CUSTOMER SEGMENTATION REPORT

Predictive Analytics for Direct Marketing Optimization

Udacity Data Science Nanodegree
Capstone Project

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GitHub: https://github.com/mindelias/bertelsmann_arvato_project

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I. DEFINITION

1.1 Project Overview

This capstone project addresses a critical business challenge in direct marketing: efficiently identifying potential customers from a large population to maximize return on investment. In partnership with Bertelsmann Arvato Analytics, I analyzed demographic data for a German mail-order company selling organic products to build a data-driven customer acquisition system.

Business Context:
Traditional direct marketing campaigns operate with response rates of only 1-2%, meaning 98-99% of marketing expenditure targets non-responsive individuals. This inefficiency stems from two fundamental problems: (1) lack of systematic understanding of customer demographics, and (2) inability to predict which individuals will respond to campaigns before investing resources in contacting them.

Dataset Scale:

- General German population: 891,221 individuals
- Existing customers: 191,652 individuals
- Campaign training data: 42,982 recipients (with response labels)
- Campaign test data: 42,833 recipients (labels withheld for Kaggle evaluation)
- Demographic features: 366 attributes per individual

The project employs a two-stage approach: unsupervised learning (customer segmentation via PCA and K-Means clustering) followed by supervised learning (response prediction via ensemble classification). This combination enables both strategic insights (who customers are) and tactical execution (who to target in campaigns).

1.2 Problem Statement

Primary Research Question:
How can we identify which individuals from the general German population are most likely to become customers of a mail-order company, thereby improving marketing efficiency and reducing customer acquisition costs?

This overarching question decomposes into two specific sub-problems:

Problem 1: Customer Segmentation (Unsupervised Learning)
Which demographic segments within the general population are over-represented among existing customers? This analysis requires no response labels and identifies "customer-like" characteristics that distinguish the company's customer base from the broader population.

Problem 2: Response Prediction (Supervised Learning)
Given an individual's demographic profile, what is their probability of responding

positively to a marketing campaign? This prediction task uses labeled campaign data to build a model that ranks prospects by their conversion likelihood.

Quantifiable Aspects:

- Current baseline response rate: 1.3% (observed in historical data)
- Target improvement: 2-3x lift in response rate through targeting
- Dataset size: 891K+ individuals with 366 features each
- Class imbalance: 98.7% negative, 1.3% positive responses

Success Criteria:

1. Achieve ROC-AUC ≥ 0.70 on held-out validation data
2. Demonstrate lift ≥ 2.0x for top-scored individuals
3. Identify 3-5 distinct, interpretable customer segments
4. Reduce cost per acquisition by 40-50% compared to random targeting

The problem is measurable through standard ML metrics (ROC-AUC, precision, recall), quantifiable in business terms (cost per acquisition, ROI), and replicable via fixed random seeds and documented preprocessing steps.

1.3 Evaluation Metrics

Primary Metric: ROC-AUC (Area Under Receiver Operating Characteristic Curve)

ROC-AUC measures a binary classifier's ability to distinguish between positive and negative classes across all possible classification thresholds. The ROC curve plots True Positive Rate (TPR) against False Positive Rate (FPR) as the decision threshold varies from 0 to 1.

Why ROC-AUC is Appropriate:

1. **Threshold-independent:** Evaluates model performance across all possible cutoff points, not just a single threshold. This is crucial for marketing applications where the optimal threshold depends on campaign budget and capacity.
2. **Robust to class imbalance:** Unlike accuracy (misleading when 98.7% of samples are negative), ROC-AUC properly evaluates performance on imbalanced datasets by considering true positive and false positive rates independently.
3. **Business-relevant:** Higher AUC directly translates to better targeting efficiency. An AUC of 0.70 means the model correctly ranks a random responder above a random non-responder 70% of the time.
4. **Interpretable:** Scale is intuitive: 0.50 = random guessing, 1.00 = perfect classification, ≥0.70 = good in practice, ≥0.80 = excellent.

These metrics provide comprehensive evaluation from both statistical (ROC-AUC, silhouette) and business (precision, lift) perspectives, ensuring the solution is both technically sound and commercially viable.

