AN EVALUATION OF THE IMPACT OF TERRORISM ON TOURISM USING TRIPADVISOR RESTAURANT REVIEWS

August 31, 2018

1 Introduction

International tourism is a major contributor to economic growth and development. In 2017 the number of tourist arrivals worldwide reached a new record with 1.3 billion arrivals. Furthermore, the exports generated through tourism increased to $1.6 trillion, making tourism the world's third-largest export sector (UNWTO, 2018). For individual countries, tourism can often play an even more prominent role. In popular travel destinations tourism accounts for significant shares of GDP and employment (WTTC, 2018). However, the dependency on the tourism sector is especially dangerous, regarding the impact of external shocks on the sector. According to Baker (2014), an decline of the tourism industry is a major concern for many countries, as it can lead to unemployment, homelessness, or an overall increase in poverty.

While the nature of external shocks on the tourism industry is manifold, research has identified events related to environmental disasters, spread of diseases, political unrest or terrorism/security threats (Zillman, 2015)[1]. The last type of shock has grown in importance in recent years. As terror attacks occurred in popular travel destinations such as France, Belgium, Turkey, Egypt and Tunisia the tourism industry within these countries was negatively affected (WTTC, 2017).

Yet, anecdotal evidence cannot be taken as proof that the threat of terrorism is increasing. Other scholars such as Smith and Zeigler (2017) argue that the world has become a less dangerous place. Yet, to explain the decrease in tourism in destinations hit by terror attacks the relevance lays not with the actual security threat but the perceived threat. Baker (2014) argues that being safe is a necessary requirement for any tourisms. Fulfilling this requirement can lead to tourists substituting their original visit destinations for one they perceive as safer (WTTC, 2017). Especially the media, plays a role in reinforcing perceptions. For example, in 2016, after the terror attacks in Paris and Brussels the New York Times published an article with the headline "Is Europe Safe for Travelers", further contributing to the "fearful misconception of overseas" (Spinks, 2017).

Statistics that estimate the impact of a terror event on tourism usually rely on traditional data sources such as household or hotel surveys, flight data or visa applications (Eurostat 2017). In our research we propose an alternative data source. Using the number and date of reviews from the popular review website TripAdvisor, we try to investigate if there is a decrease in restaurant reviews after a destination became the target of a terror attack. Such a decrease would potentially indicate a decrease in the total number of tourist visits and would therefore be in line with conclusions drawn from traditional data sources. In our data, we indeed find such a negative effect. Yet, as we explain in the discussion section our findings cannot fully be interpreted as supporting the causal link between terrorism and tourism.

As we wanted to use the TripAdvisor data for an additional analysis, we are using the content of the reviews to train a machine learning algorithm to predict the origin of that review. This could be an initial step in research that analyses how different text patterns about the same topic develop depending on external factors such as location. The algorithm that we train has relatively strong performance of 74% accuracy.

The project is structured in the following way; In Section 2 we will describe the method used. Section 3 is a descriptive analysis of the traditional data sources. Section 4 describes our data, while Section 5 represents our analysis part. In Section 6 we will discuss the limitations with the data and method, as well as further work. Section 8 gives the conclusion.

[1]This article and other similar ones cite an unknown WTTC study.

2 Web Scraping

In the following section we introduce the method that we use to analyze the effect of terrorism on tourism. The method used for the Machine Learning (ML) based text analysis of the reviews will be described in Section 5.2. Here it will be presented in direct connection with the results. We believe that this makes for a better understanding for the reader. Possible limitations of our method and its implications will be evaluated in our discussion. The code we are referring to in this section can found in the attached Jupyter notebook and in a GitHub repository[2].

In this paper, we retrieve information from TripAdvisor to analyze the effect of terrorist attacks on the number of restaurant reviews. In order to retrieve this information we used a technique called Web Scraping, which is used to extract information from websites automatically. Usually, the information is found unstructured in a HTML or XHTML format and the task of the scraper is to transform this information into a structured file that can be analyzed later.

The scraper that we built collects information such as the name of the restaurant, the address, the number of reviews and the content of each review. Yet, in order to scrape such information we first had to collect the necessary URLs of the restaurant. We did this by building a function that takes a TripAdvisor overview page as an input. A city's overview page, displays approx. 30 restaurants out of the list of all restaurants for a certain city, sorted after a criteria. For example the URL "https://www.tripadvisor.com/Restaurants-g187147-Paris_Ile_de_France.html" displays the 30 best rated restaurants in Paris. Using the pattern of the overview page's URL our function creates a list of all overview pages for a selected city. In a second step we randomly select 40 of these overview URLs and scrape them for links to all restaurants with more than 50 reviews. These links are saved in a set. Both the randomization and the limitation to restaurants with more than 50 reviews were done due to various limitations, such as computational power. The implications of these limitations will be discussed further in the discussion.

To get from the set of restaurant links to a DataFrame with the information that we plan to retrieve we built a second function ("information"). This function has a restaurant URL as input and a DataFrame with all the information as output. As each restaurant has several pages of reviews, in some cases reaching 500, our scraper needed to iterate through all pages. To solve this problem, we created a condition (while loop) which caused our algorithm to press "next page". This process was repeated until there were no more pages to access. Through this correction of the algorithm, we were able to collect all the information for each single restaurant in the set, containing the restaurant URLs. The information for all restaurants within a city were then joined into a single DataFrame. The above described process was repeated five times for each of the cites we were interested in: Paris, London, Brussels, Barcelona and Rome.

We encountered two major challenges during the web scraping of TripAdvisor, which we solved in the following ways. The first challenge we encounter was that the scraper collected the content of the reviews that were written in the language of domain suffix. Hence, when using the ".fr" domain of TripAdvisor were only able to collect the content of French reviews. Yet, this problem was of less pressing nature as the scraper was still able to collect the date information of all reviews even if these were written in a language that was different from the domain suffix. However, if we would have wanted to analyze the content of all reviews we would have had to run the scraping code several times, changing the domain suffix in the beginning according to the language we wanted to analyze. Yet, as the resources to do text analysis in another language than English are limited, we decided only to look at the content of reviews written in English, when analyzing the content of the reviews.

