Background

PA, HR, and

Margina Models Subject Specific Effects

Application Fatigability

Future Work

Scalar on Function Regression

Application: Predicting Alcohol Consumption Joint modeling of daily patterns of heart rate and physical activity data: Estimating individual heterogeneity in physiologic response to physical activity

Andrew Leroux

October 15, 2019

Motivation

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- the "big" questions:
 - What is the effect of physical activity (PA) on heart rate (HR)?
 - Can we quantify individual heterogeneity in this effect adjusting for age, health status, and diurnal patterns of both PA and HR?
 - Is this individual heterogeneity associated with outcomes of interest?
- Challenges:
 - Need (good) data (lots of it)
 - Normalize for differences in capacity ("maximum" and resting heart rate)
 - What is a sensible statistical model?

Data

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- Baltimore Longitudinal Study on Aging (BLSA)
- Actiheart chest worn uniaxial accelerometer and heart rate monitor
- Exclusion criteria
 - Ages 30-90
 - ullet Peak respiratory exchange ratio ≥ 1.1
 - Estimated $VO_2 \text{ max} \ge 10$
 - No missing data for demographic variables, several comorbidities, and alcohol consumption
 - At least 3 days of "good" Actiheart data
 - No beta blockers
- Final sample: 446 subjects, 233 male and 213 female

Defining Activity Intensity Using Heart Rate Reserve

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Application: Predicting Alcohol Consumption $\mbox{Heart Rate Reserve} = \mbox{Maximum Heart Rate} - \mbox{Resting Heart Rate}$

Vigorous: 60% or greater of HRR over resting

Moderate: 40-59% Light: 20-39%

Sedentary: <20%

We can approximate maximum heart rate using observed maximum heart rate from the treadmill test, but we need to estimate resting heart rate.

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Application: Predicting Alcohol Consumption

Resting heart rate estimation algorithm:

- Step 1: Examine 5 minute moving windows to find all 10-minute intervals between 01:00-07:00 with 0 total activity counts
 - Step 2: Calculate average heart rate of the last 5 minutes of each interval found in (1)
 - Step 3: Take the average of the heart rates found in (2)

Backgroun

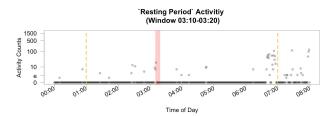
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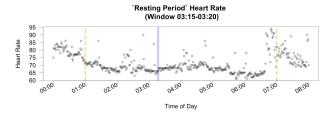
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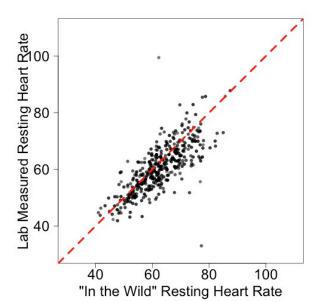
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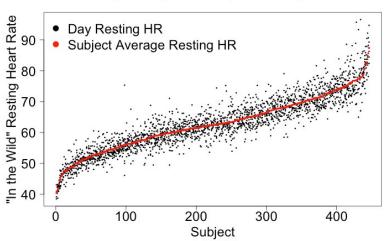
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Application: Predicting Alcohol Consumption

Day-to-day Variability in Resting RH



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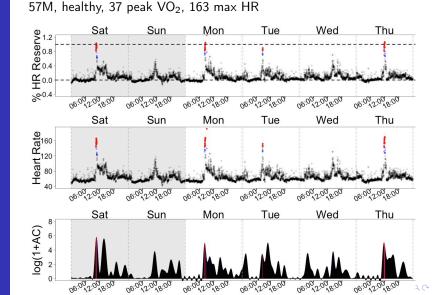
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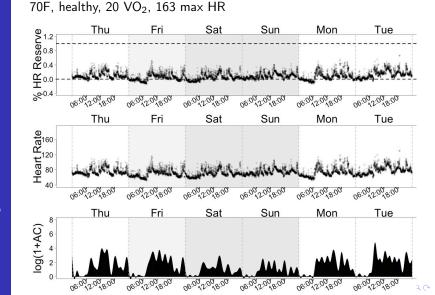
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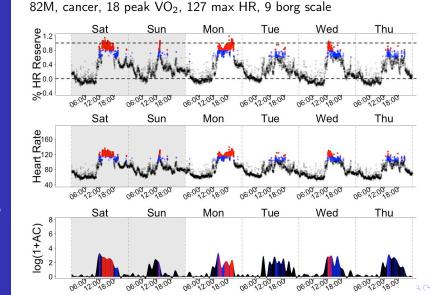
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74F, hypertension, cancer, 16 VO₂, 89 max HR, 13 borg scale

