

Heterogeneous Information Network and Deep Learning Based Music Recommender System

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Problem Definition

- Optimize top-N music recommendation to achieve higher hit rates
- INPUT: user listening history & content information
- OUTPUT: top-N songs recommendation for each user



Motivation

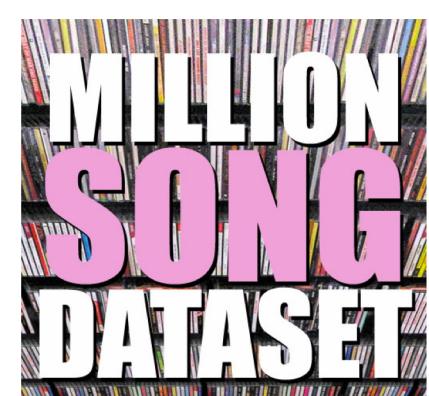


Huge numbers of choices



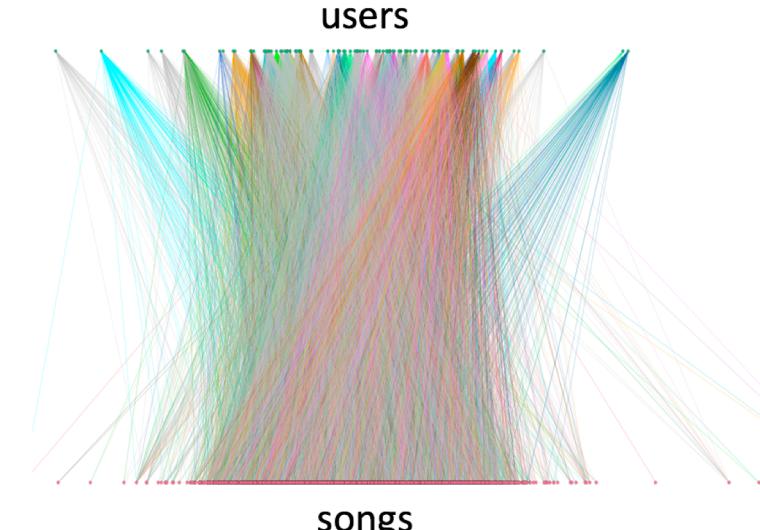
Fail to predict user preference

Datasets



Users	Songs	User-song Pairs
14516	10748	1894113
	Min	Max
	91	599
	Users per Song	Average
	3	130
	3308	176

Train	Test
80% user	20% user
Visible	Hidden
50% song	50% song



References

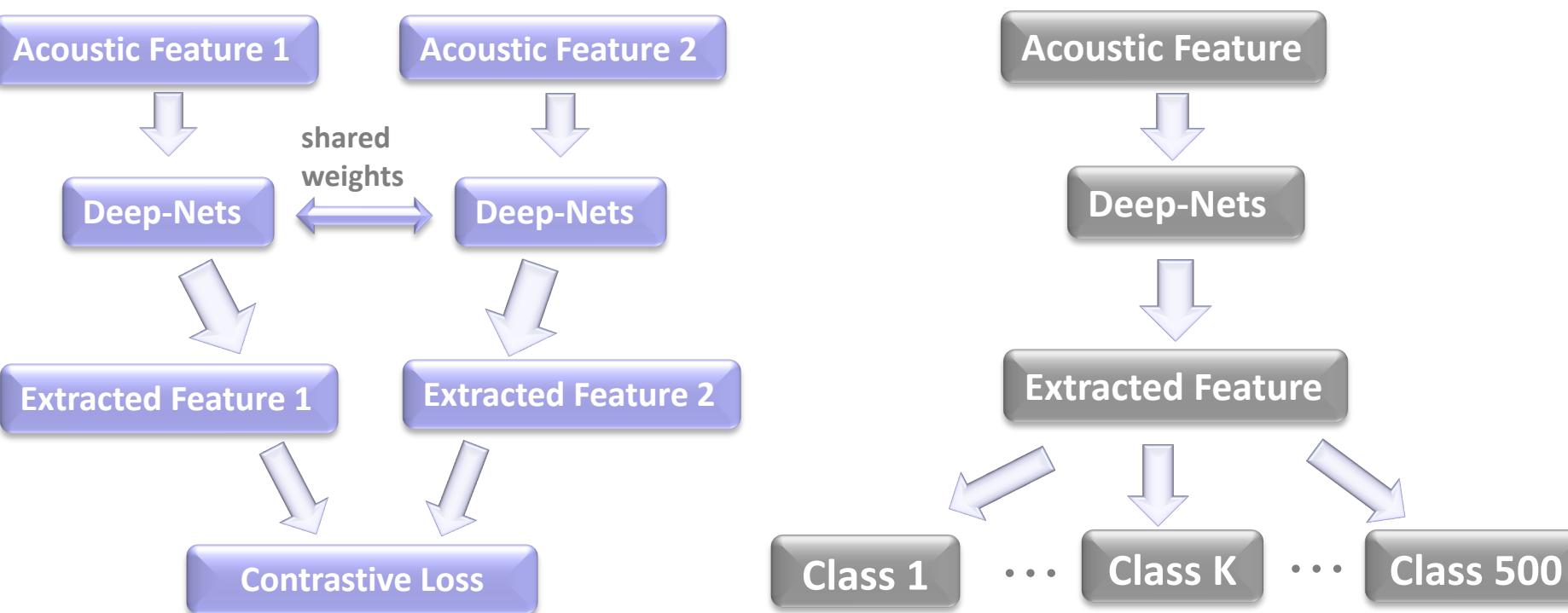
- Huan Zhao et al. Meta-Graph Based Recommender Fusion over Heterogeneous Information Network
- Danai Koutra et al. PNP: Fast Path Ensemble Method for Movie Design
- Shifu Hou et al. HinDroid: An Intelligent Android Malware Detection System Based on Structured Heterogeneous Information Network

