The Effects of Real-world Events on Music Listening Behavior: An Intervention Time Series Analysis

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ABSTRACT

We approach the research question whether real-world events, such as sport events or product launches, influence music consumption behavior. To this end, we consider events of different categories from Google Trends and model listening events as time series using Last.fm data. Performing an auto-regressive integrated moving average analysis to decompose the signal and subsequently an intervention time series analysis, we find significant signal discontinuities, in particular for the Google *news* category. We found that *news* and *events* are likely to increase the number of songs listened to per person per day by about 2%, while *tech* events commonly cause 1% less music being consumed.

CCS CONCEPTS

• **Mathematics of computing → Time series analysis**;

KEYWORDS

intervention time series analysis; music listening behavior; real-world events; Last.fm; Google Trends

1 INTRODUCTION

People spend a lot of time listening to music; however, the number of songs listened to per session differs on a daily basis [7]. A key purpose of listening to music is mood regulation [1–3, 5]. Still, previous studies in the field focus on the listeners' mood, but do not consider the cause of the mood or the mood change. In contrast, we study whether real-world events, such as natural disasters, product launches, or political elections, influence people's music listening behavior, as a presumable cause of mood changes. As an initial step in this research endeavor, the work at hand focuses on the effect of world events on the number of songs people listen to per day.

To investigate this effect, we perform an exploratory study, in which we use Google Trends[1] to obtain world-wide events, and the LFM-1b dataset[2] of listening events by users of the music streaming service Last.fm,[3] from which we obtain the number of songs listened to by all users per day.

2 DATA ELICITATION

2.1 Acquiring Listening Events

We exploit the LFM-1b dataset [7] containing over one billion listening events between 2005 and 2014, created by more than 120,000 Last.fm users. We perform an auto-regressive integrated moving average (ARIMA) analysis [4] to decompose the *absolute number of songs listened to by all users per day* into a trend, seasonal, and residuals component. Only the trend signal is considered as input to the ITSA (Section 3) to remove effects possibly caused by re-occurring events (e.g., weekends or Christmas), and the variance in the number of users who are active on Last.fm on different days.

2.2 Acquiring Real-world Events

To identify events that have an impact on a world-wide basis, we use the events published by Google Trends in their *Year in Search* overview. For various categories, this overview provides the 10 most searched terms per year. We consider the categories *tech*, *events*, *music artists*, *popular*, *trending*, and *news*. In this paper, we use the term "event" to refer to any real-world event in the dataset, while the Google Trends category *events* refers to a subset of events, for example, sport tournament, festival, or incident. For each event, we identify the calendar day on which it was most often searched for. For example, the maximum number of searches for the term "Michael Jackson" between 2004 and 2017 is reached on June 26, 2009, which is the day after he passed away.

An overview of the distribution of events in the dataset per category is given in Figure 1. Please note that before 2012, Google only published a list of the most popular search terms, without categorizing them.

3 MODELING EFFECTS CAUSED BY EVENTS

To identify effects that are possibly caused by a global event *E*, we perform an intervention time series analysis (ITSA) [4]. To this end, we define two models that indicate a significant in- or decrease of the absolute number of listening events, as a cause of the event;

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[1]https://trends.google.com/trends
[2]http://www.cp.jku.at/datasets/LFM-1b
[3]https://www.last.fm
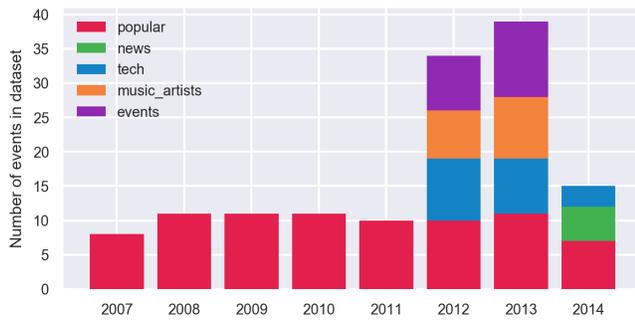
Figure 1: Distribution of events, per year and category.
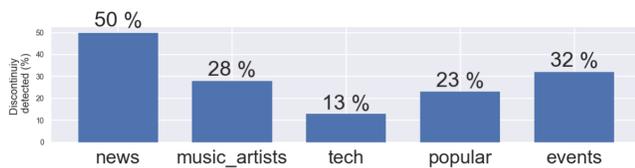
Figure 2: Relative number of events, per category, for which a discontinuity is found.

respectively, we define two predictor variables. The first predictor variable v_1 models a *linear in- or decrease of the signal*, indicating the days adjacent to the event E, starting from *-7* (a week before E), to *7* (a week after E). The second predictor variable v_2 serves as a *threshold to model sudden in- or decreases* in the absolute number of listening events on the day the event occurs. To model this, the value of v_2 is 0 for all the days before E and 1 for all days after E, including the day the event occurred. In case v_2 adds significantly ($\alpha = 0.05$) to a more accurate prediction of the *number of listening events*, a discontinuity is detected.

4 RESULTS AND DISCUSSION

Figure 2 provides an overview of the share of events per category for which a discontinuity is detected. A particularly high share of discontinuities is identified for the *news* and *events* categories. Except for *tech* events, all shares are above a baseline that performs ITSA considering each day of the time-line as an event (18%). According to a one-tailed z-test, results for *news* are significant at $p = 0.046$, while results for *events* only at $p = 0.055$.

Next, we analyze whether more or less songs are listened to as a result of the event. To this end, Figure 3 shows the relative changes in the total number of songs listened to by the entire pool of users, for those real-world events for which a discontinuity on the day of the event is identified. An *increase* is found for all events in the *news* category. This might follow from a change of the listeners' mood because the majority of the events can be considered to have a high societal impact, often combined with a low valence level (e.g., missing of Malaysia Airlines flight 370). Listeners might start to listen to more music to regulate their changed mood. In contrast, for all *tech* events, the number of listening events decreases. We speculate that the release of technical products temporarily
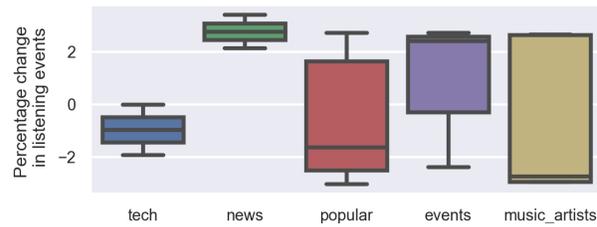
Figure 3: Box plot of the changes in listening events (in %) for real-world events that result in a discontinuity.

occupies people with activities other than listening to music, e.g., using the new product or making videos about it.

We note that the categories for which an unambiguous direction of the coefficients is found are the ones more likely to have an unambiguous level of valence, i.e., the events in the *news* category are most likely to have a low valence level, while the *popular* category contains events that can be both high and low in terms of valence. Given the predominant use of music for mood regulation [6], we argue that the valence level of the event influences whether people listen to more or less music.

5 CONCLUSION AND FUTURE WORK

We analyzed changes in listening behavior that may follow from a global real-world event. We found that *news* and *events* are likely to increase the number of songs listened to per person per day, while *tech* events are more likely to decrease it.

In future work, we will not only consider the amount of music listened to, but also study effects real-world events might have on genre and artist preferences. Also, an expansion of the event dataset with a more uniform distribution of the event types is desired. Moreover, events could be categorized according to people's emotional reactions to them. A further direction is to study regional differences of the effects.

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