



CreativeAl Deep Learning for Graphics

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



Niloy Mitra



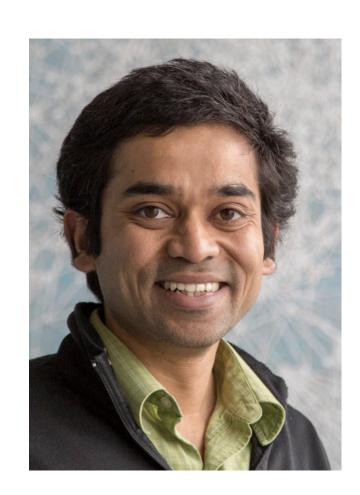


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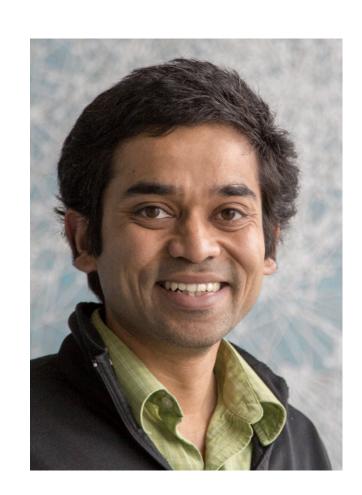


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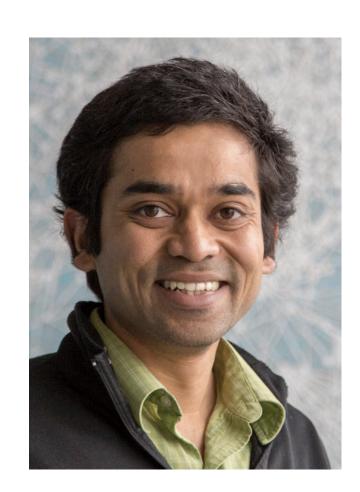


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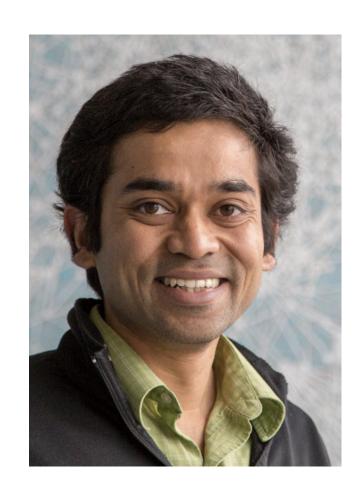


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Tobias Ritschel



Timetable

			Niloy	Paul	Nils
	Introduction	2:15 pm	X	X	X
Basics	Machine Learning Basics	~ 2:25 pm	X		
+ Ba	Neural Network Basics	~ 2:55 pm			X
Ory	Feature Visualization	~ 3:25 pm		X	
Theor	Alternatives to Direct Supervision	~ 3:35 pm		X	
		15 min. br	eak —		
Art	Image Domains	4:15 pm		X	
f the	3D Domains	~ 4:45 pm	X		
te of	Motion and Physics	~ 5:15 pm			X
State	Discussion	~ 5:45 pm	X	X	X



