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Marcin Kierczak

EXPLAINABLE(?) PREDICTIONS: INTRO TO BUILDING MODELS WITHIN THE SUPERVISED LEARNING FRAMEWORK



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Overview

- A bit of history.
- Machine Learning (ML) in general.
- Supervised learning framework.
 - Feature engineering & selection.
 - Model selection.
 - Model validation.
 - Model interpretation.
 - Uncertainty.
- General remarks.



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Artificial Intelligence & co.

Artificial Intelligence (AI)

The effort to automate intellectual tasks normally performed by humans.¹



¹ Chollet & Allaire. Deep learning with R.



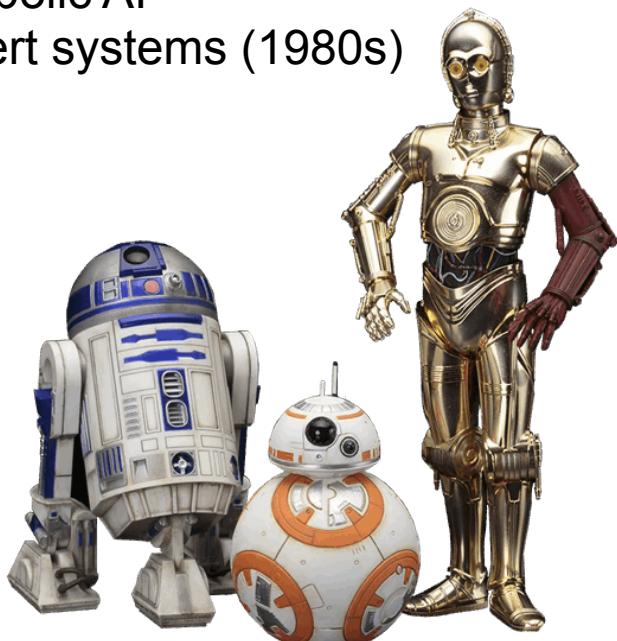
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Artificial Intelligence & co.

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The effort to automate intellectual tasks normally performed by humans.¹

- 1950s
- symbolic AI
- expert systems (1980s)



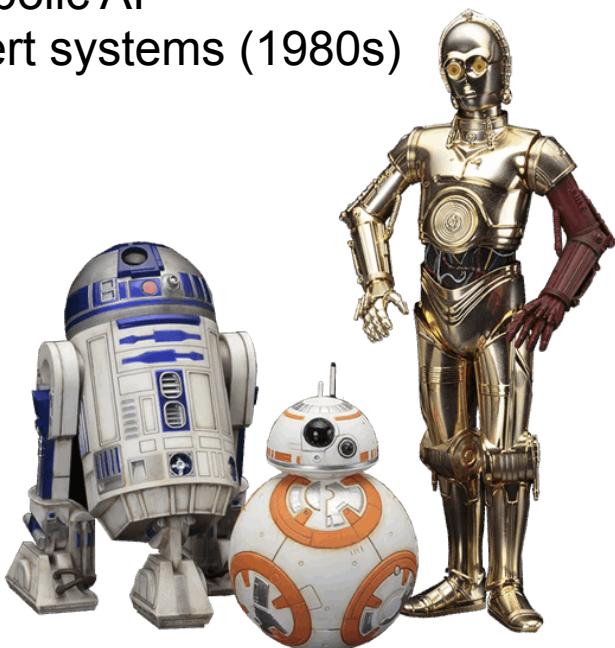
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Artificial Intelligence & co.

Artificial Intelligence (AI)

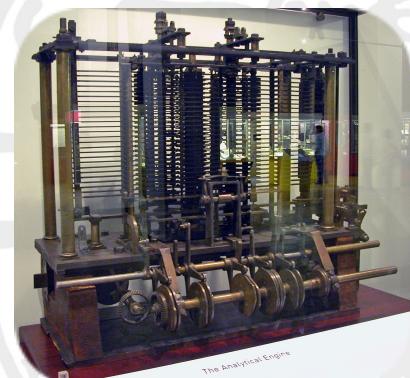
The effort to automate intellectual tasks normally performed by humans.¹

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The Analytical Engine has no pretensions whatever to originate anything. It can do whatever we know how to order it to perform...

Lady Ada Lovelace





Machine Learning

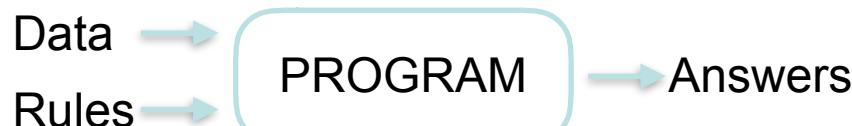
Artificial Intelligence (AI)

The effort to automate intellectual tasks normally performed by humans.¹



Allan Turing

- *Computing Machinery and Intelligence*
- Turing test





Machine Learning

Artificial Intelligence (AI)

The effort to automate intellectual tasks normally performed by humans.¹



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Machine Learning

Artificial Intelligence (AI)

The effort to automate intellectual tasks normally performed by humans.

Machine Learning (ML)

Machine Learning is a field of study that gives computers the ability to learn without being explicitly programmed.

Arthur Samuel, 1959





Overview

Artificial Intelligence (AI)

Machine Learning (ML)

