Geodätisches Institut Hannover

DFG Research Training Group i.c.sens (RTG 2159)
Integrity and Collaboration in dynamic sensor networks

Leibniz Universität Hannover

Improving Terrestrial Laser Scanning Accuracy

Modeling Distance Uncertainties with Machine Learning Techniques

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FIG Working Week 2023
Scientific Workshop on Uncertainty and Quality of Multi-Sensor Systems

2023-05-27

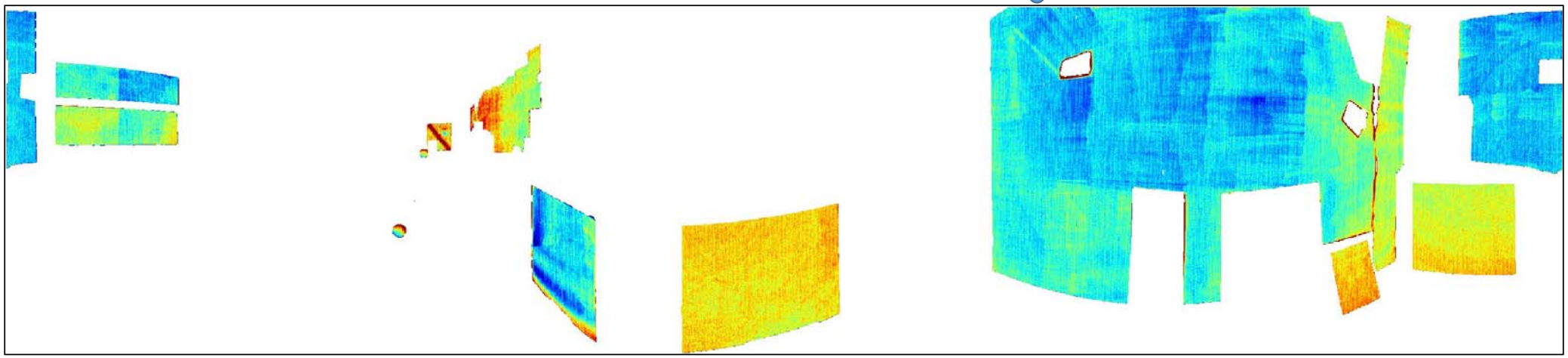
Motivation

[Z+F]

Backward Modeling

[Hexagon]

Source:
1. Sensors uncertainties
2. Object properties
3. Scan geometry



Agenda

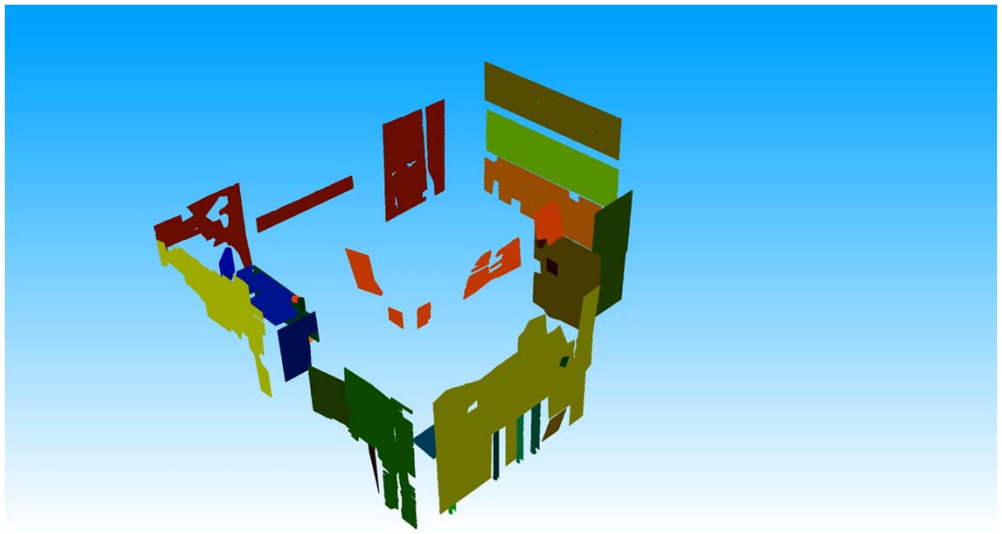
- Motivation
- Data Acquisition
- Backward Modeling
- Machine Learning Regression
- Regression Results
- Distance Calibration
- Conclusion & Outlook

Reference Point Cloud Acquisition

- Reference sensor:
  - Leica AT 960 (Laser tracker)
  - Leica LAS XL (Handheld scanner)

[Hexagon]

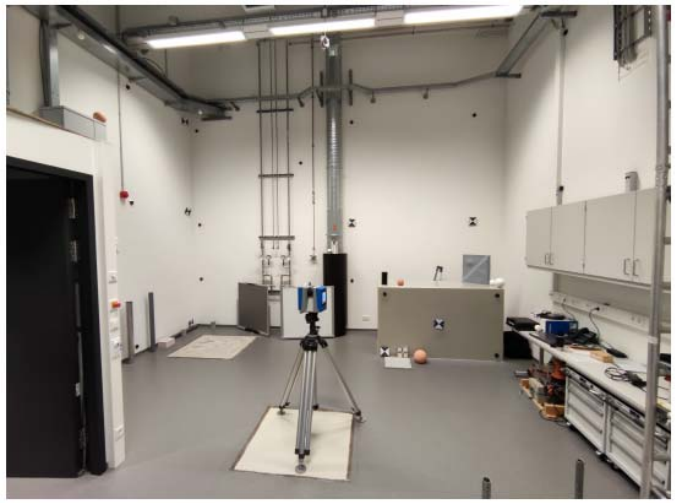
- Uncertainty in planarity $U_P = 225$ µm

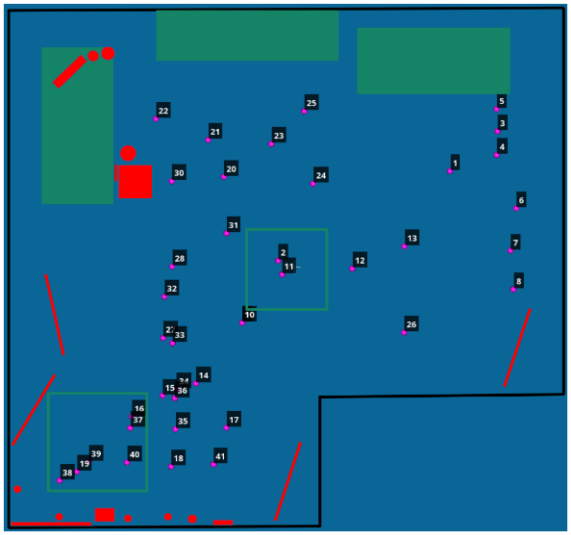


TLS Point Cloud Acquisition

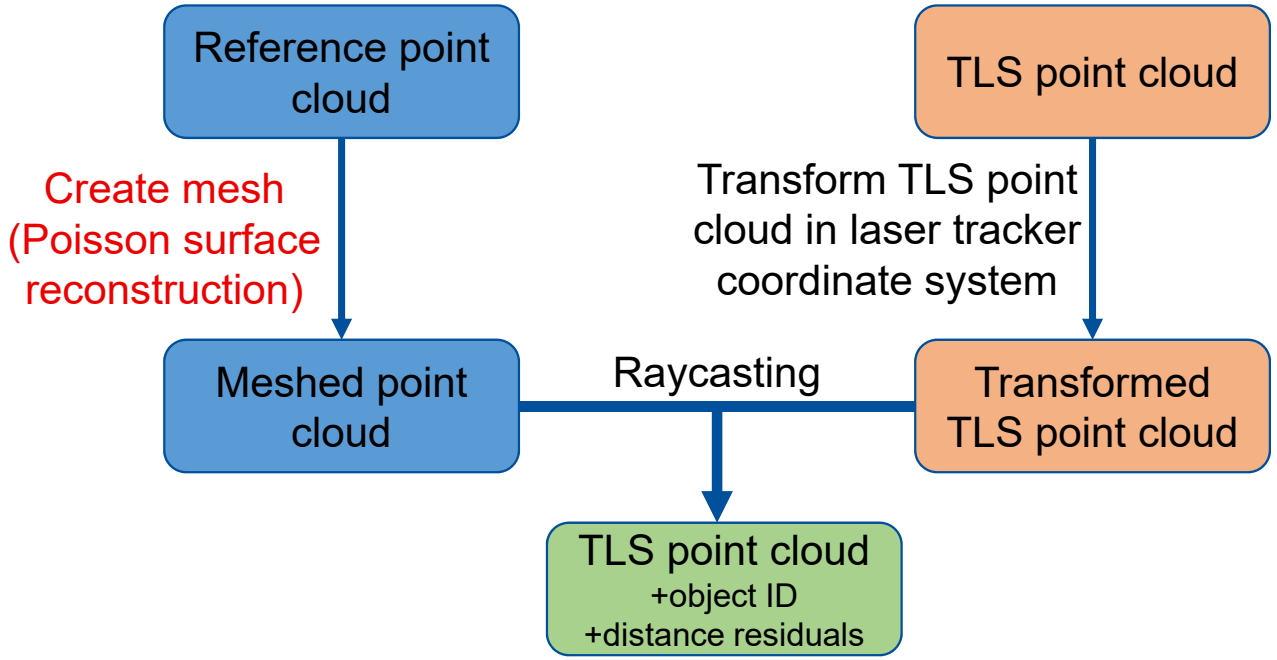
- Z+F Imager 5016
  - 50 TLS Scans inside HiTec Lab
  - Under same atmospheric conditions

Z-F Imager 5016 specifications	
Spot size	~3.5 mm @ 1 m
Divergence angle	0.3 mrad
Accuracy vertical / horizontal	0.004° rms
Linearity error	0.63 mm
Scan settings	
Scan quality	Quality +
Registration	Targets + Scantra

