Comparison of Bidding Algorithms for Simultaneous Auctions

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Bidding Problem

- Simultaneous Auctions
- Substitutable & Complementary Goods

Miami Beach

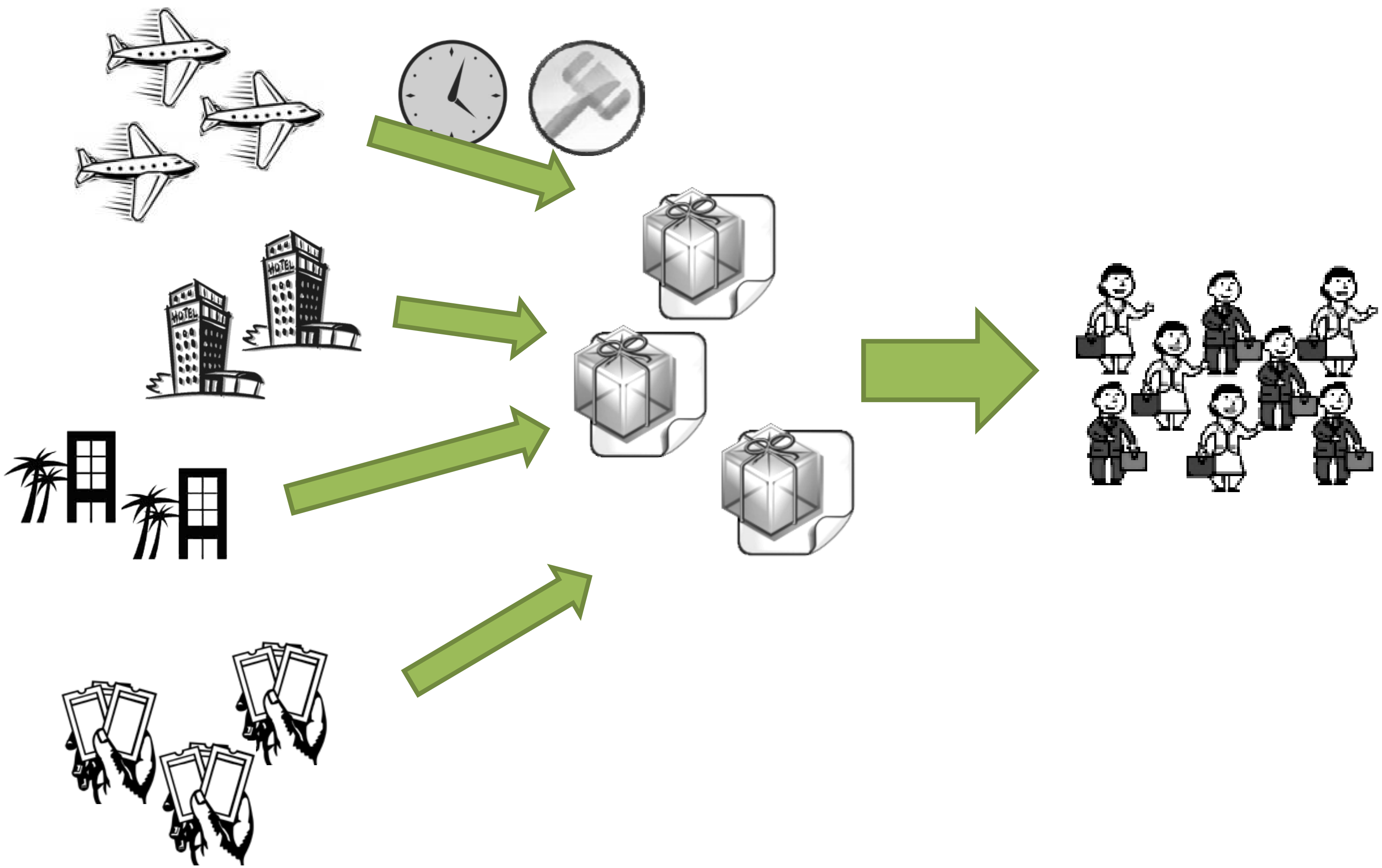
Bidding Problem: Goal

- The goal of bidding problem is to find a set of bids *B* that maximizes:

$$\int_s p(s)v(s,B)ds$$

  - *s* : clearing price.
  - *p(s)* : probability that the clearing price is *s*.
  - *v(s,B)* : value when the clearing price is *s*, and bid is *B*.

Trading Agent Competition



Algorithms

- Sample Average Approximation
- Marginal Value Bidding

Name	Performance	Algorithm
ATTac01	2000 1st, 2003 1st	Marginal Value
Walverine	2004 2nd, 2005 3rd, 2006 2nd	Marginal Value
RoxyBot	2000 2nd, 2002 final	Marginal Value
RoxyBot	2005 final, 2006 1st	SAA

Review: the Goal

- The goal of bidding problem is to find a set of bids *B* that maximizes:

$$\int_s p(s)v(s,B)ds$$

  - *s* : clearing prices.
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Sample Average Approximation

- SAA algorithm samples *S* scenarios from clearing price distribution model.

- Find a set of bids *B* that maximizes:

$$\frac{1}{|S|}\sum_{s\in S} v(s,B)$$

  - *S* : a set of sampled clearing prices.

