Bidding heuristics for ad auctions with applications to TAC AA

Jordan Berg
Amy Greenwald
Victor Naroditskiy
Eric Sodomka

BROWN

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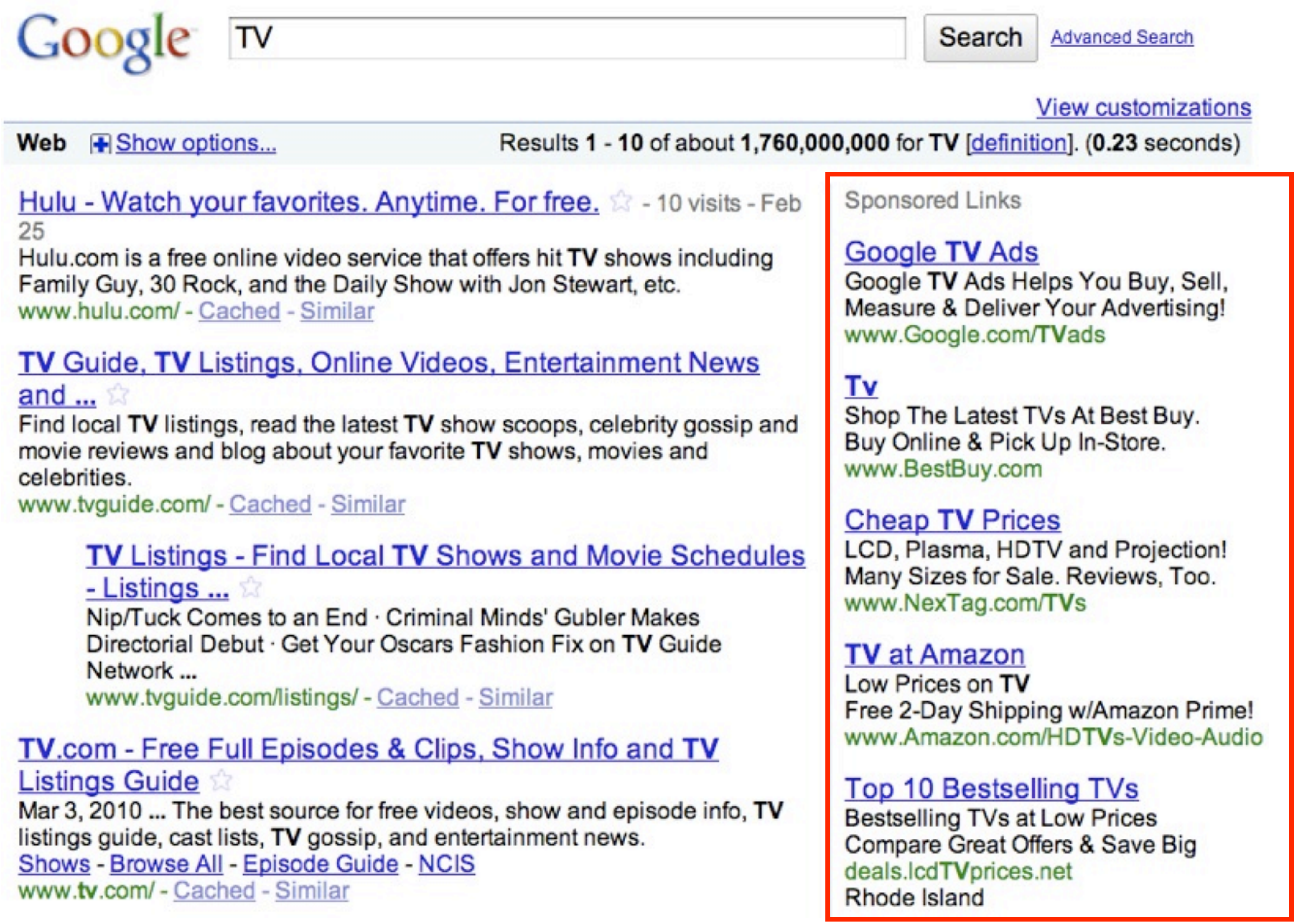
Google
TV
Search
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Results 1 - 10 of about 1,760,000,000 for TV [definition]. (0.23 seconds)
Hulu - Watch your favorites. Anytime. For free. - 10 visits - Feb 25
Hulu.com is a free online video service that offers hit TV shows including Family Guy, 30 Rock, and the Daily Show with Jon Stewart, etc.
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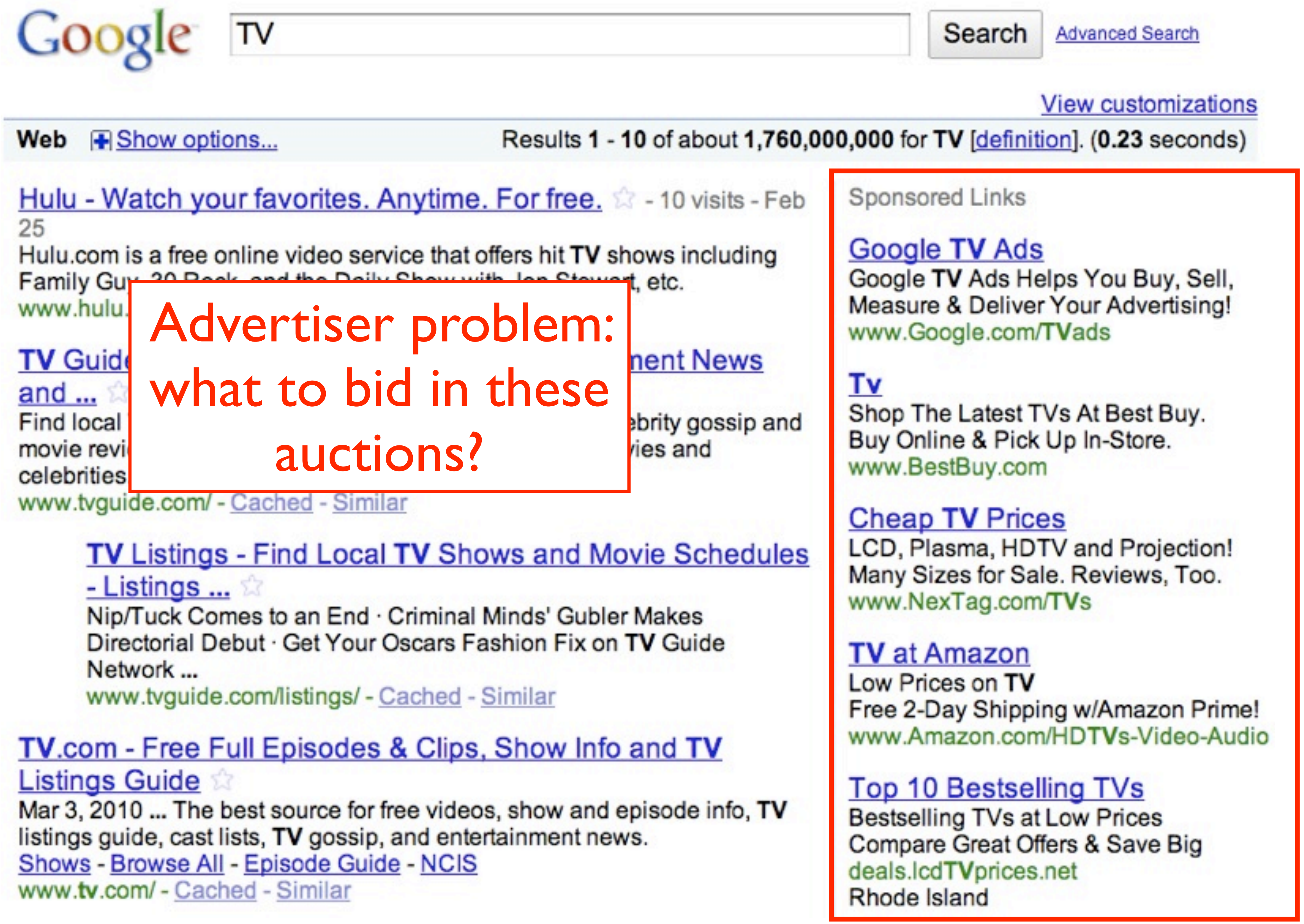
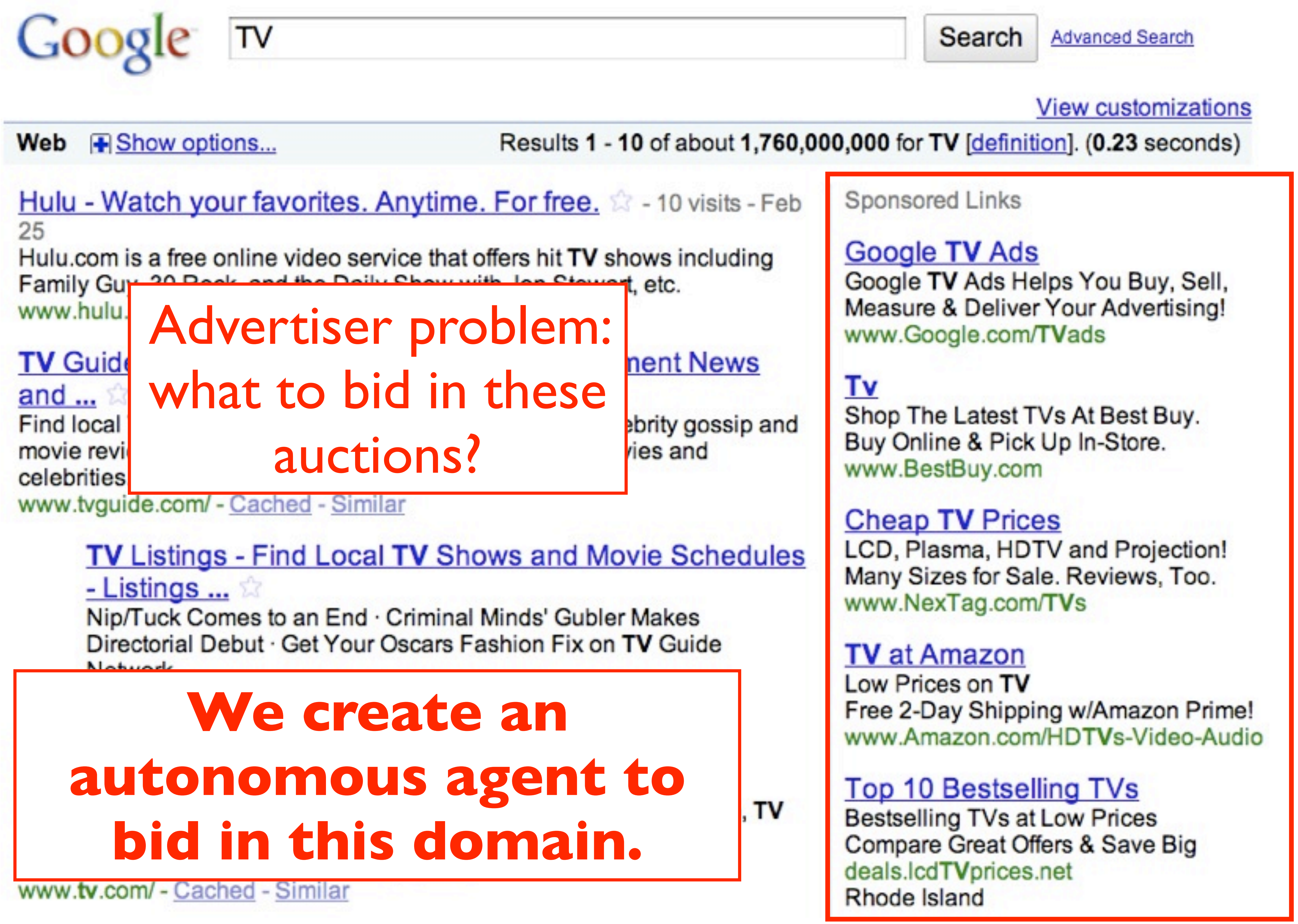


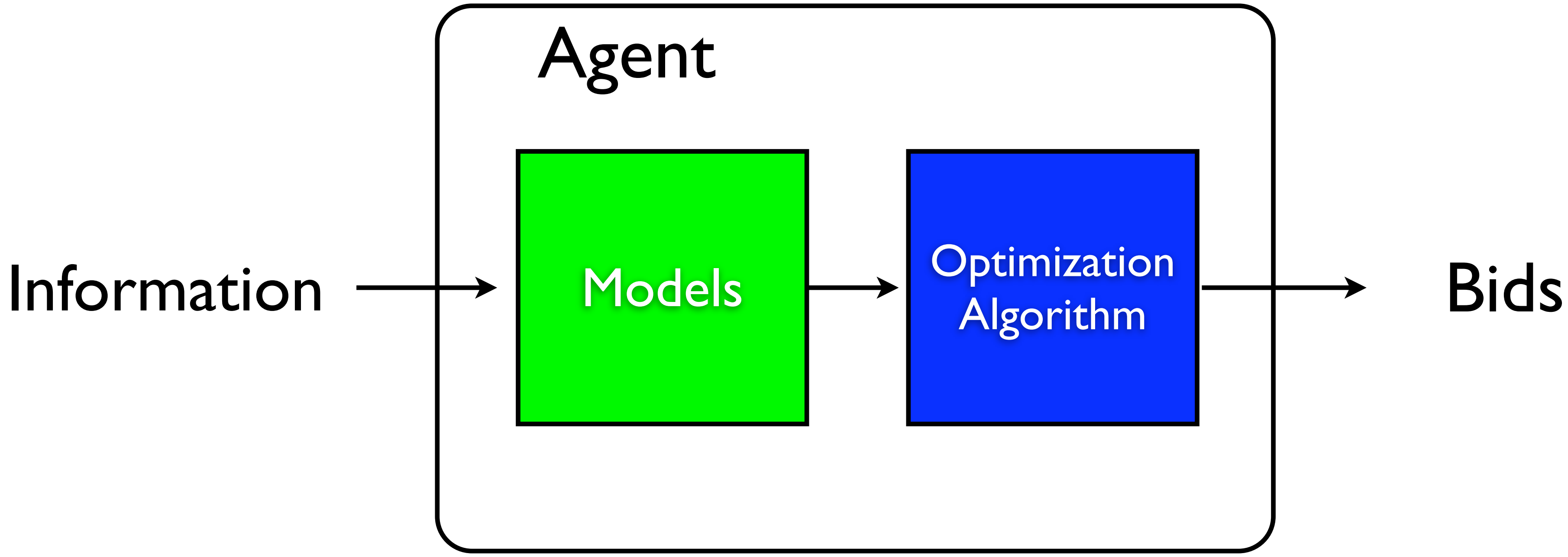
Advertiser problem: what to bid in these auctions?



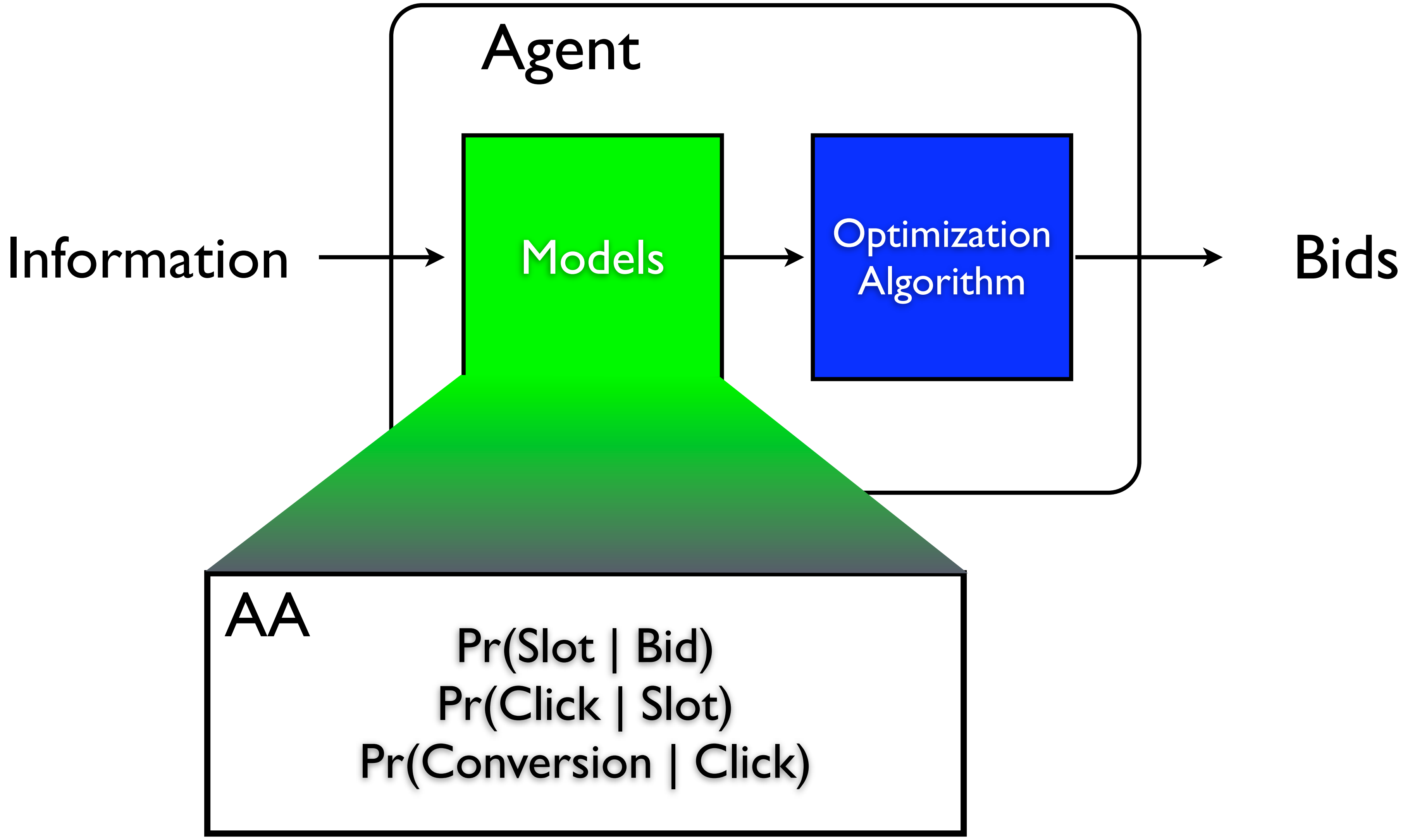
Advertiser problem: what to bid in these auctions?

We create an autonomous agent to bid in this domain.

