A Switching Kalman Filter for Modeling Classical Music Performances

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Why?

- Easy to describe musical characteristics you like: "up-tempo," "strong beat," "good lyrics," "jazzy," etc.
- Harder to describe characteristics of a performance that you like.
- In classical music, there are hundreds or thousands of recordings of the same piece.
- Why do we like some better than others?

What's different?

1. Mistakes
2. Extraneous noise
3. Recording quality
4. Articulation/Legato/Bowing/Breathing
5. Dynamics
6. Rubato/Tempo

The first three are mostly uninteresting, but the rest are about interpretation.

We like performances with "better" interpretations.

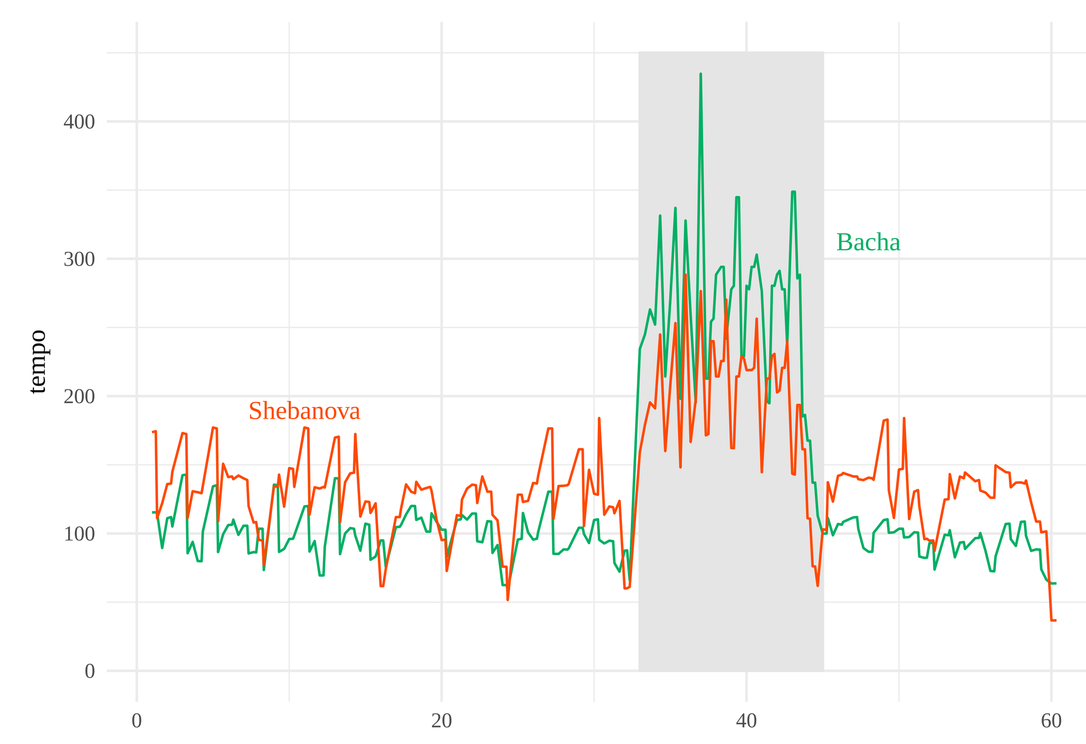
Piano music

- Can focus on dynamics and tempo
- We have quantitative data on everything from a specially equipped piano.
- This piano records keystroke velocity, pedaling, timing, duration.
- It lives in a studio at the IU Jacobs School of Music.

