Orpheus

By The Dummy Variables

Outline

- **Motivation**
- The dataset
  - EDA
- Technologies used
- Results
  - Recommender system
  - Aggregation strategy
- Final product

Motivation

Create a multi-user music recommendation system based on mood.

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The dataset

The Echo Nest Taste Profile Subset

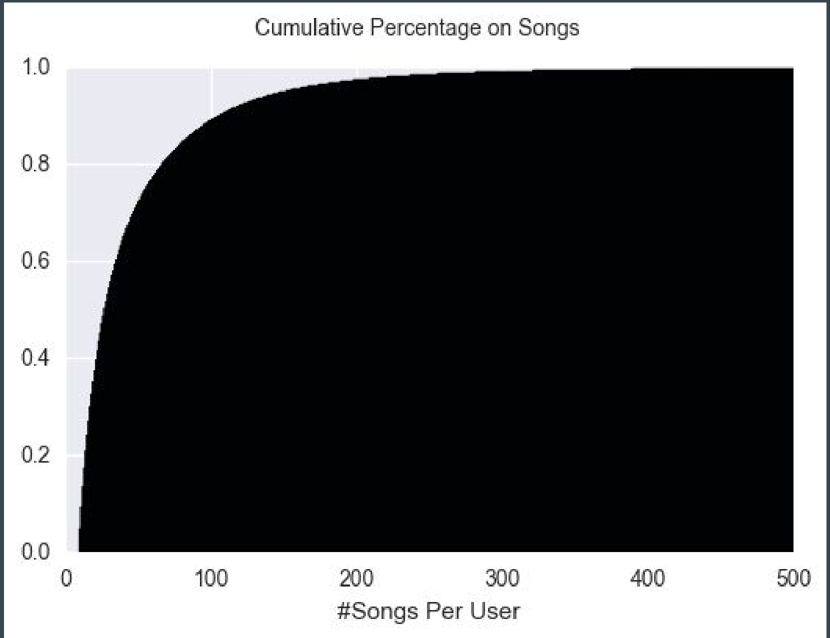
- ~5 GB
- 1,019,318 unique users
- 384,546 unique songs
- 48,373,586 unique user, song, playcount triplets

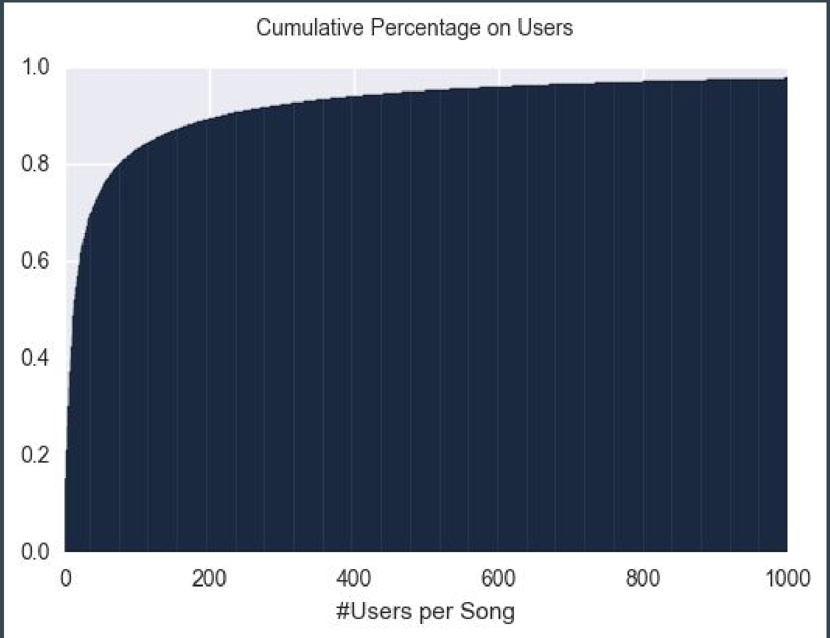
The dataset

EDA

- Listening to a Song 5 times is more common occurrence than listening to a song 4 times. 2250999 vs 1805081 occurrences
- 28,755,966 occurrences where songs were listened to once for each user, 19,617,620 occurrences where songs were listened more than one time for each user
- On Average each song is listened to by 125.79 users or 50% of songs are listened to by 13 users
- On Average each user listens to 47 unique songs or 50% of users listen to 27 unique songs
- Each user listens to at least 10 different songs
- Out of 384,546 unique songs, 31,781 songs are only listened to once.

