

# Log-time Prediction Markets for Interval Securities

---

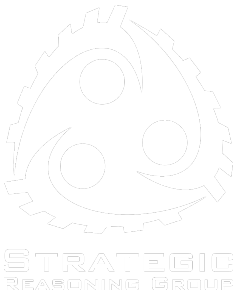
Xintong Wang *Postdoc@Harvard*

EC Mentoring Workshop, Talk Dissection, July 2022

Miro Dudík  
*Microsoft Research, NYC*

Dave Pennock  
*Rutgers University*

David Rothschild  
*Microsoft Research, NYC*



# Prediction Markets for Interval Securities

- Prediction Markets

- Offer securities whose payoff is tied to outcomes of an event.

E.g., *“the daily commercial air traffic will rise back above 100,000 flights before July 2022”*.

- Traders buy the security for some price, e.g., *\$0.32 per share*.
- One receives \$1 if **true** and \$0 if **false**.

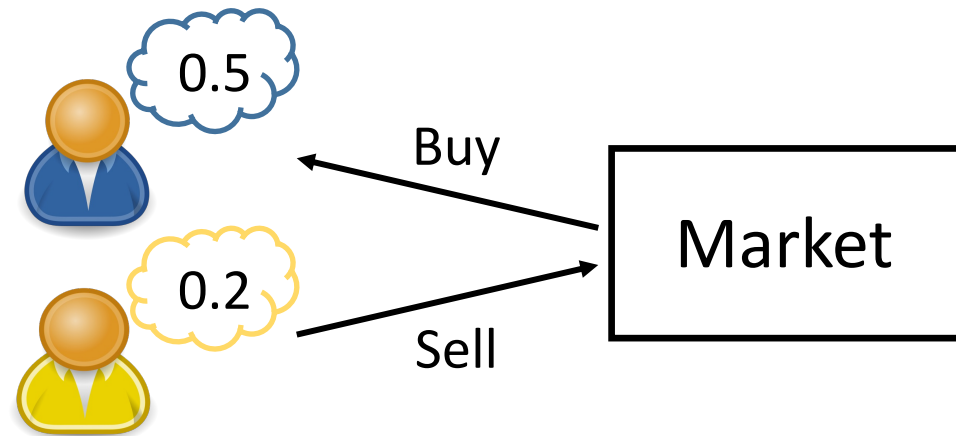
# Prediction Markets for Interval Securities

- Prediction Markets

- Offer securities whose payoff is tied to outcomes of an event.

E.g., *“the daily commercial air traffic will rise back above 100,000 flights before July 2022”*.

- Traders buy the security for some price, e.g., *\$0.32 per share*.
- One receives \$1 if **true** and \$0 if **false**.



- Market price reflects a consensus forecast for the event.

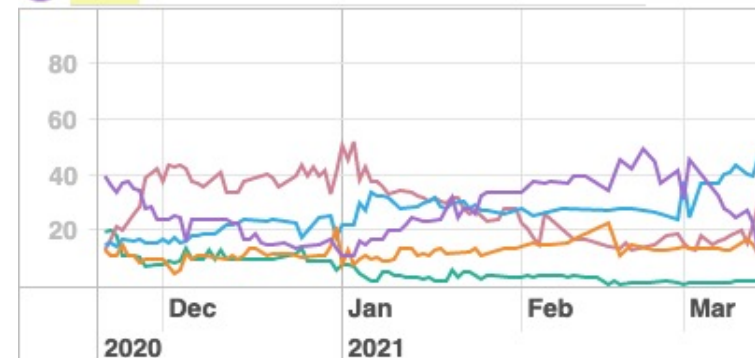
# Prediction Markets for Interval Securities

- Interval Securities: the outcome will fall into some specified interval.
  - A natural way to elicit prediction about a continuous outcome.



# Current Market Implementation

- Require predefined discretization.
- Treat as independent markets.

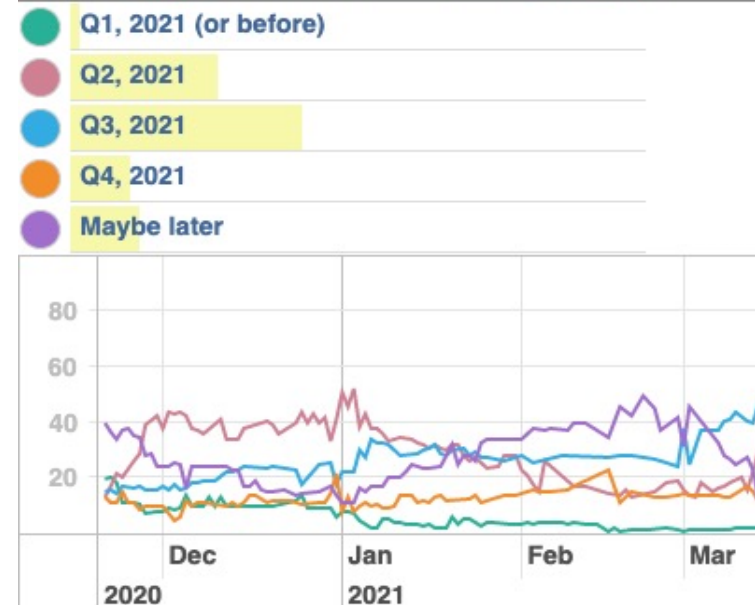


# Current Market Implementation

- Require predefined discretization.
- Treat as independent markets.

