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# CLASSIFICATION INTO TWO VON MISES DISTRIBUTIONS WITH UNKNOWN MEAN DIRECTIONS 

Kryštof Eben

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Classification procedures for directional data have been studied by Morris and Laycock [3] for the case of two von Mises distributions on the circle and two Fisher distributions on the sphere, both with known parameters. The present paper deals with two von Mises distributions with unknown mean directions and a common concentration parameter that is known. The likelihood rule and the plug-in rule are examined. For the statistic of the plug-in rule, the moment generating function is given. The moments are obtained as well but the higher ones are too complicated for practical use.

## 1. FORMULATION OF THE PROBLEM AND RELATED CLASSIFICATION RULES

In the text we use the modified Bessel functions of the first kind

$$
I_{p}(z)=\frac{1}{2 \pi} \int_{0}^{2 \pi} \cos p \theta \exp \{z \cos \theta\} \mathrm{d} \theta=\sum_{v=0}^{\infty} \frac{(z / 2)^{2 v+p}}{v!\Gamma(v+p+1)} .
$$

We need it only for whole orders $p \in Z$ and $z$ real, although it is defined more generally. Further, in our notation we shall not distinguish random variables from the arguments of the corresponding densities.

Let $I=(\cos \theta, \sin \theta)^{\prime}, 0 \leqq \theta<2 \pi$ be a random unit vector in the plane taking values on the unit circle. The density of I means the density with respect to the Lebesgue measure on the circle. Transforming the density of I to polar coordinates we obtain the density (with respect to the ordinary Lebesgue measure) of the random angle $\theta$.

I has a von Mises distribution $M(\boldsymbol{m}, \chi)$ with mean direction $\boldsymbol{m}=(\cos \mu, \sin \mu)^{\prime}$ and concentration parameter $x>0$, if the density of $I$ is given by

$$
\begin{equation*}
f(\boldsymbol{I} ; \boldsymbol{m}, x)=c(x) \exp \left\{\chi \boldsymbol{m}^{\prime} \boldsymbol{I}\right\}, \quad x>0, \quad \boldsymbol{m}^{\prime} \boldsymbol{m}=\boldsymbol{I}^{\prime} \boldsymbol{I}=1 \tag{1.1}
\end{equation*}
$$

Using the polar coordinates, we obtain this expression in the form of

$$
\begin{equation*}
g(\theta ; \mu, \chi)=c(x) \exp \{\chi \cos (\theta-\mu)\}, \quad \theta, \mu \in\langle 0,2 \pi) \tag{1.2}
\end{equation*}
$$

$c(x)=1 / 2 \pi I_{0}(\varkappa)$ being the norming constant.
Consider the problem of classification into two von Mises distributions $M\left(\boldsymbol{m}_{1}, \chi\right)$, $M\left(\boldsymbol{m}_{2}, \boldsymbol{x}\right)$, where $x$ is known, $\boldsymbol{m}_{1}=\left(\cos \mu_{1}, \sin \mu_{1}\right)^{\prime}, \boldsymbol{m}_{2}=\left(\cos \mu_{2}, \sin \mu_{2}\right)^{\prime}$. If $\boldsymbol{m}_{1}, \boldsymbol{m}_{2}$ were known, the Bayes discriminant function would be as derived in [3]:

$$
\begin{equation*}
U^{*}=\cos \left(\theta-\mu_{1}\right)-\cos \left(\theta-\mu_{2}\right) \tag{1.3}
\end{equation*}
$$

