Developing new practices for increasing transparency in social science research

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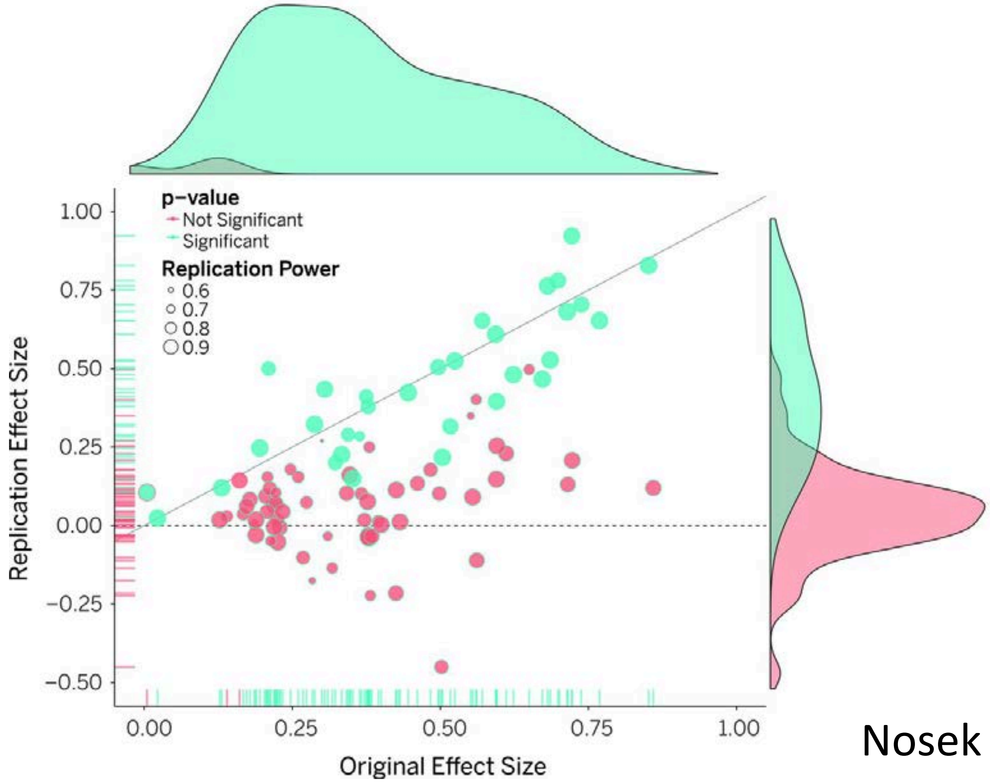
Outline

- Reproducibility crisis
- Study 1: Theoretical
- Study 2: Empirical (subjective judgment)
- Conclusion

Reproducibility Crisis

- Nosek et al. (2015) found that the results from about 100 studies, using original data, could not be replicated
  - 97% percent of original studies had significant results ($P < .05$).
  - Only 36% percent of replications had significant results



Nosek et al. (2015)

How better to evaluate design and results of studies?

- Empirical distributions, or data occurring ‘in the wild’, is often non-normal
- Yet there is no statistically robust way of quantifying the extent of non-normality between two such distributions
- Additionally, simulation studies often attempt to investigate the extent of non-normality on a certain phenomenon

Conflicting definitions of non-normality

	Values	Method of simulation
Woods, 2008	Skewness = 1.57 Kurtosis = 3.52	Mixture of two normal distributions (M1 = −0.253, M2 = 2.192, S1 = 0.609, S2 = 1.045, mp1 = .897, mp2 = .103)
Preston & Reise, 2014	Skewness = 1.75 Kurtosis = 6.75	Mixture of normal distributions Bimodal (M1 = 21.5, M2 = 3.0, S1 = 0.7, S2 = 1.5, mp1 = 1.0, mp2 = 0.7)
Savalei, 2010	Skewness = 2 Kurtosis = 7	Fleishman (1978) method
Enders, 2001	Moderate nonnormality: Skewness=1.25 Kurtosis = 7.0 Extreme nonnormality: Skewness=3.25 Kurtosis= 20.0	(Fleishman, 1978; Vale & Maurelli, 1983)

