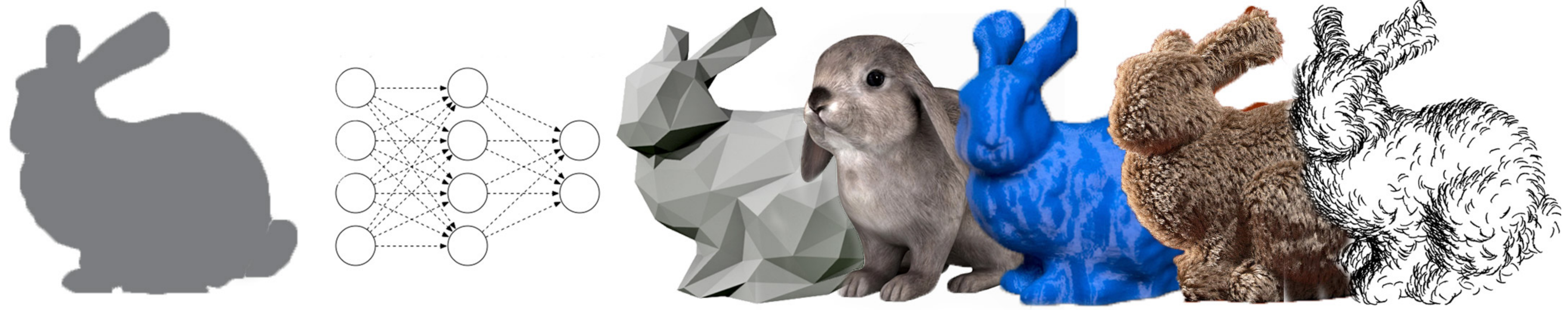

Deep Learning for Computer Graphics and Geometry Processing

Niloy Mitra — UCL

Iasonas Kokkinos — UCL

Federico Monti — USI Lugano

Emanuele Rodolà — La Sapienza

Michael Bronstein — Imperial College, USI Lugano

Or Litany — Stanford University, Facebook

Leonidas Guibas — Stanford University

http://geometry.cs.ucl.ac.uk/dl_for_CG/

Tutorial Organizers

Niloy Mitra

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Timetable

			Niloy	Federico	Iasonas	Emanuele
Theory/Basics	Introduction	9:00	X	X	X	X
	Machine Learning Basics	~ 9:05	X			
	Neural Network Basics	~ 9:35		X		
	Alternatives to Direct Supervision (GANs)	~11:00			X	
State of the Art	Image Domain	~11:45			X	
	3D Domains (extrinsic)	~13:30	X			
	3D Domains (intrinsic)	~ 14:15				X
	Physics and Animation	~ 16:00	X			
	Discussion	~ 16:45	X	X	X	X

Sessions: A. 9:00-10:30 (**coffee**) B. 11:00-12:30 [**LUNCH**] C. 13:30-15:00 (**coffee**) D. 15:30-17:00

Code Examples

PCA/SVD basis
Linear Regression
Polynomial Regression
Stochastic Gradient Descent vs. Gradient Descent
Multi-layer Perceptron
Edge Filter 'Network'
Convolutional Network
Filter Visualization
Weight Initialization Strategies
Colorization Network
Autoencoder
Variational Autoencoder
Generative Adversarial Network

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Course Objectives

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- Provide an overview of the popular **ML algorithms** used in CG

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- Provide a quick overview of **theory** and **CG applications**
  - Many extra slides in the course notes + example code
- Progress in the last 3-5 years has been dramatic
  - We have organized them to help newcomers
  - Discuss the main **challenges and opportunities** specific to CG

Two-way Communication

Scan me

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- Our aim is to convey what we found to be relevant so far
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  - Ask questions, please!

- **Thanks to many people who helped so far with slides/comments**

Scan me

Representations in Computer Graphics

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- Images (e.g., pixel grid)

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Problems in Computer Graphics

- Feature detection (image features, point features) $\mathbb{R}^{m \times m} \rightarrow \mathbb{Z}$
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synthesis

Goal: Learn a Parametric Function

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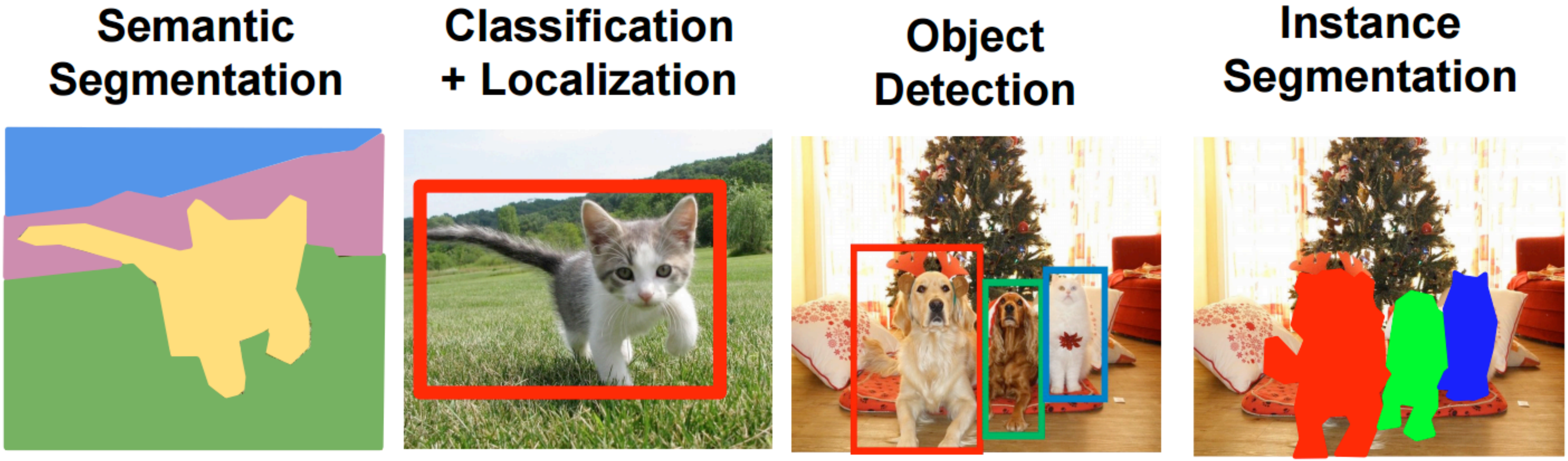
Image Synthesis: $f_\theta : \mathbb{R}^{n} \longrightarrow \mathbb{R}^{w \times h \times c}$

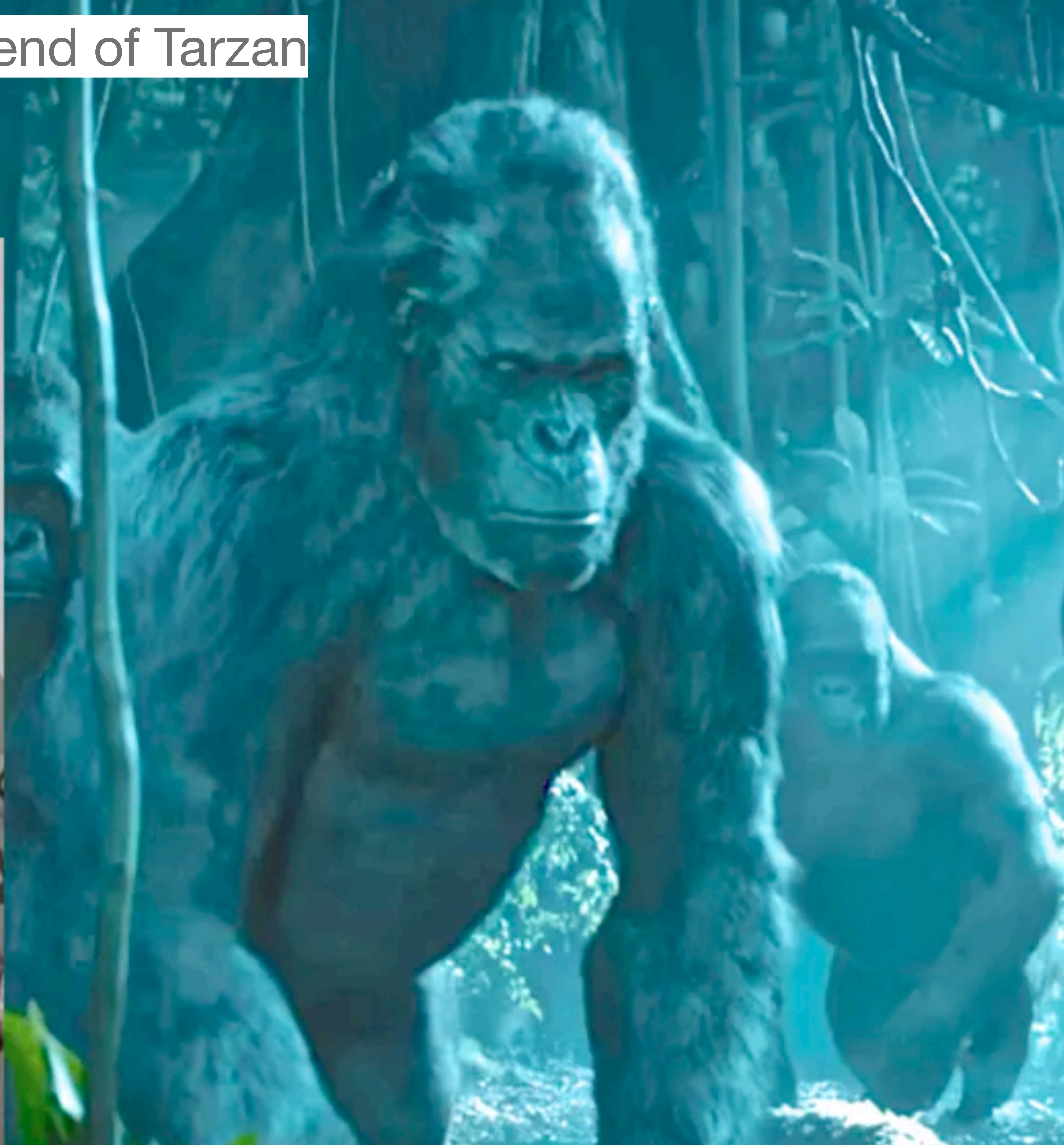
n : latent variable count $w \times h \times c$: image dimensions

Semantic Segmentation



http://cs231n.stanford.edu/slides/2017/cs231n_2017_lecture11.pdf

The Legend of Tarzan



Pose Detection using CNNs

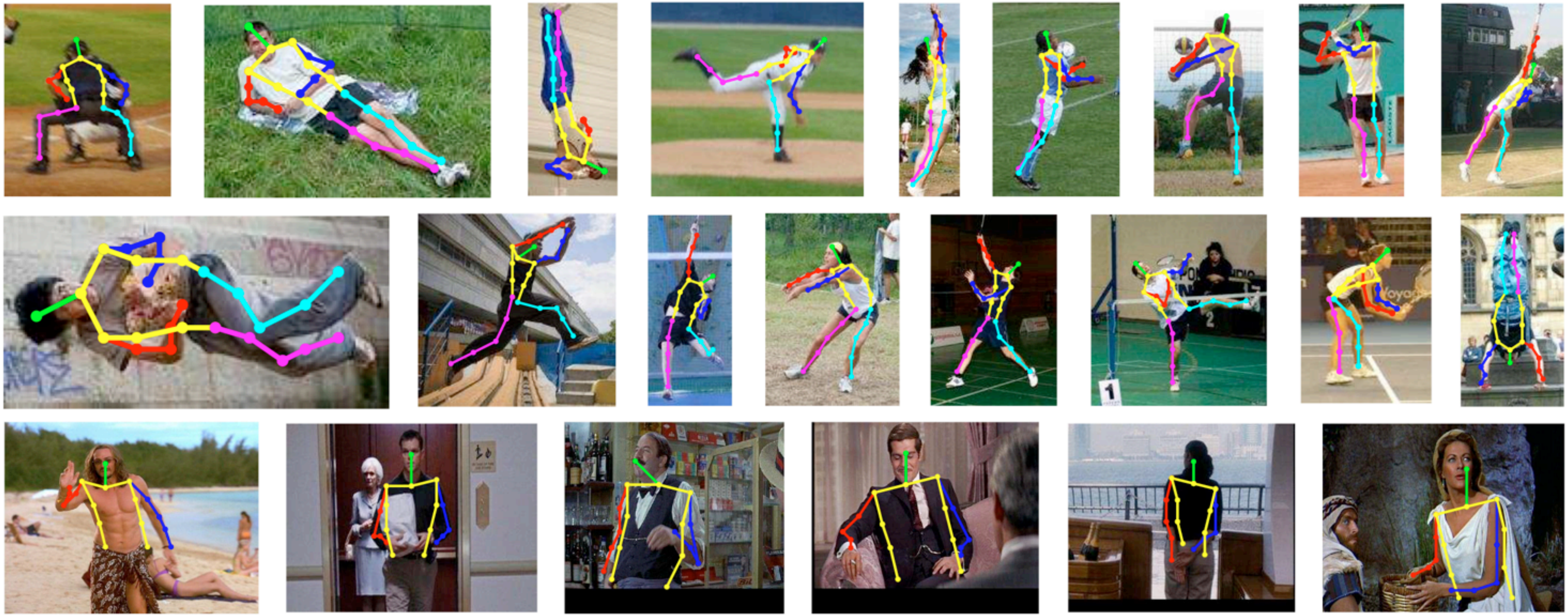


Image Denoising

[Chaitanya et al. 2017, Siggraph]

