

New Approaches To Analysing Psychological Time Series

SAA 2023 Symposium

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Extracting Dynamic Features from Irregularly Spaced Time Series

R package *expct*

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Descriptive / Exploratory Tools

- | Autocorrelation function (ACF)
- | Cross-Correlation function (CCF)

Y

y_1

y_2

y_3

y_4

y_5

y_6

y_7

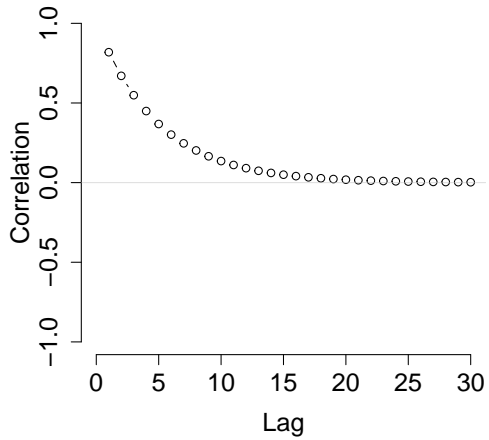
y_8

\vdots

y_T

Y	Y at lag 1	Y at lag 2
y_1		
y_2	y_1	
y_3	y_2	y_1
y_4	y_3	y_2
y_5	y_4	y_3
y_6	y_5	y_4
y_7	y_6	y_5
y_8	y_7	y_6
\vdots	\vdots	\vdots
y_T	y_{T-1}	y_{T-2}
	y_T	y_{T-1}
		y_T

Autocorrelation



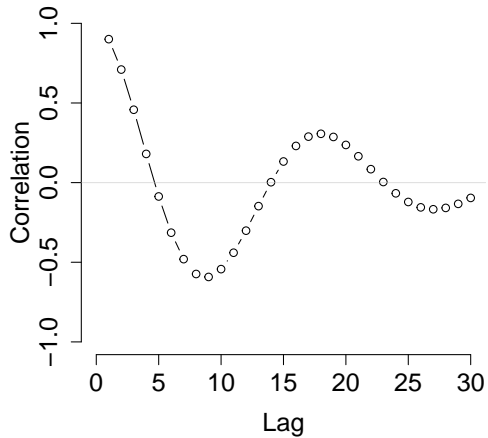
Descriptive / Exploratory Tools

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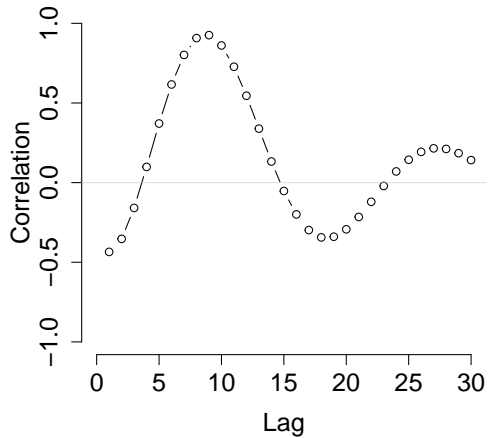
Models such as VAR and ARIMA

- | AR(1), AR(2), VAR(p)

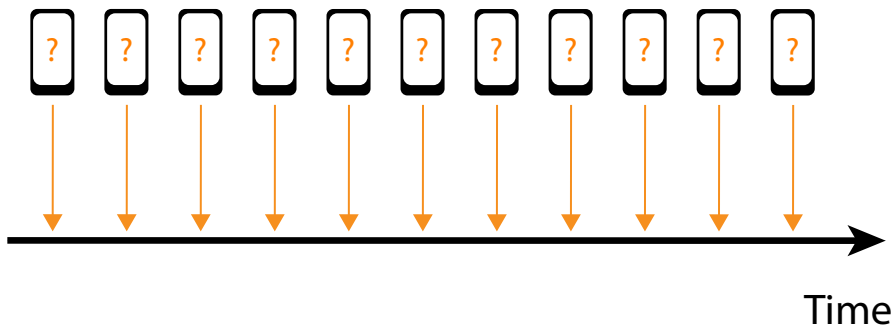
Autocorrelation



Cross-correlation



Assumption: Equally Spaced Measurements



Equally Spaced Data

Reality: Irregularly Spaced Measurements

Reality: Irregularly Spaced Measurements

Measurement Spacing in Empirical Data

Unequally Spaced Data

Continuous-Time Modeling

Avoids time-interval problems by modelling moment-to-moment dynamics directly:

$$\frac{dY(t)}{dt} = A Y(t) + G \frac{dW(t)}{dt}$$

Re-written allows us to model variable relations at different time-intervals

$$Y(t + \Delta t) = e^{A \Delta t} Y(t) + (G \Delta W)$$

Can be estimated, e.g., using the `ctsem` package (Driver et al. 2017)

- | Use $e^{A \Delta t}$ to inspect auto- and cross regression effects at different time-intervals
- | Or transform to find model-implied auto and cross correlations

Boker (2002); Oud & Delsing (2010); Voelkle et al (2012); Ryan & Hamaker (2022)

Problem: Model Misspecification

Model-based correlations accurate only if the model is correctly specified

In reality the model is never correctly specified.

