

Text-Based Price Classifier for Road Bikes on Carousell



Did you know?

Today

·-->

2030

525 km of cycling paths

1,300 km of cycling paths



From 2027: North-South Corridor

Singapore's first Integrated Transport Corridor with dedicated cycling paths





Infrastructure enhancement by the government to promote cycling for commuting and leisure purposes.

Cycling Popularity Spills Over to Carousell

CYCLING STILL MORE POPULAR NOW THAN BEFORE COVID

Cyclists and retailers said that many people who have picked up the sport have sustained an interest in it even as "normal life" resumed. Decathlon said that it is making 20 per cent more from bicycle sales now compared to pre-pandemic. 11 Mar 2023



todayonline.com

https://www.todayonline.com > singapore > cycling-bicy...

Cycling, bicycle sales on the decline after Covid boom, but ...



- Founded in Singapore
- For buying / selling new or second-hand goods.. Such as bicycles!

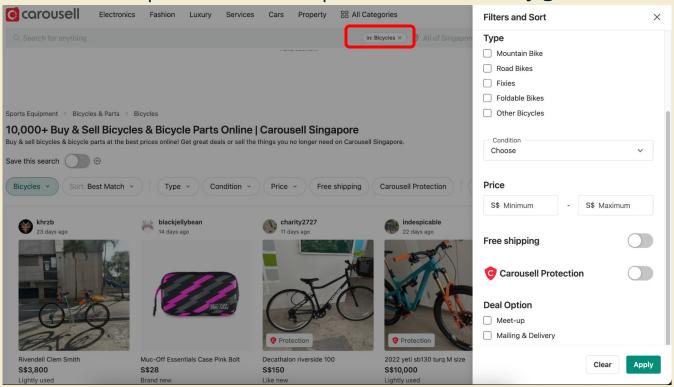






Using Carousell - Pain Points

Carousell is not specialized to each product; filters are very generic



Using Carousell - Pain Points

2. There are so many components on a road bike which affects its value!



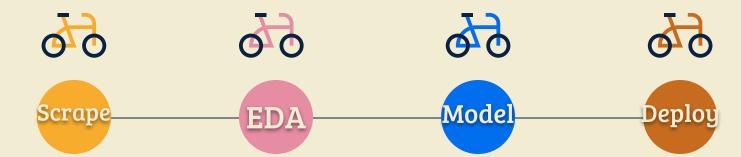
 As a buyer / seller, it is difficult to know what's a reasonable price to buy / sell at, and even more challenging as a novice

Problem Statement → Proposed Solution

- Carousell's filters are very generic
- Numerous components affect price
- Challenging to determine reasonable road bike price, especially as a novice

- Build a tool predicting road bike prices category from user-input values
- Success criteria: buyers /
 sellers can find out price to
 buy / sell at in less time than
 scrolling through Carousell to
 compare prices

Mapping the Journey



Listings were scraped from Carousell web, from the 'Bicycles' category Data cleaning and visualizations; feature engineering and finding patterns

Building classification models

Predicting the class (price level) of a road bike from text input



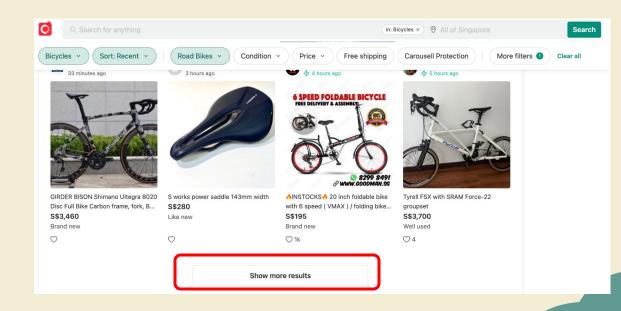






Data scraping from Carousell web

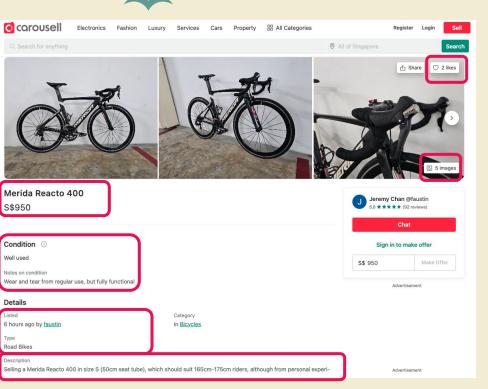
- 'Bicycles' category, with filter for 'Road Bikes'
- Beautiful Soup,
 Selenium

