

Appendix

Details of the algorithm used to estimate hyper-parameters c and π :

To maximize the likelihood

$$L(\pi, c; \mathbf{a}, \hat{s}_1^2, \dots, \hat{s}_J^2) = p(\hat{s}_1, \dots, \hat{s}_J | \pi, \mathbf{a}, c) \quad (1)$$

$$= \prod_{j=1}^J \sum_k \pi_k p(\hat{s}_j; a_k, c) \quad (2)$$

we iteratively update c and π using the following steps until they converge:

$$c^{new} = \arg \max_c \log L(c, a_1^{old}, \dots, a_K^{old}, \pi_1^{old}, \dots, \pi_K^{old}) \quad (3)$$

$$(\pi_1^{new}, \dots, \pi_K^{new}) = \left(\frac{\sum_j \tilde{\pi}_{j1}^{old}}{\sum_{j'} \sum_{k'} \tilde{\pi}_{j'k'}^{old}}, \dots, \frac{\sum_j \tilde{\pi}_{jK}^{old}}{\sum_{j'} \sum_{k'} \tilde{\pi}_{j'k'}^{old}} \right). \quad (4)$$

Because there is no analytic solution to the optimization problem (3) we approximate the optimum via the quasi-Newton method using the function `optim` in R. The updating procedure (3)-(4) is a fixed point mapping function, hence we can accelerate the overall optimization procedure by the R package `SQUAREM`, which is computationally efficient in solving fixed point problems.

Supplementary tables and figures

	A	B	C	D	E	F	G	H
baseline	70.79	131.30	57.67	49.51	47.19	60.65	56.88	40.85
limma	38.55	108.23	29.02	20.06	25.70	43.54	52.97	14.58
limmaR	38.86	103.50	29.88	20.60	25.90	41.85	39.00	14.58
vash.opt	38.54	91.39	28.56	19.86	25.69	38.60	47.34	14.31

(a) RMSE_{var} in the cases where $df=3$.

	A	B	C	D	E	F	G	H
baseline	38.73	66.01	31.50	26.98	25.82	31.25	40.43	22.36
limma	29.80	73.09	23.57	17.27	19.87	30.56	44.14	12.82
limmaR	29.88	59.13	23.19	17.18	19.92	26.33	35.47	12.78
vash.opt	29.80	60.18	22.73	16.72	19.87	26.87	39.37	12.37

(b) RMSE_{var} in the cases where $df=10$.

	A	B	C	D	E	F	G	H
baseline	17.28	37.07	14.13	12.08	11.52	16.56	14.74	10.00
limma	16.27	38.46	13.34	10.78	10.85	16.61	18.80	8.42
limmaR	16.28	36.49	12.95	10.33	10.86	16.08	14.05	8.31
vash.opt	16.27	36.89	12.85	10.19	10.85	16.27	15.68	7.80

(c) RMSE_{var} in the cases where $df=50$.

Table S1: Table of average RMSE_{var} of *limma*, *limmaR* and *vash* in the 8 simulation scenarios A-H.

	A	B	C	D	E	F	G	H
baseline	803.49	801.65	961.77	768.21	1205.23	1276.52	1223.56	1356.00
limma	16.67	17.03	13.48	12.92	25.00	32.81	30.56	28.63
limmaR	16.67	17.02	13.46	12.91	25.00	32.82	30.58	28.64
vash.opt	16.67	17.06	13.45	12.90	25.00	32.81	30.38	28.76

(a) RMSE_{prec} in the cases where $\text{df}=3$.

	A	B	C	D	E	F	G	H
baseline	35.23	34.47	35.97	38.21	52.85	57.59	52.96	50.26
limma	13.76	13.87	11.81	11.72	20.64	27.04	26.68	26.28
limmaR	13.76	13.85	11.75	11.69	20.64	27.08	26.90	26.41
vash.opt	13.76	13.85	11.72	11.70	20.64	26.48	24.85	24.74

(b) RMSE_{prec} in the cases where $\text{df}=10$.

	A	B	C	D	E	F	G	H
baseline	10.08	9.96	10.52	11.05	15.12	16.66	15.38	14.62
limma	8.20	8.18	7.97	8.40	12.29	15.46	16.27	18.10
limmaR	8.20	8.16	7.90	8.46	12.30	15.59	17.23	19.39
vash.opt	8.20	8.16	7.83	8.10	12.30	14.29	13.07	13.42

(c) RMSE_{prec} in the cases where $\text{df}=50$.

