Sponsored Search Seminar Group Project: Approach and Initial Results

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Initial Ideas

- Analyze keyword markets related by use of modifiers
  – ‘lexus’ vs. ‘used lexus’
  – ‘electrician’ vs. ‘chicago electrician’
- Develop better models for real-world bidding behavior
  – Not “uniformly at random from [a,b]”

Combined Approach

- Develop a parameterized model for bids on a single query
  - E.g., parameters are first bid and rate of falloff
- Collect bids for a wide array of keyword/modifier pairs
  - Fit the model to each bid viewer result
- Use model parameters as analysis quantities
  - E.g., the ‘free’ modifier lowers the first bid and decreases rate of falloff

Analysis

- Noise is an issue
  - Consider keywords and modifiers in groups
- Generate matrices showing effect of each modifier group on each base keyword group
  - Preliminary results today
- So far, groups created by hand
  - Can we automate this? More later…

Outline

1. Keywords and modifiers (Edi)
2. Initial results (Qian and Qiuye)
3. Ongoing work: Modeling bids (Kuzman)
4. Ongoing work: Modeling values (Jinsong)
5. Ongoing work: Automatic clustering (Alex)

Keyword Base Groups and Modifiers

- relevant, popular, diverse, and interesting
  - what some people search for
  - affected differently by modifiers
  - differ in several aspects (spatial, temporal, expense)
- eight groups with ~600 keywords total
  - one or two groups per person
- six modifier groups ~50 modifiers
  - modeling phases of consumer interaction
  - not necessarily applicable to all base keywords
- 32K base-modifier pairs
  - sparsity
  - data collection (Tales from the (s)Crypt)

Base Keywords

- **Cars** (Alex)
  - toyota camry, chevy, ford suv, porsche 911
- **Drugs, medical** (Edi)
  - zoloft, cialis, psoriasis, sciatica, liposuction
- **Electronics, software** (Jinsong)
  - xbox, mp3, pda, oracle, world of warcraft
- **Travel** (Kuzman)
  - airfare, cruise, safari, sailing, vacation
- **Local and non-local services** (Qian)
  - electrician, locksmith, ** insurance, ** loan
- **Subscription services** (Qiuye)
  - cable tv, gym membership, magazine subscription

Keyword Modifiers

- INFO:
  - info, information,
  - specs, specifications,
  - reviews, ratings,
  - prices,
  - coupon, rebate,
  - guide, news
- QUALITY:
  - best
  - luxury
  - favorite
  - inclusive, exclusive
  - preferred
  - used, new
- LOCATION:
  - 20 U.S. States
  - 20 U.S. Cities
- PRICE:
  - cheap, free
  - bargain, discount, deal
  - special, sale
  - budget, affordable
  - expensive
- ACTION:
  - buy, sell, purchase
  - lease, rent, hire
- POST:
  - support
  - parts
  - repair
  - mechanic
  - manufacturer
  - warranty

Base groups vs. modifier groups

	drugs	electronics	local service	medical	non-local service	software	subscription	travel
quality	0.2425	0.522697	0.454516	0.763077	1.38907	0.262778	0.3745283	0.718875
price	-1	0.554332	0.509529	0.558636	1.644848	0.186486	0.4626552	0.777972
post	-1	0.385122	0.713784	-1	0.730417	0.233529	0.3529545	0.11
location	-1	0.38551	1.58505	1.651934	2.829279	0.264792	0.5842331	0.729871
info	0.285461	0.259721	0.487416	1.008542	1.341488	0.223793	0.2439355	0.303883
action	-1	0.665185	0.498667	0.3125	1.409231	0.297857	0.4692941	0.323721
null	0.878548	1.026176	1.264545	1.742041	4.6692	0.662973	0.7644633	0.815219

