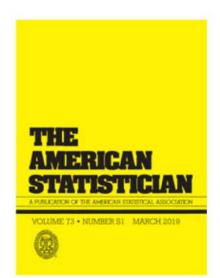




Second-Generation *p*-Values in a High Dimensional Analysis of Prostate Cancer Variants

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An Introduction to Second-Generation *p*-Values

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ABSTRACT

Second generation *p*-values preserve the simplicity that has made *p*-values popular while resolving critical flaws that promote misinterpretation of data, distraction by trivial effects, and unreproducible assessments of data. The second-generation *p*-value (SGPV) is an extension that formally accounts for scientific relevance by using a composite null hypothesis that captures null and scientifically trivial effects. Because the majority of spurious findings are small effects that are technically nonnull but practically indistinguishable from the null, the second-generation approach greatly reduces the likelihood of a false discovery. SGPVs promote transparency, rigor and reproducibility of scientific results by a priori identifying which candidate hypotheses are practically meaningful and by providing a more reliable statistical summary of when the data are compatible with the candidate hypotheses or null hypotheses, or when the data are inconclusive. We illustrate the importance of these advances using a dataset of 247,000 single-nucleotide polymorphisms, i.e., genetic markers that are potentially associated with prostate cancer.

ARTICLE HISTORY

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KEYWORDS

Likelihood ratios; Null hypothesis; p-Value; Statistical evidence

Typical concerns with standard p-value approaches

- Statistical significance ≠ clinical or practical significance
- Large p-values do not indicate support for the null hypothesis
- *p*-value adjustments for multiple comparisons
 - Often conservative
 - No universal solution
- Ranking findings by p-value may miss interesting large effects