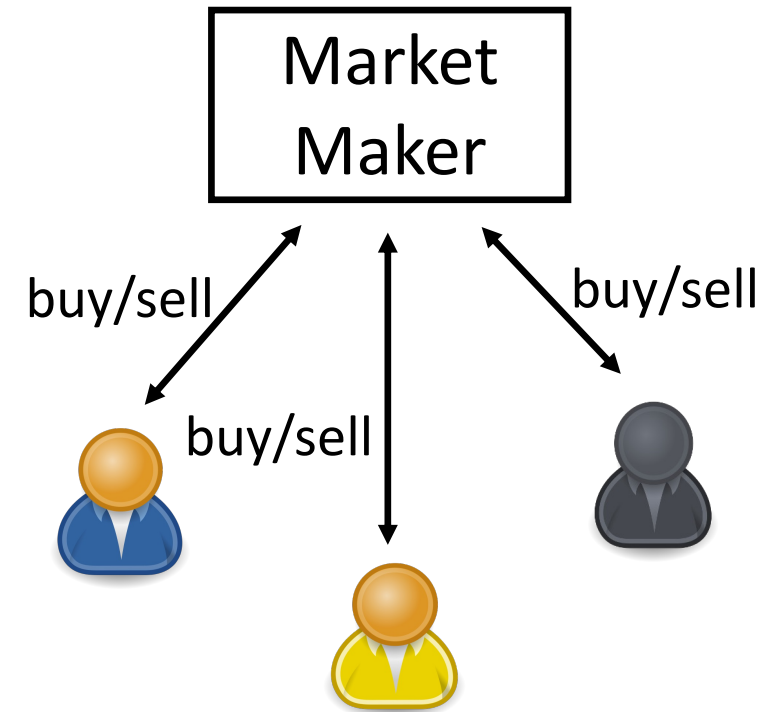
*Why not use finer discretization?*

*Challenge: the thin market problem.*



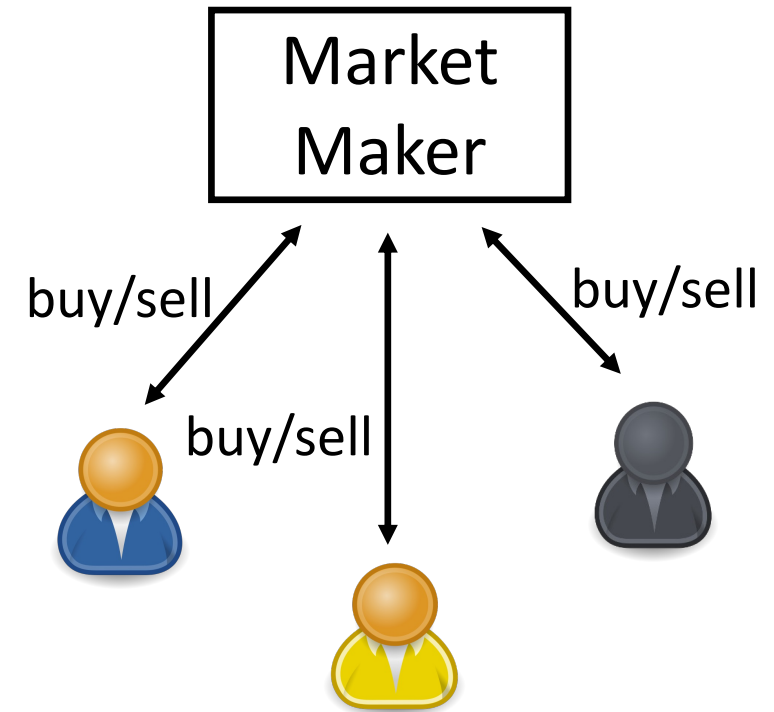
# Market Implementation: Automated Market Maker

- Set prices and offer to buy or sell *any* interval security at some price.
- If more shares are bought, increase the price of securities on the outcome.  
→ reflect a consensus forecast.
- Subsidize the market for information.



# Market Implementation: Automated Market Maker

- Set prices and offer to buy or sell *any* interval security at some price.
- If more shares are bought, increase the price of securities on the outcome.  
→ reflect a consensus forecast.
- Subsidize the market for information.
- *Challenge: market operations require time linear in the number of outcomes.*  
*E.g., quarter (2 bits of precision): runtime  $2^2$ .*  
*week (6 bits of precision): runtime  $2^6$ .*  
*day (9 bits of precision): runtime  $2^9$ .*





# Contribution Summary

*The largest amount that the MM has to pay traders across all possible trading sequences and outcomes.*

	Market Maker (MM)	Data Structure	Runtime of Market Operations	Worst-Case Loss for MM
<i>previous work</i>	Logarithmic market scoring rule (LMSR) [Hanson 2003]	array	$O(N)$ N = # distinct outcomes	$\log(N)$

# Contribution Summary

*The largest amount that the MM has to pay traders across all possible trading sequences and outcomes.*

