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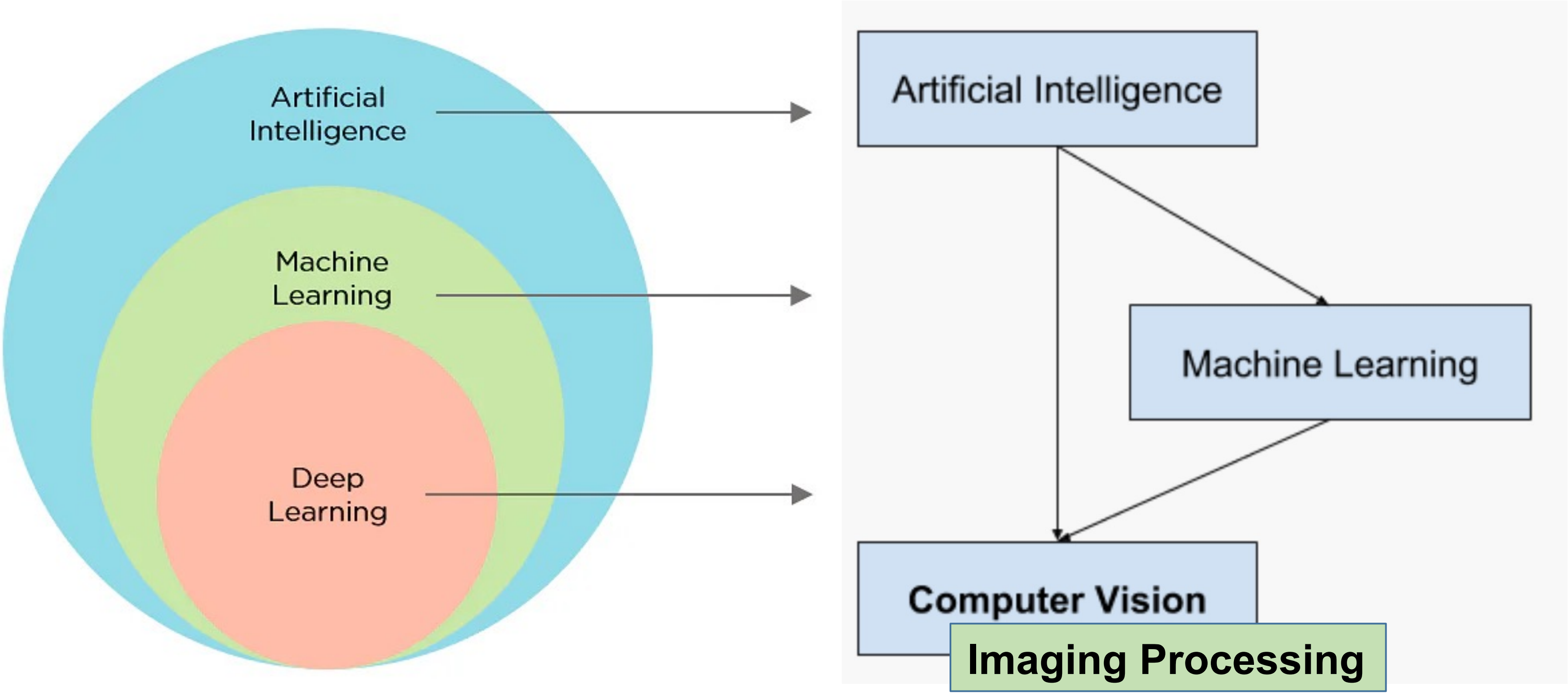
Segmentation and Classification using Deep Learning Technologies

Workshop DIPOpt, Lyon, 2023

Xiaohao Cai

VLC / ECS / UoS

AI - ML – CV – IP – MI



https://www.simplilearn.com/tutorials/artificial-intelligence-tutorial/ai-vs-machine-learning-vs-deep-learning

Xiaohao Cai

VLC / ECS / UoS

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- ➢ Computer vision
- ➢ Image processing
- ➢ Machine/deep learning
- ➢ Optimisation

Interdisciplinary

- ✓ Computer science
- ✓ Mathematics/statistics
- ✓ Physics, life science, etc.

Browse State-of-the-Art:
https://paperswithcode.com/sota

State-of-the-art Computer Vision

Data Size

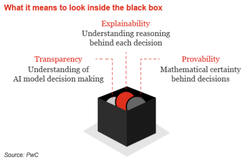
1 | 100 | 1K | 10K | 100K | 1M | 10M | > 10M

Methods

Model-driven | Data-driven

Interpretability

Strong | Weak | Black-box



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Research

Use of artifici
programmes:

BMJ 2021 ; 374 d
Cite this as: *BMJ* 2(

Article | Rel

Karoline Freeman ... *llow*[1],
Daniel Todkill , cl
Aileen Clarke, profess

Author affiliation

Correspondence t

Accepted 21 July 2

Abstract

Conclusions

Current evidence on the use of AI systems in breast cancer screening is a long way from having the quality and quantity required for its implementation into clinical practice. Well designed comparative test accuracy studies, randomised controlled trials, and cohort studies in large screening populations are needed which evaluate commercially available AI systems in combination with radiologists. Such studies will enable an

https://www.bmj.com/content/374/bmj.n1872

ARTIFICIAL INTELLI

Hundreds o... h covid. None

Some have been used in hos... pandemic could help make m...

By Will Douglas Heaven

It never happened—but not for lack of effort. Research teams around the world stepped up to help. The AI community, in particular, rushed to develop software that many believed would allow hospitals to diagnose or triage patients faster, bringing much-needed support to the front lines—in theory.

In the end, many hundreds of predictive tools were developed. None of them made a real difference, and some were potentially harmful.

That's the damning conclusion of multiple studies published in the last few months. In June, the Turing Institute, the UK's national center for data science and

https://www.technologyreview.com/2021/07/30/1030329/machine-learning-ai-failed-covid-hospital-diagnosis-pandemic

UK Parliament

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UNIVERSITY OF Southampton
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POST

UK Parliament > POST > Interpretable machine learning

Research Briefing

Interpretable machine learning

Published Tuesday, 06 October, 2020

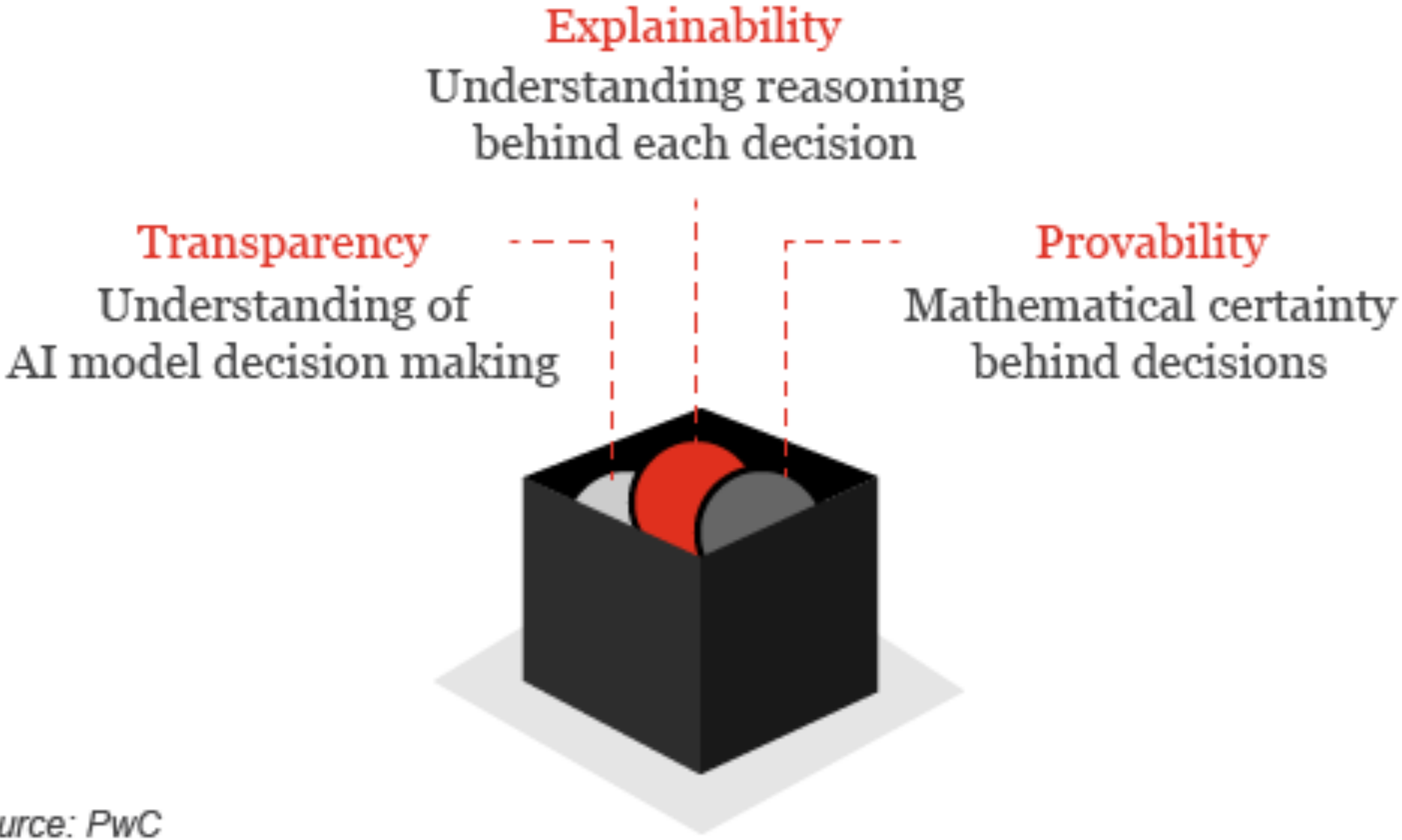
POSTnote | Crime and justice | Digital tech | Health and social care | Transport and infrastructure | Research

Lorna Christie

Machine learning (ML, a type of artificial intelligence) is increasingly being used to support decision making in a variety of applications including recruitment and clinical diagnoses. While ML has many advantages, there are concerns that in some cases it may not be possible to explain c
This POSTnote gives an overview of ML and its role in decision-
understanding how a complex ML system has reached its outp
making ML easier to interpret. It also gives a brief overview of
systems more accountable.

