

Redesigning Airplane Interiors via Data Science

DSBA X eleven strategy

TEAM 14

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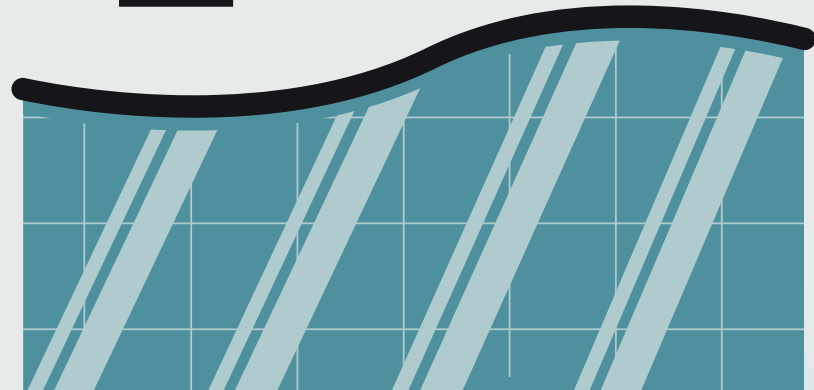
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February 18th, 2022



Agenda

1

Context

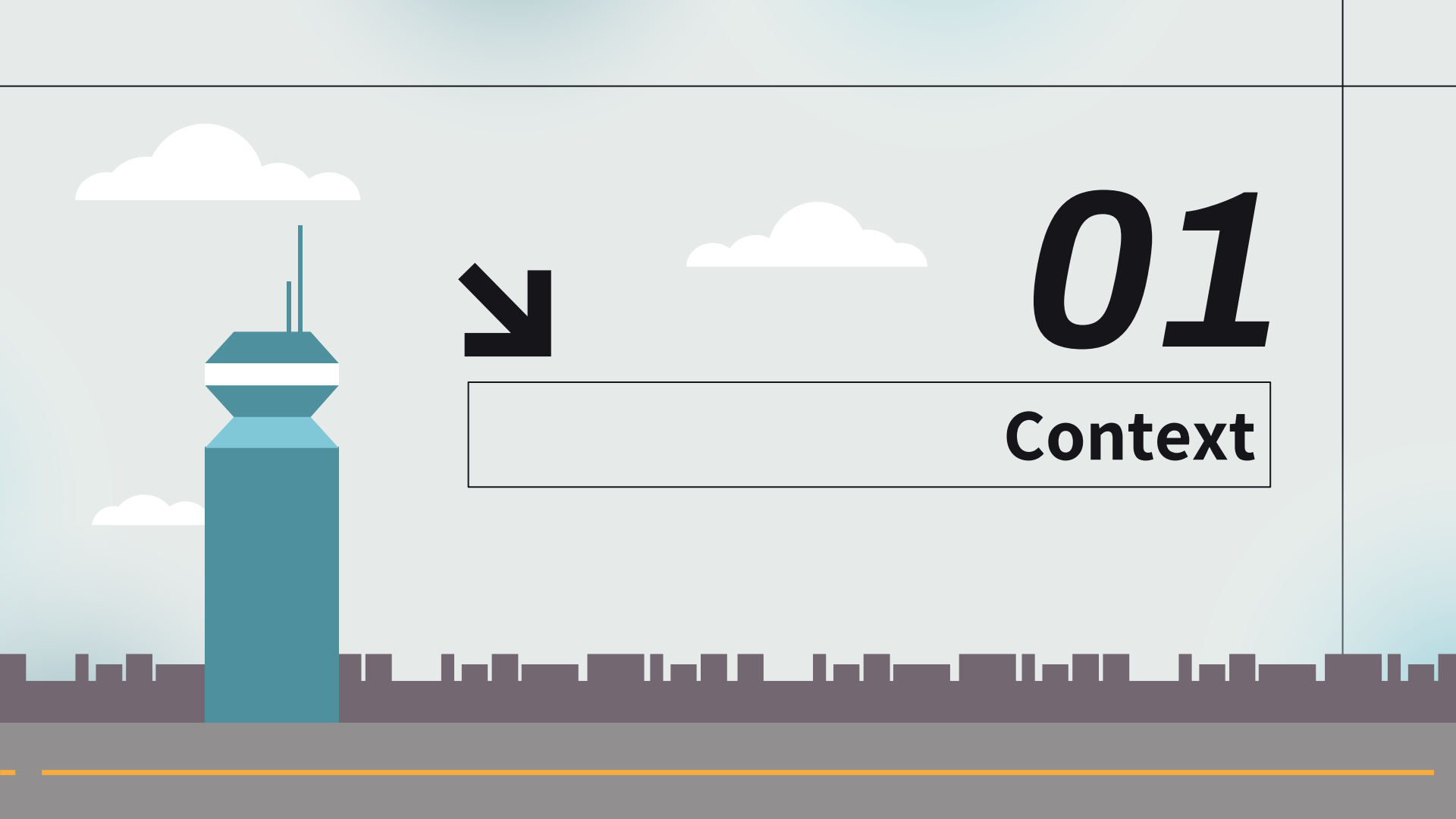
2

Methodology

3

Analysis

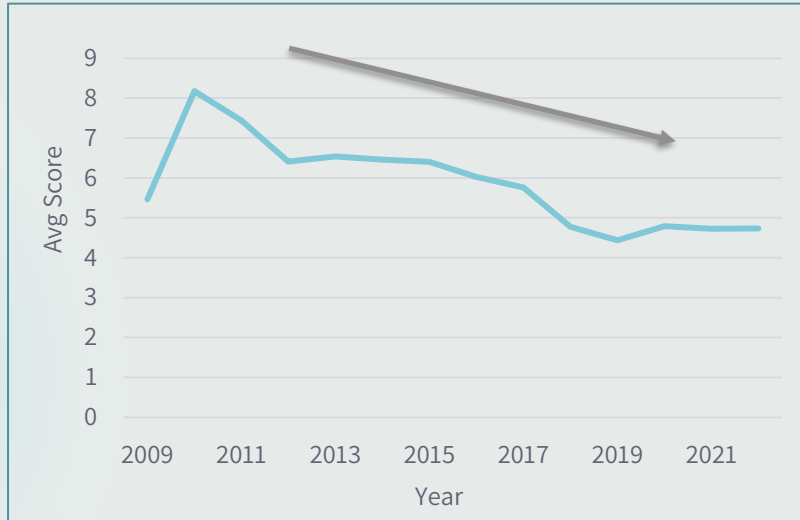




01

Context

Understand how to improve the user experience of airplane passengers

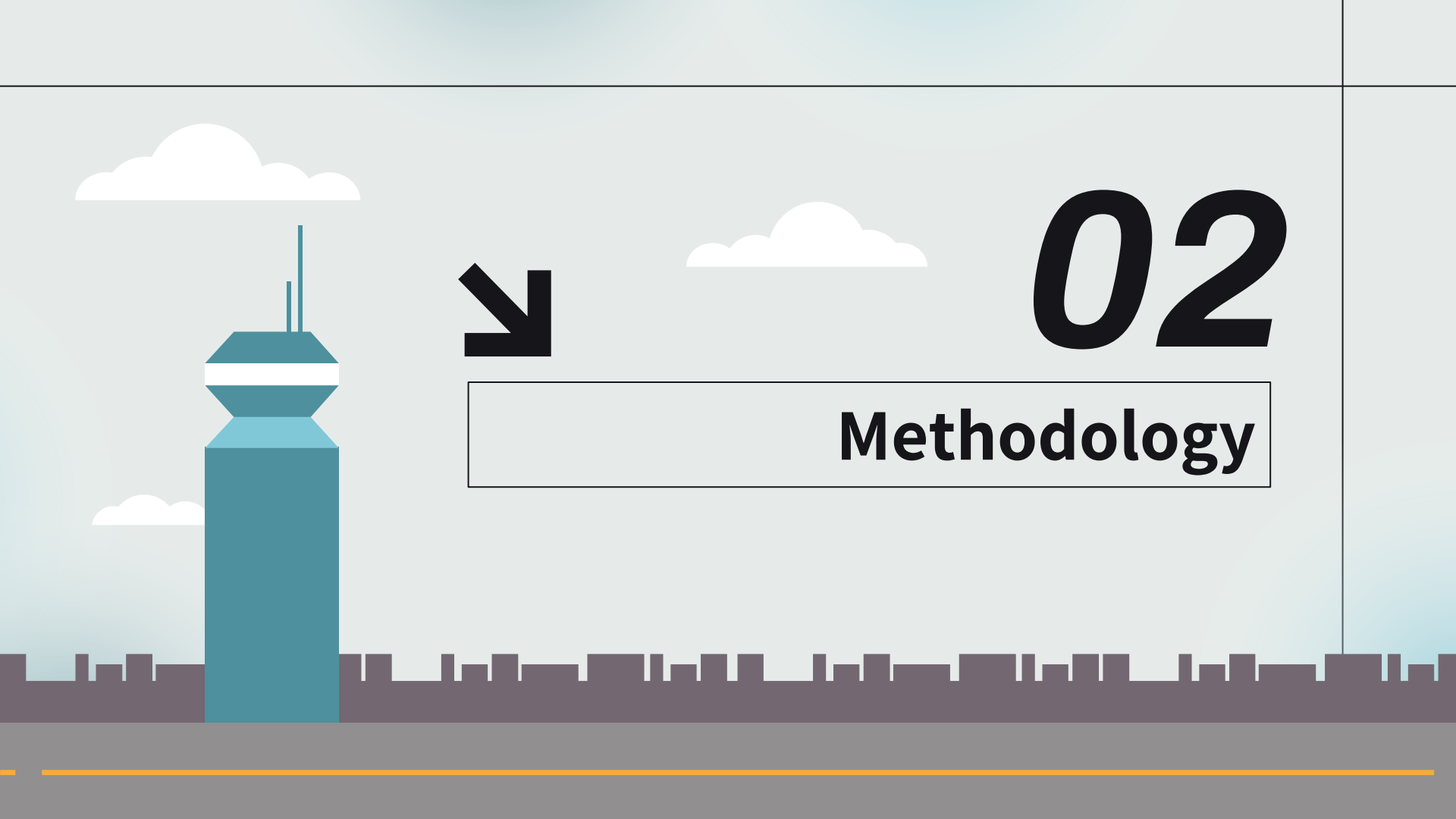


Customer experience is declining in recent years



Identify passengers' pain points about interior design