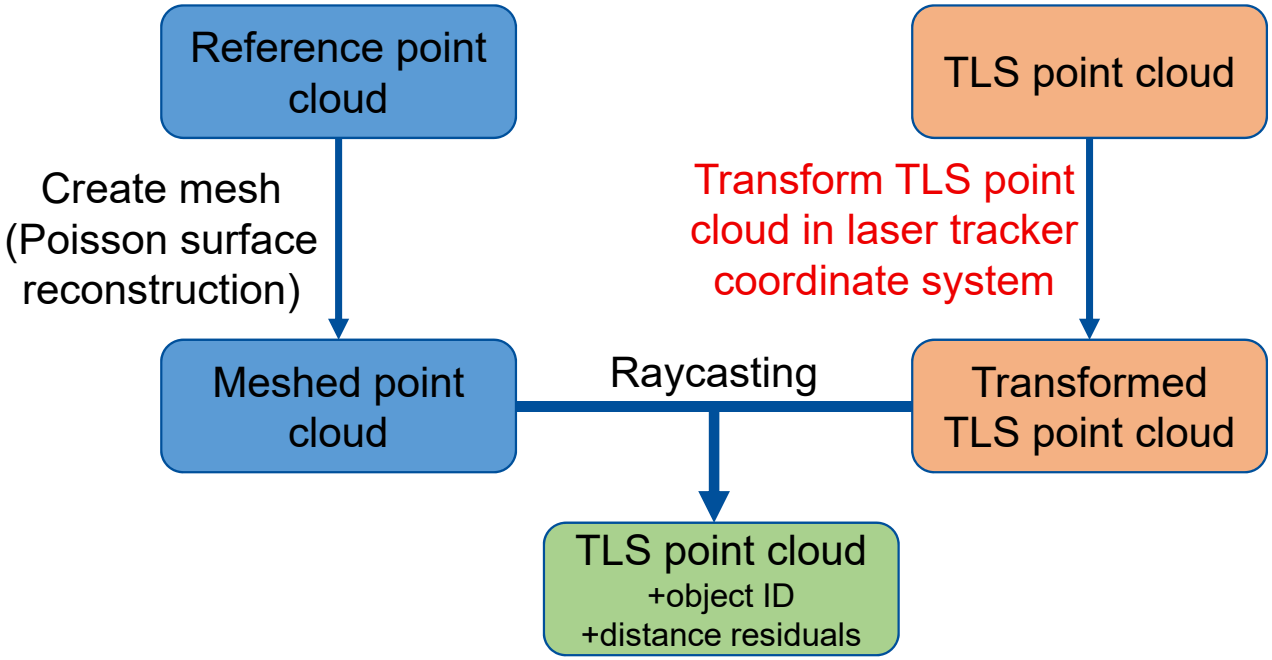




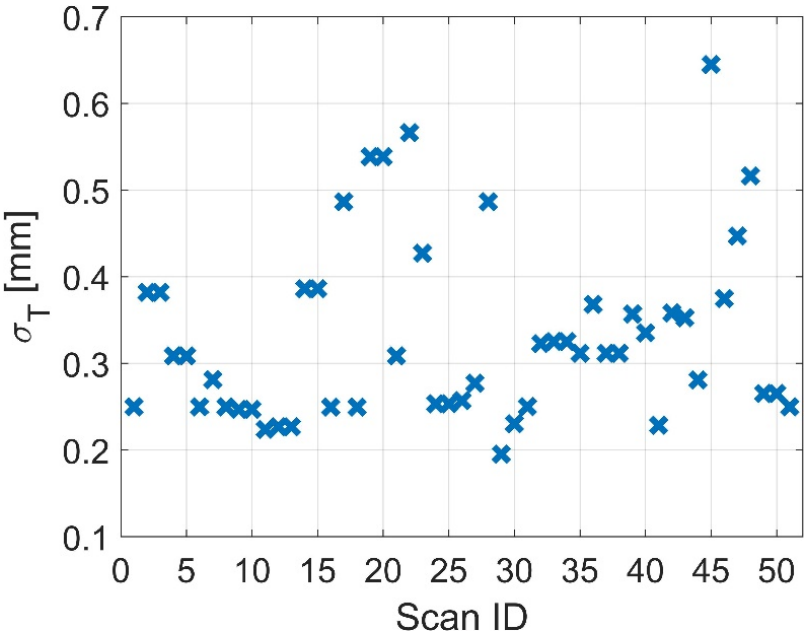
Backward Modeling



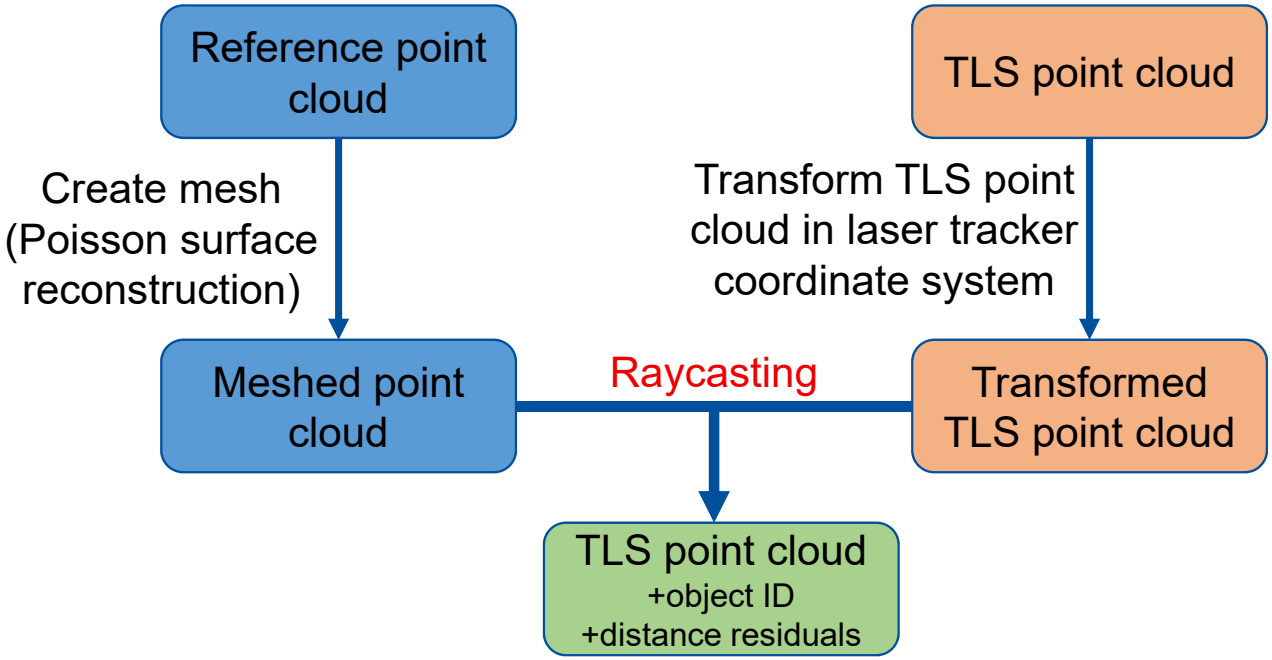
Backward Modeling

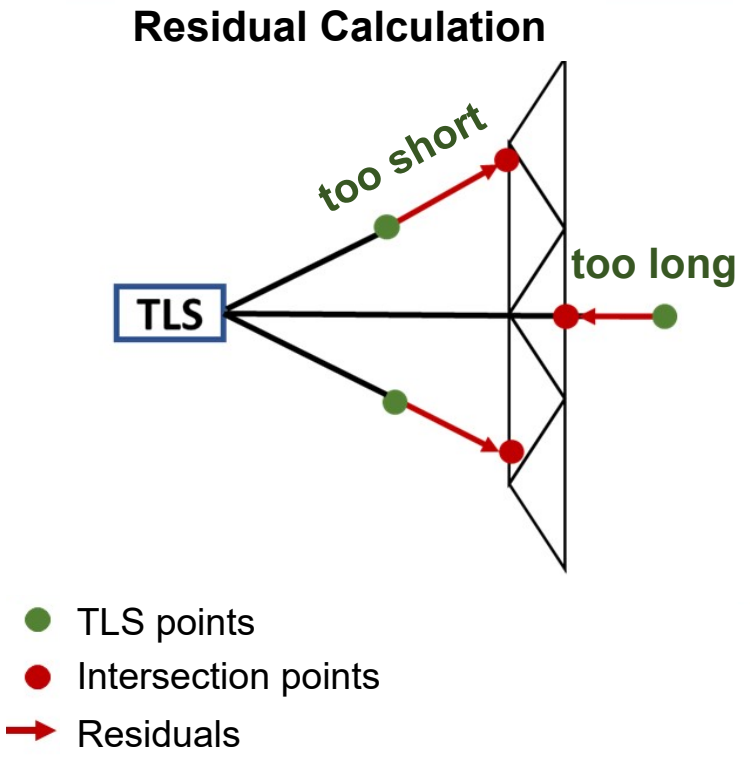


Registration via targets using Scantra (mean(σ_T) = 0.3 mm)

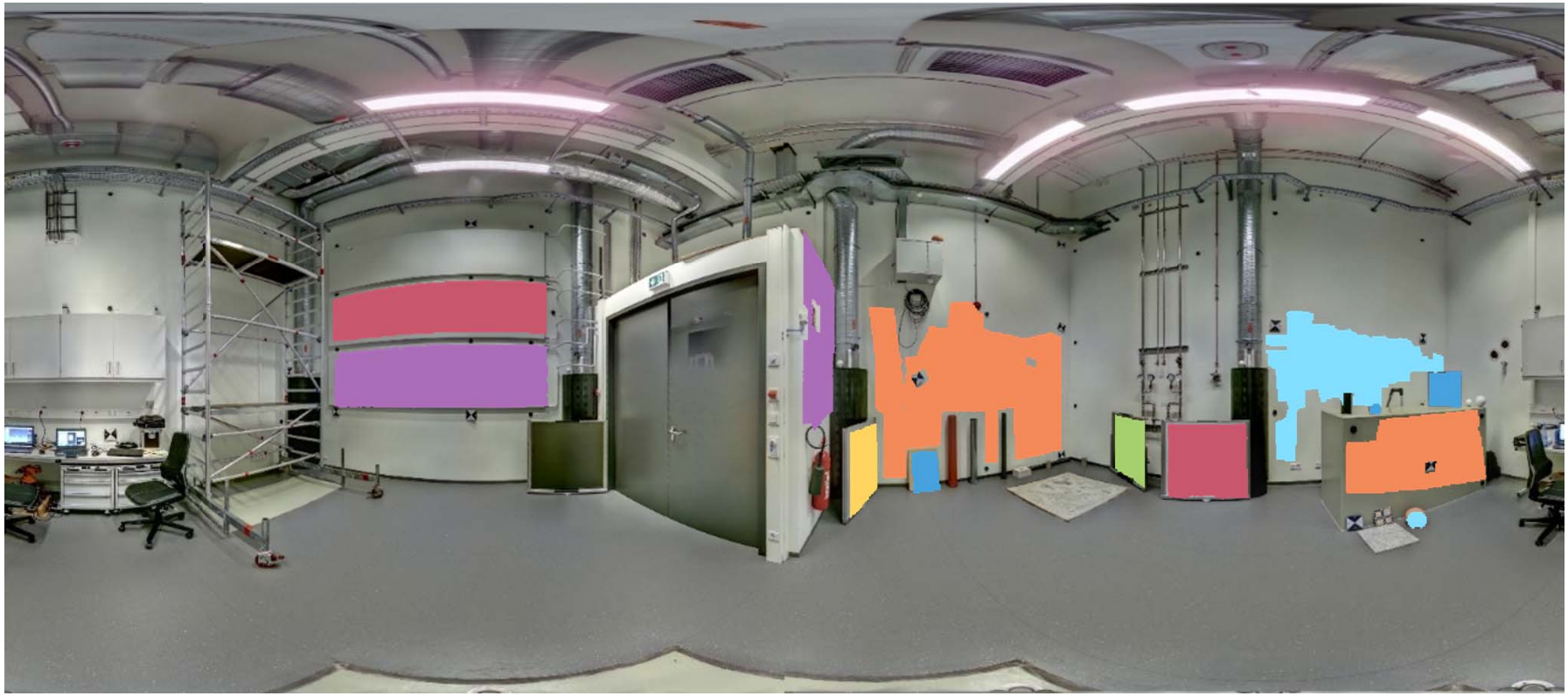


Backward Modeling

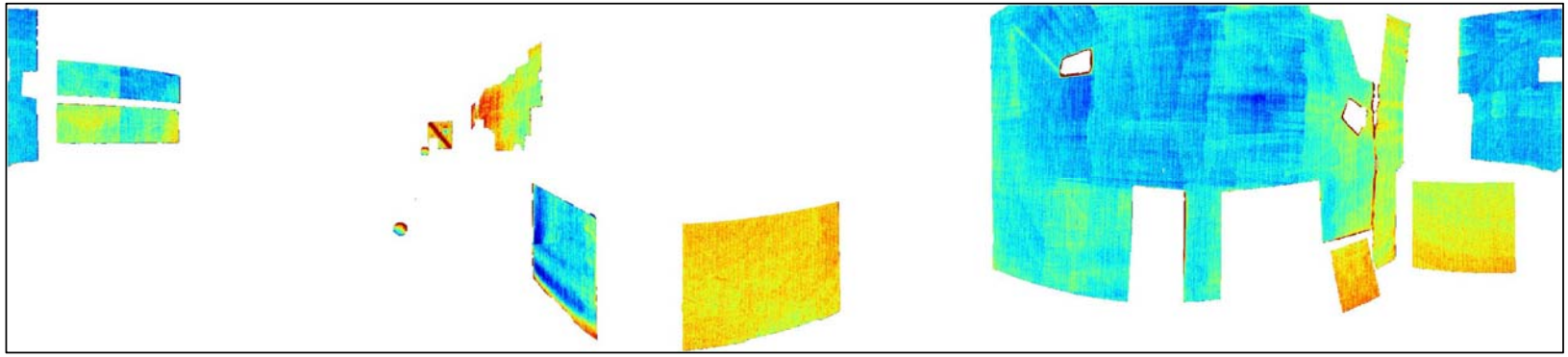




Data Set



Feature Engineering



Scan geometry:

