

Synthetic Expert:  
 **Review**  
**Helpfulness Classifier**

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Our Synthetic Expert



Data



Approach



Fine-Tuning



Application



Limitations

# Contents





## Airbnb Has Revolutionized Travel

- **Airbnb** found in 2008
- **30.18%** of the reservation and online booking market

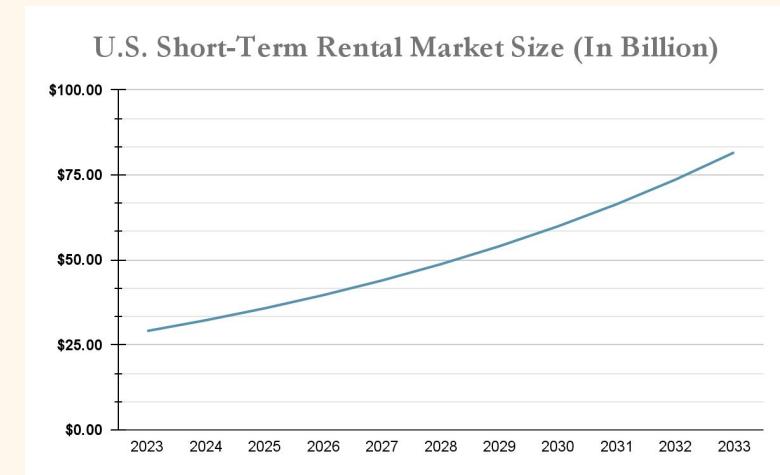


## Saturated Short-Term Rental Market

- Plenty of options for consumers
- Quality of reviews are significant
- Help customers' decision making

## Airbnb's Performance

- Q4 2023 revenue of **\$2.2 Billion**
- Increased **17%** from Q4 2022
- Demand for traveling



# Motivation

Source: 6sense (2024), Airbnb (2024), Precedence Research (2024)



# Our Synthetic Expert

- **Objective:** Evaluate and classify **Airbnb** reviews based on quality and reliability
- **Methodology:**
  - Dimensions analyzed in each review:
    - Key aspect
    - Decision-making advice
    - Expertise claim
  - Grading labels: A, B , C
- **Value Proposition:** Provides analysis of reviews to enhance decision-making for potential renters

Source: Chua Et Al. (2016)



## Cosy modern flat 16th Area

[Share](#) [Save](#)



### Entire rental unit in Paris, France

2 guests · 1 bedroom · 1 bed · 1 bath

★ 4.0 · [13 reviews](#)



Hosted by Sidney  
9 years hosting

A very cosy apartment. Very quiet with a charming view. Located at the heart of the "wealth Paris". Next to the Trocadéro, Eiffel tower, close to the Champs Elysées and the Arc de Triomphe. close to 3 subway station, good choice of restaurants around

### Add dates for prices

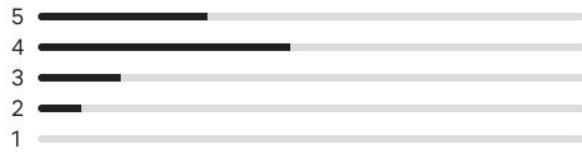
CHECK-IN Add date	CHECKOUT Add date
GUESTS 1 guest	

[Check availability](#)

 [Report this listing](#)

★ 4.0

Overall rating



Cleanliness

4.1



Accuracy

4.2



Check-in

4.8



Communication

4.8



Location

4.9



Value

4.4



13 reviews

Most recent ^

Most recent

Highest rated

Lowest rated



Fiona

Queensland, Australia

Search reviews



**Dakota**  
Indianapolis, Indiana

★★★★★ · July 2016 · Stayed over a week

Overall: Disappointing. My wife and I stayed in Sidney's flat for two weeks while we



**Jean Louis**

France

★★★★★ · September 2016 · Stayed one night

Ok

and a kitchen.