The dataset


Cumulative Percentage on Songs
1.0
0.8
0.6
0.4
0.2
0.0
0
100
200
300
400
500
#Songs Per User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Technologies used

Spark

Flask

Spotify®
WEB API

amazon
web services

databricks

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Recommender system

Types of recommender systems:

1. Content-based:
   a. Looks at characteristics of users or items. For example;
      i. Find similarity of songs based on music tempo,
      ii. Find similar users based on demographics.
   b. Difficult to collect
2. Collaborative filtering (CF):
   a. Modelling users' past behavior or the items' rating. For example;
      i. Identify users who rated the same item similarly.
   b. Cold start problem.

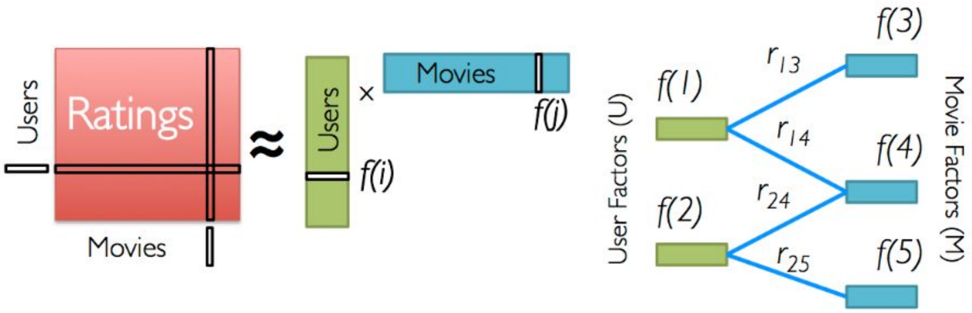
Collaborative Filtering

1. Explicit feedback
    a. User actively input their preference of the product. For example;
        i. Netflix star rating
2. Implicit feedback
    a. Based in consumption of the item.
        i. Number of times a song is heard.
        ii. Repeat purchase of product.

Collaborative Filtering

Latent factor model:

Low-Rank Matrix Factorization:



Iterate:

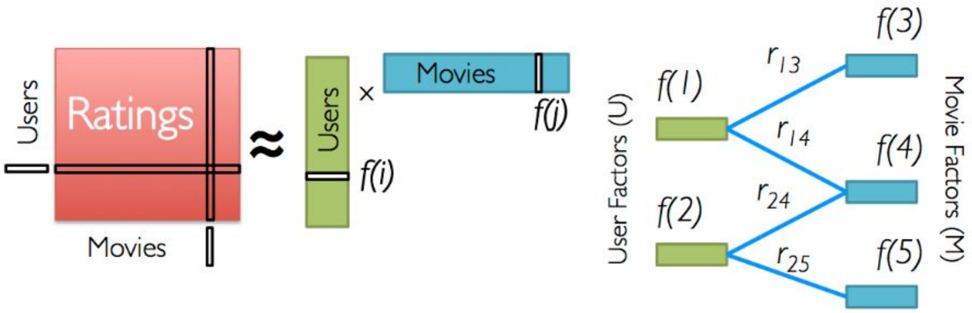
$$f[i] = \arg\min_{w \in \mathbb{R}^d} \sum_{j \in \mathrm{Nbrs}(i)} \left(r_{ij} - w^T f[j]\right)^2 + \lambda ||w||_2^2$$

