DEPARTMENT OF BIOMEDICAL DATA SCIENCE GEISEL SCHOOL OF MEDICINE

Uncovering When Dynamic Variables Optimally Predict One Another in Intensive Longitudinal Data using Novel Personalized Modeling Strategies

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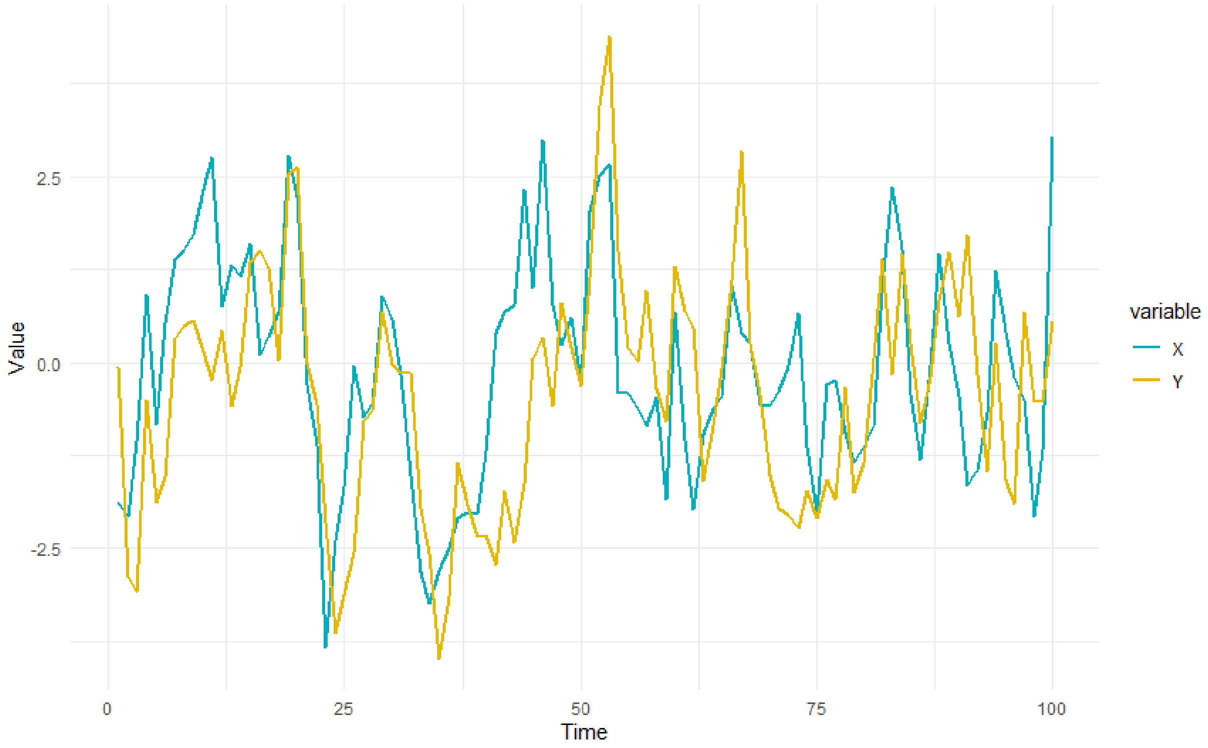
Intensive Longitudinal Data: A Powerful Tool

- The collection of intensive longitudinal data can assess dynamic processes

- Many of our psychological theories include states which change over time

- Dynamic processes: Relationships one or more variables that vary over time



Design Considerations: Timing of Active Assessments

- When we don’t know the “ground truth” and want to try to sample it periodically
  - Does not apply to event contingent designs

- Options:
- **Signal contingent:** Ping people and ask that they complete the assessments
  - **Suboption**: Can choose between random (8 prompts per day at any time) or windowed random (random time between 8 – 10 AM; 10:01 AM – 12 PM, etc)
- **Interval contingent**: Ask that persons complete assessments at a specified interval (e.g. every hour; every 15 minutes, every day)

Design Considerations: Timing of Assessments

- With dynamic processes, timing matters a LOT
- If we mis-time our data collection, it has huge implications
- **Example:** Movement of helicopter blades
- Timing of assessments (i.e. shutter speed here) can make it look like they move very slowly or not at all
  - Can change the direction of the blades

Video Credit:

BrainStuff - HowStuffWorks

How do You Choose How Often to Sample?

