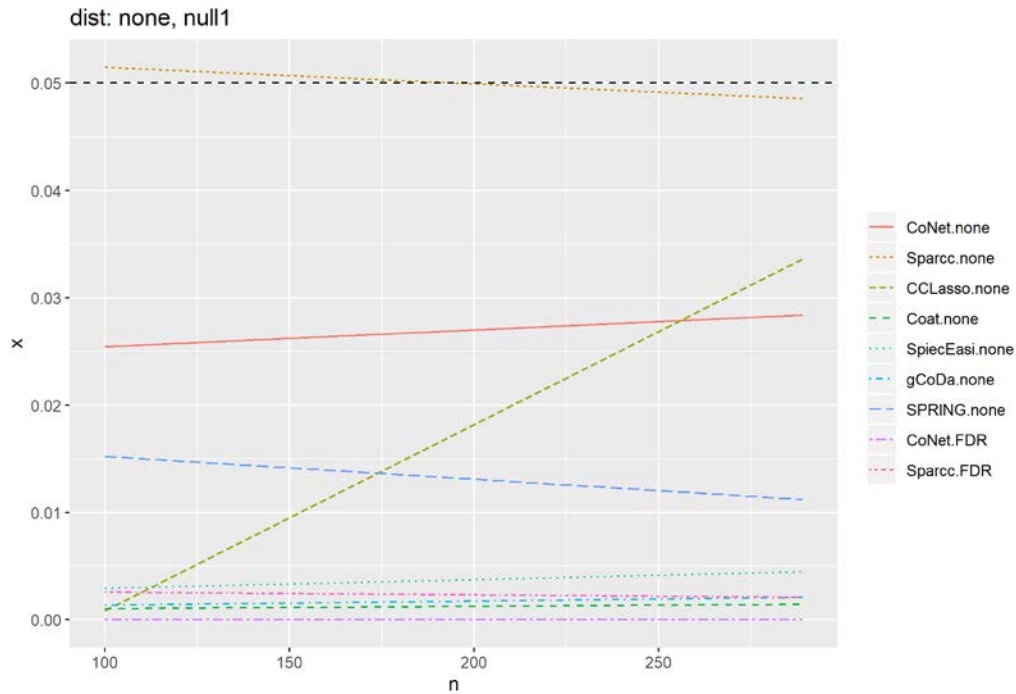


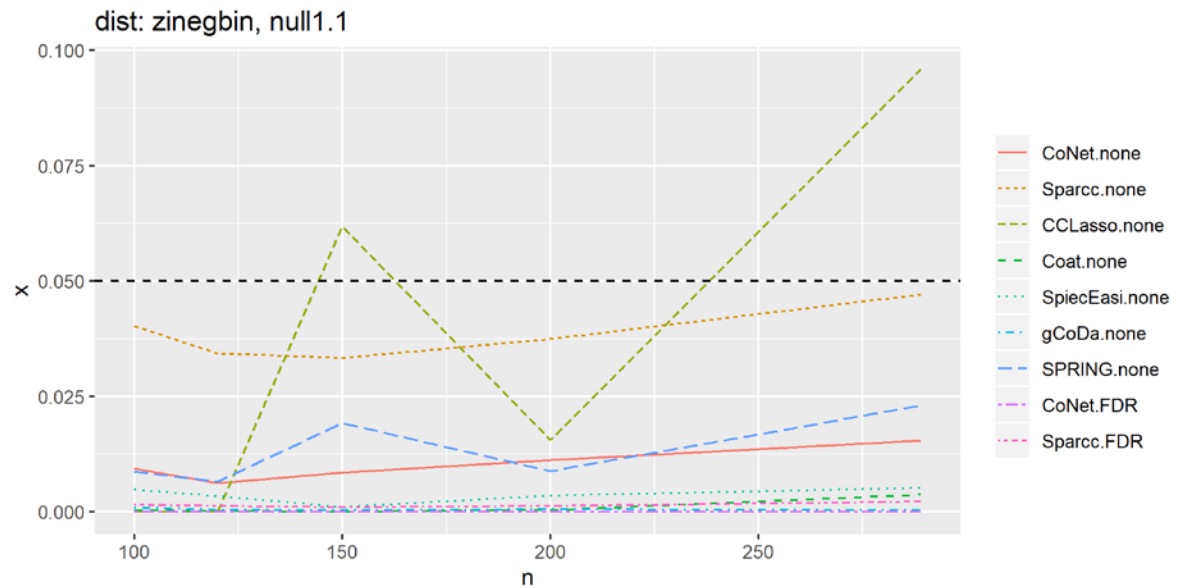
Summary for the simulation results

- Under null1 model, we directly shuffle reference data to get null data set. All methods are good.



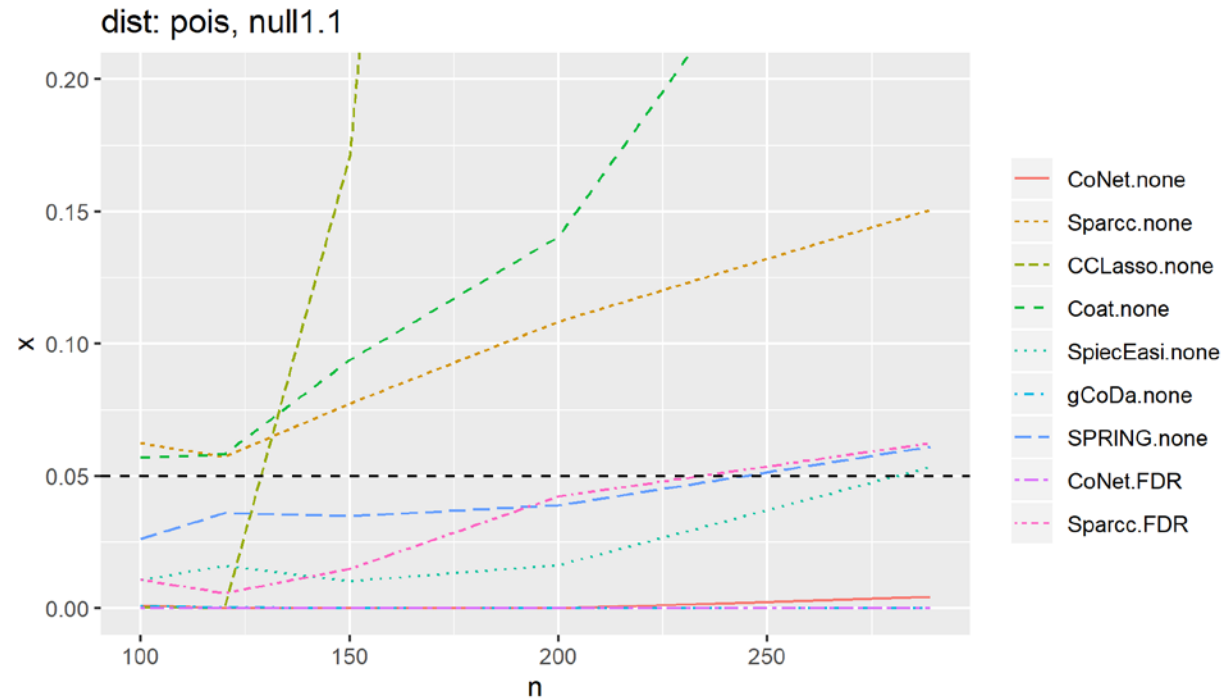
- Under null1.1 model, we generate data from copula model with a specified marginal distribution. Following plots are for false positive rate.

- Zinegbin (zero inflated negative binomial), fix $p=200$, varying n , CCLasso has slight problem

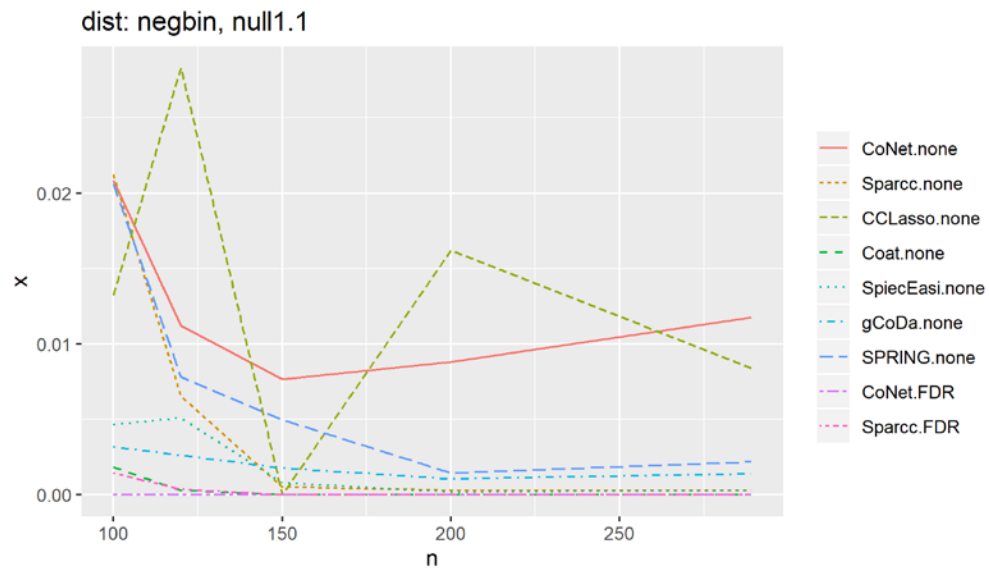


- Pois (poisson), $p=200$, varying n .

CCLasso, Coat and Sparcc have issues



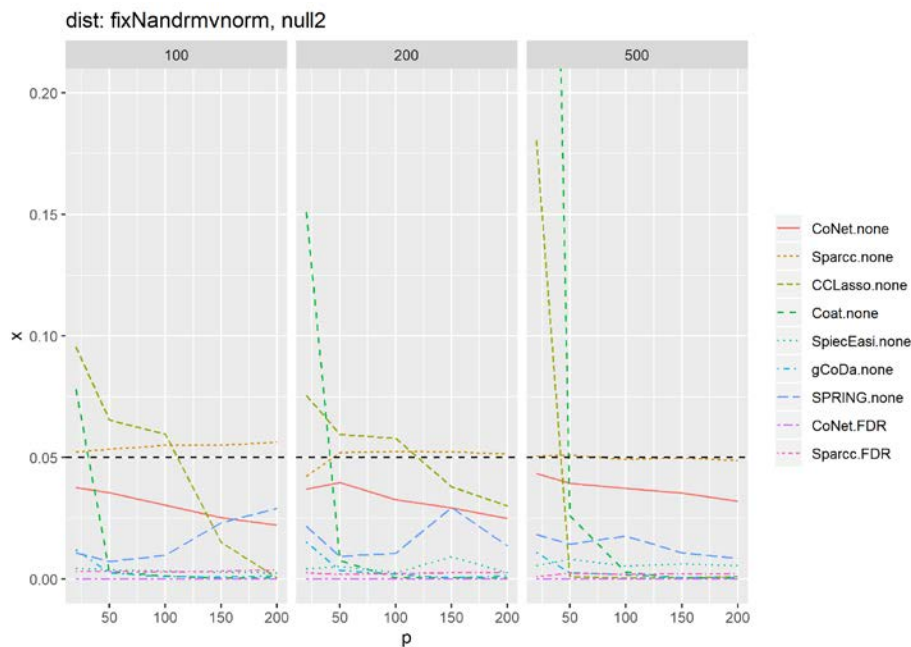
c. Negbin (negative binomial), $p=200$, n varying. All methods are good.



