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Appendix A

Estimated results for a random recommender system

For simulating the results for a system recommending random tracks from the catalog, the following numbers were used:

- Number of relevant tracks per playlist: 30
(the average playlist had ~100 tracks, and 30% of them were in the hidden section of the playlist).
- Number of playlists: 9000 (the number of test set playlists)
- Number of iterations: 100 (how many times the simulation was run per k)

Following is the source code for the simulation, and the average *recall@10*, *precision@10*, *recall@500*, and *precision@500* for the simulated random recommender.