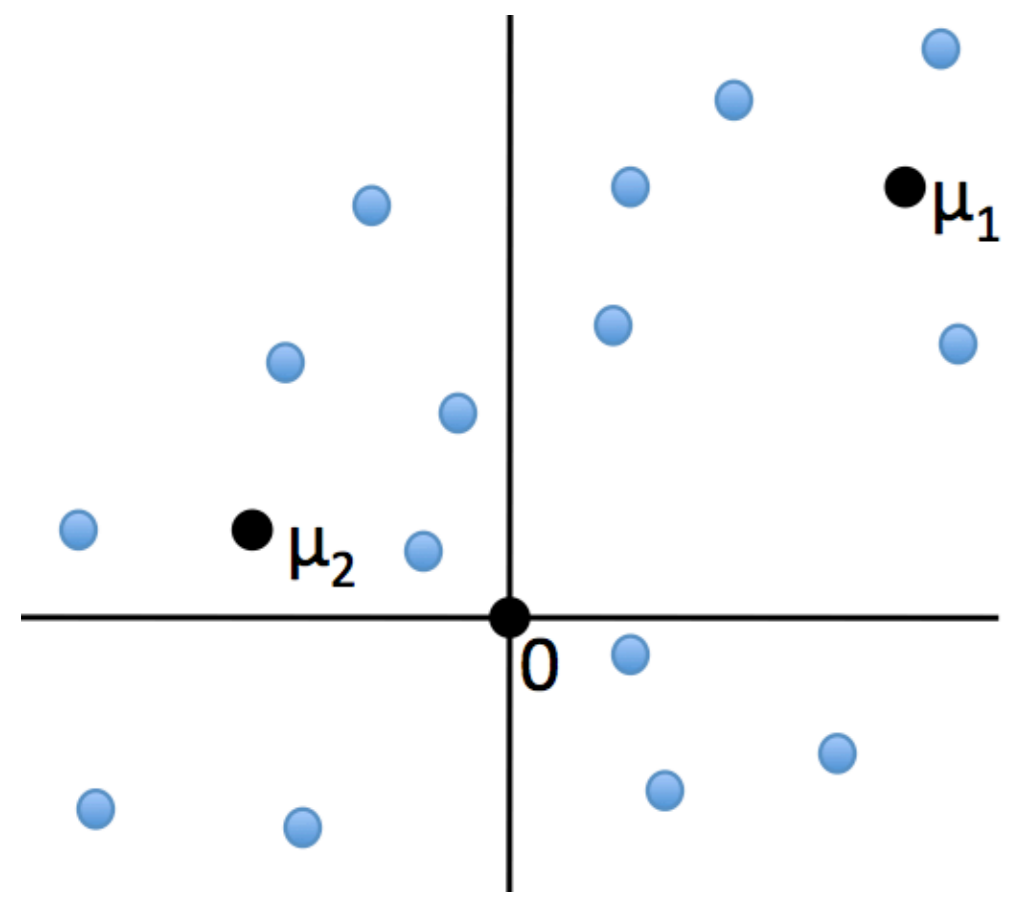


1. Tukey's halfspace depth and Mizera's tangent depth.



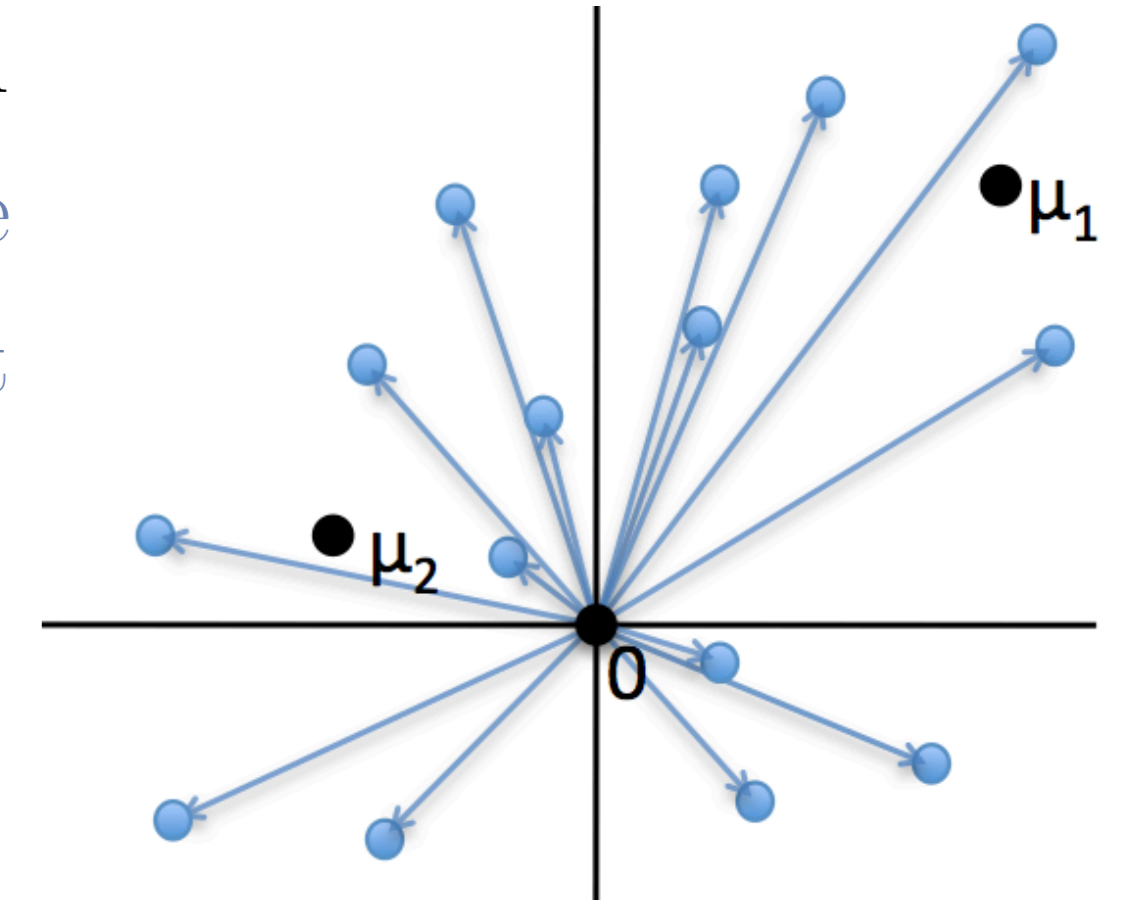
In the multivariate location setup, Tukey (1975) introduced the notion of **halfspace median** as $\operatorname{argmax}_{\mu \in \mathbb{R}^p} HD(\mu; F_{\mathbf{X}})$, the vector with maximum **halfspace depth**. Here,

$$HD(\mu; F_{\mathbf{X}}) = \inf_{\mathbf{u} \in S^{p-1}} \mathbb{P}_{F_{\mathbf{X}}} \{ \mathbf{u}'(\mathbf{X} - \mu) \geq 0 \}.$$

In the empirical setup, the halfspace depth of μ can be seen as the smallest number of observations one may remove before μ lies outside the convex hull of the remaining data.

Mizera (2002) generalized the concept of depth to any parametric model. Given a C^1 objective function $F : \Theta \times \mathcal{X} \rightarrow \mathbb{R}$, he defined the **tangent depth** of $\tilde{\theta} \in \Theta$ as

$$TD(\tilde{\theta}, F_{\mathbf{X}}) = HD(0_p; \nabla_{\theta} F(\tilde{\theta}, \mathbf{X})).$$



With respect to the construction of the maximum likelihood estimator, he suggested $F(\theta, \mathbf{X}) = \log f_{\theta}(\mathbf{X})$ as a candidate for the objective function.

2. The shape parameter.

In many classic multivariate problems, it is sufficient to know a *normalized* version of the dispersion/scatter matrix in order to perform the analysis (PCA, CCA, test of sphericity, etc.)

Definition

A scale functional is a (i) 1-homogeneous function $S : \mathcal{S}_p \rightarrow \mathbb{R}_0^+$ (i.e. $S(\lambda \Sigma) = \lambda S(\Sigma)$) such that (ii) S is differentiable, with $\frac{\partial S}{\partial \Sigma_{11}}(\Sigma) \neq 0$ for all $\Sigma \in \mathcal{S}_p$ and (iii) satisfies $S(\mathbf{I}_p) = 1$.

