Statistical Testing in NLP (II)

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Statistical variability in NLP

- How to trust experiment results, given many sources of variability?
 - How was the text data sampled?
 - How were the annotations sampled?
 - How variably do the human annotators behave?
 - How variable are the computational algorithms?
- Today: Variability due to small sample size

Text data variability

- Mathematically, the easiest case to analyze: What if we resampled the tokens/sentences/documents from a similar population as our current data sample?
- Assume units are sampled i.i.d.; then apply your favorite statistical significance/confidence interval testing technique
 - T-tests, binomial tests, ...
 - Bootstrapping
 - Paired tests
- For
 - I. Null hypothesis testing
 - 2. Confidence intervals

Null hypothesis test

- Must define a <u>null hypothesis</u> you wish to ~disprove
- pvalue = Probability of a result as least as extreme, if the null hypothesis was active
- Example: paired testing of classifiers with exact binomial test (R: binom.test)



Statistical tests

- Closed-form tests
 - t-tests, exact binomial test, chi-square tests....
- Bootstrapping
- All methods can give both p-values and confidence intervals

Bootstrapping

- Bootstrapped CI methods
 - Percentile
 - Standard error-based normal approx, etc.
- Theoretical guarantees (under various regularity conditions... for a slightly different CI method...):

$$\mathbb{P}(\theta \in C_n) = 1 - \alpha - O\left(\frac{1}{\sqrt{n}}\right)$$

- How many samples? 10,000-100,000
 (governs monte carlo error; can always make nearly 0)
- Paired bootstrap
- Bootstrapped p-values



Berg-Kirkpatrick et al. 2012

- Paired bootstrap test
 - (Subtle, debatable bug?)
- Stat. sig results may not transfer domains
- Researcher effects? Or is paired testing working correctly?



Figure 2: TAC 2008 Summarization: Confidence vs. Figure 3: CoNLL 2007 Dependency parsing: Confidence vs. ROUGE improvement on TAC 2008 test set for comparisons unlabeled dependency accuracy improvement on the Chinese between all pairs of the 58 participating systems at TAC 2008. CoNLL 2007 test set for comparisons between all pairs of the 21 participating systems in CoNLL 2007 shared task. Com-

Sec. 23 p-value	% Sys. A > Sys. B		
	Sec. 22	Sec. 24	Brown
0.00125 - 0.0025	97%	95%	73%
0.0025 - 0.005	92%	92%	60%
0.005 - 0.01	92%	85%	56%
0.01 - 0.02	88%	92%	54%
0.02 - 0.04	87%	78%	51%
0.04 - 0.08	83%	74%	48%

Table 1: **Empirical calibration:** p-value on section 23 of the WSJ corpus vs. fraction of comparisons where system A beats system B on section 22, section 24, and the Brown corpus. Note that system pairs are ordered so that A always outperforms B on section 23.

- Statistical significance != practical significance
- Cl width, statistical power, data size
- Many other confounds we don't have models for, but know can be very significant
 - Researcher bias
 - File-drawer bias
 - Generalization (e.g. across domains)
 - Tuning on test sets
 - Reusing test set over multiple papers