Base groups vs. modifier groups

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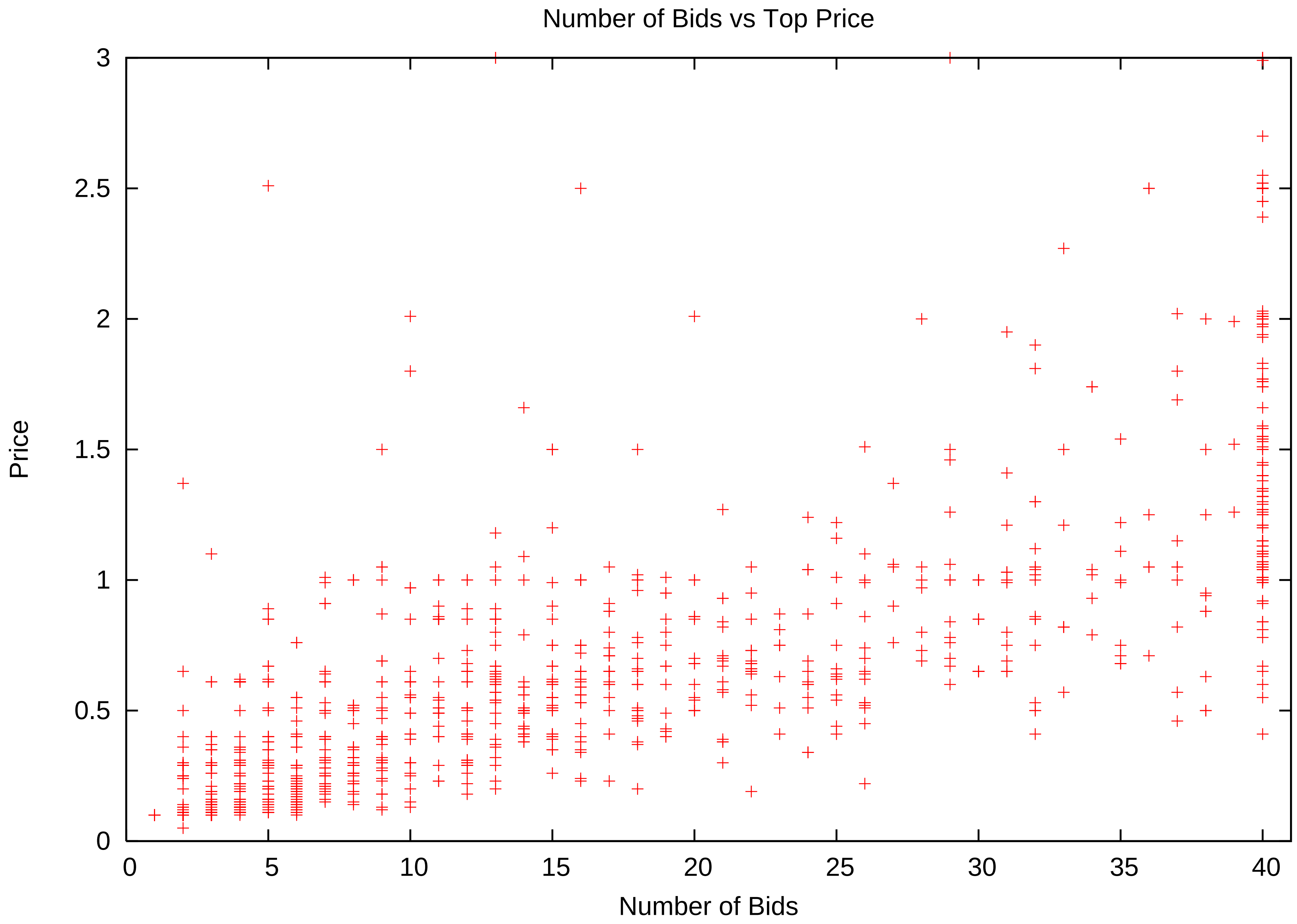
	drugs	electronics	local service	medical	non-local service	software	subscription	travel

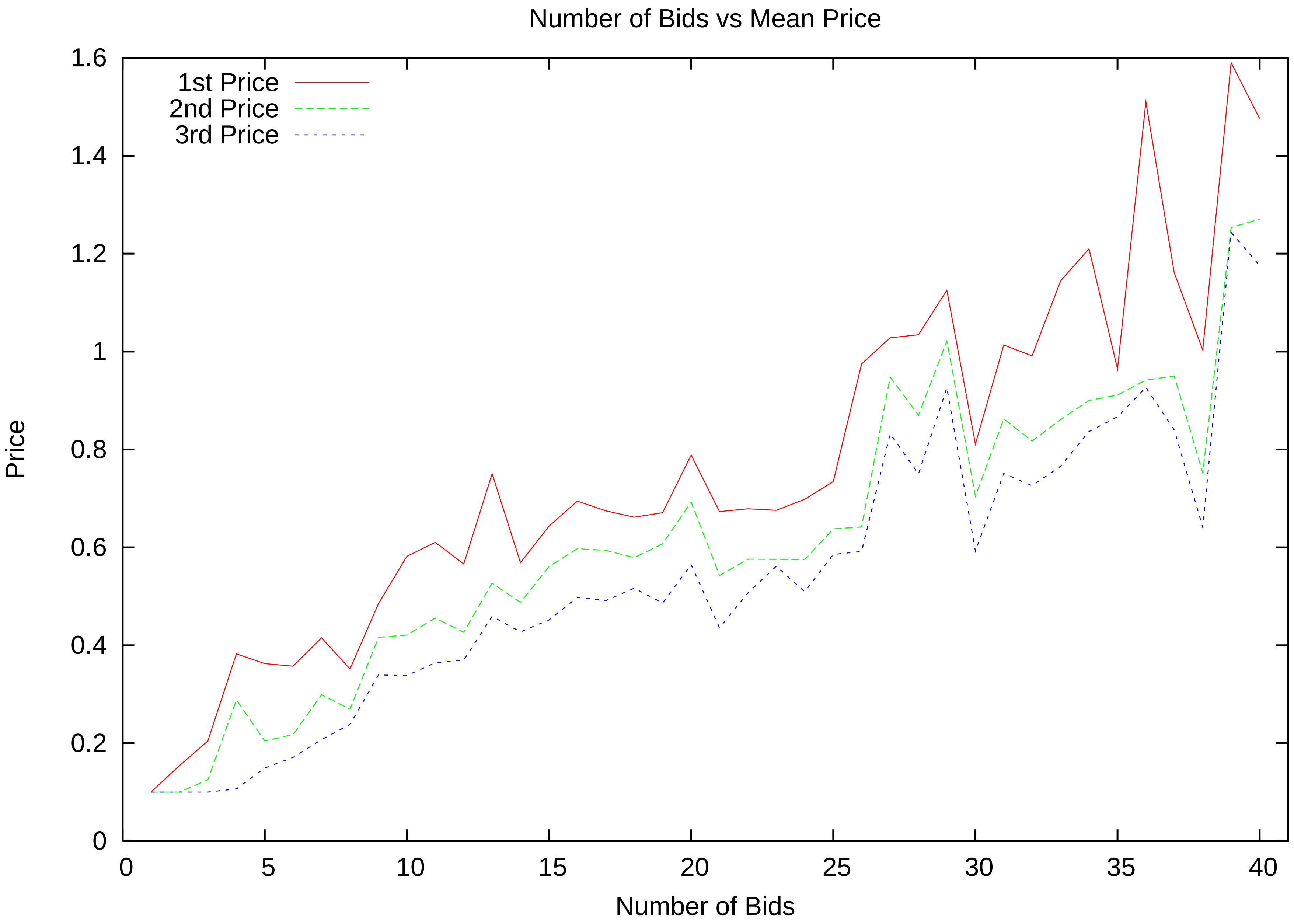
Base groups vs. price modifier sub-groups

