Physikalisch-Technische Bundesanstalt
Braunschweig und Berlin
Nationales Metrologieinstitut

Applying deep learning in metrology

An overview over some potentials and challenges

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joint with Narbota Amanova, Lara Hoffmann, Franko Schmähling, Clemens Elster

Joint European event on Digital Transformation,
20th September 2021

MATHMET

Deep learning in WG „Data analysis and measurement uncertainty“ at PTB

People

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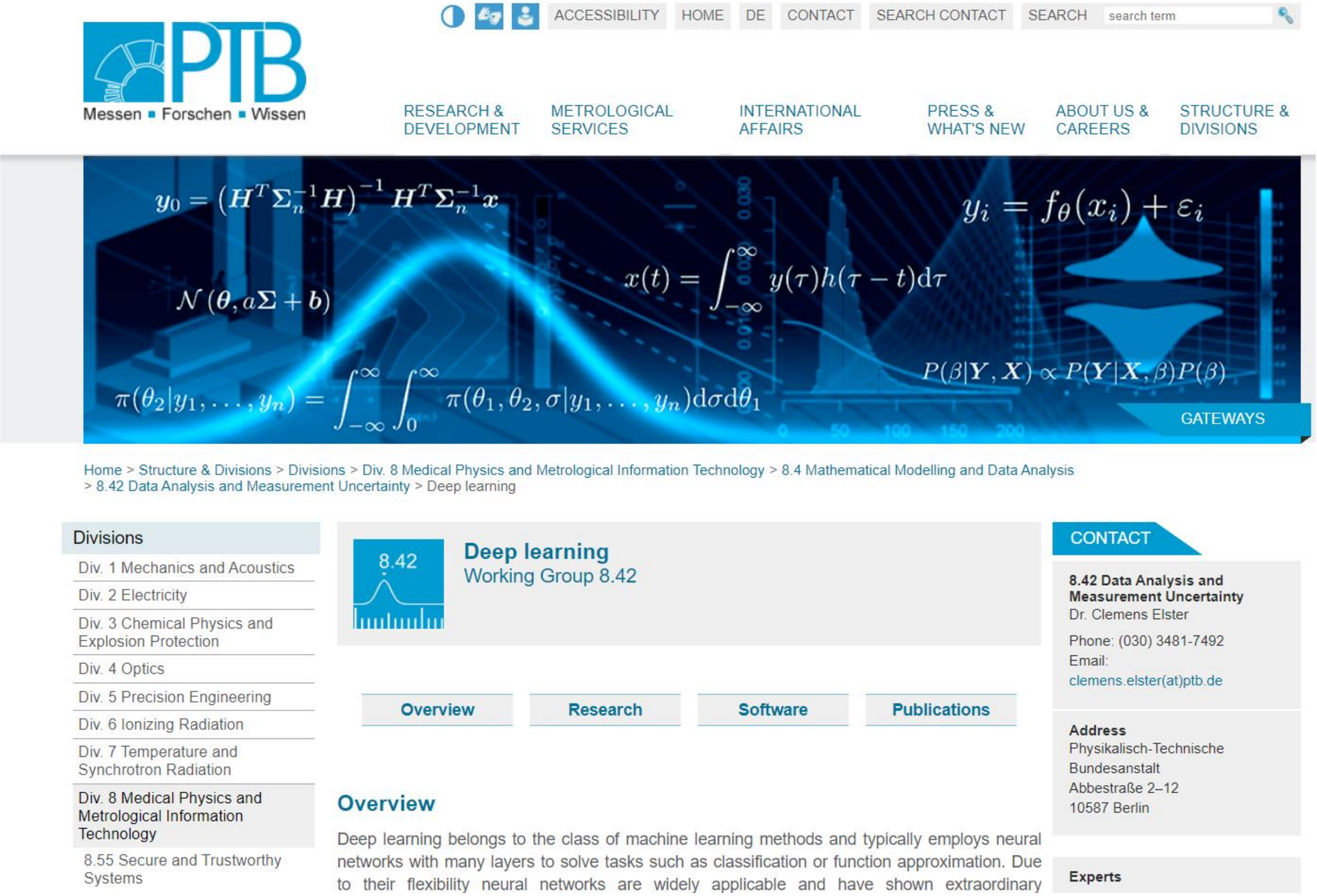
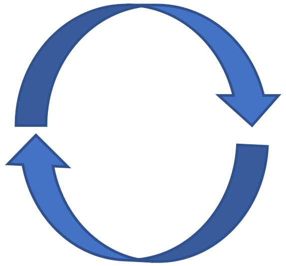
Clemens Elster



