Improving Credit Scoring Performance Using Delay-Aware Streaming Analytics

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August 2017

Imperial College London

Why Streaming/Delay and Credit Scoring?

Population **drift** remains a challenge in credit-risk classification.

- Unpredictable **changes over time** create modeling difficulties.
- Ideally, we seek to use information as soon as it becomes available.
- In principle, **streaming classification** methods can be used which are able to handle drift and incorporate information as it arrives and are **well studied**
- **Delays** in the arrival time of classification labels with respect to their corresponding feature vectors create issues for the deployment of statistical methods and are much **less studied**.

Purpose of the Talk:

This talk **is** about:

- highlighting the **importance** of **delayed labels** in streaming classification,
- showing that a **simple** classifier, that makes **realistic assumptions** on the delays, can increase performance,
- demonstrating improved performance incorporating delays for **unsecured personal loan (UPL) score cards**.

Setting the Stage:

- A **data stream** is an ordered sequence of data items arriving at **high frequency** and whose generating process is likely to **drift** (change) in time.
- **Streaming classification** is the act of mapping each observation from a data stream to a **fixed**, predetermined set of classes.
- Due to **dynamics** of the stream, streaming classifiers must be:

  ($\star$) **Sequential**,

  ($\star$) **Single-pass**,

  ($\star$) **Adaptive**.

Setting the Stage:

- **Delayed labels** are the true classes for **previously observed** feature vectors which become available after some time (or lag).
- Aspect of streaming data which is:
  - **under researched**,
  - and (most) literature assumes an **unrealistic** label-arrival process (e.g. "1-tick label arrival").

- **Example:** a stream consisting of daily **UPL applications** where the status of the loan (default or not) arrives at a later time, i.e., are **delayed**. **Incorrect** to assume that the loan status becomes available on the next day.

Notation:

- Data streams assumed to take the form:

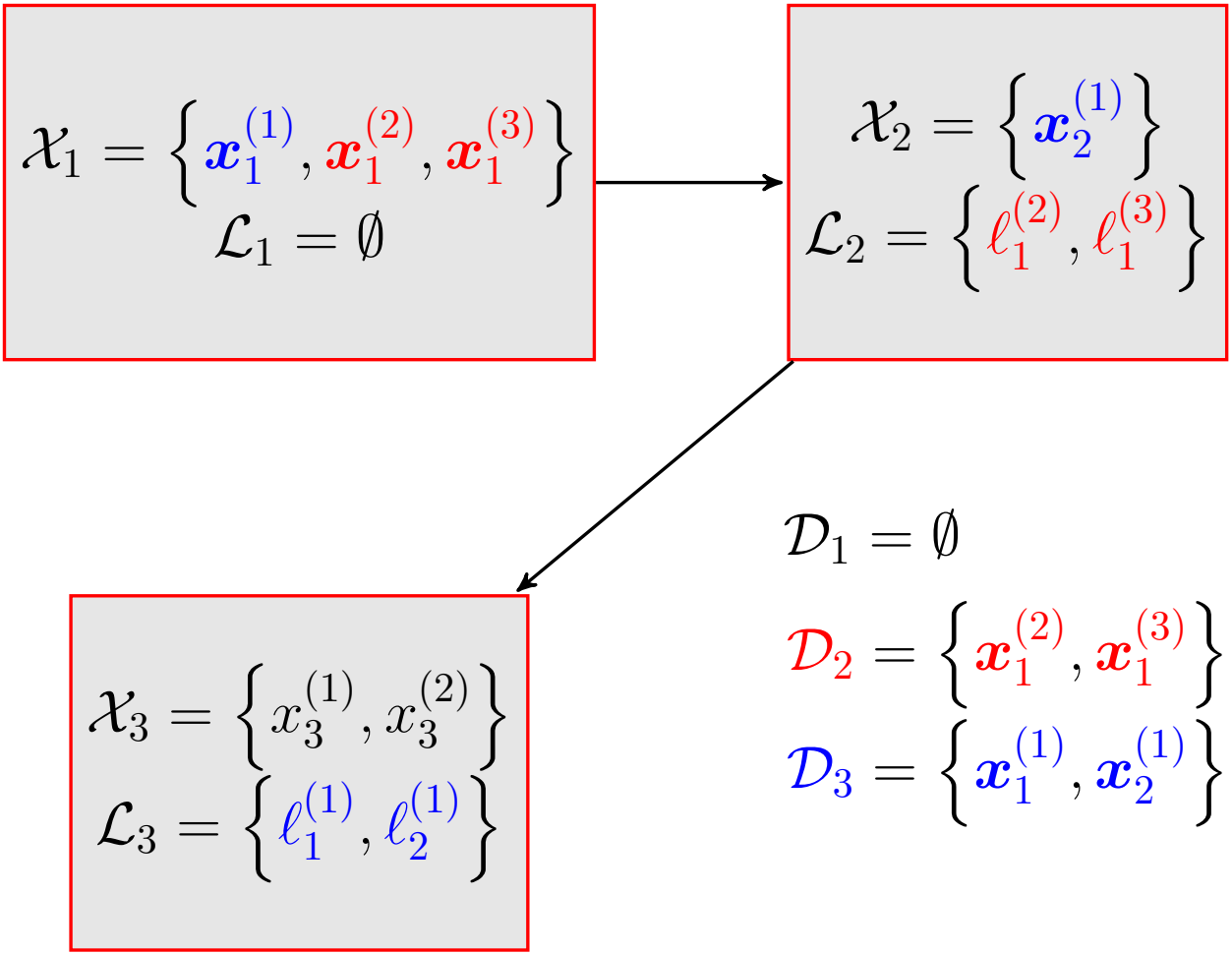
$$\langle \boldsymbol{d}_1, \ldots, \boldsymbol{d}_t, \ldots \rangle, \qquad \boldsymbol{d}_t = (\mathcal{X}_t, \mathcal{L}_t).$$

