PROBAbilistic computational intelLIGENCE

using STOCHOS inside optiSLang

PROBABILISTIC INTELLIGENCE

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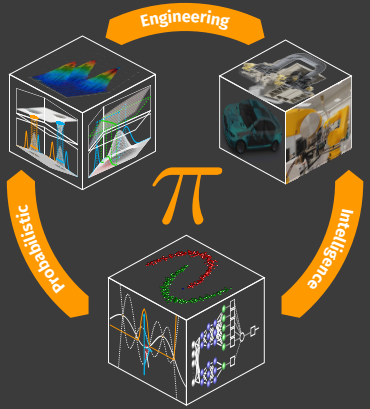
Ansys WOST CONFERENCE

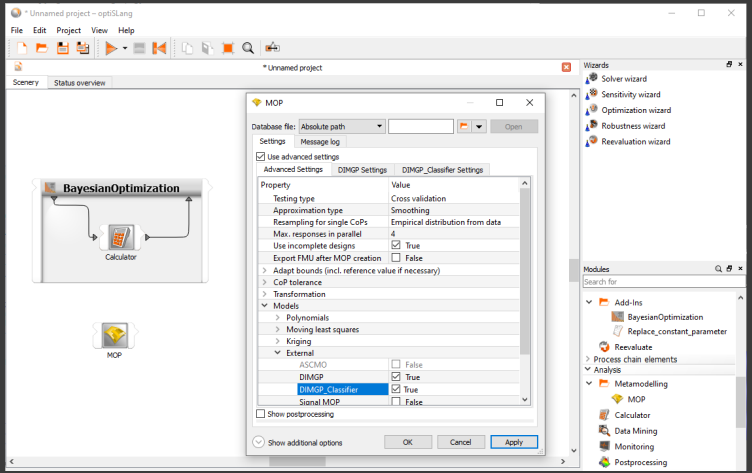
# STOCHOS inside optiSLang

# The (short) story of $\pi$ founded in late 2018

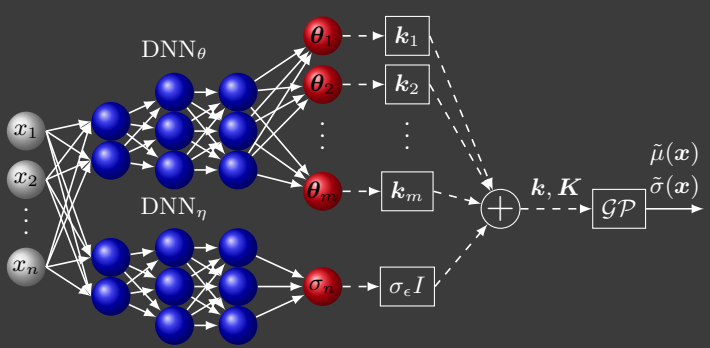
- University spin-off.
- Make research results available to industry.
- Guarantee maintenance, support and further development
- $\pi$ provides the reliability of an industry company and the innovation of an research faculty.

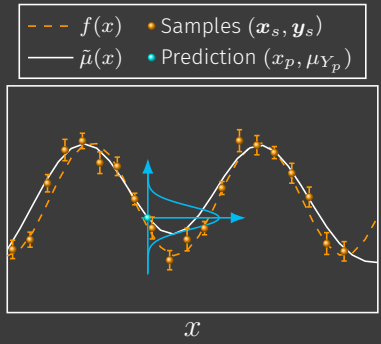


# STOCHOS inside optiSLang



# Deep Infinite Mixture Gaussian Process (DIM-GP)




| Input \ Output | Scalar | Vector | Matrix | Tensor |
|---|---|---|---|---|
| Scalar | xyz | xy | x | x |
| Vector | x | x | x | x |
| Matrix | x | x | x | x |
| Tensor | x | x | x | x |

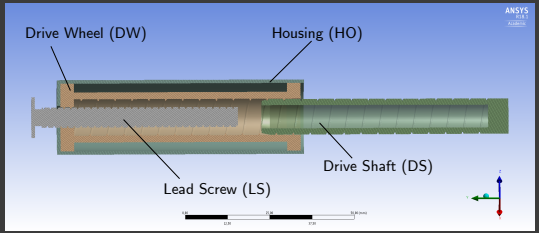
- x: Supported by STOCHOS python module
- y: Supported by BayesianOptimization - OSL
- z: Supported by MoP - OSL