- | We may have the order of the model (1st vs 2nd) wrong
- | Functional form of the relationships may not be linear at the DE level
- | Even if we have a linear 1st order model, if we have unobserved confounders or even mediators, we may run into problems

ctsem estimation: Simple Model

ctsem estimation: Misspecified Model

Traditional ACF estimation:

- | **Data-driven and exploratory** method for exploring dynamic features
- | Does not perform well with unequally spaced time series

Continuous-Time (CT) model estimation:

- | Can be estimated from **unequally spaced time series**
- | Inferences rely on correct model specification
- | Without a data-driven way of computing auto- and cross- correlations:
no easy way to check model misspecification

expct Exploratory Continuous Time Modeling

Method to estimate ACF and CCFs from unequally spaced data

R package: [github: ryanoisin/expct](#)

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Two-step procedure

1. Create a "stacked" data frame

Y	Time stamp
y_1	0
y_2	s_1
y_3	s_2
y_4	s_3
y_5	s_4
y_6	s_5
y_7	s_6
y_8	s_7
\vdots	\vdots
y_T	s_T

expct Exploratory Continuous Time Modeling

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Two-step procedure

1. Create a "stacked" data frame
2. Use Generalized Additive Model (GAM) to estimate how lagged correlations depend on the time-interval

$$Y_{t+\Delta t} = f(\Delta t)Y_t +$$

expct Exploratory Continuous Time Modeling

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$$Y_{t+\Delta t} = f(\Delta t)Y_t +$$

By rescaling $f(\Delta t)$ we estimate

$$\text{cor}(Y_t; Y_{t+\Delta t}) / f(\Delta t)$$

expct estimation: unequally spaced

Simulation Study

Time-series length: [50 - 2000]

Sampling Scheme: f Equal, Unequal Bimodal, Unequal Uniform

Data-generating models: f Simple, Oscillating, Complex (missing variables)

Methods for computing CIs:

- | Point-wise, Simultaneous, Analytic

We use "function-wide" averages to summarize performance:

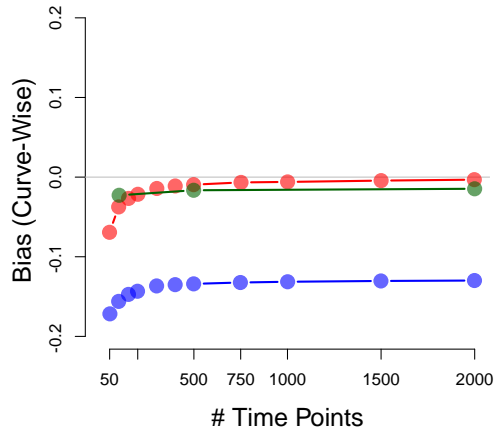
- | Function-wide bias: Average distance between true and estimated correlation function evaluated at a range of time-intervals / lags

Bias: Simple Model, Equal Spacing

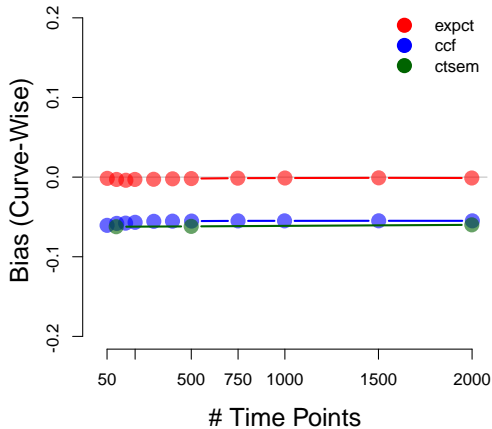
Bias: Complex Model, Equal Spacing

Bias: Complex Model, Unequal Spacing

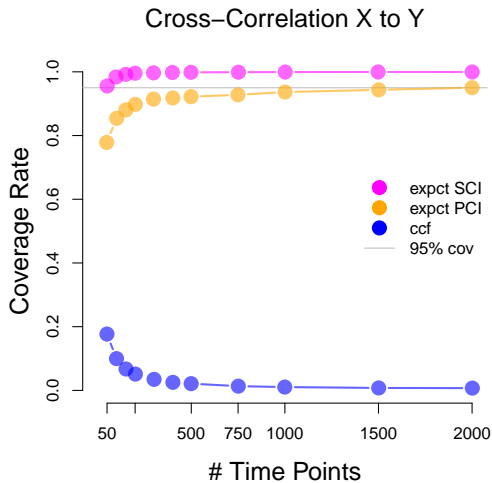
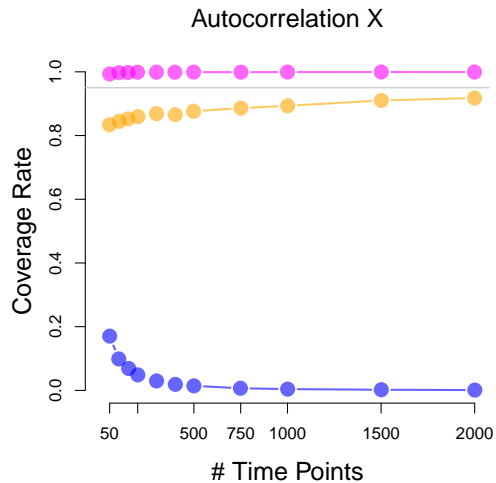
Autocorrelation Y