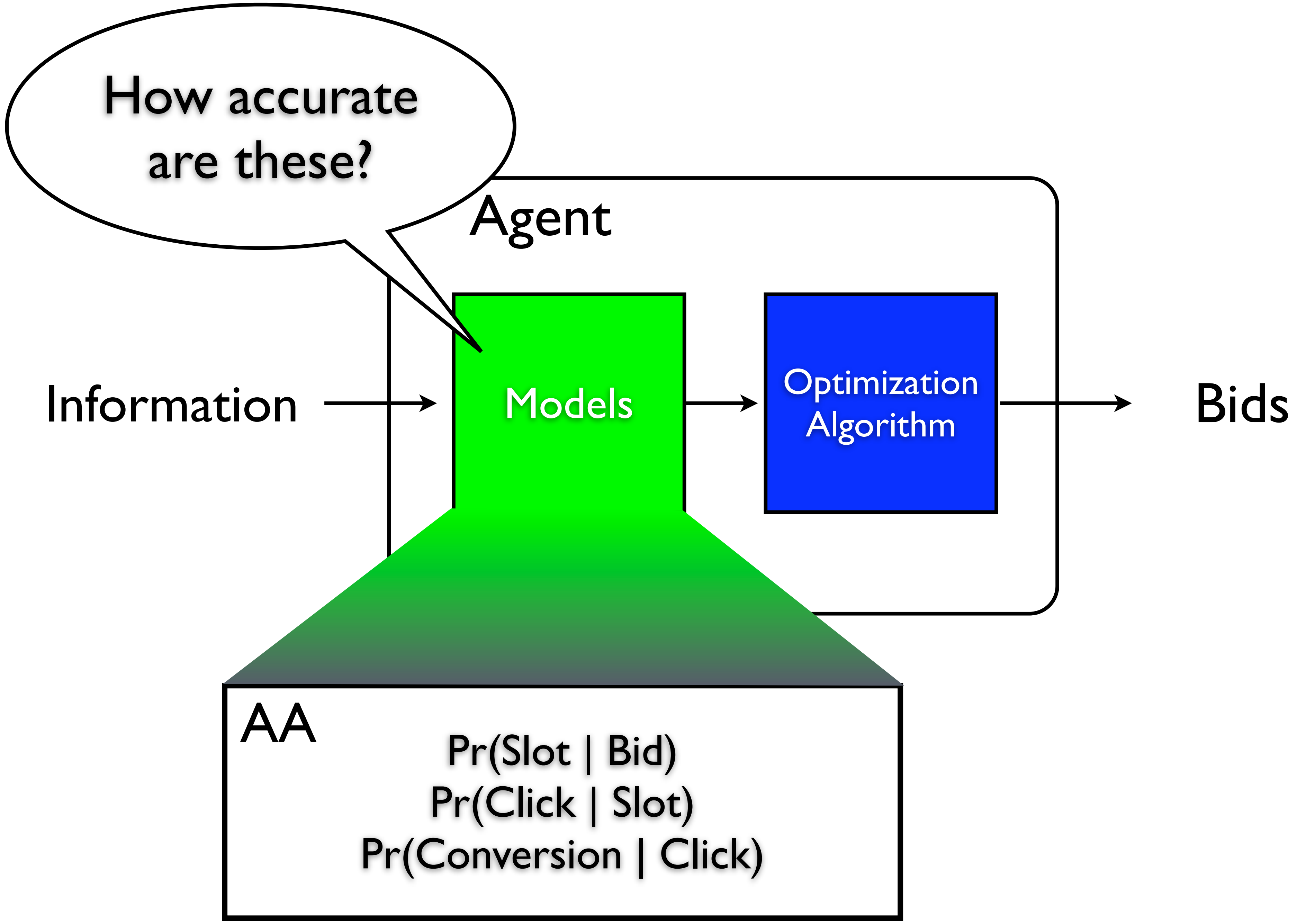
Agent Design



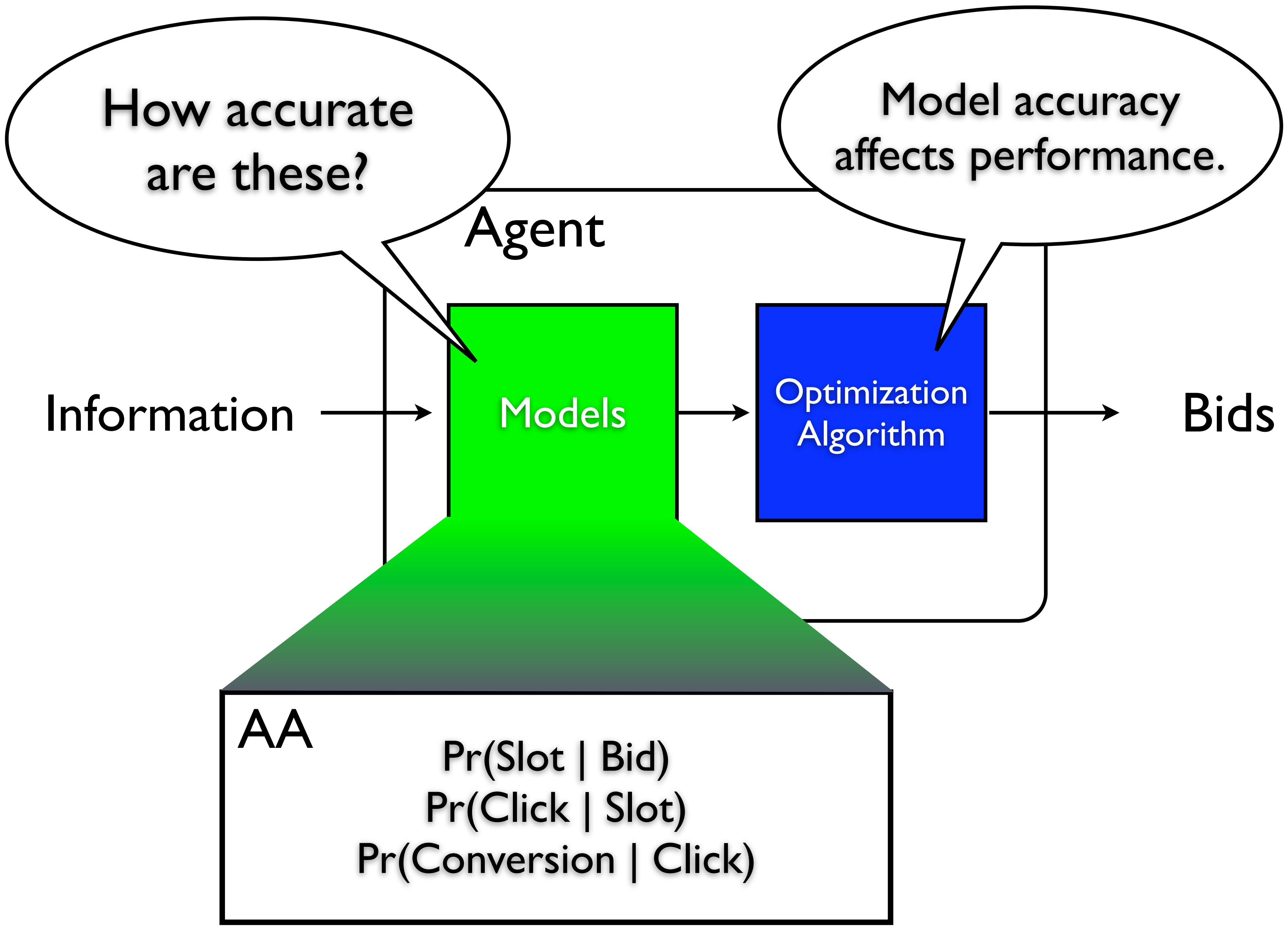
Agent Design



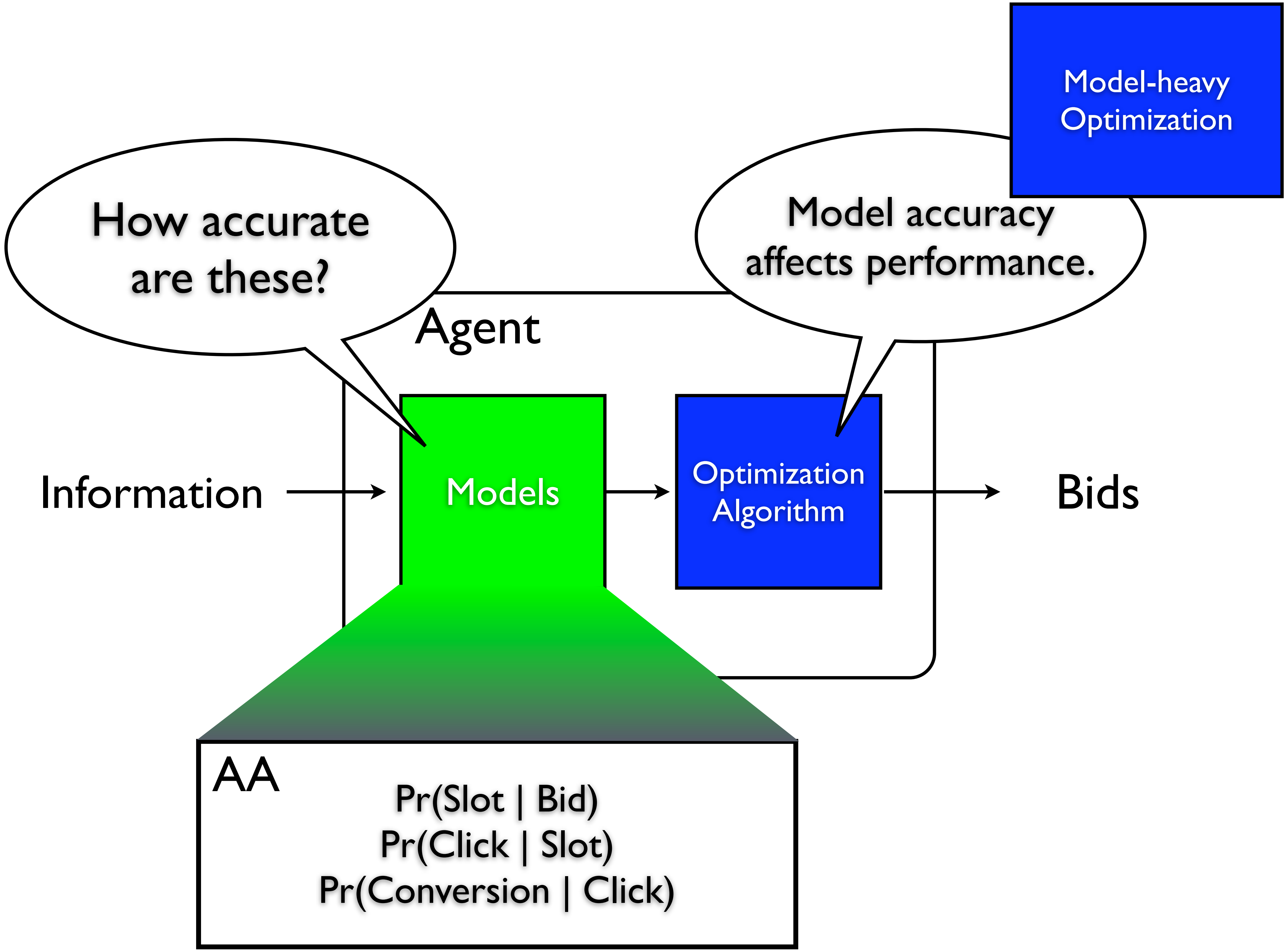
Agent Design



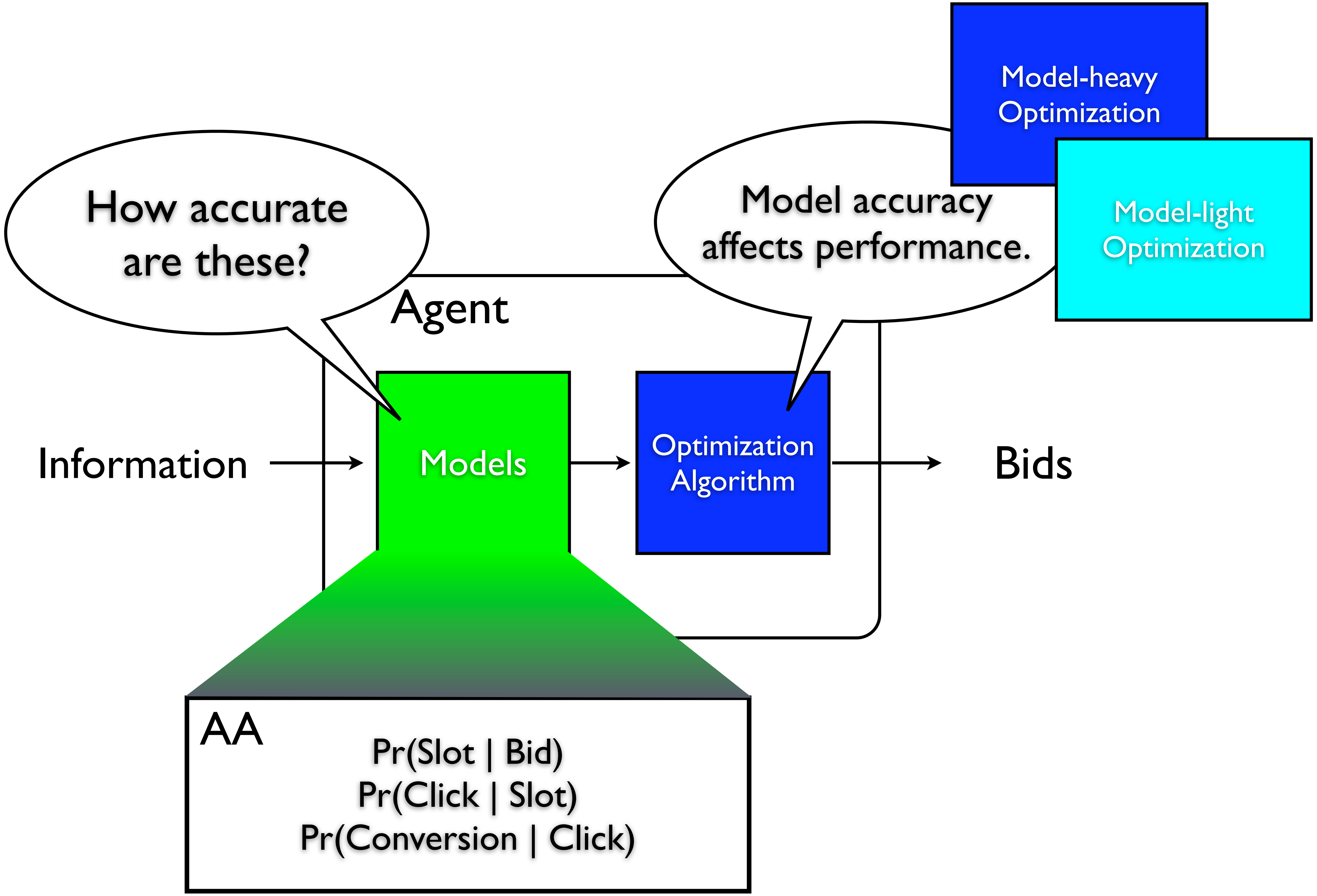
Agent Design



Agent Design



Agent Design



Agent Evaluation

Stylized $\longleftrightarrow$ Real World

Capturing interesting real-world elements?

Financial risk and market noise

Agent Evaluation

Trading Agent Competition (TAC)

Stylized ↔ Real World

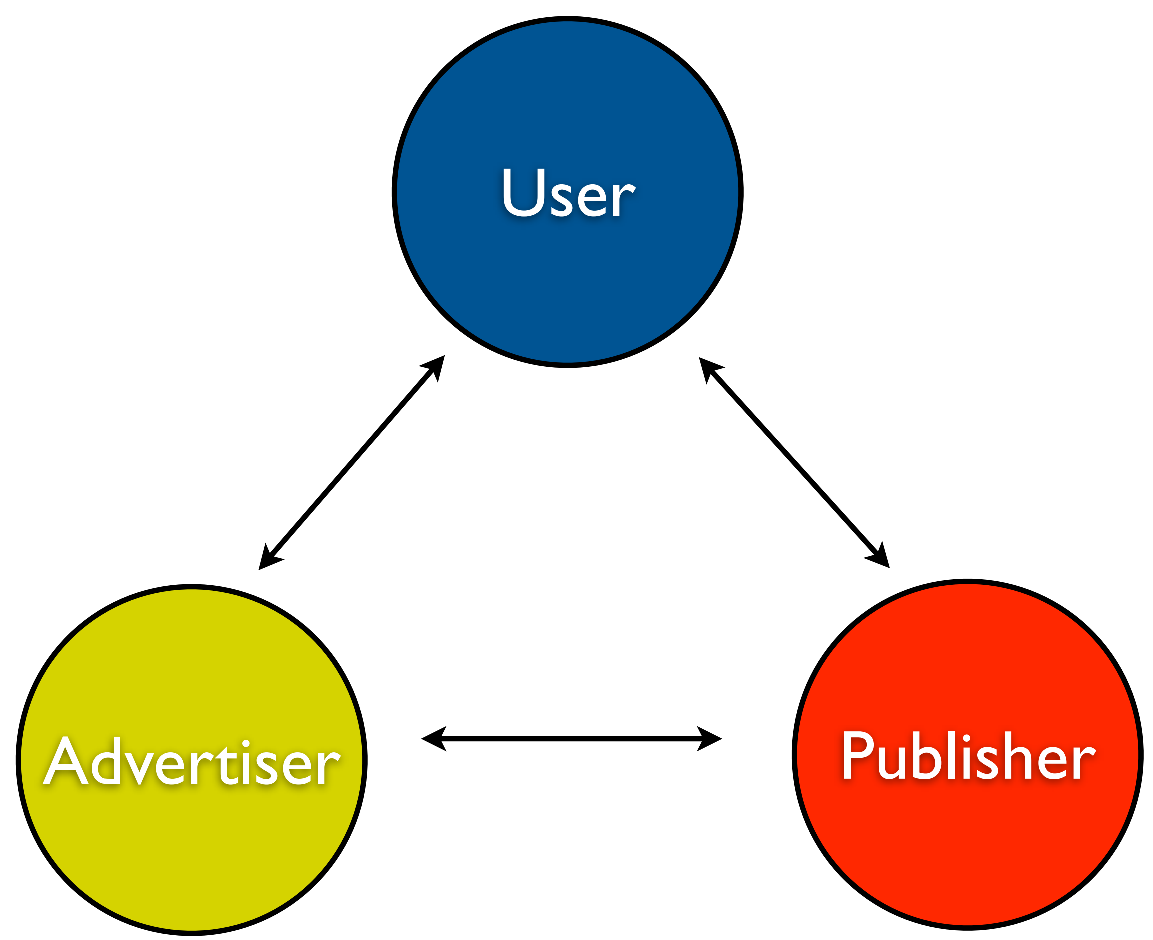
Capturing interesting real-world elements?

Financial risk and market noise

- 6-8 agents compete simultaneously
- Play many games with different market conditions
- Agent with highest average profit wins tournament

Presentation Outline

- Ad auctions game
- Optimization problem (stylized knapsack problem)
    - Model-heavy (greedy multiple choice knapsack algorithm)
    - Model-light (rule-based algorithm)
- Experiments
- Future work


User
Advertiser
Publisher

Every day:

1. Advertisers submit bids

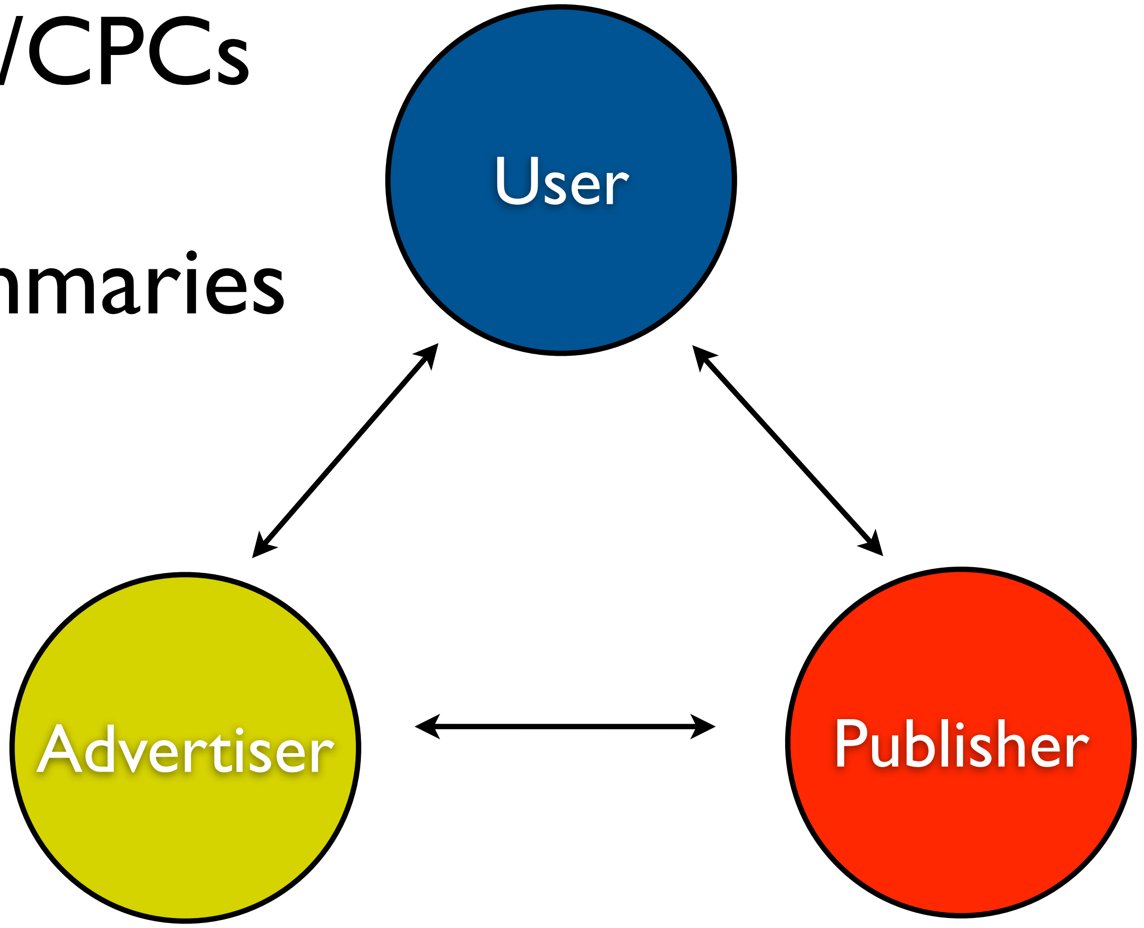
Loop:

A. Users place queries

B. Publisher assigns slots/CPCs

C. Users click/convert

2. Advertisers receive summaries



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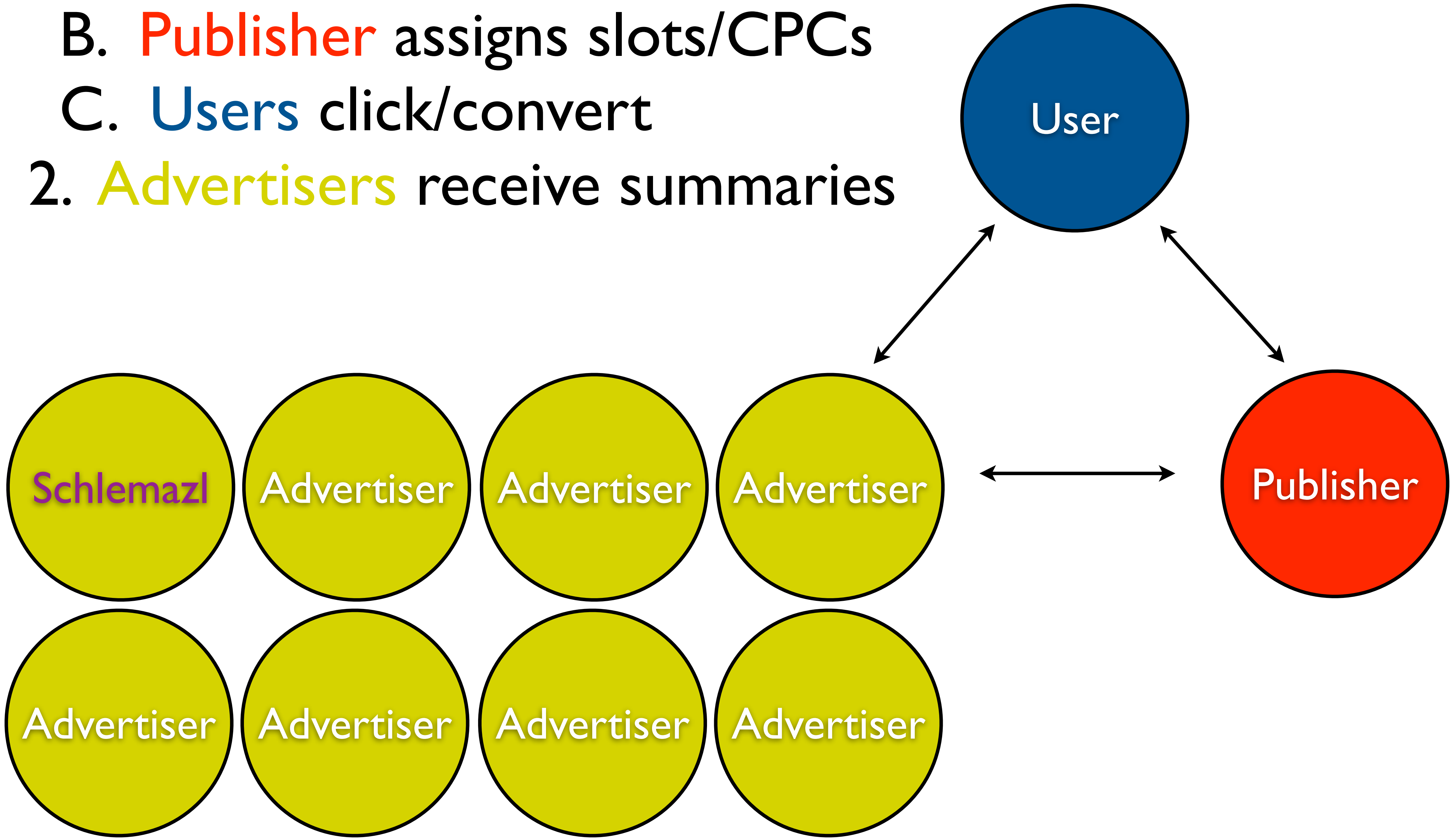
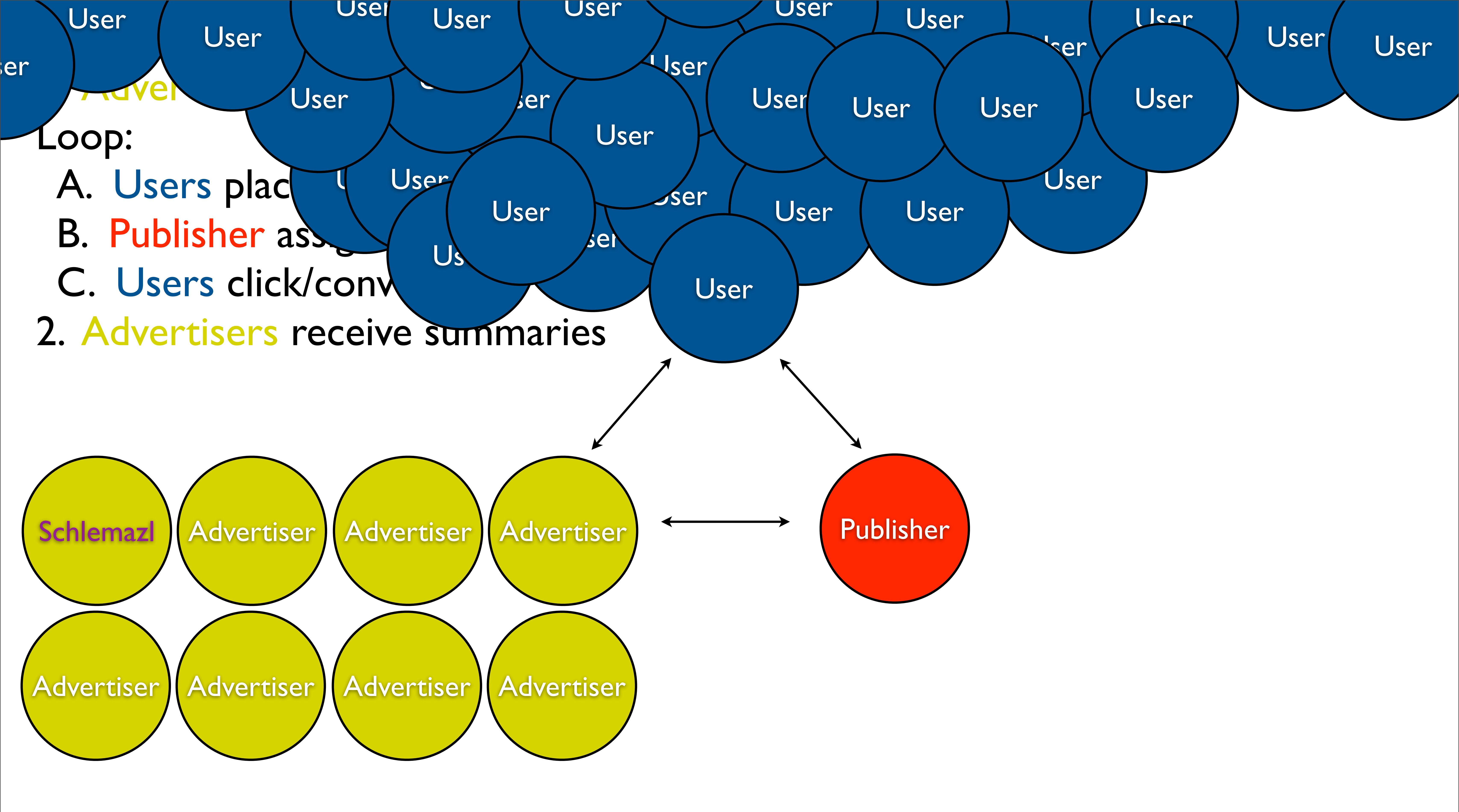



Loop:
A. Users plac
B. Publisher ass
C. Users click/conv
2. Advertisers receive summaries
User
Schlemazl
Advertiser
Publisher


Advertiser
(Retailer)

Advertiser (Retailer)

Components

TV

Audio

DVD

Advertiser (Retailer)

