Collaborative Filtering using Restricted Boltzmann Machine for Song Recommendations

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***Abstract**:* Modern technologies and advances in computing has enabled us to store and process interaction between users and items. These interactions are not some arbitrary combinations but patterns of user purchases. In any industry with vast number of products, it is of dire importance to analyse these patterns and suggest products to the user which not only help users make decisions but also help sales grow. One of these industries is music industry. An unofficial estimates states that Spotify itself provides more than 40 million songs. To select a song out of this sea is a humongous task. Recommendation engines try to solve this problem by studying the pattern of users and songs and recommend songs accordingly. In this piece of work, we have tried to implement a collaborative based filtering using a Restricted Boltzmann Machine (RBM).

1. Introduction: Millions Song Dataset [1] is a freely-available collection of audio features and metadata for a million contemporary popular music tracks. It is a set of multiple datasets collected from various sources like EchoNest, last.fm, MusiXmatch etc. One of the important dataset includes the information of around 1M users and their listening history. Using this dataset, we trained an RMB to generate a list of recommendations.

2. Data: The retrieved data from MSD is spread out into multiple datasets. The task required to merge datasets to create a single dataset for processing. The Million Song Dataset was created under a grant from the National Science Foundation, project IIS-0713334. The original data was contributed by The Echo Nest, as part of an NSF-sponsored GOALI collaboration. Subsequent donations from SecondHandSongs.com, musiXmatch.com, and last.fm, as well as further donations from The Echo Nest, are gratefully acknowledged. Due to memory constraints, the datasets were sliced and uploaded to tables on Databricks.com for faster processing and avoid memory errors. Fig 1 shows the schema of data that was followed.

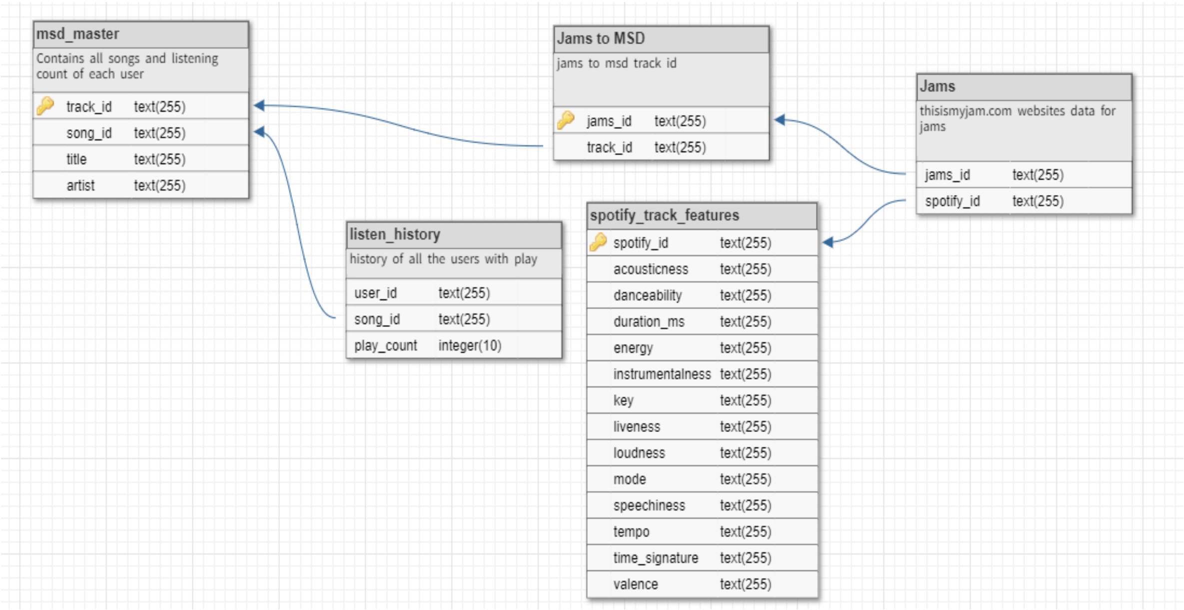

Figure 1 Schema for datasets

2.1 Song Metadata Dataset: This (msd_master) data set contains details about each track in MSD with additional details like title, artist, release year etc. The dataset is available as a SQLite database.

