INSY 669 Project: Group 5

Air Canada Reviews Analysis

based on Skytrax Reviews

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Introduction

Over the past years, the growth of the airline market has led to a lot of competitions. We believe to overcome this competition, each airline company should adopt an effective marketing strategy that will increase their customer satisfaction rates. Nowadays, with everyone having access to media, it is much easier for airlines to track and understand what people have to say about their services.

In this project, we will focus on Air Canada which is the largest domestic and international airline in Canada serving more than 200 airports on six different continents. Their vision is to connect Canada to the world and they are mainly based in Toronto, Vancouver, Calgary and Montreal. The goal of this project is to identify and analyze all the different issues related to Air Canada's customers experience, in order to provide useful insights and recommendations that will improve their customer satisfaction rates. To achieve this goal, we gathered data from **Skytrax website (**https://www.airlinequality.com/airline-reviews/air-canada/**)** via requests and BeautifulSoup packages available in Python**;** where we extracted relevant information that we used for our analysis (Please refer to the table below).

Data Dictionary

Columns Names	Description
title	Review title or subject
user	Name of reviewer/name of person writing the review
user_type	If review has been verified or not
review	Review contents/texts
publish_date	Date when review has been published
Type of traveler	# Type of travelers (Business, Solo leisure, Family leisure, Couple leisure)
Seat Type	Types of seats (economy, business, premium,
Route	Flight itinerary (City of Depart and City of Arrival)
Date Flown	Scheduled date for the flight
Seat Comfort	Rating based on the comfort of the seat (1-5)
Cabin Staff	Rating based on the service provided by crews during flight (1-5)
Food & Beverage	Rating based on food and beverage quality during flight (1-5)

Inflight Entertainment	Rating based on amusement or enjoyment during flight (1-5)
Ground Service	Rating based on the comfort of the seat (1-5)
Wifi and Connectivity	Rating based on speed of internet during flight (1-5)
Value for Money	Rating based on the total cost of flight ticket (1-5)
page	Page number where you can view review on Skytrax website

Flights and Routes Covered in Reviews

We begin our review analysis by looking into the routes traveled by customers, given that we observed mixed reviews regarding their experience with Air Canada.

To fully incorporate the data, we need to first standardize the flight information embedded in reviews. Skytrax website went through a migration process in 2015, after that reviews were structured with more flight details and title functionality. So, for all reviews before 2015, we need to extract as much route information as possible from the review itself.

Data Preprocessing to Extract Destinations Involved

As previously mentioned, data has slightly different structures before and after 2015. With old data, we noticed that some customers would provide their flight routes in the format of either city names or airport codes; but many reviews only mentioned part of their trip that they wanted to emphasize their reviews on. It is possible that a comment talked only about their experiences without mentioning their trips, for example, their experiences with customer service via phone while trying to cancel their trips. Another issue we encountered was how customers presented their route information. From our observations, there are no specific general rules for routes. Some of the customers prefer using IATA code, some prefer cities, and some even use a mix of both in case there are multiple airports in that area.

To extract route information, we performed a data cleaning process to replace IATA codes and standardize mentioned destinations. In order to do so, we extracted free online airport information data and used it as a lookup among airport codes, cities and their countries, then updated geographic information into standardized city names and map countries to these cities, so that we can decide whether customers were on board for domestic or international flights.

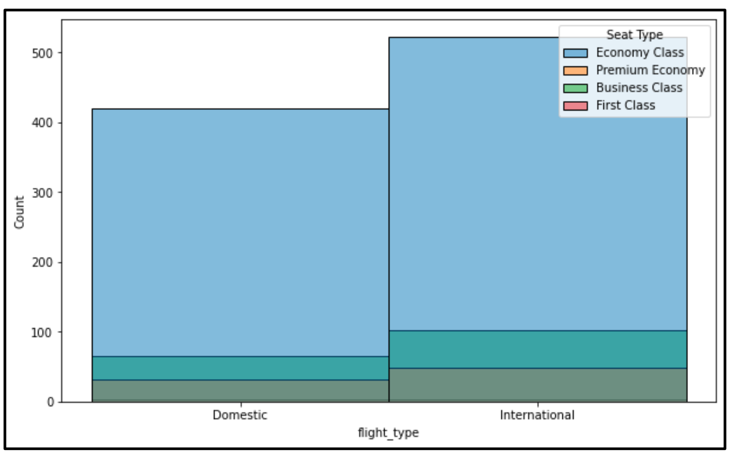
Assumption based on this approach is that, in the case of one city corresponding to multiple countries, we always map that city to the country that appeared first in the lookup search.
For reviews before 2015, we performed text searching through reviews to find any destination information possible; for reviews after 2015, we used the route information provided by customers themselves. After airports/destinations information was extracted, we replaced airport codes if any, then standardizing them into a list of cities per review for further use.

Lift Calculations and City Association via Reviews

With extracted lists of cities, we counted the occurrence of each city mentioned. Out of the top 20 cities mentioned, Canadian cities ranked high compared to international cities, but over half of the cities are outside of Canada, which can be expected considering that the airline does offer a mix of domestic and international services.
List of top 20 mentioned cities as below, ranked by count of mentions:

Toronto, Vancouver, Montreal, London, Calgary, Ottawa, Edmonton, Frankfurt, Los Angeles, Tokyo, Sydney, New York, Hong Kong, Halifax, San Francisco, Boston, Chicago, Rome, Paris, Winnipeg

The bar graph below shows the distribution of international vs domestic trips from Skytrax reviews extracted.