Sample Average Approximation

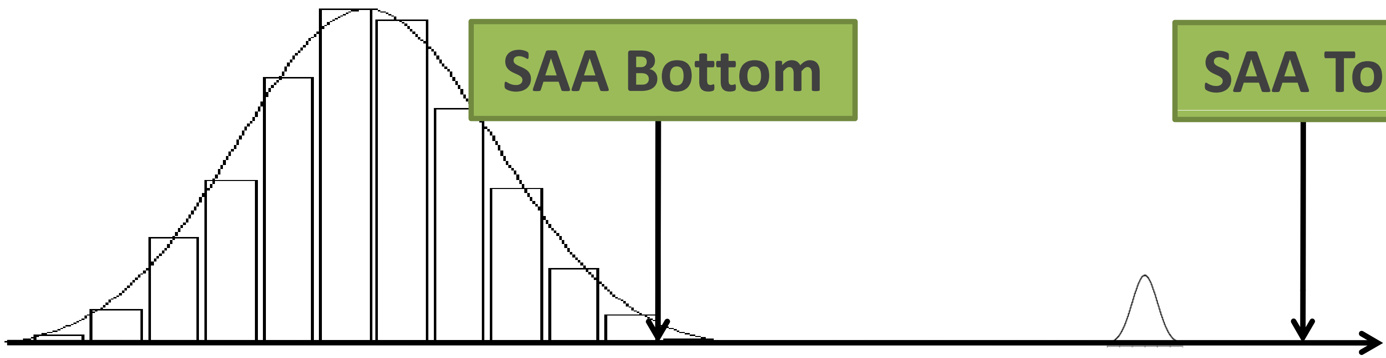
- There are infinitely many solutions!
  - e.g. *S*=1, *s*=100,
    if *B>s, v*(s,*B*)=1000-*s, else v(s,B) = 0*.
  - *B* can be any number between 100 and 1000.

- SAA Bottom: maximize $$\frac{1}{|S|}\sum_{s\in S} v(s,B) - \epsilon B$$
- SAA Top: maximize

$$\frac{1}{|S|}\sum_{s\in S} v(s,B) + \epsilon B, \quad b < c \quad \forall b \in B$$

Sample Average Approximation

- Defect
  - The highest bid SAA Bottom considers submitting may be below clearing price.
  - SAA Top may pay more than the highest price it expects.



Marginal Value based Algorithms

- Marginal Value of a good: the additional value derived from owning the good relative to the set of goods you can buy.

- Characterization Theorem [Greenwald]
  - $MV(g) > s$ if g is in all optimal sets.
  - $MV(g) = s$ if g is in some optimal sets.
  - $MV(g) < s$ if g is not in any optimal sets.

Marginal Value based Algorithms

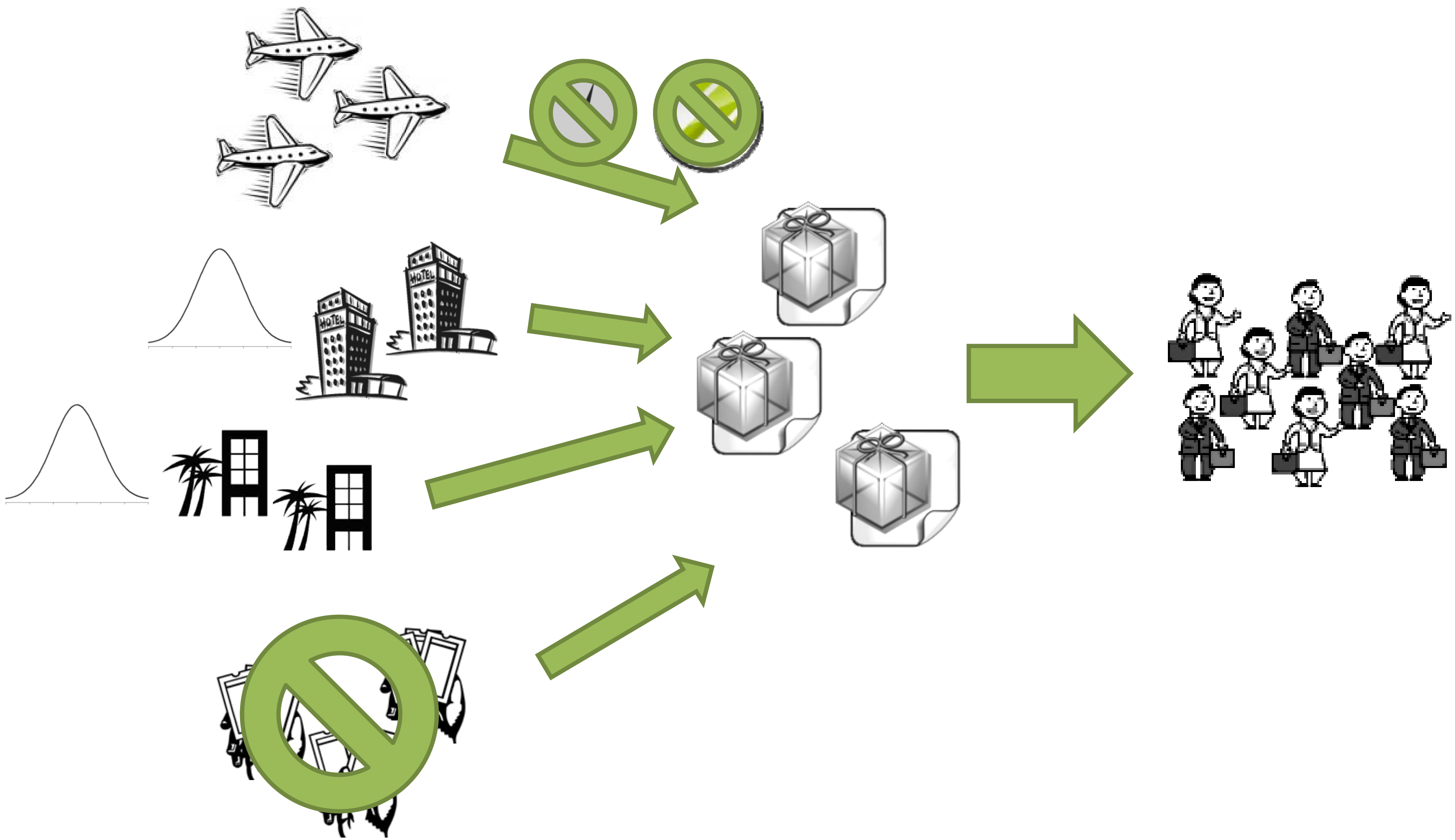
- Use MV based algorithms which performed well in the TAC:
  - TMU/TMU*: RoxyBot 2000
  - BE/BE* : RoxyBot 2002
  - AMU/SMU : ATTAC

