

Homogeneity tests of weighted samples in ROOT

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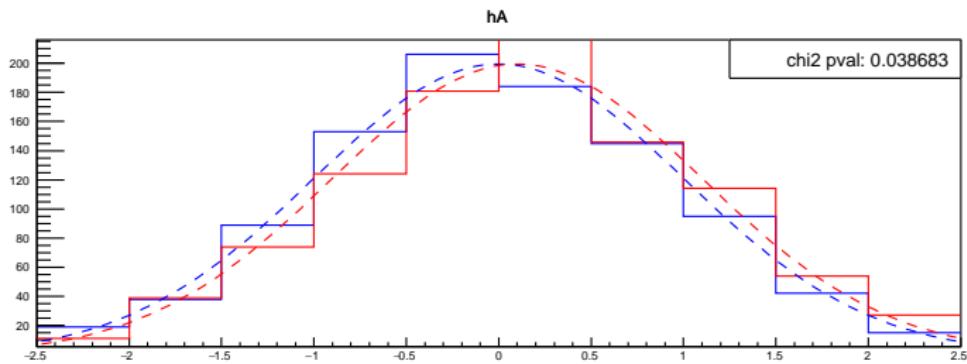
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Introduction

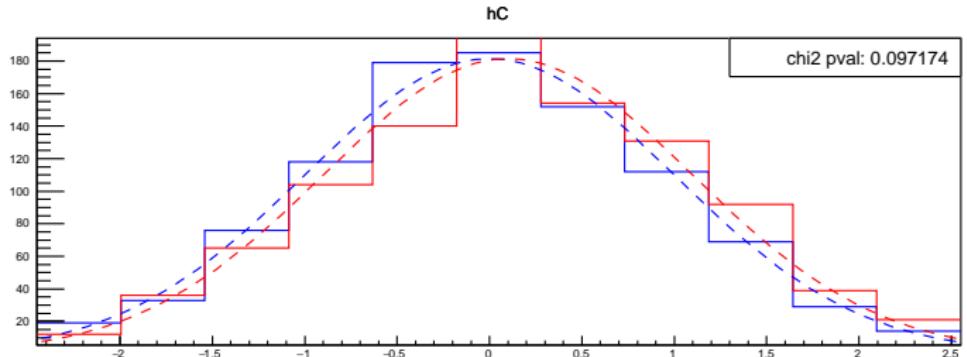
- Homogeneity testing
 - ▶ MC vs. data
 - ▶ Instability of ROOT's tests
- Weighted samples
 - ▶ $(\mathbf{X}, \mathbf{W}) = ((X_1, W_1), \dots, (X_n, W_n))^T$
 - ▶ $(\mathbf{X}, \mathbf{W}) \rightarrow \tilde{\mathbf{X}} \sim F^{(n)}$
 - ▶ weighted observations vs. weighted histogram

