

Designing Markets for Daily Deals



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GROUPON

livingsocial

Google offers

amazon local

Motivation: Daily Deals



Cambridge, MA  Search Offers e.g., pizza near san jose, ca 



Offers

RecommendedYour offersHelp 

All categories

Food & Drink

Shopping

Adventure & Activities

Events & Classes

Travel

Beauty

Health & Wellness

Automotive

Services

Jo-Ann Fabric and Craft Stores

40% off 1 regular-priced item

Burlington

VIEW OFFER



Offers

[Why these offers?](#)



L'OCCITANE

Boston

Free Hand Massage

 View offer



Chilis

Chelsea

Free jumbo soft pretzels w/
purchase of an adult entree

 View offer



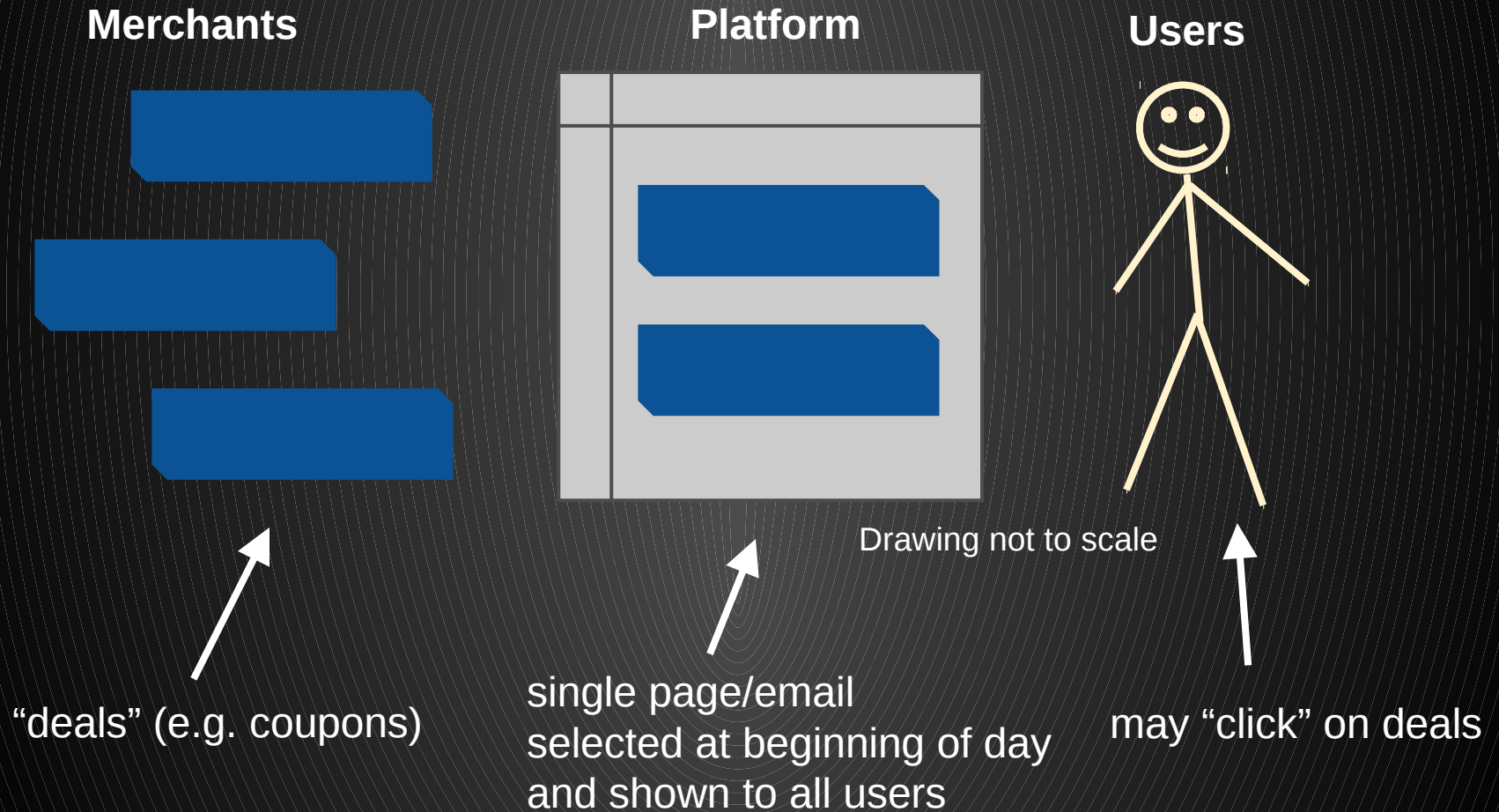
Godiva Chocolatier

Boston

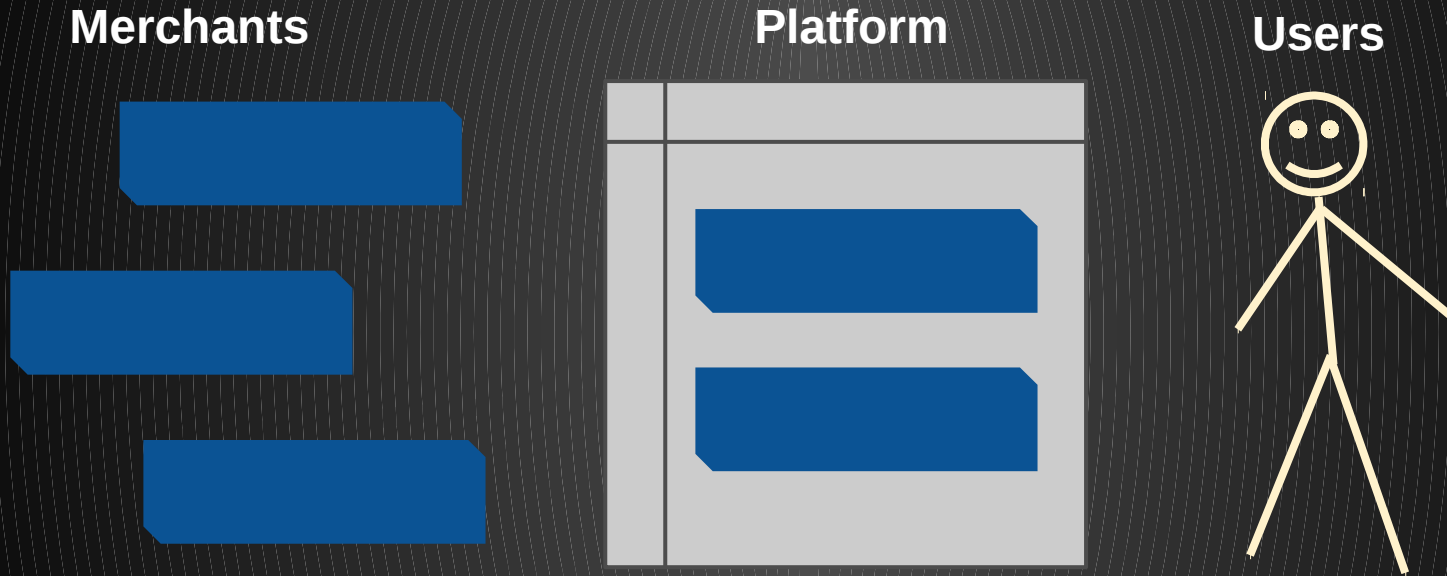
20% off entire purchase with code

 View offer

Problem statement



Problem statement



Drawing not to scale

Task: design an *auction* to pick deals

Twist: care about *users'* welfare

Challenge: merchants know value to users; platform may not

Outline

1. Really simple model for daily deals, results
2. Really general model, characterization
3. Applications and conclusion

Goals of talk: (a) state/solve daily deals problem
(b) **general** auction takeaways

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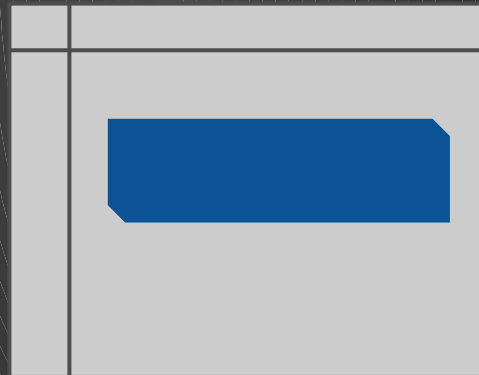
Really Simple Model

