DATA 612: Research Discussion Assignment 1 - Spotify Recommendations

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Please complete the research discussion assignment in a Jupyter or R Mark-down notebook. You should post the GitHub link to your research in a new discussion thread. Now that we have covered basic techniques for recommender systems, choose one commercial recommender and describe how you think it works (content-based, collaborative filtering, etc.). Does the technique deliver a good experience or are the recommendations off-target?

Introduction

Of the services that I use that come packaged with recommendations, Spotify is - by far - the most effective at producing recommendations that I find useful. This effectiveness has motivated my search for information over the years about how they produce such great recommendations.

Spotify - the most popular global audio streaming subscription service - operates in 79 markets, has 217 million users (including 100m paid subscribers), and streams a catalog of 50+ million tracks. Spotify's user by track matrix is simply enormous. Not only that, but there are also 3+ billion user-created playlists on the platform - a goldmine for information about what Spotify's users like.

Employees of Spotify have publicly discussed aspects of the inner workings of their recommendation platform over the years, so there is some information about how the system works. Although their recommender continues to evolve, from what I can glean from publicly available information, they use a ensemble of at several types of recommenders (as-of last 2015):

All of the images in this discussion post are taken from a presentation made by Chris Johnson on 2015-11-16, which can be found at the following URL:

https://www.slideshare.net/MrChrisJohnson/from-idea-to-execution-spotifys-discover-weekly

1. Collaborative Filtering (CF) using Matrix Factorization

From what I can gather, Spotify initially only used Collaborative Filtering (CF) to provide recommendations. This approach, which is outlined in the paper, Collaborative Filtering for Implicit Feedback Datasets (http://yifanhu.net/PUB/cf.pdf), has been presented at a handful of meetups over the years. Chris Johnson, formerly of Spotify, has even published a Python implementation of implicit matrix factorization (https://github.com/MrChrisJohnson/implicit-mf).
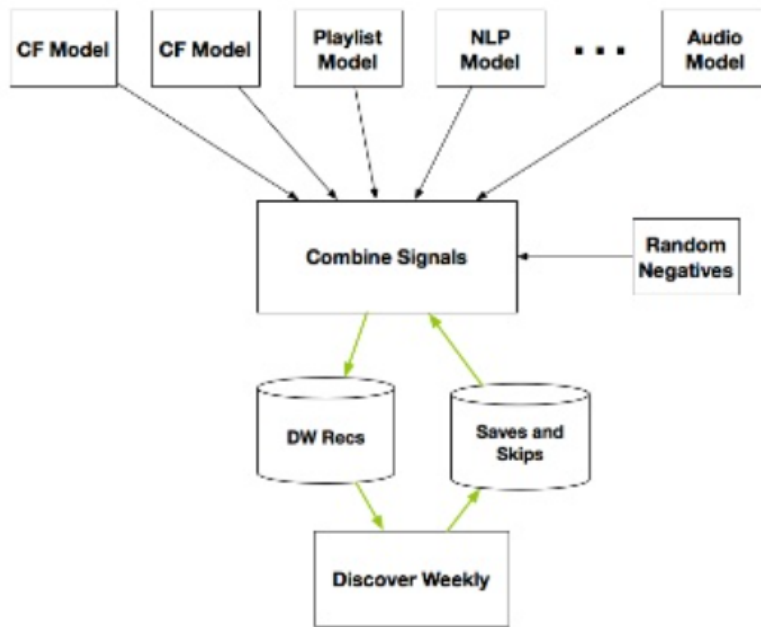
Figure 1: Recommender Structure

Figure 2: Matrix Factorization with RMSE

Implicit Matrix Factorization [1]

- Aggregate all (**user**, **track**) streams into a large matrix
- **Goal**: Approximate binary preference matrix by inner product of 2 smaller matrices by minimizing the weighted **RMSE** (root mean squared error) using a function of plays, context, and recency as weight

$$\text{Users} \begin{pmatrix} 1\,0\,0\,0\,1\,0\,0\,1 \\ 0\,0\,1\,0\,0\,1\,0\,0 \\ 1\,0\,1\,0\,0\,0\,1\,1 \\ 0\,1\,0\,0\,0\,1\,0\,0 \\ 0\,0\,1\,0\,0\,1\,0\,0 \\ 1\,0\,0\,0\,1\,0\,0\,1 \end{pmatrix} \approx \begin{pmatrix} X \end{pmatrix} \underbrace{\big(\quad Y \quad \big)}_{f} \} f$$

Songs

$$\min_{x,y} \sum_{u,i} c_{ui}(p_{ui} - x_u^T y_i - \beta_u - \beta_i)^2 + \lambda\left(\sum_u \|x_u\|^2 + \sum_i \|y_i\|^2\right)$$

- p_{ui} = 1 if user u streamed track i else 0
- $c_{ui} = 1 + \alpha r_{ui}$
- x_u = user $u's$ latent factor vector
- y_i = item $i's$ latent factor vector
- β_u = bias for user u
- β_i = bias for item i
- λ = regularization parameter

[1] Hu Y. & Koren Y. & Volinsky C. (2008) Collaborative Filtering for Implicit Feedback Datasets *8th IEEE International Conference on Data Mining*

Figure 3: Matrix Factorization with Logistic Loss

Can also use Logistic Loss! [2]

