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Score tests and **data-driven tests** in directional statistics

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Outline

1. directional statistics
2. testing uniformity
3. hypotheses
4. score tests T_k
5. simpler statistics S_k
6. data-driven versions

1. Directional statistics

Sample space

circle, sphere: S^1, S^{p-1}

projective space: $\mathbb{R}P^{p-1}$

rotation group: $SO(p)$

Stiefel manifold: (frames)

Grassmann manifold: (subspaces)

compact Riemannian manifold M

1. Directional statistics

Sample space

circle, sphere: S^1, S^{p-1}

projective space: $\mathbb{R}P^{p-1}$

rotation group: $SO(p)$

Stiefel manifold: (frames)

Grassmann manifold: (subspaces)

compact Riemannian manifold M

(or a quotient — shape spaces)

Embedding approach

$$t : M \rightarrow L^2(M)$$

vector space

Embedding approach

$$\mathbf{t}_k : M \rightarrow E_k \subset L^2(M)$$

E_k are finite-dimensional, orthogonal

E_k is k th eigenspace of Laplacian $k = 1, 2, \dots$

For S^1 ,

$$E_k = \text{span} \{ \cos(k\theta), \sin(k\theta) \}$$

$$\mathbf{t}_k(x) = \cos(k(\theta - x))$$

2. Testing uniformity

Given a_1, a_2, \dots ,

$$\mathbf{t}(x) = \sum_{k=1}^{\infty} a_k \mathbf{t}_k(x) \quad \in L^2(M)$$

Summarise sample x_1, \dots, x_n by

$$\bar{\mathbf{t}} = \frac{1}{n} \sum_{i=1}^n \mathbf{t}(x_i) \quad \in L^2(M)$$

Reject uniformity if $\|\bar{\mathbf{t}}\|^2$ large.

E.g. S^1

$$\bar{R}_k = \left\| \frac{1}{n} \sum_{i=1}^n (\cos kx_i, \sin kx_i) \right\|$$

Reject uniformity if

$$\sum_{k=1}^{\infty} a_k^2 \bar{R}_k^2 \quad \text{large}$$

generalised Rayleigh test

Problem

How to choose a_1, a_2, \dots ?

few $a_k \neq 0 \Rightarrow$ (often) simple to calculate

all $a_k \neq 0 \Rightarrow$ consistent against all alternatives

Embarrassment of choice!

Score tests of uniformity

$$(a_1, a_2, \dots) = (\underbrace{1, 1, \dots, 1}_k, 0, 0, \dots)$$

$$\mathbf{t}_{(k)}(x) = (\mathbf{t}_1(x), \dots, \mathbf{t}_k(x)) \in \bigoplus_{j=1}^k E_j \subset L^2(M)$$

$$\bar{\mathbf{t}}_{(k)} = \frac{1}{n} \sum_{i=1}^n \mathbf{t}_{(k)}(x_i)$$

$$T_k = n \|\bar{\mathbf{t}}_{(k)}\|^2$$

Reject uniformity if

$$T_k \quad \text{large}$$

Select k by BIC

\hat{k} is value of k maximising

$$T_k - \nu_k c(n)$$

$$\nu_k = \sum_{j=1}^k \dim E_j \quad c \text{ increasing, e.g. } c(n) = \log n$$

Reject uniformity for $T_{\hat{k}}$ large

‘Penalised score test’ —

penalises higher-dimensional models

Nice properties

$$P(\hat{k} = \infty) = 0$$

Under uniformity, as $n \rightarrow \infty$,

$$\begin{aligned}\hat{k} &\rightarrow 1 \\ T_{\hat{k}} &\overset{\cdot}{\sim} \chi_{\nu_1}^2\end{aligned}$$

Consistent against **all** alternatives

3. Hypotheses

uniformity

q populations equal

symmetry

group G acts on M

e.g. $M = S^2$, $G = SO(2)$, rotation about axis

independence

X on M , Y on N

goodness of fit

$f(\cdot; \theta)$

4. Score tests T_k

H_0	T_k
uniformity	$n \ \bar{\mathbf{t}}_{(k)}\ ^2$
symmetry	$n \bar{\mathbf{t}}_{(k)-}^T \mathbf{S}_{(k)-}^{-1} \bar{\mathbf{t}}_{(k)-}$
q populations	$\frac{n - q}{q - 1} \text{tr} (\mathbf{B}_{(k)} \mathbf{W}_{(k)}^{-1})$
independence	$n r_{(k)}^2$
goodness of fit	$n \bar{\mathbf{t}}_{(k)w}^T \mathbf{S}_{(k)w}^{-1} \bar{\mathbf{t}}_{(k)w}$

