## Online Portfolio Hedging with the Weak Aggregating Algorithm

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- Hedging is the act of protecting an investment against unfavorable moves in the market by trading a negatively correlated asset or investment instrument.
- Here we explore using prediction with expert advice algorithms to find optimal hedge decisions given a pool of hedging strategies.

- Cylinder Hedging Model
- 2 Weak Aggregating Algorithm
- 3 WAA for Hedging
- 4 Empirical Results





2 Weak Aggregating Algorithm

3 WAA for Hedging

Empirical Results

- We will be looking at a special case of a Financial Market Makers (MMs) hedging strategy
- The model has two main parameters:
  - A pair of long and short limits (typically specified in US dollars)
  - A hedge fraction specifying how much to hedge



Figure: Cylinder Model Position

#### Figure: Cylinder Model PnL

• Directional indicators can improve on the models ability to hedge effectively

Algorithm 1 Cylinder Hedging Model

 $\begin{array}{l} \textbf{Parameters: } \log/\text{short Limit, Hedge fraction and Skew: } L_l, L_s, H_l, H_s, S_l, S_s \\ & \text{Directional indicators Id}_t, \ t = 1, 2, \dots \end{array} \\ \textbf{for } t = 1, 2, \dots \ \textbf{do} \\ \textbf{if } Position_l^C > L_l + (L_l \times S_l \times Id_t) \ \textbf{then} \\ & \mid \text{ Hedge Fraction}_t \leftarrow H_l \\ \textbf{end} \\ \textbf{if } Position_l^C < L_s + (L_s \times S_s \times Id_t) \ \textbf{then} \\ & \mid \text{ Hedge Fraction}_t \leftarrow H_s \\ \textbf{end} \\ \textbf{else} \\ & \mid \text{ Hedge Fraction}_t \leftarrow 0 \\ \textbf{end} \end{array}$ 

end





Figure: Price of Underlying Asset









Figure: Client, Hedge and Net Drawdown



2 Weak Aggregating Algorithm

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Empirical Results

- On every step t = 1, 2, ..., the learner L produces a prediction γ<sub>t</sub> ∈ Γ, where Γ is a known prediction space.
- The nature produces a loss function λ<sub>t</sub> : Γ → ℝ and the learner suffers loss ℓ<sub>t</sub> = λ<sub>t</sub>(γ<sub>t</sub>).
- We measure the performance of *L* by the *cumulative loss* over *T* steps given by

$$\operatorname{Loss}_{\mathcal{T}}(\mathcal{L}) = \sum_{t=1}^{\mathcal{T}} \ell_t$$
.

## Prediction with Expert Advice Framework

- Suppose that there are N experts E<sub>n</sub>, n = 1, 2, ..., N, making prediction in the same environment as L.
- We want the cumulative loss  $\text{Loss}_{\mathcal{T}}(\mathcal{L})$  to be small compared to the minimum of experts' losses  $\text{Loss}_{\mathcal{T}}(\mathcal{E}_n) = \sum_{t=1}^{T} \ell_t^n$ .

Protocol 1 Prediction with Expert Advice Protocol

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 \begin{array}{l} \textbf{for } t = 1, 2, \dots, \textbf{do} \\ \text{experts } \mathcal{E}_n \text{ output predictions } \gamma_t^n \in \Gamma, \ n = 1, 2, \dots, N \\ \text{learner } \mathcal{L} \text{ outputs a prediction } \gamma_t \in \Gamma \\ \text{nature produces a function } \lambda_t : \Gamma \to \mathbb{R} \\ \text{experts } \mathcal{E}_n \text{ suffer losses } \ell_t^n = \lambda_t(\gamma_t^n), \ n = 1, 2, \dots, N \\ \text{learner } \mathcal{L} \text{ suffers loss } \ell_t = \lambda_t(\gamma_t) \\ \textbf{end} \end{array}
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- Let  $\Gamma$  be a convex set so that for any  $\gamma_1, \gamma_2, \ldots, \gamma_N \in \Gamma$  and probabilities  $p_1, p_2, \ldots, p_N$  ( $p_n \ge 0$  for  $n = 1, 2, \ldots, N$  and  $\sum_{n=1}^{N} p_n = 1$ ) the convex combination  $\gamma = \sum_{n=1}^{N} p_n \gamma_n$  is defined and belongs to  $\Gamma$ .
- In order to obtain performance bounds for WAA, one needs to assume convexity of loss functions  $\lambda_t$ ; this ensures the inequality  $\ell_t \leq \sum_{n=1}^{N} p_{t-1}^n \ell_t^n$ .
- We will also need losses to be bounded. Let  $L \in \mathbb{R}$  be such that

