# Concept Drift Adaptation for Acoustic Scene Classifier Based on Gaussian Mixture Model

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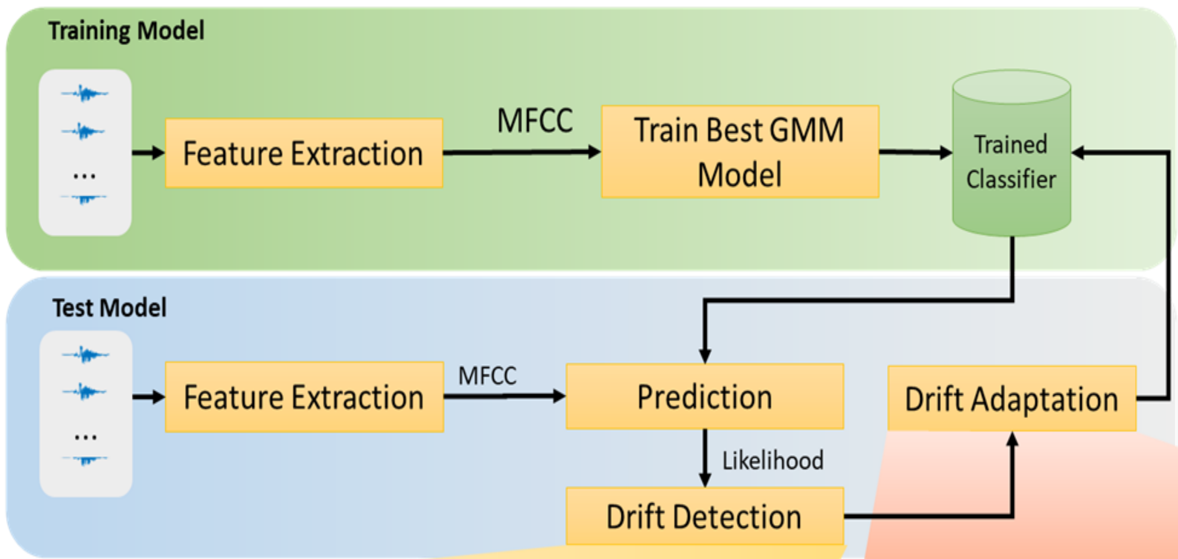
## 1. Research Background

- The environment sound can be easily **distorted** by non-stationary noise, diverse sound events, and overlapping audio events in the time or frequency domain.
- Ability to detect and adapt to concept drift in order to **prevent degradation in accuracy** is important.
- Retrain and redeploy model periodically can be **time-consuming** and **expensive,** while selecting the frequency of updates is also not a straightforward task.
- Majority of sound recognition solutions assume that data come in a sufficient amount and with a representative, **fixed underlying distribution**, which is rarely the case.

## 2. Proposed method

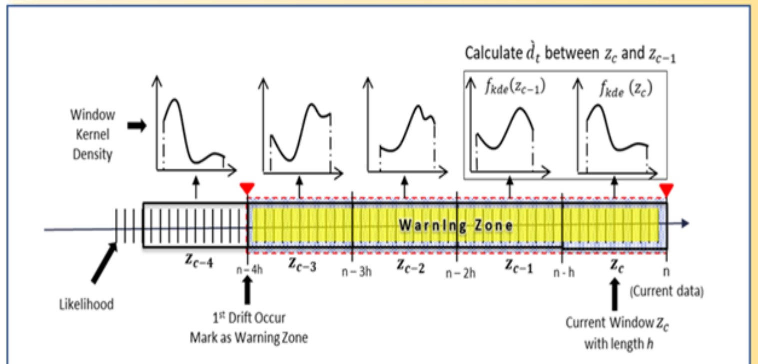



**Drift Detection Method**

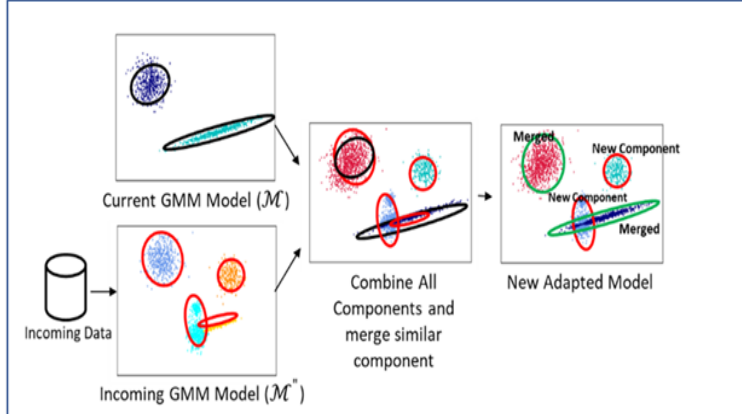
- Detect concept drift then supply data for adaptation
- Calculate Kernel Density Estimation between Current and Previous Window.
- Calculate variation between windows
- The larger window variation, the stronger Concept Drift symptom