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
```







Provide an overview of the popular ML algorithms used in CG



- Provide an overview of the popular ML algorithms used in CG
- Provide a quick overview of theory and CG applications
 - Many extra slides in the course notes + example code



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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







Our aim is to convey what we found to be relevant so far

You are invited/encouraged to give feedback





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 - Speakup. Please send us your criticism/comments/suggestions





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- You are invited/encouraged to give feedback
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 - Ask questions, please!
- Thanks to many people who helped so far with slides/comments







• Images (e.g., pixel grid)

Volume (e.g., voxel grid)



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Meshes (e.g., vertices/edges/faces)



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- Pointclouds (e.g., point arrays)
- Physics simulations (e.g., fluid flow over space/time, object-body interaction)



Problems in Computer Graphics

• Feature detection (image features, point features)

$$\mathbb{R}^{m \times m} \to \mathbb{Z}$$

• Denoising, Smoothing, etc.

$$\mathbb{R}^{m \times m} \to \mathbb{R}^{m \times m}$$

• Embedding, Distance computation

$$\mathbb{R}^{m \times m, m \times m} \to \mathbb{R}^d$$

Rendering

$$\mathbb{R}^{m \times m} \to \mathbb{R}^{m \times m}$$

Animation

$$\mathbb{R}^{3m \times t} \to \mathbb{R}^{3m}$$

Physical simulation

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Generative models

$$\mathbb{R}^d \to \mathbb{R}^{m \times m}$$



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synthesis

