The University of Texas at Austin
Aerospace Engineering
and Engineering Mechanics
Cockrell School of Engineering

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Soft Tissue Parameter Identification using Machine Learning

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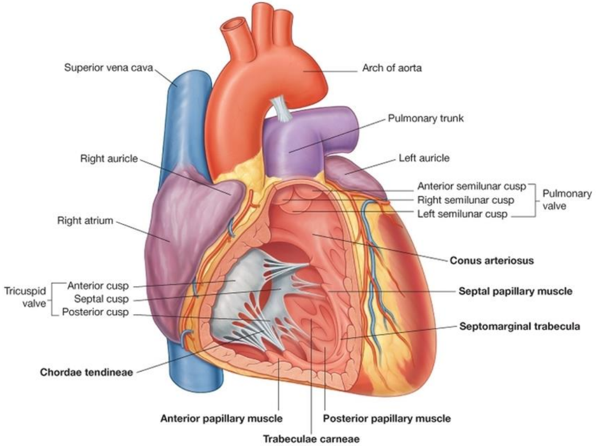
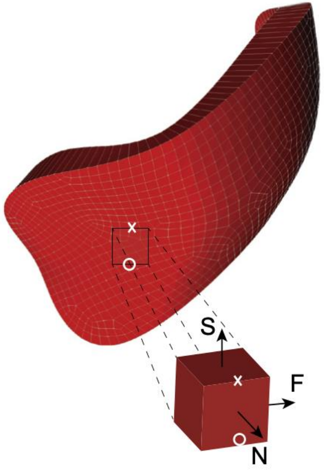
Motivation

- Biomechanical characterization
  - Blood clot
  - Right ventricular myocardium

(Sugerman et al, 2020)



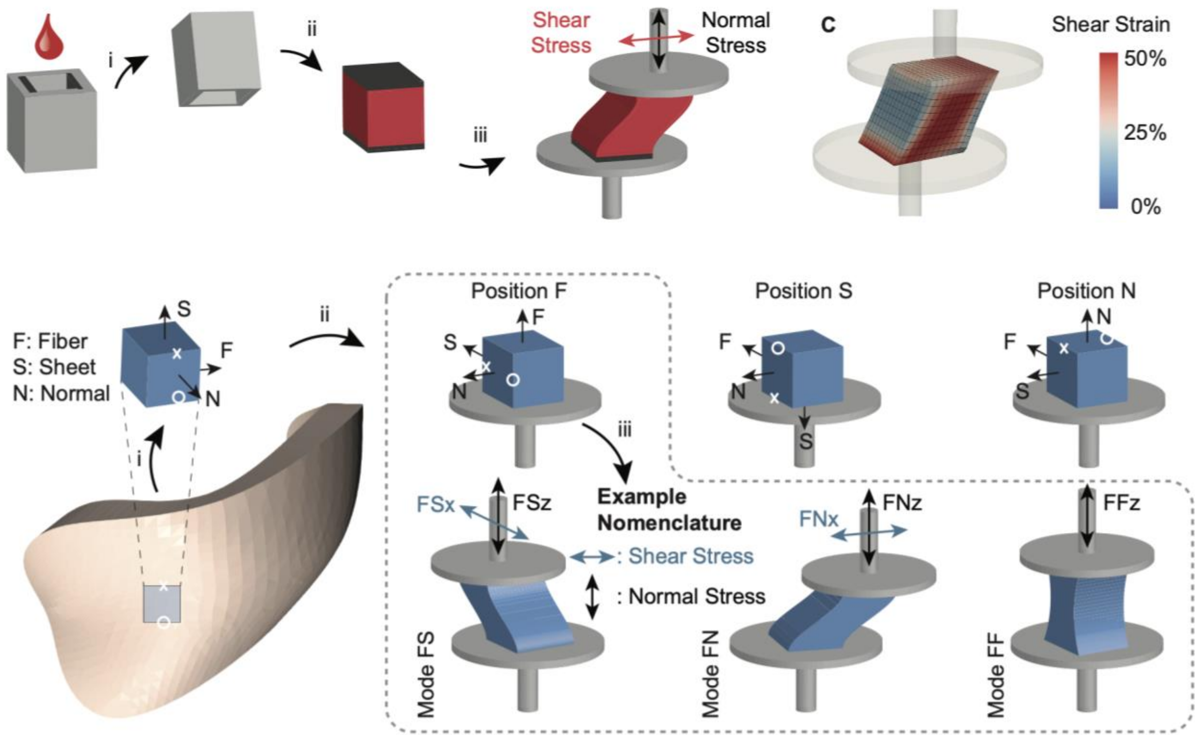
(Darke et al, 2009)

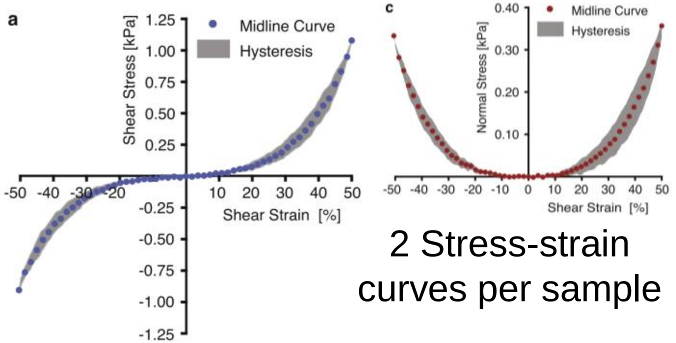


(Kakaletsis et al, 2021)

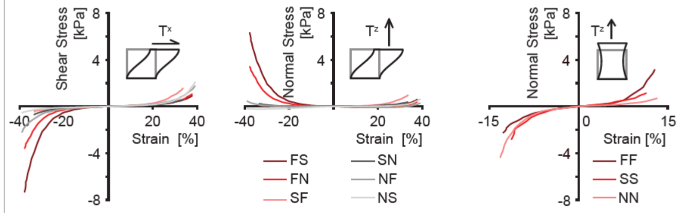
Experimental protocol

(Sugerman et al, 2020)





2 Stress-strain curves per sample



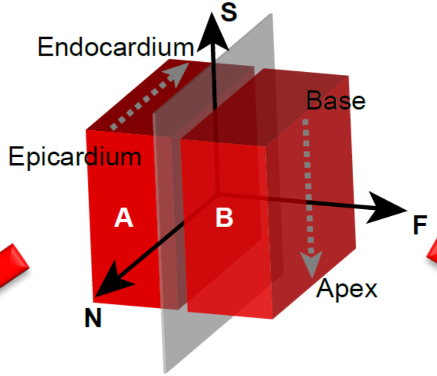
6 Simple shear modes

3 Uniaxial modes

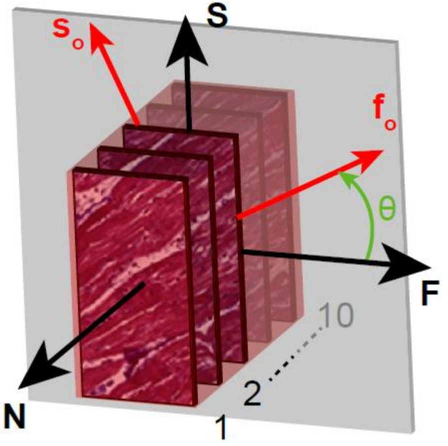
15 Stress-strain curves per sample

(Kakaletsis et al, 2021)

