

Data Stream Mining- Lecture 9

Novelty Detection in Data Streams

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Novelty Detection

Definition

Novelty detection refers to the identification of new concepts, change in the old concepts or the presence of noise.

Synonyms terms:

- Outlier detection
- One-class classification
- Anomaly detection

Definitions

Definition (Novelty)

Novelty is a concept represented by a group of examples sharing some characteristics.

Definition (Outlier)

A sparse, independent examples whose characteristics different from the normal examples are called outliers

Definition (Anomaly)

A novel concept which is unexpected, abnormal in a specific domain or application such fault detection, spam classification etc.

Desiderata for Novelty Detection

- ① **Principle of robustness:** A novelty detection method must be capable of robust performance on test data that maximizes the exclusion of novel samples while minimizing the exclusion of known samples.
- ② **Principle of generalization:** The system should be able to generalize without confusing generalized information as novel
- ③ **Principle of independence:** The novelty detection method should be independent of the number of features, and classes available.
- ④ **Principle of adaptability:** A system that recognizes novel samples during test should be able to use this information for learning new concepts
- ⑤ **Principle of computational complexity:** A number of novelty detection applications are online and, therefore, the computational complexity of a novelty detection mechanism should be as low as possible.

Basic Framework

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 - Not sufficient time in the case of streaming data.
 - Sometimes, labeling is expensive
- Build model in *Offline* phase using a small amount of labeled data.
- Use model to predict the new data point

But, how does the *novelty and concept-drifts* are handled?

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But, how does the *novelty and concept-drifts* are handled?

- ➊ First create micro-clusters using initial-set of labeled data
- ➋ Then, for each incoming data point, calculate its distance from the centroid of the micro-clusters. If the distance is more than a user-specified threshold, put in a buffer and after a enough number of points, declare as novelty.

Online Clustering for Novelty Detection and Concept Drift in Data Streams [Garcia et al., 2019]

The algorithm proposed in the above is called **Higia**.

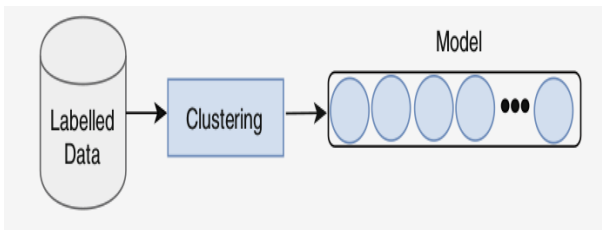


Figure: Higia Offline

Contd...

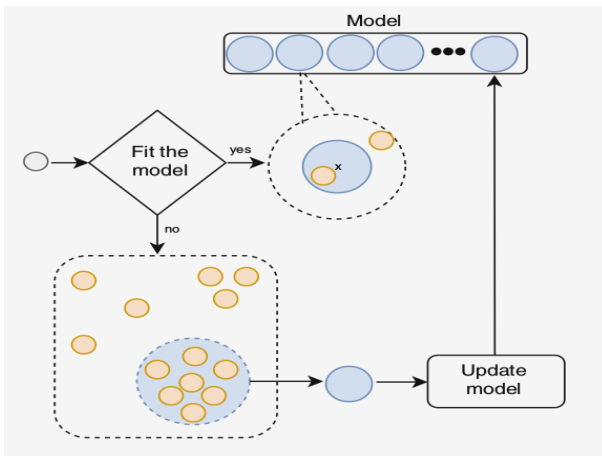


Figure: Higgs Online

Contd...

Algorithm 1. Higia: Online Phase

- 1: **input:** X_{tr} , T , k
- 2: Let ψ_k be a list of the k nearest micro-clusters to X_{tr}
- 3: **if** majority of ψ_k have the same label **then**
- 4: Let C_j be the nearest micro-cluster to X_{tr}
- 5: Let c_j be the centroid of C_j
- 6: Let $radius(C_j)$ be the radius of C_j
- 7: $dist \leftarrow EuclidianDistance(X_{tr}, C_j)$
- 8: **if** $dist \leq radius(C_j)$ **then**
- 9: update C_j with X_{tr}
- 10: classify X_{tr} with the same label of C_j
- 11: **else if** $dist \leq (radius(C_j) \times T)$ **then**
- 12: create extension of C_j with centroid X_{tr} and radius 0.5
- 13: classify X_{tr} with the same label of C_j
- 14: **else**
- 15: add X_{tr} to buffer
- 16: classify X_{tr} as unknown

Some results

Statistics	1CDT	MOA	Gear	UG	SynD	Forest Cover
Attributes	2	4	2	2	10	54
Classes	2	4	2	2	2	7
Normal classes	1	2	2	1	2	3
New classes	1	2	0	1	0	4
Instances MinCla	7199	9987	99935	44999	124660	587
Instances MajCla	7200	18180	100065	45000	125340	18350

Figure: Data set

Some results

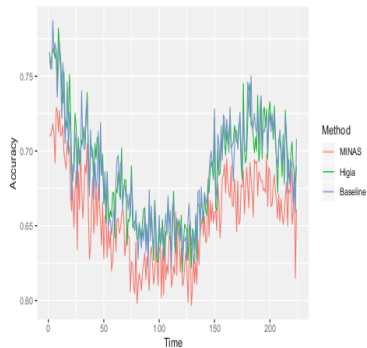
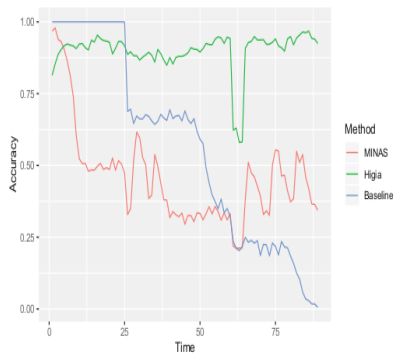


Figure: Accuracy over time

Some results

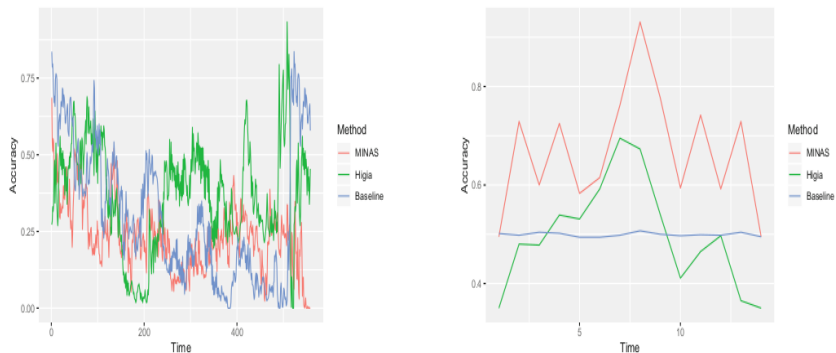


Figure: Accuracy over time

Bibliography I



Garcia, K. D., Poel, M., Kok, J. N., and de Carvalho, A. C. (2019).
Online clustering for novelty detection and concept drift in data streams.
In EPIA Conference on Artificial Intelligence, pages 448–459. Springer.