



# The Role of Transparency in Repeated 1<sup>st</sup>-Price Auctions with Unknown Valuations\*



Nicolò  
Cesa-Bianchi



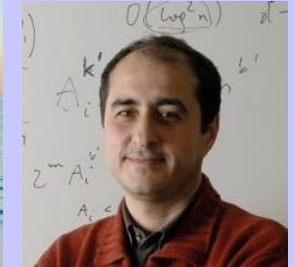
Tom  
Cesari



Roberto  
Colomboni



Federico  
Fusco



Stefano  
Leonardi

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Workshop on Learning in Games  
July 1–3, 2024

\*STOC 2024

# Repeated First-Price Auctions

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We study **repeated** first-price auctions:

- An **online learning** framework

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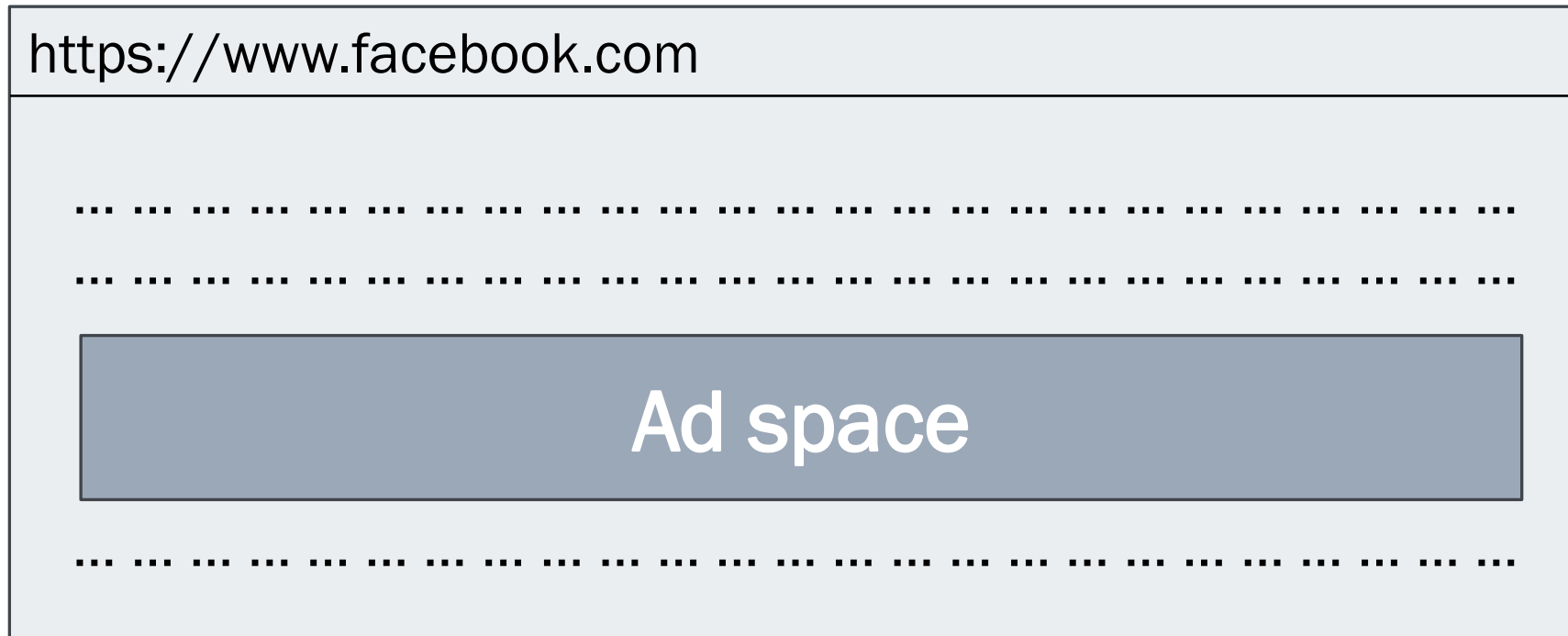
- An **online learning** framework
- From the **bidder**'s perspective
- The valuation is **unknown**

