

02 | Building Blocks of Deep Learning



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Background for Deep Learning

- Review of multi-class distributions
- Tensors for deep learning
- Basics of image data
- Introduction to Keras

Review of Binary Classification

Bernoulli distribution for probability of success

Observation: $\nu = 1$:

$$p(\nu = 1) = \Theta$$

where

$\nu = \text{an observation}$

$\Theta = \text{probability parameter}$

Review of Binary Classification

We extend the Bernoulli distribution for multiple trials with the **Binomial distribution** for k successes in n trials:

$$p(\nu = k \mid \Theta) = \binom{n}{k} \Theta^k (1 - \Theta)^{n-k}$$

Where the Binomial coefficient, pronounced n choose k is:

$$\binom{n}{k}$$

Review of Binary Classification

How do perform classification with the Bernoulli distribution?

Use the **logistic** or **sigmoid** function

$$\sigma(x) = \frac{L}{1 + e^{-k(x_0 - x)}}$$

where

L = max value

k = slope

x₀ = sigmoid midpoint

Review of Binary Classification

Simplify the logistic function if $k = 1$, $L = 1$ and $x_0 = 0$:

$$\sigma(x) = \frac{1}{1 + e^{-x}} = \frac{e^x}{1 + e^x}$$

Classification with the Categorical Distribution

- What are the distribution for multi-class problem?
- Use the **Categorical distribution** with probability mass function:

$$p(x = i \mid \boldsymbol{\theta}) = \theta_i$$

Where:

$$\boldsymbol{\theta} = (\theta_1, \dots, \theta_k)$$

And:

$$\sum_{i=1}^k \theta_i = 1.0$$

Classification with the Categorical Distribution

- How do we create a categorical classifier?
- Use a softmax function:

$$\sigma(z_i) = \frac{e^{z_i}}{\sum_{k=1}^K e^{z_k}}$$

The normalization, $\sum_{k=1}^K e^{z_k}$, ensures the probabilities sum to 1.0

Classification with the Categorical Distribution

- What is the output of softmax?
- One value for each category
 - For example, if we have 10 categories, there are 10 output values
 - Take the max as the most probable category
- Label must be one-hot encoded
 - Binary value for each possible category
 - Only one 1, others 0

Tensors for Deep Learning

For deep learning models we need a way to represent high dimensional values

- Input data
- Model parameters
- Transformations
- Output

Tensors are a generalization of multi-dimensional arrays

Not to be confused with tensors in physics and engineering

Tensors for Deep Learning

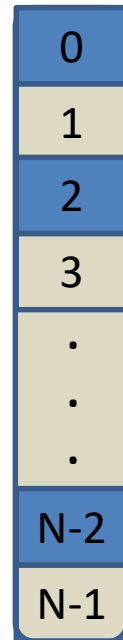
Zero dimensional tensor = scalar



0

Tensors for Deep Learning

One dimensional tensor = vector



Tensors for Deep Learning

Two dimensional tensor = matrix

0,0	0,1	...	0,M-1
1,0	1,1	...	1,M-1
2,0	2,1	...	2,M-1
3,0	3,1	...	3,M-1
.	.	.	.
.	.	.	.
.	.	.	.
N-2,0	N-2,1	...	N-2,M-1
N-1,0	N-1,1	...	N-1,M-1

Working with Image Data

Deep learning has revolutionized image analysis and understanding

Common types of image data:

- Grey scale
- Color images
- Color video

Image data is represented by tensors

Working with Image Data

A grey scale image is represented as a two dimensional tensor of pixel values

0,0	0,1	...	0,M-1
1,0	1,1	...	1,M-1
2,0	2,1	...	2,M-1
3,0	3,1	...	3,M-1
.	.	.	.
.	.	.	.
.	.	.	.
N-2,0	N-2,1	...	N-2,M-1
N-1,0	N-1,1	...	N-1,M-1

Pixel values have range {0-255}; white-black

Working with Image Data

A color image is a 3-dimensional tensor representing the three color channels

Red			Green		Blue
0 ,0,0	0 ,1,0	...	0 ,M-1,0	0 ,M-1,1	0 ,M-1,2
1 ,0,0	1 ,1,0	...	1 ,M-1,0	1 ,M-1,1	1 ,M-1,2
2 ,0,0	2 ,1,0	...	2 ,M-1,0	2 ,M-1,1	2 ,M-1,2
3 ,0,0	3 ,1,0	...	3 ,M-1,0	3 ,M-1,1	3 ,M-1,2
.
.
.
N-2 ,0,0	N-2 ,1,0	...	N-2 ,M-1,0	N-2 ,M-1,1	N-2 ,M-1,2
N-1,0,0	N-1,1,0	...	N-1,M-1,0	N-1,M-1,1	N-1,M-1,2
	N-1,0,1	N-1,1,1	...	N-1,M-1,1	N-1,M-1,2
		N-1,0,2	N-1,1,2	...	N-1,M-1,2

Intensity of color in each channel is on a scale of {0-255}

Working with Image Data

Video is represented as a 4-dimensional tensor

- 2 dimensions for each color channel
- 3rd dimension is color channel
- 4th dimension is the time sequence of images

Working with Image Data

Machine learning algorithms use one data sample at a time

For image data, we must **flatten** the image:

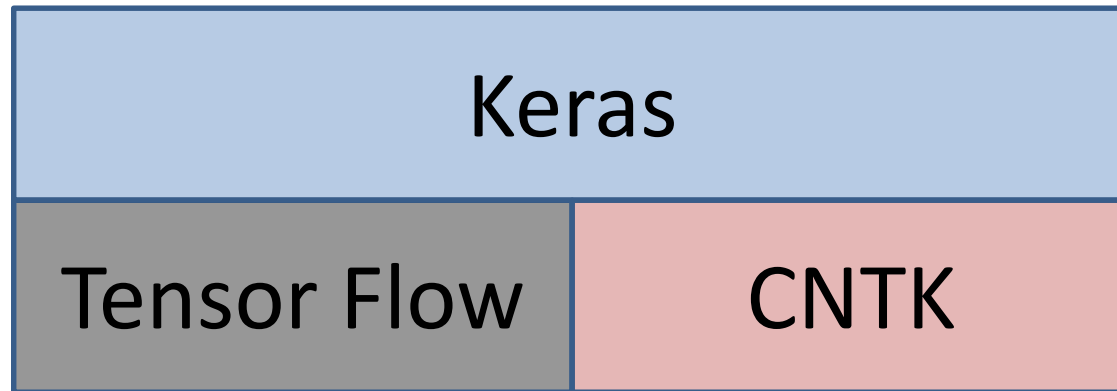
0,0	0,1	...	0,M-1
1,0	1,1	...	1,M-1
2,0	2,1	...	2,M-1
3,0	3,1	...	3,M-1
.			.
.			.
.			.
N-2,0	N-2,1	...	N-2,M-1
N-1,0	N-1,1	...	N-1,M-1

Flatten

0,0
1,0
.
.
.
N-2,0
N-1,0
.
.
.
0,M-1
1,M-1
.
.
.
N-2,M-1
N-1,M-1

Introduction to Keras

- Keras abstracts common deep learning model definitions and operations
- Use on top of deep learning framework:



- Extensive documentation at www.keras.io



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