Assume that $\boldsymbol{m}_{1}$ and $\boldsymbol{m}_{2}$ are unknown. Let $\boldsymbol{I}_{1}, \ldots, \boldsymbol{I}_{r}$ and $\boldsymbol{I}_{r+1}, \ldots, \boldsymbol{I}_{n}$ be independent random samples from $M\left(\boldsymbol{m}_{1}, \chi\right)$ and $M\left(\boldsymbol{m}_{2}, \chi\right)$. If we adopt the likelihood approach to classification, the problem may be viewed as that of testing the hypothesis (I denotes the classified vector)

$$
\begin{aligned}
H_{0}: \boldsymbol{I}_{1}, \ldots, \boldsymbol{I}_{r}, \boldsymbol{I} & \sim M\left(\boldsymbol{m}_{1}, x\right) \\
\boldsymbol{I}_{r+1}, \ldots, \boldsymbol{I}_{n} & \sim M\left(\boldsymbol{m}_{2}, x\right)
\end{aligned}
$$

against the alternative

$$
\begin{aligned}
A: & \boldsymbol{I}_{1}, \ldots, \boldsymbol{I}_{r} \sim M\left(\boldsymbol{m}_{1}, x\right) \\
& \quad \boldsymbol{I}_{\boldsymbol{r}+1}, \ldots, \boldsymbol{I}_{n} \sim M\left(\boldsymbol{m}_{2}, x\right) .
\end{aligned}
$$

The usual likelihood statistic for this kind of testing equals in our case

$$
\lambda=\frac{\max _{\boldsymbol{m}_{1}, \boldsymbol{m}_{\mathbf{2}}}[c(\varkappa)]^{n+\boldsymbol{1}} \exp \left\{\chi\left(\sum_{i=1}^{r} \boldsymbol{I}_{i}^{\prime} \boldsymbol{m}_{1}+\left(\sum_{i=r+1}^{n} \boldsymbol{I}_{i}^{\prime}+\boldsymbol{I}^{\prime}\right) \boldsymbol{m}_{2}\right)\right\}}{\max _{\boldsymbol{m}_{1}, \boldsymbol{m}_{\mathbf{2}}}[c(\varkappa)]^{n+1} \exp \left\{\chi\left(\left(\sum_{i=1}^{r} \boldsymbol{I}_{i}^{\prime}+\boldsymbol{I}^{\prime}\right) \boldsymbol{m}_{1}+\sum_{i=r+1}^{n} \boldsymbol{I}_{i}^{\prime} \boldsymbol{m}_{2}\right)\right\}} .
$$

In both the upper and the lower term of this ratio the maximum over all unit vectors $\boldsymbol{m}_{1}, \boldsymbol{m}_{2}$ is achieved for $\boldsymbol{m}_{1}, \boldsymbol{m}_{2}$ maximizing the corresponding scalar products; i.e., in the numerator for

$$
\begin{aligned}
& \left.\boldsymbol{m}_{1}^{*}=\left(\sum_{i=1}^{r} I_{i}\right) / R_{1}, \quad R_{1}=\left\|\sum_{i=1}^{r} I_{i}\right\|,{ }^{*}\right) \\
& \tilde{\boldsymbol{m}}_{2}=\left(\sum_{i=r+1}^{n} \boldsymbol{I}_{i}+\boldsymbol{I}\right) / R_{2,0}, \quad R_{2,0}=\| \|_{i=r+1}^{n} I_{i}+\boldsymbol{I} \|,
\end{aligned}
$$

and in the denominator for

$$
\begin{array}{ll}
\tilde{\boldsymbol{m}}_{1}=\left(\sum_{i=1}^{r} I_{i}+I\right) / R_{1,0}, & R_{1,0}=\left\|\sum_{i=1}^{r} I_{i}+I\right\|, \\
\boldsymbol{m}_{2}^{*}=\left(\sum_{i=r+1}^{n} I_{i}\right) / R_{2}, & R_{2}=\left\|\sum_{i=r+1}^{n} I_{i}\right\| .
\end{array}
$$

[^0]Thus we obtain

$$
\lambda=\exp \left\{\chi\left(R_{1}+R_{2,0}-R_{1,0}-R_{2}\right)\right\},
$$

which is equivalent to the statistic $R_{1}+R_{2,0}-R_{1,0}-R_{2}$.
Remark. The vectors $\boldsymbol{m}_{1}^{*}$ and $\boldsymbol{m}_{2}^{*}$ are the sample mean directions. They are maximum likelihood estimates of $\boldsymbol{m}_{1}$ and $\boldsymbol{m}_{2}$ based on the samples $\boldsymbol{I}_{1}, \ldots, \boldsymbol{I}_{\boldsymbol{r}}$ and $I_{r+1}, \ldots, I_{n}$.

