On Culture-dependent Modelling of Music Similarity

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Introduction

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- Interest in influence of **cultural context**
  for predicting users‘ opinions on musical similarity
  - culture in a wider sense

- **Current PhD thesis on: Adaptive computational music similarity measures**
  - For recommendation, analysis, indexing, ...
  - Investigation of relation between
    - cultural attributes and
    - similarity parameters

Structure of Talk

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- Similarity Modelling
  - Cultural User Data
  - Common Idea of Similarity?
- Preliminary Feasibility Study
  - The MagnaTagATune Dataset
  - Similarity data
  - Features
  - Similarity adaptation: Weight learning
- Conclusion

Concept

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- Provide a computational means of music similarity estimation
- Train / adapt a computational model to human similarity votings
- Produce models for specific user groups
- Analyse gained models

Model for Similarity Adaptation

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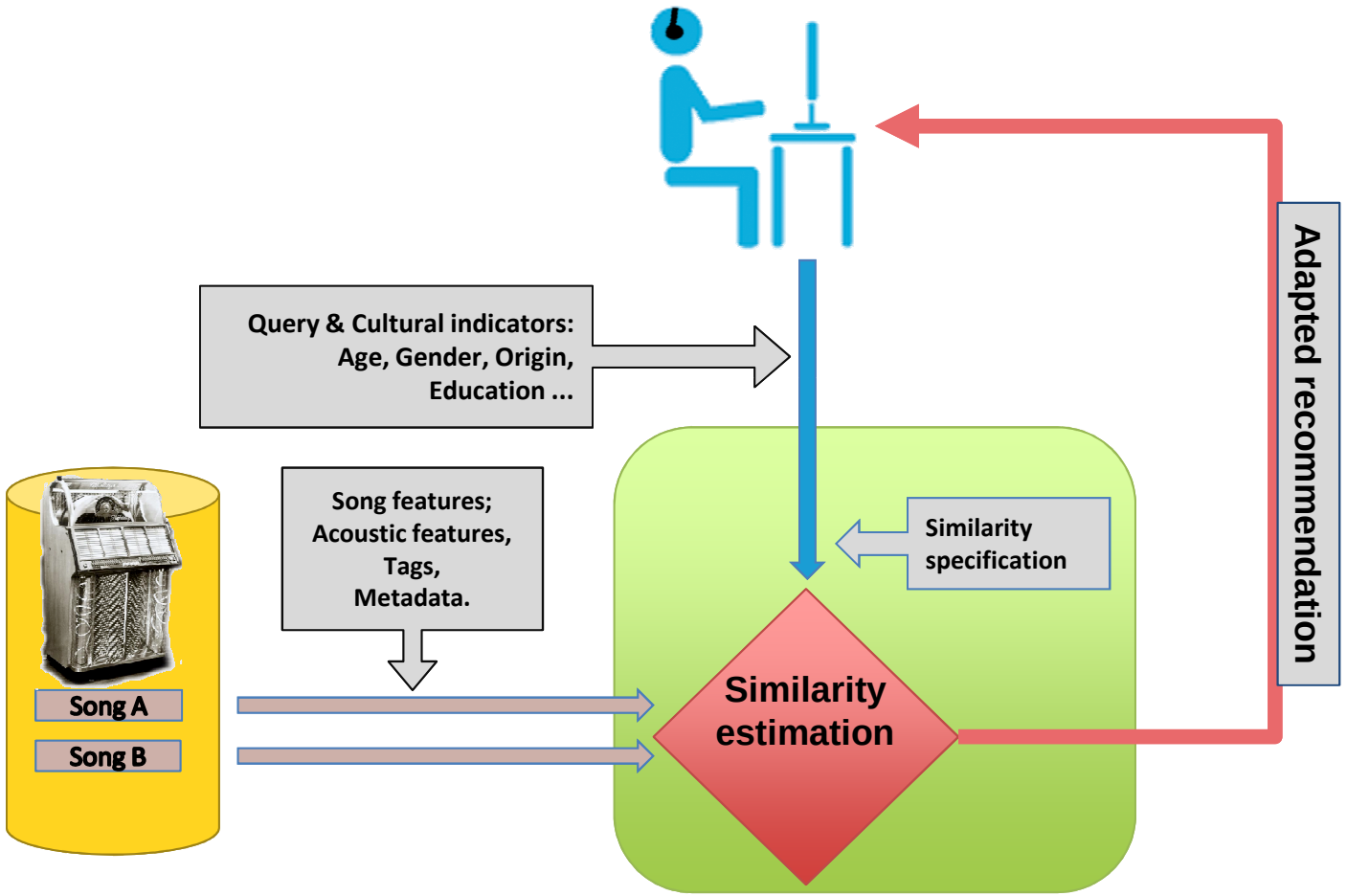

