Learning complex tasks with probabilistic population codes

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Probabilistic neural representations

Sensory cues are combined according to:
uncertainty (Ernst and Banks, 2002) and the prior (Knill, 2002)
Priors can be learned (Körding and Wolpert, 2003)
Multiple, dependent variables (Knill, 2002)

How are these computations supported by cortex?
One candidate: probabilistic population codes (PPCs)

Outstanding issues with PPC

1) No known learning method
   Adapting to a changing prior
   Learning the connection strengths
2) Complex models: multimodal/non-linear
3) Encoding multiple dependent variables

Model Details

Gaussian Prior
\( p(x|\theta) = \text{Norm}(x; \mu_x, \sigma_x^2) \)

Gaussian tuning curves
\( \lambda_{n,j}(x) = \sigma_j \text{Norm}(x; \mu_{n,j}, \sigma_j) \)

Poisson rates
\( p(r_{n,j}|x, \theta) = \text{Poisson}(r_{n,j}; \lambda_{n,j}(x)) \)

Posterior distribution
\( p(x|R, \theta) \propto \text{Norm}(x; \mu_x(R), \sigma^2_x(R)) \times \exp(- \sum_{n,j} \lambda_{n,j}(x)) \)

Variational EM

E-Step
\( q(x; r^*_n) = \text{arg min}_{r_n} \text{KL}(q(x; r^*_n)||p(x|r_1, r_2, \theta)) \)

M-Step

Supervised-like: Fill in x using \( q(x; r^*_n) \)
\( \theta^*_n = \text{arg max}_\theta \left( \log p(x; r_1, r_2, \theta) \right)_{q(x; r^*_n)} \)

vEM Interpretation of PPC

\( q(x; r^*_n) = \text{Norm}(x; \mu_n(r), \sigma_n^2(r)) \)

Extended PPC to complex learning tasks

Adapting to a changing prior and learning the network connection strengths
Viewed PPC as encoding an approximate representation of the posterior
Connected PPC to vEM which then provides learning rules

Some of the attractive properties of PPC have to be sacrificed
Updates become non-linear in general and gains must be inferred/learned
Extendedable to more complex models, but neurally plausible implementations will require further approximations

References
Ernst and Banks, Humans integrate visual and haptic information in a statistically optimal fashion, Nature, 2002
Körding and Wolpert, Bayesian integration in sensorimotor learning, Nature, 2004
Knill, Mixture models and the probabilistic structure of depth cues, Vision Research, 2003