[3] Latouche, Pierre, Etienne Birmele, and Christophe Ambroise. "Variational Bayesian inference and complexity control for stochastic block models." Statistical Modelling 12.1 (2012): 93-115.

3.1 Experimental Results for MSBM

3.1.1 Simplest Two Prototype Problem

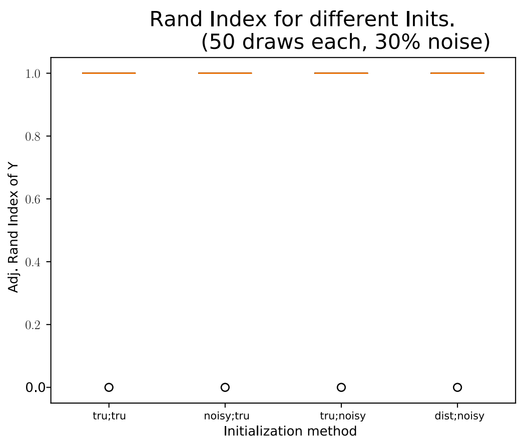
Here we compare the performance of our plain 'cavi' msbm with no annealing on a set of networks coming from two prototypes which are 'easily' distinguishable from one another. It seems that both the initializations and the order of the updates, are critical (in particular, some update orders render some initializations useless).

Below, we see the performance over 50 different runs of MSBM while doing some changes in the order of the updates as well as different initialization options:

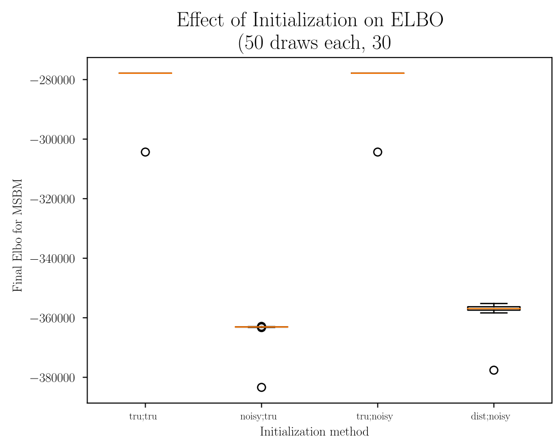
- **tru:** We initialize the multinomial as concentrated in the ground truth value. The actual posterior might not be concentrated, so this is not necessarily the best initialization, but it's a strong candidate.
- **noisy:** Refers to initializing with the 'some_truth' initialization for a multinomial, where we select a percentage λ of the correct variables and we 'flip' them, distributing the mass uniformly in the alternatives.
- **dist:** specifically for the τ variables. We select Q nodes of the network at random (trying not to select neighbors) and we assign every other node to the community of the closest of those Q 'anchors'. This procedure could probably be generalized to the μ variables.

In this first set of results, we observe the outcome of running the updates in the following order (notice how there is no Update Z): Update Π, Update γ, Update Y, Update ρ. We can see the performance of this schedule in figure **??**. Furthermore, in figure 3.2 we can see that the actual models are far from the truth.

In this first set of results, we observe the outcome of running the updates in the following order: Update Π, Update γ, Update Z, Update Y, Update ρ. We can see the performance of this schedule in figure **??**. Furthermore, in figure 3.4 we can see that the actual models are far from the truth.



(a) The rand index seems to be perfect in only one iteration for all the initializations.



(b) The ELBO is lower for the two initializations where the τ variables are noisy, these never change.

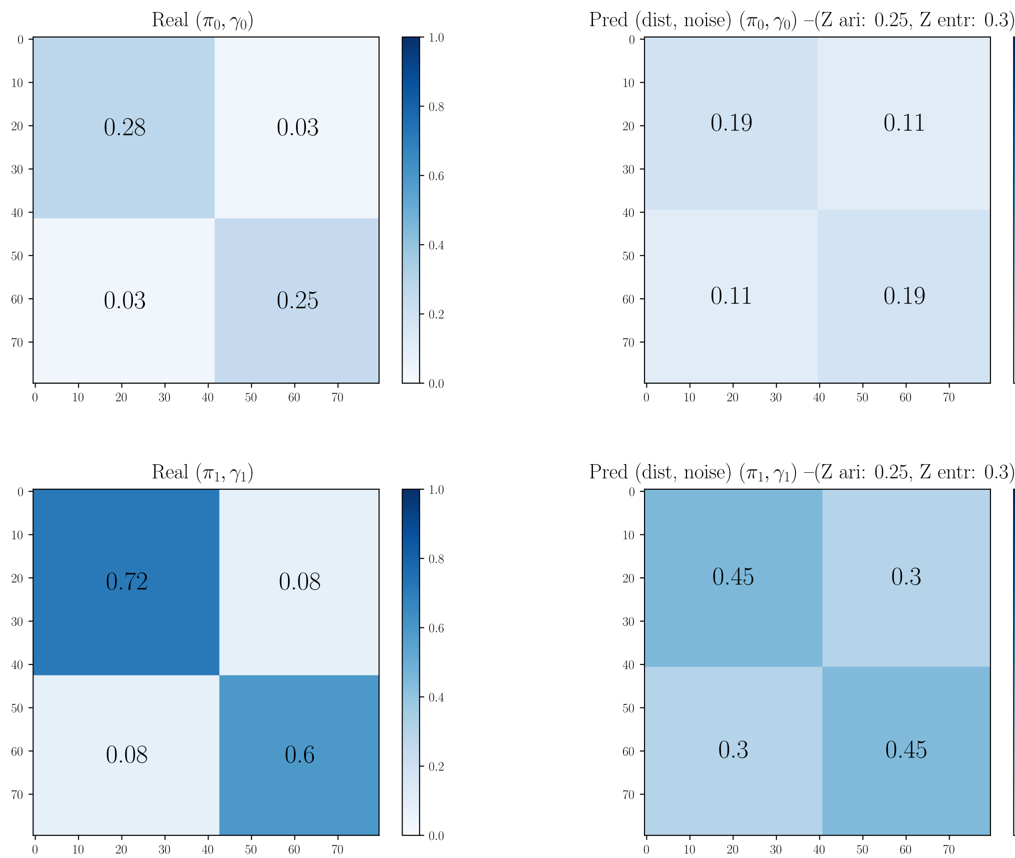
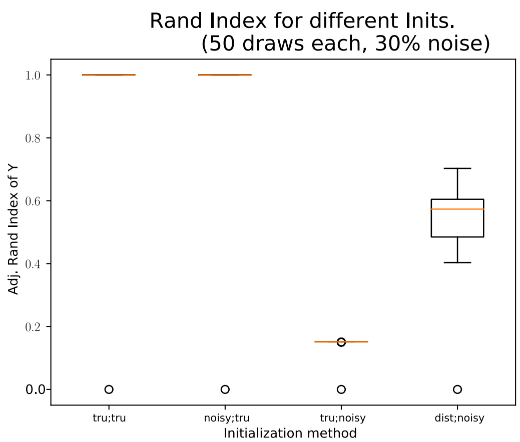
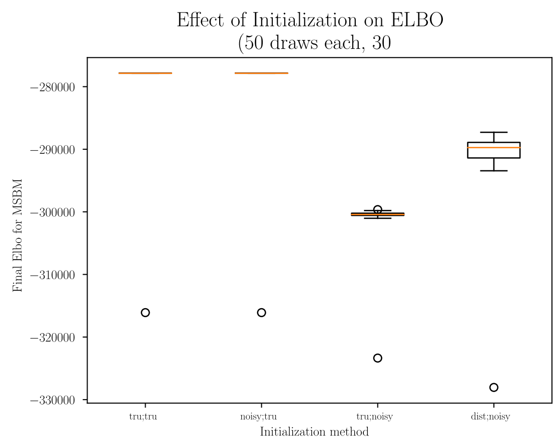


