

Project-Report

Interested in traveling again? A Timeseries-Analysis for Austria



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May, 2020*

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Outline

This report contains the methodological approaches for this project and a list of indexes for each country with their respective terms crawled from Google Trends and updated on a daily basis.

Goal of the project

The goal of the project was to develop a model for monitoring the interest in traveling again for Austria's top 16 tourism markets:

Austria, Germany, Switzerland, Belgium, France, England, USA, Hungary, Sweden, Denmark, Russia, Romania, Netherlands, Czech Republic, Poland and Italy.

Dataset

The model should be based on up-to-data, available on the Internet. One of most common sources for such a task is Google Trends, which shows search trends for terms over a number of available timeframes. Google Trends however delivers relative values only, based on the overall search behavior for this time period. This means, that eg. the values for a specific date on the term "booking" is relative to all search terms. If "Trump", "Corona" or any other search Term outperforms, "booking" is presented lower. Therefore the main task was to find a technical and mathematical solution to limit the data-bias for search results. Just crawling search terms in Google-Trends therefore wasn't an option.

As we were interested in the time period starting before the corona pandemic in 2020 the period from 8th February was chosen.

Another huge challenge in this project was to create an appropriate dataset which would include the most relevant terms, indicating when people start searching for travel purposes again like e.g. hotel, hotel Austria, flight, travel and others. This dataset was created manually. Originally a set of terms in German language was created and then translated for all 16 countries with the help of Google Translate service. These results were then checked with native speakers, resulting in a dataset which included from 41 to 139 search items with 60 terms on average per language. The large range can be explained with the peculiarity of language features and with the fact that several countries like Switzerland or Belgium have more than one official language. The dataset was iteratively filtered in order to retain only relevant and informative terms according to Google Trends data. In the preprocessing, terms where Google couldn't provide enough search volume were deleted.

Development steps

The analysis was done separately for each of the mentioned countries. Originally all terms were crawled, plotted and explored separately. The criteria of analysis for each trend line included the number of zero-values, significance of changes in the trendline and others.

After a manual inspection it was evident that some trends have similar curves. By realizing that fact it was concluded that terms having similar trends for a particular country could be merged into a single trend, i.e. an index to avoid the data-bias.

The development of an index scheme included following main steps:

- Splitting terms into groups of similar time-series and finding a mathematical representation for this task.
- Merging terms within a group into a single index
- Creating a scheme which would allow to track each index over a larger undefined period of time

Index terms

After a manual inspection it was possible to conclude, that many trends within the same country show a similar behavior, i.e. similar time-series curves, which would enable us to merge these values. However, many trends had more than 80% zero values which would force us to delete these search terms from the dataset since they were non-informative. However, non-zero values in some trends were still correlating. Examples of such terms are “hotel vienna”, “hotel tyrol” or “hotel salzburg”. To eliminate this issue, we combined such terms into one search term by using “+”: “hotel vienna + hotel tyrol + hotel salzburg” and others¹. The combination of several keywords in on query reduced the number of zero values and increased the volume of the whole trend like shown in the figure below. By applying this method, we were able to reduce the number of zero-values by nearly 80% which allowed us to retain many of the search terms thus keeping the number of terms consistent for each country. Combinations which didn’t show any improvements were then deleted from the dataset. For some combinations which still had zero-values and after conducting a number of experiments we decided to retain those keywords having less than 13% zero-values and replaced them with the mean value of the whole time frame for a particular term².

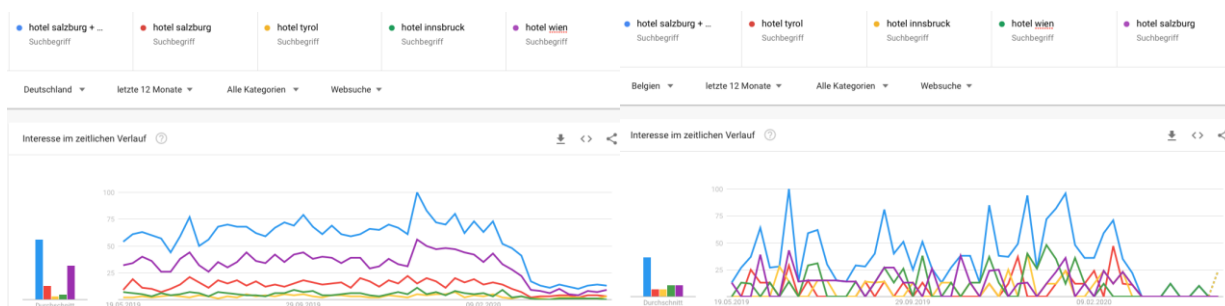


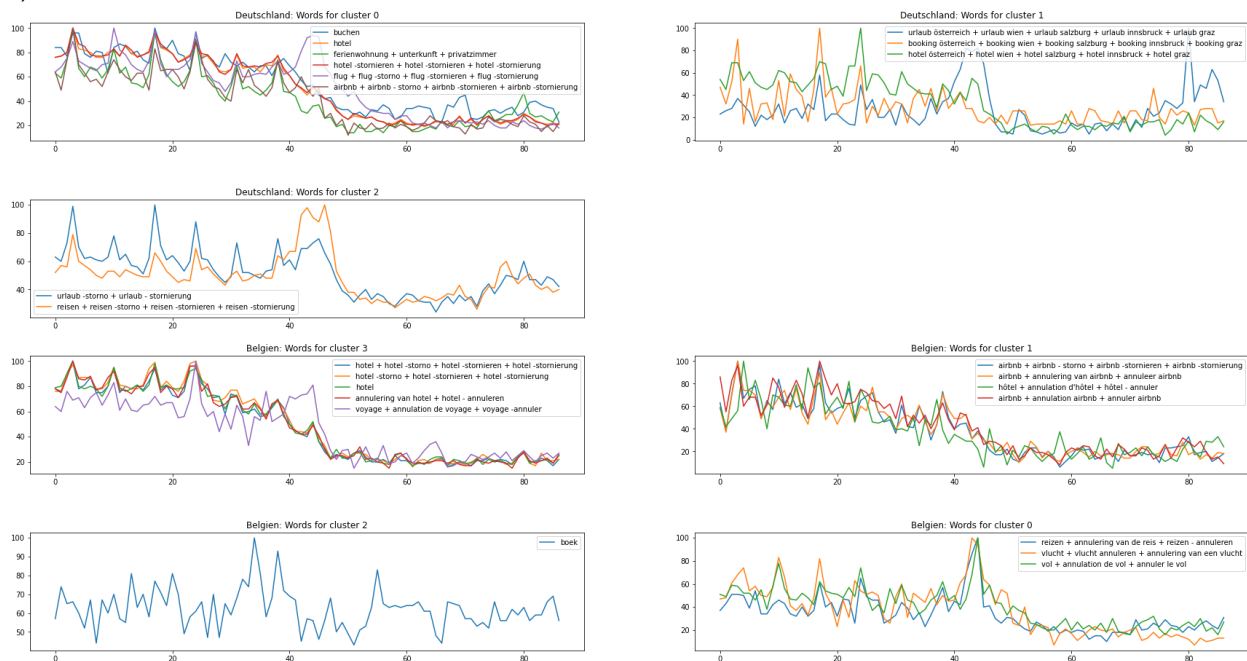
Figure 1. Examples of Germany and Belgium showing trends for “hotel salzburg”, “hotel tyrol”, “hotel innsbruck”, “hotel wien” and combination of terms “hotel salzburg + hotel tyrol + hotel innsbruck + hotel

