Paper 10574-41
Session 8: Motion, 8:00 AM - 9:40 AM, Salon B

Deep-Learning-Based CT Motion Artifact Recognition in Coronary Arteries

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innovation + you

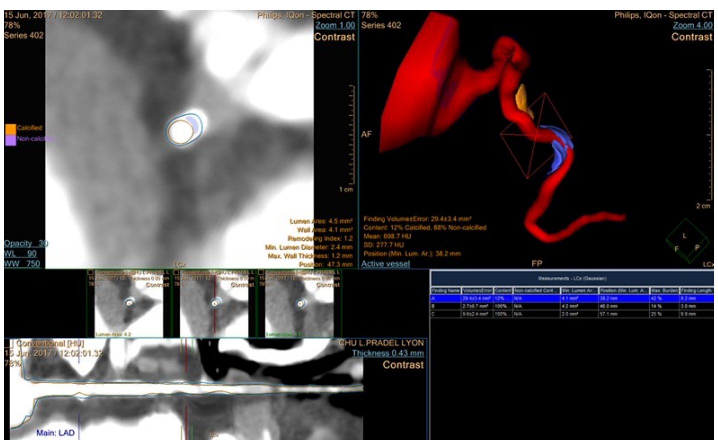
Motivation

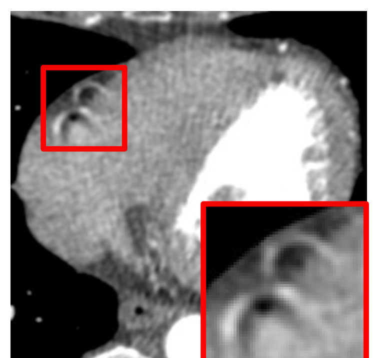
CCTA: = Coronary computed tomography angiography
- Used for detection of coronary artery disease

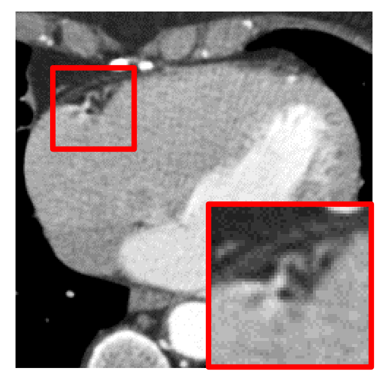
Problem:
- Cardiac motion artifacts may limit evaluation
- Potentially lead to misinterpretations

Goal:
- Motion artifact recognition at the coronary arteries by a deep-learning-based measure

Purpose:
- Assess diagnostic reliability of CCTA images
- Steering and assessment of algorithms for motion compensation (MC)







Method

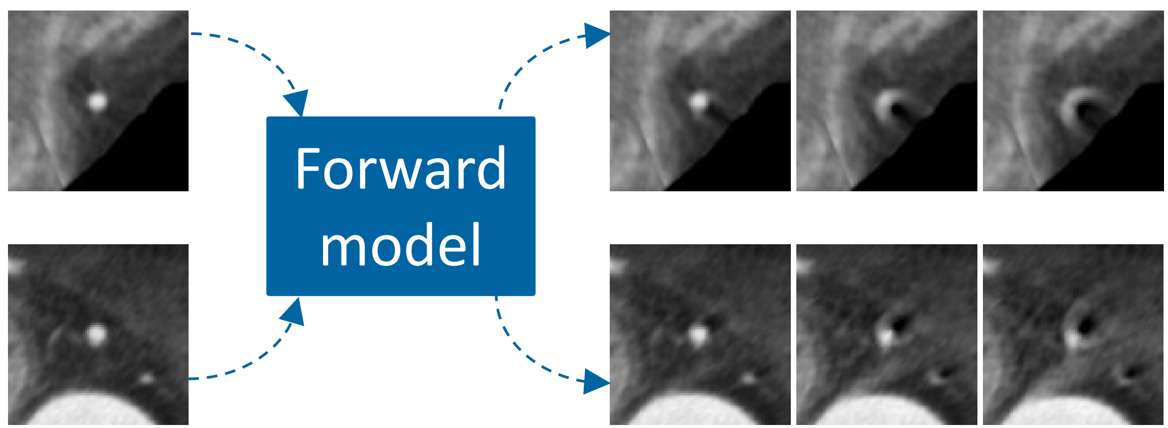
Reference data collection

Forward model

Supervised learning

Network Evaluation

<u>Main idea:</u> generate required data for supervised learning by introducing artificial motion to high quality CT cases