Supervised Learning

Deep learning

SVMs

ANNs

random forests

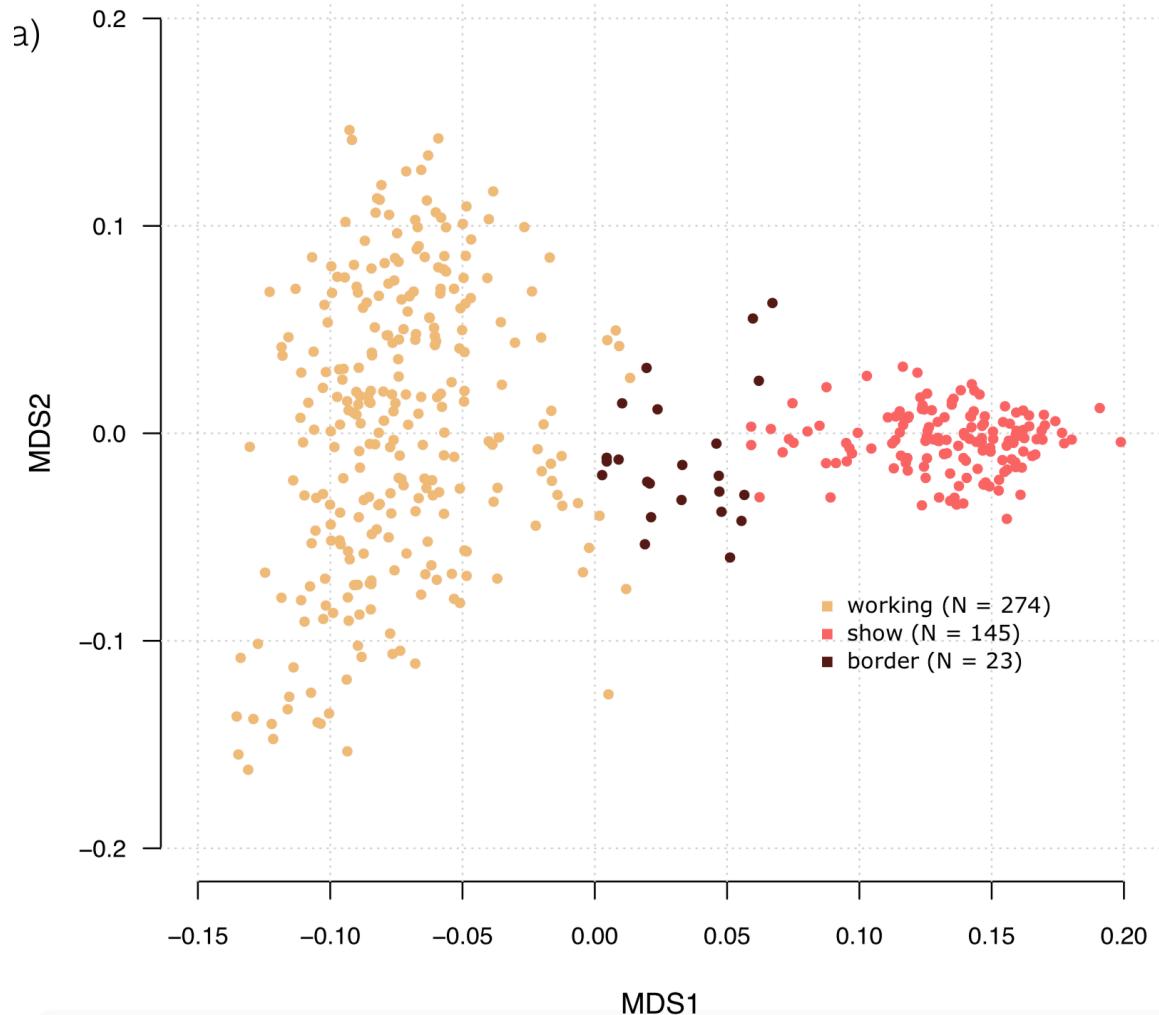
rough sets

decision trees



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Unsupervised learning





Supervised learning

A decision system

	Attr. 1	Attr. 2	...	Attr. M	d
Ex. 1	1	big	...	11.54	case
Ex. 2	4	small	...	-5.48	control
...
Ex. N	5	medium	...	7.26	control

$$\mathbf{A}_d = (U, A \cup \{d\})$$

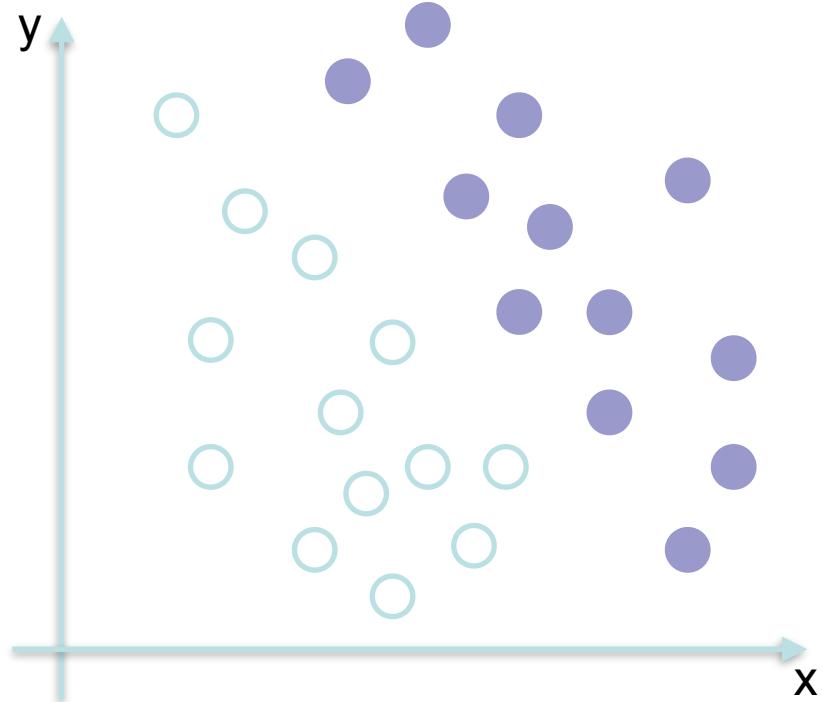
$$d \notin A$$

A – conditional attributes,
d – decision attribute(s)



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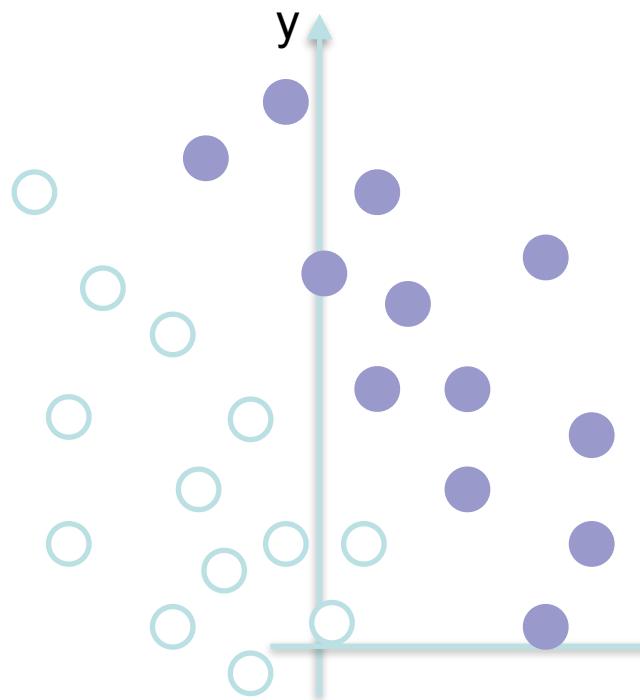
Geometric interpretation





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Geometric interpretation



IF $x < 0$ THEN white ELSE blue



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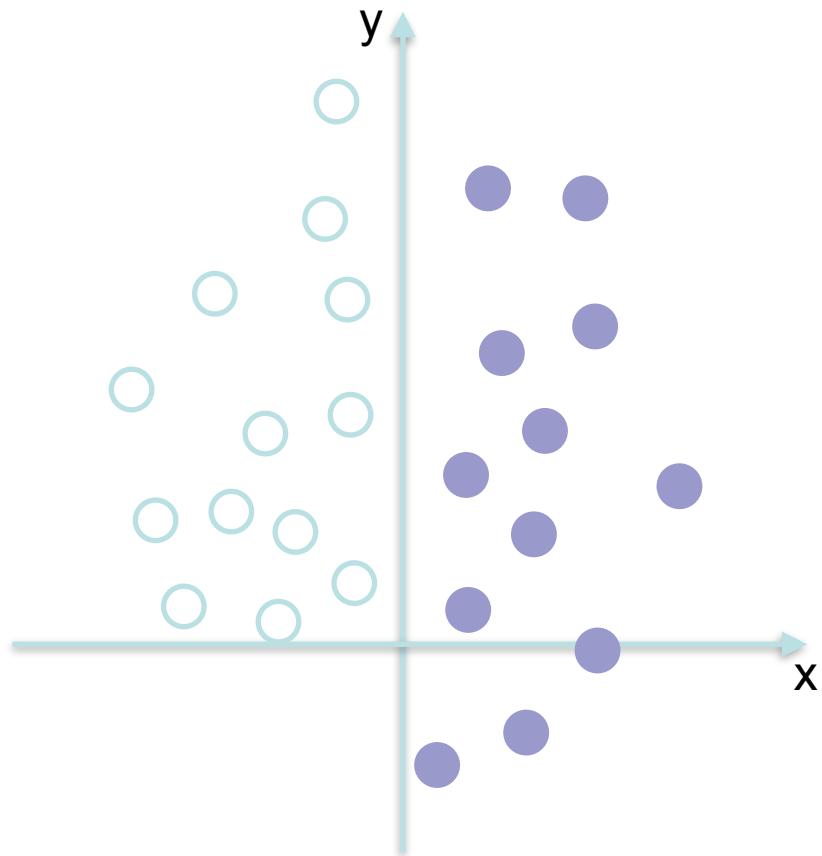
Geometric interpretation





