Encouraging Peer Grading in MOOCs

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    - Distributed Computing
    - Molecular Computing
    - Computational aspect of Games and Mechanisms

Algorithmic Game Theory and Mechanism Design

- Understanding and developing efficient algorithms for:
  - analyzing games: Algorithmic Game Theory
  - designing mechanisms: Algorithmic Mechanism Design

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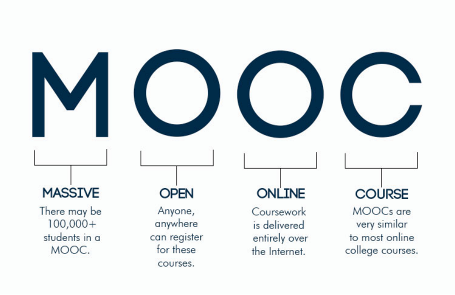
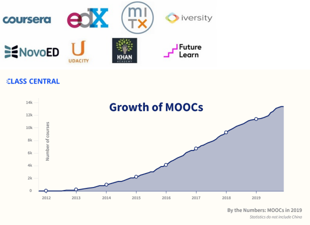
- Algorithmic Mechanism Design vs. Mechanism Design
  - Care about universal and worst-case results
  - Care about implementability, e.g., polynomial-time computable mechanisms

Outline





- Emerged as a mainstream trend of learning in 2012 (the "year of MOOCs")

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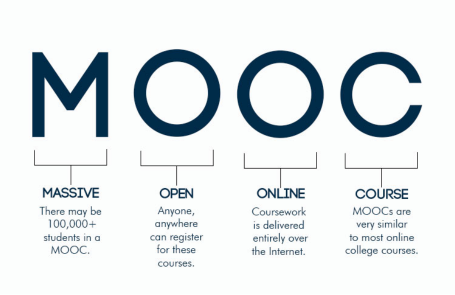

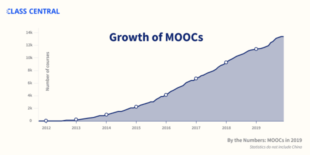

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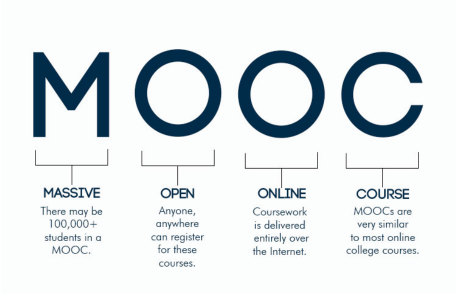

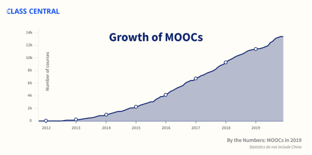

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- 13.5K courses by 900+ universities by 2019.

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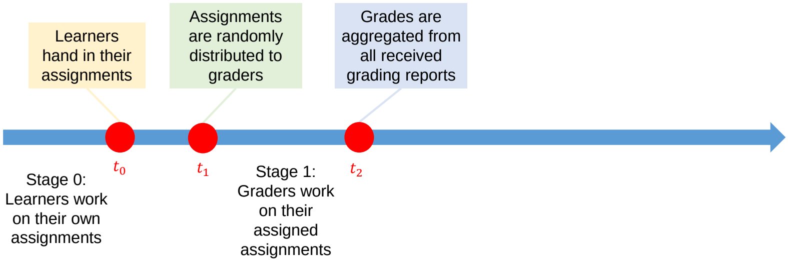
- Deployed and analyzed in Coursera.org in large-scale as early as [Piech et al., 2013]
- Still the only practical solution to grading high-level assignments in MOOCs.