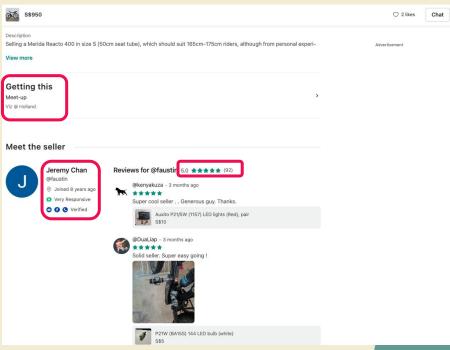


Dataset obtained: 2896 rows, 29 features













EDA

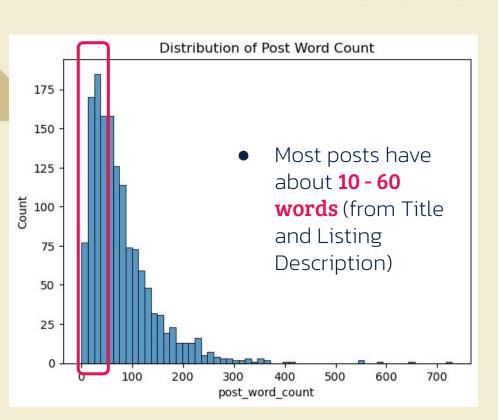
You can enter a subtitle here if you need it

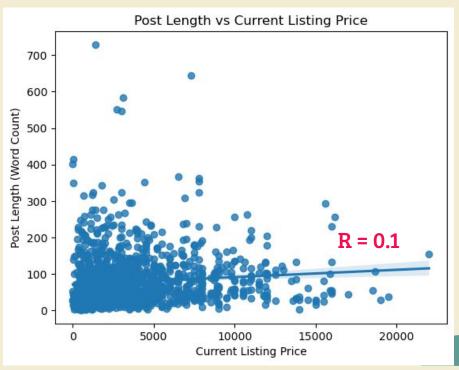
Current Listing Price



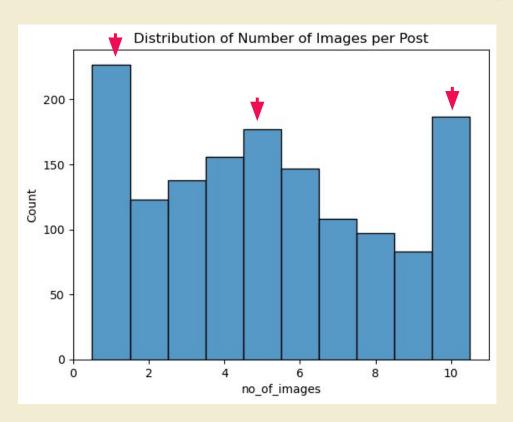
- Listings up to\$2,500 are mostcommon
- The most
 expensive listing
 is just under
 \$35,000 (outlier).

Post Word Count



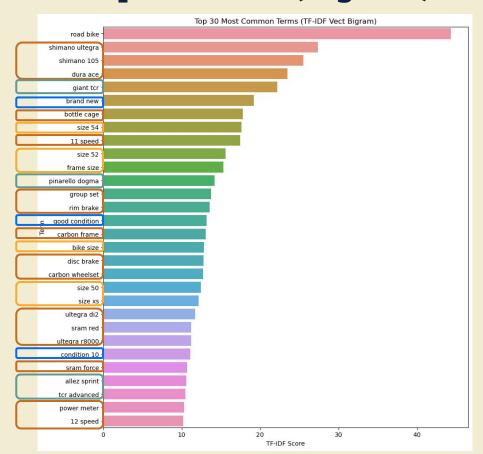


Number of Images



- Mean number of images per post is 5.
- There are listings which make full use of the 10 image limit

Top 30 Words (Bigram) - TF-IDF Vectorizer



Legend

Components

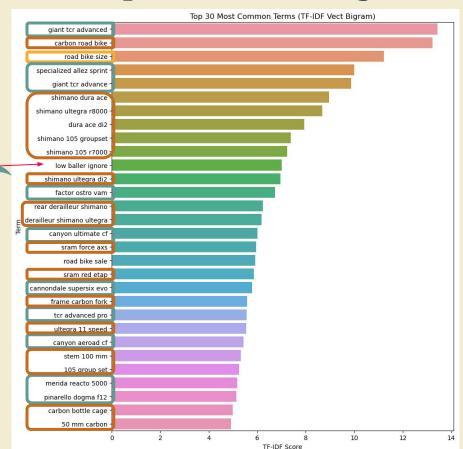
Size

Brand and/or model of bicycles

Condition

- Condition bigrams are common despite having a separate input area
- **Size 50, 52, 54** are common

Top 30 Words (Trigram) - TF-IDF Vectorizer



<u>Legend</u>

Components

Brand and/or model of bicycles

Size

- Components, brand and/or model of bicycles are most frequently mentioned
- "Low ballers will be ignored!"





