

The background features several decorative curved lines in white and red, scattered across the dark gray field. Some lines are thin and white, while others are thicker and red, creating a modern, abstract aesthetic.

Insper

Computer Vision

# **Class 12: The Simplicity and Power of Non-Linearity**

## Dense layer as affine transformation:

matrix multiplication and array addition

$$\begin{array}{ccccccc} \begin{array}{|c|} \hline \alpha_{0,0} & \alpha_{0,1} & \alpha_{0,2} & \cdots \\ \hline \end{array} & \begin{array}{|c|} \hline \alpha_{1,0} & \alpha_{1,1} & \alpha_{1,2} & \cdots \\ \hline \end{array} & \begin{array}{|c|} \hline \alpha_{2,0} & \alpha_{2,1} & \alpha_{2,2} & \cdots \\ \hline \end{array} & \vdots & \cdot & \begin{array}{|c|} \hline x_0 \\ x_1 \\ x_2 \\ \vdots \\ x_{n-1} \\ \hline \end{array} & + & \begin{array}{|c|} \hline \beta_0 \\ \beta_1 \\ \beta_2 \\ \vdots \\ \beta_{n-1} \\ \hline \end{array} & = & \begin{array}{|c|} \hline y_0 \\ y_1 \\ y_2 \\ \vdots \\ y_{n-1} \\ \hline \end{array} \\ A & & & & & x & & b & & y \end{array}$$

# Affine transformation as linear transformation:

matrix multiplication

$$\begin{bmatrix}
 \alpha_{0,0} & \alpha_{0,1} & \alpha_{0,2} & \cdots & \beta_0 \\
 \alpha_{1,0} & \alpha_{1,1} & \alpha_{1,2} & \cdots & \beta_1 \\
 \alpha_{2,0} & \alpha_{2,1} & \alpha_{2,2} & \cdots & \beta_2 \\
 \vdots & \vdots & \vdots & \ddots & \vdots \\
 \alpha_{n-1,0} & \alpha_{n-1,1} & \alpha_{n-1,2} & \cdots & \beta_{n-1}
 \end{bmatrix}
 \cdot
 \begin{bmatrix}
 x_0 \\
 x_1 \\
 x_2 \\
 \vdots \\
 x_{n-1} \\
 1
 \end{bmatrix}
 =
 \begin{bmatrix}
 y_0 \\
 y_1 \\
 y_2 \\
 \vdots \\
 y_{n-1}
 \end{bmatrix}$$

# Linear transformations

A function  $f$  is *linear* if...

- $f(\mathbf{x}_1 + \mathbf{x}_2) = f(\mathbf{x}_1) + f(\mathbf{x}_2)$ ; (*additivity*)
- $f(\lambda \mathbf{x}) = \lambda f(\mathbf{x})$  (*homogeneity*)

...and this is true if there exists a matrix  $M$  such that  $f(\mathbf{x}) = M\mathbf{x}$ .

## Example (Class 3)

The gray level conversion  $f(c) = 0.299 c_r + 0.587 c_g + 0.114 c_b$  is linear:

- $$\begin{aligned} f(c + d) &= (0.299 (c_r + d_r) + 0.587 (c_g + d_g) + 0.114 (c_b + d_b)) \\ &= (0.299 c_r + 0.587 c_g + 0.114 c_b) + (0.299 d_r + 0.587 d_g + 0.114 d_b) \\ &= f(c) + f(d); \end{aligned}$$
- $$\begin{aligned} f(\lambda c) &= (0.299 \lambda c_r + 0.587 \lambda c_g + 0.114 \lambda c_b) \\ &= \lambda (0.299 c_r + 0.587 c_g + 0.114 c_b) \\ &= \lambda f(c). \end{aligned}$$

# Examples:

- gray level conversion; (*Class 3*)
- brightness adjustment; (*Class 4*)
- contrast adjustment; (*Class 4*)
- probability dark or bright; (*Class 5*)
- convolution; (*Classes 6-8*)
- geometric transformations. (*Class 10*)