track_id	title	song_id	release	artist_name	year
TROSWPD128F14906B5	Take Time	SOPXBPA12A6D4F8492	Playing With My Heart	49ers	0
TROSWGZ128F42362F7	Cero Codazos_ Cero Cabezazos (Live)	SOEDPEP12A8C13299D	Sonora Matancera Vol. 1 - Live Broadcasts 1952...	Sonora Matancera	0
TROSWFP128EF33DB16	Die Welt schwitzt	SOBRXCQ12A67AD7251	Tricolor	K-Rings Brothers	0
TROSWIU12903CBFBA7	Woodblocker	SOMDMIH12AB018D727	Ibiza Afterparty	Fine Taste	0
TROSWFP12903CC681C	A.M. Radio	SOESLGO12A6D4FB53F	Bless You	The Court & Spark	2001

Figure 2 Song Dataset

2.2 User Listening Profile: (listen_history) contains users triplet in the form of:

<user_id> <song_id> <count>

	user_id	song_id	count
0	b80344d063b5ccb3212f76538f3d9e43d87dca9e	SOAPDEY12A81C210A9	1
1	b80344d063b5ccb3212f76538f3d9e43d87dca9e	SOBBMDR12A8C13253B	2
2	b80344d063b5ccb3212f76538f3d9e43d87dca9e	SOBFNSP12AF72A0E22	1
3	b80344d063b5ccb3212f76538f3d9e43d87dca9e	SOBFOVM12A58A7D494	1
4	b80344d063b5ccb3212f76538f3d9e43d87dca9e	SOBNZDC12A6D4FC103	1

Figure 3 User Listening Profile

2.3 Jams Dataset: For the song feature retrieval from Spotify, we require the unique spotify_uri for each song. However, the dataset itself lacked this information. A sub dataset provided by thisismyjams.com [3] was published which had the spotify_uri for the MSD songs.

	jam_id	spotify_uri	title	artist
0	c2e76bb92c7fa733fdfc9be40bb0e4ea	spotify:track:6AGhDIyDbRonzGTdbIsNXa	Rip It Up	Orange Juice
1	4849f8c893a792032dbc15eb77cfd0cd	spotify:track:2ZM9sVP0bIBj1lNIEg4dgn	Somewhere In the Night	Stereo
2	8940ff2e8e38c8f1a4676e09d152c0cd	spotify:track:096elxAmYuyAFJKPLrS5oY	I Got Her Off My Hands	The Mills Brothers
3	fb28db84e1deadae31b5d8c41353f86e	spotify:track:6W9rl3K4onX5oe2VU1HX7J	Jackie, Dressed In Cobras	The New Pornographers
4	dac2a597261068d62d9d397c697bf96c	spotify:track:7l2KfEDMVmRVj3lAvifiEd	I Was Thinking I Could Clean Up For Christmas	Aimee Mann

Figure 4 JAMS dataset

2.4 Jams to MSD: The id from Jams dataset to MSD track ids are mapped in this dataset. It contains foreign keys for the above two datasets and acted as the linking layer between them

	jam_id	track_id
0	6c63486ccec9f7a1d77b9b7db35b61ef	TRIULJC128F429EC15
1	7c7ba45c3b8f613b1887babf248e6293	TRZTLJV128F149EF6C
2	34a81ea1e4e3aa292a0d759dc0731fd3	TRMJKEU128F1457E80
3	721f626ed68d788e130a1543ba0c362b	TRENTGL128E0780C8E
4	721f626ed68d788e130a1543ba0c362b	TROSYZC128F422AA3A

Figure 5 JAMS to MSDS dataset

2.5 Spotify Track Features: - Spotify Developer API [4] provides multiple features of a song. It has the song audio analyzed and generated different parameters for the song. It helped us visualize different attributes of the song. Below are the retrieved song features:

Danceability, energy, key, loudness, mode, speechiness, acousticness, instrumentalness, liveness, valence, tempo, duration_ms, time_signature. Details about each of these attributes can be found at https://developer.spotify.com/web-api/get-audio-features/

spotify_uri	acousticness	danceability	duration_ms	energy	instrumentalness	key	liveness	loudness	mode	speechiness	tempo	time_signature	valence
124907	124900	124881	124907	124903	124899	124906	124894	124907	124906	124882	124907	124877	124879
84739	5101	1047	29669	1694	5379	12	1718	17354	2	1384	54792	4	1636
spotify:track:6niJRu59H1q2ewuVGGLU1l	0.108	0.535	237533	0.953	0	0	0.111	-7.59	1	0.0306	127.999	4	0.961
16	200	332	41	324	24155	15382	1181	40	84342	467	44	114196	413

Figure 6 Spotify Track Features

2. Data Visualization: - The song features from Spotify has been visualized. Detailed Visualization can be found at this databricks notebook. We studied the change in different parameters of song through the years. Some of them are shown below.

