Leveraging Correlations in Utility Learning

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ACC 2017

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People-Building-Grid Nexus

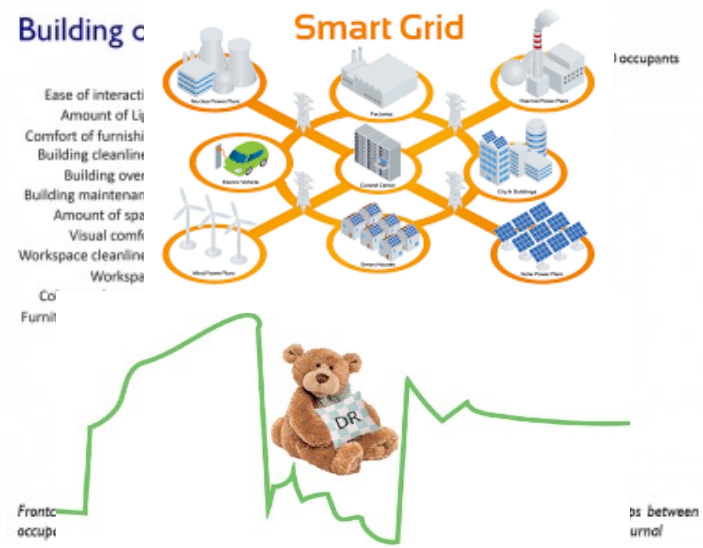
Demand Respond - Smart Grid - Occupancy Detection

Occupants' satisfaction

Internet of Things (IoT)

Smart building

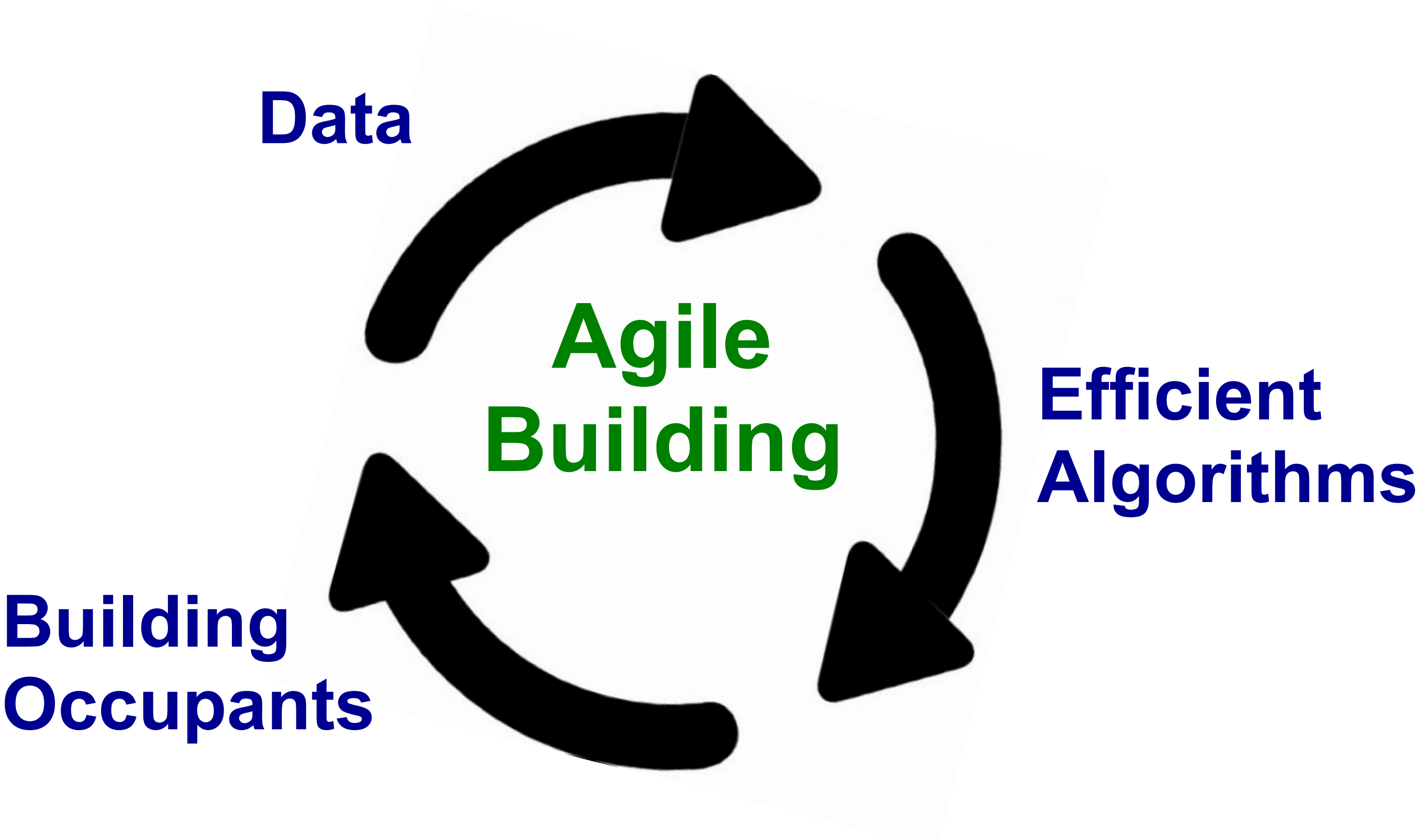


Agile operations in buildings → Occupants take real time control → Building "senses" grid – occupants actions

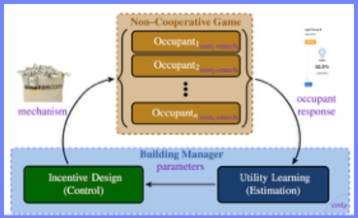
Building respects comfort, productivity, wellbeing, satisfaction

People-Building-Grid Nexus

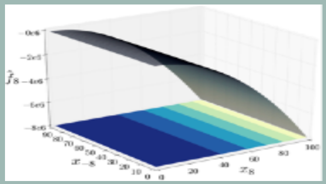


<u>The M$ question </u>–

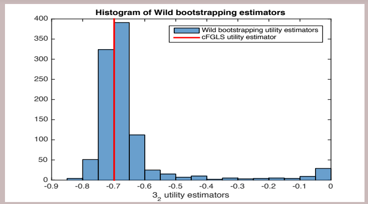
How to **learn about people's preference** from their actions?



