Hybrid Ensemble-Based Travel Mode Prediction

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Abstract. Travel mode choice (TMC) prediction, which can be formulated as a classification task, helps in understanding what makes citizens choose different modes of transport for individual trips. This is also a major step towards fostering sustainable transportation. As behaviour may evolve over time, we also face the question of detecting concept drift in the data. This necessitates using appropriate methods to address potential concept drift. In particular, it is necessary to decide whether batch or stream mining methods should be used to develop periodically updated TMC models.

To address the challenge of the development of TMC models, we propose the novel Incremental Ensemble of Batch and Stream Models (IEBSM) method aimed at adapting travel mode choice classifiers to concept drift possibly occurring in the data. It relies on the combination of drift detectors with batch learning and stream mining models. We compare it against batch and incremental learners, including methods relying on active drift detection. Experiments with varied travel mode data sets representing both city and country levels show that the IEBSM method both detects drift in travel mode data and successfully adapts the models to evolving travel mode choice data. The method has a higher rank than batch and stream learners.

Keywords: Travel mode choice · stream mining · concept drift

1 Introduction

The growth in the volume of data streams has caused data mining methods, which analyze bounded and stationary datasets, to be potentially unable to adapt to shifting data patterns and dynamic phenomena [3]. In addition to the regular fluctuations and random variations in the data, the *concept drift* phenomenon [3, 5] is frequently observed due to reasons such as seasonality [4]. A fast and potentially infinite *data stream* can be viewed as the output of a stochastic process that produces data based on a specific probability distribution at a given time [4]. This distribution may change over time. More precisely, concept drift arises when the distribution $p(x)$ and/or $p(y|x)$ changes between consecutive labelled stream instances $\{x, y\}$ [4].

The travel mode choice datasets typically include features such as duration and reason of the trip, traveller's attributes, e.g., age and gender, represented in vector $\mathbf{x}$. Each trip record includes as well a travel mode selected by the traveller [7,10,11], i.e., a class $y_i \in Y$, which includes using a car, public transport, cycling and walking. As trips are made over time, it is not obvious whether classifiers predicting travel mode should be trained with batch methods assuming stationary settings i.e., fixed $p(y|x)$ and $p(x)$ or stream mining methods addressing concept drift [8]. Stream mining algorithms offer the advantage of continuous incremental model training. This enables a model to adapt to concept drift, but it fundamentally alters the training process and the employed machine learning algorithms by including either passive or active adaptation to concept drift [3]. Alternatively, models can be trained on batches of data, a typical approach. In this scenario, models can effectively detect patterns present in batches due to the ability to iterate over data multiple times, often yielding improved outcomes. Still, their effectiveness might be reduced when the incoming data shifts [6].

Given the formulation of a TMC problem as a classification task, [10, 11], a question is posed whether online classifiers should be applied to learn possibly evolving models reflecting the evolving decisions of travellers, or whether the magnitude of concept drift(s) is not sufficient to use online learners rather than batch models. The answer is likely to depend on how stationary the process is in different cities or countries and may even change with time. Hence, we propose an ensemble method combining multiple batch and online methods to reduce the risk of selecting an under-performing method. Furthermore, the method we propose, can utilize multiple batch-learning models, bringing an extra advantage. It enables the use of distinct configurations of drift detection and batch model retraining strategies, referred to as *drift handling strategies*, for each batch learner.

Hence, in this work, we propose the novel Incremental Ensemble of Batch and Stream Models (IEBSM) method for predicting the preferred mode of transport. We evaluate both the method and baseline learners using various real datasets of successively recorded trips provided by respondents. As the distribution $p(x^i)$ of some features present in the TMC data sets is likely to change with time, trip data offer a compelling illustration of unending and changing data streams. The primary contributions of this work are as follows:

- We propose the novel IEBSM ensemble method combining drift detectors with batch and online learners. The method automates the use of multiple batch and online methods, drift detection and the retraining of batch models. The experiments we performed show that the IEBSM method yields performance gains over batch and online methods for various travel mode choice tasks. It provided highest ranked TMC models. We provide the open source implementation of the IEBSM method [1].
- We investigate whether statistically significant changes occur in travel mode choice data for a number of travel mode choice data sets and confirm that such changes occured in each of the data sets. Moreover, we confirm that

[1] All methods have been implemented with inter alia the `river` (https://riverml.xyz) and `scikit-learn` libraries.

the IEBSM method both detected changes and successfully managed the introduction of selected updated batch models.

The remainder of this work is organized as follows. In Sect. 2, we provide an overview of related works. This is followed in Sect. 3 by the proposal of the novel method aiming to automate the use of varied underlying batch and online learners under concept drifting data streams. The results of the evaluation of the method and reference methods are provided in Sect. 4. This is followed by the conclusions and summary of future works in Sect. 5.

2 Related works

TMC modelling [7, 10, 11] is concerned with predicting the travel mode most likely used by a person for their trip. Recently, the benefits arising from the use of machine learning methods for TMC tasks were discussed in [7, 10]. In [7], random forest was shown to yield the best accuracy and computational cost among the tested classifiers. Over time, aspects such as temporal changes in the environment, seasonality, and evolving human preferences are all likely to affect those choices. Hence, in some TMC datasets such as those used in [10], apart from respondent and trip attributes, such as age, education and distance travelled, the features related to weather conditions were included. Still, batch machine learning methods not considering possible changes in travel mode choice decision boundaries $p(y|x)$ are typically used both in comparative studies [7, 10] and surveys of machine learning for TMC modelling [11].

Apart from batch methods, online incremental learning methods have been developed as well, which are also suitable for learning in non-stationary environments [4]. Notable methods include adaptive random forest [8], which builds upon the random forest method to enable learning from non-stationary data streams. This way, real concept drift [4], i.e., a change in $p(y|x)$, can be addressed by changing the ensemble members. In the case of adaptive random forest, ensemble members can be replaced with new base learners better matching shifted class boundaries $p(y|x)$. Frequently, the evaluation of online models relies on first making prediction $\hat{y} = h_i(\mathbf{x}_i)$ with the current model h_i to use the instance to get a new, possibly different model $h_{i+1} = learn(h_i, \{\mathbf{x}_i, y_i\})$ through incremental training. This approach is referred to as test-then-train [3, 8]. This illustrates the fact that incremental learning methods respecting stream mining assumptions are constrained by the fact that they can inspect each example at most once [3]. This may result in models of a lower performance than the models built within a batch process relying on the access to the entire data set and the ability to iteratively revisit all instances during the training.

As traditional ML models deployed in production settings might experience performance degradation over time, their application to evolving and potentially infinite data streams called for a new approach. Hence, when Machine Learning solutions are used in IT systems, a growing emphasis on the Machine Learning Operations (MLOps) process is observed. MLOps focuses on addressing data changes through Continuous Monitoring and Continuous Training steps, ensuring models adapt to data and concept shifts to maintain performance [16]. There are multiple methods for concept drift detection, mainly focusing on monitoring data distribution [3]. Similarly, the adaptation of batch models can be performed in a number of ways, such as retraining from scratch on all available data [18] or just the latest instance window.

The combination of online and batch learning methods has been considered before. In [9], neural model training and incremental training of an online learner was proposed in the form of a hybrid model that switches between the multilayer perceptron and stream mining models based on their recent accuracy over a sliding window. In [14], the authors combined initially trained batch models (e.g. decision trees) and gradually converted them into online models. This approach leverages the simultaneous predictions from both online and batch members. However, this approach does not involve concept drift detection or model adaptation. Instead, it adds new batch learners built on recent instances over time.

Hence, the question arises of how to build TMC classifiers, while considering concept drift of unknown magnitude. Importantly, not only human preferences towards different modes can change with time (e.g. depend on the time of the year) causing $p(y|x)$ changes, but also $p(x)$ clearly changes. Examples include travel to schools less likely to happen during school holidays.

3 Ensemble of Batch and Online Learners

The method proposed in this work relies on learning an ensemble of base models including both batch and online models to respond to possible virtual drift, i.e., changes in $p(x)$, and real drift i.e., changes in $p(y|x)$. To evaluate the IEBSM ensembles as well as reference online and batch methods, the test-then-train approach is applied. Online learners are trained the same way and with the same data stream irrespective of whether they are evaluated as standalone reference learners or participate in the ensemble. Similarly, batch learners are retrained in line with Alg. 1 described below, both when they are evaluated as reference methods and when they are a part of an ensemble.

