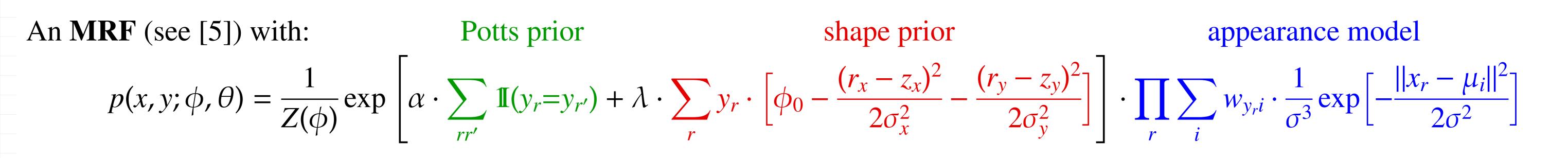
A Real-time MRF Based Approach for Binary Segmentation Dmitrij Schlesinger

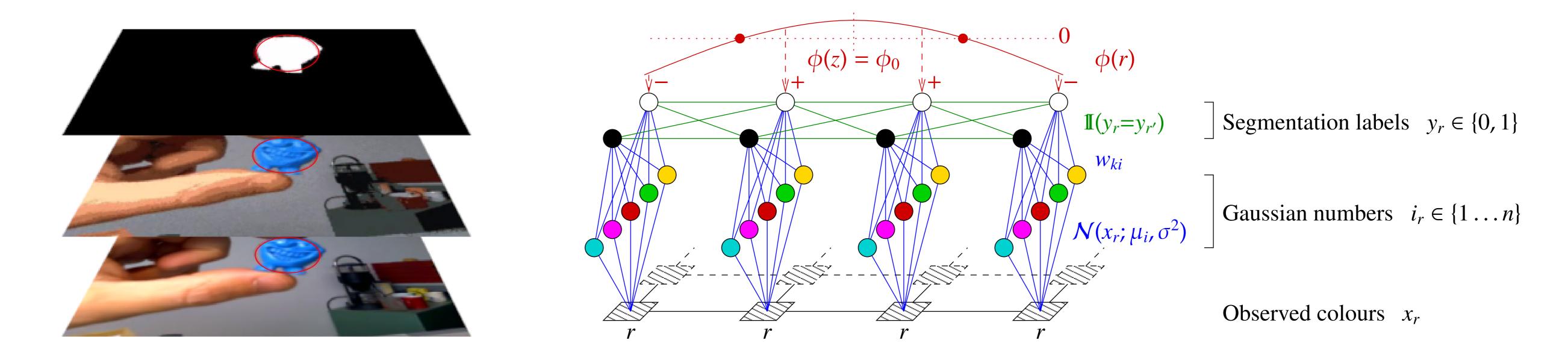


Application: real-time segmentation of live video streams

- Both inference and learning should be very fast.
- No user interactions \rightarrow fully unsupervised learning \rightarrow a generative model is necessary.

Make it right before you make it fast – model





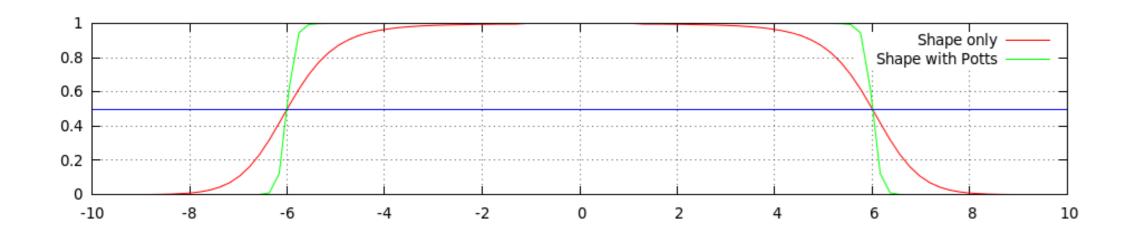
- Inference: Max-Marginal decision $y_r^* = \arg \max p(y_r = k | x; \phi, \theta) \rightarrow$ posterior sampling
- Learning: Maximum Likelihood
 - appearance model $\theta = (\mu, \sigma)$
 - Expectation-Maximization + posterior sampling - shape $\phi = (\phi_0, z_{xy}, \sigma_{xy})$ \rightarrow
 - Expectation-Maximization + posterior sampling + prior sampling

