Fairness

Yu Han

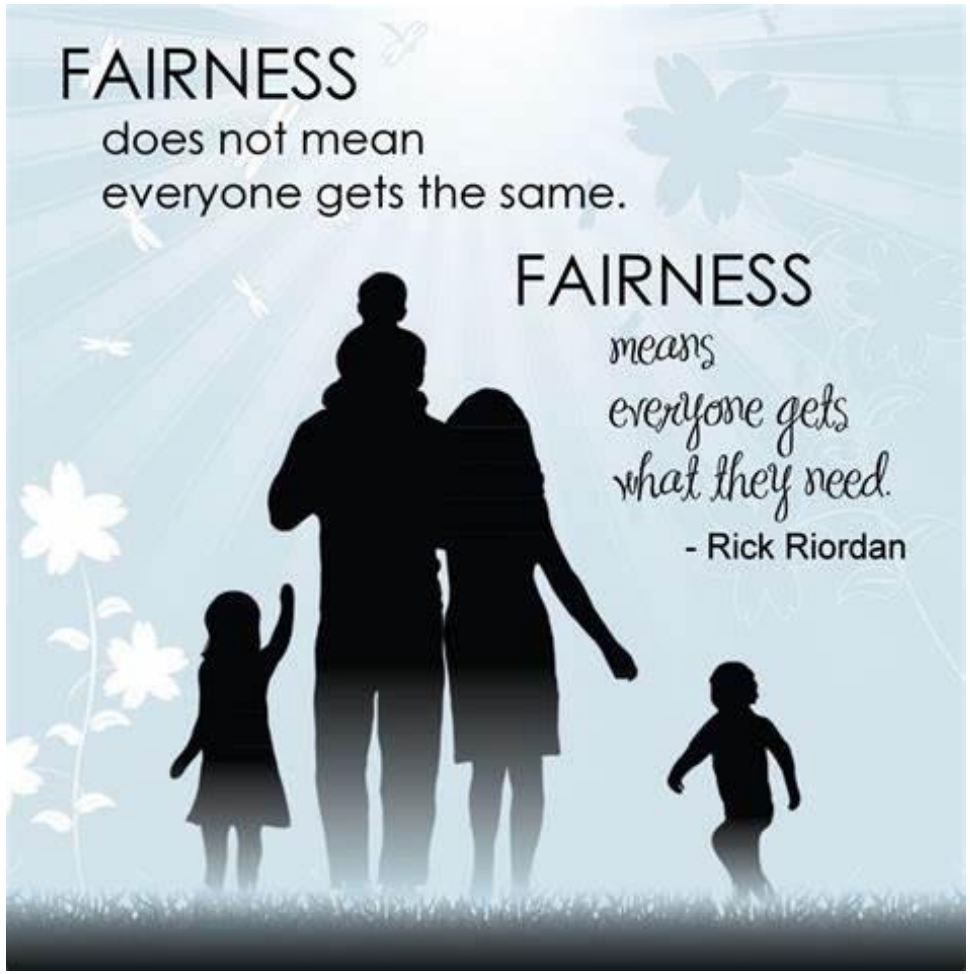
han.yu@ntu.edu.sg

Nanyang Assistant Professor
School of Computer Science and Engineering
Nanyang Technological University

