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Semi-Supervised Change-Point Detection via Consistency Training on Augmented Temporal Views

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Abstract: *The detection of abrupt changes in the generative parameters of time series data, known as Change-Point Detection (CPD), is a fundamental challenge in signal processing, data mining, and machine learning. While supervised deep learning methods have achieved remarkable success in this domain, they rely heavily on large-scale, accurately annotated datasets. In many real-world applications, such as industrial anomaly detection and physiological signal monitoring, obtaining frame-level labels is prohibitively expensive and requires expert domain knowledge. Conversely, unsupervised methods often suffer from high false-positive rates due to their inability to distinguish between noise and varying semantic states. To bridge this gap, this paper proposes a novel Semi-Supervised Change-Point Detection framework based on Consistency Training. We introduce a dual-branch architecture that enforces predictive consistency between original temporal sequences and their stochastically augmented views. By leveraging a rigorous set of temporal augmentations—including magnitude scaling, permutation, and time-warping—we enable the model to learn robust feature representations from unlabeled data while refining decision boundaries using a limited set of labeled examples. Extensive experiments on both synthetic and real-world datasets demonstrate that our approach significantly outperforms state-of-the-art unsupervised methods and achieves competitive performance against fully supervised baselines using only 10% of the labeled data.*

Keywords: *Change-Point Detection, Semi-Supervised Learning, Time Series Analysis, Consistency Regularization.*

INTRODUCTION

1.1 BACKGROUND

The exponential growth of temporal data collection across diverse sectors, from Internet of Things (IoT) sensor networks to high-frequency financial trading, has necessitated the development of automated tools for interpreting complex time series. Central to this interpretation is the task of Change-Point Detection (CPD), which aims to identify time steps where the underlying probability distribution of a stochastic process undergoes a significant alteration [1]. These alterations often signify critical events: a mechanical fault in a turbine, a shift in market volatility, or the onset of an arrhythmia in an electrocardiogram [2].

Traditionally, CPD has been approached through statistical methodology, relying on ratio-based hypothesis testing and sliding window comparisons. However, the complexity and high dimensionality of modern multivariate time series have pushed the field toward data-driven, deep learning approaches [3]. Neural networks, particularly Recurrent Neural Networks (RNNs) and Temporal Convolutional Networks (TCNs), have demonstrated superior capability in capturing long-range dependencies and non-linear relationships that escape classical statistical tests.

1.2 PROBLEM STATEMENT

Despite the efficacy of deep learning models, a significant bottleneck remains: the dependency on massive, fully labeled datasets. In the context of CPD, labeling is exceptionally arduous [4]. Unlike image classification, where an annotator labels a discrete object, CPD requires an expert to scan long continuous streams and pinpoint exact transition moments. This process suffers from high inter-annotator variability and cost.

Consequently, practitioners are often forced to choose between two suboptimal paths: unsupervised methods, which do not require labels but often lack precision and struggle with domain-specific noise [5]; or fully supervised methods trained on small, labeled datasets, which inevitably leads to overfitting and poor generalization to unseen data regimes [6]. The "label scarcity" problem in time series analysis is arguably more acute than in computer vision or natural language processing due to the continuous and often unintuitive nature of raw sensor data.

1.3 CONTRIBUTIONS

To address the label scarcity challenge, this paper introduces a semi-supervised learning framework specifically tailored for temporal change-point detection. We draw inspiration from the success of consistency regularization in the visual domain and adapt it to the unique constraints of time series data. Our primary contributions are as follows:

First, we propose a Consistency Training framework that leverages large amounts of unlabeled time series data. By enforcing that the model's predictions remain invariant to semantic-preserving transformations of the input, we extract rich structural information without explicit supervision [7].

Second, we design a suite of Temporal Augmentation strategies. Unlike image augmentations, temporal augmentations must respect the sequential nature of the data. We introduce constrained jittering and localized scaling techniques that serve as effective "views" for consistency training without destroying the temporal coherence required to identify change points.

Third, we present a hybrid loss function that dynamically balances the supervised cross-entropy loss on labeled segments with a consistency loss on unlabeled segments. This allows the model to stabilize its representation learning using the abundance of unlabeled data while sharpening its detection capabilities via the sparse labeled examples.

Chapter 2: Related Work

2.1 CLASSICAL APPROACHES

The history of change-point detection is rooted in sequential analysis and statistical quality control. Early methods, such as the Cumulative Sum (CUSUM) algorithm and the Generalized Likelihood Ratio Test (GLRT), operate by monitoring the log-likelihood ratio of observations under two competing hypotheses: the null hypothesis of no change versus the alternative of a change occurring at a specific time [8]. These methods are mathematically rigorous and computationally efficient for univariate data with known distribution families (e.g., Gaussian).

