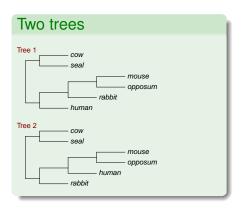
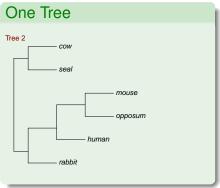
Topology Tests

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Two Main Topology Test Problems





- Is Tree 1 significantly better than Tree 2
- Is Tree 2 plausible?

Spanish Scores Before/After Course

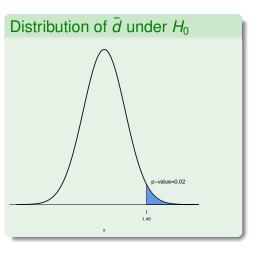
Subject	1	2	 20
Before	30	28	 29
After	29	30	 32
d _i	-1	2	 3

$$ar{d} = 1.45, \, s_d = 3.2, \\ n = 20$$

- H_0 : No significant difference Before vs After ($\mu_d = 0$)
- H_A : After scores are better ($\mu_d > 0$)
- Large \bar{d} provides evidence that H_A is true.
- $\bar{d} = 1.45$. Is this large?

- If H_0 true, Central Limit Theorem suggests \bar{d} is approximately $N(0, \sigma_d^2/n)$
- Don't know σ_d^2 but $s_d^2 \approx \sigma_d^2$
- So H_0 true, \bar{d} is approximately $N(0, s_d^2/n)$
- Compare observed $\bar{d} = 1.45$ to $N(0, s_d^2/n)$

p-values: How Large is Large?



- Is $\bar{d} = 1.45$ abnormally large under H_0 ?
- Under H_0 expect a \bar{d} as large as this $\approx 2\%$ of the time

Type I and Type II error

Types of E	rror			
		Truth	ı	
		H ₀ True (Tree 2)	H_0 False	
Decision	Reject H ₀ (Tree 2)	Type I Error		
	Do not Reject		Type II Error	

• α -level test: $P[\mathsf{Type} \mid \mathsf{Error}] \leq \alpha$ Reject H_0 : when p-value< α

Issues of Concern:

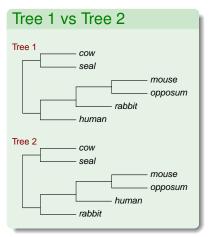
p-values in phylogenetics are approximations 0.05-level test

- ► True P[Type I Error] = 0.10. High chance that we are excluding trees (Tree 2) that is reasonable. Bad
- ► True *P*[Type I Error] < 0.05 (Conservative test) Better. Tradeoff: P(Type II Error) large.

Spanish Speaking Scores Before & After Course					
Subject	1	2	• • • •	20	
Before	30	28	• • •	29	
After	29	30	• • •	32	
d_i	-1	2		3	

- H₀: No difference between groups (μ_d = 0)
- H_0 should be $\mu_d \leq 0$

- p-value difficulty: No longer have single distribution for \bar{d} under H_0 Under H_0 , p-value depends on choice of $\mu_d \leq 0$
- Reason for calculating p-values with $\mu_d = 0$
 - If $\bar{d} > 0$, $\mu_d = 0$ is the projection of the estimate onto H_0
 - $\mu_d = 0$ gives $P(\text{Type I error}) \le 0.05$, all $\mu_d \le 0$
- $\mu_d = 0$ boundary between $H_0: \mu_d \leq 0$ and $H_A: \mu_d > 0$



One-sided Test: Is Tree 1 significantly better than Tree 2?

- Paired z-test of H_0 : $E[d_h] = 0$, H_A : $E[d_h] > 0$.
- d_h: difference in maximized site log-likelihoods (site h)

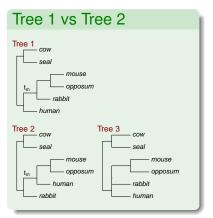
$$d_h = \log p(x_h; \tau_1, \hat{t}_1, \hat{\theta}_1) - \log p(x_h; \tau_2, \hat{t}_2, \hat{\theta}_2)$$

- Compare \bar{d} to $N(0, s_d^2/n)$
- Equivalently, compare $\sum_h d_h$ to $N(0, ns_d^2)$

