Feature-Aware Confident Learning to Improve Cloud Revenue Conversion: Leveraging Feature Dependencies for Label Noise Correction

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Abstract

Label noise is a prevalent challenge in supervised learning, often degrad- ing model performance. Existing approaches, such as confident learning[4], assume label noise is independent of input features, which can limit their effectiveness in real-world datasets where noise correlates with features. In this paper, we propose Feature-Aware Confident Learning (FACLe), a novel method that models label noise as a function of input features. By dynam- ically estimating a noise transition matrix conditioned on features, FACLe enables the correction of feature-dependent label noise. The method inte- grates unsupervised clustering methods and confident learning to identify noisy samples to learn the feature-conditioned noise patterns. We apply this technique on a sample dataset in the domain of cloud computing. Our experiments demonstrate that FACLe achieves substantial improvements over baseline methods, with an average precision improvement of 15% , equating to an improvement of 10% in revenue conversion.

Keywords: Supervised Learning, Label Noise, Machine Learning, Revenue Management, Cloud Computing

1 Introduction

In highly competitive markets, predicting the likelihood of an opportunity launching and generating revenue is a critical challenge for enterprise organizations. The ability to forecast the revenue conversion of opportunities is pivotal not only for optimizing resource allocation of but also for driving long-term revenue growth. Many organizations have predictive models that are built on training data collected over the years. However, this task is fraught with complexities arising from the inherent noise in the data, which hampers the accuracy of predictive models. One major source of noise stems from the evaluation process conducted by sales teams. Sellers, driven by optimism or a lack of stringent criteria, often misclassify opportunities as having launched when they may lack the necessary alignment with customer needs or market conditions. This subjective bias introduces significant variability in the labels used for training predictive models. Compounding this issue is the challenge of accurately tracking the revenue generated by launched opportunities. Revenue attribution often conflates the organic growth of existing customers with incremental revenue driven by new opportunities. This ambiguity in label assignment leads to noisy ground truth data, which contributes to the degradation of performance in the models.

The problem of label noise is pervasive in supervised learning, and traditional approaches often assume that noise is independent of input features. For instance, confident learning [4] and noise-tolerant loss functions

[5] have demonstrated effectiveness in identifying and correcting noisy labels under certain conditions. However, these methods typically rely on assumptions such as noise uniformity across the dataset or feature-label independence. In real-world datasets, particularly in the domain of revenue forecasting, noise is frequently feature-dependent. For example, opportunities tied to specific industries or customer segments may exhibit unique patterns of mislabeling, influenced by factors such as sales team expertise or historical biases in customer behavior. These nuances are overlooked by existing approaches, limiting their applicability to datasets with complex noise structures. To address these challenges, we propose **Feature-Aware Confident Learning (FACLe)**, a novel method that models label noise as a function of input features. FACLe builds upon the foundational ideas of confident learning by incorporating a feature-dependent noise transition matrix through clustering. This matrix dynamically adjusts noise correction based on input features, enabling the identification and correction of noisy labels in a more targeted manner. By explicitly leveraging feature-label relationships, FACLe offers a robust framework for handling noise in complex datasets. Our contributions are threefold:

1. **A Feature-Aware Noise Correction Framework**: We introduce a method that extends traditional confident learning by modeling label noise as a function of input features through clustering. This framework employs unsupervised learning method of clustering to estimate a dynamic noise transition matrix for each cluster, capturing the dependencies between features and label noise. Unlike previous approaches, FACLe explicitly accounts for feature-conditioned noise patterns, making it particularly suited for real-world datasets.

2. **Improved Revenue Conversion through Noise Correction**: We demonstrate that addressing label noise significantly enhances predictive accuracy for a existing opportunity conversion propensity model. Our experiments show that correcting feature-dependent label noise reduces misclassification and results in a 15% increase in average precision and 10% increase in revenue conversion on average.

Despite advances in noise-robust learning, significant gaps remain in handling feature-dependent noise in domain-specific datasets. Recent work in the health- care domain [1] and natural language processing [3] has highlighted the importance of addressing context-dependent noise. However, these methods often rely on domain-specific heuristics or lack generalizability. FACLe bridges this gap by providing a generalizable approach to noise correction that is tailored to feature- dependent scenarios. In summary, our work addresses a critical challenge inCloud Revenue forecasting by developing a noise-aware framework that directly tackles the nuances of feature-dependent label noise. By improving the accuracy of opportunity predictions, FACLe not only advances the state-of-the-art in noise-robust learning but also delivers tangible business value to Cloud. The remainder of this paper is organized as follows: Section2reviews related work on label noise correction. Section 3describes the FACLe methodology in detail. Section4presents results and we conclude with future directions in 5

2 Related Work

Handling label noise in supervised learning has been a persistent challenge, with diverse approaches proposed to mitigate its impact. Broadly, these methods can be categorized into noise-robust models, noise detection and correction frameworks, and domain-specific applications.