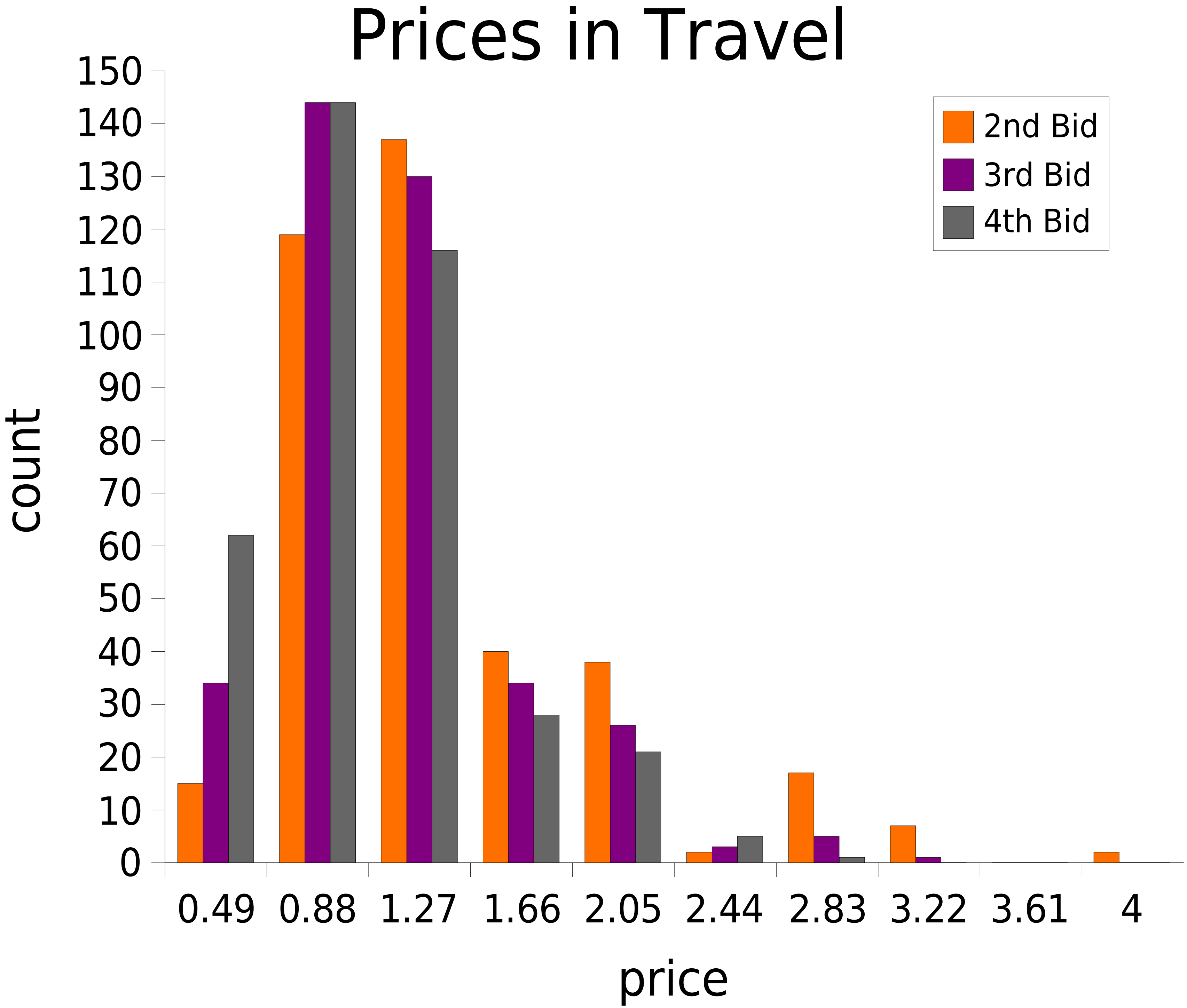
	drugs	electronics	local service	medical	non-local service	software	subscription	travel
expensive	-1	0.155556	0.115	-1	0.82	-1	0.12	0.124
sale	-1	0.63037	0.395238	0.2	0.795625	0.2525	0.3460606	0.538889
affordable	-1	0.414615	0.682	0.87375	2.181333	-1	0.3394737	0.481333
bargain	-1	0.314737	0.214286	-1	0.893846	0.1	0.4636364	0.896842
special	-1	0.213	0.346364	0.1	1.1	0.15	0.3727778	0.824286
budget	-1	0.236667	0.908571	-1	1	-1	0.173	0.618889
deal	-1	0.6528	0.321538	0.185	1.572308	0.34	0.5138235	1.119375
discount	-1	0.833214	0.550303	0.68	2.51	0.132	0.6111864	0.964681
free	-1	0.297895	0.4605	0.221538	1.115909	0.14	0.3020408	0.235
cheap	-1	0.806774	0.589722	0.781818	3.125263	0.166667	0.6505769	0.723011
null	0.878548	1.026176	1.264545	1.742041	4.6692	0.662973	0.7644633	0.815219