Manufacturers

Lioneer

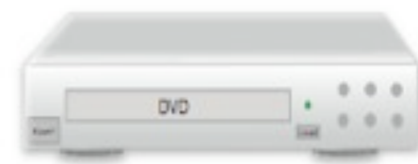
PG

Flat

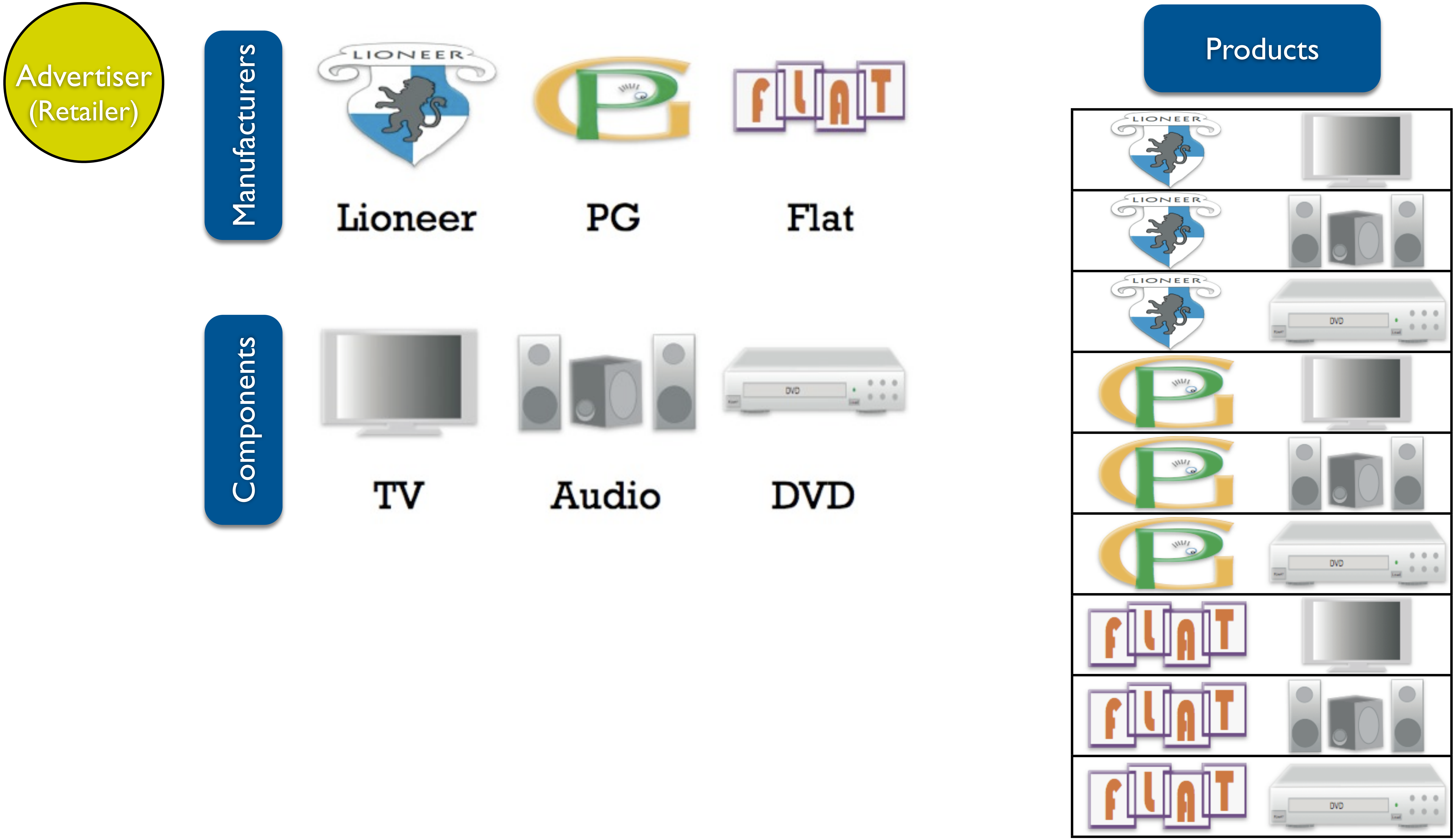
Components

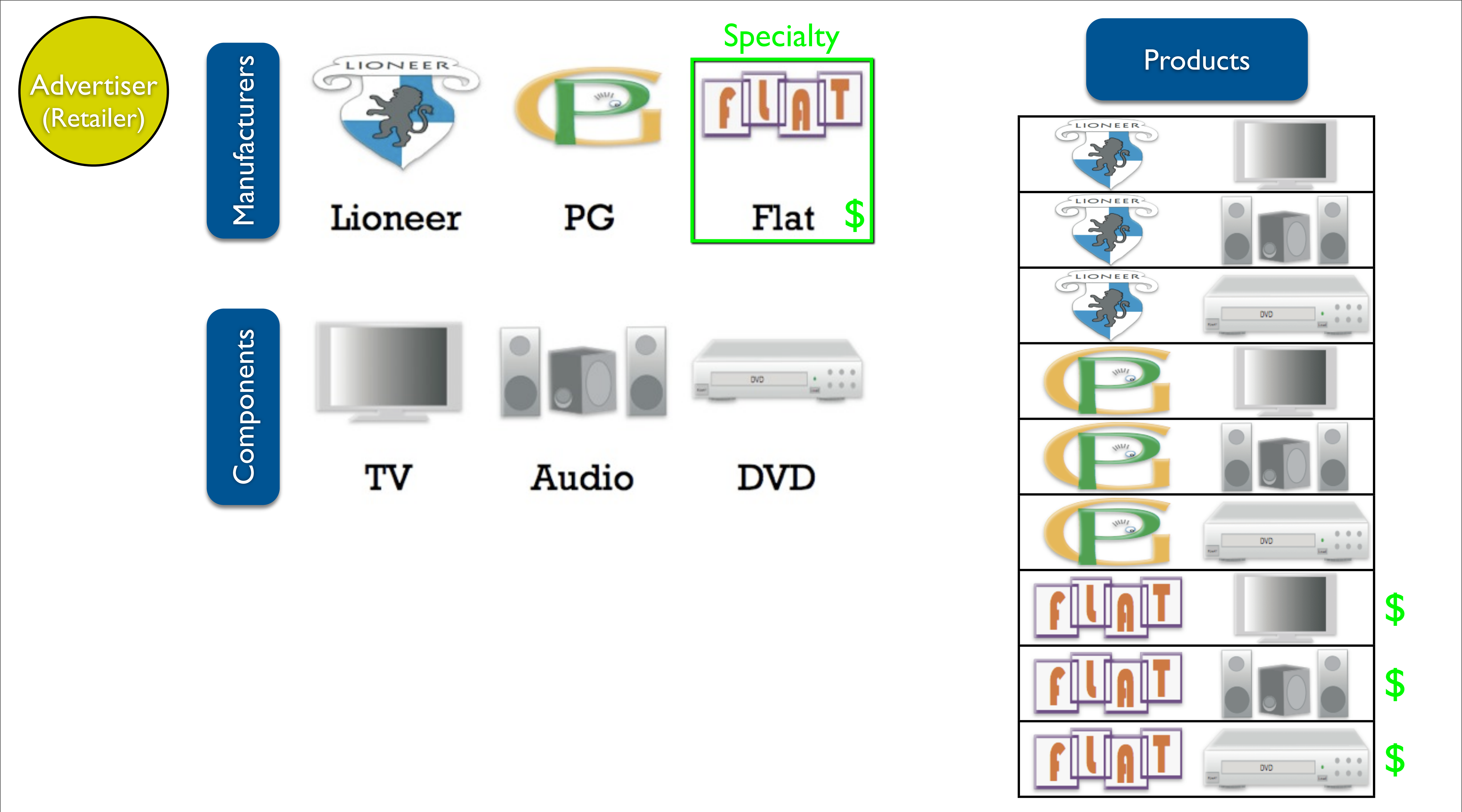
TV

Audio



DVD


Advertiser (Retailer)
Manufacturers
LIONEER
Lioneer
PG
Flat
Components
DVD
TV
Audio
DVD
Products


Advertiser (Retailer)
Manufacturers
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Components
TV
Audio
DVD
Products
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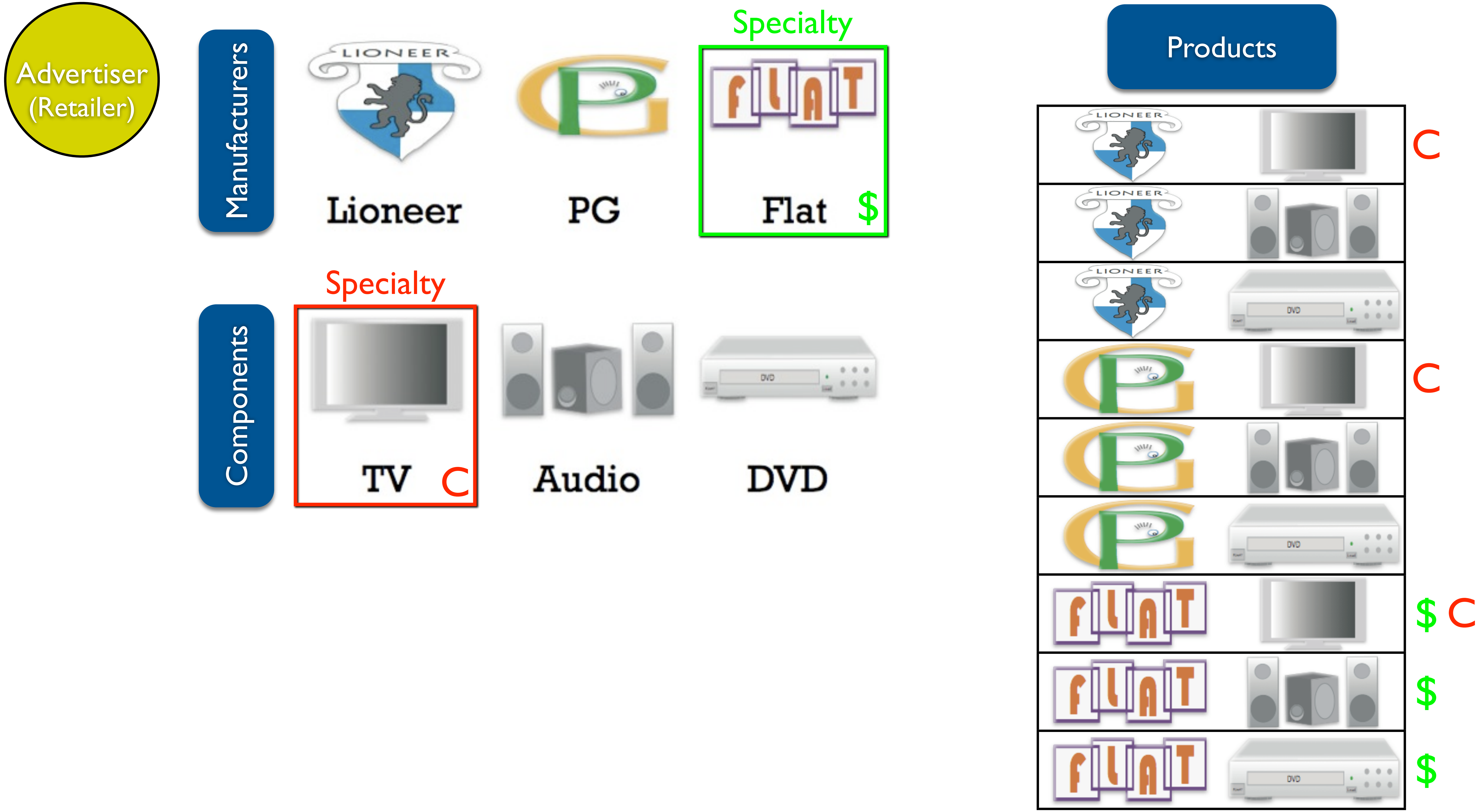
Advertiser (Retailer)
Manufacturers
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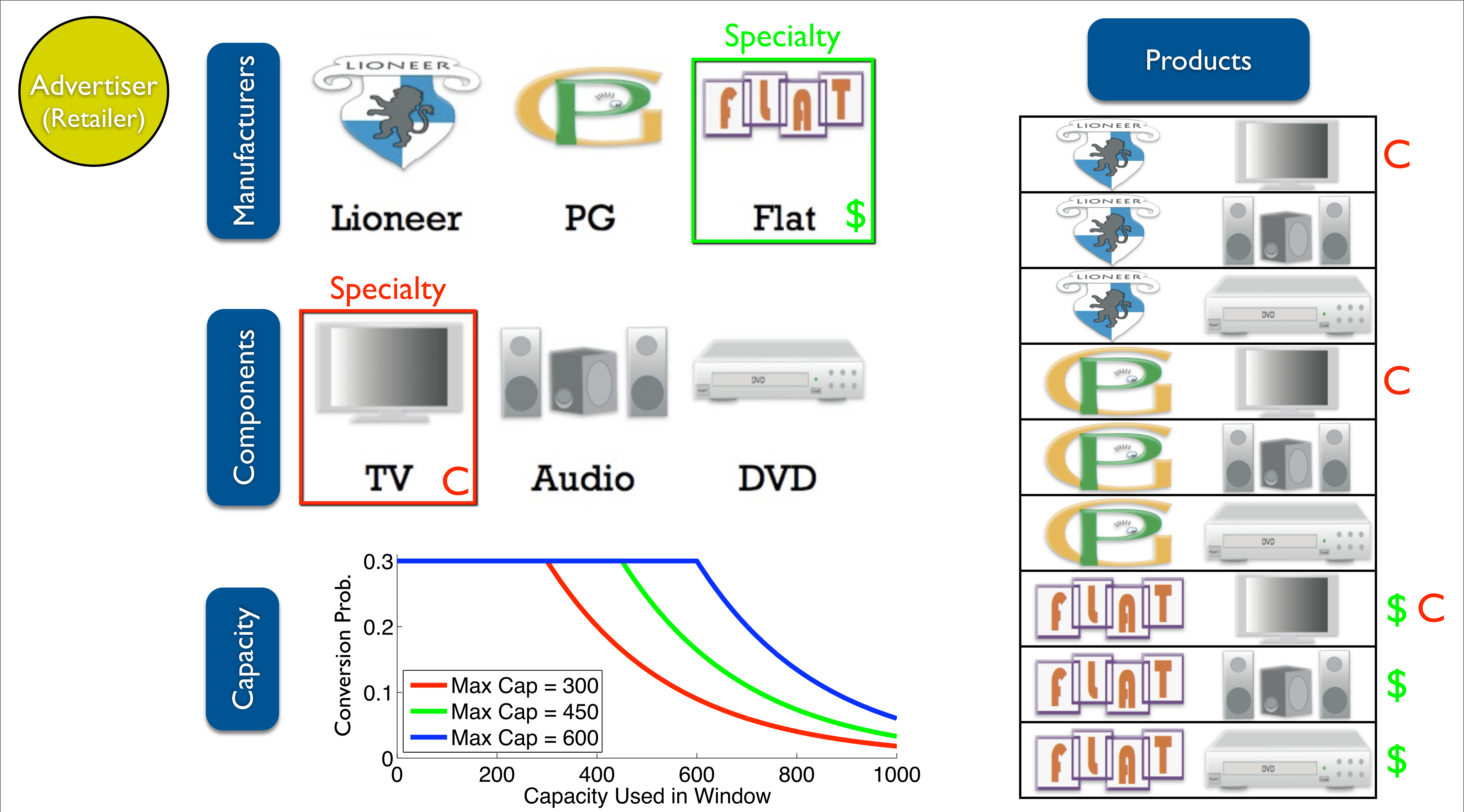

Advertiser (Retailer)
Manufacturers
Lioneer
PG
Specialty
Flat $
Components
Specialty
TV C
Audio
DVD
Capacity
Conversion Prob.
Capacity Used in Window
Max Cap = 300
Max Cap = 450
Max Cap = 600
0
0.1
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200
400
600
800
1000
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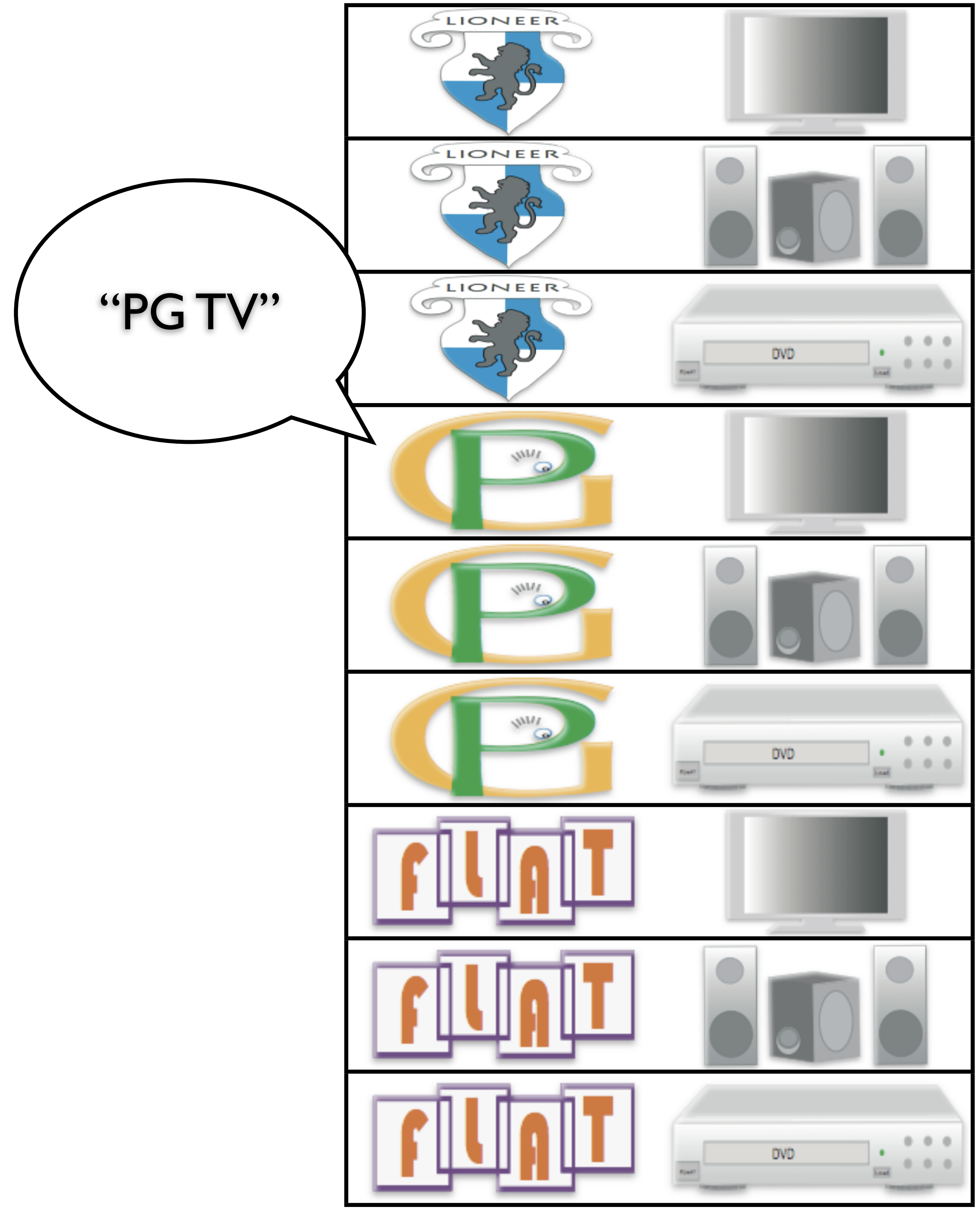
Advertiser (Retailer)

What types of queries can I bid on?

Advertiser (Retailer)

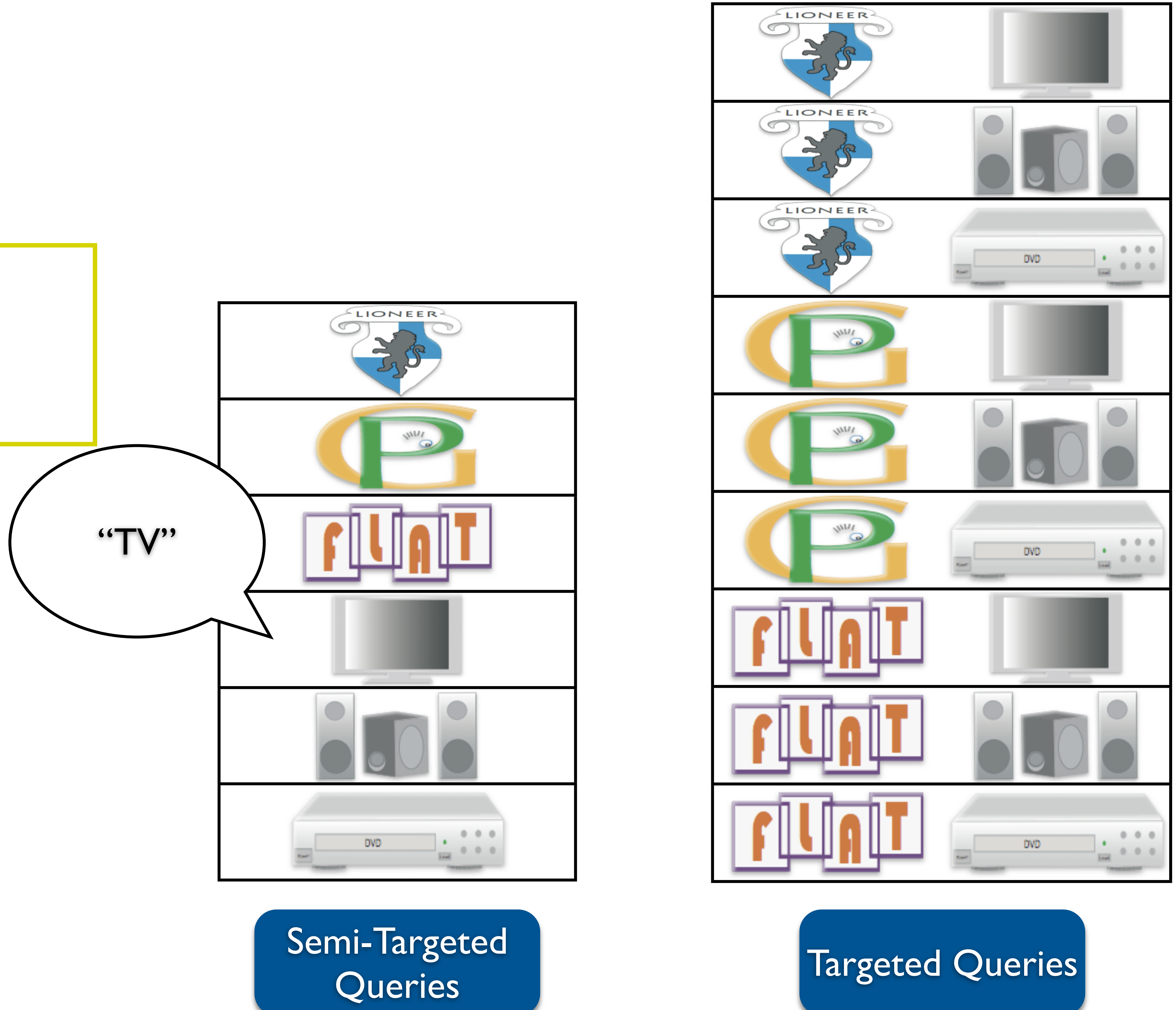
What types of queries can I bid on?
16 total



Targeted Queries

Advertiser (Retailer)

