



# Deep Learning Fundamentals

An Interactive Introduction to  
Artificial Neural Networks  
and TensorFlow

# POLL

Where are you?

- The Americas
- Europe / Middle East / Africa
- Asia-Pacific
- Extra-Terrestrial Space

# POLL

What are you?

- Developer / Engineer
- Scientist / Analyst / Statistician / Mathematician
- Other

# POLL

What's your level of experience with Deep Learning?

- Minimal
- Some theory
- Some theory and code
- Lots of theory and code

# POLL

Use of accompanying Jupyter notebooks for interactive demos and in-training exercises?

- Running them on Unix/Linux
- Running them on Mac
- Running them on Windows
- Viewing only, e.g., on GitHub
- Other

untapt

# Deep Learning Fundamentals

1. The Unreasonable Effectiveness of Deep Learning
2. Deep Learning with Keras
3. Introduction to TensorFlow
4. Deep Learning with TensorFlow

# Deep Learning Fundamentals

- 1. The Unreasonable Effectiveness of Deep Learning**
  - Intro to Neural Networks and Deep Learning
  - The Deep Learning Families and Libraries
  - Learning with Artificial Neurons
  - TensorFlow Playground
2. Deep Learning with Keras
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## Deep Learning with TensorFlow: Applications of Deep Neural Networks to Machine Learning Tasks

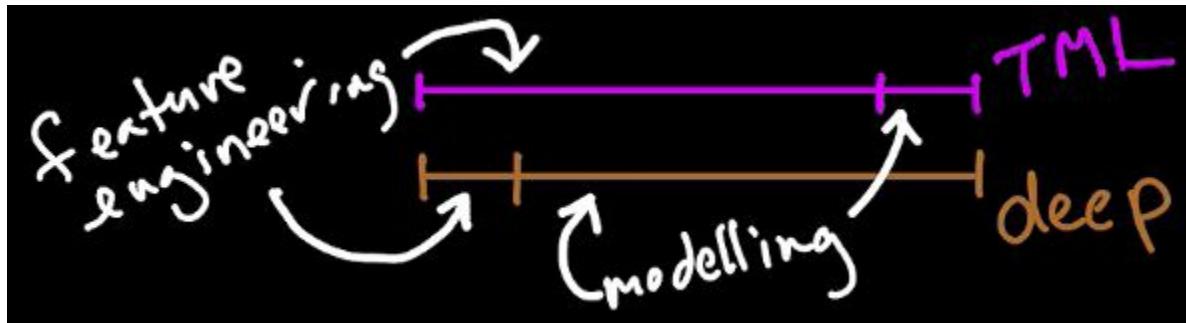
- [github.com/  
the-deep-learners/  
TensorFlow-LiveLessons](https://github.com/the-deep-learners/TensorFlow-LiveLessons)

Search *Deep Learning with TensorFlow* or *Jon Krohn* in Safari

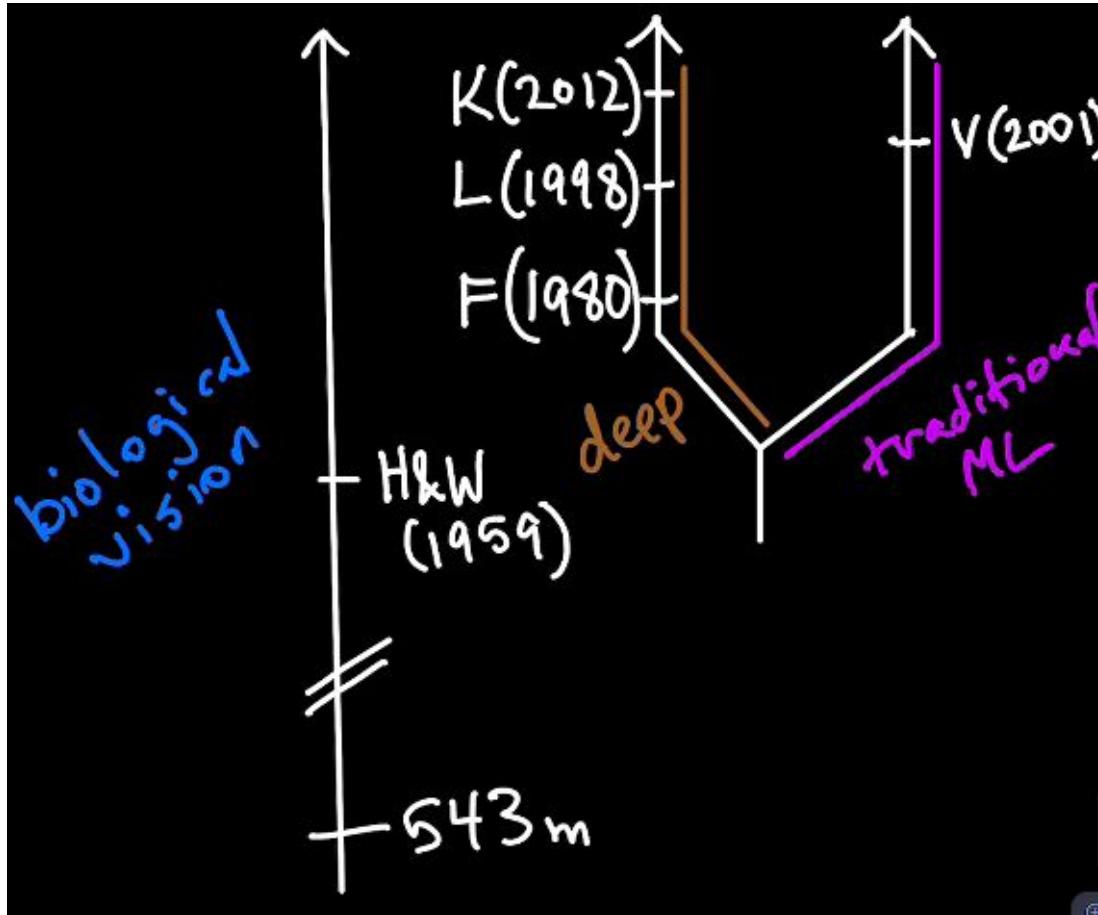
# Deep Learning Fundamentals

1. **The Unreasonable Effectiveness of Deep Learning**
  - **Intro to Neural Networks and Deep Learning**  
*(reference LiveLessons section 1.1)*
    - The Deep Learning Families and Libraries
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# Traditional ML vs Deep Learning

