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Some Problems and Solutions in the Experimental Science of Technology: The Proper Use and Reporting of Statistics in Computational Intelligence, with an Experimental Design from Computational Ethnomusicology

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Some Problems & Solutions in the Experimental Science of Technology

The Proper Use and Reporting of Statistics in Computational Intelligence, with an experimental design from Computational Ethnomusicology

Systems Science Seminar Series

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Outline

- Statistics, the Scientific Method & Critical Thinking
- Misuse of Statistical Techniques
- Statistical Significance & Statistical Power
- Problems with Statistical Significance
- What To Do?
- Cross-Validation and Related Techniques
- Dissertation Research, Data & Experimental Design

Why is Statistics Important?

- The science of Science
- Critical thinking
- Social responsibility

“ Statistical thinking will one day be as necessary for efficient citizenship as the ability to read and write.” H. G. Wells

Portland State UNIVERSITY

Critical Thinking

- Cognitive Psychology
- Philosophy
- Quantitative Literacy
- Information Literacy
- Cultural & Intercultural Competence

The Scientific Method

- Three components from ancient Greeks, Indians, Arabs, and late-Medieval/Renaissance Europe
  - Logic (resolution & composition)
  - Experimentation (measurement & repetition)
  - Theory (Greek & Arabian works)

The Scientific Method

- Early Version
    - Observation
    - Hypothesis
    - Testing
    - Reformulation or Conclusion

The Scientific Method

- The Modern Scientific Method
  - Accuracy
  - Objectivity
  - Skepticism
  - Open-mindedness

Parsimony (Skepticism) and Goodness-of-Fit

- Occam's Razor
- Laplace's principle of insufficient reason
- Einstein
- Newton's position on hypotheses
- Lendaris/Stanley conjecture

The Scientific Method

- Additional Elements for Reliable Experimentation
  - Randomization & Blocking
  - Bootstrapping
  - Double-Blinding
  - Factorial Design

Misuse of Statistical Techniques in Science, Medicine and Technology

- Hastie/Tibshirani/Friedman (2011) ‘The Elements of Statistical Learning’
- Siegfried (2010) *Science News*
- Ziliak/McCloskey (2008) ‘The Cult of Statistical Significance’
- Ioannidis (2005) *PLoS Medicine*
- Miller (2004) *The Journal of Systems and Software*
- Zucchini (2000) *Journal of Mathematical Psychology*
- Forster (2000) *Journal of Mathematical Psychology*
- Salzberg (1997) *Data Mining and Knowledge Discovery*
- Prechelt (1996) *Neural Networks*
- Flexer (1996) *Cybernetics and Systems*
- Holte (1993) *Machine Learning*

Misuse of Statistical Techniques in Model Evaluation

- Miller (2004), Zucchini (2000) & Salzberg (1997): multiplicity effect
- Salzberg (1997): nonexistent patterns
- Prechelt (1996)
  - 200 NN papers
  - 29 % not on real-world problems
  - Only 8 % with more than one alt. hypothesis
- Flexer (1996)
  - Only 3 out of 43 leading-journal NN papers used a holdout set.
- Hastie, Tibshirani, Friendman: cross-validation errors in top-rank journals
- Holte (1993): significance by accident (UCI repository)
- Ziliak (2008): 80% equate st.sig. with importance

Multiplicity/Bonferroni Example

Design:

- 14 algorithms on 11 data sets
- Those 154 combinations compared to a default classifier
- Two-tailed paired *t* test with $p < 0.05$

Problem:

- At least 99.96 % chance of incorrectly claiming statistical significance

Demo Example: the Math

154 chances to be significant.
Expected number of significant results = 154 * 0.05 = 7.7

Alpha* = P(finding at least one difference | there is no difference)
(1 – Alpha*) = P(right conclusion per experiment)
(1 – Alpha*)^n = P(making no mistakes)

