Outlier Detection, Explanation and Prediction: The influence of events on television ratings

Bachelor Thesis for Obtaining the Degree

Bachelor of Science

International Management

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Vienna, 31st of May 2019

Affidavit

I hereby affirm that this Bachelor's Thesis represents my own written work and that I have used no sources and aids other than those indicated. All passages quoted from publications or paraphrased from these sources are properly cited and attributed.

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Abstract

This thesis aims to combine the topic of outlier detection together with the prediction of television ratings. On the basis of TV audience datasets from the OTT streaming platform Zattoo an outlier detection was performed and the outliers could be matched to certain events that happened at that date and time. Additionally, it was analysed what the attributes of TV audience data are and what influence events have on television ratings. Predicting outliers in data is another topic that has been discussed in this research, in particular, what influence outliers have on the parameters of forecasting methods. Three forecasting methods are presented, exponential smoothing, Holt Winters and ARIMA (p,d,g) and how outliers can be included in the predictions. Along with that, it will be shown how events can be forecasted through performing a multiple regression. After the theoretical part follows the analysis of the datasets from OTT streaming platform Zattoo. Three German channels were investigated, ARD, ZDF and ProSieben. It was seen that events do have an influence on television ratings by causing particularly large viewing numbers that were recognized a priori through the outlier detection. Furthermore, it was found out that the category sports is the dominant category within all the events that were detected, the other categories being music and politics. The other hypotheses that were analysed revolve around what influence public holidays have on television ratings, what happens on another channel while an event is being televised and what influence the location of the channel has on the events that are streamed. For the last hypothesis two Swiss channels were chosen, SRF 1 and SRF 2.

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1 Introduction

Outliers are one of the most discussed topics in the field of Statistics. Hardly any dataset or statistic can be found that does not have any outlying observations. The concept of normality and abnormality is one that is discussed by scientists in various fields, let it be biology or anthropology, psychology or statistics. While outliers are often seen as a disturbance to the data, this thesis aims to show that irregularities can also hold valuable information when taking a closer look at them after they have been identified through an anomaly detection. At the same time, this research looks at the question, what influence events have on TV audience data. With applications like Netflix, Hulu or Amazon Prime television ratings have dropped tremendously and households have started to refrain from paying for television as a study from 2018 shows (eMarketer, 2018). However, when it comes to events that are streamed on television it can be seen that these are still widely popular to be watched on TV. The TV audience data analysed shows that at certain times viewing numbers are unusually high, in fact that these are outlying observations in the data, and the times could be matched to certain events that occurred and that were shown on television.

Furthermore, predicting outlying observations in time series is also a major issue in forecasting practices. While it is well known how to deal with seasonality, trend and cyclical behaviour, there is no method found that can include outliers into prediction methods. This thesis aims to give an overview over forecasting models that managed to predict anomalies under certain circumstances.

There are three major research questions that are being answered in this thesis:

1) What are the different mechanisms to detect anomalies?
2) Through identifying and explaining outliers, can irregularities be seen as something useful rather than a disturbance to the data?
3) Do events have an influence on television ratings?

The first part of this thesis consists of a literature review which looks at definitions of outliers and outlier detection mechanisms followed by an overview of forecasting methods, in particular Exponential Smoothing, Holt Winters, ARIMA and a multiple regression model. It will be examined what the nature of TV audience data is and what role events play in television. The second part of the thesis is the practical research, where TV audience data is being analysed and six hypotheses are tested on TV audience data from the OTT streaming platform Zattoo. This thesis is written in cooperation with the European Union funded project “ReTV”, an initiative to revise concepts of television in the Internet age.

2 Outlier Detection, Explanation and Prediction: The influence of events on television ratings

2.1 Outlier Detection and Explanation

2.1.1 Definition of Outlier

There are many different definitions that explain what outliers are. Barnett and Lewis (1994, p.4) define an outlier as “an observation (or subset of observations) which appears to be inconsistent with the remainder of that set of data”. Grubbs (1969) stated that “an outlying observation, or outlier, is one that appears to deviate markedly from other members of the sample in which it occurs”, as quoted in Barnett and Lewis (1994, p.22). Aggarwal and Yu (2001) declare that “an outlier is defined as a data point which is very different from the rest of the data based on some measure” (Aggarwal and Yu, 2001, p.211). These definitions show that for an outlier to be an outlier depends on the rest of the sample data and what is defined as normality. Zimek and Filzmoser (2018) give an interesting thought on the topic of defining outliers by pointing out that most definitions use terms like “*appear*” or “*some* measure” or “under the *suspicion*”. For decades the focus on outliers has been to create algorithms in order to detect them most efficiently, but it is also important to consider what an outlier possibly means. An outlier merely declares that there is the *suspicion* of a deviation from the norm or that it *appears* to be inconsistent from the rest of the data. These are assumptions, and even if a detection mechanism has been used it shows that outlying observations have to be handled very carefully. Kruskal (1960), as quoted in Zimek and Filzmoser (2018), uttered that:

“An apparently wild (or otherwise anomalous) observation is a signal that says: ‘Here is something from which we may learn a lesson, perhaps of a kind not anticipated beforehand, and perhaps more important than the main object of the study.’ “

This idea will be discussed further along in this research. Moreover, in this thesis the term anomaly or irregularity will be treated as a synonym for outlier, the same counts for “novelty detection, anomaly detection, noise detection, deviation detection or exception mining” (Hodge and Austin, 2004, p.85) for outlier detection.

2.1.2 Identification of Outliers: Anomaly detection methods

In this chapter it will be analysed how outliers can be detected. A variety of techniques exist and there is no model that can be applied universally (Hodge and Austin, 2004). In this research, an overview of existing techniques will be given, however, it is impossible to provide all existing approaches.

Outlier detection approaches can be categorised in different ways (Su and Tsai, 2011). Hodge and Austin (2004) differ between the three fields, Statistics, Neural Networks and Machine Learning. In Statistics, there is a differentiation between parametric and non-parametric approaches, whereas Neural Networks and Machine Learning is divided in unsupervised, supervised and semi-supervised approaches to outlier detection (Su and Tsai, 2011). In unsupervised outlier detection, there is no preceding label available for the data, thus an observation could be normal or anomalous (Su and Tsai, 2011). Hodge and Austin (2004) call this a Type 1 outlier detection model. Here outliers are detected “with no prior knowledge of the data” and the most outlying points are marked as potential anomalies (Hodge and Austin, 2004, p.88).

In supervised outlier detection, pre-labelled data is necessary for training in order to build a classifier (Hodge and Austin, 2004). The approach usually contains two phases, “a *training* phase and a *testing* phase” (Patcha and Park, 2007, p.3452). In the training phase the model learns what is normal and what is abnormal data and in the testing phase this profile can be used on new data. (Patcha and Park, 2007). This is corresponding to “supervised classification” and forms the Type 2 outlier detection model (Hodge and Austin, 2004).

A semi-supervised approach is a hybrid of Type 1 and Type 2. It can recognize normality and if a data point lies outside the borders of normality the model declares it as a novelty (Hodge and Austin, 2004). Here abnormal data does not need to be available precedingly unlike with a Type 2 model.

However, some of the earliest algorithms for detecting outliers were created in the field of *statistics*. An informal way is the Boxplot, which can “identify outliers that have extremely large or small X values” (Su and Tsai, 2011, p.262). The Boxplot shows the lower extreme, lower quartile, median, upper quartile and upper extreme (Laurikkala et al, 2000). The threshold for an upper or lower outlier is 1.5x of the interquartile range, which is an upper quartile minus the lower quartile (Laurikkala et al, 2000). Barnett and Lewis (1994) pose the rule that all data points that are three standard deviations away from the mean should be marked as outliers. This is also known as the z-score, the number of standard deviations away from the mean, which was originally created by Grubbs in 1969 (Chandola et al, 2009). The z-score is computed by the formula:

$$z = |x - \bar{x}| / s,$$

with $\bar{x}$ being the mean and s being the standard deviation. The formula for computing whether a data point is anomalous is:

$$\mathbf{z} > \frac{N-1}{\sqrt{N}} \sqrt{\frac{t^2_{\alpha/(2N),N-2}}{N-2+t^2_{\alpha/(2N),N-2}}}$$

N is the size of the test data and $t_{\alpha/(2N),N-2}$ "is a threshold used to declare an instance to be anomalous or normal" (Chandola et al, 2009, p. 31). The threshold is important as it controls the number of data points that are marked as anomalous (Chandola et al, 2009).

Anomaly detection in statistics is divided into parametric and nonparametric models. In parametric approaches, it is assumed prior to the anomaly detection that "data distributions are Gaussian in nature" (Markou and Singh, 2003, p.2483) "and certain parameters are calculated to fit the distribution" (Markou and Singh, 2003, p.2483). Nonparametric approaches have no predefined model structure, however it is figured out once the data is given (Chandola et al, 2009). Therefore nonparametric methods "give greater flexibility" (Markou and Singh, 2003, p. 2483). The most used model is the histogram based anomaly detection for a univariate dataset. This is especially used in intrusion detection (ibid.).

2.1.3 Challenges in Outlier Detection

One of the biggest challenges in outlier detection poses the issue when an outlier is close to the border of normality or a data point lies just within the normal region and is therefore not considered as an outlier but might actually be one (Singh and Upadhyaya, 2012). In other words, the borderline between normality and anomaly can be imprecise (ibid.). Furthermore, it has to be considered that the concept of what is normal can be emerging and developing, that the human tastes and preferences are changing over time and what is normal now "may not be current to be a representative in the future" (ibid.).

Another challenge is the confusion of an anomaly with noise (Chandola et al, 2009). García et al (2013) state that "in some studies outliers are also regarded as noisy data, although they are actually extreme or exceptional, but *correct*, cases" and that "noisy data may harm the learning process", whereas outliers are something that can be learnt from (García et al, 2013, p.620).

Moreover, only few anomaly detection methods are applicable universally. Most approaches are created for a specific problem, especially because the *notion* of an anomaly changes in different fields of application (Singh and Upadhyaya, 2012). As Chandola et al (2009) state:

"In the medical domain a small deviation from normal (e.g., fluctuations in body temperature) might be an anomaly, while similar deviation in the stock market domain (e.g., fluctuations in the value of a stock) might be considered as normal"

Another important aspect to consider is the labeling. Table 1 shows the difference between true and false positives. When a true inlier is marked as an apparent outlier it is a false positive and vice versa, if a true outlier is marked as an apparent inlier it is a false negative.

	Apparent outliers	Apparent inliers
True outliers	True positives	False negatives
True inliers	False positives	True negatives

Table 1: "True inliers/ outliers versus apparent inliers/outliers" (Retrieved from Zimek and Filzmoser, 2017)

2.1.4 Applications of Outlier Detection

Outlier detection has a wide range of applications, the most common fields are fraud detection, intrusion detection and fault detection (Chandola et al, 2009). Fraud detection is often used for credit card fraud and loan application fraud or in the insurance or health care sector (ibid.). Intrusion detection is used in cyber-security when "detecting unauthorized access in computer networks" (Hodge and Austin, 2004, p.88). Fault detection describes when faults are being diagnosed in "safety critical systems" (Chandola et al, 2009, p.2). An extensive list of more applications of outlier detection can be found in the survey of outlier detection methodologies by Hodge and Austin (2004).

2.1.5 The Importance of Explaining Outliers

Outlier explanation or interpretation is an equally important topic as detecting anomalies. It is important to explain outliers once they are detected as an outlier is an indication of “abnormal running conditions” (Hodge and Austin, 2004, p.86) and “offers [...] a facility to gain insights into why an outlier is exceptionally different from other regular objects” (Dang et al, 2013, p.305).

Outlying observations in data occur for one of the following reasons: “human error, instrument error, natural deviations in populations, fraudulent behaviour, changes in behaviour of systems or faults in systems” (Hodge and Austin, 2004, p.87). After its detection one is put with the question whether the outlier should be removed or retained. An answer is given by Hodge and Austin (2004): If the outlier is the result of a technical or human error, the observation should be replaced with a normal value or removed. However, if the anomaly is because of natural deviations or changes in behaviour it is crucial that the outlier is retained as it is an indication of anomaly due to external reasons. If the outlier is a result of fraudulent behaviour or fault in a system an administrator should be alarmed immediately to deal with the situation. Afterwards the data point may be corrected although in a separate file so that the original dataset is not affected but the data can be used for future work, as outliers affect the mean and median of the data.

2.2 Predicting Outliers in Time Series

Time series forecasting is an important part of any business nowadays. Through analyzing past values the aim is to predict future values. There are many models available that can recognize seasonality and trend, for example the Holt-Winters or the seasonal ARIMA model. However, including anomalies into forecasts is a topic that is still not developed entirely. In the following, an overview of different forecasting methods will be given and how they can include outliers. But first, it is necessary to look at the different types of anomalies in temporal data, which are additive outlier (AO), transitory change and level shift (Upadhyaya and Yeganeh, 2015).