Experiments

- Decision-Theoretic Setting
  - Prediction = Clearing Price (normal dist.)
  - Prediction ~ Clearing Price (normal dist.)
- Game-Theoretic Setting
  - Prediction ~ Clearing Price (CE price)

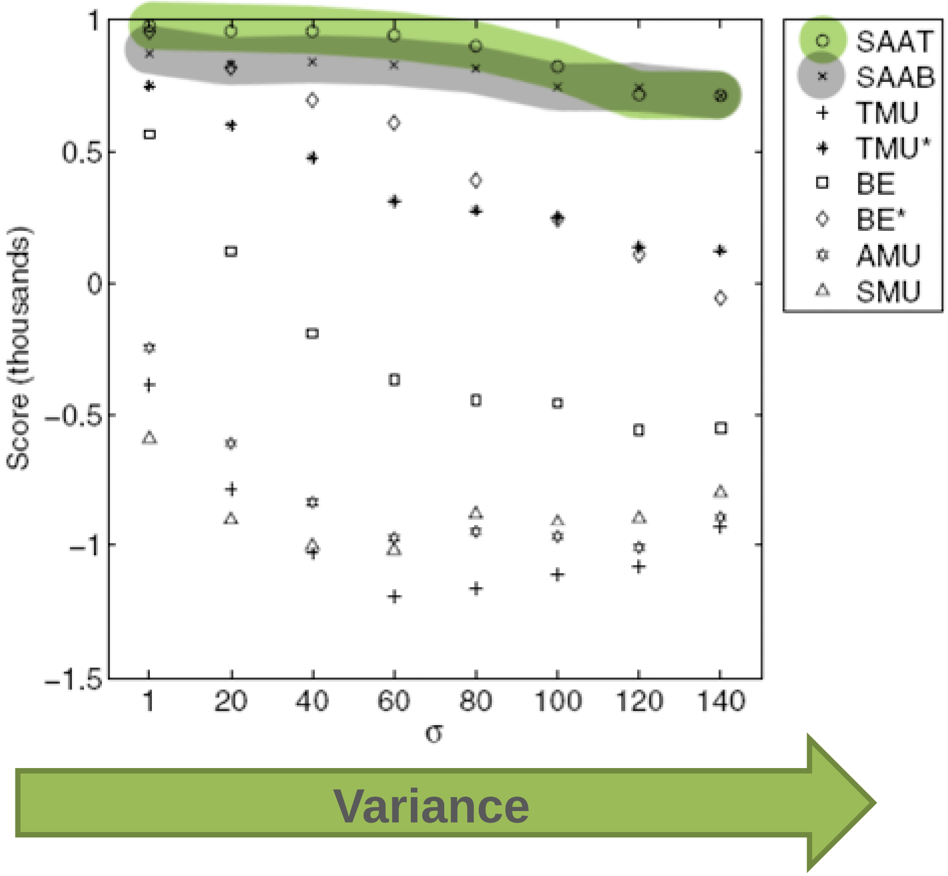