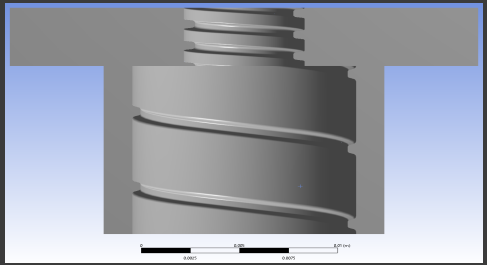


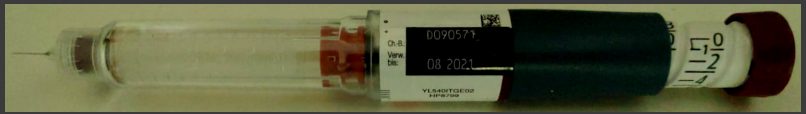
$\pi^2$

# Learning the tolerance distribution from images

# Insulin pen design

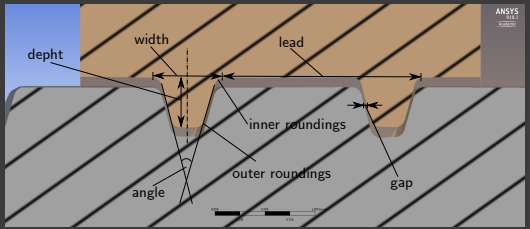


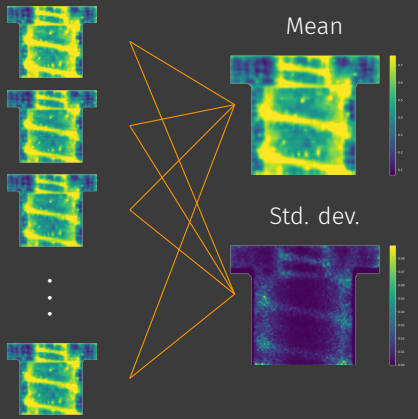





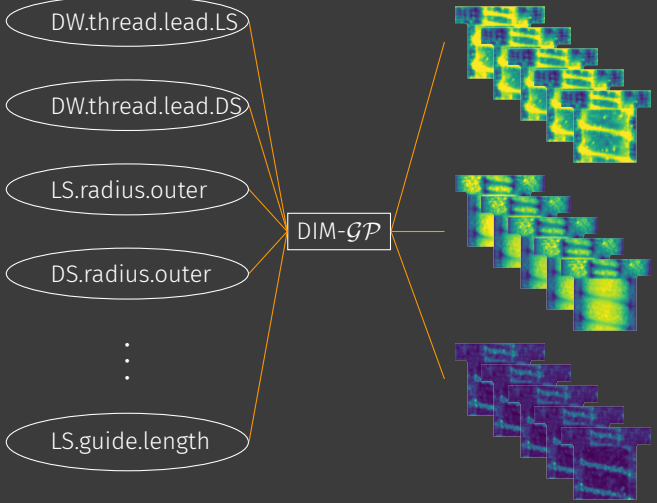
# Design and tolerance representations

| Lead Screw | Drive Shaft | Drive Wheel |
|---|---|---|
| LS.thread.x $\times 6$ | DS.thread.x $\times 6$ | DW.thread.x.LS $\times 6$ |
| LS.radius.outer | DS.radius.outer | DW.thread.x.DS $\times 6$ |
| LS.guide.length | DS.guide.length | DW.thread.gap.LS |
| LS.length | DS.length | DW.thread.gap.DS |
| LS.head.width | DS.wall.thickness | DW.length |
| LS.head.radius | | DW.wall.thickness |



# Parameters to tolerance field



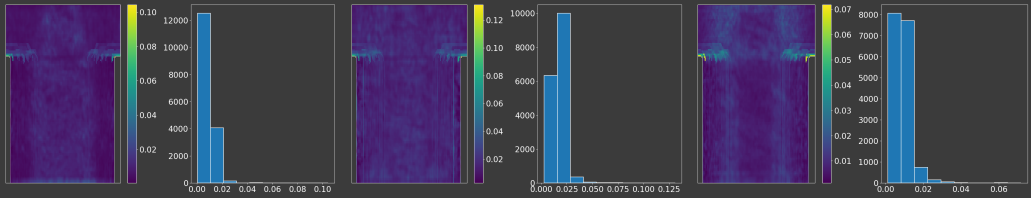

- Geometric model parameters as inputs
- Train DIMGP to predict the tolerance fields
- Input shape: (27)
- Output shape: (120, 160, 3)

