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Diversity in Ensemble Model for Classification of the Data Streams with Concept Drift

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Motivation of work

- Creation of new heterogeneous ensemble, consisting of various models trained using different base learners.
- We would like to include also the metrics to measure the diversity of the members in the ensemble.
- This metric could be used to select or improve members of model which are more diverse from other ones.

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Data stream definition

- Data stream is an unbound, ordered sequence of data elements.
- The stream elements appear from its source continuously, over time.
- Data streams may differ :
    - the format of the data elements
    - the time interval between the elements of the stream
    - the size of particular stream items
- Most of the streams are generated at high speeds.
- There are two kinds of streams: stationary and non-stationary.

Problems in processing data streams

- Limited resource for cpu, memory and time for fast predictions
    - Simpe, incremental or batch metod are used
- Phenomenon concept drift
    - Changes in data distribution in data streams
- Large volumes of data that are being continually produced at a high rate over time
- New data is constantly arriving even as the old data is being processed

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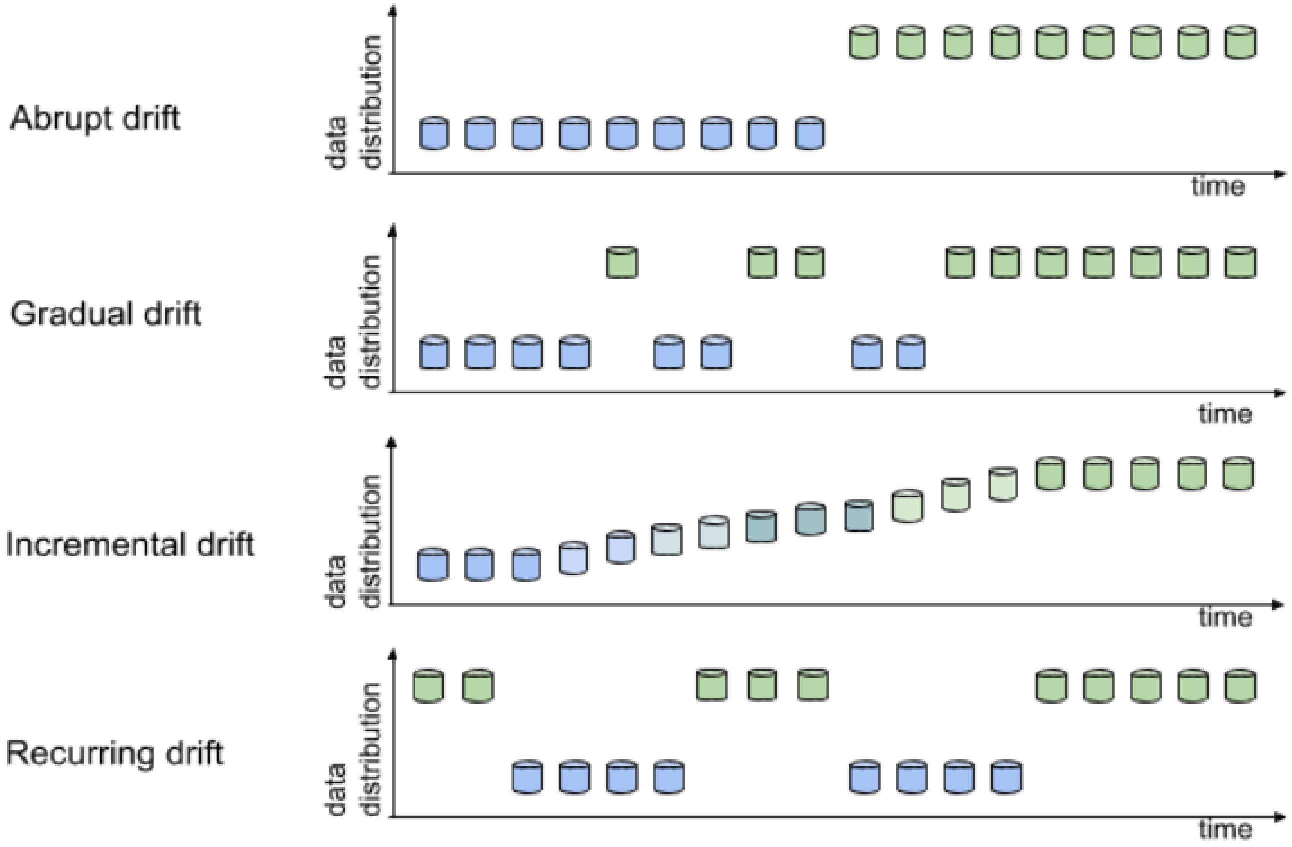
Concept drift types