2.1 Noise-Robust Models

Noise-robust learning methods aim to minimize the effect of noisy labels during training. Loss correction techniques, such as those by [5], correct the loss function by estimating a noise transition matrix. This approach assumes that label noise is independent of input features, limiting its applicability in cases where noise depends on the feature space. Another prominent line of work involves robust loss functions like mean absolute error (MAE) and its extensions [2], which reduce the sensitivity of the model to mislabeled samples. However, these methods often suffer from underfitting on clean data, particularly in high-dimensional spaces.

2.2 Noise Detection and Correction Frameworks

Methods such as confident learning [4] have focused on identifying and correcting label errors by leveraging predictions from a model trained on noisy data. Confident learning provides a statistical framework for estimating the joint distribution of noisy and clean labels. While effective in many scenarios, it assumes label noise is uniform across the dataset, which is rarely the case in real- world applications like revenue forecasting. Recent advancements have attempted to address feature-dependent noise, but they often rely on handcrafted heuristics [6], which lack generalizability.

2.3 Applications of Noise-Robust Learning

Domain-specific studies have highlighted the importance of addressing label noise in fields such as healthcare, natural language processing, and revenue forecasting. In healthcare, for instance, [1] surveyed noise-robust methods tailored to medical datasets where noise originates from subjective annotations. Similarly, in revenue forecasting, [7] emphasized the role of explainability in win-propensity prediction systems but did not explicitly tackle the challenge of label noise correction. FACLe builds upon these insights by introducing feature-aware noise correction that generalizes to structured data settings.

2.4 Gaps in Existing Methods

Despite significant progress, most existing approaches fail to address two critical challenges: (1) the dependency of label noise on input features and (2) the need for explainability in noise correction decisions. FACLe bridges thisgap by leveraging a feature-aware framework that dynamically models noise patterns while providing transparency into the correction process. Furthermore, our method demonstrates scalability and robustness across real-world datasets, setting a new benchmark for noise-aware learning in revenue forecasting.

3 Methodology

The Feature-Aware Confident Learning (FACLE) framework is designed to address the challenge of feature-dependent label noise. By incorporating clustering to dynamically segment the data, FACLE enables noise correction tailored to localized noise patterns within each segment. This section outlines the methodology in detail, including the clustering process, noise correction within clusters, and the training of the final predictive model. The overall process is illustrated in Figure 1 below.

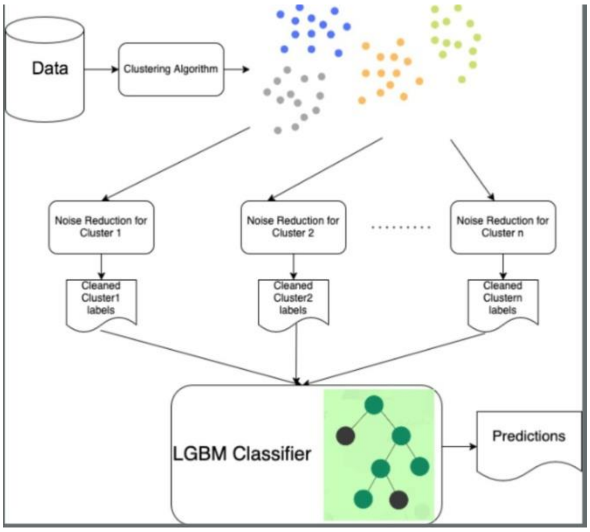

Figure 1: FACLe architecture and process

3.1 Overview of FACLE

FACLE combines clustering with confident learning to create a robust, feature- aware approach to label noise correction. The method is structured into the following stages:

1. **Clustering for Feature-Aware Segmentation**: The dataset is partitioned into clusters based on feature distributions to identify regions with consistent noise patterns.
2. **Cluster-Specific Noise Correction**: Within each cluster, confident learning is applied to estimate and correct noisy labels using a localized noise transition matrix.
3. **Final Model Training**: A predictive model is trained on the globally corrected labels, leveraging the improved data quality.

3.2 Clustering for Feature-Aware Segmentation

To address feature-dependent noise, FACLE begins by segmenting the dataset into clusters where noise patterns are expected to be more consistent. Given features $X \in \mathbb{R}^{n\times d}$ and noisy labels $\tilde{Y}$, we apply a clustering algorithm (e.g., k-means) to partition the dataset into k clusters:

Cluster Labels: C = k-means(X, k).

