TIME-SHIFT NORMALIZATION AND LISTENER PROFILING
IN A LARGE DATASET OF MUSIC LISTENING HISTORIES

Gabriel Vigliensoni
gabriel@music.mcgill.ca

Ichiro Fujinaga
ich@music.mcgill.ca

INTRODUCTION

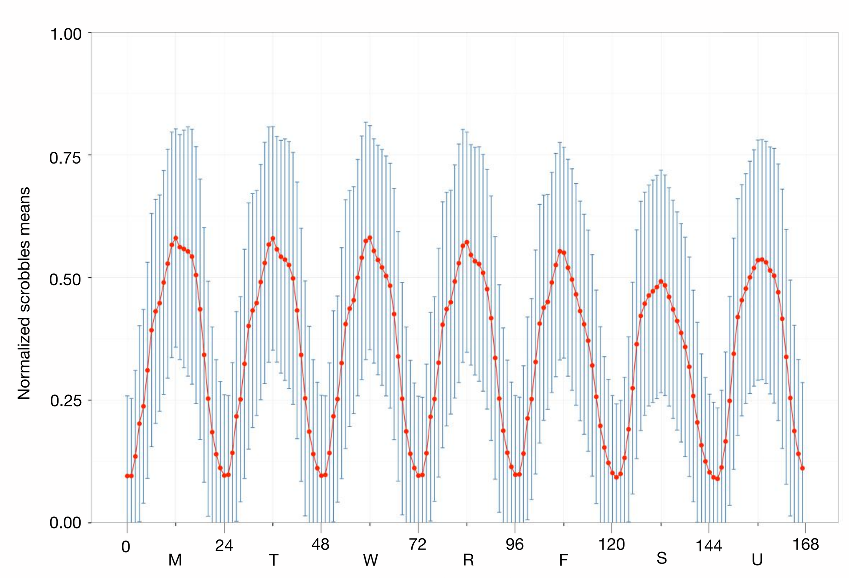
- We want to find patterns in people's music listening behaviour by studying their full music listening histories
- We have collected 594K full music listening histories from active users of the last.fm's *scrobbler* service (27MM music logs, 7M different tracks)
- However, the listening histories in our dataset are all time stamped according to a standard time zone (UTC)
- To compare people's listening behaviour according to daily or weekly periods, the music log's UTC time needs to be time shifted according to the local time zone, which is not specified in the dataset

TIME-SHIFT NORMALIZATION

- We designed an experiment to evaluate the performance of two approaches with six variants for time-shift normalization of a control dataset

Cross correlation

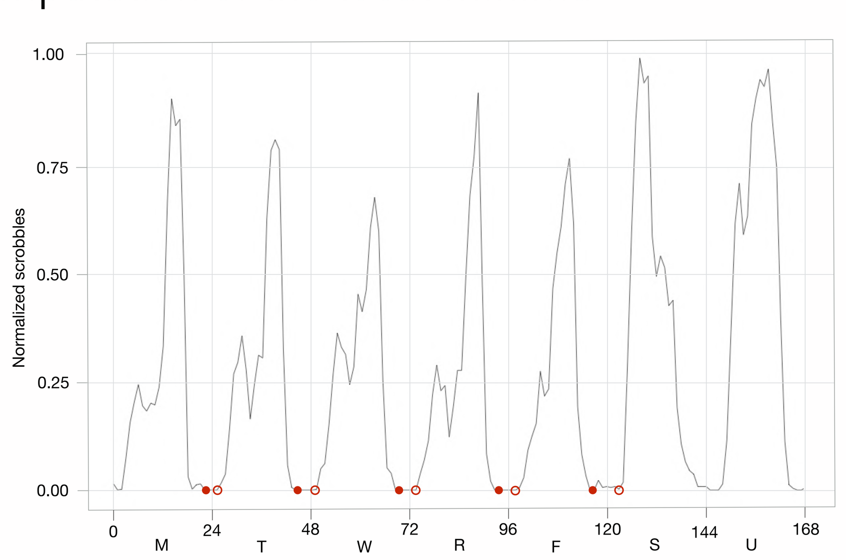
- Based on the idea that listeners share a similar listening profile
- It calculates the lag value ***k*** which returns maximum correlation between $x[t+k]$ and $y[t]$, given a cross correlation function $ccf(x,y)$
- As $y[t]$ we used aggregated listening profiles for 42K listeners in the UK



Control time series computed from weekly aggregated listening profiles from 42K listeners in the UK (mean and 95% CI error bars)

Local minima approach

- Based on the idea that listeners, in general, sleep during night time and submit fewer music logs
- It looks for the multi-local minima within a week, for weekdays only
- We also implemented a variant based on averaging the forward and the backward computation of the local minima



Forward and backward estimation of multi-local minima of weekly aggregated music listening profile