In 2018, the Lords Committee on AI calle he development of AI systems that are "intelligible to deve pers, users and regulators". It recommended that an AI system that could have a substantial impact on an individual's life should not be used unless it can produce an explanation of its decisions.[4] In a

What it means to look inside the black box



Source: PwC

“DATA IS THE NEW GOLD”

https://www.civilsdaily.com/burning-issue-data-the-new-gold/

Data
Methods
Interpretability

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Medical Imaging Problems

State of the art Computer Vision

Browse State-of-the-Art: https://paperswithcode.com/sota

[Credit Niranjan]

Dataset Size

10-20 — Not very interesting ☹

100-1000 — Few-shot learning ☺

1 – 10 K — Transfer learning ☺

100 – 200 K — Train models from scratch

> 1.0 M (ImageNet)

Methods

Model-driven

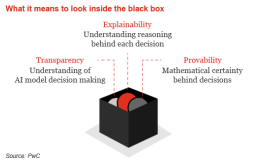
Data-driven

Interpretability

Strong

Weak

Black-box



Few-Shot Learning Framework and Subspaces

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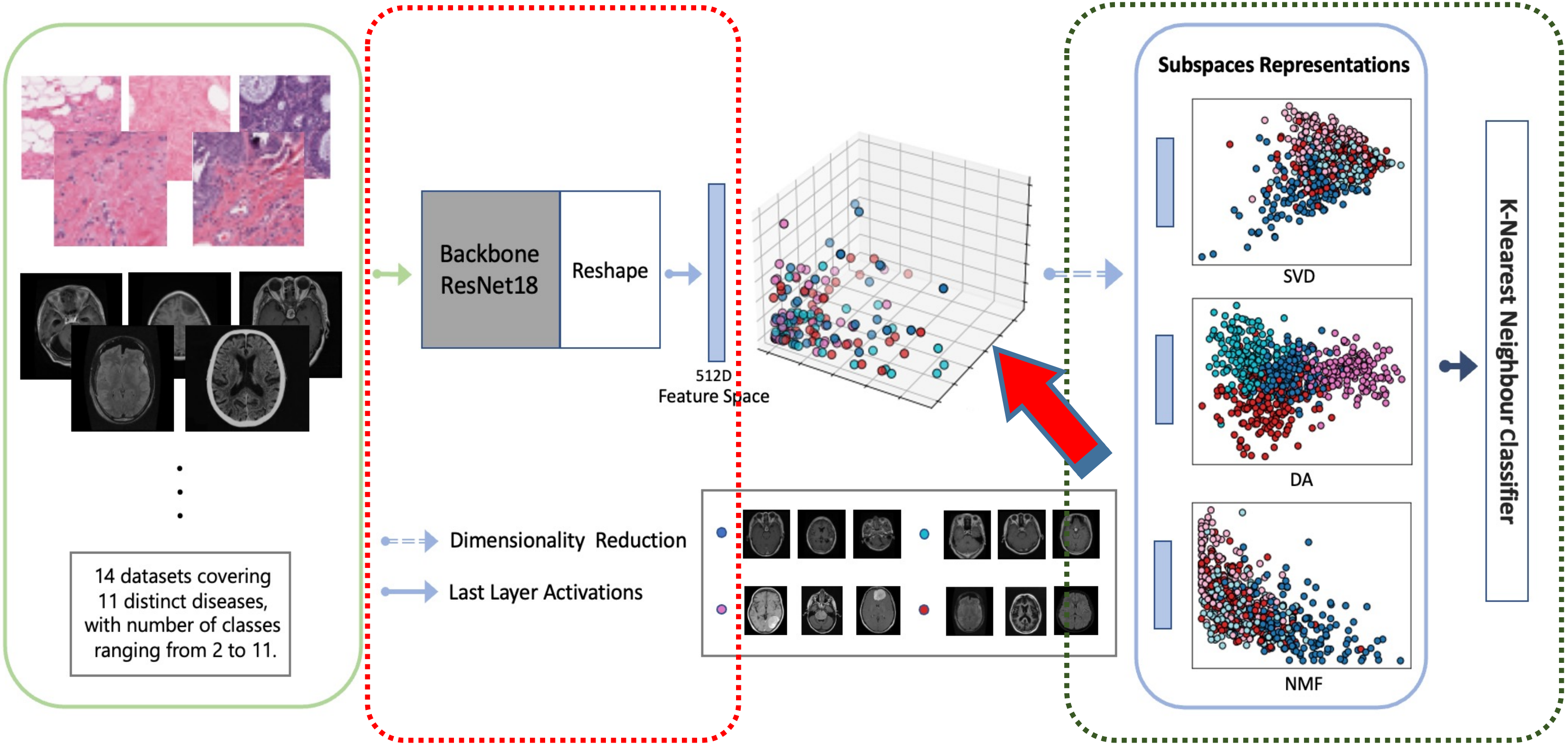
[J. Liu, K. Fan, X. Cai, and M. Niranjan, under review]



Data-driven part

Model-driven part

Classification

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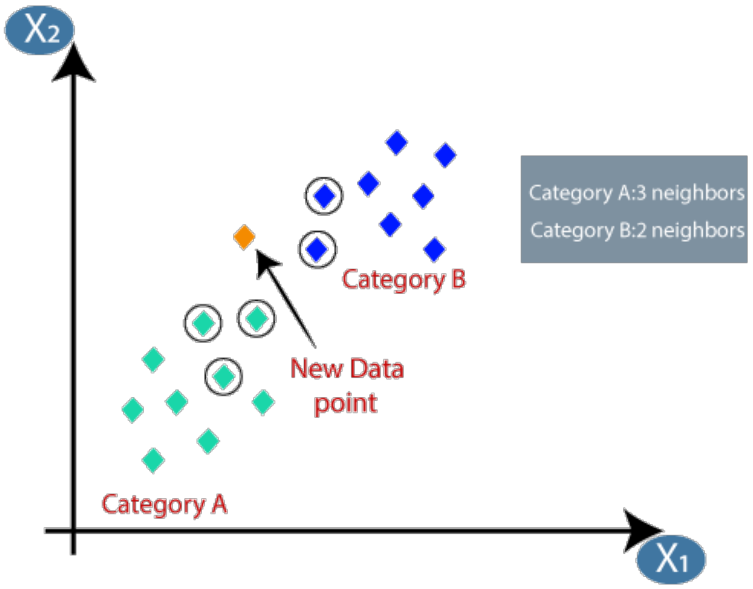
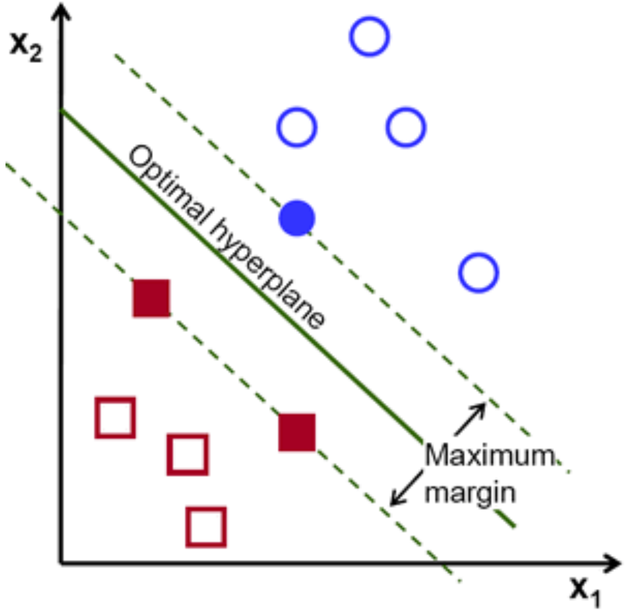


K-Nearest Neighbor (KNN)

https://www.javatpoint.com/k-nearest-neighbor-algorithm-for-machine-learning



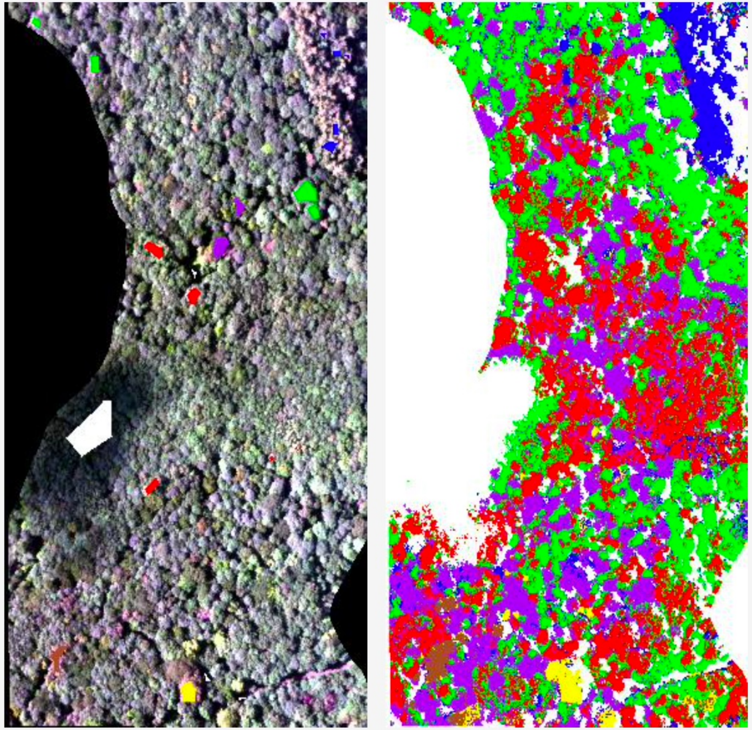
Support Vector Machine (SVM)

https://www.javatpoint.com/k-nearest-neighbor-algorithm-for-machine-learning

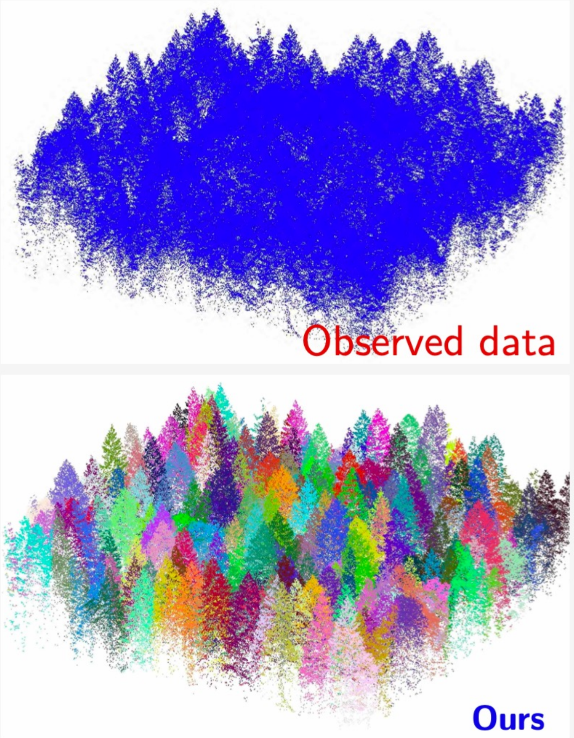
Classification

IEEE Tr., '15, '16, '19
J. Lee, X. Cai, D. Coomes
C.-B. Schönlieb, et al.

Hyperspectral



LiDAR



Classification

International Journal of Computer \
© 1987 Kluwer Academic Publishers, Boston, Manufacturec

Snakes: Active Contour Models

MICHAEL KASS, ANDREW WITKIN, and DEMETRI TERZOPOULOS
Schlumberger Palo Alto Research, 3340 Hillview Ave., Palo Alto, CA 94304

266 IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 10, NO. 2, FEBRUARY 2001

Active Contours Without Edges

Tony F. Chan, *Member, IEEE,* and Luminita A. Vese

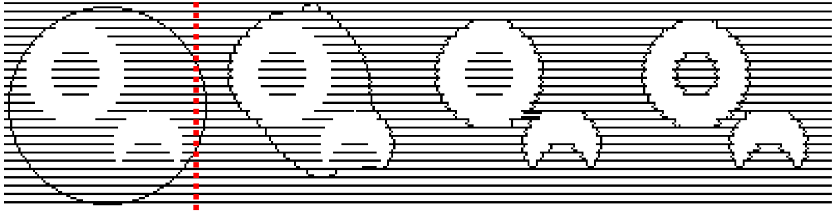
***Abstract*—In this paper, we propose a new model for active contours to detect objects in a given image, based on techniques of curve evolution, Mumford–Shah functional for segmentation and level sets. Our model can detect objects whose boundaries are not necessarily defined by gradient. We minimize an energy which can be seen as a particular case of the minimal partition problem. In the level set formulation, the problem becomes a "mean-curvature flow"-like evolving the active contour, which will stop on the desired boundary. However, the stopping term does not depend on the gradient of the image, as in the classical active contour models, but is instead related to a particular segmentation of the image. We will give a numerical algorithm using finite differences. Finally, we will present various experimental results and in particular some**

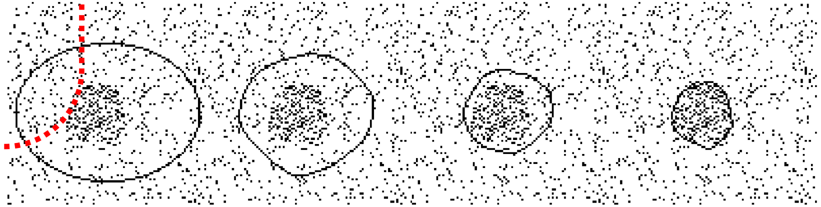
the image (the external energy). Observe that, by minimizing the energy (1), we are trying to locate the curve at the points of maxima $|\nabla u_0|$, acting as an edge-detector, while keeping a smoothness in the curve (object boundary).