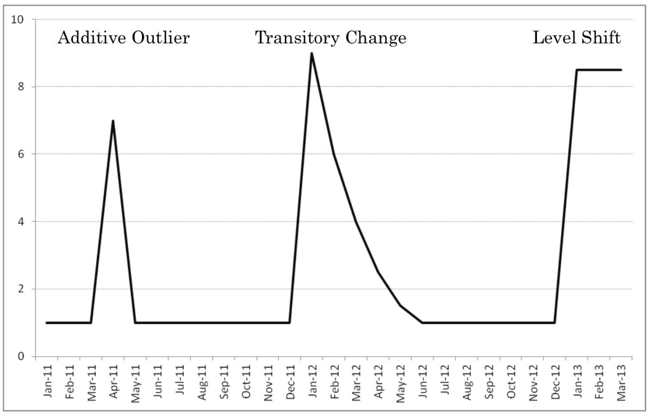


Figure 1: "Most frequent types of outliers". Retrieved from Upadhyaya and Yeganeh, 2015

In this research, the focus will be on additive outliers. Additive outliers are "single observations that are surprisingly large or small, independent of the neighbouring observations" (Talagala et al, 2018, p.5).

Time series in general can be decomposed into the following three components, the trend, seasonal and remainder component. The remainder component is also called the irregular component. Figure 2 shows the data set and its three components.

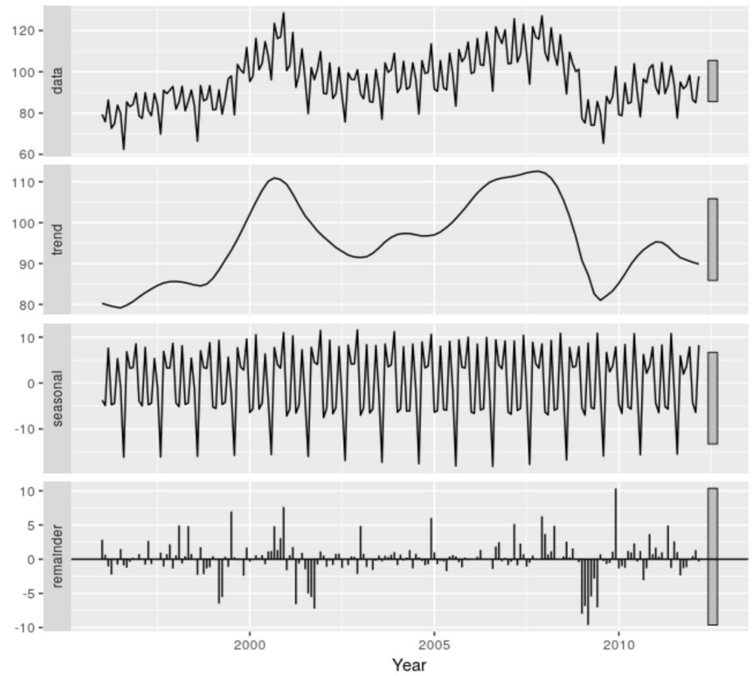


Figure 2: "The electrical equipment orders (top) and its three additive components". Retrieved from Hyndman and Athanasopoulos, 2018

Considering an additive decomposition, the formula is y_t=S_t+T_t+R_t, where "y_t is the data, S_t is the seasonal component, T_t is the trend-cycle component, and R_t is the remainder component, all at period t" (Hyndman and Athanasopoulos, 2018, p.157).

2.2.1 Exponential Smoothing Methods

Exponential smoothing is a forecasting method that uses weighted averages, which give more weight to more recent observations. Simple exponential smoothing does not allow to use data with seasonality or trend and the time series should be stationary. The smoothing parameter α with a value between 0 and 1 indicates the weight given to past observations. If α is 1, all the weight lies on the last observation, hence it would be a Naive 1 method. (Hyndman and Athanasopoulos, 2018). Double exponential smoothing can include a trend component. This method consists of the smoothing parameter α as mentioned before and a base term a and trend term b for the trend.

However, in exponential smoothing outliers can affect the parameter estimations and thus the forecasts tremendously (Koehler, 2012). Methods have been developed that allow to use exponential smoothing despite the presence of outliers. The majority of methods focus on replacing the outlier with a normal value or treating an outlier as a missing value

(Hyndman and Athanasopoulos, 2018). One exemplary procedure is presented by Koehler et al (2012). Here a so called *outlier forecasting procedure* is applied, which starts with an iterative search for all three kinds of potential outliers, namely additive outliers, a level shift or a transitory change. The search ends when no new outliers can be found. An innovative state space model is applied which assumes that there are no outliers. The outlier forecasting procedure can "adjust for outliers" and can be "applied automatically" (Koehler et al, 2012). Accommodating outliers is especially difficult when they are located towards the end of the time series. If outliers are present in the beginning of a series, exponential smoothing can work fairly well as most of the weight is given to the most recent observations and less weight to older data (Koehler et al, 2012).

2.2.2 Holt–Winters

The Holt- Winters method can accommodate trend and seasonality. The seasonality is expressed through a seasonal component s and the frequency of the seasonality is indicated by m (e.g. for monthly data m equals 12). There is an additive and a multiplicative model. The multiplicative model assumes that the seasonality is changing proportionally to the level of the time series, whereas the additive model is suggested when the seasonal changes are more or less consistent throughout the timeline (Hyndman and Athanasopoulos, 2018).

Again, both methods are unsuitable for time series that contain outliers but some procedures exist to deal with them. One way is presented by Andrysiak et al (2018), where the Holt-Winters model is combined with anomaly detection in the context of network intrusion. Rather than scanning the network traffic data for attacks, it is first defined what is the normal traffic and then any deviations from the norm are marked as possible attacks (Andrysiak et al, 2018). When all data lies "within the calculated prediction intervals, we assume that there is no attack/anomaly in out network" (Andrysiak et al, 2018, p.573). If the data outreaches the proposed interval, there is an alarm and it is noted to the log. This method is particularly created for automation.

2.2.3 ARIMA Models (Autoregressive Integrated Moving Average)

ARIMA models are the models that are most applied when it comes to dealing with outliers in time series forecasts. While exponential smoothing models "are based on a description of the trend and seasonality in the data", ARIMA models "aim to describe the autocorrelations in the data" (Hyndman and Athanasopoulos, 2018, p.221). Just like a multiple regression can use several predictors, forecasting here works by using a "linear combination of past values of the variable" (Hyndman and Athanasopoulos, 2018, p.221). These past values are also called *lagged* values. A non-seasonal ARIMA model can be written as an ARIMA (p,d,g) model, where p is the order of the autoregressive part, d is the degree of first differencing involved and g is the order of the moving average part (Hyndman and Athanasopoulos, 2018).

The forecasting method developed by Chen and Liu (1993b) is the most used and cited when it comes to predicting outliers in time series. The main issues addressed in their research is the fact that outliers have a tremendous impact on the parameter estimates which leads to inaccurate forecasts and that the masking effect results in some anomalies not being detected (Chen and Liu, 1993a). However, when *type* and *location* of the outlier are known, "one can adjust the outlier effects on the observations and the residuals" (Chen and Liu, 1993a, p.286).

2.3 Predicting Television Ratings

2.3.1 The nature of TV audience data

Predicting television ratings is surprisingly an area that has not been given much attention to by research, as Danaher et al (2011) state, even though the field is rapidly developing, from access methods like satellite and cable to the Internet and mobile phone accessibility. The number of channels is also increasing. This makes the nature of TV audience data quite complex and on top of all these challenges, the data is highly seasonal (Danaher et al, 2011). Having winter months as peaks and summer months with daylight saving making numbers drop, to weekly seasonality with more viewers on weekends than on weeknights up to a daily seasonal pattern with prime time between 8 and 10 pm (Danaher et al, 2011). Additional to that, there is also variance across days, for example "the largest total audiences at 6 pm and 8 pm are generally on Sundays and Mondays, while viewing at 10 pm is highest on a Saturday" (Danaher et al, 2011, p.1218). Furthermore, television rates or television usages are determined by additional components. There is audience availability and audience demographics on the demand side along with behavioral attributes of the viewers whereas program content and scheduling is on the supply side (Weber, 2002). Also other factors like cast demographics can play a role (Meyer and Hyndman, 2006).

Additionally, it is also important to mention how television ratings are created. The most famous way of generating television ratings is the one by Nielsen in the US. In the 1950s

Nielsen started to collect data from several households, called the "Nielsen families". These families wrote in diaries about their television viewing habits (Roussanov, 2016). Around 25 years later, in 1987, the People Meter was invented by Nielsen, a small box next to the television that was measuring when and what the household members are watching on television. Even nowadays this method is still used, with Nielsen taking the data from around 40,000 households - thus relying on a sample population in order to create overall viewing numbers (Roussanov, 2016).

2.3.2 Television Prediction Models

Predicting television ratings can be divided into two big categories, *linear* models and *non-linear* models. Linear models focus mainly on weighted averages (Weber, 2002), As the category indicates, the model is linear as time is the main predictor, thus they require evenly spaced time series (Weber, 2002). However, linear models exist that can include seasonality like time of the day and day of the week as well as predictors that indicate the content of a program like cast demographics and programm dummies (Meyer and Hyndman, 2006). Bortz (1986) for example created a "programme attractiveness index" (Weber, 2002).

Non-linear models are subdivided into technical and exploratory methods, where "technical models do not consider exogenous predictors except for the lags of the variable they are meant to predict" (Weber, 2002, p.2). These methods are mainly seasonal or distributional. Seasonal models are basic time series methods that are part of many software programs nowadays. They derive the forecasting information "exclusively from the seasonality of past TV usage" (Weber, 2002, p.2). Non-linear exploratory models consist of several predictors of TV usage. This area is fairly recent to data scientists as artificial intelligence is used and models consider not only seasonality and the program content of the forecasted channel but also the content of competing channels and the program surroundings (Weber, 2002).

Along with the traditional forecasting techniques, a Nielsen study shows how analysing social media can improve forecasts when it comes to predicting television ratings. A correlation was found between tweets and television ratings and that for example "for 18-34 year olds, an 8.5% increase in Twitter volume corresponds to a 1% increase in TV ratings for premiere episodes" (Nielsen, 2013). Using the likes, shares and comments on TV show articles on Facebook or tweets and retweets on Twitter viewers can express their opinions towards a show or episode. This is valuable information for forecasters as it represents the popularity of a series. The Nielsen study considered not only the social media buzz volume but also television factors like genre and how long the show has been televised, money spent on advertising the show and past ratings (Subramanyam, 2011). This shows how important it is to include several predictors into forecasts, with social media buzz being an innovative part when regarding the digital age of television.

2.3.3 Why is it important to predict TV audience data?

Having considered how to forecast television ratings, it is important to explain why it is important to do so. The most important reason for predicting viewing numbers is because advertising prices for television are determined based on the forecasts of audience numbers (Danaher et al, 2011). If audience numbers have not been attained as projected, media planners are refunded in an appropriate manner (Meyer and Hyndman, 2006). Nevertheless the refund does not account for the fact that their media plan has been disturbed (Meyer and Hyndman, 2006). Therefore it is important to generate as accurate forecasts as possible.

2.4 The role of events in television

Rather than the weekly occuring national sport events, major events like the Super Bowl, the Olympic Games or the Football World Cup are the ones that are having the largest audience numbers since approximately the 1970s (Whannel, 2009). Even though we live in an age of movie streaming applications like Netflix and Amazon Prime, these mega events on television are still of major importance. Live television is not only about the sport that is being seen, but also the feeling of togetherness and unitedness, sharing an experience in the intimate space of one's home (Whannel, 2009). The Super Bowl in that sense can be almost seen as a national holiday in the US. But not only in the sociological matter, but also in economic terms events play a big role in television. Events in television are especially interesting for advertisers and sponsors. Because of the huge audience numbers even a 30 second advertisement can reach millions of viewers. The most famous example is the Super Bowl in the US, with 93.1 million television viewers in 2019 (Nielsen, 2019) and advertisement costs that exceed 5 million dollars per 30 second advertisement (Statista, 2019). This form of revenue stream is essential for television channels.

Another question to consider is how other channels react to a media event being televised. Do they continue to show their regular television show or do they offer an alternative program? How do they manage to keep up television ratings? In case of the Super Bowl, some answers to these questions could be found. In 1992 Fox started to televise a show called "In Living Color" which airs directly opposite to the halftime show of the Super Bowl and ends when the football game is resumed on CBS (Meslow, 2017). Another reaction to encounter the popularity of the Super Bowl is the "Puppy Bowl" which is shown on the channel Animal Planet and where puppies play against each other rather than humans. It has become very popular as an alternative program to the football game. Other channels have also become successful at counter-programming, for example the channel Comedy Central is offering a marathon of the series "South Park" and the channel Showtime a "Twin Peaks" marathon (Meslow, 2017). Similar scenarios occurred during the FIFA Football World Cup in 2018. Rather than resigning to the football world cup, the German television channels decided to offer an alternative program. For example during the final of the FIFA world cup 2014 in Brazil, RTL was showing the movie "Kill the Boss", Sixx televised the movie "Election", RTL 2 the movie "Andromeda" and Arte the film "Loulou" with Gérard Depardieu (Neumann, 2014). It can be seen that the channels attempted to give an attractive alternative program to their viewers by televising well-known movies. However, 34.65 million viewers were watching the final game on ARD, which is making up 86.3 percent as the market share, hence 13.7 percent were watching a different channel that evening (Spiegel Online, 2014).