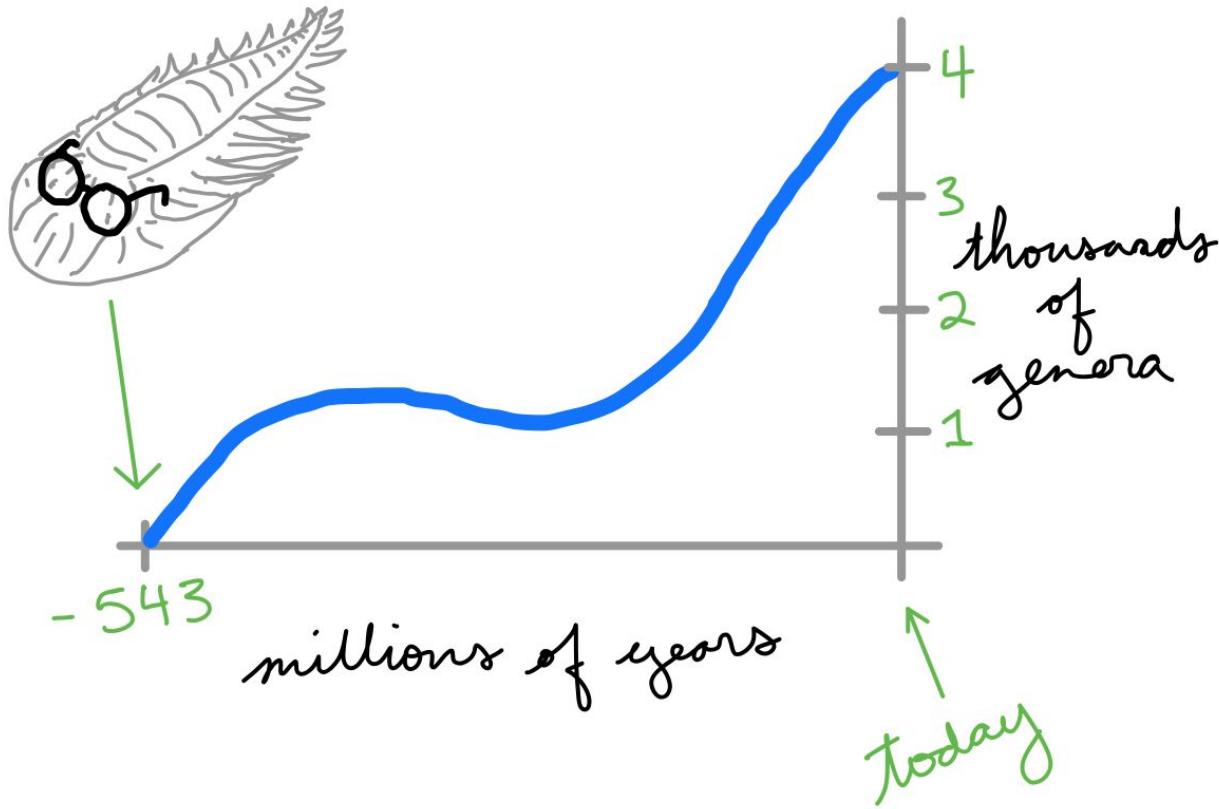


# Case Study: The History of Vision

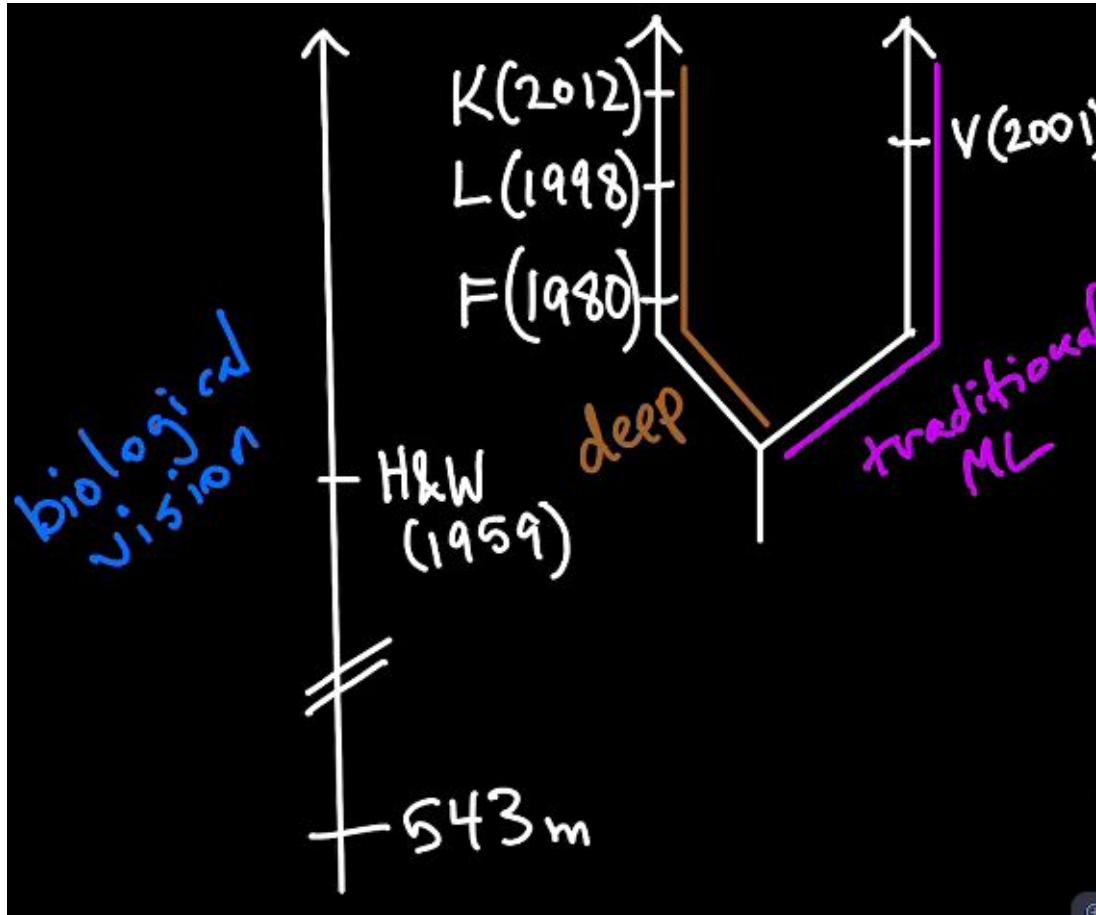






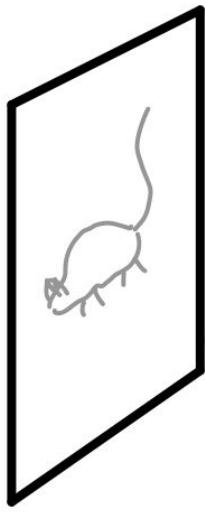


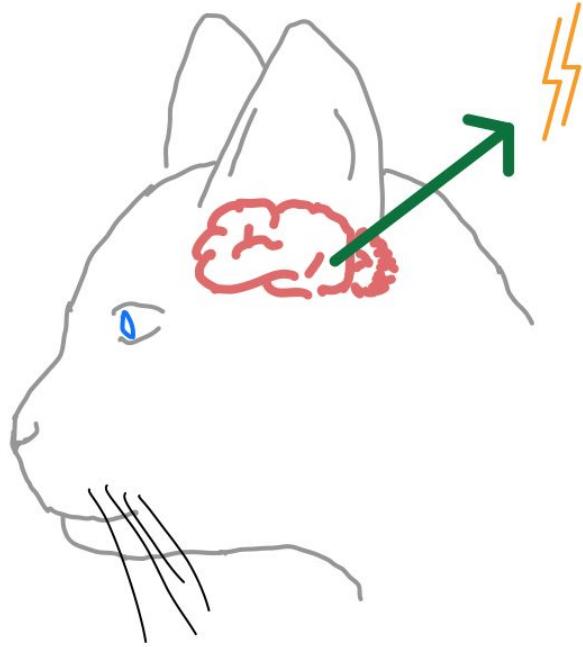
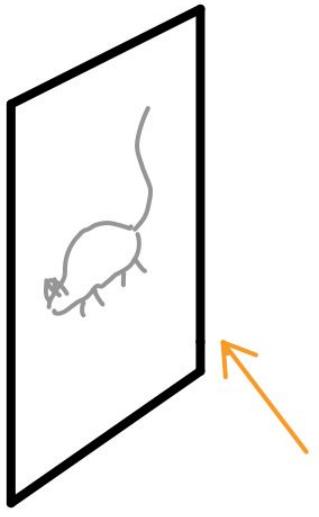
# Case Study: The History of Vision

