2021 SPES Award
"Optimal EMG Sensor Placement for Robotic Prosthetics with Sequential Adaptive Functional Estimation"

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September 2020

Optimal EMG placement for a robotic prosthesis controller with sequential, adaptive functional estimation (SAFE)

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Abstract

Robotic hand prostheses require a controller to decode muscle contraction information, such as electromyogram (EMG) signals, into the user's desired hand movement. State-of-the-art decoders demand extensive training, require data from a large number of EMG sensors and are prone to poor predictions. Biomechanical models of a single movement degree-of-freedom tell us that relatively few muscles, and, hence, fewer EMG sensors are needed to predict movement. We propose a novel decoder based on a dynamic, functional linear model with velocity or acceleration as its response and the recent past EMG signals as functional covariates. The effect of each EMG signal varies with the recent position to account for biomechanical features of hand movement, increasing the predictive capability of a single EMG signal compared to existing decoders. The effects are estimated with a multistage, adaptive estimation procedure that we call Sequential Adaptive Functional Estimation (SAFE). Starting with 16 potential EMG sensors, our method correctly identifies the few EMG signals that are known to be important for an able-bodied subject. Furthermore, the estimated effects are interpretable and can significantly improve understanding and development of robotic hand prostheses.

Citation

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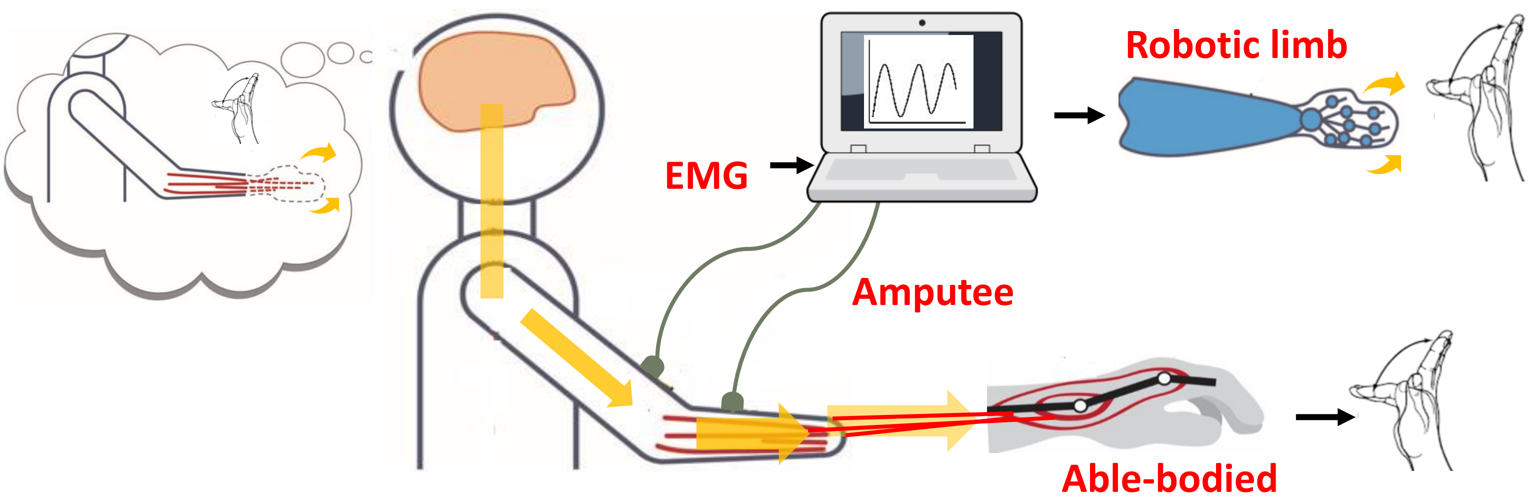
Institute of Mathematical Statistics

Robotic Hand Prosthetic

- NCSU biomedical engineers developing an **Electromyogram (EMG)-driven robotic hand prosthetic** for transradial amputees

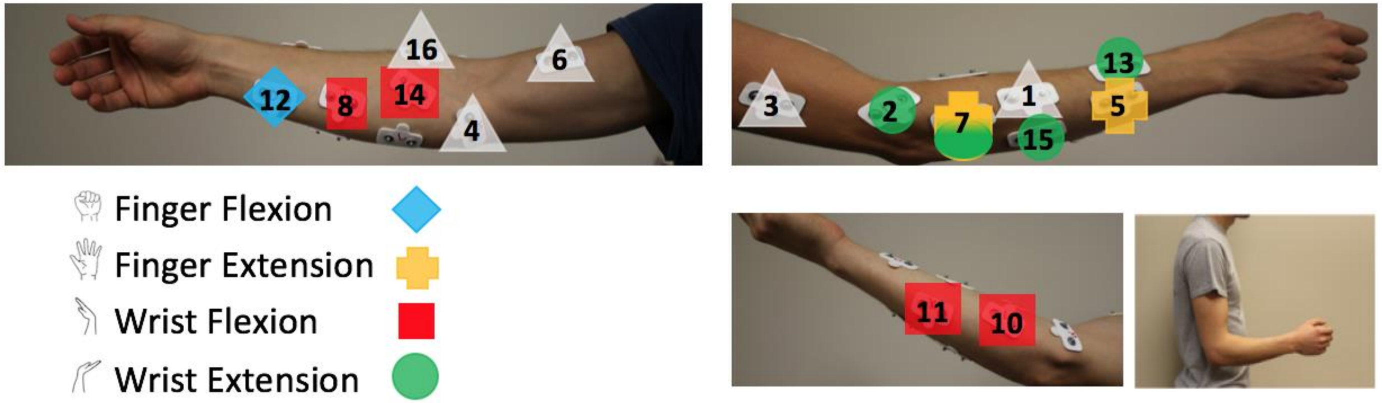
- What does EMG-driven mean? What's a transradial amputee? How does this work?

