Unsupervised Concept Drift Detection based on Parallel Activations of Neural Network

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Discovering Drift Phenomena in Evolving Landscape
ACM KDD 2024 | Barcelona, Spain

Motivation

data streams and concept drift

Data streams

Characteristics of data stream processing:

- Potentially infinite inflow of data samples:
  - in the form of individual samples (online processing),
  - **in the form of data chunks** (batch processing).
- Necessity of incremental learning and continuous adaptation.
- Maintaining low computational complexity of methods.
- Resistance to **concept drifts**.
- Possibility of **delayed labeling**.

Concept drift

Three main taxonomy axes:

- → In terms of **impact**: *virtual* and *real* drift.
- → In terms of **dynamics**: *sudden*, *gradual*, *incremental*.
- → In terms of **recurrence**: concept may re-appear after some time period.

Why should we care about concept changes?

Real changes usually result in degeneration of recognition quality.

What to do about them?

Detect and **act** upon a change.

Contribution

Proposition of *Parallel Activations Drift Detection* (PADD):

- → fully **unsupervised** and **implicit** drift detection method,
- → utilizes a deterministic, untrained Neural Network and statistical analysis of its activations to recognize changes in posterior data distribution,
- → experimental evaluation of the proposed approach:
  - analysis of hyperparameters determining the sensitivity of the method,
  - comparison with six state-of-the-art drift detection methods from supervised and unsupervised families.

Parallel Activations Drift Detector

the proposed approach to drift detection

Parallel Activations Drift Detector

For each data chunk:

- get activations at the NN output for current data
- for each NN output and for each replications:

  randomly sample s values from past activations and current activations
- calculate p-value of Student's T-Test for sampled data
- check if p-value *subceeds* alpha

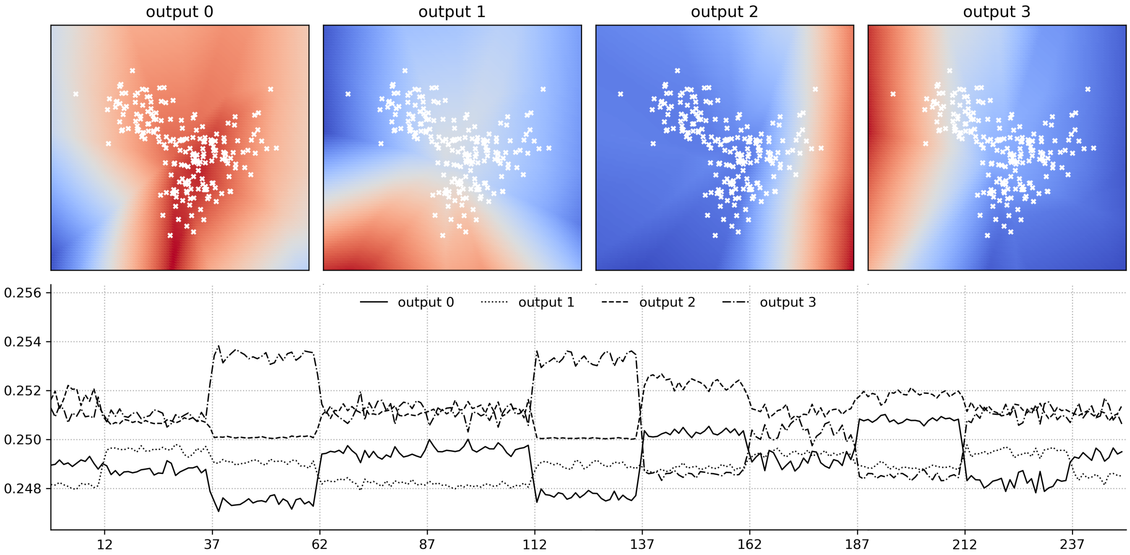
  if so, **increment a counter**
- check if counter *exceeds* threshold-based value of required test passes

  if so, **indicate drift**
- after detection, *forget* past activations

Pseudocode of the proposed approach:

for all $\mathcal{DS}_k \in \mathcal{DS}$ **do**
  $c \leftarrow \mathcal{NN}(\mathcal{DS}_k)$
  if $\mathcal{C}$ is not empty **then**
    $a \leftarrow 0$
    for all $e_i \in e$ **do**
      for all $r_i \in r$ **do**
        $cc \leftarrow$ random s from $c[e_i]$
        $pc \leftarrow$ random s from $C[e_i]$
        $p \leftarrow S(pc, cc)$
        if $p < \alpha$ **then**
          increment a
        end if
      end for
    end for
    if $a > \theta \times e \times r$ **then**
      $\mathcal{C} \leftarrow \emptyset$
      indicate drift in chunk k
    end if
  end if
  store c in $\mathcal{C}$
end for