* Samples scrapped from Skytrax



02

Methodology

Methodology



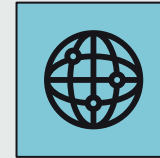
Data

- Web Scrapping
- Data Cleaning



Models

- Topic Modeling
- Sentiment Analysis



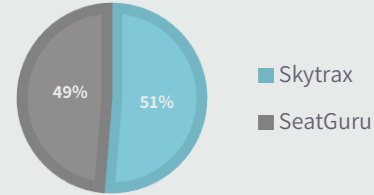
Analysis

- Pain Points
- Recommendations

Web scrapping was used to acquire data

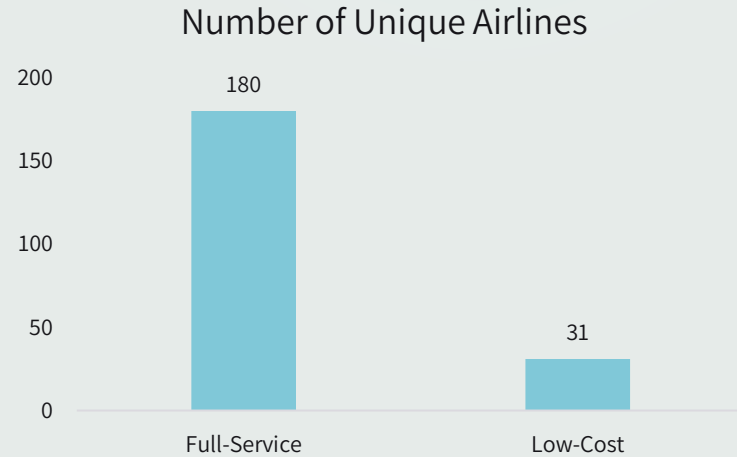
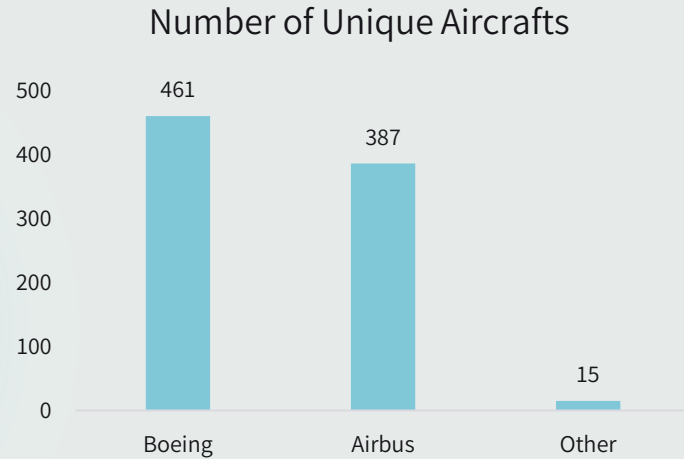


34K reviews

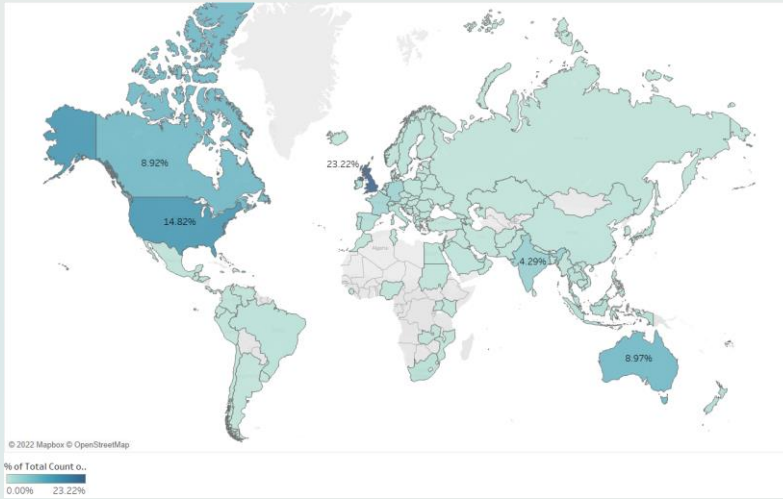


21 related attributes, including review content, scores, airline, aircraft, and etc.

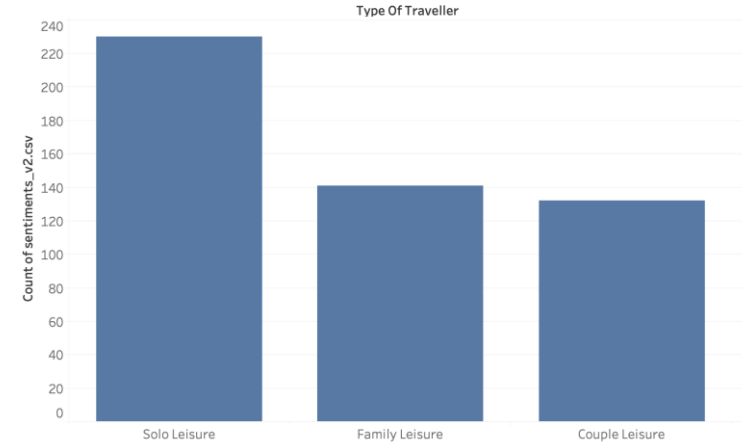
Reviews represent 211 unique airlines and 863 aircrafts