# Motivation: Real-Time Bidding

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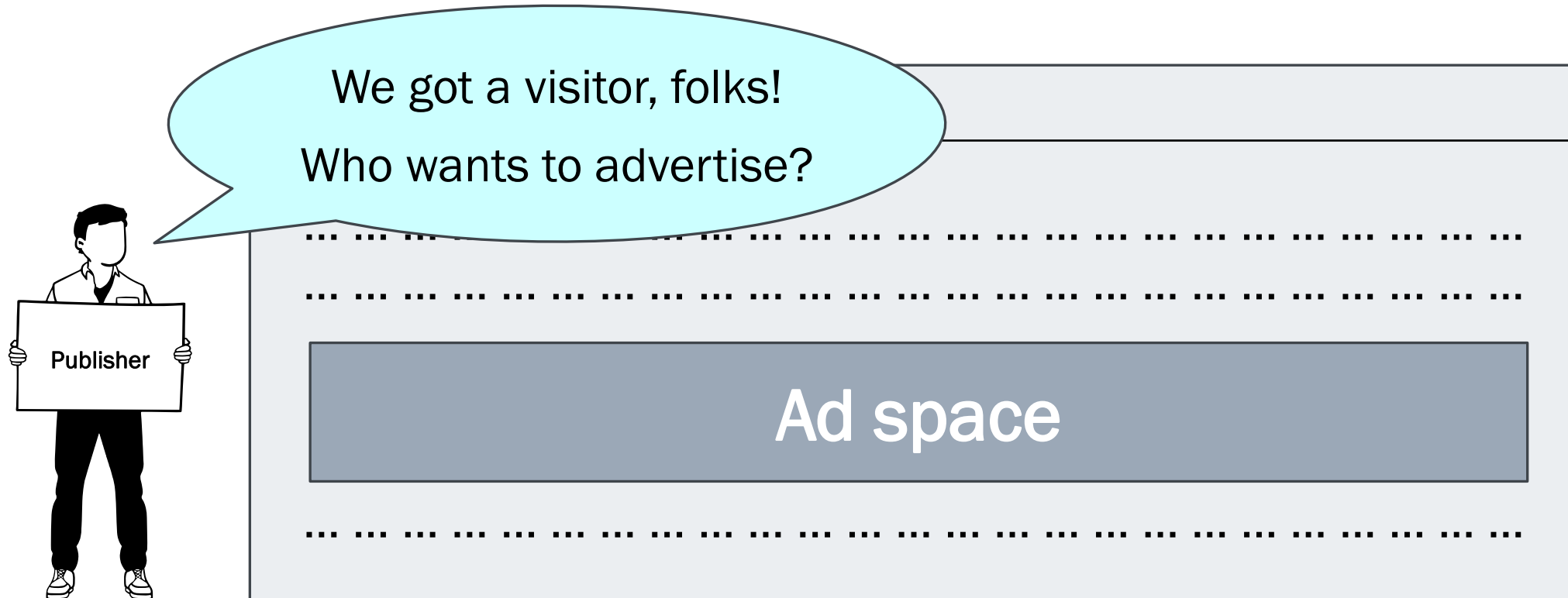
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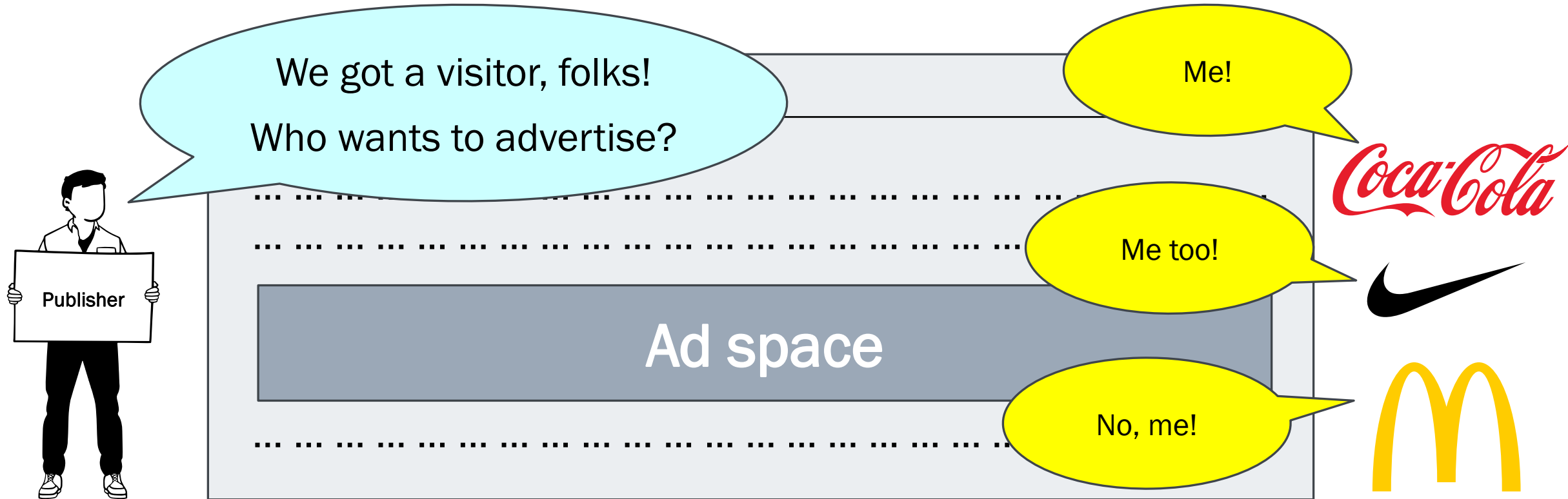


