Parameter-free Online Optimization
Part 4

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ICML 2020

Outline of the Tutorial

- Part 1: Stochastic and Online Convex Optimization
- Part 2: Parameter-free Convex Optimization
- Part 3: More Adaptivity and Applications
- **Part 4: Implementation, Experiments, Open Problems**

Somebody Won a Kaggle Competition Using Parameter-Free Algorithms!

Arturus / **kaggle-web-traffic**

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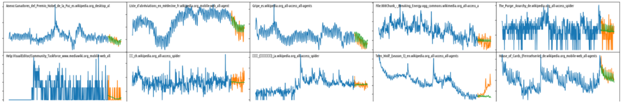
Code | Issues 12 | Pull requests 2 | Projects 0 | Wiki | Insights

1st place solution

kaggle-web-traffic · kaggle · time-series · timeseries · rnn-encoder-decoder · rnn · tensorflow · cudnn · cocob · seq2seq

Kaggle Web Traffic Time Series Forecasting

1st place solution



Training and validation

I used COCOB optimizer (see paper Training Deep Networks without Learning Rates Through Coin Betting) for training, in combination with gradient clipping. COCOB tries to predict optimal learning rate for every training step, so I don't have to tune learning rate at all. It also converges considerably faster than traditional momentum-based optimizers, especially on first epochs, allowing me to stop unsuccessful experiments early.

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  - `Pistol` uses per-coordinate updates, and guarantees the regret bound $O(\sum_{i=1}^{d} |x_i^\star| \sqrt{\sum_{t=1}^{T} |g_{t,i}| \log(|x_i^\star| T)})$.

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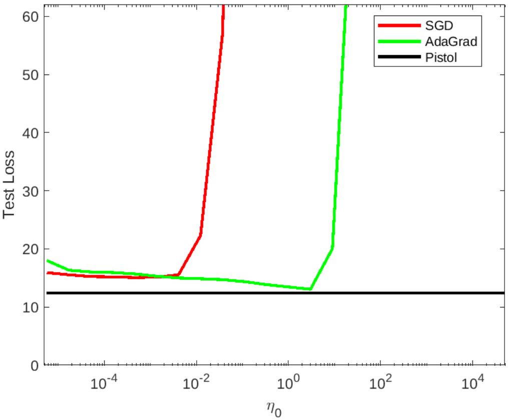
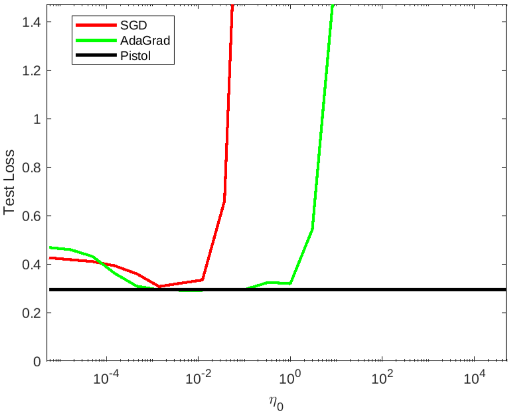
- For `AdaGrad` and `SGD`, we sweep the learning rate η_0.

[Orabona, NeurIPS'14] [`github.com/VowpalWabbit/vowpal_wabbit`]

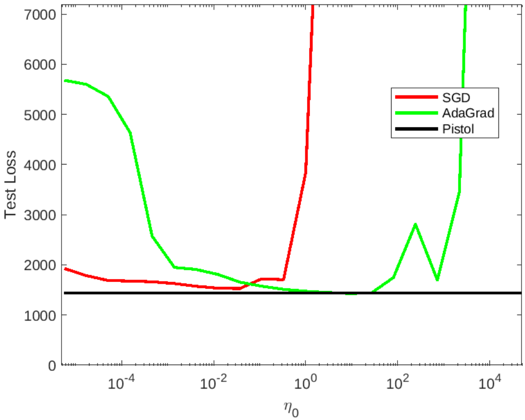
wisconsin (1187)



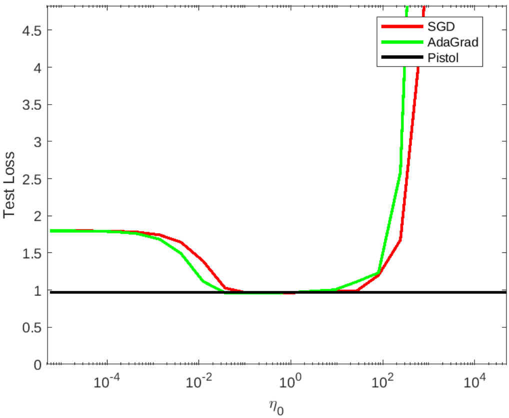
cleveland (1188)



auto price (1189)