Experiments

1. Decision-Theoretic (perfect)



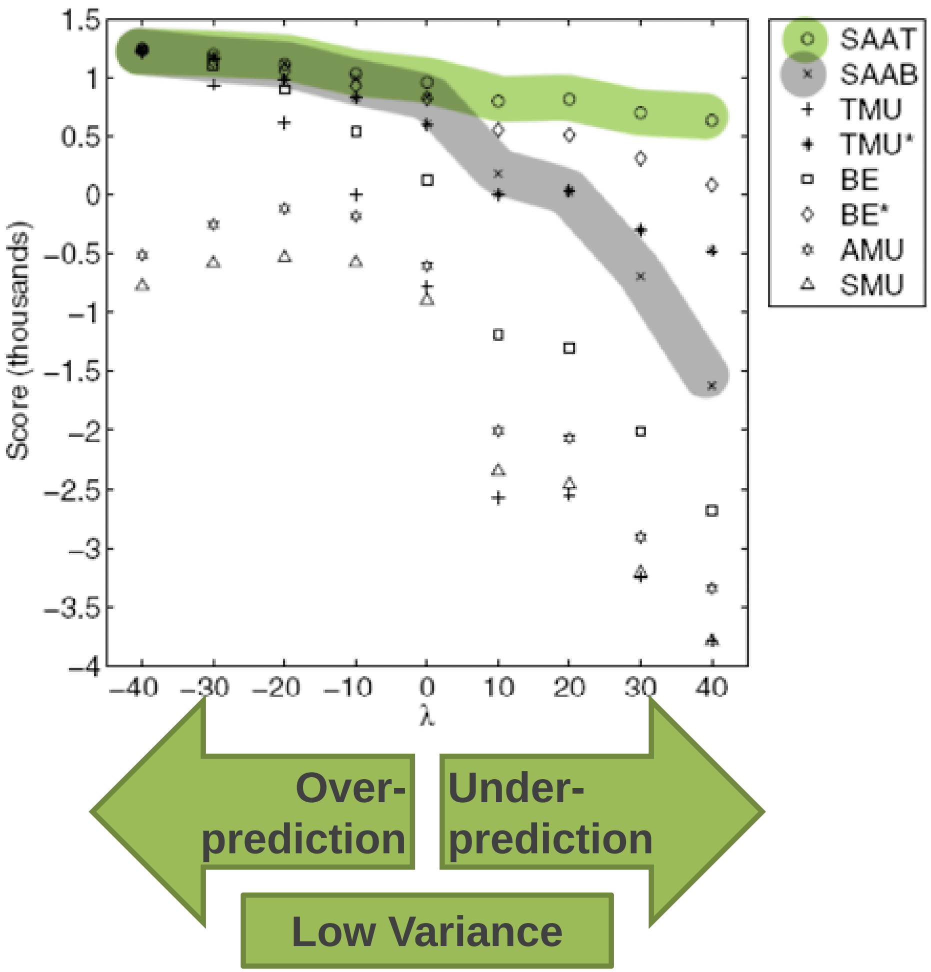
1. Decision-Theoretic (perfect)

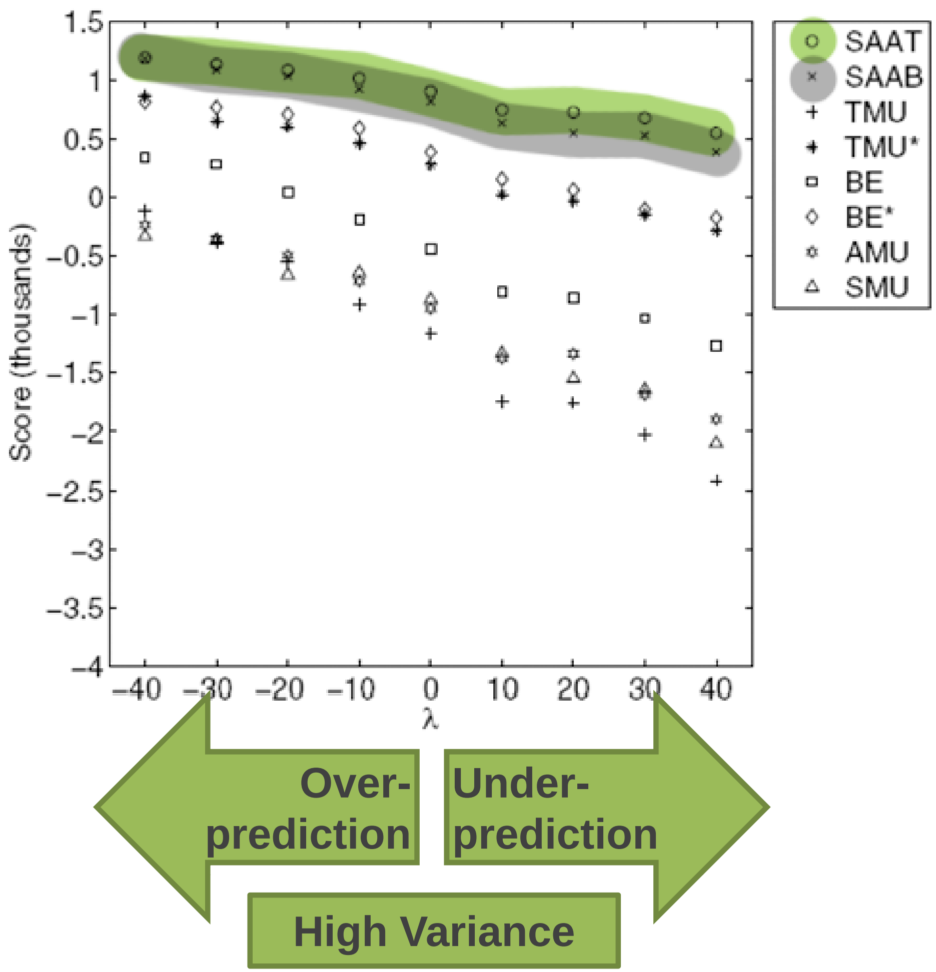
- SAAs are more tolerant to variance
- SAAT ~ SAAB at a high variance