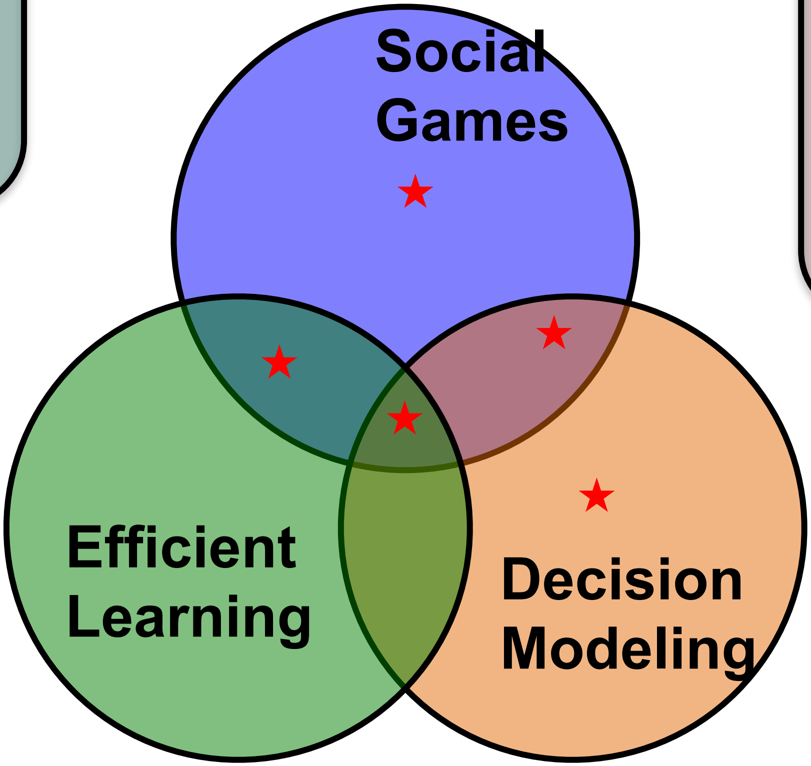
Social Game for energy efficiency (Allerton 2014)

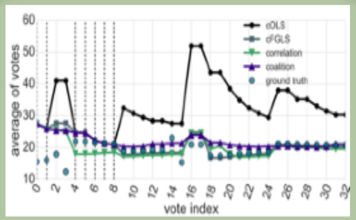


Robust Utility Learning (IEEE Transactions on Control Systems Technology)

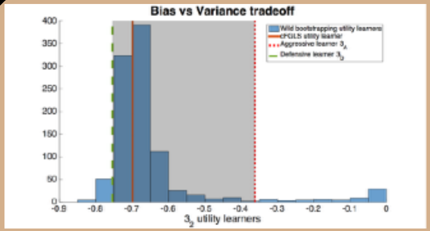


Robust Utility Learning for closing the loop (CPS Week 2016)





Leveraging correlations in utility learning (ACC 2017)



Inverse Modeling via Mixture of Utilities (CDC 2016)

Leveraging **social coalitions** can better understand/influence people’s behaviors

Engaging people in a game improves **energy efficiency** and **occupant comfort**

