

A Closer Look at Adaptive Regret

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- 1 Why adaptive regret?
- 2 Setup
- 3 Results

1 Why adaptive regret?

2 Setup

3 Results

Weather forecasting: adaptivity

Predictor



Expert



Expert



Expert



Nature



Weather forecasting: adaptivity

Predictor		
Expert		30%
Expert		90%
Expert		20%
Nature		

Weather forecasting: adaptivity

Predictor		55%
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Goal: close to the best expert overall (solution: AA)

Weather forecasting: adaptivity

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Expert		30%	40%	...	is bad on foggy days!
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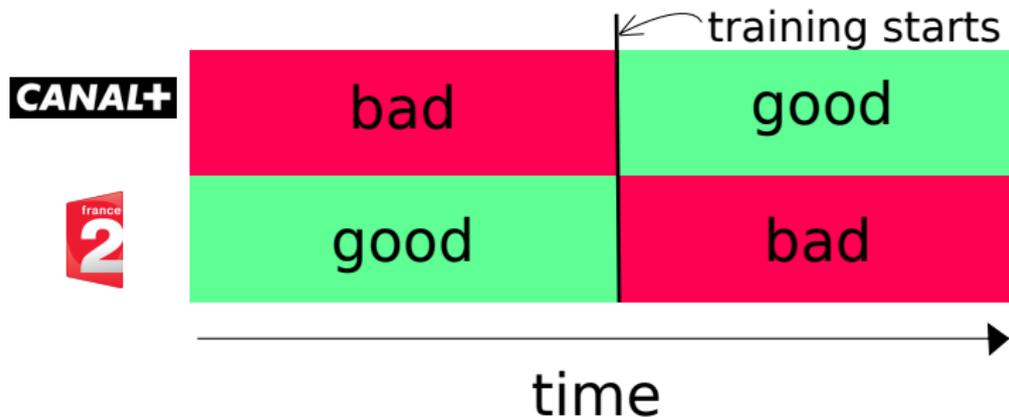
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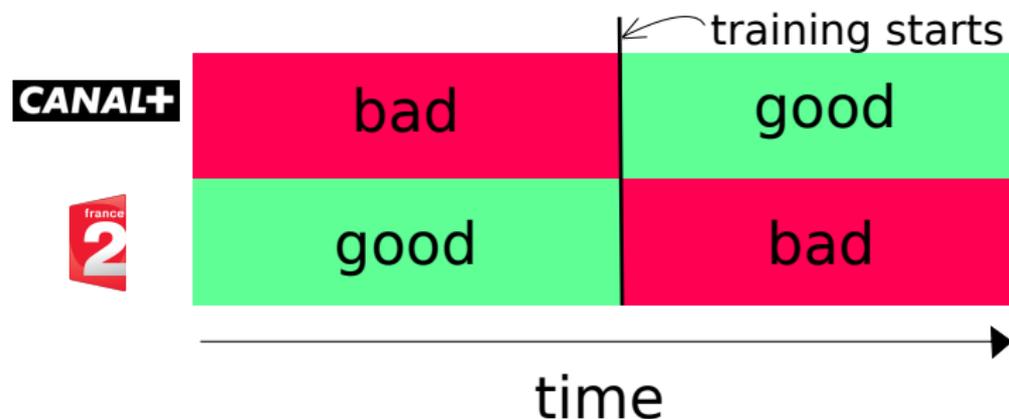
Goal: close to the best expert overall (solution: AA)

Adaptive goal: close to the best expert on **every time interval**

Example continued



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Non-adaptive predictor would lose trust in the first guy.

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- Restarting existing algorithms and combining their predictions [Hazan and Seshadhri 2009]
Also turned out to be Fixed Share!

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Our results

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Our results

- 1 Figured out the worst-case adaptive regret of Fixed Share
- 2 Proved the optimality of Fixed Share — every algorithm is dominated by a Fixed Share (i.t.o. worst-case adaptive regret)

1 Why adaptive regret?

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for $t = 1, 2, \dots$ **do**

Learner announces probability vector $\mathbf{w}_t \in \Delta_N$

Reality announces loss vector $\ell_t \in [-\infty, \infty]^N$

Learner suffers loss $\ell_t := -\ln \sum_n \mathbf{w}_t^n e^{-\ell_t^n}$

end for

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Definition

The **adaptive regret** of the algorithm on the interval $[t_1, t_2]$ is the loss of the algorithm there minus the loss of the best expert there:

$$R_{[t_1, t_2]} := L_{[t_1, t_2]} - \min_j L_{[t_1, t_2]}^j$$

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- We get **worst-case** adaptive regret by maximising over the choice of expert losses.