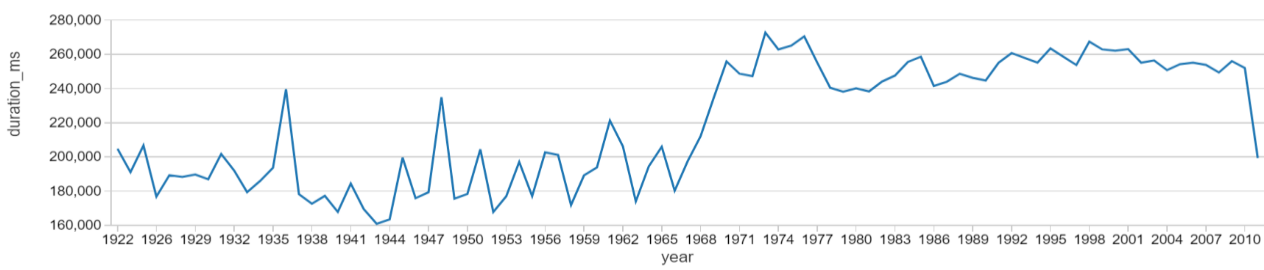

Figure 7 Average duration (in ms) of songs against years

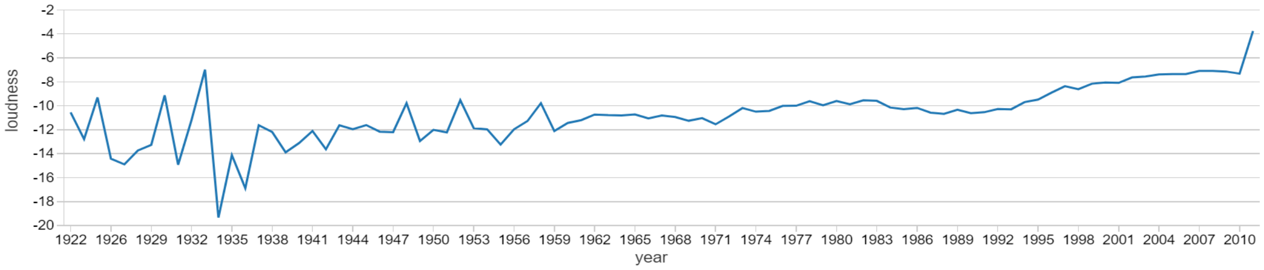

Figure 8 Maximum loudness against years

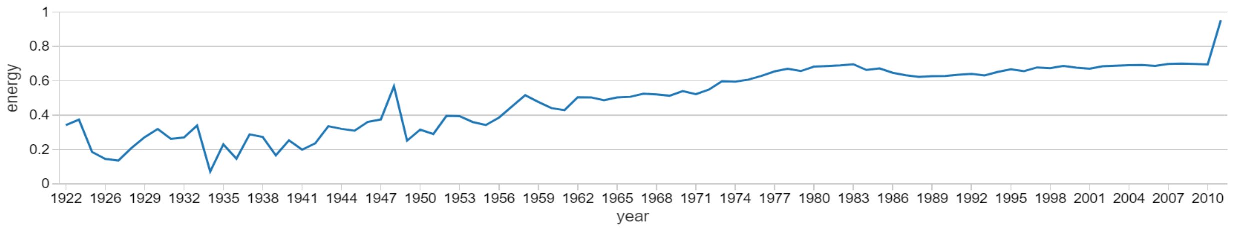

Figure 9 Average Energy

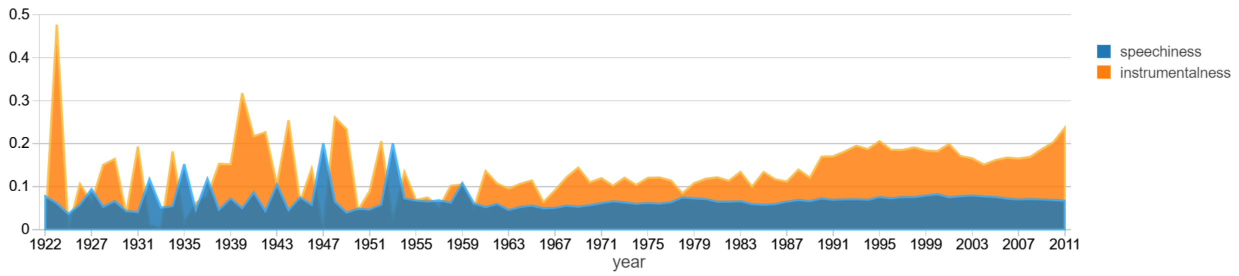

Figure 10 Speechiness and Intrumentalness

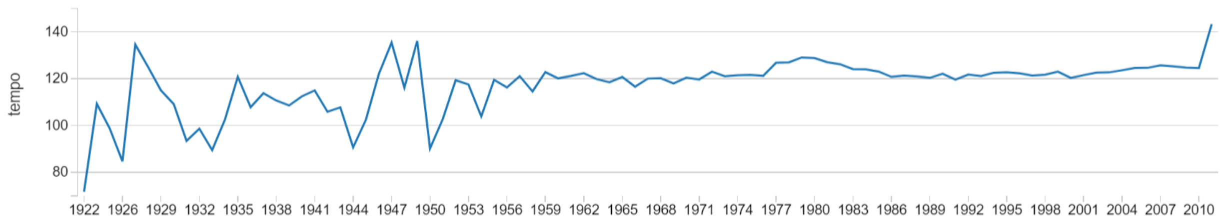

Figure 11 Tempo