$$f_{\theta}: \mathbb{X} \longrightarrow \mathbb{Y}$$

 θ : function parameters, \mathbb{X} : source domain \mathbb{Y} : target domain these are learned



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Examples:

Image Classification: $f_{\theta}: \mathbb{R}^{w \times h \times c} \longrightarrow \{0, 1, \dots, k-1\}$ $w \times h \times c : \text{image dimensions} \quad k: \text{class count}$



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Examples:

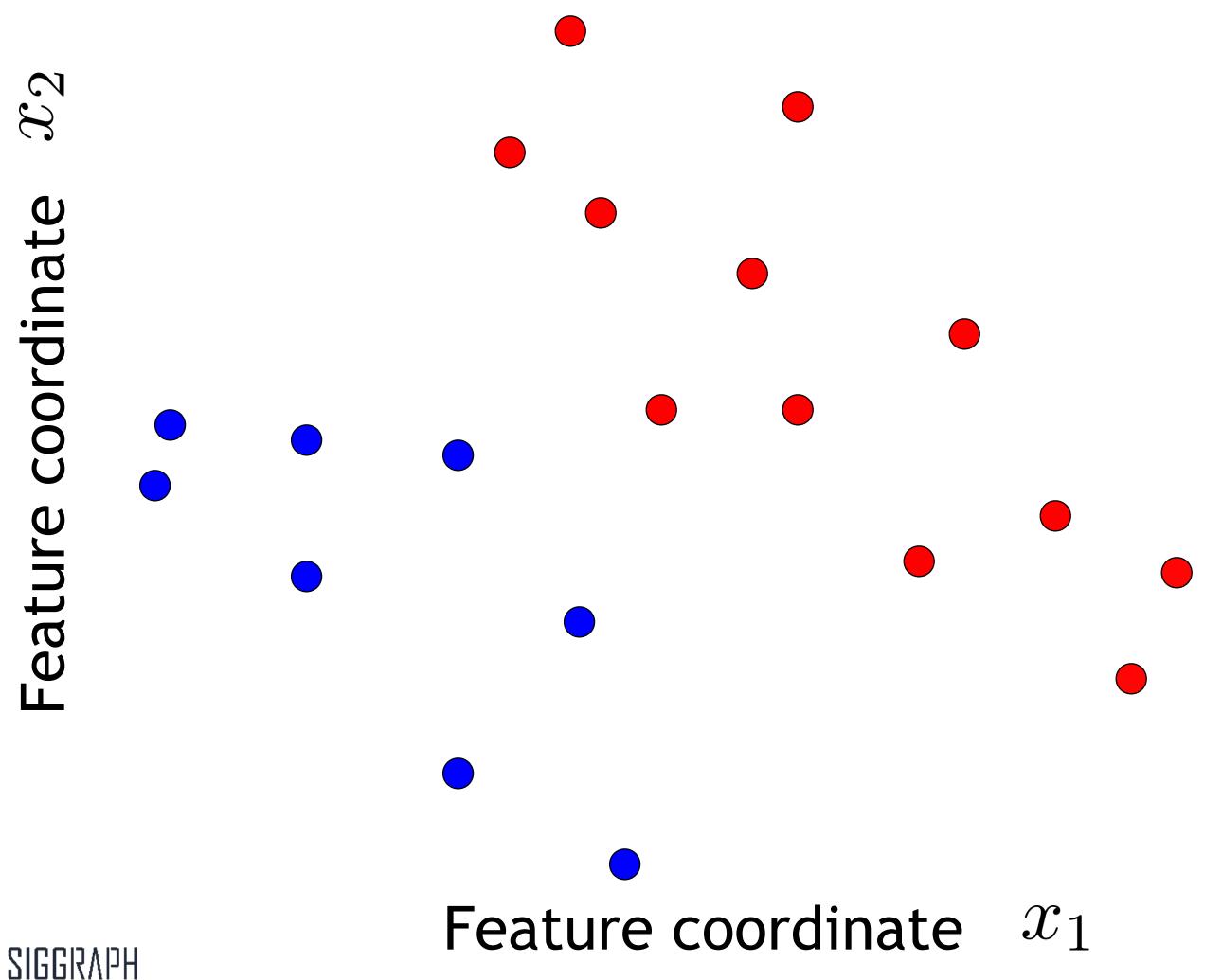
Image Classification: $f_{\theta}: \mathbb{R}^{w \times h \times c} \longrightarrow \{0, 1, \dots, k-1\}$

 $w \times h \times c$: image dimensions k: class count

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

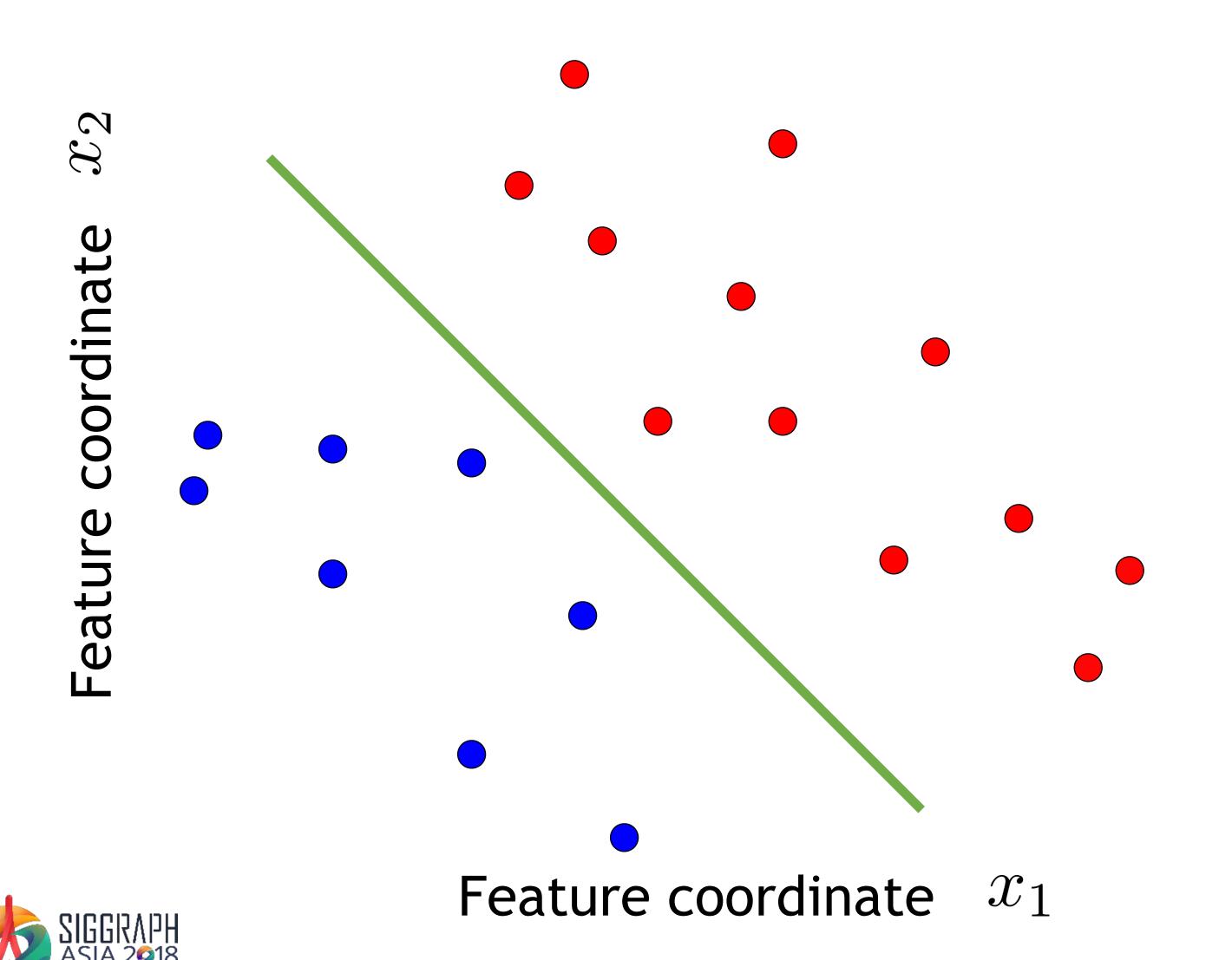




$$f_{\theta}: \mathbb{R}^n \longrightarrow \{0, 1\}$$

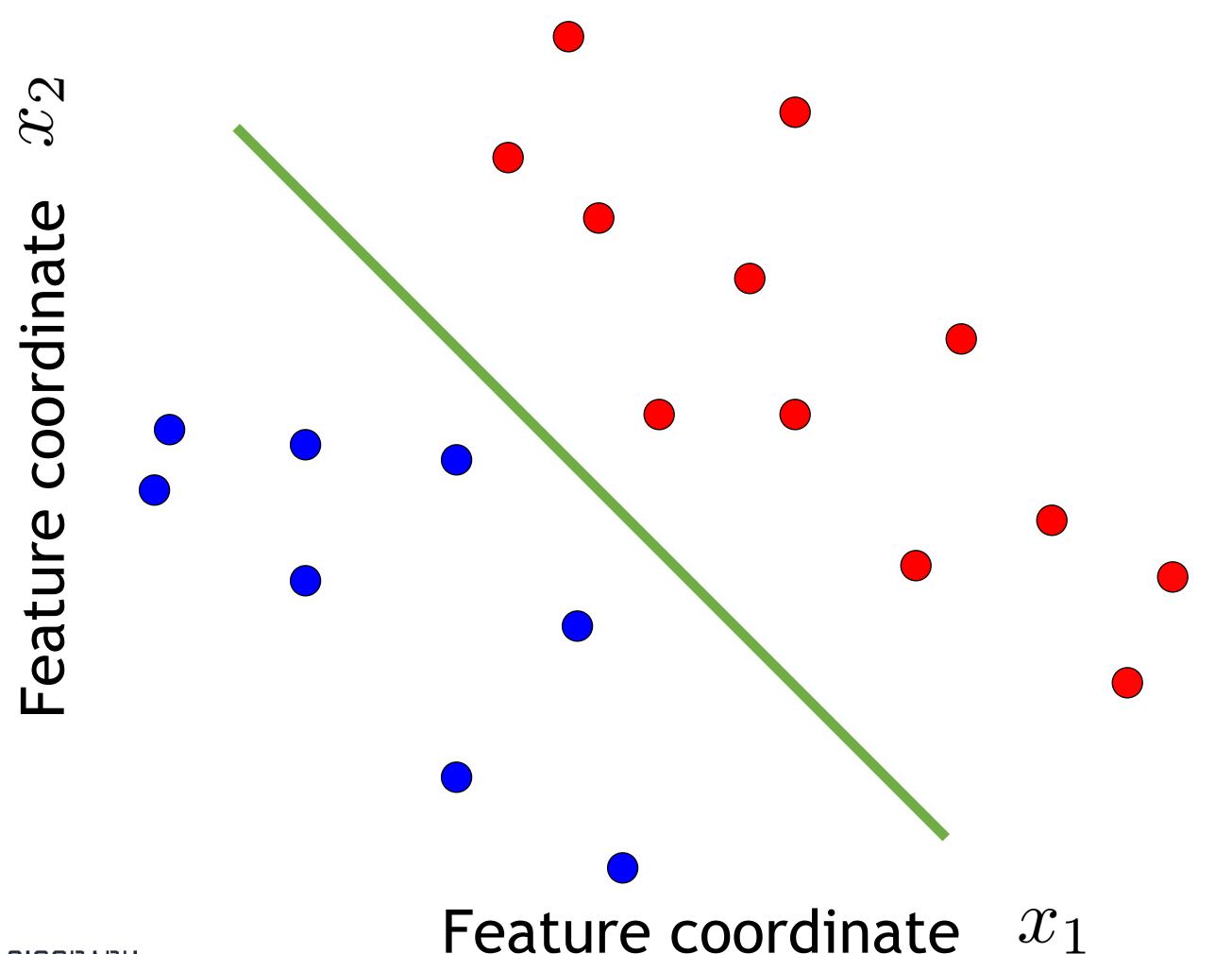
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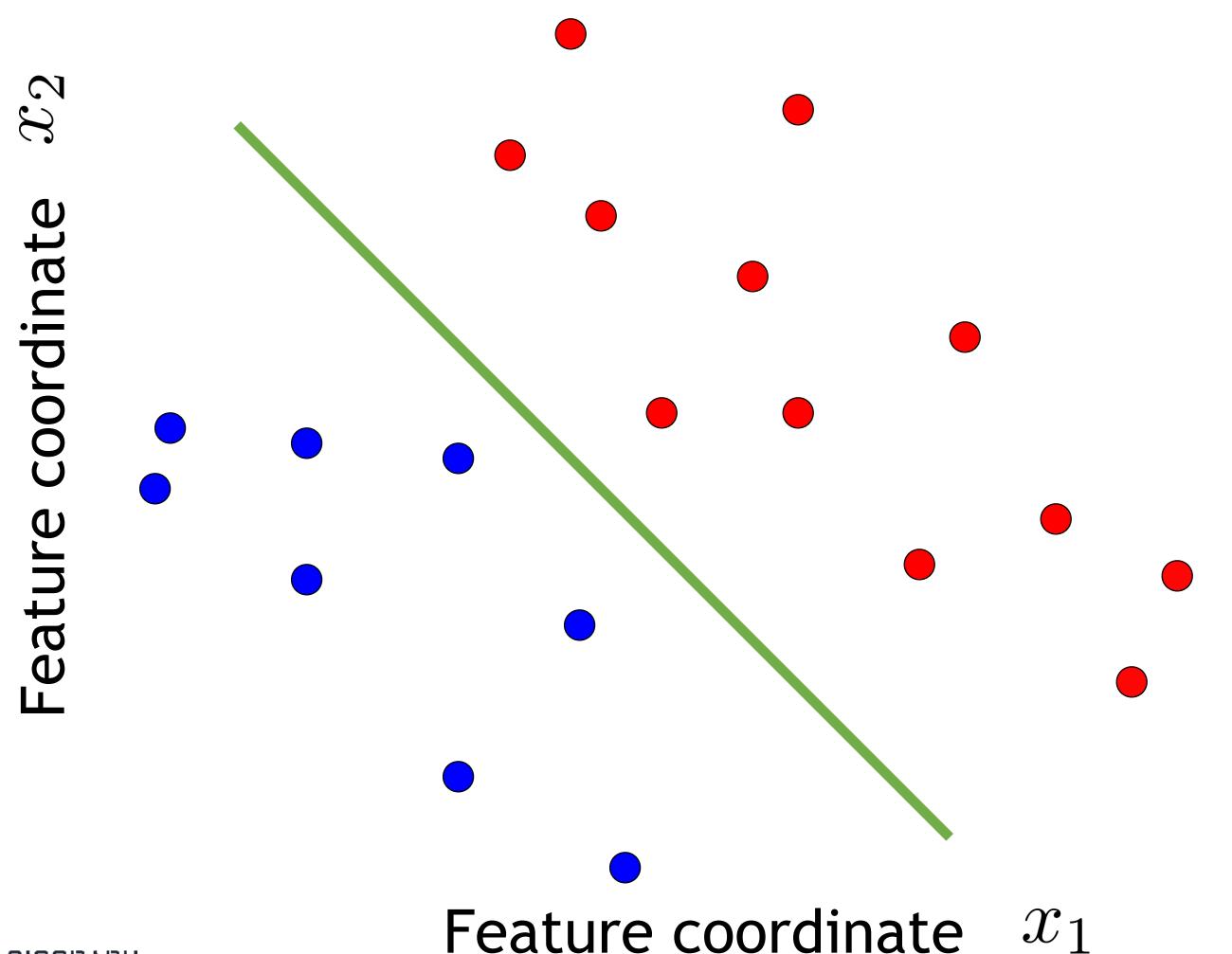


