# Advice Querying under Budget Constraint for Online Algorithms 

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## Algorithms with predictions

- Online algorithms
- Minimization (or maximization) problem
- data revealed sequentially $X=\left(x_{1}, \ldots, x_{k}\right)$
- Competitive ratio: $\operatorname{CR}(\mathrm{ALG})=\sup _{\mathcal{I}} \frac{\mathrm{ALG}(X)}{\mathrm{OPT}(X)}$


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- Learning-augmented algorithms
- predictions $Y=\left(y_{1}, \ldots, y_{k}\right)$ of $X=\left(x_{1}, \ldots, x_{k}\right), \eta=d(X, Y)$
- Robustness: $\eta \rightarrow \infty \Longrightarrow \mathrm{CR}(\mathrm{ALG}, Y)=O(\mathrm{CR}(\mathrm{ALG}))$
- Consistency: $\eta \rightarrow 0 \Longrightarrow \mathrm{CR}(\mathrm{ALG}, Y)=O(1)$
- $\lambda$ : parameter for tuning the consistency/robustness tradeoff


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- What if ...
- limited number of predictions?
- the algorithm chooses when to query them?
- guarantees on their quality?


## Related Work

Aditya Bhaskara, Ashok Cutkosky, Ravi Kumar, and Manish Purohit. Logarithmic regret from sublinear hints.
Advances in Neural Information Processing Systems, 34:28222-28232, 2021.

围 Sungjin Im, Ravi Kumar, Aditya Petety, and Manish Purohit.
Parsimonious learning-augmented caching.
In International Conference on Machine Learning, pages 9588-9601. PMLR, 2022.
R Anupam Gupta, Debmalya Panigrahi, Bernardo Subercaseaux, and Kevin Sun.
Augmenting online algorithms with $\varepsilon$-accurate predictions.
Advances in Neural Information Processing Systems, 35:2115-2127, 2022.

## Time-dependent guarantee on the prediction

## Ski-rental problem

- cost of renting $=1$, cost of buying $=b>1$
- $x=$ unknown number of snow days
- $\operatorname{OPT}(x)=\min (x, b), \operatorname{CR}(\operatorname{DET})=2-\frac{1}{b}$, $\mathrm{CR}($ RAND $)=\left(1-(1-1 / b)^{b}\right)^{-1} \rightarrow \frac{e}{e-1}$


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- Prediction
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- $p_{t}=\operatorname{Pr}\left(\mathcal{Q}_{t}=\mathbb{1}_{x-t \geq b}\right),\left(p_{t}\right)_{t}$ non-decreasing


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- Algorithm
- $\operatorname{ALG}_{t}$ Rent until $t$ then run $\operatorname{ALG}\left(p_{t}\right)$
- $\operatorname{CR}\left(\operatorname{ALG}_{t}\right) \leq \frac{t}{b}+\operatorname{CR}\left(\operatorname{ALG}\left(p_{t}\right)\right)$


## Secretary problem with recommendations

## Secretary problem

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- objective: Select the maximum
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- Algorithm
- adaptive threshold: restarted $1 /$ e-rule
- trust the recommendation if $p>p^{*}$
- $\operatorname{Pr}($ ALG succeeds $) \rightarrow 1$ for $B \rightarrow \infty$


## B-clairvoyant scheduling

## Preemptive non-clairvoyant scheduling problem

- $N$ jobs of unknown sizes to be scheduled on a single machine
- objective: minimize the sum of the completion times
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- Algorithm
- query the sizes of $B$ random jobs
- Run concurrently OPT on the $B$ jobs with known sizes and RR on the $N-B$ jobs with unknown sizes
- Competitive ratio $2-\frac{B(B-1)}{N(N-1)}$

