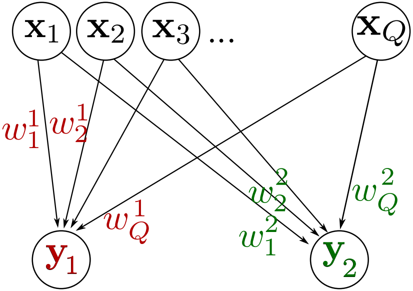
Multi-view Gaussian Processes

Jing Zhao
jzhao@cs.ecnu.edu.cn

Refer to the slide of Andreas Damianou at GPSS

Multi-view modelling (Expand the model "horizontally")

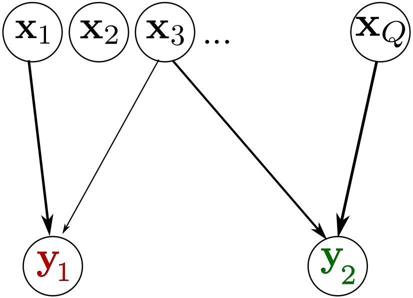
- Multi-view data arise from multiple information sources. These sources naturally contain some overlapping, or *shared* signal (since they describe the same "phenomenon"), but also have some *private* signal.
- Idea: Model such data via latent variable models



Demo: https://youtu.be/rIPX3CIOhKY

Multi-view modelling (Expand the model "horizontally")

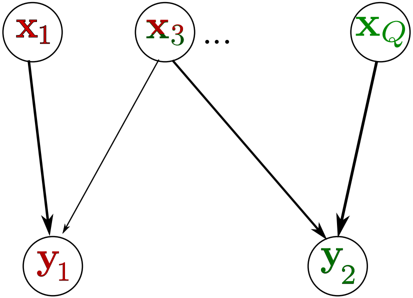
- Multi-view data arise from multiple information sources. These sources naturally contain some overlapping, or *shared* signal (since they describe the same "phenomenon"), but also have some *private* signal.
- Idea: Model such data via latent variable models



Demo: https://youtu.be/rIPX3CIOhKY

Multi-view modelling (Expand the model “horizontally”)

- Multi-view data arise from multiple information sources. These sources naturally contain some overlapping, or *shared* signal (since they describe the same “phenomenon”), but also have some *private* signal.
- Idea: Model such data via latent variable models

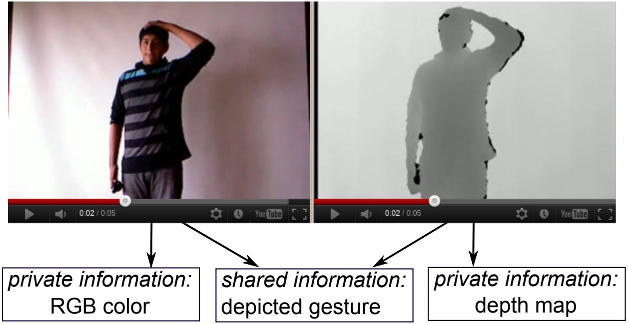


Demo: https://youtu.be/rIPX3CIOhKY

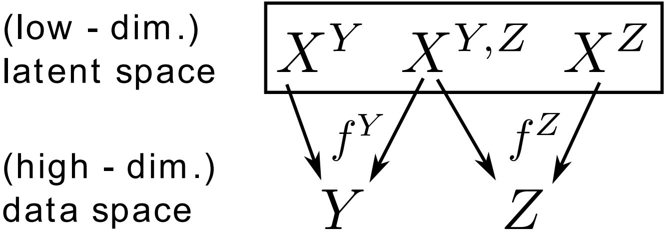
Manifold Relevance Determination *(Poster ID: 49)*

Andreas Damianou *(Univ. of Sheffield)*
Carl Henrik Ek *(KTH)*
Michalis Titsias *(Univ. of Oxford)*
Neil Lawrence *(Univ. of Sheffield)*