Deep learning in WG „Data analysis and measurement uncertainty“ at PTB

Applications

- Optical form measurements
- Image quality in mammography
- ECG diagnostics (planned)



Fundamentals

- Uncertainty
- Explainability
- Robustness

Collaborations

PTB WGs: 4.21, 4.24, 6.24, 8.13
external: TUB, Fraunhofer Heinrich-Hertz

When to apply deep learning?

Physical models

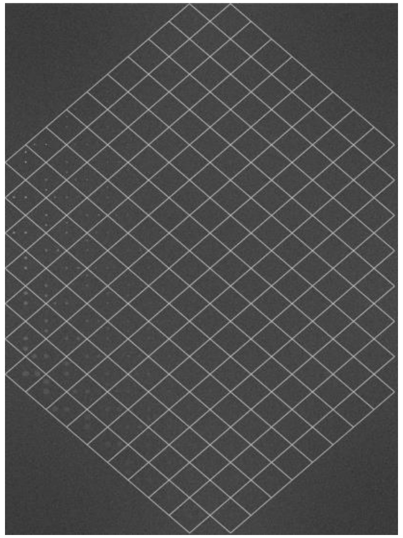
- understood
- predictable
- (often) low dimensional

Generic models

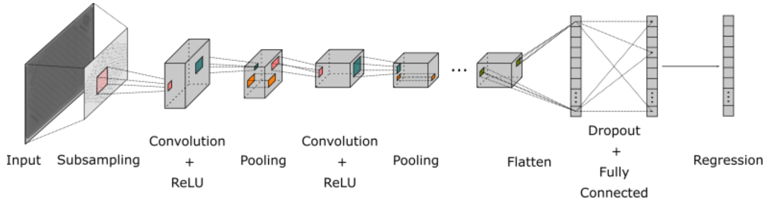
- no model needed
- sometimes more efficient
- updatable