•

$$\sum_{h=1}^{n} d_h = \triangle$$
 in max log likelihoods (Tree 1 - Tree 2) $= l_1 - l_2 = \Lambda_2$

Null Hypothesis: Tree 2 correct



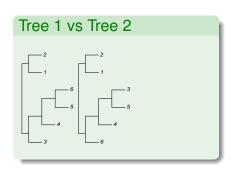
- Composite Null: H₀: T₂ (many versions of T₂)
- $P(\text{Type I Error}) \leq \alpha \text{ requires}$

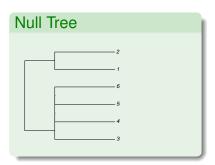
$$P_{T_2}(\text{reject } H_0) \leq \alpha$$

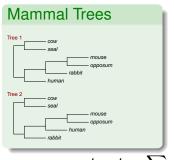
all T_2

- T_3 is on boundary between T_1 and T_2 .
- Approximate KH null: $E[d_i] \approx 0$ (large n)
 - T₃ is only version of T₂ satisfying

- Collapse as many branches as needed to make the trees equivalent.
- Don't collapse more.
- Consensus Tree of Tree 1 and Tree 2







mtREV24, 8 Gamma rate categories

site <i>i</i>	I _{1i}	I_{2i}	d_i
1	-8.533	-8.556	0.023
2	-3.775	-3.776	-0.001
÷		:	
3414	-14.053	-14.158	0.105
	-21765.04	-21766.23	1.190

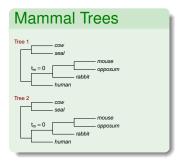
12/54

$$I_1 - I_2 = \sum_i d_i = 1.190 \quad \sqrt{3414} s_d = 9.012$$

One sided p-value = P(Z > 1.190) = 0.45

Z normal with mean 0 and standard deviation 9.012

Properties under Null Hypothesis



- Simulate 5000 data sets under mtREV24 model
- $\alpha = 0.44$, 8 Gamma categories
- Tree 2, with $t_m = 0$

	α	
	0.05	0.10
Number of Rejections	0	5
Expected (5000 $\times \alpha$)	250	500

• Very Conservative Test: $P(\text{Type I Error}) << \alpha$

 α

Bootstrapping (Paired z-test)

- Setting: d_1, \ldots, d_n iid. True distribution (P)
- What is the distribution of \bar{d} under H_0 ? Use P
- Answer: Approximately $N(0, \sigma_d^2/n)$
- True distribution P might correspond to H_A
- Generally \bar{d} approximately $N(\mu_d, \sigma_d^2/n)$
- **Centering**: Distribution of $\bar{d} \mu$ is $N(0, \sigma_d^2/n)$ Want to figure out distribution of $\bar{d} \mu$ under P

Difficulties

- Don't know P
- Centering won't always give the right distribution (eg. σ_d^2 is a function of μ_d)

- Want to figure out distribution of $\bar{d} \mu$. Don't know P
- Empirical distribution: \hat{P} assigns mass 1/n to each observed d_i .

$$\hat{P}(A) \approx P(A)$$

$$E_{\hat{P}}[d] = \sum_{d_i} p(d_i)d_i = \bar{d}$$

- Suggests: If d_1^*,\dots,d_n^* are generated from \hat{P} distribution of $\bar{d}^*-\bar{d}\approx$ distribution of $\bar{d}-\mu$
- Difficulty: Probability calculations to get $\bar{d}^* \bar{d}$ distribution is intractible

Bootstrapping in Practice

- Long run proportions match probabilities
- Select sites from $\hat{P} \iff$ Select sites with replacement eg. $d_1^* = d_{32}, d_2^* = d_{32}, \dots, d_n^* = d_3$ give a sample from \hat{P} .

$$\Rightarrow \bar{d}^* - \bar{d}$$
 gives a realization from \hat{P}

• Repeat a large number (B) of times

Proportion of
$$\bar{d}^* - \bar{d} > x \approx \hat{P}(\bar{d}^* - \bar{d} > x) \approx P(\bar{d} - \mu > x)$$