Acknowledgements

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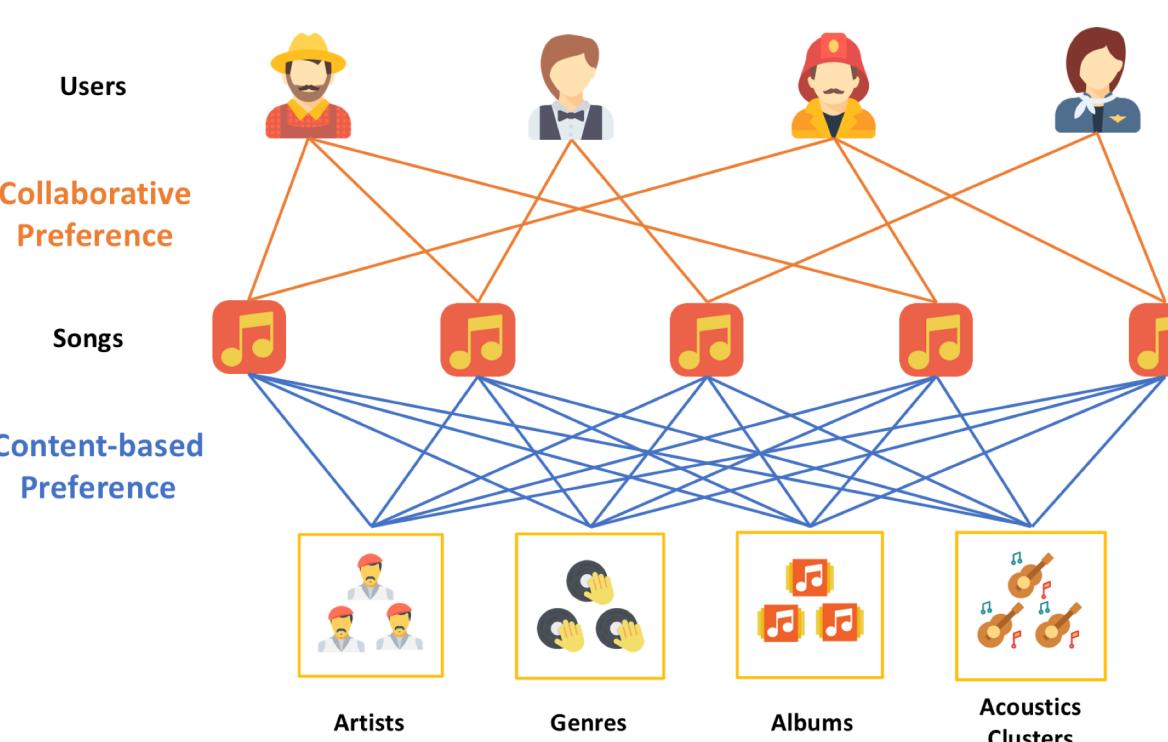
Our Approach

