

Better-Than-Chance Classification for Signal Detection— Supplementary

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1. LARGE SAMPLE

We have focused on the *high-dim–small-sample* setup because it is appropriate for many problems in neuroimaging and genetics. To show that our conclusions are not due to the *small-sample*, but rather, to the *high-dim*, we scale our basic setup ten-fold. Fixing p/n , we simulate with $p = 230$ and $n = 400$. The results, reported in Figure 1, are qualitatively similar to the *high-dim–small-sample* in the main text. In particular with respect to the dominance of two-group tests.

2. DEPARTURE FROM SPHERICITY

In the main text we have departed from the sphericity assumption by allowing Σ to be an $AR(1)$ covariance. We now try other covariance structures: a long-memory Brownian motion correlation, and an arbitrary (random) covariance structure. As seen in Figures 2 and 3, the findings in the main text hold also for the “long-memory”, and “arbitrary” correlation structures. In particular: two-group tests dominate accuracy tests, and signal is masked in the low PCs of the noise.

3. DEPARTURE FROM SHIFT ALTERNATIVES

Shift alternatives are the most common signal model in the univariate statistical literature. They are also very common in the multivariate literature, as they are implied by Fisher’s LDA problem setup, and in multivariate analysis of variance (MANOVA). On the other hand, effects may manifest themselves in many ways. We thus verify our statements in models which are not “pure

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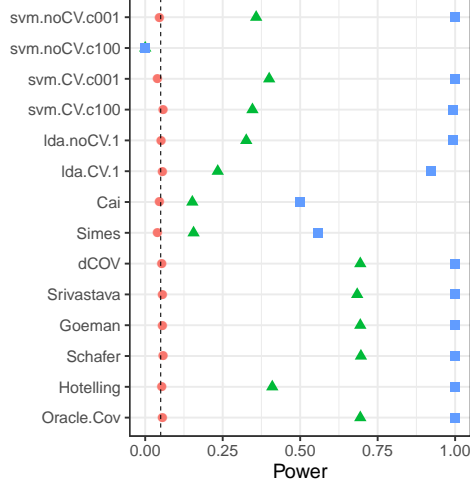


Fig. 1: **Large sample:** The basic simulation setup scaled ten-fold: $n = 400$; $p = 230$.

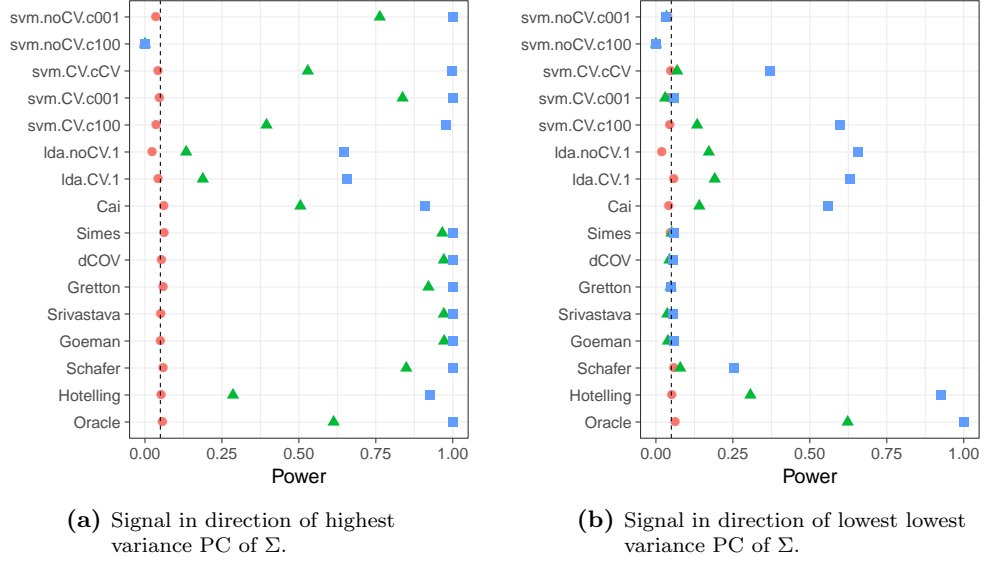


Fig. 2: Long-memory Brownian motion correlation: $\Sigma = D^{-1}RD^{-1}$ where D is diagonal with $D_{jj} = \sqrt{R_{jj}}$, and $R_{k,l} = \min\{k, l\}$.

shifts". These include logistic regression, and a mixture class.