Problems of TH1::Chi2Test – Binning effect

- nbins = 10
- min = -2.5
- max = 2.5

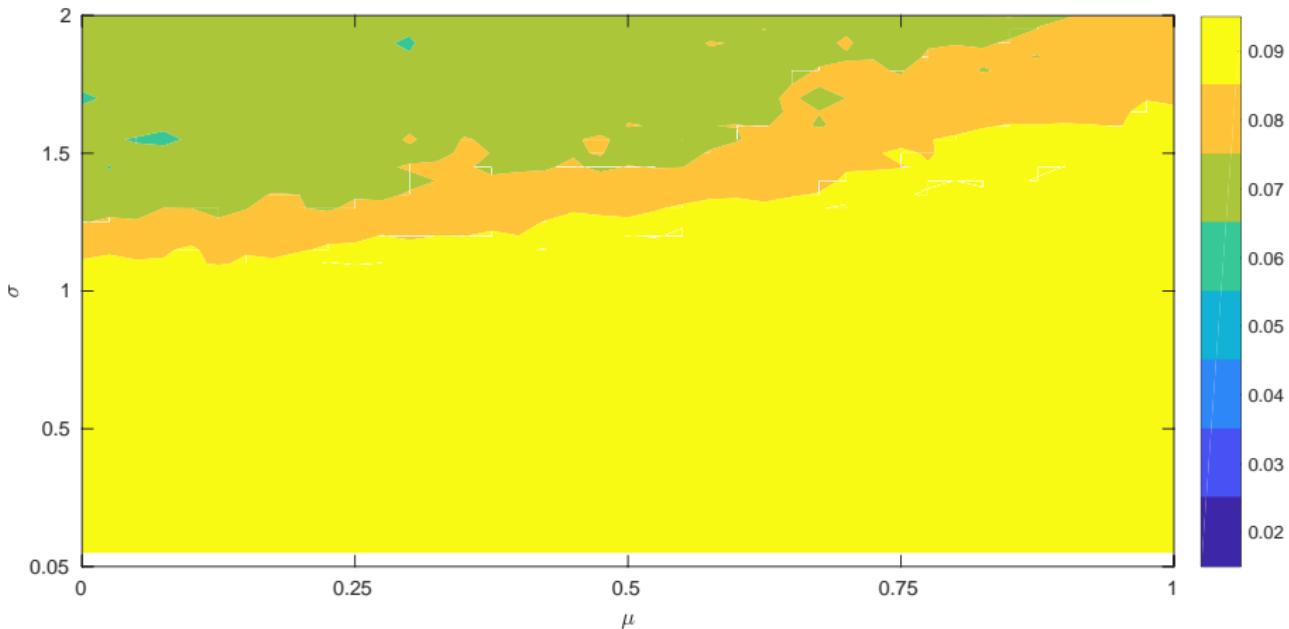


- nbins = 11
- min = -2.45
- max = 2.55



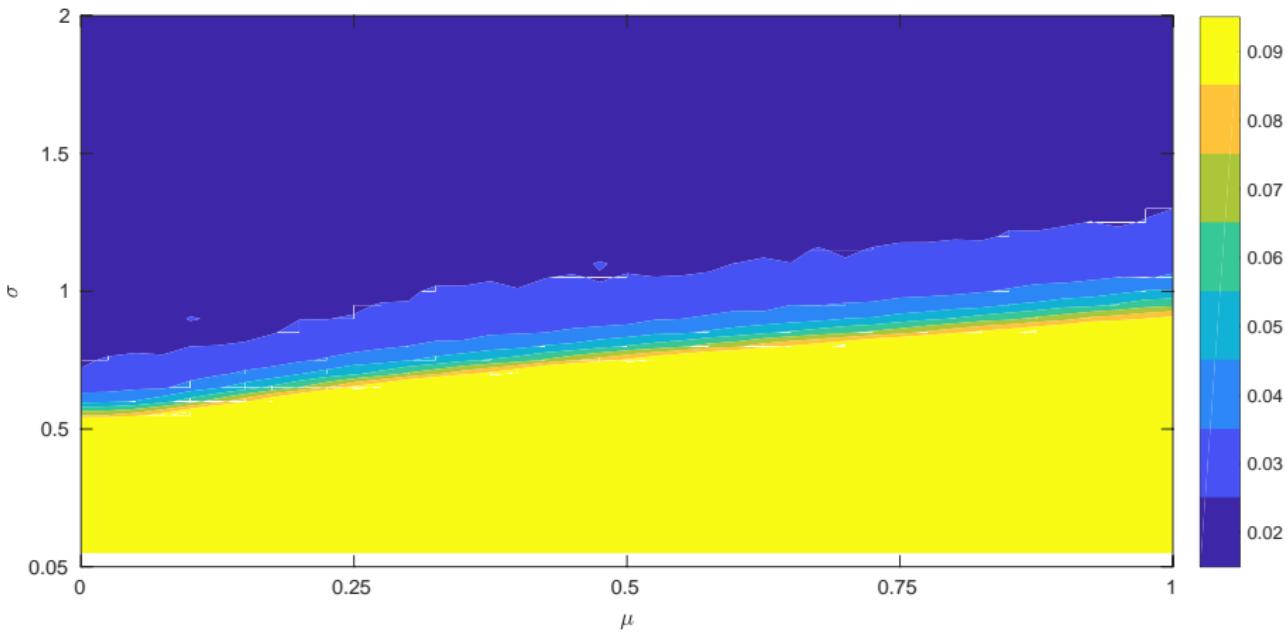
Problems of TH1::Chi2Test – Effect of weights