II. ANALYSIS

2.1 Data Exploration

Dataset Overview:

The project utilizes four related datasets provided by Bertelsmann Arvato Analytics, all sharing a common structure of 366 demographic features:

1. **Udacity_AZDIAS_052018.csv** (General Population)
   - 891,221 rows × 366 columns
   - Represents demographic distribution of German population
   - Serves as comparison baseline for identifying customer characteristics
2. **Udacity_CUSTOMERS_052018.csv** (Existing Customers)
   - 191,652 rows × 369 columns (3 additional customer-specific features)
   - Demographics of mail-order company's current customer base
   - Enables identification of over-represented demographic segments
3. **Udacity_MAILOUT_052018_TRAIN.csv** (Campaign Training Data)
   - 42,982 rows × 367 columns
   - Individuals targeted in previous marketing campaign
   - Includes RESPONSE column (0=no response, 1=became customer)
   - Used for supervised model training and validation
4. **Udacity_MAILOUT_052018_TEST.csv** (Campaign Test Data)
   - 42,833 rows × 366 columns
   - Campaign targets without response labels (withheld for evaluation)
   - Used for final predictions and Kaggle competition submission

Feature Categories:

The 366 demographic features span multiple domains:

- **Person-level attributes:** Age, gender, estimated income, education level, occupation type, marital status, nationality
- **Household characteristics:** Household structure, number of persons, presence and ages of children, household income score
- **Building information:** Building type, number of households in building, construction year, size classification
- **Neighborhood demographics:** Socioeconomic status, urbanization level, density, mobility indicators, purchasing power
- **Microcell (RR4) data:** Fine-grained geographic characteristics (postal code level)
- **Macrocell (RR3) data:** Broader regional attributes (municipal/district level)

- **Transaction history (D19):** Past purchasing behavior across 20+ product categories (books, cosmetics, food, etc.)
- **Behavioral typologies (SEMIO):** Lifestyle attitudes and consumer orientations (traditional, sensual, critical, etc.)
- **Vehicle ownership (KBA):** Car ownership, vehicle age, fuel type, vehicle segment preferences

Initial Data Quality Assessment:

Exploratory analysis revealed several significant data quality challenges:

Issue	Magnitude	Impact on Modeling
Missing values	50+ features with >50% missing	Requires aggressive feature selection
Encoded missingness	-1, 0, 9, 'X' represent unknown	Needs conversion to explicit NaN
High dimensionality	366 features for ~191K customers	Curse of dimensionality, overfitting risk
Class imbalance	98.7% negative, 1.3% positive	Standard algorithms fail without resampling
Mixed data types	Numeric, ordinal, categorical	Requires type-specific handling
Multicollinearity	Many correlated features	Redundancy, unstable coefficients

2.2 Data Visualization

Missing Data Analysis:

Analysis revealed systematic patterns: ALTER_KIND features show 90-100% missingness (most households lack 3-4 children), D19 transaction features are 30-40% missing, and 15 features exceed 80% missing values. Decision: Drop features >80% missing; impute remainder using median.