Keep it right when you make it fast – implementation

Prior label probabilities

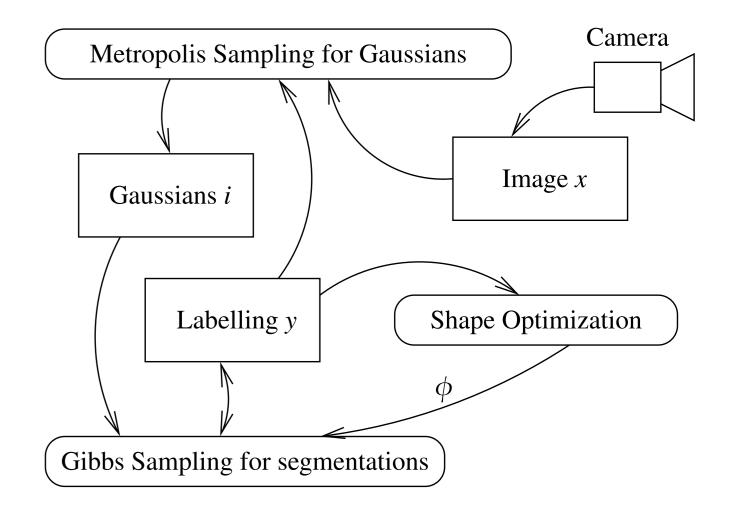
Fast generation





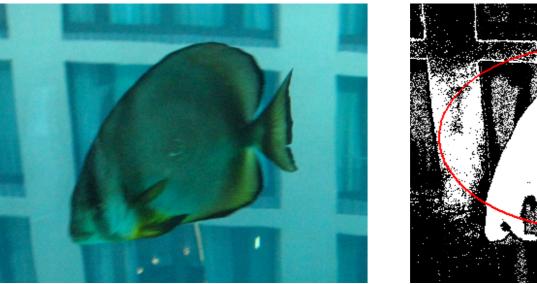
Prior label probabilities are very distinctive \rightarrow can be approximated by 0/1

- \rightarrow prior statistics can be computed explicitly
- \rightarrow prior sampling is not necessary
- Gibbs Sampling for segmentations \rightarrow the necessary energy *difference* $q(x_r, 1) - q(x_r, 0) + \phi(r) + \alpha \sum (2y_{r'} - 1)$ $r' \in N(r)$ can be computed very fast
- Metropolis Sampling for Gaussian numbers \rightarrow energy difference is a scalar product
- Look-up tables are easy to use

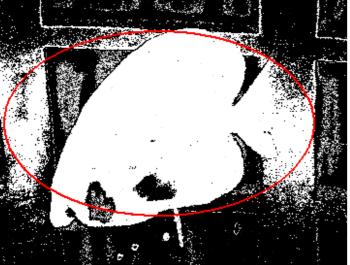


 \rightarrow working in parallel

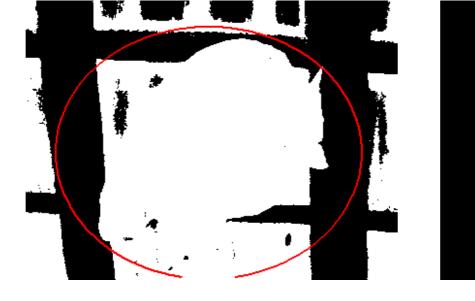
Some results



Input image



Shape prior only

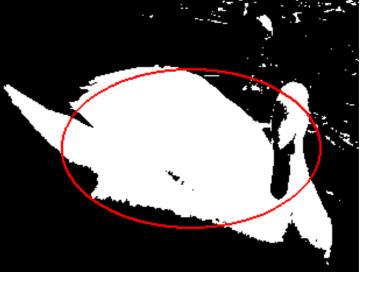


Potts prior only

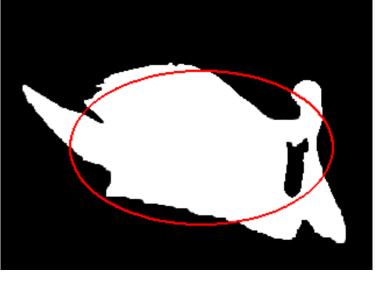
Full prior



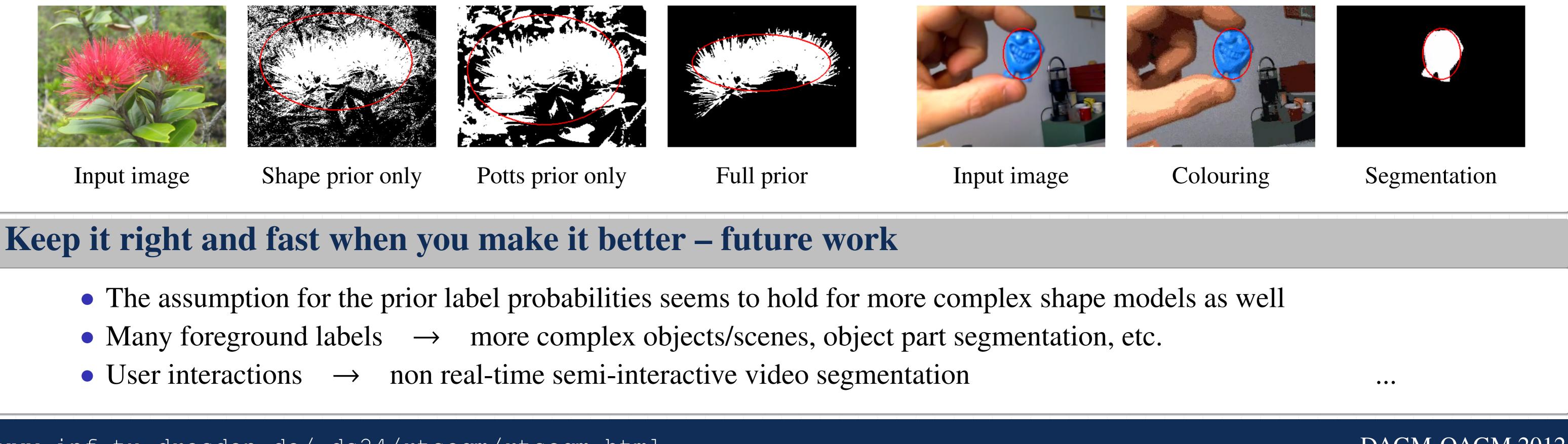
Input image



Weak prior



Strong prior



www.inf.tu-dresden.de/~ds24/rtsegm/rtsegm.html