Seasonal decomposition

- We checked if isolating cyclic seasonal data from any trend or noise would improve the performance of the time zone identification approaches

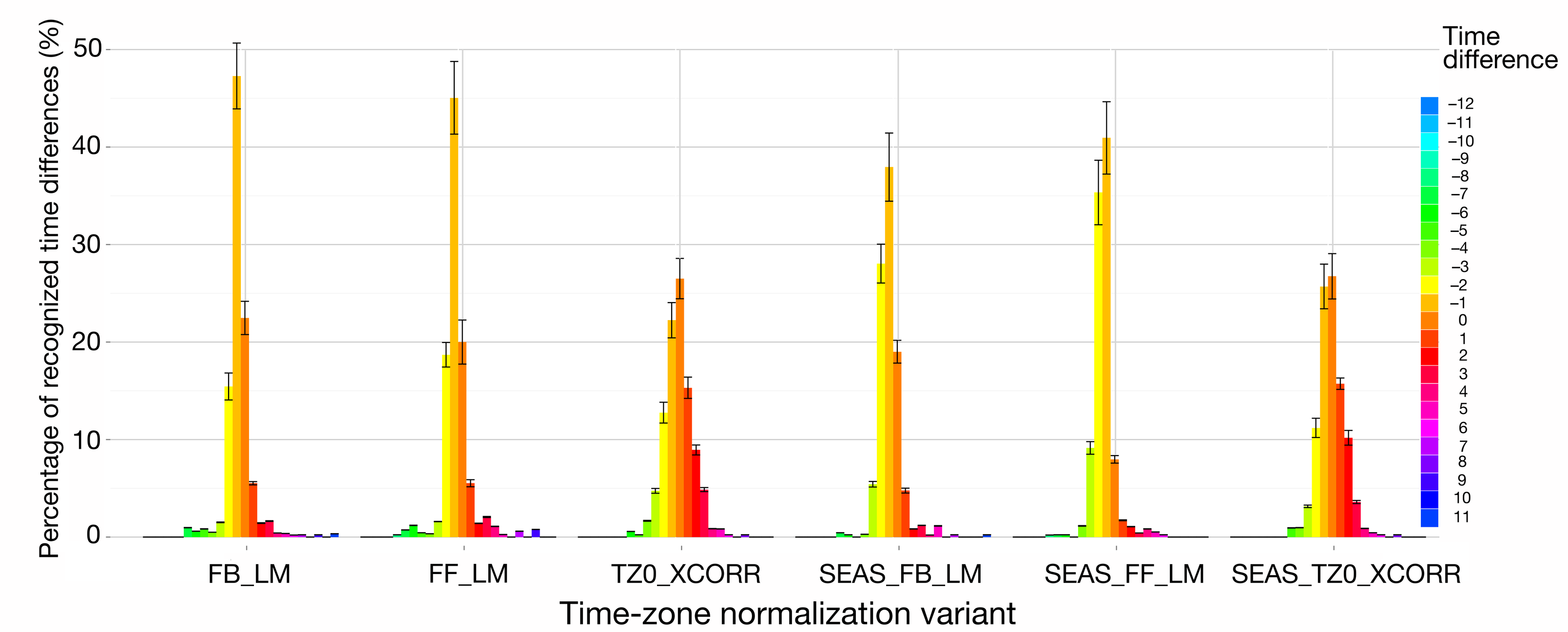
EXPERIMENT

- Control dataset created from 384 random listening histories in the dataset
- Aggregated their data into weekly listening profiles
- Manually labelled each one of these profiles in a time zone
- We evaluated the performance of each method by calculating the percentage of time differences between their computed time zone and the ones in the control dataset
- 1,000 populations replicated from the control dataset using bootstrapping method (resampling)

	Time zone 0 xcorr	Local minima-based approaches	
Raw method	TZ0_XCORR	FF_LM	FB_LM
Seasonally decomposed	SEAS_TZ0_XCORR	SEAS_FF_LM	SEAS_FB_LM

ALL SIX VARIANTS FOR TIME-ZONE NORMALIZATION

PERFORMANCE



Performance of six approaches for time-zone normalization of listening profiles. The plots are shown with error bars indicating 95% confidence interval for each time difference between manually labelled and computed time zones for 1,000 populations taken with replacement from a sample of 384 random listening histories

- TZ0_XCORR yielded the best absolute performance, but LM-based approaches performed better if ±1 hour tolerance
- SEAS approaches had poorer performance than its raw counterpart, implying losing important information

LISTENING PROFILING FEATURES

- A better understanding of people's listening behaviour might be used to improve the performance of personalized music recommendation systems
- In order to improve this understanding, we are developing features capable of expressing some aspects of people's listening habits

