# On the Potential of AI and Machine Learning for Music Performance Analysis

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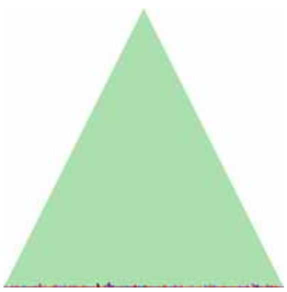
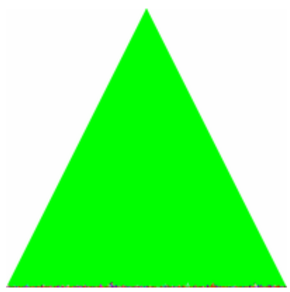
## CONGRATULATIONS TO THE MAZURKA TEAM



„Hatto, 1997"



Indjic, 2001

# OVERVIEW

**Machine Learning for the Analysis of Music Performance Data**

**A. Search for common performance principles**
1. Discovering note-level rules
2. Phrase-level learning
3. A combined model

**B. Search for characteristic differences (individual style)**
1. Pattern discovery
2. Performer identification
3. Automatic style imitation?

**A new data-intensive project**

**Opportunities for cooperation computer science ↔ musicology**

# A RECENT RESEARCH PROJECT

Artificial Intelligence Models
of Expressive Music Performance
(1999 – 2005)

**Austrian Research Institute**
**for Artificial Intelligence (OFAI), Vienna**

funded by the Austrian National Science Foundation

FWF Der Wissenschaftsfonds.

## PROJECT GOALS

- Performing **quantitative studies** of expressive music performance
- based on **large amounts** of **'real-world'** performance data
- with **AI / Machine Learning technology**

=> 'data-intensive' bottom-up approach

**Possible advantages:**

- grounding of results in substantial empirical data
- not biased by pre-conceptions, can make surprising discoveries

**Possible problems:**

- little control over experimental conditions
- studies (must) generally remain at rather general level

## TWO QUESTIONS

**Systematic similarities, general principles?**
What do 'reasonable' performances have in common?
What is predictable?

**Systematic stylistic differences between artists?**
What distinguishes great artists from each other?
Can this be characterised / quantified?

**RESTRICTIONS:**

- classical piano music
- expressive timing, dynamics, (articulation)

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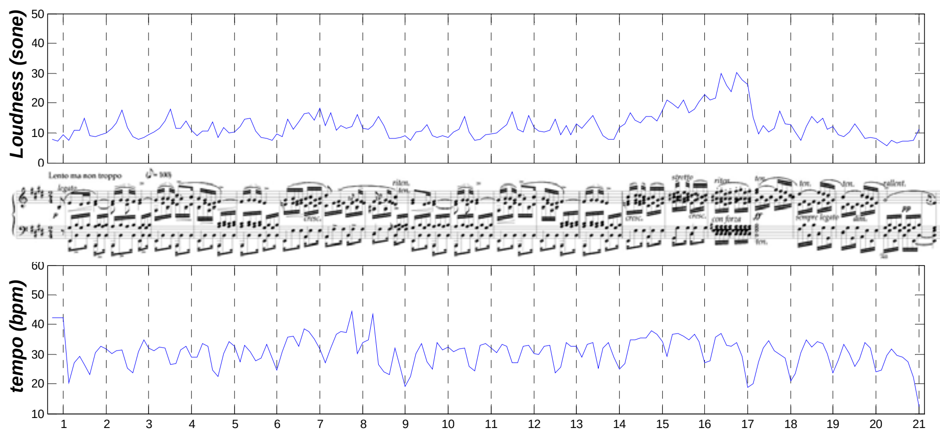
## GENERAL PRINCIPLES?

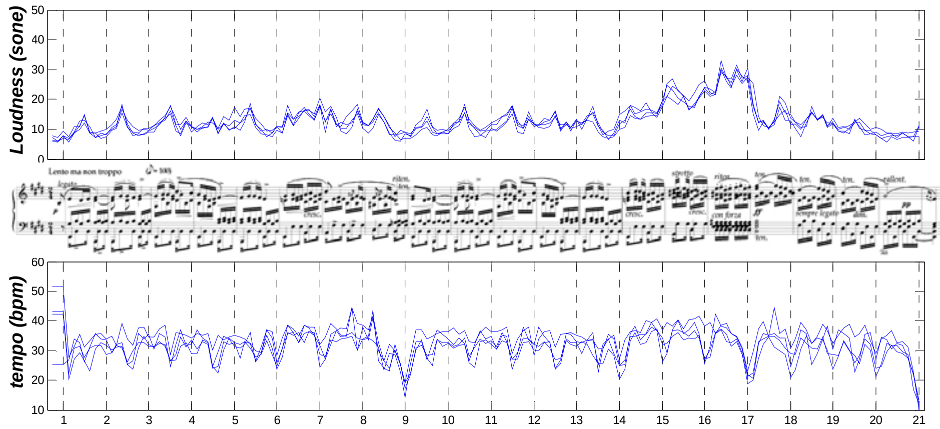
**Chopin: *Etude*, op. 10 no. 3, E major**