- $\mathcal{X}_t$ - **feature vectors** arriving at time t.
  - Each $\boldsymbol{x} \in \mathcal{X}_t$ has a **class label** $\ell \in \{c_i\}_{i=1}^{K}$.
- $\mathcal{L}_t$ - **delayed labels** for vectors observed **before** time t.

$$\mathcal{X}_t = \left\{ \boldsymbol{x}_t^{(k)} \right\}_{k=1}^{|\mathcal{X}_t|}, \quad \mathcal{L}_t = \left\{ \ell_k^{(m)} \right\}_{(k,m)\in\mathcal{I}_t}, \quad \mathcal{D}_t = \left\{ \boldsymbol{x}_k^{(m)} \right\}_{(k,m)\in\mathcal{I}_t}$$

- $(\mathcal{D}_t, \mathcal{L}_t)$ - a **labeled** collection available at time t.

Arrival Process Example:



Interpretation of Delay:

- Each feature vector is associated with the **triple** $(\boldsymbol{x}_t, \ell_t, \tau_t)$
  - ℓ_t is the true **label** for $\boldsymbol{x}_t$
  - $\tau_t \in \mathbb{Z}^+ \backslash \{0\}$ is the **delay**
- If $\tau_t = s$, then the label for $\boldsymbol{x}_t$ will arrive at time $(t + s)$:

$$\mathcal{X}_t = \boldsymbol{x}_t, \qquad \mathcal{L}_{t+s} = \ell_t.$$

- **See:** Plasse, Joshua, and Niall Adams. "*Handling Delayed Labels in Temporally Evolving Data Streams.*" IEEE International Conference on Big Data, 2016.
  - This paper proposes a much more **general** framework to streaming classification using delayed labels.