Image Denoising

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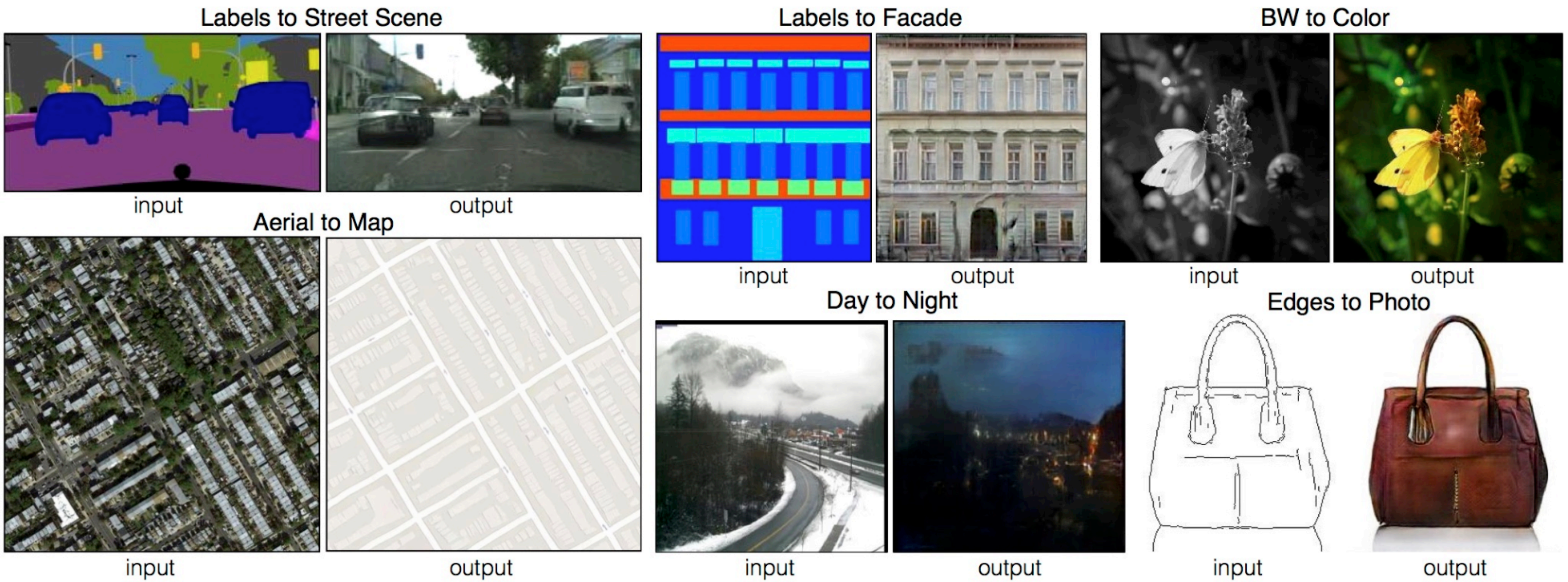
Pix2Pix (Image Translation)

[Isola et al. 2017, CVPR]



Sketch to Face!

DeepSketch2Face: A Deep Learning Based Sketching System for 3D Face and Caricature Modeling

XIAOGUANG HAN, CHANG GAO, and YIZHOU YU, The University of Hong Kong

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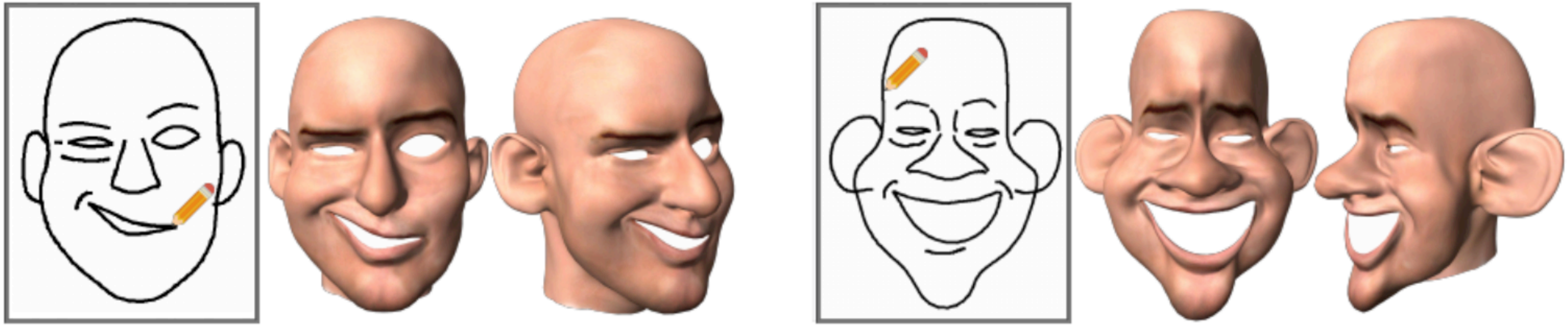

[Wang et al. 2018, Siggraph Asia]

Real Images

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Real Images

Machine Learning 101: Linear Classifier

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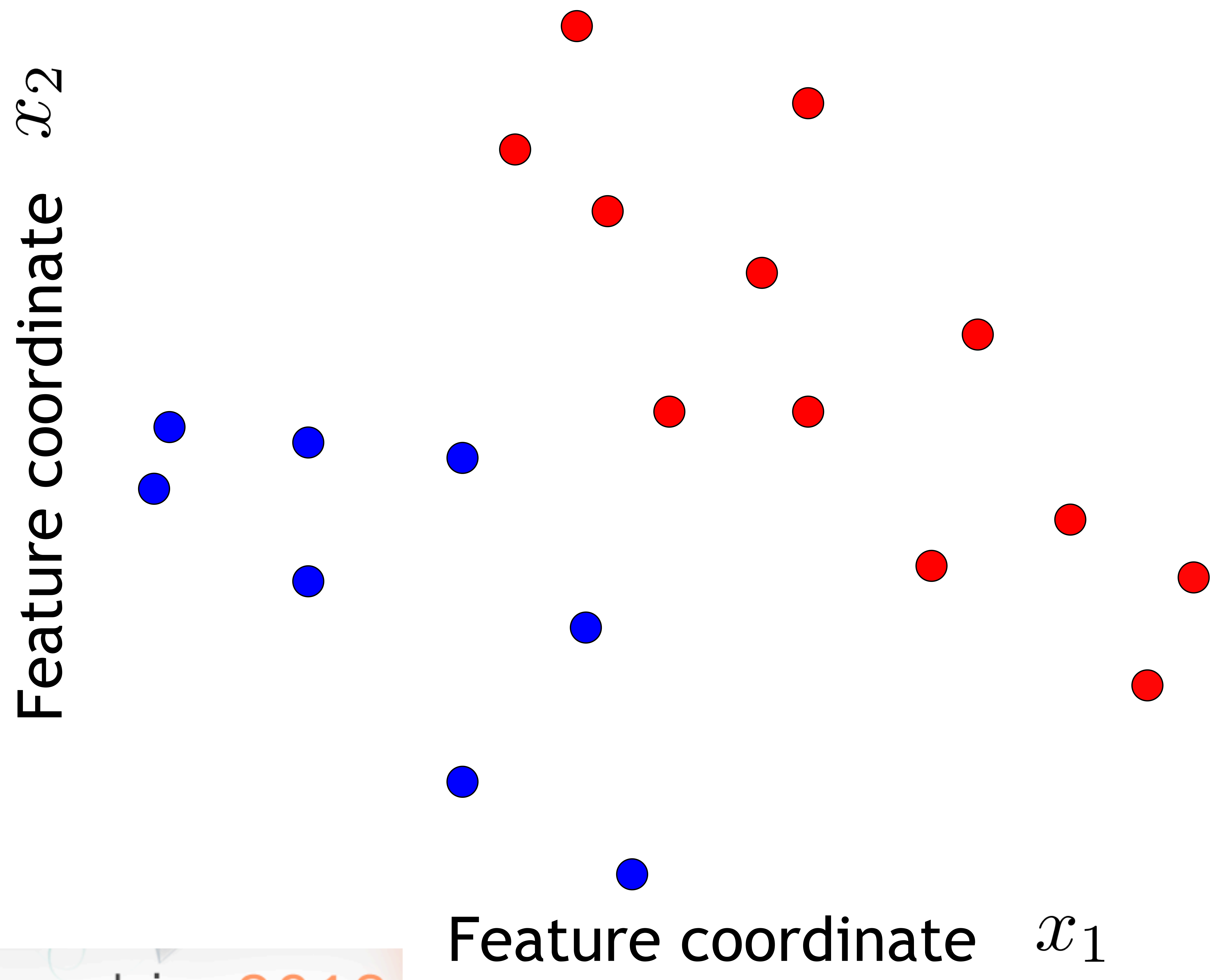

Each data point has a class label:

$$y^i = \begin{cases} 1 & (\text{red}) \\ 0 & (\text{blue}) \end{cases}$$

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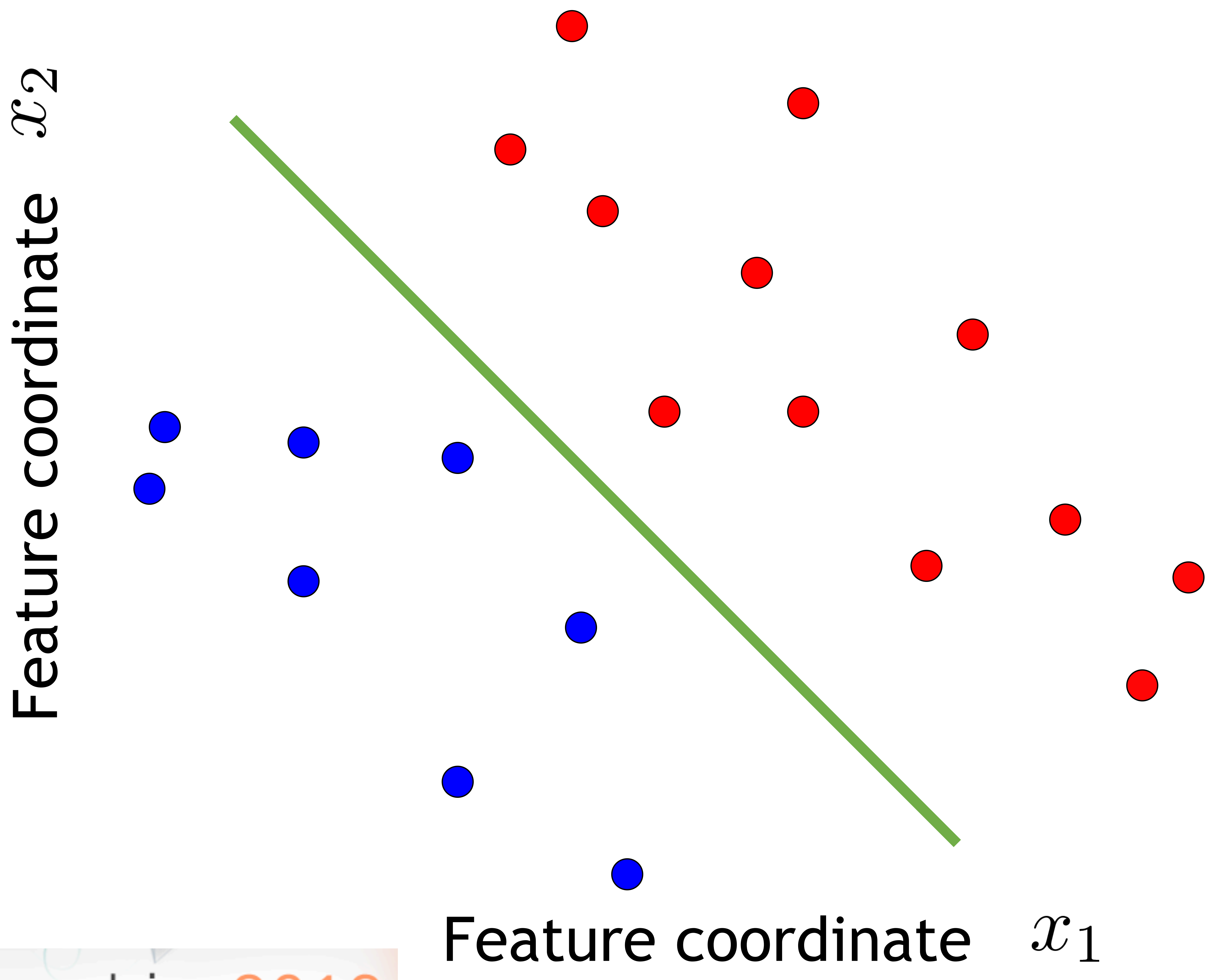