Let us denote $\boldsymbol{I}_{i}=\left(\cos \theta_{i}, \sin \theta_{i}\right)^{\prime}, i=1, \ldots, n, \theta_{i} \in\langle 0,2 \pi), \boldsymbol{m}_{1}^{*}=\left(\cos \psi_{1}, \sin \psi_{1}\right)^{\prime}$, $\boldsymbol{m}_{2}^{*}=\left(\cos \psi_{2}, \sin \psi_{2}\right)^{\prime}, \psi_{1}, \psi_{2} \in\langle 0,2 \pi)$. Then

$$
\begin{align*}
R_{1}-R_{1,0} & =R_{1}-\left(\left(R_{1} \cos \psi_{1}+\cos \theta\right)^{2}+\left(R_{1} \sin \psi_{1}+\sin \theta\right)^{2}\right)^{1 / 2}=  \tag{1.4}\\
& =\left(R_{1}^{2}\right)^{1 / 2}-\left(R_{1}^{2}+2 R_{1} \cos \left(\psi_{1}-\theta\right)+1\right)^{1 / 2}= \\
& =\frac{-2 R_{1} \cos \left(\psi_{1}-\theta\right)-1}{\left(R_{1}^{2}\right)^{1 / 2}+\left(R_{1}^{2}+2 R_{1} \cos \left(\psi_{1}-\theta\right)+1\right)^{1 / 2}}= \\
& =\frac{-2 \cos \left(\psi_{1}-\theta\right)-1 / R_{1}}{1+\left(1+\left(2 \cos \left(\psi_{1}-\theta\right)\right) / R_{1}+1 / R_{1}^{2}\right)^{1 / 2}}
\end{align*}
$$

The distribution of $R_{1}$ does not depend on $\boldsymbol{m}$ (see [2], §4.5) and it is the same as if $\boldsymbol{I}_{1}, \ldots, \boldsymbol{I}_{r}$ came from $M\left((1,0)^{\prime}, \chi\right)$. In that case

$$
\mathrm{E} \cos \theta_{i}=\frac{1}{2 \pi I_{0}(\varkappa)} \int_{0}^{2 \pi} \cos \theta \mathrm{e}^{\chi \cos \theta} \mathrm{d} \theta=\frac{I_{1}(\varkappa)}{I_{0}(\varkappa)}>0
$$

and according to the strong law of large numbers

$$
\lim _{r \rightarrow \infty} \sum_{i=1}^{r} \cos \theta_{i}=\infty \quad \text { a.s. }
$$

As $R_{1} \geqq \sum_{i=1}^{r} \cos \theta_{i}$, we have $\lim _{r \rightarrow \infty} R_{1}=\infty$ a.s. Returning back to (1.4), we obtain

$$
\lim _{r \rightarrow \infty}\left(R_{1}-R_{1,0}\right)=-\cos \left(\psi_{1}-\theta\right)
$$

Similarly we state

$$
\lim _{n \rightarrow r \rightarrow \infty}\left(R_{2}-R_{2,0}\right)=-\cos \left(\psi_{2}-\theta\right)
$$

Thus the likelihood statistic is asymptotically equivalent to the statistic $-U=$ $=\cos \left(\theta-\psi_{2}\right)-\cos \left(\theta-\psi_{1}\right)$. The statistic $U=\cos \left(\theta-\psi_{1}\right)-\cos \left(\theta-\psi_{2}\right)$ is immediately seen to be the statistic of the plug-in rule derived from (1.3) by substituting the estimates $\psi_{1}, \psi_{2}$ instead of the true parameters $\mu_{1}, \mu_{2}$.