Users are from 71 countries and solo leisure is the major traveller type



Type of Travellers



For interior design, Full-Service airlines have higher average ratings than Low-Cost airlines

5.5 / 10

for Full-Service airlines

AIRFRANCE 



AIR CANADA

American Airlines 

5.0 / 10

for Low-Cost airlines



jetBlue



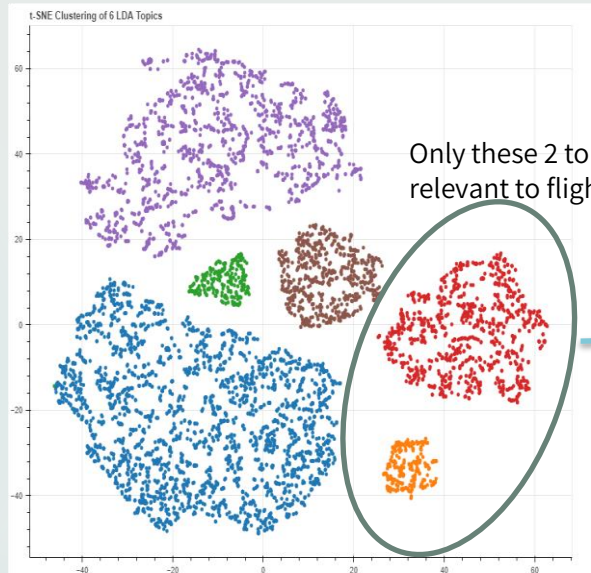
* from Skytrax

The full-service airlines seem to be only marginally better. Ratings are misleading so we need to do a deeper analysis into the text of the reviews, itself. However, it is clear from the ratings that interior design could use a face-lift