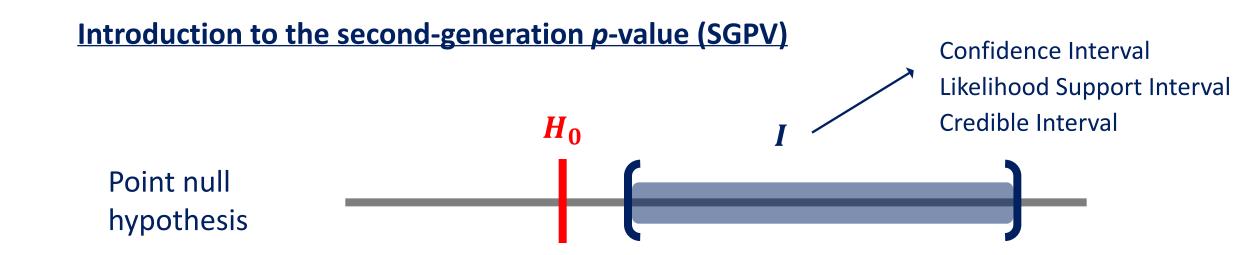
Alternatives

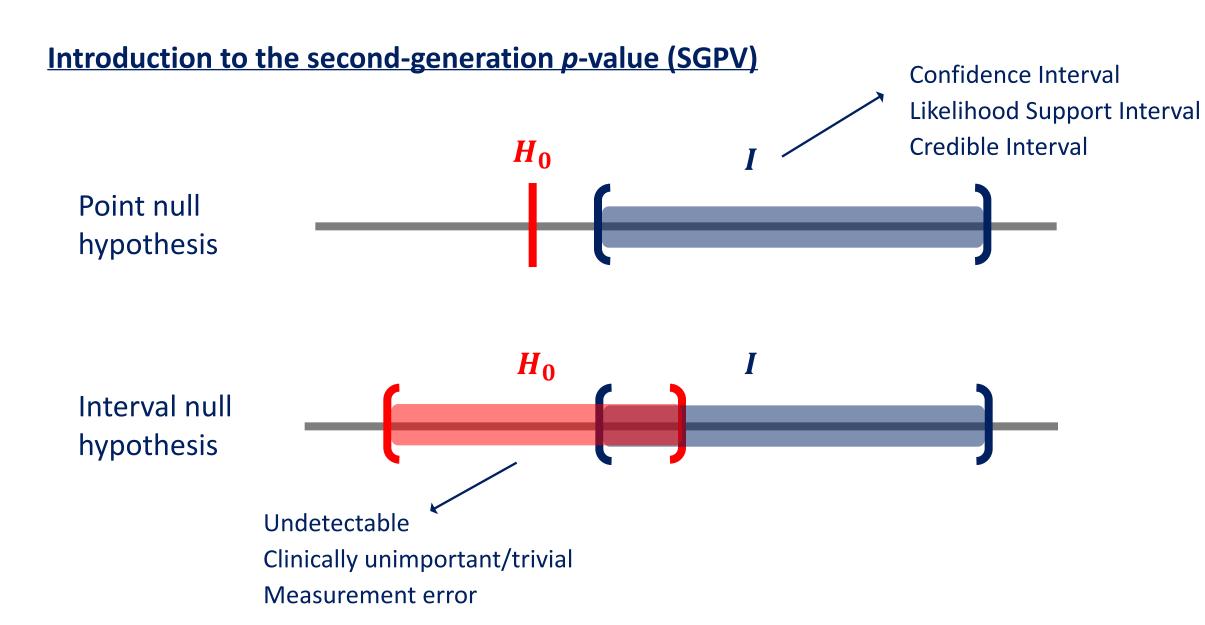
- Consider an interval null hypothesis
- Differentiate between when the data support:
 - Only alternative hypotheses
 - Only null hypotheses
 - Null and alternative hypotheses (inconclusive)
- Type I Error rate shrinks as the sample size increases
- Rank findings by clinical and statistical importance

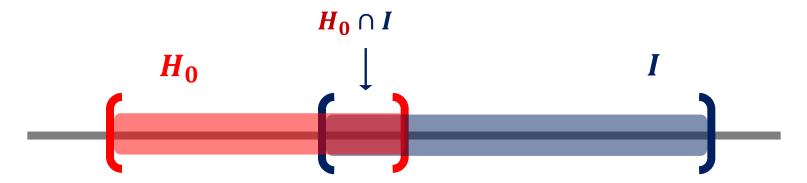
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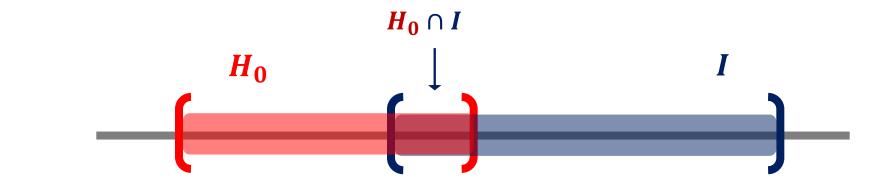
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second-generation *p*-value









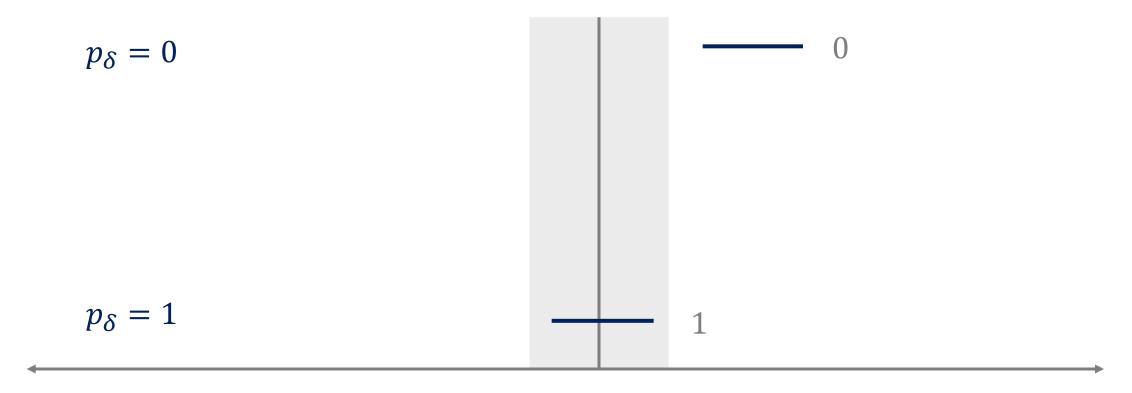
$$p_{\delta} = \frac{|I \cap H_0|}{|I|} \times \max\left\{\frac{|I|}{2|H_0|}, 1\right\}$$