Real alpha = 1–[(1 – Alpha*)^n] = 0.0003

What's Involved and What Can Be Done

- Hypothesis Testing ?
- Statistical Significance, Statistical Power & Conf. Int.
- Meta-Significance ?
- Cross-Validation, the Jackknife & the Bootstrap
- AIC, BIC, TIC, NIC, etc. (information criteria)
- Minimum Description Length (MDL)
- The Bayesian framework

Statistical Significance

- Hypothesis Testing
  - Do different treatments produce different outcomes?
  - Not feasible to study entire populations.
  - Sampling introduces uncertainty.
  - Need a measure of how much to trust results.
- Type-1 Error: no underlying difference, but observed
  - The likelihood of type-I errors is the p value. (reported)
  - α threshold must be set in advance!

Statistical Power

- Type-2 Error: difference, but not observed.
- P(Type-2 Error) $\equiv \beta$
- Typically, $\beta \leq 20$, an 80% chance of detecting a stated magnitude of difference (effect size).
- $(1 - \beta)$ is called statistical power. (controllable)
- Out of 86 clinical studies
  - 5 described power/sample size
  - 59 reported not-significant results
  - 21 of those lacked power to detect even large effects
  - In 57 studies, sample sizes ~ 15% of necessary power.

Significance & Power

- Ideal statement of the type:

  "There is at least an 80% likelihood that, had there been a 30% difference between groups, we would have found that difference with a value of *p* of less than 0.05."

- Online and other-software calculators exist.
- Find power, given sample size, α and effect size.
- Find sample size, given desired power , α and effect size.

