

Empirical Bayes Derivative Estimates

Pascal R. Deboeck
University of Utah

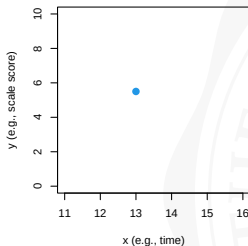
Modern Modeling Methods 2023
University of Connecticut
June 27, 2023

Introduction

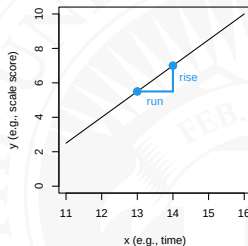
- Derivative Estimation, Empirical Bayes Derivative Estimates
- Simulations: Short, Long Time Series
- Substantive Examples

Derivatives

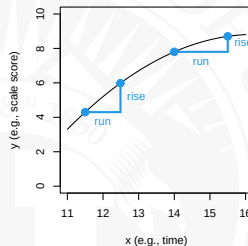
Level, Zeroth Derivative



Velocity, First Derivative

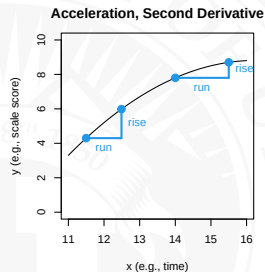
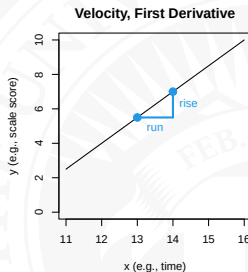
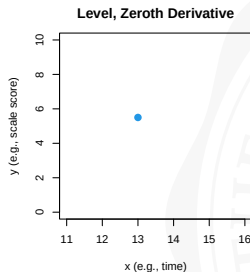


Acceleration, Second Derivative



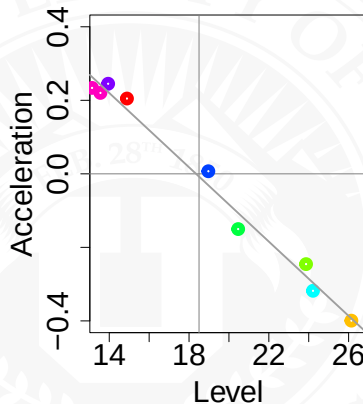
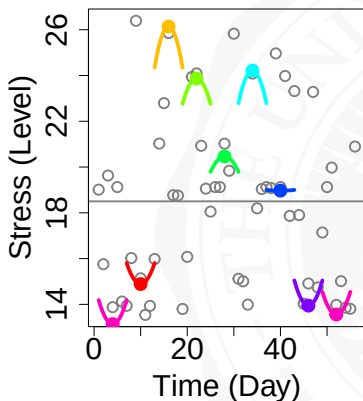
- Zeroth: x , First: dx/dt , Second: d^2x/dt^2

Derivatives



- Zeroth: x , First: dx/dt , Second: d^2x/dt^2
- Relations between derivatives

Differential Equation Modeling



Order-Plus-One

- Difference Scores ($x_t - x_{t-1}, x_{post} - x_{pre}$)
 - Zeroth Difference: x_t
 - First Difference: $x_{t+\Delta} - x_t$
 - Second Difference: $(x_{t+\Delta} - x_t) - (x_t - x_{t-\Delta})$

¹Boker & Nesselroade, 2002

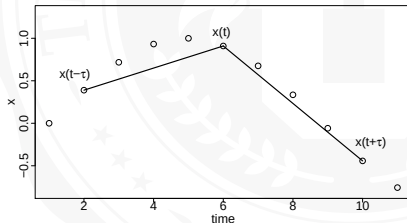
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- Local Linear Approximation¹
 - Zeroth Derivative: x_t
 - First Derivative: $(x_{t+\Delta} - x_t)/\tau\Delta$
 - Second Derivative: $(x_{t+\Delta} + x_{t-\Delta} - 2x_t)/\tau^2\Delta^2$

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 - Time explicit, τ smoothing



