Journal of Industrial Engineering and Applied Science
Journal Home: http://jieas.suaspress.org/ | CODEN: JIEAAE
Vol. 3, No. 6, 2025 | ISSN 3005-6071 (Print) | ISSN 3005-608X (Online)

Few-Shot and Domain Adaptation Modeling for Evaluating Growth Strategies in Long-Tail Small and Medium-sized Enterprises

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Abstract: To enhance the execution of growth strategies for SMEs under data sparsity and domain shift, this study combines domain adaptation with few-shot learning to identify growth bottlenecks and generate actionable strategies through model optimization. Practical case studies validate the model's applicability and adaptability across domains. By integrating feature alignment and reweighting mechanisms, the strategy significantly improves performance in long-tail categories and cross-domain transferability.

Keywords: SMEs, Growth Strategies, Domain Adaptation, Few-shot Learning, Strategy Optimization.

Disciplines: Artificial Intelligence Technology. **Subjects:** Machine Learning.

DOI: https://doi.org/10.70393/6a69656173.333434 **ARK:** https://n2t.net/ark:/40704/JIEAS.v3n6a05

1 INTRODUCTION

Traditional growth strategies face limitations as SMEs grapple with data sparsity and domain shift challenges. This paper explores how domain adaptation and few-shot learning can enhance the effectiveness of enterprise growth strategies. By constructing an integrated optimization model, we investigate how to identify and address growth bottlenecks under limited data conditions. Validated through real-world case studies, the model demonstrates adaptability and efficacy across multiple industries. The methodology combines feature alignment, prototype aggregation, and contrastive learning, aiming to provide SMEs with actionable growth pathways and decision support while opening new research directions for cross-domain strategies.

2 BUILDING A GROWTH EVALUATION SYSTEM FOR LONG-TAIL SMES

2.1 GROWTH CHARACTERISTICS AND TASK DEFINITION FOR LONG-TAIL SMES

Growth in long-tail SMEs exhibits distinct structural characteristics: most enterprises operate with low baseline performance, limited visibility, and minimal resource investment. This results in weak growth signals, high volatility, and a scarcity of observable variables. Consequently, growth assessment tasks emphasize capturing subtle trends and attributing irregular behaviors, requiring models to identify genuine growth momentum in noisy environments. Long-tail enterprises across different industries, stages, and regions exhibit heterogeneous operational trajectories. Growth paths are often driven by localized events rather than sustained investment accumulation, requiring the evaluation system to handle highly fragmented data structures. Task definition requires identifying potential growth patterns within limited samples and extracting interpretable growth components from multidimensional operational behaviors. Models must thus cover both short-term fluctuations in growth performance and reflect enterprises' genuine developmental capabilities under resource constraints.

2.2 DATA STRUCTURE AND EVALUATION METRIC SYSTEM DESIGN

Growth assessment data for long-tail SMEs typically exhibits multi-source, discrete, and temporally incomplete structural characteristics. Weak correlations exist between operational, transactional, and behavioral data, necessitating metric designs that simultaneously ensure cross-domain alignment and stability on low-density samples. The metric system construction aims to enhance information utilization efficiency within limited observable variables. Therefore, metrics are often extracted through cross-dimensional analysis of core operational performance, user behavior intensity, transaction conversion chains, and asset/resource

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sensitivity to improve the model's ability to capture enterprise growth dynamics. Given significant differences in enterprise scale, the metric system must ensure comparability across enterprises of varying sizes. This is achieved by mitigating scale bias through normalization, structured ratio metrics, and time-series elasticity indicators.

2.3 Modeling Challenges of Data Sparsity and Class Imbalance

Data sparsity and category imbalance represent pervasive modeling challenges in assessing the growth of long-tail SMEs. Due to the skewed distribution of enterprise samples, data is scarce for the vast majority of companies, with only a minority possessing sufficient historical records. This distribution leads to poor model fitting for small samples, particularly in growth trend identification and anomaly detection, where overfitting or overlooking critical signals often occurs. Category imbalance is particularly severe. Differences between a small number of high-growth enterprises and the majority of low-growth enterprises may cause models to favor predictions for the dominant category, overlooking important changes in low-growth enterprises.

