

Detecting fake product reviews



Georgios (Economics and Business)



Pedro (Economics and Business)



Marius (User Experience Design)



Objective

Create a ML- pipeline to Detect fraudulent reviews

Given these predictions, they can conduct investigations, decide whether to notify users (i.e flag fake reviews) or take corrective action.

Main Beneficiary: e-commerce platforms

Indirect beneficiaries: customers, sellers and the regulatory agencies

Project motivation

E-commerce on the rise

Reviews closely determine purchasing decisions

Dynamic environment: easier than ever to create fake content that seems believable

Fraudulent reviews damage both the platform, the seller reputation and consumers

Real world case

UK competition watchdog to probe Google and Amazon over fake reviews

Competition and Markets Authority says tech groups may not be doing enough to protect consumers.

The UK competition regulator has opened an investigation into Amazon and Google over fake reviews on their sites that may be duping consumers.

A thriving industry where potentially hundreds of thousands of reviews are bought and sold for as little as £5 each”.

“Our worry is that millions of online shoppers could be misled by reading fake reviews and then spending their money based on those recommendations,”

<https://www.ft.com/content/b7c4b9fc-116e-4681-92cb-f433f2a09aa6>



This is a real business problem

Fake online reviews cost the global economy \$152 billion a year. (WEF)

In response, there exist off-the-shelf solutions:

[Fraud detection algorithms](#) that combine behavioural analytics and text analysis e.g. Amazon Web Services (AWS):

Amazon Fraud Detector [Overview](#) [Features](#) [Pricing](#) [FAQs](#) [Resources](#) [Customers](#)

[« Machine Learning](#)

Amazon Fraud Detector

Detect online fraud faster with machine learning

[Get started with Amazon Fraud Detector](#)

Up to 30,000 fraud predictions
per month free with the [AWS Free Tier](#)

- Build, deploy, and manage fraud detection models without previous machine learning (ML) experience.
- Gain insights from your historical data, plus 20+ years of Amazon experience, to construct an accurate,
- Start detecting fraud immediately, easily enhance models with customized business rules, and deploy

Some Statistics about e-commerce

- Revenue in the eCommerce Market is projected to reach US\$3,226.00bn in 2024.
- Revenue is expected to show an annual growth rate (CAGR 2024-2029) of 9.79%, resulting in a projected market volume of US\$5,145.00bn by 2029.
- In the eCommerce Market, the number of users is expected to amount to 3.2bn users by 2029.
- Data from STATISTA (world wide in us dollars)

Some Statistics on review effect on behavior

- 95% of costumers read reviews before making the buying decision (Global Newswire)
- 88% of customers who read an online review say it influenced their buying decision (Zendesk)
- 49% of consumers trust online reviews as much as personal recommendation (Bright Local)
- Positive reviews can increase customer spending by 31% (Bright Local)
- 86% of people hesitate to do business with a company if it has too many negative customer reviews.
- If consumers found out a platform was censoring reviews, 62% of consumers would stop using it (Trustpilot)
- 52% of a company's market value is attributed to its reputation (PR Week)

Similar open source projects:

Mostly focus on NLP (analysis on text)

Sr. No.	Model Accuracy (%)	Precision Score	Recall Score	F1 Score
1	MultinomialNB	90.25	0.9325	0.8601
2	Stochastic Gradient Descent (SGD)	87.75	0.8913	0.8497
3	Logistic Regression	87.00	0.8691	0.8601
4	Support Vector Machine	56.25	0.525	0.9792
5	Gaussian Naive Bayes	63.5	0.6424	0.6169
6	K-Nearest Neighbour	57.5	0.8604	0.1840
7	Decision tree	68.5	0.6681	0.7412

[Credits: Salunkhe, Ashish. "Attention-based Bidirectional LSTM for Deceptive Opinion Spam Classification." arXiv preprint arXiv:2112.14789 \(2021\).](#)

Possible analyses

1. Analyze the reviewer, not the review

- Feature engineering: *how old the account is*, *# of reviews made*, *time stamps for behavior*, etc

2. Use review metadata: *helpfulness rank*, *verified purchase* or not.

3. Analyse the review text

- Natural Language Processing (NLP)
- Complex and beyond the scope of this course

Dataset (correction: huge database)

Yelp Dataset on Kaggle.