Secondly, we encountered significant challenges related to computational power and computational time. TripAdvisor is a webpage with a lot of data and it was impossible given our initial tools and limited time, to scrape all the information of each restaurant in each of the five cities. We therefore, decided to limit our sample for each city to the restaurants on the 40 randomly selected overview that had more than 50 reviews. The random sample accounted to approx. 5% of all restaurants in a city. At first, this may seem as a low number, yet each sample included approx. 100.000 reviews. As we analyzed 5 different cities and therefore created 5 different samples we have gathered around 500,000 reviews. We were only able to achieve this through running our scraper in Google Cloud Compute Engine. For this, we created a virtual machine instance with location "asia-southeast1" (Singapore) with 24 vCPU and 40 GB of memory[3]. This allowed us to significantly increase the speed at which we acquired the data.

3 Descriptive analysis

The aim of this part of the analysis is to present findings from research on the effect of terrorism on tourism, which use traditional data sources. Research identifies three different effects: 1) An initial decrease in tourism, 2) A spill over effect to other cities and 3) The recovery of the number of tourists.

Figure 1 shows the week-on-week change in global flight bookings to Brussels after the terror attack in March 2016. The figure shows a large decrease in the week-on-week change of flight bookings to Brussels right after the 22th of March. The number of flight bookings to Brussels decreased by 55 % compared to the week before on the day the terror attack occurred. This trend remained the same for the week following the attack, with bookings being approx. 50 % lower than the week before. The decrease in flight bookings clearly shows a strong initial negative effect of a terror attack on tourism, as the airline industry is highly associated with the tourism industry. The data indicates that people avoid a travel destination that has very recently become the target of a terror attack.

Yet, terror attacks do not only to affect the tourism in the city where the attack occurred, as other travel destinations are also affected. Figure 2 shows week-on-week change in global flight bookings to different European cities after the terror attack in Brussels on March 22nd 2016. It can be seen that in London, Paris, Amsterdam and Rome flight bookings decrease significantly compared to the week before the attack, indicating a spill over effect.

For travel destinations that have been target for terror attacks it is a high priority to make sure that their visitors do not feel insecure. Rebuilding this perceived level of security takes time. According to Schreuer (2017), tourism in Paris took a year to recover from the terror attack in 2015, as the number of tourists in the end of 2016 matched the number from 2014 in the same period. In the UK the number of tourists recovered 13 months after the terror attacks in London and Manchester (Fuller, 2017).

In the following analysis, we want to investigate if these three effects can also be found when using reviews from TripAdvisor as an indicator for tourist visits.

[3]VM instance run Debian (Linux). We installed anaconda in the VM and then opened Jupyter notebook with a port created specifically for it.

Figure 1: The initial decrease in tourism

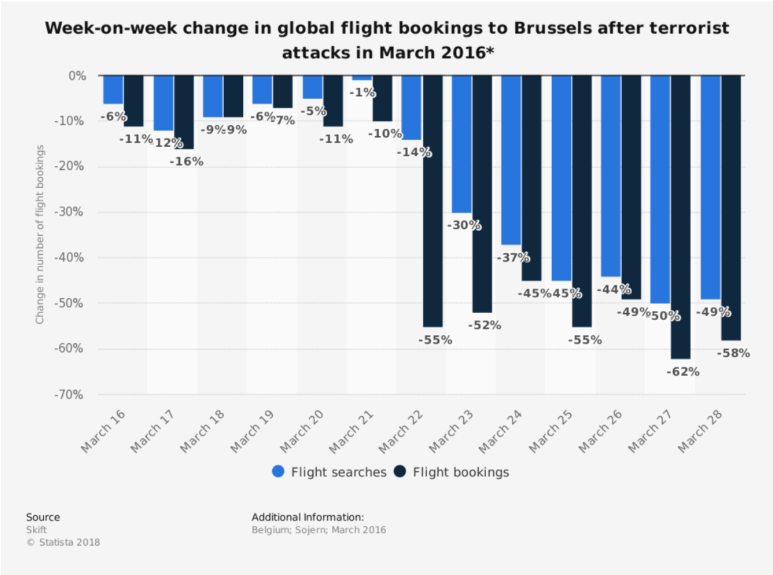
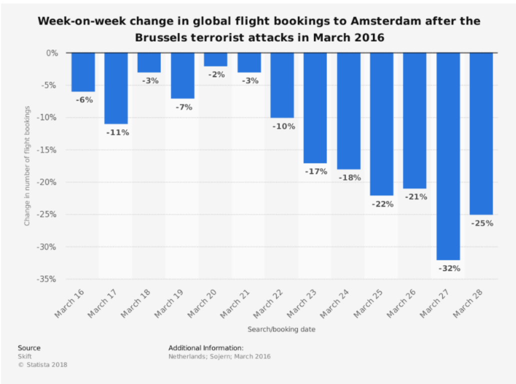
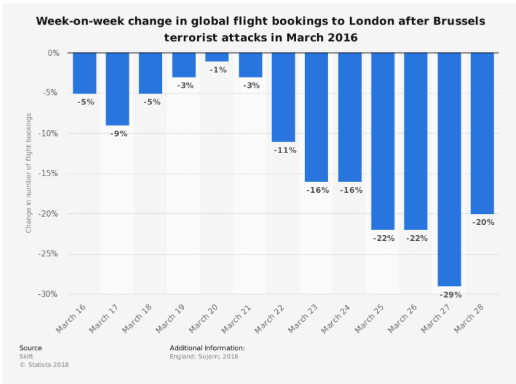