Dealing with Drift:

- **Recall:** any classifier needs to be **adaptive** to handle drift.
- Temporal adaptivity introduced through **forgetting factors** (FFs):
  - a sequence of scalars that continuously **down-weights** historical data as new data arrives,
  - can be considered as a continuous analogue of a **sliding window**.
- FFs are incorporated into parameter estimation via a **weighted-maximum likelihood** approach.
- Consider a variation of **linear discriminant analysis (LDA)**: need to consider class conditional mean vectors and covariance matrices (Gaussian) and class priors (multinomial).

Sequential Updates:

Adaptive estimates for the **mean vector** and **covariance matrix** are given, **recursively**, by:

$$
\begin{aligned}
n_t &= \lambda_{t-1} n_{t-1} + \omega_t \\
\tilde{\mu}_t &= \left(1 - \frac{\omega_t}{n_t}\right) \tilde{\mu}_{t-1} + \frac{\omega_t}{n_t} \boldsymbol{x}_t \\
\tilde{\Pi}_t &= \left(1 - \frac{\omega_t}{n_t}\right) \tilde{\Pi}_{t-1} + \frac{\omega_t}{n_t} \boldsymbol{x}_t \boldsymbol{x}_t^T \\
\tilde{\Sigma}_t &= \tilde{\Pi}_t - \tilde{\mu}_t \tilde{\mu}_t^T.
\end{aligned}
$$

- $\lambda_{t-1} \in [0, 1] \equiv$ a FF that affect how **quickly** (or slowly) the estimates react to change **(data driven)**,
- $\omega_t \equiv$ additional **weight** given to $\boldsymbol{x}_t$ **(delay driven)**.

Sequential Updates:

Adaptive estimates can also be computed for the **multinomial distribution**. Recall:

- $\{c_i\}_{i=1}^K$ are the **classes**
- $\{\ell_i\}_{i=1}^t$ are the **labels** from the stream where for every i:

$$\ell_i \in \{c_i\}_{i=1}^K \qquad \text{or} \qquad \ell_i = \emptyset \text{ (hasn't arrived)}.$$

An adaptive estimate for the j^{th} cell-probability is given by:

$$\begin{aligned} n_t &= \lambda_{t-1} n_{t-1} + \omega_t \\ \tilde{p}_t^{(j)} &= \frac{\omega_t}{n_t} I(\ell_t = c_j) + \left(1 - \frac{\omega_t}{n_t}\right) \tilde{p}_{t-1}^{(j)}, \end{aligned}$$

where we have assumed that $\ell_t \neq \emptyset$.

FF Interpretation:

- Suppose the **fixed-forgetting** case where $\lambda_{t-1} \equiv \lambda \in [0, 1]$. Then

$$\tilde{\mu}_t = \frac{1}{n_t} \left[\lambda^{t-1} \, \boldsymbol{x}_1 + \cdots + \lambda \, \boldsymbol{x}_{t-1} + \boldsymbol{x}_t \right].$$

  - $\lambda = 1 \implies \tilde{\mu}_t = \bar{\boldsymbol{x}}$, the **static** sample mean
  - $\lambda = 0 \implies \tilde{\mu}_t = \boldsymbol{x}_t$, the **most recent** observation

- Case where the FFs are functions of time is referred to as **adaptive forgetting**.