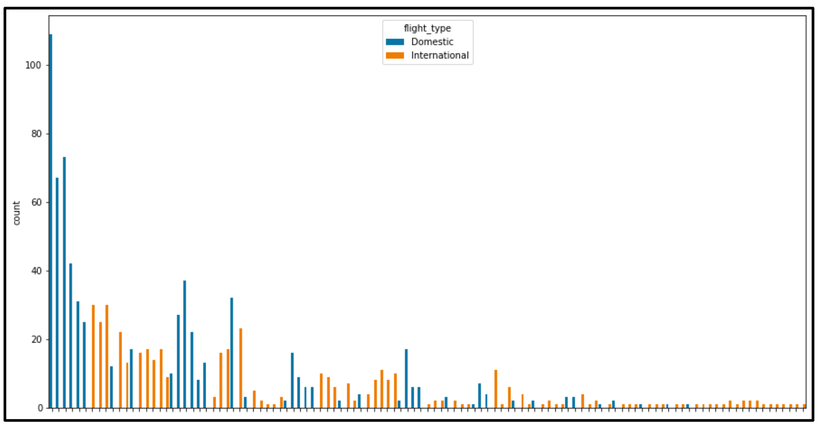
Distribution of International vs Domestic Flights, Break Down by Seat Types

From the histogram above, over 50% of reviews under Air Canada are international flight related. Looking closer to the mention of cities, international destinations are more diverse compared to domestic, which leads us towards city association computation and analysis.

Our focus for city associations is based on the top 20 cities we found previously. We calculated the lift for each of the city combos then transferred lift values into a similarity matrix for visualization. Lift calculation formula used is as below:

$$Lift = Total\ Number\ of\ Reviews \times \frac{\#\,of\ mentions\ including\ both\ city\ 1\ and\ city\ 2}{(\#\,of\ mention\ for\ city\ 1) \times (\#\,of\ mention\ for\ city\ 2)}$$

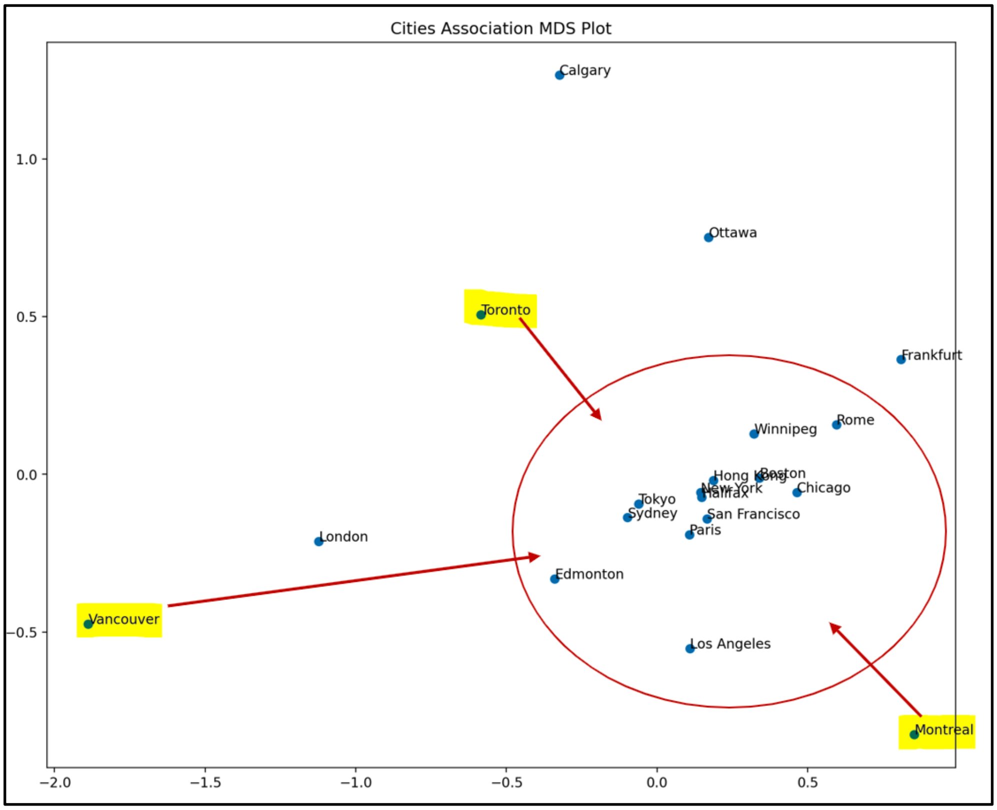
The top association combo according to Skytrax reviews is Toronto and Vancouver. Recall that international flights dominated over half of the reviews we extracted, this indicated that even though over half of the services mentioned are international lines, domestic lines demand is more saturated while international ones are more diverse; meaning that the frequency of people taking a specific set of the domestic lines is high. A great example of that is the Toronto - Vancouver line. These two cities show high counts of association, standing out of all other routes.



Distribution of Top 20 Mentioned Cities' Association in Reviews, Grouped by Flight Type

The first bar in the bar plot above is the Toronto - Vancouver line. Note that the top 5 highest city associations are all domestic (see Appendix: Table 1 for top 10 counts of city association). This shows that Air Canada should consider analyzing further on the top domestic lines taken and understanding people's concerns from there might be helpful.

With city association counts for the top 20 mentioned cities, we proceeded with lift calculation and constructed a similarity matrix, then used the matrix to visualize city association with MDS. According to the MDS plot, we noticed that international destinations (cities located outside of Canada) tend to cluster together, surrounded by the three biggest cities in Canada, located separately from each other.



