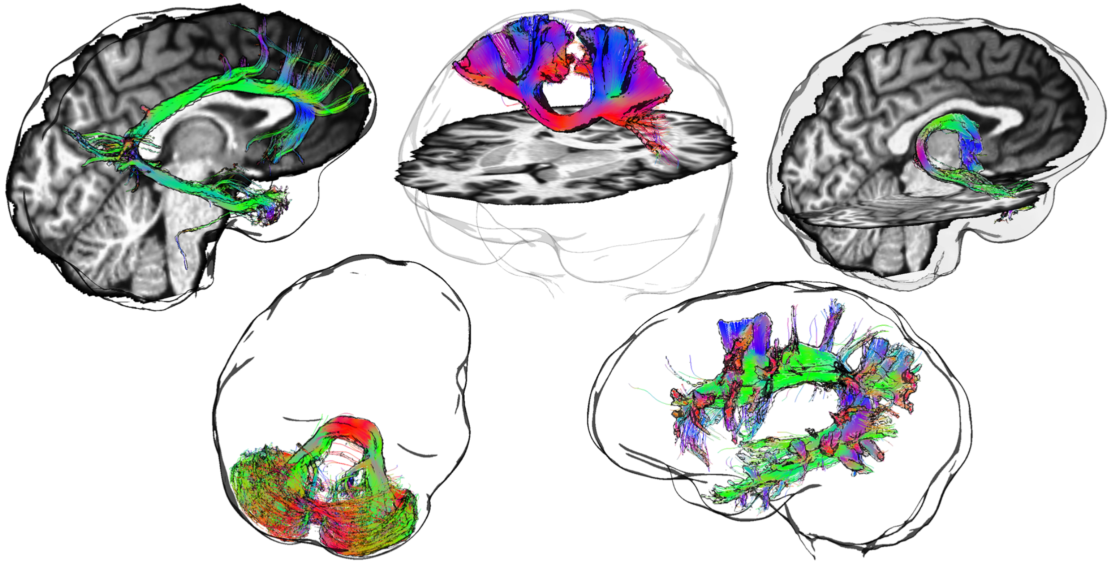
Tracking of nerve fibres in brain tumour patients

Andrey Zhylka (a.zhylka@tue.nl)[1], Josien Pluim[1], Marcel Breeuwer[1,2], Alexander Leemans[3]
[1]Medical Image Analysis Group, TU/e, [2]Philips Healthcare, [3]UMC Utrecht

- **A little on diffusion imaging…**
- **What fiber tracking is…**
- **What project is about…**
- **What it has to do with optimisation …**

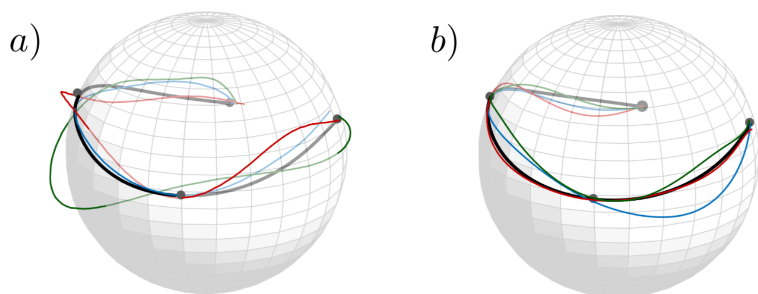


courtesy of Maxime Chamberland

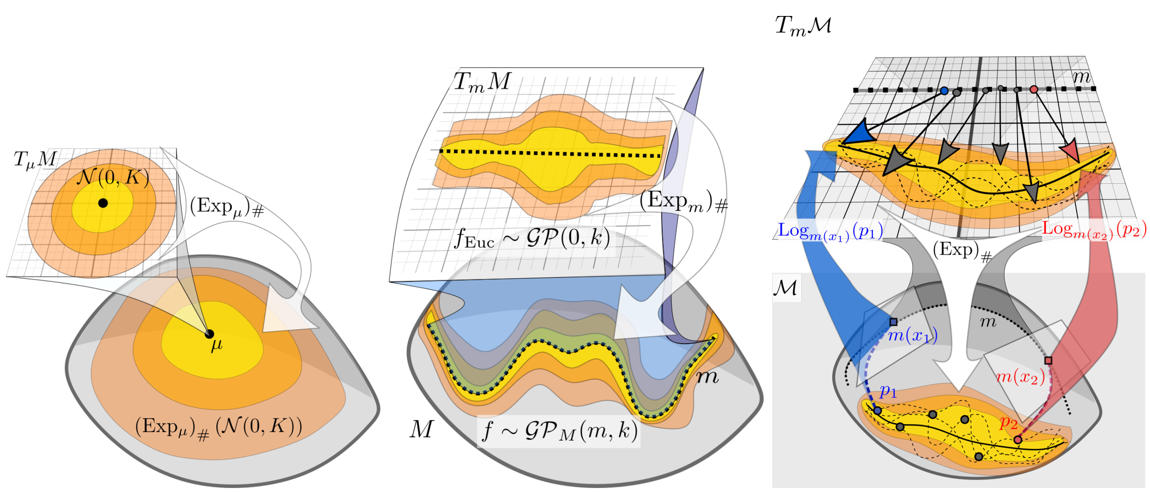
Wrapped Gaussian process regression on Riemannian manifolds

Anton Mallasto & Aasa Feragen

August 3, 2018

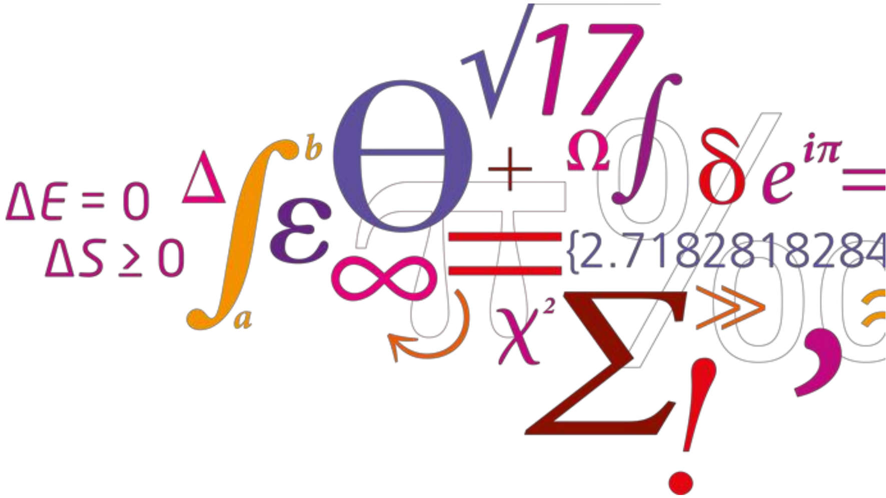


Gaussian process regression is a popular tool in non-parametric regression that provides meaningful uncertainty estimates. In this work, we consider a generalization of the method on Riemannian manifolds employing wrapped Gaussian distributions.



Optimization for multi-scale 3D reconstruction of ptychographic X-ray tomography data

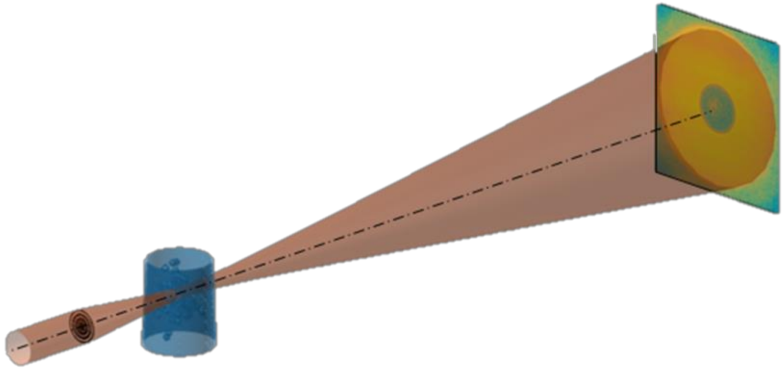
Azat M. Slyamov, Tiago Ramos, Jens W. Andreasen
Technical University of Denmark, Department of Energy Conversion and Storage, 4000 Roskilde, Denmark



DTU Energy
Department of Energy Conversion and Storage

Optimization for multi-scale 3D reconstruction of ptychographic X-ray tomography data

Direct reconstruction in 3D requires large computational recourses and/or time consuming reconstruction algorithms. Here, we propose a multi-scale approach for reducing convergence time by fast reconstruction of low-resolution image and its further application as an input guess for high-resolution reconstruction.