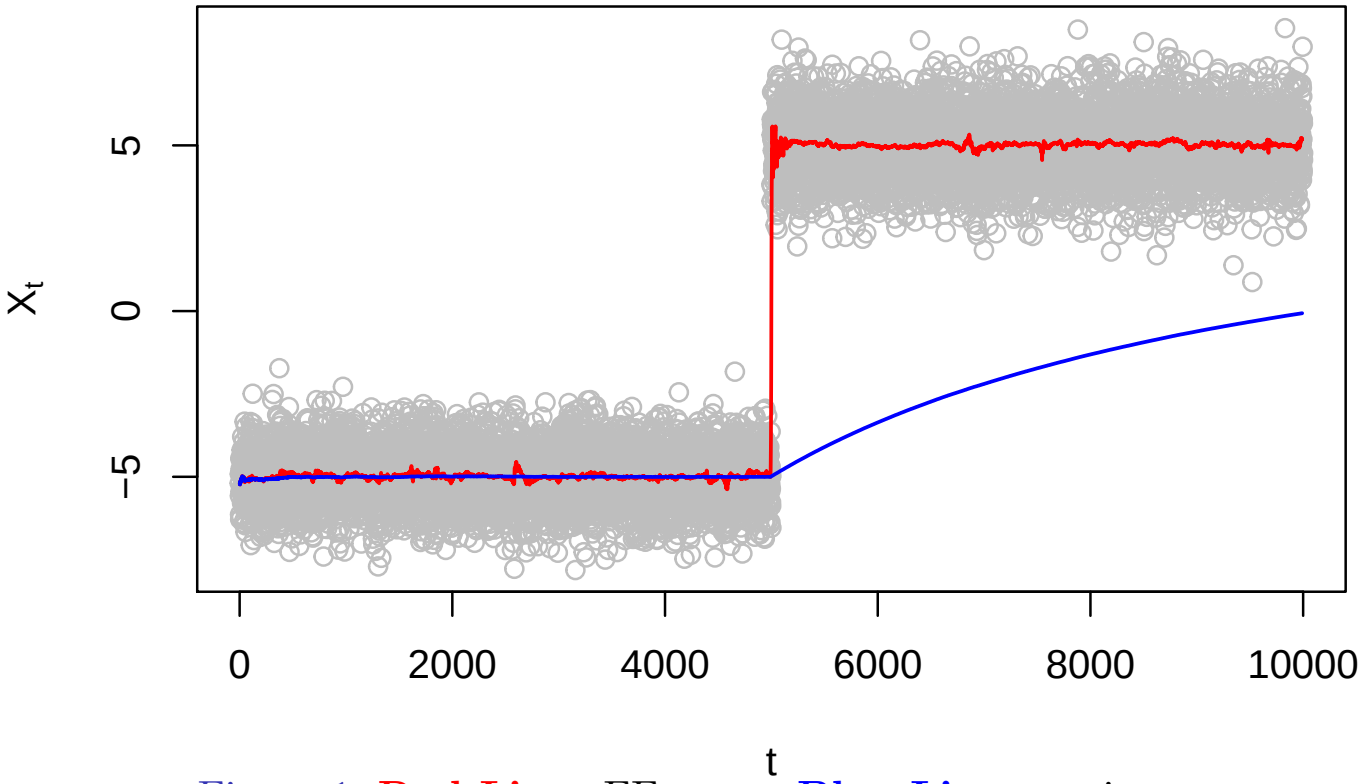


Figure 1: **Red Line:** FF mean; **Blue Line**: static mean

Streaming LDA:

The recursive estimates derived lay the groundwork for a **streaming linear discriminant analysis** algorithm.

Assumptions:

- $\mathcal{X}_t = \boldsymbol{x}_t$ (for now),
- $\ell_t \in \{0, 1\}$ – **2-class problem**,
- fixed forgetting case (for now),
- typical aggregated covariance and allocation rule used.

Constructing the Classifier:

- Suppose at time t we have the **labeled ordered set**:

$$\{(\boldsymbol{x}_k, \ell_k, \tau_k)\}_{k \in \mathcal{I}_t}, \qquad k < t.$$

- **For example:** $\boldsymbol{x}_k$ could be a feature vector corresponding to a **loan application** received on day k, ℓ_k is whether the applicant **defaults or not** and τ_k represents the **number of days** it takes to get ℓ_k.
- On the stream, the parameters associated with class ℓ_k are updated by incorporating $\boldsymbol{x}_k$ into the parameter estimation with some **specified weight**.

Constructing the Classifier:

Let

- $\lambda_j \in (0,1)$ be the **fixed** FF for class $j \in \{0,1\}$,
- $\lambda^{\text{pr}} \in (0,1)$ be the **fixed** FF for the prior probabilities.