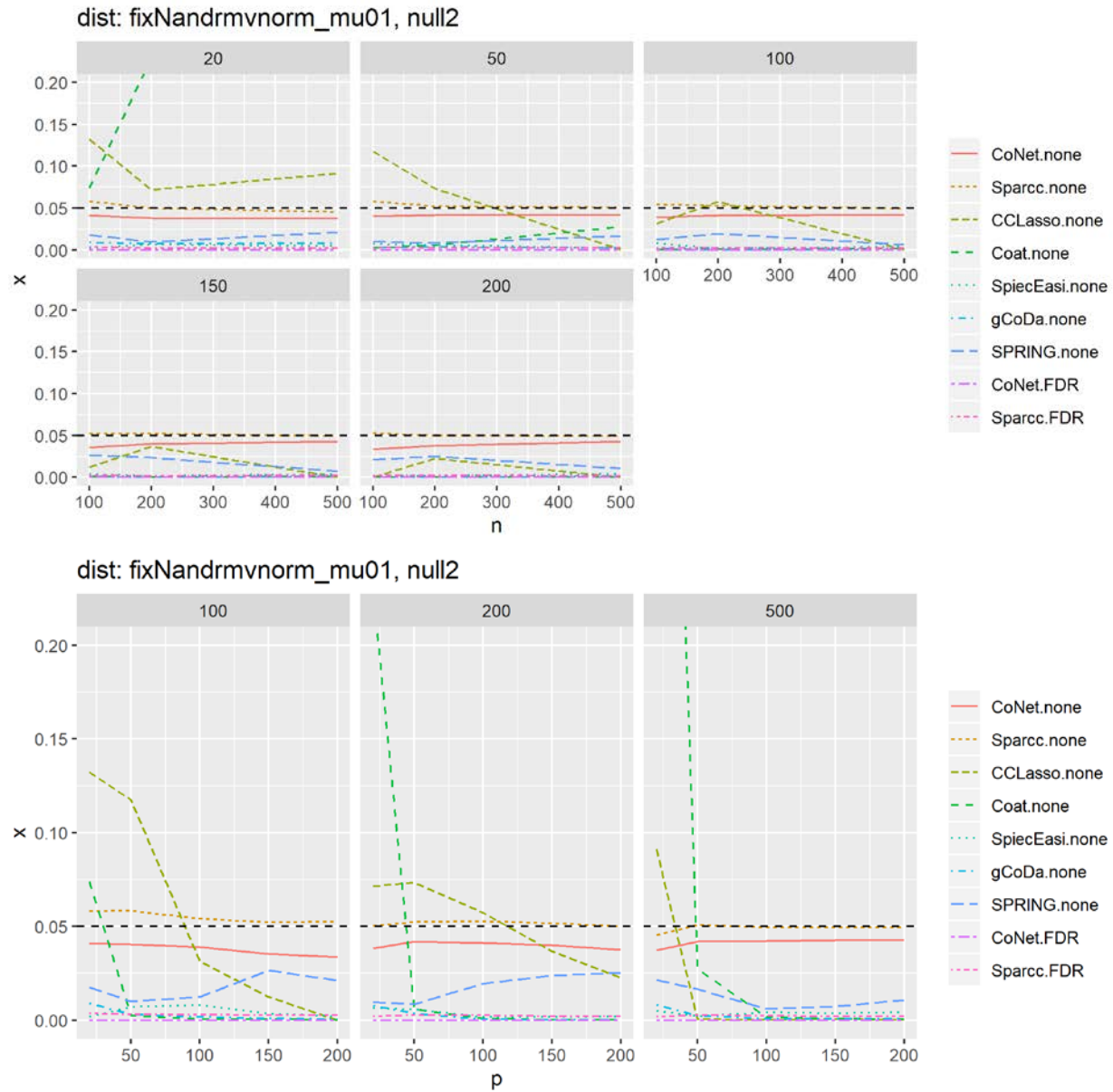
d. Had difficulty to simulate from zipois and lognorm (estimation of marginal distribution parameters did not converge).

3. Under null2 model, generate from Dirichlet distribution. $n=c(100, 200, 500)$, $p=c(20, 50, 100, 150, 200)$.

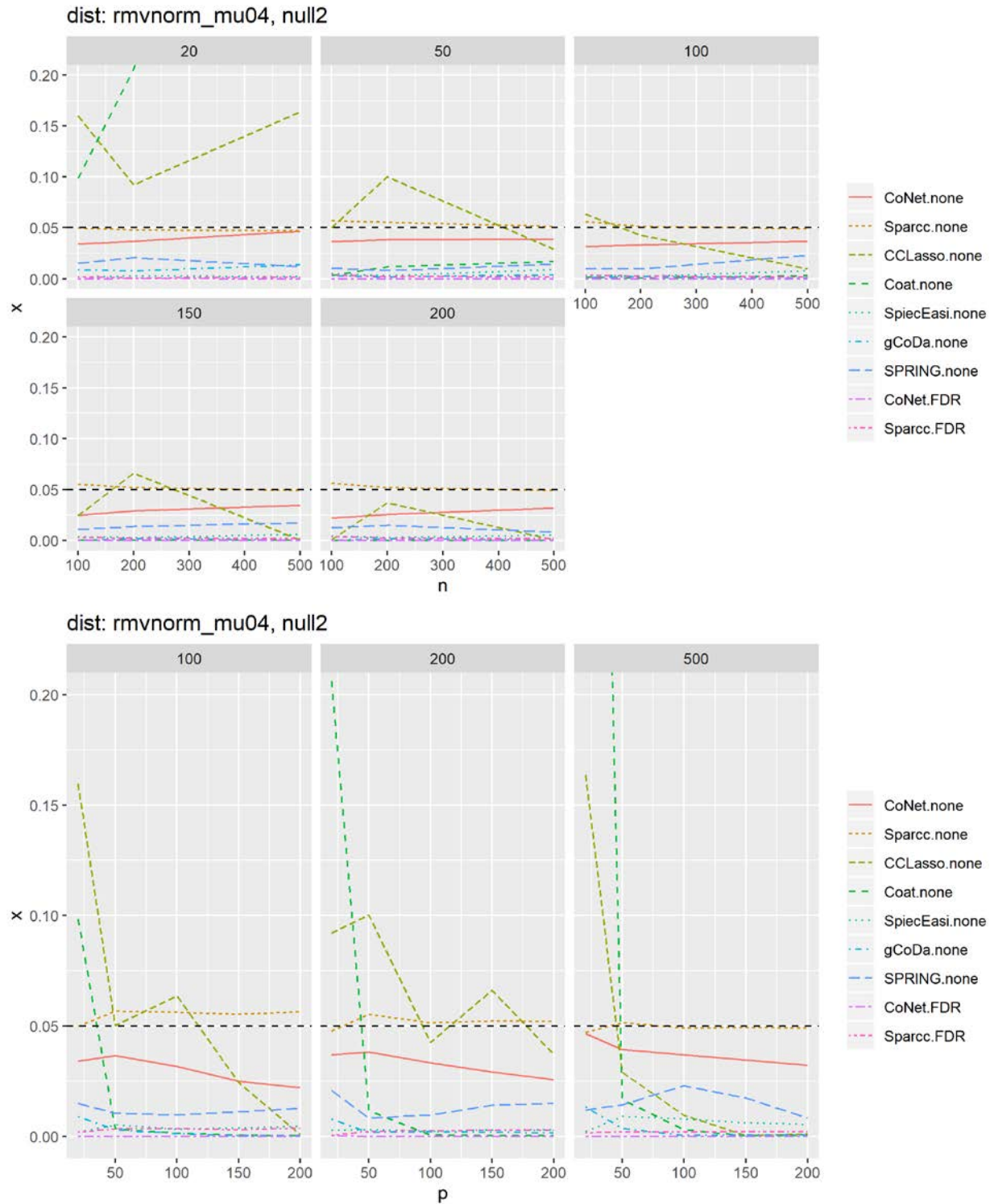
- a. use fixN (fixed library size) and also change to rmvnorm function (sorry I made a stupid mistake in my original rnorm function!!! mean mu values were added in a wrong order and things get distorted!!). Fortunately only null2 is affected). Use mu from uniform(0,4): only Coat and CCLasso fail under p=20



- b. use fixed library size and use $\mu \sim \text{uniform}(0,1)$
seems does not make much difference compared to $\mu \sim \text{uniform}(0,4)$



c. use varying library size and $\mu \sim \text{uniform}(0,4)$

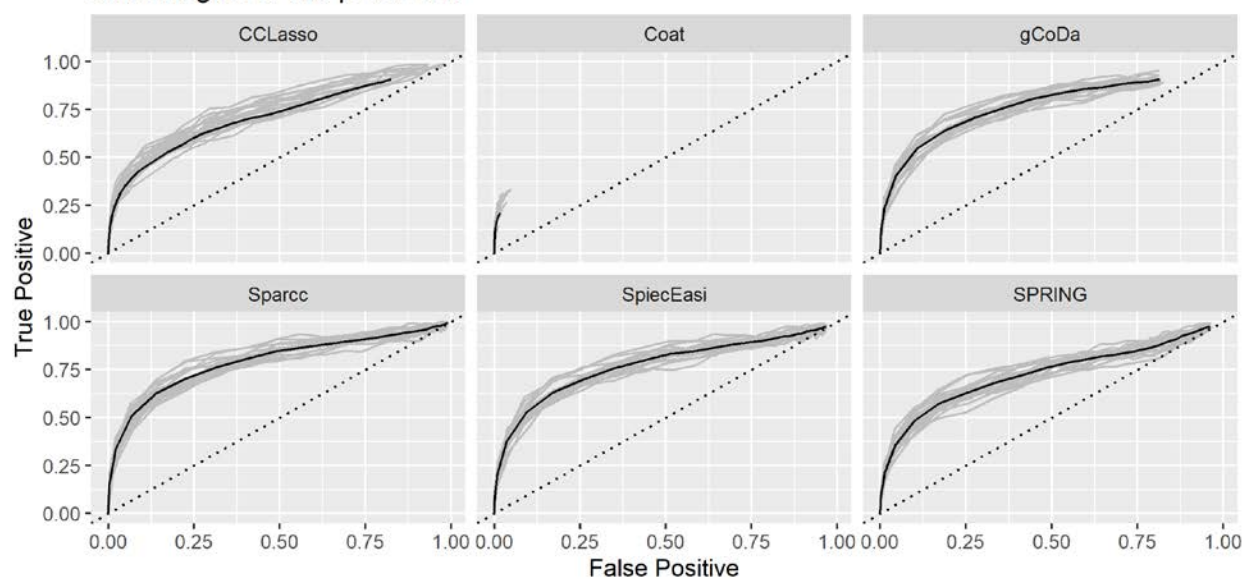


4. under alt1, generate based on copula model, the network is generated from a random graph and is set to be fixed within one setting. We vary marginal distributions. $n=c(100, 120, 150, 200, 289)$, $p=127$

