

Hotel Review in Europe

TEAM: MLB

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Agenda

Introduction

Research Question

Data and Method

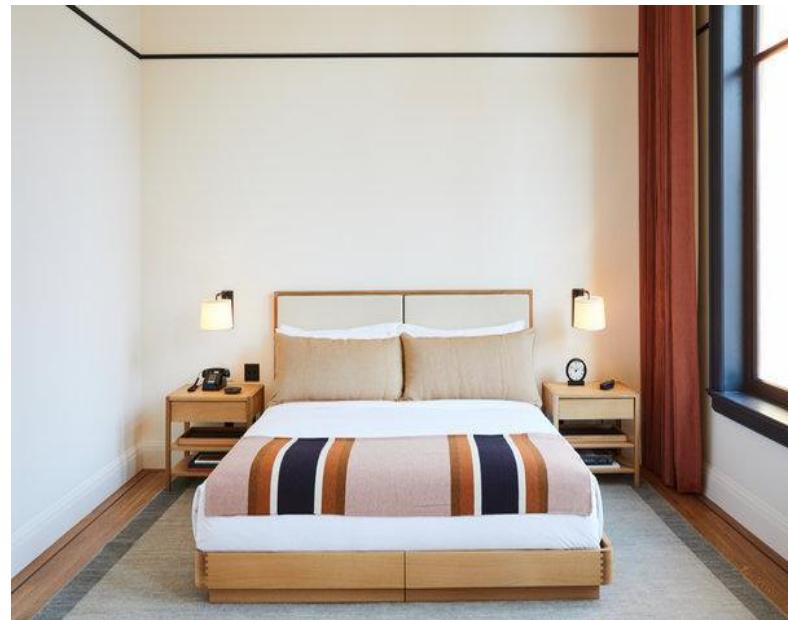
EDA visualization

Modeling result

Conclusion

Introduction

- Digital “word of mouth”
- Online reviews have significant impacts on consumers’ booking intents and perceptions of trust
- Cultural differences will affect travelers’ opinions on what the important features of hotels are
- Cultural differences also influence consumer complaint behavior (CCB)



Research Question

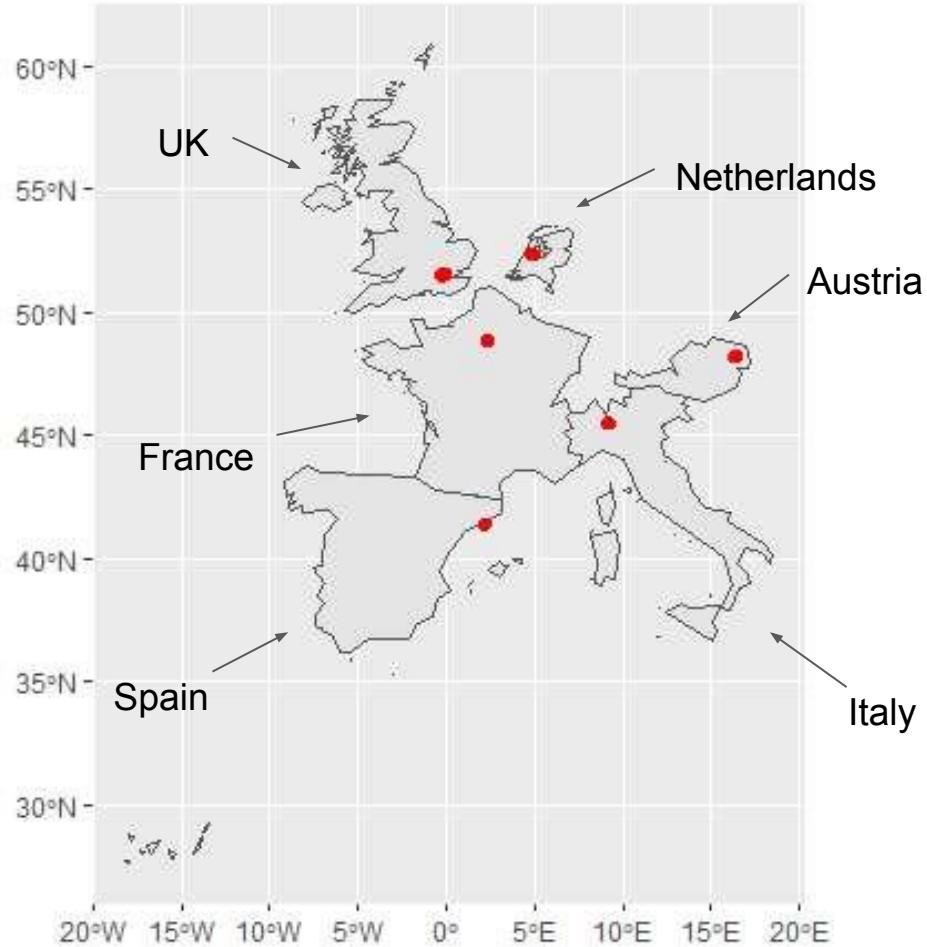
We would like to see if there is a correlation between keywords in online reviews and scores that hotels receive. The predictive power implied in this correlation could be a useful tool for hotels to cater to different needs of their customers, especially when cultural differences are at play.

Data and Method

- The dataset has 17 variables, with 515,000 reviews and scores of 1,493 luxury hotels located within 6 countries in Europe
- Choose the top 10 countries of travelers' origin
- Visualization using scatterplots, boxplot, bar charts and line graphs
- Multiple linear regressions for data analysis:
 1. review scores and influencing factors
 2. influence of keywords on positive/negative reviews
 3. regression with interaction term
- Spatial graph

Data Visualization-Spatial Analysis

1. Filter the original dataset by deleting all the duplicates from hotel_address and their associated longitudes and latitudes, and store the new data including three variable columns into a new dataset called unique.csv
2. each of the six red points on the right represents the geographical position of hotels in each of the six countries in Europe.



Limitation and Further Research of Spatial Analysis

Since the hotel address from the original dataset contains mostly only one city in each country. For example, in France, almost all hotel locations are in Paris. There is only one red point shown on the graph of each country.

