Seminar Presentation:

Review of Gaussian Processes and Machine Learning

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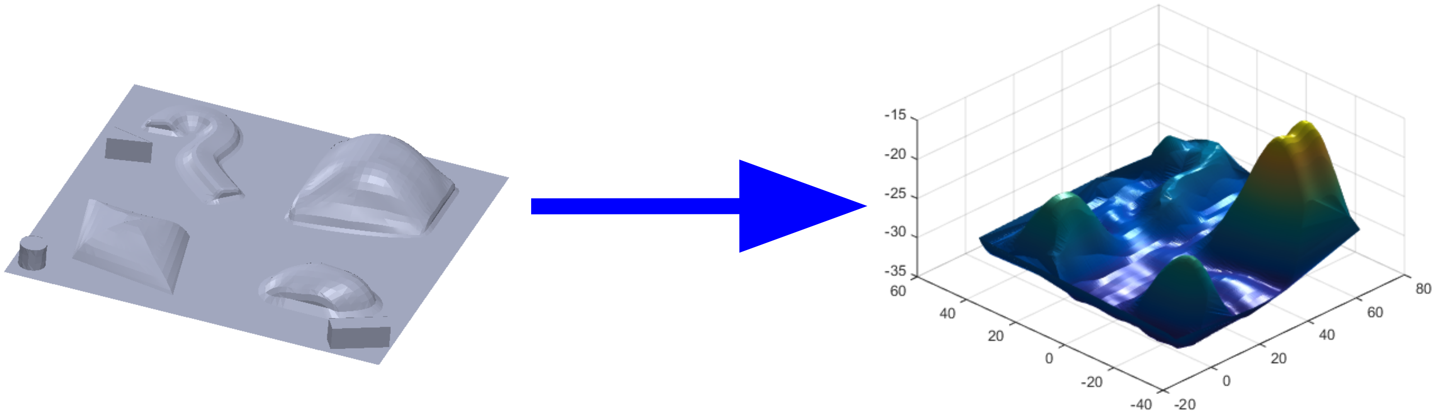
Optimized Tissue Reconstruction

Accurately reconstruct a tissue/surface from finite number of force sensor palpation readings



Reconstruction with Gaussian Processes (GP)

- Gaussian Process
  - A collection of random variables that have joint gaussian distributions
  - Can be infinite number of random variables
- For tissue reconstruction:
  - Model each force sensor palpation reading as gaussian distribution and then compute gaussian process of all palpation readings
  - Use gaussian process to model interpolated points within tissue range