- **One** winning deal
- **One** user

Merchants



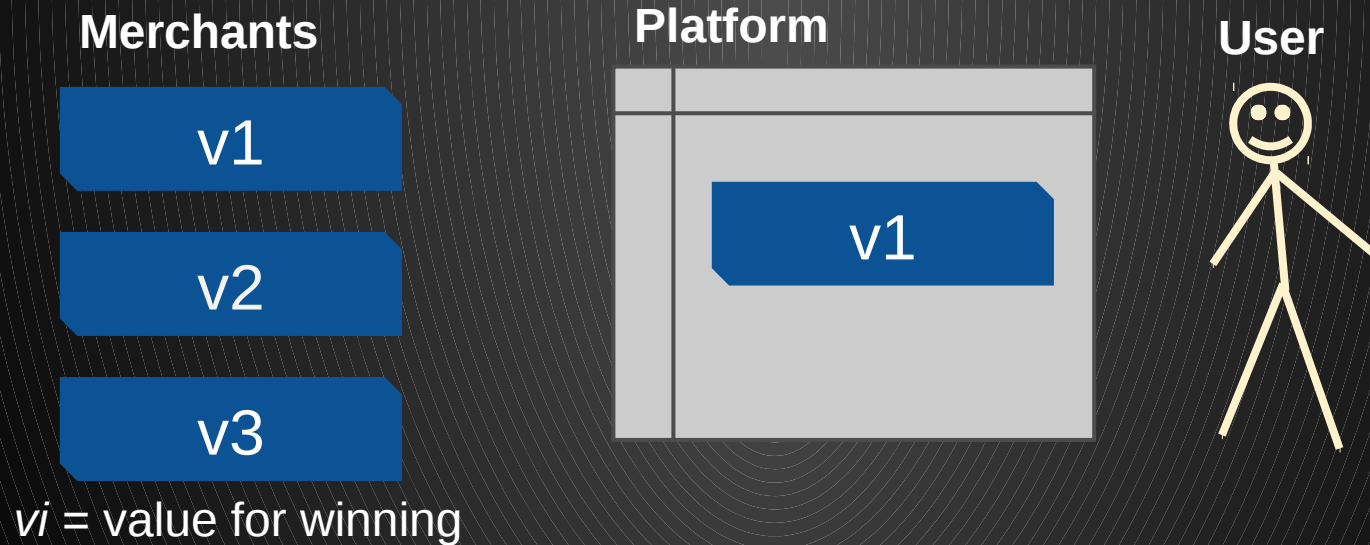
Platform



User



Prologue: Standard auction setting



Simple model for daily deals

Merchants

v_1, p_1

v_2, p_2

v_3, p_3

v_i = value for winning
 p_i = probability of click

Platform

v_1, p_1

User



Simple model for daily deals

- User welfare is related to p_i
- First try: require p_i to exceed “quality” threshold

Merchants

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Platform

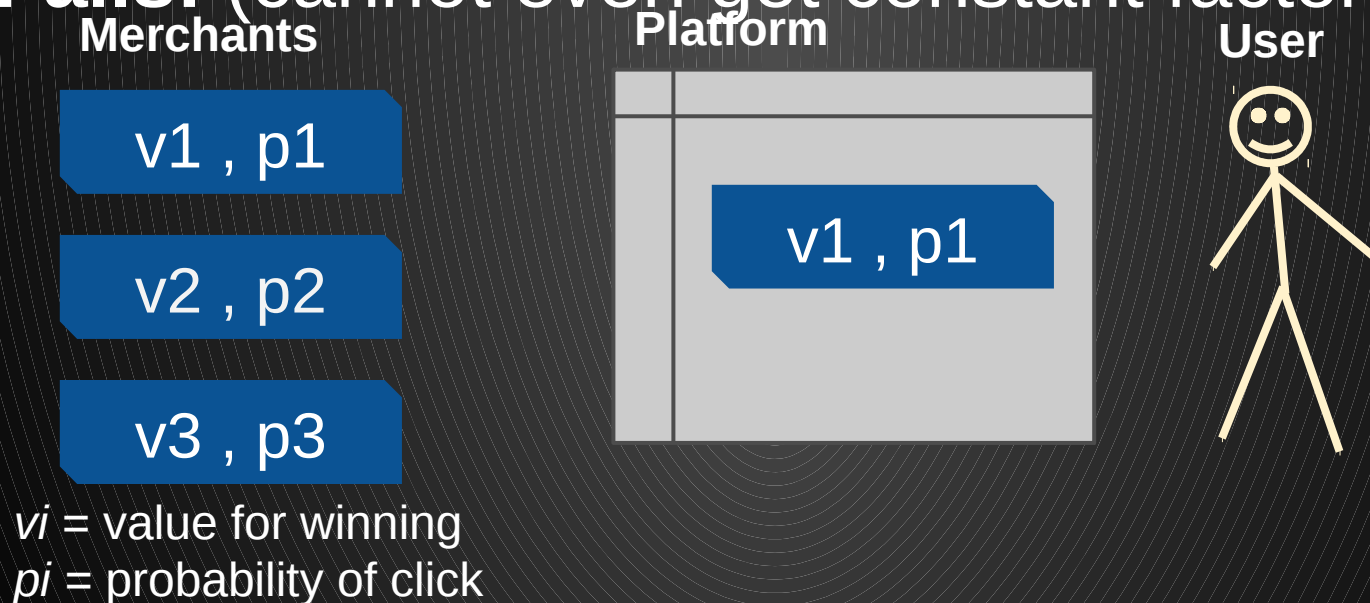
v_1, p_1

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Simple model for daily deals

- User welfare is related to p_i
- First try: require p_i to exceed “quality” threshold
- **Fails!** (cannot even get constant factor of v_i)



Maximizing total welfare

- User welfare is related to p_i
- Model relationship by a function $g(p_i)$
- Goal: maximize $v_i + g(p_i)$

Merchants

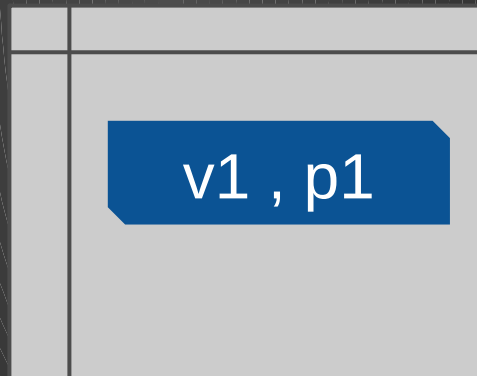
v_1, p_1

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 p_i = probability of click

Platform



User



welfare = $g(p_i)$

Q: For what user welfare functions $g(p)$ can we truthfully max welfare?

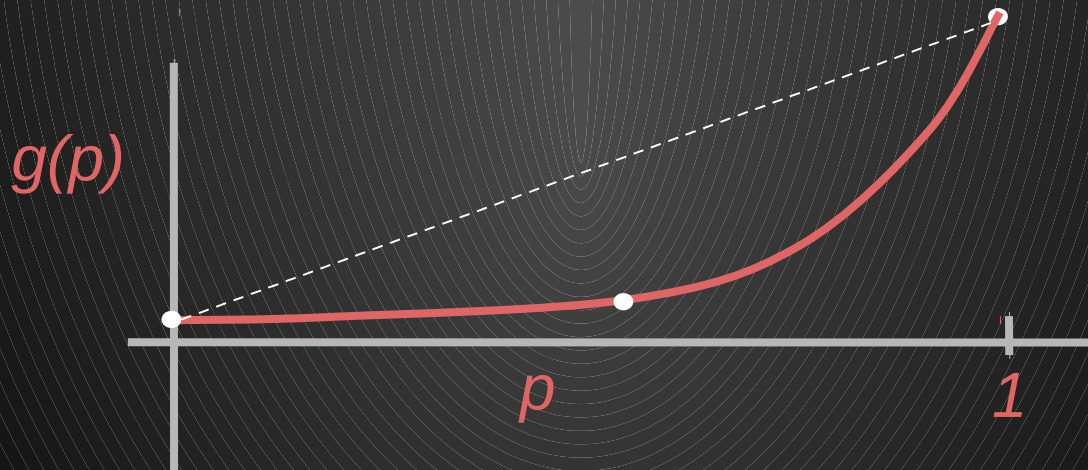
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What does convex mean?

Example: $p = 0$ on first day, $p = 1$ on second day is preferred to $p = 0.5$ on both days



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Constructing the auction

Key idea: p_i = **prediction**

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Constructing the auction

Key idea: p_i = prediction

Scoring rule: Score(prediction, outcome).

Proper: truthful prediction maximizes expected score.