symmetry

Group G acts on M , and so on each E_k

$$E_{k+} = \{f \in E_k : f(gx) = f(x), g \in G\}$$

$$E_{k-} = \left\{ f \in E_k : \int_G f(gx) dg = 0 \right\}$$

$$E_k = E_{k+} \oplus E_{k-}$$

$$\mathbf{t}_{(k)} = (\mathbf{t}_{(k)+}, \mathbf{t}_{(k)-})$$

$$\bar{\mathbf{t}}_{(k)-} = \frac{1}{n} \sum_{i=1}^n \mathbf{t}_{(k)-}(x_i)$$

score tests T_k

H_0

T_k

uniformity

$$n \|\bar{\mathbf{t}}_{(k)}\|^2$$

symmetry

$$n \bar{\mathbf{t}}_{(k)-}^T \mathbf{S}_{(k)-}^{-1} \bar{\mathbf{t}}_{(k)-}$$

q populations

$$\frac{n - q}{q - 1} \text{tr} (\mathbf{B}_{(k)} \mathbf{W}_{(k)}^{-1})$$

independence

$$nr_{(k)}^2$$

goodness of fit

$$n \bar{\mathbf{t}}_{(k)w}^T \mathbf{S}_{(k)w}^{-1} \bar{\mathbf{t}}_{(k)w}$$

q populations

$$(x_{11}, \dots, x_{1n_1}), \dots, (x_{q1}, \dots, x_{qn_q})$$

$$\mathbf{B}_{(k)} = \sum_{i=1}^q \sum_{j=1}^{n_i} (\mathbf{t}_{(k)}(x_{ij}) - \bar{\mathbf{t}}_{(k)i.}) (\mathbf{t}_{(k)}(x_{ij}) - \bar{\mathbf{t}}_{(k)i.})^T$$

$$\mathbf{W}_{(k)} = \sum_{i=1}^q n_i (\bar{\mathbf{t}}_{(k)i.} - \bar{\mathbf{t}}_{(k)..}) (\bar{\mathbf{t}}_{(k)i.} - \bar{\mathbf{t}}_{(k)..})^T$$

score tests T_k

H_0

T_k

uniformity

$$n \|\bar{\mathbf{t}}_{(k)}\|^2$$

symmetry

$$n \bar{\mathbf{t}}_{(k)-}^T \mathbf{S}_{(k)-}^{-1} \bar{\mathbf{t}}_{(k)-}$$

q populations

$$\frac{n - q}{q - 1} \text{tr} (\mathbf{B}_{(k)} \mathbf{W}_{(k)}^{-1})$$

independence

$$nr_{(k)}^2$$

goodness of fit

$$n \bar{\mathbf{t}}_{(k)w}^T \mathbf{S}_{(k)w}^{-1} \bar{\mathbf{t}}_{(k)w}$$

independence

$$\mathbf{t}_{(k)} : M \rightarrow L^2(M)$$

$$\mathbf{u}_{(k)} : N \rightarrow L^2(N)$$

$$\text{var} \begin{pmatrix} \mathbf{t}_{(k)}(x) \\ \mathbf{u}_{(k)}(y) \end{pmatrix} = \begin{pmatrix} \mathbf{S}_{(k)11} & \mathbf{S}_{(k)12} \\ \mathbf{S}_{(k)21} & \mathbf{S}_{(k)22} \end{pmatrix}$$

$$r_{(k)}^2 = \text{tr} \left(\mathbf{S}_{(k)11}^{-1} \mathbf{S}_{(k)12} \mathbf{S}_{(k)22}^{-1} \mathbf{S}_{(k)21} \right)$$