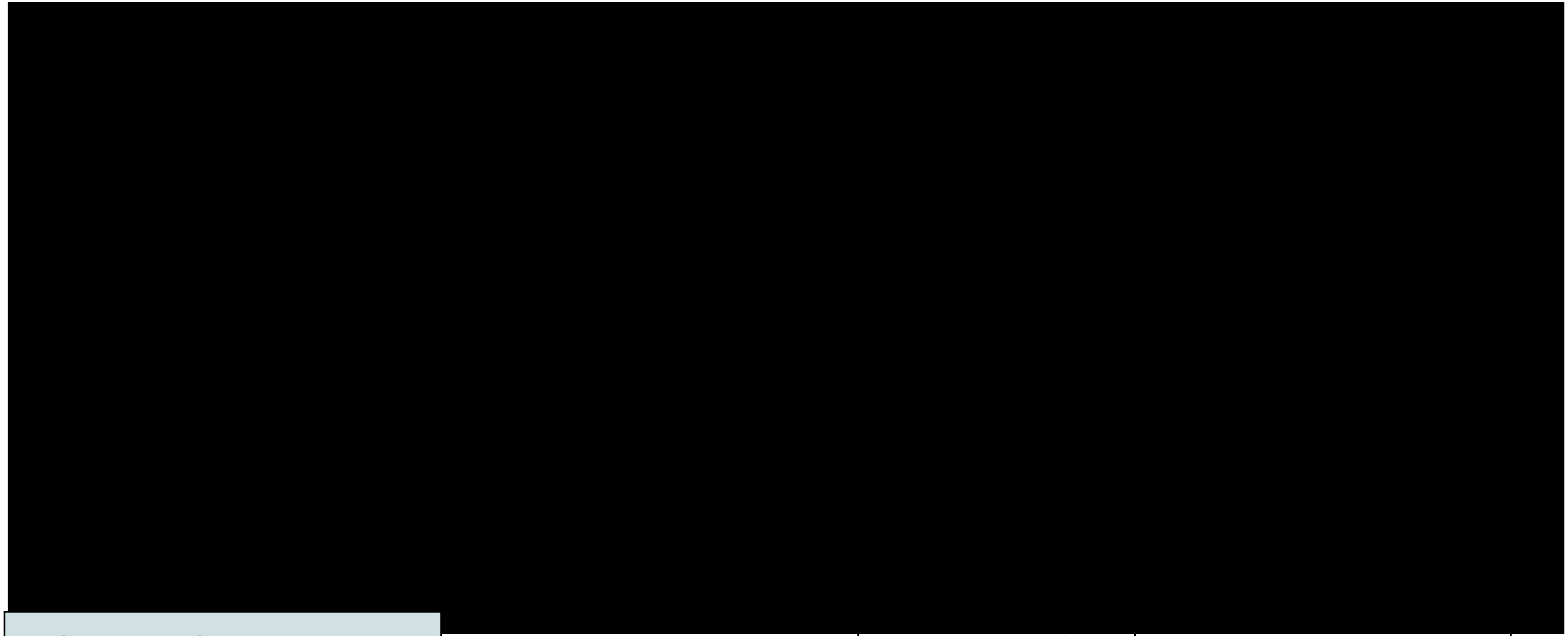
Paper Selection

- Rasmussen C. E., *Gaussian Process in Machine Learning.* Max Planck Institute for Biological Cybernetics, T¨ubingen, Germany
  - Theoretical development of GP and practical implementation
  - Our project relies on GP and a theoretical understanding is essential

Overview of paper presentation

- GP Independent of training data
- GP with Training Data
- Training a GP
- Personal Assessment

Defining a Gaussian Process



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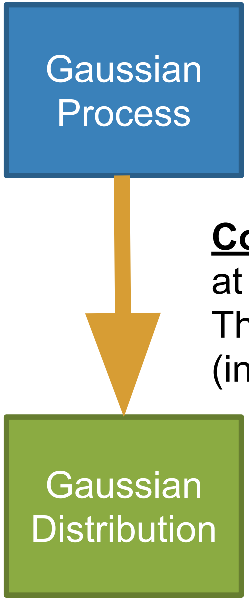
Example Conversion from GP to Gaussian Distribution

[redacted]



Conversion: Compute values of f at n distinct (finite) locations of x. This will bring you from function (infinite) to vector (finite)

[redacted]

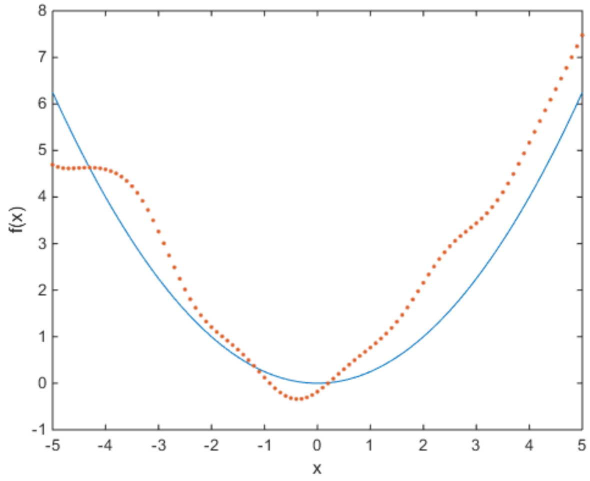
Example of Sampling from Gaussian distribution

[redacted]

[redacted]

[redacted]

