



Abstract

- Many structure learning algorithms are based on Granger causality
- Granger causality is unreliable given undersampled time series data
- We developed RASL to learn structure from undersampled data
- In simulated data, RASL algorithms reveal causal timescale structure and improved measurement timescale learning
- RASL algorithms provide additional insight on fMRI data

Problems with “Granger Causality”

- **Granger causality:** X Granger-causes $Y \equiv X$ ’s history provides information about Y ’s current state (beyond Y ’s history)
- Mathematically: $Y^t = \sum_{i=1}^k [\alpha_i Y^{t-i} + \beta_i X^{t-i}]$ is a significantly better predictor of Y^t than $Y^t = \sum_{i=1}^k \alpha_i Y^{t-i}$ (perhaps with covariates)
- Granger causality only reliable if key assumptions hold:
 - *Linearity* (but hemodynamic convolution does not create problems)
 - *Causal sufficiency* (but becoming less of a problem)
 - *Equal timescales* for both measurement and underlying causation
- **Undersampling:** Measurement timescale significantly slower than causal or communication timescale
 - Intermediate time points are unobserved
- Granger causality can be arbitrarily wrong given undersampling
 - X GC Y even though Y actually causes X
 - X GC Y even though no direct causal connection
 - X doesn’t GC Y even though X actually causes Y
- Undersampling is a ubiquitous, persistent feature of fMRI data
- **Conclusion:** Structure learning algorithms based on Granger causality are likely unreliable given fMRI data

How to Overcome the Problems

- put figure 1 here and describe succinctly

Synthetic Data

Talk about results and include pictures:

NOTE: do not forget UNM and CMU logo (already added to logo folder but not sure where to place in poster)

fMRI Data

Talk about results and include pictures:

Conclusions

Conclude stuff here

References

[1] Authors Title In *Journal*, year.