Technical Report: Investment Classification & Risk Analysis

Prepared by: Ambrus Fodor, Katharina Burtscher
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Subject: Evaluation of Predictive Models for Capital Allocation Optimization
GitHub: [Project Repository]

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1. Executive Summary

This report details the development and validation of a machine learning framework designed to optimize the screening of high-potential investments. Our primary objective was to navigate the financial asymmetry between the risk of capital loss and the opportunity cost of missed growth.

Key Results:

- **Selected Model:** Random Forest Classifier
- **Optimal Decision Threshold:** 0.60
- **Financial Performance:** The model achieved a minimum average business cost of **$63,559** on the holdout set, significantly outperforming Gradient Boosting and Logistic Regression baselines.
- **Risk Profile:** With a high **Specificity (98.04%)**, the model effectively filters out nearly all non-performing candidates while maintaining a **Precision of 76.57%** on its investment recommendations.

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2. Problem Statement & Financial Constraints

2.1 Objective

The goal is to predict the likelihood of a company being "Fast Growing" (defined as achieving 30% growth between 2012 and 2013). We treat this as a binary classification task:

- **1 (Positive):** Fast-growing firm (Target).
- **0 (Negative):** Non-performing or average firm.

2.2 Asymmetric Cost Matrix

Unlike standard academic metrics, our optimization is driven by real-world financial penalties defined by the investment committee. A "Bad Investment" (losing principal) is considered **twice as damaging** as a "Missed Opportunity."

For a one-million-dollar investment, the loss function is structured as follows:

Prediction Error	Business Context	Cost (USD)
False Negative (FN)	**Missed Opportunity:** Rejecting a future high-performer.	**$300,000**
False Positive (FP)	**Bad Investment:** Committing capital to a failing firm.	**$600,000**

Loss Function:

$$\text{Total Cost} = (\text{FN}/\text{N} \times \$300,000) + (\text{FP}/\text{N} \times \$600,000)$$

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3. Data Source

The analysis utilizes a dataset containing 287,829 records of firm-level data from a mid-sized EU country. The data covers companies registered between 2005 and 2016 within three key industries: auto manufacturing, equipment manufacturing, and hospitality (hotels and restaurants).

3.1 Sample Design

To align with our growth metric, we restricted the dataset to companies active in both 2012 and 2013. We also filtered for firms with annual sales between $10,000 and $10,000,000 to eliminate outliers and focus on our core target demographic.

```
# Get the sets of unique company IDs for each year
ids_2012 = set(data.loc[data["year"] == 2012, "comp_id"])
ids_2013 = set(data.loc[data["year"] == 2013, "comp_id"])

# Find the intersection (companies present in both years)
common_ids = ids_2012.intersection(ids_2013)

data = data[data["comp_id"].isin(common_ids)]
```

Variables with a high proportion of missing values were excluded to maintain data quality.

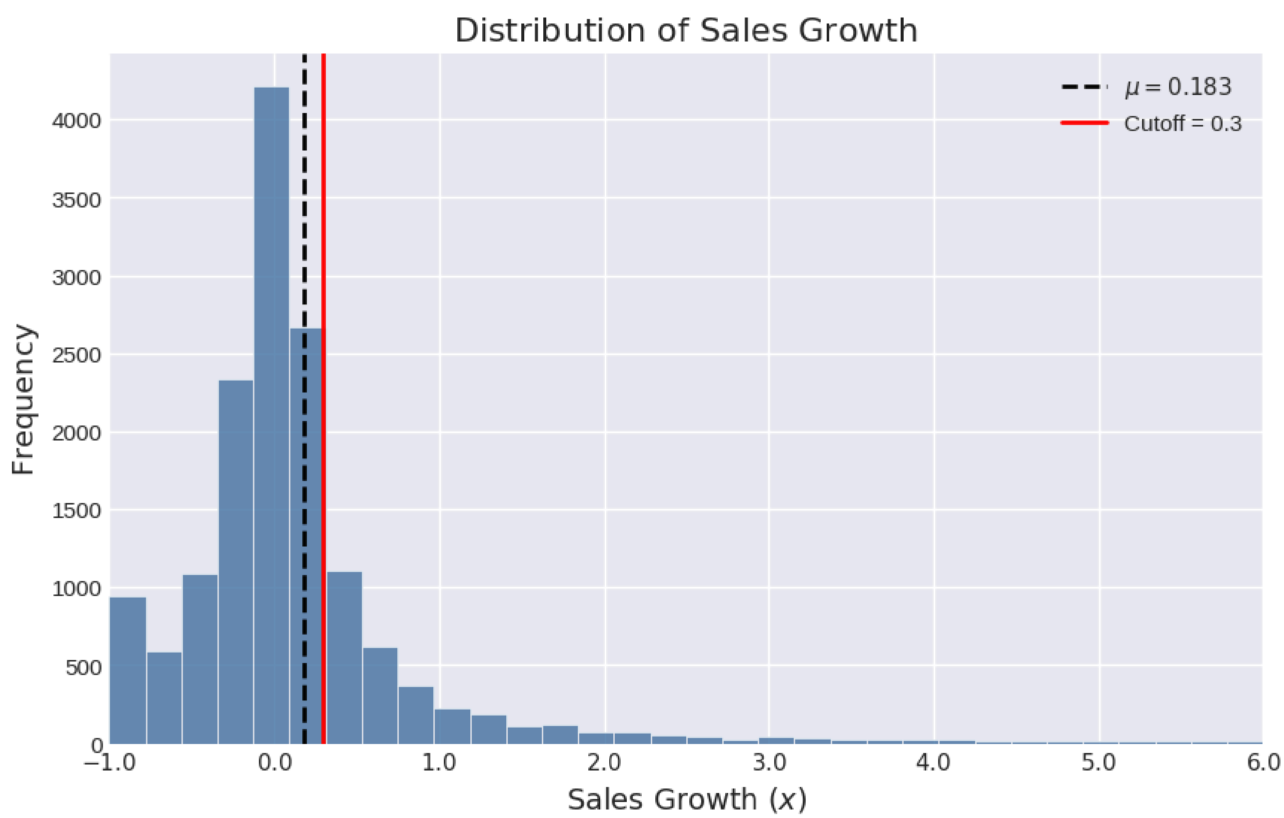
```
data = data.drop(
    columns=["COGS", "finished_prod", "net_dom_sales", "net_exp_sales",
"wages", "D", "exit_year", "exit_date"]
)
```