- Theory!
  - If you have a strongly suggestive theory about timing, great!
- But…most theories do not specify ***when***…
- **Common practice!:** Researcher X, Y, & Z each used that interval before!
  - **Do <u>not</u> do this!**
- **Best practice!:** Try to sample your process systematically – it's much better to oversample than undersample
- Incorrect timing will **<u>not</u>** allow us to test our theories

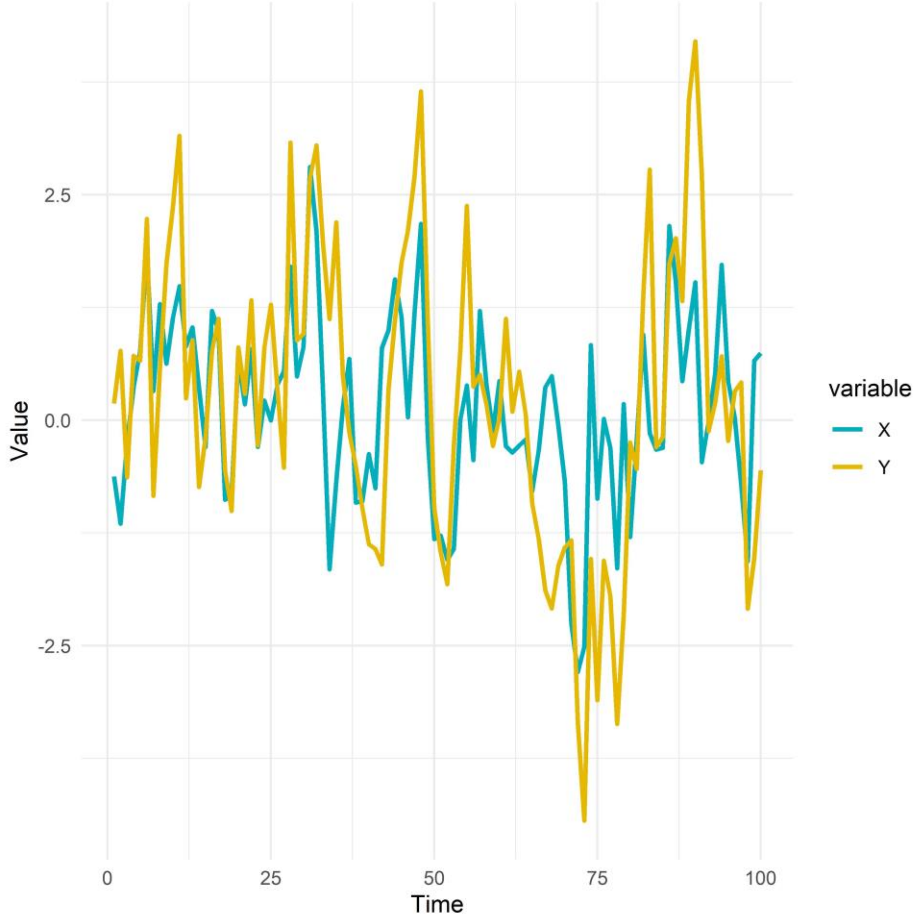
Analyzing Intensive Longitudinal Data

- **Common practice**: Look at dynamic processes concurrently or one unit in time (i.e. lag) later
  - Okay if you have a strong theory about timing
  - <u>**Not okay**</u> in the vast majority of intensive longitudinal data work