Figure 3.2: Actual vs. Predicted models for dist, noisy initialization. The models seem to be heavily undertrained (as expected), but they do show different expected degrees which is enough to tell them apart.



(a) The rand index has a better performance with non-perfect taus. This phenomenon could be explained with a smoother optimization landscape when τ is far from the truth.



(b) This effect is consistent with the ELBO which is dominated by the likelihood of the data.

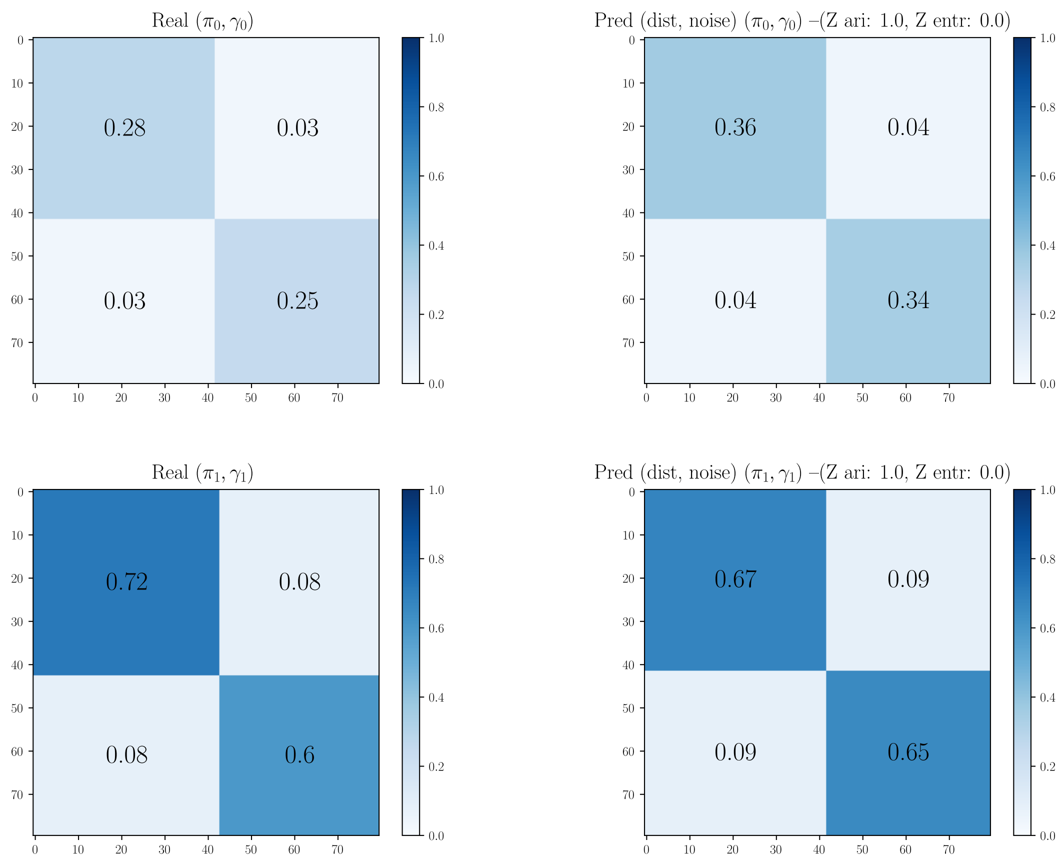


Figure 3.4: Actual vs. Predicted models for dist, noisy initialization. The models seem to be much better trained, but this does not really help the rand index of Y.