Topic Modelling

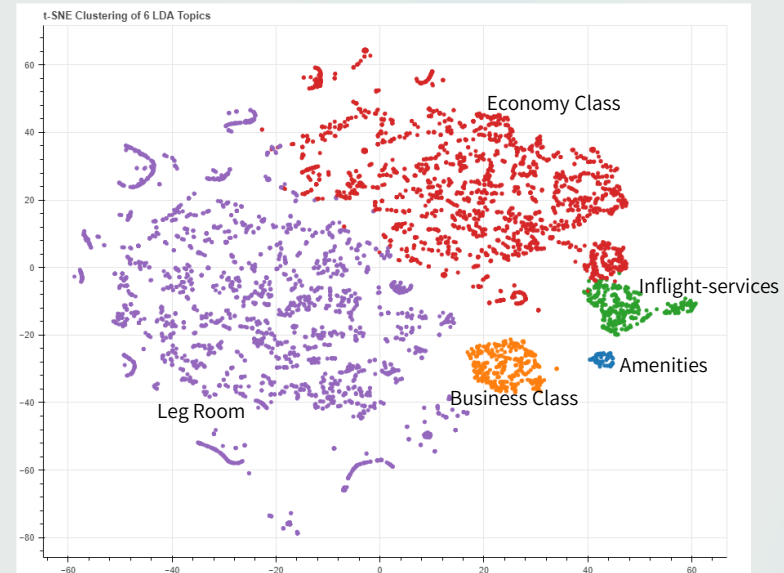


Double Topic Modelling was used to identify major topics relevant to airlines interiors

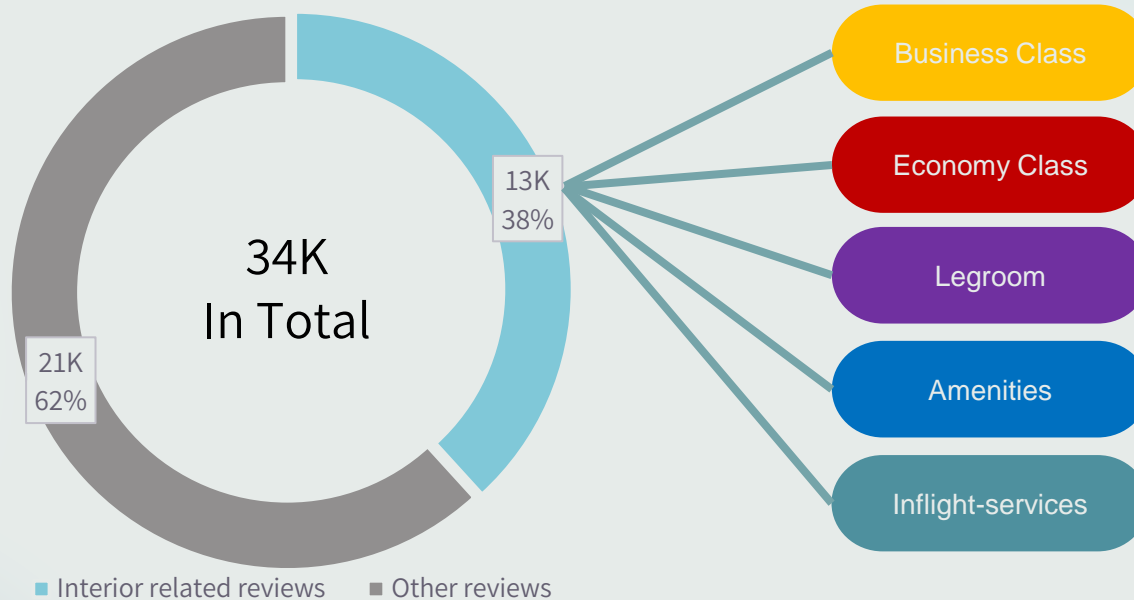


Only these 2 topics are relevant to flight interiors

6-cluster segmentation is homogeneous & identifiable



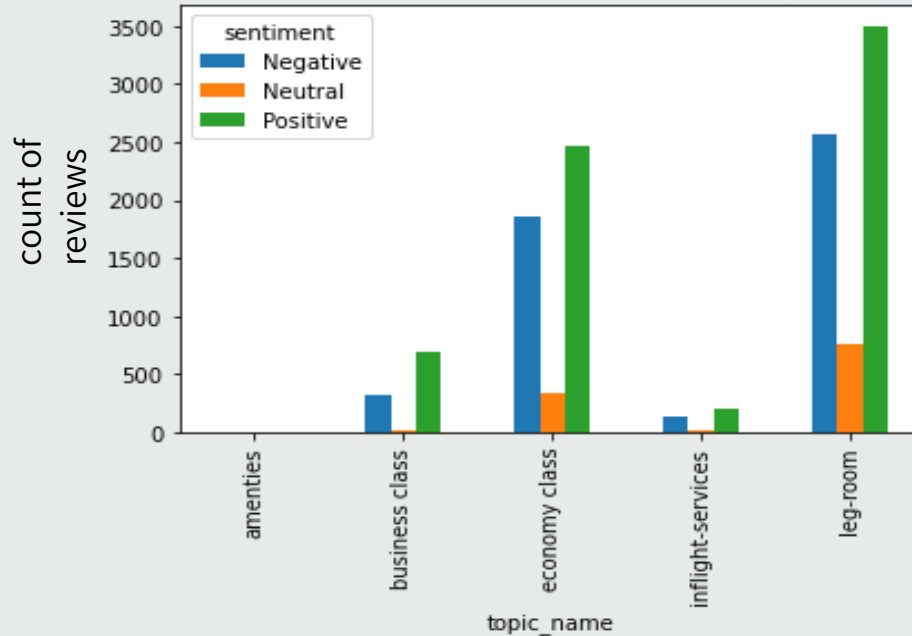
38% of scrapped data were used for sentiment analysis