Outline

Motivation

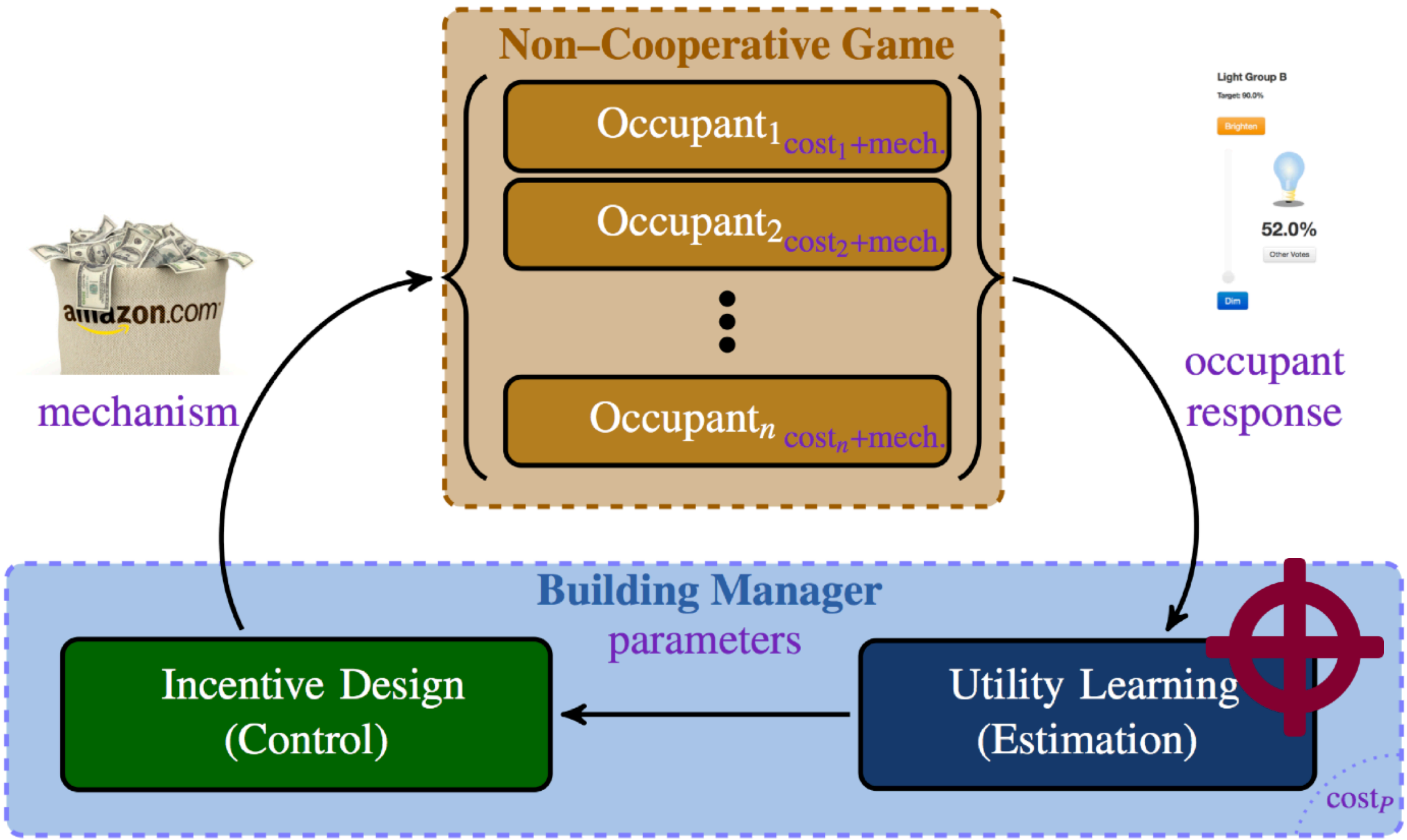
Energy efficiency via gamification

Utility learning framework

Leveraging correlations

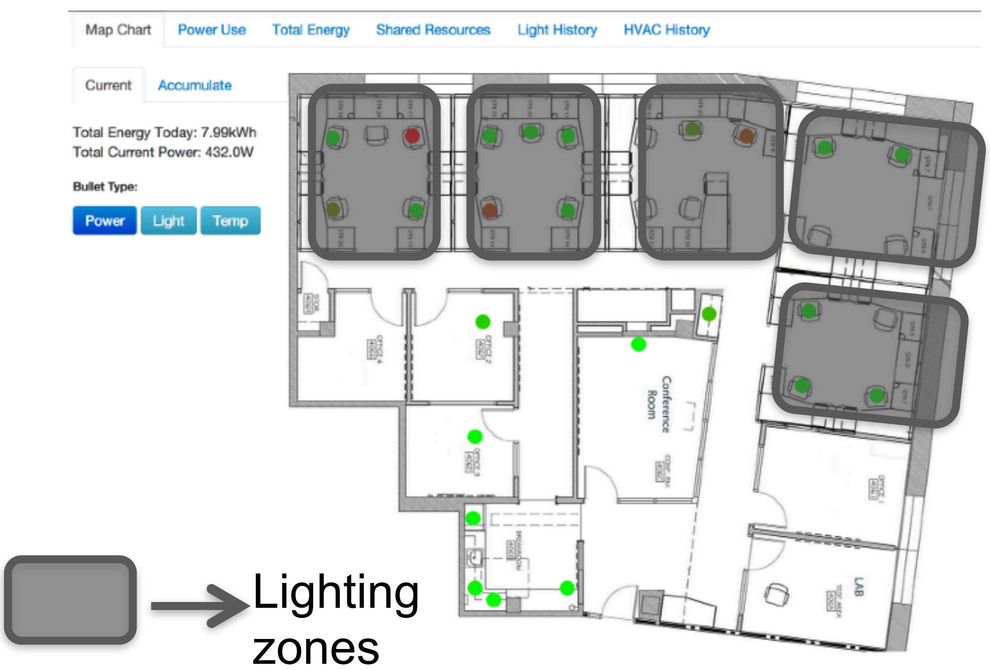
Conclusion and on-going works

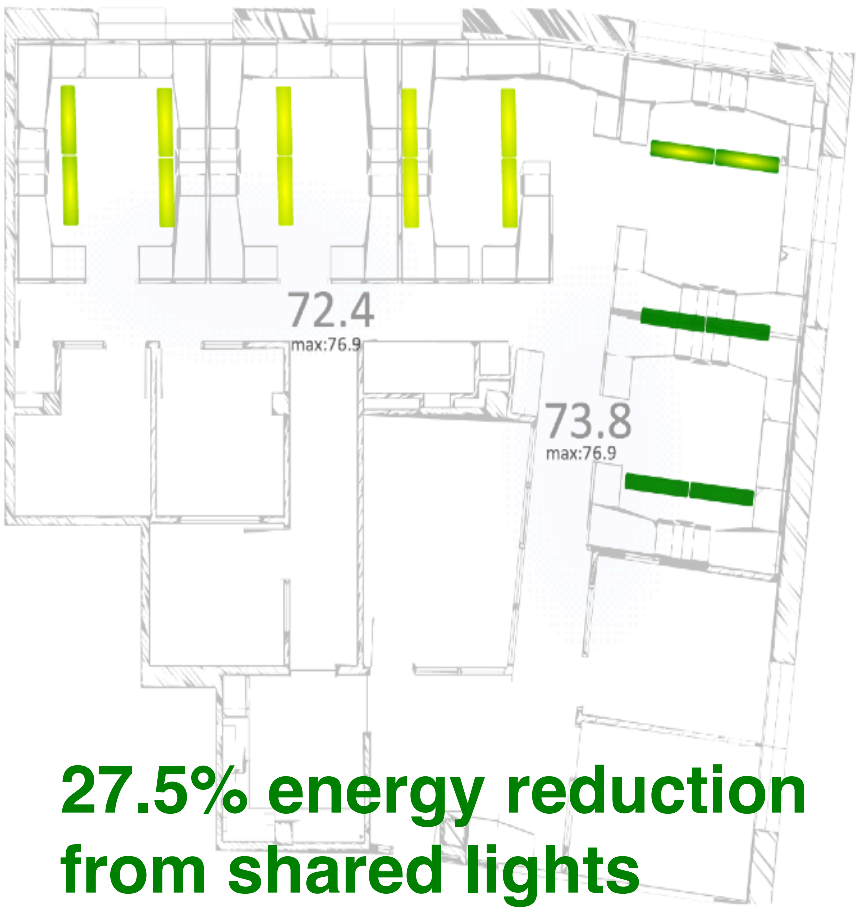
Energy efficiency via gamification



Social game for building energy efficiency

- Social game for changing occupant energy – related behaviors.
- 20 occupants
- Weekly lottery w/ Amazon cards

