A Self-adaptive 30-day Diabetic Readmission Prediction Model based on Incremental Learning

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HOSPITAL READMISSION

Definition:

- A patient is hospitalized again after being discharged from an index (initial) admission within a specified time window.

HOSPITAL READMISSION

High frequency and high associated cost:

- In the United States, the 30-day Medicare unplanned readmission rate was **15.2%** during July 2015 to June 2016 [1].
- In England, the 28-day emergency readmission rate was **11.5%** during the fiscal year 2011 to 2012 [2].
- In 2011, hospital readmissions contributed **$41.3 billion** in **total** hospital costs in the United States [3].
- Several countries have implemented programs to financially penalize readmissions, such as England, Germany, and the United States [4].

HOSPITAL READMISSION

Predictive modeling

- Numerous predictive models have been built to:
  - Predict a patient's readmission risk.
  - Predict a hospital's readmission rate.
- Problems:
  - In two systematic reviews of **99** readmission predictive models reported between 1985 and 2015, **ALL** the models are **STATIC** [5,6].
  - The static models can get outdated because the distribution of the patient population can evolve over time and it is hard to determine the "shelf life" of the model.
  - To keep up-to-date, the models need to be re-built from scratch constantly, which can be expensive in practice.

OBJECTIVE

- Build a self-adaptive 30-day readmission prediction model, which can update itself when new data become available.
  - Incremental learning: adapt to new data and extend the existing model's knowledge without retraining.

DATA & PREPROCESSING

- A de-identified inpatient encounter dataset of diabetic patients from 130 US hospitals during 1999-2008 [7].
    - 101,766 inpatient encounters
    - 11.2% encounters with 30-day readmissions
    - 50 attributes
- The dataset was balanced by down sampling the major class (encounters without 30-day readmissions).
- 22 attributes were selected.

TOOLS & ALGORITHMS

Massive Online Analysis

- Naïve Bayes [8]
- Hoeffding Tree (VFDT) [9]
- Hoeffding Adaptive Tree [10]

PREQUENTIAL EVALUATION

- When new data instances become available, they are first used to test the model and then used to improve the model [11].
- Prequential AUC: only evaluates the classifications of the most recent instances within a sliding window of size K [12].