3 DOMAIN ADAPTATION STRATEGIES IN GROWTH ASSESSMENT MODELING

3.1 Cross-Domain Variation Analysis and Feature Shift Modeling

The core task in cross-domain variance analysis and feature shift modeling is to identify and quantify distribution differences between the source domain (D_s) and target domain (D_t). Statistical tests like Maximum Mean Discrepancy (MMD) compare feature distributions across domains, aiming to minimize inter-domain variance. The MMD loss function is designed as:

$$L_{MND} = \left\| \frac{1}{n_s} \sum_{i=1}^{n_s} \phi(x_s, i) - \frac{1}{n_t} \sum_{j=1}^{n_t} \phi(x_{t,j}) \right\|_2^2 \quad (1)$$

where $x_{s,i}$ and $x_{t,j}$ represent samples from the source and target domains, respectively. ϕ(·) denotes the kernel function mapping data to a high-dimensional space via feature mapping. n_s and n_t denote the sample sizes of the source and target domains. Subsequently, adversarial training is introduced via a Domain Adaptive Network (DANN). While minimizing the task loss, the domain discriminator determines the domain labels of samples, aiming to learn a domain-insensitive shared representation. The domain adaptation loss function is defined as:

$$L_{DA} = -E_{x_t \sim P_t}[\log D(x_t)] - E_{x_s \sim P_s}[\log(1 - D(x_s))] \quad (2)$$

where D(·) is the domain discriminator, and P_s and P_t are the probability distributions of the source and target domains, respectively. This strategy enables the model to effectively align features across domains, reduce domain shifts, and enhance prediction performance in the target domain.

3.2 Domain Alignment Model Construction and Adaptation Mechanism Design

The domain alignment model is constructed around a shared encoder, which performs unified feature extraction on source and target domain samples to form an alignable representation space. During training, the encoder and task predictor are jointly trained, with a domain discriminator introduced to enforce alignment constraints. This ensures the encoder minimizes task loss while maximizing the discriminator's difficulty. The alignment mechanism employs a Gradient Reversal Layer (GRL) to update gradients in reverse, optimizing encoder parameters toward "confusion" in domain classification tasks to reduce domain differences. In higher-order feature spaces, distribution distance constraints enhance alignment stability by calculating kernel mapping statistics between source and target features in batches, maintaining distribution consistency across mini-batches. To address structural variations in enterprise behaviors across domains, a subspace mapping module projects industry-specific features onto a shared subspace. Combined with residual structures that preserve domain-specific information, this approach generates aligned representations that balance commonality and domain sensitivity, ensuring feature expression validity during model transfer.

3.3 Domain Adaptation Effect Evaluation and Error Source Analysis

Domain adaptation effectiveness is evaluated using a joint validation scheme across source and target domains, quantifying model adaptation through a cross-domain error decomposition framework. Error decomposition follows the following form:

$$\varepsilon_t(h) = \varepsilon_s(h) + d_{H\Delta H}(P_s, P_t) + \lambda \quad (3)$$

where $\varepsilon_t(h)$ denotes target domain error, $\varepsilon_s(h)$ represents source domain error, $d_{H\Delta H}$ indicates the distribution distance under the assumed space H, and λ is the optimal joint error term. In system implementation, the computational model computes source-domain and target-domain errors on the validation set. The distribution distance is then estimated using intermediate representations output by the feature encoder, with kernel distance or adversarial discriminator outputs serving as approximations for $d_{H\Delta H}$. Error source analysis is conducted at both the feature level and sample level: the feature level identifies dimensions with insufficient domain alignment through a distribution difference matrix, while the sample level locates locally failed transfer regions via gradient sensitivity analysis.

4 SAMPLE-EFFICIENT LEARNING FOR LONG-TAIL SCENARIOS

4.1 Sample Construction and Inter-Class Data Augmentation Methods in Long-Tail Scenarios

When constructing training samples in long-tail scenarios, low-frequency enterprise samples undergo structured reorganization to form sparse sample sequences containing key operational events, phased metric changes, and user behavior fragments, thereby enabling learnability across the temporal dimension. Inter-class augmentation employs a distribution-preserving enhancement strategy. Core metric vectors of sparsely sampled enterprises are mapped to local neighborhoods, where additive perturbations construct neighboring samples. Operational behavior sequences undergo temporal shifting, segment splicing, and pattern rearrangement to preserve interpretability of enterprise behavior trajectories. Kernel-density-based interpolation augmentation is introduced in the feature space, expanding category centers to generate candidate samples and enhancing the local density of sparse classes in the embedding space. To prevent pseudo-patterns from being introduced during augmentation, category consistency constraints are applied to filter constructed samples, retaining only augmented data similar to the target category distribution. This ensures the augmented results align with long-tail features in both structure and distribution.