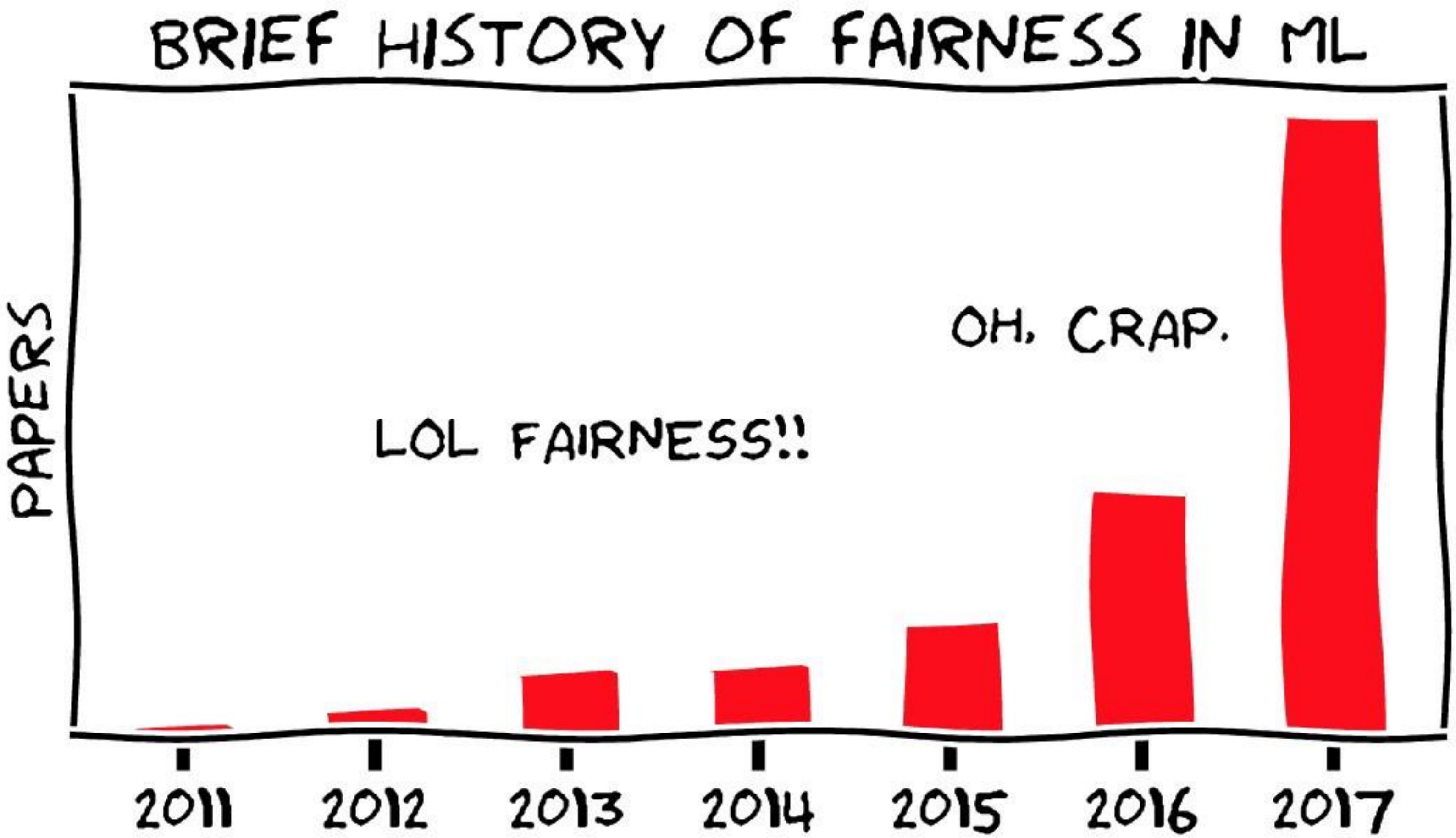
What is Fairness?

- In order to be able to achieve fairness, one should first define the notion of fairness.
- Philosophy and psychology have tried to define the concept of fairness long before computer science started exploring it.
- The fact that no universal definition of fairness exists shows the difficulty of solving this problem

What is Fairness?



Attentions on Fairness in AI



Some Basic Concepts

TP, TN, FP and FN

- A **true positive** is an outcome where the model *correctly* predicts the *positive* class.
- A **true negative** is an outcome where the model *correctly* predicts the *negative* class.
- A **false positive** is an outcome where the model *incorrectly* predicts the *positive* class.
- A **false negative** is an outcome where the model *incorrectly* predicts the *negative* class.

TP, TN, FP and FN

- Example:
  - The Confusion Matrix for the "wolf prediction" case

True Positive (TP): • Reality: A wolf threatened. • Shepherd said: "Wolf." • Outcome: Shepherd is a hero.	**False Positive (FP):** • Reality: No wolf threatened. • Shepherd said: "Wolf." • Outcome: Villagers are angry at shepherd for waking them up.
False Negative (FN): • Reality: A wolf threatened. • Shepherd said: "No wolf." • Outcome: The wolf ate all the sheep.	**True Negative (TN):** • Reality: No wolf threatened. • Shepherd said: "No wolf." • Outcome: Everyone is fine.

Protected/Sensitive Attributes

- Typically, there are some traits identified by law on which it is illegal to discriminate against
- Usually these traits are considered to be "protected" or "sensitive" attributes in computer science literature.
- E.g., age, gender, race, religion, disability, …

Categories of Fairness

- Individual Fairness:
  - Treat similar individuals similarly

- Group Fairness:
  - Treat different groups equally

Definitions of Fairness

Definition 1

- Equal Opportunity Fairness:
  - The protected (e.g., female) and unprotected (e.g., male) groups should have equal true positive rates
  - Only relevant for prediction models
  - Group Fairness

$$\frac{TP_A}{TP_A + FN_A} = \frac{TP_B}{TP_B + FN_B}$$

Definition 2

- Demographic Parity Fairness:
  - The likelihood of a positive outcome should be the same regardless of whether the person is in the protected (e.g., female) group
  - Only relevant for prediction models
  - Group Fairness

$$\frac{TP_A}{TP_A + FN_A} + \frac{FP_A}{FP_A + TN_A} = \frac{TP_B}{TP_B + FN_B} + \frac{FP_B}{FP_B + TN_B}$$

Definition 3

- Equalized Odds Fairness:
  - The protected (e.g., female) and unprotected (e.g., male) groups should have equal rates for true positives and false positives
  - Only relevant for prediction models
  - Group Fairness

$$\frac{TP_A}{TP_A+FN_A} = \frac{TP_B}{TP_B+FN_B} \text{ and } \frac{FP_A}{FP_A+TN_A} = \frac{FP_B}{FP_B+TN_B}$$