Mammography Image Quality

CDMAM Phantom



neural network



contrast detail curve

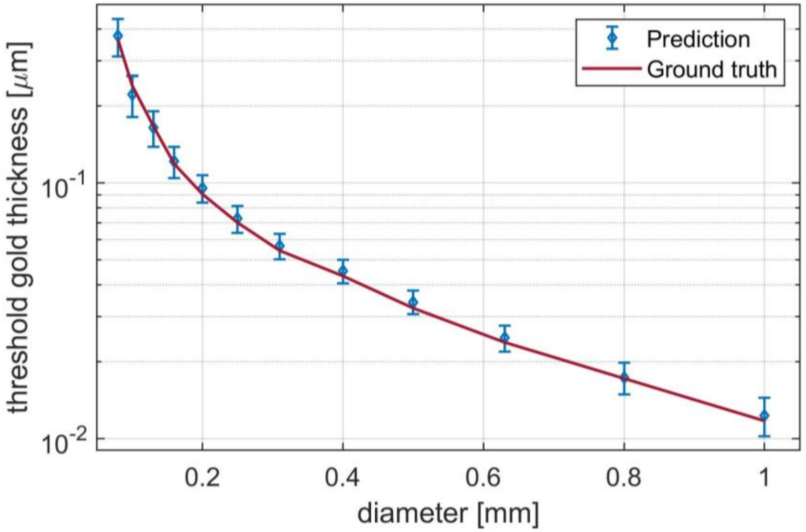
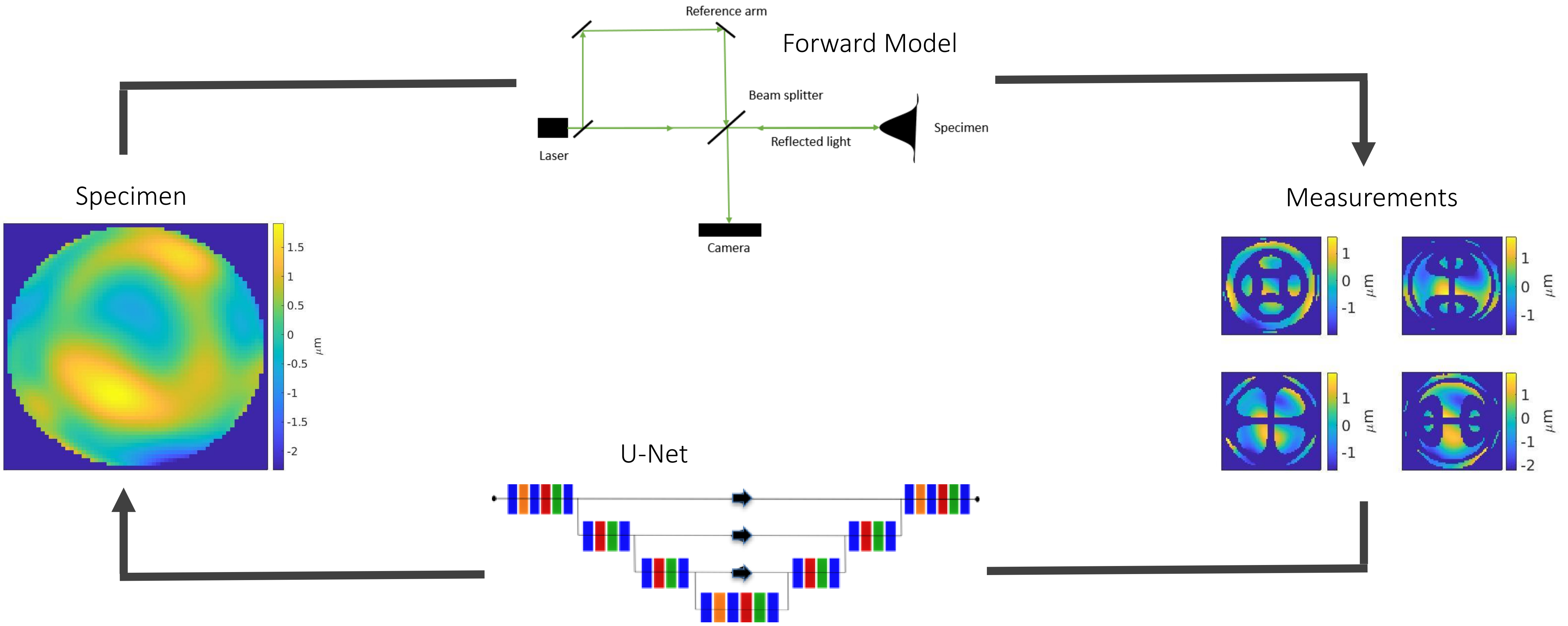


