# Autobus: Selection of Passenger Seats Based on Viewing Experience for Touristic Tours


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**Figure 1. The *East* bus tour on the island of Madeira classified with the *Autobus* system. The tour starts and ends in Machico (marked on the map) and the driving direction is counterclockwise. The pictures show scenic views that can be discovered on the trip. Base map and images ©Google, 2016.**


## ABSTRACT

Choosing a seat for traveling can be a complex evaluation of constraints depending on personal preferences. There are websites that help to choose the best seat in a bus, in a train, or on an airplane. However, these recommendations only consider seat-related factors and not the view from the window. While a scenic view rarely influences the decision for a seat on a plane, it is much more important for train rides and especially for scenic bus tours. Therefore, travel website users often discuss which side offers the best view on a specific trip. We propose an algorithm, which decides on which side of the road the view is the most scenic based on Google Street View images. These results can be used by travelers to choose a seat and by scenic tour providers to balance the scenic views between sides or add options during checkout.





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## INTRODUCTION & MOTIVATION

When planning a journey, picking the right seat can have significant influence on personal comfort during the trip. For flights, websites like SeatGuru[1] offer information on seat-related factors that might affect comfort. Besides flights, where the view out the window is only one of many factors influencing the decision for a certain seat, it is much more important for other means of transportation such as a train or a bus. As such, exploring travel destinations by bus is a common activity. Currently, while planning a tour, travelers discuss the question on which side of the bus to sit with other, previous visitors on various travel websites such as TripAdvisor[2].

[1]https://www.seatguru.com/

[2]http://www.tripadvisor.com

We present *Autobus*, a system that aims at improving the travel experience by predicting which side of the road offers the most scenic view (Fig. 1). This information is generated by a machine learning algorithm that processes images from Google Street View (GSV). Processing raster image information over alternatives ensures that the views are visible from the road, and can be applied to planned touristic routes. While the decision on the side that offers a more scenic view is highly subjective, our algorithm correctly predicts the user-informed classification for nearly 80% of road segments, as our evaluation showed. We have processed GSV images of Madeira Island as these present a wide variety of views – mountains, coasts, forests and urban sides, however, we believe that our approach is highly scalable to touristic tours anywhere in the world. This information can be used for various purposes, discussed more thoroughly later in the paper.

## RELATED WORK

Our work was highly inspired by the *Autobahn* system of Runge et al. [13]. Their system was designed to generate scenic routes using GSV images to classify route segments based on their visual characteristics in order to enhance the driving experience. It created a grid for a certain region of interest and classified each grid cell with one of six scenic attributes: "sightseeing", "mountain", "water", "nature and woods", "field", and "non-scenic". Both systems, *Autobus* and *Autobahn* use the same underlying pre-trained "Places" neural network created by Zhou et al. [25] to classify GSV images. In contrast to *Autobahn*, we do not stitch the images from GSV before classification, but instead, use the Google Pro API to retrieve higher quality images. We achieve a higher classification performance than Runge et al. as there are no stitching artifacts that negatively influence the algorithm. Therefore, we are also able to label our GSV images with a more fine-grained set of 116 tags compared to the 6 high level categories in *Autobahn*. In contrast to the main purpose of *Autobahn* of creating scenic tours, we explore how the *Autobus* system can enrich the experience on existing touristic bus tours.

In addition to the work of Runge et al. there is a large corpus of related work regarding the generation of scenic tours. Already in 1995, Golledge [4] highlighted the importance of scenic tour generators. Subsequently, scenic route generation systems were presented by various researchers [12, 17, 22]. Hochmair et al. [5, 6] use information about nearby points of interest (POIs) to detect if a route segment is scenic or not. The *GPSView* system by Zheng et al. [24] is similar to the approach of Hochmair. While Hochmair analyses the distance from certain POIs to the road, *GPSView* takes into account quantities of geo-tagged photos taken from the road to determine if a route segment is scenic or not. Similar, Lucchese et al. [9] suggested a system that generates personalized touristic tours nearby based on previously visited POIs, extracting the information from posts on Flickr and Wikipedia. Following the rising popularity of scenic route generators, Google has freshly released the Google Trips [3] application, which attaches the company's POI knowledge bases with information about the user's preferences and amount of available time in order to create a personalized tour. The system by Shen et al. [16] offers a highly customizable sightseeing navigation system that suggests routes and POIs that the user might want to see along the way using information about the user's situations.