## 2. THE MOMENT GENERATING FUNCTION AND MOMENTS OF THE STATISTIC $U$

Our starting point will be the following theorem (for the proof see [2], § 4.5):
Theorem. Let $\boldsymbol{I}_{1}, \ldots, \boldsymbol{I}_{\boldsymbol{r}}$ be a random sample from $M(\boldsymbol{m}, x), \boldsymbol{m}=(\cos \mu, \sin \mu)^{\prime}, \sum_{i=1}^{\boldsymbol{r}} \boldsymbol{I}_{\boldsymbol{i}}=$ $=R(\cos \psi, \sin \psi)^{\prime}=R \boldsymbol{m}^{* \prime}$. Then
(i) the distribution of R aoes not depend on $\mu$ (i.e. $R$ is an ancillary statistic for $\mu$ )
(ii) the conditional distribution of $\boldsymbol{m}^{*}$ given $R$ is $M(\boldsymbol{m}, \chi R)$.

Motivated by this theorem and the Fisher ancillary principle we shall assume

$$
\boldsymbol{m}_{1}^{*} \sim M\left(\boldsymbol{m}_{1}, \chi R_{1}\right), \quad \boldsymbol{m}_{2}^{*} \sim M\left(\boldsymbol{m}_{2}, \chi R_{2}\right) .
$$

We compute the moment generating function of $U$ for $I \sim M\left(\boldsymbol{m}_{1}, \chi\right)$, the other case is symmetric. Taking (1.2) for the densities,

$$
\begin{equation*}
\mathrm{E}^{t U}=c(\varkappa) c\left(\varkappa R_{1}\right) c\left(\varkappa R_{2}\right) \int_{0}^{2 \pi} \int_{0}^{2 \pi} \int_{0}^{2 \pi} \exp \left\{t\left(\cos \left(\theta-\psi_{1}\right)-\cos \left(\theta-\psi_{2}\right)\right)\right\} \times \tag{2.1}
\end{equation*}
$$

$$
\begin{gathered}
\times \exp \left\{x\left(R_{1} \cos \left(\psi_{1}-\mu_{1}\right)+R_{2} \cos \left(\psi_{2}-\mu_{2}\right)+\cos \left(\theta-\mu_{1}\right)\right)\right\} \mathrm{d} \psi_{1} \mathrm{~d} \psi_{2} \mathrm{~d} \theta= \\
=\mathrm{c}(x) c\left(\varkappa R_{1}\right) c\left(\varkappa R_{2}\right) \int_{0}^{2 \pi}\left[\int_{0}^{2 \pi} \exp \left\{t \cos \left(\theta-\psi_{1}\right)+\chi R_{1} \cos \left(\psi_{1}-\mu_{1}\right)\right\} \mathrm{d} \psi_{1}\right] \times \\
\times\left[\int_{0}^{2 \pi} \exp \left\{-t \cos \left(\theta-\psi_{2}\right)+\chi R_{2} \cos \left(\psi_{2}-\mu_{2}\right)\right\} \mathrm{d} \psi_{2}\right] \times \\
\times \exp \left\{\varkappa \cos \left(\theta-\mu_{1}\right)\right\} \mathrm{d} \theta .
\end{gathered}
$$

The first bracket in (2.1) equals to

$$
\begin{equation*}
\int_{0}^{2 \pi} \exp \left\{a \cos \psi_{1}+b \sin \psi_{1}\right\} \mathrm{d} \psi_{1} \tag{2.2}
\end{equation*}
$$

where

$$
a=t \cos \theta+\varkappa R_{1} \cos \mu_{1}, \quad b=t \sin \theta+\varkappa R_{1} \sin \mu_{1} .
$$

Settıng

$$
\varrho=\left(a^{2}+b^{2}\right)^{1 / 2}, \quad a=\varrho \cos \varphi, \quad b=\varrho \sin \varphi,
$$