kaggle.com/datasets/yelp-dataset/yelp-dataset

Clean

Popular for analysis

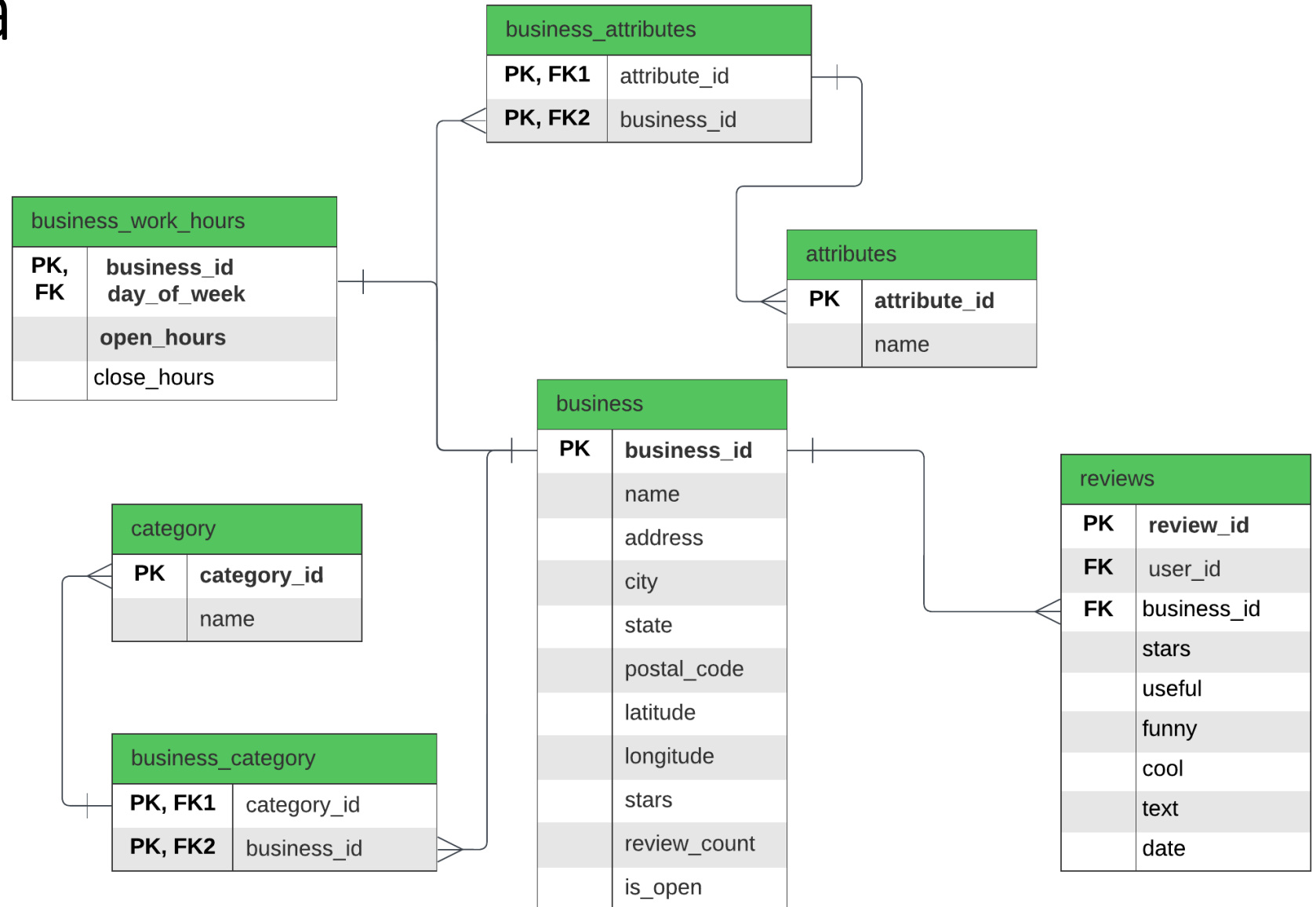
JSON (not CSV)