Explicit Model

Collaborative Filtering

Latent factor model:

Low-Rank Matrix Factorization:



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Explicit Model

$$f[i] = \arg\min_{w \in \mathbb{R}^d} \sum_{j \in \text{Nbrs}(i)} \left(r_{ij} - w^T f[j]\right)^2 + \lambda ||w||_2^2$$

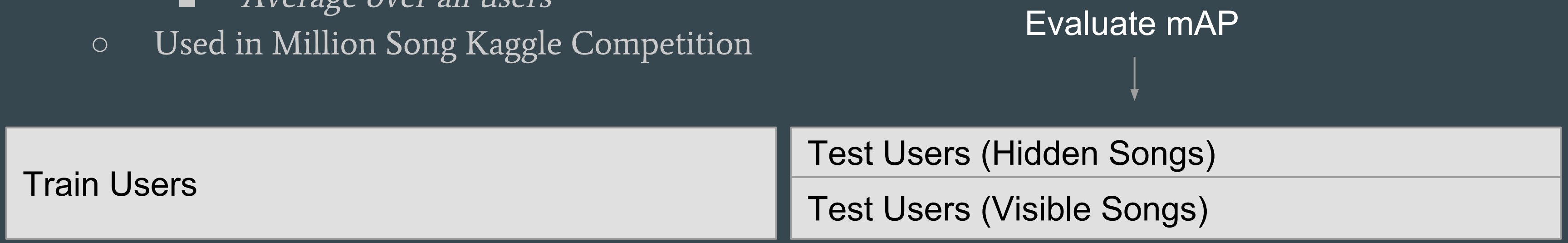
Implicit Model

$$\min_{x_\star, y_\star} \sum_{u,i} c_{ui}(p_{ui} - x_u^T y_i)^2 + \lambda \left(\sum_u \|x_u\|^2 + \sum_i \|y_i\|^2 \right)$$