- (\mathbf{X}, \mathbf{W}) vs. $(\mathbf{Y}, \mathbf{1})$
- $X_i \sim \mathcal{N}(\mu, \sigma^2)$, $Y_i \sim \mathcal{N}(0, 1)$
- $W_i = \frac{f_Y(X_i)}{f_X(X_i)} \implies H_0$ is true
- R ... ratio of rejection
- $R \approx \alpha = 0.05$ (significance level)



Problems of TH1::KolmogorovTest

- KS test is originally derived for continuous data samples
- computed p -value is higher than the true one



Possible solution: tests based on empirical distribution function

- EDF contains full information about the sample
- we need to modify some constants and functions
- invariant to scaling of weights
- is stable even if the number of events are different
- three generalized tests: KS, CvM and AD

Unweighted	Weighted
n	$n_e = \left(\sum_{i=1}^n W_i \right)^2 / \sum_{i=1}^n W_i^2$
$F_n(x) = \frac{1}{n} \sum_{i=1}^n \mathbf{1}_{(-\infty, x_i]}(x)$	$F_n^W(x) = \frac{1}{W_\bullet} \sum_{i=1}^n W_i \mathbf{1}_{(-\infty, x_i]}(x)$

Tests based on EDF

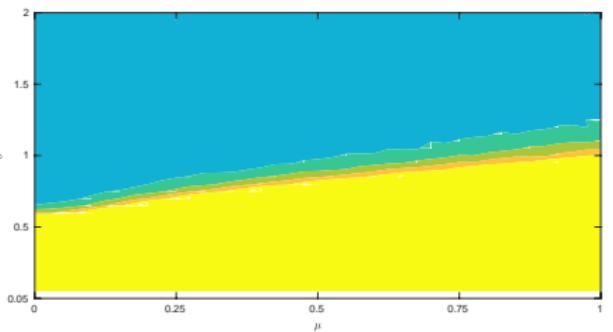


Figure: KS test

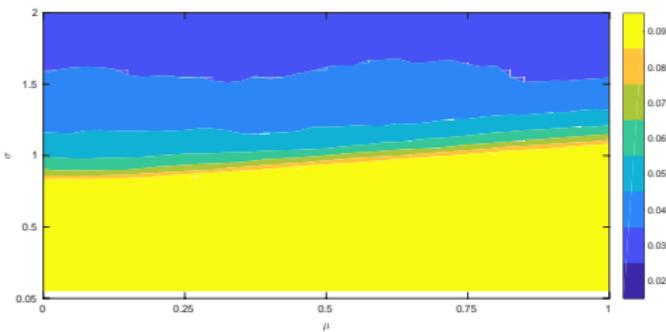


Figure: AD test

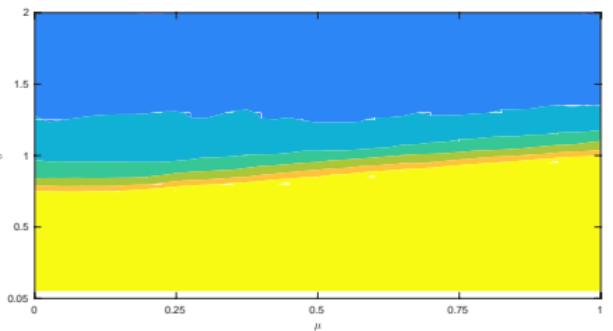


Figure: CvM test

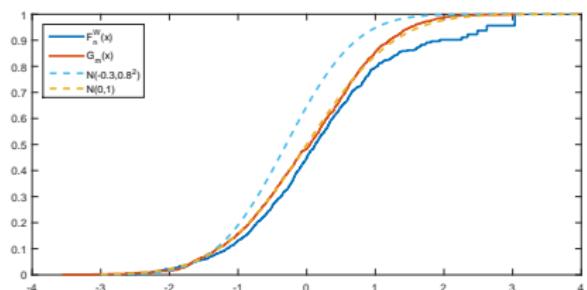


Figure: problematic configuration

Ratios of rejected tests - weights *i.i.d.*

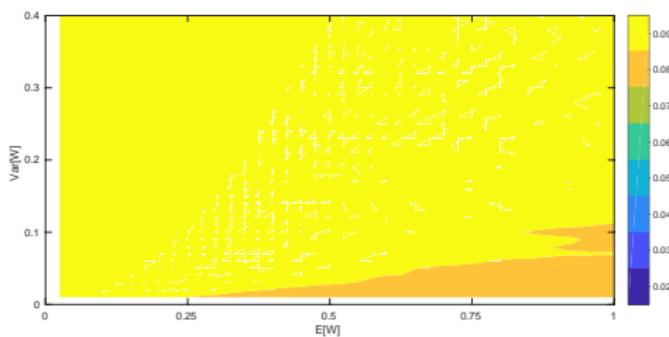


Figure: TH1::Chi2Test

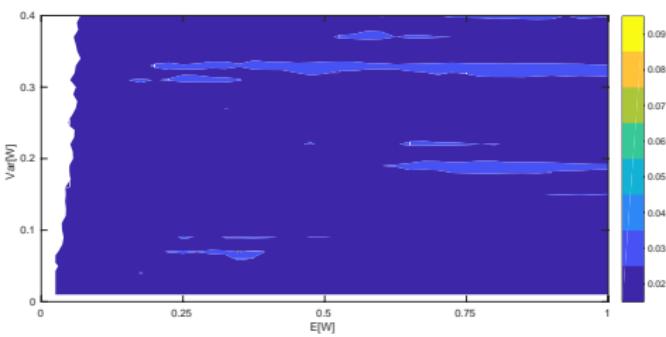


Figure: TH1::KolmogorovTest

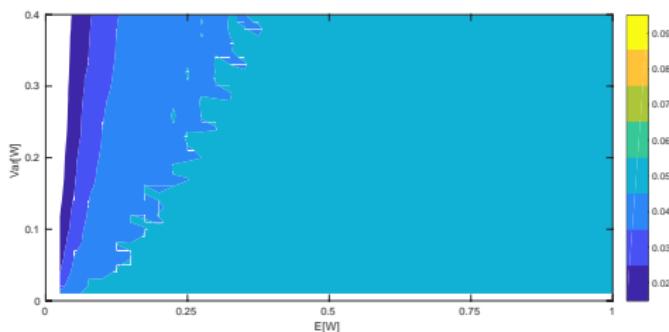


Figure: KS test

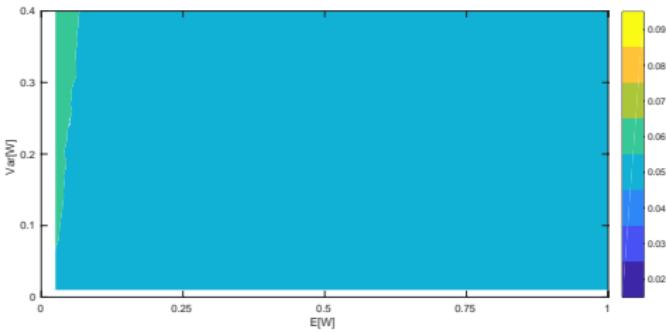


Figure: AD test

Power of test

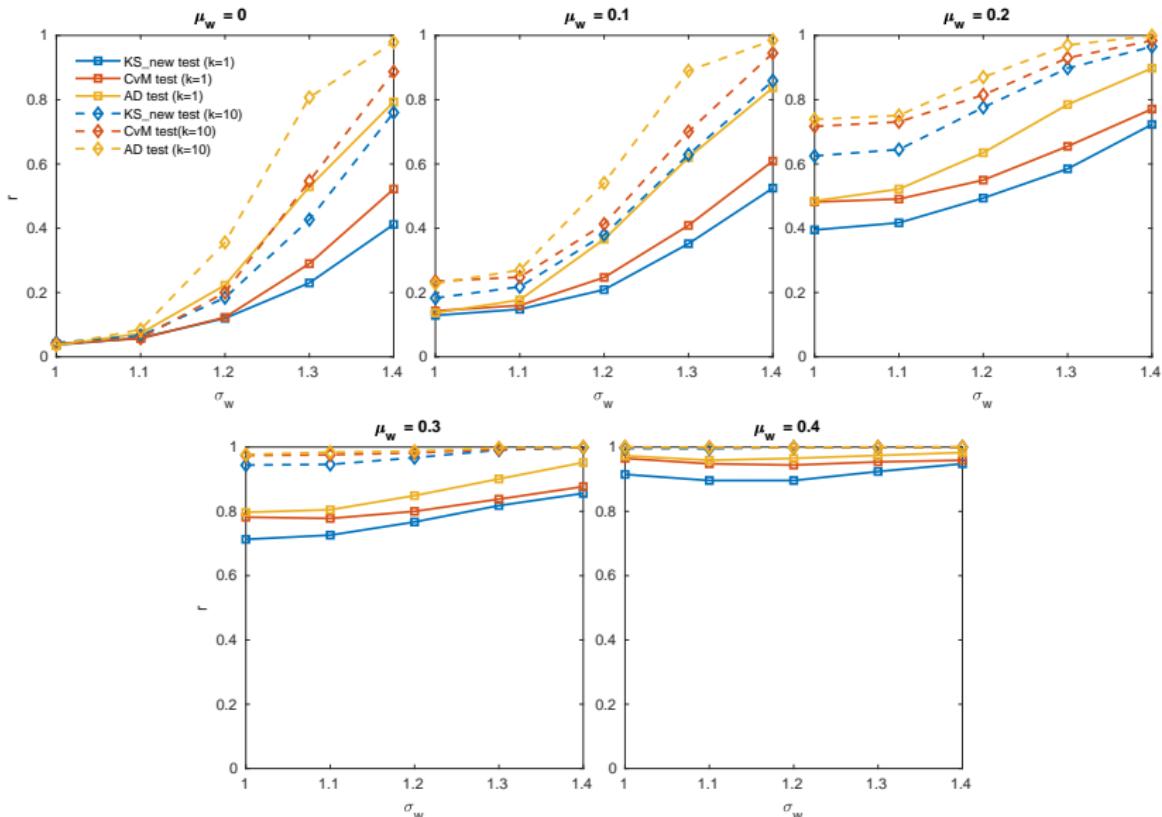


Figure: Various μ_w , σ_w , k and fixed $\mu_s = 0.2$, $\sigma_s = 1.3$, $n_{events} = 200$.

