

# Data Stream Mining

**GE461: Introduction to Data Science**

**FAZLI CAN**

**Computer Engineering Department**

**Bilkent University**

**April 28 & May 8, 2025**



# Outline

- 1. Is Future Today?**
- 2. Data stream mining**
- 3. Concept drift & Adversarial Attacks**
- 4. Data stream classification: Ensemble approach**
- 5. Measuring diversity in ensembles**
- 6. Effectiveness measures for Prediction**
- 7. Frameworks – Research Opportunities**

# Questions? Anytime is OK



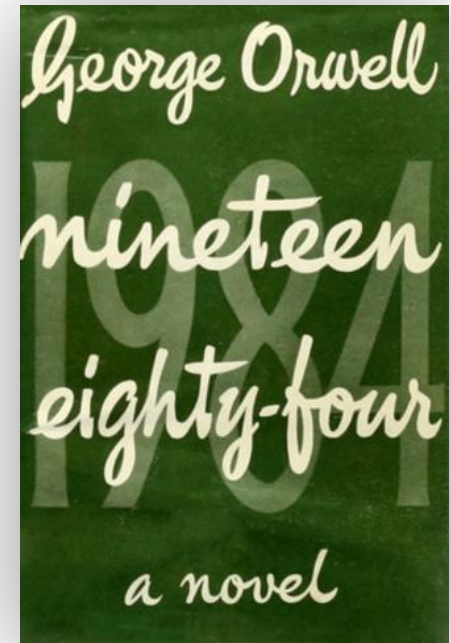
# Future: Dystopia?

## *Mad Max: Fury Road* (2015)



# Is Tomorrow Today?

We are Prisoners of Our Inventions: No Privacy



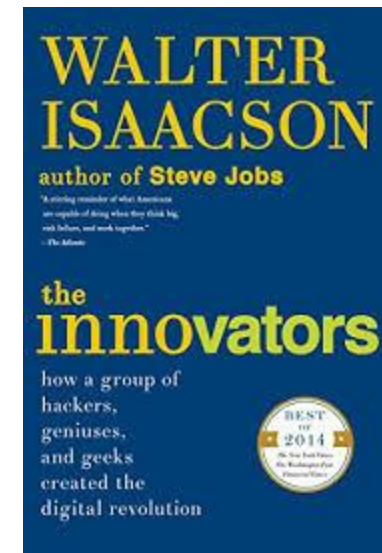
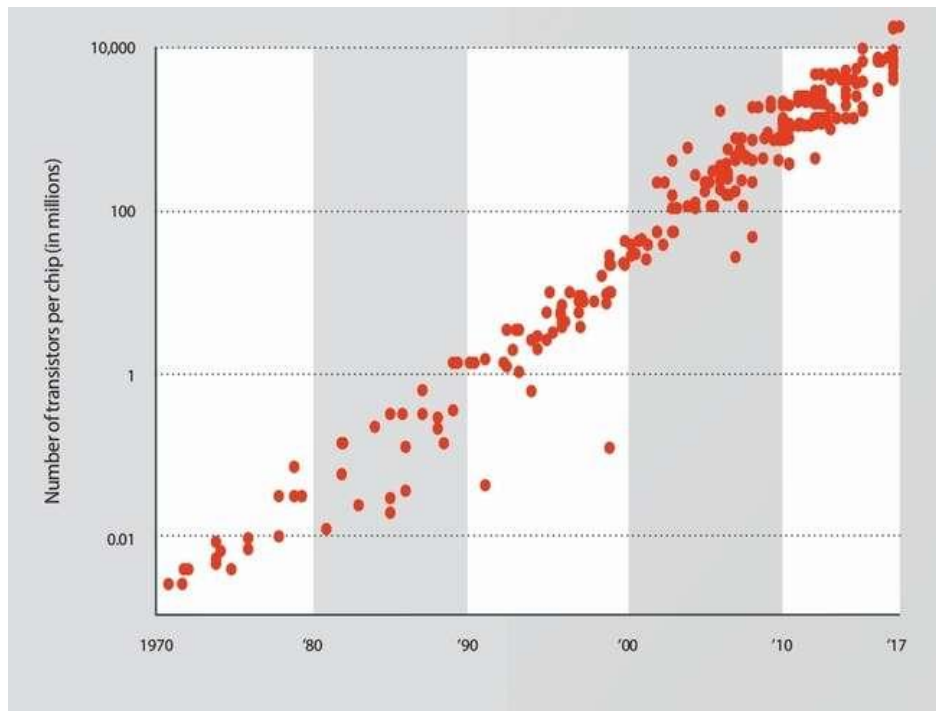
# Personalization: Google



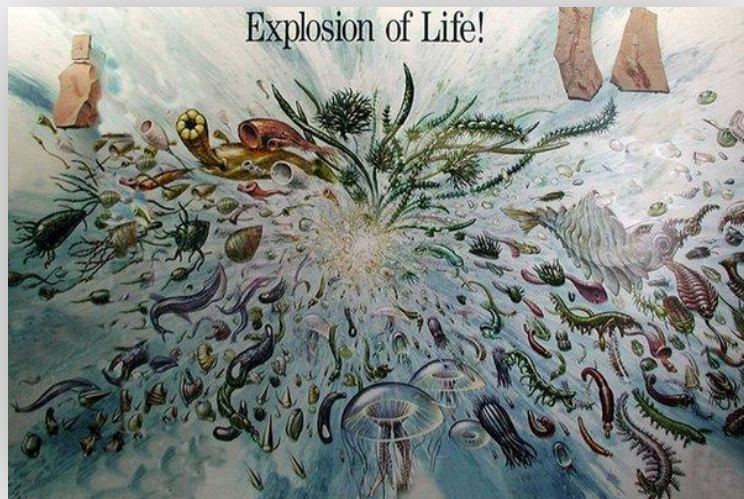
Eric Schmidt  
Was technical Advisor to Alphabet:

- “Google search will continue to become more personalized.”
- Google combines several signals: Page rank, click, similarity, ...
- “Sadece adımı bilmen yeter: Adım Alper.”

# von Neumann, Moore's Law... From Stored Program Concept To ... ?



# “A New Golden Age of Computer Architectures”: Hennessy & Patterson



Opabinia

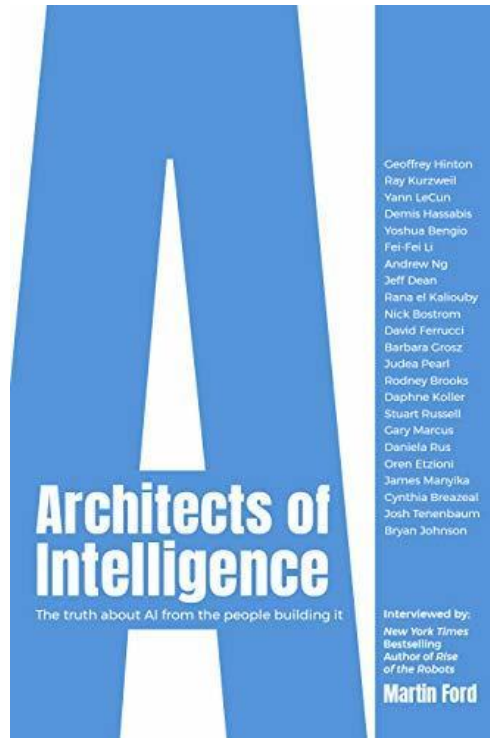
cloud.google.com > ... > Cloud TPU > Documentation  
[Cloud Tensor Processing Units \(TPUs\) | Cloud TPU | Google ...](#)  
Cloud TPU enables you to run your **machine learning** workloads on **Google's** ... The TensorFlow server running on the host machine (the **CPU** attached to the ...