$$f_{\theta}: \mathbb{R}^n \longrightarrow \{0, 1\}$$

$$f_{\theta}(x) = \begin{cases} 1 & \text{if } wx + b \ge 0 \\ 0 & \text{if } wx + b < 0 \end{cases}$$

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Data-driven Algorithms (Supervised)

Labelled data (supervision data)



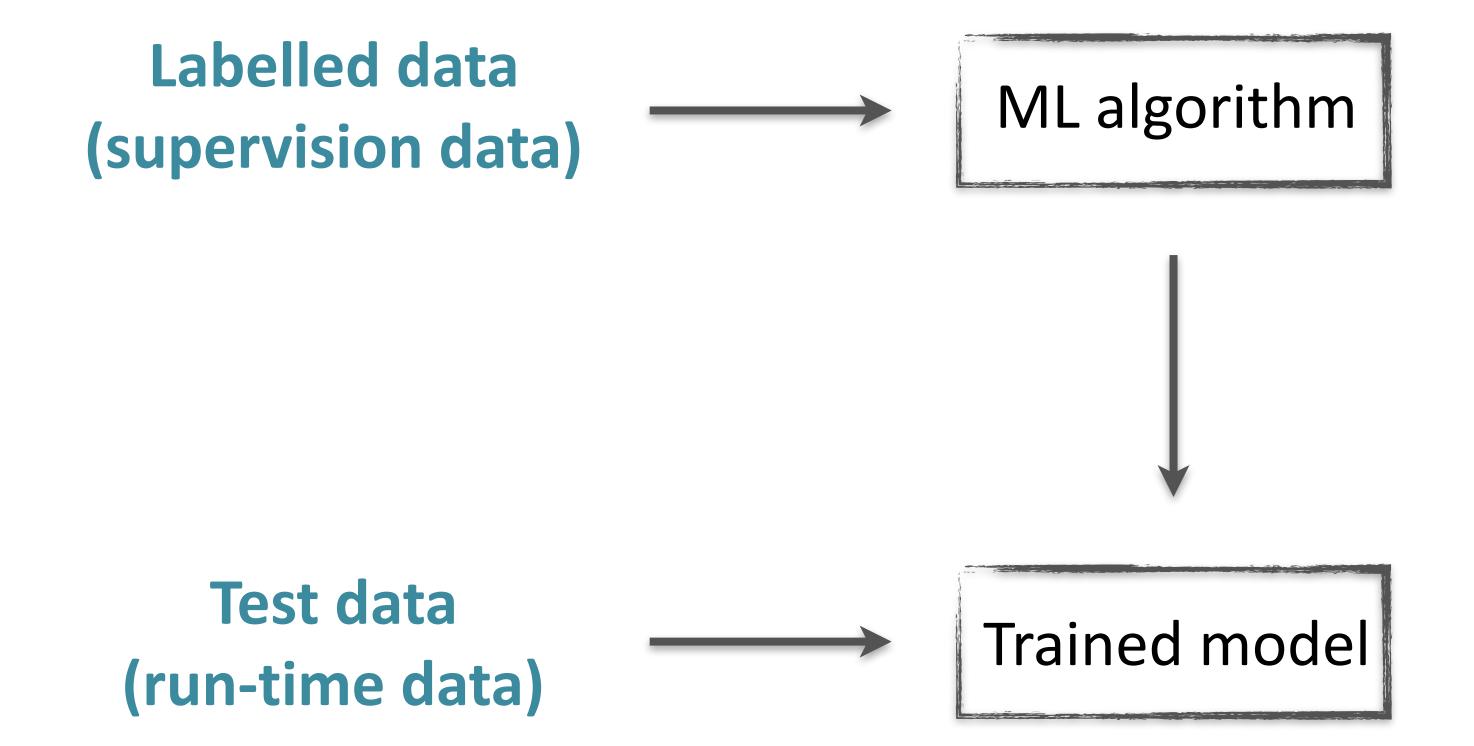
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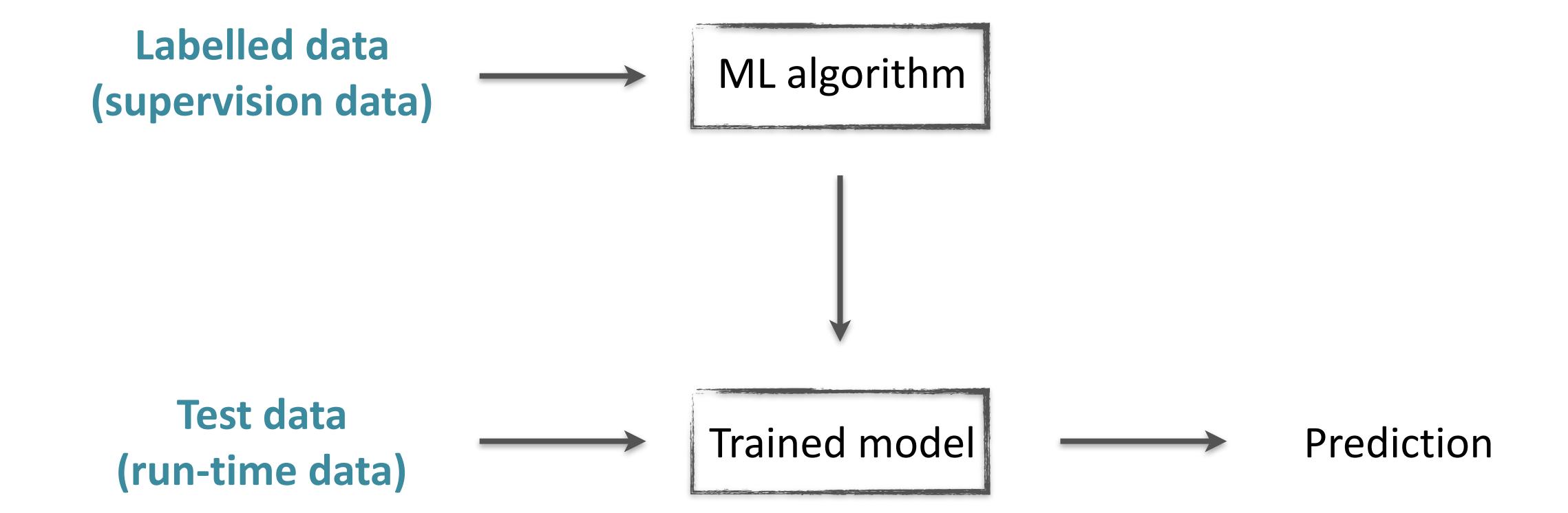
ML algorithm

Trained model

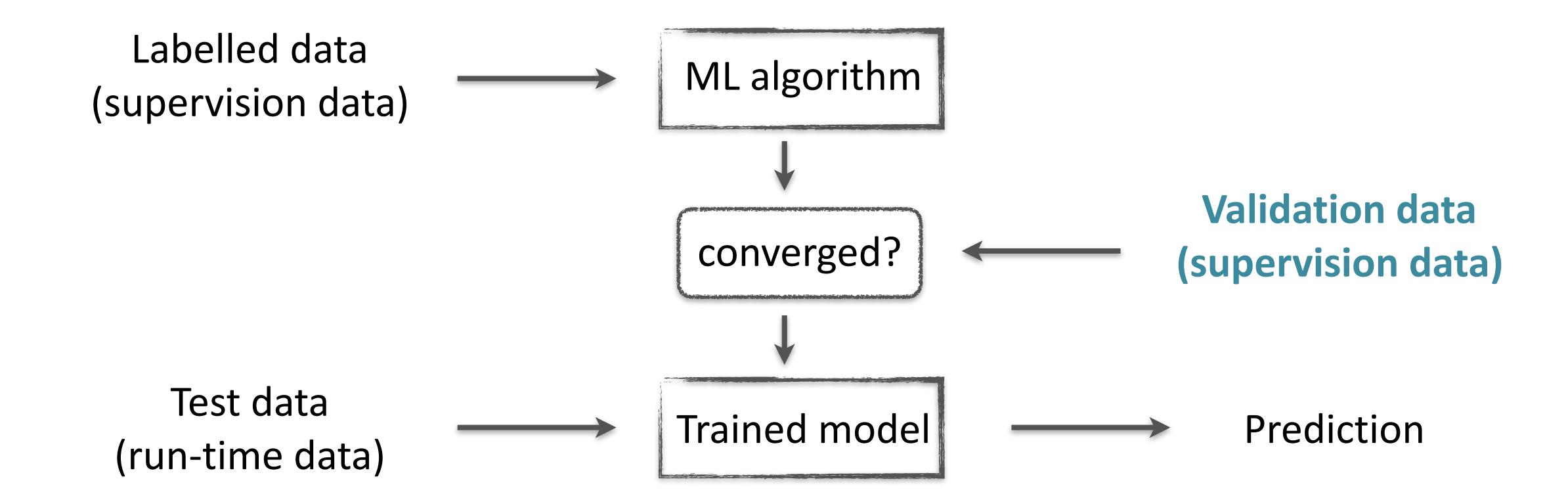




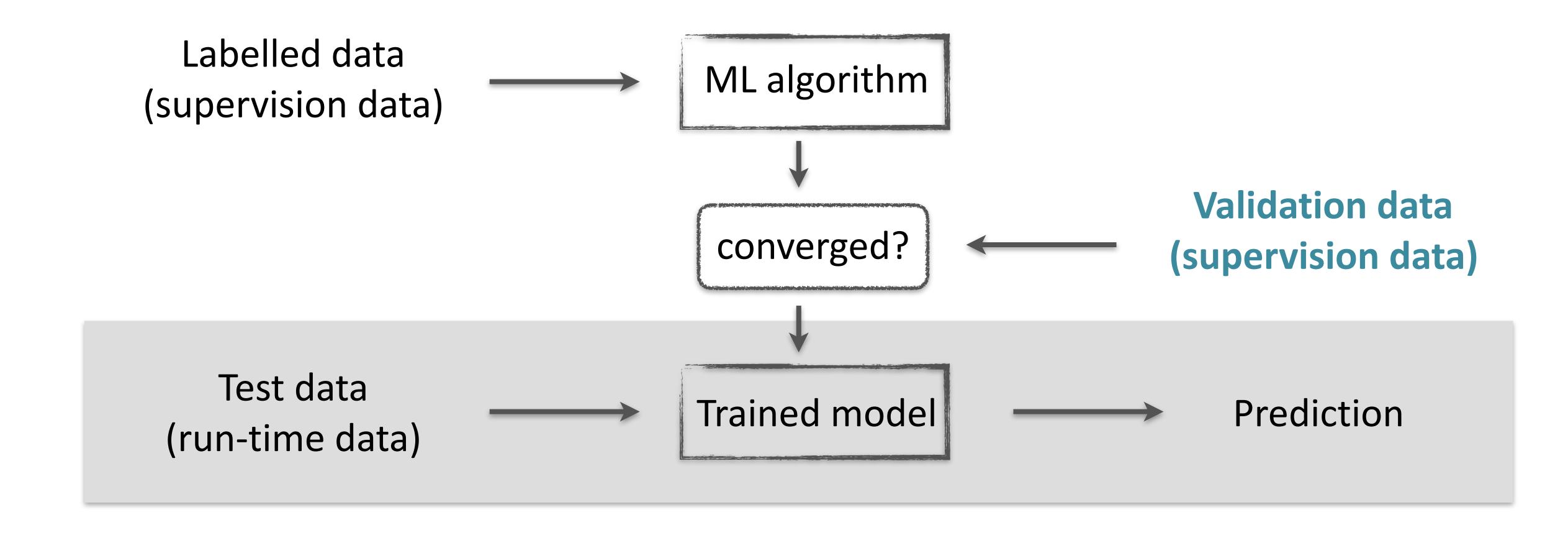




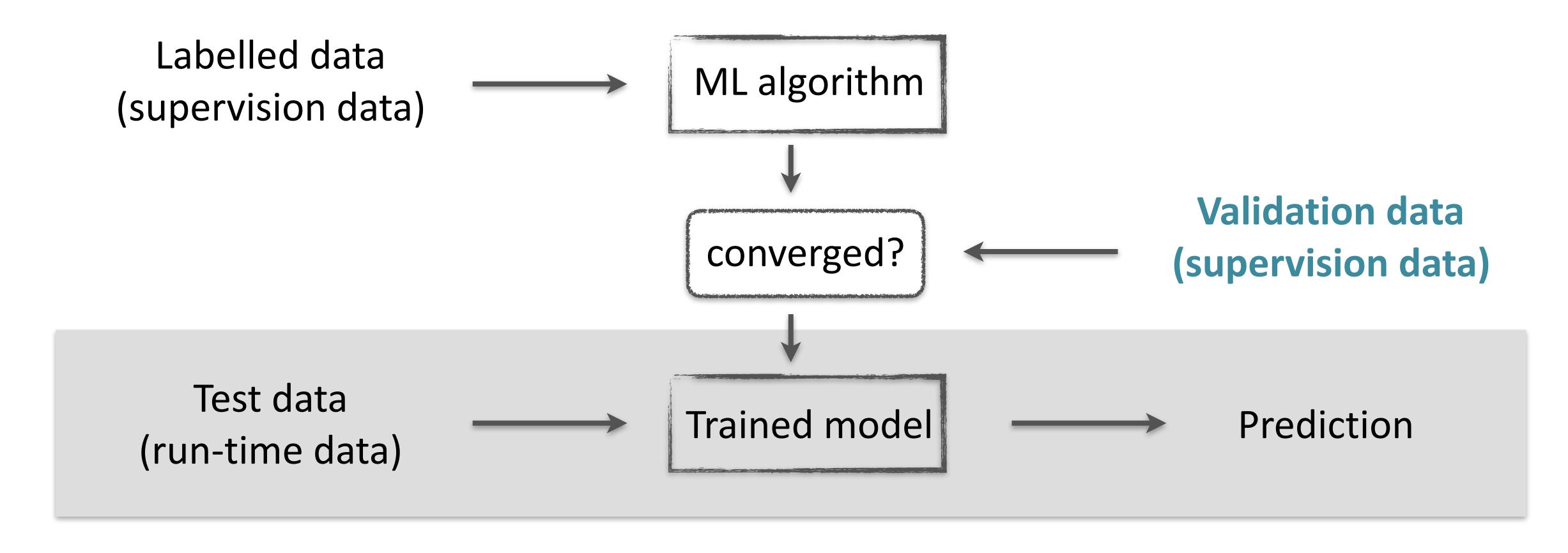






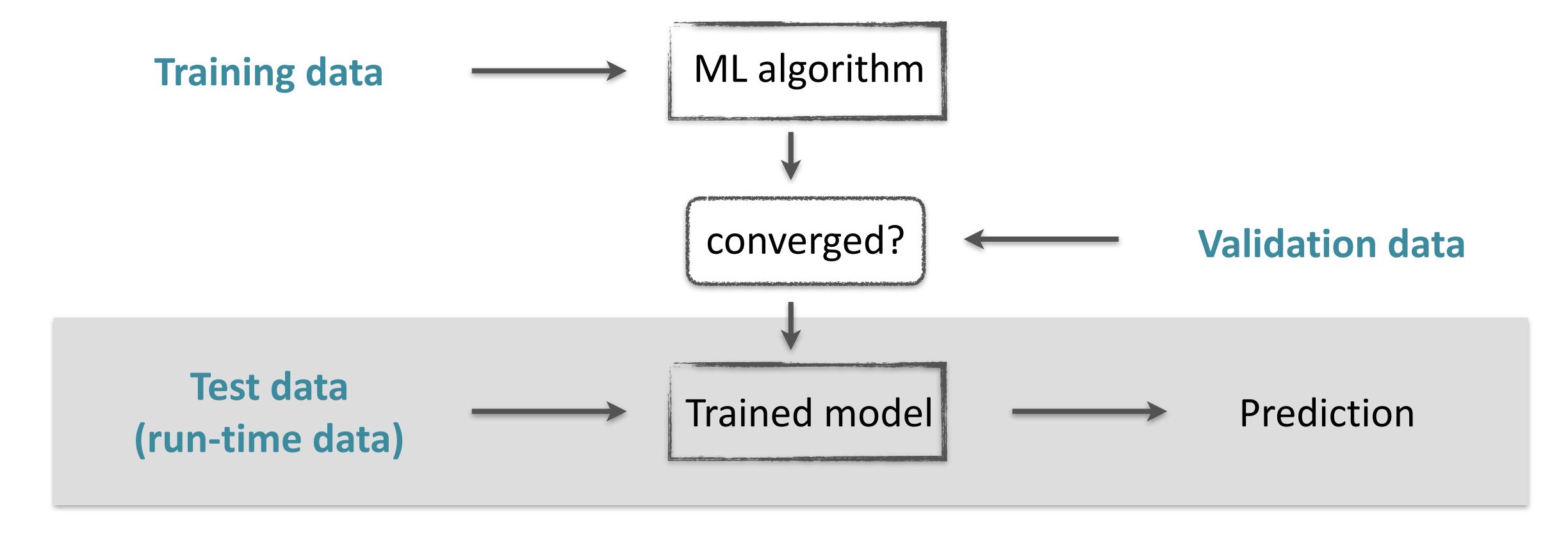






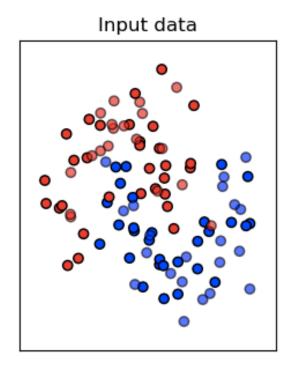
Implementation Practice: Training: 70%; Validation: 15%; Test 15%

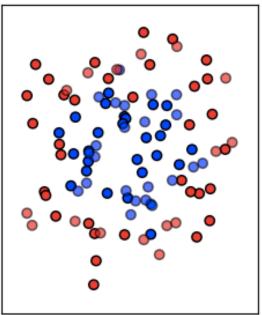


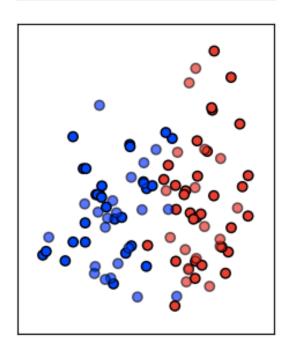


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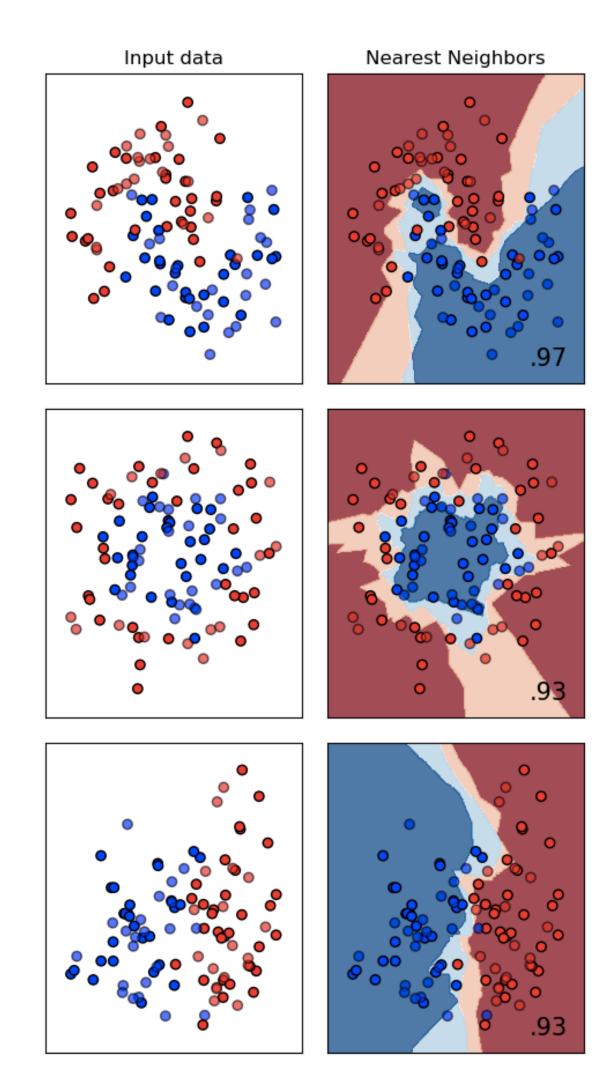