3.2 Label Engineering

Our primary "Fast Growth" label was constructed using a 30% growth cutoff, determined through a combination of domain expertise and visual analysis of growth distribution.

Decision Process:
We evaluated several metrics for growth and ultimately selected *Sales*. It provides a transparent, universal measure of traction; even venture-backed startups often prioritize sales growth before reaching profitability.

- **Functional Form:** We calculated the percentage growth in sales between 2012 and 2013. These years were chosen due to their high data density and availability.
- **Cut-off Selection:** While some definitions use 20% over three years, we applied a stricter 30% threshold for a single-year snapshot to capture truly high-velocity firms.



3.3 Feature Engineering

We re-coded industry categories based on domain insights and introduced a quadratic term for firm age to account for non-linear life-cycle effects.

```
# Consolidating industry categories
data["ind2_cat"] = np.where(data["ind2"] > 56, 60, data["ind2"])
# Capturing non-linear age effects
data["age2"] = data["age"] ** 2
```

To handle illogical negative values in asset columns (physical and intangible), we flagged these errors and capped them at zero.

```
# Flagging problematic assets and flooring at zero
data["flag_asset_problem"] = np.where((data["intang_assets"] < 0) |
(data["curr_assets"] < 0), 1, 0)
data["intang_assets"] = np.where(data["intang_assets"] < 0, 0,
data["intang_assets"])
```

To normalize for firm size, absolute currency values were converted into financial ratios.

```
# Ratio generation for Balance Sheet items
data[[col + "_bs" for col in bs_names]] =
data[bs_names].div(data["total_assets_bs"], axis="index")
```

Financial ratios often contain extreme values; we used a "flag and cap" approach for variables that theoretically reside within specific bounds (e.g., 0 to 1).

```
# Flagging and capping values > 1 (e.g., for accounting ratios)
data[col + "_flag_high"] = np.where(data[zero].isna(), np.nan, (data[zero] >
1).astype(int))
data[col] = np.where(data[zero] > 1, 1, data[zero])
```

Missing data was managed via a hybrid imputation strategy to preserve sample size without diluting signal quality.

```
# Mean imputation for CEO age
data["ceo_age"] = np.where(data["ceo_age"].isna(), data["ceo_age"].mean(),
data["ceo_age"])
```

```python
# Final cleanup of critical missing values
data.dropna(subset=["liq_assets_bs", "foreign", "ind"], inplace=True)
```

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4. Methodology & Implementation

We implemented a rigorous training pipeline to ensure model robustness and prevent common statistical pitfalls.

4.1 Preventing Data Leakage

A cornerstone of our architecture was the use of `Pipelines`. Preprocessing steps, specifically standardization (scaling), were fitted exclusively on the training folds within the Cross-Validation loop. This ensures that the test set remains strictly independent.

