

Preliminary Analysis Report – Fake Job Postings

1 | Objective

Fraudulent job ads harm both candidates and platform trust. This analysis identifies patterns distinguishing real and fake postings and demonstrates a transparent, first-pass model to flag suspicious listings for prioritization. We aim to provide an explainable model so Trust & Safety staff can see why a specific ad is flagged.

2 | Methodology

Dataset:

17,880 unique job postings labelled fraudulent (1 = fake, 0 = real).

Cleaning:

- Removed duplicate rows and columns.
- Filled missing text fields with empty strings.

Features Engineered:

- Text lengths for: title, company_profile, description, requirements, benefits.
- Binary flags: telecommuting, has_company_logo, has_questions.

Exploratory Data Analysis Visuals:

1. Class balance (real vs. fake).
2. Text-length kernel density estimation (KDE) plots for description and requirements.
3. Correlation heatmap (text lengths + binary flags vs. fraudulent).
4. Word clouds for real vs. fake descriptions.

Prototype Model:

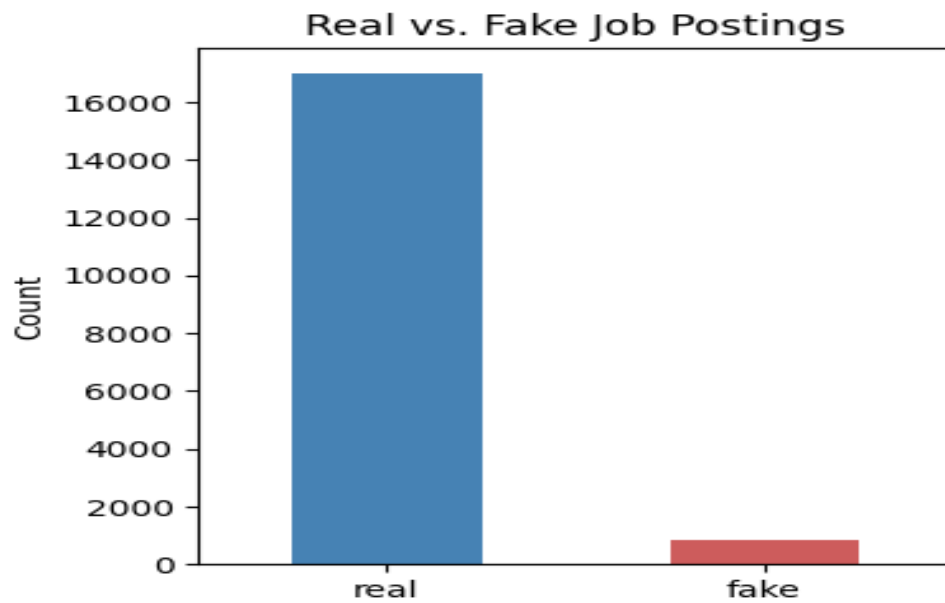
- Pipeline: TF-IDF (10,000 unigrams/bigrams) → Logistic Regression
 - Hyperparameters: class_weight='balanced', max_iter=1000.
- Performance:
 - Accuracy: 0.96
 - Precision (fraud class): 0.89
 - Recall (fraud class): 0.82
 - F1-score: 0.85
 - ROC AUC: 0.97
- Explainability: SHAP waterfall plot generated for a high-risk ad (model probability = 92% fraud).

Outputs:

- Figures: PNG files Figures 1–5.