¹Boker & Nesselroade, 2002

Regression Methods

- Generalized Local Linear Approximation (GLLA)²
 - $X = \{X_t, X_{t+1}, X_{t+2}, X_{t+3}, X_{t+4}\}$
 - $X = \beta_0 + \beta_1(Time) + \beta_2(\frac{1}{2}Time^2) + \varepsilon$
 - Derivatives: $\beta_0, \beta_1, \beta_2$

²Boker, Deboeck, Edler & Keel, 2009

³Deboeck, 2010

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- Generalized Orthogonal Local Derivative Estimates (GOLD)³
 - EQ1: $X = \beta_0 + \epsilon$
 - EQ2: $X = \beta_0 + \beta_1(Time) + \epsilon$
 - EQ3: $X = \beta_0 + \beta_1(Time) + \beta_2(\frac{1}{2}Time^2) + \epsilon$
 - Derivatives: β_0 (EQ1), β_1 (EQ2), β_2 (EQ3)

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Regression Methods

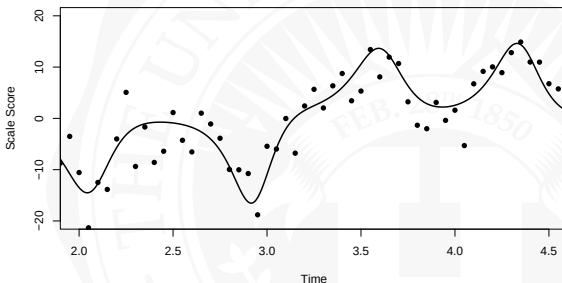
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 - Derivatives: $\beta_0, \beta_1, \beta_2$
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 - EQ1: $X = \beta_0 + \epsilon$
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 - EQ3: $X = \beta_0 + \beta_1(Time) + \beta_2(\frac{1}{2}Time^2) + \epsilon$
 - Derivatives: β_0 (EQ1), β_1 (EQ2), β_2 (EQ3)
 - Advantages are the same as GLLA, orthogonal partitioning of variance

²Boker, Deboeck, Edler & Keel, 2009

³Deboeck, 2010

Non-independent Estimation

- Functional Data Analysis⁴
- Repeated observations: complex, but smooth, process



- Polynomial segments (like GLLA), but time-adjacent polynomials the derivatives are constrained to be continuous (to specified derivative)

⁴Ramsay & Silverman, 2002, 2005

Non-independent Estimation

- Empirical Bayes Derivative Estimates

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Non-independent Estimation

- Empirical Bayes Derivative Estimates
- Panel Data (large n , few t), Developmental Psychology
- Multilevel Model, random effects for Intercepts and Slopes
- Derivatives (Level, Velocity, Acceleration) as random effects

Short Time Series Data Structure

$id(i)$	X_{it}	$Time$	$\frac{1}{2}Time^2$
1	X_{11}	-1.5	1.125
1	X_{12}	-0.5	0.125
1	X_{13}	0.5	0.125
1	X_{14}	1.5	1.125
2	X_{21}	-1.5	1.125
2	X_{22}	-0.5	0.125
2	X_{23}	0.5	0.125
2	X_{24}	1.5	1.125
⋮	⋮	⋮	⋮

Long Time Series Data Structure

id	$Windows(i)$	X_{it}	$Time$	$\frac{1}{2}Time^2$
1	1	X_{11}	-1.5	1.125
1	1	X_{12}	-0.5	0.125
1	1	X_{13}	0.5	0.125
1	1	X_{14}	1.5	1.125
1	2	X_{12}	-1.5	1.125
1	2	X_{13}	-0.5	0.125
1	2	X_{14}	0.5	0.125
1	2	X_{15}	1.5	1.125
1	3	X_{13}	-1.5	1.125
1	3	X_{14}	-0.5	0.125
1	3	X_{15}	0.5	0.125
1	3	X_{16}	1.5	1.125
⋮	⋮	⋮	⋮	⋮