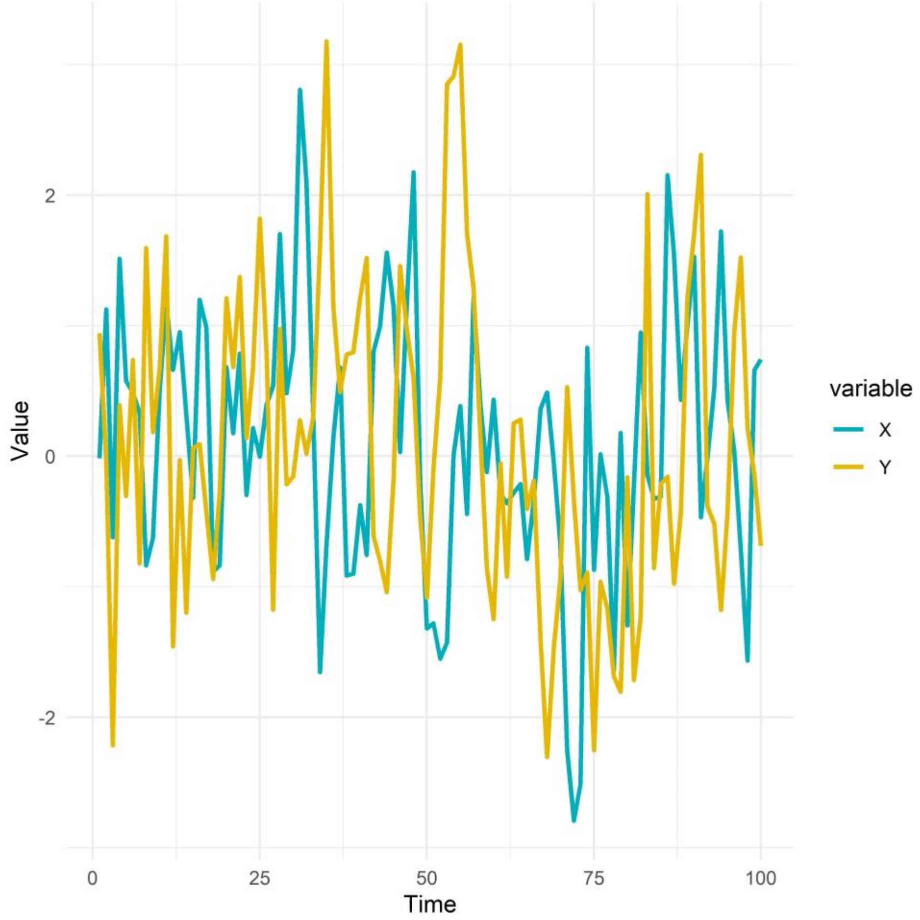
- **Best practice**: Investigate the times in which processes optimally predict one another

I would just see it in my data, right?

- Yes with small lag:
- Lag 1



- **<u>No</u>** with large lags:
- Lag 10



New Alternative:
The Differential Time-Varying Effect Model

- Automated R package which fits smooth curves to the data to explore potential higher order lags, strongly backed by simulation studies

- Next: subsequently performs confirmatory analyses using gold-standard state-space modeling routines

- Usages: One to many predictors, one to many outcomes, one to many people
- Uses full information maximum likelihood for missing data

Behavior Research Methods
https://doi.org/10.3758/s13428-018-1101-0

CrossMark

The Differential Time-Varying Effect Model (DTVEM): A tool for diagnosing and modeling time lags in intensive longitudinal data

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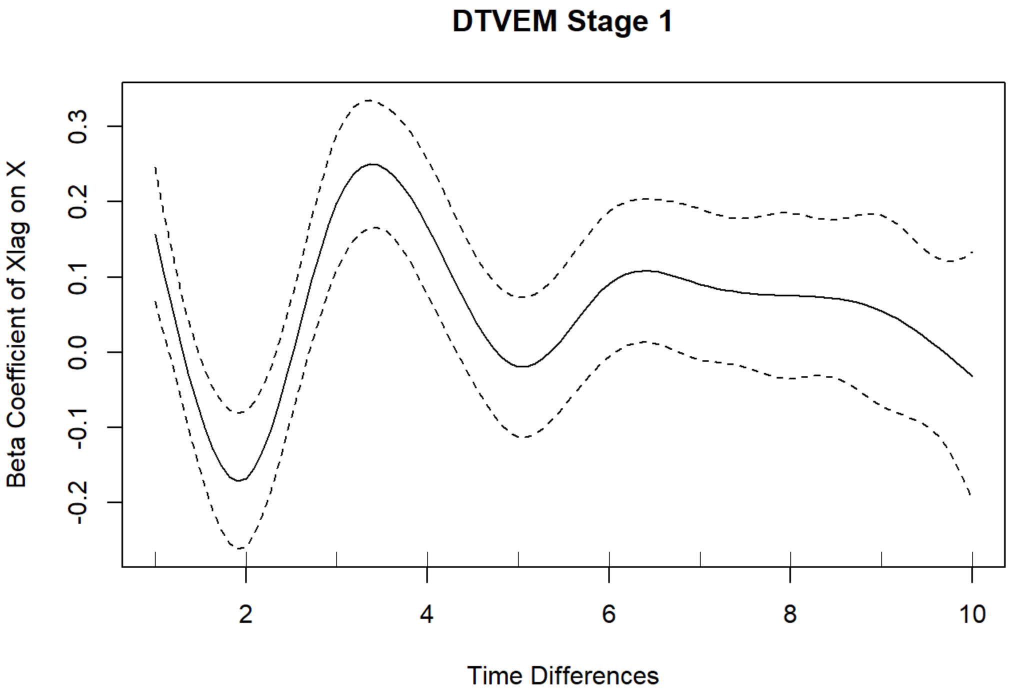
Output