A general edge-detector can be defined by a positive and decreasing function g, depending on the gradient of the image u_0, such that

$$\lim_{z\to\infty} g(z) = 0.$$

For instance





T-ROF *(Thresholded-ROF)*

arXiv: 1905.08538
X. Cai, et al.

Image Restoration

ROF model
(1992, citation > 15,700)

thresholding

$$\min_{u\in BV(\Omega)} \left\{ TV(u) + \tfrac{\mu}{2}\int_\Omega (f-u)^2 dx \right\},$$

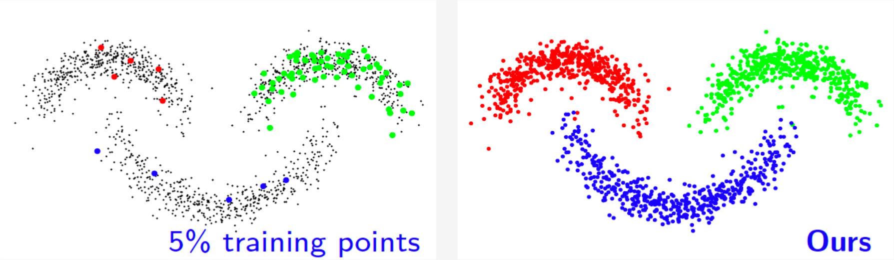
$TV(u)$: total variation of u

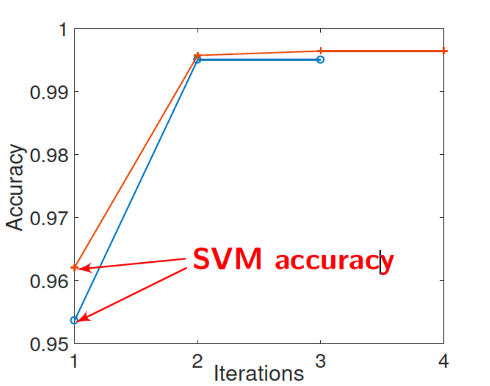
Pe

Theorem

(Relation between ROF and Chan-Vese model) *Let*
model. For given $0 < m_0 < m_1 \le 1$, *let* $\tilde\Sigma := \{x \in \Omega$
$0 < |\tilde\Sigma| < |\Omega|$. *Then* $\tilde\Sigma$ *is a minimizer of the Chan-V*
and fixed m_0, m_1. *In particular,* $(\tilde\Sigma, m_0, m_1)$ *is a parti*
Chan-Vese model if $m_0 = \mathrm{mean}_f(\Omega\backslash\tilde\Sigma)$ *and* $m_1 = \mathrm{me}$

Point clouds





Method	Acc.
MBO ('14)	99.1
GC-1 ('14)	98.4
GC-2 ('17)	98.7
GC-3 ('18)	98.6
GC-4 ('18)	98.4
Ours	**99.4**

Parallelism computation

Models

Models proposed in our work, e.g.:

- $\min_x \left\{ \frac{\lambda}{2}\|y - \mathcal{A}x\|_2^2 + \|\mathcal{W}x\|_1 \right\}$
- $\min_g \left\{ \frac{\lambda}{2}\|f - \mathcal{A}g\|_2^2 + \frac{\mu}{2}\|\nabla g\|_2^2 + \|\nabla g\|_1 \right\}$
- $\mu\Phi(f, \mathcal{A}g) + \lambda\Psi(g, u_i, c_i) + \sum_{i=1}^{K} \int_\Omega |\nabla u_i|$
  s.t. $\sum_{i=1}^{K} u_i(x) = 1, u_i(x) \in \{0, 1\}$
- $\min_{u \in S} \left\{ \frac{1}{2}\|f - \mathcal{B}u\|_2^2 + \lambda\|\nabla u\|_0 \right\}$
- $\min_\psi \left\{ D[T(\psi), R] + \alpha\|\Delta\psi\|_2^2 \right\}$

Convex optimisation algorithms

- ADMM
- Primal-dual
- Split-Bregman
- Augmented Lagrangian

Sparse regularizations

- $\|\cdot\|_0$, $\|\cdot\|_1$, $\|\cdot\|_2$
- with $\nabla, \Delta, \mathcal{W}$
- $\mathcal{W}$: Wavelet transform

Model Selection

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Statistics and Computing (2022) 32:87
https://doi.org/10.1007/s11222-022-10152-9

Proximal nested sampling for high-dimensional Bayesian model selection

Xiaohao Cai[1,2] · Jason D. McEwen[1,3] · Marcelo Pereyra[4]

Received: 15 April 2022 / Accepted: 9 September 2022 / Published online: 5 October 2022

Model Selection

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Article

Proximal nested sampling with data-driven priors for physical scientists

Jason D. McEwen [1,2*], Tobías I. Liaudat [1,3], Matthew A. Price[1], Xiaohao Cai [4] and Marcelo Pereyra [5]

[1] Mullard Space Science Laboratory, University College London (UCL), Dorking, RH5 6NT, UK;
[2] Alan Turing Institute, London, NW1 2DB, UK;
[3] Department of Computer Science, University College London (UCL), London, WC1E 6BT, UK;
[4] School of Electronics and Computer Science, University of Southampton, Southampton, SO17 1BJ, UK;
[5] School of Mathematical and Computer Sciences, Heriot-Watt University, Edinburgh, EH14 4AS, UK;
* Correspondence: jason.mcewen@gmail.com

28 Jul 2023

Abstract: Proximal nested sampling was introduced recently to open up Bayesian model selection for high-dimensional problems such as computational imaging. The framework is suitable for models with a log-convex likelihood, which are ubiquitous in the imaging sciences. The purpose of this article is two-fold. First, we review proximal nested sampling in a pedagogical manner in an attempt to elucidate the framework for physical scientists. Second, we show how proximal nested sampling can be extended in an empirical Bayes setting to support data-driven priors, such as deep neural networks learned from training data.

Keywords: Bayesian model selection; nested sampling; proximal calculus.

Model Selection

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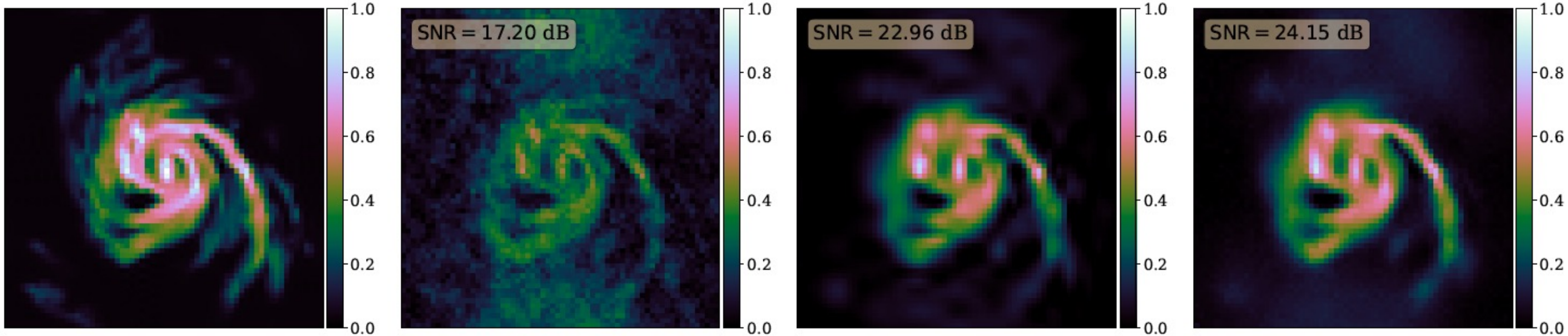
School of Electronics and Computer Science

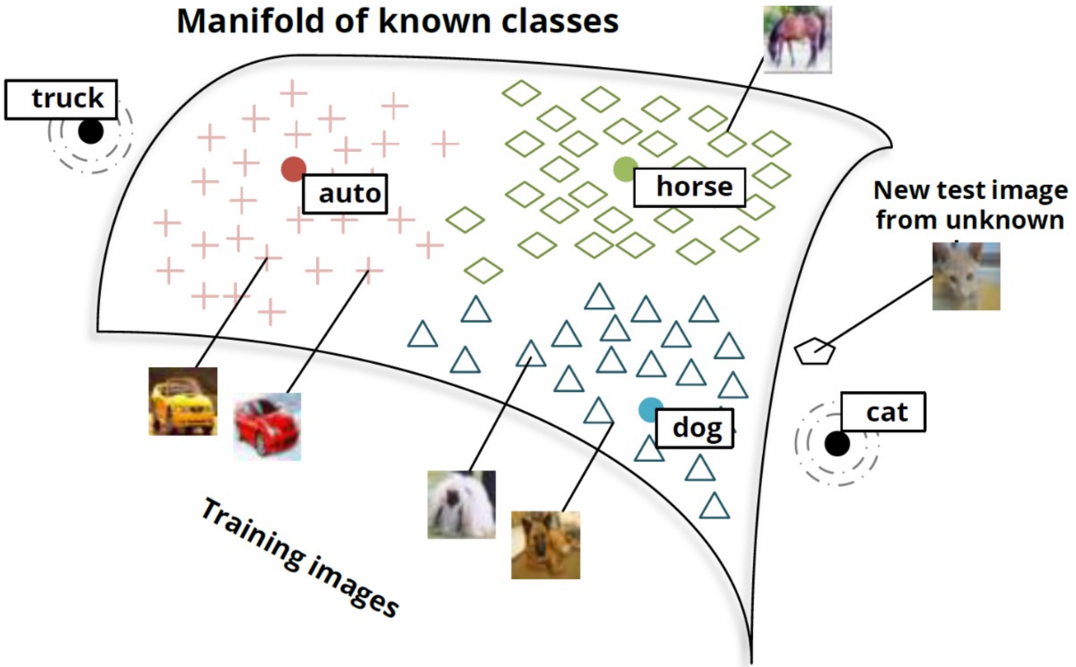


(a) Ground truth **(b)** Dirty **(c)** Hand-crafted prior **(d)** Data-driven prior

−2.96x1E3 −1.35x1E3

Log evidence

Subspace Representation / Embedding



Socher et al. (2013b)

Subspace feature representations (SVD *vs* DA)