² <https://medium.com/@pewresearch/using-google-trends-data-for-research-here-are-6-questions-to-ask-a7097f5fb526>

wien” indicated by blue line in both figures. The blue line shows the combined search volume of “hotel salzburg + hotel wien + hotel tyrol + hotel graz + hotel innsbruck” which is significantly above zero.

To measure the similarity of time-series the Python package “tslearn”, which is a kind of K-Means clustering developed for time-series, was used³. The results of initial experiments confirmed our expectations, so that we continued with the selection of individual cluster numbers for each country. First, the ideal cluster number was chosen by comparing the silhouette scores, however, this approach led to confusion in results - some trends which were evidently suitable for one cluster were assigned to a wrong one. The second approach for identifying the best number of clusters, was the K-Means rule of thumb: $k = \sqrt{n/2}$, where n is number of samples and k is resulting cluster number. This resulted in a much better separation and acted as a base for manual fine-tuning of clusters. We also compared the performance of classical K-Means with K-Means for time series. Unlike K-Means which normally uses cosine or euclidean distance as similarity measure, K-Means for time series is more robust towards outliers. However, since this algorithm didn’t give us any improvement in terms of a better cluster separation, we decided to use results obtained initially with the regular K-Means algorithm. Some experiment-examples of clustering results produced with classical K-Means and with K-Means for time series are provided in the figure below:

a)



³ <https://tslearn.readthedocs.io/en/stable/>

b)



Figure 2. a) Examples of K-Means clustering for Germany and Belgium; b) Examples of K-Means clustering for time series for Germany and Belgium.

Finally, we defined each cluster, i.e. each index manually, eliminating errors produced by K-Means. Again, terms which were not suitable for any index were deleted from the dataset. Depending on the country and its individual search terms, an iterative filtering was done which resulted in 1 to 5 indexes per country. The full list of search terms and their respective indices are available in the appendix.

Scaling scheme

After the dataset was iteratively filtered and each search-term was assigned to an index, the next task was to choose an appropriate statistical method to combine trends into indexes. First of all, the terms from the same index were crawled together. As Google Trends allows a maximum five keywords to be compared simultaneously and we had up to 9 keywords falling into the same index, we tested the two following options: split one index into two or three new indexes or to reduce the number of keywords through the union of several keywords having identical curves. For example, keywords “hotel -storno”, “hotel -stornieren” and “hotel -stornierung” showed nearly identical trends and search volumes when compared to each other, so we reduced them to a single search term using “+”: “hotel -storno + hotel -stornieren + hotel -stornierung” which allowed us to keep maximum five search terms per index. Some examples are provided in the figure below.

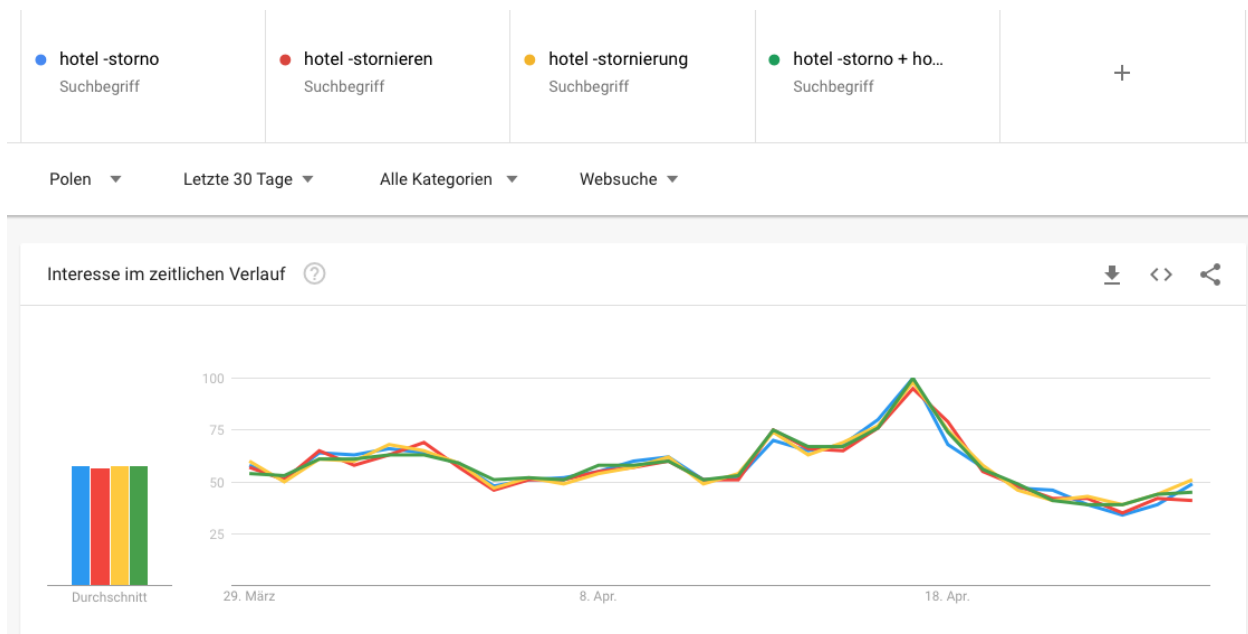


Figure 3. Examples of terms “hotel -storno”, “hotel -stornieren”, “hotel -stornierung” and combined search term “hotel -storno + hotel -stornieren + hotel -stornierung” indicated by green line.

