Crowd-Learning: Improving the Quality of Crowdsourcing Using Sequential Learning

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The power of crowdsourcing

Tapping into enormous resources in sensing and processing:

• Data collection: participatory sensing, user-generated map
• Data processing: image labeling, annotation
• Recommendation: rating of movies, news, restaurants, services
• Social studies: opinion survey, the science of opinion survey
Scenario I: recommender systems

E.g., Yelp, movie reviews, news feed

- A user shares experience and opinion
- Measure of quality subjective: not all ratings should be valued equally
Scenario II: crowdsourcing markets

E.g., using AMTs

- Paid workers perform computational tasks.
- Measure of quality objective but hard to evaluate: competence, bias, irresponsible behavior, etc.
Our objective

To make the most effective use of the crowdsourcing system

- Cost in having large amount of data labeled is non-trivial
- There may also be time constraint

A sequential/online learning framework

- Over time learn which labelers are more competent, or whose reviews/opinion should be valued more.
- Closed-loop, causal.
Multiarmed bandit (MAB) problems

A sequential decision and learning framework:

- **Objective**: select the best of a set of choices ("arms")
- **Principle**: repeated sampling of different choices ("exploration"), while controlling how often each choice is used based on their empirical quality ("exploitation").
- **Performance measure**: “regret” – difference between an algorithm and a benchmark.

Challenge in crowdsourcing: ground truth

- True label of data remains unknown
- If view each labeler as a choice/arm: unknown quality of outcome ("reward").
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Key ideas and features

Dealing with lack of ground truth:

- Recommender system: input from others is calibrated against one’s own experience
- Labeler selection: mild assumption on the collective quality of the crowd; quality of an individual is estimated against the crowd.

Online and offline uses:

- Learning occurs as data/labeling tasks arrive.
- Can be equally used offline by processing data sequentially.

Performance measure

- Weak regret: comparing against optimal static selections.
- Will also compare with offline methods.
Outline of the talk

The recommender system problem
- Formulation and main results
- Experiments using MovieLens data

The labeler section problem
- Formulation and main results
- Experiments using a set of AMT data

Discussion and conclusion
Model

Users/Reviewers and options:

- $M$ users/reviewers: $i, j \in \{1, 2, ..., M\}$.
- Each has access to $N$ options $k, l \in \{1, 2, ..., N\}$.
- At each time step a user can choose up to $K$ options: $a^i(t)$.

Rewards:

- An IID random reward $r^i_l(t)$, both user and option dependent.
- Mean reward (unknown to the user): $\mu^i_l \neq \mu^i_k, l \neq k, \forall i$, i.e., different options present distinct values to a user.
Performance measure

Weak regret:

\[ R^{i,a}(T) = T \cdot \sum_{k \in N^i_K} \mu^i_k - \mathbb{E} \left[ \sum_{t=1}^{T} \sum_{k \in a^i(t)} r^i_k(t) \right] \]

A user’s optimal selection (reward-maximization): top-\( K \) set \( N^i_K \).

- General goal is to achieve \( R^{i,a}(T) = o(T) \).
- Existing approach can achieve log regret uniform in time.
Example: UCB1 [Auer et all 2002]

Single-play version; extendable to multiple-play

Initialization: for \( t \leq N \), play arm/choice \( t \), \( t = t + 1 \)

While \( t > N \)

- for each choice \( k \), calculate its sample mean:

\[
\bar{r}_k^i(t) = \frac{r_k^i(1) + r_k^i(2) + \ldots + r_k^i(n_k^i(t))}{n_k^i(t)}
\]

- its index:

\[
g_{k,t,n_k^i(t)}^i = \bar{r}_k^i(t) + \sqrt{\frac{L \log t}{n_k^i(t)}}, \; \forall k
\]

- play the arm with the highest index; \( t = t + 1 \)
Key observation

A user sees and utilizes its own samples in learning.

- Can we improve this by leveraging other users’ experience?
- Second-hand learning in addition to first-hand learning.

Basic idea:

- Estimate the difference between two users.
- Use this to calibrate others’ observations or decisions so that they could be used as one’s own.
How to model information exchange

Full information exchange:

• Users share their decisions and subsequent rewards \((k, r_k^i(t))\).

