COURT DECISIONS ON MUSIC PLAGIARISM AND THE PREDICTIVE VALUE OF SIMILARITY ALGORITHMS

Dr. Marc Pendzich
Institute of Musicology
University of Hamburg

Dr. Daniel Müllensiefen
Goldsmiths College
University of London

AGENDA

1 Introduction

2 Method

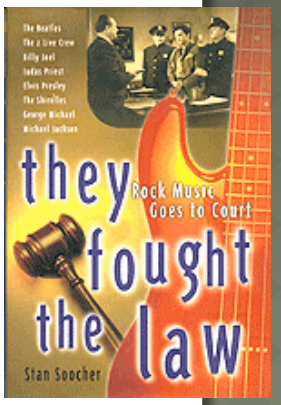
3 Empirical Study

4 Summary/next steps

1 INTRODUCTION

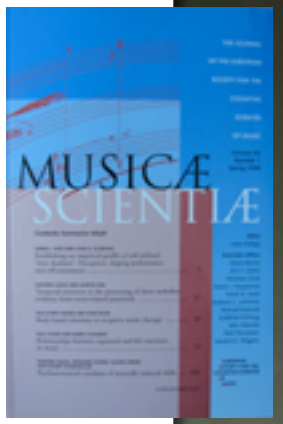
- Melodic Plagiarism: Huge public interest, importance for pop industry – little research

- Exceptions:
  - Stan Soocher: They Fought The Law, 1999
  - Charles Cronin: Concepts of Melodic Similarity in Music-Copyright, 1998



1 INTRODUCTION

- The aim of the study is
  - to explore how melodic similarity as measured by modern algorithms is related to court decisions in individual cases
  - to measure the similarity of the melody pairs in a sample of cases taken from a collection of court cases and
  - to evaluate the predictive power of the algorithmic measurements when compared to the court ruling.



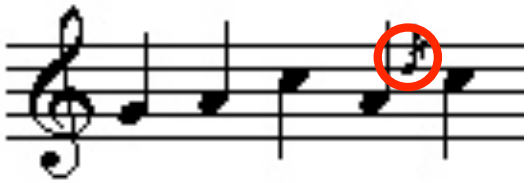
2 METHOD

- 20 cases spanning the years from 1970 to 2005 – with a focus on *melodic* aspects of music copyright infringement.
- *Creation* of monophonic MIDI files,
- *analysis* of the written opinions of the judges,
- *reduction* of the court decisions to only two categories
  - „pro plaintiff“ = melodic plagiarism
  - „contra plaintiff“ = no infringement

BRIGHT TUNES VS. HARRISONGS (1976)

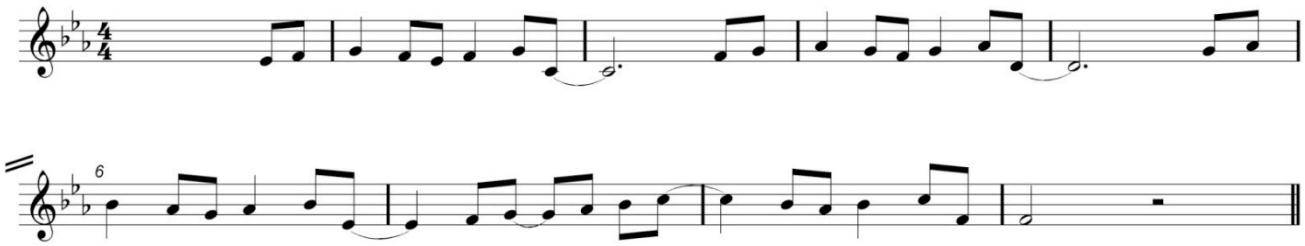
- The Chiffons „He‘s So Fine“, 1963
  - No. 1 in US, UK highest position 11

- George Harrisson, „My Sweet Lord“ Single published in 1971
  - No.-1-Hit in US, UK & (West-)Germany