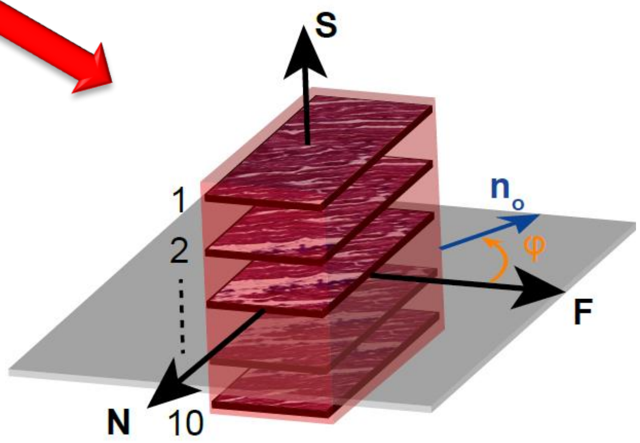
Histology



Epicardium to Endocardium Sections



Base to Apex Sections



Constitutive models

- Blood clot (hyperelastic, isotropic)

$$W = \frac{a}{b^2}\left(\lambda_1^b + \lambda_2^b + \lambda_3^b - 3\right)$$

(Ogden, 1973)

- Myocardium (hyperelastic, anisotropic)

(Holzapfel et al, 2009)

Isotropic term (amorphous matrix) | Fiber stiffness contribution | Sheet stiffness contribution | Shear coupling (fiber-sheet interaction)

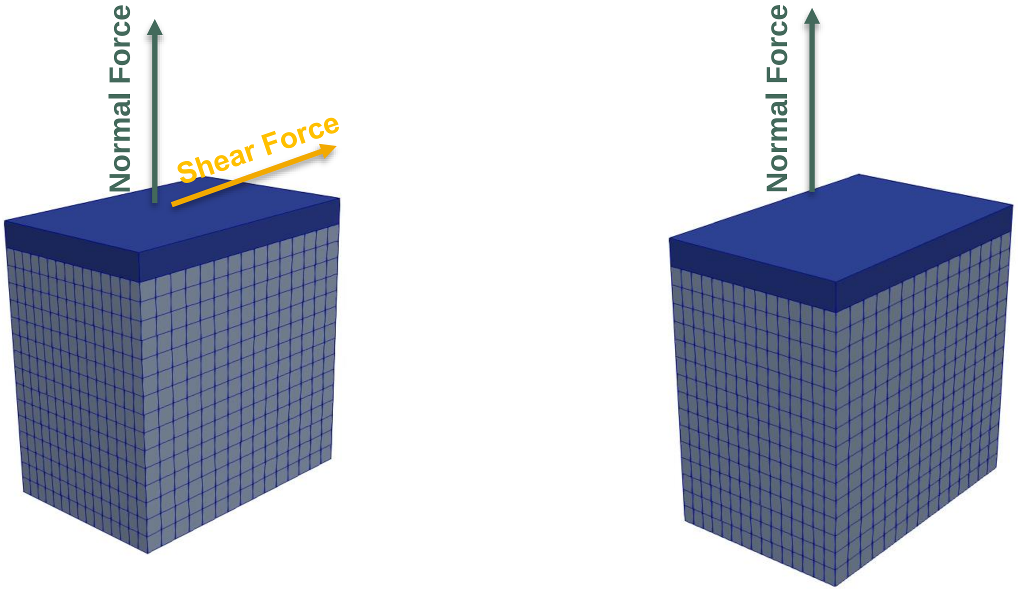
$$W = \frac{a}{2b}(\exp[b(I_1 - 3)] - 1) + \frac{a_f}{2b_f}\left(\exp\left[b_f(I_{4f} - 1)^2\right] - 1\right) + \frac{a_s}{2b_s}(\exp[b_s(I_{4s} - 1)^2] - 1) + \frac{a_{fs}}{2b_{fs}}\left(\exp\left[b_{fs}I_{8fs}^2\right] - 1\right)$$

$$\int_0^{2\pi} H(I_{4f} - 1)\left\{\frac{a_f}{2b_f}\left(\exp\left[b_f(I_{4f} - 1)^2\right] - 1\right)\right\} R(\theta)\, d\theta$$

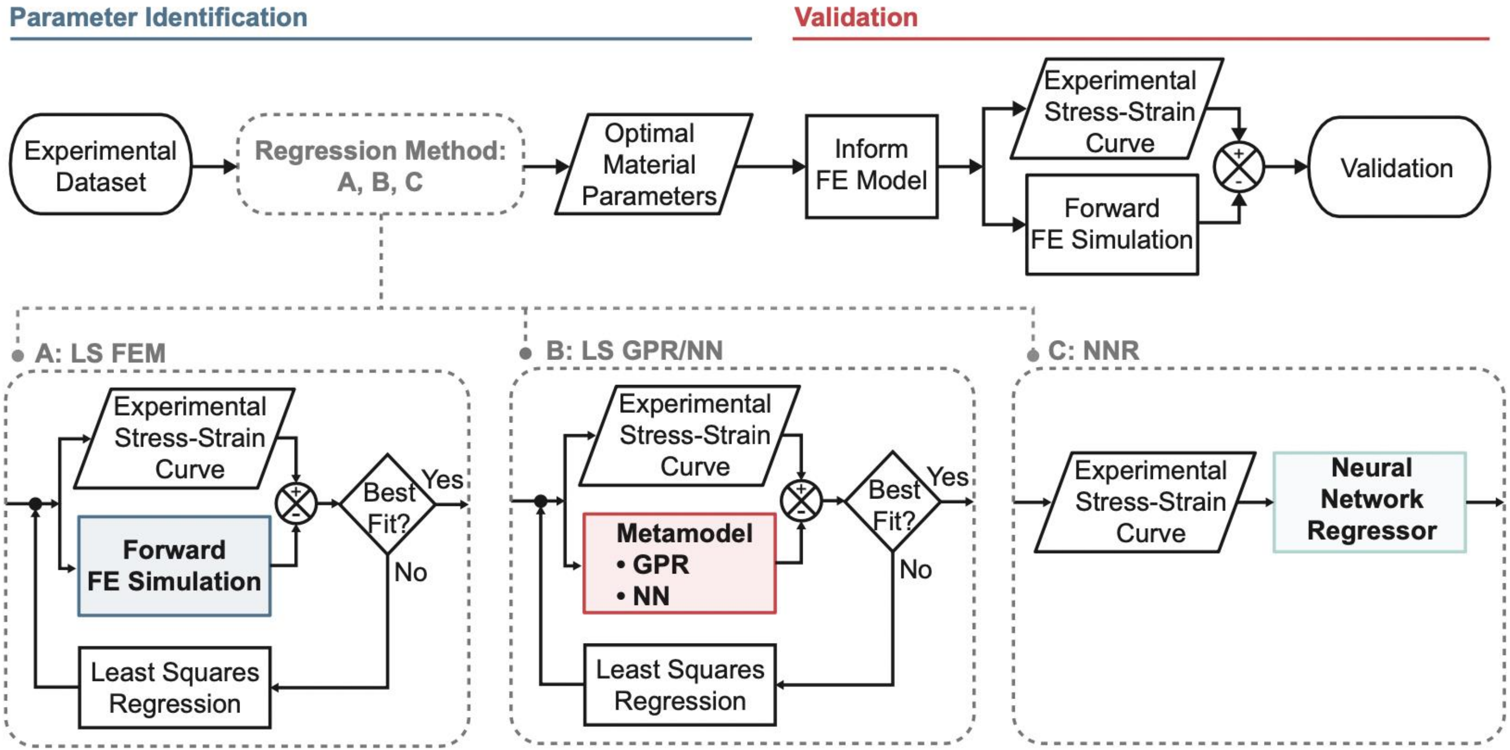
In-plane fiber dispersion

Objective

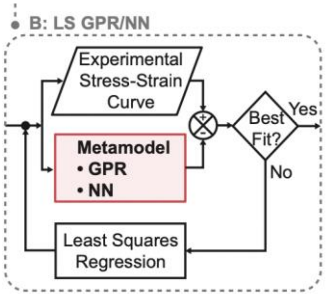
- Can we accelerate material parameter estimation using machine learning metamodels?