Rolling stones being the longest running band in the history of music, they proved to be informative as they represent the trend of the music industry.

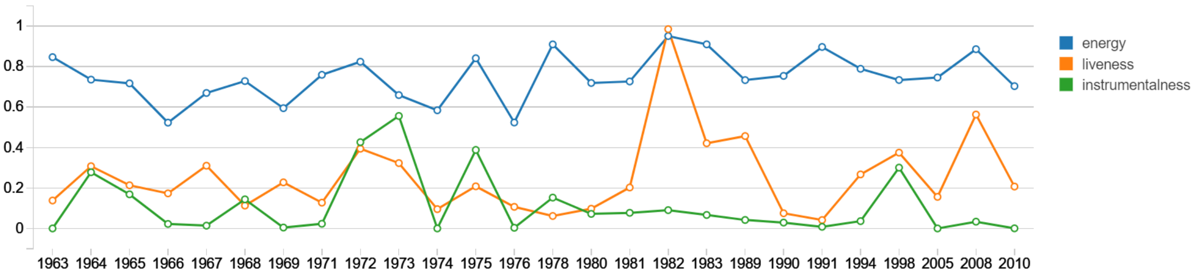

Figure 12 Rolling Stone progression through years

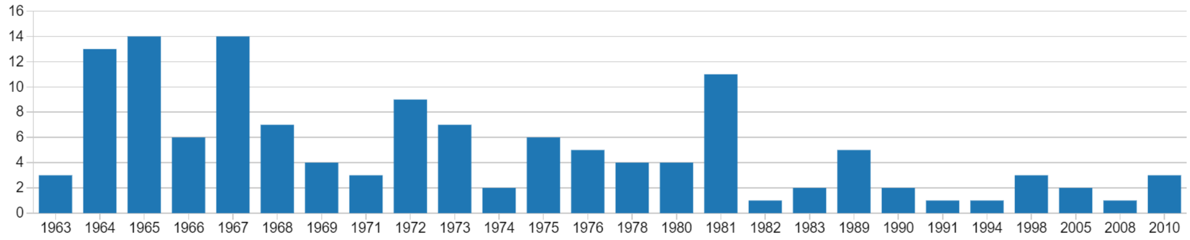

Figure 13 Rolling stones' songs released per year

We tried to create a World cloud from the dataset. The stopwords relevant to music industry were filtered out. E.g.:-band, featuring, version, live, feat, Remastered, Digital etc.