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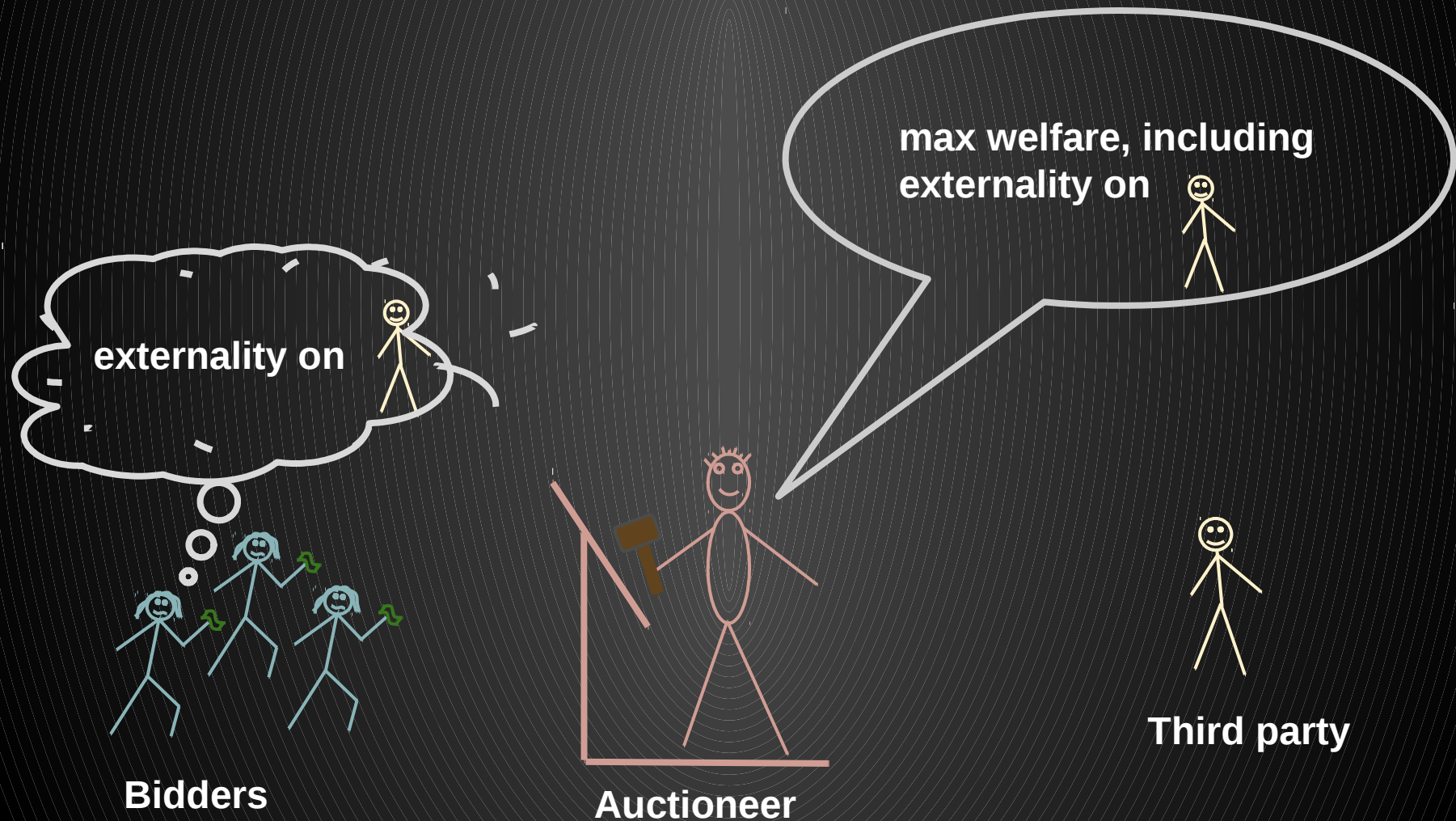
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$$E[\text{utility for winning}] = v_1 + g(p_1) - (v_2 + g(p_2))$$

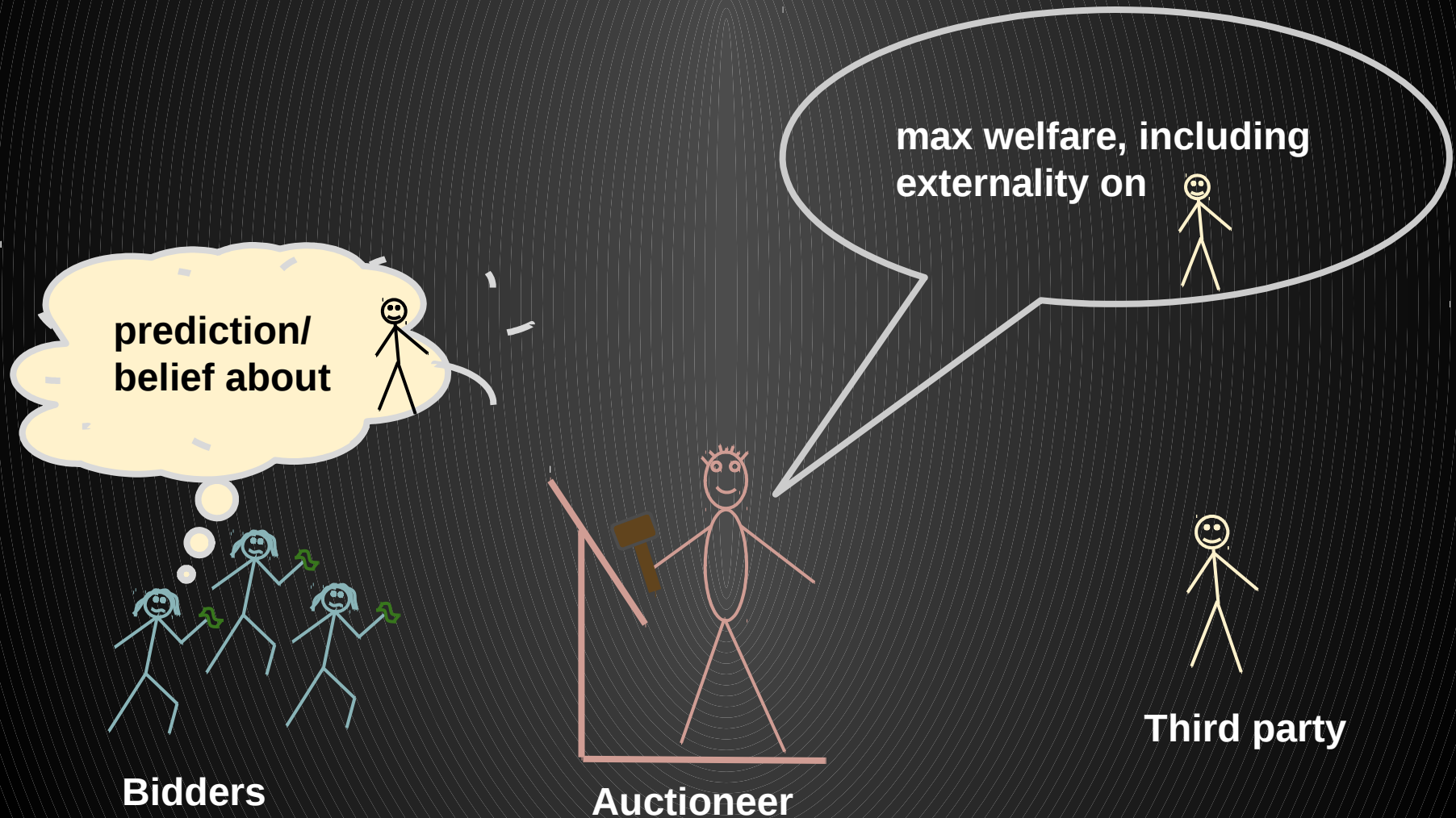
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Takeaways from simple model