- Deep-learning based Acoustic Feature Extraction
- Multi-classification model



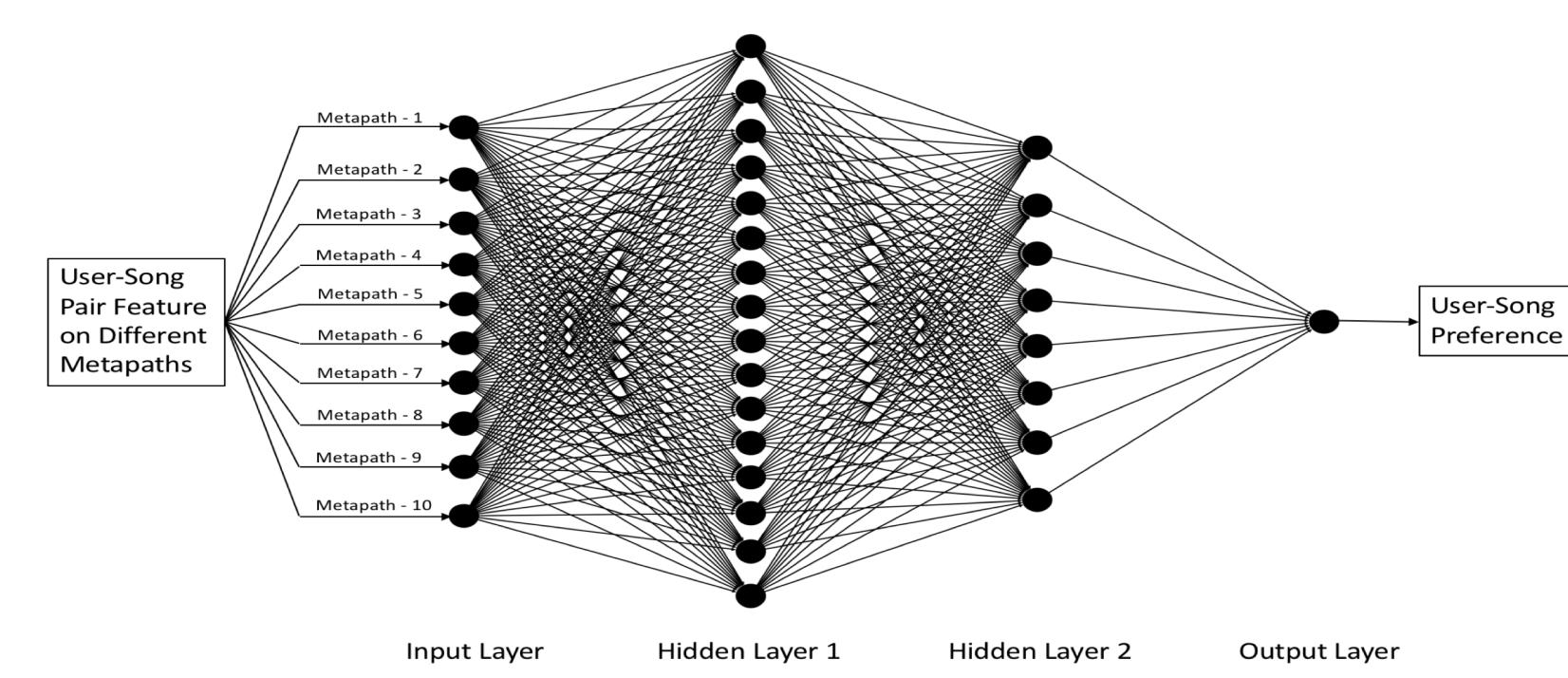
Heterogeneous Graph based Recommendation using Metapaths

- In Heterogeneous graph, we define **Metapaths** in different relationships to model the preference between entities
- Entities:** User, Song
- Relationships:**
 - User-Song: R
 - Song-Artist: T
 - Song-Genre: E
 - Song-Album: M
 - Song-Acoustic: C



Combination of Metapaths by using Machine Learning Techniques

- We combine different Metapaths by using **Multi-layer Perceptron Regression** with 2 hidden layers on listening history of user-item pairs
- Supervised Learning** helps us automatically learn from observed history then effectively select useful Metapath features