3.1 Logistic Regression

In Figure 4 we report the usual power simulation, when generating from a logistic regression setup with both main effects, and second order interactions. This exact setup is also reported in the main text.

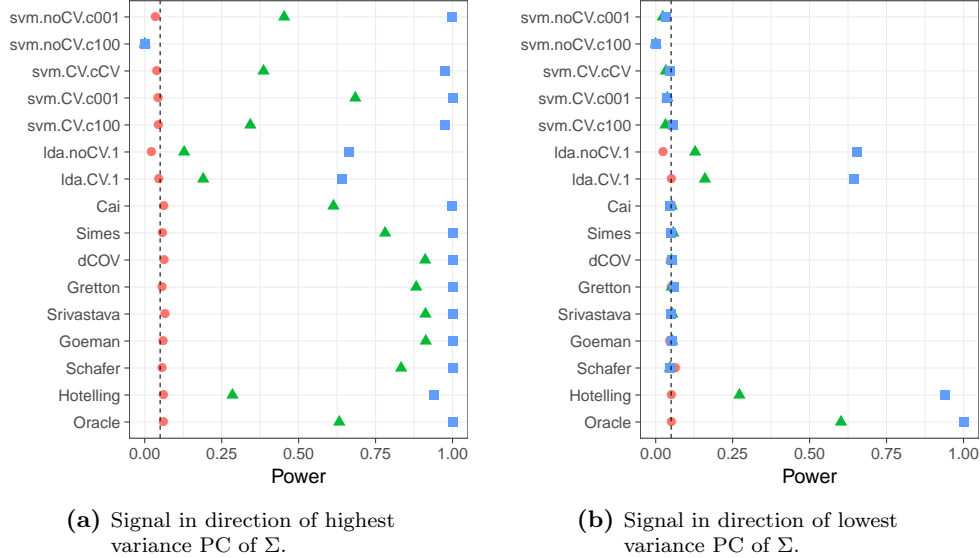


Fig. 3: Arbitrary Correlation. $\Sigma = D^{-1}RD^{-1}$ where D is diagonal with $D_{jj} = \sqrt{R_{jj}}$, and $R = A'A$ where A is a Gaussian $p \times p$ random matrix with independent $\mathcal{N}(0, 1)$ entries.

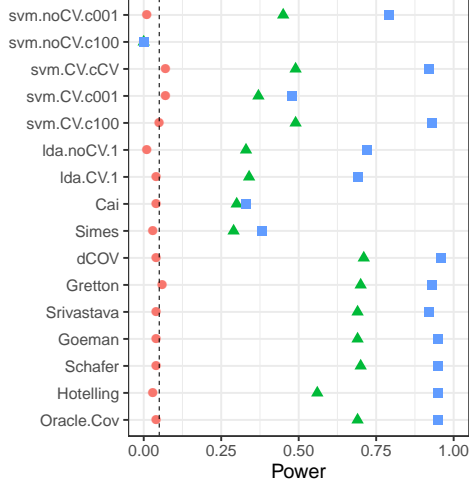
Formally, the logistic assumption implies that $P(y = 1|x) = \exp(\eta)/[1 + \exp(\eta)]$. Main-effects and second order interaction imply that $\eta = x'\beta + x'Bx$, for some p -vector β , and symmetric $p \times p$ matrix B . We also assume $x \sim \mathcal{N}(0, I_{p \times p})$. We perform the various tests in the original space, x , but also in the 276 dimensional space of main effects and second order interactions:

$$\tilde{x} := \Phi(x) = (x_1, \dots, x_j, \dots, x_p, \dots, x_1x_1, \dots, x_jx_{j'}, \dots, x_px_p).$$