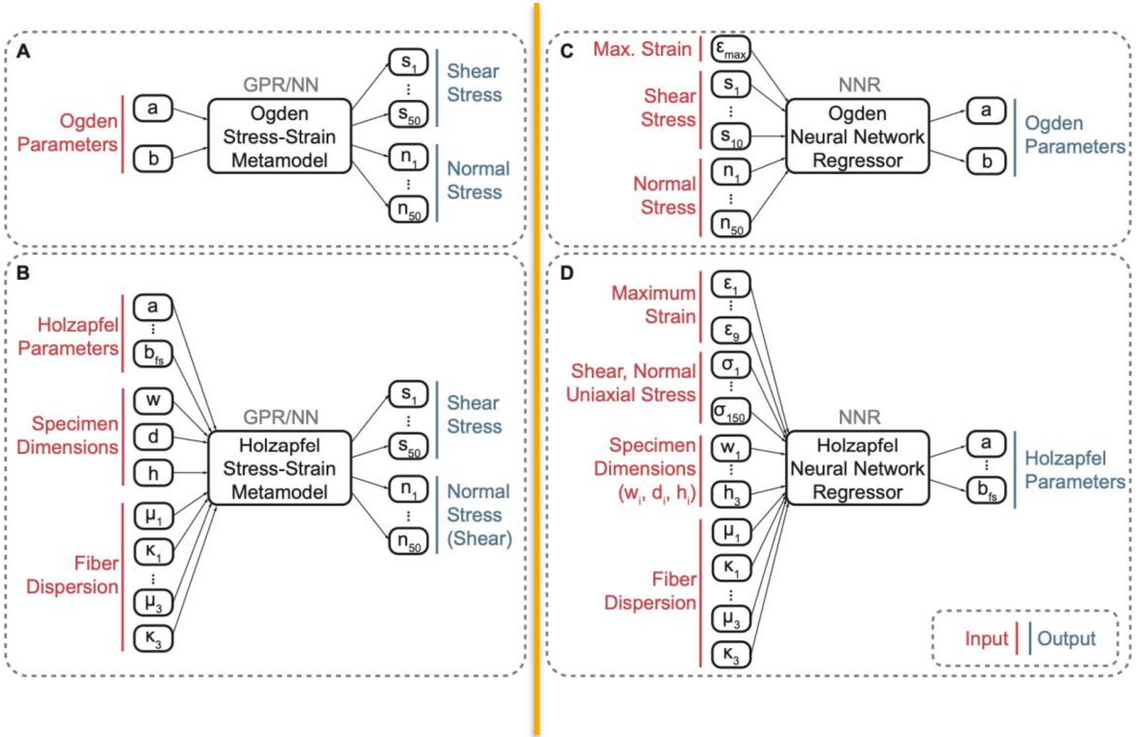


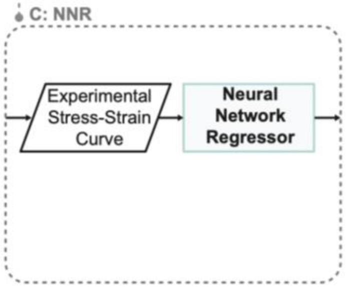
Pipeline


Parameter Identification
Validation
Experimental Dataset
Regression Method: A, B, C
Optimal Material Parameters
Inform FE Model
Experimental Stress-Strain Curve
Forward FE Simulation
Validation
A: LS FEM
Experimental Stress-Strain Curve
Forward FE Simulation
Best Fit?
Yes
No
Least Squares Regression
B: LS GPR/NN
Experimental Stress-Strain Curve
Metamodel
• GPR
• NN
Best Fit?
Yes
No
Least Squares Regression
C: NNR
Experimental Stress-Strain Curve
Neural Network Regressor

