

psycholR: Relevance Prediction

WP3, Probabilistic modeling for multi-source fusion (Task 3.2)

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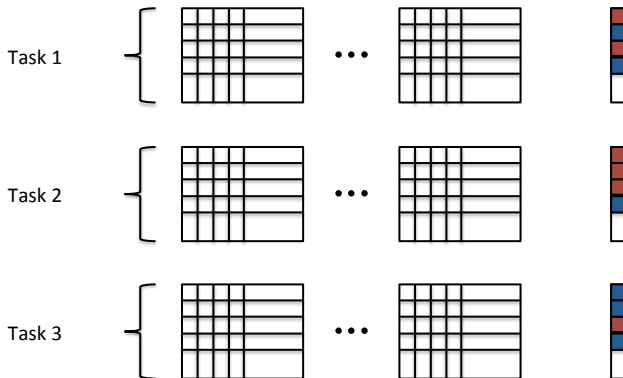
MindSee Kickoff Meeting
Berlin, Oct 28-29, 2013

Setup

Per Subject:

20 views based on fEMG,
EDA, Eye-tracking, EEG signals

Relevance
judgments



Research questions

1. Can we predict relevance from physiological signals?
2. What is the predictive power of different physiological signals?
3. What features of a physiological signal are important?
4. Is the relevance prediction task-dependent?
5. Is the relevance prediction subject-dependent?

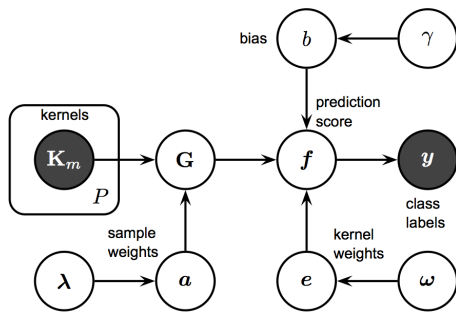
Multiple kernel learning

Compute a kernel for each view and use, e.g., a weighted sum of the P kernels $\{\mathbf{k}_m : \mathcal{X} \times \mathcal{X} \rightarrow \mathbb{R}\}_{m=1}^P$:

$$f(\mathbf{x}_*) = \alpha^t \left(\sum_{i=1}^P \mathbf{e}_m \mathbf{k}_{m,*} \right) + b$$

where \mathbf{x}_* is an unseen sample, $\mathbf{k}_{m,*}$ is the vector of kernel weights, $\mathbf{k}_{m,*} = [k_m(\mathbf{x}_1, \mathbf{x}_*), \dots, k_m(\mathbf{x}_N, \mathbf{x}_*)]^t$, α is the vector of sample weights, b is the bias, and $\{\mathbf{x}_i \in \mathcal{X}\}_{i=1}^N$ are the training samples.

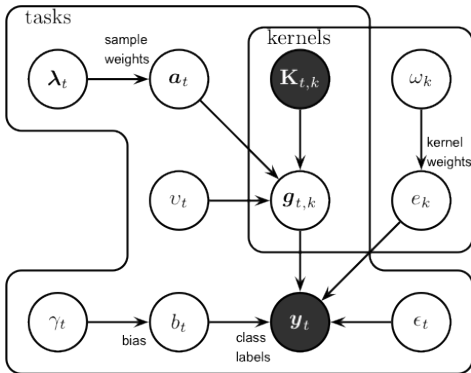
Bayesian Multiview MKL



$$\begin{aligned}
 \lambda_i &\sim \mathcal{G}(\lambda_i; \alpha_\lambda, \beta_\lambda) & \forall i \\
 a_i | \lambda_i &\sim \mathcal{N}(a_i; 0, \lambda_i^{-1}) & \forall i \\
 g_i^m | \mathbf{a}, \mathbf{k}_{m,i} &\sim \mathcal{N}(g_i^m; \mathbf{a}^\top \mathbf{k}_{m,i}, 1) & \forall (m, i) \\
 \gamma &\sim \mathcal{G}(\gamma; \alpha_\gamma, \beta_\gamma) \\
 b | \gamma &\sim \mathcal{N}(b; 0, \gamma^{-1}) \\
 \omega_m &\sim \mathcal{G}(\omega_m; \alpha_\omega, \beta_\omega) & \forall m \\
 e_m | \omega_m &\sim \mathcal{N}(e_m; 0, \omega_m^{-1}) & \forall m \\
 f_i | b, e, \mathbf{g}_i &\sim \mathcal{N}(f_i; \mathbf{e}^\top \mathbf{g}_i + b, 1) & \forall i \\
 y_i | f_i &\sim \delta(f_i y_i > \nu) & \forall i
 \end{aligned}$$

Gönen (2012): Novel kernel combination formulation with a fully conjugate probabilistic model, which leads to a very efficient variational approximation.

Bayesian Multitask/Multiview MKL



$$\begin{aligned}
 \lambda_{t,i} &\sim \mathcal{G}(\lambda_{t,i}; \alpha_\lambda, \beta_\lambda) \quad \forall(t, i) \\
 a_{t,i} | \lambda_{t,i} &\sim \mathcal{N}(a_{t,i}; 0, \lambda_{t,i}^{-1}) \quad \forall(t, i) \\
 v_t &\sim \mathcal{G}(v_t; \alpha_v, \beta_v) \quad \forall t \\
 g_{t,k} | a_t, K_{t,k}, v_t &\sim \mathcal{N}(g_{t,k}; K_{t,k} a_t, v_t^{-1} I) \quad \forall(t, k) \\
 \gamma_t &\sim \mathcal{G}(\gamma_t; \alpha_\gamma, \beta_\gamma) \quad \forall t \\
 b_t | \gamma_t &\sim \mathcal{N}(b_t; 0, \gamma_t^{-1}) \quad \forall t \\
 \omega_k &\sim \mathcal{G}(\omega_k; \alpha_\omega, \beta_\omega) \quad \forall k \\
 e_k | \omega_k &\sim \mathcal{N}(e_k; 0, \omega_k^{-1}) \quad \forall k \\
 \epsilon_t &\sim \mathcal{G}(\epsilon_t; \alpha_\epsilon, \beta_\epsilon) \quad \forall t \\
 y_t | b_t, e, G_t, \epsilon_t &\sim \mathcal{N}\left(y_t; \sum_{k=1}^K e_k g_{t,k} + b_t \mathbf{1}, \epsilon_t^{-1} I\right)
 \end{aligned}$$

TeamFIN (2013): Extension to tasks with shared kernel weights; TeamFIN won “The NCI-DREAM Drug Sensitivity Prediction Challenge”.

Selected references:

Mehmet Gönen. Bayesian efficient multiple kernel learning. In *Proceedings of the 29th International Conference on Machine Learning*, 2012. URL <http://users.ics.aalto.fi/gonen/icml12.php>.

TeamFIN. Bayesian multitask multiple kernel learning. Members of HIIT (Helsinki Institute for Information Technology) and FIMM (Institute for Molecular Medicine Finland): Elisabeth Georgii and Mehmet Gönen and Muhammad Ammad-ud-din and Petteri Hintsanen and Suleiman A Khan and John-Patrick Mpindi and Olli Kallioniemi and Antti Honkela and Tero Aittokallio and Krister Wennerberg and Samuel Kaski, 2013.

More information, including papers and code, at:

<http://research.ics.aalto.fi/mi/>