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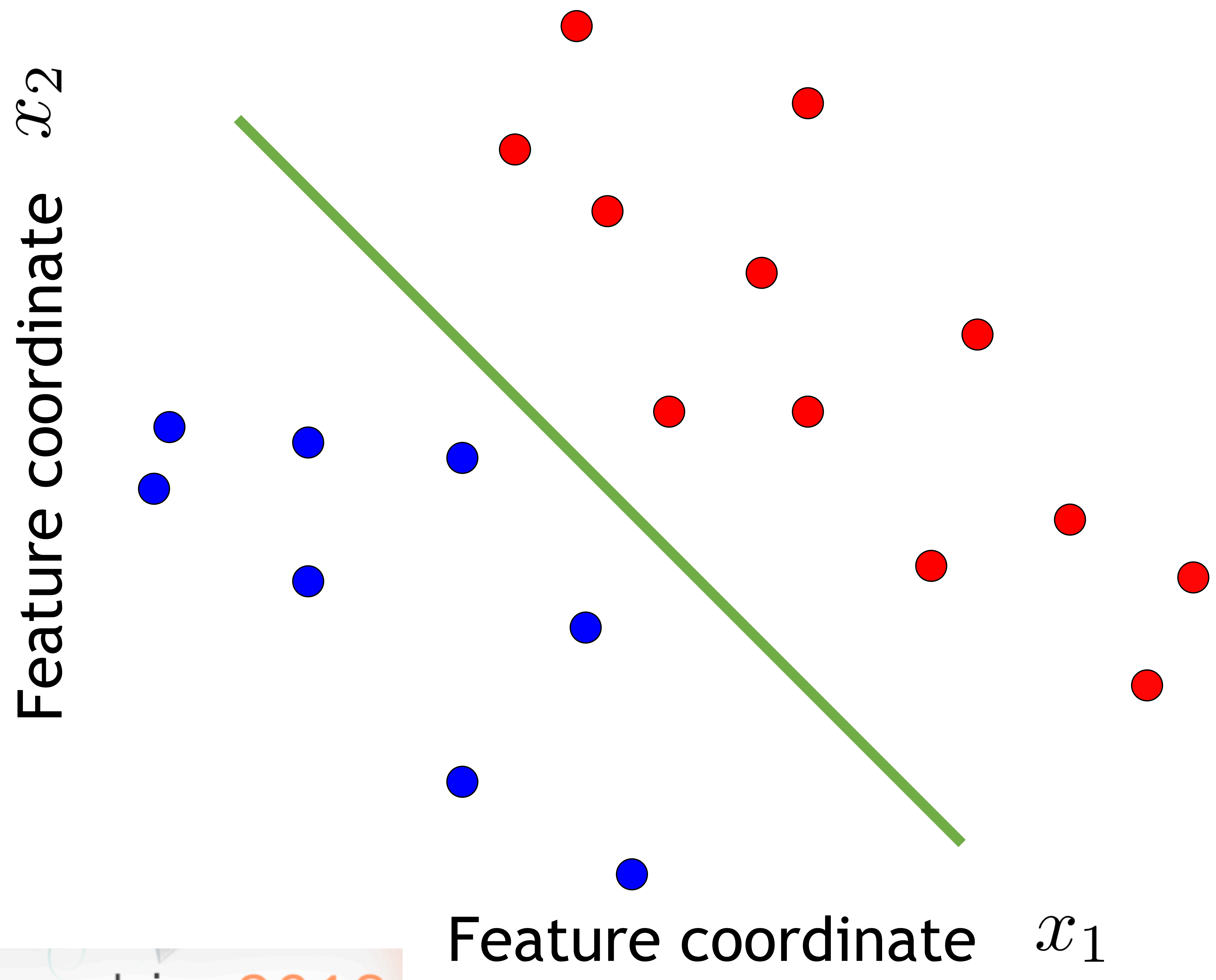

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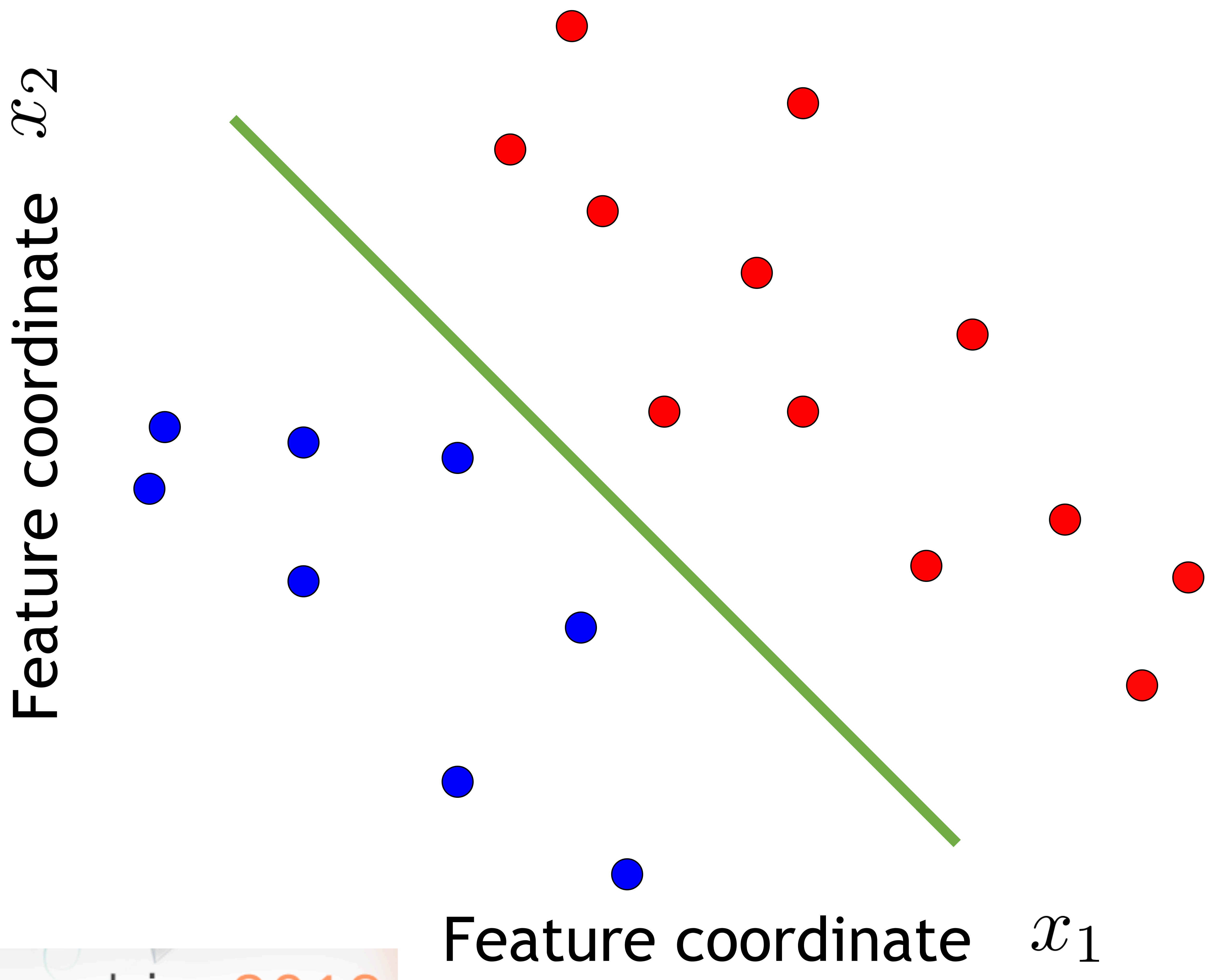

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Data-driven Algorithms (Supervised)

Labelled data
(supervision data)

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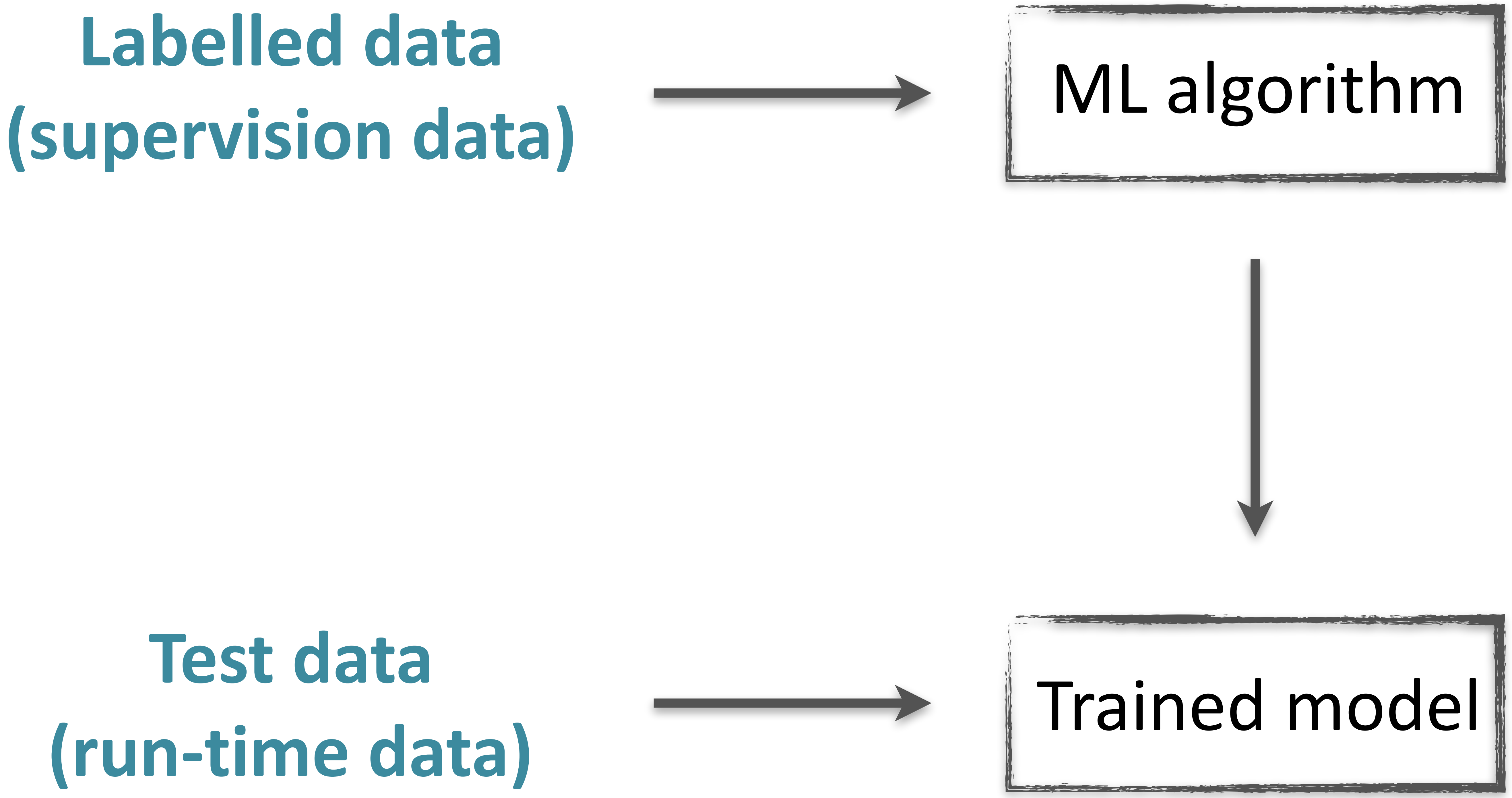
ML algorithm

Trained model

Data-driven Algorithms (Supervised)



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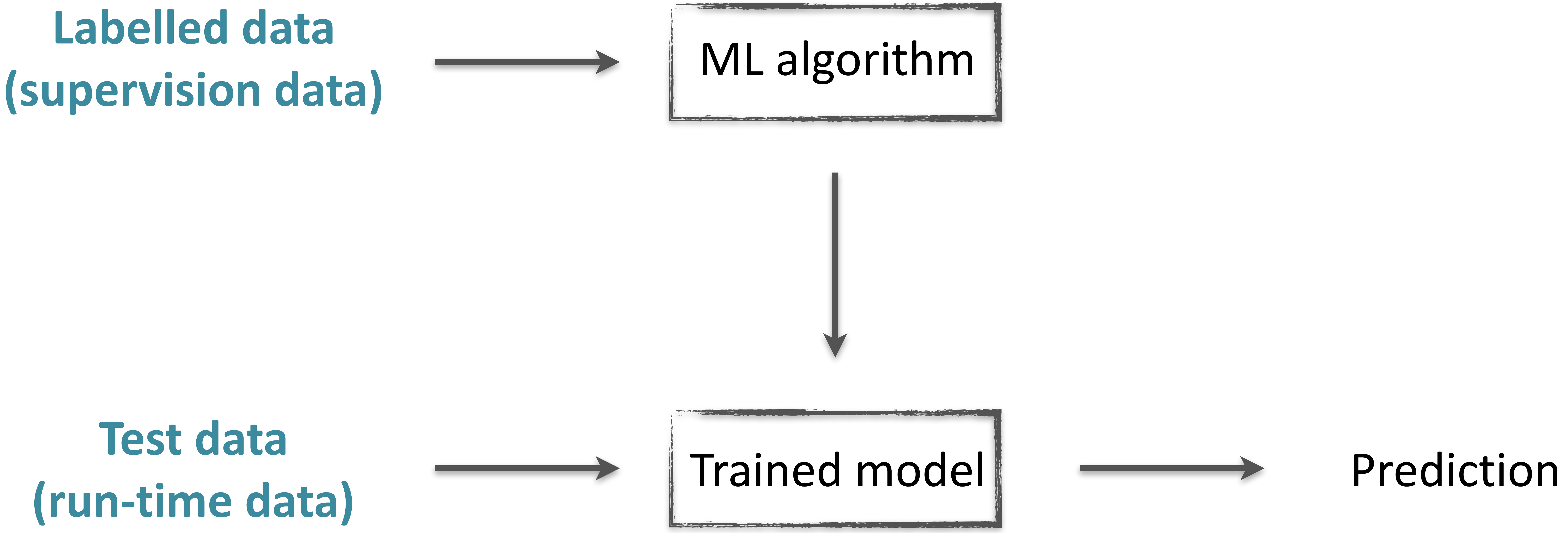