An additional problem was how to make trends within the same index comparable. When comparing trends with Google it often happens that some trends get very close to zero (for these numbers Google returns a “<1” value which was not informative and invalid for our research) when compared with other trends having significantly higher search volumes. For some indices this issue was eliminated by the approach proposed above, i.e. combine some trends with similar curves together into a single search term to increase overall search volume. This made some search terms more comparable to those like “hotel” or “buchten”. However, there were still many indices which needed an improvement. Again, we tested a huge number of options. One possible solution was to reveal absolute search volumes, i.e. real numbers for each search term, so that we could calculate with appropriate proportions of terms from the same index. Google provides the Google Ads service, which returns absolute search volumes for a particular search term. The proposed solution was to compare time series from Google Trends (GT) with Google Ads (GA). If curves for the same term were identical, we could use these absolute numbers to convert the data obtained from Google Trends into real numbers and thus make all trends comparable to each other regardless of their proportion displayed in Google Trends. To test how data from GT matches with the data from GA we collected data for our initial dataset for the period of the last year with monthly values. Since the data from GA contains real values and GT contains relative values varying from 0 to 100, we transformed GA values into a [0;100] range and plotted GA and GT time series together in order to make initial assumptions about trends similarity. We could identify many keywords where GA and GT for the respective term match together showing correlation close to 1. However, some trends showed opposite trends and thus had correlation about -1. As a baseline we used RSS (residual sum of squares) and RMSE (root mean squared error) scores to measure how well patterns match together. Because of the mentioned problem of opposite trends, RMSE score wasn’t informative for our research, although it was very close to

0 which is a great indicator but invalid because patterns don't match together. The illustration of the problem is provided in the figure below.

Correlations for Niederlande with thresh < 0.15

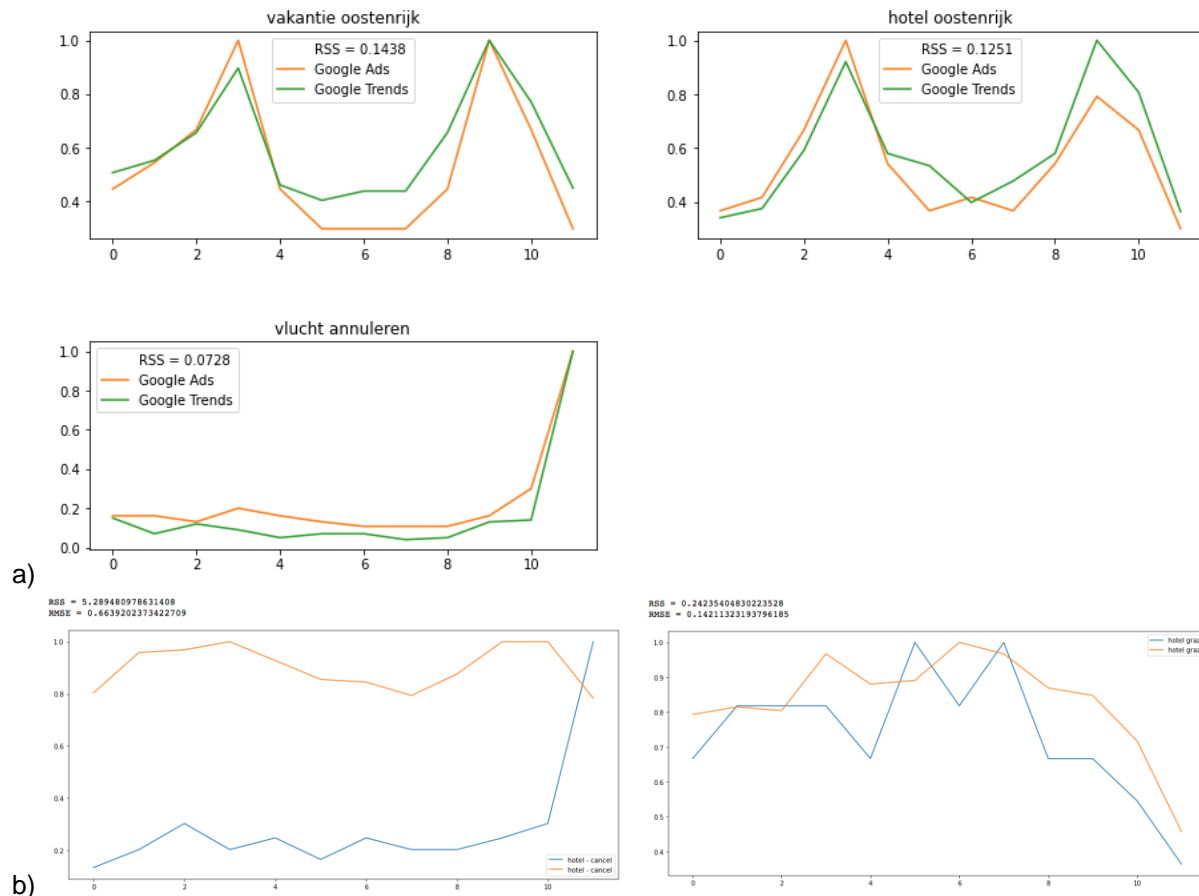


Figure 4. Examples of comparing trends from Google Ads vs. Google Trends having low RSS - value: a) examples of good pattern match; b) examples of opposite trends although the RSS value is low.

After testing a variety of time series comparison techniques, we concluded that the strategy to convert GT data by comparable GA data into real numbers was applicable to only a small number of search terms, because according to our experiments most of the patterns didn't match together. We retrieved the needed GA-Data from Keywords.io. However, finally we had to conclude, that the numbers from Google Ads can't be compared with those from Google Trends because of the following reasons:

a) Google Trends uses a random unbiased sample of relative-popularity on a 100-point scale -- the data shown has nothing whatever to do with absolute-search-volume. Generally, keyword-planners' absolute-volumes do not match the relative-popularity-scales, nor absolute actual traffic...

b) popular terms, during popular time-frames, tend to show an increased competition and cost much more per click, or require much higher quality, or usually some combination of both, to surface impressions -- bids alone may not be enough”⁴.

Due to these factors we decided to omit GA data for our further research and rely only on data we collected daily from Google Trends.