Types of concept drift

Models for data stream processing

Models with drift detection

- Main idea is to detect concept drift what triggers action in model structure:
  - Update of model classifiers
  - Actual classifiers set is replaced by new one
- Popular drift detectors:
  - DDM
  - EDDM
  - ADWIN
- Example models:
  - Diversity for Dealing with Drifts (DDD)
  - OnlineBoosting (Aboost)

Ensemble models

- Based on set of multiple simple classifiers
  - Ensemble create powerful model with diverse classifiers
  - This classifiers are updated or replaced dynamically based on model performance
  - Heterogeneous or homogeneous
- Final classification is based on voting rule
  - Majority voting, Weighted voting, stacking
- Popular models
  - Accuracy Weighted Ensemble (AWE)
  - Dynamic Weighted Majority (DWM)
  - Online Bagging (OzaBagging)

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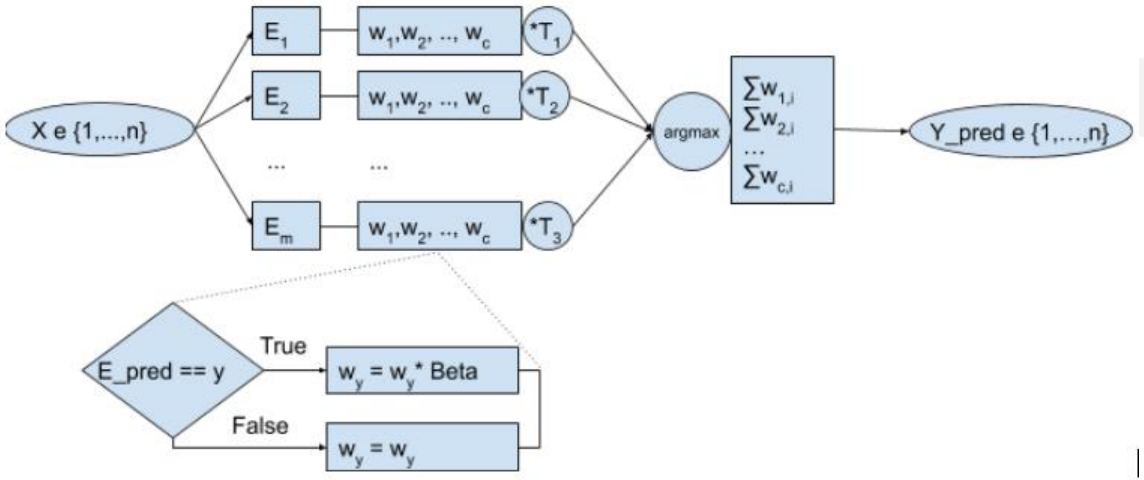
Our proposed model

Diversified Dynamic Class Weighted (DDCW)

- Heterogenous ensemble model based on simple online classificators (experts)
    - Naive Bayes, KNN, Hoeffding Tree
- Experts score is decreased based on expert life in model – number of period
- After each period the experts weights are updated based on
    - expert accuracy
    - internal metric pair diversity Q statistic (between each pair of experts)
- The size of model is dynamic
    - experts are removed according its score
    - added when overall model performance is lower



Overall scheme of the proposed ensemble model.