(2.2) becomes

$$
\begin{gathered}
\int_{0}^{2 \pi} \exp \left\{\varrho \cos \left(\psi_{1}-\varphi\right)\right\} \mathrm{d} \psi_{1}=2 \pi I_{0}(\varrho)= \\
= \\
2 \pi I_{0}\left(\left(t^{2}+x^{2} R_{1}^{2}+2 t \varkappa R_{1} \cos \left(\theta-\mu_{1}\right)\right)^{1 / 2}\right) .
\end{gathered}
$$

By the same argument, the second bracket in (2.1) equals to

$$
2 \pi I_{0}(\tilde{\varrho})=2 \pi I_{0}\left(\left(t^{2}+\varkappa^{2} R_{2}^{2}+2 t \varkappa R_{2} \cos \left(\theta-\mu_{2}-\pi\right)\right)^{1 / 2}\right)
$$

and (2.1) simplifies to

$$
\begin{equation*}
\mathrm{E}^{t U}=\left[2 \pi I_{0}(\varkappa) I_{0}\left(\varkappa R_{1}\right) I_{0}\left(\varkappa R_{2}\right)\right]^{-1} \int_{0}^{2 \pi} I_{0}(\varrho) I_{0}(\varrho) \exp \left\{\varkappa \cos \left(\theta-\mu_{1}\right)\right\} \mathrm{d} \theta . \tag{2.3}
\end{equation*}
$$

Lemma. (a) The von Neumann summation formula. For $x_{1}, x_{2}, \theta$ reul,

$$
\begin{gather*}
I_{0}\left(\left(x_{1}^{2}+x_{2}^{2}+2 x_{1} x_{2} \cos \theta\right)^{1 / 2}\right)=  \tag{2.4}\\
=I_{0}\left(x_{1}\right) I_{0}\left(x_{2}\right)+2 \sum_{p=1}^{\infty} I_{p}\left(x_{1}\right) I_{p}\left(x_{2}\right) \cos p \theta .
\end{gather*}
$$

(b) The sum on the right-hand side of (2.4) is absolutely convergent.
(c) For every $p \in Z, x>0$,

$$
\int_{0}^{2 \pi} \sin p \theta \exp \{\varkappa \cos \theta\} \mathrm{d} \theta=0 .
$$

(d) For $p, q \in Z, \mu_{1}, \mu_{2}$ real, $x>0$,

$$
\begin{gathered}
\int_{0}^{2 \pi} \cos p\left(\theta-\mu_{1}\right) \cos q\left(\theta-\mu_{2}-\pi\right) \exp \left\{\varkappa \cos \left(\theta-\mu_{1}\right)\right\} \mathrm{d} \theta=\frac{(-1)^{q}}{2} \times \\
\times \int_{0}^{2 \pi}\left[\cos \left((p+q)\left(\theta-\mu_{1}\right)+q\left(\mu_{1}-\mu_{2}\right)\right)+\cos \left((p-q)\left(\theta-\mu_{1}\right)-q\left(\mu_{1}-\mu_{2}\right)\right)\right] \times \\
\times \exp \left\{\varkappa \cos \left(\theta-\mu_{1}\right)\right\} \mathrm{d} \theta=\frac{(-1)^{q}}{2} \cos q\left(\mu_{1}-\mu_{2}\right) 2 \pi\left(I_{p+q}(\chi)+I_{p-q}(\chi)\right) .
\end{gathered}
$$

For the derivation of (2.4) see e.g. [1] § 7•6. The absolute convergence may be obtained for example from the rough inequality

$$
\left|I_{p}(x)\right| \leqq \sum_{v=0}^{\infty} \frac{|x / 2|^{2 v+p}}{v!(v+p)!} \leqq \frac{|x / 2|^{p}}{p!} \exp (x / 2)^{2}
$$

(c) is self-evident and (d) may be easily checked with the help of (c).