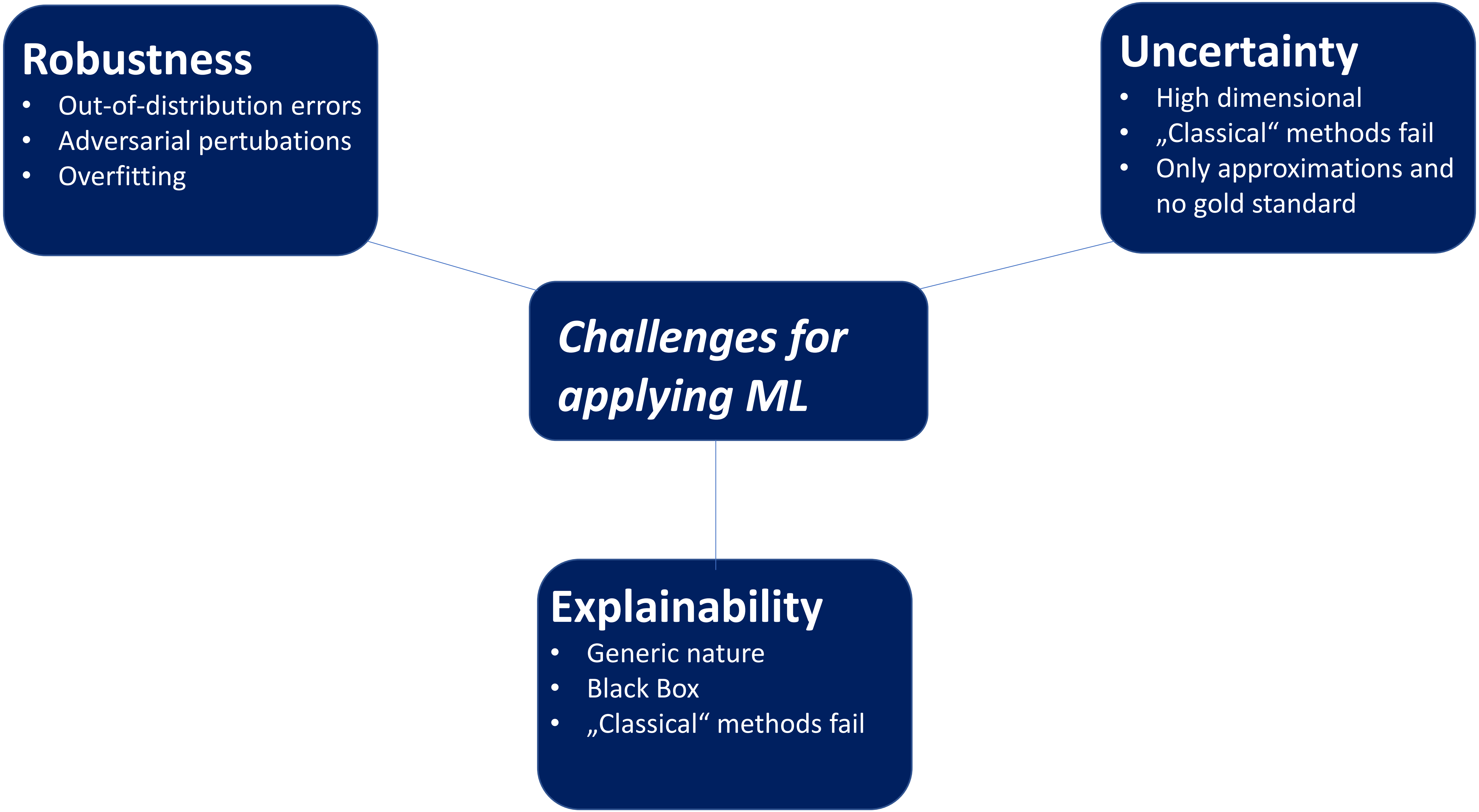
Image quality from images of CDMAM Phantoms via ML

T. Kretz, K-R Müller, T. Schäffter & C. Elster. *Mammography Image Quality Assurance Using Deep Learning*, IEEE Transactions on Biomedical Engineering 2020.