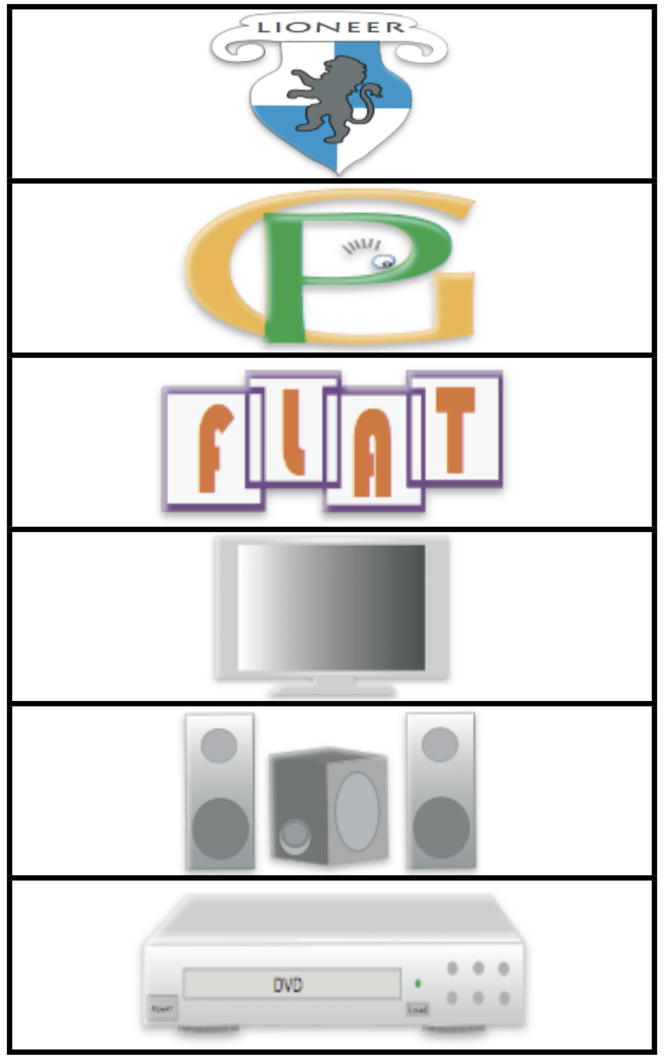
What types of queries can I bid on?
16 total

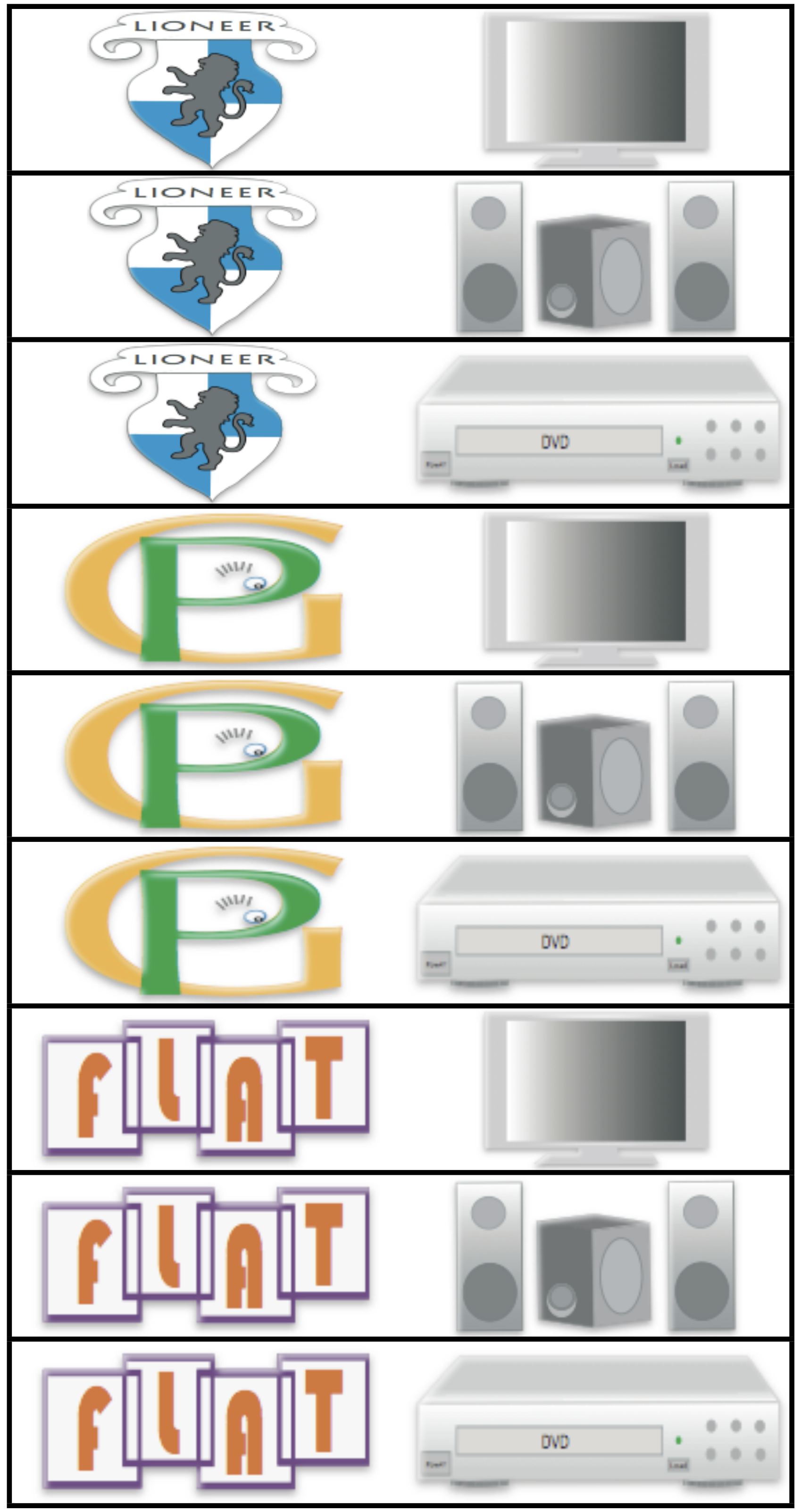


Advertiser (Retailer)

What types of queries can I bid on?
16 total

“Electronics”



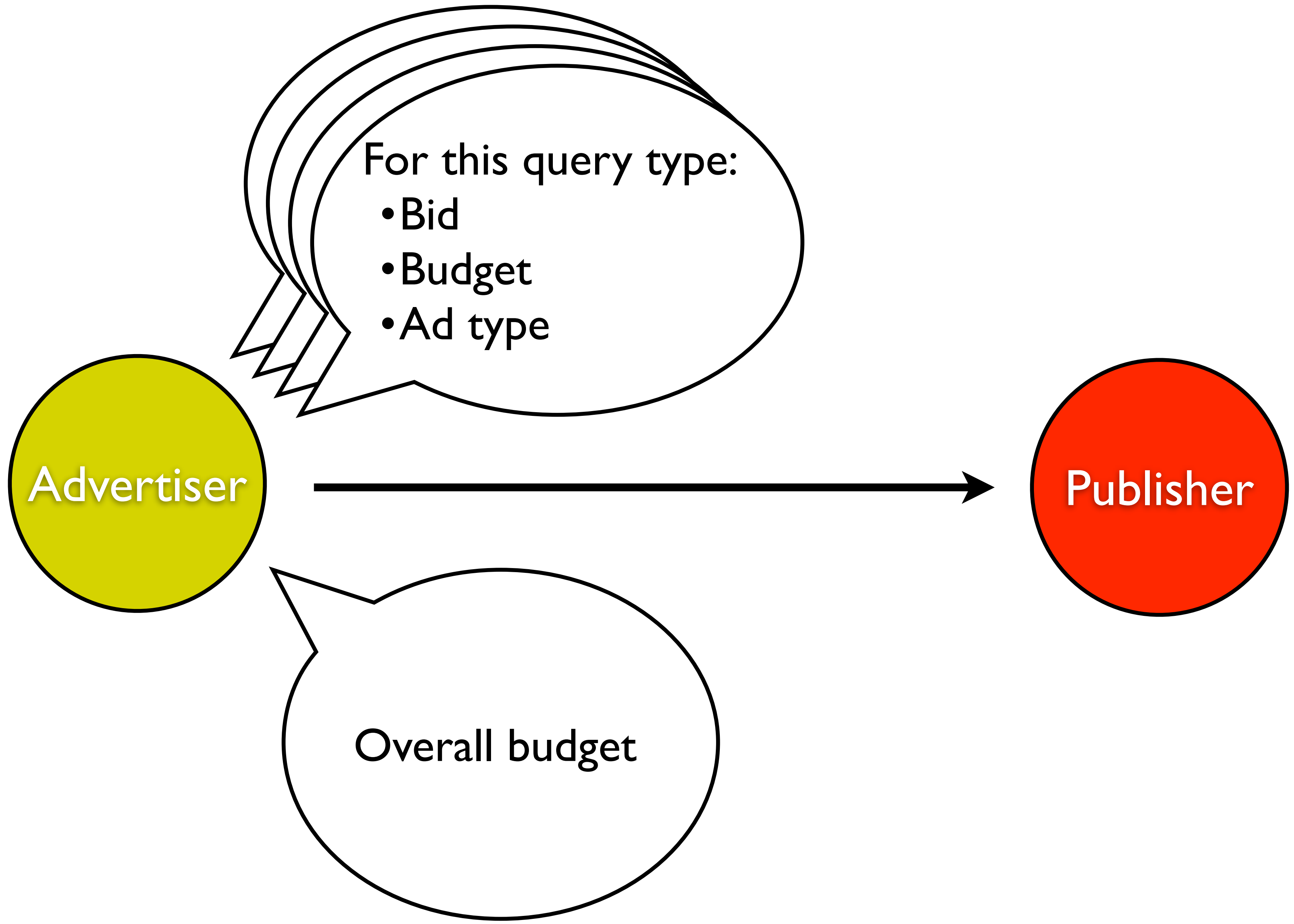


Generic Query

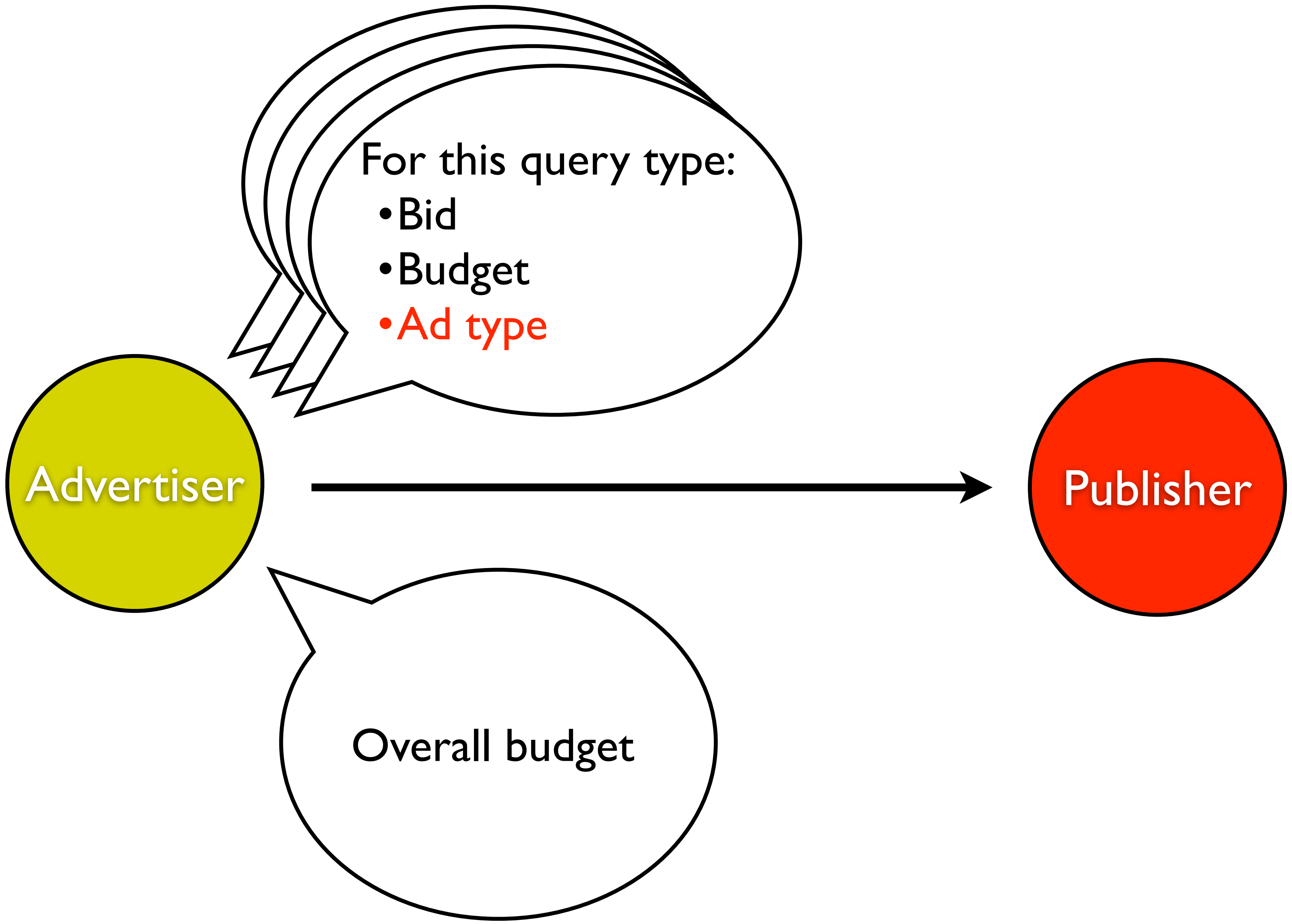
Semi-Targeted Queries

Targeted Queries

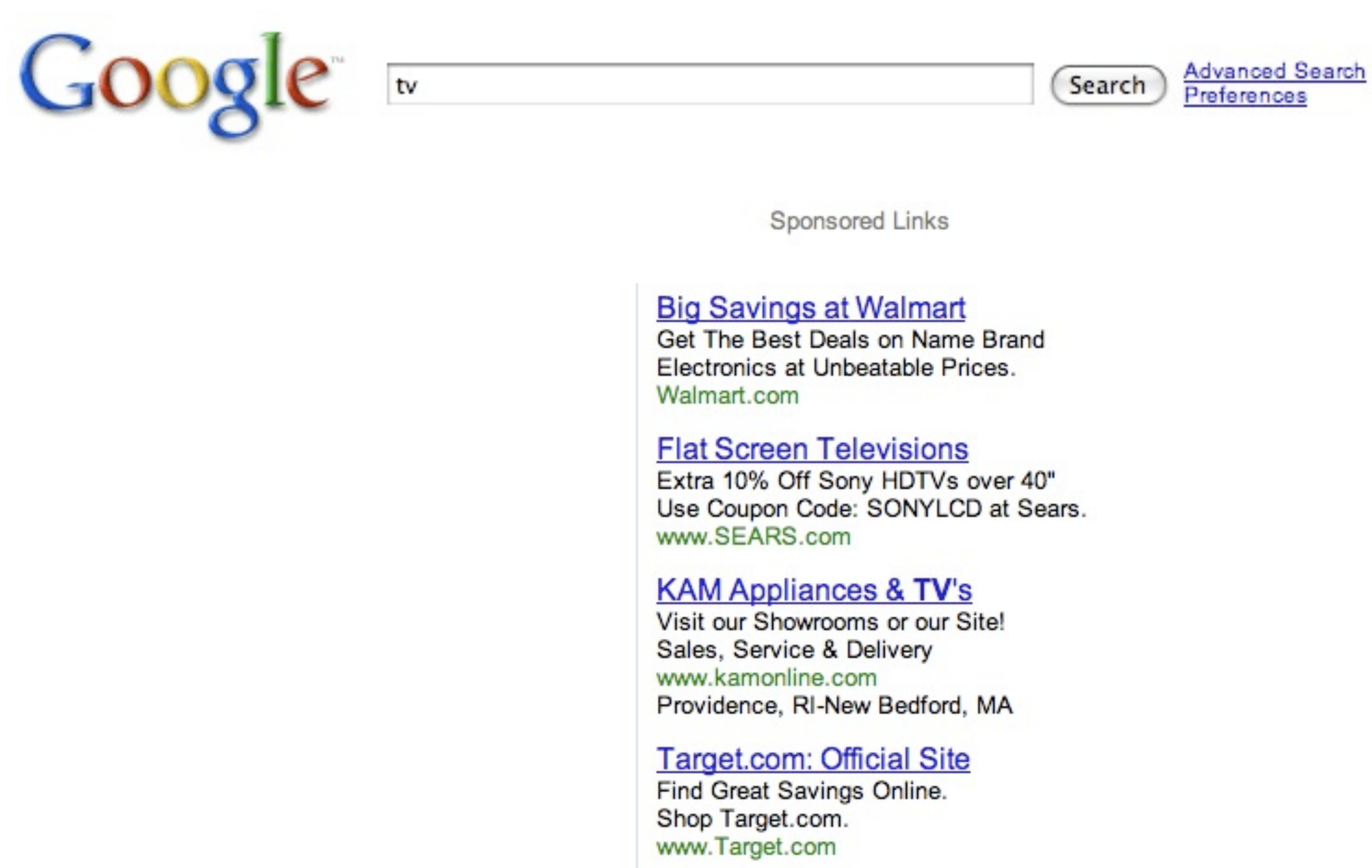
Advertiser decisions



Advertiser decisions




Google
tv
Search
Advanced Search
Preferences


Google
tv
Search
Advanced Search
Preferences
Sponsored Links
Big Savings at Walmart
Get The Best Deals on Name Brand
Electronics at Unbeatable Prices.
Walmart.com
Flat Screen Televisions
Extra 10% Off Sony HDTVs over 40"
Use Coupon Code: SONYLCD at Sears.
www.SEARS.com
KAM Appliances & TV's
Visit our Showrooms or our Site!
Sales, Service & Delivery
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Providence, RI-New Bedford, MA
Target.com: Official Site
Find Great Savings Online.
Shop Target.com.
www.Target.com

Google

tv

Search

Advanced Search
Preferences

Sponsored Links

Generic Ad

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Providence, RI-New Bedford, MA

Generic Ad

Target.com: Official Site
Find Great Savings Online.
Shop Target.com.
www.Target.com

Google

tv

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Find Great Savings Online.
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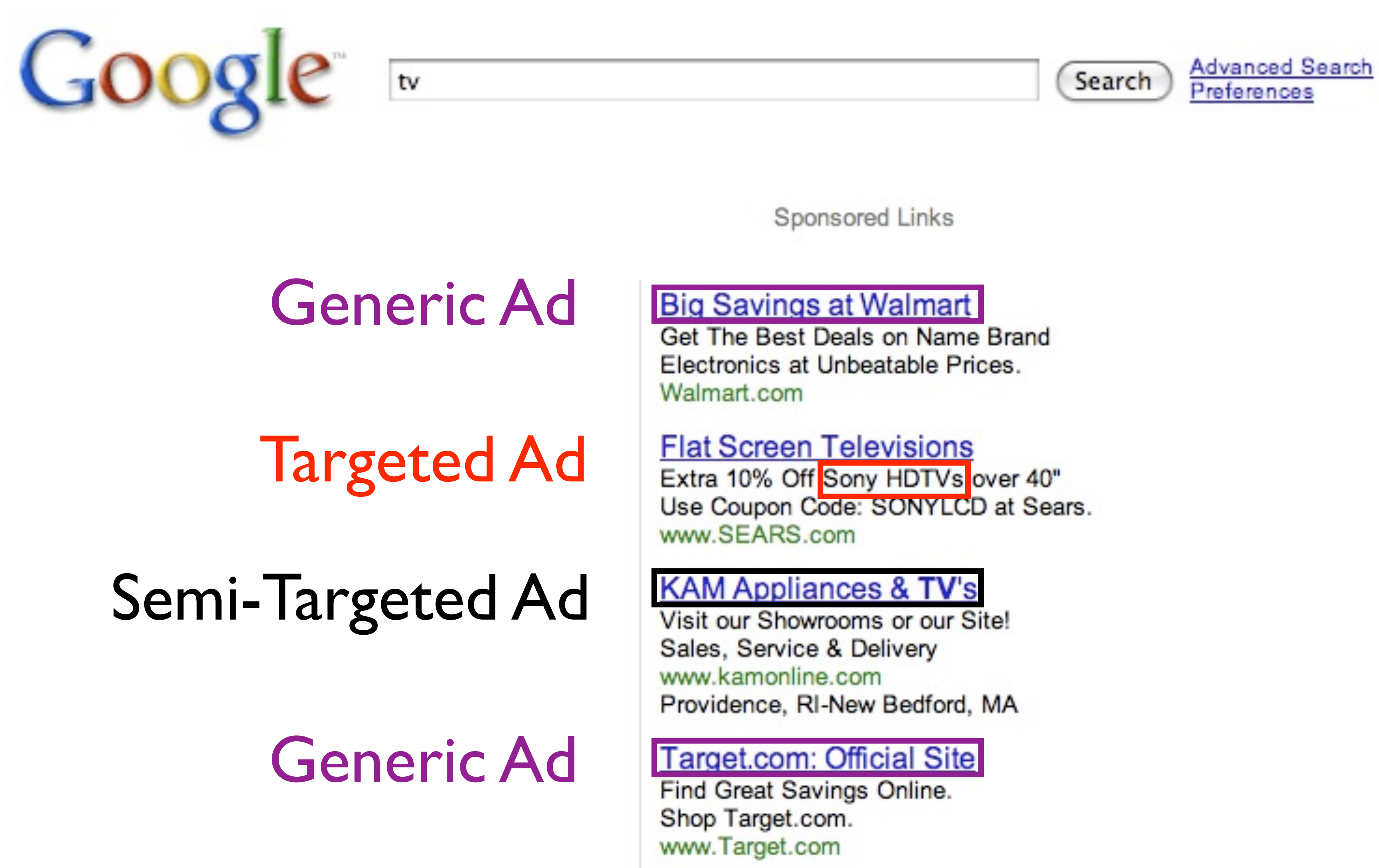
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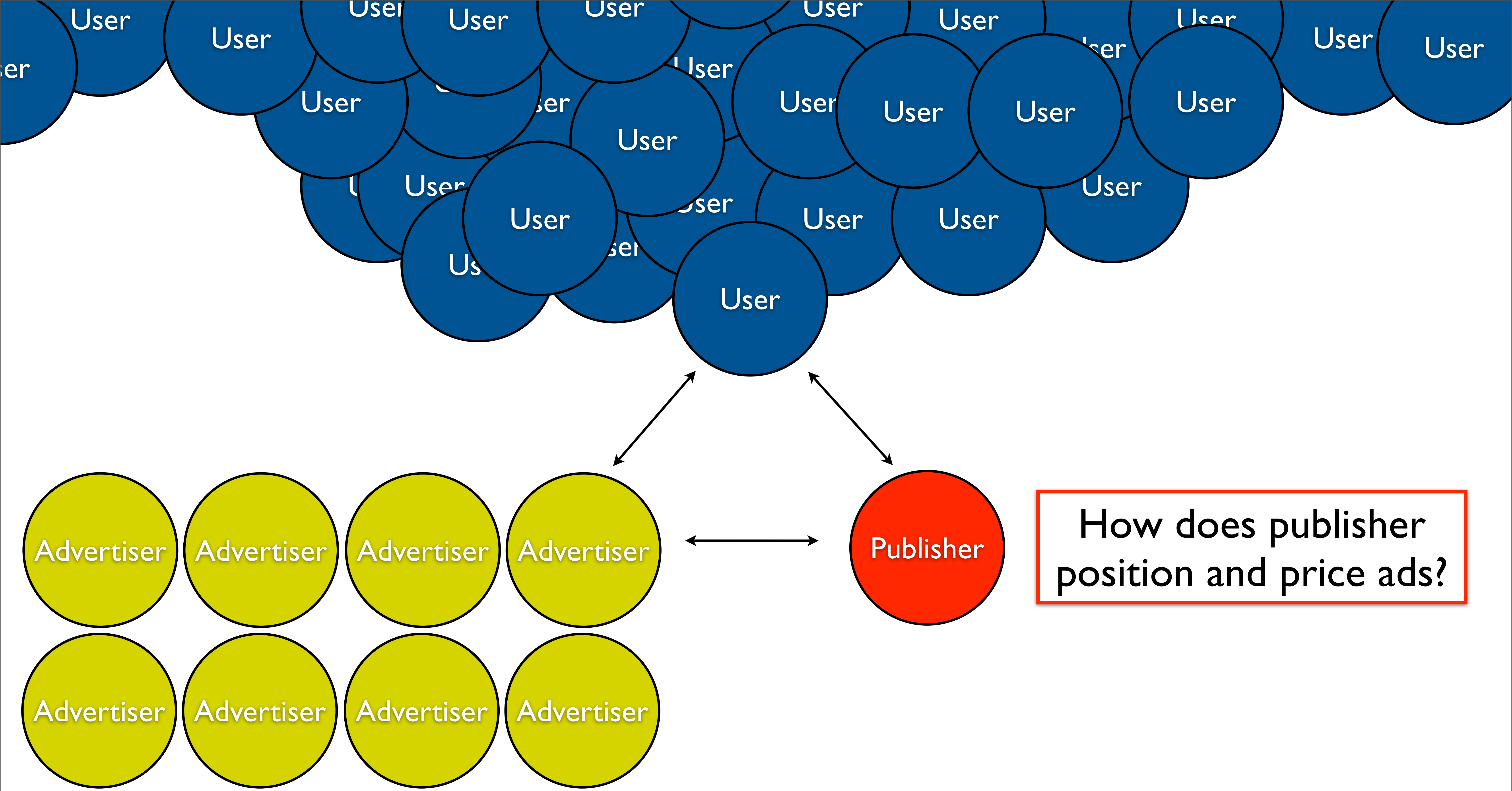
Generic Ad
Target.com: Official Site
Find Great Savings Online.
Shop Target.com.
www.Target.com

Advertiser Summaries

Advertiser	Ad Type	Average Slot	Average CPC	Impressions	Clicks	Conversions
	Generic	1.0				
		1.2	2.57	1000	200	50
		2.6				



How does publisher position and price ads?

