

# Effective parameter inference for a mathematical model of the left ventricle

RSS Glasgow

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Alan Lazarus

Joint with: Dirk Husmeier, Hao Gao and Xiaoyu Luo

February 9, 2021

University of Glasgow

Background

The mathematical model

Statistical emulation

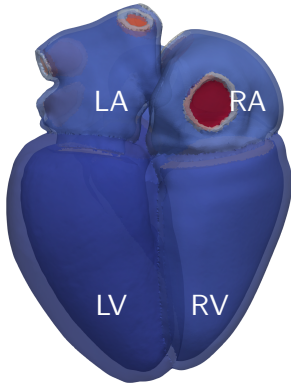
Emulation for multiple geometries

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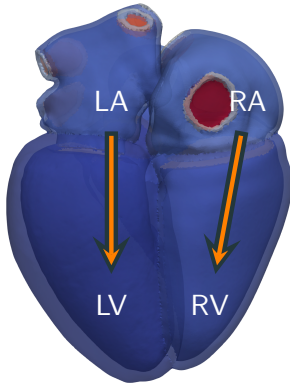
Using ex-vivo information

Ongoing work

# Heart function

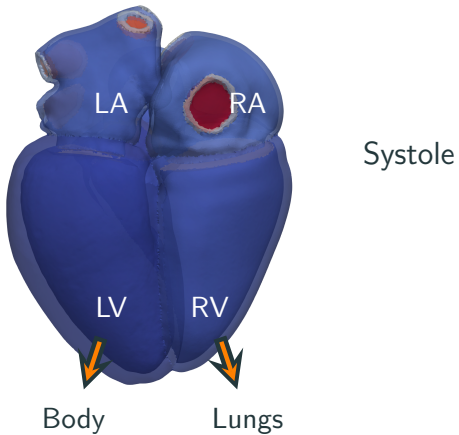


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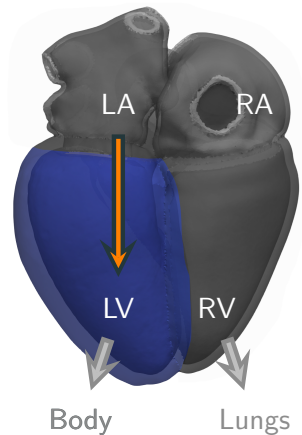


Diastole

# Heart function



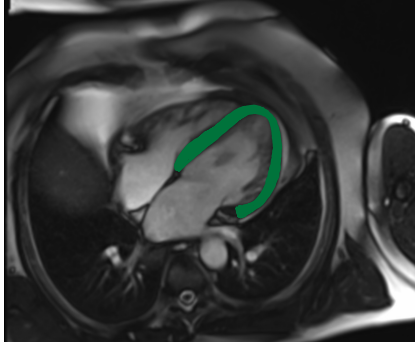
# Heart function



Our interest: left  
ventricle in diastole

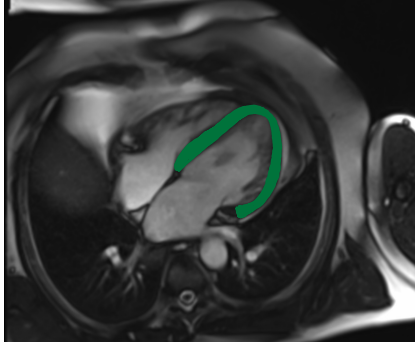
# Left ventricle function

- Left ventricle function is guided by the myocardium.
- Relaxation of the muscle—passive behaviour— allows filling in diastole.
- With diastolic heart failure this filling reduces.
- Inferring the stiffness properties of the myocardium could help identify disease.



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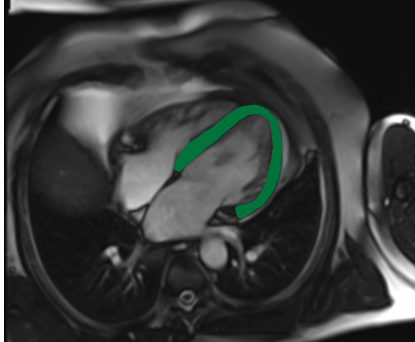
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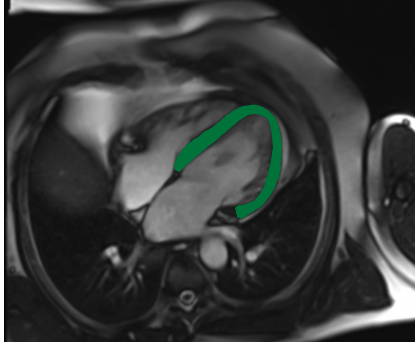
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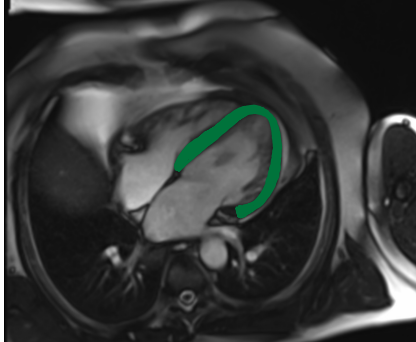
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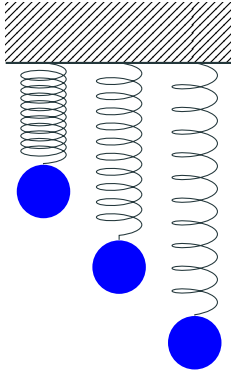


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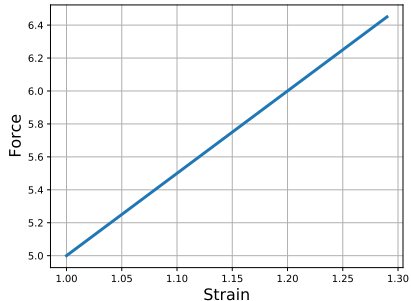


# Describing material behaviour



$$F = kx$$

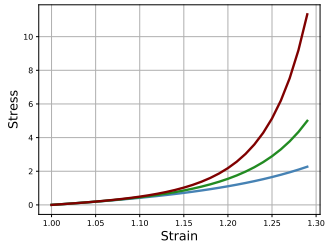
- Hooke's law is the stress-strain relation for linear materials.
- Describes the behaviour of the spring under external force.
- $k$  is the material property—**stiffness of the spring**



# Parameterized description of left ventricle passive behaviour

- Stress strain relation for myocardium provided by the Holzapfel Ogden law.
- A **parameterized** description of the myocardium.
- Parameters give us the stiffness properties!