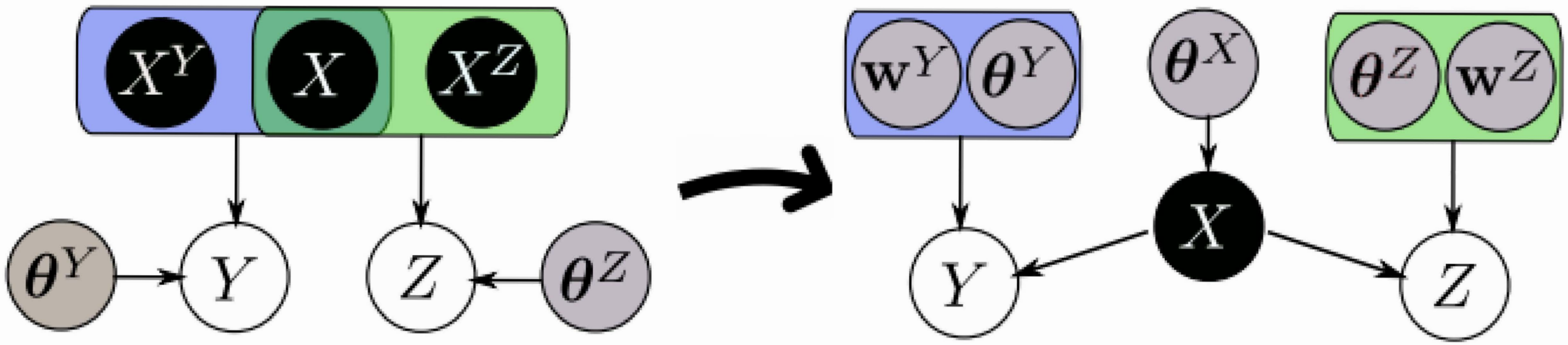
- Motivation *(just an example)*:



Generative model: multiple views



- The **aim** of our model is to learn the mappings f and the factorisation of X *automatically*.

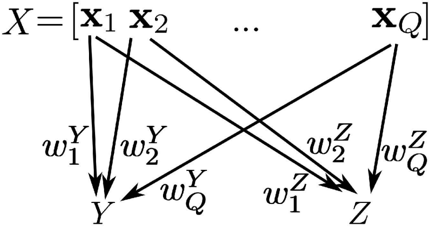


$$
\begin{aligned}
y_{nd} &= f_d^Y(\mathbf{x}_n) + \epsilon_{nd}^Y \\
z_{nd} &= f_d^Z(\mathbf{x}_n) + \epsilon_{nd}^Z,
\end{aligned}
\qquad
k^Y(\mathbf{x}_i, \mathbf{x}_j) = (\sigma_{ard}^Y)^2 e^{-\frac{1}{2}\sum_{q=1}^{Q} w_q^Y (x_{i,q} - x_{j,q})^2}
$$

$$
P(Y, Z | X, \boldsymbol{\theta}) = \prod_{\mathcal{K}=\{Y,Z\}} \int p(\mathcal{K}|F^{\mathcal{K}}) p(F^{\mathcal{K}}|X, \boldsymbol{\theta}^{\mathcal{K}}) \mathrm{d}F^{\mathcal{K}}.
$$

$$
\begin{aligned}
F_v(q) &= \int q(\Theta) q(X) \log\left(\frac{p(Y|X)p(Z|X)}{q(\Theta)} \frac{p(X)}{q(X)}\right) \mathrm{d}X \\
&= \mathcal{L}_Y + \mathcal{L}_Z - \mathbf{KL}\left[q(X) \parallel p(X)\right],
\end{aligned}
\tag{6}
$$

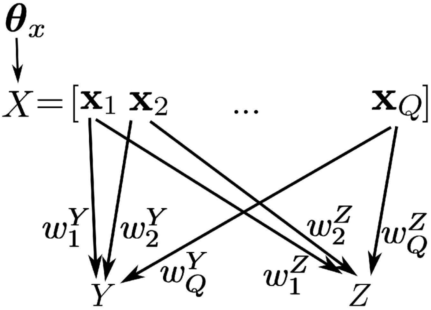
Main idea



$$f^Y \sim \mathcal{GP}\left(\mathbf{0}, k^Y(X,X)\right), \ k^Y = g(\mathbf{w}^Y)$$