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Geometric interpretation



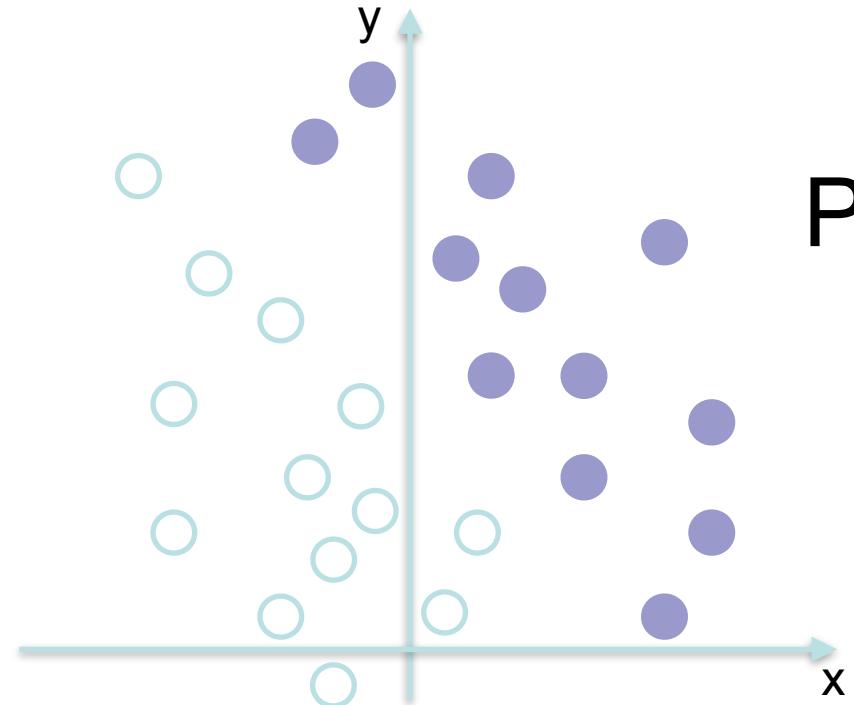


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Formal definition of ML

A computer program is said to learn from experience E with respect to some task T and some performance measure P , if its performance on T , as measured by P , improves with E .

Tom Mitchell, 1997



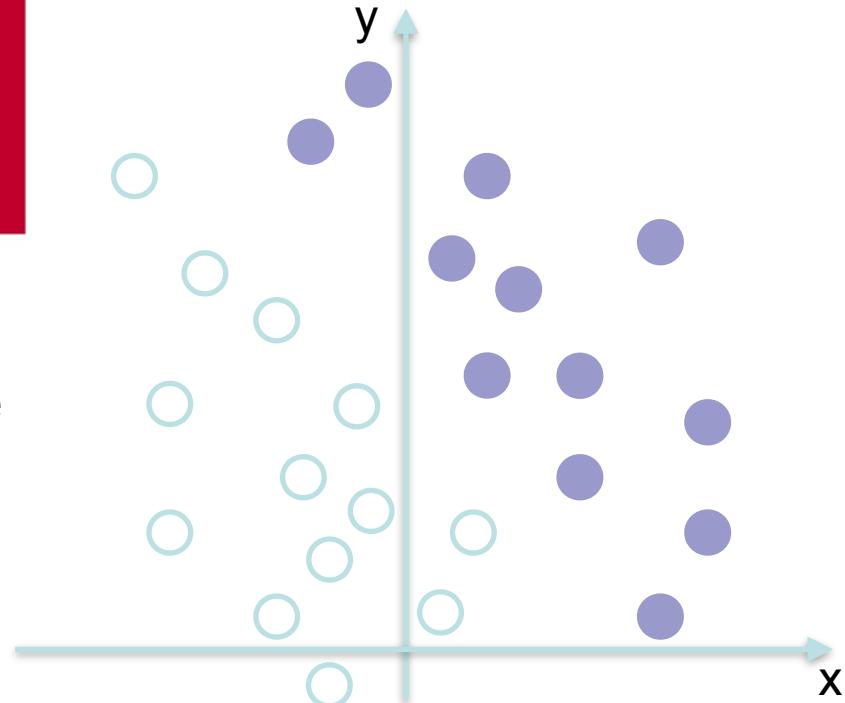
Performance P

		Actual	
		TP	FP
Predicted	●	TP	FP
	○	FN	TN



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13 white
12 blue

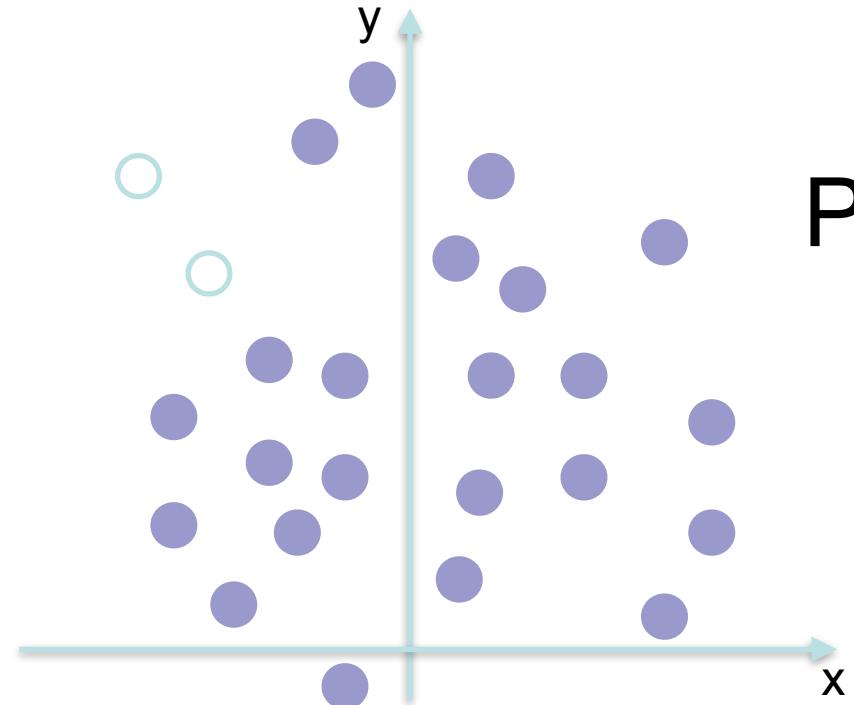


Performance P

- class bias
- misclassification cost

		Actual	
		White	Blue
Predicted	White	10	2
	Blue	2	11

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} = \frac{10 + 11}{10 + 11 + 2 + 2} = \frac{21}{25} = 0.84$$



Performance P

		Actual	
		P	N
Predicted	P	23	2
	N	0	0

$$Acc = \frac{TP + TN}{TP + TN + FP + FN} = \frac{23 + 0}{23 + 0 + 2 + 0} = \frac{23}{25} = 0.92$$