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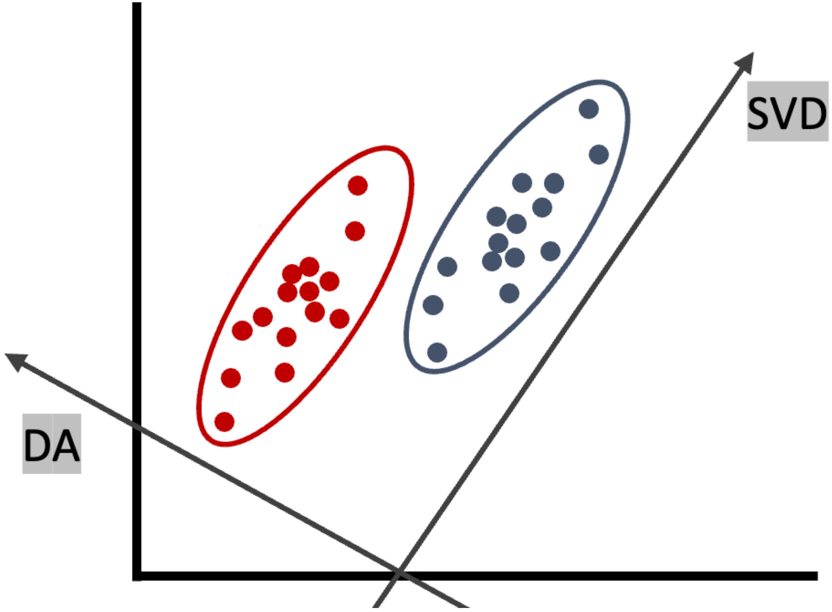
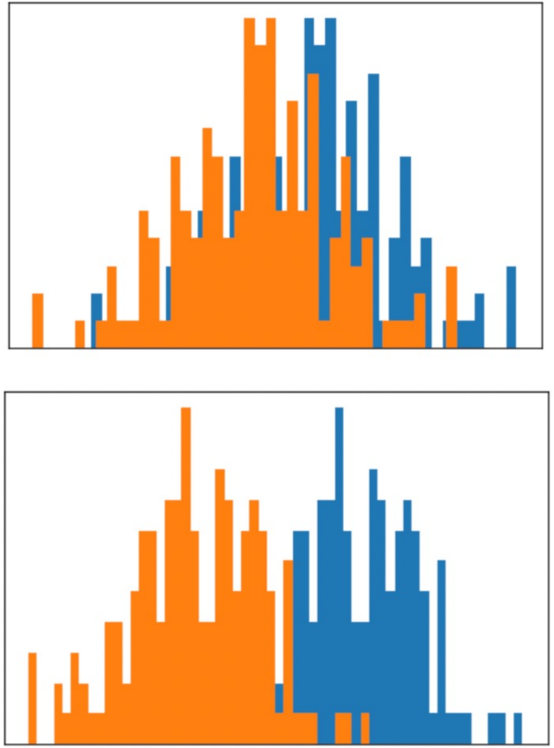




DA (Linear discriminant analysis)

Maximise: $$\mathcal{R}(\boldsymbol{d}) = \frac{\boldsymbol{d}^\top \boldsymbol{S}_{\mathrm{B}} \boldsymbol{d}}{\boldsymbol{d}^\top \boldsymbol{S}_{\mathrm{W}} \boldsymbol{d}}$$

No. of classes

Mean of class *j*

Mean of the whole data

$$\boldsymbol{S}_{\mathrm{B}} = \sum_{j=1}^{C} (\bar{\boldsymbol{y}}_j - \bar{\boldsymbol{y}})(\bar{\boldsymbol{y}}_j - \bar{\boldsymbol{y}})^\top, \quad \boldsymbol{S}_{\mathrm{W}} = \sum_{j=1}^{C} \boldsymbol{S}_{\mathrm{W}}^j,$$

$$\boldsymbol{S}_{\mathrm{W}}^j = \sum_{k=1}^{N_j} (\boldsymbol{y}_k^j - \bar{\boldsymbol{y}}_j)(\boldsymbol{y}_k^j - \bar{\boldsymbol{y}}_j)^\top,$$

Inter-class scatter

Intra-class scatter

DA (Linear discriminant analysis)

University of Southampton
School of Electronics and Computer Science

[arXiv:2305.14568]

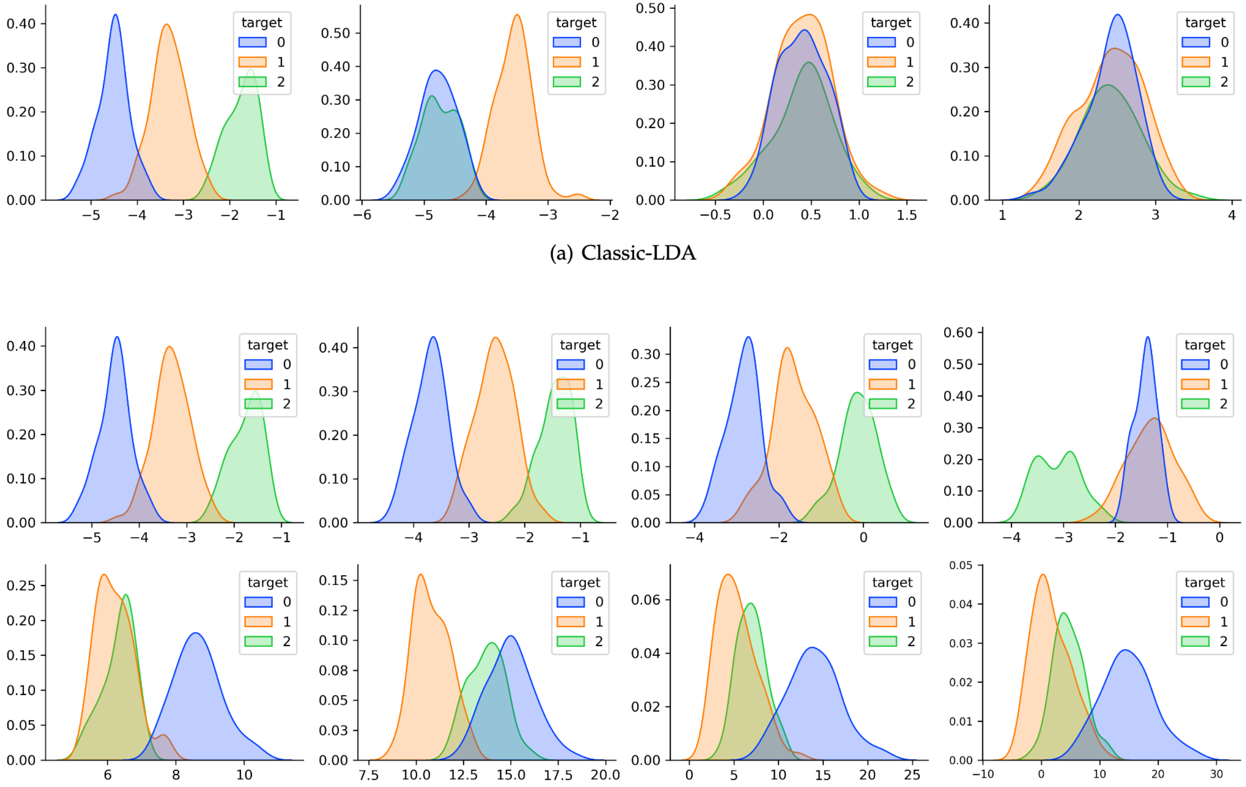
Maximise: $\mathcal{R}(\boldsymbol{d}) =$

JOURNAL OF LATEX CLASS FILES, VOL. XX, NO. X,

GO-LDA:
D

Jiah

Abstract—Linear discriminant analysis (
While linearity of class boundaries cann
served to map complex data onto feature
which is variance preserving, LDA maxir
class on a subspace. The solution to bin
It is well known that the multiclass LDA i



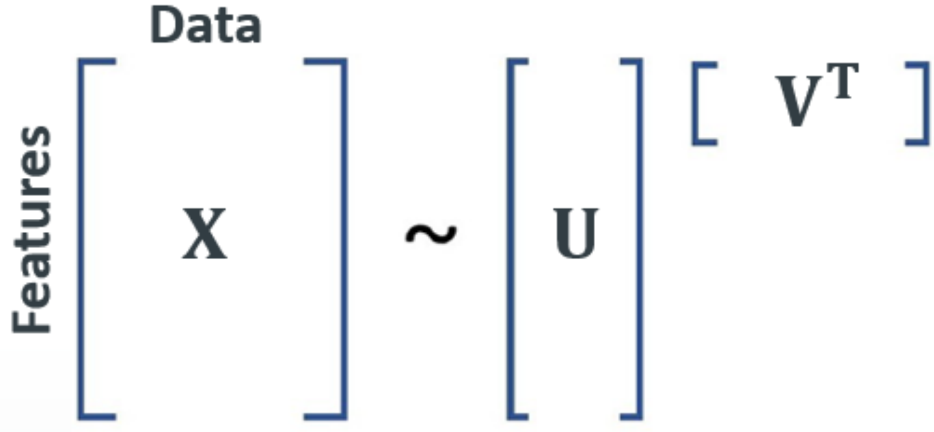
(a) Classic-LDA

(b) GO-LDA

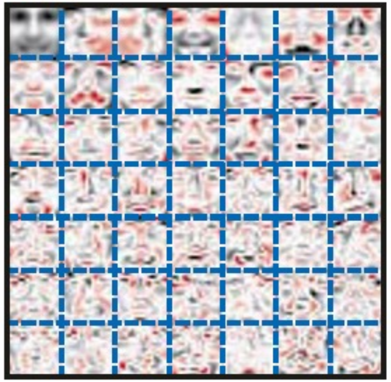
NMF (Non-negative matrix factorization)

[Lee & Seung, 1999]

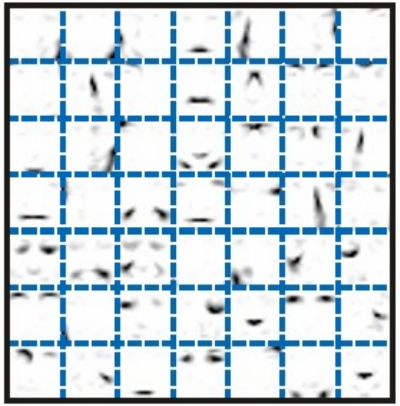
$$\min_{\boldsymbol{U},\boldsymbol{V}} \|\boldsymbol{X} - \boldsymbol{U}\boldsymbol{V}^\top\|_F^2, \text{ s.t. } \boldsymbol{U} \geq \mathbf{0}, \boldsymbol{V} \geq \mathbf{0}$$



PCA



NMF



Supervised NMF (DNMF, SCNMFS)

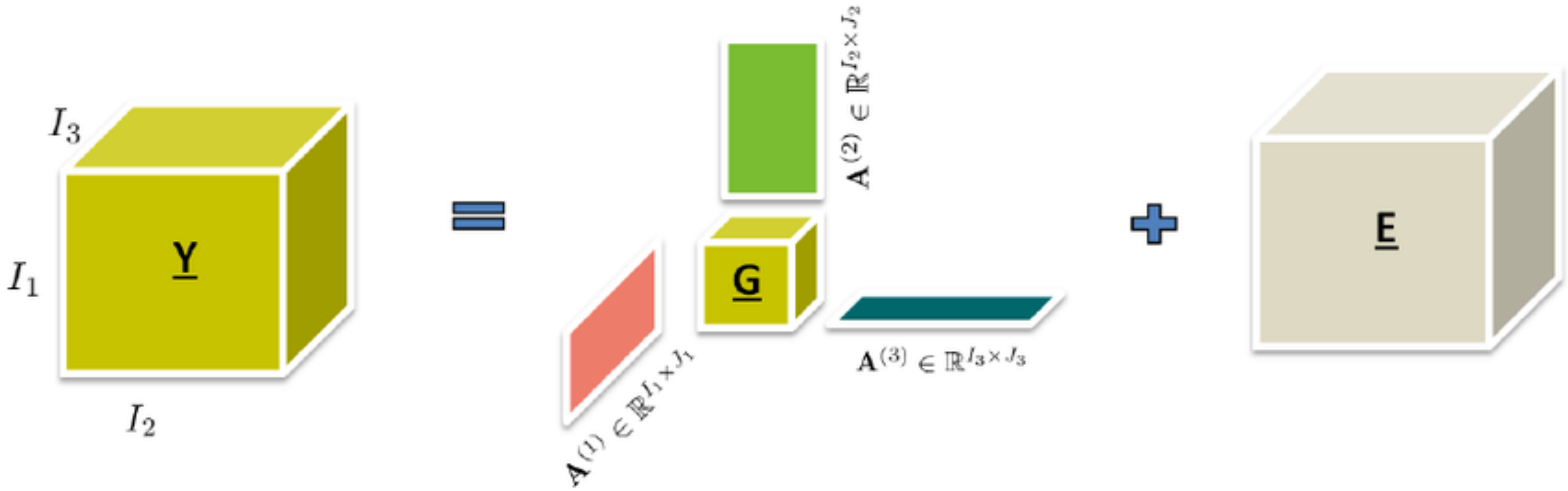
DNMF (Discriminative NMF)
[M. Babaee, 2016]:

$$\min_{\boldsymbol{U},\boldsymbol{V},\boldsymbol{A}} \|\boldsymbol{X} - \boldsymbol{U}\boldsymbol{V}^\top\|_F^2 + \alpha\|\boldsymbol{Q} - \boldsymbol{A}\boldsymbol{V}^\top\|_F^2,$$
$$\text{s.t. } \boldsymbol{U} \geq \boldsymbol{0}, \boldsymbol{V} \geq \boldsymbol{0}$$