Figure 2: The spill over effect to other cities

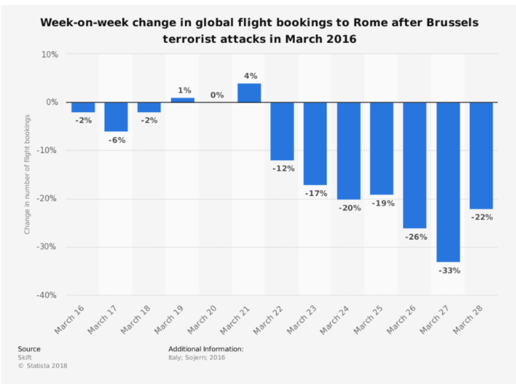
(a) Amsterdam



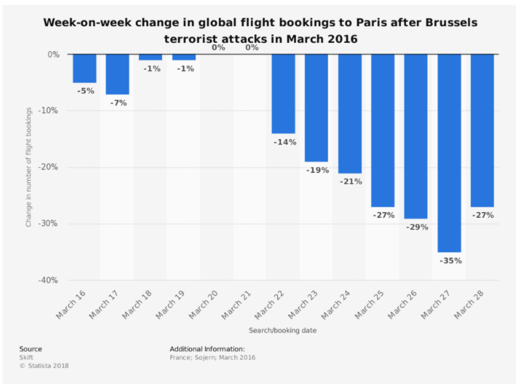
(b) London



(c) Rome



(d) Paris



4 Data

The following section presents the data that we have collected and are using in the analysis part. First, we briefly describe the terror attacks we will consider, followed by summary statistics of our dataset.

The number of terror attacks in the world has increased rapidly since the '9/11' attack in the US back in 2001 (Roser et al., 2018). In 2017, the UK experienced the most terror attacks in Europe according to Dearden (2018). While the deadliest attack in western Europe took place in Paris back in 2015 (Hanrahan & Wang, 2017). Our motivation to use terror attacks as an external shock to tourism is the relatively easy distinction between before and after a terror attack. Other types of external shock such as political instability or disease outbreak are more difficult to precisely date.

We will consider four different cities which were all targets for some of the largest terror attacks in the recent years in Europe, namely Paris, Brussels, London and Barcelona. At the same time, these cities are very popular travel destinations. According to O'Hara (2017), Paris and London were among the top tourist destinations among international travelers in 2017. Table 1 presents an overview of the terror attacks that occurred in the four cities: The table shows that Paris and Brussels experienced the largest terror attacks of the four cities with 550 and 305 casualties, respectively. In comparison, the terror attacks in London and Barcelona caused 59 and 119 causalities, respectively.

Table 1: Terror attacks in Europe

	Paris, France	Brussels, Belgium	London, UK		Barcelona, Spain
Date	13 Nov 2015	22 Mar 2016	22 Mar 2017	3 June 2017	17 Aug 2017
Number of killed	137	35	6	11	15
Number of injured	413	270	50	48	104

Source: https://www.start.umd.edu/gtd/

The reason we are considering these cities within Europe is twofold. Firstly, they are very popular travel destinations and secondly, Europe as a whole is seen to be more safe compared other parts of the world. This leads us to believe that a terror attack would lead to a more visible shock to tourism. Furthermore, the stronger media coverage of terror attacks in the West might further contribute to a stronger impact on the perceived safety, which in turn influences travelers for whom safety is a high priority.

We are using Rome as a control city to investigate the spill over effect. This way we can observe if the number of restaurant reviews in Rome is impacted by terror attacks in other European cities.

The analysis throughout the paper relies solely on the data scraped from TripAdvisor. We are using TripAdvisor as it's large number of reviews makes it one of the largest travel websites worldwide. TripAdvisor has more than 661 million reviews, 456 million unique monthly visitors on average and has information on 7.7 million accommodations, airlines, experiences and restaurants[4]. In particular, we focus specifically on reviews of restaurants. Restaurants provide an alternative source of data to hotels and flights, which is not commonly used when measuring tourist activity.

Table 2 presents the summary statistics of our sample. The dataset spans from week 43, 2007 to week 35, 2018. The total number of reviews, hence observations, range from 170,265 (Rome) to 65,763 (Brussels). The total number of reviews is 551,908 and the average number of reviews per restaurant is approx. 253.75 reviews.

[4] https://tripadvisor.mediaroom.com/US-about-us

The most active city is Rome with a weekly activity of 306 reviews on average, whereas the least active city is Brussels with 116 weekly reviews on average. Furthermore, there seems to be significant fluctuations as seen by an average standard deviation of 185.39 reviews. This might be a result of the volatility associated with effects of different seasons on the number of reviews.

Table 2: Summary statistics

	Paris, France	Brussels, Belgium	London, UK	Barcelona, Spain	Rome, Italy
Total number of reviews	102,041	65,763	91,013	122,826	170,265
Total number of restaurants	494	377	397	420	487
Average number of reviews per restaurant	206.56	174.44	229.25	292.44	305.68
Mean	179.65	115.78	164.88	218.55	305.68
Max	573	401	551	876	921
Min	1	1	1	1	1
Std.	173.95	104.57	154.89	225.18	268.38

Source: TripAdvisor.com

Note: Data has been scraped in the period: 25th of August – 29th of August, 2018.

5 Analysis

In this section, the aim is to provide an analysis from the data gathered using the web scraping method. The analysis is divided into two parts. In the first part, we make a graphical analysis of the impact of terror attacks on the weekly number of reviews for each city. The second part focuses on our machine learning algorithm that analyses the content of the reviews.

5.1 Graphical analysis

In the graphical analysis, we are analysing the number of reviews per week over a timespan of 8 years, from the first week of 2011 to the 34th week of 2018. We hereby make two changes to our original dataset. Firstly, we remove all reviews before 2011, as the number of reviews on TripAdvisor at this point was still very low. This can be seen in figure 10 in the appendix. Secondly, we drop the data of week 35, as this week was not yet completed when we conducted the web scraping. We gather the number of reviews per day, and collect them into week, as it removed the day-to-day fluctuation (naturally there are more reviews on a Saturday than on a Monday). This change therefore allows for a clearer picture of the trends. The number of reviews per week are calculated for all five cities.

