

Insights into p-values and Bayes Factors through False-Positive and False-Negative Bayes Factors

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Introduction

- Bayes Factor and p-values often lead to different conclusions about a null hypothesis
 - ◆ Example: GWAS of prostate cancer
 - ◆ Bayes Factors may be more theoretically-justified, but yield no insight about false positive or negative results
- I introduce the
 - ◆ False Positive and False Negative Bayes Factors
 - ◆ These are functions of the p-value and power vs. an alternative hypothesis
 - ◆ Their ratio is approximately the Bayes Factor
 - ◆ They help reveal the 2 SNP mutations declared positive that, with later data, are now known to be negative

Bayes Factor

$$BF = \frac{P(T = t_{obs} | H_0)}{P(T = t_{obs} | H_1)}$$

- ◆ Likelihood of observing the study data under the null to the alternative
- ◆ Based on $Posterior = P(H_0 | T = t_{obs})$
- ◆ Uses all the study information
- ◆ Has ancient history
 - Jeffreys, 1939
 - Lindley, 1957
 - Cox and Hinkley, 1974
 - Lindley and Scott, 1984

p-values

$$P(T > t_{obs} | H_0) \quad \text{vs.} \quad P(|T| > t_{obs} | H_0)$$

- Two major differences between Bayes Factors and p-values
 - ◆ P-values don't account for alternative hypotheses H_1
 - P-value may be small, but if the alternatives are even less likely, the p-value does not provide evidence against the null
 - ◆ P-values use tail probabilities, not the point of data observed
 - P-values consider more extreme values of the test statistic that are not observed. Seems irrelevant for drawing inferences from the value of the observed test statistic.

False Positive Report Probability



Sholom Wacholder

$$FPRP = P(H_0 | T > t_{obs})$$

- P-value spirit: use tail probability (1- or 2- sided)
 - ◆ Only uses the information: “Is the study significant?”
 - Doesn't use all the study data
 - ◆ Has long history:
 - Jeffreys (1939) – Bayesian interpretation of p-values
 - Morton (1955) -- LOD scores in linkage studies
 - Peto et al (1976) -- Interpret p-values from clinical trials
 - Lee and Zelen (2000) -- Determine sample size
 - Storey (2003) – Bayesian interpretation of False Discovery Rates
 - Wacholder et al (2004) -- Interpret p-values in data analyses

False Positive Bayes Factor

$$FPBF = \frac{P(T > t_{obs} | H_0)}{P(T > t_{obs} | H_1)} = \frac{p}{p_1}$$

- FPBF is the p-value divided by the “power”
 - ◆ “If I declare my study significant, how much evidence is there against the null hypothesis?”
 - $FPBF \leq 1$
 - ◆ “power” is computed after observing data; not unconditional frequentist power

False Negative Report Probability

$$FNRP = P(H_1 | T < t_{obs})$$

- Two decisions/mistakes are possible
 - ◆ Only uses the information: “Is the study not significant?”
 - ◆ Decision to declare significance is merely conventional, so both possibilities must be considered
 - ◆ Need to trade off with FPRP; complements FPRP
 - ◆ The Bayes Factor doesn't have a complement since

$$Posterior = P(H_1 | T = t_{obs}) = 1 - P(H_0 | T = t_{obs})$$

False Negative Bayes Factor

$$FNBF = \frac{P(T < t_{obs} | H_1)}{P(T < t_{obs} | H_0)} = \frac{1 - p_1}{1 - p}$$

- FNBF

- ◆ Complement of power divided by complement of p-value

- How to declare 'significant' vs 'insignificant'?

- ◆ If both FPBF and FNBF are low, how to choose?
- ◆ If $FPBF = FNBF$ (happens when one-sided $p + p_1 = 1$; $BF = 1$)
 - Indecision region
 - If you declare significance, study favors H_0 over H_1 with same strength as that if you declared insignificance the study favors H_1 over H_0
- ◆ Small FPBF requires large FNBF to constitute evidence against the null

Reconcile BF with FPBF and FNBF

- If $FPBF = FNBF$:
 - ◆ When H_0 and H_1 are close, so $p \approx p_1$
 - ◆ For hypothesis-driven alternative: one-sided $p + p_1 = 1$
- In both cases, $BF = 1$ as well
- Thus reconcile BF with FPBF and FNBF:

$$S = \frac{FPBF}{FNBF} = BF$$

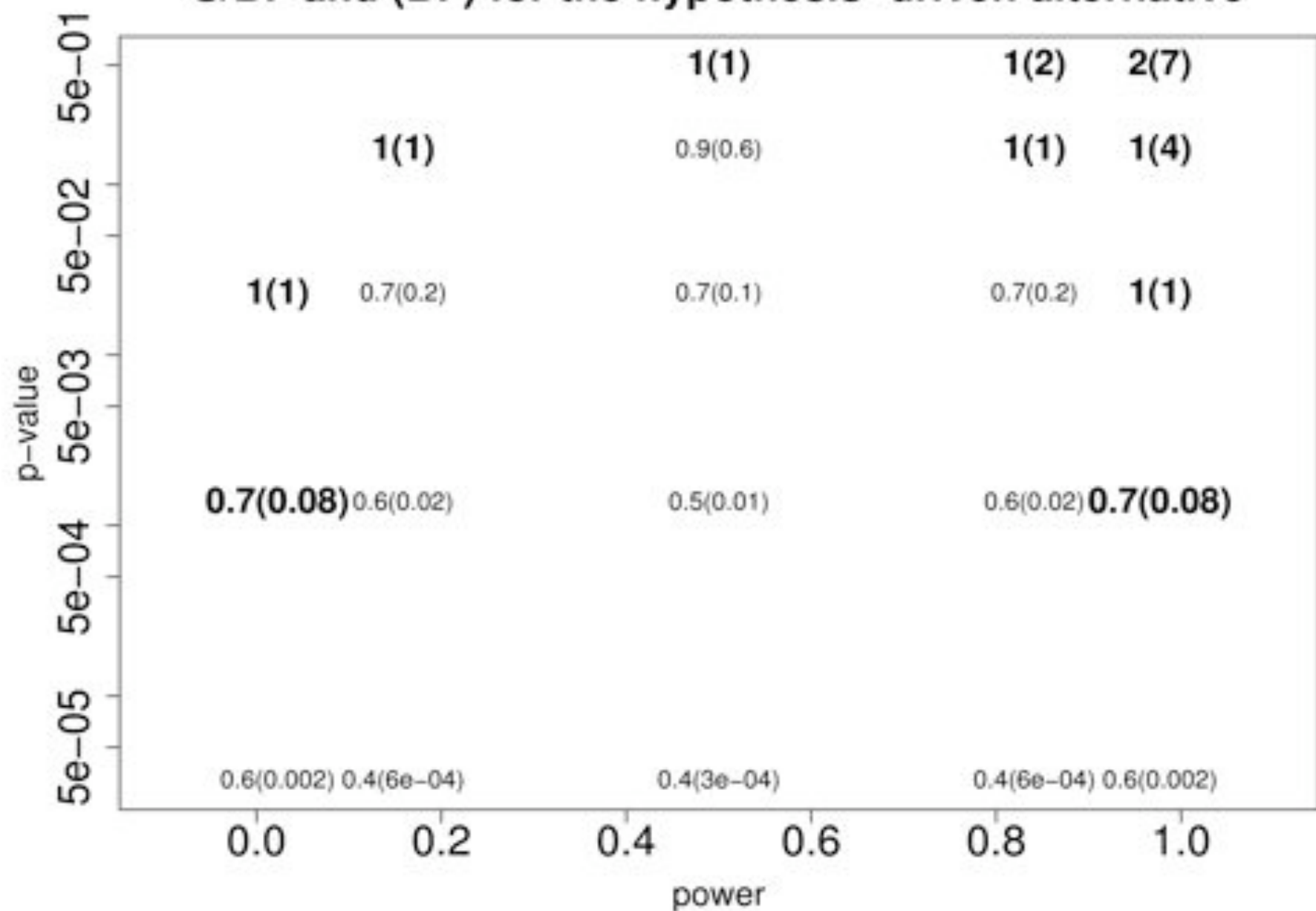
Reconcile BF with FPBF and FNBF

$$P(Z > z) \approx \frac{\exp(-z^2/2)/\sqrt{2\pi}}{z + 0.8\exp(-0.4z)}$$

- Under Hart's approximation,

$$\begin{aligned} S = \frac{FPBF}{FNBF} &\approx \frac{\exp(-z_0^2/2) |z_1| + 0.8(\exp(-0.4|z_1|))}{\exp(-z_1^2/2) |z_0| + 0.8(\exp(-0.4|z_0|))} \\ &= BF \times \frac{\sigma_0 |z_1| + 0.8(\exp(-0.4|z_1|))}{\sigma_1 |z_0| + 0.8(\exp(-0.4|z_0|))} \\ (z_0 = \hat{\beta}/\sigma_0; \quad z_1 = (\hat{\beta} - \beta_1)/\sigma_1) \end{aligned}$$

S/BF and (BF) for the hypothesis-driven alternative



Wilcox's Example

	OR	CI	p-value
Factor A	2.0	(1.2 - 3.3)	0.0067
Factor B	4.0	(1.3 - 12)	0.013

- Set Alternative $OR=3$
- Assume test statistics under null and alternative are
 - ◆ Centered at $OR=1$ and $OR=3$
 - ◆ Normally distributed with equal variances
 - ◆ Back the variance out of the CI

Wilcox's Example: What Happened?

	OR	p-value	FPBF	BF	FNBF	S
Factor A	2.0	0.0067	1/278	1/11	1/17	1/16
Factor B	4.0	0.013	1/45	1/19	1/1.4	1/32

- Both FPBF and FNBF favor Factor A
 - ◆ 1/17 is between 1/8 ('fairly strong') and 1/32 ('quite strong') evidence.
 - ◆ Warns us that the BF and the p-value will disagree
 - ◆ The BF and S are close, justifying using FPBF & FNBF
- Bayes Factors do not yield insight about why they disagree with p-values
 - ◆ But FPBF and FNBF show us this insight

CGEMS: Cancer GEnetic Markers of Susceptibility



- Over 500,000 SNP genetic mutations
 - ◆ Single Nucleotide Polymorphism (SNP): mutation at a single base-pair
 - ◆ Can be 4 possibilities (A,C,G,T), but almost always binary
- Focus on Chromosome 8 in 8q24
 - ◆ PLCO: ~1200 prostate cancers, ~1200 controls per SNP
- Analysis
 - ◆ Odds ratios (OR) associating each SNP with presence of prostate cancer (binary)