In the field of transportation science, the majority of related work [19, 20] focuses on improving the efficiency of urban bus journeys, aiming to improve the overall travel experience as well. As such, Stamboulis et al. [18] showed that even mass-oriented tourism is shifting towards personalized tours, often with the help of widely accessible information on the Internet and tour generation applications.

Improving touristic experiences was also in the scope of HCI researchers in the past. The REXplorer mobile game designed by Ballagas et al. [1] aimed at bringing "serious games" and location-based gaming to the domain of tourism, targeting a young audience. The game encourages sightseeing and interest in the history of the user's city by engaging the gamer with virtual spirits of the city's main historic figures, fighting the belief that "guided tours are boring", but, at the same time, not replacing the actual tours but raising the user's interest in those. Similarly, Schöning et al. [15] evaluated how information generated on-the-fly about a POI can be presented interactively using an augmented reality approach. The research of Marshall et al. [10] analyses, how tangible multi-touch surfaces could be adapted to multi-user interactions between users in a touristic center in the planning phase of a trip. Kinoshita et al. [8] looked at the POI suggestion problem from a different perspective and introduced an approach that recommends streets with touristic atmosphere rather than POIs. Very recent work of Zhang et al. [23] investigates, how generating touristic trips differs when performed by a group of people, including inter-group communication, labor & information search division, and cultural difference between the tourists.

In contrast to the related work, rather than generating scenic tours, the *Autobus* approach aims at improving existing tours by allowing tourists as well as tour providers to examine the scenic qualities of these tours. By combining methods from computer vision and machine learning, our system has a main goal to improve existing touristic bus experiences by letting the stakeholders explore their options.

To conclude the related work analysis, we need to note that besides approaches to routing, there is other work on determining if a view is scenic or not, such as the *ScenicOrNot* dataset by Workman et al. [21]. Instead of explicitly processing the image to find out what is portrayed in it, their system specifically answers the question if a view is scenic, comparing the image to others that have been rated by people on a scale from 1 to 10 (3.0 or less counted as "non-scenic" and 7.0 or more meant that the view was enjoyed). Designed to answer the question whether a view is scenic, we expect that this method might have comparable or even better results in finding scenic images than our machine learning approach with the "Places" database, but it is less adjustable to the end users, who might want to specifically see, e.g., mountains or ocean views.

## THE AUTOBUS PIPELINE

### KML Bus Tour Information (a)

We used the island of Madeira, Portugal, as a test case for our application but in general, it can classify all tours available

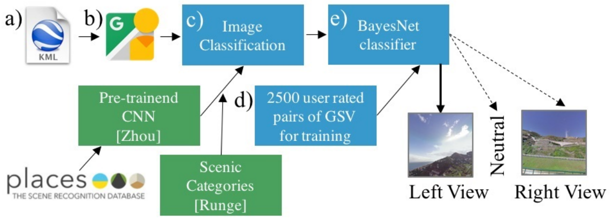


**Figure 2. The *Autobus* pipeline: GSV images are classified with a CNN. A BayesNet classifier predicts the most scenic views with an overall accuracy of 79.52%.**

in the form of a Keyhole Markup Language (KML) file (see Figure 2a). The landscape of Madeira offers a wide variety of views, from city streets in the capital of Funchal to rural areas with fields and wild nature, and from coastal views to picturesque mountain peaks over 2000m above sea level [11]. In addition, tourism is a very important part of the island's economy [2]. Should users be interested in qualities that are not represented on Madeira Island – e.g., processing a bus tour through the Rocky Mountains in Canada or Patagonia in South America – they might need to repeat step d) of the pipeline, so that our system could learn the scenic properties of that area.

### Extracting GSV images (b)

After the KML file had been generated, we extracted GSV images along four major bus tours on Madeira (Figure 2b). The tours, labeled by their provider as *Blue* and *Red*, circulate around the Funchal area and are about 17km long. The other two tours that we used for our analysis start in Funchal and cover the island round trips through Porto Moniz (*West*) and Porto da Cruz (*East*). These two tours are about 115km long. For all these tours we downloaded a total of 2500 pairs of GSV images (one pair of images every 50m) that show the views from the left and the right sides of the bus (we removed the cases where the tours lead through tunnels or had no GSV available) through the Google Pro API. The resolution of the extracted images is 2048x2048. The images were downloaded on the left and right side from the driving direction with pitch of 0° and field of view of 90° (see Figure 3 for examples).