- The additional weight given to $\boldsymbol{x}_k$ is chosen according to:

$$\omega_k = \lambda_j^{\tau_k} \text{ or } (\lambda^{\text{pr}})^{\tau_k}.$$

- Observations get **less** weight the **larger** the delay.

Blocking and Averaging:

- Suppose now that **multiple** feature vectors arrive at each time t

  $\Longrightarrow$ several delayed labels can arrive for feature vectors that were observed **at the same time**.

- These vectors should be given the **same weight** in the parameter updating.
- Repeated application of the recursive update equations does **not** allow for this!

Blocking and Averaging:

- To alleviate this problem consider the **blocks**

$$B_k^{(j)} = \left\{ \boldsymbol{x}_k^{(m)} \in \mathcal{D}_t \,|\, \ell_k^{(m)} = j \right\}, \qquad \forall\, (k,m) \in \mathcal{I}_t, \;\; j \in \{0,1\}.$$

- Just ordering feature vectors by **arrival time** and **label**.

- **Idea:** average over the blocks to get **one** feature vector to use in the updating of each class, for every k.
- In credit scoring for an application $\boldsymbol{x} \in B_k^{(j)}$ it must be the case that:
  - the application $\boldsymbol{x}$ was received on day k,
  - the status of the loan was revealed on day t
  - the label for $\boldsymbol{x}$ is class $j \in \{0,1\}$.
- Weights **previously discussed** can be scaled by the **cardinality** of the block.

Demonstration:

The Data:

- Over 36,000 **unsecured personal loans** from a major UK bank recorded over 1994-1995.
- Binary response gives the **loan status** of the applicant.
- **Features**: age of applicant, loan amount etc.
- Not high frequency, so why relevant?!
  - Exhibits **population drift**
  - Delay mechanism is **inherent** in the application.

The Delays:

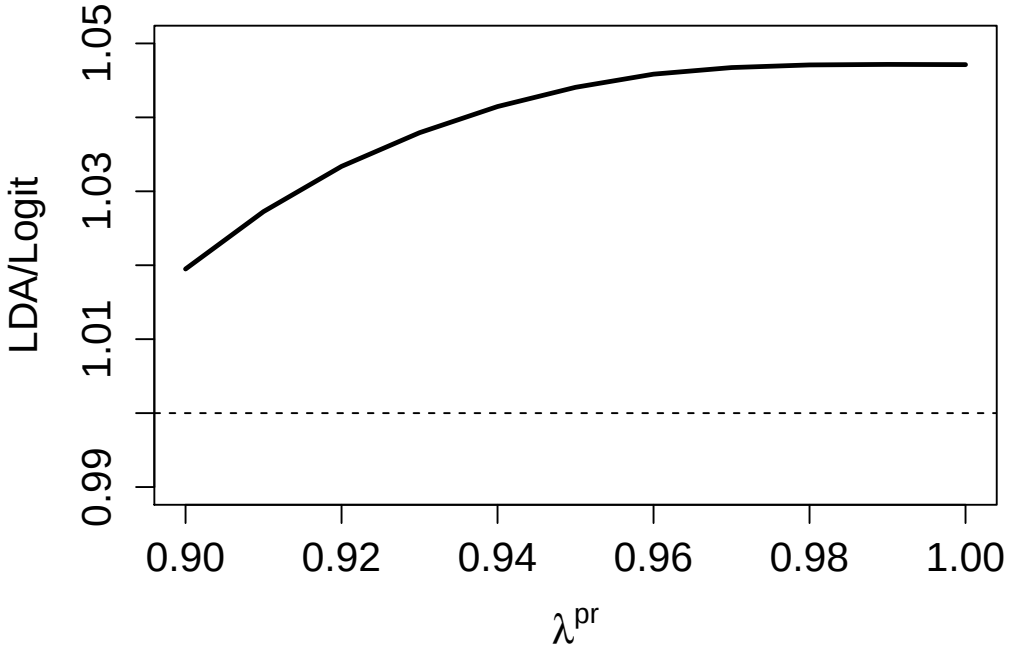
- The data considered has no timing information associated with the labels.
- **Fix:** synthetically introduce the delays which mimic how they may occur in reality:
  - ($\star$) Any loan granted in the **last three months never** has their label arrive.
  - ($\star$) Any loan granted in the **first nine months** has two options:
    - Bad (defaults) labels arrive randomly a **minimum of three months** from the start date.
    - Good (non-defaults) labels only arrive randomly in the **last three months** of the year.
- Streaming LDA was trained on 94 and tested on 95 and is compared to the **baseline** logistic regression classifier using **area under the ROC curve** as a performance measure.