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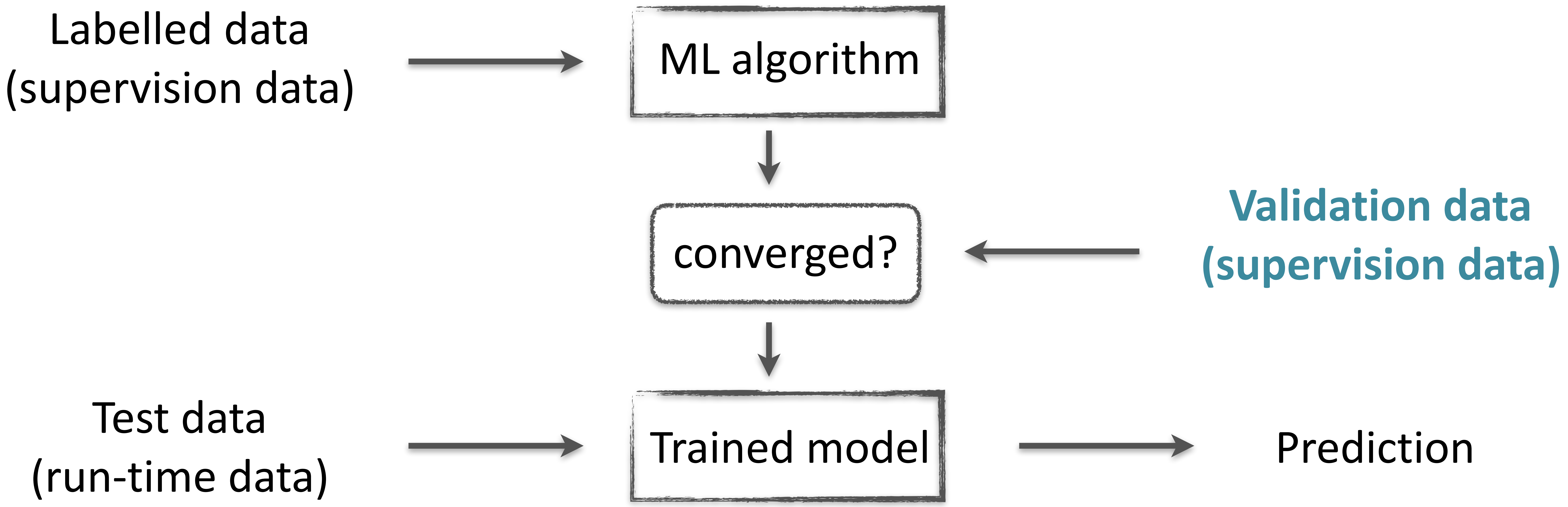

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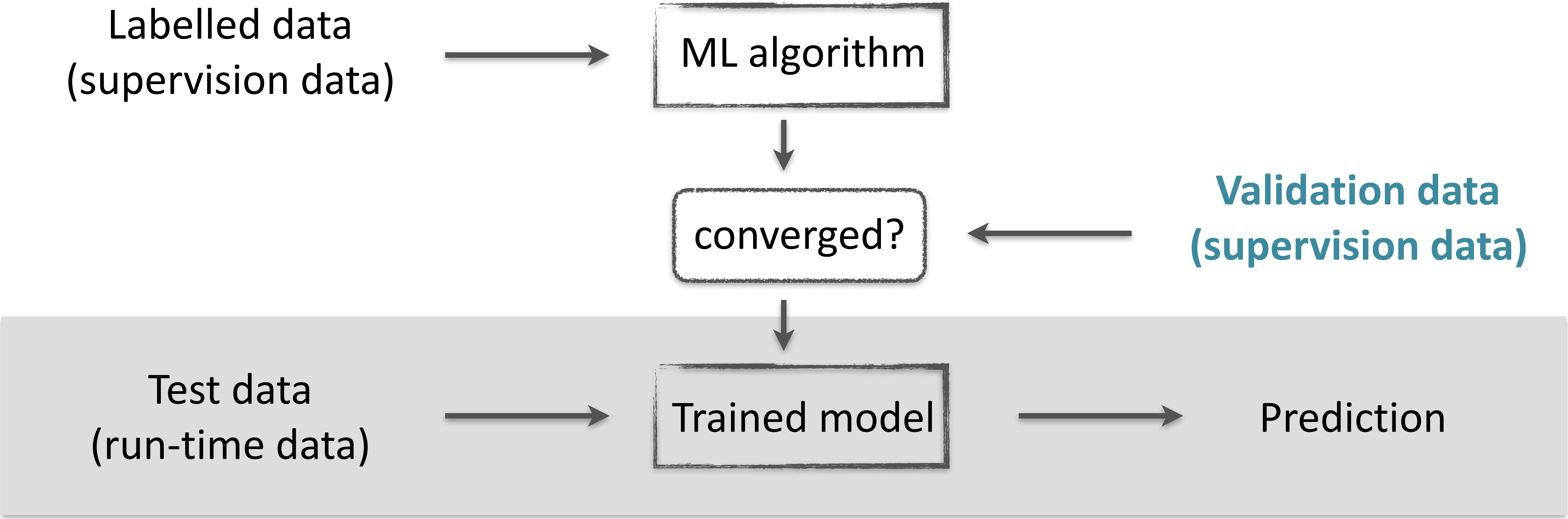

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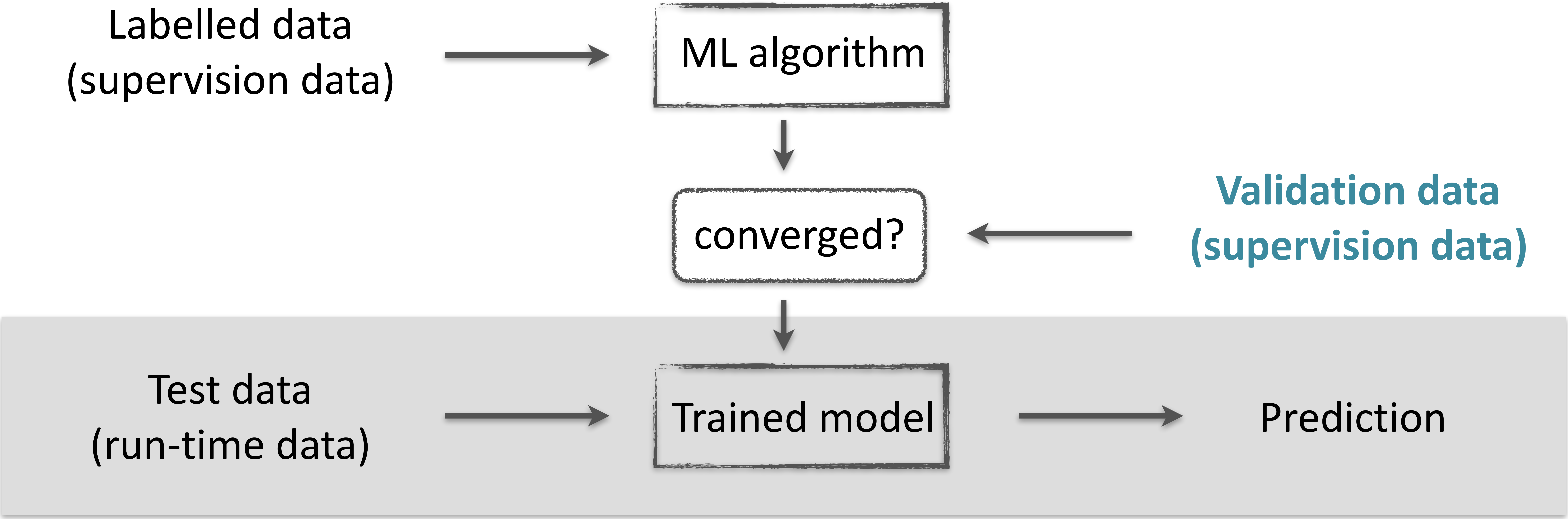
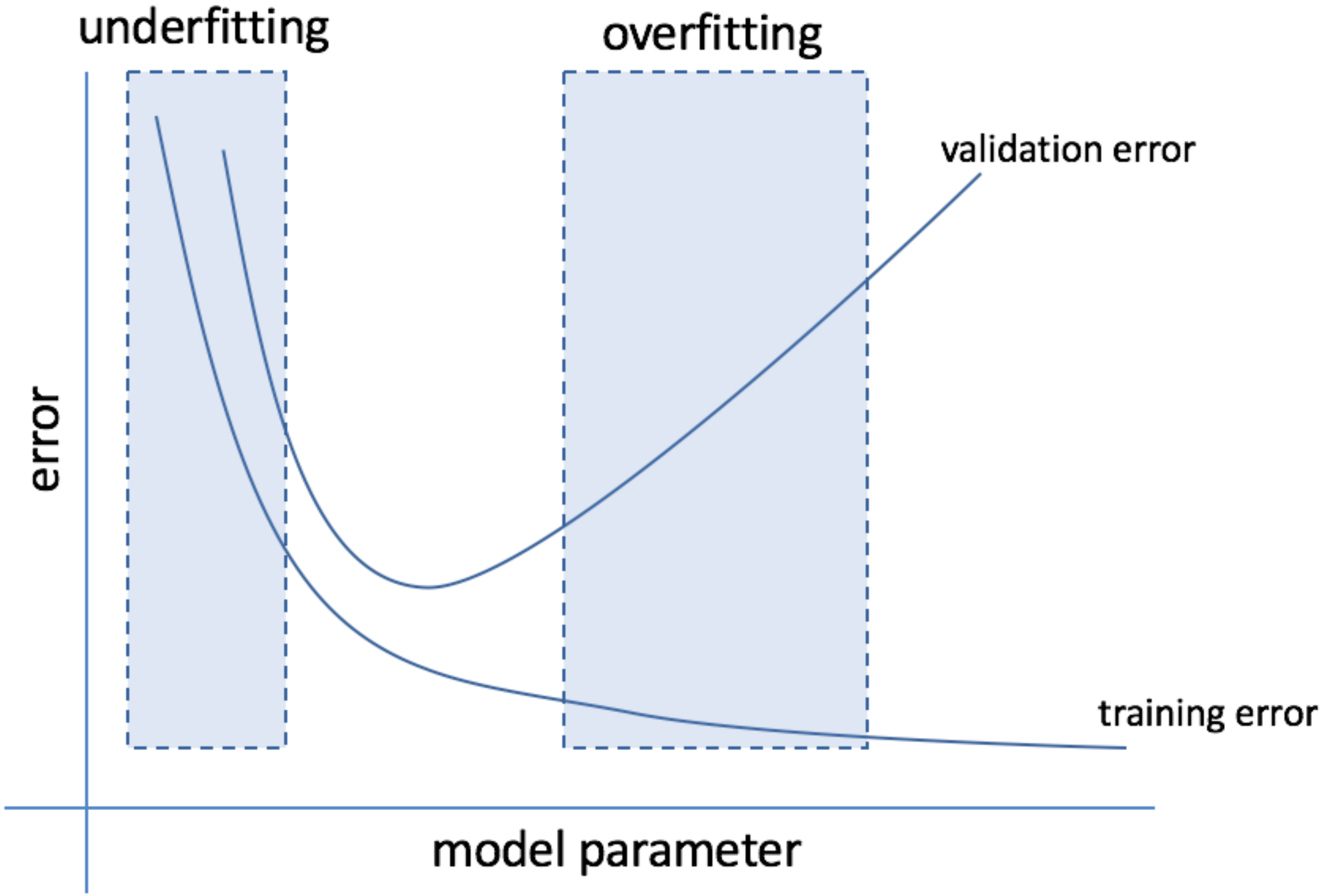