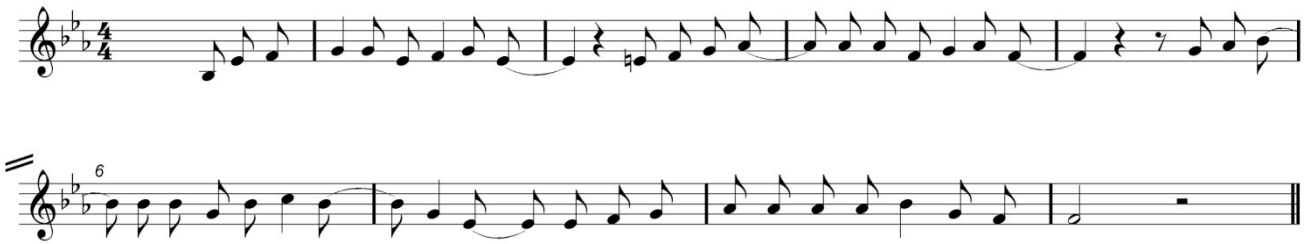


SELLE VS. GIBB (1984)

- Ronald Selle, “Let It End”



- Bee Gees, “How Deep Is Your Love” (1977)



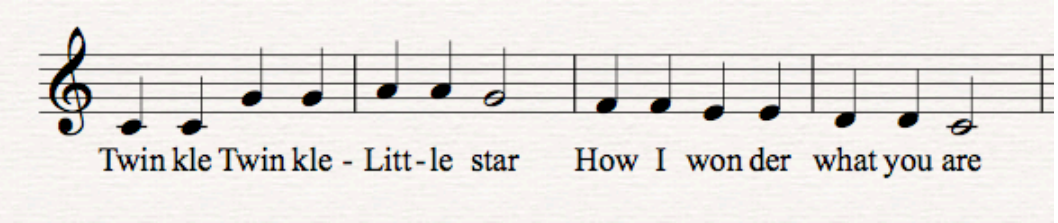
3 EMPIRICAL STUDY

- How do court decision relate to melodic similarity?
- What is the frame of reference (directionality of comparisons)?
- How is prior musical knowledge taken into account?

STATISTICALLY INFORMED ALGORITHMS

- Idea: Frequency of melodic elements important for similarity assessment
- Inspired from computational linguistics (Baayen, 2001), text retrieval (Manning & Schütze, 1999)
- Conceptual Components:
  - *m-types* (aka n-grams) as melodic elements
  - Frequency counts: Type frequency (TF) and Inverted Document Frequency (IDF)

MELODIC ELEMENTS: M-TYPES



Word Type *t*	Frequency *f(t)*,	Melodic Type τ (pitch interval, length 2)	Frequency *f(τ)*,
Twinkle	2	0, +7	1
little	1	+7, 0	1
star	1	0, +2	1
How	1	+2, 0	1
I	1	0, -2	3
wonder	1	-2, -2	1
what	1	-2, 0	2
you	1	0, -1	1
are	1	-1, 0	1

TYPE / INV. DOCUMENT FREQ.

C Corpus of melodies

m melody

τ Melodic type

τ T # different melodic types

|m:τ ∈ m| # melodies containing τ

$$TF(m,\tau) = \frac{f_m(\tau)}{\sum_{i=1}^{T} f_m(\tau_i)} \qquad IDF_C(\tau) = \log\left(\frac{|C|}{|m:\tau \in m|}\right)$$

Melodic Type τ (pitch interval, length 2)	Frequency $f(\tau)$
0, +7	1
+7, 0	1
0, +2	1
+2, 0	1
0, -2	3
-2, -2	1
-2, 0	2
0, -1	1
-1, 0	1

TYPE / INV. DOCUMENT FREQ.