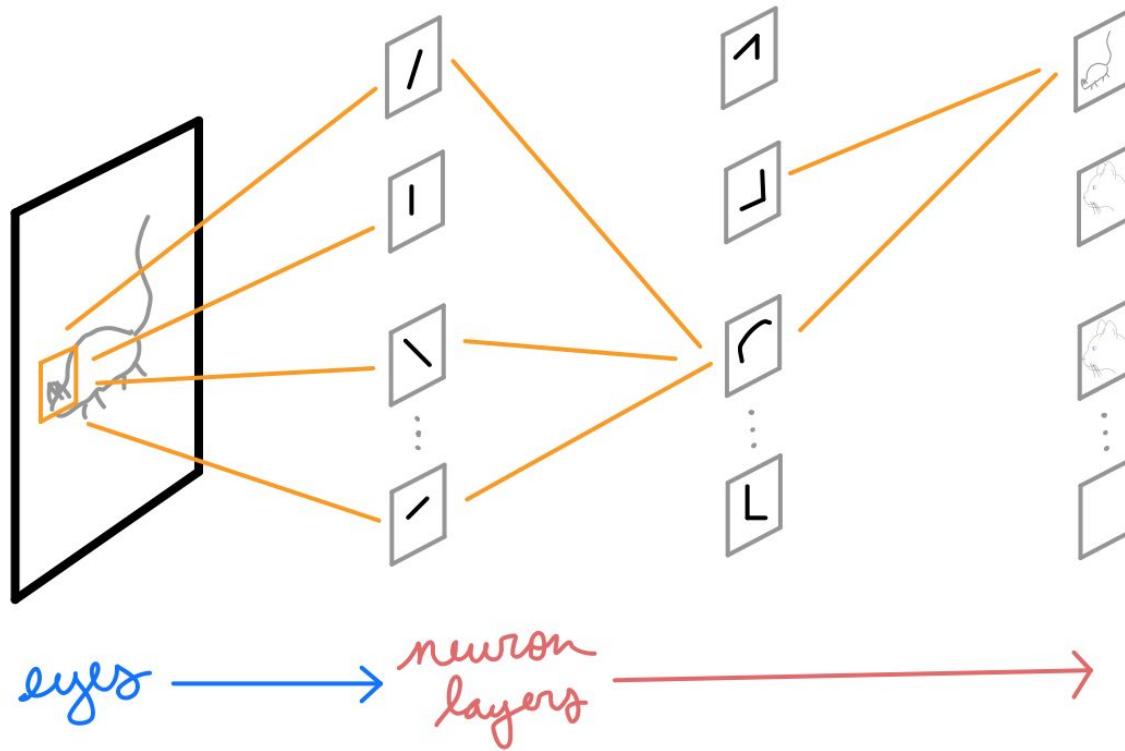




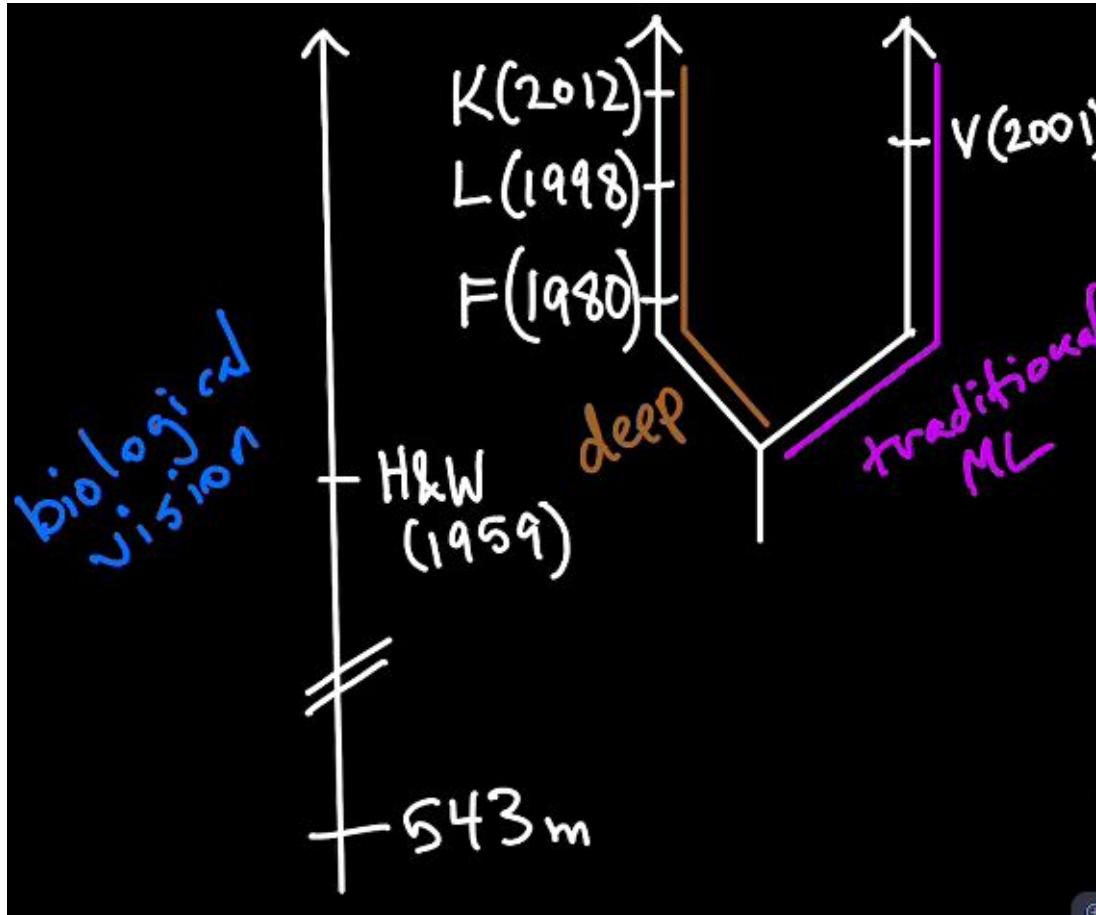








# Case Study: The History of Vision



# Neurocognitron (Fukushima, 1980)

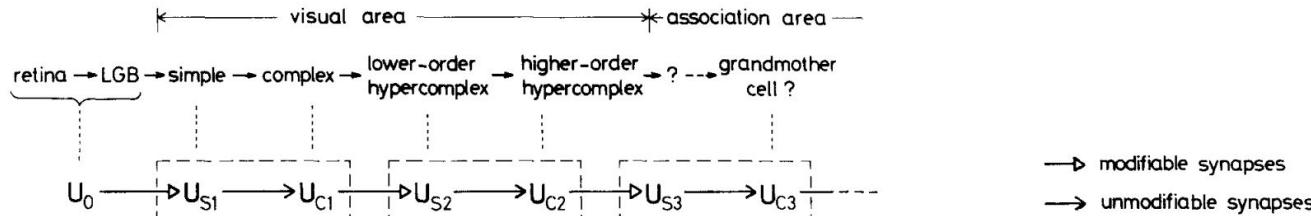


Fig. 1. Correspondence between the hierarchy model by Hubel and Wiesel, and the neural network of the neocognitron