Coherent X-ray diffraction imaging

$$I_{\boldsymbol{\Theta}} \cong |\mathcal{F}\{\psi_{\boldsymbol{\Theta}}\}|^2 = |\Psi_{\boldsymbol{\Theta}}|^2$$

$$\psi_{\boldsymbol{\Theta}} = P O_{\boldsymbol{\Theta}}$$

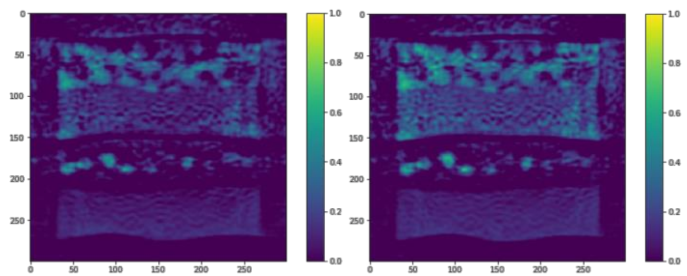
$$O_{\boldsymbol{\Theta}} = \exp\left[\mathbf{i}k \int_{\Theta} -\delta + \mathbf{i}\beta\right],$$

Phase-retrieval

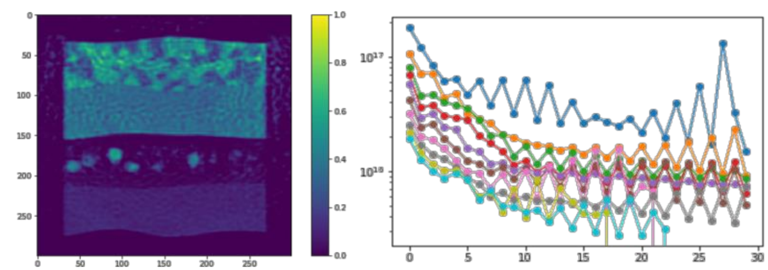
$$\min(I_{\boldsymbol{\Theta}}^{\boldsymbol{g}} - I_{\boldsymbol{\Theta}}^{m})$$

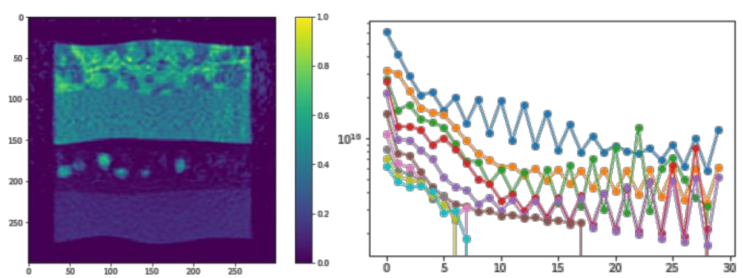
Optimization for multi-scale 3D reconstruction of ptychographic X-ray tomography data

Single-scale reconstruction

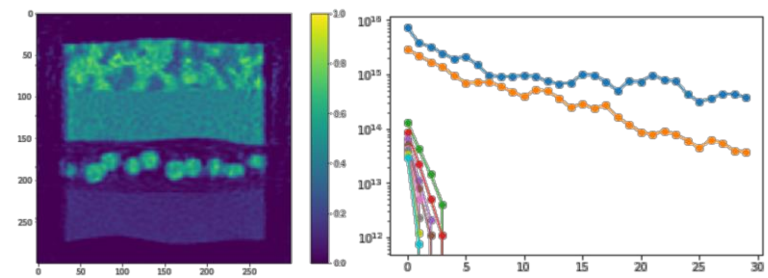


Reconstruction from scaled data





Multi-scale reconstruction



Physical Model Based Segmentation

A method for assessing uncertainty in tomographic structural analysis result

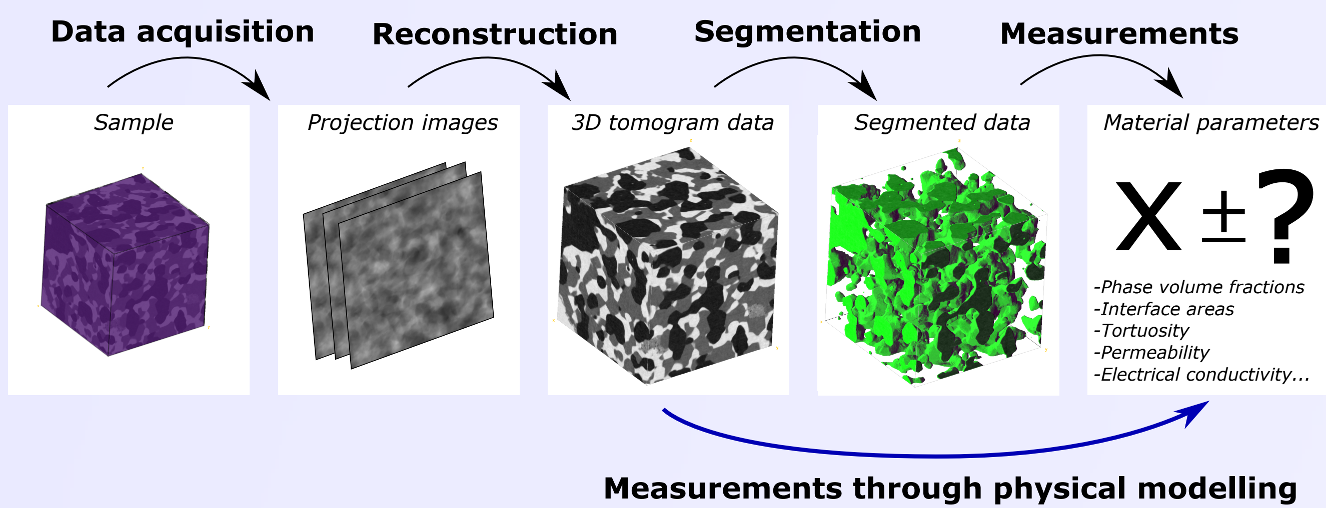
Elise Otterlei Brenne*
elbre@dtu.dk

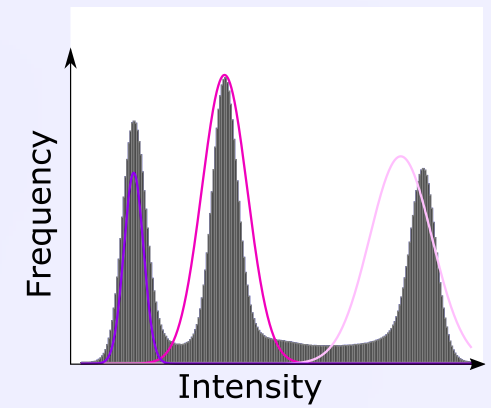
Supervisors: Peter Stanley Jørgensen*, Vedrana Andersen Dahl*, Ali Chirazi#

*Department of Energy Conversion and Storage, Technical University of Denmark, Frederiksborgvej 399, 4000 Roskilde, Denmark
#Thermo Fisher Scientific, Bordeaux, France

Problem

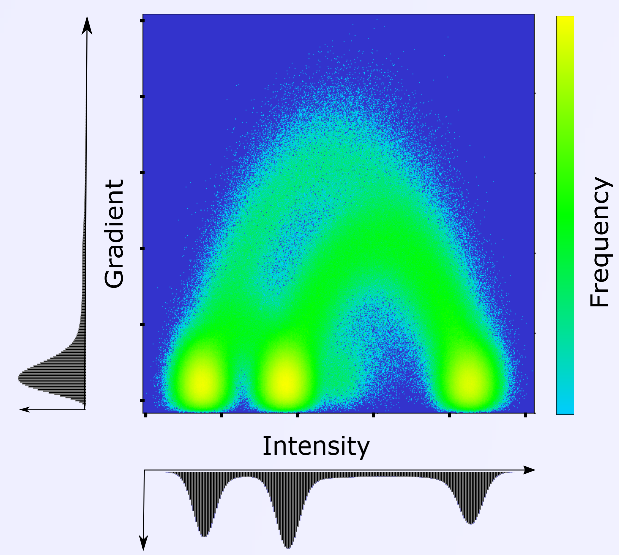
- Errors will occur and propagate through the sifferent steps of the tomographic pipeline
- This makes it challenging to assess the uncertainty in the final result
- How to assign meaningful error bars to the extracted material parameters?





Basic physical model:
Gaussian mixture model and added Gaussian noise, fitted to 1D intensity histogram

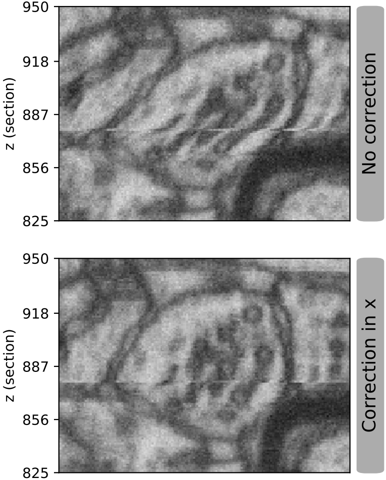
Parameters:
- Phase volume fractions
- Noise levels



Extended physical model:
Model fitted to 2D intensity-gradient histogram

Parameters:
- Interface areas
- Resolution

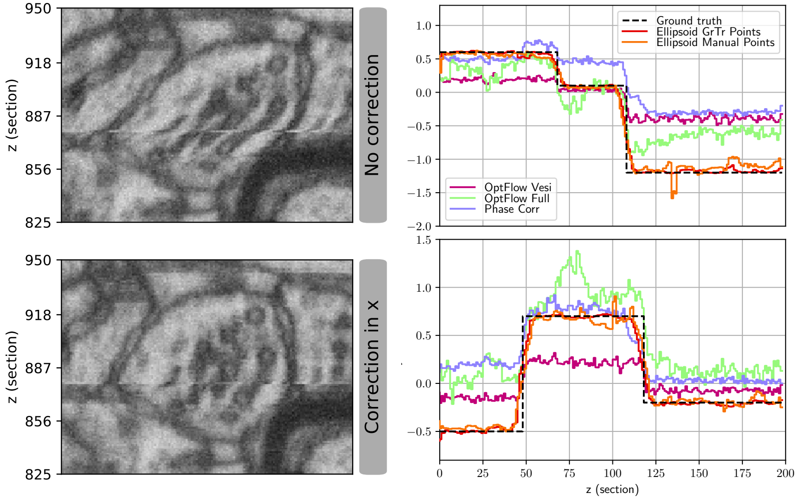
Correcting Drifted FIB-SEM Images using a Model-Based Registration Approach