Large: 3GB + 5GB databases

Data schema

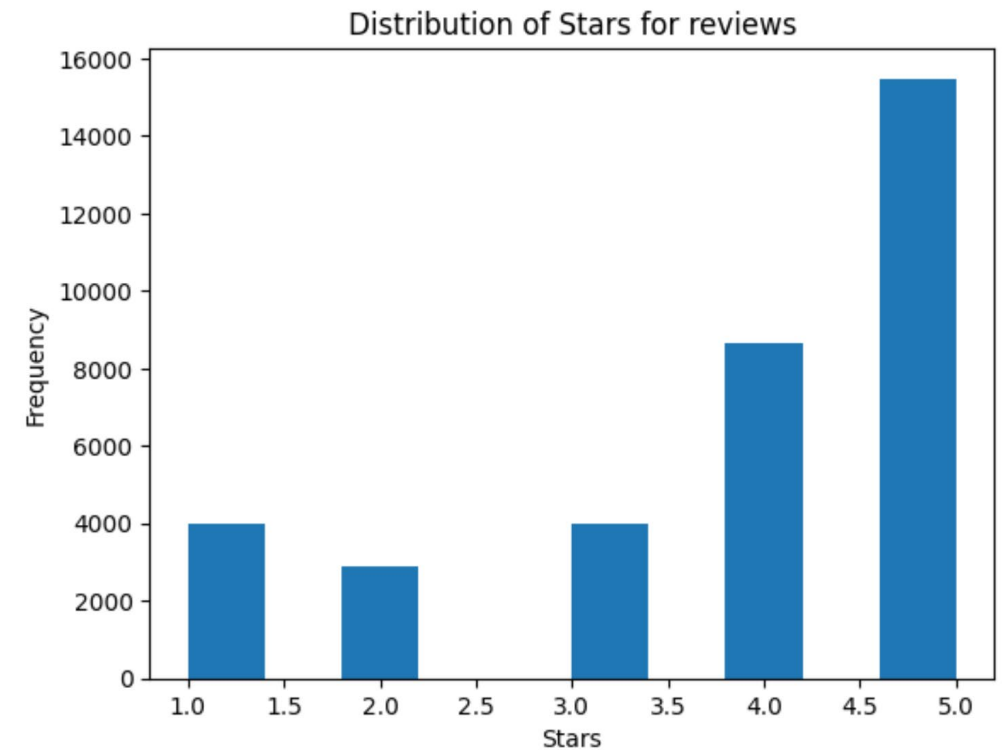
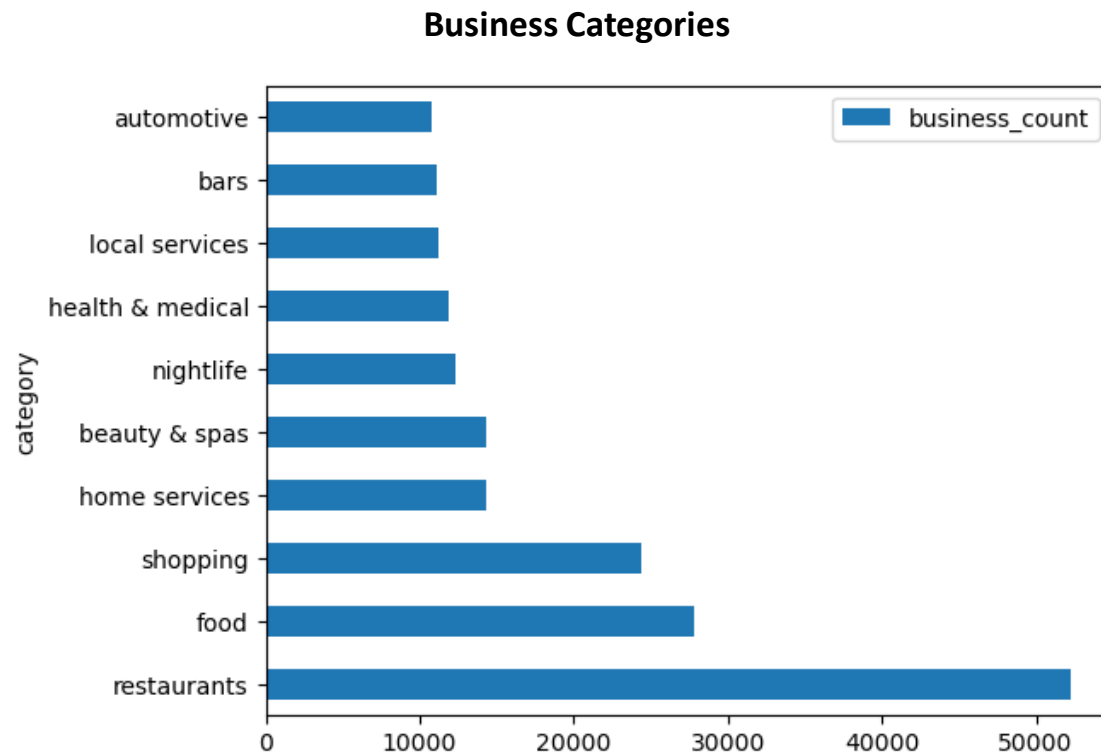
Covers:

- Businesses
- Reviews
- Users



[Credits: An Hoang Vo, Kaggle, Business Analysis using SQL and Spark](#)

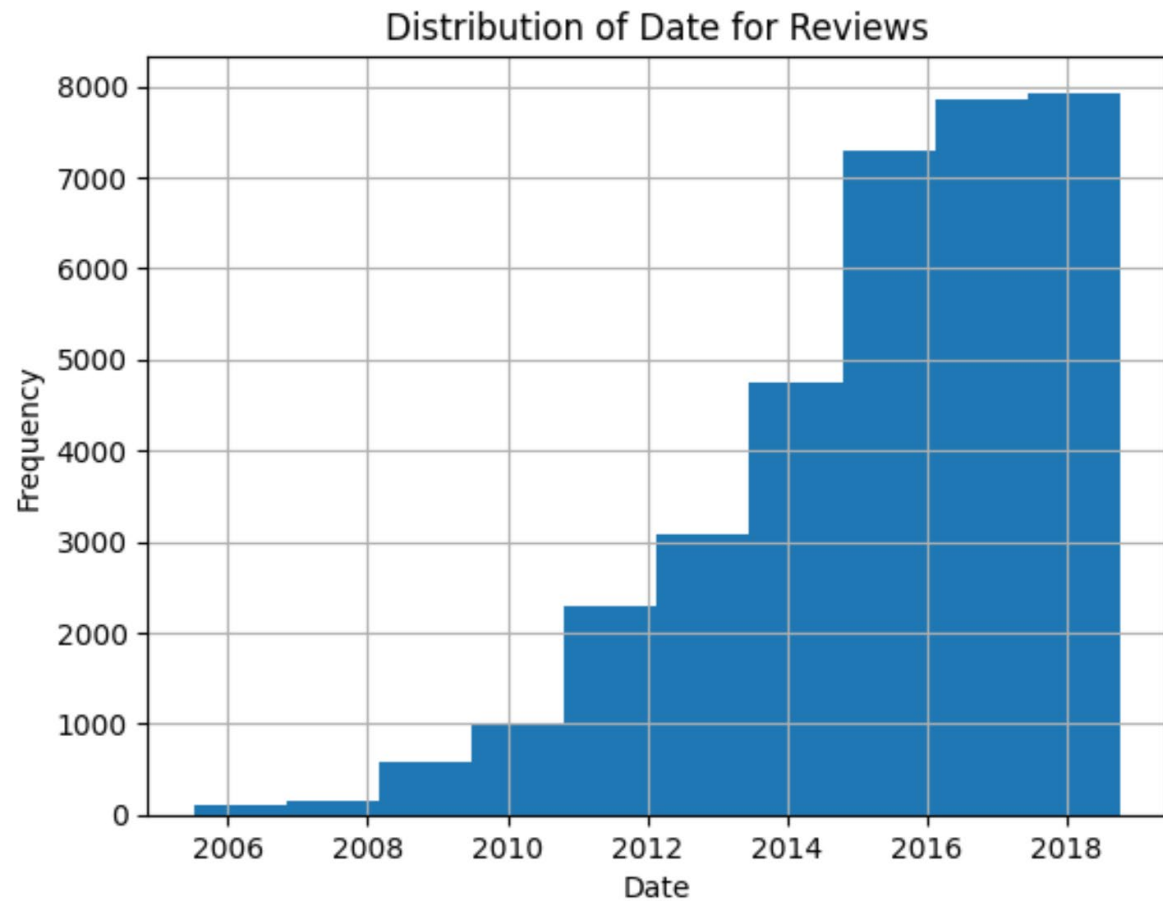
Exploratory data analysis (EDA). Part 1/3