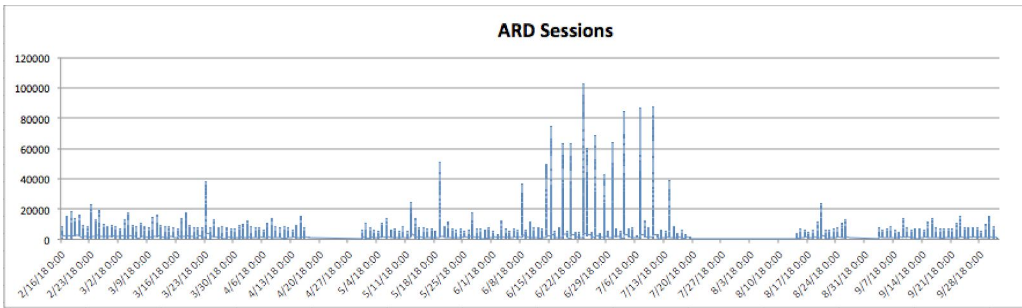
2.5 Predicting Events and Public Holidays

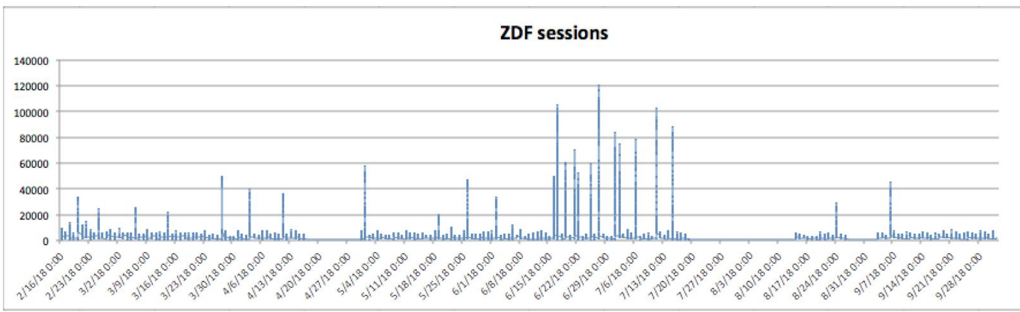
One successful method presented by Hyndman and Athanasopoulos (2018) for predicting events and public holidays in time series is using a multiple regression. For example, when tourist arrivals are forecasted for South Africa in 2010, one should consider the impact of the Football World Cup in that year. This can be done using dummy variables. The dummy variable will indicate through 1 = "yes" and 0 = "no" whether a special event has occurred that day or not. The same accounts for public holidays. This method can also be used when outliers occur in the data, with the dummy variable removing the effect of the outlier rather than having to replace the outlier (Hyndman and Athanasopoulos, 2018).

Regression models can be linear or multiple. A linear regression only considers one predictor, whereas a multiple regression takes several predictors into account. The forecast variable y is the explained variable, while the predictor variable is the explanatory variable. A linear regression can be expressed through the formula $y_t=\beta_0+\beta_1 x_t+\varepsilon_t$ where β_0 indicates the intercept, β_1 the slope, x is the predictor and ε the error term (Hyndman and Athanasopoulos, 2018).

2.6 The Experiment: Combining Anomaly Detection with Prediction of Events in Television

The TV audience dataset used for the experiment is derived from the project “ReTV”, which is funded by the European Union. The project was initiated in January 2018 with the goal to “re-invent TV for the interactive age” (ReTV, n.d.). There is a separate dataset for each channel and each dataset contains two variables, “time” and “number of sessions”. The time variable is evenly spaced as the data has been collected every five minutes. All datasets start on February the 16th and end on October the 2nd 2018. The data is from several TV channels from Germany and Switzerland. For the experiment three German channels have been chosen due to their popularity and representativity, namely ARD, ZDF and ProSieben, and two Swiss channels have been analysed for the fourth hypothesis, SRF 1 and SRF 2. There is a period of missing values between April 17-30 and July 19 until August 14 on every channel. However, this does not affect the results of the experiment. Below is a summary of the data from each channel. Due to data protection and privacy reasons the full TV audience dataset will not be published in this thesis. Furthermore, the dataset will be considered as a representative sample for the television viewing behaviour of the respective home country of the channel.





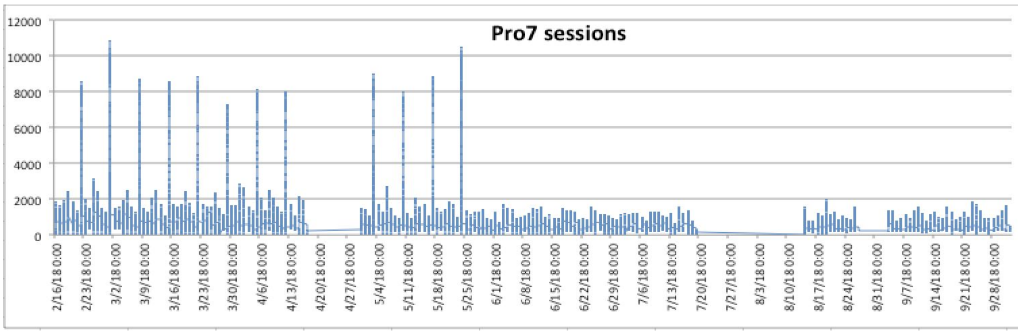


Figure 3: Overview of the Data from the Channels ARD, ZDF and ProSieben

Six hypotheses were created and tested. The method and results for each hypothesis will be reported individually.

H_1: *Events have an influence on television ratings*

H_2: *Sport events influence television ratings more than political events*

H_3: *Sport events influence television ratings more than music events*

H_4: *The detected anomalies in Swiss television are linked to different events than in German television*

H_5: *With an event being televised on one channel, ratings on another channel decrease*

H_6: *Public holidays have an influence on the number of television ratings*

2.6.1 Events have an influence on television ratings

In order to test this hypothesis an anomaly detection has been conducted with the program SPSS Statistics by IBM. With the command “DETECTANOMALY” or “identify unusual cases” from the menu bar under DATA the algorithm searches for cases that deviate “from the norms of their cluster groups” (IBM, n.d.).

The anomaly detection performed through SPSS can additionally report the anomalies based on peer groups. For example, the channel ZDF has 3 peer groups, with 6.5% forming the third peer group, 56.6% the second and 36.9% the first adding up to 100% in total. Below is the result of the anomaly detection case peer ID list for ZDF.

Anomaly Case Peer ID List				
Case	slice_start	Peer ID	Peer Size	Peer Size Percent
33832	27-JUN-18	3	3362	6.5%
33831	27-JUN-18	3	3362	6.5%
33830	27-JUN-18	3	3362	6.5%
33829	27-JUN-18	3	3362	6.5%
33833	27-JUN-18	3	3362	6.5%
33828	27-JUN-18	3	3362	6.5%
33826	27-JUN-18	3	3362	6.5%
33819	27-JUN-18	3	3362	6.5%
33818	27-JUN-18	3	3362	6.5%
33825	27-JUN-18	3	3362	6.5%
33817	27-JUN-18	3	3362	6.5%
33816	27-JUN-18	3	3362	6.5%
30967	17-JUN-18	3	3362	6.5%
33824	27-JUN-18	3	3362	6.5%
30966	17-JUN-18	3	3362	6.5%
33815	27-JUN-18	3	3362	6.5%
30964	17-JUN-18	3	3362	6.5%
37906	11-JUL-18	3	3362	6.5%

Table 2: Anomaly Case Peer ID List for the Channel ZDF

After the anomaly detection has been performed, it was necessary to remove the duplicates, as the goal is to find the *date* with abnormal numbers of sessions and not the session per se. The anomaly detection for the third peer group looks as following:

	AnomalyCasePeerIDList	V2	V3	V4	V5
1	30967	17-Jun-2018	3	3362	6.5%
2	33832	27-Jun-2018	3	3362	6.5%
3	37906	11-Jul-2018	3	3362	6.5%
4	38998	15-Jul-2018	3	3362	6.5%

Table 3: List of Anomalies After Removal of Duplicates for the Channel ZDF

The process for removing the duplicates was: SELECT CASES under the condition that the peer group = 3, so that only the third peer group is shown. With the command IDENTIFY DUPLICATE CASES and the first case in each group being primary, duplicates are being removed. Then SELECT CASES again with the condition that only the first primary case is shown will give back the dates. The full anomaly detection and duplicate removal process is explained in Appendix 1.

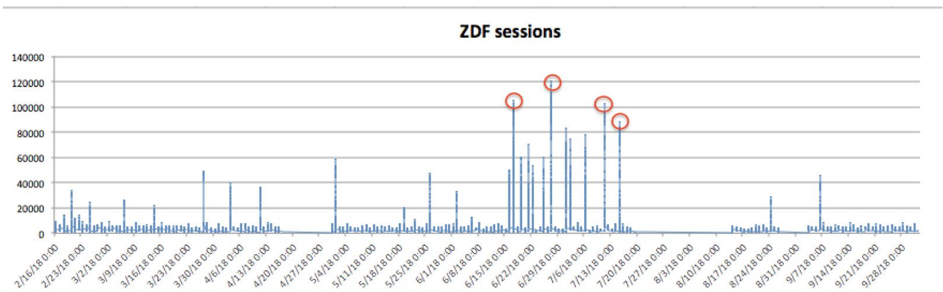


Figure 4: Result of the Anomaly Detection for the 3rd Peer Group for the Channel ZDF

The four dates indicated are the largest unusual cases detected by SPSS for the channel ZDF. Together they make up 6.5% of the data. However, when lowering the threshold and considering the second peer group as well, there are 25 outliers in total.

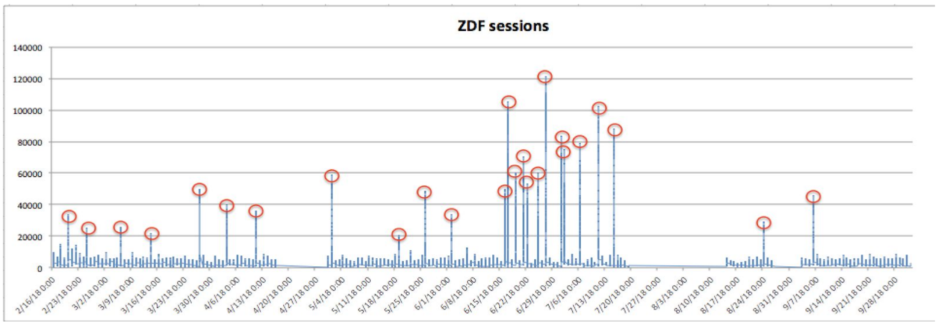


Figure 5: Result of the Anomaly Detection for the Channel ZDF After Lowering the Threshold

Manually the dates have been associated with events that match the streaming time. The results as shown below demonstrate that most outliers were associated to a specific event on that day. The table with the source indication can be found in Appendix 2.

20-Feb-18	UEFA Champions League Game Bayern Munich : Beşiktaş
25-Feb-18	IIHF Ice Hockey Final Germany : Russia
6-Mar-18	UEFA Champions League Game Paris Saint Germain : Real Madrid
14-Mar-18	UEFA Champions League Game Beşiktaş : Bayern Munich
27-Mar-18	FIFA Football World Cup Test Game Germany : Brazil
3-Apr-18	UEFA Champions League Quarter Final Sevilla : Bayern Munich
11-Apr-18	UEFA Champions League Quarter Final Bayern Munich : Sevilla
1-May-18	UEFA Champions League Semi Final Bayern Munich : Real Madrid
19-May-18	The Royal Wedding Live
26-May-18	UEFA Champions League Final
2-Jun-18	FIFA Football World Cup Test Game Germany : Austria
16-Jun-18	FIFA Football World Cup Second Game Day
17-Jun-18	FIFA Football World Cup Game Germany : Mexico
19-Jun-18	FIFA Football World Cup Game Russia : Egypt
21-Jun-18	FIFA Football World Cup Game Day
22-Jun-18	FIFA Football World Cup Game Day
25-Jun-18	FIFA Football World Cup Game Iran : Portugal
27-Jun-18	FIFA Football World Cup Game Germany : South Korea
1-Jul-18	FIFA Football World Cup Round of 16; Spain : Russia / Croatia :Denmark
2-Jul-18	FIFA Football World Cup Round of 16; Brazil : Mexico / Belgium : Japan
6-Jul-18	FIFA Football World Cup Quarter Finals
11-Jul-18	FIFA Football World Cup Semi Finals
15-Jul-18	FIFA Football World Cup Finals
24-Aug-18	German Premier League Opening Bayern Munich : Hoffenheim
6-Sep-18	Nations League Football Game Germany : France

Table 4: List of Events That Matched Anomalies for the Channel ZDF

For the channel ARD the anomaly detection by SPSS gave two peer groups with one anomaly making up the second one.