Top 20 Mentioned Cities Association MDS Plot

Toronto, Vancouver and Montreal are known as the top three cities with a large-scale international airport that hosted lots of domestic and international flights. There are quite a lot of flights among these three, while there are many flights going between these three cities and the international destination cluster we identified. Note that Toronto appeared in many of the associations as its home to one of the largest airports in Canada. From this perspective, though we notice a high volume of international flights, Air Canada should not disregard domestic flights involving Toronto, Vancouver and Montreal, as there are large transactions among them as well.

Sentiment Analysis Based on Routes in Reviews

With the understanding of what kind of lines are discussed among customers, we took these routes information and further proceeded with the actual text contents in each of the reviews. To do so, we performed concatenation between title and review contents, so that both inputs are considered by the sentiment model. However, note that for the old data before 2015, titles are not as structured compared to newer data. To ensure high quality of content, all these reviews before 2015 were not concatenated with the review contents. Based on a set of complete reviews, we then performed stop words removal, tokenization and lemmatization on review texts. The sentiment computation library we apply is TextBlob available in Python. TextBlob returns a score for subjectivity and polarity(sentiment) for each review.

The matrix we used to determine positive vs negative:

Positive reviews	**Negative reviews**
Sentiment score > 0	Sentiment score <= 0

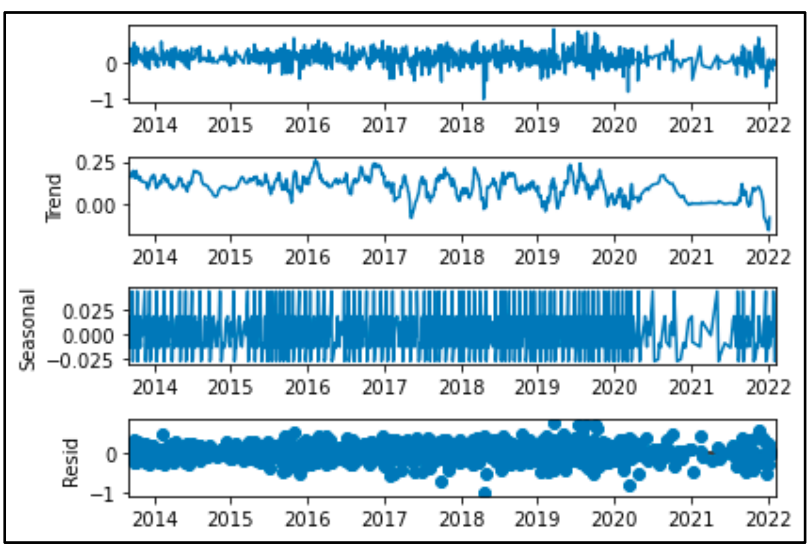
The matrix we used to determine subjective vs objective:

Subjective reviews	**Objective reviews**
Subjective score > 0.5	Subjective score <= 0.5

Out of all 1644 reviews, we noticed 761 of them passed the subjective criteria. To have enough data points for sentiment analysis, we keep all reviews to get a complete view of reviewers' opinions.

Time Series Analysis of Sentiment Scores and Covid-19 Impact

Considering that our dataset has time series characteristics as well, we grouped reviews by date and took the mean of reviews' sentiment posted on that day; then we performed a decomposition on this time series consisting of average sentiment scores. The results of decomposition are shown below.



Time Series Decomposition for Average Sentiment Overtime

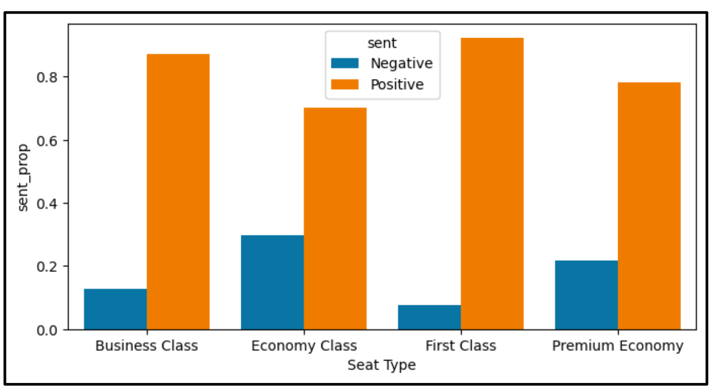
The average sentiment scores generally displayed annual seasonality. Notice that review sentiment scores trend fluctuate each year then start to have a downward trend, especially after the Covid-19 pandemic kicked off in 2020. The Number of reviews after pandemic kick-off is not as much compared to previous years and has an obvious decreasing trend starting from the second half of 2021. This could be understood as the pandemic downgraded customer's experiences as many trips were canceled during that time. In the middle of 2020, as Covid-19 policy loosened, people started to travel again. Near the end of 2020, Covid variants hit the world including Canada, lots of trips are canceled due to strict travel restrictions. Similar situations occurred again at the end of 2021 and the beginning of 2022. People started to book trips and travel due to the loosened travel policy, then encountered large cancellations after Omicron hit globally.

Sentiment Analysis Based on Reviews' Flight Information

In general, Air Canada received most of their reviews on Skytrax as positive based on our model output and matrix we defined above. With each review classified as positive or negative reviews, we can analyze sentiments based on flight information provided by reviewers and apply business understanding to these results.

1. Seat Type

By breaking reviews into different cabin types, we noticed that customers' sentiment distributions behave differently for each class. Below is a bar graph of negative review proportion vs positive for each type of cabin.