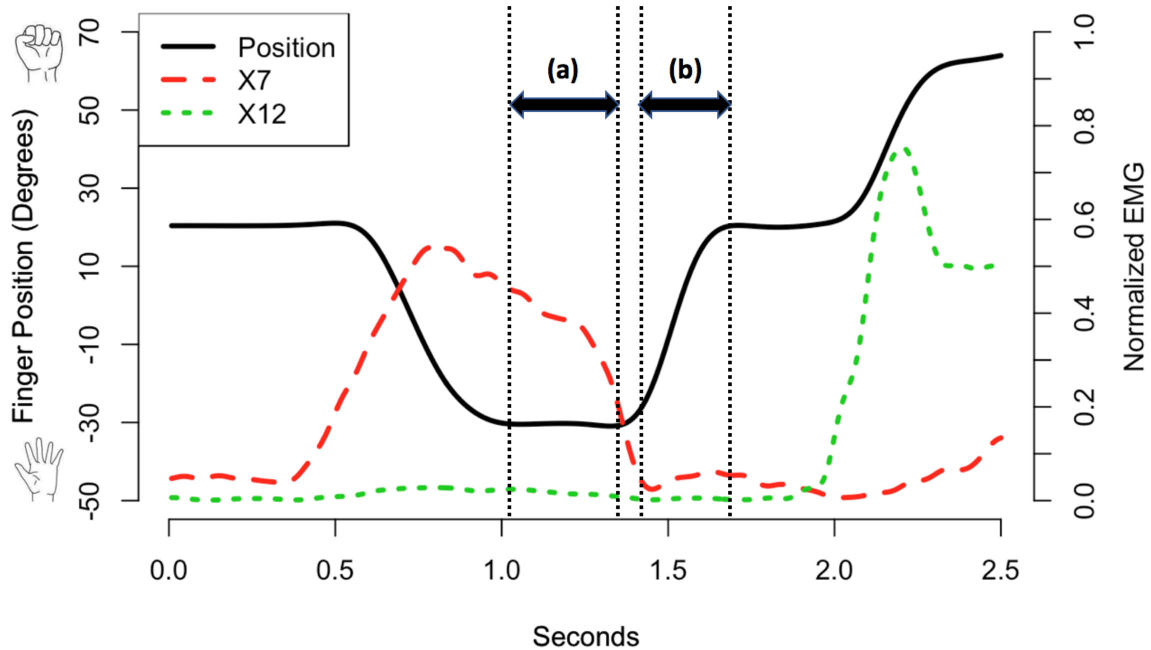


Identify research goals

- Able-bodied subjects require **few forearm muscles** to generate finger and wrist movement
  - **Starts with internal biomechanical** representation of movement
- Amputees have **altered** internal representation
- Still believe few muscles needed to predict movement, but where to put the sensors?
- **Goal:** determine optimal EMG sensor placement from high density EMG data that reliably predicts movement

Data collection and visualization



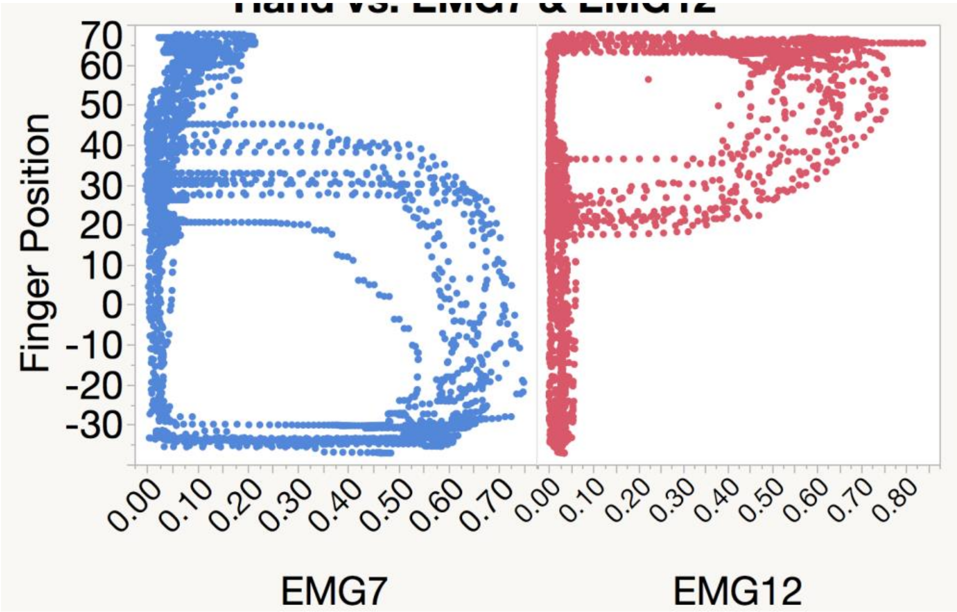


Data exploration

- Sounds like a variable selection problem…but for **what model**?
- If the model is poor, selection will be poor too