## GENERAL PRINCIPLES?

**Chopin:** ***Etude*****, op. 10 no. 3, E major**

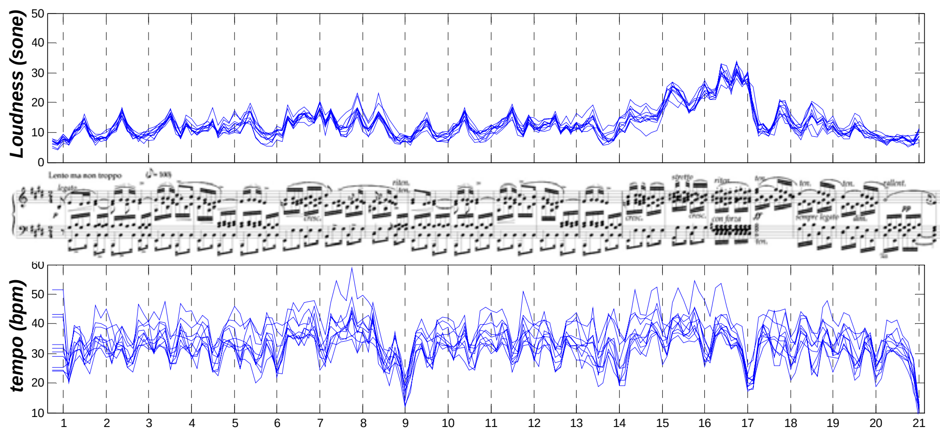
***Pianists 1-4***




## GENERAL PRINCIPLES?

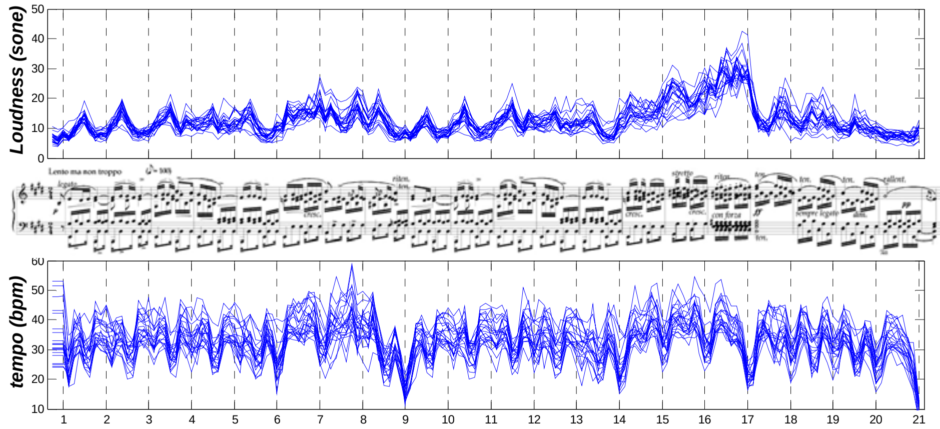
**Chopin:** ***Etude*****, op. 10 no. 3, E major**

***Pianists 1-10***



## GENERAL PRINCIPLES?

**Chopin: *Etude*, op. 10 no. 3, E major** ***Pianists 1-22***




## Bösendorfer SE 290

## STUDY 1:
## LEARNING NOTE-LEVEL PERFORMANCE RULES

**The Data:**

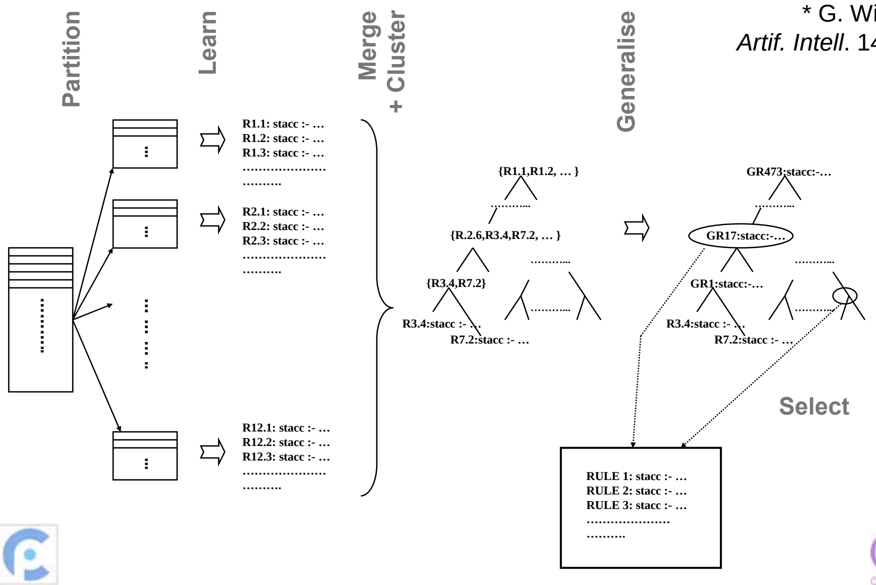
- 13 complete Mozart piano sonatas ( > 100,000 notes)
- performed by concert pianist on a Bösendorfer SE290 computer-controlled grand piano
- plus explicit encoding of the musical score
- plus 1-to-1 correspondence between played notes and written notes