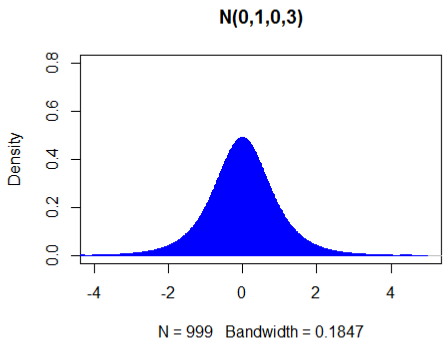
Theoretical

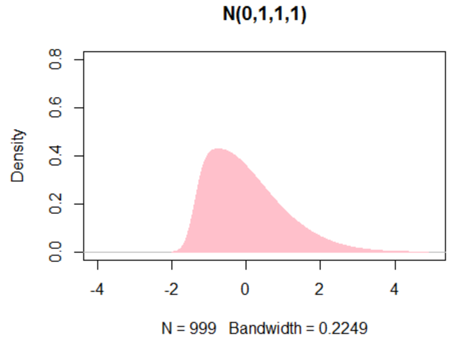
- Goal: to evaluate a suite of theoretical distances, as applied to constructed non-normal distributions

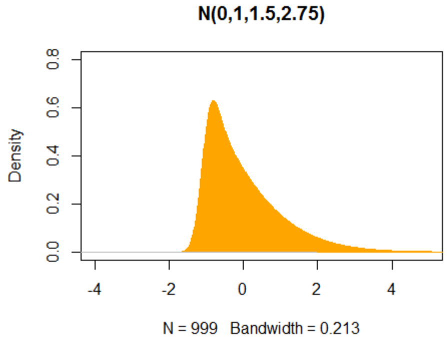
- Using the Fleishman (1978) method of constructing non-normal distributions, we simulate 107 distributions of the form F~(0,1,x,y))

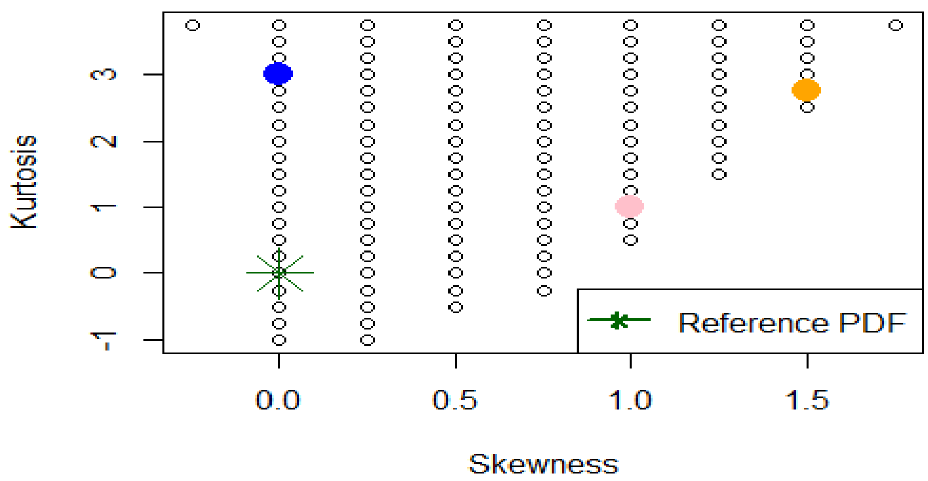
- x = Skewness: ranged from [-0.25, 1.75]
- y = Kurtosis: ranged from [-1, 3.75]