Modeling

Pre-Modeling Preparation

1 Identify columns to send for modeling

Narrow down
dataframe to listings
up to \$2000

2

Use **BERTopic** for topic identification:

 Obtain top 10 words for each topic and append to dataframe

4

Feature engineer price:

- Class O (\$0 \$600)
- Class 1 (\$601 \$1200)
- Class 2 (\$1201 \$2000)

Topics from BERTopic

```
Topic 0: bike, size, carbon, shimano, frame, mm, road, new, cm, ultegra
Topic 1: specialized, bike, mm, carbon, tarmac, shimano, size, saddle, sram, ultegra
Topic 2: giant, tcr, shimano, advanced, size, pro, disc, carbon, wheelset, advance
Topic 3: merida, reacto, carbon, bike, shimano, ultegra, scultura, size, frame, road
Topic 4: trek, madone, bontrager, oclv, bike, slr, size, aeolus, emonda, carbon
Topic 5: canyon, cf, bike, ultimate, endurace, aeroad, size, sl, shimano, new
Topic 6: pinarello, dogma, size, di2, f12, dura, ace, bike, wheelset, f10
```

Each topic has a mixture of **brand** and **model** name, **components**, **properties** of the bike

Modeling Summary

	Accuracy (Train)	Accuracy (Test)	AUC	Recall	Precision	F1
Gradient Boosting Classifier (baseline)	0.8365	0.8276	1.0000	0.8276	0.8918	0.8348
Logistic Regression	0.9406	0.9212	0.9869	0.9212	0.9211	0.9210
k-nearest Neighbours	0.9682	0.9655 ↑ 17%	0.9981	0.9655	0.9675	0.9658





Deployment

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Streamlit demo







Key Insights & Impact

Key Insights

Components maketh the bike

Sellers: list your bike components, ensuring to use keywords

Buyers: know what components you want/need, and search by keywords

Bike sizes 50, 52, 54 are listed frequently

Sellers: if you're selling a bike of this size make sure to have a USP / good price

Buyers: many choices if you are looking for bicycles of these sizes

Post quality

Sellers: aim to use up to 100 words and upload 5 images

Buyers: avoid posts which are too brief; it will be difficult to ascertain pricing



Problem Statement

- Carousell's filters are very generic
- Numerous components affect price
- Challenging to determine reasonable road bike price, especially as a novice

Proposed Solution

 Build a tool predicting road bike prices category from user-input values

Impact

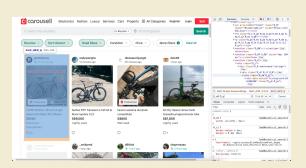
- Users are able to save
 10 15 min of
 'research' time
- Takes less than 2 min
 to input keywords and
 get a recommended
 price range





here if you need it

Challenges & Solutions



Data scraping html class changes every day

Re-inspect soup and update code before scraping
Use div-id where

possible



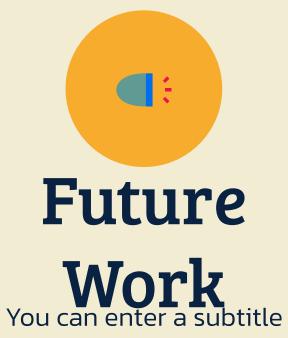
Limited to about 2,500 listings scraped per run

Scrape data every few days to get newer listings



Feature engineered a 'brands' dictionary containing bicycle brands





here if you need it

Future Work

Increase size of dataset for Road
Bikes, with higher price ranges

Decrease price window of predicted class for more actionability

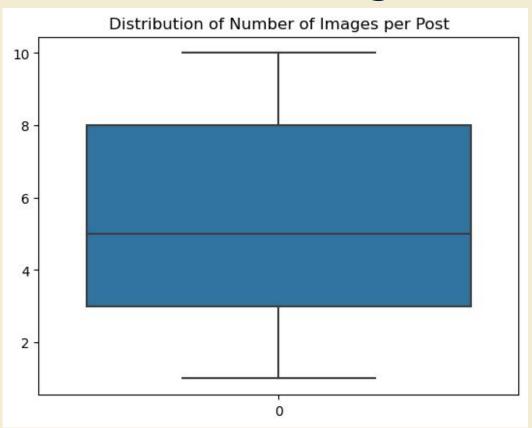
Expand analysis to **other types of bicycles** as well (Mountain Bikes, Foldies, Hybrid)







