Detecting fake product reviews

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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,"

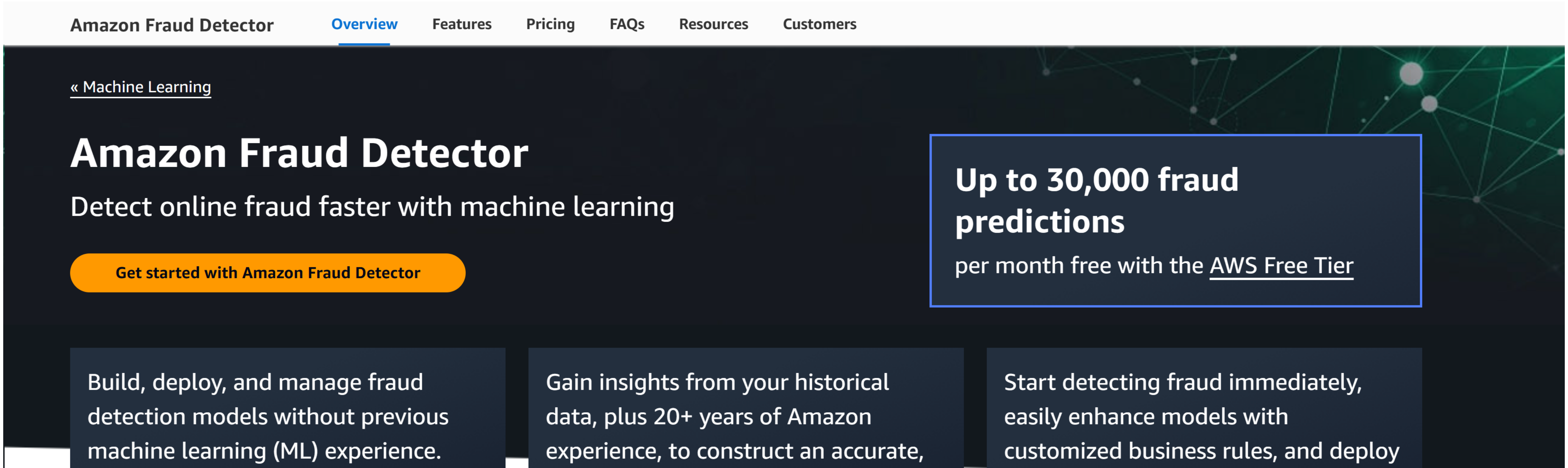
https://www.ft.com/content/b7c4b9fc-116e-4681-92cb-f433f2a09aa6

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):



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 dolars)

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

Re-framing the objective:

Detecting suspicious reviews based on account behavior

Less focus on the content of the review (text), and more on the behavior of the user (numbers)

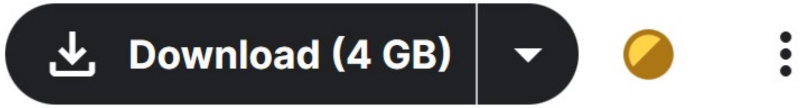
Data from Yelp covers this

Success metrics:

- Precision (works even with a skewed dataset)
- Compared to random chance
- Compared to other analyses done on this dataset

Dataset (correction: huge database)

Yelp Dataset on Kaggle.