Power of test

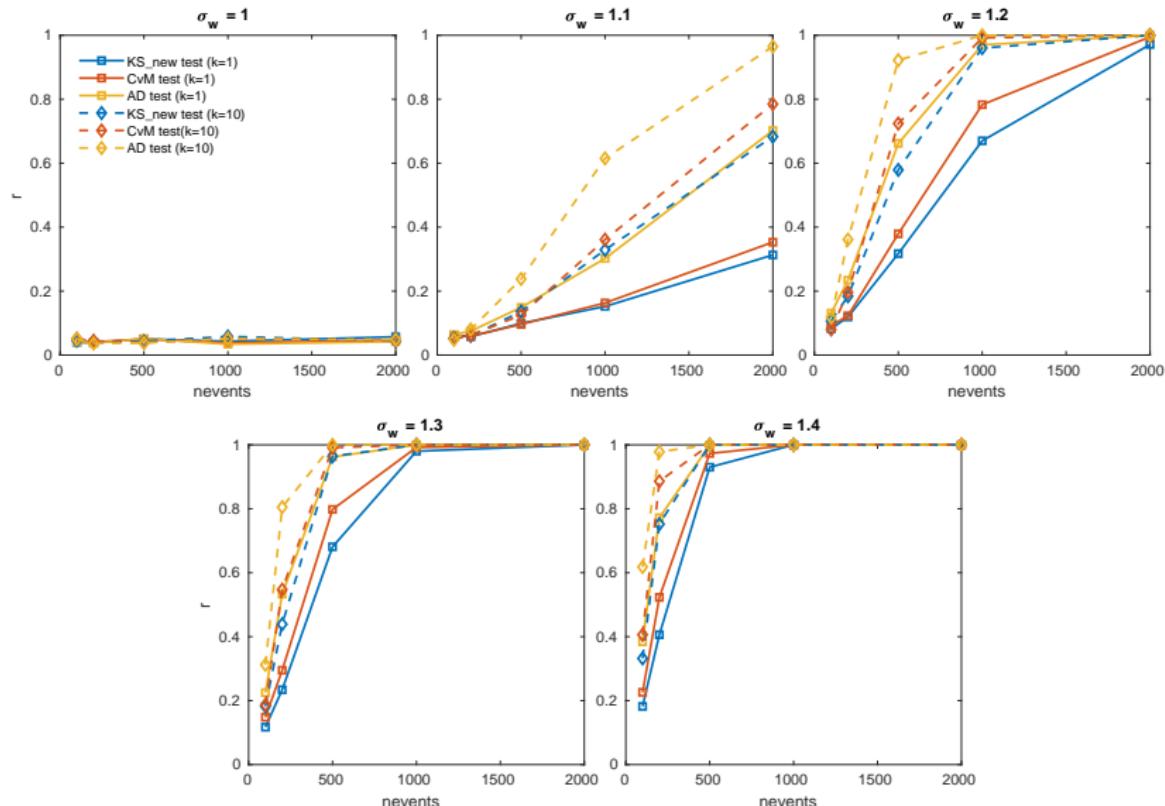


Figure: Various σ_w , $nevents$, k and fixed $\mu_s = 0.1$, $\sigma_s = 1.2$, $\mu_w = 0$.