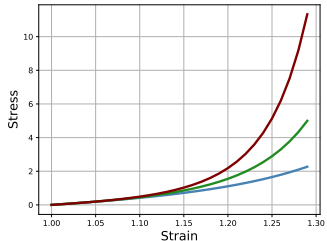
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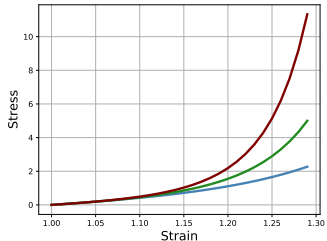
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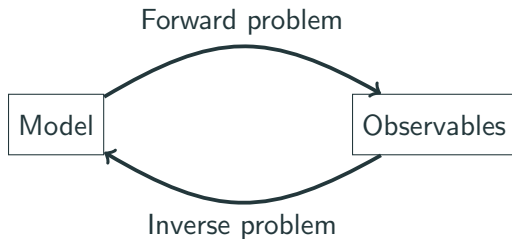
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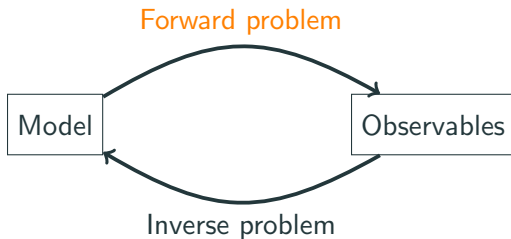


# Forward and inverse problems





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The mathematical model

Statistical emulation

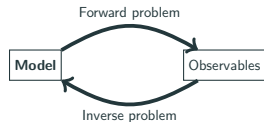
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# The mathematical model as a black box



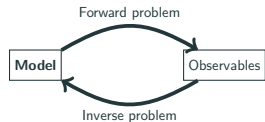
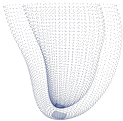
Geometry at early diastole

Boundary conditions

Material properties of myocardium

End of diastole

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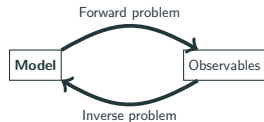
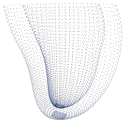
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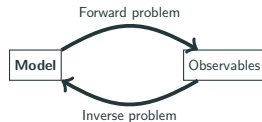
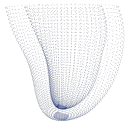
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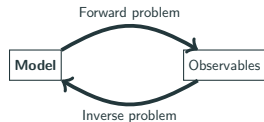
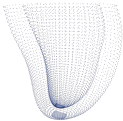
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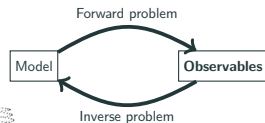
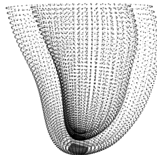
# What do we get from the model?

We have two reference points:

Early diastole



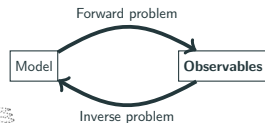
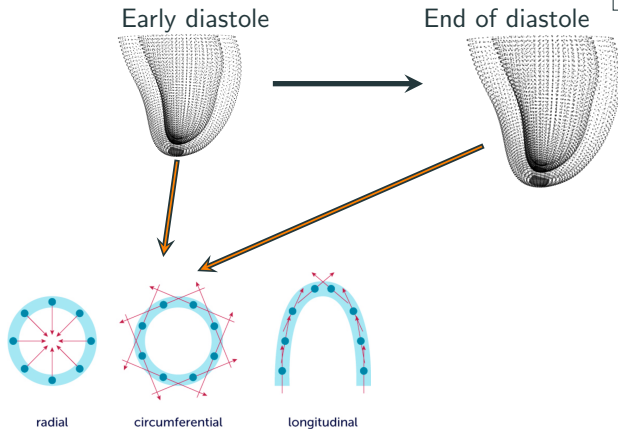
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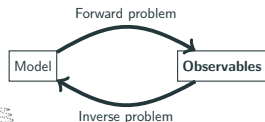
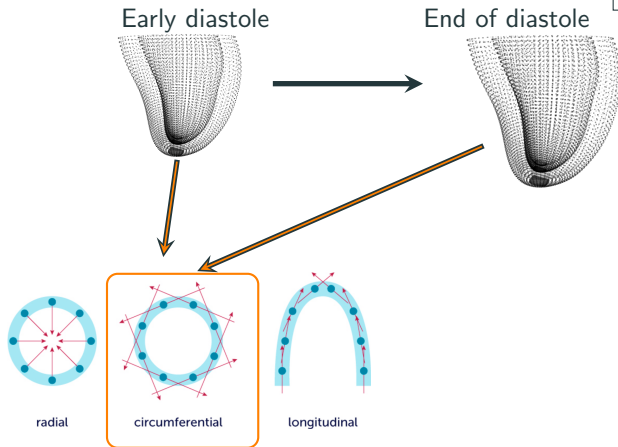
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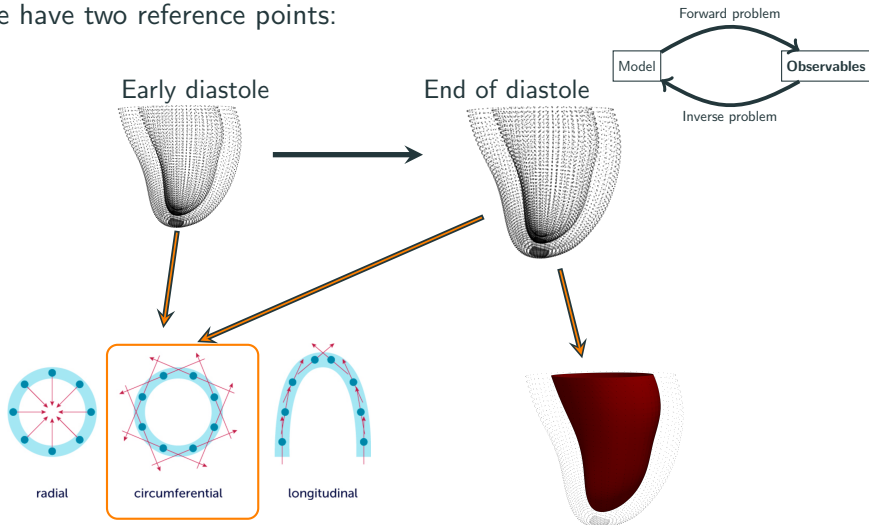
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Currently, only **circumferential strains** can be accurately measured.