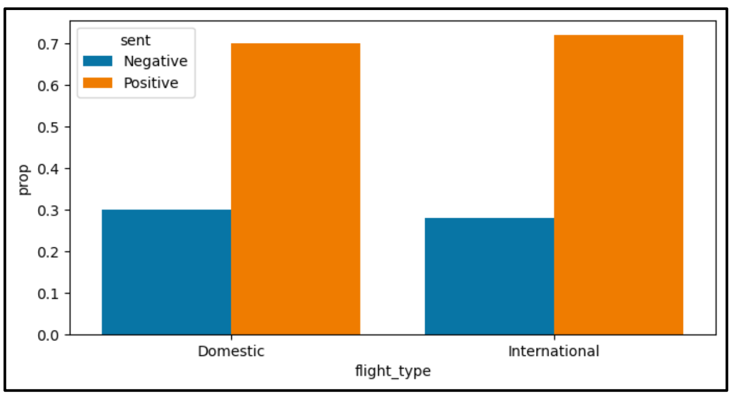


Sentiment Proportion Categorized by Seat Type

Notice that as cabins get upgraded, customers tend to be more satisfied with Air Canada's services. Nearly ⅓ of the economy class customers left negative reviews on Skytrax. As economy class customers take the majority of all services, Air Canada should consider analyzing economy class customers and further looking into the causes behind customers' dissatisfaction in order to improve service quality and customer stickiness.

2. Domestic vs International Lines

Recall that we noticed international lines took over half of the reviews we extracted. However, the proportions of negative reviews vs. positive for both are very similar with around ⅓ of total reviews on Skytrax being negative. Note that the proportion of negative reviews for domestic flights is slightly higher compared to international flights. See the plot below for the proportion bar graph between domestic and international flights.



Sentiment Proportion Categorized by Flight Type

3. Transfer Impact on Sentiment

Out of all reviews we analyzed, 75% of them are related to direct flights and the remaining 25% are transfers related. Proportions of positive and negative reviews for direct and transferred flights are very similar as well, with direct flights having a slightly higher negative sentiment proportion (Table 2 in Appendix).

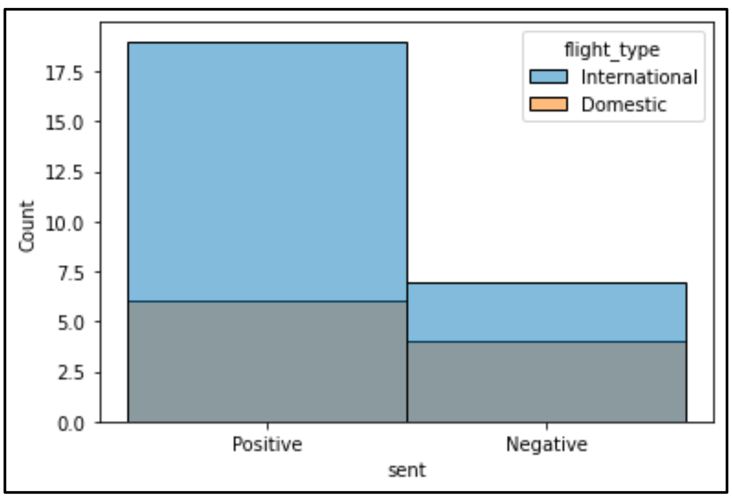
The reasons behind this might be caused by customers who took connecting flights tend to experience multiple airlines at the same time, thus their reviews are based on a comparison between a series of airlines and hence more objective; while direct flights customers only accessed Air Canada services and tend to give relatively subjective reviews.

Cosine Similarity Based on Review Context

To access cosine similarity for extracted reviews, we first computed word frequency in each review, then performed TF-IDF transformation on it. With the word frequency matrix, we then computed the cosine similarity matrix as well as a cosine dissimilarity matrix.

Based on the previous dissimilarity matrix, we can try to visualize the position of each review on a MDS plot and see how sentiment behaved there. Note that based on the visualization, we did not notice specific clusters or an obvious separation between positive and negative reviews. This is caused by people sharing their feedback on a specific set of keywords which we will further look into in the attribute discovery section, either in a positive or negative way. Another consideration here is that MDS might not be a good way to visualize cosine similarity in our case, thus any separation between clusters is not presented well.

With a similarity score defined, we further divided into the most similar reviews identified by cosine similarity which had a similarity score over 0.15. In this set of reviews, the top 5 most mentioned are all Canadian cities. The distribution of positive vs negative reviews with flight type information is shown below.



This demonstrated that around 17% of the reviews have a negative sentiment, lower than what we observed previously over the whole set of reviews, hence review owners in this group were more satisfied on average compared to overall reviewers. However, the ratio of negative over positive reviews for domestic flights is way higher than that of international flights. This shows that within this group, international flights customers tend to be more satisfied with Air Canada services.

Aside from flight characteristics, we also did a keyword frequency analysis based on the most mentioned nouns to get a sense of what these reviewers talked about in their reviews, the result of the top 5 discussed noun keywords are as follows with a descending order of counts:

Customer Service, Line, Hour, Luggage, Time

Line, hour, time are wait time or schedule-related terms, while customer service is a broad topic to explore. This leads us towards topic modeling to further understand what reviewers discussed in their reviews.

Topic Modeling

In order to get more insights into the comments, we conducted a topic modeling. The topic_modeling_3.ipynb contains the code for this part of the project. The pre-processing steps involved looking at all the columns to identify the relevant features that could be included in our LDA analysis. Based on the initial look, we thought it would be interesting to examine the topics mentioned in the reviews and titles columns to take into account different types of customers, seats and flight dates.

Exploratory Word Analysis

We started by taking a look at the word clouds for the titles of the reviews and removing prevalent stop words such as ‘Canada’ or ‘air’ (left: before stop words removal, right: after).