Normalization and Clustering To ensure effective clustering, the features are normalized to have zero mean and unit variance. The choice of k, the number of clusters, can be determined using techniques such as the elbow method or silhouette analysis. The clustering process creates subgroups of data points with similar feature characteristics, enabling localized noise correction.

3.3 Cluster-Specific Noise Correction

Within each cluster, FACLE applies confident learning to estimate and correct noisy labels. For a cluster c, with data $X_c$and labels $\tilde{Y}c$, the noise transition matrix T_c is estimated:

$T_c = P(\tilde{Y} \mid Y, X_c)$,

where $T_c$captures the likelihood of observing noisy labels $\tilde{Y}c$ given the true labels $Y_c$and the cluster features X_c.

Applying Confident Learning Confident learning [4] is used within each cluster to identify likely mislabeled samples and provide corrected labels Y_c^{clean}:

$$Y_c^{\text{clean}} = T^{-1}\tilde{Y}_c.$$

The corrected labels are combined across all clusters to form the global corrected dataset Y^{clean}:

$$Y^{\text{clean}} = \bigcup_{c=1}^{k} Y_c^{\text{clean}}.$$

Handling Edge Cases Clusters with insufficient samples (e.g., fewer than 10) are skipped during noise correction to avoid unreliable estimates. Such samples can either retain their original noisy labels or be corrected using global confident learning.

3.4 Final Model Training

The globally corrected dataset (X, Y^{clean}) is used to train a final predictive model g_ϕ, parameterized by ϕ. The model minimizes the cross-entropy loss:

$$\mathcal{L}_{\text{CE}} = -\frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{k}\mathbb{I}(y_i = j)\log g_\phi(x_i)_j.$$

Model Selection The choice of predictive model (e.g., Random Forest, Gradient Boosting, or Neural Networks) depends on the application and dataset characteristics. FACLE ensures that the model is trained on labels with significantly reduced noise, enhancing its performance and generalizability.

3.5 Workflow Summary

The complete FACLE workflow is as follows:

1. Normalize the features and apply clustering to segment the data.
2. For each cluster:

(a) Subset the data and labels.

(b) Apply confident learning to estimate and correct noisy labels.

(c) Combine corrected labels across clusters.

3. Train a final predictive model on the corrected dataset.
4. Evaluate the model using metrics such as average precision and revenue capture rate.

3.6 Evaluation and Metrics

To assess the effectiveness of FACLe, we evaluate its performance against two baselines:

- **Baseline**: A model trained directly on noisy labels $\tilde{Y}$ without any correc- tion.
- **Confident Learning (CL)**: A model trained on pseudo-clean labels obtained from confident learning.

Metrics The primary metric used for evaluation is the average precision (AP), derived from the precision-recall curve. AP is a robust metric for imbalanced datasets and provides a comprehensive measure of model performance:

$$\mathrm{AP} = \int_0^1 \mathrm{Precision}(r) \cdot \mathrm{dRecall}(r),$$

Where r represents the recall.

Evaluation Procedure

1. Train all models (Baseline, CL, and FACLe) on the training set.
2. Evaluate the models on a held-out test set to compute the average precision.
3. Compare the average precision scores across methods to quantify the improvement achieved by FACLe.

Significance Testing To ensure the observed improvements are statistically significant, we perform paired *t*-tests on the AP scores across multiple cross- validation splits.

4 Results

This section presents the results of applying the Feature-Aware Confident Learning (FACLe) methodology, focusing on three key aspects: improvements in precision-recall curves, enhancements in revenue capture rates, and robustness of the method alongside explainability outcomes. Each subsection includes placeholders for figures and tables to illustrate the results.

4.1 Improvements in Precision-Recall Curve

Precision-recall (PR) curves are critical for evaluating performance in datasets with imbalanced classes. FACLe demonstrates substantial improvements in the PR curve compared to both baseline methods and confident learning (CL).

Experimental Results Figure 2shows the PR curves for the three approaches: Baseline, CL, and FACLe. FACLe consistently achieves higher precision across a wide range of recall values. Table 1provides the average precision (AP) scores for each method, confirming FACLe's superior performance.