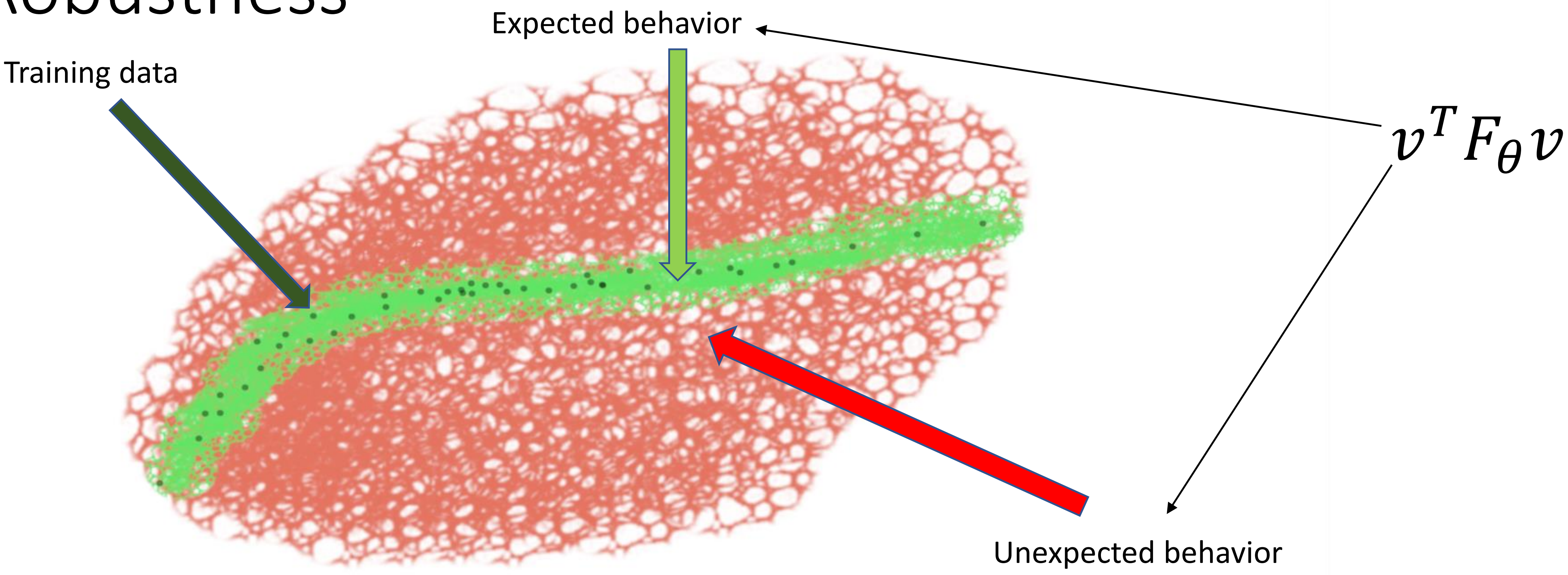
Tilted-Wave Interferometer



L. Hoffmann, C. Elster. *Deep Neural Networks for Computational Optical Form Measurements.* Journal of Sensors and Sensor Systems, 2020.
L. Hoffmann, I. Fortmeier, C. Elster. *Uncertainty Quantification by Ensemble Learning for Computational Optical Form Measurements.* Machine Learning: Science and Technology, 2021.


Robustness
• Out-of-distribution errors
• Adversarial pertubations
• Overfitting
Uncertainty
• High dimensional
• „Classical“ methods fail
• Only approximations and no gold standard
Challenges for applying ML
Explainability
• Generic nature
• Black Box
• „Classical“ methods fail