**The Target:**

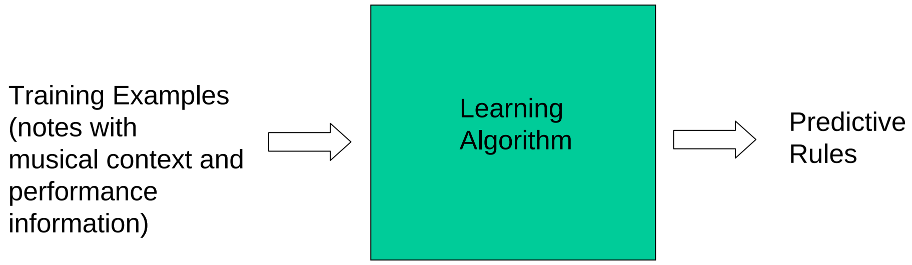
- rules predicting the performer's decisions in (local) timing, dynamics, and articulation
  - Timing: *lengthen* vs. *shorten*
  - Dynamics: *louder* vs. *softer*
  - Articulation: *staccato* vs. *legato*

## THE LEARNING ALGORITHM

* G. Widmer
*Artif. Intell.* 146(2), 2003



# THE LEARNING ALGORITHM




| Rule | Action | Conditions | pos. coverage (slow+fast) | | Precision slow | Precision fast | Precision total |
|---|---|---|---|---|---|---|---|
| **TL1** | lengthen IF | abstr_dur_context = equal-longer | 2,665 | (19.87 %) | .870 | .686 | .746 |
| **TL2** | lengthen IF | next_dur_ratio ≤ 0.334 | 1,788 | (13.33 %) | .846 | .708 | .758 |
| **TL2a*** | lengthen IF | next_dur_ratio ≤ 0.99 & metr_strength ≤ 2 | 1,121 | (8.36 %) | .820 | — | .820 |
| **TL3** | lengthen IF | dir_next = up & int_next > p4 & metr_strength ≤ 2 & int_prev ≤ maj2 | 259 | (1.93 %) | .714 | .636 | .662 |
| **TS1*** | shorten IF | prev_dur_ratio ≤ 0.67 & next_dur_ratio > 1.0 | 354 | (2.66 %) | .669 | — | .669 |
| **TS2**** | shorten IF | tempo = fast & meter = 3/8 & prev_dur_ratio > 2.0 & dur ≤ 0.5 & next_dur_ratio ≤ 0.99 | 43 | (0.32 %) | — | .915 | .915 |
| **DL1** | louder IF | dir_prev = up & int_prev > p4 & metr_strength > 2 | 747 | (6.42 %) | .847 | .761 | .782 |
| **DL2** | louder IF | mel_contour = up_down & int_prev > min3 & metr_strength > 2 | 890 | (7.65 %) | .734 | .731 | .731 |
| **DL3**** | louder IF | prev_dur_ratio ≤ 0.5 & dir_prev = up & metr_strength > 3 | 359 | (3.09 %) | — | .709 | .709 |
| **DS1** | softer IF | prev_dur_ratio > 5.0 | 377 | (4.00 %) | .764 | .675 | .710 |
| **DS2** | softer IF | dir_prev = down & int_prev > maj3 & metr_strength ≤ 1 & dur_prev > 0.33 | 173 | (1.83 %) | .745 | .811 | .783 |
| **DS3** | softer IF | dir_prev = down & int_prev > p5 & metr_strength ≤ 1 | 169 | (1.79 %) | .840 | .797 | .813 |
| **AS1** | staccato IF | marked_staccato = yes | 3,071 | (13.88 %) | .916 | .938 | .934 |
| **AS2** | staccato IF | int_next = unison | 2,929 | (13.23 %) | .981 | .996 | .934 |
| **AS3** | staccato IF | int_next > p4 & dir_next = up & metr_strength ≤ 2 | 1,237 | (5.59 %) | .656 | .796 | .756 |
| **AS4** | staccato IF | next_dur_ratio ≤ 0.4 & dir_prev = down | 1,215 | (5.49 %) | .571 | .809 | .717 |
| **AL1** | legato IF | staccato = no & mel_contour = up_down | 687 | (7.42 %) | .593 | .513 | .537 |

* G. Widmer, *J.New.Mus.Res.* 31(1), 2002

## DISCOVERED RULES

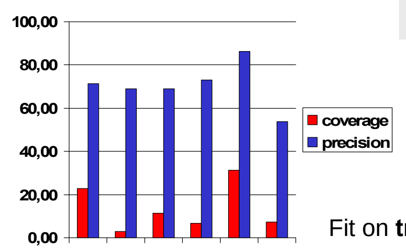
**RULE TL2:**

**<u>lengthen</u> IF**
**abstr_dur_context = short-short-long &**
**metr_strength ≤ 1**

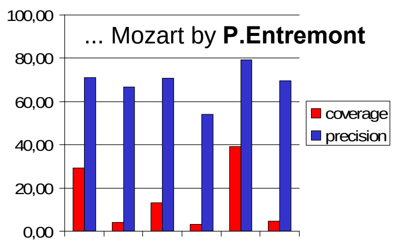
"Given two notes of equal duration followed by a longer note, lengthen the note (i.e., play it more slowly) that precedes the final, longer one, if this note is in a metrically weak position."

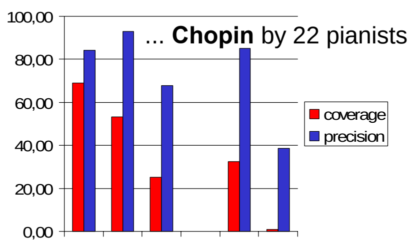
TP = 1,894 (14.12%), FP = 588 (2.86%), $\pi$ = .763

## QUANTITATIVE EVALUATION




Fit on **training data** (Mozart by R.Batik) vs. ...