The above lemma enables us to expand the term $I_{0}(\varrho) I_{0}(\varrho)$ in the integrand of (2.3):

$$
\begin{gathered}
I_{0}(\varrho) I_{0}(\tilde{\varrho})=I_{0}^{2}(t) I_{0}\left(\varkappa R_{1}\right) I_{0}\left(\varkappa R_{2}\right)+ \\
+2 I_{0}(t) I_{0}\left(\varkappa R_{1}\right) \sum_{q=1}^{\infty} I_{q}(t) I_{q}\left(\varkappa R_{2}\right) \cos q\left(\theta-\mu_{2}-\pi\right)+ \\
+2 I_{0}(t) I_{0}\left(\varkappa R_{2}\right) \sum_{p=1}^{\infty} I_{p}(t) I_{p}\left(\varkappa R_{1}\right) \cos p\left(\theta-\mu_{1}\right)+ \\
+4 \sum_{p=1}^{\infty} \sum_{q=1}^{\infty} I_{p}(t) I_{q}(t) I_{p}\left(\varkappa R_{1}\right) I_{q}\left(\varkappa R_{2}\right) \cos p\left(\theta-\mu_{1}\right) \cos q\left(\theta-\mu_{2}-\pi\right) .
\end{gathered}
$$

Since the series involved are absolutely convergent, we can integrate termwise. The calculation needs only (c) and (d) of the lemma and is omitted here. As a result we obtained the following expression for the moment generating function of the statistic $U$ :

$$
\mathrm{E} \mathrm{e}^{t U}=\sum_{p=0}^{\infty} \sum_{q=0}^{\infty} a_{p q} I_{p}(t) I_{q}(t)
$$

where the coefficients $a_{p q}$ are defined in subsequent manner: let us denote $\alpha_{p}(\varkappa)=$ $=I_{p}(x)\left|I_{0}(\varkappa), \delta=\left|\mu_{1}-\mu_{2}\right| ;\right.$ then

$$
\begin{aligned}
a_{00} & =1 \\
a_{0 q} & =(-1)^{q} 2 \alpha_{q}(\varkappa) \alpha_{q}\left(\varkappa R_{2}\right) \cos q \delta, \\
a_{p 0} & =2 \alpha_{p}(\varkappa) \alpha_{p}\left(\varkappa R_{1}\right), \\
a_{p q} & =(-1)^{q} 2 \alpha_{p}\left(\varkappa R_{1}\right) \alpha_{q}\left(\varkappa R_{2}\right)\left(\alpha_{p+q}(\varkappa)+\alpha_{p-q}(\varkappa)\right) \cos q \delta, \\
& p, q \geqq 1 .
\end{aligned}
$$

## 3. THE MOMENTS OF THE STATISTIC $U$

For the functions $I_{p}(t)$ we have (see [1] 7.2.5, resp. §7.11)

$$
\begin{gather*}
I_{p}(0)=0 \quad \text { for } p \neq 0  \tag{3.1}\\
=1 \quad \text { for } p=0 \\
\frac{\mathrm{~d}}{\mathrm{~d} t} I_{p}(t)=\frac{1}{2}\left(I_{p-1}(t)+I_{p+1}(t)\right) . \tag{3.2}
\end{gather*}
$$

Let us consider derivatives of the term $I_{p}(t) I_{q}(t)$. According to (3.1) and (3.2),

$$
\left.\frac{\mathrm{d}^{k}}{\mathrm{~d} t^{k}} I_{p}(t) I_{q}(t)\right|_{t=0}=c_{p q}^{(k)}
$$

where $c_{p q}^{(k)}$ is the coefficient standing by $I_{0}(t) I_{0}(t)$ in the expression for $\left(\mathrm{d}^{k} / \mathrm{d} t^{k}\right) I_{p}(t) I_{q}(t)$. Obviously $c_{p q}^{(k)}=0$ for $p+q>k$ and the $k$-th moment of $U$ equals

$$
\mathrm{E} U^{k}=\left.\frac{\mathrm{d}^{k}}{\mathrm{~d} t^{k}} \mathrm{E} e^{t v}\right|_{t=0}=\sum_{\substack{p, q \geqq 0 \\ p+q \leqq k}} \sum_{p q} c_{p q}^{(k)} a_{p q} .
$$

It remains to find the coefficent $c_{p q}^{(k)}$. From (3.2) it follows
(3.3) $\frac{\mathrm{d}}{\mathrm{d} t} I_{p}(t) I_{q}(t)=\frac{1}{2}\left(I_{p-1}(t) I_{q}(t)+I_{p+1}(t) I_{q}(t)+I_{p}(t) I_{q-1}(t)+I_{p}(t) I_{q+1}(t)\right)$.