Method

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↓

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↓

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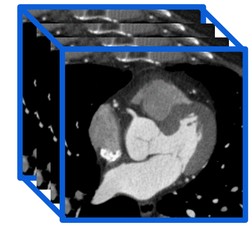
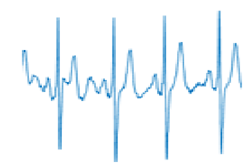
Input of the forward model:

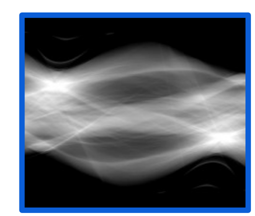
- Cardiac CT data sets with excellent image quality (no motion reference)



- Coronary artery tree including centerline and lumen contour

- Corresponding ECG-triggered projection data





➢ 9 step-and-shoot cases included

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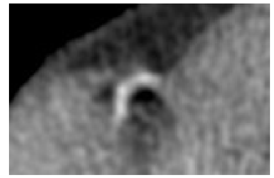
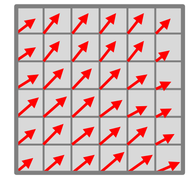
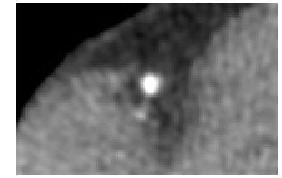
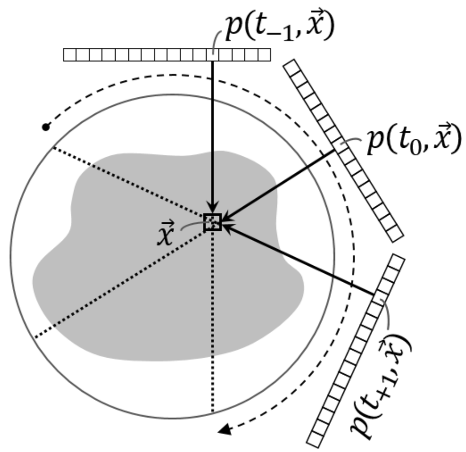
Application of the MC-FBP[1] algorithm

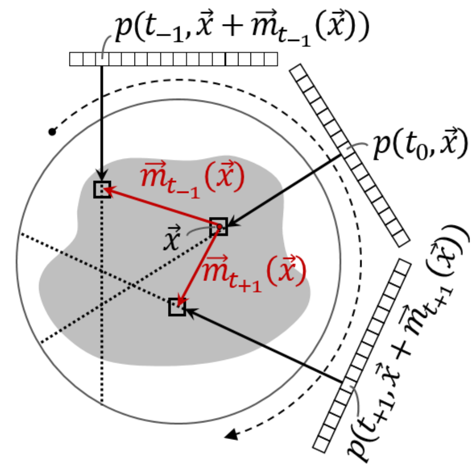
- blurred image + true MVF = sharp image

- takes estimated motion $\vec{m}_t(\vec{x})$ of each voxel $\vec{x}$ into account during reconstruction



Usual back projection



Motion compensated back projection

[1] U. van Stevendaal et al., "A motion-compensated scheme for helical cone-beam reconstruction in cardiac CT angiography", 2008.