[redacted]



Prior and posterior

GP with training data

Prior [redacted]

[redacted]

Posterior [redacted]

f ➔ known function values from training cases
f* ➔function values for test set inputs
μ ➔ means for training sets
μ* ➔ means for test sets
Σ ➔ training set covariances
Σ* ➔ Training-test set covariances
Σ** ➔ test set covariances

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GP Conditional distribution

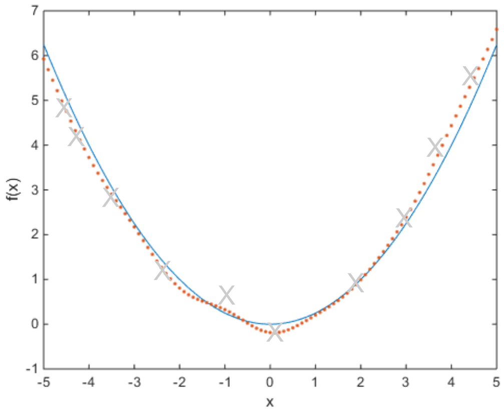
The training points allow us to compute the distribution of test points given the training points (with goal of increasing accuracy of model) as follows:

[redacted]

-or-

[redacted]

Sample points from conditional distribution



Updating the prior with training data

- In most applications, an exact prior (as was the case in all preceding examples) is not known
- Use hyperparemeters (set of parameters) that can be 'tuned' on training data
- An example of this would be if we knew the mean function resembles a second order polynomial:

[redacted]

[redacted]

[redacted]

hyperparameters

[redacted]

Updating the prior with training data

[redacted]

- Given this system, we want to tune the hyperparameters in order for the prior to fit the training data
- To tune, we will utilize the marginal log likelihood:

[redacted]

- Calculate value of each hyperparameter that maximizes the log likelihood function
  - Can use gradient descent to do this

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Log likelihood and fitting

[redacted]

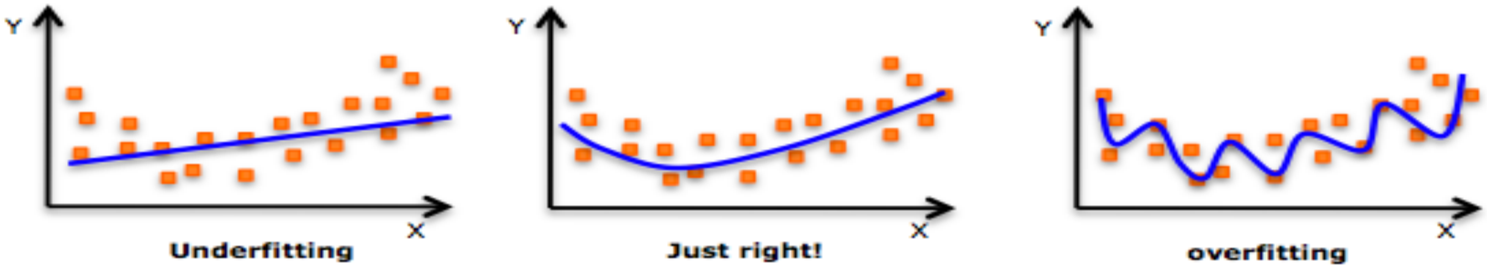
Decreases log likelihood if system is complex

Deceases log likelihood if prior does not fit data

Relatively unimportant to the idea of fitting

As can be observed by the first two terms there is a trade off between complexity of your model and goodness of fit.

Log likelihood and fitting



Low Complexity
Poor fit to test points

High Complexity
Hits most test points

Relation to tissue reconstruction

Paper

[redacted]

[redacted]

[redacted]

[redacted]

Our Model

[redacted]

[redacted]

[redacted]

Criticism

- The author made many assumptions that he assumed the reader would know. It required a high level of mathematics background

Implications for our project

- Increased understanding of GP should help with:

1. Ensuring our GP code is working properly
2. Increasing the efficiency of our GP code

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QUESTIONS???