Implementation Practice: Training: 70%; Validation: 15%; Test 15%

Training versus Validation Loss/Accuracy



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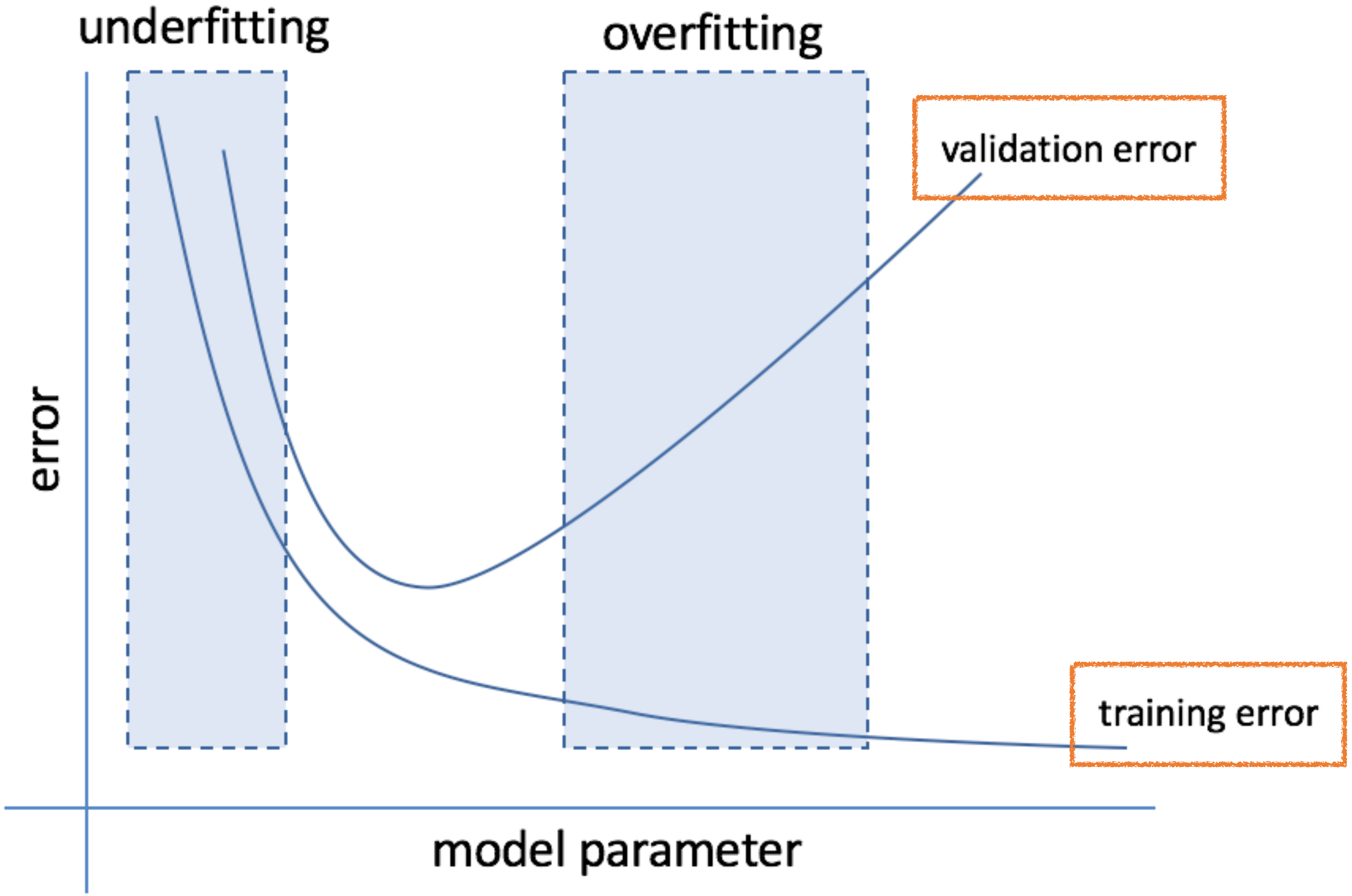
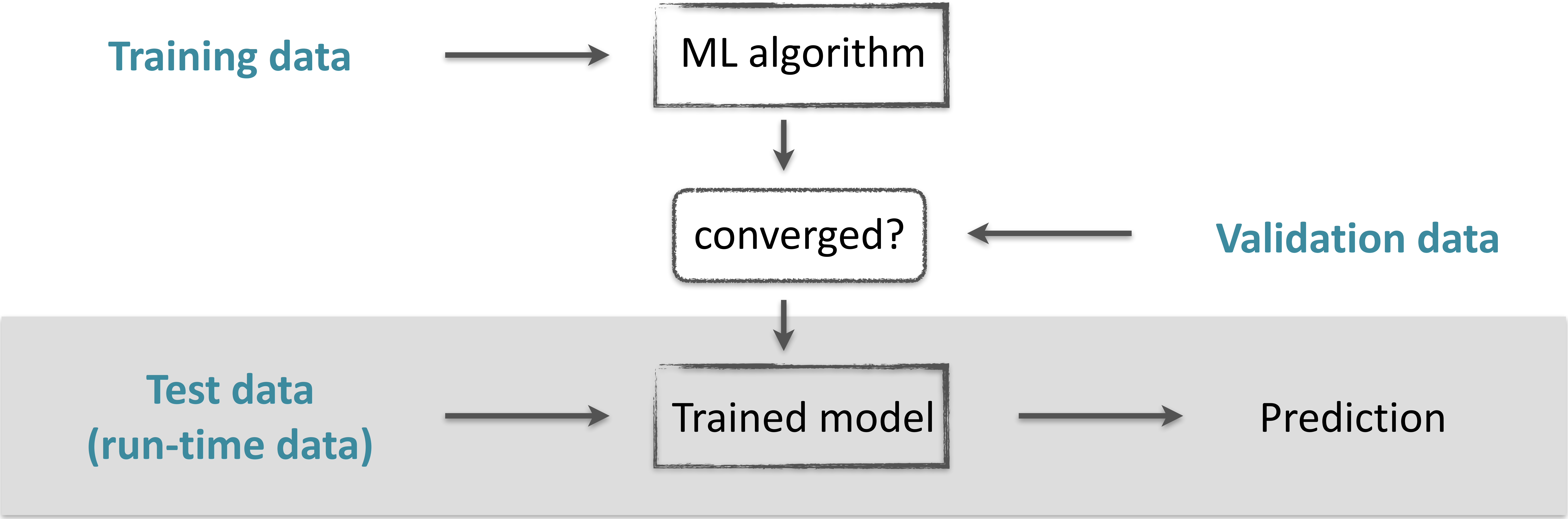


Data-driven Algorithms (Unsupervised)



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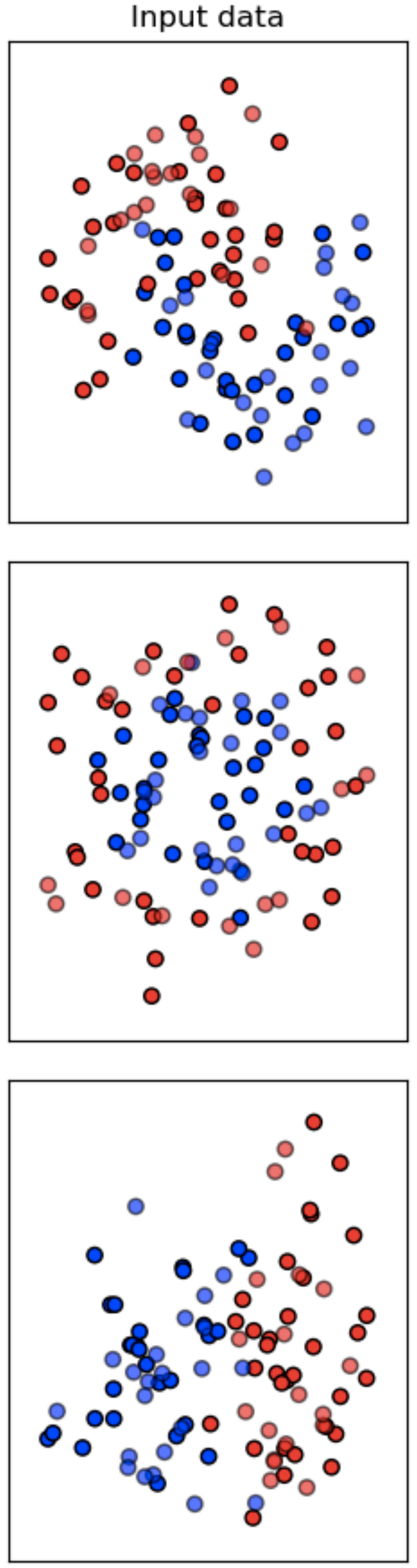
Various ML Approaches (Supervised approaches)



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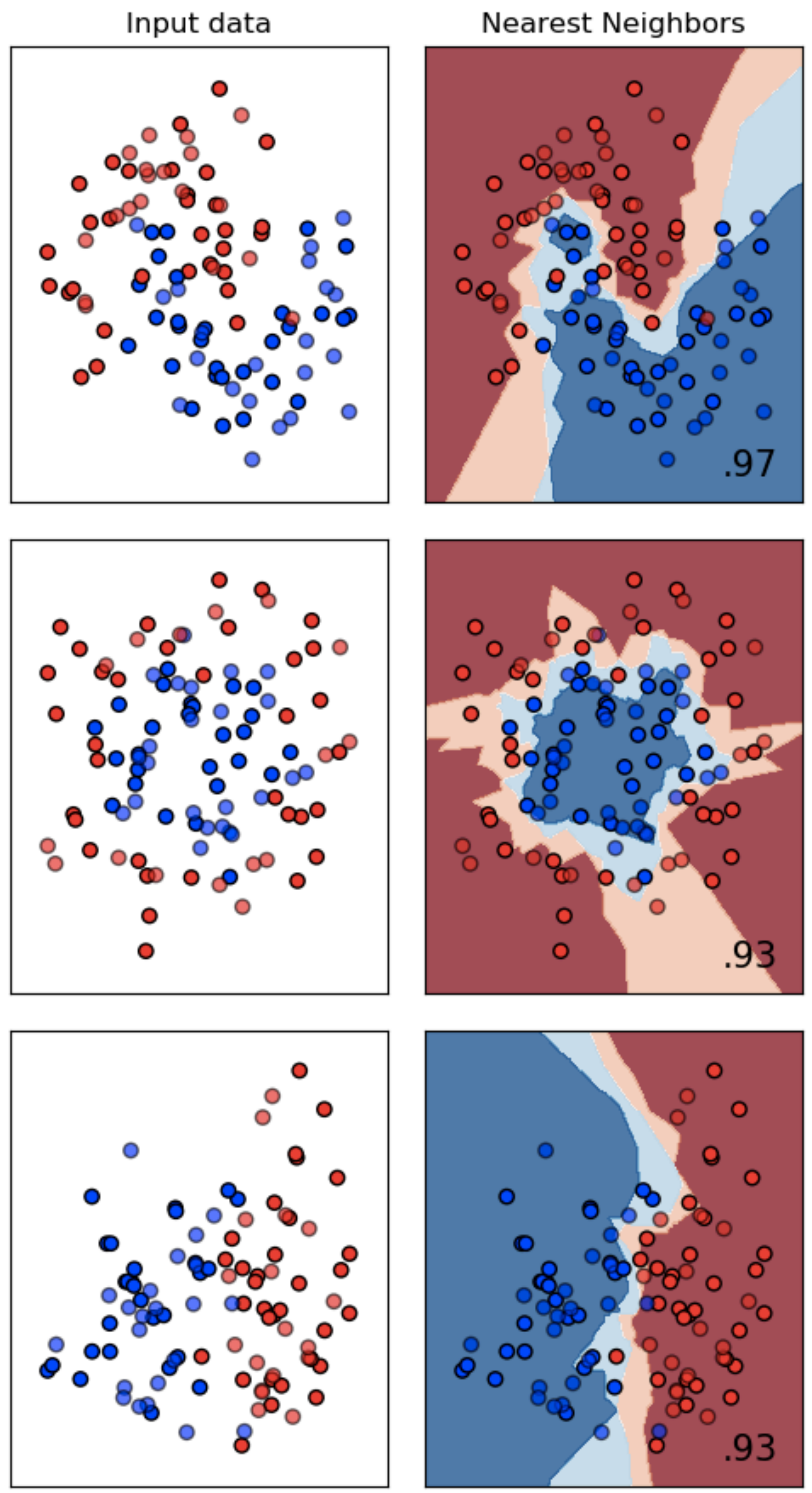

