LAZADA VERACITY CHECKER

By: InternshipSeekers

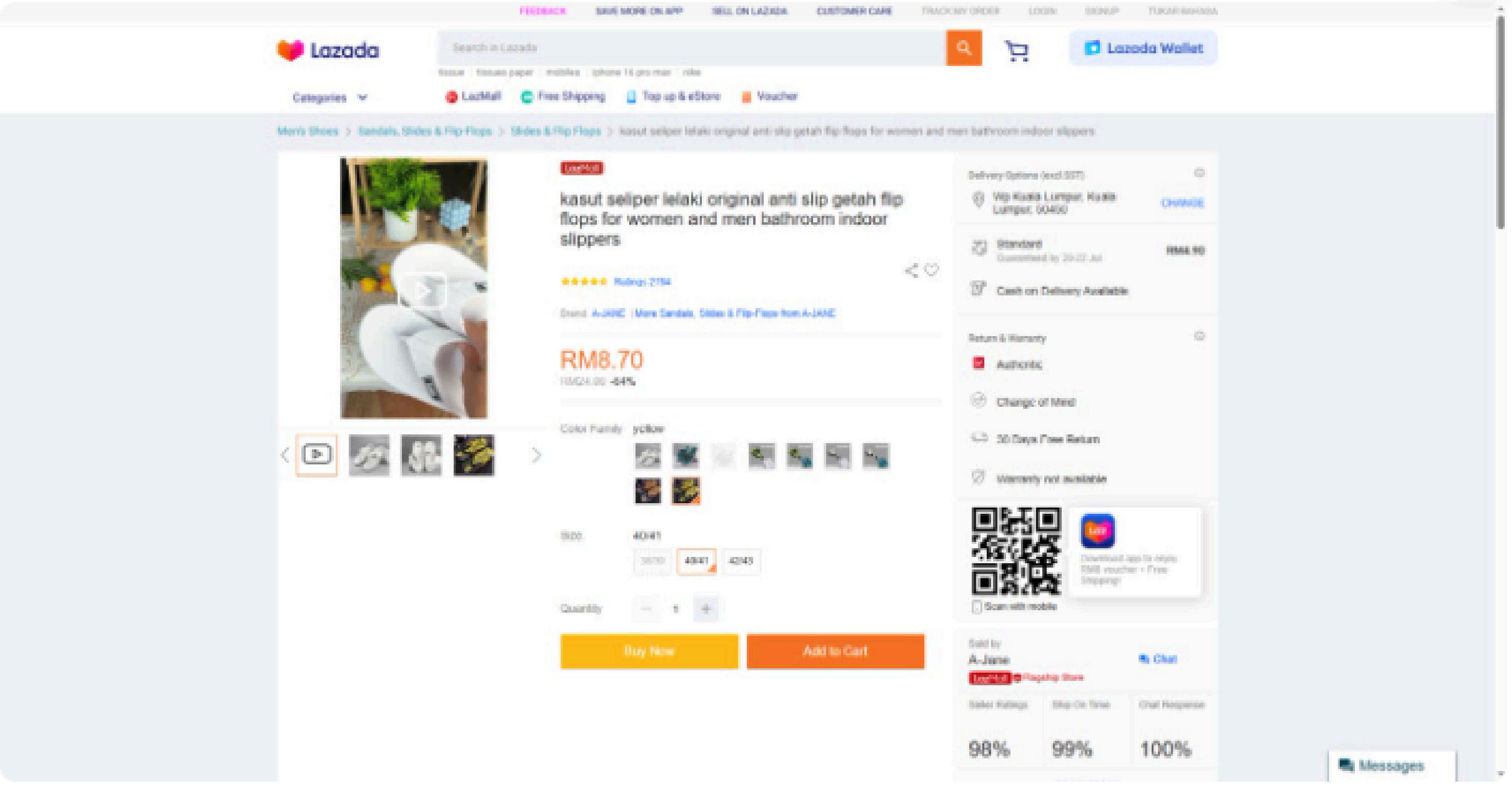
A project that aims to ensure integrity of Lazada products and reviews

Lazada Veracity Checker

Enter Lazada product URL:

https://www.lazada.com.my/products/kasut-seliper-lelaki-original-anti-slip-getah-flip-flops-for-womei