Machine Learning Approach



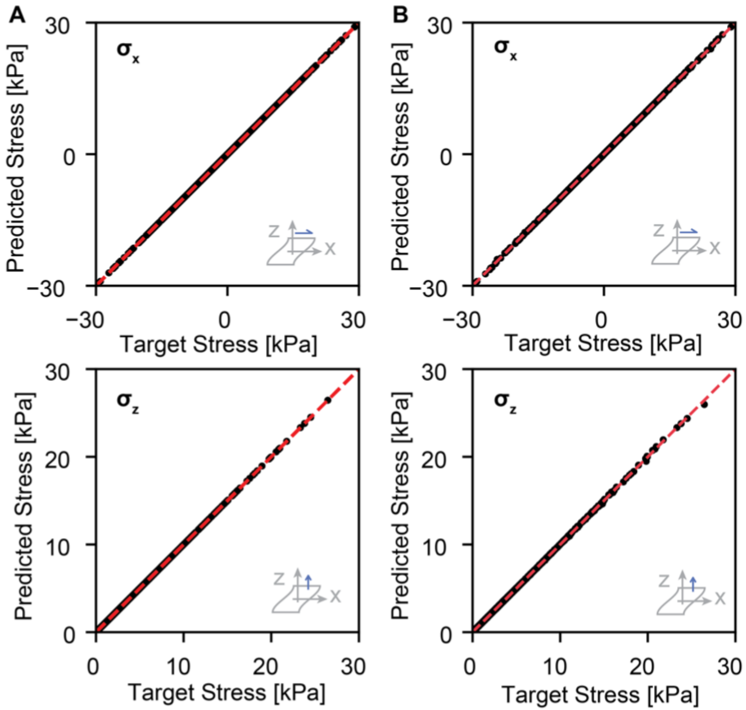




Training on Synthetic Data – Blood Clot

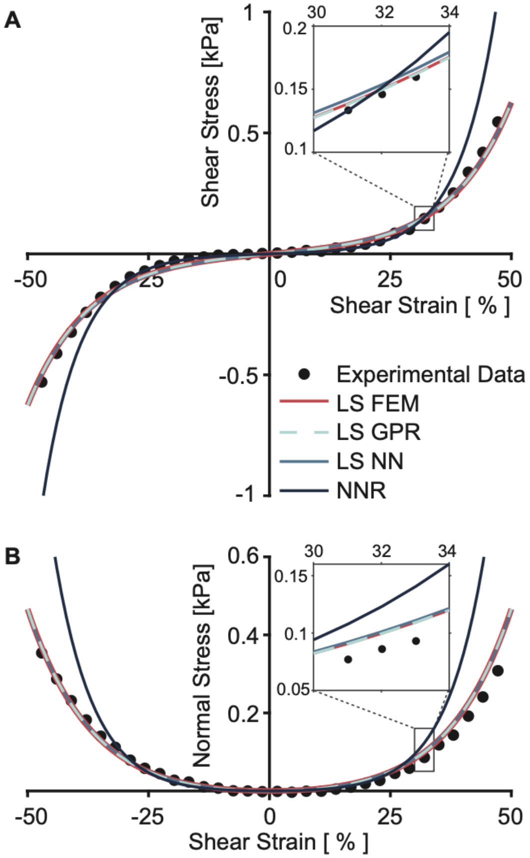
GPR

NN

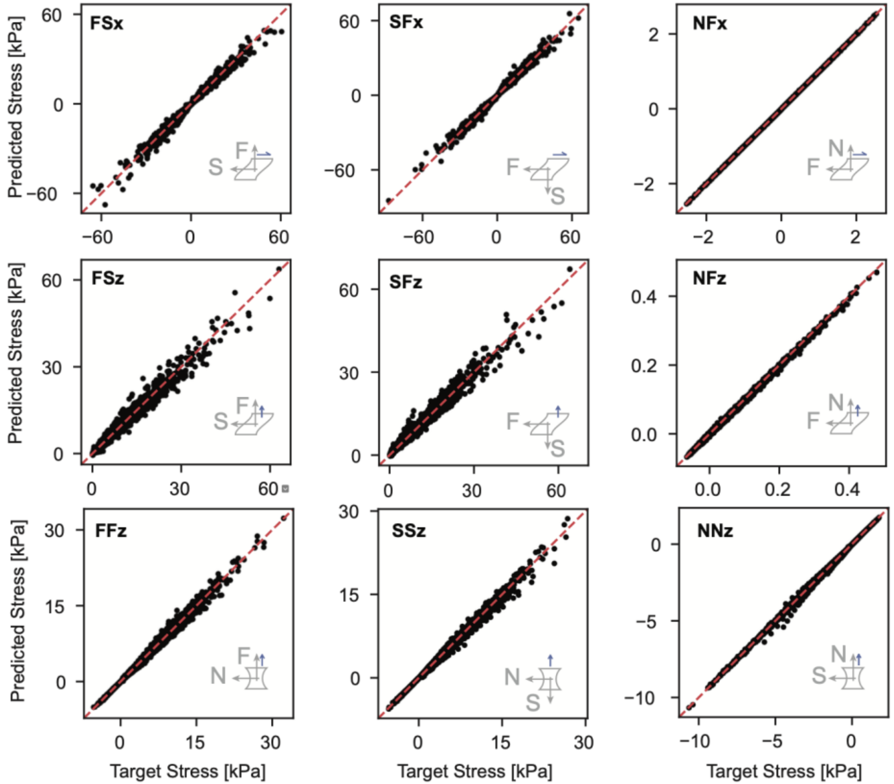


Validation-Blood Clot

Sample	Method	a (Pa)	b (-)	NMSE (-)	Acc. Loss (%)
Best	LS FEM	657.78	16.17	0.981	0.00
	LS GPR	627.25	16.49	0.980	0.01
	LS NN	656.99	16.24	0.980	0.01
	NNR	91.94	26.35	0.904	7.86
Median	LS FEM	530.39	16.32	0.989	0.00
	LS GPR	527.16	16.36	0.989	0.00
	LS NN	558.05	16.03	0.989	0.01
	NNR	194.67	26.21	-0.272	127.47
Worst	LS FEM	847.24	15.38	0.988	0.00
	LS GPR	845.42	15.39	0.988	0.00
	LS NN	881.57	15.14	0.988	0.01
	NNR	398.96	29.56	-23.212	2449.85

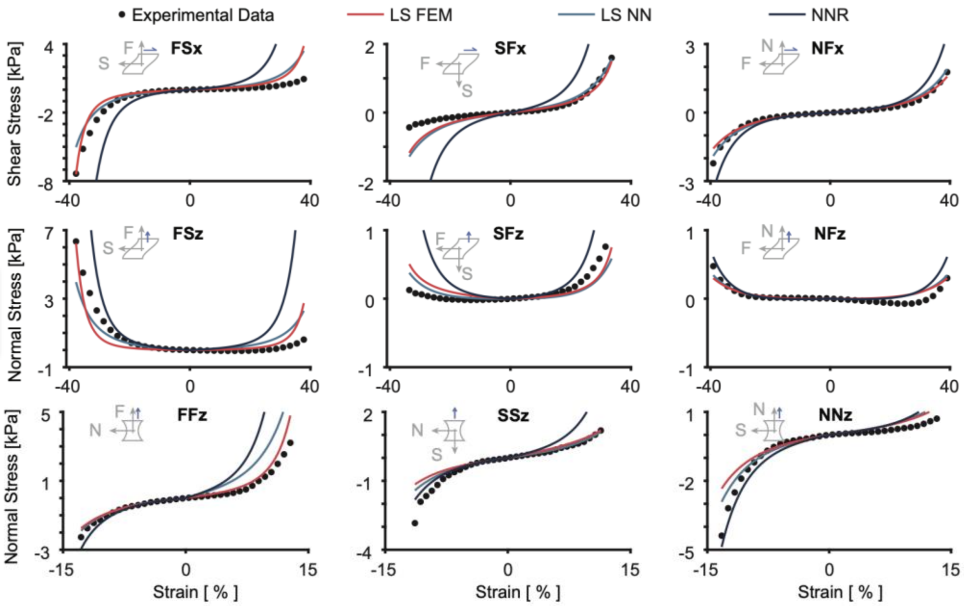


Training on Synthetic Data – Myocardium



Validation- Myocardium

Subject	Method	a (Pa)	b (-)	a_f (Pa)	b_f (-)	a_s (Pa)	b_s (-)	a_{fs} (Pa)	b_{fs} (-)	NMSE (-)	Acc. Los (%)
Best	LS FEM	1928.4	9.29	3925.4	19.42	1592.0	0.00	1587.8	0.00	0.878	0.0
	LS NN	2065.4	11.04	11580.1	8.72	780.1	0.03	0.1	18.59	0.758	13.7
	NNR	2319.3	18.88	3215.9	27.24	410.0	24.20	162.8	29.96	0.275	68.7
Median	LS FEM	1238.8	10.28	487.6	29.14	610.2	0.00	0.0	0.00	0.781	0.0
	LS NN	1259.7	11.50	2418.6	15.31	31.7	16.72	102.2	9.39	0.701	10.3
	NNR	1121.8	16.64	2787.2	27.06	794.0	20.96	1445.4	29.29	-8.349	1168.4
Worst	LS FEM	726.6	7.80	17707.5	0.00	0.2	0.12	0.0	0.00	0.713	0.0
	LS NN	765.8	10.89	15542.2	0.03	219.3	11.65	0.3	10.41	0.360	49.5
	NNR	1835.2	14.49	13346.3	27.00	7997.8	17.04	680.2	19.04	-Inf	Inf



Conclusions

- Can machine learning accelerate soft tissue parameter identification? –It depends.
  - Complexity of the corresponding experimental protocol
  - Feature space dimension
- Publicly available experimental and synthetic dataset
  - Future advances that further improve similar methods or follow entirely different approaches

References

- Kakaletsis S, Lejeune E, Rausch MK. Can machine learning accelerate soft material parameter identification from complex mechanical test data?***(Under Review)***

- Sugerman GP, Kakaletsis S, Thakkar P, Chokshi A, Parekh SH, Rausch MK. A whole blood clot thrombus mimic: Constitutive behavior under simple shear. *Journal of the Mechanical Behavior of Biomedical Materials*, 2021.

- Kakaletsis S, Meador WD, Mathur M, Sugerman GP, Jazwiec M, Lejeune E, Timek TA, Rausch MK. Right ventricular myocardial mechanics: Multi-modal deformation, microstructure, and modeling. *Acta Biomaterialia*, 2021.

Thank you!