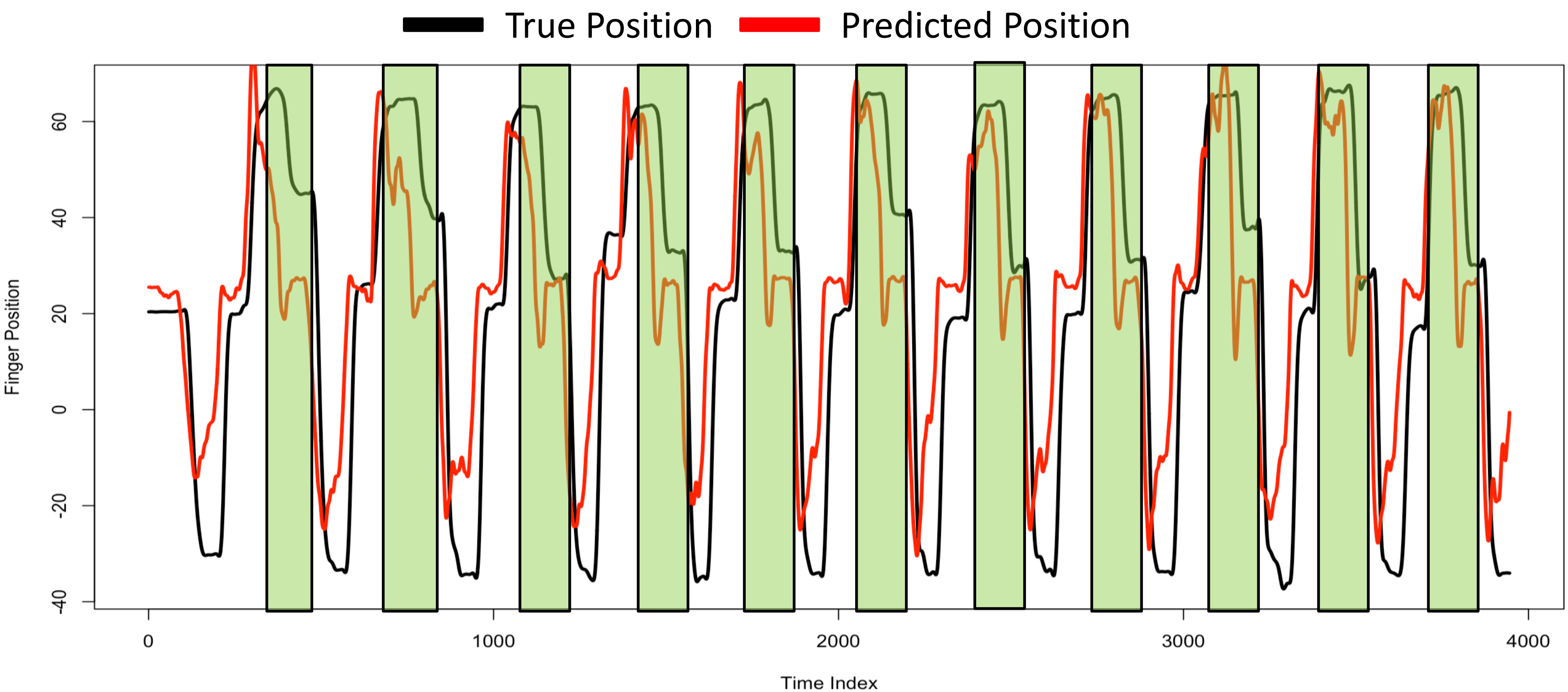
- Attempt 1: Model **finger position** using **concurrent EMG**