- Distance
- Angle of impact

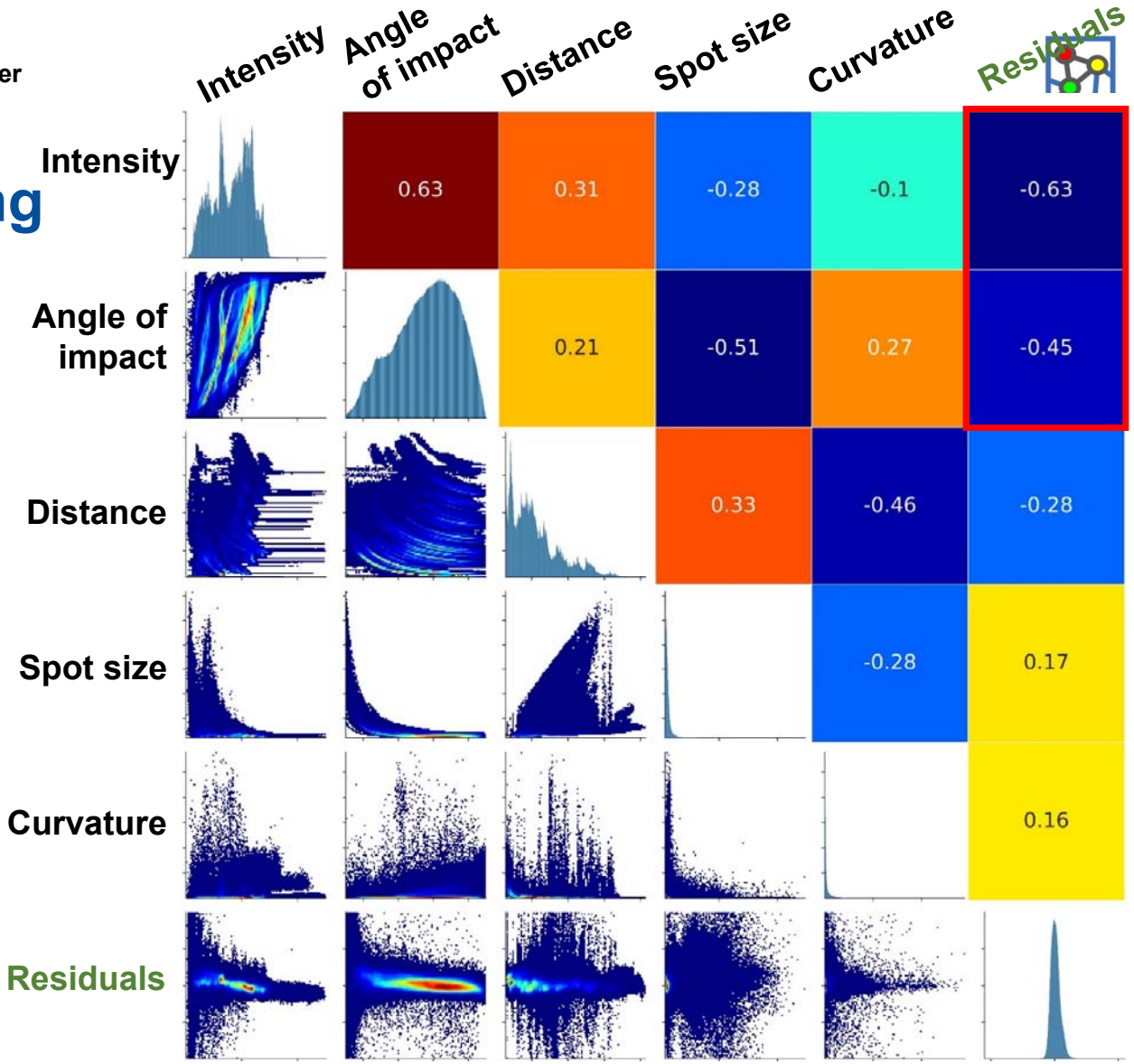
→ Spot size

Object properties

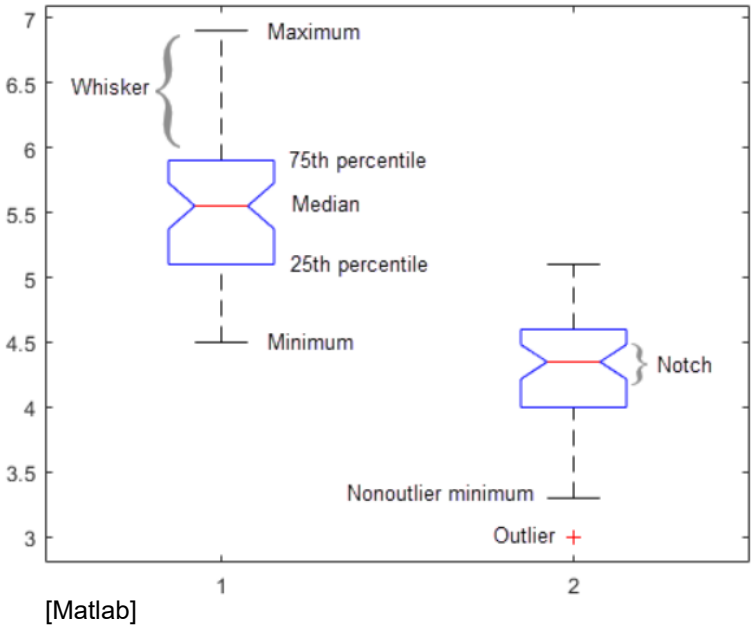
- Penetration depth
- Form → Curvature
- Reflectivity → Intensity

Correlated

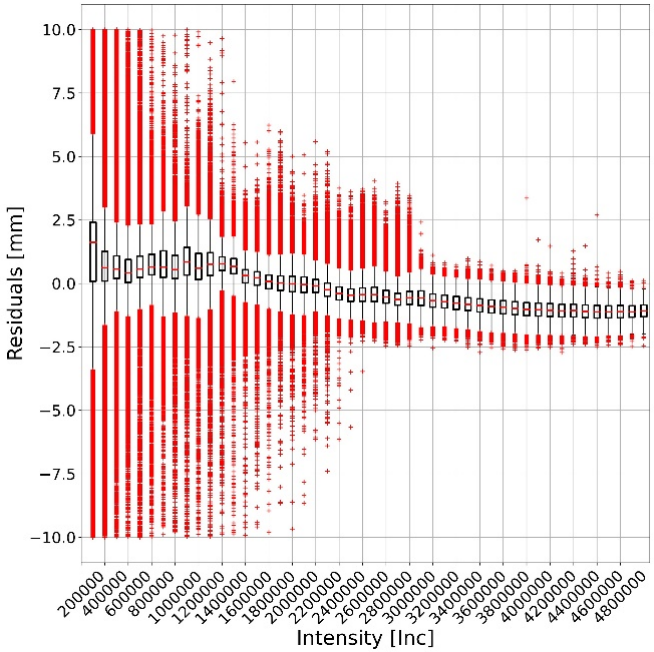
Data Preprocessing

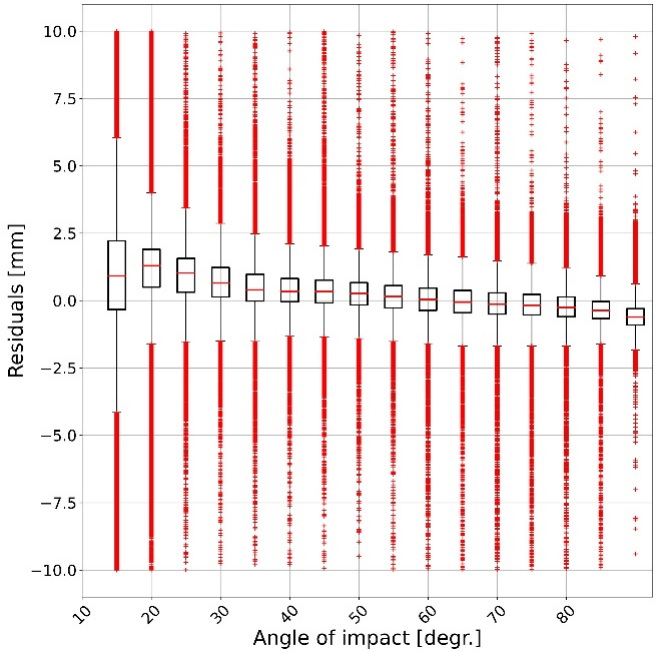


Data Processing – Principle of Outlier Removal

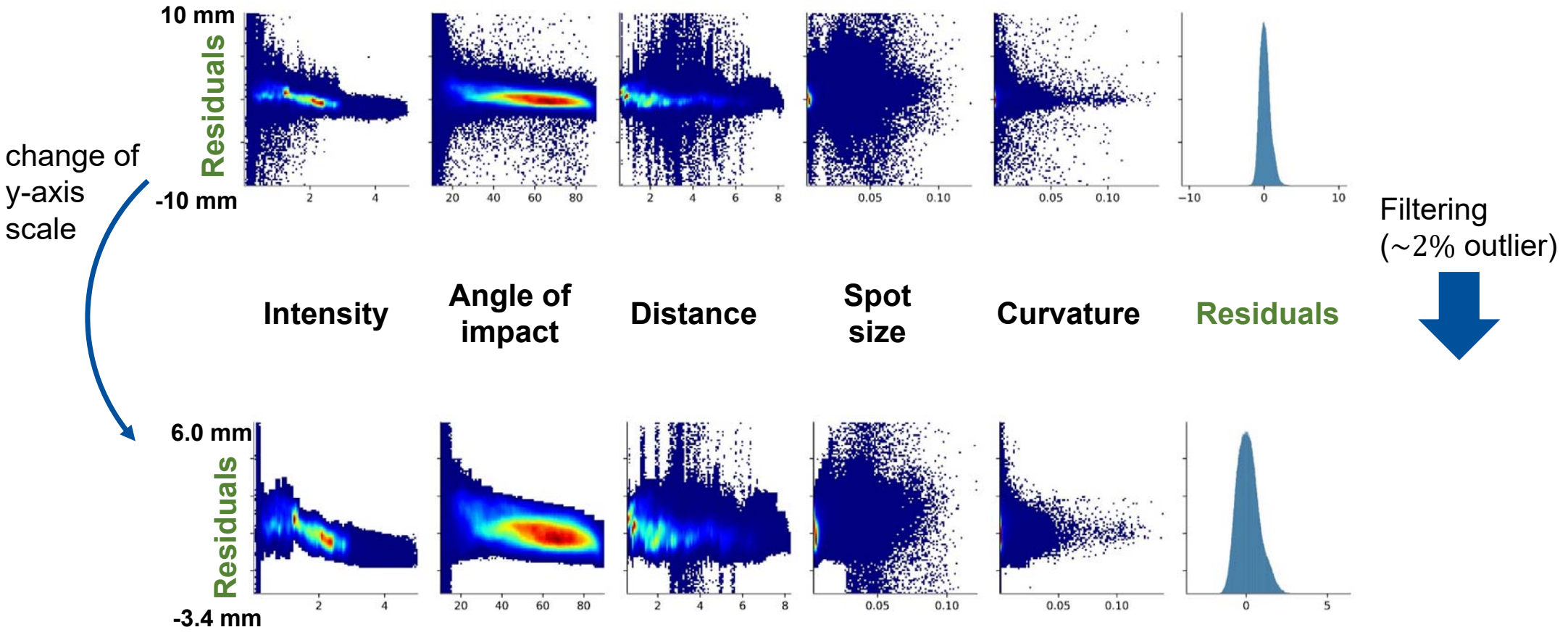


[Matlab]