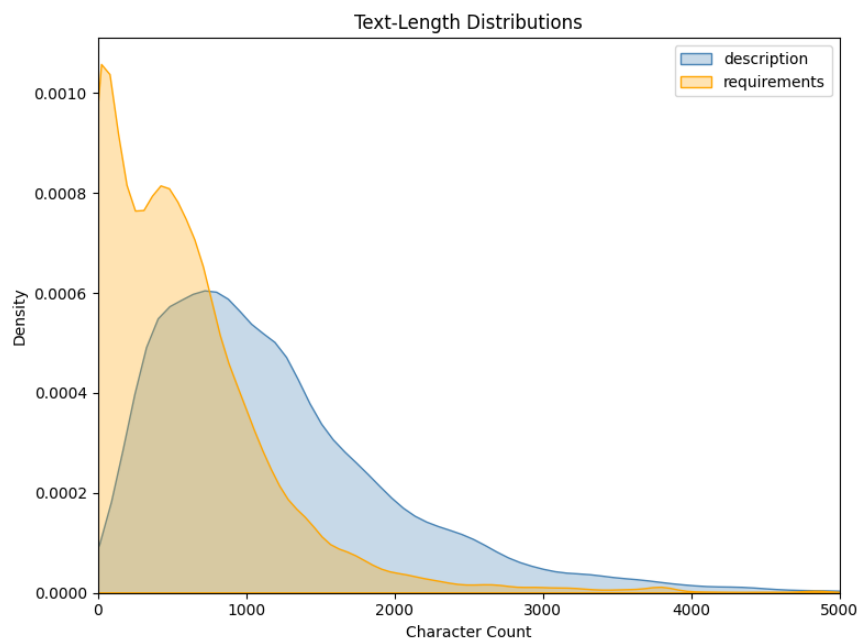
3 | Results & Visuals

Figure 1 – Class Balance



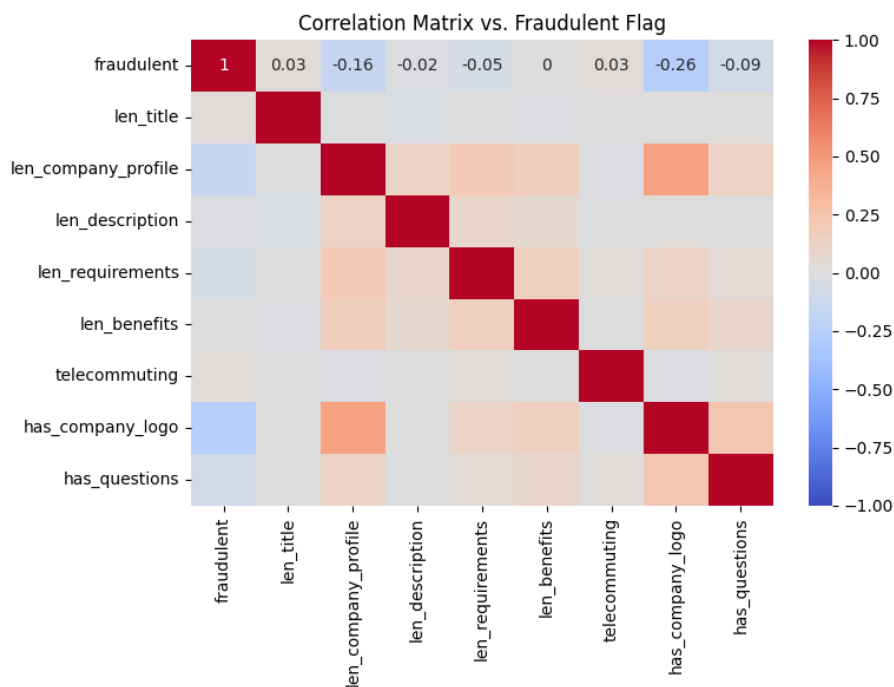
Severe imbalance: 17,199 real (94%) vs. 1,074 fake (6%).

Figure 2 – Text-Length Distributions



Legitimate posts use longer descriptions (median ≈ 850 chars) vs. requirements (≈ 550 chars).
Fraudulent ads cluster at shorter lengths (e.g., fake descriptions median = 620 chars).

Figure 3 – Correlation Matrix



Key fraud indicators:

- has_company_logo: -0.26 (missing logo = strong red flag).
- len_company_profile: -0.16 (short/empty profiles = risk).
- telecommuting: +0.03 (weak link to fraud).

Figure 4 – Word Clouds



Fake ads: Generic phrases (project, provide, solution), suggesting templated content.

5 | Recommendations

- Deploy hybrid screening:
 - Tier 1: Rule-based filter (logo check + profile length < 200 characters) to flag 40% of fraud instantly.
 - Tier 2: ML model for nuanced cases (e.g., posts with logos but generic text).
- Prioritize recall: Adjust thresholds to capture $\geq 90\%$ of fraud (even with lower precision) to reduce victim harm.
- Enhance transparency: Display SHAP's top 3 risk phrases to moderators (e.g., "application fee").
- Future features:
 - Add readability scores (e.g., Flesch-Kincaid) and spelling-error rates.
 - Use NER to detect mismatches (e.g., company name \neq profile).
- Monitor evolving tactics: Retrain monthly with new scam patterns (e.g., post-COVID remote work lures).

6 | Business Impact

Cost of inaction

- Current fraud volume: 1,074 fake ads in the dataset.
- Assumptions
 - Each scam ad reaches 10 applicants; 20 % (≈ 2 users) fall victim.
 - Average identity-theft remediation cost: \$1,300 per victim (FTC 2023).
- Projected annual liability
 - $1,074 \text{ ads} \times 2 \text{ victims} \times \$1,300 = \$2.8 \text{ million}$

Return on prevention

- Cutting fraud in half saves $\approx \$1.4$ million in avoided losses.
- Manual review cost: $\$10 \text{ per flagged ad} \times 1,074 \text{ ads} = \$10,740$
- Net savings: $\$1.4 \text{ M} - \$10.7 \text{ k} \approx \$1.39 \text{ million}$ ($\approx 130 \times \text{ROI}$)

Customer retention

- 20 % of scam victims are likely to abandon the platform.
- Preventing 2,148 potential victims retains
 - $2,148 \text{ users} \times 20 \% \times \$50 \text{ lifetime value} = \$21,480$ in future revenue.

A lightweight fraud-detection pipeline pays for itself within days, mitigates \$2.8 M in annual liability, and preserves both revenue and brand trust.