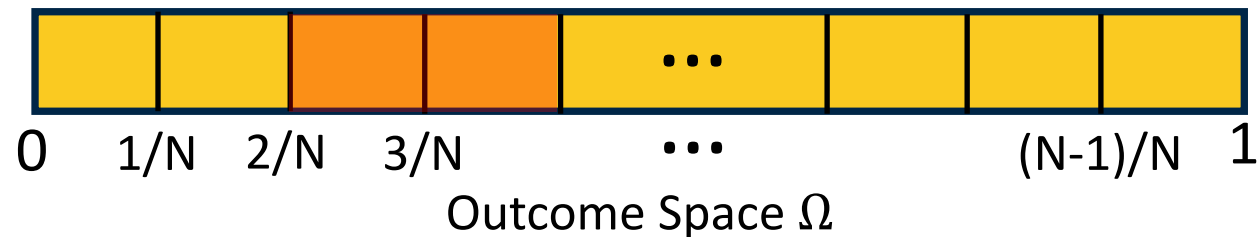
	Market Maker (MM)	Data Structure	Runtime of Market Operations	Worst-Case Loss for MM
<i>previous work</i>	Logarithmic market scoring rule (LMSR) [Hanson 2003]	array	$O(N)$ N = # distinct outcomes	$\log(N)$
<i>this work</i>	Log-time LMSR MM			
	Multi-resolution linearly constrained MM (LCMM)			

# LMSR Market Maker - Intuition

# LMSR Market Maker - Intuition

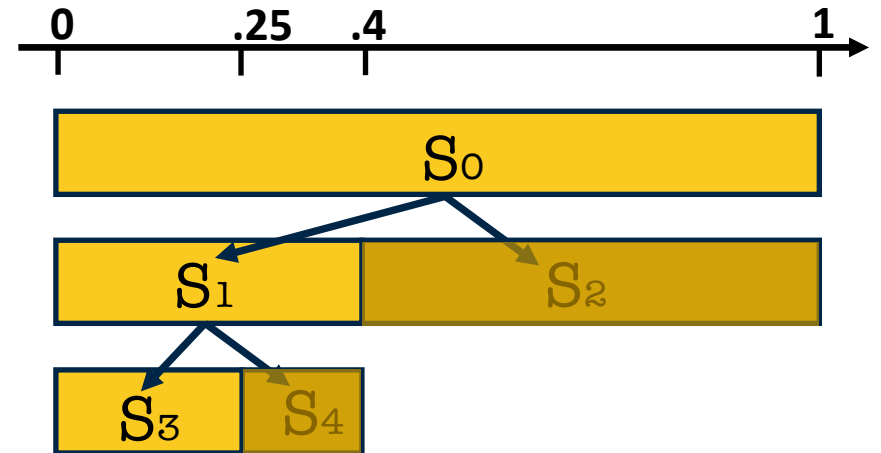
- ***price(I)***
  - Keep track of price for each outcome  $\omega \in \Omega$ .
  - Sum up the prices of all outcomes in the interval, i.e.,  $\mathbf{price}(I) = \sum_{\omega \in I} \mathbf{price}(\omega)$ .
- ***buy(I, s)***
  - Increase the prices of outcomes  $\omega \in I$  by a factor of  $e^{s/b}$ .
  - Renormalize across all prices: prices of bought outcomes  $\uparrow$ , prices of others  $\downarrow$ .
- ***Challenge: price(I) and buy(I, s) take time linear in the number of outcomes.***

*Liquidity parameter set by the market designer.*



# Contribution: Log-time LMSR Market Maker

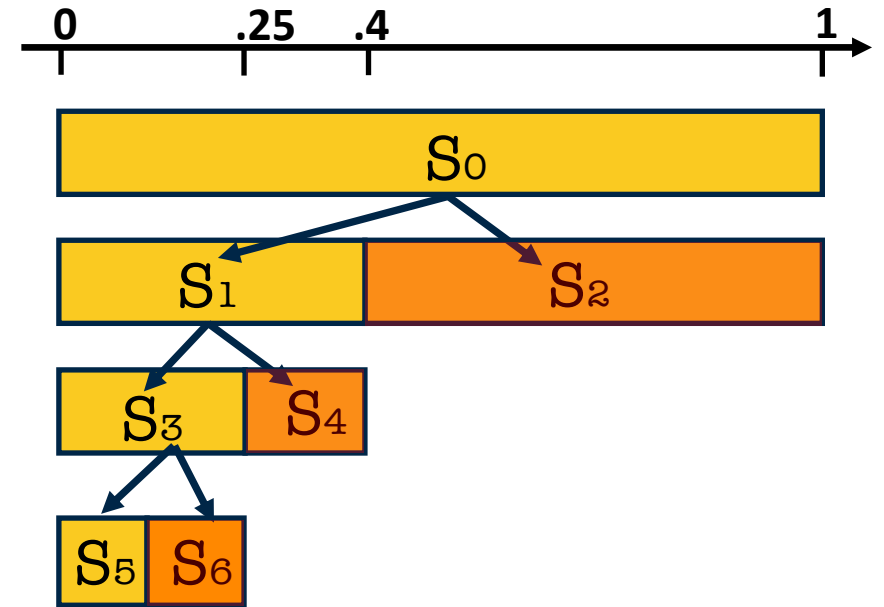
- A balanced binary tree
  - Construct nodes from queried intervals.
  - Decompose LMSR computations along the tree nodes.
  - Keep track of unnormalized prices (in each node) and partial sums (in parent nodes).
- **price**( $I$ ), e.g.,  $I = [.25, 1)$ 
  - Sum up the prices of relevant subintervals (at most  $\log n$ ) along the search path.
  - Normalize by the overall sum (in the root).