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DDCW – matrix of weights

- Matrix of weights is used to store weight from each expert to each target class
  - Weights are dynamically updated based on expert performance
  - One expert can predict some classes very well but others poorly
  - This makes model suitable for unbalanced data streams
- Class score
  - Contribution of experts weight to target class
- Experts score
  - Sum of experts weights

	target class #1	target class #2	target class #3	experts score
expert #1	0,1	0,2	0,2	0,5
expert #2	0,4	0,6	0,1	1,1
expert #3	0,5	0,2	0,7	1,4
class score	0,5	0,0	0,7	

Table of weight matrix

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Comparting to other models

Proposed model DDCW

- Heterogeneous – based on different classifiers
- Incremental online model with small periods
- Updating weights after each period
- Matrix of weights
- Removing old and weak expert by new one
- Internal metrics for Q stat diversity

Other ensemble models

- Mostly homogeneous – one type of classifier
- Incremental or batch type with sliding window
- Voting based or weight based
- Different types of updating weights
- Dynamic or stable ensemble models

Experiments

- In first sets of experiment, we compare DDCW model with enabled and disabled model updates based on diversity
    - Goal was to determine impact of diversity to model behaviour and performance
- The other set of experiment was about comparsion DDCW model performance with other well know models
    - Similar dynamic models (AWE, DWM)
    - More robust models (OzaBagging, OnlineBoosting)

Datasets

- Selected Datasets are from two categories:
  - Synthetic
  - Real
- Datasets covers tasks for binary and multiclass classification
- Datasets contains different types of concept drift
- We use **Gini Index** per windows of 1000 samples to visualize changes of concepts in datasets

Dataset	Dataset type	Drift type	Samples	Features	Classes
Eletricity	real	?	45 312	8	2
KDD99_10%	real	?	489 000	41	23
Stagger	synthetic	abrupt	100 000	3	2
LED	synthetic	gradual	100 000	24	10

Datasets used in the experiments.

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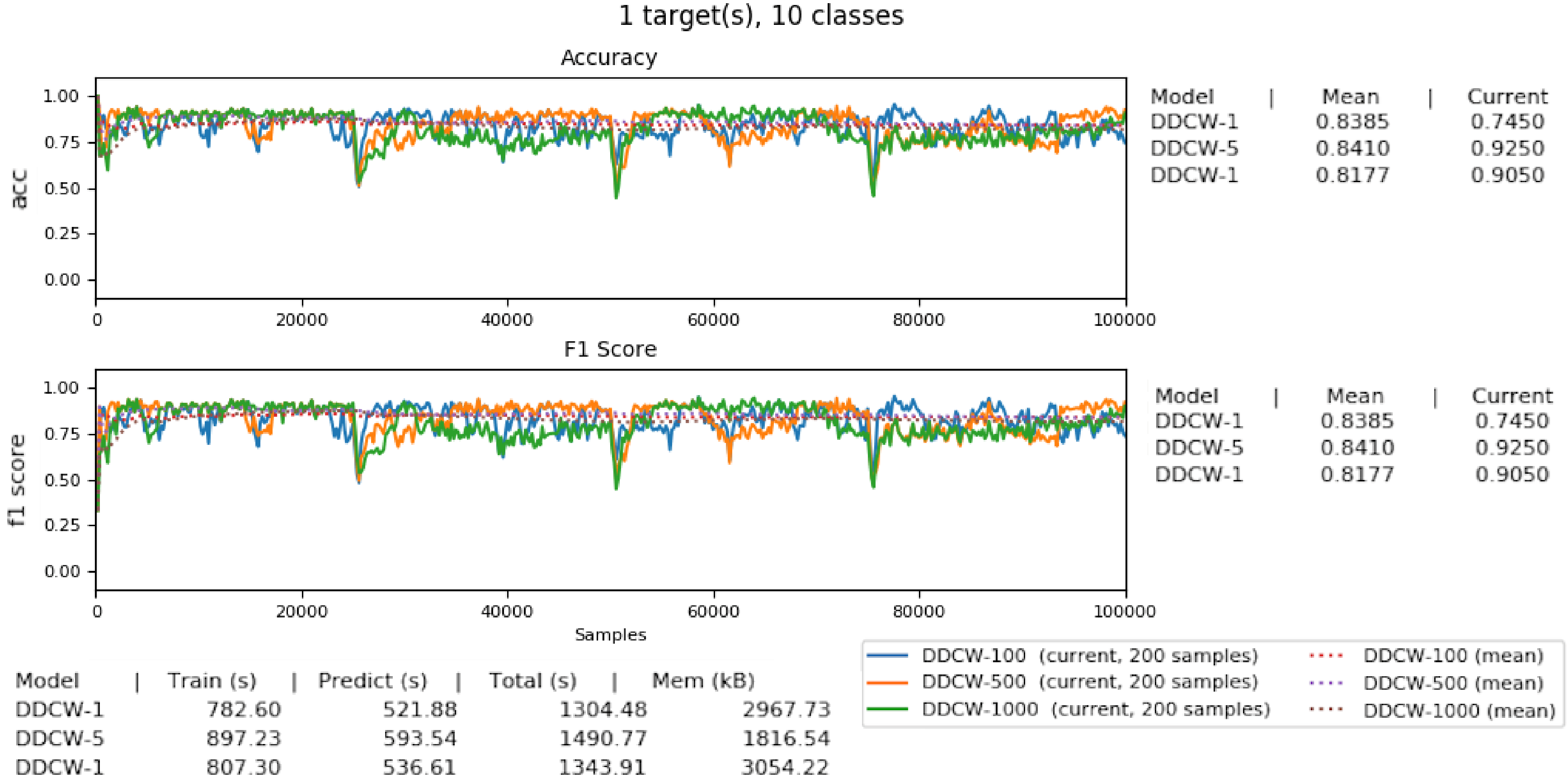
Results of experiments with changing period size of model DDCW on dataset LED