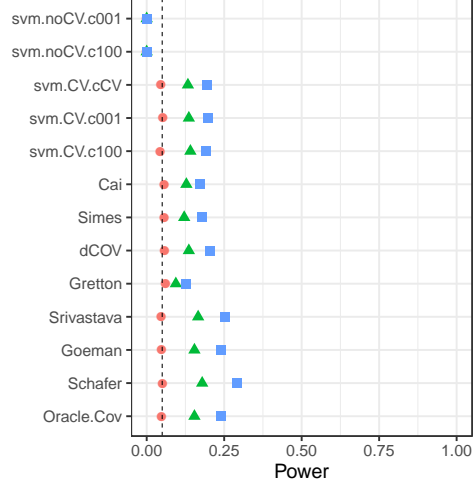
From Figure 4 we learn that two-group tests dominate accuracy tests also in the logistic setup. Was this to be expected, given our conclusions on multivariate shifts? In the logistic setup x_1 is not a shifted version of x_0 , but their means certainly differ. The larger the main effects, the larger the difference in means. This suggests that a main-effect-only model ($B = 0$) will be similar to a shift class, and a second-order-interactions-only model may be very different than a shift class. To isolate these two cases, we simulate a main-effects-only setup (Fig. 5), and an interaction-only setup (Fig. 6).

The main-effect-only case in Figure 5 is not very surprising: the groups differ in their first moment, so that our conclusions are almost identical to the “pure shift” examples in the main text. Analyzing the data in the augmented 276 dimensional space decreases power, since the problems increase in dimension, and many more parameters need to be estimated.

The second-order-interactions-only case in Figure 6 is interesting. From Figure 6a we see that in this setup x_1 is roughly a scaled version of x_0 . In the context of machine-learning, and in particular learning in kernel spaces, this is sometimes known as a *ring problem*. Because B is a scaled matrix of ones, and thus has the same symmetries as x , then x_0 and x_1 have the same first moment. We thus expect that tests for shifts would have poor performance. This is indeed the case: no test has any power. Surprisingly, the two-group GOF tests have no power either. [TODO: file46 for large sample verification. can we offer some intuition?]

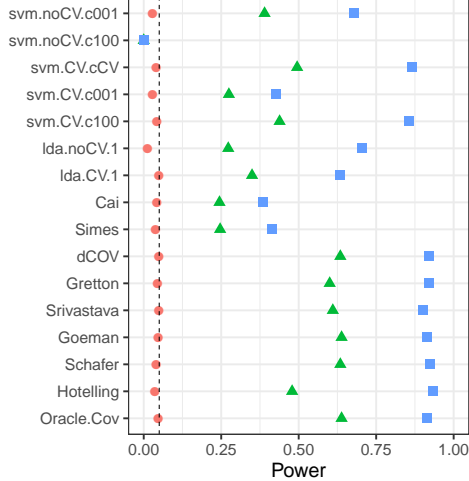


(a) Data analyzed in the original space (x).

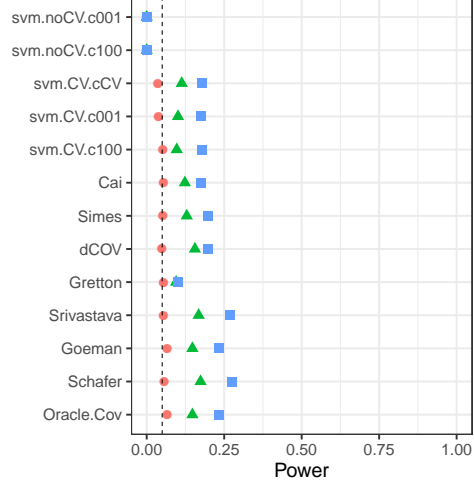


(b) Data analyzed in augmented interactions space (\tilde{x}).

Fig. 4: Logistic regression with second order interactions. Data generated via $y|x \sim \text{Binom}(1, p(x)); p(x) = \exp(\eta)/[1 + \exp(\eta)]; \eta = x'\beta + x'Bx; x \sim \mathcal{N}(0, I_{p \times p})$.



(a) Data analyzed in the original space (x).