- The washer doesn't work. We were told that the washer didn't work after we checked in via text message.
- There is no AC. When we asked about it, we were told it was an old building and there is not any. Max did try and find a portable unit 10 days into our stay but was unsuccessful.
- The wifi is spotty. It wasn't unbearable but it would go out for hours at a time.
- The hotplates are broken. Portable hotplates were provided but the unit took up the only counter space available as it is a small kitchen.
- We never met or communicated with Sidney. Max was fantastic but we found it strange to never communicate with the listed host.
- Some essentials were missing. The towels, sheets, and toilet paper were abundant but all of the soap containers (shower, hand, dish) were empty. Cleaning supplies were also empty (paper towels, general cleaning solvent).

Overall, we were disappointed. The flat is not as advertised and would have never come up in our search had the description been accurate. For the price, we could have stayed in a place with all of the items we needed for a good trip. We made do, and if you don't need a washer, AC, wifi, kitchen, and/or essentials, then this place is great. But if you do need those items, I strongly advise you communicate with Sidney or Max with your precise needs, even if they are listed, before paying.



# Data

## Airbnb Listings & Reviews

Airbnb data for 250,000+ listings across 10 major cities, with 5 million reviews.

- **Data Set:** Airbnb data for **250,000+** listings across 10 major cities
  - From [kaggle](#)
  - Cities: Paris, New York, Rome etc.
- **Method:**
  - Built a scraper for Airbnb comments using listing ids in the dataset
  - Link: [www.airbnb.com/rooms/listing\\_id](http://www.airbnb.com/rooms/listing_id)
  - Scrapped first **5k** Airbnb reviews
  - Used Open AI's API to label **4500** reviews

# Construct and Grading

- We adapted a three-layered rubric developed by Chua Et Al. in 2015
- Rubric:
  - Score on 3 metrics out of 5 and bucket the sum into **A**, **B**, or **C**
    - Key Aspects: How many specific aspects of the listing were mentioned?
    - Decision-Making Advice:
      - Was their review vague?
      - Or, did they offer explicit advice?
    - Expertise Claims: How knowledgeable/qualified was the reviewer of the property?



# Detailed Grading Rubric

Table 1. Coding scheme of a given AirBnB review in terms of the three manually coded measures.

<b>Scores</b>	<b>Key aspects</b>	<b>Decision-making advice</b>	<b>Expertise claims</b>
1	Indicates no specific aspect of the AirBnB listing.	Describes personal experiences vaguely without advising on renting decisions.	Makes no claims of the reviewer's expertise.
2	Indicates one specific aspect of the AirBnB listing.	Describes personal experiences clearly without advising on renting decisions.	Suggests familiarity of the reviewer with listing similar to the one under review.
3	Indicates two specific aspects of the AirBnB listing.	Offers an implicit advice on whether to rent the listing.	Suggests familiarity of the reviewer with the listing under review.
4	Indicates three specific aspects of the AirBnB listing.	Offers an explicit advice on whether to rent the listing.	Makes claims of the reviewer's expertise without justification.
5	Indicates four or more specific aspects of the AirBnB listing.	Explicitly advises who should, and who should not rent the listing.	Makes claims of the reviewer's expertise with justification.

Source: Chua Et Al. (2016)



# Classification Target Labels

Overall Score (X)	Label	Class Label Description
$3 \leq X \leq 6$	C	Least Helpful Reviews
$7 \leq X \leq 10$	B	Moderately Helpful Reviews
$11 \leq X \leq 15$	A	Most Helpful Reviews

- Why did we choose to bucket reviews in this fashion?
  - Class Representation
  - Intuitive Application for Consumers



# Approach : Fine-Tuning



- Link to Our Airbnb Helpfulness Classifier (Hugging Face):

<https://huggingface.co/lihuicham/airbnb-reviews-helpfulness-classifier-roberta-base>

1

## Data Labelling



### - Train Set :

4560 samples synthetically labelled by GPT-4 Turbo

### - Test Set:

500 samples manually labelled, majority vote applies

2

## Pre-Trained LLM Selection

FacebookAI/roberta-base

- Transformer architecture
- Trained on English corpus
- Task : Sequence (text) classification

3

## Prepare the Data for Fine-Tuning

- Oversampling on Training Set
- Preprocess with `LabelEncoder()`
- Tokenization
- `id2label {0: 'A', 1: 'B', 2: 'C'}`