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

Clean

Popular for analysis

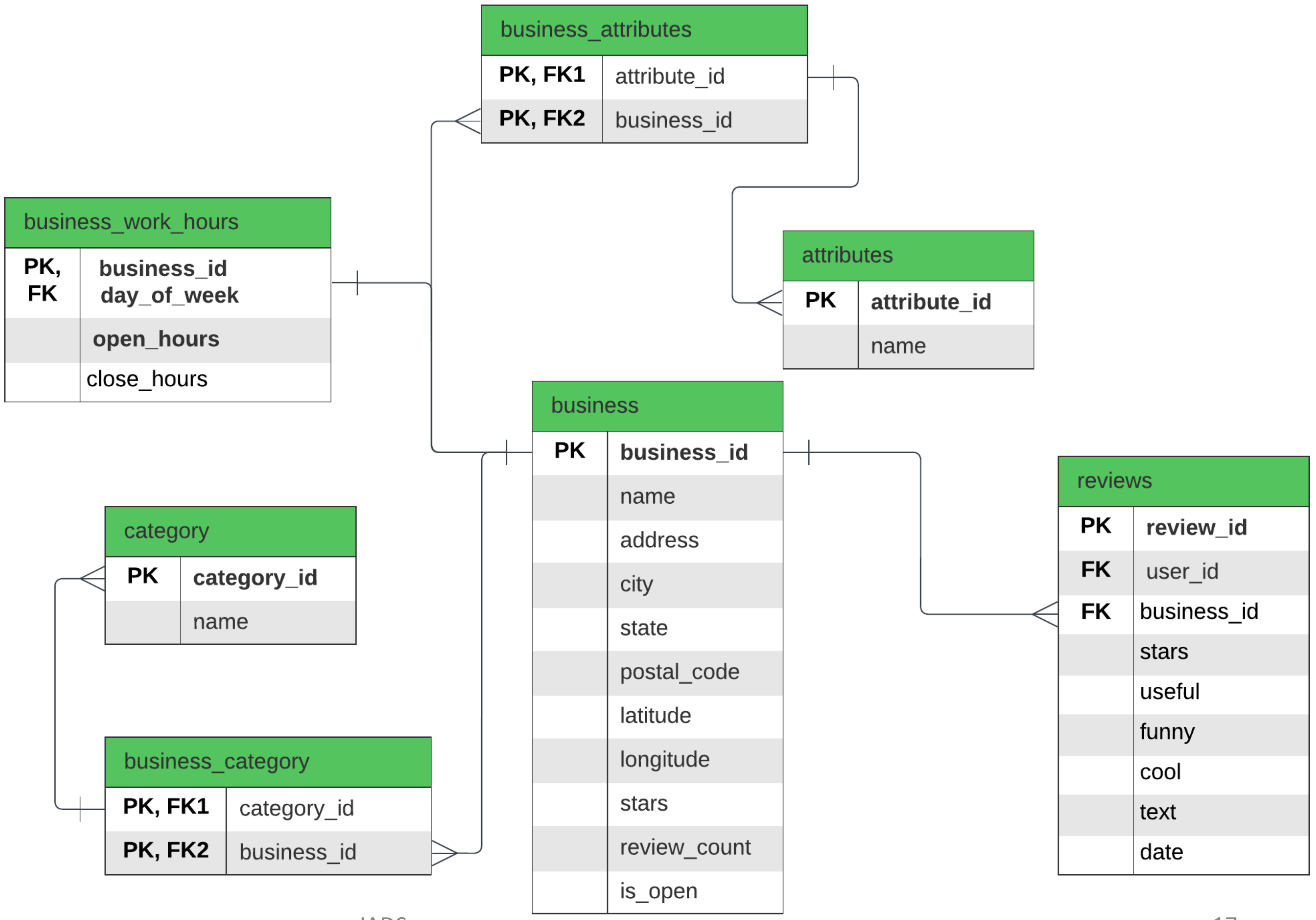
JSON (not CSV)