As mentioned before, Google Trends allows the comparison of a maximum of five different search terms simultaneously. An example of terms falling into one of indexes for Austria is provided below. When compared to each other, a trend having a maximum value over a given period is treated as an absolute value for other trends. This results for some trends to be placed close to zero, because their absolute values account for less than 1% of the search volume of the trend with the maximum value. This gives to many trends a very low weight which makes trends nearly incomparable. To eliminate this issue, we tried an approach based on an anchoring strategy⁵. This approach intends to use anchor words in order to rescale terms having low numbers and thus make them comparable with other trends. The anchor word should be a term which has a stable dynamic in Google Trends with as little change across a certain time frame as possible. Also an anchor word should be selected in the way that its search volumina is not much higher than that for the term which needs to be rescaled. Good examples of such anchor words are “water”, “magazine”, “journal” and others. The behavior of those trends is displayed in the Figure 5 below. Considering the fact that anchor words were necessary for indices of nearly each country, we had to select anchor words which were easy to translate in any language and showed a similar search behavior regardless of the country.

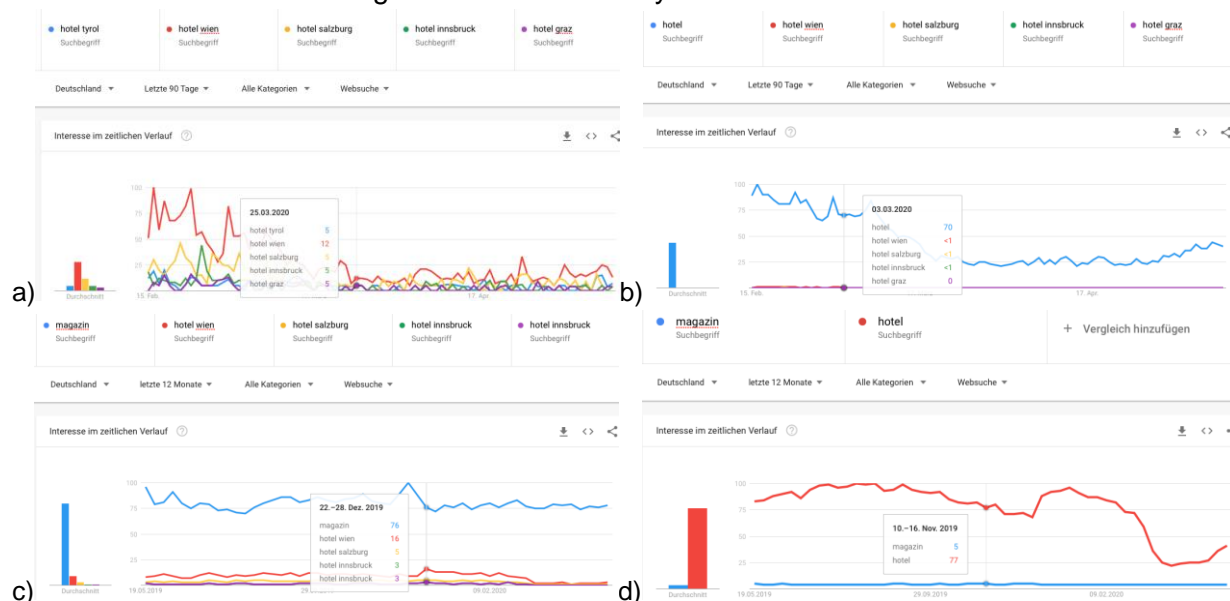


Figure 5. Examples of anchor words used to rescale trends having “<1 %” values towards the “hotel” search term: a) terms “hotel tyrol”, “hotel wien”, “hotel salzburg”, “hotel innsbruck” and “hotel graz”; b) terms from

⁴ <https://support.google.com/google-ads/thread/9052927?hl=en>, <https://mudd.com/google-trends-vs-keyword-planner/>

⁵ <https://towardsdatascience.com/using-google-trends-data-to-leverage-your-predictive-model-a56635355e3d>

p.a) with added term “hotel” indicated by blue line; c) terms from p.a) with “magazin” as anchor word; d) anchor word “magazin” indicated by blue line and “hotel” indicated by red line.

We can see that the word “magazin” has a quite stable dynamics and can be used as an anchor word in order to rescale search terms “hotel tyrol”, “hotel salzburg”, “hotel innsbruck”, “hotel graz” and “hotel wien” towards a search term “hotel” which has the biggest search volume in the index. A scaling factor using an anchor word is computed like shown in the formulas below⁶:

$$SF_1 = \frac{anchor^1}{med(anchor^1)}.$$

$$SF_i = SF_{i-1} \cdot anchor_{i-1}^i = \frac{\prod_{j=0}^{i-2} anchor_{i-j-1}^{i-j}}{med(anchor^1)} \quad \forall i > 1$$

$$x_{scaled} = x \cdot SF_i$$

Formulas above propose a solution which is applicable to any number of anchor words used for rescaling. This means that anchor words with increasing search volume can be used till the necessary scaled volume is reached. The first scaling factor SF_1 is normalized by its median across the selected timeframe. Each following scaling factor SF_i can be created by multiplying values of the next anchor words and again by normalizing the resulting value by the median of the first scaling factor. The resulting scaling value x_{scaled} is produced by multiplying the original search volume of a term and a respective scaling factor.

This approach could be used to compare any number of terms instead of the five, mentioned above. However, although this approach seemed to be quite stable, we still faced the issue of many trends having many missing, i.e. zero-values. This led us to combine terms having zero-values together into a single search term like described in the beginning of the report. By doing this we were able to keep the number of terms per index with a maximum of five. In addition, terms which needed to be rescaled using anchor words became comparable to other trends, through the increase of search volumes for composite search terms. This allowed us to compare and weight trends in the index without using anchor words. However, trends which still had more than 13% zero-values were deleted from the dataset, while trends having less than 13% zero-values were filled with their mean value, which made our approach stable. As shown during our experiment, the number of zero-values in trends remained stable regardless of the selected time frame which made our approach reliable for further rescaling.

After we solved the problem with incomparable search volumes and exceeding numbers of possible terms falling into an index, we developed a scaling scheme which allowed us to daily update each index and to extend it to any number of updates per day. One of the necessary conditions was, that Google-Trends data is provided on a daily scale, i.e. with search volumes for every day which can be extended to any future period of time. Google Trends provides daily data for a maximum of the last 90 days. For us, the most recent available period started on the 8th of February. We used the data crawled for this period using our final dataset (see appendix in this report) to test different techniques for creating an index from a number of trends falling into it.

⁶ <https://towardsdatascience.com/using-google-trends-data-to-leverage-your-predictive-model-a56635355e3d>

Some of the index terms are provided in the figures below (zero-values are already replaced with the mean value):



Figure 6. Example of index terms for Austria and Belgium (each graph in the figure represents a separate index).

It can be seen, that none of the trends has incomparable values with the maximum value, when compared to each other. To merge trend lines into a single index - trend we applied the following techniques:

- PCA (Principal Component Analysis)
- t-SNE (t-distributed Stochastic Neighbor Embedding)
- an average trend.