Anomaly Case Peer ID List

Case	slice_start	Peer ID	Peer Size	Peer Size Percent
32728	23-JUN-18	2	7096	13.7%
32729	23-JUN-18	2	7096	13.7%
32727	23-JUN-18	2	7096	13.7%
46733	14-SEP-18	1	44756	86.3%
28706	09-JUN-18	1	44756	86.3%
31896	20-JUN-18	1	44756	86.3%
50191	26-SEP-18	1	44756	86.3%
2090	23-FEB-18	1	44756	86.3%
2366	24-FEB-18	1	44756	86.3%
9626	21-MAR-18	1	44756	86.3%

Table 5: Anomaly Case Peer ID List for the Channel ARD

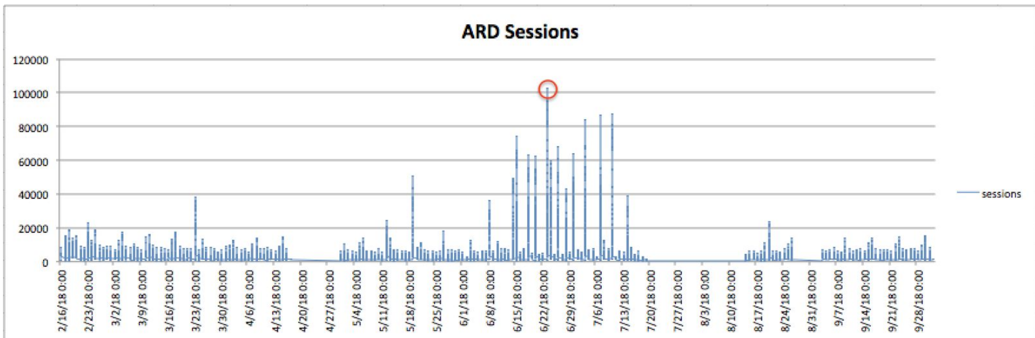


Figure 6: Result of the Anomaly Detection for the 3rd Peer Group for the Channel ARD

After lowering the threshold another time to the second peer group, 18 anomalies have been detected.

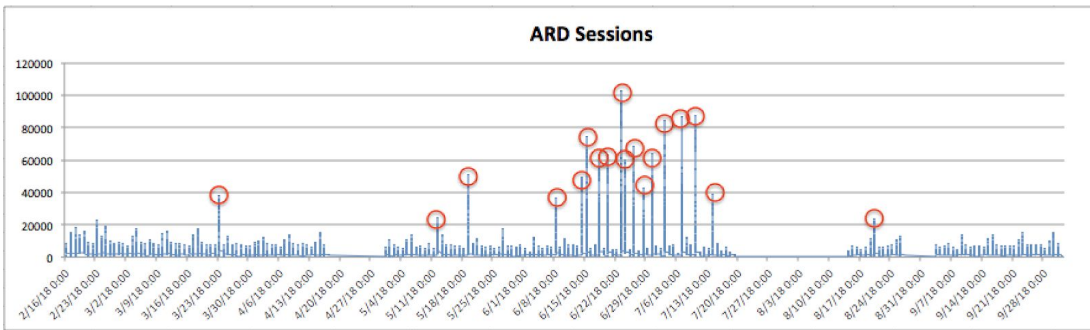


Figure 7: Result of the Anomaly Detection for the Channel ARD After Lowering the Threshold

Again, the anomalies have been matched manually with certain events that fit the exact streaming time on ARD. The table with the source indication is to be found in Appendix 3.

23-Mar-18	FIFA Football World Cup Test Game Germany : Spain
12-May-18	European Song Contest Final
19-May-18	DFB Cup Final Bayern Munich : Eintrach Frankfurt
8-Jun-18	FIFA Football World Cup Test Game Germany : Saudi Arabia
14-Jun-18	FIFA Football World Cup Opening Game Russia : Saudi Arabia
15-Jun-18	FIFA Football World Cup Game Day (Portugal : Spain)
18-Jun-18	FIFA Football World Cup Game Day
20-Jun-18	FIFA Football World Cup Game Day
23-Jun-18	FIFA Football World Cup Game Day Germany : Sweden
24-Jun-18	FIFA Football World Cup Game Day
26-Jun-18	FIFA Football World Cup Game Day
28-Jun-18	FIFA Football World Cup Game Day
30-Jun-18	FIFA Football World Cup Round of 16
3-Jul-18	FIFA Football World Cup Round of 16
7-Jul-18	FIFA Football World Cup Quarter Final
10-Jul-18	FIFA Football World Cup Semi Final Game France : Belgium
14-Jul-18	FIFA Football World Cup 3rd Place Belgium : England
20-Aug-18	DFB Cup Game Greuther Fürth : Borussia Dortmund

Table 6: List of Events That Matched Anomalies for the Channel ARD

For the channel ProSieben the results are the following:

	AnomalyCasePeerIDList	V2	V3	V4	V5	PrimaryFirst
1	1860	22-Feb-2018	2	14281	27.5%	1
2	3875	01-Mar-2018	2	14281	27.5%	1
3	5893	08-Mar-2018	2	14281	27.5%	1
4	7908	15-Mar-2018	2	14281	27.5%	1
5	9919	22-Mar-2018	2	14281	27.5%	1
6	11828	29-Mar-2018	2	14281	27.5%	1
7	13838	05-Apr-2018	2	14281	27.5%	1
8	15811	12-Apr-2018	2	14281	27.5%	1
9	18046	03-May-2018	2	14281	27.5%	1
10	20062	10-May-2018	2	14281	27.5%	1
11	22078	17-May-2018	2	14281	27.5%	1
12	24106	24-May-2018	2	14281	27.5%	1

Table 7: List of Anomalies Detected for the Channel ProSieben

Twelve anomalies have been detected by SPSS in the second peer group, making up 27.5% of the data. In this case, there was no need to lower the threshold as all expected outliers were detected sufficiently.

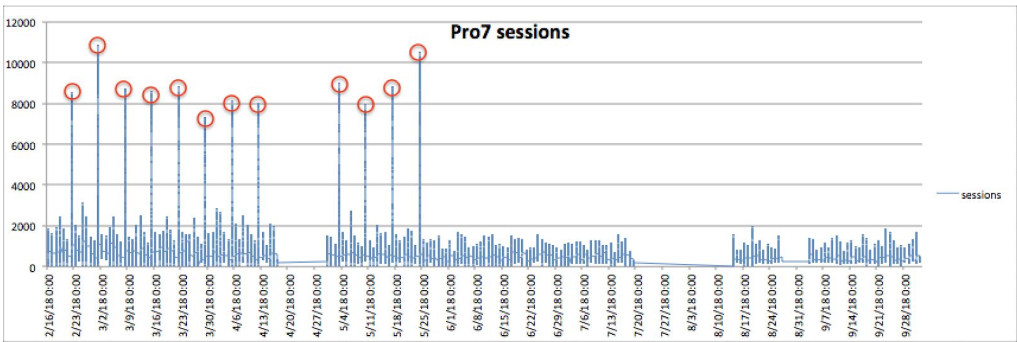


Figure 8: Result of the Anomaly Detection for the Channel ProSieben

All twelve dates could be associated to the TV show “Germany’s Next Topmodel”, as the TV ratings increased rapidly during the time when the show has been streamed on ProSieben. The show was running from the 8th of February 2018 until the 24th of May 2018 once a week every Thursday between 8.15 pm until approximately 10.30 pm (ProSieben, n.d.). “Germany’s Next Topmodel” is a German casting show that was airing every year since 2006. In 2018 the average viewing number of the season was 2.38 million viewers (Statista, 2018).

The graph below shows one example on the 22nd of February 2018 from 0.00 am to 11.55 pm.

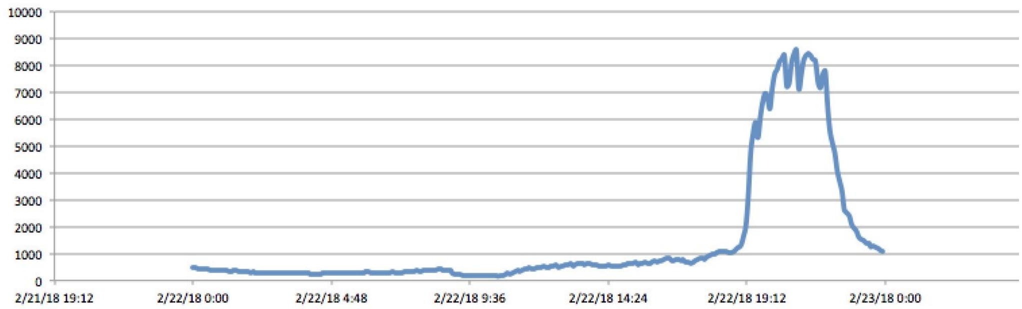


Figure 9: The Dataset from the 22nd of February 2018 on ProSieben

It is unclear whether the twelve dates should be considered as anomalous observations or rather a temporal pattern or a trend. The TV show “Germany’s Next Topmodel” is not considered as an event per se. It is assumed that the anomaly detection recognized the dates as outliers because of the extremely large viewer numbers but in fact it is a recurring weekly pattern that is occuring due to the TV scheduling at that time.

Furthermore, it is interesting to see the small drops in the dataset above. It is assumed that these exist because of the advertisement breaks, where people decide to switch to another channel for a while in order to avoid the commercials. However, this could not be verified in the data, therefore it remains purely an assumption.

To conclude the first hypothesis, the results from the channels ARD and ZDF show that events do have a strong influence on television ratings. Each detected anomaly was associated to an event that occurred at that date and time. However, on the channel ProSieben the outliers were not associated to an event but to a TV show that was recurring weekly.

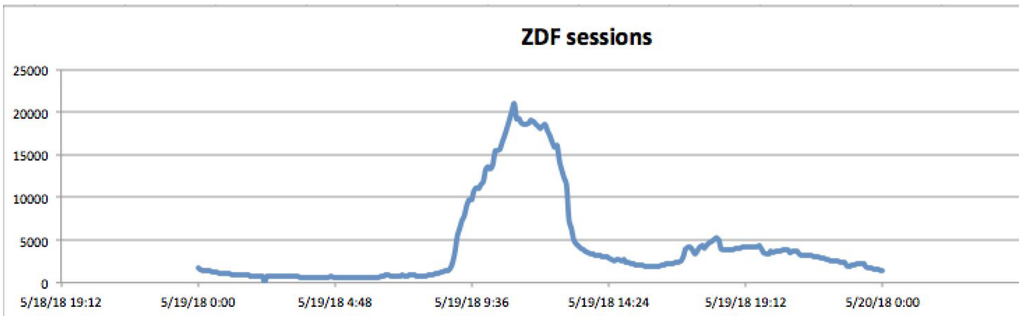
2.6.2 Sport events influence television ratings more than political events

In order to test this hypothesis the results from H_1 will be used. For the channel ZDF 25 outliers were detected. Out of those 24 were associated with a sport event and one was associated to a political event, namely the royal wedding of Prince Harry and Meghan Markle on the 19th of May 2018. Out of the 24 sport events, one was categorized "other than football", which was the ice hockey final between Germany and Russia on the 25th of February 2018.

20-Feb-18	UEFA Champions League Game Bayern Munich : Beşiktaş
25-Feb-18	Ice Hockey Final Germany : Russia
6-Mar-18	UEFA Champions League Game Paris Saint Germain : Real Madrid
14-Mar-18	UEFA Champions League Game Beşiktaş : Bayern Munich
27-Mar-18	FIFA Football World Cup Test Game Germany : Brazil
3-Apr-18	UEFA Champions League Quarter Final Sevilla : Bayern Munich
11-Apr-18	UEFA Champions League Quarter Final Bayern Munich : Sevilla
1-May-18	UEFA Champions League Semi Final Bayern Munich : Real Madrid
19-May-18	The Royal Wedding Live
26-May-18	UEFA Champions League Final
2-Jun-18	FIFA Football World Cup Test Game Germany : Austria
16-Jun-18	FIFA Football World Cup Second Game Day
17-Jun-18	FIFA Football World Cup Game Germany : Mexico
19-Jun-18	FIFA Football World Cup Game Russia : Egypt
21-Jun-18	FIFA Football World Cup Game Day
22-Jun-18	FIFA Football World Cup Game Day
25-Jun-18	FIFA Football World Cup Game Iran : Portugal
27-Jun-18	FIFA Football World Cup Game Germany : South Korea
1-Jul-18	FIFA Football World Cup Round of 16; Spain : Russia / Croatia : Denmark
2-Jul-18	FIFA Football World Cup Round of 16; Brazil : Mexico / Belgium : Japan
6-Jul-18	FIFA Football World Cup Quarter Finals
11-Jul-18	FIFA Football World Cup Semi Finals
15-Jul-18	FIFA Football World Cup Finals
24-Aug-18	German Premier League Opening Bayern Munich : Hoffenheim
6-Sep-18	Nations League Football Game Germany : France
	Category: Sport event (Football)
	Category: Sport event (other than football)
	Category: Political

Table 8: List of Events That Matched Anomalies for the Channel ZDF by Categories

Taking a closer look at one specific example from the 19th of May 2018. ZDF showed from 11 am onwards the Royal Wedding of Prince Harry and Meghan Markle. ARD started streaming from 8.15 pm the DFB Cup Final. Below are the ratings from both channels on that day. While ZDF had a peak with around 20 000 viewers, ARD reached more than 50 000 with the sports game.