Basic Peer Grading Mechanism



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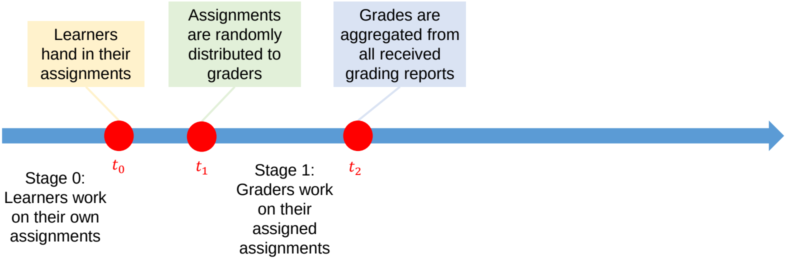

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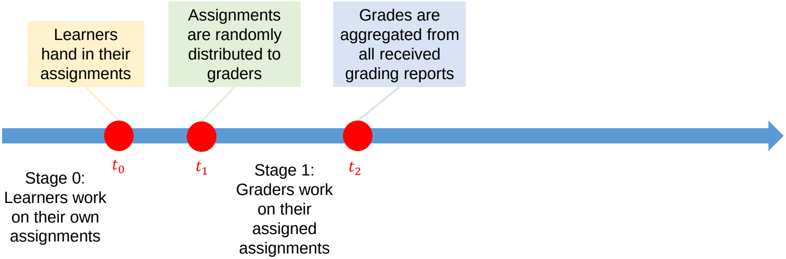

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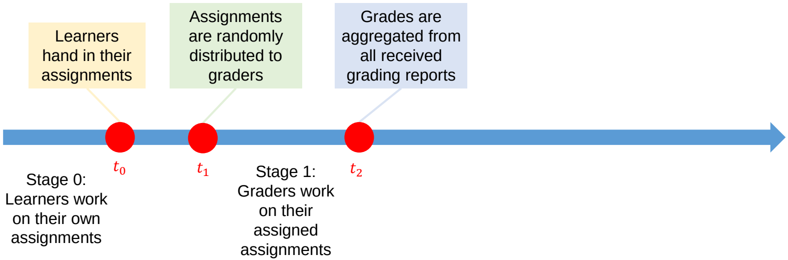

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  - Incentives

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- Efforts put in grading others' work were not reflected in concrete reward
- Only absent graders, instead of ineffective ones, were punished
- An improved mechanism that incentivizes effort in peer grading is necessary.

Proposed approaches

- Through punishment: a Stackelberg game that limited TA resources are efficiently allocated to double check the grading [Carbonara et al., 2015]

[2] https://www.crowdgrader.org/

Proposed approaches

- Through reward: Crowdgrader[2]: incentivizing accurate graders directly [de Alfaro and Shavlovsky, 2014]

crowdgrader

CrowdGrader lets students submit and collaboratively grade their solutions to homework assignments.

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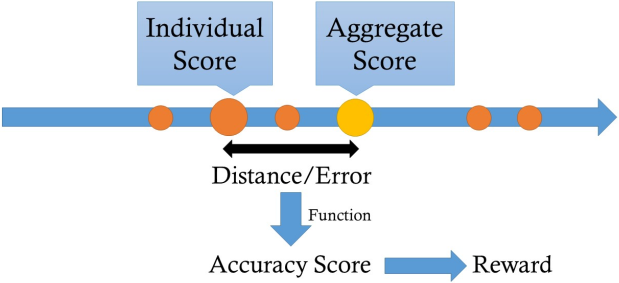
Crowdgrader in a Nutshell



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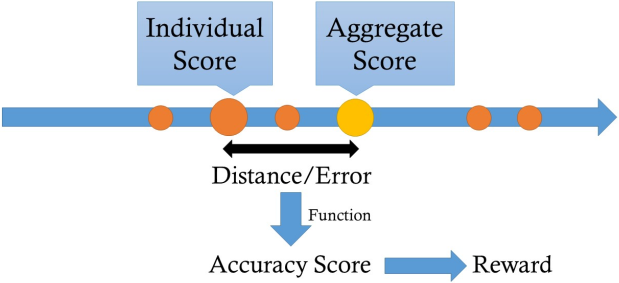
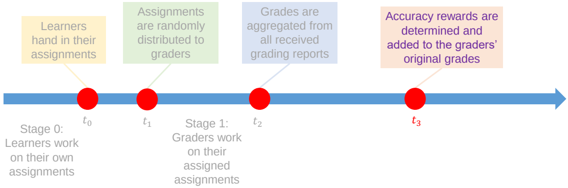