SCNMFS (Supervised and Constrained NMF with Sparseness) [Xibiao Cai, 2018]:

$$\min_{\boldsymbol{U},\boldsymbol{Z}} \|\boldsymbol{X} - \boldsymbol{U}\boldsymbol{Z}^\top\boldsymbol{Q}\|_F^2 + \beta \parallel \boldsymbol{U} \parallel_F^2,$$
$$\text{s.t. } \boldsymbol{U} \geq \boldsymbol{0}, \boldsymbol{Z} \geq \boldsymbol{0}$$

Subspace Representation / Tensor Decomposition



[Credit: Guoxu Zhou and Andrzej Cichocki]

Subspace Representation / Tensor Decomposition

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School of Electronics and Computer Science

Journal of Scientific Computing (2023) 95:52
https://doi.org/10.1007/s10915-023-02172-y

Check for updates

Practical Sketching Algorithms for Low-Rank Tucker Approximation of Large Tensors

Wandi Dong[1] · Gaohang Yu[1] · Liqun Qi[1,2] · Xiaohao Cai[3]

Received: 24 October 2022 / Revised: 27 January 2023 / Accepted: 28 February 2023 /
Published online: 29 March 2023

Subspace Representation / Tensor Decomposition

A Randomized Block Krylov Method for Tensor Train Approximation

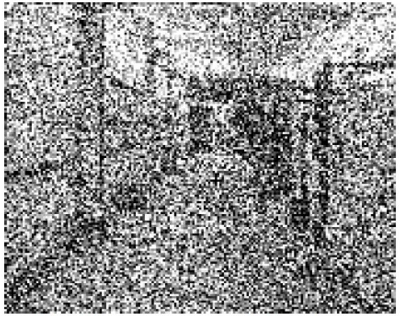
Gaohang Yu[1*], Jinhong Feng[1], Zhongming Chen[1], Xiaohao Cai[2], Liqun Qi[1,3]

[1]Department of Mathematics, Hangzhou Dianzi University, China.
[2]School of Electronics and Computer Science, University of Southampton, Southampton, UK.
[3]Huawei Theory Research Lab, Hong Kong, China.

*Corresponding author(s). E-mail(s): maghyu@163.com;
Contributing authors: fengjinhong0502@163.com; zmchen@hdu.edu.cn;
x.cai@soton.ac.uk; liqun.qi@polyu.edu.hk;

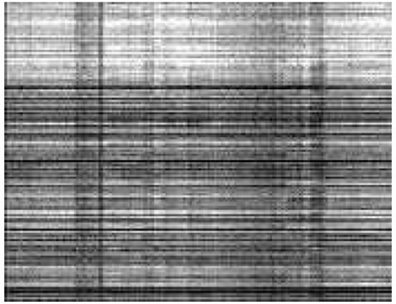
Subspace Representation / Tensor Decomposition

(a) Original gray video frame

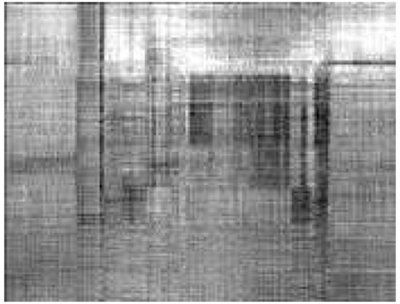


(b) Noisy gray video frame
PSNR: 7.6099

(c) TT-SVD
CPU: 0.29; PSNR: 22.9434



(d) TT-rSVD
CPU: 0.03; PSNR: 15.4260



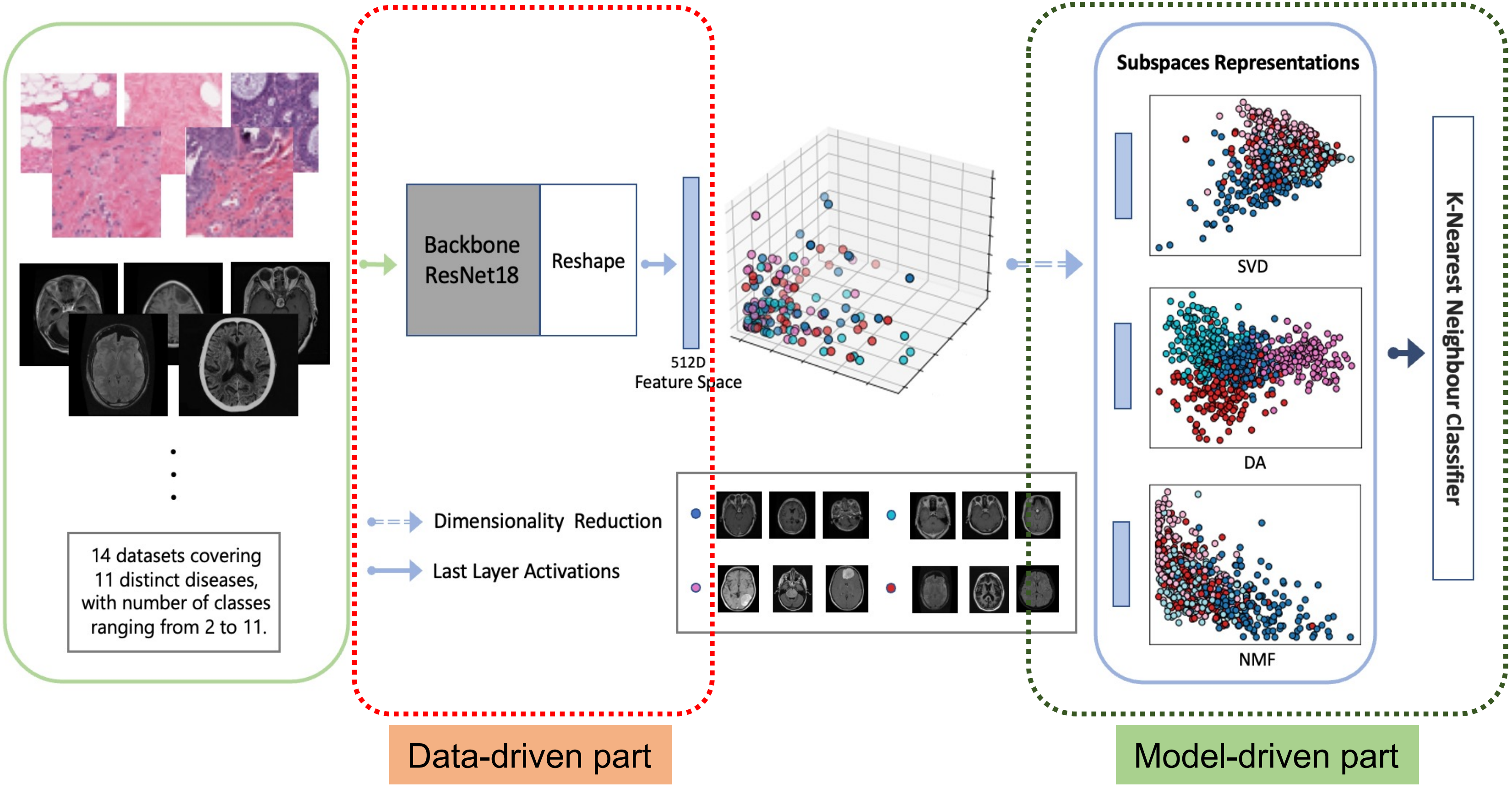
(e) TT-rSI
CPU: 0.07; PSNR: 20.4777

(f) TT-rBKI
CPU: 0.10; PSNR: 22.0651

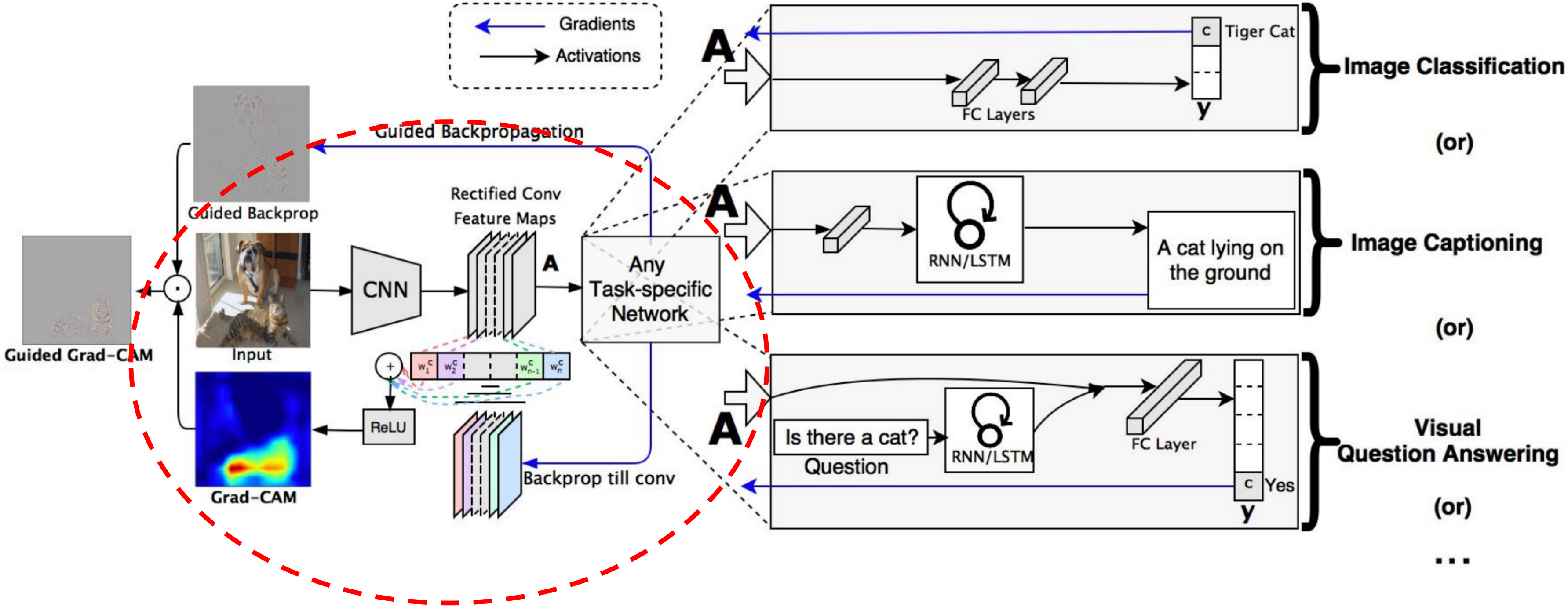
Few-Shot Learning Framework and Subspaces

UNIVERSITY OF Southampton
School of Electronics and Computer Science

[J. Liu, K. Fan, X. Cai, and M. Niranjan, under review]



Explainable AI (XAI) methods – Grad-CAM



Grad-CAM: Visual Explanations from Deep Networks via Gradient-based Localization, IJCV, ’19