Linear model definitely not a good idea…but we do see some patterns



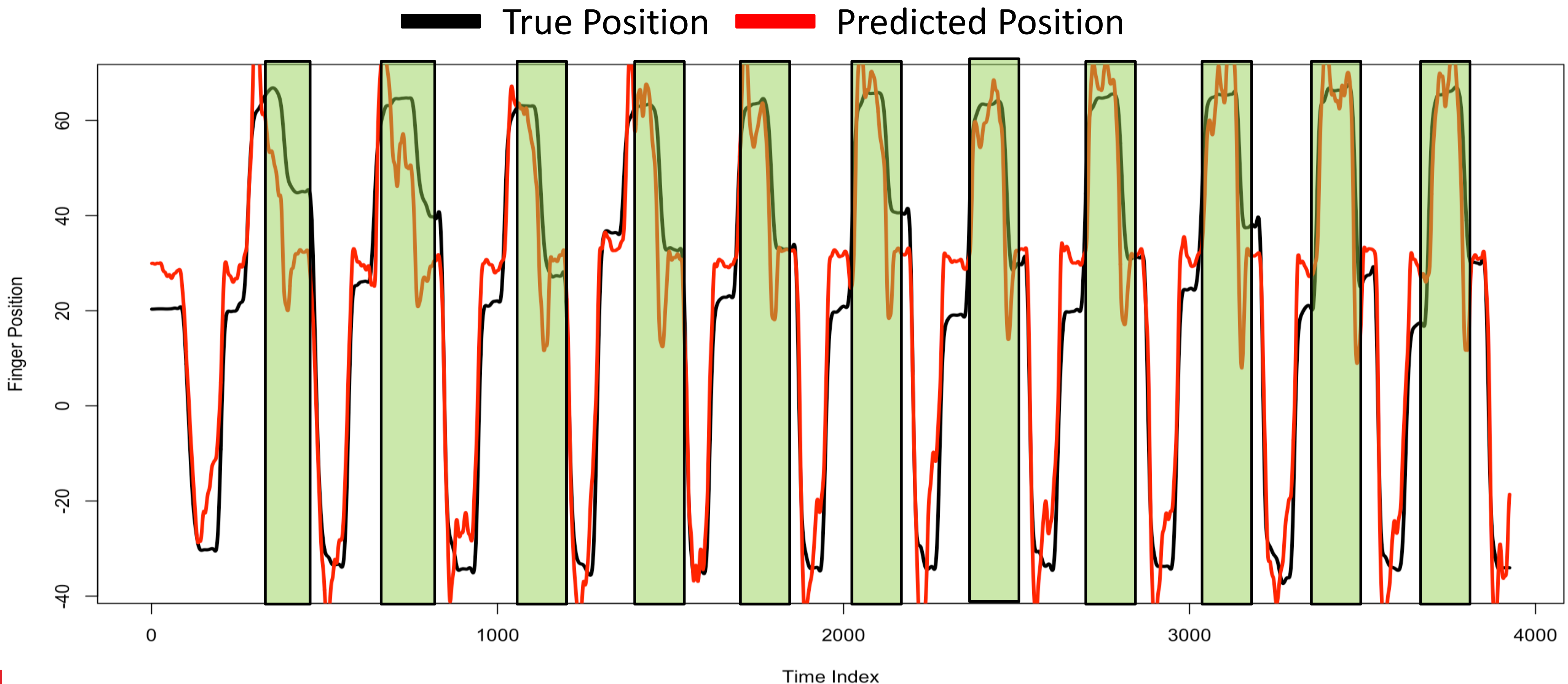
Attempt 1: Concurrent Linear Model

- Knew X7 and X12 were most important, how well does linear model work?



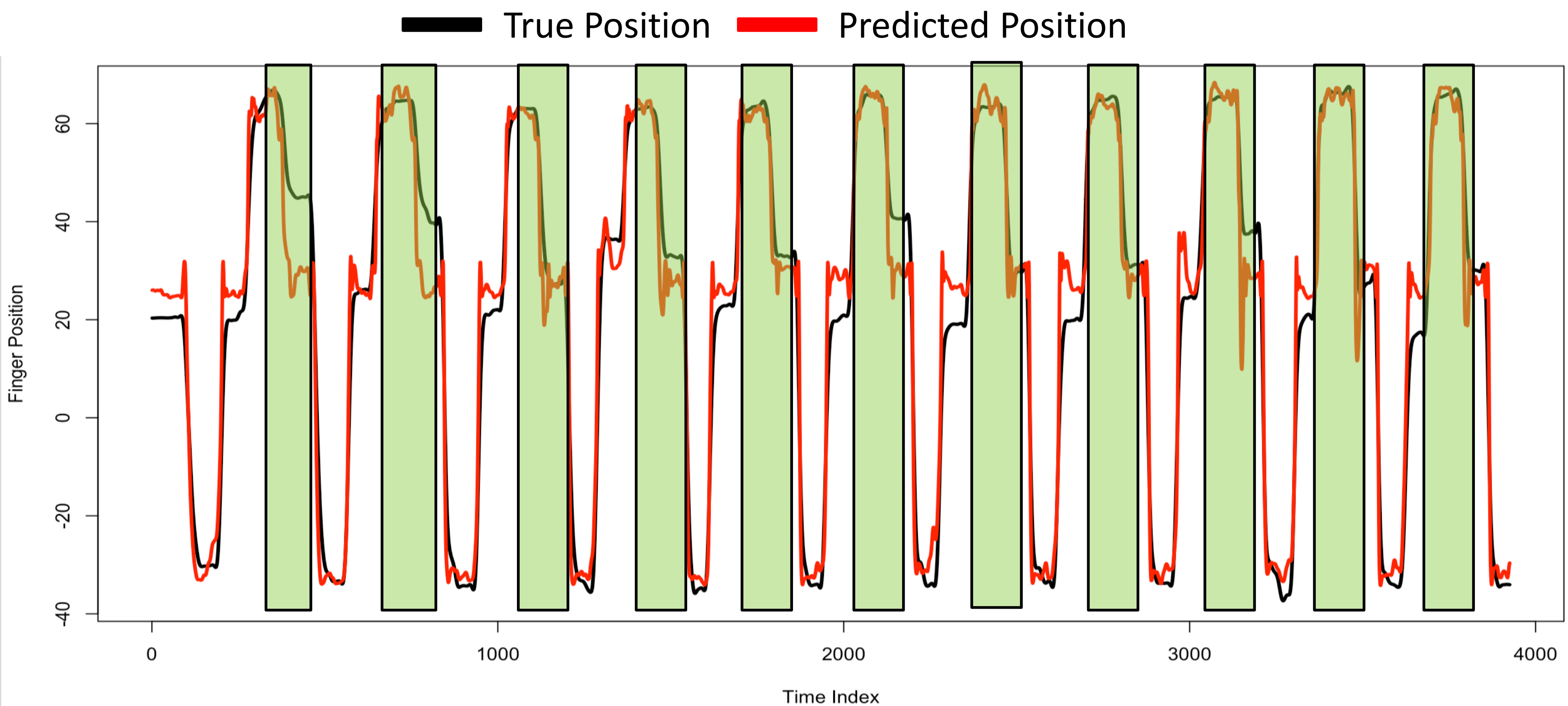
Attempt 2: Lagged Linear Model

- Collaborators told us concurrent model doesn't always make sense, there is a **lagged movement response** to EMG