John L. Hennessy, David A. Patterson: A new golden age for computer architecture. *Commun. ACM* 62(2): 48-60 (2019).



# Book Recommendation

## *Architects of Intelligence*, Martin Ford



Opabinia

# Each Person Creates Multiple Data Streams

- I was talking about my foot pain 2 hours later I received a WebMD email about reasons for foot pain. We provide too much information about ourselves in our web searches, skype conversations, etc.

- Foot pain
- Face pain
- How old is ...?



# Three Vs of Data Streams

- Velocity
- Variety
- Volume



Big data what is big data 3 Vs of big data volume, velocity and variety  
day 2 of 21, <https://blog.sqlauthority.com/2013/10/02/big-data-what-is-big-data-3-vs-of-big-data-volume-velocity-and-variety-day-2-of-21/>

# What is Data Stream?

- Data stream is a sequence of temporal data.
- Sources : news portals, social media, stock market data (Twitter, Facebook, ...)
- Data types : image, text, signal,  
anything in digital form

# Data Stream Types

- Social media posts
- Stock tickers
- Sensor data
- News articles
- Intelligence reports
- Customer feedback
- Web clicks
- ...

# Data Stream Characteristics

- Temporal
- Unbounded
- Time Constraint: See *Flash Boys*
- Memory Constraint
- Concept drift
- Evolving: Concept drift, new classes, new features, missing features, missing data items
- Adversarial attacks
- Measuring Effectiveness: Interleaved-Test-then-Train

# Data Stream Characteristics

- Continuous flow (data arrives over time)
- Huge amount of data (infinite data items)
- Data distribution may change over time
- Batch learning vs. incremental online learning
- Rapid arrival rate

# Verizon

## <https://www.marketsmedia.com/>

- Frequent Trades
- New York – Chicago: under 15 ms
- With Light Speed? 13.3 ms

04.02.2013  
By Terry Flanagan

Banks

### Chicago-New York Link Edges Closer to Speed of Light

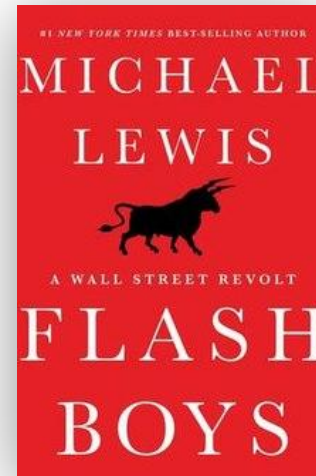
Share this on:



A direct high speed trading link between Chicago and New York will cut the round trip time by more than half a millisecond, to just under 15 milliseconds.

That's a significant boost, given that it takes light 13.3 milliseconds to travel from Chicago to New York and back again.

The link, constructed by Verizon, will connect CME Group's data center in Aurora, Ill. to New York metro financial markets, offering an ultra-low latency round-trip route that bypasses traditional area "data hotels."





# Data Stream Mining: Four Major Problems

1. Class prediction: What is it?
2. Concept drift: Evolving data items and relationships
3. Evolving classes: New classes, Dying Classes
4. Adversarial attacks: Making the learner learn incorrectly

# Data Stream Mining Problems

## 1. Class Prediction

- Unary: From us vs. not from us (anomaly detection)
- Multi-class: Choose one out of many (comedy)
- Multi-label: Choose more than one out of many (comedy, action, spy, drama...)

# Data Stream Mining:

## 2. Concept Drift Detection

- Y: Output, X: input,  $P(Y/X)$ : class prediction for X
- Real Concept Drift
  - Classification boundary changes (X remains the same,  $P(Y/X)$  changes)
    - Esad → Esed
    - David Lean movie: *Bridge over the River Kwai*
- Virtual Concept
  - Data items of a class change: Virtual Concept Drift
    - For people definition of beauty changes



# What is It?

## Real Concept Drift

- Concept drift is the change in the relationships between input and output data in the underlying problem over time.

Decision:  $P(Y/X)$ , Input:  $P(X)$

- Real Concept Drift:

A user may be interested in a movie genre and become uninterested later.

X: Input (genre) remains the same

Y: Output (class) changes

In politics it happens a lot (Esad vs. Esed)

# What is It?

## Virtual Concept Drift

- $P(Y/X)$ , Input:  $P(X)$
- Virtual Concept Drift:

165 cm: definition of tall man in 19<sup>th</sup> century

175 cm: definition of tall man in 20<sup>th</sup> century

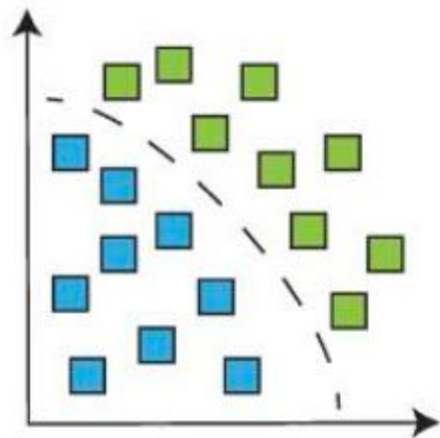
185 cm: definition of tall man in 21<sup>st</sup> century

X: Input changes

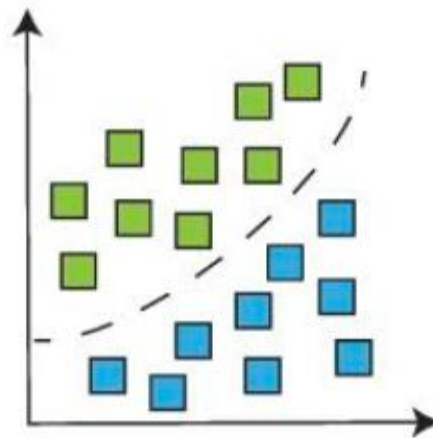
Y: Output remains the same

# Data Stream Mining:

## 2. Concept Drift Detection



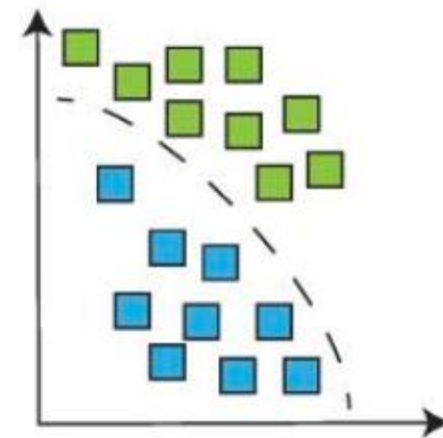
Original Data



Real Concept Drift

- change in  $p(y|X)$

**Decision boundary changes**



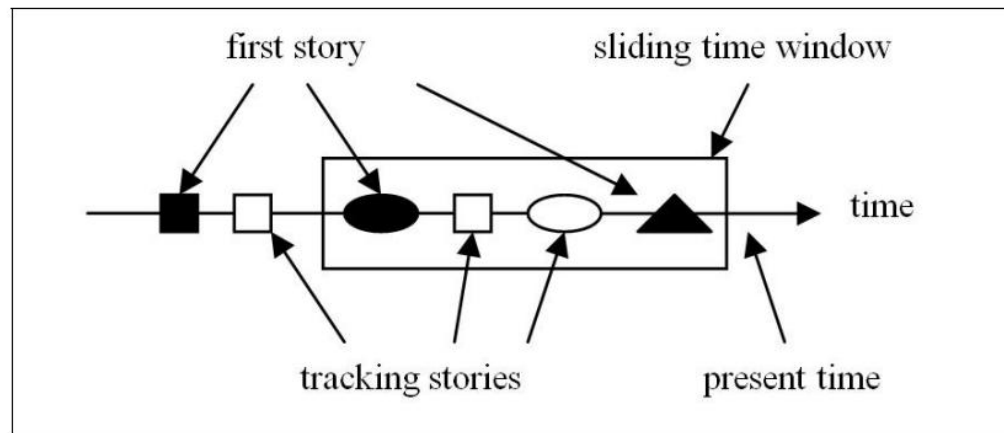
Virtual Drift

- change in  $p(X)$  but not  $p(y|X)$

**Input characteristics changes**

# Data Stream Mining: 3. Evolving Classes

- Discover new patterns: New classes
- New Becomes Old: New event detection and tracking