3.1 Training of online and batch learners with TMC data streams

For online learning algorithms, the learners are provided with new labelled examples and updated incrementally, as defined in the test-then-train approach. In the case of batch learning algorithms, newly arriving $\{\mathbf{x}_i, y_i\}$ instances are placed in the cache of the most recent instances. Then, drift detectors assess the cache to identify concept drift following the predefined drift handling strategy. If a drift is detected, the batch model undergoes retraining, using data from the cache under the chosen retraining strategy. Subsequently, the newly trained model and the previous model are evaluated on the successive n_{comp} instances. If the retrained model demonstrates superior performance compared to the old model, it replaces the previous model in use. This illustrates the challenge of batch learning adapted to an online setting, i.e., its dependence on hyperparameters such as n_{comp}. The batch learning models are trained for the first time using the initial n_{first_fit} instances. Prior to the collection of all these instances, a majority class model generates prediction output as the label of the class that has been observed most frequently up to that point. In this way, batch and stream models can be evaluated with the same instances $\{\mathbf{x}_i, y_i\}, i = 1, \ldots$ irrespective of the duration of the *warm-up* period of n_{first_fit} instances.

In our approach, the monitoring strategies used to detect drift rely on the analysis of the most recent instances. To achieve this, we partition these instances into two equal batches of s instances i.e., the reference batch and the current batch. Every s instances, we then compare the distributions of these two batches by applying statistical tests. A test is applied to each feature separately to detect possible changes in the distribution of the values of j-th feature x^j and label y. We associate a threshold θ with those tests, the interpretation of which varies depending on the drift detection method. As the tests to be applied depend on feature types, we discuss them in detail in Sect. 4. Besides testing for changes in the input feature/target distribution, we utilise detection techniques that monitor the performance of a model. A performance drop, defined as the F_1 macro score on the current batch falling below α of the F_1 macro score on a reference batch, suggests a concept drift. To initiate retraining, at least one drift detection method identifying a change in the data distribution of some feature or a change in model performance must detect a concept drift.

3.2 Building an ensemble of batch and online learners

As defined in Alg. 1, we propose an ensemble-based method that aims to maximise the performance of travel mode choice predictions by combining predictions of both batch and online learners. The method builds an ensemble of N base learners, some of which can be online learners such as adaptive random forest [8], while the remaining ones can be batch learners. In line with the test-then-train approach, for every new instance, each base learners generates a prediction first. In the case of batch models, we propose to rely on majority class prediction prior to the collection of a sufficiently large training data set.

The IEBSM ensemble generates the ultimate prediction by aggregating the outputs from all member models, as shown in lines 16-22 of Alg 1. We propose two approaches for combining predictions. In both approaches, we record the value of a performance measure such as F_1 for every ensemble member in the prequential approach, i.e., over a sliding window of instances. Under the **Weighted Voting (WV)** approach we combine predictions using weights w_i assigned to each member m_i of ensemble M according to their recent performance calculated on the sliding window of instances. In the case of the **Dynamic Switching (DS)** approach, the final prediction of the ensemble is the prediction from the recently top-performing ensemble member. This corresponds to assigning $w_i = 1$ to the best model m_i, and $w_j = 0, j \neq i$ otherwise.

Next the training of base learners is considered. In the case of online learners, they are simply provided with the new instance $(\mathbf{x}_i, y_i)$, which may trigger updates of a model m. In the case of batch learners, first a cache of recent instances is updated. This is to store data to be used for potential retraining of a batch model based on a recent data set. Next, drift handling strategy $S(m)$ is used to define the way drift detection is performed, e.g. whether it is focused on virtual drift only and/or the performance of model m, and how sensitive drift detection is, which is defined by the settings of statistical tests. This illustrates the complexity of using batch learners in the case of concept drifting data streams.

In case a drift is detected, a new model is developed and stored as a shadow model to potentially replace the original one. This happens once its performance is found to be actually superior to the performance of the original model. Hence, in line 33, the new pair of true and predicted labels is used to update the performance of the shadow model $m.shadow\_model$, if any, and compare it to the performance of the original model m and decide whether it should replace the model m or not. In this way, drift detection is combined with the checking of the performance of a newly developed shadow model over a window of new instances not used to train it.

4 Results

4.1 Data streams and libraries

The experiments performed with online, batch, and combined methods were assessed on real travel mode data streams, with the overview provided in Table 1. The datasets vary in the number of features, classes, i.e., travel modes, and instances. Each instance corresponds to an actual trip reported by a survey participant, with the employed travel mode designated as the target variable. For a more comprehensive description of data stream preparation, please refer to the supplementary material, where additional description is provided.

To implement the proposed methods and the evaluation framework, we used the library River [13] (online learning methods), and the LightGBM package (the LGBM classifier). For the batch learning methods, except for LGBM, the scikit-learn library was used, while the concept drift detection implementation relied on the EvidentlyAI [1].

4.2 Experiments

We conducted a series of experiments for each data stream, which included online learning experiments, batch learning experiments, and experiments using the IEBSM method. The precise configurations of online and batch learning methods are detailed in the supplementary material accompanying this work.

For online learning, we employed the Hoeffding Adaptive Tree (HAT), Adaptive Random Forest (ARF), Streaming Random Patches (SRP), Online Gaussian Naive Bayes ((O)NB), and Online Logistic Regression ((O)LR) algorithms. The batch learning experiments made use of the Logistic Regression (LR) (with prior standardization of the training batch), Gaussian Naive Bayes (NB), Decision

Input: $\{x_1, y_2\}, \ldots, \{x_i, y_i\}, \ldots$ - a labelled data stream, c - a method combining predictions of members, e - a method evaluating members, $S = \{S_1, \ldots, S_K\}, K \leq N$ - a set of drift handling strategies (one per each batch base learner), each defined by a vector of hyperparameter values controlling the way drift is detected and a batch model retrained

Data: $M = \{m_1, \ldots, m_N\}$ - an ensemble of base learners

```
foreach {x_i, y_i} ∈ data_stream do
    Ŷ_i ← [], scores_i ← []
    foreach m ∈ M do
        if m.type == batch  and  i <= n_first_fit then
            Ŷ_i[m] ← get_majority_class(m.cache)
            if i == n_first_fit then
                m = m.first_fit()
            end
        end
        else
            Ŷ_i[m] ← m.predict(x_i)
        end
        e.update_model_score(y_i, Ŷ_i[m])
    end
    if c == DS then
        weigths ← zeros(len(members))
        weights[argmax(scores_i)] ← 1
    end
    if c == WV then
        weights ← (scores_i / sum(scores_i))
    end
    ŷ_i ← argmax_{c∈classes} {Σ_{j←0, Ŷ_i[j]==c}^{m_len − 1} weights[j]}
    foreach m ∈ M do
        if m.type == online then
            m = m.update_model(x_i, y_i)
        end
        if m.type == batch then
            m.update_cache(x_i, y_i)
            if m.has_concept_drift_occurred(S(m)) then
                m.shadow_model ← train_on_cached_instances(m, S(m))
            end
            m ← evaluate_shadow_model(m, m.shadow_model, x_i, y_i, Ŷ_i[m])
        end
    end
    update_performance_metrics(y_i, ŷ_i)
end
```

Algorithm 1: Training and evaluation of IEBSM models.

Tree Classifier (DT), LGBM, and Random Forest (RF) algorithms. Furthermore, we applied each batch learning algorithm to the data streams using three distinct drift handling strategies:

- S1: Basic drift detection of changes in input features, target and model performance drift with $\theta = 0.03$, $s = 10,000$, $\alpha = 0.2$
- S2: Performance drift detection only with $s = 10,000$, $\alpha = 0.2$
- S3: Frequent drift detection of changes in input features, target and model performance with $\theta = 0.02$, $s = 5,000$, $\alpha = 0.2$, i.e., relying on smaller windows of $5,000$ instances than in S1.

Batch experiments were equivalent to running Alg. 1 with one batch base learner and its drift handling strategy. We have chosen the values for the hyperparameters θ and s through preliminary tests aimed at determining the values resulting

Table 1. The summary of data streams

Data stream	Instances	Features	Classes	Description
Ohio (OHI)	122,331	156	12	2001-2003 Ohio survey [15]
London (LON)	81,086	41	4	London Travel Demand Survey [12]
Optima (OPT)	2,265	497	4	Suiss survey data [2]
NTS	230,608	17	4	Dutch National Travel Survey with environment and weather features [7, 10]
N-MW	144,905	2,571	21	The National Household Travel Survey (NHTS) conducted in 2016 and 2017 [17], divided into five regions of the US
N-NE	145,564	2,437	21	
N-SE	209,485	2,586	21	
N-SW	190,279	2,505	21	
N-W	233,323	2,553	21	

in possibly high performance of the models. In the batch-learning experiments, we employed a retraining strategy, which involved training a new model using all historical instances that arrived after the last model replacement. After each retraining, we assessed the performance of a shadow model relative to the old one, over the following $n_{comp} = 500$ instances. Depending on their performance, we would replace the old model with the new one. The first training took place after the initial $n_{first\_fit} = 2500$ examples.