(b) Data analyzed in augmented interactions space (\tilde{x}).

Fig. 5: Logistic Regression. Main effects only. Data generated via $y|x \sim \text{Binom}(1, p(x)); p(x) = \exp(\eta)/[1 + \exp(\eta)]; \eta = x'\beta; x \sim \mathcal{N}(0, I_{p \times p})$.

3.2 Mixture Class

Another example where x_1 is not a shifted version of x_0 is a mixture class. Golland and Fischl [2003] and Golland et al. [2005] study accuracy-tests using simulation, neuroimaging data, genetic data, and analytically. The finite Vapnik–Chervonenkis dimension requirement [Golland et al.,

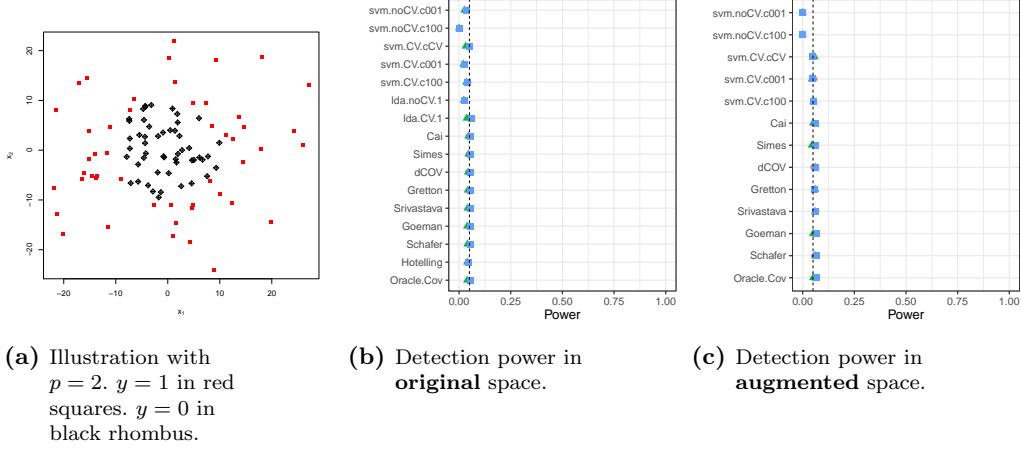


Fig. 6: Logistic regression. Second order interactions only. Data generated via $y|x \sim \text{Binom}(1, p(x)); p(x) = \exp(\eta)/[1 + \exp(\eta)]; \eta = \beta_0 + x'x; x \sim \mathcal{N}(0, \sigma^2 I_{p \times p})$.

2005, Sec 4.3] implies a the problem is low dimensional and prevents the permutation p-value from (asymptotically) concentrating near 1. They find that the power increases with the size of the test set. This is seen in Fig.4 of Golland et al. [2005], where the size of the test-set, K , governs the discretization. We attribute this to the reduced discretization of the accuracy statistic.

When discussing the power of the resubstitution accuracy, Golland et al. [2005] simulate power by sampling from a Gaussian mixture family of models. Under their model (with some abuse of notation)

$$\begin{aligned} x_1 &\sim \pi \mathcal{N}(\mu_1, I) + (1 - \pi) \mathcal{N}(\mu_2, I), \\ x_0 &\sim (1 - \pi) \mathcal{N}(\mu_1, I) + \pi \mathcal{N}(\mu_2, I). \end{aligned}$$

Varying π interpolates between the null distribution ($\pi = 0.5$) and a location shift model ($\pi = 0$). We now perform the same simulation as Golland et al. [2005], but in the same dimensionality of our previous simulations. We re-parameterize so that $\pi = 0$ corresponds to the null model:

$$\begin{aligned} x_1 &\sim (1/2 - \pi) \mathcal{N}(\mu_1, I) + (1/2 + \pi) \mathcal{N}(\mu_2, I), \\ x_0 &\sim (1/2 + \pi) \mathcal{N}(\mu_1, I) + (1/2 - \pi) \mathcal{N}(\mu_2, I). \end{aligned} \tag{3.1}$$

From Figure 7, we see that for the mixture class of Golland et al. [2005] locations tests are still preferred over accuracy-tests.