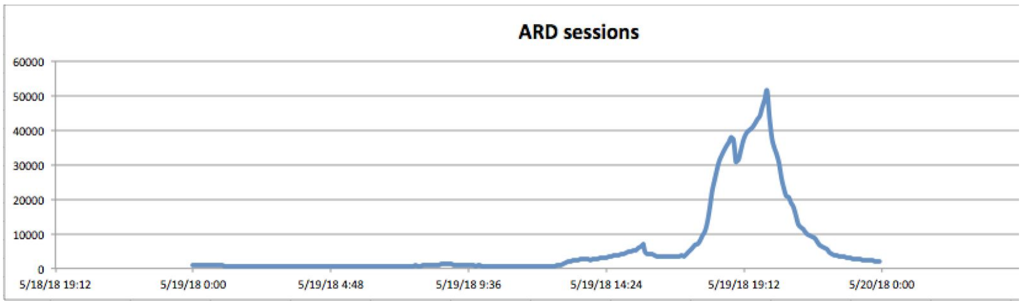


Figure 10: The Datasets from ZDF and ARD on the 19th of May 2018

It can be seen that the sport event reached a higher quota than the political event in one specific case, but also in the overall number of detected outliers that were associated to events as one out of 25 was linked to a political event and 24 to a sport event.

2.6.3 Sport events influence television ratings more than music events

On the channel ZDF 18 outliers were detected. Out of those 17 werde associated with a sport event and one was in the category of music events, the Eurovision Song Contest on the 12th of May 2018.

23-Mar-18	FIFA Football World Cup Test Game Germany : Spain
12-May-18	European Song Contest Final
19-May-18	DFB Cup Final Bayern Munich : Eintracht Frankfurt
8-Jun-18	FIFA Football World Cup Test Game Germany : Saudi Arabia

14-Jun-18	FIFA Football World Cup Opening Game Russia : Saudi Arabia
15-Jun-18	FIFA Football World Cup Game Day (Portugal : Spain)
18-Jun-18	FIFA Football World Cup Game Day
20-Jun-18	FIFA Football World Cup Game Day
23-Jun-18	FIFA Football World Cup Game Day Germany : Sweden
24-Jun-18	FIFA Football World Cup Game Day
26-Jun-18	FIFA Football World Cup Game Day
28-Jun-18	FIFA Football World Cup Game Day
30-Jun-18	FIFA Football World Cup Round of 16
3-Jul-18	FIFA Football World Cup Round of 16
7-Jul-18	FIFA Football World Cup Quarter Final
10-Jul-18	FIFA Football World Cup Semi Final Game France : Belgium
14-Jul-18	FIFA Football World Cup 3rd Place Belgium : England
20-Aug-18	DFB Cup Game Greuther Fürth : Borussia Dortmund
	Category: Sport event (Football)
	Category: Music

Table 9: List of Events That Matched Anomalies for the Channel ARD by Categories

It can be seen that in the data that has been worked with the category sport event (football) is dominant. Therefore it has been shown that sport events have a greater influence on television ratings in the sample data than music events.

2.6.4 The detected anomalies in Swiss television are linked to different events than in German television

Additional to the German channels two Swiss channels have been analysed, SRF 1 and SRF 2. Both datasets are in the same time frame as the German channels and the data is retrieved from the same source, ReTV and the application Zattoo. The data for SRF 1 looks as following:

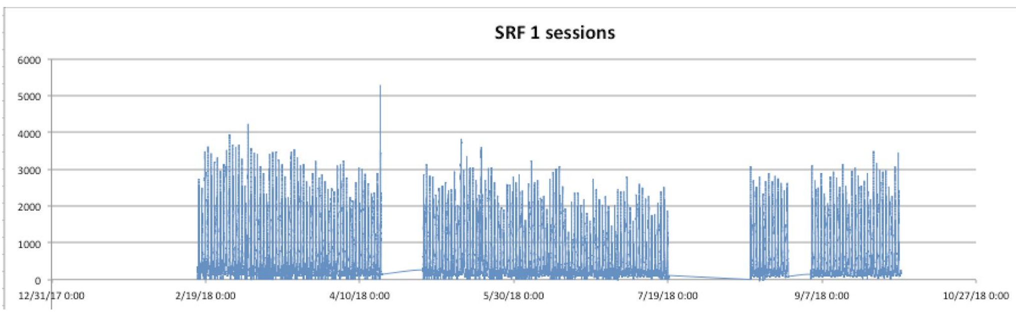


Figure 11: Overview of the Data from SRF 1

An anomaly detection has been performed with SPSS. For SRF 1 there are three peer groups, with one big anomaly making up the first peer group with a peer sice of 25%.

Anomaly Case Peer ID List

Case	slice_start	Peer ID	Peer Size	Peer Size Percent
16914	16-APR-18	1	12940	25.0%
16913	16-APR-18	1	12940	25.0%
16912	16-APR-18	1	12940	25.0%
4482	03-MAR-18	2	25569	49.3%
9594	21-MAR-18	2	25569	49.3%
10174	23-MAR-18	2	25569	49.3%
18294	04-MAY-18	2	25569	49.3%
18930	06-MAY-18	2	25569	49.3%
20017	10-MAY-18	2	25569	49.3%

Table 10: Anomaly Case Peer ID List for the Channel SRF 1

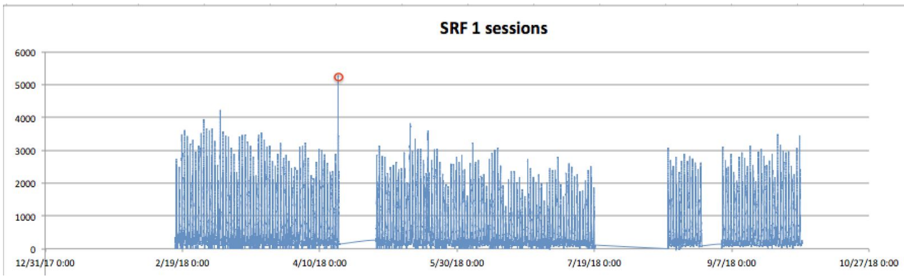


Figure 12: Result of the Anomaly Detection for the Channel SRF 1

The outlier was linked to the 16th of April 2018 and associated to a public holiday in Switzerland, the Spring Celebration in Zurich, also called “Sechseläuten”.

Taking a closer look at the data from that day, the ratings start to increase around 3 pm with 1232 viewers and the peak was at 4.20 pm with 5245 viewer ratings. SRF1 was live streaming the festive parade in Zurich for three hours starting at 3.35 pm, which explains the increase in ratings during that time(SRF, n.d.).

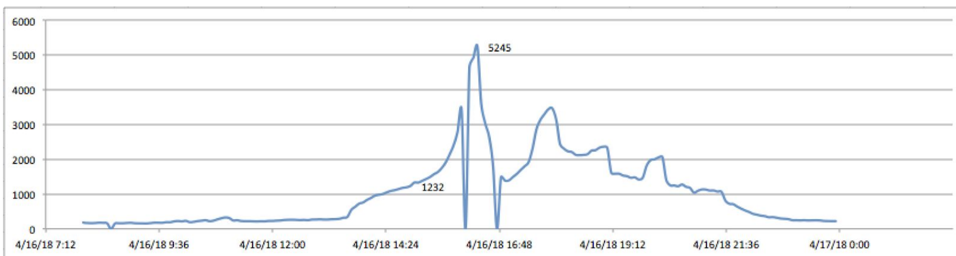


Figure 13: The Dataset on the 16th of April 2018 on SRF 1

For SRF 2, the data looks as following:

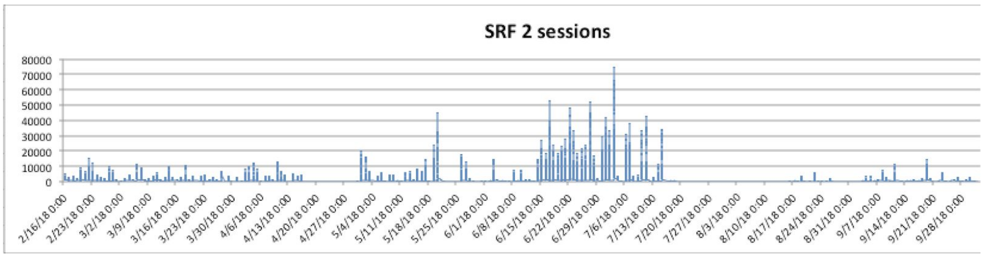


Figure 14: Overview of the Data from SRF 2

The result of the anomaly detection with SPSS gave two peer groups, the second one is made up of six anomalies accounting for 11.2 % of the data.

AnomalyCasePeerIDList	V2	V3	V4	V5
22956	20-MAY-18	2	5799	11.2%
31004	17-JUN-18	2	5799	11.2%
32440	22-JUN-18	2	5799	11.2%
33880	27-JUN-18	2	5799	11.2%
35560	03-JUL-18	2	5799	11.2%
37906	11-JUL-18	2	5799	11.2%

Table 11: Anomaly Case Peer ID List for the Channel SRF 2

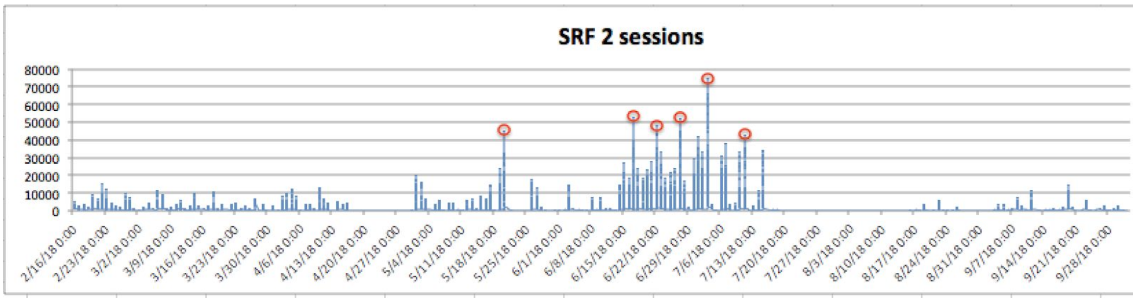


Figure 15: Result of the Anomaly Detection for the Channel SRF 2

Manually the dates were associated to events that match what has been shown on SRF2 during the outlying time slot. The table with the source indication is to be found in Appendix 4.

20-May-18	Ice Hockey World Cup Final Sweden : Switzerland
17-Jun-18	FIFA Football World Cup Game Switzerland : Brazil
22-Jun-18	FIFA Football World Cup Game Switzerland : Serbia
27-Jun-18	FIFA Football World Cup Game Switzerland : Costa Rica
03-Jul-18	FIFA Football World Cup Round of 16 Switzerland : Sweden
11-Jul-18	FIFAFootball World Cup Semi Final Croatia : England

Table 12: List of Events That Matched Anomalies for the Channel SRF 2

The associated events are all sport events that Switzerland was part of except for the last one, the Semi Final of the FIFA Football World Cup. From this example it can be seen that the location of the channel has an influence on the events that cause the viewing numbers to reach an anomalous level as most anomalies were associated to events that Switzerland was a part in.

2.6.5 With an event being televised on one channel, ratings on another channel decrease

The goal of the fifth hypothesis is to find out whether an event on one channel influences the viewer ratings of another channel. The month from the 14th of June until the 14th of July 2018 has been chosen to compare the two channels ARD and ZDF with each other. As a result, it could be seen that during that month the spikes of viewing numbers take turn, meaning that if there is a peak of ratings on ARD, the channel ZDF has a low number of sessions and vice versa.

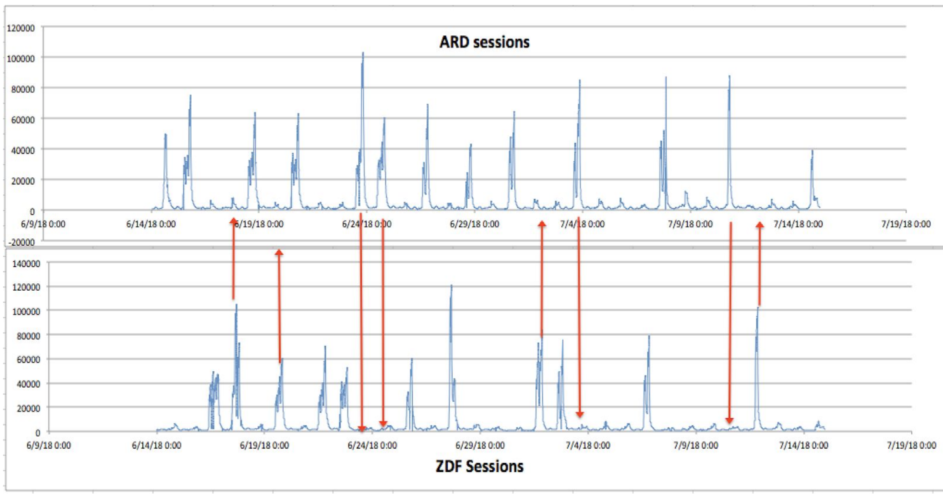


Figure 16: A Comparison of the Data from the Channels ARD and ZDF from the 14th of June Until the 14th of July 2018

Taking a closer look, the graphs below show the week from the 19th of June until the 25th of June 2018.

