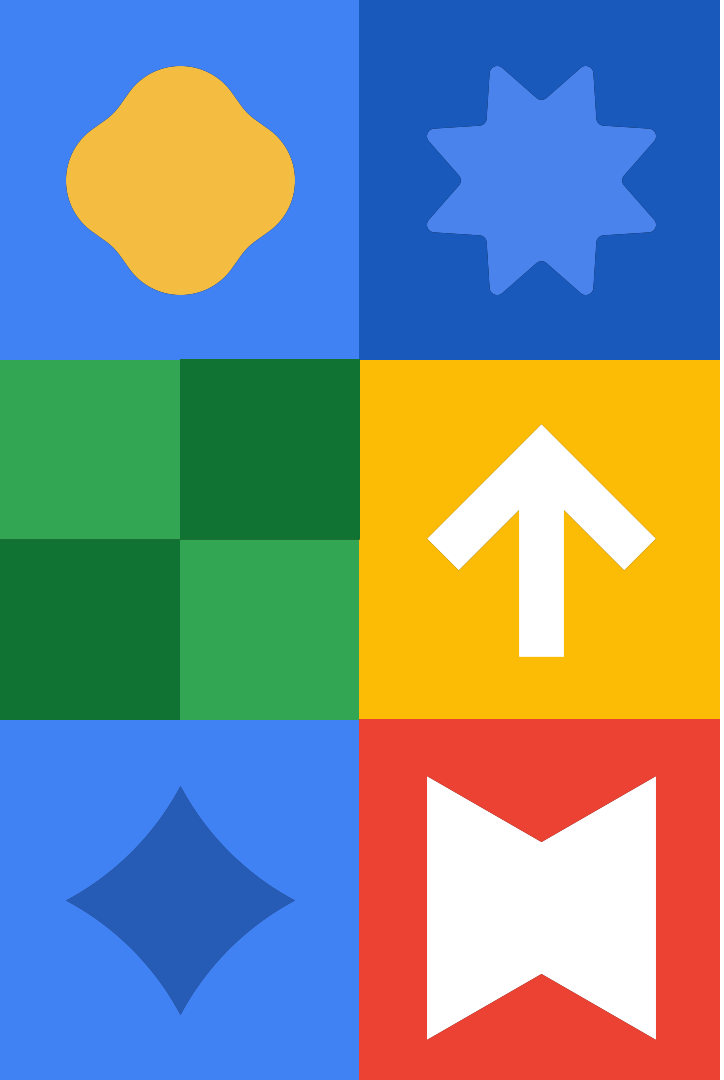
Epoch 1: Accuracy: 65%

Epoch 2: Accuracy: 78% — Learning!