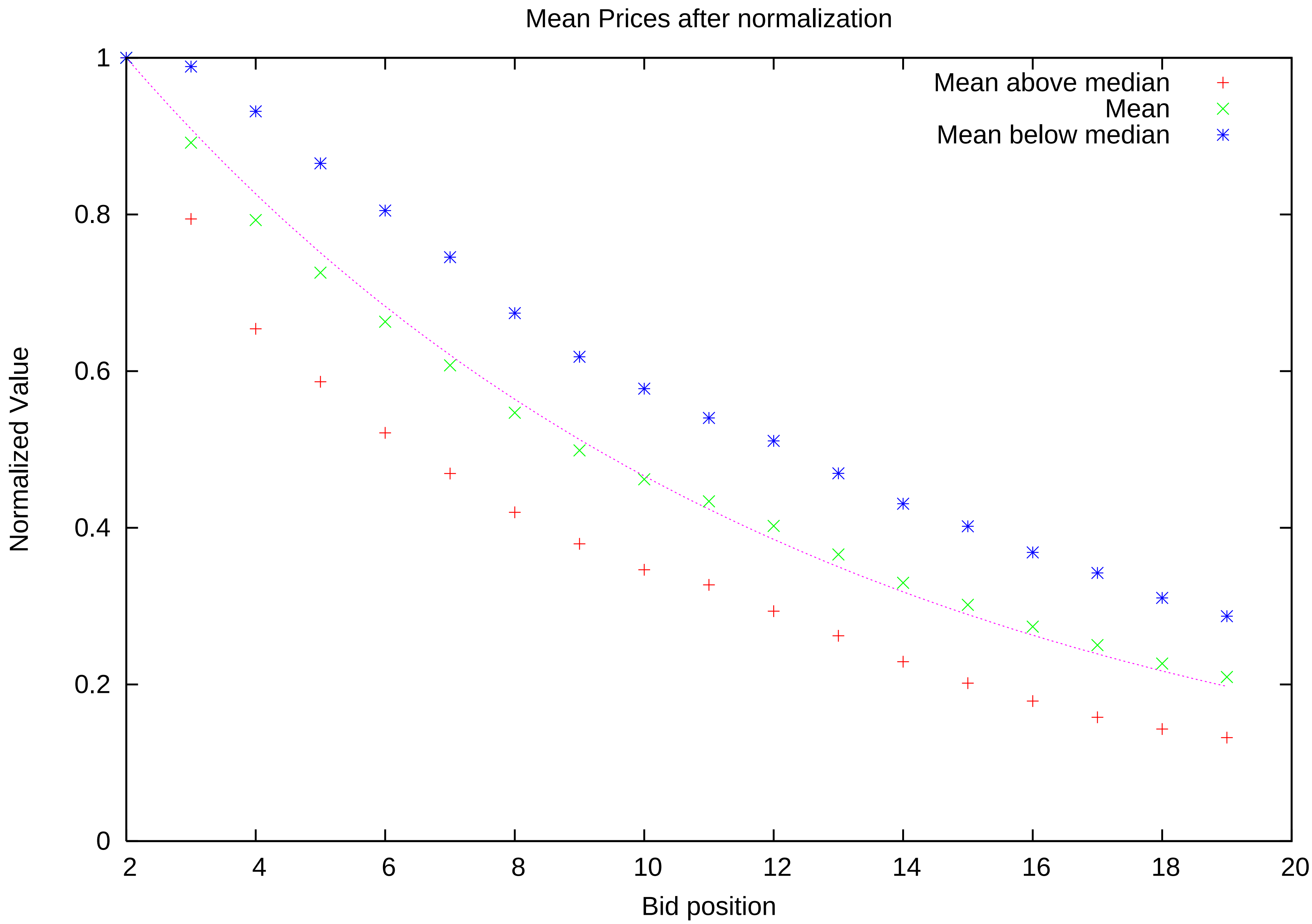
Base groups vs. location modifier sub-groups

