Data Exploration Findings

1. Peak into data

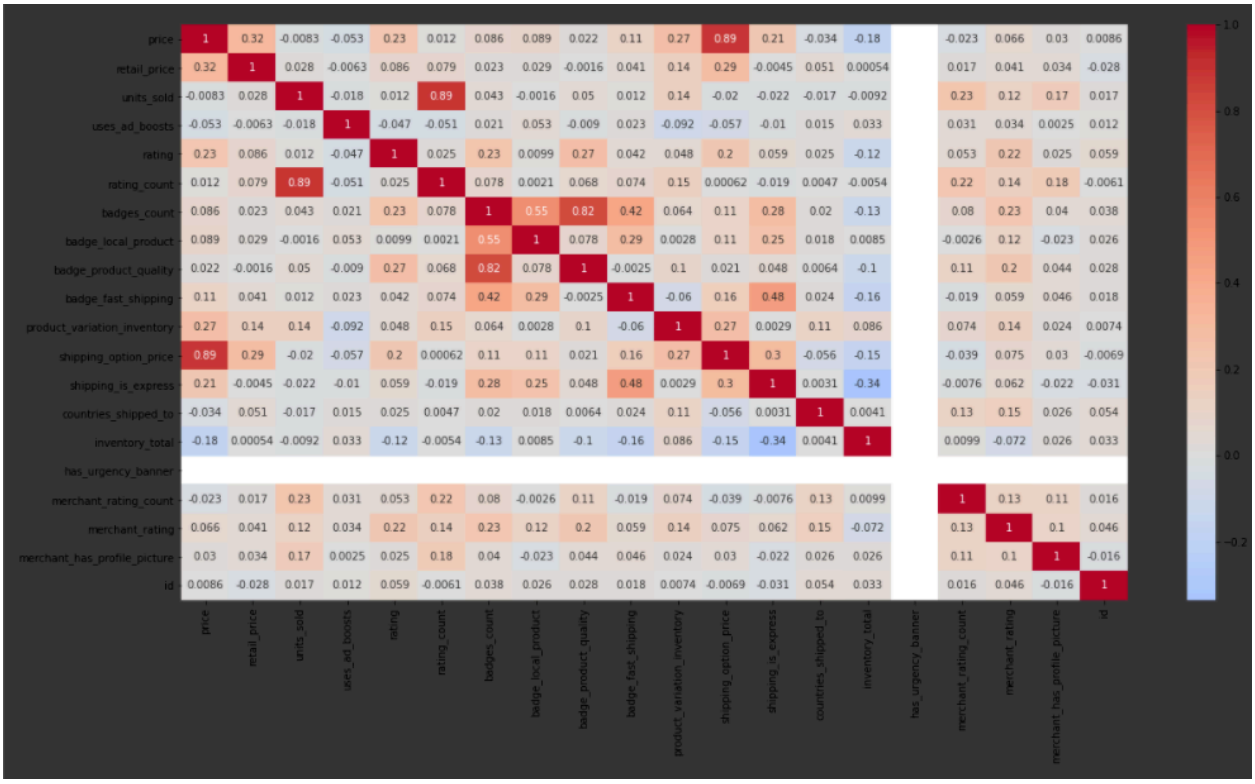
We start with 32 features with ratings being the target feature.

2. Using a heat correlation map:

Columns price and shipping option price has a correlation of 0.89. Decisions: if correlation was higher, I would consider removing but 0.89 is still too low in my opinion and needs further consideration.

Columns rating count and units sold also have a correlation of 0.89. Decisions: if correlation was higher, I would consider removing but 0.89 is still too low in my opinion and needs further consideration. It also makes sense that these two are positively correlated.

Has urgency banner and urgency text have a correlation of 1 (determined after some preprocessing). Decisions: I first fixed the columns and missing values so they represent a binary feature and then re did the heat map to find that these two had a correlation of 1 and should therefore be removed.