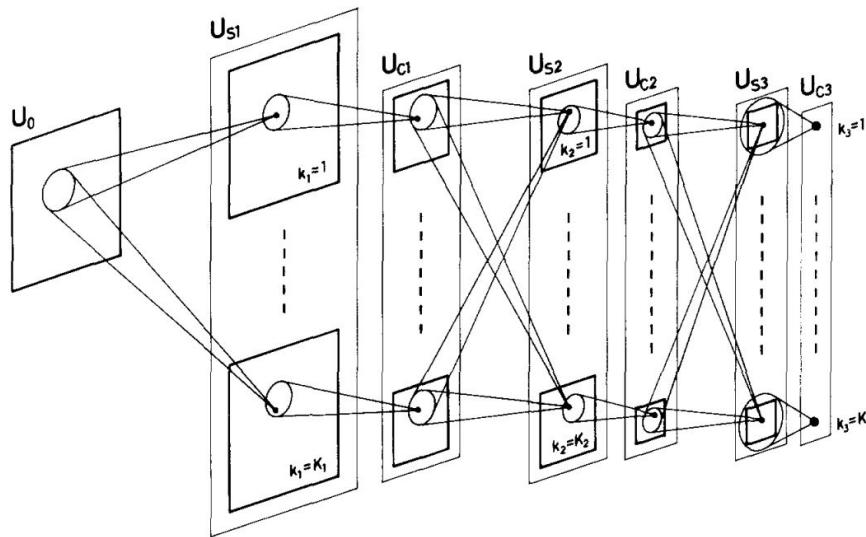
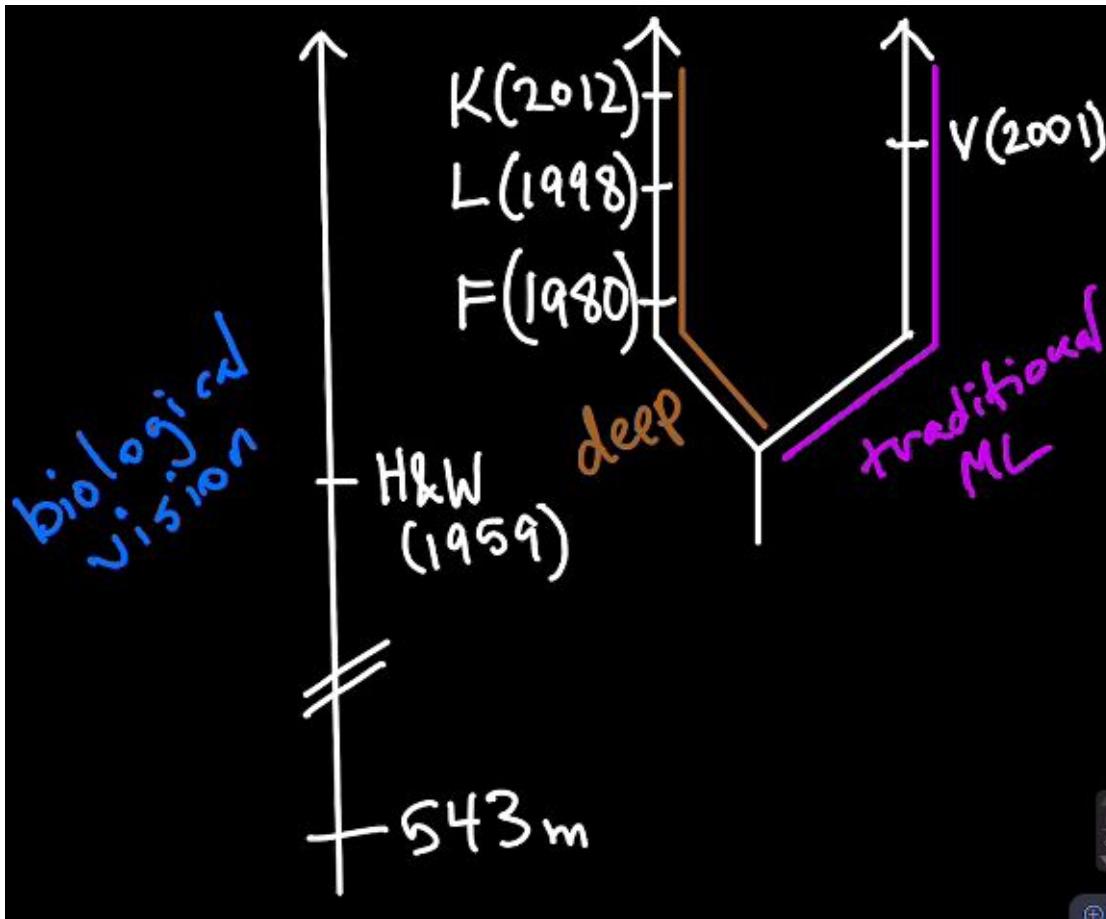
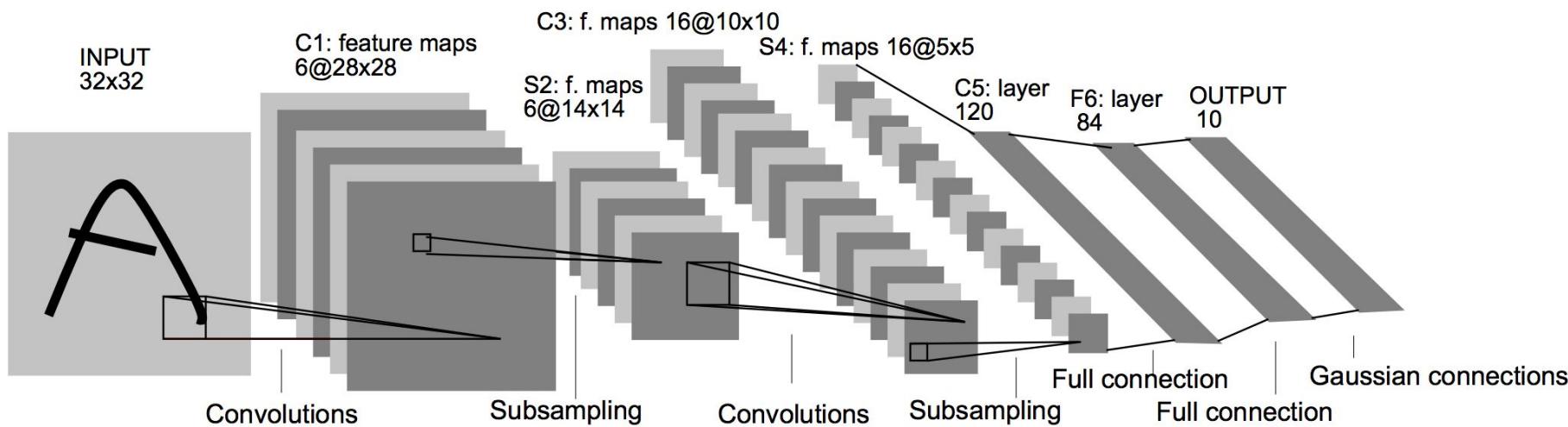
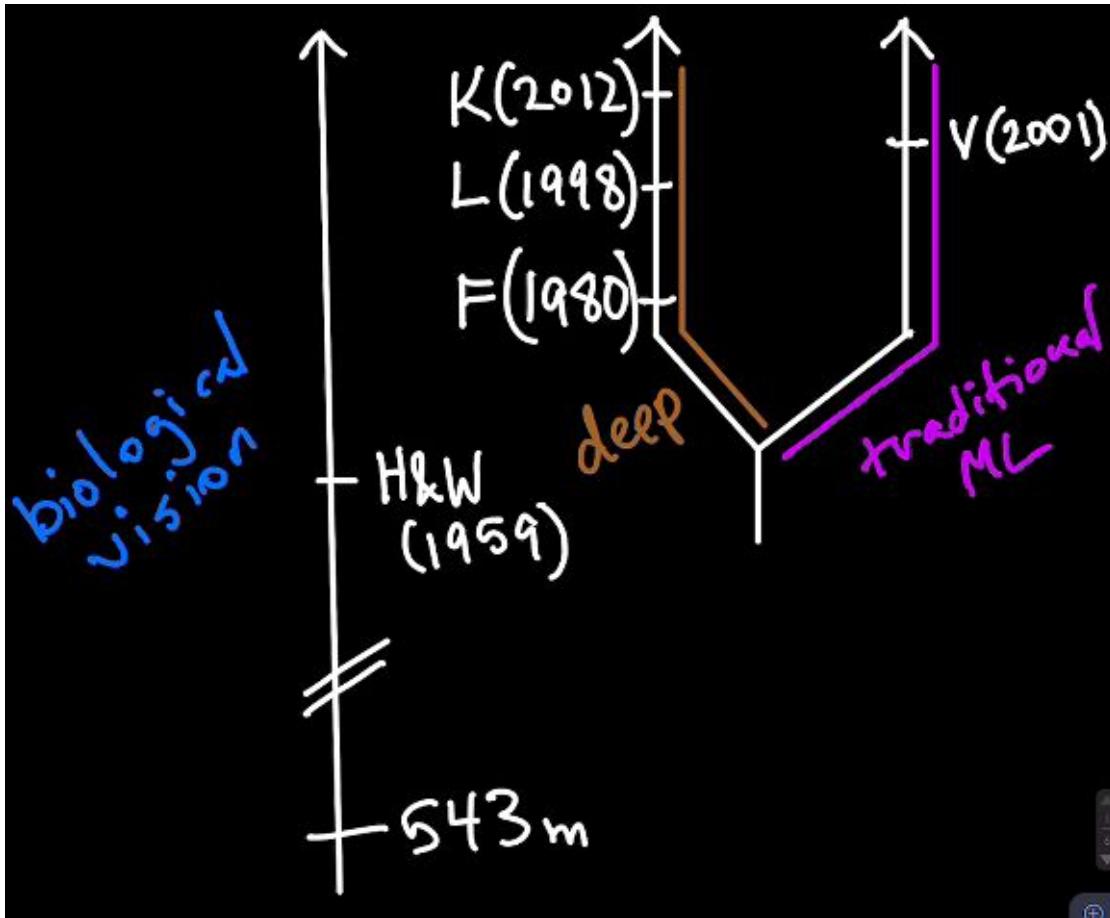


Fig. 2. Schematic diagram illustrating the interconnections between layers in the neocognitron

