Project: Detecting fake reviews

- Team members
  - Georgios (Economics and Business)

  - Pedro (Economics and Business)

  - Marius (User Experience Design)

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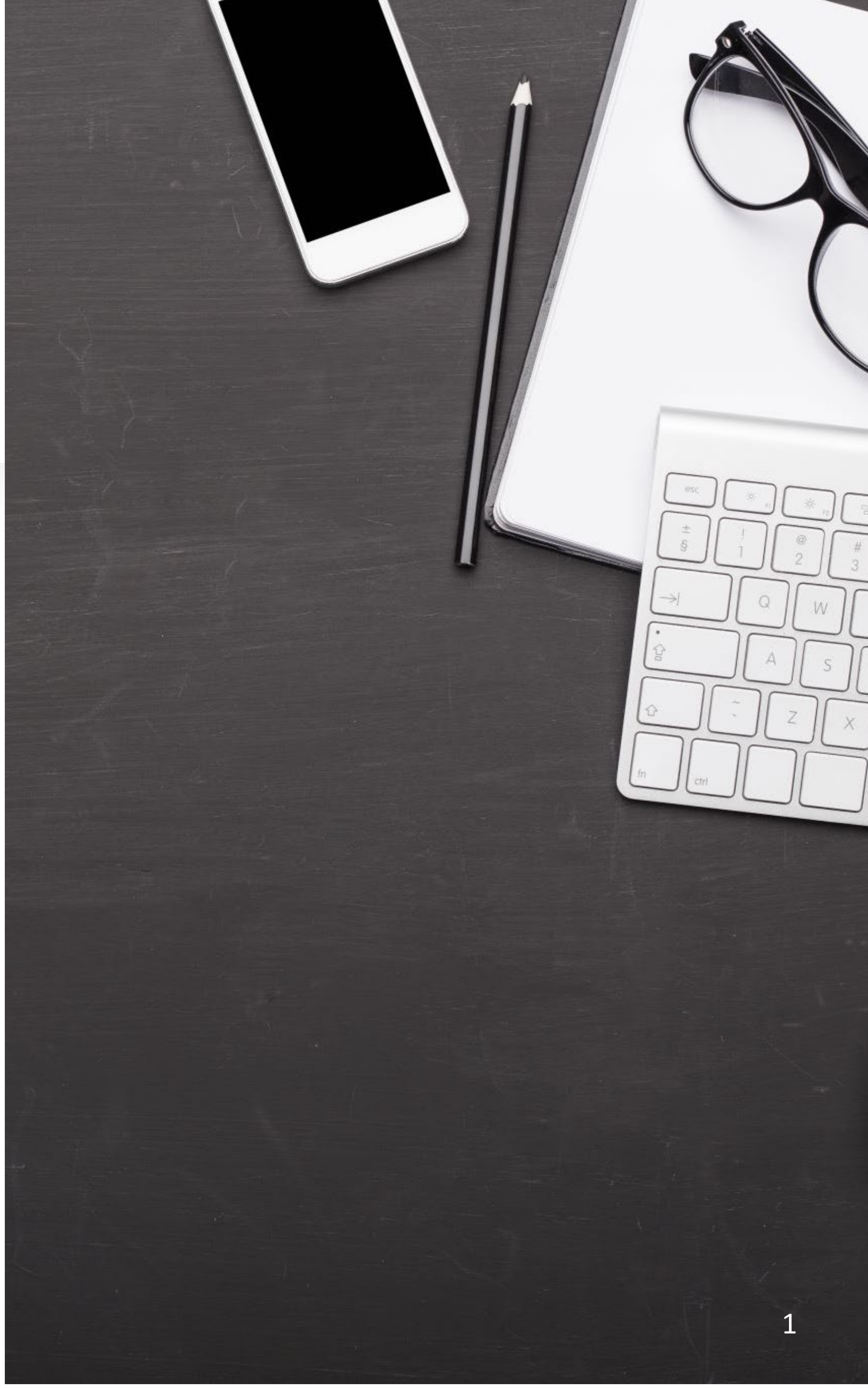


Objective

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 Financial Times

- 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,"