If we can find hotel addresses from more diverse cities in each country, for example, London, Manchester, Liverpool in UK, we may later implement clustering algorithm (where k=3 chosen) to do clustering on the points.

Example of pseudocode on the right.

```
# assign three clusters
from sklearn.cluster import KMeans
kmeans = KMeans(n_clusters=3)
kmeans.fit(X)
y_kmeans = kmeans.predict(X)

# import library
from sklearn.metrics import pairwise_distances_argmin
def find_clusters(X, n_clusters, rseed=3):

    # 1. randomly choose clusters
    rng = np.random.RandomState(rseed)
    i = rng.permutation(X.shape[0])[:n_clusters]
    centers = X[i]

    while True:

        # 2. assign labels based on closest center
        labels = pairwise_distances_argmin(X, centers)

        # 3. find new centers from means of points
        new_centers = np.array([X[labels == i].mean(0) for i in range(n_clusters)])

        centers, labels = find_clusters(X, 3)
        plt.scatter(X[:, 0], X[:, 1], c=labels, s=50, cmap='viridis')

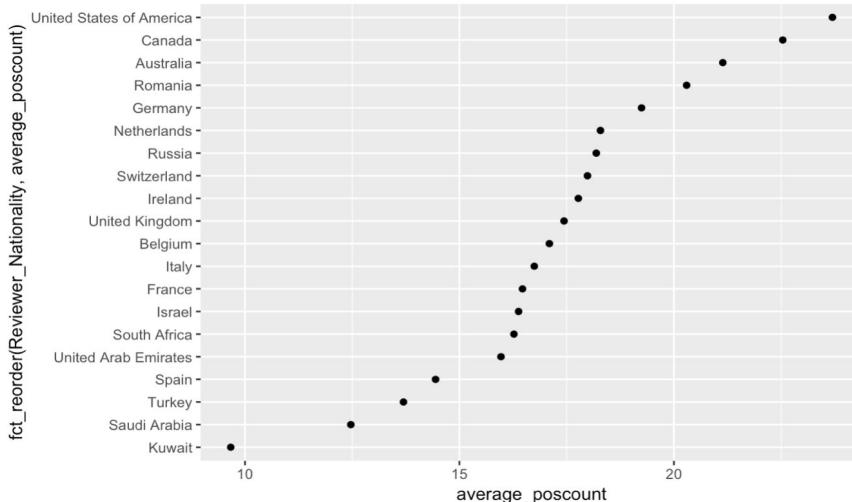
        if np.all(centers == new_centers):
            break
    centers = new_centers
return centers, labels
```

EDA Results/Data Visualization

Reviewer_Nationality

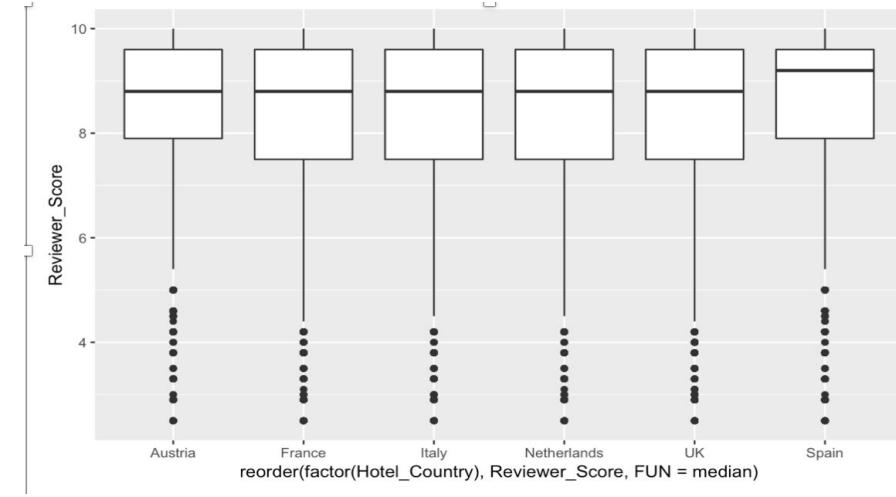
| Reviewer_Nationality | num_tourist_by_nation |
|--------------------------|-----------------------|
| United Kingdom | 245246 |
| United States of America | 35437 |
| Australia | 21686 |
| Ireland | 14827 |
| United Arab Emirates | 10235 |
| Saudi Arabia | 8951 |
| Netherlands | 8772 |
| Switzerland | 8678 |
| Germany | 7941 |
| Canada | 7894 |

fct_reorder(Reviewer_Nationality, average_poscount)