PCA and t-SNE are dimensionality reduction techniques which are used to project a multi-dimensional space into a lower-dimensional space with a predefined number of components. For example, if an index has 5 terms like in the figure, by using PCA and t-SNE we were able to reduce the number of components to 1 which would represent a particular index. However, when plotting the results, we realized that the pattern of the resulting trend don't match the original pattern anymore. This is due to the fact, that dimensionality reduction methods try to keep as much as possible variance in the data while not keeping the original patterns. After we used an average trend for creating indexes, we were satisfied with the results as the original pattern was still preserved in the resulting time series. Some of the results are provided in the Figure 7. below:

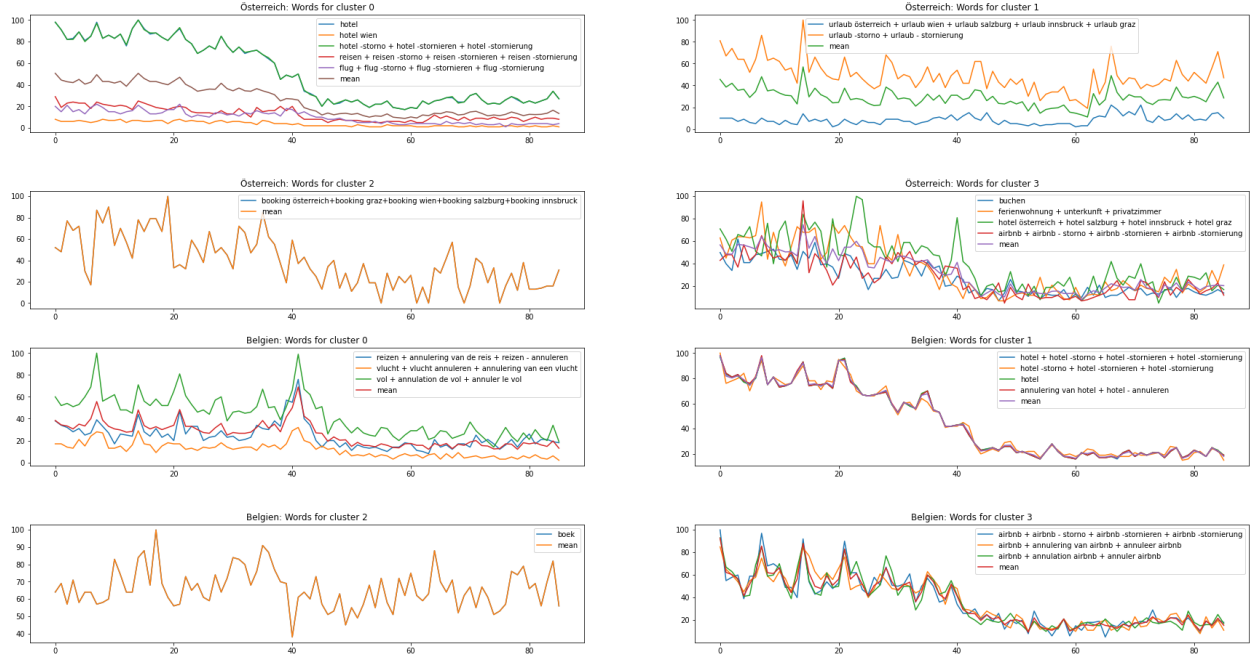


Figure 7. Examples of index terms for Austria and Belgium with an index as mean between index terms.

The mean trend for each index is indicated as “mean” in the legend. One can see that the index pattern is well-preserved and has smoothed values. The example of resulting indexes are provided below:

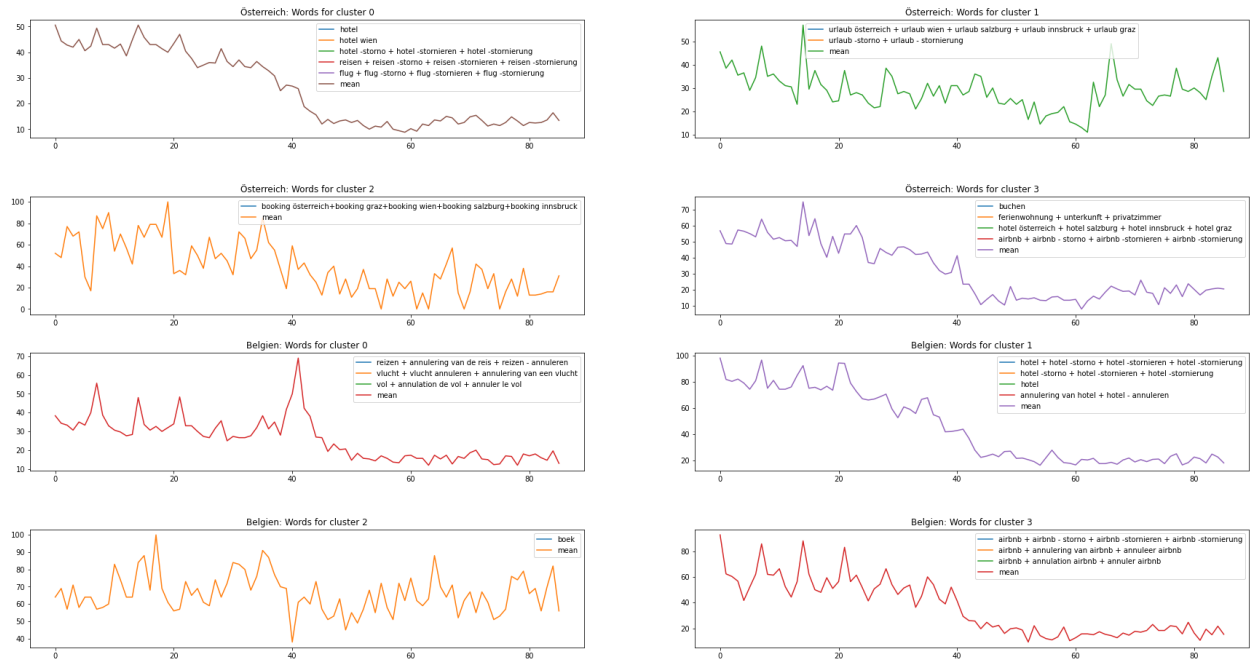


Figure 8. Examples of index terms for Austria and Belgium created a mean curve between all terms falling into their respective index.

