High Enough? Explaining and Predicting Traveler Satisfaction Using Airline Reviews

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Introduction

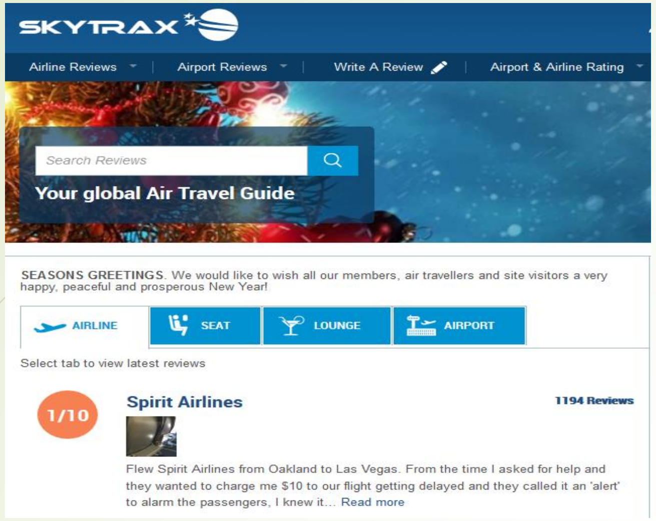
Air travel is one of the most frequently used means of transportation in our every-day life. In the last decades, air travel has become one of the most frequently used means of transportation. The International Air Transport Association (IATA) expects traveler numbers to reach 7.3 billion by 2034, representing a 4.1% average annual growth in demand for air connectivity.

Thus, it is not surprising that an increasing number of travelers share their experiences with airlines and airports in form of online reviews on the Web. In this work, we thrive to explain and uncover the features of airline reviews that contribute most to traveler satisfaction.

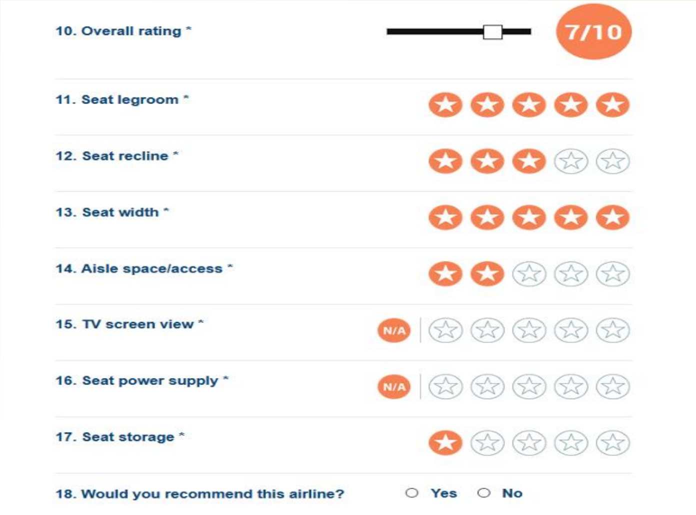
Each review category consists of several five-star ratings as well as free-text review content.

Keywords

- Airlines reviews
- Skytrax
- Traveler satisfaction
- User satisfaction prediction
- Features analysis



a) reviews



b) ratings

A growing number of customers share their experiences and viewpoints on airlines and airports in form of online reviews in order to help others to better judge airline and airport quality. Such reviews may consist of free-text reviews combined with ratings.

Specially our goal is work on travelers ratings and reviews satisfaction up in the following two research questions that guide our work:

RQ1: Which airline review features are most indicative for traveler satisfaction?
RQ2: To what extent can we predict traveler satisfaction using the available rating and inferred sentiment of airline reviews?

EXPLAINING TRAVELER SATISFACTION and Methodology

In this section, we aim to answer the first research question of our work (RQ1) and determine the review features that contribute the most to traveler satisfaction.

We use the overall rating to evaluate how the different review features influence the traveler's satisfaction.

- ✓ Overall scores
- ✓ Rating and inferred features with the overall ratings by user
- ✓ Reviews on Airport, Lounge, Airlines Seat.