2dplanes (215)



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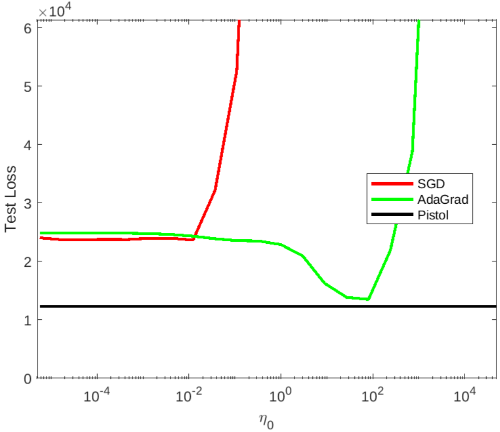
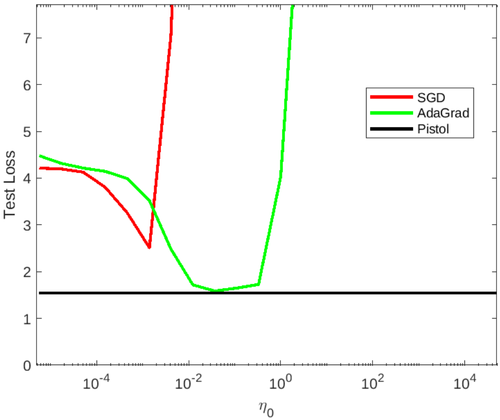
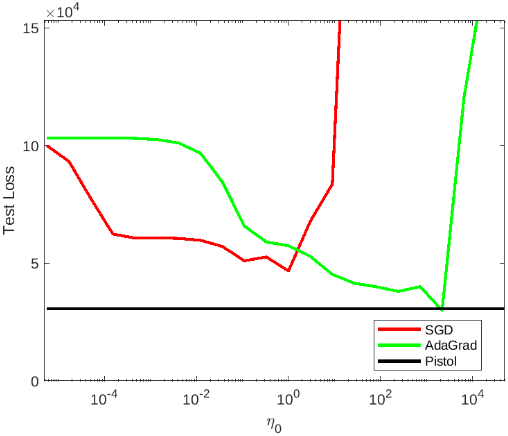


house 8L (344)


Test Loss
0
1
2
3
4
5
6
7
10^{-4}
10^{-2}
10^{0}
10^{2}
10^{4}
η_0
SGD
AdaGrad
Pistol

houses (573)



$\times 10^4$
15
10
5
0
Test Loss
10^{-4}
10^{-2}
10^{0}
10^{2}
10^{4}
η_0
SGD
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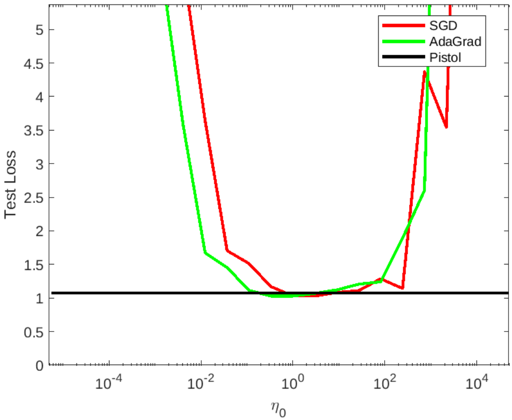
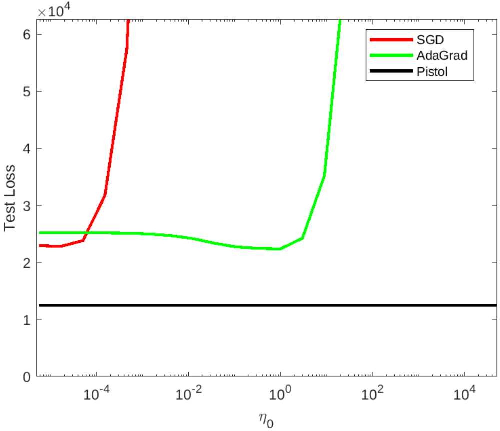
fried (564)



SGD
AdaGrad
Pistol
Test Loss
5
4.5
4
3.5
3
2.5
2
1.5
1
0.5
0
10^{-4}
10^{-2}
10^{0}
10^{2}
10^{4}
η_0

house 16H (574)



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2. There is no single “common default” learning rate that can work for all datasets.
3. Often, the parameter-free algorithm will outperform even a tuned gradient descent!