Intuition behind the proposed approach



Experiment design

data streams, evaluation criteria, planned experiments

Experiment design

- Implementation in *Python* programming language.
- Libraries: *stream-learn*, *numpy*.
- Synthetic non-stationary data streams generated using *stream-learn* generator.

Two planned experiments

- Analysis of method's hyperparameters influencing its sensitivity (*alpha* and *threshold*).
- Comparison with reference approaches.

Parameter	Configuration
Number of chunks	250
Chunk size	200
Number of features	30, 60, 90 (30% informative)
Drift frequency	3, 5, 10, 15 drifts
Drift dynamics	sudden, gradual
Replications	10

Drift Detection Errors

The evaluation of drift detection:

- → Classification quality is not a good indicator of detector's performance.
- → Hence, the evaluation was based on three **drift detection error** measures:
  - **D1** – The average distance of each detection to the nearest drift,
  - **D2** – The average distance of each drift to the nearest detection,
  - **R** – The adjusted ratio of the number of drifts to the number of detections.

Results of experiments

Hyperparameter selection

- The evaluated hyperparameters were *alpha* and *threshold*, responsible for method's sensitivity.
- The results of three measures are interpreted as an RGB image, where red channel shows D1, green channel – D2 and blue channel – R error.

  The best results across three measures are indicated as dark regions.
- There's a range of two hyperparameters offering a optimal drift detection across all three measures.
- The following parameter combinations were selected for the comparison experiment: for *gradual* drifts $\alpha = 0.13$, $\theta = 0.26$; for *sudden* drifts $\alpha = 0.07$, $\theta = 0.0.19$.

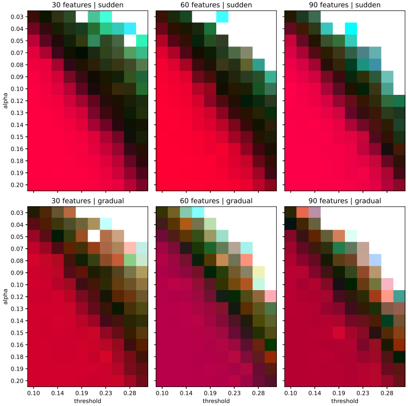


Figure: Results of hyperparameter selection experiment for all data streams, presented as an RGB image

Comparison with reference approaches

Acronym	Name and reference	Category
MD3	**Margin Density Drift Detector** [T. Sethi and M. Kantardzic, 2015]	Unsupervised with label request
OCDD	**One-class Drift Detector** [Ö. Gözüaçık and F. Can, 2021]	Unsupervised
CDDD	**Centroid Distance Drift Detector** [J. Klikowski, 2022]	Unsupervised
ADWIN	**Adaptive Windowing** [A. Bifet and R. Gavalda, 2007]	Supervised
DDM	**Drift Detection Method** [J. Gama et al., 2004]	Supervised
EDDM	**Early Drift Detection Method** [M. Baena-Garcia et al., 2006]	Supervised

Comparison with reference approaches

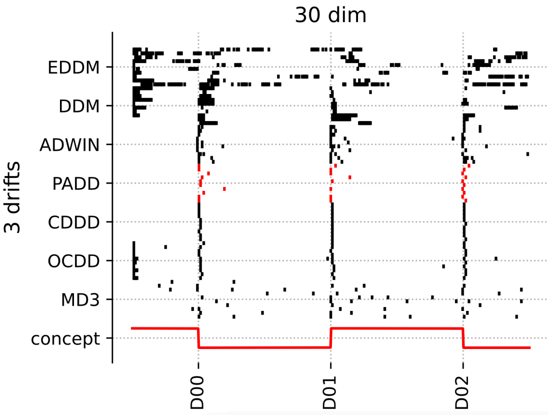


Figure: Results for a single stream type – the moments of drift detection across all ten replications of evaluation. Ideal detection is indicated with vertical lines overlapping with ticks on x-axis.