	drugs	electronics	local service	medical	non-local service	software	subscription	travel
pacific	-1	0.365	1.481158	1.494248	3.099717	0.179	0.553864	0.875042
mountain	-1	0.231905	1.449853	1.376667	2.850753	0.575	0.520769	0.633766
central	-1	0.344068	1.631514	1.684847	2.793631	0.217391	0.562696	0.68305
eastern	-1	0.590606	1.718561	1.961528	2.767216	0.188571	0.710263	0.77661
null	0.87855	1.02618	1.26455	1.74204	4.6692	0.66297	0.76446	0.81522

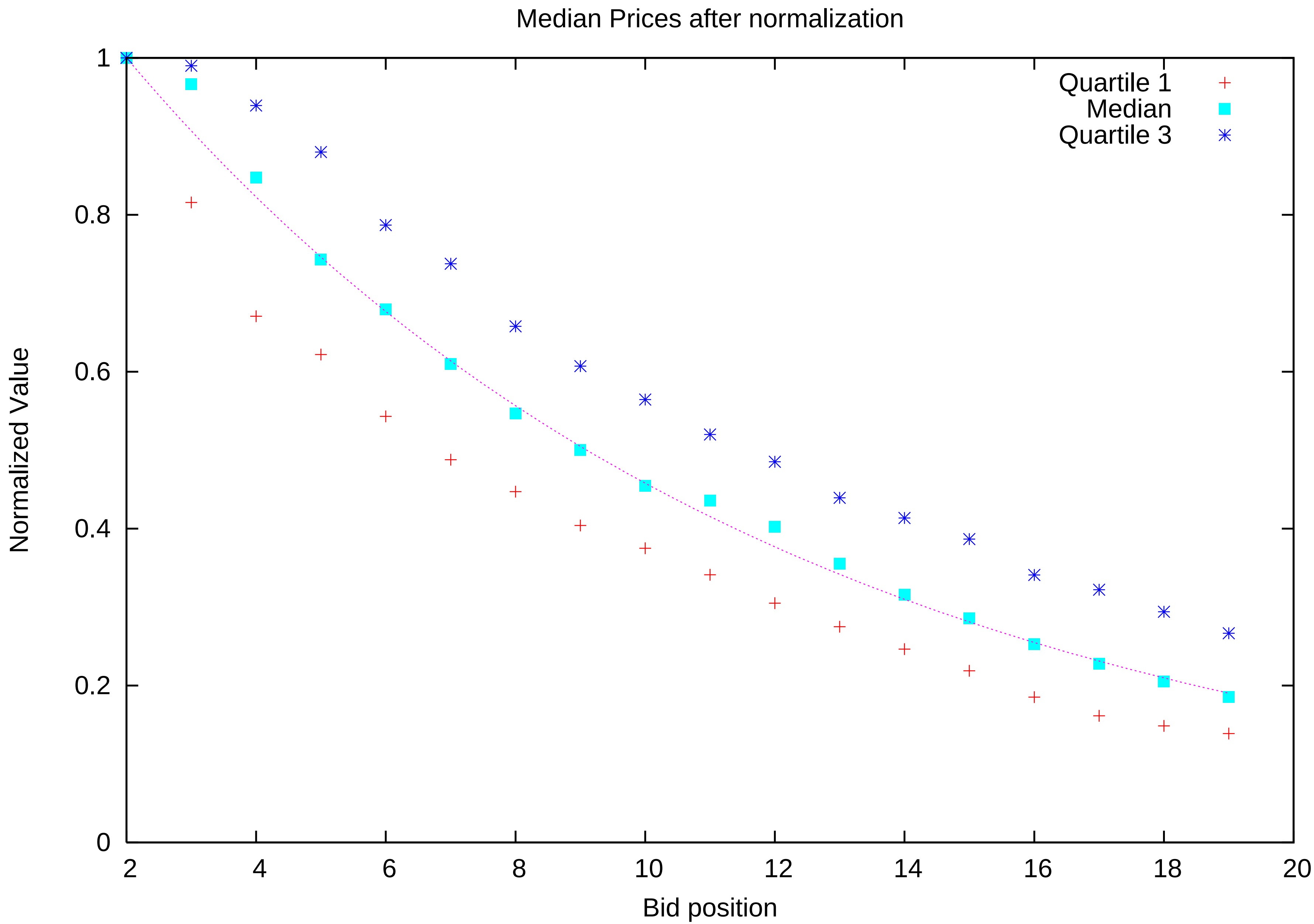

Number of Bids vs Top Price
Price
Number of Bids
0
0.5
1
1.5
2
2.5
3
0
5
10
15
20
25
30
35
40


Number of Bids vs Mean Price
1st Price
2nd Price
3rd Price
Price
Number of Bids
0
0.2
0.4
0.6
0.8
1
1.2
1.4
1.6
0
5
10
15
20
25
30
35
40