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Progress of accuracy and f1 in DDCW model with and without diversity on dataset LED

Results of comparing models in table

dataset	$p = 100$ Div acc/F1	$p = 100$ acc/F1	$p = 500$ Div acc/F1	$p = 500$ acc/F1	$p = 1000$ Div acc/F1	$p = 1000$ acc/F1
Eletricity	**0.82/0.78**	0.81/0.77	**0.81/0.76**	0.79/0.73	**0.80/0.73**	0.79/0.72
KDD99_10%	0.99/0.64	0.99/0.64	0.99/0.63	0.99/0.63	0.99/0.63	0.99/0.63
Stagger	0.94/0.95	0.94/0.95	0.94/0.94	**0.95/0.95**	**0.94/0.95**	0.94/0.94
LED	0.85/0.85	**0.86/0.86**	0.87/0.87	0.87/0.87	**0.86/0.86**	0.84/0.84

Accuracy and f1 of DDCW model with enabled and disabled diversity using different model periods.

dataset	DDCW acc/F1	DWM acc/F1	AWE acc/F1	OnlineBoosting acc/F1	OzaBagging acc/F1
Eletricity	**0.82/0.77**	0.81/0.76	0.77/0.70	0.79/0.75	0.78/0.74
KDD99_10%	**0.99/0.64**	0.98/0.51	0.43/0.05	0.99/0.64	0.99/0.63
Stagger	0.94/0.94	0.94/0.94	**0.95/0.95**	0.93/0.93	0.95/0.95
LED	0.84/0.84	0.83/0.34	**0.89/0.89**	0.85/0.85	0.84/0.84

Comparsion of accuracy and f1 metrics of evaluated ensemble models.

Conclusion

- New heterogenous ensemble model DDCW with diversity mechanism
- Various base learners – Naive Bayes, k-NN and Hoeffding tree
- Class-weighted scheme and matrix of weights

- Various experiments on multiple datasets
- Model perform better compared to other tested models

- Future plans – experiments more in depth and wide range of datasets

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Thank you