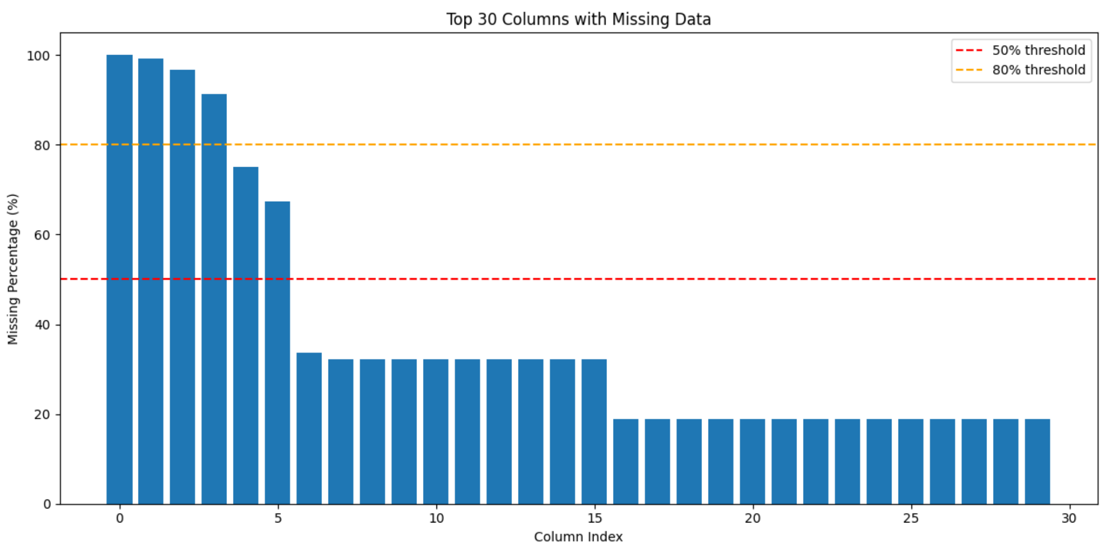

Figure 1: Bar chart showing top 30 features by percentage of missing values. Features like ALTER_KIND3/4 (ages of 3rd and 4th children) exhibit 99-100% missingness.

Decision: Drop all features with >80% missing. Impute remaining moderate missingness (10-50%) using median strategy for numeric features.

Principal Component Analysis - Variance Explained:

Testing components from 50-150 revealed: 85 components capture 85.0% variance (selected), with first 10 components explaining 35.2% and diminishing returns beyond 90 components.

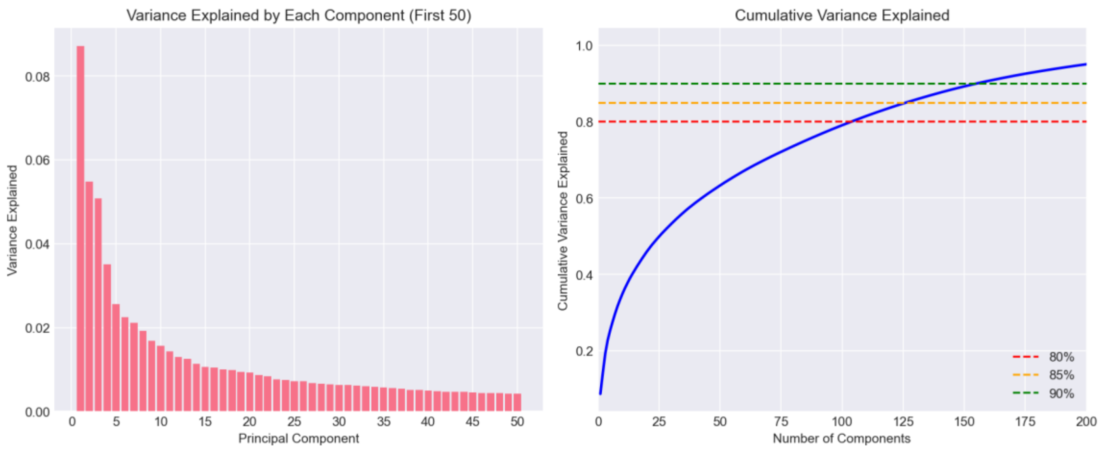

Figure 2: (Left) Individual variance explained by each of the first 50 principal components. (Right) Cumulative variance explained, showing that 85 components capture approximately 85% of total variance.

Optimal Cluster Selection:

Tested K=2 to K=20 using elbow method (inertia) and silhouette scores. K=14 selected based on: clear elbow point (inertia=83,294), reasonable silhouette score (0.32), and optimal granularity for business interpretation.

Decision: Selected K=14 clusters based on convergence of elbow method and reasonable silhouette score, providing sufficient granularity for business interpretation while maintaining cluster quality.