# Counterexample *(Class 3)*

The HSV conversion, which uses  $f(c) = \max(c_r, c_g, c_b)$ , is **not** linear:

- $f((1, 2, 3) + (5, 3, 1)) = \max(1 + 5, 2 + 3, 3 + 1) = \max(6, 5, 4) = 6;$
- $f((1, 2, 3)) + f((5, 3, 1)) = \max(1, 2, 3) + \max(5, 3, 1) = 3 + 5 = 8.$

# Counterexamples:

- boolean dark or bright; (*Class 1*)
- template matching; (*Class 1*)
- HSL conversion; (*Class 3*)
- Harris-Stephens detector. (*Class 9*)



*Non-linearity can also give some alternatives to linear algorithms.*

*So let's revisit previous problems.*

## Gaussian noise:

variations are rarely extreme



## Impulse noise:

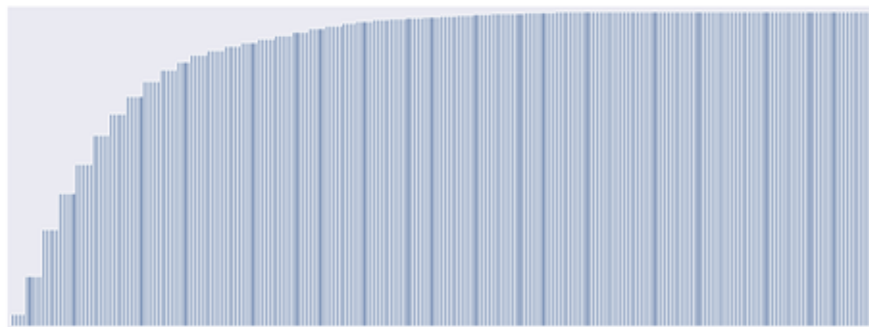
variations are always extreme



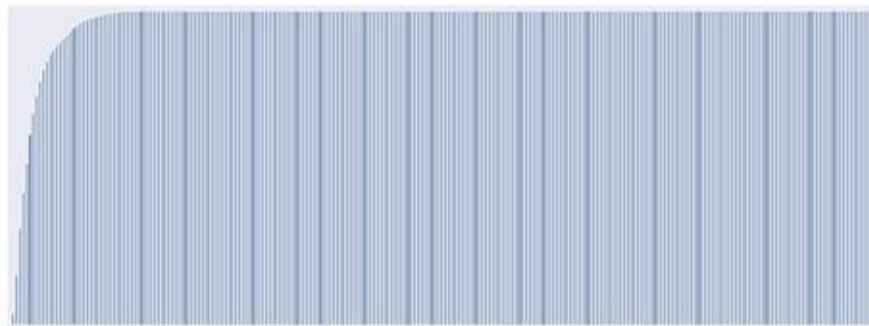




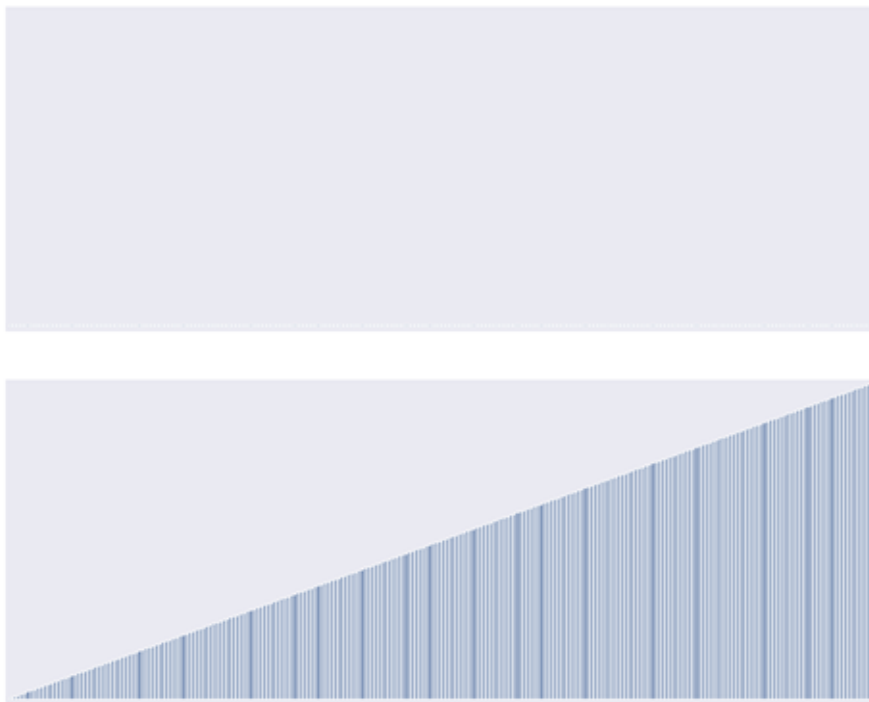


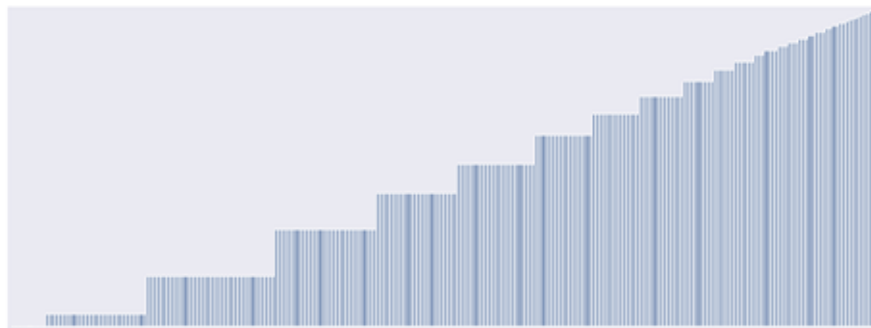
















The background of the slide consists of numerous horizontal, wavy lines in two shades of pink, creating a rhythmic, undulating pattern.

**handout**

# Toolkit

- **Language:** Mathematics
- **Library:** None
- **Platform:** Pencil and Paper





# Instructions

1. Organize in groups of 2 or 3 members. No more, no less.
1. Take a copy of the handout, read it, and do the activities.
1. Register the member names and return it to the professor.

# Neural network mysteries

- How can we separate a dataset in training data and testing data?
- ~~What is a hidden layer?~~