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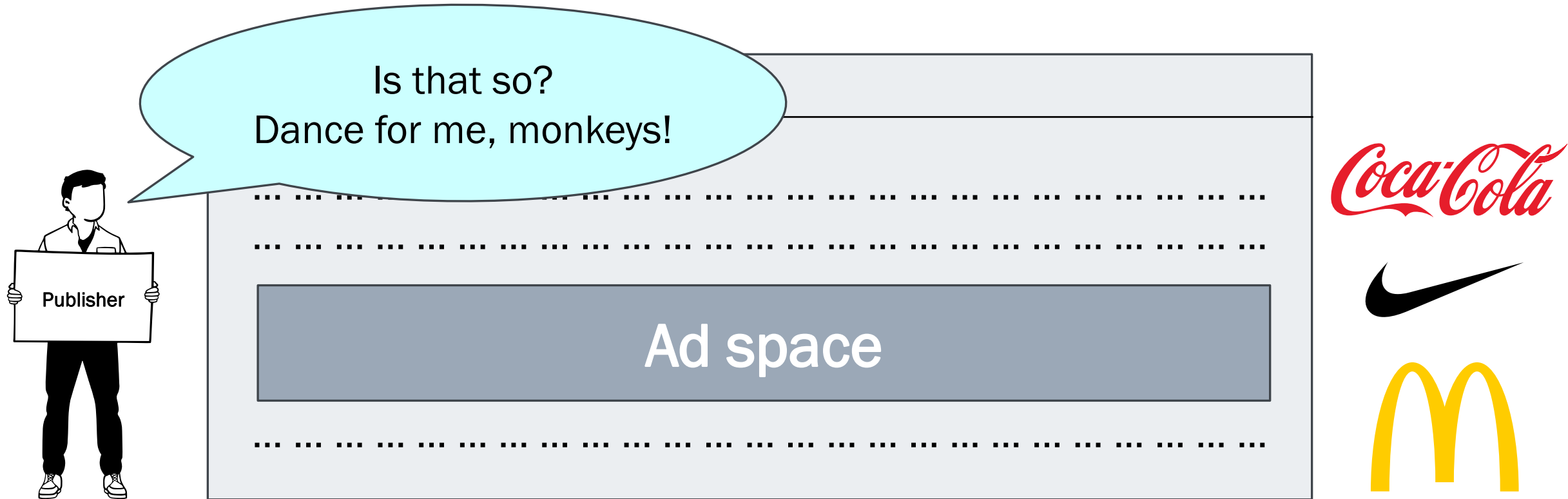
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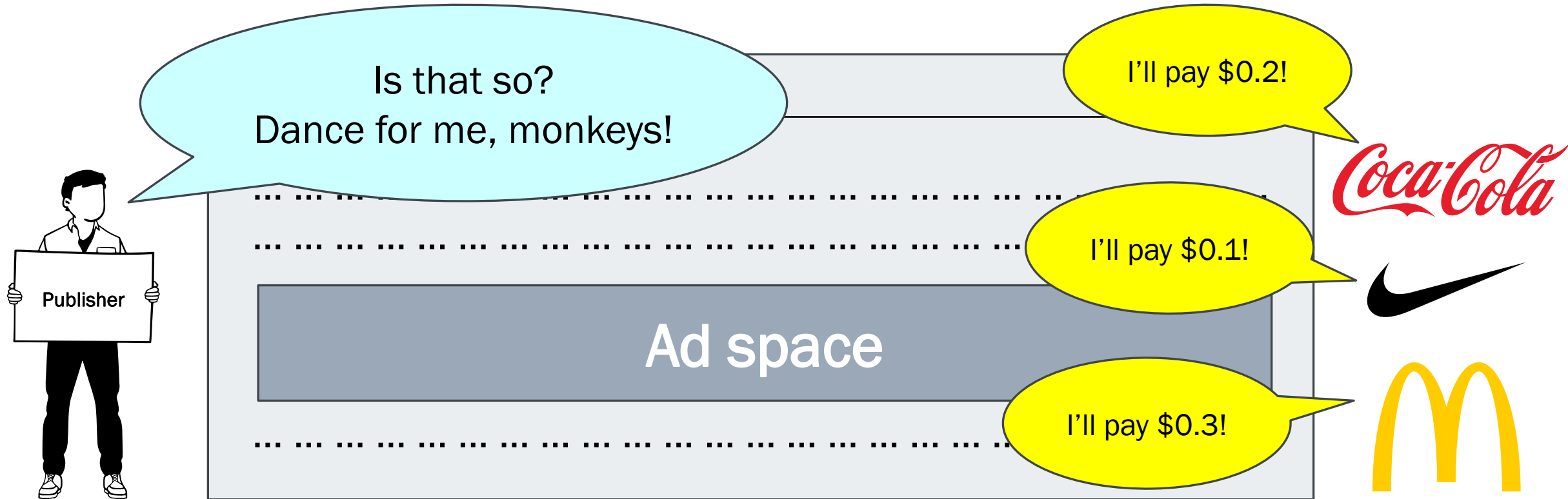