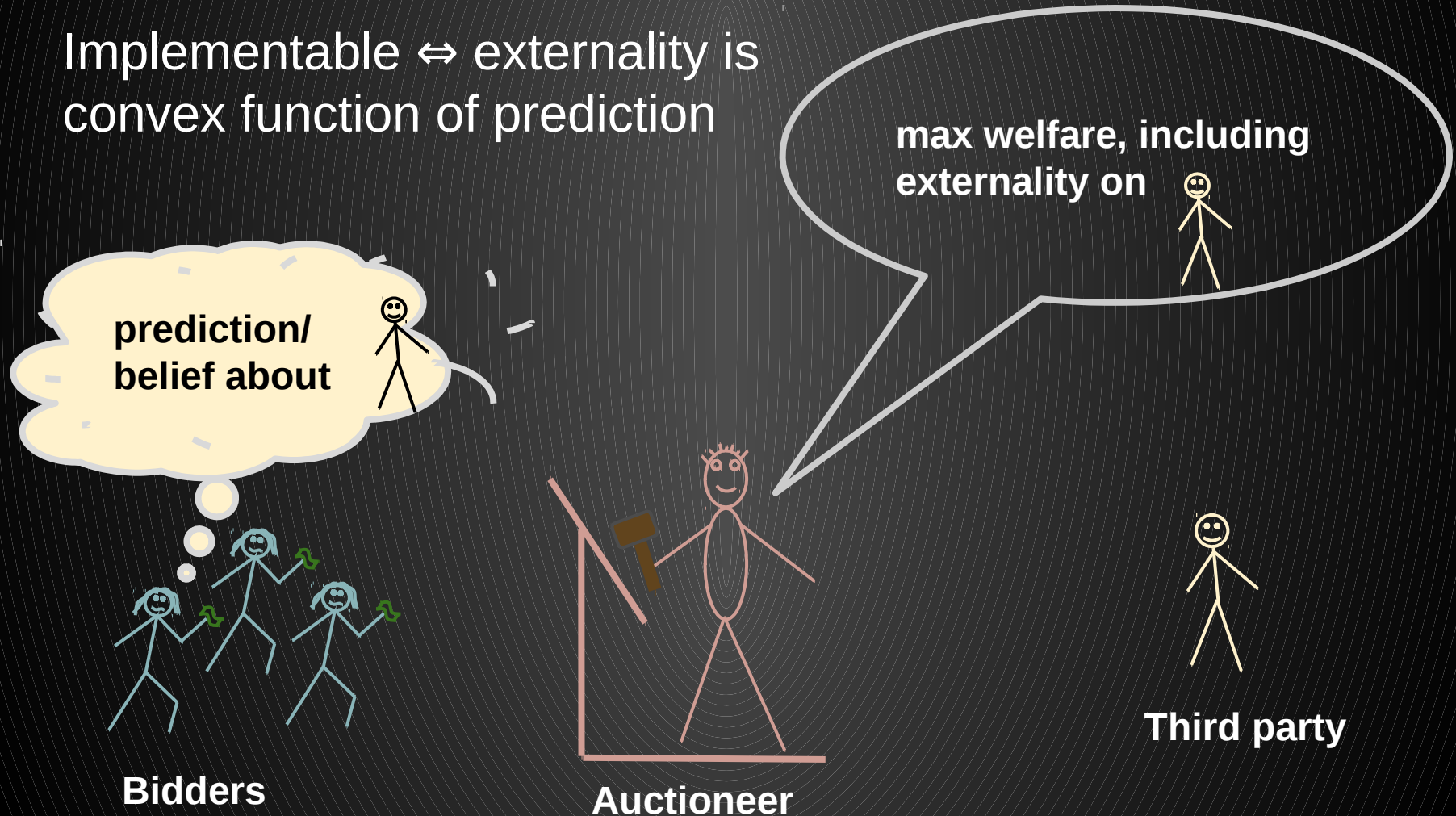


Takeaways from simple model



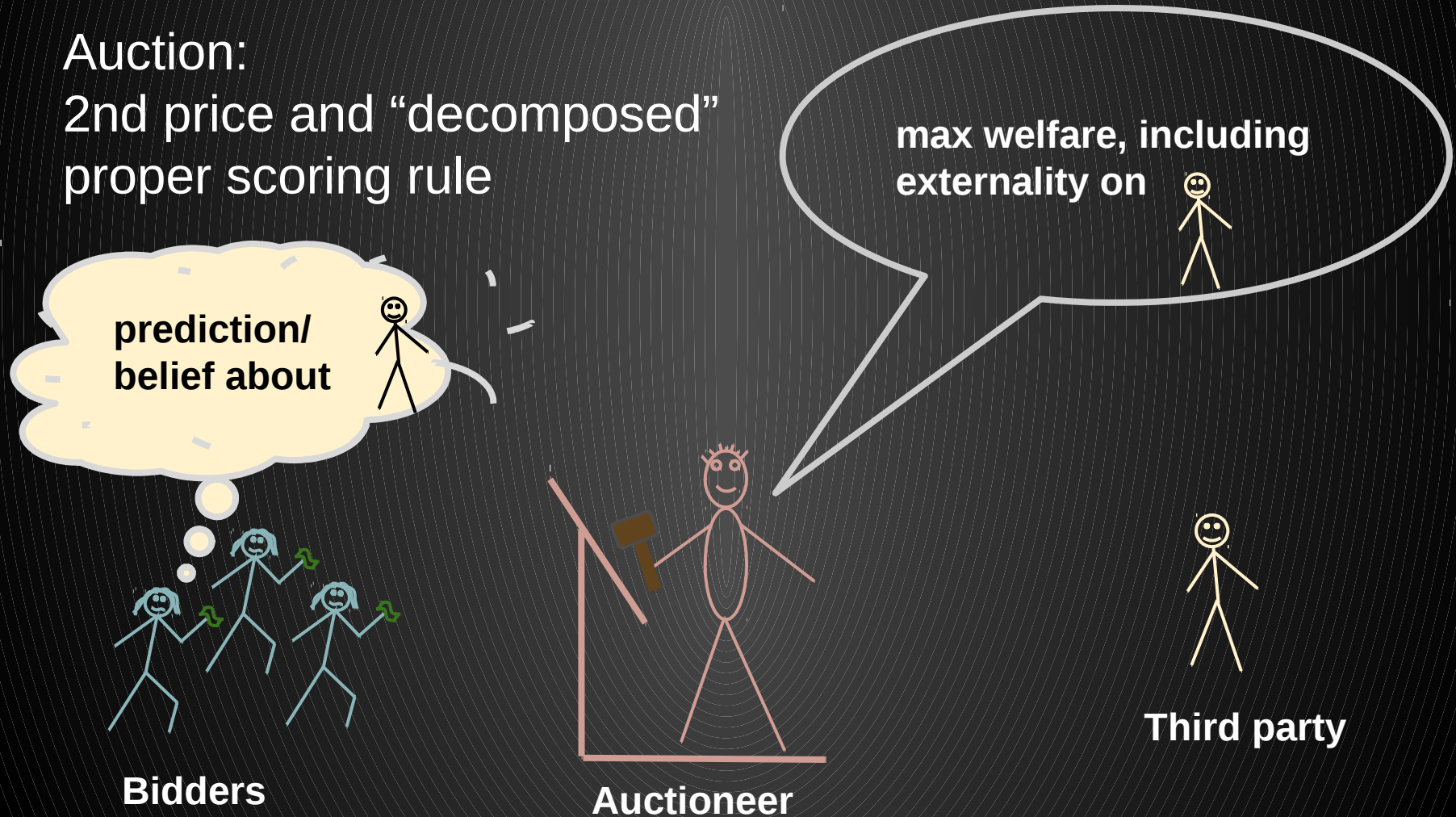
Takeaways from simple model

Implementable $\Leftrightarrow$ externality is convex function of prediction



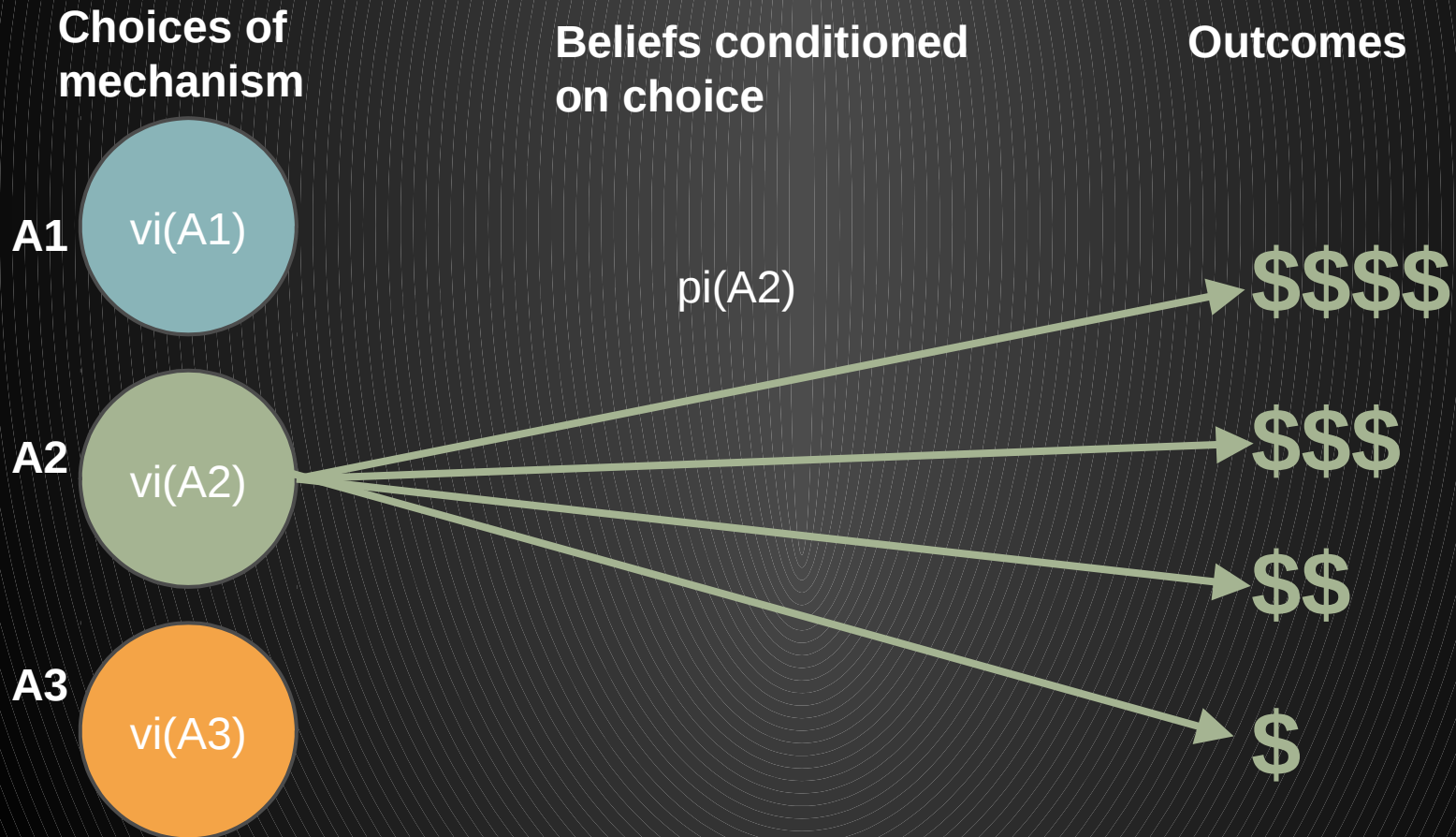
Takeaways from simple model

Auction:
2nd price and “decomposed”
proper scoring rule



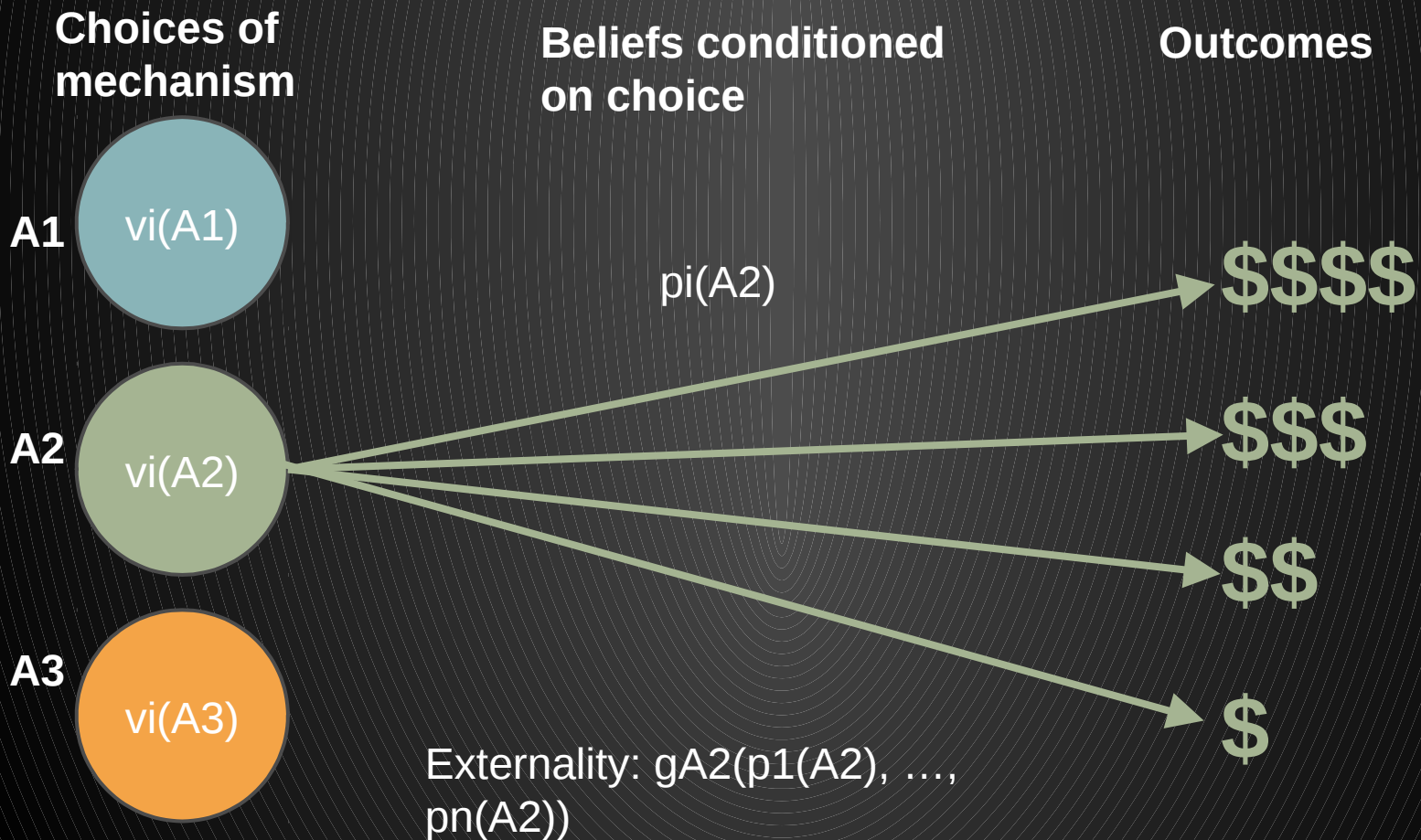
“Really General Model”

Example: “full” daily deals.



“Really General Model”

