

## Evaluating scoring streaks and game excitement using in-match trend estimation

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#### Roadmap

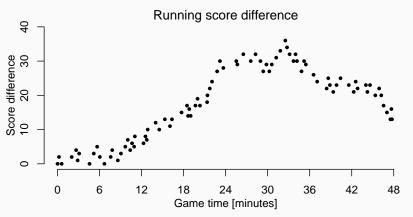
- 1. Introduction (CE)
- 2. Latent dynamics GP Regression (AKJ)
- 3. The 2019–2020 NBA season (CE)
- 4. Conclusion

### Introduction (CE)

#### Introduction

#### Motivating example

Game development in the final match of the NBA 2019–2020 season between Los Angeles Lakers and Miami Heat at October 11, 2020. Positive values  $\Rightarrow$  LA Lakers are leading.



How exciting was this match?

# Latent dynamics GP Regression (AKJ)

#### Gaussian Process regression with latent dynamics

$$\mathcal{Z}_{m} \mid \mathbf{\Psi}_{m}, \mathbf{t}_{m} \sim H(\mathcal{Z}_{m} \mid \mathbf{\Psi}_{m})$$

$$d_{m}(t) \mid \mathcal{Z}_{m} \sim \mathcal{GP}(\mu_{\beta_{m}}(t), C_{\boldsymbol{\theta}_{m}}(s, t))$$

$$D_{m}(t_{mi}) \mid d_{m}(t_{mi}), t_{mi}, \mathcal{Z}_{m} \stackrel{iid}{\sim} N\left(d_{m}(t_{mi}), \sigma_{m}^{2}\right)$$

$$\begin{bmatrix} d_m(s) \\ d'_m(t) \\ d''_m(u) \end{bmatrix} | \, & \qquad & \mathcal{GP} \left( \begin{bmatrix} \mu_{\beta_m}(s) \\ \mu'_{\beta_m}(t) \\ \mu'_{\beta_m}(u) \end{bmatrix}, \begin{bmatrix} C_{\theta_m}(s,s') & \partial_2 C_{\theta_m}(s,t) & \partial_2^2 C_{\theta_m}(s,u) \\ \partial_1 C_{\theta_m}(t,s) & \partial_1 \partial_2 C_{\theta_m}(t,t') & \partial_1 \partial_2^2 C_{\theta_m}(t,u) \\ \partial_1^2 C_{\theta_m}(u,s) & \partial_1^2 \partial_2 C_{\theta_m}(u,t) & \partial_1^2 \partial_2^2 C_{\theta_m}(u,u') \end{bmatrix} \right)$$

#### Gaussian Process regression with latent dynamics

The posterior distribution of the latent processes conditional on the hyper-parameters is the multivariate Gaussian process

$$\begin{bmatrix} d_m(s) \\ d'_m(t) \\ d''_m(u) \end{bmatrix} \mid \mathcal{D}_m, \textcircled{2}_m \sim \mathcal{GP} \left( \begin{bmatrix} \mu_{d_m}(s) \\ \mu_{d'_m}(t) \\ \mu_{d''_m}(u) \end{bmatrix}, \begin{bmatrix} \Sigma_{d_m}(s,s') & \Sigma_{d_m d'_m}(s,t) & \Sigma_{d_m d''_m}(s,u) \\ \Sigma_{d'_m d_m}(t,s) & \Sigma_{d'_m}(t,t') & \Sigma_{d'_m d''_m}(t,u) \\ \Sigma_{d''_m d_m}(u,s) & \Sigma_{d''_m d'_m}(u,t) & \Sigma_{d''_m}(u,u') \end{bmatrix} \right)$$

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Where the components evaluated at any  $\mathbf{t}^*$  are given by