Aggregating Algorithm [Vovk 1990] updates weights as:

$$w_{t+1}^n := \frac{w_t^n e^{-\ell_t^n}}{\sum_n w_t^n e^{-\ell_t^n}}.$$

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Fixed Share (family) is defined by a sequence of “switching rates” α_t .
The weight update is

$$w_{t+1}^n := \frac{\alpha_{t+1}}{N-1} + \left(1 - \frac{N}{N-1} \alpha_{t+1}\right) \frac{w_t^n e^{-\ell_t^n}}{\sum_n w_t^n e^{-\ell_t^n}}.$$

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Adaptivity hides in the first term.

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Fixed Share Worst-Case Adaptive regret data

We proved that the worst case data for Fixed Share looks like this:

	1	...	$t_1 - 1$	t_1	...	t_2
Expert 1	?	?		0	0	0
Expert 2	?	?	?			
...	?	?	?			
Expert N	?	?	?			

where  denotes infinite loss, 0 – zero loss and '?' – losses that don't matter.

Fixed Share Worst-Case Adaptive regret formula

Knowing the worst-case data, we can plug it in and calculate the regret:

Theorem

The worst-case adaptive regret of Fixed Share with N experts on interval $[t_1, t_2]$ equals

$$-\ln \left(\frac{\alpha_{t_1}}{N-1} \prod_{t=t_1+1}^{t_2} (1 - \alpha_t) \right).$$

Different α -s: examples

- Classic Fixed Share ($\alpha_t = \text{const}$):

$$\begin{aligned} & \ln(N - 1) - \ln \alpha - (t_2 - t_1) \ln(1 - \alpha) && \text{for } t_1 > 1, \text{ and} \\ & \ln N - (t_2 - 1) \ln(1 - \alpha) && \text{for } t_1 = 1. \end{aligned}$$

Linear in length $t_2 - t_1$

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Linear in length $t_2 - t_1$

- Slowly decreasing $\alpha_t = 1/t$ leads to regret of

$$\begin{array}{ll} \ln(N - 1) + \ln t_2 & \text{for } t_1 > 1, \text{ and} \\ \ln N + \ln t_2 & \text{for } t_1 = 1. \end{array}$$

Logarithmic in end-time t_2

- Quickly decreasing switching rate.

If we set $\alpha_t = t^{-2}$ we have the upper bound for regret

$$\ln N + 2 \ln t_1 + \ln 2.$$

Logarithmic in start-time t_1

For $t_1 = 1$ this is very close to classical AA regret!

Combining adaptive stuff to get tracking bounds

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Time	Interval 1				Interval 2				Interval 3			
Expert 1	0	0	...	0			...				...	
Expert 2			...		0	0	...	0			...	
Expert 3			...				...		0	0	...	0

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Expert 2			...		0	0	...	0			...	
Expert 3			...				...		0	0	...	0

And the tracking bound can be recovered!

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Theorem

The worst-case adaptive regret of any algorithm is dominated by that of a Fixed Share.

Theorem (Lower bound)

Let N be the number of experts. If $\phi(t_1, t_2)$ is the worst-case adaptive regret of an algorithm, then

$$\phi(t, t) \geq \ln N \quad \text{for all } 1 \leq t \text{ and}$$

$$\phi(t_1, t_2) \geq \phi(t_1, t_1) - \sum_{t=t_1+1}^{t_2} \ln \left(1 - (N-1)e^{-\phi(t,t)} \right) \quad \text{for all } 1 \leq t_1 < t_2.$$

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Fixed Share with

$$\alpha_t = (N-1)e^{-\phi(t,t)}.$$

will have the second line with **equality**.

- We studied two intuitive methods to obtain adaptive algorithms.
- They turned out to be Fixed Share.
- We studied the worst-case Adaptive Regret of Fixed Share.
- We showed that Fixed Share is optimal.

Thank you!