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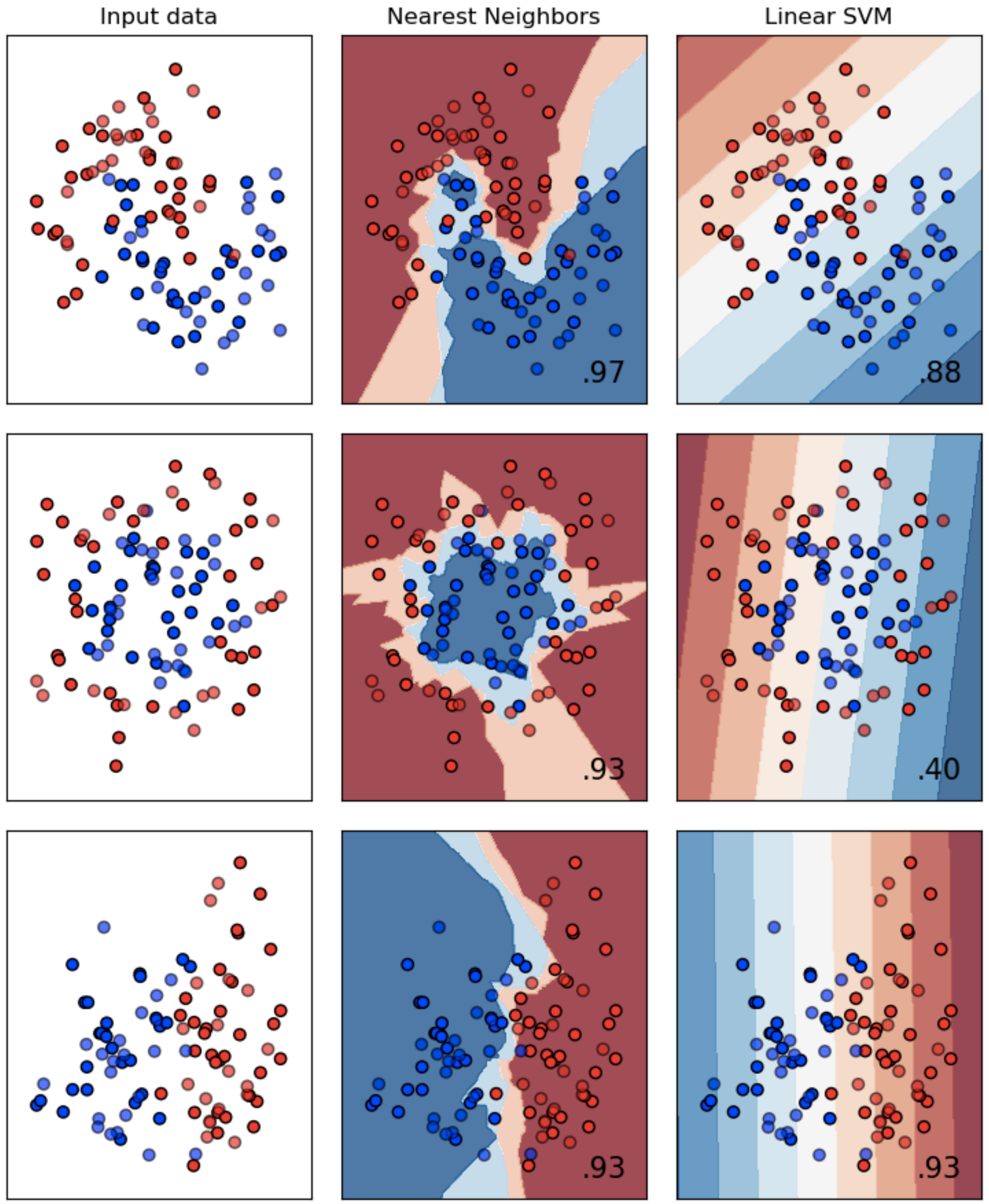

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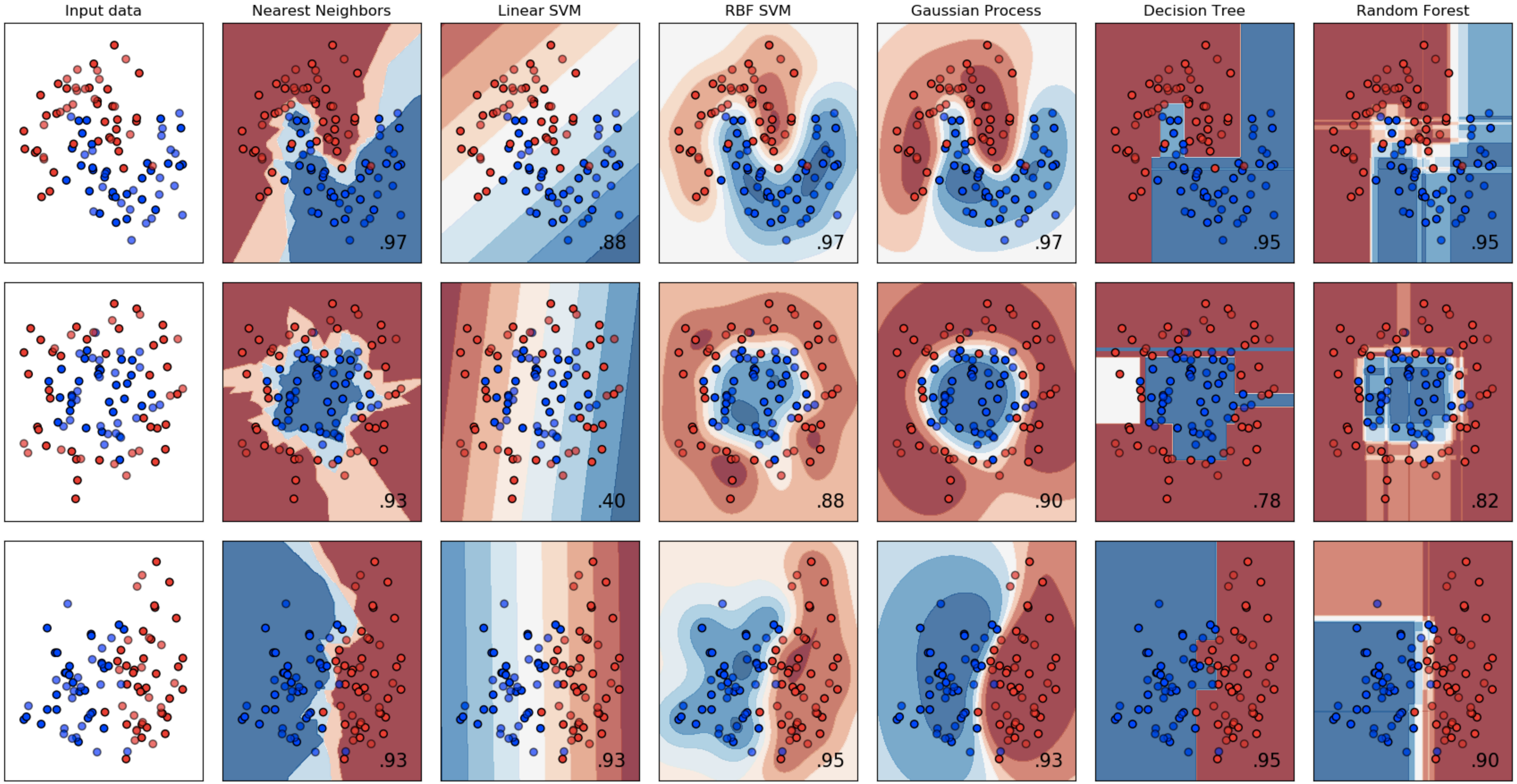

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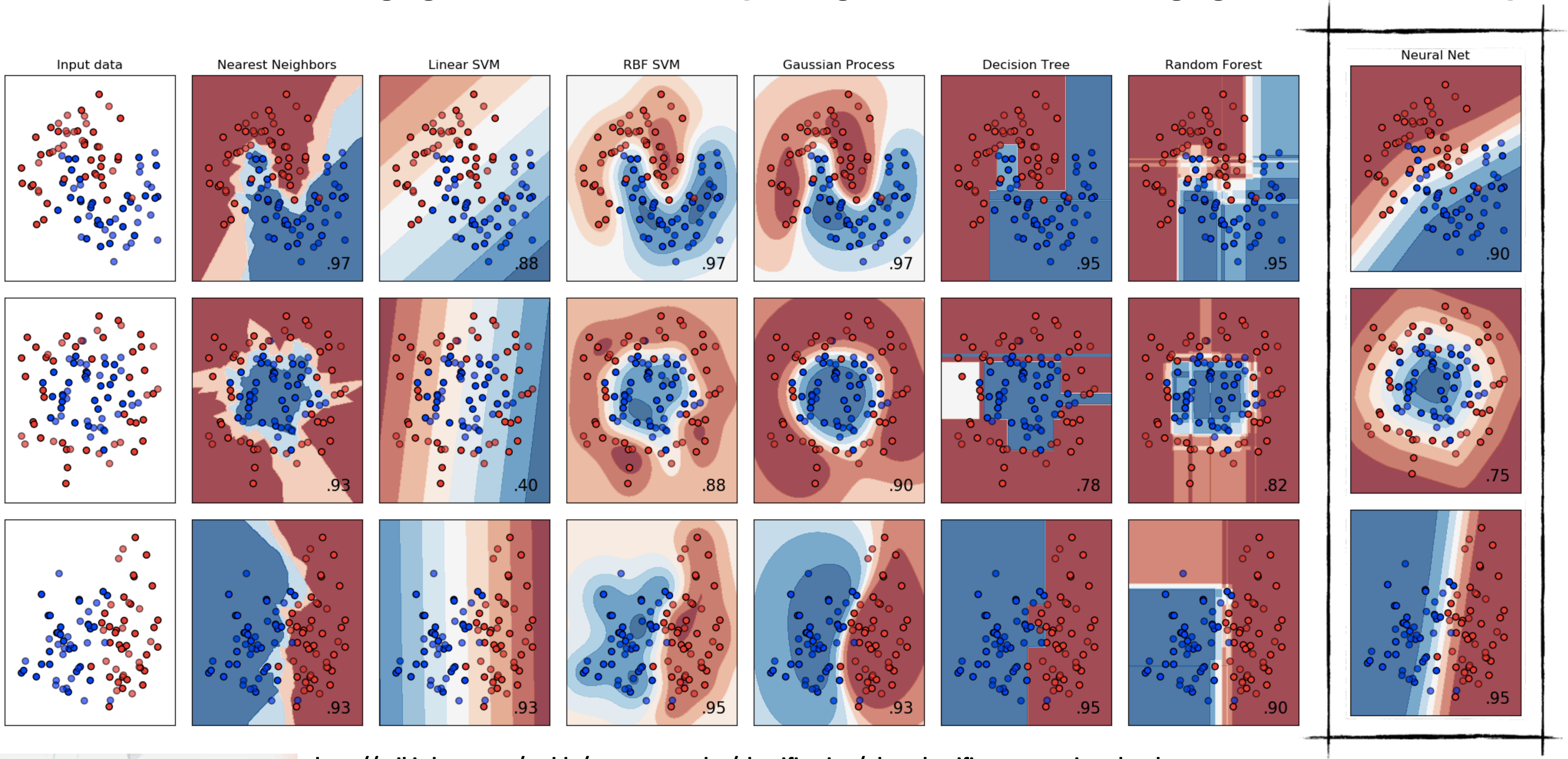

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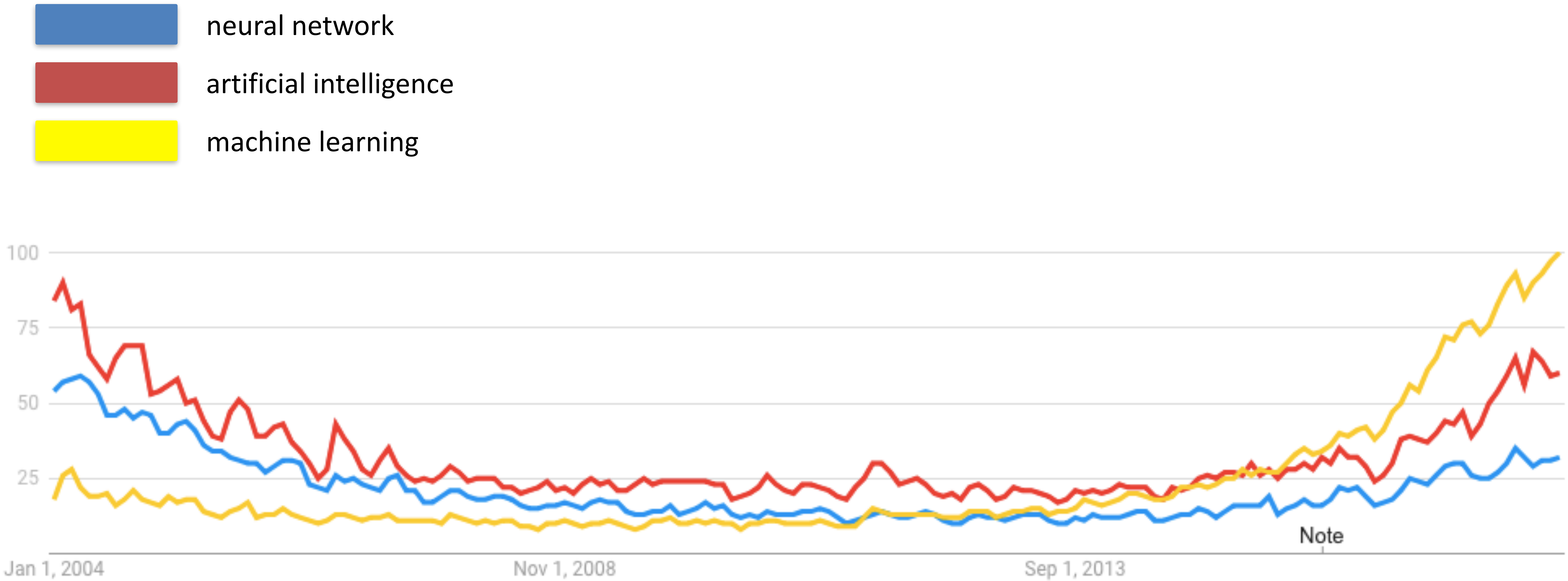
Rise of Learning

- 1958: Perceptron
- 1974: Backpropagation
- 1981: Hubel & Wiesel wins Nobel prize for ‘visual system’
- 1990s: SVM era
- 1998: CNN used for handwriting analysis
- **2012: AlexNet wins ImageNet**