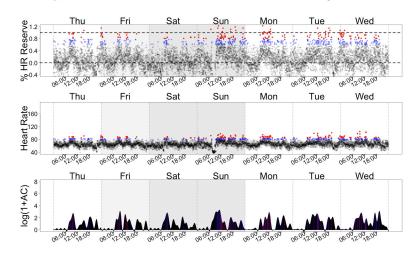


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PA, HR, and HRR vs Age

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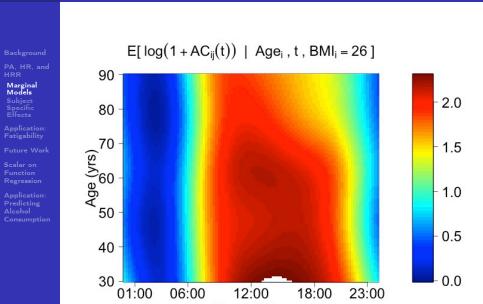
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Application: Predicting Alcohol Consumption Model daily patterns of PA, HR, and HRR as a function of age

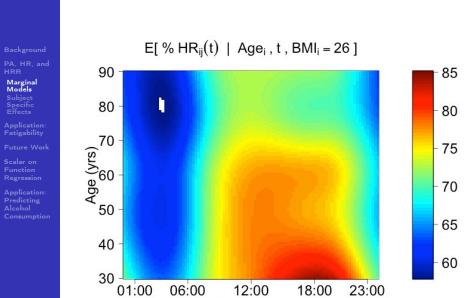
• Fit 3 separate models:

$$E[Y_{ij}(t)|\mathbf{X}_i, \mathsf{Age}_i, t] = f_0(t) + \sum_{p=1}^P X_{ip} f_p(t) + \beta(\mathsf{Age}_i, t)$$

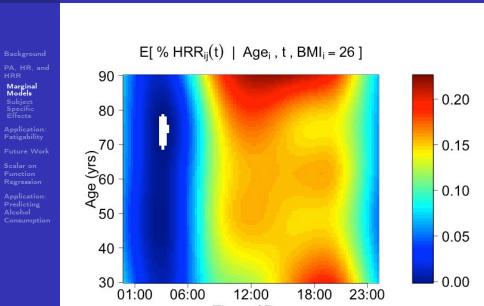
- $i=1,\ldots,N$ subject, $j=1,\ldots,J_i$ day, $t=1,\ldots,1440$ minute of the day
- X_{ip} are scalar covariates (BMI, comorbidities, etc.)
- $\beta(Age_i, t)$ allows for outcome to vary smoothly in time and age



HR vs Age



HRR vs Age



PA, HR, and HRR vs Age

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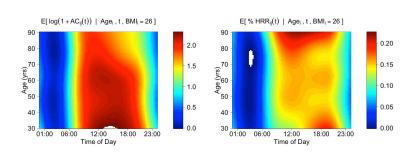
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PA, HR, and HRR vs Age

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Application: Predicting Alcohol Consumption Attempt to adjust for PA at a given time

$$E[\mathsf{HRR}_{ij}(t)|\cdot] = f_0(t) + \sum_{
ho=1}^P X_{i
ho} f_
ho(t) + eta(\mathsf{Age}_i,t) + \gamma_1(t) \mathsf{LAC}_{ij}(t)$$

- Concurrent effect of activity on heart rate
- Historical effect of PA?

HRR adjusting for PA

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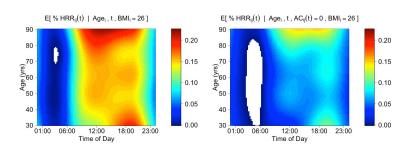
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Application: Predicting Alcohol



PA, HR, and HRR vs Age

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- HRR at rest will vary from person-to-person (latent health status) and day-to-day (hydration, mental state, etc.)
- For now ignore day-to-day variability

PA, HR, and HRR vs Age

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Application: Predicting Alcohol Consumption HRR at rest will vary from person-to-person (latent health status) and day-to-day (hydration, mental state, etc.)

• For now ignore day-to-day variability

$$\mathsf{HRR}_{ij}(t) = \eta_i(t) + \gamma(t)\mathsf{LAC}_{ij}(t) + b_{0i}(t) + b_{1ij}(t)\mathsf{LAC}_{ij}(t) + \epsilon_{ij}(t)$$

- $\eta_i(t) = f_0(t) + \sum_{p=1}^{P} X_{ip} f_p(t) + \beta(Age_i, t)$
- $b_{0i}(t)$ represents subject i's average HRR difference from the population at rest
- $b_{1i}(t)$ represents subject i's deviation from the population in response to PA

Estimating $b_{1i}(t)$

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PA, HR, and HRR Marginal Models Subject Specific

Effects Application Fatigability

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Scalar on Function Regression

- How to estimate subject specific responses?
 - Fit marginal model, obtain residuals, fit N separate regressions
 - Fit marginal model, obtain residuals, GLS, fit N separate regressions
 - 3 Fit the "full" model (functional mixed effects model)
- Choice of estimation procedure depends on goals.