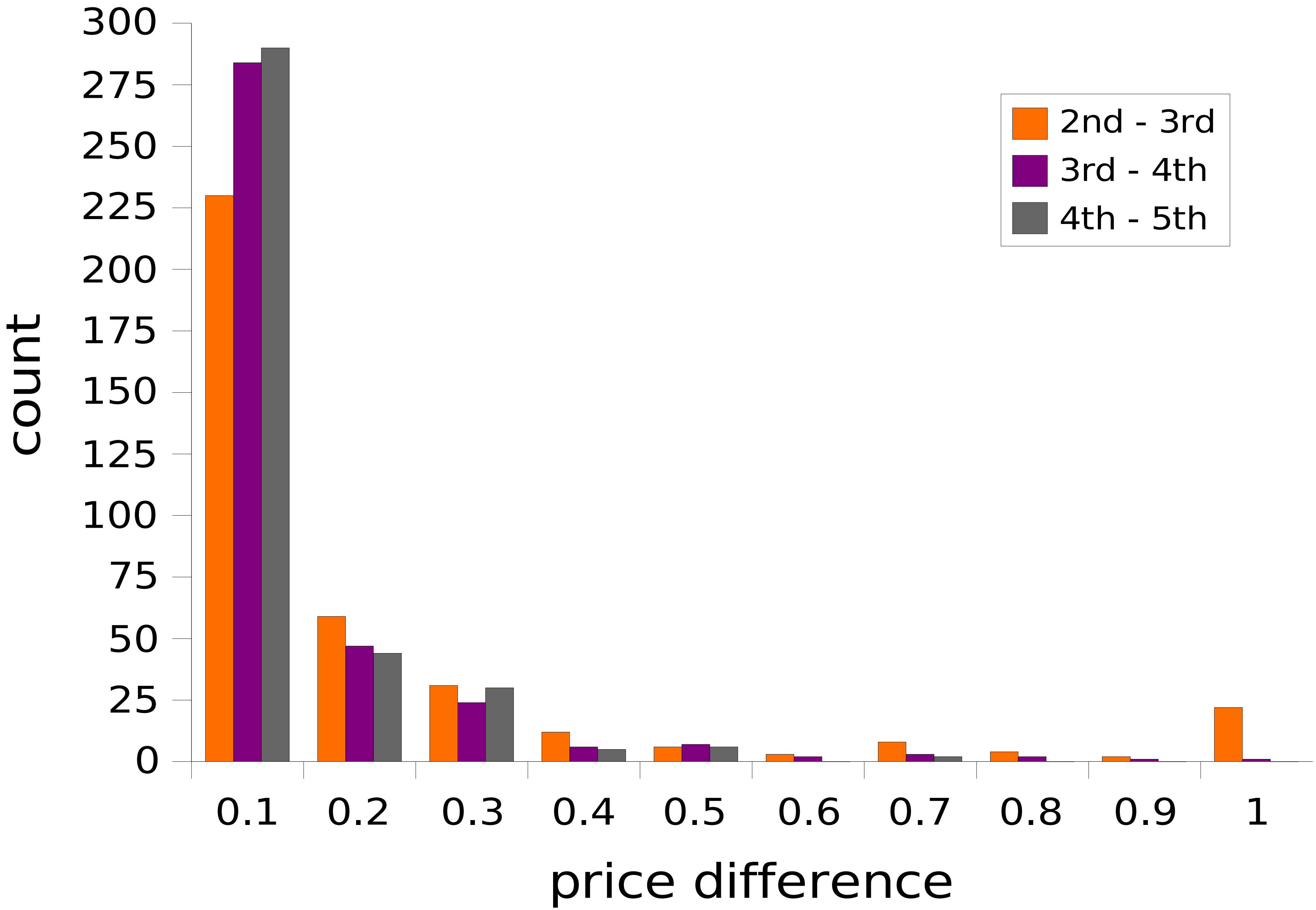

Prices in Travel
count
150
140
130
120
110
100
90
80
70
60
50
40
30
20
10
0
0.49
0.88
1.27
1.66
2.05
2.44
2.83
3.22
3.61
4
price
2nd Bid
3rd Bid
4th Bid