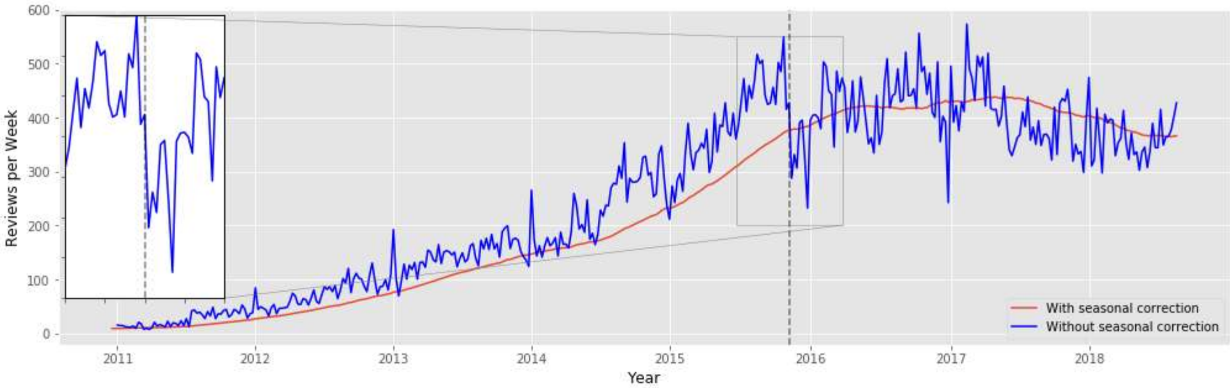
The x-axis of the graphs is a timeline, with annual markers. The y-axis is the number of reviews per week. The graphs include two curves. The blue curve represents the absolute number of reviews per week, while the red curve is corrected for seasonality. We correct for the seasons by taking the rolling mean on an annual basis. We do this, as we assume that the number of restaurant reviews on TripAdvisor are affected by the seasons. For example, there probably will be more reviews in the summer season compared to other seasons.

Our main focus when analysing the graphs will be to look for the three effects we identified in the literature: 1) An initial decrease in tourism after a terror attack, 2) A spill over effect to other cities and 3) The recovery of the number of tourists to before the attack. In the graphical analysis of the individual cities, we will focus on the immediate effect of the terror attack and the recovery of tourism. The spill over effect will be analysed by looking at the number of reviews per week in Rome, which has not been a target for terror attacks. We are using Rome as a control city to investigate whether the terror attacks in the other European cities had a spill over effect on the tourism in Rome.

Figure 3 shows the development in the weekly number of reviews in Paris from TripAdvisor. We consider the number of reviews from week 1 in 2011 to week 34 in 2018. The overall trend is increasing, which might also have to do with the increasing popularity of TripAdvisor. In 2016 the trend is more stable and starting from mid 2017 we see a decrease in weekly reviews.

The terror attack in Paris took place the 13th of November 2015, which is marked by the vertical line in the figure. We magnify this period in the left side of the graph. There is a visible immediate effect of the terror attack on the weekly number of restaurant reviews in Paris. In week number 46, the week of the terror attack, the number of reviews were 427. In the week after the attack the number was reduced to 287 reviews per week. This represents a 32,7 % decrease in the weekly number of reviews.

Figure 3: The number of restaurant reviews per week in Paris, 2011-2018



Source: TripAdvisor.com

When analysing the period after the terror attack, the level of the number of reviews is lower than it was in the period right before the terror attack. The number of reviews peer week in the period before the attack was around 450-500 reviews. The level is returning to the initial level approx. 2.5 months after the attack. Exactly a year after the attack the number of weekly reviews is 482, which indicates that the tourism in Paris is fully recovered after a year.

The red curve corrects for seasonal effects on the number of weekly reviews, that is clearly present. We can see that the trend of the curve is increasing in the period before the terror attack, while the increase is less strong after the attack. Overall, we can see that the number of weekly reviews is strongly affected by the seasons, for example in most years there is a strong increase around the new years celebration. The rolling mean method corrects for this.

The numbers of restaurant reviews per week for Barcelona is presented in figure 4. The overall trend is similar to that of Paris. We first see an overall increase and then a decrease at the end of the timespan. Again this might be related to developments in the popularity of TripAdvisor. The terror attack in Barcelona happened the 17th of August 2017. The blue curve shows a significant decrease in the number of reviews in the week after the attack, which continues for a long period after the attack. Both curves indicate that the general trend in this period is decreasing. However, the sharp decrease in the blue curve might point towards an immediate effect of the terror attack on the number of reviews. This is also supported by literature and other data sources. For example, an article from Bremner (2017) estimates the short term impact of the Barcelona terror attack as being a loss of 200,000 tourist.

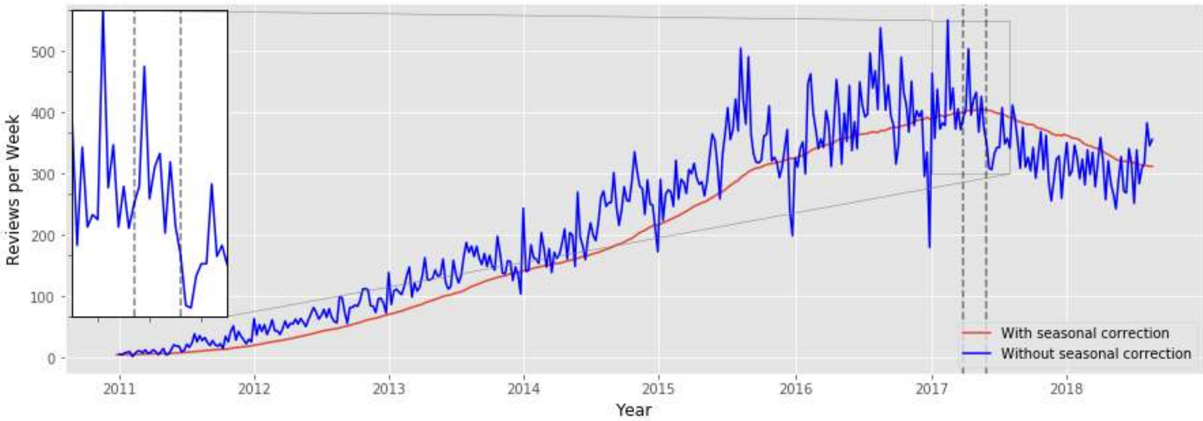
Figure 4: The number of restaurant reviews per week in Barcelona, 2011-2018

Source: TripAdvisor.com

According to the data the number of weekly reviews remains lower in the period after the attack than before. This might indicate that tourism in Barcelona has not yet recovered from the attack. Yet, when looking at the very end of the curve without seasonal correction, there seems to be an increase in the number of reviews per week. As Barcelona is a popular travel destination in the summer we see a strong seasonal effect. We therefore cannot be sure whether the increase in the blue curve at the end of the timespan is due to the recovery or just seasonality, as the same increase is not present in the red curve.