Proportion of data-supported hypotheses that are also null hypotheses

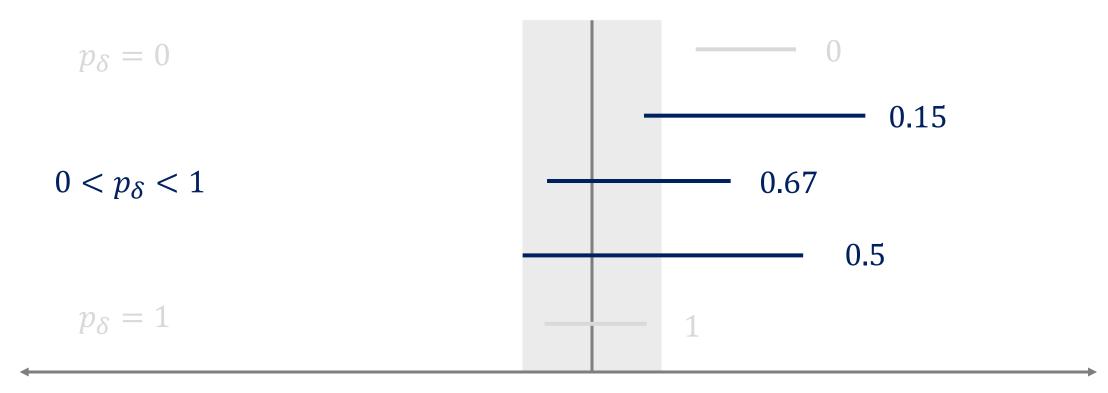
Small-sample correction factor

shrinks proportion towards $\frac{1}{2}$ when |I| is greater than $2|H_0|$

 Provides a single-number summary of when the data support only null effects, only meaningful alternative effects, or are inconclusive

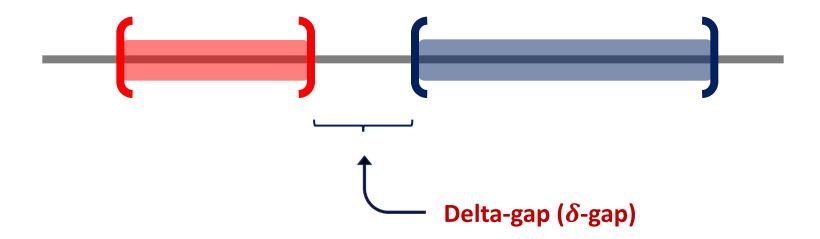


 Provides a single-number summary of when the data support only null effects, only meaningful alternative effects, or are inconclusive



Ranking second-generation *p*-values

• When $p_{\delta}=0$, there is a gap between the intervals. The length of that gap is the delta-gap



Allows refined differentiation among findings

Example with prostate cancer variants

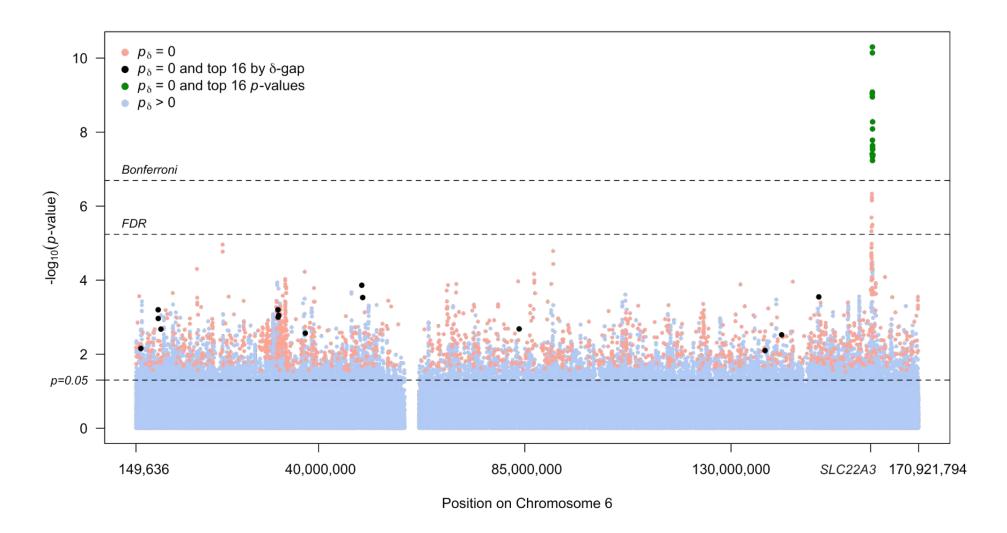
 International Consortium for Prostate Cancer Genetics (Schaid and Chang 2055; ICPCG 2018)

