KAGGLE COMPETITION

Thea Boge

Introduction

1. DATA UNDERSTANDING AND FEATURE SELECTION
2. BASELINE MODEL
3. MODEL SELECTION AND DEVELOPMENT
4. FINAL MODEL AND RESULTS
5. LIMITATIONS AND FUTURE WORK

Dataset

From 56 raw columns → 10 relevant, interpretable features

Textual

- title
- descriptions

Contains seller language that directly expresses product condition (e.g. “nuevo”, “sin uso”, “usado”)

Numerical

- price
- base_price
- sold_quantity
- available quantity

Capture pricing patterns and product demand, which differ between new and used items.

Categorical

- listing_type_id
- buying_mode
- category_id

Describe how items are sold and categorized, adding contextual variation.

Text Cleaning and Preprocessing

Implemented two functions:

- clean_text()
  - lowercased text
  - removed punctuation and special characters
  - normalized accented characters
- preprocess()
  - combine titles and descriptions
  - apply the clean_text function
  - feature engineering for the numeric and categorical variables

Feature groups

Three feature groups for later preprocessing tequniques.

Preprocessing techniques:

- TF-IDF Vectorizer
- StandardScaler
- OneHotEncoder

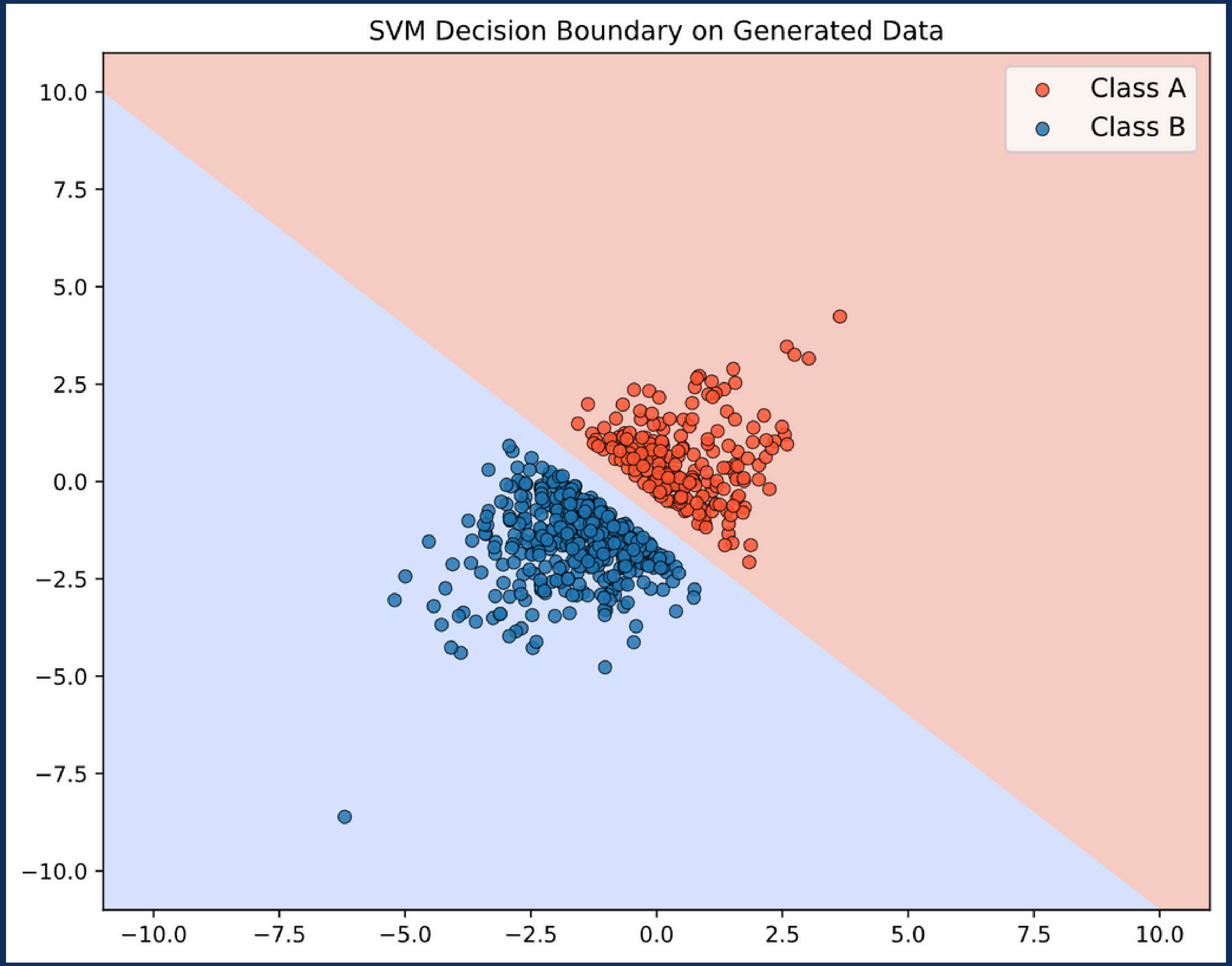
```
# Feature columns
text_col = "text"
num_cols = ["price", "base_price", "sold_quantity", "available_quantity",
            "price_ratio", "sold_ratio", "price_diff", "log_price"]
cat_cols = ["listing_type_id", "buying_mode", "category_id"]
```