$\rightarrow$ scalar to tensor model

# Parameters to tolerance field - Train Errors (80 designs, 874 samples)

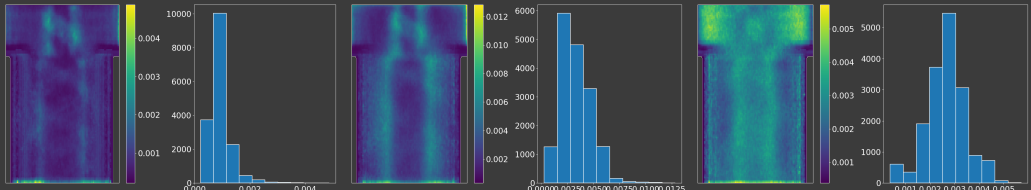
Mean

$R^2 = 0.971$ $R^2 = 0.986$ $R^2 = 0.995$



Std. Dev.

$R^2 = 0.815$ $R^2 = 0.777$ $R^2 = 0.675$

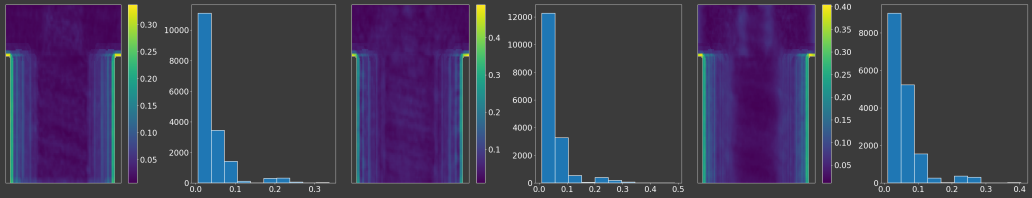


Channel 1 Channel 2 Channel 3

# Parameters to tolerance field - Test Errors (20 designs, 217 samples)

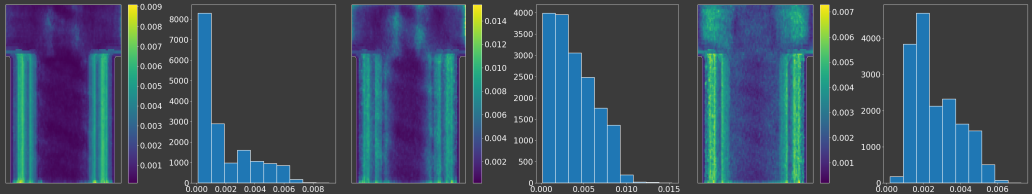
Mean

$R^2 = 0.504$ $R^2 = 0.871$ $R^2 = 0.848$



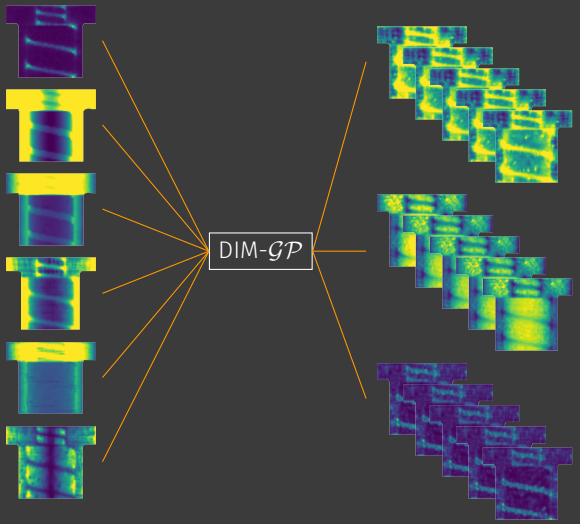
Std. Dev.