C Corpus of melodies

m melody

τ Melodic type

τ T # different melodic types

|m:τ ∈ m| # melodies containing τ

$$TF(m,\tau) = \frac{f_m(\tau)}{\sum_{i=1}^{T} f_m(\tau_i)}$$

$$IDF_C(\tau) = \log\left(\frac{|C|}{|m:\tau \in m|}\right)$$

Melodic Type τ (pitch interval, length 2)	Frequency $f(\tau)$	TF(m, τ)
0, +7	1	0.11
+7, 0	1	0.11
0, +2	1	0.11
+2, 0	1	0.11
0, -2	3	0.33
-2, -2	1	0.11
-2, 0	2	0.22
0, -1	1	0.11
-1, 0	1	0.11

TYPE / INV. DOCUMENT FREQ.

C Corpus of melodies

m melody

τ Melodic type

τ T # different melodic types

|m:τ ∈ m| # melodies containing τ

$$TF(m,\tau) = \frac{f_m(\tau)}{\sum_{i=1}^{T} f_m(\tau_i)} \qquad IDF_C(\tau) = \log\left(\frac{|C|}{|m:\tau \in m|}\right)$$

Melodic Type τ (pitch interval, length 2)	Frequency $f(\tau)$	TF(m, τ)	$IDF_C(\tau)$
0, +7	1	0.11	1.57
+7, 0	1	0.11	1.36
0, +2	1	0.11	0.23
+2, 0	1	0.11	0.28
0, -2	3	0.33	0.16
-2, -2	1	0.11	0.19
-2, 0	2	0.22	0.22
0, -1	1	0.11	0.51
-1, 0	1	0.11	0.74

TYPE / INV. DOCUMENT FREQ.

C Corpus of melodies

m melody

τ Melodic type

τ T # different melodic types

|m:τ ∈ m| # melodies containing τ

$$TF(m,\tau) = \frac{f_m(\tau)}{\sum_{i=1}^{T} f_m(\tau_i)} \qquad IDF_C(\tau) = \log\left(\frac{|C|}{|m:\tau \in m|}\right)$$

Melodic Type τ (pitch interval, length 2)	Frequency $f(\tau)$	TF(m, τ)	$IDF_C(\tau)$	$TFIDF_{m,C}(\tau)$
0, +7	1	0.11	1.57	0.1727
+7, 0	1	0.11	1.36	0.1496
0, +2	1	0.11	0.23	0.0253
+2, 0	1	0.11	0.28	0.0308
0, -2	3	0.33	0.16	0.0528
-2, -2	1	0.11	0.19	0.0209
-2, 0	2	0.22	0.22	0.0484
0, -1	1	0.11	0.51	0.0561
-1, 0	1	0.11	0.74	0.0814

TF-IDF CORRELATION

$$\sigma_C(s,t) = \frac{\sum_{\tau \in s_n \cup t_n} TFIDF_{s,C}(\tau) \cdot TFIDF_{t,C}(\tau)}{\sqrt{\sum_{\tau \in s_n \cup t_n} \left(TFIDF_{s,C}(\tau)\right)^2 \cdot \sum_{\tau \in s_n \cup t_n} \left(TFIDF_{t,C}(\tau)\right)^2}}$$

FEATURE-BASED SIMILARITY

Ratio Model (Tversky, 1977): Similarity $\sigma(s,t)$ related to

- # features in *s* and *t* have common
- salience of features *f()*

$$\sigma(s,t) = \frac{f(s_n \cap t_n)}{f(s_n \cap t_n) + \alpha f(s_n \setminus t_n) + \beta f(t_n \setminus s_n)}, \alpha, \beta \geq 0$$

- features => m-types
- salience => IDF and TF
- different values of α, β to change frame of reference
- Variable m-type lengths (n=1,…,4), entropy-weighted average