Baseline Model

Support Vector Machines

- Baseline model for comparison
- Uses TF-IDF text features
- Linear SVM: fast, interpretable, effective for high-dimensional sparse data
- Accuracy: 0.8692

- Non-linear kernel (RBF) could model complex patterns, but too heavy for this dataset.

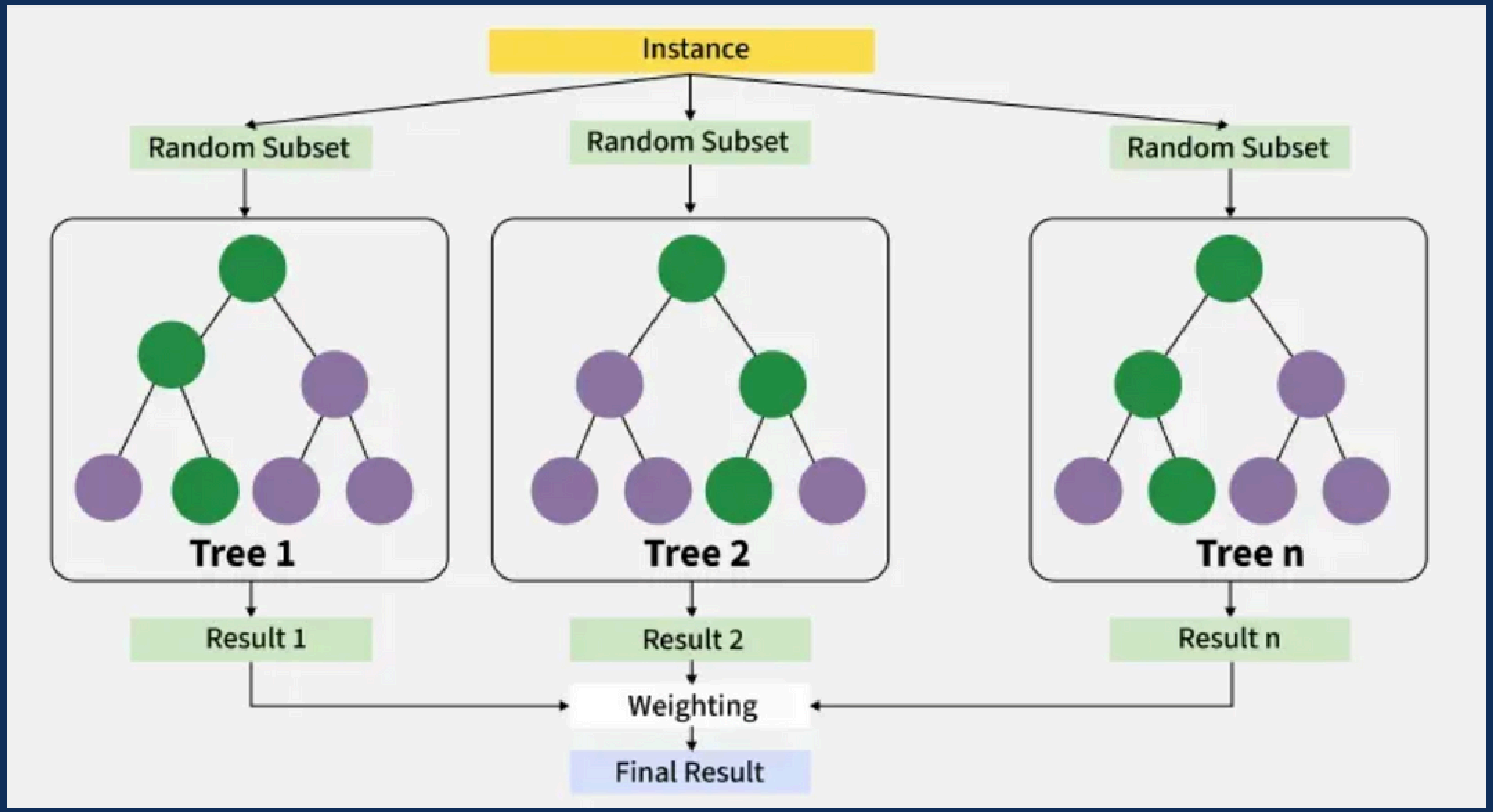


XGBoost

- Gradient boosting algorithm
  - builds trees sequentially
- Corrects previous errors
  - strong performance on mixed features
- Hist tree method: groups continuous features into bins
  - faster and memory-efficient

- Accuracy: 0.8828 (↑ from SVM)

Moving forward → improving the XGBoost



https://www.geeksforgeeks.org/machine-learning/xgboost/

Improvement

- ColumnTransformer → clean structure
- Added pipeline → end-to-end training
- Tuned hyperparameters
  - learning rate
  - max_depth
  - n_estimators
- Added feature engineering to preprocess() to capture economic behaviour

Improved model → 0.89

```python
# XGBoost model
xgb_model = XGBClassifier(
    n_estimators=7000,
    learning_rate=0.03,
    max_depth=9,
    subsample=0.85,
    colsample_bytree=0.7,
    reg_lambda=1.5,
    reg_alpha=0.5,
    tree_method="hist",
    random_state=42,
    n_jobs=-1,
    eval_metric="logloss"
)
```

