Evaluating strategies of phylogenetical analyses by the coherence of their results

Blaise Li

Journées de la SFS - Paris - 10/10/2012

Frequent approach:

 A priori decision, based on a compromise between complexity of the operations and expected accuracy of the results.

Frequent approach:

- A priori decision, based on a compromise between complexity of the operations and expected accuracy of the results.
- Use of a testing tool, like jModelTest (Posada, 2008), that makes likelihood calculations on trees obtained by fast methods.

Frequent approach:

- A priori decision, based on a compromise between complexity of the operations and expected accuracy of the results.
- Use of a testing tool, like jModelTest (Posada, 2008), that makes likelihood calculations on trees obtained by fast methods.

My proposition:

Apply various methods.

Frequent approach:

- A priori decision, based on a compromise between complexity of the operations and expected accuracy of the results.
- Use of a testing tool, like jModelTest (Posada, 2008), that makes likelihood calculations on trees obtained by fast methods.

My proposition:

- Apply various methods.
- Look how coherent the results obtained are when a given method is used on several datasets.

Frequent approach:

- A priori decision, based on a compromise between complexity of the operations and expected accuracy of the results.
- Use of a testing tool, like jModelTest (Posada, 2008), that makes likelihood calculations on trees obtained by fast methods.

My proposition:

- Apply various methods.
- Look how coherent the results obtained are when a given method is used on several datasets.
- Choose a posteriori the method that generated the most coherent results.

Only the results count, so the thing to select can be a whole analysis pipeline, including such things as:

Data selection and pre-processing (alignment, trimming, recoding, ...)

- Data selection and pre-processing (alignment, trimming, recoding, ...)
- Model (sustitution rates, composition, heterogeneities, correlations, . . .)

- Data selection and pre-processing (alignment, trimming, recoding, ...)
- Model (sustitution rates, composition, heterogeneities, correlations, . . .)
- ▶ Method of inference (distance, parsimony, likelihood, ...)

- Data selection and pre-processing (alignment, trimming, recoding, ...)
- Model (sustitution rates, composition, heterogeneities, correlations, . . .)
- Method of inference (distance, parsimony, likelihood, ...) and it implementation (program, options, tunings, ...)

- Data selection and pre-processing (alignment, trimming, recoding, ...)
- Model (sustitution rates, composition, heterogeneities, correlations, . . .)
- Method of inference (distance, parsimony, likelihood, ...) and it implementation (program, options, tunings, ...)
- Support evaluation (bootstrapping, ...)

- Data selection and pre-processing (alignment, trimming, recoding, ...)
- Model (sustitution rates, composition, heterogeneities, correlations, . . .)
- Method of inference (distance, parsimony, likelihood, ...) and it implementation (program, options, tunings, ...)
- Support evaluation (bootstrapping, ...)
- <Insert your favourite strategy item here>

Why?:

The most accurate strategies should extract more historical signal than the others.

- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies.

- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies.



- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies.



Why?:

- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies.

results





- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies. Good method results



- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies. Good method results



- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies. Good method results



- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies. Good method results



- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies.
 Bad method results



- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies.
 Bad method results



- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies.
 Bad method results



- The most accurate strategies should extract more historical signal than the others.
- So the different datasets should produce more similar trees whith these strategies.
 Bad method results



But:

But:

But:

But:



But:





But:



But:



But:



But:


But:



But:



But:



But:



But:

But:



But:



But:

 Strategies prone to reconstruction errors will produce wrong results in a consistent manner if the datasets share the error-inducing characteristics (false positive).

results





But:



But:



But:



But:



Data

- 42 cyanobacteria and plastids
- 73 protein-coding genes

Data

- 42 cyanobacteria and plastids
- 73 protein-coding genes
- 4 sets of congruent markers according to concaterpillar (Leigh et al., 2008)

Data

- 42 cyanobacteria and plastids
- 73 protein-coding genes
- 4 sets of congruent markers according to concaterpillar (Leigh et al., 2008)

Due to the internals of concaterpillar the analyses of the 4 sets should yield results with some degrees of incoherence, at least for standard maximum likelihood under a GTR + I + Γ model.

- Maximum likelihood bootstrap (200 pseudo-replicates):
 - RAxML (Stamatakis, 2006), GTR + I + Γ

- Maximum likelihood bootstrap (200 pseudo-replicates):
 - RAxML (Stamatakis, 2006), GTR + I + Γ
 - recodings to eliminate signal associated with synonymous substitutions

- Maximum likelihood bootstrap (200 pseudo-replicates):
 - RAxML (Stamatakis, 2006), GTR + I + Γ
 - recodings to eliminate signal associated with synonymous substitutions
- Bayesian MCMC inference:

- Maximum likelihood bootstrap (200 pseudo-replicates):
 - RAxML (Stamatakis, 2006), GTR + I + Γ
 - recodings to eliminate signal associated with synonymous substitutions
- Bayesian MCMC inference:
 - Phylobayes (Lartillot and Philippe, 2004), GTR + I + Γ + CAT (site-wise composition heterogeneity)