• For observed test statistic \bar{d} , approximate p-value

Proportion of
$$\bar{d}^* - \bar{d} > \operatorname{obs}(\bar{d})$$

Nonparametric bootstrap: P does not involve a model

- Test statistic: d̄
- Original KH p-value= $P[D > obs(\bar{d})]$, $D \sim N(0, s_d^2/n)$.
- RELL version: $P[D > \text{obs}(\bar{d})]$, calculated using bootstrap distribution of $\bar{d}^* \bar{d}$

p-value = Proportion of
$$\bar{d}^* - \bar{d} > \mathsf{obs}(\bar{d})$$

- Minor adjustment: \bar{d} replaced by ave_b \bar{d}^*
- Results are almost always identical to paired z-test version

RELL and Bootstrap Principle

RELL: Resampling estimated log likelihoods:

$$d_1^*, \ldots, d_n^*$$
 sampled with replacement from d_1, \ldots, d_n

- Bootstrap principle: Mimic what is done with original data
- d_1, \ldots, d_n were not the original data

Nonparametric and Parametric Bootstrap

Nonparametric bootstrap

- **1** Site columns x_1^*, \ldots, x_n^* sampled with replacement from x_1, \ldots, x_n
- 2 Estimate \hat{t}_j^* , $\hat{\theta}_j^*$, ...

$$\Lambda_2^* = \sum_h \log[p(x_h; \tau_1, \hat{t}_1^*, \hat{\theta}_1^*)] - \log[p(x_h; \tau_1, \hat{t}_2^*, \hat{\theta}_2^*)]$$

3

p-value = Proportion of
$$\Lambda_2^*$$
 - ave $(\Lambda_2^*) >= I_1 - I_2 = \Lambda_2$

Parametric bootstrap:

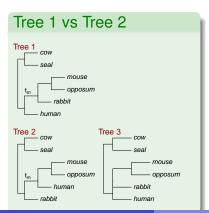
Replace Step 1 with: Generate x_1^*, \ldots, x_n^* from $p(x; \tau_j, \hat{t}_j, \hat{\theta}_j)$ (eg. seq-gen)

- Pros and Cons:
 - Both much more computationally expensive than RELL
 - Nonparametric robust to model misspecification (sort of)
 - Parametric less variable

Parametric Bootstrap

Swofford et al (1996) Molecular Systematics

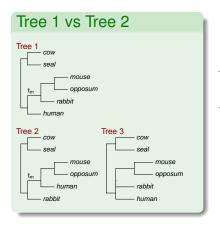
- Centering: x_1^*, \ldots, x_n^* from $\hat{P} \approx P$ We use $l_1^* - l_2^* - \text{ave}(l_1^* - l_2^*)$ instead of $l_1^* - l_2^*$
- H_A might be true \Longrightarrow mean $I_1^* I_2^*$ not ≈ 0 as under H_0
- Difficulty: If H_A true, other parts of distribution might differ (eg Standard Deviation)



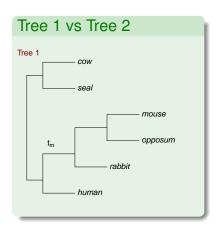
- Parametric bootstrap: Can generate from H₀: Tree 3
- Centering not needed
- KHns approximates parametric bootstrap Tree 3 using simple normal simulation

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Comparison of P-values Mammal Data

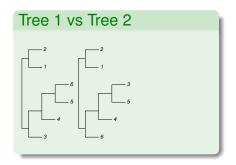


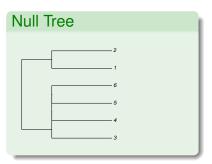
Test	p-value
KH	0.45
Nonpar (center)	0.45
Par, Tree 3 (uncenter)	0.05
Par, Tree 3 (center)	0.05
KHns	0.05



- Null hypothesis Tree 2 is a special case of Tree 1
 ⇒ Conventional parametric model test
- $H_0: t_m = 0 \text{ vs } H_A: t_m > 0$

- General Case
- Tree 2 is special case of Tree 1
- But $t_m = 0$ where t_m is p-dimensional





- Null Hypothesis H₀: t_m = 0, H_A: t_m > 0
 t_m p-dimensional. Edges set to 0 in consensus tree
- LR Statistic

$$2\Lambda_3 = 2\{I_1 - I_3\}$$

 I_3 maximized log likelihood for T_1 holding $t_m = 0$ fixed Equivalently, maximized log likelihood for T_3