Standard Image Registration Methods

source: thestar.com/opinion/editorial_cartoon/2018/03/25/greg-perry-faceplant.html

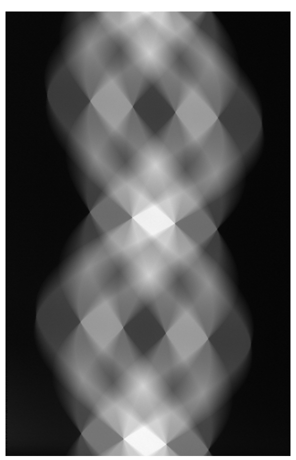
Correcting Drifted FIB-SEM Images using a Model-Based Registration Approach

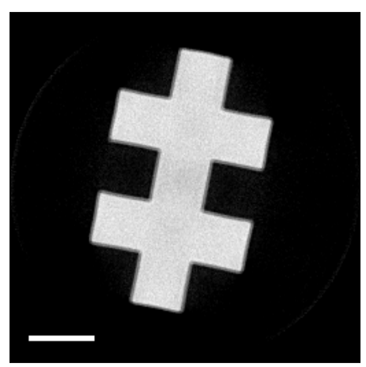


Direct Segmentation from Projections

Existing reconstruction approach

$$\hat{p} = Wx$$



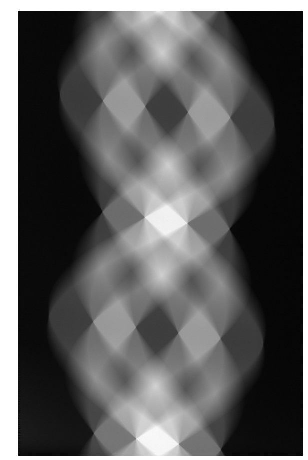


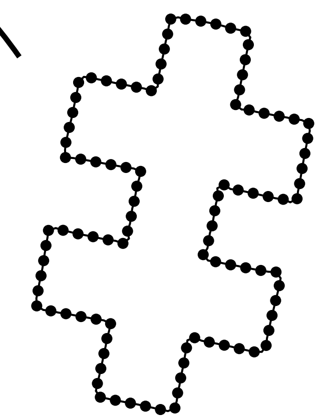
p $\qquad$ x

$$\min_{x} ||p - \hat{p}||$$

Our approach

$$\hat{p}(C)$$





p $\qquad$ C

$$\min_{C} ||p - \hat{p}||$$

Optimize an energy involved in a curve

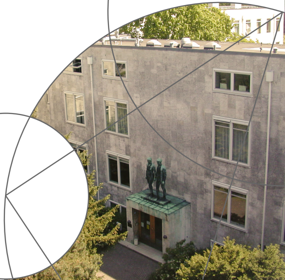
$$\min E(C) = \sum_{\theta} \int_{S} (p(\theta, s) - \mu \hat{p}(\theta, s))^2 ds$$

$$\hat{p}(\theta, s) = \int_{\mathrm{int}(C)} \delta(L_\theta(x, y) - s)\, \mathrm{d}x\mathrm{d}y$$

Faculty of Science

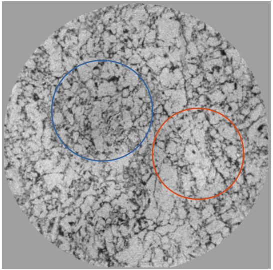
Multiphase Local Mean Geodesic Active Regions

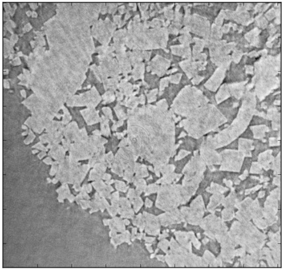
Jacob Daniel Kirstejn Hansen & François Bernard Lauze
Department of Computer Science

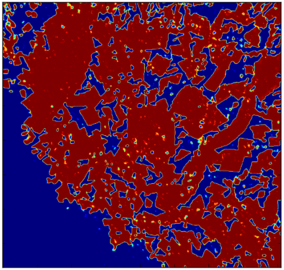


August, 2018

Addressed problem







Proposed methods

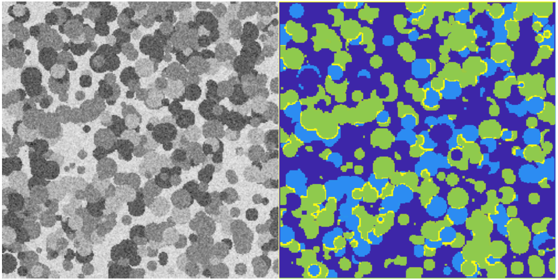
$$\mathcal{E}_{wTV}(\mathbf{c},\mathbf{v}) = \frac{1}{2}\sum_{i=1}^{n}\int_\Omega g * \left[(u - c_i(\boldsymbol{x}))^2\mathbf{v}_i\right](\boldsymbol{x})\,d\boldsymbol{x} + \mu\mathcal{J}_h(\mathbf{v}),$$

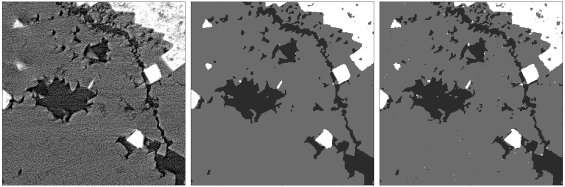
$$\mathcal{E}_{wQ}(\mathbf{c},\mathbf{v}) = \frac{1}{2}\sum_{i=1}^{n}\int_\Omega g * \left[(u - c_i(\boldsymbol{x}))^2\mathbf{v}_i\right](\boldsymbol{x})\,d\boldsymbol{x} + \frac{\mu}{2}||D\mathbf{v}||_h^2$$

$$\mathbf{v} \in \Sigma_n(a.e.)$$

Using a modified (now more general) version of the Chambolle, Crembers, and Pock's framework and a simple proximal method to optimize the two energy functions, respectively.

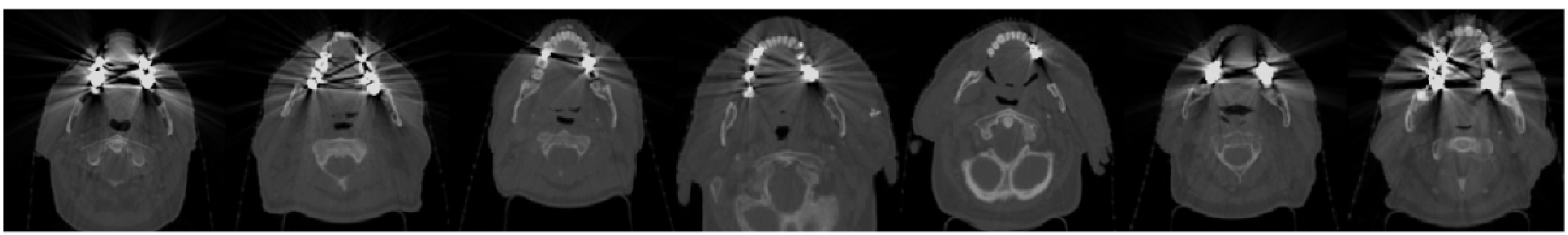
Results





Tuning the hyperparameters in an MR patch-based CT metal artifact reduction algorithm

Jonathan Scharff Nielsen (DTU, RGH), Jens M. Edmund (RGH, NBI) and Koen Van Leemput (DTU, MGH)



- Metal implants lead to CT metal artifacts
- We've created a generative model of CT values, corrupted CT values and MR patches for estimating CT values using Bayesian inference

Hyperparameters

- The model uses kernel density estimation along with a noise model of the CT artifacts
- The problem: Hyperparameters need picking; an optimisation problem! Come hear about Empirical Bayes and the EM-algorithm.

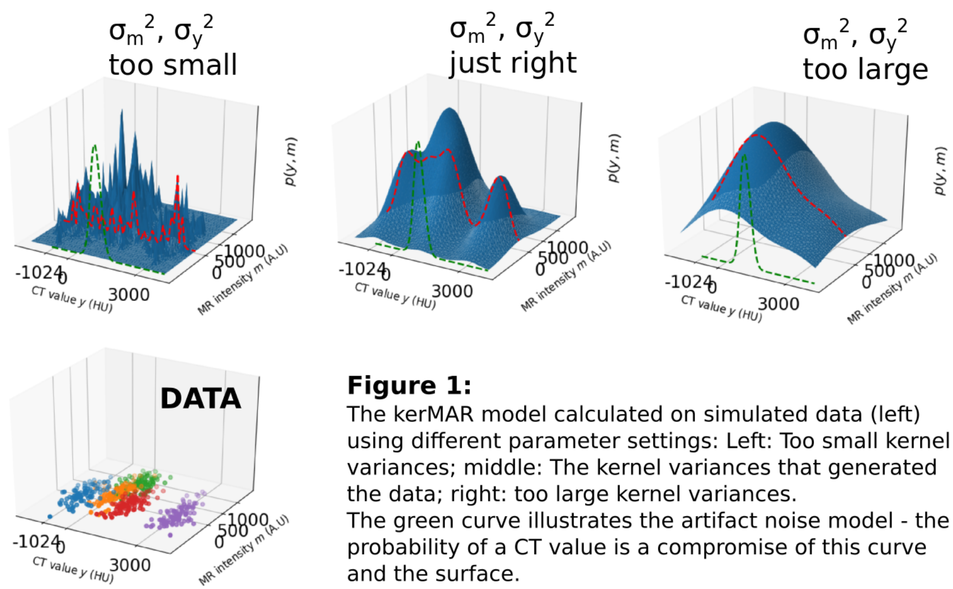
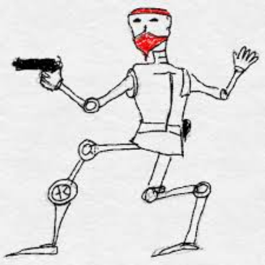


Figure 1:
The kerMAR model calculated on simulated data (left) using different parameter settings: Left: Too small kernel variances; middle: The kernel variances that generated the data; right: too large kernel variances.
The green curve illustrates the artifact noise model - the probability of a CT value is a compromise of this curve and the surface.