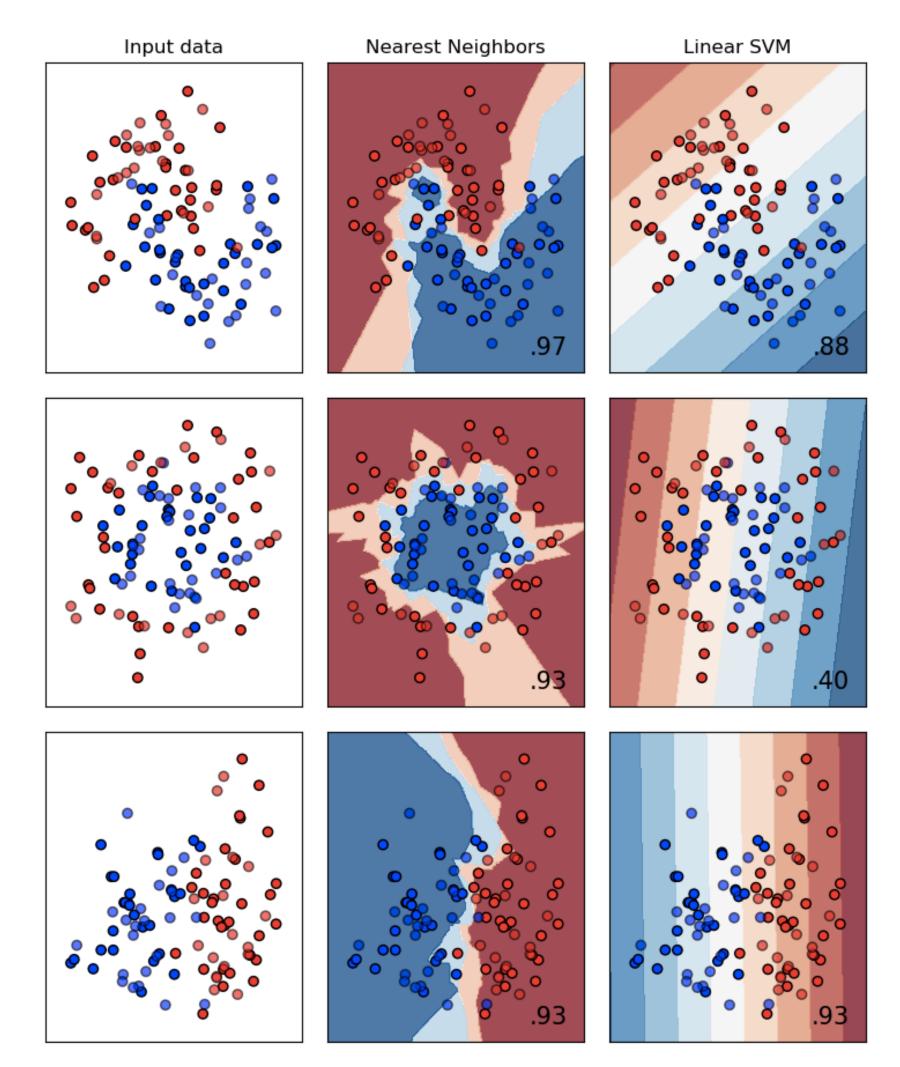




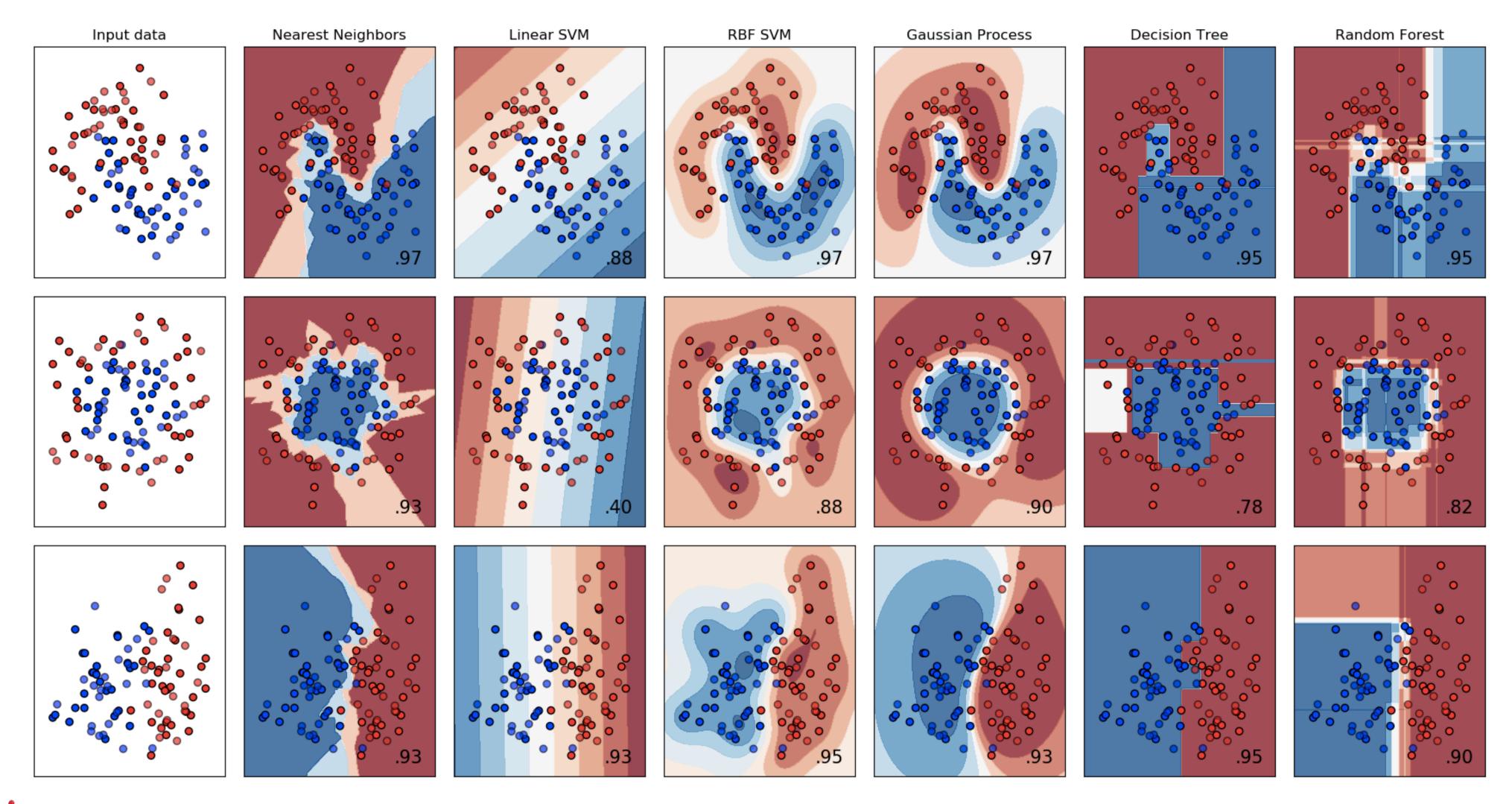




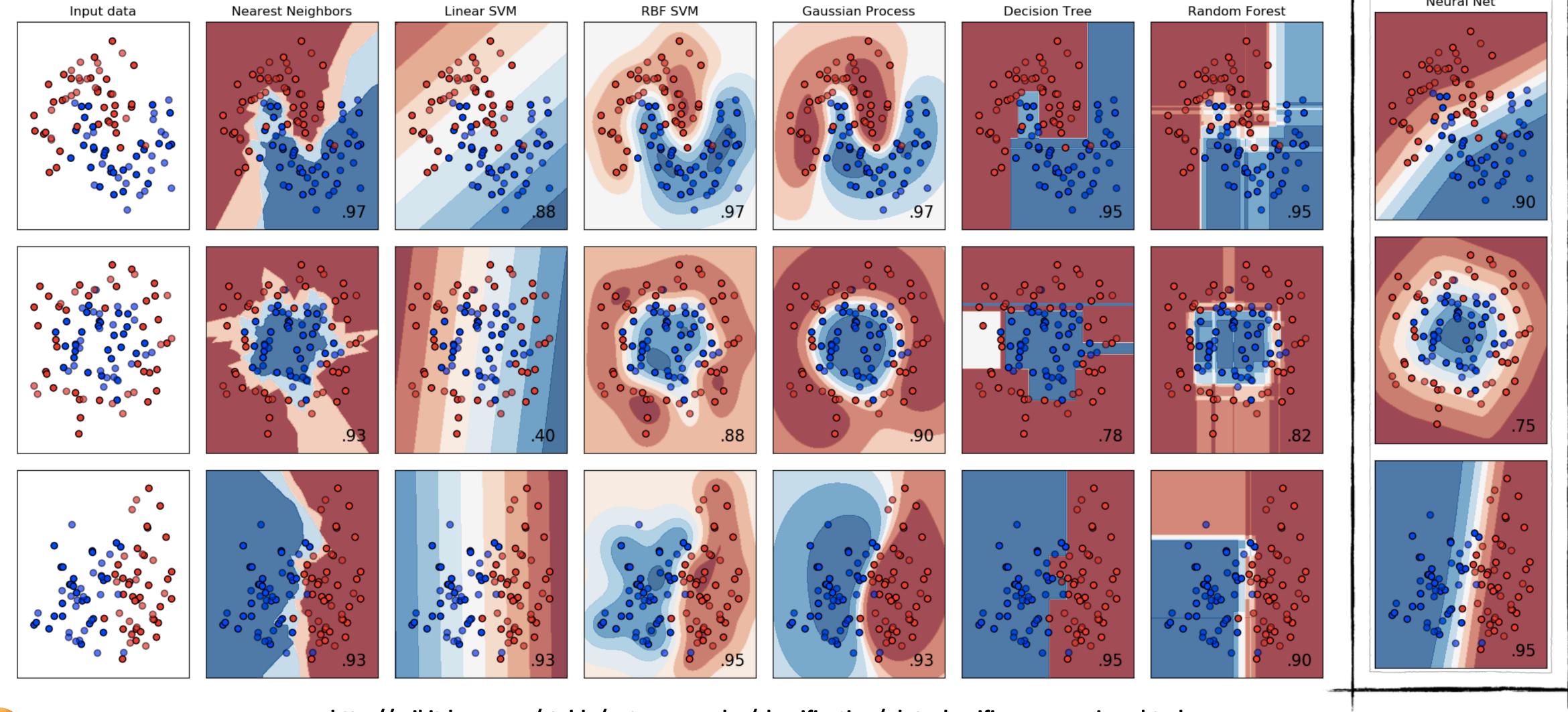














Rise of Learning

• 1958: Perceptron

• 1974: Backpropagation

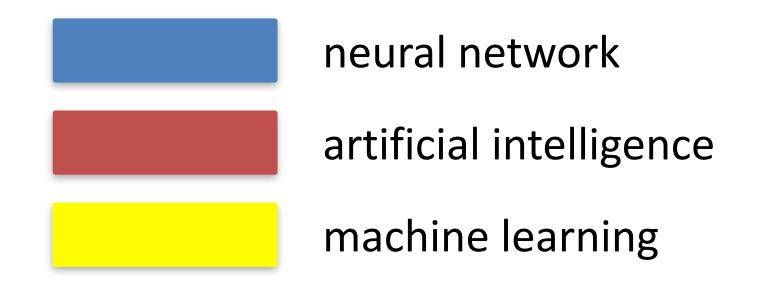
• 1981: Hubel & Wiesel wins Nobel prize for 'visual system'

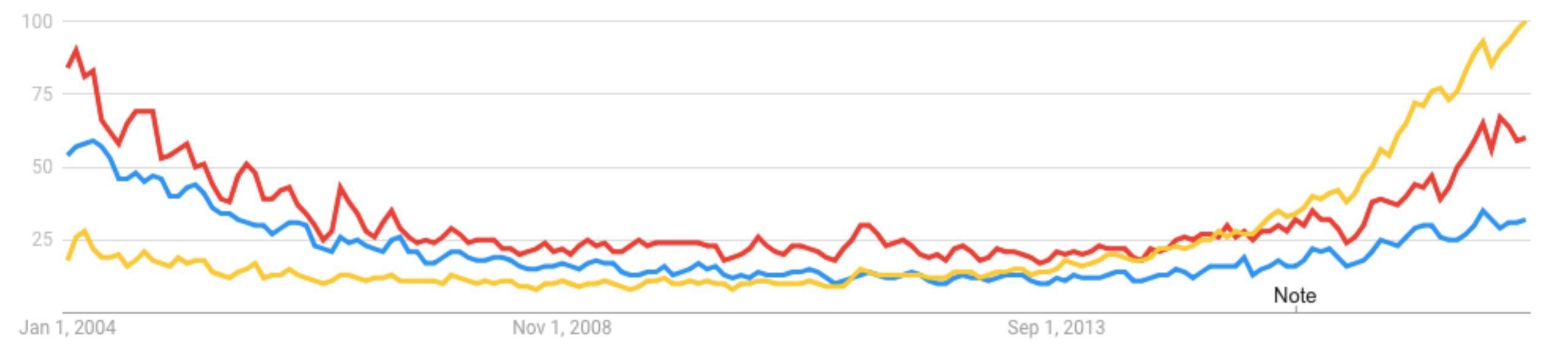
• 1990s: SVM era

• 1998: CNN used for handwriting analysis

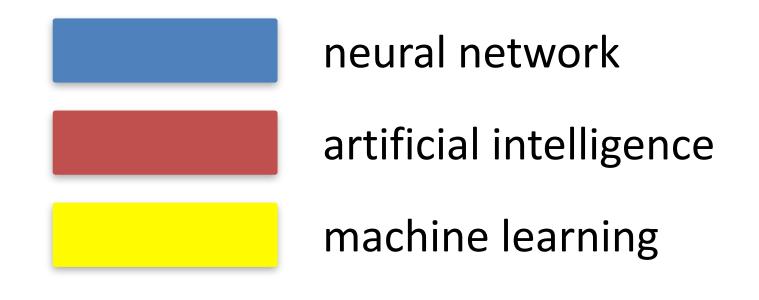
2012: AlexNet wins ImageNet



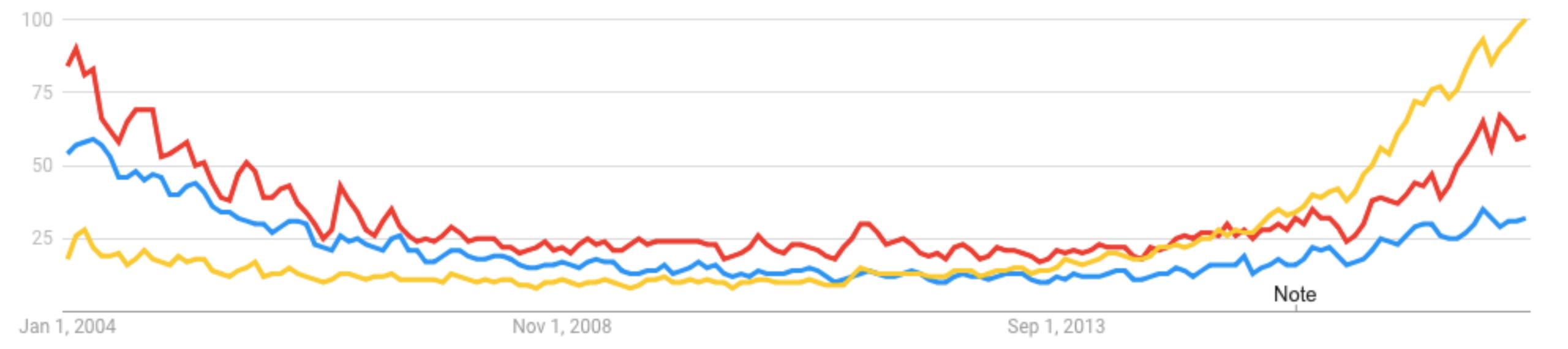




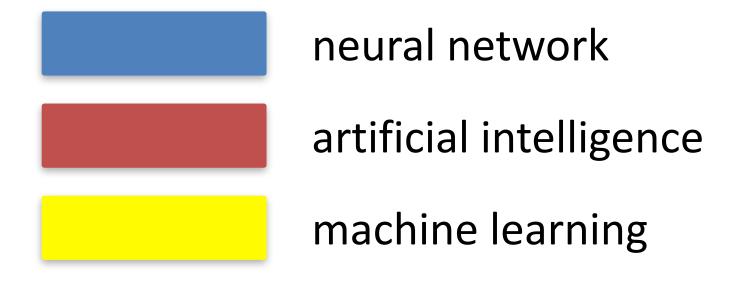


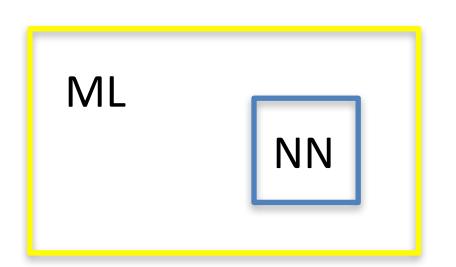


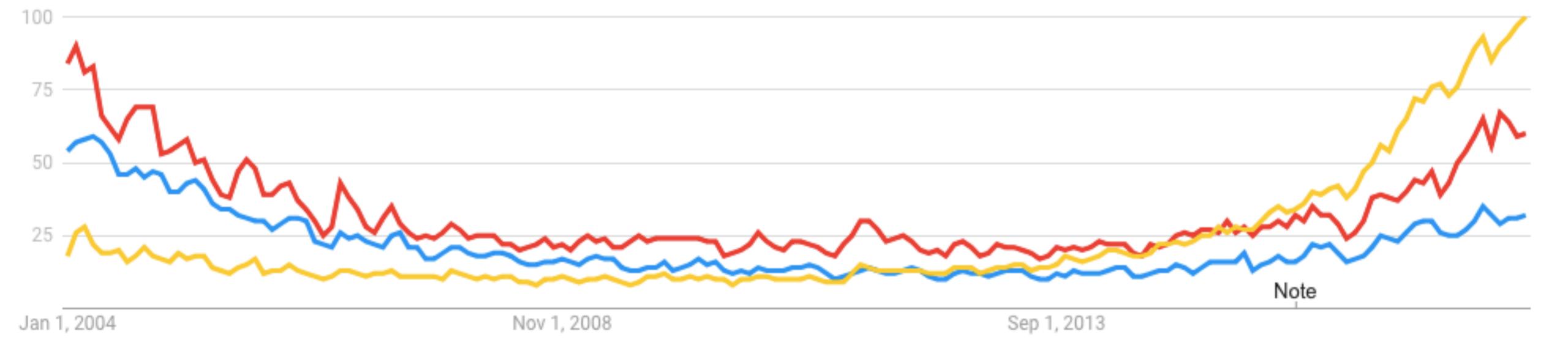




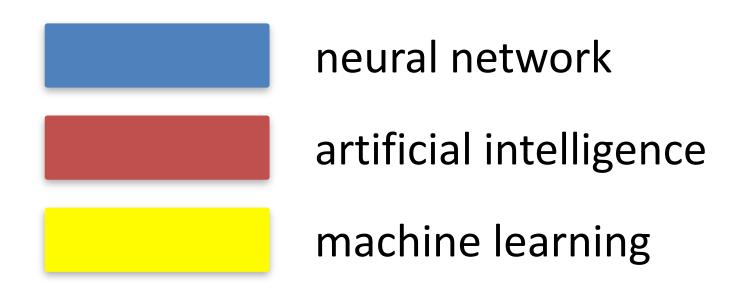


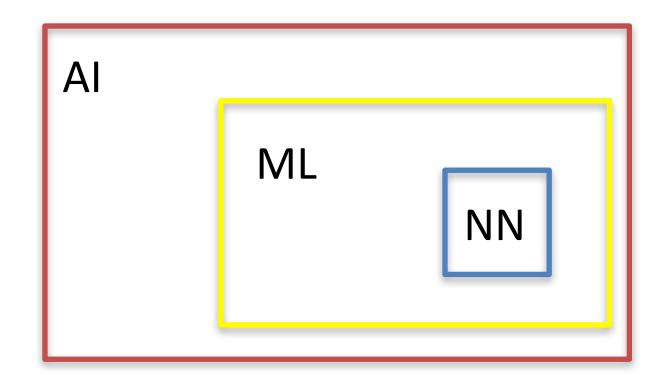


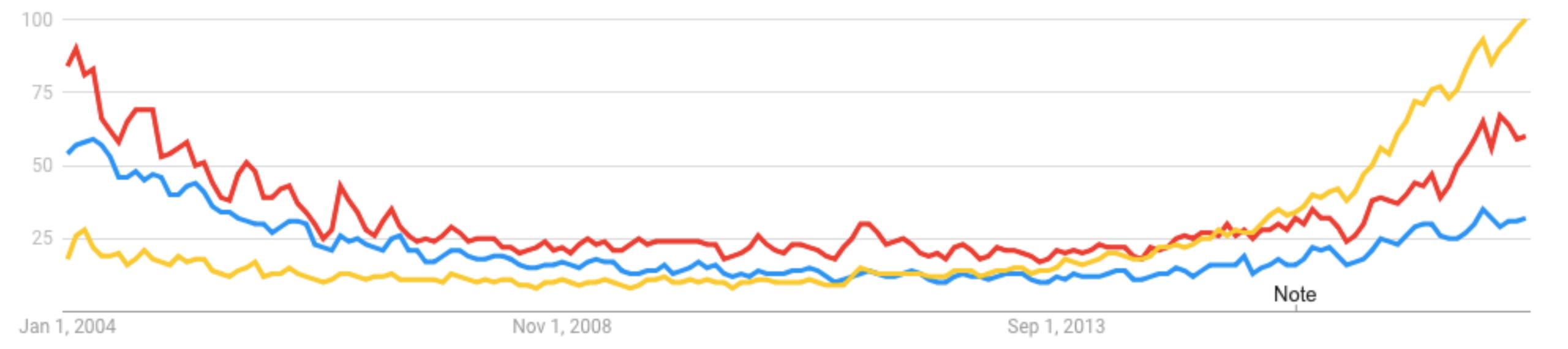






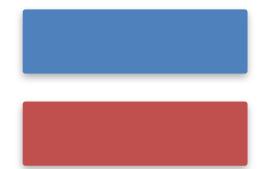






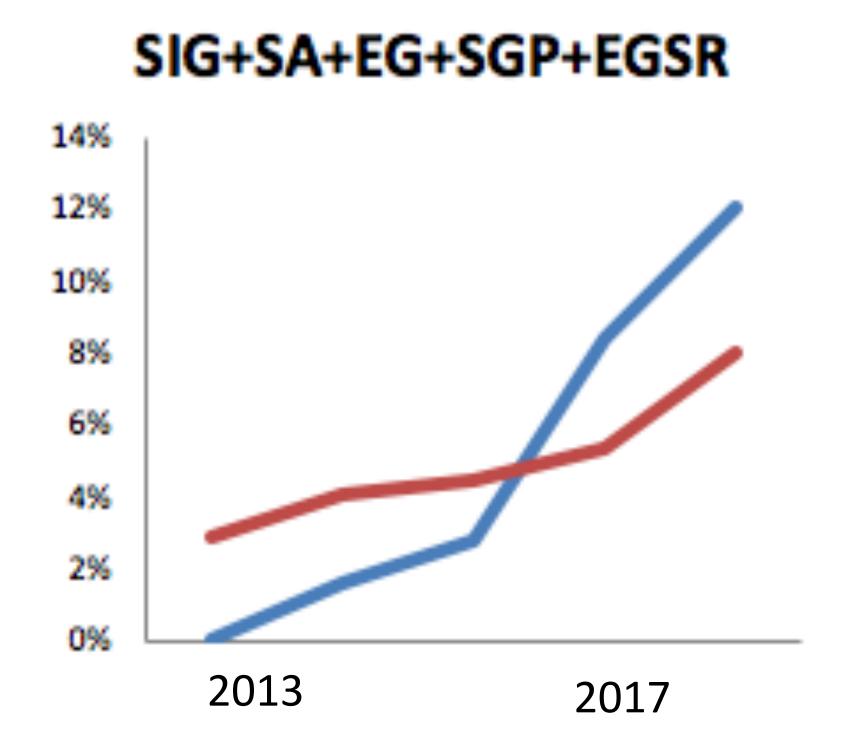


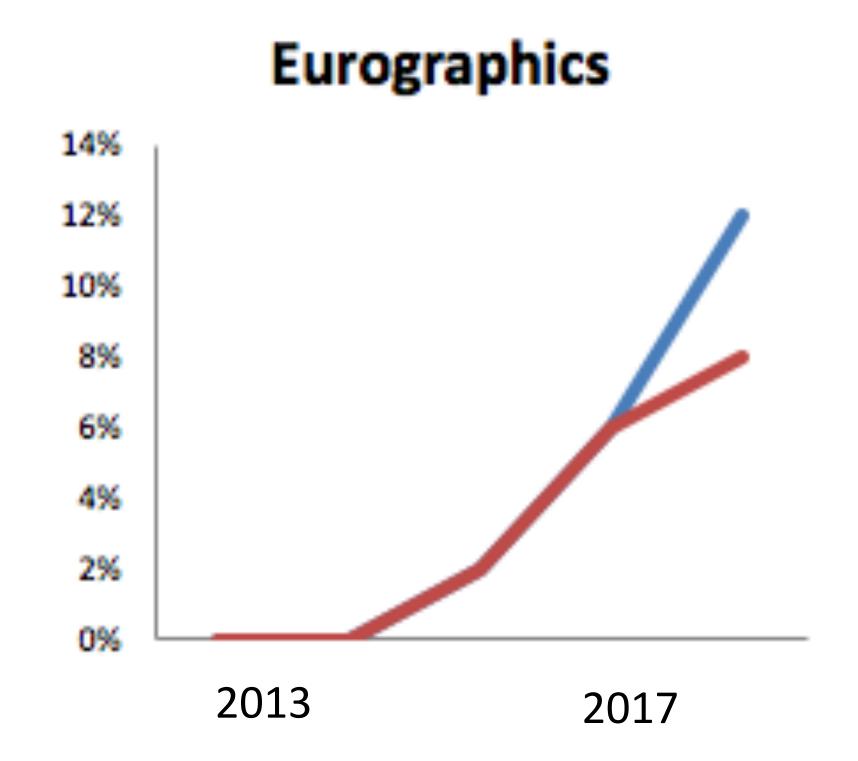