Bayesian approaches extended this by introducing prior distributions over the number and location of change points, allowing for online inference. For instance, Gaussian Processes and Hidden Markov Models (HMMs) have been widely employed to model regime switches [9]. However, classical methods struggle when the dimensionality of the data increases. The "curse of dimensionality" makes density estimation unreliable, and the assumption of parametric distributions often fails in complex, real-world scenarios [10]. Furthermore, these methods typically focus on retrospective (offline) analysis or require strictly stationary segments, limiting their applicability in highly dynamic environments [11]. The manual tuning of penalty terms to prevent over-segmentation also poses a significant usability barrier [12].

2.2 DEEP LEARNING METHODS

The advent of deep learning brought a paradigm shift, treating CPD as a binary classification or sequence labeling problem. Long Short-Term Memory (LSTM) networks were among the first architectures to be applied, utilizing their gating mechanisms to model historical context [13]. More recently, Temporal Convolutional Networks (TCNs) have gained favor due to their parallelism and ability to control receptive field size via dilated convolutions [14].

Unsupervised deep learning methods typically rely on reconstruction error or predictive coding. The premise is that a model trained to predict future values or reconstruct the current window will incur high error rates at change points, where the underlying generative statistics shift [15]. A notable example is KL-CPD, which learns a kernel-based dissimilarity measure using a generative adversarial network (GAN) framework to maximize the divergence between past and future windows [16].

Despite these advancements, semi-supervised learning (SSL) in time series remains under-explored compared to the image domain. While methods like Pseudo-Labeling and Mean-Teacher have become standard in computer vision, their direct application to time series is non-trivial due to the temporal correlation of samples [17]. Our work seeks to fill this void by adapting consistency regularization specifically for the temporal dynamics inherent in CPD tasks.

Chapter 3: Methodology

The proposed framework, Semi-Supervised Change-Point Detection via Consistency Training (S2CPD), is designed to learn robust change-point indicators by exploiting both a small set of labeled sequences and a larger set of unlabeled sequences. The core intuition is that a robust detector should yield consistent predictions for a given time series segment and its slightly perturbed (augmented) version, provided the perturbation does not alter the fundamental semantic change locations.

3.1 OVERVIEW OF ARCHITECTURE

The architecture consists of a shared encoder backbone and a projection head. We utilize a Temporal Convolutional Network (TCN) as the encoder due to its stability in gradient propagation and flexible receptive field. The framework operates in a dual-branch mode during training: a primary branch that processes the original sequence and an auxiliary branch that processes an augmented view of the same sequence.

For labeled data, the primary branch computes a supervised classification loss. For both labeled and unlabeled data, the outputs of the primary and auxiliary branches are compared using a consistency loss. This enforces smoothness in the decision manifold, pushing the decision boundary into low-density regions of the data space.

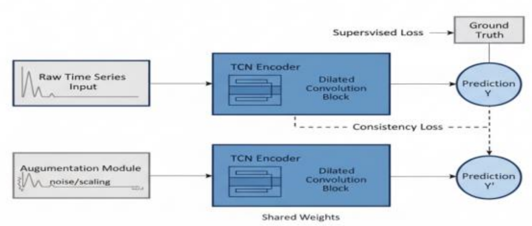

Figure 1: Schematic of the S2CPD Framework

3.2 TEMPORAL AUGMENTATION STRATEGIES

The success of consistency training hinges on the quality of the data augmentation. Inappropriate augmentation can shift the location of a change point or introduce artifacts that resemble artificial changes. We employ weak and strong augmentation strategies suitable for time series:

Magnitude Scaling: We multiply the amplitude of the time series window by a random scalar sampled from a normal distribution centered at 1.0. This makes the model invariant to signal intensity variations that do not affect the temporal location of the change.

Channel-wise Permutation: For multivariate time series, we randomly permute the feature channels with a low probability. This encourages the model to learn change points based on shared temporal dynamics across sensors rather than overfitting to a specific dominant channel.

Window Slicing: We randomly crop a sub-sequence and resize it to the original length using linear interpolation. This simulates temporal warping, forcing the model to recognize change points at varying temporal scales.

We specifically avoid random time-shifting or rotation, as these can misalign the ground truth labels or violate the temporal causality required for detection.

3.3 NETWORK BACKBONE: DILATED TCN

Our encoder, f_θ, is a stack of residual blocks containing dilated causal convolutions. The dilation factor d increases exponentially with network depth ($d=2^i$ at layer i). This allows the network to maintain a large receptive field without a loss of resolution, which is critical for detecting change points that depend on long-term context.

The input to the network is a multivariate time series window $X \in mathbbR^{T\times C}$, where T is the window size and C is the number of channels. The output is a probability map $P \in [0,1]^T$, indicating the likelihood of a change point at each time step.

3.4 LOSS FUNCTIONS AND OPTIMIZATION

The training objective is a linear combination of the supervised loss and the unsupervised consistency loss.