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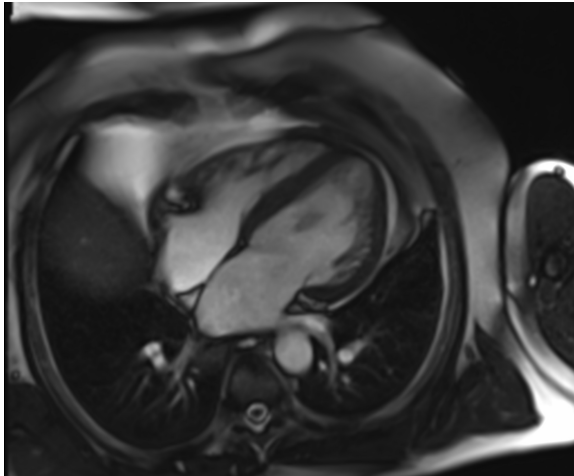
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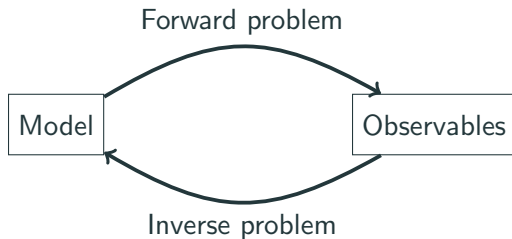
Currently, only **circumferential strains** can be accurately measured.

End diastolic volume of the cavity.

## How are strains and volume measured?

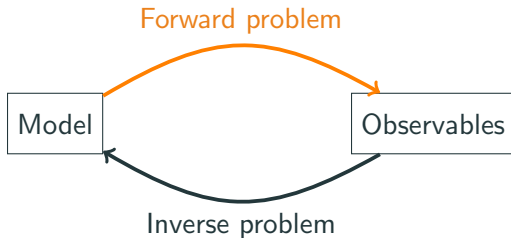


## Can we now solve the inverse problem?



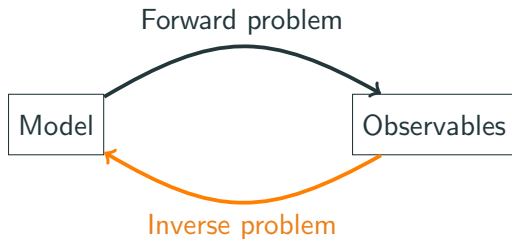
Can we now solve the inverse problem?

Expensive!



Can we now solve the inverse problem?

Very expensive!



We can solve if the patient can wait 2 days and we ignore our uncertainty...

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**Statistical emulation**

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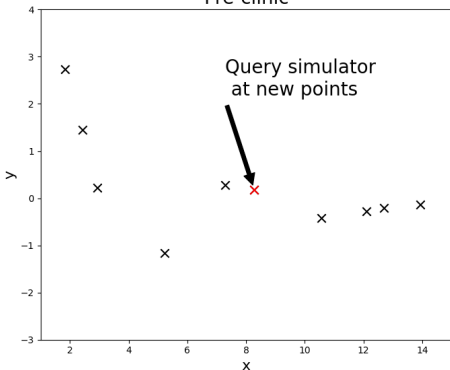
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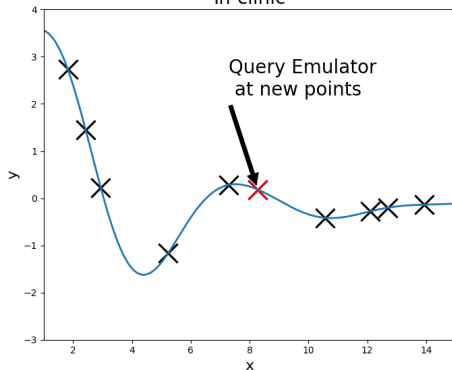
# Emulation

Move the expensive simulations to the pre-clinic phase.

Pre-clinic



In-clinic

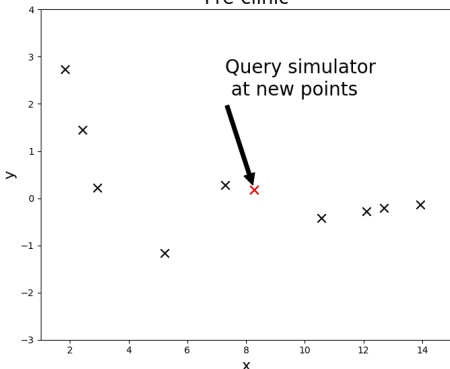


**Two questions:** what is our input space and how do we obtain our emulator?

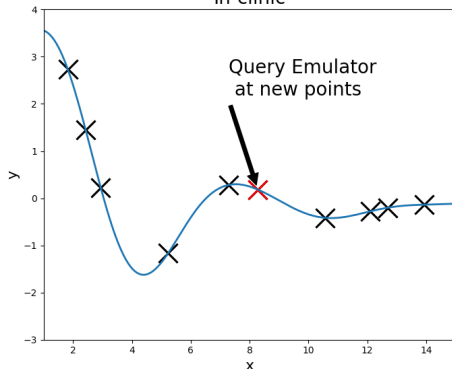
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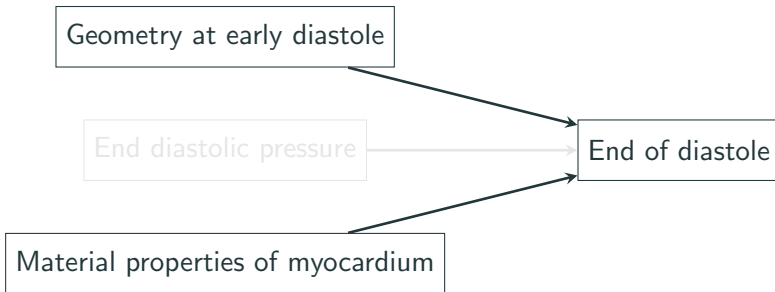


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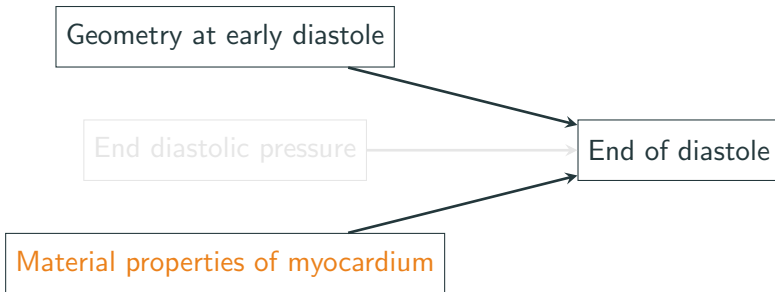


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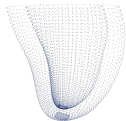


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# Where do we run our simulator?



