

# Fluid Dynamics Models for Low Rank Discriminant Analysis

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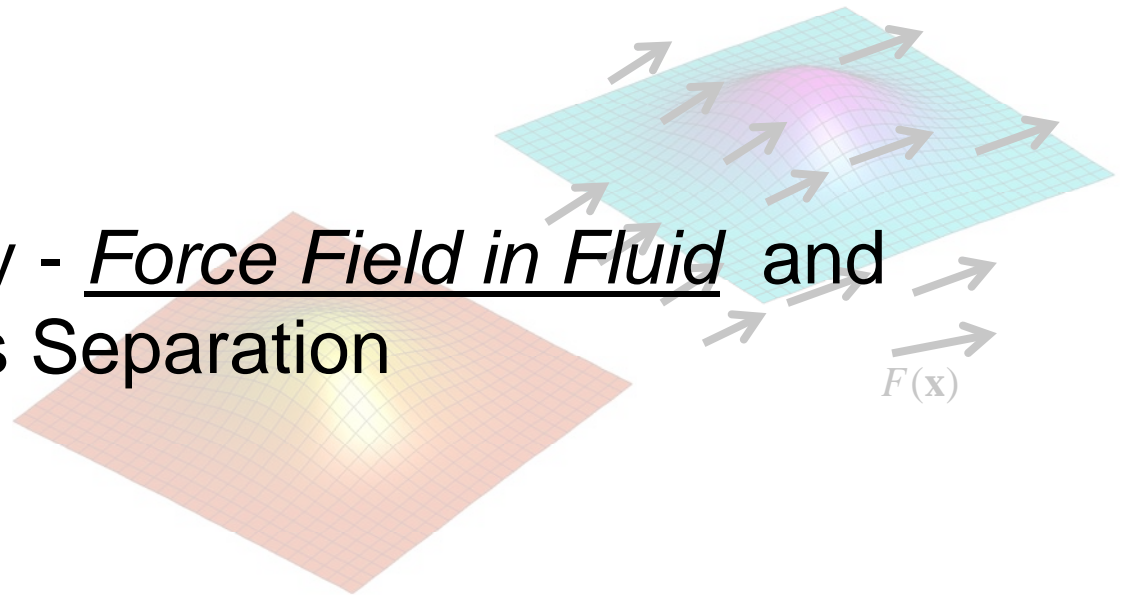
AI & Statistics 2010

The logo for AI & Statistics 2010 features a stylized sun and palm trees in the background, with the word "Statistics" written in a light blue, cursive font across the middle. The entire logo is enclosed in a thin blue rectangular border.

# Overview

- Dimensionality Reduction Problem for Classification – Bhattacharyya Analysis

- Physics Analogy - Force Field in Fluid and Motion for Class Separation



- Discrimination of Gaussian Processes

# Discriminant Analysis

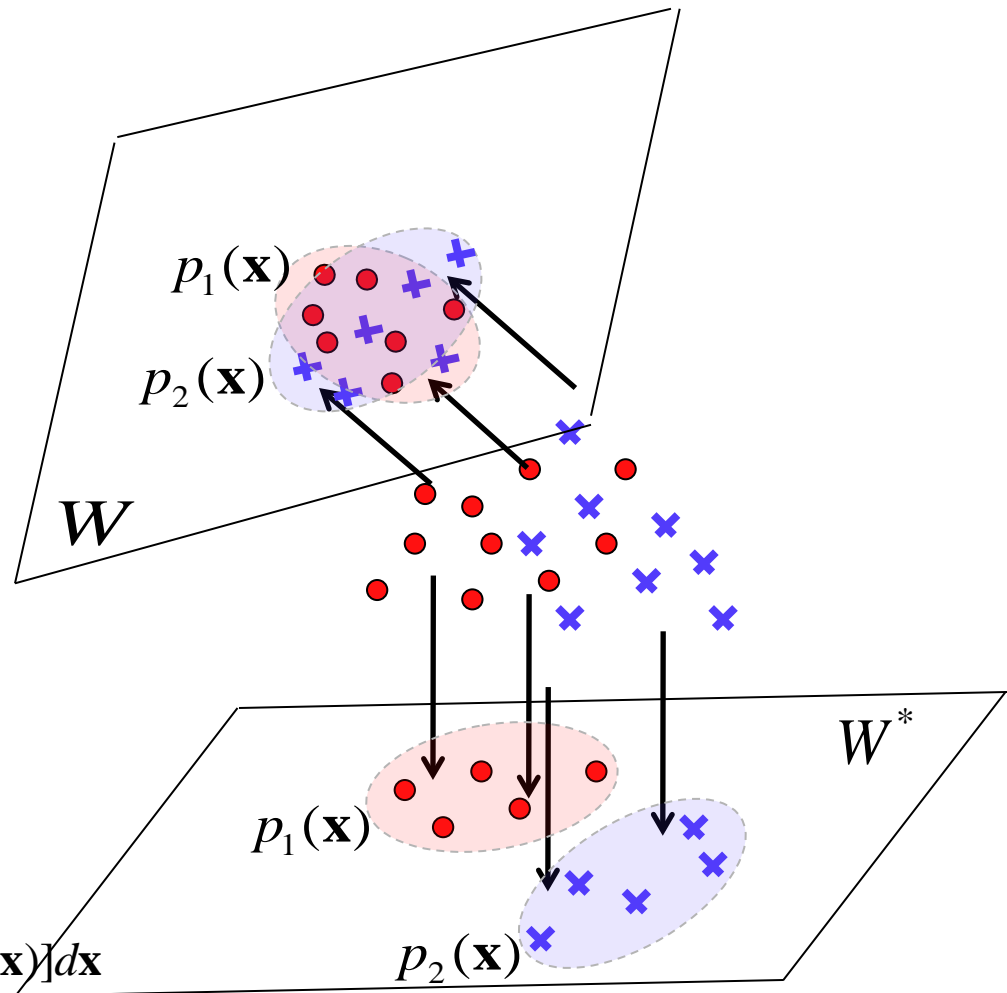
- Maximize class separation for classification.

Optimal subspace

$$W^* = \arg \min_W E_{Bayes}(W)$$

Objective function

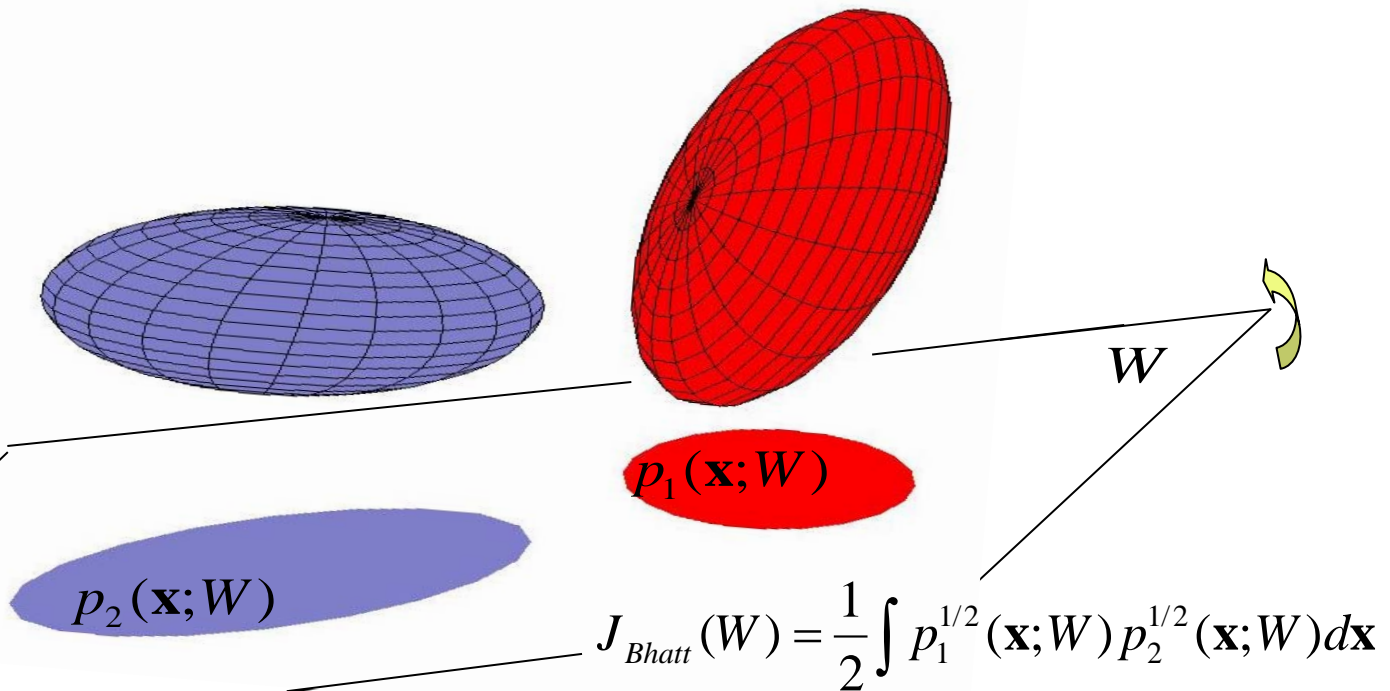
$$E_{Bayes} = \frac{1}{2} \int \min[p_1(\mathbf{x}), p_2(\mathbf{x})] d\mathbf{x}$$