Similarity Modelling

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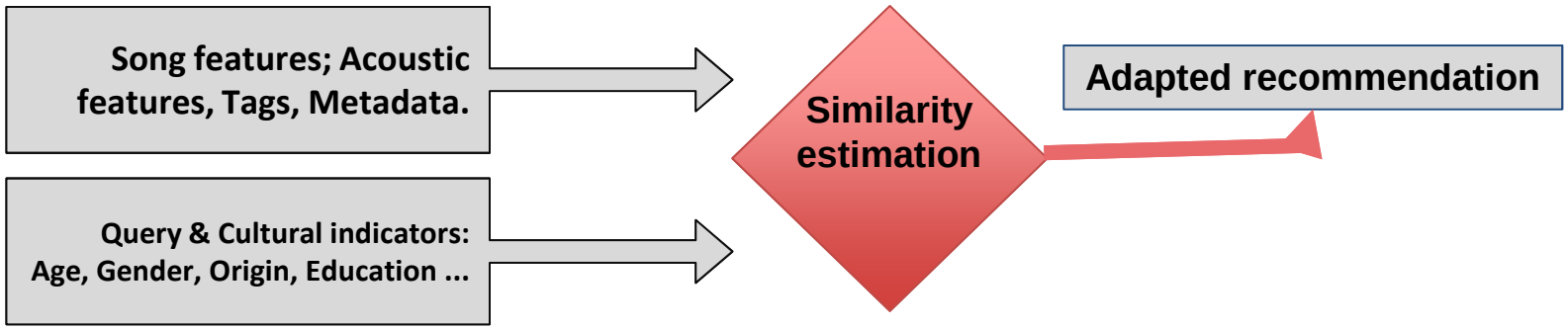
- Similarity measure is defined as a function on
  - two music clips
  - culture-related user attributes

- The result is a similarity estimate



Model Training

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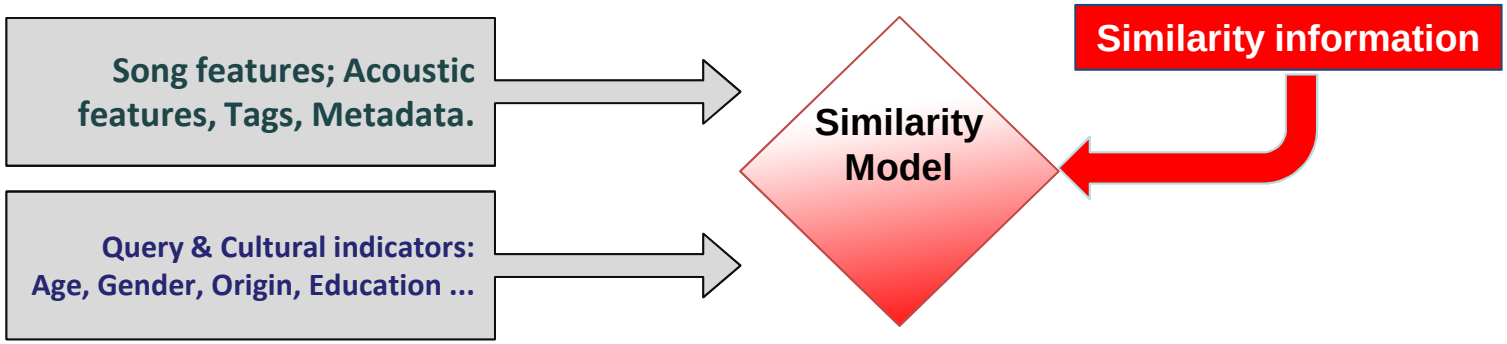
- Mathematical model is tuned to human input
- Data needed:
  - clip features
  - similarity information
  - user attributes



Cultural User Attributes

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- Exemplary list of collectable attributes

- Personal data
  - origin, gender, age
- Socio-economic background
  - education, occupation, income
- Musical background
  - musical education, listening habits, familiarity with style, “fan”