4. FIXED SNR

For a fair comparison between simulations, in particular between those with different Σ , we needed to fix the difficulty of the problem. We fix the Kullback–Leibler Divergence between distributions of sample means. Formally, the Kullback–Leibler Divergence between two Gaussian populations is given by

$$KL[x_1, x_0] = \frac{1}{2} \left(\log \frac{\det \Sigma_0}{\det \Sigma_1} - p + \text{Tr}(\Sigma_0^{-1} \Sigma_1) + (\mu_0 - \mu_1)' \Sigma_0^{-1} (\mu_0 - \mu_1) \right), \tag{4.2}$$

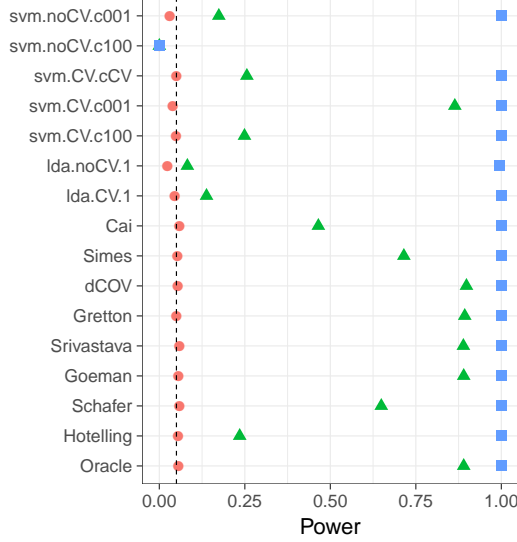


Fig. 7: Mixture Alternatives. \mathbf{x}_i is distributed as in Eq.(3.1). μ is a p -vector with $3/\sqrt{p}$ in all coordinates. The effect, π , is color and shape coded and varies over 0 (red circle), $1/4$ (green triangle) and $1/2$ (blue square).

where $x_y \sim \mathcal{N}(\mu_y, \Sigma_y)$. In the case of the sample means of two shifted groups of size n , then

$$KL[\bar{x}_1, \bar{x}_0] = \frac{n}{2} \mu' \Sigma^{-1} \mu = \frac{n}{2} \|\mu\|_{\Theta}^2, \quad (4.3)$$

where $\mu := \mu_1 - \mu_0$.

In most of our simulations we fixed $n\|\mu\|_{\Theta}^2$. The logistic regression setup is an exception because... [TODO: relate to logistic regression]

Fixing $n\|\mu\|_{\Theta}^2$ implies that the Euclidean norm of μ varies with Σ , with the sample size, and with the direction of the signal. An initial intuition may suggest that detecting signal in the low variance PCs is easier than in the high variance PCs. This is true when fixing $\|\mu\|_2$, but not when fixing $\|\mu\|_{\Theta}$.

For completeness, Figure 8 reports the power analysis under $AR(1)$ correlations, but with $\|\mu\|_2$ fixed. We compare the power of a shift in the direction of some high variance PC (Figure 8a), versus a shift in the direction of a low variance PC (Figure 8b). The intuition that it is easier to detect signal in the low variance directions is confirmed.

Other authors have also observed the need for fixing the SNR for a fair comparison between tests. In Ramdas et al. [2015], authors prefer to use sparse alternatives. With sparse alternatives, the difficulty of the problem is governed by the sparsity of the signal and not only the dimension of the data. In Chen et al. [2010], authors fix $\|\mu\|_2^2 / \|\Sigma\|_{Frob}^2$ where $\|\Sigma\|_{Frob}^2 = \text{Tr}(\Sigma' \Sigma)$ is the Frobenius matrix norm. Clearly, $\|\mu\|_2^2 / \|\Sigma\|_{Frob}^2$ is invariant to the direction of the signal with respect to the noise. For this reason, we prefer fixing $\|\mu\|_{\Theta}$.