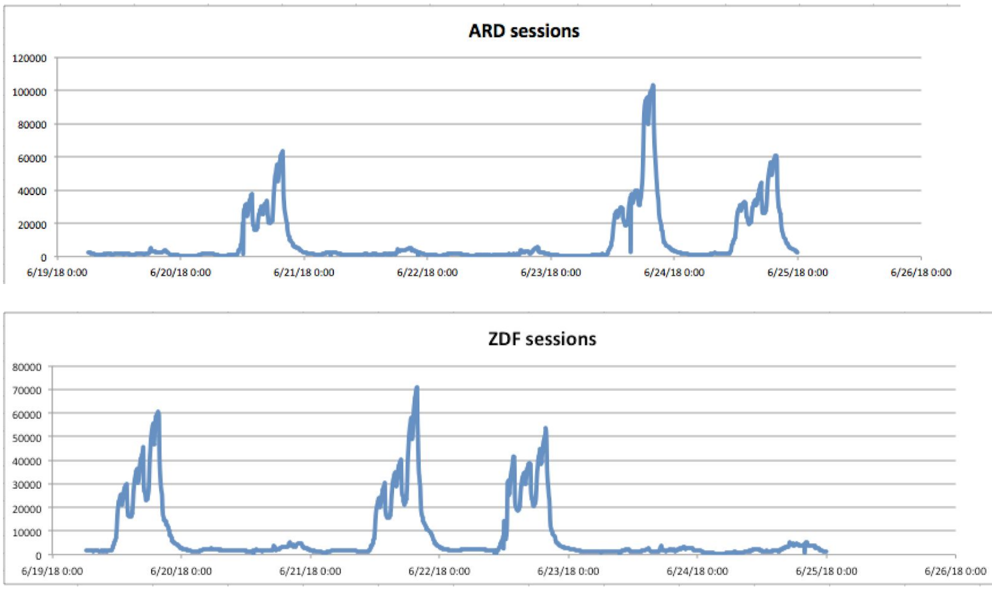


Figure 17: A Comparison of the Data from the Channels ARD and ZDF from the 19th Until the 25th of June 2018

It shows more clearly that every time an event is shown on one channel, the ratings on the other channel stay low. Furthermore, the goal was also to see whether if viewers watch one channel, they decide to switch to the other channel or whether they would continue to watch the regular program that they have been watching at that time. However, in the dataset no such evidence was found where viewers decide to switch the channel. The data rather shows tendencies that viewers specifically start to stream the event that they want to see instead of switching the channel from a previous watched TV show or event. A few examples will be shown below.

First, an example of the 19th of June 2018 can be seen below. ZDF was streaming the FIFA Football World Cup Game Russia vs. Egypt.

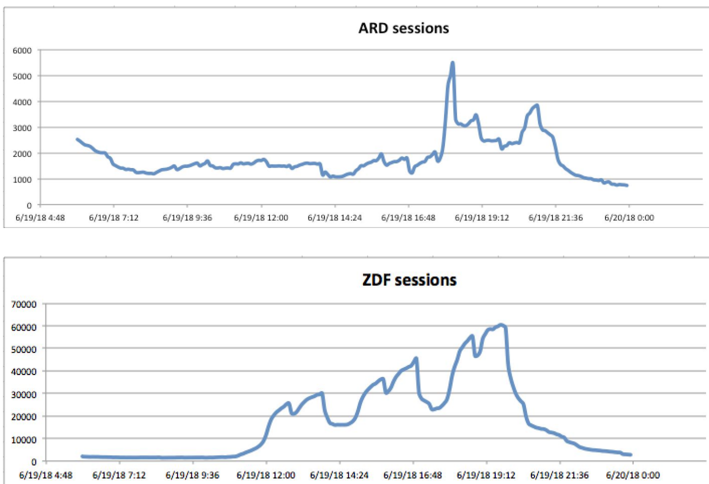


Figure 18: A Comparison of the Data from the Channels ARD and ZDF from the 19th of June 2018

The ratings on ARD stay relatively the same until a rapid increase at 6.15 pm to over 5 000 viewers, followed by a decrease and another increase again until the numbers drop towards midnight. No significant drop on the channel ARD was witnessed, there was even a sharp increase. However, it is important to consider the significant difference in the number of ratings, as ZDF experiences almost 60 000 ratings while the peak of viewing numbers on ARD is at 5 000.

Below the expected curve of ARD is shown. The data from ARD is fictional as this is what was expected if viewers decide to change the channel.

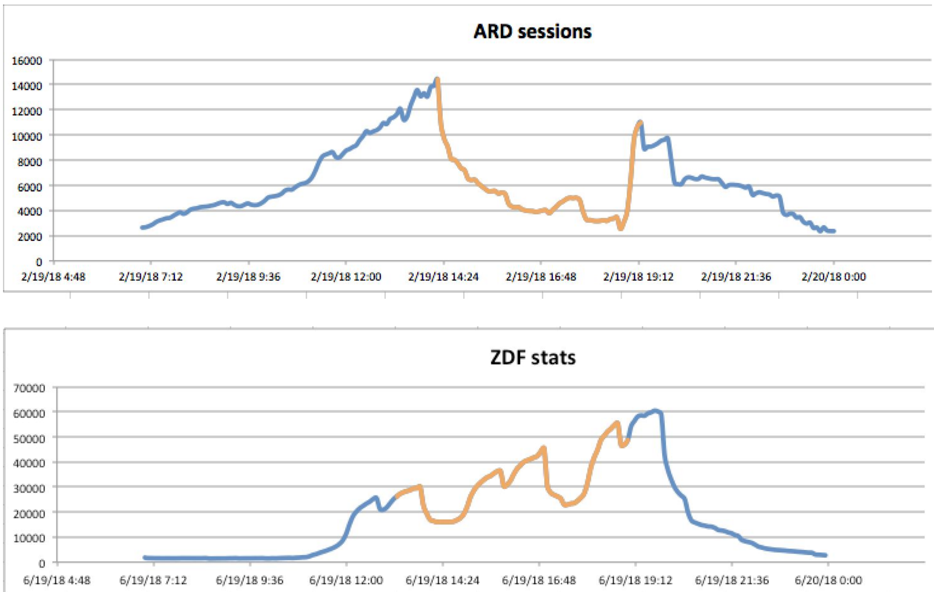


Figure 19: The Expected Curve from the Channel ARD in Comparison With the Data from ZDF from the 19th of June 2018

This is the expected scenario. Television viewers that are watching ARD are changing the channel to see the event streamed on ZDF. ZDF ratings increase, while ARD ratings are declining at the same time.

In the next example as seen on the next page from the 23rd of June 2018, ARD was streaming the FIFA Football World Cup Game Germany vs. Sweden. The sessions that day on ARD had a peak at around 7.45 pm with 103 179 sessions. On ZDF the number of sessions revolves in a range between 172 and 3608 sessions on the same day. In this case again no significant change was experienced on ZDF, even though the viewing numbers on ARD were peaking.

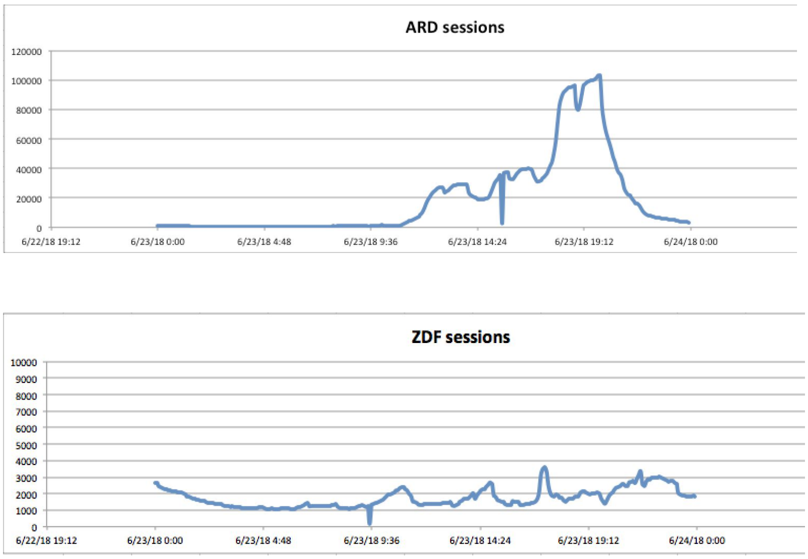


Figure 20: A Comparison of the Data from the Channels ARD and ZDF from the 23rd of June 2018

To conclude this hypothesis, it could be seen that if one channel televised an event, the ratings on another channel are low. However, there was no evidence found that viewers decide to switch from another channel to the event. This indicates a tendency that viewers decide to specifically turn on the television to watch an event.

2.6.6 Public holidays have an influence on the number of television ratings

It was expected that public holidays have an influence on television ratings as people are off work and could spend more time watching television that day. In the data that has been analysed three public holidays come up as anomalies, the 1st of May as the Workers' Holiday, the 16th of April as the Swiss holiday "Sechseläuten" and the 20th of May as the Whitsunday.

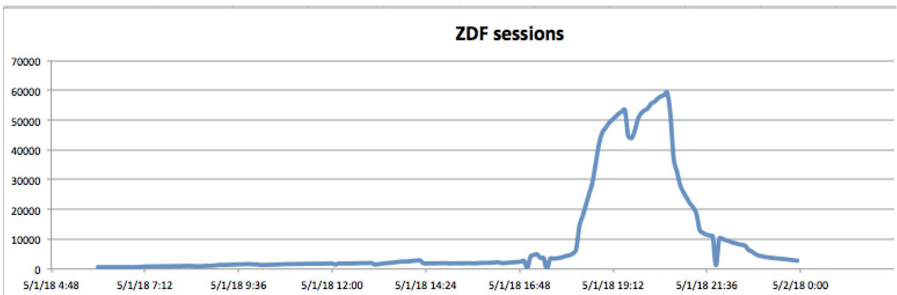


Figure 21: The Dataset from the 1st of May 2018 on ZDF

On the 1st of May 2018 the channel ZDF streamed the UEFA Champions League semi-final Bayern Munich vs. Real Madrid. The first of May is also a public holiday called the workers' day which fell on a tuesday that year. It can be seen that the ratings were low during the day. In the evening when ZDF was streaming the football game the numbers were increasing rapidly and had a peak at 20.15 with 59 249 viewers on Zattoo.

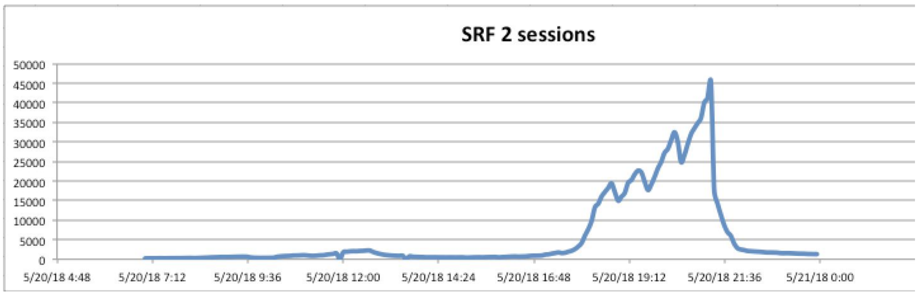


Figure 22: The Dataset from the 20st of May 2018 on SRF 2

On the 20th of May 2018 SRF 2 was streaming from 7.30 pm onwards the final of the Ice Hockey World Cup between Sweden and Switzerland. Television ratings were low during the day and rose sharply towards the evening, yet in a slower manner than on ZDF.

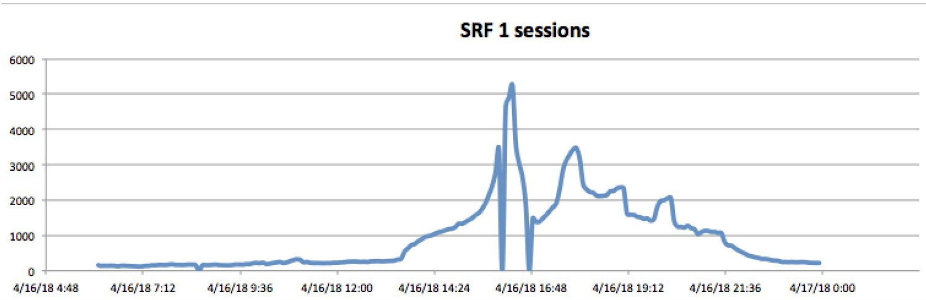


Figure 23: The Dataset from the 16th of April 2018 on SRF 1

The 16th of April is a public holiday in Switzerland called “Sechseläuten”. SRF 1 was streaming the festive parade in Zurich starting at 3.35 pm that which is also the same time as the ratings were peaking on SRF 1.

