Ste Stein: perform best when eigenvalues are approximately equal or forms clusters that are theed nearly equal inside. Generally outperform original minimax. E.B. & original S.

JS & : have several variants. I based on correlation motor) too tedious to look into.

(Improved minimax. [Dipak 1985)

Use same old setting.
minimizing Risk obtained with Stein's Loss.

invarance: orthogonal matrix.

$$|| \mathcal{D}| \text{Recall} : \text{Original minimax estimator.}$$

$$| S = KK^T \implies \varphi(S) = K\Delta K^T \quad \Delta_{V} = \frac{1}{n+p-2V+1} \qquad \text{R} \left(\hat{\Sigma}_{JS}(S), \hat{\Sigma} \right).$$

$$|| \hat{\Sigma}_{JS}(S) || \text{Oliveady minimax}$$

Claim $\hat{\Sigma}^m$ to be minimax by saying $R(\hat{\Sigma}^m, \Sigma) \leqslant R(\hat{\Sigma}_{1S}, \Sigma)$. Why: estimator that's invariant under orthogonal transformation is a special case of estimator invariant under lower triongular.

$$\sup_{\Sigma} R(\hat{\Sigma}_{Js}, \Sigma) = \inf_{\hat{\Sigma} = K\Delta^{k}K^{T}} \sup_{\Sigma} R(\hat{\Sigma}, \Sigma)$$

then must equal

otherwise $S^m = \mathbb{R} B(\mathcal{V}^m(L)B)$ is another class of estimator, con't make conclusion.

$$\frac{\triangle m}{\sum} = S = B L B^{T} = K K^{T}$$

$$= (B L^{\frac{1}{2}}) (B L^{\frac{1}{2}})^{T} \implies K = B L^{\frac{1}{2}} \implies \sum_{m=1}^{\infty} B \varphi^{m}(L) B^{T}$$

$$= K L^{-\frac{1}{2}} \varphi^{m}(L) Q L^{\frac{1}{2}} K^{T}.$$

$$= K L^{-\frac{1}{2}} \varphi^{m}(L) Q L^{\frac{1}{2}} K^{T}.$$
Some worst cose section

Same worst case serscenario but risk domintes JS. original minimow.

other improvement: Very tedious to look into

T (4) fraction 5.t.) 0 < T(4) < 12/22)/5(k+)-1

Note: still need isotonizing procedur

The non-decrease in I Ell'(1)] < a