Partial information exchange:

• Only share decisions on which options were used without revealing evaluation \((k)\).
Full information exchange

how to measure pairwise difference

Estimated distortion:

\[ \hat{\delta}^{i,j}_k(t) = \frac{\sum_{s \leq t} \log r^{i}_k(s)/n^{i}_k(t)}{\sum_{s \leq t} \log r^{j}_k(s)/n^{j}_k(t)} . \]

Converted average reward from \( j \):

\[ \pi^{i,j}(\bar{r}^{j}_k(t)) = \sum_{s \leq t} \left( r^{j}_k(s) \hat{\delta}^{i,j}_k(t) / n^{j}_k(t) \right) . \]
An index algorithm

Original UCB1 index: $\bar{r}_k^i(t) + \sqrt{\frac{2\log t}{n_k^i(t)}}$

Modified index: choose $K$ highest in this value

$\bar{r}_k^i(t) \cdot n_k^i(t) + \sum_{j \neq i} \pi^{i,j}(\bar{r}_k^i(t)) \cdot n_k^j(t)$

(U_full): $\frac{\sum_j \pi^{i,j}(\bar{r}_k^i(t)) \cdot n_k^j(t)}{\sum_j n_k^j(t)} + \sqrt{\frac{2\log t}{\sum_j n_k^j(t)}}$,

- Converted average reward from $j$:

$\pi^{i,j}(\bar{r}_k^i(t)) = \sum_{s \leq t} (r_k^j(s)) \tilde{\delta}_k^{i,j}(t) / n_k^i(t)$
The weak regret of user $i$ under $U_{\text{full}}$ is upper bounded by

$$R_{U_{\text{full}}}(T) \leq \sum_{k \in \overline{N}_i^i} \left[ \frac{4(\sqrt{2} + \kappa M^\gamma)^2 \log T}{M \cdot \Delta_k^i} \right] + \text{const.}$$

where $\Delta_k^i = \mu_k^i - \mu_{\overline{N}_i}^i$, assuming $\min_j \{ E[\log r_{ij}^j] - \delta_k^i \} > 0$, and

$$r_k^i = (r_k^j)^{\delta_k^i}.\$$

Compared with UCB1: $R_{\text{ucb1}}(T) \leq \sum_{k \in \overline{N}_K^i} \left[ \frac{8 \log T}{\Delta_k} \right] + \text{const.}$

- When $M$ large roughly $\sqrt{M}$-fold improvement.
Regret bound

Theorem

The weak regret of user $i$ under $U_{\text{full}}$ is upper bounded by

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- When $M$ large roughly $\sqrt{M}$-fold improvement.
Partial information exchange

Only sees others’ choices, not rewards

- Will further distinguish users by their *preference groups*.
- Within the same preference group users have the same preference ordering among all choices: $\mu_{1}^{i} > \mu_{2}^{i} > \cdots > \mu_{N}^{i}$ for all $i$ in the group.
Uniform group preference

Keep track of sample frequency:

- Track $n_k(t) = \sum_i n'_k(t)$; compute frequency
  
  $$\beta_k(t) := \frac{n_k(t)}{\sum_l n_l(t)}$$

Modified index:

$$(U_{\text{part}}): \bar{r}_k^i(t) - \alpha(1 - \beta_k(t)) \sqrt{\frac{\log t}{n'_k(t)}} + \sqrt{\frac{2 \log t}{n'_k(t)}}$$

Group recommendation

- $\alpha$: the weight given to others' choices.
Non-uniform group preferences

Additional technical hurdles:

- Assume known set of preferences but unknown group affiliation.
- Need to perform group identification
  - Keep track of the number of times user $j$ chooses option $k$.
  - Estimate $j$’s preference by ordering the sample frequency.
  - Place $j$ in the group with best match in preference ordering.
  - Discount choices made by members of a different group.
- Similar results can be obtained.
Experiment I: $M = 10, N = 5, K = 3$

Uniform preference; rewards exp rv; distortion Gaussian

(L) comparing full information exchange with UCB1 applied individually, and applied centrally with known distortion.

(R) comparing partial information exchange with UCB1 applied individually.
Experiment II: MovieLens data

A good dataset though not ideal for our intended use

- Collected via a movie recommendation system
- We will use MovieLens-1M dataset: containing 1M rating records provided by 6040 users on 3952 movies from 18 genres, from April 25, 2000 to February 28, 2003.
- Each rating on a scale of 1-5.
- In general, each reviewer contributes to multiple reviews: ~70% have more than 50 reviews.