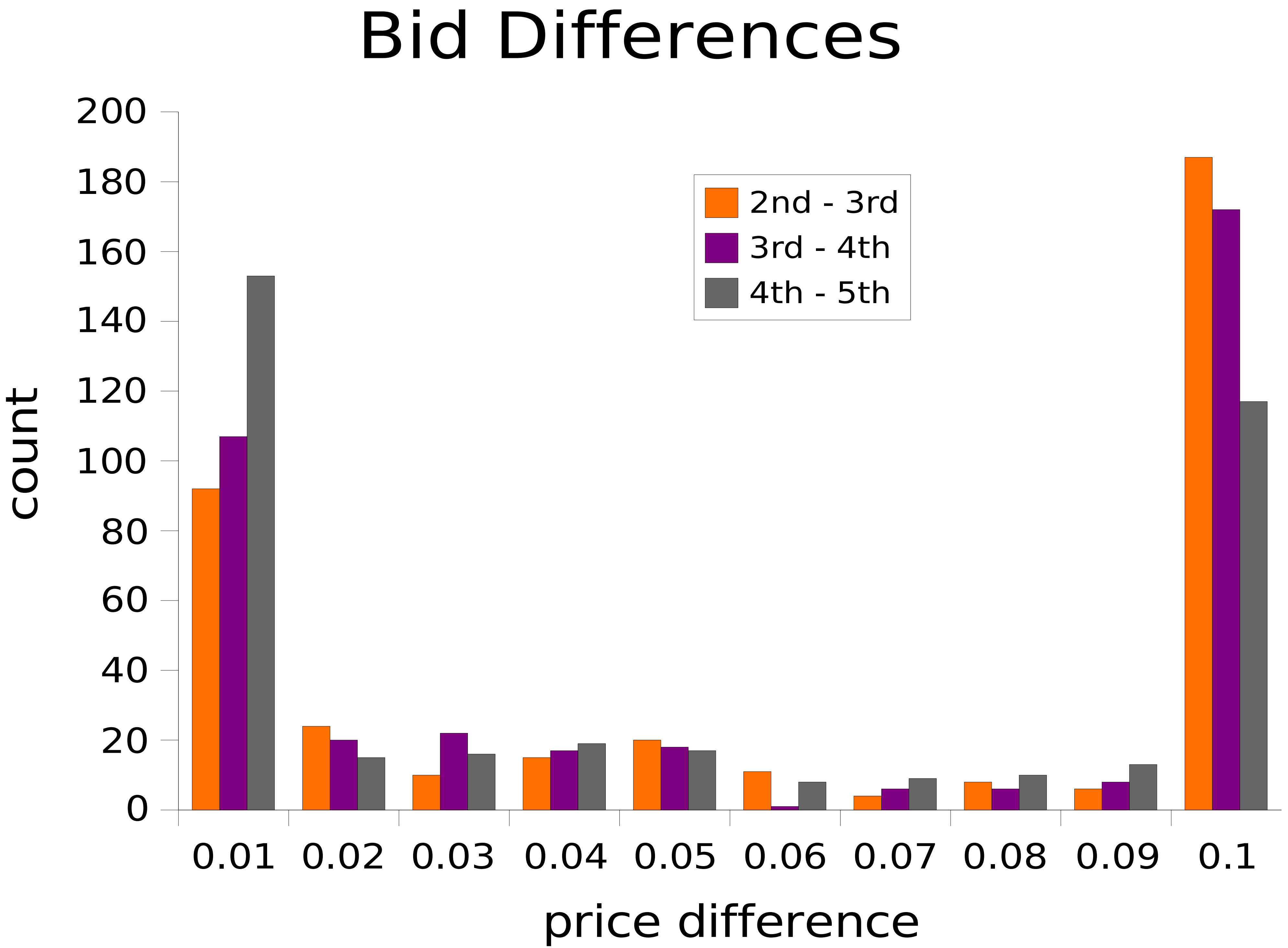


Mean Prices after normalization
Mean above median
Mean
Mean below median
Normalized Value
Bid position
0
0.2
0.4
0.6
0.8
1
2
4
6
8
10
12
14
16
18
20