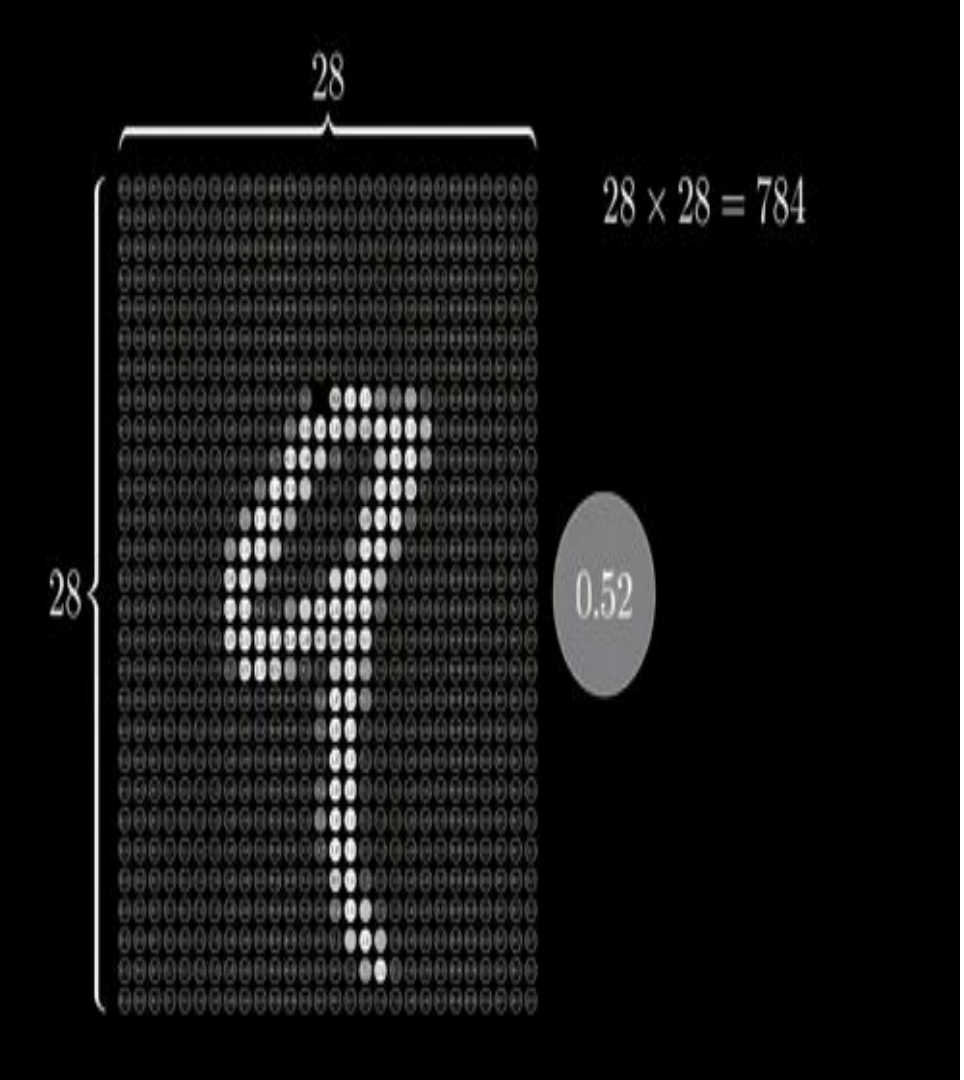
Epoch 3: Accuracy: 84%

Epoch 4: Accuracy: 89%


COLLEGE



Hands-On Project *Building a Real Neural Network*



PROJECT OVERVIEW

Handwritten Digit Recognition

Goal: Classify handwritten digits (0-9)