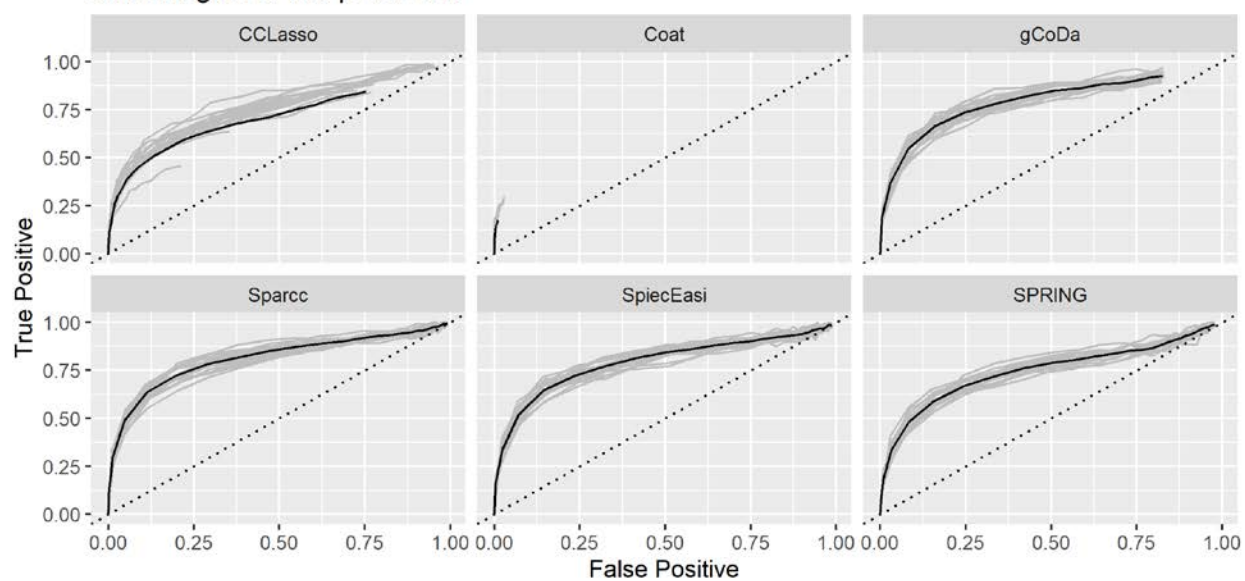
- a. Zinegbin

The tuning parameter sequence is problematic for COAT

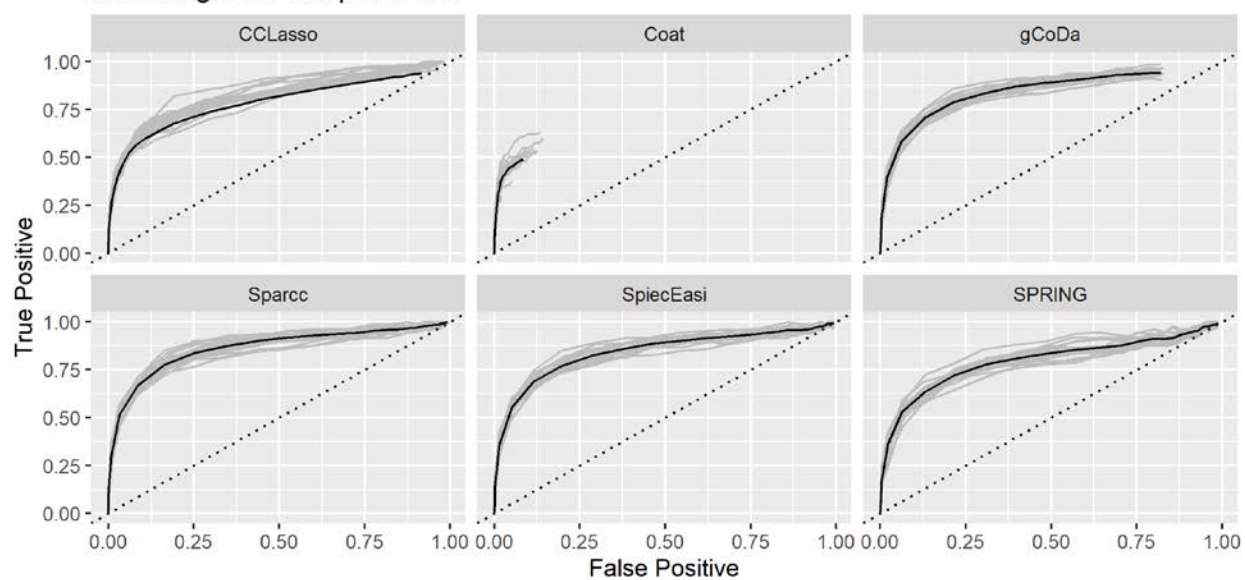
dist zinegbin n 100 p 127 alt1



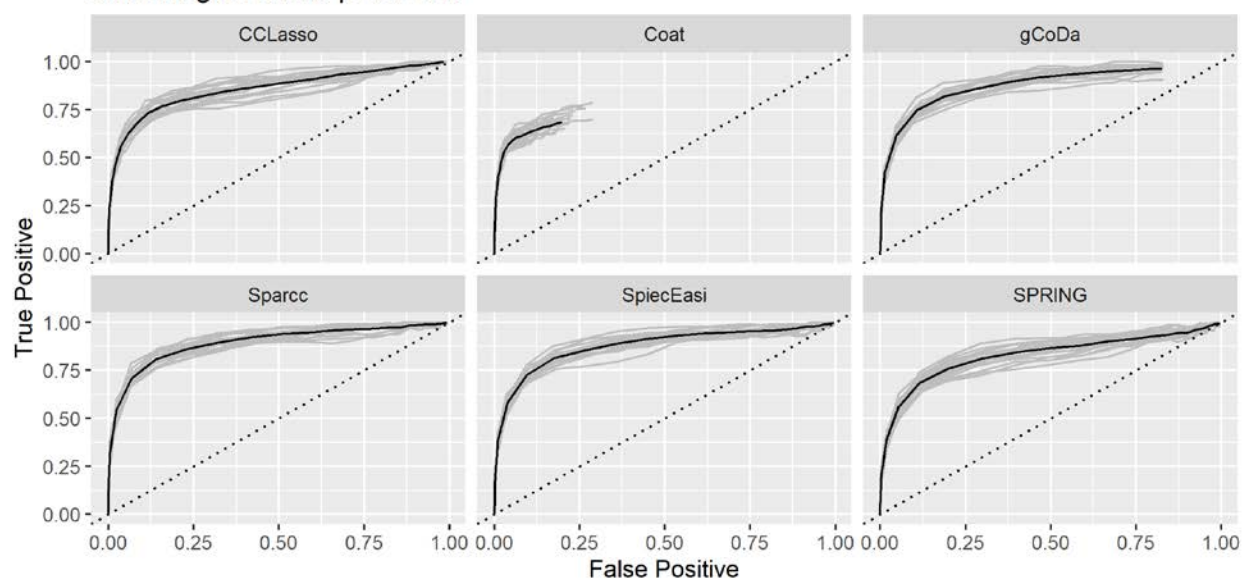
dist zinegbin n 120 p 127 alt1

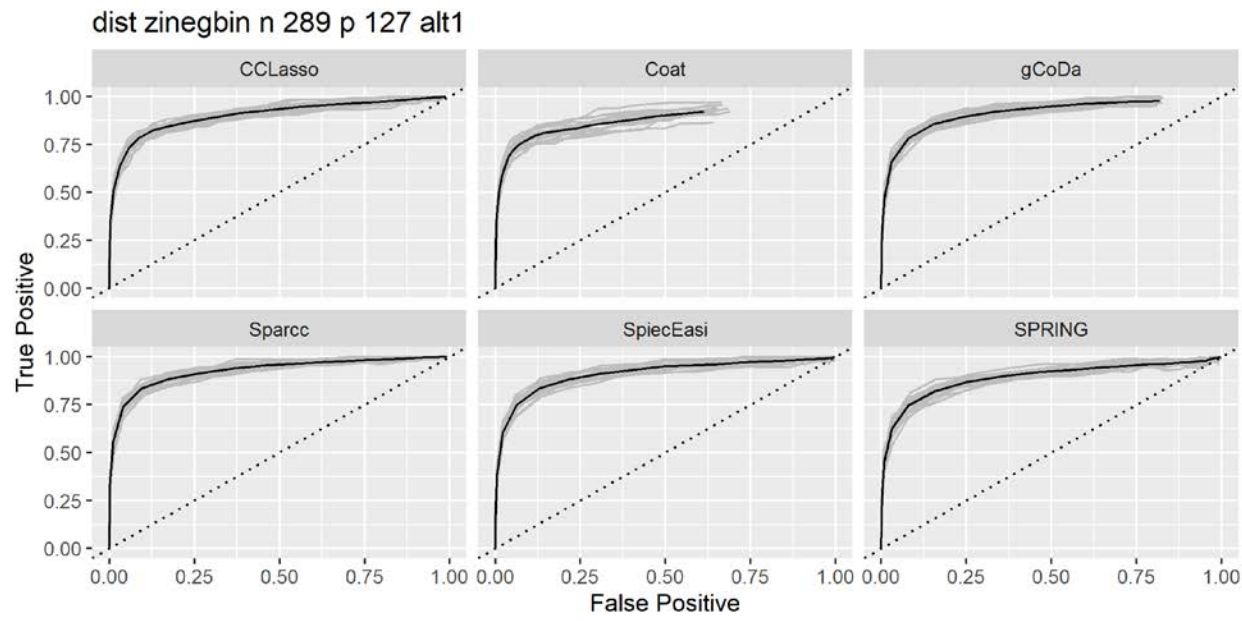