Performance P

		Actual	
		Sick	Healthy
Predicted	Sick	10	2
	Healthy	11	2

$$Acc = \frac{TP + TN}{TP + TN + FP + FN}$$

$$Precision = \frac{TP}{TP + FP}$$

fraction of correctly predicted sick to all predicted to be sick

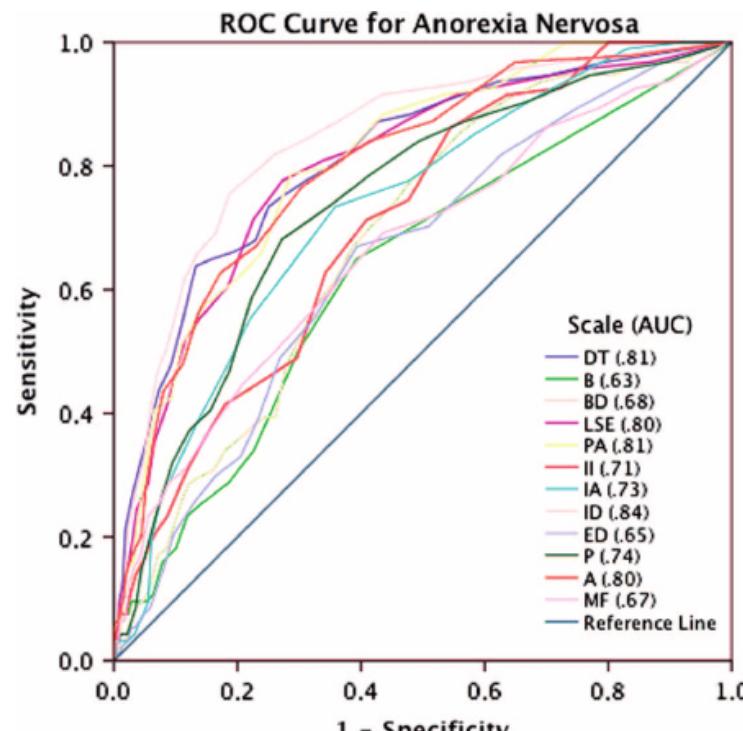
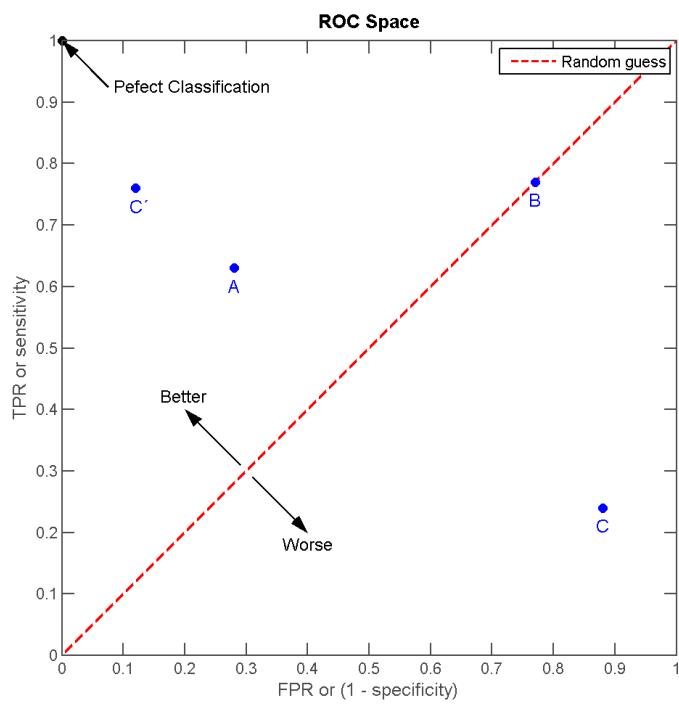
$$Sensitivity = \frac{TP}{TP + FN}$$

fraction of correctly predicted sick to all sick

$$Specificity = \frac{TN}{TN + FP}$$

fraction of correctly predicted healthy to all healthy

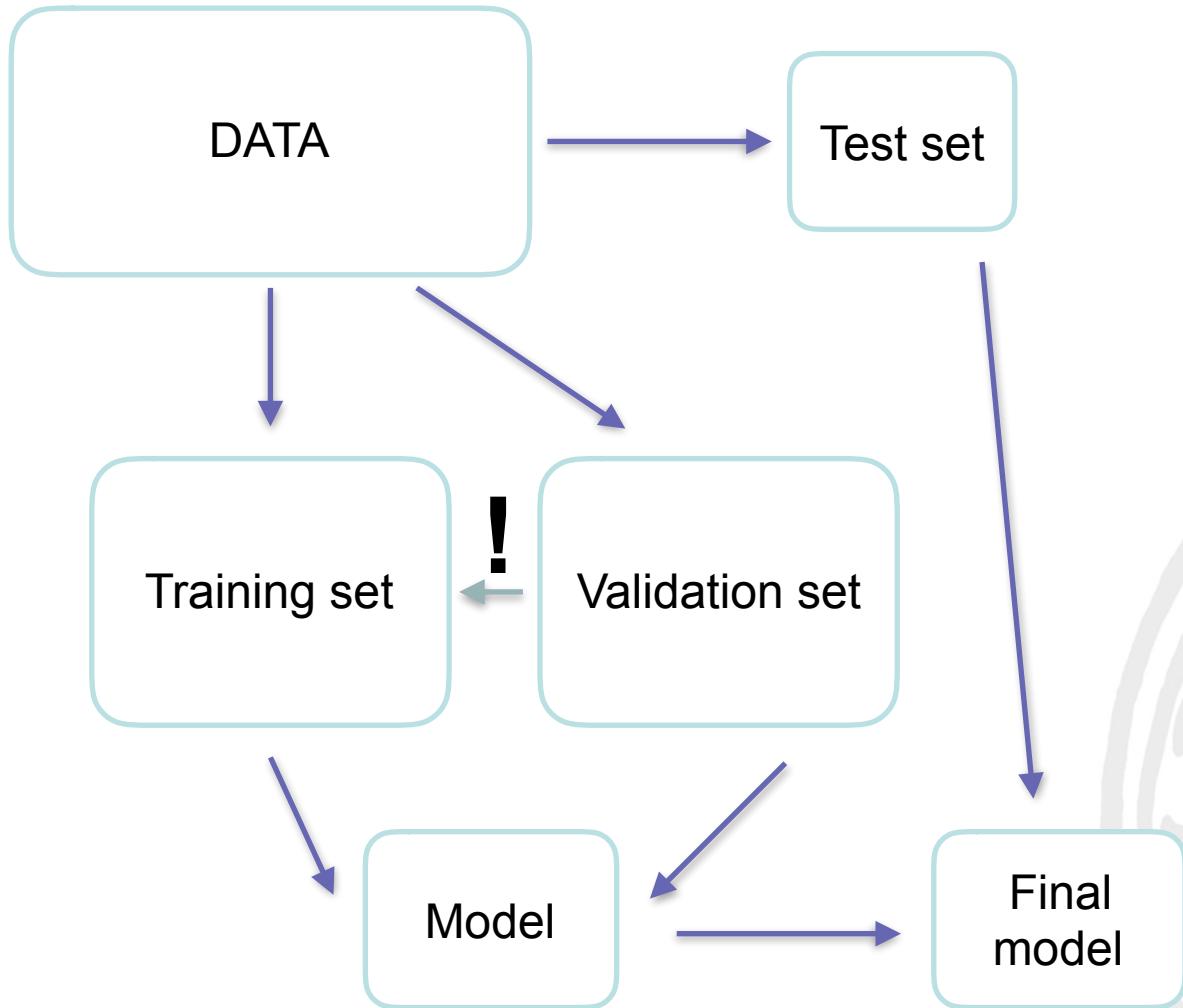
Performance P – ROC & AUC



Nyman-Carlsson, et al. (2014). Eating Disorder Inventory-3: Validation in Swedish patients with eating disorders, psychiatric outpatients and a normal control sample. Nordic Journal of Psychiatry. 68. 1-10.



Measuring performance



- class distribution
- information leaks
- temporal leaks
- duplication leaks



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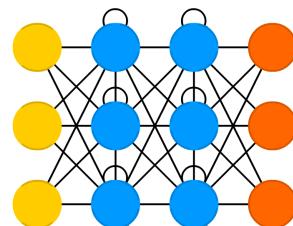
Performance baseline

IF $x < 0$ THEN white ELSE blue

Acc = 0.74



Acc = 0.54



Acc = 0.72

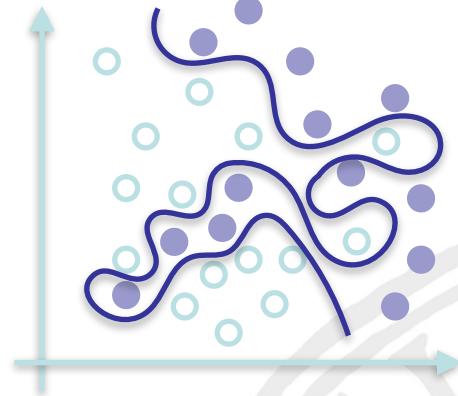
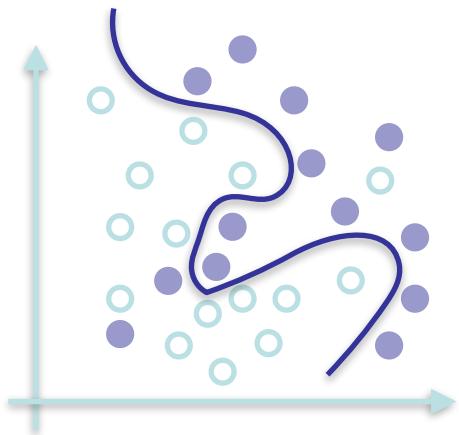
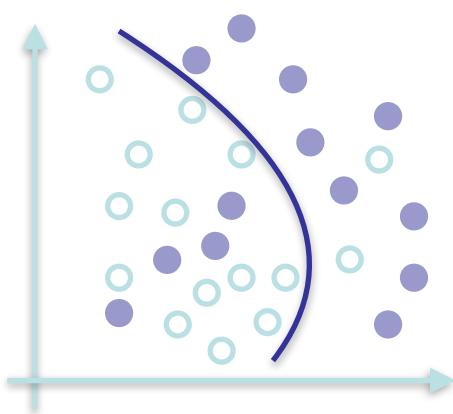