$\in \mathbb{R}^{17k}$

Geometry at early diastole

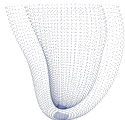
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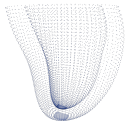
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Need to fill a  $17k+8$   
dimensional space...

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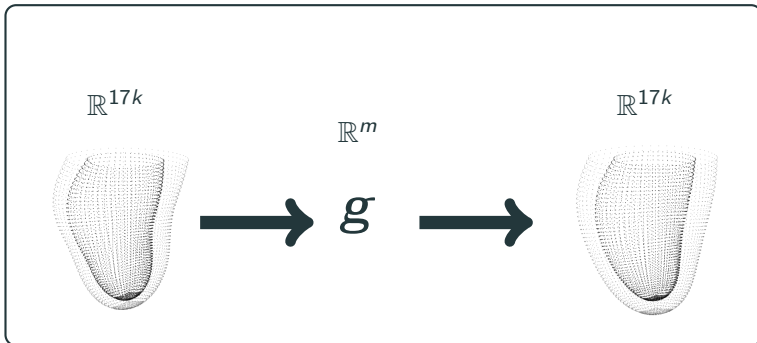
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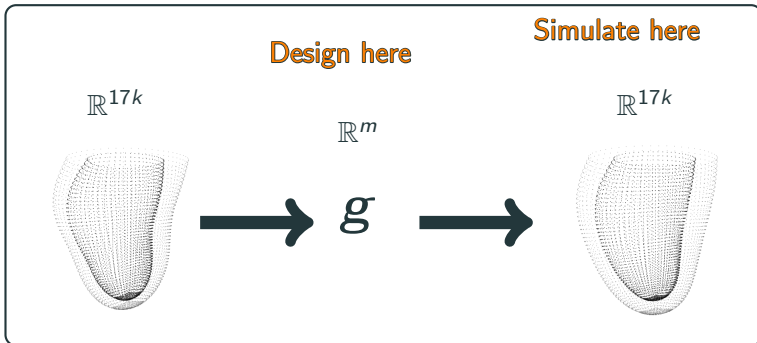
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- Dimensionality reduction allows us to find a low dimensional representation of the LV geometry from  $n$  training left ventricles.
- Design in the low dimensional space and run the simulator on the reconstructed geometries
- These can be fully represented by the  $m$  dimensional projection.
- For our data (**small n**) PCA outperforms more sophisticated methods.



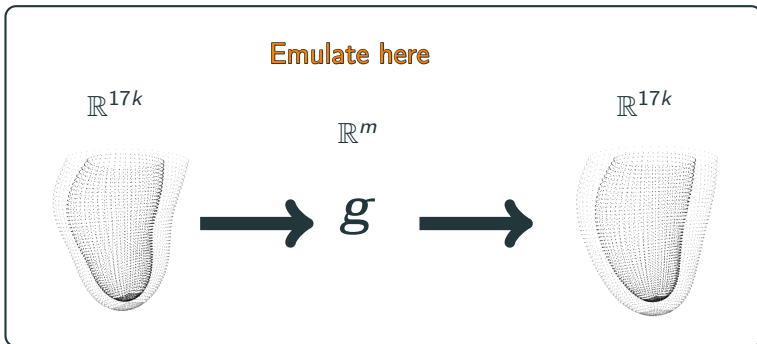
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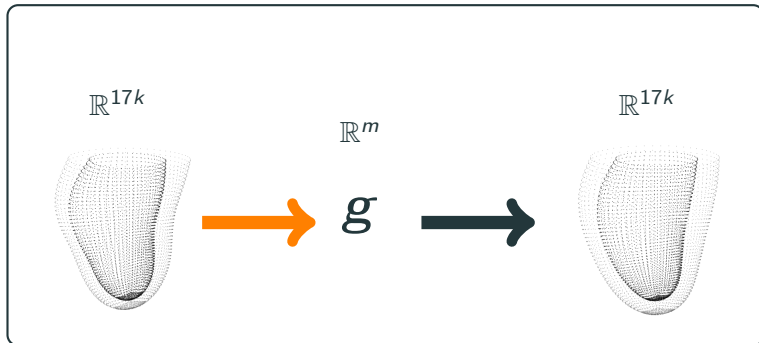
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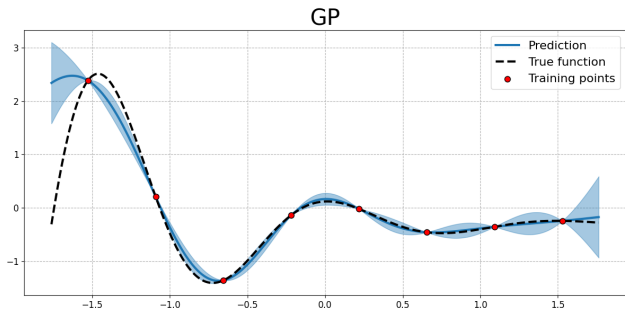
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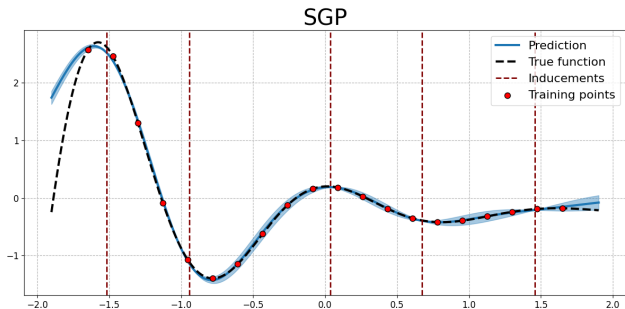
# The problem with GPs

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- With large datasets they rely on approximations.
- Computational costs are only as low as the number of inducement points.
- Neural networks are parametric: prediction costs do not grow with training set size.