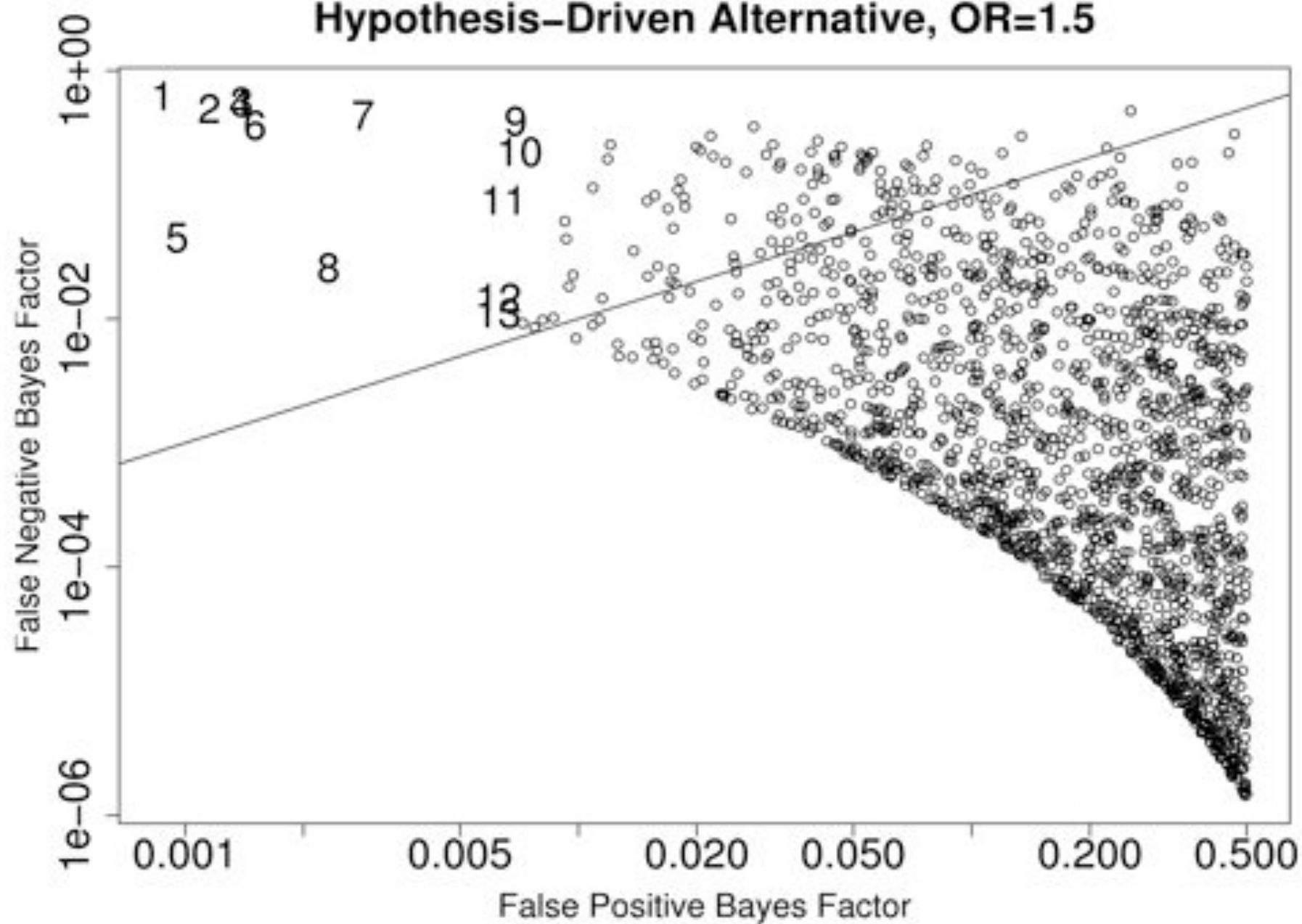
CGEMS: Cancer GEnetic Markers of Susceptibility

#	OR	stderr logOR	p-value	Bayes Factor
1	1.56	0.13	0.00066	0.0031
2	1.49	0.12	0.0012	0.0052
3	1.52	0.13	0.0012	0.0055
4	1.52	0.13	0.0013	0.0055
5	1.30	0.08	0.0018	0.0329
6	1.43	0.11	0.0019	0.0087
7	1.46	0.13	0.0032	0.0133
8	1.27	0.08	0.0045	0.11
9	1.44	0.14	0.0085	0.0325
10	1.37	0.12	0.011	0.0534
11	1.30	0.10	0.012	
12	1.24	0.09	0.012	
13	1.24	0.08	0.012	