Acc = 0.80

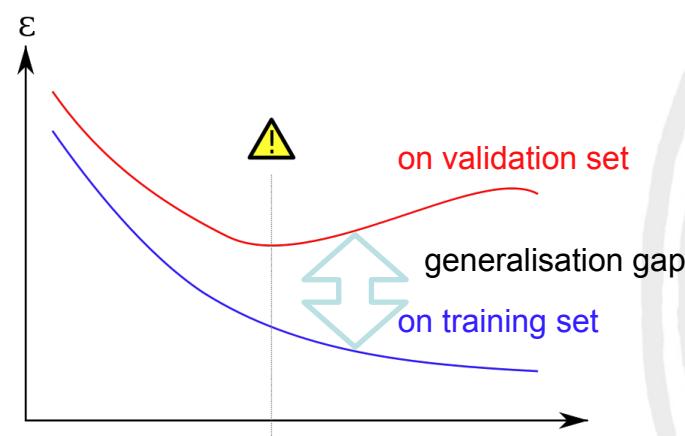
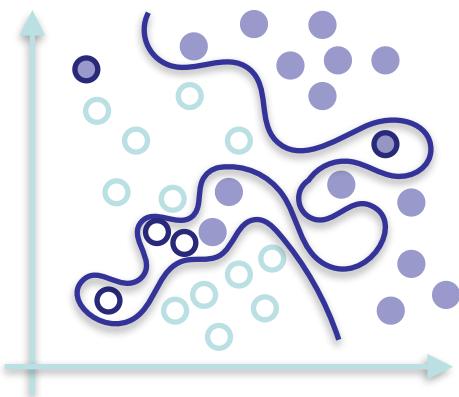


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Overfitting

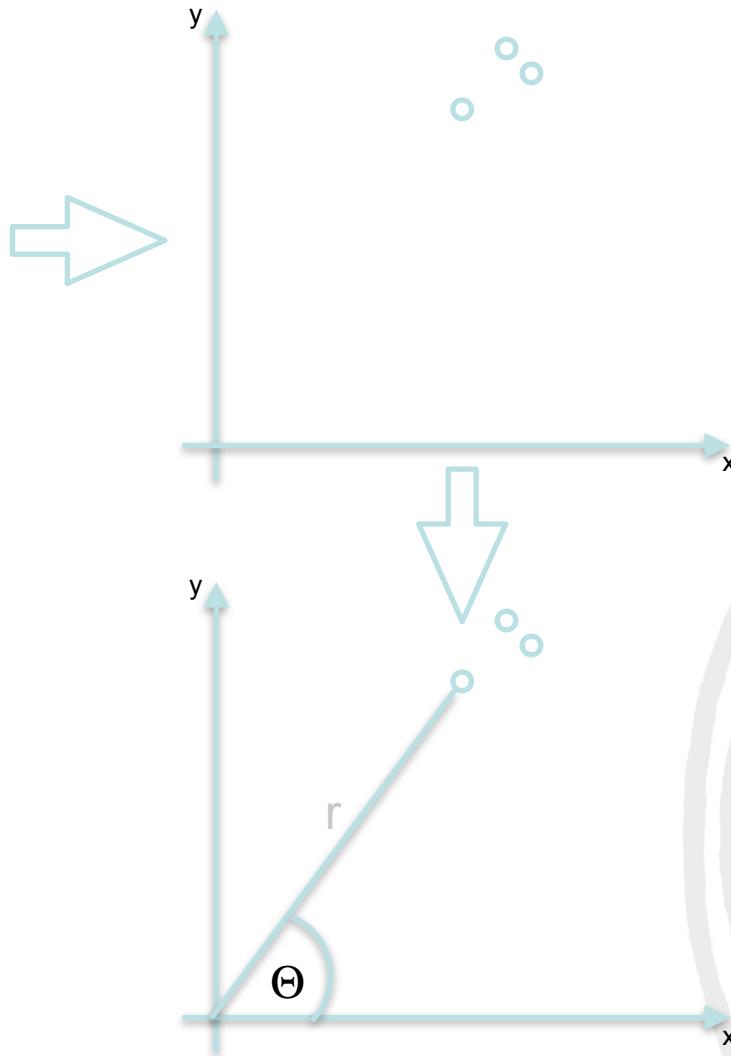


On new data



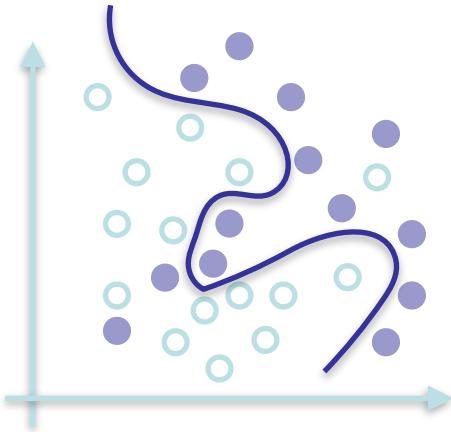


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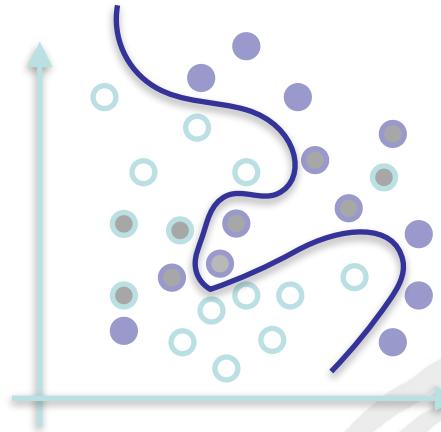
Feature engineering

Interpretability



Input image

a couple of bears are
standing in a field

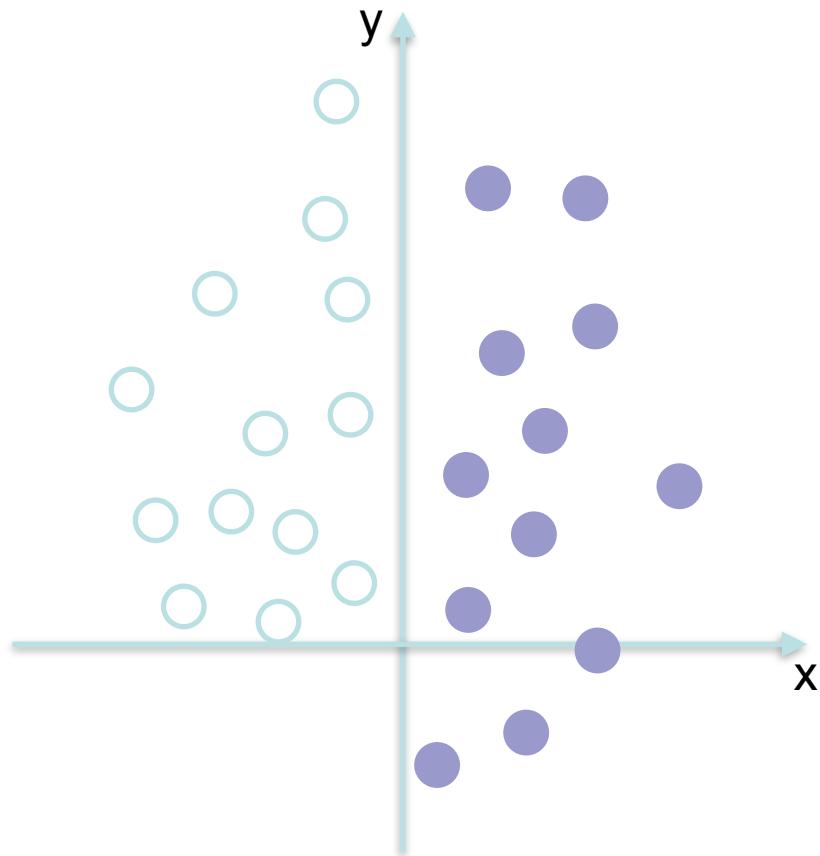


Importance map



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Feature selection





Feature selection

	a1	a2	d
Ex. 1	1	7.45	case
Ex. 2	0	3.24	control
...
Ex. N-1	1	8.72	case
Ex. N	0	11.5	control

