Business continuity management in the sharing economy: Insights from Airbnb online reviews

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Business continuity management

Business continuity management (BCM) is the strategic response to internal or external disruptions that pose a substantive risk to critical business operations.

Prior literature has investigated how large firms and organisations as well as SMEs respond to major market disruption (Widianti et al., 2024), but business continuity in the sharing economy is currently under-researched.

Sharing economy

Sharing economy is a socio-economic system centered on resource sharing, usually through digital platforms, enabling peer-to-peer (P2P) exchange of underutilized assets or services, with the key characteristics:

- Digital platforms
- P2P interaction
- Flexible and on-demand services
- Monetization of idle assets

airbnb

Anywhere | Any week | Add guests

Airbnb your home

Private room in central London penthouse flat

Share Save

Room in Greater London, United Kingdom

1 king bed · Shared bathroom

Guest favourite — One of the most loved homes on Airbnb, according to guests — 4.91 ★★★★★ — 76 Reviews

£96 night

CHECK-IN 14/11/2024

GUESTS 1 guest

Overall rating
5
4
3
2
1

Cleanliness	Accuracy	Check-in	Communication	Location	Value
4.7	5.0	5.0	5.0	4.9	4.8

Marie
7 years on Airbnb
★★★★★ · 4 days ago
Very good stay with Tom. The accommodation is pleasant and quiet in the heart of a very lively neighborhood. Tom is available and very responsive. Great stay!

Sage
8 years on Airbnb
★★★★★ · 1 week ago
The apartment was clean and quiet and Tom was very responsive to all messages. The apartment is in a central location only a 10-15 minute walk to Covent Garden and Soh...
Show more

Ben
Vancouver, Canada
★★★★★ · 2 weeks ago
I had a lovely one night's stay in Tom's place. I appreciated Tom's flexibility with the check-in time and the clear instructions he provided for accessing the flat. The room wa...
Show more

Clarence
Frisco, Texas
★★★★★ · 3 weeks ago
Can't beat the location; travel to anywhere in London with ease. Tom is a great host, I had a wonderful time there.

Why focus on London’s Airbnb market?

- London’s visitor economy contributed £36 billion a year in revenue and employed 700,000 people pre-Covid (London & Partners, 2017)
- London had the highest volume of active rentals in major cities worldwide in 2018 and was previously considered the world's Airbnb capital (Statista, 2021).

Data

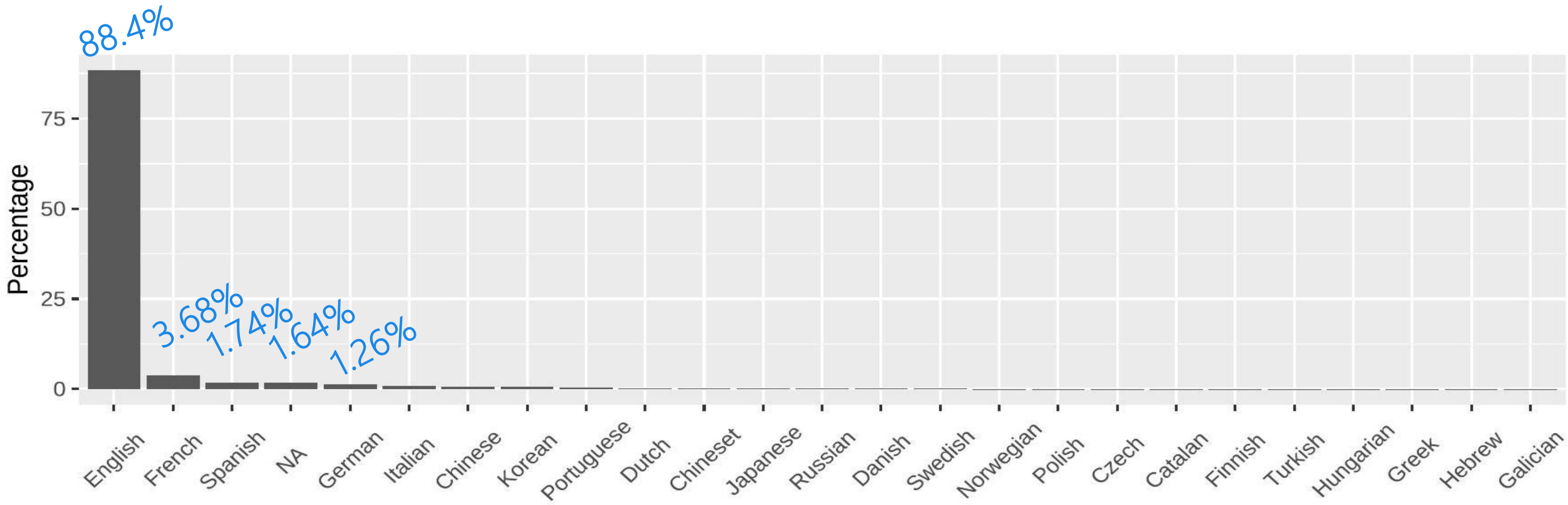
Two datasets from Inside Airbnb were used, which cover reviews and listing information between 21 December 2009 and 31 March 2022 in London.

- listing.csv is a tabular data that contains the key information related to Airbnb: listing id, name, description, neighbourhood, URL, latitude, longitude, room type, facilities, average review rating, host name, host id, host response time, and so on.
- reviews.csv contained guest reviews.

https://insideairbnb.com/

Data pre-processing

- Remove HTML codes like **⟨br /⟩**, **⟨br⟩**.
- Separate emoticons :-) and emojis ☺ from online reviews.
- Detect languages of reviews using the Google Compact Language Detector 2 (CLD2)† and remove non-English reviews.



† CLD2 is a Naïve Bayesian classifier (https://github.com/CLD2Owners/cld2), which has shown an impressive accuracy of 98.82% in language detection tests, as reported by Michael McCandless.

