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 tth subgradient of A_{1D}
  Optimize A_{1D}
  Set g_t as tth subgradient of A_S
  Optimize A_S
end for

5 Computer Vision

Hopefully To be filled in the future.

6 Conclusion

References

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