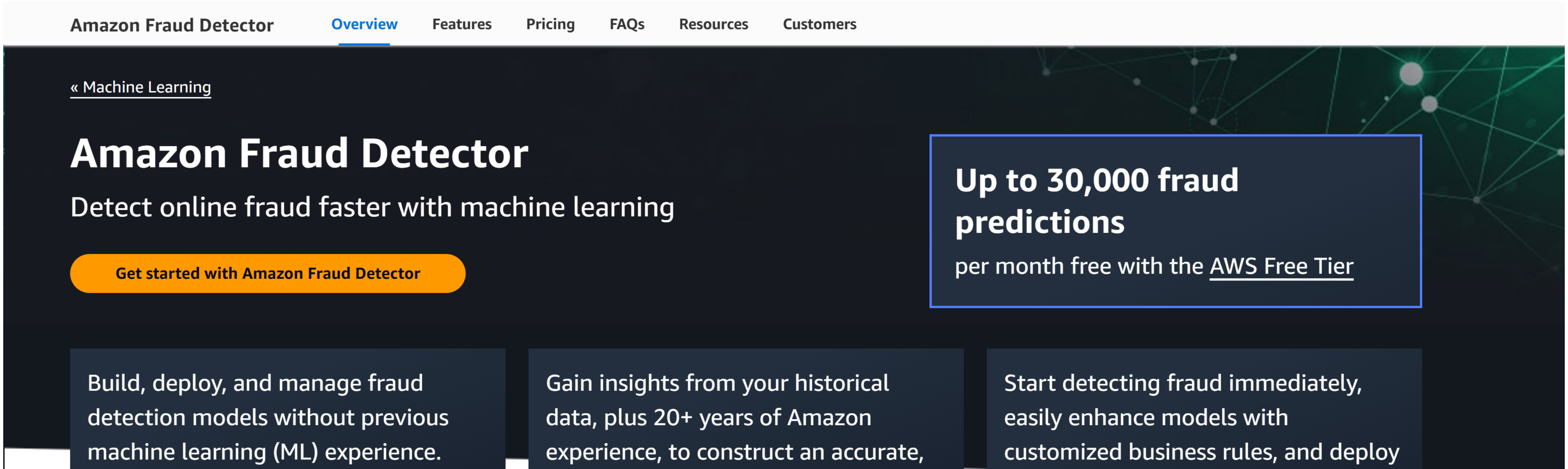
https://www.ft.com/content/b7c4b9fc-116e-4681-92cb-f433f2a09aa6

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

Detect online fraud faster with machine learning

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 the e-commerce market)

- 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)

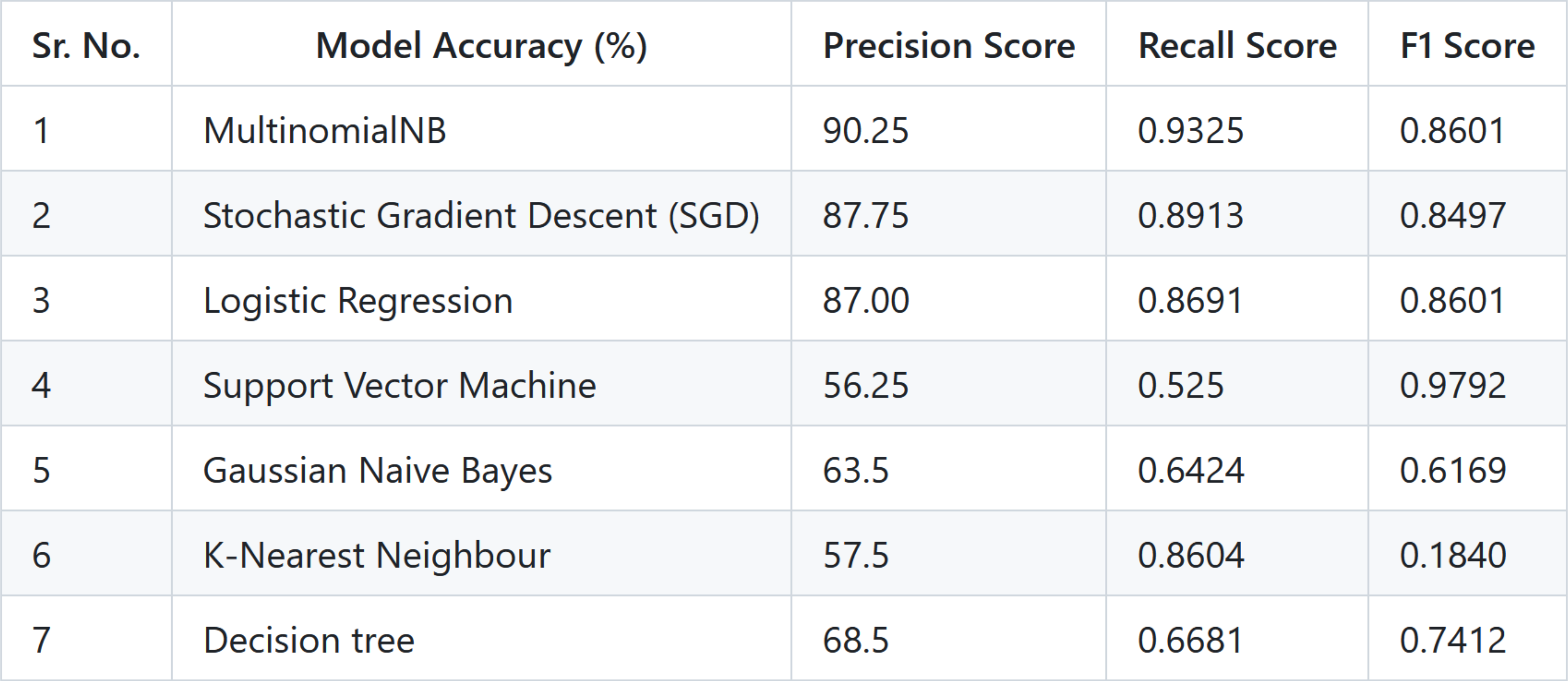
Some Statistics (about the role of reviews in the buying process)