Pre-Covid, during lockdowns & upon reopening

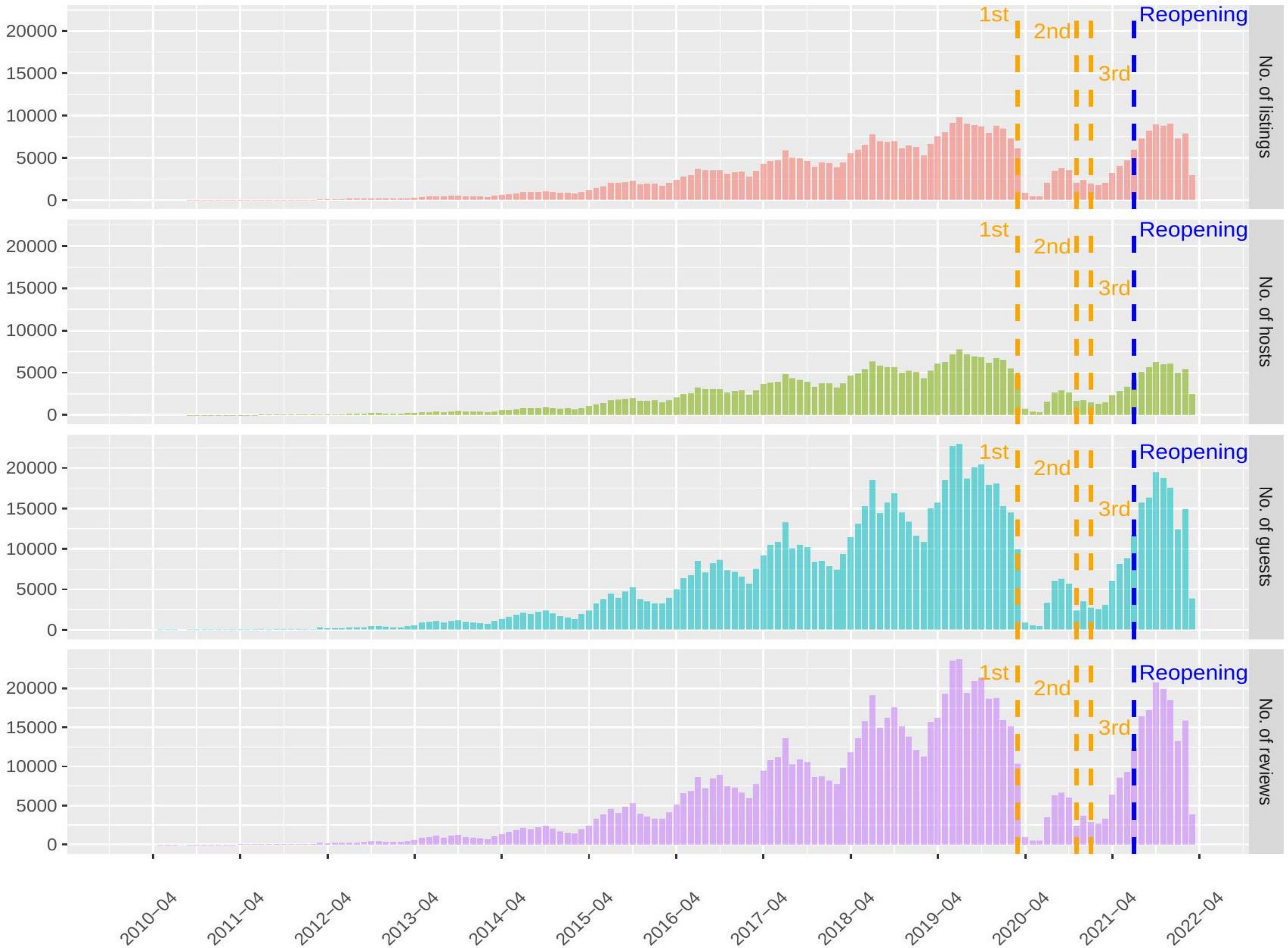
Our analysis included 894,686 English reviews posted by 755,524 guests on 46,175 listings from 32,139 hosts in 33 London boroughs over 145 months.

Period	Year	Dates	No. of months	No. of listings	No. of hosts	No. of reviews	No. of reviewers
Pre-Covid	2009-2016	[2009-12-21, 2016-12-31]	82	9,921	8,485	152,205	139,378
	2017	[2017-01-01, 2017-12-31]	12	12,554	10,169	114,586	105,312
	2018	[2018-01-01, 2018-12-31]	12	16,765	13,068	163,618	148,401
	2019	[2019-01-01, 2019-12-31]	12	21,442	15,789	220,756	199,023
	2020	[2020-01-01, 2020-03-22]	3	12,451	9,150	40,697	37,681
During lockdowns	2020	[2020-03-23, 2020-12-31]	9†	9,358	6,422	31,550	28,099
	2021	[2021-01-01, 2021-07-18]	7	9,827	6,292	40,407	35,601
Upon reopening	2021	[2021-07-19, 2021-12-31]	5‡	17,803	11,000	97,869	87,189
	2022	[2022-01-01, 2022-03-31]	3	12,011	7,887	32,998	30,133

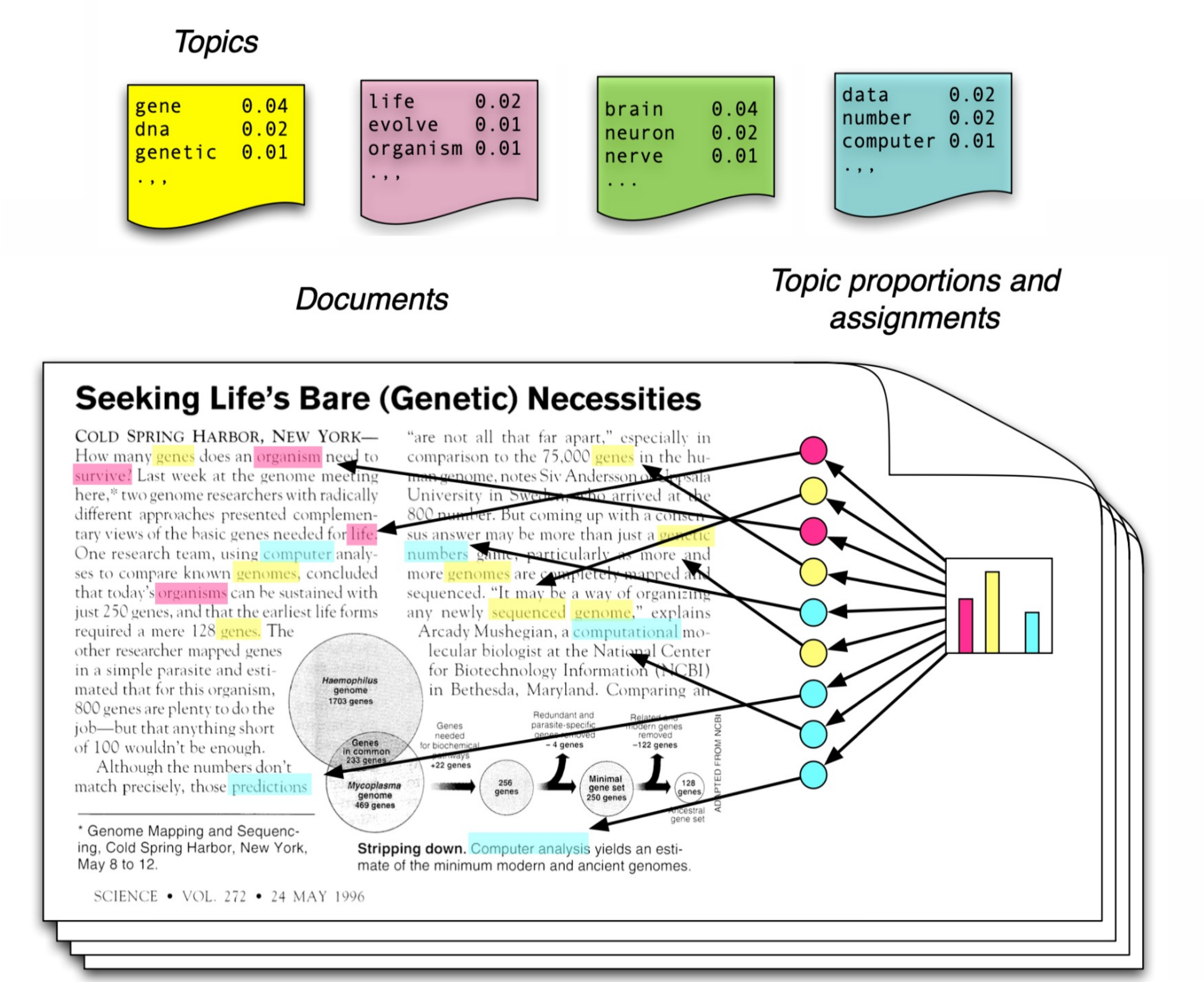
† On 2020-03-23, PM announces the first lockdown in the UK, so the 9 days from 2020-03-23 to 2020-03-31 are not accounted for a full month.