After we successfully created an index-scheme we continued with the scaling scheme. This would allow us to extend indexes to every period of time in the future. Our scaling scheme is based on

an overlapping period between different time frames⁷. The idea is to take a time series for the same search term from different time periods, showing some overlapping points. We then calculated a scaling factor based on these overlapping time frame.

We finally used the following scaling approach:

Timeframe 1: $TF_1 = [T_0, \dots, T_k], k > 0$

Timeframe 2: $TF_2 = [T_i, \dots, T_{t+1}], i < k, t+1 > k, i \geq 0, t+1 > i$

Overlapping period: $[T_0, \dots, T_k] \cap [T_i, \dots, T_{t+1}] = [T_i, \dots, T_k]$

Overlapping period from T1: $[T_i, \dots, T_k]_1$

Overlapping period from T2: $[T_i, \dots, T_k]_2$

Scaling factor: $scaling = \frac{1}{n} \sum_i^k \frac{[T_i, \dots, T_k]_1}{[T_i, \dots, T_k]_2}$, where

n = number of overlapping points.

Resulting timeframe: $[T_0, \dots, T_{t+1}] = [T_0, \dots, T_{k-1}, scaling * [T_i, \dots, T_{t+1}]]$.

By using this scaling scheme, we were able to scale each “next time frame” to the previous one. We are using an average scaling factor, because this approach is robust and stable towards outliers.

The next challenge was to identify appropriate time periods, which we would crawl everyday in order to make daily updates available. The initial suggestion was to crawl the data for the last 30 or 90 days which would allow to have 28 or 88 overlapping points respectively thus ensuring that the scaling factor is stable and has insignificant changes. However, the data for the last month and for the last 3 months is updated only each week and not everyday. This has led us to switch to weekly data which is updated every day. The data for the “last week” contains hourly values for each day of the week which means there are 24 values available for each day. Using this data we create a daily value by averaging the search volume of the day. Each index term is crawled and rescaled separately, after which a new index point is created. Each index is updated every day at 12 p.m. One should note here, that at 12 p.m. only partial data for any term is available, i.e. from 12 a.m. till 12 p.m. To avoid any inconsistencies, we use a two-step rescaling scheme: Everyday we first recollect the data for the last week ending with the day “yesterday” so that the data for the last day is complete and contains values for all 24 hours of that day. After that we drop the last index point which was created for 12 p.m. of that day and scale time frames again. Then we collect the data for the last week ending again with the day “today 12 p.m.” and so on. We tested our approach during 13 days and found it stable. Each day we crawled search volumes for the last week and rescaled them with the data collected on the previous day. Examples are shown in the figure below:

⁷ <https://github.com/e-271/pytrends/blob/master/pytrends/renormalize.py>,
<https://towardsdatascience.com/reconstruct-google-trends-daily-data-for-extended-period-75b6ca1d3420>

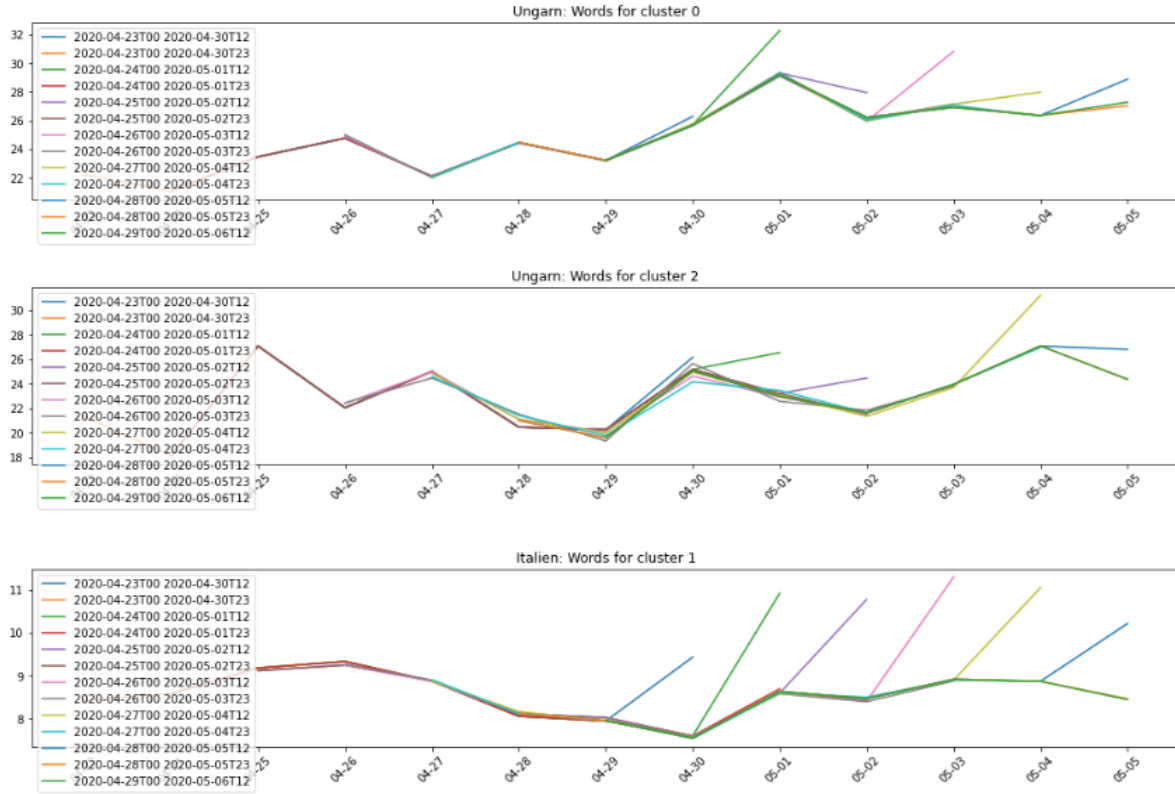


Figure 9. Example of index rescaling for Hungary and Italy rescaled over 13 days with sharp tails indicating 12 p.m. of each day.

In figure 9 one can see an example of Hungary with 3 different indexes. Each index contains the data crawled each day within the “last week”. For each day, the overlapping period accounts for 6 days, where we can see from the figure 9 that this is a satisfying method. The ‘tails’ going sharply up or down depict the values from 12 p.m. which we delete every next day in order to make an appropriate rescaling.