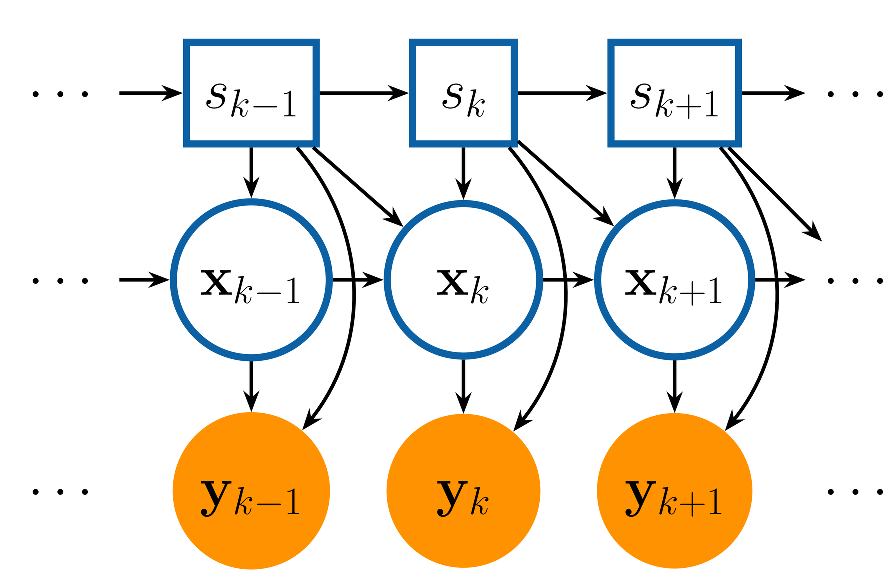
Data

- CHARM Mazurka Project
- Focus on timing only (dynamics also available)
- 50 recordings: Chopin Mazurka Op. 68 No. 3
- Recorded between 1931 and 2006
- 45 different performers

measure	1	9	17	25	33	37	41	45	53
section	a	a′	b	a′	pedal	c	c′	a	a′



Switching Kalman filter



Intentional tempo

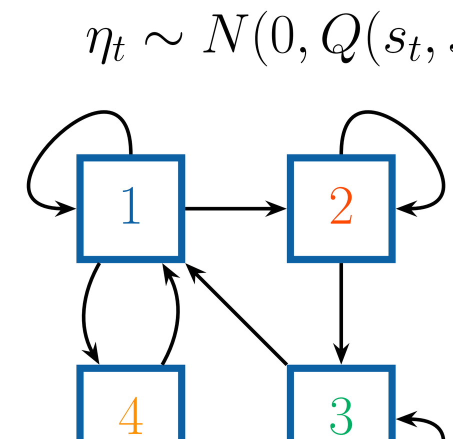
$$x_t = d(s_t, s_{t-1}) + T(s_t, s_{t-1})x_t + R(s_t, s_{t-1})\eta_t$$

Observed tempo

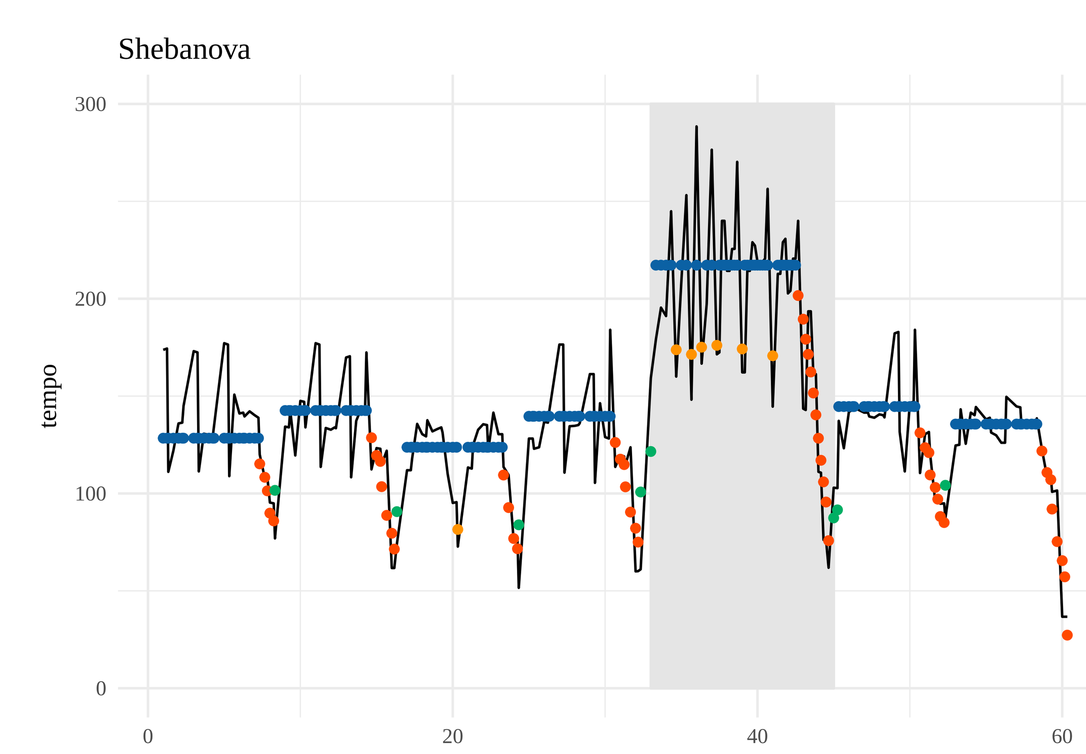
$$y_t = c(s_t) + Z(s_t)x_t + \epsilon_t$$