3. Checking for missing values

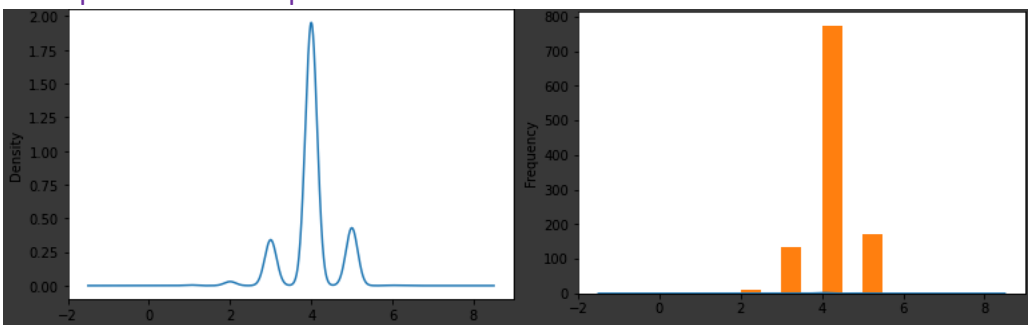
Product color, product variation size id, has urgency banner, urgency text, origin country, merchant name, merchant profile picture are the only columns with missing values. Decisions: required further look into features to determine how to deal with missing values.

Checking for uni-value columns (columns with the same values for each row or composed MAINLY (95% +) of one value. (also double checked with excel filter)

- Currency buyer's only value is EUR, theme and crawl_month only have one value as well. Decisions: these features are removed.
- Shipping_option_name only has 3 categories however they are mainly China or US very disproportionately. Decisions: these features are removed.
- Shipping_is_express almost all the rows had a value of 0 and only a few 1s. Decisions: these features are removed.

4. Checking feature (and target variable) distribution

Checking the distribution of ratings to see what is considered a good rating. Seems that most ratings are approximately 4 and a good rating is anything above 4.3 let's say. The two graphs represent the distribution of the target variable (rating). It seems that it is a binomial distribution with majority of ratings at 4. Decisions: I can try a data sampling method to deal with the slightly unbalanced data. It seems that a big proportion of rating is 4 so that class has the most amount of data oversampling (since we don't have too much data) could be used to see if performance improves.



Checking distribution of numeric features (following are positively skewed)

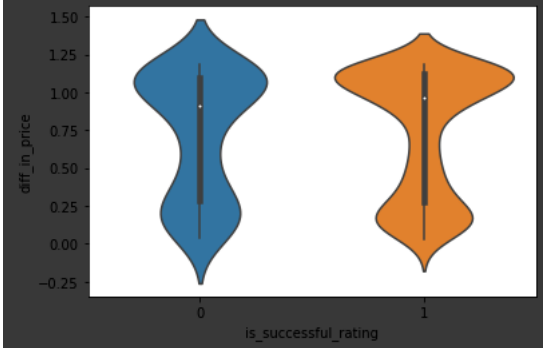
Feature	Mean	Median
retail_price	24	10
units_sold	4519	1000
rating_count	916.0	143.5
merchant_rating_count	26784	8225

The above features are all positively skewed as they have a mean higher than their median. Decisions: to improve performance we could try cube/cube square to sort of improve the distribution of the feature.

5. checking for significant relationships between features/features and features/target

Wanted to see if there is a difference between price and retail_price. And I also wanted to see if that difference has an effect of ratings. First, I set 4 as a threshold for a successful rating then compared difference in price and retail price with product rating. As you can see there is no different between high and low rated products in terms of price vs retail price. Decisions: Since there is no significant correlation, these two features could be removed if needed to improve model performance

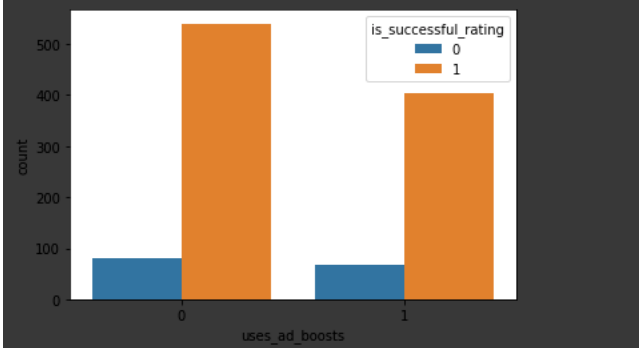
```
Overall stats:
8.320786106032902
23.712065813528337
----------------------
Stats for successful products:
8.544814814814815
24.404232804232805
----------------------
Stats for unsuccessful products:
6.899932885906042
19.322147651006713
<matplotlib.axes._subplots.AxesSubplot at 0x7faf
```



