Factoring in What Gets Listened To

Performance of Factorisation Machine using Musical Features for Children

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Background

- Many recommender systems are well researched for "normal" users¹
- Children and other non-normative listeners often have traditional recommenders perform worse²
- Children's listening behaviour has been studied, but no recommender has been evaluated³

Research Question

How well does a music recommender system using matrix factorisation leveraging various audio features perform for child users?



Resources

Dataset of users' listening behaviour: LFM-2b

- filtered for children, at least 10 listens
- Songs' feature values, extracted from Spotify:
- Tempo
- Average Loudness
- Time signature Musical mode

Experiment

- Use 0.1% of user's listening events for training, 99.9% for heuristics (nDCG, MRR) (hardware limitations)
- Factorisation Machine without features as control, evaluate extension with all features and all combinations of 3 features

Results		Fea	Features used		MRR	
					1 0 31161	
		Δ1	1 features	0.15000	0.01101	-
			loudnoss	0.15900	0.32223)
		INO		0.15974	0.37828)
		Γ	lo mode	0.15369	0.35678	5
		Ν	o tempo	0.18303	0.49598	8
		No tii	me signature	0.17544	0.41342	
0.6					•	
0.0						
0.5						
0.4						
				_		
		_				
0.3						
0.2						
0.2						
01						
0						
	Control	All features	No loudness	No mode	No tempo	No time sig.

- · All recommenders with added features performed better than the control, but fewer features tend to cause better scores
- Removing mode has little to no positive effect
- Using no tempo values significantly improves the scores

nDCG MRR

1. Schedl et al.. Music Recommender Systems, pages 453-492. Springer US, Boston, MA, 2015. 2. Kowald et al.. Support the underground: characteristics of beyondmainstream music listeners. EPJ Data Science, 10, 2021. 3. Spear et al.. Baby shark to barracuda: Analyzing children's music listening behavior. In Proceedingsof the 15th ACM Conference on Recommender Systems, RecSys '21, page 639-644, New York, NY, USA, 2021. Association for Computing Machinery.



Supervisors: Robin Unruh, Sole Pera

Discussion

· Quality over quantity for selecting features, some features may oppose each other · Very small training set due to demanding performance of FM

· Because of the low split, comparison of the results to similar research is not advisable

Conclusion

· Do features improve the recommender? Yes, but...

· For better results, this experiment should be repeated with a larger training set (80%) • What other features can be used to improve the recommender?

 How do features extracted through other means (e.g. signal processing) perform? · How good is this recommender for recommending music to adults?