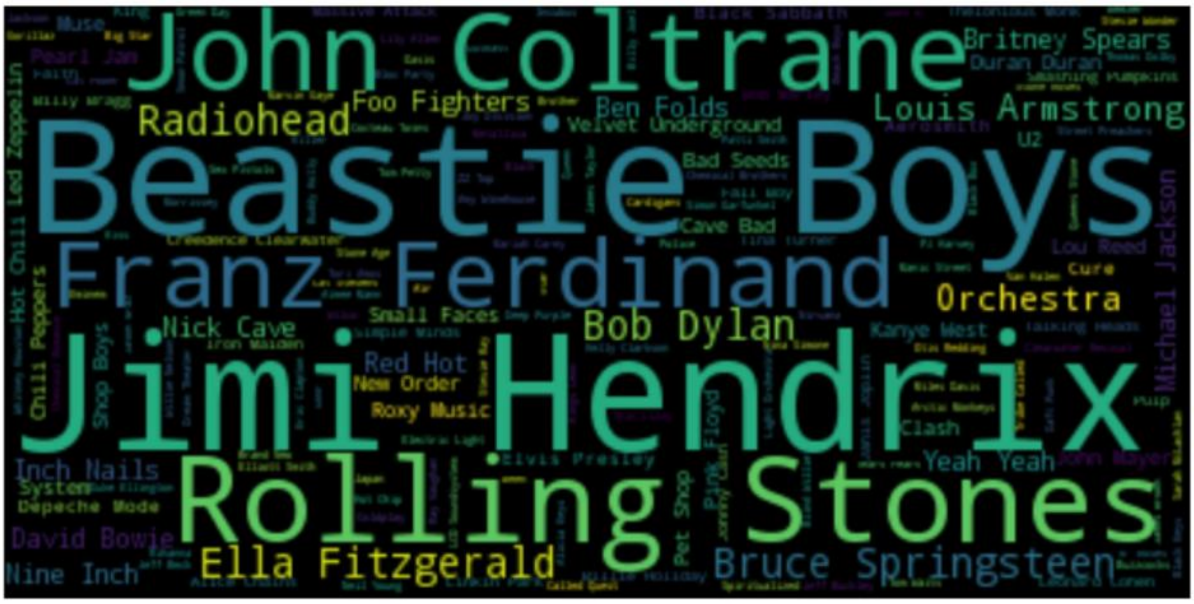

Figure 14 Word Cloud of Band names

Figure 15 Word Cloud of Song names

3. RBM Model

RBMs are shallow, two-layer neural nets, the first layer of the RBM is called the visible, or input, layer, and the second is the hidden layer. In RBM, we try to generate the original input during the reconstruction phase or the backward pass. In our model, the input is the listening history of the users. We train the network to learn these patterns and predict the output for a given user's listening history. The number of input units are equal to the number of songs in the dataset.

3.1 Data Preparation

To feed our data to the model, we have created a matrix of user-song interactions [18]. The data was converted in to a low dimension, a single matrix containing interaction between all users and songs. The row of the matrix represents the users while columns represents the songs. As the ids of the users or song will make it difficult to process, their position in the dataset was used as their unique identifier. For e.g.: consider the history of 4 users. 0 represents no interaction and 1 is positive recommendation.

Table 1 Original Feedback Matrix

user_id\track_id	Track1	Track2	Track3	Track4
User1	0	0	1	0
User2	1	0	0	1
User3	1	1	1	0
User4	0	0	0	1

Table 2 Converted Feedback Matrix

user_index\track_index	1	2	3	4
1	0	0	1	0
2	1	0	0	1
3	1	1	1	0
4	0	0	0	1

3.2 Training

A Sampled feedback matrix of 1000 users was selected for training. The data was split into batches of 100 records. The root mean square difference of the predicted output and actual output was minimized in the training. 20 epochs showed the maximum accurate model and no overfitting.