Cross-Correlation X to Y



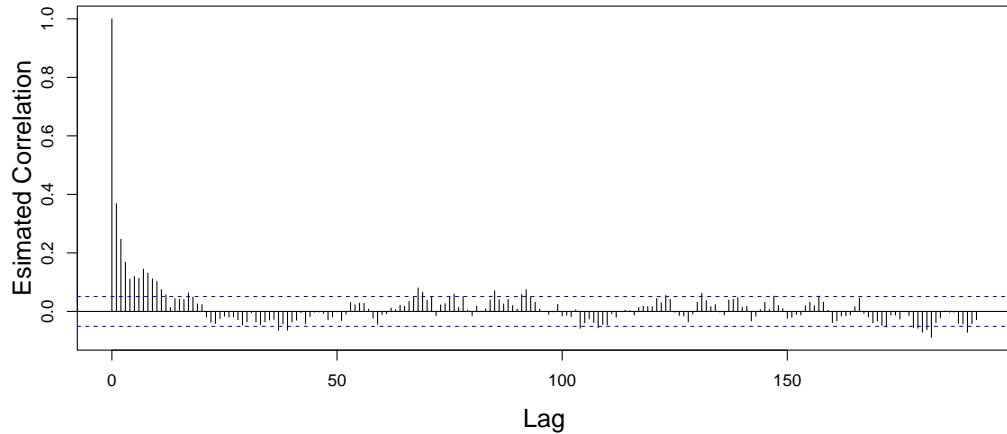
Coverage: Complex Model, Unequal Spacing



Empirical Data

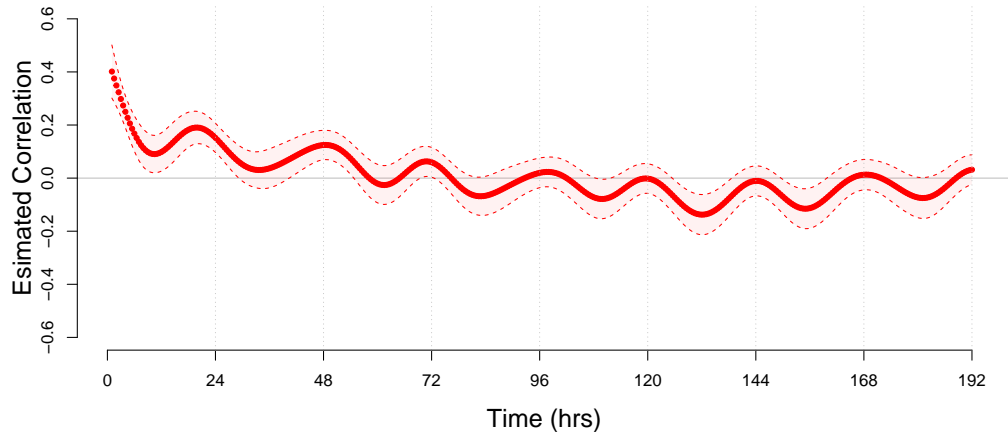
Empirical Data

Autocorrelation Self-Doubt (acf)



Empirical Data

Autocorrelation Self-Doubt (expct)



Future work

In principle this method can be used in other situations than those studied here

- | Systems of variables measured at different timescales (e.g., daily diary vs hourly ratings vs minute-to-minute physiological measurements)
- | “Panel” data: multi-subject low repeated measures

Extensions in progress:

- | Multi-level time-series data (random effects)
- | Partial relationships (PACF, PCCF)

Extracting Dynamic Features from Irregularly Spaced Time Series

expct: Exploratory continuous-time modeling

- | Available as an R package [github: ryanoisin/expct](#)
- | Overcomes equal-interval limitation of traditional ACF/CCF estimation
- | Avoids reliance on correct lagged model specification in confirmatory continuous-time models
 - | *ctsem*, *dynr*

Ryan O., Wu, K., & Jacobson, N.K. (in preparation). Exploratory Continuous-Time Modeling (*expct*): Extracting Dynamic Features from Irregularly Spaced Time Series

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