- Aggregate all (**user**, **track**) streams into a large matrix
- **Goal**: Model probability of user playing a song as **logistic**, then maximize **log likelihood** of binary preference matrix, weighting positive observations by a function of plays, context, and recency

$$
\text{Users} \begin{pmatrix} 1\,0\,0\,0\,1\,0\,0\,1 \\ 0\,0\,1\,0\,0\,1\,0\,0 \\ 1\,0\,1\,0\,0\,0\,1\,1 \\ 0\,1\,0\,0\,0\,1\,0\,0 \\ 0\,0\,1\,0\,0\,1\,0\,0 \\ 1\,0\,0\,0\,1\,0\,0\,1 \end{pmatrix} \approx \begin{pmatrix} X \end{pmatrix} \underbrace{\big(\quad Y \quad \big)}_{f} \Big\}\, f
$$

Songs

$$
\max_{X,Y} \sum_{u,i} \alpha r_{u,i} \log(\sigma(x_u.y_i + \beta_u + \beta_i)) + \log(1 - \sigma(x_u.y_i + \beta_u + \beta_i)) - \lambda(\sum_u \|x_u\|^2 + \sum_i \|y_i\|^2)
$$

- x_u = user $u's$ latent factor vector
- y_i = item $i's$ latent factor vector
- β_u = bias for user u
- β_i = bias for item i
- λ = regularization parameter

[2] Johnson C. (2014) Logistic Matrix Factorization for Implicit Feedback Data *NIPS Workshop on Distributed Matrix Computations*

Essentially, matrix factorization is applied to a binary representation of user/track preference where each element of the matrix represents whether a user has streamed a track. (Details can be found here https://www.slideshare.net/MrChrisJohnson/algorithmic-music-recommendations-at-spotify/19-Implicit_Matrix_Factorization19Replace_Stream_counts). The output of the method is a lower dimensional representation the universe of users and tracks. Each user has a vector that uniquely represents their musical preferences (i.e., it maps them to this space). An approximate nearest neighbors implementation is then used to search for similar users/items to get fast recommendations for each user (https://www.slideshare.net/erikbern/approximate-nearest-neighbor-methods-and-vector-models-nyc-ml-meetup). A Python implementation is again available (https://github.com/MrChrisJohnson/annoy)

2. Content-Based Filtering using Natural Language Processing (NLP)

NLP is applied to meta data associated with playlists.

3. Applications of Deep Learning

There appear to be two uses of Deep Learning in the Spotify recommender system:

Content-Based Filtering using Deep Learning: One part of the system does Deep Learning on Audio files to find representations of the tracks that can be used in recommendations.

Collaborative Filtering using Deep Learning: Another part of the system appears to learn latent embeddings for users and items, using implicit user/track feedback data. The network takes as input a user's history of implicit ratings (i.e., whether they stream a track for longer than a minimum time) and attempts to predict their listening history (approximately 2 weeks).

Figure 4: Ratio Data Flow

Figure 5: Discover Weekly Data Flow

Python Implementation Links

The following URLs provide Python implementations for some of the methods used in the ensemble:

```
https://github.com/MrChrisJohnson/implicit-mf
https://github.com/MrChrisJohnson/logistic-mf
https://github.com/MrChrisJohnson/deep-mf
https://github.com/MrChrisJohnson/annoy
```

Presentation Links

The following URLs provide fancinating details about featurs of the Spotify
recommender system:

[2014-01-13] https://www.slideshare.net/MrChrisJohnson/algorithmic-music-recommendations-at-spotify

[2014-05-09] https://www.slideshare.net/MrChrisJohnson/collaborative-filtering-with-spark

[2014-06-27] https://www.slideshare.net/MrChrisJohnson/music-recommendations-at-scale-with-spark

[2015-01-06] https://www.slideshare.net/MrChrisJohnson/scala-data-pipelines-for-music-recommendations

[2015-09-25] https://www.slideshare.net/MrChrisJohnson/interactive-recommender-systems-with-netflix-and-spotify

[2015-09-25] https://www.slideshare.net/erikbern/approximate-nearest-neighbor-methods-and-vector-models-ny

[2015-11-16] https://www.slideshare.net/MrChrisJohnson/from-idea-to-execution-spotifys-discover-weekly

Key Papers

The following URLs provide details of matrix factorization on implicit data:

http://yifanhu.net/PUB/cf.pdf

http://stanford.edu/~rezab/nips2014workshop/submits/logmat.pdf

https://papers.nips.cc/paper/5004-deep-content-based-music-recommendation.pdf

Software

This discussion post was created using base R [R Core Team, 2018] and the R
markdown [Allaire et al., 2018], tint [Eddelbuettel, 2018], kableExtra [Zhu, 2018],
and tidyverse [Wickham, 2017] libraries.

References

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R Core Team. *R: A Language and Environment for Statistical Computing*. R
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   //www.R-project.org/.

Hadley Wickham. *tidyverse: Easily Install and Load the 'Tidyverse'*, 2017. URL
   https://CRAN.R-project.org/package=tidyverse. R package
   version 1.2.1.

Hao Zhu.   *kableExtra: Construct Complex Table with 'kable' and
   Pipe Syntax*, 2018.   http://haozhu233.github.io/kableExtra/,
   https://github.com/haozhu233/kableExtra.