Detecting heterogeneity in phylogenetic inference

> Daisy Shephero

Introduction & Motivatior

Methods & Data

Results & Key Findings

Current work

Detecting heterogeneity in phylogenetic inference

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The Proposed Solution



Methods & Data

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- Alignments simulated from Seqgen
- Model: JC69 + γ + I
- 8 taxa
- Used three different topologies:
 a) Balanced, b) Caterpillar, and c) Intermediate



Analysis in PhyML

Results Difference in log-likelihoods



Results Site likelihoods for individual trees



Key Findings

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Current work

- AIC, BIC suggested neither model consistently preferred.
- AIC favoured the simplicity of the proposed model.
- Wide Cls Large variation.

But... Is it really necessary to implement the more complex model for little improvement?

Current Work Main Ideas

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Ability to detect heterogeneity on a genomic scaleCase Study: Sliding Window Approach



Preliminary findings & Future work

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Full Alignment Analysis:

Heterogeneous model over Homogenous model 75% of time

Sliding Window Analysis:

Accurate in detection & parameter estimation

So where to next?

Acknowledgements

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