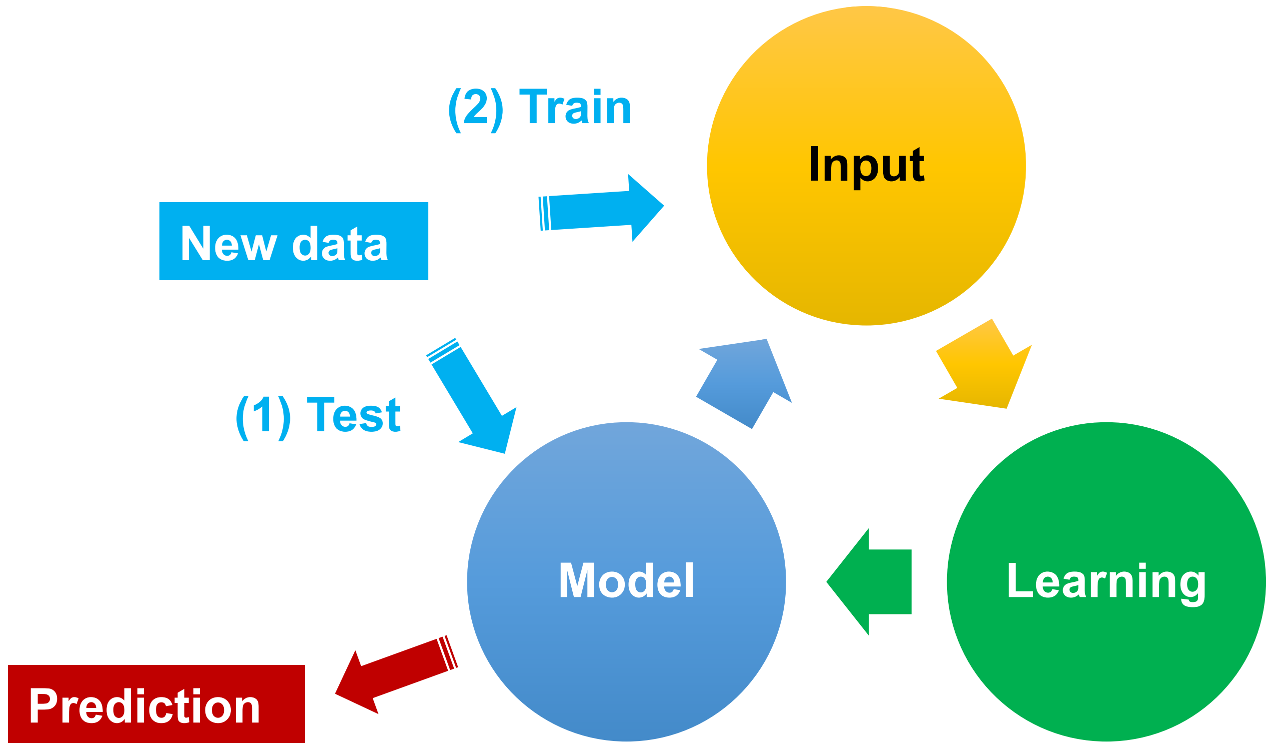
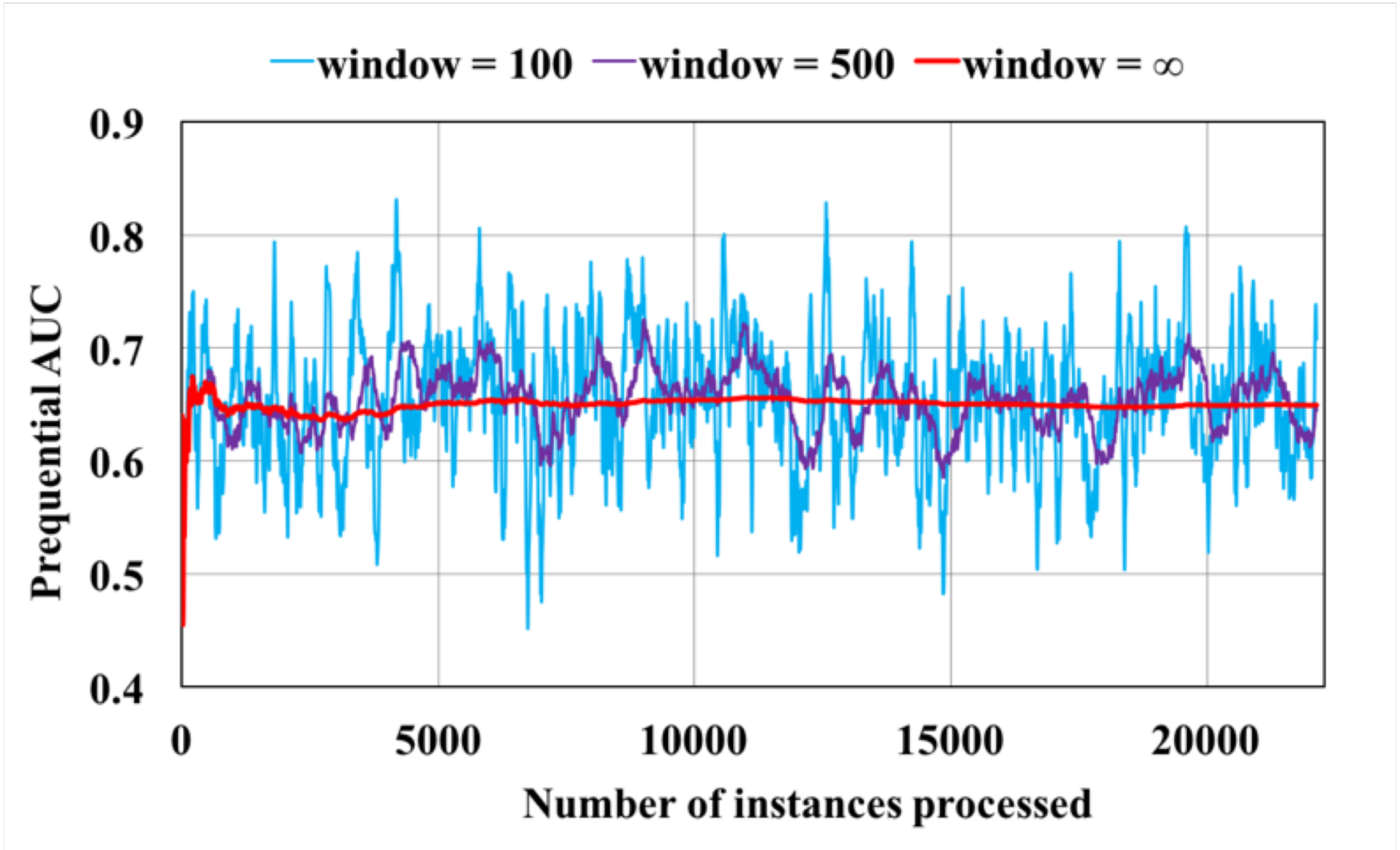