Table S2: Table of average RMSE_{prec} of *limma*, *limmaR* and *vash* in the 8 simulation scenarios A-H.

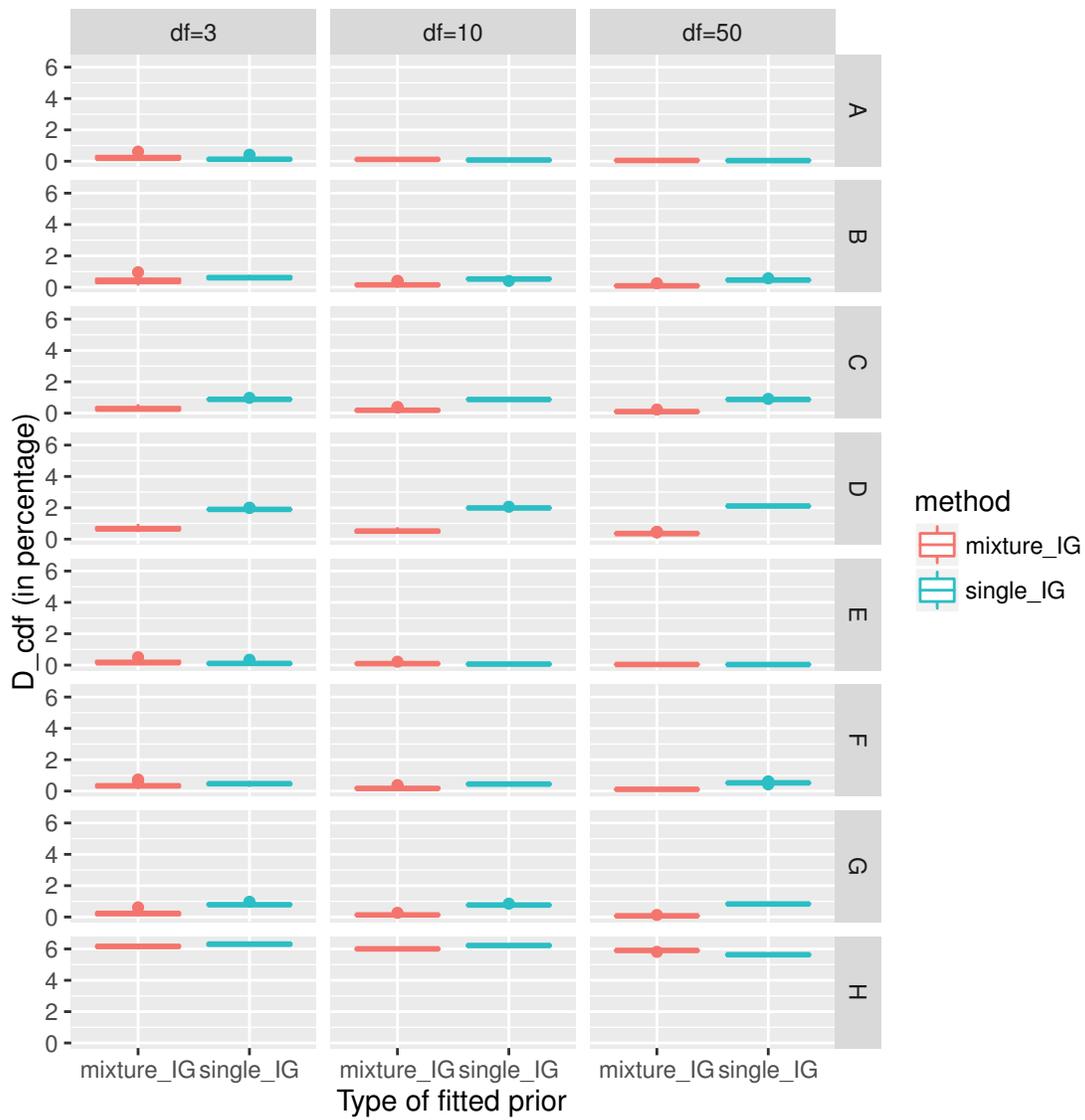


Figure S1: D_{cdf} , the average distance between the cdfs of true variance prior and estimated prior by mixture prior model or single component prior model.