Comparison with reference approaches

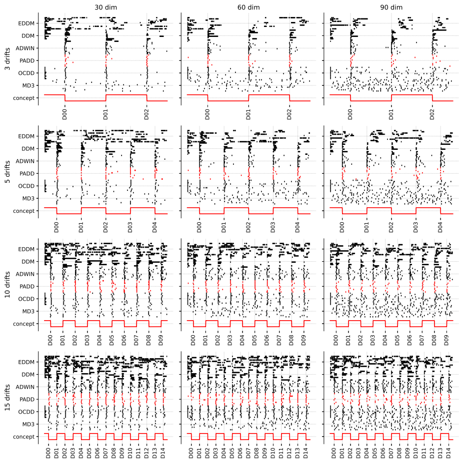


Figure: All results for *sudden* drift

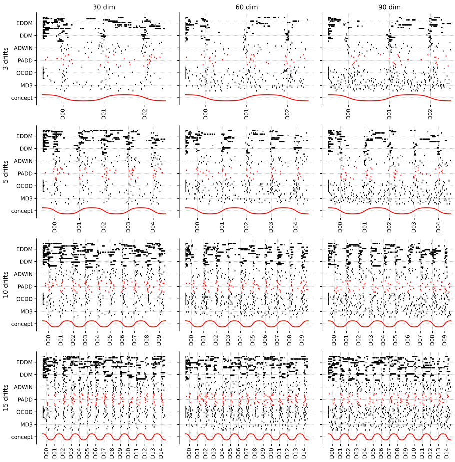
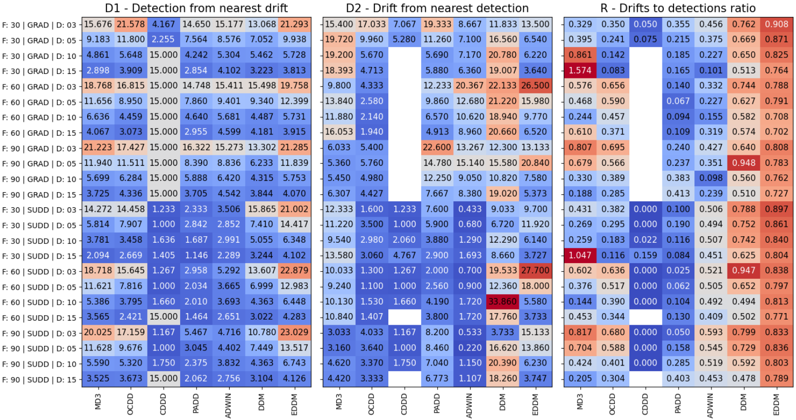