We did the same for reviews and obtained the below word clouds (left: before stop words removal, right: after).


LDA

In the next step, we feed the data (reviews and titles separately) into the topic_generator() function. This function turns a column into a list of words, removes the stopwords before creating a bag of words and running the LDA topic modeling.

We started by generating the topics from the reviews. The word proportions appear really low for the reviews and so we decided to focus on the titles which are more concise.

For the titles, we generated 4 topics with higher word proportions. These 4 topics could be summarized as follow:

- Customers with great experience: mostly positive comments and nothing negative to report
- Customers with a bad experience: with mentions of delays, cancellations and uncomfortable seats
- Customers with a mixed experience: mixed feelings about the experience but great customer experience.

In order to evaluate the topics for the different categories of customers, we also ran the topic generator for each customer category separately. Overall, the topics do not differ much for the different categories.

Sentiment and Attributes Analysis

Sentiment Analysis could help provide deeper insight into public reviews and opinions. Here we are using it to get the most frequently used words to understand more about the attributes that matter the most to the customers. As part of our analysis we used two approaches to classify both reviews and titles into sentiments (positive and negative).

Assigning Sentiments

Approach 1: Using TextBlob library

Based on polarity values returned by TextBlob libraries, we will be classifying reviews into positive and negative sentiments. (Polarity > 0 => Positive, Polarity < 0 => Negative).

We are not using the reviews and titles that were assigned neutral values since the word frequency being built is based on the polarity of the review.

Approach 2: Using Average ratings

As we have ratings on multiple parameters available as part of our dataset, we are using them to classify the reviews as positive or negative.

Calculations Logic:

We have seven different parameter ratings in our dataset, namely, 'Seat Comfort', 'Cabin Staff Service', 'Food & Beverages', 'Inflight Entertainment', 'Ground Service', 'Wifi & Connectivity' and 'Value For Money'. Assuming that a zero rating for any of the above parameters is indicative of the reviewer not submitting any review for that category, we added a column called 'count_ratings' to note the number of individual parameter ratings that are greater than zero. Next we summed up all the individual parameter ratings into column 'sum_ratings'. Finally, average ratings were calculated and stored in 'avg_rating' using the above two columns.

Classification:

- Average ratings >=3 => Positive Sentiment
- Average ratings < 3 => Negative Sentiment

Getting top frequent words

Now that we have our reviews classified into sentiments, we focus on building word frequency dictionaries based on those sentiments. However, to get these words, we first need to preprocess data to get the tokens.

1. Pre-processing

Following steps were followed to get tokens which were stored in two new columns - 'review_tokens' and 'title_tokens'

- Any null values were replaced by blanks.
- NLTK's stopwords were stored in a list and a new stop words list was created to supplement the NLTK list.
- To remove the mention of cities (location / destinations) from word frequency, all the unique cities from the 'Route' column were stored in a list using the GeoText library.

- NLTK was used to split the text into tokens (words) and if the token is not included in stopwords, custom stopwords list and in list of unique cities, the lemmatized form of the word in lower case was added to the list of tokens.

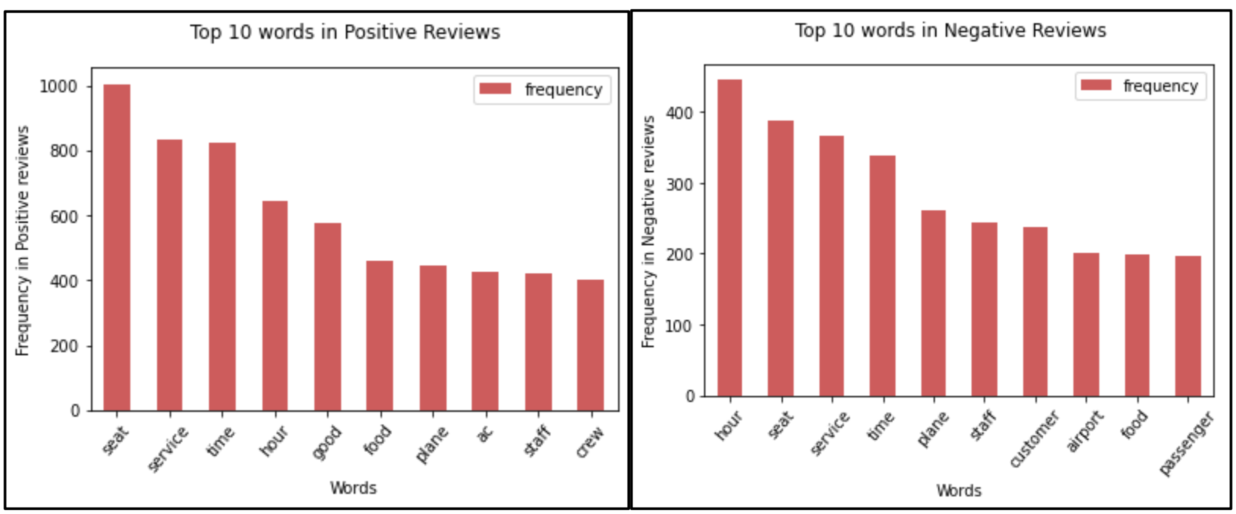
2. Building Word Frequency Dictionaries

The 'build_word_freq' was used to get the word frequency dictionaries. Based on the above sentiments, we pass two lists to this function, one with positive sentiment and other with negative. For each token a key is created in the form of (token, label). Here, the label is zero for tokens appearing in the negative list and one for tokens in the positive list. For every occurrence of a token in a particular sentiment, its frequency is incremented by one. Finally, we obtain the frequency word dictionary at the end.