Empirical Bayes Derivative Estimates

$$X_{it} = \beta_{0i} + \beta_{1i}(\text{Time}) + \beta_{2i}(\tfrac{1}{2}\text{Time}^2) + \varepsilon_{it}$$

$$\beta_{0i} = \gamma_{00} + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + u_{1i}$$

$$\beta_{2i} = \gamma_{20} + u_{2i}$$

- Multivariate normal distribution of derivatives: $\beta_{0i}, \beta_{1i}, \beta_{2i}$

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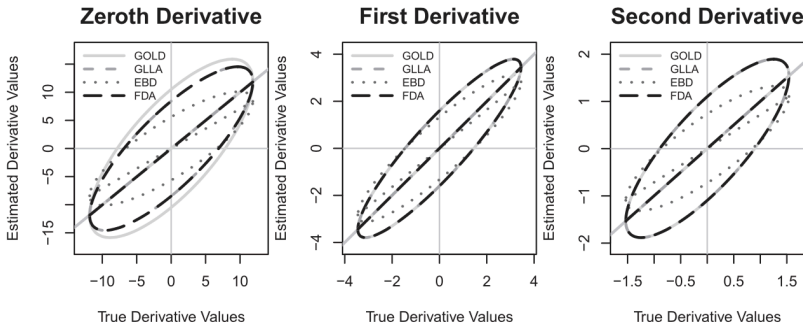
$$\beta_{2i} = \gamma_{20} + u_{2i}$$

- Multivariate normal distribution of derivatives: $\beta_{0i}, \beta_{1i}, \beta_{2i}$
- Subsequent estimation of random effects: "Conditional mean/mode" estimates
- Application of Bayes' formula with model estimates as known prior, data for each "group"

Simulations

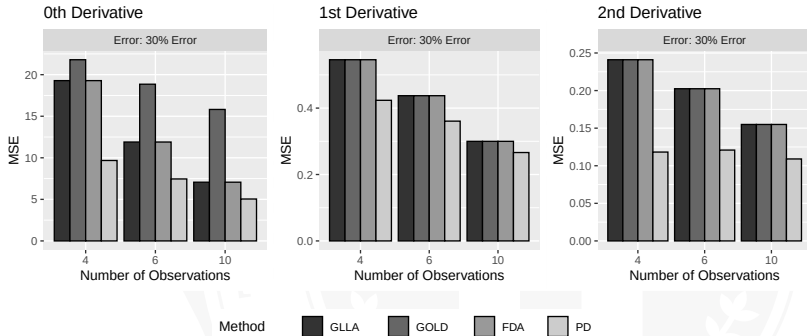
- Two Simulations: Short, Long time series
- GLLA, GOLD, FDA, EBD
- Short Time Series
 - Quadratic time series
 - 4-10 observations per time series
 - 25, 50, 100, 500 time series (i.e., many individuals)
 - Measurement error: 10%, 30%, 50%