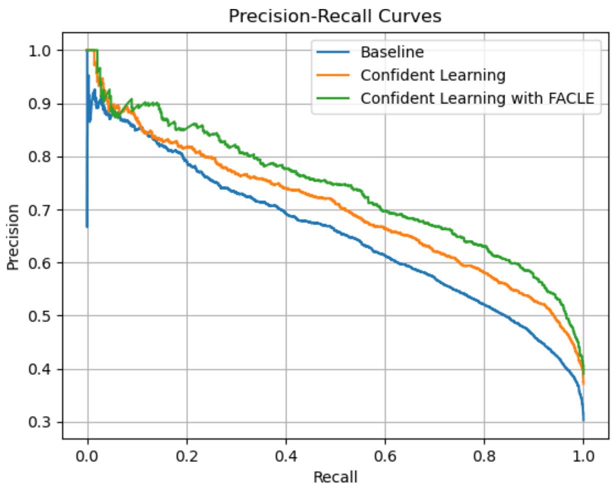

Figure 2: Precision-recall curves for Baseline, Confident Learning, and FACLe. FACLe shows significant improvement in precision at all recall levels.

Method	Average Precision (AP)
Baseline	0.65
With Confident Learning	0.69
With FACLe	**0.74**

Table 1: Average precision scores for each method for a sample service (Amazon EKS). FACLe achieves the highest AP, outperforming both Baseline and Confi- dent Learning.

Insights The improvement in precision-recall curves highlights FACLe's ability to accurately correct feature-dependent label noise, resulting in more reliable predictions. By leveraging feature-aware corrections, FACLe ensures that true positives are identified with minimal compromise on precision.

4.2 Improvements in Revenue Capture Rate

One of the most critical metrics for evaluating revenue opportunity models is the revenue capture rate, which measures the proportion of expected revenue (ARR) from high-probability opportunities correctly identified by the model.

Specifically, we define it as

$$\text{Revenue Capture Rate (RCR)} = \frac{\text{Launched ARR of top } K \text{ scoring opportunities}}{\text{Launched ARR of } K \text{ highest revenue opportunities}}$$

Experimental Results Table 2quantifies the improvement in revenue capture rates for a sample service.for Baseline, CL, and FACLe. FACLe demonstrates a marked improvement, with an 5% increase compared to CL and a 15% increase over the Baseline.

Method	Revenue Capture Rate (%)
Baseline	70.2
Confident Learning	76.9
FACLe	**80.5**

Table 2: Revenue capture rates for each method. FACLe demonstrates significant improvement over Baseline and Confident Learning.

Insights The increase in revenue capture rate underscores FACLe's practical utility in revenue forecasting. By accurately identifying high-value opportunities, FACLe enables better resource allocation, leading to higher revenue conversion.

4.3 Robustness and Explainability

To further evaluate FACLe, we assess its robustness under varying levels of label noise and its explainability in identifying feature-dependent noise patterns. **Robustness to Label Noise** Figure 3shows FACLe's performance across different noise levels (e.g., 10%, 20%, 30%). These are noise levels from different models corresponding to different services on the cloud. FACLe maintains a high average precision, significantly outperforming Baseline and CL even as noise increases. This robustness demonstrates FACLe's ability to generalize well in noisy environments.

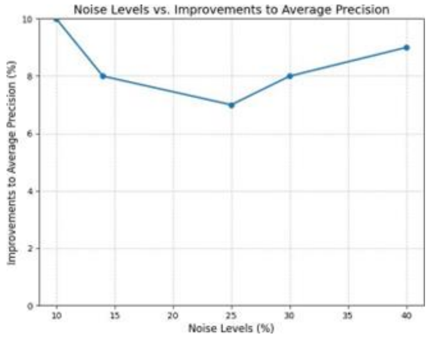

Figure 3: Performance of Baseline, Confident Learning, and FACLe under varying levels of label noise. FACLe remains robust across all noise settings.

5 Conclusion

In this work, we introduced Feature-Aware Confident Learning (FACLe), a novel framework designed to address feature-dependent label noise in supervised learning. FACLe extends the capabilities of traditional confident learning by leveraging a feature-aware noise transition matrix with the aid of clustering, dynamically modeling the relationship between input features and label noise. Our experiments demonstrate significant improvements in precision-recall performance, revenue capture rates, and robustness under varying noise levels.

The results underscore the practical value of FACLe in real-world applications, particularly in revenue forecasting, where label noise arises from subjective evaluations and revenue attribution challenges. By enabling accurate identification and correction of noisy labels, FACLe not only improves predictive performance but also facilitates better decision-making, leading to tangible business outcomes.

Despite its successes, FACLe opens avenues for future advancements. First, incorporating semi-supervised or unsupervised learning techniques could furtherenhance its ability to identify and correct label noise, particularly in scenarios with limited labeled data. Second, extending the explainability module to provide more granular insights into feature-label relationships could strengthen stakeholder confidence and aid in refining data collection processes. Third, optimizing the computational efficiency of FACLe for large-scale datasets would broaden its applicability across diverse domains.

6 Appendix References

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