Theoretical





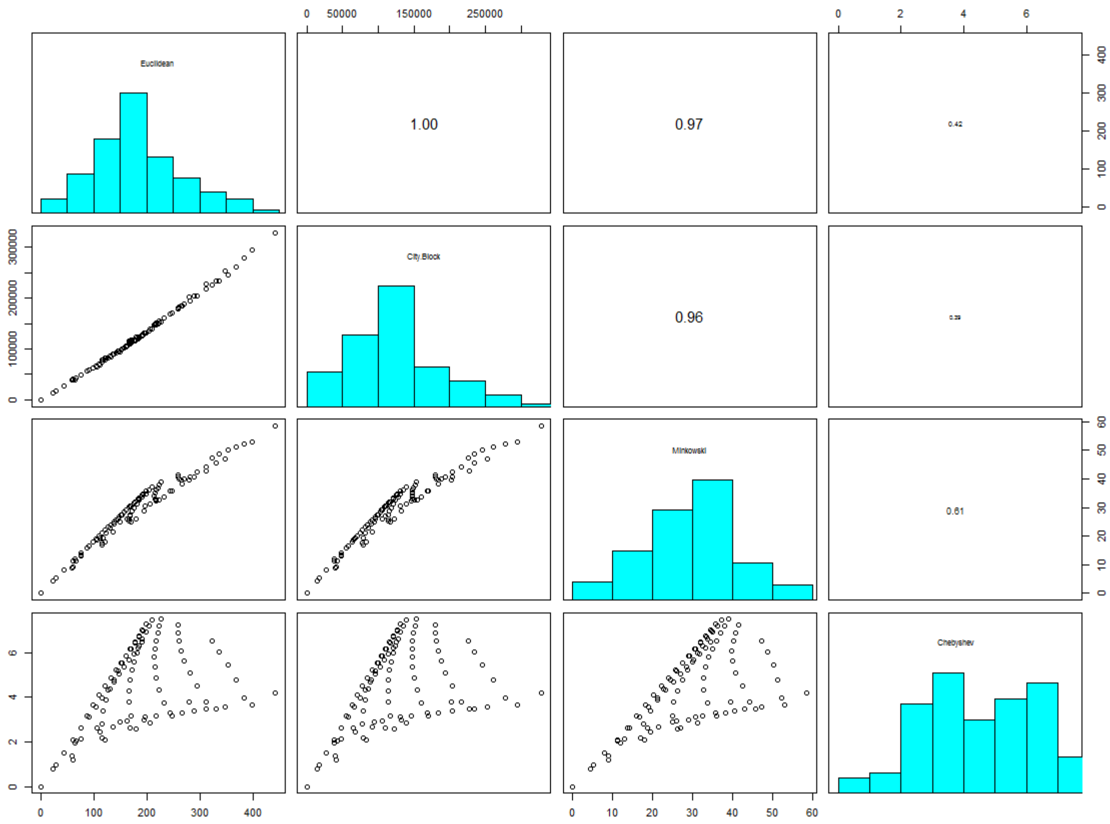




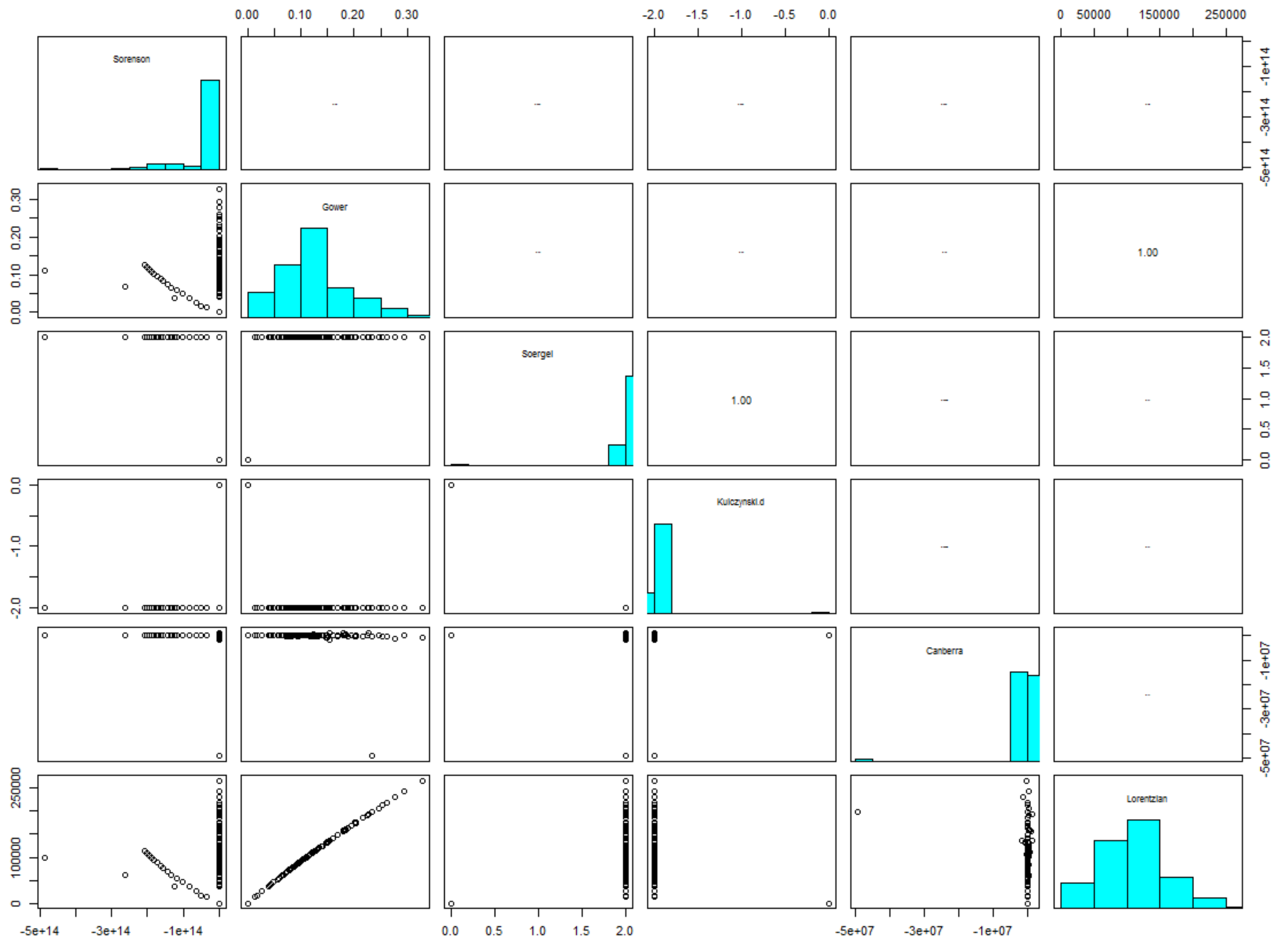
Theoretical

- Using 17 measure s from 3 classes, we calculated the distance between 107 non-normal distributions and the standard normal, X~N(0,1,0,0).