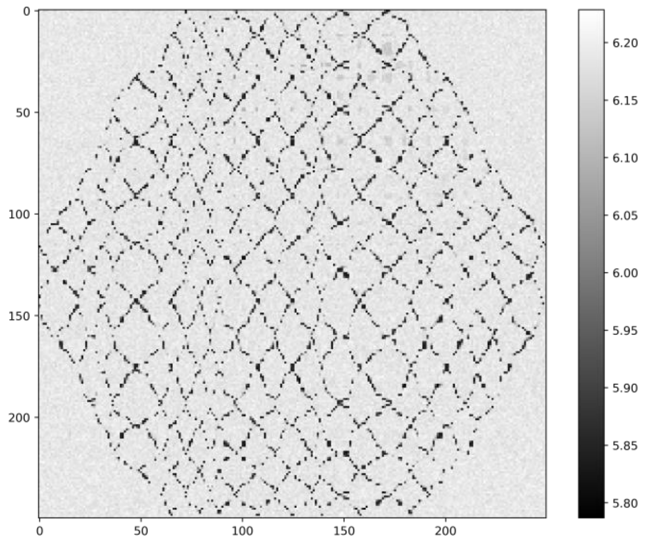
Robustness

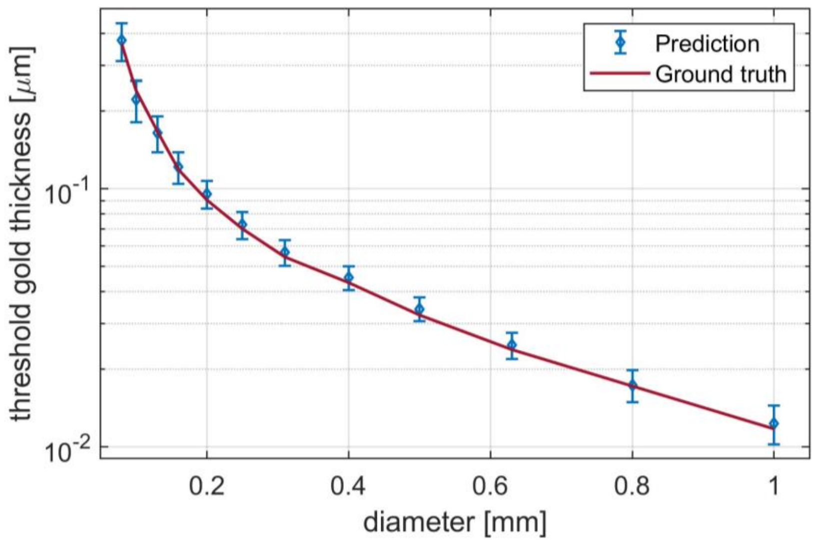


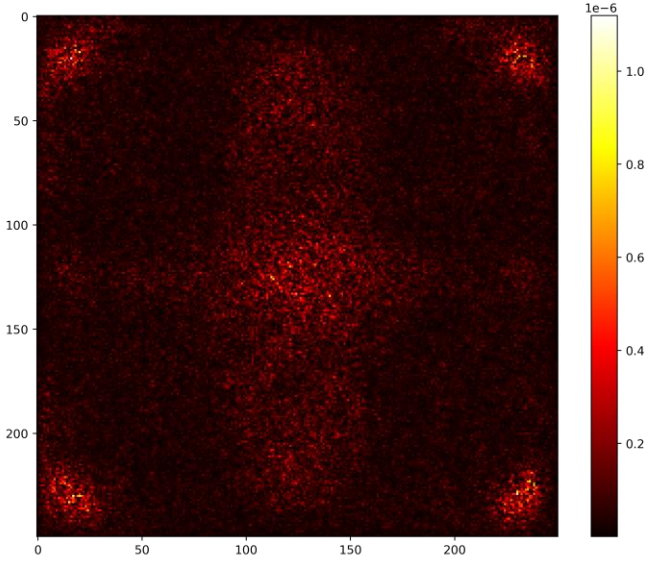
J. Martin, C. Elster. *Inspecting adversarial examples using the Fisher information*. Neurocomputing, 2020.