Attempt 3: Lagged General Additive Model

- Relationship isn't linear due to positional boundaries so we tried a general additive model (GAM)



Data exploration leads to questions

- What we learned:
  1. **Lag** in the EMG activation and muscle contraction
  2. Threshold for each EMG where **no more movement can occur**
  3. Movement occurs due to muscle **activation** and **relaxation**

- GAM + Lag approach took care of (1) and (2)

- **Differentiate** movements from activation and relaxation

- Model effects as **position dependent**, use velocity as response

Choosing response and model

- Covariates are **recent past of EMG** for a given time window

$X_{ik}(s) \quad s \in \mathcal{S} = [-\delta, 0] \quad X_{ik}(0)$ = concurrent EMG signal

- Model velocity, y_i , with **historical, position-dependent effects** for each EMG

$$E(y_i | X_{i1}, \ldots, X_{iK}, z_i) = \sum_{k=1}^{K} \int_{-\delta}^{0} X_{ik}(s) \boxed{\gamma_k(s, z_i)} ds$$

- Knew nothing about functional data analysis, but now I had a reason to learn about it

Functional variable selection

- Standard variable selection methods find $\beta_k = 0$
- Approximate $\gamma_k(s, z_i)$; each *k* has **group of coefficients**

$$\gamma_k(s, z_i) \approx \sum_{l=1}^{L} \sum_{m=1}^{M} \omega_l(s)\tau_m(z_i)\beta_{klm}$$

- Need estimation method that:
  - Encourages sparsity for selection ($\hat{\gamma}_k = 0$)
  - Smooth, interpretable estimates by controlling curvature

$$\hat{\gamma}''_{k,s} = \frac{\partial^2 \hat{\gamma}_k}{\partial s^2} \qquad \hat{\gamma}''_{k,z} = \frac{\partial^2 \hat{\gamma}_k}{\partial z^2}$$

- Gertheiss et al (2013), Pannu and Billar (2017), Callazos et al (2015), and many others have studied this research problem

Group LASSO penalty

- Penalty is combination of magnitude and curvature measures

$$P_\phi(\gamma_k) = (||\gamma_k||^2 + \phi_s||\gamma''_{k,s}||^2 + \phi_z||\gamma''_{k,z}||^2)^{1/2}$$

$$||\gamma_k||^2 = \int_{\mathcal{S}}\int_{\mathcal{Z}} \gamma_k(s,z)^2 dzds$$

- Large ϕ_s encourages near linear estimates in *s* direction
- Group LASSO minimize sum of squared error (**SSE**) plus penalty

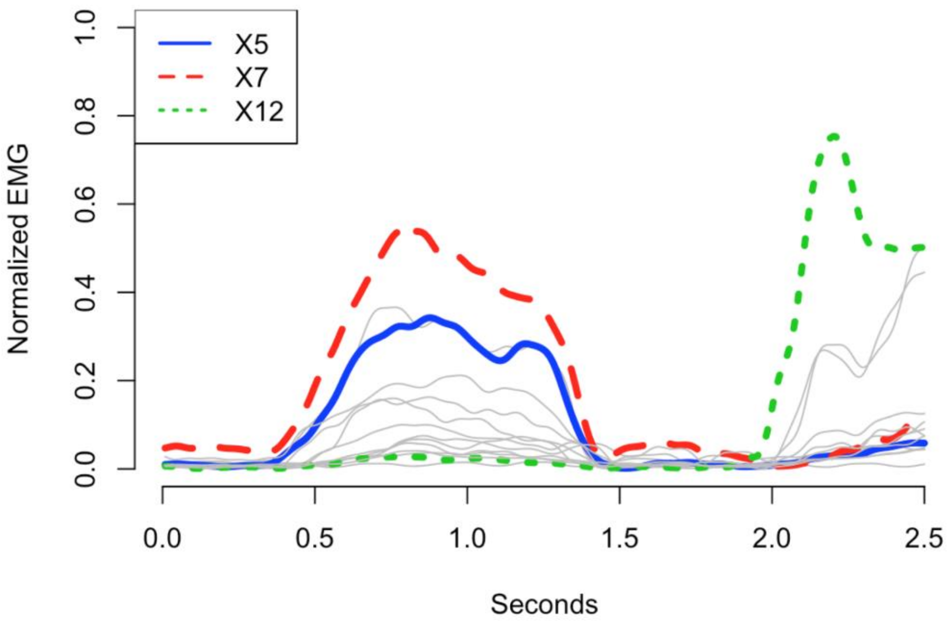
$$\text{argmin}_{\gamma_1,\ldots,\gamma_k}\ SSE + \lambda\sum_k P_\phi(\gamma_k)$$