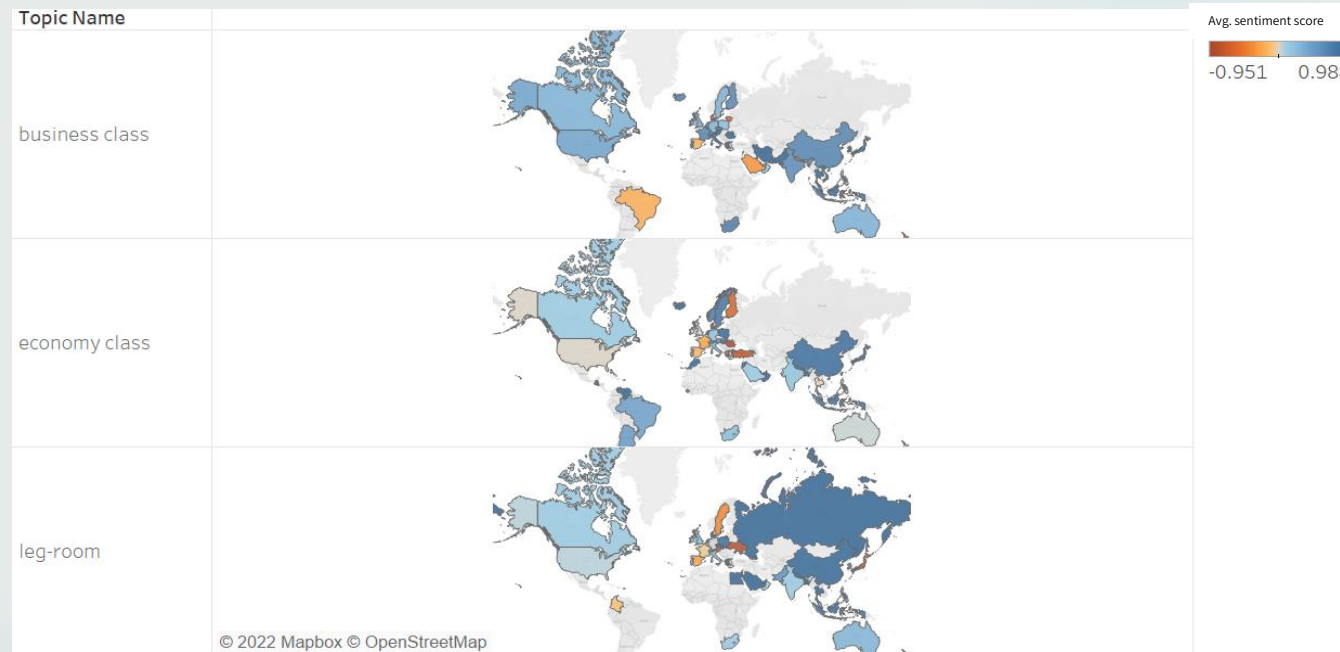
Sentiment Analysis



The proportion of negative reviews is considerable across all topics, showing there is room for significant improvements.