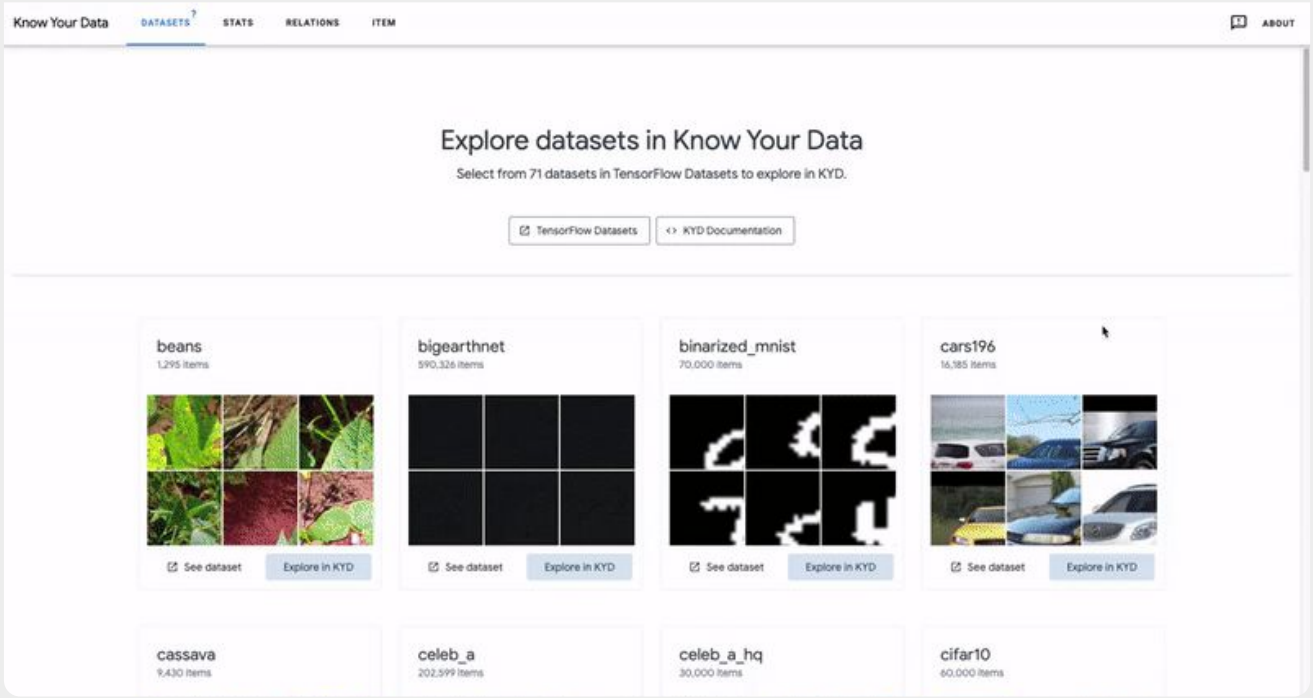
Dataset: MNIST (60,000 training images)

Input: 28×28 pixel grayscale images

Output: Digit class (0, 1, 2, ..., 9)

Success Metric: >87% accuracy

TensorFlow Datasets



kaggle

Search datasets

Filters

Computer Science | Education | Classification | Computer Vision | NLP | Data Visualization | Pre-Trained Model

Trending Datasets

See All

F1 Schedule 2022

Vivo Vinco · Updated 4 hours ago
Usability **9.4** · 2 kB
2 Files (CSV)

7

World Happiness Report 2022

Mathurin Aché · Updated 12 hours ago
Usability **10.0** · 2 MB
4 Files (other, CSV)

13

Vinello.eu Wine Catalogue

efimpolianskii · Updated 13 hours ago
Usability **9.4** · 42 kB
1 File (CSV)

5

Youtube Videos Dataset (~3400 videos)

Rajat Chaudhari · Updated 15 hours ago
Usability 8.8 · 661 kB
1 File (CSV)