In 2017, two terror attacks happened within 3 months in London. The first happened the 22nd of March and the second on the 3rd of June. Both are included in figure 5 through the vertical lines. We find no immediate effect of the first terror attack on the number of reviews per week. However, we see a clear decrease in the number of reviews per week after the second terror attack occurred. This decrease is also present in the curve with seasonal correction. The decrease after the second terror attack might be an accumulated reaction to the two attacks, as the timespan between the attacks was small. The increase of the blue curve approx. a year after the attacks might indicate a recovery effect in London. Yet, as our dataset ends at this point no final conclusions can be drawn.

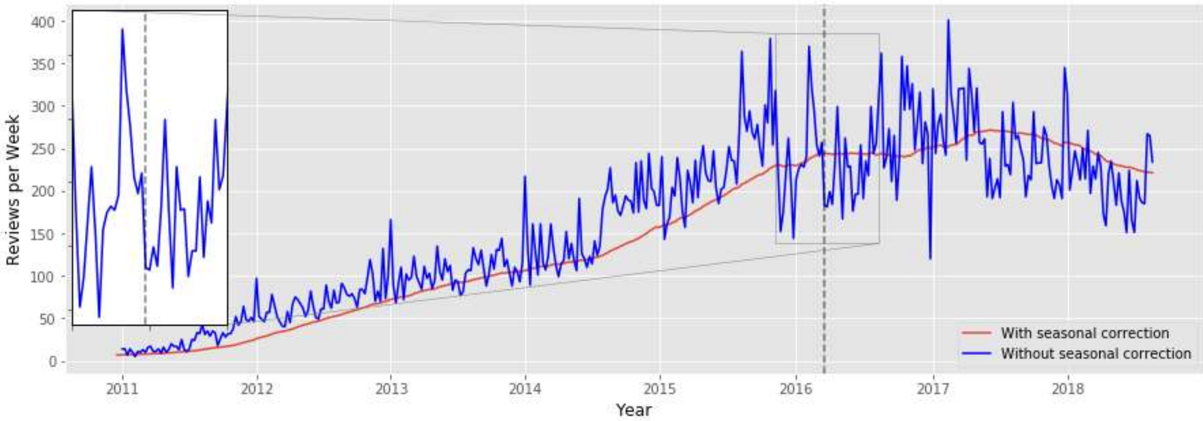
Figure 5: The number of restaurant reviews per week in London, 2011-2018



Source: TripAdvisor.com

The terror attack in Brussels took place the 22nd of March 2016. Figure 6 shows the weekly number of restaurants reviews for the period 2011-2018. The impact of the terror attack on the number of reviews is less clear in Brussels than in the other cities. While we see a decrease for the weeks immediately following the attack, the weekly number of reviews returns to the benchmark from before the attack in approx. half a year. In the curve with seasonal correction is suggested to have a stable number of reviews the time-period after the attack. Approx. a year after the attack, in the first months of 2017, the number of weekly reviews is increasing again. This might indicates that the tourism in Brussels has fully recovered from the terror attack.

Figure 6: The number of restaurant reviews per week in Brussels, 2011-2018



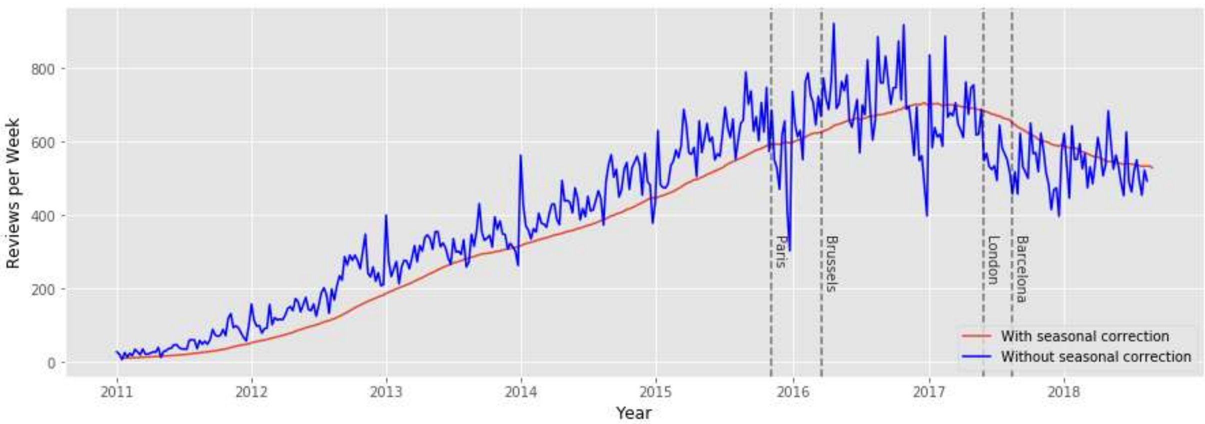
Source: TripAdvisor.com

To investigate whether a terror attack in one European city had an impact on the tourism in other European cities, we look at the number of review per week in Rome. We have included the four different terror attacks that occurred in the other cities as vertical lines in figure 7.