Power of test

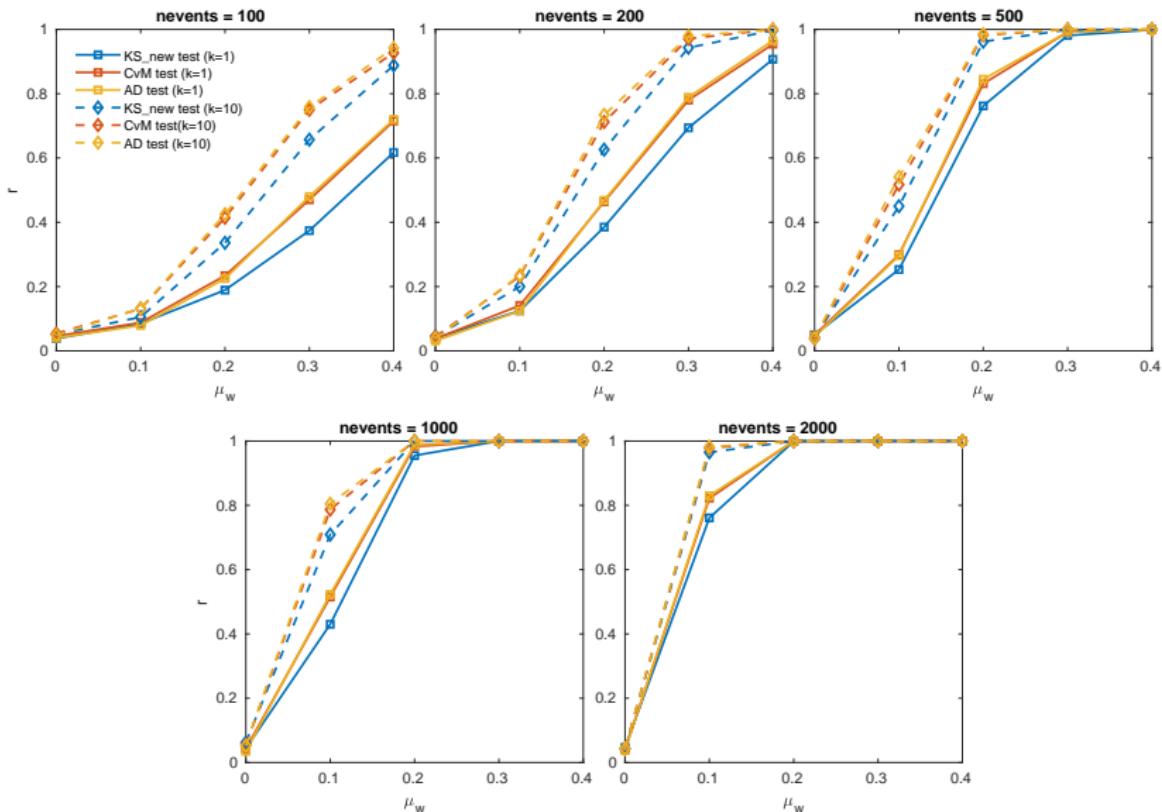


Figure: Various $nevents$, μ_w , k and fixed $\mu_s = 0$, $\sigma_w = 1.4$, $\sigma_w = 0$.

