So Who Won?
Dynamic Max Discovery with the Crowd

Stephen Guo, Aditya Parameswaran, Hector Garcia-Molina

Vipul Venkataraman
Sep 9, 2015
Outline

• Why Crowdsourcing?
• Finding Maximum
  • Judgement Problem
  • Next Votes Problem
• Conclusion
• References
Why Crowdsourcing?

To solve problems that are difficult for computers

- Sort / Max [1]
- Graph search [5]
- Categorize [4]
- Filter [3]

Tradeoffs [3]

- Latency
- Cost
- Uncertainty
Why Crowdsourcing?

To solve problems that are difficult for computers

• Sort / Max [1]  focus of this talk  Tradeoffs [3]
• Graph search [5]
• Categorize [4]
• Filter [3]

• Latency
• Cost
• Uncertainty
Closest point?
Best profile picture?
Best profile picture?
Best profile picture?
Max Problem

• Goal: Find object with maximum quality
• How: ask pairwise comparisons - votes
• Workers vote correctly with probability $p$
• Variants
  • Structured
  • Unstructured
Max Problem

• Goal: Find object with maximum quality

• How: ask pairwise comparisons - votes

• Workers vote correctly with probability $p$

• Variants
  • Structured
  • Unstructured
Max Problem

• Goal: Find object with maximum quality
• How: ask pairwise comparisons - votes
• Workers vote correctly with probability $p$
• Variants
  • Structured
  • Unstructured
Unstructured setting

- *Judgement Problem*: what is our current best estimate for the overall max winner?

- *Next Votes Problem*: how to choose most effective votes to invoke, given current standing?
Unstructured setting

Both problems are:

• NP-Hard

• Good heuristics exists! #phew

• More on this soon
Judgement Problem

Current best estimate for the overall max winner?

 Representation: weighted directed graphs

![Directed Graph](image)

\[
W = \begin{pmatrix}
0 & 2 & 0 & 0 \\
0 & 0 & 2 & 3 \\
0 & 1 & 0 & 1 \\
0 & 0 & 1 & 0 \\
\end{pmatrix}
\]

Figure: [1]
ML Formulation

Let $\pi$ denote a permutation function

For object $i$, $\pi(i)$ denotes its rank

$$P(\pi^{-1}(k) = j|W) = \frac{\sum_{d: \pi_d^{-1}(k) = j} P(W|\pi_d)}{\sum_{l} P(W|\pi_l)}$$

ML Formulation: Given $W$ and $p$, determine:

$$\text{arg max}_j P(\pi^{-1}(1) = j|W)$$
Heuristic Strategies

- Indegree Strategy
- Local Strategy
- PageRank Strategy
- Iterative Strategy
Indegree Strategy

- Need to know worker accuracy $p$
- Scoring function - represents number of in-degrees
- Transform graph such that $l(i,j) + l(j,i) = 1$
  
- $l(j,i) = P(\pi(i) < \pi(j) | w(i,j), w(j,i))$
- Find node with highest sum of in-degree weights
Local Strategy

Use local evidence

\[ \text{wins}(i) = \sum_j w_{ji} \quad \text{losses}(i) = \sum_i w_{ij} \]

\[ s(i) = \text{wins}(i) - \text{losses}(i) + \sum_j [1(w_{ji} > w_{ij})\text{wins}(j)] \]

\[ - \sum_j [1(w_{ij} > w_{ji})\text{losses}(j)] \]

We now consider evidence 2 steps away
PageRank Strategy

Use global evidence

$$pr_{t+1}(i) = \sum_j \frac{w_{ji}}{d^+(j)} pr_t(j) \quad d^+(i) = \sum_j w_{ij}$$

The probability masses concentrate on the Strongly Connected Components

Subtle differences from original PageRank

Does not always converge. How to handle this?
Iterative Strategy

Rank objects using a scoring metric (which one?)

Remove lower ranked objects

Repeat until final object is obtained

Any metric can be used
Iterative Strategy

Rank objects using a scoring metric (which one?)