- **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)**

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

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

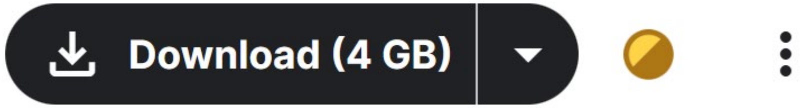
1. Analyze the reviewer, not the review
   - Feature engineering: *how old the account is*, *# of reviews made*, *time stamps for behavior*, etc

2. Use review metadata: helpfulness ranking, 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.



Download (4 GB)

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

Clean

Popular for analysis

JSON (not CSV)

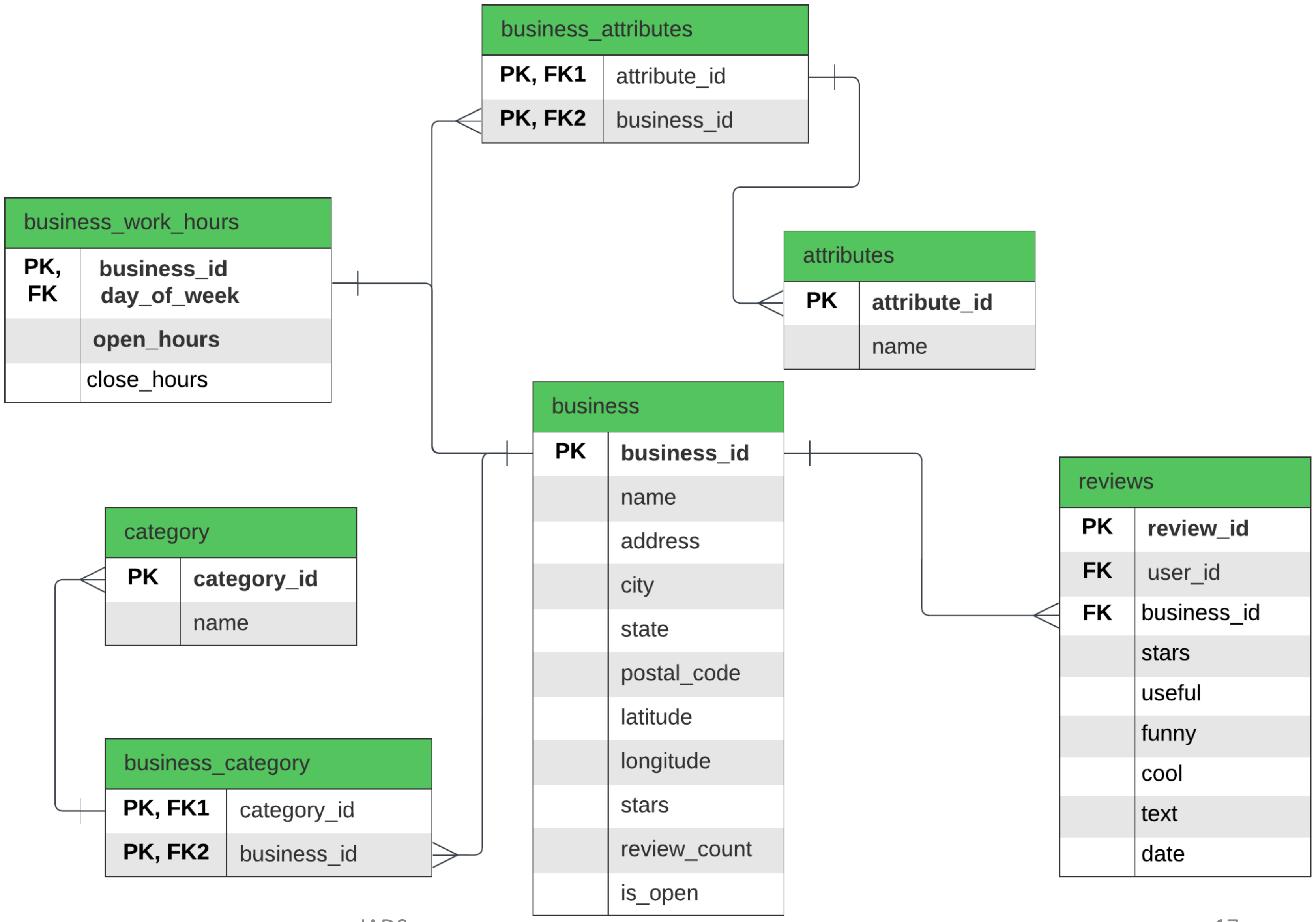
Large: 3GB + 5GB databases

Credits: An Hoang Vo, Kaggle, Business Analysis using SQL and Spark

Data schema

Covers:

- Businesses,
- Reviews
- Users



business_attributes	
PK, FK1	attribute_id
PK, FK2	business_id

business_work_hours	
PK, FK	business_id day_of_week
	open_hours
	close_hours

attributes	
PK	attribute_id
	name

business	
PK	business_id
	name
	address
	city
	state
	postal_code
	latitude
	longitude
	stars
	review_count
	is_open

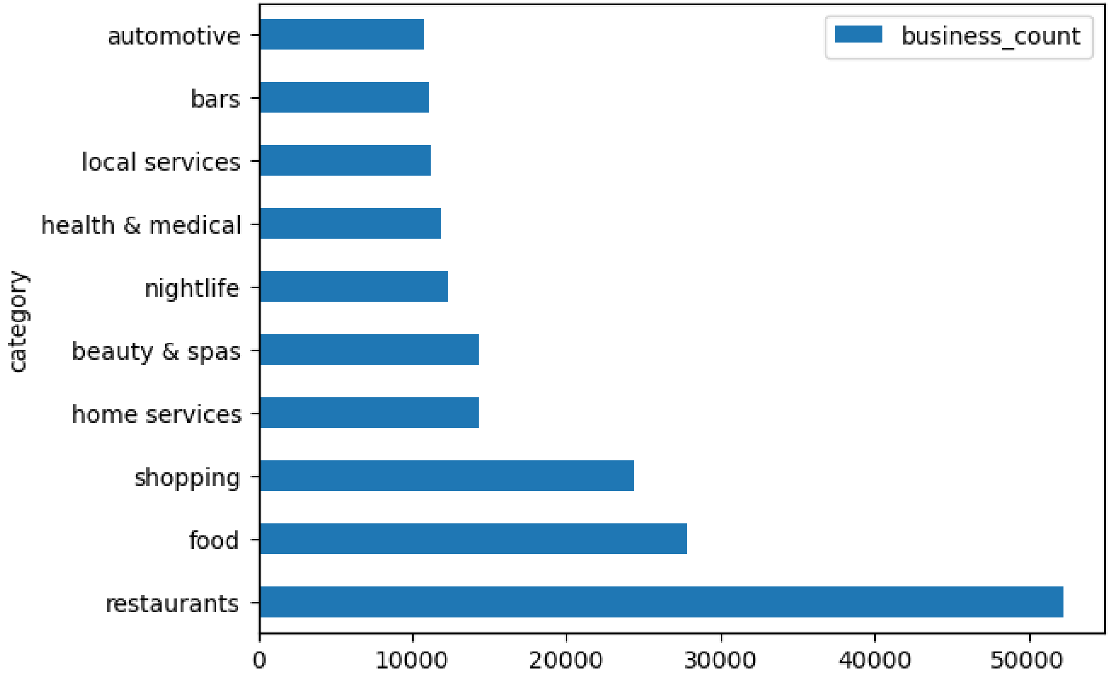
reviews	
PK	review_id
FK	user_id
FK	business_id
	stars
	useful
	funny
	cool
	text
	date