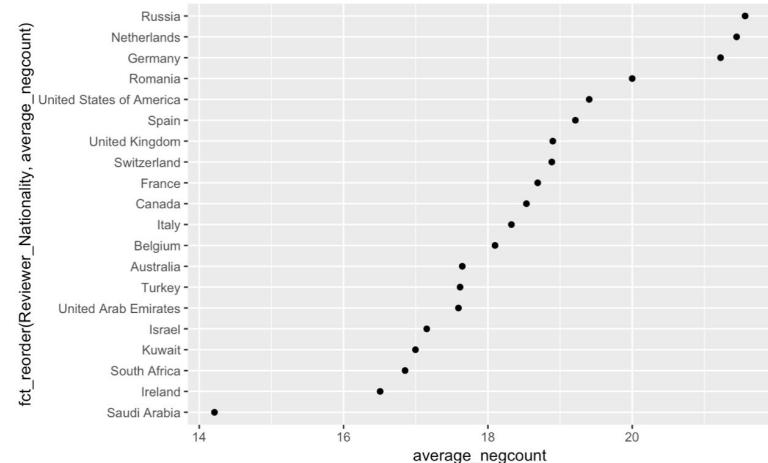


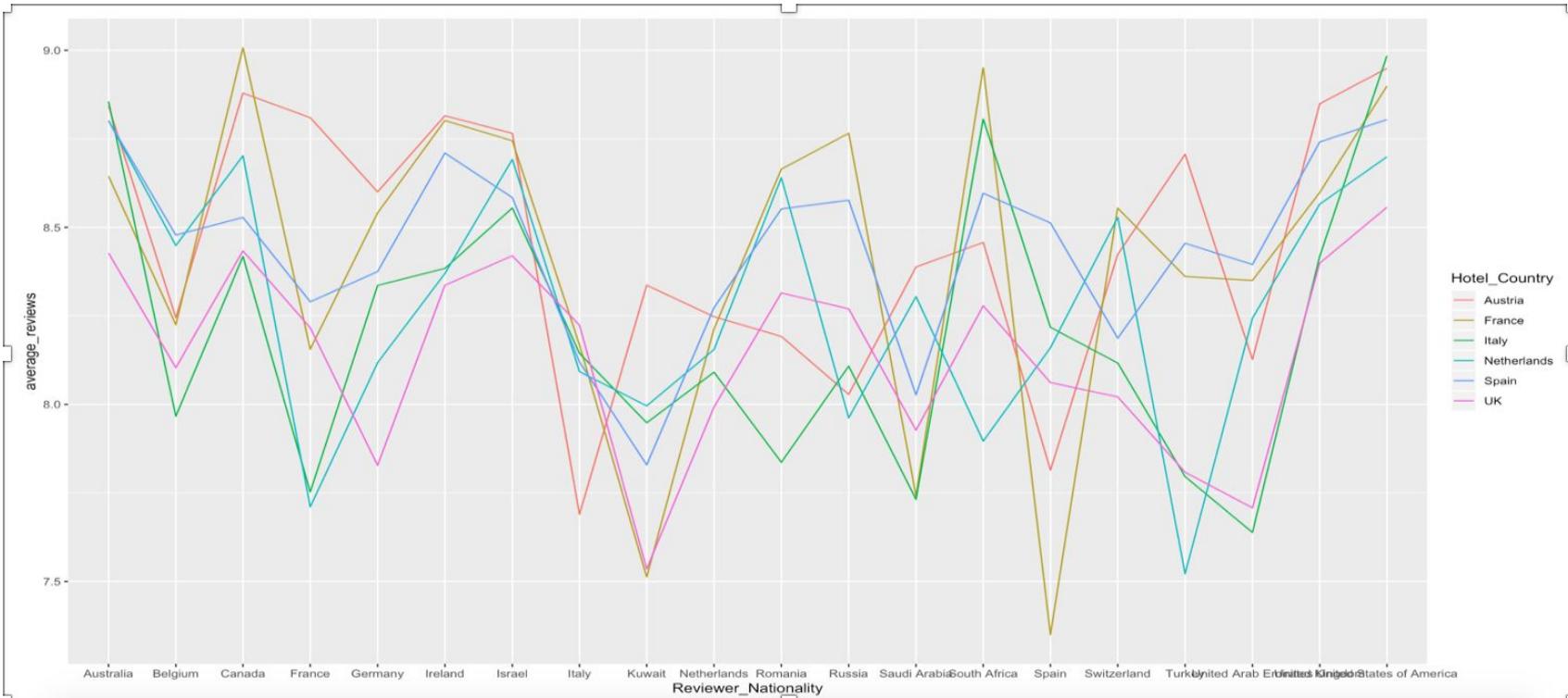
num_tourist_by_nation

<chr>
United Kingdom
United States of America
Australia
Ireland
United Arab Emirates
Saudi Arabia
Netherlands
Switzerland
Germany
Canada

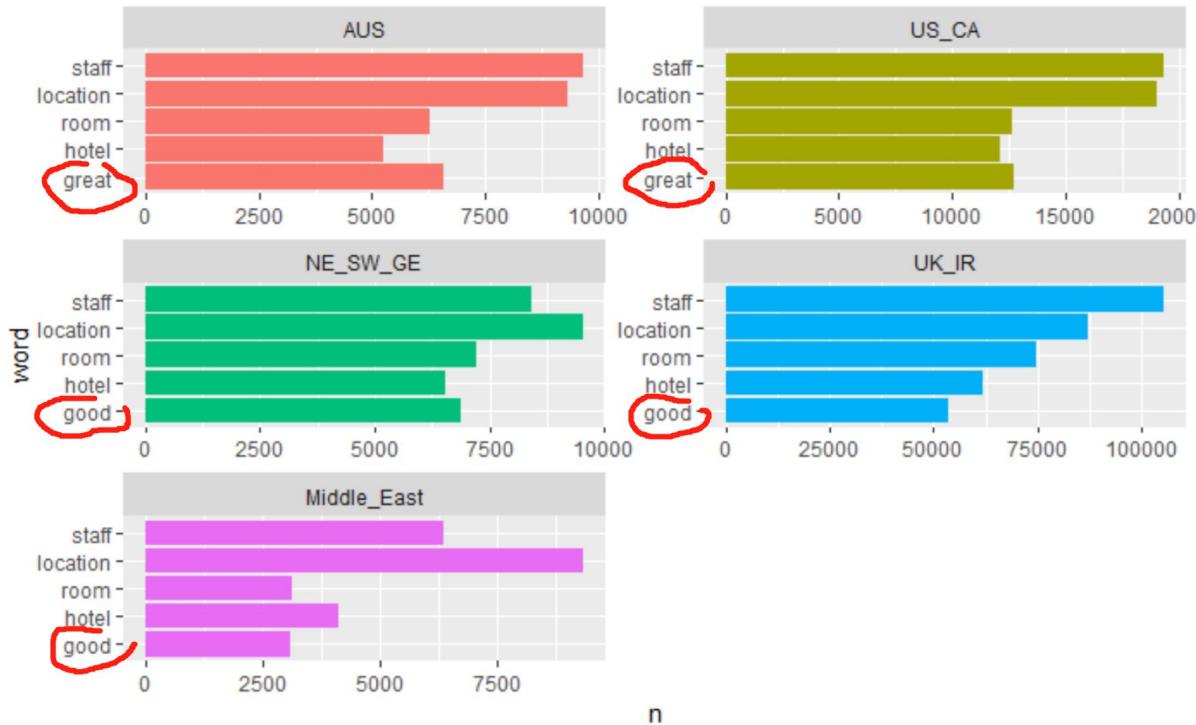


fct_reorder(Reviewer_Nationality, average_negcount)