Scrape



Product

Product Name: kasut seliper lelaki original anti slip getah flip flops for women and men bathroom indoor slippers

Price: 8.70

Total Purchase: 2194

Seller Ratings: `4.9`

Core Features

01

Counterfeit Product Detection

02

Bot-Generated Review Detection

03

Review Sentiment Analaysis

04

Malicious Words Detection

05

Review Similarity Analysis

Counterfeit Product Detection

1. Input Data

Used **counterfeit_products.csv** which contains a dataset with e-commerce related data as well as the counterfeit labels

2. Data Cleaning

Drops all columns that could be acquired in Lazada, and identifies which columns to use as features. Eventually chosen price, seller_rating, and purchases column. Columns such as product_images, seller_reviews, description_length, shipping_time_days, and wishlist_adds is excluded because they are too significant, which will lead to bias and overfitting.

3. Model Training

Data is splited into train, validation, and test set for training. We utilize the XGBClassifier model for classification tasks. **RandomizedSearchCV** is also utilized to fine the best hyper parameters. Which is:

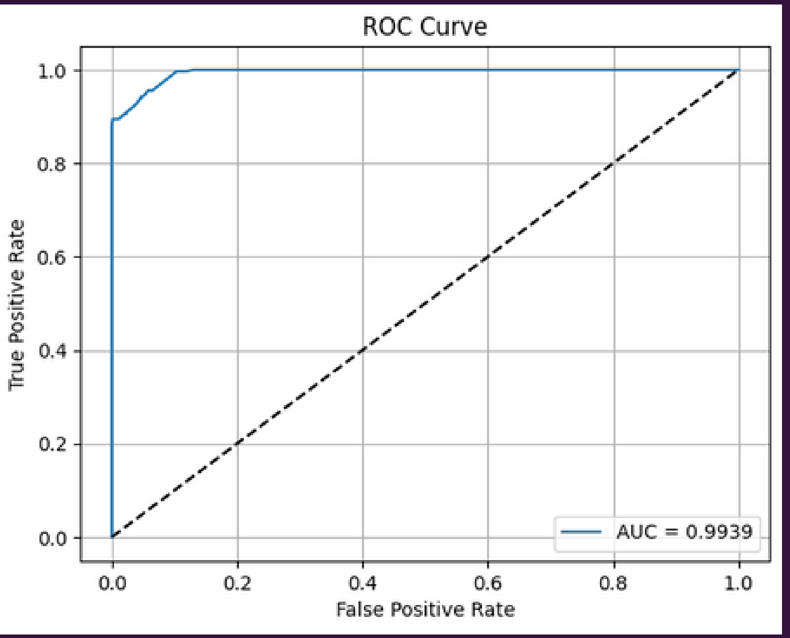
{'subsample': 1.0, 'scale_pos_weight': 2.4, 'reg_lambda': 0.5, 'reg_alpha': 0.5, 'n_estimators': 100, 'min_child_weight': 3, 'max_depth': 3, 'learning_rate': 0.05, 'gamma': 5, 'colsample_bytree': 1.0}

4. Accuracy Interpret

Based on the confusion matrix, we can see the model accuracy is excellent with no overfitting.

	precision	recall	f1-score	support
0	0.9807	0.9348	0.9572	706
1	0.8593	0.9558	0.9050	294
accuracy			0.9410	1000
macro avg	0.9200	0.9453	0.9311	1000
weighted avg	0.9450	0.9410	0.9419	1000

ROC-AUC: 0.9939



Bot-Generated Review Detection

1. Input Layer

- Review Text
- Rating

2. Preprocessing

- Clean text (lowercase, remove stopwords & punctuation)