I wanted to see the relationship between ad_boosts and product rating. There seems to be no significant relationship between using ad boosts and ratings. Decisions: could be removed if needed to improve model performance

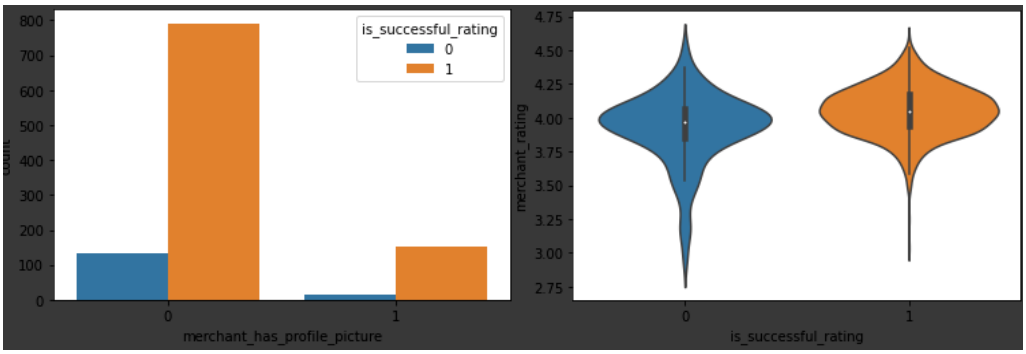
```
Percent of products using ad boosts:  43.235831809872025
```

is_successful_rating	0	1
uses_ad_boosts		
0	81	540
1	68	405



I wanted to see the relationship between merchant profile and merchant rating with product rating. There seems to be no significant association between merchant rating and rating of the product as seen in the violinplot (right). However, there is a relationship between merchant

profile and product ratings (left). It seems that presence of merchant profile picture is significantly associated with higher ratings.



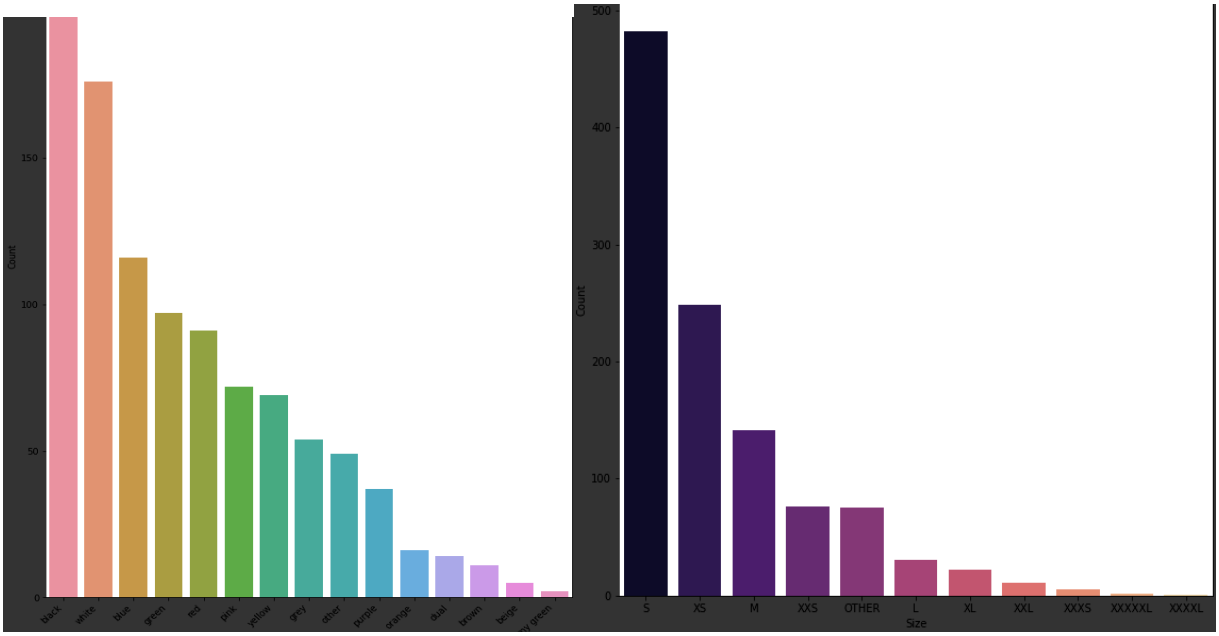
Data cleaning and pre-processing

6. Editing 'string' columns to binary

Both 'urgency_text' and 'has_urgency_banner' contained missing values and one had tex and needed to be pre-processed. Decisions: both were fixed in terms of missing values and changed to binary e.g. 1 if text or banner was present and 0 if not.