Acc = 0.98

Ex. 1	1	7.45	case
Ex. 2	1	3.24	control
...
Ex. N-1	0	8.72	case
Ex. N	0	11.5	control

Acc = 0.95

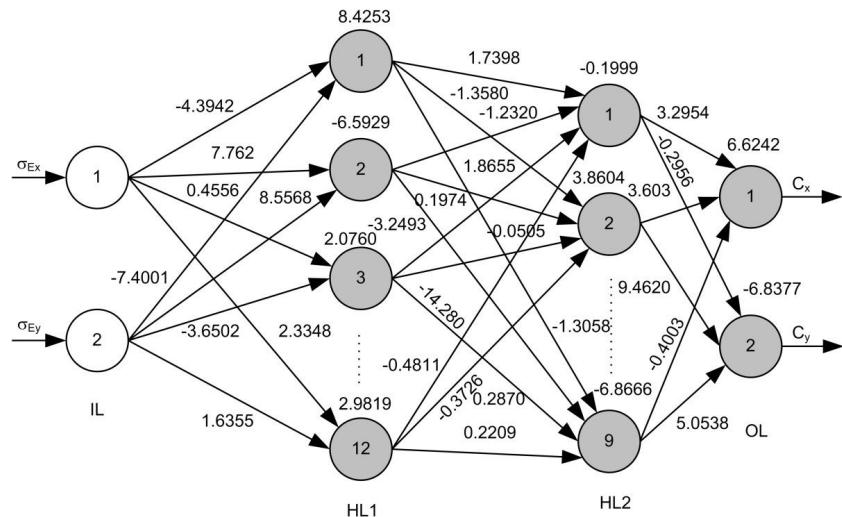
$I(a_2) > I(a_1)$

Ex. 1	1	8.72	case
Ex. 2	0	11.5	control
...
Ex. N-1	1	7.45	case
Ex. N	0	3.24	control

Acc = 0.75

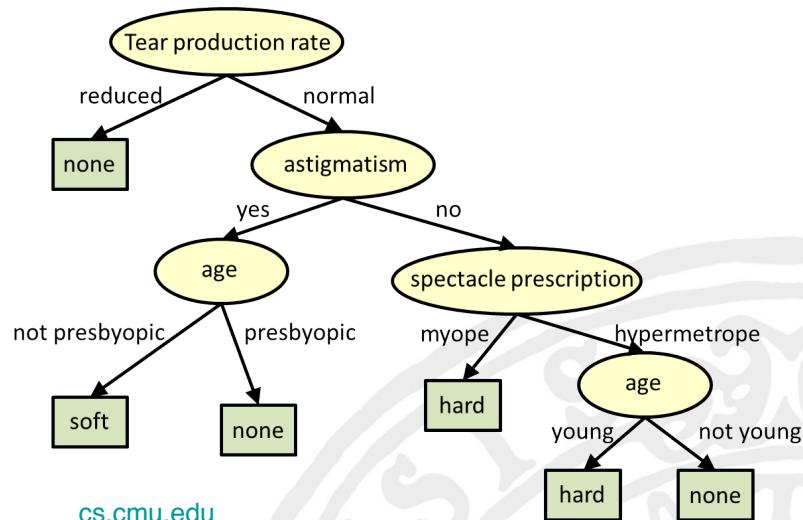


Explainability

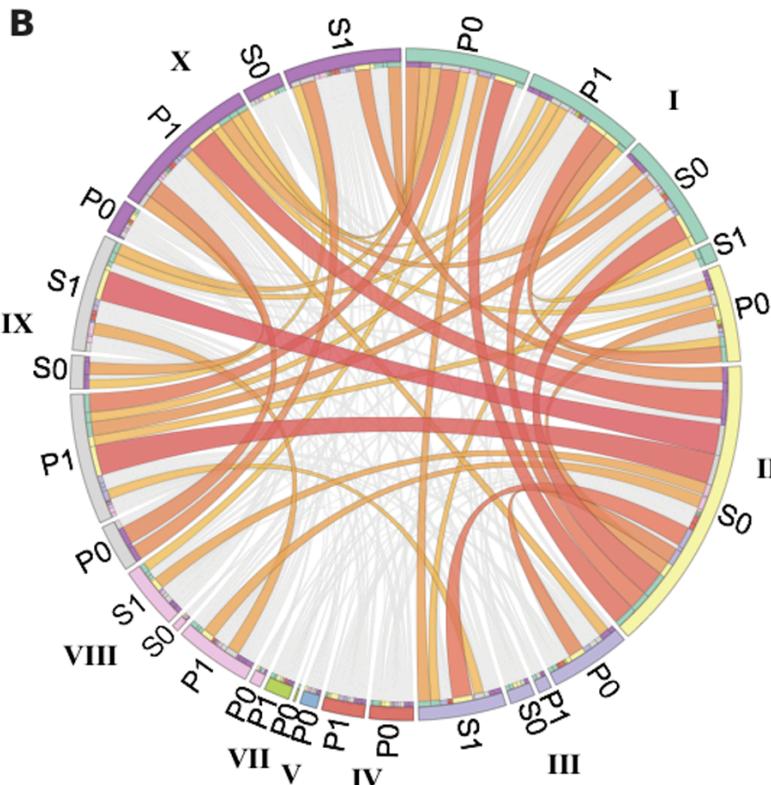
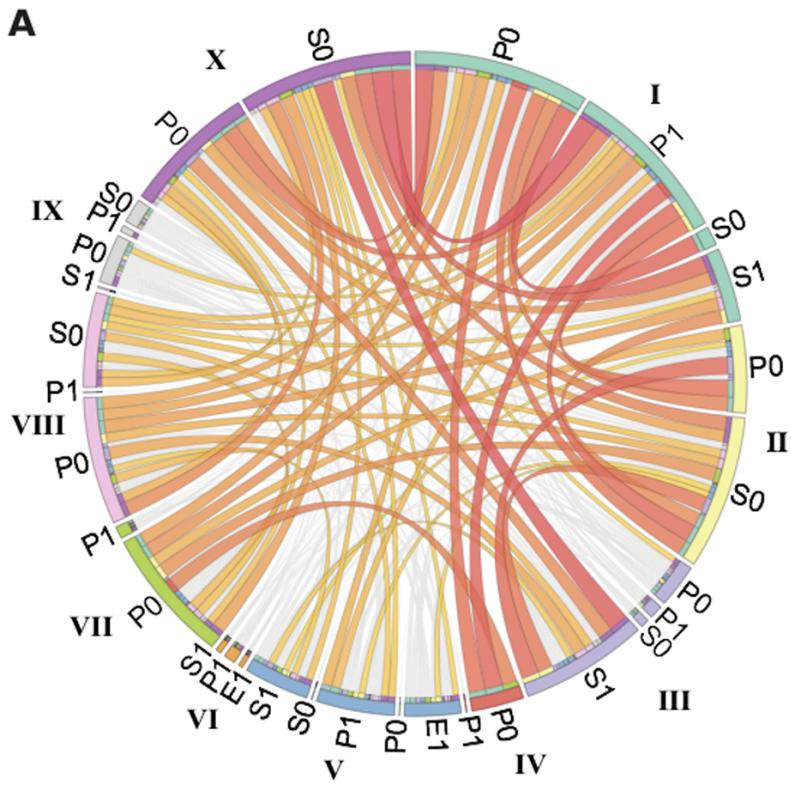


Arockia et al. Journal on Wireless Communications and Networking 2014:160

IF tear prod. rate = normal & astigmatism = yes & age != presbyopic THEN lenses = soft