Exploratory

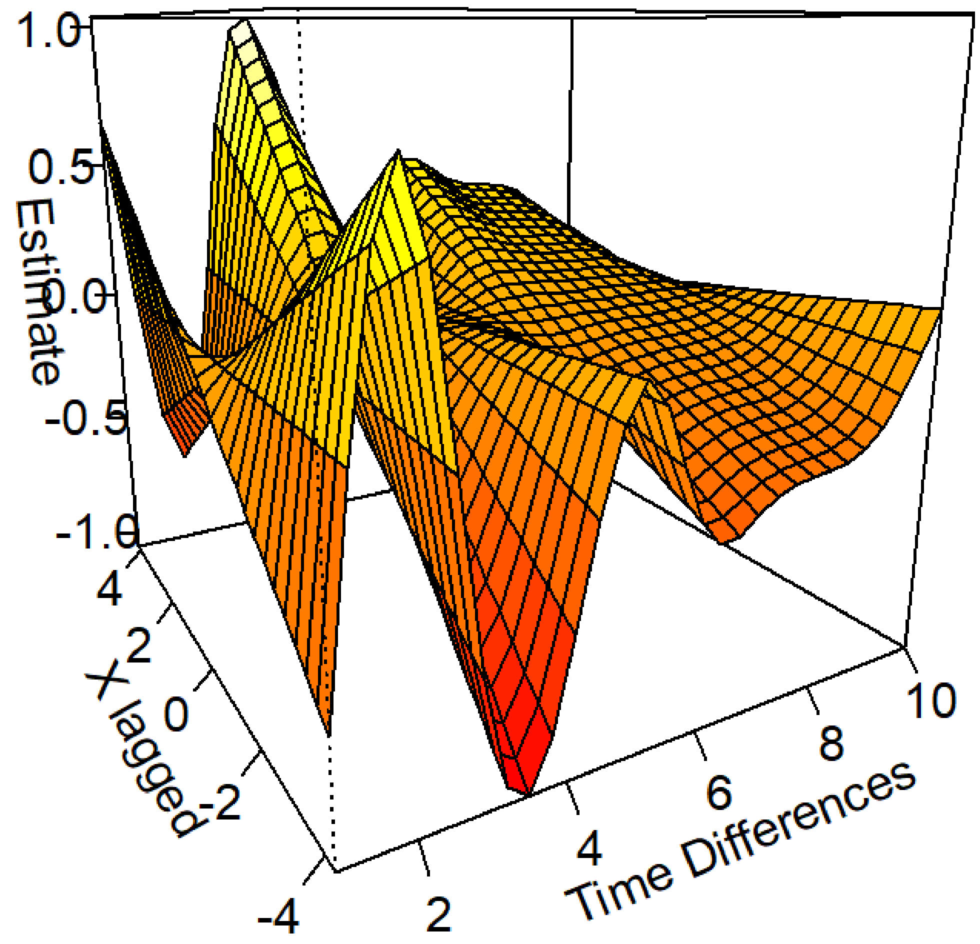


Confirmatory

```
##          name matrix row col   Estimate  Std.Error lbound ubound lboundMet
## 1 XlagonXlag1   s1.A   1   1  0.2360088 0.04461888     NA     NA     FALSE
## 2 XlagonXlag2   s1.A   1   2 -0.2485319 0.04220480     NA     NA     FALSE
## 3 XlagonXlag3   s1.A   1   3  0.2835748 0.04300307     NA     NA     FALSE
##   uboundMet     tstat       pvalue  sig
## 1     FALSE  5.289438 1.226928e-07 TRUE
## 2     FALSE -5.888712 3.892167e-09 TRUE
## 3     FALSE  6.594293 4.272871e-11 TRUE
```