Rise of Machine Learning (in Graphics)



machine learning

neural network









1. Image Processing (image translation tasks)



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- 2. Many sources of input data model building (e.g., images, scanners, motion capture)



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- 3. Many sources of synthetic data can serve as supervision data (e.g., rendering, animation)
- 4. Many problems in generative models





1. Representation: How is the data organised and structured?



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- 4. Loss functions: Hand-crafted or learned from data?

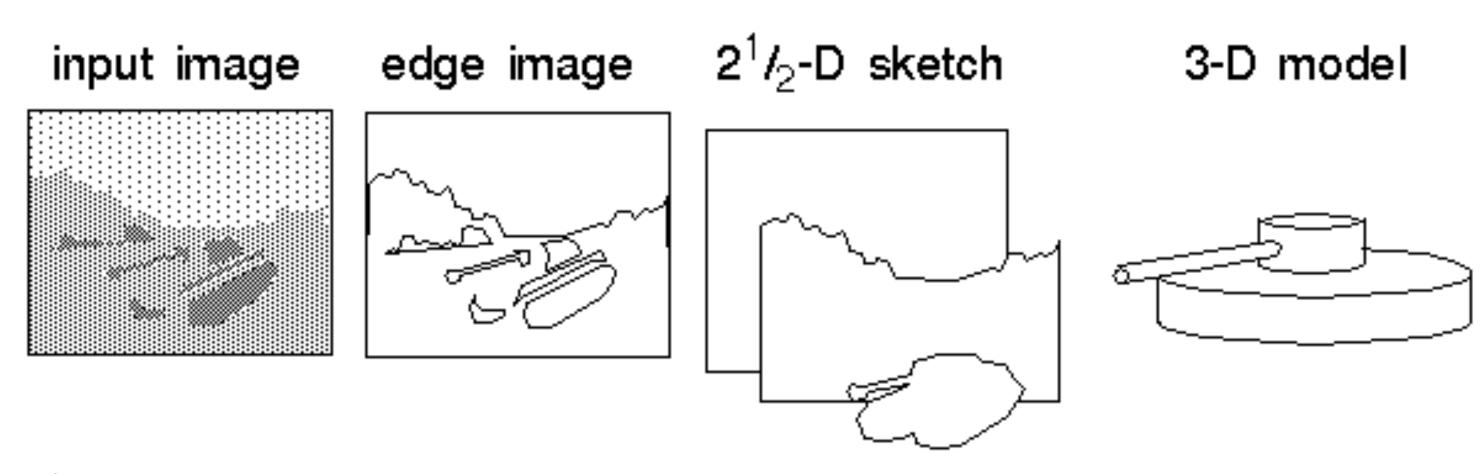


End-to-end: Learned Features



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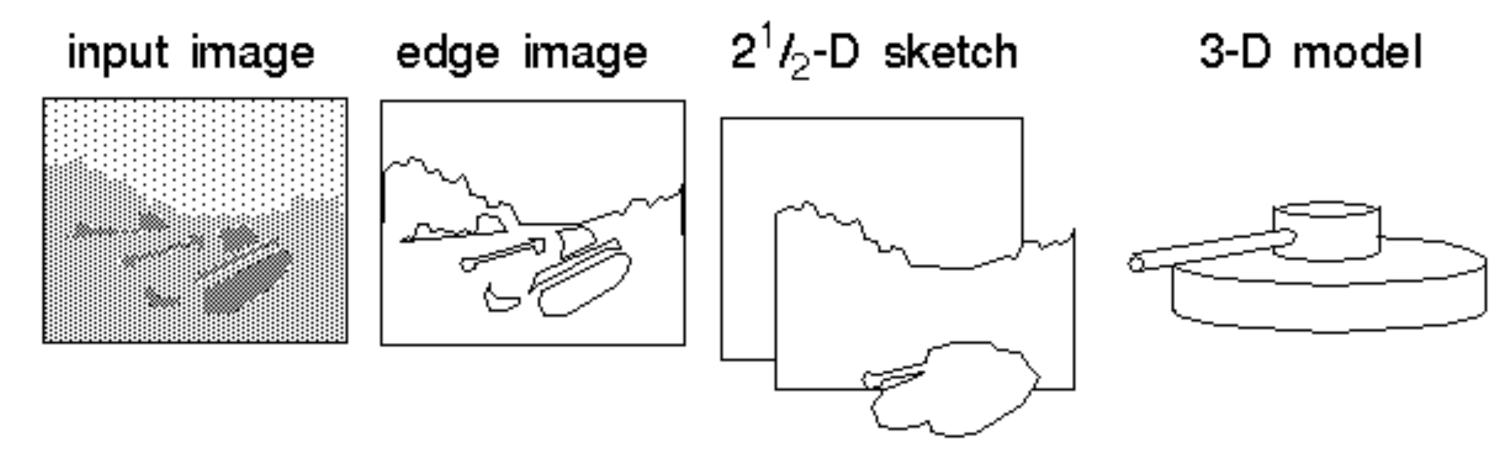
- Old days
 - Handcrafted feature extraction, e.g., edges or corners (hand-crafted)
 - Mostly with linear models (PCA, etc.)