Estimating $b_{1i}(t)$

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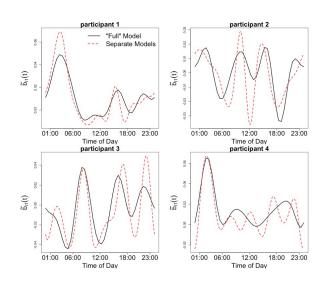
Subject Specific Effects

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Application: Predicting Alcohol



Using Estimated $\tilde{b}_{1i}(t)$

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Scalar on Function

- $\tilde{b}_{1i}(t)$ as a functional predictor
- ullet scalar summary (e.g. $\int_{\mathcal{T}} \tilde{b}_{1i}(t) dt$, the average across the day)

Fatigability

Backgroun

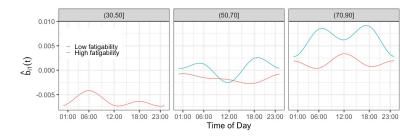
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Application: Fatigability

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Scalar on Function



Fatigability

Application:

Fatigability

Alcohol

```
Residuals:
    Min
                Median
                                   Max
             10
                            30
-2.8233 -1.2287 -0.3259
                        0.9551 5.5196
Coefficients:
             Estimate Std. Error t value Pr(>|t|)
(Intercept) 6.173061
                        0.885410
                                  6.972 1.24e-11 ***
                       0.007577
            0.038331
                                  5.059 6.37e-07 ***
age
bmi
            0.011762
                       0.019528
                                  0.602 0.547284
                       0.161772
sexMale
            -0.728330
                                  -4.502 8.76e-06 ***
TAC mu
            -0.025157
                       0.007552
                                  -3.331 0.000943 ***
            18.951565
                       6.392608
                                  2.965 0.003206 **
b2i mu
Signif. codes:
                        0.001 '**' 0.01 '*' 0.05 '.' 0.1
Residual standard error: 1.636 on 413 degrees of freedom
```

Multiple R-squared: 0.1978, Adjusted R-squared: 0.1881 F-statistic: 20.37 on 5 and 413 DF, p-value: < 2.2e-16

Next steps/Open questions

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PA, HR, and HRR Marginal

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Future Work

Scalar on Function Regression

- What does it mean when $\gamma(t) + b_{i1}(t) \leq 0$? Individual thresholds? Bad data?
- Day-to-day variability?
- Building in a historical effect of activity (of heart rate?)

Scalar on Function Regression

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Scalar on Function Regression

Application: Predicting Alcohol Consumption Scalar on function regression can take many forms

 Functional Generalized Linear Model¹(FGLM): Association varies with time of day, but scales linearly with (log) activity count

$$g(E[Y_i]) = X_i'\beta + \int_T f(t)Z_i(t)dt$$

 Functional Generalized Additive Model²(FGAM):
 Association varies smoothly with both time of day and value of (log) activity count

$$g(E[Y_i]) = X_i'\beta + \int_T f[t, Z_i(t)]dt$$

²McLean MW, Hooker G, Staicu AM, Scheipl F, Ruppert D. Functional Generalized Additive Models. J Comput Graph Stat. 2014;23(1):249-269.



²Müller HG, Stadtmüller U. Generalized functional linear models. Annals of Statistics. 2005;33(2):774-805.

Scalar on Function Regression

 In both FGLR and FGAM estimation is done by applying a spline basis to the coefficient and then approximating the functional term numerically.

$$\begin{split} \int_{\mathcal{T}} f(t) Z_i(t) dt &= \int_t \sum_{k=1}^K \xi_k \phi_k(t) Z_i(t) dt \quad \text{Apply spline basis} \\ &\approx \sum_{l} \delta_l \sum_{k=1}^K \xi_k \phi_k(l) Z_i(l) \quad \text{Numeric Approximation} \\ &= \sum_{k=1}^K \xi_k \left[\sum_{l} \delta_l \phi_k(l) Z_i(l) \right] \\ &= \sum_{k=1}^K \xi_k \tilde{Z}_i(k) \end{split}$$

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SoFR: Heavy Drinkers

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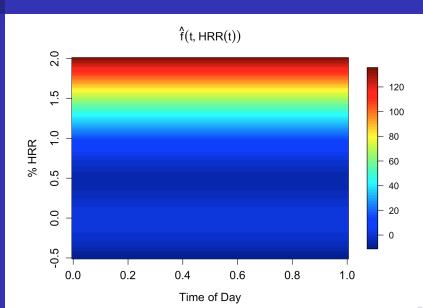
Application: Predicting Alcohol Consumption • Let Y_i be the binary indicator that subject i self reports heavy drinking

Logistic regression

• FGLR: logit $(p_i|X_i, \mathbf{Z}_i) = X_i'\beta + \int_T f(t)Z_i(t)dt$

• FGAM: $logit(p_i|X_i, \mathbf{Z}_i) = X_i'\beta + \int_T f[t, Z_i(t)]dt$

- Estimation via using refund::pfr() function
- Adjust for linear effects of age, body mass index, and sex



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FGAM

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Scalar on Function Regression

- Estimated coefficient surface seems to imply high heart rate at any time of the is associated with increased log odds of drinking heavily
- Very few "high" HRR during the early morning hours
- Consider a transformation to reduce data sparsity. Here we use the empirical CDF $\hat{g}_t(x) = \frac{1}{N} \sum_{i=1}^{N} I(Z_i(t) < x)$ for all t.

$$logit(p_i|X_i, \mathbf{Z}_i) = X_i'\beta + \int_T f[t, g_t(Z_i(t))]dt$$

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