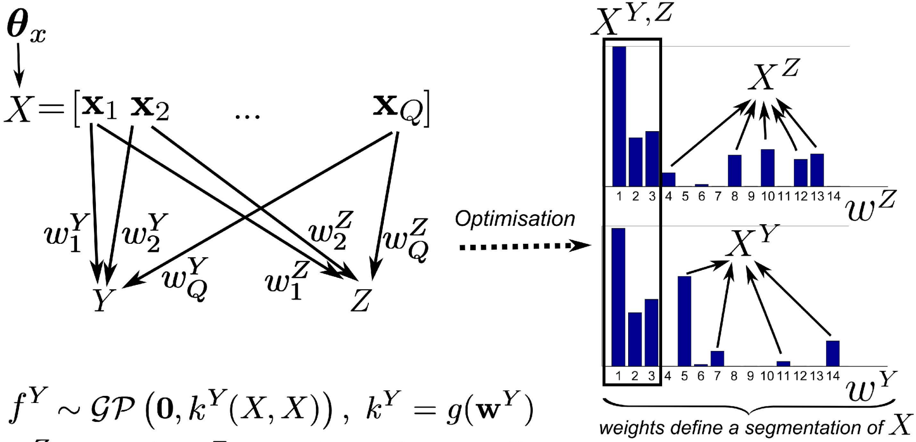
$$f^Z \sim \mathcal{GP}\left(\mathbf{0}, k^Z(X,X)\right), \ k^Z = g(\mathbf{w}^Z)$$

Main idea



$$f^Y \sim \mathcal{GP}\left(\mathbf{0}, k^Y(X,X)\right), \ k^Y = g(\mathbf{w}^Y)$$
$$f^Z \sim \mathcal{GP}\left(\mathbf{0}, k^Z(X,X)\right), \ k^Z = g(\mathbf{w}^Z)$$

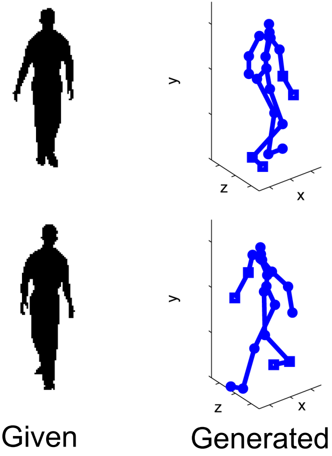
Main idea



$$f^Y \sim \mathcal{GP}\left(\mathbf{0}, k^Y(X,X)\right), \;\; k^Y = g(\mathbf{w}^Y)$$
$$f^Z \sim \mathcal{GP}\left(\mathbf{0}, k^Z(X,X)\right), \;\; k^Z = g(\mathbf{w}^Z)$$

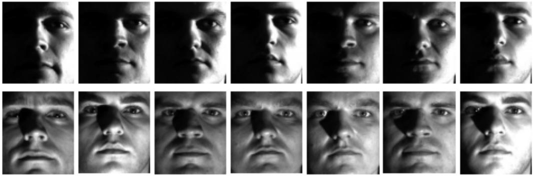
Demonstration

- Generate in the one modality, given data from the other (also works for classification)



- Y contains the pictures corresponding to all 64 different illumination conditions for each one of 3 subjects; similarly for Z for 3 different subjects.
- aligned with the same illumination condition
- shared latent space? private space?

- neighbours from the shared subspace



- sample from the private subspaces

Model properties

1. Soft segmentation of the latent space
2. Fully Bayesian (X is marginalised out), approximation of the full posterior
3. Can incorporate prior information in the latent space
4. Subspace segmentation and dimensionality automatically discovered
5. Non-linear method