Results



- 100 time series, 30% measurement error, 6 observations/time series

Results, MSE

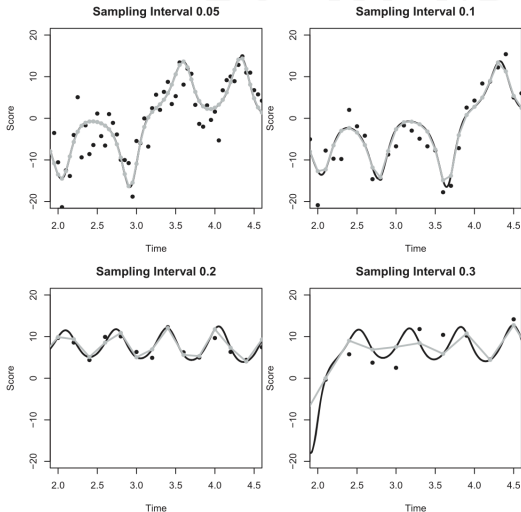


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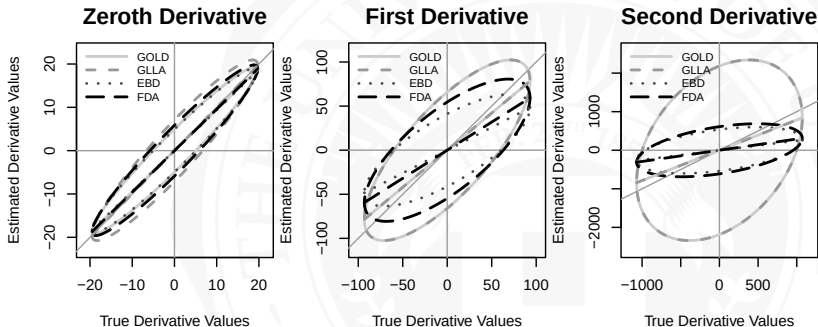
Long Time Series Simulation

- “x” component of Lorenz Attractor
- Varied sampling rate (0.05, 0.10, 0.20, 0.30)
- Embedding 5
- Time series of 25, 50, 100, 500 observations
- Measurement error: 10%, 30%, 50%

Long Time Series, Sampling Rates

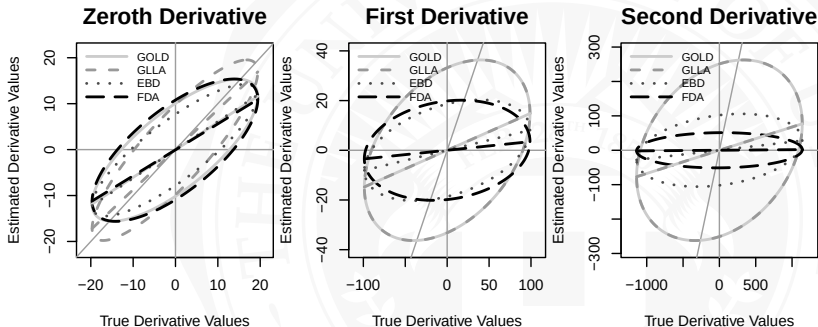


Results: High Fidelity, Sampling Rate 0.05



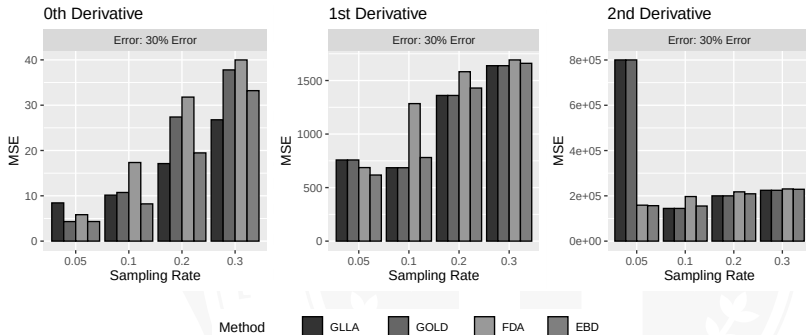
- Time series length of 100, 30% error

Results: Low Fidelity, Sampling Rate 0.20



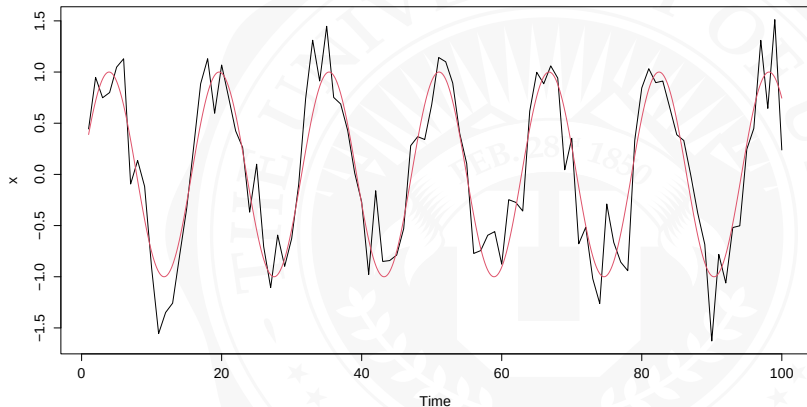
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Results, MSE