Exploratoryness

- To represent how much a listener explores different music instead of being listening to the same music repeatedly we defined *exploratoryness* e_x for listener x as:

$$e_x = 1 - \frac{1}{t_x}\sum_{i=1}^{k_x}\frac{s_i}{i}$$

- where t_x is the total number of music logs for user x,
- k_x is the total number of different music item keys for user x,
- and s_i is the number of music logs for a specific key at ranking i for user x

Mainstreamness

- To express how similar a listener's listening history is to what everyone else is listening to, we compared a listener's listening history music items with the overall ranking of music items, looking for the co-occurrences.
- We defined the *mainstreamness* m_x for listener x as:

$$m_x = \frac{1}{N_1 t_x}\sum_{i=1}^{k_x} O_k l_k$$

- where N_1 is the total number of music logs for the music item in rank 1 in the overall ranking,
- t_x is the total number of music logs for user x,
- O_k is the number of music logs of key k in the overall ranking,
- l_k is the number of scrobbles of key k in the listener's ranking,
- and k_x is the total number of keys for user x

Genderness

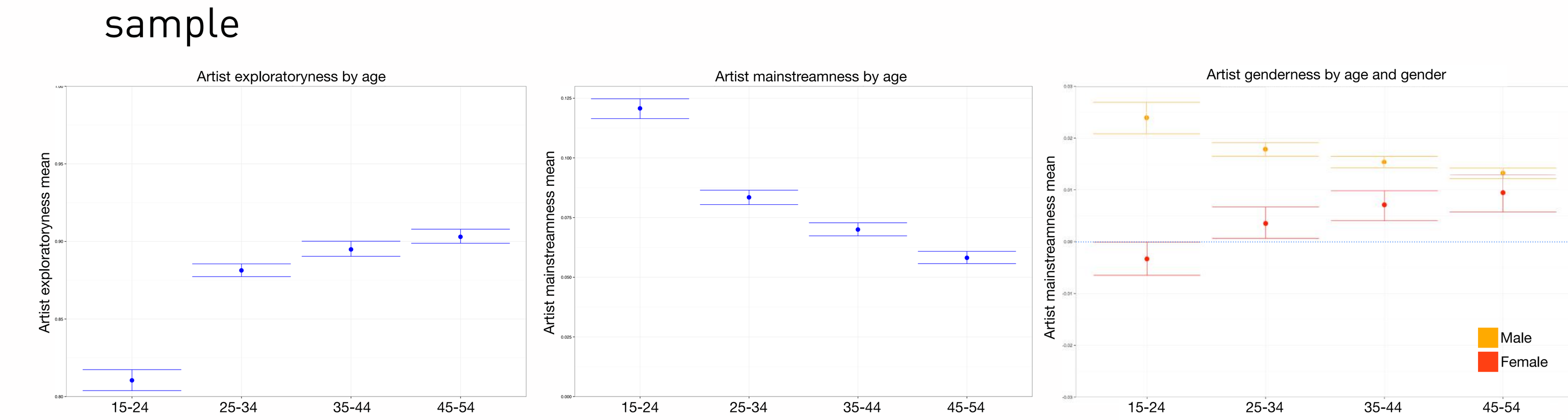
- With the aim of expressing how close a listener's listening history is to what female or men are listening to, we defined the feature *genderness* g_x as listener x:

$$g_x = m_{mx} - m_{fx}$$

- where m_{mx} is the *mainstreamness* of listener x with the male ranking,
- and m_{fx} is the *mainstreamness* of listener x with the female ranking

Profiling listeners by age

- We calculated the listeners' features in relation with artists, and the interaction with their age group
- We created balanced groups of 100 listeners for each age, and created 10-year groups
- We applied the bootstrap technique with 1,000 replications of the original sample



Feature means and 95% CI bars for random group of listeners. Each age group has 1,000 listeners, and error bars were calculated by taking 1,000 populations replicated from the original sample using bootstrap

RESULTS

- While younger people listen more often to the same performers than adults, older listeners tend to explore more artists while they are getting older
- While younger people listen more to the same artists everyone is listening to, older people tend to listen to less common performers
- While self-declared males tend to listen more to music that is ranked higher in the "male" ranking, females listen more to artist ranked higher in the female ranking only when they are young
- Men and women have opposite trends of *genderness*, which seems to stabilize when they are mature

Acknowledgements

This research has been supported by BecasChile Bicentenario, CONICYT, and the Social Sciences and Humanities Research Council of Canada. Important part of this work was made using ComputeCanada's High Performance Computing resources

CIRMMT Centre for Interdisciplinary Research in Music Media and Technology
McGill
DDMAL DISTRIBUTED DIGITAL MUSIC ARCHIVES & LIBRARIES LAB
Social Sciences and Humanities Research Council of Canada
Conseil de recherches en sciences humaines du Canada
Canada