Learning-Augmented Dynamic Power Management with Multiple States via New Ski Rental Bounds Antonios Antoniadis, Christian Coester, Marek Eliáš, Adam Polak, Bertrand Simon

DYNAMIC POWER MANAGEMENT WITH MULTIPLE STATE						
Machine with mu	Itiple sleep states:		Sx			
			50	Active		
			50ix	Low Po		
			51	Power		
			52	CPU po		
				Standb		
Deeper sleep \rightarrow higher wake-up cost			54	Hibern		
			55	Soft Of		
Input: sequence of idle periods						
20s	5min	10	S			

Our task: choose sleep states during each idle period

duration not known in advance!

RAISON D'ÊTRE OF LEARNING-AUGMENTED ALGORI	ТΗ
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	worst-case	ty
classical algorithms		
machine-learned predictions	××	
learning-augmented algorithms		

DESIDERATA OF LEARNING-AUGMENTED ALGORITHMS = ALGORITHMS WITH PREDICTIONS

Consistency

close-to-optimal performance when predictions accurate

Robustness

worst-case guarantees, even when predictions adversarial

Smoothness

performance degrades slowly in the prediction error



- Other ingredients:
 - Reduction from DPM to ski-rental
 - extension of [Lotker et al. '12] to the learning-augmented setting
 - Online learning for hyperparameter optimization

SKI RENTAL

Previous algorithms:

- deterministic 2-competitive
- randomized e/(e-1)-competitive





During a ski season of unknown length, each day either

per day cost $\alpha \rightarrow rent$ or buy \sim one-time cost β

[folklore] [Karlin et al. '90] • learning-augmented [Purohit et al. '18], [Angelopoulos et al. '20] • optimal consistency/robustness trade-off, no smoothness

Our new ski rental algorithm is $(\rho, \mu(\rho))$ -competitive, i.e.

 $cost(ALG) \leq \rho \cdot cost(OPT) + \mu(\rho) \cdot \eta$

where
$$\rho \in [1, \frac{e}{e-1}], T^2 e^{-T} = 1 - \frac{1}{\rho}$$

 $\mu(\rho) = \max\left\{\frac{1-\rho\frac{e-1}{e}}{\ln 2}, \rho(1-T)e^{-T}\right\}$