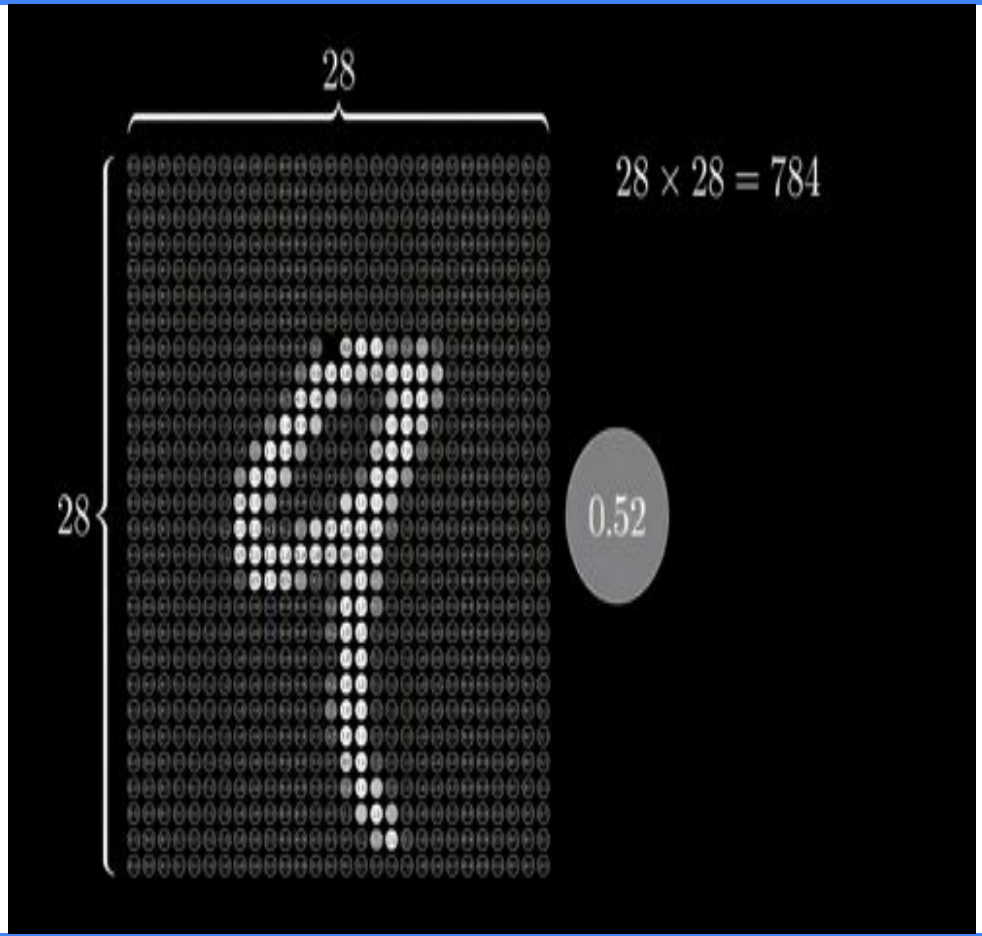
6

Popular Datasets

See All



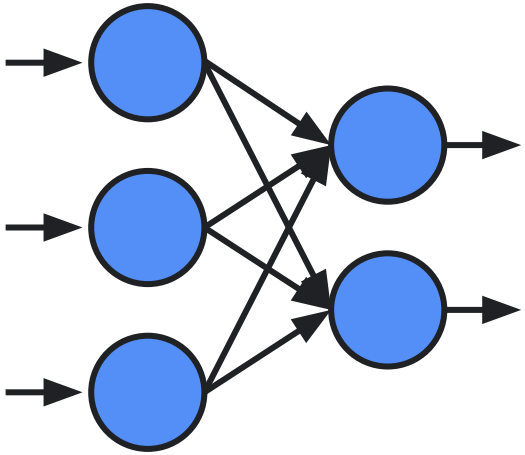

DATA EXPLORATION


28
28
28 × 28 = 784
0.52

```python
# Load and explore MNIST dataset
import tensorflow as tf

# Load dataset
(x_train, y_train), (x_test, y_test) = tf.keras.datasets.mnist.load_data()

print(f"Training images: {x_train.shape}")  # (60000, 28, 28)
print(f"Training labels: {y_train.shape}")  # (60000,)
print(f"Label range: {y_train.min()} to {y_train.max()}")  # 0 to 9

# Normalize pixel values to 0-1 range
x_train = x_train / 255.0
x_test = x_test / 255.0
```

DATA EXPLORATION

Keras



```
model = tf.keras.Sequential([
  layers.Flatten(),
  layers.Dense(3, activation='relu'),
  layers.Dense(2)
])
```

```
# Build our neural network architecture
model = tf.keras.Sequential([
    tf.keras.layers.Flatten(input_shape=(28, 28)),    # 784 features
    tf.keras.layers.Dense(128, activation='relu'),    # Hidden layer 1
    tf.keras.layers.Dropout(0.2),                     # Prevent overfitting
    tf.keras.layers.Dense(64, activation='relu'),     # Hidden layer 2
    tf.keras.layers.Dense(10, activation='softmax')   # Output layer
])

# Print model architecture
model.summary()
```