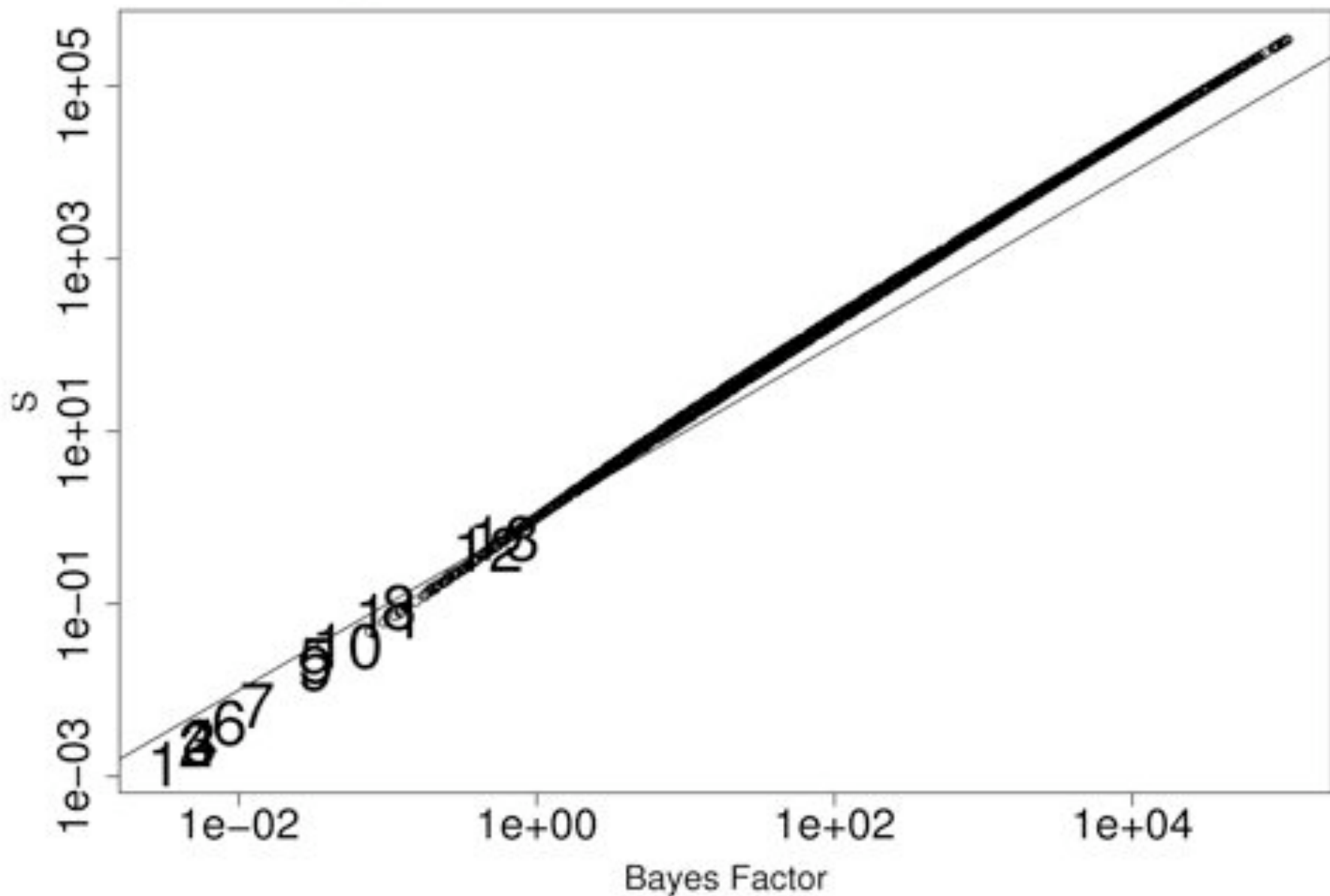
CGEMS Alternative Hypotheses

- Fix variance of null to be that observed for that SNP
- Two hypothesis-driven alternatives
 - ◆ Minimally-important effect sizes we want to test against
 - ◆ Set $\beta_1 = \log(\text{OR}) = \log(1.5)$
 - ◆ Set $\beta_1 = \log(\text{OR}) = \log(1.3)$
- Two hypothesis-generating alternatives
 - ◆ Presume 95% of findings should be in $(1/1.5, 1.5)$: $W=0.04$
 - ◆ Presume 95% of findings should be in $(1/1.1, 1.1)$: $W=0.002$