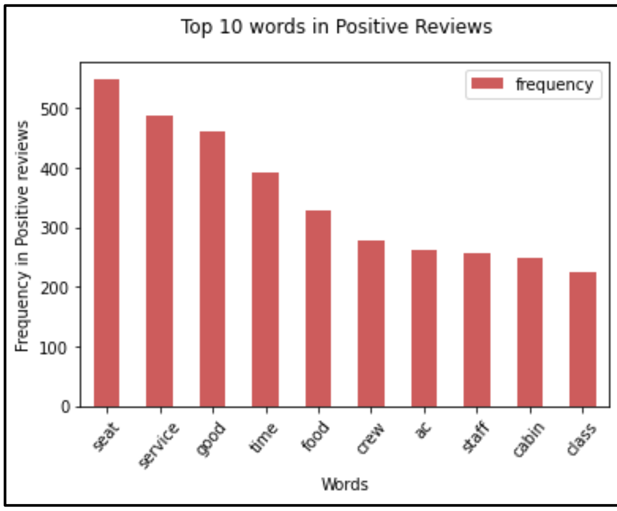
Results based on word frequencies

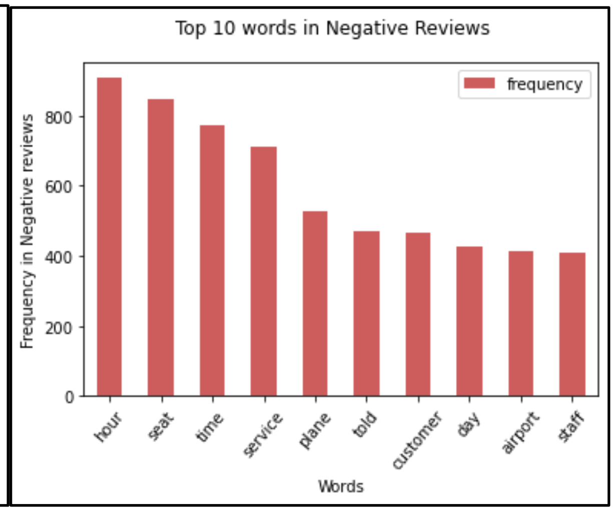
Based on sentiment classification approach, here are the top 10 words found in reviews, based on polarity (positive/negative).

1. Sentiment classification based on TextBlob library



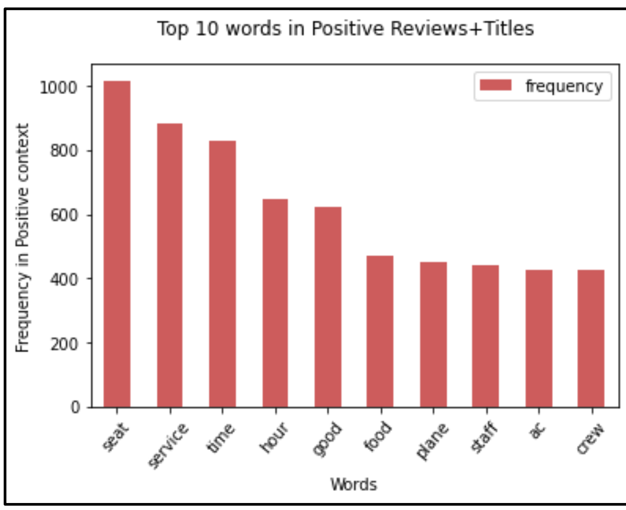
2. Sentiment classification based on Average Ratings

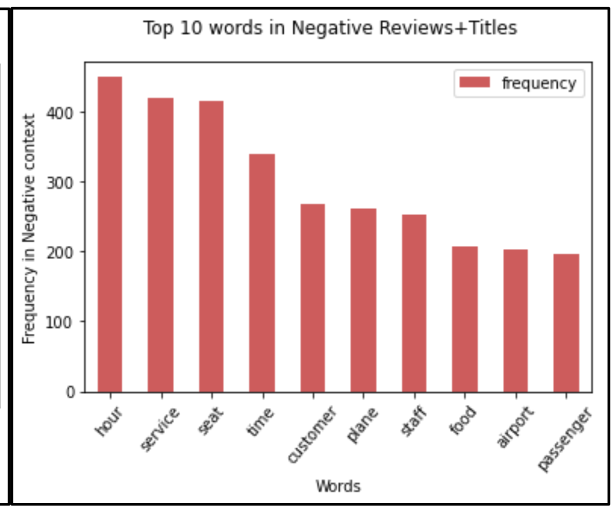




Combining Reviews and Titles

In addition to the above distribution, the following word frequency was noted based on a combination of reviews and titles.





Analyzing sentiment analysis results based on word frequencies

To be specific in terms of good and bad for Air Canada, our observations show that AC and Crew are two of the most frequent words in positive context and are not that frequent in negative context. While words like Customer and Airport come up more frequently in negative contexts. Both these words suggest relation to customer experience at the airport and possibly with staff and services provided there.

On a more general level, an overlook at the results shows that most words are common across sentiments and approach. This shows that those attributes are paramount to customer experience while traveling with Air Canada. Intuitively speaking, time (delays and cancellations), hours (scheduling), food, seat (comfort and arrangement), customer and staff (ground staff and customer support) play a crucial part of customer experience and consequentially part of their reviews and feedback. Though these services are similar for all customers, its satisfactory level would be highly subjective, thus resulting in similar words in both the sentiments. Although, what works in favor of Air Canada here is that numerically speaking, the frequency count of these words is higher in positive context than in negative. However, these are certainly the factors that Air Canada can look into to further enhance their customer experience.