category	
PK	category_id
	name

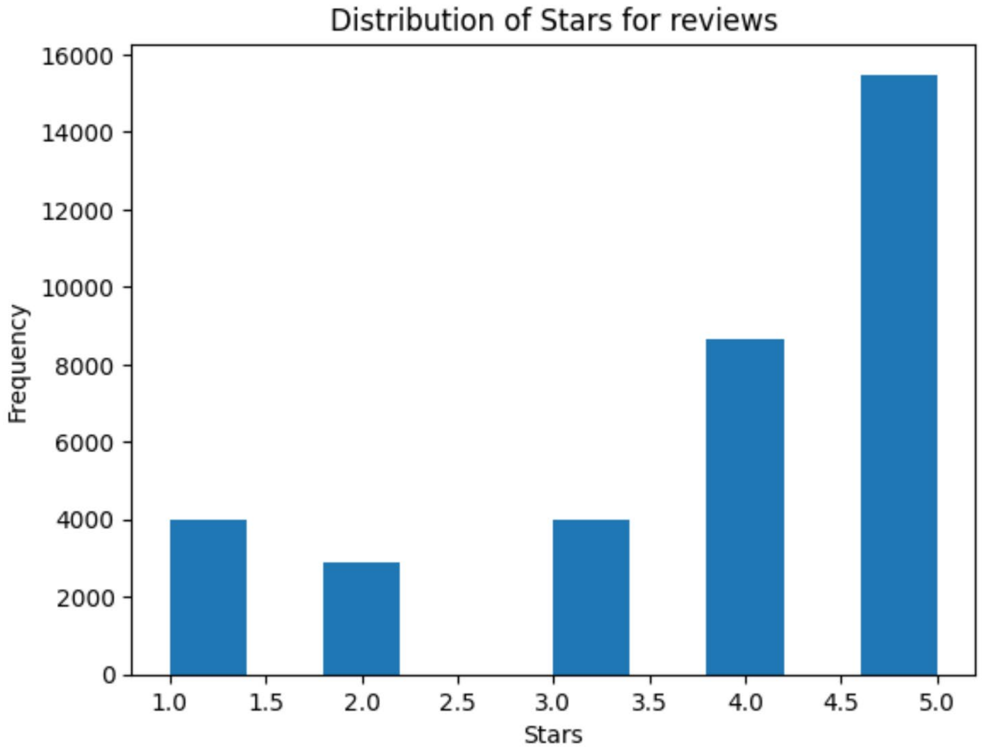
business_category	
PK, FK1	category_id
PK, FK2	business_id