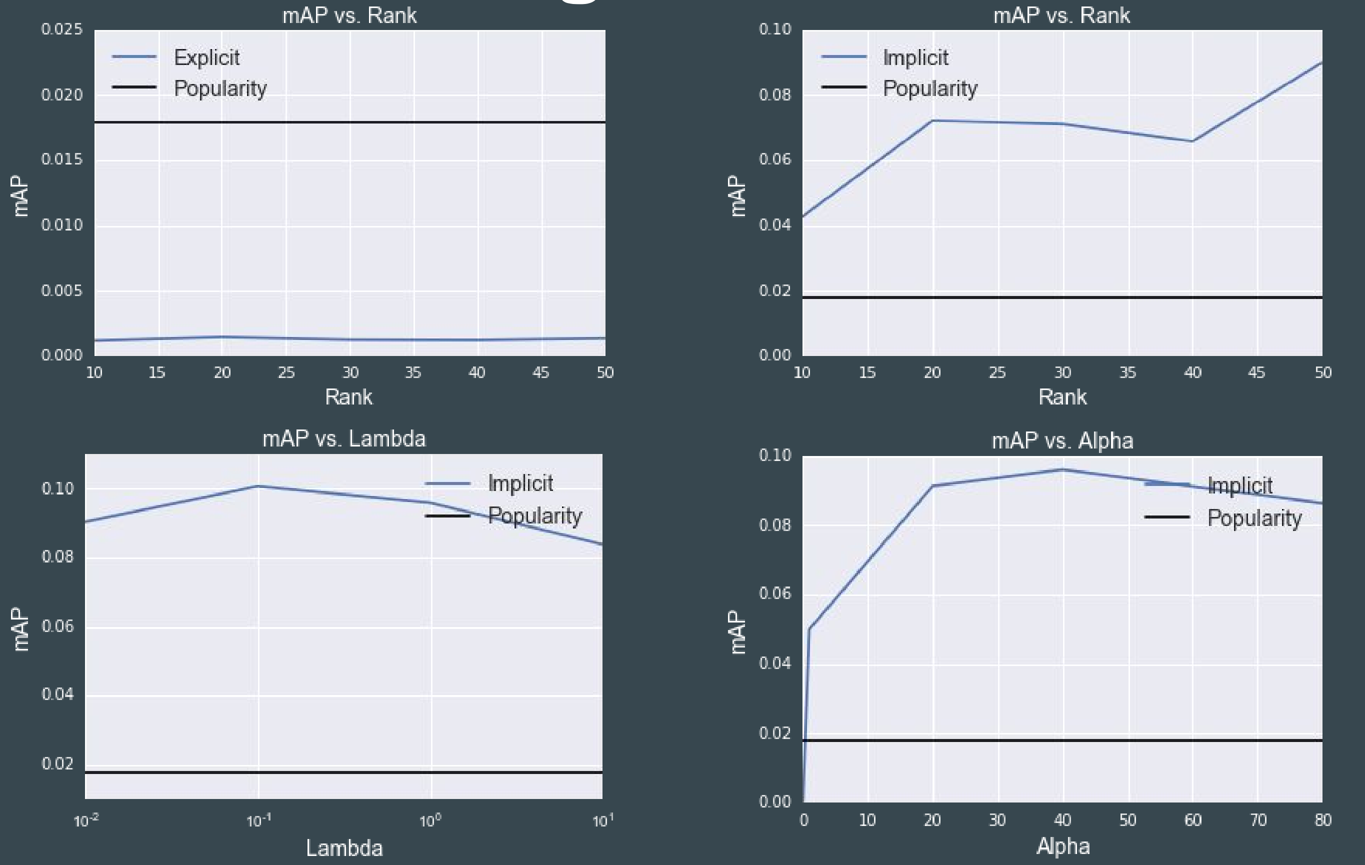
$$c_{ui} = 1 + \alpha r_{ui}$$

Collaborative Filtering

- How to Evaluate Implicit Model?
  - RMSE doesn't make sense!
  - Neither regression nor classification
- Mean Average Precision (mAP)
  - Precision-at-k (P)
    - *Proportion of correct recommendations within top-k of the predicted ranking*
  - Average Precision (AP)
    - *Precision at each recall point k*
  - Mean Average Precision (mAP)
    - *Average over all users*
  - Used in Million Song Kaggle Competition



Collaborative Filtering



Collaborative Filtering

20	↓1	WiscoDisco	0.11206	5	Tue, 26 Jun 2012 01:21:55 (-28.5h)
21	↓1	sedielem	0.10952	11	Thu, 09 Aug 2012 17:52:45 (-50.4d)
22	↓1	Francie	0.10812	3	Fri, 08 Jun 2012 11:27:52
23	↓1	MML	0.10778	16	Wed, 06 Jun 2012 07:33:46 (-15.3h)
24	—	Superman89	0.10117	5	Fri, 20 Jul 2012 15:20:35 (-18.4h)
25	—	eggershead	0.09923	5	Thu, 17 May 2012 00:41:58
26	—	AppleCakeMining	0.09655	12	Mon, 21 May 2012 10:29:26 (-34.8h)
27	—	Andrew Ostapets	0.09132	17	Sun, 29 Jul 2012 21:13:41 (-10d)
28	↑69	seventeen	0.08998	4	Thu, 09 Aug 2012 16:32:37
29	↓1	holy shit	0.08657	13	Mon, 30 Jul 2012 03:09:46 (-46.1d)
30	↓1	jose	0.08657	6	Sat, 30 Jun 2012 17:33:16 (-14.4d)

25th out of 150 teams!

Collaborative Filtering

User: 193650

- Listening History

Radiohead - Talk Show Host	Radiohead - Just	Radiohead - Sail To The Moon	Lifehouse - Near Life Experience	Lifehouse - How Long

- Recommendations

Radiohead - Karma Police	Radiohead - (Nice Dream)	Lifehouse - All In	Lifehouse - From Where You Are	Lifehouse - Whatever It Takes

Aggregation strategy

- How to adapt recommendations to a group based on individual members' preference?