Hypothesis-Driven Alternative, OR=1.5



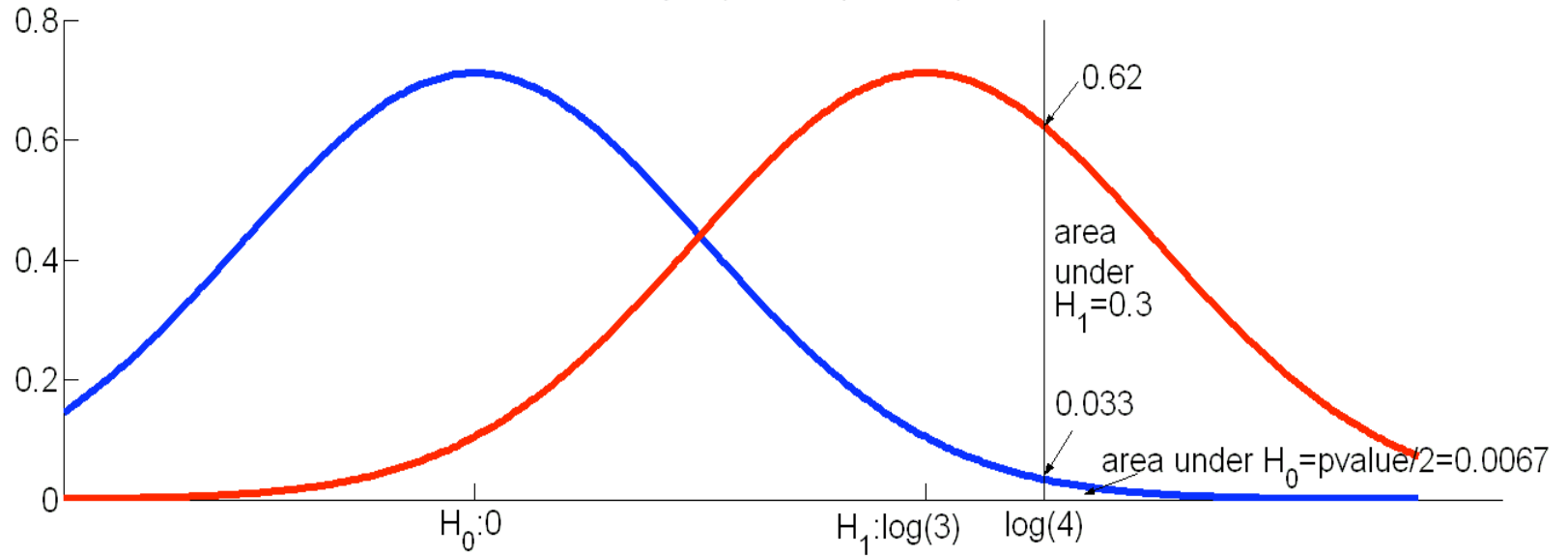
Hypothesis-Driven Alternative, OR=1.5



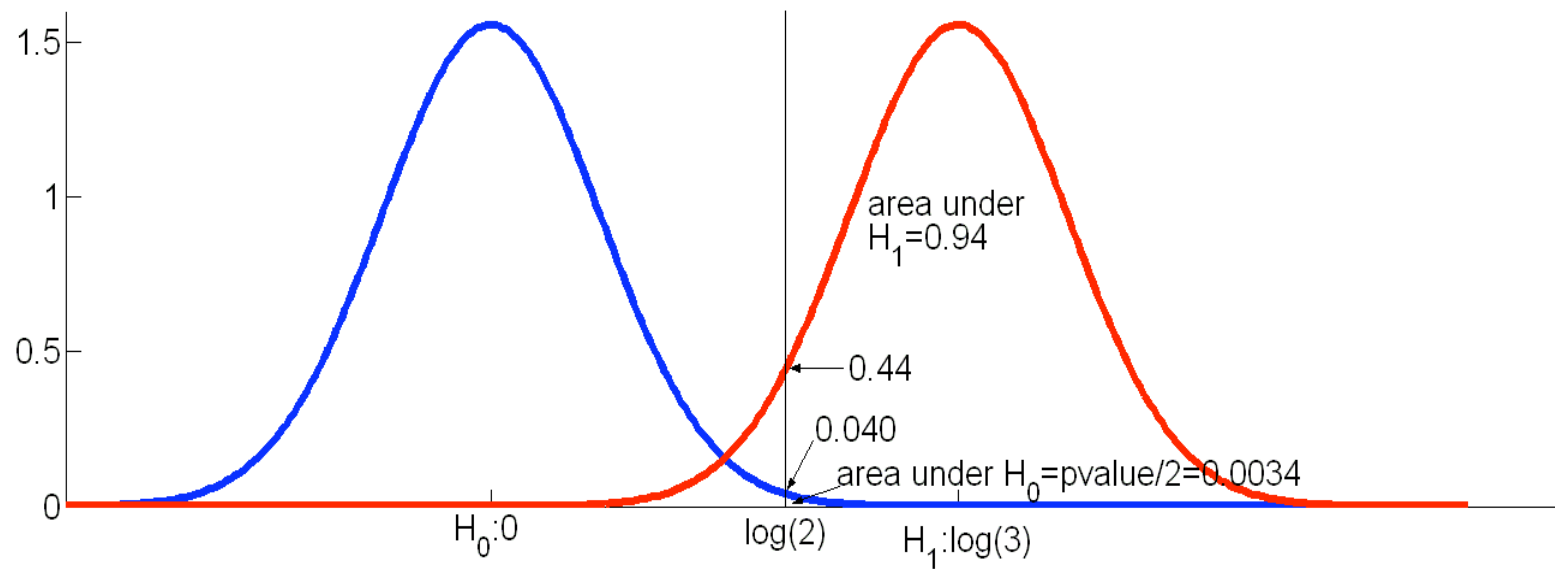
Recap

- False Positive/Negative Bayes Factors
 - ◆ Are approximately the two components of the Bayes Factor
 - ◆ Explain disagreements between p-values and Bayes Factors
 - ◆ Complement p-values and Bayes Factors
- FPBF and FNBF require dichotomization
 - ◆ Scientists often dichotomize study results anyway
 - “If I declare my findings positive, what is the chance that I'm wrong?”
 - “If I declare my findings negative, what is the chance that I'm wrong?”
 - ◆ Relationship to Bayes Factor alleviates concern
 - ◆ Need to consider FPBF jointly with FNBF
- P-values and Bayes Factors can't be reconciled
 - ◆ But the *evidential interpretation of the p-value via False Positive/Negative Bayes Factors* can be approximately reconciled with the Bayes Factor

Study B (2-sided $p=0.013$)



Study A (2-sided $p=0.0067$)



Wilcox's Example: What Happened?

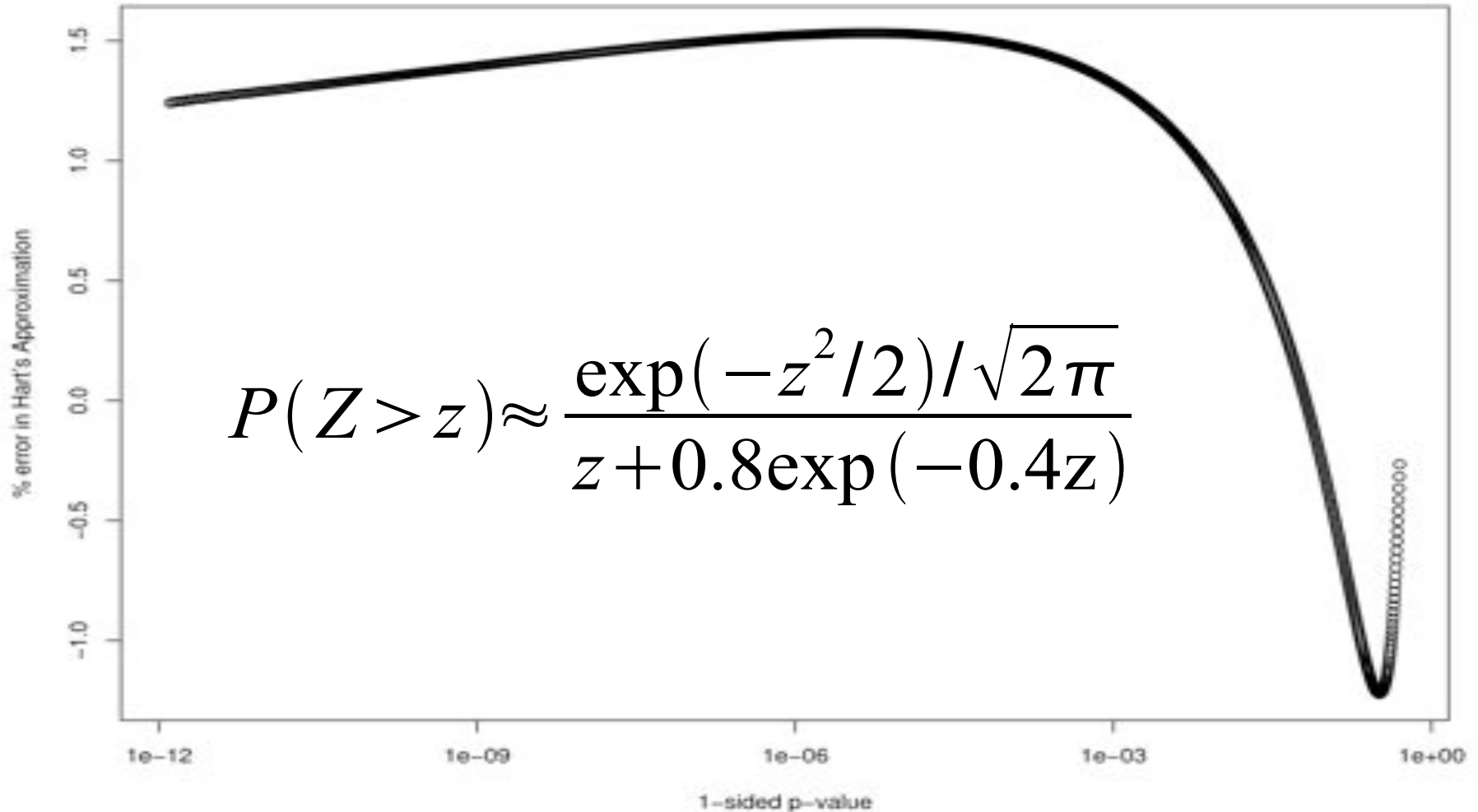
	OR	CI	p-value	FPBF	BF
Factor A	2.0	(1.2 - 3.3)	0.0067	1/278	1/11
Factor B	4.0	(1.3 - 12)	0.013	1/45	1/19