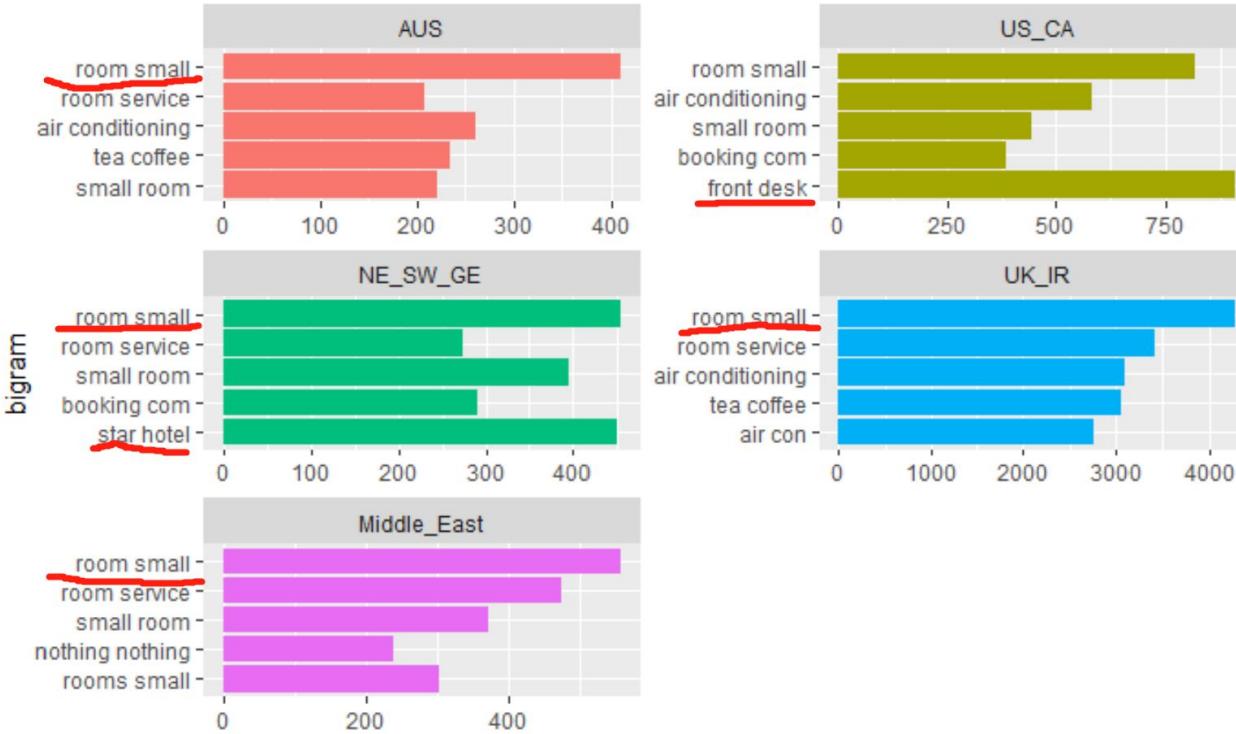


EDA Visualization: Positive Review



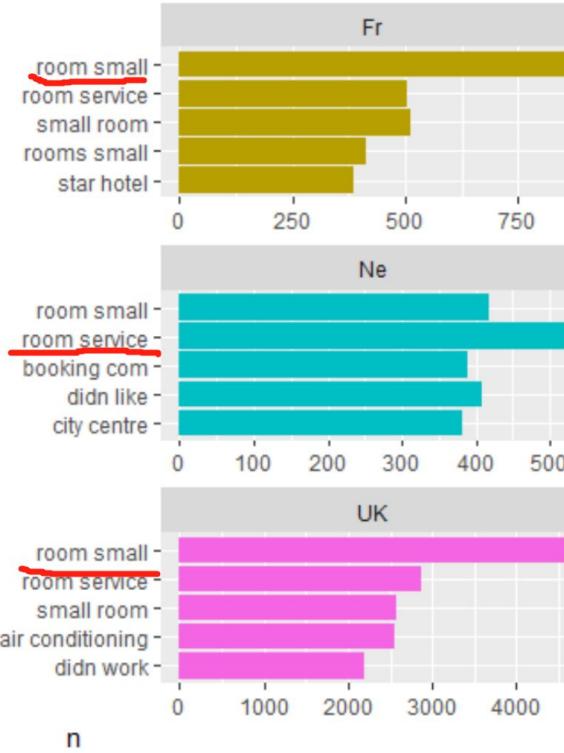
- Cultural Similarity
- Great VS Good
- Friendly Staff
- Good Location

EDA Visualization: Negative Review (1)

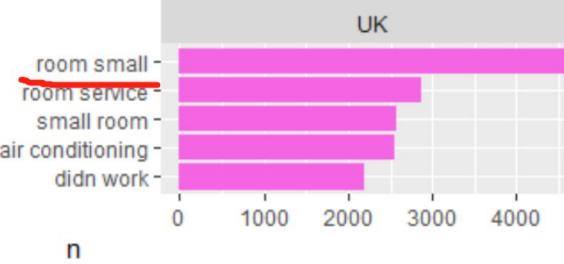
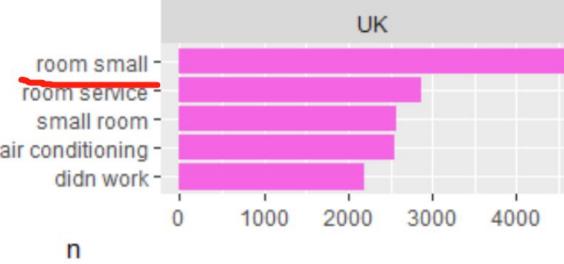
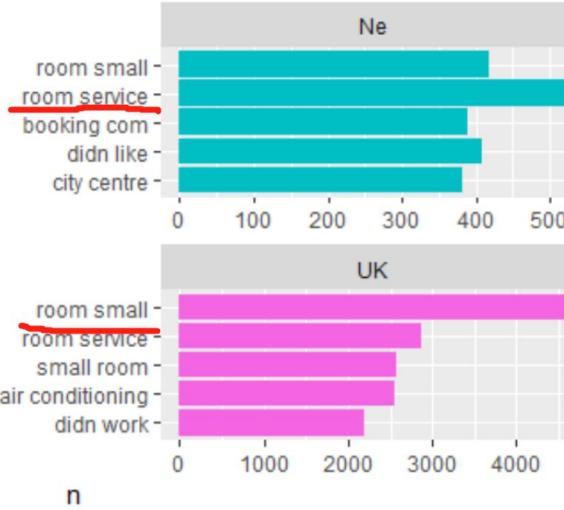