# Analysis with Bhattacharyya Bound

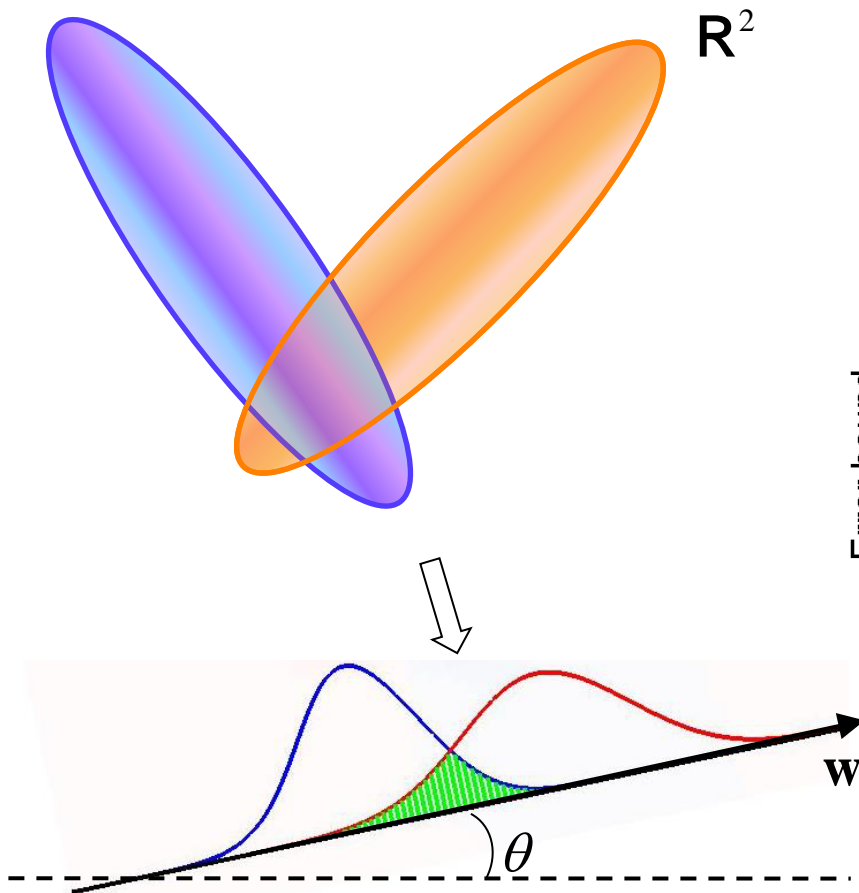
- Bhattacharyya bound with Gaussian distributions is integrable.

$$\min[p_1, p_2] \leq p_1^{1/2} p_2^{1/2}$$

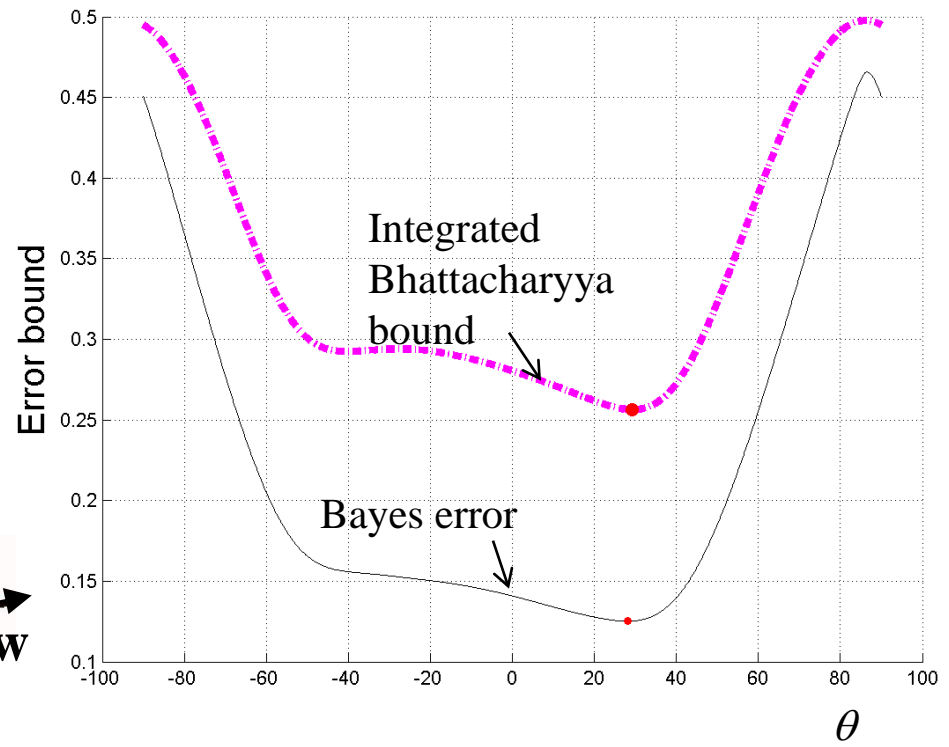


# Characteristic 1:

- Non-convex Function with Global Minimum Near Bayes Optimal.



$$E_{Bayes} \leq J_{Bhatt}$$



## Characteristic 2:

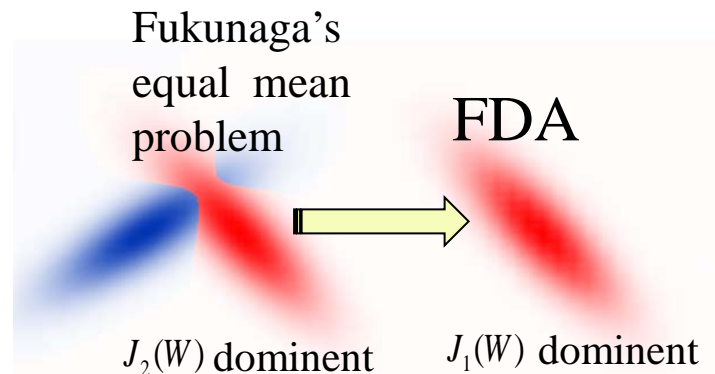
- Optimizing Integrated Bhattacharya Bound.

$$-\ln[2J_{Bhatt}(W)] = J_1(W) + J_2(W) \quad [\text{Fukunaga 1990}]$$

$$J_1(W) = \frac{1}{8} \text{Tr} \left[ \underbrace{\left( \frac{W^T \Sigma_1 W + W^T \Sigma_2 W}{2} \right)^{-1}}_{\substack{\text{Minimizing} \\ \text{within class} \\ \text{variance}}} \underbrace{W^T (\mu_1 - \mu_2)(\mu_1 - \mu_2)^T W}_{\substack{\text{Maximizing} \\ \text{mean difference}}} \right]$$

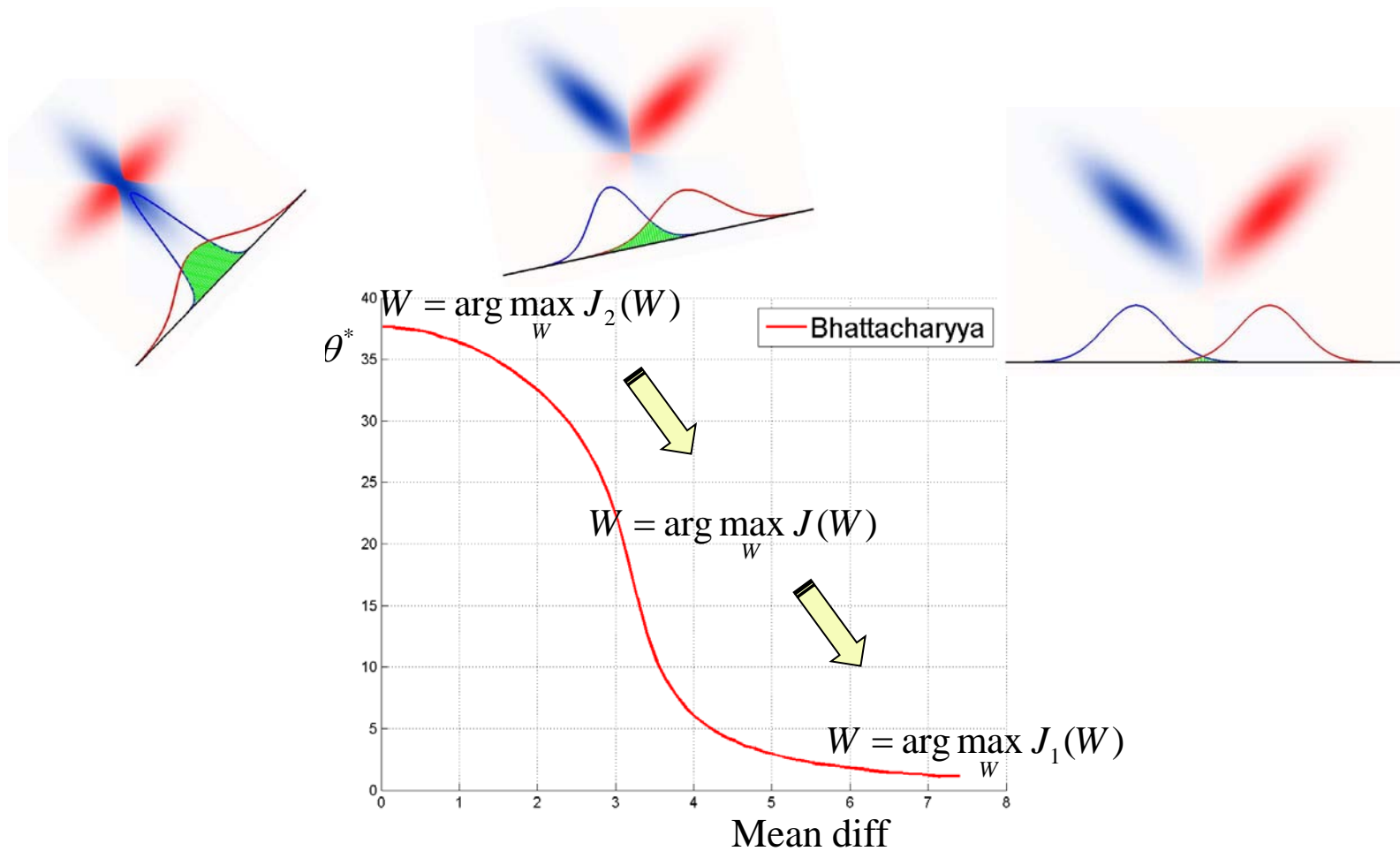
$\mu_i$ : mean  
 $\Sigma_i$ : Cov.

$$J_2(W) = \frac{1}{2} \ln \left( \underbrace{\left| \frac{W^T \Sigma_1 W + W^T \Sigma_2 W}{2} \right| / \left| W^T \Sigma_1 W \right|^{1/2} \left| W^T \Sigma_2 W \right|^{1/2}}_{\text{Maximizing covariance difference}} \right)$$



# Characteristic 3:

- Transition of the Optimal Direction.