- Crowd-grading is found as effective and satisfactory (to the learners) as TA-grading [de Alfaro and Shavlovsky, 2014]

Revamped Peer Grading Mechanism



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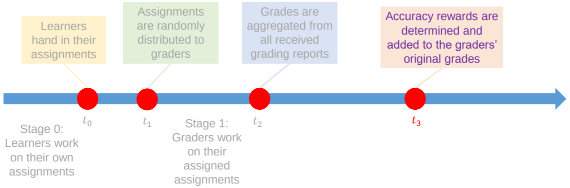

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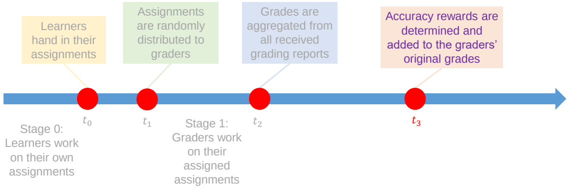

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  - While the settings in Crowdgrader work empirically, are they theoretically robust as well?

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  - Finding real settings that satisfy the necessary conditions

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Motivation

Model

Players and Actions

Mechanism

Results

Encouraging Conditions and Existence of Pure Equilibria

Controlling Pure Equilibria from Mechanism Parameters

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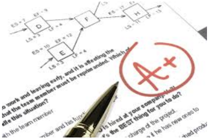
- N learners, $\{a_1, a_2, ...a_N\}$



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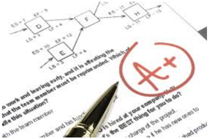

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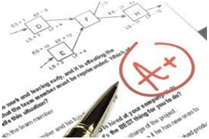

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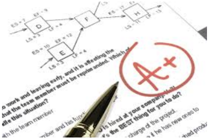

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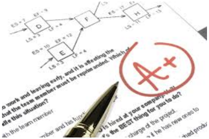

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- Efforts are unobservable

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- We assume truthfulness, i.e., a_j directly reports S_j^i to the mechanism without manipulation

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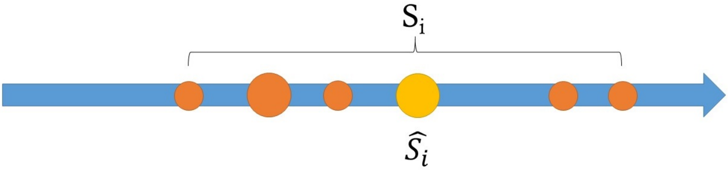
  - Examples: Average, Median, Olympian Average, etc.



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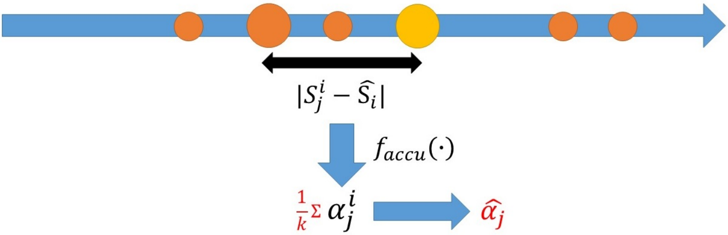

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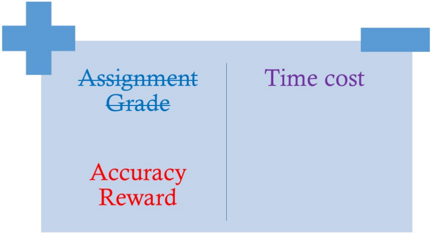