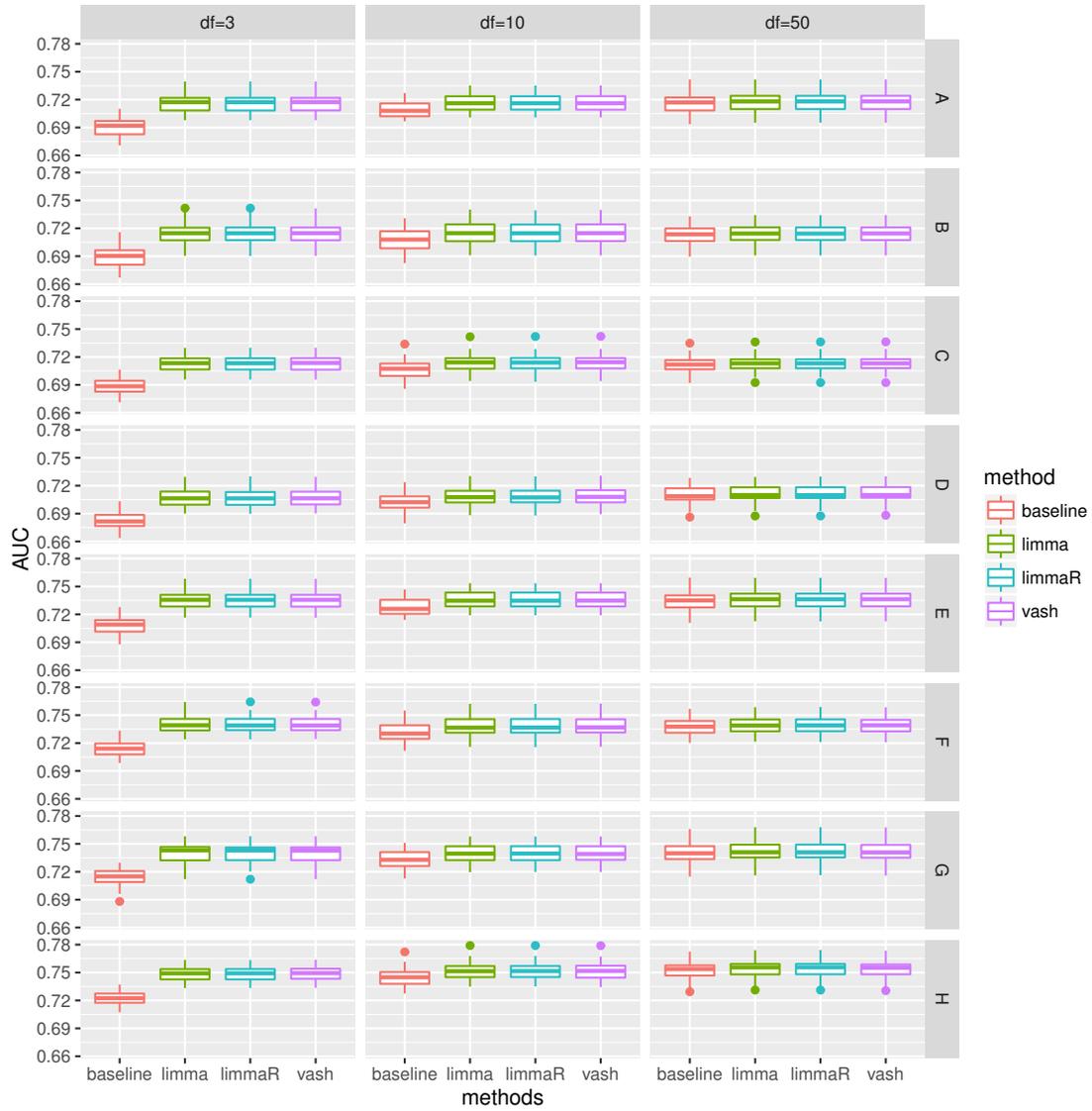


Figure S2: AUC (area under ROC curve) of *limma*, *limmaR* and *vash* and baseline method (original t-test) in the 8 simulation scenarios A-H.