Hybrid music recommender using content-based and social information

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Outline

"Music doesn't have any special meaning; it depends what it's attached to." (Oliver Sacks 1933-2015)

Aim and Motivations

Design and implement a hybrid music recommender to mitigate the cold-start problem in a content-based recommendation strategy.

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Design and implement a hybrid music recommender to mitigate the cold-start problem in a content-based recommendation strategy.

- Implement a convolutional deep neural network (CDNN) to obtain high-level representation of an audio file.
- Investigate Estimation of Distribution Algorithms (EDAs) to model user profiles in terms of probabilities of music genres preferences.

Recommender Systems

Hybrid music recommender (Yoshii et al. 2008)

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- Three-way aspect model: "unobserved" genre

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- CDNN for latent vector representation
- Million Song Dataset

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Hybrid recommender based on EDA (Liang, T. et al. 2014)

- TF-IDF for item attributes
- Movielens dataset
- Permutation EDA

Hybrid music recommender design

Fundamental tasks:

- User modelling
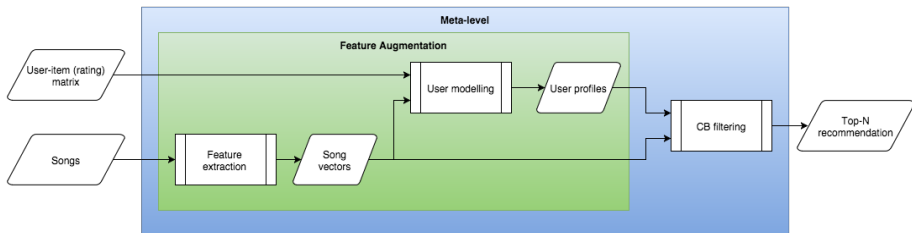- Information filtering

Required data:

- User-item matrix: Taste profile dataset (53 users)
- Audio clips: 7digital UK catalogue (640 clips)

Song representation:

- 10-dimensional vector
- Probability to belong to a music genre

Hybrid music recommender approach

- Feature augmentation
- Meta-level

Probability of music genre
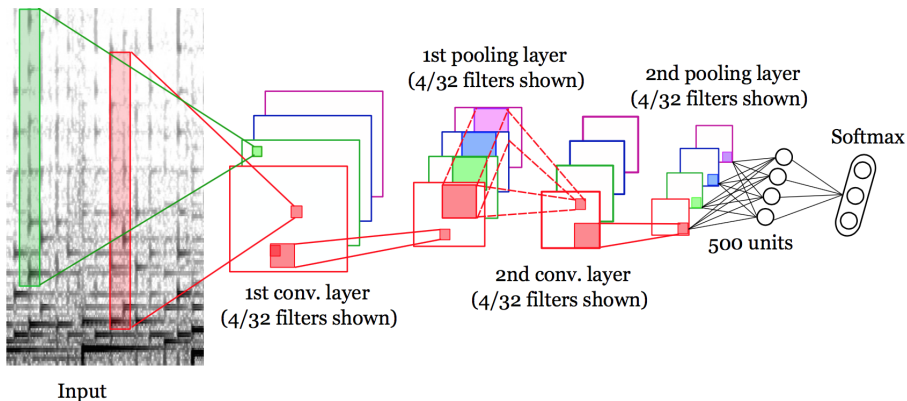
Figure: CDNN for music genre classification (Kereliuk et al. 2015)

Estimation of Distribution Algorithms (EDAs)
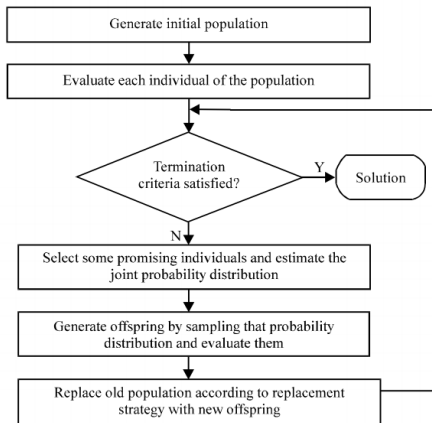
Figure: Flowchart for EDA (Ding et al. 2015)

User profile modelling

With permutation EDA:

- 10 tags (GTZAN) equivalent to keywords
- 50 weights: evenly spaced over the inverval $[0.1, \dots, 0.9]$

With continuous EDA:

- Each genre considered as a dimension
- Compute mean and covariance for each dimension along individuals
- Sample from normal distribution

Genre classification

Table: Genre classification results

Trial	Validation error (%)	Test error (%)	Iter.	Time elapsed (min.)
1	58.0	65.2	650	7.00
2	37.6	46.0	2150	13.07
3	39.6	46.0	700	7.54
4	35.6	36.8	550	6.01
5	36.4	40.0	250	5.47
6	40.4	44.8	150	5.41
7	32.4	40.4	800	8.64
8	36.0	38.8	250	5.42
9	34.0	38.8	850	9.14

Top - N recommendation

Table 5.2: Evaluation of recommender systems (N=5)

Recommender	Precision	Recall	F1	Accuracy
Content-based (baseline)	0.275 ± 0.087	0.010 ± 0.003	0.020 ± 0.007	0.681 ± 0.008
Hybrid (permutation EDA)	$\mathbf{0.391 \pm 0.182}$	$\mathbf{0.013 \pm 0.007}$	$\mathbf{0.025 \pm 0.013}$	$\mathbf{0.685 \pm 0.009}$
Hybrid (continuous UMDA)	0.318 ± 0.142	0.011 ± 0.005	0.021 ± 0.011	0.683 ± 0.009

Table 5.3: Evaluation of recommender systems (N=10)

Recommender	Precision	Recall	F1	Accuracy
Content-based (baseline)	0.301 ± 0.059	0.022 ± 0.007	0.041 ± 0.012	0.678 ± 0.007
Hybrid (permutation EDA)	$\mathbf{0.370 \pm 0.073}$	$\mathbf{0.024 \pm 0.007}$	$\mathbf{0.045 \pm 0.013}$	$\mathbf{0.682 \pm 0.009}$
Hybrid (continuous UMDA)	0.309 ± 0.100	0.019 ± 0.007	0.036 ± 0.013	0.679 ± 0.009

Table 5.4: Evaluation of recommender systems (N=20)

Recommender	Precision	Recall	F1	Accuracy
Content-based (baseline)	0.281 ± 0.052	0.041 ± 0.006	0.071 ± 0.010	0.666 ± 0.006
Hybrid (permutation EDA)	$\mathbf{0.363 \pm 0.041}$	$\mathbf{0.047 \pm 0.008}$	$\mathbf{0.084 \pm 0.014}$	$\mathbf{0.676 \pm 0.007}$
Hybrid (continuous UMDA)	0.302 ± 0.067	0.039 ± 0.011	0.070 ± 0.019	0.671 ± 0.010

Conclusions and future work

- CDNN produce similar results to long-established music genre classifiers
- Hybrid permutation EDA outperforms CB
- Investigate unsupervised deep learning
- Online evaluation

Questions?