Moreover, we conducted baseline experiments in which we trained each batch algorithm on the initial 2,500 instances (strategy B1) and subsequently used that model for predictions on the remaining data stream. We also repeated the baseline experiments using an initial training set of 25,000 instances (strategy B2) for a more comprehensive analysis.

Finally, in the experiments including batch models and involving drift detection and model adaptation we dynamically selected a specific statistical test based on the input feature/target column. For numerical columns with the number of unique values $n\_unique > 5$ we used Wasserstein Distance when $s > 1,000$; and two-sample Kolmogorov-Smirnov test otherwise. For categorical columns or numerical (with $2 < n\_unique <= 5$), Jensen–Shannon divergence when $s > 1,000$; or chi-squared test were used otherwise. Finally, for binary categorical features ($n\_unique = 2$): Jensen–Shannon divergence was used when $s > 1,000$; and proportion difference test for independent samples based on Z-score otherwise.

Combining online and batch learning with the IEBSM method The experiments using IEBSM included an ensemble of four instances of the same batch learning classifier, each utilizing a distinct drift handling (DH) strategy, along with three online learning classifiers: (O)NB, HAT, and ARF. We tested the LGBM and RF as the batch learning algorithms. We employed a single batch learning algorithm for all batch members within each IEBSM experiment to reduce variation arising from diverse algorithms. This allowed us to single out the impact of distinct drift handling strategies, namely:

– S4: investigating changes in input features, target, and model performance with $\theta = 0.02$, $s = 2,500$, $\alpha = 0.2$
– S5: investigating changes in model performance only with $s = 2,500$, $\alpha = 0.2$
– S6: investigating changes in input features, target, and model performance with $\theta = 0.03$, $s = 10,000$, $\alpha = 0.2$
– S7: investigating changes in input features, target, and model performance with $\theta = 0.02$, $s = 10,000$, $\alpha = 0.2$

In the S5 and S7 settings, the retraining batch corresponds to the window of last s instances. In contrast, for S4 and S6, all instances since the last model replacement are considered for retraining. The other hyperparameter values (e.g., n_{first_fit}, n_{comp}) were the same as in the single online/batch learning experiments. The seven ensemble members described above were combined using two methods c outlined in Section 3.2.

After conducting experiments, it became evident that online learning methods exhibited significantly inferior performance compared to batch learning methods. To demonstrate the effect of model combination with the IEBSM method and eliminate the impact of under-performing online models, we conducted additional IEBSM experiments: DS-BATCH and WV-BATCH experiments utilizing only LGBM S4, S5, S6, and S7 models. Moreover, we performed DS-ONLINE and WV-ONLINE experiments combining HAT, ARF, and (O)NB models solely. For the nine data streams, we calculated each method's average ranking position based on the value of F_1 macro score. Table 2 shows the obtained results for the selected experiments (all experiment results are provided in the supplementary material).

4.3 Discussion

It follows from Table 2 that batch-learning experiments RF-S3 and LGBM-S3 employing DH strategies to possibly adapt batch models, outperformed the baseline experiments RF-B* and LGBM-B* in which RF and LGBM models trained once on initial batch of data were used next to predict travel modes for all the remaining instances (B1 and B2 strategies, sample results in Table 2 provided inter alia for RF as RF-B1 results). This finding demonstrates that implementing the aforementioned DH strategies significantly benefits batch-learning models when faced with travel mode choice data. Among different ways the RF and LGBM models can be updated, strategy S3 stood out as the most effective.

Surprisingly, the online learning methods yielded the poorest performance results, as illustrated by the SRP results. One potential explanation could be the abundance of features in our data streams, among which many might be irrelevant. The SRP classifier emerged as the most effective online learning method, albeit with the trade-off of longer execution times.

The use of IEBSM, evaluated in the DS-* and WV-* experiments, enhanced performance compared to individual batch and online model setups, and provided the best overall results. This combination successfully mitigated the challenges caused by the need to choose online and batch learning methods. More-

Table 2. Ranks of selected methods across all streams and F_1 macro score for each data stream. Data streams were arranged in order based on the increasing number of features. A ranking score combined with the corresponding position in the overall ranking (in brackets). † - For the OPT data stream, hyperparameters values set to $s = 100$ and $s = 250$ (instead of 2,500 and 10,000), $n_{first\_fit} = 150$, and $n_{comp} = 50$. For N-* data streams, the input feature drift detection disabled in DH strategies S1, S3, S4, S6, S7 due to the performance issues caused by a large number of features.

Method	Rank	*Data stream*								
	(pos.)	NTS	LON	OHI	OPT†	N-NE	N-SW	N-W	N-MW	N-SE
DS-RF	4.33(1)	0.532	0.544	0.206	0.393	**0.464**	**0.464**	**0.453**	**0.476**	0.453
WV-RF	5.78(2)	0.534	0.546	0.197	0.362	0.460	0.460	0.435	0.458	**0.456**
DS-LGBM	7.78(3)	0.540	**0.549**	**0.224**	0.436	0.377	0.358	0.320	0.368	0.316
RF-S3	8.11(4)	0.520	0.530	0.205	0.382	0.414	0.421	0.417	0.403	0.428
DS-BATCH	8.44(5)	0.541	0.538	**0.224**	0.446	0.379	0.357	0.320	0.365	0.314
WV-LGBM	9.00(6)	**0.542**	0.546	0.215	0.438	0.359	0.357	0.306	0.352	0.316
WV-BATCH	10.83(12)	0.539	0.531	0.216	**0.459**	0.358	0.356	0.307	0.349	0.314
LGBM-S3	12.39(13)	0.530	0.533	0.213	0.453	0.358	0.339	0.302	0.349	0.314
LGBM-B1	18.61(19)	0.355	0.512	0.213	0.307	0.358	0.339	0.302	0.349	0.314
RF-B2	23.11(23)	0.486	0.426	0.196	0.274	0.279	0.229	0.197	0.232	0.220
LGBM-B2	25.00(24)	0.506	0.433	0.162	0.299	0.167	0.179	0.183	0.118	0.142
WV-ONLINE	25.44(26)	0.481	0.504	0.166	0.338	0.077	0.071	0.066	0.081	0.069
SRP	26.22(27)	0.375	0.430	0.177	0.234	0.231	0.161	0.210	0.210	0.195
RF-B1	26.33(28)	0.356	0.516	0.164	0.199	0.253	0.211	0.146	0.189	0.167
DS-ONLINE	26.78(29)	0.375	0.432	0.162	0.312	0.084	0.080	0.074	0.090	0.078

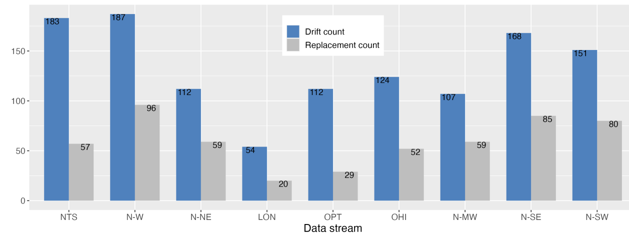
over, utilising multiple batch members with varied DH strategies and varied hyperparameters in turn reduced the need to pre-select the optimal strategy. While the Random Forest algorithm used to develop batch ensemble members yielded superior results, as shown by the DS-RF outcome, the DS-LGBM demonstrated faster operation despite the inferior performance.

Interestingly, the IEBSM ensembles comprised solely of batch-learning LGBM classifiers ([DS/WV]-BATCH) resulted in a worse global rank than the corresponding experiments that combined both LGBM and online classifiers ([DS/WV]-LGBM). These findings underscore that, even in cases where online learning demonstrates suboptimal performance, IEBSM ensembles can benefit from the diversity their members offer. Similarly, when using combining ensembles solely with online learners ([DS/WV]-ONLINE), a notable enhancement in performance, compared to the performance of the experiments utilizing single instances of HAT, ARF, and O(NB), was observed.

Finally, the role of drift detections and shadow models in the IEBSM approach can be analyzed. Fig. 1 presents the total number of drift detections and actual model replacements for all batch members for the highest-ranked method, i.e., the IEBSM-based DS-RF [2] ensemble, which notably included both online and random forest models. It follows from the figure, that detections of statisti-

[2] Due to the extensive number of experiments conducted, detailed results for all experiments are provided in the supplementary materials.