 Standard statistical theory indicates p-values should be calculated as

$$P(\chi_p^2 > 2\{I_1 - I_3\}$$

Chi-square test

- Standard theory condition: t_m be in the interior of the parameter space
- Null Hypothesis $H_0: t_m = 0, H_A: t_m > 0$
- t_m is on the boundary of the parameter space
- Shapiro (1985)

$$P(2\{l_1-l_3\}>y)=\sum_{j=0}^p w_j P(\chi_j^2>y)$$

Chi-bar test

• Consensus Tree with p zero-length edges. Shapiro (1985) \Rightarrow

$$\text{p-value} = \sum_{j=0}^{p} w_j P(\chi_j^2 > 2\Lambda_3)$$

- p = 1, Ota et al. (2000) Mol Biol Evol 17:793: $w_1 = w_2 = 1/2$
- p = 2,3: w_j can be approximated using second derivatives of log likelihood.
- $p \ge 4$: no expression for w_j .

Ignore boundary issue: Under H_A, p additional parameters.

naive p-value
$$= P(\chi_p^2 > 2\Lambda_3)$$

$$P(\chi_{\rho}^2 > 2\Lambda_3) \leq \sum_{j=0}^{\rho} w_j P(\chi_j^2 > 2\Lambda_3) = \text{correct p-value}$$
 (1)
 $P(\text{Type 1 Error}) \leq \alpha$

Using KH test statistic

- Λ₂ available from any software.
- Since consensus tree T_3 is special case of Tree 2, $I_2 > I_3$. So

$$\Lambda_2 = I_1 - I_2 < I_1 - I_3 = \Lambda_3$$

• So using Λ_2 with Λ_3 -based thresholds gives a conservative test.

Naiive (Chi-square) Test using KH Test Statistic

https://www.mathstat.dal.ca/ tsusko/software.html Susko (2014)

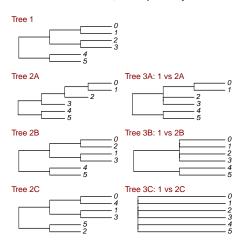
```
$ cat mammal-2trees
(human, (seal, cow), (rabbit, (opposum, mouse)));
(human, (rabbit, (seal, cow)), (opposum, mouse));
$ iqtree -s mtprot.phy -z mammal-2trees \
      -m mt.REV+F+G8 -n 0
$ cat mtprot.phy.trees
[ tree 1 lh=-21765.1 ] (human:0.2731,...
[ tree 2 lh=-21766.2341157180 ] (human:0.26588,...
$ trees2df -n 6 < mtprot.phy.trees</pre>
1 1
. . .
In R
> 2*(-21765.1-(-21766.2341157180))
[1] 2.268231
> 1-pchisq(2.268231,1)
 [1] 0.1320506
```

Test	p-value
KH	0.45
Nonpar (center)	0.45
Par, Tree 3 (center)	0.05
Par, Tree 3 (uncenter)	0.05
KHns	0.05
Naive (KH)	0.13
Chi-bar (KH)	0.07
Naive (Λ ₃)	0.00
Chi-bar (Λ_3)	0.00

Test	Comments
KH	Highly Conservative Type I
KHns	Approximate Type I
chi-bar	Approximate Type I
chi-bar(KH)	Conservative Type I
	NA $p \geq 4$
naive	Conservative
	Simple Calculation
naive(KH)	Simplest calculation

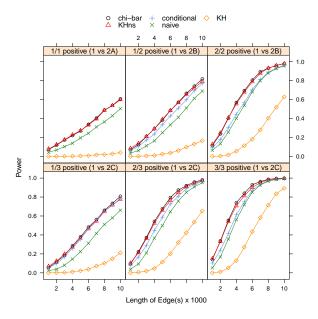
Trees in Simulations

- 1000 simulated data sets, 1000 sites each.
- HKY, $\kappa = 2$,, frequency of A, C, G and T 0.1, 0.2, 0.3 and 0.4.