# Optimizing Bhattacharrya Bound

- A Good Approximation of the Bayes Optimum Subspace
  - Analytically Integrable for Gaussians
- Non-Convex, Many Local Minima
  - ‘ $W$ ’ Matrix Cannot be Optimized by Optimizing Basis Vectors. (Deflation Cannot be Applied.)

How to address these problems?



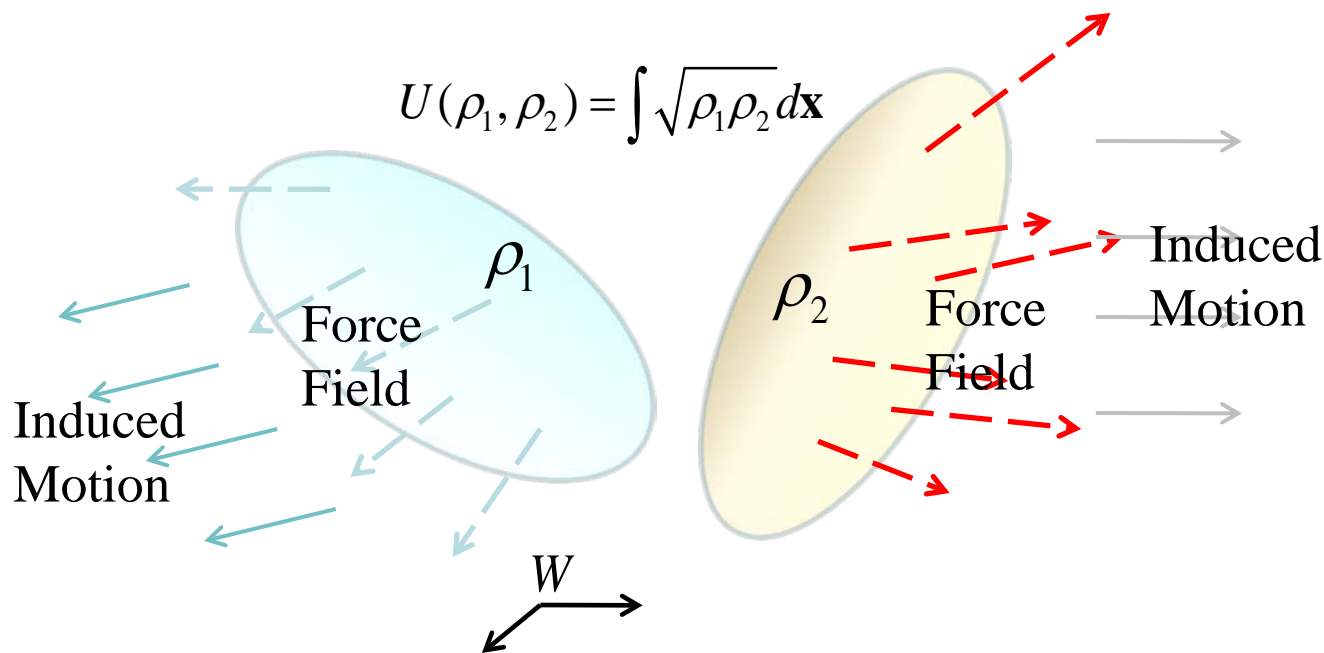


# Fluid Dynamics Model

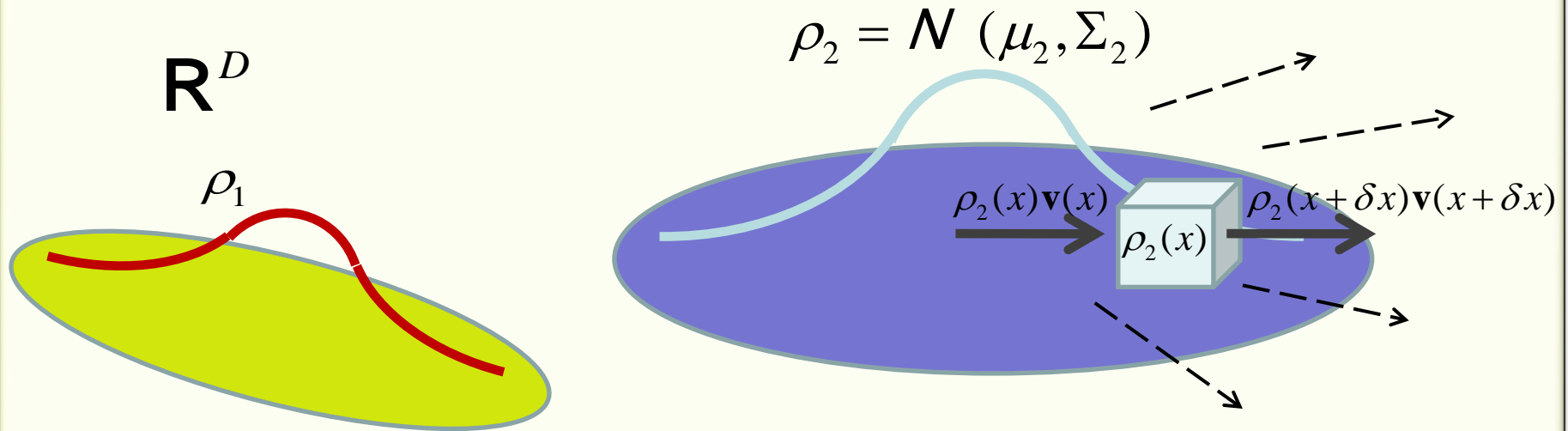


# Physics-Based Model for Bhattacharyya Optimization

- Bhattacharyya potential over high dimensional distributions to reduce the overlap
  - Generate the motion
  - Motion & Low dimensional space



# Fluid Model

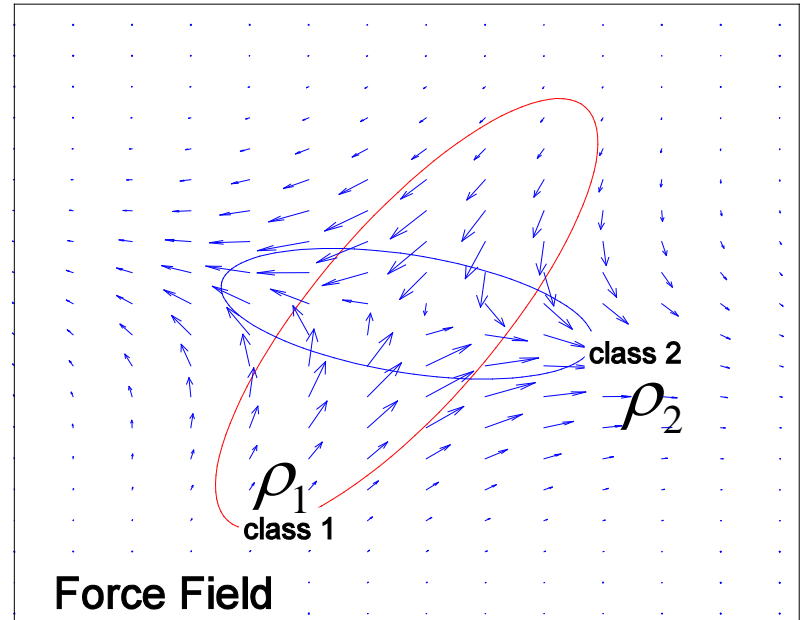
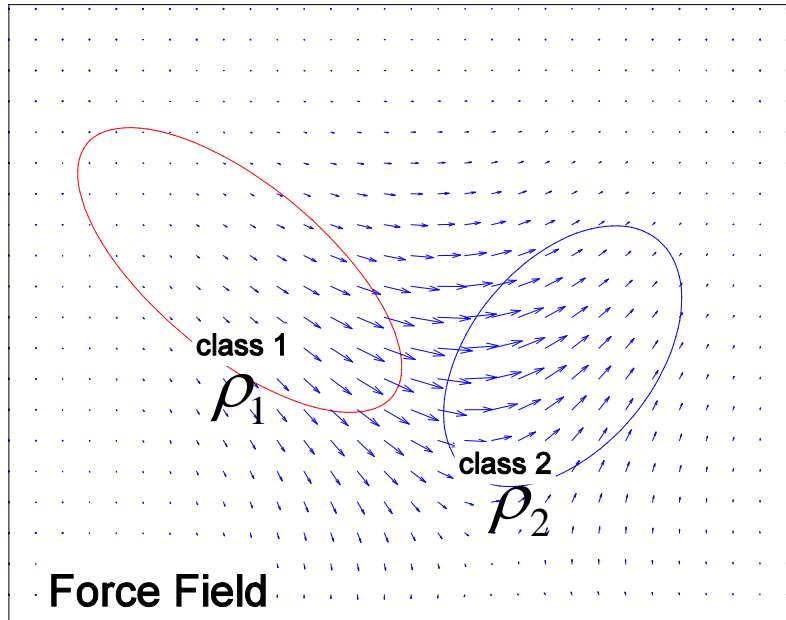