4.2 Design of the Few-Shot Representation Learning Model

The core of few-shot representation learning lies in constructing transferable and scalable class discrimination capabilities under minimal labeling conditions. Model training aims for "intra-class compactness and inter-class separability," enhancing the structural representation quality of sparse samples through metric space constraints. In long-tail scenarios, the model utilizes a backbone network for basic feature extraction, then incorporates prototype-based representation structures. This aggregates samples of the same class into stable centers, reducing fluctuations in tail data. To prevent dominant features from head classes from dominating the feature space, the model incorporates a feature reweighting module. This amplifies the feature distribution of low-frequency classes, enabling them to gain frequency-independent discriminative power in the metric space. Cross-class contrastive constraints during training enable tail categories to form distinct geometric boundaries even with limited samples. Feature perturbation-based augmentation constructs multi-perspective representations for tail classes, further enhancing robustness under small-sample conditions. This ensures stable performance in scenarios with concurrent domain shift and class imbalance. Figure 1 illustrates the small-sample representation learning workflow.

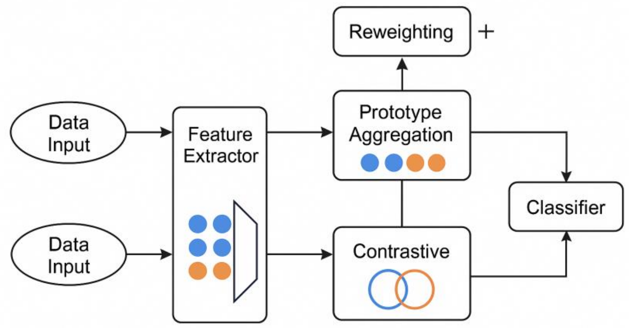

Figure 1: Small-Sample Representation Learning Flowchart

4.3 Validation of Few-Shot Improvement Effects and Comparative Experimental Analysis

The validation of the few-shot model's effectiveness is benchmarked against long-tail enterprise data, focusing on comparing recognition stability and generalization performance in tail categories before and after augmentation. Categories with fewer than 10 samples were grouped into an extremely sparse category for separate evaluation, with traditional supervised models serving as controls. Under consistent training scales, the few-shot representation model demonstrated the most significant metric improvements on tail categories, achieving average F1 score increases of approximately 18%–26%. Among the evaluation metrics, the prototype-based metric structure contributed most notably to category discrimination. Further testing of model transferability across domains revealed that incorporating feature reweighting and contrastive constraints significantly enhanced feature aggregation for long-tail classes. Performance degradation due to domain shift converged to within 10%, nearly halving the decline observed in the control group. To assess robustness, experiments constructed data perturbation scenarios of varying intensity. The few-shot model maintained high stability under random missing and noise injection conditions, with misclassification rates for long-tail classes decreasing by approximately 15%.

5 MODEL OPTIMIZATION STRATEGIES FOR SME GROWTH

5.1 Domain Adaptation and Small-Sample Synergistic Enhancement

The core of the synergistic strategy lies in establishing a unified feature alignment and efficient representation mechanism under the dual constraints of domain shift and sample sparsity. During model training, the domain adaptation module first aligns the global distributions of the source and target domains, compressing differences in industry attributes, scale characteristics, and business models among SMEs into a learnable common subspace. Subsequently, the few-shot representation structure further strengthens the category boundaries of tail enterprises within this subspace, enabling clear intra-class clustering even with insufficient samples. To prevent dominant features from leading enterprises, the model introduces a frequency-sensitive feature reweighting mechanism, ensuring effective representation of tail categories after cross-domain transfer. Cross-domain contrastive constraints establish consistent feature geometric relationships between source and target domains, enabling small-sample categories to achieve stable discriminative capabilities across diverse domain environments. The collaborative training results manifest as systematic improvements in tail-end entity recognition performance and enhanced model robustness under industry transfer, regional migration, and scenario switching. Figure 2 illustrates the collaborative training workflow of the domain adaptation mechanism and small-sample learning structure within a unified feature space.