‡ Since 2021-07-19, most legal limits on social contact removed in England, and the final closed sectors of the economy reopened so the 13 days from 2021-07-19 to 2021-07-31 are not accounted for a full month.

Changes in London's Airbnb market



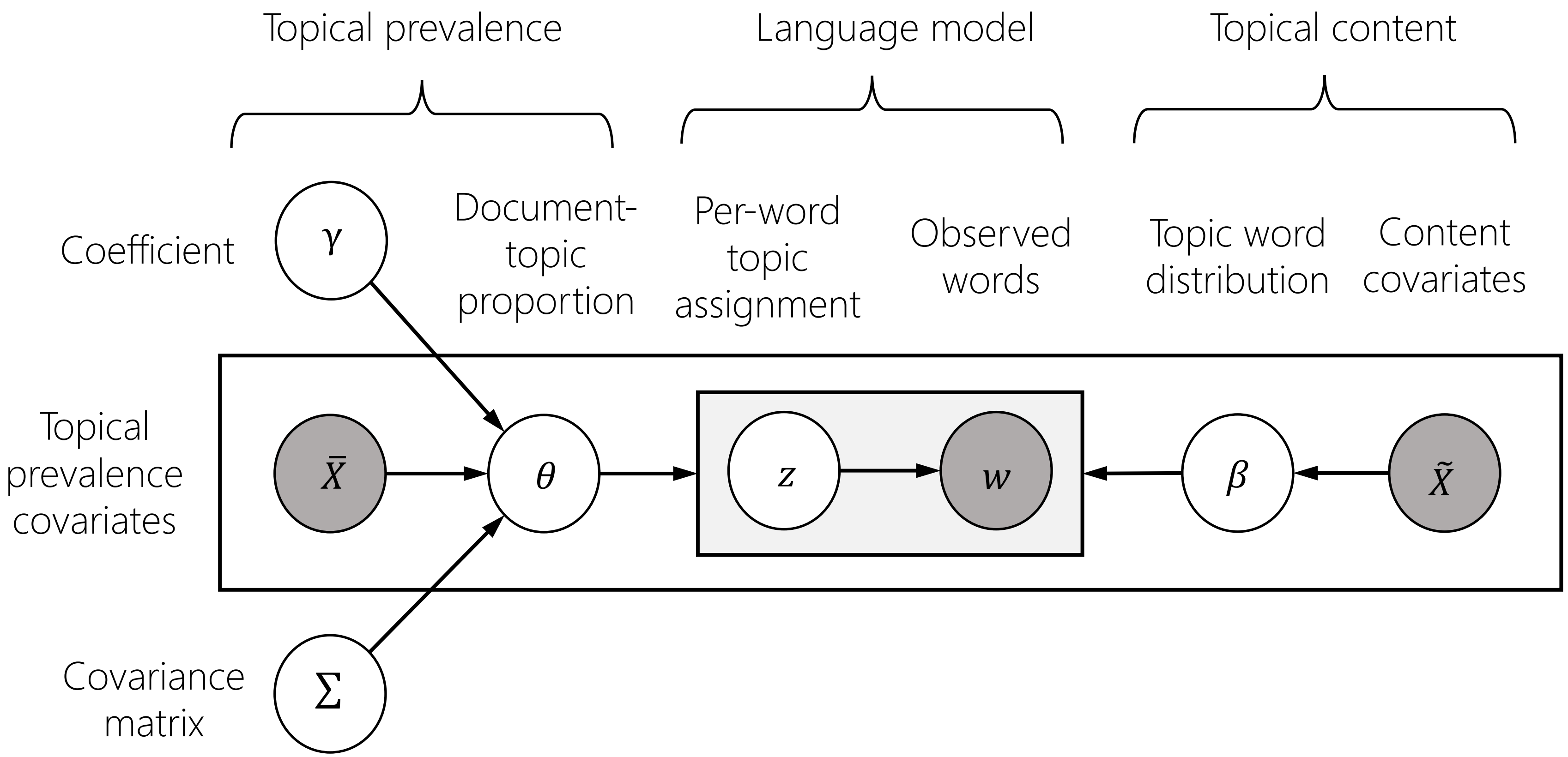
Topic modelling



- Each document is a mixture of several topics
- Each topic is characterized by a specific distribution of words.

David Blei. "Probabilistic topic models". Communications of the ACM 55.4 (2012), pp. 77–84.

Structural topic model (STM)