5. SPARSE ALTERNATIVES

In our set of simulations we discussed “dense” alternatives. Dense alternatives are motivated by neuroimaging where most brain locations in a region carry signal. In a genetic application, a

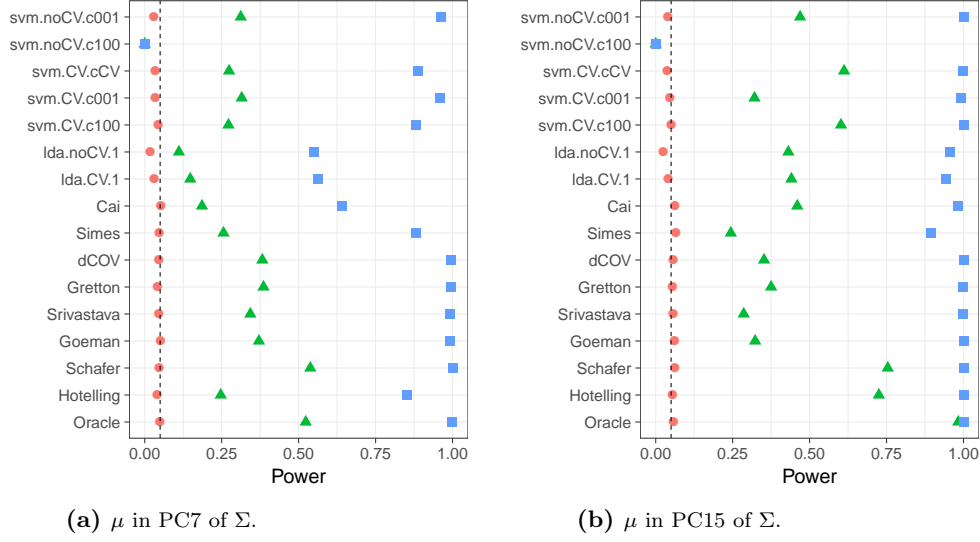


Fig. 8: Short memory, AR(1) correlation. $\|\mu\|_2$ fixed.

sparse alternative may be more plausible. Figure 9 reports power when μ is sparse. As usual, two-group tests dominate accuracy-tests, only this time, the winners are not the T^2 type statistics, but rather, the tests for sparse shifts (*Cai*, *Simes*).

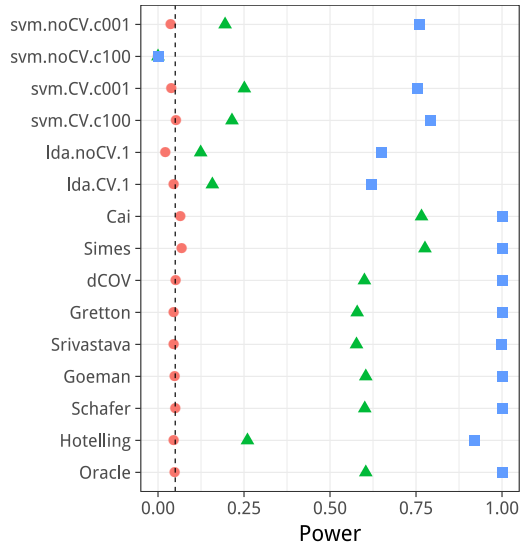


Fig. 9: Sparse μ .

6. DEPARTURE FROM HOMOSKEDASTICITY AND SCALAR INVARIANCE

Our previous simulations assume variables have unit variance (diagonal Σ). Practitioners are already accustomed to z-score features before learning a regularized predictor (e.g. ridge regression) so this is not an unrealistic setup. Implicit z-scoring is sometime an integral part of a test statistic. This is known as *scalar invariance*. The *Srivastava* statistic, for instance, is scalar invariant. It can be (roughly) thought of as the l_2 norm of the p -vector of coordinate-wise t-statistics. The *Goeman* statistic, for instance, is not scalar invariant. It can be (roughly) thought of as the l_2 norm of the p -vector of variable-wise mean differences. Under heteroskedasticity, the *Goeman* statistic will give less importance to signal in the high-variance directions than signal in the low-variance directions. *Srivastava* will give all coordinates the same importance.