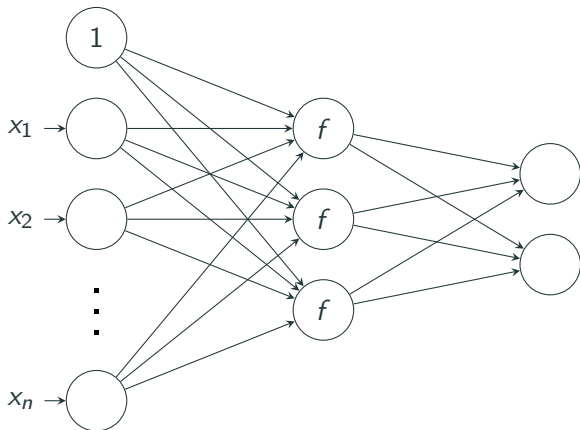
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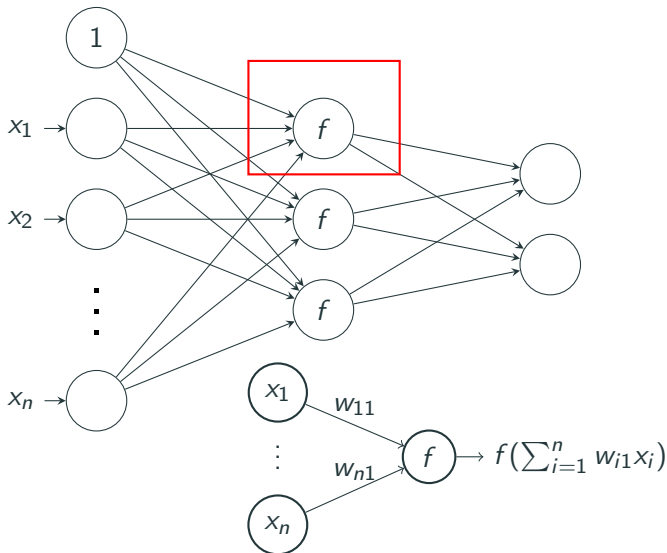
Standard network architecture.





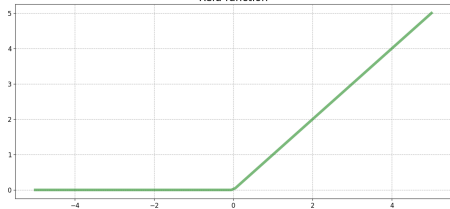
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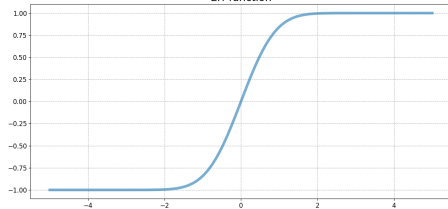


# Effect of activation function

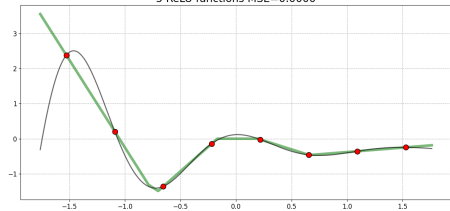
Relu function



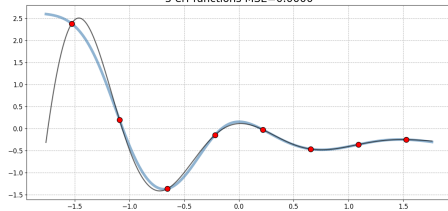
Erf function



5 ReLU functions MSE=0.0000

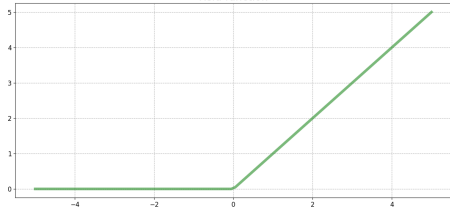


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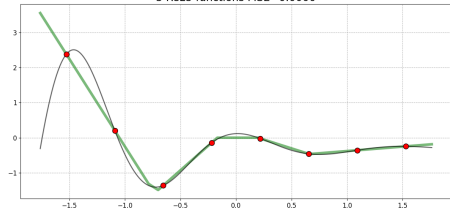


# Effect of activation function

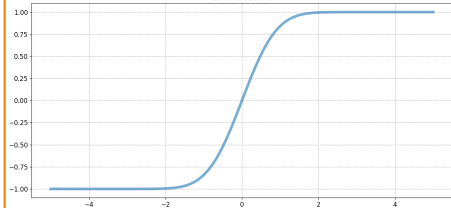
Relu function



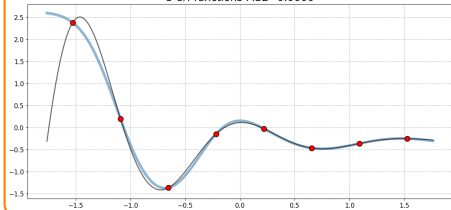
5 ReLU functions MSE=0.0000



Erf function



5 erf functions MSE=0.0000



# Plan

Background

The mathematical model

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Parameter inference for different geometries

Using ex-vivo information

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## Recall: the simulator model



Geometry at early diastole

End diastolic pressure

End of diastole

Material properties of myocardium

$$\begin{aligned} \Psi = & \frac{a}{2b} [\exp \{b(l_1 - 3)\} - 1] \\ & + \sum_{i \in \{f, s\}} \frac{a_i}{2b_i} [\exp \{b_i(l_{4i} - 1)^2\} - 1] \quad \in \mathbb{R}^8 \\ & + \frac{a_{fs}}{2b_{fs}} \left\{ \exp \left( b_{fs} l_{8fs}^2 \right) - 1 \right\} \end{aligned}$$

## Recall: the simulator model



$$\mathbf{g} \in \mathbb{R}^m$$

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Need to fill an  $m + 8$   
dimensional space...

## Recall: the simulator model



$$\mathbf{g} \in \mathbb{R}^m$$

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End diastolic pressure

End of diastole

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Tractable, but can  
we do better?

8 dimensional space...



## A further reduction in complexity

$$\begin{aligned}\Psi = & \frac{a}{2b} \{ \exp[b(l_1 - 3)] - 1 \} + \sum_{i \in \{f, s\}} \frac{a_i}{2b_i} \{ \exp[b_i(l_{4i} - 1)^2] - 1 \} \\ & + \frac{a_{fs}}{2b_{fs}} [\exp(b_{fs} l_{8fs}^2) - 1] + \frac{1}{2}\end{aligned}$$

$$\begin{array}{ll}a = \theta_1 a_0, & b = \theta_1 b_0 \\ a_f = \theta_2 a_{f0}, & a_s = \theta_2 a_{s0} \\ b_f = \theta_3 b_{f0}, & b_s = \theta_3 b_{s0} \\ a_{fs} = \theta_4 a_{fs0}, & b_{fs} = \theta_4 b_{fs0}\end{array}$$