FEATURE-BASED SIMILARITY

Tversky.equal measure (with $\alpha = \beta = 1$)

$$\sigma(s,t) = \frac{\sum_{\tau \in s_n \cap t_n} IDF_C(\tau)}{\sum_{\tau \in s_n \cap t_n} IDF_C(\tau) + \sum_{\tau \in s_n \setminus t_n} IDF_C(\tau) + \sum_{\tau \in t_n \setminus s_n} IDF_C(\tau)}$$

Tversky.plaintiff.only measure (with $\alpha = 1$, $\beta = 0$)

$$\sigma_{\text{plaintiff.only}}(s,t) = \frac{\sum_{\tau \in s_n \cap t_n} IDF_C(\tau)}{\sum_{\tau \in s_n \cap t_n} IDF_C(\tau) + \sum_{\tau \in s_n \setminus t_n} IDF_C(\tau)}$$

Tversky.defendant.only measure (with $\alpha = 0$, $\beta = 1$)

$$\sigma_{defendant\ .only}(t,s) = \frac{\sum_{\tau \in s_n \cap t_n} IDF_C(\tau)}{\sum_{\tau \in s_n \cap t_n} IDF_C(\tau) + \sum_{\tau \in t_n \setminus s_n} IDF_C(\tau)}$$

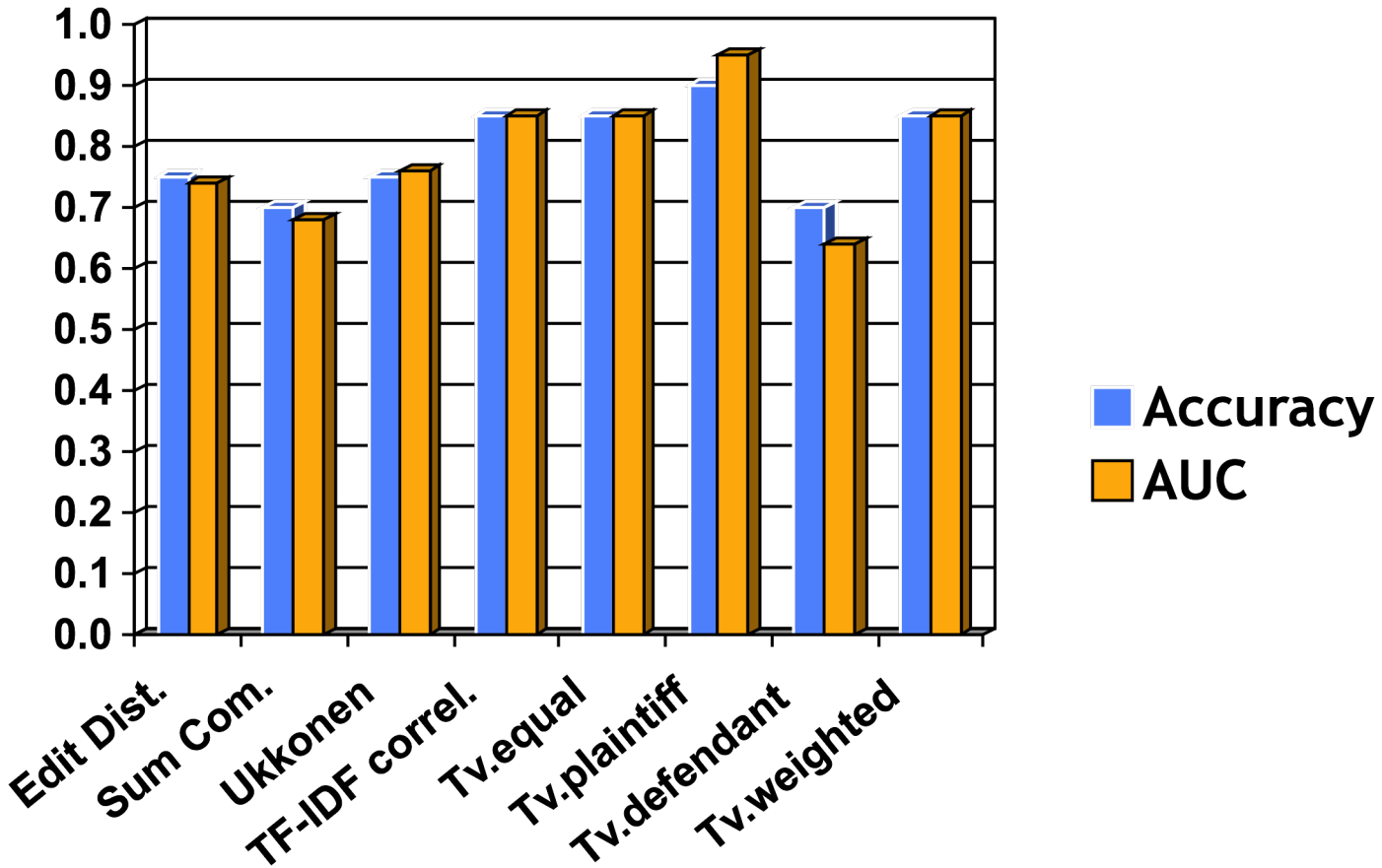
Tversky.weighted measure with $\alpha = \frac{\sum_{\tau \in s_n \cap t_n} TF_s(\tau)}{\sum_{\tau \in s_n} TF_s(\tau)}$ and $\beta = \frac{\sum_{\tau \in s_n \cap t_n} TF_t(\tau)}{\sum_{\tau \in t_n} TF_t(\tau)}$