Exploratory data analysis (EDA). Part 1/3

Business Categories

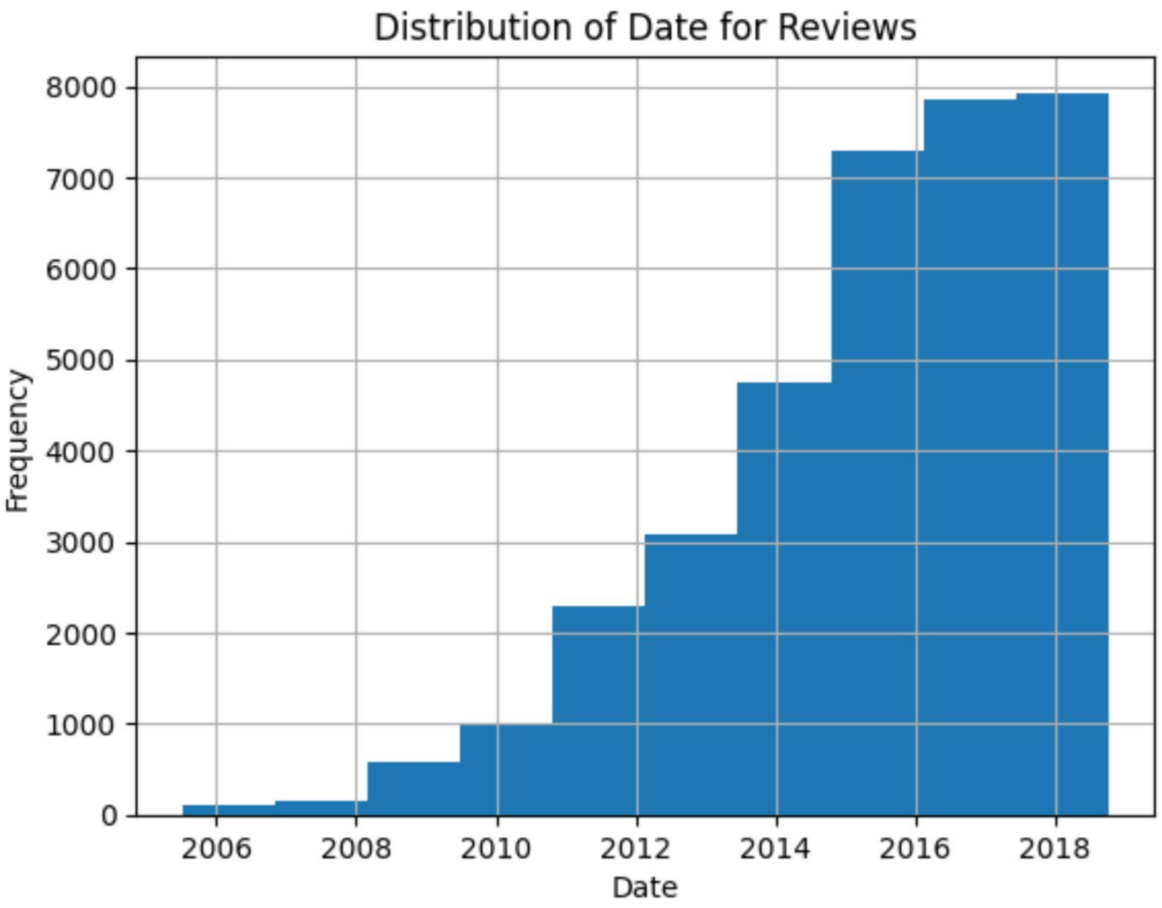


Credits: An Hoang Vo on Kaggle, Business Analysis using SQL

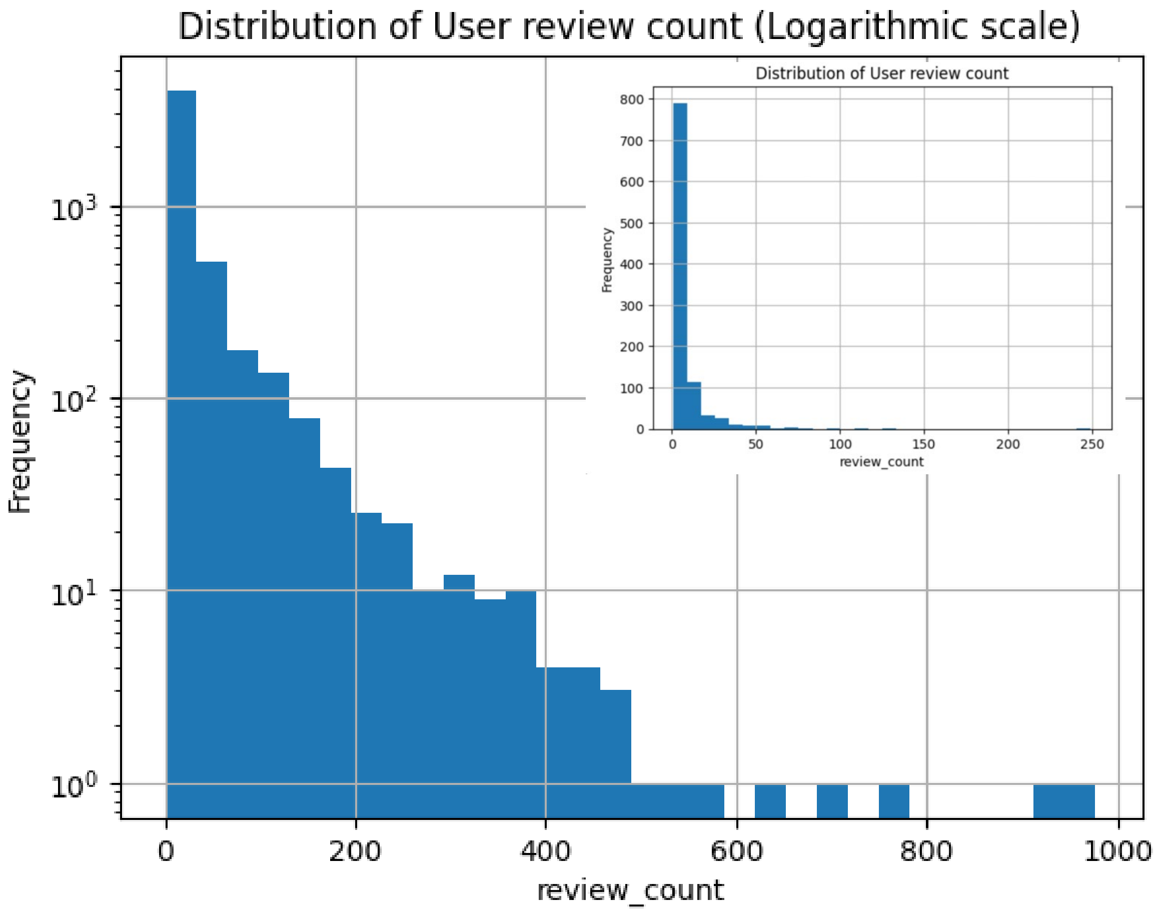


Analysis of a fragment of 35k random (?) entries of ‘reviews’