XAI Application

frontiers | Frontiers in Marine Science

TYPE Original Research
PUBLISHED 27 July 2023
DOI 10.3389/fmars.2023.1167818

Check for updates

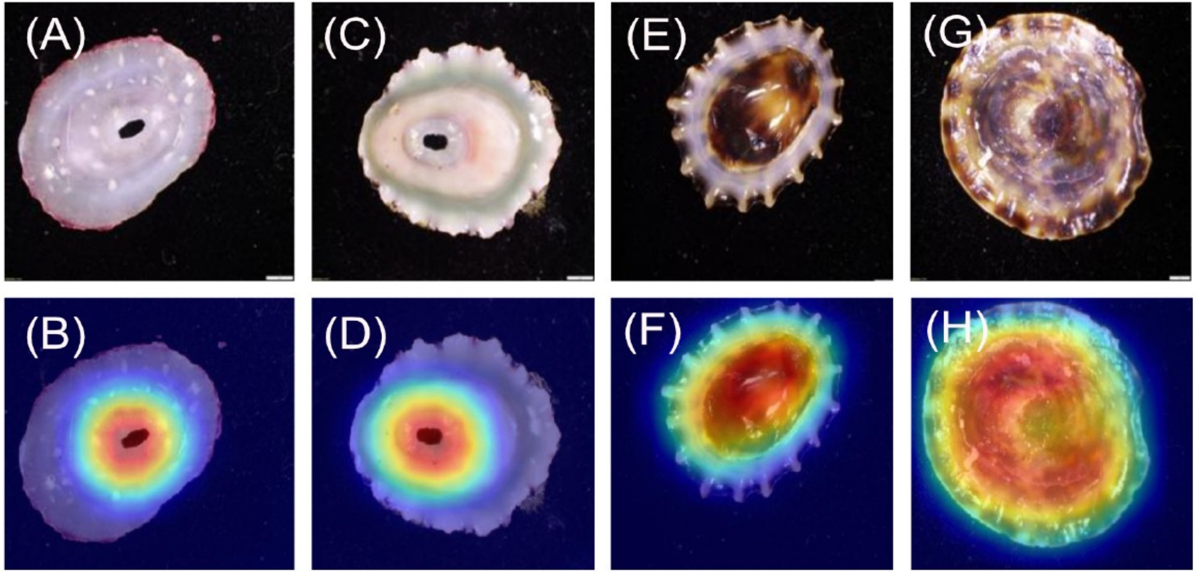
OPEN ACCESS

EDITED BY

Using computer vision to identify limpets from their shells: a case study using four species from ja California peninsula

ister[1,2,3]*, Xiaohao Cai[1], Tammy Horton[2,3],
. Price[3], Karolina M. Zarzyczny[1,3]
. Fenberg[1,3]

nd Earth Sciences, University of Southampton, Southampton, United Kingdom,
nces, National Oceanography Centre, Southampton, United Kingdom, [3]Natural
ondon, United Kingdom

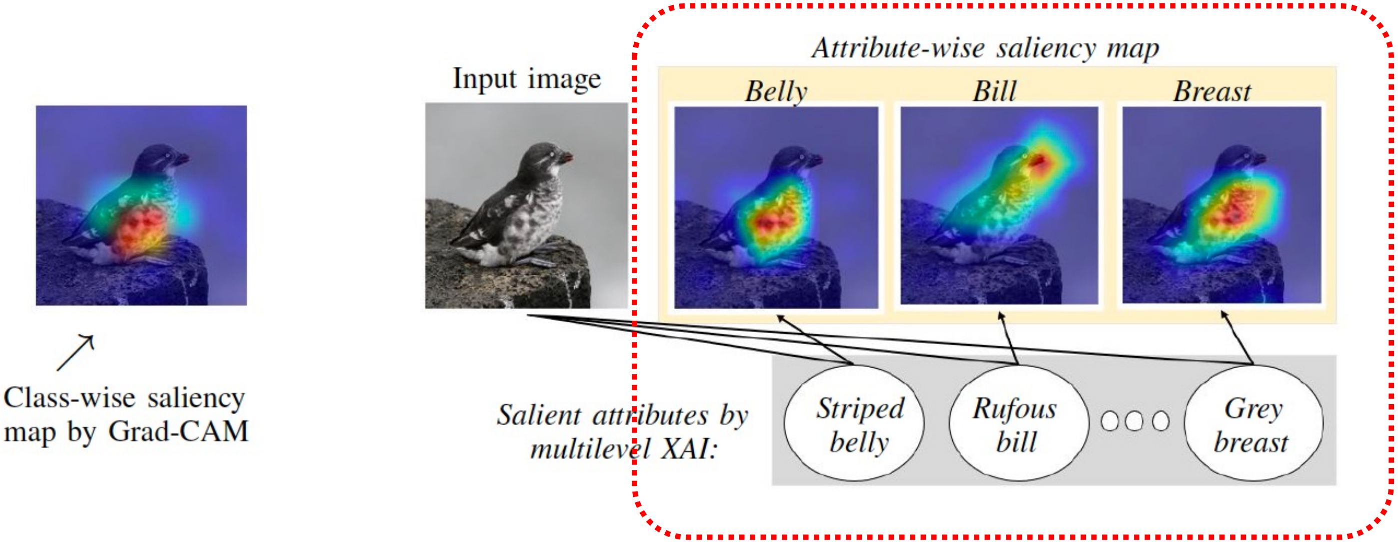


Multilevel XAI

JOURNAL OF IEEE TRANSACTIONS ON ARTIFICIAL INTELLIGENCE, VOL. 00, NO. 0, MON [2023]

Multilevel Explainable Artificial Intelligence: Visual and Linguistic Bonded Explanations

Halil Ibrahim Aysel, Xiaohao Cai, and Adam Prugel-Bennett

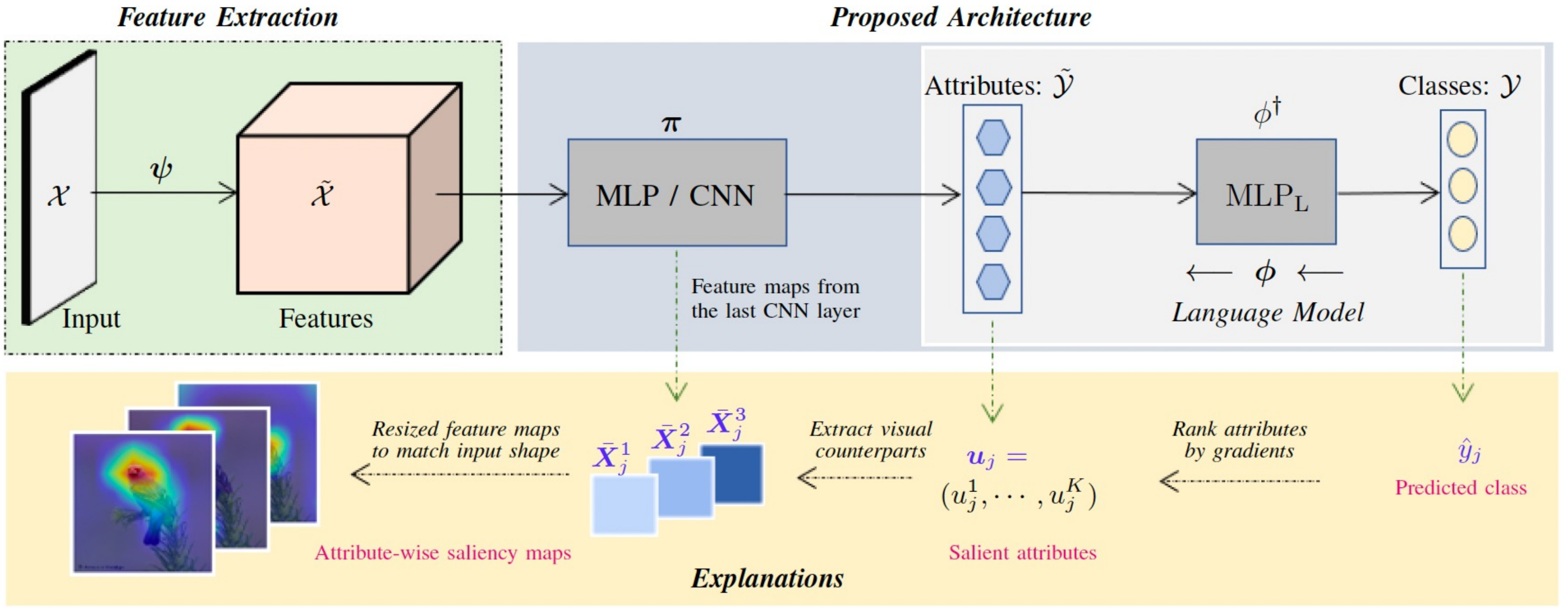


Multilevel XAI

JOURNAL OF IEEE TRANSACTIONS ON ARTIFICIAL INTELLIGENCE, VOL. 00, NO. 0, MON[2023]

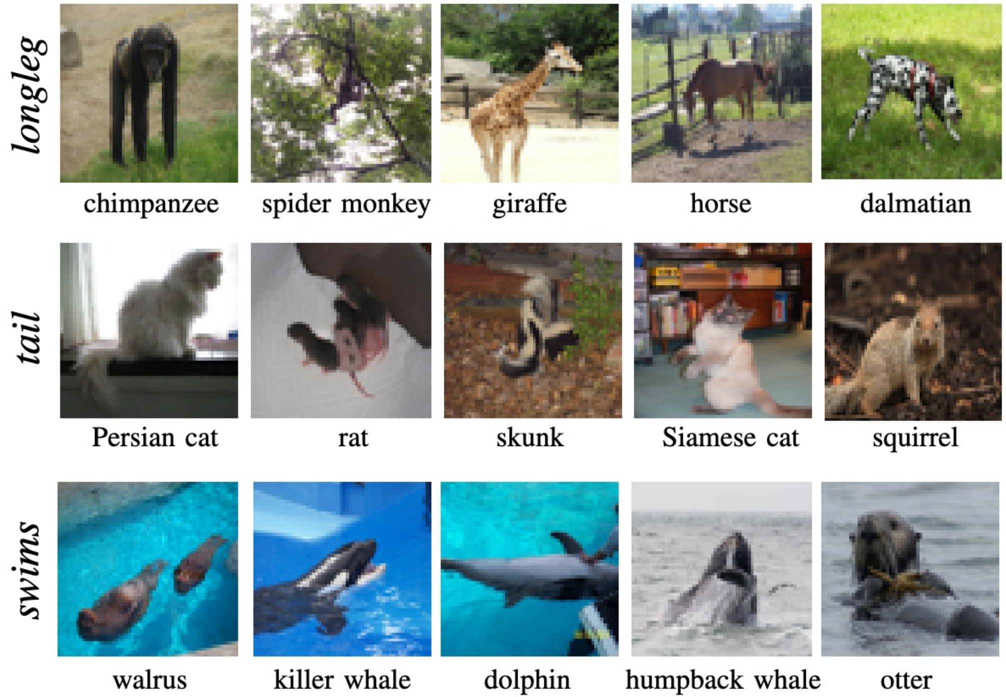
Multilevel Explainable Artificial Intelligence: Visual and Linguistic Bonded Explanations