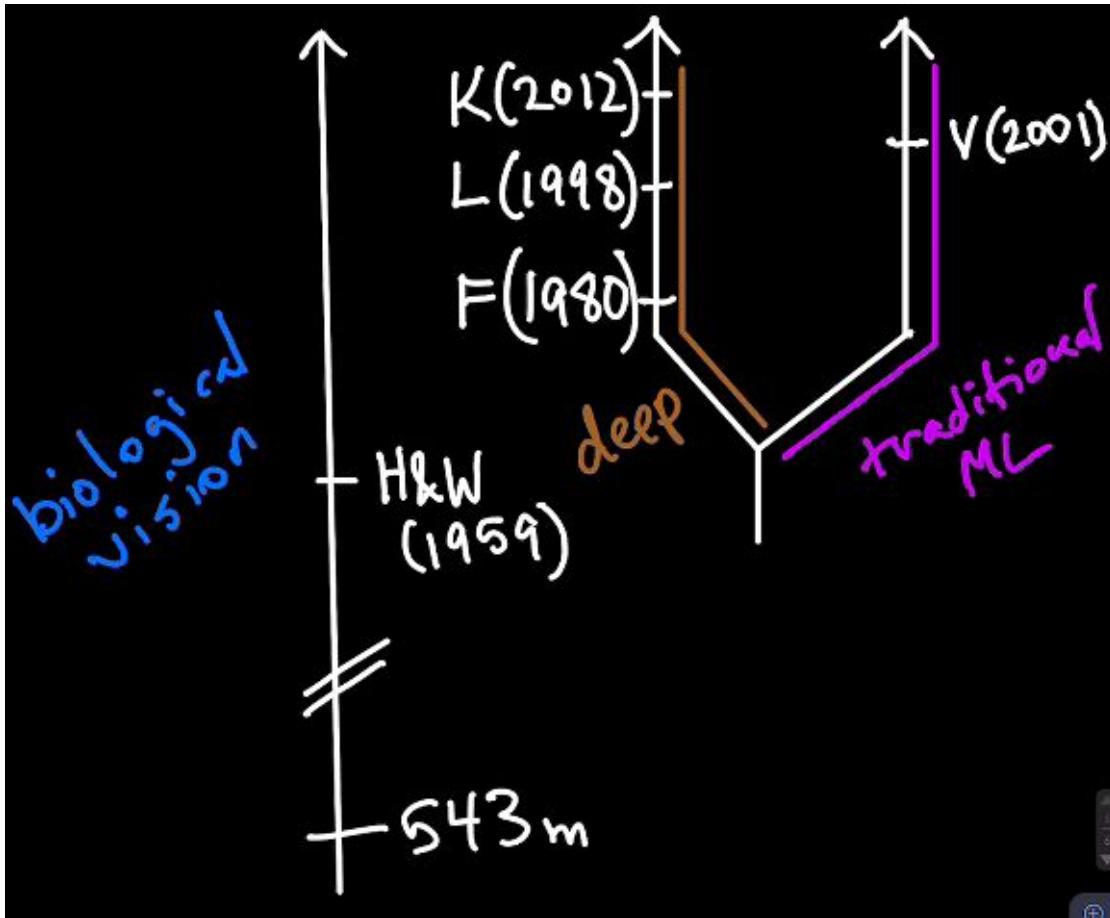


# LeNet-5 (LeCun et al., 1998)

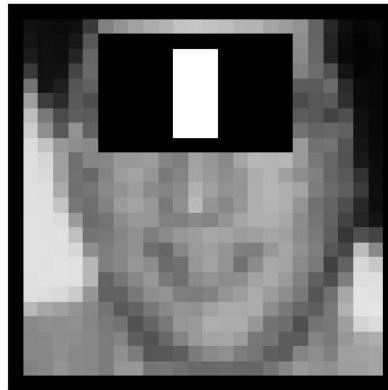
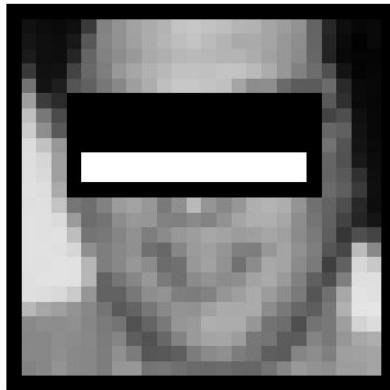
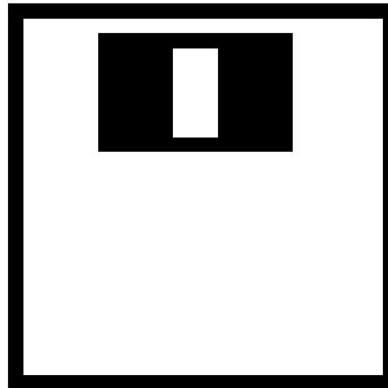
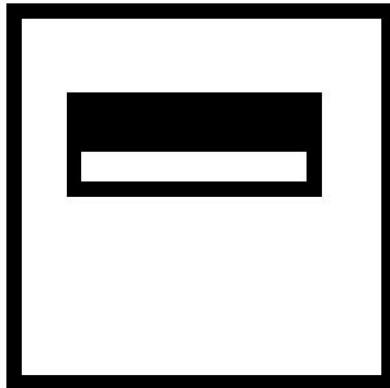