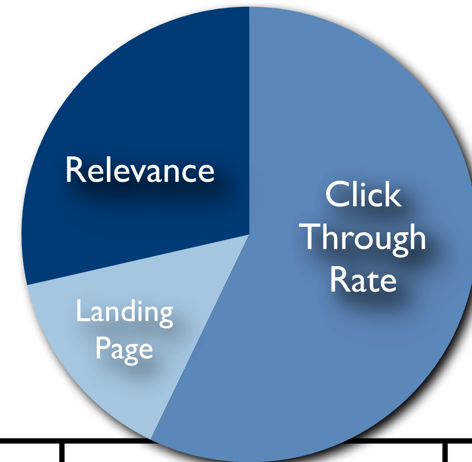
Publisher

Query

Advertiser	Bid	Quality	Score	Slot	CPC
	$4				
	$3				
	$2				
	$1				

Publisher

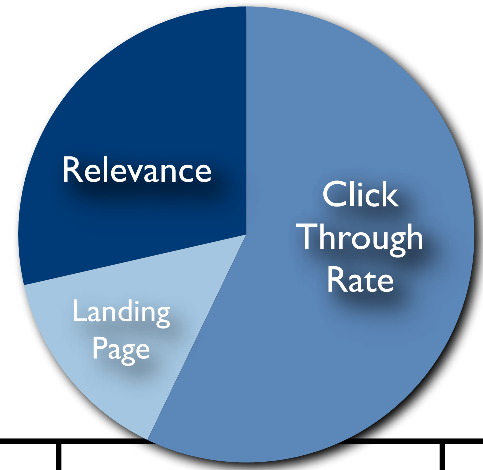
Query



Advertiser	Bid	Quality	Score	Slot	CPC
	$4	1			
	$3	3			
	$2	6			
	$1	8			

Publisher

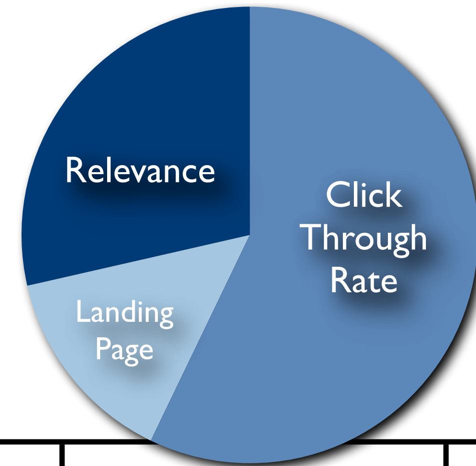
Query



Advertiser	Bid	x Quality	= Score	Slot	CPC
	$4	1	4		
	$3	3	9		
	$2	6	12		
	$1	8	8		

Publisher

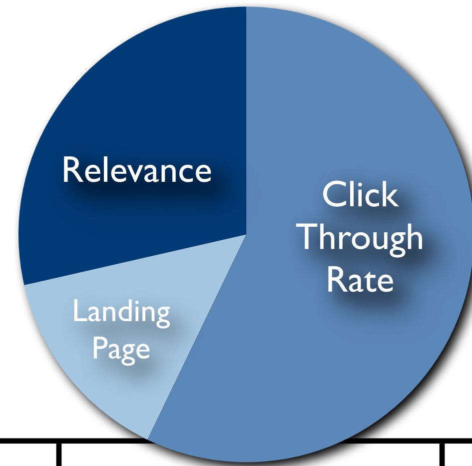
Query



Advertiser	Bid x	Quality =	Score	Slot	CPC
	$4	1	4	X	
	$3	3	9	2	
	$2	6	12	1	
	$1	8	8	3	

Publisher

Query

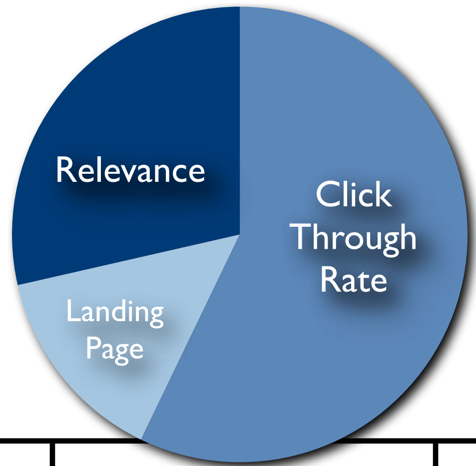


(Minimum bid to retain slot)

Advertiser	Bid x	Quality =	Score	Slot	CPC
	$4	1	4	X	
	$3	3	9	2	
	$2	6	12	1	(9/6) = $1.50
	$1	8	8	3	

Publisher

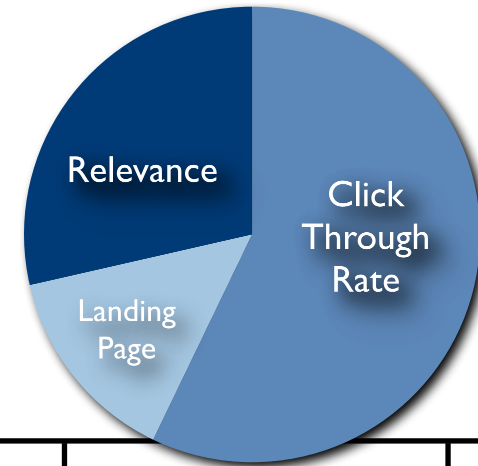
Query



(Minimum bid to retain slot)

Advertiser	Bid	x Quality	= Score	Slot	CPC
	$4	1	4	X	
	$3	3	9	2	(8/3) = $2.67
	$2	6	12	1	(9/6) = $1.50
	$1	8	8	3	

Publisher

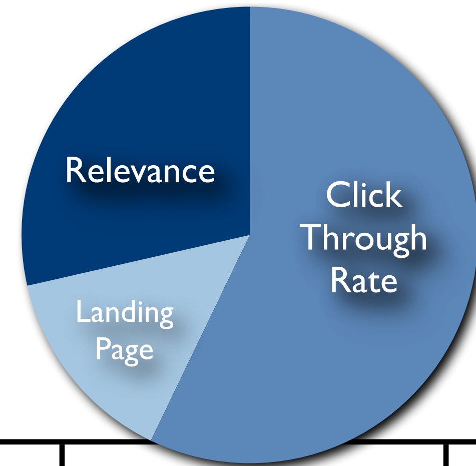


(Minimum bid to retain slot)

Advertiser	Bid	x Quality	= Score	Slot	CPC
	$4	1	4	X	
	$3	3	9	2	(8/3) = $2.67
	$2	6	12	1	(9/6) = $1.50
	$1	8	8	3	(4/8) = $0.50

Publisher

Query

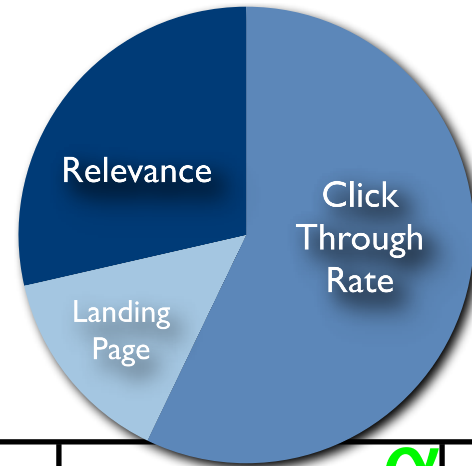


(Minimum bid to retain slot)

Advertiser	Bid	x Quality	= Score	Slot	CPC
	$4	1	4	X	X
	$3	3	9	2	(8/3) = $2.67
	$2	6	12	1	(9/6) = $1.50
	$1	8	8	3	(4/8) = $0.50

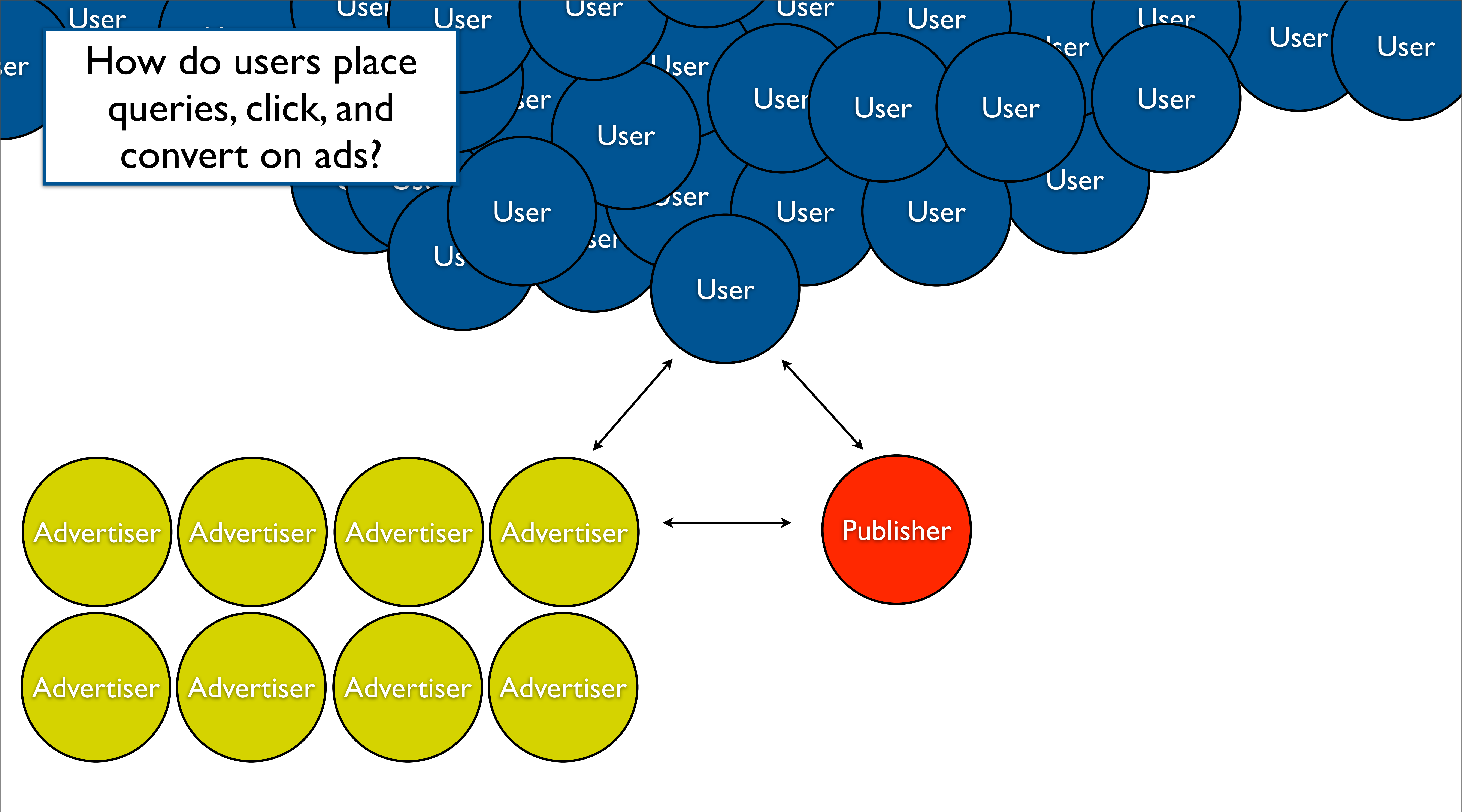
Publisher

Query



(Minimum bid to retain slot)

Advertiser	Bid	$\times(\text{Quality})^{\alpha} =$	Score	Slot	CPC
	\$4	1	4	X	X
	\$3	3	9	2	(8/3) = \$2.67
	\$2	6	12	1	(9/6) = \$1.50
	\$1	8	8	3	(4/8) = \$0.50


How do users place queries, click, and convert on ads?
User
User
User
User
User
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User
User
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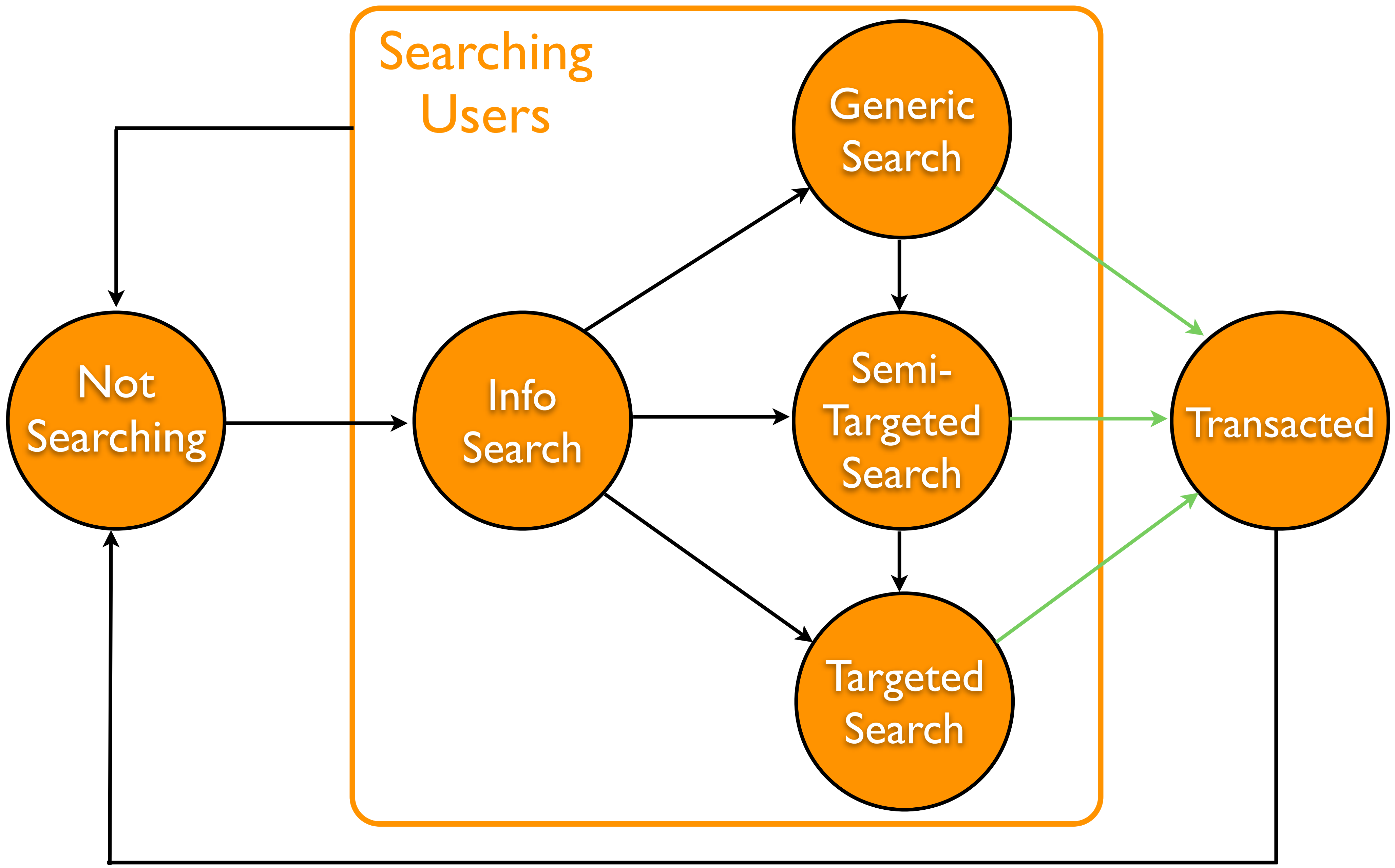
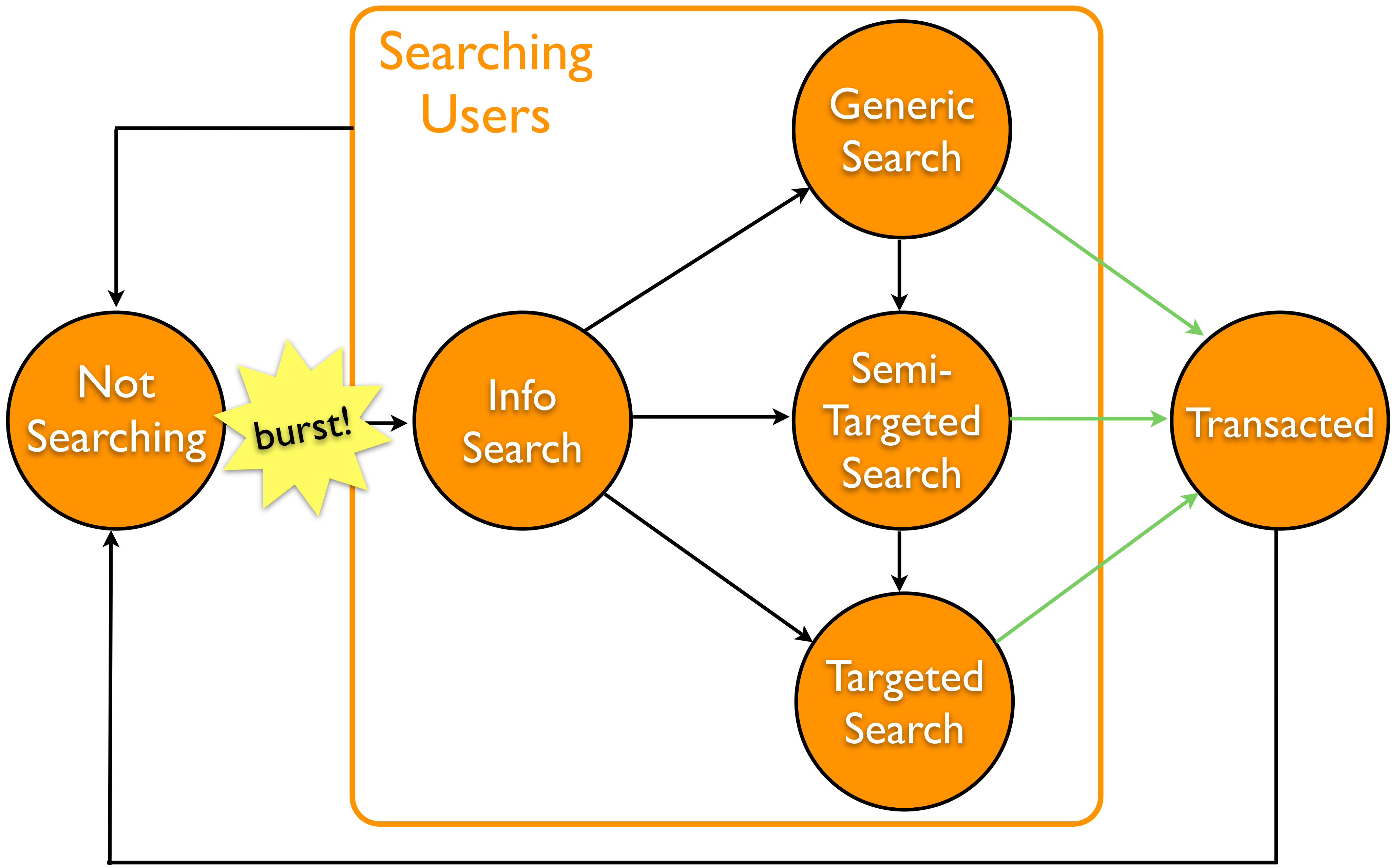
User
Advertiser
Advertiser
Advertiser
Advertiser
Advertiser
Advertiser
Advertiser
Advertiser
Publisher

