eXplainable Artificial Intelligence Application in Metrology

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Optical Industrial Metrology - Background

Industrial Quality Control

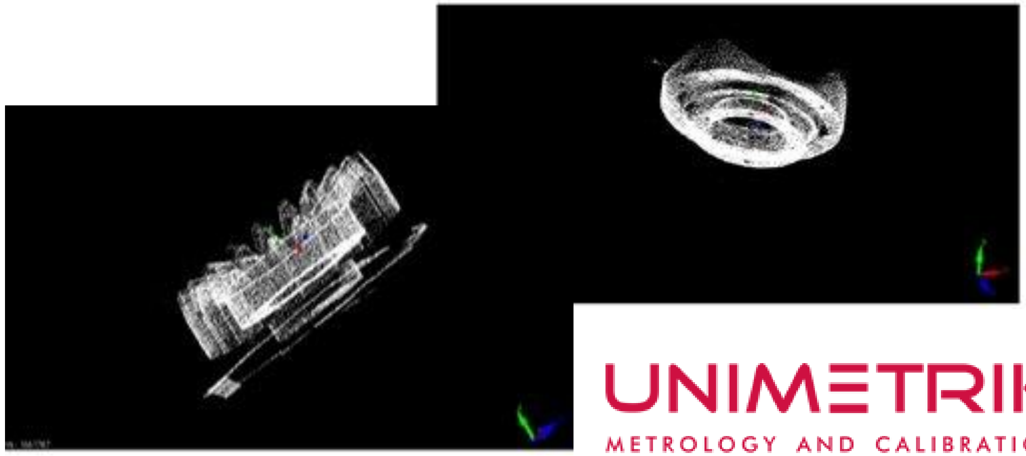
- Manufactured parts for automotive, aeronautic, energy sectors
- Dimensional/positional measurements: Definition of dimension/position & tolerance

Instrument: 3D laser scanner

- User-defined parametrization of scanning conditions
- Point Cloud generation

Software: M3 metrological software

- Point cloud processing
- Measurement using two methods (complete Point Cloud / geometry definition points)

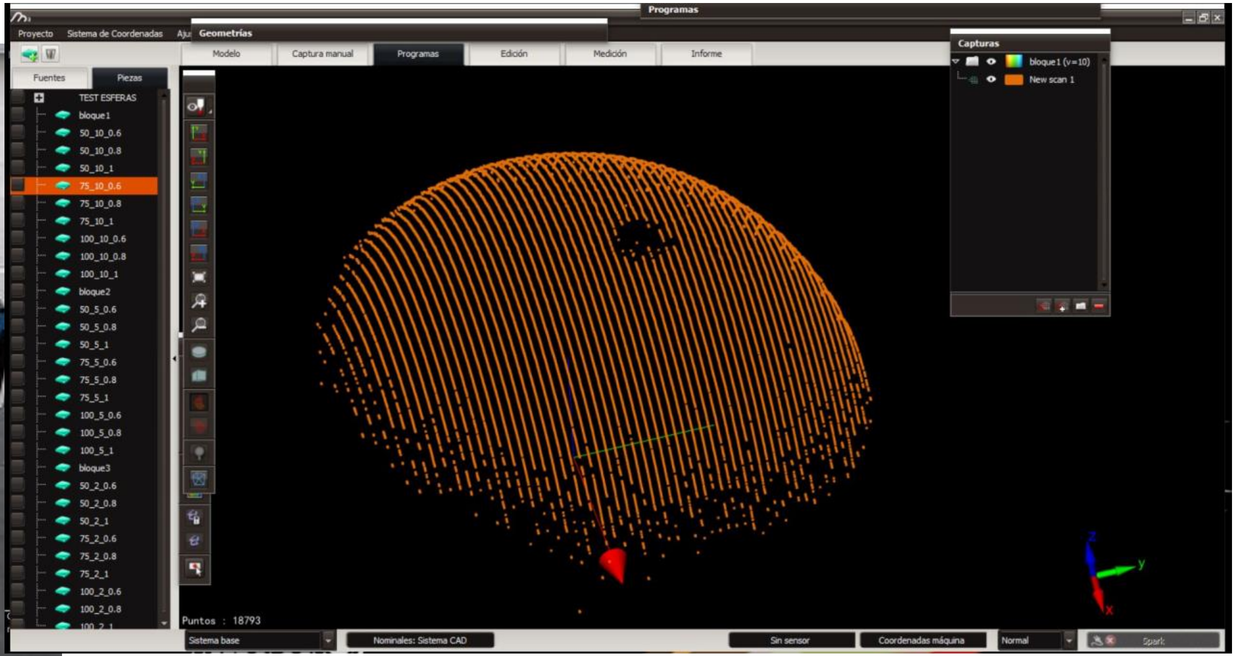


UNIMETRIK
METROLOGY AND CALIBRATION

Measurement Workflow

Step 1: Preliminary analysis of the object under study & selection of laser setup

- ➢ scanning parameters & laser orientation



Step 2: Configuration of scanning conditions & generation of Point Cloud

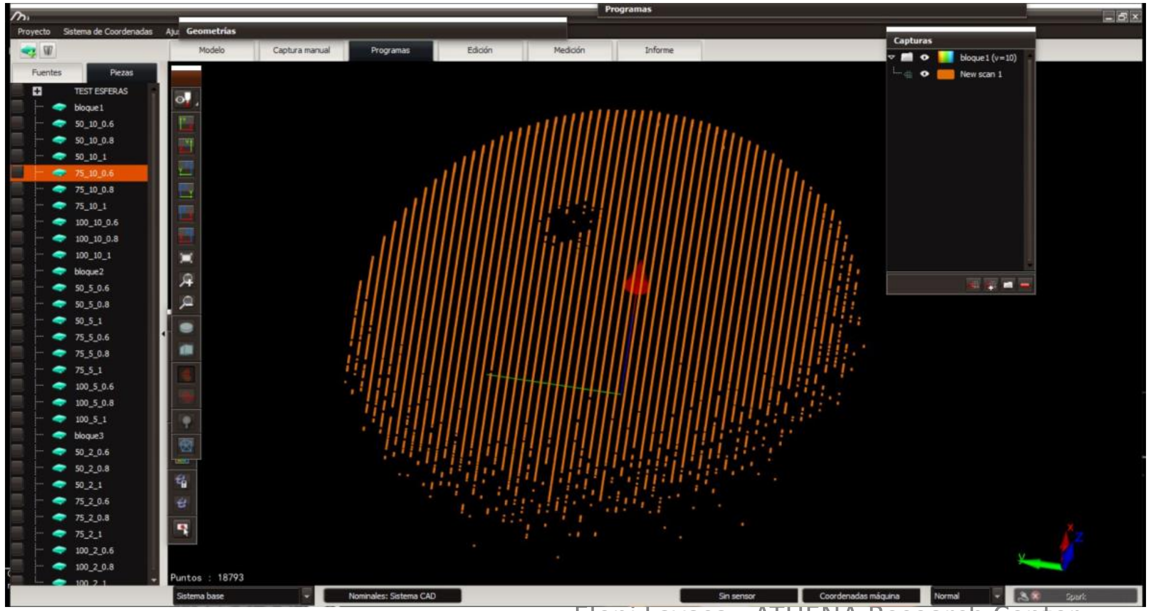
Measurement Workflow

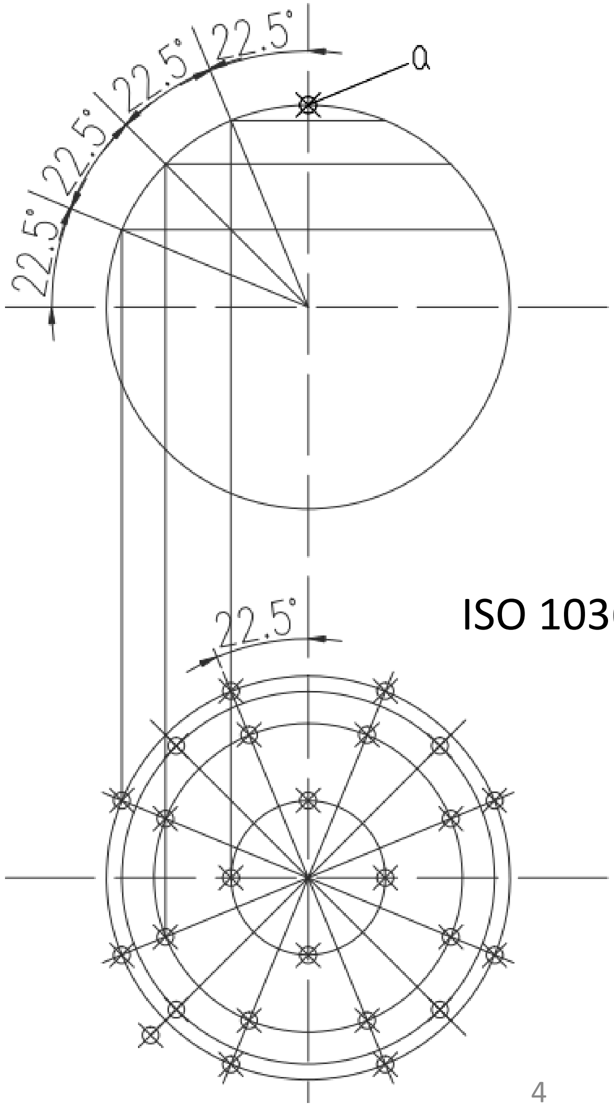
Step 3: Point cloud preprocessing

- Outlier removal
- Noise filtering
- Surface Segmentation

Step 4: Dimensional/positional measurement

- Method#1 (CONSTRUCT) (Geometry definition points)
- Method#2 (EXTRACT) complete Point Cloud





ISO 10360

Use case description

Issues:
- Results depend on metrologist's experience (inconsistency of results)
- Wasted time on iterative analysis, each project from scratch

Use Case 1: Measurement plan parameter optimization

Objective: Optimization of scanning parameters, to achieve minimum error/uncertainty in dimensional measurement

Accelerate/Facilitate ***Step 1: Preliminary analysis***

Use Case 2: Point Cloud optimization

Objective: Optimization of the 3D point cloud in terms of quality & size

- **Size**: minimum # of points sufficient to perform accurate measurement, & preserve shape/geometry information
- **Quality**: Point cloud denoising / filtering / segmentation

Accelerate/Facilitate ***Steps 3&4: Point Cloud pre-processing & Dimensional measurement***

Initial Approach: Supervised Learning Setting

Objective: Model instrument's anisotropic accuracy

- in response to *different surface orientations*
- in relation to *scanning parameters*

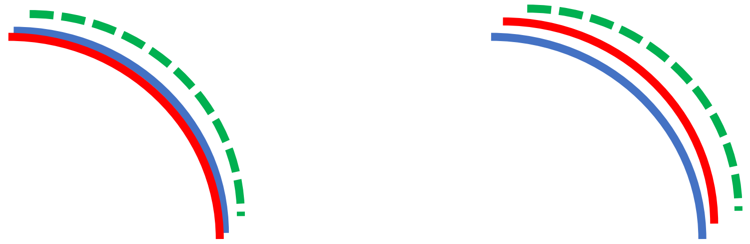
Approach: Supervised Regression task

- Prediction of error in Point capturing
- Access to *Ground Truth* needed

Method: Use measurements of *Calibrated artifacts*

- Actual dimensions precisely known (~1μm), i.e. actual ≈ nominal
- Validated shape perfection
- Ground Truth: actual Point positions located on artifact's nominal surface

calibrated *non-calibrated*



Nominal => dimension in CAD design
Actual => true dimension
Measured => dimension estimated by measurement

target variable

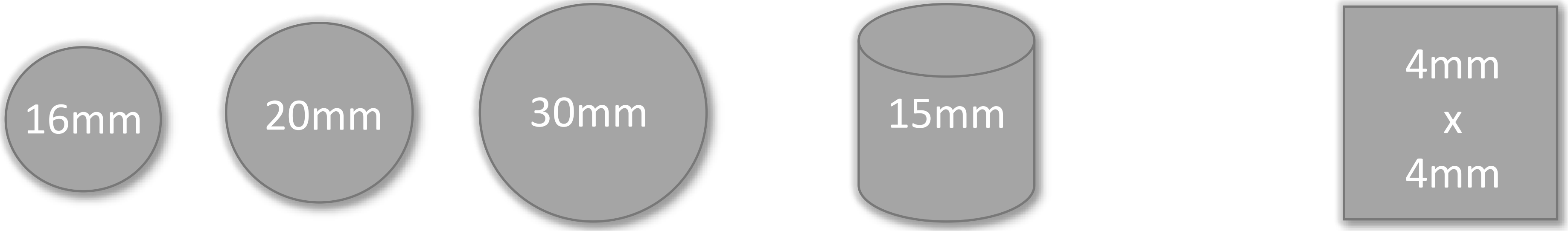
Point Measurement deviation (error):

PointDev = measured - nominal

Data Sources Description

Geometries: Sphere | Cylinder | Plane

Ground truth: Diameter | Diameter | Distance to laser



Scanning parameters

1. *Lateral Density* — low (50), medium (75), high (100)
2. *Scan Direction Density* — low (2), medium (5), high (10)
3. *Exposure time* — low (0.6), medium (0.8), high (1.0)

Laser setup

Source orientation $\vec{L}$

$\vec{L}$ *= constant (Sphere & Plane)*

$\vec{L}1, \vec{L}2$ *= constant & symmetrical wrt axis (Cylinder)*

Detector (CMOS) viewing direction $\vec{V}$

Vertical distance $Z_l \approx 90mm$

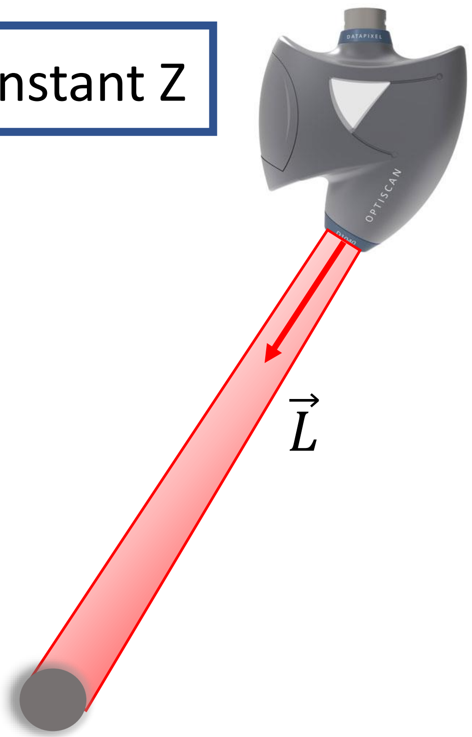
$\vec{V}$ *at 30° wrt* $\vec{L}$ *(rotate over axis of movement)*