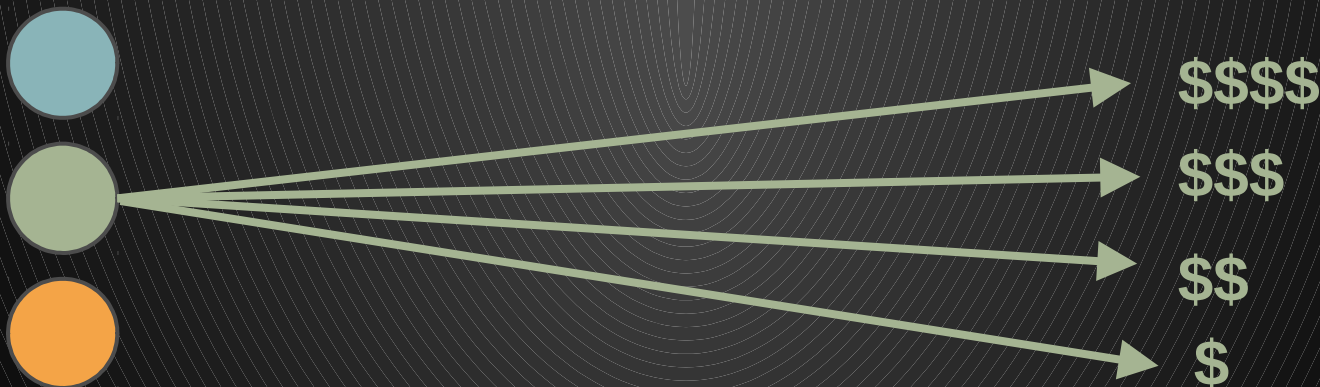
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$g_A(p_1(A), \dots)$ are **convex** in each argument $\Leftrightarrow$ we can maximize welfare = $g_A(p_1(A), \dots) + \sum_i v_i(A)$.

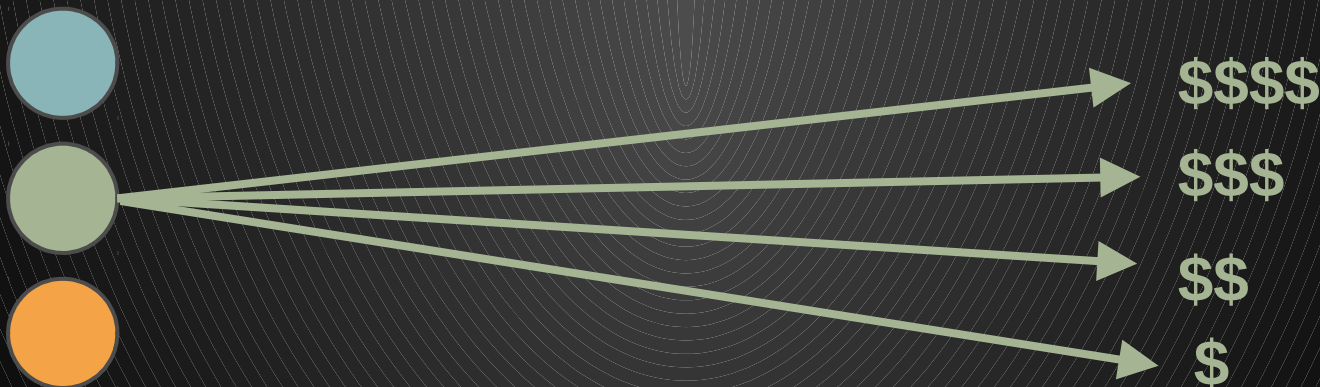


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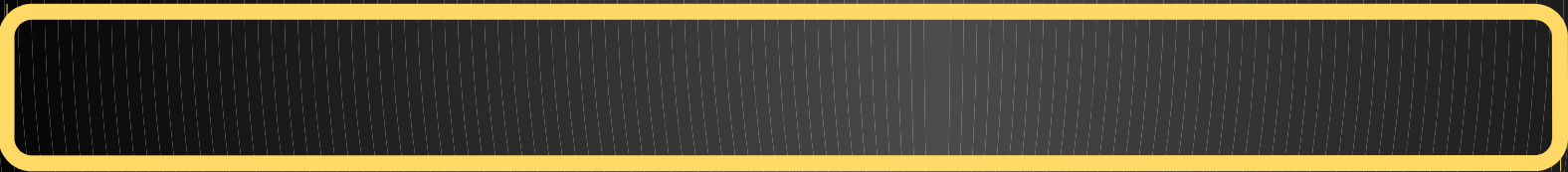
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Auction: VCG and carefully constructed scoring rules.