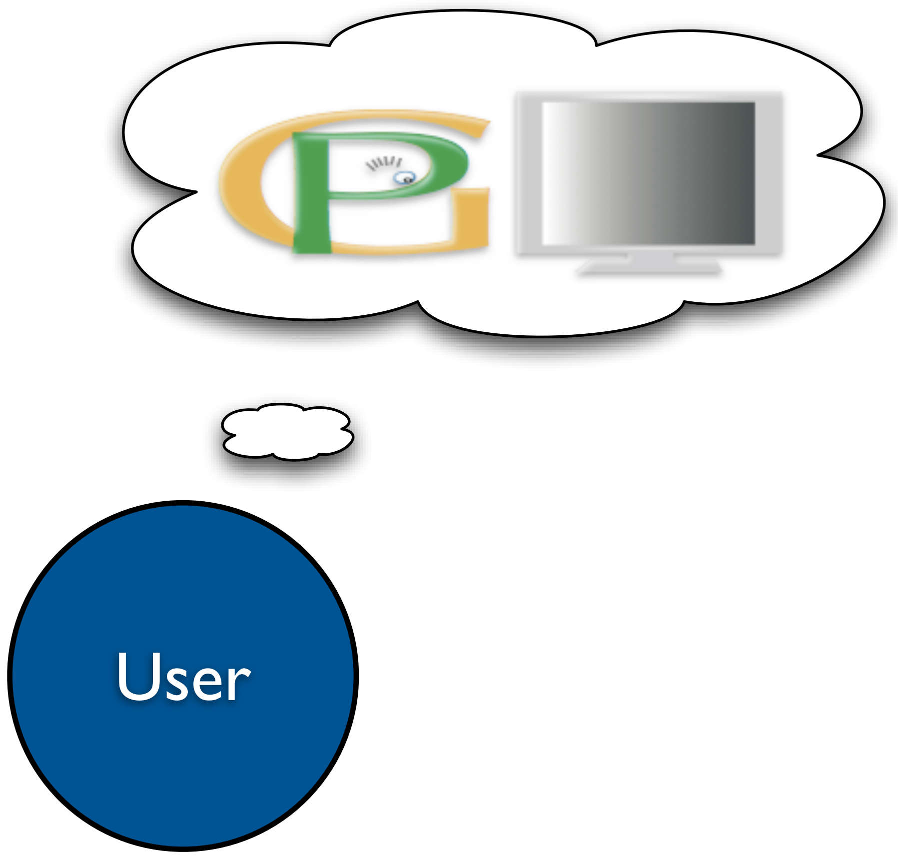
User State Model



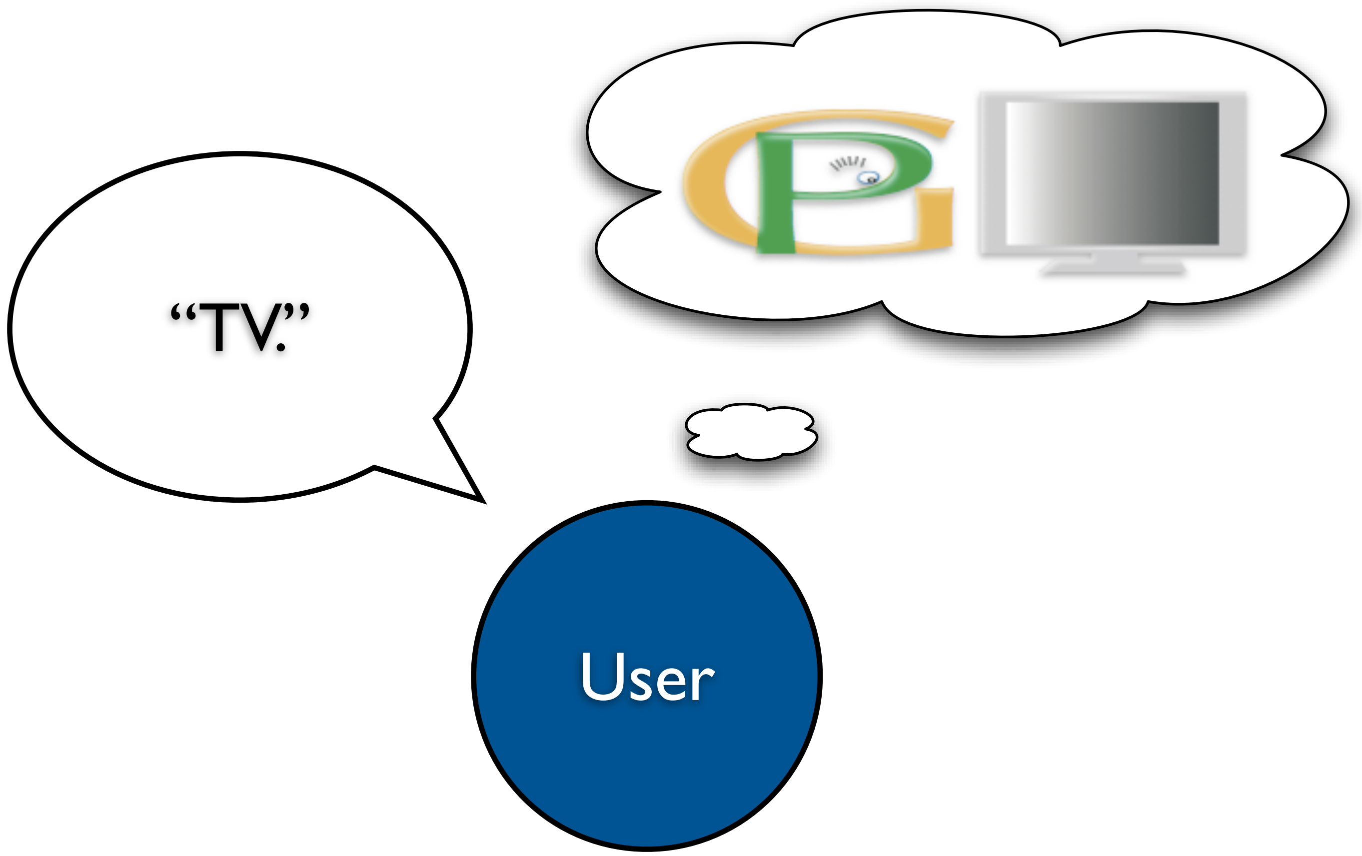
User State Model



User Click Model



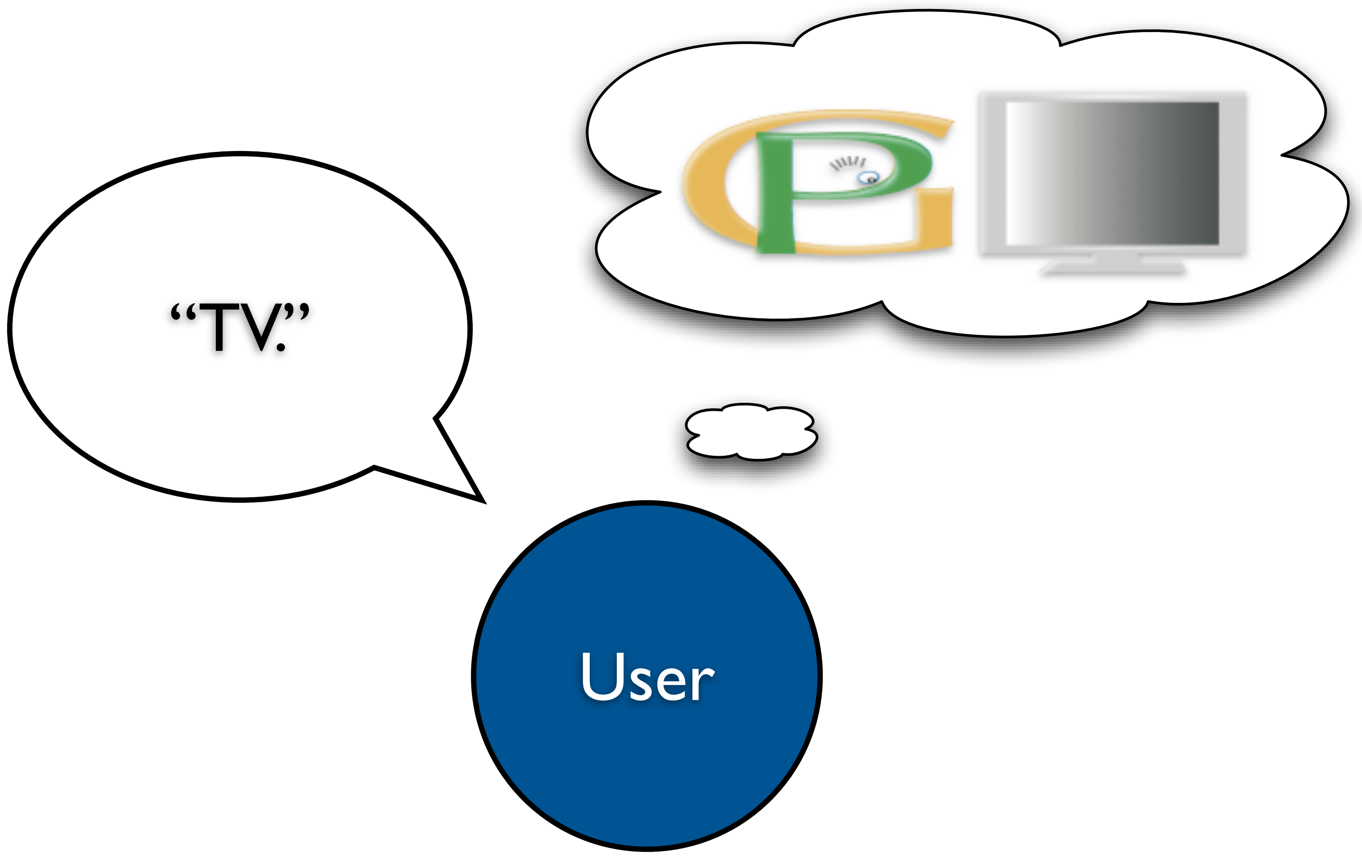
User Click Model



User Click Model

Query

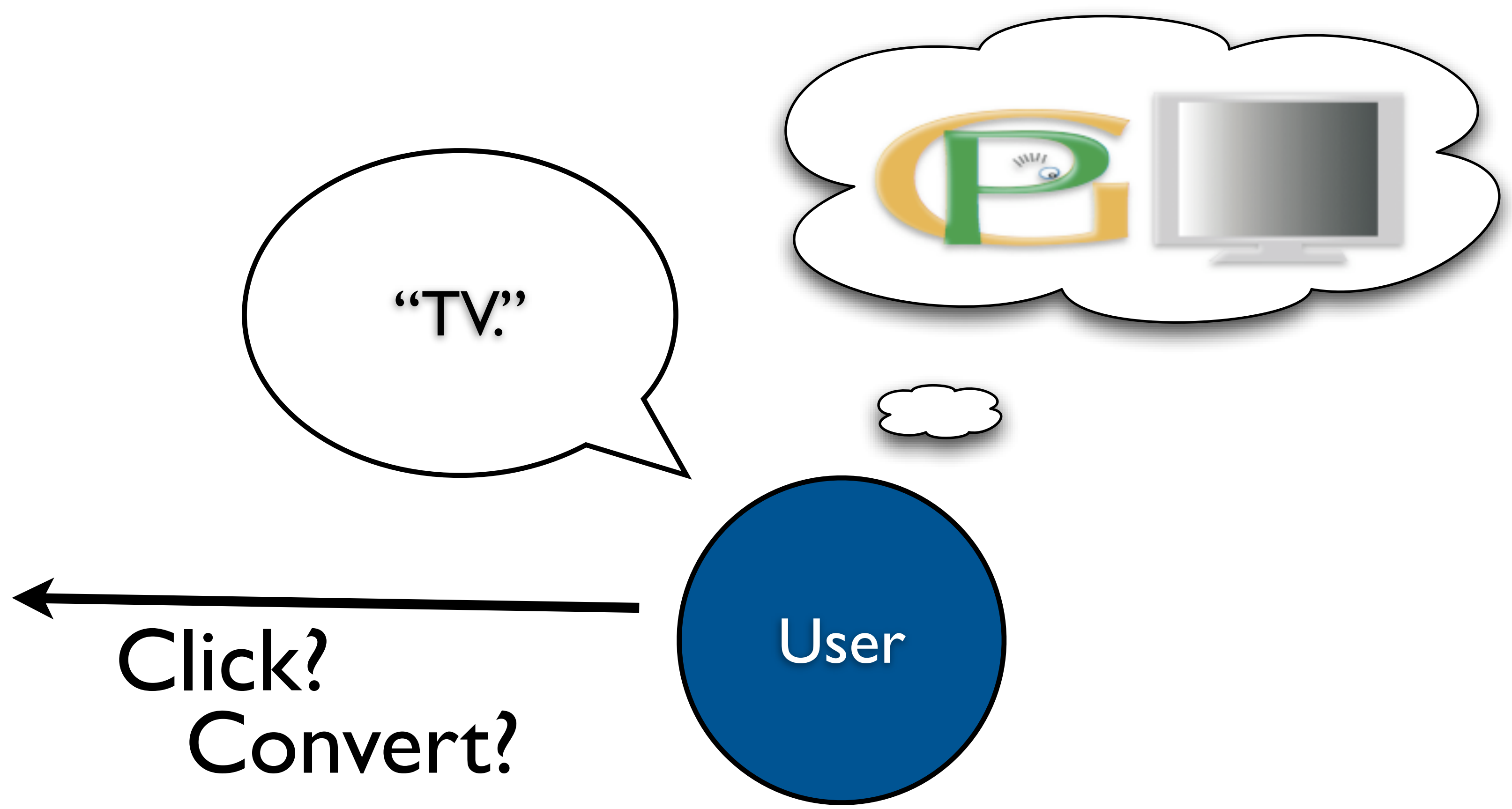
Slot	Advertiser	Ad Type
1		Generic
2		
3		



User Click Model

Query

Slot	Advertiser	Ad Type
1		Generic
2		LIONEER
3		



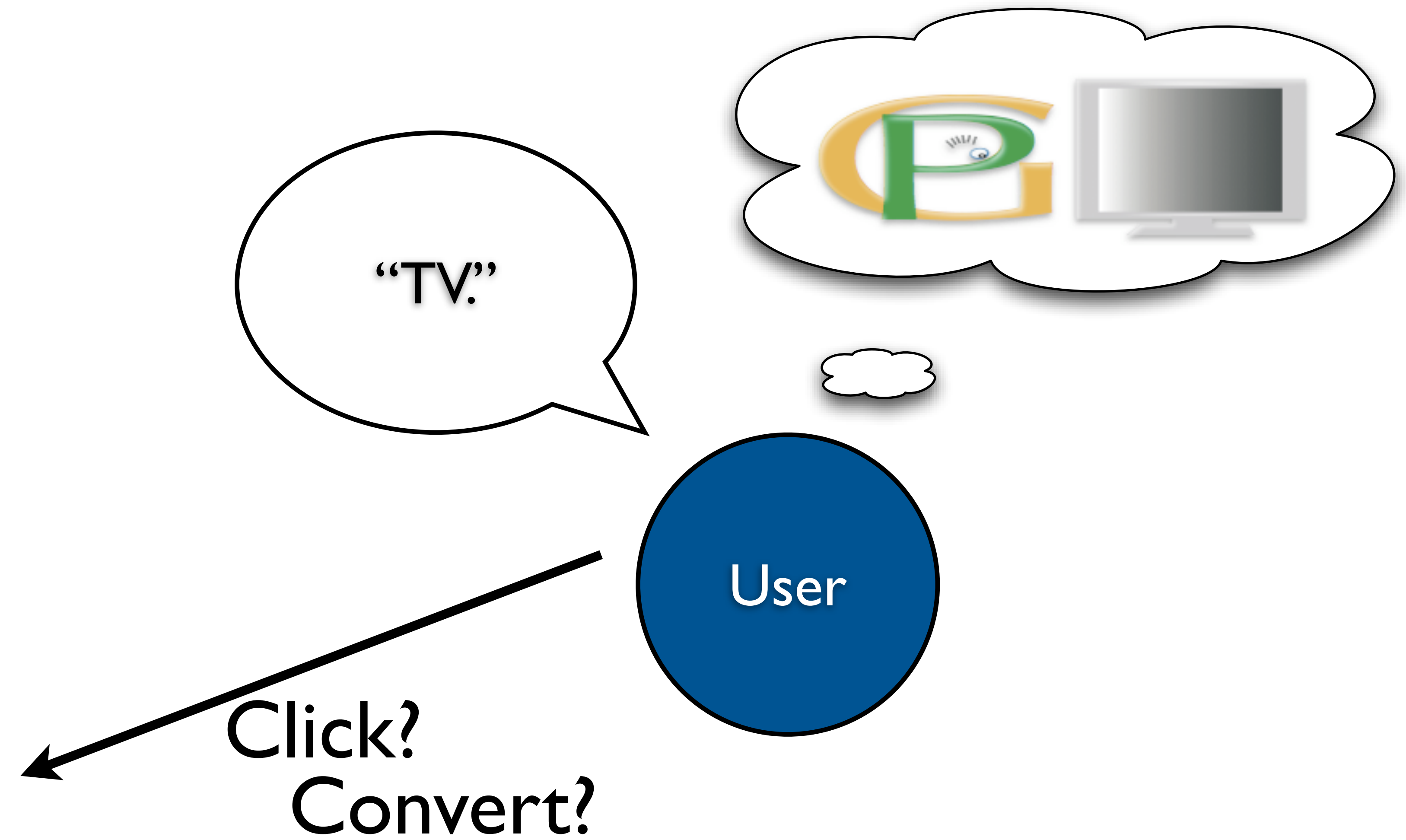
Pr(Click): advertiser quality, ad type

Pr(Convert): user state, capacity, comp. specialty

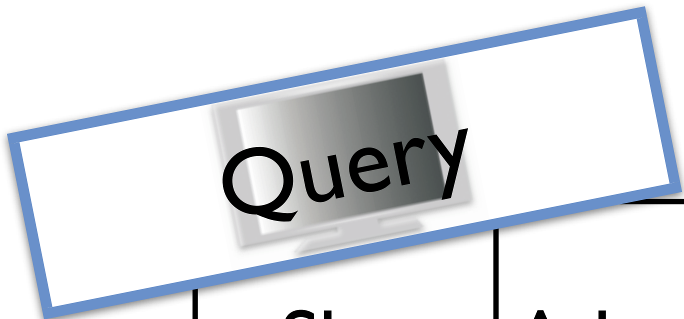
User Click Model

Query

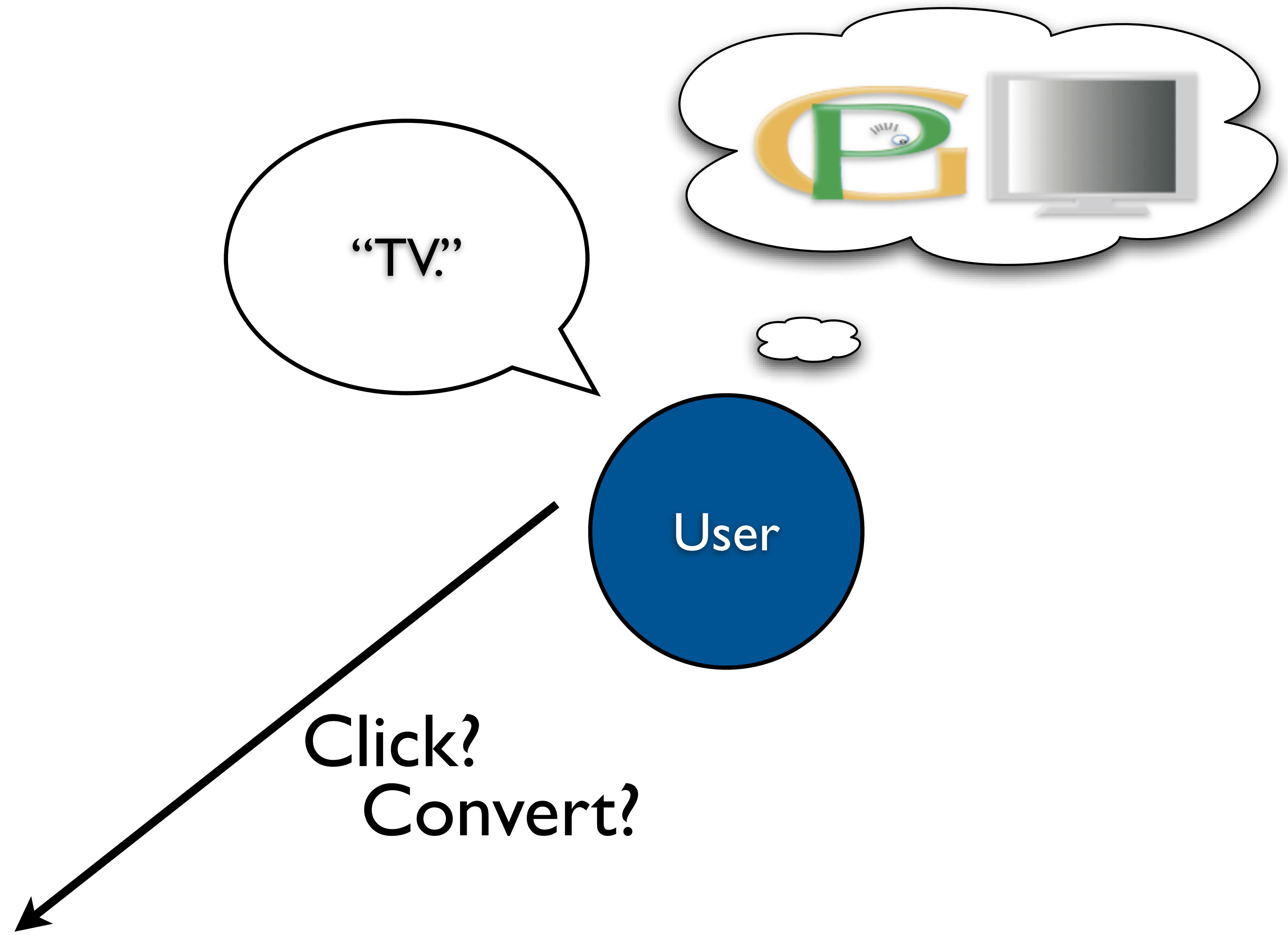
Slot	Advertiser	Ad Type
1		Generic
2		LIONEER 
3		



User Click Model



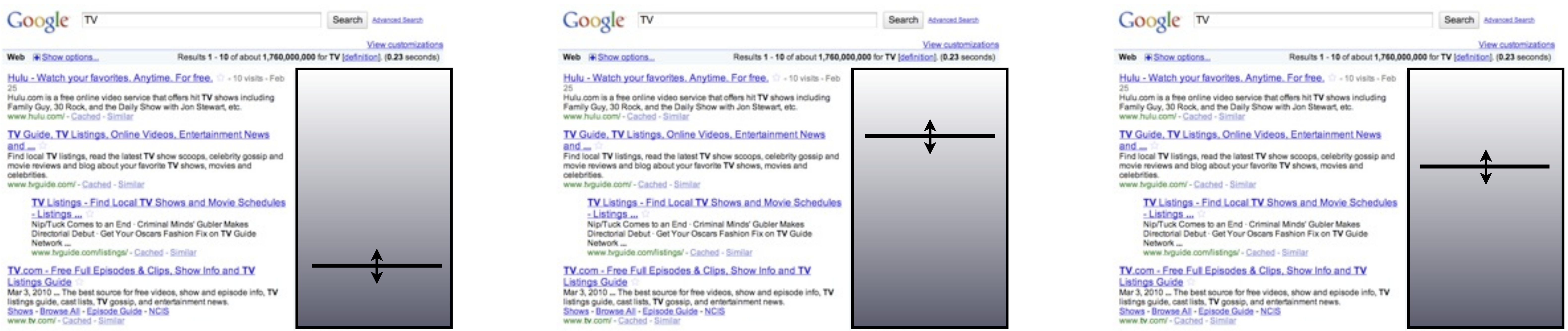
Slot	Advertiser	Ad Type
1		Generic
2		
3		



Presentation Outline

- Ad auctions game
- Optimization problem (stylized knapsack problem)
  - Model-heavy (greedy multiple choice knapsack algorithm)
  - Model-light (rule-based algorithm)
- Experiments
- Future work

Stylized Knapsack Problem



Assume: capacity constraint is hard.

Stylized Knapsack Problem

$$\max_{\vec{s}\in\mathbb{R}^n_+} \sum_{q\in Q} (rev_q(\bar{s}_q) - cost_q(\bar{s}_q)) \quad \text{s.t.}$$

$$\sum_{q\in Q} sales_q(\bar{s}_q) \leq C$$

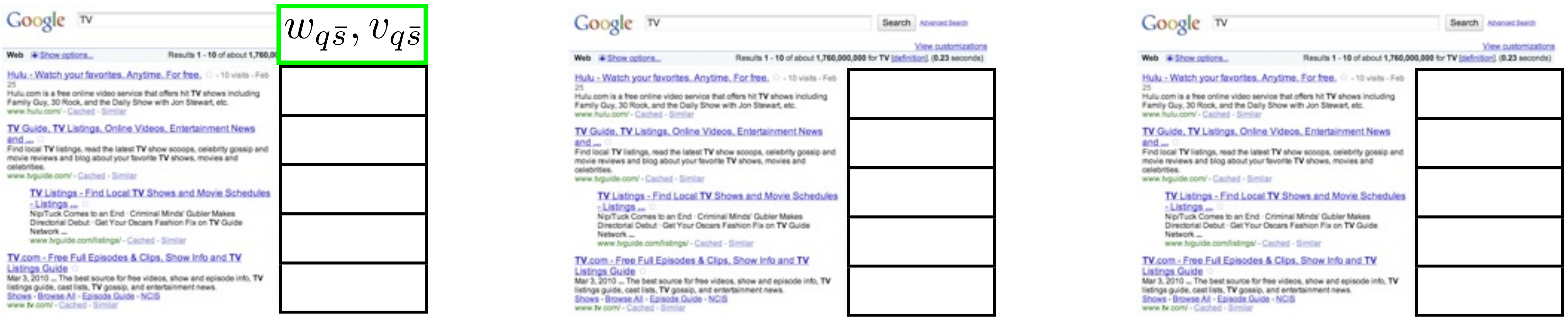
- Equimarginal principle: equating marginal return on investment (marginal ROI) across uses (queries) maximizes profit, assuming diminishing marginal returns.

$$\begin{aligned} rev_q(\bar{s}_q) &= sales_q(\bar{s}_q)\,USP_q \\ cost_q(\bar{s}_q) &= numClicks(\bar{s}_q)\,CPC_q(\bar{s}_q) \\ sales_q(\bar{s}_q) &= numClicks(\bar{s}_q)\,PrConv_q(\bar{s}_q) \\ numClicks(\bar{s}_q) &= i_q PrClick_q(\bar{s}_q) \end{aligned}$$

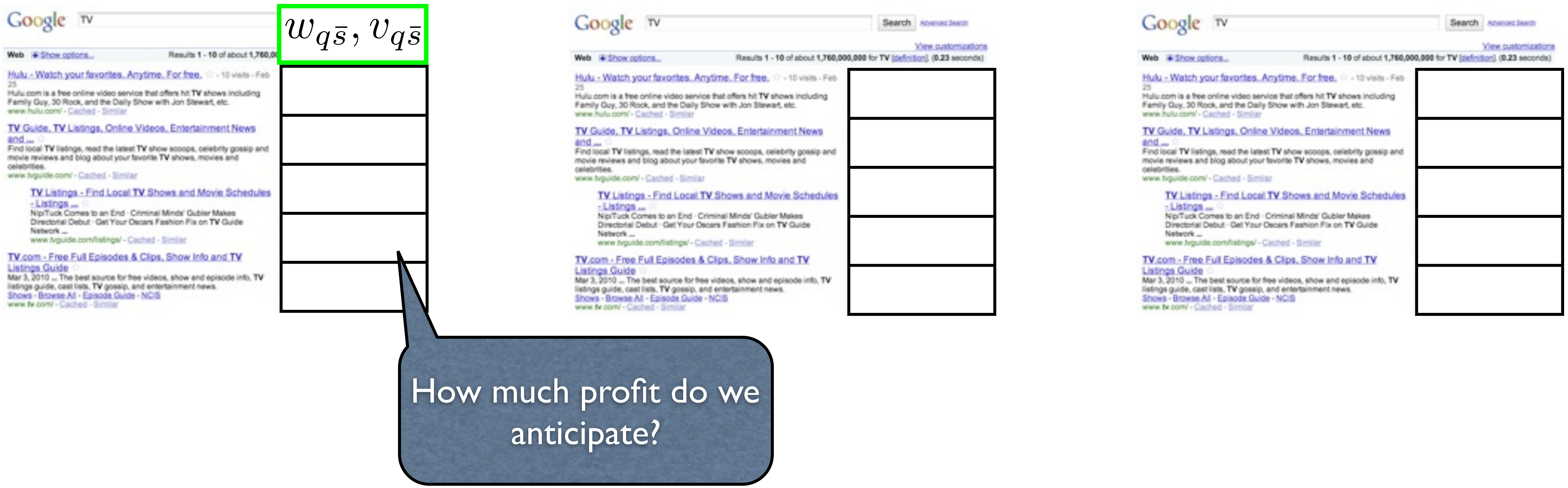
Presentation Outline

- Ad auctions game
- Agent architecture
- Optimization problem (stylized knapsack problem)
  - Model-heavy (greedy multiple choice knapsack algorithm)
  - Model-light (rule-based algorithm)
- Experiments
- Future work