	INDIVIDUAL RECOMMENDATIONS: p(u,i)				
USER	Lifehouse - Whatever It Takes	Lifehouse - From Where You Are	Lifehouse - Falling In	Lifehouse - Storm	Lifehouse - All In
84250	0.95	0.98	1.00	0.97	0.97
92650	0.86	0.77	0.71	0.64	0.75
193650	0.86	0.86	0.89	0.84	0.88

- When forming recommendations for the group:
  - Average strategy: average happiness of the members.
  - Most pleasure: happiness of the most happy member.
  - Least misery: happiness of the least happy member.
  - Multiplicative: product of each member's happiness.

Aggregation strategy

Example of Least Misery aggregation strategy:

	INDIVIDUAL RECOMMENDATIONS				
USER	Lifehouse - Whatever It Takes	Lifehouse - From Where You Are	Lifehouse - Falling In	Lifehouse - Storm	Lifehouse - All In
84250	0.95	0.98	1.00	0.97	0.97
92650	0.86	0.77	0.71	0.64	0.75
193650	0.86	0.86	0.89	0.84	0.88
	GROUP RECOMMENDATIONS				
LM	0.86	0.77	0.71	0.64	0.75

Aggregation strategy

- Which strategy performs best?
- What strategy to use based on group characteristics?
  - Best strategy for a group with very similar members?
  - Best strategy for a small group vs big group?
- How to measure group satisfaction?

$$S(u,R) = \frac{\sum_{i \in R} \hat{p}(u,i)}{|R|}$$

$$S(g,R) = \frac{\sum_{u \in g} S(u,R)}{|g|}$$

- Cluster users
  - K-means clustering using latent features.
  - Create homogeneous and heterogeneous groups of 3, 5, and 7 members.
  - Derive S(g,R) for each aggregation strategy.

Aggregation strategy analysis

> homogenous: 3-members

	LM	MP	AV	MU
means	0.51	0.49	0.56	0.52
sds	0.14	0.13	0.12	0.16
ANOVA p-value	0.548			

> homogenous: 5-members

	LM	MP	AV	MU
means	0.48	0.45	0.53	0.51
sds	0.11	0.09	0.09	0.12
ANOVA p-value	0.0719			

> homogenous: 7-members

	LM	MP	AV	MU
means	0.51	0.46	0.56	0.52
sds	0.15	0.15	0.13	0.18
ANOVA p-value	0.277			

> heterogenous: 3-members

	LM	MP	AV	MU
means	0.39	0.38	**0.47**	0.35
sds	0.08	0.07	0.08	0.15
ANOVA p-value	**0.00481**			
TukeyHSD Post-hoc test: p-value < 0.05				
variables	**AV-MP**	**MU-AV**		

> heterogenous: 5-members

	LM	MP	AV	MU
means	0.25	0.23	**0.36**	0.19
sds	0.06	0.06	0.06	0.1
ANOVA p-value	**3.86E-10**			
TukeyHSD Post-hoc test: p-value < 0.05				
variables	**AV-LM**	**MU-LM**	**AV-MP**	**MU-AV**

> heterogenous: 7-members

	LM	MP	AV	MU
means	0.2	0.19	**0.32**	0.17
sds	0.04	0.04	0.04	0.07
ANOVA p-value	**8.83E-16**			
TukeyHSD Post-hoc test: p-value < 0.05				
variables	**AV-LM**	**AV-MP**	**MU-AV**	

- Average aggregation strategy works best especially for heterogenous groups!

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Final product

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References

- Carvalho, L., Macedo, H.: Users' Satisfaction in Recommendation Systems for Groups: an Approach Based on Noncooperative Games (2013)
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