Results:

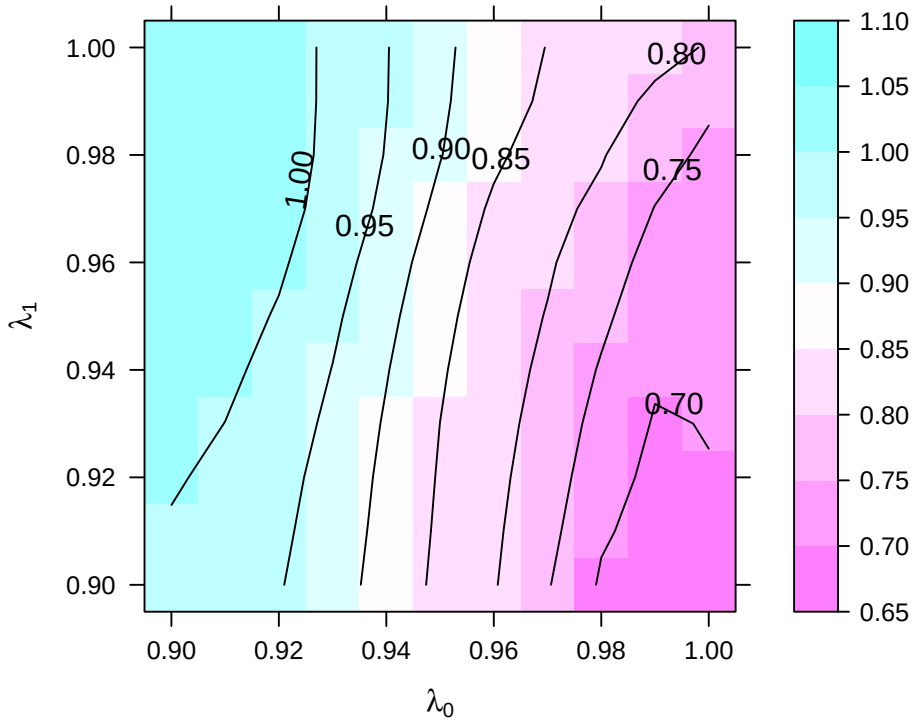
- Consider a **grid** $G = \{0.9, 0.91, ..., 1\}$.
- LDA was run for every combination of $(\lambda_0, \lambda_1, \lambda^{\text{pr}}) \in G^3$.
- For each triple $(\lambda_0, \lambda_1, \lambda^{\text{pr}})$ the AUC from streaming LDA was compared to the AUC from logistic regression.
- The upcoming plots report:

  (LDA AUC)/(Logistic AUC).
- Any value **greater than one** indicates that our method has a higher AUC when compared to logistic regression.

λ^{pr} Results:



(λ_0, λ_1) Results:



Current Work: Tuning the FFs

- In the streaming paradigm a grid search may not always be possible.
- Consider **adaptively tuning** the FFs according to a **stochastic gradient descent (SGD) step:**

$$\lambda_t = \lambda_{t-1} - \eta \nabla_\lambda \left[J \left(\lambda_{t-1} | \boldsymbol{x}_t, \tilde{\theta}_{t-1} \right) \right]$$

  - $\eta \equiv$ a **step-size**
  - $J \equiv$ a continuous and differentiable **cost function**
  - λ_t could be for the class conditionals or the priors.
- Applying SGD **and** incorporating delays is **tricky**.