Experiments

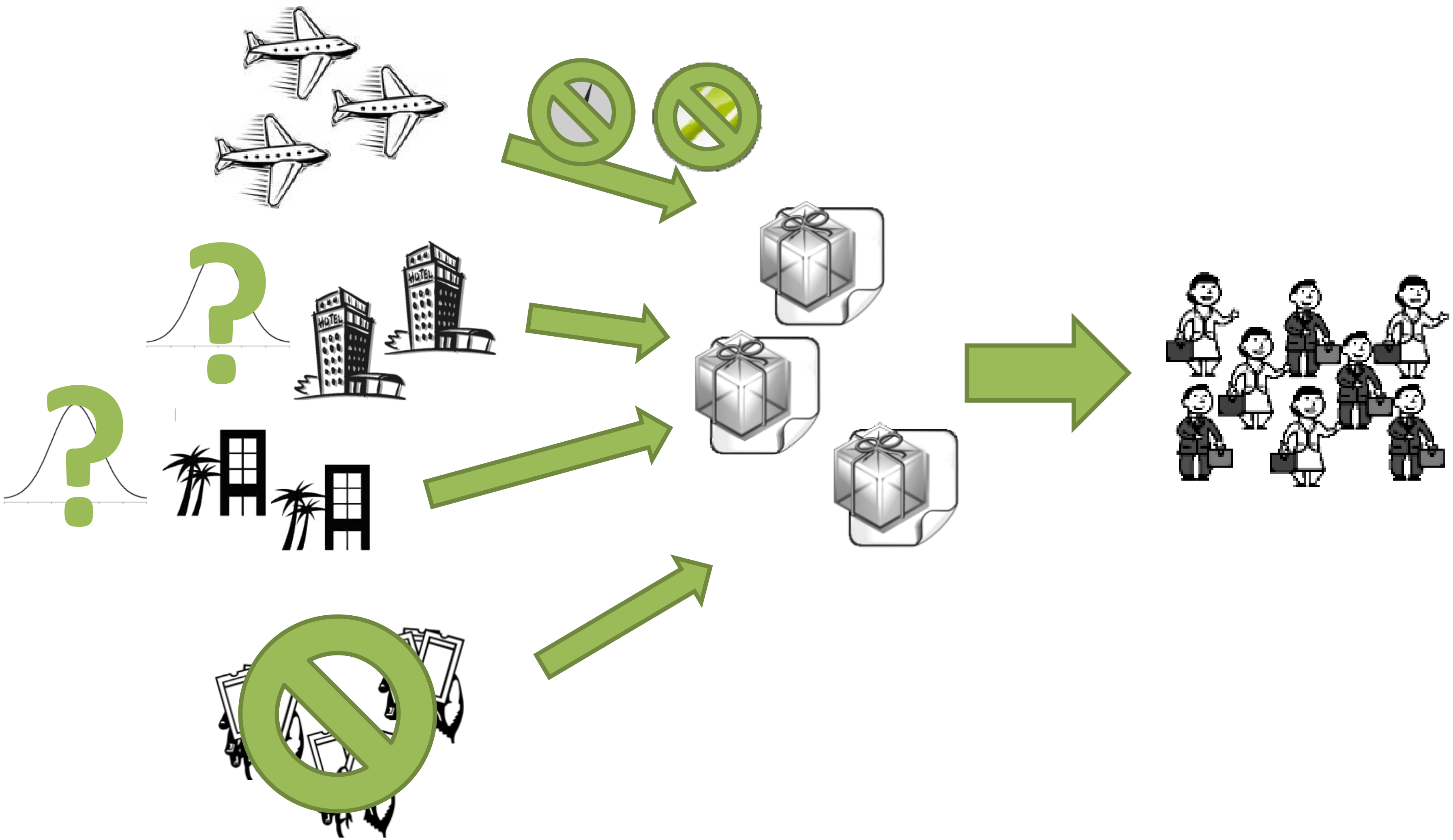
2. Decision-Theoretic (noise)





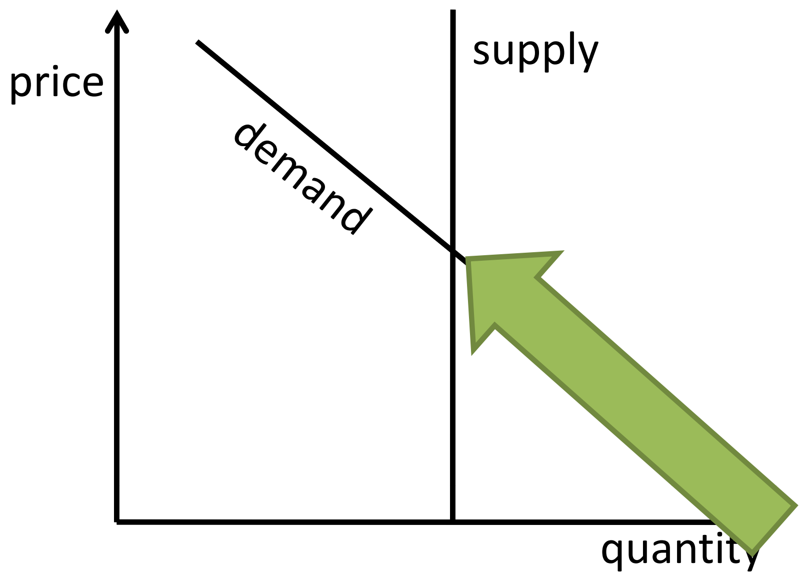
Experiments

3. Game-Theoretic (CE prices)



3. Game-Theoretic (CE prices)

- Competitive Equilibrium [Wellman '04]
- $P_{n+1} = P_n + \mathrm{MAX}(0, \alpha P_n(\text{demand - supply}))$