Halil Ibrahim Aysel, Xiaohao Cai, and Adam Prugel-Bennett

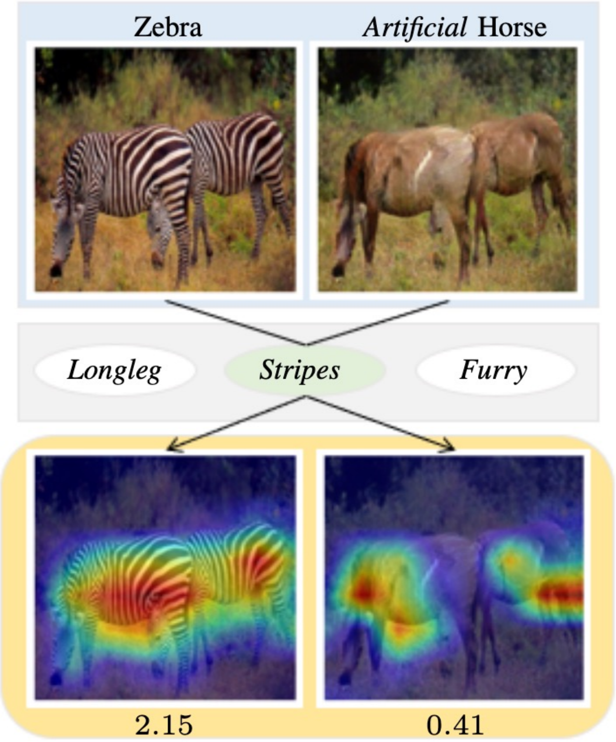


Multilevel XAI

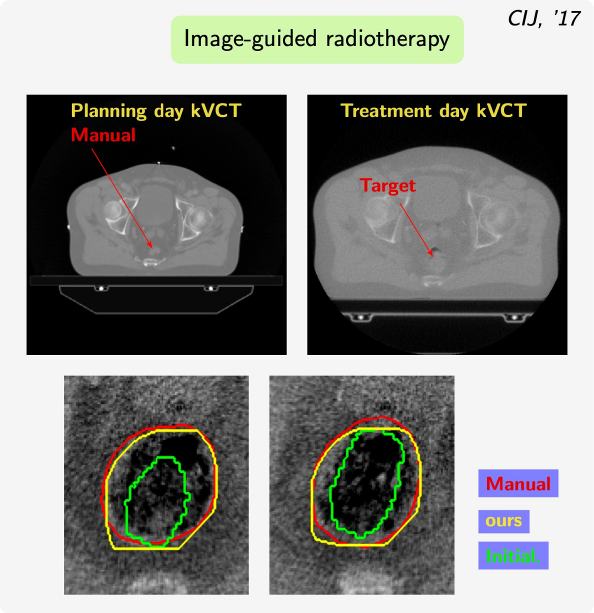
UNIVERSITY OF Southampton
School of Electronics and Computer Science



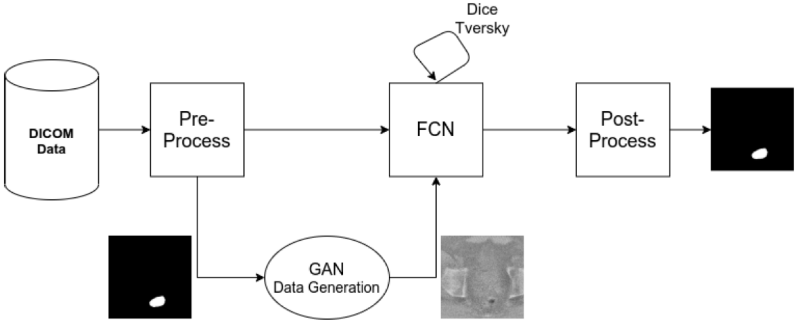
The top five classes that maximally activate the given individual attribute on the left



Data Augmentation



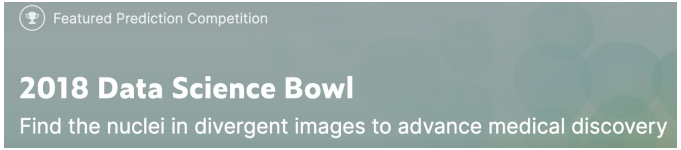
http://www.componc org/research/voxtox

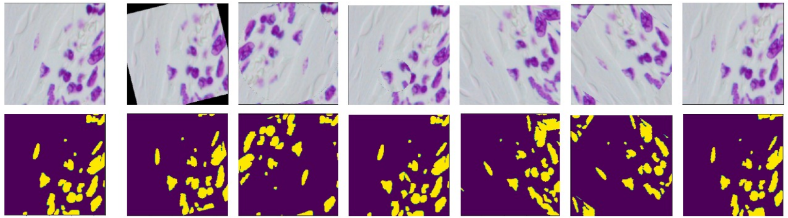


Use cGAN for data augmentation

D. Mallios and X. Cai, EUSIPCO, 2021

Data Augmentation





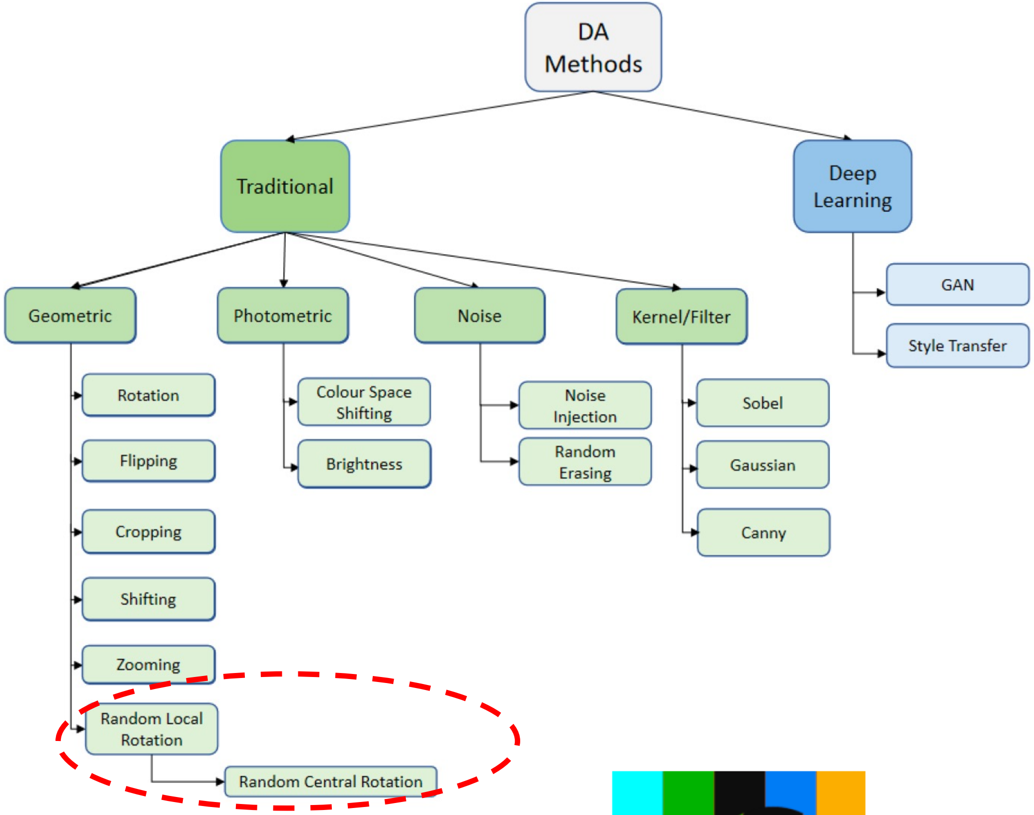
Given image TR RCR RLR RRR RWR RNR

Journal of *Imaging* 2023

Article

Data Augmentation in Classification and Segmentation: A Survey and New Strategies

Khaled Alomar *, Halil Ibrahim Aysel and Xiaohao Cai



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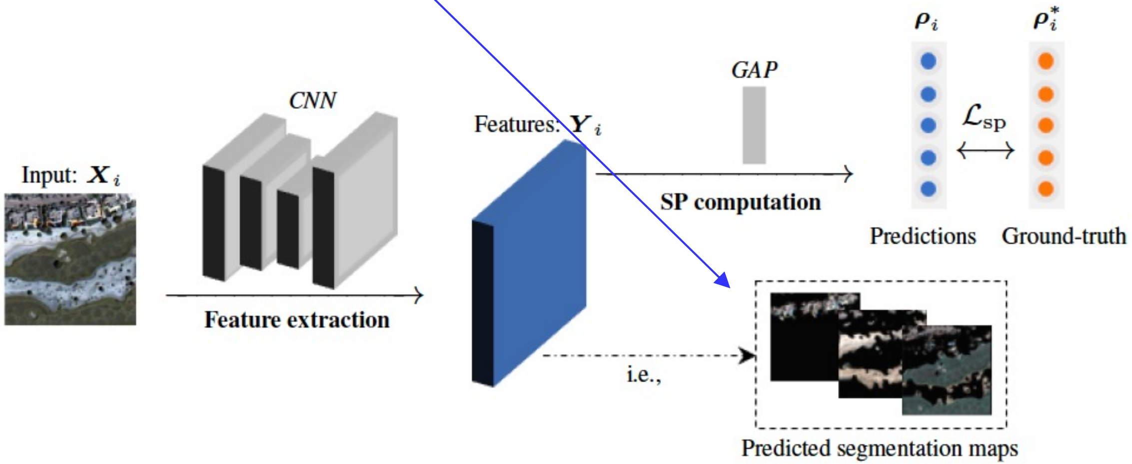
Semantic Segmentation by Semantic Proportions

[arXiv:2305.15608]

Halil Ibrahim Aysel[1*] **Xiaohao Cai**[1] **Adam Prügel-Bennett**[1]
[1]School of Electronics and Computer Science, University of Southampton, UK



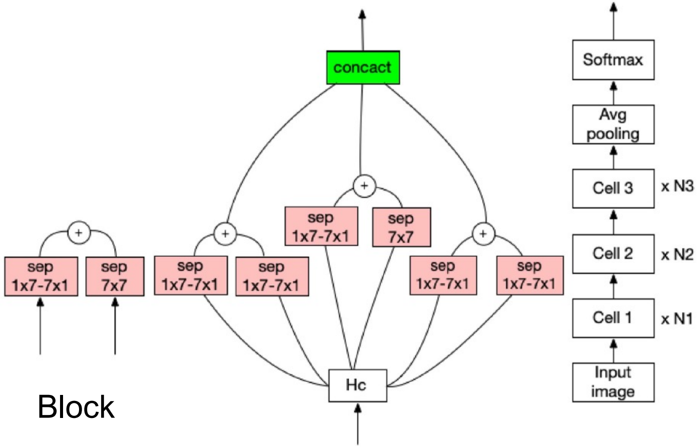
Balanced Neural Architecture Search

UNIVERSITY OF Southampton
School of Electronics and Computer Science

IEEE TRANSACTIONS ON SIGNAL PROCESSING, VOL. 69, 2021

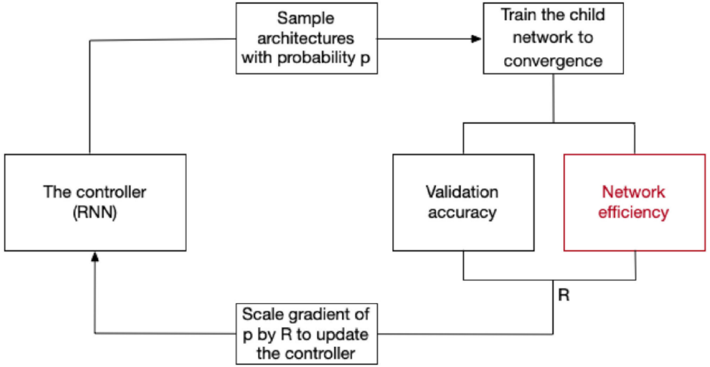
Balanced Neural Architecture Search and Its Application in Specific Emitter Identification

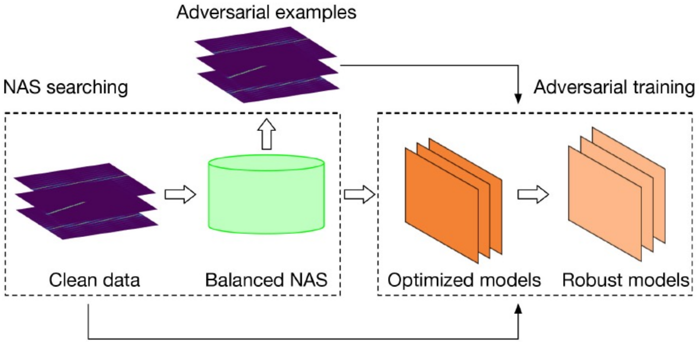
Mingyang Du, Xikai He, Xiaohao Cai, and Daping Bi



