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UniODA *vs.* Student's t-Test: Comparing Two Migraine Treatments

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This study evaluates the number of migraine attacks experienced in a clinical trial of two alternative treatments, for a sample of 67 patients. Several conventional statistical methods were used to compare the number of attacks between treatments, but all of these methods were compromised by violations of their underlying assumptions. Only an exact test motivated by an eyeball spline was revealing. UniODA was used to compare treatments, and identified the latter effect.

Appleton[1] evaluated the number of migraine attacks experienced in a clinical trial of two alternative treatments, for a sample of 67 patients (Table 1), using several methods.

Table 1: Data for 67 patients from a clinical trial of two migraine treatments (Appleton, 1995).

Number of Attacks	Treatment 1	Treatment 2
0	13	5
1	9	13
2	4	6
3	2	1
4	1	2
5	1	3
6	3	3
7	0	1

Note: Tabled are frequency counts.

Student's t-test was first used to compare the mean number of attacks between treatments, but the result wasn't statistically significant (p<0.14). Student's t-test was employed again to compare the data after modification using a square root transformation (p<0.06), and then a log transformation (p<0.07), and again failed to identify a reliable mean difference. And, crucial assumptions underlying Student's t-test were violated by the data.[1,2]

The nonparametric Mann-Whitney U-test was attempted next (p<0.07), but again the requirements of the test weren't met (too many tied values). A normal test assuming a Poisson distribution was attempted next, and it identified a statistically significant effect (p<0.04), but the Poisson assumption was untenable.[1]

Such failure of real-world samples to comply with the restrictive assumptions which underlie suboptimal paradigms—such as general linear model and maximum-likelihood—is more the rule than the exception.[2,3]

Appleton decided to use Fisher's exact test, but a methodology to spline the number of migraine attacks into a binary indicator was needed: "…after discretizing the data at some point, probably between no attacks and one or more" (p. 242). For a cut-off between 0 and 1 it was reported, exact p<0.029.

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In contrast to conventional statistical methods, with ODA one has no worries about parent distributions (*p* is always exact), or about where to spline (cut) an ordered attribute (ODA always finds the model which maximizes the classification accuracy).[2,3] In the present application UniODA analysis[2] was performed with MegaODA[4-7] software. The class variable was treatment group (dummy-coded as 1 and 2), and the ordered attribute was the number of migraine attacks. Consistent with Appleton's eyeball spline, the UniODA model identified was: if Number of Attacks>0 then predict class=Treatment 2; otherwise predict class= Treatment 1. The model achieved a moderate ESS of 24.7, and the result was marginally significant (exact $p<0.085$). The model correctly classified 13 (39%) of 33 patients undergoing treatment 1, and 29 (85%) of 34 patients undergoing treatment 2. The model was correct 72% of the time that it predicted a patient experienced treatment 1, and 59% of the time it predicted a patient experienced treatment 2.

Stable classification performance was obtained in "leave-one-out" (jackknife) validity analysis, but was statistically significant (exact $p<0.0218$) because the UniODA model is applied *a priori* to the jackknife sample.[2]

Unlike the conventional tests employed earlier, UniODA provided a valid (there are no required population-based assumptions that may be violated by data), exact Type I error rate; a normed measure of classification accuracy relative to chance (ESS) for the specific data at hand; and a statistical model which explicitly maximizes (weighted) classification accuracy for the sample. Conventional statistical methods are rarely valid, but UniODA is always exact. Conventional methods omit classification accuracy from their formulation, but UniODA identifies the model which explicitly maximizes classification accuracy for the sample. There is little rational motivation to continue using conventional suboptimal methods to perform approximate statistical analyses.[2,3]

References

[1]Appleton DR (1995). Pitfalls in the interpretation of studies: III. *Journal of the Royal Society of Medicine, 88*, 241-243.

[2]Yarnold PR, Soltysik RC (2005). *Optimal data analysis: A guidebook with software for Windows*. Washington, DC: APA Books.

[3]Yarnold PR, Soltysik RC (2010). Optimal data analysis: A general statistical analysis paradigm. *Optimal Data Analysis*, *1*, 10-22.

[4]Soltysik RC, Yarnold PR. (2013). MegaODA large sample and BIG DATA time trials: Separating the chaff. *Optimal Data Analysis*, 2, 194-197.

[5]Soltysik RC, Yarnold PR (2013). MegaODA large sample and BIG DATA time trials: Harvesting the wheat. *Optimal Data Analysis*, 2, 202-205.

[6]Yarnold PR, Soltysik RC (2013). MegaODA large sample and BIG DATA time trials: Maximum velocity analysis. *Optimal Data Analysis*, 2, 220-221.

[7]UniODA analysis was accomplished using the following MegaODA code (commands are indicated in red; non-directional exploratory analysis is conducted as there was no *a priori* hypothesis):

```
open data;
output migraine.out;
vars group attacks;
data;
1 0 (repeated 13 times)
1 1 (repeated 9 times)
1 2 (repeated 4 times)
1 3 (repeated 2 times)
1 4 (repeated 1 time)
1 5 (repeated 1 time)
1 6 (repeated 3 times)
2 0 (repeated 5 times)
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```
2 1 (repeated 13 times)
2 2 (repeated 6 times)
2 3 (repeated 1 time)
2 4 (repeated 2 times)
2 5 (repeated 3 times)
2 6 (repeated 3 times)
2 7 (repeated 1 time)
end;
class group;
attr attacks;
mcarlo iter 25000;
loo;
go;
```

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