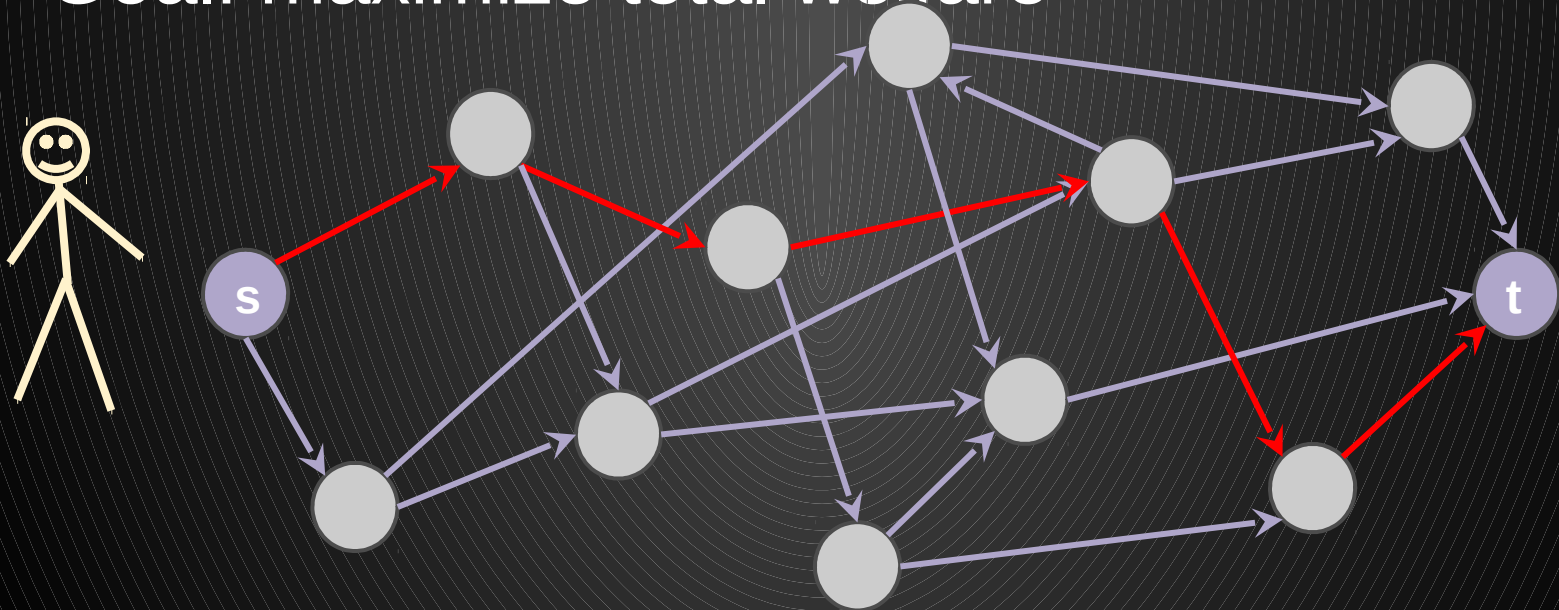
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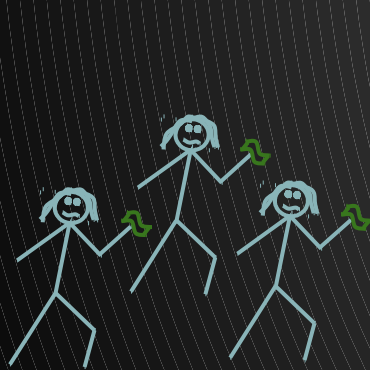
Application of Characterization: Network Problems

- Each edge has:
 - cost v_i
 - stochastic delay $\sim p_i$
- Utility of traveler: $g(p_1, \dots, p_m)$ for path $1 \dots m$
- Goal: maximize total welfare

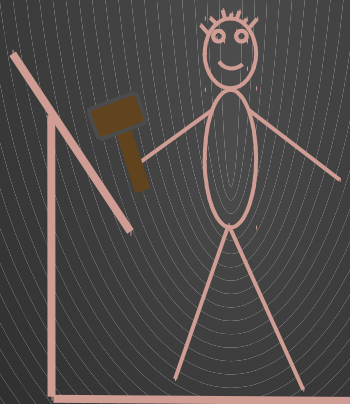


General takeaways

- Welfare includes **externality** on 
- ... depending on private **predictions** of bidders
- Implementable $\Leftrightarrow$ externality is convex function of prediction
- Auction = VCG + “decomposed” scoring rules



Bidders



Auctioneer



Third party

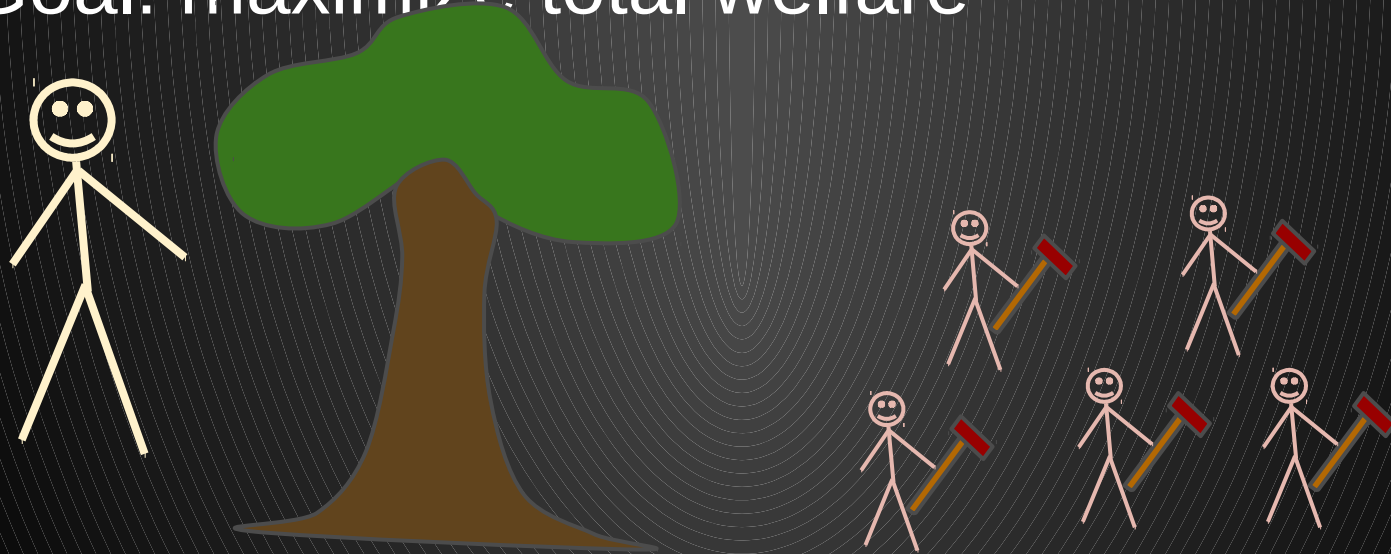
Future work

- Practicality
- Assumptions to avoid negative results
- Applications
- Revenue maximization
- Explore: convexity, implementable allocation functions, and implementable objective functions. c.f. Frongillo and Kash, *General Truthfulness Characterizations via Convex Analysis*



Extension: Principal-agent problems

- Each worker has a set of efforts, each with:
 - cost
 - stochastic quality
- Externality: observed quality of work
- Goal: maximize total welfare



Designing Markets for Daily Deals



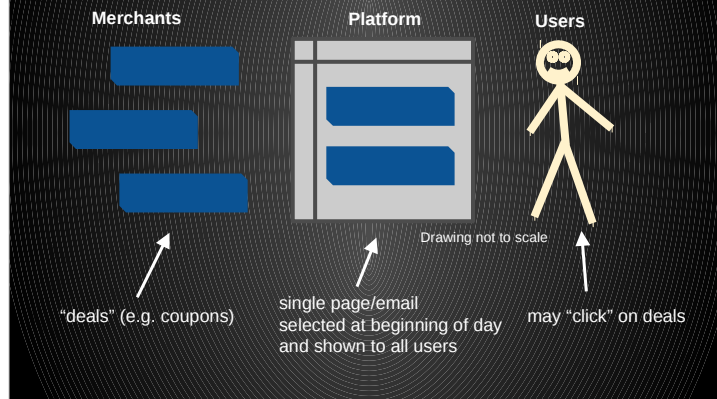
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WINE 2013

The screenshot shows the Google Offers interface. At the top, there are logos for Groupon and Amazon Local. The main heading is "Motivation: Daily Deals". Below this is a search bar with the text "Search Offers e.g., pizza near san jose, ca". To the left of the main content area is a sidebar with the heading "Offers" and a list of categories: Food & Drink, Shopping, Adventure & Activities, Events & Classes, Travel, Beauty, Health & Wellness, Automotive, and Services. The main content area features a large featured offer from "Jo Ann Fabric and Craft Stores" for "40% off 1 regular-priced item" with a "VIEW OFFER" button. Below this are three smaller offers: "L'Occitane Free Hand Massage" (Boston), "Chila Free jumbo soft pretzels w/ purchase of an adult entree" (Chicago), and "Grafica Chocolaterie 20% off entire purchase with code" (Boston). Each offer includes a small image and a "View offer" link.

Daily deals sites are coupon aggregators.