Block

Cell

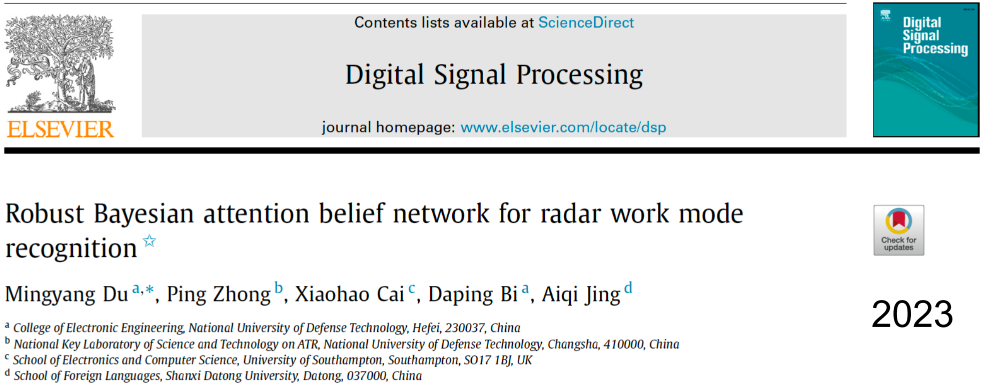




Adversarial training

Bayesian Attention Belief Network

UNIVERSITY OF Southampton
School of Electronics and Computer Science


Contents lists available at ScienceDirect

Digital Signal Processing

journal homepage: www.elsevier.com/locate/dsp

ELSEVIER

Robust Bayesian attention belief network for radar work mode recognition ☆

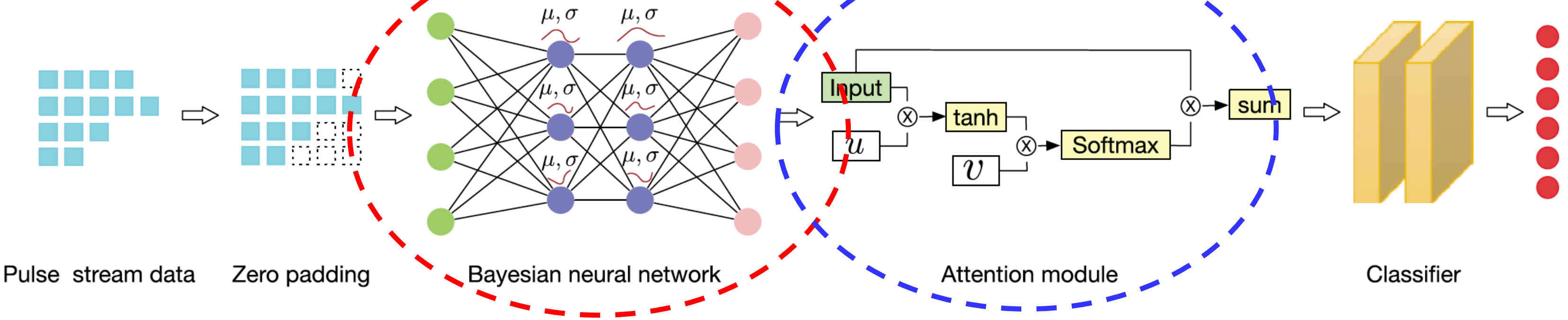
Mingyang Du [a,*], Ping Zhong [b], Xiaohao Cai [c], Daping Bi [a], Aiqi Jing [d]

[a] College of Electronic Engineering, National University of Defense Technology, Hefei, 230037, China
[b] National Key Laboratory of Science and Technology on ATR, National University of Defense Technology, Changsha, 410000, China
[c] School of Electronics and Computer Science, University of Southampton, Southampton, SO17 1BJ, UK
[d] School of Foreign Languages, Shanxi Datong University, Datong, 037000, China

2023

Better robustness and generalisation

More efficient and effective



Structure of the proposed BABNet

Denoising and Classification

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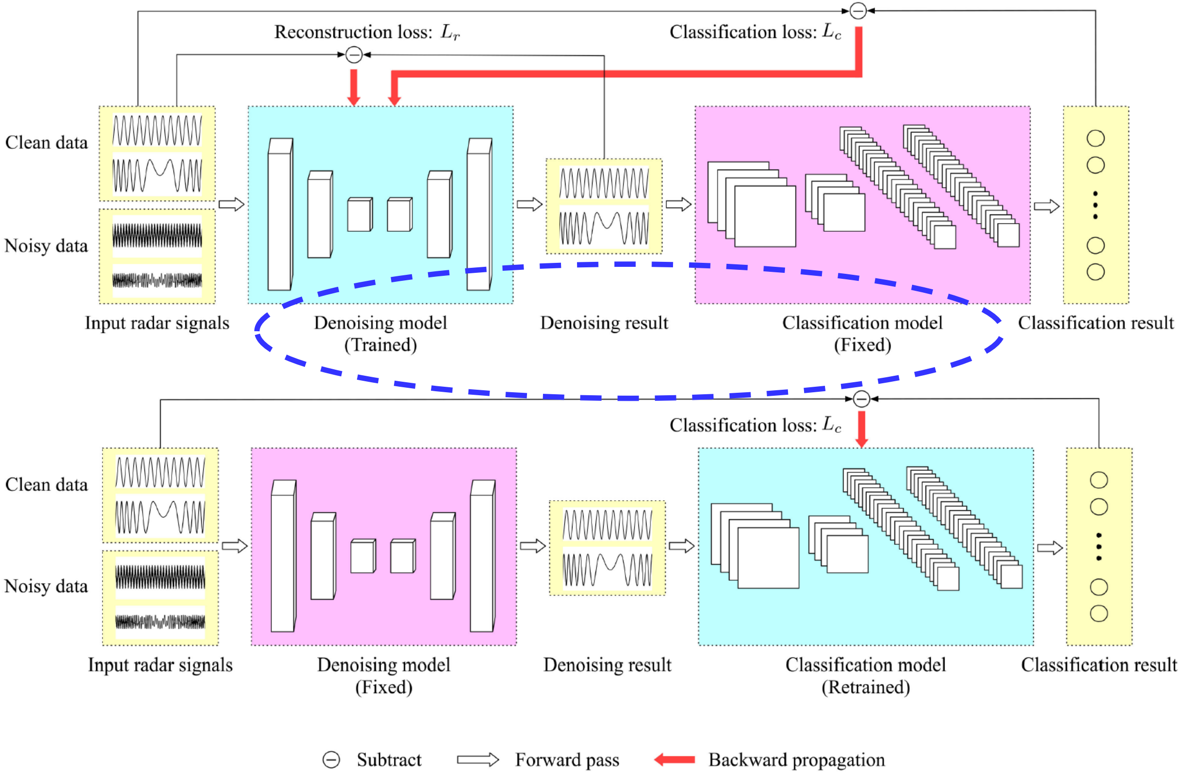


IEEE Transactions on Aerospace and Electronic Systems, 2022

DNCNet: Deep Radar Signal Denoising and Recognition

MINGYANG DU
National University of Defense Technology, Hefei, China

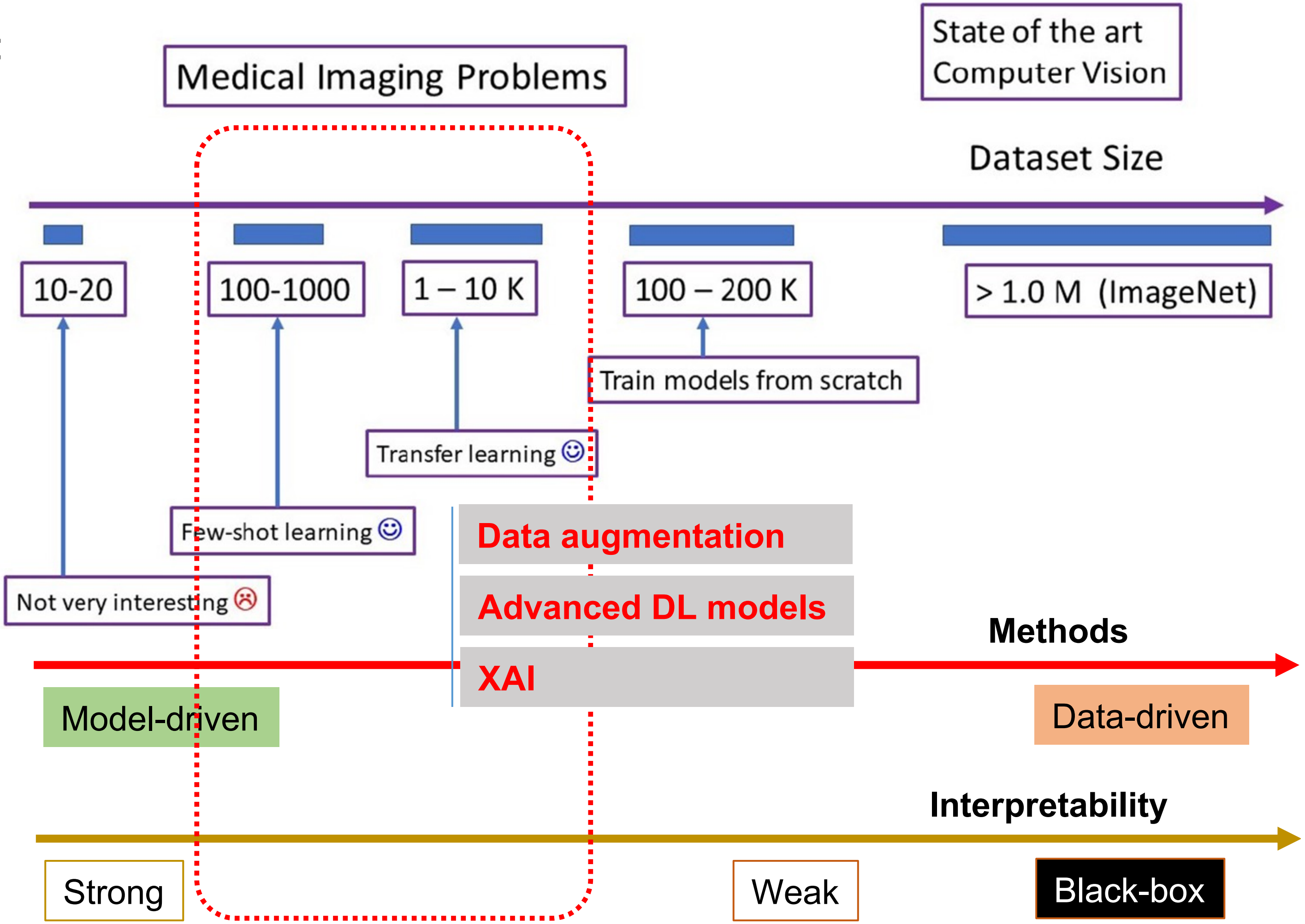
PING ZHONG, Senior Member, IEEE
National University of Defense Technology, Changsha, China

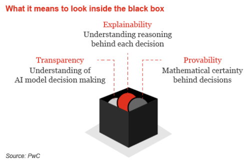
XIAOHAO CAI
University of Southampton, Southampton, U.K.

DAPING BI
National University of Defense Technology, Hefei, China

Better robustness and generalisation

Recap:


Medical Imaging Problems
State of the art Computer Vision
Dataset Size
10-20
100-1000
1 – 10 K
100 – 200 K
> 1.0 M (ImageNet)
Train models from scratch
Transfer learning ☺
Few-shot learning ☺
Not very interesting ☹
Data augmentation
Advanced DL models
XAI
Methods
Model-driven
Data-driven
Interpretability
Strong
Weak
Black-box


What it means to look inside the black box
Explainability
Understanding reasoning behind each decision
Transparency
Understanding of AI model decision making
Provability
Mathematical certainty behind decisions
Source: PwC