- Group by Tourists' Country
- Room Small
- Peculiarities

EDA Visualization: Negative Review (2)



- Group by Hotel
- Country
- Room Small
- Air Conditioner
- Peculiarity



EDA Visualization: Average Score

| Reviewer_Nationality | AvSC |
|----------------------|----------|
| <fctr> | <dbl> |
| US_CA | 8.421511 |
| AUS | 8.285644 |
| UK_IR | 8.191468 |
| NE_SW_GE | 7.791922 |
| Middle_East | 7.628262 |

Is the above result consistent with people's intuition?

Multiple Linear Regression #1

$$\widehat{Y} = 0.1345 - 6.538X_1 - 0.0002616X_2 - 0.01169X_3 - 0.001308X_4$$

Call:

```
lm(formula = Reviewer_Score ~ negative_ratio + days_since_review +
  difference + Total_Number_of_Reviews_Reviewer_Has_Given,
  data = reviews_ed2)
```

Residuals:

| Min | 1Q | Median | 3Q | Max |
|---------|---------|--------|--------|--------|
| -7.0246 | -0.8766 | 0.2525 | 1.1420 | 6.2529 |

Coefficients:

| | Estimate | Std. Error | t value | Pr(> t) |
|--|------------|------------|----------|--------------|
| (Intercept) | 1.345e+01 | 4.528e-02 | 297.091 | < 2e-16 *** |
| negative_ratio | -6.538e+00 | 5.834e-02 | -112.077 | < 2e-16 *** |
| days_since_review | →2.616e-04 | 2.015e-05 | -12.983 | < 2e-16 *** |
| difference | -1.169e-02 | 1.389e-04 | -84.190 | < 2e-16 *** |
| Total_Number_of_Reviews_Reviewer_Has_Given | -1.308e-03 | 3.741e-04 | -3.496 | 0.000472 *** |

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.526 on 130954 degrees of freedom
Multiple R-squared: 0.1344, Adjusted R-squared: 0.1344
F-statistic: 5084 on 4 and 130954 DF, p-value: < 2.2e-16 ←

Comparatively Significant Covariates in terms of estimates and p-value:

- negative_ratio (ratio of negative reviews)
- difference (word count differences between positive/negative reviews)