Problem statement



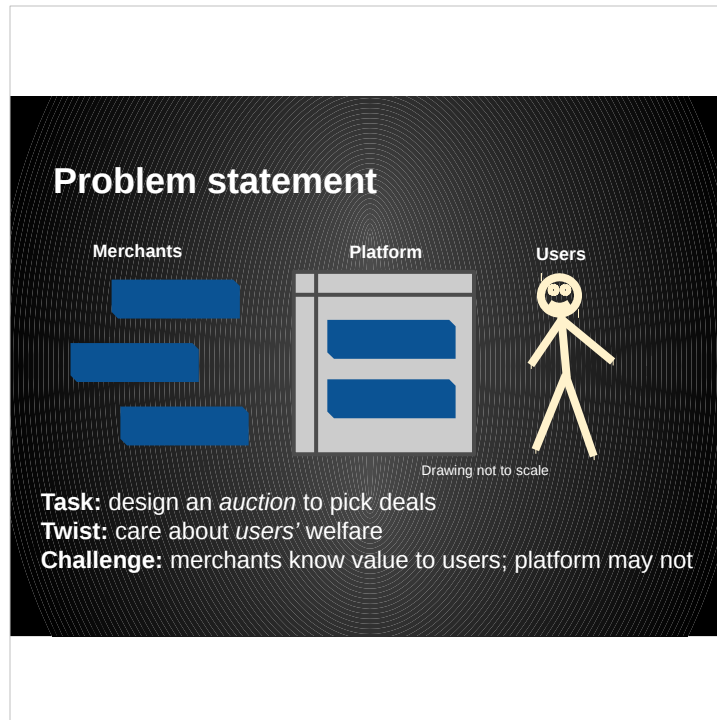
Merchants have deals (coupons) they want to offer users.

The platform, at beginning of the day, must select a single subset of deals to display on a website or send in a mass email to all users.

Users arrive, and obtain the deal in some fashion, and we just call this a click.

Crucially, the platform observes this decision.

The goal is to automate the procedure of selecting deals with some sort of mechanism.



Whereas a standard auction only would concern the merchants and platform, here we want to pick deals that have good utility for the users; if the merchants have high values but the deals are terrible, users won't come back and the platform will fail.

Challenge in our setting: care about users, but impact on users is private information of merchants (many reasons, for example we've never seen this deal before today and have to make a final decision before we see its performance).

For instance, if you're familiar with ad auctions, in those models the platform has all information about the "quality" of the bidders, but here we want to understand what is possible with the opposite information asymmetry: bidders are completely informed and auctioneer is not.

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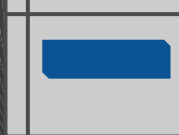
Really Simple Model

- **One** winning deal
- **One** user

Merchants



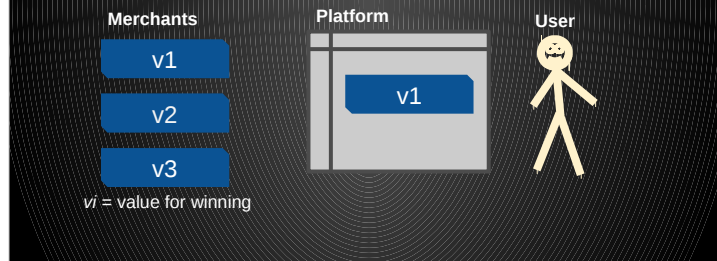
Platform



User

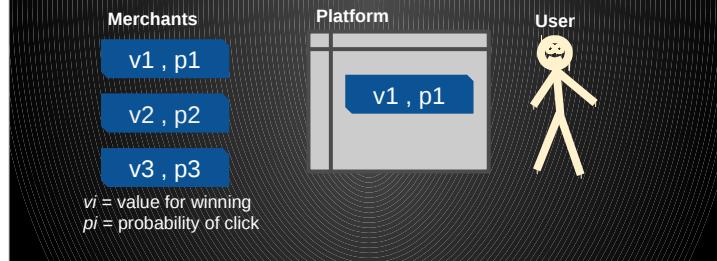


Prologue: Standard auction setting



Standard auction model, each merchant has as private information a scalar v_i , the value for winning the slot.

Simple model for daily deals



Now, merchants also have a parameter p , also private info, which is the probability that the user clicks on the deal.

v still = valuation for winning slot (hasn't changed!).

Of course, v and p can be related in some arbitrary way; doesn't matter to us, just two fixed parameters known to the merchant with these well-defined meanings.

Simple model for daily deals

- User welfare is related to p_i
- First try: require p_i to exceed “quality” threshold

Merchants

v_1, p_1

v_2, p_2

v_3, p_3

Platform

v_1, p_1

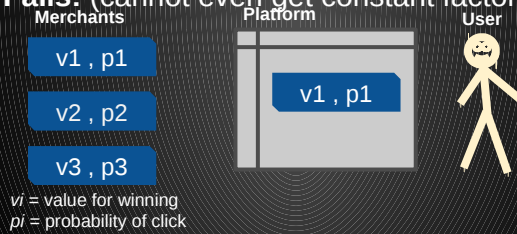
User



v_i = value for winning
 p_i = probability of click

Simple model for daily deals

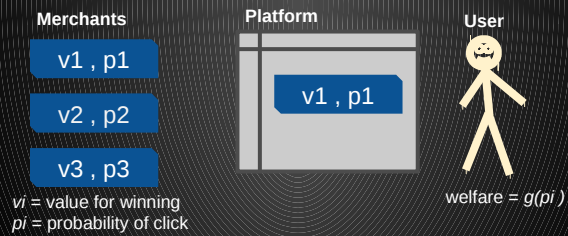
- User welfare is related to pi
- First try: require pi to exceed “quality” threshold
- **Fails!** (cannot even get constant factor of v_i)



See the paper for the exact result, but the takeaway is that it seems hard to run a good auction by imposing any sort of threshold on pi (even a relatively soft one).

Maximizing total welfare

- User welfare is related to p_i
- Model relationship by a function $g(p_i)$
- Goal: maximize $v_i + g(p_i)$



Bidders impact social welfare by both value *and* by their impact on the user; let's model this impact with a function g , thought of as “externality” on user, and now total welfare is $v + g(p)$.

Q: For what user welfare functions $g(p)$ can we truthfully max welfare?

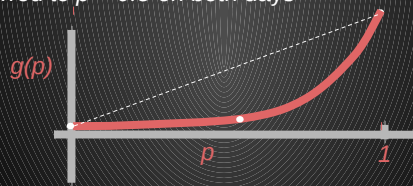
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What does convex mean?

Example: $p = 0$ on first day, $p = 1$ on second day is preferred to $p = 0.5$ on both days



I claim that convex functions $g(p)$ intuitively correspond to risk aversion (even though we are used to associating risk-aversion with concave functions, which are functions of wealth!).

The reason: We'd rather take something for certain than a lottery with same expectation. In this case, the user would prefer to click on exactly one deal out of the two days than face some lotteries with one click in expectation.

In general, you might think of $g(p)$ as the "certainty equivalent" function for a lottery p ; it is known that a convex $g(p)$ corresponds to a concave utility function, i.e. risk-aversion.

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Theorem 1. $g(p)$ is **convex** $\Leftrightarrow$ there exists a deterministic, truthful auction maximizing $v_i + g(p_i)$.

Constructing the auction

Key idea: p_i = prediction

Q: For what user welfare functions $g(p)$ can we truthfully max welfare?

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Constructing the auction

Key idea: p_i = prediction

Scoring rule: Score(prediction, outcome).

Proper: truthful prediction maximizes expected score.

Example scoring rule: The log scoring rule.

Score(p, yes) = log(p).

Score(p, no) = log(1-p).

(Can be shifted/multiplied by a constant, of course!)

Of course, we can't simply apply scoring rules and auctions separately; we need to carefully combine them.

Q: For what user welfare functions $g(p)$ can we truthfully max welfare?

Theorem 1. $g(p)$ is **convex** $\Leftrightarrow$ there exists a deterministic, truthful auction maximizing $v_i + g(p_i)$.

1. Sort by $v_i + g(p_i)$ from highest to lowest.
2. Pick bidder 1.
3. Bidder 1 pays platform: $v_2 + g(p_2)$
4. Platform pays bidder 1: $\text{Score}(p_1, \text{outcome})$

Here's the mechanism; the question is, which scoring rule do we pick for Step 4? It must be chosen carefully!

Q: For what user welfare functions $g(p)$ can we truthfully max welfare?

Theorem 1. $g(p)$ is **convex** $\Leftrightarrow$ there exists a deterministic, truthful auction maximizing $\sum v_i + g(p_i)$.

Lemma (Savage '71). For all convex $g(p)$, there exists a proper scoring rule with expected score $g(p)$ for truthfully reporting p .

Example: For the log scoring rule,

$g(p) = p \log(p) + (1-p)\log(1-p)$, i.e. the entropy function.

Note that this is convex in p and is equal to the expected score of an agent with belief p who reports truthfully.

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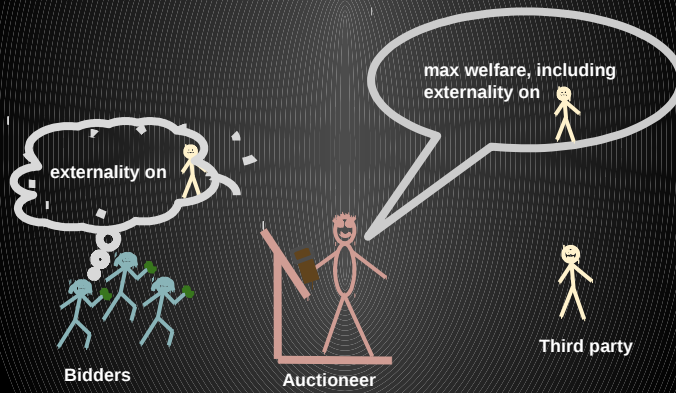
$$E[\text{utility for winning}] = v_1 + g(p_1) - (v_2 + g(p_2))$$

You can easily check that bidder 1 wants to win only if $v_1 + g(p_1)$ is higher than $v_2 + g(p_2)$, and furthermore, prefers telling the truth to lying when she does win. This implies truthfulness of the auction.