The **scale parameter** associated with Σ is $\sigma_S^2 = S(\Sigma)$. The **shape parameter** is $\mathbf{V}_S = \Sigma / S(\Sigma)$. Denote $\mathcal{V}_p^S = \{\mathbf{V} \in \mathcal{S}_p \mid S(\mathbf{V}) = 1\}$. Classical choices of scale functionals are $S_O(\Sigma) = \Sigma_{11}$, $S_T(\Sigma) = \operatorname{tr}(\Sigma)/p$ and $S_D(\Sigma) = |\Sigma|^{1/p}$. We are interested in the *shape parameter* of p -variate elliptical distributions, with general density

$$\mathbf{x} \mapsto \frac{c_{p,g_1}}{|\Sigma|^{1/2}} g_1(d(\mathbf{x}, \theta; \Sigma)) = \frac{\tilde{c}_{p,g}}{|\mathbf{V}_S|^{1/2}} g(d(\mathbf{x}, \theta; \mathbf{V}_S)) = f_{\theta, \mathbf{V}_S, g}(\mathbf{x}),$$

where $d(\mathbf{x}, \theta; \Sigma) = ((\mathbf{x} - \theta)' \Sigma^{-1} (\mathbf{x} - \theta))^{1/2}$, $\Sigma \in \mathcal{S}_p$.

3. Shape depth.

Hallin and Paindaveine (2006) showed that the score is given by

$$\nabla_{\mathbf{V}} F(\mathbf{V}, \mathbf{X}) \propto \mathbf{M}_S^{\mathbf{V}} (\mathbf{V}^{\otimes 2})^{-1/2} \operatorname{vec} \left(\varphi_{g_1} \left(\frac{d}{\sigma_S} \right) \frac{d}{\sigma_S} \mathbf{U} \mathbf{U}' - \mathbf{I}_p \right),$$

with $d = d(\mathbf{X}, \theta; \mathbf{V})$, $\mathbf{U} = \mathbf{V}^{-1/2}(\mathbf{X} - \theta)/d$ and $\varphi_g = -g'/g$. $\mathbf{M}_S^{\mathbf{V}}$ is the $(p(p+1)/2 - 1) \times p$ matrix such that $(\mathbf{M}_S^{\mathbf{V}})'(\operatorname{vech}(\mathbf{v})) = \operatorname{vec}(\mathbf{v})$ for all matrix $\mathbf{v} \in \mathcal{S}_p$ such that $(\nabla S(\operatorname{vech}(\mathbf{V})))'(\operatorname{vech}(\mathbf{v})) = 0$. The unspecification of scale σ_S^2 leads to rather consider the **efficient scores** (obtained from projections along tangent spaces)

$$\nabla_{\mathbf{V}}^* F(\mathbf{V}, \mathbf{X}) \propto \mathbf{M}_S^{\mathbf{V}} (\mathbf{V}^{\otimes 2})^{-1/2} \varphi_{g_1} \left(\frac{d}{\sigma_S} \right) \frac{d}{\sigma_S} \operatorname{vec} \left(\mathbf{U} \mathbf{U}' - \frac{1}{p} \mathbf{I}_p \right).$$

Definition

Let S be a scale functional, and $\mathbf{V} \in \mathcal{V}_p^S$. Define the vector $\mathbf{W} = \mathbf{M}_S^{\mathbf{V}} (\mathbf{V}^{\otimes 2})^{-1/2} \operatorname{vec} \left(\mathbf{U} \mathbf{U}' - \frac{1}{p} \mathbf{I}_p \right)$. Then the **shape depth** of \mathbf{V} is