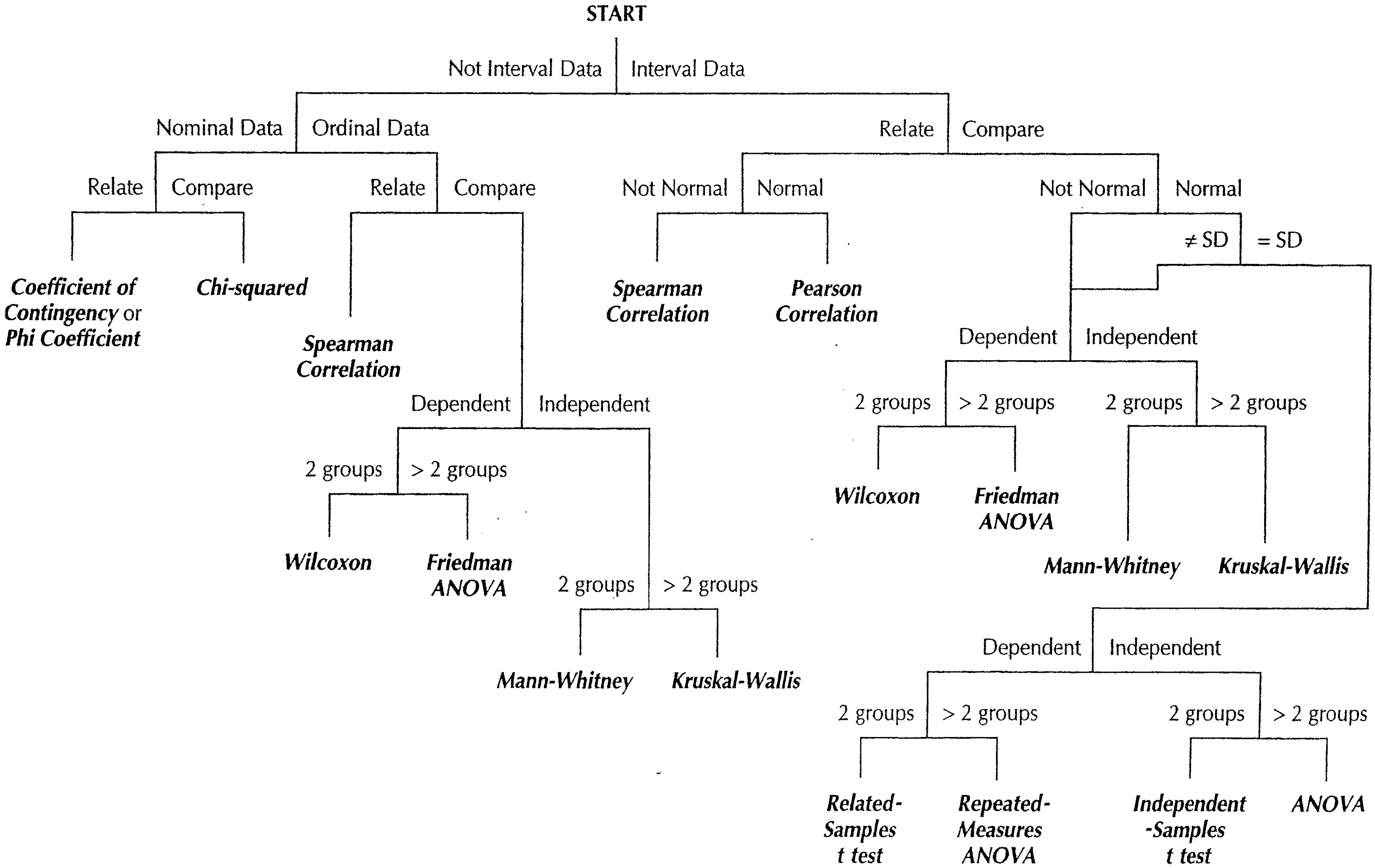
Meta-Significance & Other Problems

- Is statistical significance itself statistically significant?
- The standard 0.05 and 0.01 thresholds are arbitrary.
- Not the same as practical significance.
- Publication bias
- Encourages dismissal of observed differences in favor of the null.
- Regression to the mean (Tversky/Kahneman, 1971)
- Using a single *p* value from a single study is irrational.
- If not significant, maybe study wasn't powerful enough to find a small effect.

What To Do?

Even more important to understand what we're doing and what it means.

- Correct methodology
  - Choice of Tests: ANOVA, Wilcoxon, …
  - Design: Cross-Validation, Bootstrap, …
  - Selection Criteria: penalty schemes (AIC, BIC, …)
- Sufficient data
- Checking assumptions against requirements
- Careful interpretation
- Suspension of judgment when appropriate



START

- Not Interval Data
  - Nominal Data
    - Relate
      - ***Coefficient of Contingency*** or ***Phi Coefficient***
    - Compare
      - ***Chi-squared***
  - Ordinal Data
    - Relate
      - ***Spearman Correlation***
    - Compare
      - Dependent
        - 2 groups
          - ***Wilcoxon***
        - > 2 groups
          - ***Friedman ANOVA***
      - Independent
        - 2 groups
          - ***Mann-Whitney***
        - > 2 groups
          - ***Kruskal-Wallis***
- Interval Data
  - Relate
    - Not Normal
      - ***Spearman Correlation***
    - Normal
      - ***Pearson Correlation***
  - Compare
    - Not Normal
      - Dependent
        - 2 groups
          - ***Wilcoxon***
        - > 2 groups
          - ***Friedman ANOVA***
      - Independent
        - 2 groups
          - ***Mann-Whitney***
        - > 2 groups
          - ***Kruskal-Wallis***
    - Normal
      - ≠ SD
      - = SD
        - Dependent
          - 2 groups
            - ***Related-Samples t test***
          - > 2 groups
            - ***Repeated-Measures ANOVA***
        - Independent
          - 2 groups
            - ***Independent-Samples t test***
          - > 2 groups
            - ***ANOVA***

Cross-Validation

- What is it?
- What types are there?
- What are related techniques and equivalencies?
- What are the alternatives?

Cross-Validation: What is it?

The use of separate data sets for training, tuning and assessment.

Cross-Validation: What types are there?

- Holdout (basic)
- Multifold (*k*-fold, Geisser, 1975)
- Leave-One-Out (LOO)

Cross-Validation: Related techniques

- The Bootstrap
- The Jackknife

Cross-Validation: Equivalences & Performance

- Holdout → unbiased estimate of generalization performance.
- AIC, LOO & Bootstrap → asymptotically equivalent, except
    - LOO degrades as *n* increases.
    - LOO overfits in model selection.
- *k*-fold Cross-Validation superior to Holdout & LOO.
- 10-fold is better than any Bootstrap, but Stratified is best.
- Use lower *k* with plentiful data; higher *k* with few data.
- BIC > AIC for model selection when data plentiful.