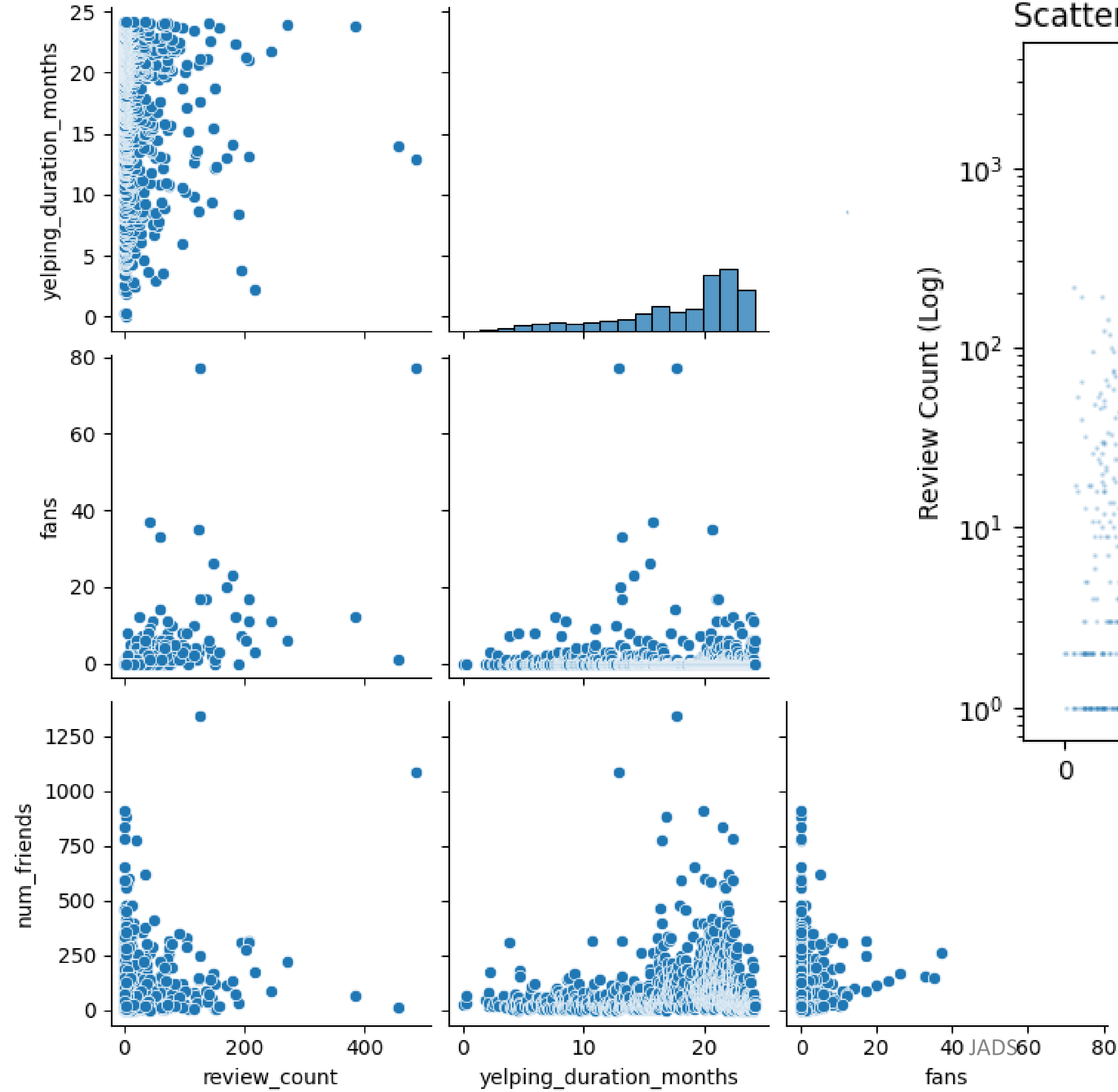
EDA 2/3

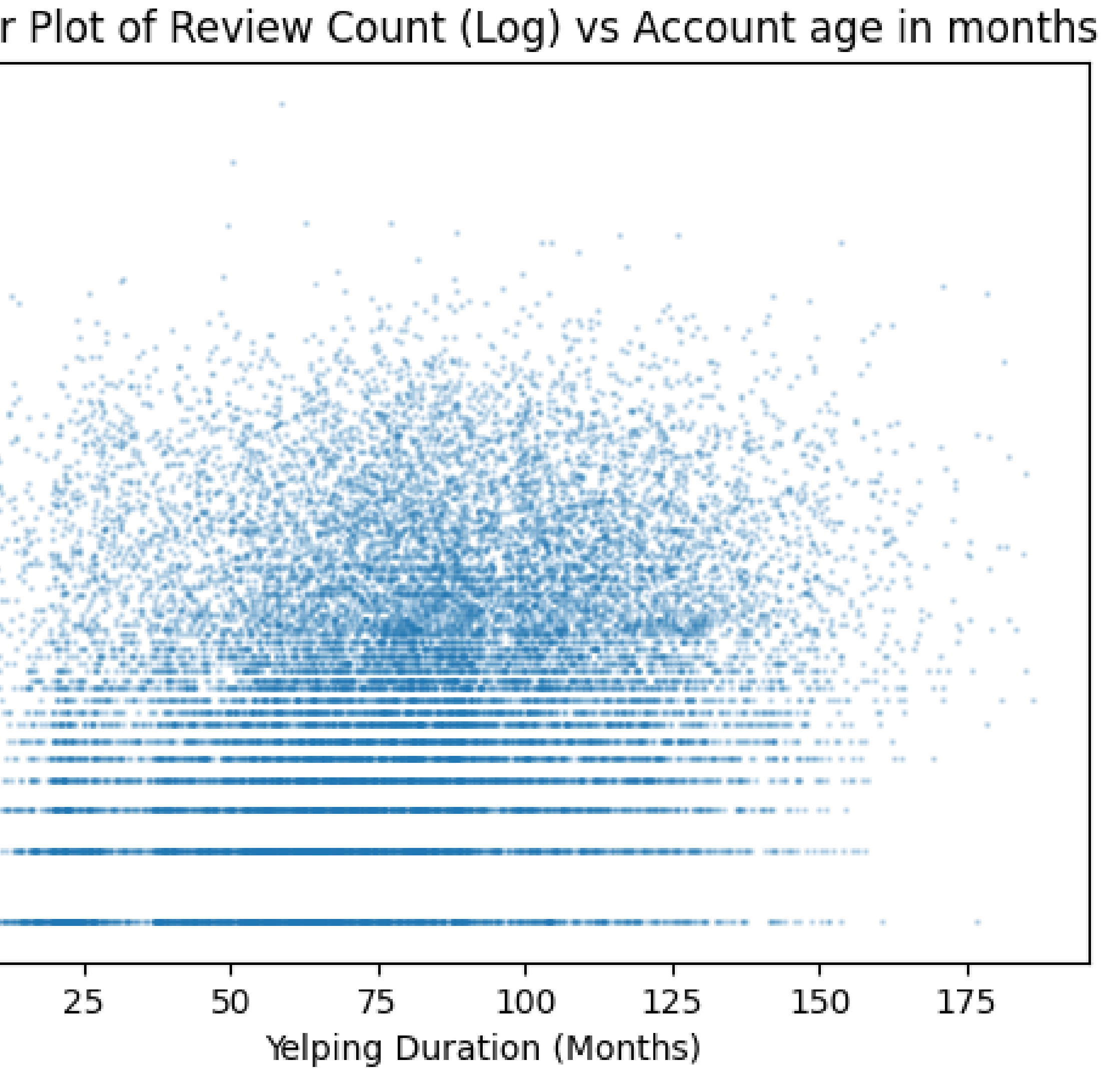


Our analysis of a fragment of 35k random (?) entries of ‘Reviews’



Our analysis of a fragment of 1000 random entries of ‘Users’





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.com/ursumarius/review-analysis-intro-ml-jads/

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

Slides:

- Thanks for your time.
  - Marius
  - Pedro
  - Georgios

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