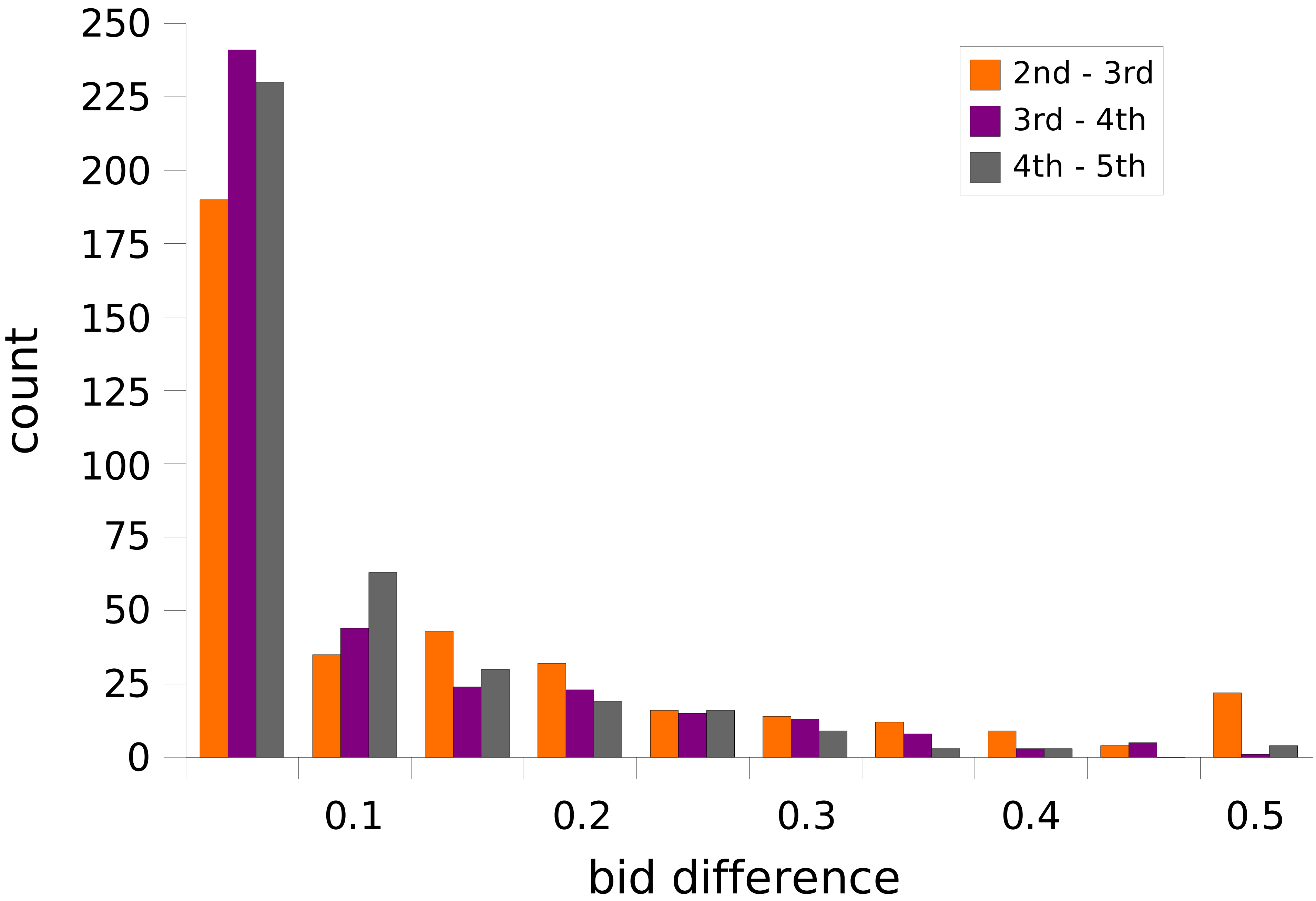

Median Prices after normalization
Quartile 1
Median
Quartile 3
Normalized Value
Bid position
0
0.2
0.4
0.6
0.8
1
2
4
6
8
10
12
14
16
18
20

Bid differences




Bid Differences
count
200
180
160
140
120
100
80
60
40
20
0
2nd - 3rd
3rd - 4th
4th - 5th
0.01
0.02
0.03
0.04
0.05
0.06
0.07
0.08
0.09
0.1
price difference

Normalized price differences



Modeling Bidder Values

- The questions:
  - What is the distribution of values (of all potential bidders) for a random keyword?
  - What is the distribution of values for a keyword from a specific category?
  - How does a modifier affects the distribution of value?
- In the current literature, such distributions are often assumed to be uniformly distributed over some interval [a,b]
  - An oversimplification
- Our experiments set to answer these questions

Modeling bidder values

- The problem:
  - bidder values are *never* directly observable
- Estimate bidder b_i*'s* value with the maximum bid ever observed during some period of time
- Assumptions:
  - 1. the Max bid is highly correlated with her value (and positively).
  - 2. the bid value of any bidder does not vary too much over the period of time we observe

Experiment Setup

- 1. sample a set of keywords;
- 2. observe the bids over, say, a few weeks for each keyword X;
- 3. record the max bid, *max*(b_i,X) for each bidder b_i
- 4. normalize these data according to some criteria
  - e.g. by dividing by the highest max bid for X among all bidders
    - $max(b_i,x) \rightarrow max(b_i,x)/max_j\{ max(b_j,x) \}$
  - Or by further take into consideration n_X, the avg num of bidders for X
    - $max(b_i,x) \rightarrow \mathbf{[\ (n_X+1)/n_X\ ]} * [\ max(b_i,x)/max_j\{ max(b_j,x) \}\ ]$
  - now each (keyword, bidder value) pair maps to a point in [0,1]
- 5. plot all such data points in [0,1] will give us a rough idea of the "prior" distribution of bidder values for a random keyword.
- 6. come up with some statistical model that fits the data
  - Hopefully also come up with a theory explains it

Automatic Clustering

- Can we choose keyword/modifier groups automatically?
- Idea: use data to guide clustering
  - Modifiers that have similar effects should be grouped together
  - Base keywords that are effected similarly should be grouped together
- Might rediscover original groups, or find interesting new ones (or garbage)

Algorithmic Ideas

- Suppose l fixed base keyword groups
- Compute vector of length l per modifier
  - i^{th} dimension is average effect of modifier on keyword group i
- Can run k-means (or something else…)
  - Should produce clusters with desired property
- Now suppose k fixed modifer groups
  - Can do the same thing for base keywords

Algorithmic Ideas

- Idea: alternate k/l-means steps for base keywords and modifiers
  - Recompute vectors at each step

Randomly initialize prototypes

Assign modifiers to clusters

Re-center keyword prototypes

Assign keywords to clusters

Re-center modifier prototypes