# Data Stream Mining:

## 4. Adversarial Attacks

- With a small perturbation Panda prediction of 57.7% confidence is predicted as Gibbon with 99.3% confidence.

Goodfellow et al. Explaining and harnessing adversarial examples, ICTIR 2015 Conf.





# Data Stream Processing

- Destination: human or application
- Personalized vs. public
- What is the intended use: summarization...
- Flow size and time constraint
- Scalability: Centralized vs. distributed
- Congestion: Resource adaptive
- Dynamic/incremental processing

# Data Stream Classification

- Updated Data Feeding
- Scheduled Feeding of Ensemble Members
- Add/Drop Classifiers
- Feature Regulation (e.g. scaling: fixed range)

# How to Handle Data Streams

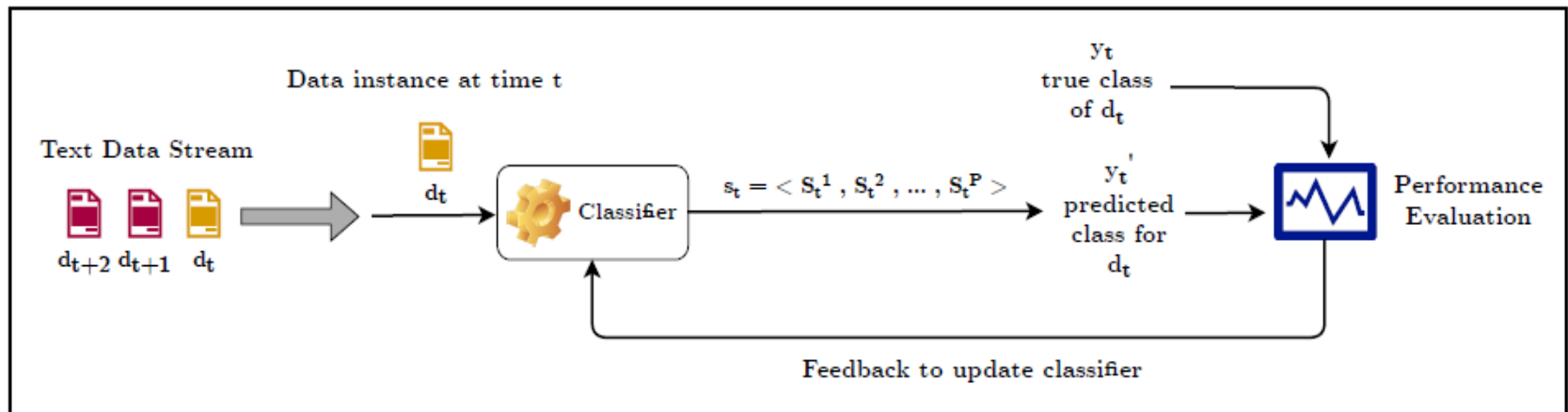
1. Process one example at a time and inspect it only once
2. Use a limited amount of memory
3. Be ready to predict at any time
4. Be able to react to concept drift in case of evolving data streams

# Online Learning vs. Batch Learning

- Online learning techniques are used to handle data stream classification
- Online vs Batch learning :
  1. Data is not stored in the memory
  2. The system sees the data once
  3. Algorithm should be much faster than batch learning

# Data Stream Classification Evaluation

- No separate train and test sets
- We can use interleaved-test-then-train method
- Simple idea : we use each instance first to **test** the model, and **then** to **train** the model



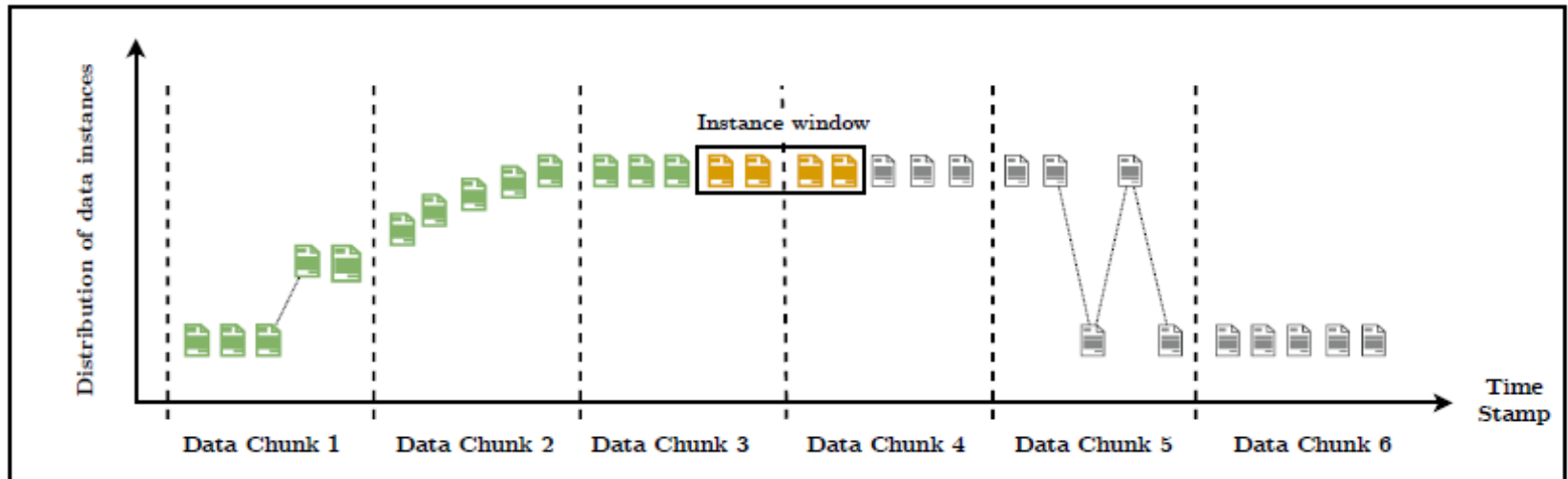
# Now More on: Concept Drift

- What is concept drift?
- Concept drift types
- Concept drift detection:
  - Prediction performance decrease
  - Using an Algorithm: supervised vs. unsupervised
- Concept drift handling
  - Active: Detect and retrain
  - Passive: Let the system handle