- ~~Does it matter if the input tensors are 3D, 2D, or 1D?~~
- ~~What is a dense layer?~~
- ~~How do we calculate the number of parameters in a dense layer?~~
- ~~How do we calculate the number of steps in a training process?~~
- ~~How do we calculate the number of steps in a testing process?~~
- Does the number of layers matter?
- ~~Does the size of a dense layer matter?~~
- What exactly activation='relu' does?
- ~~Can classic vision algorithms be represented by dense layers?~~
- ~~In a dense layer, are all the weights and biases always necessary?~~
- ~~How do we calculate the number of parameters in a convolutional layer?~~

*Deep learning is not simply  
about adding extra layers.*

*Deep learning is about ensuring  
that the extra layers are relevant.*

# Next class:

- non-linear classic vision.

# Credits

This material was based on the work of other professors, listed below.

- Fabio Miranda ([fabiomiranda@insper.edu.br](mailto:fabiomiranda@insper.edu.br))
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Well, except for the errors. Any errors you might find are probably my fault.

# Images

[https://en.wikipedia.org/wiki/Histogram\\_equalization](https://en.wikipedia.org/wiki/Histogram_equalization)

<https://acidcow.com/pics/15485-mindfuck-pictures-74-pics.html>

[https://en.wikipedia.org/wiki/Thresholding\\_\(image\\_processing\)](https://en.wikipedia.org/wiki/Thresholding_(image_processing))