Thus the term $I_{p}(t) I_{q}(t)$ "produces" the four terms on the right-hand side. Proceeding in this way we see that differentiation is analogous (in the sense of (3.3)) to producing all the paths of the symmetric random walk on $Z \times Z$ starting at the point $(p, q)$. The probability of reaching the point $(0,0)$ after $k$ steps from $(p, q)$ is of course the same as that of reaching $(p, q)$ when starting from $(0,0)$. Let us denote this probability by $P_{k}(p, q)$ and assume for a while that the starting point is $(0,0)$. Then

$$
2^{-k} c_{p q}^{(k)}=P_{k}(p, q) .
$$

For $P_{k}(p, q)$ we have

$$
\begin{equation*}
P_{0}(0,0)=1, \tag{3.4}
\end{equation*}
$$

$$
\begin{gathered}
P_{k}(p, q)=\frac{1}{4}\left[P_{k-1}(p-1, q)+P_{k-1}(p+1, q)+P_{k-1}(p, q-1)+\right. \\
\left.+P_{k-1}(p, q+1)\right]
\end{gathered}
$$

(3.4) defines $P_{k}(p, q)$ uniquely and one easily checks that it is fulfilled if $P_{k}(p, q)$ is given by

$$
\begin{equation*}
P_{k}(p, q)=4^{-k}\binom{k}{2}\binom{k}{\frac{k-p-q-q}{2}} \tag{3.5}
\end{equation*}
$$

for both $p, k-q$ odd or both $p, k-q$ even, $P_{k}(p, q)=0$ otherwise.
Let us write the first two moments:

$$
\begin{aligned}
\mathrm{E} U= & \alpha_{1}(\varkappa)\left(\alpha_{1}\left(\varkappa R_{1}\right)-\alpha_{1}\left(\varkappa R_{2}\right) \cos \delta\right), \\
\mathrm{E} U^{2}= & 1-\left(\alpha_{1}\left(\varkappa R_{1}\right) \alpha_{1}\left(\varkappa R_{2}\right)\left(\alpha_{2}(\varkappa)+1\right) \cos \delta\right)+ \\
& +\frac{1}{2} \alpha_{2}(\varkappa)\left(\alpha_{2}\left(\varkappa R_{1}\right)+\alpha_{2}\left(\varkappa R_{2}\right) \cos 2 \delta\right) .
\end{aligned}
$$

For practical purposes, the approximate formulas for $\alpha_{1}($.$) and \alpha_{2}($.$) may be used$ as given in [2] 3.4.9d.

## References

[1] H. Bateman, A. Erdélyi: Higher transcendental functions, vol. 2, McGraw-Hill 1953.
[2] K. V. Mardia: Statistics of directional data. Academic Press, London and New York 1972.
[3] J. E. Morris, P. J. Laycock: Discriminant analysis of directional data, Biometrika 61 (1974), 335-342.

Souhrn

# KLASIFIKACE DO DVOU TŘÍD S VON MISESOVÝM ROZLOŽENÍM A NEZNÁMÝMI STŘEDNÍMI SMĚRY VE TŘÍDÁCH 

## Kryštof Eben

Článek se zabývá klasifikačním pravidlem založeným na věrohodnostním poměru a pravidlem založeným na výběrových středních směrech (plug-in rule). Pro diskriminační funkci tohoto pravidla je nalezena momentová vytvořující funkce a jsou zjištěny momenty.

Parametr koncentrace se považuje za známý a totožný v obou třídách.
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[^0]:    *) We use to exclude the event $\sum \boldsymbol{I}_{\boldsymbol{i}}=0$ which is of measure zero.

