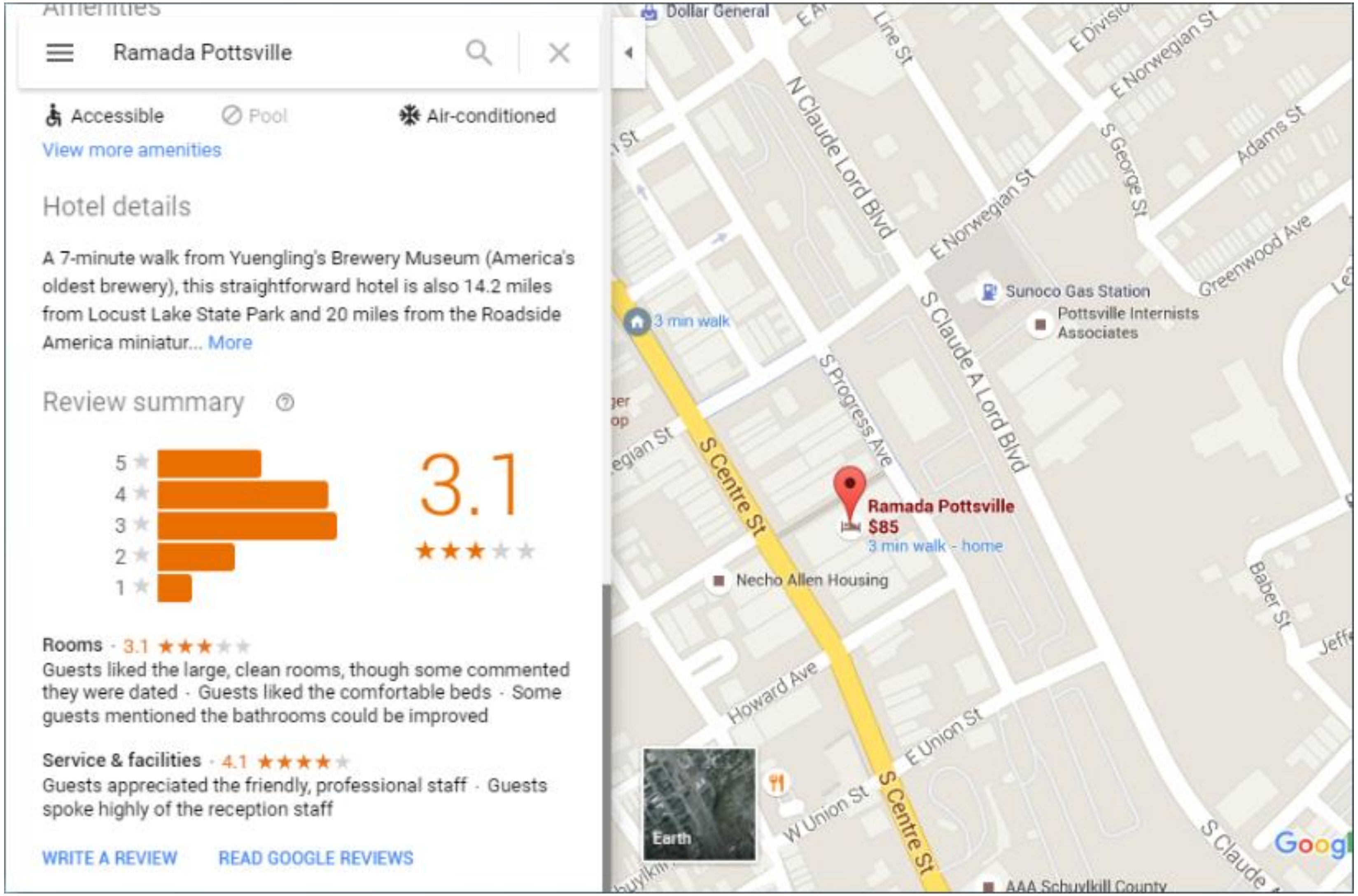
Peer Prediction on Peer Grading System

National Taiwan University,
Department of Electrical Engineering
R07921036@ntu.edu.tw
Cheng-Yu Shih

Outline

- Peer Prediction
- Previous Work
- Peer Grading Re-model
- Truthfulness
- Conclusion
- Reference