Building Model

```
# Configure training process
model.compile(
    optimizer='adam',                    # Smart learning rate adjustment
    loss='sparse_categorical_crossentropy',    # For multi-class classification
    metrics=['accuracy']                 # Track accuracy during training
)

# Train the model
history = model.fit(
    x_train, y_train,
    epochs=10,                # 10 complete passes through data
    validation_split=0.2,       # Use 20% of training data for validation
    batch_size=32,            # Process 32 images at once
    verbose=1                 # Show training progress
)
```

TRAINING CONFIGURATION

```
# Configure training process
model.compile(
    optimizer='adam',                    # Smart learning rate adjustment
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```

TRAINING CONFIGURATION

LIVE DEMO TIME!

🚀 LIVE CODING DEMONSTRATION
Let's build this neural network together!

Demo Environment: Google Colab
Repository: Link
Follow along: Colab Notebook Link

LIVE DEMO TIME!

Training Results

Final Training Accuracy: 98.7%
Final Validation Accuracy: 97.2%
Test Accuracy: 96.8%

Model Performance:

- Epoch 1: 92.1% accuracy
- Epoch 5: 96.5% accuracy
- Epoch 10: 97.2% accuracy

Success!

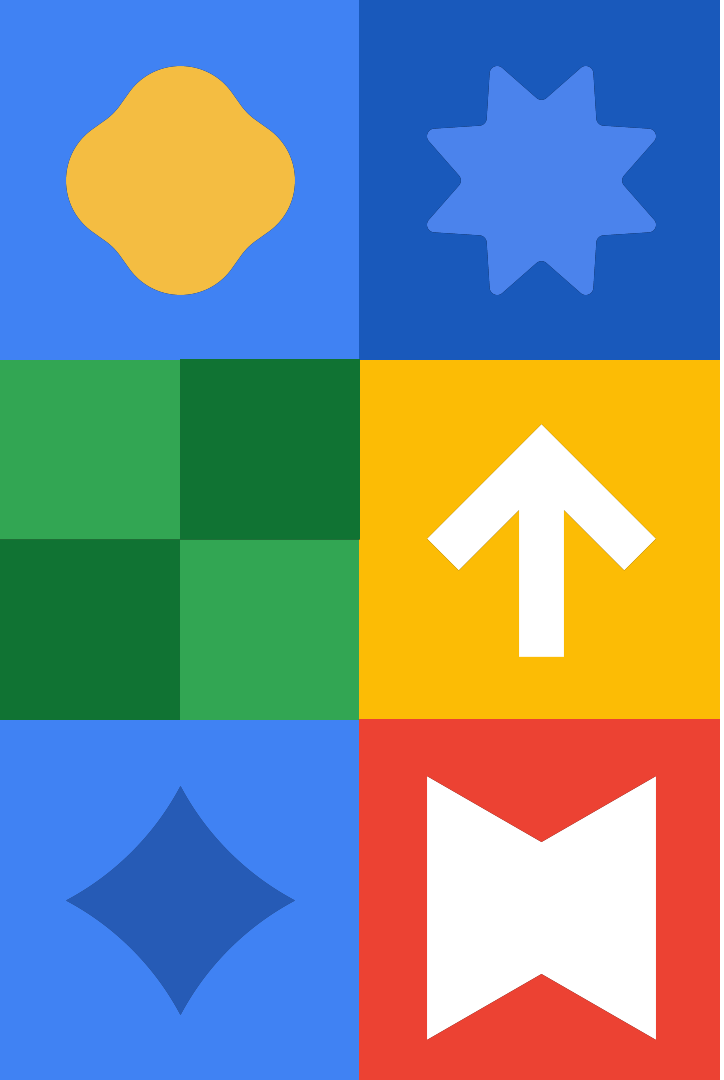
```python
# Make predictions on new data
import matplotlib.pyplot as plt