Null Simulations - Number of False Positives

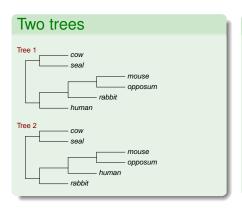
Tree	KHns	chi-bar		naive		KH
		Λ_3	KH	Λ_3	KH	
3A	48	44	40	24	23	0
3B	50	39	31	18	15	0
3C	40	31	23	10	6	0

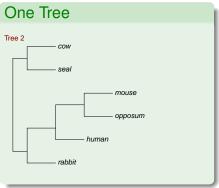


Summary (Two Tree Tests)

- KHns & chi-bar best performers
 - Implementation is complicated
- KH simple but very conservative
- Parametric Bootstrapping should be applied with consensus tree

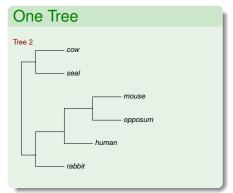
Two Main Topology Test Problems





- Is Tree 1 significantly better than Tree 2
- Is Tree 2 plausible?

Confidence Sets of Trees are Equivalent to Tests



 Given a test, 95% confidence set of trees C: All trees giving p ≥ 0.05

 $P[\text{True Tree in } C] \ge 0.95$

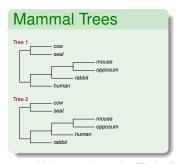
- Coverage: proportion of times true tree is in confidence set
- If a test has P(Type I error) = 0.02 then the coverage of the confidence set is 0.98

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37/54

SH Test

Shimodaira & Hasegawa (1999) Mol Biol Evol 16:1114



T₁ and T₂ fixed a priori:

 Q_{KH} : T_1 significantly better than T_2 ?

If instead, only T₂ is fixed a priori,

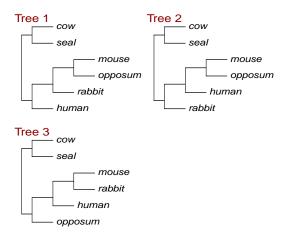
 Q_{SH} : ML tree significantly better than T_2 ?

Selection Bias: Tree 1 is selected based on the data

- If Tree 1 fixed and H_0 true $I_1 I_2 < 0$ approximately 50% of time
- $I_1 I_2$ never < 0 if Tree 1 is ML tree

- **Setting**: T_1 and T_2 become $T_1, \ldots, T_M \Rightarrow I_1, \ldots, I_M$
 - ▶ Mammal data. 6 taxa \Rightarrow M = 105 trees.
- Test statistic I₁ I₂ replaced by I_m I₁
 m indice of MLE.
- RELL Bootstrapping
 - ► Replace I_1^*, \dots, I_M^* by $I_1^* ave_b I_1^*, \dots, I_M^* ave_b I_M^*$
 - ▶ Use observed $l_{m^*}^* l_2^*$ from bootstrapping for null distribution. m^* : indice of MLE for bootstrap sample.

Mammal Data Example - Three trees



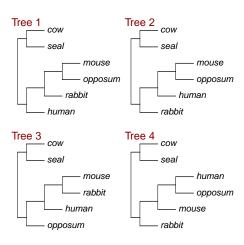
Tree 1 was the ML tree for this data

- $I_1 I_2 = 1.19$
- I_i^* (after centering), first three bootstrap samples

$$pKH = \text{proportion of } I_1^* - I_2^* > 1.19 = 0.44$$

$$pSH = \text{proportion of } I_{m^*}^* - I_2^* > 1.19 = 0.59$$

Mammal Data Example - Four trees



•
$$B = 5000$$
. $M = 4$

$$I_1 - I_2 = 1.19$$

$$pKH$$
 = proportion of $l_1^* - l_2^* > 1.19 = 0.44$
 pSH_3 = proportion of $l_{m_3^*}^* - l_2^* > 1.19 = 0.59$
 pSH_4 = proportion of $l_{m_4^*}^* - l_2^* > 1.19 = 0.74$
 pSH_{105} = proportion of $l_{m_{105}^*}^* - l_2^* > 1.19 = 0.95$

- Bootstrap Principle: Bootstrapping should mimic what is being done with original data.
- If exhaustive search for ML tree, M = 105
- Impossible with large number of taxa
 - Best 100 or 1000 trees found in tree searching
 - Collection of bootstrap trees
 - **.** . . .