Question: Cultural Grouping

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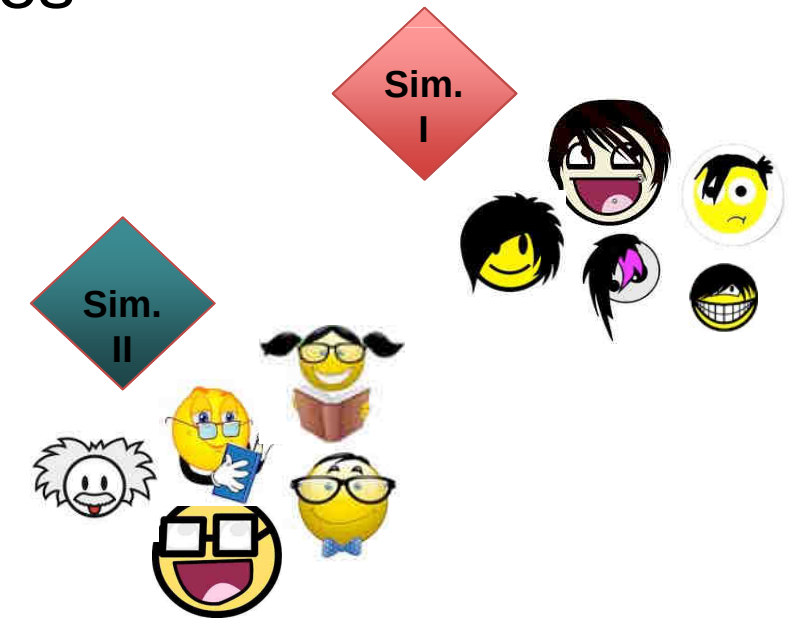
- Later analysis:
  - group users by similarity models and cultural attributes
  - influential user attributes
  - model differences



Data Collection

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Data Collection

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- Get attributes and similarity data:
  - surveys
  - user profiles
  - social networks

- **G**ames **W**ith **A** **P**urpose
  - gaming helps collect valuable data
  - tagging massive media (pictures, music)
  - web-based
  - Game rewards consensus
    - (discourage idiosyncrasy)

GWAP Example: HerdIt

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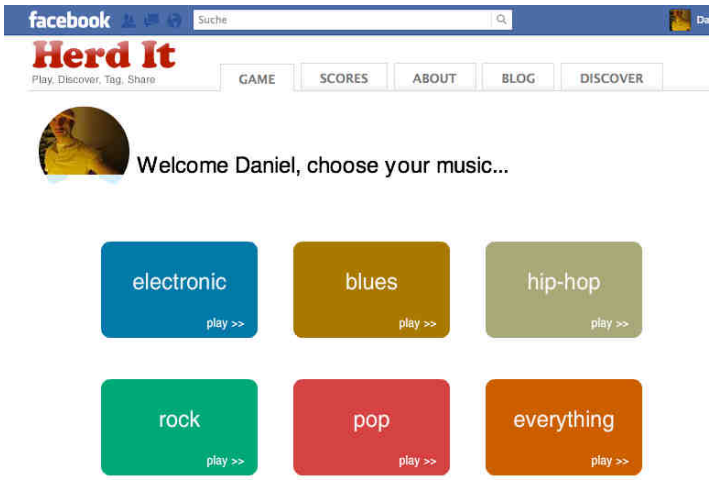

Barrington et al. 2009

GWAP Example: HerdIt

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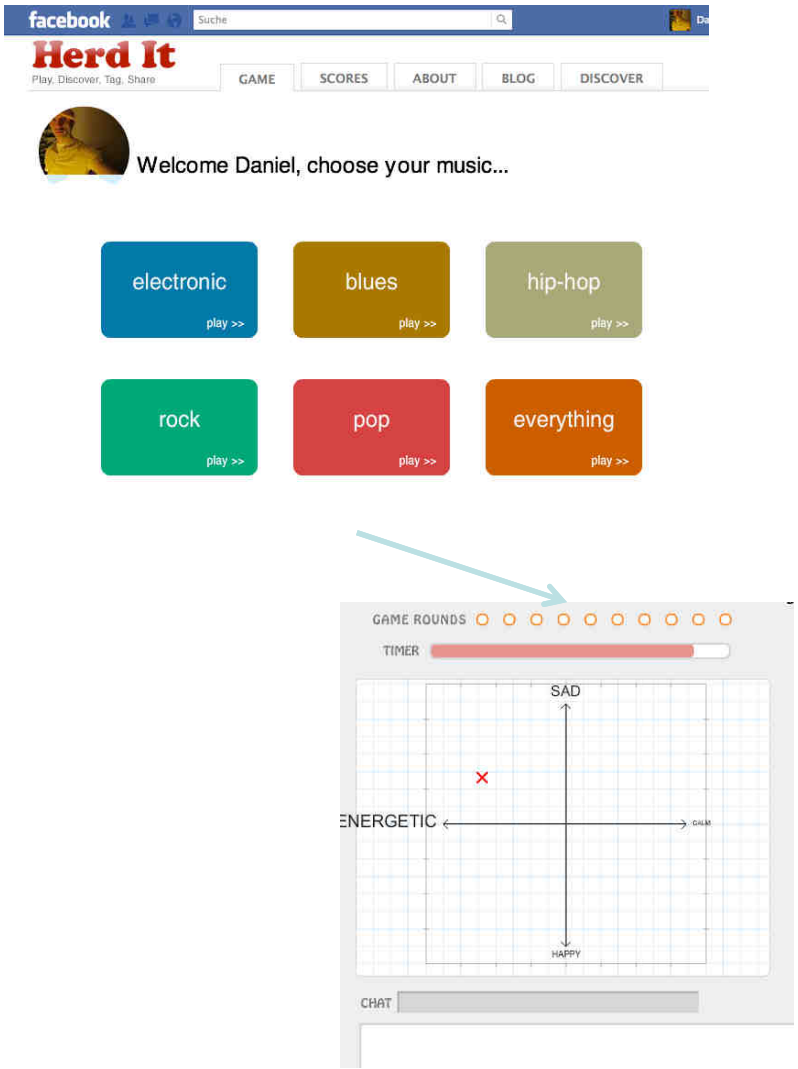