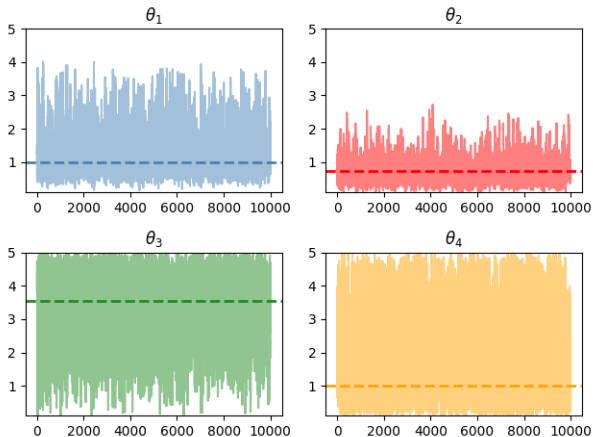
Infer  $\theta_1, \theta_2, \theta_3$  and  $\theta_4$

Emulation problem is now  $m + 4$  dimensional

# Sampling with MCMC

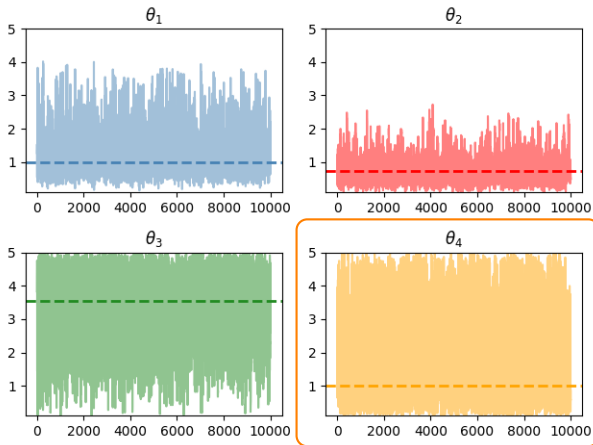
- We will use MCMC to quantify our uncertainty about the parameters.
- Two properties of the statistical emulator allow sampling with more sophisticated MCMC procedures:
  1. **Efficiency**: prediction in order of milliseconds instead of 8 minutes.
  2. **Differentiability** of the function
- However, we use an approximation (emulator) of the true function.
- Error is compounded by our approximation of the geometry.
- How does this affect our inference?

# Inferring material parameters of a real geometry



Inference time: **15 seconds**

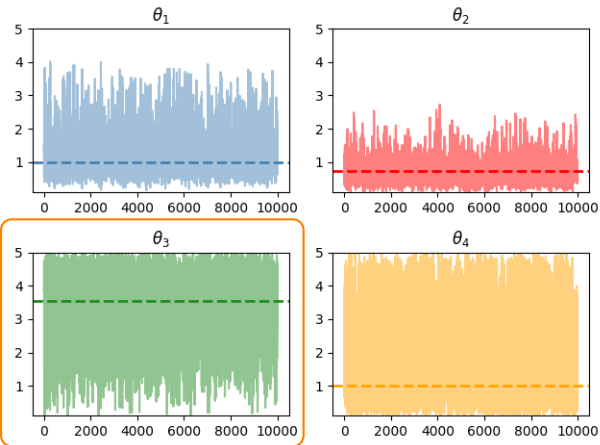
# Inferring material parameters of a real geometry



Circumferential strains  
and volume are not  
sensitive to  $\theta_4$

Inference time: **15 seconds**

# Inferring material parameters of a real geometry

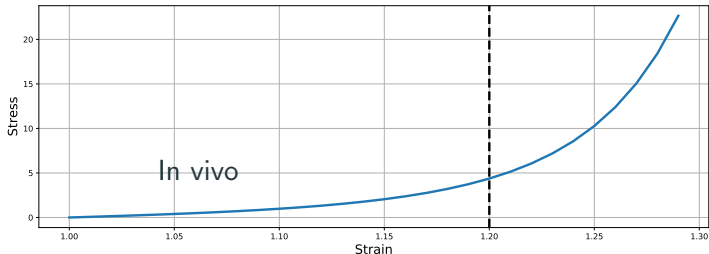


Inference time: **15 seconds**



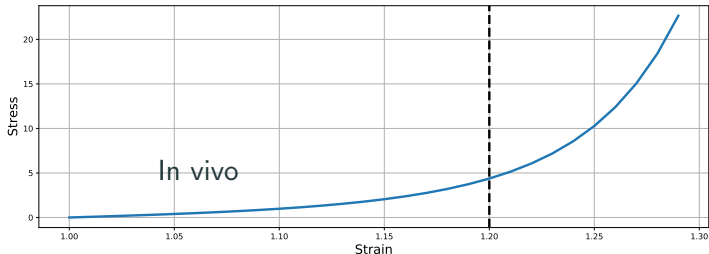
# Problem with parameter identifiability

- Myocardium is a complicated material.
- Different components in material take effect at different stretches.
- Parameters of HO law reflect this changing behaviour.
- Observed data are only informative about small stretch regime.



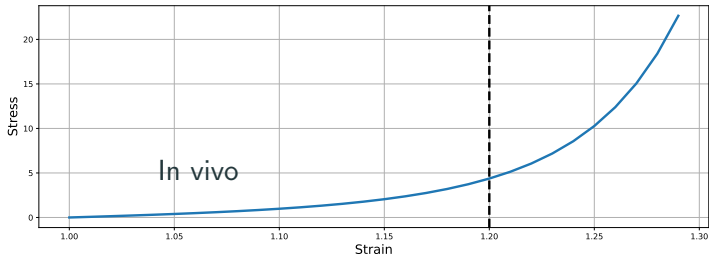
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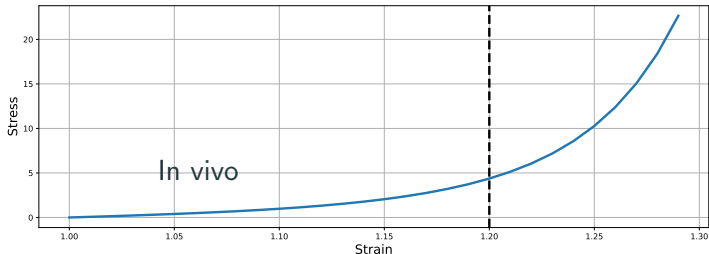
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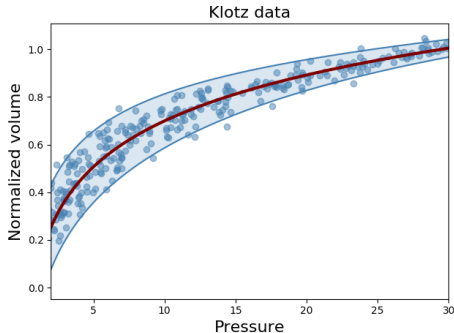
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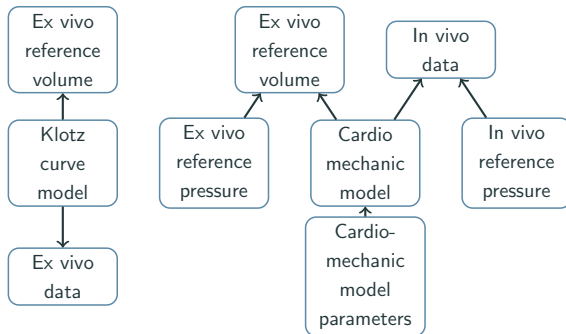
Ongoing work