J. Martin, C. Elster. *Detecting unusual input to neural networks*, Applied Intelligence, 2021.

Explainability



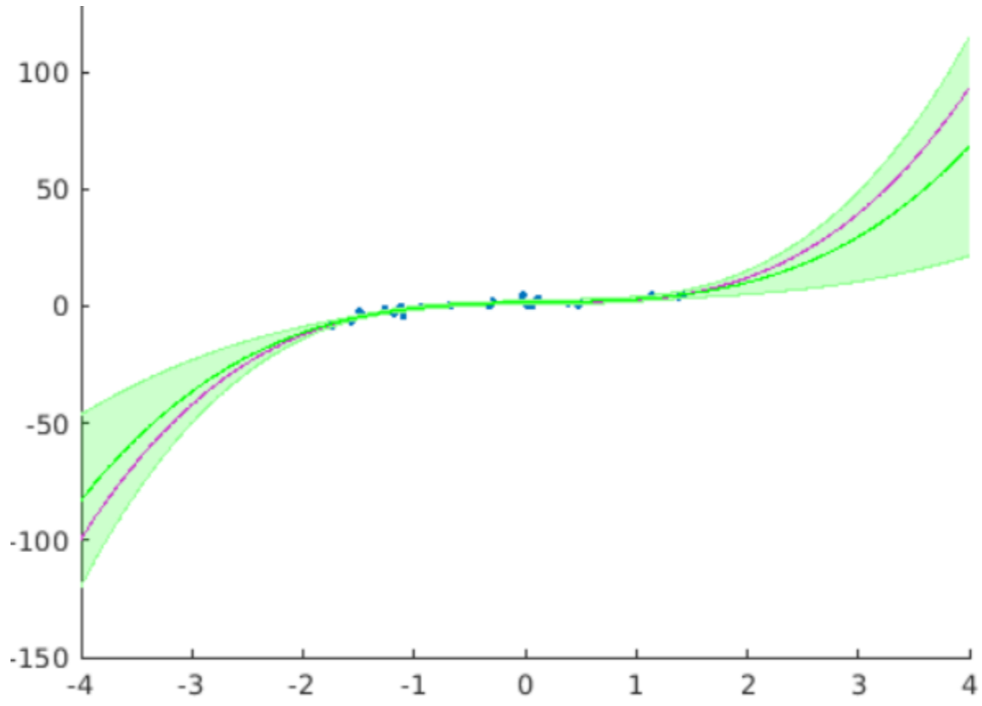




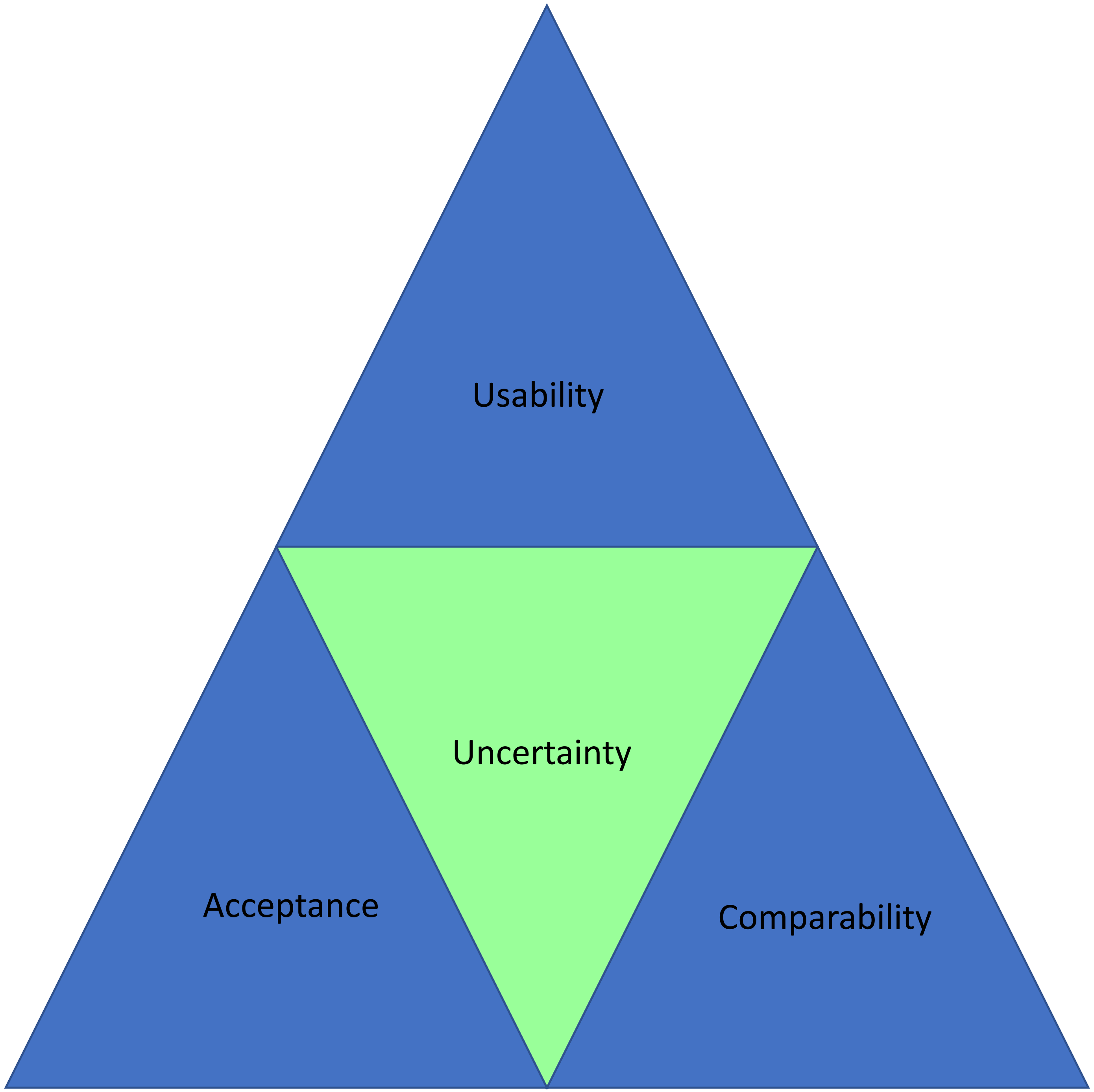
Relevant areas for prediction

work in progress by N. Amanova, J. Martin, C. Elster

Uncertainty



- Various approaches
- No gold standard



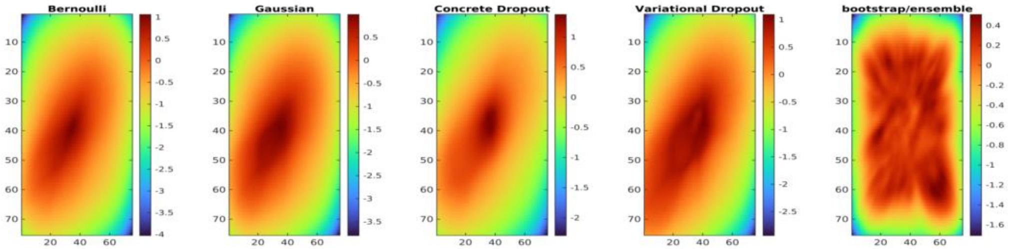
Uncertainty

Research in PTB‘s WG „Data analysis and measurement uncertainty“

Variational Inference

Errors-in-Variables for deep learning: rethinking aleatoric uncertainty, Martin & Elster (ArXiv)

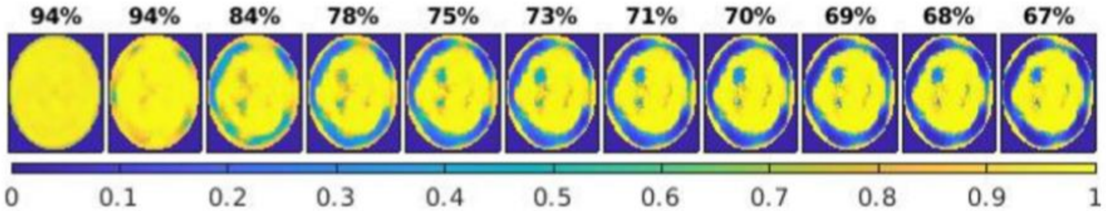
A framework for benchmarking uncertainty in deep regression, Schmähling, Martin & Elster (ArXiv)



$$q_{\phi}(\theta) \approx \pi(\theta|D)$$

Deep Ensembles

Uncertainty Quantification by Ensemble Learning for Computational Optical Form Measurements, Hoffmann, Fortmeier & Elster (Mach. Learn: Sci. T.)



Deep ensembles form a Bayesian perspective, Hoffmann & Elster (ArXiv)

Generative Models

About the regularity of the discriminator in CWGANs, Martin (ArXv)

$$\mathcal{L}_{\theta} = \mathbb{E}_{y\sim\pi(y)}[\mathcal{W}(\mathcal{G}(y), \pi(x|y))]$$

Conclusions

- Deep learning can be a useful tool in metrology
- Its generic nature raises the need for evaluating and understanding
    - ➢Robustness
    - ➢Explainability
    - ➢Uncertainty