Fig. 1. The number of drift detections and model replacements. DS-RF experiments.



cally significant changes in data have occurred in all data streams. These were followed by the replacement of batch models. Hence, the shadow models built with more recent data were found to be superior to the original models they replaced. Newly developed models were only in some cases found to yield better performance, as the drift count significantly exceeds the actual model replacement count. This confirms that both detection and the evaluation of shadow models are vital components of the highest-ranked approach to building TMC models i.e., the DS-RF approach.

5 Conclusions

In the prevailing majority of cases, modelling of travel mode choices is performed with batch learning methods. However, factors such as seasonality suggest that when predicting TMC decisions incorporating concept drift detection and adaptation could be justified. On the other hand, change detection could occur too frequently and reduce the potential of newly developed models in turn. A possible solution to the problem can rely on the use of both online and batch learners. Our experiments performed with multiple travel mode choice data sets confirm the need for continuous monitoring and retraining of TMC models. Combining batch and online learning clearly yields improved performance of the models. Furthermore, the IEBSM method eases the challenge of choosing a learning method and drift detection settings by employing multiple base members including both online and batch learners with different drift handling strategies. This resulted in the best rank of the IEBSM approach.

Future works entail exploring various combining approaches, such as different ways of assigning member weights. Furthermore, travel mode choice data sets can be used to foster the development of future stream mining methods.

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Supplement to the article: *Hybrid Ensemble-Based Travel Mode Prediction*

1 Global ranking

Table 1 illustrates the comprehensive ranking of methods. Across the 9 data streams, all 38 methods were organized based on their F_1 macro scores in descending order. Subsequently, we computed the *Ranking score* for each method by computing their average ranking position across these nine rankings. The ultimate *Ranking position* represents the sequential number of these averages, sorted from the smallest to the nearest value.

Table 1: Table with the global ranking of used methods

Ranking position	Method abbr.	Ranking score	Ranking position	Method abbr.	Ranking score
1	DS-RF	4.33	20	DT B2	19.56
2	WV-RF	5.78	21	DT B1	21.67
3	DS-LGBM	7.78	22	LR B2	22.11
4	RF S3	8.11	23	RF B2	23.11
5	DS-BATCH	8.44	24	LGBM B2	25.00
6	WV-LGBM	9.00	25	LR B1	25.11
7	RF S1	9.00	26	WV-ONLINE	25.44
8	LR S3	9.78	27	SRP	26.22
9	DT S1	9.83	28	RF B1	26.33
10	DT S3	10.28	29	DS-ONLINE	26.78
11	LR S1	10.33	30	NB S1	30.44
12	WV-BATCH	10.83	31	HAT	30.78
13	LGBM S3	12.39	32	NB S3	31.22
14	LGBM S1	12.56	33	NB B2	31.78
15	RF S2	13.06	34	ARF	32.00
16	LGBM S2	13.28	35	NB S2	32.50
17	LR S2	14.00	36	NB B1	34.39
18	DT S2	16.39	37	ONB	35.56
19	LGBM B1	18.61	38	OLR	37.22

2 Data stream preparation

If any of the nine data streams included variables related to the date and time of the journey, the instances were arranged chronologically. In each original data stream, we removed variables that might lead to knowledge leakage and conducted one-hot encoding for categorical variables. The datasets had minimal missing values, and for categorical variables, we converted these to a category indicating *'Don't know / Refuse to answer'*. Numerical missing values were replaced with the mode value computed across the entire dataset. Instances with missing target values were excluded.

3 Online and batch learning models configuration

All batch learning models were initialized with their default hyperparameter values, except for setting the *random_ seed* to 42 where applicable. Within Listings 1 to 5, you'll find code snippets that define online learning models using the River library.

```python
from river.linear_model import LogisticRegression as LROnline
from river import compose
from river.preprocessing import StandardScaler
from river import optim

lr_online = compose.Pipeline(
    StandardScaler(
        with_std=True
    ),
    LROnline(
        optimizer=optim.SGD(
            lr=0.005
        ),
        loss=optim.losses.Log(
            weight_pos=1.,
            weight_neg=1.
        ),
        l2=1.0,
        l1=0.,
        intercept_init=0.,
        intercept_lr=0.01,
        clip_gradient=1e+12,
        initializer=optim.initializers.Zeros()
    )
)
```

Listing 1: Online Logistic Regression (OLR) model definition

```python
from river import forest

arf = forest.ARFClassifier(seed=42, leaf_prediction="mc")
```

Listing 2: Adaptive Random Forest (ARF) model definition

```python
from river.tree import HoeffdingAdaptiveTreeClassifier

hat = HoeffdingAdaptiveTreeClassifier(
    grace_period=100,
    delta=0.01,
    leaf_prediction='nb',
    nb_threshold=10,
    seed=42
)
```

Listing 3: Hoeffding Adaptive Tree (HAT) model definition

```python
from river.tree import HoeffdingTreeClassifier
from river import ensemble

base_model = HoeffdingTreeClassifier(grace_period=100, delta=0.01)
srp_model = ensemble.SRPClassifier(model=base_model, n_models=3, seed=42)
```

Listing 4: Streaming Random Patches (SRP) model definition

```python
from river.naive_bayes import GaussianNB as GNBOnline

nb_online = GNBOnline()
```

Listing 5: Online Gaussian Naive Bayes (ONB) model definition

4 Detailed results

Within Table 2, you'll find a comprehensive breakdown of experiment outcomes across various data streams. The rows are arranged based on both the data stream and F_1 macro score. For ensembles, the presented drift/replacement values represent the aggregated sum across all ensemble members. Additionally, with respect to both online and baseline methods, the count of drifts and replacements is zero since these methods do not utilize our monitoring and retraining strategies. Figure 1 presents the F_1 macro score values for selected methods on all data streams. The data streams were arranged in order based on the increasing number of features.

Table 2: Table with detailed results for all experiments

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
0	London	3	DS-LGBM	0.5492	0.7347	0.5830	45.0	17.0	1083.41
1	London	6	WV-LGBM	0.5464	0.7339	0.5838	45.0	17.0	1045.94
2	London	2	WV-RF	0.5455	0.7317	0.5804	54.0	20.0	5789.70
3	London	1	DS-RF	0.5445	0.7331	0.5795	54.0	20.0	5778.41
4	London	5	DS-BATCH	0.5378	0.7198	0.5633	22.0	11.0	583.30
5	London	14	LGBM S1	0.5332	0.7157	0.5580	15.0	8.0	143.40
6	London	13	LGBM S3	0.5331	0.7180	0.5606	6.0	2.0	125.21
7	London	16	LGBM S2	0.5324	0.7144	0.5552	1.0	1.0	100.41
8	London	12	WV-BATCH	0.5306	0.7151	0.5561	22.0	11.0	499.85
9	London	4	RF S3	0.5303	0.7156	0.5578	6.0	1.0	1608.12
10	London	11	LR S1	0.5299	0.6943	0.5312	14.0	9.0	149.13
11	London	7	RF S1	0.5281	0.7137	0.5532	14.0	9.0	1579.17
12	London	8	LR S3	0.5274	0.7065	0.5446	8.0	2.0	158.33
13	London	17	LR S2	0.5163	0.6811	0.5124	1.0	1.0	84.32
14	London	15	RF S2	0.5163	0.6951	0.5295	0.0	0.0	1458.65
15	London	28	RF B1	0.5163	0.6951	0.5295	0.0	0.0	1231.51
16	London	25	LR B1	0.5160	0.6808	0.5119	0.0	0.0	51.99
17	London	19	LGBM B1	0.5118	0.6921	0.5217	0.0	0.0	1278.48
18	London	26	WV-ONLINE	0.5042	0.6584	0.4892	0.0	0.0	536.18
19	London	10	DT S3	0.4534	0.5853	0.3696	6.0	5.0	98.58
20	London	9	DT S1	0.4534	0.5858	0.3708	14.0	5.0	89.98
21	London	21	DT B1	0.4429	0.5645	0.3440	0.0	0.0	38.39
22	London	18	DT S2	0.4411	0.5650	0.3425	0.0	0.0	53.19