- Our theoretical analysis relies strongly on global convexity properties.

Deep Learning

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- Some tweaks are necessary to get the best performance.
- Providing a solid theoretical foundation here is a great open problem!

Dynamics of Coin Betting (Recall from Section 2)

- Remember the optimal gradient descent tuning:

$$\boldsymbol{x}_{t+1} = \boldsymbol{x}_t - \frac{\|\boldsymbol{x}^\star\|}{G\sqrt{T}}\boldsymbol{g}_t$$

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- Supposing a 1-d problem with $x_t \geq 0$ always, we have:

$$\begin{aligned} x_{t+1} &= \beta \text{Wealth}_t = \beta \text{Wealth}_{t-1} - \beta g_t x_t \\ &= x_t - \frac{g_t |x_t|}{\sqrt{T}} \end{aligned}$$

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- Conclusion: parameter-free algorithms behave similarly to gradient descent with learning rate $\eta_t = \frac{\|\boldsymbol{x}_t\|}{G\sqrt{T}}$.
- Coincidentally, scaling the "learning rate" by the magnitude of the weights has been recently suggested as an empirically useful heuristic in deep learning [You et al., 2017, 2019; Bernstein et al., arXiv'20].

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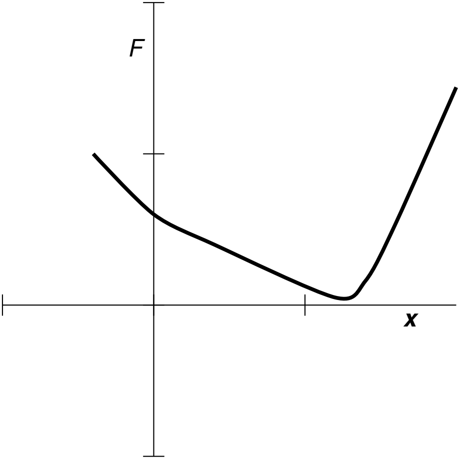
- In non-convex problems, this may not be true.
- Neural network initialization schemes seem to be important in training - we don’t want to destroy this initialization with some bad early updates.

Parameter-Free Algorithms as Binary Search



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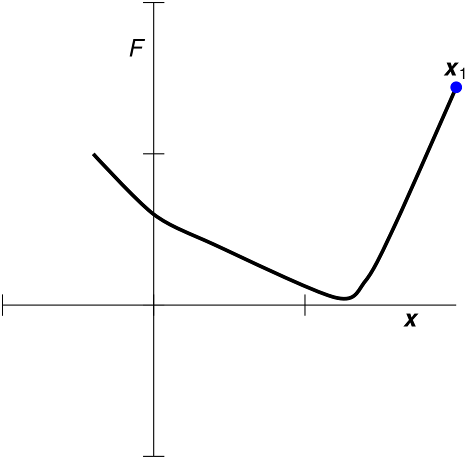

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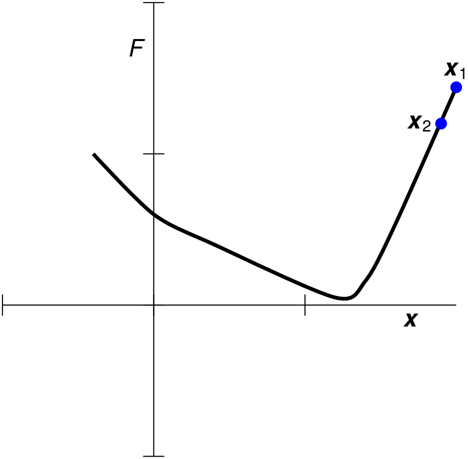

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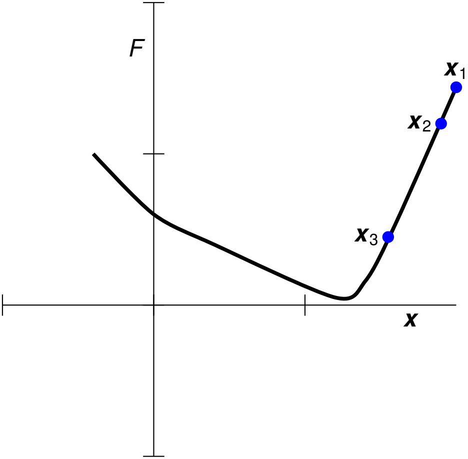