The effect of two terror attacks is visible in data on the weekly reviews for restaurants in Rome. After the terror attack in Paris the 13th of November and the second attack in London on 3rd of June 2017 we see a decrease in reviews (blue line). In the red line the decrease is also visible for the attack in Paris. For the attack in London the curve with seasonal correction is unclear, as there was an overall decrease in number of reviews in this period. The reactions to the attacks in Paris and London might be indicators of a spill over effect. However, we cannot see any visible negative changes in the number of reviews per week to the terror attacks in Brussels and Barcelona. This would speak against the negative spill over effect, that was for example measured in flight bookings (see Section 3.1).

In general, we cannot draw any clear conclusions about a negative spill over effect from our data on restaurant reviews from Rome. We believe that one of the reasons might be that there are two opposite effects occurring after a terror attack happens. On the one hand, there might be an overall decrease in the willingness to travel to an entire area e.g. Europe, as potential travelers perceive a higher level of threat. One the other hand, there might be a substitution effect of travelers that had originally intended to go to a specific city e.g. Paris, instead going to a city in this region where no terror attack occurred as for example Rome. These two effects would have an opposite impact on tourism in Rome and if our key assumption is correct on the number of reviews.

Figure 7: The number of restaurant reviews per week in Rome, 2011-2018



Source: TripAdvisor.com

5.2 Text Analysis & Machine Learning

In this section we present a way to analyse the content of the reviews with a combination of techniques used in Natural Language Processing (NLP) and Machine Learning (ML). Our goal is to build an algorithm that is able to classify the reviews depending on the country from which they come. This task is interesting as it will help us understand if people write different reviews depending on the country they visit and if there are patterns that the algorithm can use to predict which country each comment belongs to.

We will use the Bag of Words (BoW), which is widely used in NLP. The advantage of this model is that it has relatively simple implementation, in addition to good performance in many cases.

Using text as data is challenging as machine learning algorithms are not capable of interpreting information the same way humans do. We therefore have to transform this information into well-defined fixed-length inputs and outputs before we can use them. BoW does this by transforming the text into numbers or more precisely vector of numbers. Hence, BoW can be understood as a way to represent text as numerical feature vectors for later use in ML algorithms.

According to Raschka and Mirjalili (2017), BoW can be summarized into two steps. Firstly, we built a vocabulary of unique tokens (in our case, words) from all the documents (reviews). Secondly, we create a feature vector for each document, which measures the presence of the words that will be used as input in the construction of the classifier in later stages.

To illustrate this model, we will explain it through an example. There are three reviews called R1, R2 and R3.

- R1: "I like the restaurant"
- R2: "The restaurant was horrible"
- R3: "I like the restaurant even though the food was horrible"

The vocabulary is a dictionary of unique tokens (words). In this case, it would be: Vocabulary: "I", "the", "restaurant", "was", "food", "horrible", "is", "like", "even", "though". Then, we build our feature vectors for each review. A "1" means the word appears in the review and "0" if it does not:

- Vector1: [1 1 1 0 0 0 1 0 0]
- Vector2: [0 1 1 1 0 1 0 0 0]
- Vector3: [1 2 1 1 1 1 1 1 1]

Feature vectors (also called sparse vectors due to the amount of 0´s they have) measure the raw term frequency (tf), which calculates the number of times a word occurs in a document. This approach has a problem when there are many documents. In this case highly frequent words dominate in the document even if they do not contribute any information. Therefore, a weighting scheme called TF-IDF (Term Frequency – Inverse Document Frequency) is usually applied. TF-IDF rescales the frequency of words by how often they appear in the documents. This means that words that appear in a lot of documents such as "the" will be down-weighted. After applying TF-IDF, the feature vectors can be introduced into a ML algorithm.

Before explaining the implementation of the machine learning classifier and showing the results, it is important to further clarify one aspect. In the above example we built the vocabulary in blocks of one word. However, one can create a vocabulary in which each block is a set of words, for example, a set of two words. Following the example from above, the vocabulary of R1 would be "I like", "like the" and "the restaurant". This usually means that BoW will be able to capture more meaning in the reviews. Using this approach, each token is called a gram and creating a vocabulary of two-word pairs is called a bigram model. It is possible to create a N-gram model in which N refers to the number of words in each group. When we build our classifier we will create a vocabulary that consists of blocks of one word as well as two words.

Once we have constructed the vocabulary and the feature vectors representing each review, we build a classifier to see if we can predict the origin of a review using its content as an input. Our data consists of approx. 100,000 reviews in English distributed between 5 different cities (Paris, London, Brussels, Barcelona and Rome). The first step is to factorize all cities for the classifier to be able to recognize them (0: London, 1: Barcelona, 2: Rome, 3: Brussels and 4: Paris). After that, we convert all our data (content of the reviews) into the feature vectors as described earlier.

It is important to mention that we will consider both unigrams and bigrams to try to capture more meaning. The result is a vocabulary of 91.867 features. This means that each of the 100,000 reviews are represented as a vector of 91,867 dimensions. We must hereby highlight that this process is incredibly memory-intensive. Therefore, we increased the memory of our server in Google Cloud Compute Engine to 150 Gb[5].

To build our ML algorithms we implement three types of classifiers, which are widely used in ML: 1) Linear Support Vector Machine, 2) Logistic Regression and 3) Multinomial Naive Bayes. In the following we will analyze and compare how well they perform on our dataset.

To evaluate their performance, we first split the data between training set (75 %) and test set (25 %). Afterwards, we fit the model and compute the accuracy using our classifying algorithm on the test set. To remove any bias, we use 3-fold cross validation. The results are shown below in table 3.

In table 3, we can observe the accuracy of each model depending of the number of the folds we use (cross validation). Linear Support Vector Machine and Logistic Regression perform much better than the Multinomial Naive Bayes model. Between the first two, we choose Linear SVC as it has the highest accuracy. The accuracy is shown graphically in figure 8.