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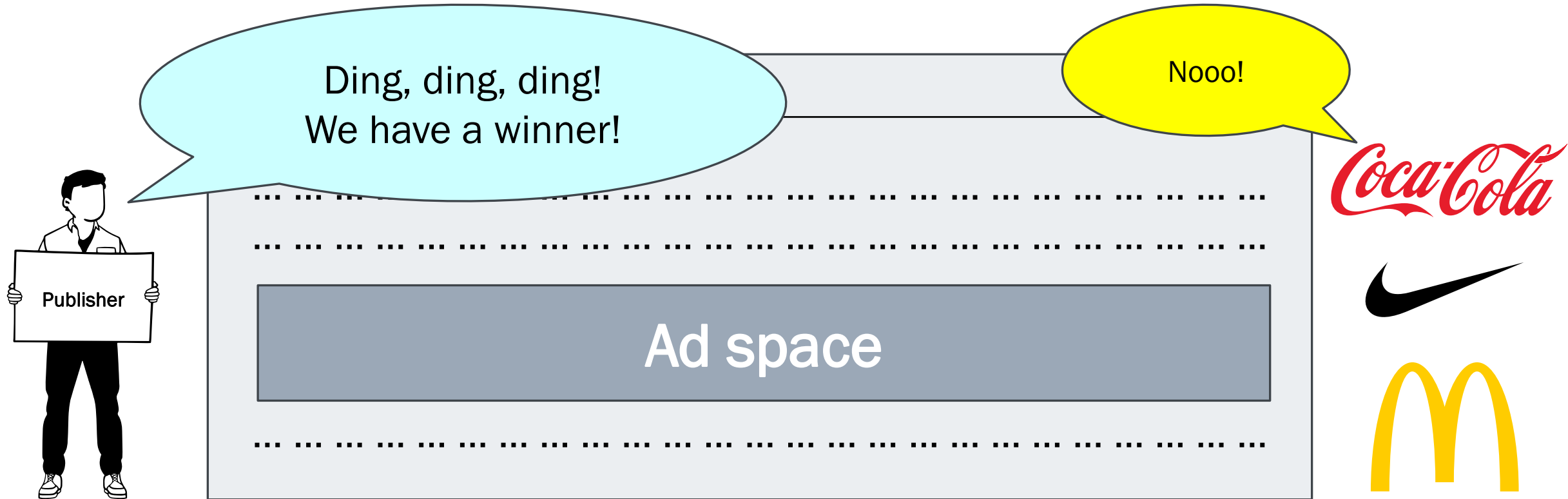