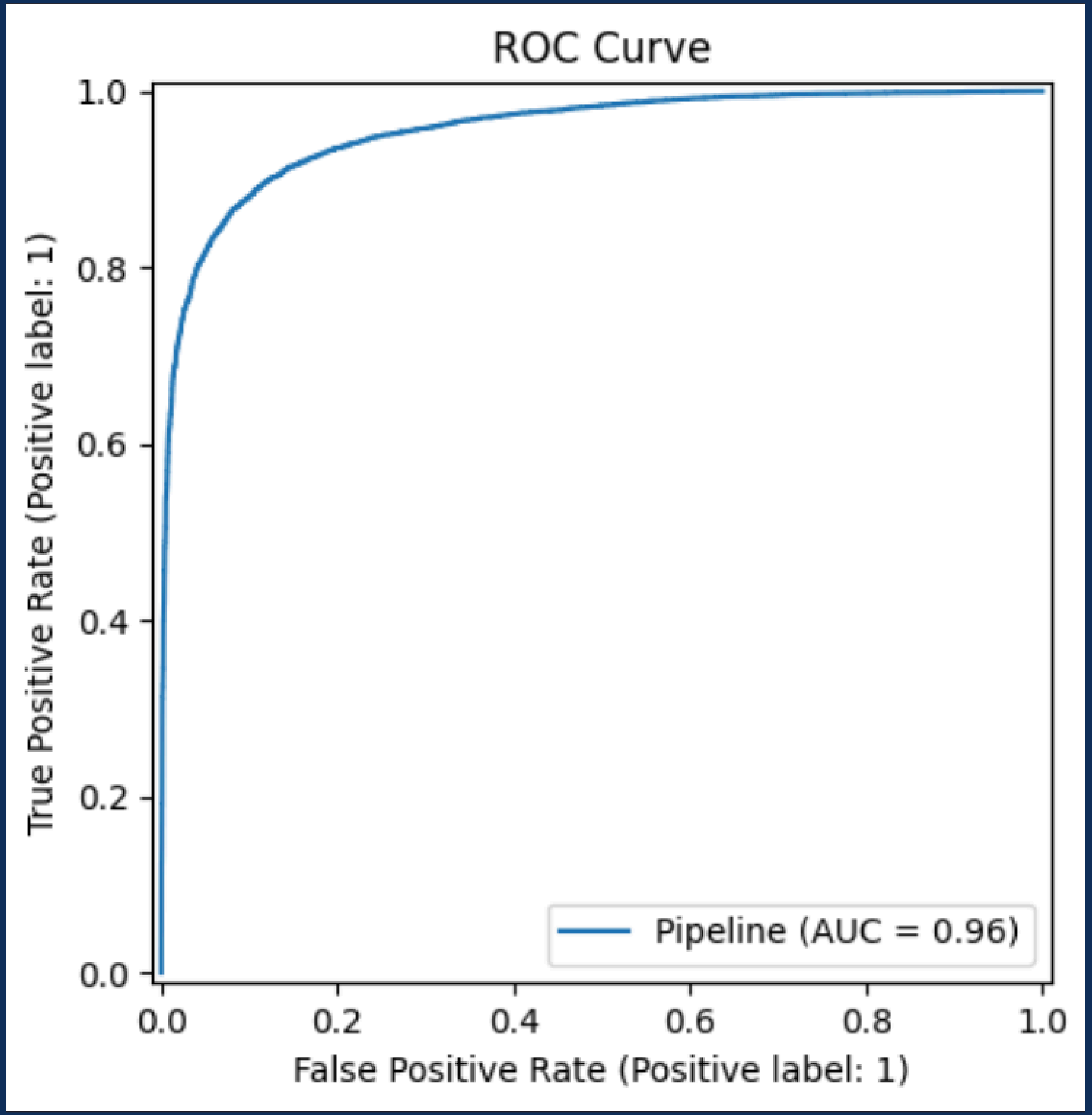
```python
df["price_ratio"] = df["price"] / (df["base_price"] + 1)
```