- Dr. Manuel Rausch, UT Austin (www.manuelrausch.com)
- Dr. Emma Lejeune, Boston University
- Soft Tissue Biomechanics Lab, UT Austin

- Funding sources

The Dataverse® Project

GitHub

American Heart Association®

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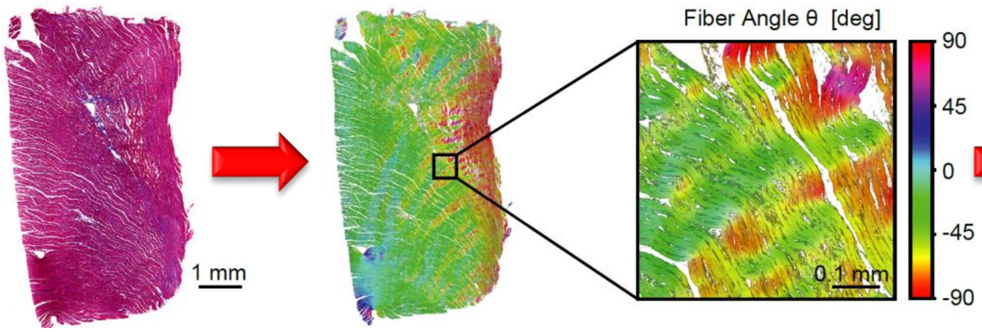
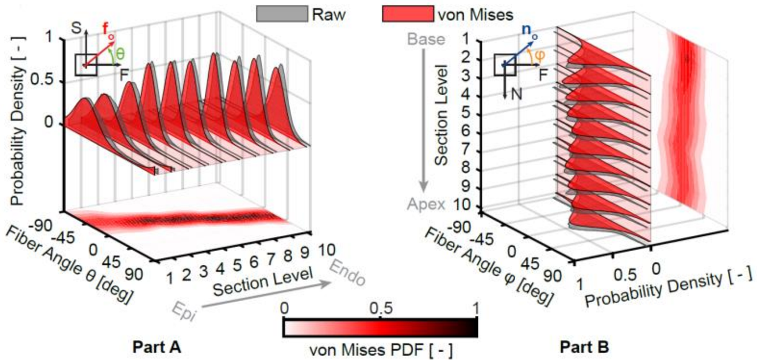
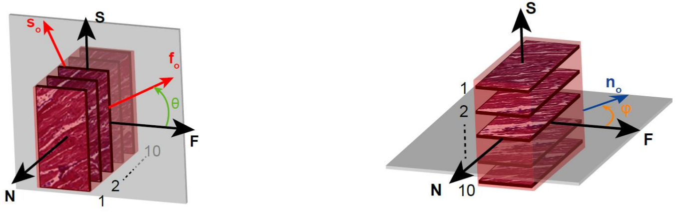
Fiber Orientation

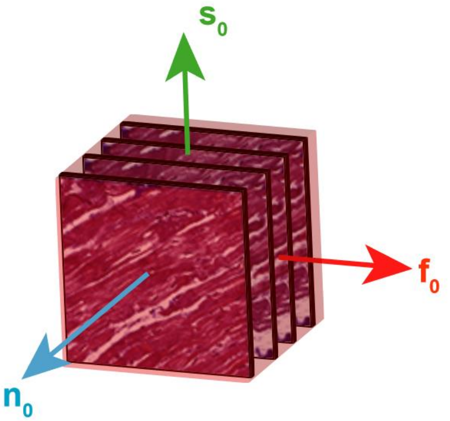




- High resolution images of histology slides
- Directional image analysis (ImageJ / OrientationJ)
- π-periodic von Mises distributions of fiber orientation angles through section levels



Holzapfel-Ogden Model



Right ventricular myocardium exhibited:

- Nonlinear response
- Anisotropic behavior
- Heterogeneous properties.

Structurally based constitutive model by Holzapfel & Ogden (2009):

$$W = \frac{a}{2b}(\exp[b(I_1 - 3)] - 1) + \frac{a_f}{2b_f}\left(\exp\left[b_f\left(I_{4f} - 1\right)^2\right] - 1\right) + \frac{a_s}{2b_s}(\exp[b_s(I_{4s} - 1)^2] - 1) + \frac{a_{fs}}{2b_{fs}}\left(\exp\left[b_{fs}I_{8fs}^2\right] - 1\right)$$

Isotropic term (amorphous matrix)	Fiber stiffness contribution	Sheet stiffness contribution	Shear coupling (fiber-sheet interaction)

Where the anisotropic **invariants** of the deformation tensor are given by:

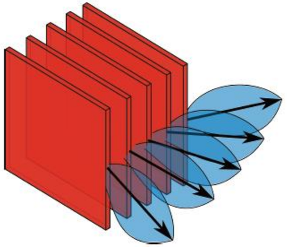
$$I_{4f} = \boldsymbol{f}_0 \cdot (\boldsymbol{C}\boldsymbol{f}_0) \qquad I_{4s} = \boldsymbol{s}_0 \cdot (\boldsymbol{C}\boldsymbol{s}_0) \qquad I_{8fs} = \boldsymbol{f}_0 \cdot (\boldsymbol{C}\boldsymbol{s}_0)$$

Include fiber dispersion

Modify strain energy to account for in-plane fiber dispersion:

$$W = \frac{a}{2b}(\exp[b(I_1 - 3)] - 1) + \frac{a_f}{2b_f}\left(\exp\left[b_f\left(I_{4f} - 1\right)^2\right] - 1\right) + \frac{a_s}{2b_s}(\exp[b_s(I_{4s} - 1)^2] - 1) + \frac{a_{fs}}{2b_{fs}}\left(\exp\left[b_{fs}I_{8fs}^2\right] - 1\right)$$

$$\int_0^{2\pi} H\left(I_{4f} - 1\right)\left\{\frac{a_f}{2b_f}\left(\exp\left[b_f\left(I_{4f} - 1\right)^2\right] - 1\right)\right\} R(\theta)\, d\theta$$



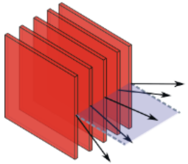
where

- $H\left(I_{4f} - 1\right)$ the Heaviside step function to ensure fibers contribute **only under tension**
- $R(\theta)$ is π-periodic von Mises function with $R(\theta) = \frac{\exp(b\cos(2[\theta - \mu]))}{2\pi I_0(b)}$
- Angular integration approach

Model Classes

Model Class 1

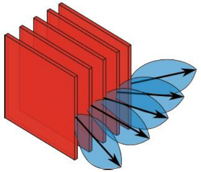
No dispersion



$$\frac{a_f}{2b_f}\left(\exp\left[b_f\left(I_{4f}-1\right)^2\right]-1\right)$$

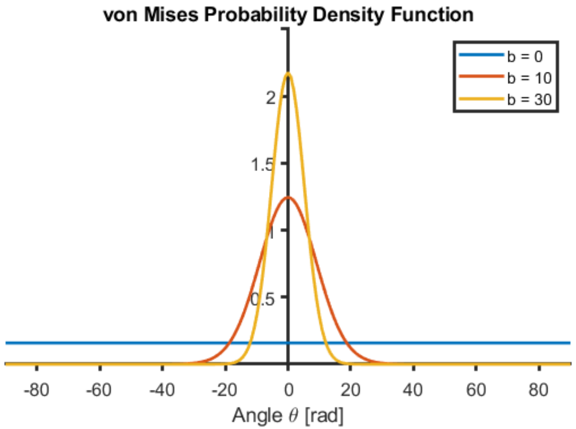
Model Class 2

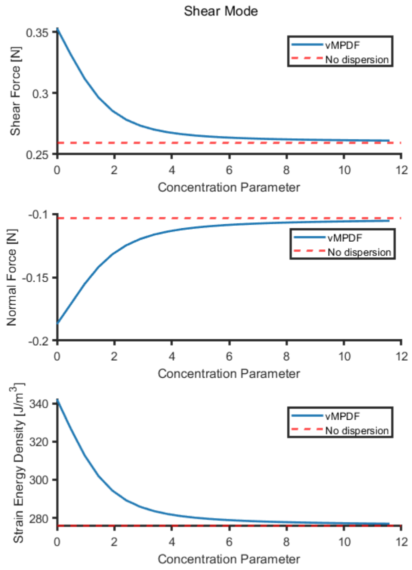
2D von Mises Distribution



$$\int_0^{2\pi} H\left(I_{4f}-1\right)\left\{\frac{a_f}{2b_f}\left(\exp\left[b_f\left(I_{4f}-1\right)^2\right]-1\right)\right\}R(\theta)\,d\theta$$