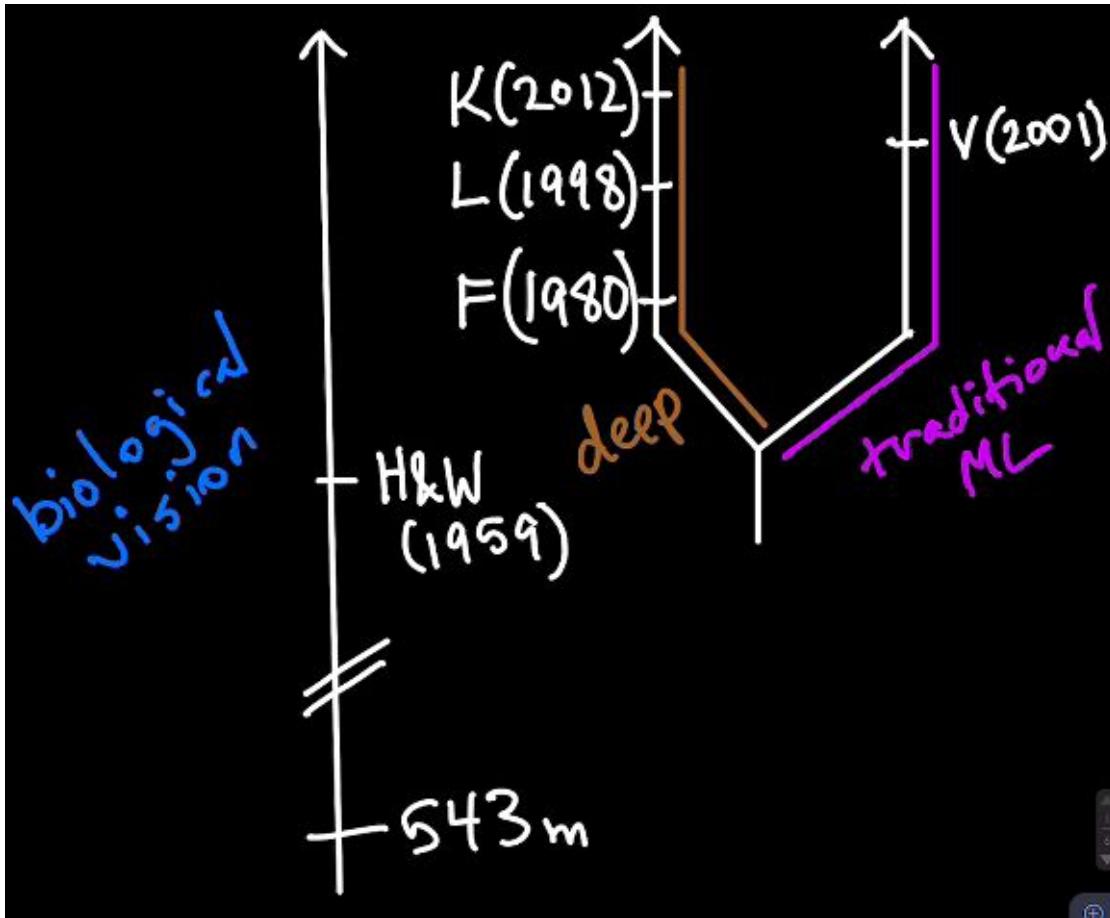




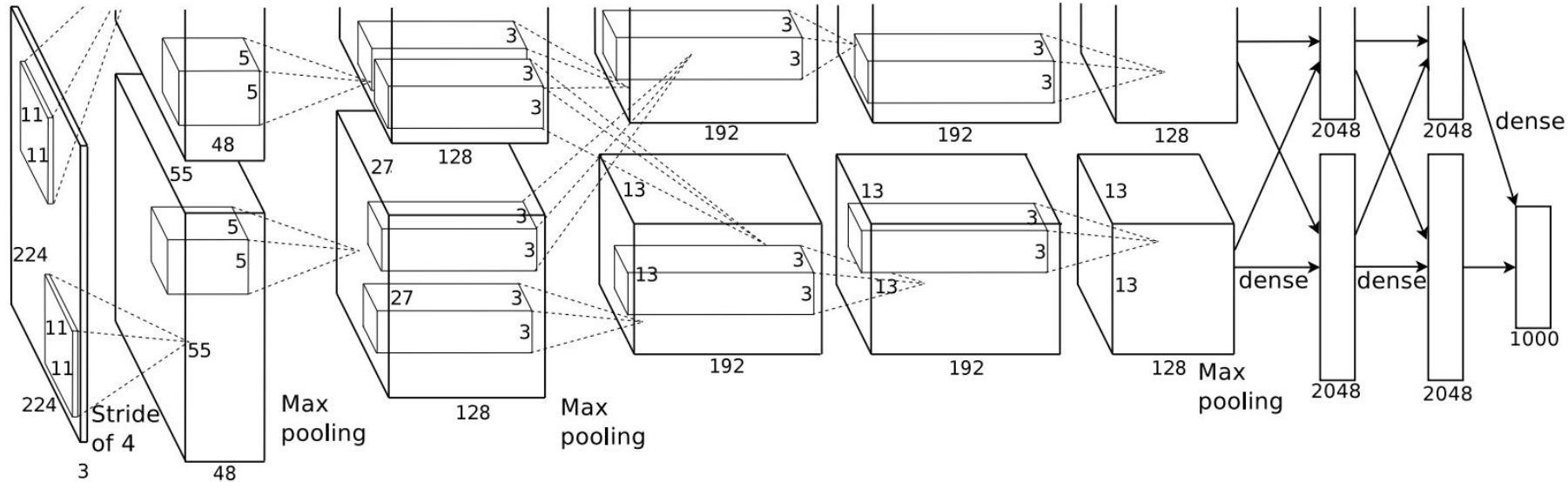


# Viola & Jones (2001)





# AlexNet (Krizhevsky et al., 2012)



# POLL

If a voice recognition algorithm is fed audio of speech as inputs, given corresponding text as the outputs (labels) to learn, and no features are explicitly programmed, is this a:

- Traditional Machine Learning Algorithm
- Deep Learning Algorithm
- I Don't Know

# Deep Learning Fundamentals

## 1. The Unreasonable Effectiveness of Deep Learning

- Intro to Neural Networks and Deep Learning
- **The Deep Learning Families and Libraries**  
*(reference LiveLessons sections 2.1 & 4.1)*
- Learning with Artificial Neurons
- TensorFlow Playground

2. Deep Learning with Keras

3. Introduction to TensorFlow

4. Deep Learning with TensorFlow

# Dense Networks



# ConvNets: Convolutional Networks



# RNNs: Recurrent Neural Networks



# Deep Reinforcement Learning



# GANs: Generative Adversarial Networks



# POLL

If you were designing an algorithm to learn to play Tetris by maximizing its score, which of these Deep Learning approaches would be most appropriate?

- Convolutional Neural Network
- Recurrent Neural Network
- Deep Reinforcement Learning
- Generative Adversarial Network

# POLL

If you were designing an algorithm to recognise tumours in medical images, which of these Deep Learning approaches would be most appropriate?

- Convolutional Neural Network
- Recurrent Neural Network
- Deep Reinforcement Learning
- Generative Adversarial Network

# POLL

If you were designing an algorithm to predict stock price movements based on time series data, which of these Deep Learning approaches would be most appropriate?

- Convolutional Neural Network
- Recurrent Neural Network
- Deep Reinforcement Learning
- Generative Adversarial Network

# Leading Deep Learning Libraries

	Caffe	Torch	MXNet	TensorFlow
<i>Language</i>	Python, Matlab	Lua, C	Python, R, C++ Julia, Matlab JavaScript, Go Scala, Perl	Python, R, C++ C, Java, Go
<i>Programming Style</i>	Symbolic	Imperative	Imperative	Symbolic
<i>Parallel GPUs: Data</i>	Yes	Yes	Yes	Yes
<i>Parallel GPUs: Model</i>		Yes	Yes	Yes
<i>Pre-Trained Models</i>	Model Zoo	ModelZoo	Model Zoo	<a href="https://github.com/tensorflow/models">github.com/tensorflow/models</a>
<i>For RNNs</i>				Best
<i>High-Level APIs</i>		PyTorch	in-built	Keras, TFLearn

# Deep Learning Fundamentals

## 1. The Unreasonable Effectiveness of Deep Learning

- Intro to Neural Networks and Deep Learning
- The Deep Learning Families and Libraries
- **Learning with Artificial Neurons (reference  
*LiveLessons sections 2.2, 2.3 & 3.1*)**
- **TensorFlow Playground (2.4)**

2. Deep Learning with Keras
3. Introduction to TensorFlow
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# Your Arsenal

## Neurons

- sigmoid
- tanh
- ReLU

# Your Arsenal

## Neurons

- sigmoid
- tanh
- ReLU

## Cost Functions

- quadratic cost

$$\sum_i (y_i - \hat{y}_i)^2$$

# Your Arsenal

## Neurons

- sigmoid
- tanh
- ReLU

## Cost Functions

- quadratic cost
- cross-entropy

# Your Arsenal

## Neurons

- sigmoid
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## Cost Functions

- quadratic cost
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## Gradient Descent

