Exploiting Music Play Sequence for Music Recommendation

CSE/ECE471 | SPRING 2019

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PROJECT PRESENTATION 30 Apr 2019

Base Paper

This project is an implementation of the following base paper:

- Title: Exploiting Music Play Sequence for Music Recommendation
- Author: Zhiyong Cheng and Jialie Shen, Lei Zhu, Mohan Kankanhalli, Liqiang Nie
- Publication: Proceedings of the Twenty-Sixth International Joint Conference on Artificial Intelligence (IJCAI-17)

Flow of presentation

 Motivation • Problem Statement Intro • Proposed Solution • Data Preprocessing MF and BMF Module Song2Vec • Experimental Setup • Results Project • Future Directions References Contributions Misc.

Introduction

- Users leave digital footprints when interacting with various music streaming services.
- Music play sequence (MPS), contains rich information about personal music preference and song similarity.
- MPS has been largely ignored in previously developed music recommender systems.



Motivation

 Include the much neglected Music Play Sequence (MPS) to make the song recommendation more relevant



Problem Statement:

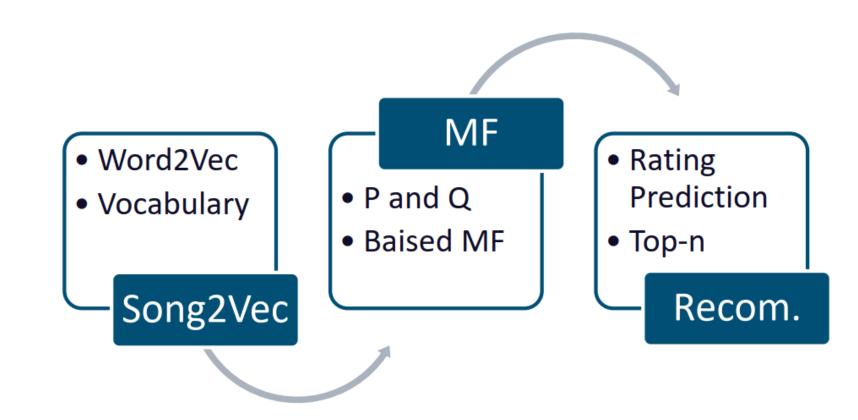
• Incorporate the effect of Music Play Sequence (MPS) along with Matrix Factorization (MF) methods to generate more relevant music recommendations.

Proposed Solution:

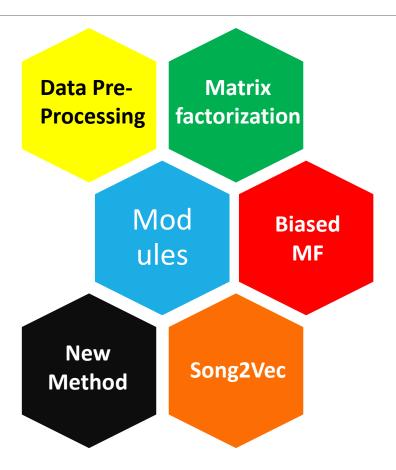
- Use word embedding techniques in MPS to estimate the similarity between songs.
- Embed learned similarity into matrix factorization
- k-nearest songs in the learning process to avoid the increase in time complexity



Overview:



Modules



Data Processing

We are using Last.fm dataset, which has the following characteristics:

• No. of data points : 4752899

• No. of unique songs: 72678

• No. of unique users: 249



Snapshot of Raw Data

user_000001 d86e2 Elysian	2009-05-03T15:10:18Z Fields	463a94f1-2713-40b1-9c88-dcc9c0170cae	Minus 8 4e78efo	:4-e545-47af-9617-05ff816
user_000001 -77ec38d66859	2009-05-03T15:04:31Z Planetary Deadlock	ad0811ea-e213-451d-b22f-fa1a7f9e0226	Beanfield	fb51d2c4-cc69-4128-92f5
user_000001 -23fd157f9347	2009-05-03T14:56:25Z Good Morning Love Coffe	309e2dfc-678e-4d09-a7a4-8eab9525b669 e Is Ready	Dj Linus	4277434f-e3c2-41ae-9ce3
user_000001 -8a4605ce456c	2009-05-03T14:50:51Z Deadly Species	6f3d4a7b-45b2-4c08-9306-8d271e92cb4f	Alif Tree	1151b040-8022-4965-96d2
user_000001 6854e Cold Fu	2009-05-03T14:46:29Z sion	463a94f1-2713-40b1-9c88-dcc9c0170cae	Minus 8 f78c95a	a8-9256-4757-9a9f-213df5c
user_000001 935c2 Clouds	2009-05-03T14:39:20Z	45bdb5be-ec03-484f-b58d-d22afc944b24	Wei-Chi c4fc880	02-d186-4c4d-85cd-d5d063b

Data Processing

The following are the preprocessing steps used before using the data to train the model.

- 1. Exclude the users only listened to less than 10 songs
- 2. Exclude the songs which have been played by less than 10 users.
- 3. Exclude the irrelevant data columns i.e. song id, artist id, artist name

	UserID	TimeStamp	Song
0	1	2009-05-04T23:08:57Z	Fuck Me Im Famous (Pacha Ibiza)-09-28-2007
1	1	2009-05-04T13:54:10Z	Composition 0919 (Live_2009_4_15)
2	1	2009-05-04T13:52:04Z	Mc2 (Live_2009_4_15)
3	1	2009-05-04T13:42:52Z	Hibari (Live_2009_4_15)
4	1	2009-05-04T13:42:11Z	Mc1 (Live_2009_4_15)
4	1	2009-05-04T13:42:11Z	Mc1 (Live_2009_4_15)

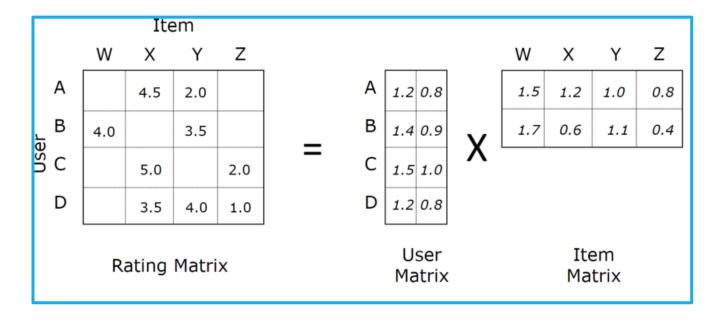
Music Play Sequence (MPS)

- Play event to be part of a session if it occurs no later than 800 seconds
- We only keep the listening sessions with no less than 10 songs.
- Number of sessions 125181 (with each session having 10 or more songs)

{1: [['Lust', 'The Essence', 'Idioteque', 'Change Of Seasons', idal Reprise', 'Landing', 'Detchibe', 'Watching Windows', 'Rid less', 'Id', 'Zazen Bo', 'What You Gonna Do?', 'Rusty Gears Lo '], ['Ozma', 'Hint Oyaji', 'Cow', 'Cow', 'Extra Ignored', 'Hib n The Forest (Interlude Mix)', 'Waltz For Jason (Full Nine Yar ', 'Gum', 'Clap & Whistle & Walking', 'The Star Spangle-Gayo'] Tune', 'More Than Ever People', 'Appreciation (Radio Mix)', 'P re Is The Line', 'Vökuró', 'Öll Birtan', 'Who Is It', 'Submari ss', 'Where Is The Line', 'Vökuró', 'Öll Birtan', 'Who Is It', e Down', 'Surrender', 'Misunderstanding', '花狂()', 'Element Wa de Mix)', 'Waltz For Jason (Full Nine Yards Re-Edit) (2 Banks gle-Gayo', 'Music', 'Gum', 'Clap & Whistle & Walking', 'The St