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
23	London	24	LGBM B2	0.4333	0.5718	0.3819	0.0	0.0	1102.58
24	London	34	ARF	0.4319	0.7292	0.5698	0.0	0.0	383.62
25	London	29	DS-ONLINE	0.4317	0.7278	0.5685	0.0	0.0	587.02
26	London	27	SRP	0.4304	0.7092	0.5424	0.0	0.0	899.10
27	London	30	NB S1	0.4292	0.5202	0.3408	14.0	7.0	109.38
28	London	23	RF B2	0.4264	0.5672	0.3748	0.0	0.0	1072.53
29	London	22	LR B2	0.4248	0.5646	0.3717	0.0	0.0	49.88
30	London	32	NB S3	0.4236	0.5125	0.3323	6.0	4.0	132.09
31	London	35	NB S2	0.4194	0.5110	0.3305	0.0	0.0	78.13
32	London	36	NB B1	0.4194	0.5110	0.3305	0.0	0.0	52.06
33	London	20	DT B2	0.3840	0.4856	0.2695	0.0	0.0	37.40
34	London	37	ONB	0.3545	0.5518	0.3650	0.0	0.0	125.82
35	London	33	NB B2	0.3523	0.4226	0.2356	0.0	0.0	49.99
36	London	31	HAT	0.3385	0.5092	0.3168	0.0	0.0	319.72
37	London	38	OLR	0.0208	0.0319	0.0020	0.0	0.0	54.64
38	NHTS-MW	1	DS-RF	0.4760	0.7497	0.6402	107.0	59.0	84720.46
39	NHTS-MW	2	WV-RF	0.4577	0.7435	0.6284	107.0	59.0	67835.22
40	NHTS-MW	7	RF S1	0.4424	0.7299	0.6133	34.0	16.0	3796.36
41	NHTS-MW	8	LR S3	0.4237	0.5872	0.4435	11.0	10.0	1089.48
42	NHTS-MW	11	LR S1	0.4161	0.6145	0.4713	31.0	19.0	1420.77
43	NHTS-MW	9	DT S1	0.4105	0.7464	0.6559	32.0	20.0	601.91
44	NHTS-MW	10	DT S3	0.4036	0.7330	0.6374	11.0	9.0	281.73
45	NHTS-MW	15	RF S2	0.4027	0.7137	0.5873	10.0	9.0	3312.46
46	NHTS-MW	4	RF S3	0.4027	0.7137	0.5873	12.0	9.0	2548.20
47	NHTS-MW	17	LR S2	0.3858	0.5747	0.4308	7.0	7.0	818.72

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
48	NHTS-MW	3	DS-LGBM	0.3679	0.7605	0.6610	48.0	1.0	65638.91
49	NHTS-MW	5	DS-BATCH	0.3651	0.7533	0.6536	58.0	1.0	8220.94
50	NHTS-MW	6	WV-LGBM	0.3524	0.7537	0.6507	48.0	1.0	71879.20
51	NHTS-MW	16	LGBM S2	0.3487	0.7465	0.6433	2.0	0.0	585.15
52	NHTS-MW	14	LGBM S1	0.3487	0.7465	0.6433	17.0	0.0	2337.83
53	NHTS-MW	13	LGBM S3	0.3487	0.7465	0.6433	4.0	0.0	655.64
54	NHTS-MW	12	WV-BATCH	0.3487	0.7465	0.6433	58.0	1.0	8219.19
55	NHTS-MW	19	LGBM B1	0.3487	0.7465	0.6433	0.0	0.0	3390.72
56	NHTS-MW	20	DT B2	0.3255	0.6127	0.4939	0.0	0.0	233.86
57	NHTS-MW	21	DT B1	0.2952	0.6805	0.5657	0.0	0.0	329.61
58	NHTS-MW	18	DT S2	0.2948	0.6627	0.5416	0.0	0.0	203.15
59	NHTS-MW	22	LR B2	0.2719	0.3981	0.2659	0.0	0.0	717.05
60	NHTS-MW	23	RF B2	0.2320	0.5948	0.4415	0.0	0.0	2476.18
61	NHTS-MW	27	SRP	0.2097	0.7014	0.5672	0.0	0.0	70330.61
62	NHTS-MW	25	LR B1	0.2092	0.3503	0.2077	0.0	0.0	633.07
63	NHTS-MW	28	RF B1	0.1886	0.6073	0.4082	0.0	0.0	3061.13
64	NHTS-MW	24	LGBM B2	0.1177	0.3566	0.1949	0.0	0.0	2794.48
65	NHTS-MW	29	DS-ONLINE	0.0901	0.3852	0.1730	0.0	0.0	83130.95
66	NHTS-MW	31	HAT	0.0835	0.3012	0.1508	0.0	0.0	36687.71
67	NHTS-MW	26	WV-ONLINE	0.0814	0.4320	0.1386	0.0	0.0	84483.09
68	NHTS-MW	33	NB B2	0.0675	0.0947	0.0208	0.0	0.0	1076.56
69	NHTS-MW	35	NB S2	0.0611	0.1259	0.0301	3.0	0.0	918.80
70	NHTS-MW	32	NB S3	0.0611	0.1259	0.0301	5.0	0.0	1220.80
71	NHTS-MW	36	NB B1	0.0611	0.1259	0.0301	0.0	0.0	681.23
72	NHTS-MW	34	ARF	0.0561	0.4690	0.1121	0.0	0.0	2560.09
73	NHTS-MW	30	NB S1	0.0500	0.0999	0.0281	34.0	12.0	1357.63

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
74	NHTS-MW	37	ONB	0.0267	0.4159	-0.0000	0.0	0.0	23804.50
75	NHTS-MW	38	OLR	0.0128	0.0233	0.0107	0.0	0.0	1773.06
76	NHTS-NE	1	DS-RF	0.4641	0.7792	0.6832	112.0	59.0	87765.85
77	NHTS-NE	2	WV-RF	0.4599	0.7767	0.6777	112.0	59.0	87051.09
78	NHTS-NE	9	DT S1	0.4357	0.7775	0.6969	38.0	17.0	307.42
79	NHTS-NE	7	RF S1	0.4251	0.7543	0.6476	41.0	20.0	2732.06
80	NHTS-NE	11	LR S1	0.4207	0.6539	0.5242	37.0	18.0	669.07
81	NHTS-NE	10	DT S3	0.4162	0.7609	0.6738	16.0	8.0	290.92
82	NHTS-NE	4	RF S3	0.4142	0.7555	0.6488	16.0	9.0	2528.74
83	NHTS-NE	20	DT B2	0.4021	0.6584	0.5486	0.0	0.0	251.94
84	NHTS-NE	5	DS-BATCH	0.3787	0.7813	0.6948	64.0	2.0	7595.85
85	NHTS-NE	3	DS-LGBM	0.3770	0.7851	0.6982	53.0	2.0	65082.30
86	NHTS-NE	17	LR S2	0.3759	0.6412	0.5009	10.0	6.0	437.09
87	NHTS-NE	8	LR S3	0.3750	0.6415	0.5058	18.0	7.0	619.50
88	NHTS-NE	6	WV-LGBM	0.3588	0.7791	0.6888	53.0	2.0	61123.38
89	NHTS-NE	16	LGBM S2	0.3580	0.7750	0.6850	1.0	0.0	1388.38
90	NHTS-NE	14	LGBM S1	0.3580	0.7750	0.6850	27.0	0.0	3097.06
91	NHTS-NE	13	LGBM S3	0.3580	0.7750	0.6850	9.0	0.0	1126.49
92	NHTS-NE	12	WV-BATCH	0.3580	0.7750	0.6850	64.0	2.0	6545.09
93	NHTS-NE	19	LGBM B1	0.3580	0.7750	0.6850	0.0	0.0	3383.84
94	NHTS-NE	15	RF S2	0.3252	0.7225	0.5976	4.0	4.0	2353.08
95	NHTS-NE	18	DT S2	0.3092	0.7174	0.6153	0.0	0.0	141.83
96	NHTS-NE	21	DT B1	0.3089	0.7089	0.6031	0.0	0.0	345.22
97	NHTS-NE	23	RF B2	0.2787	0.6444	0.5067	0.0	0.0	2502.35
98	NHTS-NE	22	LR B2	0.2683	0.4299	0.2942	0.0	0.0	808.16