- FPBF: “You could’ve seen something huge!”
- BF: “Both hypotheses are unlikely!”
- Both agree that alternative is favored
 - ◆ Disagree on how much more it’s favored
- Famous unresolved paradox:
 - ◆ Royall, American Statistician (1986)

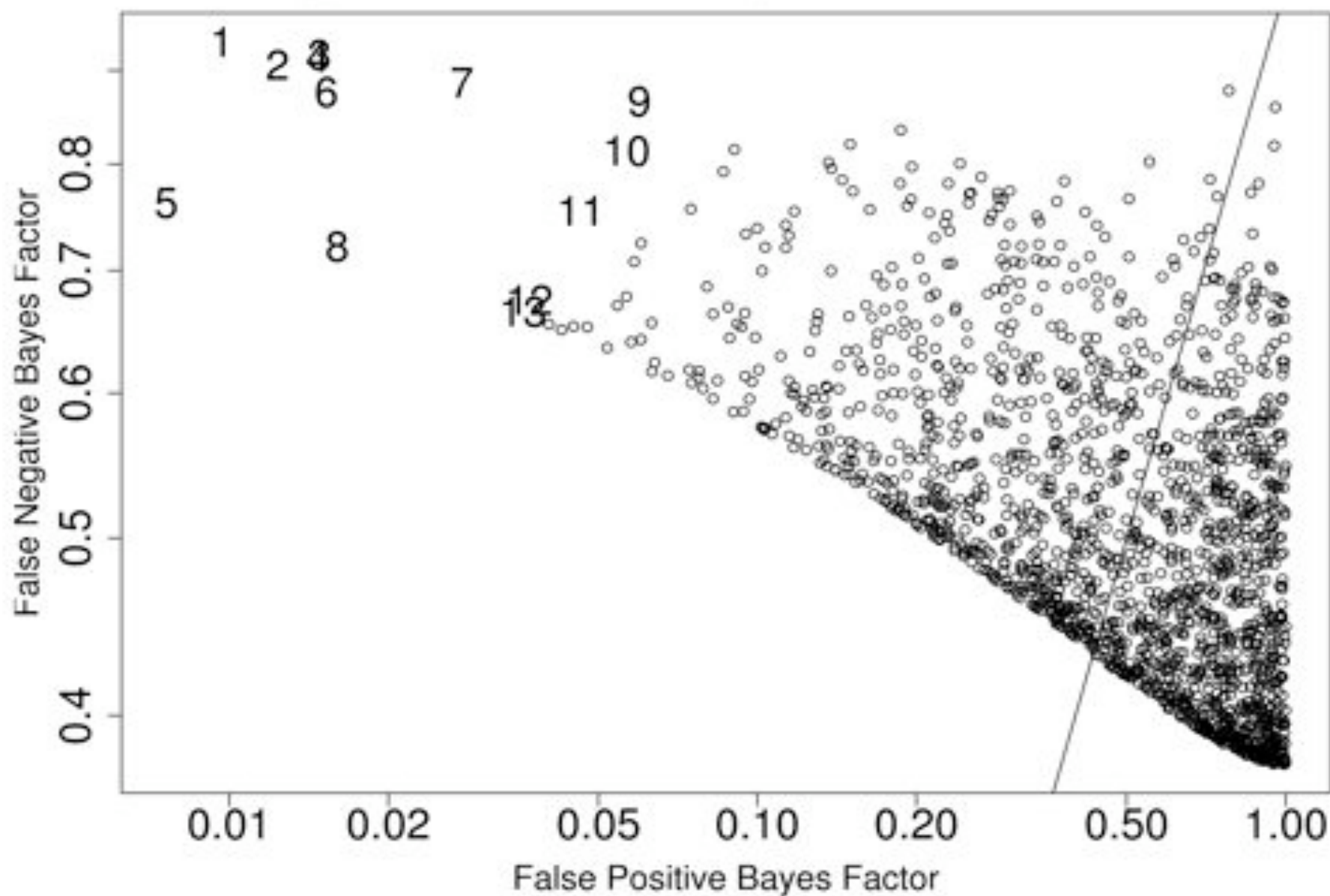
Future Work

- Choice of alternative hypothesis
 - ◆ For Wilcoxon example, if chose alternatives centered at $\log(1.5)$ or $\log(5)$, there are no problems
 - ◆ Critical choice of W in hypothesis-generating alternative
 - ◆ Empirical Bayes: Estimate null and alternative hypotheses from data (Efron 2004)
- Relationship to False Discovery Rates (FDR)
 - ◆ The FPRP estimates the same estimand as the FDR, only forcing you to propose a specific alternative
 - FPBF is akin to an evidential measure implicitly used by FDR
 - ◆ Similarly for FNRP and FNBF for the False Non-Discovery Rate