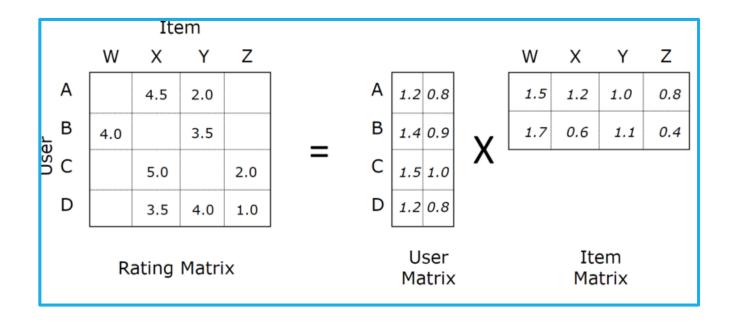
Matrix Factorization

- Collection of feedback can be represented in a form of a matrix.
- Row represents users
- Column represents different songs.
- Sparse Matrix
- It can incorporate implicit feedback (derived by analyzing user behavior.)



Matrix Factorization

- Predicted user Rating : $\hat{r}_{ui} = q_i^T p_u$
- Optimization Objective : $\min_{q^*,p^*} \sum_{(u,i) \in \mathit{K}} \bigl(r_{ui} q_i^T p_u \bigr)^2 + \lambda (\|q_i\|^2 + \|p_u\|^2)$



Matrix Factorization

Regularization term:

$$\lambda(\|q_i\|^2 + \|p_u\|^2)$$

- Avoid decomposed matrix q and p to over-fit to the original matrix.
- Goal is to generalize the previous ratings in a way that predicts future-unknown ratings.

MF Learning Method

- Stochastic gradient descent
- Squared error loss function :

$$e_{ui} \triangleq r_{ui} - q_i^T p_u$$

• Update rule :

$$q_i \leftarrow q_i + \gamma \cdot (e_{ui} \cdot p_u + \lambda \cdot q_i)$$

 $p_u \leftarrow p_u + \gamma \cdot (e_{ui} \cdot q_i + \lambda \cdot p_u)$

Biased Matrix Factorization

- Some songs are biased in that it is widely perceived better (or worse) than other song.
- Some users may be biased too.
- Include the bias terms into our original equation.

$$\hat{r}_{ui} = \mu + \boldsymbol{b}_i + \boldsymbol{b}_u + \boldsymbol{q}_i^T \boldsymbol{p}_u$$

The new objective function would look something like below

$$\min_{q^*,p^*,b^*} \sum_{(u,i)\in K} (r_{ui} - \mu - b_u - b_i - p_u^T q_i)^2 + \lambda (\|p_u\|^2 + \|q_i\|^2 + b_u^2 + b_i^2)$$

Song2Vec

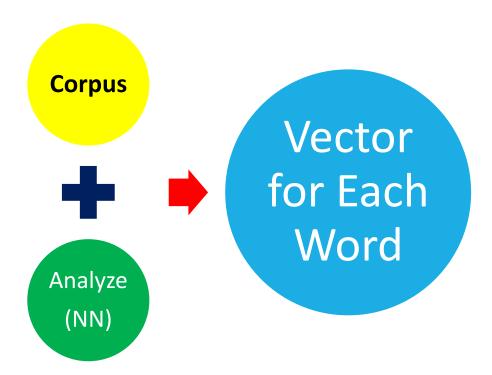
- Capture what songs are listened to frequently together in very similar contexts.
- This is where Word2Vec comes in.



song2vec

Word2Vec

- Word2vec is a class of neural network models.
- Introduced for learning word embedding's that are highly useful for NLP.