Experimental Results

Single Metapaths Comparison in Music Recommendation

Metapaths	Single Path Average Hit Rate
$RR^T R$	20.07%
RTT	25.30%
REE^T	0.82%
RMM^T	26.93%
RCC^T	6.94%
$RR^T RTT^T$	13.49%
$RR^T REE^T$	0.46%
$RR^T RMM^T$	15.17%
$RR^T RCC^T$	1.65%
$REE^T TT^T$	2.11%
$REE^T MM^T$	1.69%
$REE^T CC^T$	0.25%
$RTT^T MM^T$	23.41%
$RTT^T CC^T$	7.79%
$RMM^T CC^T$	8.03%

We choose 5 best Metapaths to perform Metapath (5), and 10 best Metapaths to perform Metapaths (10). Red stands for Metapaths used in Metapaths (5), Blue stands for Metapaths used in Metapaths (10).

Comparison with Other Baseline Models in Music Recommendation

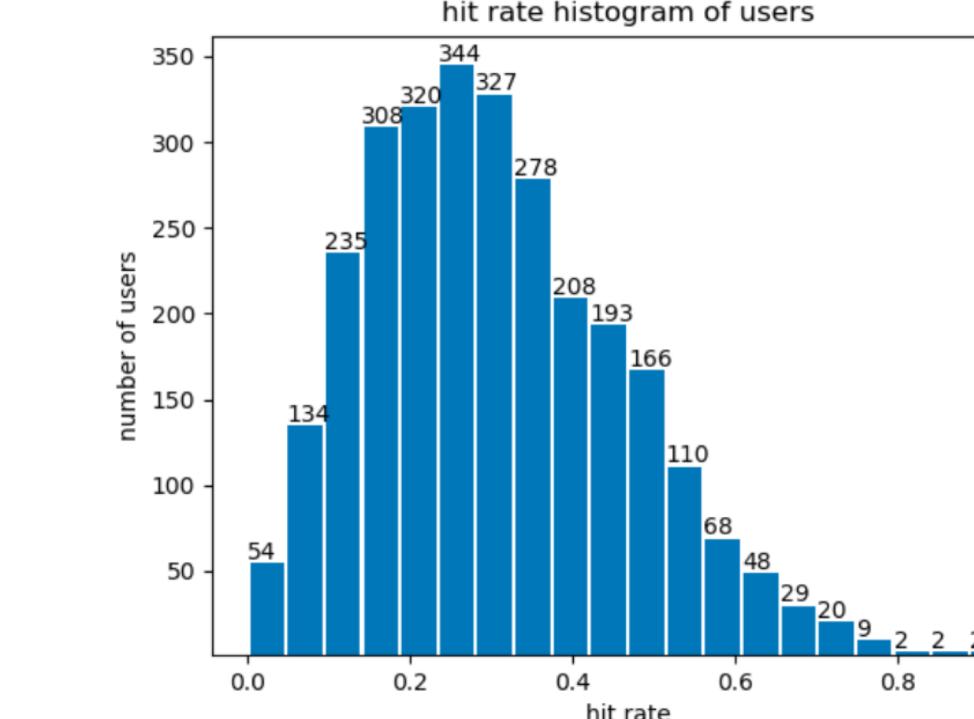
Observation:

- Metapath-based recommendation** outperforms traditional collaborative filtering and matrix factorization methods
- By utilizing **machine learning** techniques, Metapath-based recommendation achieves higher hit rates

Methods	Average Hit Rate
Random Guess	0.62%
Popular-based Recommendation	7.30%
Collaborative Filtering	14.11%
Metapaths (5) + Matrix Factorization	12.11%
Metapaths (10) + Matrix Factorization	12.67%
Metapaths (5) + Linear Regression	28.97%
Metapaths (10) + Linear Regression	30.29%
Metapaths (5) + Neural Network	29.73%
Metapaths (10) + Neural Network	32.28%

Metapaths (5): Using 5 best Metapaths features; Metapaths(10): Using 10 best Metapaths features

Distribution of Metapaths (10) + Neural Network on Hit Rates for Different Users



Observation:
The prediction satisfies Gaussian distribution with mean=32.28% and standard derivation=15.02%

Conclusions

- Doing **multi-label classification** over acoustic features works better than grouping them according to hyper dimensional distance using listeners' preference
- Heterogeneous Information Network** based recommendation by combining collaborative preference and content-based preference outperforms other methods
- Metapaths** combination through **Supervised Learning** yields higher hit rate