EVALUATION

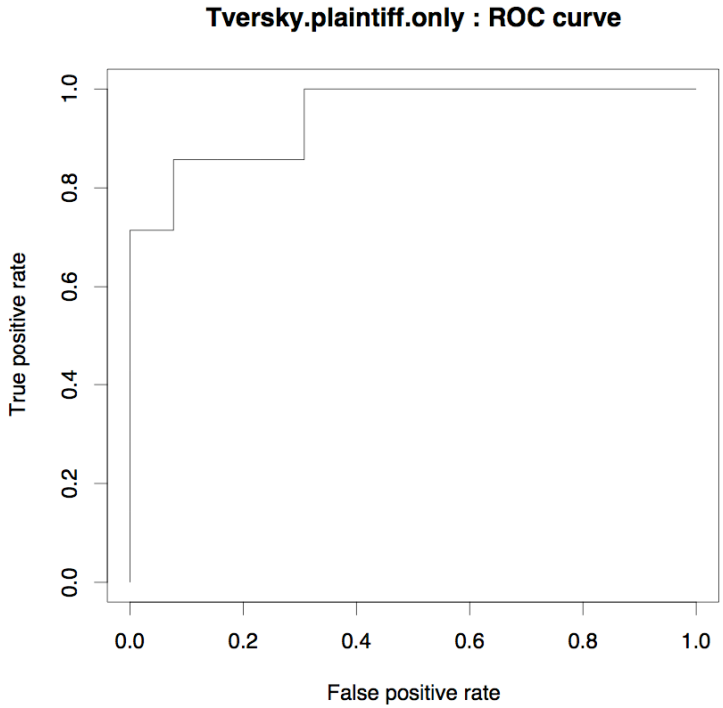
- Ground Truth:
  20 cases with yes/no decision (7/13)