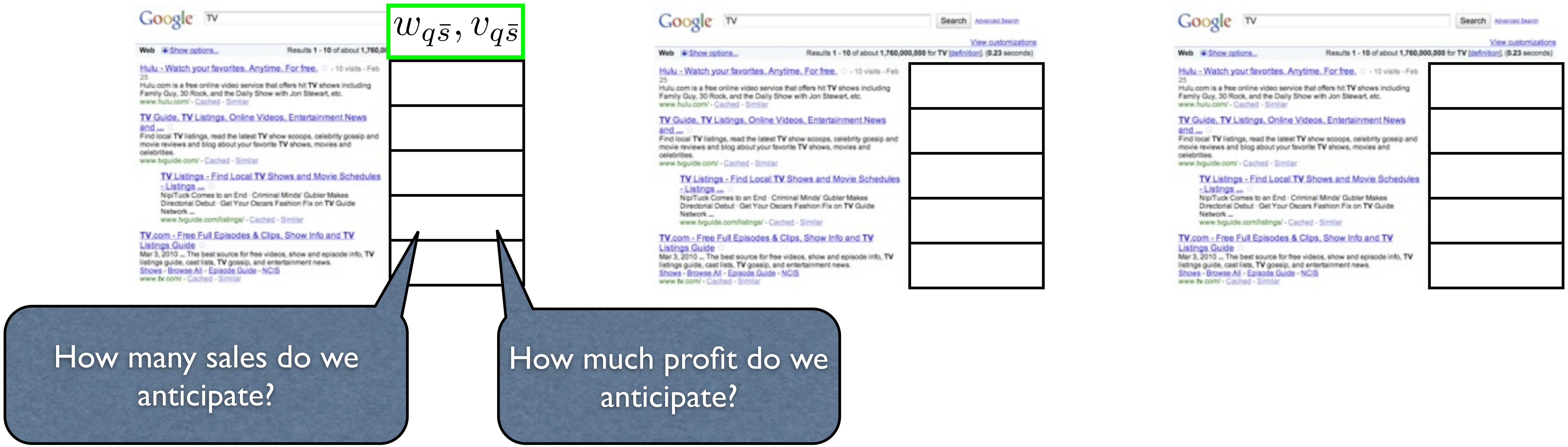
Model-heavy optimization



Model-heavy optimization

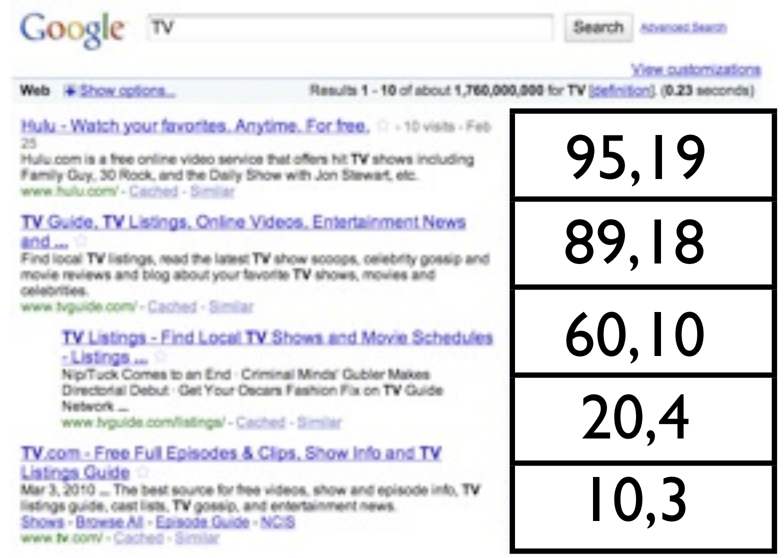


Model-heavy optimization



Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
90,20
89,18
60,10
20,4
10,3



95,19
89,18
60,10
20,4
10,3

67,18
65,13
60,10
20,4
10,3

How many sales do we anticipate?

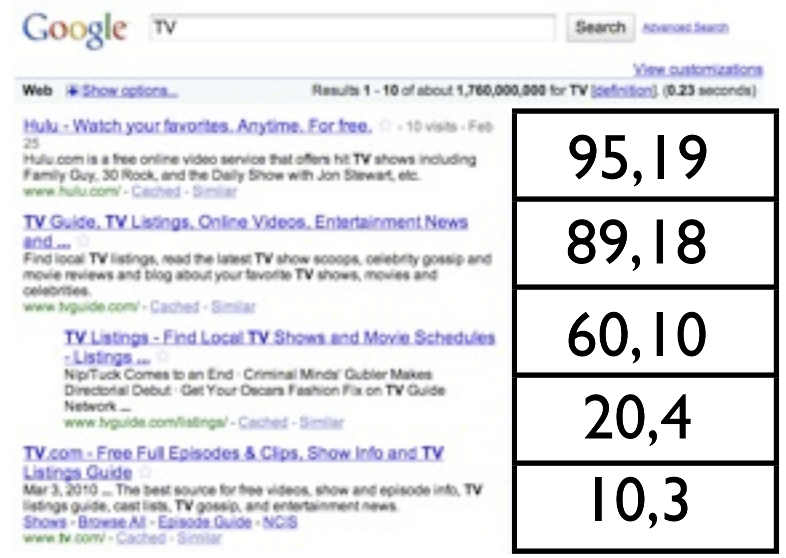
How much profit do we anticipate?

Models give us these values.

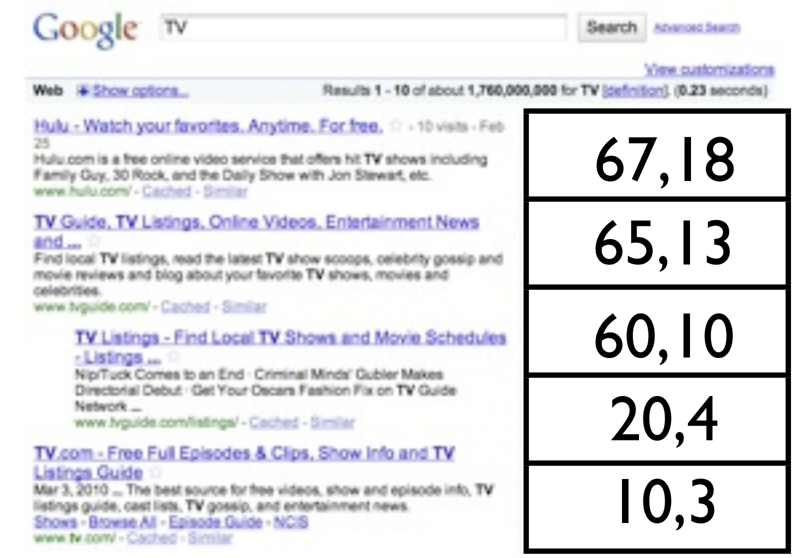
$$
\begin{aligned}
v_{q\bar{s}} &= i_q PrClick_{q\bar{s}}(PrConv_q USP_q - CPC_{q\bar{s}}) \\
w_{q\bar{s}} &= i_q PrClick_{q\bar{s}} PrConv_q
\end{aligned}
$$

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
90,20
89,18
60,10
20,4
10,3



95,19
89,18
60,10
20,4
10,3



67,18
65,13
60,10
20,4
10,3

How many sales do we anticipate?

How much profit do we anticipate?

Models give us these values.

But what slots should we choose, given this information?

$$v_{q\bar{s}} = i_q PrClick_{q\bar{s}}(PrConv_q USP_q - CPC_{q\bar{s}})$$
$$w_{q\bar{s}} = i_q PrClick_{q\bar{s}} PrConv_q$$

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
90,20
89,18
60,10
20,4
10,3

95,19
89,18
60,10
20,4
10,3

67,18
65,13
60,10
20,4
10,3

How many sales do we anticipate?

How much profit do we anticipate?

Models give us these values.

But what slots should we choose, given this information?

Assume: capacity constraint is hard.
This is a multiple-choice knapsack problem (MCKP)!

Multiple Choice Knapsack Problem (MCKP)

$$
\begin{aligned}
\max_{x_{q\bar{s}}} \quad & \sum_{q \in Q} \sum_{\bar{s} \in S} v_{q\bar{s}} x_{q\bar{s}} \\
\text{subject to} \quad & \sum_{q \in Q} \sum_{\bar{s} \in S} w_{q\bar{s}} x_{q\bar{s}} \ \leq \ C \\
& \sum_{\bar{s} \in S} x_{q\bar{s}} \ \leq \ 1 \quad \forall q \in Q \\
& x_{q\bar{s}} \in \{0, 1\}, \quad \forall q \in Q, \bar{s} \in S
\end{aligned}
$$

MCKP Greedy Algorithm

- Remove (LP) dominated items
  - Item (1,100) dominates item (5,20) $\boxed{w_{q\bar{s}}, v_{q\bar{s}}}$
- Create incremental items
  - (5,20), (8, 35) → (5, 20), (3, 15)
- Run a greedy knapsack algorithm on incremental items: i.e., take incremental items in nonincreasing order of efficiency
- Convert incremental items taken back into items

Kellerer 2004

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$70
5, \$75
3, \$60
2, \$50
1, \$30

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$76
5, \$75
3, \$60
2, \$40
1, \$30

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
6, $70
5, $75
3, $60
2, $50
1, $30

$w_{q\bar{s}}, v_{q\bar{s}}$
6, $76
5, $75
3, $60
2, $40
1, $30

- Remove (LP) dominated items

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $70	Dominated
5, $75	
3, $60	
2, $50	
1, $30	

$w_{q\bar{s}}, v_{q\bar{s}}$
6, $76
5, $75
3, $60
2, $40
1, $30

- Remove (LP) dominated items

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, \$70	Dominated
5, \$75	
3, \$60	
2, \$50	
1, \$30	

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, \$76	
5, \$75	
3, \$60	.5
2, \$40	LP Dominated
1, \$30	.5

- Remove (LP) dominated items

C=5

Model-heavy optimization

- Remove (LP) dominated items
- Create incremental items

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $70	Dominated
5, $75	2, $15
3, $60	1, $10
2, $50	1, $20
1, $30	1, $30

$w_{q\bar{s}}, v_{q\bar{s}}$		
6, $76		1, $1
5, $75		2, $15
3, $60	.5	2, $30
2, $40	LP Dominated	
1, $30	.5	1, $30

- Remove (LP) dominated items
- Create incremental items

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, \$70	Dominated
5, \$75	2, \$15
3, \$60	1, \$10
2, \$50	1, \$20
1, \$30	1, \$30

$w_{q\bar{s}}, v_{q\bar{s}}$		
6, \$76		1, \$1
5, \$75		2, \$15
3, \$60	.5	2, \$30
2, \$40	LP Dominated	
1, \$30	.5	1, \$30

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items: i.e., take incremental items in nonincreasing order of efficiency

C=5

Model-heavy optimization

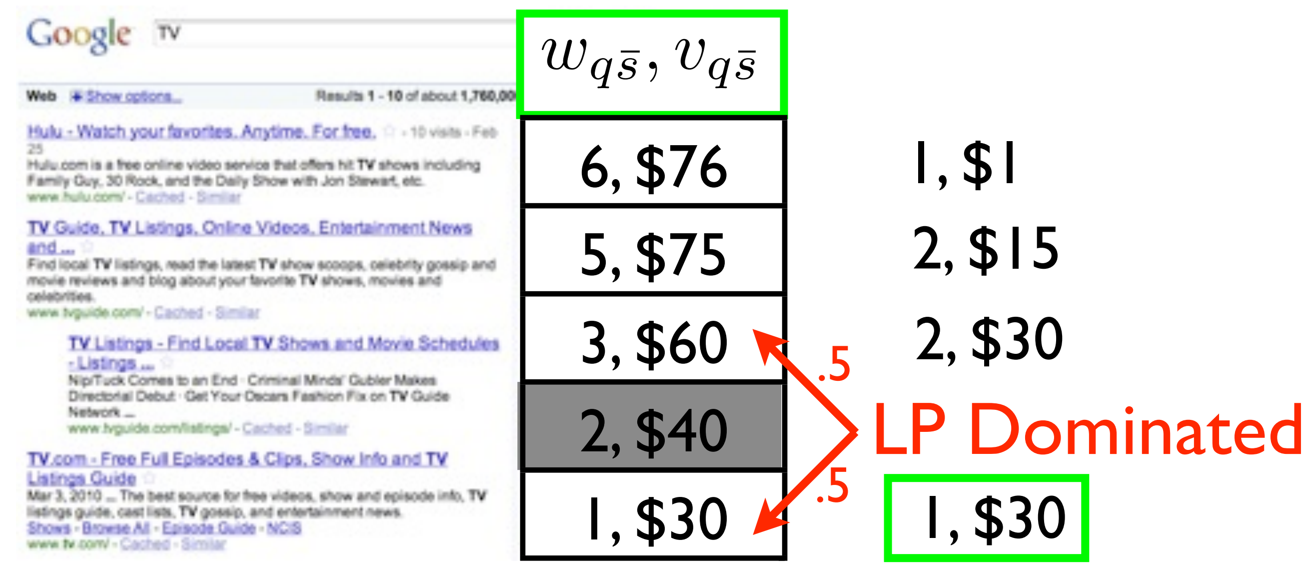
$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $70	Dominated
5, $75	2, $15
3, $60	1, $10
2, $50	1, $20
1, $30	1, $30

$w_{q\bar{s}}, v_{q\bar{s}}$		
6, $76		1, $1
5, $75		2, $15
3, $60	.5	2, $30
2, $40	LP Dominated	
1, $30	.5	1, $30

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items: i.e., take incremental items in nonincreasing order of efficiency

C=5

Model-heavy optimization



- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items: i.e., take incremental items in nonincreasing order of efficiency

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $70	Dominated
5, $75	2, $15
3, $60	1, $10
2, $50	1, $20
1, $30	1, $30

$w_{q\bar{s}}, v_{q\bar{s}}$		
6, $76		1, $1
5, $75		2, $15
3, $60	.5	2, $30
2, $40		LP Dominated
1, $30	.5	1, $30

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items: i.e., take incremental items in nonincreasing order of efficiency

C=5

Model-heavy optimization

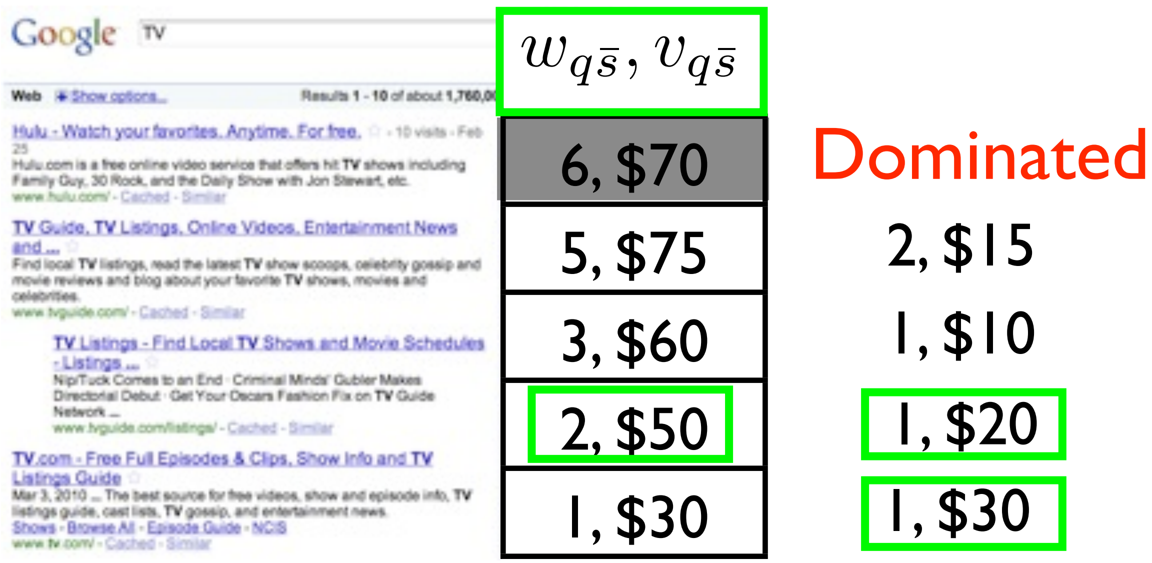
$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $70	Dominated
5, $75	2, $15
3, $60	1, $10
2, $50	1, $20
1, $30	1, $30

$w_{q\bar{s}}, v_{q\bar{s}}$		
6, $76		1, $1
5, $75		2, $15
3, $60	.5	2, $30
2, $40	LP Dominated	
1, $30	.5	1, $30

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items: i.e., take incremental items in nonincreasing order of efficiency

C=5

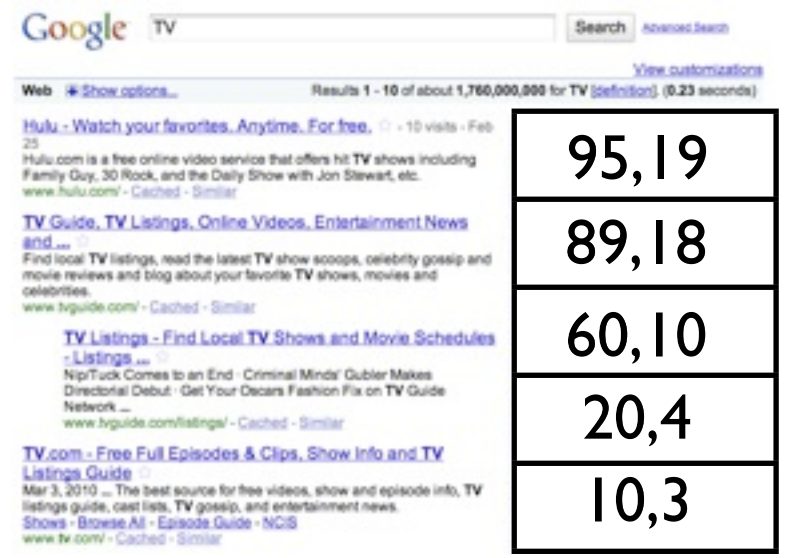
Model-heavy optimization



- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items: i.e., take incremental items in nonincreasing order of efficiency
- Convert incremental items taken back into items

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
90,20
89,18
60,10
20,4
10,3



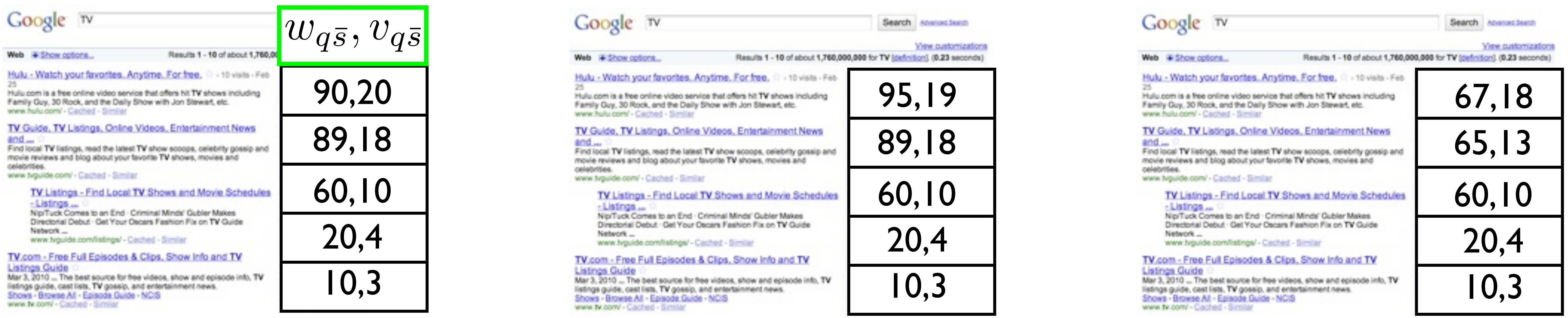
95,19
89,18
60,10
20,4
10,3

67,18
65,13
60,10
20,4
10,3

Assume: capacity constraint is hard.

This is a multiple-choice knapsack problem (MCKP)!

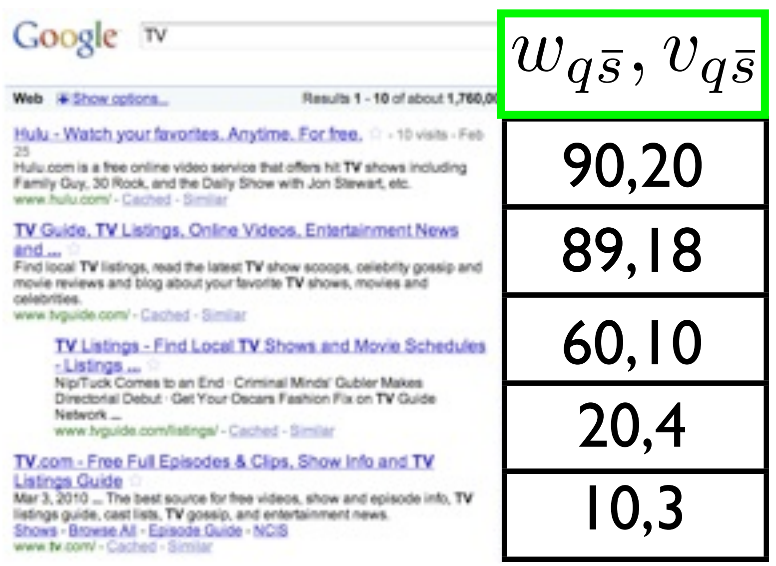
Model-heavy optimization

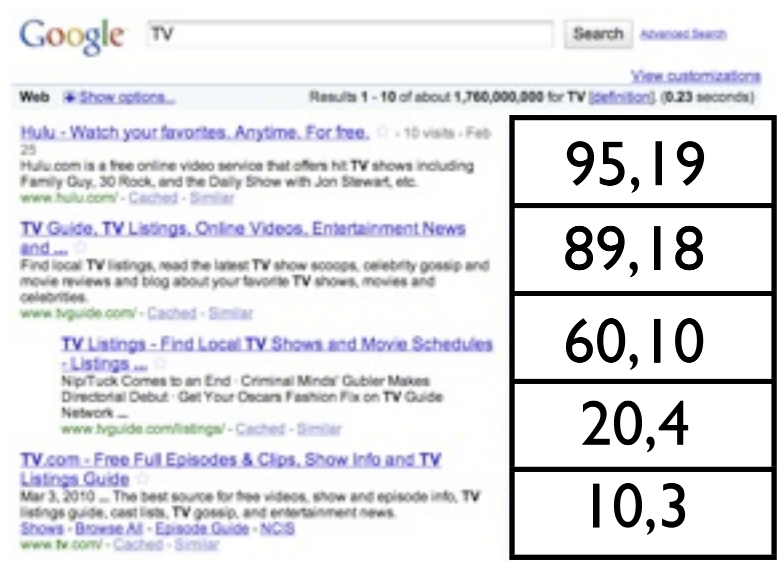


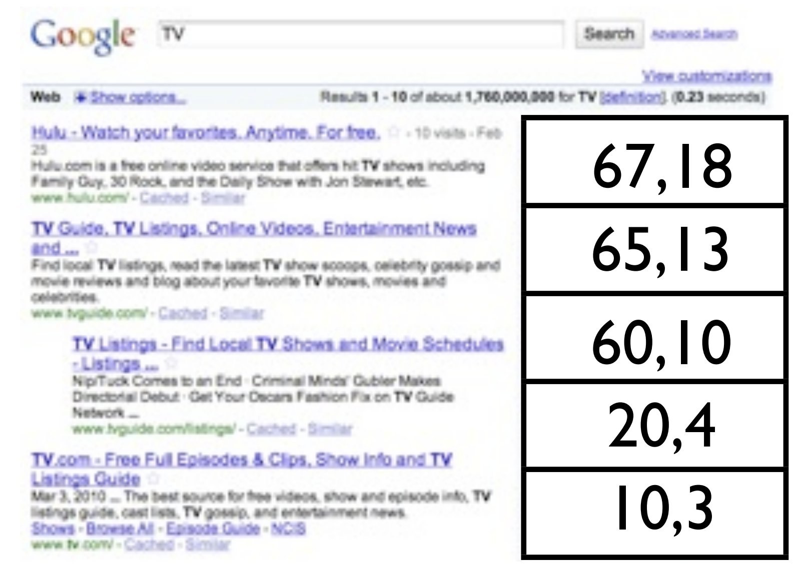
Bad assumption!