$R^2 = 0.011$ $R^2 = 0.650$ $R^2 = 0.449$



Channel 1 Channel 2 Channel 3

# Geometry image to tolerance field



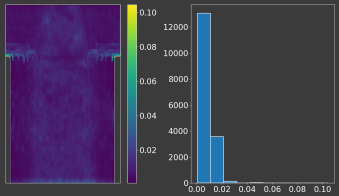

- Geometric properties (coordinates, normal vector components, curvature) as input image channels
- Train DIMGP to predict the tolerance fields
- Input shape: (120, 160, 6)
- Output shape: (120, 160, 3)

$\rightarrow$ tensor to tensor model

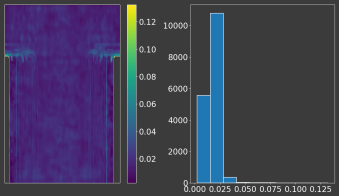
# Geometry image to tolerance field - Train Errors (80 designs, 874 samples)

Mean

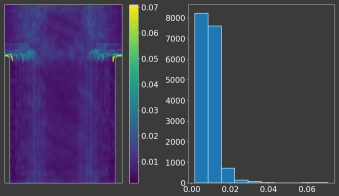
$R^2 = 0.971$ (0.000)



$R^2 = 0.986$ (0.000)

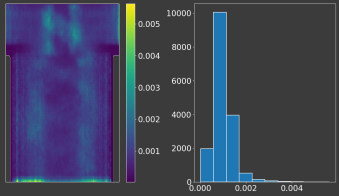


$R^2 = 0.995$ (0.000)

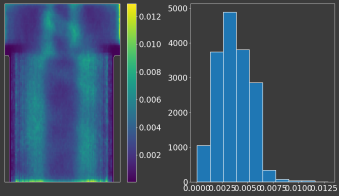


Std. Dev.

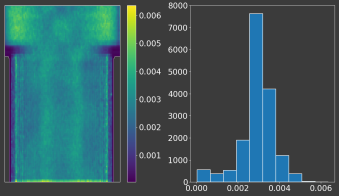
$R^2 = 0.787$ (+0.776)



$R^2 = 0.736$ (−0.040)



$R^2 = 0.626$ (−0.049)

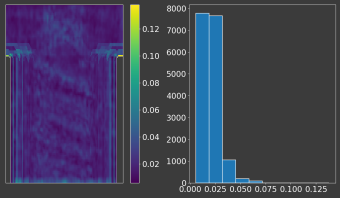


Channel 1 Channel 2 Channel 3

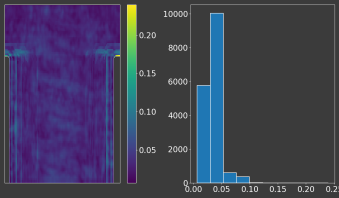
# Geometry image to tolerance field - Test Errors (20 designs, 217 samples)

Mean

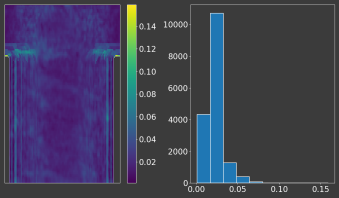
$R^2 = 0.845$ (+0.341)



$R^2 = 0.939$ (+0.068)

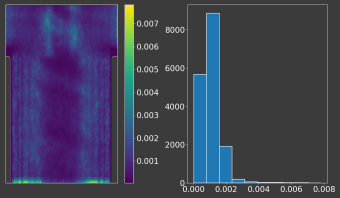


$R^2 = 0.969$ (+0.121)

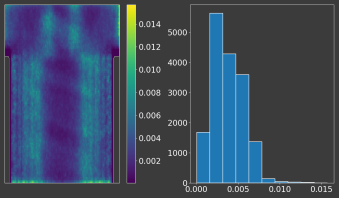


Std. Dev.

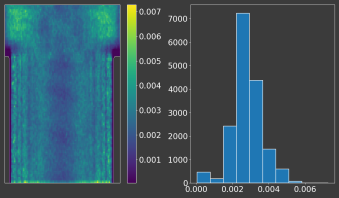
$R^2 = 0.785$ (+0.774)



$R^2 = 0.733$ (+0.083)



$R^2 = 0.676$ (+0.227)

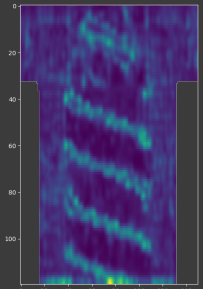


Channel 1 Channel 2 Channel 3

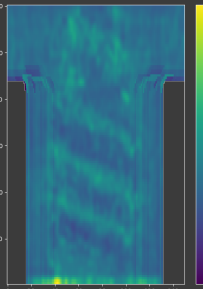
# Comparative results (Median sample) - Channel 1