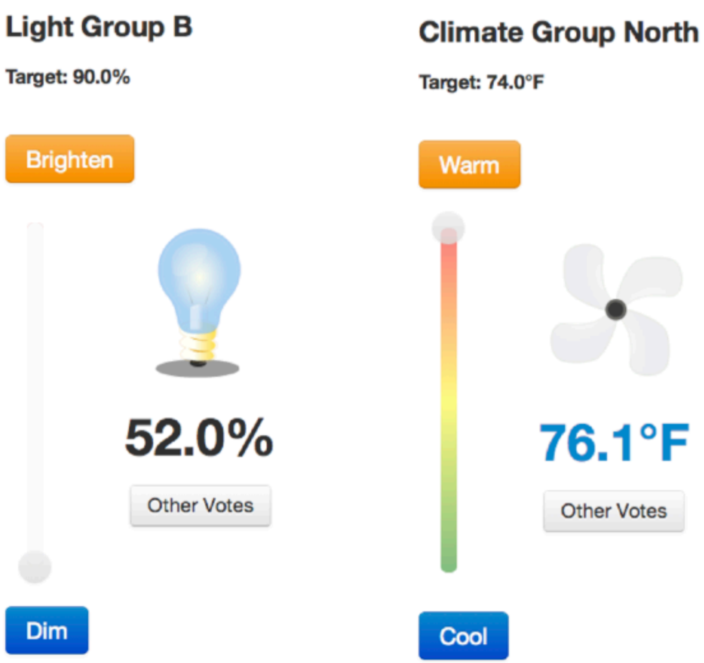


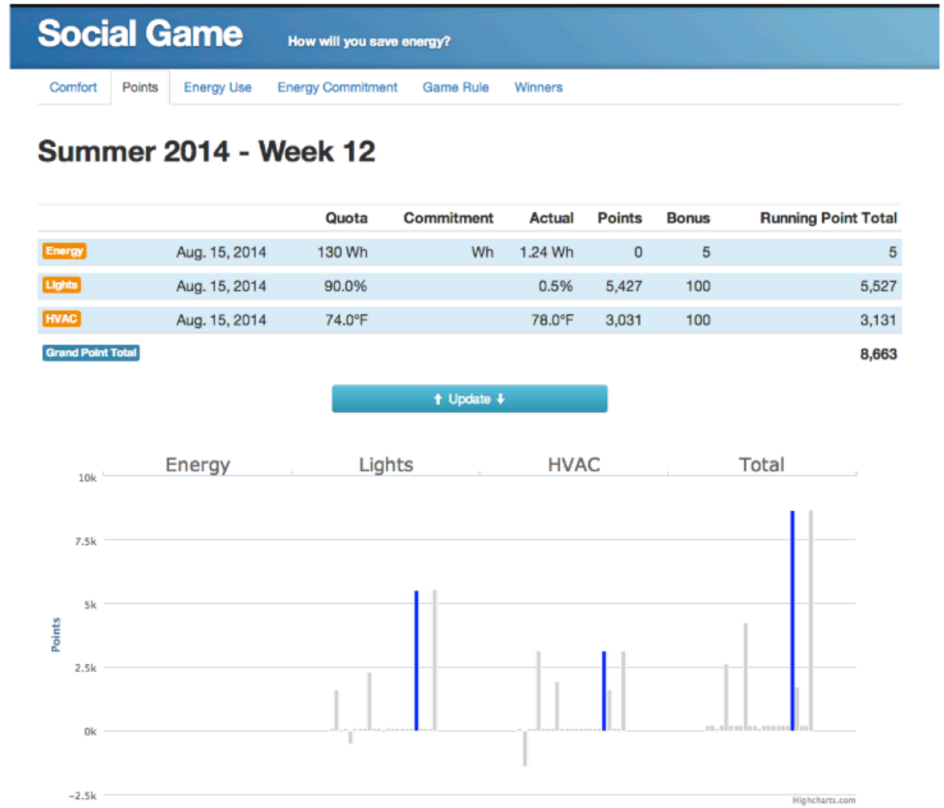


27.5% energy reduction from shared lights

Social game for building energy efficiency

Real time control for shared lights and HVAC





○ Points are used to determine probability of winning in lottery

"Use less to gain more"

People play Nash equilibrium

Each occupant selects

$$\underbrace{\textbf{vote}}_{x_i} \in [\underbrace{\textbf{min light setting}}_{0}, \underbrace{\textbf{max light setting}}_{100}]$$

in order to maximize

$$\underbrace{\textbf{occupant utility}}_{f_i(x_1, x_2, \cdots, x_n)} = \underbrace{\textbf{comfort}}_{-(\frac{1}{n}\sum_{j=1}^{n} x_j - x_i)^2} + \theta_i \underbrace{\textbf{desire to win}}_{-\rho(\frac{x_i}{100})^2}$$