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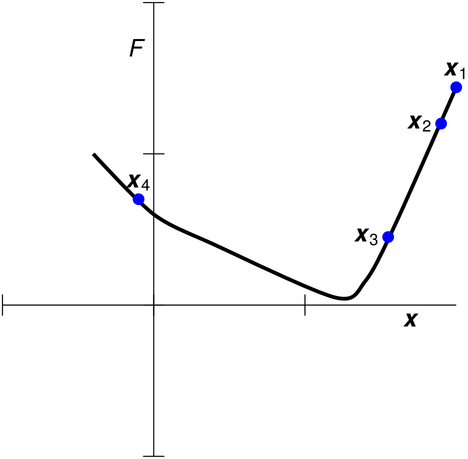

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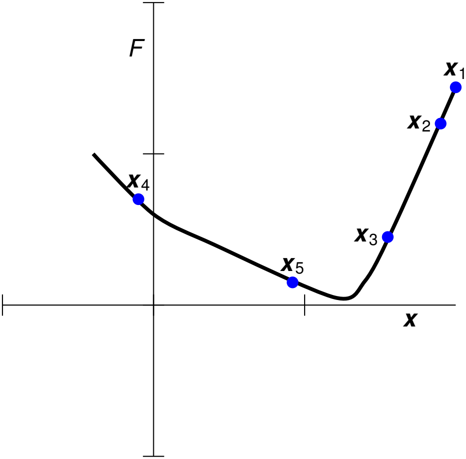

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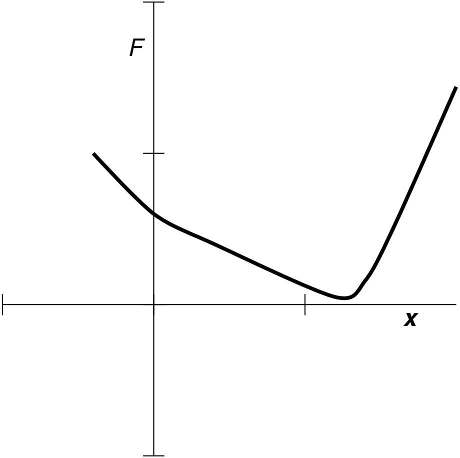
What if we use a different search factor?



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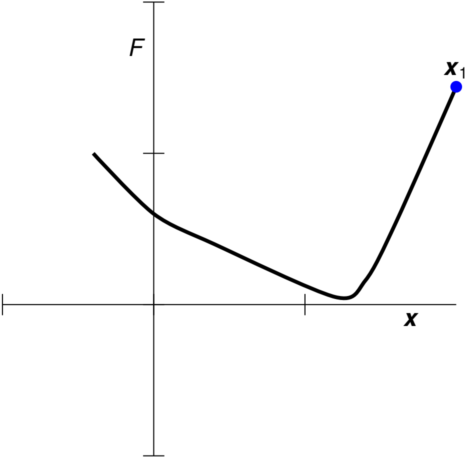

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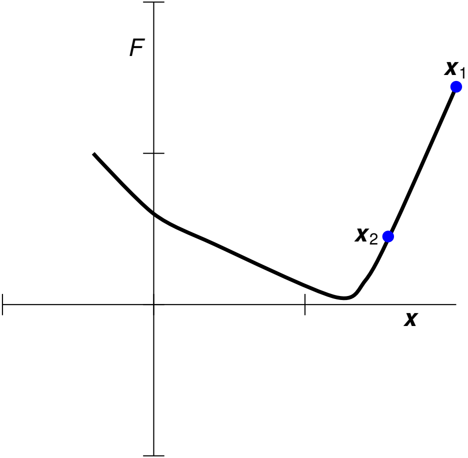

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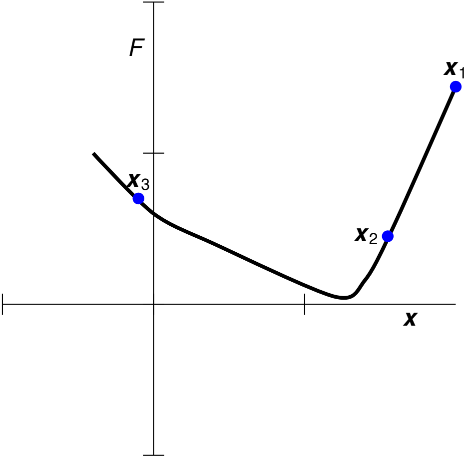