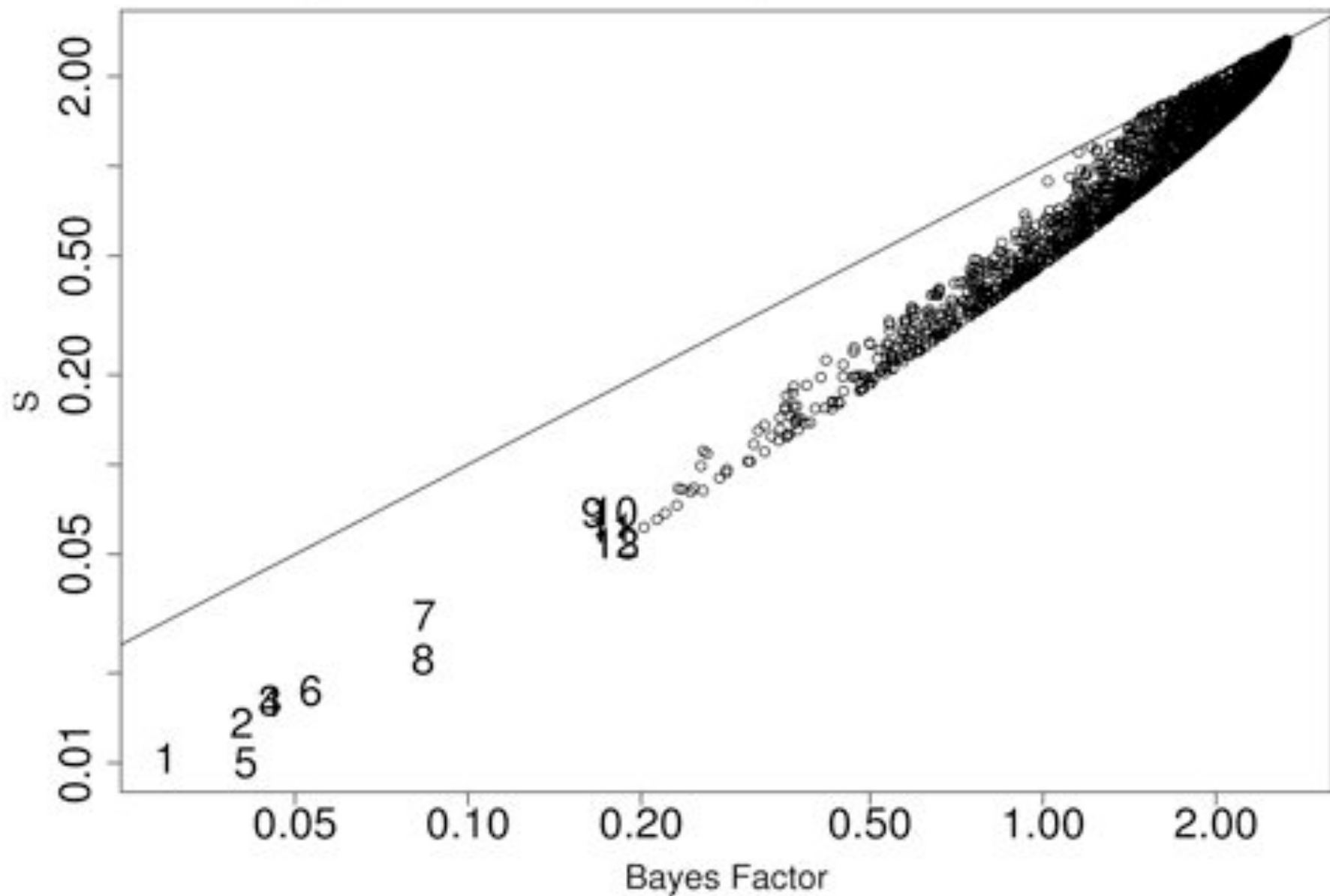
Reconcile BF with FPBF and FNBF: Hart's Approximation (1957)



Hypothesis-Generating Alternative, OR=1.5



Hypothesis-Generating Alternative, OR=1.5



Reconcile BF with FPBF and FNBF

$$P(Z > z) \approx \frac{\exp(-z^2/2)/\sqrt{2\pi}}{z + 0.8\exp(-0.4z)}$$

- S is approximately a ratio of tail probabilities
 - ◆ $p < p_1 < 0.5$: If both p, p_1 are small then $S \approx \text{FPBF} = p/p_1$ for both alternatives
 - ◆ $p < 0.5, p_1 > 0.5$: If p is small, p_1 is large, then $S \approx p/(1-p_1)$ for hypothesis-driven alternative
 - ◆ $p > 0.5, p_1 < 0.5$: Impossible since $p < p_1$ for both alternatives
 - ◆ $p_1 > p > 0.5$: If both p, p_1 are large then $S \approx 1/\text{FPBF} = (1-p)/(1-p_1)$ for both alternatives