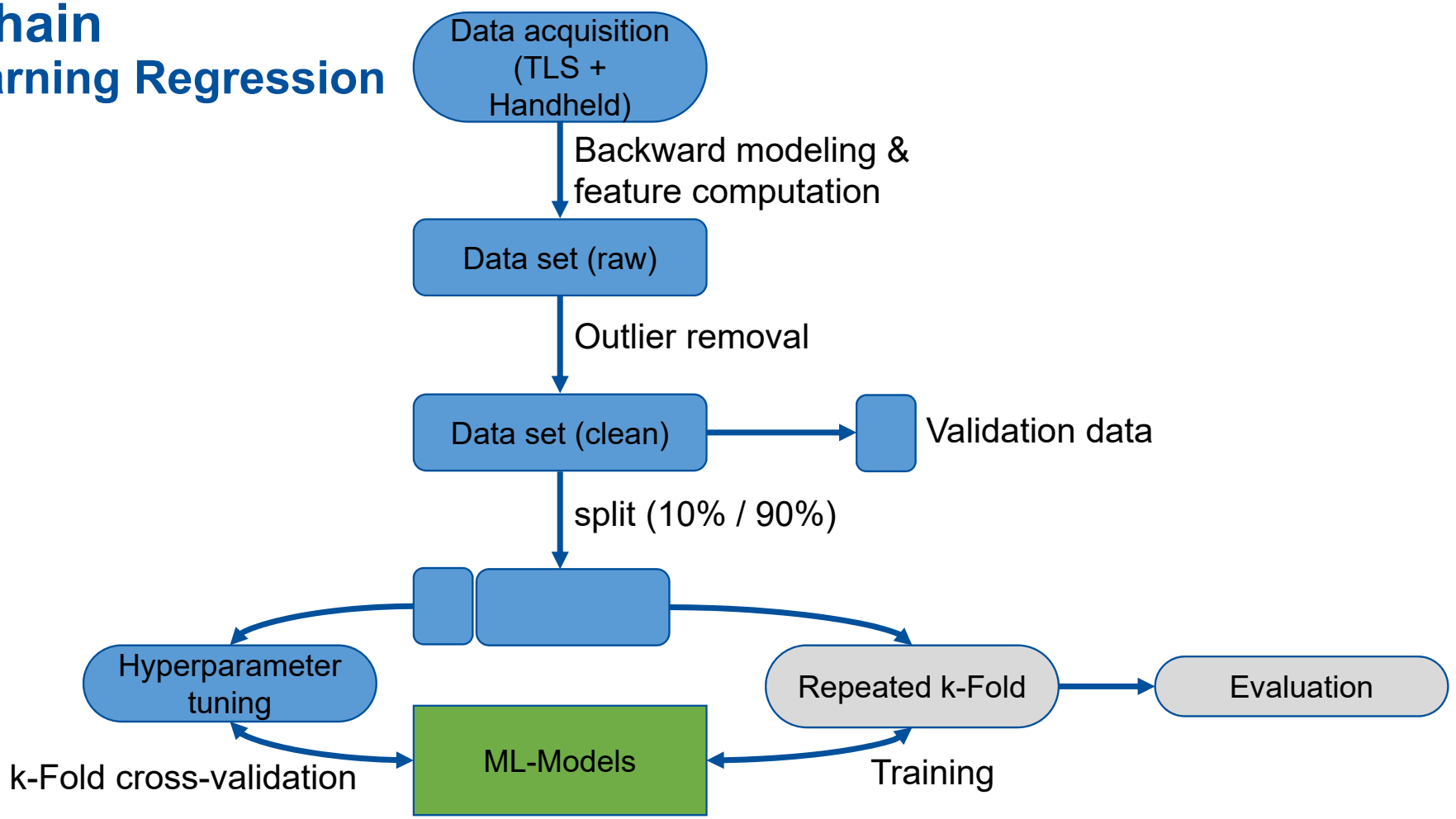




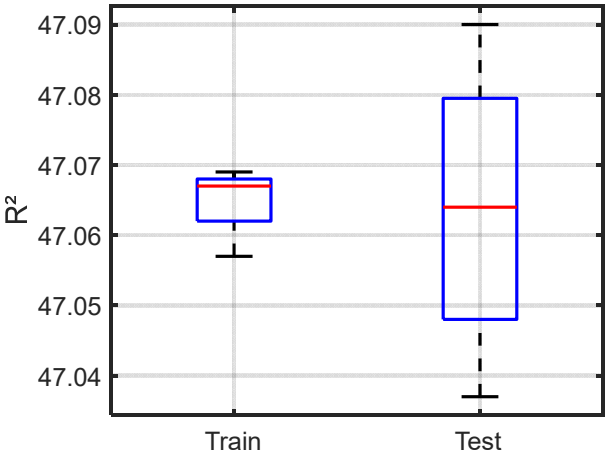
Data Processing – Outlier Removal by IQR-method

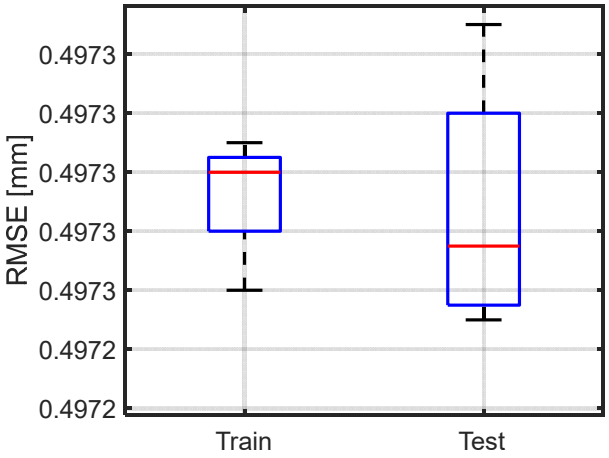


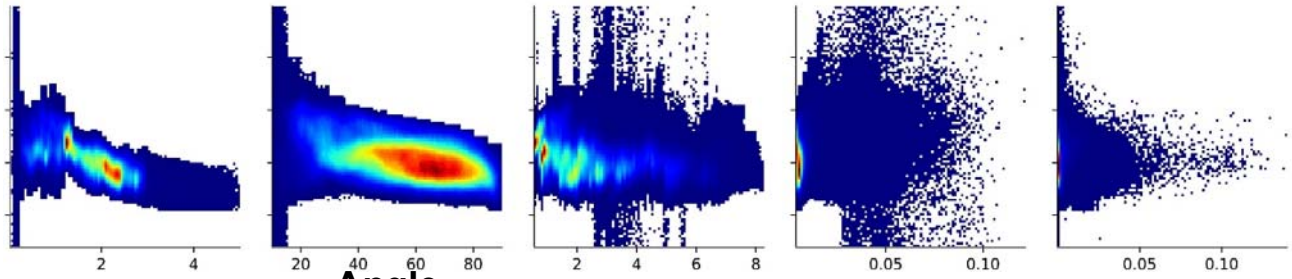
Process Chain
Machine Learning Regression



1st Model: Multiple Linear Regression







Intensity | **Angle of impact** | **Distance** | **Spot size** | **Curvature**

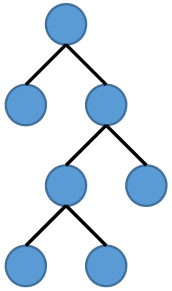
Results not sufficient:

- Multicollinearity
- Nonlinear relationships

Improved Models
Dealing with Nonlinearity and Multicollinearity

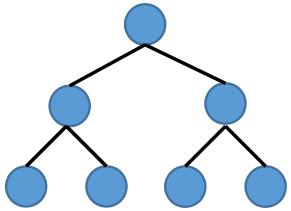
Gradient boosting trees

XGBoost & LightGbm (LGBM)