Code Snippet: Pipeline Implementation

```python
from sklearn.pipeline import Pipeline

# We use a Pipeline to scale data INSIDE the CV loop (prevents leakage)
lasso_rmse_pipe = Pipeline([
    ('scaler', StandardScaler()),
    ('lasso', LogisticRegressionCV(
        Cs=Cs_values,
        penalty='l1',
        cv=k,
        scoring='neg_brier_score',
        solver='liblinear',
        random_state=42,
        n_jobs=-1
    ))
])
```

4.2 Hyperparameter Tuning

We utilized `GridSearchCV` to optimize the Random Forest and Gradient Boosting models. Our primary scoring metric was the Brier Score (mean squared error of probabilities), ensuring our models provide well-calibrated probability estimates rather than just binary labels.

Code Snippet: Grid Search Configuration

```python
from sklearn.model_selection import GridSearchCV

# Define RF Grid & Model
grid = {
    'max_features': [5, 6, 7, "sqrt"],
    'criterion': ['gini'],
    'min_samples_split': [11, 16],
    'n_estimators': [500]
}

prob_forest = RandomForestClassifier(
    random_state=42,
    n_estimators=100,
    oob_score=True
)

# Run Grid Search
prob_forest_grid = GridSearchCV(
    prob_forest,
    grid,
    cv=5,
    refit='neg_brier_score',
    scoring=['accuracy', 'roc_auc', 'neg_brier_score'],
    n_jobs=-1
)
```

4.3 Custom Business Cost Function

To finalize model selection, we moved beyond standard AUC metrics. We developed a custom loss function to evaluate models based on our specific $300k / $600k penalty structure.

Code Snippet: Financial Loss Calculation

```python
def calculate_business_cost(y_true, y_probs, threshold):
    # Convert probabilities to binary predictions based on threshold
    y_pred = (y_probs >= threshold).astype(int)

    # Calculate False Positives and False Negatives
    fp = np.sum((y_pred == 1) & (y_true == 0))
    fn = np.sum((y_pred == 0) & (y_true == 1))

    # Apply Financial Costs
    cost_fn = 300_000
    cost_fp = 600_000
```

```
    total_loss = (fn * cost_fn) + (fp * cost_fp)
    return total_loss
```

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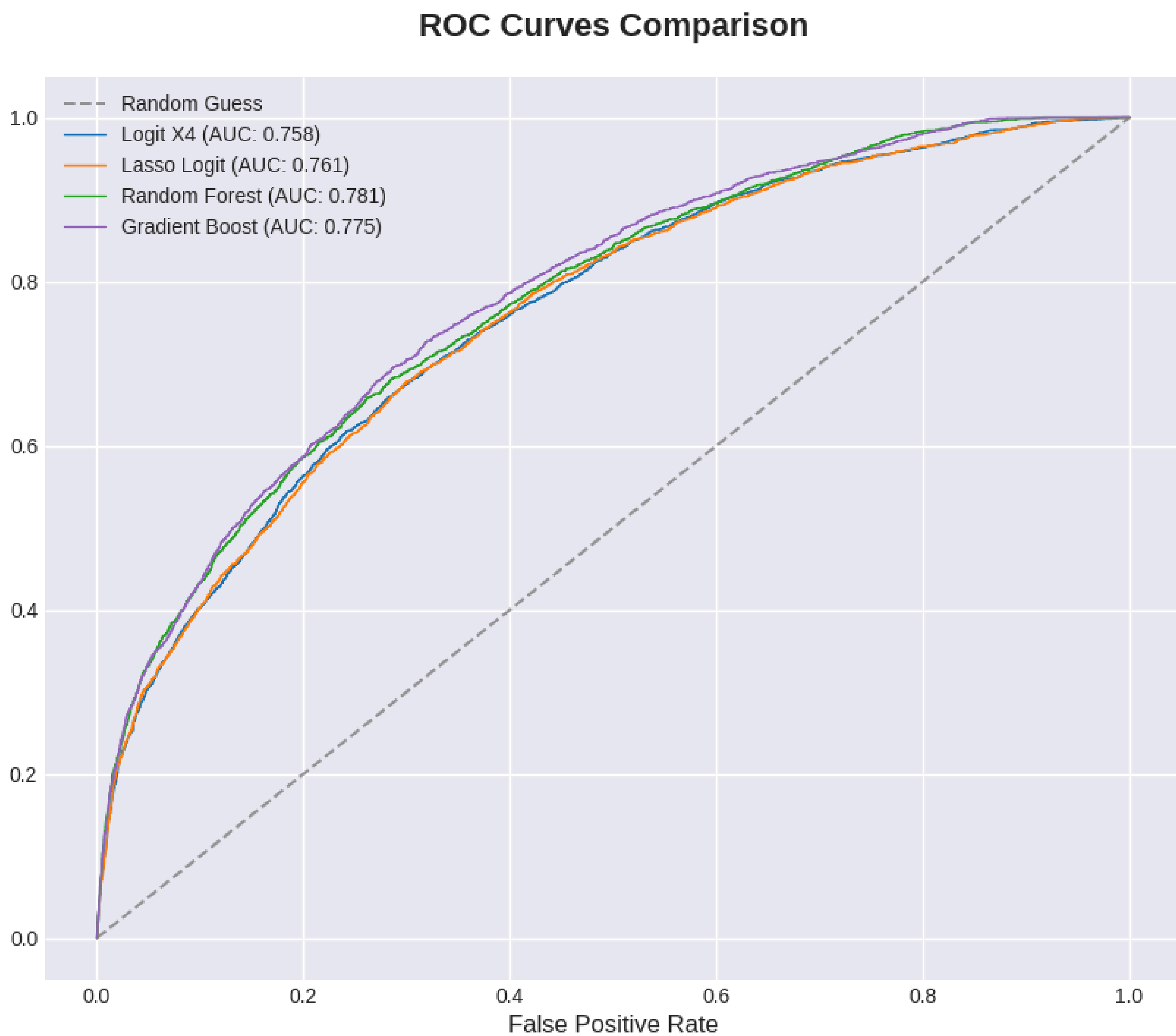
5. Model Comparison & Selection