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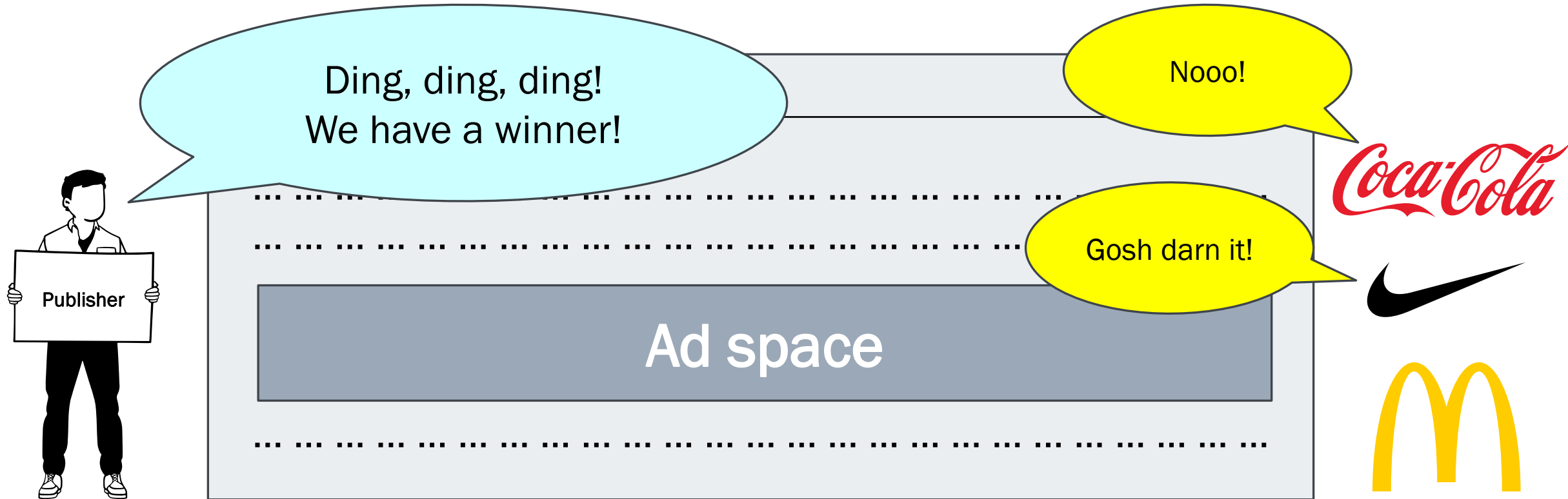


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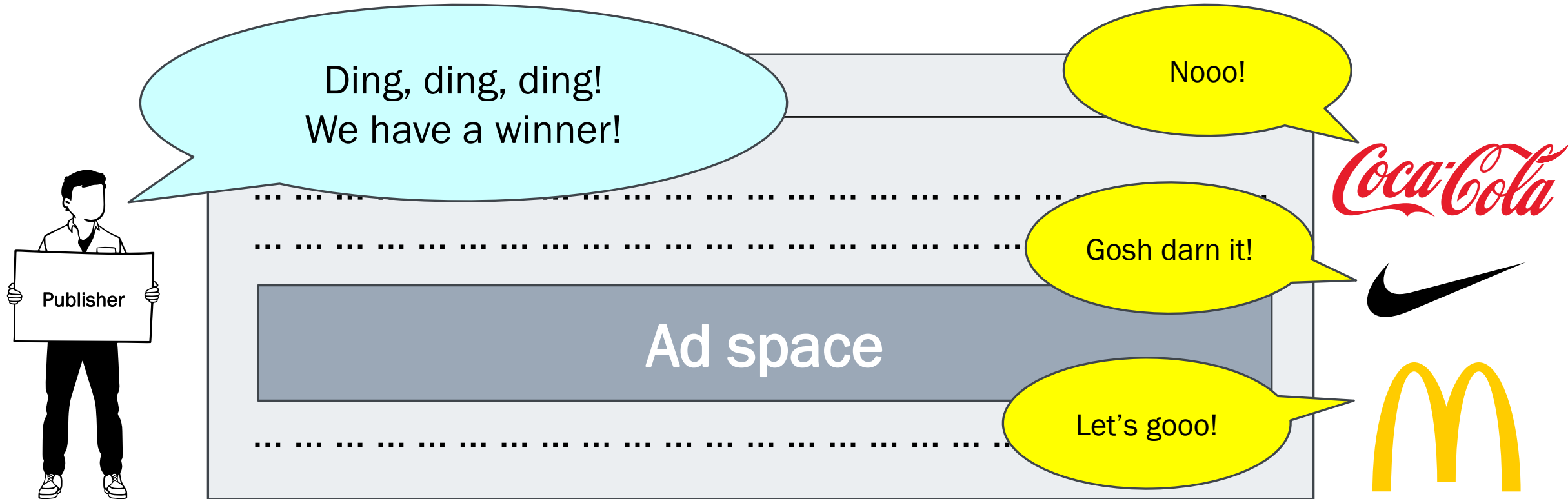
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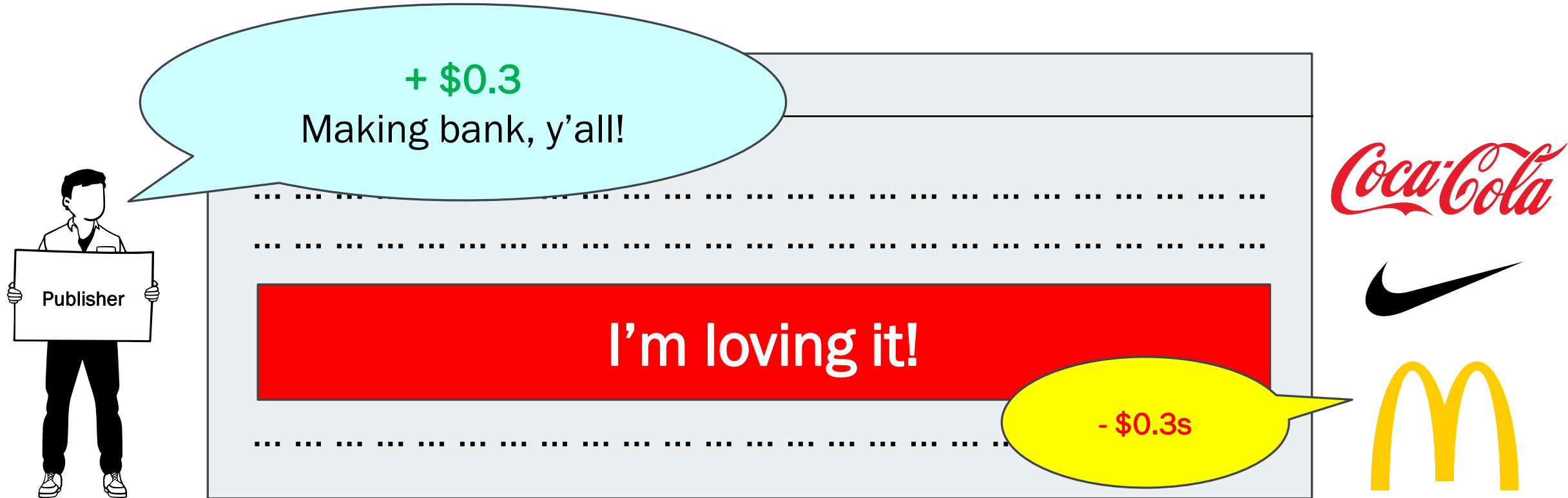