The schema below illustrates the full scaling algorithm used to create and update any index on the next day (consider index points instead of single term-points):

1. Existing data: $[T_0, \dots, T_t]$,
2. Delete point T_t , where T_t indicates “yesterday 12 p.m.”,
3. Recollect data for period $[T_0, \dots, T_t]$, where T_t indicates “yesterday” and has now the data for all 24 hours,
4. Rescale the data $[T_0, \dots, T_t]$ from p.3 based on overlapping period $[T_0, \dots, T_{t-1}]$,
5. Collect data for time period $[T_1, \dots, T_{t+1}]$, where T_{t+1} indicates the point “today 12 p.m.”,
6. Rescale data from p.5 based on overlapping period $[T_1, \dots, T_t]$,

7. Create a new index point at T_t using the scaling factor.

After we rescaled all weekly time frames and started the time frame for the last 90 days, we are monitoring daily updates as shown on the figure below:

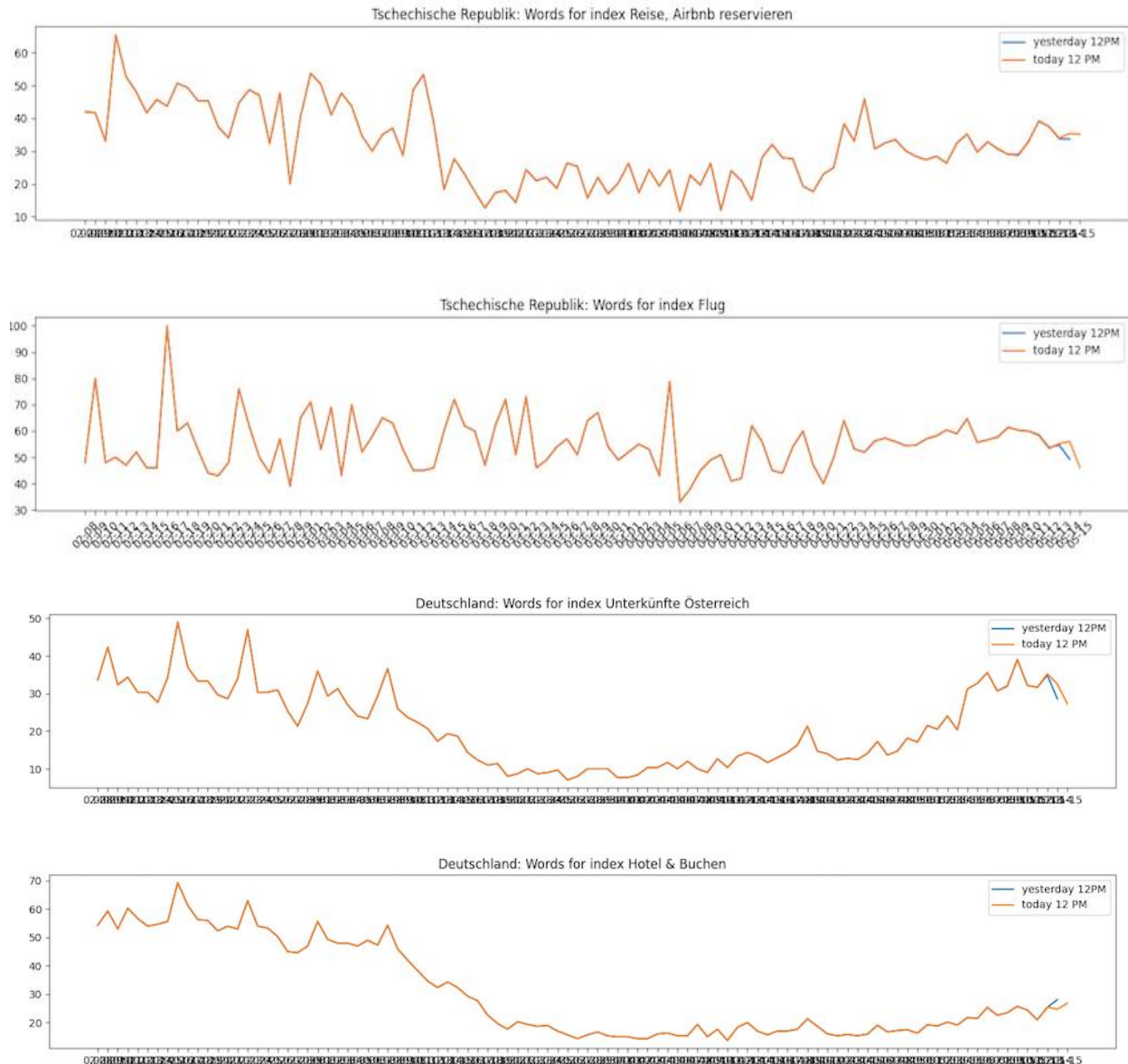


Figure 10. Example of indexes for Czech Republic and Germany. The blue line overlaps with the orange line till the last day where the new index value is created. The last point of the blue line indicates the previous day at “yesterday 12 p.m.”. The orange line shows an updated index with the last point being “today 12 p.m.”.

Each figure represents its own index and contains index values from the previous day and today respectively. On the last day we can see small changes, which are due to our scaling scheme: a blue “tail” which indicates “yesterday 12 p.m.” is deleted on the next day and the new index point

is created. Each day we have 6 overlapping points and as one can see from in the figure, this scaling scheme is stable.

Appendix

The dataset containing indexes for each country and their respective terms:

Index terms	Land	Index Name
<ul style="list-style-type: none"> reizen + annulering van de reis + reizen - annuleren vlucht + vlucht annuleren + annulering van een vlucht vol + annulation de vol + annuler le vol 	Belgien	Reisen & Flug
<ul style="list-style-type: none"> hotel + hotel -storno + hotel -stornieren + hotel -stornierung hotel -storno + hotel -stornieren + hotel -stornierung hotel annulering van hotel + hotel - annuleren 	Belgien	Hotel
<ul style="list-style-type: none"> boek 	Belgien	Buchen
<ul style="list-style-type: none"> airbnb + airbnb - storno + airbnb -stornieren + airbnb -stornierung airbnb + annulering van airbnb + annuleer airbnb airbnb + annulation airbnb + annuler airbnb 	Belgien	Airbnb
<ul style="list-style-type: none"> buchen Hotel hotel -stornieren + hotel -stornieren + hotel -stornierung 	Deutschland	Hotel & Buchen
<ul style="list-style-type: none"> urlaub österreich + urlaub wien + urlaub salzburg + urlaub innsbruck + urlaub graz booking österreich + booking wien + booking salzburg + booking innsbruck + booking graz 	Deutschland	Österreich Urlaub
<ul style="list-style-type: none"> urlaub -storno + urlaub - stornierung reisen + reisen -storno + reisen -stornieren + reisen -stornierung 	Deutschland	Urlaub & Reisen
<ul style="list-style-type: none"> hotel österreich + hotel wien + hotel salzburg + hotel innsbruck + hotel graz ferienwohnung + unterkunft + privatzimmer airbnb + airbnb - storno + airbnb -stornieren + airbnb -stornierung 	Deutschland	Unterkünfte Österreich
<ul style="list-style-type: none"> rejse + rejse aflysning + rejse - annullere 	Dänemark	Reisen
<ul style="list-style-type: none"> hotel hotel annullering + hotel - annullering 	Dänemark	Hotel
<ul style="list-style-type: none"> booking fly + aflysning af fly + annuller flyvning airbnb + airbnb-annulering + annuller airbnb 	Dänemark	Buchen, Flug, Airbnb
<ul style="list-style-type: none"> booking hotel hotel cancellation + hotel - cancel airbnb + airbnb cancellation + cancel airbnb 	England	Unterkunft buchen
<ul style="list-style-type: none"> to travel + travel cancellation + travel - cancel flight + flight cancellation + cancel flight 	England	Reise & Flug