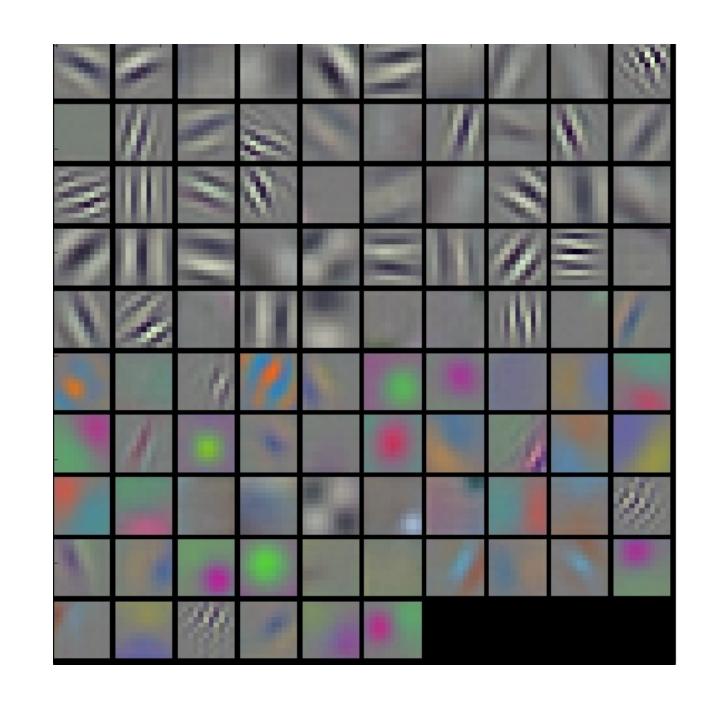




End-to-end: Learned Features

- Old days
 - Handcrafted feature extraction, e.g., edges or corners (hand-crafted)
 - Mostly with linear models (PCA, etc.)
- Now
 - End-to-end
 - Move away from hand-crafted representations









- Old days
 - Evaluation came after
 - It was a bit optional
 - You might still have a good algorithm without a good way of quantifying it
 - Evaluation helped publishing



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- If the loss is not good, the result is not good
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 - Evaluation helped publishing
- Now
 - It is essential and build-in
 - If the loss is not good, the result is not good
 - (Extensive) Evaluation happens automatically
- While still much is left to do, this makes graphics much more reproducible



End-to-end: Real/Generated Data





End-to-end: Real/Generated Data

- Old days
 - Test with some toy examples
 - Deploy on real stuff
 - Maybe collect some performance data later





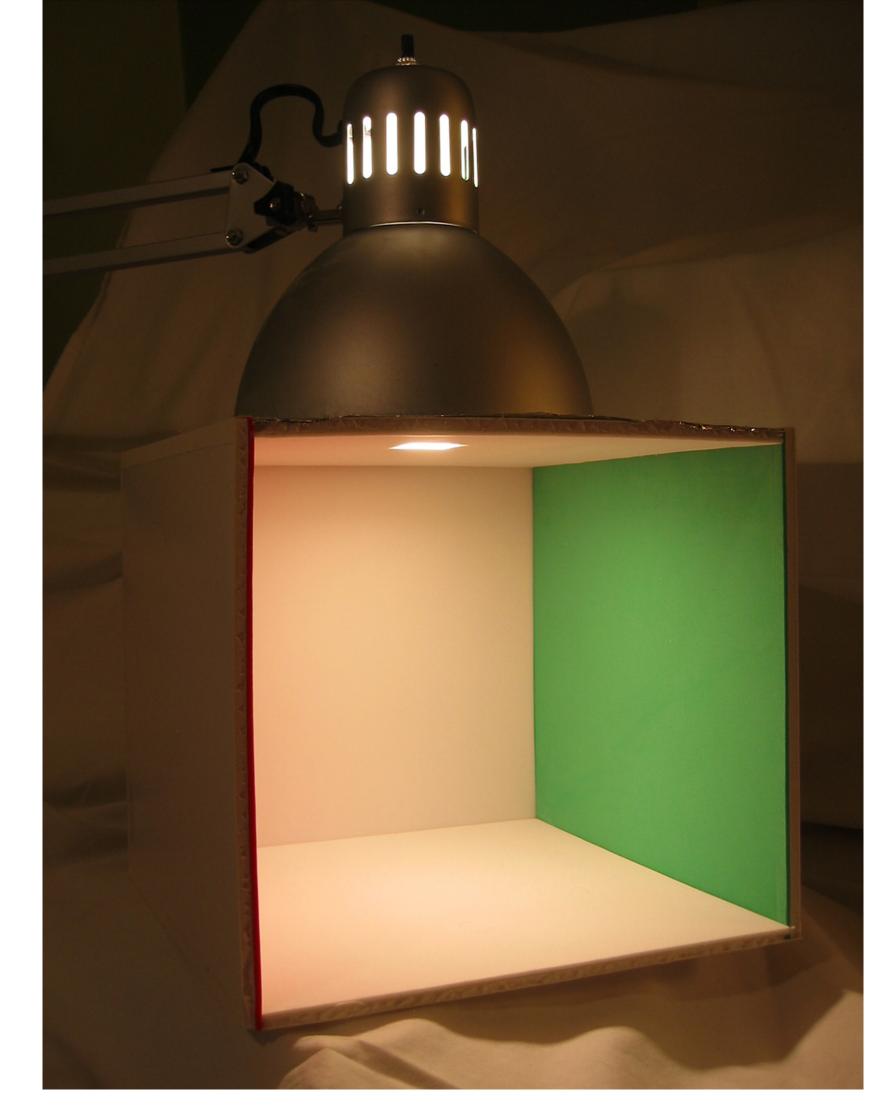
End-to-end: Real/Generated Data

Old days

- Test with some toy examples
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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

Rendering

Animation



Examples in Graphics

Geometry

Colorization

Image

manipulation

BRDF estimation

Real-time rendering

Sketch

simplification

Rendering

Procedural modelling

Mesh segmentation

Learning deformations

Animation

Boxification Fluid

Animation

Denoising

Facial animation

PCD processing



Examples in Graphics



Sketch simplification



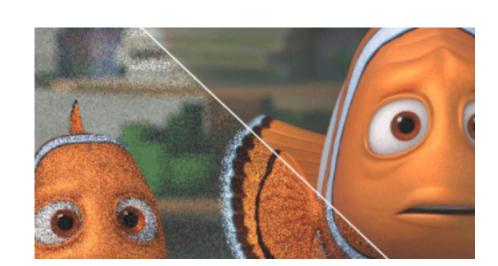
Real-time rendering



Colorization



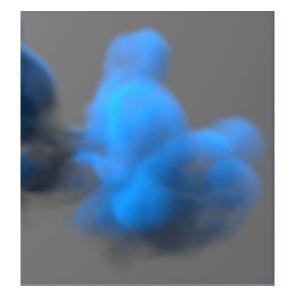
BRDF estimation



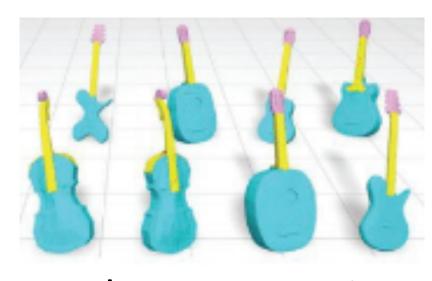
Denoising



Procedural modelling



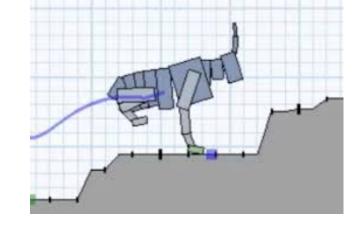
Fluid



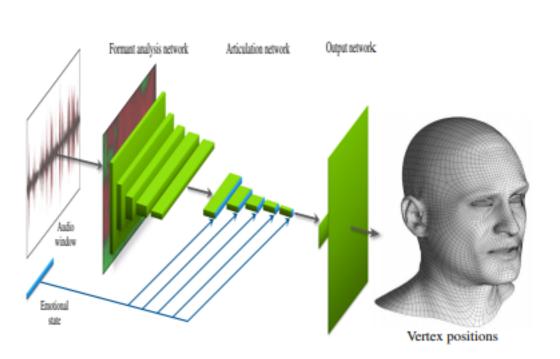
Mesh segmentation



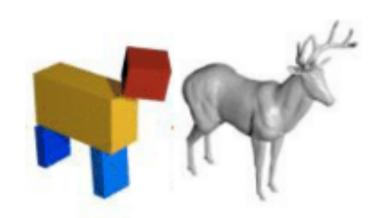
Learning deformations



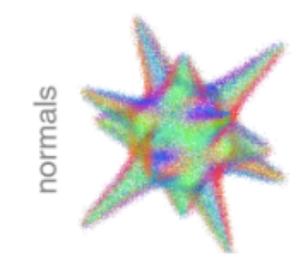
Animation



Facial animation



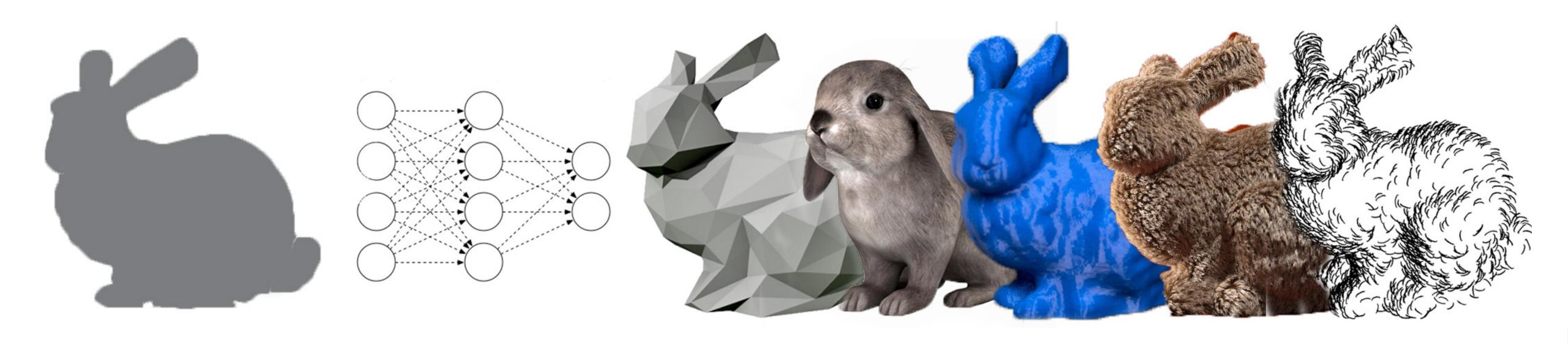
Boxification



PCD processing



Course Information (slides/code/comments)



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