# Your Arsenal

## Neurons

- sigmoid
- tanh
- ReLU

## Cost Functions

- quadratic cost
- cross-entropy

## Gradient Descent

## Backpropagation

# Your Arsenal

## Neurons

- sigmoid
- tanh
- ReLU

## Cost Functions

- quadratic cost
- cross-entropy

## Gradient Descent

## Backpropagation

## Layers

- dense
- softmax

# Your Arsenal

## Neurons

- sigmoid
- tanh
- ReLU

## Initialization

- Glorot normal
- Glorot uniform

## Cost Functions

- quadratic cost
- cross-entropy

## Gradient Descent

## Backpropagation

## Layers

- dense
- softmax

# Your Arsenal

## Neurons

- sigmoid
- tanh
- ReLU

## Cost Functions

- quadratic cost
- cross-entropy

## Stochastic Gradient Descent

- mini-batch size
- learning rate
- second-order, e.g., Adam

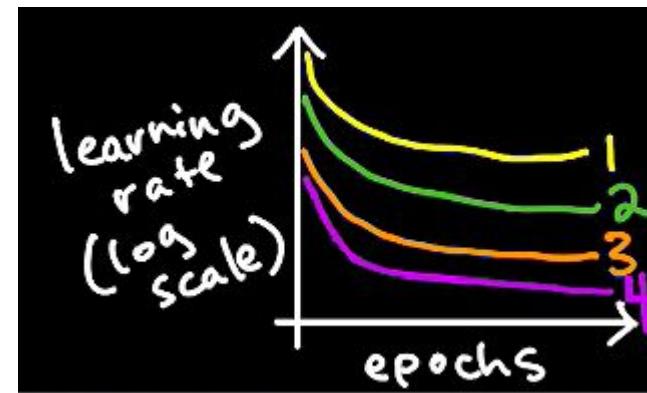
## Backpropagation

## Initialization

- Glorot normal
- Glorot uniform

## Layers

- dense
- softmax



# Your Arsenal

## Neurons

- sigmoid
- tanh
- ReLU

## Cost Functions

- quadratic cost
- cross-entropy

## *Stochastic Gradient Descent*

- mini-batch size
- learning rate
- second-order, e.g., Adam

## Backpropagation

## Initialization

- Glorot normal
- Glorot uniform

## Layers

- dense
- softmax

## Avoiding Overfitting

- L1/L2 Regularization
- Dropout
- Data Expansion

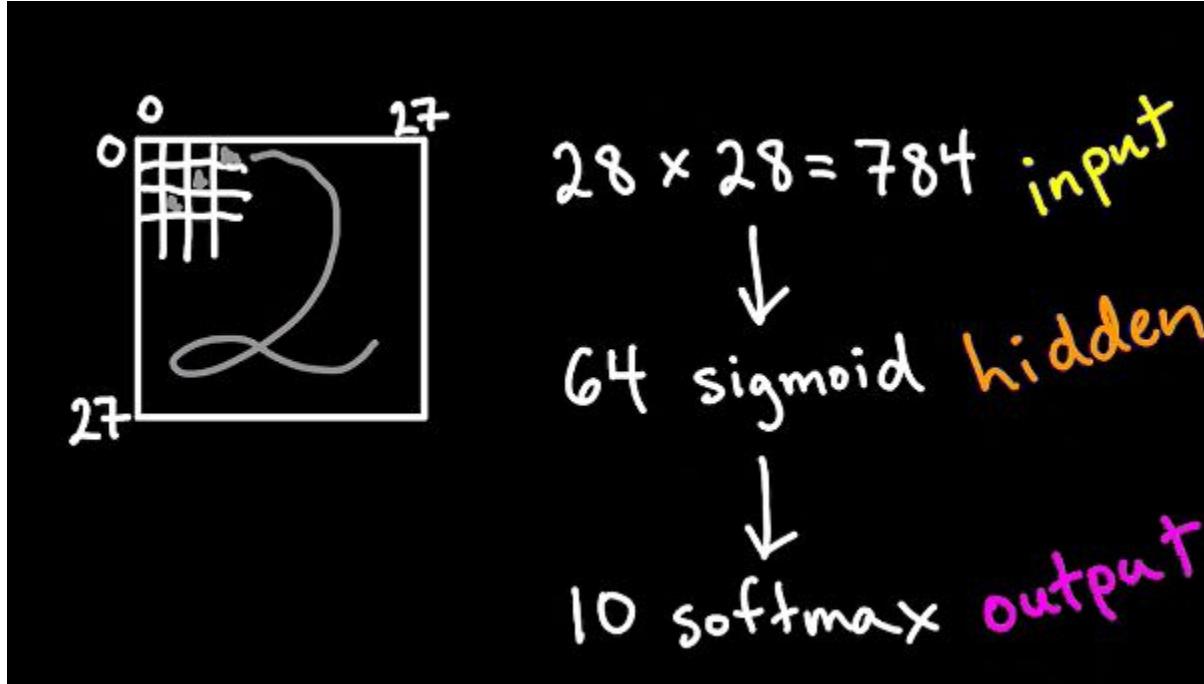
# Deep Learning Fundamentals

1. The Unreasonable Effectiveness of Deep Learning
2. **Deep Learning with Keras**
  - **Shallow Neural Networks**
  - **Deep Neural Networks**
  - **How to Build Your Own Project**
3. Introduction to TensorFlow
4. Deep Learning with TensorFlow

# Deep Learning Fundamentals

1. The Unreasonable Effectiveness of Deep Learning
2. **Deep Learning with Keras**
  - **Shallow Neural Networks** (*LiveLessons 1.3 & 2.5*)
  - Deep Neural Networks
  - How to Build Your Own Project
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# MNIST Digits



# Deep Learning Fundamentals

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  - Shallow Neural Networks
  - Deep Neural Networks (*LiveLessons section 3.2*)
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# Deep Learning Fundamentals

1. The Unreasonable Effectiveness of Deep Learning
- 2. Deep Learning with Keras**
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  - Deep Neural Networks
  - How to Build Your Own Project (*LiveLessons 5.1 & 5.2*)
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# How to Build Your Own DL Project

1. Define Task
2. Define Data Set
3. Define Metric
4. Split Data
5. Establish Baseline
6. Implement Existing
7. Improve...

# Tuning Hyperparameters

1. Get Above Chance
2. Experiment with Layers (Count, Variety)
3. Glorot Initialization
4. Choose Cost Function
5. Avoid Overfitting
6. Vary Learning Rate
7. Epochs
8. Regularization  $\lambda$
9. Batch Size
10. Automation

# Deep Learning Fundamentals

1. The Unreasonable Effectiveness of Deep Learning
2. Deep Learning with Keras
- 3. Introduction to TensorFlow**
  - **TensorFlow Graphs**
  - **Neurons in TensorFlow**
4. Deep Learning with TensorFlow

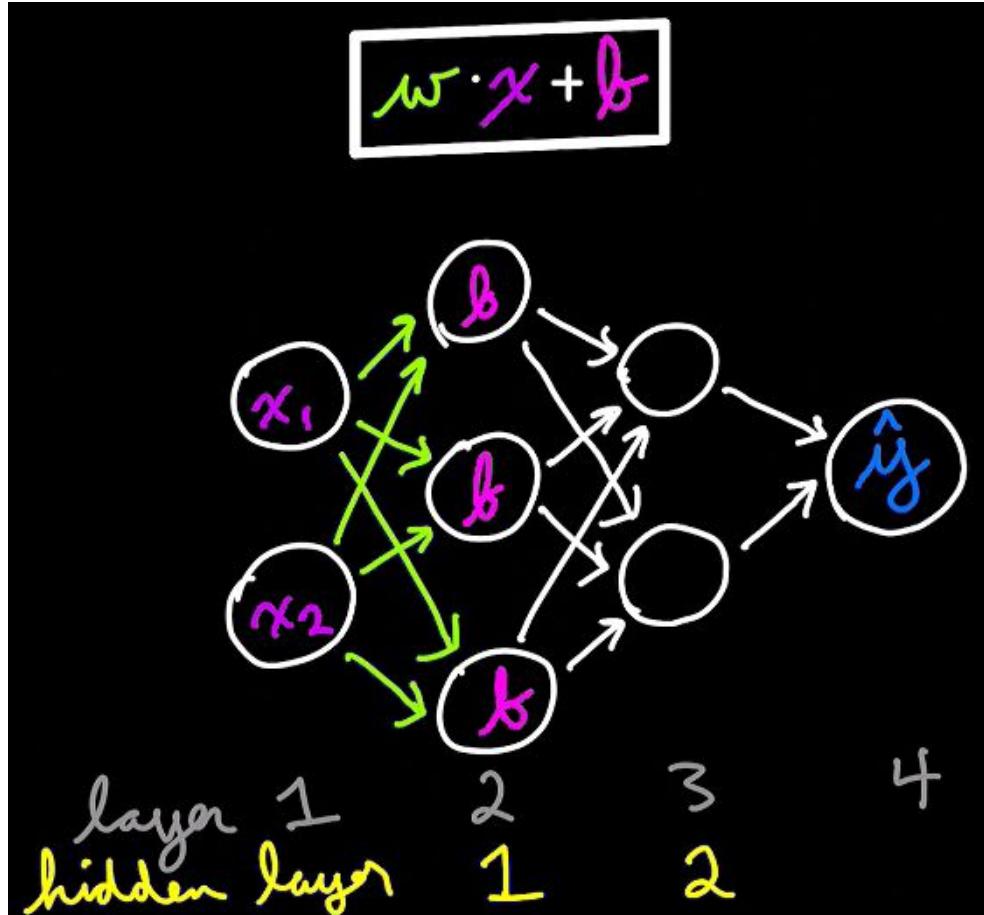
# Deep Learning Fundamentals

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  - **TensorFlow Graphs** (*LiveLessons section 4.2*)
  - Neurons in TensorFlow
4. Deep Learning with TensorFlow

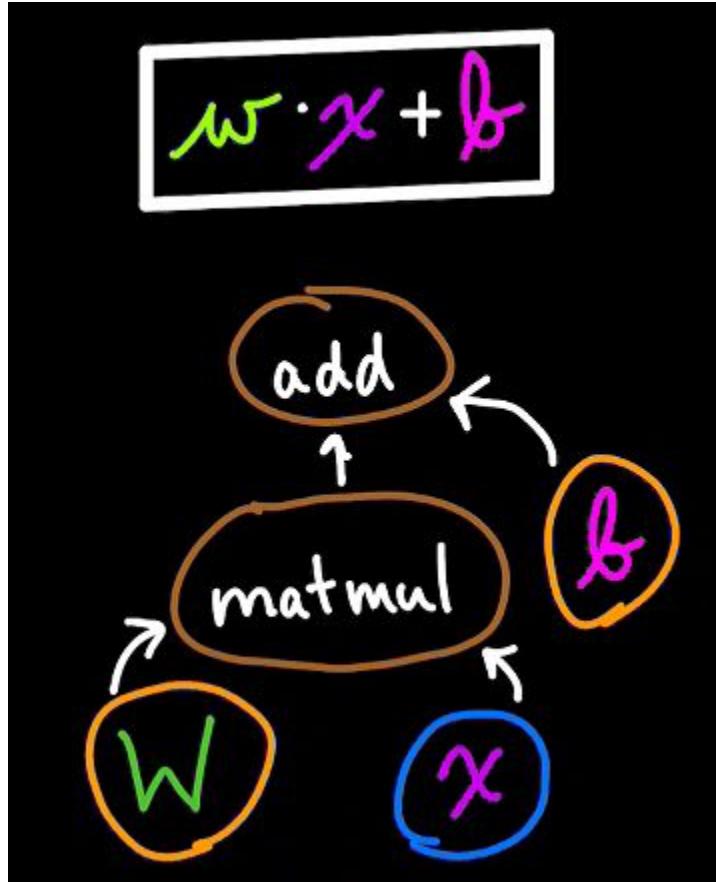
# TensorFlow Graphs

1. build graph
2. initialize session
3. fetch and feed data

# A Familiar Equation



# TensorFlow Graphs



# POLL

in a TensorFlow graph, the calculation of a mean is best associated with:

- an operation
- a Variable tensor
- a placeholder tensor

# POLL

in a TensorFlow graph, the labels we're predicting with our model are best associated with:

- an operation
- a Variable tensor
- a placeholder tensor

# POLL

in a TensorFlow graph, the slope of a regression line is best associated with:

- an operation
- a Variable tensor
- a placeholder tensor

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  - TensorFlow Graphs
  - **Neurons in TensorFlow** (*LiveLessons section 4.2*)
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- 4. Deep Learning with TensorFlow**
  - Model-Fitting
  - Deep Neural Nets

# Deep Learning Fundamentals

1. The Unreasonable Effectiveness of Deep Learning
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- 4. Deep Learning with TensorFlow**
  - **Model-Fitting** (*LiveLessons 4.3*)
  - Deep Neural Nets

# Deep Learning Fundamentals

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- 4. Deep Learning with TensorFlow**
  - Model-Fitting
  - **Deep Neural Nets (*LiveLessons 4.4*)**

# Sneak Peak at *LiveLessons* 3.5

## Design neural network architecture

```
In [4]: model = Sequential()

model.add(Conv2D(96, kernel_size=(11, 11), strides=(4, 4), activation='relu', input_shape=(224, 224, 3)))
model.add(MaxPooling2D(pool_size=(3, 3), strides=(2, 2)))
model.add(BatchNormalization())

model.add(Conv2D(256, kernel_size=(5, 5), activation='relu'))
model.add(MaxPooling2D(pool_size=(3, 3), strides=(2, 2)))
model.add(BatchNormalization())

model.add(Conv2D(256, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(384, kernel_size=(3, 3), activation='relu'))
model.add(Conv2D(384, kernel_size=(3, 3), activation='relu'))
model.add(MaxPooling2D(pool_size=(3, 3), strides=(2, 2)))
model.add(BatchNormalization())

model.add(Flatten())
model.add(Dense(4096, activation='tanh'))
model.add(Dropout(0.5))
model.add(Dense(4096, activation='tanh'))
model.add(Dropout(0.5))

model.add(Dense(17, activation='softmax'))
```

# Sneak Peak at *LiveLessons* 4.5

## Design neural network architecture

```
In [7]: def network(x, weights, biases, n_in, mp_psize, mp_dropout, dense_dropout):

    # reshape linear MNIST pixel input into square image:
    square_dimensions = int(np.sqrt(n_in))
    square_x = tf.reshape(x, shape=[-1, square_dimensions, square_dimensions, 1])

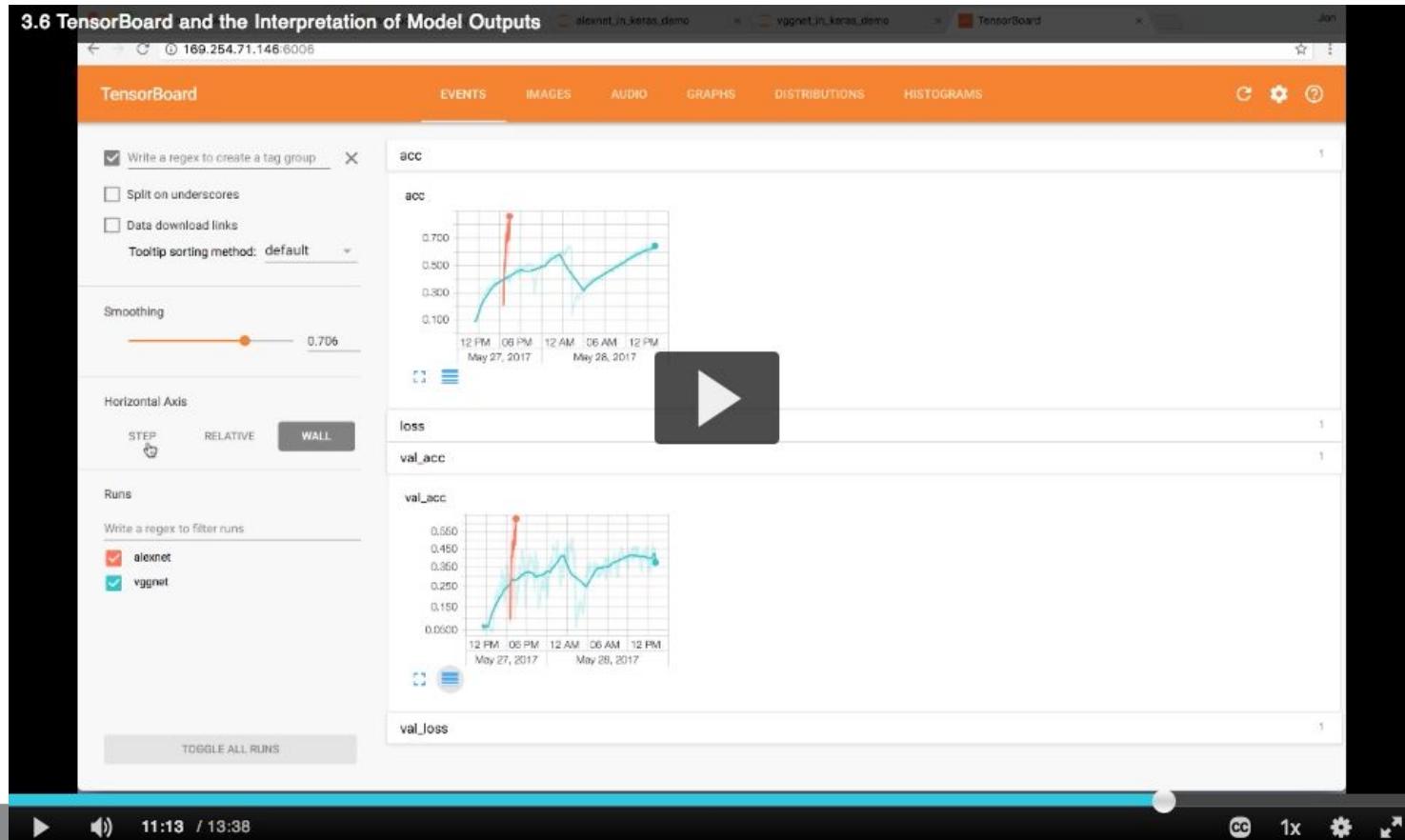
    # convolutional and max-pooling layers:
    conv_1 = conv2d(square_x, weights['W_c1'], biases['b_c1'])
    conv_2 = conv2d(conv_1, weights['W_c2'], biases['b_c2'])
    pool_1 = maxpooling2d(conv_2, mp_psize)
    pool_1 = tf.nn.dropout(pool_1, 1-mp_dropout)

    # dense layer:
    flat = tf.reshape(pool_1, [-1, weights['W_d1'].get_shape().as_list()[0]])
    dense_1 = dense(flat, weights['W_d1'], biases['b_d1'])
    dense_1 = tf.nn.dropout(dense_1, 1-dense_dropout)

    # output layer:
    out_layer_z = tf.add(tf.matmul(dense_1, weights['W_out']), biases['b_out'])

    return out_layer_z
```

# Sneak Peak at *LiveLessons* 3.6



# POLL

what's most useful for follow-up?

- CNNs and Machine Vision
- Sequences: RNNs, LSTMs, NLP, Financial Time Series
- Generative Adversarial Networks
- Reinforcement Learning
- TensorBoard
- more detail on fundamental theory
- Something Else

## Deep Learning for Natural Language Processing



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 Pearson

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