GWAP Example: HerdIt

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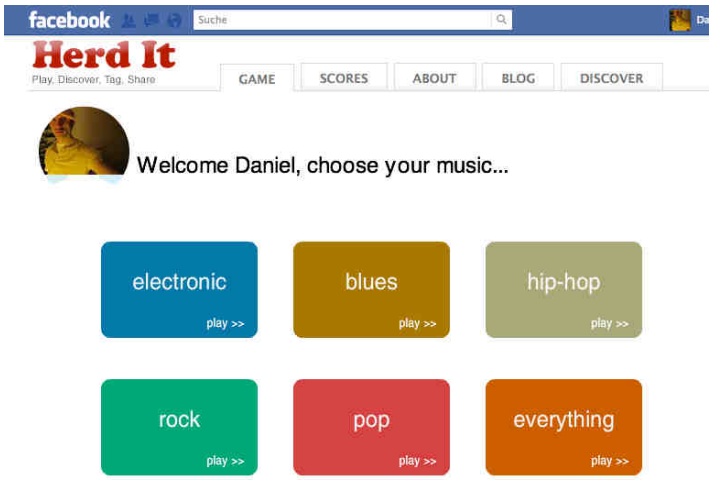

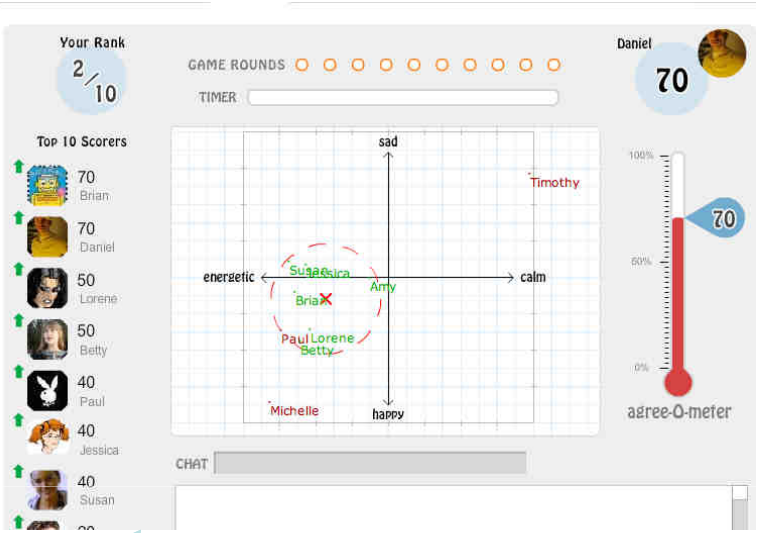

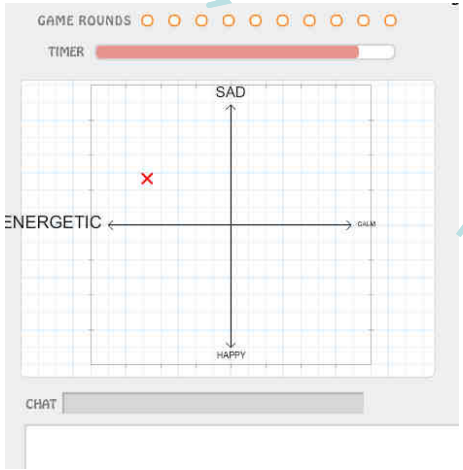

GWAP Example: HerdIt

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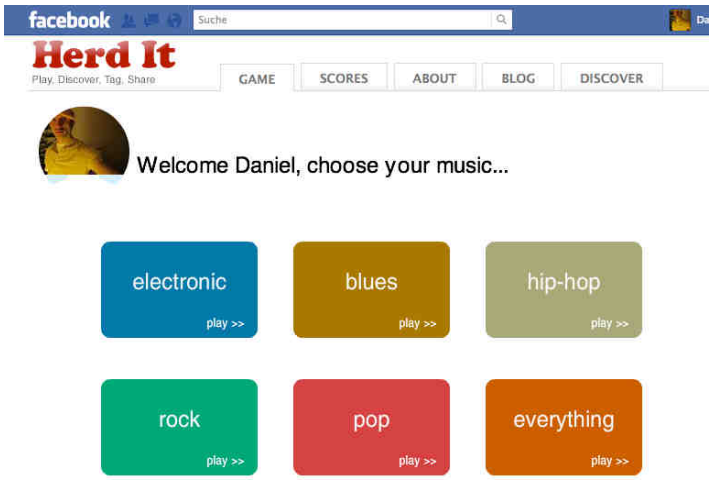

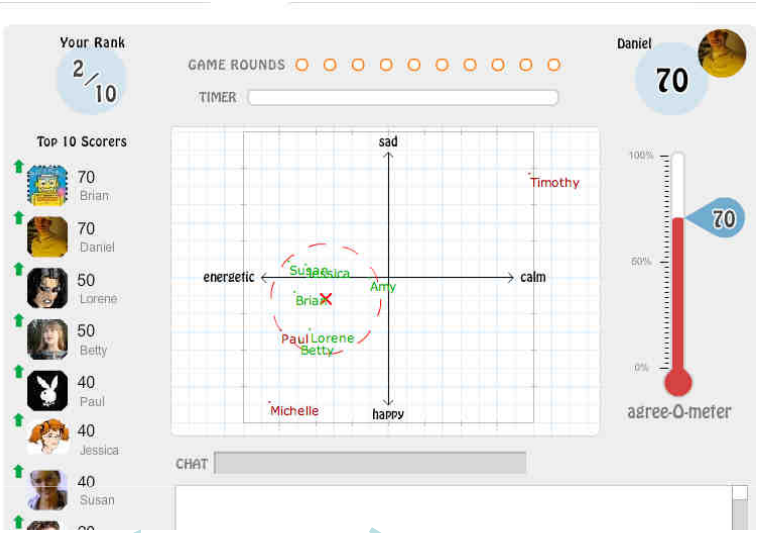

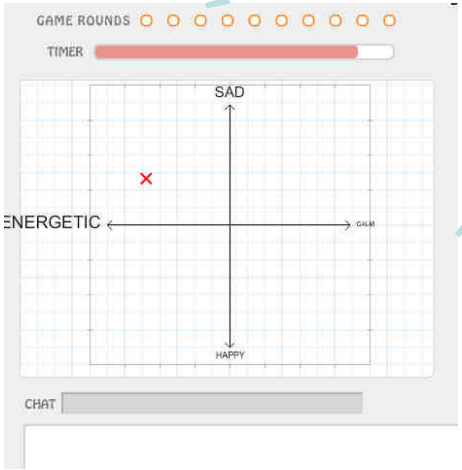

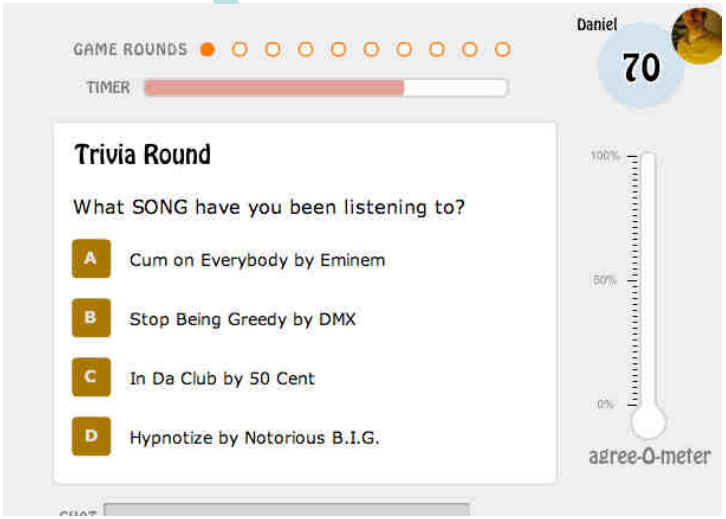

Music Similarity Perception?

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- Data collection
  - **statements / opinions** about musical properties
    - similarity
  - approaches (especially GWAPS) come with different, partly unknown biases
  - Psychological factors / biases in games to be considered

- Training may give some results:
  - Is there a consensous / generally consistent opinion on similarity
  - For a subgroup?