  - Minkowski (includes Euclidean, Chebyshev distance)
  - L1 (includes Sorenson)
  - Intersection (includes WavesHedges)

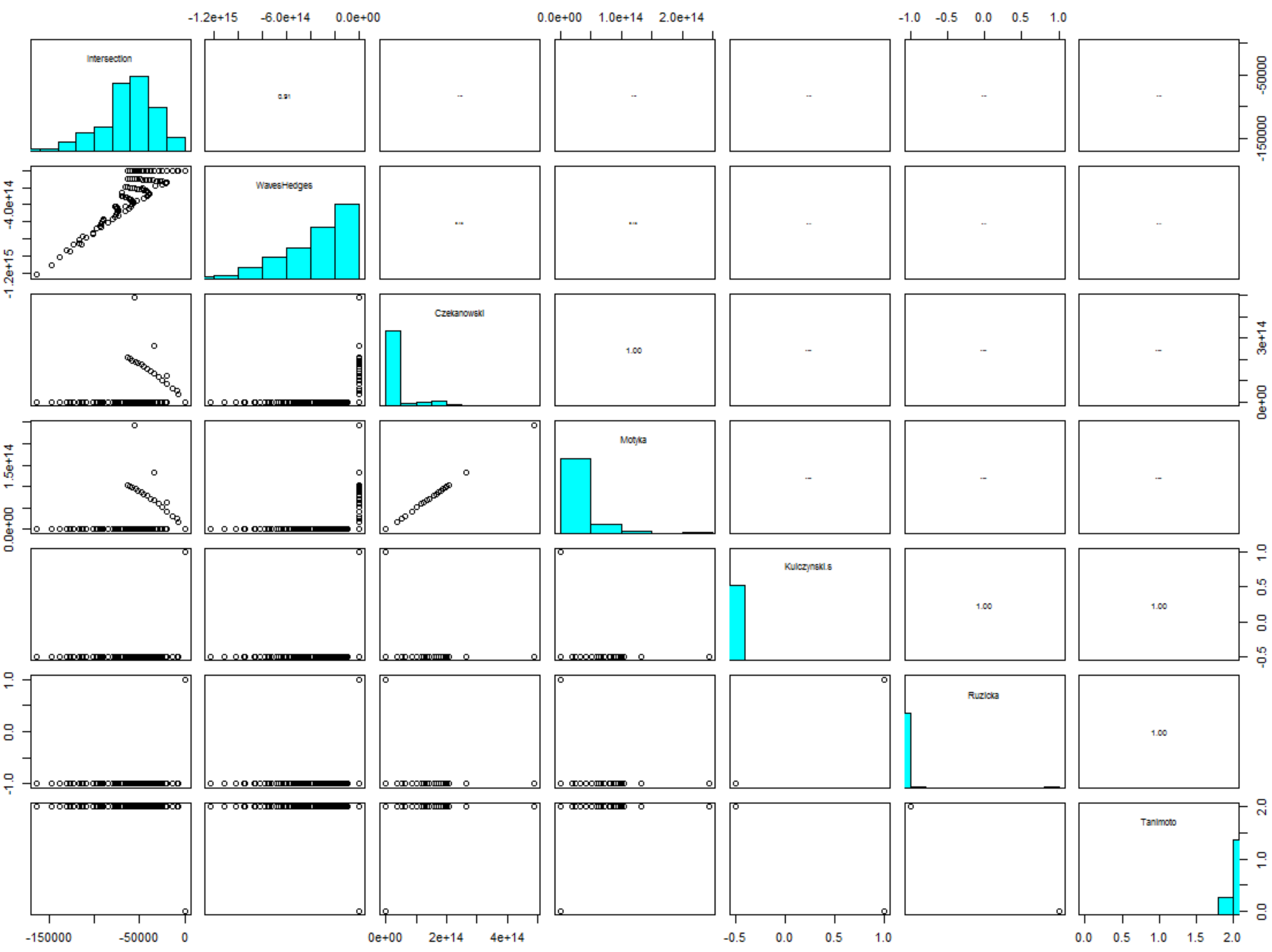
Theoretical (Minkowski)



