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

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Zalando SE

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Overview

- 🚺 Online game playing, portfolio and bandit
 - Prediction with Experts' advice
 - Game settings
 - Universal portfolio
 - Bandit: playing games with limited feedbacks
- Contextual bandit Optimization
 - Gaussian process bandit
 - General Bayesian optimization
 - Time-varing surface-responce optimization
 - FashionFlow: sequential classification instead of search
- Sku Proposal in FashionFlow
 - No dummy experts
 - Tracking the best (set of) experts
 - Online detection of concept drifts



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- Loss: $I(\hat{y}_t, y_t) = \mathbf{1}_{\hat{y}_t \neq y_t}$, $I(f_{n,t}, y_t) = \mathbf{1}_{f_{n,t} \neq y_t}$

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A simple policy

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

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Cummulative loss:

$$\hat{L}_t = \sum_{i=t}^t I(\hat{y}_t, y_t) \le \log_2 N; \tag{1}$$

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Regret $R_{n,t}$: the extra losses the forecaster made without exclusively following the expert E_n up to time t:

$$R_{n,t} = \hat{L}_t - L_{n,t} = \sum_{i=t}^t I(\hat{y}_t, y_t) - \sum_{i=t}^t I(f_{n,t}, y_t)$$
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A new metric: the upper bound of regret

$$R_t^* = \max_{n \in [1,N]} R_{n,t} = \hat{L}_t - \min_{n \in [1,N]} L_{n,t}$$

One player game

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.

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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

- Statement
- ② Explanation
- 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