Table 3: Accuracy measures

Model	Fold	Accuracy
Linear SVC	0	0.741857435
Linear SVC	1	0.739344306
Linear SVC	2	0.742395235
Multinomial NB	0	0.62739624
Multinomial NB	1	0.625993778
Multinomial NB	2	0.628669432
Logistic Regression	0	0.733615166
Logistic Regression	1	0.730277327
Logistic Regression	2	0.732211232

To conclude, we present the confusion matrix for the Linear SVC model in figure 9. A confusion matrix is a simple way to assess the performance of a model. The matrix is to be read in the following way. On the x-axis one can see the prediction of our model and on the y-axis the actual value of that prediction. This means the cases in the diagonal are the ones where the model predicted the value (the origin) of a review correctly. We see that the majority of the predictions end up on the diagonal.

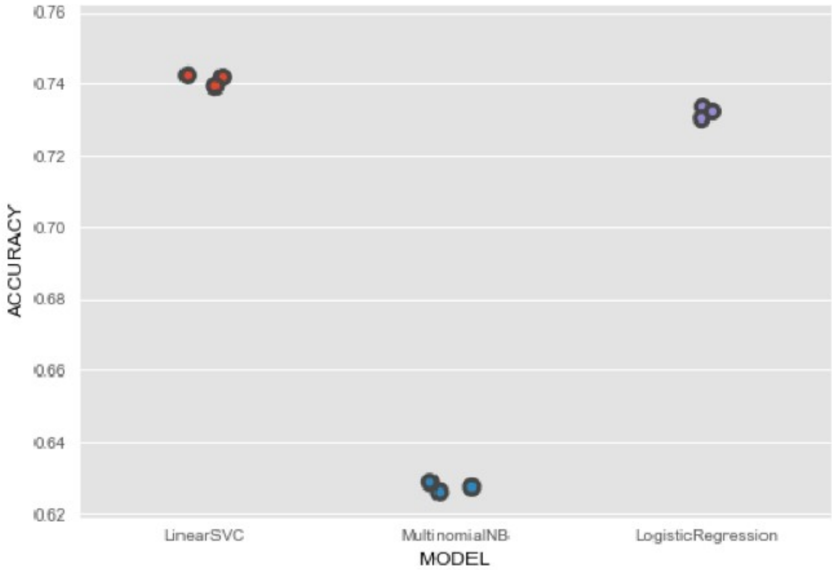
More specifically, we observe that the classifier predicts London much better than the other cities. London has a 10.22 % error rate [666 + 302 + 350 + 256 / 666 + 302 + 350 + 256 + 13820] while Barcelona, Brussels, Rome and Paris have 32.07 %, 49.80 %, 30.52 % and 41.20 % error rates, respectively. This might be a result of the bigger amount of comments in London compared to the other cities.

Furthermore, it is possible that the name of the country or city appears in some of the reviews. It would therefore be interesting to implement a classifier that removes the reviews where they appear. Further research could also focus on the reasons of the misclassifications. Another interesting aspect would be the the implementation of topic modeling (Linear Dirichlet allocation, for example) to try to unravel hidden patterns

[5]Alternatively, we could have reduced the dimensionality of our dataset through a stemming algorithm (usually Porter stemming algorithm) or with the feature hashing algorithm/hashing trick as an efficient way to store feature vectors.

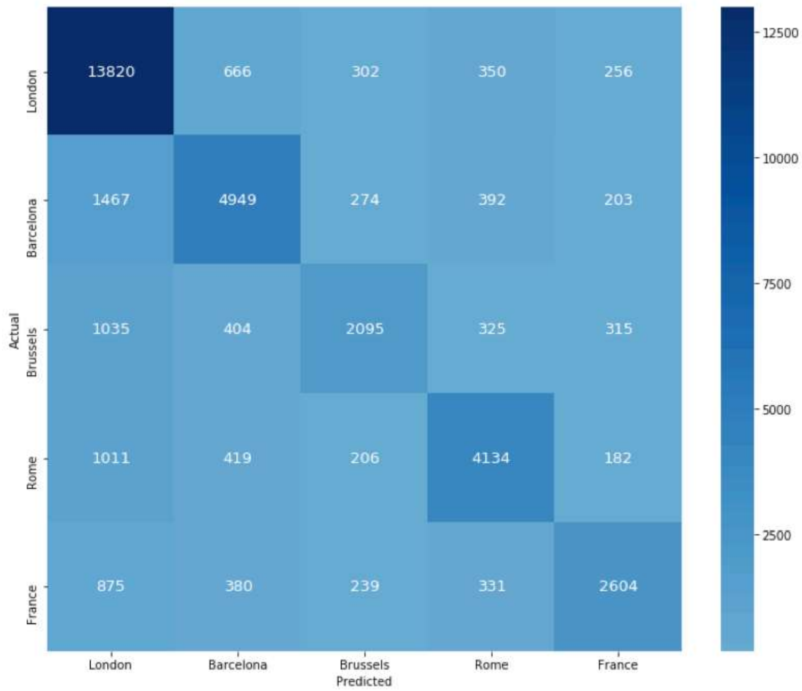
in the data that could help us gain a deeper understanding of the topics.

Figure 8: Accuracy of the models



Source: TripAdvisor.com

Figure 9: Confusion matrix



Source: TripAdvisor.com
Note: France refers to Paris

6 Discussion

In the following section, we will discuss possible limitations of our research. Hereby, we will focus on limitations regarding the methods we used and the dataset we obtained through it. We will then propose improvements and suggest further research. We will conclude this section by discussing ethical aspects that are of relevance to our research.

One of the key assumptions of our research is that the number of reviews on TripAdvisor for a city is a good indicator for how many tourists visited that city. This assumption allows us to interpret a decrease in the number of reviews after a terror attack, as a direct effect of the attack on the number of tourist visits. In multiple of the cities in our dataset, we see that the number of weekly reviews is lower in the period directly following a terror attack. This might suggest a negative effect of a terror attack on the number of reviews. In the previous sections we have shown, that the same immediate negative effect can be found when looking at different data sources, such as data on flight bookings or hotel surveys. The alignment of the results of the different data sources therefore supports our key assumption.