▹ **rules generalise well to other performers and other musical styles!**

## RELATION TO SUNDBERG PERFORMANCE RULES

```
RULE TL3: lengthen IF dir_next = up &
                      int_next > p4 &
                      metr_strength ≤ 2 &
                      int_prev ≤ maj2
```

"Lengthen a note if it precedes an upward melodic leap larger than a perfect fourth, if it is in a metrically weak position, and if it is preceded by (at most) stepwise motion."

slow: TP = 95 (2.60%), FP = 38 (0.64%), $\pi$ = .714
fast: TP = 164 (1.68%), FP = 94 (0.64%), $\pi$ = .636
all: TP = 259 (1.93%), FP = 132 (0.64%), $\pi$ = .662

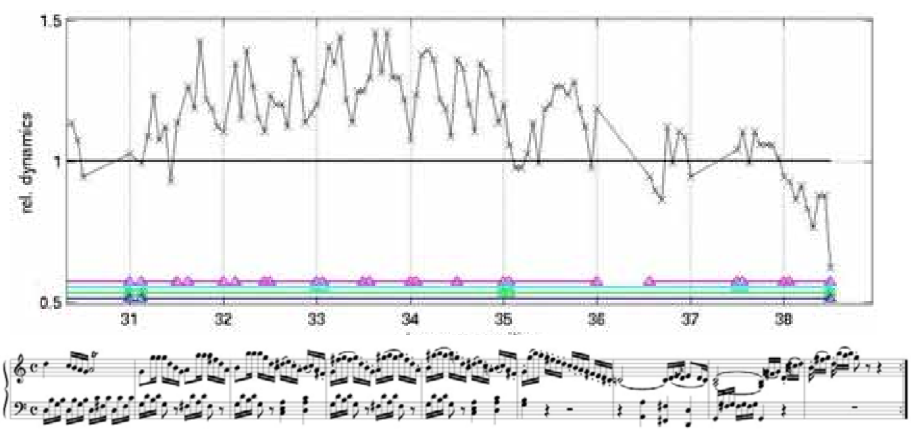
**=> cf. "Leap Tone Duration" and "Leap Articulation" rules (Friberg, 1995)**

```
RULE AS3: staccato IF int_next > p4 &
                      dir_next = up &
                      metr_strength ≤ 2
```

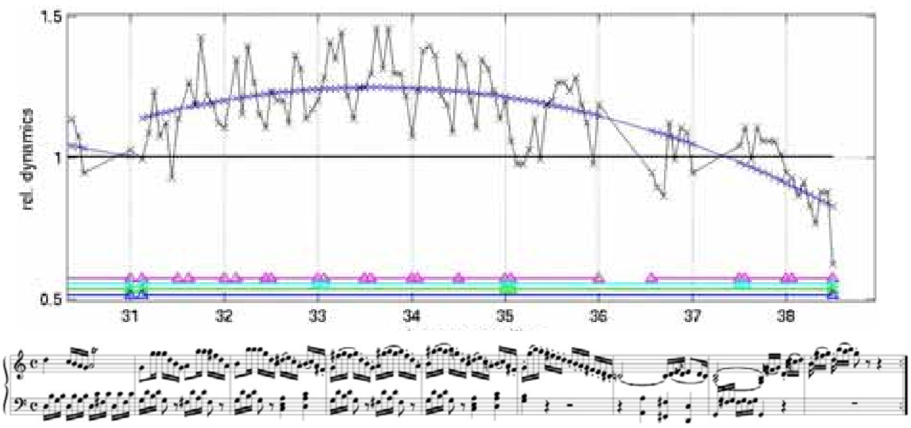
"Insert a micropause after a note if it precedes an upward melodic leap larger than a perfect fourth and is metrically weak."

slow: TP = 307 (6.27%), FP = 161 (2.31%), $\pi$ = .656
fast: TP = 930 (5.39%), FP = 239 (1.99%), $\pi$ = .796
all: TP = 1,237 (5.59%), FP = 400 (2.11%), $\pi$ = .756