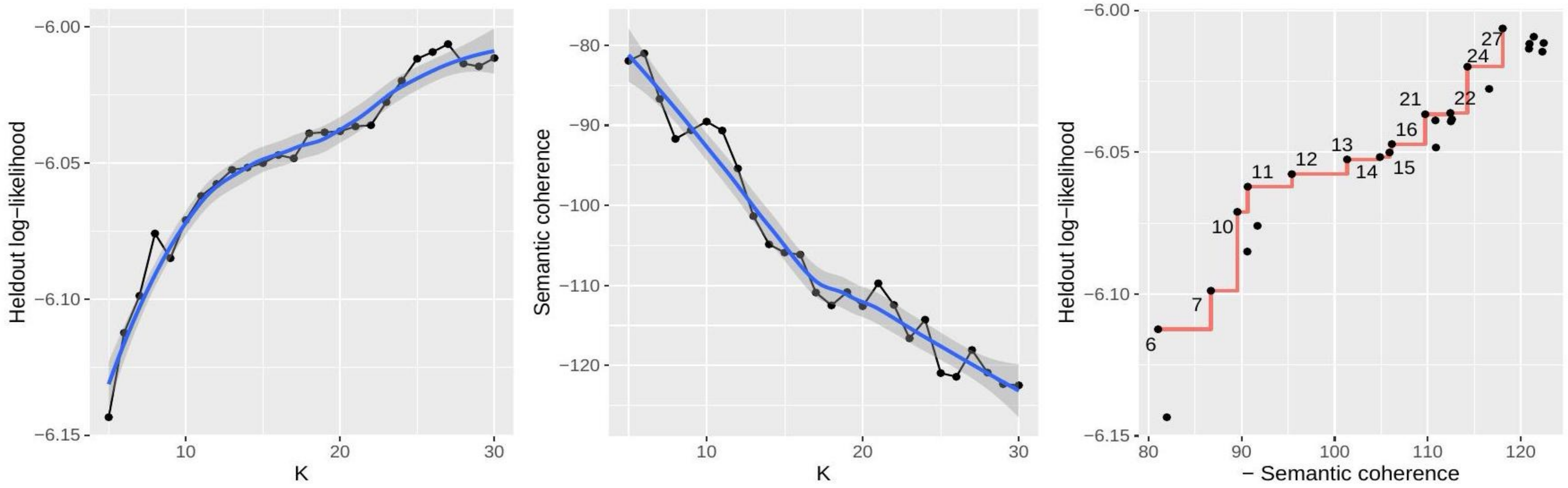


$$p(\beta_{1:K}, \theta_{1:D}, z_{1:D}, w_{1:D}) = \prod_{k=1}^{K} p(\beta_k) \prod_{d=1}^{D} p(\theta_d) \left(\prod_{n=1}^{N} p(z_{d,n}|\theta_d) p(w_{d,n}|\beta_{1:K}, z_{d,n}) \right)$$

Margaret E. Roberts, Brandon M. Stewart, and Edoardo M. Airoldi. "A model of text for experimentation in the social sciences". Journal of the American Statistical Association 111.515 (2016), pp. 988–1003

Determining the optimal number of topics in the STM

- Held-out likelihood: Which words the model believes will be in a given document and comparing this to the document's actual word composition
- Semantic coherence: How frequently the most probable words in a topic co-occur in the same documents?
- Exclusivity: How unique a topic's top words are?



Margaret E. Roberts, Brandon M. Stewart, and Dustin Tingley. "STM: An R package for structural topic models". Journal of Statistical Software 91 (2019), pp. 1–40. ISSN: 15487660.

Topics in online reviews

Topic	Description	Top words †	Topic proportion
1	Check-in & check-out	evening, day, arrive, time, get, first, didn't	6.77%
2	Public transportation	station, nice, london, bus, walk, minute, city	7.50%
3	Host communication	host, great, location, help, friend, excellent, accommod	12.33%
4	Cleanliness	stay, place, recommend, clean, definitely, really, comfortable	15.28%
5	Decent location	great, location, easily, london, close, flat, love	11.47%
6	Room facilities	bed, room, bathroom, kitchen, small, bedroom, shower	8.00%
7	Local amenities	walk, park, restaurant, shop, tube, street, minute	7.74%
8	Accuracy	everything, apart, perfect, need, thank, flat, well	9.34%
9	Value	good, room, value, price, money, hotel, check	4.81%
10	Food service	home, house, love, welcome, room, feel, beautiful	13.47%
11	Room size & good feeling	space, well, airbnb, place, clean, comfortable, flat	3.30%

† Words within each topic with the highest probability inferred from the topic-word distribution parameter.

Changes in guest review topics before, during, and after the pandemic

		Topic proportion			Difference of means (p-value)		
Topic	Description	Pre-Covid (2018-2020) †	During lockdowns	Upon reopening	Pre-Covid (2018-2020) vs during lockdowns	Pre-Covid (2018-2020) vs upon reopening	During lockdowns vs upon reopening
1	Check-in & check-out	6.17%	6.19%	6.21%	0.72	0.15	0.51
2	Public transportation	7.82%	5.16%	5.89%	0***	0***	5.75e-157***
3	Host communication	12.68%	13.63%	13.01%	4.85e-101***	7.31e-21***	4.30e-36***
4	Cleanliness	15.69%	16.47%	15.63%	4.20e-109***	0.01*	2.46e-99***
5	Decent location	11.89%	11.89%	12.28%	0.83	1.81e-42***	1.96e-22***
6	Room facilities	8.01%	8.37%	9.03%	5.27e-16***	3.60e-171***	2.40e-36***
7	Local amenities	7.63%	7.14%	7.43%	1.59e-48***	2.27e-13***	4.93e-14***
8	Accuracy	8.96%	9.77%	9.61%	2.48e-229***	3.81e-242***	1.90e-07***
9	Value	4.68%	6.71%	6.46%	0***	0***	2.76e-10***
10	Food service	13.15%	11.36%	11.23%	0***	0***	0.01*
11	Room size & good feeling	3.30%	3.34%	3.21%	1.46e-05***	2.79e-31***	1.99e-32***

† 16 March 2018 to 22 March 2020, matches the 738 days of observations in the post-Covid period. In total, we analysed 607,469 reviews, including 404,645 reviews from the pre-Covid period, 71,957 reviews during lockdowns, and 130,867 reviews upon reopening.

Sentiment analysis

- Online review text -> AFINN lexicon[†]
- Emoticons, for example, :-), :-(-> AFINN lexicon[‡]
- Emoji, for example, ☺, ☹ -> text description using emoji dictionary* -> AFINN lexicon

AFINN lexicon is a list of English words manually rated for valence with an integer between -5 (negative) and +5 (positive) by Finn Årup Nielsen between 2009 and 2011.