Figure 1: Summary of Parameter Estimates

Multiple Linear Regression #1: Modeling Assumptions

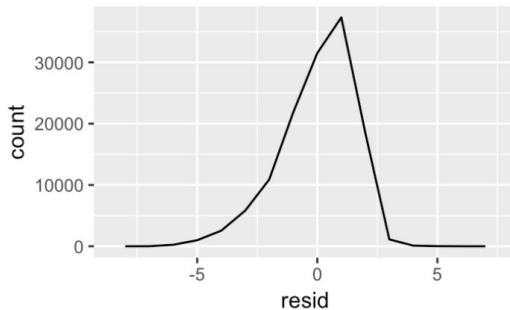


Figure 2: The Frequency Distribution of Residuals

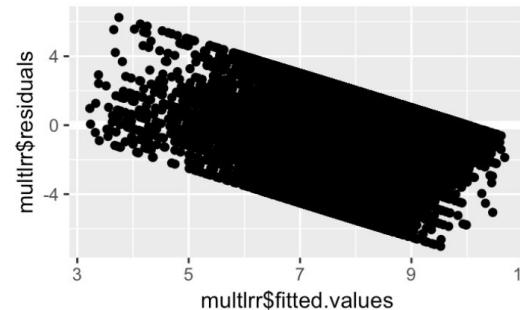


Figure 3: Residuals vs. Fitted Values

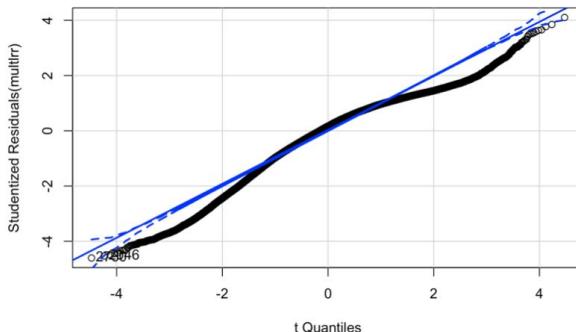


Figure 4: QQ Plot of Multiple Linear Regression #1

Regression Tree Modeling

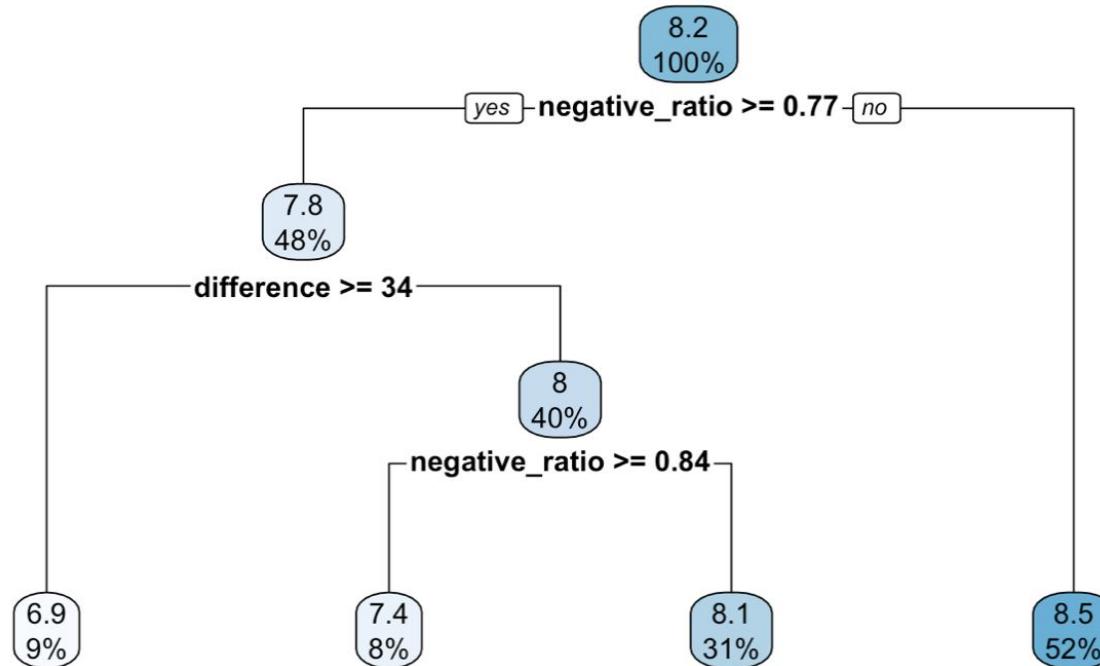
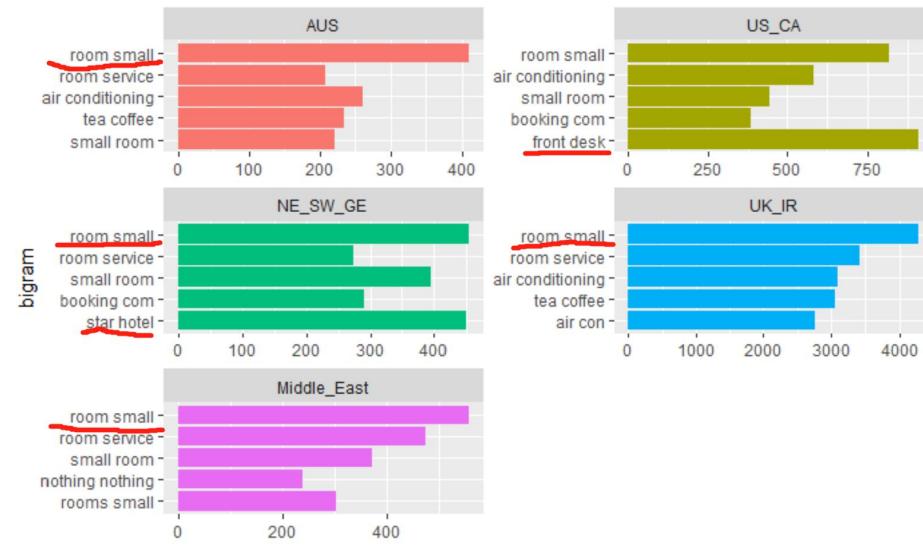


Figure 5: Regression Tree of Multiple Linear Regression #1

Modelling Results: Multiple Linear Regression for Negative Review

| | Estimate | Std. Error | t value |
|---------------------------------|------------|------------|---------|
| small | -5.345e-01 | 8.419e-03 | -63.492 |
| breakfast | -2.813e-01 | 9.238e-03 | -30.451 |
| bed | -8.722e-01 | 1.027e-02 | -84.918 |
| bathroom | -5.994e-01 | 1.257e-02 | -47.674 |
| coffee | -2.586e-01 | 1.783e-02 | -14.506 |
| Reviewer_NationalityAUS | 8.810e+00 | 1.961e-02 | 449.221 |
| Reviewer_NationalityUS_CA | 8.923e+00 | 1.720e-02 | 518.950 |
| Reviewer_NationalityNE_SW_GE | 8.334e+00 | 1.857e-02 | 448.844 |
| Reviewer_NationalityUK_IR | 8.782e+00 | 1.573e-02 | 558.381 |
| Reviewer_NationalityMiddle_East | 8.115e+00 | 1.952e-02 | 415.756 |
| Hotel_CountryFr | -2.215e-01 | 1.722e-02 | -12.863 |
| Hotel_CountryIt | -2.598e-01 | 1.976e-02 | -13.145 |
| Hotel_CountryNe | -2.044e-01 | 1.706e-02 | -11.983 |
| Hotel_CountrySp | -6.464e-02 | 1.708e-02 | -3.784 |
| Hotel_CountryUK | -3.498e-01 | 1.495e-02 | -23.406 |
| days_since_review | -1.048e-04 | 1.493e-05 | -7.017 |
| Pr(> t) | | | |
| small | < 2e-16 | *** | |
| breakfast | < 2e-16 | *** | |
| bed | < 2e-16 | *** | |
| bathroom | < 2e-16 | *** | |
| coffee | < 2e-16 | *** | |
| Reviewer_NationalityAUS | < 2e-16 | *** | |
| Reviewer_NationalityUS_CA | < 2e-16 | *** | |
| Reviewer_NationalityNE_SW_GE | < 2e-16 | *** | |
| Reviewer_NationalityUK_IR | < 2e-16 | *** | |
| Reviewer_NationalityMiddle_East | < 2e-16 | *** | |
| Hotel_CountryFr | < 2e-16 | *** | |
| Hotel_CountryIt | < 2e-16 | *** | |
| Hotel_CountryNe | < 2e-16 | *** | |
| Hotel_CountrySp | 0.000154 | *** | |
| Hotel_CountryUK | < 2e-16 | *** | |
| days_since_review | 2.27e-12 | *** | |

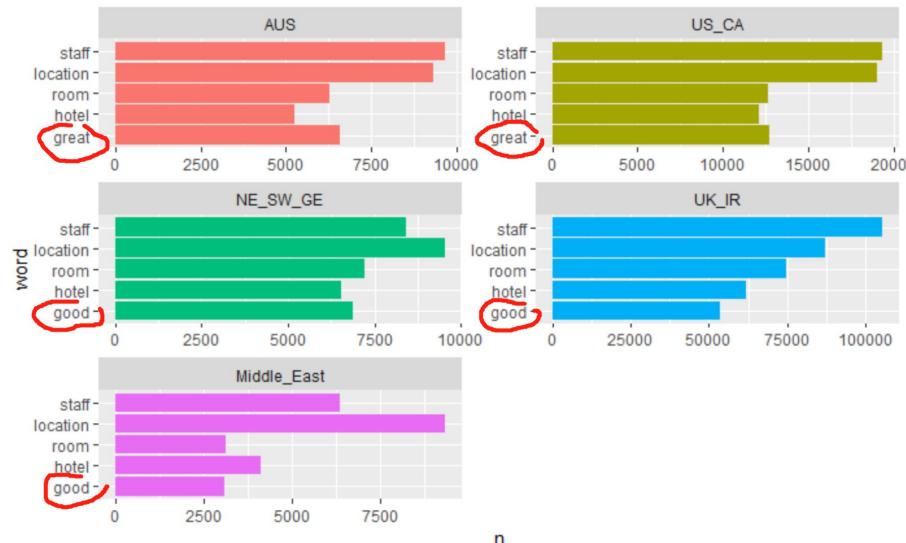
- Those closely related to living experience are ‘powerful’



