RL in the industry (Applications of bandits and recommendation systems)

Nicolas Le Roux

Google Brain

Presenter: Tianlu Wang
1 Introduction
   • Background

2 Finding a bidding strategy
   • Previous solution
   • Problem
   • Dealing with confounding variables
   • Counterfactual Questions
   • From evaluation to optimization

3 Summary
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3 Summary
Two main components in RL

- Multi-step episodes
- **Reward evaluation and maximization** (in one episode)
Retargeting in online advertising

- A user lands on a webpage
- Website contacts an ad-exchange
- Ad-exchange contacts the retargeter
- It's an **auction**: each competitor tells how much it bids
- Highest bidder wins the right to display an ad
Details of auction

- Real-time bidding (RTB)
- 2nd -price auction: the highest bidder wins but pays the second highest bid
- Optimal strategy: bid the expected gain
- \( E[gain] = \text{price per click (CPC)} \times \text{Probability(click)}(\text{CTR}) \)
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3 Summary
We wish to estimate the probability of click
We have access to labelled data (for won auctions)
X: information about the user
Y: click / no click
First reaction is to build a classifier for this
Pick a better model

- Two-arm bandit: system A (current) vs. B (new)
- Split the population for some period of time
- Choose the system with the best average reward
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3 Summary
Test error vs. true revenue
Because of implicit assumptions

- The log-loss is a good proxy for the revenue?:
  - people only care about what is the optimal when they define the loss function but we should also consider how much we need to pay if we make wrong decision (white board)

- The input distribution is the same?:
  - Labelled data is on the won auctions
  - The bidding algorithm impacts input distribution
  - The best model can change
Simpson’s paradox

<table>
<thead>
<tr>
<th></th>
<th>Top banner</th>
<th>Side banner</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>CTR</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall</td>
<td>60/9000 (0.67%)</td>
<td>50/7000 (0.71%)</td>
</tr>
<tr>
<td>High-value-users</td>
<td>48/8000 (0.6%)</td>
<td>2/1000 (0.2%)</td>
</tr>
<tr>
<td>Low-value-users</td>
<td>12/1000 (1.2%)</td>
<td>48/6000 (0.8%)</td>
</tr>
</tbody>
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3 Summary
Possible methods

- Add as many variables as possible in the model: Too complicated
- Run online A/B tests: Smaller companies take longer to collect data
- **Exploration** (demonstration):
  - Exploration converges to the optimum when the model is well-specified!
  - It almost never is. (In most cases, bandit algorithms don’t work)
- Perform counterfactual analyses: What would have happened if we had taken another decision?
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3 Summary
Current distribution over actions: \( p(a|s) \)

Expected value of new distribution \( q(a|s) \)?

\[
G(q) = \int_{s} \int_{a} p(s)q(a|s)r(a, s) \, da \, ds
\]

\[
= \int_{s} \int_{a} p(s) \frac{q(a|s)}{p(a|s)} p(a|s) r(a, s) \, da \, ds
\]

\[
\approx \frac{1}{N} \sum_{i} \frac{q(a_{i}|s_{i})}{p(a_{i}|s_{i})} r_{i}
\]
Estimated reward vs. Real reward
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3. Summary
Evaluation is underrated

- Importance sampling allows us to evaluate $q$
- We may now optimize over $q$
- Rolling out a new policy is expensive
- How to optimize with few updates?
Robustness and efficiency are critical
This includes pipeline efficiency
Improving the model is useless w/o good reward
RL deals with tangible quantities.