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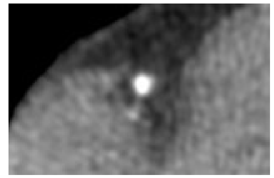
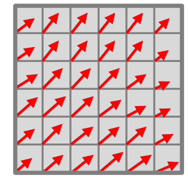
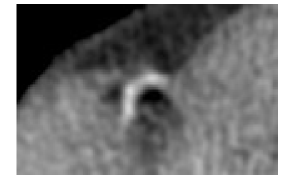
Application of the MC-FBP[1] algorithm

- sharp image + artificial MVF = blurred image

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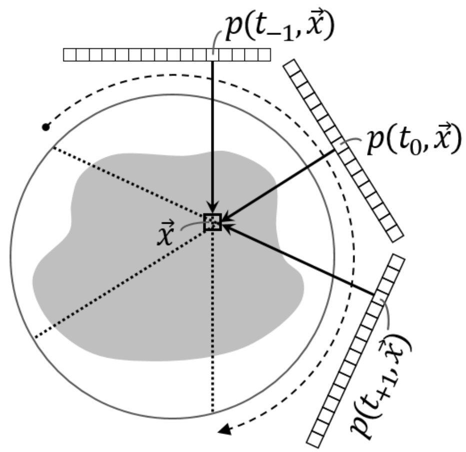
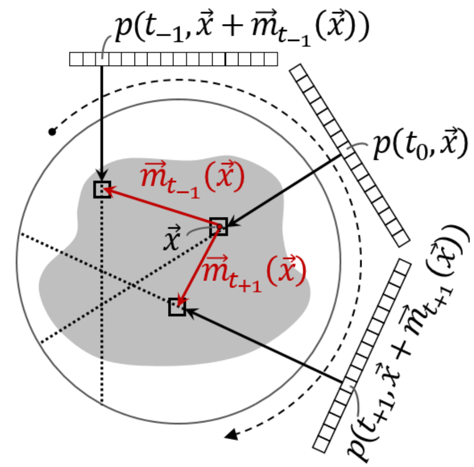


Usual back projection



Motion compensated back projection

[1] U. van Stevendaal et al., “A motion-compensated scheme for helical cone-beam reconstruction in cardiac CT angiography”, 2008.

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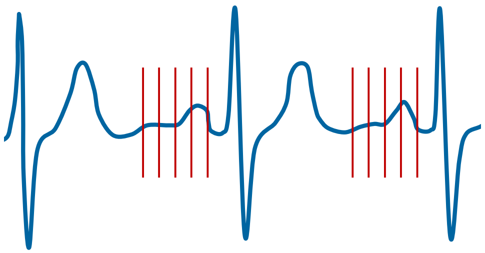
Network Evaluation

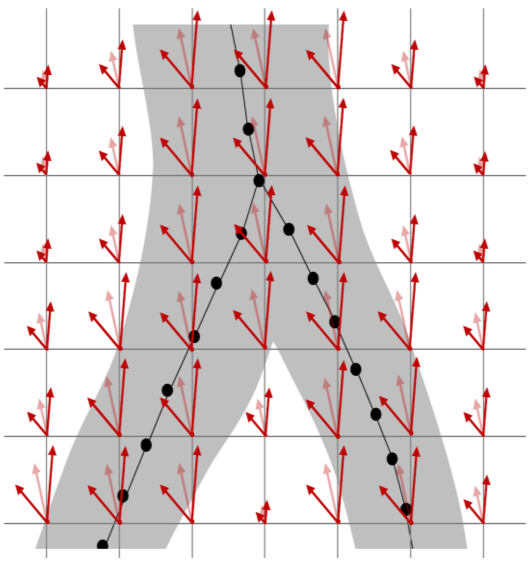
Generation of the MVF

$$\boxed{\vec{m}_{t_i}(\vec{x})} = \boxed{w(\vec{x})} \cdot \boxed{\frac{\vec{\rho}_i}{\rho_{\text{norm}}}} \cdot \boxed{s} \quad , \; i \in \{1, \dots, 5\}$$



displacement sample vectors:
define 5 motion states

weight mask $w(\vec{x}) \in [0,1]$:
limits motion area
forces smoothness



displacement direction:
random ($\vec{\rho}_i \in U[-1,1]^3$)