Rise of Machine Learning



Rise of Machine Learning

neural network

artificial intelligence

machine learning

NN

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neural network

artificial intelligence

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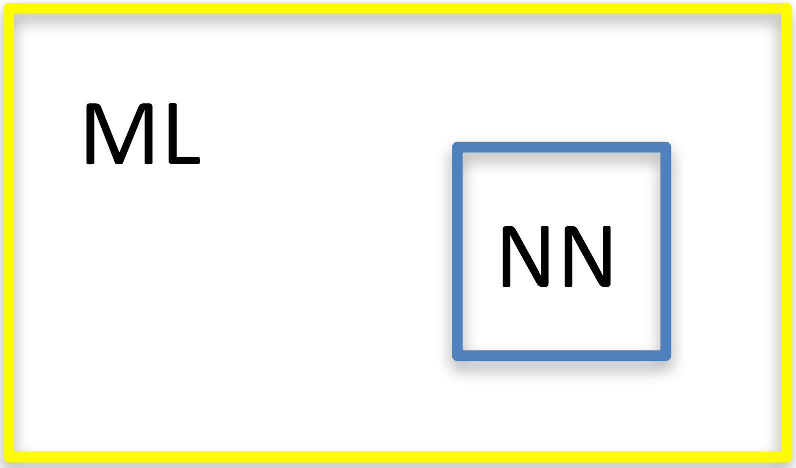

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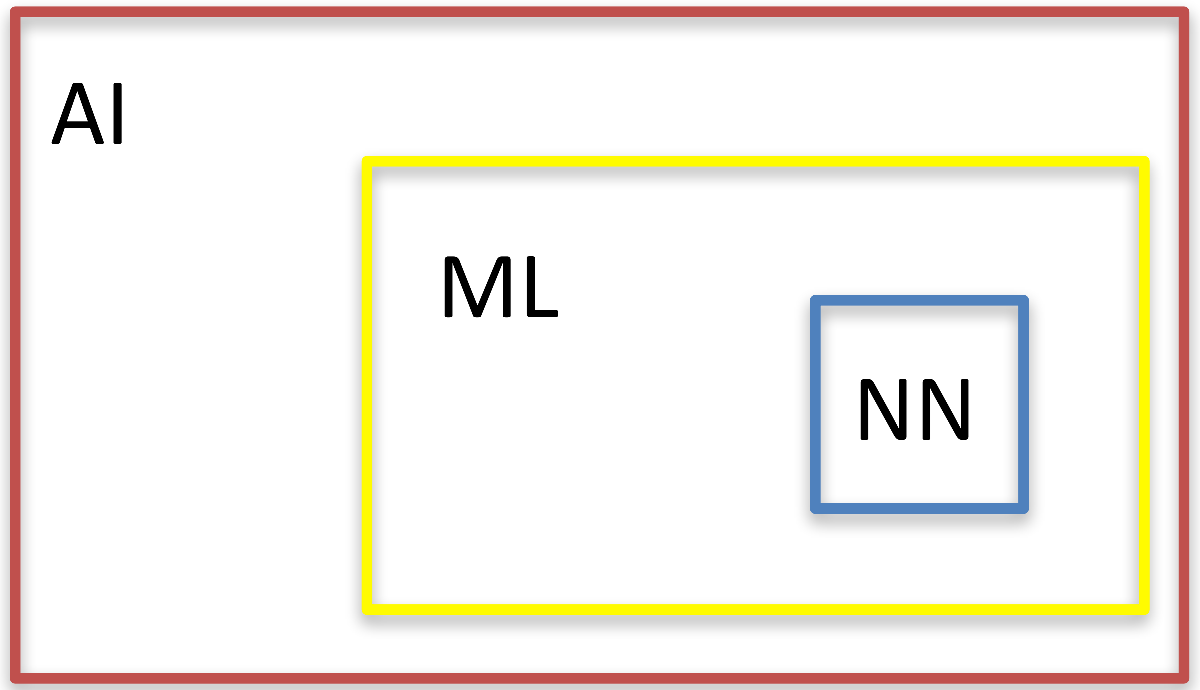
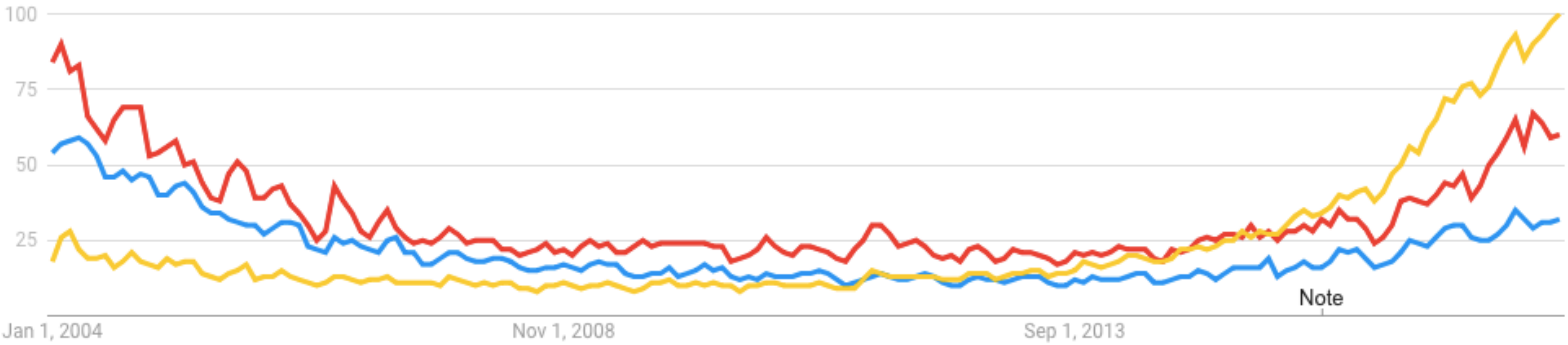
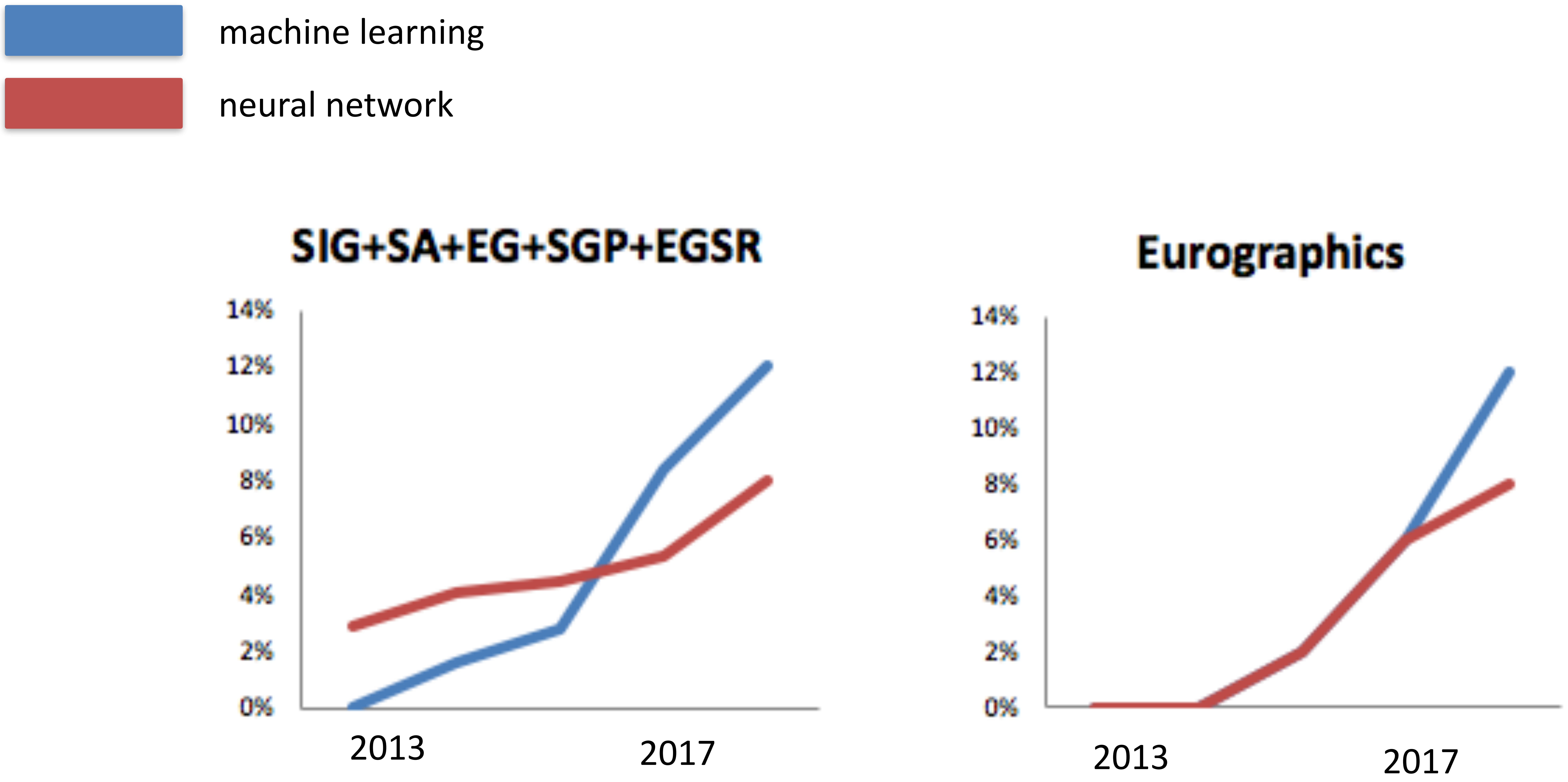




Rise of Machine Learning (in Graphics)



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4. Many problems in **generative models**

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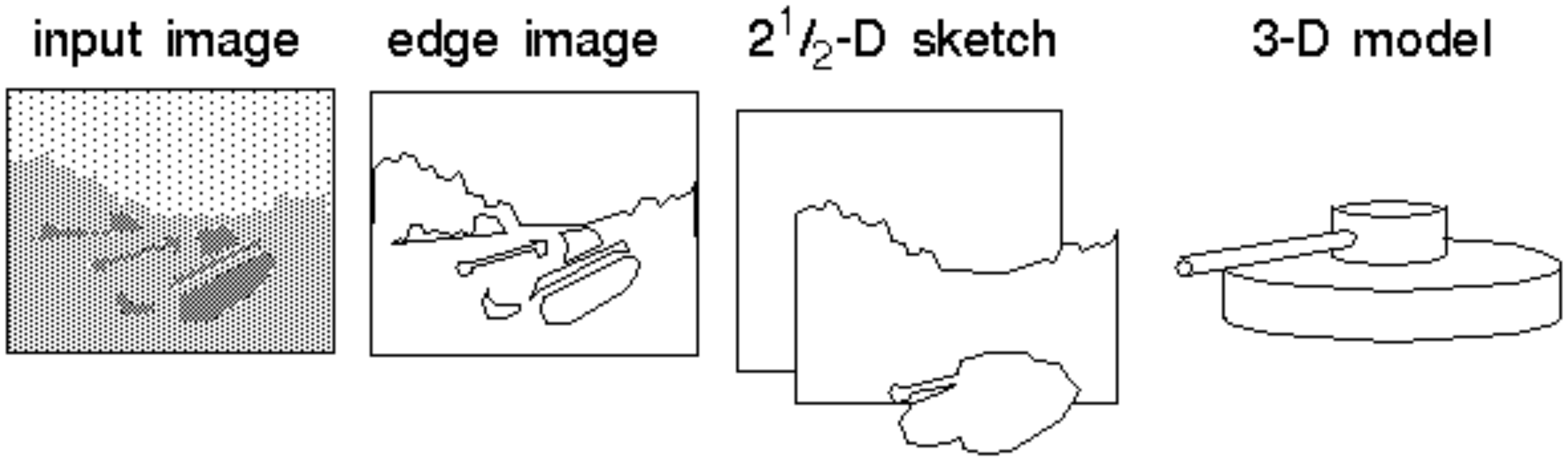

