# Minimalistic Predictions for Online Class Constraint Scheduling

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## Context

## Scheduling

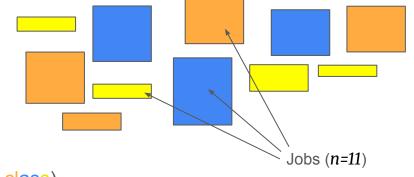
- Assigning jobs to machines while minimizing some metric.
- Applications: product planning, data placement, load balancing, ...

#### Online

- Jobs are revealed one after the other
- An irrevocable decision has to be taken before learning about the next one

Given:

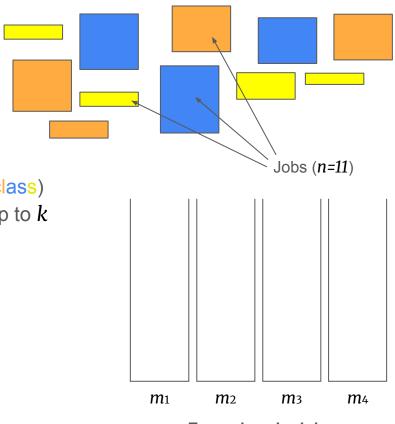
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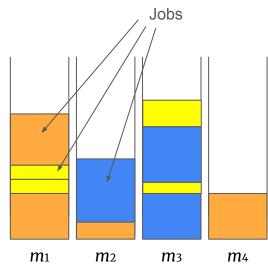
Example schedule: 4 machines (*m*=4)

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#### Goal:

Schedule the jobs efficiently (minimize the makespan)



#### **Example schedule:**

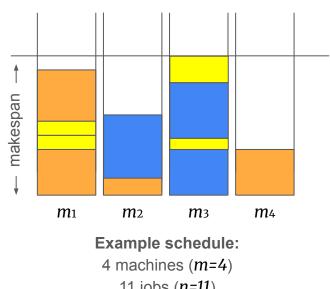
4 machines (*m*=4) 11 jobs (*n*=11) max 2 colors/machine (*k*=2)

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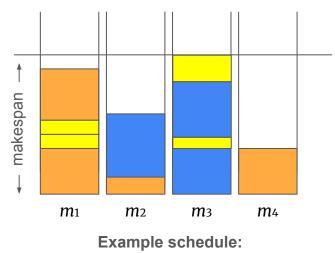
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#### Hurdles:

 Hard lower bounds: can't do better than m times the optimal offline solution



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## Learning-augmented algorithms

#### Predict some of the unknown information where:

- Good predictions lead to a performance close to the offline problem (consistency)
- Bad predictions lead to an acceptable performance (robustness)

### What information **could** we predict?

- Classical: input, actions (information to predict is O(n))
- Specific: number of classes (and their sizes): information to predict is O(k)

### What information is **necessary**?

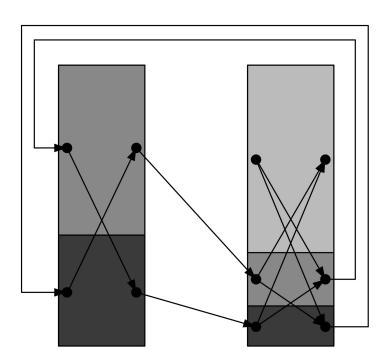
- Number of classes (has to be exact)
- The size of each class (predicted)

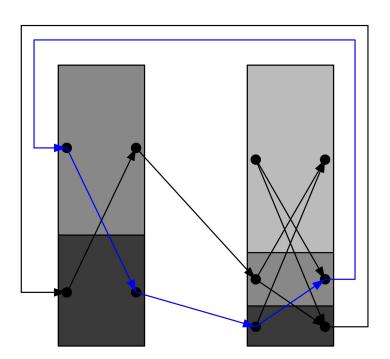
## Our approach

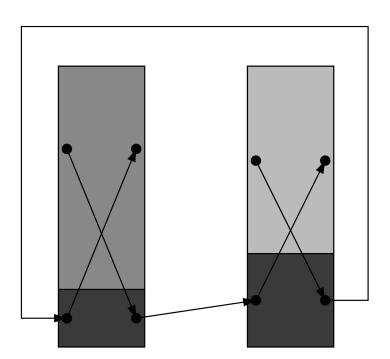
- 1. Predict the class sizes (with some error L)
- 2. Compute a schedule based on the predictions
- 3. Manipulate/structure the schedule to minimize the impact of *L*
- 4. Place the incoming jobs according to the resulting schedule

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## Result

Competitive ratio:  $2 + \varepsilon + L/OPT$ 

- Does not depend on *m*
- Scales gracefully with L

# Thank you!