Predicting Traveler Satisfaction

In this section, we aim to address our second research question (RQ2:To what extent can we predict traveler satisfaction using the available rating and inferred sentiment of airline reviews?) in order to determine the features that can be exploited to predict the final traveler satisfaction.

- Formulate the task a binary classification problem.
- Given reviews marked as either positive or negative satisfaction.

Predicting Traveler Satisfaction Methodology:

We performed our experiments using several standard classification algorithms:

- ✓ NaiveBayes
- ✓ C4.5
- ✓ Random Forest
- ✓ CART
- In this work, however, we report the results of the Hoeffding

Tree.

We chose this algorithm due to its practical advantage for real-time data mining.

Methodology

- To determine the best performing features for traveler satisfaction prediction, we trained and evaluated the classification model in the following three settings.

1. for each single rating feature, we created a separate classifier and evaluated its performance.
2. we used a combination of features that highly correlate with the traveler satisfaction while having a low inter-correlation
3. we trained a model solely based on the inferred review text sentiment.

Methodology

we report the prediction accuracy by means of the F1-score(F1) and Area Under the ROC curve (AUC)

Airport reviews

Feature	F1	AUC
Overall	0.963	0.948
Queuing	0.869	0.875
Airport shopping	0.859	0.876
Terminal cleanliness	0.828	0.814
Terminal seating	0.791	0.534
Food beverages	0.792	0.530
WiFi connectivity	0.774	0.519
Terminal signs	0.800	0.502
Airport staff	0.678	0.499
Combination	**0.967**	**0.976**
Airport Sentiment	0.719	0.715

Lounge reviews

Feature	F1	AUC
Overall	0.834	0.878
Comfort	0.762	0.839
Staff service	0.768	0.819
Bar beverages	0.783	0.838
Catering	0.783	0.829
Cleanliness	0.773	0.817
Washrooms	0.750	0.826
WiFi	0.743	0.795
Combination	**0.837**	**0.884**
Lounge Sentiment	0.773	0.822

Airline reviews

Feature	F1	AUC
Overall	0.838	0.971
Value money	**0.863**	0.940
Cabin staff	0.794	0.884
Seat comfort	0.750	0.843
Food beverages	0.741	0.827
Inflight entertainment	0.693	0.754
Ground service	0.622	0.533
WiFi connectivity	0.615	0.509
Combination	0.842	**0.975**
Airlne Sentiment	0.839	0.896

Seat reviews

Feature	F1	AUC
Overall	**0.939**	**0.985**
Seat legroom	0.872	0.919
Seat width	0.847	0.890
Aisle space	0.840	0.895
Seat recline	0.802	0.855
Viewing TV	0.730	0.759
Seat storage	0.711	0.576
Power supply	0.647	0.529
Combination	0.925	0.984
Seat Sentiment	0.812	0.849

Result

- **Runtime considerations:** When training and testing the different classification approaches, we achieved the best accuracy performance using the Hoeffding Tree algorithm. Moreover, we found a maximum model training runtime of 0.06 seconds for this classifier in case of the rating feature combination for airline reviews.
- **Individual rating features:** Our prediction results based on the review categories are shown in Table 2(lounge).using the value-for-money feature (F1 = 0.863) in airline reviews provides higher prediction accuracy than using the overall rating (F1 = 0.838).
- **Combination of rating features:** Overall, the combination of rating features results in strong prediction results with respect to F1-score and AUC. The best performance is achieved with airport and lounge reviews.

CONCLUSION AND FUTUREWORK

In this paper, we discuss how online reviews can be an important source of information to explain (RQ1) and predict (RQ2) traveler satisfaction. We utilized data crawled from the Skytrax portal in order to show that rating features such as airport queuing time, lounge comfort, airline cabin staff quality and seat legroom size highly contribute to the overall traveler satisfaction.

Based on these findings, we trained several classifiers and we report the results of the Hoeffding Tree algorithm. The algorithm is especially suited for real-world settings, where the goal is to continuously mine and predict traveler satisfaction using online reviews.

In our opinion, a limitation of this work is the lack of a direct comparison with other incremental classifiers such as Incremental Tree Induction (i.e., ITI, the successor of ID5R) or FlexDT (Flexible Decision Tree based on fuzzy logic).

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And some more.

Thank you