target motion strength $s \in \mathbb{R}^+$:
scales displacement lengths

Method

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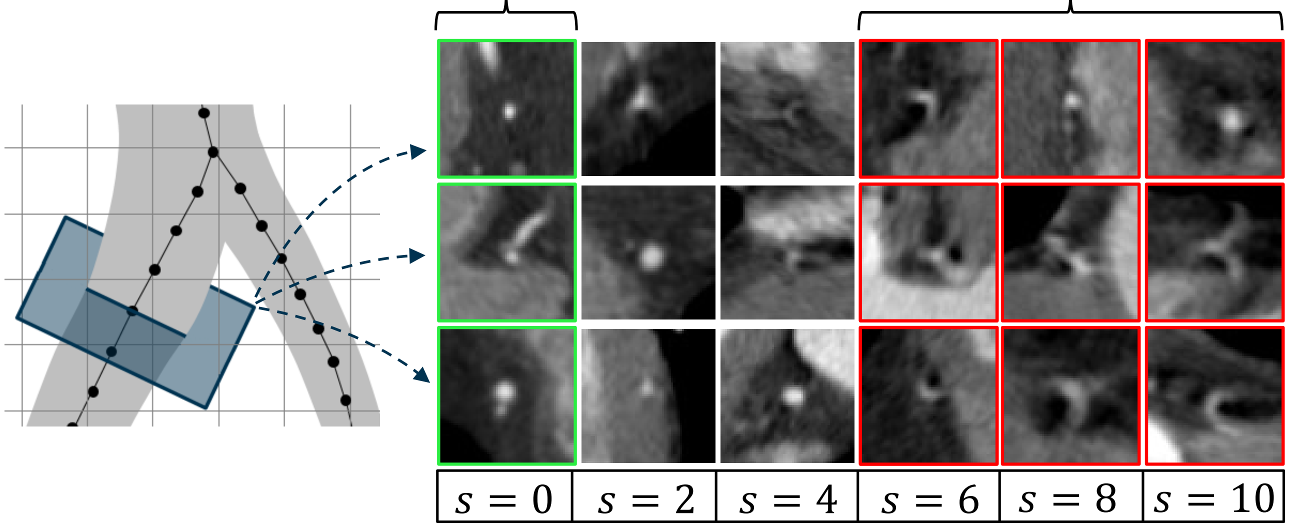
Network Evaluation

Task: Separate cross-sectional image patches into classes <u>no artifact</u> and <u>artifact</u>



- Database: ca. 18k samples of size 96x96 pixels
  - balanced classes, case-wise separation
  - augmentation: rotation, mirroring, cropping (60x60)
- Setup: 20-layer ResNet[1], Adam optimizer[2]

[1] K. He et al., “Deep residual learning for image recognition”, 2016.
[2] D. Kingma et al., “Adam: A method for stochastic optimization”, 2014.