$$\begin{split} \mu_{d_{m}}(\mathbf{t}^{*}) &= \mu_{\beta_{m}}(\mathbf{t}^{*}) + C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}_{m}) \left( C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}_{m}) + \sigma_{m}^{2} I \right)^{-1} \left( \mathbf{D}_{m} - \mu_{\beta_{m}}(\mathbf{t}_{m}) \right) \\ \mu_{d_{m}'}(\mathbf{t}^{*}) &= \mu_{\beta_{m}'}'(\mathbf{t}^{*}) + \partial_{1}C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}_{m}) \left( C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}_{m}) + \sigma_{m}^{2} I \right)^{-1} \left( \mathbf{D}_{m} - \mu_{\beta_{m}}(\mathbf{t}_{m}) \right) \\ \mu_{d_{m}''}(\mathbf{t}^{*}) &= \mu_{\beta_{m}'}''(\mathbf{t}^{*}) + \partial_{1}^{2}C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}_{m}) \left( C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}_{m}) + \sigma_{m}^{2} I \right)^{-1} \left( \mathbf{D}_{m} - \mu_{\beta_{m}}(\mathbf{t}_{m}) \right) \\ \Sigma_{d_{m}}(\mathbf{t}^{*}, \mathbf{t}^{*}) &= C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}^{*}) - C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}_{m}) \left( C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}_{m}) + \sigma_{m}^{2} I \right)^{-1} C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}^{*}) \\ \Sigma_{d_{m}'}(\mathbf{t}^{*}, \mathbf{t}^{*}) &= \partial_{1}\partial_{2}C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}^{*}) - \partial_{1}C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}_{m}) \left( C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}_{m}) + \sigma_{m}^{2} I \right)^{-1} \partial_{2}C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}^{*}) \\ \Sigma_{d_{m}'}(\mathbf{t}^{*}, \mathbf{t}^{*}) &= \partial_{1}^{2}\partial_{2}^{2}C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}^{*}) - \partial_{1}^{2}C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}_{m}) \left( C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}_{m}) + \sigma_{m}^{2} I \right)^{-1} \partial_{2}^{2}C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}^{*}) \\ \Sigma_{d_{m}d_{m}'}(\mathbf{t}^{*}, \mathbf{t}^{*}) &= \partial_{2}^{2}C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}^{*}) - C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}_{m}) \left( C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}_{m}) + \sigma_{m}^{2} I \right)^{-1} \partial_{2}^{2}C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}^{*}) \\ \Sigma_{d_{m}'}d_{m}''(\mathbf{t}^{*}, \mathbf{t}^{*}) &= \partial_{1}^{2}\partial_{2}^{2}C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}^{*}) - C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}_{m}) \left( C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}_{m}) + \sigma_{m}^{2} I \right)^{-1} \partial_{2}^{2}C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}^{*}) \\ \Sigma_{d_{m}'}d_{m}''(\mathbf{t}^{*}, \mathbf{t}^{*}) &= \partial_{1}^{2}\partial_{2}^{2}C_{\theta_{m}}(\mathbf{t}^{*}, \mathbf{t}^{*}) - \partial_{1}^{2}C_{\theta}(\mathbf{t}^{*}, \mathbf{t}_{m}) \left( C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}_{m}) + \sigma_{m}^{2} I \right)^{-1} \partial_{2}^{2}C_{\theta_{m}}(\mathbf{t}_{m}, \mathbf{t}^{*}) \end{split}$$

#### Trend Direction Index (TDI)

$$TDI_{m}(t \mid \mathcal{E}_{m}) = P\left(d'_{m}(t) > 0 \mid \mathcal{D}_{m}, \mathcal{E}_{m}\right)$$
$$= \frac{1}{2} + \frac{1}{2} \operatorname{Erf}\left(\frac{\mu_{d'_{m}}(t)}{2^{1/2} \Sigma_{d'_{m}}(t, t)^{1/2}}\right)$$

#### Excitement Trend Index

$$\begin{aligned} \text{ETI}_{m} \mid & \bigstar_{m} = \mathbb{E} \left[ \# \left\{ t \in \mathcal{I}_{m} : d'_{m}(t) = 0 \right\} \mid \mathcal{D}_{m}, & \bigstar_{m} \right] \\ &= \int_{\mathcal{I}_{m}} \int_{-\infty}^{\infty} |v| \, f_{d'_{m}(t), d''_{m}(t)}(0, v \mid \mathcal{D}_{m}, & \bigstar_{m}) \mathrm{d}v \mathrm{d}t \\ &= \int_{\mathcal{I}_{m}} d \text{ETI}_{m}(t \mid & \bigstar_{m}) \mathrm{d}t \end{aligned}$$

#### Excitement Trend Index

?