4

## Fine-Tuning & Evaluate

- Experiment (next slide) with different hyperparameters
- Evaluate model on loss, accuracy, f1, precision and recall



Synthetic  
Expert

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Fine-Tuning

Experiment  
& Results

Applications

Limitations

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# Experiments & Results

- Final Hyperparameters :

```
hyperparameters =
{'learning_rate': 3e-05,
'per_device_train_batch_size': 16,
'weight_decay': 1e-04,
'num_train_epochs': 4,
'warmup_steps': 500}
```

- Results :

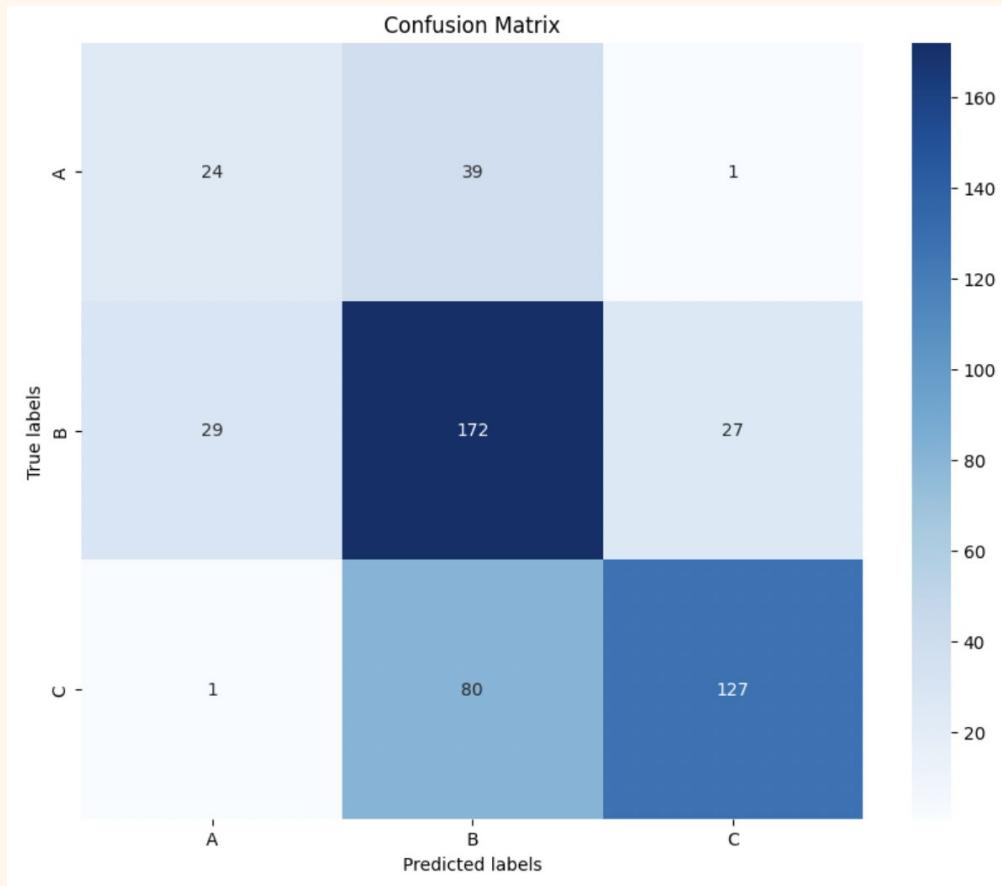
- Good overall precision and accuracy
- Least overfitting

Epoch	Training Loss	Validation Loss	Accuracy	F1	Precision	Recall
1	0.533900	1.249057	0.502000	0.497464	0.574362	0.562057
2	0.409200	0.980797	0.646000	0.589772	0.618288	0.579988
3	0.166500	1.759467	0.618000	0.569187	0.654116	0.569163
4	0.147100	2.322143	0.602000	0.551476	0.619609	0.550396

- Learnings :

- Increase learning rate to overcome model bias
- Increase weight decay for regularization to combat overfitting
- More epochs != better performance





## Interpretation :

- Class A has the lowest recall since more As are misclassified as B
- Class C has good precision since not many other classes are misclassified as C
- Class B 

## Recap of Knowledge

**Precision** - predicted class A is actually class A

**Recall** - find as many class A as possible

## ⚡ Inference API ⓘ

Text Classification

Examples ▾

This was my first time getting an Airbnb and won't be the last! The location was so peaceful and quiet, perfect for a weekend getaway. The space was modern and clean. I was able to cook a whole breakfast buffet in the kitchen. The hosts were extremely helpful and friendly, 10/10 highly recommend! Definitely will be returning when the weather gets warmer!!