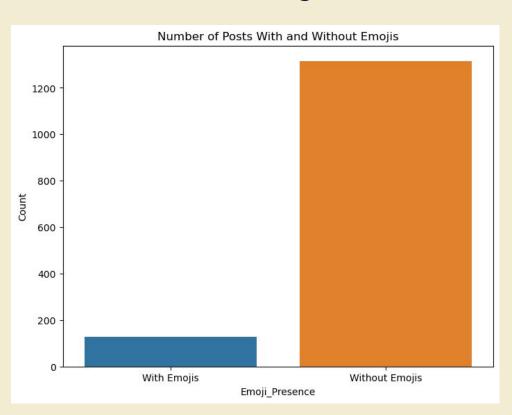
Number of Images



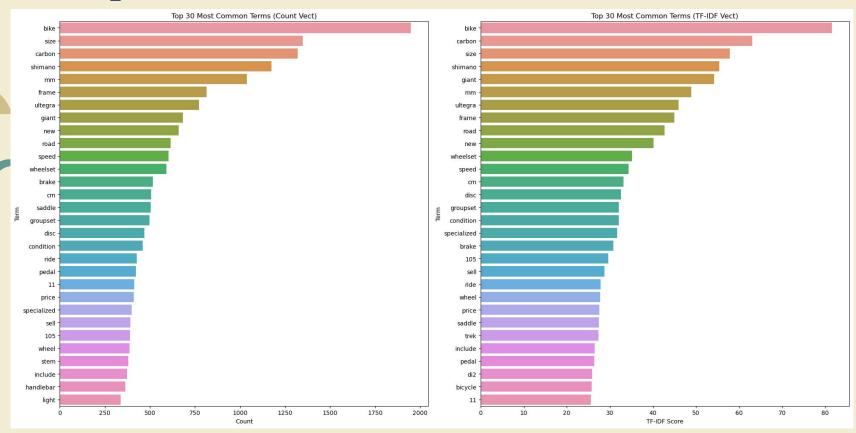
Features of scraped dataset

```
no of likes
                          2885 non-null
                                         object
   no_of_images
                         2885 non-null
                                          object
   title
                         2885 non-null
                                          object
   listing price
                         2885 non-null
                                          object
                         2885 non-null
   item condition
                                          object
   deal method
                          2885 non-null
                                          object
   post date
                          2885 non-null
                                          object
   category_type
                          2885 non-null
                                          object
   post type
                          2885 non-null
                                          object
   condition subtext
                          2884 non-null
                                          object
   listing description
                          2885 non-null
                                          object
   mailing option
                                          object
                          2885 non-null
   delivery options
                          435 non-null
                                          object
   mail_speed
                          435 non-null
                                          object
   meetup_option
                          2885 non-null
                                          object
   meetup_location
                          2566 non-null
                                          object
   seller_id
                          2885 non-null
                                         object
   seller join date
                          2885 non-null
                                         object
   seller response
                          2796 non-null
                                         object
   seller verif
                          2885 non-null
                                          object
   verified_by_email
                          2189 non-null
                                         float64
   verified_by_facebook 2189 non-null
                                          float64
   verified_by_mobile
                          2189 non-null
                                          float64
   seller_stars_rating
                         2608 non-null
                                          float64
   reviews_of_seller
                          2608 non-null
                                          object
25
   url
                          2885 non-null
                                          object
   deal location lat
                          647 non-null
                                          float64
   deal location lon
                         647 non-null
                                          float64
28
   posts
                          2885 non-null
                                          object
```