To conclude this hypothesis, it can not be clearly said whether the increase in television ratings on these three dates was a result of the days being public holidays and viewers having more time to watch television or out of the interest of the viewers in the events that were being streamed. However, as the ratings are low during the day but only increase when the event is being streamed it can be said that for the analysed data the fact that the day was a public holiday was not the reason why television ratings were increasing but rather the content that was being shown.

3 Conclusion

In the beginning of this research, it was defined what an outlier is, what the reasons for the existence of outliers are and that they should not be rejected or removed without careful consideration. Different anomaly detection methods were shown and also their challenges, applications and why it is important to explain an anomaly that has been detected. When it comes to predicting outliers, it was seen what influence outliers can have on the parameters, for example in exponential smoothing. It was shown why TV audience data can be difficult to predict due to its daily and weekly seasonality, but also that other factors have to be taken into account like viewer demographics, their behavioral patterns and content scheduling. Also social media data can have an influence on television rating predictions as the amount of social media buzz around a show correlates with the number of ratings for a particular episode. The influence of events on TV audience data was analyzed. It was shown that events can cause extremely large viewing numbers and that these were identified as outliers by an anomaly detection mechanism. A method for predicting events and public holidays was presented. This can be done using a multiple regression and a dummy variable as the predictor for events.

The second part of the thesis consisted of the analysis of several datasets that were retrieved from the OTT streaming platform Zattoo. It follows a summary of the results that were found. The first hypothesis showed that events do have an influence on television ratings. An anomaly detection was performed and the detected outliers were associated to events that were streamed on the television channel that day. Each anomaly could be associated to an event. However, on the channel ProSieben the anomalies were not linked to an event but rather a recurring TV show named “Germany’s Next Topmodel”, where the pattern of the time series reminds that of a trend rather than a time series with outliers. Out of 25 associated events on ARD, one was linked to a political event, the Royal Wedding of Meghan Markle and Prince Harry on the 19th of May 2018. 24 events fall in the category “Sport”. In the sample that was analysed, sport events influence television ratings more than political events. Out of 18 events on ZDF, one falls in the category of music events, which was the Eurovision Song Contest on the 12th of May 2018. 17 events are in the category “Sport”. Therefore it can be said that sport events influence television ratings more than music events in the sample data that was analysed.

It could be seen that there are local differences in the events that were detected as the most anomalous days in the dataset. On SRF 1 the anomaly detected was related to the Swiss public holiday “Sechseläuten” and its televised parade on that day. On SRF 2 the anomalies account for six sport events. Five out of the six events were sport events that Swiss national teams took part in.

The fifth hypothesis tested gave two main takeaway points. The data that was analysed showed that if there is an event streamed on one channel, the other channel has low viewing figures. However, no evidence was found in the data whether viewers are watching one channel and decide to switch to another channel for the particular event that was popular that day.

The result of the last hypothesis is that in the data that has been worked with public holidays did not influence the viewing behaviour as much as the content that was being streamed. The television ratings were low during the day but at the starting time of the event stream the ratings increased which shows that the event was the trigger for a rise in viewing figures and not the public holiday per se.

4 Future work and limitations

There are certain limitations to this research that makes the results that were retrieved applicable to the available dataset only. As the data was measured on the OTT streaming platform Zattoo it can only represent the sample that was analysed. If data was made available from the national or private television channels results could be more generalized for the whole country of Germany or Switzerland. However, some tendencies can be seen that can represent the total population.

Furthermore, the events that were associated to the anomalies have been assigned manually. It was planned to use an event calendar to link anomalies to events but only a small percentage of the events that were listed matched the anomalies that were found in the dataset. For future research it would be very complicated to continue assigning the events manually as it can be time-consuming so a mechanism to combine an event calendar with anomaly detection is an idea for future work.

Moreover, the idea was to find a prediction model that can include anomalies into forecasts. A multiple regression is a model that could include anomalies that are known of as future events into forecasts but creating this forecasting model would go over the extent of this research.

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Appendices

Appendix 1: The Anomaly Detection Process in SPSS

The anomaly detection in SPSS is done with the command “Identify Unusual Cases” which is found under “Data”. “Sessions” is chosen as the analysis variable and “slice_start” as the case identifier in order to match the session to the appropriate date and time.

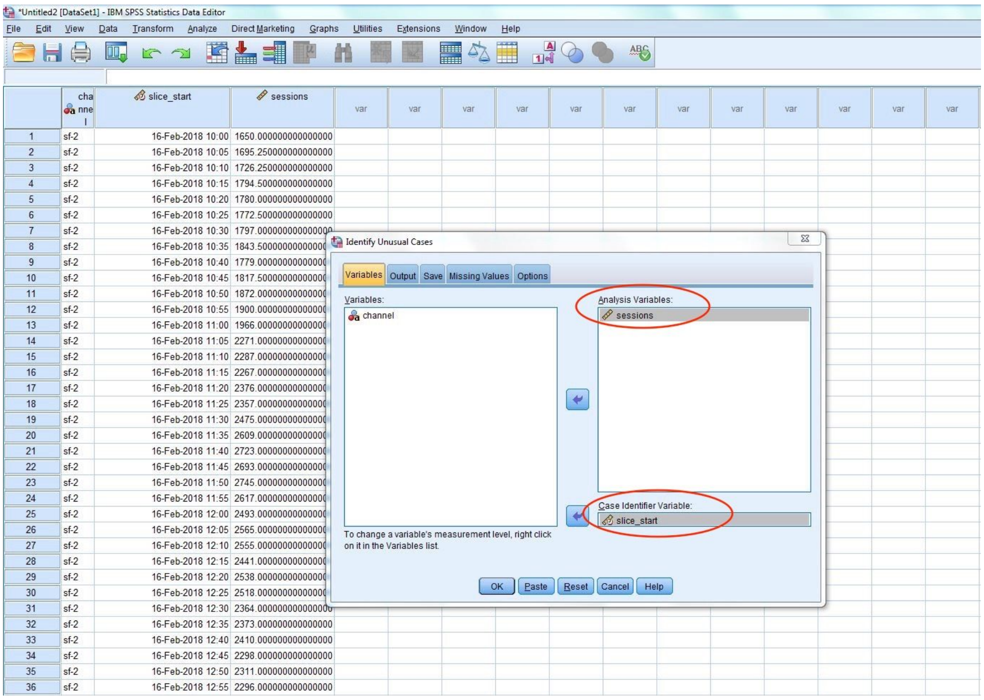


Figure 24: An example of “Identify Unusual Cases” in SPSS

Once the anomaly detection has been performed, the table with the peer groups was chosen from the output and imported as a separate file into SPSS as seen below.

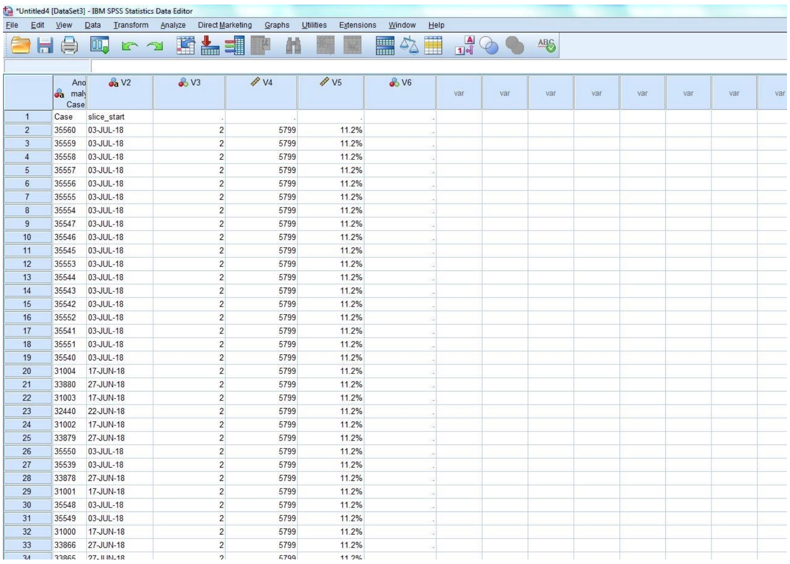


Figure 25: The Imported Table of the Peer Groups in SPSS

Now all the outlying observations are in one table sorted by peer group. As the interest was only in the second peer group with it containing the most outlying observations, through the command “Select Cases” under “Data” it was chosen to only show the second peer group by creating the condition that V3 = 2. Note that in this case it was intended to delete the unselected cases.

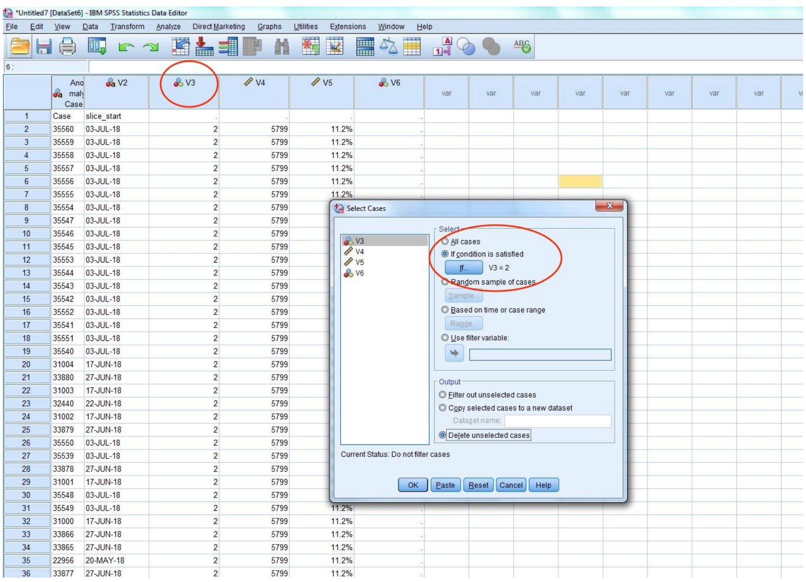


Figure 26: An Example of the Command “Select Cases”

Now only the results from the second peer group are visible. The next step is to eliminate dates that are listed multiple times. This was done with the command "Identify Duplicate Cases" and the first diagnosed case was the one to keep marked as Primary First.

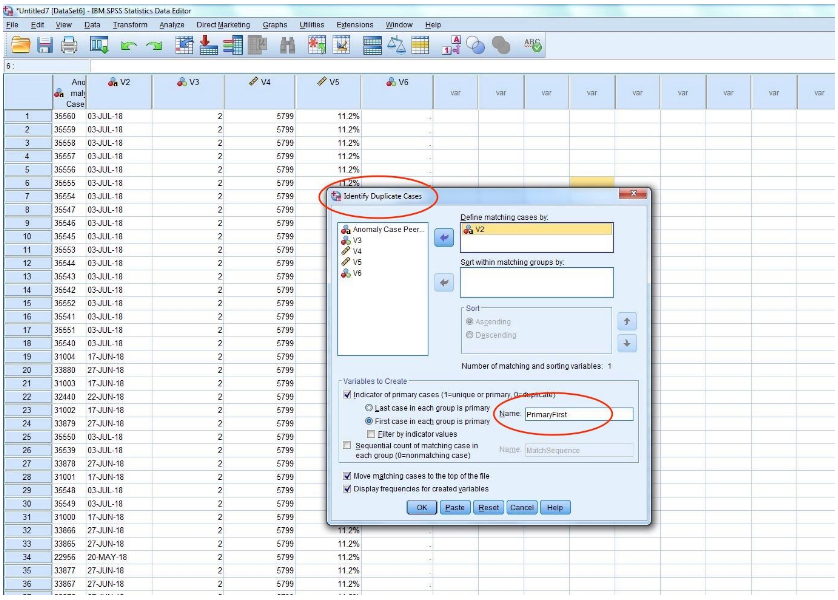


Figure 27: An Example of the Command "Identify Duplicate Cases"

Now the duplicate cases have been pointed out but not removed yet. This is done using "Select Cases" another time. Only cases are being chosen that fulfill the condition that they are labeled Primary First, the unselected cases are deleted again.