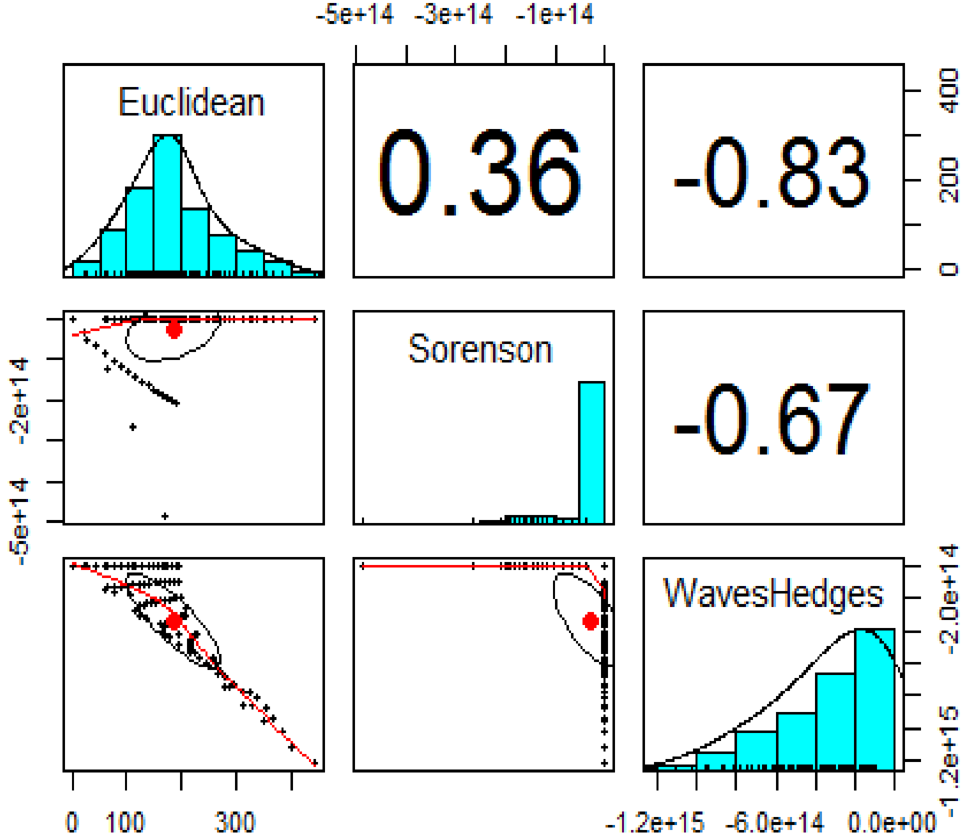
Theoretical (Lp family)