Experiments

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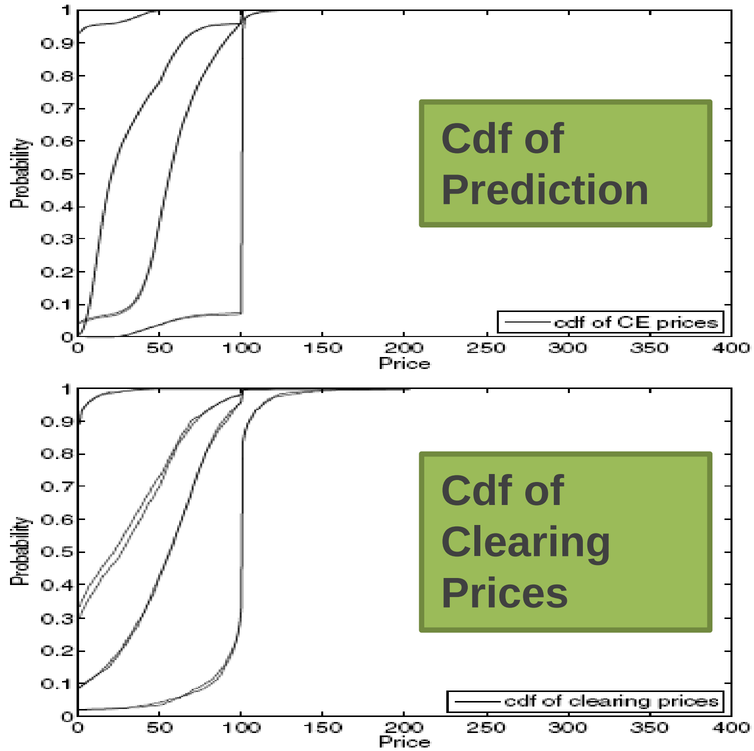
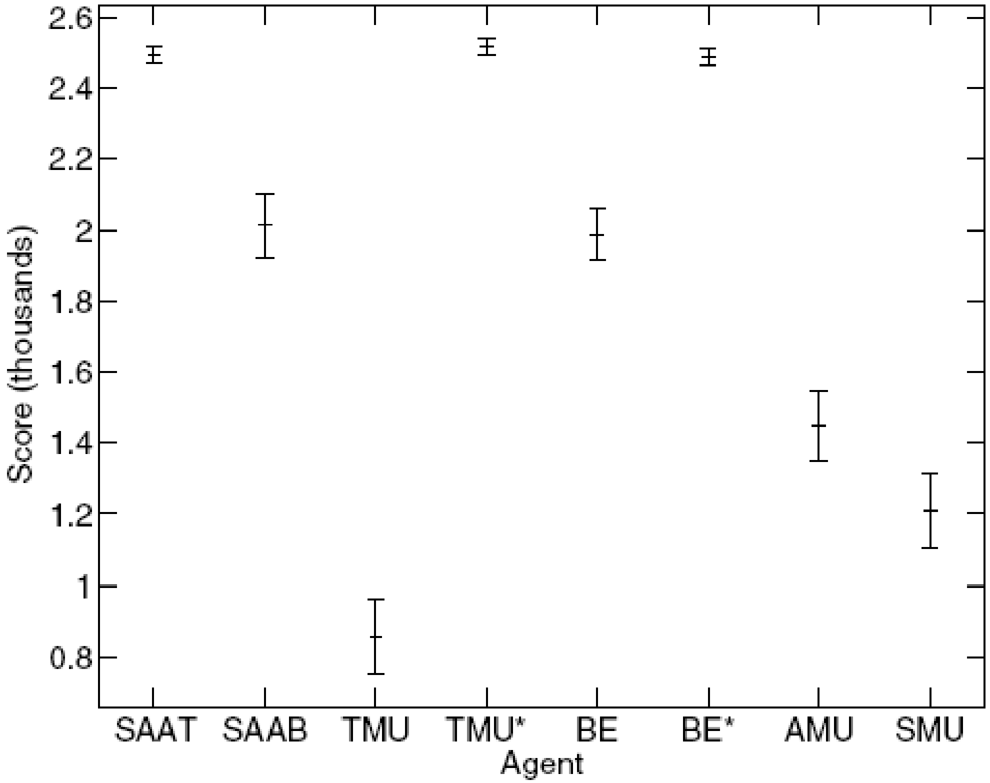
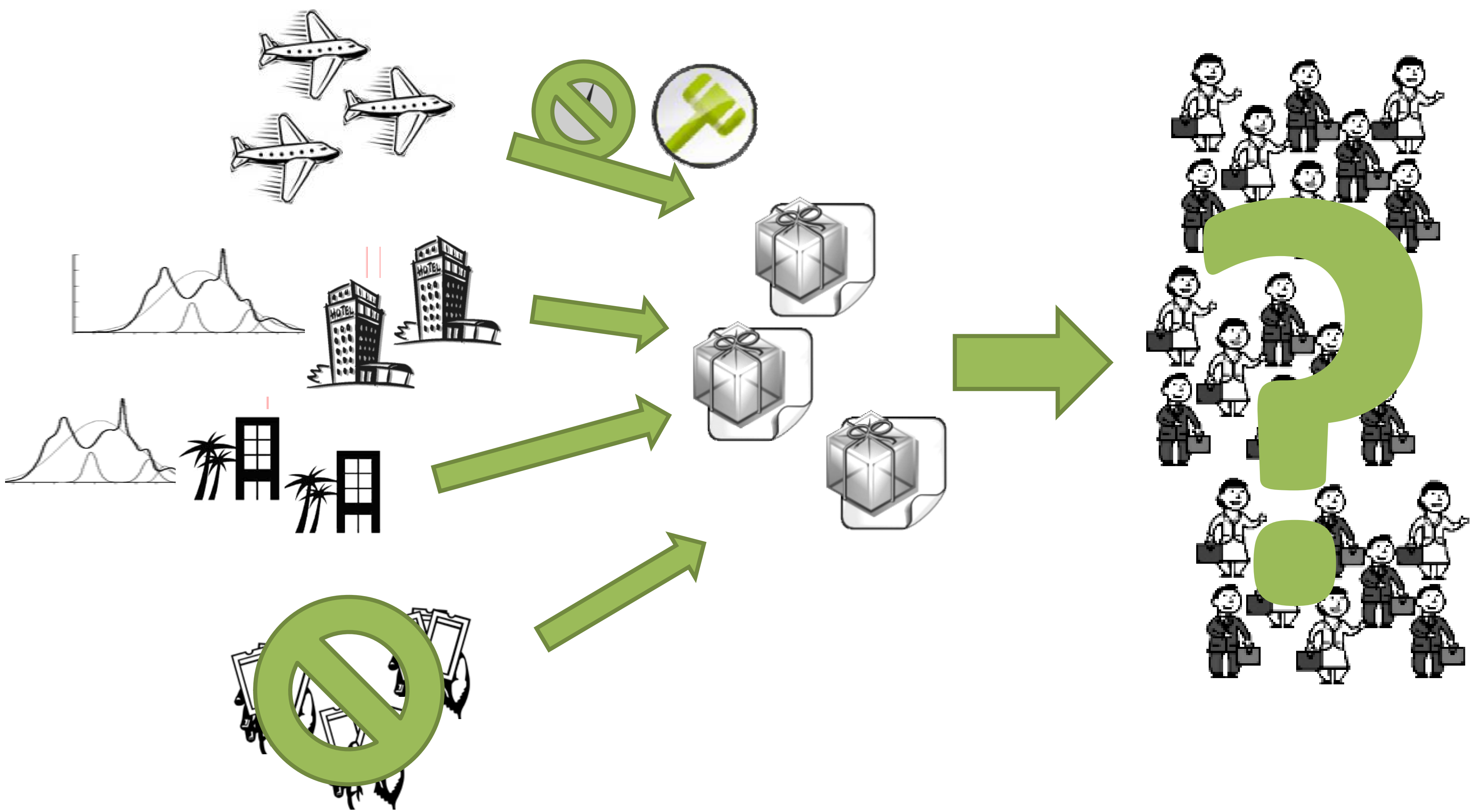