An Optimal Algorithm for Stochastic and Adversarial Bandits

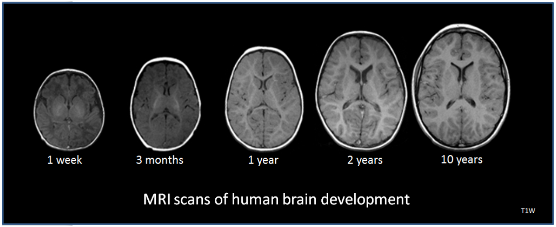


Julian Zimmert & Yevgeny Seldin

August 6, 2018

University of Copenhagen

Modelling Time Evolution of Medical Images

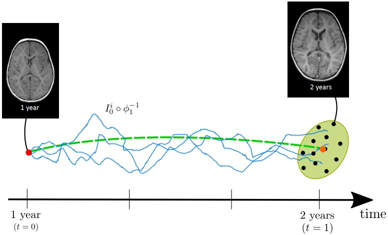


Minimize:

$$E(v_t) = \int_0^1 \|v_t\|^2 dt + \|I_0 \circ \phi_1^{-1} - I_1\|_{L^2}^2$$

With deformations:

$$d\phi_t^{-1} = -D\phi_t^{-1} v_t dt - \sum_{k=1}^{d} D\phi_t^{-1} \sigma_k \circ_S dB_t^k$$



Limitations of Cross-Lingual Learning from Image Search

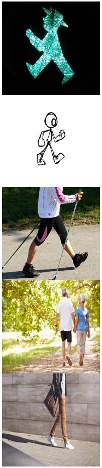
Lexicon induction from image data: Does it work for adjectives and verbs?

mug:

Tasse:

traurig:

gehen:



Multigrain crystallography: Indexing algorithms for multiphase polycrystalline Cu_2ZnSnS_4 solar cells

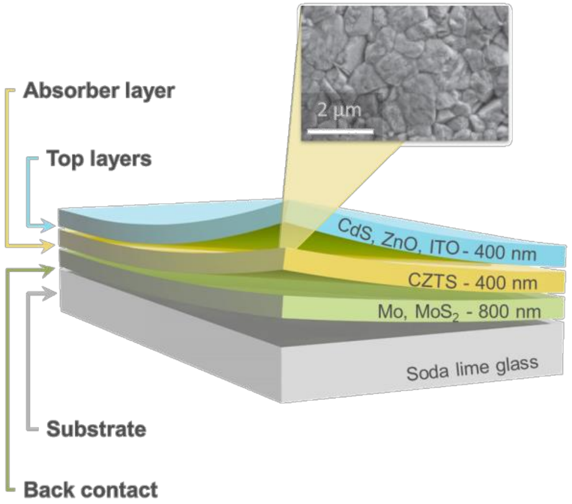
Mariana Mar Lucas

DTU Energy

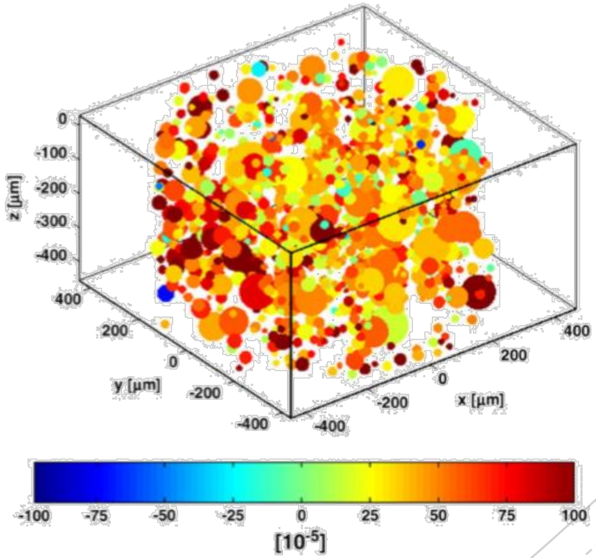
Technical University of Denmark

Main topics:

- Kesterite (CZTS) solar cells
  - Structural characterization of the absorber layer
  - Crystallographic phases of the absorber layer



- Multigrain crystallography
  - 3D X-ray diffraction
  - Indexing algorithms
  - Grain mapping



(Oddershedde, 2011)

Motivation - Is there a problem?

Cluster failure: Why fMRI inferences for spatial extent have inflated false-positive rates

Anders Eklund[a,b,c,1], Thomas E. Nichols[d,e], and Hans Knutsson[a,c]

Essay

Why Most Published Research Findings Are False

John P. A. Ioannidis

PLoS Medicine | www.plosmedicine.org 0696 August 2005 | Volume 2 | Issue 8 | e124

ANALYSIS

Power failure: why small sample size undermines the reliability of neuroscience

Katherine S. Button[1,2], John P. A. Ioannidis[3], Claire Mokrysz[1], Brian A. Nosek[4], Jonathan Flint[5], Emma S. J. Robinson[6] and Marcus R. Munafò[1]

NATURE REVIEWS | NEUROSCIENCE VOLUME 14 | MAY 2013 | 365

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Science 28 August 2015:
Vol. 349 no. 6251
DOI: 10.1126/science.aac4716

RESEARCH ARTICLE

Estimating the reproducibility of psychological science

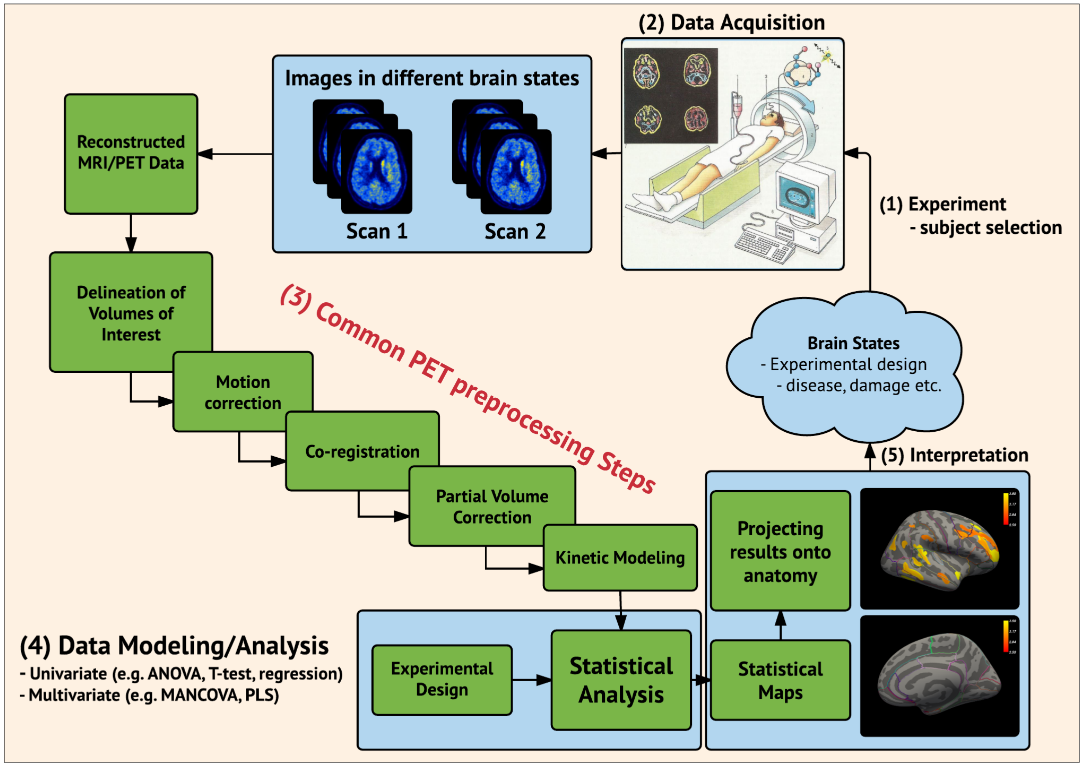
Open Science Collaboration*,†

+ Author Affiliations

†Corresponding author. E-mail: nosek@virginia.edu

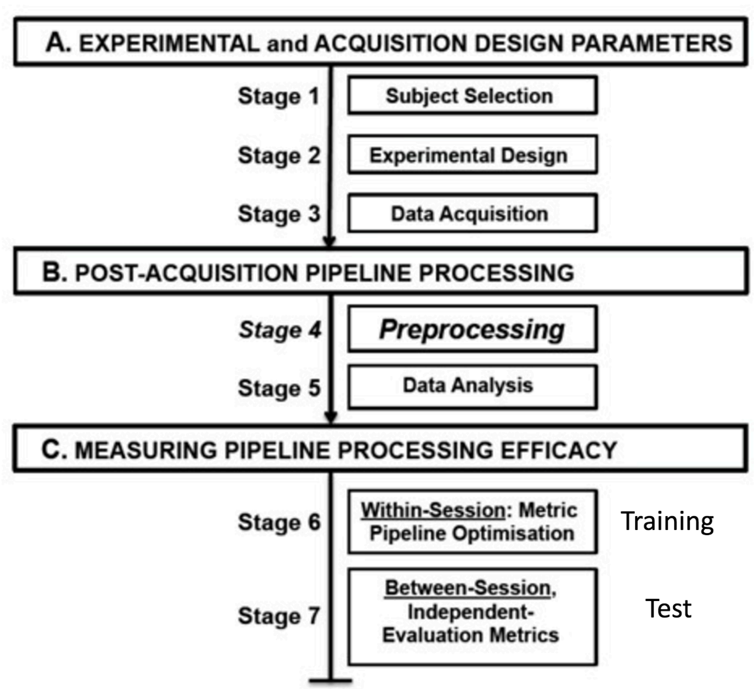
Optimization of Preprocessing Strategies in Positron Emission Tomography (PET): A [11C]DASB Study