Z_l *= constant for all measurements*

Data Sources Description

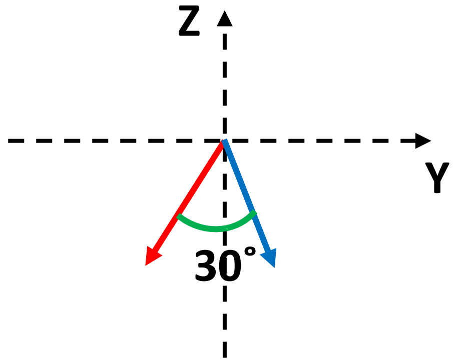
Rotary Head of Optical System

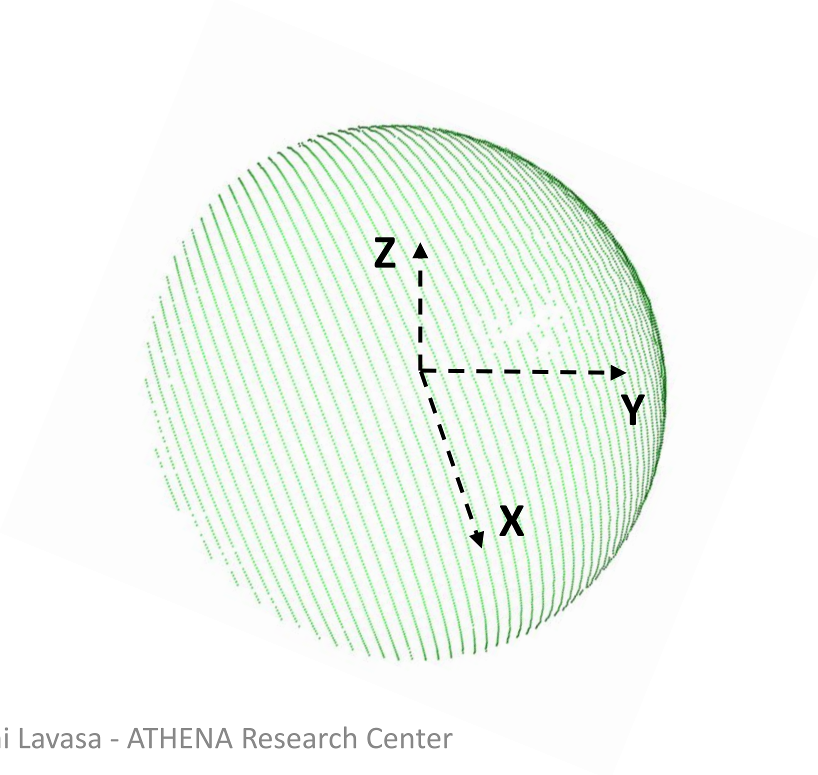
Head moves along Y-axis at constant Z



$\vec{L}$ = *Laser Source orientation vector*

$\vec{V}$ = *Detector (CMOS) viewing direction*



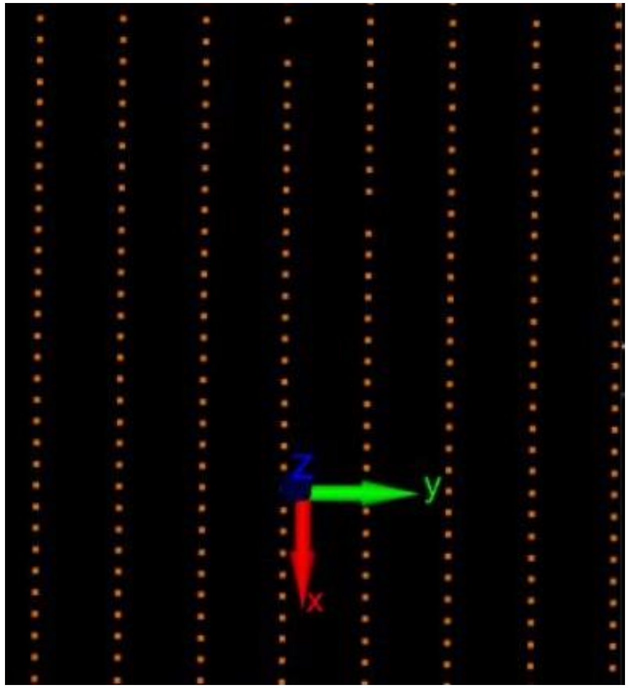


Data Sources Description

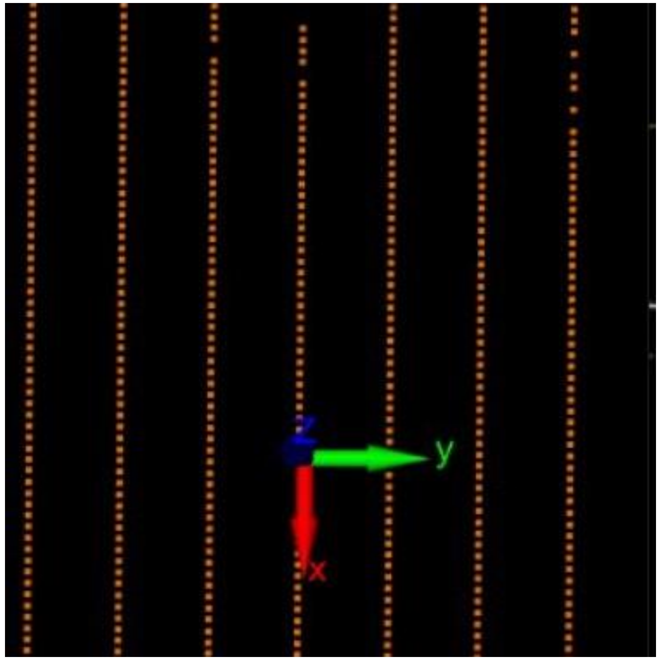
Scanning Parameters: ***Lateral Density***

Increasing point density along each line (lateral direction)

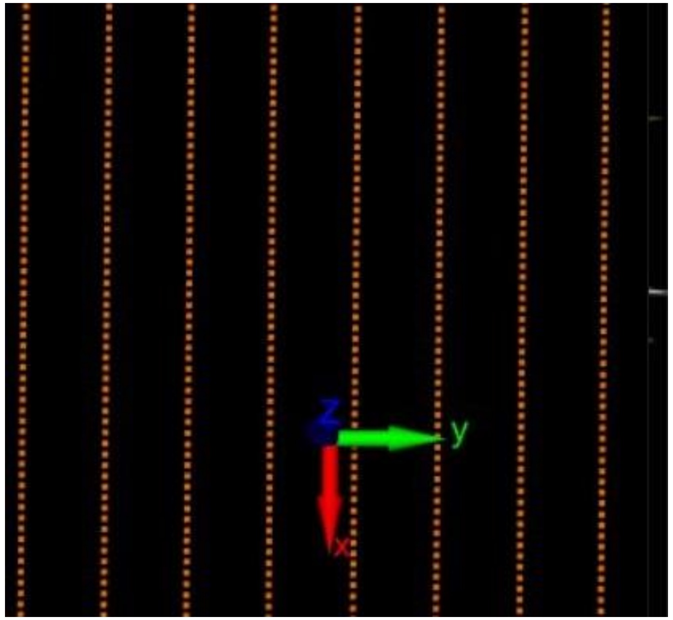
50



75



100



Data Sources Description

Scanning Parameters: *Scan Direction Density*

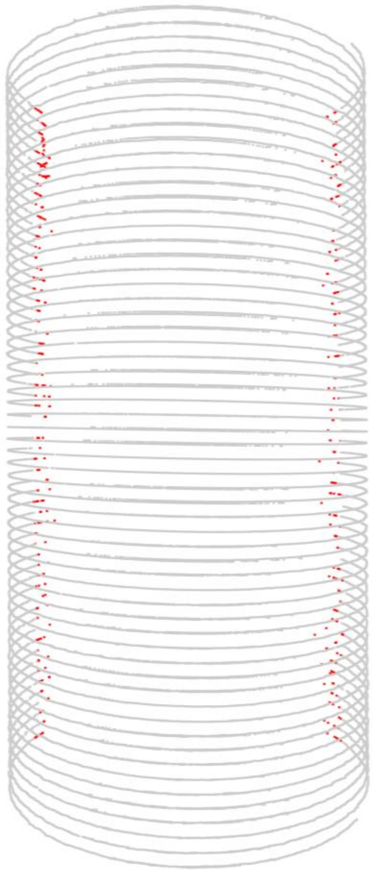
Decreasing point density in the direction of movement (sparse lines)

..increasing velocity of rotary head movement

10

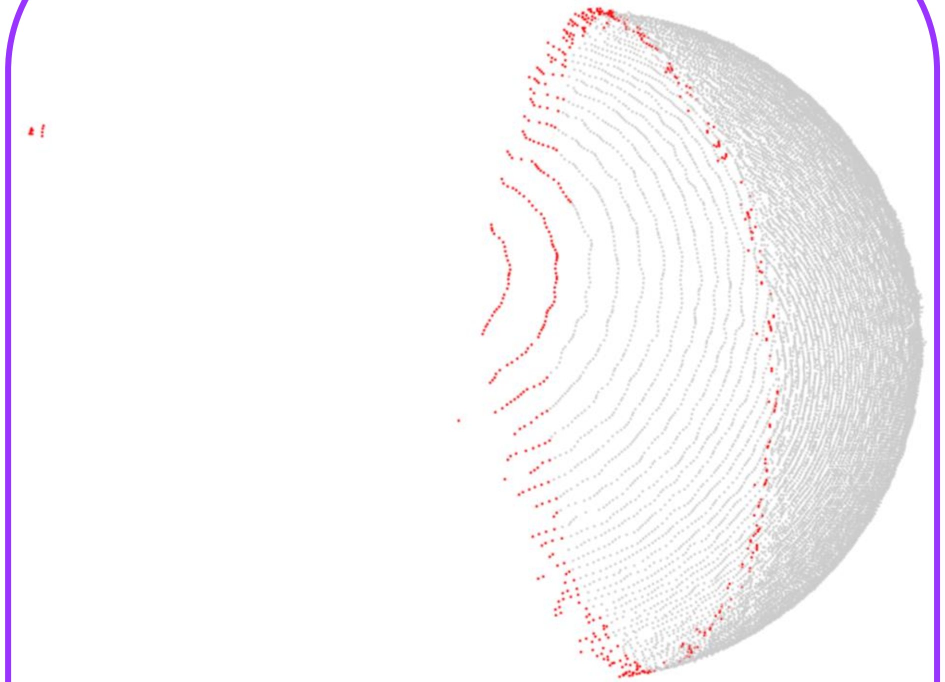
5

2



Statistical outlier removal

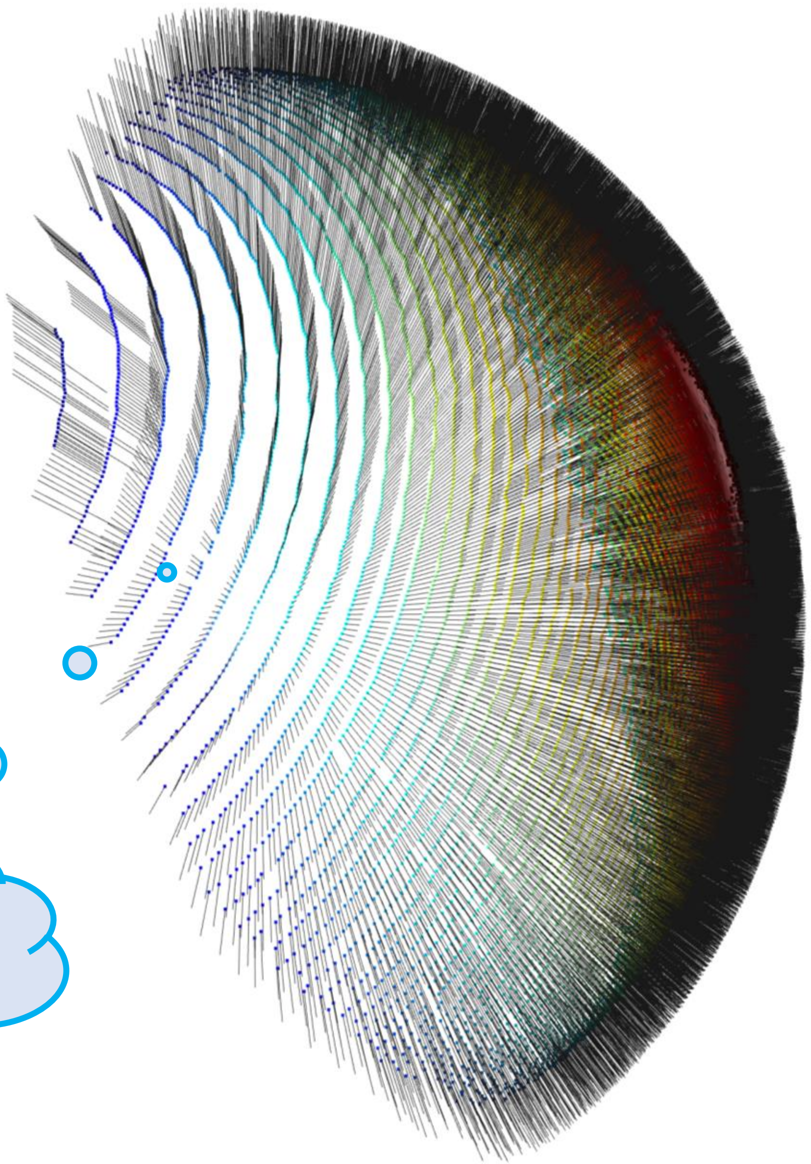
- Based on distance to nearest neighbors (number of NN, std)
- inliers: red
- outliers: grey



Estimation of normal vectors $\vec{N} = [Nx, Ny, Nz]$

- **surface orientation** at each point
- Based on nearest neighbors within a given radius (number of NN, radius)

Ensure alignment of normal vectors !