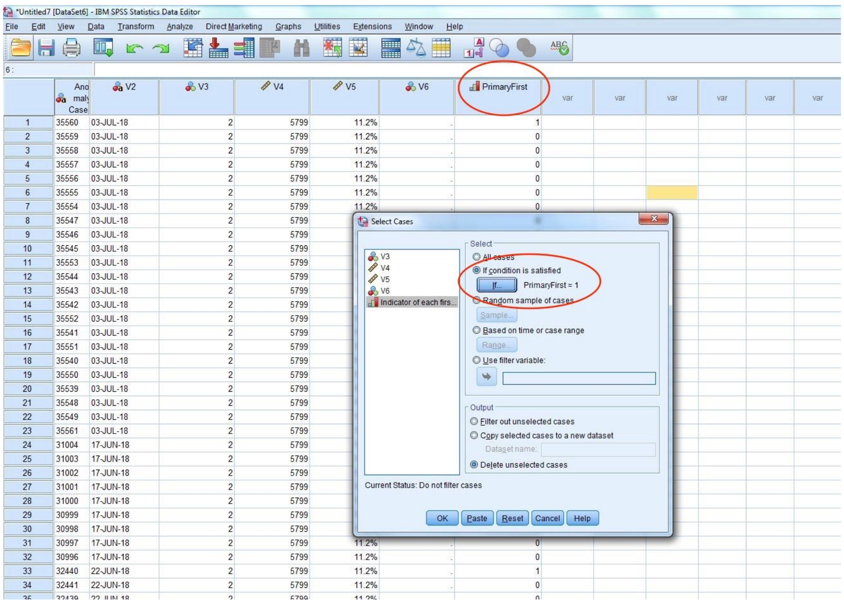
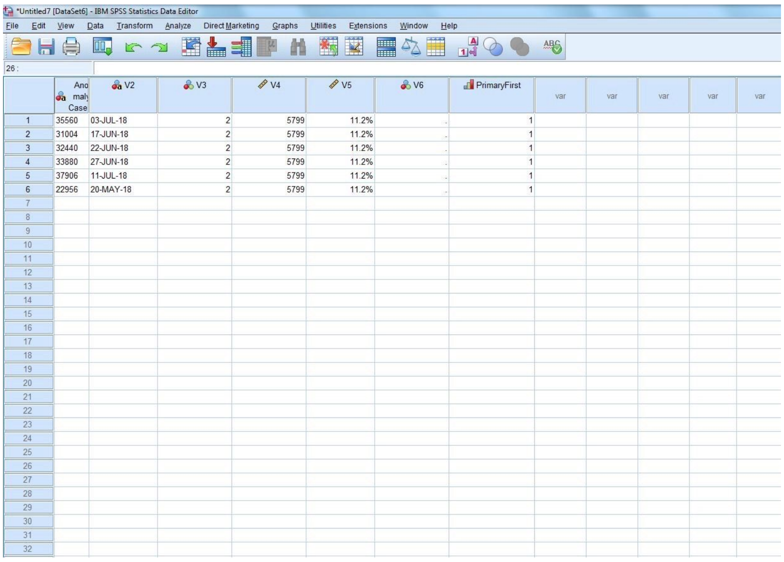


Figure 28: Selecting Duplicate Cases

The result is seen on the below. It is the final table including only the most anomalous cases of the dataset and no duplicate dates.



*Untitled7 [DataSet6] - IBM SPSS Statistics Data Editor

	AnomalyCase	V2	V3	V4	V5	V6	PrimaryFirst	var	var	var	var	var
1	35560	03-JUL-18	2	5799	11.2%	.	1					
2	31004	17-JUN-18	2	5799	11.2%	.	1					
3	32440	22-JUN-18	2	5799	11.2%	.	1					
4	33880	27-JUN-18	2	5799	11.2%	.	1					
5	37906	11-JUL-18	2	5799	11.2%	.	1					
6	22956	20-MAY-18	2	5799	11.2%	.	1					

Figure 29: The Result of the Anomaly Detection After Removal of Duplicates

Appendix 2: ZDF Event Calendar

20-Feb-18	UEFA Champions League Game Bayern Munich : Beşiktaş	https://www.uefa.com/uefachampionsleague/news/newsid=2525734.html
25-Feb-18	IIHF Ice Hockey Final Germany : Russia	https://olympia.zdf.de/aktuelles/2018-tagesvorschau-100/
06-Mar-18	UEFA Champions League Game Paris Saint Germain : Real Madrid	https://www.presseportal.de/pm/7840/3881498
14-Mar-18	UEFA Champions League Game Beşiktaş : Bayern Munich	https://www.uefa.com/uefachampionsleague/news/newsid=2525734.html
27-Mar-18	FIFA Football World Cup Test Game Germany : Brazil	https://presseportal.zdf.de/pressemitteilung/mitteilung/zdf-uebertraegt-wm-test-deutschland-brasilien-live-aus-berlin/
03-Apr-18	UEFA Champions League Quarter Final Sevilla : Bayern Munich	https://www.uefa.com/uefachampionsleague/news/newsid=2525734.html
11-Apr-18	UEFA Champions League Quarter Final Bayern Munich : Sevilla	https://www.uefa.com/uefachampionsleague/news/newsid=2525734.html
01-May-18	UEFA Champions League Semi Final Bayern Munich : Real Madrid	https://www.presseportal.de/pm/7840/3916044
19-May-18	The Royal Wedding Live	https://www.sendungverpasst.de/content/zdf-royal-1
26-May-18	UEFA Champions League Final	https://presseportal.zdf.de/pressemitteilung/mitteilung/finale-in-der-champions-league-real-madrid-fc-liverpool-live-im-zdf/select_category/17/
02-Jun-18	FIFA Football World Cup Test Game Germany : Austria	https://www.zdf.de/sport/zdf-sportextra/fussball-laenderspiel---oesterreich---deutschland-100.html

16-Jun-18	FIFA Football World Cup Second Game Day	https://www.zdf.de/sport/fifa-wm-2018/vorschau-16-juni-100.html
17-Jun-18	FIFA Football World Cup Game Germany : Mexico	https://www.zdf.de/sport/zdf-sportextra/wm-spiele-verteilung-100.html
19-Jun-18	FIFA Football World Cup Game Russia : Egypt	https://www.shz.de/sport/fussball/fussball-wm/Russland-Aegypten-live-im-TV-und-Live-Stream-WM-2018-live-id20174397.html
21-Jun-18	FIFA Football World Cup Game Day	https://www.shz.de/sport/fussball/fussball-wm/Russland-Aegypten-live-im-TV-und-Live-Stream-WM-2018-live-id20174397.html
22-Jun-18	FIFA Football World Cup Game Day	https://www.shz.de/sport/fussball/fussball-wm/Russland-Aegypten-live-im-TV-und-Live-Stream-WM-2018-live-id20174397.html
25-Jun-18	FIFA Football World Cup Game Iran : Portugal	https://presseportal.zdf.de/pressemitteilung/mitteilung/aufteilung-wm-parallelspieltag-fuer-zdf-und-zdfinfo-festgelegt/seite/26/
27-Jun-18	FIFA Football World Cup Game Germany : South Korea	https://www.pokalzeit.de/fussball-wm-2018-tv-programm-uebertragung-sender/
01-Jul-18	FIFA Football World Cup Round of 16; Spain : Russia / Croatia :Denmark	https://www.morgenpost.de/sport/fussball-wm/article214720603/WM-Achtelfinale-im-Fernsehen-So-uebertragen-ARD-und-ZDF.html
02-Jul-18	FIFA Football World Cup Round of 16; Brazil : Mexico / Belgium : Japan	https://www.morgenpost.de/sport/fussball-wm/article214720603/WM-Achtelfinale-im-Fernsehen-So-uebertragen-ARD-und-ZDF.html
06-Jul-18	FIFA Football World Cup Quarter Finals	https://www.pokalzeit.de/fussball-wm-2018-tv-programm-uebertragung-sender/
11-Jul-18	FIFA Football World Cup Semi Finals	https://www.pokalzeit.de/fussball-wm-2018-tv-programm-uebertragung-sender/
15-Jul-18	FIFA Football World Cup Finals	https://www.pokalzeit.de/fussball-wm-2018-tv-programm-uebertragung-sender/
24-Aug-18	German Premier League Opening Bayern Munich : Hoffenheim	https://www.zdf.de/sport/spielplan-106.html
06-Sep-18	Nations League Football Game Germany : France	http://news-dg.de/deutschland-frankreich-fussball-6-september-2018-live-im-zdf/

Table 13: List of Events That Matched Anomalies for the Channel ZDF with Source Indication

Appendix 3: ARD Event Calendar

23-Mar-18	FIFA Football World Cup Test Game Germany : Spain	https://rp-online.de/sport/fussball/nationale laenderspiel-2018-deutschland-gegen-spani -in-duesseldorf-ausverkauft_aid-16446321
12-May-18	Eurovision Song Contest Final	https://www.tz.de/tv/esc-2018-eurovision-song-contest-finale-heute-live-tv-live-stream-uebersicht-sendungen-zr-9848974.html
19-May-18	DFB Cup Final Bayern Munich : Eintracht Frankfurt	https://www.daserste.de/sport/sportschau/dfb-pokal-finale-2018-berlin-100.html

08-Jun-18	FIFA Football World Cup Test Game Germany : Saudi Arabia	https://www.eurosport.de/fussball/fifa-wm/2018/deutschland-saudi-arabien-heute-live-im-tv-und-im-livestream-und-liveticker_sto6785138/story.shtml
14-Jun-18	FIFA Football World Cup Opening Game Russia : Saudi Arabia	https://www.daserste.de/specials/ueber-uns/fifa-wm-2018-eroeffnungsspiel-live-im-ersten100.html
15-Jun-18	FIFA Football World Cup Game Day (Portugal : Spain)	https://www.goal.com/de/meldungen/wm-2018-tv-live-plan-ard-zdf-sky-fernsehen-weltmeisterschaft/haxmnfj99hcs138k404hn07bh
18-Jun-18	FIFA Football World Cup Game Day	https://www.goal.com/de/meldungen/wm-2018-tv-live-plan-ard-zdf-sky-fernsehen-weltmeisterschaft/haxmnfj99hcs138k404hn07bh
20-Jun-18	FIFA Football World Cup Game Day	https://www.goal.com/de/meldungen/wm-2018-tv-live-plan-ard-zdf-sky-fernsehen-weltmeisterschaft/haxmnfj99hcs138k404hn07bh
23-Jun-18	FIFA Football World Cup Game Day Germany : Sweden	https://www.goal.com/de/meldungen/wm-2018-tv-live-plan-ard-zdf-sky-fernsehen-weltmeisterschaft/haxmnfj99hcs138k404hn07bh
24-Jun-18	FIFA Football World Cup Game Day	https://www.goal.com/de/meldungen/wm-2018-tv-live-plan-ard-zdf-sky-fernsehen-weltmeisterschaft/haxmnfj99hcs138k404hn07bh
26-Jun-18	FIFA Football World Cup Game Day	https://www.goal.com/de/meldungen/wm-2018-tv-live-plan-ard-zdf-sky-fernsehen-weltmeisterschaft/haxmnfj99hcs138k404hn07bh
28-Jun-18	FIFA Football World Cup Game Day	https://www.goal.com/de/meldungen/wm-2018-tv-live-plan-ard-zdf-sky-fernsehen-weltmeisterschaft/haxmnfj99hcs138k404hn07bh
30-Jun-18	FIFA Football World Cup Round of 16	https://www.daserste.de/specials/ueber-uns/wm-achtelfinals-frankreich-argentinien-portugal-england-live-im-ersten100.html
03-Jul-18	FIFA Football World Cup Round of 16	https://www.daserste.de/specials/ueber-uns/wm-achtelfinals-frankreich-argentinien-portugal-england-live-im-ersten100.html
07-Jul-18	FIFA Football World Cup Quarter Final	https://www.daserste.de/specials/ueber-uns/viertelfinals-der-fifa-wm-2018-im-ersten-100.html
10-Jul-18	FIFA Football World Cup Semi Final Game France : Belgium	http://www.spiegel.de/sport/fussball/wm-2018-tv-spielplan-wo-sie-das-achtelfinale-live-sehen-koennen-a-1215718.html
14-Jul-18	FIFA Football World Cup 3rd Place Belgium : England	http://www.spiegel.de/sport/fussball/wm-2018-tv-spielplan-wo-sie-das-achtelfinale-live-sehen-koennen-a-1215718.html
20-Aug-18	DFB Cup Game Greuther Fürth : Borussia Dortmund	https://www.presseportal.de/pm/6694/4036497

Table 14: List of Events That Matched Anomalies for the Channel ARD with Source Indication

Appendix 4: SRF 2 Event Calendar

20-May-18	IIHF Ice Hockey World Cup Final Sweden : Switzerland	https://www.srf.ch/sport/eishockey/wm/die-schweiz-vor-dem-wm-final-das-puzzle-fuer-den-wm-titel
17-Jun-18	FIFA Football World Cup Game Switzerland : Brazil	https://www.srf.ch/sport/fussball/fifa-wm-2018/in-eigener-sache-neun-von-zehn-fussballfans-schauten-die-wm-auf-srf-zwei
22-Jun-18	FIFA Football World Cup Game Switzerland : Serbia	https://www.srf.ch/sport/fussball/fifa-wm-2018/schweizer-wm-fahrplan-der-countdown-laeuft
27-Jun-18	FIFA Football World Cup Game Switzerland : Costa Rica	https://www.srf.ch/sport/fussball/fifa-wm-2018/schweizer-wm-fahrplan-der-countdown-laeuft
03-Jul-18	FIFA Football World Cup Round of 16 Switzerland : Sweden	https://www.srf.ch/sport/mehr-sport/in-eigener-sache/in-eigener-sache-bis-zu-1-9-mio-sahen-schweizer-achtelfinaleinzug-auf-srf-zwei
11-Jul-18	FIFA Football World Cup Semifinal Croatia : England	https://www.srf.ch/sport/fussball/fifa-wm-2018/2-1-sieg-in-der-verlaengerung-mandzukic-schiesst-kroatien-in-den-final

Table 15: List of Events That Matched Anomalies for the Channel SRF 2 with Source Indication