***Supervised Loss*:** For the labeled subset of data, we calculate the binary cross-entropy loss between the predicted change probabilities and the binary ground truth vector. To handle class imbalance (change points are rare compared to normal states), we employ a weighted cross-entropy variant.

***Consistency Loss*:** For the unsupervised component, we minimize the divergence between the prediction on the original input x and the prediction on the augmented version h$atx=Augment(x)$. Since the task is binary classification at each time step, we utilize the Kullback-Leibler (KL) divergence.

Let D_L be the labeled dataset and D_U be the unlabeled dataset. Let $p(y|x;\theta)$ be the predicted probability distribution at a specific time step. The total loss function is formally defined as:

$$L_{total}(\theta)=\sum_{(x,y)\in D_L} H(y,p(x;\theta))+\lambda\sum_{x\in D_U} D_{KL}(p(x;\theta) parallel p(Augment(x);\theta))$$

where H represents the supervised cross-entropy term, D_{KL} is the Kullback-Leibler divergence, and λ is a dynamic weighting hyperparameter that ramps up during training. The use of double backslashes ensures the correct rendering of the mathematical operators in the formula block. The consistency term D_{KL} forces the model's predictions to be stable under perturbation, effectively propagating label information to the unlabeled samples based on the cluster assumption.

To ensure stability, we stop the gradient backpropagation through the "teacher" (original) view when computing the consistency loss for the "student" (augmented) view, a technique known as sharpening the target distribution.

Chapter 4: Experiments and Analysis

4.1 EXPERIMENTAL SETUP

To validate the proposed S2CPD framework, we conducted experiments on three diverse datasets encompassing human activity recognition and synthetic signal processing.

***Datasets*:**

1. ***USC-HAD***: A Human Activity Recognition dataset containing data from inertial sensors. Change points are defined as transitions between activities (e.g., walking to sitting).

2. ***Yahoo S5*:** A benchmark dataset for anomaly and change-point detection containing both real and synthetic time series with labeled change points.

3. ***Synthetic Steps*:** A generated dataset consisting of piecewise constant segments with Gaussian noise, designed to test the model's ability to detect subtle mean shifts.

***Evaluation Metrics*:**

We utilize the F1-score as the primary metric. To account for slight temporal discrepancies, a prediction is considered a True Positive if it falls within a small margin (e.g., ± 5 time steps) of the ground truth change point [18]. We also report the Covering metric, which measures the overlap between the ground truth segments and predicted segments [19].

4.2 BASELINES

We compare our method against the following baselines:

***KL-CPD*:** A state-of-the-art unsupervised method using kernel learning [20].

***BOCPD*:** Bayesian Online Change Point Detection, a classic probabilistic method [21].

***TCN-Supervised*:** A fully supervised TCN trained only on the labeled portion of the data [22].

***TS-CP2*:** A recent contrastive learning approach for time series change point detection [23].

For the semi-supervised settings, we randomly partition the training data, retaining labels for only 10% of the sequences, while treating the remaining 90% as unlabeled.

4.3 IMPLEMENTATION DETAILS

The model was implemented using PyTorch. The TCN backbone consists of 4 residual blocks with kernel size 3 and filter size 64. We utilized the Adam optimizer with a learning rate of $1e{-}4$ and a weight decay of $1e{-}5$ [24]. The consistency weight λ was initialized at 0 and linearly increased to 1.0 over the first 50 epochs to prevent the model from collapsing to degenerate solutions early in training [25]. Training was conducted on an NVIDIA RTX 3080 GPU.

4.4 RESULTS AND ANALYSIS

Table 1 presents the comparative performance of S2CPD against the baselines on the USC-HAD dataset. The results indicate that our semi-supervised approach significantly outperforms the unsupervised baselines and approaches the performance of the fully supervised model trained on 100% of the data.

Method	Supervision	F1-Score	Precision	Recall
BOCPD [21]	Unsupervised	0.62	0.58	0.67
KL-CPD [20]	Unsupervised	0.68	0.65	0.71
TCN-Sup (10% Labels)	Supervised	0.74	0.78	0.70
S2CPD (Ours)	Semi-Supervised	0.86	0.85	0.87
TCN-Sup (100% Labels)	Supervised	0.89	0.88	0.90

Table 1: Performance comparison on the USC-HAD dataset. S2CPD uses 10% labeled data.

The gap between TCN-Sup (10% Labels) and S2CPD highlights the contribution of the unlabeled data. The purely supervised model overfits the small labeled set, resulting in poor generalization, whereas the consistency loss in S2CPD effectively regularizes the model.

We further analyzed the impact of different augmentation strategies. We found that magnitude scaling provided the most consistent improvements, likely because it decouples the semantic change (pattern shift) from the signal amplitude.