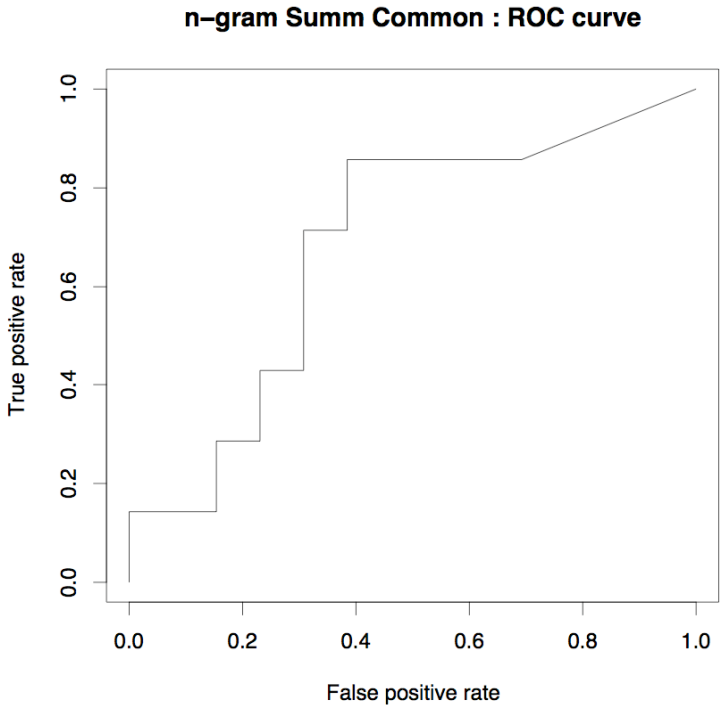
- Evaluation metrics
  - Accuracy (% correct at optimal cut-off on similarity scale)
  - AUC (Area Under receiver operating characteristic Curve)

EVALUATION

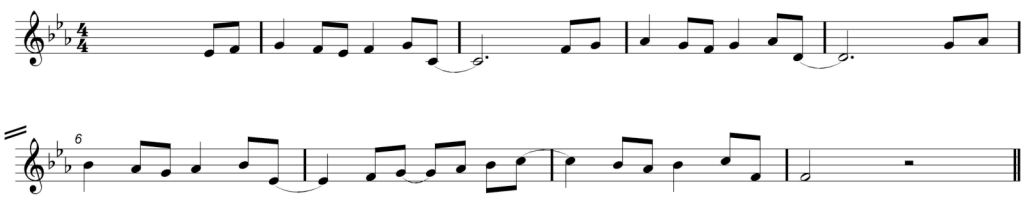

1.0
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
Edit Dist.
Sum Com.
Ukkonen
TF-IDF correl.
Tv.equal
Tv.plaintiff
Tv.defendant
Tv.weighted
Accuracy
AUC

EVALUATION: ROC CURVES

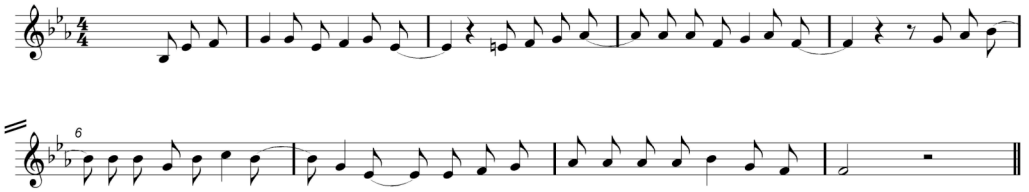




A QUALITATIVE LOOK



Ronald Selle, “Let It End”



Bee Gees, “How Deep Is Your Love”

Observations:

- Decision sometimes based on ‘characteristic motives’
- High-level form can be important (e.g. call-and-response structure)
- Reference point can be different

4 SUMMARY/NEXT STEPS

- Court decisions can be related closely to melodic similarity
- Plaintiff's song is often frame of reference
- Statistical information about commonness of melodic elements is important

4 SUMMARY/NEXT STEPS

- More US cases
- UK and German cases (from the “big” western markets)
- Include rhythm in m-types
- Compare to more similarity algos from literature

Thank you for your attention!

COURT DECISIONS ON MUSIC PLAGIARISM AND THE PREDICTIVE VALUE OF SIMILARITY ALGORITHMS

Dr. Marc Pendzich
Institute of Musicology
University of Hamburg

Dr. Daniel Müllensiefen
Goldsmiths College
University of London