Project 4

Fake Job Postings **Detection**

Group 2

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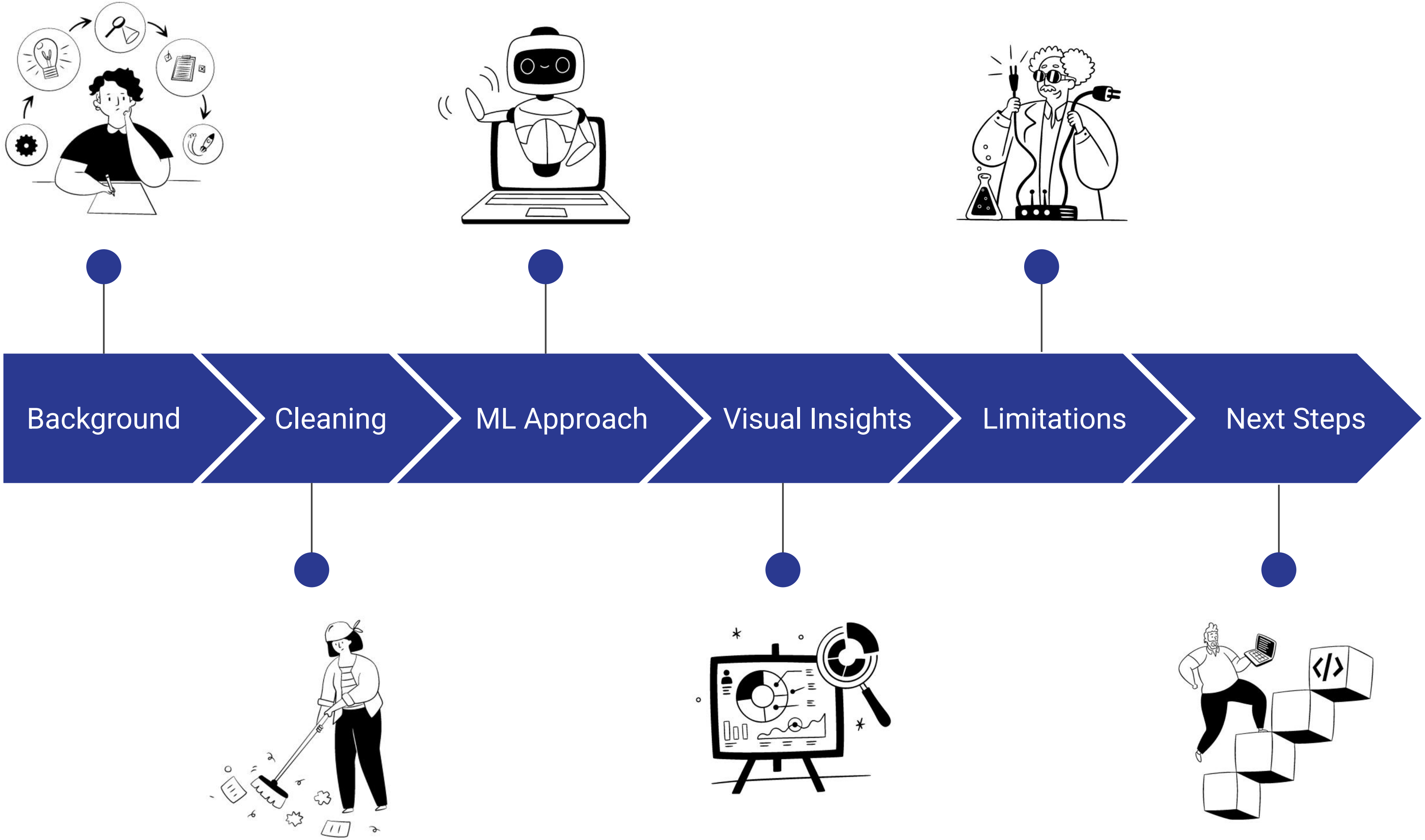

Background
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Background

Problem

Why do fake job postings matter?