We benchmarked four candidate models using 5-fold cross-validation. While Gradient Boosting achieved the highest raw AUC, the Random Forest model generated the lowest expected financial loss when applied to our cost matrix.

Table 1: Model Performance Summary (Holdout Set)

Model	AUC	Classification Threshold	False Positives (Bad Inv)	False Negatives (Missed Opp)	Total Expected Loss
Logit X4	0.758	0.65	42	501	$64,665
Lasso Logit	0.761	0.62	48	493	$65,107
Gradient Boosting	0.781	0.68	45	491	$64,223
Random Forest (Selected)	**0.775**	**0.60**	**41**	**493**	**$63,559**

Selection Logic: Although Gradient Boosting showed a marginal edge in AUC, the Random Forest model's probability distribution allowed for a more efficient threshold (0.60). By minimizing expensive False Positives (41 vs 45), it provides a **$700 cost saving** over the next best alternative.



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6. Final Model Evaluation: Random Forest

The Random Forest model was evaluated on the complete holdout dataset ($N \approx 2,714$).

6.1 Confusion Matrix Analysis

At the selected probability threshold of **0.60**:

-	Actual Success (1)	Actual Failure (0)
Predicted Investment (1)	134 (TP)	41 (FP)
Predicted Rejection (0)	493 (FN)	2,046 (TN)

- **True Positives (134):** Correctly identified high-growth firms.
- **False Positives (41):** "Value Traps"—investments that failed to perform.
- **True Negatives (2,046):** Successfully avoided poor performers.

Classification Metrics:

Metric	Value
Accuracy	80.32%
Precision	76.57%
Recall	21.37%
Specificity	98.04%

6.2 Financial Impact Breakdown

Cost of Missed Opportunities (FN):

$$493 \text{ Missed Deals} \times \frac{\$300,000}{2,714} = \mathbf{\$54,495}$$

Analysis: This represents the largest cost component. The model is intentionally conservative, prioritizing capital preservation over deal volume.

Cost of Bad Investments (FP):

$$41 \text{ Failed Investments} \times \frac{\$600,000}{2,714} = \mathbf{\$9,064}$$

Analysis: Direct capital loss is strictly minimized. Only ~16% of the total expected cost stems from actual cash loss; the remainder is theoretical "lost profit."

Total Business Cost (per applicant):

$$\frac{\$172,500,000}{2,714} = \mathbf{\$63,559}$$

6.3 Sector Analysis

A post-hoc analysis revealed significant performance variance across industries:

- **Manufacturing Sector:** The model struggled, yielding a Recall of only 11.05%.
- **Services Sector:** Performance was significantly stronger here, with a Recall of 25.56%.

Recommendation: The model is best suited for Service-sector candidates. Manufacturing firms may require a lower threshold or qualitative human intervention.

7. Conclusion & Recommendations

The Random Forest model serves as a "Capital Shield." By achieving 98.04% Specificity, it protects the firm's principal investment at the expense of potential deal volume.

Action Plan:

1. **Automated Filtering:** Deploy the model to automatically filter out applicants with a probability score below 0.60. This safely removes ~80% of the deal pipeline (mostly True Negatives).
2. **Strategic Due Diligence:** Focus investment analysts on the remaining ~20% of applicants. With a Precision of 76.6%, 3 out of every 4 of these firms are likely high-growth winners.
3. **Sector-Specific Tuning:** Exercise caution in Manufacturing; consider lowering the decision threshold to 0.50 for this sector to improve opportunity capture.

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8. Environment Details

- **Python Version:** 3.12.4
- **Core Packages:** numpy, pandas, matplotlib, sklearn, patsy