$$ShD(\mathbf{V}, S, F_{\mathbf{X}}) = HD(\mathbf{0}_p, \mathbf{W}).$$

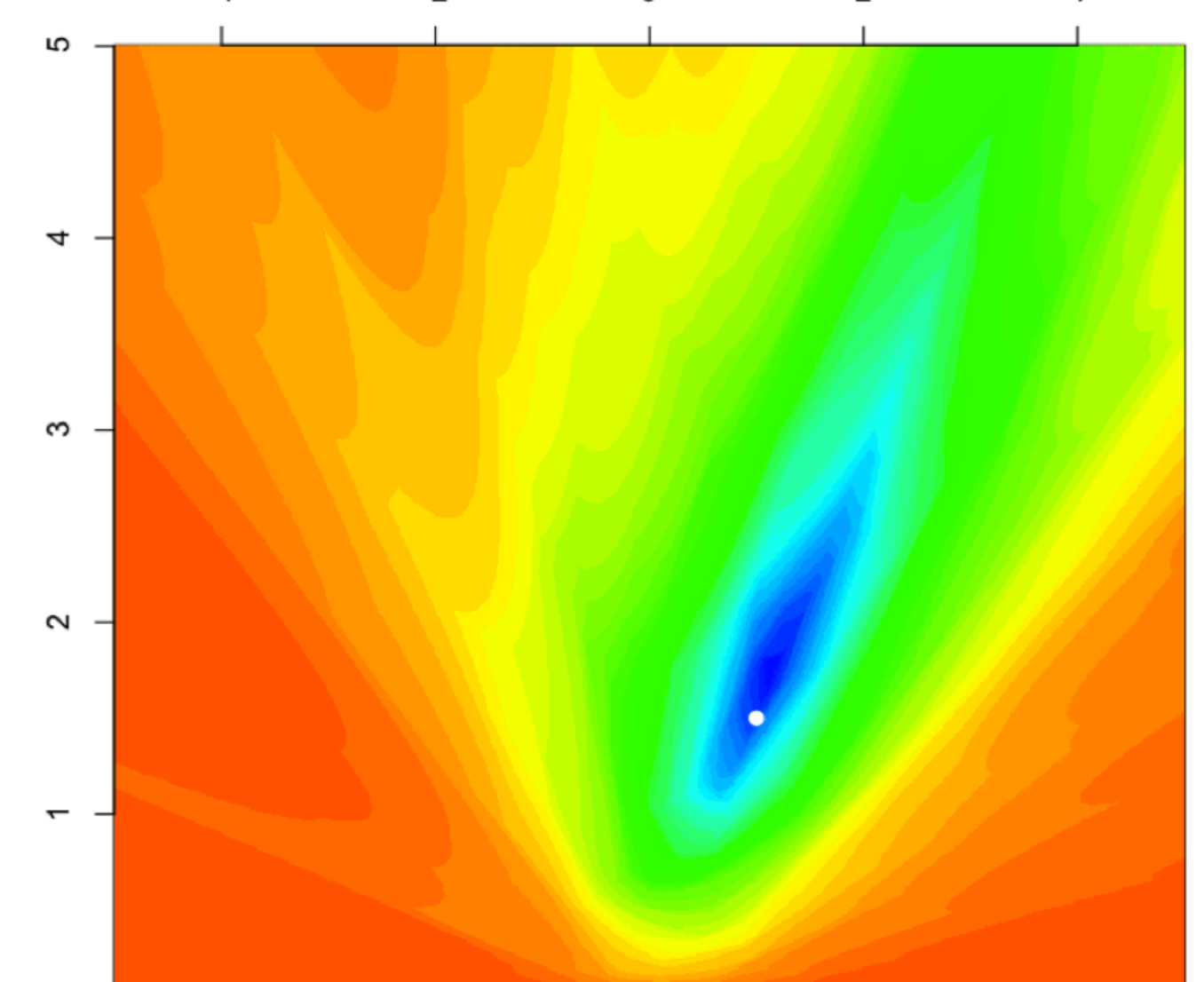