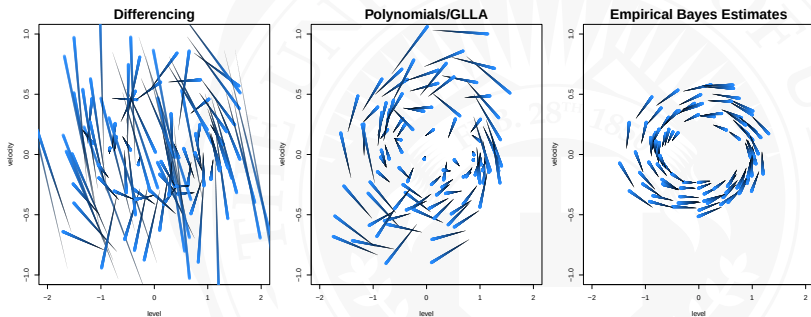


- Time series length of 100, 30% error

Differencing — GLLA — EBD



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Limitations

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- Fairly robust to non-normality of random effects
- Same mean/covariance matrix across all estimates
 - People with Different Dynamics
 - Non-stationary Time Series
- Linear relations between derivatives

Variations

- Multilevel Modeling Advantages

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- Generalized Linear Mixed Models (Categorical, Poisson data)

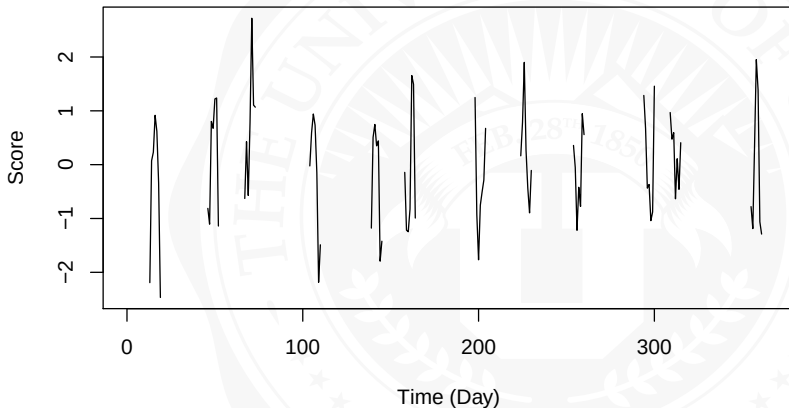
Variations

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- Simultaneously Detrend Data

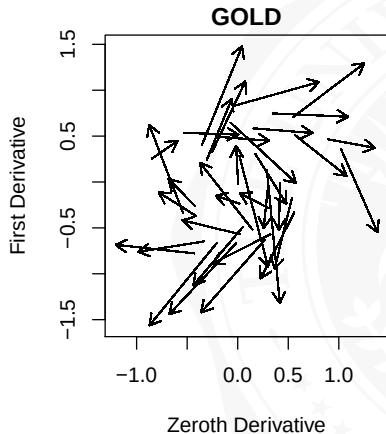
Variations

- Multilevel Modeling Advantages
- Unequal Observation Intervals/Missing Data
- Generalized Linear Mixed Models (Categorical, Poisson data)
- Simultaneously Detrend Data
- New intensive sampling schemes

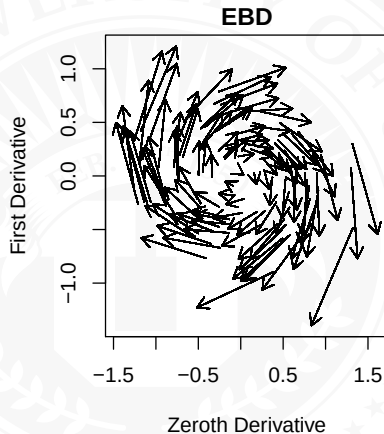
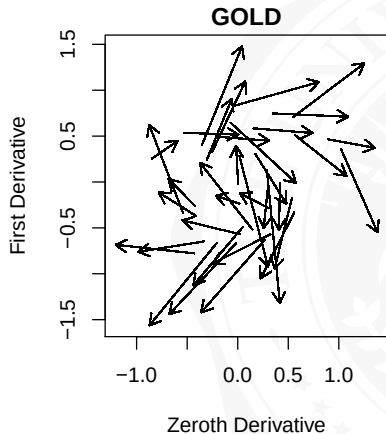
7/30 Sampling Scheme