Explainability

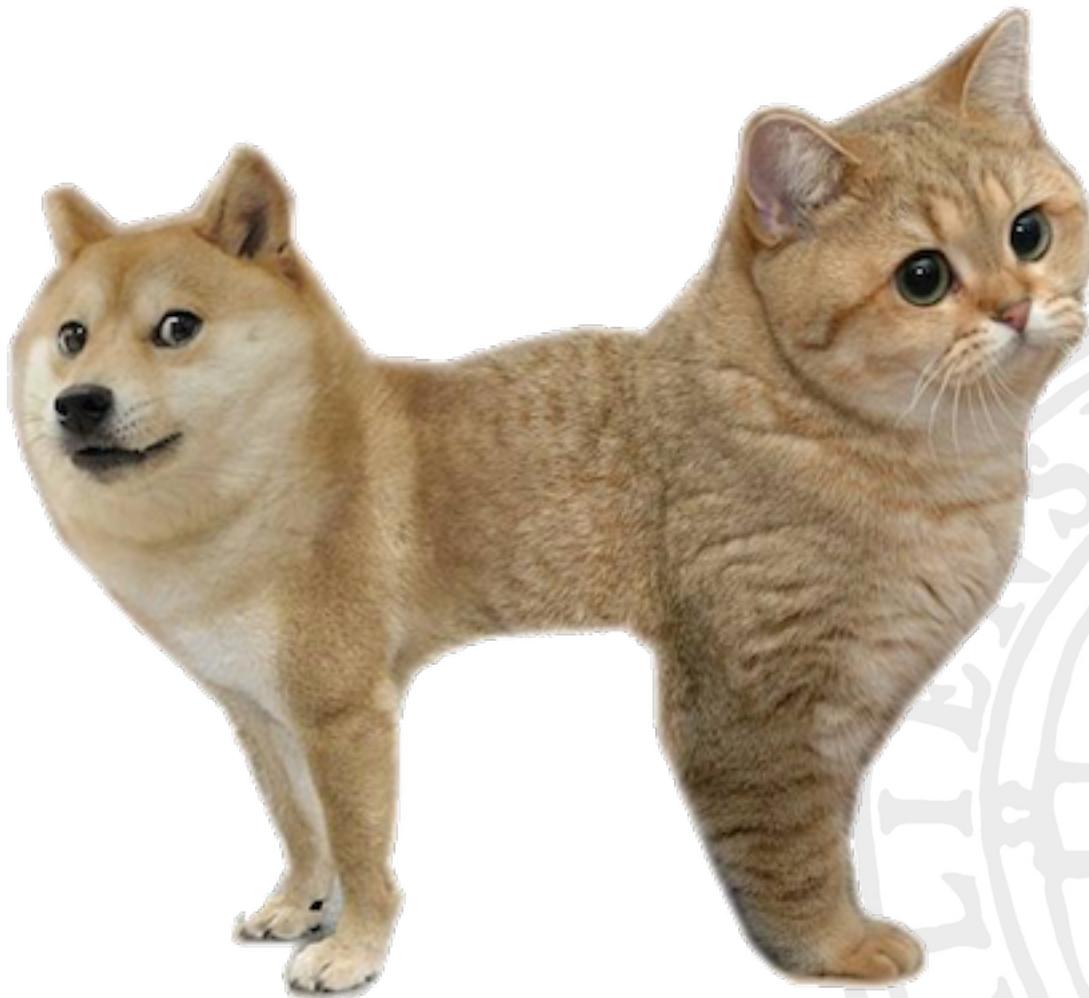


"I P0" is interpreted as "H2BK5me1 preceding the exon is absent"



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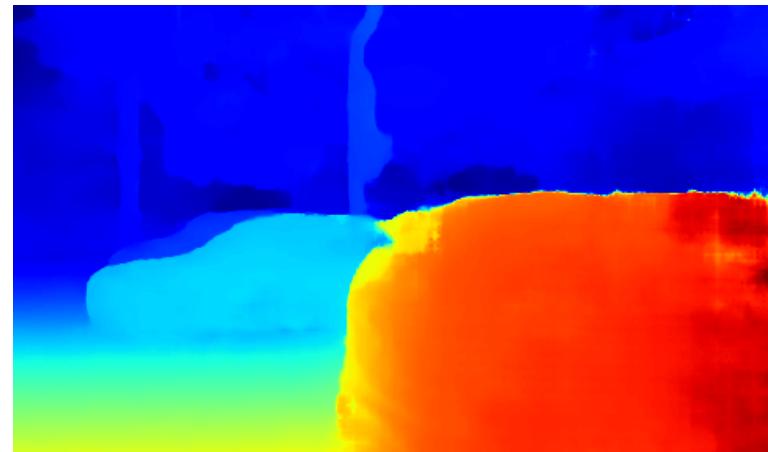
Dealing with uncertainty





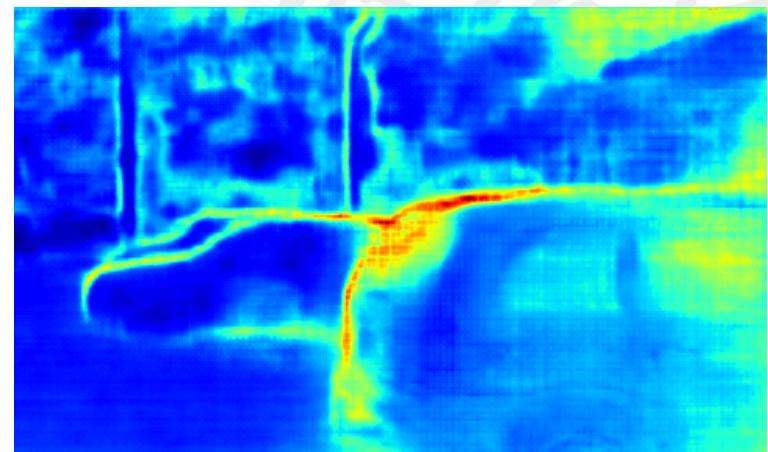
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Uncertainty



Uncertainty of depth estimation:

1. Original picture.
2. Estimated depth.
3. Estimation uncertainty.



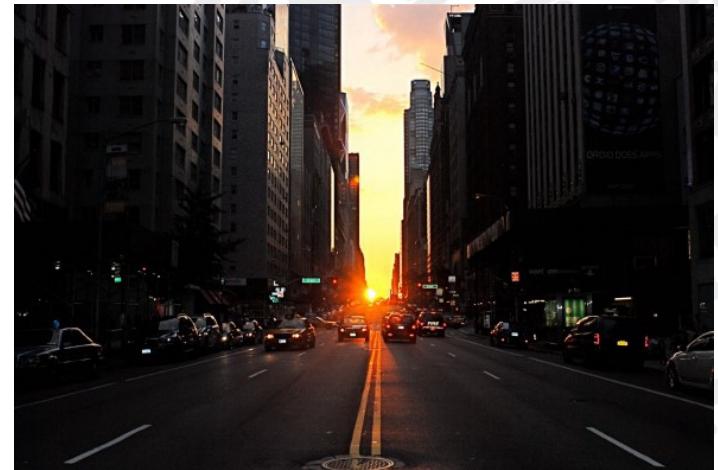


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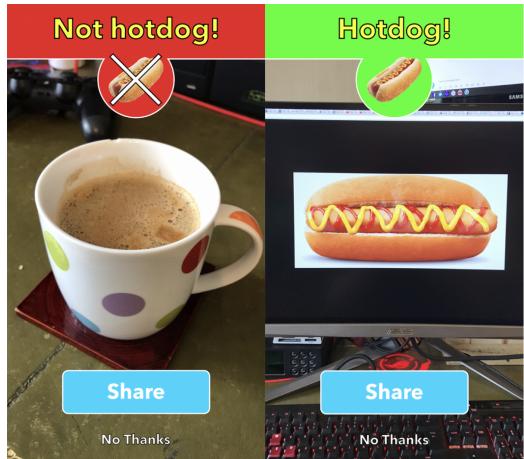
Aleatoric uncertainty



Aleatoric uncertainty is the sensing uncertainty.