## STUDY 2: LEARNING PHRASE-LEVEL TIMING AND DYNAMICS



## STUDY 2:
## LEARNING PHRASE-LEVEL TIMING AND DYNAMICS





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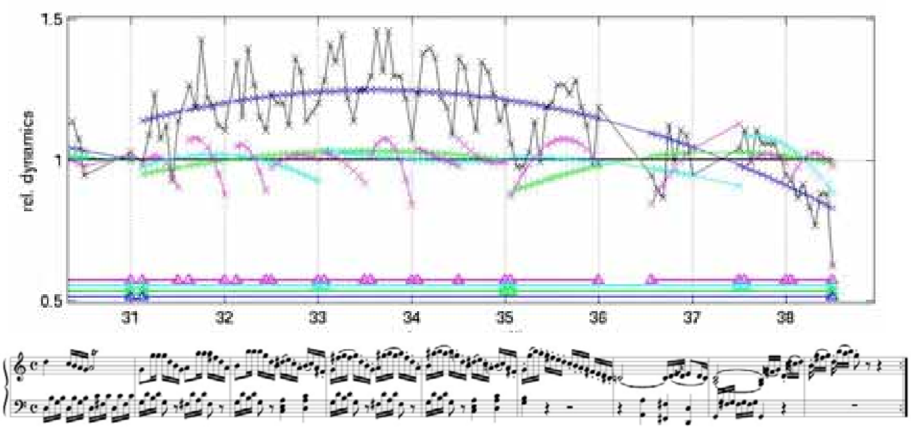
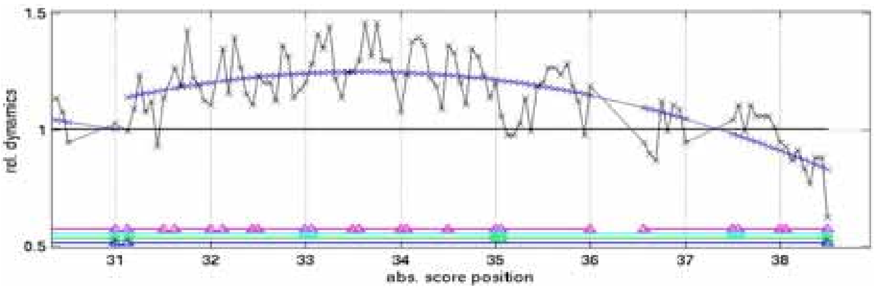


## DERIVING TRAINING INSTANCES: MULTI-LEVEL DECOMPOSITION

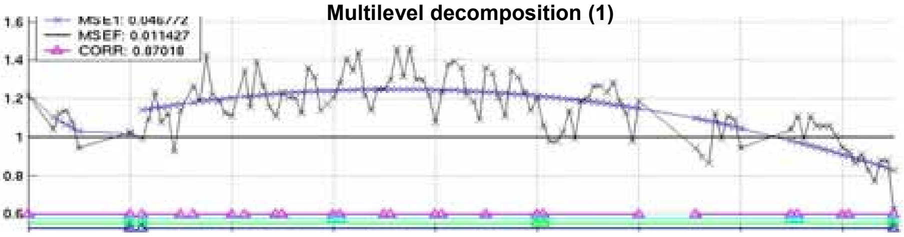
**Model class for phrase-level expressive 'shapes':**
quadratic functions (2nd degree polynomials)