### Image Classification and Assigning Place Tags (c)

In the next step, the views were processed using the Caffe Deep Learning Framework for neural networks [7] and the "Places" database by MIT [25]. The database creators used crowdworkers to assign place tags to different images, including both indoor (conference room, fire escape, etc.) and outdoor classifications (from a gas station to a palace). Their convolutional neural network was trained with 2,448,873 images of the ImageNet Dataset and showed an accuracy of slightly above 50% on the evaluation dataset. As an output of their classification, each processed image is assigned probabilities for each of the 205 place tags. We have selected 116 characteristics out of these 205 that reflect outdoor views one could see from the bus (e.g., ocean view, forest, mountain, highway, parking lot, and similar) – indoor and irrelevant place tags were not considered. As a result of this step, each GSV image was assigned five top place tags from these 116 predicted by the neural network, as well as their probabilities.

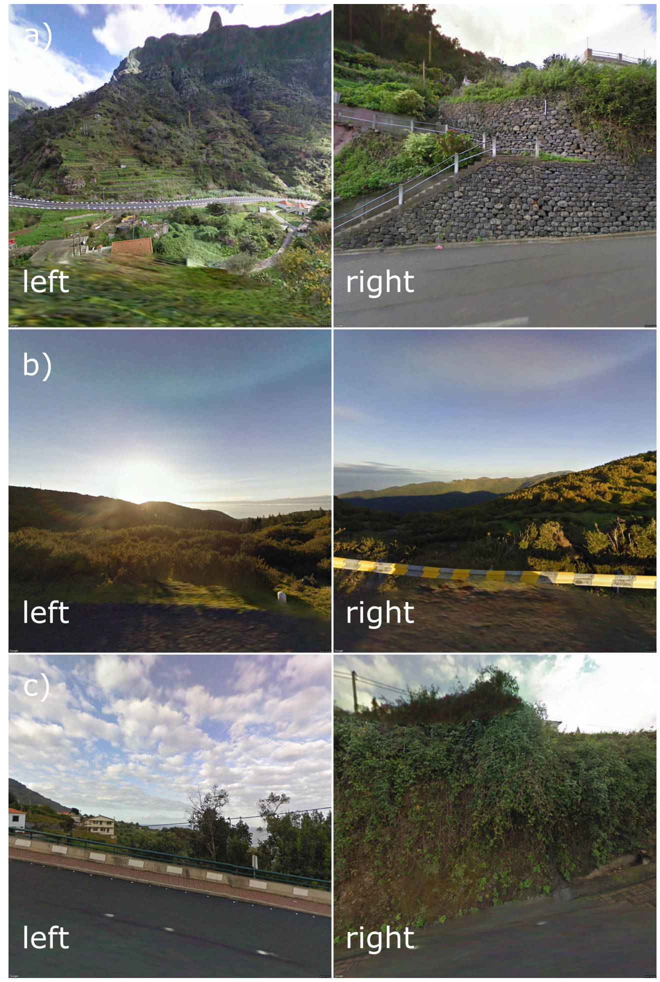


**Figure 3. Three pairs of GSV images from the survey: a) typical pair of images where the left side was preferred by the survey participants, b) typical pair of images where users did not agree as both sides were rated as scenic and c) both sides were rated as not very scenic. ©Google**

### Collecting Training Data (d)

To train our classifiers, we asked 50 volunteers to rate 2500 pairs of GSV images using an online survey. We asked the participants to choose the more scenic image from a pair and rate their preference on a 7-point Likert scale, from "strong preference for the left image"(1) to "strong preference for the right image"(7) for 100 pairs of images. The order in which the image pairs were presented was chosen randomly.

The survey showed, that even though *scenic* is a highly subjective category, the participants agreed on over 47% of the images that they belong to one of the of the classes "Left" (1-3 on the Likert scale), "Neutral" (4) and "Right" (5-7). In Figure 3a) we expose an example of image pairs from the survey, on which participants agreed on the class "Left". For the remaining cases, where disagreement between the users has occurred, often both images showed a scenic landscape as shown in Figure 3b), or both images pictured rather non-scenic views as shown in Figure 3c). These cases of disagreement between the users have been added to the "Neutral" class for the classifier training purposes.