In Figure 10a we can see the difference between the scalar-invariant *Srivastava* and *Goeman* statistics. We also see that two-group tests dominate accuracy-tests also in the heteroskedastic case.

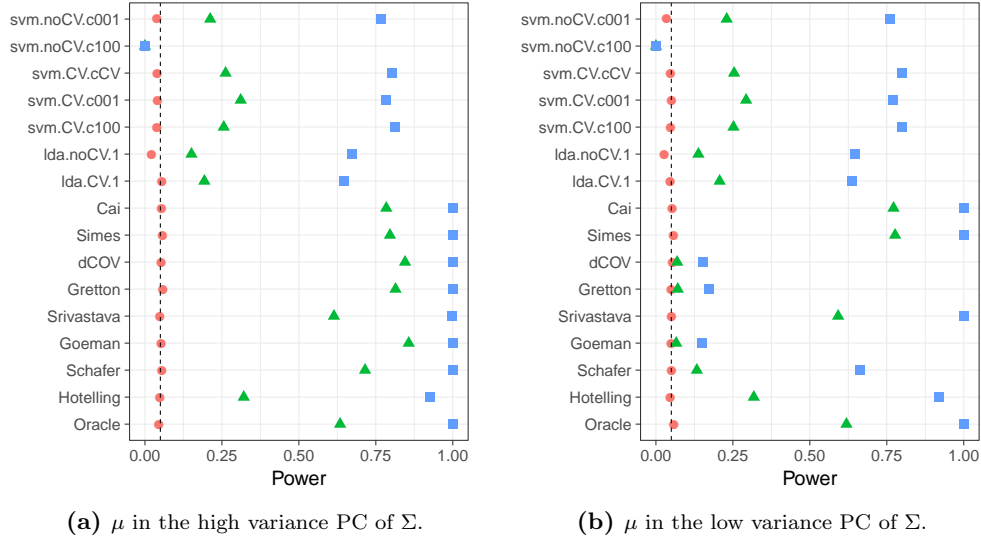


Fig. 10: Heteroskedasticity: Σ is diagonal with $\Sigma_{jj} = j$.

7. TIE BREAKING

Discrete test statistics lose power by not exhausting the permissible false positive rate. A common remedy is a *randomized test*, in which the rejection of the null is decided at random in a manner that exhausts the false positive rate. Formally, denoting by \mathcal{T} the observed test statistic, by \mathcal{T}_π , its value after under permutation π , and by $\mathbb{P}\{A\}$ the proportion of permutations satisfying A then the randomized version of our tests imply that if the permutation p-value, $\mathbb{P}\{\mathcal{T}_\pi \geq \mathcal{T}\}$, is greater than α then we reject the null with probability

$$\max \left\{ \frac{\alpha - \mathbb{P}\{\mathcal{T}_\pi > \mathcal{T}\}}{\mathbb{P}\{\mathcal{T}_\pi = \mathcal{T}\}}, 0 \right\}.$$

Figure 11 reports the basic simulation setup while allowing for random tie breaking. It demonstrates that the power disadvantage of accuracy-tests cannot be remedied by random tie breaking.

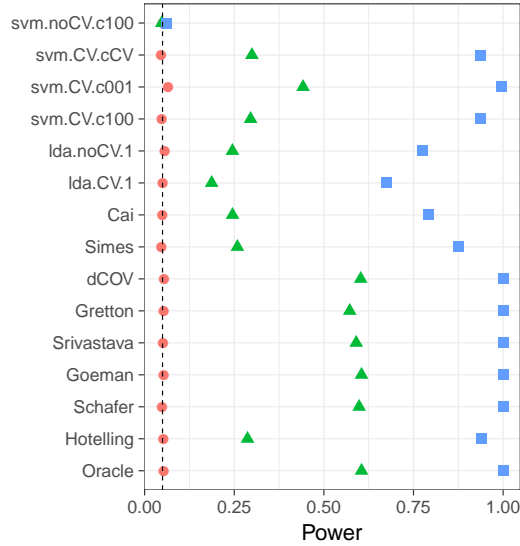


Fig. 11: **Tie breaking:** The basic simulation setup with random tie breaking.

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