dist zinegbin n 150 p 127 alt1



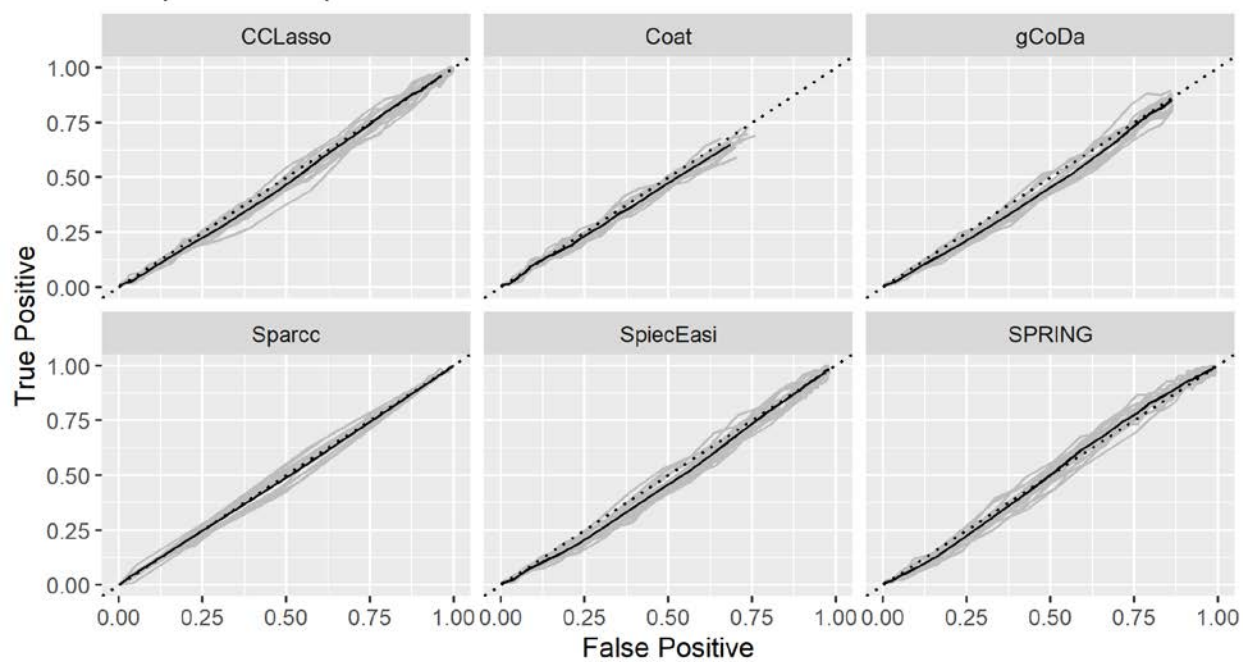
dist zinegbin n 200 p 127 alt1



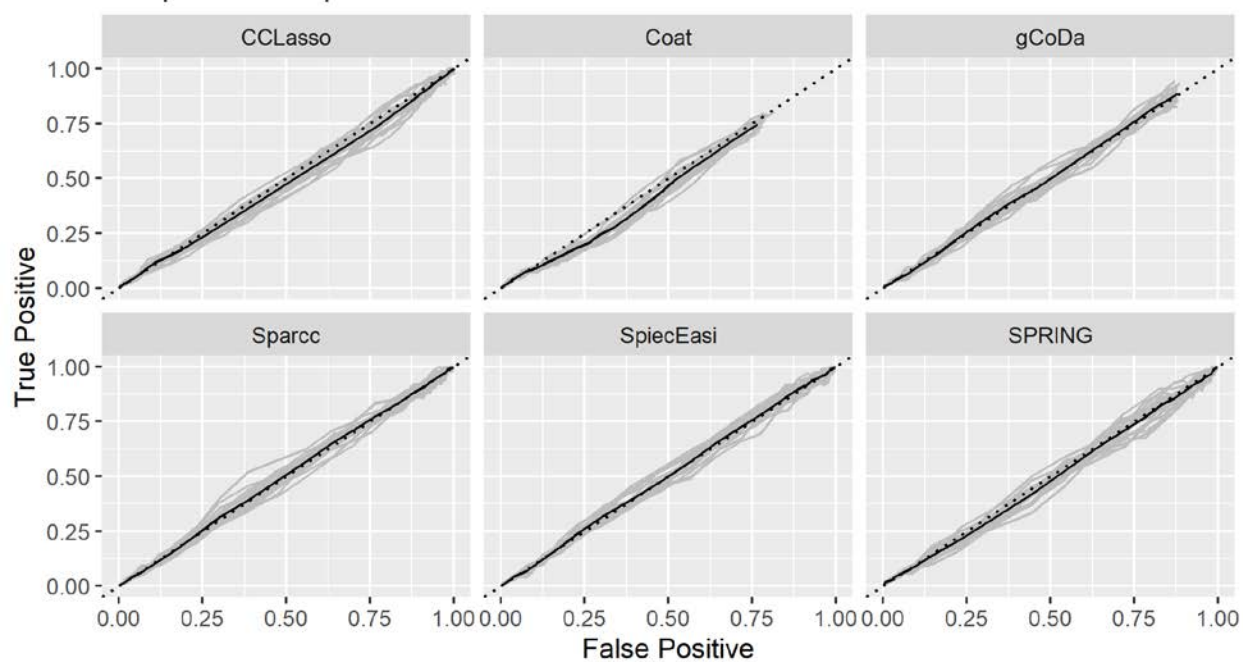


b. Pois. None of the methods work

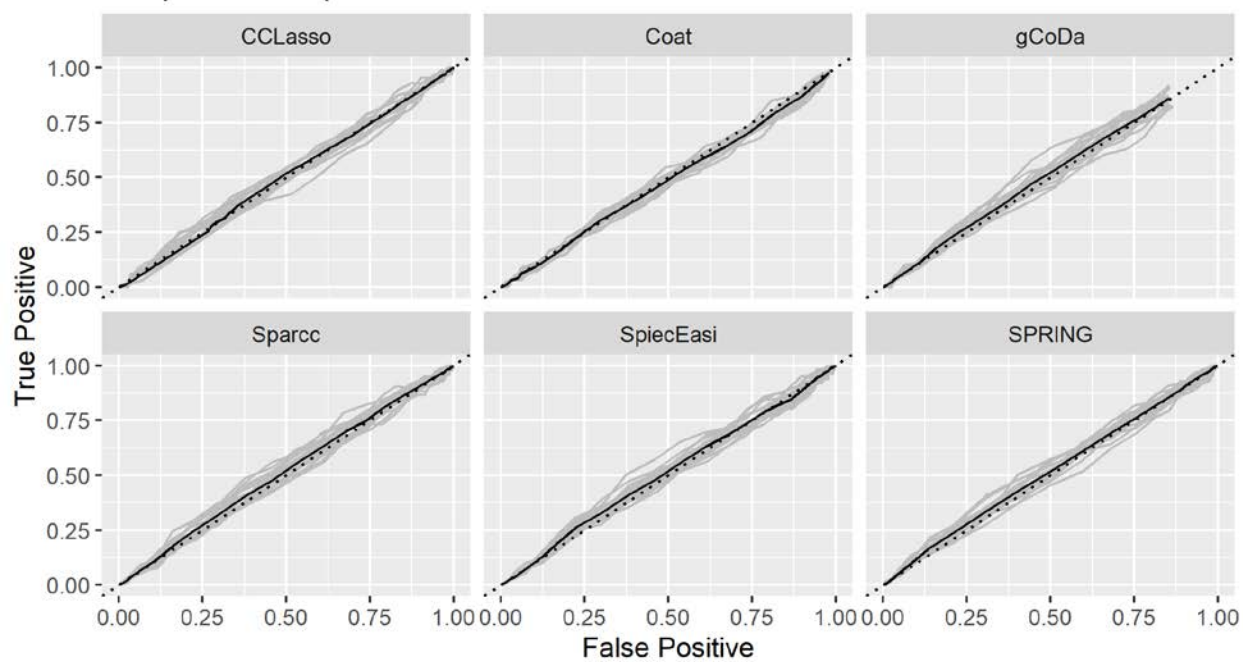
dist pois n 100 p 127 alt1



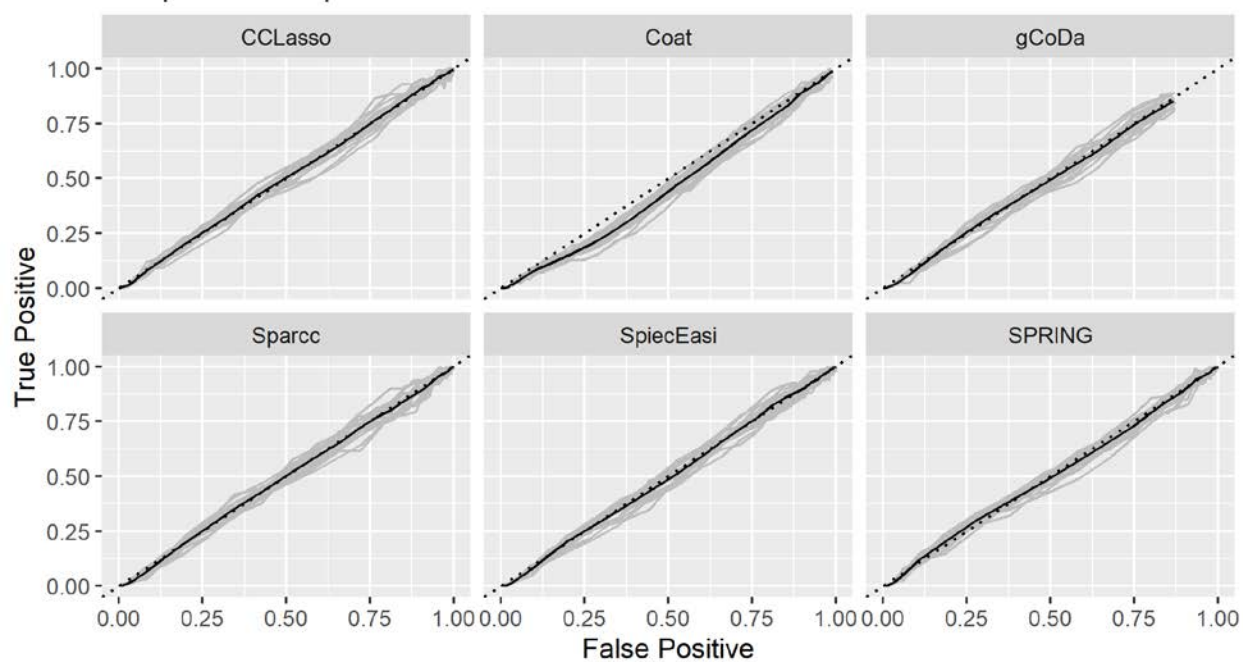
dist pois n 120 p 127 alt1