$$y = ax^2 + bx + c$$

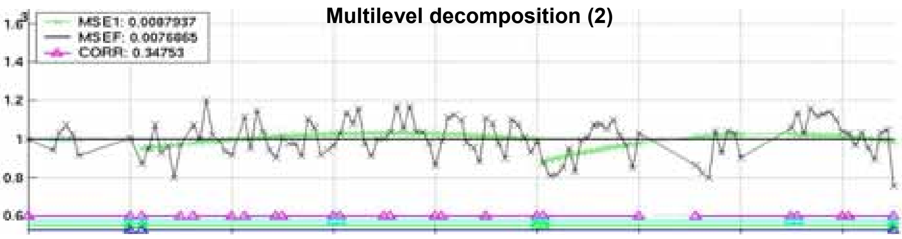



## DERIVING TRAINING INSTANCES: MULTI-LEVEL DECOMPOSITION

**Multilevel decomposition (1)**

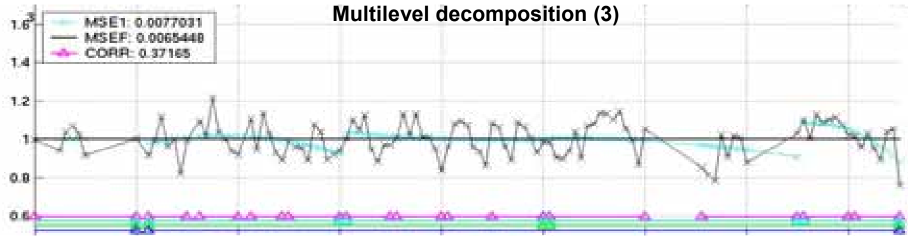


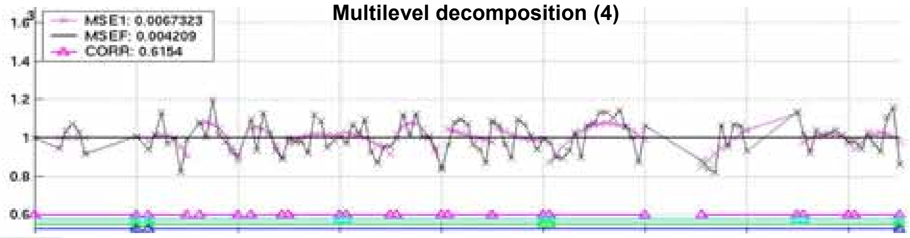

**Multilevel decomposition (2)**




W.A.Mozart: Piano Sonata K. 279 (C major), 1st mvt., mm.31-38: dynamics

# DERIVING TRAINING INSTANCES: MULTI-LEVEL DECOMPOSITION

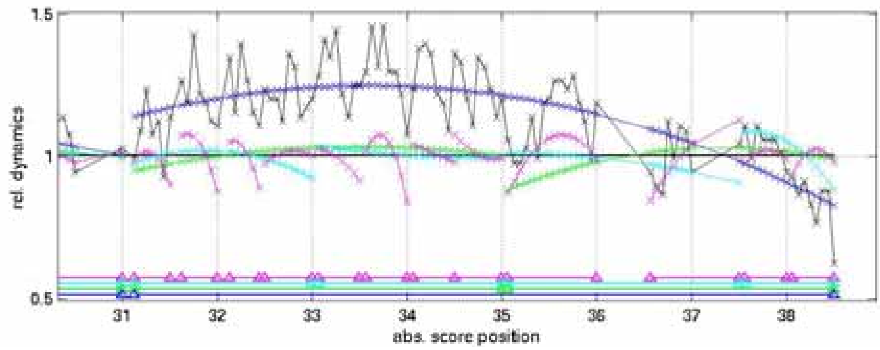



W.A.Mozart: Piano Sonata K. 279 (C major), 1st mvt., mm.31-38: dynamics

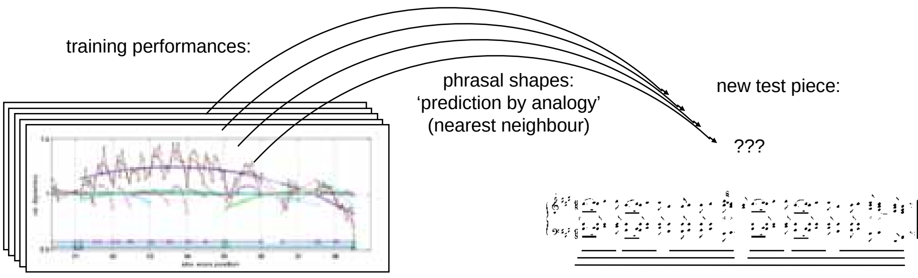
# DERIVING TRAINING INSTANCES: MULTI-LEVEL DECOMPOSITION

**Multilevel decomposition: All levels**




W.A.Mozart: Piano Sonata K. 279 (C major), 1st mvt., mm.31-38: dynamics

# CASE-BASED LEARNING




# EXPERIMENTS: THE DATA

| sonata movement | 'melody' notes | phrases at level 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| K.279:1:1 fast 4/4 | 391 | 50 | 19 | 9 | 5 |
| K.279:1:2 fast 4/4 | 638 | 79 | 36 | 14 | 5 |
| K.280:1:1 fast 3/4 | 406 | 42 | 19 | 12 | 4 |
| K.280:1:2 fast 3/4 | 590 | 65 | 34 | 17 | 6 |
| K.280:2:1 slow 6/8 | 94 | 23 | 12 | 6 | 3 |
| K.280:2:2 slow 6/8 | 154 | 37 | 18 | 8 | 4 |
| K.280:3:1 fast 3/8 | 277 | 28 | 19 | 8 | 4 |
| K.280:3:2 fast 3/8 | 379 | 40 | 29 | 13 | 5 |
| K.282:1:1 slow 4/4 | 165 | 24 | 10 | 5 | 2 |
| K.282:1:2 slow 4/4 | 213 | 29 | 12 | 6 | 3 |
| K.282:1:3 slow 4/4 | 31 | 4 | 2 | 1 | 1 |
| K.283:1:1 fast 3/4 | 379 | 53 | 23 | 10 | 5 |
| K.283:1:2 fast 4/4 | 428 | 59 | 32 | 13 | 6 |
| K.283:3:1 fast 3/8 | 326 | 52 | 30 | 12 | 3 |
| K.283:3:2 fast 3/8 | 558 | 78 | 47 | 19 | 6 |
| K.332:2 slow 4/4 | 477 | 49 | 23 | 12 | 4 |
| **Total:** | **5506** | **712** | **365** | **165** | **66** |