[Norgaard et al., 2018 in prep]



[Tabachnick and Fidell, 2001] – "Do not expect garbage in, roses out"

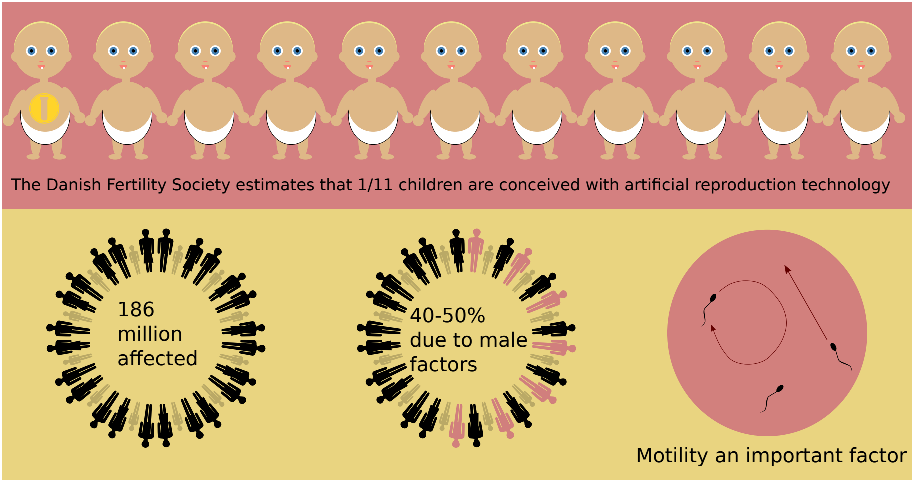
Optimization?



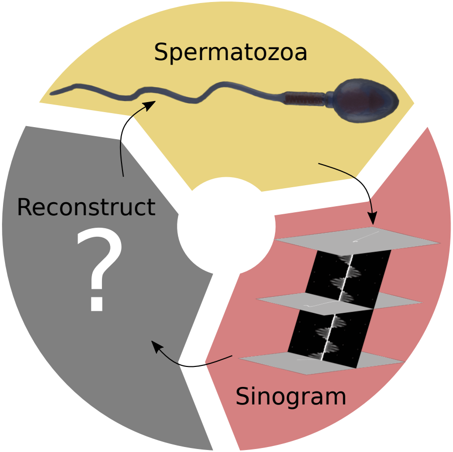
[Churchill and Strother, 2016]

Martin Nørgaard
NRU, Copenhagen University Hospital, Rigshospitalet

Sperm quality is declining



First ever 4D tomographic reconstruction of a sperm cell



Reconstructing images from in situ small angle x-ray scattering experiments

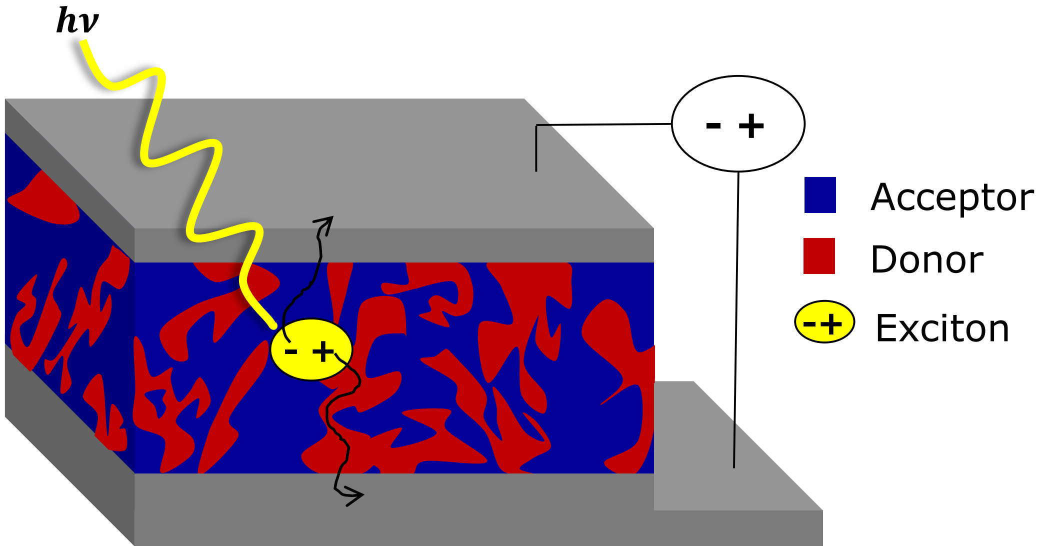
Michael Korning Sørensen, DTU Energy

Organic solar cells are:
Cheap, non-toxic, flexible, colourful, and shows the potential to mass produced.

Few pioneering companies, can not sustain with out founding.

Efficiency and life times are too low at this stage.

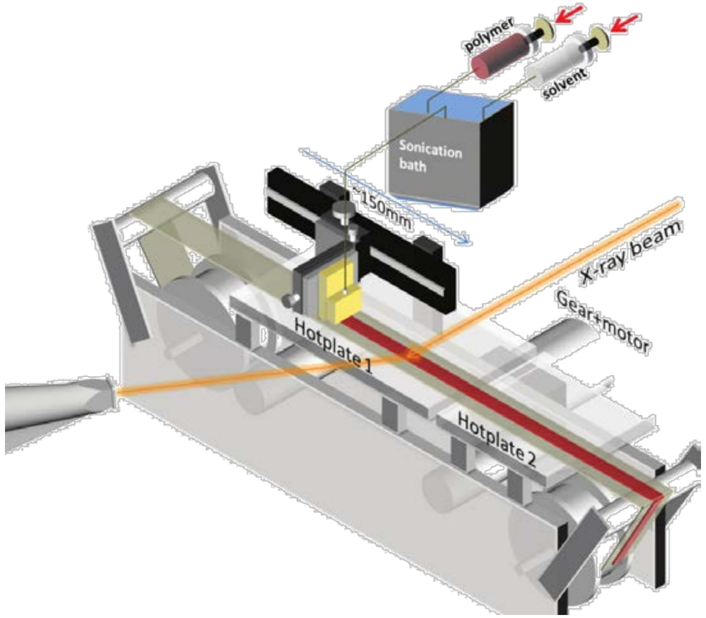
Understand the morphology of the active layer and how to tweak it.

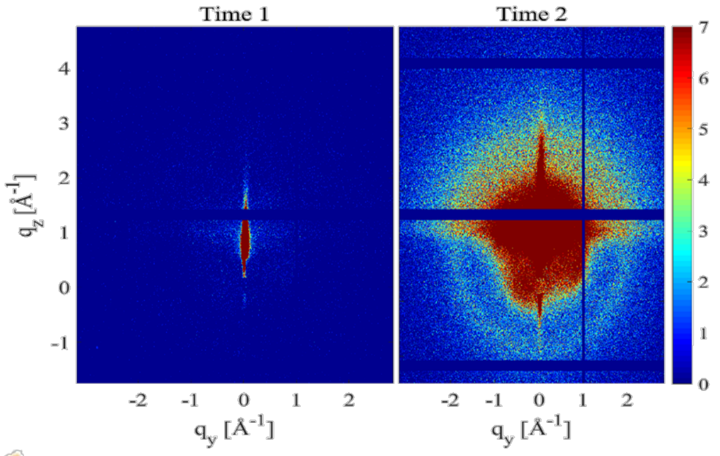


What we do, and why I am here

Roll to roll printing in situ x-ray scattering.

Several parameters at ‘one’ experiment.





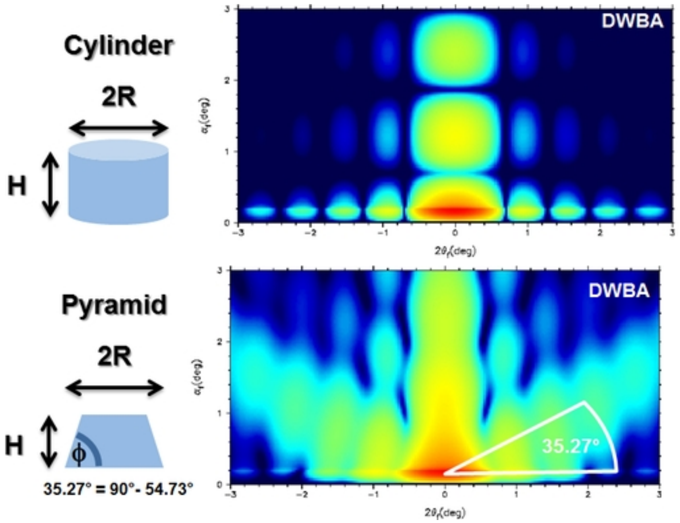
2D – detector with temporal information.