Definition 4

- Treatment Equality Fairness:
  - Treatment equality is achieved when false negative and false positive ratios are the same for both protected (e.g., female) and unprotected (e.g., male) groups
  - Only relevant for prediction models
  - Group Fairness

$$\frac{FN_A}{FN_A+TP_A} = \frac{FN_B}{FN_B+TP_B} \text{ and } \frac{FP_A}{FP_A+TN_A} = \frac{FP_B}{FP_B+TN_B}$$

Definition 5

- Fairness through Awareness:
  - Any two individuals who are similar with respect to a similarity metric defined for a particular task should receive a similar outcome
  - Relevant for both prediction models and resource allocation models
  - Individual Fairness

Definition 6

- Fairness through Unawareness:
  - An algorithm is fair as long as no protected attribute is explicitly used in the decision-making process
  - Relevant for both prediction models and resource allocation models
  - Individual Fairness

Definition 7

- Counterfactual Fairness:
  - A decision is fair towards an individual if it is the same in both the actual world and a counterfactual world where the individual belonged to a different demographic group
  - Relevant for both prediction models and resource allocation models
  - Individual Fairness

Getting Focused:
Balancing Fairness and Efficiency in Decision Support Systems

Decision Support Systems

- After analyzing patterns or making predictions with machine learning algorithms (e.g. deep learning), we still need to make decisions
- This often involves some types of resource allocation
- Reasons:
  - Agents face resource constraints
    - Not enough budget to execute all possible actions
    - Not enough time to try all possible alternatives
    - … …

Our Scenario: The Sharing Economic

Sharing of Private Resources

When I buy a car, how often do I really use it?

The car is not used for over **90%** of the time

Source: The future business is the "mesh"

Sharing Economy (those with resources)

Sharing of Private Resources

High Cost + Idling Capacity + Critical Mass

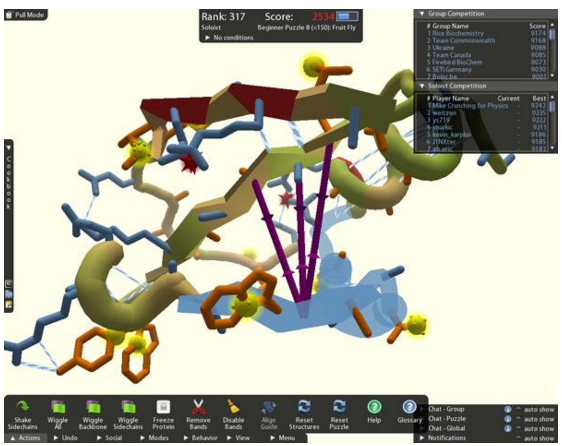
UBER
EVERYONE'S PRIVATE DRIVER™

airbnb

Side·car
a whole new way to get around

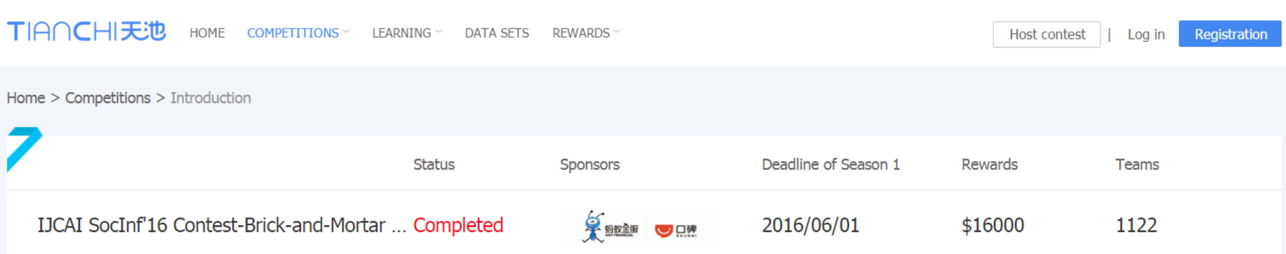
GRABTAXI

Sharing Economy (those with skills)



Foldit – a game to crowdsource complex protein structures (***Nature* 466**, 756–760, 2010).

reCAPTCHA – digitalizing books via crowd-powered online security (***Science* 321**, 1465–1468, 2008).