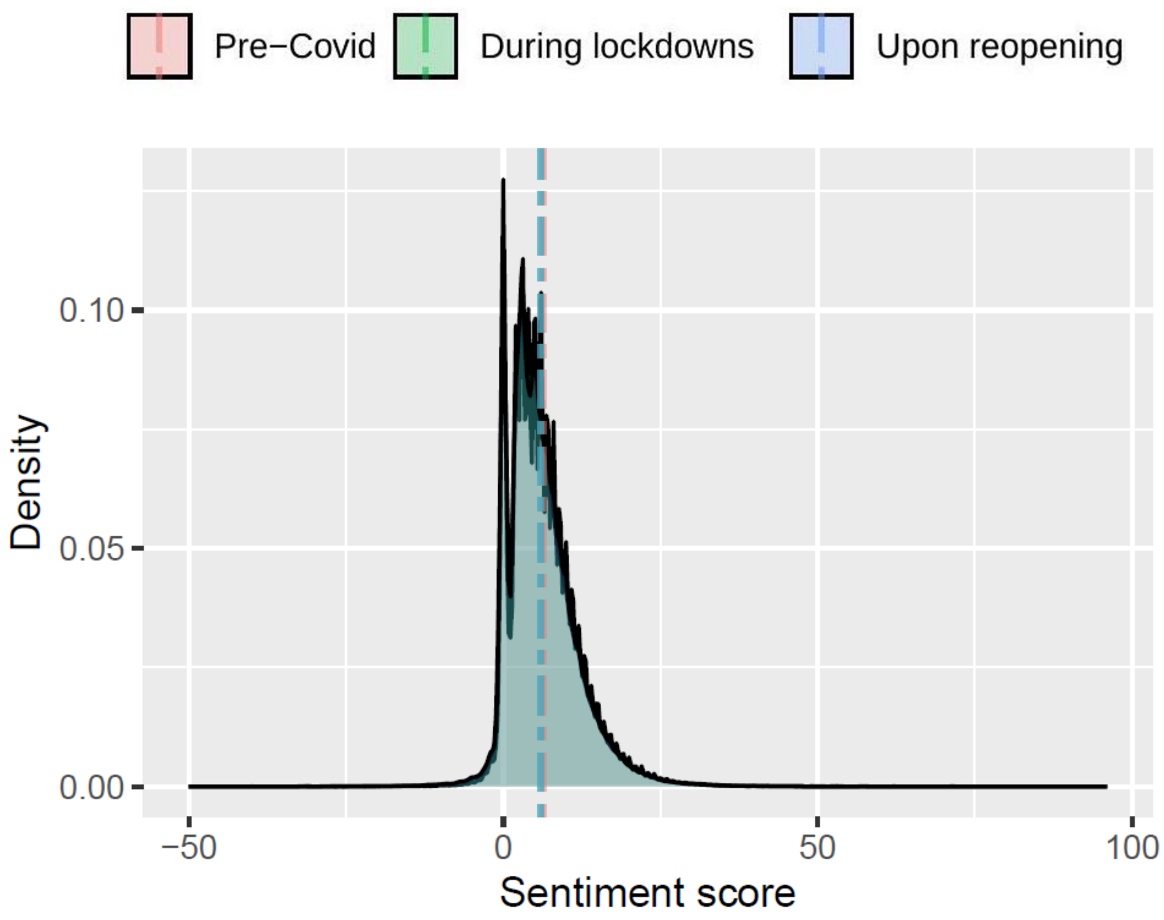
A tibble: 2,477 x 2

word <chr>	value <dbl>
abandon	-2
abandoned	-2
abandons	-2
abducted	-2
abduction	-2
abductions	-2
abhor	-3
abhorred	-3
abhorrent	-3
abhors	-3

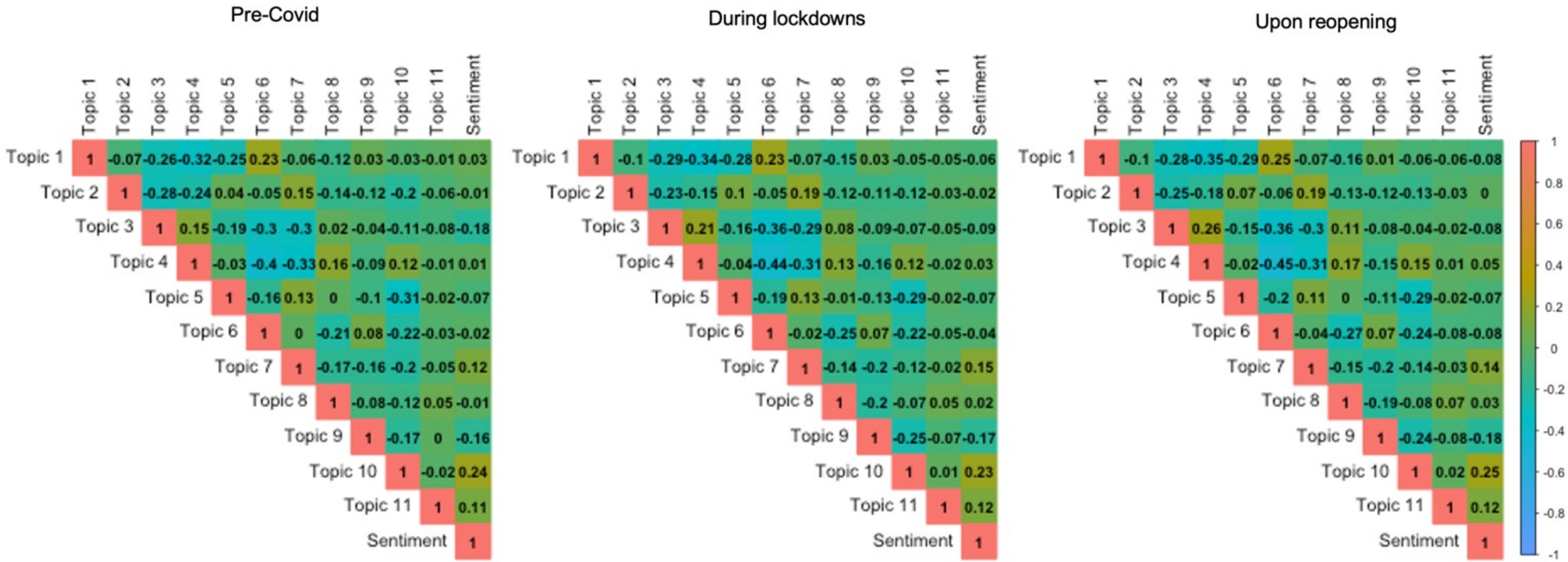
† https://github.com/fnielsen/afinn
‡ https://github.com/fnielsen/afinn/blob/master/afinn/data/AFINN-emoticon-8.txt
* https://github.com/today-is-a-good-day/emojis/blob/master/emDict.csv

Changes in guest review sentiment before, during, and after the pandemic

- No significant difference in hypothesis testing between the means for lockdowns and upon reopening.
- Both lockdowns and upon reopening exhibit significantly lower sentiment compared to the pre-Covid.



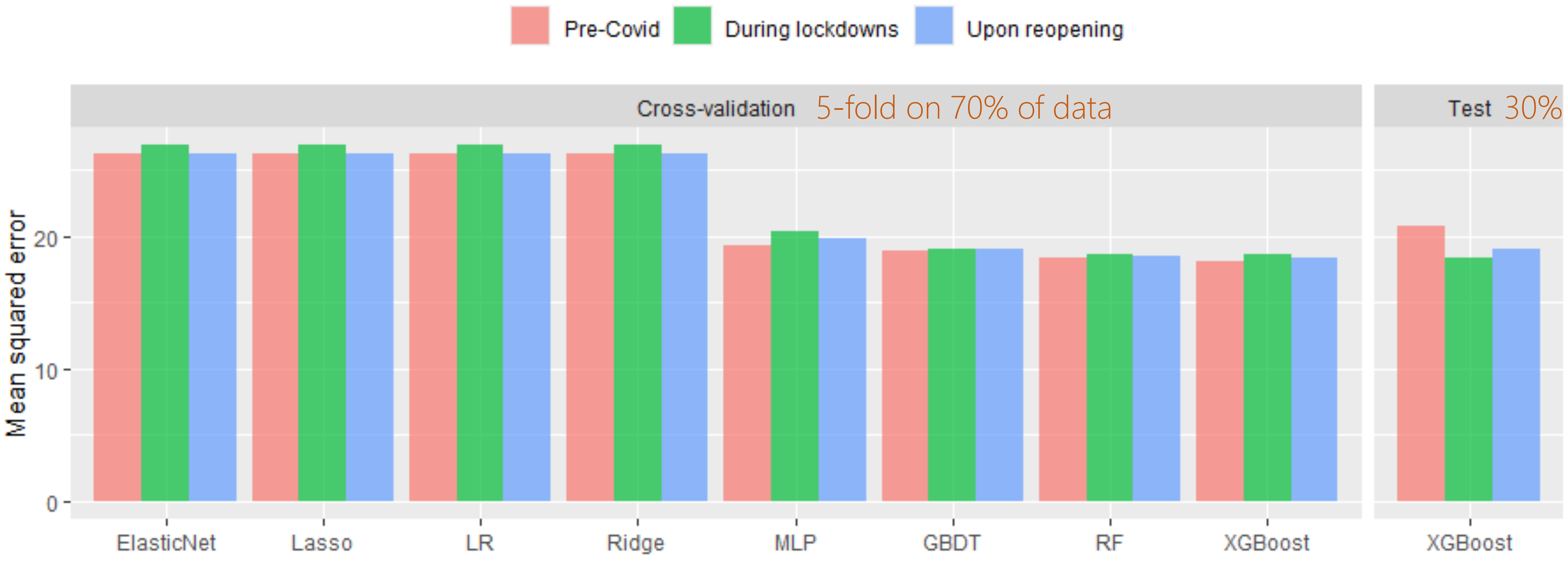
Correlations of topic proportions and sentiment scores across three periods