Compute

Computation time on cpu: 0.063 s



⟨/⟩ JSON Output

Maximize

## Scoring rubrics for our model

Key Aspects, Decision-Making Advice, Expertise Claims

← Review

← Predicted Label

Try our model at  
Hugging Face !



Link: [lihuicham/airbnb-reviews-helpfulness-classifier-roberta-base](https://lihuicham/airbnb-reviews-helpfulness-classifier-roberta-base)

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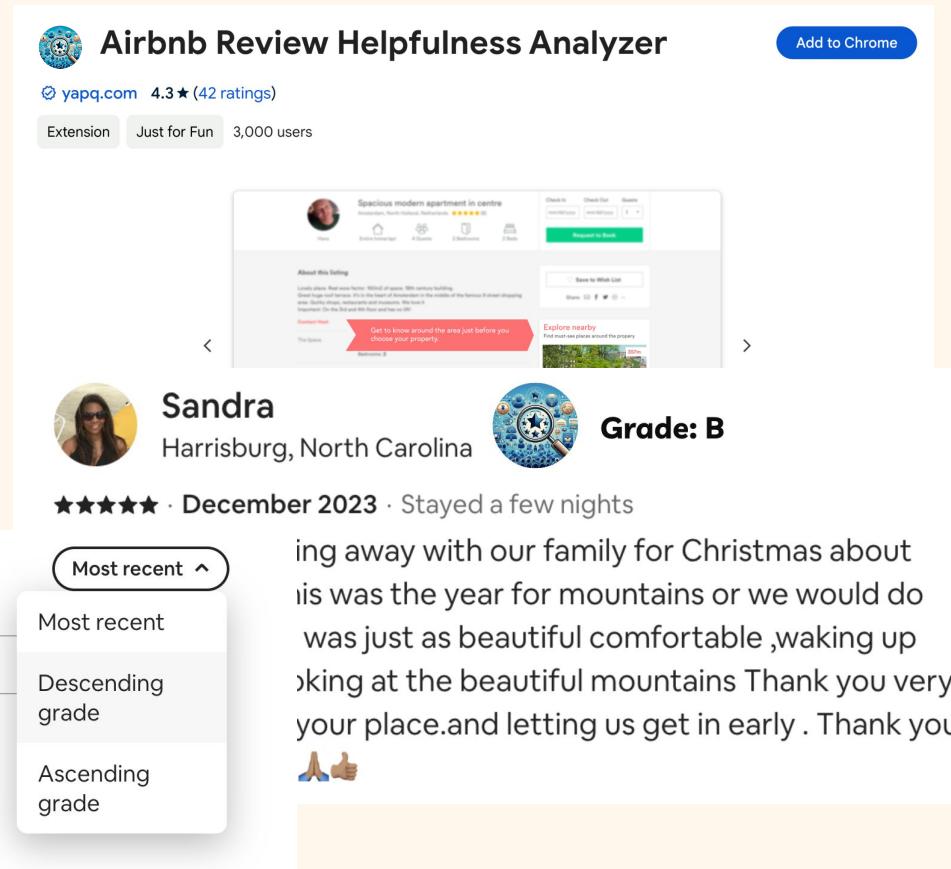
# Applications - Usage

- **Browser Extensions**
  - Chrome extension
  - Safari extension
  - Firefox Add-on
- **Embedded Inside Airbnb**
  - No need for installation
  - Convenient to use
  - Easy to read and analyze

**Airbnb Review Helpfulness Analyzer**

[yapq.com](https://yapq.com) 4.3 ★ (42 ratings)