US$335 Billion

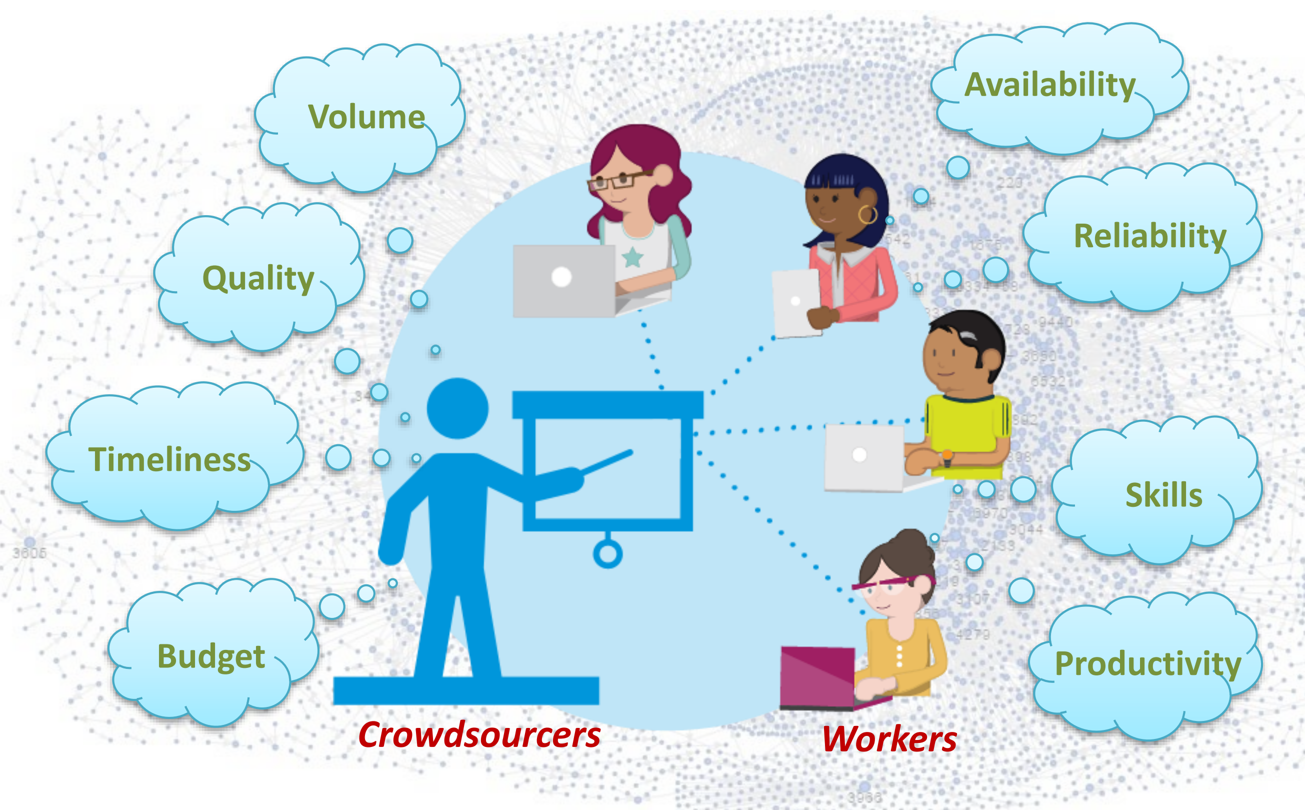
by 2025

Challenges in Decision-making

amazon mechanical turk
Artificial Artificial Intelligence

40% of the results are deemed to be of low quality

Lack of Efficiency & Quality Control



Difficulties

1. Large-scale congestion game
2. Uncertainty & temporal variations in situational factors
3. Limited time for decision-making

Challenges in Decision-making

- Crowdsourcing systems need efficiency in order to attract crowdsourcer who pay for their services

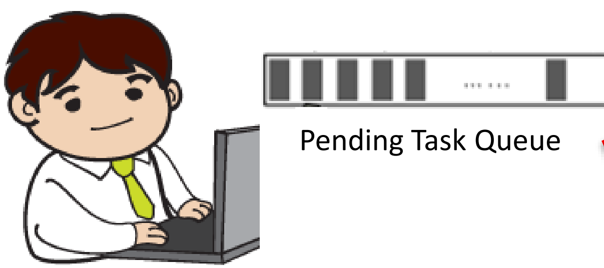
- Crowdsourcing systems need to treat workers fairly in order to attract and retain a large pool of skilled workers to satisfy crowdsourcers' requests

- How to match tasks to workers to achieve these two (possibly conflicting) long-term goals?

Balancing Efficiency and Fairness

- Here:
  - We adopt the definition of "Fairness through Unawareness"
  - Develop a smart task allocation algorithm that balances efficiency and fairness considerations
  - Allow "human-over-the-loop" intervention through individual preference statements