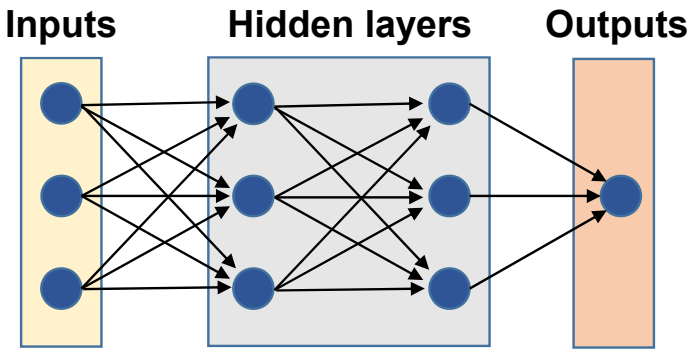
Asymmetric Tree

Catboost

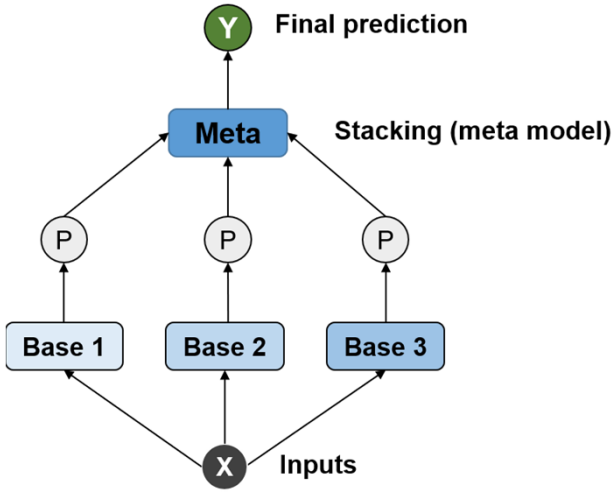


Symmetric Tree

Deep Learning



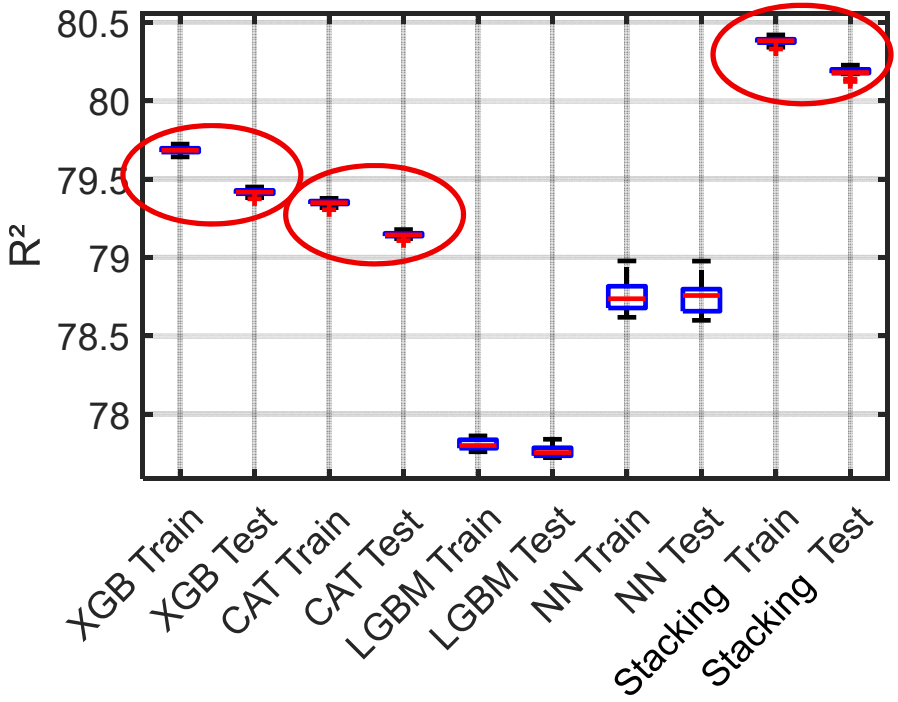
Stacking

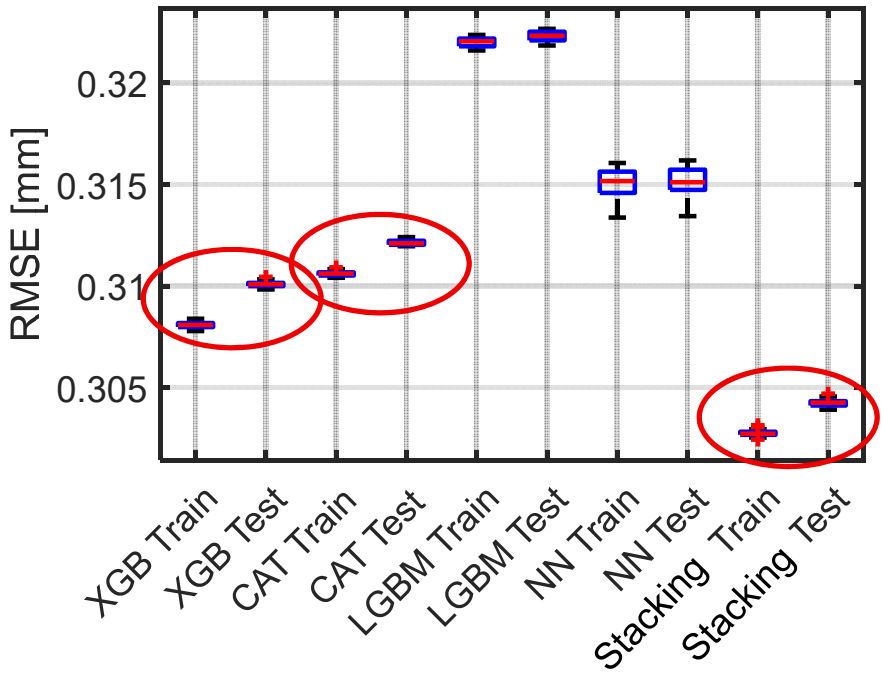


Base model:
- All previous trained ML-models

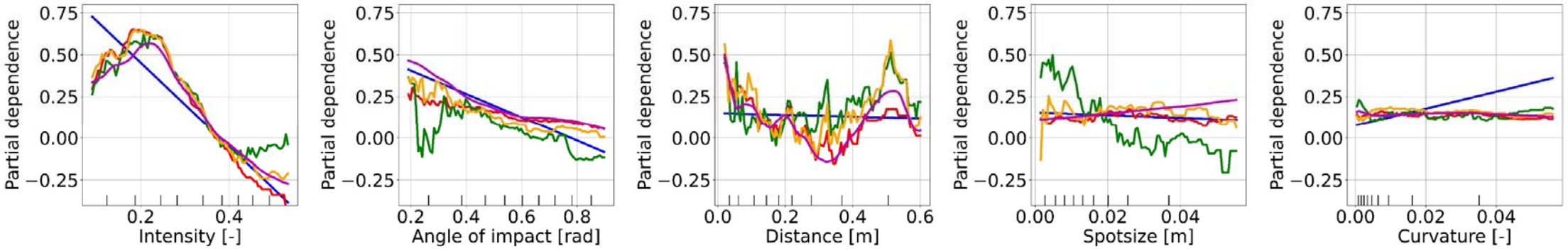
Meta model:
- XGBoost

Regression Results





Partial & Feature Importance

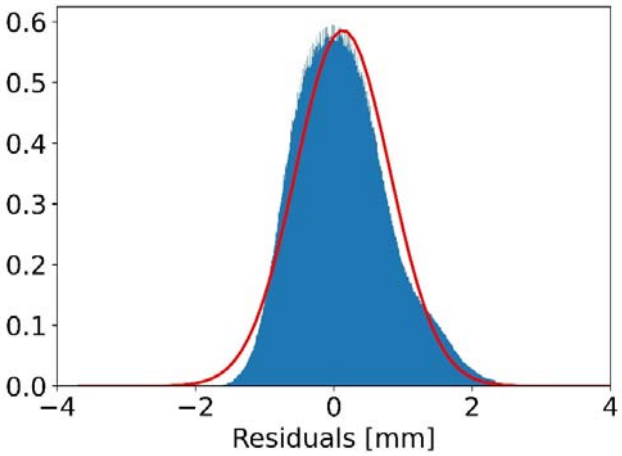


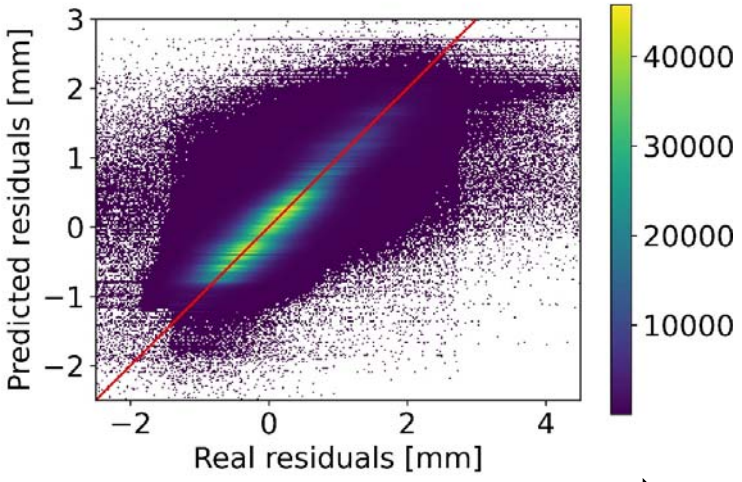
Stacking model (XGBoost): Feature importance

Linear Regression	XGBoost	Catboost	LightGBM	Deep Learning

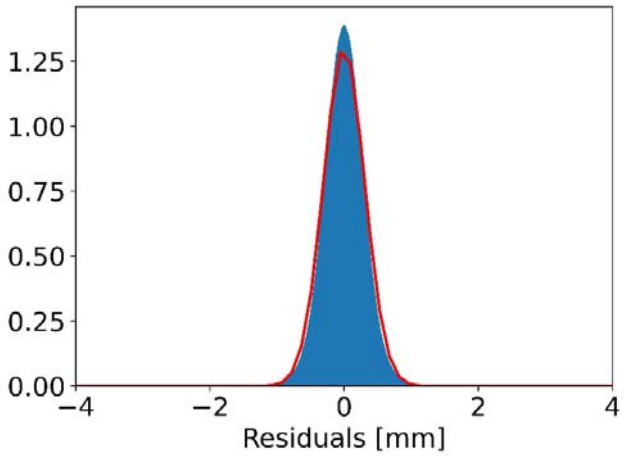
Stacking Model – Detailed Results Test Data

Real Residuals





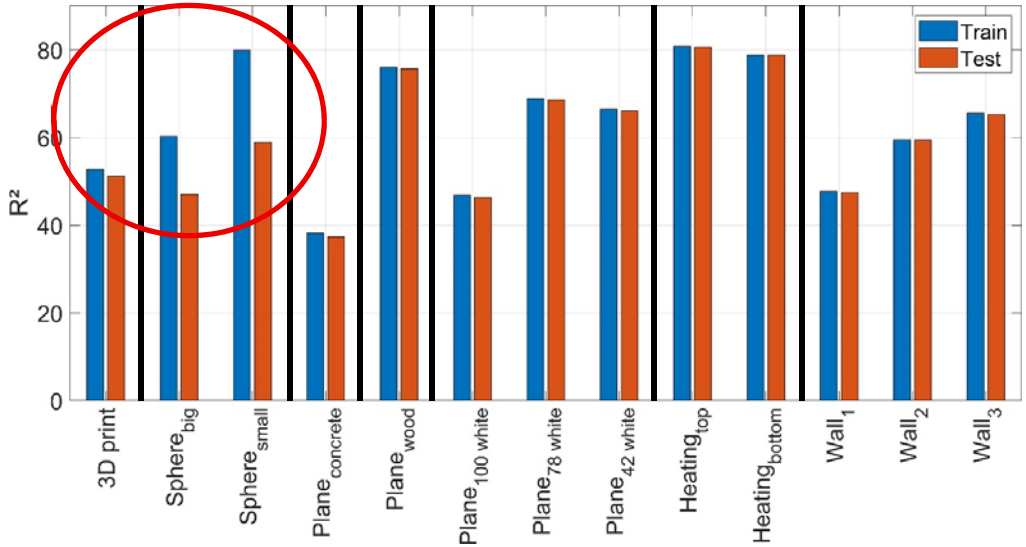
Residuals after calibration

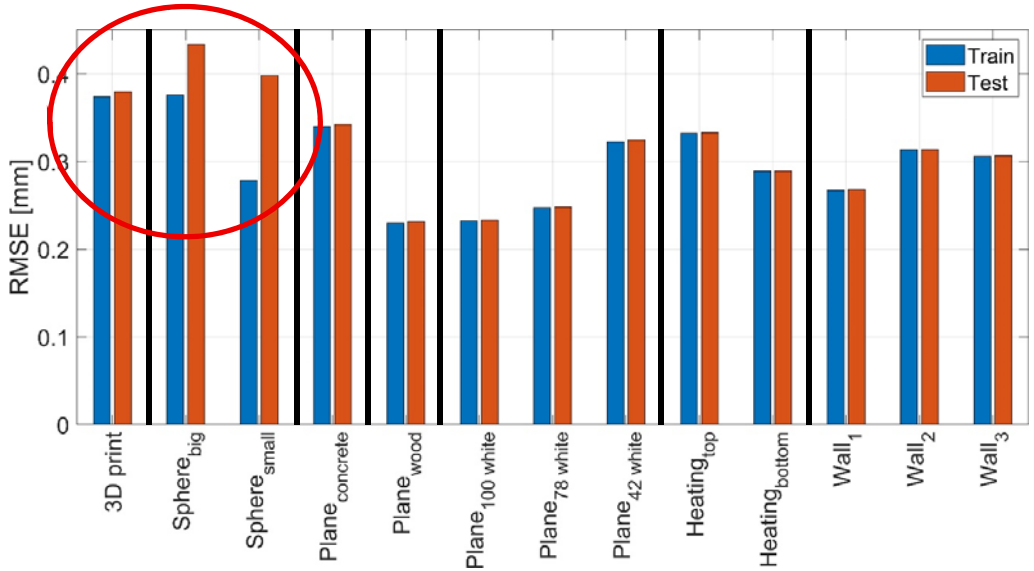


Calibration

$\mu = 0.13$ mm	$\mu = 0.00$ mm ⇨100% Improvement
$\sigma = 0.68$ mm	$\sigma = 0.30$ mm ⇨55% Improvement