Large: 3GB + 5GB databases

Data schema

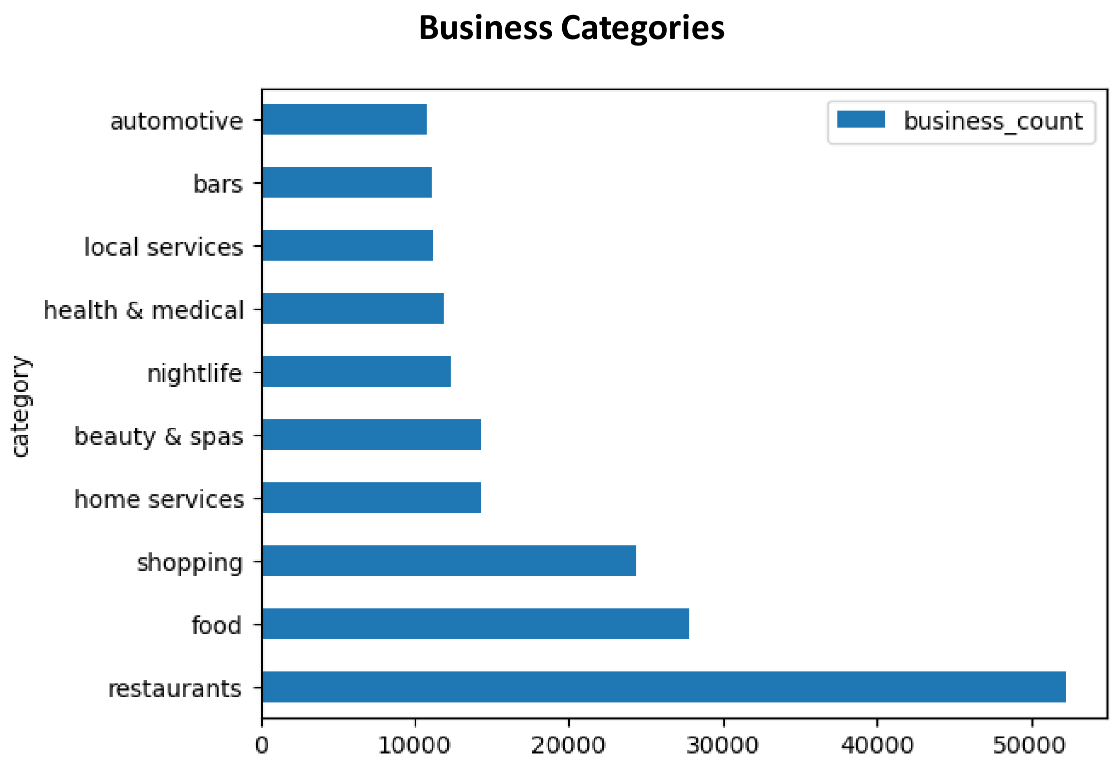
Covers:

- Businesses
- Reviews
- Users



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

Exploratory data analysis (EDA). Part 1/3



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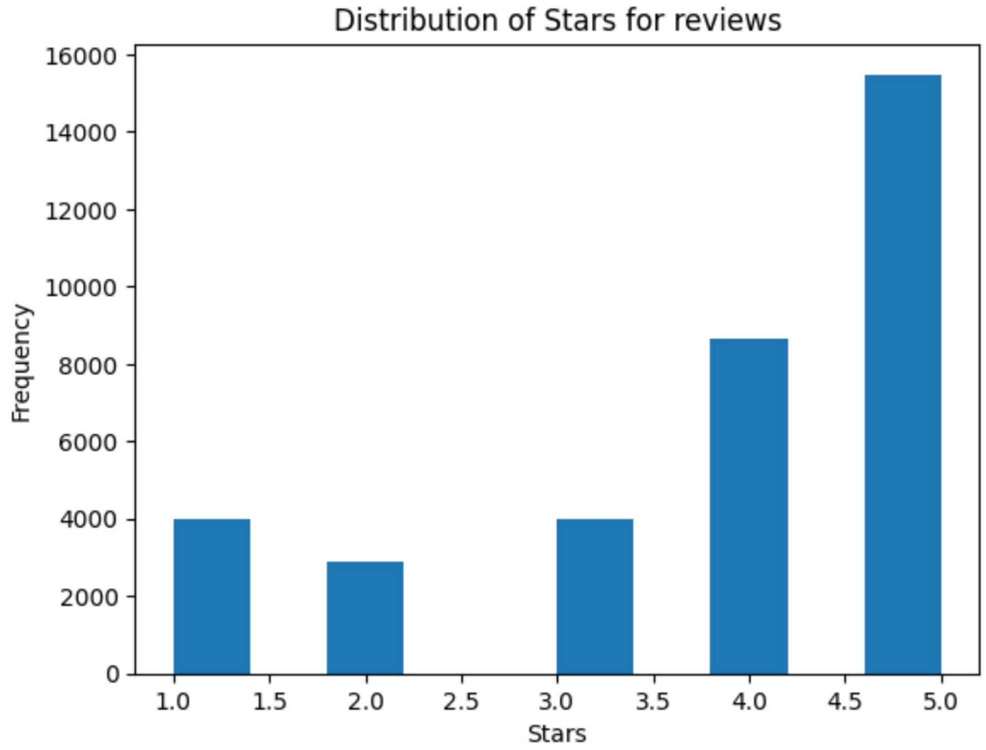
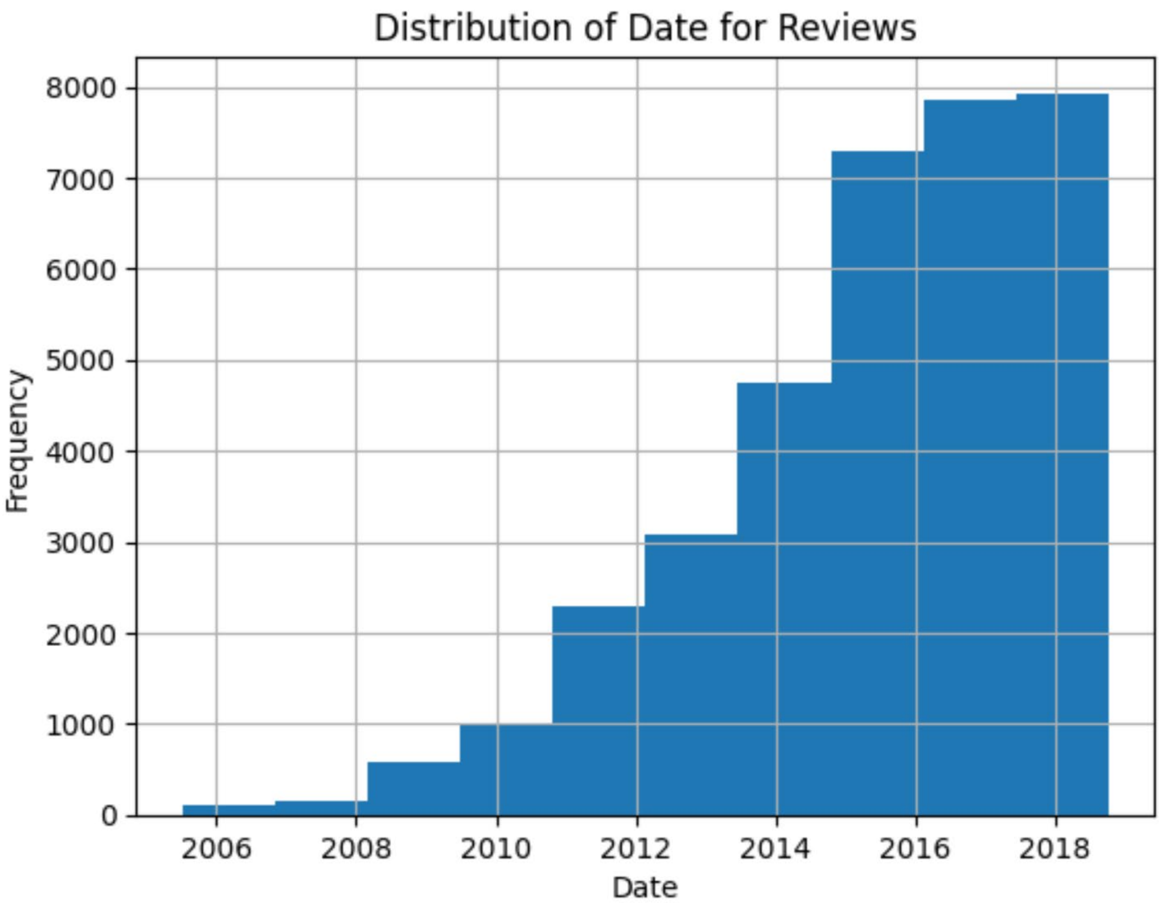