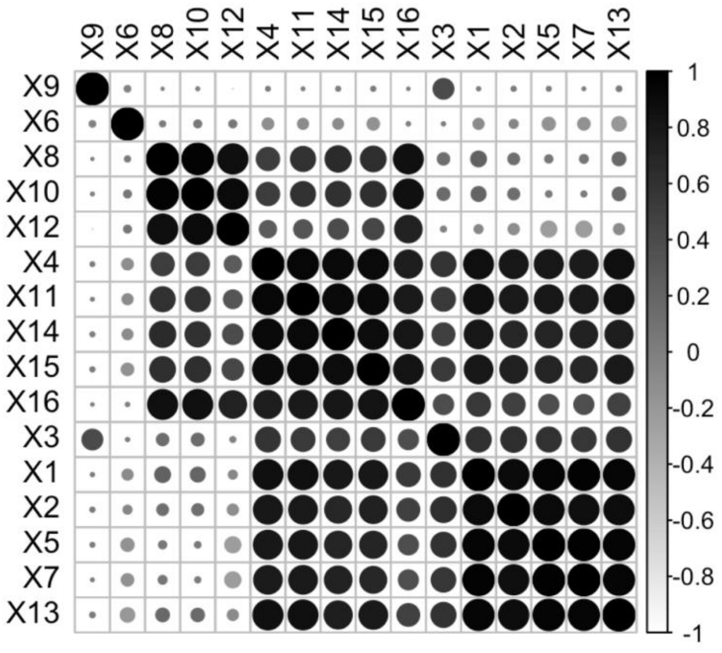
- Optimal tuning parameters with 5-fold CV + 1SE**

Functional variable selection…applied

- Applied to able-bodied data with known ground truth
- Found the correct EMG signals, but many false positives
- **Issue 1:** Latent variable structure split true effects across multiple sensors
- **Issue 2:** Random cross validation folds gives similar training/test sets and led to overfitting
  - **Block cross validation** solved this issue

Latent variable structure





Sequential, adaptive estimation

- **Adaptive LASSO:** Zou (2006) recommend adaptive weights for each variable to improve variable selection performance

$$P_{\phi,w}(\gamma_k) = (f_k||\gamma_k||^2 + g_k\phi_s||\gamma''_{k,s}||^2 + h_k\phi_z||\gamma''_{k,z}||^2)^{1/2}$$

$$f_k = 1/||\tilde{\gamma}_k|| \qquad g_k = 1/||\tilde{\gamma}''_{k,s}|| \qquad h_k = 1/||\tilde{\gamma}''_{k,z}||$$

- **Relaxed LASSO:** Meinshausen (2007) recommends running LASSO again but with subset of variables from first stage
- **Combine these two ideas into a new functional variable selection procedure**

Sequential Adaptive Functional Estimation

- **S**equential **A**daptive **F**unctional **E**stimation (**SAFE**)
  1. Stage 1: Group LASSO with all weights equal to 1
  2. Remove insignificant covariates from analysis
  3. Generate weights from previous stage's important effects
  4. Perform adaptive Group LASSO on reduced covariate set
  5. Repeat (2)-(4) for ***R* stages**

- Six data sets: 3 consistent (FC1-FC3) and 3 random (FR1-FR3)
- Compared to three existing methods with simpler model
  - **AGL** (Gertheiss et al (2013))
  - **FAR** (Fan et al (2015))
  - **LAD** (Pannu and Billar (2017))

Variable selection results: Stage 1

True Positive (2 or 3) / False Positive

	AGL	LAD	FAR	SAFE(z)
FC1	3/10	3/10	3/0	2/2
FC2	3/ 7	3/ 9	3/1	2/1
FC3	3/ 9	3/ 2	3/0	2/2
FR1	3/ 7	3/ 1	2/1	3/2
FR2	3/ 1	3/ 1	3/1	3/1
FR3	2/ 1	3/ 7	3/4	3/1

Typically have overselection in initial stage (no weighting)