Modelling Results: Multiple Linear Regression for Positive Review

| | Estimate | Std. Error | t value |
|---------------------------------|------------|------------|---------|
| location | 5.262e-02 | 5.716e-03 | 9.206 |
| staff | 6.191e-01 | 5.470e-03 | 113.181 |
| bed | 2.274e-01 | 7.680e-03 | 29.609 |
| clean | 1.819e-01 | 7.619e-03 | 23.867 |
| breakfast | 1.750e-01 | 7.855e-03 | 22.279 |
| Reviewer_NationalityAUS | 8.519e+00 | 1.598e-02 | 533.203 |
| Reviewer_NationalityUS_CA | 8.662e+00 | 1.411e-02 | 613.878 |
| Reviewer_NationalityNE_SW_GE | 8.138e+00 | 1.538e-02 | 529.292 |
| Reviewer_NationalityUK_IR | 8.500e+00 | 1.302e-02 | 653.060 |
| Reviewer_NationalityMiddle_East | 7.921e+00 | 1.643e-02 | 482.152 |
| Hotel_CountryFr | -1.420e-01 | 1.384e-02 | -10.262 |
| Hotel_CountryIt | -1.604e-01 | 1.594e-02 | -10.060 |
| Hotel_CountryNe | -1.227e-01 | 1.383e-02 | -8.873 |
| Hotel_CountrySp | -3.886e-02 | 1.376e-02 | -2.824 |
| Hotel_CountryUK | -2.564e-01 | 1.207e-02 | -21.236 |
| days_since_review | 9.000e-06 | 1.223e-05 | 0.736 |
| Pr(> t) | | | |
| location | < 2e-16 | *** | |
| staff | < 2e-16 | *** | |
| bed | < 2e-16 | *** | |
| clean | < 2e-16 | *** | |
| breakfast | < 2e-16 | *** | |
| Reviewer_NationalityAUS | < 2e-16 | *** | |
| Reviewer_NationalityUS_CA | < 2e-16 | *** | |
| Reviewer_NationalityNE_SW_GE | < 2e-16 | *** | |
| Reviewer_NationalityUK_IR | < 2e-16 | *** | |
| Reviewer_NationalityMiddle_East | < 2e-16 | *** | |
| Hotel_CountryFr | < 2e-16 | *** | |
| Hotel_CountryIt | < 2e-16 | *** | |
| Hotel_CountryNe | < 2e-16 | *** | |
| Hotel_CountrySp | 0.00474 | ** | |
| Hotel_CountryUK | < 2e-16 | *** | |
| days_since_review | 0.46182 | | |

- Friendly staffs do matter!



Interaction Term

Later, we add an interaction term Review_Total_Negative_Word_Counts:countrydummy to test whether the effect of Review_Total_Negative_Word_Counts on Reviewer_Score depends on the state of countrydummy, where countrydummy is denoted shown at the bottom.

```
mutate(countrydummy = ifelse(Hotel_Country == 'France', 1,  
                             ifelse(Hotel_Country == 'Italy', 2,  
                                   ifelse(Hotel_Country == 'Netherlands', 3,  
                                         ifelse(Hotel_Country == 'Spain', 4,  
                                               ifelse(Hotel_Country == 'UK', 5, 0))))))  
|
```