OPEN3D

Data Sources Description

Calculation of the target variable

at point P:

$P(X, Y, Z) =$ *measured point coordinates*

$P'(Xnom, Ynom, Znom) =$ *projected point coordinates*

(nominal surface)

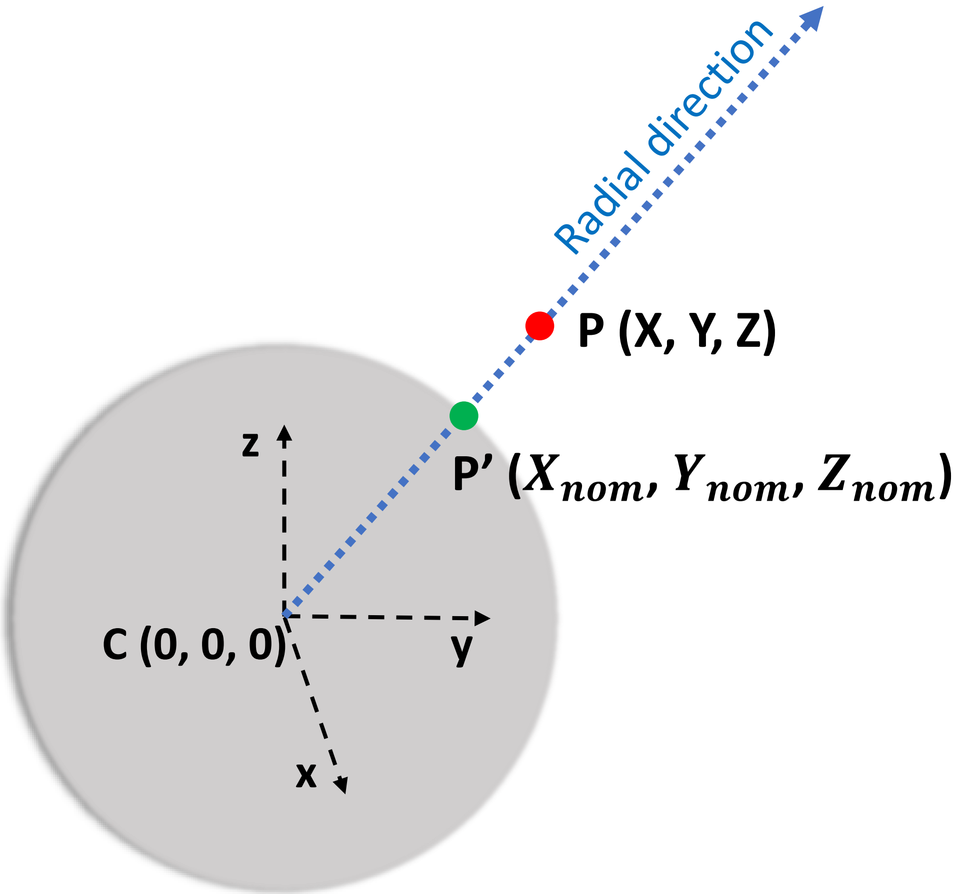
|CP| = R = **measured** point radial distance (spheres)

(cylinder: axial, plane: vertical)

|CP'| = Rnom = **nominal** radial distance = Nominal Radius

PointDev = |P'P| = R – Rnom

= **point deviation from nominal surface**



$\vec{L}$ = *Laser Source orientation vector*
$\vec{V}$ = *Detector (CMOS) viewing direction*

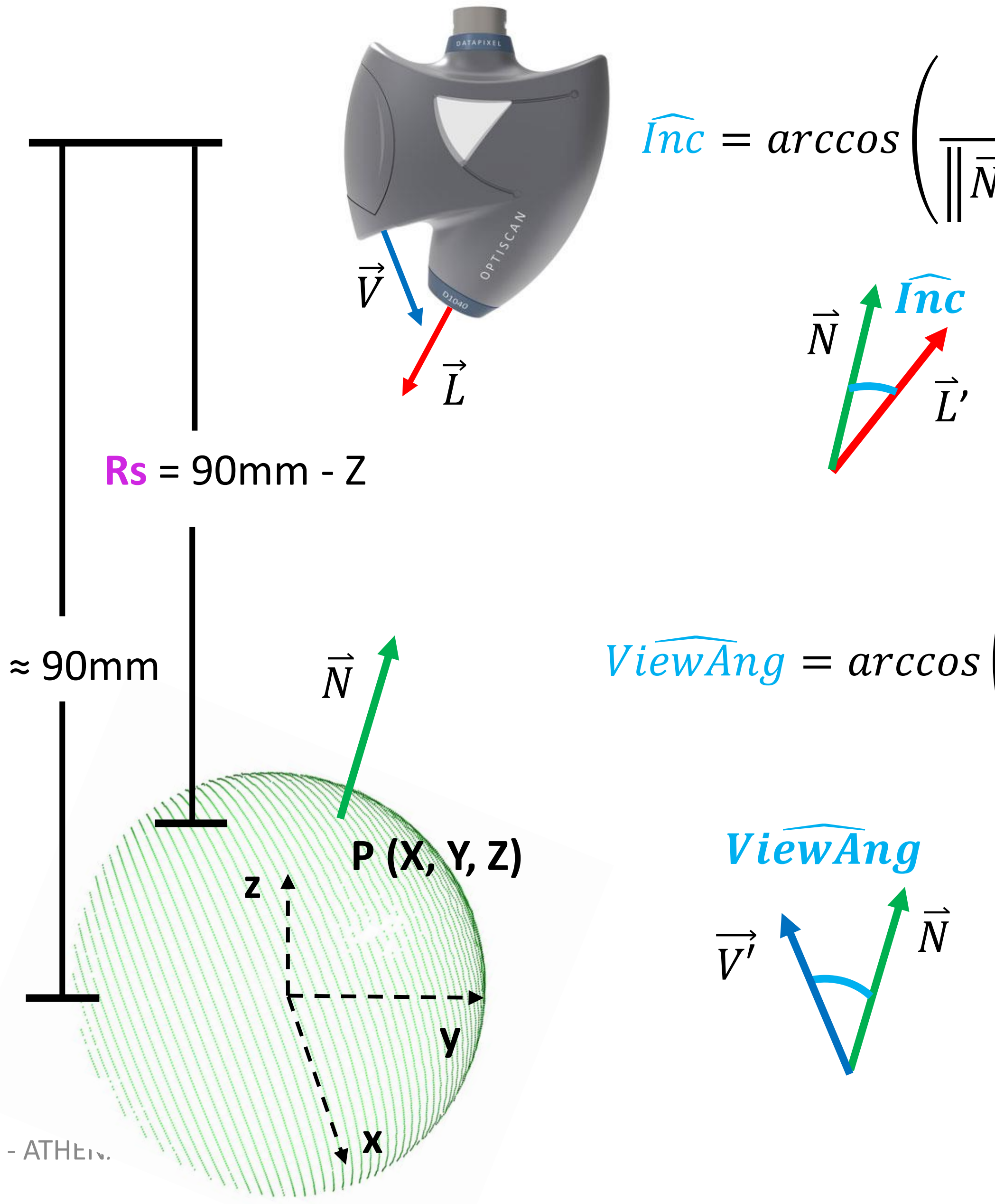
at point P:

$\vec{N} = [Nx, Ny, Nz] =$ *surface orientation*

$\widehat{Inc}$ = *incidence angle of light on surface*

$\widehat{ViewAng} = viewing\ angle\ from\ CMOS$

R_s = *Vertical distance to laser source*



$$\widehat{Inc} = arccos\left(\frac{\vec{N}.\vec{L}'}{\|\vec{N}\|.\|\vec{L}'\|}\right)$$

$$\widehat{ViewAng} = arccos\left(\frac{\vec{N}.\vec{V}}{\|\vec{N}\|.\|\vec{V}\|}\right)$$

Data Sources Description

$\vec{L}$ = *Laser Source orientation vector* $= [I, J, K]$

$\vec{V}$ = *Detector (CMOS) viewing direction* $= [I, J', K]$

at point P:

$\vec{N} = [Nx, Ny, Nz]$ $=$ *surface orientation*

$\overrightarrow{Ori} = \vec{N} - \vec{L}$ = *[OriX, OriY, OriZ]*

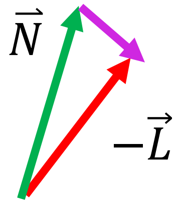
= *Orientation difference vector (surface & laser)*

$\overrightarrow{OriCMOS} = \vec{N} - \vec{V}$ = *Orientation difference vector*

(surface & CMOS sensor)

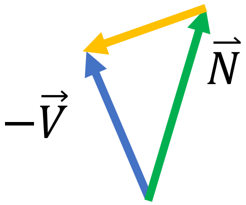
OriYcmos = *Ny – J'*

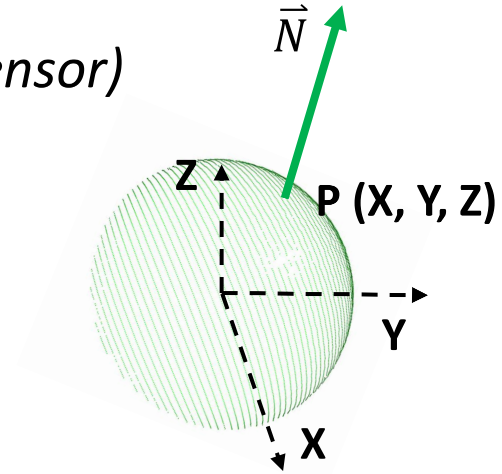
$\widehat{Ang}$ = *4-quadrant angle*



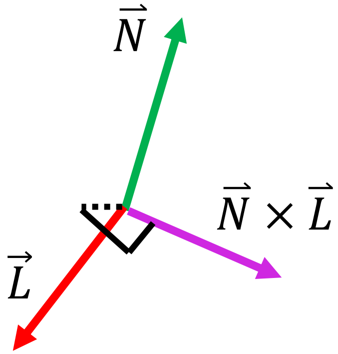
$\overrightarrow{Ori} = \vec{N} - \vec{L}$

$\overrightarrow{OriCMOS} = \vec{N} - \vec{V}$





$$\widehat{Ang} = arctan2d\left(\vec{N} \times \vec{L}, \vec{N}.\vec{L}\right)$$

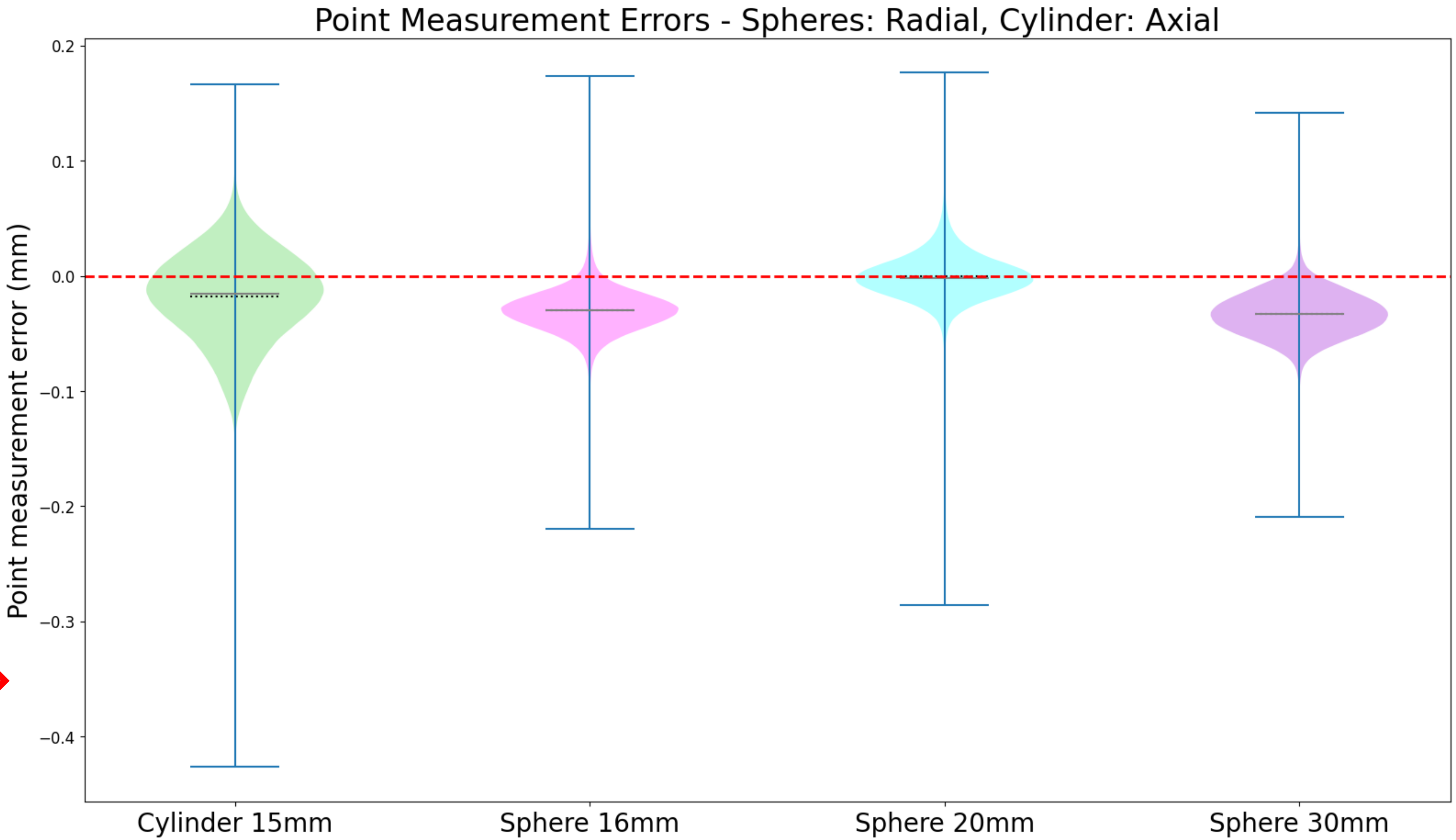


Data exploration & Analysis

Studying the behavior of the instrument

- Errors in point capture tend to be negative
- Instrument tends to under-estimate the dimension of objects