Experiments

3. Game-Theoretic (CE prices)

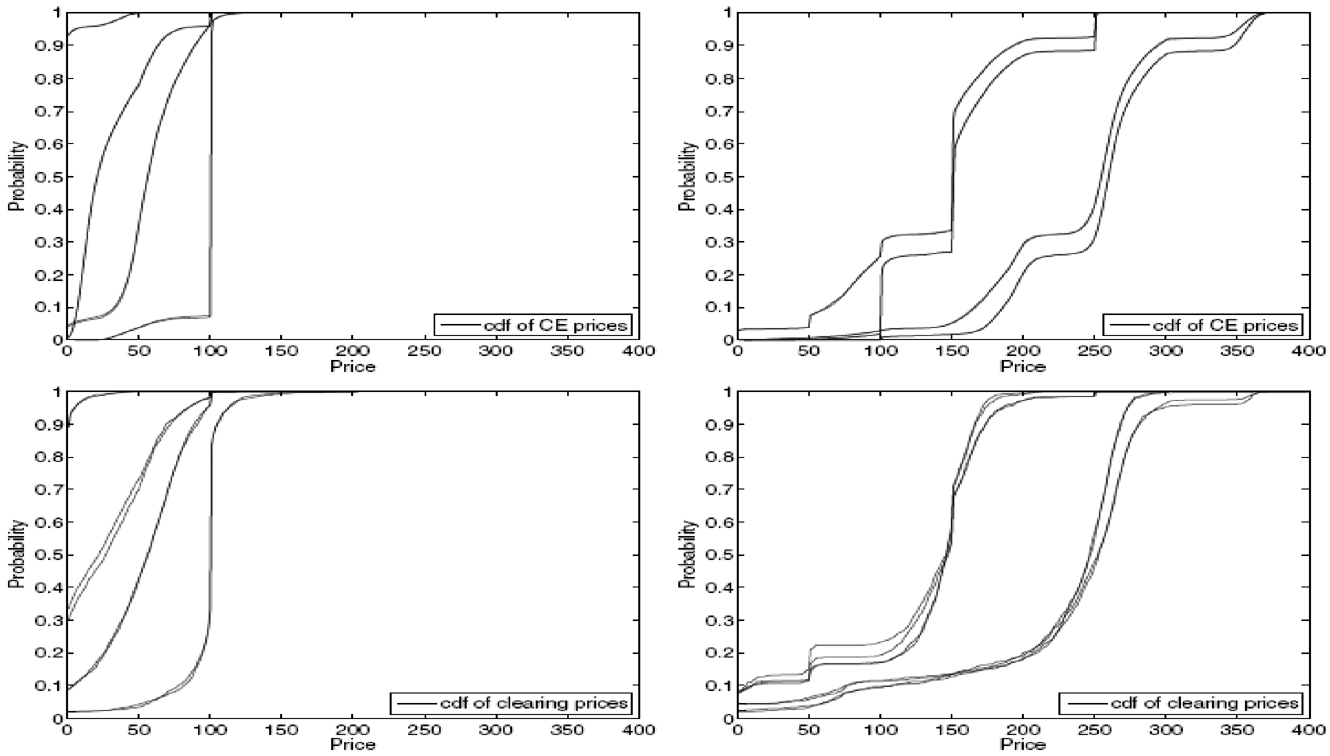


Experiments

3. Game-Theoretic (CE prices)

Cdf of Prediction

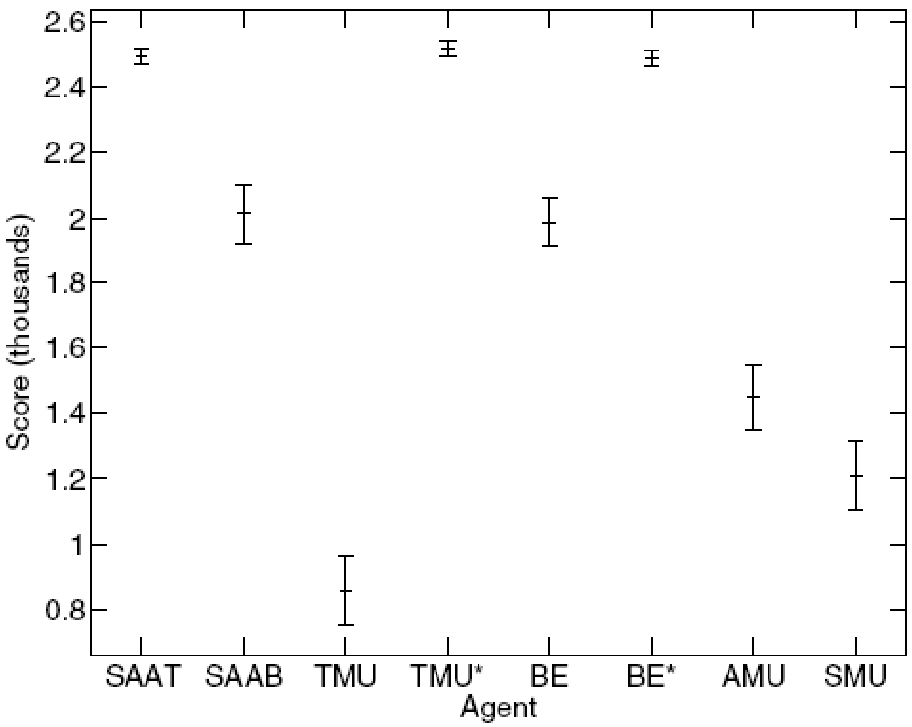
Cdf of Clearing Prices



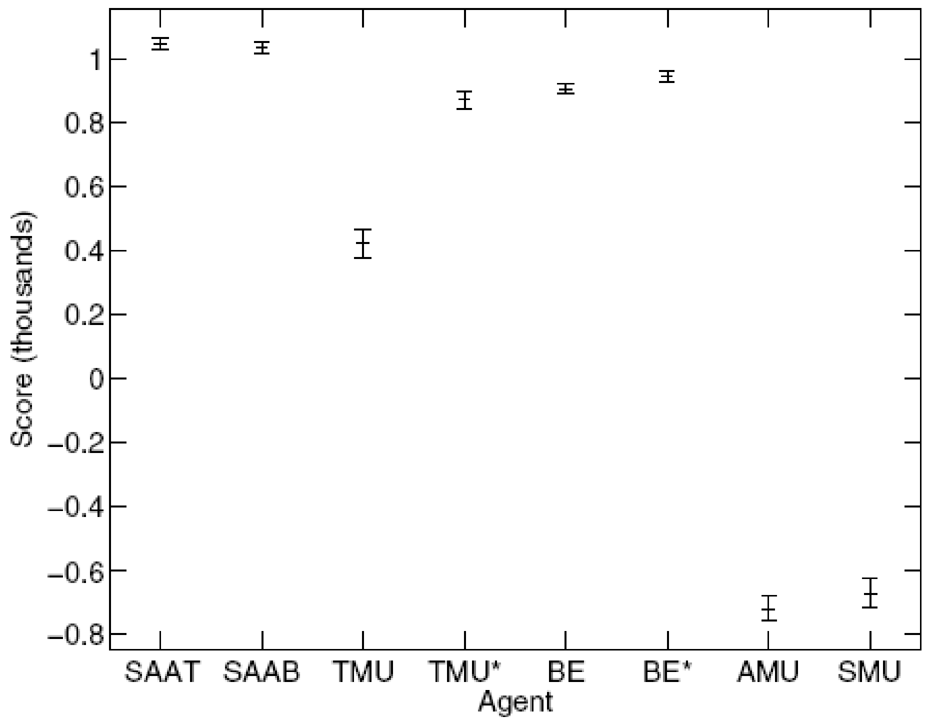
Low Variance

High Variance

3. Game-Theoretic (CE prices)



Low Variance



High Variance

Conclusion

- Sample Average Approximation
  - Optimal for decision-theoretic setting, with infinite number of scenarios.
  - More tolerant to variance.
  - More tolerant to noise.
    - SAA Top is tolerant to noise in general.
    - SAA Bottom is tolerant to noise in high variance.
  - Showed a better performance even in a game-theoretic setting.

Questions?

Acknowledgements

- Andries van Dam
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