Fake job listings can waste applicants' time, expose them to financial scams, and even lead to identity theft.

In a job market where people are already vulnerable, these scams exploit hope and urgency — often leaving real harm in their wake.

The Data

2016 Data

Contains ~18,000 job postings

Each listing is labeled as “real” or fraudulent”

Kaggle does not provide documentation on how these labels were created

2023-2024 Data

Contains recent job postings scraped from LinkedIn

Does not include labels for “fake” vs. real postings

Used to test model performance on more recent job postings

The Data: Shared Columns

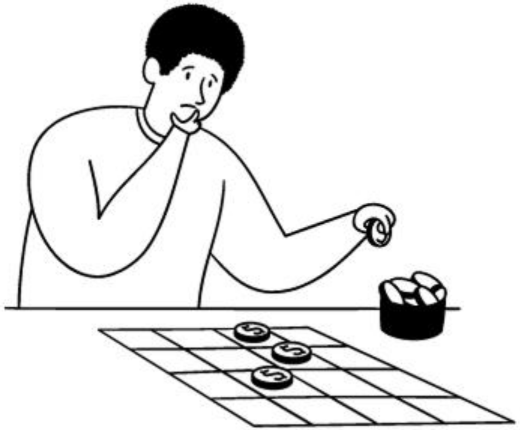
Job Title | Employment Type | Industry

Challenges - Only 4.3% of Postings Are Fake

Challenge

Imbalanced Dataset

- We can't rely on accuracy alone.
- We’ll look at precision, recall, and F1 score.



Cleaning the Data

Preprocessing for Better Results

2016 Data

- Loaded and duplicated raw CSV for safe editing
- Checked value counts and flagged low-variance columns
- Selected relevant features (e.g. title, description, location, education, experience)
- Split location column into country, region, and city
- Renamed columns for clarity and consistency
- Exported cleaned data to new CSV for modeling

Our ML Approach

Machine Learning

approach

- Combined multiple text fields into a single input
- Used TF-IDF vectorization to convert text to numeric format
- Trained a Random Forest Classifier using GridSearchCV
- Tuned n_estimators and max_depth for best F1 score

Model Performance & Metrics

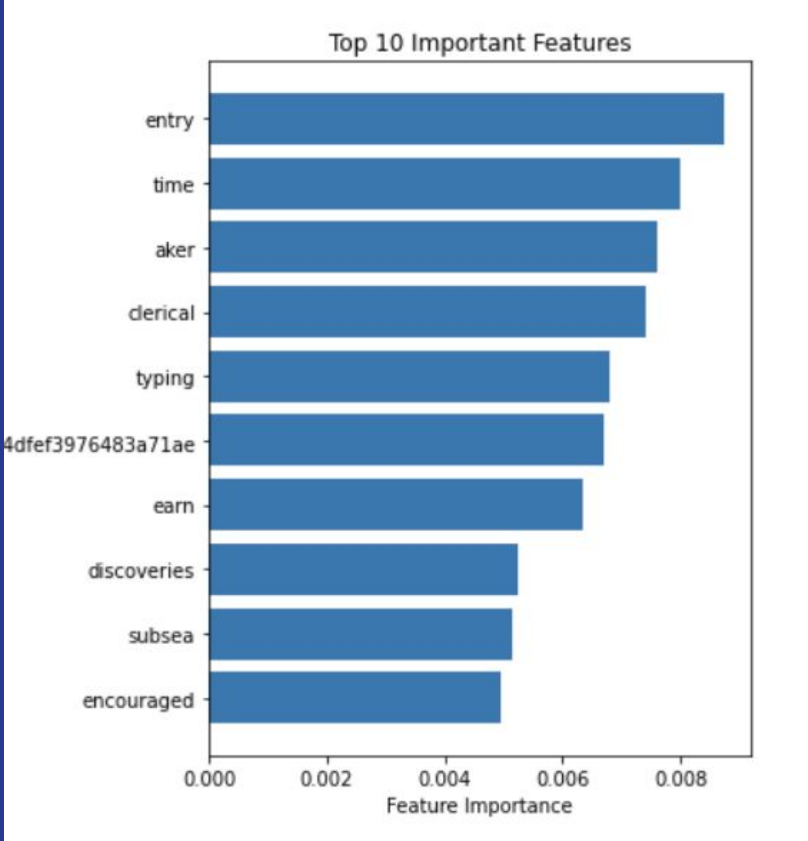
Accuracy, Precision, Recall, F1

Classification Report:

	precision	recall	f1-score	support
0	0.98	1.00	0.99	3403
1	1.00	0.60	0.75	173
accuracy			0.98	3576
macro avg	0.99	0.80	0.87	3576
weighted avg	0.98	0.98	0.98	3576

How the Model “Thinks”

- Top features included keywords, company descriptions, and location signals
- Feature importance chart generated from Random Forest model

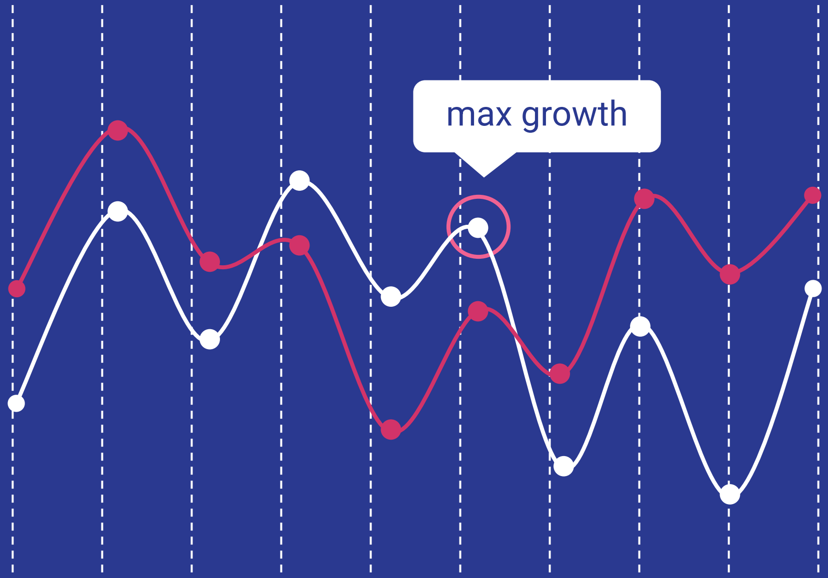


Insights

2016

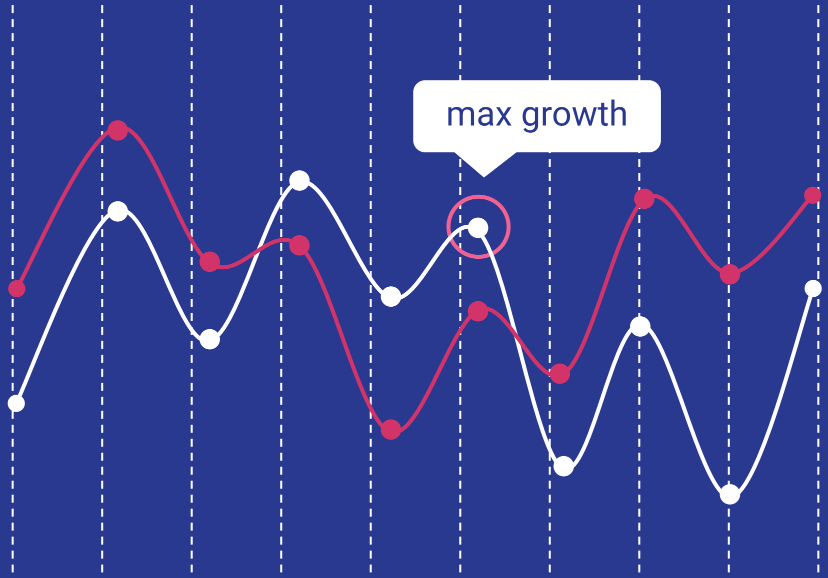
Y/N

Real vs Fake