# Contribution: Log-time LMSR Market Maker

- **buy**( $I, s$ )

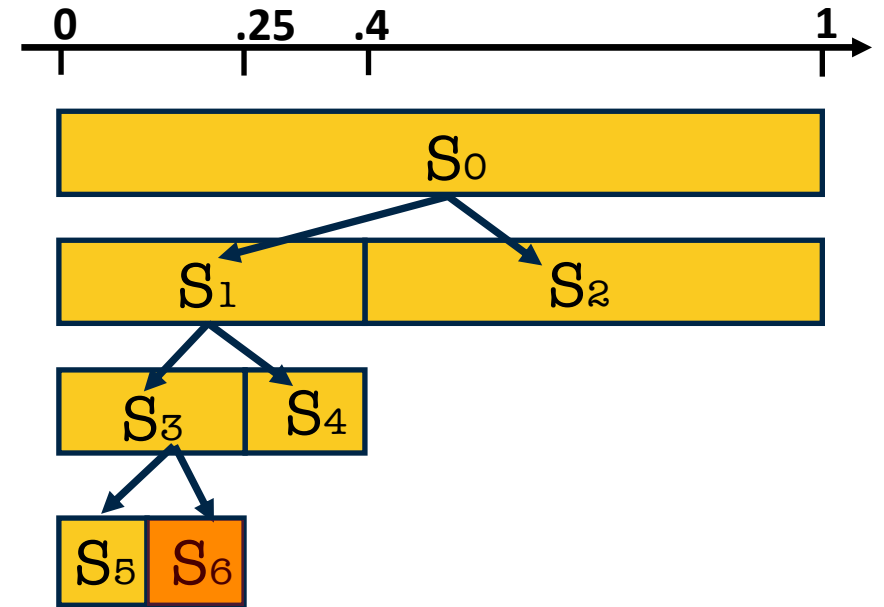
- Update the corresponding multipliers of subintervals by  $e^{s/b}$  along the search path.
- Update the partial sums back up.
- *Challenge: the tree may no longer be balanced!*



# Contribution: Log-time LMSR Market Maker

- ***buy***( $I, s$ )

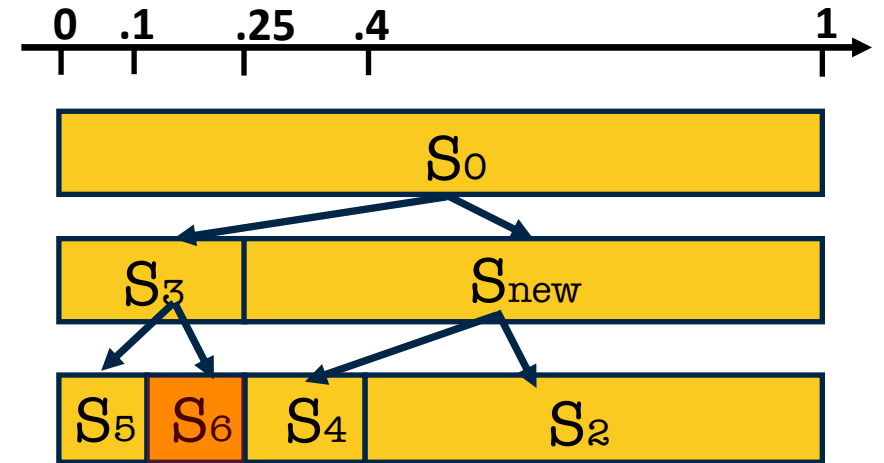
- Update the corresponding multipliers of subintervals by  $e^{s/b}$  along the search path.
- Update the partial sums back up.
- *Challenge: the tree may no longer be balanced!*
- Rely on rotation to rebalance which requires constant time.



# Contribution: Log-time LMSR Market Maker

- ***buy***( $I, s$ )

- Update the corresponding multipliers of subintervals by  $e^{s/b}$  along the search path.
- Update the partial sums back up.
- *Challenge: the tree may no longer be balanced!*
- Rely on rotation to rebalance which requires constant time.





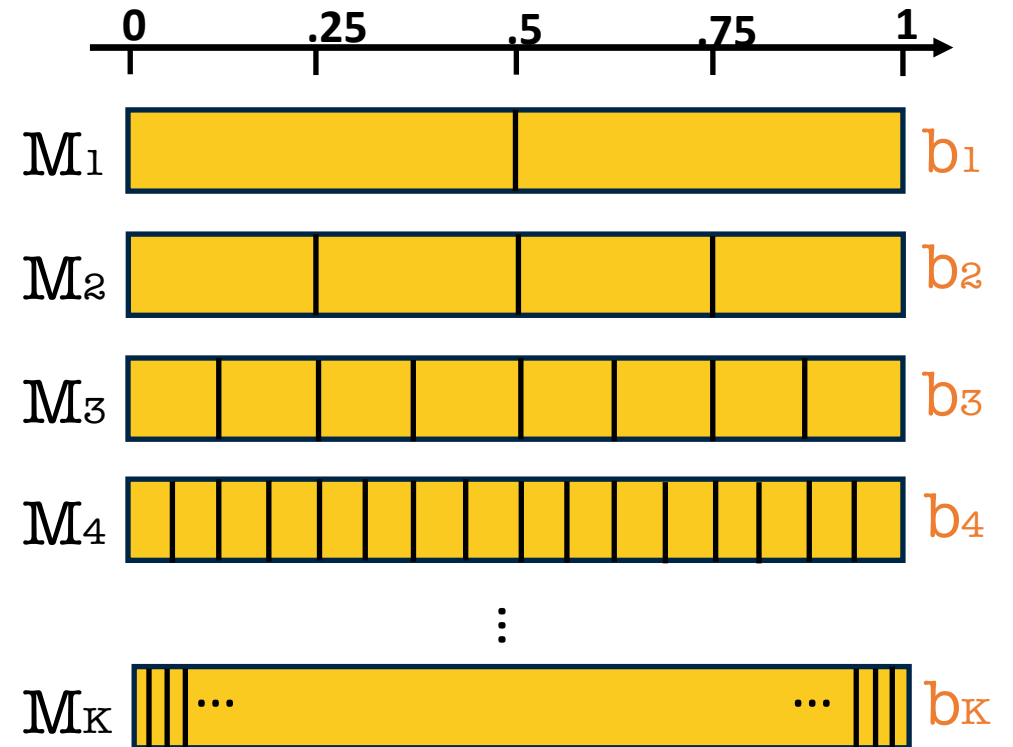
# Contribution: Log-time LMSR Market Maker