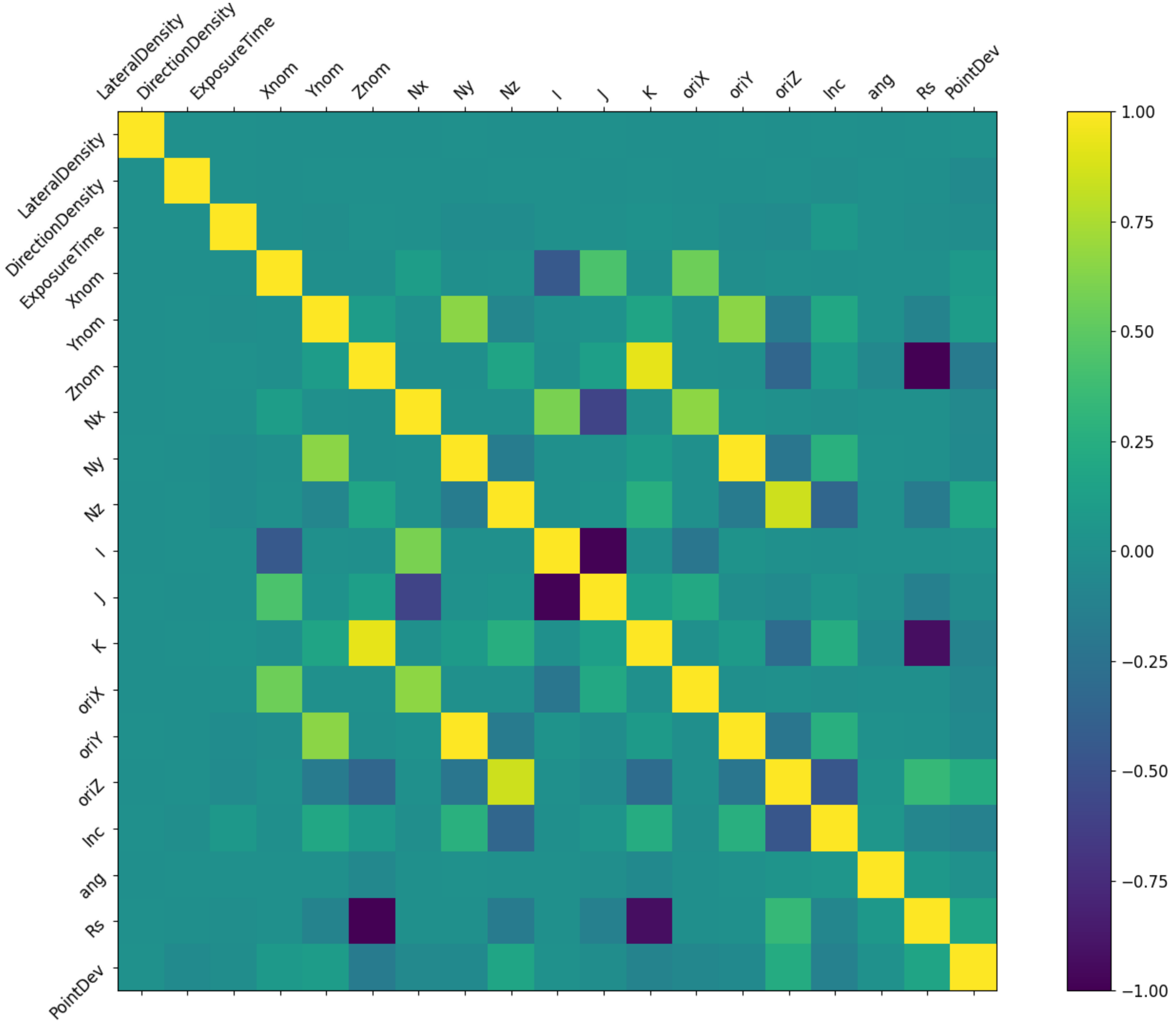
__Mean Point Error__
-0.024 ± 0.053 mm



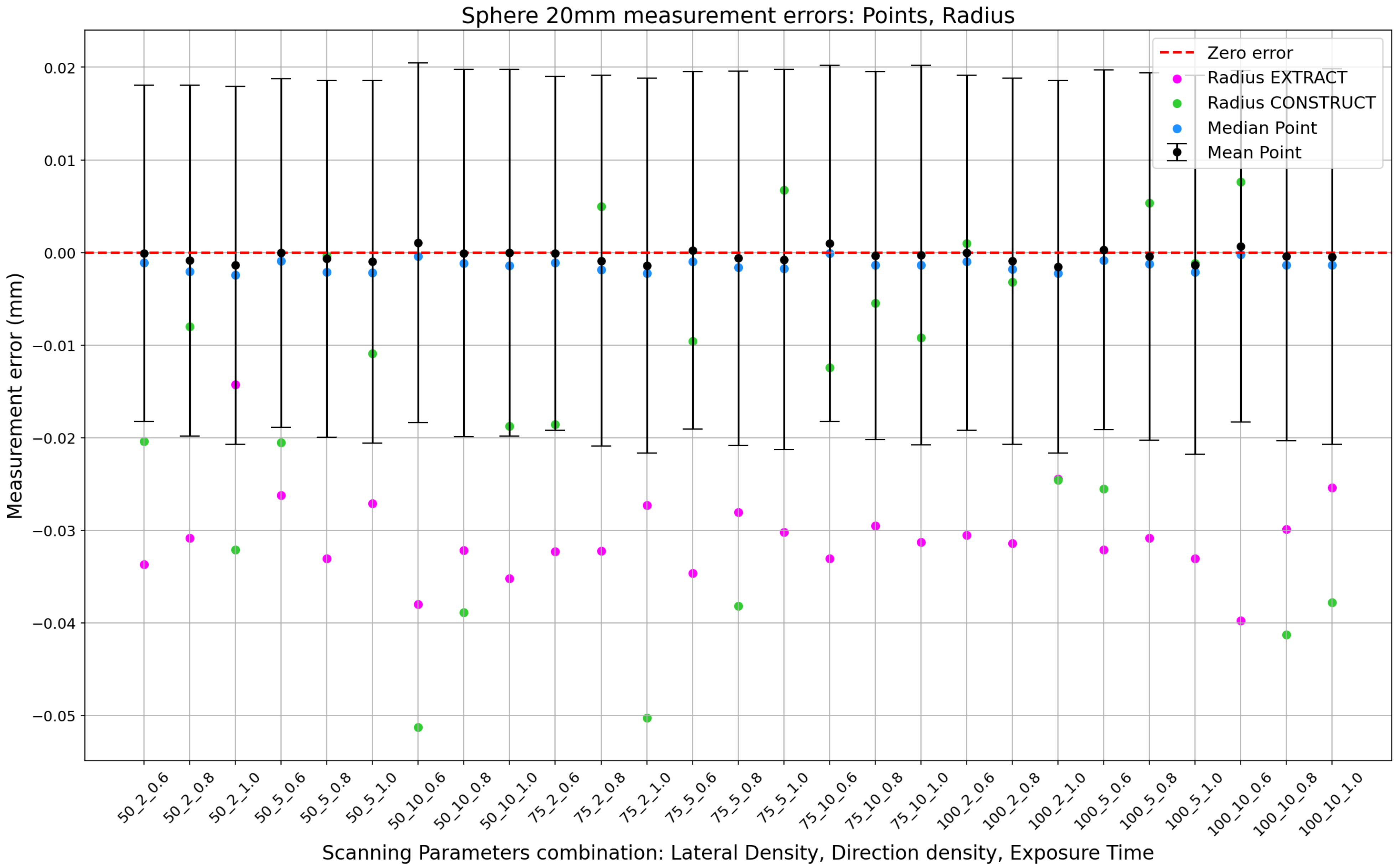
Data exploration & Analysis

Investigating (anti)correlations amongst features

- Scanning parameters (Lateral Density, Direction Density, Exposure Time) are not related to the target variable, Point measurement error (PointDev)
- The z-component of the normal vector (Nz) and the orientation difference vector (oriZ) show minor correlation to PointDev
- Strong correlations are due to calculation formulas or bias induced by specific geometries (sphere & cylinder)

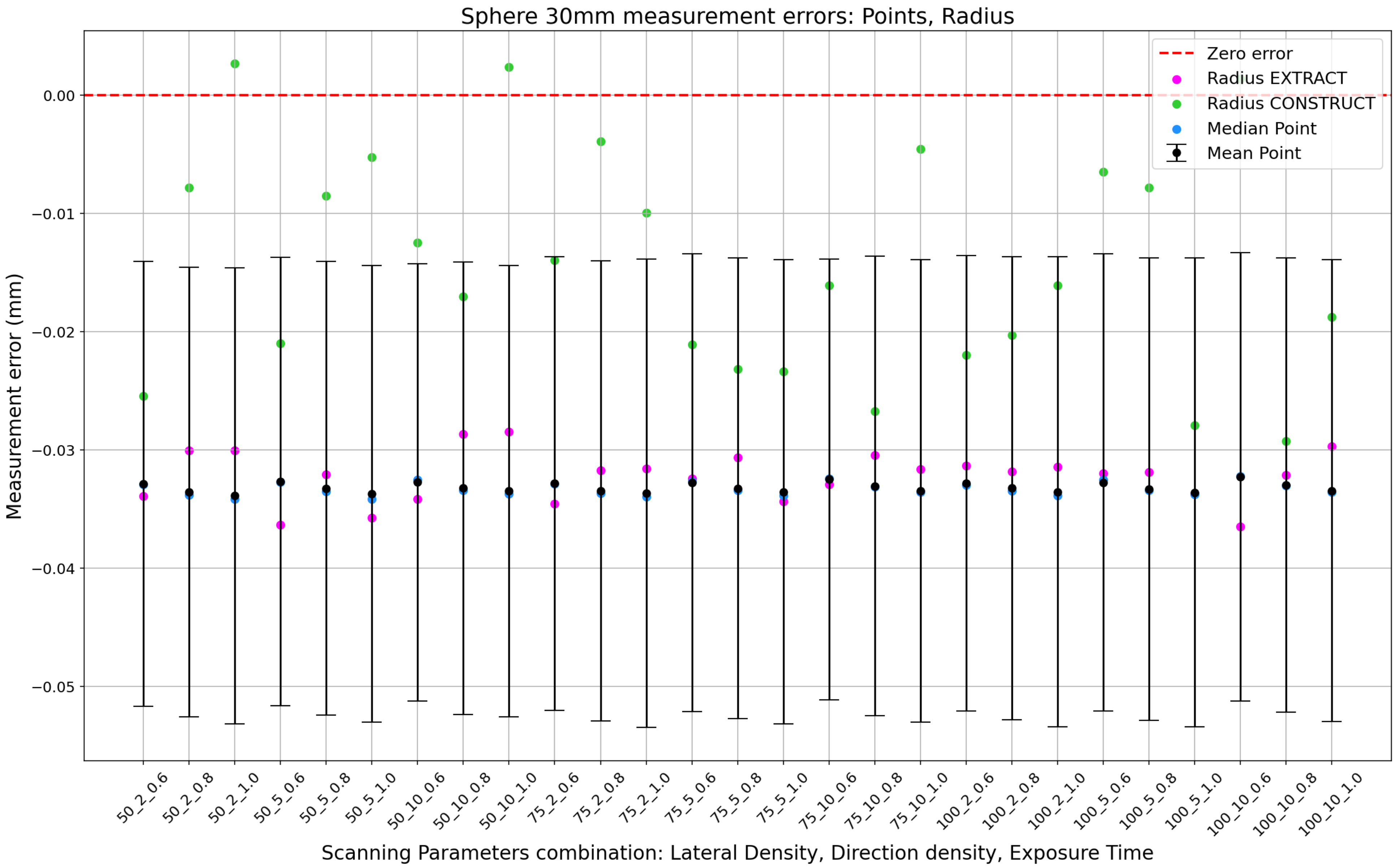


Data exploration & Analysis



- Statistical distribution of points: captures well actual surface
- Mean of radial distribution: good estimate of actual radius
- Both methods under-estimate sphere radius, method EXTRACT (Point Cloud) performs worse

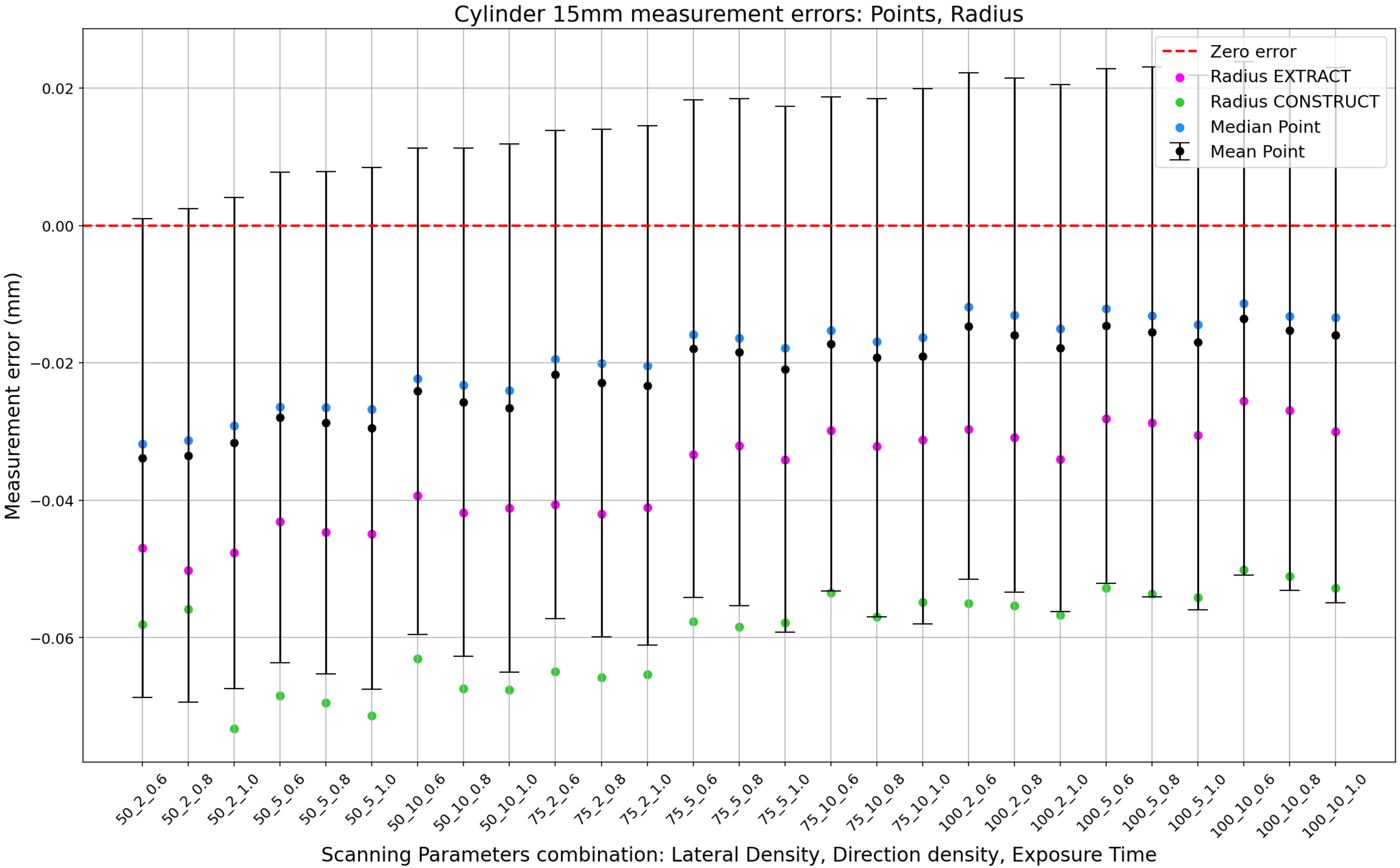
Data exploration & Analysis



- ➢ Statistical point distribution: well below actual surface
- ➢ Mean of distribution: bad estimate of radius

- ➢ Method EXTRACT (Point Cloud) under-estimates radius
- ➢ Method CONSTRUCT (Geometry Definition points) performs better

Data exploration & Analysis



- ➢ Statistical point distribution: below actual surface
- ➢ Mean of point radial distribution: good estimate of radius

- ➢ Both methods consistently under-estimate radius, Method EXTRACT (Point Cloud) performs better
- ➢ Cylinder captured better with high Lateral Density

Machine Learning Pipeline

Step 1

- Random selection of N points/point cloud
- Feature & target scaling to [0, 1] interval

Step 2

- Selection of algorithms (SVM, MLP, Decision Tree, Random Forest)
- Wide hyper-parameter grid

Step 3

- Randomized Grid search cross-validation
- Nested Cross-Validation scheme (10 fold)