Assume: capacity constraint is hard.
This is a multiple-choice knapsack problem (MCKP)!

Model-heavy optimization







Bad assumption!

You can go over capacity.

~~Assume: capacity constraint is hard.~~

This is a multiple-choice knapsack problem (MCKP)!

Penalized

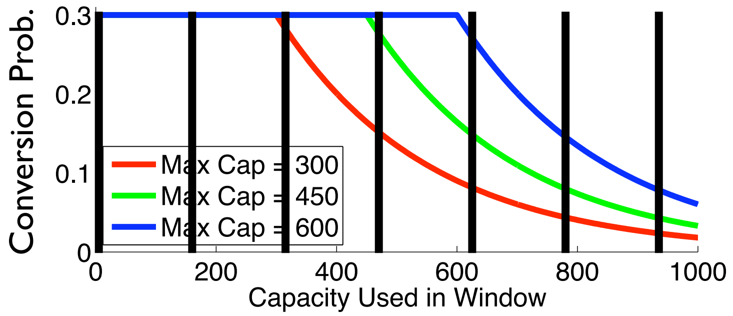
Multiple Choice Knapsack Problem (PMCKP)

$$\max_{\vec{x}} \quad \sum_{q\in Q}\sum_{\bar{s}\in S} v_{q\bar{s}}(\rho,\kappa)x_{q\bar{s}}$$

$$\kappa = \sum_{q\in Q}\sum_{\bar{s}\in S} w_{q\bar{s}}(\rho,\kappa)x_{q\bar{s}}$$

$$\sum_{\bar{s}\in S} x_{q\bar{s}} \leq 1 \quad \forall q \in Q$$

$$x_{q\bar{s}} \in \{0,1\}, \quad \forall q \in Q, \bar{s} \in S$$



PMCKP Algorithms

$w_{q\bar{s}}, v_{q\bar{s}}$
6, $70
5, $75
3, $60
2, $50
1, $30

$w_{q\bar{s}}, v_{q\bar{s}}$
6, $76
5, $75
3, $60
2, $40
1, $30

Exhaustive PMCKP

- For each capacity level,
  - get capacity-adjusted values
  - solve MCKP with these values

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$70
5, \$75
3, \$60
2, \$50
1, \$30

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$76
5, \$75
3, \$60
2, \$40
1, \$30

Hybrid PMCKP

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$70
5, \$75
3, \$60
2, \$50
1, \$30

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$76
5, \$75
3, \$60
2, \$40
1, \$30

Hybrid PMCKP

- Remove (LP) dominated items

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$70
5, \$75
3, \$60
2, \$50
1, \$30

Dominated

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$76
5, \$75
3, \$60
2, \$40
1, \$30

Hybrid PMCKP

- Remove (LP) dominated items

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$70
5, \$75
3, \$60
2, \$50
1, \$30

Dominated

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$76
5, \$75
3, \$60
2, \$40
1, \$30

.5

LP Dominated

.5

Hybrid PMCKP

- Remove (LP) dominated items

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$70
5, \$75
3, \$60
2, \$50
1, \$30

Dominated

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$76
5, \$75
3, \$60
2, \$40
1, \$30

.5

LP Dominated

.5

Hybrid PMCKP

- Remove (LP) dominated items
- Create incremental items

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$		
6, \$70	Dominated	
5, \$75		2, \$15
3, \$60		1, \$10
2, \$50		1, \$20
1, \$30		1, \$30

$w_{q\bar{s}}, v_{q\bar{s}}$		
6, \$76		1, \$1
5, \$75		2, \$15
3, \$60	.5	2, \$30
2, \$40	LP Dominated	
1, \$30	.5	1, \$30

Hybrid PMCKP

- Remove (LP) dominated items
- Create incremental items

Sunday, September 5, 2010

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $70	Dominated
5, $75	2, $15
3, $60	1, $10
2, $50	1, $20
1, $30	1, $30

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $76	1, $1
5, $75	2, $15
3, $60	2, $30
2, $40	LP Dominated
1, $30	1, $30

.5
.5

Hybrid PMCKP

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items, penalizing values as capacity is used

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $70	Dominated
5, $75	2, $15
3, $60	1, $10
2, $50	1, $20
1, $30	$\boxed{1, \$30}$

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $76	1, $1
5, $75	2, $15
3, $60	2, $30
2, $40	LP Dominated
1, $30	1, $30

.5

.5

$ 30=30

Hybrid PMCKP

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items, penalizing values as capacity is used

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	Dominated
6, \$70	
5, \$75	2, \$15
3, \$60	1, \$10
2, \$50	1, \$20
1, \$30	1, \$30

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, \$76	1, \$1
5, \$75	2, \$15
3, \$60	2, \$30
2, \$40	.5 .5 LP Dominated
1, \$30	1, \$30

\$ 60=30+30

Hybrid PMCKP

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items, penalizing values as capacity is used

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, \$70	Dominated
5, \$75	2, \$15
3, \$60	1, \$10
2, \$50	1, \$20
1, \$30	1, \$30

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, \$76	1, \$1
5, \$75	2, \$15
3, \$60	2, \$30
2, \$40	LP Dominated
1, \$30	1, \$30

\$ 80=30+30+20

Hybrid PMCKP

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items, penalizing values as capacity is used

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $70	Dominated
5, $75	2, $15
3, $60	1, $10
2, $50	1, $20
1, $30	1, $30

$w_{q\bar{s}}, v_{q\bar{s}}$		
6, $76		1, $1
5, $75		2, $15
3, $60	.5	2, $30
2, $40	LP Dominated	
1, $30	.5	1, $30

Hybrid PMCKP

$110=30+30+20+30

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items, penalizing values as capacity is used

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$65
5, \$71
3, \$57
2, \$48
1, \$29

Dominated

2, \$14

1, \$9

1, \$19

1, \$29

$w_{q\bar{s}}, v_{q\bar{s}}$
6, \$72
5, \$71
3, \$57
2, \$38
1, \$29

1, \$1

2, \$14

2, \$28

.5

LP Dominated

.5

1, \$29

~~\$110=30+30+20+30~~

$\$114=\underbrace{29+29+19+28}_{-5}+9$

Hybrid PMCKP

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items, penalizing values as capacity is used

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, \$60	Dominated
5, \$63	2, \$11
3, \$52	1, \$8
2, \$44	1, \$18
1, \$26	1, \$26

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, \$63	1, \$0
5, \$63	2, \$11
3, \$52	2, \$26
2, \$34	.5 LP Dominated .5
1, \$26	1, \$26

$\cancel{\$110=30+30+20+30}$

$\cancel{\$114=\underbrace{29+29+19+28}_{-5}+9}$

$\$114=\underbrace{26+26+18+26+8}_{-10}+11$

Hybrid PMCKP

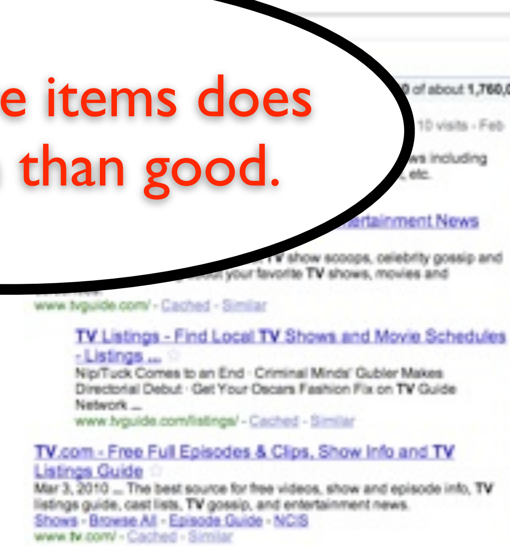
- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items, penalizing values as capacity is used

C=5

Model-heavy optimization

$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $54	Dominated
5, $57	2, $10
3, $47	1, $6
2, $41	1, $17
1, $24	1, $24

Adding more items does more harm than good.



$w_{q\bar{s}}, v_{q\bar{s}}$	
6, $56	1, $-1
5, $57	2, $10
3, $47	2, $23
2, $34	LP Dominated
1, $24	1, $24

.5

.5

$\cancel{\$110=30+30+20+30}$

$\cancel{\$114=\underbrace{29+29+19+28}_{-5}+9}$

$\cancel{\$114=\underbrace{26+26+18+26+8}_{-10}+11}$

$\$114=\underbrace{24+24+17+23+6+10}_{-11}+10$

Hybrid PMCKP

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items, penalizing values as capacity is used

C=5

Model-heavy optimization

Hybrid PMCKP

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items, penalizing values as capacity is used
- Convert incremental items taken back into items

~~$110=30+30+20+30~~

~~$114=29+29+19+28+9~~

$\underbrace{29+29+19+28}_{-5}$

$114=26+26+18+26+8+11

$\underbrace{26+26+18+26+8}_{-10}$

PMCKP Algorithms

MCKP Greedy (Kellerer 2004)

- Remove (LP) dominated items
  - Item (1,100) dominates item (5,20) $\boxed{w_{q\bar{s}}, v_{q\bar{s}}}$
- Create incremental items
  - (5,20), (8, 35) → (5, 20), (3, 15)
- Run a greedy knapsack algorithm on incremental items: i.e., take incremental items in nonincreasing order of efficiency
- Convert incremental items taken back into items

Exhaustive PMCKP

- For each capacity level,
  - get capacity-adjusted values
  - solve MCKP with these values

Hybrid PMCKP

- Remove (LP) dominated items
- Create incremental items
- Run a greedy knapsack algorithm on incremental items, penalizing values as capacity is used
- Convert incremental items taken back into items

Dynamic PMCKP

Loop:

- For each query,
  - Get next undominated item
  - Calculate incremental value and weight of this item
- Greedily take highest-efficiency incremental item
- Adjust values after each incremental item is taken

Convert incremental items taken back into items

Presentation Outline

- Ad auctions game
- Agent architecture
- Optimization problem (stylized knapsack problem)
  - Model-heavy (greedy multiple choice knapsack algorithm)
  - Model-light (rule-based algorithm)
- Experiments
- Future work

Model-~~heavy~~ light optimization

$w_{q\bar{s}}, v_{q\bar{s}}$
90,20
89,18
60,10
20,4
10,3

How many sales do we anticipate?

...and how much profit?

~~Models give us these values.~~

- Model-heavy algorithms equated marginal ROI
- Model light algorithms equate some *proxy* of marginal ROI using less information

Equate ROI

Input: $sales$, $targetROI$, $targetSales$
Output: $\forall q, bid_q$
  if $sales > targetSales$ **then**
    $targetROI = targetROI(d) * \text{INC\_ROI}$
  else
    $targetROI = targetROI(d) \,/\, \text{INC\_ROI}$
  for all q **do**
    $CPC_q = (USP_q - targetROI) * PrConv_q$
    $bid_q = cpc2bid(CPC_q)$

$$
\begin{aligned}
ROI_q(s_q) &= \frac{rev_q(s_q) - cost_q(s_q)}{sales_q(s_q)} \\
&= USP_q - \frac{CPC_q(s_q)numClicks_q(s_q)}{sales_q(s_q)} \\
&= USP_q - CPC_q(s_q)\frac{1}{PrConv_q}
\end{aligned}
$$

Borgs 2007

Equate ROI

If sold more than desired, reduce tomorrow's sales (by increasing target ROI).

Input: $sales$, $targetROI$, $targetSales$
Output: $\forall q$, bid_q
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for all q **do**
  $CPC_q = (USP_q - targetROI) * PrConv_q$
  $bid_q = cpc2bid(CPC_q)$

ROI = "profit per sale"

$$ROI_q(s_q) = \frac{rev_q(s_q) - cost_q(s_q)}{sales_q(s_q)}$$

$$= USP_q - \frac{CPC_q(s_q) numClicks_q(s_q)}{sales_q(s_q)}$$

$$= USP_q - CPC_q(s_q) \frac{1}{PrConv_q}$$

Borgs 2007

Equate ROI

If sold more than desired, reduce tomorrow's sales (by increasing target ROI).

Input: $sales$, $targetROI$, $targetSales$
Output: $\forall q, bid_q$
if $sales > targetSales$ **then**
  $targetROI = targetROI(d) * \text{INC\_ROI}$
else
  $targetROI = targetROI(d) \,/\, \text{INC\_ROI}$
for all q **do**
  $CPC_q = (USP_q - targetROI) * PrConv_q$
  $bid_q = cpc2bid(CPC_q)$

Approximates equating marginal ROI across queries--solution characterized by equimarginal principle

ROI = "profit per sale"

$$
\begin{aligned}
ROI_q(s_q) &= \frac{rev_q(s_q) - cost_q(s_q)}{sales_q(s_q)} \\
&= USP_q - \frac{CPC_q(s_q)numClicks_q(s_q)}{sales_q(s_q)} \\
&= USP_q - CPC_q(s_q)\frac{1}{PrConv_q}
\end{aligned}
$$

Borgs 2007

Equate PM

Input: $sales$, $targetPM$, $targetSales$
Output: $\forall q, bid_q$

if $sales > targetSales$ **then**
  $targetPM = targetPM(d) * \text{INC\_PM}$
else
  $targetPM = targetPM(d) \,/\, \text{INC\_PM}$
for all q **do**
  $CPC_q = (USP_q - targetPM) * PrConv_q$
  $bid_q = cpc2bid(CPC_q)$

$$PM_q(s_q) = \frac{rev_q(s_q) - cost_q(s_q)}{rev_q(s_q)}$$
$$= 1 - \frac{cost_q(s_q)}{rev_q(s_q)}$$
$$= 1 - \frac{CPC_q(s_q)}{PrConv_q USP_q}$$

Equate PM

PM = "profit as a fraction of revenue"

Input: $sales$, $targetPM$, $targetSales$
Output: $\forall q, bid_q$
  if $sales > targetSales$ **then**
    $targetPM = targetPM(d) * \text{INC\_PM}$
  else
    $targetPM = targetPM(d) \,/\, \text{INC\_PM}$
  for all q **do**
    $CPC_q = (USP_q - targetPM) * PrConv_q$
    $bid_q = cpc2bid(CPC_q)$

$$PM_q(s_q) = \frac{rev_q(s_q) - cost_q(s_q)}{rev_q(s_q)}$$

$$= 1 - \frac{cost_q(s_q)}{rev_q(s_q)}$$

$$= 1 - \frac{CPC_q(s_q)}{PrConv_q USP_q}$$

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Experiments

- TAC AA games
- Optimization challenge
    - Is it representative of TAC AA games?
    - Model accuracy tests
    - Fixed vs. dynamic capacity tests

TAC AA Experiments

Agent	Set 1	Set 2	Set 3
TacTex	80.76	79.86	81.84
HybridMCKP	77.83		
EquateROI		75.67	
astonTAC	76.30	75.32	77.25
munsey	73.41	72.40	72.01
epflagent	72.43	73.05	72.46
EquatePM			69.63
QuakTAC	70.61	70.53	68.38
MetroClick	70.15	68.73	69.10
mertacor	68.31	68.08	67.63

Optimization algorithms that approximately equate marginal ROI are competitive

EquatePM is not competitive

Opponent scores/rankings are similar, regardless of our agent

Optimization Challenge

Agent	Profit	Avg Pos	CPC	ClickPr	ConvPr	Sales in CS	Sales in MS	OverCap
DynamicMCKP	75.93	2.49	0.46	0.21	0.17	0.41	0.85	1.38
HybridMCKP	75.85	2.42	0.48	0.22	0.17	0.40	0.86	1.40
ExhaustiveMCKP	75.01	2.70	0.42	0.20	0.14	0.41	0.78	1.45
EquateROI	73.47	2.33	0.48	0.20	0.14	0.38	0.86	1.40
EquatePM	64.70	3.06	0.34	0.13	0.11	0.44	0.38	1.53

Agent	Set 1	Set 2	Set 3
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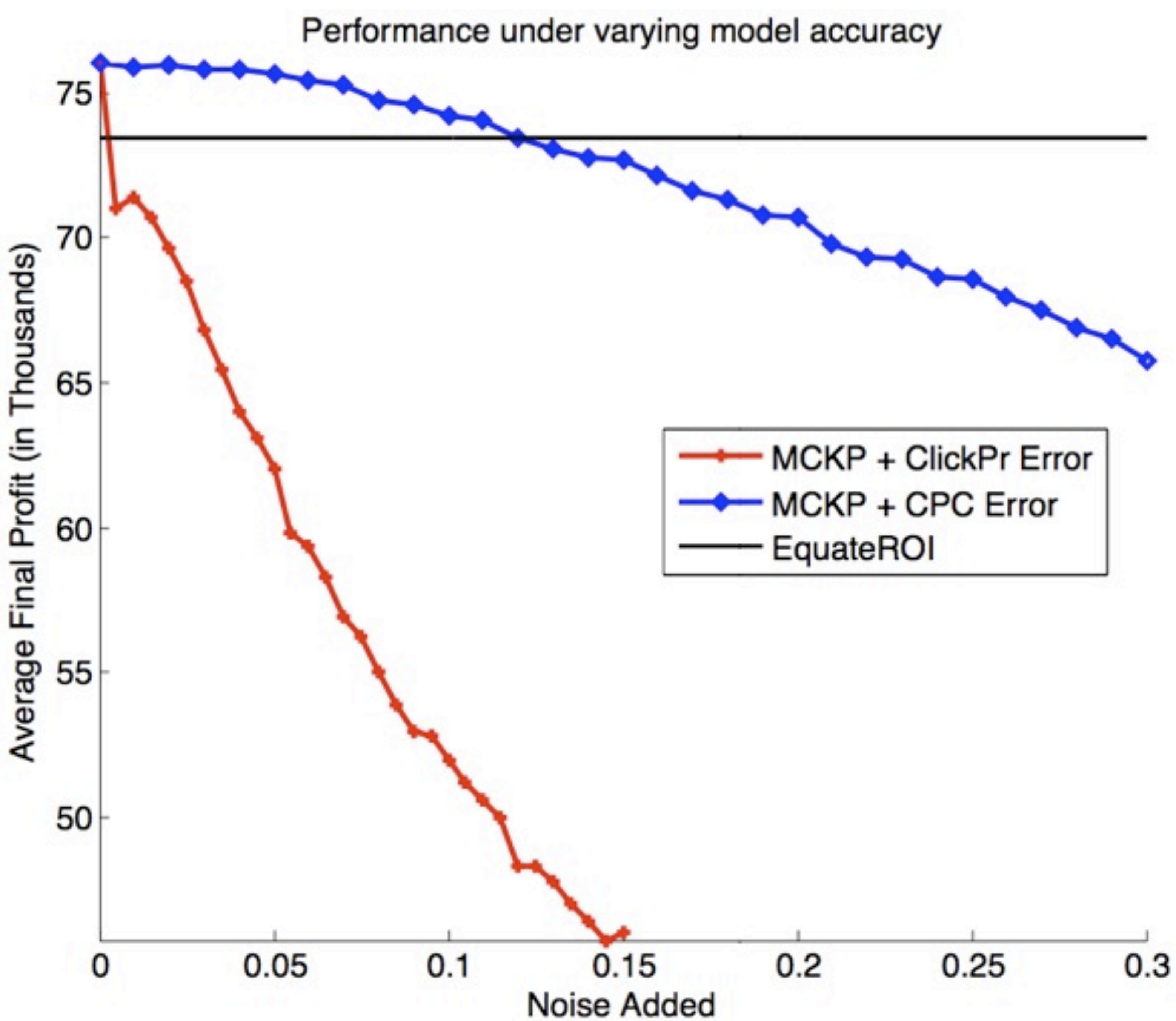
mertacor	68.31	68.08	67.63

- Exhaustive, Hybrid, and Dynamic MCKP earn about the same profit
- Optimization Challenge scores/rankings similar to TAC AA games
    - different opponents
    - different market conditions
    - opponents not responding to our agent

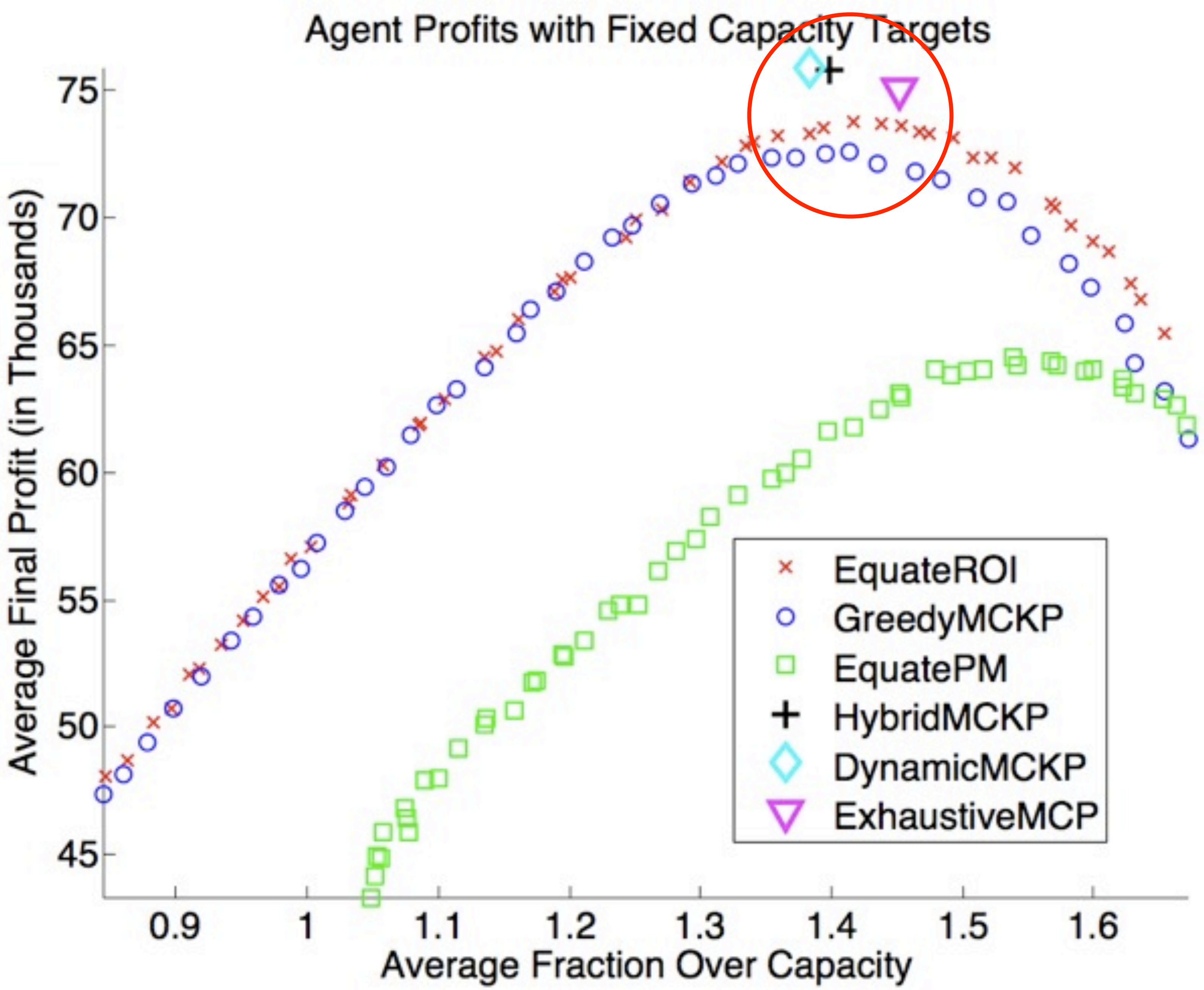
Model Accuracy Experiments



- Add noise to answer:
  - is there a point at which rule-based algorithms are more profitable?
  - which model improvements will result in highest profits?

- As model accuracy decreases, rules-based algorithms perform better than Hybrid MCKP
- ClickPr accuracy appears to be more important than CPC

Capacity Experiments



- Exhaustive, Hybrid, and Dynamic MCKP all have similar average capacities
- These average capacities are similar to the best fixed capacity
- Value in adjusting capacity dynamically

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Future Work

- Models
  - user state predictions
  - opponent bid predictions
- Optimization
  - Multi-day problem
  - Game-theoretic problem
- Controlled testing environments

Questions?