# How Does It Happen: Concept Drift Types

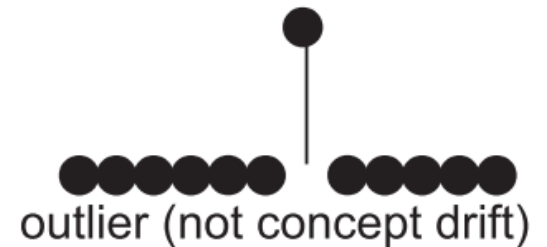
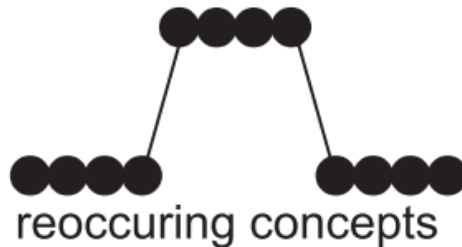
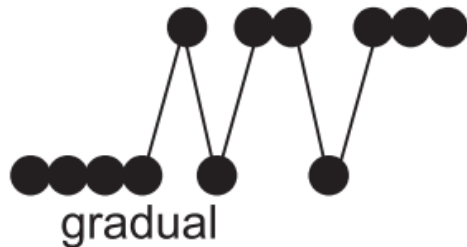
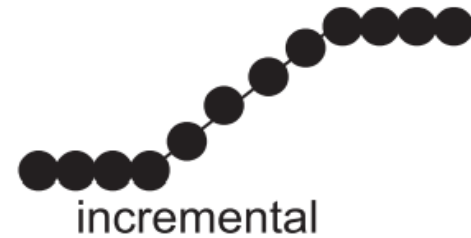
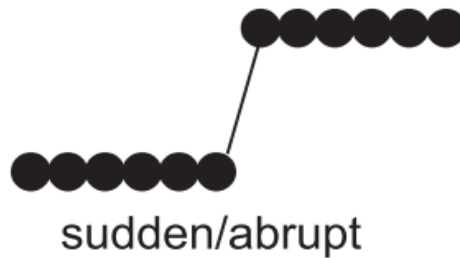
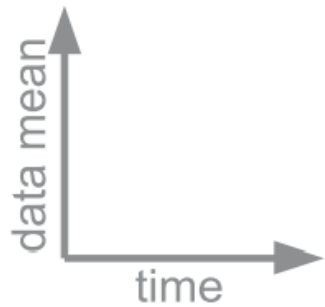
- Abrupt /Sudden
- Gradual
- Incremental
- Reoccurring

# Concept Drift Types





# Concept Drift Types



Gama, J., Zliobaite, I., Bifet, A., Pechenizkiy, M., Bouchachia, A. A survey on concept drift adaptation. *ACM Computing Surveys*, 46(4), 44:1–44:37 (2014).

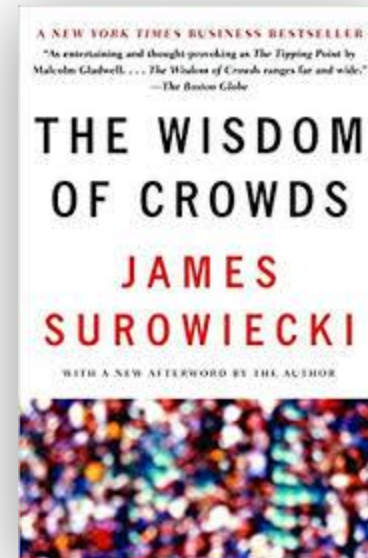
# Concept Drift Detection

- Concept drift detection algorithms find the drift point in a data stream.
- They usually detect the change based on the changes in the distribution of data over time.
- Detectors send an alarm in case of any changes and the system adapts to the changes based on a concept drift adaptation algorithm.

# Concept Drift Handling: Single Classifiers vs. Ensembles

1. Update the model over time in certain time order. For example, update the model every week and learn the new data.
2. Incrementally learn the new data over time.
3. Assign more weights to incoming data right after the drift.
4. Restart learning from the drift point
5. Use ensemble of weak classifiers to adjust to the changes

# Ensemble Approach: *The Wisdom Of Crowds*



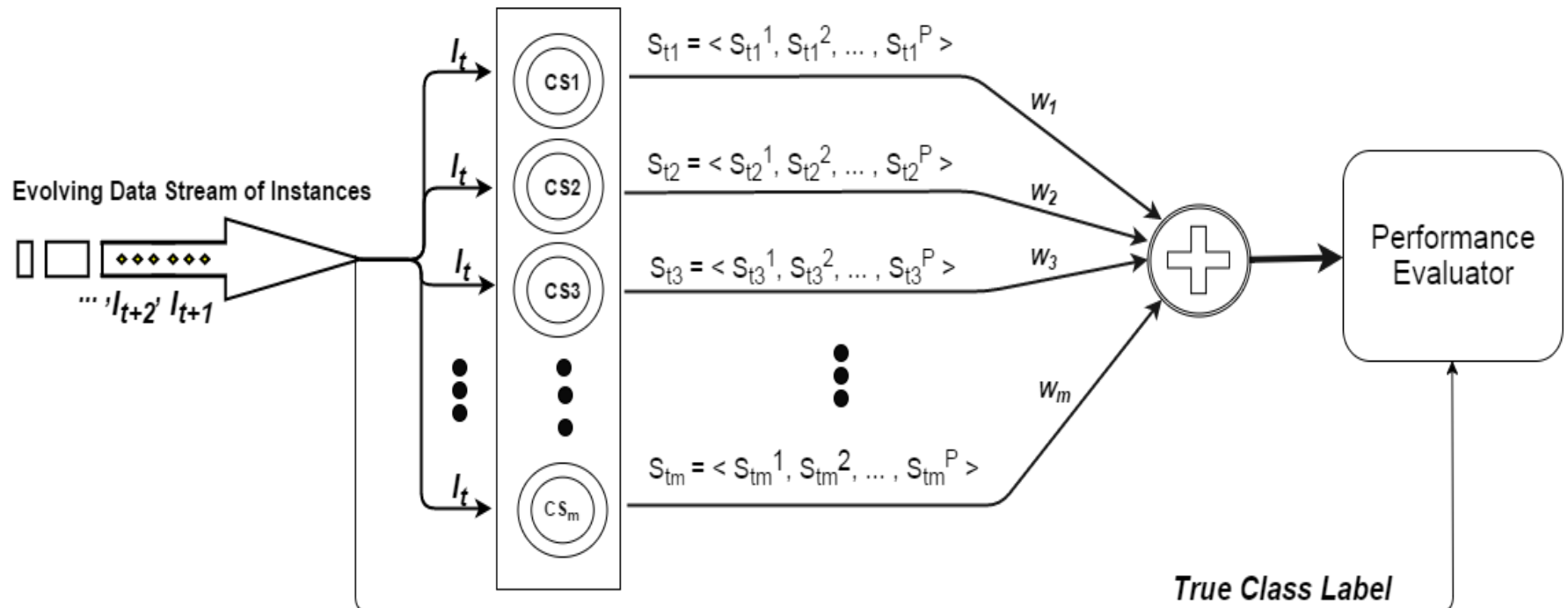
# Using Ensemble Methods

- Ensemble learning is a paradigm where multiple machine learning algorithms or better to say, weak learners are combined to get better results.
- Some Ensemble methods:
  1. Bagging: sampling with replacement and averaging
  2. Boosting: combine weak learners to obtain a strong learner
  3. Stacking: a learner that learns classifiers
- Using these methods and voting systems like majority voting, the system can adapt to new changes.

