1. The Setup

- Choose comparison class of predictors, called experts.
- A Master Algorithm combines the predictions of experts to make its own predictions.
- Experts and Master incur loss.

For example: (see above) Suppose experts are meteorologists, predicting the weather (0=sun, 1=rain). Weather forecasts are made daily, and some experts are better than others.

The protocol for the Expert Framework is as follows:

Loop for each trial $t = 1, \ldots, T$
- Get next instance $x_t$
- Make prediction $\hat{y}_t = w_1 x_t, \ldots, w_k x_t$
- Incur loss $L_{t,i}$

4. Results

The following plots illustrate how the Master Algorithms “adapt” when the best expert changes over time.

The figure on the right is a total loss plot.
- $T = 1400$ trials, $n = 20000$ experts
- $k = 6$ shifts (every 200 trials)

Notice how the share algorithms fixate on a new expert when it starts performing well. The Static Expert algorithm stays with the best expert in the first segment.

The figure on the left shows the weights of experts under the Fixed Share to Start Vector update.
- Same setup as in the figure above.

Weights switch quickly when a new expert starts performing well.

The figure on the right shows the weights of experts under the Fixed Share to Decaying Past share update.
- Again, same setup as above.

Notice how the weights of experts which had high weight previously recover weight even more quickly when they become useful again.

The figure on the left shows a log-plot of the weights of experts under the Fixed Share to Decaying Past update.
- Good expert’s weights are picked up exponentially (linearly in the plot).
- Experts which had high weight in the past maintain a higher weight than other experts while dormant.

3. Share Update

A second update helps the weight of newly successful experts recover. After the loss update the past weight vectors are mixed:

$$w_{t+1} = \frac{w_{t+1|i}^{\text{norm}}}{\sum_{q=0}^{T} \gamma_{t+1,q} w_{t,q}^{\text{norm}}}$$

where $\sum_{q=0}^{T} \gamma_{t+1,q} = 1$

The chosen mixture scheme influences the recovery properties of the Master Algorithm.

5. Relative Loss Bounds

Using the share updates we get bounds that have the following forms: We pay extra for the encoding of the partition $P$ (location of boundaries, and subset of “successful” experts).

$$L_{t,i} \leq \min_{P} \left( L_{t,i|P} + O(\text{bits for encoding } P) \right)$$

$\rightarrow$ Finding the best partition (off-line) in general is NP-complete.

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The protocol

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