θ_i : **tradeoff between comfort and desire to win**

Definition

A collection of lighting settings $x = (x_1, \cdots, x_n)$ is a **Nash equilibrium if no occupant can increase his utility by selecting a different lighting setting** x_i' i.e. for each $i \in \{1, \ldots, n\}$

$$f_i(x_i, x_{-i}) \geq f_i(x_i', x_{-i},) \quad \forall \; x_i' \in [0, 100] \tag{1}$$

Nash characterized by KKT conditions

- Occupant *i*'s parameterized utility function:

$$f_i(x_1^{(k)}, x_2^{(k)}, \cdots, x_n^{(k)}) = \underbrace{-(\frac{1}{n}\sum_{j=1}^{n} x_j^{(k)} - x_i^{(k)})^2}_{\text{comfort}} - \theta_i \underbrace{\rho(\frac{x_i^{(k)}}{100})^2}_{\text{desire to win}}$$

- Each $x_i^{(k)}$ is approximately a Nash equilibrium point.
- Residuals defined by the stationarity and complementary slackness conditions:

$$r_{s,i}^{(k)}(\theta_i, \mu_i) = D_i\, f_i(x_1^{(k)}, x_2^{(k)}, \cdots, x_n^{(k)}) + \sum_{j=1}^{2} \mu_i^j D_i h_{i,j}(x_i^{(k)})$$

$$r_{c,i}^{j,(k)}(\mu_i) = \mu_i^j h_{i,j}(x_i^{(k)}),\;\; j \in \{1, 2\}$$

where $h_{i,1}(x_i^{(k)}) = 100 - x_i^{(k)}, h_{i,2}(x_i^{(k)}) = x_i^{(k)}$

Learning with constrained Ordinary Least Squares (cOLS)

From the KKT conditions of Nash, one can formulate cOLS:

$$Y = X\beta + \epsilon, \;\; \beta \in \mathcal{B}$$

where $E(\varepsilon|X) = 0^{n_d \times 1}, \mathrm{cov}(\varepsilon|X) = \sigma^2 I^{n_d \times n_d}$ is “spherical” noise.

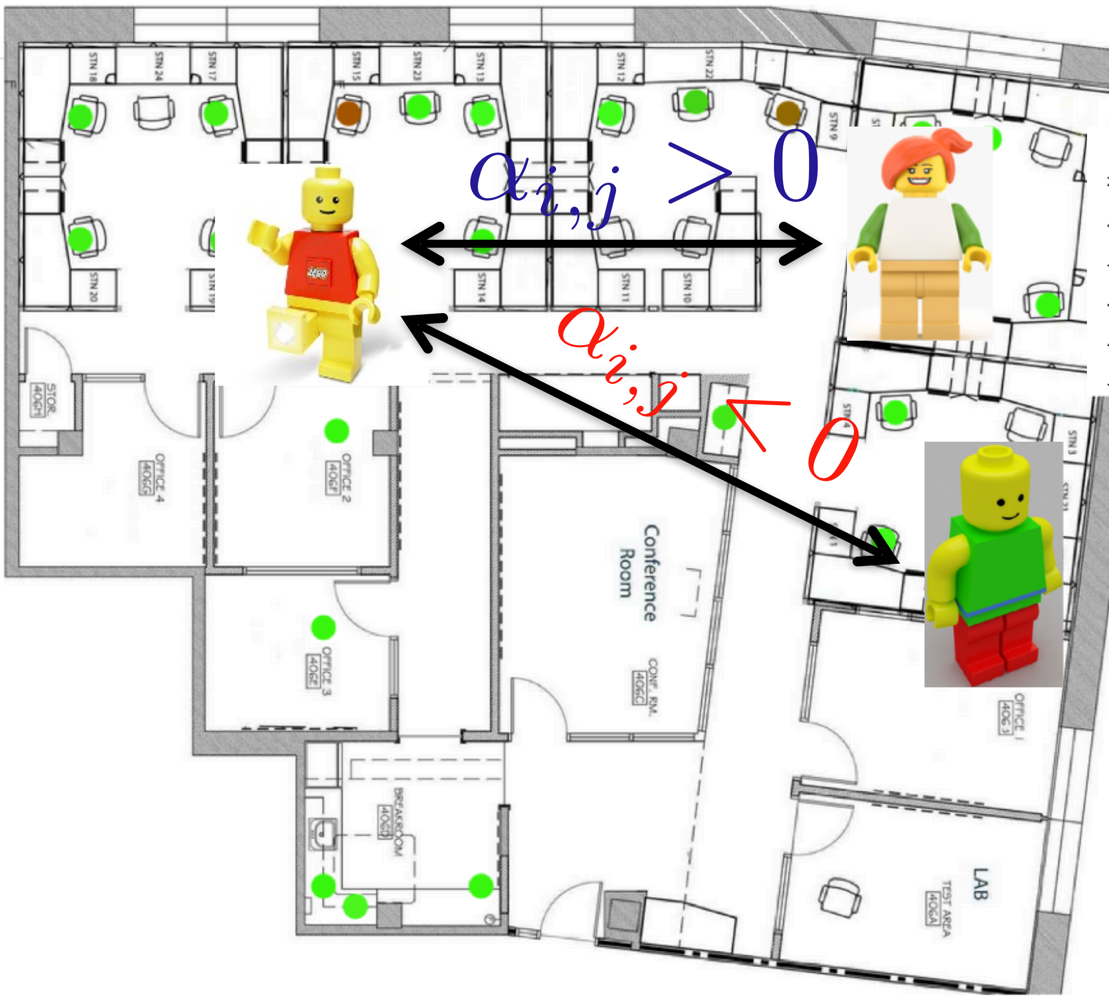
However, this estimator often performs “poorly”, due to this strong assumption on *“spherical noise structure”*.

Besides, data is often expensive and *limited*!

People often vote as a group..

We can design *utility with player coalition* based on the ***correlation matrix***.