A second line of code to visualize

- vis.gam(out$stage1out$mod,xlab="Time Differences",ylab="X lagged",zlab="Estimate",theta=-30,ticktype="detailed")



Variable Predicting Itself Over Time

- A single line of code:

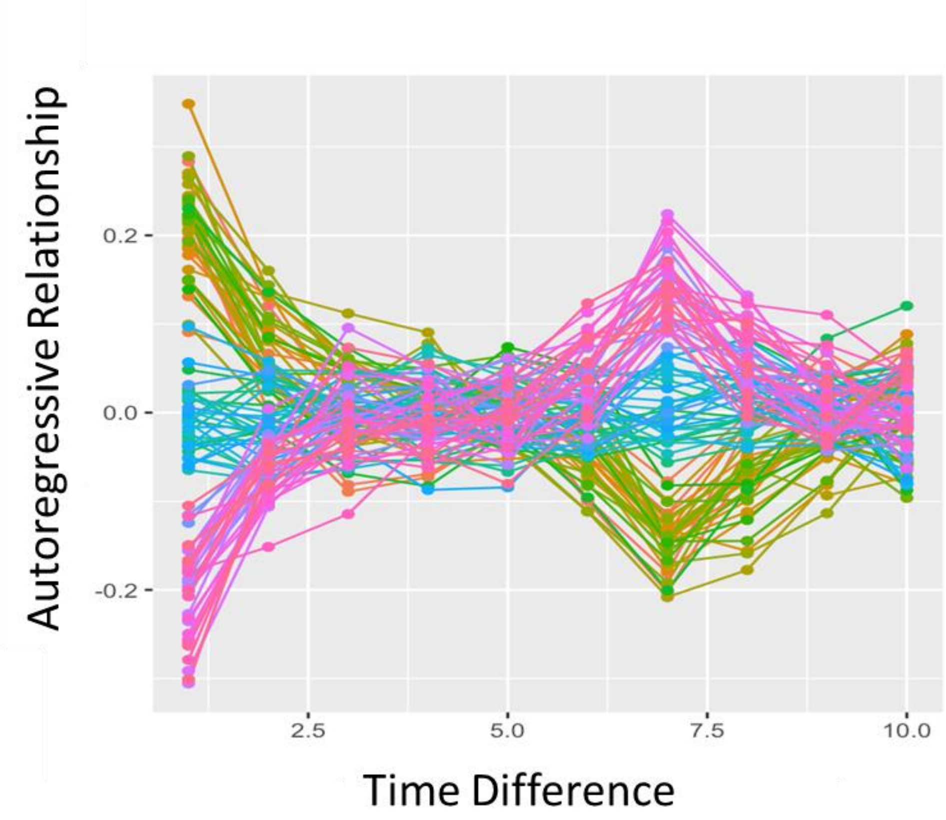
- out=LAG("X",differntialtimevaryingpredictors=c("X"),outcome=c("X"), data=exampledat1,ID="ID",Time="Time",k=9,standardized=FALSE,pre dictionstart = 1,predictionsend = 10,predictionsinterval = 1)

Our Prior Work

- Assumes that you have processes that are either person-specific (n = 1) or common to the entire sample (N)

Current Extension

- Can detect subgroups of persons with common lag dynamics
  - Fit a generalized additive mixed model with a random smooth, such that each person can have unique dynamic relationships
  - Use hierarchical clustering to detect subgroups of the random smooth estimates
  - Estimate the subgroups together



Thank you to my lab!

Postdocs

PhD Students

Research Assistants

Masters Students

Visiting Scholar

Undergraduate research assistants

Where do I get this?

- Idiographic and group work

- http://www.nicholasjacobson.com/project/dtvem/