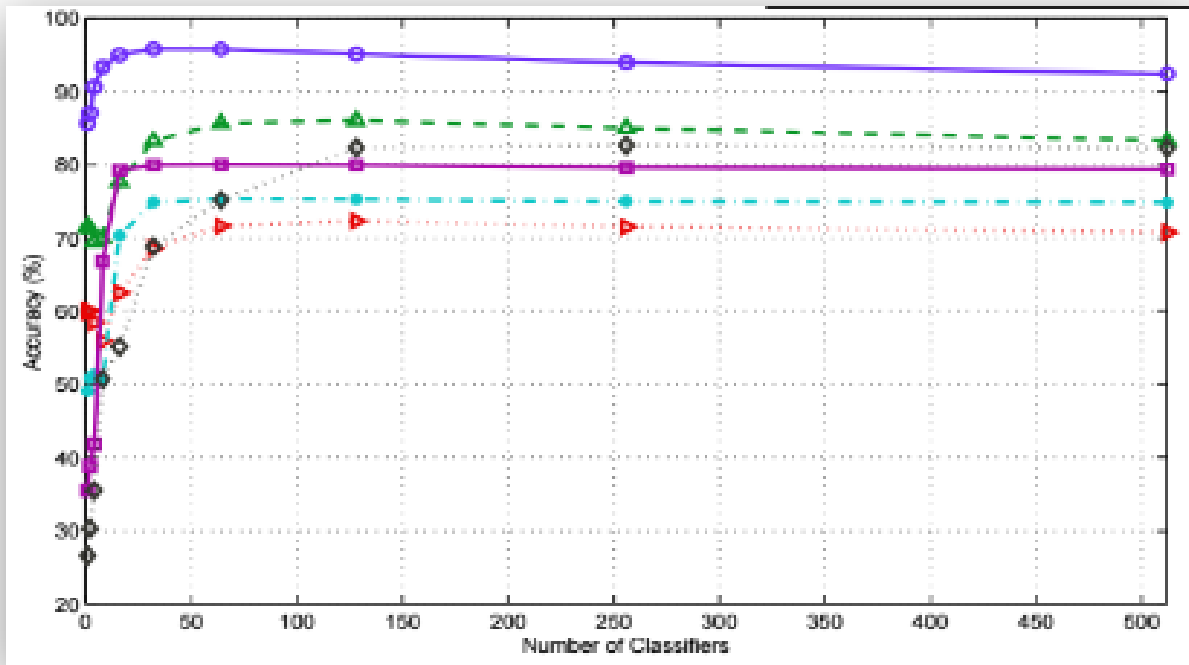
# GOOWE

- Notations and Assumptions:
  - **p class labels** as  $C = (C_1, C_2 \dots C_p)$   
multi-class problem
  - **m classifier** systems as  $CS = (CS_1, CS_2 \dots CS_m)$
  - For each of these Instances ( $I_i$ ), every classifier system  $CS_j$  returns a set of scores as  $S_{ij} = (S_{ij}^1, S_{ij}^2 \dots S_{ij}^p)$

# GOOWE (Cont.)



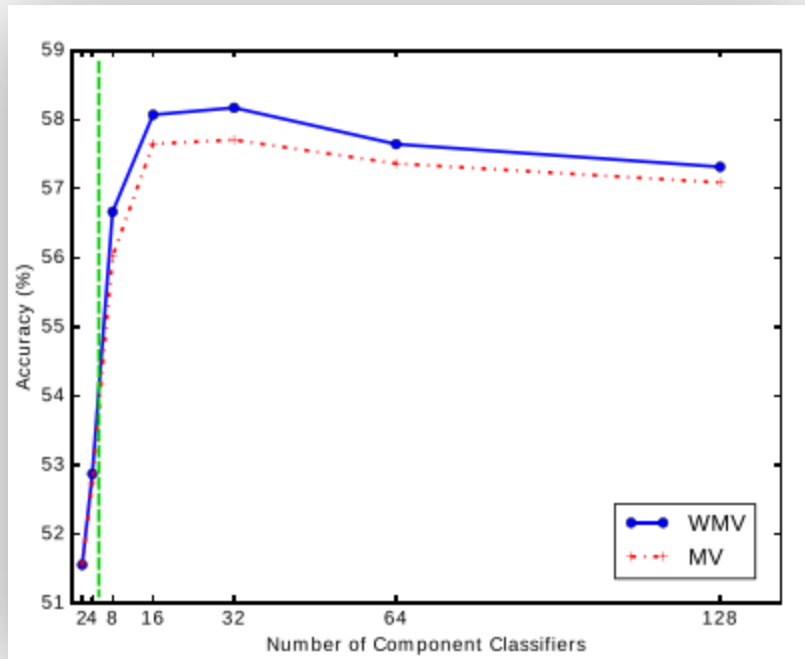
# Law Of Diminishing Returns



Bonab, H., Can, F. GOOWE: Geometrically optimum and online-weighted ensemble classifier for evolving data streams. *ACM Transactions on Knowledge Discovery from Data*, 12(2), 1-25:33 (2018).



# Components must be Independent and Diverse ( $m = p$ )



The highest effectiveness is observed much closer to the theoretically ideal  $m=p$  green line rather than the maximum number of components.

H. Bonab, F. Can: Less Is More: A Comprehensive Framework for the Number of Components of Ensemble Classifiers. *IEEE Transactions on Neural Networks and Learning Systems*, 30(9), 2735-2745 (2019).

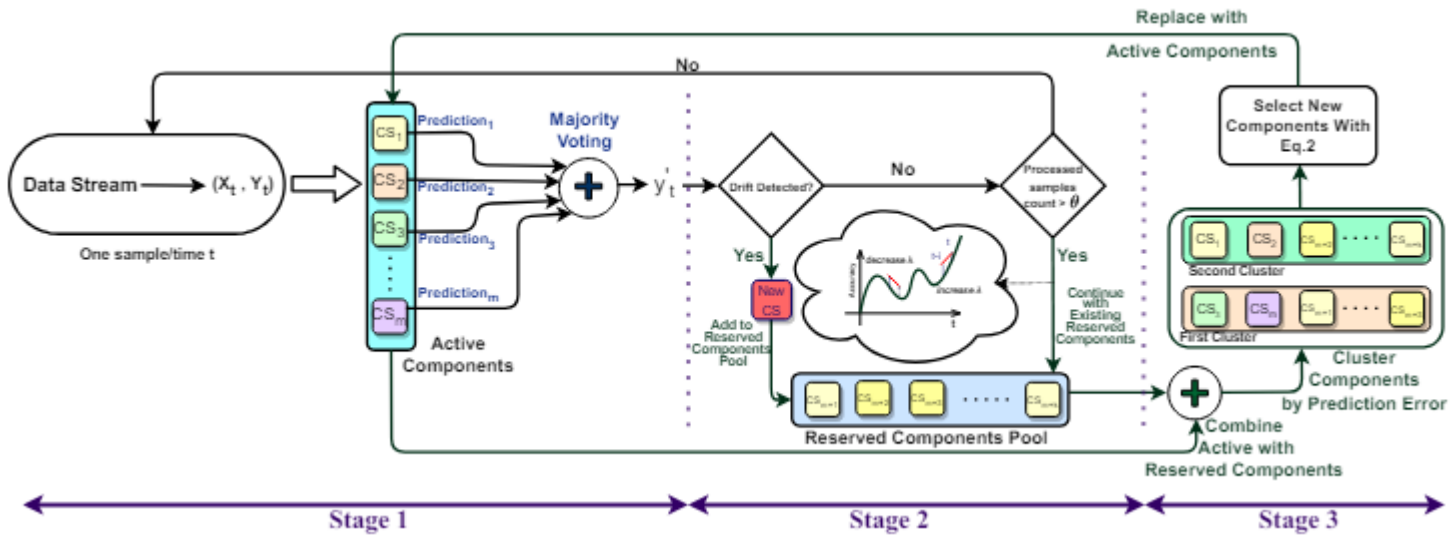
# What Is Diversity Measure in Ensemble Learning?