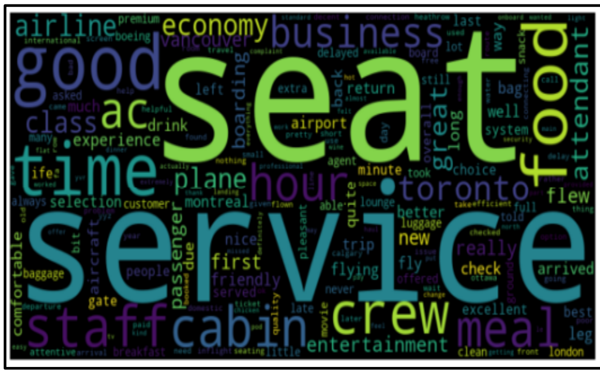
Additional analysis on review parameters

As mentioned we had various review parameters which were used to find the positive and negative reviews based on rating in order to know on which parameters customers were happy and where there is scope for improvement across seat types and types of travelers. Customers with review ratings of 3 and above were considered and findings for few important parameters could be found below and remaining in appendix (table 3,4 and plot 3,4). Here most of Business and First class passengers were happy while customers in the Premium economy segment were happy on some parameters which shows there is some scope of improvements in the economy category. It was difficult to get a clear picture on traveler types to target who were not satisfied with the services due to considerable mixed feelings.

1. Positive vs Negative reviews across Seat and traveler types and word clouds on Value for money:

Seat Type	Reviews on Value For Money	Good raters	Positive reviews (%)	Negative reviews (%)
Business Class	262	170	65	35
Economy Class	1286	504	39	61
First Class	13	8	62	38
Premium Economy	83	45	54	46

Type Of Traveller	Reviews on Value For Money	Good raters	Positive reviews (%)	Negative reviews (%)
Business	226	77	34	66
Couple Leisure	292	113	39	61
Family Leisure	243	107	44	56
Solo Leisure	444	189	43	57

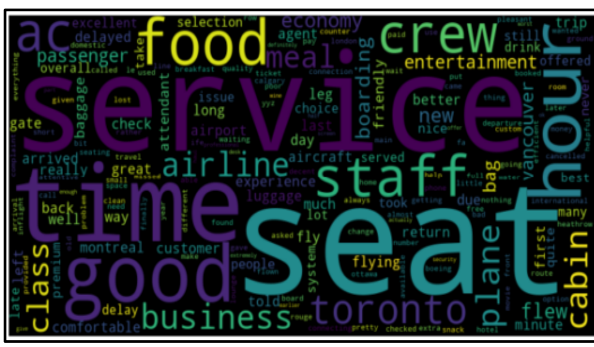


Positive Negative

2. On Cabin Staff Service:

Seat Type	Reviews on Cabin Staff Service	Good raters	Positive reviews (%)	Negative reviews (%)
Business Class	258	209	81	19
Economy Class	1216	638	52	48
First Class	13	10	77	23
Premium Economy	80	46	57	43

Type Of Traveller	Reviews on Seat Comfort	Good raters	Positive reviews (%)	Negative reviews (%)
Business	216	116	54	46
Couple Leisure	270	134	50	50
Family Leisure	232	115	50	50
Solo Leisure	420	237	56	44



Positive Negative

3. On Seat Comfort:

Seat Type	Reviews on Seat Comfort	Good raters	Positive reviews (%)	Negative reviews (%)
Business Class	258	198	77	23
Economy Class	1226	600	49	51
First Class	13	11	85	15
Premium Economy	80	50	63	38

Type Of Traveller	Reviews on Seat Comfort	Good raters	Positive reviews (%)	Negative reviews (%)
Business	216	116	54	46
Couple Leisure	270	134	50	50
Family Leisure	232	115	50	50
Solo Leisure	420	237	56	44

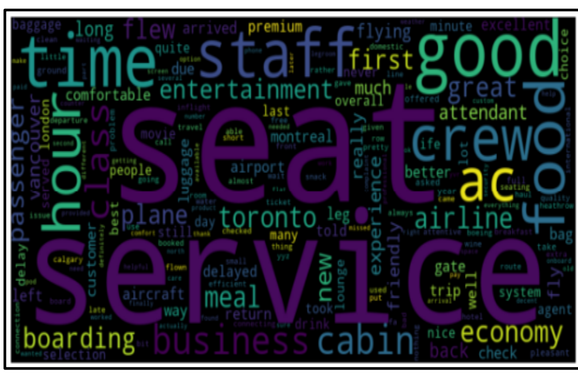
Positive

Negative

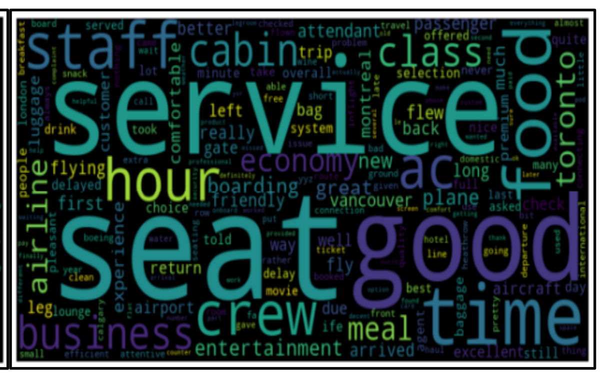
4. On Food & Beverages:

Seat Type	Reviews on Food & Beverages	Good raters	Positive reviews (%)	Negative reviews (%)
Business Class	248	174	70	30
Economy Class	1003	406	40	60
First Class	12	8	67	33
Premium Economy	76	42	55	45