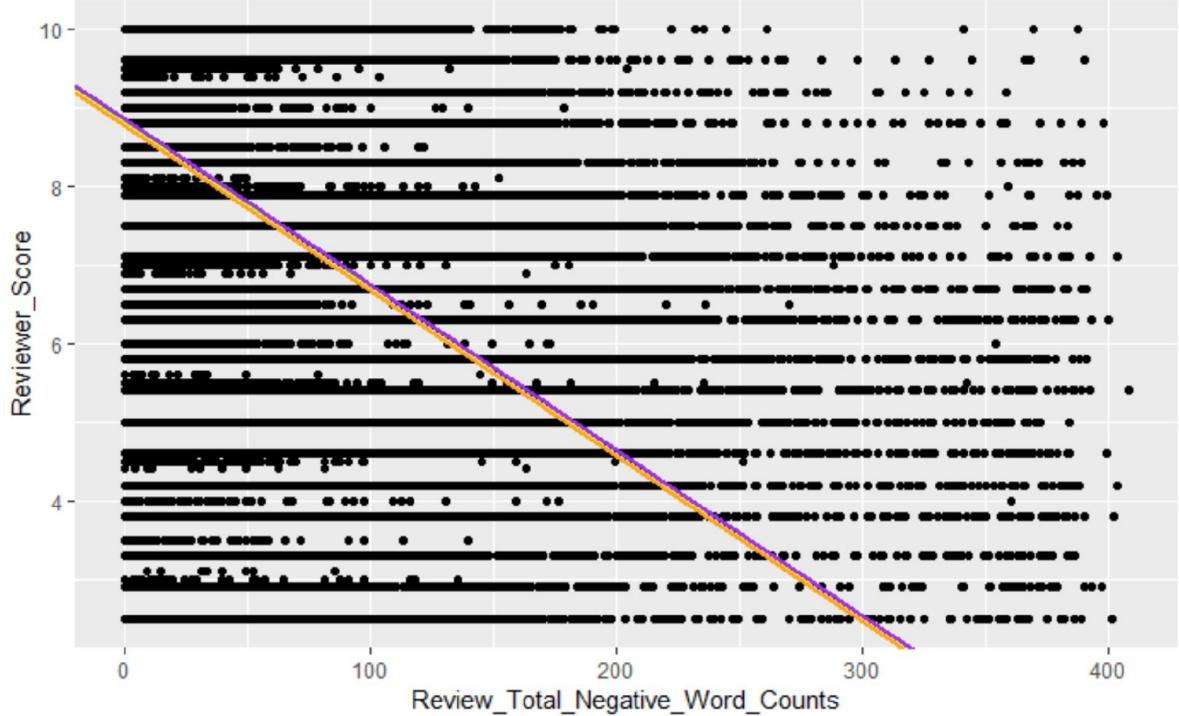
From the table, the p-value is 0.785, which is insignificant. Therefore, we decide to remove the interaction term.

```
Call:
lm(formula = Reviewer_Score ~ Review_Total_Negative_Word_Counts +
    countrydummy + Review_Total_Negative_Word_Counts:countrydummy,
    data = dummyset)

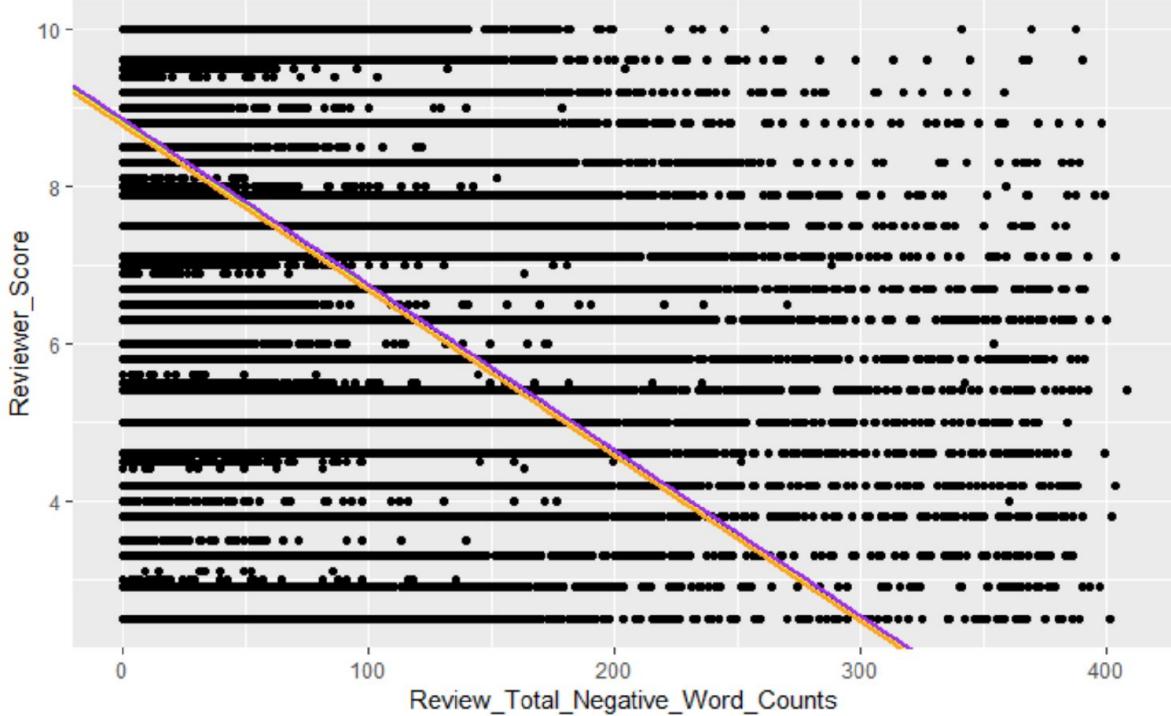
Residuals:
    Min      1Q  Median      3Q     Max 
-6.357 -0.833  0.442  1.183  9.389 

Coefficients:
                                         Estimate
(Intercept)                         8.857e+00
Review_Total_Negative_Word_Counts      -2.111e-02
countrydummy                          -1.980e-02
Review_Total_Negative_Word_Counts:countrydummy 1.150e-05
                                         Std. Error
(Intercept)                         5.674e-03
Review_Total_Negative_Word_Counts     1.699e-04
countrydummy                          1.426e-03
Review_Total_Negative_Word_Counts:countrydummy 4.207e-05
                                         t value
(Intercept)                         1561.075
Review_Total_Negative_Word_Counts     -124.255
countrydummy                          -13.879
Review_Total_Negative_Word_Counts:countrydummy 0.273
                                         Pr(>|t|) 
(Intercept)                         <2e-16 ***
Review_Total_Negative_Word_Counts     <2e-16 ***
countrydummy                          <2e-16 ***
Review_Total_Negative_Word_Counts:countrydummy 0.785
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.513 on 515734 degrees of freedom
Multiple R-squared:  0.1467,    Adjusted R-squared:  0.1467 
F-statistic: 2.956e+04 on 3 and 515734 DF,   p-value: < 2.2e-16
```



We use six colors to represent six countries. From the graph on the left, we find that six lines are in high superposition.



Additionally, there is an interesting pattern that at lower reviewer scores, the negative word counts are more widely distributed whereas they are highly concentrated at lower values when the review scores are becoming larger. We think the reasons could be travelers who are more dissatisfied with the hotel experience might write more negative comments to abreact their negative emotions.

Conclusion

Residual standard error: 1.623 on 278209 degrees of freedom
Multiple R-squared: 0.9621, Adjusted R-squared: 0.9621
F-statistic: 4.416e+05 on 16 and 278209 DF, p-value: < 2.2e-16

- Joint Significance of Coefficients, and the Overall Goodness of Fit for Negative Words

Residual standard error: 1.491 on 345906 degrees of freedom
Multiple R-squared: 0.9707, Adjusted R-squared: 0.9707
F-statistic: 7.154e+05 on 16 and 345906 DF, p-value: < 2.2e-16

- Joint Significance of Coefficients, and the Overall Goodness of Fit for Positive Words
- Finally, hotels/restaurants should give tourists a hospitable ambience, regardless of where the tourists come from!

Thank You !

- Q & A