Predictive models for sentiment vs topics

Type	Model	Pros	Cons
Linear model	Linear regression	• Simple to implement • Interpretable	• Limited to linear relationships • Sensitive to outliers
	Ridge regression	• Reduces overfitting by adding regularization	• Requires tuning of regularization parameters
	Lasso regression		
	ElasticNet		
Neural network	Multi-layer perceptron (MLP)	• Capable of modelling complex, non-linear relationships	• Requires large amounts of data, • Prone to overfitting • Longer training time
Tree-based ensemble method	Random forest (RF)	• Handles non-linear data well • Robust to overfitting • Good accuracy	• Slower to train and predict, less interpretable • Can overfit if not tuned properly, longer training time
	Gradient boosting decision tree (GDBT)		
	Extreme gradient boosting (XGBoost)		

Model performance



Explainable machine learning/AI (XML/XAI)

Types and/or aspects:

- Intrinsic/ante-hoc or post-hoc
- Model specific or model-agnostic
- Local or global

Post-hoc explanations refer to methods that are applied after a machine learning model has made predictions to explain how or why the model arrived at those decisions. These explanations are essential when using complex, often “black-box” models like deep neural networks or ensemble methods that are difficult to interpret directly.

Shapley additive explanations (SHAP)

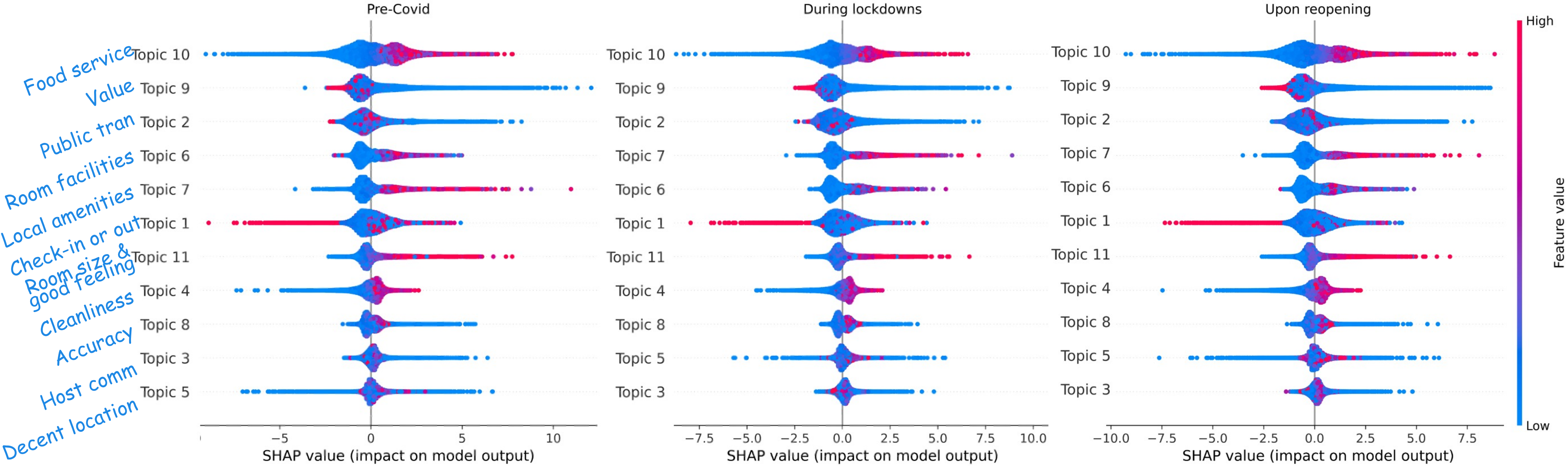
- The idea behind SHAP is to compute Shapley values from game theory to gain local and global understanding of the contributions from feature values in the given data.
- For feature j, we compute it as a weighted sum reflecting each feature's impact averaged across all possible feature combinations added to the model.

$$\xi_j(f,x) = \sum_{W \subseteq \{1,\ldots,J\} \setminus \{j\}} \underbrace{\frac{|W|!(J-|W|-1)!}{J!}}_{=\textit{Weight}} \underbrace{\left[f_x(W \cup \{j\}) - f_x(W)\right]}_{=\textit{Contribution}},$$

where J is the size the feature vector, and W is the subsect of $\{1,\ldots,J\}\setminus\{j\}$.

Lundberg, S. M., & Lee, S. I. (2017). "A unified approach to interpreting model predictions". Proceedings of the 31st International Conference on Neural Information Processing Systems, 12, 4768–4777.

Global and local feature importance summary



Implications

- Transportation: Hosts can improve business continuity by incorporating micro-mobility options (e.g., bikes, e-bike, e-scooters). Offering micromobility assets provides psychological benefits for consumers and supports sustainable urban practices.
- Cleanliness and healthy eating: Hosts have a competitive advantage by encouraging 'home cooking' and maintaining a clean, well-equipped kitchen for health-conscious guests. Personalising the kitchen setup with specific foods can cater to individual preferences, enhancing guest satisfaction.
- Technological innovation: Self-service technology can partially or fully automate these processes, providing convenience and flexibility.

Thanks!