Stacking Model – Detailed Results

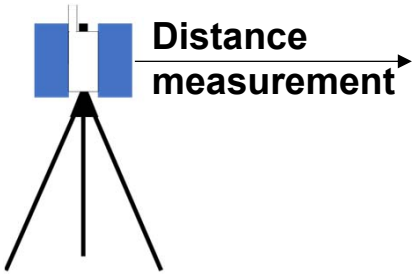




- R^2: 39% - 80.5%
- RMSE: 0.22 mm – 0.44 mm
- Highest RMSE for objects with high curvature (spheres, 3D print)

Distance Calibration

Record point cloud → **Calculate features** → **Predict distance residuals** → **Calibrate distance measurement**



1. Intensity
2. Angle of impact
3. Distance
4. Spot size
5. Curvature

Input:
- Features
- ML models

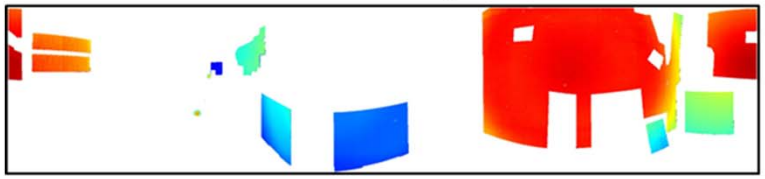
Output:
- Distance residuals d_{pred}

$$d_{cal} = d_{raw} - d_{pred}$$

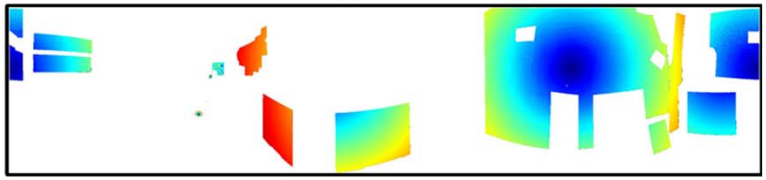
Distance Calibration (Features)

Record point cloud → **Calculate features** → Predict distance residuals → Calibrate distance measurement

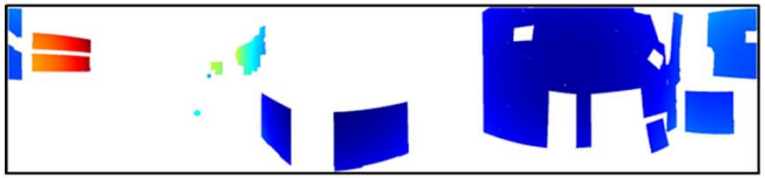
Intensity



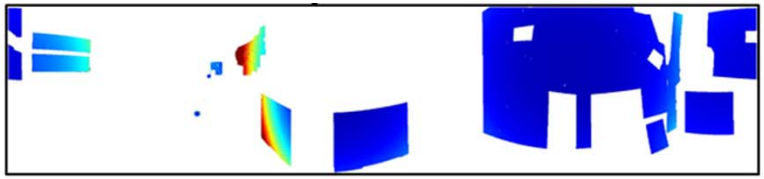
Angle of impact



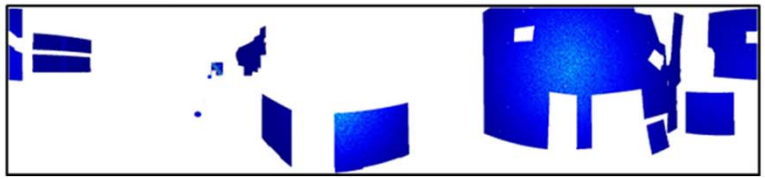
Distance



Spot size

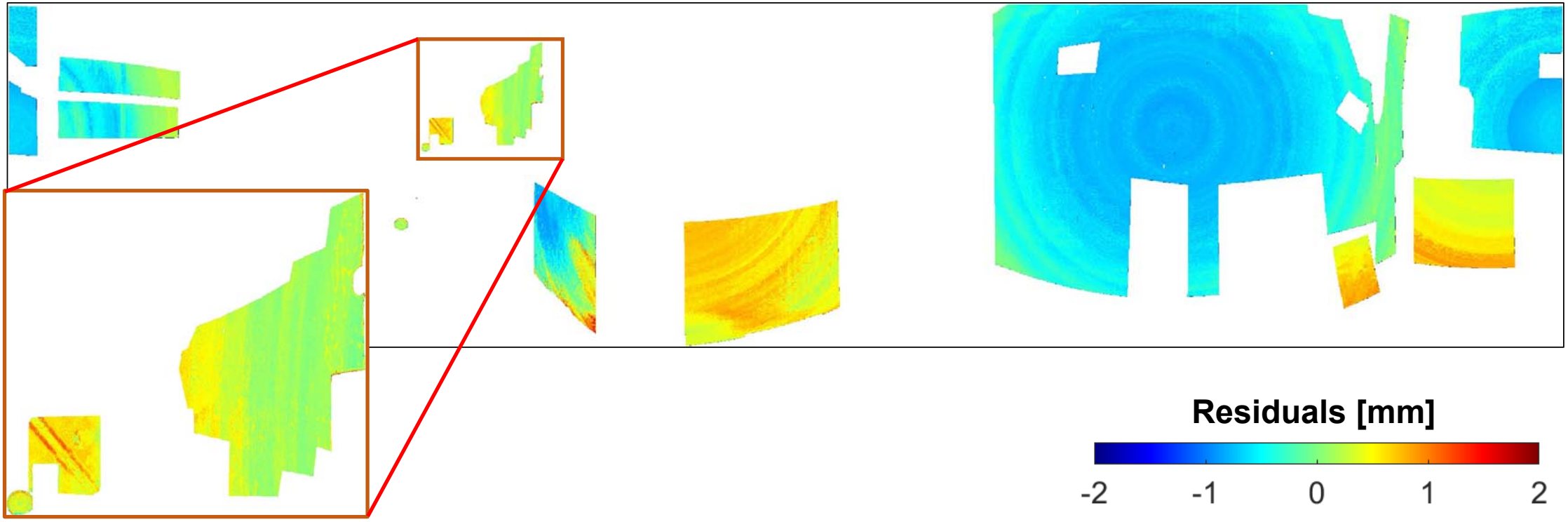


Curvature



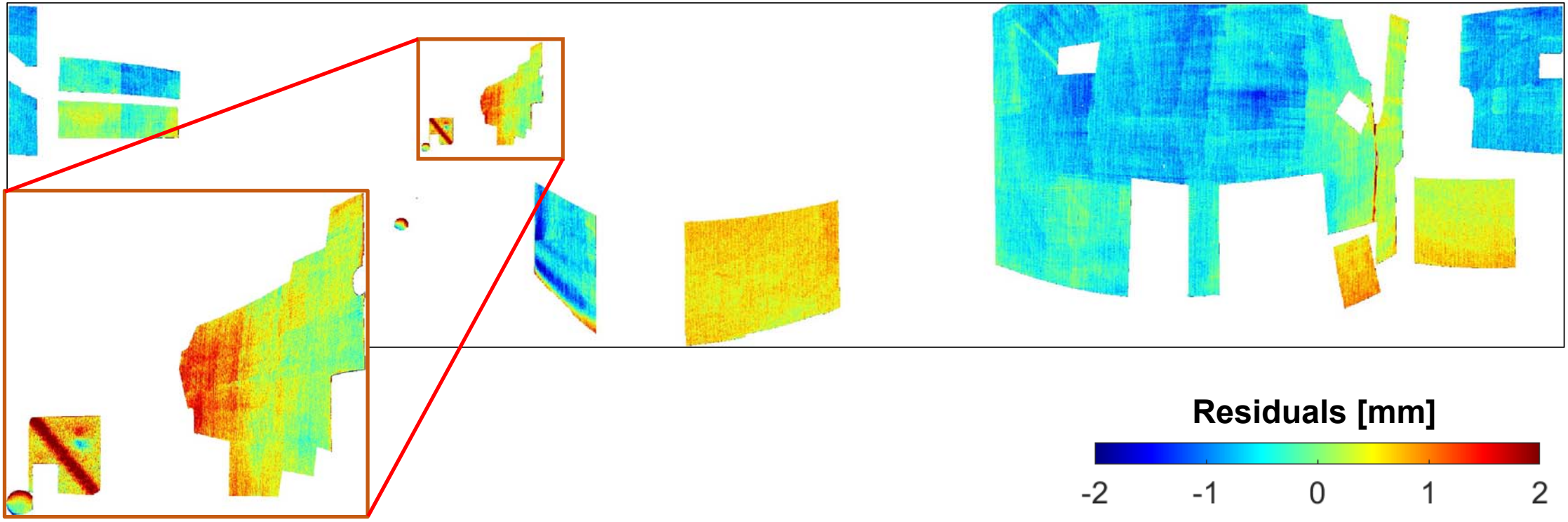
Distance Calibration (Predicted Residuals)

Record point cloud → Calculate features → **Predict distance residuals** → Calibrate distance measurement



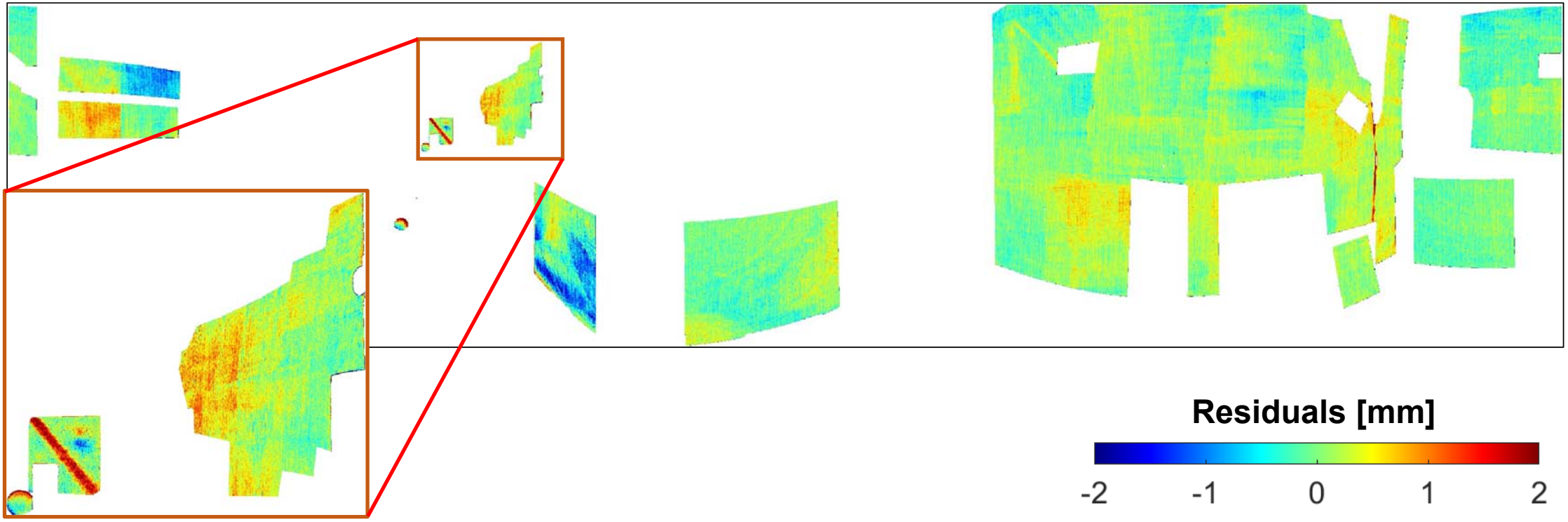
Distance Calibration (Raw Residuals)

