The lecture on January 17 cannot take place due to a lack of electricity and heating in the B-IT building. Fortunately, we managed to cover the theory behind Markov Random Fields (up to Chapter 8, Slide 52) already on January 10. With the few remaining slides and the following comments, you should be able to solve this week's practical assignment. In the next lecture, we will continue with the next chapter. In case of questions, feel free to use the mailing list or ask in the lecture on January 24.

- The basic idea behind Markov Random Fields for image segmentation is that they allow us to penalize segmentation results with lots of isolated pixels or very small groups of pixels, which are typically a result of image noise.
- They do so by combining the same Gaussian data likelihood term that we used previously with a novel prior term whose probability decreases with each pair of neighboring pixels that are assigned different labels (Potts Model).
- We again take the logarithm to replace the computationally inconvenient product required to compute the joint probability with a simple sum. In order to relate *maximizing* the probability of our model to other segmentation methods that involve energy *minimization,* we multiply the logarithm by minus one. This results in what we call a *potential.*
- The potential for the prior (Potts Model) are given on Slide 51. They are called *binary* potentials, because they involve two labels (from two adjacent pixels). Since several students last year had trouble deriving the unary potentials, which link the segmentation to the image intensities, the derivation is now spelled out on the novel Slide 53.
- The task of maximum a posteriori probability (MAP) estimation is to find a hard segmentation that optimizes the sum of external energy (sum of unary potentials) and internal energy (sum of binary potentials). Several algorithms for MAP estimation exist and are listed on Slide 56. In today's sheet, we ask you to implement the simplest one, Iterated Conditional Modes (ICM), for which pseudocode is listed on Slide 55. Its idea is to repeatedly iterate over all pixels. Each time, we assume all neighboring labels are fixed, use them to compute the overall energy for each possible label for the current pixel, and select the label that results in the lowest energy. The correspondingly modified EM algorithm is shown on Slide 57.
- It can be seen from Slide 58 that adding binary potentials greatly reduces the effect of image noise on the segmentation. However, we have to select a parameter (which we call β in our model) that balances internal and external energies. Putting too much weight on the internal energy can lead to a loss of fine structures in the segmentation, as shown on Slide 59.
- An additional benefit of our probabilistic model is that the prior can depend not only on smoothness (as in the Potts model), but it is easy to also account for atlases that indicate where in a typical brain we are likely to find the several tissue types. This is shown on Slide 60, but not required for the assignment.