$$d\mathrm{ETI}_m(t\mid \boldsymbol{\mathscr{Z}}_m) = \lambda_m(t)\phi\left(\frac{\mu_{d_m'}(t)}{\Sigma_{d_m'}(t,t)^{1/2}}\right)\left(2\phi\left(\zeta_m(t)\right) + \zeta_m(t)\,\mathrm{Erf}\left(\frac{\zeta_m(t)}{2^{1/2}}\right)\right)$$

$$\lambda_m(t) = \frac{\sum_{d'_m}(t,t)^{1/2}}{\sum_{d'_m}(t,t)^{1/2}} \left(1 - \omega_m(t)^2\right)^{1/2}, \quad \omega_m(t) = \frac{\sum_{d'_m}d''_m(t,t)}{\sum_{d'_m}(t,t)^{1/2}\sum_{d''_m}(t,t)^{1/2}}$$
$$\zeta_m(t) = \frac{\mu_{d'_m}(t)\sum_{d'_m}(t,t)^{1/2}\omega_m(t)\sum_{d'_m}(t,t)^{-1/2} - \mu_{d''_m}(t)}{\sum_{d'_m}(t,t)^{1/2}\left(1 - \omega_m(t)^2\right)^{1/2}}$$

#### Estimation

$$\mu_{\beta_m}(t) = \beta_m, \quad C_{\theta_m}(s, t) = \alpha_m^2 \exp\left(-\frac{(s - t)^2}{2\rho_m^2}\right)$$

The hyper-parameters are given the following prior distribution

$$H(\mathscr{F}_m \mid \Psi_m) = H(\beta_m \mid \Psi_{\beta_m})H(\alpha_m \mid \Psi_{\alpha_m})H(\rho_m \mid \Psi_{\rho_m})H(\sigma_m \mid \Psi_{\sigma_m})$$

with

$$\beta_m \sim T_4\left(\widehat{\beta_m^{\mathrm{ML}}}, 5\right), \ \alpha_m \sim T_4^+\left(\widehat{\alpha_m^{\mathrm{ML}}}, 5\right), \ \rho_m \sim T_4^+\left(\widehat{\rho_m^{\mathrm{ML}}}, 5\right), \ \sigma_m \sim T_4^+\left(\widehat{\sigma_m^{\mathrm{ML}}}, 5\right)$$

Super-script ML indicates the marginal maximum-likelihood estimate (empirical Bayes).

#### Empirical bayes

To find the empirical Bayes estimate of the hyper-parameters we maximize the marginal log-likelihood function. This can be written as

$$\log L(\mathcal{E}_m \mid \mathcal{D}_m) \propto -\frac{1}{2} \log |C_{\theta_m}(\mathbf{t}_m, \mathbf{t}_m) + \sigma_m^2 I|$$

$$-\frac{1}{2} (\mathbf{D}_m - \mu_{\beta_m}(\mathbf{t}_m))^T \left[ C_{\theta_m}(\mathbf{t}_m, \mathbf{t}_m) + \sigma_m^2 I \right]^{-1} (\mathbf{D}_m - \mu_{\beta_m}(\mathbf{t}_m))$$

The solution  $\mathcal{E}_m^{\mathrm{ML}} = \arg\sup_{\mathcal{E}} \log L(\mathcal{E} \mid \mathcal{D}_m)$  can be obtained by numerical optimization.

Our model is implemented in Stan and for each match we ran 4 chains for 50,000 iterations with half of them for warm-up.

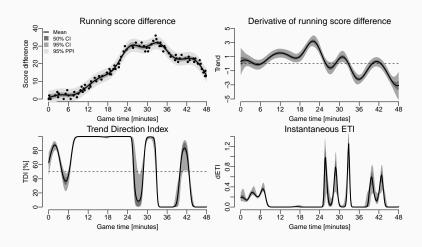
## The 2019–2020 NBA season (CE)

#### The 2019–2020 NBA season

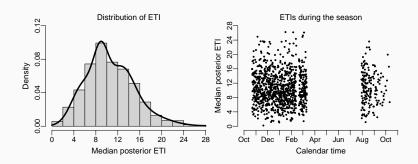
We applied our method for all 1143 matches from the 2019–2020 NBA basketball season.

We disregarded overtime.