For highly concentrated fiber distributions (high concentration parameter b) the two classes are equivalent:





Incompressibility

- Decompose deformation gradient into volumetric and isochoric part:

$$\boldsymbol{F} = \left(J^{1/3}\boldsymbol{I}\right) \cdot \left(J^{-1/3}\boldsymbol{F}\right) = \boldsymbol{F}_{\boldsymbol{vol}} \cdot \widetilde{\boldsymbol{F}}$$

Note: $\det(\boldsymbol{F}_{\boldsymbol{vol}}) = J$ and $\det(\widetilde{\boldsymbol{F}}) = 1$

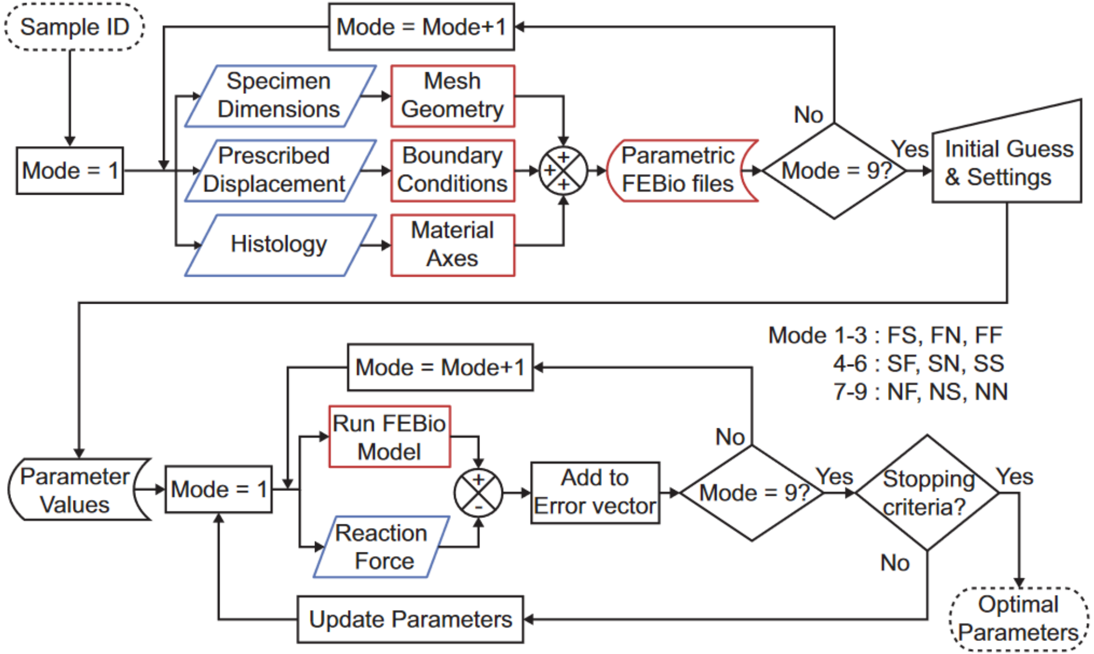
- Volumetric-Isochoric split of strain energy function

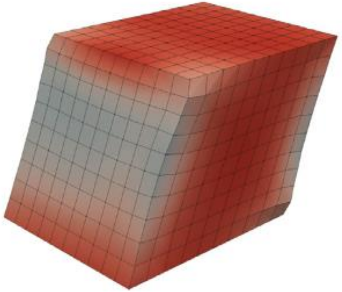
$$W(\boldsymbol{C}) = U(J) + W_{iso}(\widetilde{\boldsymbol{C}})$$

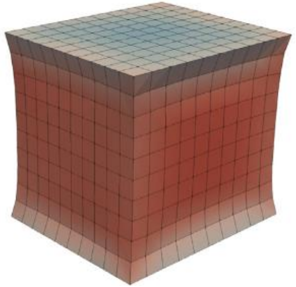
where $U(J) = K/2\ln(J)^2$, $\widetilde{\boldsymbol{C}} = \widetilde{\boldsymbol{F}}^T\widetilde{\boldsymbol{F}}$ and W_{iso} as presented previously, by substituting the isochoric invariants

$$I_{4f} = \boldsymbol{f}_0 \cdot (\widetilde{\boldsymbol{C}}\boldsymbol{f}_0) \qquad I_{4s} = \boldsymbol{s}_0 \cdot (\widetilde{\boldsymbol{C}}\boldsymbol{s}_0) \qquad I_{8fs} = \boldsymbol{f}_0 \cdot (\widetilde{\boldsymbol{C}}\boldsymbol{s}_0)$$