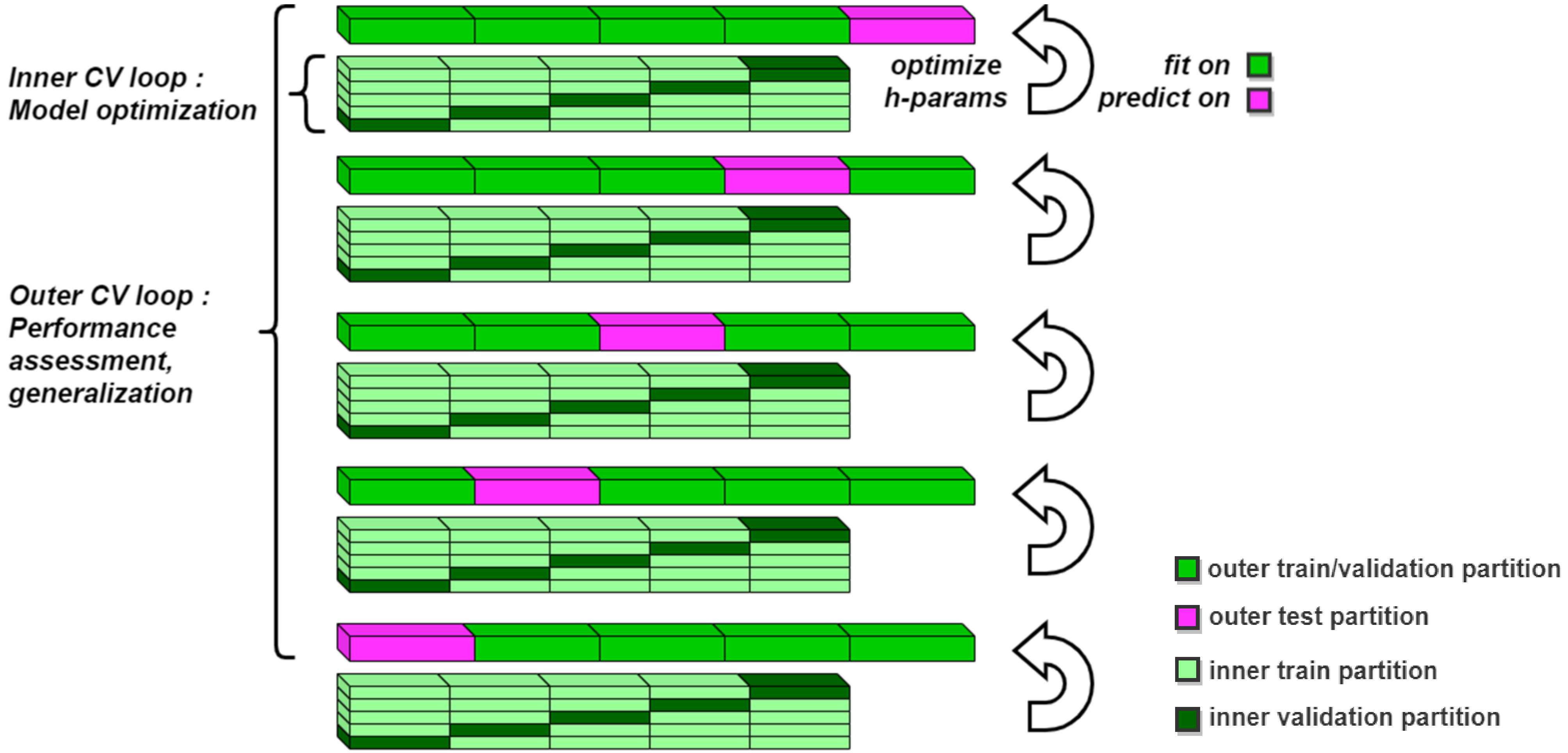
Step 4

- Optimal model retrieval based on mean validation scores

Model training, optimization & Validation

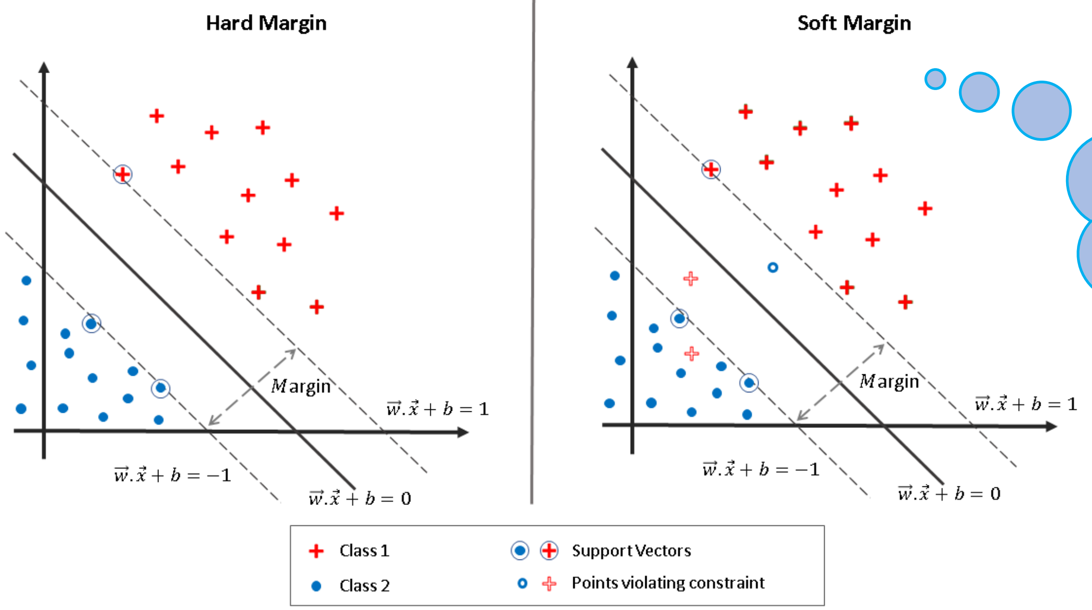
Nested Cross-Validation scheme

Self-consistent methodology to train/optimize models & assess their performance

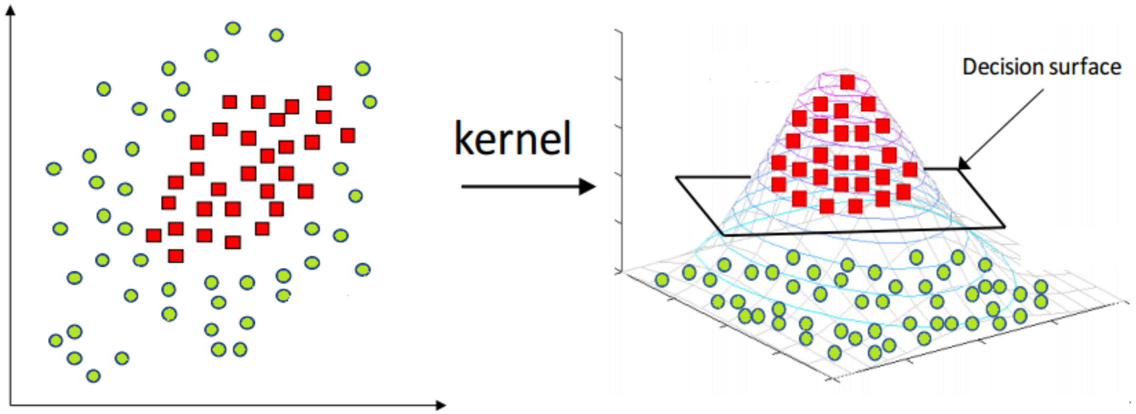


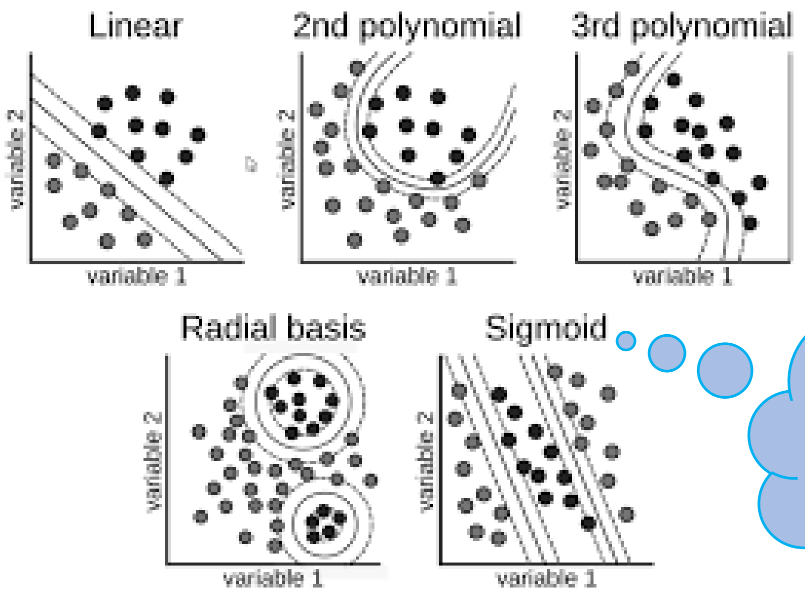
Model intuition – Support Vector Machine (SVM)

- Finds Optimal separating hyperplane (decision surface) for linearly separable patterns
- Optimal Hyperplane => maximum margin
- Support vectors => data points closest to the decision surface (points most difficult to discriminate – specify optimum location of decision surface)
- Extend to not linearly separable patterns: transformations of original data into new space – Kernel function



Hyper-parameter ***C*** controls margin
Large C => small margin



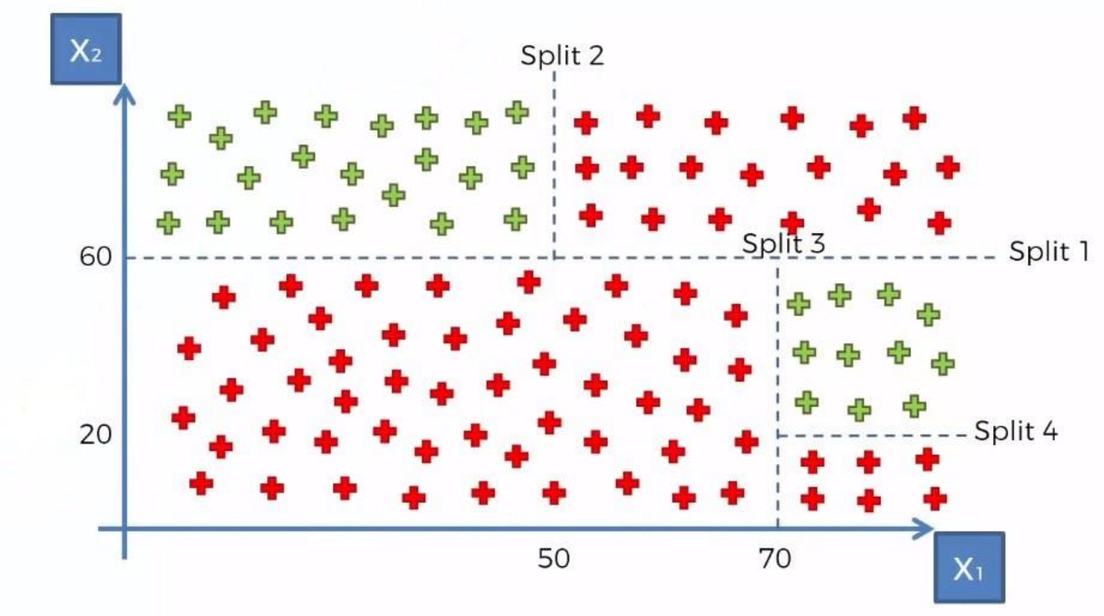


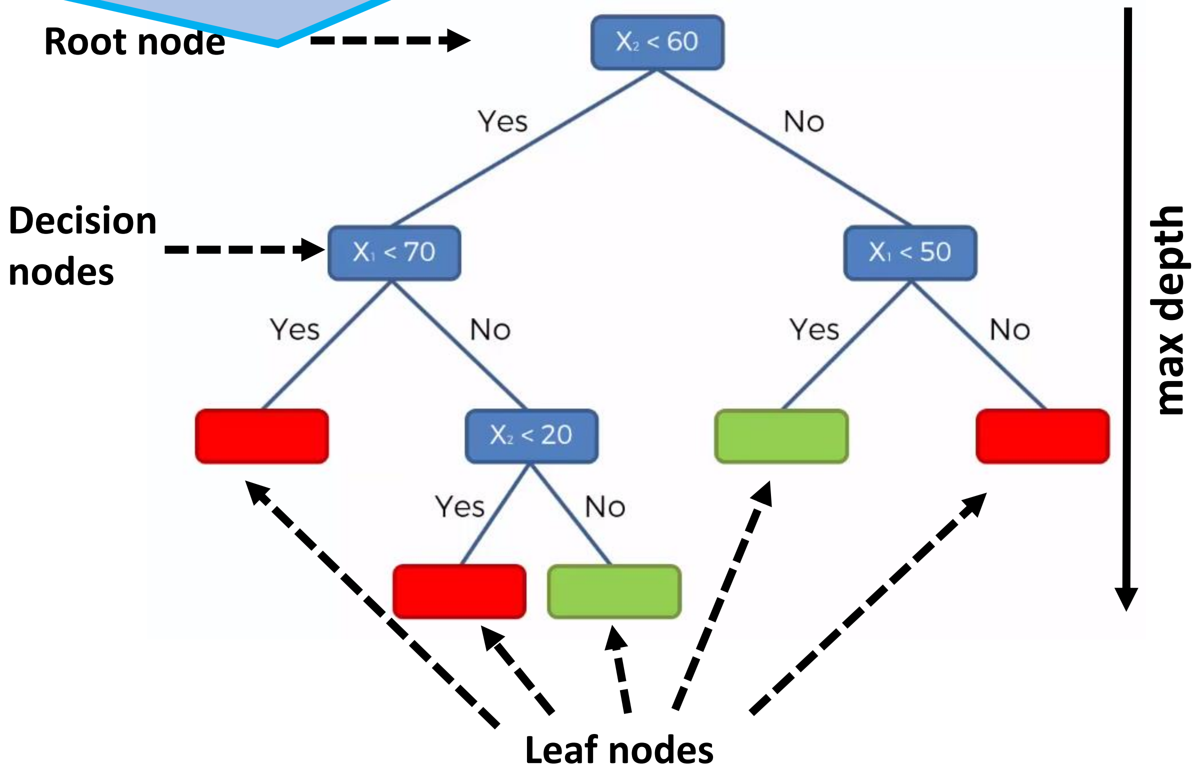
H-parameter ***kernel*** controls kernel function

Model intuition - Decision Tree

- Splits data points to maximize information gain (minimize impurity) in the resulting data partitions
- Optimal partitions contain as much as possible information and less randomness

Hyper-parameters (regression)
- *max_depth*: maximum depth of the tree (max # of decision levels)
- *splitter*: strategy to perform splits (“best”, “random”)
- *split_criterion*: function to measure quality of split (“squared_error”, …)
- *min_samples_split*: minimum # of samples to split decision nodes
- *min_samples_leaf*: minimum # of samples at leaf nodes

