Online Decision-making with a Expert Committee and Its Application on FahsionFlow

Zalando Search Team

Zalando SE

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Overview

1. Prediction with experts, game playing and portfolio management
   - Prediction with Experts' advice
   - Online repeated game playing
   - Universal portfolio
2. Bandit Optimization in metric spaces
   - Bandit: play games with limited feedbacks
   - Gaussian process bandit optimization
   - General Bayesian optimization
3. Concept drift in online decision
   - Stability v.s. adaptivity
   - Explicite detection of concept drifts
   - Adaptive regret for tracking the best expert
   - Time-varing suface-responce bandit optimization
4. Sku Proposal in FashionFlow
   - Expert setting v.s. Bandit setting
   - From a good classifier to a good proposer

A gentle start

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A simple policy

The final decision is made with the majority voting from the expert committee: $\hat{y}^{(t)} = \textbf{sign}(\frac{\sum_{n=1}^{N} f_i^{(t)}}{N} - 0.5)$;

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$w_n^{(t)} \leftarrow 0$ if expert E_n makes a mistake at time $t-1$, *i.e.* kick E_n out of the committee;

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Cummulative loss:

$$\hat{L}^{(t)} = \sum_{i=t}^{t} l(\hat{y}^{(t)}, y^{(t)}) \leq \log_2 N; \quad (1)$$

Generalized committee

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$$R_n^{(t)} = \hat{L}^{(t)} - L_n^{(t)} = \sum_{i=t}^{t} l(\hat{y}^{(t)}, y^{(t)}) - \sum_{i=t}^{t} l(f_n^{(t)}, y^{(t)}) \tag{2}$$

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the upper bound of regret

$R^{(t)*} = \max_{n \in [1,N]} R_n^{(t)} = \hat{L}^{(t)} - \min_{n \in [1,N]} L_n^{(t)}$

Weighted majority algorithm

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$$w_n^{(t+1)} = (1-\eta) w_n^{(t)} \tag{3}$$

where $\eta \leq \frac{1}{2}$.

Analysis on weighted majority algorithm

Theorem (Regret bound using weighted majority)

After T steps, $\hat{L}^{(T)} \leq 2(1+\eta)\min_{1 \in [1,N]} L_n^{(T)} + \frac{2\ln N}{\eta}$

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Proof: Let $\Gamma^{(t)} = \sum_{n\in[1,N]} w_n^{(t)}$, then $\Gamma^{(1)} = N$. Also, if the forecaster makes a mistake, $\hat{y}^{(t)} \neq y^{(t)}$

$$\Gamma^{(t+1)} \leq \Gamma^{(t)}(\frac{1}{2} + \frac{1}{2}(1-\eta) = \Gamma^{(t)}(1-\frac{\eta}{2}) \tag{4}$$

therefore:

$$\Gamma^{(T+1)} \leq N(1-\frac{\eta}{2})^{\hat{L}^{(T)}} \tag{5}$$

for any individual expert n

$$w_n^{(T+1)} = (1-\eta)^{L_n^{(T)}} \tag{6}$$

since $w_n^{(T+1)} \leq \Gamma^{(T+1)} \implies (1-\eta)^{L_n^{(T)}} \leq N(1-\frac{\eta}{2})^{\hat{L}^{(T)}}$

Analysis on weighted majority algorithm, cont.

$$
\begin{aligned}
(1-\eta)^{L_n^{(T)}} &\leq N(1-\tfrac{\eta}{2})^{\hat{L}^{(T)}} \\
\Leftrightarrow L_n^{(T)} \ln(1-\eta) &\leq \ln N + \hat{L}^{(T)} \ln(1-\tfrac{\eta}{2}) \\
\Leftrightarrow -\ln(1-\tfrac{\eta}{2}) &\leq -L_n^{(T)} \ln(1-\eta) + \ln N \\
\xRightarrow{x \leq -\ln(1-x)} \tfrac{\eta}{2}\hat{L}^{(T)} &\leq -L_n^{(T)} \ln(1-\eta) + \ln N \\
\xRightarrow{-\ln(1-x) \leq x+x^2, \text{when } x \leq 1/2} \tfrac{\eta}{2}\hat{L}^{(T)} &\leq L_n^{(T)} \eta(1+\eta) + \ln N \\
\Leftrightarrow \hat{L}^{(T)} &\leq 2(1+\eta) L_n^{(T)} + \frac{2\ln N}{\eta}
\end{aligned}
\tag{7}
$$

Randomized weighted majority algorithm

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After T steps, $\hat{L}^{(T)} \leq (1+\eta) \min_{1 \in [1,N]} L_n^{(T)} + \frac{\ln N}{\eta}$

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Proof: Let $\Gamma^{(t)} = \sum_{n\in[1,N]} w_n^{(t)}$, then $\Gamma^{(1)} = N$.