Our analysis of a fragment of 35k random (?) entries of ‘reviews’

EDA 2/3



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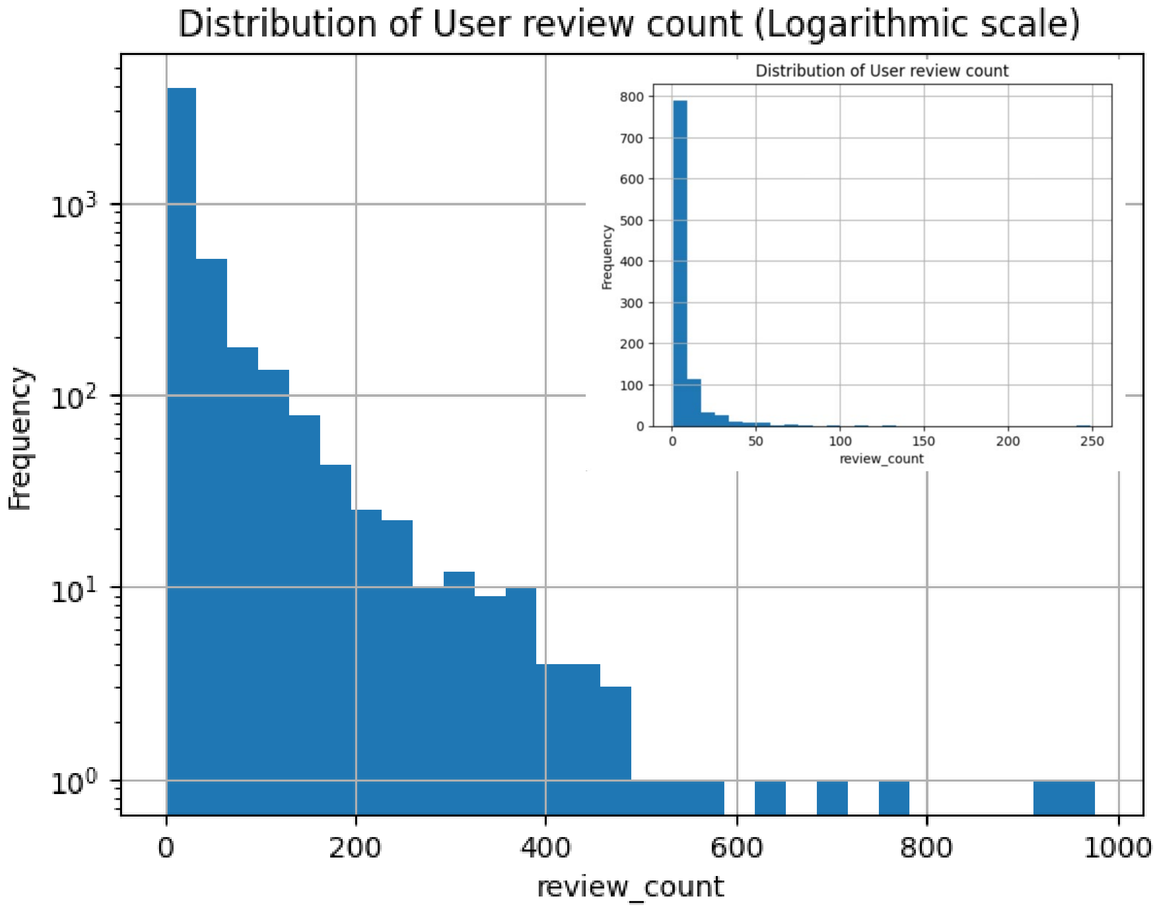
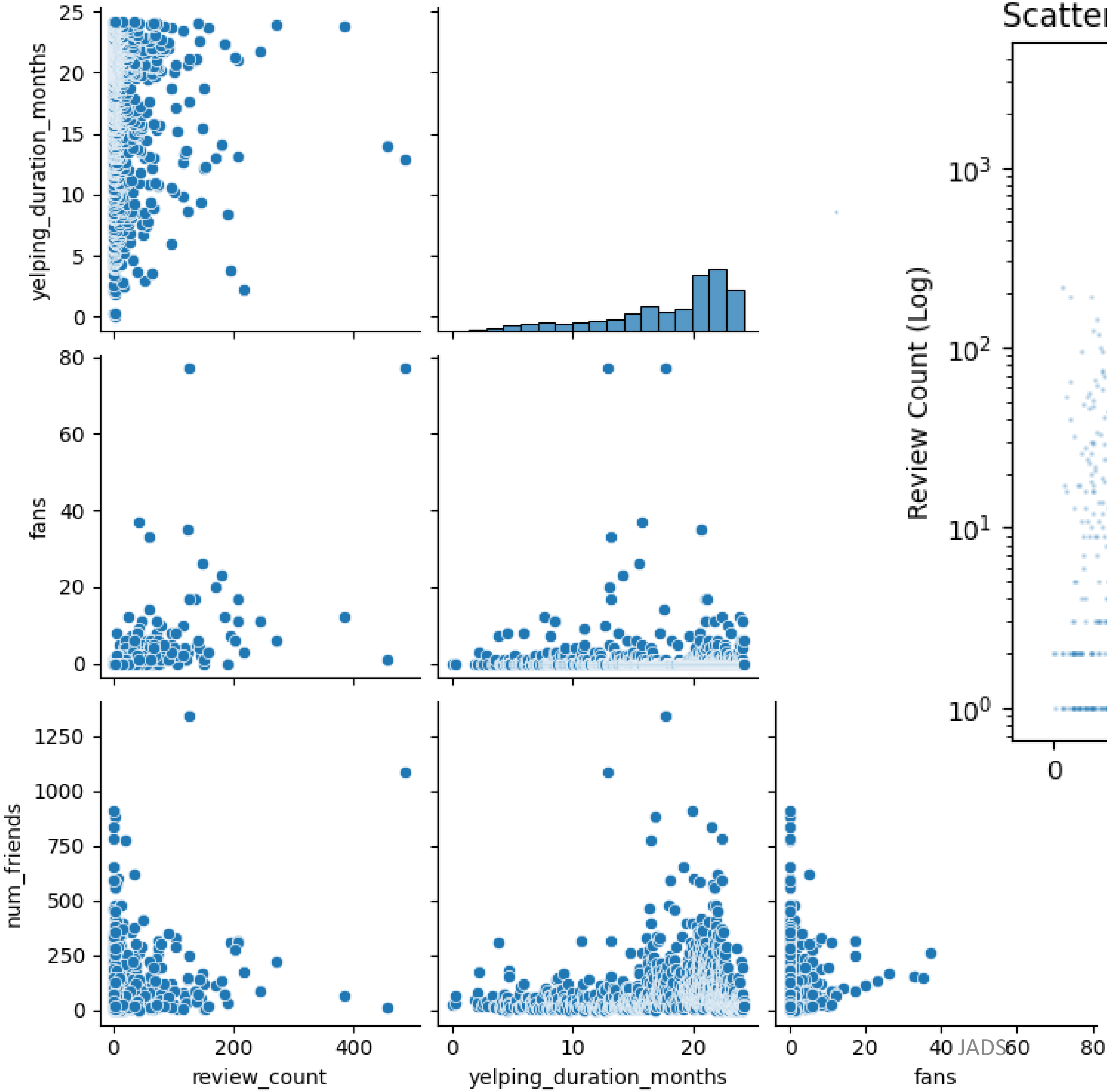
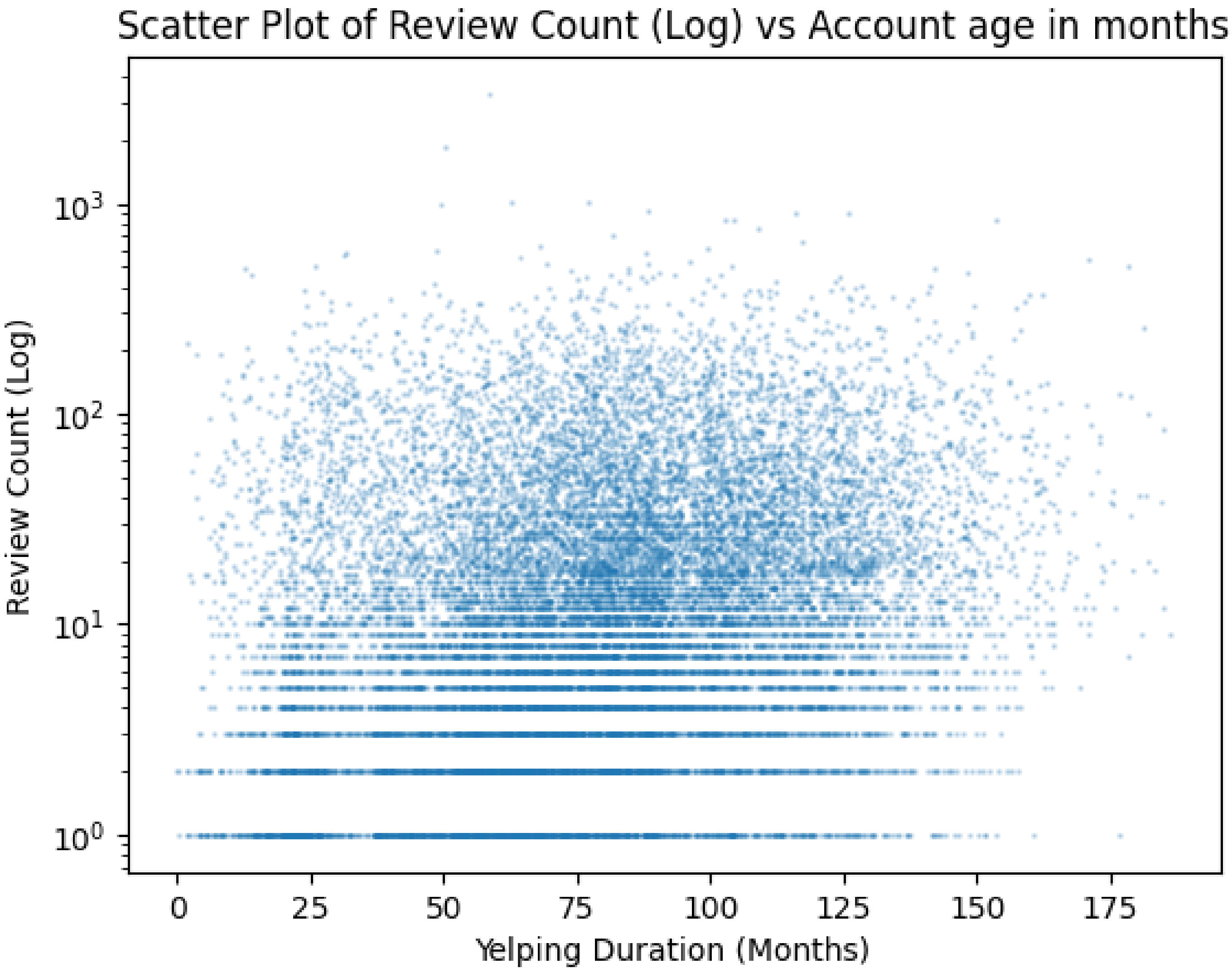


Our analysis of a fragment of 1000 random entries of 'Users'





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

EDA 3/3

Pipeline

1. Extract

- Option 1: Spark and SQL for working with databases

```
from pyspark.sql
```

[Learn joining data in SQL on datacamp]

- Option 2: Split the dataset using:

```
! split -l 35000 ../input/yelp-dataset/
```

```
/yelp_academic_dataset_review.json review_
```

2. Data wrangling

- No cleaning needed
- No imputation needed
- Compute *age* from *date*
- Compute *total nr* of friends from a list of their *id*'s

3. Feature engineering

- Question time

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