Results – 2D

Reference data collection

↓

Forward model

↓

Supervised learning

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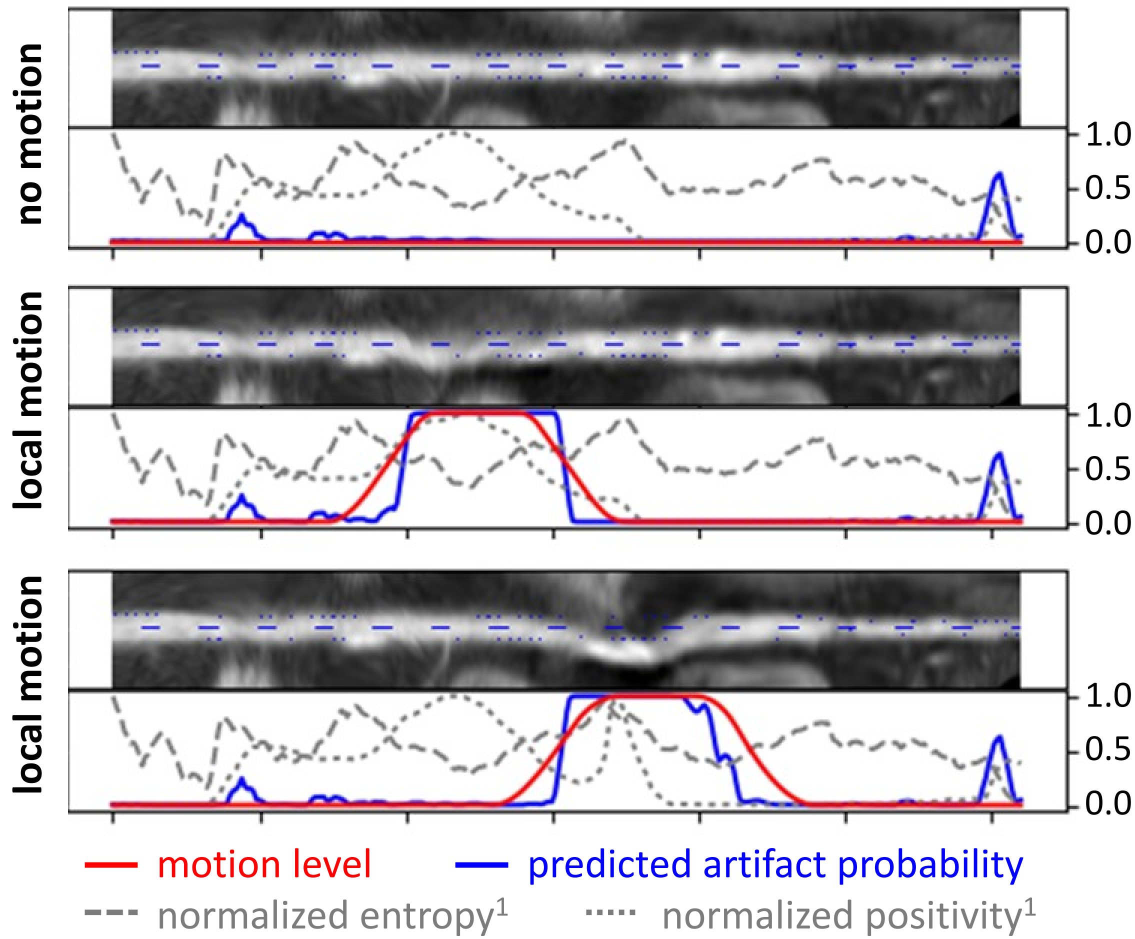
Network Evaluation

4-fold cross-validation (60x60)

mean classification accuracy: $94.4\% \pm 2.9\%$



[1] C. Rohkohl et al., "Improving best-phase image quality in cardiac CT by motio correction with MAM optimization", 2013.