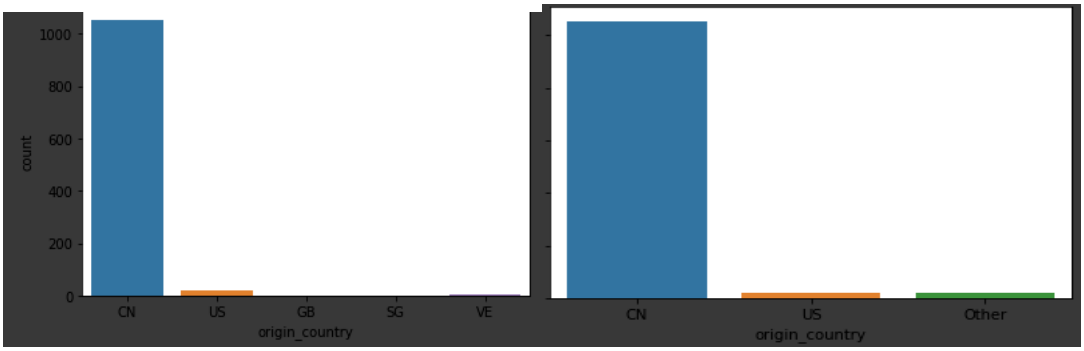
7. Unify name variations

The features 'product_variation_size_id' and 'product_color' both name variations refereeing to the same thing e.g. 'light blue' 'blue' 'Blue' 'Dark blue' 'bluee' are all variations of blue. Decisions: this was fixes by grouping major variations under one category e.g. 'blue' and categorizing minor variations as 'OTHER'. This was done for both of these features. There were a lot of variations in the color category in terms of spelling and abbreviations of same colors. Decisions: I grouped all variation into the respective color. Missing values or indistinguishable color names were categorized under OTHER. I also made a distribution of colors (left) just to see what color is the most popular. It seems that the most popular colors are black and white. Most popular sized are small and extra small.



8. Combining minority groups due to highly skewed distribution

For the feature origin_country it is mostly composed of US, China and minor others. Decisions: I preprocessed the data so that I keep CN and US and group the rest into others along with those with missing values.



Units_sold has few values below then first majority are above . Decisions: i combined anything below 10 as 10.

```
Median of units sold is 1000.0
Mean of units sold is 4518.6617915904935
100       353
1000      280
5000      139
10000     125
20000      79
50         54
10         47
50000      12
100000      5
```

9. Duplicate row removal

Duplicate rows were found. Decisions: they were removed going from 1094 to 1081.

10. Column removal

Duplicate rows Different features (columns) were removed and added back to observe the performance of the model. The list shown in the accompanying Jupyter code consists of features that consistently produced better results. Decisions: the table below shows all the features and the final decision made for the feature after playing around with model performance (Table 1).

price	Kept but change to int from float
retail_price	Kept
currency_buyer	Removed all values within the column were the same
units_sold	Kept
uses_ad_boosts	Kept
rating	Target attribute
rating_count	Kept
badges_count	Kept but not sure what it is
badge_local_product	Kept but not sure what it is
badge_product_quality	Kept but not sure what it is
badge_fast_shipping	Kept but not sure what it is
tags	Kept but changed to number of tags per row
product_color	Removed due to low significance determined using feature selection and model performance score
product_variation_size_id	Removed due to low significance determined using feature selection and model performance score
product_variation_inventory	Kept
shipping_option_name	Removed cause it only had 3 categories and they were mainly china or US
shipping_option_price	Kept
shipping_is_express	Removed cause almost all the rows had a value of 0 and only a few has 1s so best practive is to remove it
countries_shipped_to	Remove due to similar 'values'
inventory_total	Removed cause almost all the rows had a value of 50 and only a few had other values best practive is to remove it
has_urgency_banner	Kept but changed to binary and then int
urgency_text	Removed due to being synonym columns with 'has urgency banner' and also lowered performance score
origin_country	Kept but dummy encoded
merchant_title	Removed because keeping merchant is enough, it's just different ways of identifying the merchant so no need to keep them all
merchant_name	Removed because keeping merchant is enough, it's just different ways of identifying the merchant so no need to keep them all
merchant_info_subtitle	Removed
merchant_rating_count	Kept
merchant_rating	Kept but change to int from float
merchant_id	Removed
merchant_has_profile_picture	Kept
merchant_profile_picture	Removed
theme	Removed all values within the column were the same
crawl_month	Removed all values within the column were the same
id	Removed cause it's unique categorical column