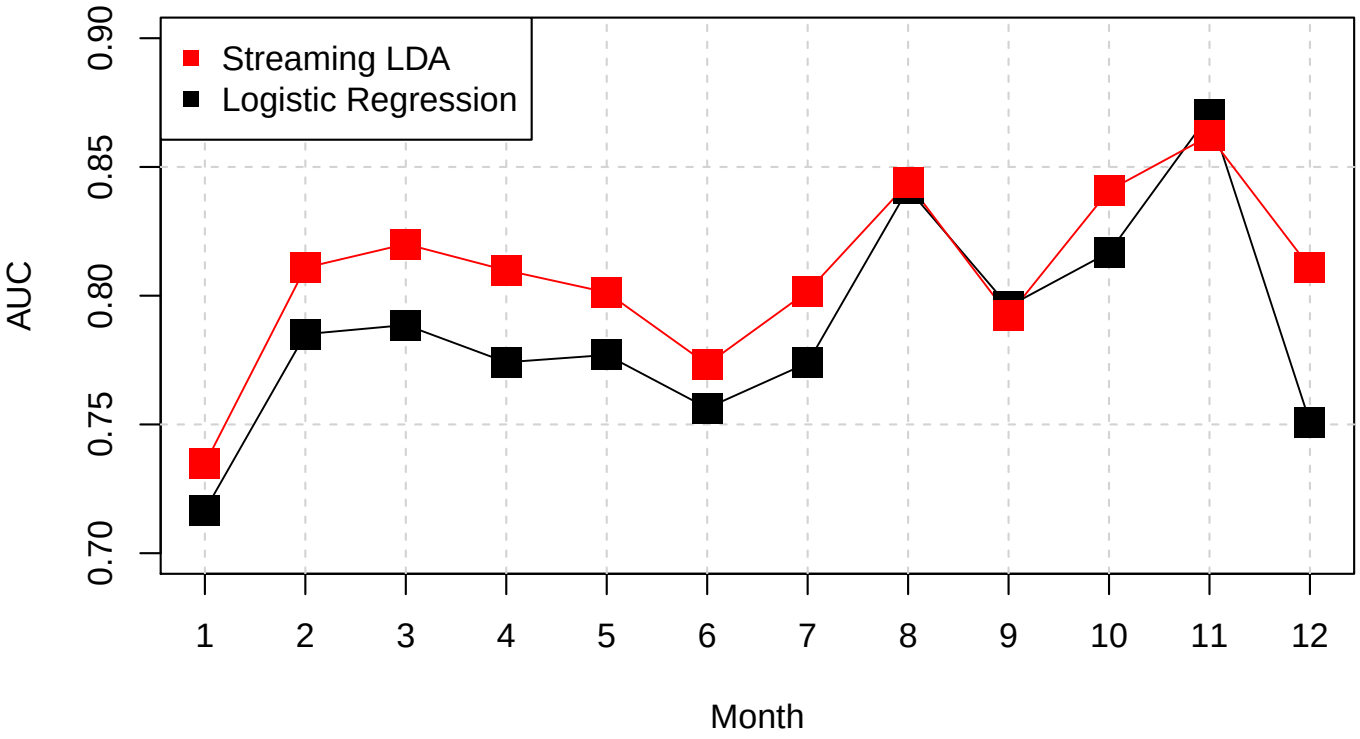


Figure 2: Overall AUC: **0.785**, **0.768**

Conclusions:

- Handling delays in the proposed way has some **promise** for credit scoring and warrants **further research**.
- Delayed labels can be incorporated into a **simple** online classifier which:
  - better matches the structure of the real problem,
  - can perform better than a common classifier used in industry,
  - can remove the burden of having to subjectively choose the forgetting factors.

Acknowledgment: Research was supported by an Imperial College President's PhD Scholarship.