	Market Maker (MM)	Data Structure	Runtime of Market Operations	Worst-Case Loss for MM
<i>previous work</i>	Logarithmic market scoring rule (LMSR) [Hanson 2003]	array	$O(N)$ $N = \#$ distinct outcomes	$\log(N)$
<i>this work</i>	Log-time LMSR MM	binary tree (adaptive)	$O(\log n) \leq O(\log N)$ $n = \#$ distinct queries	$\log(N)$

- *Challenge: worst-case loss is dependent on the number of outcomes.*

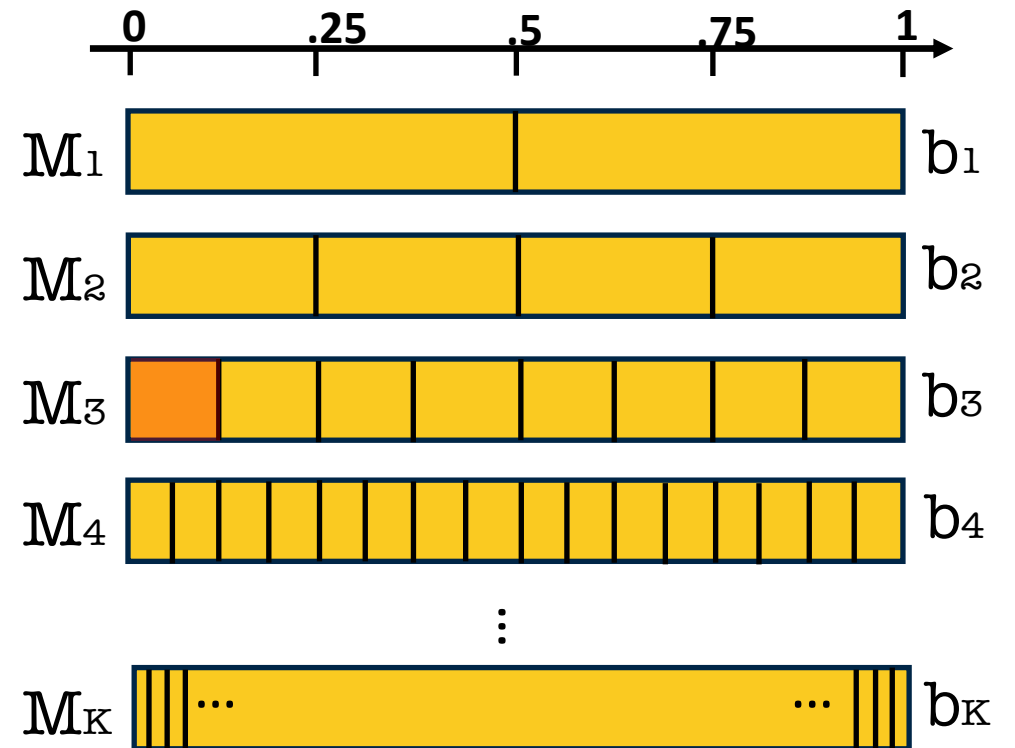
# Contribution: Multi-resolution Linearly Constrained Market Maker

- Use multiple LMSRs with different *liquidity parameters* to mediate markets offering interval securities at different resolutions.
- The liquidity parameter controls
  - How fast the price moves, i.e.,  $e^{s/b}$ ;
  - The worst-case loss for MM, i.e.,  $b \log N$ .
- Achieve constant loss bound by choosing proper liquidity values.
  - Total worst-case loss:  
$$\sum_{k=1}^K b_k \log N_k = \sum_{k=1}^K b_k \log(2^k).$$
    - E.g.,  $b_k = O(k^{-2.01})$ .