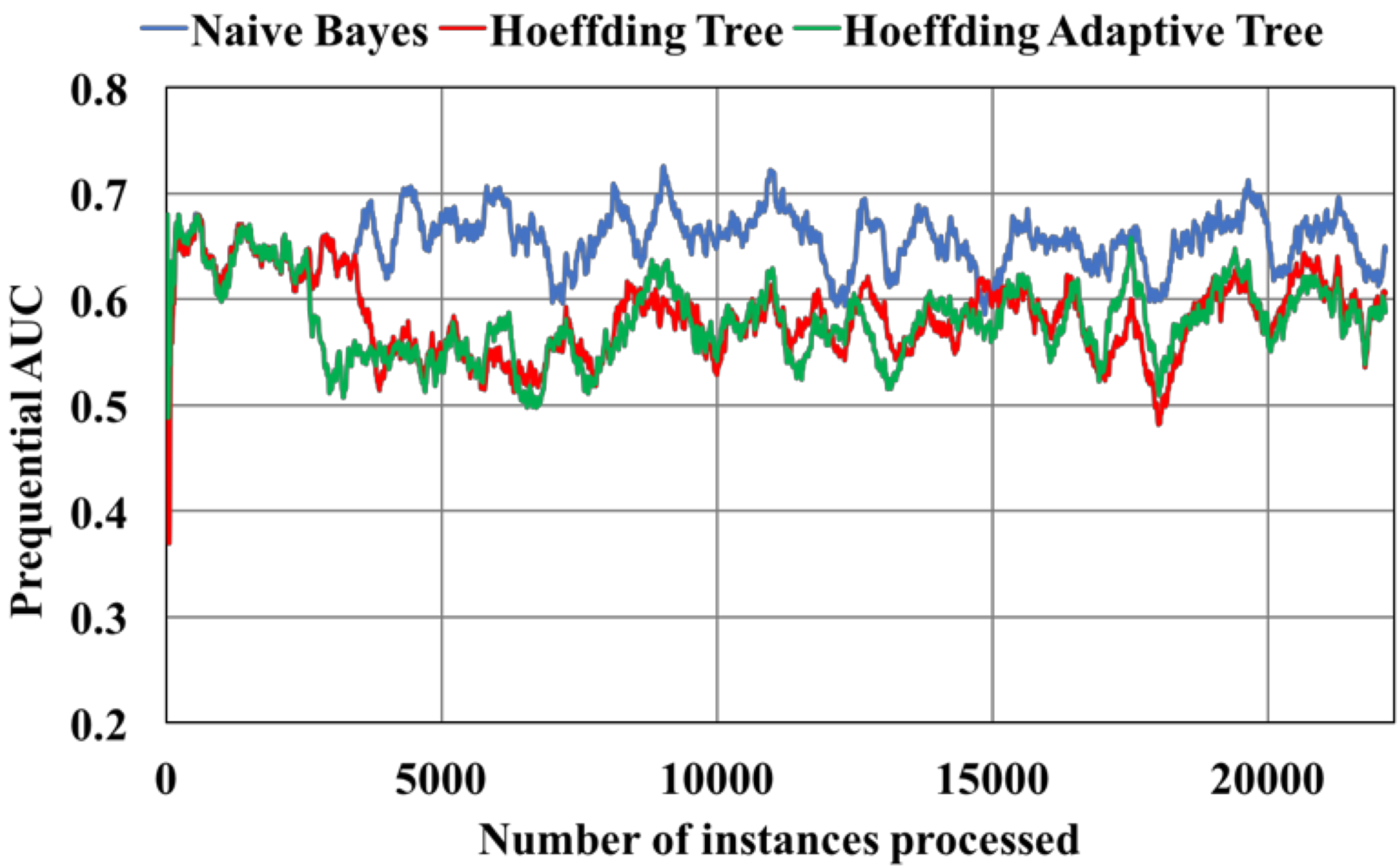
Image adapted from: https://moa.cms.waikato.ac.nz/tutorial-1-introduction-to-moa/

RESULTS



Graph 1. Effects of the sliding-window size K on the prequential AUC curves of the Naïve Bayes model.

RESULTS



Graph 2. The prequential AUC curves of the three algorithms. K = 500

RESULTS

- Benchmark: compare the performance of the self-adaptive model with a static model.

Table 1. The AUC of the incremental and static models trained with the same data.

Models	AUC
Naïve Bayes (incremental)	0.655 ± 0.078 (average)
Naïve Bayes (static)	0.660
Naïve Bayes (static) [13]	0.657

CONCLUSION

- A self-adaptive 30-day diabetic hospital readmission prediction model has been developed based on incremental learning.
- The global performance of the incremental model is nearly identical to that of the static models built with the same dataset.

ACKNOWLEDGEMENT

- PhD advisor:
  - Illhoi Yoo, PhD
- PhD committee:
  - Abu Mosa, PhD
  - Mihail Popescu, PhD
  - Suzanne Boren, PhD

Questions?

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ALGORITHMS

Naïve Bayes

$$P(C|X) = \frac{P(X|C)P(C)}{P(X)}$$

- Naturally incremental.
- Constantly updates counts according to incoming training instances.