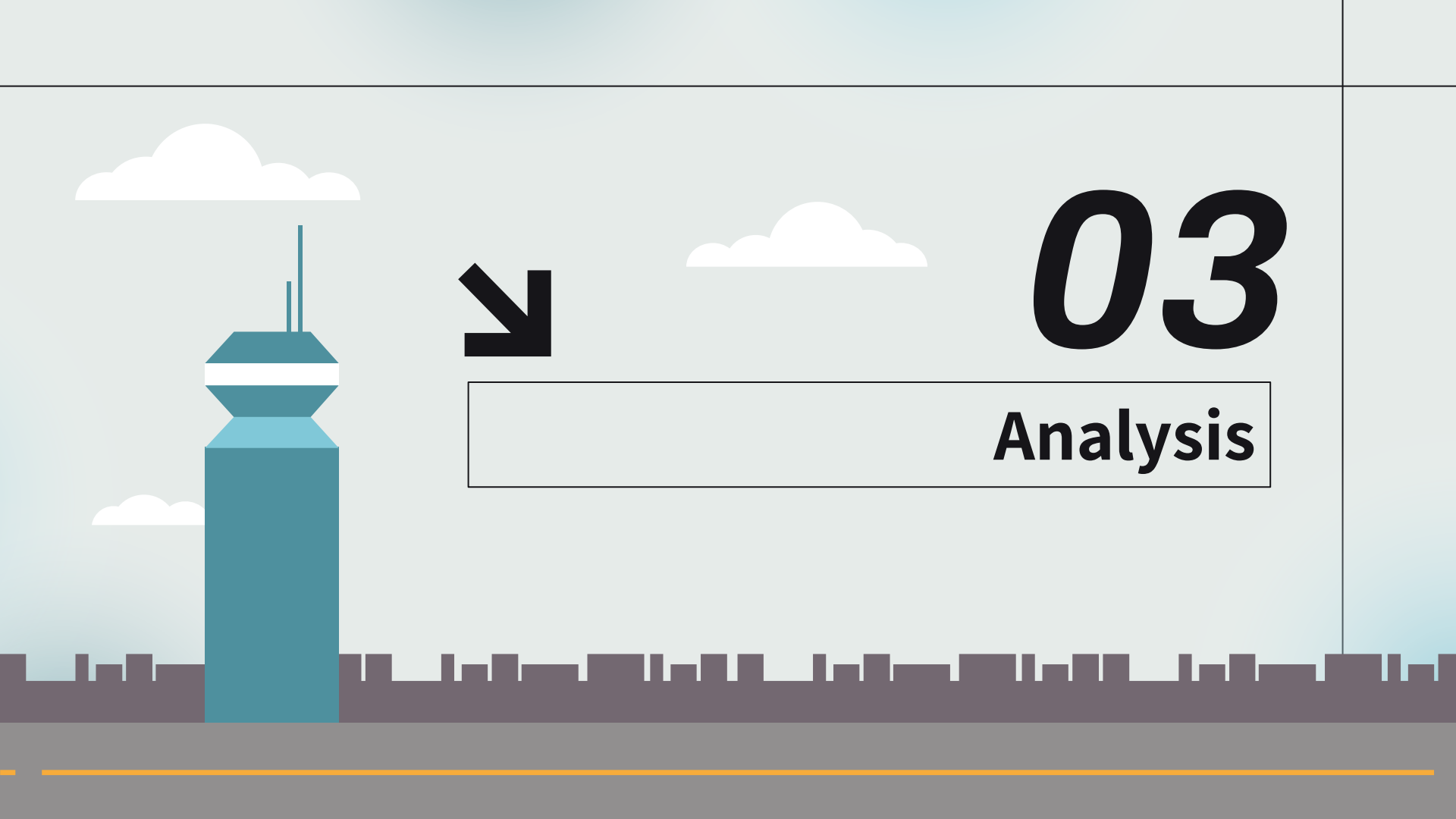


Sentiments for economy class and leg-room are generally negative or less-positive in developed economies, possibly due to higher expectations from customers.



Boeing offers a better legroom in low budget airline, but people prefer the Airbus Economy





Analysis

03

Pain Points Highlighted Per Topic



Uncomfortable flat beds in Business Class

“Seat when adjusted to be flat bed was not comfortable”



Broken seats & unfriendly entertainment UI in Economy

“Lousiest flight I ever took the seat was broken and the airline can't find any replacement the tv-equipment at some of the aisle were also broken”



Cramped Seats with little legroom

“The B777 on the Brisbane to Dubai leg was cramped and dirty. The A380 on the Dubai-Birmingham leg had more leg room.”



- 'good': 383
- 'first': 255
- 'comfortable': 237,
- 'great': 210



- Excellent food, entertainment and inflight-services
- Polite, friendly and professional staff
- Comfortable seating

“Seats were comfortable, WiFi worked very well, and crew were lovely.”

- 'first': 90
- 'flat': 71
- 'uncomfortable': 59
- 'bad': 53



- Flight Delays, slow moving boarding-queues
- Uncomfortable seats or flat-beds
- Bad food quality

“Seat when adjusted to be flat bed was not comfortable”



- 'good': 792
- 'comfortable': 698
- 'great': 601
- 'premium': 475



- Attentive and friendly-crew
- Generous leg-room and retractable foot-rests
- Ergonomic reclining seats with armrests
- Overhead luggage storage capacity

"Purchased seat 6A that is an economy and was surprised to find quite a nice leg room , probably at least 32"

- 'uncomfortable': 406
- 'premium': 310
- 'other': 298
- 'disappointing': 131



- Uncomfortable or non-reclining seats
- Poor leg-room
- Broken entertainment-units
- Hard seats

“Lousiest flight i ever took the seat was broken and the airline can t find any replacement the tv-equipment at some of the aisle were also broken”



Analysis of Topic: Leg-room

Most commonly occurring words:

- 'good': 1054
- 'great': 795
- 'comfortable': 781
- 'extra': 620



Positive reviews stems from:

- Good leg-space
- Seats designed for tall people
- Premium economy seats with extra leg-room
- Option to pay for seats with extra leg-space

Example:

“Mumbai to Bangalore was a very smooth flight and I was surprised that the check in agent was happy to provide me with an exit row seat with extra leg-room.”

Most commonly occurring words:

- 'uncomfortable': 462
- 'extra': 414
- 'narrow': 243
- 'bad': 220



Negative reviews stems from:

- Crammed seats with little leg-room
- No options to buy seats with extra leg-room
- Lower than standard leg-space
- Long-haul flights

Example:

“The B777 on the Brisbane to Dubai leg was cramped and dirty. The A380 on the Dubai-Birmingham leg had more leg room.”