# The Klotz curve

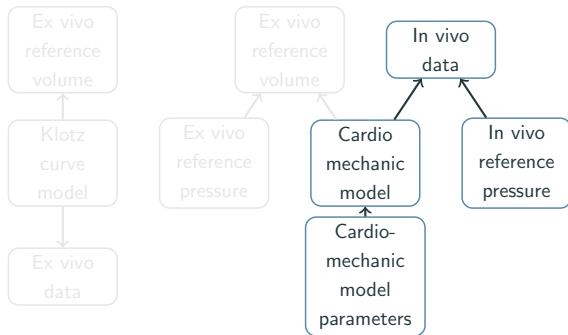
- Klotz et al inflated left ventricles (ex vivo) from volume  $V_0$  at pressure 0 to volume  $V_P$  and pressure  $P$ .
- Measuring also the volume at pressure 30,  $V_{30}$ , they found a relationship between normalized volume  $\tilde{V} = \frac{V_P - V_0}{V_{30} - V_0}$  and pressure  $P$  :
$$\tilde{V} = \frac{\log \frac{P}{\alpha}}{\beta}$$
- Can we use this relationship to include the behaviour at high stretch?



## A first attempt: the non empirical Klotz prior

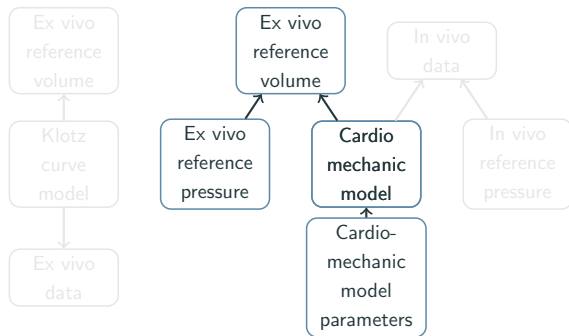


## A first attempt: the non empirical Klotz prior



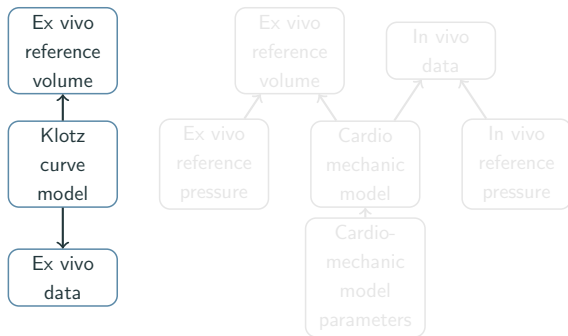
Our likelihood: this comes from our model of the in vivo left ventricle.

## A first attempt: the non empirical Klotz prior



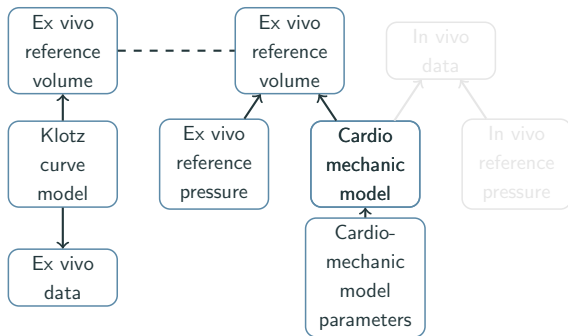
This distribution,  $\pi_E(\tilde{V}_{20})$ , comes from emulators trained to predict volume at pressure 20 and pressure 30 (with associated uncertainty).

## A first attempt: the non empirical Klotz prior



This distribution,  $\pi_{\text{KL}}(\tilde{V}_{20})$ , comes from enforcing the Klotz relationship on the left ventricle.

## A first attempt: the non empirical Klotz prior

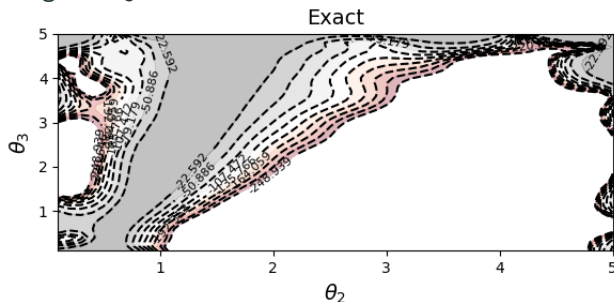


Match these with **product of experts**:  $\mathcal{F} = \int \pi_E(\tilde{V}_{20}) \pi_{KL}(\tilde{V}_{20}) d\tilde{V}_{20}$ .

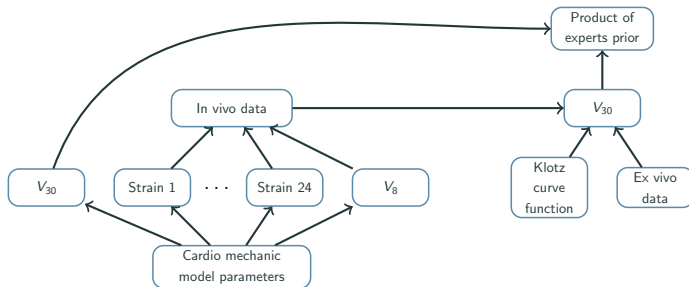


# Problem with the non empirical Klotz prior

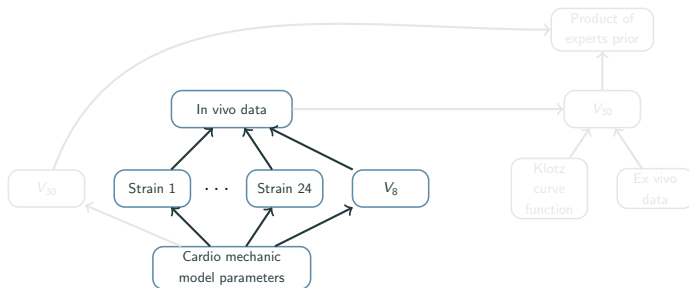
Ridge in  $\theta_3$  direction.