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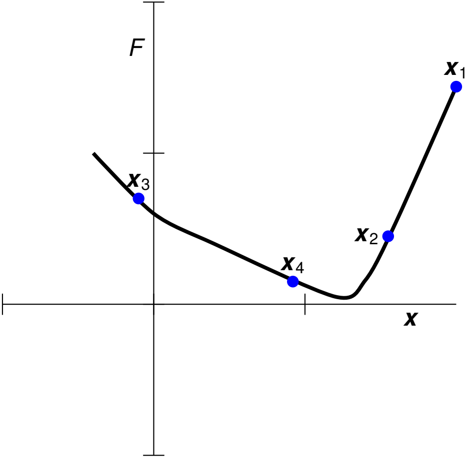

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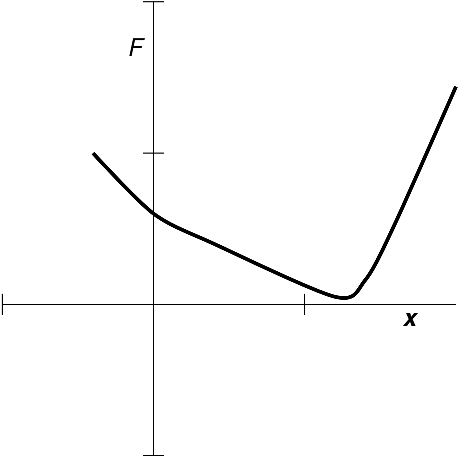

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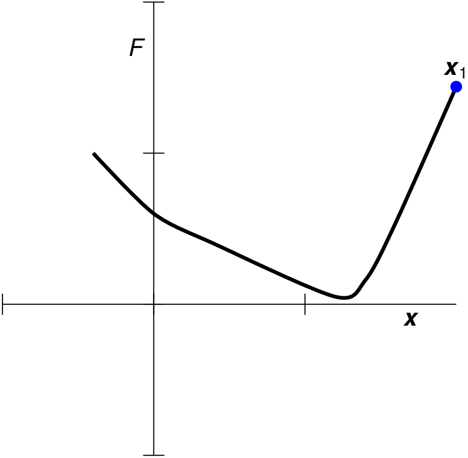

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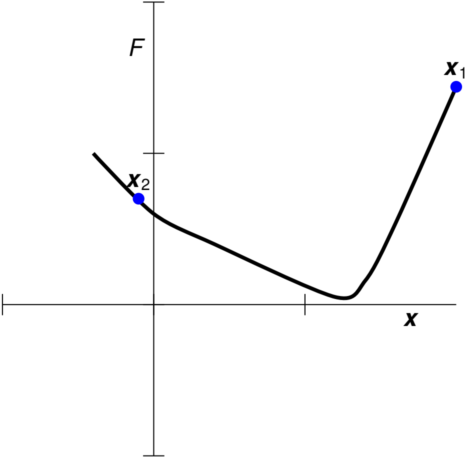

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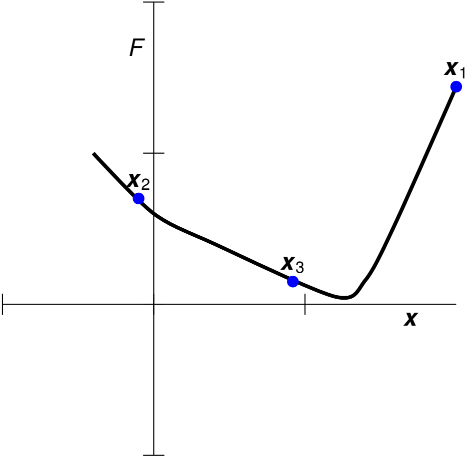
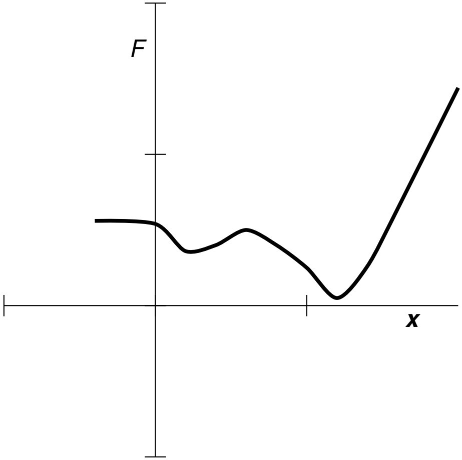