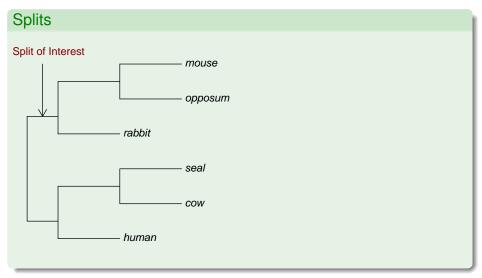
Selection bias corrected parametric bootstrap

- Full parametric bootstrapping from current tree (Tree 2) considered for confidence set
- Calculate I_m^* ML Tree for each bootstrap sample
- p_{SOWH} = Proportion of $I_m^* I_2^* > I_m I_2$
- *p_{SOWH}* << *p_{SH}*
- Sometimes, SOWH will generate from a fully-resolved Tree 2 Under fully-resolved Tree 2, less likely to see large $l_m l_2$

Test	p-value
KH	0.45
Par, Tree 3	0.05
Chi-bar (KH)	0.07
SOWH	0.00

- SOWH gets smaller p-value even though it adjusts for selection bias
- Should apply SOWH with Tree 3 as simulating tree

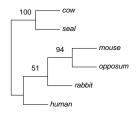
Features of a Topology



• Significant evidence that the split is present?

Bootstrap Support

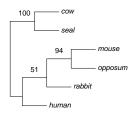
- For each bootstrap sample x_1^*, \ldots, x_n^* obtain \hat{T}^*
- BP for opposum, mouse and rabbit = proportion of T* with that split.



- By far the most frequent measure of uncertainty
- How large of BP is large?

- Felsenstein (1985): Bootstrap Support (BP) introduced
- Hillis and Bull (1993): BP is probability split is correct. 70% is large.
- Felsenstein and Kishino (1993): 1-BP is p-value for hypothesis that split is not present. 95% is large.
- Efron, Halloran and Holmes (1996) 1-BP is first order correct.
 - Efron and Tibshirani (1998) proof for analogous problem of regions
- Susko (2009) E & T result correct for problem of regions but not phylogenetics
 - ► Fixed Tree: 1-BP is conservative: Expect 95% BP less than 5% of time

Bootstrap Support for Splits



- Fixed Tree: BP is conservative:
 - Expect >95% BP less than 5% of time
 - Expect < 40% BP more than 40% of time</p>
- Selection Bias: ML tree is not fixed a priori. Very unlikely BP < 40%

Bootstrap Support for Trees

- For each bootstrap sample x_1^*, \ldots, x_n^* obtain \hat{T}^*
- BP for tree T is proportion of times $\hat{T}^* = T$
- BP for Tree always ≤ BP for each of its splits
 ⇒ conservative. Expect 95% BP less than 5% of time
- AU Test (Shimoadiara (2002) Syst Biol 5:492). Bootstrap correction
 - ▶ Bootstraps with differing fractions of original sample size $\Rightarrow BP(r_1)...,BP(r_m)$.
 - ▶ AU p-value is transformation of $BP(r_1)...,BP(r_m)$
 - ► The correction relies on 1-BP being first-order correct
 - ★ Works for the analogous problem of regions
 - ★ Not justified in phylogenetics

```
AU Test: 6 Trees
(human,(seal,cow),(rabbit,(opposum,mouse)));
(opposum,(human,(rabbit,(seal,cow))),mouse);
(opposum,((rabbit,human),(seal,cow)),mouse):
((opposum,human),(rabbit,(seal,cow)),mouse);
(opposum,human,((rabbit,mouse),(seal,cow)));
(seal,cow,(opposum,(human,(rabbit,mouse))));
KH Test: Same as AU Test
SH Test: 15 Trees: All Trees with (cow.seal)
Naive (Chi-square) Test: 2 Trees
(human,(seal,cow),(rabbit,(opposum,mouse)));
(opposum,(human,(rabbit,(seal,cow))),mouse);
```

- SH is fast but extremely conservative. Values depends on number of input trees M
- BP is conservative
- AU is not justified. Properties unclear.
- SOWH more accurate but intensive and should use consensus tree (Tree 3)
- KH test is very conservative as two tree test.
- Chi-square (Naive) reasonable but does not adjust for selection bias
- Working on alternatives