Early Feasibility Experiment

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Early Feasibility Experiment

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- **Adapt metric parameters** to **human similarity judgements** from a human computation game.
- Evaluate quality of adaptation
  - adaptation to data
  - prediction of unseen data
- Here: No information about user attributes
  - general model

The MagnaTagATune Dataset

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- Music clips from the Magnatune label
  - about 30 seconds long, most prominent genres:
    - ”electronica” (30%), ”classical” (28%), ”world” (15%) and ”rock” (17%)
- Similarity votings
- Audio features:
  - Vector representations of audio
  - Precomputed by the echonest

Similarity data

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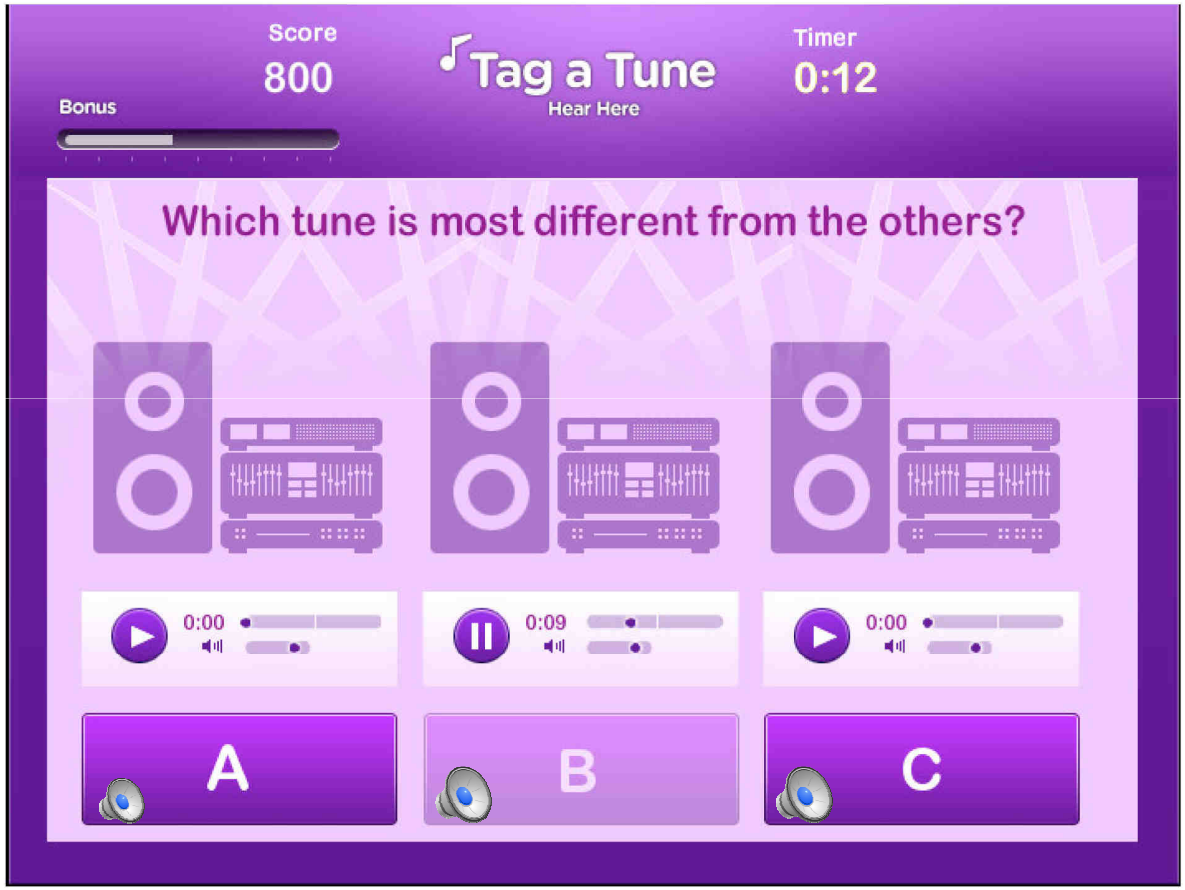

Bonus Round

Law et al. 2009

Similarity data

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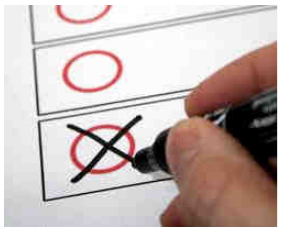
- Data collected via bonus round in TagATune game
  - Users aim to agree on **outlying (most dissimilar) clip** out of three
  - **533 triplet votings**, 1019 clips
  - On average **14 votes** per triplet
  - Some triplets reappear as permutation



  - Genre distribution favors „electronic“ genre
  - Most triplets contain 2 or 3 different genres