Conclusion

- Weighted homogeneity tests for binned data are generally unstable
- Tests based on EDF compute p -values correctly
 - ▶ ROOT code: <http://gams.fjfi.cvut.cz/homtests>
 - ▶ Implementation in ROOT::Math::GoFTest soon

Backup – Weighted samples

$$\begin{aligned}(\mathbf{X}, \mathbf{W}) &= ((X_1, \dots, X_n)^T, (W_1, \dots, W_n)^T) \\ (\mathbf{Y}, \mathbf{V}) &= ((Y_1, \dots, Y_m)^T, (V_1, \dots, V_m)^T)\end{aligned}$$

Effective entries size

$$n_e = \left(\sum_{i=1}^n W_i \right)^2 / \sum_{i=1}^n W_i^2$$

Weighted empirical distribution function (WEDF)

$$F_n^{\mathbf{W}}(x) = \frac{1}{W_*} \sum_{i=1}^n W_i \mathbf{1}_{(-\infty, X_i]}(x)$$

WEDF of mixed sample

$$H_{n_e, m_e}^{\mathbf{W}, \mathbf{V}}(x) = \frac{n_e F_n^{\mathbf{W}}(x) + m_e F_m^{\mathbf{V}}(x)}{n_e + m_e}$$

1. Weights – i.i.d.

$$W_i \sim P^W$$

2. Weights – ratio of PDFs

$$W_i = \frac{g(X_i)}{f(X_i)}$$

3. Weights – CDF

$$W_i = G(X_i) - G(X_{i-1})$$

Backup – Properties of WEDF

Weights – i.i.d.

$F_n^W(x)$ is an unbiased and strongly consistent estimate of $F_X(x)$.

Weights – ratio of PDFs

$F_n^W(x)$ is asymptotically unbiased and strongly consistent est. of $F_Y(x)$.

Weights – CDF

$F_n^W(x)$ is strongly consistent estimate of $F_Y(x)$.

Generalized Glivenko-Cantelli theorem

Let $\mathbf{X} = (X_1, \dots, X_n)^T$ be i.i.d. random vector from F . Let $\mathbf{W} = (W_1, \dots, W_n)^T$ be its weights. Let F_n^W be their WEDF which value $F_n^W(x)$ is for all $x \in \mathbb{R}$ strongly consistent estimate of value $G(x)$. Then

$$\sup_{x \in \mathbb{R}} |F_n^W(x) - G(x)| \xrightarrow{\text{s.j.}} 0.$$

Backup –Homogeneity tests of weighted samples

Kolmogorov-Smirnov test

$$\begin{aligned} T_{n,m}^{W,V} &= \sqrt{\frac{n_e m_e}{n_e + m_e}} \sup_{x \in \mathbb{R}} |F_n^W(x) - F_m^V(x)| \\ K(\lambda) &= 1 - 2 \sum_{k=1}^{+\infty} (-1)^{k+1} e^{-2k^2 \lambda^2} \end{aligned}$$

Cramér-von Mises test

$$\begin{aligned} T_{n,m}^{W,V} &= \frac{n_e m_e}{n_e + m_e} \int_{\mathbb{R}} (F_n^W(x) - F_m^V(x))^2 dH_{n_e, m_e}^{W, V} \\ L(z) &= \frac{1}{\pi \sqrt{z}} \sum_{k=0}^{+\infty} (-1)^k \binom{-\frac{1}{2}}{k} \sqrt{1 + 4k} \exp\left(-\frac{(1+4k)^2}{16z}\right) K_{\frac{1}{4}}\left(\frac{(1+4k)^2}{16z}\right) \end{aligned}$$

Anderson-Darling test

$$\begin{aligned} T_{n,m}^{W,V} &= \frac{n_e m_e}{n_e + m_e} \int_{0 < H_{n_e, m_e}^{W, V}(x) < 1} \frac{(F_n^W(x) - F_m^V(x))^2}{H_{n_e, m_e}^{W, V}(x)(1 - H_{n_e, m_e}^{W, V}(x))} dH_{n_e, m_e}^{W, V} \\ M(z) &= \frac{\sqrt{2\pi}}{z} \sum_{k=0}^{+\infty} \binom{-\frac{1}{2}}{k} (1 + 4k) \exp\left(-\frac{(1+4k)^2 \pi^2}{8z}\right) \\ &\quad \int_0^{+\infty} \exp\left(\frac{z}{8(w^2+1)} - \frac{(1+4k)^2 \pi^2 w^2}{8z}\right) dw \end{aligned}$$