**Drift Adaptation Method**

- Train the incoming data then combine it to current model
- Merge all similar component based on Kullback Leiber Divergence before and after merge



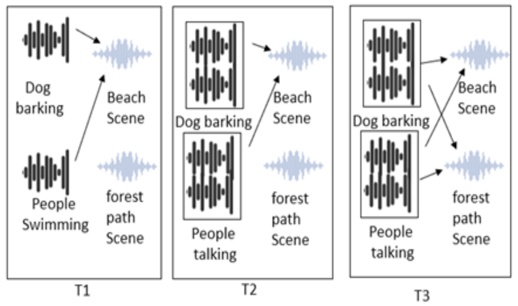

Kernel Density Drift Detection




Combine Merge Gaussian Mixture Model

## 3. Experiment Setup

The overall dataset consisted of 12,000 audio segments of ten seconds each, equally distributed between 15 different scenes and annotated with their ground-truth labels. Based on that dataset we generate T1,T2 and T3. Two Test Scenario Used, namely Active Scenario and Passive Scenario




## 4. Result & Discussion

- The experimental results demonstrated that the proposed algorithms work well in detecting and adapting to three types of drift scenarios.
- KD3 demonstrated a better performance than ADWIN except for T1. This is mainly because KD3 takes the entire data distribution into account, while ADWIN uses only its average.
- The drawback of KD3 is its high computational cost
- The adaptation cycle (i.e., the number of data points to update) plays an important role in achieving a good performance in the passive approach
- By comparing the active and passive approaches to detecting concept drifts, the number of data to adapt to the model is a crucial factor impacting the method's accuracy.

**ACTIVE APPROACH**

| ADAPTOR | DETECTOR | OVERALL ACCURACY | | | F1 SCORE | | | EXECUTION TIME | | | Drift |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | T1 | T2 | T3 | T1 | T2 | T2 | T1 | T2 | T3 | |
| CMGMM* | KD3* | 0.8373 | **0.7962** | **0.7409** | 0.8432 | **0.7993** | **0.7460** | 128.06 | 115.07 | 110.49 | 39 |
| | ADWIN | 0.8471 | 0.6415 | 0.6332 | 0.8518 | 0.6379 | 0.6379 | 83.07 | 84.22 | 85.44 | 32 |
| | HDDM | 0.2762 | 0.2627 | 0.2990 | 0.3184 | 0.2992 | 0.3406 | 84.81 | 84.53 | 83.11 | 373 |
| IGMM | KD3* | 0.8283 | 0.7574 | 0.6622 | **0.8173** | 0.7499 | 0.6488 | 120.04 | 128.75 | 120.50 | 35 |
| | ADWIN | **0.8419** | 0.5711 | 0.6057 | 0.8329 | 0.5722 | 0.6063 | 82.80 | 84.219 | 83.08 | 21 |
| | HDDM | 0.2363 | 0.2507 | 0.2032 | 0.2436 | 0.3055 | 0.2675 | 84.37 | 87.55 | 84.87 | 350 |

**PASSIVE APPROACH**

| ADAPTOR | ADAPTATION CYCLE | OVERALL ACCURACY | | | F1 SCORE | | | EXECUTION TIME | | | Drift |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | | T1 | T2 | T3 | T1 | T2 | T3 | T1 | T2 | T3 | |
| CMGMM* | 50 | 0.5621 | 0.4451 | 0.4003 | 0.5719 | 0.4615 | 0.4373 | 83.178 | 82.945 | 83.163 | - |
| | 100 | 0.7424 | 0.6547 | 0.6434 | 0.7451 | 0.6583 | 0.6476 | 83.688 | 82.265 | 83.704 | - |
| | 150 | 0.8002 | **0.7437** | **0.7301** | 0.8043 | 0.7482 | 0.7327 | 84.527 | 82.298 | 89.555 | - |
| | 200 | 0.7602 | 0.7073 | 0.6904 | 0.7663 | 0.714 | 0.7001 | 83.414 | 85.922 | 84.594 | - |
| IGMM | 50 | 0.5365 | 0.4209 | 0.3687 | 0.5458 | 0.4319 | 0.3888 | 84.467 | 82.776 | 82.655 | - |
| | 100 | 0.7324 | 0.643 | 0.6371 | 0.736 | 0.6448 | 0.6388 | 82.693 | 82.652 | 82.199 | - |
| | 150 | **0.8056** | 0.7401 | 0.7291 | 0.8107 | 0.7431 | 0.7223 | 83.659 | 82.645 | 83.453 | - |
| | 200 | 0.7528 | 0.7149 | 0.6899 | 0.7609 | 0.722 | 0.6981 | 84.597 | 84.228 | 85.797 | - |

(*) Proposed Method