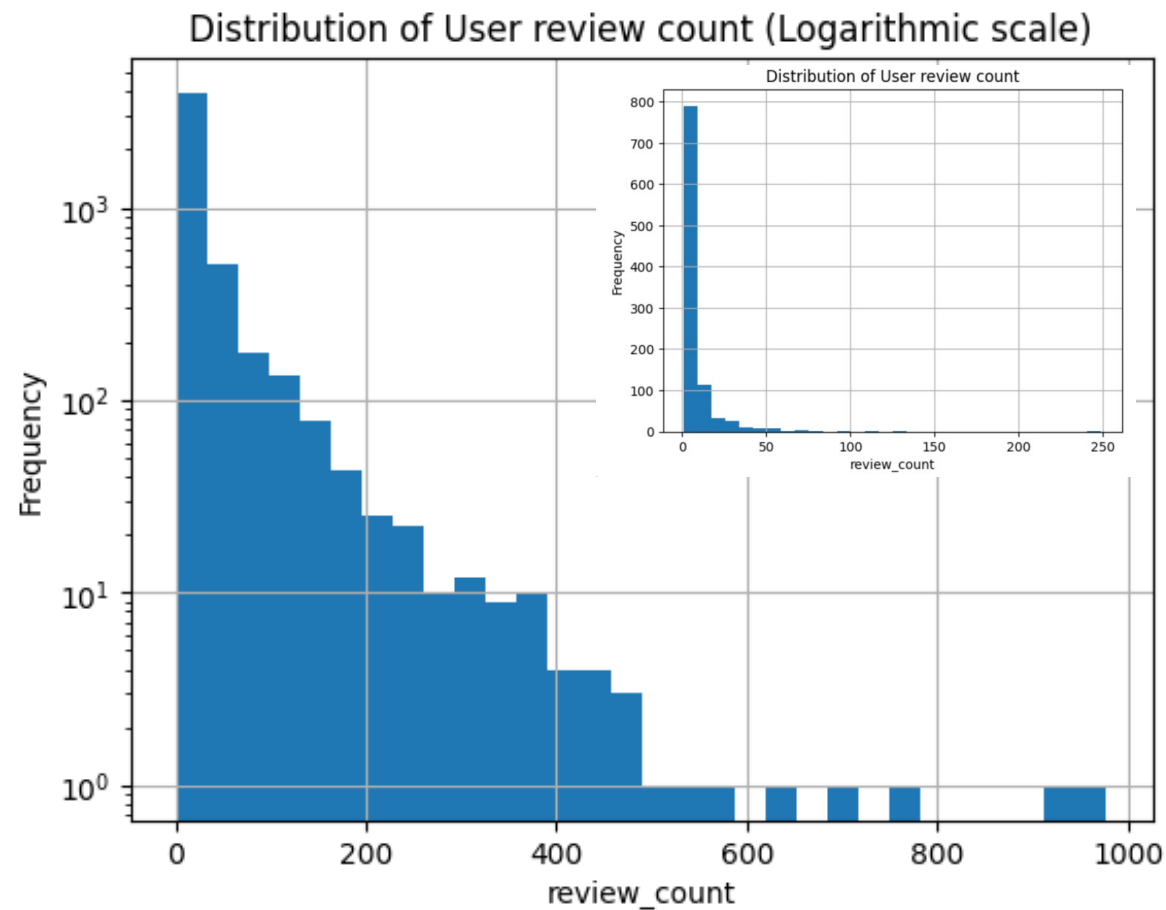
[Credits: An Hoang Vo, Kaggle, Business Analysis using SQL and Spark](#)

Our analysis of a fragment of 35k random (?) entries of 'reviews'