Variable selection results: Stage 5

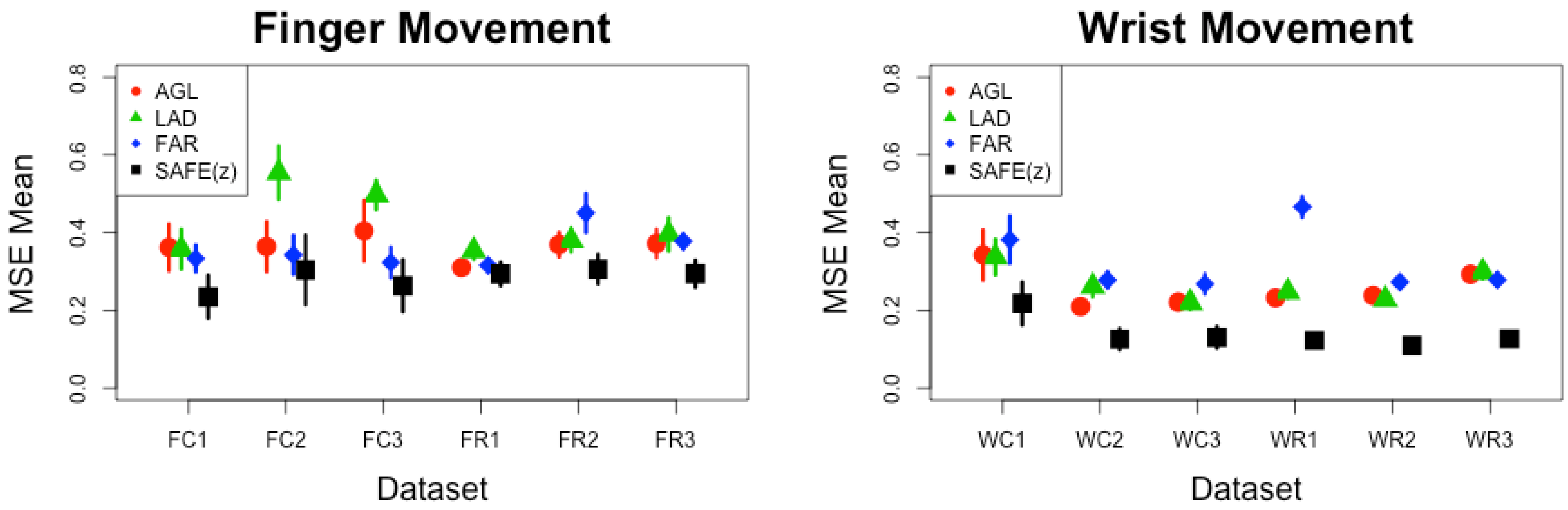
True Positive (2 or 3) / False Positive

	AGL	LAD	FAR	SAFE(z)
FC1	2/7	2/4	3/0	2/0
FC2	3/5	2/0	3/1	2/0
FC3	2/6	2/0	3/0	2/0
FR1	2/2	2/0	2/1	2/0
FR2	2/0	3/0	3/1	3/0
FR3	2/0	2/0	3/4	2/0

SAFE(z) never misses important EMG and no false positives

Out-sample prediction

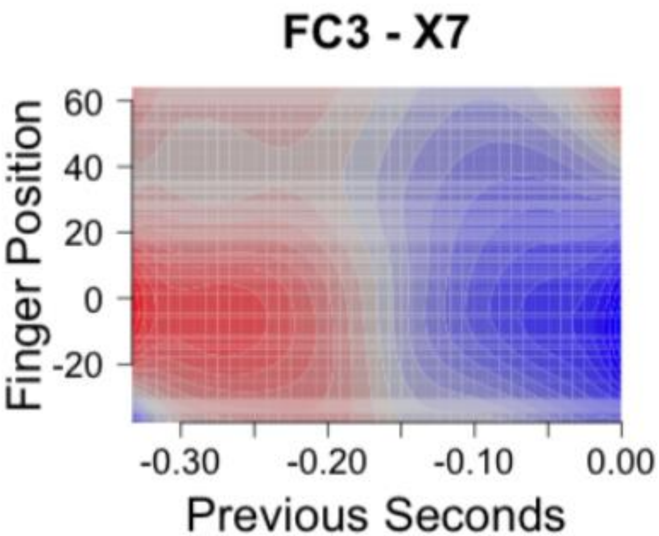
- Used each data set's estimates to predict other 5 data sets