Two types of Alternative Hypotheses

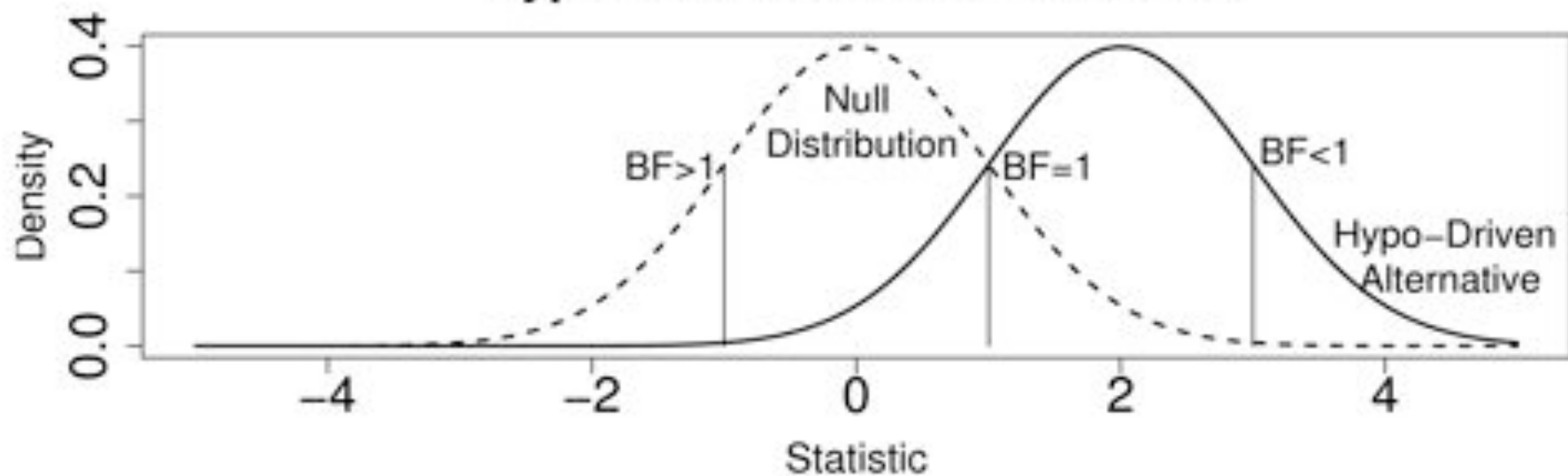
- Hypothesis-Driven Alternative

- ◆ $H_{1d}: \hat{\beta} \sim N(\beta_1, \sigma_1^2)$, *WLOG* $\beta_1 > 0$; $\sigma_0 = \sigma_1$
- ◆ Specification of β_1 suggests the investigator has an *a priori* hypothesis or a minimally-interesting effect size

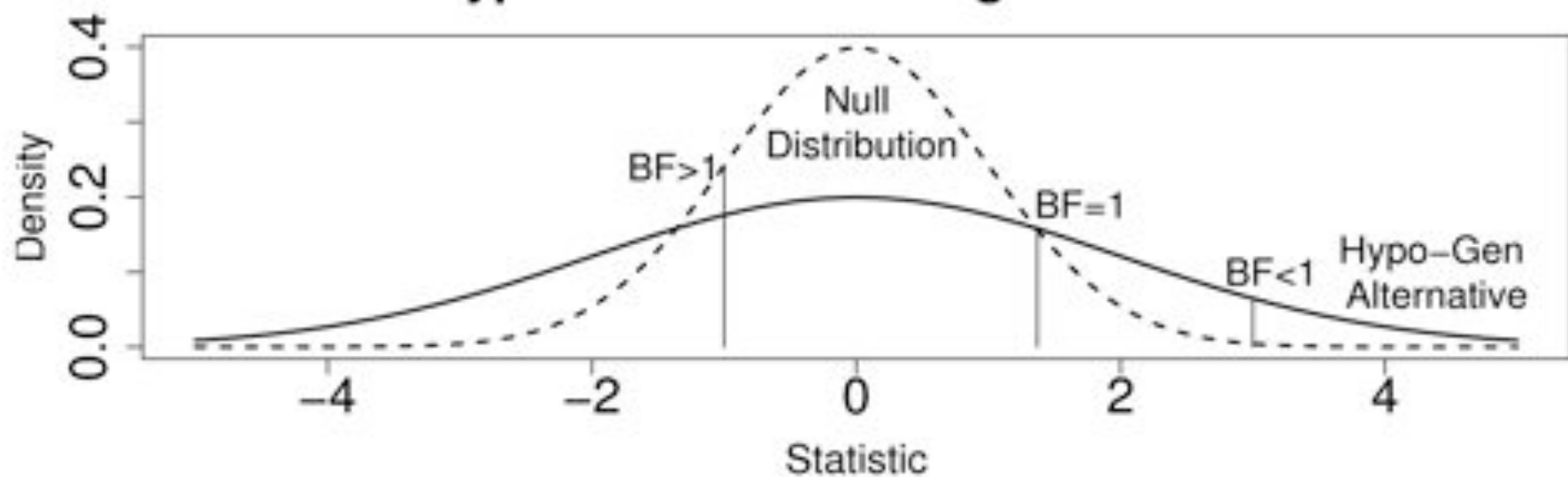
- Hypothesis-Generating Alternative

- ◆ $H_{1g}: \hat{\beta} \sim N(0, \sigma_1^2 = \sigma_0^2 + W)$
- ◆ Marginal distribution of: $\hat{\beta} \sim N(\beta_1, \sigma_0^2)$, $\beta_1 \sim N(0, W)$
- ◆ Often used in bioinformatic situations where there are no *a priori* hypotheses about which factors will have an effect, but the vast majority of factors are expected to have no effect

Hypothesis-Driven Alternative



Hypothesis-Generating Alternative



Two types of Alternative Hypotheses

- Hypothesis-Driven Alternative Bayes Factor

$$\begin{aligned}BF_d(\hat{\beta}) &= \frac{\exp(-0.5((\hat{\beta}-0)^2/\sigma_0^2))}{\exp(-0.5((\hat{\beta}-\beta_1)^2/\sigma_1^2))} \\ &= \exp(-0.5(2\hat{\beta}\beta_1 - \beta_1^2)/\sigma_0^2)\end{aligned}$$

- Hypothesis-Generating Alternative Bayes Factor

$$\begin{aligned}BF_d(\hat{\beta}) &= \frac{\exp(-0.5((\hat{\beta}-0)^2/\sigma_0^2))}{\exp(-0.5((\hat{\beta}-0)^2/\sigma_1^2))} \\ &= \sigma_0^{-1} \sqrt{\sigma_0^2 + W} \exp(-0.5(\hat{\beta}^2/\sigma_0^2 - \hat{\beta}^2/(\sigma_0^2 + W)))\end{aligned}$$

Use of FPBF to interpret p-values



Richard Royall

- Consider betahat where densities cross ($BF=1$)
 - ◆ By BF, neither null nor alternative can be preferred
 - ◆ However, p-value can be very small: contradiction
 - ◆ Under either alternative, $FPBF < 1$: alternatives preferred
 - ◆ As p-value $\rightarrow 0$, $FPBF \ll 1$: alternatives strongly preferred
 - ◆ Easy to construct such contradictions: Royall (1986)
 - ◆ Basis for much argument that Bayes Factors and p-values draw different conclusions

S/BF and (BF) for the hypothesis-generating alternative