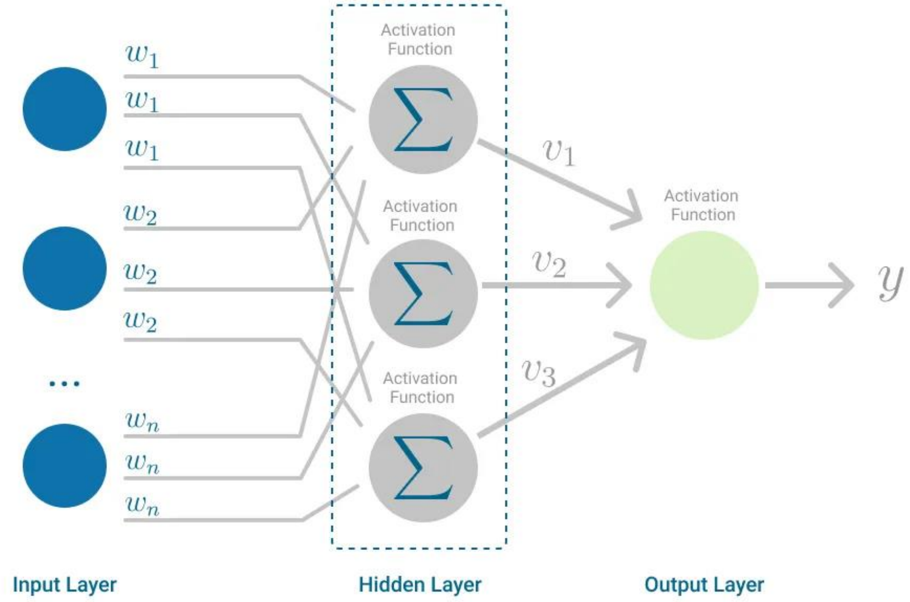


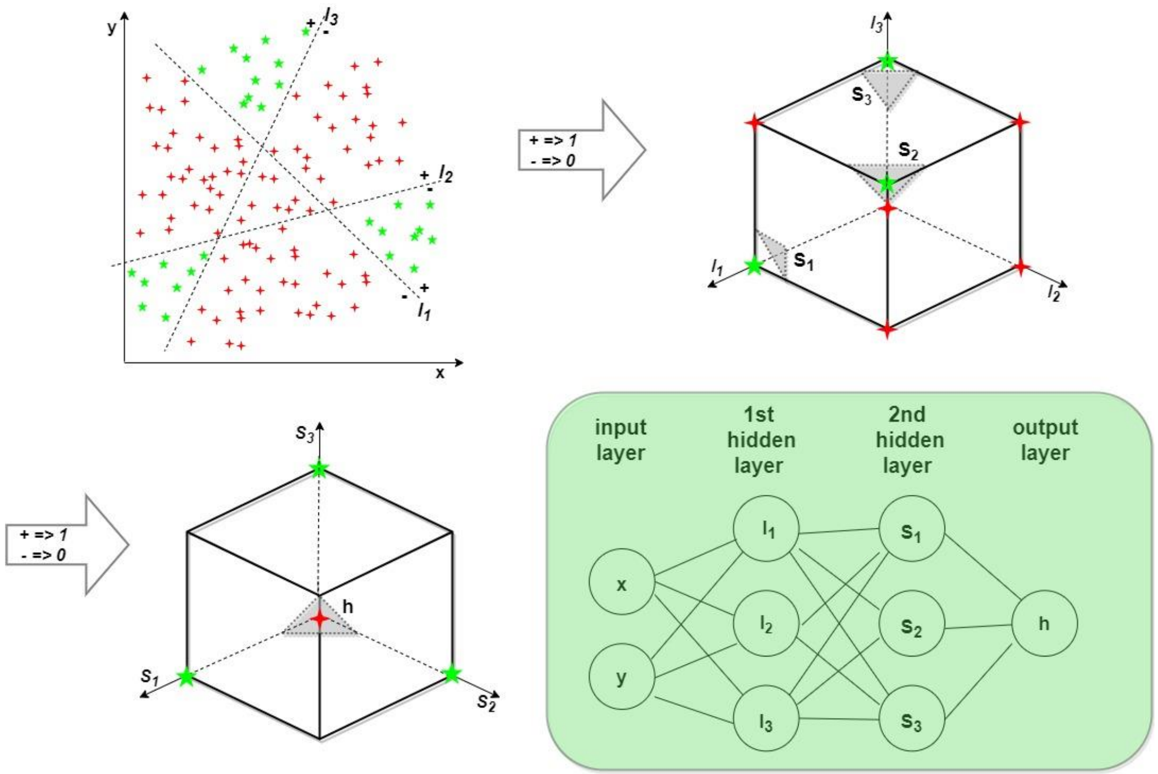


Model intuition - Multi-layer Perceptron (MLP)

- Sequentially transforms input into higher dimensional spaces: samples can be discriminated
- Neuron: basic unit of computation, receives inputs & weights (for each input)
- At each neuron: inputs combined in a weighted sum
- If weighted sum exceeds predefined threshold: neuron activation, output production
- Threshold represented by activation function

Hyper-parameters
- *hidden_layer_sizes*: the number of neurons in each hidden layer
- *activation*: Activation function(“logistic”, “relu”…)
- *solver*: the algorithm for weight optimization (“sgd”, “adam”, …)





ML Experimental results – Model performance

Optimal SVM model

Hyperparameters = {

kernel: RBF,

C: 10.0}

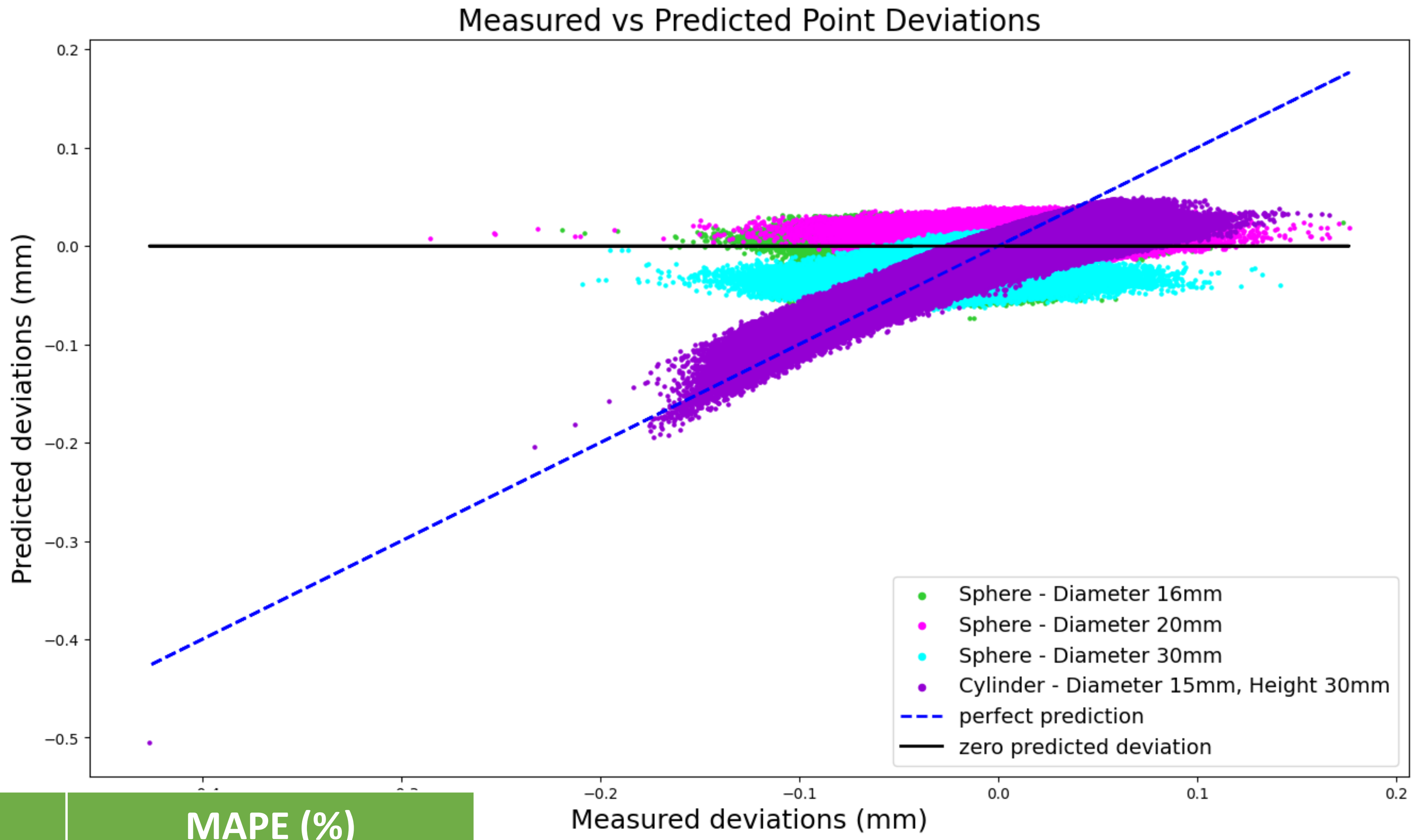
Predictions on spheres

Large deviations from actual

Flat distribution

Predictions on cylinder

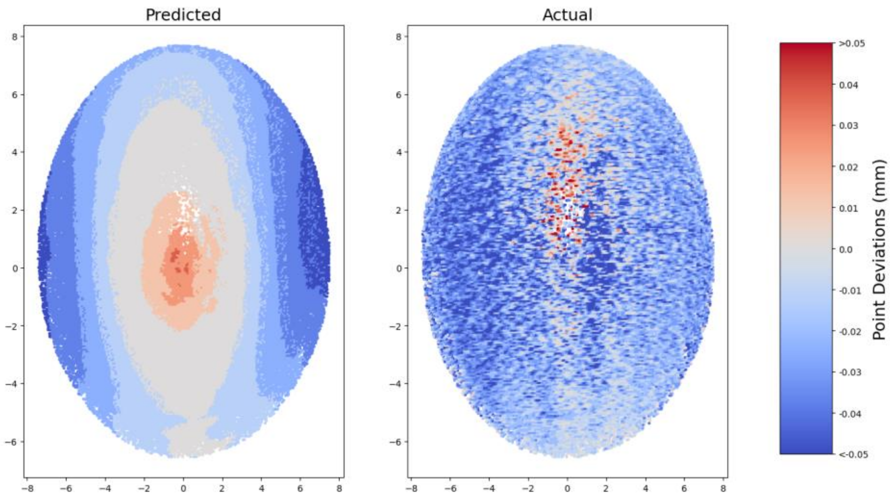
better approximation of truth



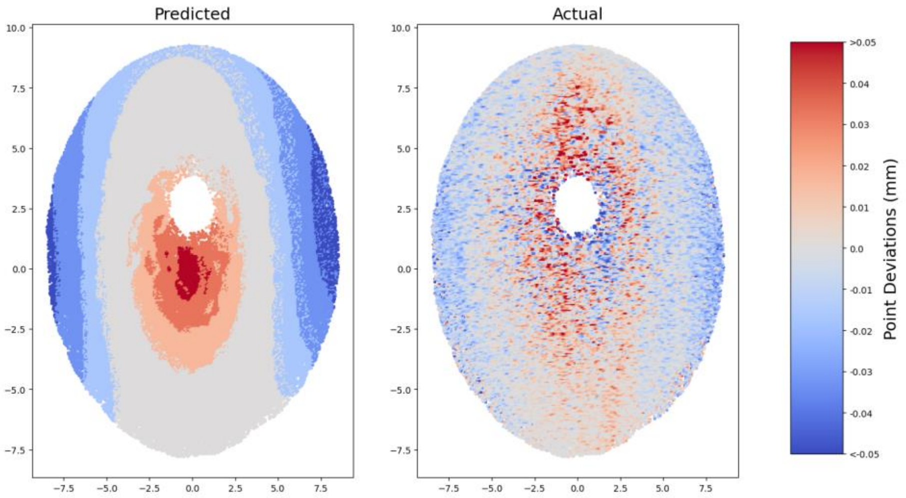
	MAE (mm)	MAPE (%)
Mean Validation score	0.026 ± 0.002	3.24 ± 0.03
Mean Test score	0.028 ± 0.004	3.4 ± 0.1

ML Experimental results – Visualize predictions

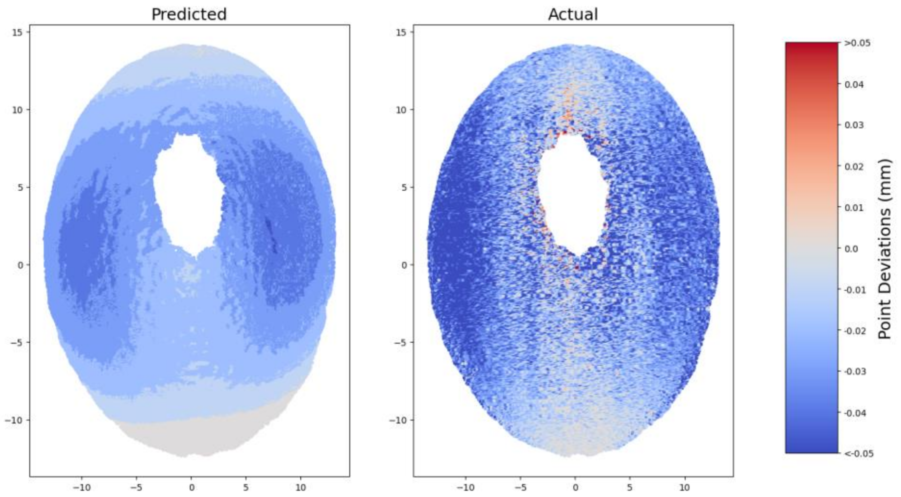
Sphere 16.0026mm, Lateral Density=50, Direction Density=2, Exposure Time=1.0



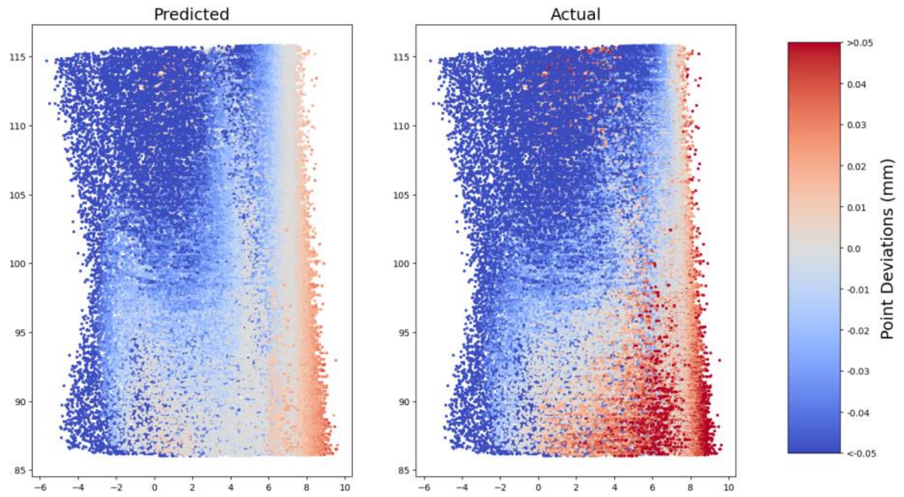
Sphere 20.0118mm, Lateral Density=50, Direction Density=2, Exposure Time=1.0