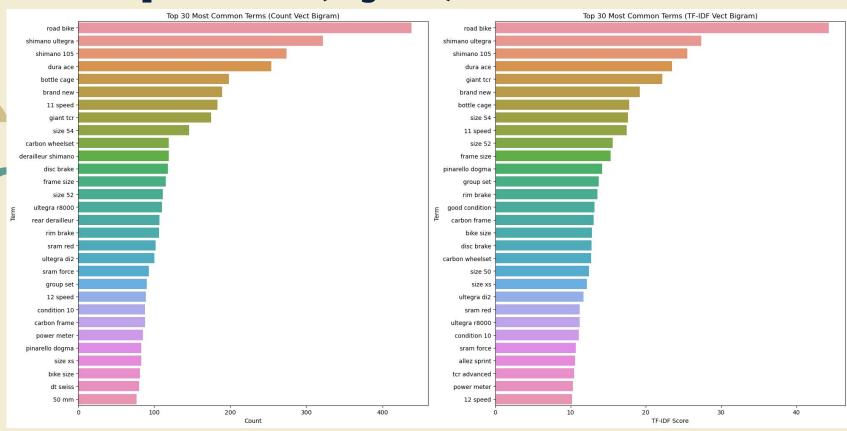
Emoji Use



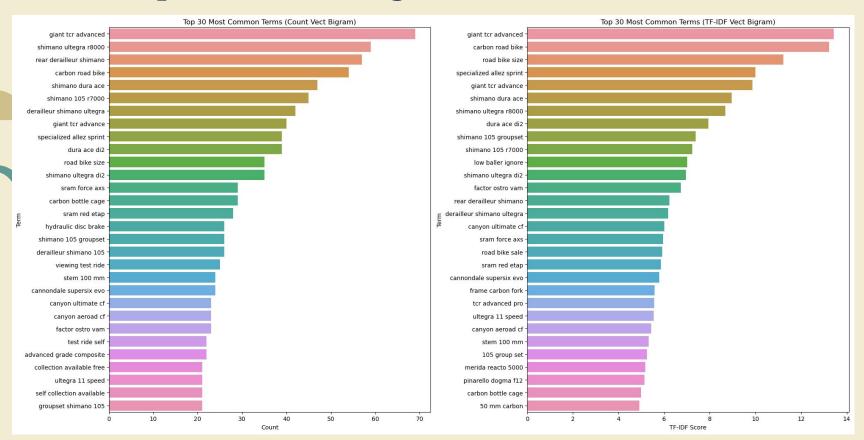
Top 30 Words - Count & TF-IDF Vectorizer



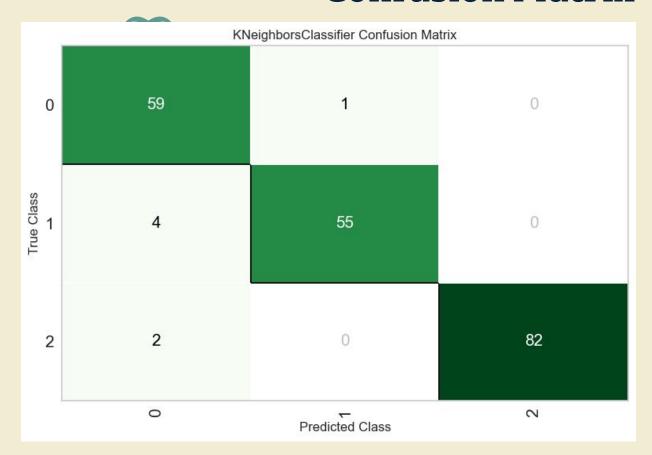
Top 30 Words (Bigram) - TF-IDF Vectorizer



Top 30 Words (Trigram) - TF-IDF Vectorizer

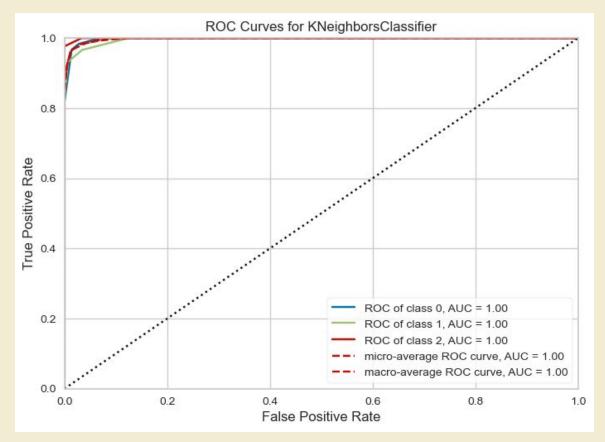


Confusion Matrix



- Class 1: Low (\$0 \$600)
- Class 2: Med (\$601 \$1200)
- Class 0: High (\$1201 \$2000)

ROC AUC



- Class 1: Low (\$0 \$600)
- Class 2: Med (\$601 \$1200)
- Class 0: High (\$1201 \$2000)

Brands Dictionary

```
brands = [
r'\bArgon(18)?\b',
r'\b(Giant|Qiant)\b',
r'\bScott\b',
r'\bBianchi\b',
r'\bTrek\b',
r'\bStandert\b',
r'\bOrbea\b',
r'\bFactor\b',
r'\bCanyon\b',
r'\b(Pinarello|Pina|Dogma)\b',
r'\bEddy Merckx\b',
r'\bColnago\b',
r'\b(Specialized|Specilized|Specialize|Specialised)\b',
r'\bS[-\s]?[Ww]ork\b',
r'\bMerida\b',
r'\bDean\b',
```