Queueing System Modelling



Worker

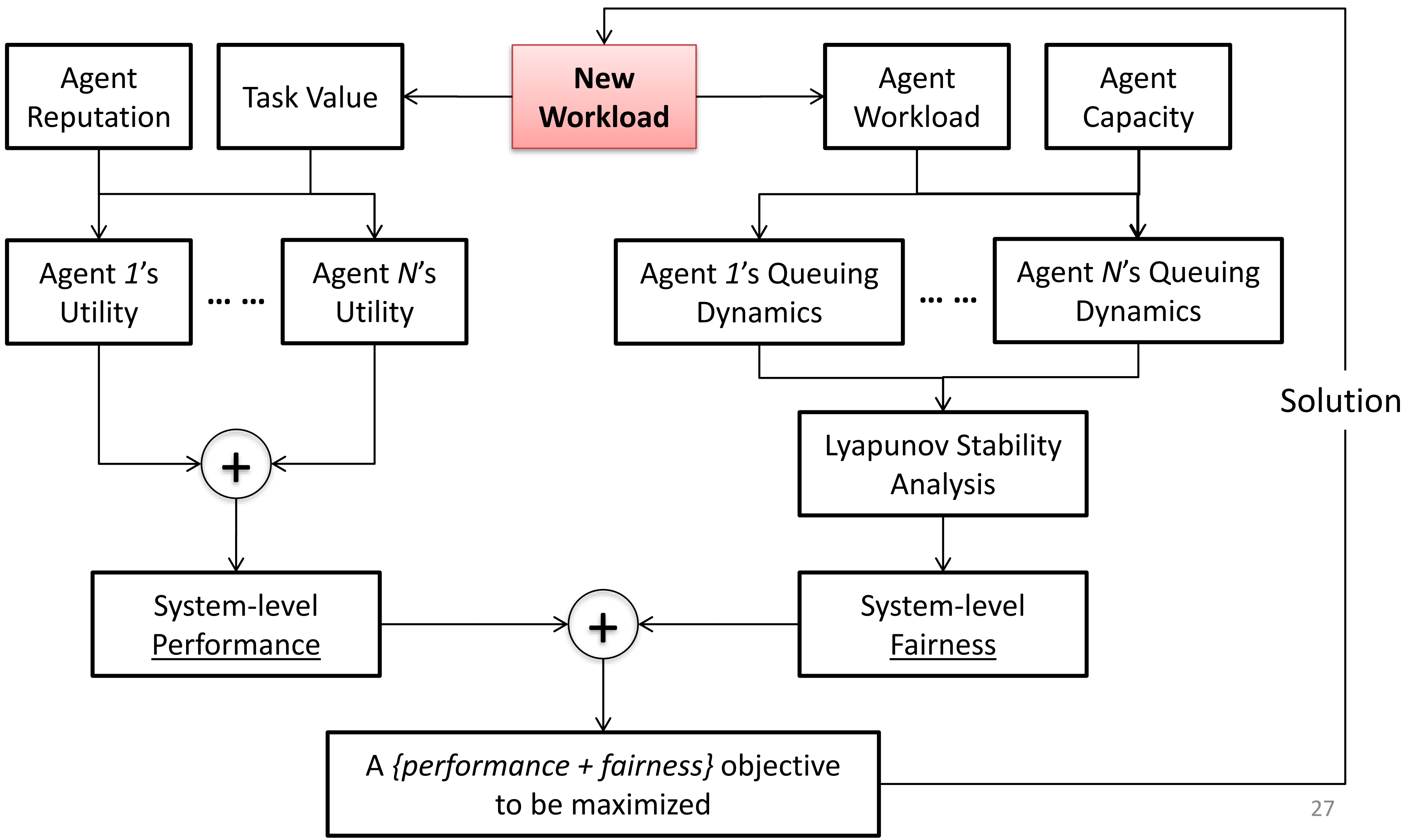
- Reliability
- Productivity
- Availability

No. of tasks accepted by *w* at time *t*.

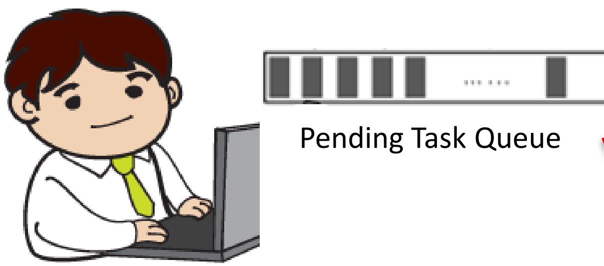
No. of tasks completed by *w* at time *t*.

$$\boxed{q_w(t+1)} = \max[0, \boxed{q_w(t)} + \boxed{a_w(t)} - \boxed{c_w(t)}]$$

Overall Decision-making Flow



Formulating Optimization Objective



Worker

- Reliability
- Productivity
- Availability

No. of tasks accepted by *w* at time *t*.

No. of tasks completed by *w* at time *t*.

$$\boxed{q_w(t+1)} = \max[0, \boxed{q_w(t)} + \boxed{a_w(t)} - \boxed{c_w(t)}]$$

Lyapunov functions: scalar functions that may be used to prove the stability of an equilibrium of an ordinary differential equations.

$$L(t) = \frac{1}{2}\sum_{w=1}^{N} q_w^2(t)$$

What's Captured by Lyapunov Function

- Example:
  - Case 1: three workers having been allocated 5, 5 and 65 tasks, respectively.
  - Case 2: three workers having been allocated 25, 25 and 25 tasks, respectively.
  - 5 + 5 + 65 = 25 + 25 + 25 = 75
  - No difference? Tasks in Case 2 is obviously more evenly distributed than in Case 1!