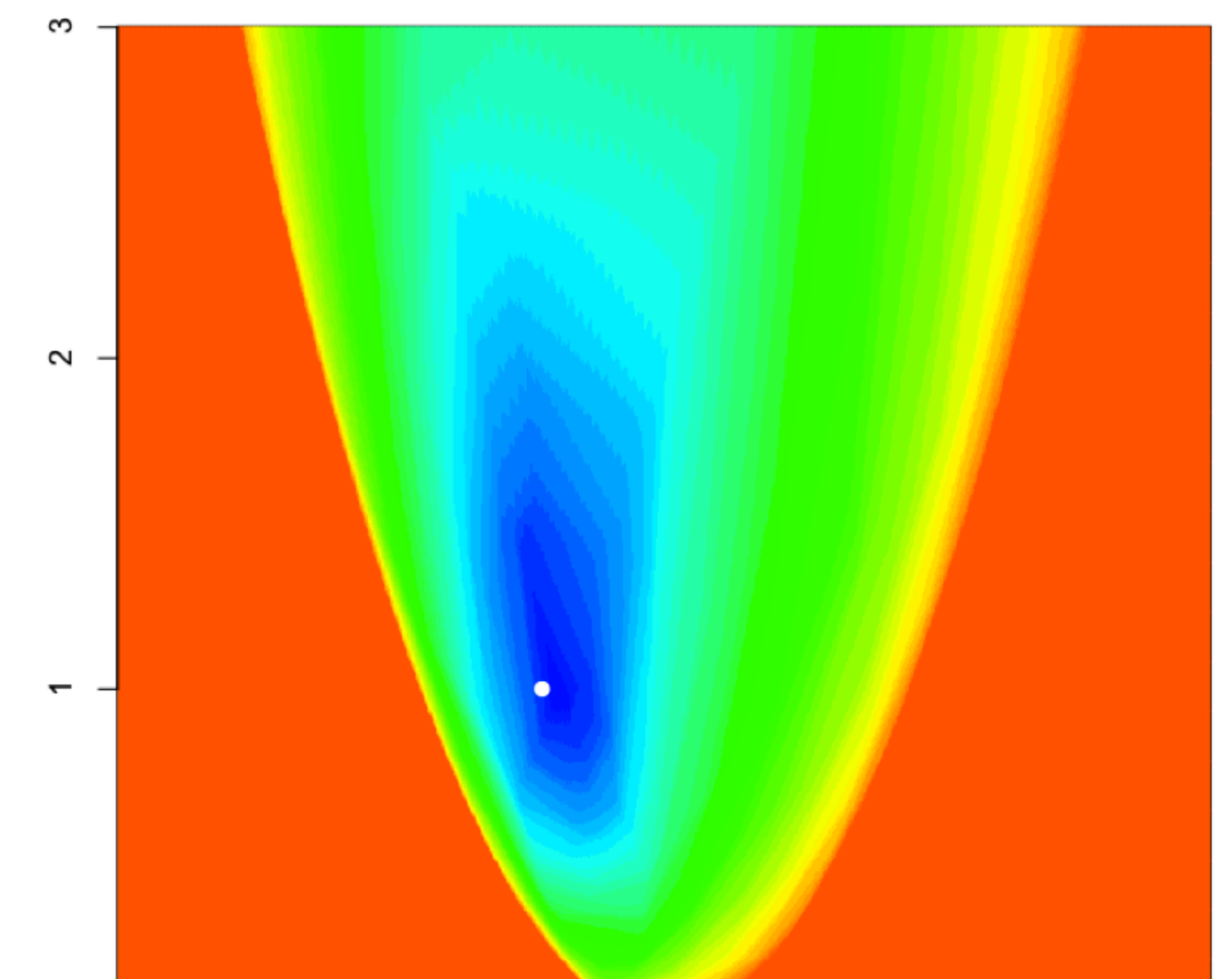
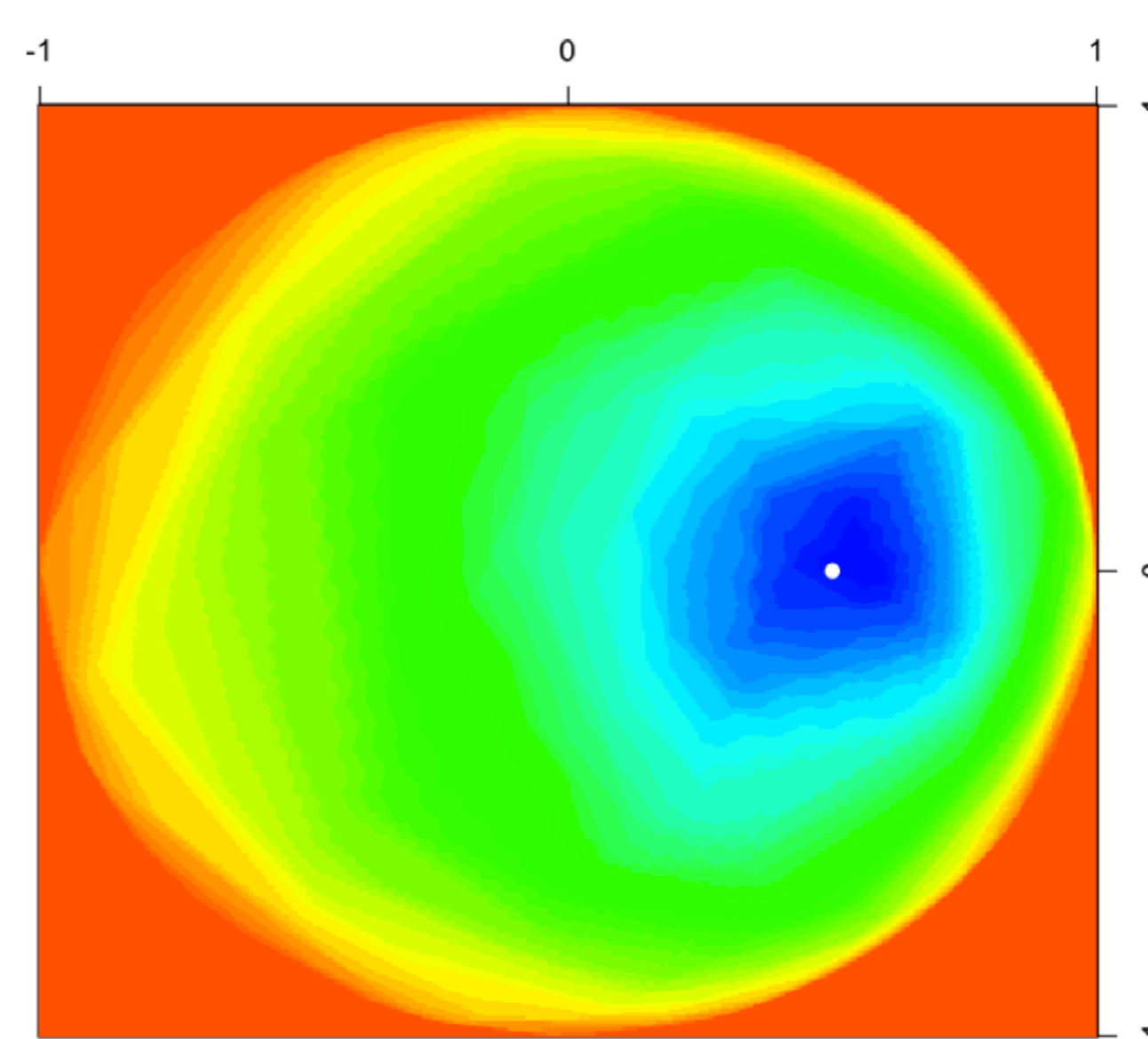
Dimension 2 allows for representations since