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<https://www.facebook.com>

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.....

**I'm loving it!**

.....

# How do advertisers quantify value?

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- Metric 1: **Click-through rate**
- Metric 2: **Conversion** of curiosity to sales
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**All happening only if the auction is won!**

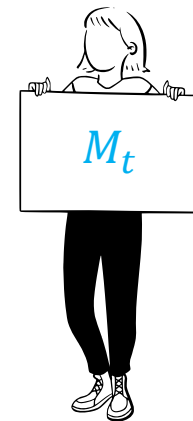
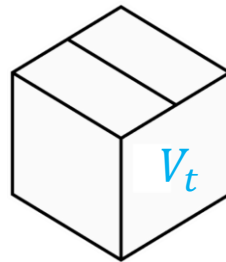
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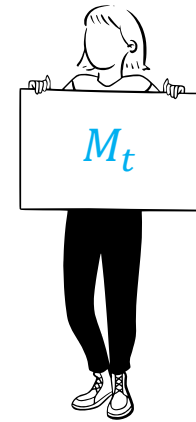
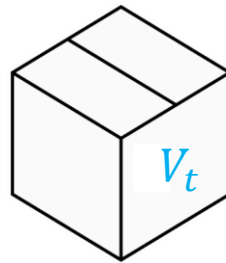
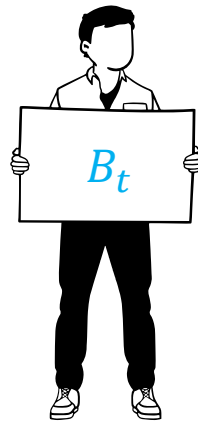
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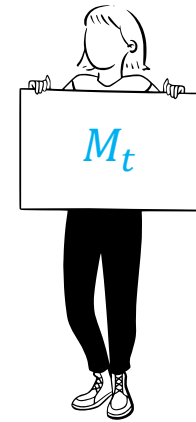
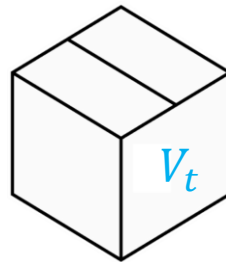
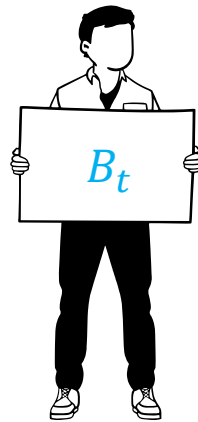
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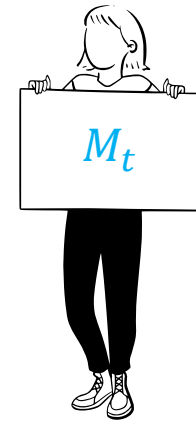
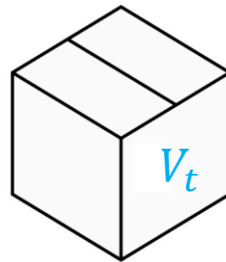
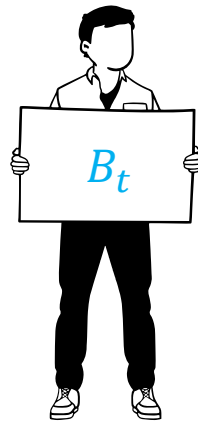