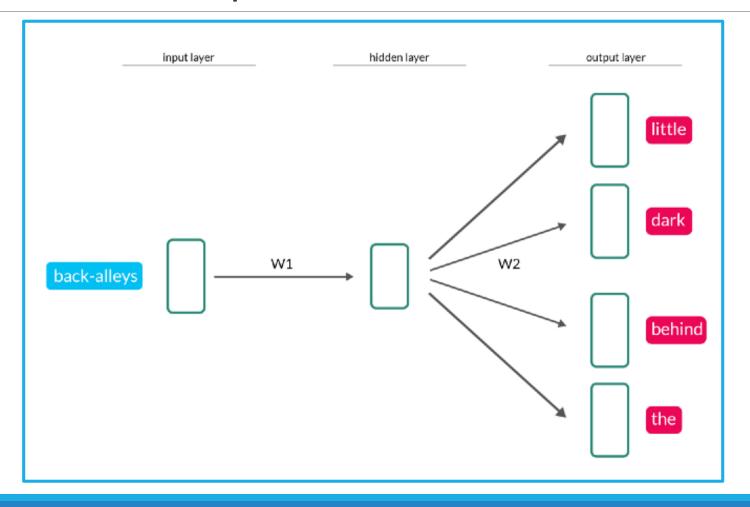
Word2Vec: Skip Gram Model

- Shallow neural network with a single hidden layer.
- Word as input and tries to predict the context

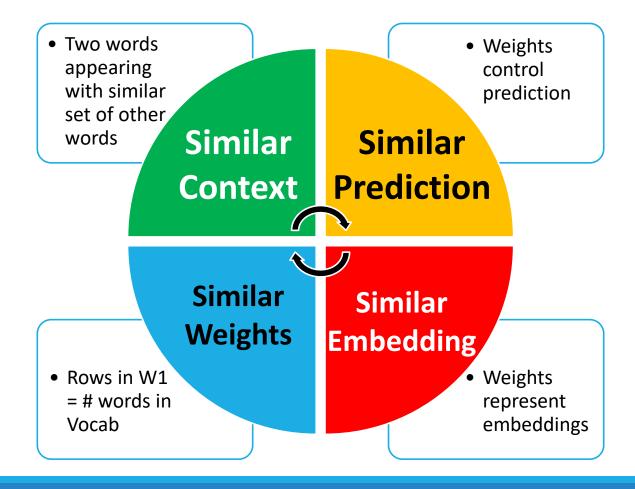
But I always liked side-paths, little dark back-alleys behind the main road - there one finds adventures and surprises, and precious metal in the dirt.