Figure: All results for *gradual* drift

Comparison with reference approaches



D1 - Detection from nearest drift

	MD3	OCDD	CDDD	PADD	ADWIN	DDM	EDDM
F: 30 | GRAD | D: 03	15.676	21.578	4.167	14.650	15.177	13.068	21.293
F: 30 | GRAD | D: 05	9.183	11.800	2.255	7.564	8.576	7.052	9.938
F: 30 | GRAD | D: 10	4.861	5.648	15.000	4.242	5.304	5.462	5.728
F: 30 | GRAD | D: 15	2.898	3.909	15.000	2.854	4.102	3.223	3.813
F: 60 | GRAD | D: 03	18.768	16.815	15.000	14.748	15.411	15.498	19.758
F: 60 | GRAD | D: 05	11.656	8.950	15.000	7.860	9.401	9.340	12.399
F: 60 | GRAD | D: 10	6.636	4.459	15.000	4.640	5.681	4.487	5.731
F: 60 | GRAD | D: 15	4.067	3.073	15.000	2.955	4.599	4.181	3.915
F: 90 | GRAD | D: 03	21.223	17.427	15.000	16.322	15.273	13.302	21.285
F: 90 | GRAD | D: 05	11.940	11.511	15.000	8.390	8.836	6.233	11.839
F: 90 | GRAD | D: 10	5.699	6.284	15.000	5.888	6.420	4.315	5.753
F: 90 | GRAD | D: 15	3.725	4.336	15.000	3.705	4.542	3.844	4.070
F: 30 | SUDD | D: 03	14.272	14.458	1.233	2.333	3.506	15.865	21.002
F: 30 | SUDD | D: 05	5.814	7.907	1.000	2.842	2.852	7.410	14.417
F: 30 | SUDD | D: 10	3.781	3.458	1.636	1.687	2.991	5.055	6.348
F: 30 | SUDD | D: 15	2.094	2.669	1.405	1.146	2.289	3.244	4.102
F: 60 | SUDD | D: 03	18.718	15.645	1.267	2.958	5.292	13.607	22.879
F: 60 | SUDD | D: 05	11.621	7.816	1.000	2.034	3.665	6.999	12.983
F: 60 | SUDD | D: 10	5.386	3.795	1.660	2.010	3.693	4.363	6.448
F: 60 | SUDD | D: 15	3.565	2.421	15.000	1.464	2.651	3.022	4.283
F: 90 | SUDD | D: 03	20.025	17.159	1.167	5.467	4.716	10.780	23.029
F: 90 | SUDD | D: 05	11.628	9.676	1.000	3.045	4.402	7.449	13.517
F: 90 | SUDD | D: 10	5.590	5.320	1.750	2.375	3.832	4.363	6.743
F: 90 | SUDD | D: 15	3.525	3.673	15.000	2.062	2.756	3.104	4.126

D2 - Drift from nearest detection

	MD3	OCDD	CDDD	PADD	ADWIN	DDM	EDDM
F: 30 | GRAD | D: 03	15.400	17.033	7.067	19.333	8.667	11.833	13.500
F: 30 | GRAD | D: 05	19.720	9.960	5.280	11.260	7.100	16.560	6.540
F: 30 | GRAD | D: 10	19.200	5.670		5.690	7.170	20.780	6.220
F: 30 | GRAD | D: 15	18.393	4.713		5.880	6.360	19.007	3.640
F: 60 | GRAD | D: 03	9.800	4.333		12.233	20.367	22.133	26.500
F: 60 | GRAD | D: 05	13.840	2.580		9.860	12.680	21.220	15.980
F: 60 | GRAD | D: 10	11.880	2.140		6.570	10.620	18.940	9.770
F: 60 | GRAD | D: 15	16.053	1.940		4.913	8.960	20.660	6.520
F: 90 | GRAD | D: 03	6.033	5.400		22.600	13.267	12.300	13.133
F: 90 | GRAD | D: 05	5.360	5.760		14.780	15.140	15.580	20.840
F: 90 | GRAD | D: 10	5.450	4.980		12.250	9.050	10.820	7.580
F: 90 | GRAD | D: 15	6.307	4.427		7.667	8.380	19.020	5.373
F: 30 | SUDD | D: 03	12.333	1.600	1.233	7.600	0.433	9.033	9.700
F: 30 | SUDD | D: 05	11.220	3.500	1.000	5.900	0.680	6.720	11.920
F: 30 | SUDD | D: 10	9.540	2.980	2.060	3.880	1.290	12.290	6.140
F: 30 | SUDD | D: 15	13.580	3.060	4.767	2.900	1.693	8.660	3.727
F: 60 | SUDD | D: 03	10.033	1.300	1.267	2.000	0.700	19.533	27.700
F: 60 | SUDD | D: 05	9.240	1.100	1.000	2.560	0.900	12.360	18.000
F: 60 | SUDD | D: 10	10.130	1.530	1.660	4.190	1.720	33.860	5.580
F: 60 | SUDD | D: 15	10.840	1.407		3.800	1.720	17.760	3.733
F: 90 | SUDD | D: 03	3.033	4.033	1.167	8.200	0.533	3.733	15.133
F: 90 | SUDD | D: 05	3.160	3.640	1.000	8.460	0.220	16.620	13.860
F: 90 | SUDD | D: 10	4.620	3.370	1.750	7.040	1.150	20.390	6.230
F: 90 | SUDD | D: 15	4.420	3.333		6.773	1.107	18.260	3.747