Sphere 30.0085mm, Lateral Density=50, Direction Density=2, Exposure Time=1.0

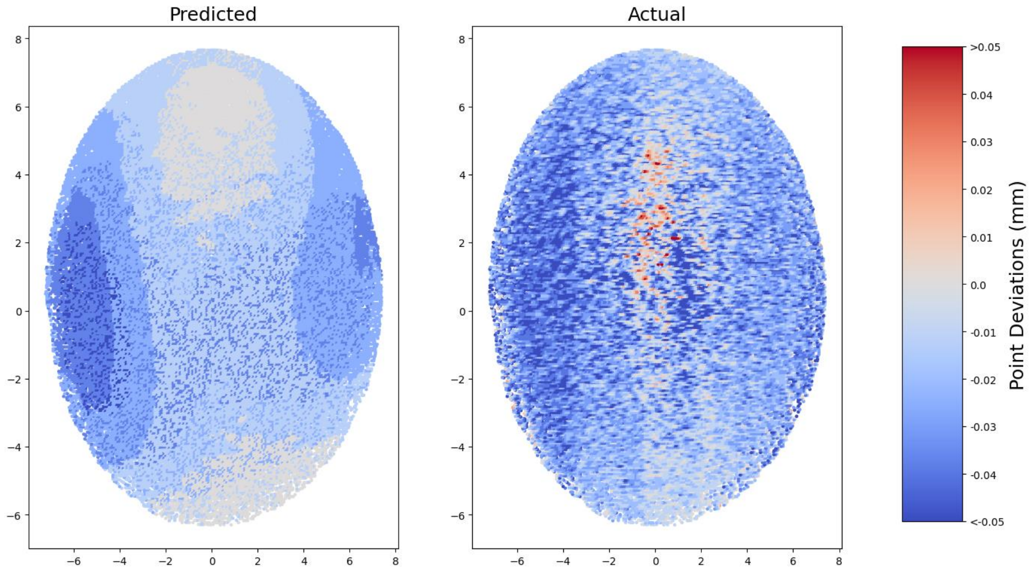


Cylinder 15.0219mm, Lateral Density=50, Direction Density=2, Exposure Time=1.0

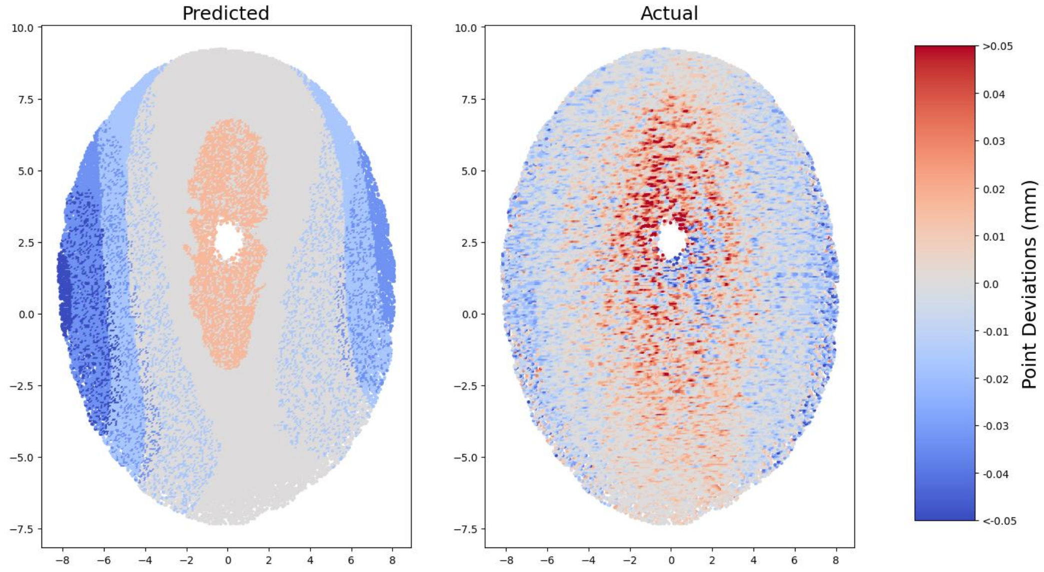


ML Experimental results – Visualize predictions

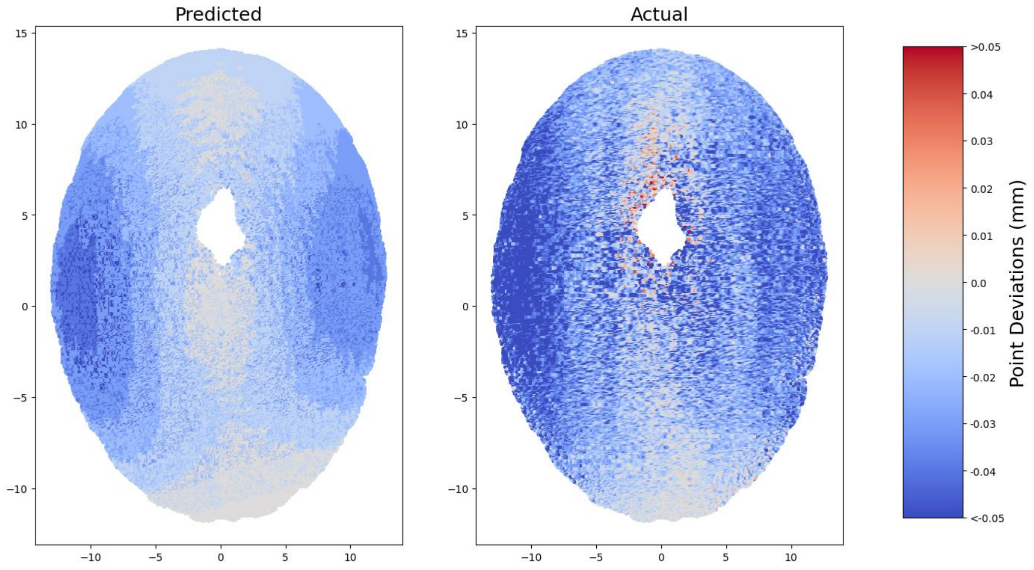
Sphere 16.0026mm, Lateral Density=50, Direction Density=2, Exposure Time=0.6



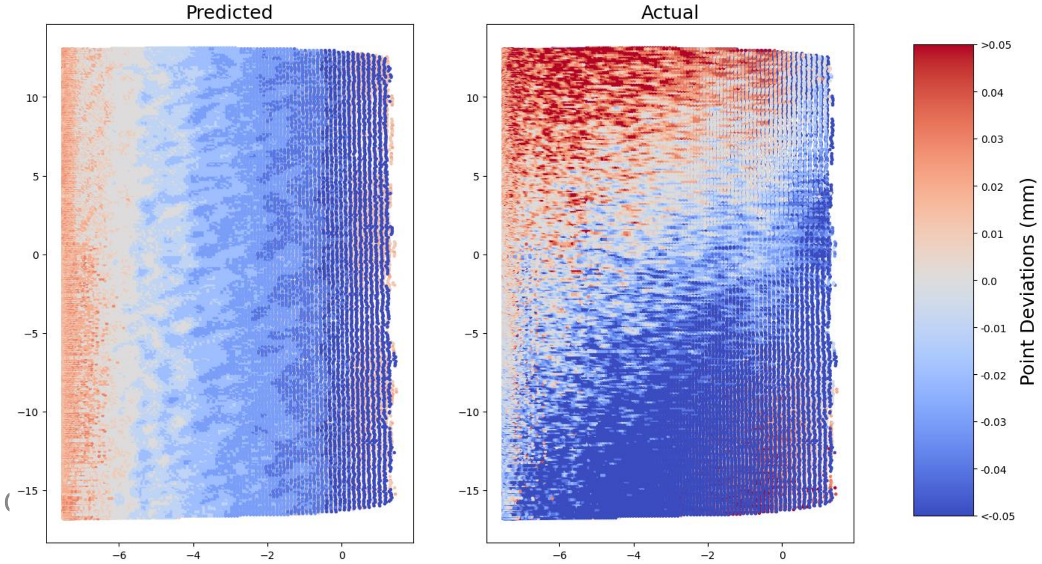
Sphere 20.0118mm, Lateral Density=50, Direction Density=2, Exposure Time=0.6



Sphere 30.0085mm, Lateral Density=50, Direction Density=2, Exposure Time=0.6



Cylinder 15.0219mm, Lateral Density=50, Direction Density=2, Exposure Time=0.6



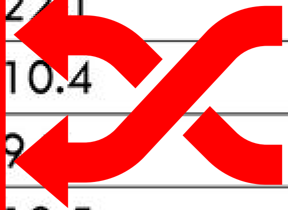
Model Explanations - Feature Importance methods

Permutation Feature Importance

- Permute each feature by random shuffle of values
- Compute the decrease in model performance scores
- Repeat N times
- Calculate mean decrease & std in performance scores

Computed independently for each feature …
Permutation Importance scores **do not** add up to 1

	TV	Radio	Newspaper	Sales
0	230.1	37.8	69.2	22.1
1	44.5	39.3	45.1	10.4
2	17.2	45.9	69.3	9
3	151.5	41.3	58.5	18.5
4	180.8	10.8	58.4	12.9

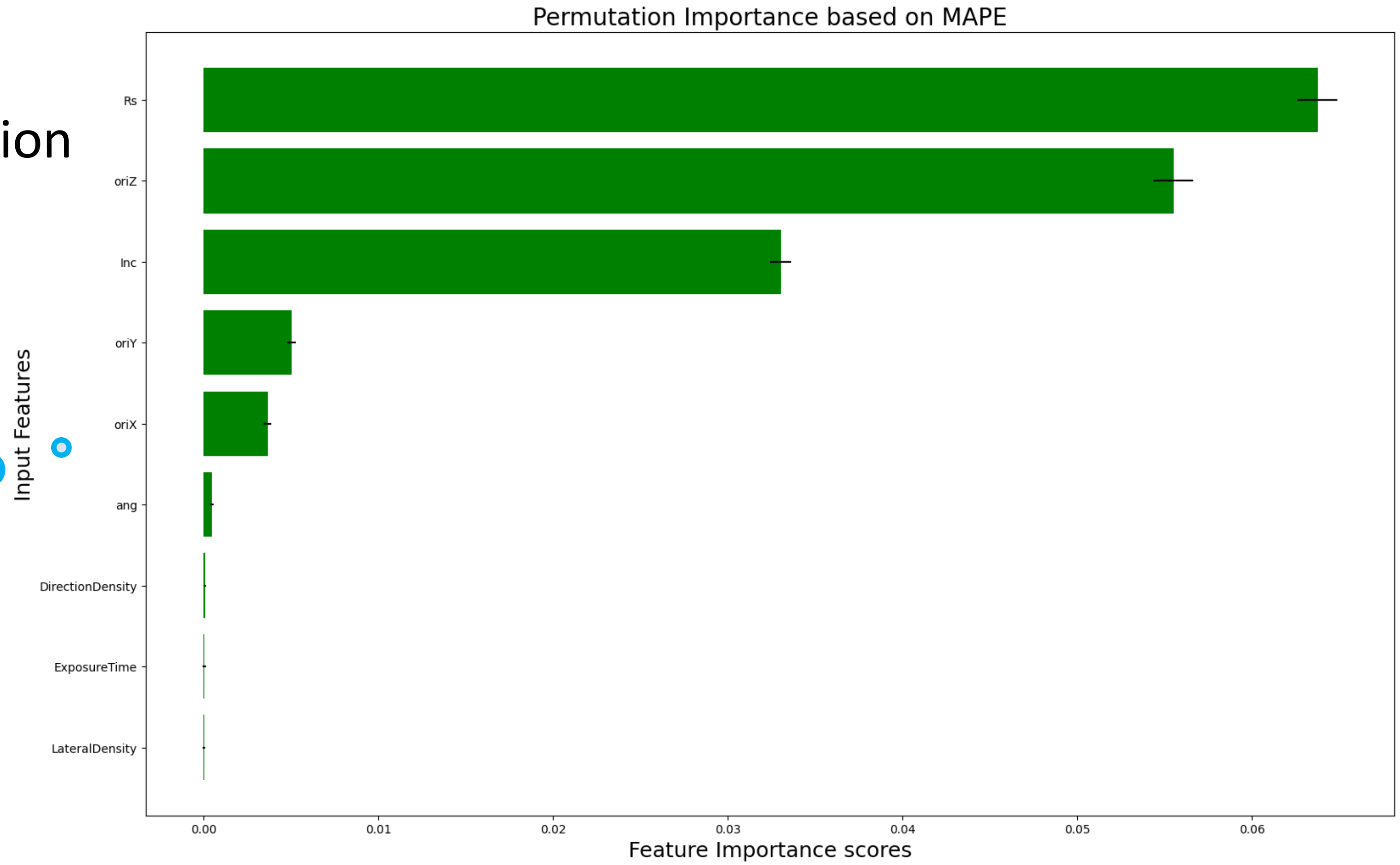


Model Explanations

Features with high effect on model's output:

- *Rs* = Distance to laser source
- *oriZ* = z-component of Orientation difference vector
- *Inc* = Incidence angle

Very low importance scores **< 7%**

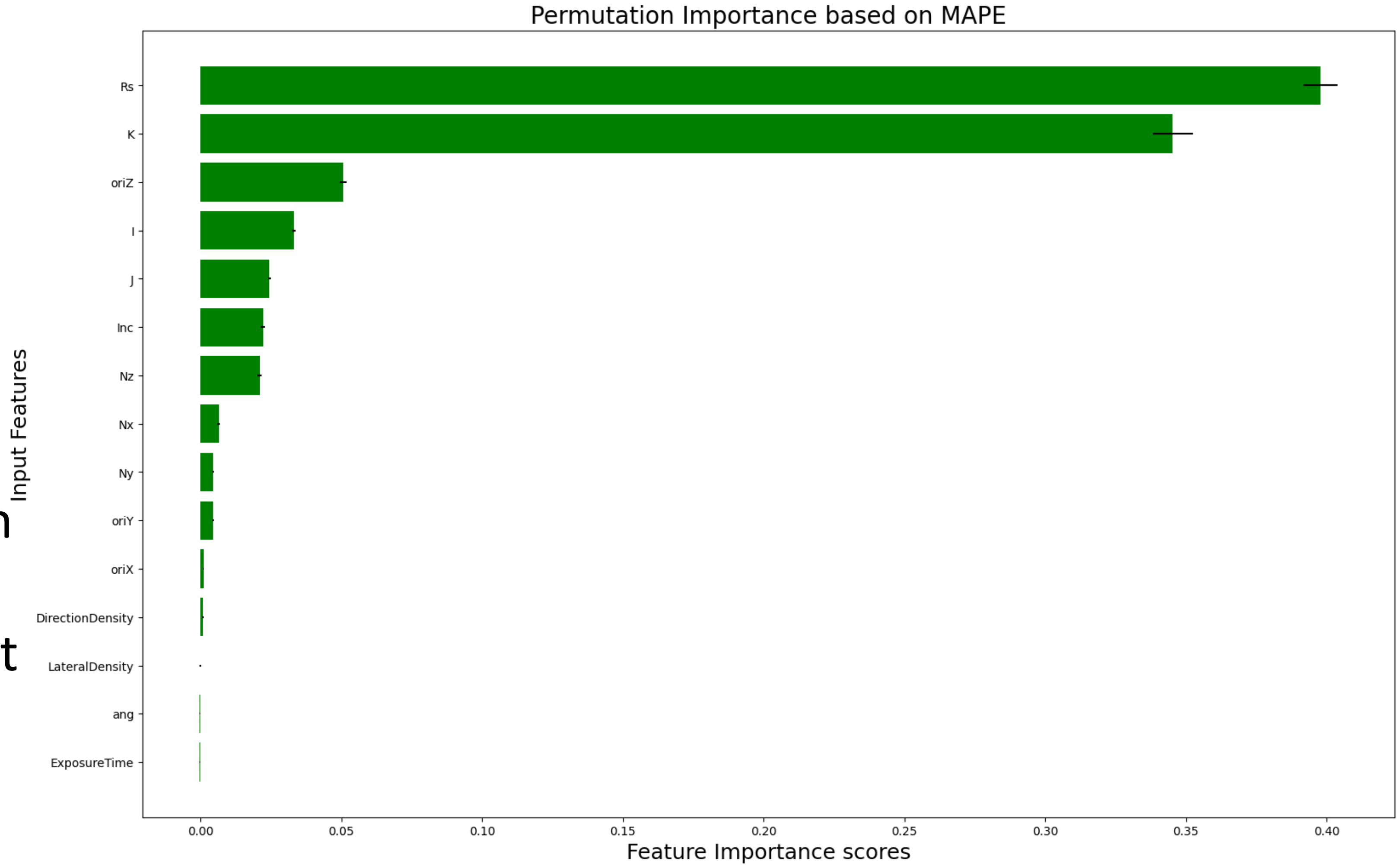


Model Explanations

Features with high effect on model's output:

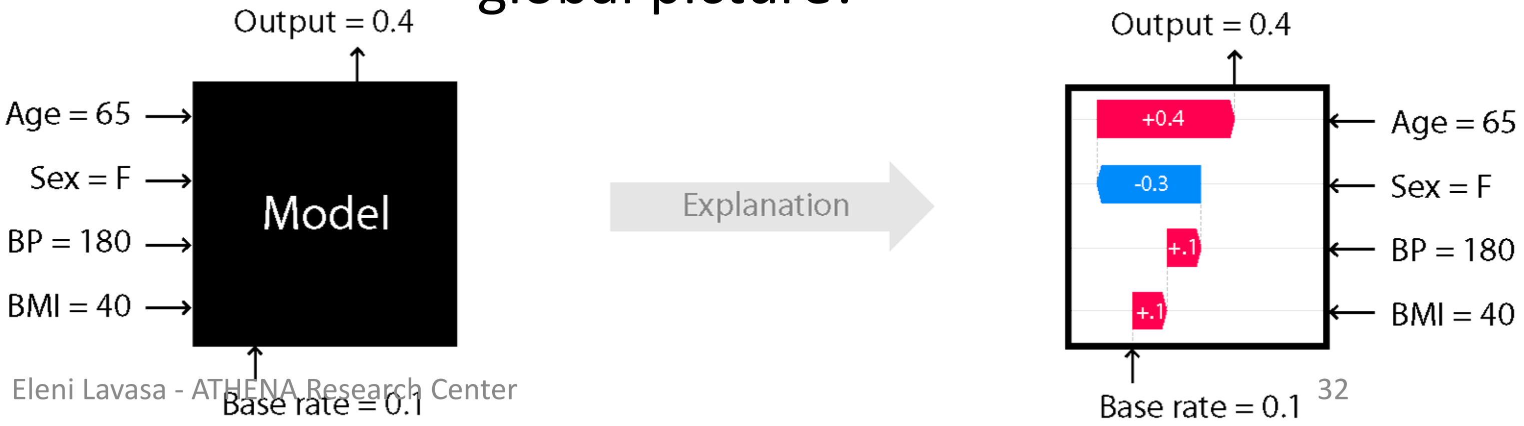
- ➢ Rs = Distance to laser source
- ➢ K = z-component of laser source direction

- ➢ Features *Rs, K* have ~8-10 times higher importance than the rest
- ➢ Features *Rs, K* have significant impact on model's predictions: 35-40%



SHAP – SHapley **A**dditive ex**P**lanations

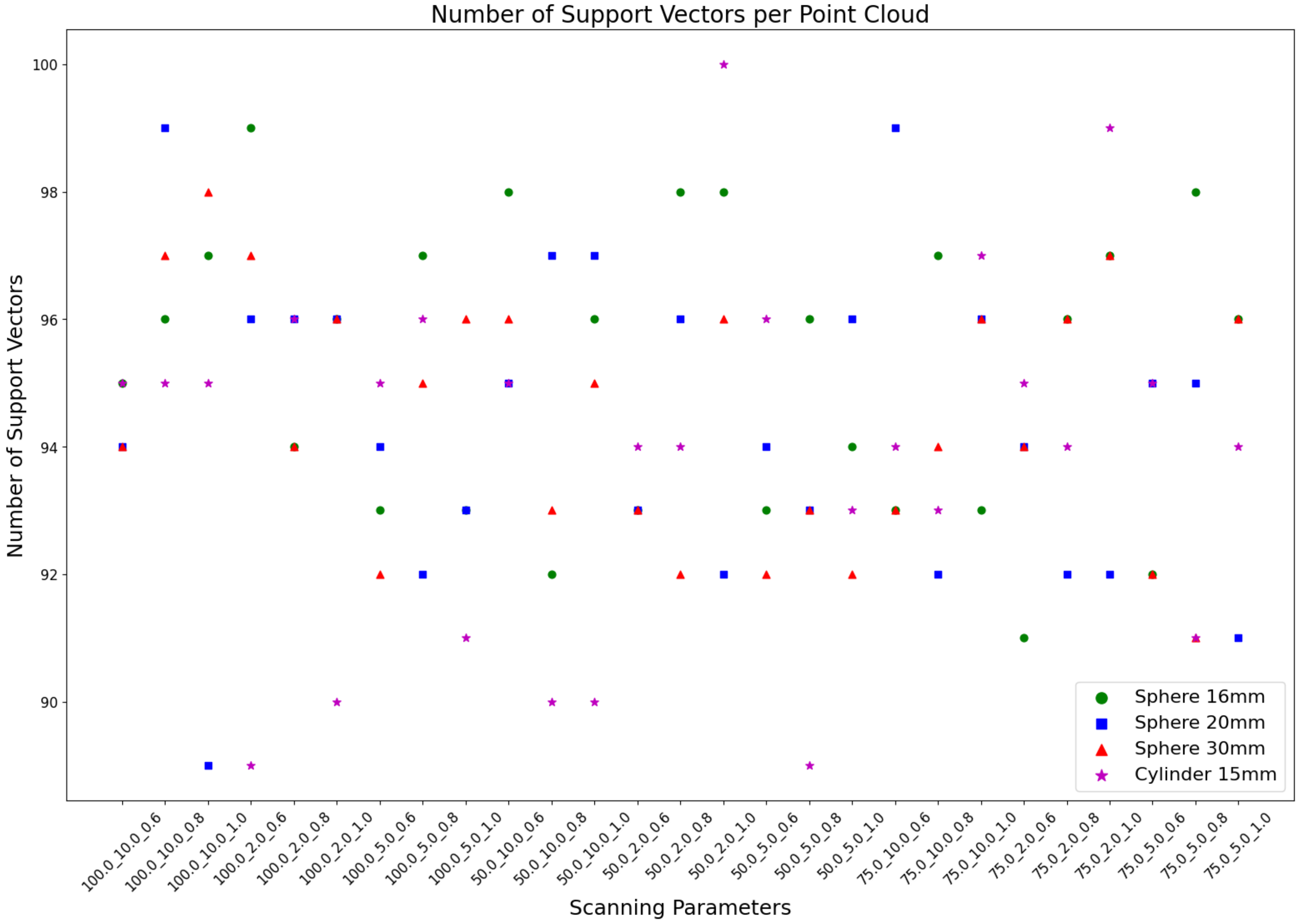
- Based on Shapley values from cooperative game theory
- Shapley quantifies the contribution of each player to the outcome of the game, considering every possible coalition of players
- SHAP quantifies the contribution each feature brings to each prediction of the ML model, considering all possible combinations of input features
- Builds one predictive model per combination of features, sequentially including more features: estimates the marginal contribution of each feature to the final outcome
- Aggregation of local explanations: global picture!



Model Explanations

Retrieve Support Vectors (SV):

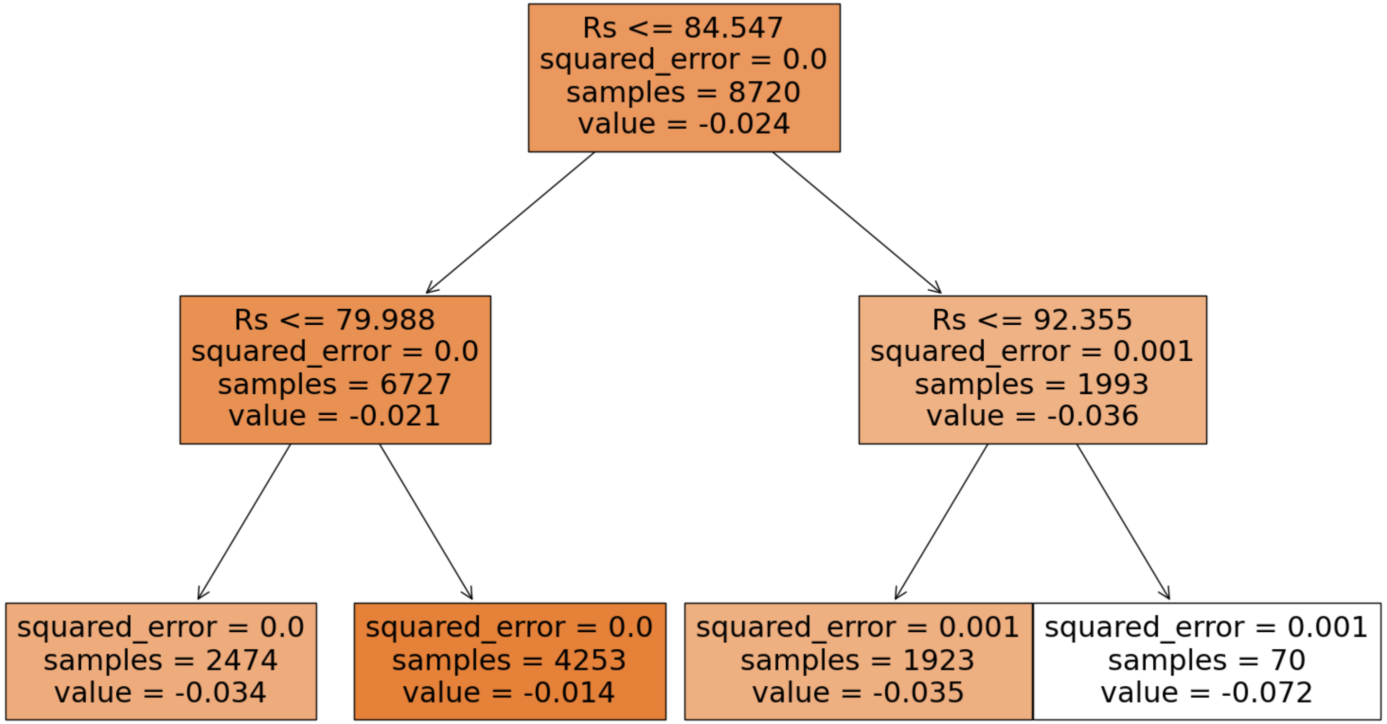
- 90-100 SVs per Point Cloud
- Training samples per Point Cloud = 100
  - SVs ≈ training samples!



Model Explanations – Global surrogate

Decision Tree to explain trained SVM

- Depth = 2
- MAE = 0.014 (mm)



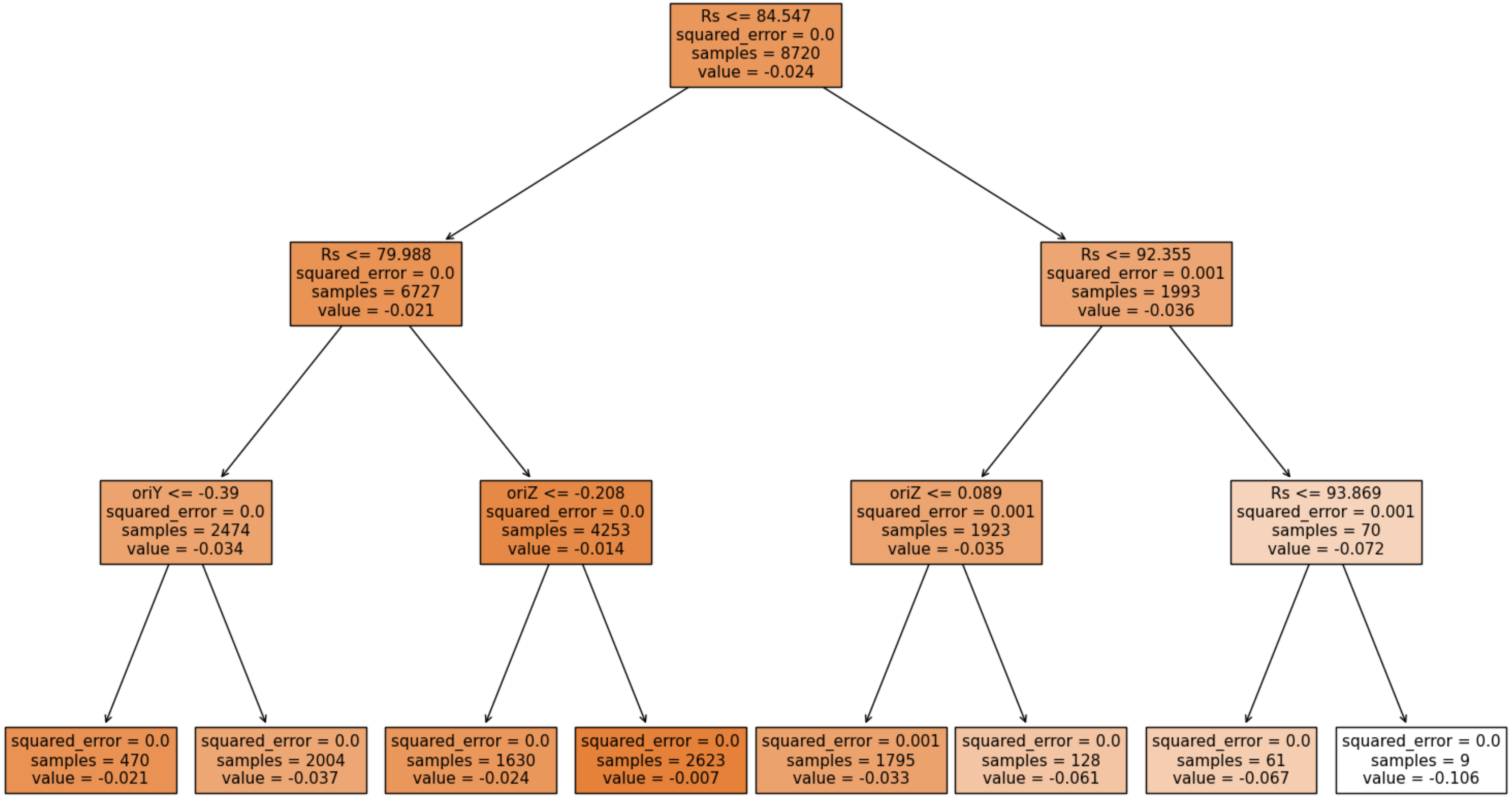
Decision Rules

```
|--- Rs <= 84.55
|   |--- Rs <= 79.99
|   |   |--- value: [-0.03]
|   |--- Rs >  79.99
|   |   |--- value: [-0.01]
|--- Rs >  84.55
|   |--- Rs <= 92.35
|   |   |--- value: [-0.03]
|   |--- Rs >  92.35
|   |   |--- value: [-0.07]
```

Model Explanations – Global Surrogate

Decision Tree to explain trained SVM

- Depth = 3
- MAE = 0.012 (mm)



Decision Rules

```
|--- Rs <= 84.55
|   |--- Rs <= 79.99
|   |   |--- oriY <= -0.39
|   |   |   |--- value: [-0.02]
|   |   |--- oriY >  -0.39
|   |   |   |--- value: [-0.04]
|   |--- Rs >  79.99
|   |   |--- oriZ <= -0.21
|   |   |   |--- value: [-0.02]
|   |   |--- oriZ >  -0.21
|   |   |   |--- value: [-0.01]
|--- Rs >  84.55
|   |--- Rs <= 92.35
|   |   |--- oriZ <= 0.09
|   |   |   |--- value: [-0.03]
|   |   |--- oriZ >  0.09
|   |   |   |--- value: [-0.06]
|   |--- Rs >  92.35
|   |   |--- Rs <= 93.87
|   |   |   |--- value: [-0.07]
|   |   |--- Rs >  93.87
|   |   |   |--- value: [-0.11]
```

Conclusions – Next Steps

Prediction of point-wise measurement accuracy

- Extraction of additional features
- More measurements needed (different geometries, fine granulation of scanning parameters)
- Repeat experiments for concave/complex geometries (different laser setup)

Relate point deviations to the target of the measurement

- Use Open3D to fit nominal geometries, calculate dimension & estimate uncertainty

New problem statement

- Unsupervised / semi-supervised learning methods
- Model data on graphs & apply Graph ML techniques

Thank you for your attention!