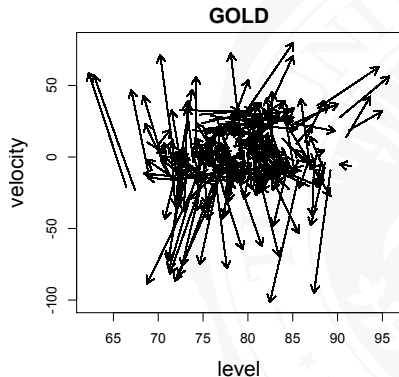
7/30 Sampling Scheme



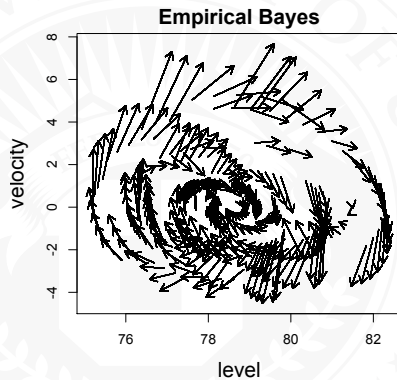
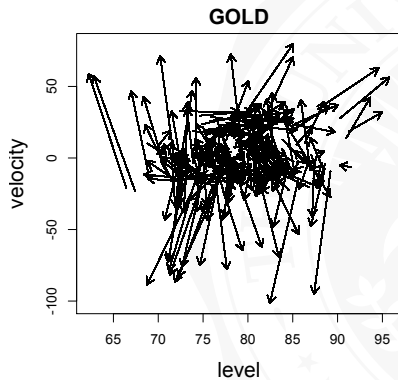
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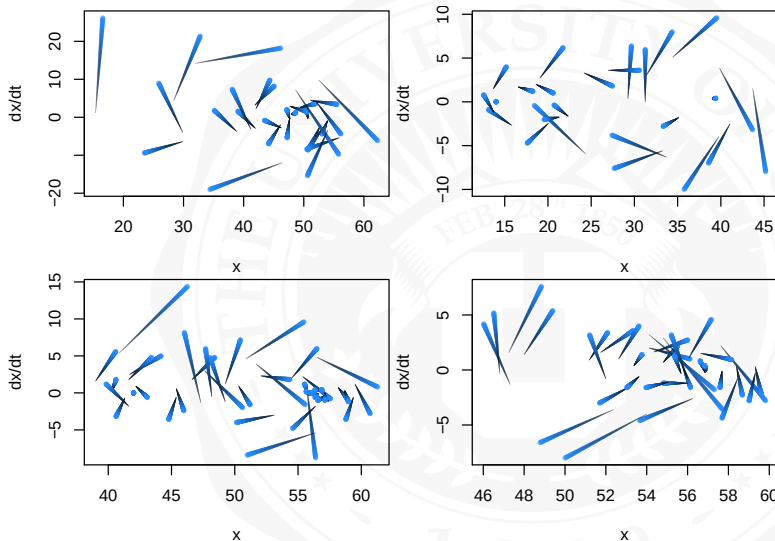
Heart Rate Data