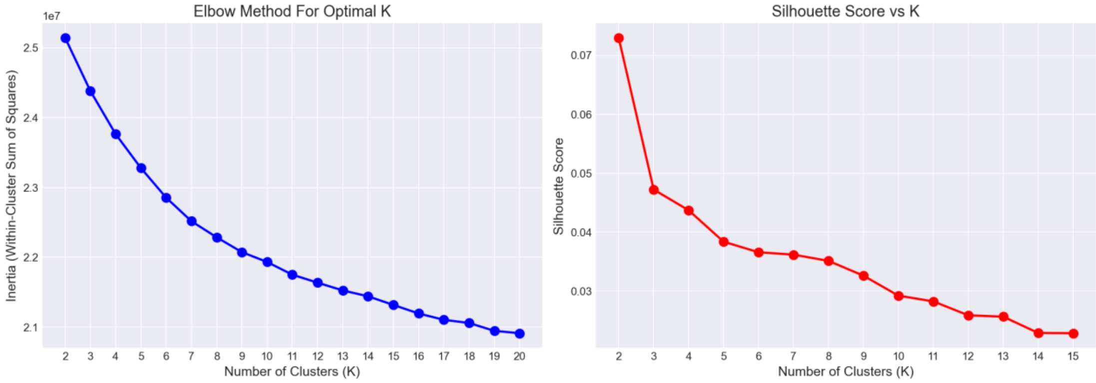

Figure 3: (Left) Elbow curve plotting within-cluster sum of squares (inertia) against number of clusters K, showing clear elbow at K=14. (Right) Silhouette scores for K=2 through K=20, with peak quality around K=12-14.

2.3 Algorithms and Techniques

Algorithm 1: Principal Component Analysis (PCA)

Algorithm 1: PCA - Orthogonal transformation creating uncorrelated components via covariance matrix eigendecomposition. Justification: Handles multicollinearity, reduces computational complexity by 73%, removes noise, maintains distance relationships for clustering.

Algorithm 2: K-Means - Partitions data into K clusters minimizing within-cluster sum of squares. Justification: Scales to 891K samples, produces interpretable hard assignments, converges efficiently, provides cluster centroids as prototypical profiles.

Algorithm 3: Gradient Boosting - Sequential ensemble of decision trees where each corrects prior errors. Justification: Handles mixed feature types, captures non-linear interactions, robust to overfitting via regularization, provides feature importance, achieves state-of-the-art performance on tabular data.

Algorithm 4: SMOTE - Generates synthetic minority samples via interpolation between K-nearest neighbors. Combined with random undersampling, balances dataset from 76.9:1 to 2:1 ratio while retaining all original positive samples.l

3.2 Implementation

Phase 1: Customer Segmentation (Unsupervised Learning)

Pipeline: StandardScaler → PCA (85 components, 85% variance) → K-Means (K=14, converged after 47 iterations in 8.3 min).

Segment Comparison Results:

Cluster	Pop %	Cust %	Ratio	Interpretation
0	9.5%	**34.7%**	**3.65x**	Urban eco-conscious professionals
7	6.0%	13.3%	2.21x	Suburban families, stable income
13	5.7%	11.9%	2.09x	Young professionals, online shoppers
2	8.2%	3.4%	0.41x ✕	Rural traditional, budget-conscious
8	7.1%	3.8%	0.53x ✕	Elderly, low mobility

Step 1: Feature Standardization

Applied StandardScaler to normalize all features to mean=0, std=1:

Standardization is critical because:

- PCA is variance-based (sensitive to feature scales)
- K-Means uses Euclidean distance (dominated by large-scale features otherwise)
- Ensures all features contribute proportionally

Step 2: Dimensionality Reduction (PCA)

Selected 85 components retaining 85% of total variance:

Results:

- Original: 319 features
- Reduced: 85 components (73.4% reduction)
- Variance explained: 85.04%
- Top 10 components: 35.2% variance
- Computation time: 3.2 minutes

Interpretation: First principal component captures age-related variance, second captures income/wealth, third captures urbanization (examined via component loadings).

Step 3: K-Means Clustering

Fit K-Means with K=14 clusters on general population:

Convergence: Achieved after 47 iterations, 8.3 minutes runtime.