At each time t, let $F^(t) = \frac{\sum_{n:f_n^{(t)}\neq y^{(t)}} w_n^{(t)}}{\sum_n w_n^{(t)}}$, then

$$\Gamma^{(t+1)} = \Gamma^{(t)}\Big(1 - F^{(t)} + F^{(t)}(1-\eta)\Big) = \Gamma^{(t)}(1 - F^{(t)}\eta) \tag{9}$$

therefore:

$$\Gamma^{(T+1)} = N\prod_{t=1}^{T}(1 - F^{(t)}\eta) \tag{10}$$

for any individual expert n : $w_n^{(T+1)} = (1-\eta)^{L_n^{(T)}}$,
since $w_n^{(T+1)} \leq \Gamma^{(T+1)} \Longrightarrow (1-\eta)^{L_n^{(T)}} \leq N\prod_{t=1}^{T}(1 - F^{(t)}\eta)$

Go beyond 0-1 loss

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\xRightarrow{x \leq -\ln(1-x)} \eta \underbrace{\sum_{t=1}^{T} F^{(t)}}_{\mathbb{E}\{\hat{L}^{(T)}\} \approx \hat{L}^{(T)}} &\leq -L_n^{(T)} \ln(1-\eta) + \ln N \qquad (12) \\
\xRightarrow{-\ln(1-x) \leq x+x^2, \text{when } x \leq 1/2} \eta \hat{L}^{(T)} &< L_n^{(T)} \eta (1+\eta) + \ln N \\
\Leftrightarrow \hat{L}^{(T)} &\leq (1+\eta) L_n^{(T)} + \frac{\ln N}{\eta}
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One-player game

- One player plays a game, at time t he takes one action $a^{(t)} = i \in [1, N]$, then the environment releases the cost for each action $\mathbf{m}^{(t)} = [m_1^{(t)}, m_2^{(t)}, \cdots, m_N^{(t)}]^\top$,

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- the player takes actions with some

Two-player game

Two-person zero-sum: two players ($K = 2$) play a game which is defined by a $N \times N$ cost matrix $\mathbf{C}$ (N is the number of possible actions for players) , where each entry c_{ij} defines the loss to the row player when the row player takes the action $i \in [1, N]$ and the column player takes the action $j \in [1, N]$.

An example cost matrix:
$$\begin{array}{c c} & \begin{array}{cccc} 1 & 2 & 3 & 4 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \\ 4 \end{array} & \begin{bmatrix} c_{11} & c_{12} & c_{13} & c_{14} \\ c_{21} & c_{22} & c_{23} & c_{24} \\ c_{31} & c_{32} & c_{33} & c_{34} \\ c_{41} & c_{42} & c_{43} & c_{44} \end{bmatrix} \end{array}$$

The row player's goal is to minimize its loss while the objective of the column player is to maximize it

Nash Equilibrium

- no player has an incentive of changing his strategy if the player does not change his, i.e. every player is happy about current status;

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-

Hanan's theorem

follow the perturbed leading expert;

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Nonlinear loss

$f_t i = \log(-\langle \mathbf{p}_i, \Delta x_t \rangle)$

Han

Paragraphs of Text

Sed iaculis dapibus gravida. Morbi sed tortor erat, nec interdum arcu. Sed id lorem lectus. Quisque viverra augue id sem ornare non aliquam nibh tristique. Aenean in ligula nisl. Nulla sed tellus ipsum. Donec vestibulum ligula non lorem vulputate fermentum accumsan neque mollis.

Sed diam enim, sagittis nec condimentum sit amet, ullamcorper sit amet libero. Aliquam vel dui orci, a porta odio. Nullam id suscipit ipsum. Aenean lobortis commodo sem, ut commodo leo gravida vitae. Pellentesque vehicula ante iaculis arcu pretium rutrum eget sit amet purus. Integer ornare nulla quis neque ultrices lobortis. Vestibulum ultrices tincidunt libero, quis commodo erat ullamcorper id.

Bullet Points

- Lorem ipsum dolor sit amet, consectetur adipiscing elit
- Aliquam blandit faucibus nisi, sit amet dapibus enim tempus eu
- Nulla commodo, erat quis gravida posuere, elit lacus lobortis est, quis porttitor odio mauris at libero
- Nam cursus est eget velit posuere pellentesque
- Vestibulum faucibus velit a augue condimentum quis convallis nulla gravida

Blocks of Highlighted Text

Block 1

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Integer lectus nisl, ultricies in feugiat rutrum, porttitor sit amet augue. Aliquam ut tortor mauris. Sed volutpat ante purus, quis accumsan dolor.

Block 2

Pellentesque sed tellus purus. Class aptent taciti sociosqu ad litora torquent per conubia nostra, per inceptos himenaeos. Vestibulum quis magna at risus dictum tempor eu vitae velit.

Block 3

Suspendisse tincidunt sagittis gravida. Curabitur condimentum, enim sed venenatis rutrum, ipsum neque consectetur orci, sed blandit justo nisi ac lacus.

Multiple Columns

Heading

1. Statement
2. Explanation
3. Example

Lorem ipsum dolor sit amet, consectetur adipiscing elit. Integer lectus nisl, ultricies in feugiat rutrum, porttitor sit amet augue. Aliquam ut tortor mauris. Sed volutpat ante purus, quis accumsan dolor.

Table

Treatments	Response 1	Response 2
Treatment 1	0.0003262	0.562
Treatment 2	0.0015681	0.910
Treatment 3	0.0009271	0.296

Table : Table caption

Theorem

Theorem (Mass–energy equivalence)

$E = mc^2$

Verbatim

Example (Theorem Slide Code)

```
\begin{frame}
\frametitle{Theorem}
\begin{theorem}[Mass--energy equivalence]
$E = mc^2$
\end{theorem}
\end{frame}
```

Figure

Uncomment the code on this slide to include your own image from the same directory as the template .TeX file.

Citation

An example of the `\cite` command to cite within the presentation:

This statement requires citation [Smith, 2012].

References

John Smith (2012)
Title of the publication
Journal Name 12(3), 45 – 678.

The End