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
99	NHTS-NE	28	RF B1	0.2528	0.6730	0.5200	0.0	0.0	3169.13
100	NHTS-NE	27	SRP	0.2313	0.7322	0.6144	0.0	0.0	55738.82
101	NHTS-NE	25	LR B1	0.2028	0.4620	0.3152	0.0	0.0	714.31
102	NHTS-NE	24	LGBM B2	0.1666	0.5065	0.3584	0.0	0.0	3561.00
103	NHTS-NE	29	DS-ONLINE	0.0845	0.4079	0.1869	0.0	0.0	78882.46
104	NHTS-NE	31	HAT	0.0829	0.3189	0.1707	0.0	0.0	30021.90
105	NHTS-NE	26	WV-ONLINE	0.0772	0.4524	0.1551	0.0	0.0	76859.47
106	NHTS-NE	33	NB B2	0.0668	0.0839	0.0149	0.0	0.0	960.97
107	NHTS-NE	32	NB S3	0.0655	0.0867	0.0261	15.0	5.0	513.10
108	NHTS-NE	34	ARF	0.0614	0.4816	0.1269	0.0	0.0	1463.03
109	NHTS-NE	30	NB S1	0.0589	0.0866	0.0285	43.0	14.0	523.56
110	NHTS-NE	35	NB S2	0.0511	0.0811	0.0247	5.0	0.0	1560.00
111	NHTS-NE	36	NB B1	0.0511	0.0811	0.0247	0.0	0.0	788.83
112	NHTS-NE	37	ONB	0.0272	0.4279	-0.0000	0.0	0.0	23059.12
113	NHTS-NE	38	OLR	0.0117	0.0250	0.0135	0.0	0.0	1619.25
114	NHTS-SE	2	WV-RF	0.4557	0.7653	0.6543	168.0	85.0	118115.13
115	NHTS-SE	1	DS-RF	0.4530	0.7662	0.6586	168.0	85.0	118014.45
116	NHTS-SE	15	RF S2	0.4285	0.7432	0.6233	18.0	16.0	3600.94
117	NHTS-SE	4	RF S3	0.4285	0.7432	0.6233	23.0	16.0	3690.82
118	NHTS-SE	9	DT S1	0.4277	0.7641	0.6738	47.0	24.0	525.47
119	NHTS-SE	18	DT S2	0.4271	0.7564	0.6628	16.0	12.0	366.81
120	NHTS-SE	17	LR S2	0.4208	0.6426	0.4979	12.0	10.0	580.04
121	NHTS-SE	8	LR S3	0.4201	0.6400	0.4972	12.0	10.0	573.24
122	NHTS-SE	7	RF S1	0.4125	0.7389	0.6166	61.0	28.0	4028.50
123	NHTS-SE	10	DT S3	0.4061	0.7446	0.6465	12.0	7.0	427.95

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
124	NHTS-SE	11	LR S1	0.4012	0.6290	0.4866	55.0	28.0	998.26
125	NHTS-SE	6	WV-LGBM	0.3165	0.7544	0.6478	91.0	2.0	108938.05
126	NHTS-SE	3	DS-LGBM	0.3159	0.7522	0.6455	91.0	2.0	119122.05
127	NHTS-SE	20	DT B2	0.3151	0.6398	0.5197	0.0	0.0	591.60
128	NHTS-SE	16	LGBM S2	0.3141	0.7509	0.6446	2.0	0.0	476.56
129	NHTS-SE	13	LGBM S3	0.3141	0.7509	0.6446	7.0	0.0	996.73
130	NHTS-SE	12	WV-BATCH	0.3141	0.7509	0.6446	91.0	2.0	11946.93
131	NHTS-SE	19	LGBM B1	0.3141	0.7509	0.6446	0.0	0.0	4694.60
132	NHTS-SE	5	DS-BATCH	0.3135	0.7501	0.6436	91.0	2.0	11022.63
133	NHTS-SE	22	LR B2	0.2646	0.4001	0.2605	0.0	0.0	1315.21
134	NHTS-SE	21	DT B1	0.2400	0.6682	0.5370	0.0	0.0	315.66
135	NHTS-SE	23	RF B2	0.2200	0.6321	0.4746	0.0	0.0	4485.57
136	NHTS-SE	25	LR B1	0.2093	0.3930	0.2317	0.0	0.0	279.89
137	NHTS-SE	14	LGBM S1	0.2049	0.6460	0.5059	36.0	6.0	1240.84
138	NHTS-SE	27	SRP	0.1947	0.6935	0.5481	0.0	0.0	92934.53
139	NHTS-SE	28	RF B1	0.1670	0.6251	0.4237	0.0	0.0	4228.90
140	NHTS-SE	24	LGBM B2	0.1424	0.4900	0.3432	0.0	0.0	4700.93
141	NHTS-SE	29	DS-ONLINE	0.0775	0.3746	0.1400	0.0	0.0	124328.69
142	NHTS-SE	31	HAT	0.0691	0.2547	0.1085	0.0	0.0	51264.47
143	NHTS-SE	26	WV-ONLINE	0.0686	0.4416	0.1202	0.0	0.0	126428.51
144	NHTS-SE	33	NB B2	0.0675	0.0800	0.0151	0.0	0.0	1280.62
145	NHTS-SE	30	NB S1	0.0603	0.0885	0.0234	63.0	24.0	938.44
146	NHTS-SE	34	ARF	0.0514	0.4801	0.1063	0.0	0.0	2179.29
147	NHTS-SE	32	NB S3	0.0447	0.0763	0.0214	14.0	7.0	802.59
148	NHTS-SE	35	NB S2	0.0433	0.0745	0.0197	9.0	5.0	693.19
149	NHTS-SE	36	NB B1	0.0398	0.1059	0.0226	0.0	0.0	686.33

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
150	NHTS-SE	37	ONB	0.0274	0.4325	-0.0000	0.0	0.0	36869.95
151	NHTS-SE	38	OLR	0.0108	0.0154	0.0083	0.0	0.0	2448.38
152	NHTS-SW	1	DS-RF	0.4643	0.7807	0.6864	151.0	80.0	99704.80
153	NHTS-SW	2	WV-RF	0.4595	0.7790	0.6819	151.0	80.0	102847.74
154	NHTS-SW	4	RF S3	0.4211	0.7587	0.6553	21.0	14.0	3345.15
155	NHTS-SW	8	LR S3	0.4048	0.6290	0.4918	18.0	14.0	608.19
156	NHTS-SW	11	LR S1	0.4021	0.6386	0.5018	47.0	22.0	1398.39
157	NHTS-SW	9	DT S1	0.3939	0.7632	0.6747	54.0	25.0	433.37
158	NHTS-SW	7	RF S1	0.3920	0.7454	0.6343	54.0	26.0	3677.16
159	NHTS-SW	10	DT S3	0.3859	0.7514	0.6591	13.0	8.0	310.39
160	NHTS-SW	18	DT S2	0.3818	0.7484	0.6551	8.0	7.0	242.74
161	NHTS-SW	3	DS-LGBM	0.3584	0.7827	0.6970	93.0	19.0	85107.34
162	NHTS-SW	5	DS-BATCH	0.3574	0.7789	0.6934	93.0	19.0	7613.78
163	NHTS-SW	6	WV-LGBM	0.3568	0.7873	0.7012	93.0	19.0	104524.58
164	NHTS-SW	12	WV-BATCH	0.3557	0.7833	0.6984	93.0	19.0	7228.98
165	NHTS-SW	20	DT B2	0.3469	0.6540	0.5398	0.0	0.0	249.26
166	NHTS-SW	17	LR S2	0.3442	0.6132	0.4684	9.0	7.0	551.88
167	NHTS-SW	16	LGBM S2	0.3391	0.7721	0.6808	1.0	0.0	596.61
168	NHTS-SW	13	LGBM S3	0.3391	0.7721	0.6808	6.0	0.0	928.74
169	NHTS-SW	19	LGBM B1	0.3391	0.7721	0.6808	0.0	0.0	4628.27
170	NHTS-SW	14	LGBM S1	0.3364	0.7710	0.6793	38.0	1.0	5438.19
171	NHTS-SW	15	RF S2	0.2992	0.7069	0.5762	7.0	5.0	3343.71
172	NHTS-SW	22	LR B2	0.2783	0.5194	0.3395	0.0	0.0	1243.45
173	NHTS-SW	21	DT B1	0.2543	0.6982	0.5878	0.0	0.0	524.11
174	NHTS-SW	23	RF B2	0.2289	0.6303	0.4847	0.0	0.0	4704.03