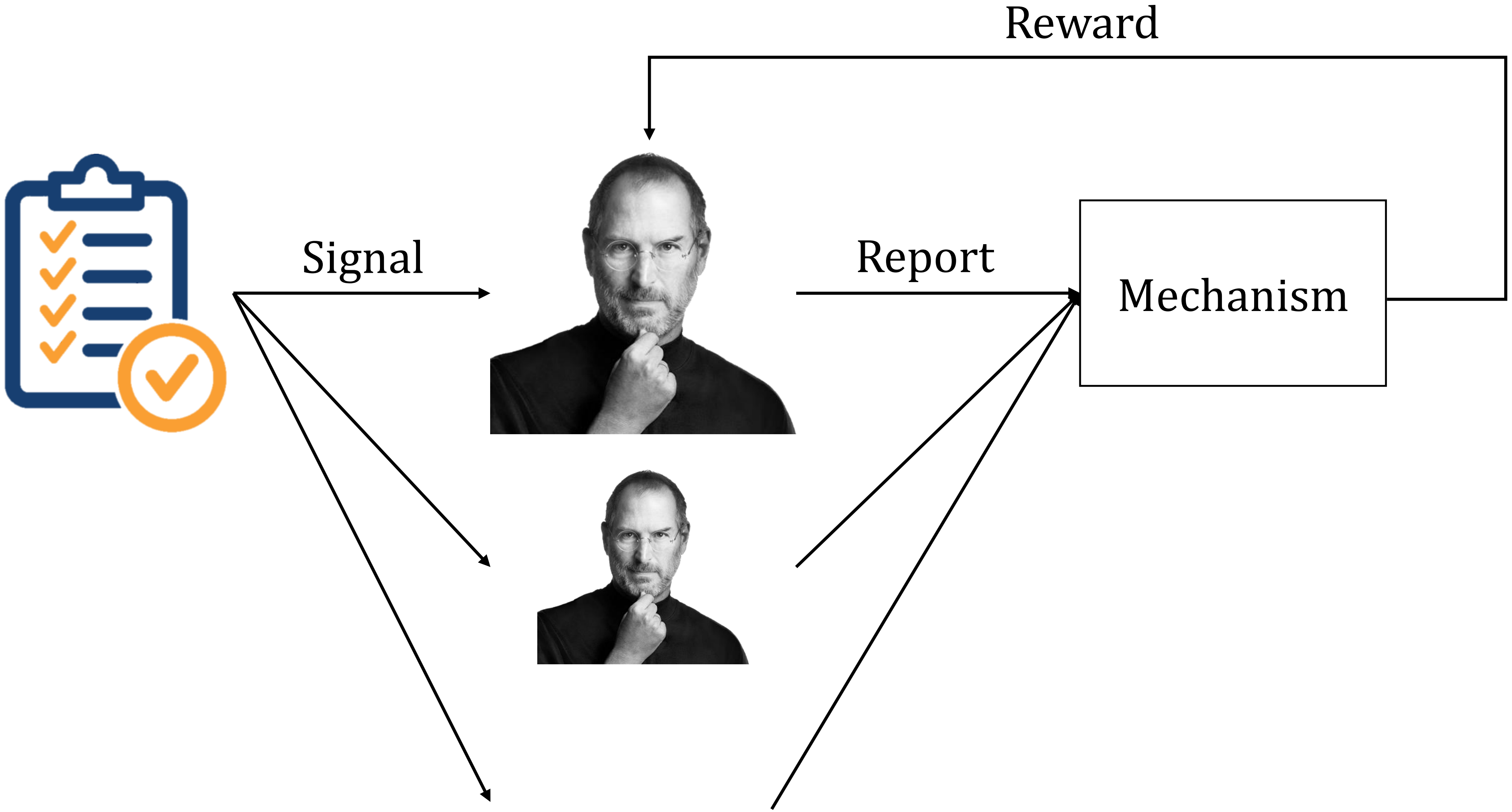
Peer Prediction



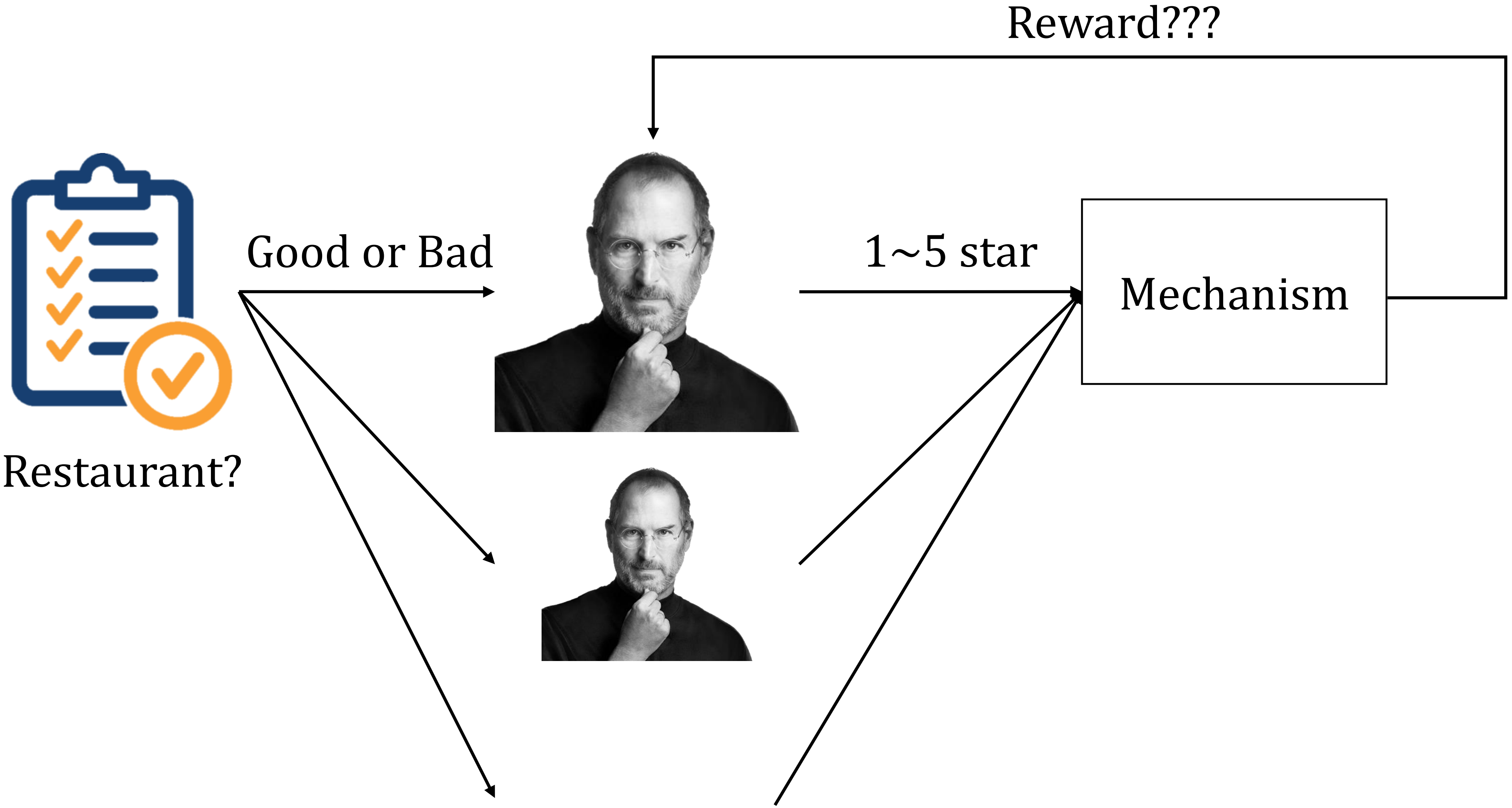
Peer Prediction

- Ask participants for feedback on questions
  - Elicit information without verification
- Example:
  - Peer-grading
  - Labeling in a machine learning task
- Encourage truthfulness and efforts