Record point cloud → Calculate features → Predict distance residuals → Calibrate distance measurement



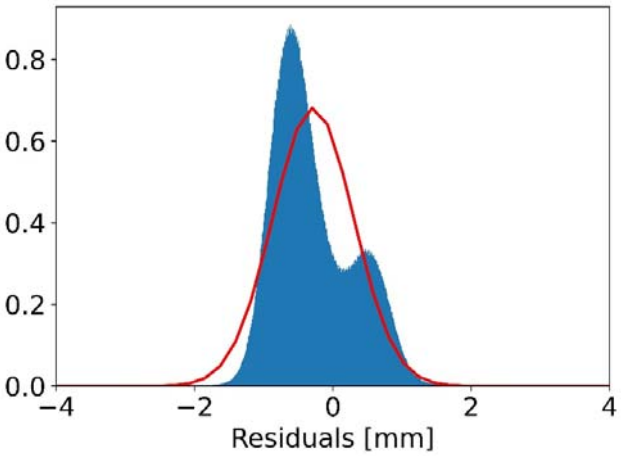
Distance Calibration (Residuals after Calibration)

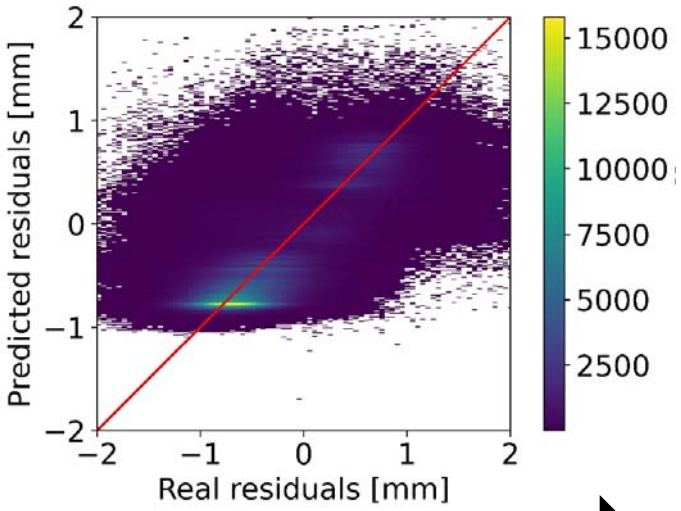
Record point cloud → Calculate features → Predict distance residuals → Calibrate distance measurement



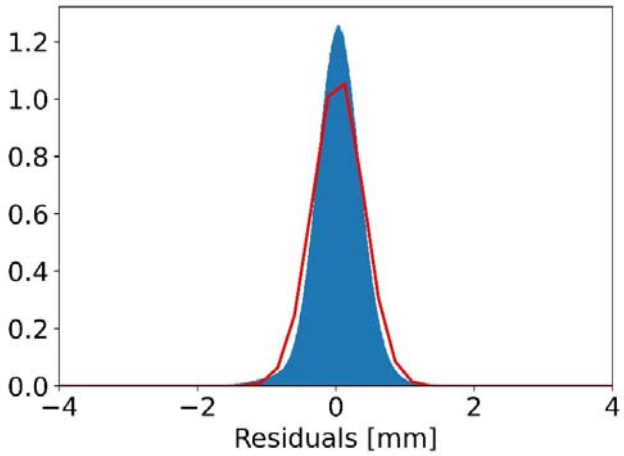
Stacking Model – Detailed Results Validation Data

Real Residuals





Residuals after calibration



Calibration

$\mu = -0.28$ mm	$\mu = 0.03$ mm ⇨88% Improvement
$\sigma = 0.58$ mm	$\sigma = 0.36$ mm ⇨37% Improvement

Conclusion & Outlook

Conclusion

- ML models achieve satisfactory results
  - $R^2 > 77\%$
  - RMSE < 0.33 mm
- *Stacking* improves the results slightly
- Joint modeling of objects of different material and shape in one model works well
- Real scan shows the applicability of the ML models to improve accuracy
  - Residuals are normally distributed after calibration
  - Mean residuals and standard deviation decreases

Outlook

- Development of an efficient calibration environment to train ML models
- Investigation of effects from angle measurements

References

1. [Hexagon] https://hexagon.com/de/products/leica-absolute-tracker-at960-scanner-bundle
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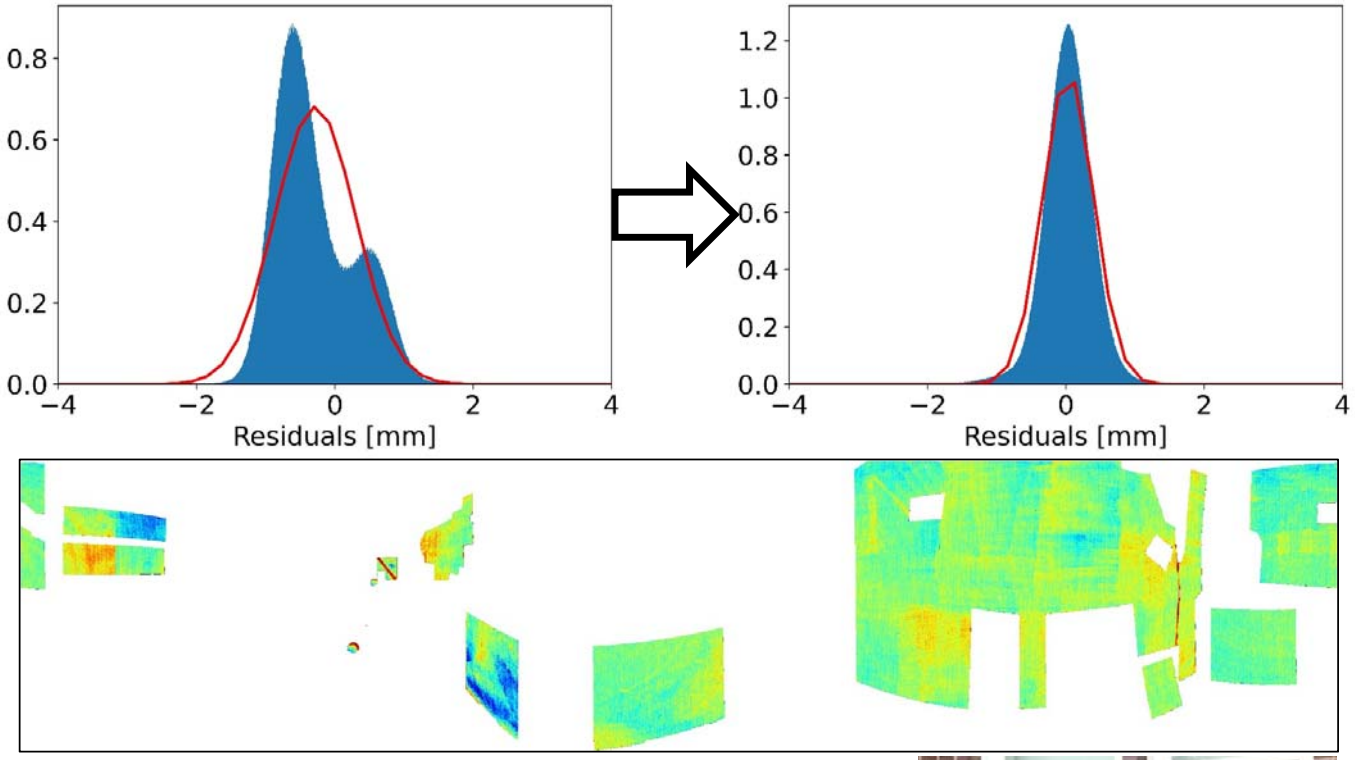
Summary

- Usage of ML methods to calibrate distance measurements of a TLS
- Joint modeling of shape and material
- Results:
  - $R^2 > 77\%$
  - RMSE < 0.33 mm



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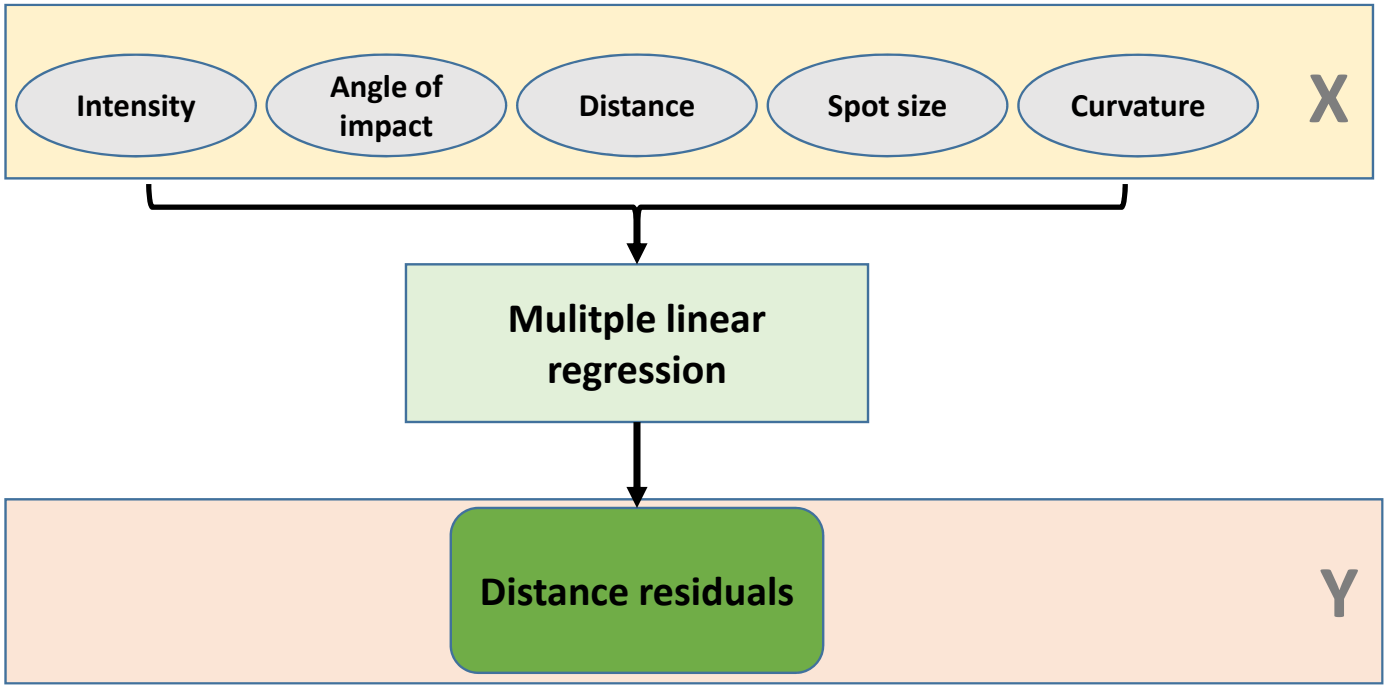
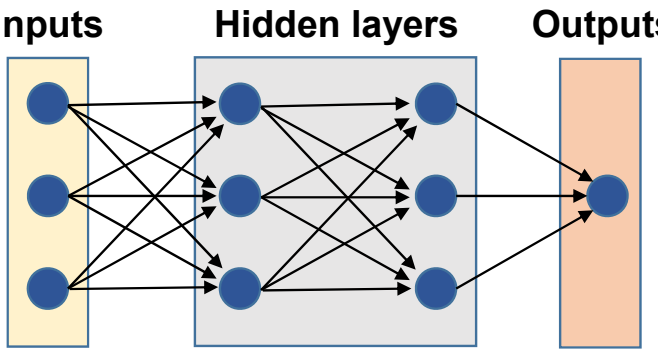
Appendix