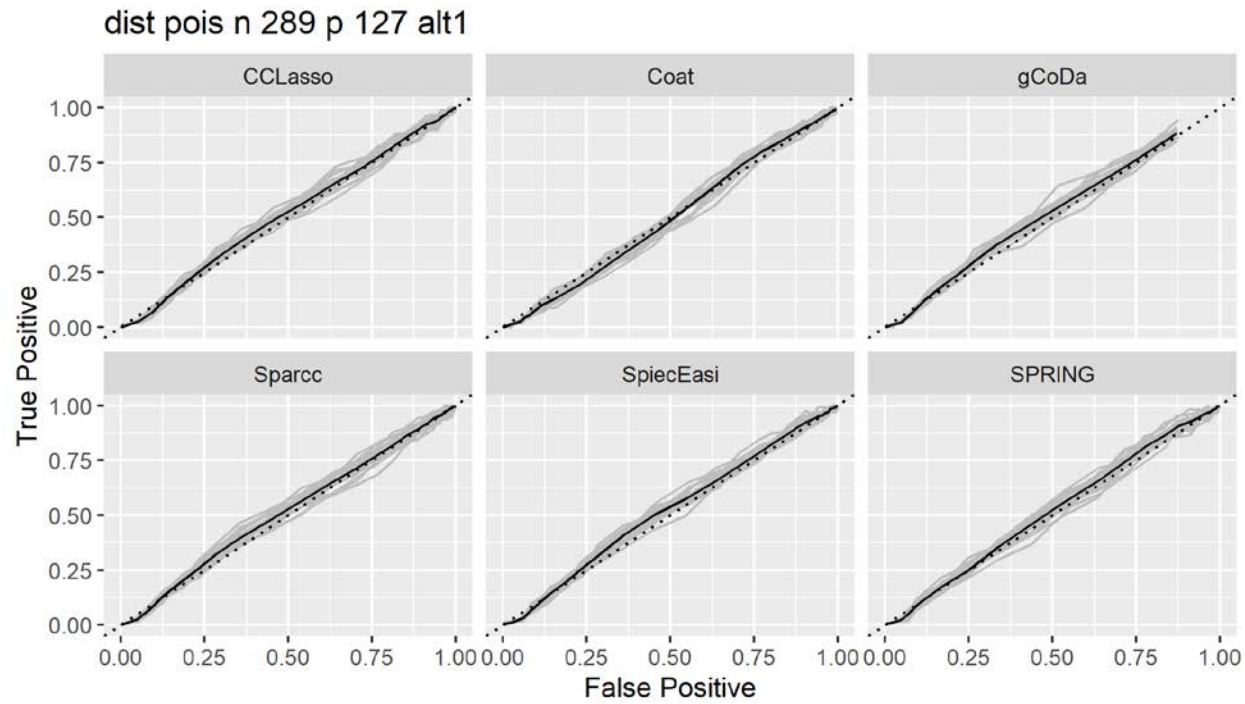


dist pois n 150 p 127 alt1



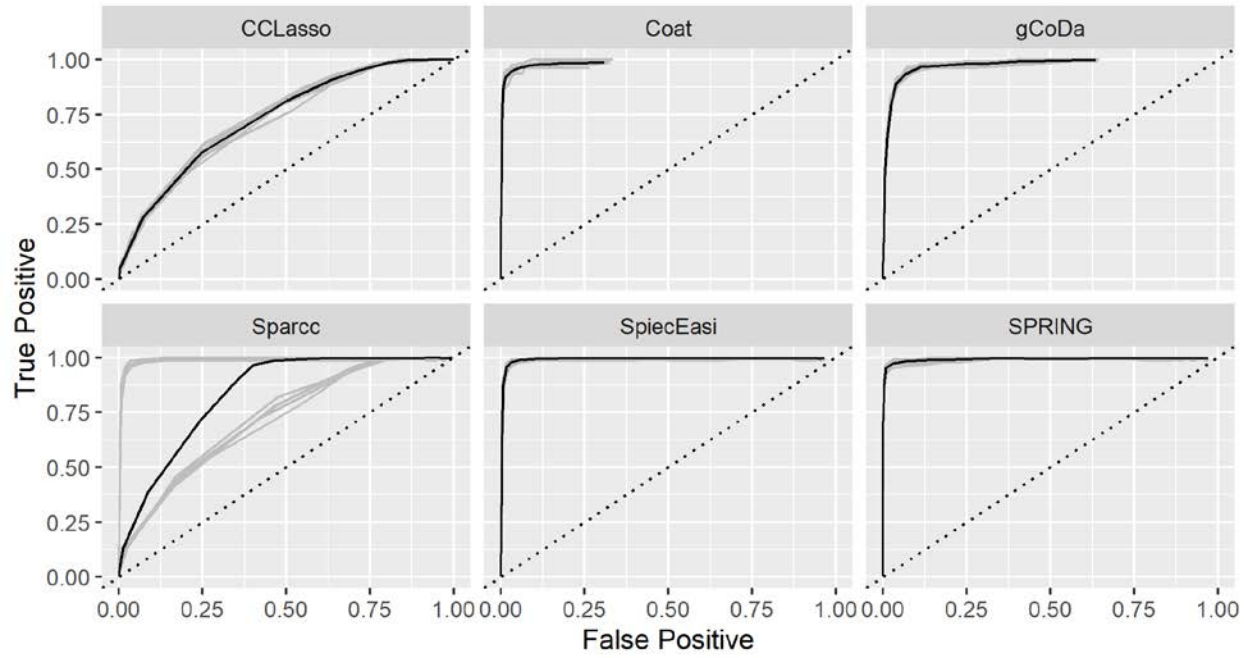
dist pois n 200 p 127 alt1



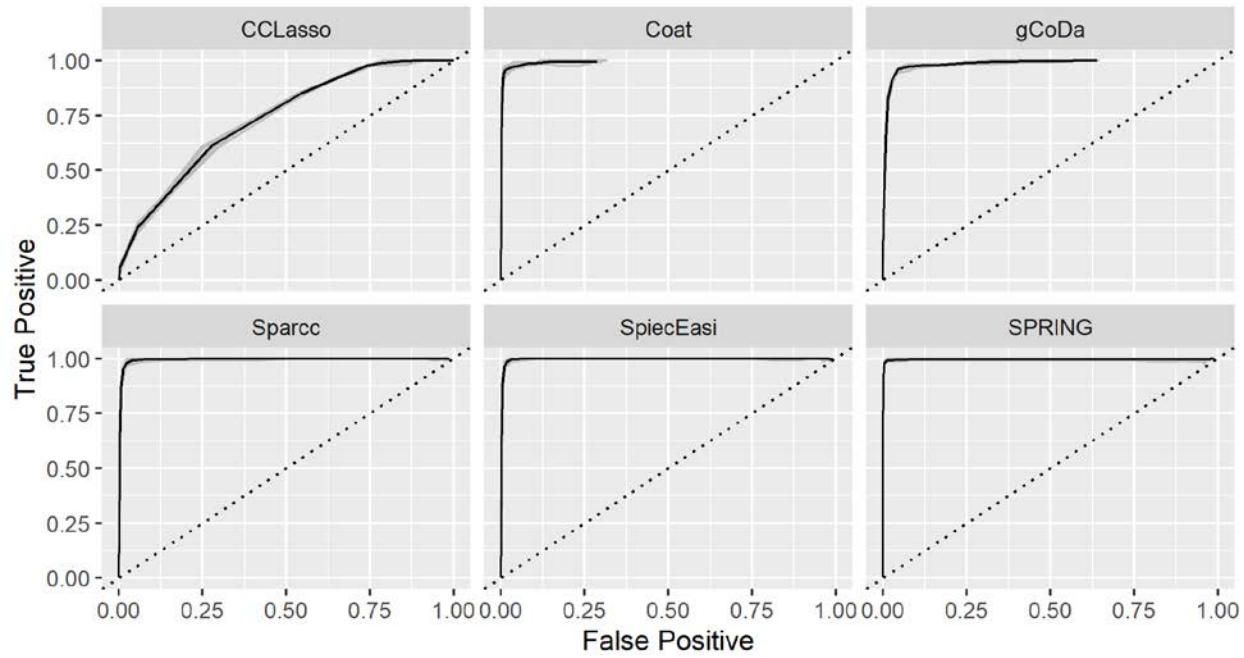


- c. Negbin. Might need closer investigation for CCLasso and SparCC. The last plot for gcodea might have some error, not yet investigated.