Recommendations

Solutions



1 More reliable flat-bed technology

2 Privacy curtains

3 Update layout of hallways to facilitate on/off-boarding



4 Ergonomically designed seats (leather)

5 Improve UI for Entertainment systems

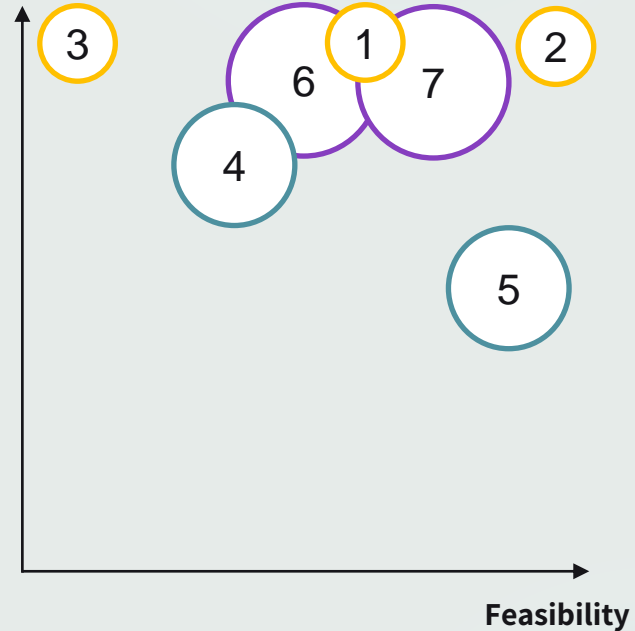


6 Staggered seats

7 Design few seats for taller people (maybe also for smaller people)



Customer Value



Recommendations

Solutions



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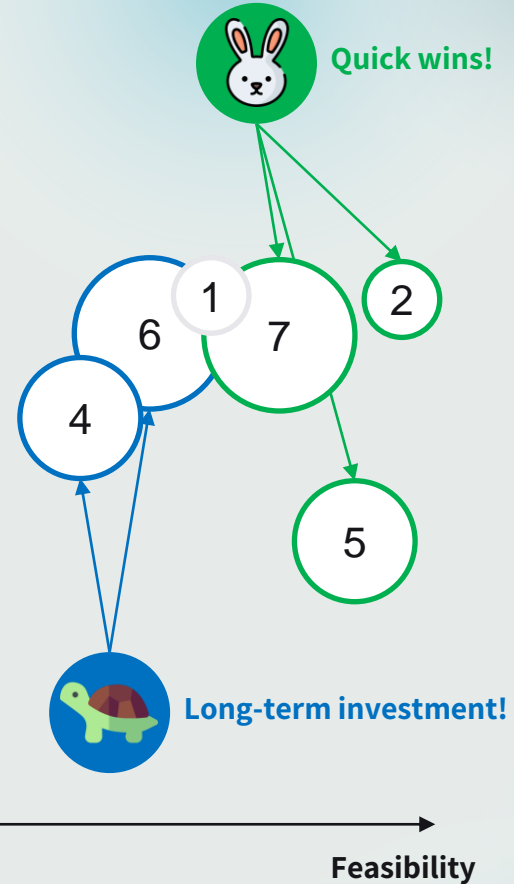


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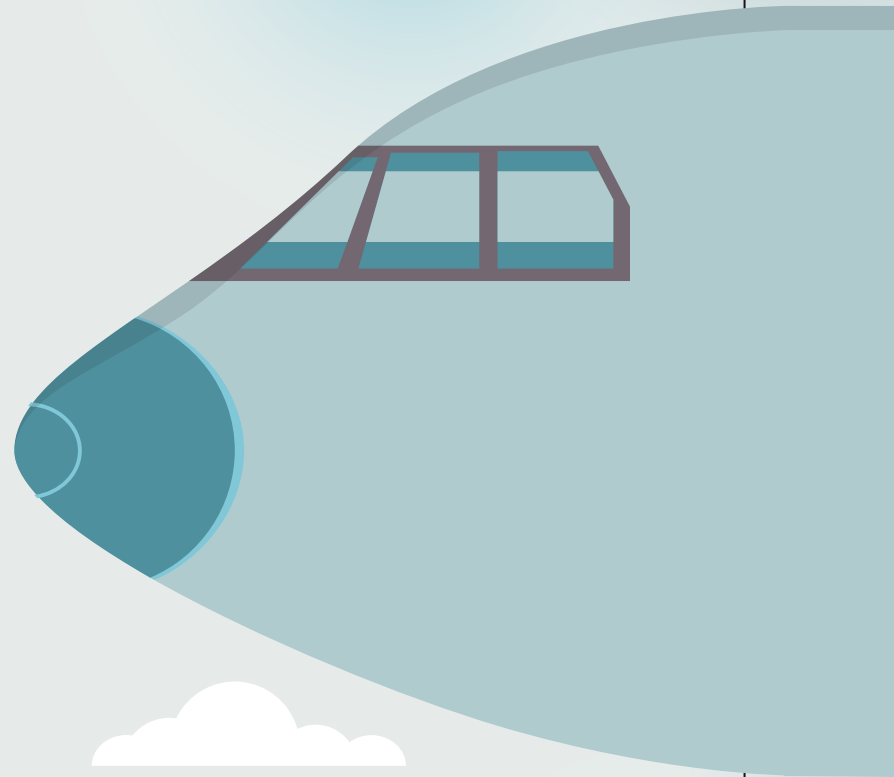
Customer Value