Extension Just for Fun 3,000 users



**Sandra**  
Harrisburg, North Carolina

Grade: B

★★★★★ · December 2023 · Stayed a few nights

ing away with our family for Christmas about  
iis was the year for mountains or we would do  
was just as beautiful comfortable ,waking up  
oking at the beautiful mountains Thank you very  
your place.and letting us get in early . Thank you  
🙏👍

Most recent ▾

- Most recent
- Descending grade
- Ascending grade

Source: Chrome Web Store (2024), Airbnb (2024)

# Business Applications

1

## For Airbnb Customers:

- Informed Decisions
- Time-Saving
- Customization

2

## For Airbnb Platform:

- Enhance Customer Experience
- Improve Search Functionality
- Quality Control
- Data-Driven Decision Making

3

## For Airbnb Hosts:

- Reputation Management
- Targeted Improvements
- Competitive Advantage

4

## For Airbnb's Business Intelligence:

- Market Insights
- Service Design
- Strategic Planning

# Business Applications

- First apply in Paris, then generalize
-  Customer experience (CX)
-  Customer satisfaction rate,  customer churn rate
-  Revenue

**Revenue of customer experience (CX) leaders and laggards over time, index (100 = 2016)**

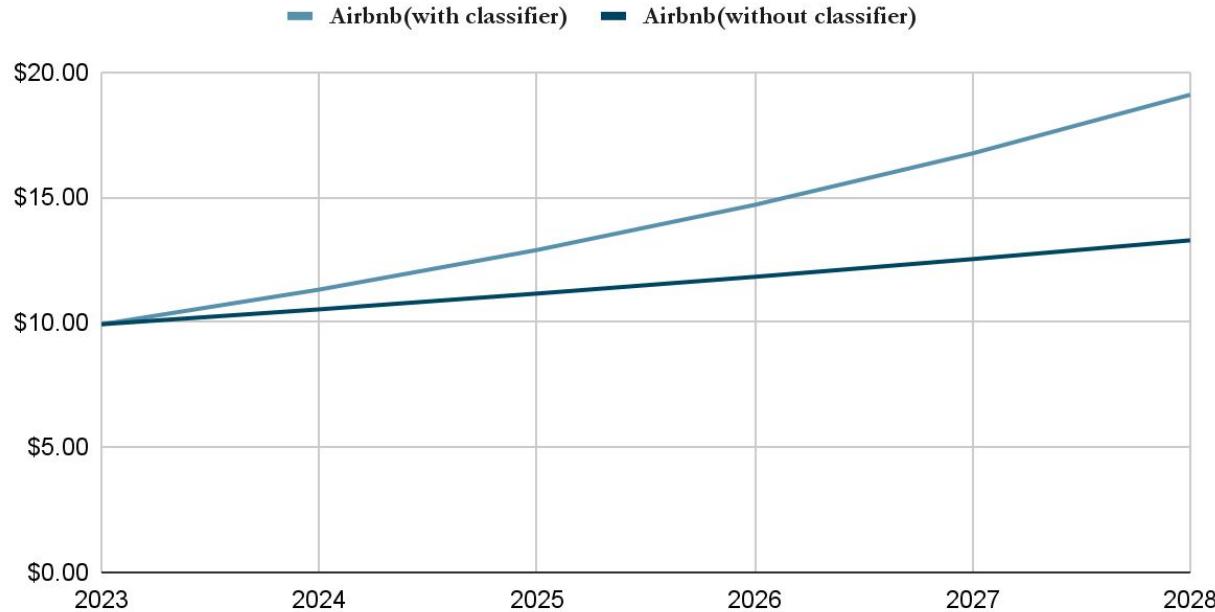


Source: McKinsey (2023)



# Business Applications

## Forecasted Revenue of Airbnb (In Billion)



# Limitations

- **Lack of Generalization**
  - Only trained on Parisian reviews, may not generalize well outside of Paris
    - Retrained using more diverse geographic data if the user is interested in more generalized applications in regards to the classification of **Airbnb** reviews globally
- **Information Loss**
  - Some information may have been lost in translation
- **High Computational Cost**
  - Paid for Colab Pro \$9.99; ~45 mins for 4 epochs.



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Thank  
You !

Do you have any questions?