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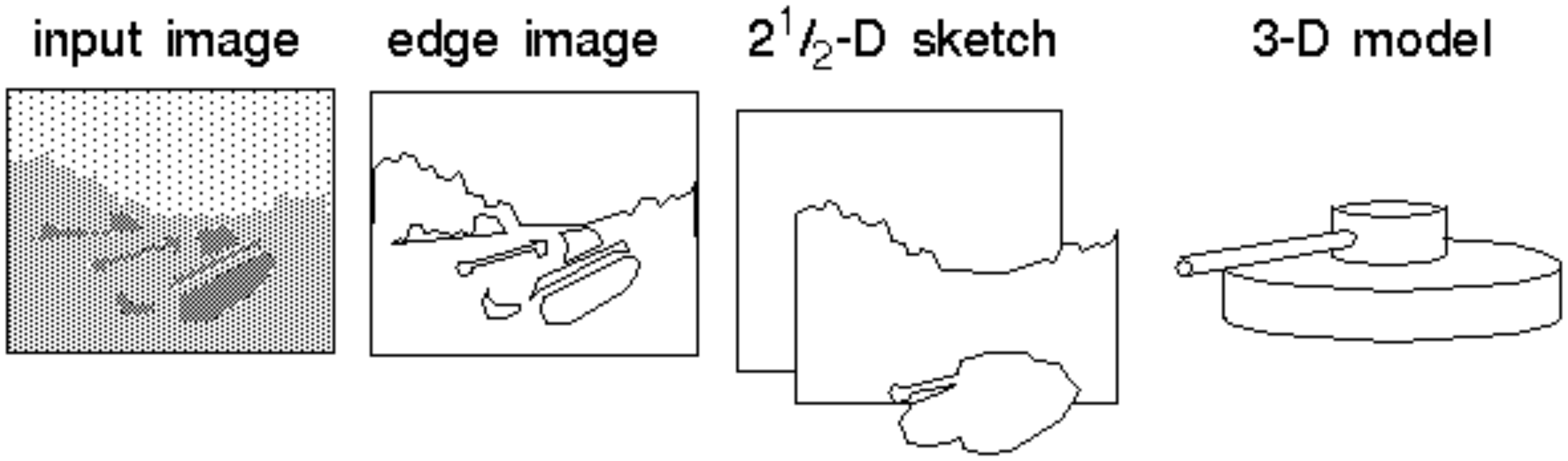
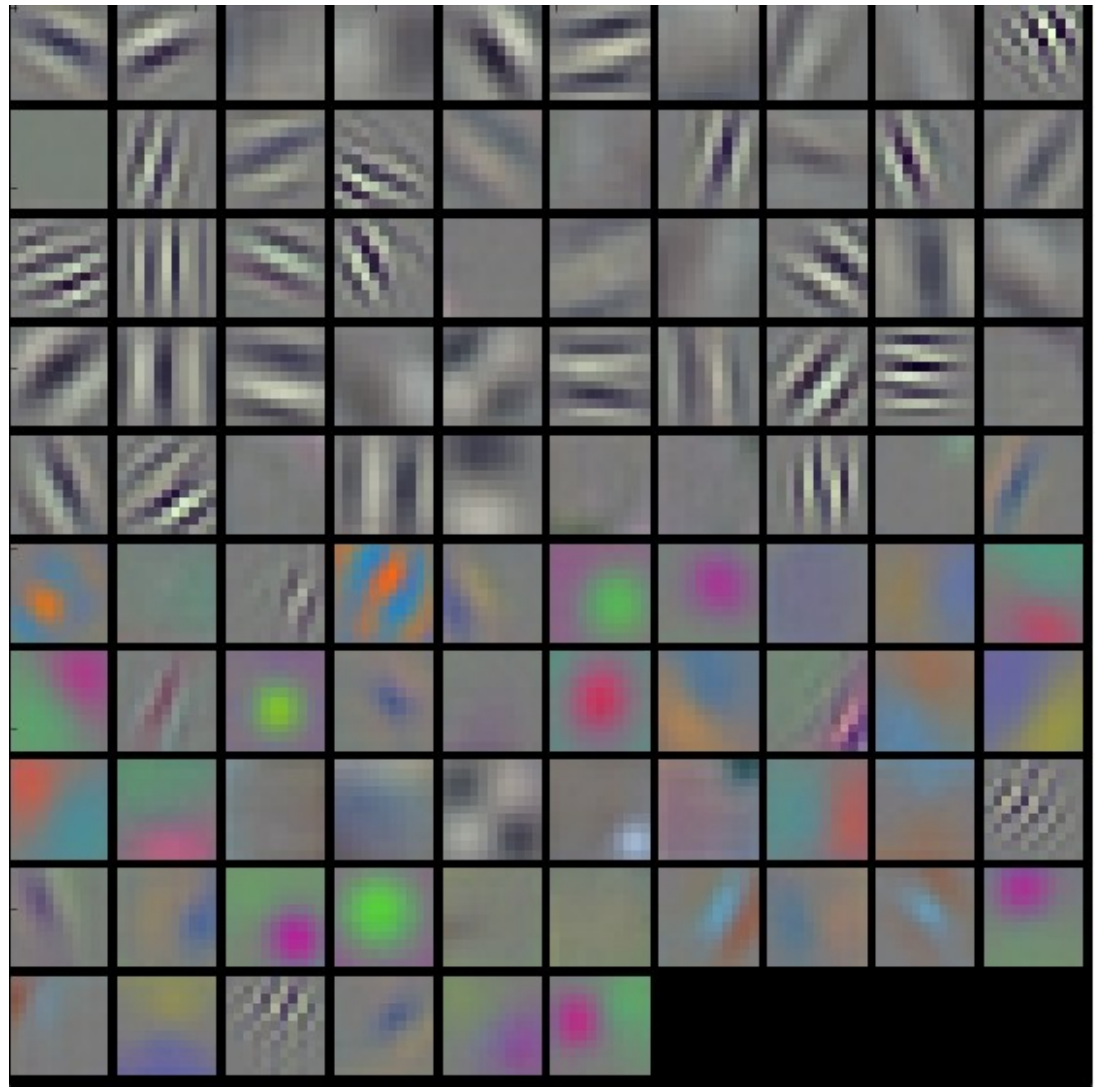
- *Now*
  - End-to-end
  - Move away from hand-crafted representations





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- While still much is left to do, this makes graphics much more reproducible

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  - Deploy on real stuff
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  - Deploy on real stuff
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- *Now*
  - Test and deploy need to be as identical **(in distribution)**
  - Need to collect data first
  - No two steps

Examples in Graphics

Geometry

Image manipulation

Animation

Rendering

Examples in Graphics

Geometry

Procedural modelling

Mesh segmentation

Learning deformations

Colorization

Sketch simplification

Image manipulation

Animation

BRDF estimation

Boxification

Fluid

Real-time rendering

Animation

Rendering

Denoising

Facial animation

PCD processing

Examples in Graphics

Sketch simplification

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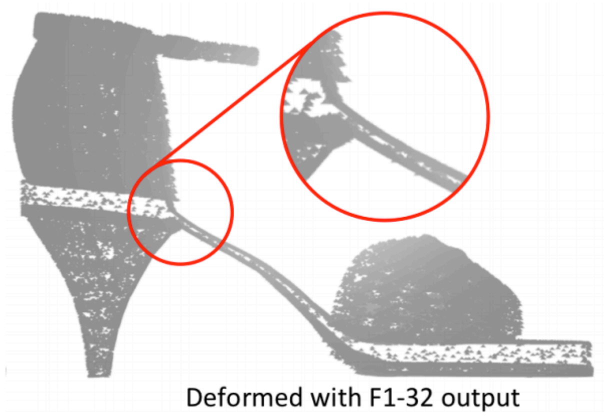

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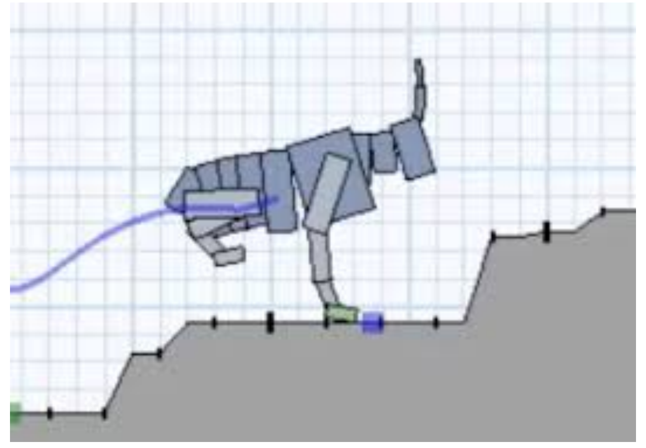
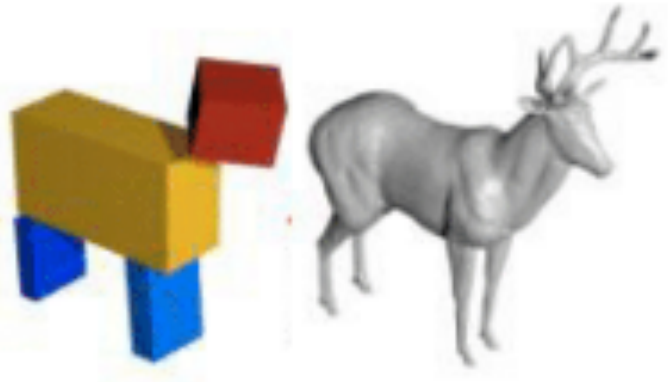
BRDF estimation

Fluid



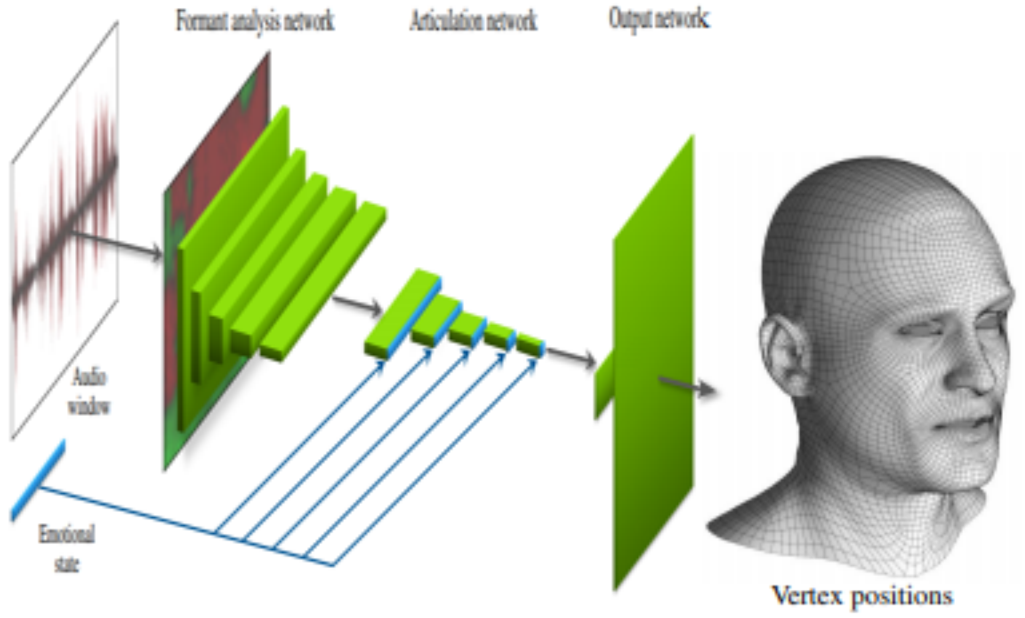
Animation



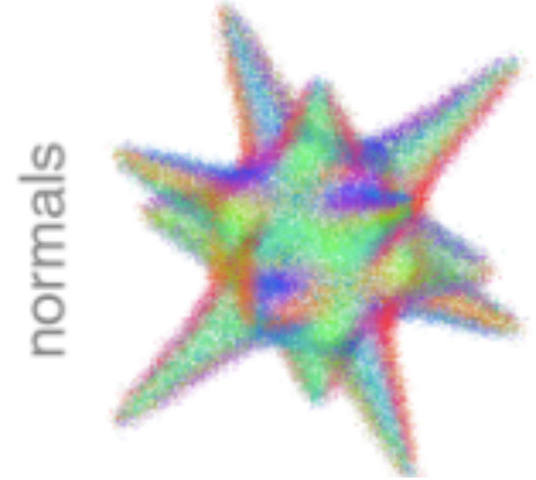
Boxification

Real-time rendering

Denoising

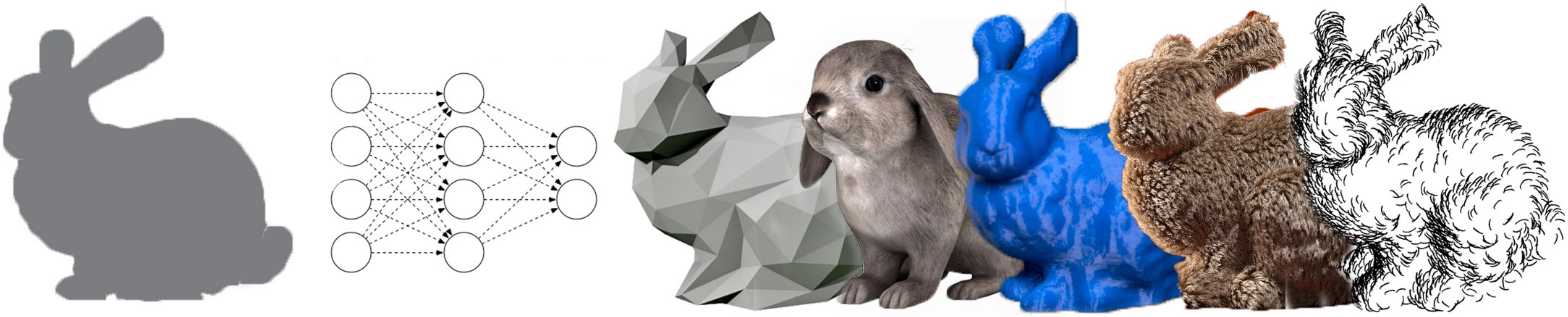


Facial animation



PCD processing

Course Information (slides/code/comments)



http://geometry.cs.ucl.ac.uk/dl_for_CG/

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