What's Captured by Lyapunov Function

- Example:
  - Case 1: three workers having been allocated 5, 5 and 65 tasks, respectively.
  - Case 2: three workers having been allocated 25, 25 and 25 tasks, respectively.
  - With the Lyapunov function, we have:
  - $\frac{1}{2}(5^2 + 5^2 + 65^2) = 2137.5$
  - $\frac{1}{2}(25^2 + 25^2 + 25^2) = 937.5$

Formulating Optimization Objective

Let $\mathbf{q}(t)$ be a vector of all workers' pending task queues during time slot t. Using the *Lyapunov drift*, $\Delta(\mathbf{q}(t))$, the variation in workers' workload can be expressed as:

$$
\begin{aligned}
\Delta(\mathbf{q}(t)) &= \mathbb{E}\{L(t+1) - L(t) | \mathbf{q}(t)\} \\
&= \sum_{w=1}^{N} \left(\frac{1}{2} q_w^2(t+1) - \frac{1}{2} q_w^2(t) \right) \\
&\leqslant \sum_{w=1}^{N} \left(q_w(t) a_w(t) - q_w(t) c_w(t) + \frac{1}{2}[a_w^2(t) + c_w^2(t)] \right)
\end{aligned}
$$

$$\frac{1}{2}[(a_w^{\max})^2 + (c_w^{\max})^2]$$

Formulating Optimization Objective

- Let $U(t)$ be the expected overall utility (i.e., the sum of the expected task success rate) of a strategy which distributes tasks among a given set of N workers in a given way during time slot t. We have:

$$U(t) = \sum_{w=1}^{N} r_w(t) a_w(t)$$

Worker w's reputation
(i.e. probability of successfully completing a task)

Formulating Optimization Objective

Weightage

$$\frac{1}{T}\sum_{t=0}^{T-1}(\sigma\mathbb{E}\{U(t)|\mathbf{q}(t)\} - \Delta(\mathbf{q}(t)))$$

Collective Utility Unfairness

Maximize:

$$\frac{1}{T}\sum_{t=0}^{T-1}\sum_{w=1}^{N} a_w(t)\left[\sigma_w(t) r_w(t) - q_w(t)\right]$$

Subject to:

$$r_w(t) \geqslant r_{\min},\ \forall w,\ \forall t$$

$$a_w(t) \leqslant n c_w^{\max},\ \forall w,\ \forall t$$

Suitability Ranking Index

Personal eagerness to work

Current workload

$$\Psi_w(t) = \sigma_w(t) r_w(t) - q_w(t)$$

Current reputation

- A simple greedy algorithm
  - greedy in the sense that decisions are made without considering future values of the relevant variables
- leads to a solution that has regret
  - compared to the *optimal solution*
- which decreases with increasing **σ**
  - where **σ** > 0 is the average eagerness to work expressed by workers

Centralized Implementation

Require: New tasks in the crowdsourcing task at time slot t, $Q(t)$; the average deadline of the new requests, $\bar{d}$; $\sigma_w(t)$, $q_w(t)$, $c_w^{\max}$ and $r_w(t)$ values for all workers.

Compute $\Psi_w(t)$ for all w;
Rank all w in descending order of $\Psi_w(t)$;
for each worker w **do**
    if $\Psi_w(t) > 0$ **and** $r_w(t) \geqslant r_{\min}$ **then**
        if $Q(t) < \bar{d}c_w^{\max} - q_w(t)$ **then**
            $a_w(t) = Q(t)$;
        else
            $a_w(t) = \max[0, \lfloor \bar{d}c_w^{\max} - q_w(t) \rfloor]$;
        end if
    else
        $a_w(t) = 0$;
    end if
    $Q(t) \leftarrow Q(t) - a_w(t)$;
end for
return $(a_1(t), a_2(t), \ldots, a_N(t))$;

Distributed Implementation

Require: New tasks pending worker w's acceptance at time slot t, $Q_w(t)$; the average deadline of the new requests for worker w, $\bar{d}_w$; $\sigma_w(t)$, $q_w(t)$, $c_w^{\max}$ and $r_w(t)$ values for worker w.

Compute $\Psi_w(t)$ for w;
if $\Psi_w(t) > 0$ **then**
    if $Q_w(t) < \bar{d}_w c_w^{\max} - q_w(t)$ **then**
        $a_w(t) = Q_w(t)$;
    else
        $a_w(t) = \max[0, \lfloor c_w^{\max} \bar{d}_w - q_w(t) \rfloor]$;
    end if
else
    $a_w(t) = 0$;
end if
if $Q_w(t) - a_w(t) > 0$ **then**
    Send the remaining $Q_w(t) - a_w(t)$ task requests to the crowdsourcers;
end if
return $a_w(t)$;

Further Reading

Y. Zheng, H. Yu, L. Cui, C. Miao, C. Leung & Q. Yang, "SmartHS: An AI Platform for Improving Government Service Provision," in *Proceedings of the 30th AAAI Conference on Innovative Applications of Artificial Intelligence (IAAI-18)*, pp. 7704–7711, 2018.