Alternatives: Penalty Schemes

- AIC (an information criterion, or Akaike inf. criterion)
- BIC
- others (Takeuchi's TIC, etc.)

Alternatives: Penalty Schemes

- AIC
- BIC (Bayes information criterion, or Schwartz inf. criterion)
- others (Takeuchi, et al.)

The Bayesian Framework is not discussed here due to time constraints.

My Research

- Fields:
  - Computational Intelligence (Neural Networks)
  - Information Theory (RA)
  - Music Information Research (Computational Ethnomusicology)
- Populations:
  - 65536 binary attack-point rhythm vectors
  - The space of all MLPs and all prestructured MLPs
  - All RA-derived mathematical models partido-alto clave direction
- Variables of Interest:
  - Generalization performance on holdout data as measured by GGR
  - Explanatory power of RA models tempered by penalty factors
  - A random selection of vectors for representativeness & stat. power
  - Selection of human experts and non-experts

My Research

- Description of Samples:
  - One-hidden-layer fully connected MLPs
  - One-hidden-layer prestructured MLPs, selected according to OCCAM3 searches
  - Models of rhythm data selected according to heuristics and RA decision criteria (AIC, BIC, etc.)
  - RNG-ordering of vectors (traditional patterns added if missing)
  - 4 out of 7 local mid-level human experts on partido-alto clave direction for the "ceiling" benchmark
  - Self-selected convenience sample of available "clueless" human testers for the "floor" benchmark
- Description of Inference(s):

Based on factorial design, with batches of different random-number seeds:

  - Generalization performance of fully connected neural networks
  - Generalization performance of prestructured neural networks
  - Generalization performance of RA models
  - Generalization performance of mid-level experts (as guideline)
  - Generalization performance of clueless testers (as guideline)

Factors in Neural-Net Experimentation

- Output encoding
- Training/Test regimes
- Network-design parameters
    - Learning rate (step size) & momentum
    - Epoch size
    - Derivative offset
    - Number of hidden layers
    - Number of processing elements per hidden layer
    - Learning schedules
- Spatial Crosstalk (separate concepts in one network)
- Decision-making instruments
- Early-stopping
- Bumping and jogging network weights

My Data

- 2^16 = 65536 possible input patterns (idealized rhythms)
- Three musical-teaching contexts (teacher types) for classification
    - Lenient
    - Firm
    - Strict
- Four output classes
    - Incoherent
    - Forward
    - Reverse
    - Neutral
- Three membership degrees in each output class
    - Strong
    - Average
    - Weak

My Data

- “Firm” teacher context selected.
- Data stabilized July 4, 2010, with 10,811 vectors.
- Two types of holdout sets created
    - Standard (random) holdout
        - Design data: 8651
            - Strong: 4745
            - Average: 2010
            - Weak: 1896
        - Holdout data: 2160
    - Weak holdout
        - Design data: 8442
            - Strong: 5931
            - Average: 2511
        - Holdout data: 2369

Experimental Design

- Five-fold stratified cross-validation is the best approach to performance estimation.
- Minimum training-set size for good generalization (Haykin):
  - $N = O(W/\varepsilon)$
    - 20 hidden elements → O(4413) examples
    - 40 hidden elements → O(8813) examples
  - These numbers are beyond the notion of parsimony.
- NeuralWare NeuralWorks manual gives higher numbers for my set size.

Eight Choices or Actions

- Output encoding
- Training classes
- Testing classes
- Training membership degrees
- Testing membership degrees
- Thresholding (NN) or Fitting (RA)
- Controls
    - Randomization testing for NNs
    - Random "structure" for RA models
    - Human floor and ceiling
- Random-Number Initialization

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Questions & Discussion