# On Testing the Hypothesis of Equality of Two Bernoulli Regression Functions <br> Elizbar Nadaraya, Petre Babilua 

Ivane Javakhishvili Tbilisi State University, Department of Mathematics

elizbar.nadaraya@tsu.ge; petre.babilua@tsu.ge
Let randon variables $Y^{(i)}, i=1,2$, take two values 1 and 0 with probabilities $p_{i}$ (succes) and $1-p_{i}$, $i=1,2$ (failure), respectively. Assume that the probability of success $p_{i}$ is the function of an independent variable $x \in[0,1]$, i.e. $p_{i}=p_{i}(x)=\mathbb{P}\left\{Y^{(i)}=1 \mid x\right\}(i=1,2)$ (see [1]-[3]). Let $t_{j}, j=1, \ldots, n$, be the devision points of the interval $[0,1]: t_{j}=\frac{2 j-1}{2 n}, j=1, \ldots, n$

Let further $Y_{i}^{(1)}$ and $Y_{i}^{(2)}, i=1, \ldots, n$, be mutually independent random Bernoulli variables with $\mathbb{P}\left\{Y_{i}^{(k)}=1 \mid t_{i}\right\}=p_{k}\left(t_{i}\right), \quad \mathbb{P}\left\{Y_{i}^{(k)}=0 \mid t_{i}\right\}=1-p_{k}\left(t_{i}\right), \quad i=1, \ldots, n, \quad k=1,2 . \quad$ Using $\quad$ the samples $Y_{1}^{(1)}, \ldots, Y_{n}^{(1)}$ and $Y_{1}^{(2)}, \ldots, Y_{n}^{(2)}$ we want to chek the hypothesis

$$
H_{0}: p_{1}(x)=p_{2}(x)=p(x), \quad x \in[0,1],
$$

against the sequence of "close" alternatives of the form

$$
H_{1 n}: p_{k}(x)=p(x)+\alpha_{n} u_{k}(x)+o\left(\alpha_{n}\right), \quad k=1,2 .
$$

where $\alpha_{n} \rightarrow 0$ relevantly, $u_{1}(x) \neq u_{2}(x), x \in[0,1]$ and $o\left(\alpha_{n}\right)$ uniformly in $x \in[0,1]$.
We consider the crietrion of testing the hypothesis $H_{0}$ based on the statistic function

$$
\begin{aligned}
T_{n} & =\frac{1}{2} n b_{n} \int_{\Omega_{n}(\tau)}\left[\hat{p}_{1 n}(x)-\hat{p}_{2 n}(x)\right]^{2} p_{n}^{2}(x) d x= \\
& =\frac{1}{2} n b_{n} \int_{\Omega_{n}(\tau)}\left[p_{1 n}(x)-p_{2 n}(x)\right]^{2} d x, \quad \Omega_{n}(\tau)=\left[\tau b_{n},(1-\tau) b_{n}\right], \quad \tau>0,
\end{aligned}
$$

Where

$$
\hat{p}_{i n}=p_{i n}(x) p_{n}^{-1}(x), \quad p_{i n}(x)=\frac{1}{n b_{n}} \sum_{j=1}^{n} K\left(\frac{x-t_{j}}{b_{n}}\right) Y_{j}^{(i)}, \quad i=1,2, \quad p_{n}(x)=\frac{1}{n b_{n}} \sum_{i=1}^{n} K\left(\frac{x-t_{i}}{b_{n}}\right),
$$

$K(x)$ is some distribution density and $b_{n} \rightarrow 0$ is a sequence of positive numbers, $\hat{p}_{i n}(x)$ is the kernel estimator of the regression function.

We assume that a kernel $K(x) \geq 0$ is chosen so that it is a function of bounded variation and satisfies the conditions: $K(x)=K(-x), K(x)=0$ for $|x| \geq \tau>0, \int K(x) d x=1$. The class of such functions is denoted by $H(\tau)$.

Theorem Let $K(x) \in H(\tau)$ and $p(x), u_{1}(x), u_{2}(x) \in C^{1}[0,1]$. If $n b_{n}^{2} \rightarrow \infty, \alpha_{n} b_{n}^{-1 / 2} \rightarrow 0$ and $n b_{n}^{1 / 2} \alpha_{n}^{2} \rightarrow c_{0}, 0<c_{0}<\infty$, then for the hypothesis $H_{1 n}$

$$
b_{n}^{-1 / 2}\left(T_{n}-\Delta(p)\right) \sigma^{-1}(p) \xrightarrow{d} N(a, 1),
$$

where $\Delta(p)$ and $\sigma^{2}(p)$ are defined in Lemma 2 and $\xrightarrow{d}$ denotes convergence in distribution and $N(a, 1)$ is a random variable having the standard normal distribution with parameters $(a, 1)$,

$$
a=\frac{c_{0}}{2 \sigma(p)} \int_{0}^{1}\left(u_{1}(x)-u_{2}(x)\right)^{2} d x .
$$