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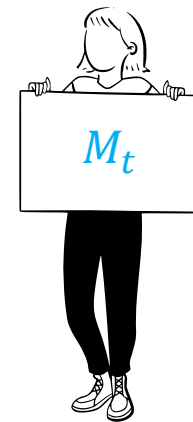
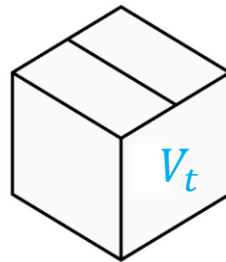
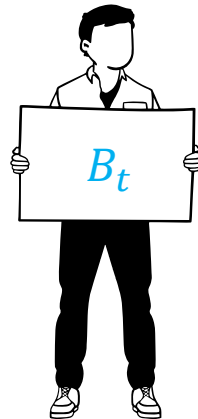
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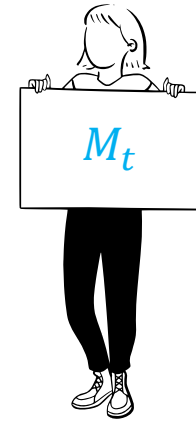
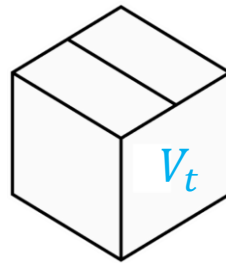
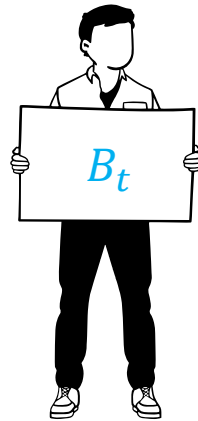
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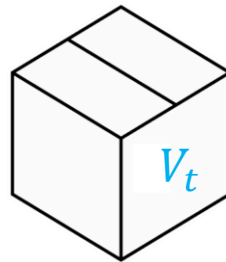
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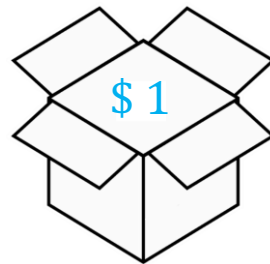
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# Regret

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Goal: minimize the **regret**

$$R_T := \max_{b \in [0,1]} \mathbb{E} \left[ \sum_{t=1}^T \text{Util}_t(b) \right] - \mathbb{E} \left[ \sum_{t=1}^T \text{Util}_t(B_t) \right]$$

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Our contribution: We fully characterize the **minimax** regret rate for various **feedback** and **data generation** models

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	$M_t$	$V_t$
Full	Always observed	Always observed
Transparent	Always observed	Observed if auction is won

# Transparent Feedback

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The following bidders participated to the auction:

- Anonymous 1 bid \$ 0.79 and won the auction
- Anonymous 2 bid \$ 0.75
- Anonymous 3 bid \$ 0.73
- Anonymous 4 bid \$ 0.34
- Anonymous 5 bid \$ 0.12

# Feedback Models

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	$M_t$	$V_t$
Full	Always observed	Always observed
Transparent	Always observed	Observed if auction is won
Semi-Transparent	Observed if auction is lost	Observed if auction is won

# Semi-Transparent Feedback

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Anonymous bid \$ 0.79 and won the auction

# Feedback Models

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	$M_t$	$V_t$
Full	Always observed	Always observed
Transparent	Always observed	Observed if auction is won
Semi-Transparent	Observed if auction is lost	Observed if auction is won
Bandit	Never observed	Observed if auction is won

# Semi-Transparent Feedback

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I ain't no snitch, fool. Buzz off!