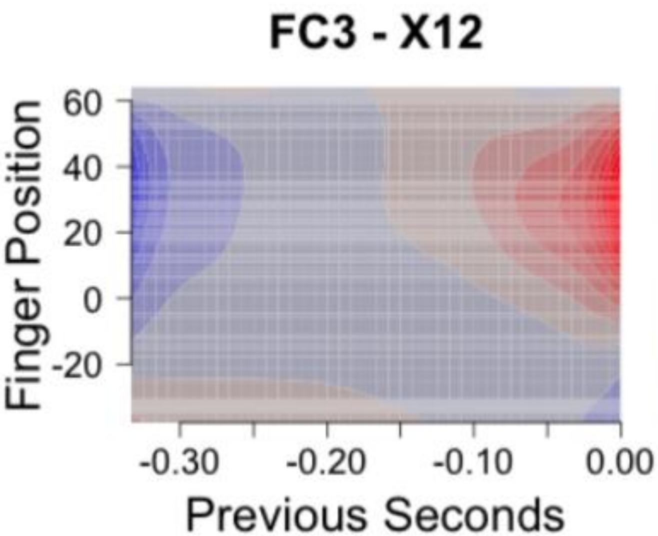


- SAFE(z) had superior prediction with fewer EMG sensors

Interpreting $\gamma_k(s, z_i)$

- Look at coefficient estimates for FC3

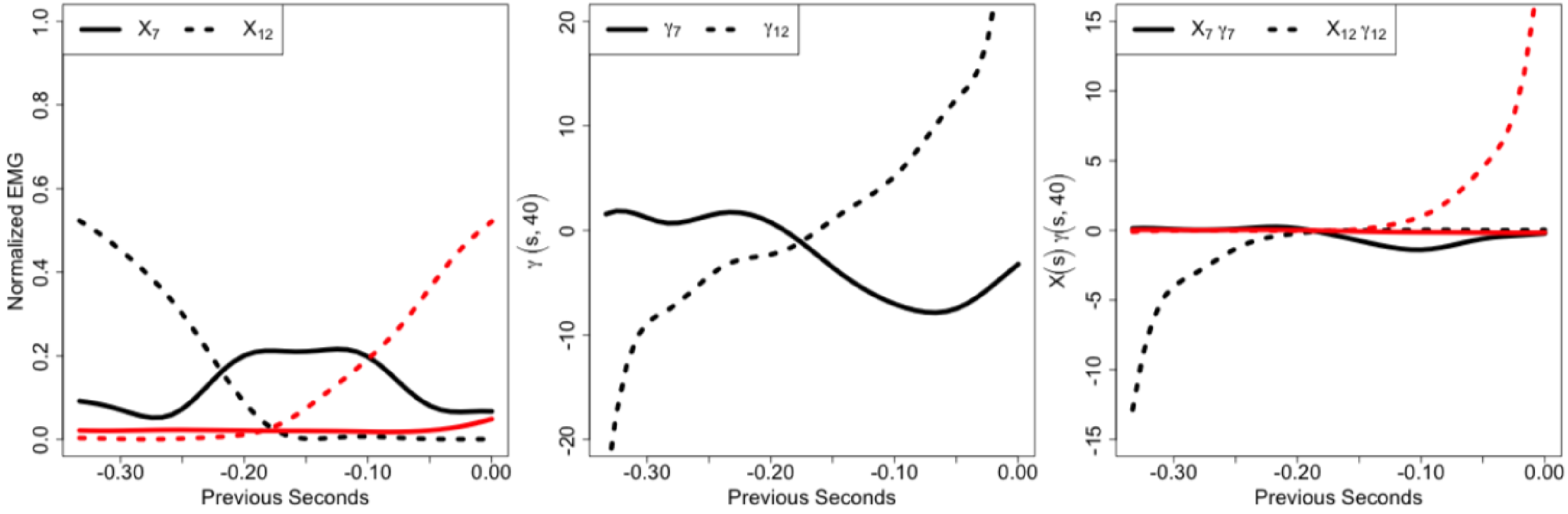




- Concurrent activation of X7 → **negative velocity (extension)**
- Past activation of X7 → **positive velocity (flexion)**

Interpreting $\gamma_k(s, z_i)$ – Slicing position

- Look at coefficient estimates for FC3, $z = 40$ (flexion)



- Concurrent activation of X12 → **positive velocity (flexion)**
- Past activation of X12 → **negative velocity(extension)**
- X7 nonzero, but no effect on velocity prediction

EMG project – Future work

- Apply to amputee data
- Implement model (called a decoder) in prosthesis controller

- **Rebecca North:**
  - Different penalty functions that separate sparsity and smoothness
  - Employ multivariate functional PCA to account for latent activity

- **Julia Holter:**
  - New tuning parameter selection method to mimic relaxed LASSO
  - Systematic tuning parameter exploration to circumvent group LASSO computational demands

References

- Bliss, D. I. (1969),"Communication Between Biologists and Statisticians, A Case Study," *The American Statistician,* 2, 3, pp. 15-20.
- Box, G. E. P. (1976), "Science and Statistics", *Journal of the American Statistical Association*, 71, 356, pp. 791-799.
- —— (1979), "Robustness in the strategy of scientific model building", *Robustness in Statistics,* ed. Launer, R. L., and Wilkinson, G. N. *Academic Press,* pp. 201-235.
- Callazos, J. A. A. and Zambom, A. Z. (2015), "Consistent variable selection for functional regression models", arXiv.1506.03426.
- Gertheiss, J., Maity, A., and Staicu, A.-M. (2013), "Variable selection in generalized functional linear models", *Stat*, 2, 86-101.
- Hinkelman, K., and Kempthorne, O. (2008), *Design and Analysis of Experiments Volume 1: Introduction to Experimental Design* (2nd Ed). Hoboken, New Jersey: Wiley.
- Hunter, W. G. (1981), "The Real World is an Idea Whose Time Has Come," *The American Statistician*, Vol. 35, No. 2 pp. 72-76.
- Meinshausen, N. (2007), "Relaxed lasso", *Computational Statistics and Data Analysis*, 52, 374-393.
- Pannu, J. and Nedret, B. (2017), "Robust group-lasso for functional regression model", *Communications in Statistics-Simulation and Computation*, 46, 3356-374.
- Zahn, D. A., and Isenberg, D. J. (1983), "Nonstatistical Aspects of Statistical Consulting" *The American Statistician*, 37, 4, 1, pp. 297-302.

Thank you!

Latent Factors and Selection

- Say really two latent factors $L_1(s)$ and $L_2(s)$ with true model

$$\int L_1(s)\boldsymbol{\beta_1(s)}ds + \int L_2(s)\boldsymbol{\beta_2(s)}ds$$

- K observed covariates where $X_k(s) = \alpha_{k1}L_1(s) + \alpha_{k2}L_2(s)$

- Fit model with $X_k(s)$ gives model equivalence

$$\sum_k \int X_k(s)\gamma_k(s)ds = \int L_1(s) \boldsymbol{\sum_k \alpha_{k1}\gamma_k(s)}\, ds + \int L_2(s) \boldsymbol{\sum_k \alpha_{k2}\gamma_k(s)}\, ds$$

- True effects **partitioned** across the $\gamma_k(s)$, need to encourage sparsest partitioning

New 1SE Rule

- One tuning parameter: larger parameters imply sparser models
  - 1SE rule: pick largest tuning parameter in 1SE set
  - Does not extend to multiple tuning parameters
- Larger parameters have estimates with smaller penalty value
  - 1SE rule: pick tuning parameters with smallest penalty value
  - Does extend to multiple tuning parameters!
- Pick set of tuning parameters with smallest penalty measure:

$$P_\phi(\gamma_k) = (||\gamma_k||^2 + \quad ||\gamma''_{k,s}||^2 + \quad ||\gamma''_{k,z}||^2)^{1/2}$$