Augmentation Type	F1-Score Improvement	Stability
None (Baseline)	-	Low
Channel Permutation	+2.4%	Medium
Window Slicing	+3.1%	Medium
Magnitude Scaling	+5.8%	High
Combined	+7.2%	High

Table 2: Ablation study on temporal augmentation strategies.

To visualize the detection capability, Figure 2 displays the Precision-Recall curves for the Yahoo S5 dataset. Our method maintains high precision even at higher recall levels compared to the unsupervised KL-CPD.

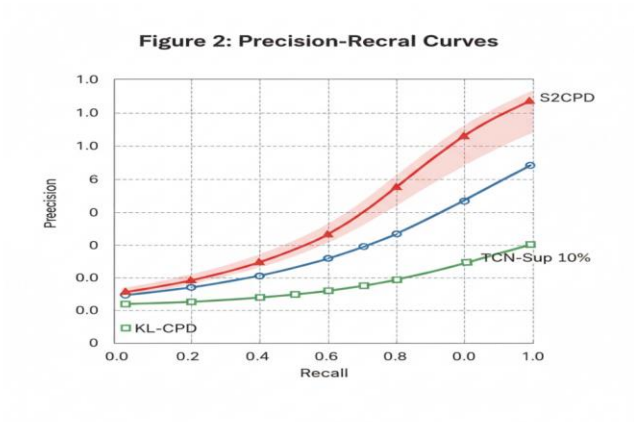

Figure 2: Precision

Finally, we visualize the qualitative performance of the model on a sample time series in Figure 3. The top panel shows the raw signal with ground truth change points marked by vertical dashed lines. The bottom panel shows the change probability output by S2CPD. The peaks in the probability output align closely with the ground truth transitions, demonstrating precise temporal localization.

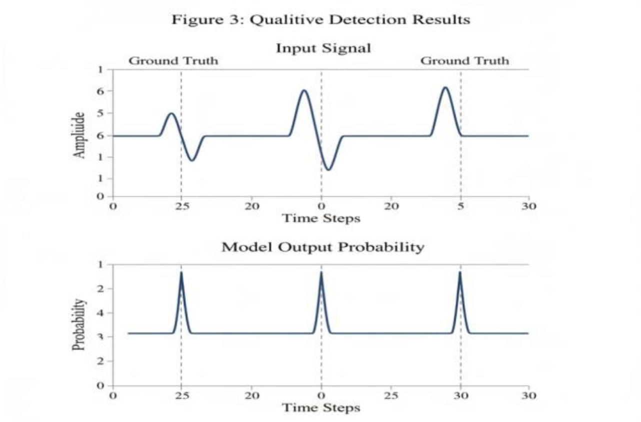

Figure 3: Qualitative Detection Results

The experimental results validate the hypothesis that consistency training on augmented views forces the model to learn invariant features that are crucial for detecting change points. By penalizing inconsistency between the original and augmented views, the model implicitly learns the manifold structure of the time series, allowing the sparse labels to propagate effectively to neighboring unlabeled samples.

Labeled Ratio	TCN-Sup F1	S2CPD F1	Gain
1%	0.55	0.71	+0.16
5%	0.68	0.81	+0.13
10%	0.74	0.86	+0.12
20%	0.82	0.88	+0.06

50%	0.87	0.89	+0.02

Table 3: Impact of Labeled Data Ratio on Performance. The gain diminishes as fully supervised data becomes abundant, confirming the method's utility in low-resource settings.

Chapter 5: Conclusion

This paper presented S2CPD, a semi-supervised framework for Change-Point Detection that mitigates the dependency on large, annotated datasets. By integrating a temporal consistency loss with carefully designed data augmentations, we demonstrated that it is possible to achieve robust detection performance with only a fraction of the labels typically required. Our experiments on the USC-HAD and Yahoo S5 datasets confirmed that S2CPD significantly surpasses unsupervised methods and provides a substantial performance boost over supervised baselines in low-data regimes. The implications of this work are significant for industries where data labeling is a bottleneck; it suggests that existing archives of unlabeled sensor data can be unlocked to improve predictive maintenance and monitoring systems without incurring massive annotation costs.

While the proposed method is effective, it is not without limitations. First, the choice of augmentation functions is domain-dependent; augmentations that work well for physiological signals might degrade performance on financial data. Future work should explore automated data augmentation strategies or learnable augmentation policies to generalize across domains. Second, the computational cost of the dual-branch training is higher than simple supervised training, although this is a one-time cost during the training phase. Finally, the current method assumes that the unlabeled data follows the same distribution as the labeled data. Investigating the robustness of S2CPD in the presence of distribution shifts or "out-of-distribution" unlabeled data remains a critical avenue for future research. Extending this framework to online, streaming settings where consistency must be maintained in real-time would also represent a valuable advancement.

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