## A second attempt: the empirical Klotz prior

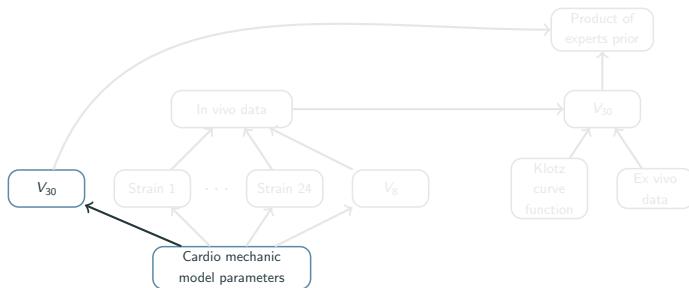


## A second attempt: the empirical Klotz prior



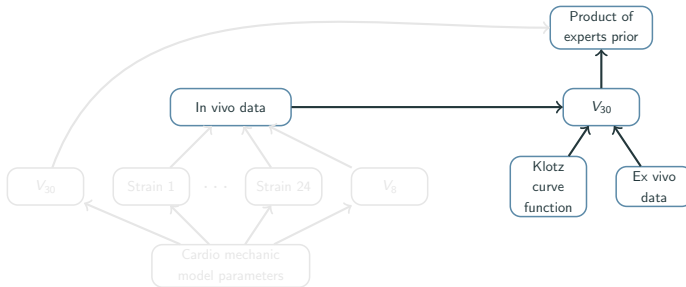
Likelihood function for in vivo data comes from emulated cardiac model.

## A second attempt: the empirical Klotz prior



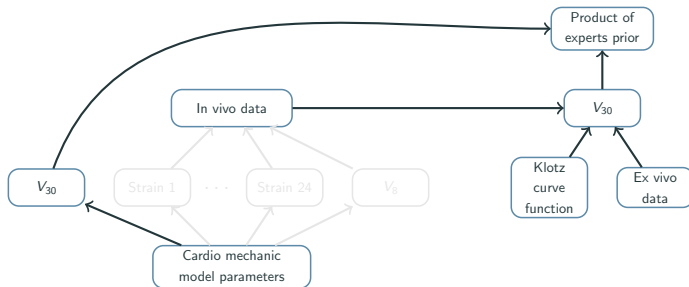
A prediction of  $V_{30}$  comes from a pressure 30 volume emulator.

## A second attempt: the empirical Klotz prior



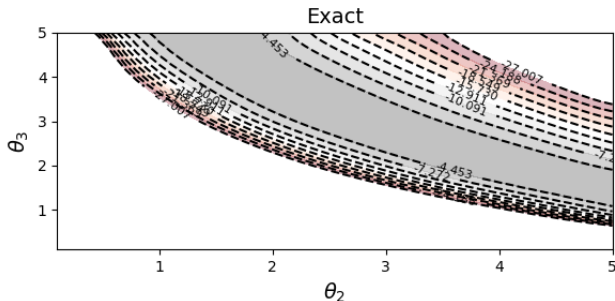
A prediction of volume at pressure 30 from Klotz function, this time related to the in vivo volume measurement.

## A second attempt: the empirical Klotz prior



Match with product of experts: now we have an empirical Klotz prior (relies on the measured volume)

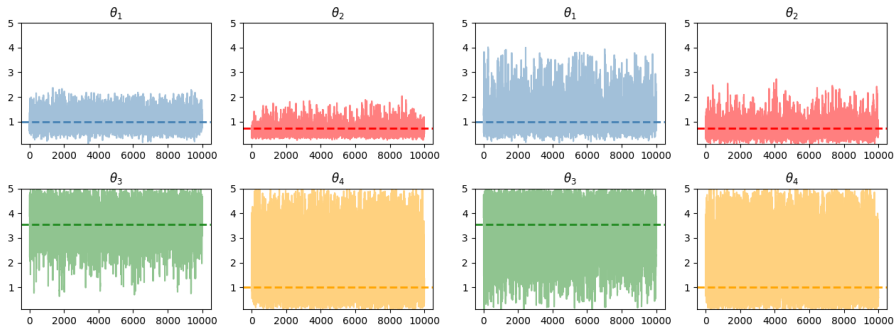
# Assessing performance of the Klotz prior



Ridge in the prior is aligned with the  $\theta_2$  axis.

# Does Empirical Klotz make a difference?

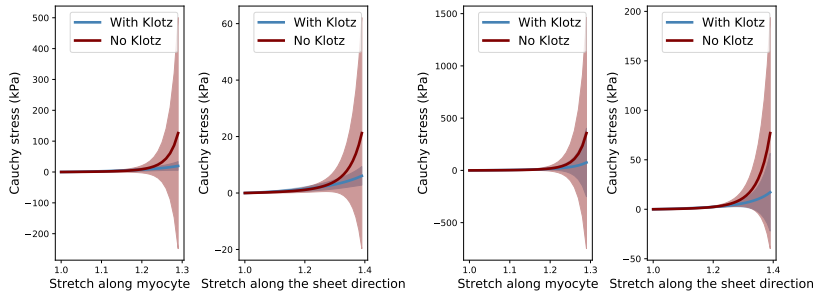
Yes, if our data are generated in line with the Klotz curve



But we do not know how closely the in vivo heart follows the Klotz curve



# How about real data?



## Summary so far

- The parameters from the reparameterized HO law are difficult to estimate
- Klotz is probably not the answer to the problem—do we really want to rely so heavily on ex vivo data?
- Instead, we should try new parameterizations
- Or accept lack of identifiability and try to use only those parameters we can learn

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## Alternative parameterization

$$\begin{aligned}\Psi &= \frac{a}{2b} [\exp \{b(l_1 - 3)\} - 1] \\ &+ \sum_{i \in \{f, s\}} \frac{a_i}{2b_i} \left[ \exp \left\{ b_i (l_{4i} - 1)^2 \right\} - 1 \right] \\ &+ \frac{a_{fs}}{2b_{fs}} \left\{ \exp (b_{fs} l_{8fs}^2) - 1 \right\}\end{aligned}$$

$a, b, a_f, b_f$  inferred,  $a_s, b_s, a_{fs}, b_{fs}$  constant

$a$  and  $a_f$  are more identifiable, can we use these for predicting tissue health?

Thank you!

# PC performance