- Equation of continuity

$$\frac{\partial \rho_c}{\partial t} + \nabla \cdot (\rho_c \mathbf{v}) = 0$$

– Conservation of mass

# Force Field for Class Separation



- Potential to reduce interaction

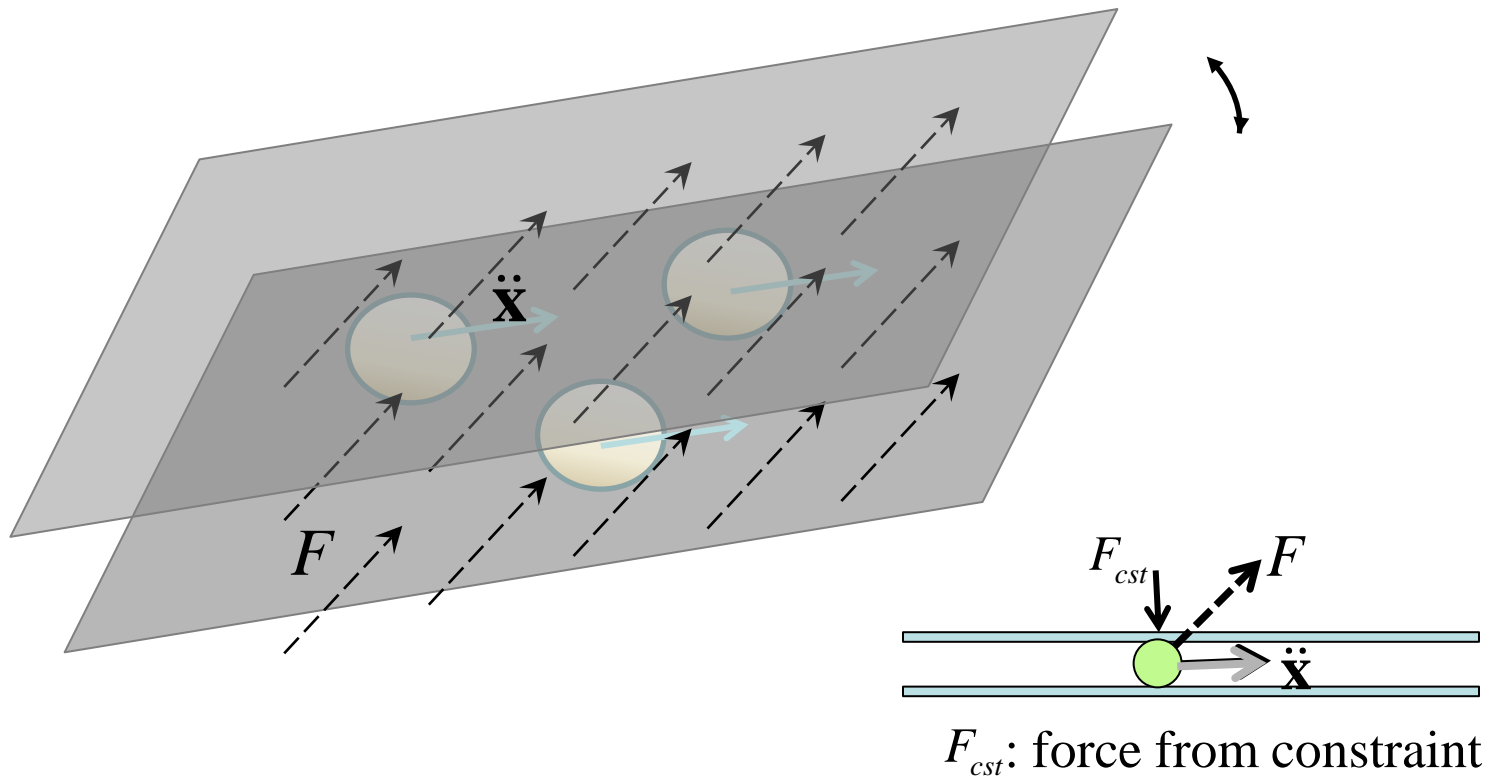
$$U(\rho_1, \rho_2) = \int \sqrt{\rho_1 \rho_2} d\mathbf{x} \quad \leftarrow \text{Bhattacharyya bound}$$

- Decrease of potential by movement of  $\rho_2$

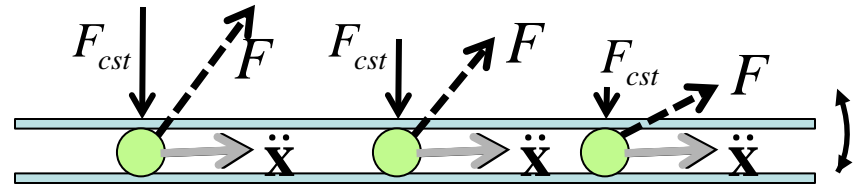
$$F_{1 \rightarrow 2}(\mathbf{x}) = -\frac{1}{2} \rho_2 \nabla \sqrt{\frac{\rho_1}{\rho_2}}$$

# Constrained Fluid Model

- Acceleration is optimized under force field and given constraint.



# Gauss Principle of Least Constraint



$F_{cst}$ : force from constraint

- Minimize  $L$

$$L = \frac{1}{2} \int \rho(\mathbf{x}) \left( \ddot{\mathbf{x}} - \frac{F(\mathbf{x})}{\rho(\mathbf{x})} \right)^2 d\mathbf{x}$$

$F_{cst}(\mathbf{x}) / \rho(\mathbf{x})$

- Minimizing total constraint forces
- Motion of multiple objects with multiple constraints.

# Acceleration Field with Constraint

- Constraint on motion

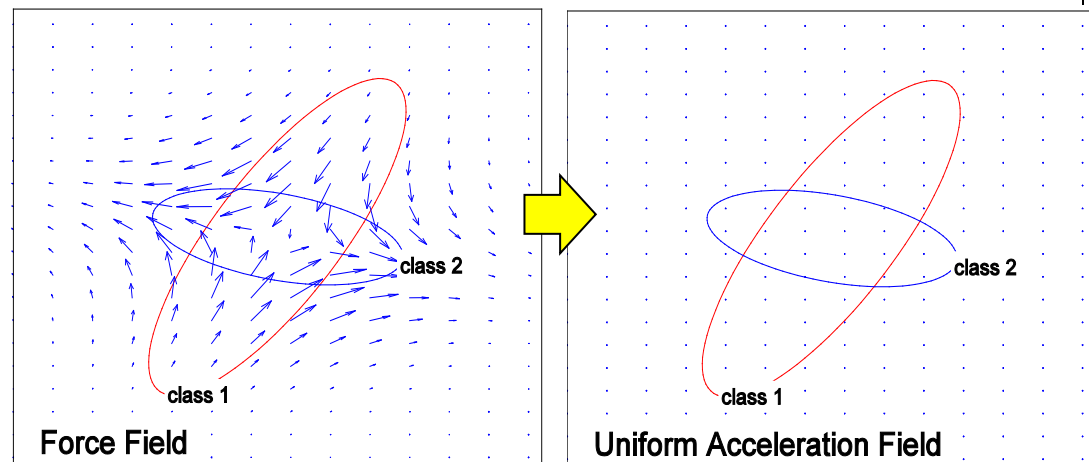
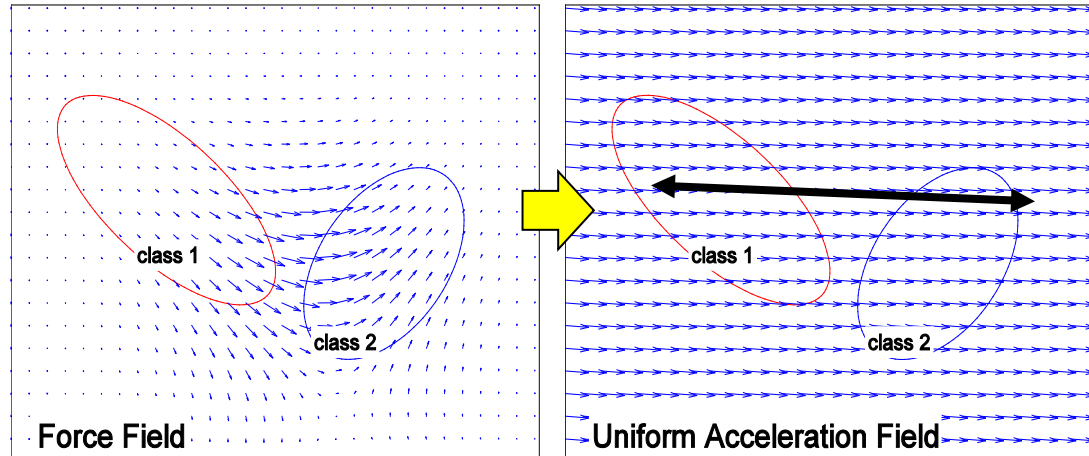
Uniform translational movement

$$\ddot{\mathbf{x}} = \mathbf{w}$$



$$\begin{aligned} \mathbf{w} &= \int F d\mathbf{x} \\ &= C_2 \left( \frac{\Sigma_1 + \Sigma_2}{2} \right)^{-1} (\mu_1 - \mu_2) \end{aligned}$$