Data preparation

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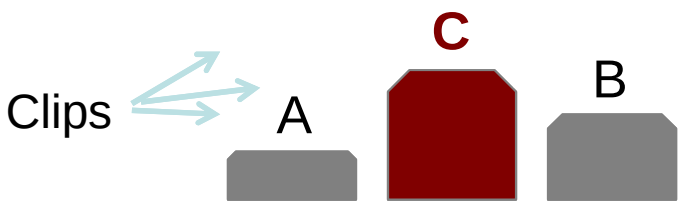
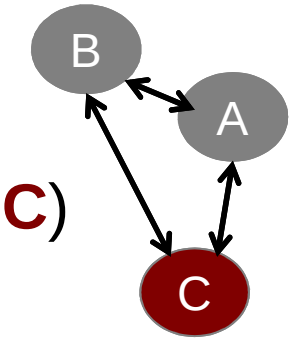
- Simplify data:
  - determine **winning outlier** where possible
  - discard votings without clear winner



- Derive similarity constraints:
  - **C** being the outlier implies
  - sim(A, B) > sim(A, **C**) AND sim(A, B) > sim(B, **C**)



Feature Data

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- Timbre
- Pitch class
- Rhythm
- Genre information.

- 120 features

- Similarity / metric space is defined on the feature space

Timbre / Chroma Features

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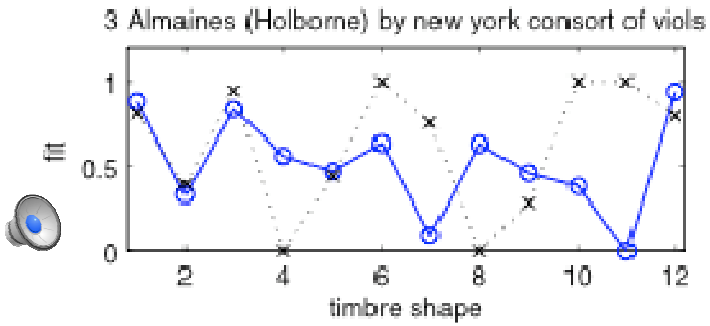
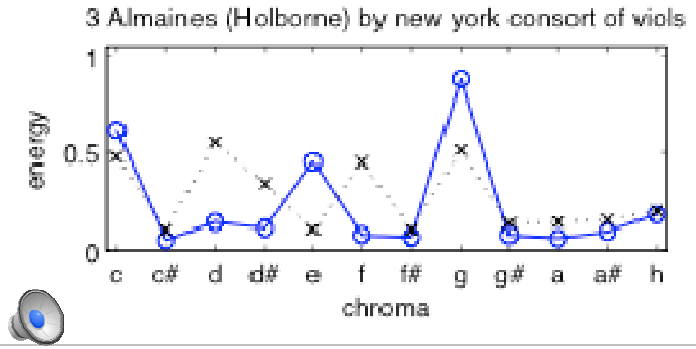
- Timbre of clip: 2 representative feature vectors
  - sorted according to accumulated time.

- Harmonic content: 2 sorted feature vectors
  - feature data contains strength of each well-tempered pitch-class
  - transposed to root note C





Rhythm Features

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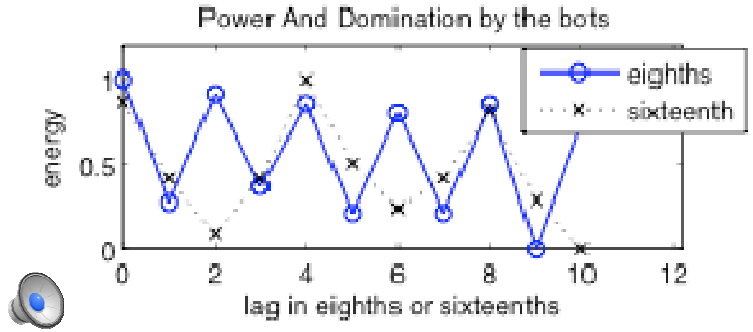
- MagnaTagATune contains beat positions and meter information.
- Analyse accentuation of eighths / sixteenths
  - By analysing repetitions in the clip‘s energy curve
  - For 11 of each of these positions



