Top-N Protocols and Unary Data

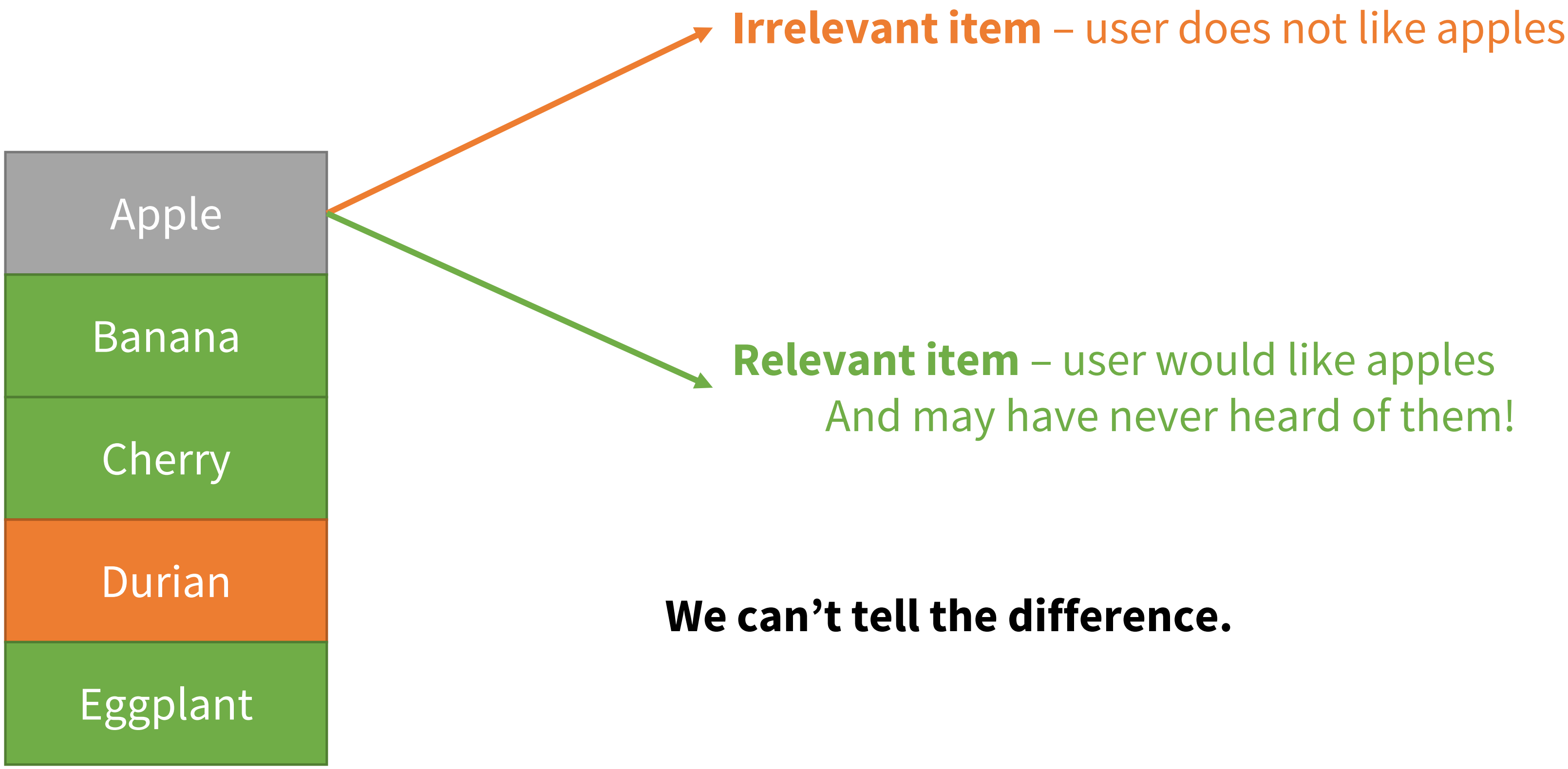
一元数据

Introduction

- We’ve seen
  - Prediction metrics
  - Top-N metrics
  - Cross-validation protocols
- Now: some particular protocol considerations for top-N evaluation,
  - Particularly for unary data
- Unfortunately, some deep unsolved problems

Missing Data

- Most of our data is missing
  - Unrated items
  - Unpurchased items
- What do we know about items with no record?
  - User *probably* doesn't like item…
  - … but if they do, it might be a *really good* recommendation



We can’t tell the difference.

Popularity Bias

- Popular items have the most ratings/purchases
- So 'Popular' recommender can automatically do very well
  - Popular is a good baseline recommender anyway
  - But if we want the recommender to find less-known items the user might like…
- Recommenders that effectively find relevant but less-popular items perform poorly on metrics

Studied by Alejandro Bellogin

Problem Summary

- Penalizing good recommendations due to missing data
- Data favors ‘most popular’
  - Correlation between bias and performance unknown

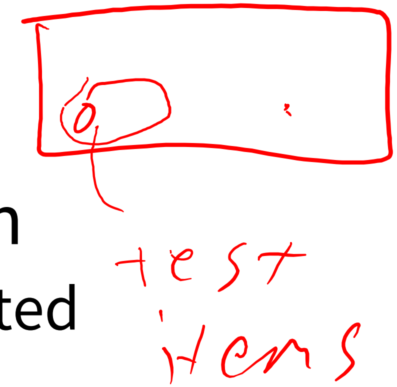
Solution 1: Rank Effectiveness

If we have ratings, or other negative feedback:

1. Ask recommender to rank test items, rather than recommend from entire universe.
2. Measure if rank is consistent with user ratings
   - MAP
   - nDCG
   - NDPM

Requires ratings, so no good on unary data.

Proposed Solution 2: Limit Domain



- Limit *candidate set* for recommendation
  - Recommend from test + N randomly-selected unknown items
  - Introduced by Koren (2008)
- Good-but-unknown items are *probably not* in candidate set
  - Assuming sufficiently low prevalence of good items
- However: seems to exacerbate popularity bias
  - Randomly-selected items probably aren't popular
  - Found by Mahant (2016)

Best Known Practices

- These are the best we have
- Use them
  - But be aware of limitations when reporting
- Look for alternatives
  - User testing
  - Try to get negative data
  - Corroborate with additional evidence

Promising Directions

- One-sided classification
- New metrics and protocols (e.g. clarity)

Conclusion

- Evaluating recommenders is hard
- Offline evaluation doubly so
- We don’t have great methods right now
- Be aware of problems when making claims

Top-N Protocols and Unary Data