Normalizing / Scaling / Encoding features / feature engineering

11. Encoding non int features

Features such as ‘product_color’ , ‘product_variation_size_id’ and ‘origin_country’ were ended using the get_dummies pandas function. Also the feature ‘tags’ were modified to count how many tags were in each record (using commas) and that number was saved as ‘tag_count’ and added as a feature and ‘tags’ was removed.

12. Min/Max normalization

All features except for the target variables ‘rating’ were normalized using the MinMaxScaler function from sklearn. Models were trained with both normalized and un-normalized features to check for performance.

13. Feature Engineering

After running the sklearn feature importance function with my random forest model I saw that most consistently important features were ratings and rating counts. I wanted to create a feature that distinguishes high rating with low rate counts and vice versa. I created this feature for rating_count and merchant_rating_count. Both features were used in the prediction model and evaluated using feature importance function.

```
Feature ranking:
1. feature 4 (rating_count) (0.182981)
2. feature 12 (merchant_rating) (0.135871)
3. feature 11 (merchant_rating_count) (0.124843)
4. feature 0 (price) (0.079496)
5. feature 1 (retail_price) (0.076236)
6. feature 17 (tag_count) (0.072905)
7. feature 14 (diff_in_price) (0.072249)
8. feature 2 (units_sold) (0.062142)
9. feature 8 (product_variation_inventory) (0.050085)
10. feature 9 (shipping_option_price) (0.037819)
11. feature 6 (badge_product_quality) (0.028629)
12. feature 5 (badges_count) (0.021484)
13. feature 10 (has_urgency_banner) (0.018654)
14. feature 3 (uses_ad_boosts) (0.017830)
15. feature 13 (merchant_has_profile_picture) (0.008844)
16. feature 7 (badge_fast_shipping) (0.004895)
17. feature 15 (country__Other) (0.002853)
```

Final data preparations

14. train / test split

I created 4 sets of X and y. first is X_no_split , y_no_split which is used for cross validation later on. Second is X_not_nor , y_not_nor which contains un-normalized data. Third is X_nor , y_nor which contains normalized data. Fourth and last (which only takes the training set) us called X_res , y_res which represents oversampled training data (running this cell was optional to observe change in performance).I mainly created these to make it easier to run models multiple times without having to keep manually changing variables to observe change in performance. I wanted to see the effect of normalization, over-sampling, cross validation on model performance.

Model evaluation

General feature patterns:

Wanted I observed the performance of all models using by removing and adding various features. Some general patterns I observed were slightly better performance for all models when color and size attributes were removed. I further confirmed these when I ran feature evaluation using the sklearn random forest feature evaluation and saw that features such as color, size, shipping is express, badge_local_product had the lowest priority (significance). These columns were then dropped. The remaining are 17 features used for modeling in order of importance in the following figure.

```
Feature ranking:
1. feature 4 (rating_count) (0.196857)
2. feature 12 (merchant_rating) (0.142623)
3. feature 11 (merchant_rating_count) (0.130748)
4. feature 0 (price) (0.095118)
5. feature 1 (retail_price) (0.083802)
6. feature 16 (tag_count) (0.078523)
7. feature 2 (units_sold) (0.066838)
8. feature 8 (product_variation_inventory) (0.052005)
9. feature 9 (shipping_option_price) (0.036222)
10. feature 6 (badge_product_quality) (0.035555)
11. feature 5 (badges_count) (0.024280)
12. feature 10 (has_urgency_banner) (0.019765)
13. feature 3 (uses_ad_boosts) (0.019073)
14. feature 13 (merchant_has_profile_picture) (0.011094)
15. feature 7 (badge_fast_shipping) (0.003352)
16. feature 15 (country__US) (0.002308)
17. feature 14 (country__Other) (0.001837)
```

Normalized vs un-normalized:

Model	Mean F1 score	
	Normalized	Un-normalized
Decision Tree	0.647	0.647
Random Forest	0.704	0.704
Adaboost	0.703	0.704
Neural net	0.24	0.193
Ensemble learning	0.708	0.708

There was no significance improve in performance except for a slight improvement for the neural net and ensemble learning. Since no negative effects were observed I will use normalized values for prediction.