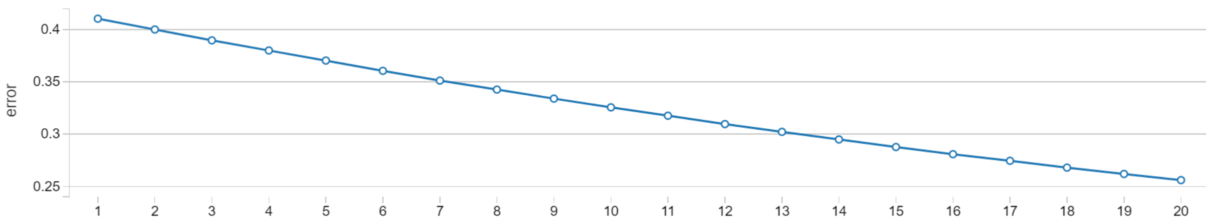

Figure 16 Epoch vs Error

3.3 Generating Recommendations

After the model has been trained with low error. A sample, normalized listening history can be fed to the model and it produces a recommendation matrix for all the songs. We pick up the top 20 items and display them to the user.

	track_id	song_name	artist_name	index	Recommendation Score
107581	TRGXQES128F42BA5EB	Undo	Björk	107581	0.999415
42132	TRONYHY128F92C9D11	Revelry	Kings Of Leon	42132	0.999294
75825	TRDMBIJ128F4290431	Sehr kosmisch	Harmonia	75825	0.998614
59654	TRHKJNX12903CEFCDF	Dog Days Are Over (Radio Edit)	Florence + The Machine	59654	0.995901
50363	TROAQBZ128F9326213	Secrets	OneRepublic	50363	0.968848
121604	TREQNRF12903CF2405	Drop The World	Lil Wayne / Eminem	121604	0.942155
61977	TRZJNDO128EF343498	The Gift	Angels and Airwaves	61977	0.937435
90933	TRSLDDC12903CC36E7	OMG	Usher featuring will.i.am	90933	0.906739
21580	TRQFXKD128E0780CAE	The Scientist	Coldplay	21580	0.795930
121038	TRDTWWZ12903CC36D8	Tighten Up	The Black Keys	121038	0.748728
250	TRJRECT12903CBADA3	Make Love To Your Mind	Bill Withers	250	0.738949
108210	TRIDPEB12903CCEB4B	All I Do Is Win (feat. T-Pain_ Ludacris_ Snoop...	DJ Khaled	108210	0.704728
69354	TRTEHXL128F931687B	Use Somebody	Kings Of Leon	69354	0.686372
68686	TRRUVLO128F92DE6F7	Bulletproof	La Roux	68686	0.686152
99483	TRUFTBY128F93450B8	Alejandro	Lady GaGa	99483	0.682605
101833	TRRJLQW128F4257946	Just Dance	Lady GaGa / Colby O'Donis	101833	0.677907
3600	TRIEXMF128F92FDD60	Use Somebody	Kings Of Leon	3600	0.674714
22646	TRHIVEJ128F14749AD	Le Courage Des Oiseaux	Dominique A	22646	0.671292
46455	TRJWVCU128F14581FF	Strut (1993 Digital Remaster)	Sheena Easton	46455	0.669025
117567	TREMDNV12903CAC420	I Gotta Feeling	Black Eyed Peas	117567	0.665784

Figure 17 Sample Recommendation Matrix

3.4 Evaluation

To check the accuracy of the model, we assume that the system generates a recommendation score close to 1 for the songs which the user has already interacted with. We calculate the average of recommendation scores for the positive interactions (user had positive feedback) and average score of negative interactions (user had no feedback). For the model to have better accuracy and precision, the positive mean needs to be greater than the negative mean [19]. In our RBM, the positive mean was around 0.3 and negative mean was 0.2. The means were generated on random 1000 users from the dataset.

4. Conclusion and future scope:

This project has given keen insight on the recommendation systems. Simple algorithms like RBM and other Autoencoders can be very efficient in creating a collaborative filtering systems. However, the collaborative filtering faces a problem of cold start where the user has low or no item interaction history making it difficult to give recommendations. Future scope would be to include item and user metadata embeddings to further help increase the accuracy and provide truly personal recommendations. Techniques like Ensembling [17] can further increase the accuracy by combining multiple algorithms. The developed RBM has a lower precision. This can be improved by creating multiple RMB models for each user which share the same hidden layers [16] but different input layers. Each user's input layer has same number of units as the songs he has interacted with. This way only positive interactions are used for training and is independent on the number of songs in the system.

5. References

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