Peer Prediction



Peer Prediction



Previous Work

- Shao-Heng Ko [2017]
  - Peer Grading
  - Encouraging Conditions

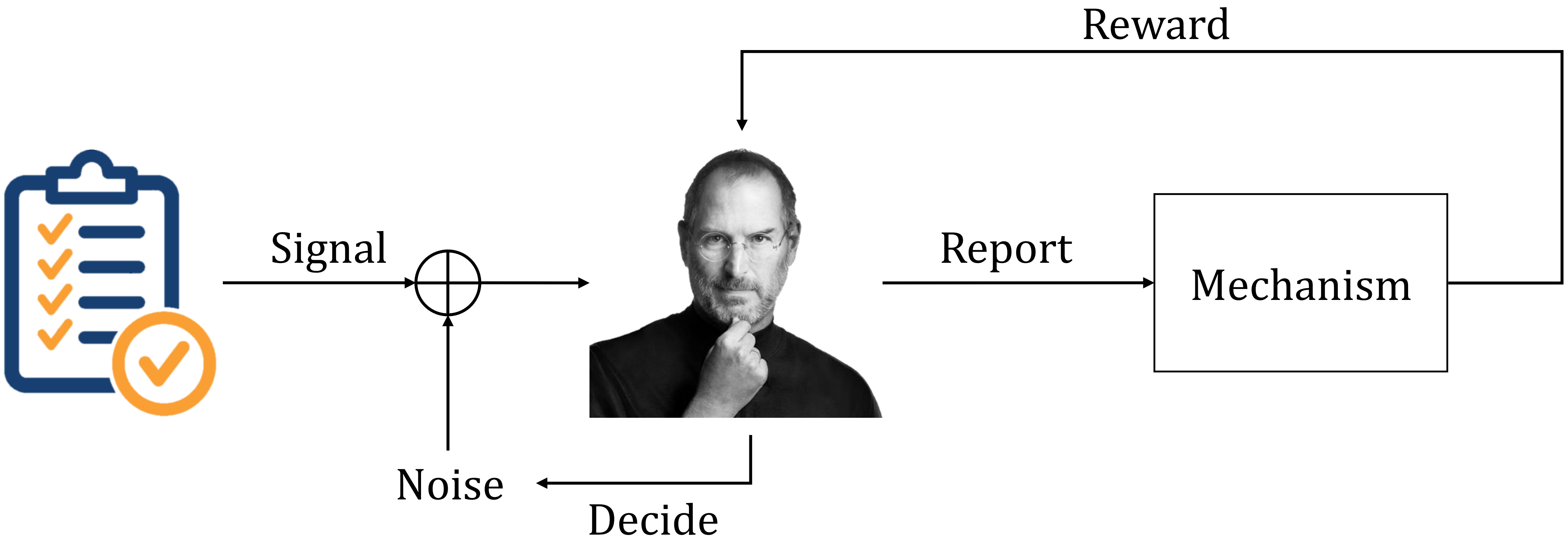
    $\Rightarrow$ At least one pure Nash equilibrium
  - Homogeneous

    $\Rightarrow$ pure Nash $\{t_1^*, t_2^*, \dots, t_N^*\}$, $t_1^* = t_2^* = \cdots = t_N^*$

Peer Grading Re-model

- Agents: $a_0, a_1, \dots, a_n$
- Signals: $(s_0, s_1, \dots, s_n) \sim \mathrm{S}$
- <u>**Noise**</u>: $\epsilon_i, \forall i \in [0, n]$
  - Mean $= 0$, variance $= \sigma_i^2$
  - Independent
  - No-bias
  - Effort time $t_i \Uparrow \Rightarrow \sigma_i \Downarrow$
- Received Signal $= \mathrm{s_i} + \epsilon_i =$ Report $\mathrm{r_i}$
  - Always Truthful

Peer Grading Re-model



Peer Grading Re-model

- Mechanism
  - Each agent is paired with another agent randomly
  - Difference in reports $\Uparrow \Rightarrow$ Reward $\Downarrow$
  - Mean Square Error:

$$E\left[\left(r_i - r_j\right)^2\right]$$

Peer Grading Re-model

- Expected Utility:

$$U_i = U - C_i - f(t_i)$$

  - U: constant
  - C_i: report difference
  - $f(t_i)$: effort cost
- $\max U_i$
  - Unrelated to others ⇒ **Dominant Strategy**
  - If σ, f are homogeneous to every agent ⇒ $t_0^* = t_1^* = \cdots = t_n^*$

Peer Grading Re-model

- Encouraging Condition
  - (O) EC-1
    - Suppose $\sigma_i(t_i)$ is positive, convex, decreasing
  - (X) EC-2

