Manifold Relevance Determination *(Poster ID: 49)*

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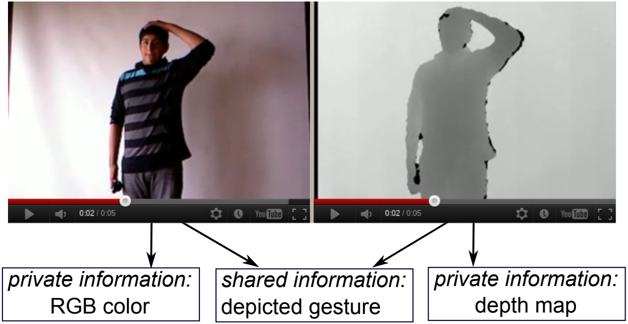
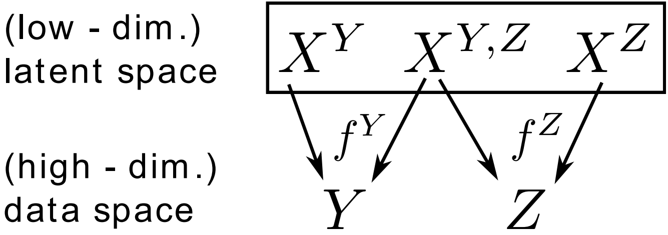
- Motivation *(just an example)*:

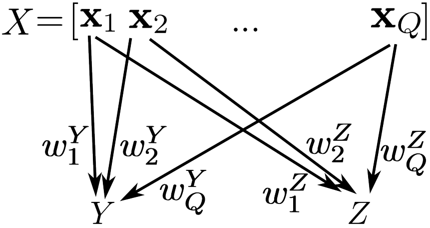


Generative model: multiple views



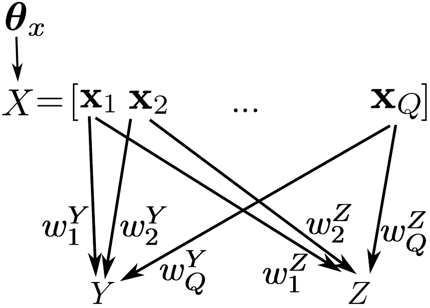
- The **aim** of our model is to learn the mappings f and the factorisation of X *automatically*.

Main idea



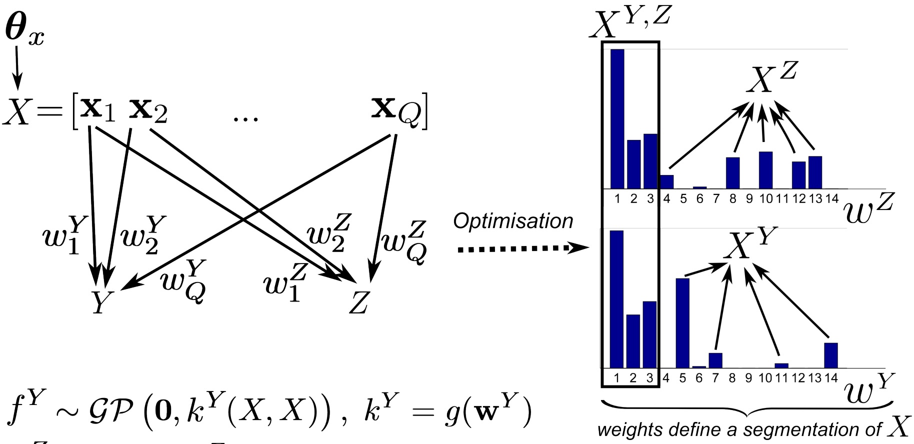
$$f^Y \sim \mathcal{GP}\left(\mathbf{0}, k^Y(X,X)\right), \; k^Y = g(\mathbf{w}^Y)$$
$$f^Z \sim \mathcal{GP}\left(\mathbf{0}, k^Z(X,X)\right), \; k^Z = g(\mathbf{w}^Z)$$

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



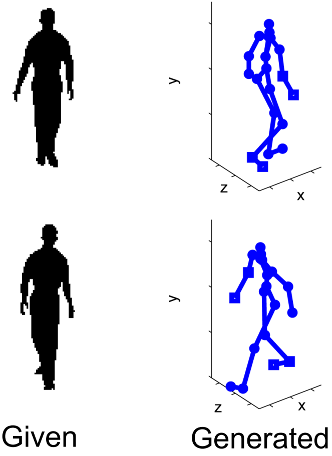
$$f^Y \sim \mathcal{GP}\left(\mathbf{0}, k^Y(X,X)\right),\ k^Y = g(\mathbf{w}^Y)$$
$$f^Z \sim \mathcal{GP}\left(\mathbf{0}, k^Z(X,X)\right),\ k^Z = g(\mathbf{w}^Z)$$

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

Demonstration

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



- Sampling from the discovered latent spaces to produce *novel outputs*