R - Drifts to detections ratio

	MD3	OCDD	CDDD	PADD	ADWIN	DDM	EDDM
F: 30 | GRAD | D: 03	0.329	0.350	0.050	0.355	0.456	0.762	0.908
F: 30 | GRAD | D: 05	0.395	0.241	0.075	0.215	0.375	0.669	0.871
F: 30 | GRAD | D: 10	0.861	0.142		0.185	0.227	0.650	0.825
F: 30 | GRAD | D: 15	1.574	0.083		0.165	0.101	0.513	0.764
F: 60 | GRAD | D: 03	0.576	0.656		0.140	0.332	0.744	0.788
F: 60 | GRAD | D: 05	0.468	0.590		0.067	0.227	0.627	0.791
F: 60 | GRAD | D: 10	0.244	0.457		0.094	0.155	0.582	0.708
F: 60 | GRAD | D: 15	0.610	0.371		0.109	0.319	0.574	0.702
F: 90 | GRAD | D: 03	0.807	0.695		0.240	0.427	0.640	0.808
F: 90 | GRAD | D: 05	0.679	0.566		0.237	0.351	0.948	0.783
F: 90 | GRAD | D: 10	0.330	0.389		0.383	0.098	0.560	0.762
F: 90 | GRAD | D: 15	0.188	0.285		0.413	0.239	0.510	0.727
F: 30 | SUDD | D: 03	0.431	0.382	0.000	0.100	0.506	0.788	0.897
F: 30 | SUDD | D: 05	0.269	0.295	0.000	0.190	0.494	0.752	0.861
F: 30 | SUDD | D: 10	0.259	0.183	0.022	0.116	0.507	0.742	0.840
F: 30 | SUDD | D: 15	1.047	0.116	0.159	0.084	0.451	0.625	0.804
F: 60 | SUDD | D: 03	0.602	0.636	0.000	0.025	0.521	0.947	0.838
F: 60 | SUDD | D: 05	0.376	0.517	0.000	0.062	0.505	0.652	0.797
F: 60 | SUDD | D: 10	0.144	0.390	0.000	0.104	0.492	0.494	0.813
F: 60 | SUDD | D: 15	0.453	0.344		0.130	0.409	0.502	0.771
F: 90 | SUDD | D: 03	0.817	0.680	0.000	0.050	0.593	0.799	0.833
F: 90 | SUDD | D: 05	0.704	0.588	0.000	0.158	0.545	0.729	0.836
F: 90 | SUDD | D: 10	0.424	0.401	0.000	0.285	0.519	0.592	0.803
F: 90 | SUDD | D: 15	0.205	0.304		0.403	0.453	0.478	0.789

Figure: Color-coded table showing averaged results for all methods and data streams. Blue cells indicate low errors, while red cells – a high error.

Comparison with reference approaches

→ In the case of $D1$ error, the presented method is significantly the **best lone leader** of comparison.

→ For the R error, the presented solution – while having the best ranking value – is statistically significantly **co-dependent to the ADWIN and OCDD**.

→ For the $D2$, the best results were obtained by the OCDD method, and the **PADD results are statistically dependent on the second method in terms of quality** (ADWIN) with the minimal difference in ranks.

→ It is worth emphasizing that those criteria **should not be used independently** to evaluate methods, and it is the juxtaposition of all three that describes the proper and effective method operation.

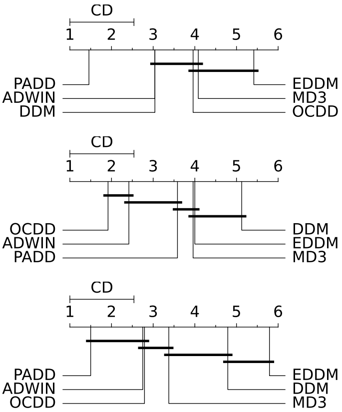


Figure: Results of a post-hoc *Nemenyi* test based on *Wilcoxon Signed Rank* across all three errors: D1 (top), D2 (center), R (bottom).

Conclusions and future works

- This work proposed an unsupervised *Parallel Activations Drift Detector* that utilizes an **untrained neural network** to recognize significant changes in the posterior distribution of the data stream to signal concept drift according to the result of a **statistical test** stabilized by **a pool of replications**.
- The conducted experimental evaluation allowed to demonstrate that the proposed PADD method states a valuable tool in the context of reference methods.

- As part of future work, it is planned to expand the hyperparameter calibration study – considering the introduction of a non-parametric version of the method.

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