Binary Search on Non-Convex Objectives

First-order methods on non-convex objectives can be sensitive to large jumps:



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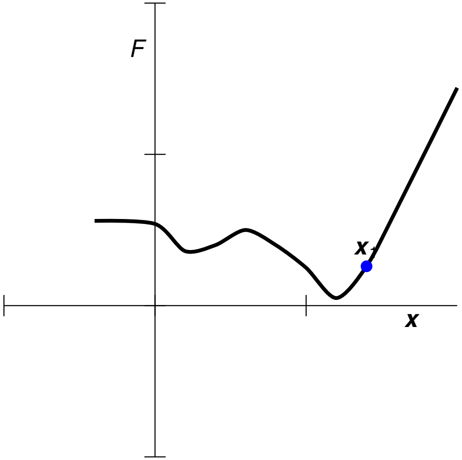

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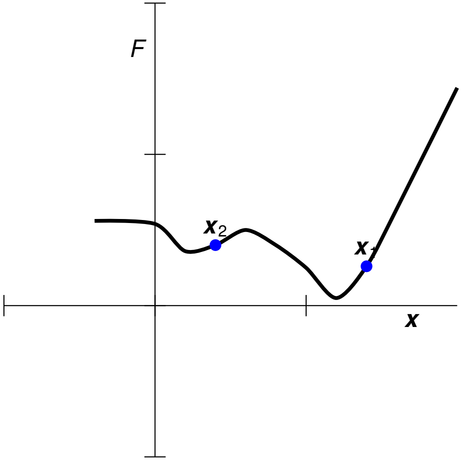

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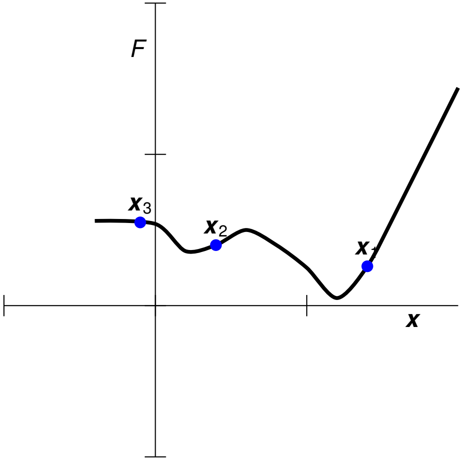

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Early-stage Dynamics of Coin-Betting Algorithms

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- Small initial wealth means we will make very small changes at first, while large initial wealth allows for large changes.
- The wealth changes exponentially fast, so one expects the algorithm to be very insensitive to the initial value.
- Unfortunately, since we cannot recover from bad behavior in the non-convex setting, we may need to be more conservative and start with smaller initial wealth.

Stability and Initialization

- For some large language models, it is necessary to decrease the initial wealth smaller than 1.
- Keep initial betting fraction from being too large initially:

```
beta = clip(true_beta, -0.1 * sum_grad, 0.1 * sum_grad)
```

- This formula is motivated by the fact that most algorithms set:

```
true_beta =  sum_grad * some_multiplier
```

Tweaks

- Neural networks are NOT initialized to zero. Record the initial value of the weights and translate the optimizer outputs by these values
- Normalize gradients by the maximum gradient.

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```
def apply_gradient(grad, var):
    max_grad = max(grad, max_grad)
    grad = grad/max_grad
    offset = get_param_free_output(grad, var)
    initial_value = get_initial_value(var)
    var.assign(initial_value + offset)
```

More Tweaks

- Add average of previous outputs (similar to the reduction for strongly-convex adaptivity)