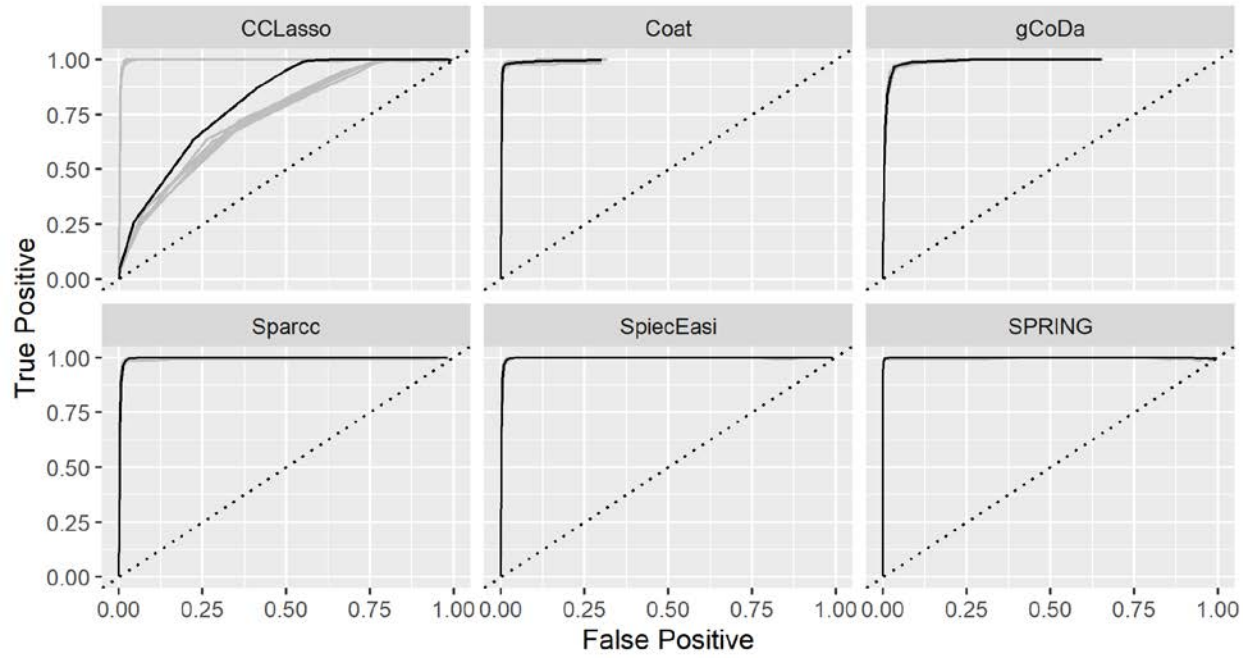
dist negbin n 100 p 127 alt1



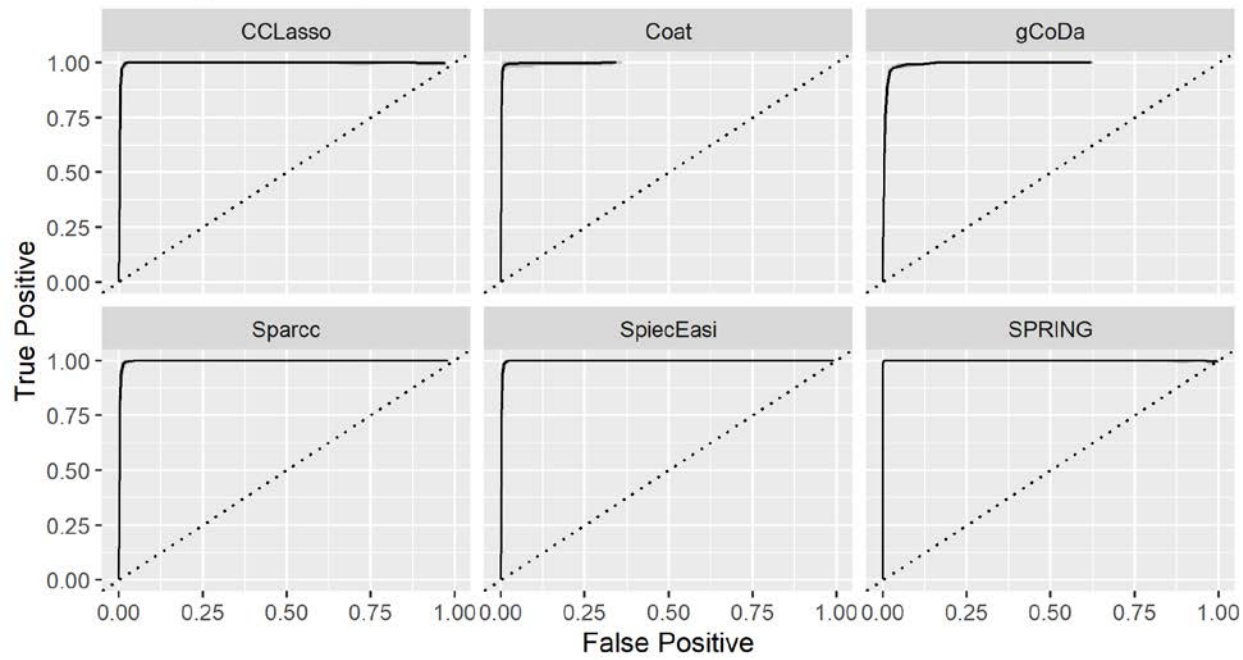
dist negbin n 120 p 127 alt1

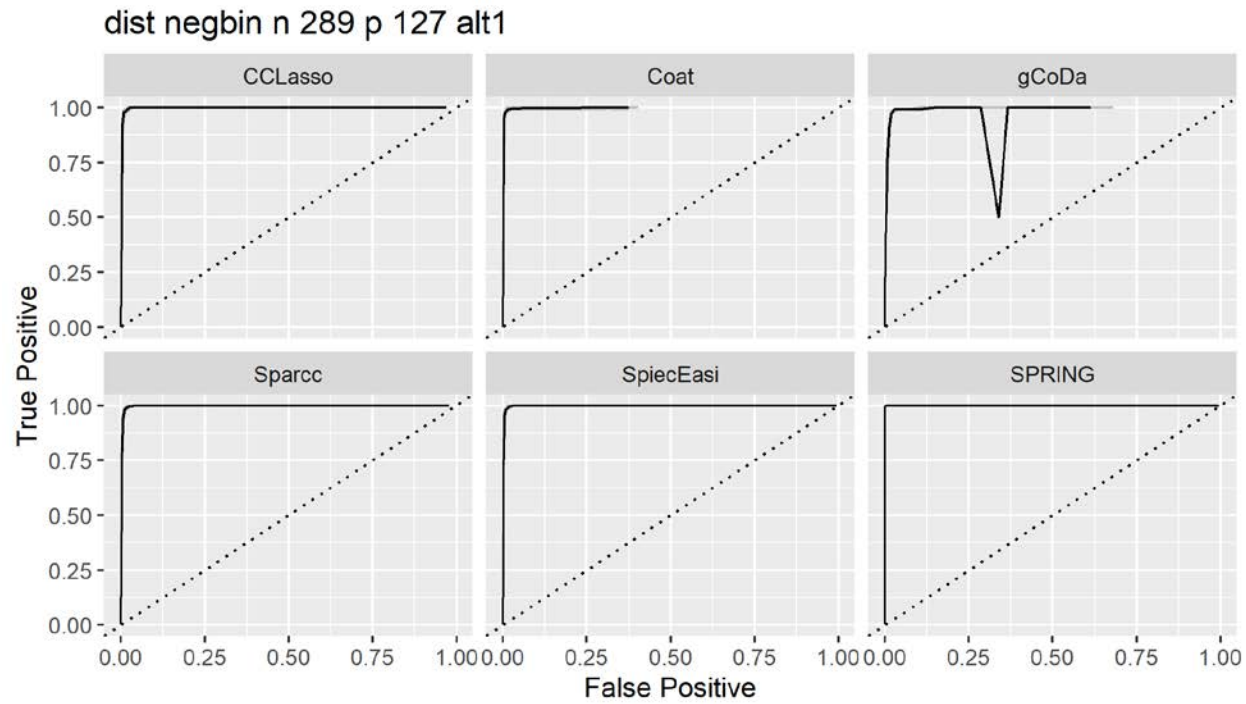


dist negbin n 150 p 127 alt1



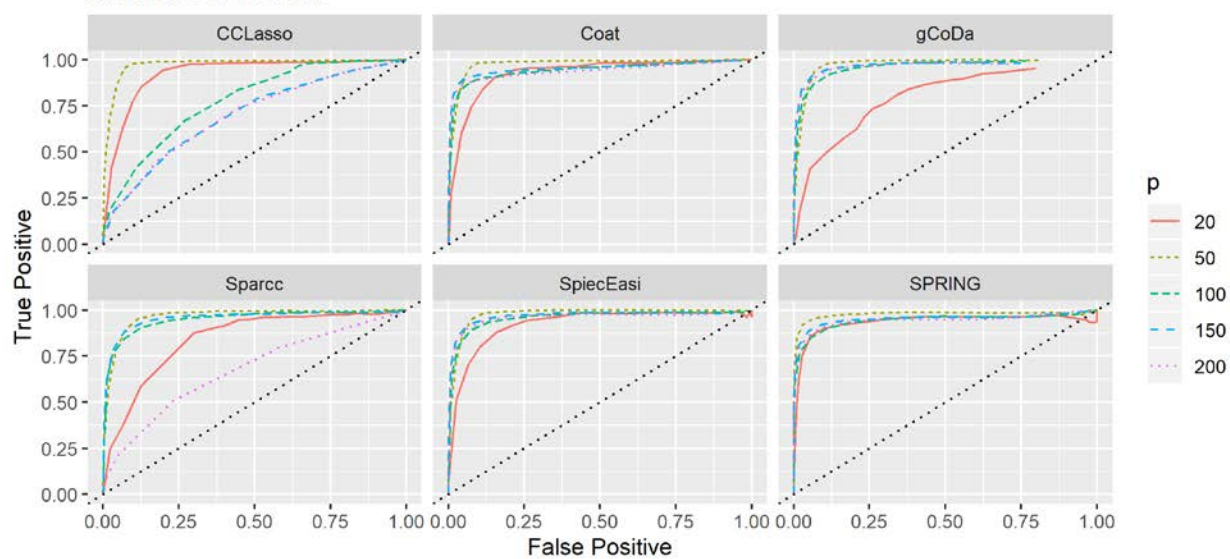
dist negbin n 200 p 127 alt1



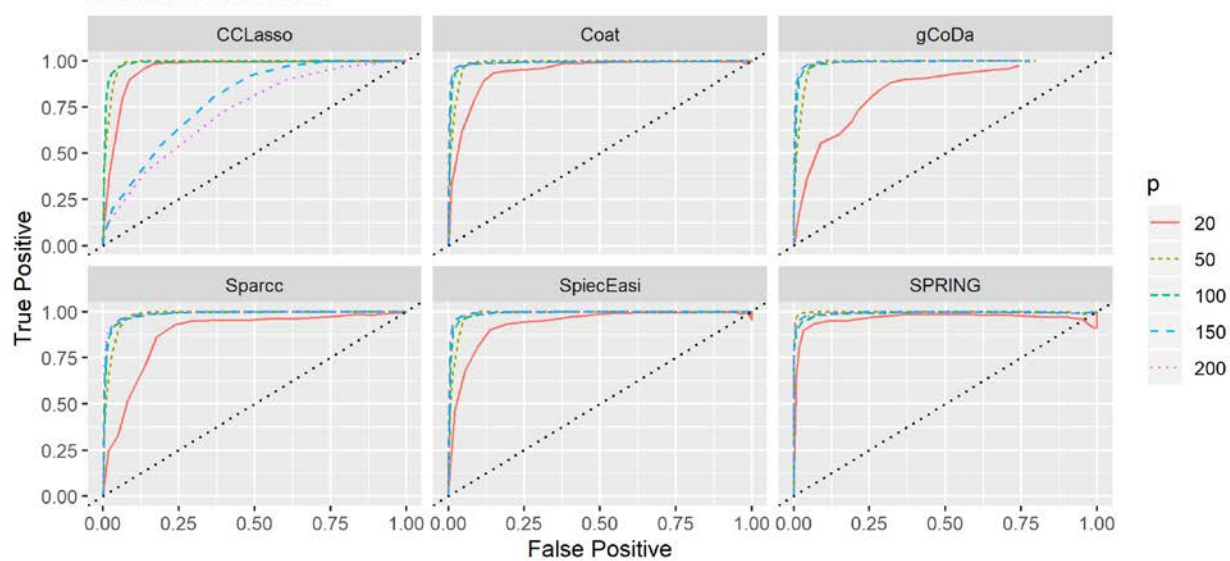


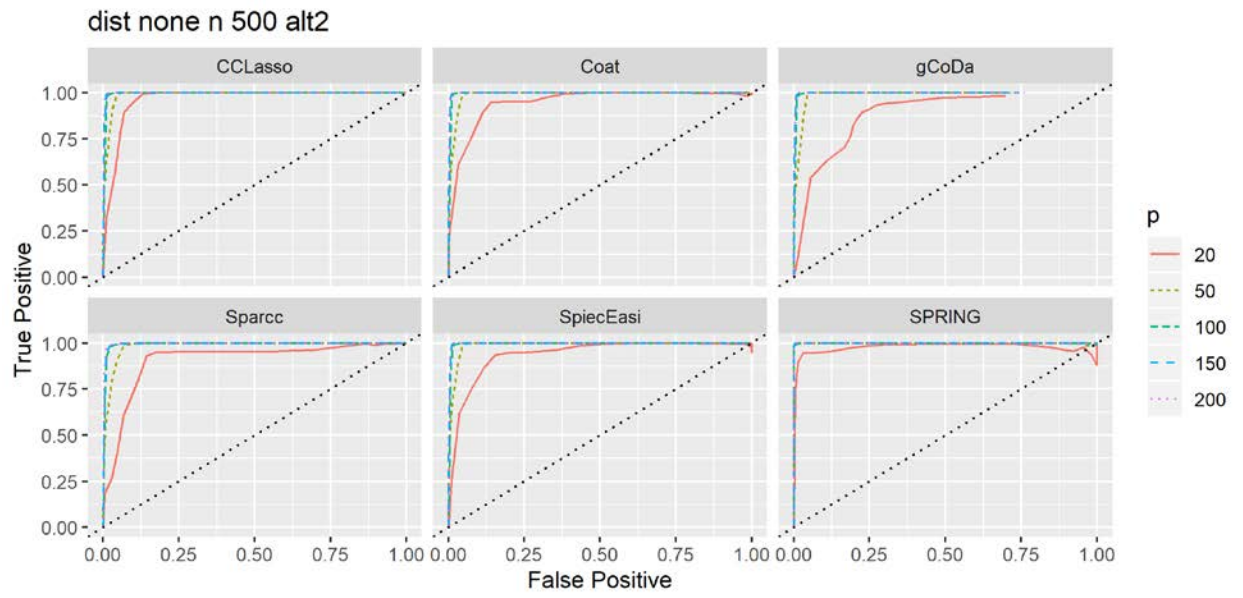