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
175	NHTS-SW	28	RF B1	0.2110	0.6742	0.5250	0.0	0.0	4091.52
176	NHTS-SW	25	LR B1	0.2108	0.4252	0.2500	0.0	0.0	814.19
177	NHTS-SW	24	LGBM B2	0.1787	0.5422	0.3811	0.0	0.0	5410.17
178	NHTS-SW	27	SRP	0.1613	0.6864	0.5467	0.0	0.0	79355.50
179	NHTS-SW	29	DS-ONLINE	0.0803	0.4301	0.1710	0.0	0.0	109513.14
180	NHTS-SW	26	WV-ONLINE	0.0711	0.4591	0.1493	0.0	0.0	109645.59
181	NHTS-SW	31	HAT	0.0637	0.2021	0.0831	0.0	0.0	57760.73
182	NHTS-SW	34	ARF	0.0611	0.4957	0.1767	0.0	0.0	2899.39
183	NHTS-SW	35	NB S2	0.0565	0.0819	0.0279	9.0	4.0	727.22
184	NHTS-SW	30	NB S1	0.0554	0.0750	0.0270	58.0	25.0	691.29
185	NHTS-SW	32	NB S3	0.0534	0.0674	0.0267	17.0	9.0	639.35
186	NHTS-SW	36	NB B1	0.0506	0.0837	0.0285	0.0	0.0	937.72
187	NHTS-SW	33	NB B2	0.0470	0.0571	0.0185	0.0	0.0	704.75
188	NHTS-SW	37	ONB	0.0263	0.4074	-0.0000	0.0	0.0	38147.17
189	NHTS-SW	38	OLR	0.0114	0.0152	0.0083	0.0	0.0	3322.76
190	NHTS-W	10	DT S3	0.4848	0.7722	0.6836	28.0	14.0	566.05
191	NHTS-W	1	DS-RF	0.4532	0.7744	0.6654	187.0	96.0	143264.35
192	NHTS-W	9	DT S1	0.4527	0.7682	0.6780	50.0	25.0	594.09
193	NHTS-W	2	WV-RF	0.4353	0.7687	0.6537	187.0	96.0	141365.07
194	NHTS-W	15	RF S2	0.4173	0.7470	0.6217	20.0	17.0	4178.44
195	NHTS-W	4	RF S3	0.4173	0.7470	0.6217	30.0	17.0	4214.24
196	NHTS-W	11	LR S1	0.4115	0.6556	0.5178	47.0	29.0	897.65
197	NHTS-W	8	LR S3	0.4095	0.6627	0.5189	21.0	12.0	902.13
198	NHTS-W	7	RF S1	0.3808	0.7412	0.6121	66.0	34.0	4245.50
199	NHTS-W	17	LR S2	0.3802	0.6363	0.4906	9.0	6.0	628.01

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
200	NHTS-W	20	DT B2	0.3685	0.6631	0.5399	0.0	0.0	421.93
201	NHTS-W	18	DT S2	0.3432	0.6910	0.5743	0.0	0.0	198.67
202	NHTS-W	21	DT B1	0.3390	0.6877	0.5709	0.0	0.0	559.44
203	NHTS-W	5	DS-BATCH	0.3204	0.7635	0.6590	99.0	8.0	7590.45
204	NHTS-W	3	DS-LGBM	0.3200	0.7661	0.6615	99.0	8.0	123308.00
205	NHTS-W	14	LGBM S1	0.3175	0.7481	0.6406	36.0	4.0	2099.50
206	NHTS-W	12	WV-BATCH	0.3072	0.7589	0.6516	99.0	8.0	8258.08
207	NHTS-W	6	WV-LGBM	0.3064	0.7638	0.6556	99.0	8.0	110823.18
208	NHTS-W	16	LGBM S2	0.3024	0.7546	0.6454	3.0	0.0	976.63
209	NHTS-W	13	LGBM S3	0.3024	0.7546	0.6454	13.0	0.0	2646.26
210	NHTS-W	19	LGBM B1	0.3024	0.7546	0.6454	0.0	0.0	5477.02
211	NHTS-W	22	LR B2	0.2538	0.4007	0.2539	0.0	0.0	953.67
212	NHTS-W	27	SRP	0.2096	0.7146	0.5687	0.0	0.0	96165.77
213	NHTS-W	23	RF B2	0.1970	0.6438	0.4712	0.0	0.0	4565.17
214	NHTS-W	25	LR B1	0.1921	0.4242	0.2373	0.0	0.0	1291.27
215	NHTS-W	24	LGBM B2	0.1831	0.5814	0.4264	0.0	0.0	4757.49
216	NHTS-W	28	RF B1	0.1465	0.6215	0.3937	0.0	0.0	5196.77
217	NHTS-W	29	DS-ONLINE	0.0739	0.3853	0.1586	0.0	0.0	133554.11
218	NHTS-W	33	NB B2	0.0723	0.0575	0.0176	0.0	0.0	885.35
219	NHTS-W	31	HAT	0.0717	0.2745	0.1379	0.0	0.0	52504.42
220	NHTS-W	26	WV-ONLINE	0.0656	0.4623	0.1293	0.0	0.0	131808.03
221	NHTS-W	30	NB S1	0.0605	0.0861	0.0297	64.0	17.0	1177.87
222	NHTS-W	32	NB S3	0.0554	0.0774	0.0256	25.0	11.0	966.08
223	NHTS-W	35	NB S2	0.0552	0.0815	0.0266	13.0	7.0	887.78
224	NHTS-W	36	NB B1	0.0465	0.0752	0.0194	0.0	0.0	662.44
225	NHTS-W	34	ARF	0.0455	0.4828	0.0712	0.0	0.0	2759.94

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
226	NHTS-W	37	ONB	0.0284	0.4553	0.0000	0.0	0.0	33103.23
227	NHTS-W	38	OLR	0.0135	0.0327	0.0150	0.0	0.0	2684.69
228	NTS	6	WV-LGBM	0.5415	0.6787	0.4374	141.0	39.0	2601.83
229	NTS	5	DS-BATCH	0.5412	0.6642	0.4229	57.0	24.0	1314.61
230	NTS	3	DS-LGBM	0.5397	0.6655	0.4257	141.0	39.0	2706.23
231	NTS	12	WV-BATCH	0.5386	0.6658	0.4241	57.0	24.0	1192.17
232	NTS	2	WV-RF	0.5345	0.6782	0.4312	183.0	57.0	16451.08
233	NTS	14	LGBM S1	0.5343	0.6602	0.4141	54.0	16.0	354.19
234	NTS	1	DS-RF	0.5324	0.6673	0.4226	183.0	57.0	16392.98
235	NTS	13	LGBM S3	0.5299	0.6571	0.4087	25.0	11.0	313.80
236	NTS	7	RF S1	0.5260	0.6628	0.4108	53.0	15.0	4568.37
237	NTS	4	RF S3	0.5202	0.6587	0.4056	25.0	7.0	3900.09
238	NTS	16	LGBM S2	0.5107	0.6465	0.3880	2.0	2.0	281.23
239	NTS	24	LGBM B2	0.5059	0.6253	0.3754	0.0	0.0	3280.94
240	NTS	15	RF S2	0.4916	0.6415	0.3790	2.0	2.0	4200.99
241	NTS	23	RF B2	0.4855	0.6218	0.3626	0.0	0.0	4014.39
242	NTS	8	LR S3	0.4813	0.6437	0.3724	25.0	12.0	225.38
243	NTS	26	WV-ONLINE	0.4806	0.6393	0.3673	0.0	0.0	1184.56
244	NTS	11	LR S1	0.4668	0.6357	0.3539	53.0	24.0	267.63
245	NTS	17	LR S2	0.4547	0.6362	0.3639	2.0	1.0	166.85
246	NTS	22	LR B2	0.4403	0.6026	0.3220	0.0	0.0	143.17
247	NTS	32	NB S3	0.4280	0.5330	0.2650	24.0	9.0	213.61
248	NTS	10	DT S3	0.4236	0.5380	0.2513	24.0	11.0	167.05
249	NTS	9	DT S1	0.4235	0.5360	0.2513	53.0	23.0	207.70
250	NTS	30	NB S1	0.4233	0.5268	0.2572	52.0	15.0	270.74