Leveraging correlations among players



- Estimate correlations between occupants

Id	2	6	8	14	20
2	0.04	**0.06**	-2.80	-5.19	**0.03**
6	0.06	7.84	-16.8	0.84	-0.02
8	-2.80	-16.8	6.4×10^4	**4.28×10^4**	-7.60
14	**-5.19**	0.84	**4.28×10^4**	8.84×10^4	-12.6
20	0.03	-0.02	-7.60	-12.6	0.07

Contributions

- Boost performance using OLS
- Reduce computational complexity
- Transfer to online learning

Gradient Boosting to estimate noise structure

Original fitting residuals

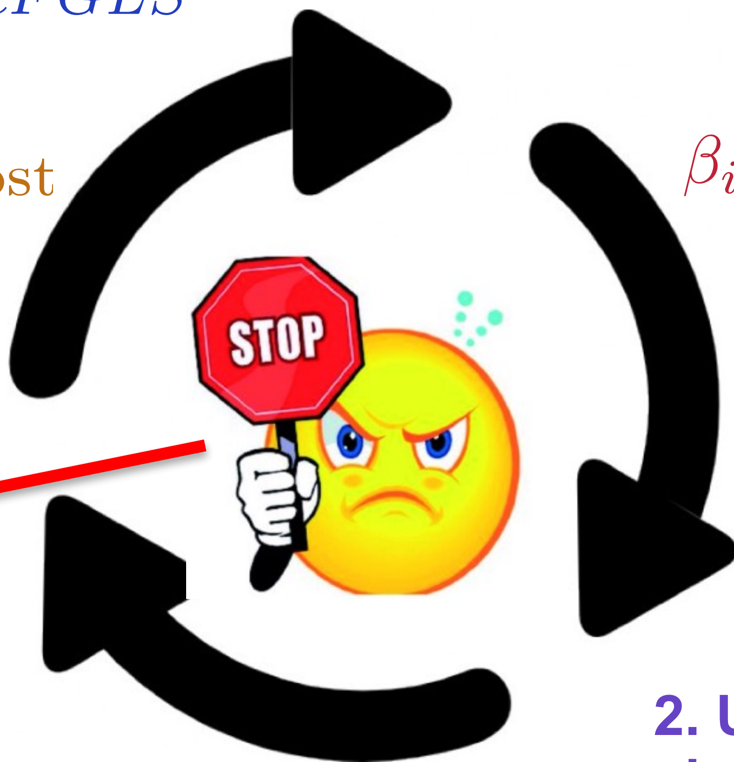
e, β_{cFGLS}

$e \leftarrow Y - X\beta_{\text{boost}}$

3. Residuals update

$\beta_i \leftarrow (X^\top X)^{-1} X^\top e$

1. Residual fitting

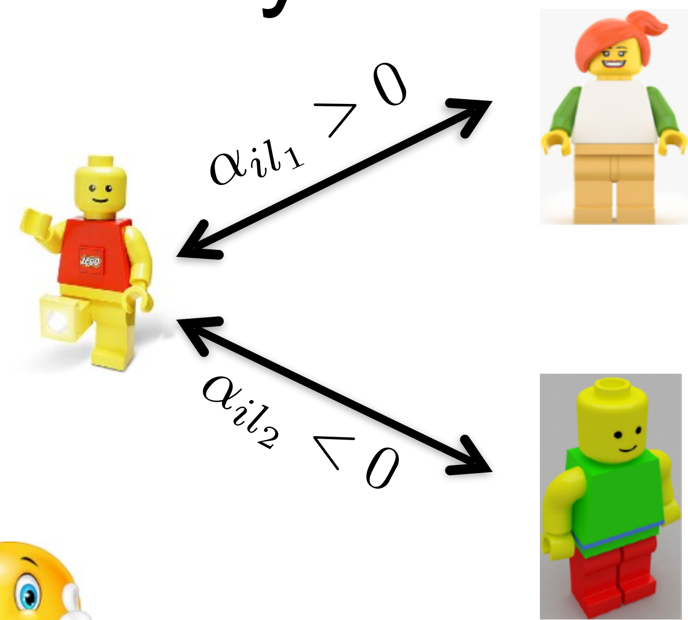


- AIC criterion
- Fixed iterations
- Prevent overfitting

$\beta_{\text{boost}} \leftarrow \beta_{\text{boost}} + \nu\beta_i$

2. Update with shrinkage parameter *v* in (0,1]

Utility function based on correlation



Correlation utility

$$\hat{g}_i(x_i, x_{-i}) = \sum_{l \in Q_i} \frac{\alpha_{il}}{c_{il}} \hat{f}_l(x_i, x_{-i})$$

Coalition utility

$$\tilde{g}_{M_i}(x_{M_i}, x_{-M_i}) = \sum_{j \in M_i} f_j(x_{M_i}, x_{-M_i})$$

Happiness Metric: $\mathrm{H} = \hat{f}_i^{\mathrm{coal}}(x^{(k)}; \theta_i^{\mathrm{coal}}) - \hat{f}_i(x^{(k)}; \theta_i^{\mathrm{cOLS}})$