Can we provide better recommendation?

- Predict how a user is going to rate movies given his and other users’ reviews in the past.
- The decision aspect of the learning algorithm is not captured.
MovieLens: methodology

- Discrete time steps clocked by the review arrivals.
- Bundle movies into 18 genres (action, adventure, comedy, etc), each representing an option/arm:
  - ensure that each option remains available for each reviewer
  - lose the finer distinction between movies of the same genre
  - prediction is thus for a whole genre, used as a proxy for a specific movie within that genre.
- Use full information exchange index
  - we will only utilize users estimated to be in the same group (same preference ordering).
- Prediction performance measured by error and squared error averaged over the total number of reviews received by time $t$. 
The recommendation algorithm

At time $t$, given $i$’s review $r_i^k(t)$ for movie $k$:

- update $i$’s preference ranking over options/genres;
- update $i$’s similarity group: reviewers that share the same set of top $K$ preferred options as $i$;
- estimate the distortion between $i$ and those in its similarity group;
- update $i$’s rating for each option by including rating from those in its similarity group corrected by the estimated distortion;
- repeat for all reviews arriving at time $t$.

At the end of step $t$, obtain estimated rating for all reviewers and all genres.
Algorithm used online

Prediction at each time step

- Prediction becomes more accurate with more past samples.
- Group learning outperforms individual learning.
- Downward trend not monotonic due to arrivals of new movies.
Algorithm used offline

Offline estimation result; comparison with the following

- SoCo, a social network and contextual information aided recommendation system. A random decision tree is adopted to partition the original user-item-rating matrix (user-movie-rating matrix in our context) so that items with similar contexts are grouped.

- RPMF, Random Partition Matrix Factorization, a contextual collaborative filtering method based on a tree constructed by using random partition techniques.

- MF, basic matrix factorization technique over the user-item matrix.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Crowd</th>
<th>Ind.</th>
<th>SoCo</th>
<th>RPMF</th>
<th>MF</th>
</tr>
</thead>
<tbody>
<tr>
<td>Avg. Error</td>
<td>0.6880</td>
<td>0.8145</td>
<td>0.7066</td>
<td>0.7223</td>
<td>0.7668</td>
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<tr>
<td>RMSE</td>
<td>0.9054</td>
<td>1.0279</td>
<td>0.8722</td>
<td>0.8956</td>
<td>0.9374</td>
</tr>
</tbody>
</table>
Discussion

Combination of learning from direct and indirect experience

- Estimation of similarity groups and pairwise distortion effectively allows us to utilize a larger set of samples.

Our algorithm does not rely on exogenous social or contextual information

- However, the estimation of similarity groups introduces a type of social connectivity among users.

In settings where it’s unclear whether preferences are uniform or non-uniform:

- can simply assume it to be the latter and do as we did in the MovieLens experiment.
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Discussion and conclusion
Labeler selection

- $M$ labelers; labelers $i$ has accuracy $p_i$ (can be task-dependent).
  - No two exactly the same: $p_i \neq p_j$ for $i \neq j$, and $0 < p_i < 1$, $\forall i$.
  - Collective quality: $\bar{p} := \sum_i p_i / M > 1/2$.

- Unlabeled tasks arrive at $t = 1, 2, \cdots$.
  - User selects a subset $S_t$ of labelers for task at $t$.
  - Labeling payment of $c_i$ for each task performed by labeler $i$. 
Labeling outcome/Information aggregation

Aggregating results from multiple labelers:

- A task receives a set of labels: \( \{L_i(t)\}_{i \in S_t} \).
  - Use simple majority voting or weighted majority voting to compute the label output: \( L^*(t) \).

- Probability of correct labeling outcome: \( \pi(S_t) \); well defined function of \( p_i \)s.
  - Optimal set of labelers: \( S^* \) that maximizes \( \pi(S) \).

Accuracy of labeling outcome:

- Probability that a simple majority vote over all \( M \) labelers is correct: \( a_{\text{min}} := P(\sum_i X_i / M > 1/2) \).
  - If \( \bar{p} > 1/2 \) and \( M > \frac{\log 2}{\bar{p} - 1/2} \), then \( a_{\text{min}} > 1/2 \).
Obtaining $S^*$

Assuming we know $\{p_i\}$, $S^*$ can be obtained using a simple linear search.