- The key point in defining an ensemble of classifiers is to choose diverse classifiers.
- There is no universal definition for diversity in ensemble methods
- This make it hard to measure diversity

# Key Questions in Diversity Measurement

1. How do we define and measure diversity?
2. How are the various measures of diversity related to each other?
3. How are the measures related to the accuracy of the team?
4. Is there a measure that is best for the purposes of developing committees that minimize error?
5. How can we use the diversity measures in designing the classifier ensembles?

# DynED: Dynamic Ensemble Diversification in Data Stream Classification



# What is Q-statistics?

- Yul's Q statistic :

For two classifiers  $D_i$  and  $D_k$  we have:

- $$Q_{i,k} = \frac{N^{11}N^{00} - N^{01}N^{10}}{N^{11}N^{00} + N^{01}N^{10}}$$

	$D_k$ correct (1)	$D_k$ wrong (0)
$D_i$ correct (1)	$N^{11}$	$N^{10}$
$D_i$ wrong (0)	$N^{01}$	$N^{00}$
Total, $N = N^{00} + N^{01} + N^{10} + N^{11}$ .		

# What is Q-statistics?

- For instance, suppose that for  $D_i$  and  $D_k$  we have the following predictions for 10 instances :

- *Predictions of  $D_i$*  =  $\langle 0, 1, 0, 1, 0, 0, 1, 1, 1, 1 \rangle$

- *Predictions of  $D_k$*  =  $\langle 0, 0, 0, 0, 0, 1, 1, 0, 1, 1 \rangle$

- *Ground Truth* =  $\langle 1, 0, 0, 1, 0, 0, 1, 1, 1, 1 \rangle$

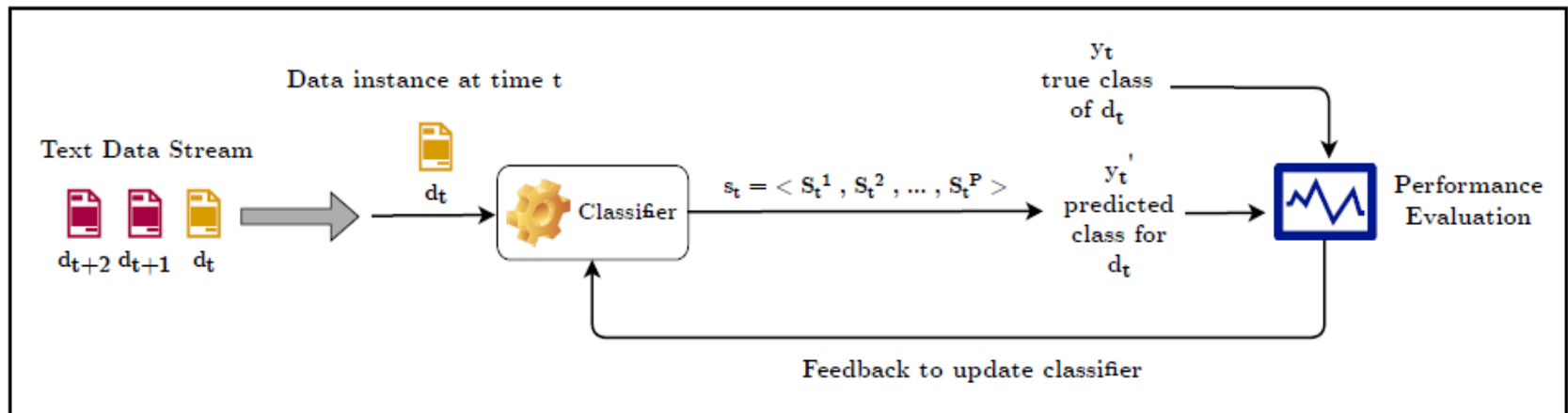
- $N^{11} = 5, N^{10} = 3, N^{01} = 1, N^{00} = 1$

- $$Q_{i,k} = \frac{N^{11}N^{00} - N^{01}N^{10}}{N^{11}N^{00} + N^{01}N^{10}} = \frac{5*1 - 1*3}{5*1 + 1*3} = \frac{2}{8}$$

	$D_k$ correct (1)	$D_k$ wrong (0)
$D_i$ correct (1)	$N^{11}$	$N^{10}$
$D_i$ wrong (0)	$N^{01}$	$N^{00}$
Total, $N = N^{00} + N^{01} + N^{10} + N^{11}$ .		

# Prediction Effectiveness Measures

- No separate train and test sets
- We can use interleaved-test-then-train method
- Simple idea : we use each instance first to **test** the model, and **then** to **train** the model



# Prequential Evaluation

- While calculating prequential accuracy, each data instance is used for two purpose. First we use it for testing then for training.
- Overall accuracy at time  $t$ , is the accumulated prequential accuracy calculated for all the stream data until time  $t$ .

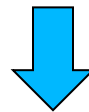


# Window Size is Important

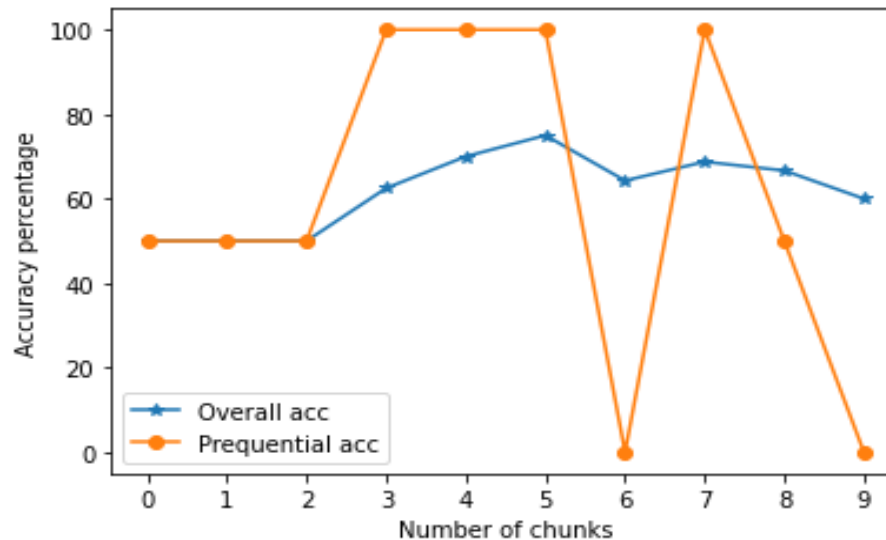
- Narrow window: Minor swings can be labeled as concept drift
  - Observing a student during a semester
- Wide window: Major swings can be missed
  - Just looking at student overall GPA

# Prequential Evaluation Example 1

Prediction	1,0	0,1	1,0	1,1	1,1	1,1	0,0	1,1	0,1	0,0
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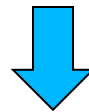


Prequential acc	50%	50%	50%	100%	100%	100%	0%	100%	50%	0%
Overall acc	50%	50%	50%	62.50%	70%	75%	64.28%	68.75%	66.66%	60%