- Maximum likelihood bootstrap (200 pseudo-replicates):
 - RAxML (Stamatakis, 2006), GTR + I + Γ
 - recodings to eliminate signal associated with synonymous substitutions
- Bayesian MCMC inference:
 - Phylobayes (Lartillot and Philippe, 2004), GTR + I + Γ + CAT (site-wise composition heterogeneity)
 - P4 (Foster, 2004), GTR + I + Γ + NDCH (clade-wise composition heterogeneity)

- Maximum likelihood bootstrap (200 pseudo-replicates):
 - RAxML (Stamatakis, 2006), GTR + I + Γ
 - recodings to eliminate signal associated with synonymous substitutions
- Bayesian MCMC inference:
 - Phylobayes (Lartillot and Philippe, 2004), GTR + I + Γ + CAT (site-wise composition heterogeneity)
 - P4 (Foster, 2004), GTR + I + Γ + NDCH (clade-wise composition heterogeneity)
- A priori less accurate strategies (using Phylip, Felsenstein, 2005):

- Maximum likelihood bootstrap (200 pseudo-replicates):
 - RAxML (Stamatakis, 2006), GTR + I + Γ
 - recodings to eliminate signal associated with synonymous substitutions
- Bayesian MCMC inference:
 - Phylobayes (Lartillot and Philippe, 2004), GTR + I + Γ + CAT (site-wise composition heterogeneity)
 - P4 (Foster, 2004), GTR + I + Γ + NDCH (clade-wise composition heterogeneity)
- A priori less accurate strategies (using Phylip, Felsenstein, 2005):
 - parsimony bootstrap (200 pseudo-replicates)

- Maximum likelihood bootstrap (200 pseudo-replicates):
 - RAxML (Stamatakis, 2006), GTR + I + Γ
 - recodings to eliminate signal associated with synonymous substitutions
- Bayesian MCMC inference:
 - Phylobayes (Lartillot and Philippe, 2004), GTR + I + Γ + CAT (site-wise composition heterogeneity)
 - P4 (Foster, 2004), GTR + I + Γ + NDCH (clade-wise composition heterogeneity)
- A priori less accurate strategies (using Phylip, Felsenstein, 2005):
 - parsimony bootstrap (200 pseudo-replicates)
 - distance bootstrap (Jukes-Cantor and LogDet, 200 pseudo-replicates)

Principles Application Results Conclusion

Robinson-Foulds distance (a.k.a symmetric difference)



A: bipartitions defined by the branches of one tree

Robinson-Foulds distance (a.k.a symmetric difference)



A: bipartitions defined by the branches of one treeB: bipartitions defined by the branches of the other tree

Robinson-Foulds distance (a.k.a symmetric difference)



A: bipartitions defined by the branches of one tree B: bipartitions defined by the branches of the other tree Distance between the trees: $RF = |A \cap \overline{B}| + |\overline{A} \cap B|$





Full distribution:

- 200² × 6 Robinson-Foulds distances
- Coherence assessed using the distribution and average of these distances





Between consensus:

- 6 Robinson-Foulds distances
- Coherence assessed using these distances and their average












Results



Blaise Li

 To some extent, coherence seems correlated to phylogenetic accuracy.

- To some extent, coherence seems correlated to phylogenetic accuracy.
- But the discriminative power of the Robinson-Foulds based coherence measure is low

- To some extent, coherence seems correlated to phylogenetic accuracy.
- But the discriminative power of the Robinson-Foulds based coherence measure is low and this measure may be subject to biases related to the degree of resolution that a strategy of analysis typically produces.

- To some extent, coherence seems correlated to phylogenetic accuracy.
- But the discriminative power of the Robinson-Foulds based coherence measure is low and this measure may be subject to biases related to the degree of resolution that a strategy of analysis typically produces. (Is this a bug or a feature?)

- To some extent, coherence seems correlated to phylogenetic accuracy.
- But the discriminative power of the Robinson-Foulds based coherence measure is low and this measure may be subject to biases related to the degree of resolution that a strategy of analysis typically produces. (Is this a bug or a feature?)
- Could better measures of coherence be designed?

- To some extent, coherence seems correlated to phylogenetic accuracy.
- But the discriminative power of the Robinson-Foulds based coherence measure is low and this measure may be subject to biases related to the degree of resolution that a strategy of analysis typically produces. (Is this a bug or a feature?)
- Could better measures of coherence be designed?
- Including in the pannel a priori poorly performing analysis strategies may help to detect false positives.

Thanks for your attention

- This work was supported by a Fundação para a Ciência e a Tecnologia (FCT, Portugal) grant to Cymon J. Cox, Centro de Ciencias do Mar (CCMAR) - CIMAR-Lab. Assoc., (PTDC/BIA-BCM/099565/2008).
- I'm currently looking for a job, so if you think I can be useful in your lab, feel free to contact me.
- Contact: blaise.li@normalesup.org

This work relied heavily on the Python programming language.