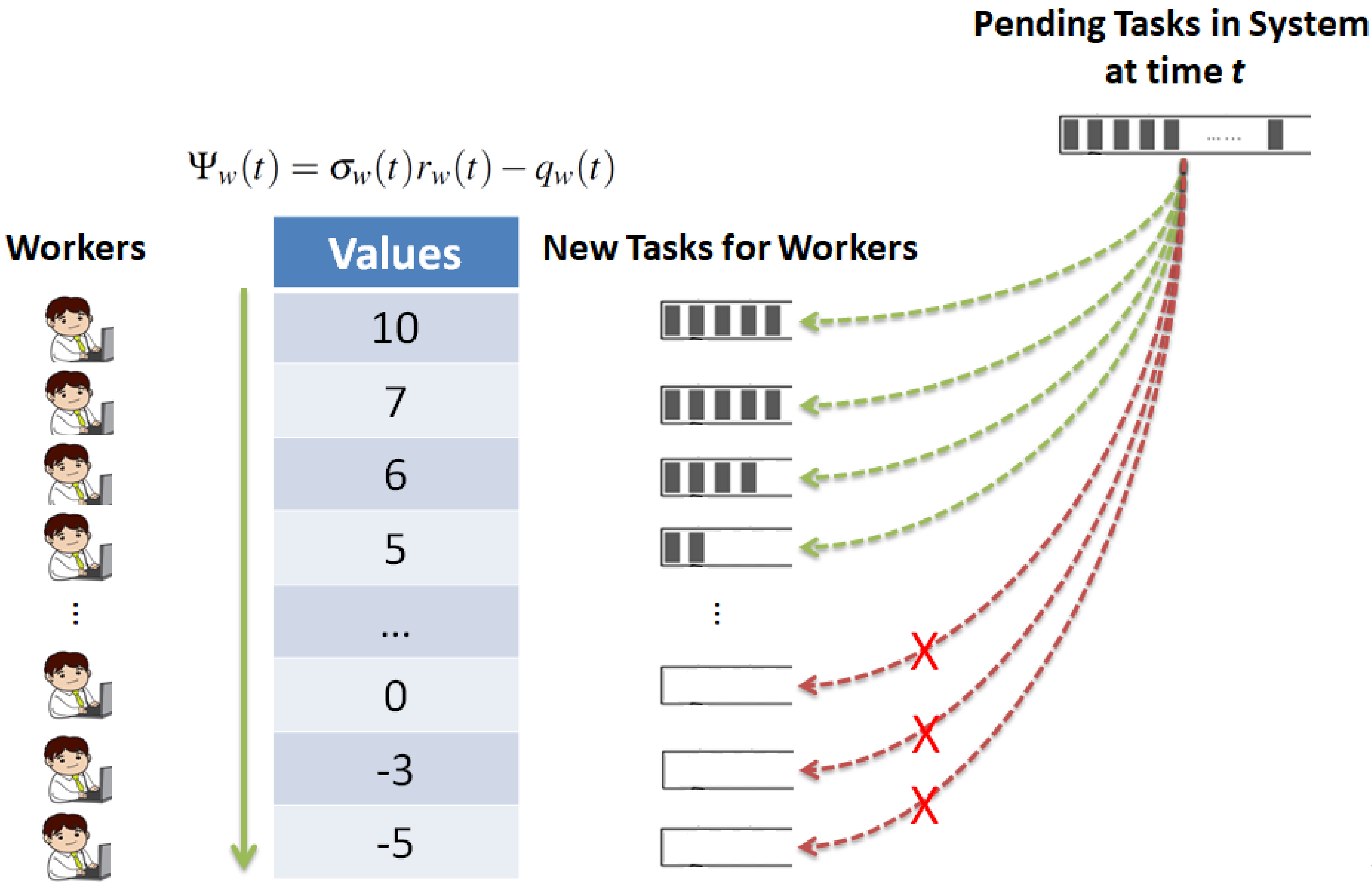
Yu, H., Miao, C., Chen, Y., Fauvel, S., Li, X. & Lesser, V. R. Algorithmic management for improving collective productivity in crowdsourcing. *Scientific Reports*, vol. 7, no. 12541, Nature Publishing Group (2017).

Yu, H., Miao, C., Leung, C., Chen, Y., Fauvel, S., Lesser, V. R. & Yang, Q. Mitigating herding in hierarchical crowdsourcing networks. *Scientific Reports*, vol. 6, no. 4, Nature Publishing Group (2016).