5. Alternative 2 model, generate from log normal model. Plot the mean ROC only for each p under the same n.
 - a. did not use fixN/fix library size, using mu from uniform(0,4).

dist none n 100 alt2



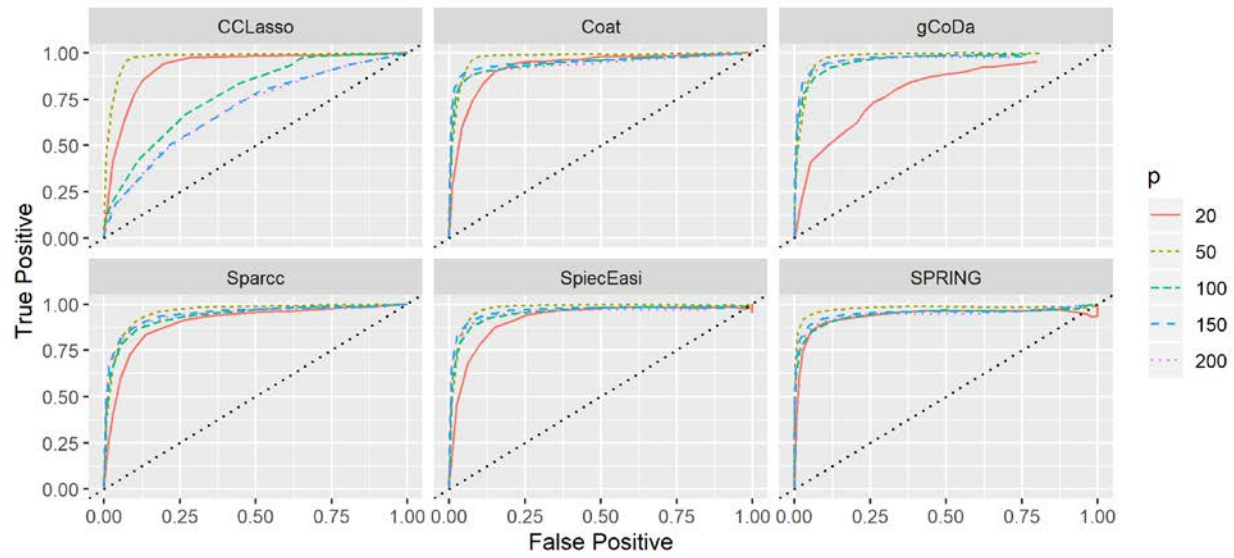
dist none n 200 alt2



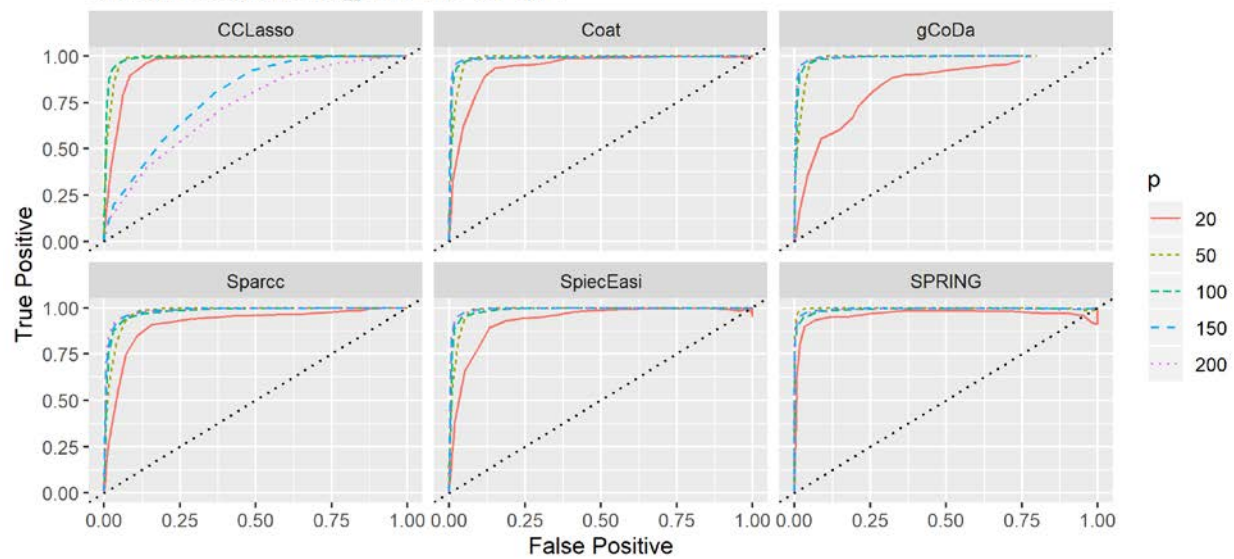


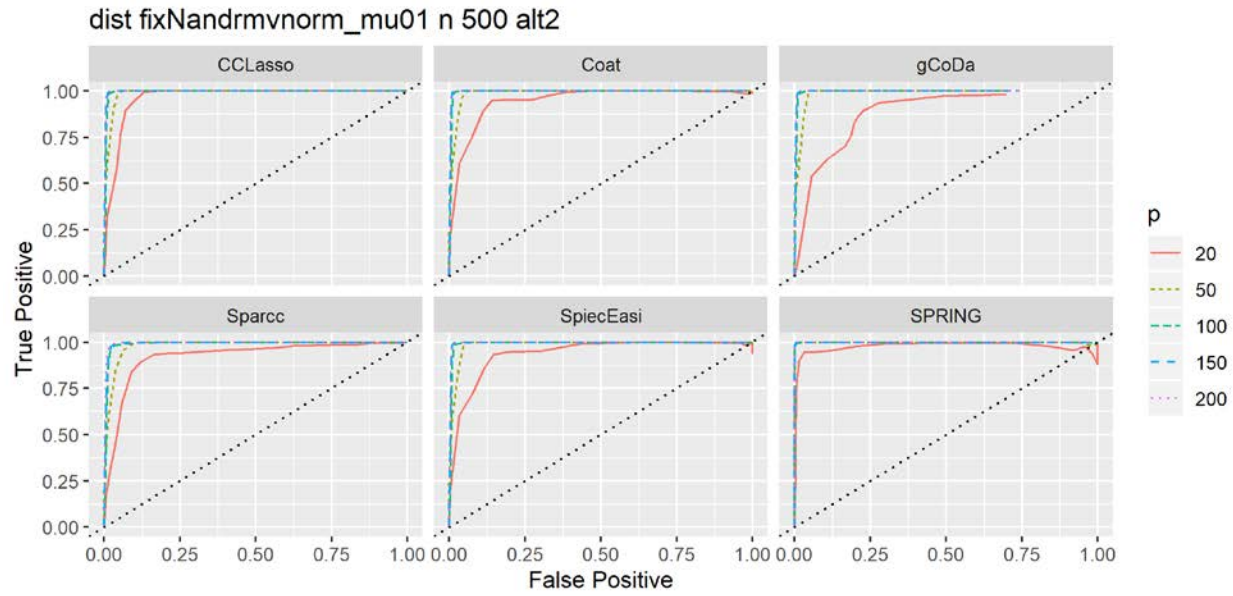
b. Use fixed library size, and also use $\mu \sim \text{uniform}(0,1)$: similar results.