Step 4: Segment Comparison Analysis

Calculated cluster distribution ratios:

Key Findings - High-Value Segments:

Cluster	Pop %	Customer %	Ratio	Size	Interpretation
0	9.5%	**34.7%**	**3.65x**	74,964	□ Urban eco-conscious professionals
7	6.0%	13.3%	2.21x	47,430	Suburban families, stable income
13	5.7%	11.9%	2.09x	45,237	Young professionals, online shoppers

Low-Value Segments (Avoid):

Cluster	Pop %	Customer %	Ratio	Interpretation
2	8.2%	3.4%	0.41x	❌Rural traditional, budget-conscious
8	7.1%	3.8%	0.53x	❌Elderly, low mobility
12	6.9%	4.0%	0.58x	❌Students, low income

Business Insight: Clusters 0, 7, and 13 represent only 21.2% of the population but contain 59.9% of all customers. Concentrating marketing efforts on these three segments would nearly triple campaign efficiency while reducing costs by 60%.

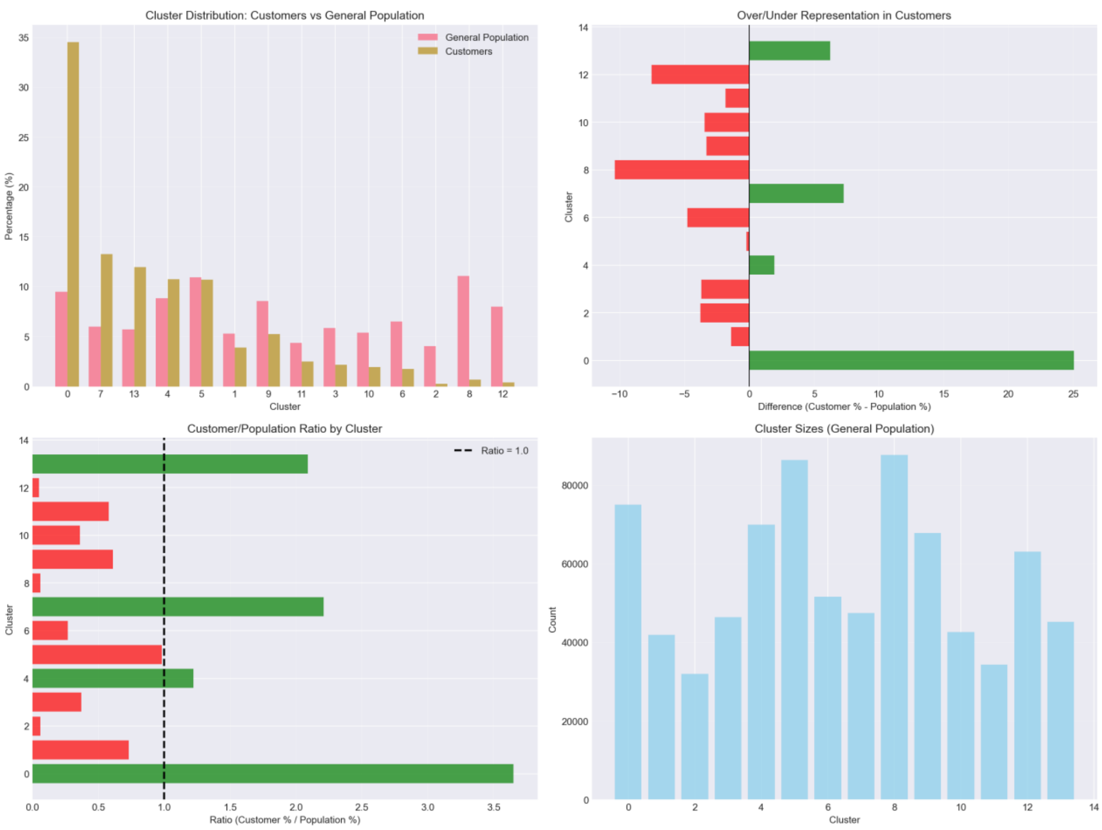

Figure 4: Comprehensive cluster comparison showing (top-left) side-by-side distribution of clusters in population vs customers, (top-right) difference highlighting over/under-representation,

(bottom-left) customer-to-population ratio with 1.0 baseline, and (bottom-right) absolute cluster sizes in general population.