The subspace is the FDA solution



# Acceleration Field with Constraint

- Constraint on motion

*Low rank  
affine acceleration*

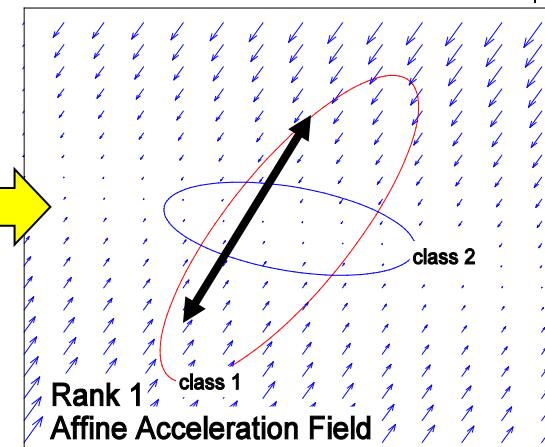
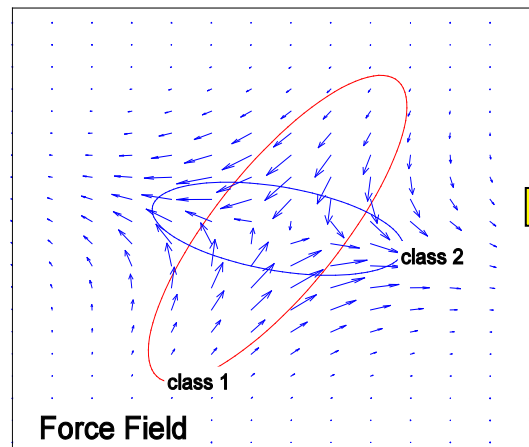
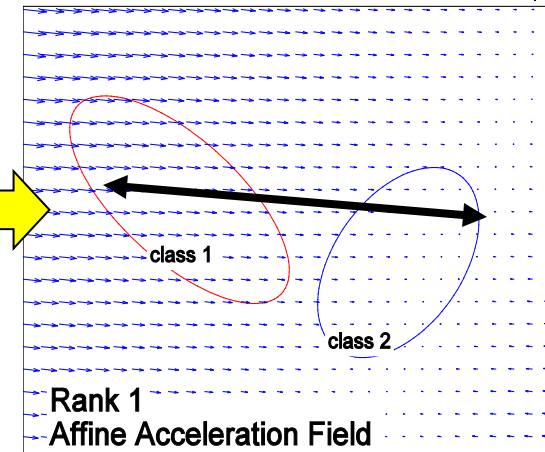
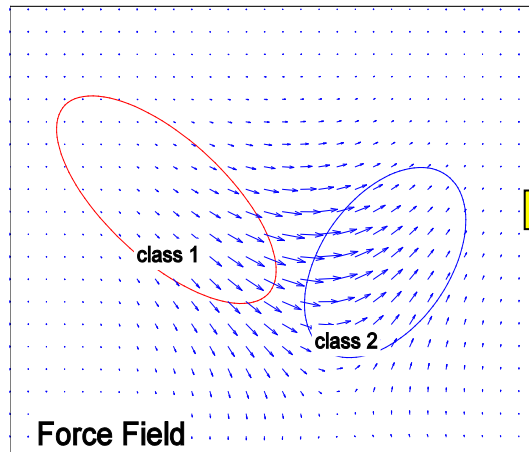
$$\ddot{\mathbf{x}} = W U_c^T \mathbf{x}_e \quad \mathbf{x}_e = \begin{bmatrix} \mathbf{x} \\ 1 \end{bmatrix}$$



$W$ : e-vectors of

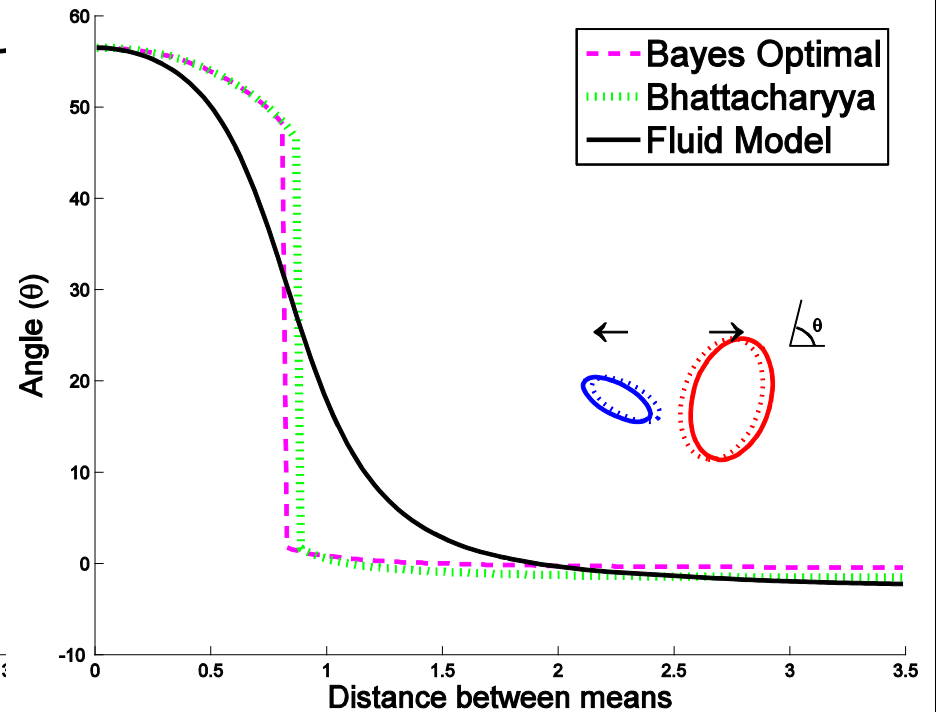
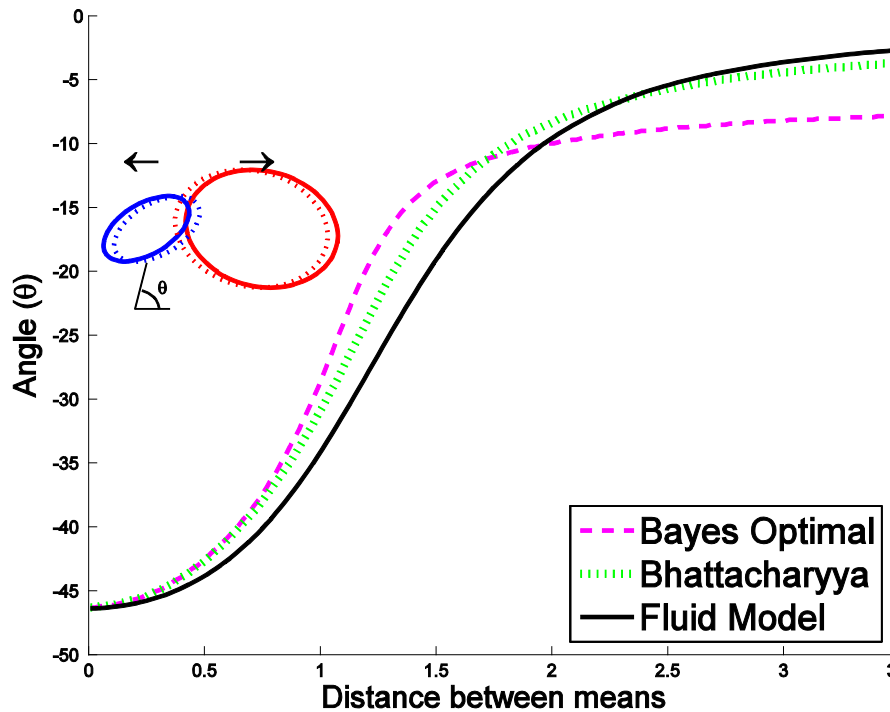
$$\sum_c \langle F_c \mathbf{x}_e^T \rangle \langle \mathbf{x}_e \mathbf{x}_e^T \rangle_{\rho_c}^{-1} \langle \mathbf{x}_e F_c^T \rangle$$

*The subspace approximates  
two analytical Bhattacharyya  
solution*





# Optimal Direction for Rank-one Affine Constraint



# Real Dataset Performance

(%)

Dataset	# classes	Fukunaga	FDA	Fluid
SpectF	2	78.50	80.20	<b><u>81.70</u></b>
Ionosphere	2	86.83	85.96	<b><u>87.54</u></b>
Parkinsons	2	86.83	82.33	<b><u>89.33</u></b>
Ozone	2	71.27	<b><u>84.54</u></b>	84.20
Breast Cancer	2	93.83	97.87	<b><u>97.92</u></b>
Glass	6	--	52.53	<b><u>55.67</u></b>
USPS	10	--	90.38	<b><u>91.48</u></b>

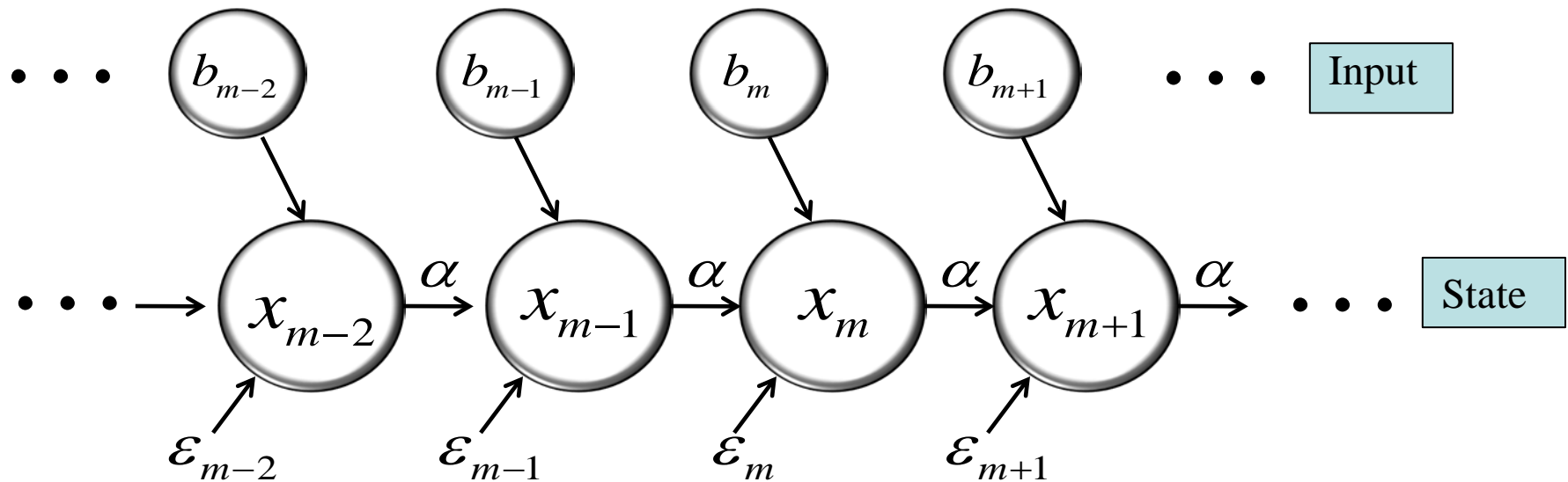
- Average of 100 realizations for UC Irvine datasets
- Average of 20 realizations for USPS dataset
- Number of dimensions of subspace is (number of classes – 1)
- Empirical covariance matrix is regularized with isotropic matrix
- Cross validation is used for each algorithm to choose regularization parameter