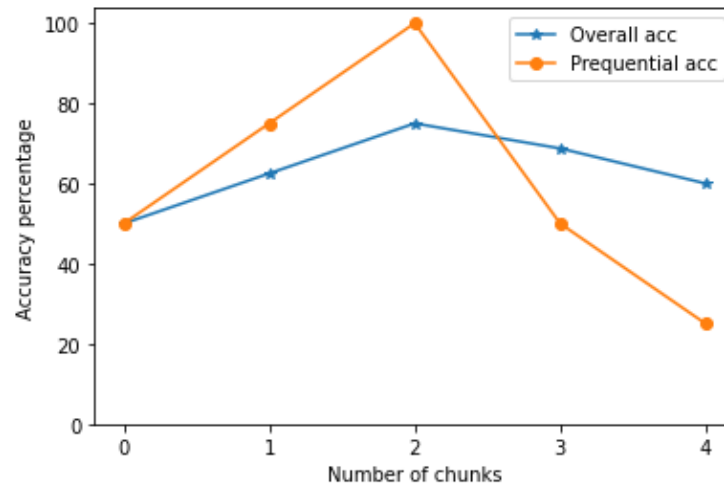


# Prequential Evaluation Example 2

Prediction	1,0,0,1	1,0,1,1	1,1,1,1	0,0,1,1	0,1,0,0
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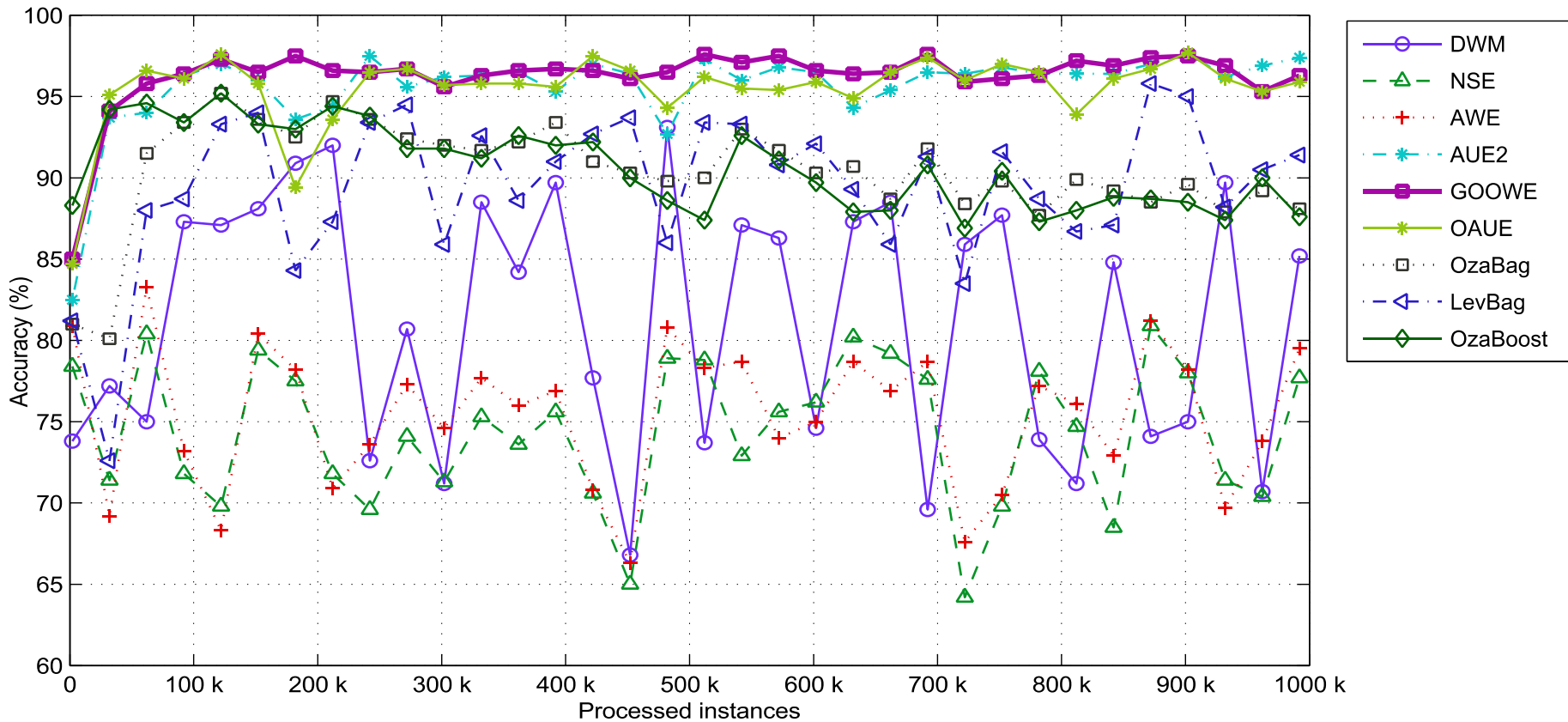


Prequential acc	50%	75%	100%	50%	25%
Overall acc	50%	62.50%	75%	68.75%	60%



# Behavior of Different Classifiers

## Rigorous Concept Drift: Gradual Change RBF-G-4-F



(a) accuracy

# Multi-label Classification

- In multi-label classification each data instance may belong to several classes.
- For instance, a movie may belong to several genres.
- For multi-label classification we can use single classifier or ensemble method.

# Online Multi-label Classification

- Most of the Online multi-label classification algorithms are based on ensemble methods :
  1. GOOWE-ML-based methods:
  2. A classifier for each class
  3. Online Bagging (OzaBagging)-based methods
  4. ADWIN Bagging-based methods

# Multi-label Classification Evaluation

- Evaluation metrics :
  1. Instance-Based Metrics
  2. Label-Based Metrics
  3. Efficiency Metrics: Time and Space

# Instance-based Metrics

Instance-based metrics are evaluated for every instance and averaged over the whole dataset

1. Exact Match
2. Hamming Score,
3. Instance-Based (Accuracy, Precision, Recall, F1-Score)



# Instance-based Metrics

$$\textit{Exact match} = \frac{1}{N} \sum_{i=1}^N \llbracket y^i = \hat{y}^i \rrbracket$$

$$\textit{Hamming score} = \frac{1}{LN} \sum_{i=1}^N \sum_{j=1}^L \llbracket y_j^i = \hat{y}_j^i \rrbracket$$

# Instance-based Metrics

Example based accuracy, precision, recall and F1 scores\*

$$Acc_{ex} = \frac{1}{N} \sum_{i=1}^N \frac{|y^i \cap \hat{y}^i|}{|y^i \cup \hat{y}^i|}$$

$$Pr_{ex} = \frac{1}{N} \sum_{i=1}^N \frac{|y^i \cap \hat{y}^i|}{|\hat{y}^i|}$$

$$Re_{ex} = \frac{1}{N} \sum_{i=1}^N \frac{|y^i \cap \hat{y}^i|}{|y^i|}$$

$$F1_{ex} = \frac{2 * Pr_{ex} * Re_{ex}}{Pr_{ex} + Re_{ex}}$$

\* Precision= (TP) / (TP + FP), Recall= (TP) / (TP + FN), Search Web for more explanation.

# Instance-based Metrics Example

- Assume a labelset with 5 labels for a given instance we have :
- *Prediction:*  $\hat{y} = \langle 1, 1, 0, 0, 0 \rangle$
- *Ground Truth*  $y = \langle 0, 1, 1, 1, 0 \rangle$
- Exact match = 0 , because two vectors are not completely the same
- Hamming score =  $2/5$  , because there are two matching bits between the vectors
- $Acc_{ex} = 1/4$  , because 1 relevant bit is mutual among the relevant bits of two vectors
- $Pr_{ex} = 1/2$  , because 1 relevant bit is the same among 2 predicted relevant bits
- $Re_{ex} = 1/3$  , because 1 relevant bit is the same among 3 correct bits from the ground truth.