ALGORITHMS

Hoeffding Tree (VFDT)

Choose **a** as the split attribute if: $G(a) - G(b) > \sqrt{\frac{R^2 ln\left(\frac{1}{\delta}\right)}{2n}}$

a, b	Attributes with the best and second best G
G	Information gain of choosing an attribute
R	Range of observed independent instances on a leaf
n	Number of observed independent instances on a leaf
$1 - \delta$	Confidence

- It uses a small number of instances to choose the split attribute.
- The output is nearly identical to that of a non-incremental decision tree.

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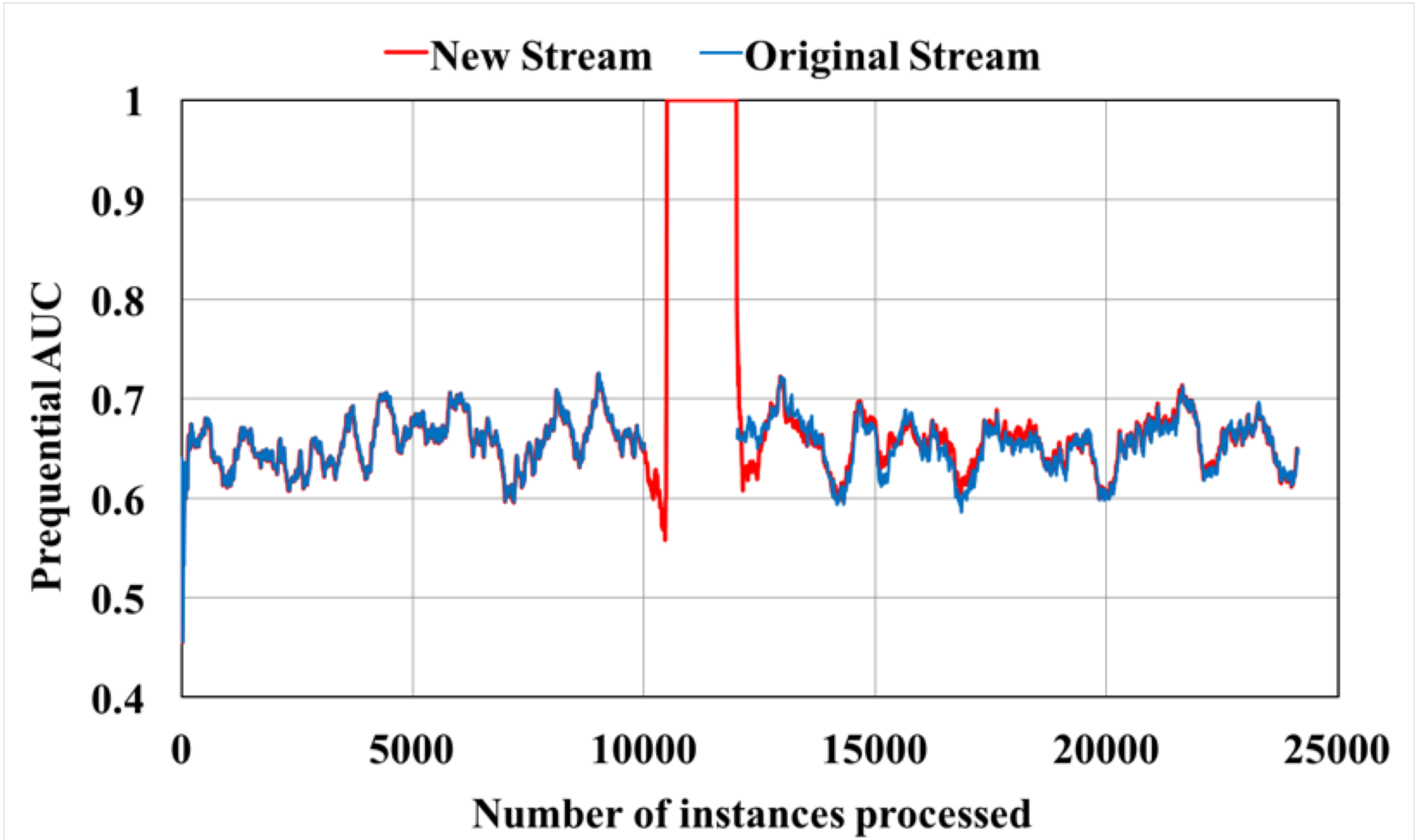
ALGORITHMS

Hoeffding Adaptive Tree

- Based on Hoeffding Tree.
- It monitors the performance of branches and replaces them with more accurate new branches if their accuracy decreases.

[1] Bifet et al. Adaptive learning from evolving data streams. Ricard Gavaldà. IDA 2009: Advances in Intelligent Data Analysis VIII pp 249-260

RESULTS



Graph 3. The prequential AUC curves of the Naïve Bayes models for the modified data stream and the original data stream. K = 500