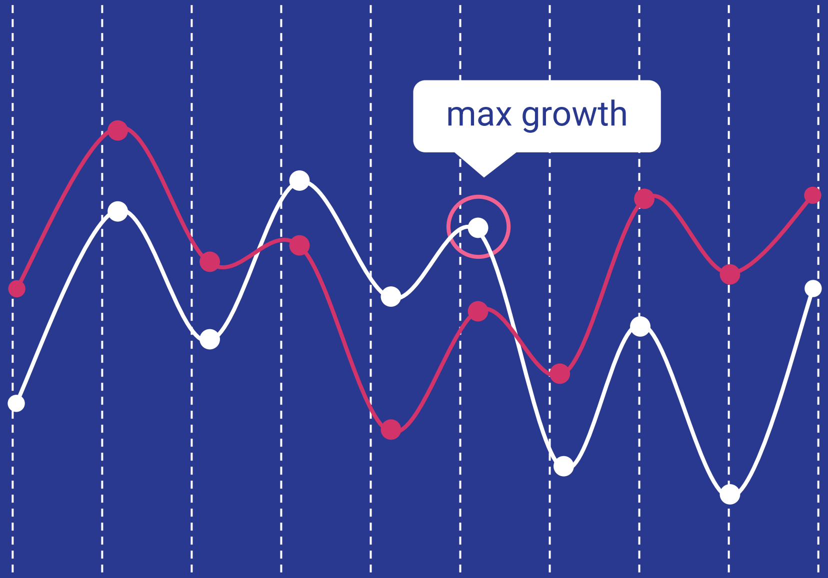
2016 Job Titles

Real vs Fake



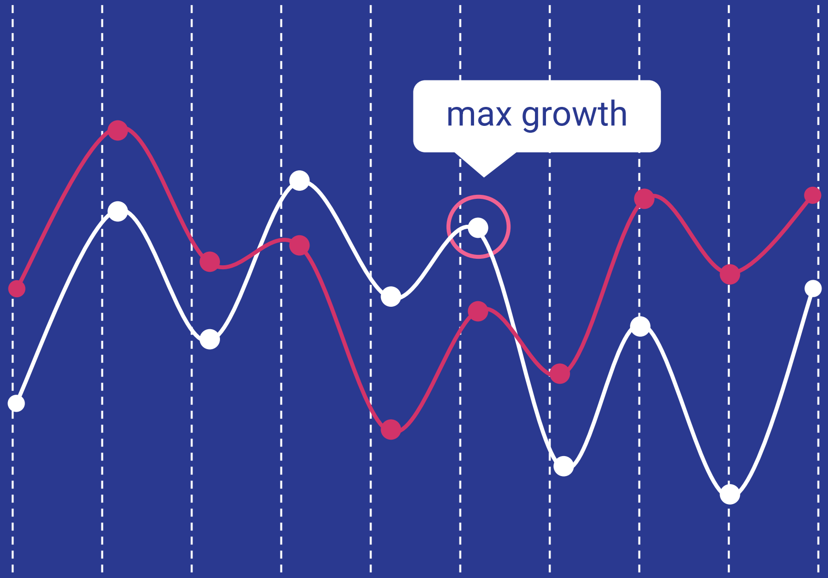
2016 Keywords

Fake vs Real



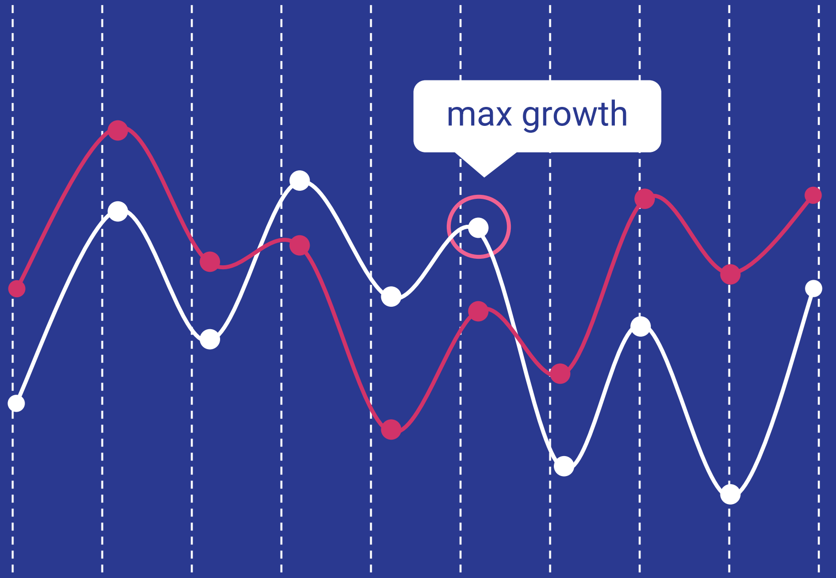
2023-24
Y/N

Real vs Fake



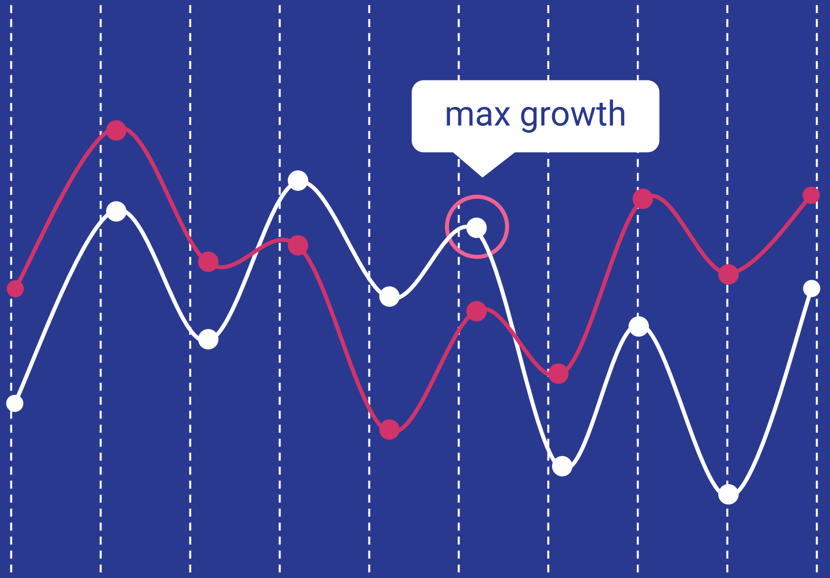
2023-24 Keywords

Real vs Fake



2023-24 Job Titles

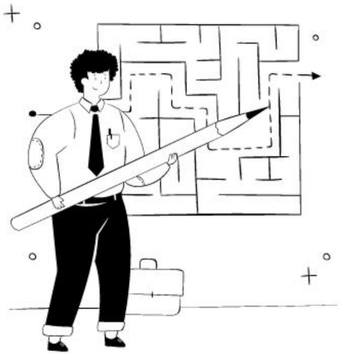
Real vs Fake



Key Differences Between the Datasets

2016 Data	2023-2024 Data
Point 1	Point 1
Point 2	Point 2
Point 3	Point 3

Limitations



Challenges & Caveats

Warning!

- Outdated training data — scammers evolve fast.
- Small proportion of fake listings (~4.3%)
- Manual labeling may introduce bias
- We're building intuition, not a perfect detector

What’s Next/Final Thoughts

Next Steps

Real World Use Cases

- Re-train on updated job datasets
- Explore more advanced NLP (e.g., BERT)
- Integrate as a flagging tool for job platforms ?
- Use for scam-awareness education & training?