- Encourage efforts?
  - Suppose $f(t_i) = k \cdot t_i$
  - Effort cost ratio $k \Downarrow \Rightarrow$ effort time $t_i \Uparrow$

Peer Grading Re-model

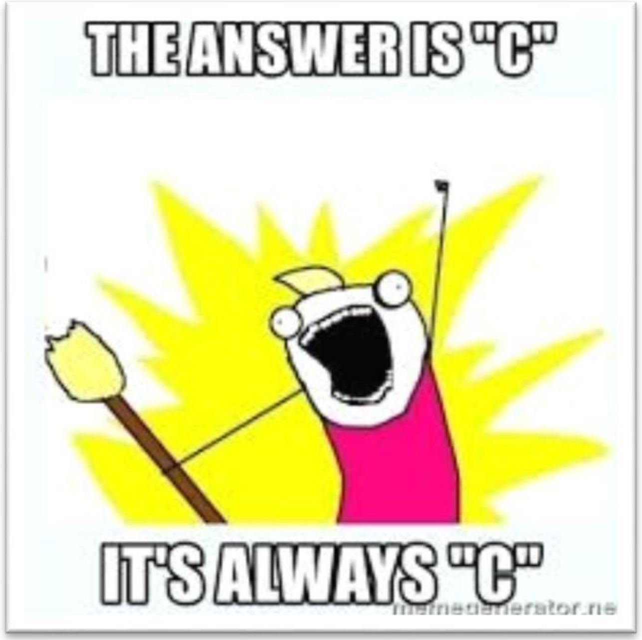
- What's the difference

	Shao-Heng Ko [2017]	This Work
Signal Distribution	$F_p(v_i, t_j^i)$	$\mathrm{s_i} + \epsilon_i$
Encouraging Conditions	Yes	No
Settings	Gaussian Distributions	ϵ_i is independent

- What's the same
  - Pure Nash Equilibrium exists
  - homogeneous $\Rightarrow$ symmetric equilibrium
  - Encourage efforts

Truthfulness

- What if agents can be untruthful
  - Everyone always reports the same feedback
  - (No effort, r^*) ← Best equilibrium



Truthfulness

- Dasgupta and Ghosh [2013]
  - Reward $=$ agreement on **common tasks** – agreement on **separate tasks**
  - (All effort, truthful) and (no effort, random guess) are both equilibrium
  - (All effort, truthful) $\leftarrow$ Best equilibrium
- Kong and Schoenebeck [2016]
  - Mutual Information $MI(X;Y)$
  - $MI(M(X);Y) \leq MI(X;Y)$

Truthfulness

- Allow verification
  - TA score in peer grading
  - Minimize TA's workload
- Dasgupta and Ghosh [2013]
  - Reward $=$ agreement on **<u>common tasks</u>** – agreement on **<u>separate tasks</u>**

    $\propto \rho(r_i, r_j)$
  - Assume: $\rho(M(r_i), r_j) \leq \rho(r_i, r_j)$
    - Any **<u>independent</u>** modification $\nRightarrow$ the correlation coefficient ⇧
    - Mutual Information (Kong and Schoenebeck [2016])

Truthfulness

	Dasgupta and Ghosh [2013]	This Work
Signal Type	Discrete	Continuous
Agreement	Exactly the same	Negative correlation to Squared Euclidean Distance
Assumption	$\Pr[s_j = s \mid s_i] < \Pr[s_j = s]$, $\forall s \neq s_i$	$\rho(M(r_i), r_j) \leq \rho(r_i, r_j)$
Best Equilibrium (no effort cost)	(All effort, truthful)	(All effort, truthful)

Conclusion

- Describe effort as a noise to the real signal
- No need to be Gaussian
- Always truthful $\Rightarrow$ relaxed
- Discrete $\Rightarrow$ Continuous

Reference

[1] Dasgupta, Anirban, and Arpita Ghosh. "Crowdsourced judgement elicitation with endogenous proficiency." Proceedings of the 22nd international conference on World Wide Web. ACM, 2013.

[2] Kong, Yuqing, and Grant Schoenebeck. "An information theoretic framework for designing information elicitation mechanisms that reward truth-telling." ACM Transactions on Economics and Computation (TEAC) 7.1 (2019): 2.