3



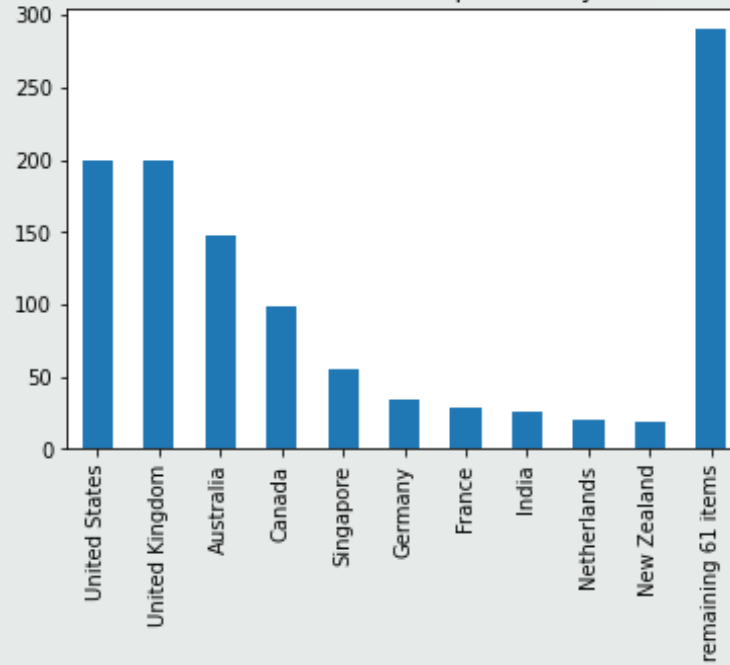
Feasibility

Q&A

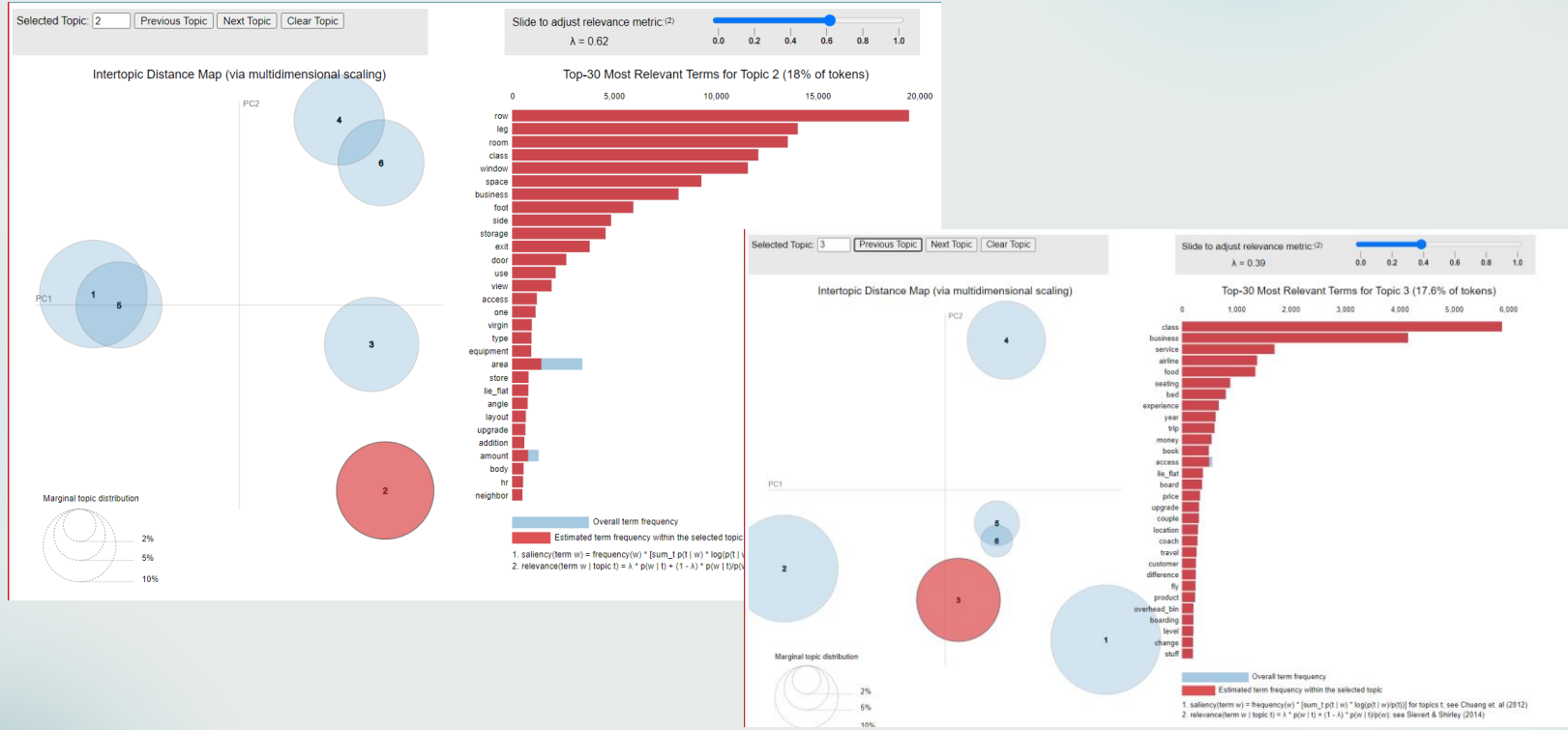


Appendix

Number of Reviews per country



Interactive segmentation plot



Selected Topic: 3

Previous Topic

Next Topic

Clear Topic

Slide to adjust relevance metric: (2)

λ = 0.39

0.0 0.2 0.4 0.6 0.8 1.0

Intertopic Distance Map (via multidimensional scaling)

Top-30 Most Relevant Terms for Topic 3 (17.6% of tokens)

Marginal topic distribution

Overall term frequency

Estimated term frequency within the selected topic

$$1. \text{saliency}(\text{term } w) = \text{frequency}(w) \cdot \left(\sum_{t=1}^T p(t|w) \cdot \log(p(t|w)) \right)$$

$$2. \text{relevance}(\text{term } w | \text{topic } t) = \lambda \cdot p(w | t) + (1 - \lambda) \cdot p(w | \text{Topic})$$

Topic weights

Word Count and Importance of Topic Keywords

Word Count and Importance of Topic Keywords