$$\max_{n=1,2,\ldots,N} \ell_t^n - \min_{n=1,2,\ldots,N} \ell_t^n \le L$$

## Weak Aggregating Algorithm

• A learner following the WAA protocol with equal initial weights and a learning rate  $\eta_t = c/\sqrt{t}$  where  $c = 2\sqrt{\ln N}/L$ , can ensure the following bound on loss:

$$\operatorname{Loss}_{\mathcal{T}}(\mathcal{L}) \leq \operatorname{Loss}_{\mathcal{T}}(\mathcal{E}_n) + L\sqrt{\mathcal{T}\ln N}$$

for all T = 1, 2, ..., N and all experts  $\mathcal{E}_n$ , n = 1, 2, ..., N.

Algorithm 2 Weak Aggregating Algorithm

 $\begin{aligned} & \textbf{Parameters: Initial distribution } q_1, q_2, \dots, q_N, q_n \geq 0 \text{ for } n = 1, 2, \dots \text{ and } \sum_{n=1}^N = 1 \\ & \text{Learning rates } \eta_t > 0, t = 1, 2, \dots \end{aligned} \\ & \textbf{let } L_0^n = 0, n = 1, 2, \dots, N \\ & \textbf{for } t = 1, 2, \dots \textbf{do} \\ & \textbf{calculate weights } w_{t-1}^n = q_n e^{-\eta_t L_{t-1}^n}, n = 1, 2, \dots, N \\ & \text{normalise the weights } p_{t-1}^n = w_{t-1}^n / \sum_{i=1}^N w_{t-1}^i, n = 1, 2, \dots, N \\ & \text{normalise the weights } p_{t-1}^n = w_{t-1}^n / \sum_{i=1}^N w_{t-1}^i, n = 1, 2, \dots, N \\ & \text{normalise the weights } p_{t-1}^n = m_{t-1}^n / \sum_{i=1}^N w_{t-1}^i, n = 1, 2, \dots, N \\ & \text{normalise the weights } p_{t-1}^n = m_{t-1}^n / \sum_{i=1}^N w_{t-1}^i, n = 1, 2, \dots, N \\ & \text{normalise the weights } p_{t-1}^n + p_{t-1}$ 

## Discounted Loss

Suppose that we are given coefficients α<sub>1</sub>, α<sub>2</sub>, ... ∈ (0, 1]. Let the cumulative discounted loss for a learner *L* be given by

$$\widetilde{\text{Loss}_{T}}(\mathcal{L}) = \sum_{t=1}^{T} \lambda(\gamma_{t}) \left( \prod_{s=t}^{T-1} \alpha_{s} \right) = \alpha_{T-1} \widetilde{\text{Loss}_{T-1}}(\mathcal{L}) + \lambda(\gamma_{T}) ;$$

• If *L* is known in advance and all discounting factors are equal and less than 1, one can take

$$\eta_t = \eta = \frac{2\sqrt{2(1-\alpha)\ln N}}{L}$$

and ensure for equal weights  $q_1=q_2=\ldots=q_N=1/N$  the bound

$$\operatorname{Loss}_{\mathcal{T}}(\mathcal{L}) \leq \operatorname{Loss}_{\mathcal{T}}(\mathcal{E}_n) + L \sqrt{\frac{\ln N}{2(1-\alpha)}}$$
 (1)

for all T = 1, 2, ..., N.