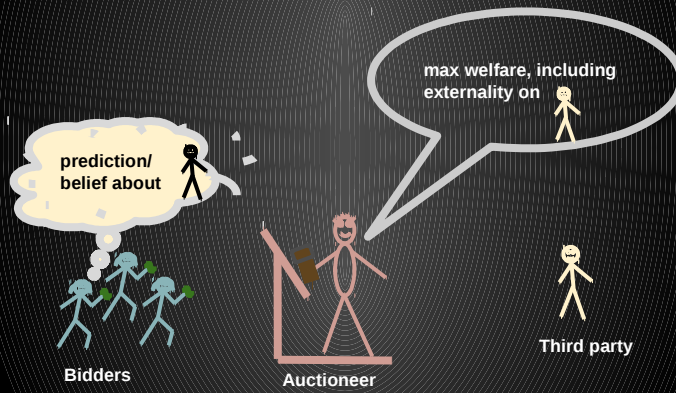
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Takeaways from simple model

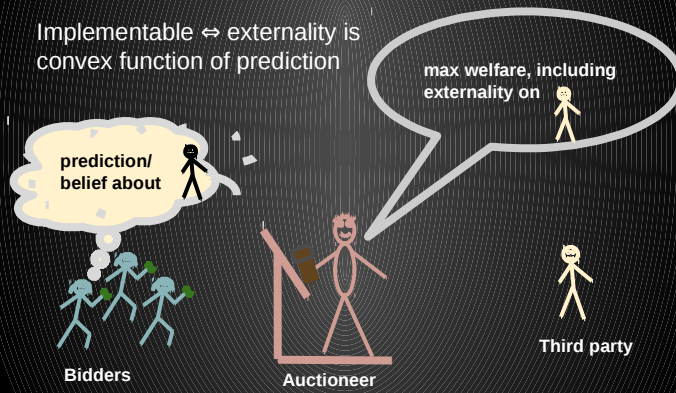


Takeaways from simple model



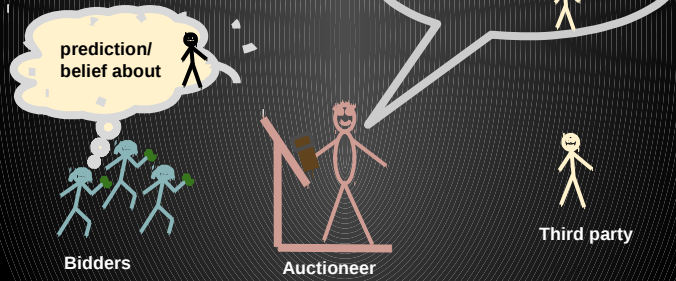
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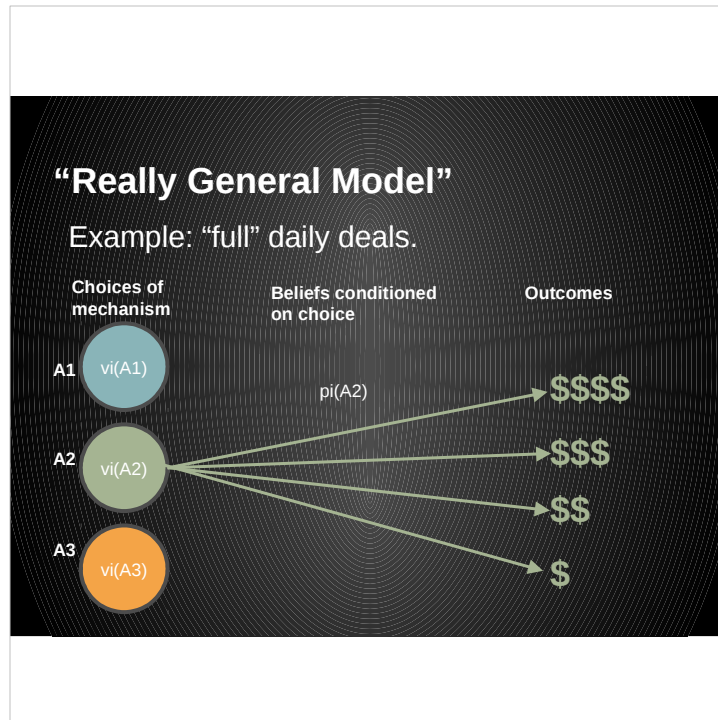
Implementable $\Leftrightarrow$ externality is
convex function of prediction



Takeaways from simple model

Auction:
2nd price and “decomposed”
proper scoring rule





Example: a daily deals setting with multiple slots on the page for sale and many arriving users.

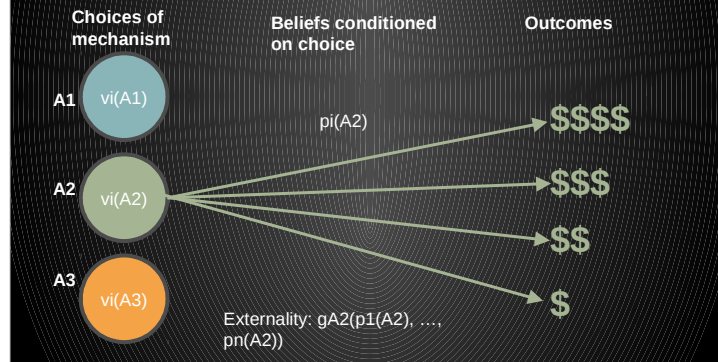
The choices of the mechanism are the possible page layouts: An assignment of slots to merchants.

The outcomes for bidder i could be, for instance, total number of clicks on i 's advertisements (if any).

i has beliefs conditional on the mechanism's choice: Given that the mechanism chooses layout A2, i has a distribution over the total number of clicks she will get.

“Really General Model”

Example: “full” daily deals.

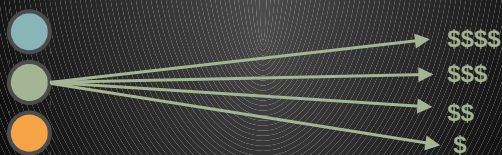


The “third party”’s welfare is modeled by a function of all the predictions.
There could be a different function for each possible choice of the mechanism.

Q: For what externality functions g can we truthfully max welfare?

Theorem 2.

$g_A(p_1(A), \dots)$ are **convex** in each argument $\Leftrightarrow$ we can maximize welfare = $g_A(p_1(A), \dots) + \sum_i v_i(A)$.



There exists a deterministic, truthful, welfare-maximizing auction if and only if all $g_A(p_1(A), \dots)$ are convex in each argument.

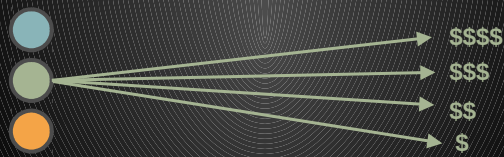
Note that this is a weaker condition than convexity: The function $f(x, y) = x \cdot y$ is convex in each argument, but is not a convex function.

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Auction: VCG and carefully constructed scoring rules.



The auction relies on, for each agent, carefully decomposing $g_A(p_1(A), \dots)$ into a scoring rule for that particular agent, after plugging in the predictions of all other agents. Then, the form of the auction looks like VCG.

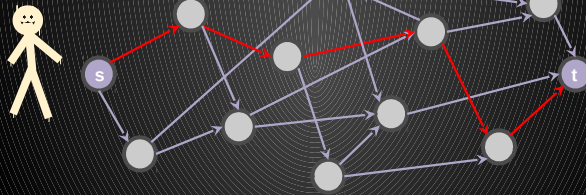
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Application of Characterization: Network Problems

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stochastic delay $\sim p_i$
- Utility of traveler: $g(p_1, \dots, p_m)$ for path $1 \dots m$
- Goal: maximize total welfare



This is an unrelated problem. However, once we write it down formally, we can notice that it fits our general model, and therefore our results apply (both positive and negative).

Note that a convex function g corresponds to a risk-averse traveler: One who prefers a more certain travel time to a more uncertain one, even with a higher expected travel time.

General takeaways

- Welfare includes **externality** on 
- ... depending on private **predictions** of bidders
- Implementable $\Leftrightarrow$ externality is convex function of prediction
- Auction = VCG + “decomposed” scoring rules



Bidders



Auctioneer



Third party

Future work

- Practicality
- Assumptions to avoid negative results
- Applications
- Revenue maximization
- Explore: convexity, implementable allocation functions, and implementable objective functions. c.f. Frongillo and Kash, *General Truthfulness Characterizations via Convex Analysis*



Extension: Principal-agent problems

- Each worker has a set of efforts, each with:
cost
stochastic quality
- Externality: observed quality of work
- Goal: maximize total welfare



Another quick example of unrelated areas where our results apply. Take a principal-agent problem where the agents hold private information about their quality, i.e. the quality is picked from a distribution known to the agents but not the principal. The externality here is on the principal (whom we might also think of as the auctioneer, but this is no problem for the model). If the principal is risk-averse with respect to quality, our auction applies.