Genre Features

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Genre Features

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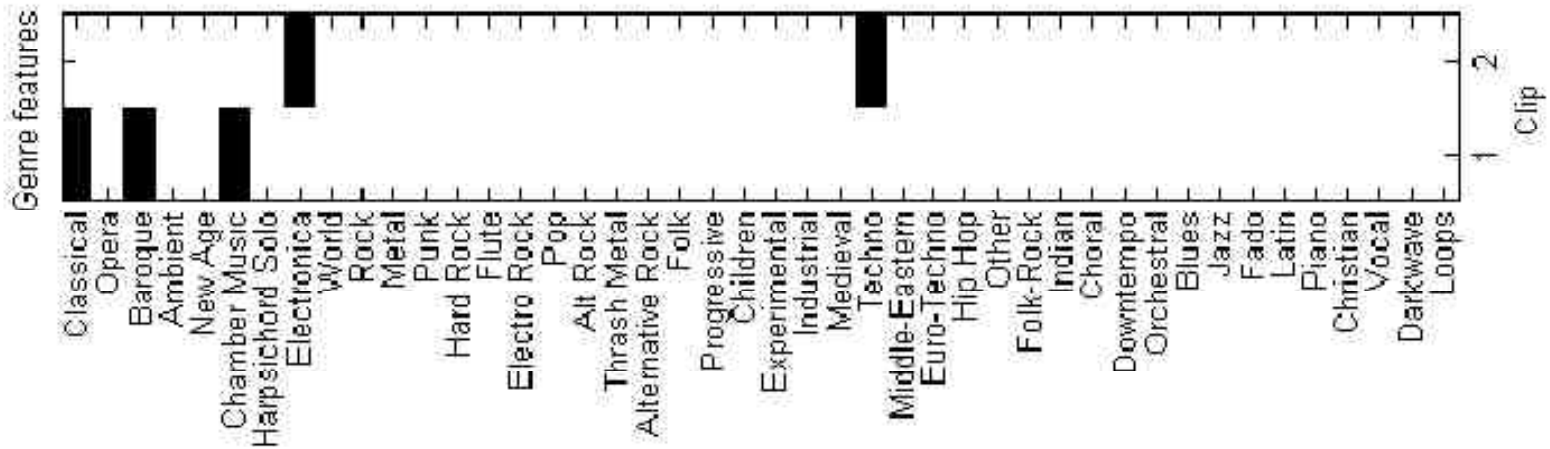
- Genre information from the Magnatune label
  - Small vocabulary: 44 genres for the whole set

- **Binary vector** per clip (0 or 1 per genre)

Two vectors:



Similarity Metric Learning

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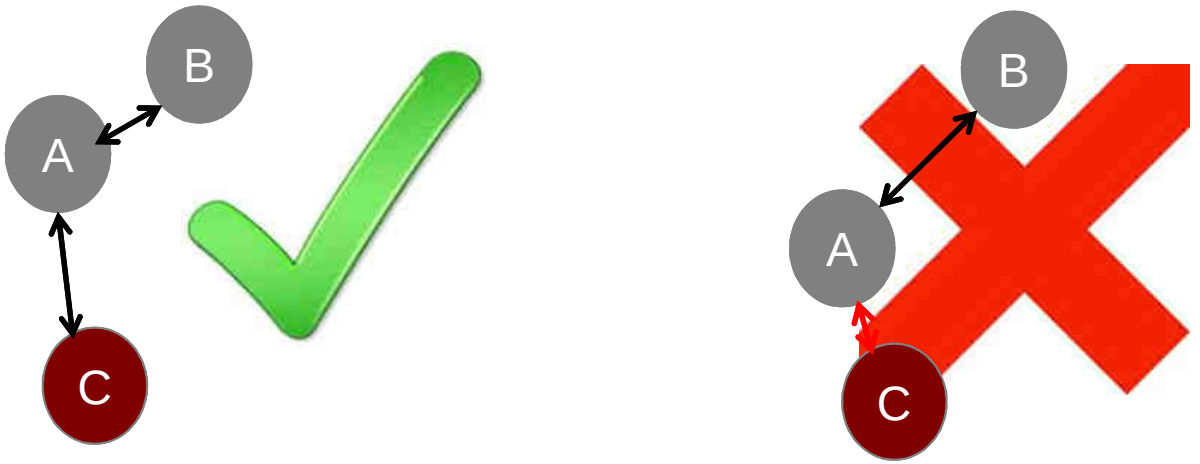
- Optimise a weighted metric using constraints:
  1. **Define** a distance metric
  2. For each training triplet, **determine** distance using the new metric: **Compare** pairs (A, B), (A, **C**) to data in training set
  3. **Optimise feature weights** for violated constraints



Evaluation Method

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- 5-fold cross-validation
  - (adapt and test on different subsets)

- 106 test constraints
- 427 training constraints

Results

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- Weighted similarity measure gives improved results
- Baseline: equal-weighted Euclidean metric

	Euclidean mean	**Weighted mean**	**Weighted std deviation**
Training	64.1%	91.0%	1%
Test		75.2%	4.2%

Conclusions and Future Work

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- Similarity and cultural context
- Basic experiment: **similarity adaptation** using weighted Euclidean metrics works
- Future work
  - more elaborate features
  - different algorithms for metric adaptation
  - Currently testing more elaborate **processing of similarity votes**
  - Gather similarity data with more context information
  - Comparison of user groups

Fin

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Thank you