<ul style="list-style-type: none"> • hotel austria + hotel tyrol + hotel vienna + hotel salzburg + hotel innsbruck 	England	Hotels in Österreich
<ul style="list-style-type: none"> • réservation • vol + annulation de vol + annuler le vol 	Frankreich	Buchen & Flug
<ul style="list-style-type: none"> • hôtel + hôtel - annuler • voyage + annulation de voyage + voyage -annuler • airbnb + annulation airbnb + annuler airbnb 	Frankreich	Unterkunft & Reise
<ul style="list-style-type: none"> • albergo • viaggio + annullamento del viaggio + viaggio - annulla 	Italien	Hotel & Reise
<ul style="list-style-type: none"> • hotel + hotel -annulla • volo + cancellazione del volo • airbnb 	Italien	Unterkunft & Flug
<ul style="list-style-type: none"> • reizen + annulering van de reis + reizen - annuleren • vlucht + vlucht annuleren 	Niederlande	Flug & Reisen
<ul style="list-style-type: none"> • boek 	Niederlande	Buchen
<ul style="list-style-type: none"> • hotel + annulering van hotel + hotel - annuleren • airbnb + annulering van airbnb + annuleer airbnb 	Niederlande	Unterkunft
<ul style="list-style-type: none"> • lot + odwołanie lotu + anuluj lot + loty 	Polen	Flug
<ul style="list-style-type: none"> • hotel • anulowanie hotelu + hotel - anuluj 	Polen	Hotel
<ul style="list-style-type: none"> • Rezerwacja • airbnb + anulowanie airbnb + anuluj airbnb 	Polen	Buchen & Airbnb
<ul style="list-style-type: none"> • hotel + hotel - anulare • airbnb + airbnb -anulare 	Rumänien	Unterkunft
<ul style="list-style-type: none"> • бронирование + бронирование -отмена 	Russland	Buchen
<ul style="list-style-type: none"> • отель + отель - отмена • авиабилеты + авиабилеты -возврат • airbnb + airbnb -отмена + airbnb -возврат 	Russland	Unterkunft & Flug
<ul style="list-style-type: none"> • путешествие + путешествие -отмена 	Russland	Reise
<ul style="list-style-type: none"> • hotell + hotell -avboka • flyg + flyg -avboka • airbnb + airbnb -avboka 	Schweden	Unterkunft & Flug
<ul style="list-style-type: none"> • bokning 	Schweden	Buchen
<ul style="list-style-type: none"> • hotel • hotel -storno + hotel -stornieren + hotel -stornierung • cancellazione dell'hotel + hotel - annulla 	Schweiz	Hotel
<ul style="list-style-type: none"> • buchen • ferienwohnung + unterkunft + privatzimmer • urlaub -storno + urlaub - stornierung • airbnb + airbnb - storno + airbnb -stornieren + airbnb -stornierung • airbnb + cancellazione di airbnb + annulla airbnb 	Schweiz	Unterkunft, Urlaub buchen

<ul style="list-style-type: none"> reisen + reisen -storno + reisen -stornieren + reisen -stornierung flug + flug -storno + flug -stornieren + flug -stornierung 	Schweiz	Reisen & Flug
<ul style="list-style-type: none"> viaggio + viaggio - annulla 	Schweiz	Reise
<ul style="list-style-type: none"> volo + cancellazione del volo +annulla il volo 	Schweiz	Flug
<ul style="list-style-type: none"> rezervace cestování + zrušení cesty + cestování - zrušit airbnb + zrušení airbnb + zrušit airbnb 	Tsch.Rep	Reise, Airbnb reservieren
<ul style="list-style-type: none"> let + zrušení letu + zrušit let 	Tsch.Rep	Flug
<ul style="list-style-type: none"> hotel zrušení hotelu + hotel - zrušit 	Tsch.Rep	Hotel
<ul style="list-style-type: none"> booking hotel hotel cancellation + hotel - cancel airbnb + airbnb cancellation + cancel airbnb 	USA	Unterkunft buchen
<ul style="list-style-type: none"> hotel austria + hotel vienna + hotel salzburg + hotel innsbruck + hotel graz to travel + travel cancellation + travel - cancel flight + flight cancellation + cancel flight 	USA	Reise, Flug, Hotel Österreich
<ul style="list-style-type: none"> hotel a szálloda lemondása + hotel - visszavonás utazás + utazás törlése + utazás - visszavonás 	Ungarn	Hotel & Reise
<ul style="list-style-type: none"> foglalás airbnb + airbnb lemondás 	Ungarn	Buchen & Airbnb
<ul style="list-style-type: none"> járat 	Ungarn	Flug
<ul style="list-style-type: none"> hotel hotel wien hotel -storno + hotel -stornieren + hotel -stornierung reisen + reisen -storno + reisen -stornieren + reisen -stornierung flug + flug -storno + flug -stornieren + flug -stornierung 	Österreich	Hotel, Reisen & Flug
<ul style="list-style-type: none"> urlaub österreich + urlaub wien + urlaub salzburg + urlaub innsbruck + urlaub graz urlaub -storno + urlaub - stornierung 	Österreich	Österreich Urlaub
<ul style="list-style-type: none"> booking österreich+booking graz+booking wien+booking salzburg+booking innsbruck 	Österreich	Österreich Buchen
<ul style="list-style-type: none"> buchen ferienwohnung + unterkunft + privatzimmer hotel österreich + hotel salzburg + hotel innsbruck + hotel graz airbnb + airbnb - storno + airbnb -stornieren + airbnb -stornierung 	Österreich	Unterkünfte Österreich buchen