3. Feature Extraction

- TF-IDF (Top 5000 tokens)
- Review Length
- Rating

4. Model

- Logistic Regression

5. Output

- Prediction: Human or Bot
- Probability Score

Review & Rating Sentiment Analysis

1. Input Layer
- **Ratings**
- **Reviews**

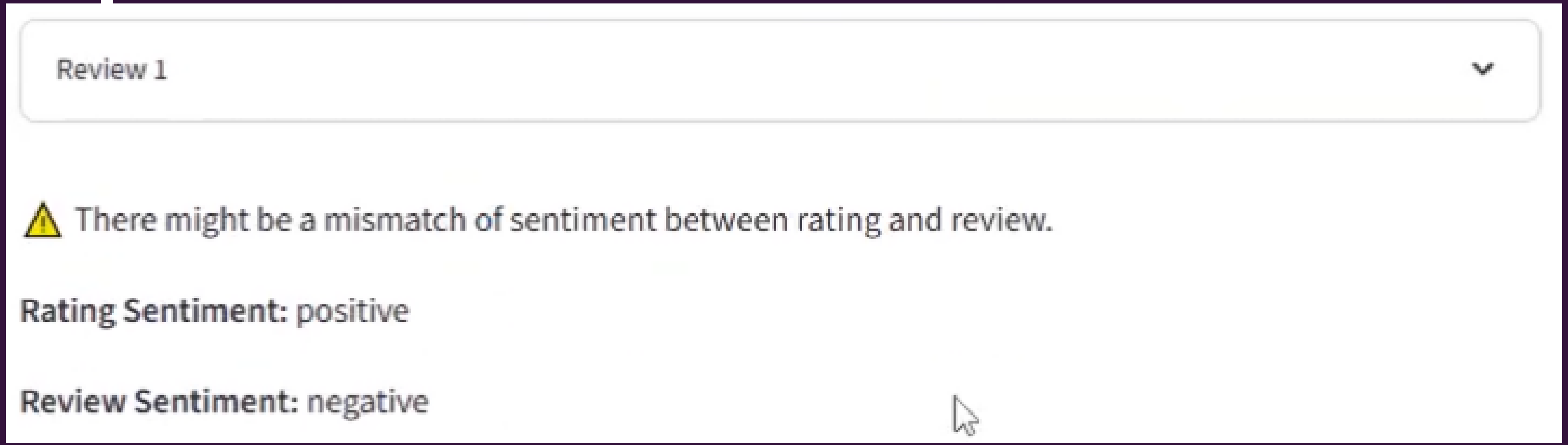
2. Data Preprocessing
- Clean text (lowercase, remove stopwords & punctuation)
- Convert given ratings to expected sentiment:
  - Ratings ≥ 4 → "positive"
  - Ratings ≤ 2 → "negative"

3. Feature Extraction
- TF-IDF Vectorizer to convert review text into a numerical matrix
- Review Length
- VADER sentiment analyzer to calculate a sentiment score on the review text

4. Model Training
- *LinearSVC*
- Balance dataset using RandomOverSampler (from imblearn)

5. Output
- Predicts rating sentiment of each product review
- Compares with actual rating to flag mismatches

Expected Result:



Malicious Words Detection

Rule-Based Malicious Word Detection Module

- Detect malicious, rude, offensive words in product reviews
- Cover both English and Malay version product reviews

Regex-based function:

- Scan each product review
- Match the malicious words in the product review with preset malicious keywords
- Return True and display matched malicious keywords in website

Sample Output Exported:

	A	B	C	D	E
1	ratings	review	language	cleaned_review	is_malicious
2	1	Your fuc	english	your fucking size is a bullshit im gonna donate these shorts not gonna buy again	TRUE

Review Similarity Analysis

Goal: Detect highly similar or duplicated reviews to identify potentially malicious or spam content.

Methodology

- Data Limitation: Used the latest 1,000 reviews for efficiency.
- Vectorization: Applied TF-IDF to convert review texts into numerical features.
- Similarity Engine: Used FAISS for fast and memory-efficient similarity detection.
- Threshold: Filtered results with cosine similarity > 0.85.

Sample output

cosine_similar_reviews_faiss

review_id_1	review_id_2	similarity_score	product_id
0	0	1.0	eng_product
1	1	1.0	eng_product
4	4	1.0	eng_product
46	457	1.0	eng_product
46	46	1.0	eng_product
130	4	1.0	eng_product
146	557	0.8833030462265020	eng_product
158	158	0.9999999403953550	eng_product
177	897	0.8980520367622380	eng_product
177	206	0.8980520367622380	eng_product

Outcome

- Able to flag repeated or potentially malicious reviews efficiently.
- Scalable to larger datasets using FAISS.
- Supports fake review detection pipeline.