### Classifier Training & Testing (e)

In the next step, we used the tagged images to train a classifier to predict whether the left or the right view offers a more scenic outlook. As the input to the classifier, we used probabilities of 116 place tags from the convolutional neural network. The probabilities for the same place tag from the left image were subtracted from the right image and used for learning. As an output, the classifier had to rate the pair of images as one of 3 classes ("Left", "Neutral" or "Right"). 10-fold cross-validation testing showed that the REPTree classifier was able to predict, to which of the 3 classes a pair of images belongs with an accuracy of 62.04% (precision$_M$ = 44.81%, recall$_M$ = 56.69%, $F_{1_M}$ = 50.05%)

In order to boost the accuracy of the classifier, we decided to re-run the learning and testing on sets of neighboring images. We opted to train a classifier on route segments of 10 pairs of images each. These segments are about 450m long: a bus driving at 60km/h (37.28mph) would need around 30 seconds to travel one segment. The classifications for route segments were generated by averaging values of the contained images. We tested the segments with 10-fold cross-validation as well, and it showed that this fusion has increased the overall accuracy when using a Bayes Network classifier to 79.52% (precision$_M$ = 66.74%, recall$_M$ = 70.00%, $F_{1_M}$ = 68.33%). Therefore, due to the increased accuracy, we believe that the replacement of individual points with route segments is favorable for purposes of overall route analysis.

It is important to note that no views from the "Left" class were classified as "Right", and vice versa (which would be the worst type of error for our classifier).

To conclude, our *Autobus* pipeline is able to predict with an accuracy of 79.52% on segments of 450m, whether the right or the left view offers a better lookout. An example result of our system is shown in the centre of Figure 1. It is interesting that *Autobus* recognized the whole coastal path as being more scenic on the right (the direction towards the seaside). On the *Red* and *Blue* routes, which drive around the city and screenshots of which we decided not to include in this paper, the views were rated as almost exclusively "Neutral", which means that for city bus tours an approach looking for points of interest is likely to be more informative, while *Autobus* is more interesting in rural areas, where POIs are rather sparse.

## AUTOBUS APPLICATION SCENARIOS

The *Autobus* pipeline opens a large set of application scenarios. The most interesting application in our opinion is an extension to seat selection systems that would take into account the scenic values from the windows on different sides on bus tour routes. As such, the *East* bus tour (see Figure 1) generally offers better views on the right side of the bus, mainly because of the coastal scenes. Our system can also reveal interesting segments on which it is not obvious from the map, which side offers a better view. Another use case would be an application for smartphones or wearables that alerts the tourists about upcoming magnificent views in advance.

For the bus tour providers, there are several possible application scenarios for *Autobus* as well. Tour providers could check their tours in advance and revise in order to balance scenic views on both sides. As such, the abovementioned *East* route could be modified to show the sea views to passengers on the left, or to compensate for the coastal scenes with more mountain views. Using *Autobus* functionality, a selection of N best views on both sides can be automatically generated to help the user decide which side they want to sit on. Balancing views on the sides of the vehicle is a completely new routing paradigm, not researched as intensively as shortest or fastest path or other methods proposed by Golledge [4]. Alternatively, the price of the seats could be adjusted to reflect the view from the window. The automatic approach can be also extended by surveying real users of touristic bus tours about their scenic view experience and their seat.

Alternatively, the functionality could be extended to support other means of transportation, such as non-touristic buses or trains that cross a scenic landscape.

As passengers in an autonomous car do not have to concentrate on the road and thus may look around and enjoy the view, *Autobus* could also be integrated in its navigation algorithms as the fastest route is not always a primary requirement [14].

## CONCLUSION & DISCUSSION

We presented our *Autobus* system, a computer vision and machine learning pipeline that is able to suggest seating places on bus tours based on their scenic quality. The system predicts, from which side of the bus the view is better with an accuracy of 62.04% for a single pair of images and 79.52% for 450m long segments of the route. We reported the results of an online survey with 50 participants which was used to train the classifier. Image classification was performed using the Caffe network pre-trained with the "Places" database from MIT. We trained *Autobus* with images from Madeira Island as it features a wide selection of scenic qualities, but our method is scalable to the whole world. In addition, we outlined possible applications for our system, targeted at novel end-user applications and bus tour improvement.

The reported accuracy of the system is satisfactory to draw generic conclusions about a bus route, but not high enough for in-depth analysis, especially when considering only one image at a time. In our opinion, the main reason for sub-par accuracy of the method is the subjectivity of scenic qualities, which results in disagreements between participants of the survey and noisy input data which, in turn, always decreases performance of any types of classifiers. Nevertheless, the *Autobus* system shows satisfactory results for route segments and overall route analysis.

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