# Interpretation in Gaussian Processes



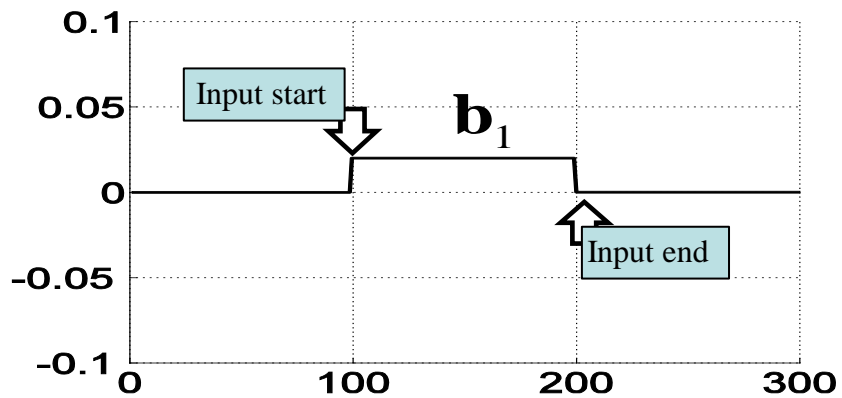
# Application to Gaussian Processes



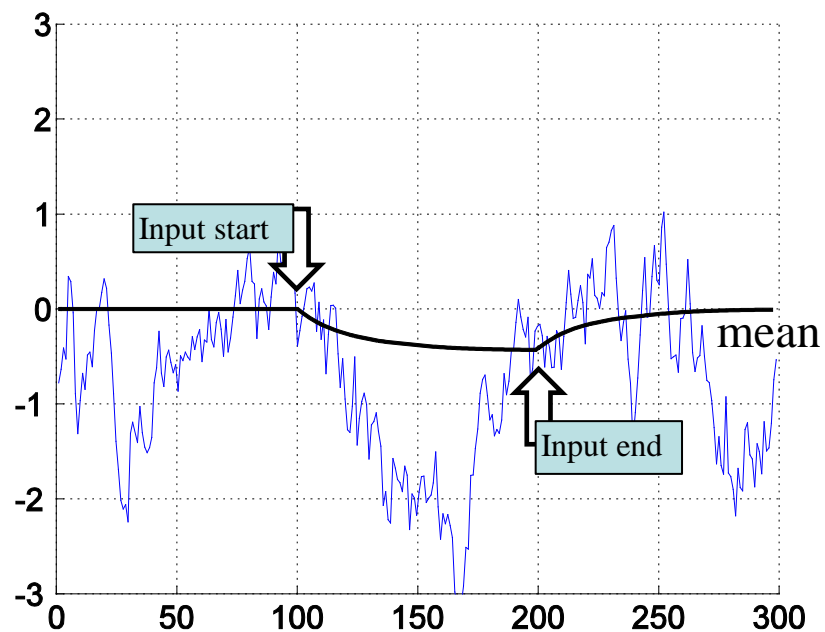
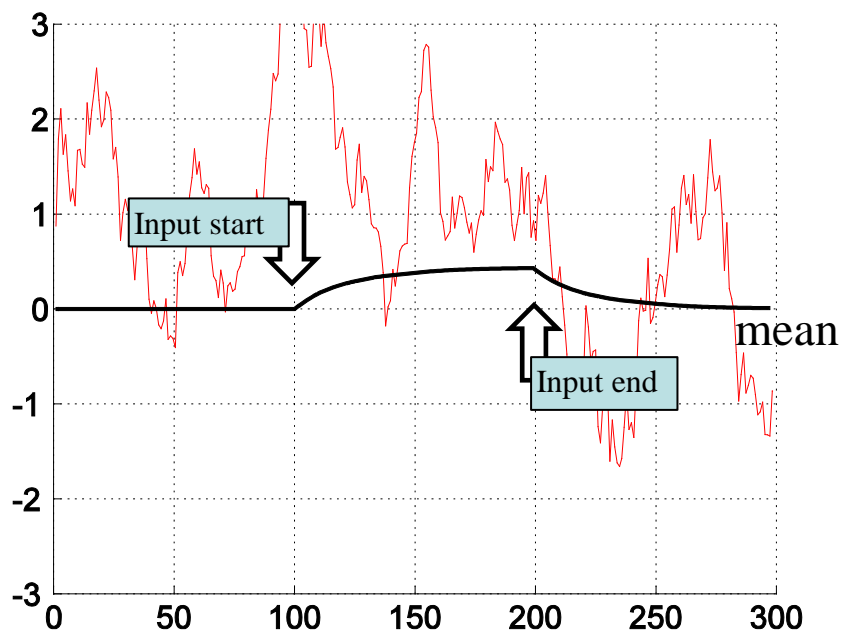
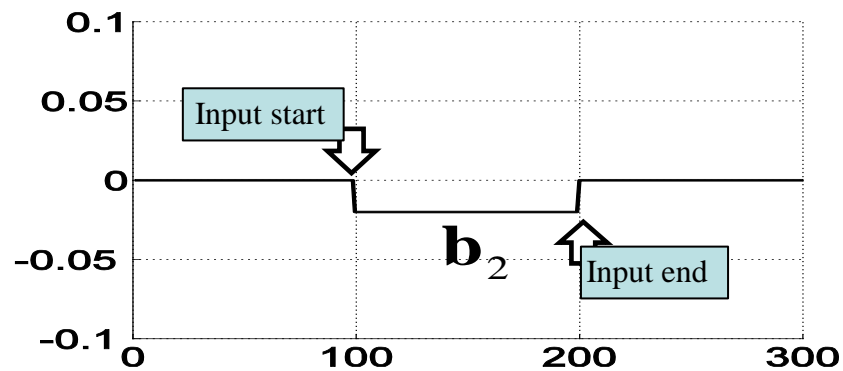
$$\text{Update rule: } x_m = \alpha x_{m-1} + b_m + \varepsilon_m$$

$$0 < \alpha < 1 \quad \varepsilon_m \sim \mathcal{N}(0, \sigma^2)$$

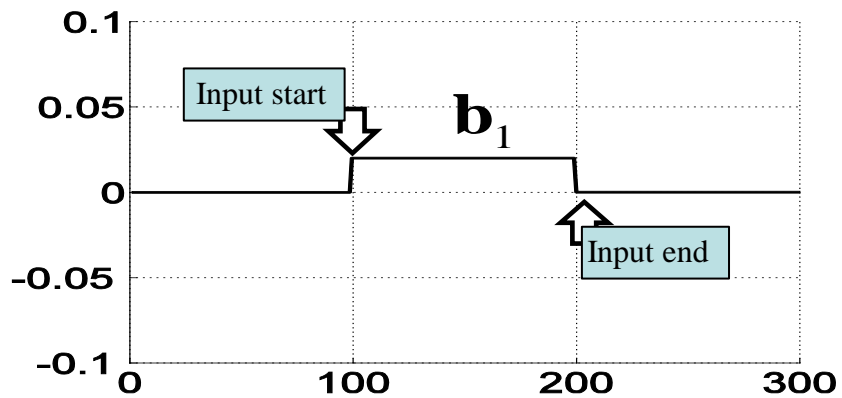
$$GP_1(\mathbf{x} | \alpha, \mathbf{b}_1)$$



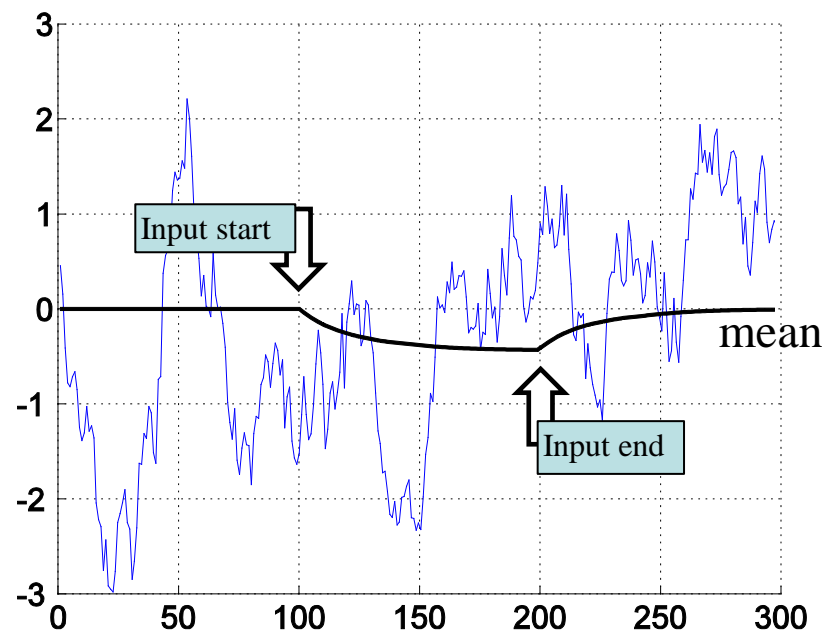
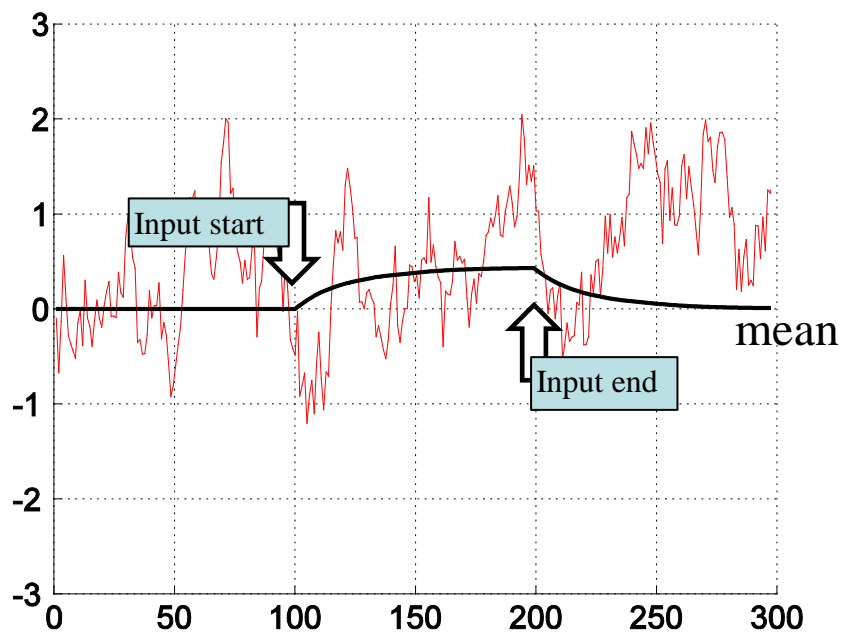
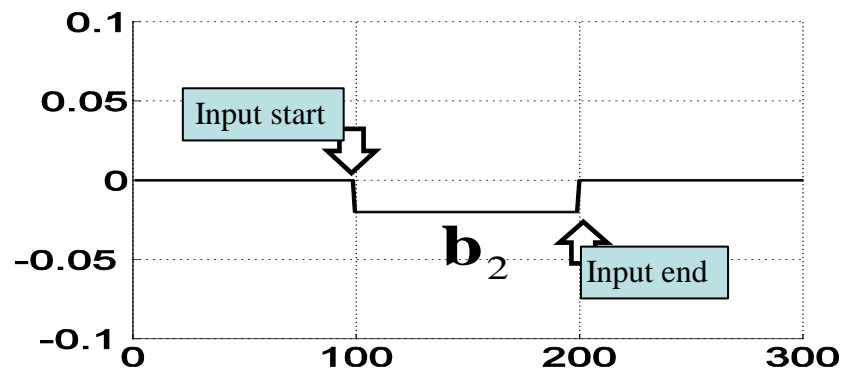
$$GP_2(\mathbf{x} | \alpha, \mathbf{b}_2)$$