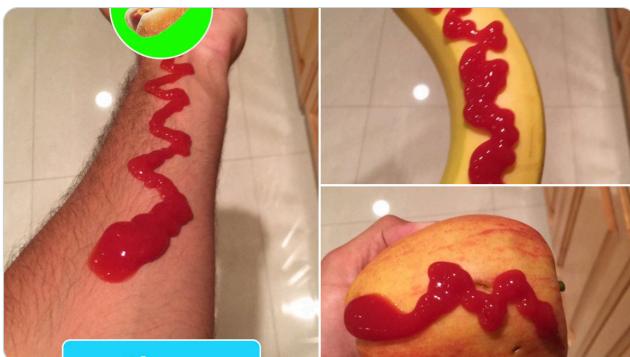


Epistemic uncertainty



 David Khachatryan
@david_kha

If there's ketchup, it's a hotdog @FunnyAsianDude
#nohotdog #NotHotdogchallenge



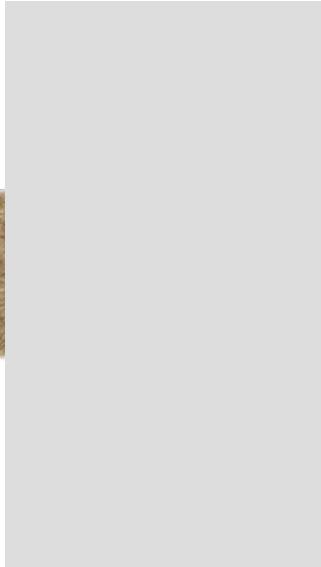
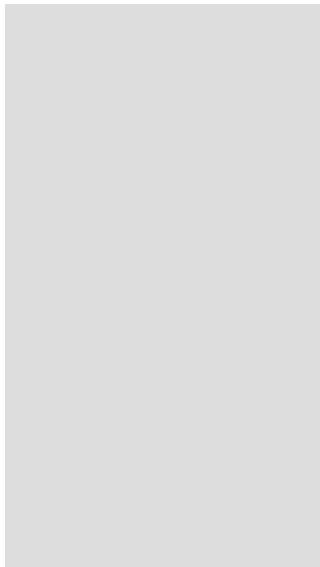
Epistemic uncertainty – related to the model.

- can be fixed given more training data



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Assessing uncertainty

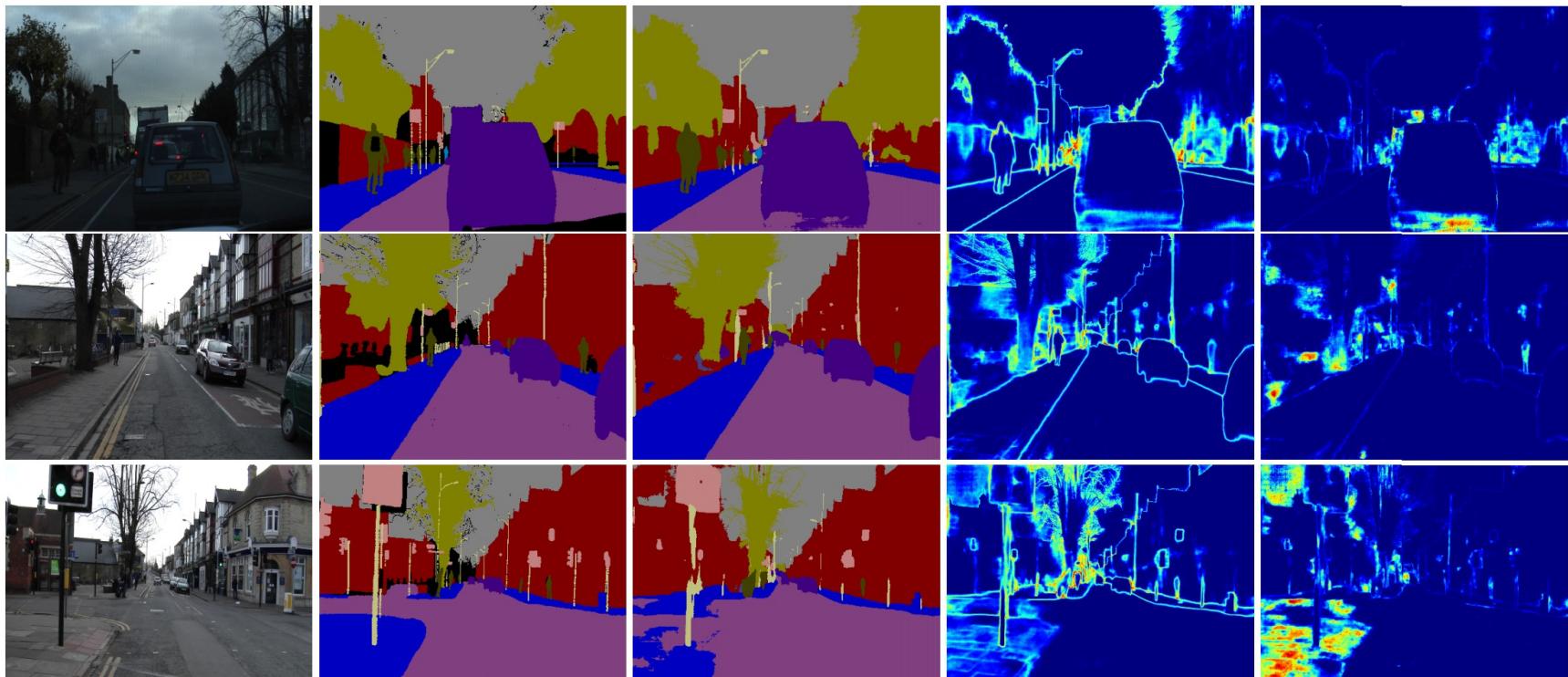


100% cat

high epistemic uncertainty

100% dog

Uncertainty – applications



(a) Input Image

(b) Ground Truth

(c) Semantic Segmentation

(d) Aleatoric Uncertainty

(e) Epistemic Uncertainty



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History

Machine
Learning

Feature
engineering

Feature
selection

Overfitting

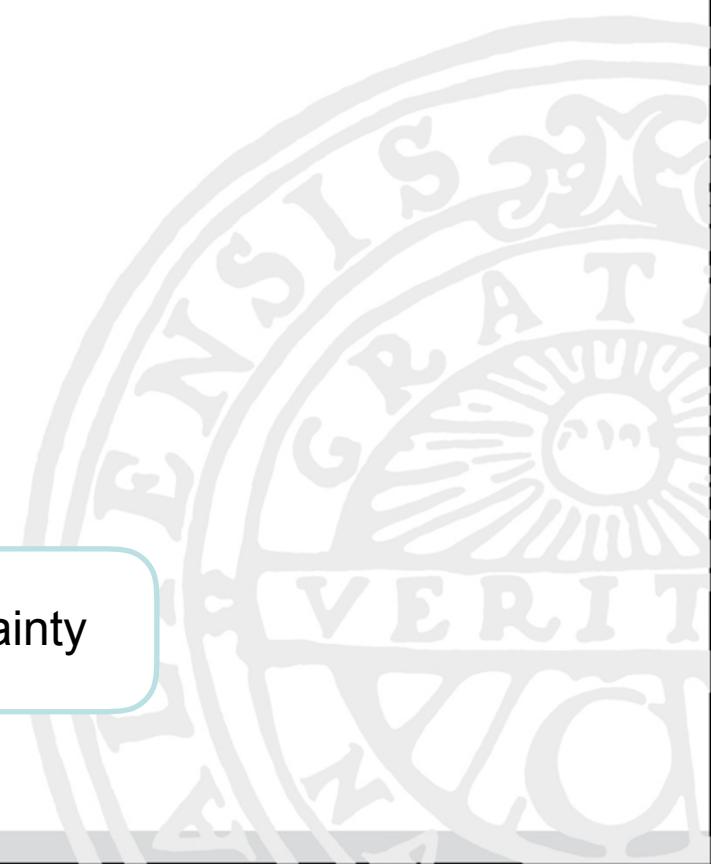
Performance

Interpretability

Explainability

Uncertainty

Final remarks





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Thank You!