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
251	NTS	20	DT B2	0.4104	0.5138	0.2319	0.0	0.0	105.36
252	NTS	33	NB B2	0.4072	0.5040	0.2351	0.0	0.0	155.73
253	NTS	29	DS-ONLINE	0.3751	0.6511	0.3742	0.0	0.0	1313.52
254	NTS	27	SRP	0.3748	0.6486	0.3625	0.0	0.0	1091.14
255	NTS	34	ARF	0.3727	0.6766	0.3961	0.0	0.0	1152.61
256	NTS	35	NB S2	0.3643	0.4481	0.2106	0.0	0.0	176.59
257	NTS	36	NB B1	0.3643	0.4481	0.2106	0.0	0.0	147.09
258	NTS	25	LR B1	0.3633	0.6037	0.2988	0.0	0.0	132.41
259	NTS	28	RF B1	0.3555	0.5957	0.2969	0.0	0.0	4155.82
260	NTS	19	LGBM B1	0.3552	0.5817	0.2852	0.0	0.0	4552.39
261	NTS	21	DT B1	0.3492	0.4916	0.1784	0.0	0.0	141.69
262	NTS	18	DT S2	0.3488	0.4899	0.1753	0.0	0.0	123.73
263	NTS	37	ONB	0.3477	0.5436	0.2793	0.0	0.0	153.35
264	NTS	31	HAT	0.2724	0.4438	0.1682	0.0	0.0	473.12
265	NTS	38	OLR	0.1799	0.5534	0.0026	0.0	0.0	80.24
266	Ohio	5	DS-BATCH	0.2242	0.8724	0.6808	50.0	8.0	1074.72
267	Ohio	3	DS-LGBM	0.2239	0.8728	0.6824	94.0	9.0	7419.69
268	Ohio	14	LGBM S1	0.2173	0.8674	0.6678	34.0	2.0	1732.27
269	Ohio	10	DT S3	0.2164	0.8233	0.5893	13.0	9.0	1722.45
270	Ohio	12	WV-BATCH	0.2156	0.8686	0.6684	50.0	8.0	1004.59
271	Ohio	6	WV-LGBM	0.2146	0.8707	0.6685	94.0	9.0	7295.75
272	Ohio	9	DT S1	0.2138	0.8192	0.5756	34.0	17.0	1782.37
273	Ohio	16	LGBM S2	0.2130	0.8664	0.6623	4.0	0.0	193.32
274	Ohio	13	LGBM S3	0.2130	0.8664	0.6623	15.0	0.0	1501.06
275	Ohio	19	LGBM B1	0.2130	0.8664	0.6623	0.0	0.0	2354.07

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
276	Ohio	8	LR S3	0.2068	0.8412	0.6110	12.0	7.0	1726.50
277	Ohio	1	DS-RF	0.2059	0.8712	0.6601	124.0	52.0	16161.06
278	Ohio	18	DT S2	0.2051	0.8179	0.5756	3.0	2.0	111.39
279	Ohio	4	RF S3	0.2051	0.8706	0.6581	16.0	7.0	4002.08
280	Ohio	11	LR S1	0.2021	0.8376	0.6024	36.0	17.0	1992.12
281	Ohio	22	LR B2	0.2014	0.8155	0.5206	0.0	0.0	99.06
282	Ohio	7	RF S1	0.2002	0.8659	0.6421	38.0	18.0	4093.52
283	Ohio	21	DT B1	0.1975	0.8189	0.5752	0.0	0.0	81.40
284	Ohio	2	WV-RF	0.1970	0.8658	0.6390	124.0	52.0	15978.95
285	Ohio	23	RF B2	0.1961	0.8478	0.5767	0.0	0.0	1841.63
286	Ohio	17	LR S2	0.1877	0.8159	0.5585	3.0	2.0	153.50
287	Ohio	20	DT B2	0.1873	0.7963	0.5039	0.0	0.0	73.81
288	Ohio	15	RF S2	0.1871	0.8600	0.6269	5.0	5.0	2372.49
289	Ohio	27	SRP	0.1771	0.8658	0.6481	0.0	0.0	4149.69
290	Ohio	25	LR B1	0.1756	0.7879	0.4946	0.0	0.0	104.80
291	Ohio	26	WV-ONLINE	0.1660	0.8439	0.5689	0.0	0.0	2411.53
292	Ohio	28	RF B1	0.1636	0.8503	0.5969	0.0	0.0	2262.79
293	Ohio	29	DS-ONLINE	0.1619	0.8465	0.5773	0.0	0.0	2506.60
294	Ohio	24	LGBM B2	0.1616	0.7557	0.4283	0.0	0.0	1925.58
295	Ohio	34	ARF	0.1573	0.8483	0.5806	0.0	0.0	722.21
296	Ohio	38	OLR	0.1217	0.7947	0.4823	0.0	0.0	176.67
297	Ohio	37	ONB	0.1131	0.8156	0.4839	0.0	0.0	1170.22
298	Ohio	31	HAT	0.0780	0.3376	0.1058	0.0	0.0	1858.16
299	Ohio	33	NB B2	0.0711	0.3344	0.0759	0.0	0.0	141.96
300	Ohio	35	NB S2	0.0629	0.2798	0.0848	7.0	2.0	200.55
301	Ohio	32	NB S3	0.0629	0.2798	0.0848	18.0	2.0	1951.37

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
302	Ohio	30	NB S1	0.0629	0.2798	0.0848	42.0	2.0	2091.38
303	Ohio	36	NB B1	0.0598	0.3172	0.0886	0.0	0.0	161.69
304	Optima	12	WV-BATCH	0.4590	0.6110	0.3013	117.0	22.0	2541.97
305	Optima	13	LGBM S3	0.4533	0.5894	0.2905	17.0	4.0	717.30
306	Optima	5	DS-BATCH	0.4461	0.5700	0.2606	117.0	22.0	2548.02
307	Optima	6	WV-LGBM	0.4384	0.6547	0.3379	117.0	22.0	8179.01
308	Optima	3	DS-LGBM	0.4365	0.6013	0.2922	117.0	22.0	2684.22
309	Optima	16	LGBM S2	0.4286	0.5603	0.2460	51.0	8.0	926.28
310	Optima	14	LGBM S1	0.4283	0.5603	0.2460	17.0	7.0	12.04
311	Optima	18	DT S2	0.3943	0.5082	0.2047	47.0	10.0	978.93
312	Optima	1	DS-RF	0.3933	0.5978	0.2797	112.0	29.0	2997.41
313	Optima	15	RF S2	0.3915	0.5974	0.2547	49.0	8.0	1019.55
314	Optima	7	RF S1	0.3835	0.5947	0.2527	13.0	9.0	45.91
315	Optima	4	RF S3	0.3823	0.5907	0.2264	15.0	4.0	784.60
316	Optima	8	LR S3	0.3724	0.5395	0.2296	18.0	5.0	756.07
317	Optima	2	WV-RF	0.3617	0.6340	0.2725	112.0	29.0	3000.15
318	Optima	10	DT S3	0.3539	0.4627	0.1647	18.0	3.0	751.16
319	Optima	9	DT S1	0.3537	0.4693	0.1478	13.0	7.0	9.89
320	Optima	11	LR S1	0.3413	0.5139	0.1734	14.0	10.0	13.09
321	Optima	26	WV-ONLINE	0.3384	0.6137	0.2360	0.0	0.0	90.86
322	Optima	17	LR S2	0.3293	0.5161	0.1579	47.0	16.0	974.94
323	Optima	30	NB S1	0.3139	0.4830	0.1445	17.0	7.0	10.76
324	Optima	29	DS-ONLINE	0.3115	0.5700	0.2972	0.0	0.0	70.54
325	Optima	19	LGBM B1	0.3070	0.5143	0.0843	0.0	0.0	34.98
326	Optima	31	HAT	0.3057	0.5492	0.2784	0.0	0.0	43.67

	Data stream	Global rank pos.	Method abbr.	F_1 macro	Accuracy	Kappa	Drift count	Replacement count	Time [s]
327	Optima	21	DT B1	0.3048	0.4344	0.0974	0.0	0.0	2.67
328	Optima	35	NB S2	0.3030	0.4728	0.1141	50.0	11.0	974.51
329	Optima	22	LR B2	0.3002	0.4552	0.1467	0.0	0.0	2.15
330	Optima	24	LGBM B2	0.2989	0.5042	0.1263	0.0	0.0	31.50
331	Optima	32	NB S3	0.2929	0.4464	0.0892	14.0	3.0	750.43
332	Optima	25	LR B1	0.2911	0.4949	0.1185	0.0	0.0	2.86
333	Optima	20	DT B2	0.2813	0.4026	0.0965	0.0	0.0	2.17
334	Optima	23	RF B2	0.2739	0.5064	0.0941	0.0	0.0	29.85
335	Optima	37	ONB	0.2643	0.6137	0.2252	0.0	0.0	20.02
336	Optima	33	NB B2	0.2622	0.4358	0.0686	0.0	0.0	2.10
337	Optima	27	SRP	0.2340	0.5907	0.1727	0.0	0.0	135.40
338	Optima	36	NB B1	0.2161	0.4680	-0.0100	0.0	0.0	2.54
339	Optima	28	RF B1	0.1991	0.5143	-0.0218	0.0	0.0	33.54
340	Optima	34	ARF	0.1883	0.5691	0.0677	0.0	0.0	15.12
341	Optima	38	OLR	0.1495	0.2512	0.0251	0.0	0.0	7.01

Figure 1: Visualization of F_1 macro score for selected methods.