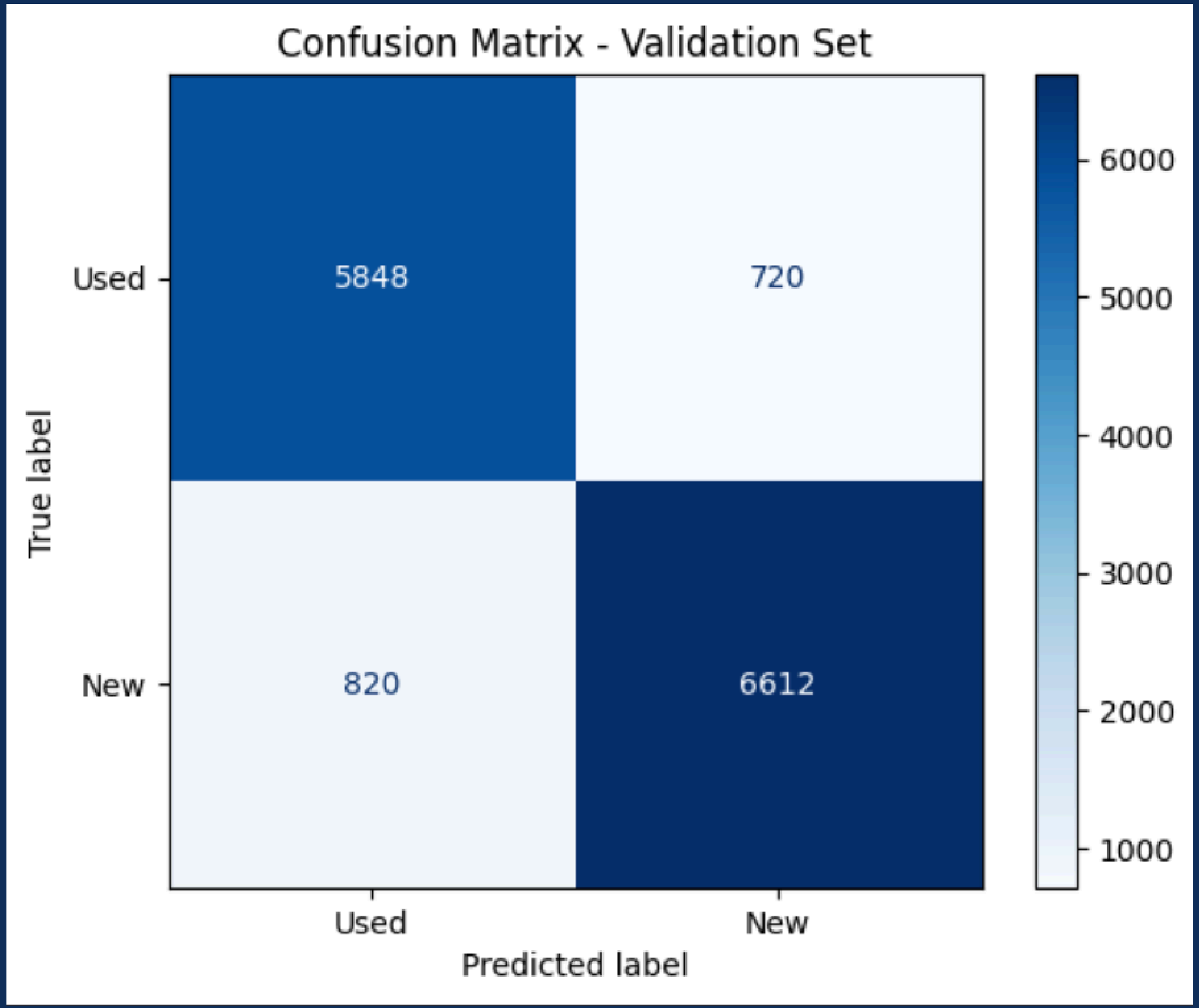
```python
df["log_price"] = np.log1p(df["price"].fillna(0))
df["log_sold"] = np.log1p(df["sold_quantity"].fillna(0))
```

```python
df["sold_ratio"] = df["sold_quantity"] / (df["available_quantity"] + 1)
```

Final Model Validation

XGBoost with histogram-based tree method, combining TF-IDF text, scaled numeric, and one-hot categorical features





Limitations and further work

- GridSearchCV() or Optuna for model tuning
  - Automate the search for optimal hyperparameters instead of manual tuning.
- Test additional boosting frameworks (e.g., LightGBM, CatBoost)
  - Compare performance and training efficiency on mixed feature data.
- Use richer text embeddings
  - Replace TF-IDF with word embeddings such as FastText or BERT to capture semantic meaning.
- Feature importance and interpretability
  - Analyze the most influential features to better understand what drives the model’s predictions.

Gracias por su atención!