```python
def apply_gradient(grad, var):
    max_grad = max(grad, max_grad)
    grad = grad/max_grad
    offset = get_param_free_output(grad, var)
    grad_norm_sq = squared_norm(grad)
    sum_squared_grad += grad_norm_sq
    weighted_sum_offset += grad_norm_sq * offset
    average_offset = weighted_sum_offset/sum_squared_grad
    initial_value = get_initial_value(var)
    var.assign(initial_value + average_offset + offset)
```

One More Algorithm: Parameter-Free Preconditioning

- A preconditioned regret bound looks like:

$$\sum_{t=1}^{T} \langle \boldsymbol{g}_t, \boldsymbol{x}_t - \boldsymbol{x}^\star \rangle \leq \sqrt{d \sum_{t=1}^{T} \langle \boldsymbol{g}_t, \boldsymbol{x}^\star \rangle^2}$$

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- Algorithms that achieve this typically require expensive matrix calculations.
- Recent work has suggested that such algorithms are helpful in optimizing neural networks [Gupta et al., ICML'18; Agarwal et al., ICML'19]

[Koren&Livni, NeurIPS'17; Kotlowski, ALT'17]

Faster Preconditioning (Sometimes) Using Coin-Betting

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- If $\left|\sum_{t=1}^{T} \langle \boldsymbol{g}_t, \boldsymbol{x}^\star \rangle\right| \ge \|\boldsymbol{x}_\star\|_2 \sqrt{\sum_{t=1}^{T} \|\boldsymbol{g}_t\|_2^2}$, then:

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- The algorithm runs in linear time (same as SGD).

[Cutkosky&Sarlos, ICML'19]

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- In the previous sections, we focused on 1-dimensional coin-betting algorithms, but this is not necessary.
- All the coin-betting framework seamlessly generalizes to vector betting:

$$\text{Wealth}_T = 1 - \sum_{t=1}^{T} \langle \boldsymbol{g}_t, \boldsymbol{x}_t \rangle$$

$$\boldsymbol{x}_t = \boldsymbol{\beta}_t \text{Wealth}_{t-1}, \ \|\boldsymbol{\beta}_t\| \leq 1$$

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- Unfortunately, taking advantage of exp-concavity is slow for learning high-dimensional quantities.

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- When $\left|\sum_{t=1}^T \langle \boldsymbol{g}_t, \boldsymbol{x}^\star \rangle\right| \geq \|\boldsymbol{x}_\star\|_2 \sqrt{\sum_{t=1}^T \|\boldsymbol{g}_t\|_2^2}$, a more refined analysis using the vector betting fractions shows that we even get the preconditioned bound.

[Cutkosky&Sarlos, ICML'19]

Recursive Optimizer

Initialize "inner" parameter-free algorithm $\mathcal{A}$.
Initialize $\text{Wealth}_0 = 1$
for $t = 1$ **to** T **do**