Yet, there are limitations to the assumption. Our method only captures a very small set of tourists, those who write reviews on TripAdvisor. Tourists that do not write reviews are therefore excluded in our dataset, which might lead to a strong selection bias. Our method fails to capture entire demographic groups, such as people who are less familiar with reviewing restaurants online (e.g. people of higher age). In addition, people from countries where TripAdvisor is not very popular are excluded. This selection bias is especially of importance as different types of tourists might react differently to the change in perceived level of security that follows a terror attack. For example Arlt (2016) reports that many Chinese tourists decided to travel to non-European destinations, as they were concerned about safety in Europe. As TripAdvisor has multiple more popular competitors in China (Xiang, 2014) this trend might be invisible in our data set.

Another aspect worth considering is that a declining number of reviews on TripAdvisor are probably not the result of a decrease in number of tourist visits but may instead be TripAdvisor losing popularity. In all five cities, we notice a decline in weekly TripAdvisor reviews after approx. mid 2017. Yet, this does not align with other data sources, which measure an increase in tourism in Europe in 2017 (Sprinks, 2018). The decline might therefore be an indicator that users are leaving TripAdvisor for different platforms (Horton, 2018). The overall number of active TripAdvisor user would therefore need to be taken into account when analysing changes in weekly number of reviews.

Regarding our data and its collection we have identified three limitations. First, choosing only restaurants with more than 50 reviews might have resulted in a selection bias. We were unable to capture smaller, lesser-known or newer restaurants in our dataset. Yet, we do not believe that this selection bias has impacted our analysis. It seems unlikely that visitors of less-reviewed restaurants would be affected differently by a terror attack than visitors of more-reviewed restaurants. Secondly, for the machine learning based text analysis we only used reviews in English. This was mainly due to the way TripAdvisor's HTML was structured, which we explained in the methods section. We found a solution to also scrape the content from reviews written in other languages, however as we had limited computational capacities we decided against proceeding with it. Furthermore, as most text analysis tools are available for English it remains unclear how much the inclusion of the reviews in other languages would have added. Lastly, our sample only accounts for approx. 5% of the reviews in the five cities we selected. This raises questions whether the representativeness are legitimate. As we had limited computational power we were only able to mitigate this limitation by randomizing the selection of our sample.

To address these limitations, we propose that further research considers multiple aspects. To achieve a higher level of representativeness a bigger, less restricted sample would be needed. Furthermore, we believe TripAdvisor data should be used in combination with other data sources. These include data sources that are traditionally used to measure tourism such as number of flight bookings and visa application or hotel survey. These multiple data sources should be used within a regression model, capable of better isolating the effect of terrorism on tourism. Further steps towards establishing causality would be the inclusion of variables that control for the overall number of active TripAdvisor users. Hereby, it might also be of advantage to include a second similar website such as Yelp as a data source to additional control for a change in popularity of TripAdvisor.

Finally, we would like to address aspects of the ethical considerations of our research. As we are dealing with non-sensitive, publicly available data we do not believe that specific privacy- or data-protective measures are necessary. Yet we must acknowledge our shortcomings in not informing TripAdvisor about our intentions and proceedings to scrape their website. Even though web scraping itself it not illegal, the fact that TripAdvisor is very restricted in giving access to their API, makes us believe that our undertaking might have been something that TripAdvisor does not agree with.

7 Conclusion

Using the number of weekly TripAdvisor reviews, we find that for Paris, Barcelona and London the number of reviews decreases after a terror attack occurred. This could indicate an overall decrease in tourist visits to this city, which is in line with conclusions from other data sources. Furthermore, we find that approx. a year after a terror attack the number of reviews has returned to the level of before the attack. This supports the recovery effect, which was identified by other researchers. Finally, when we look at Rome, a city that was not hit by a terror attack, we find a potential negative spill over effect on the number of reviews when terror attacks in Paris and London occurred. We conclude that while our findings are in line with effects identified by researchers using different data sources, we cannot draw any final conclusions on the impact of terrorism on tourism, as TripAdvisor reviews only capture tourism with limitations. Yet, as our findings look promising we propose further research that uses TripAdvisor data in addition to other data sources, to achieve a more complete understanding of the relationship between terrorism and tourism.

The algorithm that we trained to predict the origin of a review, based on it's content shows a relatively strong performance with an accuracy of 74 %. We find that the more comments the algorithm gets from a specific city, the better it becomes in predicting correctly, if a review is from this city.

8 Literature

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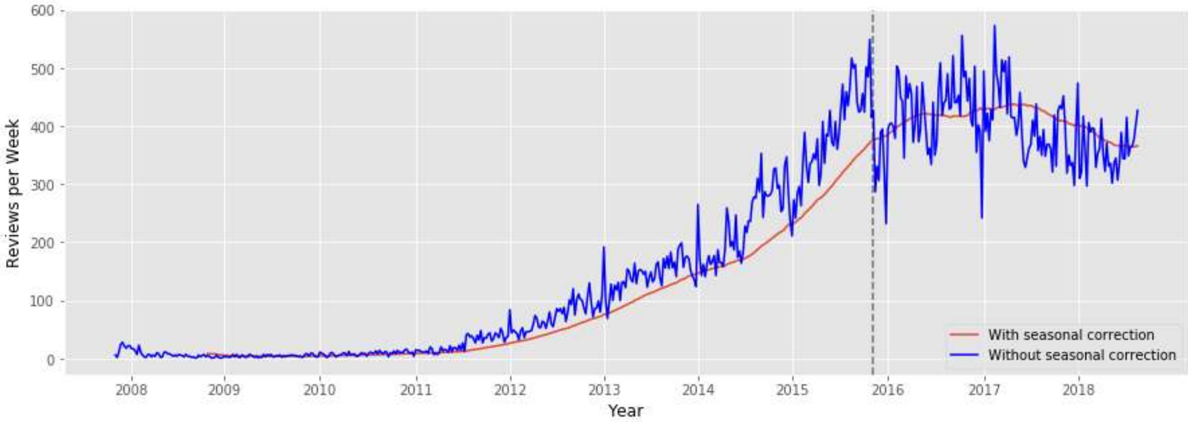
9 Appendix

A.1 Figure for the whole timespan

Figure 10: The number of restaurant reviews per week in Paris, 2008-2018



Source: TripAdvisor.com