Table 1: Sonata movements used in experiments

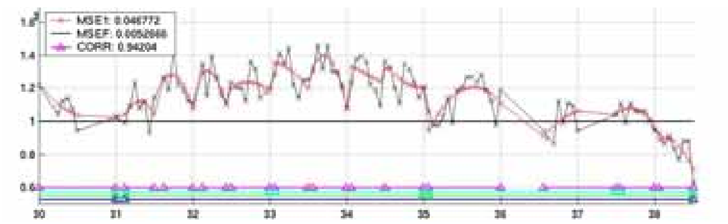
## EXPERIMENTS: QUANTITATIVE RESULTS

| | dynamics | | | | | tempo | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $MSE_D$ | $MSE_L$ | $MAE_D$ | $MAE_L$ | $Corr_L$ | $MSE_D$ | $MSE_L$ | $MAE_D$ | $MAE_L$ | $Corr_L$ |
| K.279:1:1 | .0383 | **.0214** | .1643 | **.1100** | .6714 | .0348 | .0375 | .1220 | .1257 | .3061 |
| K.279:1:2 | .0318 | .0355 | .1479 | **.1384** | .5744 | .0244 | .0291 | .1004 | .1133 | .3041 |
| K.280:1:1 | .0313 | **.0195** | .1432 | **.1052** | .6635 | .0254 | **.0188** | .1053 | **.0934** | .5611 |
| K.280:1:2 | .0281 | .0419 | .1365 | .1482 | .4079 | .0250 | .0290 | .1074 | .1111 | .3398 |
| K.280:2:1 | .1558 | **.0683** | .3498 | **.2064** | .7495 | .0343 | .0373 | .1189 | **.1157** | .5888 |
| K.280:2:2 | .1424 | **.0558** | .3178 | **.1879** | .7879 | .0406 | .0508 | .1349 | .1443 | .4659 |
| K.280:3:1 | .0334 | **.0168** | .1539 | **.0979** | .7064 | .0343 | **.0260** | .1218 | **.1179** | .5136 |
| K.280:3:2 | .0226 | .0313 | .1231 | .1267 | .4370 | .0454 | **.0443** | .1365 | .1388 | .3361 |
| K.282:1:1 | .1076 | **.0412** | .2719 | **.1568** | .7913 | .0367 | .0376 | .1300 | **.1196** | .3267 |
| K.282:1:2 | .0865 | **.0484** | .2420 | **.1680** | .7437 | .0278 | .0474 | .1142 | .1436 | .2072 |
| K.282:1:3 | .1230 | **.0717** | .2595 | **.2172** | .6504 | .1011 | **.0463** | .2354 | **.1575** | .8075 |
| K.283:1:1 | .0283 | **.0263** | .1423 | **.1067** | .7007 | .0183 | .0202 | .0918 | .1065 | .3033 |
| K.283:1:2 | .0371 | **.0221** | .1611 | **.1072** | .7121 | .0178 | **.0171** | .0932 | .0960 | .4391 |
| K.283:3:1 | .0404 | **.0149** | .1633 | **.0928** | .8247 | .0225 | **.0183** | .1024 | **.0954** | .4997 |
| K.283:3:2 | .0424 | **.0245** | .1688 | **.1156** | .6881 | .0256 | .0308 | .1085 | .1184 | .2574 |
| K.332:2 | .0919 | .0948 | .2554 | **.2499** | .3876 | .0286 | .0630 | .1110 | .1767 | .2389 |
| **WMean** | **.0486** | **.0360** | **.1757** | **.1370** | **.6200** | **.0282** | **.0326** | **.1108** | **.1202** | **.3600** |

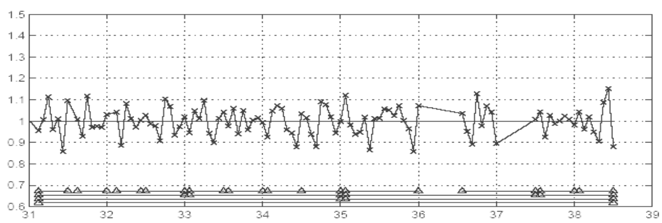
**Table 2: Results (by sonata sections) of cross-validation experiment with DISTALL *(depth=2, k=1)*. Measures subscripted with D refer to the 'default' (mechanical, inexpressive) performance, those with L to the performance produced by the learner.**

## STUDY 3: A COMBINED MODEL

**Approximation of original curve by 4 levels of polynomial shapes**



**=> "Residuals":**

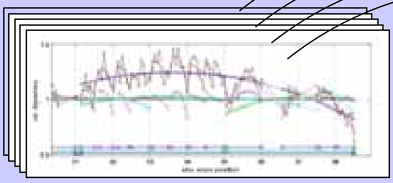


## STUDY 3: A COMBINED MODEL

** Widmer & Tobudic, J. New Mus. Res. 32(3), 2003*

training performances:

***Phrase level***



phrasal shapes:
'prediction by analogy'

'residuals':

rule learning algorithm PLCG

note-level rules

***Note level***

## THE COMBINED MODEL IN ACTION

**W.A.Mozart, Piano Sonata K.280, F major, 1st Movement**


**Second Prize, RENCON Contest, Tokyo, Sept. 2003**

## INSIGHTS (1)

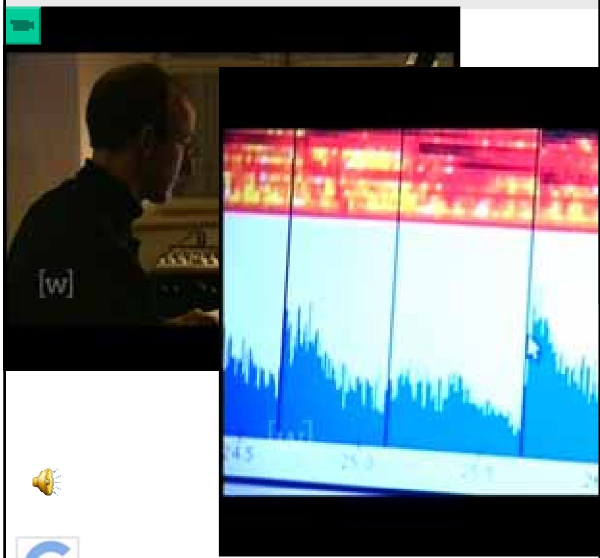
- There *are* predictable aspects of expressive performance
- Machine learning can (help us) discover some of them
- Expressive performance is a multi-level phenomenon and needs multi-level models
- Open question: the boundary of predictability …

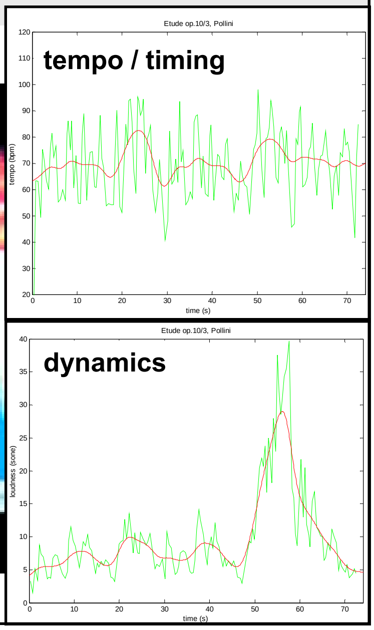
## TWO QUESTIONS

**Systematic similarities, general principles?**
What do ‘reasonable’ performances have in common?
What is predictable?

**Systematic stylistic differences between artists?**
What distinguishes great artists from each other?
Can this be characterised / quantified?