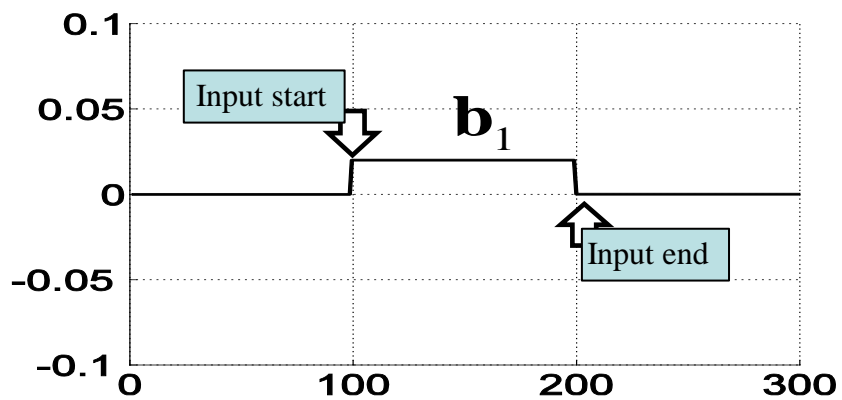
$$GP_1(\mathbf{x} | \alpha, \mathbf{b}_1)$$



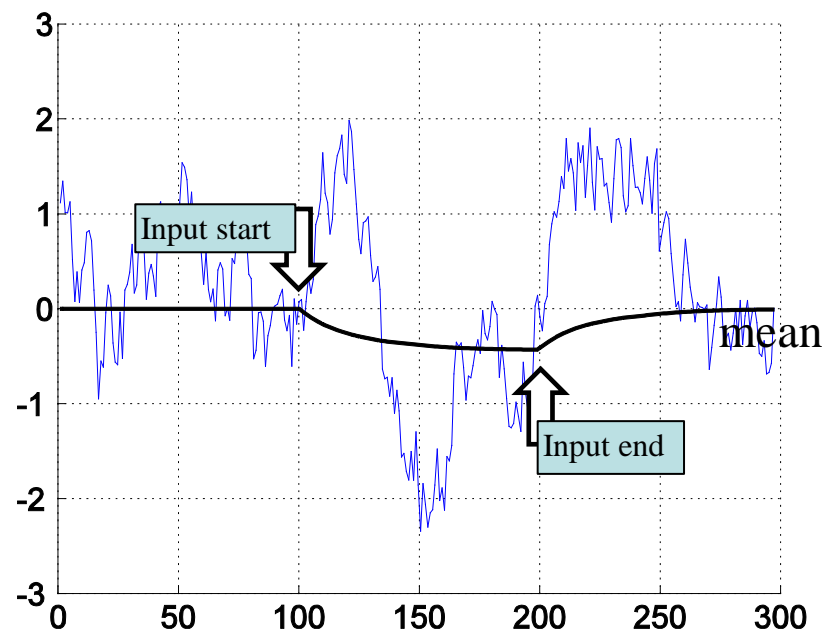
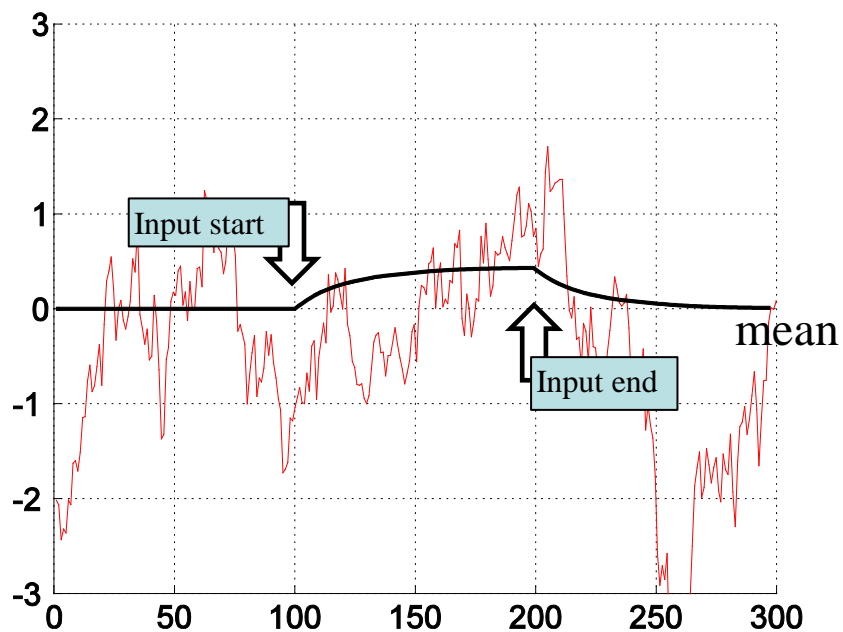
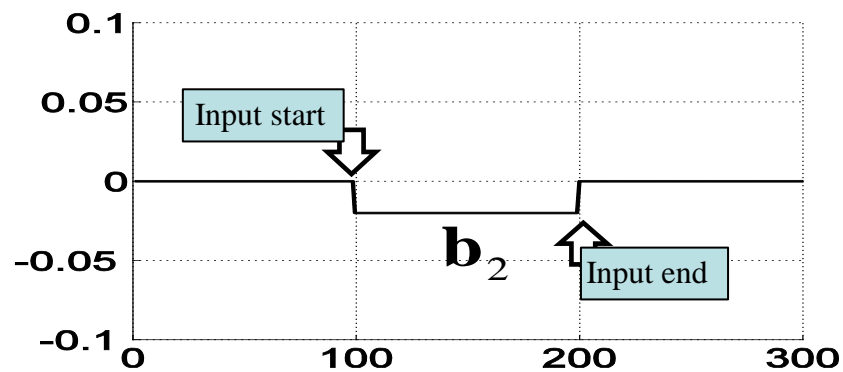
$$GP_2(\mathbf{x} | \alpha, \mathbf{b}_2)$$