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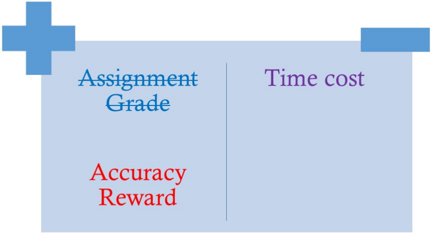

- $r_i \geq 0$: a_i's time-to-grade ratio
- $\pi_i = \cancel{(1-\lambda)M\hat{S}_i} + \lambda M\hat{\alpha}_i - r_i \sum_j t_i^j$.: final utility of learner i

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Controlling Pure Equilibria from Mechanism Parameters

Definition: EC-1

A setting satisfies **EC-1** if:
Given the others' strategies $T_{-j} = [t_1, t_2, ..., t_{j-1}, t_{j+1}, ..., t_k]$,
$\mathbf{E}[\alpha_j](T_{-j}, t_j)$ is non-decreasing and concave on $t_j \in [0, U]$.

More effort means more accuracy, with diminishing marginal increment.

Definition: EC-2

A setting satisfies **EC-2** if:
For any pair of two strategy profiles T_{-j} and T'_{-j} s.t.:

- $t_p < t'_p$ for some p,
- $t_q = t'_q \, \forall \, q \neq p$,

it holds that $\frac{\partial}{\partial t_j}\mathbf{E}[\alpha_j](T_{-j}, t_j) < \frac{\partial}{\partial t_j}\mathbf{E}[\alpha_j](T'_{-j}, t_j), \; \forall t_j$.

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- A positive reinforcement.

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Theorem

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Proposition

Define $\mathrm{f}_{\mathrm{avg}}(\mathbf{S}) = \frac{1}{k}\sum_j (S_j)$. Suppose that $\mathrm{f_g} \sim N(v, g^2)$ where $g = g(t_j)$ is a non-increasing convex function. If $\mathrm{f}_{\mathrm{agg}}(\cdot) = \mathrm{f}_{\mathrm{avg}}(\cdot)$, $\mathrm{f}_{\mathrm{accu}}(\cdot)$ is non-increasing piecewise continuous, then for any values of $(M, k, \mathbf{r}, U, \lambda)$, $(M, k, \mathbf{r}, U, \lambda, \mathrm{f_g}(\cdot), \mathrm{f}_{\mathrm{agg}}(\cdot), \mathrm{f}_{\mathrm{accu}}(\cdot))$ satisfies both EC-1 and EC-2.

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- decreases when λ(peer grading importance) increases
- decreases when M(the full grade) increases
- Closely related to Nash equilibria

Encouraging Grading

Theorem

- Assume k is fixed, both EC satisfied in G_1 with $\bar{r} = \bar{r}_1$
- G_3 differs with G_1 only in $\bar{r}_3 < \bar{r}_1$
- $T_1 = [t_{1\,i}]$ is an equilibrium in G_1

$\Longrightarrow$ There exists an equilibrium T_3 in G_3 where $t_{3\,i} \geq t_{1\,i}\, \forall i$.
If the i-th equality holds, then $t_{1\,i} = U$.

- Decreasing $\bar{r}$ distorts the entire equilibria upwards!

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    then every grader gives identical level of effort in pure NE.
  - If some graders have fixed strategies (think of TA paddings),
    then the equilibria holds as long as
    irrational players' strategies are public information.

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- Special case: homogeneous grading
- Extension: irrational graders, TAs, biased grading, etc

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    - The ground truth (production) is also not perfectly observable.
    - Therefore, aggregation significantly affects the peer grading game.

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- Truthfulness is an assumption
- Application is limited, while other similar scenarios exist: peer grading is actually very similar to other peer assessment scenarios, e.g., peer reviewing in academics, or crowdsourcing.


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