Results – 3D

Reference data collection

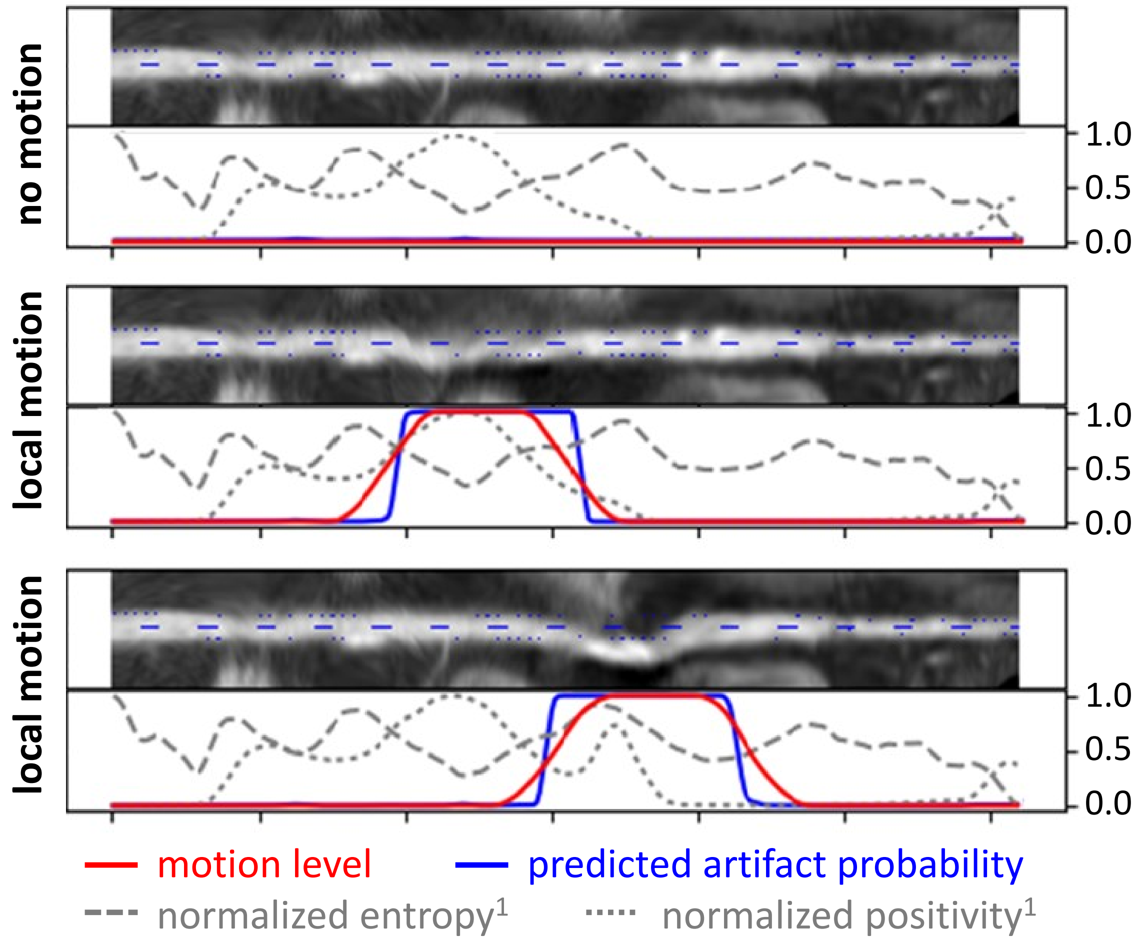
Forward model

Supervised learning

Network Evaluation

4-fold cross-validation (60x60x11)

mean classification accuracy: $95.6\% \pm 2.7\%$

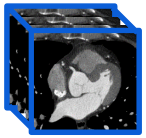


[1] C. Rohkohl et al., "Improving best-phase image quality in cardiac CT by motio correction with MAM optimization", 2013.

Summary

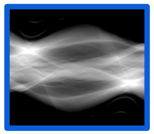
Step 1: Preprocessing

Reference data collection

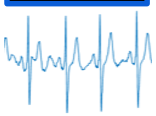


3D cardiac CT volume

coronary artery tree



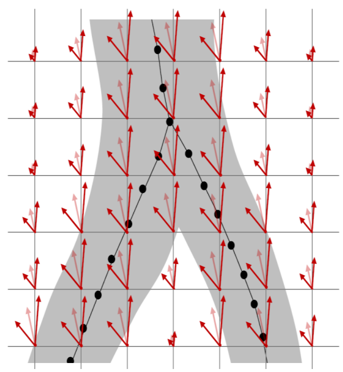
projection data



ECG data

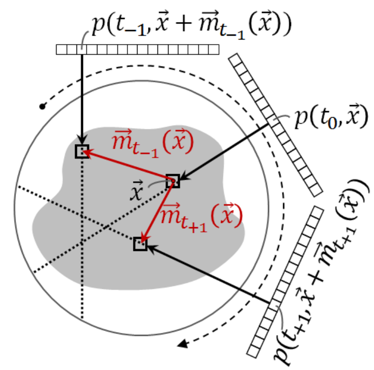
Step 2: Forward model

Artificial motion introduction



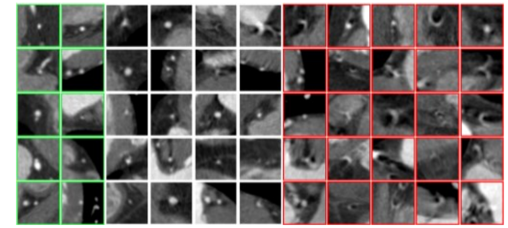
artificial MVF

+

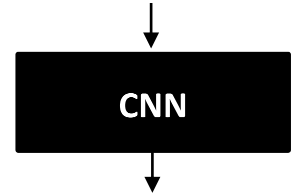


MC-FBP

Step 3: Supervised Learning



sampled cross-sectional patches



no artifact or artifact

Conclusions

- Demonstrated feasibility of accurate motion artifact recognition in CCTA images using deep learning
- Future work:
  - Increase robustness
  - Artifact level regression
  - Testing on real artifacts

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