Algorithm 3 Weak Aggregating Algorithm with Discounting

 $\begin{aligned} & \textbf{Parameters: Initial distribution } q_1, q_2, \dots, q_N, q_n \geq 0 \text{ for } n = 1, 2, \dots \text{ and } \sum_{n=1}^N = 1. \\ & \text{Discounting factors } \alpha_1, \alpha_2, \dots \in (0, 1]. \\ & \text{Learning rates } \eta_t > 0, t = 1, 2, \dots \end{aligned} \\ & \textbf{let } L_0^n = 0, n = 1, 2, \dots, N \\ & \textbf{for } t = 1, 2, \dots \textbf{do} \\ & \textbf{calculate weights } w_{t-1}^n = q_n e^{-\eta_t \alpha_{t-1} L_{t-1}^n}, n = 1, 2, \dots, N \\ & \textbf{normalise the weights } p_{t-1}^n = w_{t-1}^n / \sum_{i=1}^N w_{t-1}^i, n = 1, 2, \dots, N \\ & \textbf{normalise the weights } p_t^n = \eta_n e^{-\eta_t \alpha_{t-1} L_{t-1}^n}, n = 1, 2, \dots, N \\ & \textbf{normalise the weights } p_{t-1}^n = w_{t-1}^n / \sum_{i=1}^N w_{t-1}^i, n = 1, 2, \dots, N \\ & \textbf{notput } \gamma_t = \sum_{n=1}^N p_{t-1}^n \gamma_t^n \\ & \textbf{read experts losses } \ell_t^n, n = 1, 2, \dots, N \\ & \textbf{update } L_t^n = \alpha_{t-1} L_{t-1}^n + \ell_t^n, n = 1, 2, \dots, N \end{aligned} \\ & \textbf{end} \end{aligned}$ 

2 Weak Aggregating Algorithm

3 WAA for Hedging

Empirical Results

- Our pool of experts are a set of cylinder models
- A hedge decision is represented by  $\gamma \in [-1, 0]$ , where  $\gamma_t = -1$  implies hedging out the entire client position and  $\gamma_t = 0$  corresponds to a decision not to hedge over trial t
- It is natural to define loss in terms of the the MM's PnL resulting from facilitating client orders
- As PnL represents the MM's gain, we need to take its inverse when defining the loss. We can therefore take the loss at time t to be  $\lambda(\gamma_t) = -\text{PnL}_t\gamma_t$

 Here we will take a similar approach considering the loss function with the coefficients u ≥ 0 and v ≥ 0:

$$\lambda(\gamma) = -\left(\frac{u}{u+v}\mathsf{PnL}\gamma + \frac{v}{u+v}\min(\mathsf{PnL}\gamma,0)\right)$$

• This allows a the learner to adjust their risk appetite adding more focus on losses that profit and minimise drawdown

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## Data Set

- Real-world currency exchange price data and client order data based on the trading behaviour of individuals opening positions with an FX MM
- EUR/USD over a 41 month period (Feb 2014 June 2017) represented in hourly epochs



### **Experts**

• Our pool of experts is the hedge fraction predictions from 100 unique cylinder models.



#### Figure: EUR/USD PnL

Online Portfolio Hedging

### Results

EUR/USD PnL against Max Drawdown.**Discount Key** Red: 0%, Cyan: 2.5%, Purple: 5%, Black: 7.5%, Pink: 10%, Orange: 20%



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- We have shown that the Weak Aggregating Algorithm (WAA) can be used to combine the predictions from a pool of cylinder hedging models to improve key performance metrics - namely the overall profit (PnL) - whilst simultaneously not compromising on the smoothness of returns by minimising drawdowns
- We have further introduced a method for applying discounted loss to the WAA





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