# Contribution: Multi-resolution Linearly Constrained Market Maker

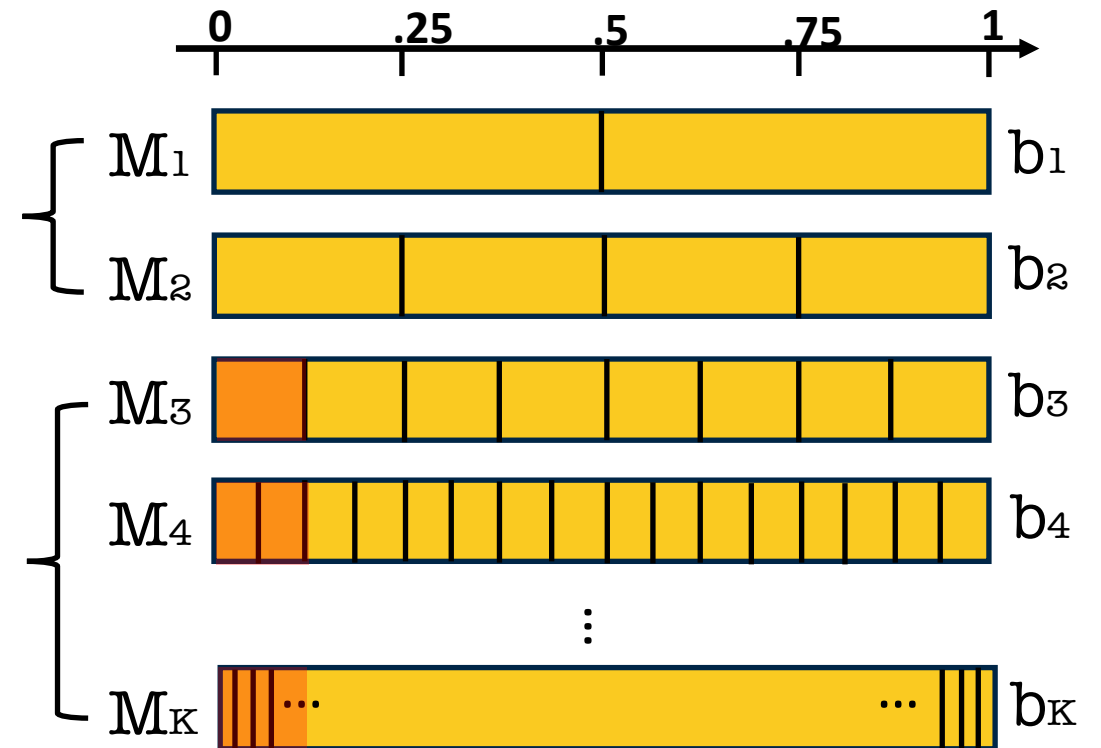
- *Challenge: keep prices coherent across different markets.*
- **buy**( $I, s$ )
  - Example: **buy**( $I=[0,.125), 1$ ) in  $M_3$   
→ price incoherence between  $M_3$  and other markets.



# Contribution: Multi-resolution Linearly Constrained Market Maker

- The LCMM can remove price incoherence (arbitrage) efficiently across markets.

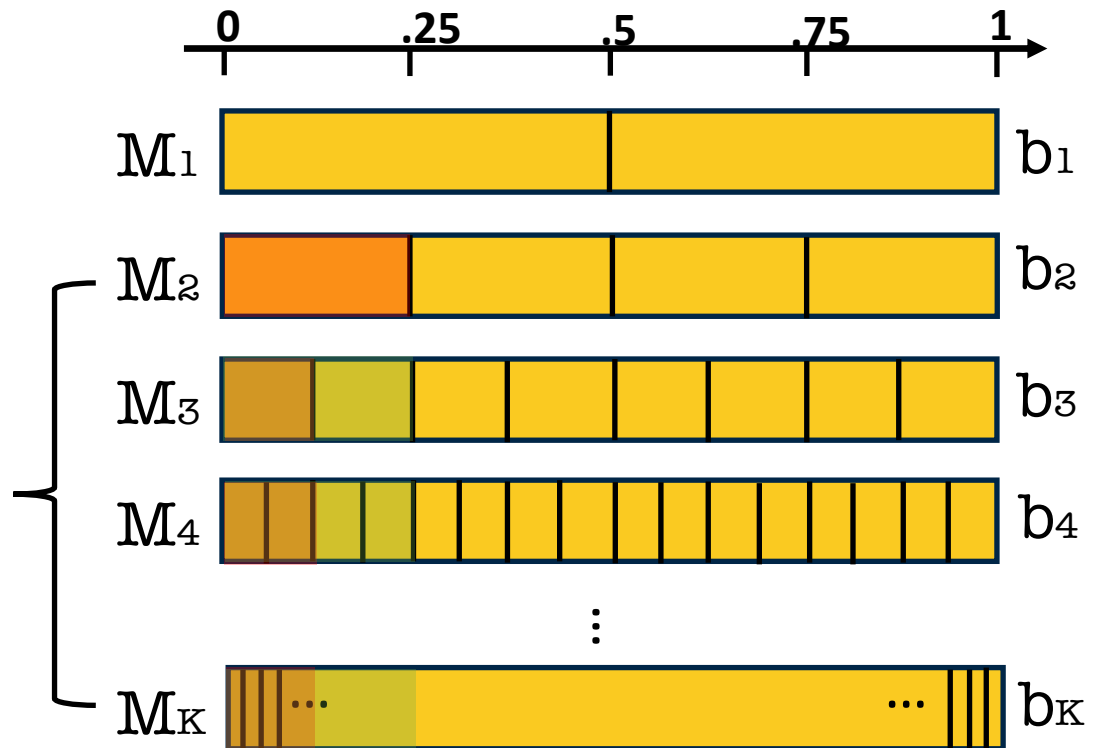
*Intuition: split the 1 share among  $M_3 \dots M_k$  according to liquidity ratio to maintain price coherence.*



# Contribution: Multi-resolution Linearly Constrained Market Maker

- The LCMM can remove price incoherence (arbitrage) efficiently across markets.