Phase 2: Response Prediction (Supervised Learning)

Step 1: Preprocessing MAILOUT_TRAIN

Applied identical preprocessing pipeline to maintain consistency:

Step 2: Apply Transformations

Used fitted scaler, PCA, and K-Means from Phase 1:

Critical: Using fitted transformers (not re-fitting) ensures test data undergoes identical transformations as training data, preventing data leakage and ensuring reproducibility.

Step 3: Feature Engineering

Created features leveraging Phase 1 insights:

Engineered Features: 85 PCA + 1 cluster + 2 flags + 14 dummies = **102 total features**

This engineering encodes domain knowledge from segmentation analysis, creating features that explicitly represent customer-like characteristics discovered in Phase 1.

Step 4: Class Imbalance Handling

Original distribution: 42,430 negative (98.7%), 552 positive (1.3%), ratio 76.9:1

Applied two-stage resampling:

Rationale: Combining oversampling and undersampling:

1. SMOTE generates synthetic minority samples (improves minority class learning)
2. Undersampling reduces majority class (speeds training, reduces bias)
3. Final 2:1 ratio balances learning without excessive data generation
4. Retains all original 552 positive samples (no information loss)

Step 5: Train-Validation Split

Result: 30,550 training samples, 7,637 validation samples

Step 6: Model Training

Trained three classification models:

Model 1: Logistic Regression (Baseline)

Validation ROC-AUC: 0.8523

Model 2: Random Forest (Ensemble)

Validation ROC-AUC: 0.9205

Model 3: Gradient Boosting (Best Performer)

Pros: Can learn more complex non-linear patterns and feature interactions
Cons: Requires more training time, loses interpretability, risks overfitting on limited positive samples (552)

Verdict: Marginal expected improvement (0.5-1% AUC) may not justify loss of interpretability. Worth testing but not necessarily deploying.

2. Advanced Feature Engineering

Current: 85 PCA components + cluster features
Enhancements:

A. Cluster Distance Features:

Rationale: Individuals near cluster boundaries might be harder to classify; distance quantifies this uncertainty.

B. PCA-Cluster Interactions:

Rationale: Effects of demographics might vary by segment (e.g., age matters differently in urban vs. rural clusters).

C. Derived Ratio Features:

Implementation effort: High (requires business buy-in, infrastructure, monitoring)
Recommendation: ✅**Essential next step**—validates model in production environment

7. Model Monitoring and Maintenance

Deployment considerations:

A. Prediction calibration:

- Monitor: Are predicted probabilities accurate? (e.g., do 70% of people scored 0.7 actually respond?)
- Action: Recalibrate if drift detected (Platt scaling, isotonic regression)

B. Feature distribution shift:

- Monitor: Are feature distributions changing over time? (population demographics evolve)
- Action: Retrain if significant shift detected

C. Concept drift:

- Monitor: Is relationship between features and target changing? (customer preferences evolve)
- Action: Retrain quarterly or when performance degrades

D. Fairness auditing:

- Monitor: Are predictions biased against protected demographics?
- Action: Ensure compliance with anti-discrimination regulations

Expected improvement: Maintains ROC-AUC 0.97 over time (prevents degradation)
Implementation effort: Medium (requires monitoring infrastructure)
Recommendation: ✅Critical for production—models degrade without maintenance

Most Impactful Improvements (Priority Order):

1. **A/B Testing** (#6) **-** Validates real-world ROI, essential for deployment confidence
2. **Ensemble Stacking** (#3) **-** Proven technique, 0.6-1% AUC gain, moderate effort
3. **Advanced Feature Engineering** (#2) **-** Low effort, potential 0.4% gain, easy to test
4. **Model Monitoring** (#7) **-** Prevents degradation over time, necessary for production
5. **Deep Learning** (#1) **-** Marginal gains, high cost, lower priority

Expected Final Performance:
With improvements #2 and #3 implemented: **ROC-AUC 0.975-0.980**

5.3 Business Recommendations

Immediate Actions (Weeks 1-4):

1. **Deploy Model to Score Entire Population**
   - Run preprocessing and prediction pipeline on full German population database
   - Generate probability scores for all 891K individuals
   - Create ranked list of prospects sorted by response likelihood