#### Final match between LA Lakers and Miami Heat

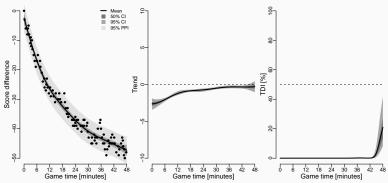


#### Distribution of the 1143 median posterior ETIs



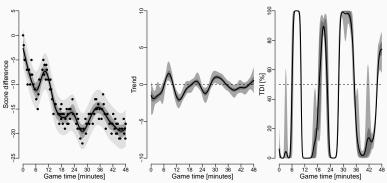
#### Season minimum ETI



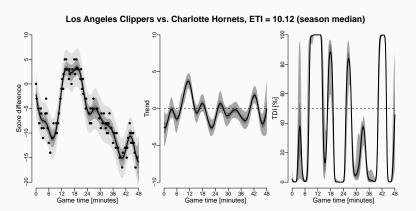


#### Season 25% percentile ETI

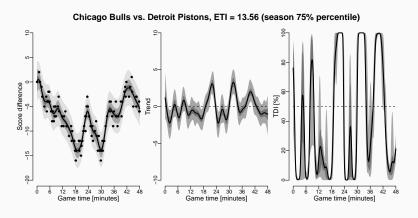




#### Season median ETI

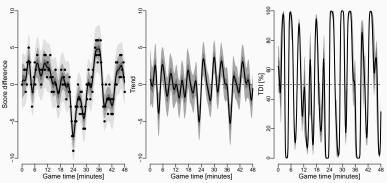


#### Season 75% percentile ETI



#### Season maximum ETI



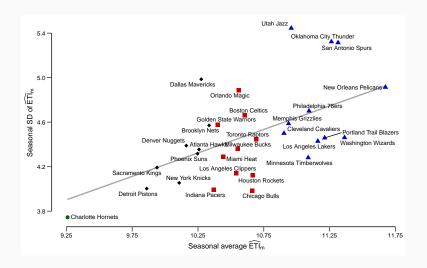


#### An algorithm for collapsing a factor into sub-groups

#### Clustering results

	Average	SD	2.5%	50%	97.5%	Group
	Average	3D	2.070	3070	31.070	Group
New Orleans Pelicans	11.67	4.91	3.10	11.59	23.54	A
Washington Wizards	11.36	4.46	2.98	11.63	18.28	A
San Antonio Spurs	11.31	5.31	3.52	9.88	23.44	A
Oklahoma City Thunder	11.26	5.32	1.68	11.55	23.74	A
Portland Trail Blazers	11.21	4.46	3.31	10.82	18.48	A
Los Angeles Lakers	11.16	4.43	3.61	10.52	19.79	A
Philadelphia 76ers	11.09	4.70	2.73	10.28	21.53	A
Minnesota Timberwolves	11.09	4.28	4.01	10.69	19.46	A
Utah Jazz	10.96	5.44	3.09	9.76	23.54	A
Memphis Grizzlies	10.94	4.59	3.04	10.36	20.84	A
Cleveland Cavaliers	10.90	4.50	4.93	10.39	22.36	A
Toronto Raptors	10.69	4.44	3.48	10.33	21.79	В
Houston Rockets	10.67	4.12	3.52	10.74	19.17	В
Chicago Bulls	10.66	3.98	2.95	10.65	17.49	В
Boston Celtics	10.61	4.66	2.81	10.19	20.92	В
Orlando Magic	10.56	4.89	2.72	10.41	21.01	В
Milwaukee Bucks	10.55	4.36	2.77	9.59	18.13	В
Los Angeles Clippers	10.54	4.14	4.05	10.72	20.56	В
Miami Heat	10.44	4.29	3.28	9.91	18.54	В
Golden State Warriors	10.40	4.58	3.37	10.24	18.72	В
Indiana Pacers	10.37	3.99	3.31	10.22	18.54	В
Brooklyn Nets	10.33	4.57	3.07	10.06	18.89	C
Dallas Mavericks	10.27	4.99	3.00	9.04	22.09	C
Atlanta Hawks	10.26	4.35	2.50	9.75	18.31	C
Phoenix Suns	10.25	4.32	3.78	9.29	19.81	C
Denver Nuggets	10.16	4.39	3.42	9.59	19.61	C
New York Knicks	10.11	4.05	2.84	9.87	18.47	C
Sacramento Kings	9.94	4.19	3.66	9.30	18.93	C
Detroit Pistons	9.86	4.00	3.73	9.44	17.08	C
Charlotte Hornets	9.26	3.74	1.96	9.22	15.95	D

#### Team specific seasonal SD vs. average ETIs



## Conclusion

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