

Manifold Relevance Determination (Poster ID: 49)

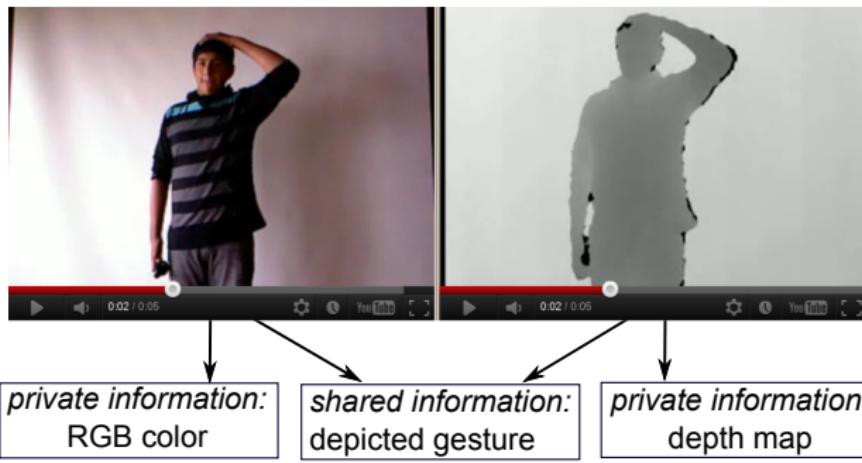
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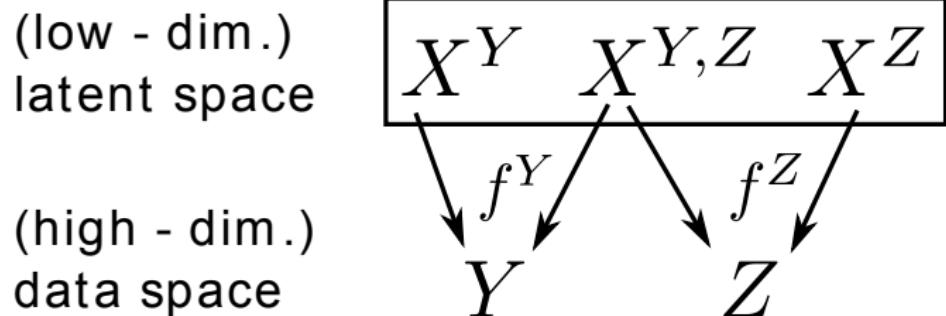
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- Motivation (*just an example*):



Generative model: multiple views



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

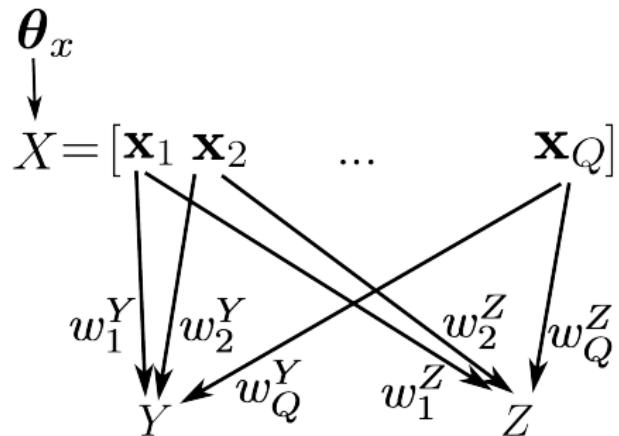
Main idea

$$X = [\mathbf{x}_1 \ \mathbf{x}_2 \ \dots \ \mathbf{x}_Q]$$

The diagram illustrates the structure of matrix X . It consists of a matrix X with columns labeled $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_Q$. Below the matrix, two nodes are shown: Y on the left and Z on the right. Arrows labeled w_1^Y, w_2^Y, w_Q^Y point from the first three columns of X to node Y . Arrows labeled w_1^Z, w_2^Z, w_Q^Z point from the same three columns to node Z .

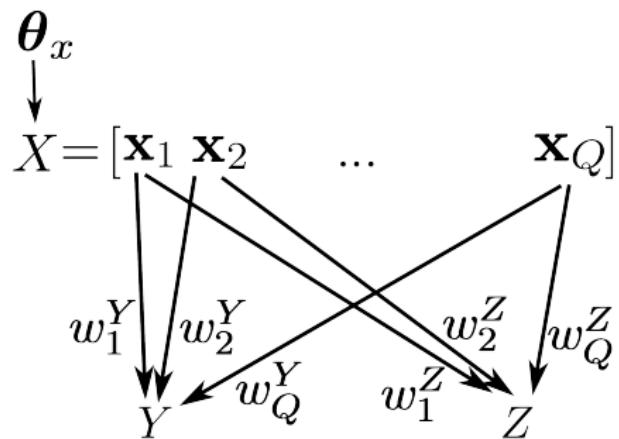
$$f^Y \sim \mathcal{GP}(\mathbf{0}, k^Y(X, X)), \quad k^Y = g(\mathbf{w}^Y)$$
$$f^Z \sim \mathcal{GP}(\mathbf{0}, k^Z(X, X)), \quad k^Z = g(\mathbf{w}^Z)$$

Main idea

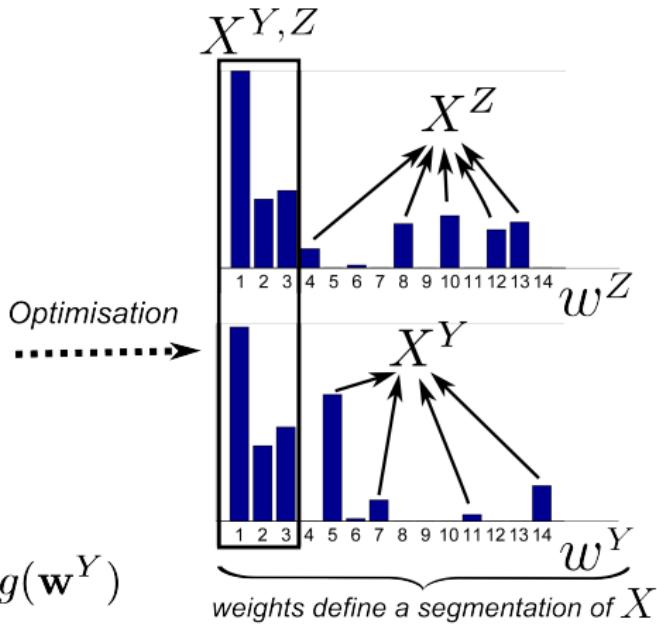


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Main idea



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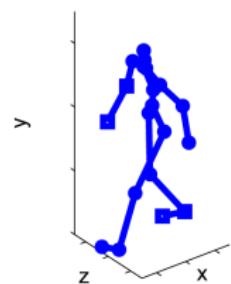
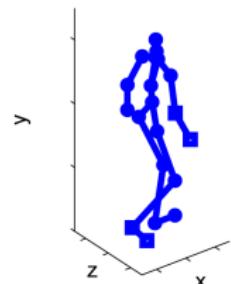


Model properties

- 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)



Given

Generated

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