Contain information of the morphology.

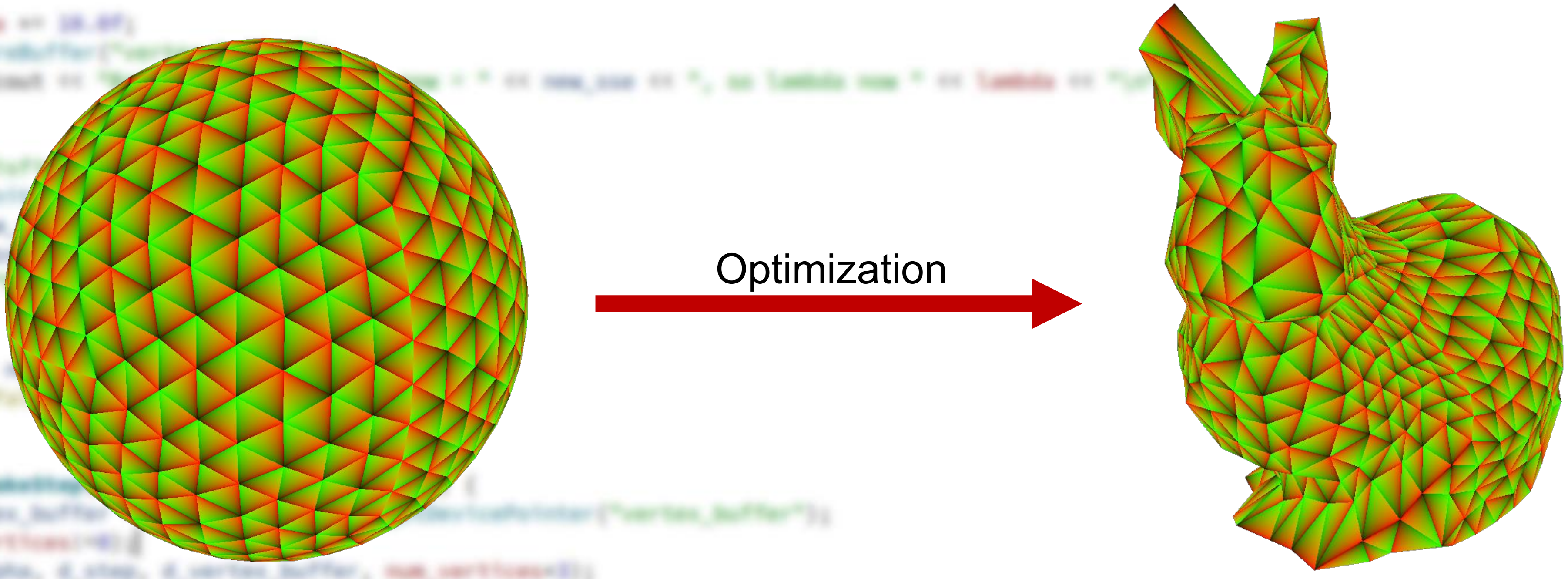
Every element and shape scatters differently.

Currently: an iterative model.

Aim: rewrite as a convex optimisation problem.



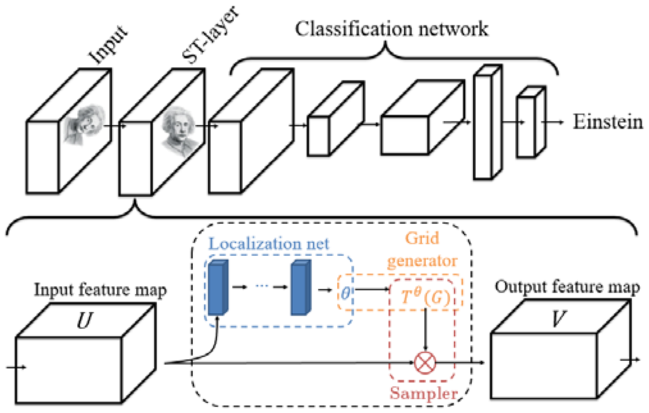
Direct Surface Reconstruction for Structured Light



Deep Diffiomorphic Transformer Networks (DDTN)

Nicki Skafte Detlefsen, Oren Freifeld, Søren Hauberg

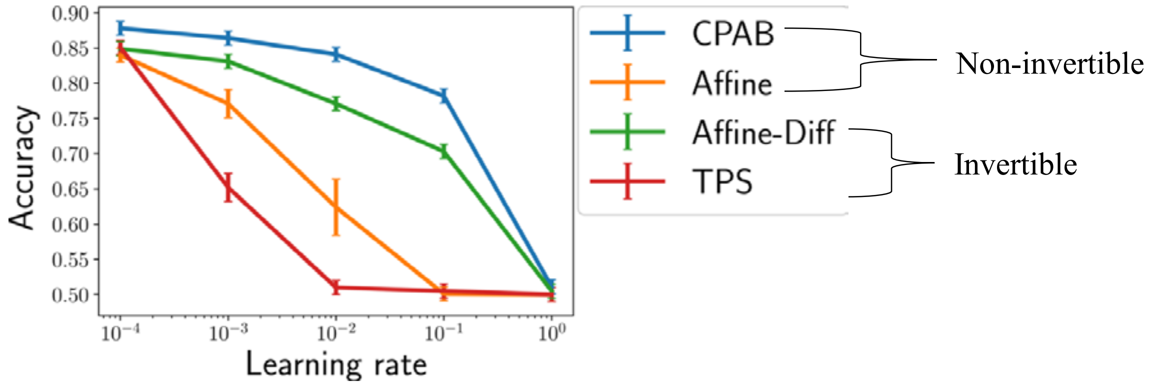
Spatial transformer networks (STN's)



Basic idea: Incorporate *diffiomorphic transformations* into STN's

The network learns a squarification of facial images

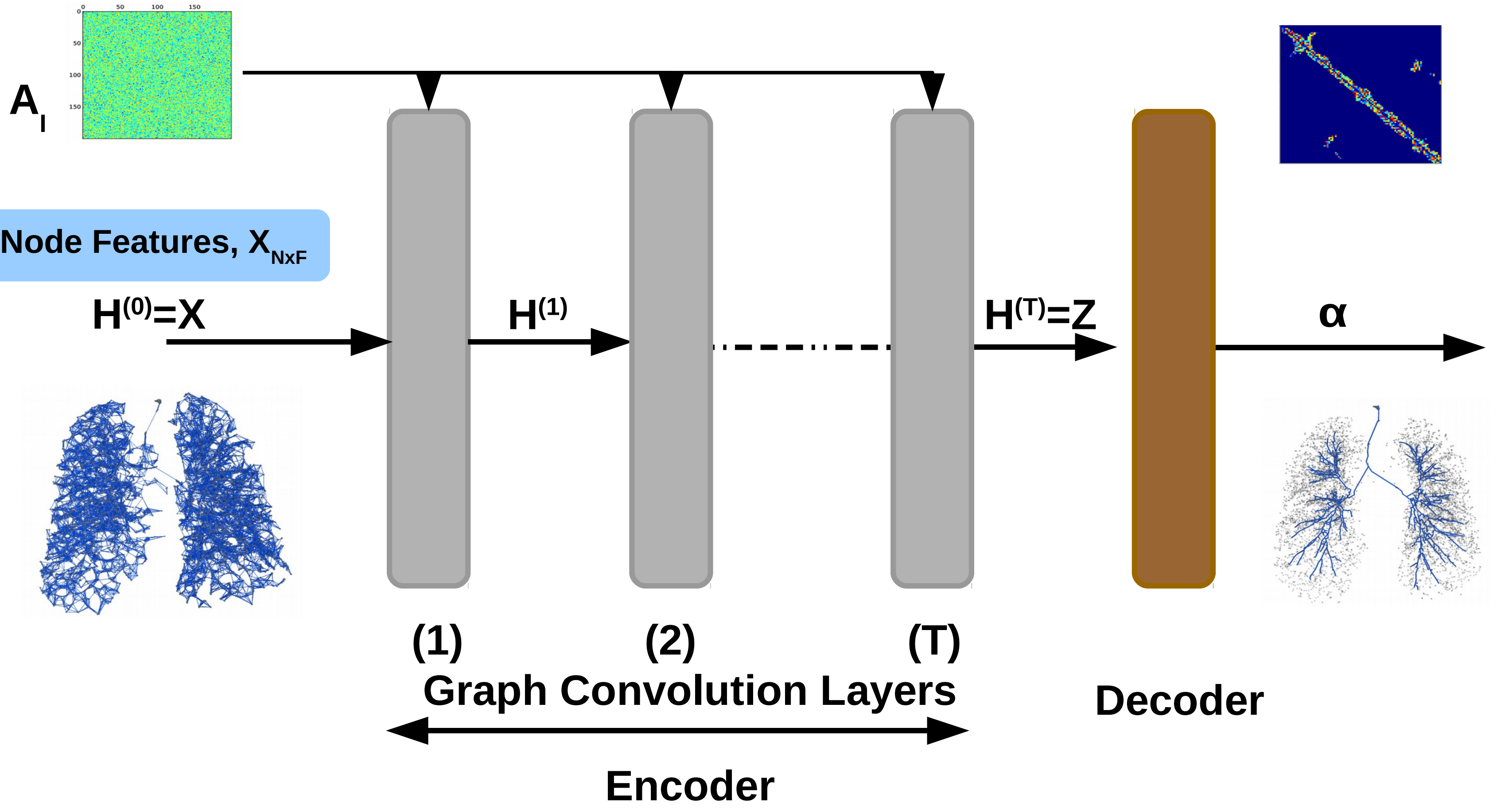
Optimization experiment:



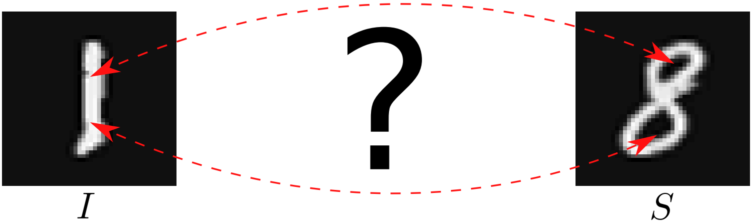
”Revertability↔Invertability” hypothesis
Optimizing non-invertible STNs is prone to instability

Extraction of Airways using Graph Neural Networks

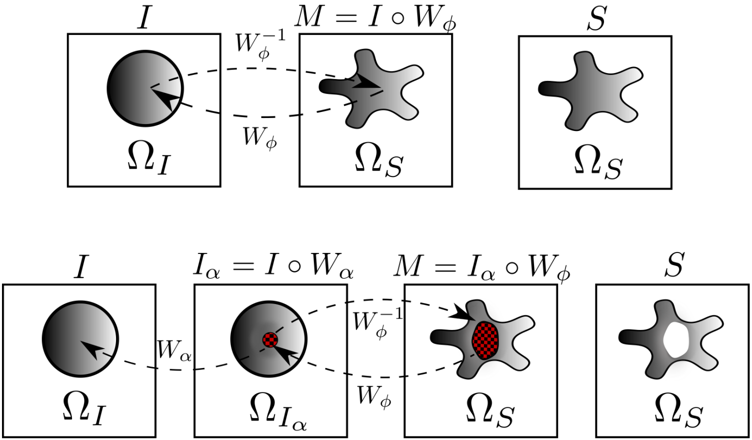
Raghavendra Selvan



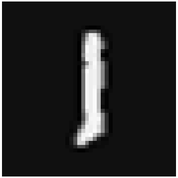
Topological Differences in Deformable Registration



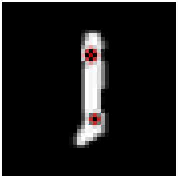
Composition with explicit topology changing deformation



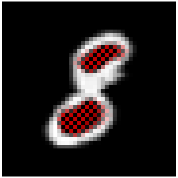
Result



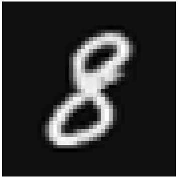
I



I_α



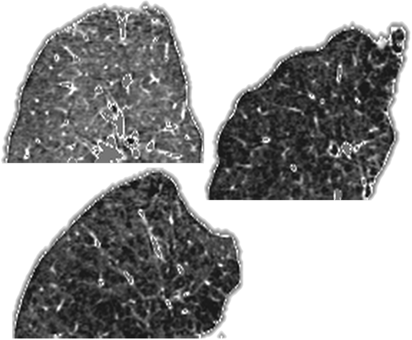
M



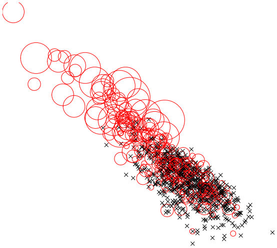
S

Feature learning based on visual similarity triplets in medical image analysis

A case study of emphysema in chest CT scans



$\overset{?}{\mapsto}$

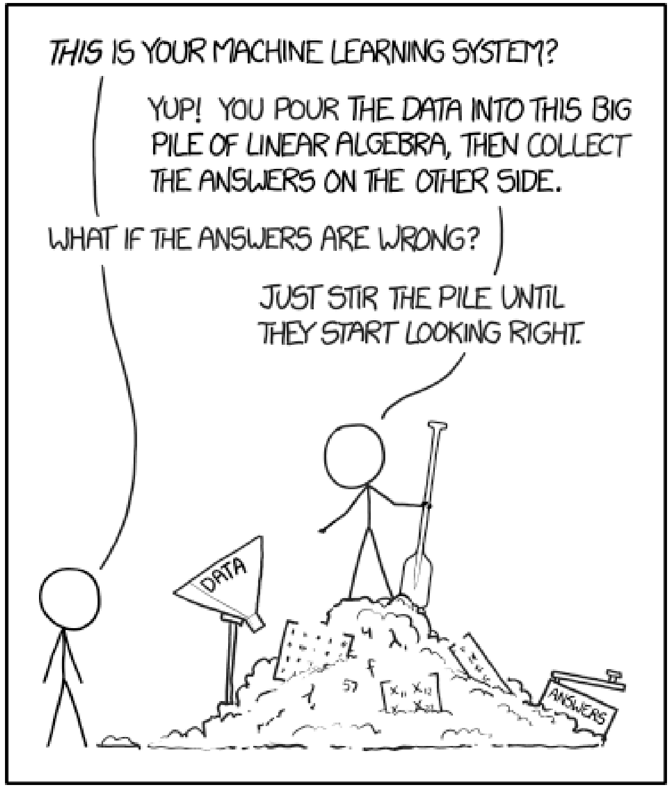


Silas N Ørting, Jens Petersen, Veronika Cheplygina, Laura H Thomsen, Mathilde M W Wille, Marleen de Bruijne

PRODUCING ARTIFICIAL DATA SAMPLES USING GENERATIVE ADVESARIAL NETWORKS

Motivation:

- Performance of machine learning algorithms depends heavily on the available data
- Data acquisition and annotation is tedious, time-consuming and error-prone.



Source: https://xkcd.com/1429/

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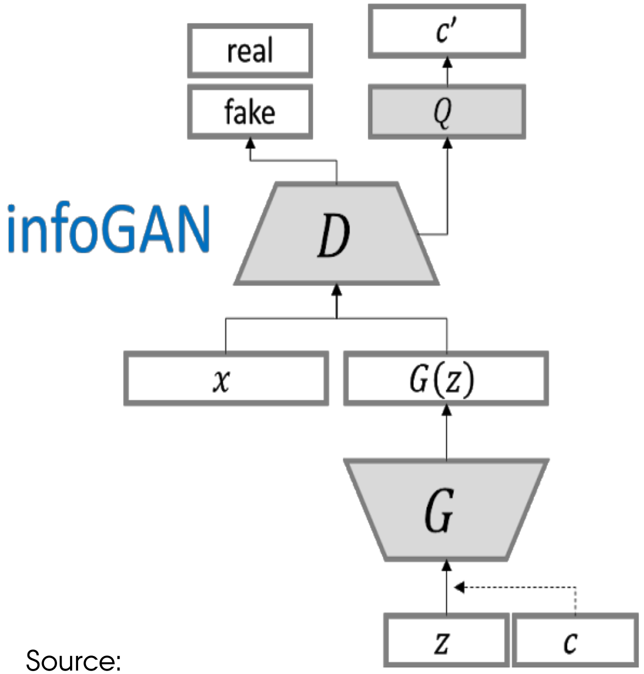
Method:



Source:
https://github.com/hwalsuklee/tensorflow-generative-model-collections

Results:

PREDICTING DRY MATTER COMPOSITION OF GRASS CLOVER LEYS USING DATA SIMULATION AND CAMERA-BASED SEGMENTATION

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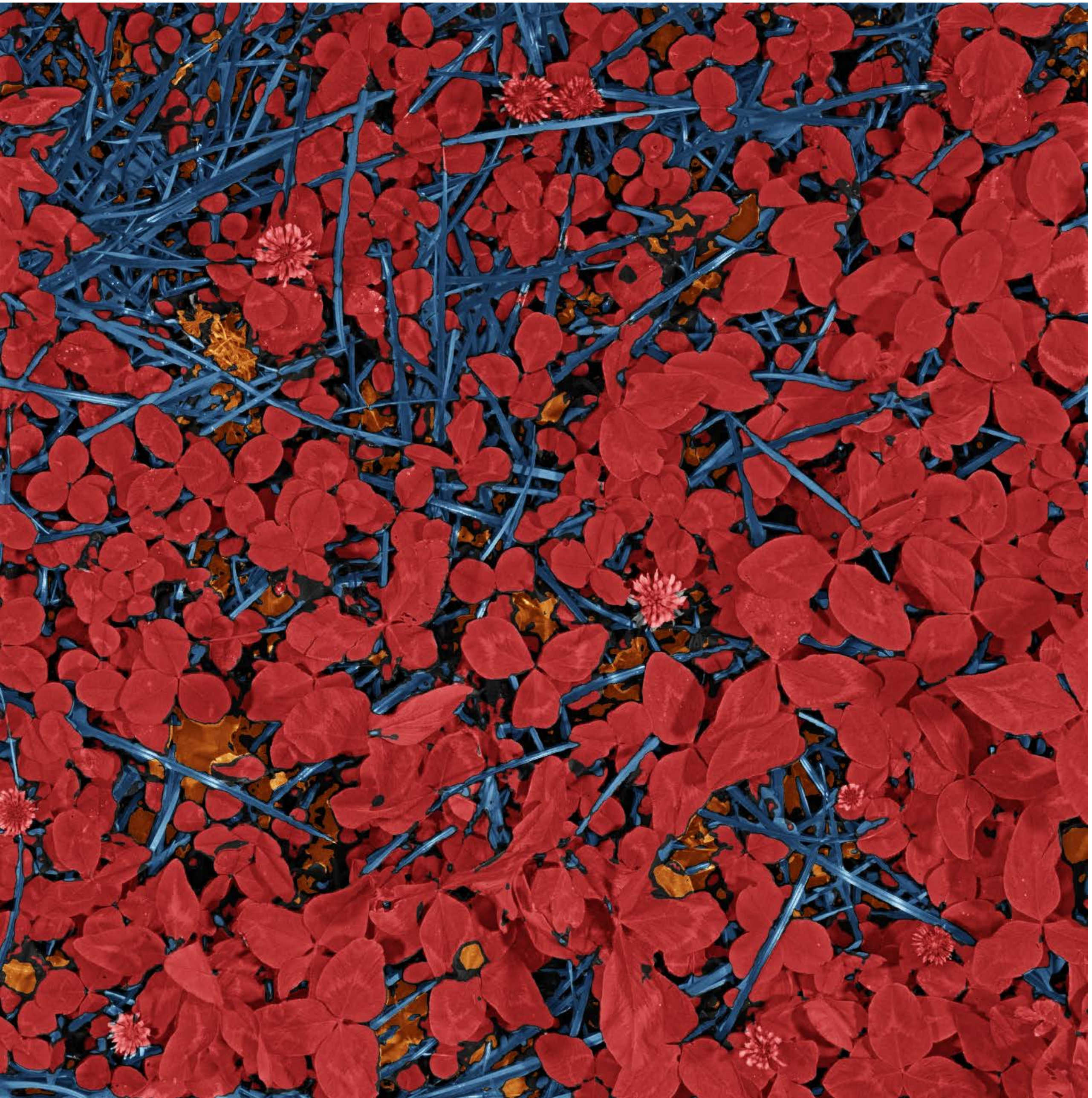
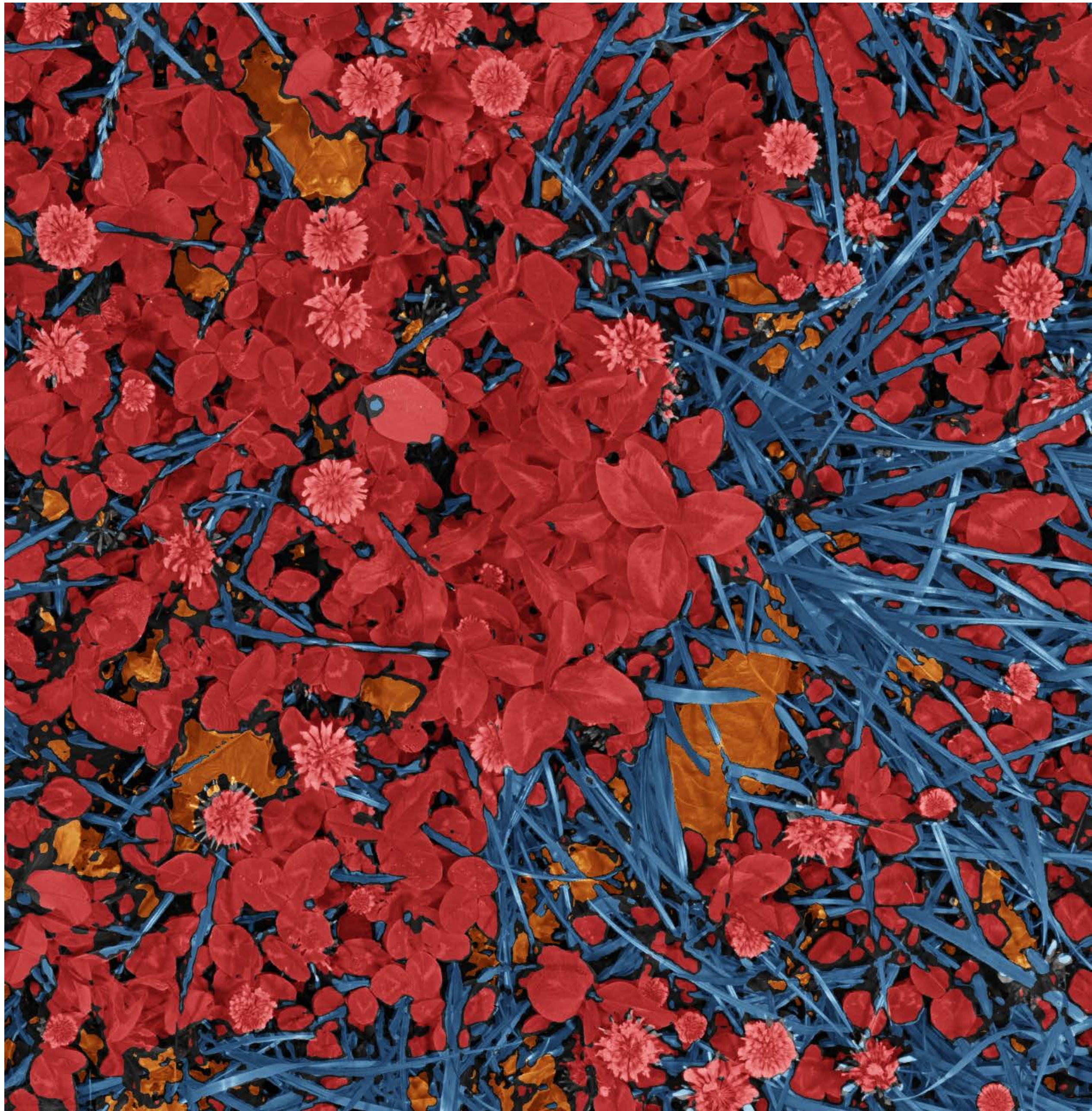
SEGMENTATION ON REAL IMAGES

SEGMENTATION ON REAL IMAGES





Adaptation to Easy Data in Prediction with Limited Advice

Tobias Sommer Thune & Yevgeny Seldin

Multi-armed bandits (online convex optimisation)

Regret for easy data:

effective loss range

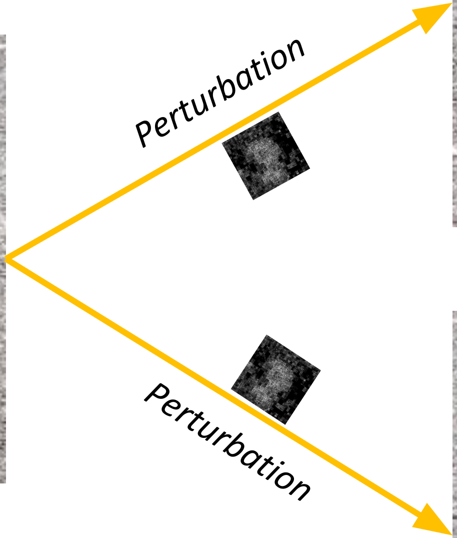
$$\mathcal{R}_T \le \mathcal{O}\left(\varepsilon\sqrt{(K-1)T\ln K}\right)$$

This is NOT possible with bandit feedback (Gerchinovitz and Lattimore, 2016).

How much more information do we need?

What are adversarial examples?

Original Image
Predicted as: Bird
Confidence: 96%



Adversarial Image (Maximization)
Predicted as: Rat
Confidence: 99%

Adversarial Image (Minimization)
Confidence of Bird: 7.6e-14%
(Least probable outcome)

Utku Ozbulak, Arnout Van Messem and Wesley De Neve

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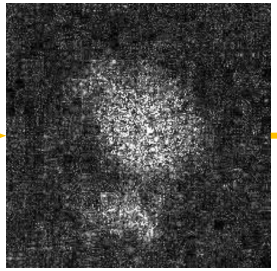
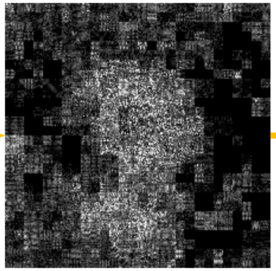
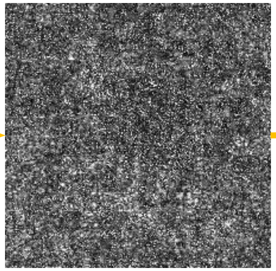
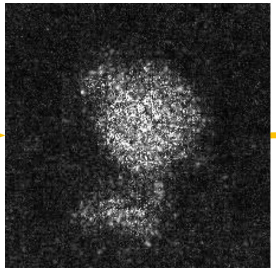
Adversarial Attack Techniques and Perturbation Intensity

Attack Technique	Perturbation	Model Transferability from Resnet50 to AlexNet	VGG	ResNet152
Gradient Ascent Optimization [2] $X' = \arg max\ g(\theta, X)_c$		36%	21%	13%
L-BFGS Attack [3] minimize $\alpha \cdot \|X - X'\|_2^2 + J(g(\theta, X')_c)$		32%	20%	9%
I-FGS Attack [4] $X_i = X_{i-1} - \alpha \cdot sign(\nabla_x\ J(g(\theta,\ X)_c))$		35%	20%	12%
Carlini & Wagner Attack [5] $minimize\ \|X - X'\|_2^2 + \alpha \cdot \ell(X')$		**51%**	**38%**	**25%**

Embedded Information in Surfaces

Utilizing Engineered Surface Microstructure

Viggo Falster (PhD Student)

Microstructure

?

Information in a surface
(e.g. a code)