# Machine Learning Paper Reviews

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## 1 Introduction

To prepare for the incoming master thesis project and the research work at laboratory, bunch of machine learning papers would be my daily reading material in next stage. I will write down summaries about all the papers I read and elaborate my ideas (if any) . Since my current work and master thesis mainly focus on the online learning optimization problem, section 2 might be the most important part in this document.

Besides this, section 3 takes notes regarding (deep) reinforcement learning, which is a promising sub field of machine learning. Section 4 and 5 summarize the papers in the field of natural language processing and computer vision.

## 2 Optimization

### 2.1 Online Learning Without Prior Information

Cutkosky and Boahen [2017] gives a new frontier *lower* bounds of regret for online optimization problems in the case of without any prior information (i.e., the diameter of $W$ or the bound of gradients $L_{\max}$ of loss function). They prove that the lower bound they provide is already the optimal one if with no prior information.

The second part of the paper uses Follow-the-Regularized-Leader (FTRL) framework (Shalev-Shwartz et al. [2012]) to find a way whose *upper* bound of regret can be aligned with the previous *lower* bound, which means they decrease the upper bounds to the already known lower bounds (i.e., optimal upper bound of regret). At the end, they give a explicit description of this algorithm which is called FreeRex (**Free**-Information **R**egret **ex**ponetial updates, see algorithm 1).

**Algorithm 1** FreeRex

**Input:** $k$

**Initialize:** $\frac{1}{\eta_0^2} \leftarrow 0, a_0 \leftarrow 0, w_1 \leftarrow 0, L_0 \leftarrow 0, \psi(w) = (\|w\| + 1)\log(\|w\| + 1) - \|w\|$.

**for** $t = 1$ **to** $T$ **do**
  Play $w_t$, receive subgradient $g_t \in \partial l_t(w_t)$.
  $L_t \leftarrow \max(L_{t-1}, \|g_t\|)$.
  $\frac{1}{\eta_t^2} \leftarrow \max\left(\frac{1}{\eta_{t-1}^2} + 2\|g_t\|^2, L_t\|g_{1:t}\|\right)$.
  $a_t \leftarrow \max(a_{t-1}, 1/(L_t\eta_t)^2)$.
  //Set $w_{t+1}$ using FTRL update
  $w_{t+1} \leftarrow -\frac{g_{1:t}}{a_t\|g_{1:t}\|}\left[\exp\left(\frac{\eta_t\|g_{1:t}\|}{k}\right) - 1\right]$.
**end for**

### 2.2 Black-Box Reductions for Parameter-free Online Learning in Banach Spaces

Cutkosky and Orabona [2018] introduces several new parameter-free online learning algorithms using the reduction technique. For a convex loss $l$ and parameter $w \in W$ in which $W$ is a convex set,

$$
\begin{aligned}
R_T(w^*) &= \sum_{t=1}^{T} l_t(w_t) - l_t(w^*) \\
&\leq \sum_{t=1}^{T} \langle g_t, (w_t - w^*)\rangle \\
&= \sum_{t=1}^{T} \langle g_t, z_t y_t\rangle - \langle g_t, w^*\rangle \\
&= \sum_{t=1}^{T} \langle g_t, y_t\rangle z_t - \langle g_t, y_t\rangle\|w^*\| + \|w^*\|(\langle g_t, y_t\rangle - \langle g_t, \frac{w^*}{\|w^*\|}\rangle) \\
&= \sum_{t=1}^{T} \langle\langle g_t, y_t\rangle, z_t - \|w^*\|\rangle + \|w^*\|\langle g_t, y_t - \|w^*\|w^*\rangle \\
&= R_T^{1D}(\|w^*\|) + \|w^*\|R_T^{S}(\frac{w^*}{\|w^*\|})
\end{aligned}
\tag{1}
$$

The origin problem is unknown with both the diameter $D$ of $w$ and the bounds of gradients $L_{\max}$ of gradients.

However, after reduced it to 2 sub-problems, the diameters for both are known. For the first term, it is a one-Dimension optimization problem, designing a 1D optimization algorithm $A^{1D}$ could solve this problem (FreeRex mentioned in subsection 2.1 could be applied here). For the second term, the parameter $\frac{w^*}{\|w^*\|}$ is a unit ball which means $D^S = 1$.

Simply speaking, the algorithm reduces $w$ of origin problem into $zy$, in which $z \in \mathbb{R}$ and $y \in \mathbb{R}^d$ whose diameter is 1. The reduction algorithm is described in algorithm 2.

This paper also introduces other fancy reduction technique but it is out of my research range so I just skip it.

## 3 Reinforcement Learning

Hopefully To be filled in the future.

## 4 Natural Language Processing

Hopefully To be filled in the future.

**Algorithm 2** 1D Reduction algorithm

**Input:** a 1D online learning algorithm $A_{1D}$ and a online learning algorithm $A_S$ whose domain is a ball with radius $r$ defined in Banach space, as well as loss $l$ of origin problem.

**for** $t = 1$ **to** $T$ **do**
  Get $z_t$ from $A_{1D}$
  Get $y_t$ from $A_S$
  $w_t = z_t y_t$
  $g_t = \frac{\partial l}{\partial w_t}$
  Set $\langle g_t, y_t \rangle$ as $t$th subgradient of $A_{1D}$
  Optimize $A_{1D}$
  Set $g_t$ as $t$th subgradient of $A_S$
  Optimize $A_S$
**end for**

# 5 Computer Vision

Hopefully To be filled in the future.

# 6 Conclusion

# References

A. Cutkosky and K. Boahen. Online Learning Without Prior Information. *Proceedings of Machine Learning Research*, 65:1–35, 2017. URL `https://arxiv.org/pdf/1703.02629.pdf`.

A. Cutkosky and F. Orabona. Black-Box Reductions for Parameter-free Online Learning in Banach Spaces. feb 2018. ISSN 1477-8920. doi: http://dx.doi.org/10.2166/wh.2016.230. URL `http://arxiv.org/abs/1802.06293`.

S. Shalev-Shwartz et al. Online learning and online convex optimization. *Foundations and Trends® in Machine Learning*, 4(2):107–194, 2012.