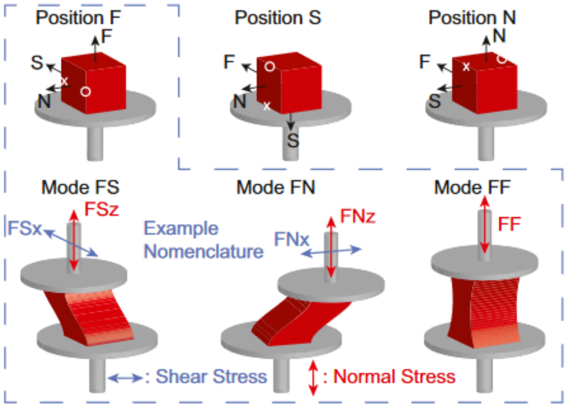
Material Parameter Estimation

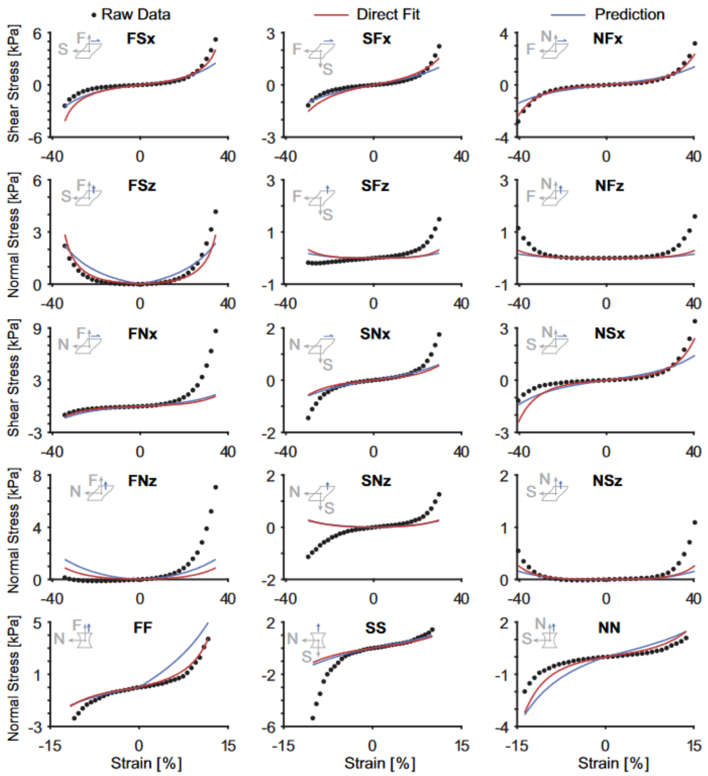






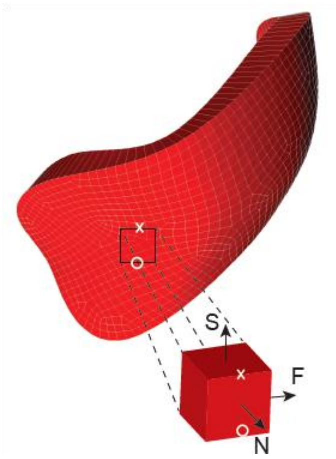
Material Parameter Estimation



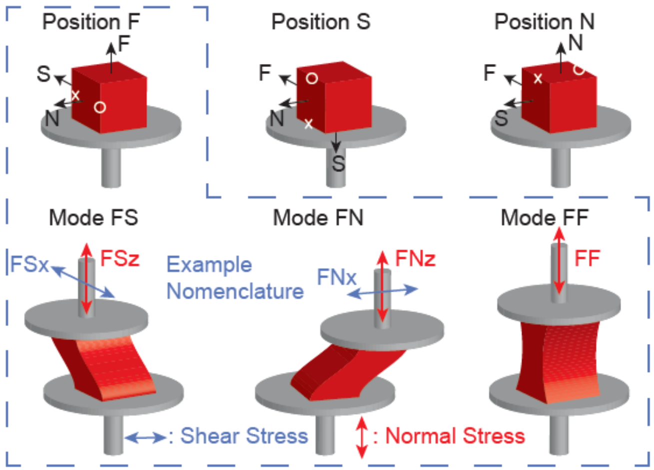


Mechanical Testing

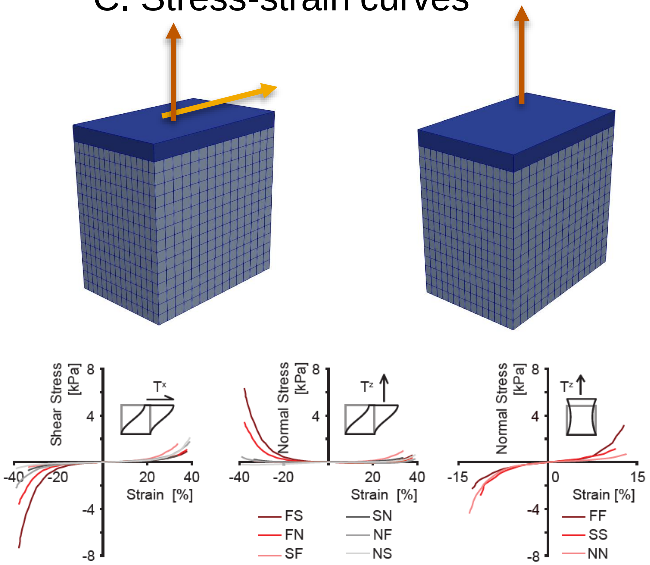
A. Excise specimens (10x10x10mm cubes)



B. Test in 9 different modes



C. Stress-strain curves

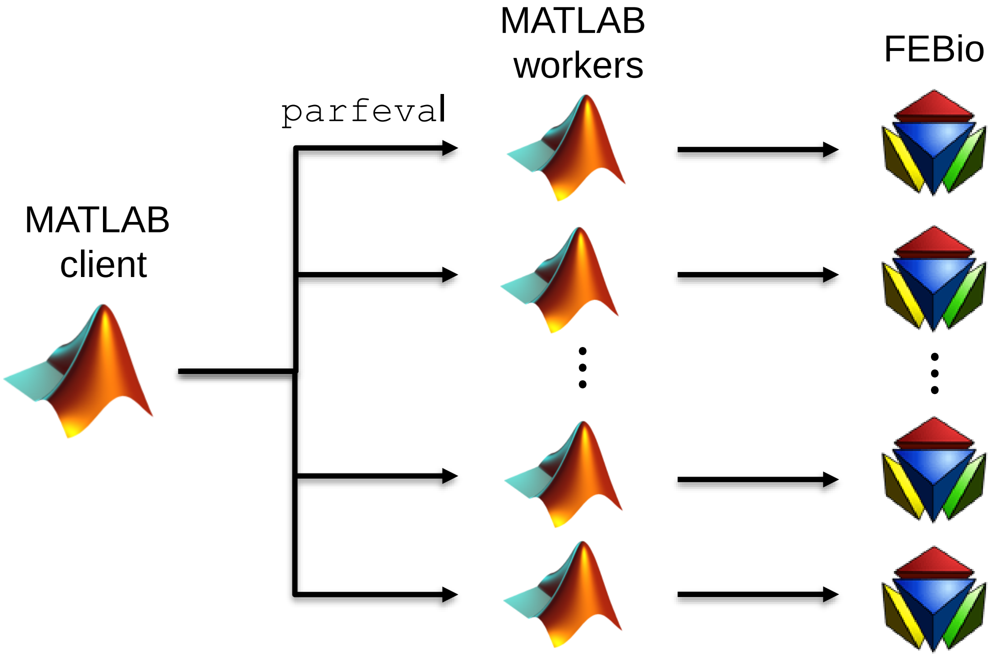


6 Simple shear modes

3 Uniaxial modes

15 Stress-strain curves per sample

Practical Aspects



Run all 9 modes in parallel

	Element Type	Run Time 9 modes [sec]	Run Time 9 modes [min]	Run time for 15 iterations [h]
Class 1	Linear	23.2	0.4	**0.9**
	Quad	167.8	2.8	**6.3**
Class 2	Linear	70.3	1.2	**2.6**
	Quad	184.7	3.1	**7.0**

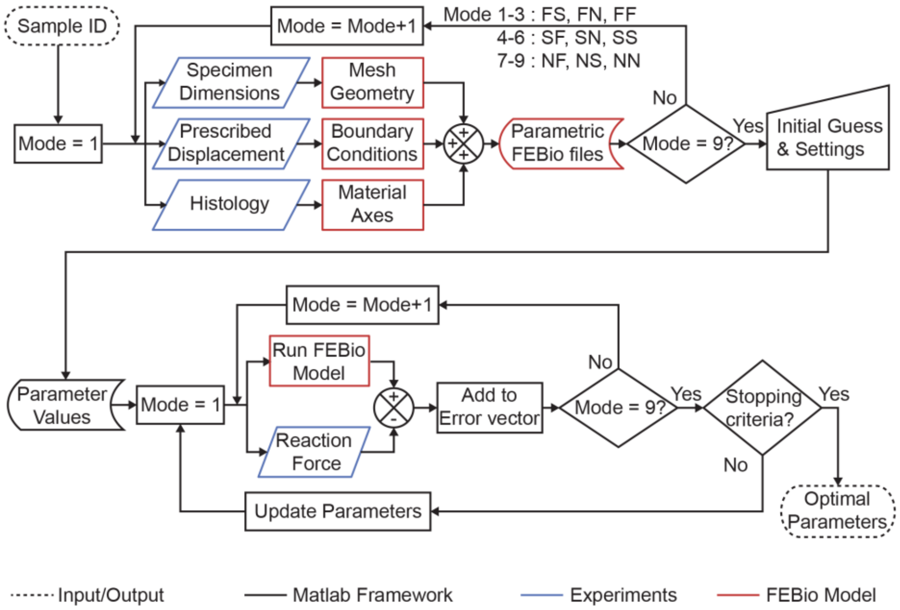
9 modes * 9 param var. = **81 FEBio runs / iteration**

15 iter. * 81 = **1,215 FEBio runs for converged parameters**

Expensive!

https://www.mathworks.com/ ; www.febio.org

Machine Learning Approach



Substitute forward FE simulations by a ML metamodel. Motivation:

- A gradient-based inverse method using FE simulations is very expensive!
- Even more expensive for continuous fiber distribution materials using the angular integration method.
- Predictive power: replace the entire pipeline to estimate material parameters.