# Feedback Models

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- **Stochastic** model:  $(V_t, M_t)$  drawn **i.i.d.** from a **fixed** but **unknown** distribution
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We might want to **avoid “atoms”**

## Definition ( $\sigma$ -smoothness)

A measure  $\mu$  on  $[0,1]^2$  is  **$\sigma$ -smooth** if it admits a **density** (w.r.t. Lebesgue) **bounded** by  $1/\sigma$

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The **size** and **structure** of the **action space**

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The **quality** of the **feedback**

- Transparency regulates the ability to reconstruct **counterfactual information**

The **size** and **structure** of the **action space**

- We typically know how to handle **finite** action spaces
- We typically know how to handle **regular** objectives

# The Utility Function

---

Recall that the **utility** as a function of the bid  $b$  is

$$\text{Util}_t(b) := (V_t - b) \cdot \mathbb{I}\{b \geq M_t\}$$

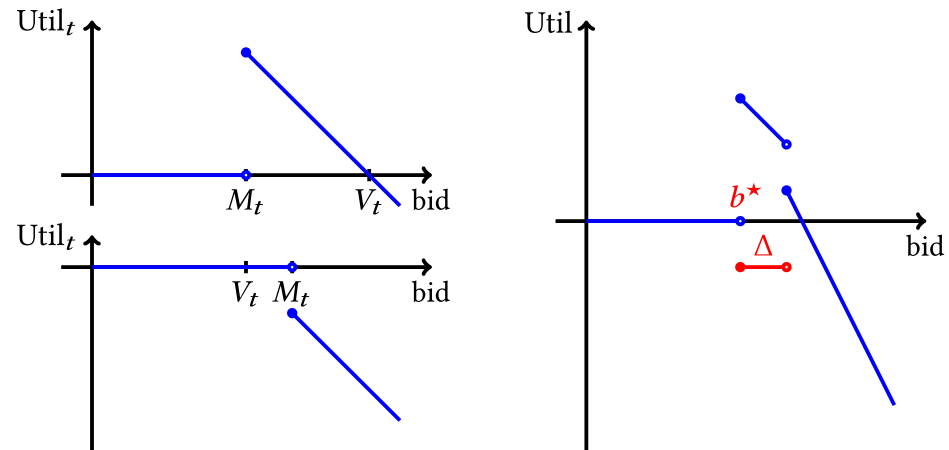


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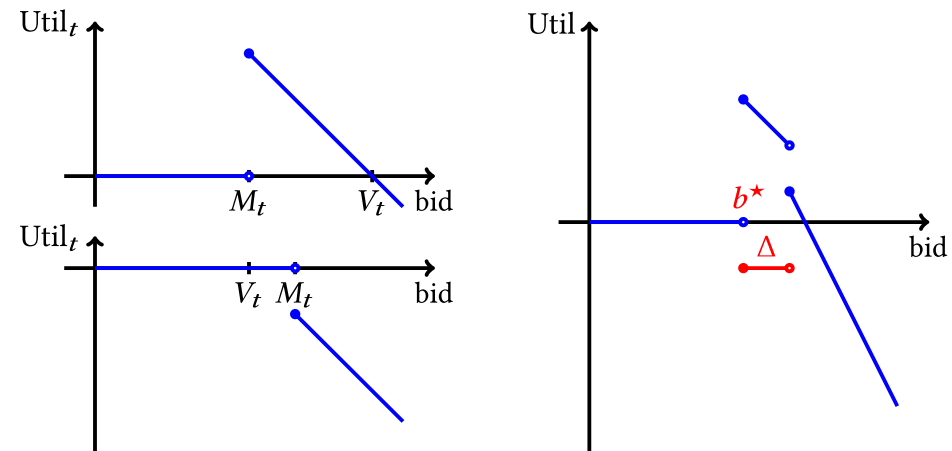


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It is **not** (one-sided) **Lipschitz nor** (semi) **continuous!**

# Our Results

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	Smooth	General	Smooth	General
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- THM 2. Beyond that, revealing the winning bid avoids pathologies
- THM 3. In particular, revealing all bids drastically improves learnability (to full-info levels)

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Thank  
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