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Chen, B. , Anker, T. B. and Liang, X. (2025) "Business continuity management in the sharing economy: insights from Airbnb online reviews". Tourism Management, 107, 105067. doi: 10.1016/j.tourman.2024.105067

Appendix: Timeline of the UK government Covid-19 lockdowns and measures from March 2020 to December 2021

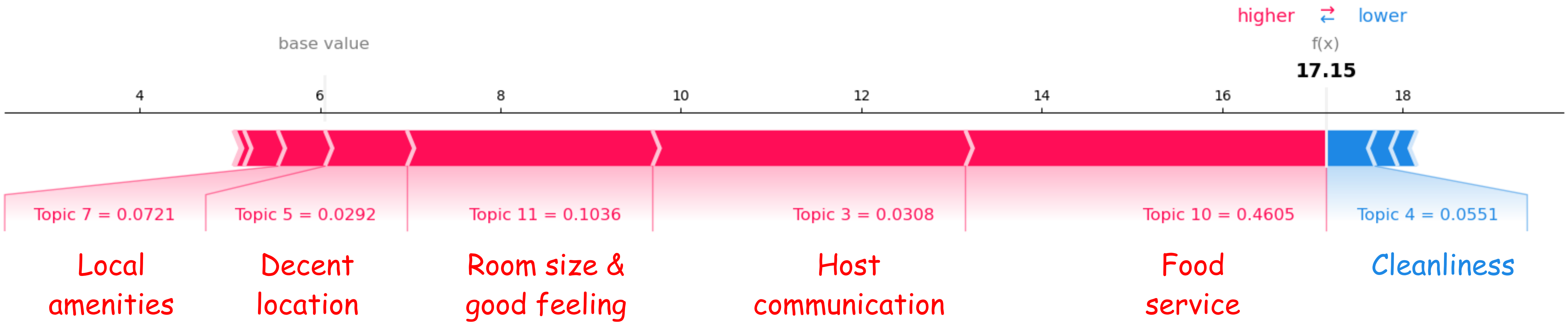
31 January 2020	The first two cases of Covid-19 in the UK reported.
16 March 2020	PM says "now is the time for everyone to stop non-essential contact and travel".
23 March 2020	PM announces the first lockdown in the UK, ordering people to "stay at home".
26 March 2020	Lockdown measures legally come into force.
16 April 2020	Lockdown extended for "at least" three weeks. Government sets out five tests that must be met before restrictions are eased.
23 June 2020	PM says UK's "national hibernation" coming to an end – announces relaxing of restrictions and 2m social distancing rule.
04 July 2020	UK's first lockdown comes into force in Leicester and parts of Leicestershire. More restrictions are eased in England, including reopening of pubs, restaurants, hairdressers.
14 August 2020	Lockdown restrictions eased further, including reopening indoor theatres, bowling alleys, soft play.
04 October 2020	A new three-tier system of Covid-19 restrictions starts in England.
31 October 2020	PM announces a second lockdown in England to prevent a "medical and moral disaster" for the NHS.
05 November 2020	Second national lockdown comes into force in England.
24 November 2020	PM announces up to three households will be able to meet up during during a five-day Christmas period of 23 to 27 December.

02 December 2020	Second lockdown ends after four weeks and England returns to a stricter three-tier system of restrictions.
19 December 2020	PM announces tougher restrictions for London and South East England, with a new Tier 4: "Stay at Home" alert level. Christmas mixing rules tightened.
21 December 2020	Tier 4 restrictions come into force in London and South East England.
26 December 2020	More areas of England enter Tier 4 restrictions.
06 January 2021	England enters third national lockdown.
15 February 2021	Hotel quarantine for travellers arriving in England from 33 high-risk countries begins.
22 February 2021	PM publishes a roadmap for lifting the lockdown.
08 March 2021	Step 1: Schools in England reopen for primary and secondary school students. Recreation in an outdoor public spaces will be allowed between two people. "Stay at home" order remains in place.
29 March 2021	Step 1: Outdoor gatherings of either six people or two households will be allowed, including in private gardens. Outdoor sports facilities also reopen. "Stay at home" order ends but people encouraged to stay local.
12 April 2021	Step 2: Non-essential retail, hairdressers, public buildings (e.g. libraries and museums) reopen. Outdoor venues, including pubs and restaurants, zoos and theme parks also open, aswell as indoor leisure (e.g. gyms). Self-contained holiday accommodation opens. Wider social contact rules continue to apply in all settings – no indoor mixing between different households allowed.

17 May 2021	Step 3: Limit of 30 people allowed to mix outdoors. "Rule of six" or two households allowed for indoor social gatherings. Indoor venues will reopen, including pubs, restaurants, cinemas. Up to 10,000 spectators can attend the very largest outdoor-seated venues like football stadiums.
19 July 2021	Step 4: Most legal limits on social contact removed in England, and the final closed sectors of the economy reopened (e.g. nightclubs).
14 September 2021	PM unveils England's winter plan for Covid – "Plan B" to be used if the NHS is coming under unsustainable pressure, and includes measures such as face masks.
08 December 2021	PM announces a move to 'Plan B' measures in England following the spread of the Omicron variant.
10 December 2021	Face masks become compulsory in most public indoor venues under Plan B.
15 December 2021	NHS Covid Pass becomes mandatory in specific settings (e.g., nightclubs under Plan B).

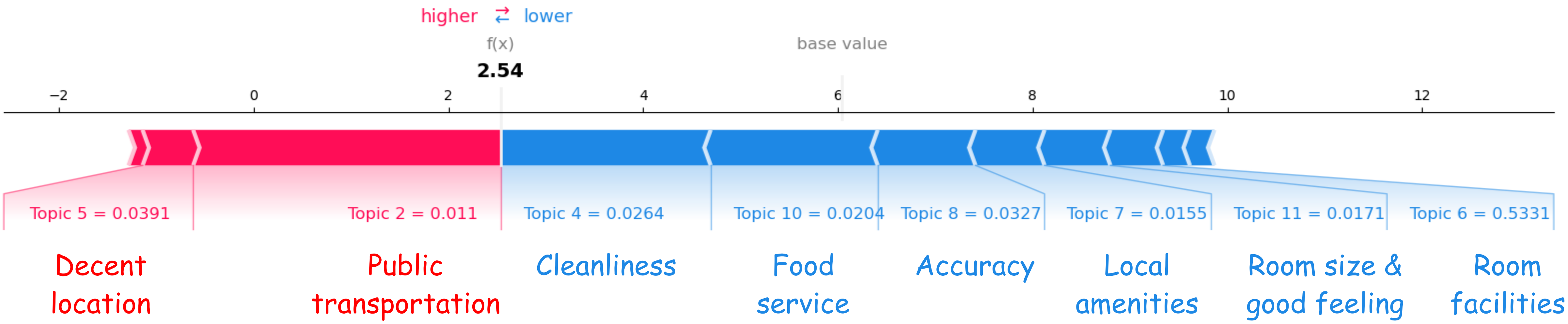
Appendix: Local explanations example

"super host is an understatement, laurence and suzanne's is one of the best airbnb stays i've had. they were incredibly lovely and accomodating when my travel plans fell through and made me feel so welcome. it was nice to sit with them a few times and have tea and breakfast or to even watch the birds in the garden from the kitchen window. the room was as described, clean (they often offered fresh towels and bedding!) and cosy with little touches that made it homey. the area is well serviced by buses and trains but if you like to walk, like me, you'll be delighted by all the lovely parks and sights nearby. as a first time, solo female traveller i felt very safe. many, many thanks again to suzanne and laurence for everything ❤️"