A Walkthrough Example

Example

$$\Psi_w(t) = \sigma_w(t) r_w(t) - q_w(t)$$



Example

- Suppose we have 5 workers, *w1* to *w5*:

ID	Reputation	Eagerness to Work	Productivity (tasks per round)
w1	0.9	10	5
w2	0.8	15	8
w3	0.7	10	15
w4	0.4	20	20
w5	0.2	50	25

Round 1

- All workers start with 0 workload
- Compute their suitability ranking indices

$$\Psi_w(t) = \sigma_w(t) r_w(t) - q_w(t)$$

ID	Reputation	Eagerness to Work	Suitability Ranking Index
w1	0.9	10	9
w2	0.8	15	12
w3	0.7	10	7
w4	0.4	20	8
w5	0.2	50	10

Round 1

- Suppose we only want workers with reputation scores above 0.6 to work on our tasks:

ID	Reputation	Eagerness to Work	Suitability Ranking Index
w1	0.9	10	9
w2	0.8	15	12
w3	0.7	10	7
w4	0.4	20	8
w5	0.2	50	10

Round 1

- Rank the remaining workers in descending order of their suitability ranking indices:

ID	Reputation	Eagerness to Work	Suitability Ranking Index
w2	0.8	15	12
w1	0.9	10	9
w3	0.7	10	7

Round 1

- Rank the remaining workers in descending order of their suitability ranking indices.
- Suppose we have 20 new tasks, all with deadlines = 2 rounds:

ID	Suitability Ranking Index	Productivity (tasks per round)	New Tasks Assigned
w2	12	8	16
w1	9	5	4
w3	7	15	0

Round 2

- Suppose w2 completed 8 tasks during round 1, and w1 completed 4 tasks during round 1:

ID	Reputation	Eagerness to Work	Remaining Tasks	Suitability Ranking Index
w1	0.9	10	0	9
w2	0.8	15	8	4
w3	0.7	10	0	7
w4	0.4	20	0	8
w5	0.2	50	0	10

Round 2

- Suppose we only want workers with reputation scores above 0.6 to work on our tasks:

ID	Reputation	Eagerness to Work	Remaining Tasks	Suitability Ranking Index
w1	0.9	10	0	9
w2	0.8	15	8	4
w3	0.7	10	0	7
w4	0.4	20	0	8
w5	0.2	50	0	10

Round 2

- Rank the remaining workers in descending order of their suitability ranking indices.
- Suppose we have 10 new tasks, all with deadlines = 1 round:

ID	Suitability Ranking Index	Productivity (tasks per round)	New Tasks Assigned
w1	9	5	5
w3	7	15	5
w2	4	8	0

Measuring Fairness

Jain's Fairness Index

- Raj Jain's equation:

$$\mathcal{J}(x_1, x_2, \ldots, x_n) = \frac{\left(\sum_{i=1}^{n} x_i\right)^2}{n \cdot \sum_{i=1}^{n} {x_i}^2}$$

- x_i denotes the amount of resources allocated to *i*.
- It is useful to evaluation fairness of resource allocation among recipients.
- The range of values for *J* is between 0 and 1. The larger the value, the fairer the allocation.

Example

- [Case 1]:
  - Consider workers *a*, *b* and *c*.
  - Their reputation scores (r) are 0.9, 0.5 and 0.2, respectively.
  - The values of the tasks (v) being allocated to them are 25, 12 and 20, respectively.
  - How fair is the allocation?

- Solution using Jain's Fairness Index:
  - In this case, we want to see if more reputable workers are allocated more valuable tasks
  - Thus, we set $x_i = \frac{v_i}{r_i}$
  - $J = \frac{\left(\frac{25}{0.9}+\frac{12}{0.5}+\frac{20}{0.2}\right)^2}{3\left[\left(\frac{25}{0.9}\right)^2+\left(\frac{12}{0.5}\right)^2+\left(\frac{20}{0.2}\right)^2\right]} = \frac{23036.49}{34042.81} = 0.677$

Example

- [Case 2]:
  - Consider workers *a*, *b* and *c*.
  - Their reputation scores (r) are 0.9, 0.5 and 0.2, respectively.
  - The values of the tasks (v) being allocated to them are 25, 20 and 12, respectively.
  - How fair is the allocation?

- Solution using Jain's Fairness Index:
  - In this case, we want to see if more reputable workers are allocated more valuable tasks
  - Thus, we set $x_i = \frac{v_i}{r_i}$
  - $J = \frac{\left(\frac{25}{0.9}+\frac{20}{0.5}+\frac{12}{0.2}\right)^2}{3\left[\left(\frac{25}{0.9}\right)^2+\left(\frac{20}{0.5}\right)^2+\left(\frac{12}{0.2}\right)^2\right]} = \frac{16327.16}{17914.81} = 0.911 > 0.677$
  - Thus, Case 2 is fairer than Case 1.

Example

- What about [Case 3]:
  - Consider workers *a*, *b* and *c*.
  - Their reputation scores (r) are 0.9, 0.5 and 0.2, respectively.
  - The values of the tasks (v) being allocated to them are 12, 20 and 25, respectively.
  - How fair is the allocation?

- Try it yourself

Fairness

Yu Han

han.yu@ntu.edu.sg

Nanyang Assistant Professor
School of Computer Science and Engineering
Nanyang Technological University