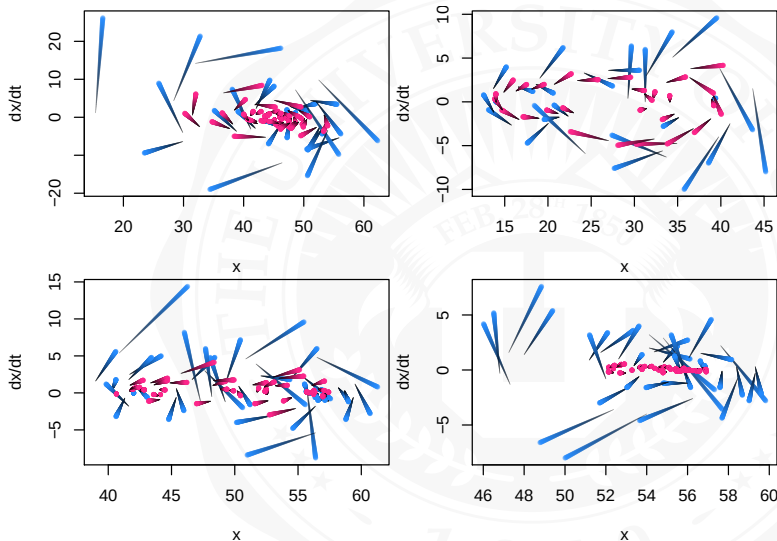
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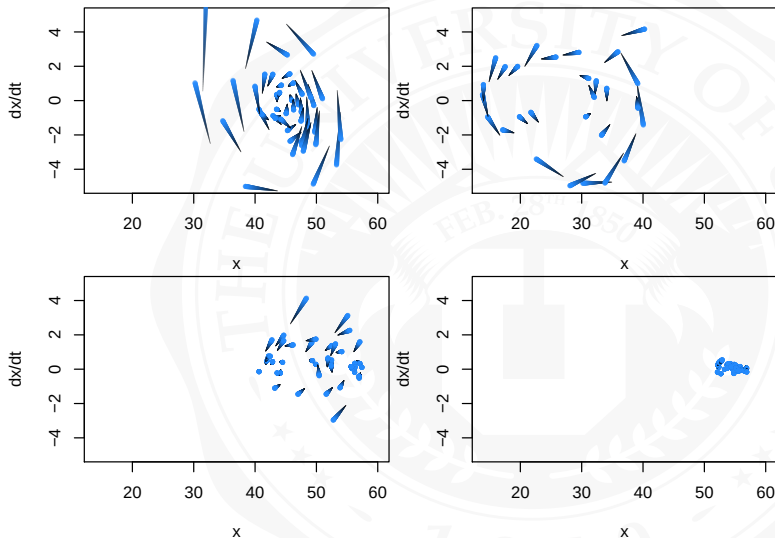
Positive Affect, Daily for 56 Days (GOLD)



Positive Affect, Daily for 56 Days (GOLD, EBD)



Positive Affect, Daily for 56 Days (EBD)



Conclusion

- Derivative Estimation
 - Order-Plus-One (Differences, LLA), Regression Methods (GLLA, GOLD), Non-independent Estimation (FDA)
 - Empirical Bayes Derivative Estimates (Multilevel Models, random effects)
 - Simulations highlight attenuation, greatly reduced variance
 - Generally as efficient or better than GLLA/GOLD/FDA
- Variations
 - Unequal Observation Intervals/Missing Data
 - Generalized Linear Mixed Models (Categorical, Poisson data)
 - Simultaneously Detrend Data
 - New intensive sampling schemes (7/30 for a year)
- Substantive: Heart Rate, Positive Affect



- Paper: Deboeck, P. R. (2020). Empirical Bayes Derivative Estimates. *Multivariate Behavioral Research*, 55:3, 382–404.
- Substantive State-Space Modeling: Montpetit, M. A., Bergeman, C. S., Deboeck, P. R., Tiberio, S. S. & Boker, S. M. (2010) Resilience-As-Process: Negative Affect, Stress, and Coupled Dynamical Systems. *Psychology and Aging*, 25 (3), 631–640.
- GLLA: Boker, S. M., Deboeck, P. R., Edler, C. & Keel, P. K. (2009). Generalized Local Linear Approximation of Derivatives from Time Series. In S. Chow, E. Ferrer & F. Hsieh (Eds.), *Statistical Methods for Modeling Human Dynamics: An Interdisciplinary Dialogue*, pp. 161–178. New York, NY: Taylor & Francis Group.
- GOLD: Deboeck, P. R. (2010). Estimating Dynamical Systems, Derivative Estimation Hints from Sir Ronald A. Fisher. *Multivariate Behavioral Research*, 43 (4), 725–745.