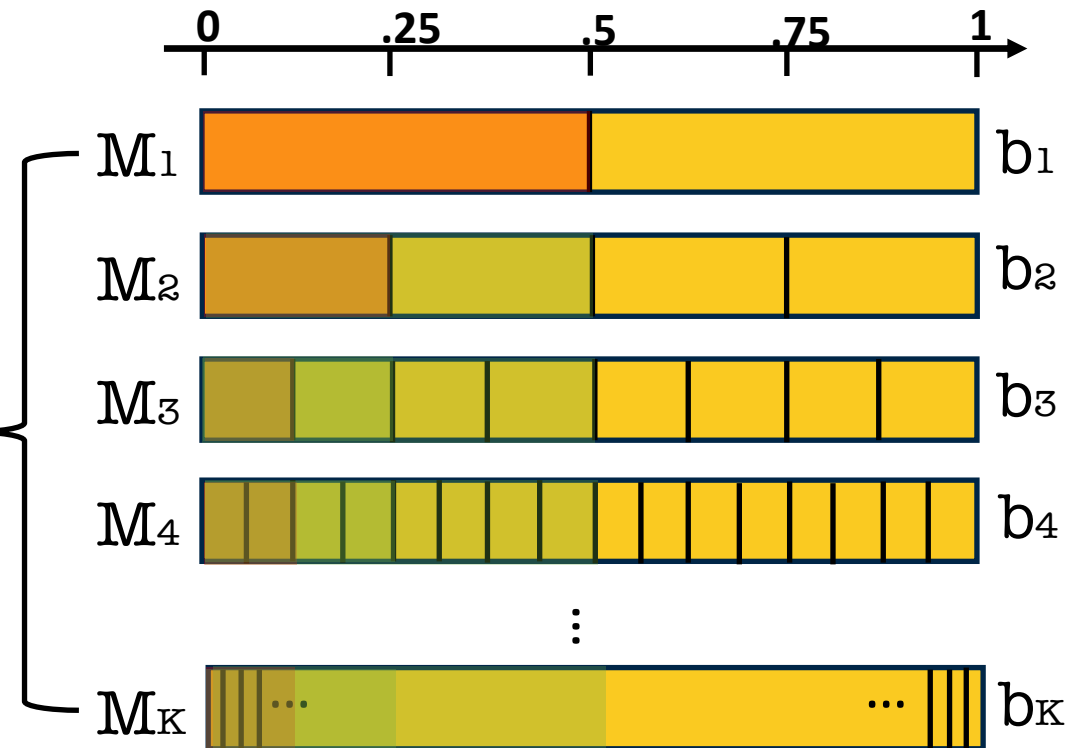
*Intuition: remove arbitrage level by level*



# Contribution: Multi-resolution Linearly Constrained Market Maker

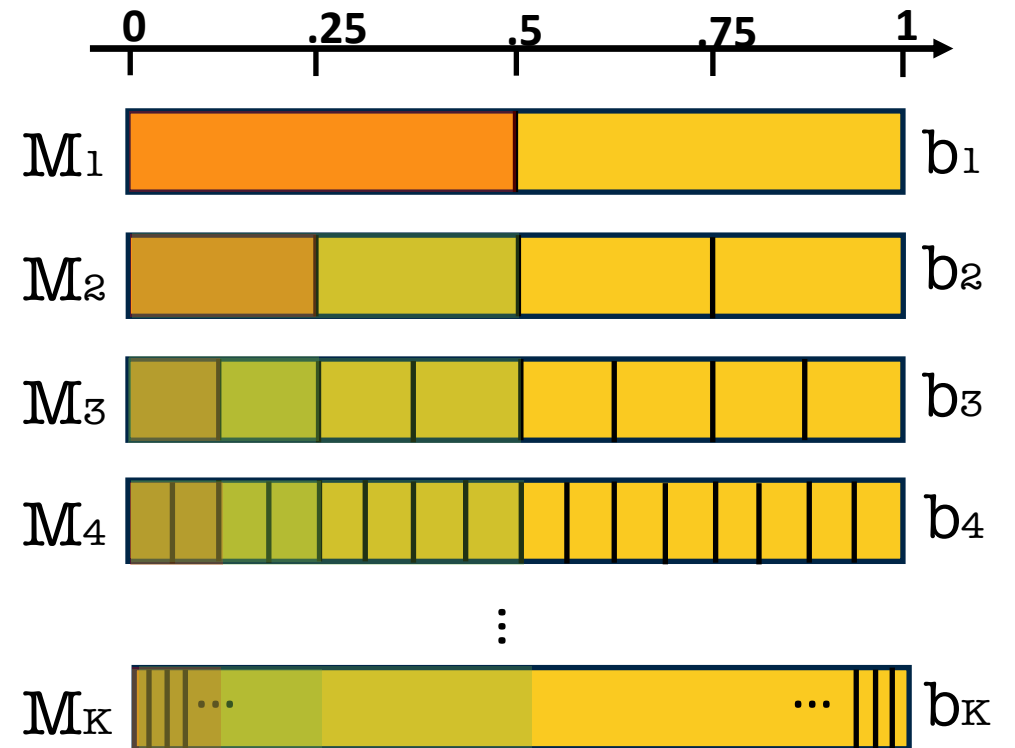
- The LCMM can remove price incoherence (arbitrage) efficiently across markets.

*Intuition: remove arbitrage level by level (e.g., **buy s' share** [0,.5) in  $M_1$  and **split sell s' share** among  $M_2 \dots M_k$ ).*



# Contribution: Multi-resolution Linearly Constrained Market Maker

- The LCMM can remove price incoherence (arbitrage) efficiently across markets.
- A single static binary tree
  - Keep track of (1) trader purchases and (2) automatic purchases made by the LCMM for price coherent.