# Get predictions for test set
predictions = model.predict(x_test)

# Visualize a prediction
def plot_prediction(image, prediction, true_label):
    plt.figure(figsize=(6, 3))
    plt.subplot(1, 2, 1)
    plt.imshow(image, cmap='gray')
    plt.title(f'True Label: {true_label}')
    plt.subplot(1, 2, 2)
    plt.bar(range(10), prediction)
    plt.title(f'Predicted: {np.argmax(prediction)}')
    plt.xlabel('Digit Class')
    plt.ylabel('Probability')

# Test on a random image
idx = 42
plot_prediction(x_test[idx], predictions[idx], y_test[idx])
```

MAKING PREDICTIONS



Beyond the Basics *Where to Go Next*

ADVANCED ARCHITECTURES

Next-Level Neural Networks

Convolutional Neural Networks (CNNs)

→ *Image recognition, computer vision*

Recurrent Neural Networks (RNNs)

→ *Text processing, language models*

Transformers

→ *Large language models, ChatGPT*

Generative Adversarial Networks (GANs)

→ *Image generation, deepfakes*

REAL-WORLD APPLICATIONS

Neural Networks in Action

Healthcare: Medical image analysis, drug discovery

Autonomous Vehicles: Object detection, path planning

Finance: Fraud detection, algorithmic trading

Entertainment: Game AI, content recommendation

Climate: Weather prediction, climate modeling

Education: Personalized learning, automated grading

Your AI Learning Journey

Month 1-2: Master the Fundamentals

- Linear algebra & calculus review
- Python programming proficiency
- Complete Andrew Ng's courses

Month 3-4: Specialized Architectures

- CNNs for computer vision
- RNNs for natural language processing
- Practice with real datasets

Month 5-6: Advanced Topics

- Transfer learning & fine-tuning
- Model optimization & deployment
- Contributing to open source projects

ESSENTIAL LEARNING RESOURCES

📚 **Courses:**
- Andrew Ng's Deep Learning Specialization (Coursera)
- MIT 6.034 Artificial Intelligence
- Google's Machine Learning Crash Course

📖 **Books:**
- "Deep Learning" by Ian Goodfellow
- "Hands-On Machine Learning" by Aurélien Géron
- "Neural Networks and Deep Learning" by Michael Nielsen

💻 **Practice:**
- Kaggle competitions and datasets
- Google Colab notebooks
- TensorFlow tutorials and documentation

CONNECT & CONTINUE LEARNING

🌐 Online Communities:

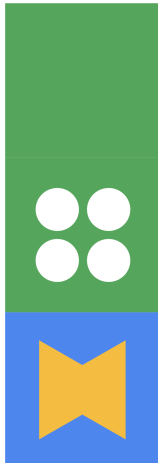
- ➔ *r/MachineLearning (Reddit)*
- ➔ *AI/ML Discord servers (e.g. Kaggle)*
- ➔ *TensorFlow Community Forum*
- ➔ *Join Offbeats!*

🏢 Local Groups:

- ➔ *AI/ML Meetups in your city*
- ➔ *University research groups*
- ➔ *Tech company events and workshops*

📱 Follow & Learn:

- ➔ *@AndrewYNg (Twitter)*
- ➔ *Google AI Blog*
- ➔ *Distill.pub for visual explanations*
- ➔ *Newsletters*



Gracias!
Questions?

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BONUS - WHAT'S NEXT

Your Next Challenge

Build a Neural Network for:

🖼️ Image Classification (cats vs dogs)

📝 Text Analysis (sentiment classification)

📈 Time Series Prediction (stock prices)

🎮 Game AI (tic-tac-toe)

The Journey Continues...

Start Coding Today! 🚀


THANK YOU
dhanyavad
THANK YOU
THANK YOU
THANK YOU
ock 5 minutes before work ends:
THANK YOU