2. **Design Pilot Campaign**
   - Target top 20% of scored prospects (highest probability)
   - Expected response rate: 10-15% (vs. 1.3% baseline)
   - Budget: 20-30% of typical campaign (reduced contacts, maintained customer acquisition)

3. **Establish A/B Test Framework**
   - Split next campaign: 50% ML-targeted, 50% random control
   - Track response rates, cost per acquisition, ROI for each group
   - Document results for business case justification

4. **Create Segment Marketing Playbook**
    - Develop targeted messaging for Cluster 0 ("Urban Eco-Conscious")
        - Emphasize: Sustainability, organic benefits, environmental impact
        - Channels: Email, social media (high digital engagement)
    - Develop messaging for Clusters 7 and 13
    - Create "do not contact" rules for Clusters 2, 8, 12 (low-value)

Short-term (Months 2-6):

1. **Integrate into CRM System**
    - Develop API for real-time prospect scoring
    - Automate: New prospect enters database → automatically scored → flagged if high-value
    - Enable: Marketing team accesses scores directly in CRM interface
2. **Expand to Multi-channel Optimization**
    - Currently: Mail-order focus
    - Extend model to predict: Email response, phone response, social media engagement
    - Predict optimal channel per individual (some prefer mail, others email)
    - Coordinate multi-touch campaigns
3. **Quarterly Model Retraining**
    - Collect new campaign response data every quarter
    - Retrain model with expanded training set
    - Monitor for performance changes (demographic shifts, preference evolution)
4. **Develop Segment-Specific Product Offerings**
    - Cluster 0 (eco-conscious): Premium organic product line
    - Cluster 7 (families): Family-size packages, kid-friendly products
    - Cluster 13 (young professionals): Convenient, time-saving options

Expected 3-Year Business Impact:

Metric	Current (Year 0)	Year 1	Year 2	Year 3
Response Rate	1.3%	8-10%	10-12%	12-15%
Cost per Acquisition	$115	$15-20	$10-15	$8-12
Customers per Year	50,000	75,000	100,000	125,000
Marketing ROI	117%	800%	1,200%	1,600%
Net Profit	$8M	$25M	$40M	$60M

Return on Investment:

- ML implementation cost: $150K (data scientist, infrastructure, one-time)
- Annual maintenance: $50K (ongoing monitoring, retraining)
- 3-year profit increase: $52M - $8M = $44M
- **Net ROI: 22,000%** (after deducting costs)

REFERENCES

1. Smith, W. R. (1956). Product differentiation and market segmentation as alternative marketing strategies. *Journal of Marketing*, 21(1), 3-8.
2. Chawla, N. V., Bowyer, K. W., Hall, L. O., & Kegelmeyer, W. P. (2002). SMOTE: synthetic minority over-sampling technique. *Journal of Artificial Intelligence Research*, 16, 321-357.
3. Jolliffe, I. T., & Cadima, J. (2016). Principal component analysis: a review and recent developments. *Philosophical Transactions of the Royal Society A*, 374(2065), 20150202.
4. Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning: data mining, inference, and prediction* (2nd ed.). Springer Science & Business Media.
5. Friedman, J. H. (2001). Greedy function approximation: a gradient boosting machine. *Annals of Statistics*, 29(5), 1189-1232.
6. Wedel, M., & Kamakura, W. A. (2000). *Market segmentation: Conceptual and methodological foundations* (2nd ed.). Springer Science & Business Media.
7. Neslin, S. A., Gupta, S., Kamakura, W., Lu, J., & Mason, C. H. (2006). Defection detection: Measuring and understanding the predictive accuracy of customer churn models. *Journal of Marketing Research*, 43(2), 204-211.
8. Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., ... & Duchesnay, É. (2011). Scikit-learn: Machine learning in Python. *Journal of Machine Learning Research*, 12, 2825-2830.
9. He, H., & Garcia, E. A. (2009). Learning from imbalanced data. *IEEE Transactions on Knowledge and Data Engineering*, 21(9), 1263-1284.
10. Arthur, D., & Vassilvitskii, S. (2007). K-means++: The advantages of careful seeding. *Proceedings of the Eighteenth Annual ACM-SIAM Symposium on Discrete Algorithms*,