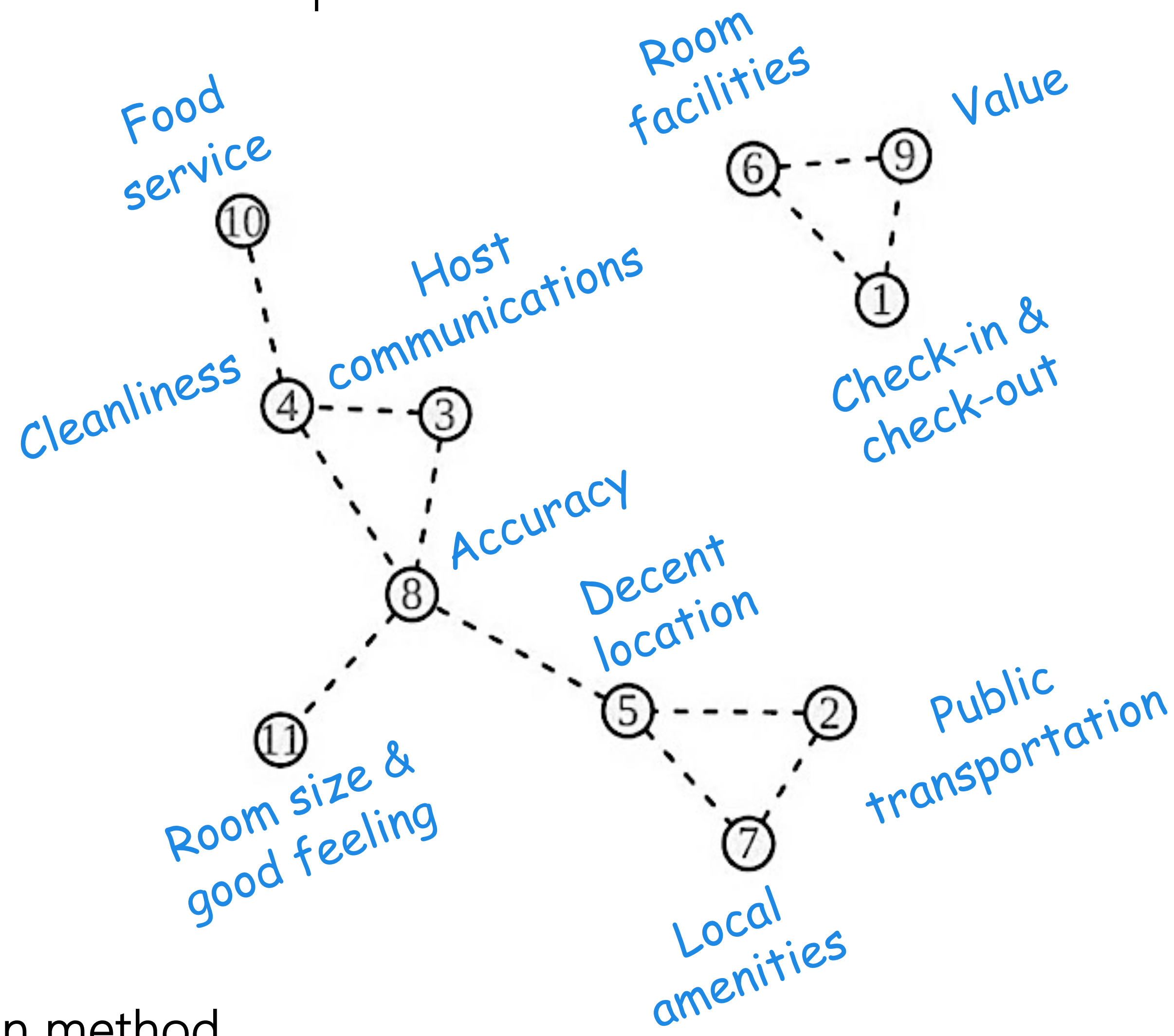


Appendix: Local explanations example

"positives: the apartment at night was quiet although you do hear the neighbours as the move around or come in and out up the stairs. the flat is in a great central location. negatives: apartment was not up to the stated standard at all. wifi was very poor. no signal in the bedrooms at all. lamps were missing bulbs or not working. the double bed collapsed as we were sleeping and we had to move beds. the furniture is worn and tired with lots of stains. there is significant construction directly opposite the flat which made doing anything in the flat during the day impossible. huge lorries, drilling, flashing lights, shouting. overall the quality, cleanliness and consideration for people renting the apartment isn't very well thought through for considerate. that kind of major disruption with the construction should be stated upfront, it's unacceptable. we didn't stay the second night we had booked and went elsewhere. not a great airbnb experience :("



Appendix: Correlations of topics



Meinshausen-Buhlmann method

Tuo Zhao et al. “The huge package for high-dimensional undirected graph estimation in R”. Journal of Machine Learning Research 13 (2012), pp. 1059–1062.

Appendix: Hyperparameter tuning for predictive models

Type	Model	Hyper-parameter settings
Linear model	Linear regression	NA
	Ridge regression	"alpha": [0.001, 0.01, 0.5, 1]
	Lasso regression	"alpha": [0.001, 0.01, 0.5, 1]
	ElasticNet	"alpha": [0.001, 0.01, 0.5, 1], "l1_ratio": [0.001, 0.01, 0.5, 1]
Neural network	Multi-layer perceptron (MLP)	"hidden_layer_sizes": [(100, 100, 100), (200, 200, 200), (200,)], "activation": ["relu", "tanh", "logistic"]
Tree-based ensemble method	Random forest (RF)	"max_depth": [10, 25, 50], "min_samples_leaf": [1, 5, 10] "min_samples_split": [2, 5, 10], "n_estimators": [300, 400, 500]
	Gradient boosting decision tree (GDBT)	"learning_rate": [0.05, 0.1, 0.15], "n_estimators": [300, 400, 500]
	Extreme gradient boosting (XGBoost)	"max_depth": [10, 25, 50], "learning_rate": [0.05, 0.1, 0.15], "min_child_weight": [2, 3, 4], "n_estimators": [300, 400, 500]

Appendix: Popular post-hoc explanation methods

Model	Pros	Cons
Impurity-based feature importance	• Fast and efficient • Built-in to tree-based models • Globally interpretable	• Biased towards features with more categories • only applicable to tree-based models, • feature interaction ambiguity
Permutation feature importance	• Model-agnostic • Less biased	• Can be computationally expensive • Feature interaction ambiguity
Local interpretable model-agnostic explanations (LIME)	• Model-agnostic • Provide local interpretability	• Sensitivity to parameter settings • Computationally expensive • Only local explanations
Shapley additive explanations (SHAP)	• Theoretically sound and consistent • Handles interactions well	• Computationally expensive, especially for large datasets