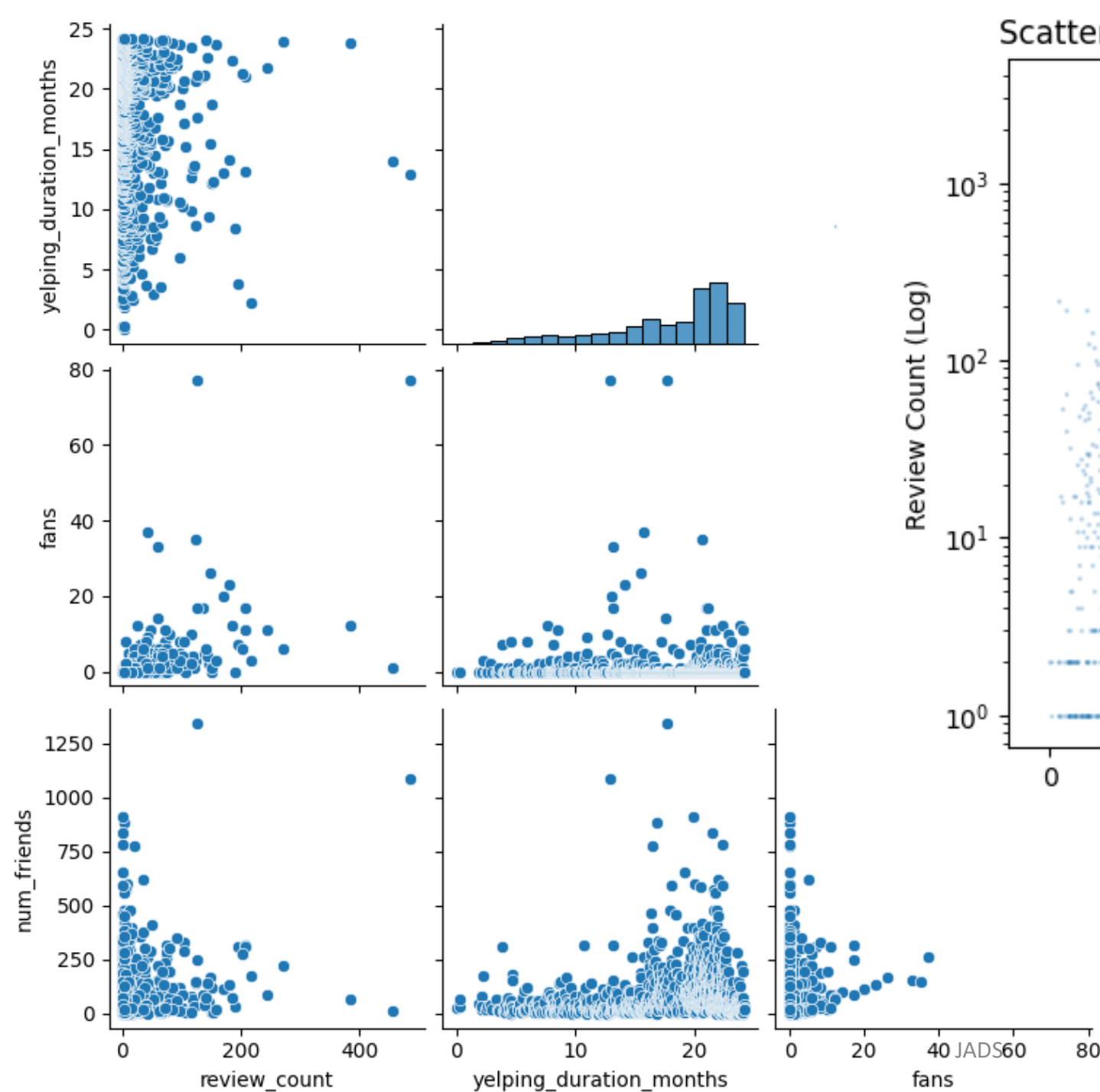
EDA 2/3



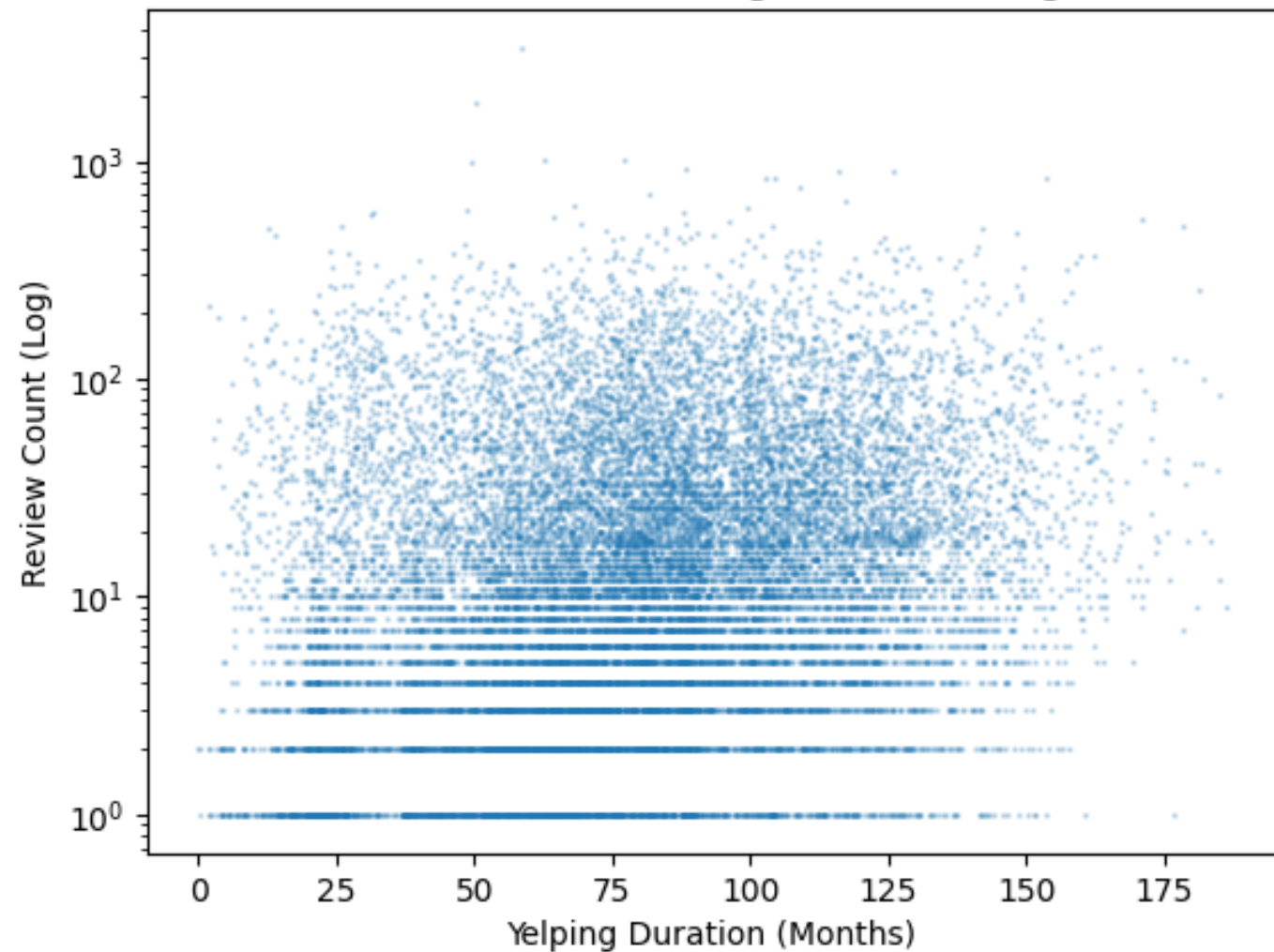
Our analysis of a fragment of 35k random (?) entries of 'Reviews'



Our analysis of a fragment of 1000 random entries of 'Users'



Scatter Plot of Review Count (Log) vs Account age in months



Both analyses performed on a random (?) sample of 20k Users

EDA 3/3

Questions we need help with:

1. Dealing with a large dataset: in practice vs for this course.

Is 'split' acceptable ?

How can we see how randomly distributed it is now ?

2. Should we continue working with a large dataset that requires significant JOINS between different datasets ?

3. How can we evaluate the model if real world data does not contain a label: fake/real. Prediction tested by what ?

Next actions

- Closer look at how others evaluate their result given data not labelled on authenticity
- Replicating another project to see what we learn
- Comparing 3 key algorithms and decide on one

OR

Coaching session w/ teacher + Plan B for a more manageable objective.

Follow our progress

Github: github.com/ursumarius/review-analysis-intro-ml-jads/

Kaggle: kaggle.com/code/mariusursu/review-analysis-intro-ml-jads

Slides: github.com/ursumarius/review-analysis-intro-ml-jads/blob/main/Intro-ML-Presentation-Med-Muscle.pdf