Remove lower ranked objects

Repeat until final object is obtained

Any metric can be used, eg: $\text{wins}(i) - \text{losses}(i)$
## Comparison

<table>
<thead>
<tr>
<th>Heuristic</th>
<th>Prediction</th>
</tr>
</thead>
<tbody>
<tr>
<td>ML</td>
<td>((D, C, B, A)) and ((C, D, B, A))</td>
</tr>
<tr>
<td>Indegree</td>
<td>((D, C, B, A))</td>
</tr>
<tr>
<td>Local</td>
<td>((D, C, B, A))</td>
</tr>
<tr>
<td>PageRank</td>
<td>Maximum object = (C)</td>
</tr>
<tr>
<td>Iterative</td>
<td>((C, D, B, A), (C, D, A, B), (D, C, B, A), or)</td>
</tr>
<tr>
<td></td>
<td>((D, C, A, B))</td>
</tr>
</tbody>
</table>

Table: [1]
Experiments

- ML has best performance
- Iterative is best when votes sampled are high
- PageRank bad with low worker accuracy
- PageRank best when votes sampled are low, with high worker accuracy

Figures: [1]
Next Votes Problem

Given current standing and an additional vote budget $b$, what votes to invoke?

- Adaptive
- One-shot

\[ W = \begin{pmatrix}
0 & 2 & 0 & 0 \\
0 & 0 & 2 & 3 \\
0 & 1 & 0 & 1 \\
0 & 0 & 1 & 0
\end{pmatrix} \]

Figure: [1]
Next Votes Problem

Given current standing and an additional vote budget b, what votes to invoke?

• Adaptive
• One-shot

\[ W = \begin{pmatrix}
0 & 2 & 0 & 0 \\
0 & 0 & 2 & 3 \\
0 & 1 & 0 & 1 \\
0 & 0 & 1 & 0 \\
\end{pmatrix} \]

Figure: [1]
ML Formulation

Q: a vote multiset; |Q| = b

A(Q): corresponding answer multiset for Q

\[ P_{\text{max}}(a \land W) = \max_i P(\pi^{-1}(1) = i | a \land W) \]

ML Formulation: Given b, W and p, determine Q, that maximizes:

\[ \sum_{a \in A(Q)} \max_i P(\pi^{-1}(1) = i, a \land W) \]
Evaluation

We use the following framework to evaluate additional votes:

• Use $W$ to score all objects with a scoring function

• Select a batch of $b$ votes to request

• Compute new scores and find maximum object
Evaluation

We use the following framework to evaluate additional votes:

• Use $W$ to score all objects with a scoring function $\text{which one?}

• Select a batch of $b$ votes to request

• Compute new scores and find maximum object
Evaluation

We use the following framework to evaluate additional votes:

- Use $W$ to score all objects with a scoring function
- Select a batch of $b$ votes to request
- Compute new scores and find maximum object
Heuristic Strategies

- Paired Vote Selection
- Max Vote Selection
- Greedy Vote Selection
- Complete Tournament Vote Selection
Paired Vote Selection

• Greedy

• No object chosen twice

• Performs well when objects have similar scores

• Good/bad - why?
Max Vote Selection

- More focus on finding top ranked object
- Should be better than Paired Vote
- Good/bad - why?
Greedy Vote Selection

- Find product of scores of pairs
- Choose $b$ highest weighted pairs
- Good/bad - why?
Complete Tournament

- Take top K objects
- Do round-robin among them (choose K accordingly)
- Given K, should we choose an even lower value? Why?
- Good/bad - why?
Experiments

- ML-ML has best performance
- Prediction performance increases with $b$ (concave)
- Prediction performance increases with $p$ (convex)
- Complete Tournament and Greedy are clear winners

Figures: [1]
Experiments

Greedy v Complete Tournament

- Objects of different types
- Initial votes across same types more likely
- We assume no initial votes across different types
- Complete Tournament is the winner
- Complete Tournament works better with fewer objects

Figures: [1]
Experiments

Greedy v Complete Tournament

- Objects of different types

- Initial votes across same types more likely

- We assume no initial votes across different types

- Complete Tournament is the winner

- Complete Tournament works better with fewer objects

Figures: [1]
Discussion

• Can the first round of votes be invoked better?

• How about performance of the iterative strategy with other scoring metrics?

• Theoretical basis for the behavior of heuristics

• Why does PageRank work well with fewer initial votes?

• Why is Complete Tournament better than Greedy?
Conclusion

• Judgement Problem
• Next Votes Problem
• Effective Heuristics
  • PageRank
• Complete Tournament
References

[1] So who won?: dynamic max discovery with the crowd, S Guo, A Parameswaran, H Garcia-Molina


Questions?
Thank you