Theoretical (Intersection Family)



Theoretical (summary)



Theoretical

- The intra-class distance measures exhibit little agreement with each other, with some measures appearing to be minimally affected by skewness and kurtosis
- To more clearly delineate a ‘new’ grouping of distances based on their sensitivity to skewness and kurtosis, polynomial regression was conducted:

$$Distance = Intercept + Skewness + Kurtosis + Skewness^2 + Kurtosis^2 + Skewness * Kurtosis$$

Prescribed Taxonomy

Distance	Int	Skew	Kurt	Skew^2	Kurt^2	Skew*Kurt	R^2
Euclidean	1	1	0	1	1	1	0.93
City.Block	1	1	0	1	1	1	0.94
Minkowski	1	1	0	1	1	1	0.9
Chebyshev	1	1	1	1	1	0	0.92
Sorenson	1	1	0	1	0	0	0.42
Gower	1	1	0	1	1	1	0.94
Soergel	1	0	0	0	0	0	0.06
Kulczynski.d	1	0	0	0	0	0	0.06
Canberra	0	0	0	0	0	0	0.58
Lorentzian	1	1	0	1	1	1	0.93
Intersection	1	1	0	1	1	1	0.94
WavesHedges	0	1	1	1	1	1	0.98
Czekanowski	1	1	0	1	0	0	0.42
Motyka	1	1	0	1	0	0	0.42
Kulczynski.s	1	0	0	0	0	0	0.06
Ruzicka	1	0	0	0	0	0	0.06
Tanimoto	1	0	0	0	0	0	0.06

Variance Explained Taxonomy

x	Int	Skew	Kurt	Skew^2	Kurt^2	Skew*Kurt	R^2
Euclidean	1	1	0	1	1	1	0.93
City.Block	1	1	0	1	1	1	0.94
Minkowski	1	1	0	1	1	1	0.9
Gower	1	1	0	1	1	1	0.94
Lorentzian	1	1	0	1	1	1	0.93
Intersection	1	1	0	1	1	1	0.94
Sorenson	1	1	0	1	0	0	0.42
Czekanowski	1	1	0	1	0	0	0.42
Motyka	1	1	0	1	0	0	0.42
Chebyshev	1	1	1	1	1	0	0.92
Canberra	0	0	0	0	0	0	0.58
WavesHedges	0	1	1	1	1	1	0.98

The Soergel, Kulczynski.d, Kulczynski.s, Ruzicka, and Tanimoto were predicted only by the intercept, $R^2 = 0.06$

Theoretical: Summary

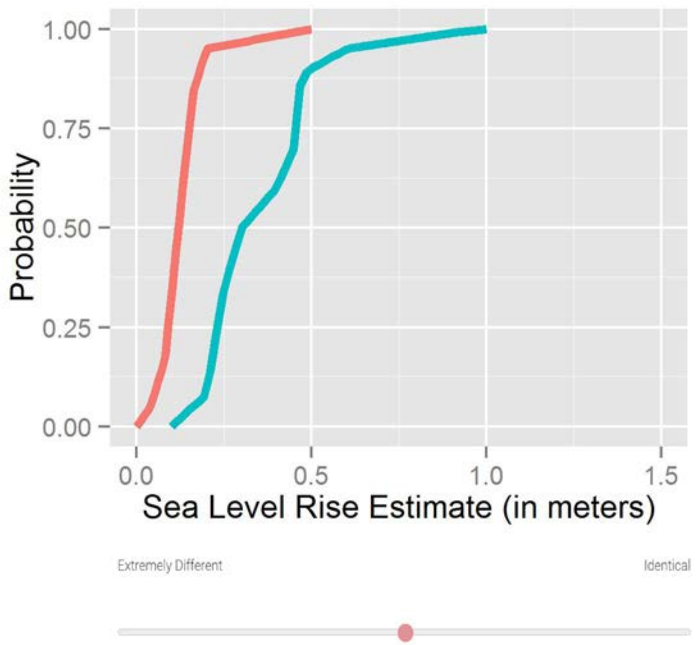
- Theoretical distances do not cleanly map onto the non-normal distributions of varying skewness and kurtosis
- The distances are, in some cases, completely insensitive to these moments
- A variance explained taxonomy of distances reveals very different groupings than the theoretical classes