$$GP_1(\mathbf{x} | \alpha, \mathbf{b}_1)$$

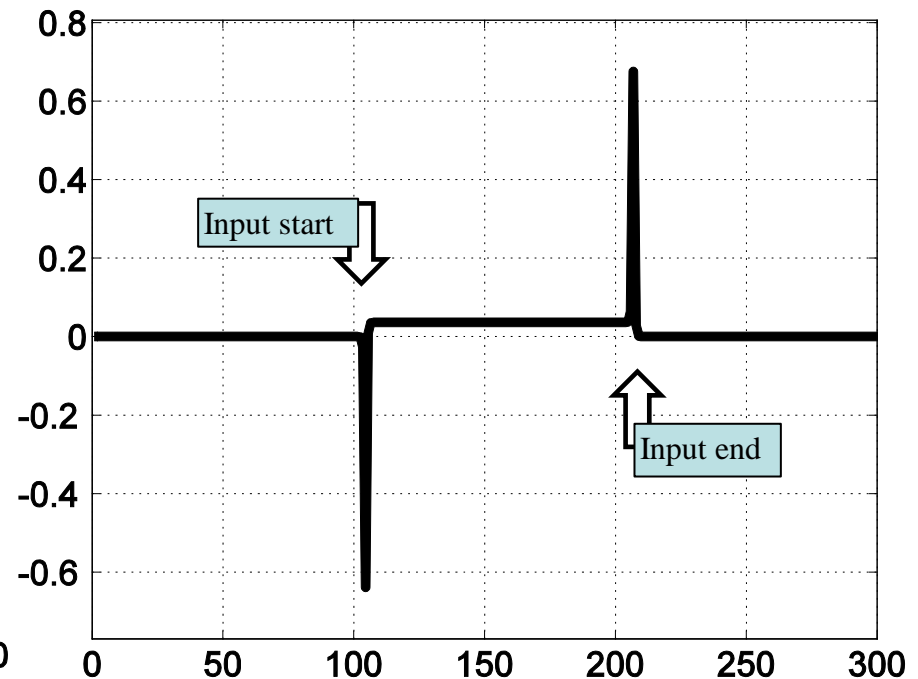
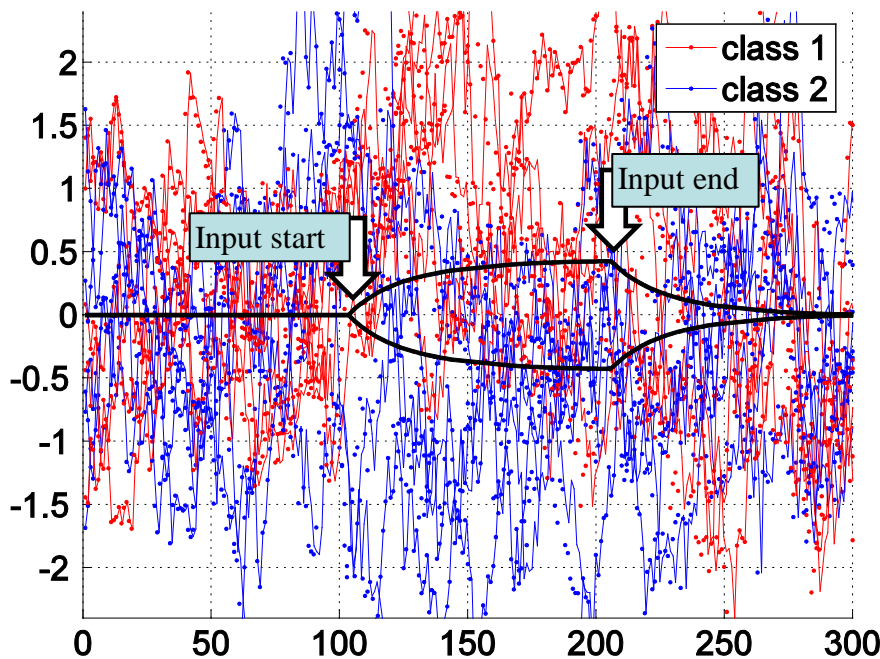
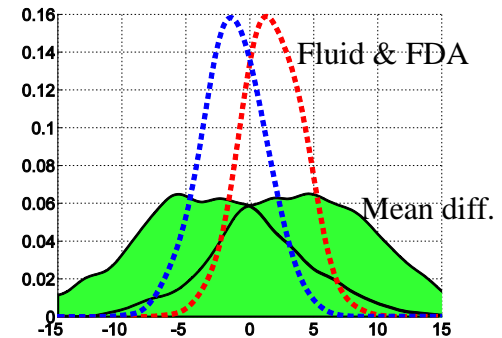


$$GP_2(\mathbf{x} | \alpha, \mathbf{b}_2)$$



# Optimal Filter for GP

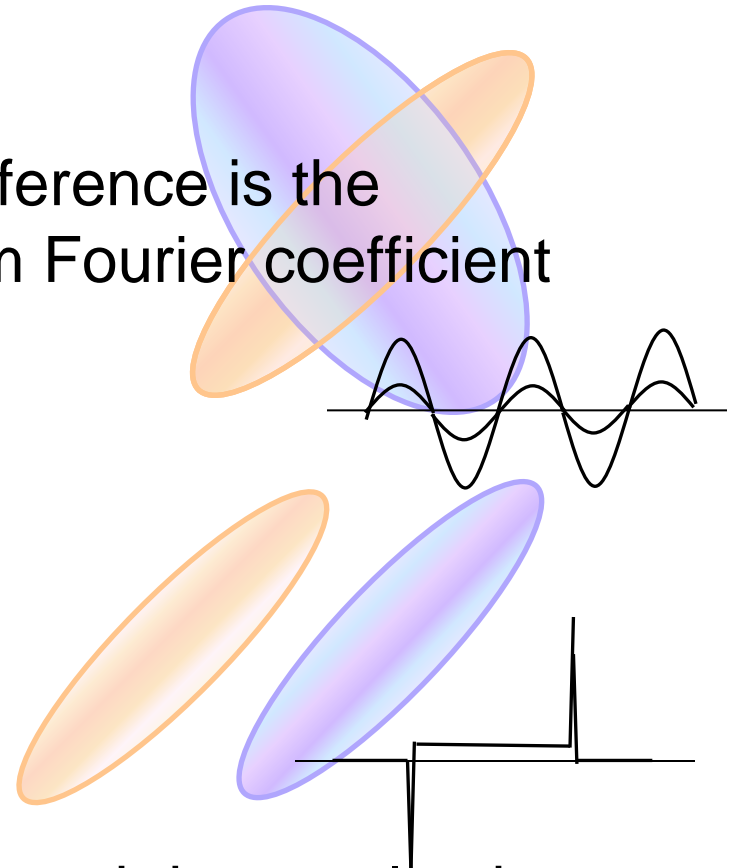
- Same decay rate  $\alpha$ 
  - Equal cov. function case





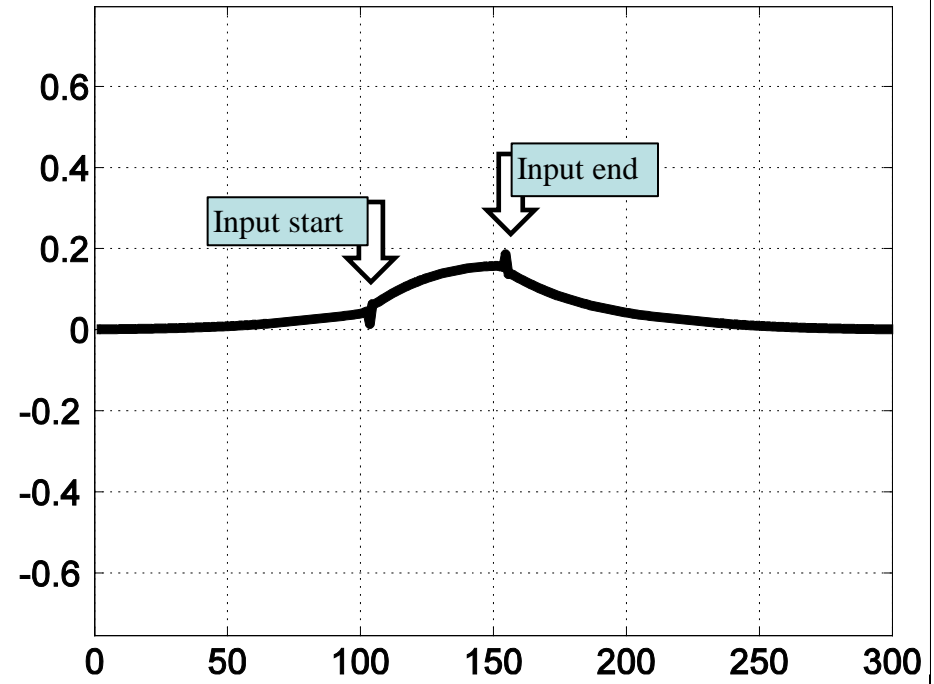
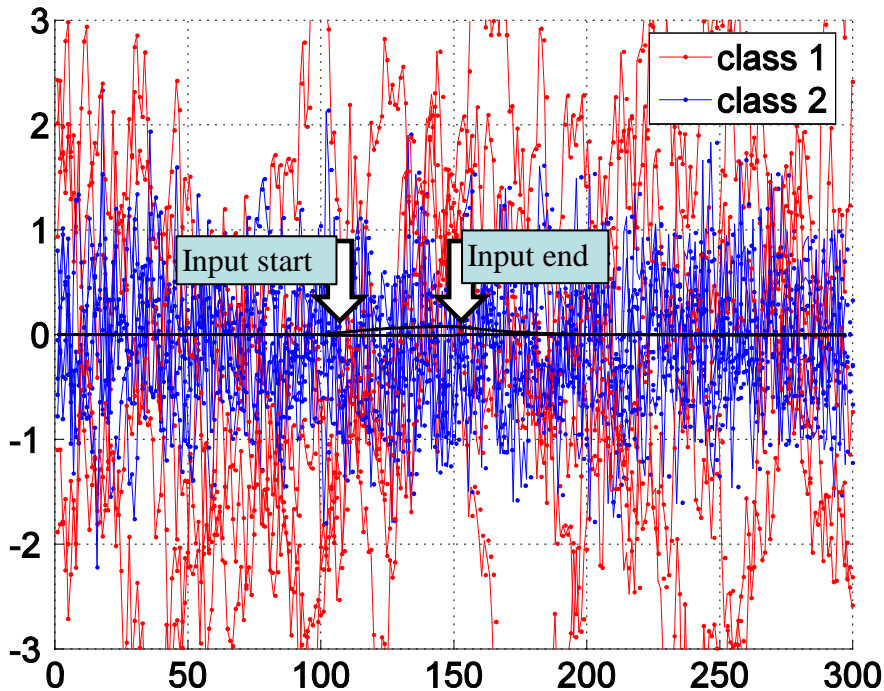
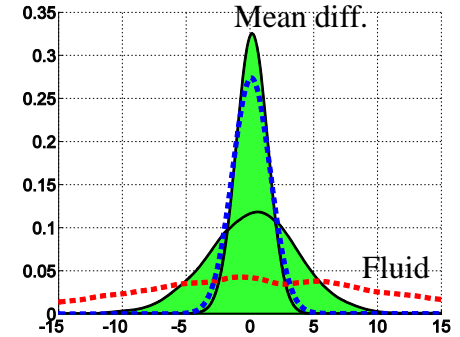
# Gaussian Process Interpretation

- Equal mean:
  - Filter of maximum variance difference is the Fourier mode having maximum Fourier coefficient difference.
- Equal cov.:
  - Deconvolved input.
- Optimal filter in general:
  - Combination of Fourier modes and deconvolved input (calculated in Fourier domain).



# Optimal Filter for GP (Fluid Model)

- Different decay rate  $\alpha$  and  $b$ .
  - Different mean function
  - Different cov. function



# Summary

- Bhattacharyya Analysis
- Physics-based approach (Fluid model) that approximates Bhattacharyya solution.
- Optimal filter approximation for Gaussian Processes.



Thank You

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