Type Of Traveller	Reviews on Food & Beverages	Good raters	Positive reviews (%)	Negative reviews (%)
Business	166	74	45	55
Couple Leisure	208	94	45	55
Family Leisure	191	89	47	53
Solo Leisure	335	166	50	50



Positive



Negative

Recommendations from Analysis

1. Pricing can be competitive for economy and premium economy class to compete with other airlines and have high occupancy. Business and First-class people seem to be comfortable with the services provided but it was not the same for the other two classes.
2. Seat comfort can be improved for economy class in long haul flights keeping in mind the route profitability and number of potential customers

3. Food options specific to routes can make travel more enjoying and give an edge against competing airlines on the route
4. Delays and cancellation can be reduced by introducing buffer time in flight time (example: if flight is of eight hours, it can be made of 9 hours and additional 1 hour can be used to prepare for next flight or to make up the delay) and less contact points for customers during travel to save time and make it more comfortable

Conclusion

Overall, in our analysis we were able to understand the sentiment, more precisely the experience of passengers regarding the services Air Canada offers. From these diverse opinions of customers, it will be easy for airlines to understand all their customers' concerns and figure out a better strategy to enhance their service in the future. As we took a deep dive into the reviews, we noticed that most of the keywords associated with negative reviews are “delayed, cancellations, time, lines, luggages”; however, those associated with positive reviews are usually related to passengers’ inflight experience (staff service, food, entertainment, etc..).

Surprisingly, our findings and insights matched with most recent news, articles and blogs on Air Canada; where people are complaining about the nightmare they have been through in the airport due to Air Canada flights delays and lack of customer support. Then, we strongly recommend Air Canada to develop a strategy that will mainly focus on improving customers' experience at the airport.

There is still a scope for improvement in our analysis. In the future, we are planning to expand our analysis by building sentiment classifier models to predict whether or not a review has a positive or negative sentiment. We will take advantage of the pipeline class from the Scikit-learn library to transform all review texts into numerical values before performing ML classifiers to predict the sentiments of each review.

Appendix

Table 1: Top 10 City Association, Counts and Corresponding Lift; order by count

City 1	City 2	Count	Lift
Toronto	Vancouver	109	0.579939
Toronto	London	73	0.924877
Toronto	Montreal	67	0.568274
Toronto	Calgary	42	0.649919
Vancouver	London	37	0.997835
Vancouver	Sydney	32	3.731858
Toronto	Ottawa	31	0.924131
Toronto	Frankfurt	30	1.085961
Toronto	Tokyo	30	1.126182
Vancouver	Montreal	27	0.487464

Table 2: Count of Reviews under Transfer and Direct Flights with Sentiment Proportion

Flight Type	Count of Reviews under Each Type	Sentiment	Proportion
Transfer	1235	Negative	29%
		Positive	71%
Direct	413	Negative	26%
		Positive	74%

Table 3: Distribution of positive and negative reviews across seat and traveler types for ground services

Seat Type	Reviews on Ground Service	Good raters	Positive reviews (%)	Negative reviews (%)
Business Class	170	118	69	20
Economy Class	910	332	36	39
First Class	7	4	57	36
Premium Economy	78	48	62	25

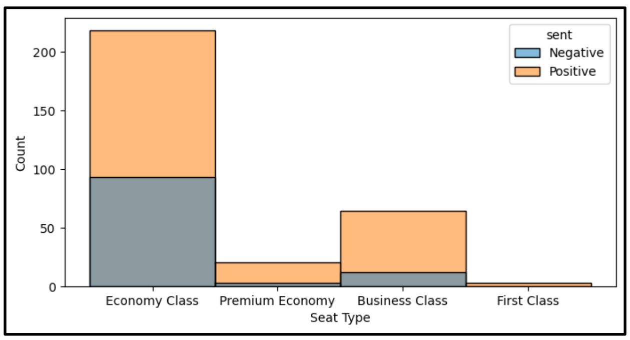
Type Of Traveller	Reviews on Ground Service	Good raters	Positive reviews (%)	Negative reviews (%)
Business	221	78	35	65
Couple Leisure	278	114	41	59
Family Leisure	236	106	45	55
Solo Leisure	430	204	47	53

Table 4: Distribution of positive and negative reviews across seat and traveler types for entertainment

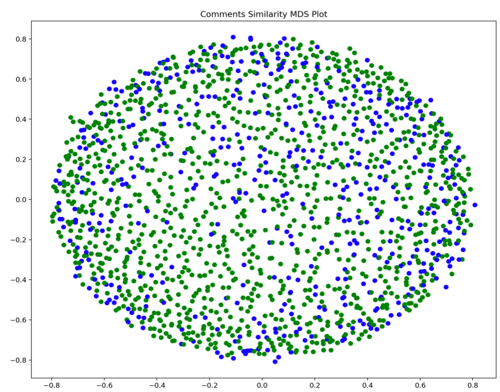
Seat Type	Reviews on Inflight Entertainment	Good raters	Positive reviews (%)	Negative reviews (%)
Business Class	240	192	80	20
Economy Class	951	581	61	39
First Class	11	7	64	36
Premium Economy	73	55	75	25

Type Of Traveller	Reviews on Inflight Entertainment	Good raters	Positive reviews (%)	Negative reviews (%)
Business	154	87	56	44
Couple Leisure	201	136	68	32
Family Leisure	178	123	69	31
Solo Leisure	303	213	70	30

Plot 1: Counts of Seat Type with Sentiment



Plot 2: Cosine Similarity Visualization on MDS



Plot 3: Word cloud of positive and negative reviews for ground services

Plot 4: Word cloud of positive and negative reviews for entertainment