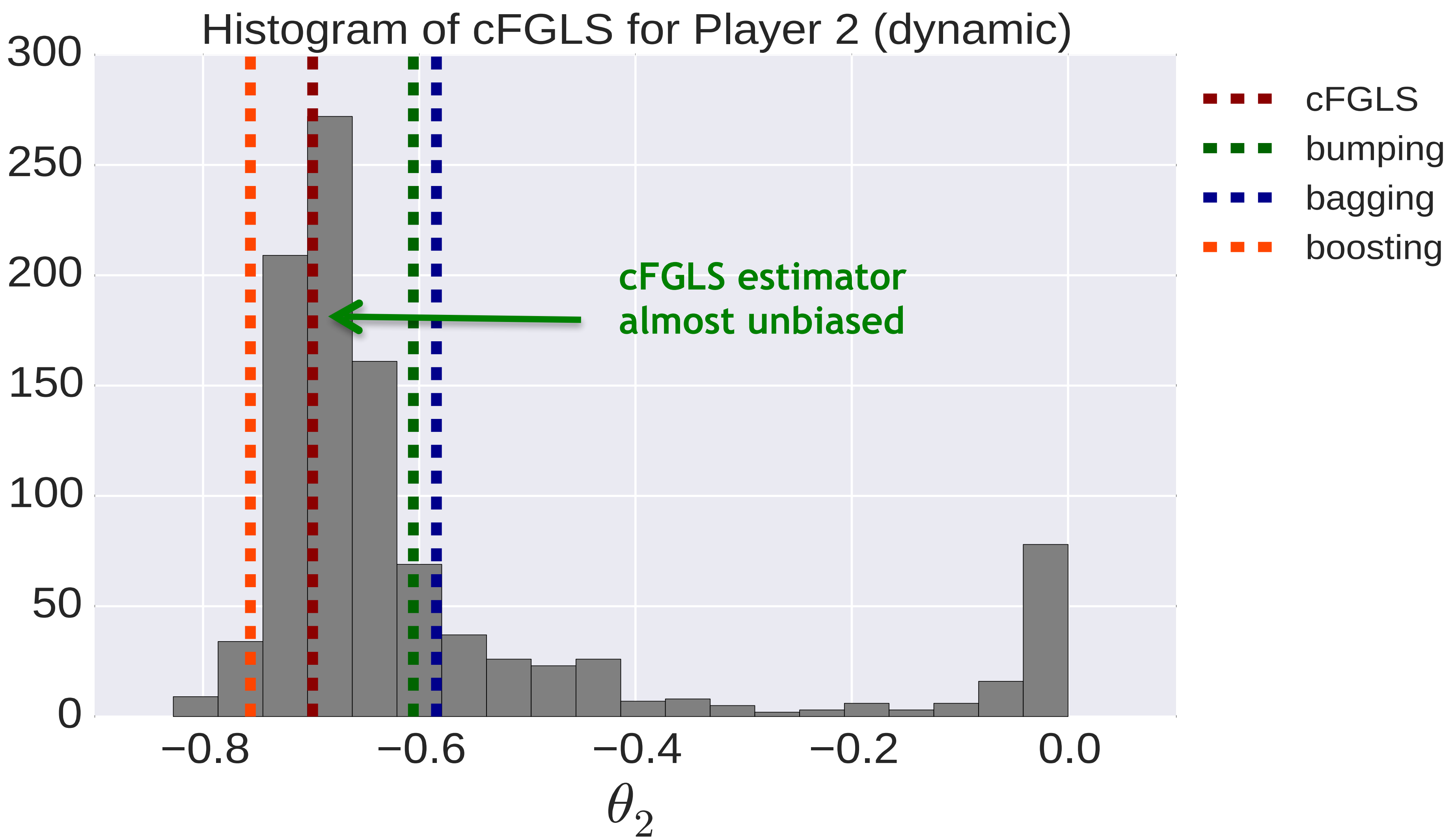
Coalition utility per player: $\hat{f}_i^{\mathrm{coal}}(x^{(k)}; \hat{\theta}_i^{\mathrm{coal}}) = \dfrac{1}{|M_1|} \tilde{g}_{M_i}(x^{(k)}; \hat{\theta}_{M_i}^{\mathrm{coal}})$

