Recommender Models for Items in the game '*Destiny 2*'

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Background, Aim and Applications

Background: When dealing with non-ranking recommendation models, or popularity-based systems, platform operators have a wealth of data on how the things they recommend are actually used. This data could improve and further inform the AI models they use. The game 'Destiny 2' is used as a case study thanks to its open API access and Player-vs-Player environment facilitating popularity labeling for items.

Aim:
Investigating how to take advantage of characteristics specific to recommendation applications.

Applications:
Improvement in training of Recommendation models. Aligning objective function to production goals.

Lifecycle

Data collection → Model Proposal and Development → Evaluation Metrics → Live Performance Evaluation → Conclusions

Literature Review

The topics explored were the following:

- Previous work...
  - In other games [1, 2]
  - In *'Destiny 2'* [3, 4]
  - In other recommendation systems [5]
- Suitable models to the domain
- Constrains preventing Synthetic Data Generation [6]

Data Collection

The dataset is gathered with a script, using the available set of public API services the game developers provide. The strategy is based on a snowballing 3-stage crawling search:

1. Gather new, unseen players
2. Get the account's matches and used items
3. Get other players to process in the matches

Evaluation Metrics for Recommenders

Heuristic metrics for recommenders [7]

- Accuracy-based metrics are not the best suited because only one class is relevant
- Heavily discourage the model from recommending 'unpopular'
- 'Punish' the model as a function of the gravity of the error

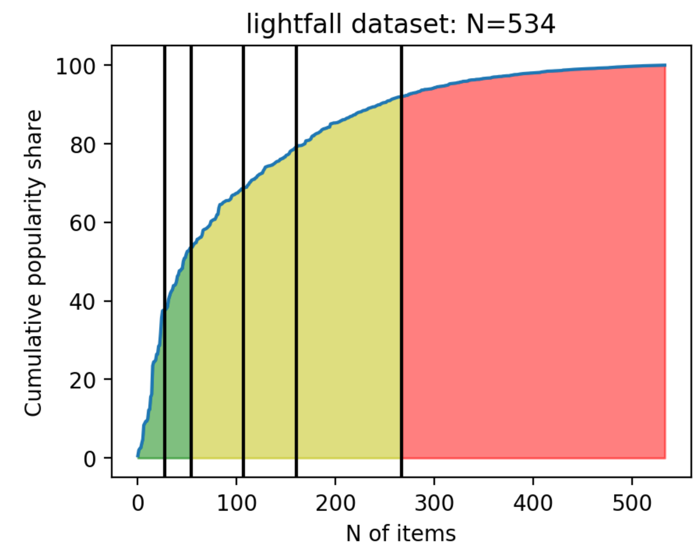

Figure 1: Cumulative popularity sum of items

To achieve these goals, the following objective function is proposed:

$$H = q_0 * TP_{\mathcal{C}_0} + \sum_{i \in \mathcal{C}}^{N} q_i * FP_{\mathcal{C}_i \ misclassified \ as \ \mathcal{C}_0}, \ where \ q_0 > q_1 \geq ..q_{N-1} \geq q_N \quad (1)$$

With $\mathcal{C}_0$ as the Popular class with $q_0 = 1$ and $\mathcal{C}_1$ as the Niche class, and used the combined ratio of $\mathcal{C}_0 + \mathcal{C}_1$ over the entire dataset as q_1 in Equation 1 we obtain:

$$WFPC = TP_{Popular} + ((N_{Niche} + N_{Popular})/Total) * FP_{Niche} \quad (2)$$

Performance evaluation and metric results comparison

Model	10-Fold CV	Full Training
Decision Tree	**57.45**	75.53
Random Forest	07.47	23.40
Boosted Decision Tree	31.51	88.30
Support Vector Machine	38.30	**91.49**
Multi-Layer Perceptron	13.83	17.02

Table 1: WFPC Training metrics

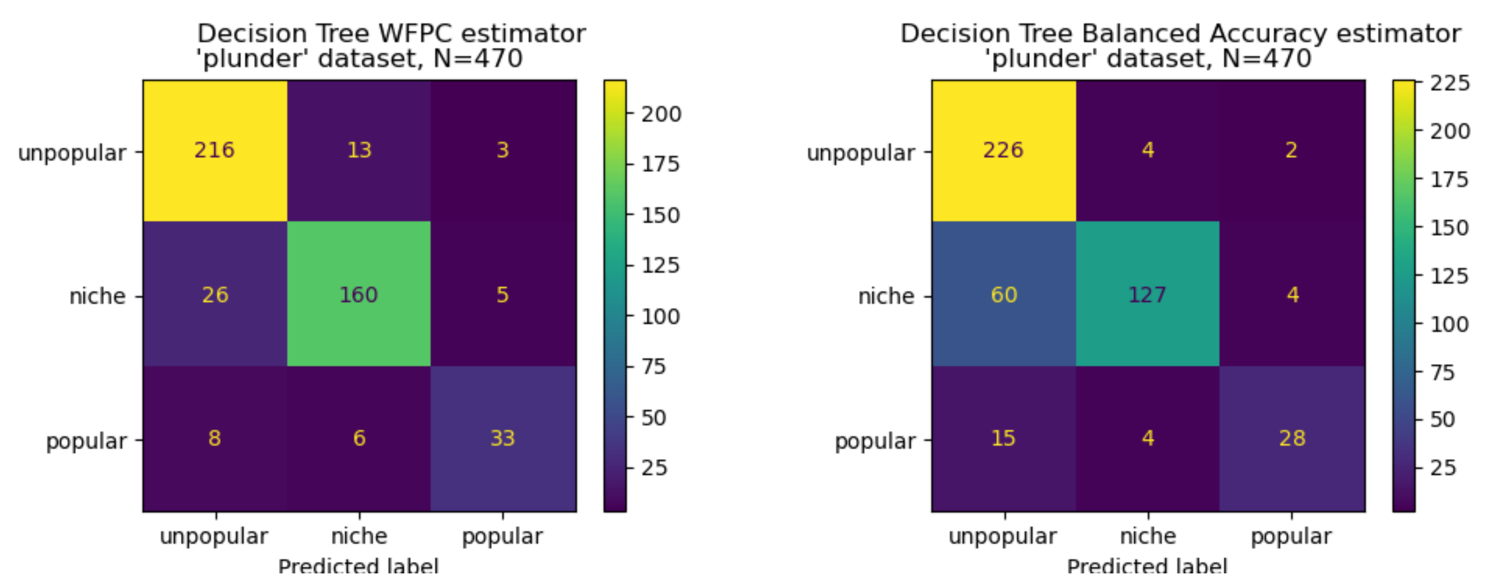

Figure 2: WFPC-vs-Balanced Accuracy trained Decision Trees

Conclusions and summary

Conclusion
The models trained on the heuristic *WFPC* metric exhibit better accuracy for the 'popular' class and shows less instances of missclassification of 'unpopular' items as 'popular' than the commonly used *Balanced Accuracy* metric.

Contributions:
A novel, heuristic-based metric for developing AI systems that deal with recommendations.

Limitations:
Careful tuning of the class factors q_i is needed to ensure the discounted reward does not bias the model towards class i when it is prevalent in the data.

Future Work:
Further development of heuristic metrics, Analysis of size reduction for models trained with the metric. Study the effects of poor q_i choices and strategies for choosing them.

Repository and References

[1] Paul Bertens et al. "A Machine-Learning Item Recommendation System for Video Games". In: *2018 IEEE Conference on Computational Intelligence and Games (CIG)*. 2018.

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