The problem

Input

8 Material Parameters: a, b, a_f, b_f, a_s, b_s, a_{fs}, b_{fs}

2 Fiber Angles: φ, θ

→ **Meta-model** →

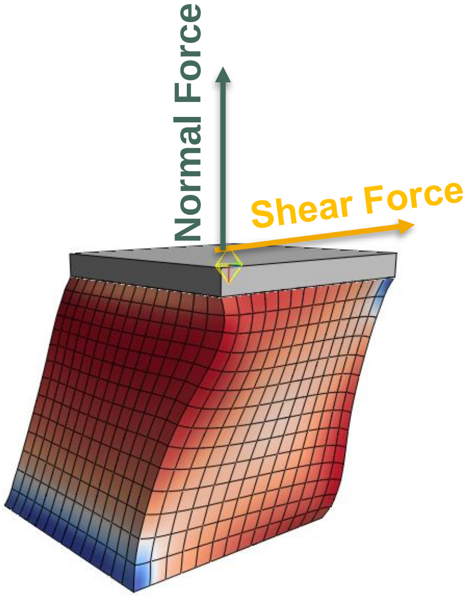
Target

F_x @ -40%
F_x @ -38%
⋮
F_x @ $+40\%$

Shear force at 50 strain values

F_z @ -40%
F_z @ -38%
⋮
F_z @ $+40\%$

Normal force at 50 strain values

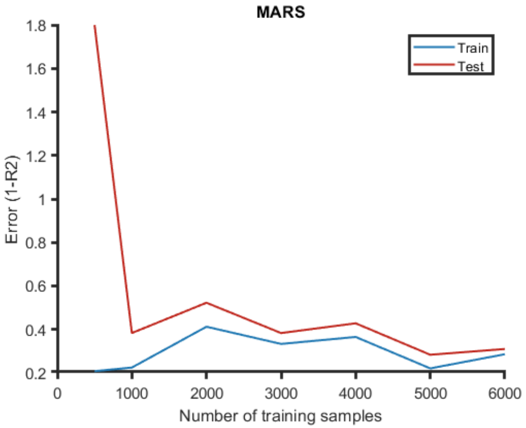


10,000 Samples

100 values / sample

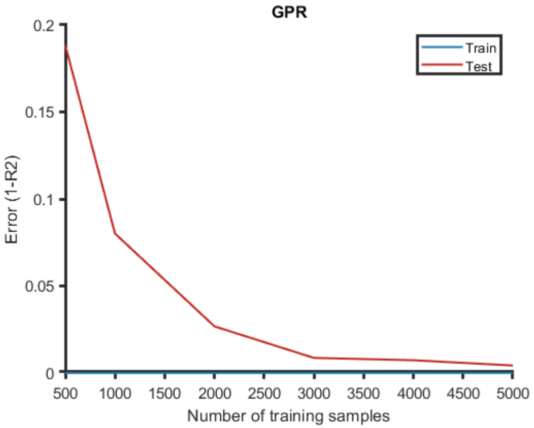
Metamodel Selection

Multivariate Adaptive Regression Splines



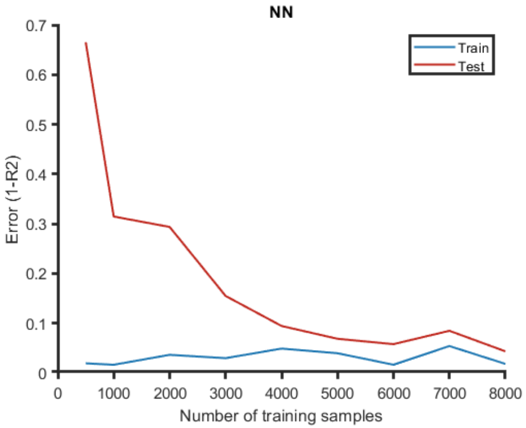
Gaussian Process Regressor

Anisotropic RBF kernel

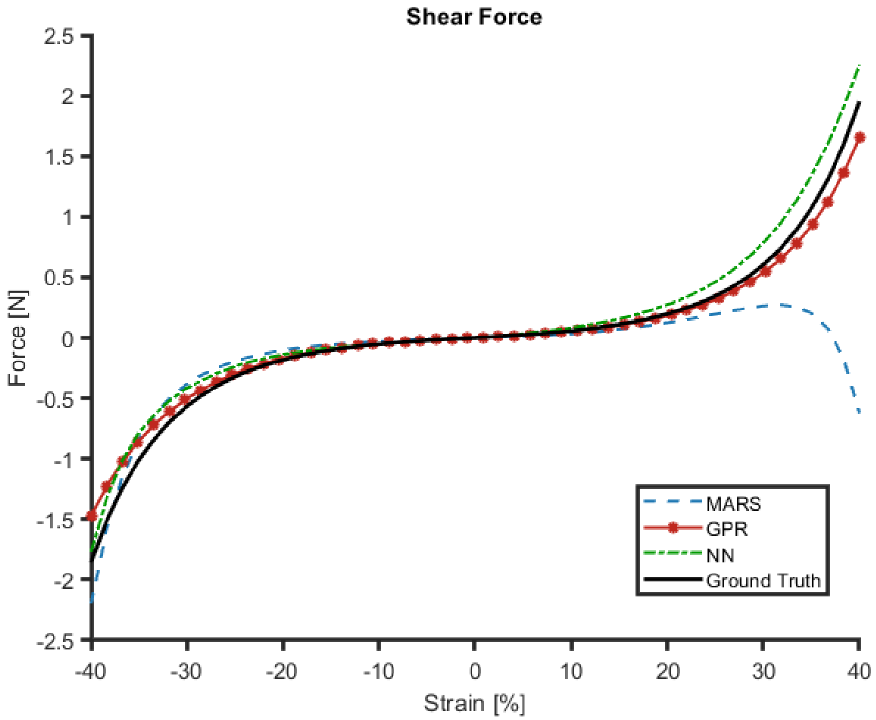


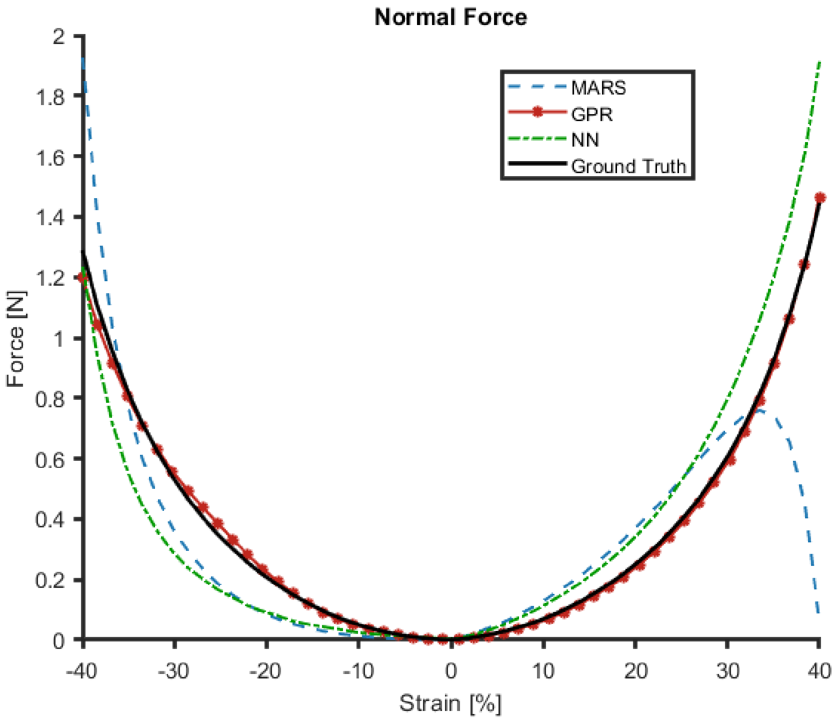
Neural Network

Multi-layer Perceptron Regressor



Preliminary Results





Stress-strain prediction of one sample in validation set, trained with 5,000 samples

The University of Texas at Austin
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