# Statistical Tests

For selling your ideas statistical tests are essential in the comparison of methods

1. Show statistical significance of your results: To show that which method is significant better than the baselines
2. Use strong baselines (avoid straw man)
3. Use accessible datasets
4. Make sure that other people can repeat your experiments
5. Remember important keywords of CS research: Scalability, Dynamism, Robustness

# MOA

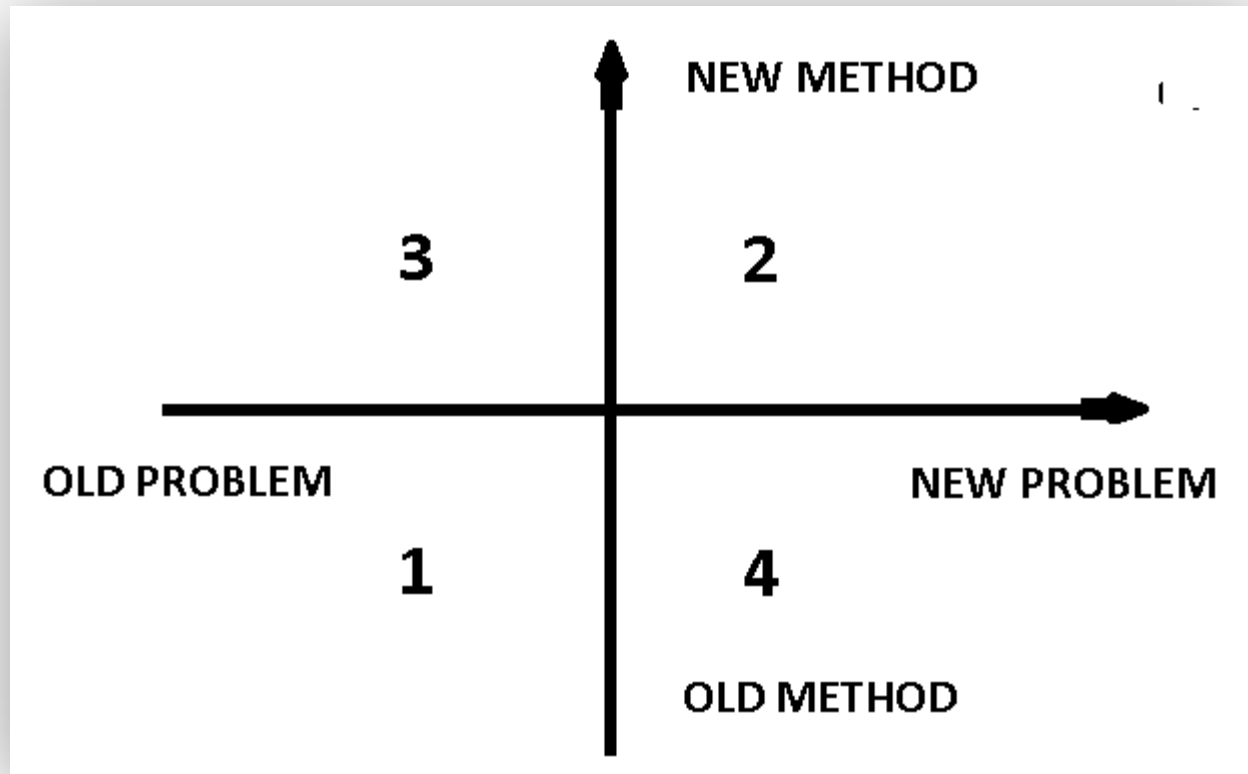
- MOA (Massive Online Analysis) is one of the popular frameworks for data stream analysis in JAVA.
- MOA contains some of the most famous machine learning algorithms e.g. Hoeffding Tree, Naïve Bayes,...
- There are generators in MOA which simulate the stream environment by generating the data over time.
- <https://moa.cms.waikato.ac.nz/>



# Scikit-multiflow

- Scikit-learn is a famous machine learning framework in python
- However, scikit-learn doesn't contain any module for handling data streams
- Scikit-multiflow is a framework which is the equivalent of MOA in python
- It also has the capabilities of scikit-learn
- <https://scikit-multiflow.github.io/>

# New Research Opportunities: Research Principles



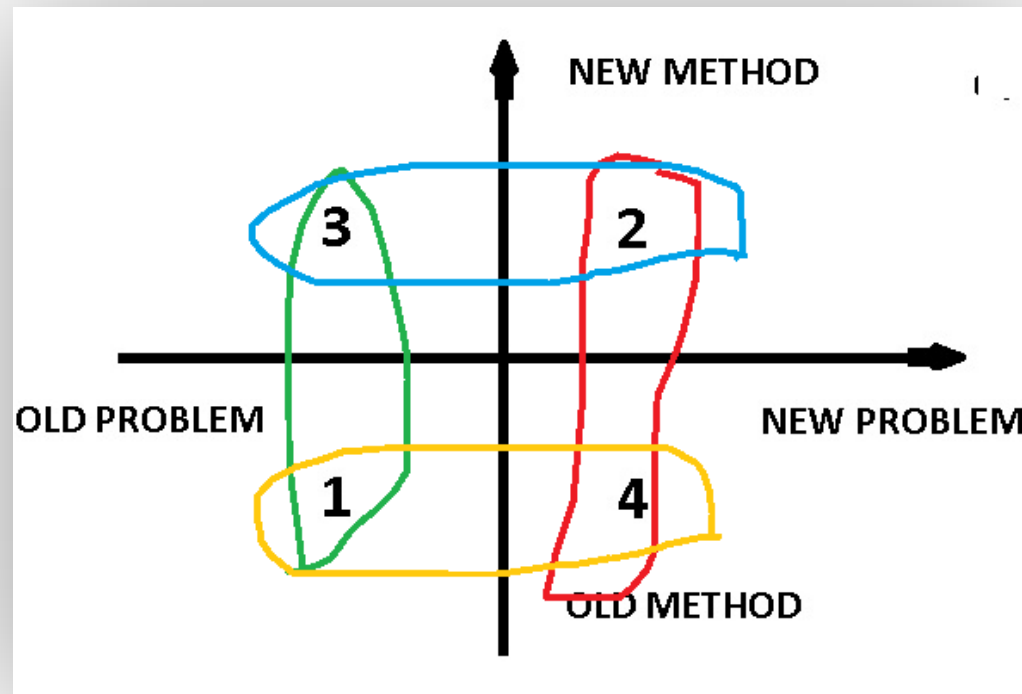
# Types of Research

1. Old Problem : Old Method (Shannon: Training)
2. New Problem : New Method (New Technologies)
3. Old Problem : New Method (Unsolved Problems)
4. New Problem : Old Method (Shannon: Seek Similar Prob.)





# Types of Research Problem – Method



# Current Research Opportunities

- Ensemble pruning: which components to delete - DynED
- Concept drift detection: supervised vs. unsupervised
- Multi stream environment: fusing different streams
- Construction of ensemble of ensembles: a possibility
- Lifelong learning for data streams without forgetting the past (rehearsal...)

# REFERENCES

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- Bifet, A., et al. MOA: Massive online analysis. *Journal of Machine Learning Research* 11.May (2010): 1601-1604.
- Big data what is big data 3 Vs of big data volume, velocity and variety day 2 of 21.  
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