Cross validated vs not cross validated:

Model	Mean F1 score	
	Cross validated	Not cross validated
Decision Tree	0.495	0.647
Random Forest	0.555	0.704
Adaboost	0.555	0.704
Neural Net	0.194	0.193
Ensemble Learning	0.543	0.708

** Adaboost took a very long time to run for cross validated (like… very long)

Since scores were lowered after cross validating results it shows that my model might not be as good as I thought right now. For a more realistic gasp of model performance I will be using cross validation to double check my model performance to make sure a good performance value isn't just by chance.

Over-sampling vs not over-sampling:

Model	Mean F1 score	
	Over-sampled	Not over-sampled
Decision Tree	0.615	0.647
Random Forest	0.668	0.704
Adaboost	0.677	0.704
Neural net	0.265	0.193
Ensemble learning	0.650	0.708

And I decided to try over sampling the data because we had an un-even number of records per class, there were many records for rating 4 and not as much for the other ratings. However, over-sampling data did not seem to increase model performance therefore will be not be implemented.

Decision Tree

- Gini performs better than entropy
- Splitter='random' improved performance
- Increases max-depth increases performance but has the risk of overfitting
- Model performs best when max_features includes all features. Performs worse if you decrease it.

Random Forest

- Increasing number of estimators improved model performance
- Gini performs better than entropy
- Setting bootstrap to False increases model performance. Also boostrap is better to use than out of bag sampling.
- Setting warm_start to True slightly increases model perfomance

Adaboost

- Lowering learning_rate to 0.01 increases model performance.
- Lowering n_estimators slightly increases performance

The table below shows difference pre-processing techniques used for each model variance. These models were also ran with varying set of features, new features were included and removed to observe performance.

Version	Model		
	XG Boost	Random Forest	Ensemble Learning
1	Not normalized Not oversampled	Not normalized Not oversampled	Not normalized Not oversampled
2	Normalized Not oversampled	Normalized Not oversampled	Normalized Not oversampled
3	Not normalized Oversampled	Not normalized Oversampled	Not normalized Oversampled
4	Normalized Oversampled	Normalized Oversampled	Normalized Oversampled
5	Normalized Undersampled	Normalized Undersampled	Normalized Undersampled

The highest score achieved uses training dataset was 0.7698 (on Kaggle) was using ensemble learning which contained the algorithms random forest, XGboost, Adaboost. The list of features used to achieve this is shown below.

#	Column	Non-Null Count	Dtype
0	price	1094 non-null	float64
1	retail_price	1094 non-null	float64
2	units_sold	1094 non-null	float64
3	uses_ad_boosts	1094 non-null	float64
4	rating	1094 non-null	float64
5	rating_count	1094 non-null	float64
6	badges_count	1094 non-null	float64
7	badge_product_quality	1094 non-null	float64
8	badge_fast_shipping	1094 non-null	float64
9	product_variation_inventory	1094 non-null	float64
10	shipping_option_price	1094 non-null	float64
11	has_urgency_banner	1094 non-null	float64
12	merchant_rating_count	1094 non-null	float64
13	merchant_rating	1094 non-null	float64
14	merchant_has_profile_picture	1094 non-null	float64
15	diff_in_price	1094 non-null	float64
16	country__CN	1094 non-null	float64
17	country__Other	1094 non-null	float64
18	country__US	1094 non-null	float64
19	tag_count	1094 non-null	float64

The dataset was normalized and cross validated and was not oversampled, in fact I noticed no significant difference with an oversampled dataset. In general ensemble learning and random forest and adaboost performed the best. XGboost and decision tree were next. Models such as neural net (MLP), KNN, and SVM did not perform well at all and were not further considered.