# Contribution: Multi-resolution Linearly Constrained Market Maker

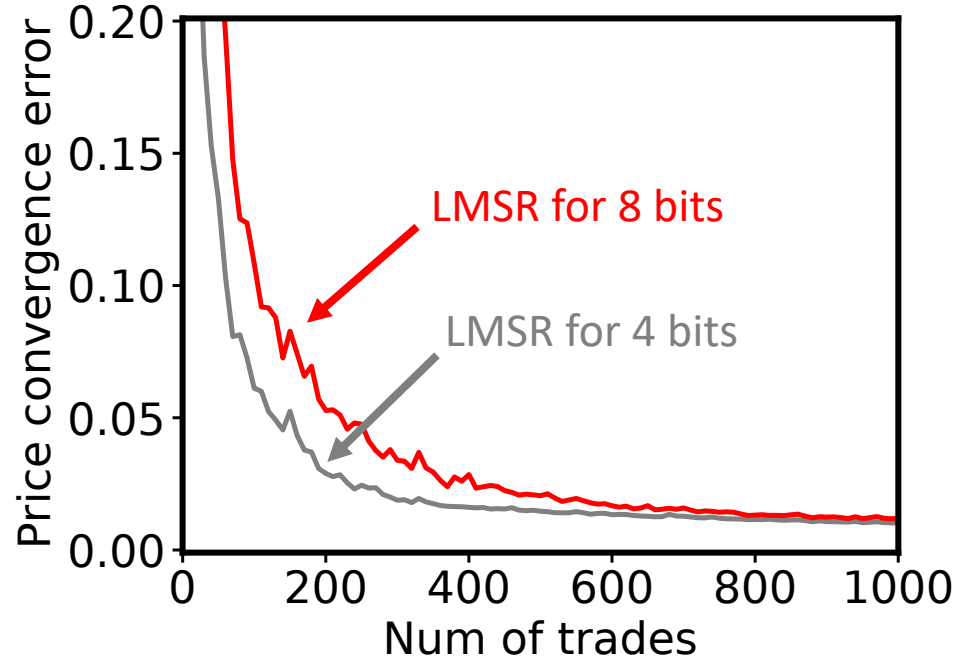
	Market Maker (MM)	Data Structure	Runtime of Market Operations	Worst-Case Loss for MM
<i>previous work</i>	Logarithmic market scoring rule (LMSR) [Hanson 2003]	array	$O(N)$ N = # distinct outcomes	$\log(N)$
<i>this work</i>	Log-time LMSR MM	binary tree (adaptive)	$O(\log n) \leq O(\log N)$ $n = \# \text{ distinct queries}$	$\log(N)$
	Multi-resolution linearly constrained MM (LCMM)	binary tree (static)	$O(\log N)$ N = # distinct outcomes	<b>constant</b>



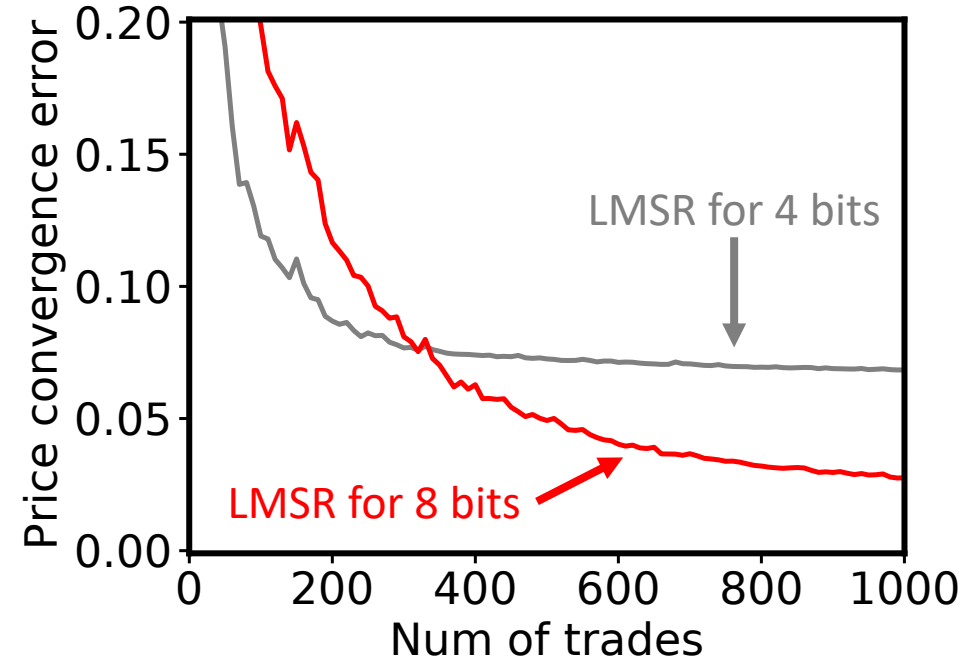
# Log-time LMSR vs. Multi-resolution LCMM

- Simulate trading in prediction markets where the MM has a fixed budget.
- Evaluate how fast prices converge to reach “consensus”.

Outcome at 4 bits



Outcome at 8 bits



# Log-time LMSR vs. Multi-resolution LCMM

- Compare to **LCMM** that equally splits the budget to two resolutions.
- **LCMM achieves the best of both worlds:**  
elicit forecasts at the finer level & obtain a fast convergence at the coarser level.

# Recap & Summary

	Market Maker (MM)	Data Structure	Runtime of Market Operations	Worst-Case Loss for MM
<i>previous work</i>	Logarithmic market scoring rule (LMSR) [Hanson 2003]	array	$O(N)$ N = # distinct outcomes	$\log(N)$
<i>this work</i>	Log-time LMSR MM	binary tree (adaptive)	$O(\log n) \leq O(\log N)$ $n = \# \text{ distinct queries}$	$\log(N)$
	Multi-resolution linearly constrained MM (LCMM)	binary tree (static)	$O(\log N)$ N = # distinct outcomes	<b>constant</b>

*Thank you!*