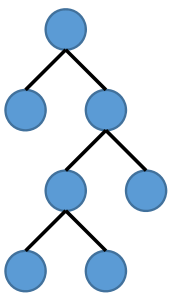
Objects

3D Print

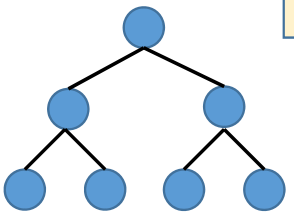
Bildervorlagen



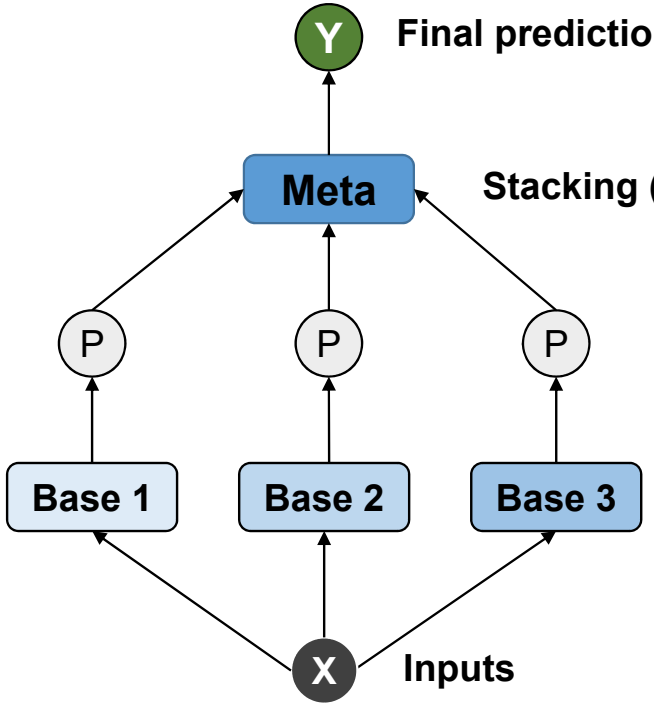




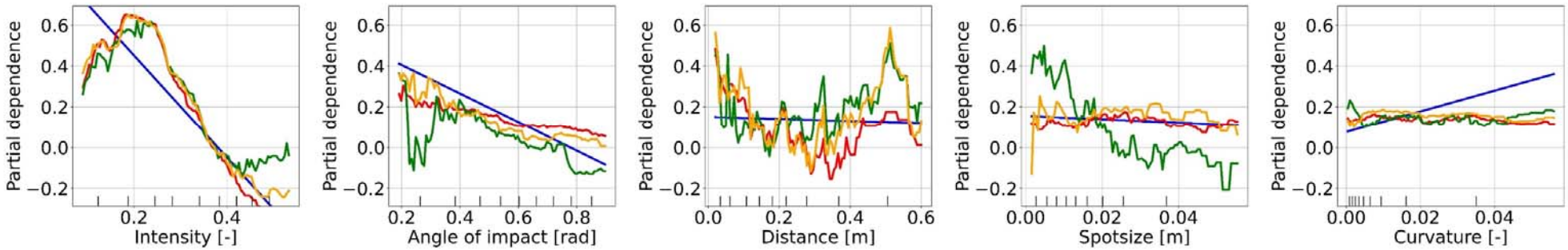
Asymmetric Tree



Symmetric Tree



Detailed Results



Linear Regression
XGBoost
Catboost
LightGbm
Deep Learning

Linear Regression
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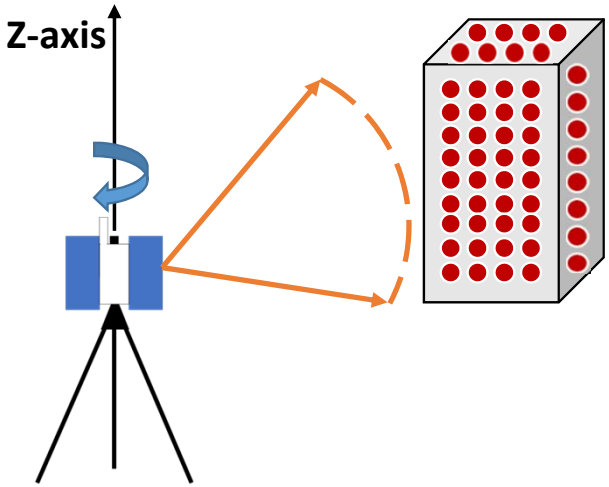
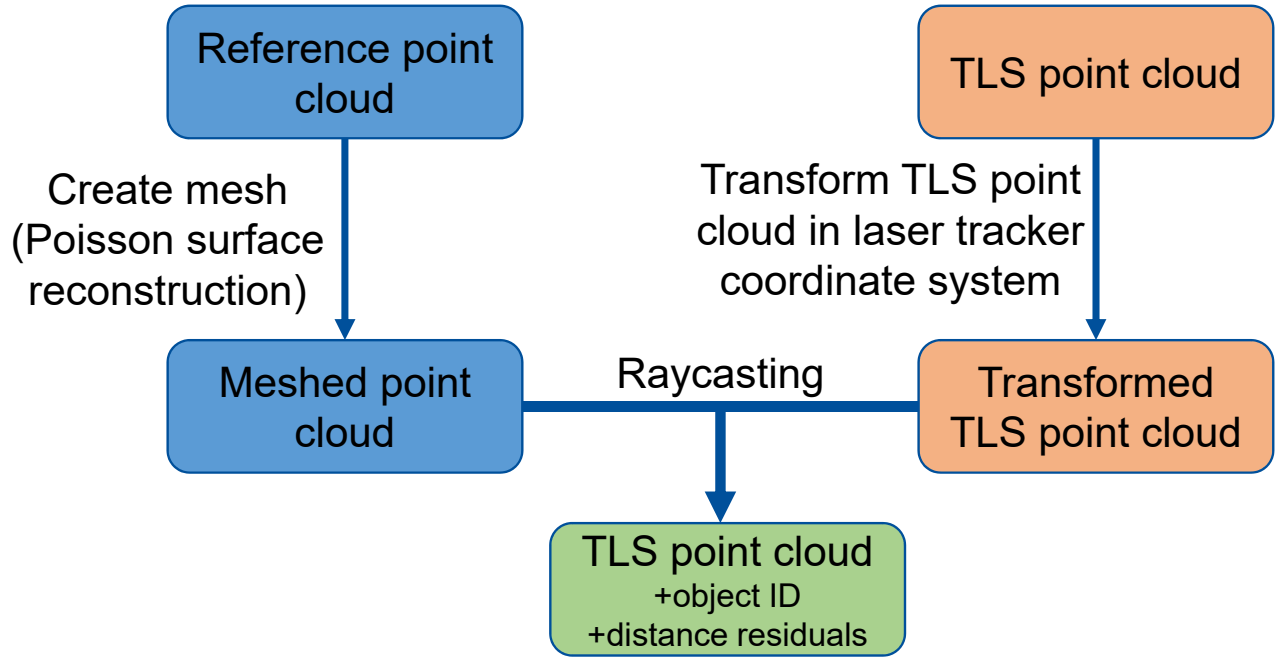
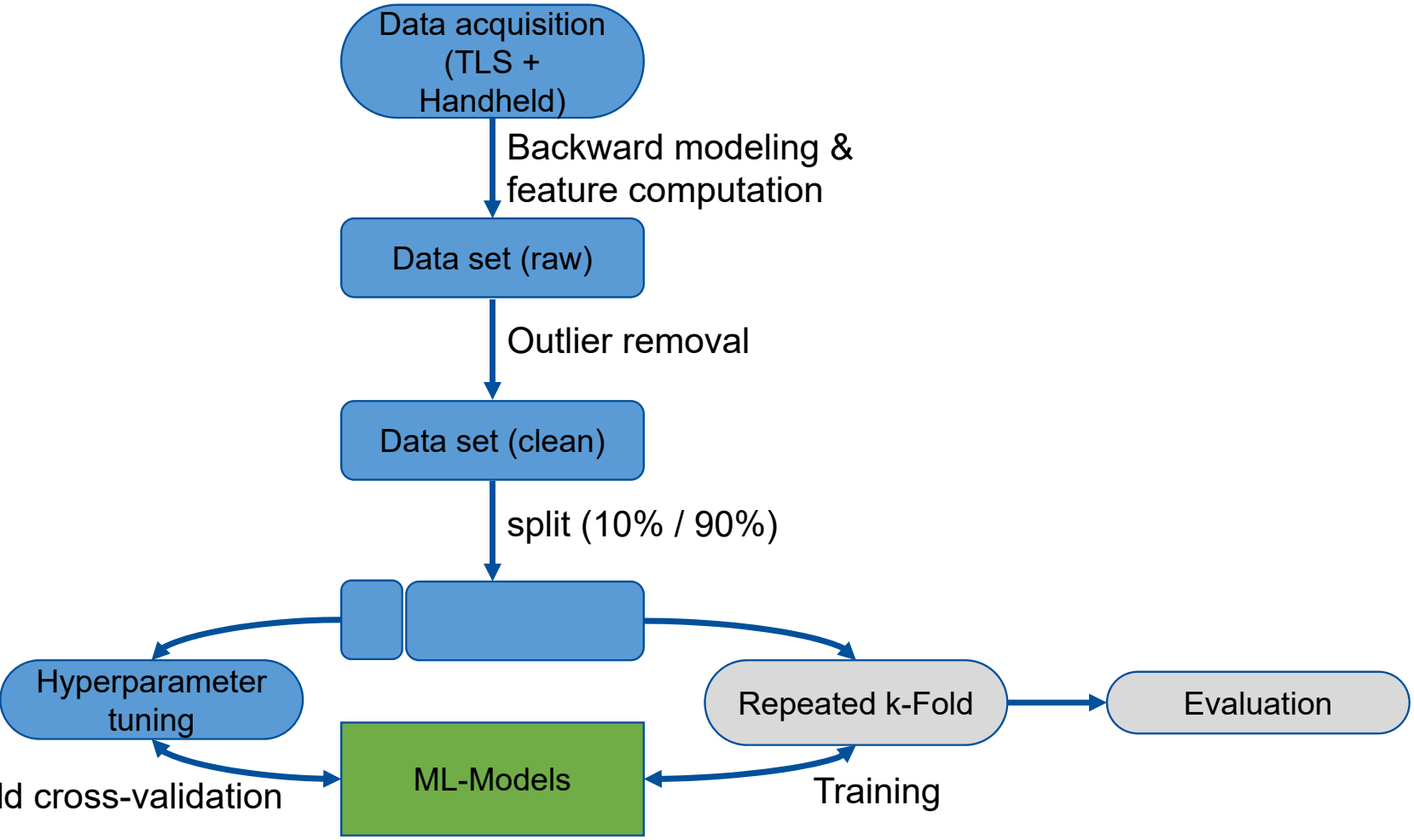

Z-axis


Reference point cloud
Create mesh (Poisson surface reconstruction)
Meshed point cloud
TLS point cloud
Transform TLS point cloud in laser tracker coordinate system
Transformed TLS point cloud
Raycasting
TLS point cloud
+object ID
+distance residuals


Data acquisition (TLS + Handheld)
Backward modeling & feature computation
Data set (raw)
Outlier removal
Data set (clean)
split (10% / 90%)
Hyperparameter tuning
Repeated k-Fold
Evaluation
ML-Models
ld cross-validation
Training