Fyodor Dostoyevsky, The Brothers Karamazov

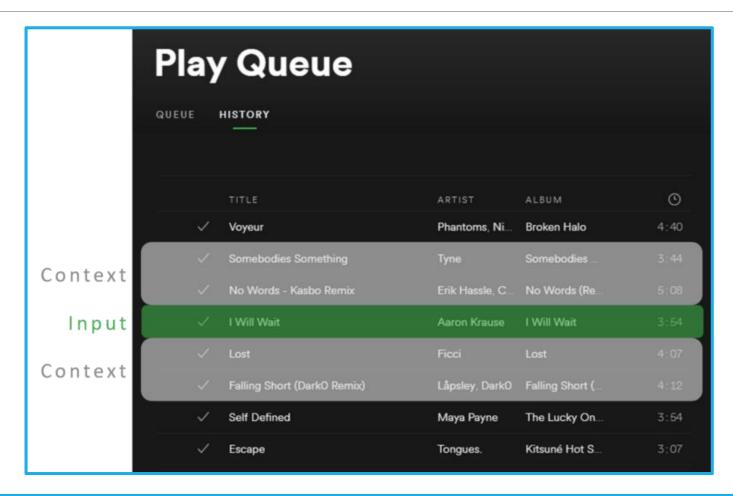
Word2Vec: Skip Gram Model



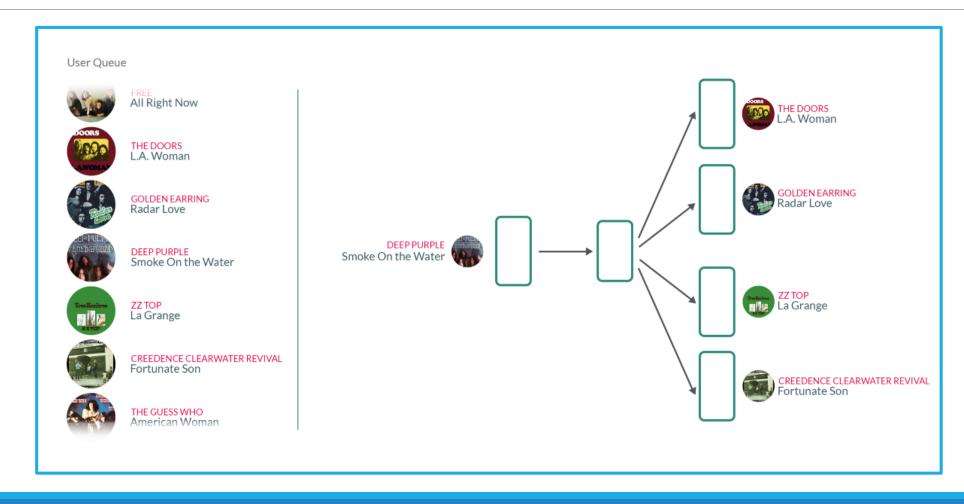
Word2Vec: Skip Gram Model



Song2Vec

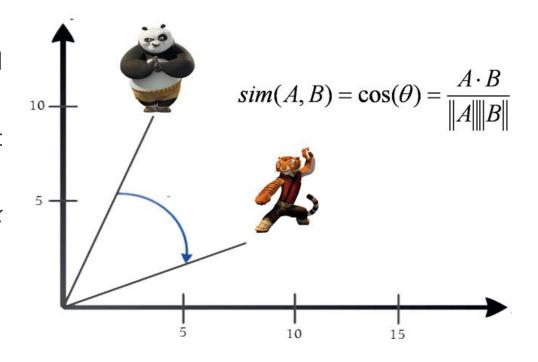


Song2Vec

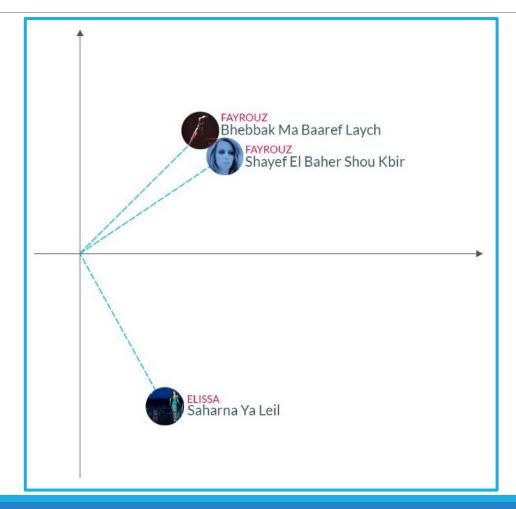


Song2Vec: Use Case

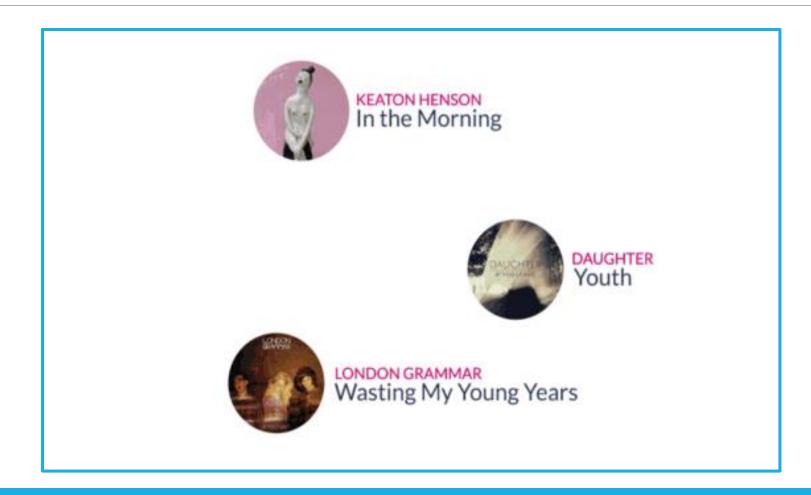
- Transformed problem of finding song similarity into mathematical numbers.
- Weights as coordinates in a high dimensional space.
- Each song being represented by a point in that space.
- Given a particular seed song, we can find k other similar songs (cosine similarity).