Parameters to tolerance field

True

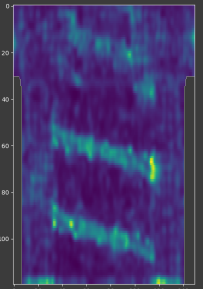


Prediction

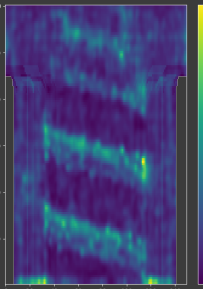


Geometry image to tolerance field

True



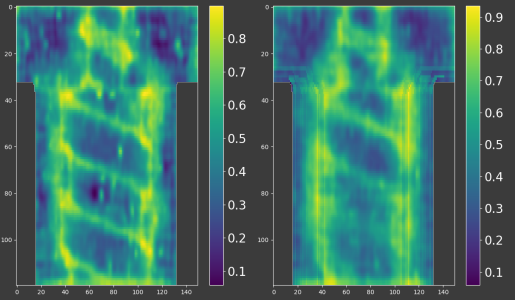
Prediction



# Comparative results (Median sample) - Channel 2

Parameters to tolerance field

True

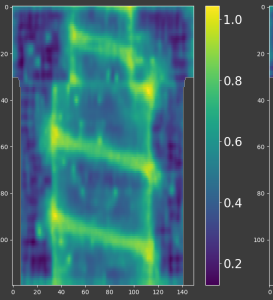



Prediction

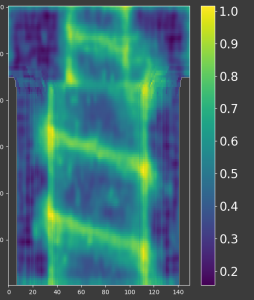



Geometry image to tolerance field

True



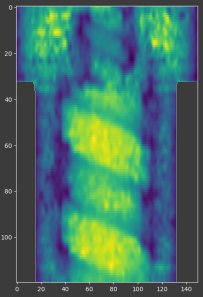

Prediction



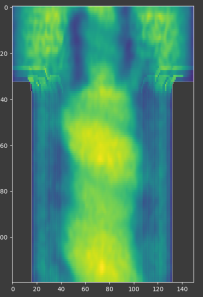
# Comparative results (Median sample) - Channel 3

Parameters to tolerance field

True

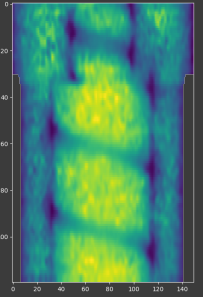



Prediction

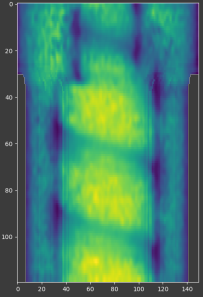



Geometry image to tolerance field

True




Prediction



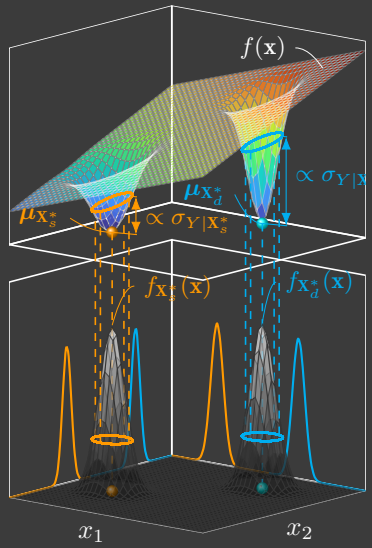
# Conclusion and Outlook

# Conclusion

- DIM-GP can be trained using arbitrarily shaped data
- Image representation may be more informative than CAE parameters
- Other parametrizations may achieve better results
- Using a better parametrization scheme enables using RDO tools in optiSLang
- WIP: Support non-scalar data in STOCHOS inside optiSLang
- Next step: RDO

# Outlook

- BayesianOptimization add-in for sample efficient optimization
- Sobol-index embedded Bayesian optimization (SIEMBO) can be used for optimization in high dimensional image space instead of the parametric one
- WIP: Bayesian robust design optimization for STOCHOS inside optiSLang
- STOCHOS license includes both models and algorithms



# Contact

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