dist fixNandrmvnorm_mu01 n 100 alt2



dist fixNandrmvnorm_mu01 n 200 alt2



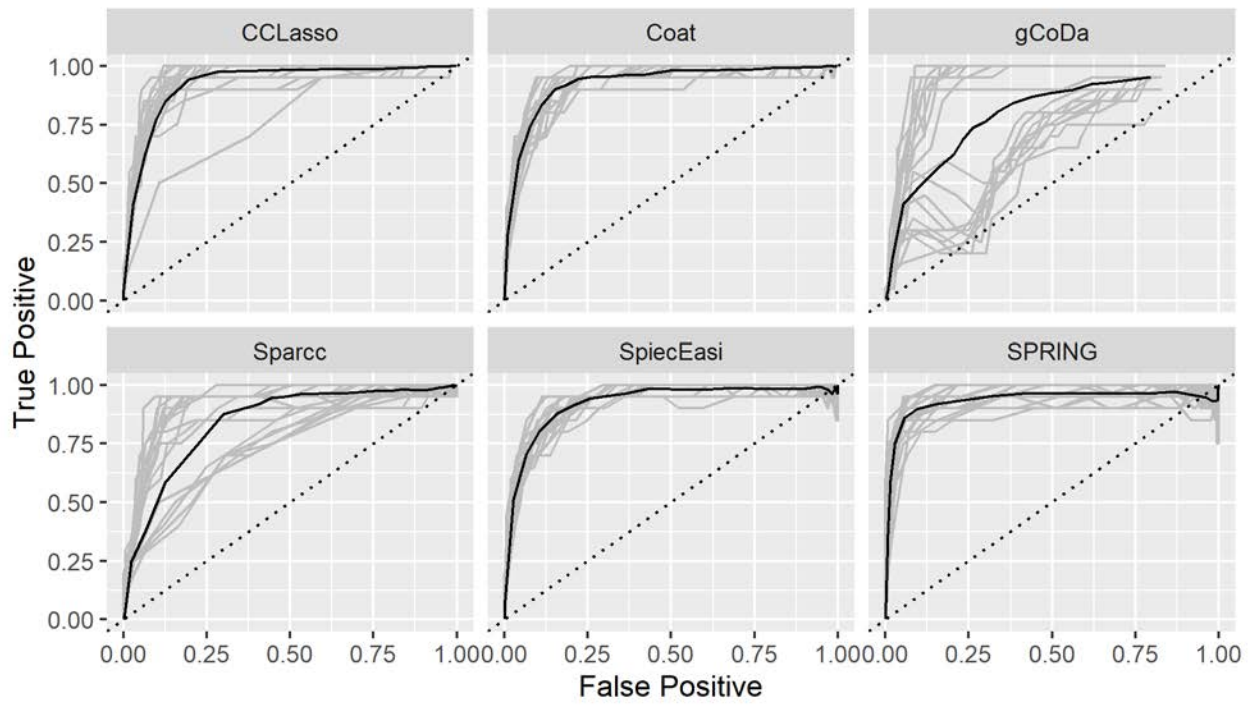


6. Some more exploration for CCLasso behavior under alt2, varying library scale and $\mu \sim \text{uniform}(0,4)$:

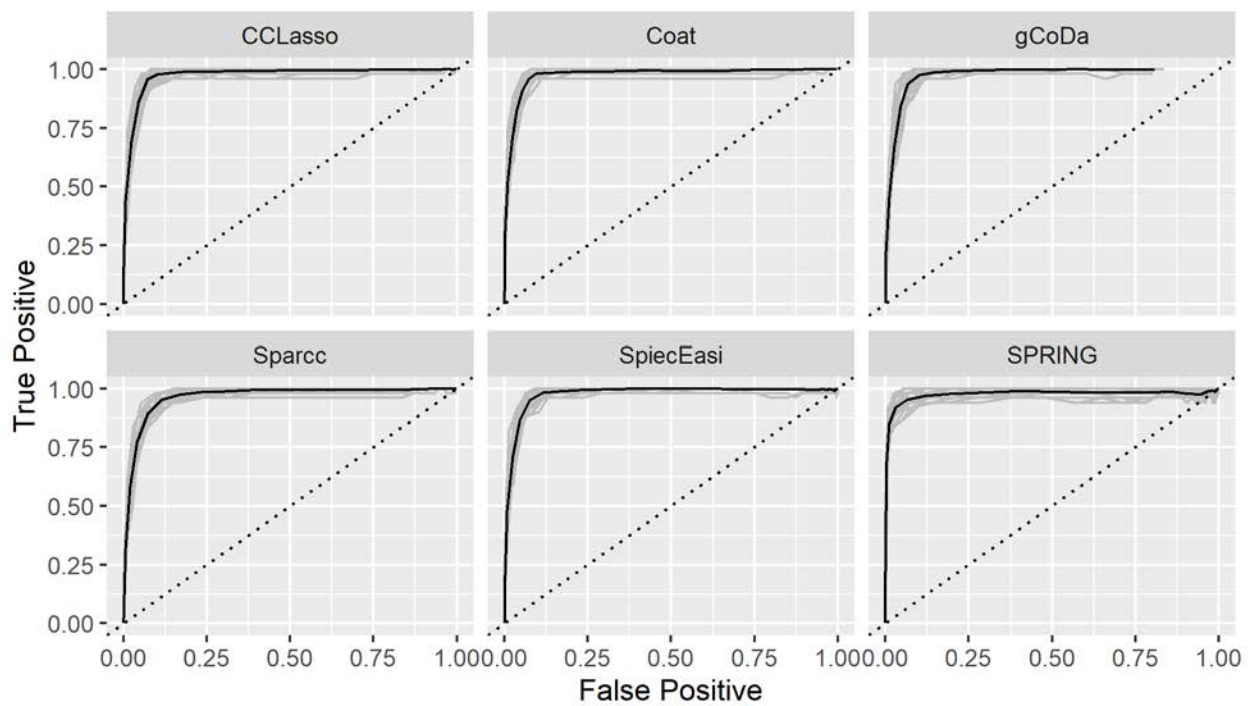
Tuning parameter by CCLasso is not at the boundary (assume no issue here)

By separately looking at each n p combination, the grey lines represent ROCs from different replicates. For these replicates tuning parameter is fine (not at the boundary supplied). However we can see large variation in ROCs.

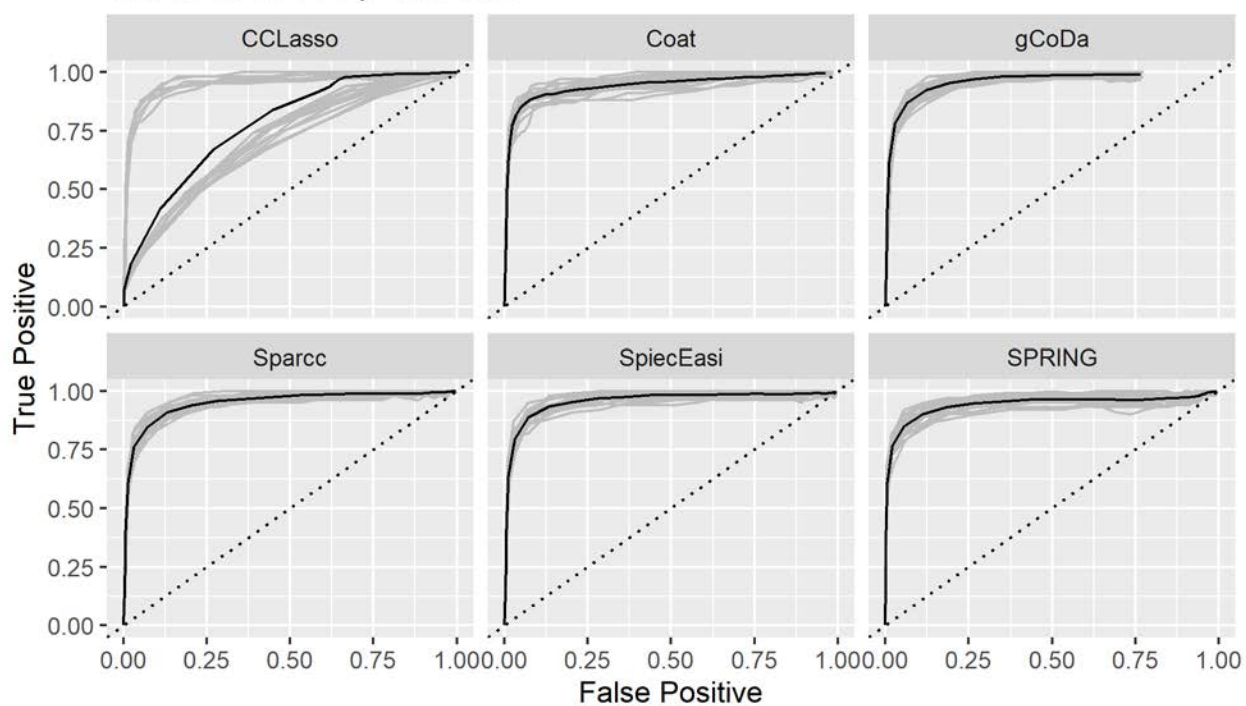
dist none n 100 p 20 alt2



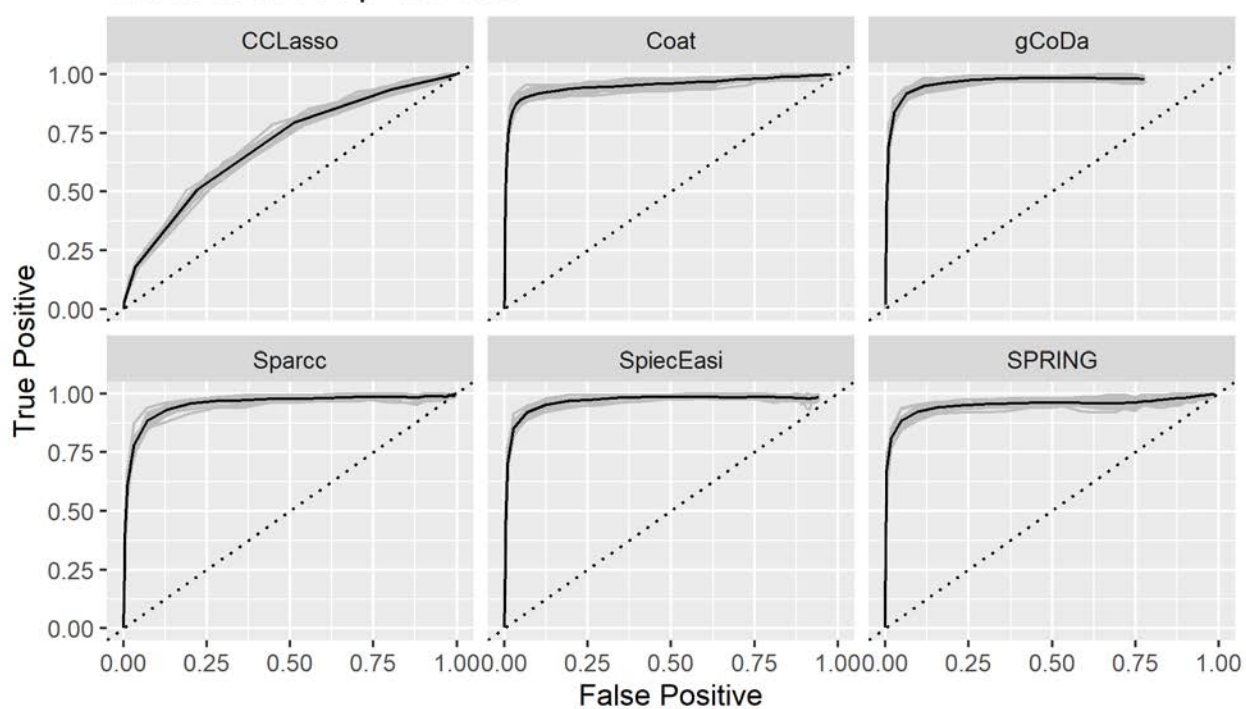
dist none n 100 p 50 alt2



dist none n 100 p 100 alt2



dist none n 100 p 150 alt2



dist none n 100 p 200 alt2