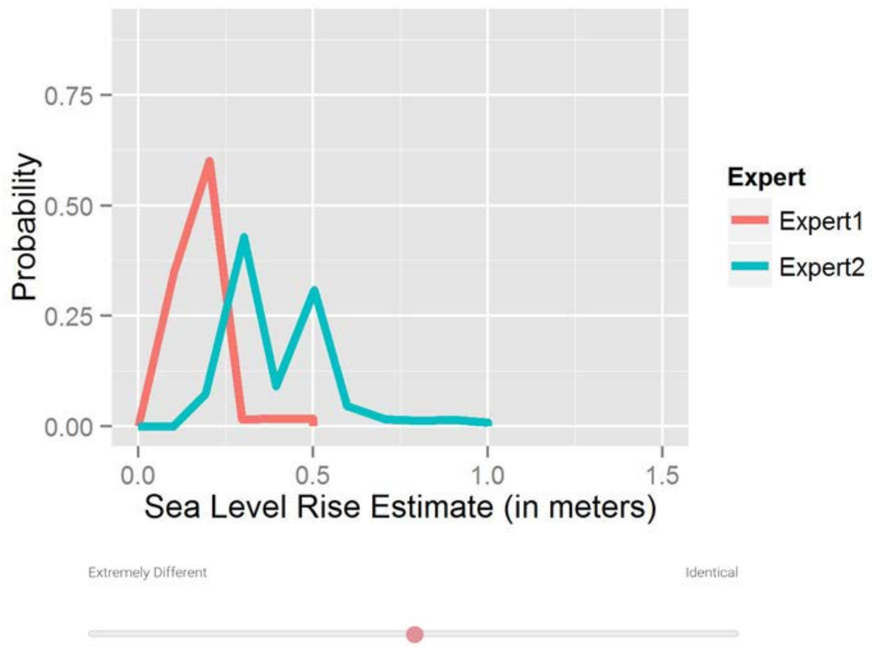
- Future work: more distance classes, different ways of producing non-normal distributions (e.g., mixture proportions), different distribution parameters (hyper-moments, tail weights)

Empirical (psychophysical)

- How well can laypeople distinguish differences between distributions?
- Thomas et al (2015) asked 6 experts their assessment of sea level rise in the year 2050.
- Using two display formats (cumulative distribution functions and probability density functions), we asked laymen to evaluate their perceived distance between two experts