Experimental

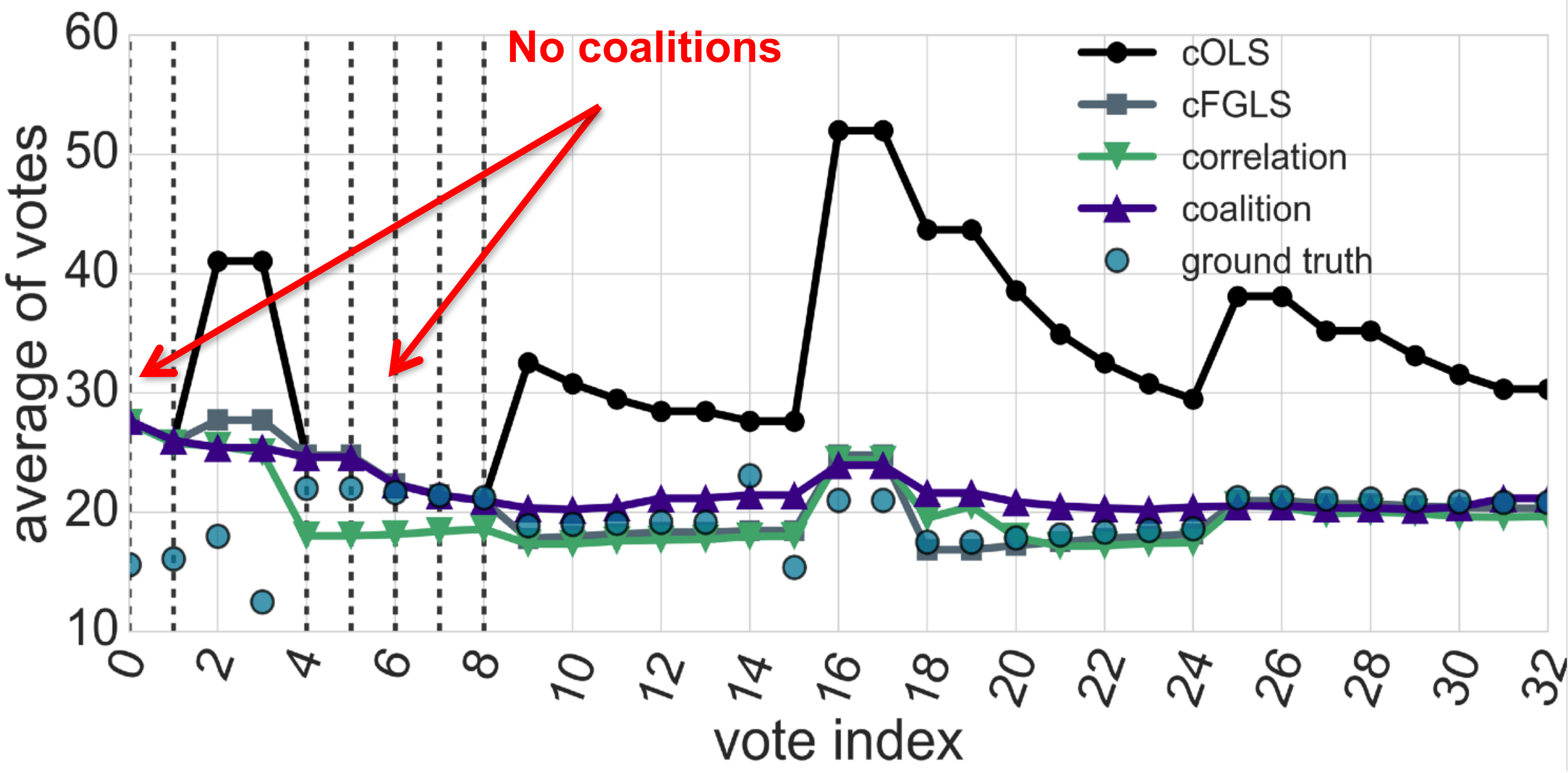
Results

Gradient boosting gives unbiased estimator

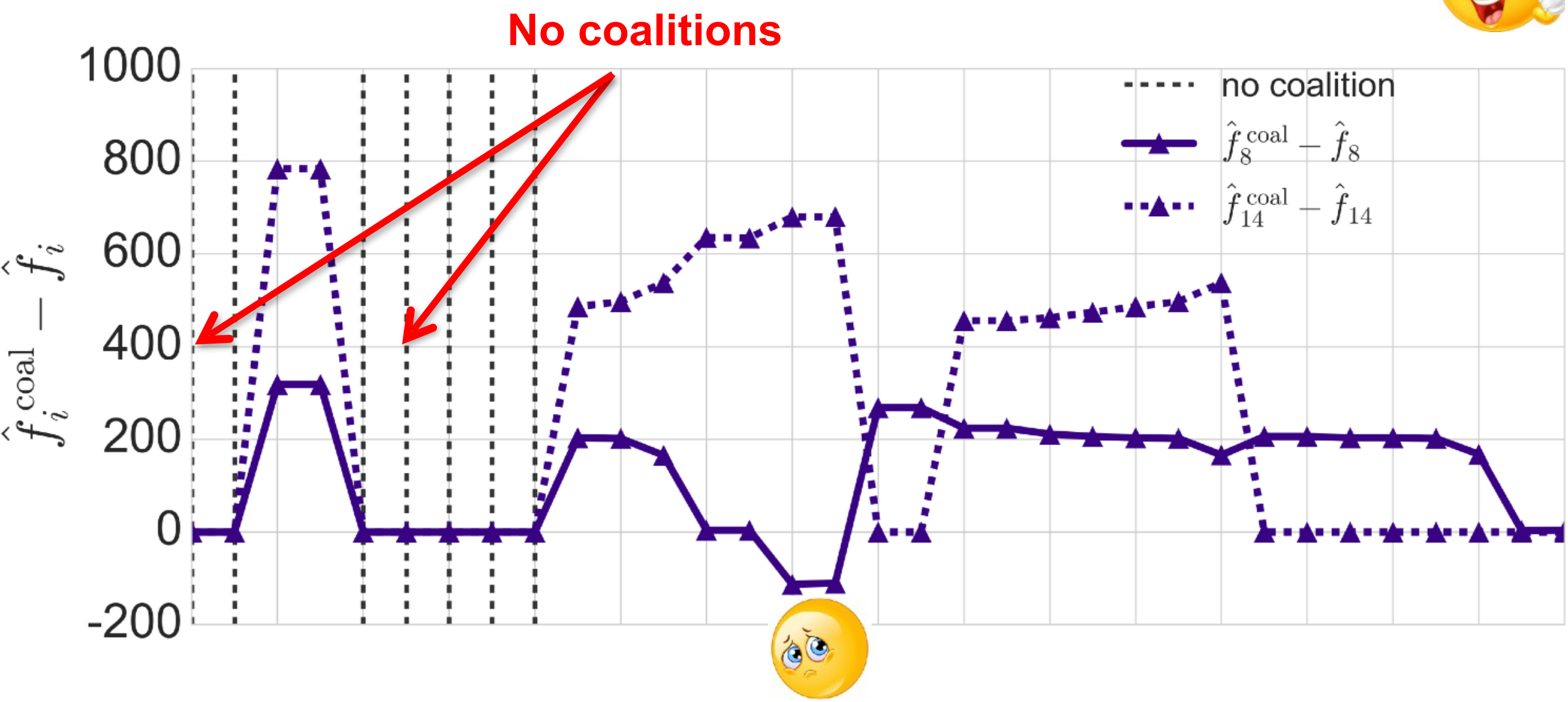
Asymptotic bias estimation via bootstrapping



Leveraging correlation improves forecasting



Happiness metric indicates collusion between users 8 and 14



Conclusion

Unknown noise structure

Limited sample size

Correlated players' actions

NEW GAMES, MORE GAMES !!!

Shared lighting experiment at Sutardja Dai Hall with 200 occupants (4th and 7th floor)

Shared lighting – personal desk electrical equipment experiment at CREATE Tower (11th floor) in Singapore with 50 occupants

Personal room lighting at Graduate Hall dorms in Eco Campus in Singapore with 100++ occupants

Acknowledgement

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