score tests T_k

H_0

T_k

uniformity

$$n \|\bar{\mathbf{t}}_{(k)}\|^2$$

symmetry

$$n \bar{\mathbf{t}}_{(k)-}^T \mathbf{S}_{(k)-}^{-1} \bar{\mathbf{t}}_{(k)-}$$

q populations

$$\frac{n - q}{q - 1} \text{tr} (\mathbf{B}_{(k)} \mathbf{W}_{(k)}^{-1})$$

independence

$$nr_{(k)}^2$$

goodness of fit

$$n \bar{\mathbf{t}}_{(k)w}^T \mathbf{S}_{(k)w}^{-1} \bar{\mathbf{t}}_{(k)w}$$

goodness of fit

$$\mathbf{t}_{(k)w}(x) = \frac{1}{f(x; \hat{\theta})} \mathbf{t}_{(k)}(x)$$

$$\bar{\mathbf{t}}_{(k)w} = \frac{1}{n} \sum_{i=1}^n \mathbf{t}_{(k)w}(x_i)$$

Aside: cubic corrections

Under H_0 ,

$$T_k \overset{\cdot}{\sim} \chi_{\nu_k}^2 \quad \text{error } O(n^{-1})$$

$$T_k^* = \left\{ 1 + \frac{1}{n} [c_0 + c_1 T_k + c_2 T_k^2] \right\} T_k$$

Under H_0 ,

$$T_k^* \overset{\cdot}{\sim} \chi_{\nu_k}^2 \quad \text{error } O(n^{-2})$$

5. Simpler statistics S_k

H_0

S_k

uniformity

$$n \|\bar{\mathbf{t}}_{(k)}\|^2$$

symmetry

$$n \|\bar{\mathbf{t}}_{(k)-}\|^2$$

q populations

$$\text{tr}(\mathbf{B}_{(k)})$$

independence

$$\text{tr}(\mathbf{S}_{12(k)}\mathbf{S}_{21(k)})$$

goodness of fit

$$\|\bar{\mathbf{t}}_{(k)w}\|^2$$

6. Data-driven versions

Select k by BIC

\hat{k} is value of k maximising $T_k - \nu_k c(n)$

or

\hat{k} is value of k maximising $S_k - \hat{\nu}_k c(n)$

Data-driven versions of T_k

$$1 \leq k \leq K$$

\hat{k} is value of k maximising $T_k - \nu_k c(n)$

H_0	T_k	ν_k
symmetry	$n \bar{\mathbf{t}}_{(k)-}^T \mathbf{S}_{(k)-}^{-1} \bar{\mathbf{t}}_{(k)-}$	ν_{k-}
q pop'ns	$\frac{n-q}{q-1} \text{tr} (\mathbf{B}_{(k)} \mathbf{W}_{(k)}^{-1})$	$(q-1)\nu_k$
indep'ce	$nr_{(k)}^2$	$\sum_{r+s=k} \nu_{M,r} \nu_{N,s}$
g.o.f.	$n \bar{\mathbf{t}}_{(k)w}^T \mathbf{S}_{(k)w}^{-1} \bar{\mathbf{t}}_{(k)w}$	ν_k

Nice properties of $T_{\hat{k}}$

Under H_0 , as $n \rightarrow \infty$,

$$\begin{aligned}\hat{k} &\rightarrow 1 \\ T_{\hat{k}} &\overset{\cdot}{\simeq} \chi_{\nu_1}^2\end{aligned}$$

Consistent against alternatives with

$$E [\mathbf{t}_{(K)}(x)] \neq \mathbf{0}.$$

Data-driven versions of S_k

$$1 \leq k \leq K$$

\hat{k} is value of k maximising $S_k - \hat{\nu}_k c(n)$

H_0	S_k	$\hat{\nu}_k$
symmetry	$n \ \bar{\mathbf{t}}_{(k)-}\ ^2$	$\text{tr}(\mathbf{S}_{(k)-})$
q populations	$\text{tr}(\mathbf{B}_{(k)})$	$\frac{q-1}{n-q} \text{tr}(\mathbf{W}_{(k)})$
independence	$\text{tr}(\mathbf{S}_{12(k)} \mathbf{S}_{21(k)})$	$\text{tr}(\mathbf{S}_{11(k)}) \text{tr}(\mathbf{S}_{22(k)})$
goodness of fit	$\ \bar{\mathbf{t}}_{(k)w}\ ^2$	$\frac{1}{n} \sum_{i=1}^n \frac{\ \mathbf{t}_{(k)}(x_i)\ ^2}{f(x_i; \hat{\theta})}$

Nice properties of $S_{\hat{k}}$

Under H_0 , as $n \rightarrow \infty$,

$$\hat{k} \rightarrow 1$$

$$S_{\hat{k}} \rightsquigarrow \text{non-degenerate distribution}$$

Consistent against alternatives with

$$E [\mathbf{t}_{(K)}(x)] \neq \mathbf{0}.$$