    Get $\boldsymbol{\beta}_t$ from $\mathcal{A}$.
    Play $\boldsymbol{x}_t = \boldsymbol{\beta}_t \text{Wealth}_{t-1}$
    Get gradient $\boldsymbol{g}_t$, define $\ell_t(\boldsymbol{\beta}) = -\log(1 - \langle \boldsymbol{\beta}, \boldsymbol{g}_t \rangle)$
    Compute $\boldsymbol{z}_t = \ell_t'(\boldsymbol{\beta}_t) = \frac{\boldsymbol{g}_t}{1 - \langle \boldsymbol{\beta}_t, \boldsymbol{g}_t \rangle}$
    Send $\boldsymbol{z}_t$ to $\mathcal{A}$.
    Set $\text{Wealth}_t = \text{Wealth}_{t-1} - \langle \boldsymbol{g}_t, \boldsymbol{x}_t \rangle$
end for

Two Lessons

1. The property of having small regret for small comparators can be used in surprising and non-intuitive ways.
2. Parameter-free algorithms can obtain bounds which are better than any currently known gradient-descent-like method, <u>even with oracle tuning</u>.

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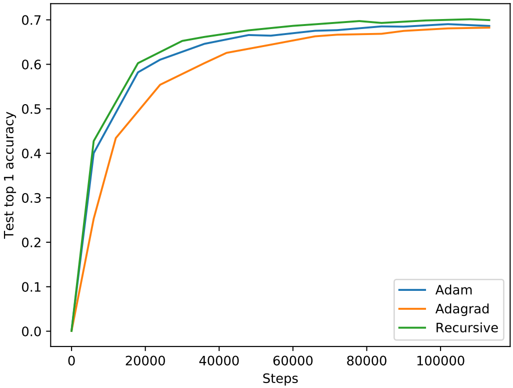
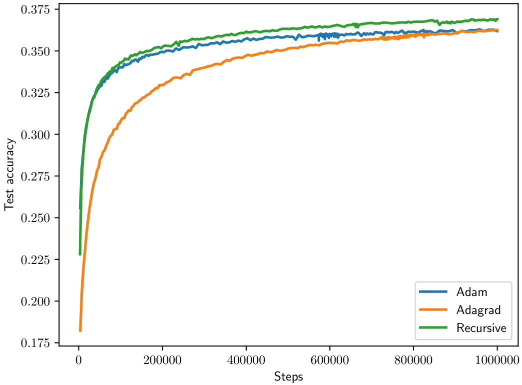
- We compare to `Adam` and `Adagrad` with fixed learning rates (no warm-up and decay or other complicated schedules).
- Caveat: if one does tune a more complicatedschedule it is possible to get better results than we'll show.

`github.com/google-research/google-research/tree/master/recursive_optimizer`

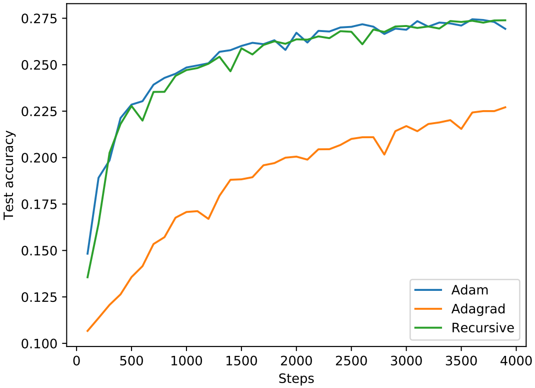
ResNet50 Imagenet



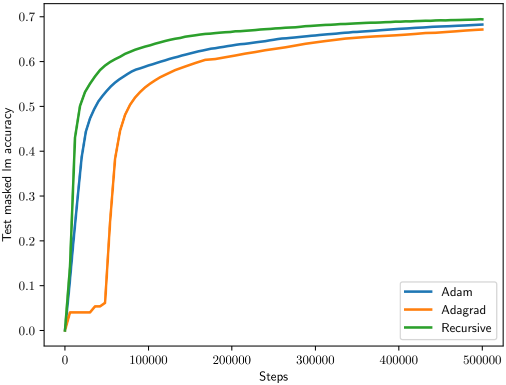
Transformer LM1B



Transformer Penn Tree Bank



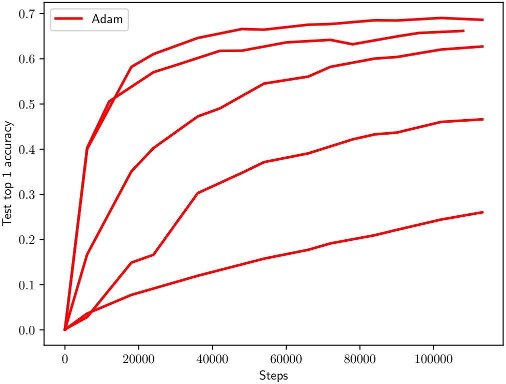
BERT-Base Pretraining



Robustness to Initial Wealth

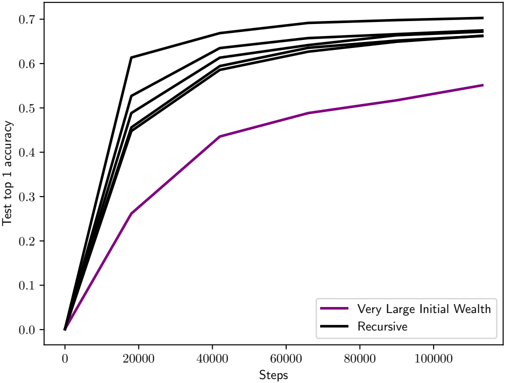
- Unfortunately, we now needed to make sure that initial wealth is not too big.
- This is a parameter, but since wealth changes exponentially fast, we might hope that the algorithm is very robust to making the initial wealth very small.

ResNet50 Imagenet Robustness



Robustness to learning rate.

ResNet50 Imagenet Robustness



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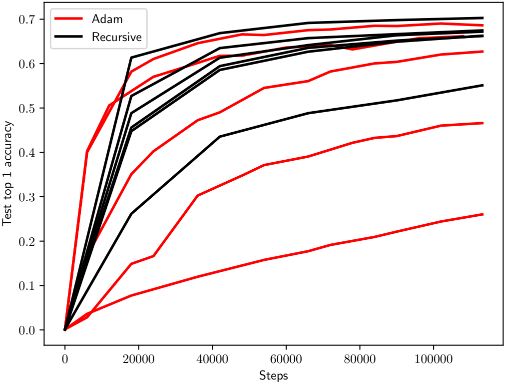

Robustness to initial wealth or learning rate.

Other Topics

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- Scale Invariant learning [Kotlowski, ALT'17; Kempka et al., ICML'19; Mhammedi&Koolen, COLT'20]

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- High probability bounds?

Section 4 Summary

1. Parameter-Free Algorithms work well on benchmark tasks in convex and even non-convex settings!
2. Sometimes Parameter-Free bounds can <u>exceed</u> tuned SGD bounds.
3. There are lots of good open problems to solve!