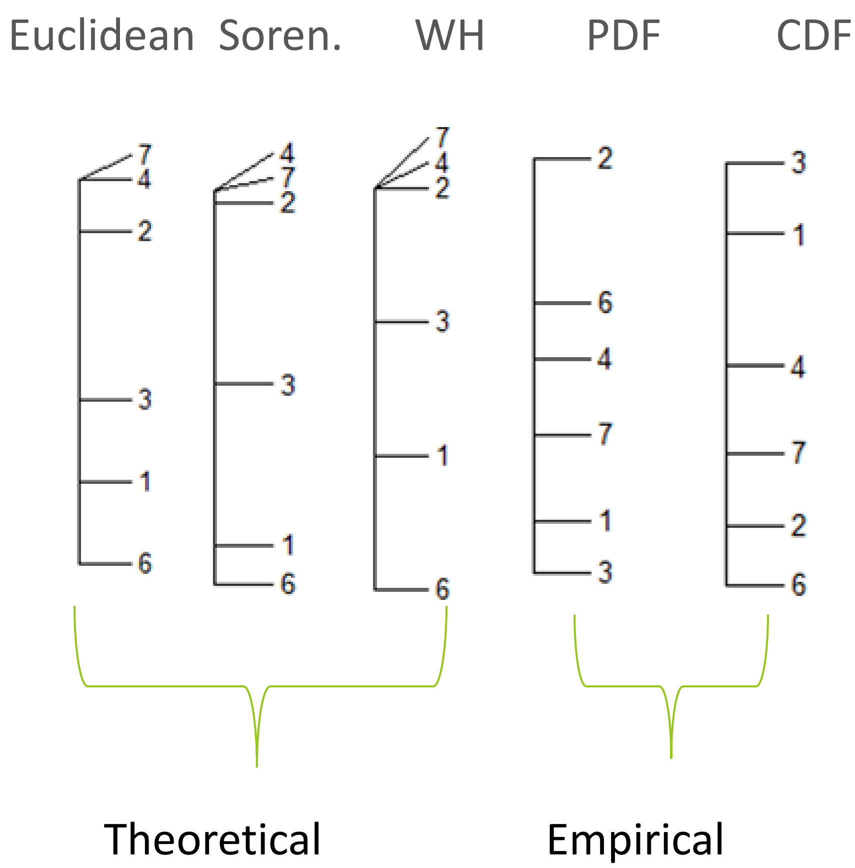
Experiment Display





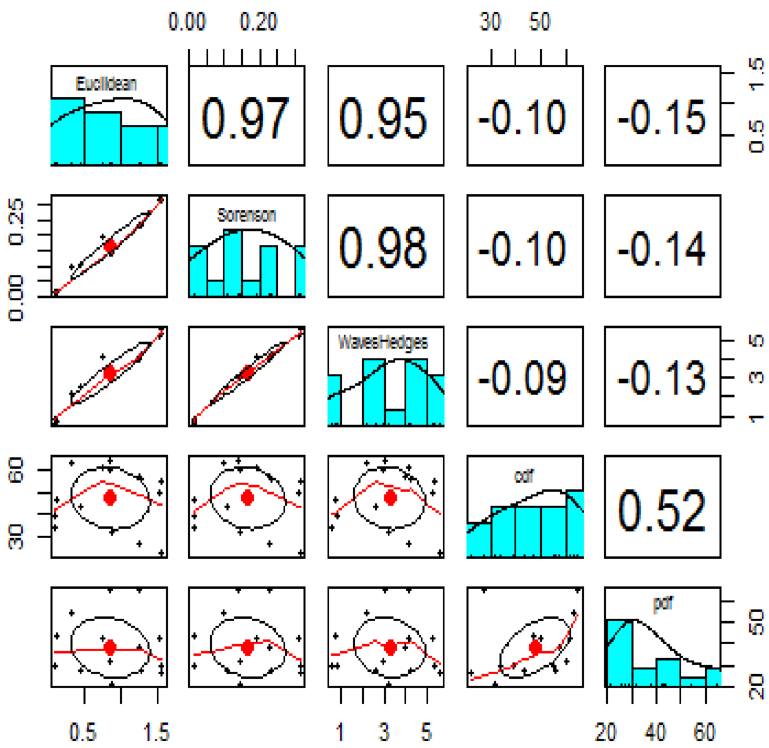
Empirical

- Unidimensional scaling of the theoretical distances (same used in Study 1) and the median subjective judgments (pdf and cdf)



Empirical

- The theoretical metrics agree on the clustering of expert judgments
- The empirical metrics have moderate agreement



Conclusion

- Theoretical metrics perform non-uniformly when assessing the extent of systematic deviance from a standard normal distribution
- In the empirical study, we found (a) high agreement between theoretical metrics, (b) moderate agreement (r=0.5) between empirical judgments based on pdfs and cdfs, and (c) low agreement between empirical judgments and the theoretical metrics
- Psychophysical methods do not agree with purely statistical methods
- Future experiments will use theoretical distributions (as in those generated by the Fleishman method) to compare more directly psychophysical and statistical judgments

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Theoretical Distance Formulas

- Euclidean (of the Minkowski family)- "straight-line" metric distance

$$d_{Euc} = \sqrt{\sum_{i=1}^{d} | P_i - Q_i |^2}$$

- Sorenson (of the L_1 family) – a proportion coefficient of overlap that is semi-metric (can have two distinct points with a distance of 0); more sensitive to outliers

$$d_{sor} = \frac{\sum_{i=1}^{d} | P_i - Q_i |}{\sum_{i=1}^{d} (P_i + Q_i)}$$

- WavesHedges (of the Intersection family) – metric distance used as a measure of overlap; sensitive to histogram binning
-

$$d_{WH} = \sum_{i=1}^{d} \left(1 - \frac{\min(P_i, Q_i)}{\max(P_i, Q_i)}\right)$$

$$= \sum_{i=1}^{d} \frac{| P_i - Q_i |}{\max(P_i, Q_i)}$$