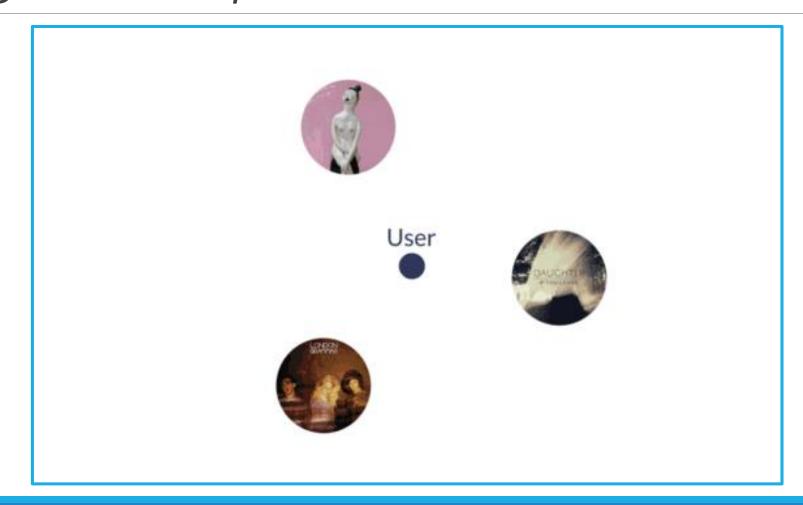
Song2Vec : Use Case



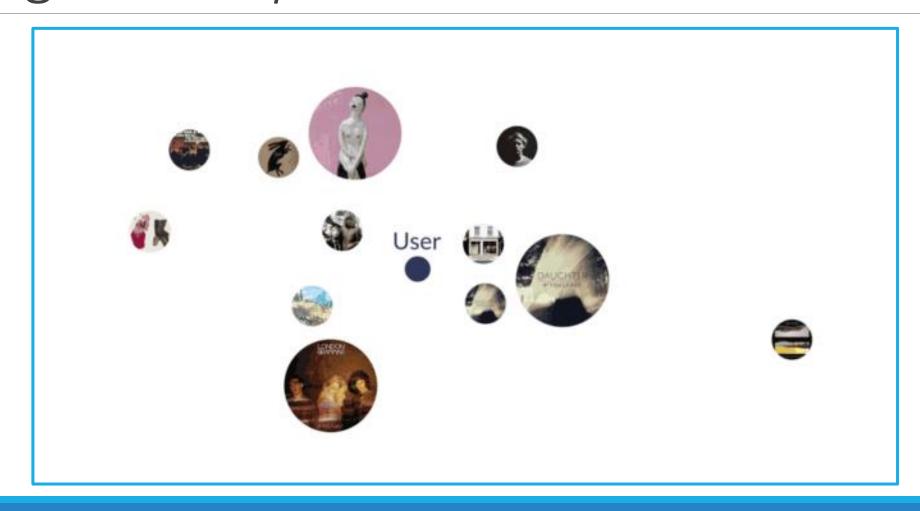
Song2Vec: Top-n Recommendation



Song2Vec: Top-n Recommendation



Song2Vec: Top-n Recommendation



Final Objective Function

$$\min_{q^*,p^*,b^*} \sum_{(u,i)\in K} (r_{ui} - \hat{r}_{u,i})^2 + \frac{\alpha}{2} \sum_{i,j\neq i} (s_{i,j} - q_i^T q_j)^2 + \frac{\lambda}{2} \Omega(\Theta)$$

Song2Vec: Experimental Method

- Top-n recommendation
 - Given a song from the vocabulary, generate the top n recommended song for the user.
- Rating Prediction
 - Predict rating $\hat{r}_{u,i}$ (predicted rating of u song for i user)
 - Given d is the dimension of the latent feature vectors learned by MF, what is its effect on RMSE.