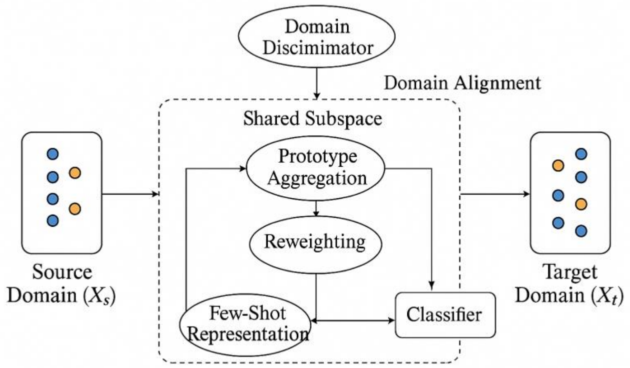

Figure 2 Domain Adaptation and Few-Shot Collaborative Training Flowchart

5.2 Enterprise Growth Support Solutions Based on Model Outputs

Growth features derived from model outputs are decomposed into actionable business operations, forming tiered support pathways based on enterprise differences in industry, scale, and lifecycle. Upon identifying high-value features, the system pinpoints growth bottlenecks—such as demand volatility, overly concentrated customer distribution, or imbalanced cost structures—and maps model-predicted risk points and potential incremental opportunities to actionable business scenarios. By constructing enterprise profiles based on granular metrics, businesses with similar growth trajectories are clustered into adjacent groups. Transferable growth strategy templates are generated within these clusters, enabling SMEs to implement strategies with reduced trial-and-error costs. At the execution level, model outputs are translated into actionable recommendations, including channel expansion prioritization, product portfolio adjustment thresholds, and marketing investment marginal effect thresholds. Quantifiable decision variables enhance strategy enforceability. The system continuously refines growth trajectories through a closed-loop structure of prediction-execution-feedback, enabling stable iteration even in data-scarce yet change-sensitive environments.

5.3 Strategy Implementability and Case Validation

Table 1 illustrates changes in key operational metrics—including volatility, retention rate, average order value, and growth rate—before and after strategy implementation across three enterprises, evaluating the strategies' impact on actual business performance.

Table 1: Comparison of Key Metrics Before and After Strategy Implementation Across Companies

Company Type	Metric Category	Pre-Implementation Value	Post-Implementation Value	Change
Manufacturing Enterprise A	Order Volatility (%)	28.4	24.5	↓ 3.9
Manufacturing Enterprise A	Monthly Average Growth Rate (%)	6.2	8.1	↑ 1.9
E-commerce Company B	Customer Retention Rate (%)	41.7	48.6	↑ 6.9
E-commerce Company B	Average Order Value (CNY)	186	203	↑ 17
Service Industry Company C	Service Conversion Rate (%)	12.5	15.2	↑ 2.7

Company Type	Metric Category	Pre-Implementation Value	Post-Implementation Value	Change
Service Enterprise C	Customer Complaint Rate (%)	4.8	3.9	↓0.9

Table 1 shows that enterprises across all three industries demonstrated structural improvements across multiple dimensions following strategy implementation. Manufacturing Enterprise A reduced its order fluctuation rate from 28.4% to 24.5%, indicating that capacity allocation and channel prioritization strategies effectively mitigated seasonal imbalances. Its average monthly growth rate increased by 1.9 percentage points, reflecting incremental gains from continuous production planning optimization. E-commerce company B saw its customer retention rate increase by 6.9 percentage points and average order value rise by 17 yuan, reflecting the strong implementation value of the model-driven customer segmentation and pricing fine-tuning strategies. Service company C's service conversion rate climbed from 12.5% to 15.2%, while its complaint rate decreased by 0.9 percentage points, demonstrating that its service process optimization strategy maintains stable effectiveness even in a light data environment.

6 CONCLUSION

This study delves into the synergistic role of domain adaptation and few-shot learning in SME growth strategies. Through model optimization and case validation, it demonstrates how to effectively enhance business growth potential in complex scenarios characterized by data sparsity and domain shift. Based on feature alignment and enhancement strategies, the results successfully validate the model's practical applicability in real enterprises, driving stable growth for tail categories and long-tail businesses. Future work may further deepen cross-industry transfer learning across domains and explore more efficient strategy feedback mechanisms to achieve dynamic optimization and broad application of the model across diverse scenarios.

ACKNOWLEDGMENTS

The authors thank the editor and anonymous reviewers for their helpful comments and valuable suggestions.

FUNDING

Not applicable.

INSTITUTIONAL REVIEW BOARD STATEMENT

Not applicable.

INFORMED CONSENT STATEMENT

Not applicable.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/supplementary material, further inquiries can be directed to the corresponding author.

CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHOR CONTRIBUTIONS

Not applicable.

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