- $\sim 3,900 \text{ subjects } (2,500 \text{ cases } \& 1,400 \text{ controls})$
- $\succ \sim 247,000$ single-nucleotide polymorphisms (SNPs) from Chromosome 6

Goal: Identify 'interesting' SNPs potentially associated with prostate cancer

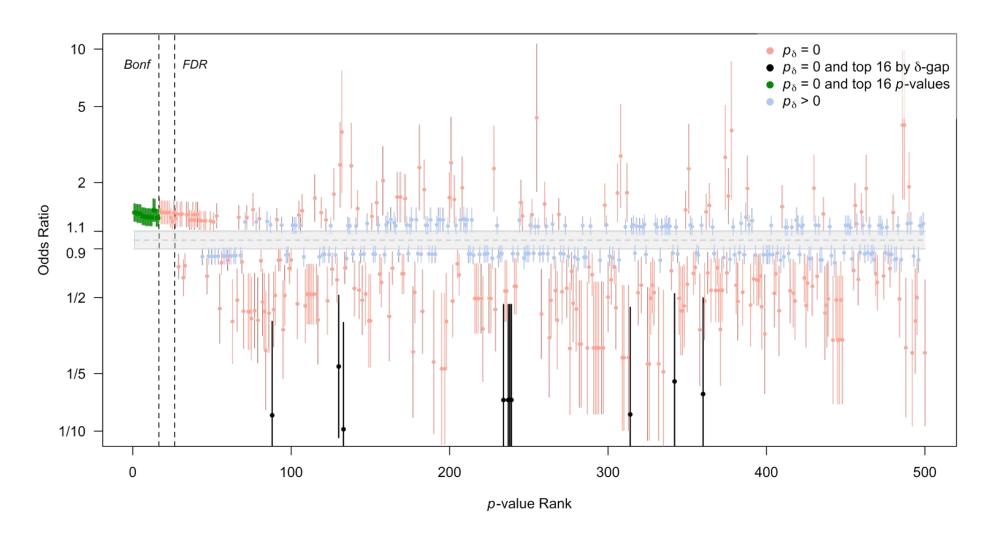
$$H_0: OR \in [0.9, 1.11]$$

Manhattan Plot

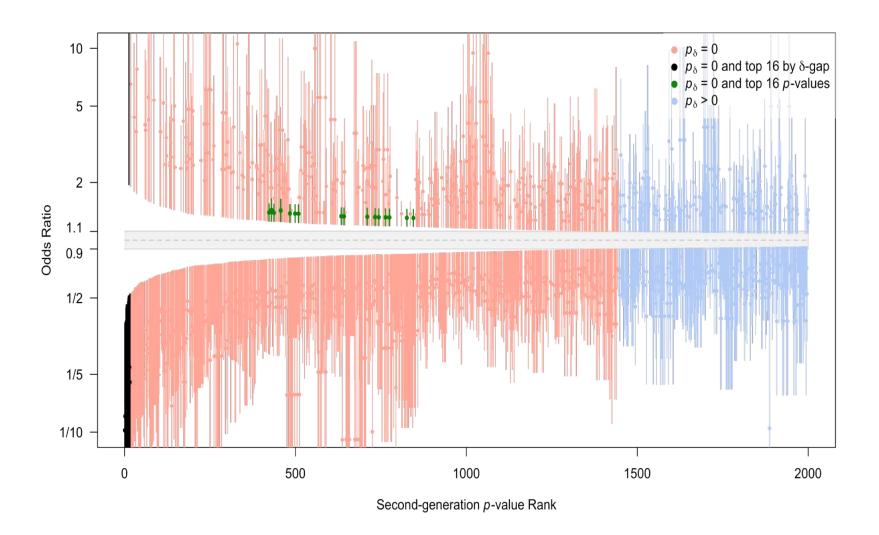


Second-generation *p*-values Welty, ENAR 2019

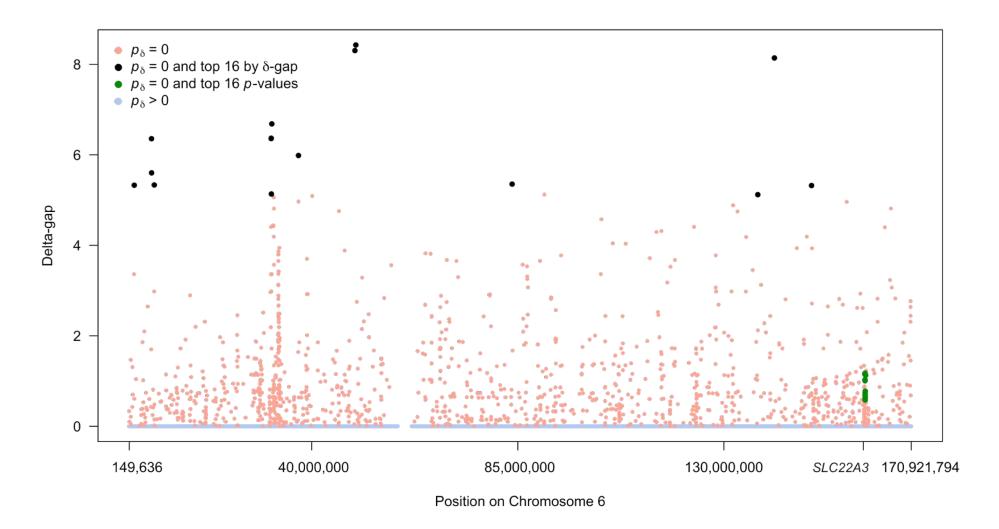
Top 500 support intervals by p-value ranking



Top 2,000 support intervals by SGPV ranking



SGPV Manhattan plot



Discussed in papers (Blume et al. 2018, Blume et al. 2019)

- SGPV error rate profile
 - ➤ Both Type I and II Error rates converge to 0 with sample size
- False discovery rate profile
 - ➤ Maintains FDR improvement associated with multiple comparisons adjustments while lowering the false confirmation rate

Ongoing work

- SGPV false discovery rates (FDR_{δ})
 - > Estimation methods
 - \triangleright Rank SGPV findings by FDR_{δ}

Recommendations

- Report all finding where $p_{\delta}=0$ and $p_{\delta}=1$ ("discoveries" and "confirmations")
- Identify top findings among those with $p_{\delta}=0$ by large delta-gaps or low FDR_{δ} values
 - Prioritizes clinical impact over precision
 - Incorporates reliability of findings
 - \rightarrow Above set of findings is very different from those of classical p-value approaches
- R package available at github.com/weltybiostat/sgpv

sgpvalue plotsgpv sgpower fdrisk

Support and References

TREAT Research Group (Dept. of Thoracic Surgery) and Statistical Evidence in Data Science (SEDS) Lab

- Thomas Stewart
- Megan Hollister

Blume JD, Greevy RA, Welty VF, Smith JR, Dupont WD (2019) An Introduction to Second-Generation *p*-Values, The American Statistician, 73:sup1, 157-167, DOI: 10.1080/00031305.2018.1537893

Blume JD, D'Agostino McGowan L, Dupont WD, Greevy RA Jr (2018) Second-generation *p*-values: Improved rigor, reproducibility, & transparency in statistical analyses. PLoS ONE 13(3): e0188299. https://doi.org/10.1371/journal.pone.0188299