• Top 6 recommendation for the song "The Fox"

<pre>get_song("The Fox")</pre>					
Top 6 Songs for: The Fox					
Name	Similarity Score				
Start Toge Milkshake Let'S Call Leave You The End Of One Song F	0.8167651891708374 0.7961223125457764 0.795258641242981 0.7926040291786194 0.7861700057983398 0.7859086394309998				

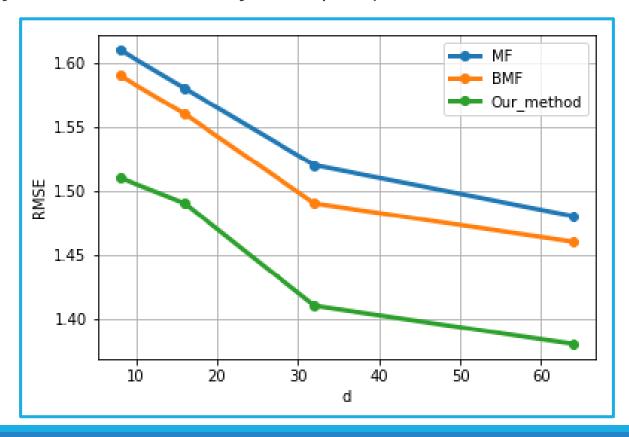
• Top 6 recommendation for the song "Bedragaren I Murmansk"

get_song("Bedragaren I Murmansk")				
Top 6 Songs for:	Bedragaren I Murmansk			
Name	Similarity Score			
Ännu Mera Bilder Av M Som I Sån Hur Många Trösta Mig	0.9780382513999939 0.9775434732437134 0.9768289923667908 0.9757107496261597 0.9739065170288086 0.9728430509567261			

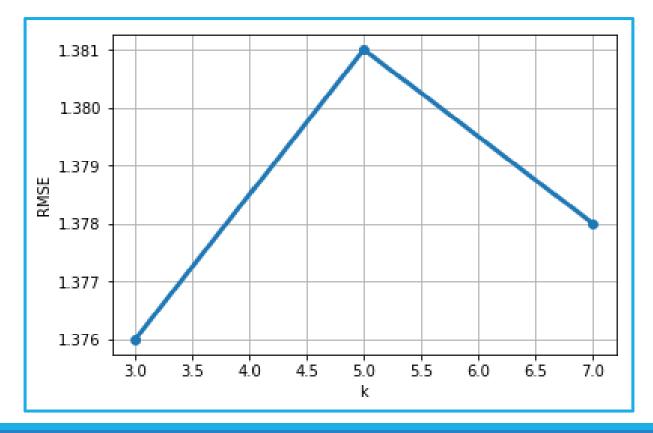
• Top 6 recommendation for the song "A little Bit Of Pain"

<pre>get_song("A Little Bit Of Pain")</pre>	
Top 6 Songs for: A Little Bit Of Pain	
Name Similarity Sc	ore
Make You L0.96422922611Ilfracombe0.95224893093Autumn'S H0.93321287631Silent Tra0.93295848369I Would Fo0.92487215995Aphrodite0.92182528972	10913 98853 59839 78857

• RMSE vs d (No. of dimensions in latent factor space)



• Variation of RMSE vs k (No. of nearest neighbors)



Future Direction

- Why not Artist2Vec ?
- Prediction based on lyrics.
- Develop dataset with more features like demographic information, language etc.



References

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- 3. [KeunhoChoia, DongheeYoob, GunwooKimc, YongmooSuha], A hybrid online-product recommendation system: Combining implicit rating-based collaborative filtering and sequential pattern analysis, Electronic Commerce Research and Applications, Volume 11, Issue 4, July–August 2012, Pages 309-317
- 4. Song2Vecimplementation: https://github.com/0411tony/Yue/blob/master/recommender/advanced/Song2vec.py
- 5. Create corpus for Song2Vec: https://github.com/WQtong/MusicRecsys/blob/master/create_song_corpus.ipynb

Thank You!