$$-\mathcal{V}_2^{S_O} \cong \{(x, y) \in \mathbb{R}^2 \mid y > x^2\},$$

$$-\mathcal{V}_2^{S_T} \cong \{(x, y) \in \mathbb{R}^2 \mid x^2 + y^2 < 1\}$$

and

$$-\mathcal{V}_2^{S_D} \cong \{(x, y) \in \mathbb{R}^2 \mid y > 0\}.$$



4. Some results.

Theorem 1

For any $\Sigma \in \mathcal{S}_p$ and any scale functionals S_1 and S_2 ,

$$ShD\left(\frac{\Sigma}{S_1(\Sigma)}, S_1, F_{\mathbf{X}}\right) = ShD\left(\frac{\Sigma}{S_2(\Sigma)}, S_2, F_{\mathbf{X}}\right).$$

Theorem 2

Let S be a scale functional, \mathbf{A} a non-singular $p \times p$ matrix and $\mathbf{V} \in \mathcal{V}_p^S$. Then, for all distributions $F_{\mathbf{X}}$,

$$ShD(\mathbf{V}, S, F_{\mathbf{X}}) = ShD\left(\frac{\mathbf{A} \mathbf{V} \mathbf{A}'}{S(\mathbf{A} \mathbf{V} \mathbf{A}')}, S, F_{\mathbf{A} \mathbf{X}}\right).$$

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- (1) Hallin, M. and Paindaveine, D. (2006). Semiparametrically efficient rank-based inference for shape I: Optimal rank-based tests for sphericity. *Annals of Statistics*, Vol. 34, pp. 2707-2756.
- (2) Mizera, I. (2002). On depth and deep points: a calculus. *Annals of Statistics*, Vol. 30, No. 6, pp. 1681-1736.
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