- PTB‘s WG „Data analysis and measurement uncertainty“:
  focus on generic methods (e.g. uncertainty) and specific applications

Publications DL - WG Data analysis and measurement uncertainty

Publications

- L. Hoffmann, I. Fortmeier, C. Elster. *Uncertainty Quantification by Ensemble Learning for Computational Optical Form Measurements.* Mach. Learn.: Sci. Technol., 2021.
- J. Martin, C. Elster. *Detecting unusual input to neural networks*. Applied Intelligence, 2021.
- T. Kretz. *Development of model observers for quantitative assessment of mammography image quality*. PhD Thesis, 2020.
- L. Hoffmann, C. Elster. *Deep Neural Networks for Computational Optical Form Measurements*. JSSS, 2020.
- T. Kretz, K.-R. Müller, T. Schäffter, C. Elster. *Mammography Image Quality Assurance Using Deep Learning*. IEEE Transactions on Biomedical Engineering, 2020.
- J. Martin, C. Elster. *Inspecting adversarial examples using the fisher information*. Neurocomputing, 2020.

Preprints

- J. Martin. *About the regularity of the discriminator in conditional WGANs*. ArXiv, 2021.
- J. Martin, C. Elster. *Errors-in-Variables for deep learning: rethinking aleatoric uncertainty*. ArXiv, 2021.
- L. Hoffmann, C. Elster. Deep ensembles form a Bayesian perspective, ArXiv, 2021.
- F. Schmähling, J. Martin, C. Elster, *A framework for benchmarking uncertainty in deep regression*, ArXiv, 2021.