**Theorem**

*Under the simple majority voting rule, $|S^*|$ is an odd number. Furthermore, $S^*$ is monotonic: if $i \in S^*$ and $j \notin S^*$, then we must have $p_i > p_j$.***
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An online learning algorithm

There is a set of tasks $E(t) \sim \log t$ used for testing purposes.

- These or their independent and identical variants are repeatedly assigned to the labelers $\sim \log t$. 
Two types of time steps:

- **Exploration**: all $M$ labelers are used. Exploration is entered if (1) the number of testers falls below a threshold ($\sim \log t$), or if (2) the number of times a tester has been tested falls below a threshold ($\sim \log t$).

- **Exploitation**: the estimated $\tilde{S}^*$ is used to label the arriving task based on the current estimated $\{\tilde{p}_i\}$.
Three types of tasks:

- **Testers**: those arriving to find (1) true and (2) false. These are added to $E(t)$ and are repeatedly used to collect independent labels whenever (2) is true subsequently.

- **Throw-aways**: those arriving to find (2) true. These are given a random label.

- **Keepers**: those arriving to find both (1) and (2) false. These are given a label outcome using the best estimated set of labelers.
**Accuracy update**

- Estimated label on tester $k$ at time $t$: majority label over all test outcomes up to time $t$.
- $\tilde{p}_i$ at time $t$: the % of times $i$’s label matches the majority vote known at $t$ out of all tests on all testers.
Regret

Comparing with the optimal selection (static):

\[ R(T) = T \pi(S^*) - E\left[\sum_{t=1}^{T} \pi(S_t)\right] \]

Main result:

\[ R(T) \leq \text{Const}(S^*, \Delta_{\text{max}}, \Delta_{\text{min}}, \delta_{\text{max}}, \delta_{\text{min}}, a_{\text{min}}) \log^2(T) + \text{Const} \]

- \( \Delta_{\text{max}} = \max_{S \neq S^*} \pi(S^*) - \pi(S) \), \( \delta_{\text{max}} = \max_{i \neq j} |p_i - p_j| \).
- First term due to exploration; second due to exploitation.
- Can obtain similar result on the cost \( C(T) \).
Discussion

Relaxing some assumptions

• Re-assignment of the testers after random delay
• Improve the bound by improving $a_{\text{min}}$: weed out bad labelers.

Weighted majority voting rule

• Each labeler $i$’s decision is weighed by $\log \frac{p_i}{1-p_i}$.
• Have to account for additional error in estimating the weights when determining label outcome.
• A larger constant: slower convergence to a better target.
Experiment I: simulation with $M = 5$

Performance comparison: labeler selection v.s. full crowd-sourcing (simple majority vote)
Comparing weighted and simple majority vote

![Graph comparing weighted and simple majority voting](image)
Experiment II: on a real AMT dataset

• Contains 1,000 images each labeled by the same set of 5 AMTs.
• Labels are on a scale from 0 to 5, indicating how many scenes are seen from each image.
• A second dataset summarizing keywords for scenes of each image: use this count as the ground truth.

<table>
<thead>
<tr>
<th></th>
<th>AMT1</th>
<th>AMT2</th>
<th>AMT3</th>
<th>AMT4</th>
<th>AMT5</th>
</tr>
</thead>
<tbody>
<tr>
<td># of disagree</td>
<td>348</td>
<td>353</td>
<td>376</td>
<td>338</td>
<td>441</td>
</tr>
</tbody>
</table>

Table: Total number of disagreement each AMT has
(L) AMT 5 was quickly weeded out; eventually settled on the optimal set of AMTs 1, 2, and 4.

(R) CDF of all images’ labeling error at the end of this process.
Conclusion

We discussed two problems

- How to make better recommendation for a user by considering more heavily opinions of other like-minded users.
  - UCB1-like group learning algorithms.
  - Outperforms individual learning.

- How to select the best set of labelers over a sequence of tasks.
  - An algorithm that estimates labeler’s quality by comparing against (weighted) majority vote.
  - New regret bound.

Currently under investigation

- Lower bound on the regret in the labeler selection problem.
- Generalization to sequential classifier design.
References