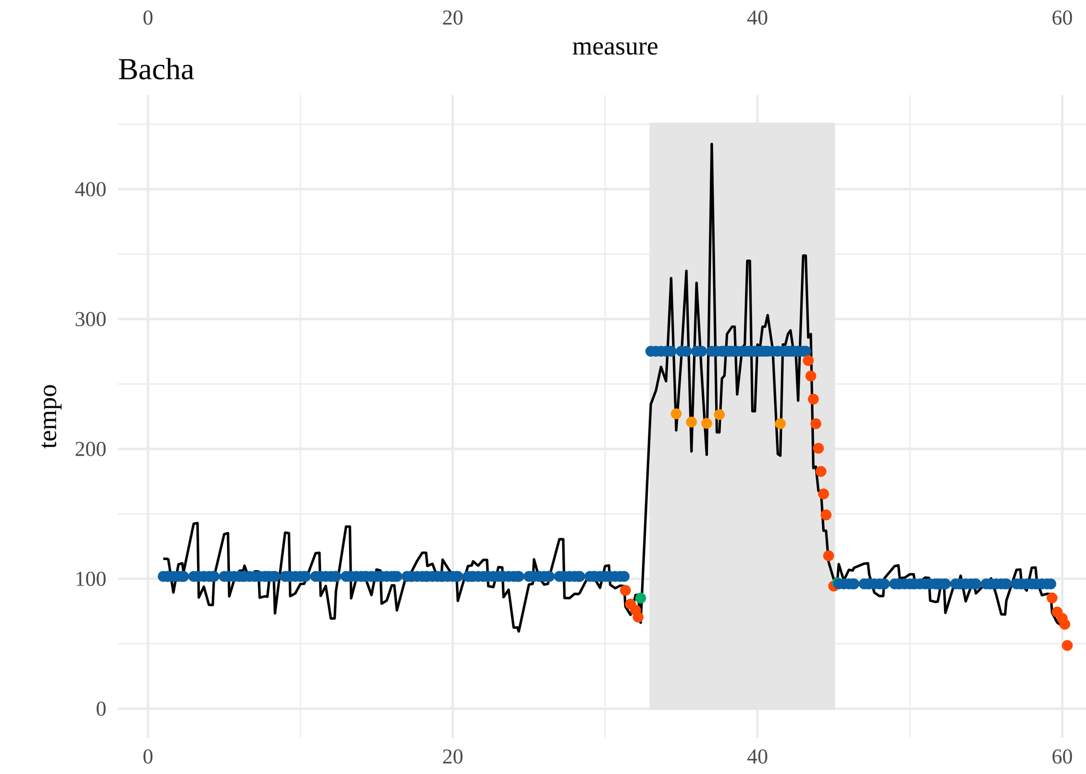
Error distribution

$$\eta_t \sim N(0, Q(s_t, s_{t-1})) \qquad \epsilon_t \sim N(0, G(s_t))$$



1. Constant tempo
2. Slowing down
3. Speeding up
4. Tenuto (emphasis)





Algorithm (Greedy discrete particle filter)

1: **Input:** A distribution w on S_0. Parameters of matrices. Number of particles B.
2: **for** $t = 1$ **to** N **do**
3: For each current path, calculate the 1-step likelihood for moving to each potential S_t
4: Multiply the likelihood by the transition probability $p(S_{t-1}, S_t)$
5: Multiply by weights w
6: If $\|w\|_0 > B$, resample to B non-zero weights and renormalize
7: Keep only those paths corresponding to the non-zero weights
8: **end for**
9: Return path with largest weight w.

Future work

- Using dynamic information
- Bayesian hierarchical clustering
- Musical structure recovery
- Looking at tempo tracks for multiple recordings displays obvious structure
- Testing in real people

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