## INTERACTIVE BEAT TRACKING



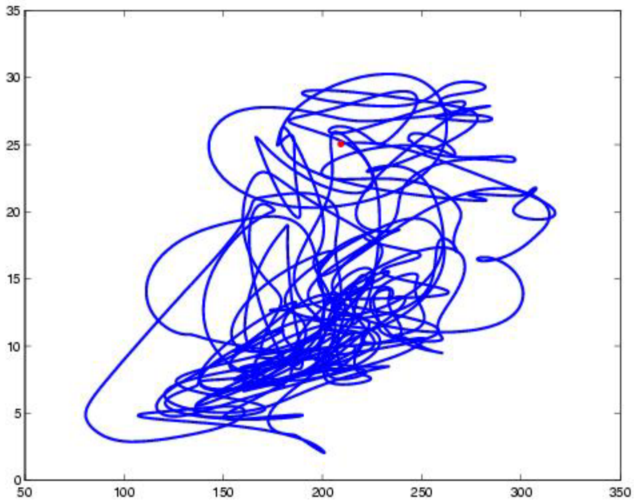



## THE PERFORMANCE WORM

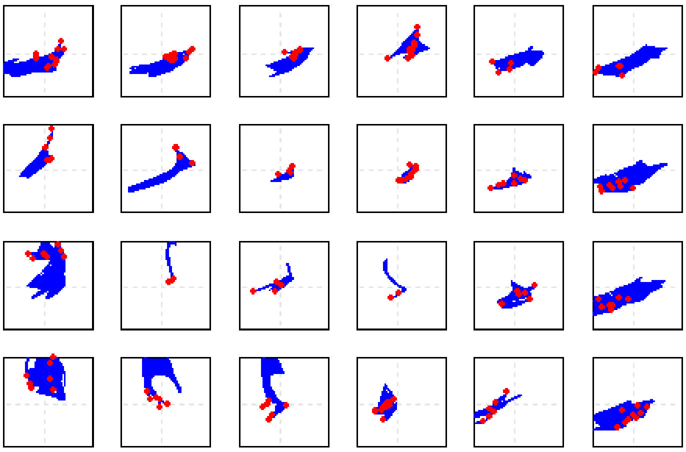
* Langner & Goebl, *Comp.Mus.J.* 27(4), 2003

## PERFORMANCE TRAJECTORIES

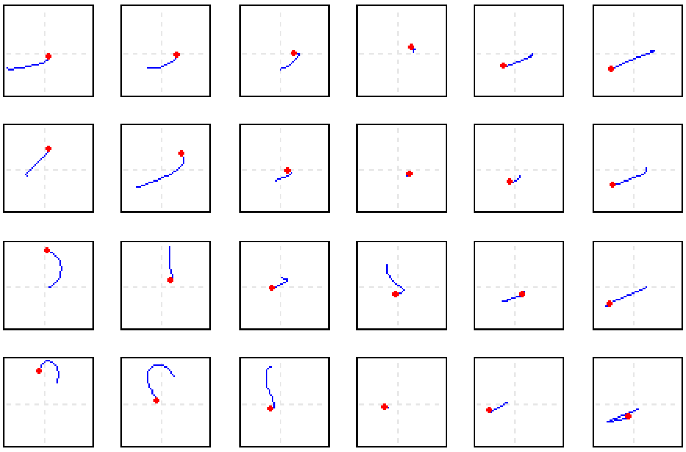
Artur Rubinstein: Frédéric Chopin, Ballade op.27, $A^b$ major



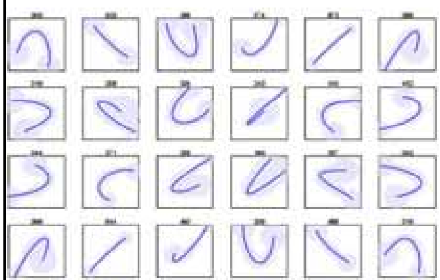

## PERFORMANCE ALPHABETS

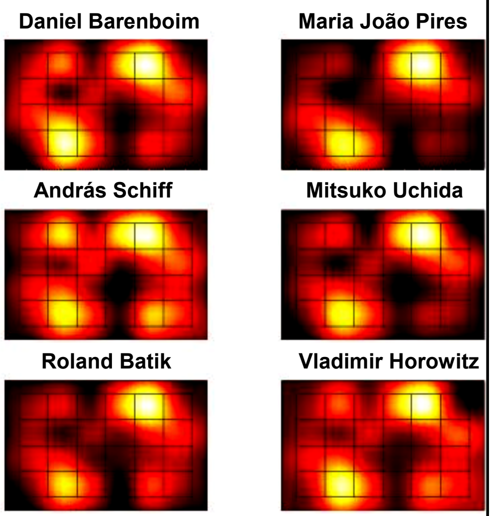


# PERFORMANCE ALPHABETS



# SOME SIMPLE STATISTICS





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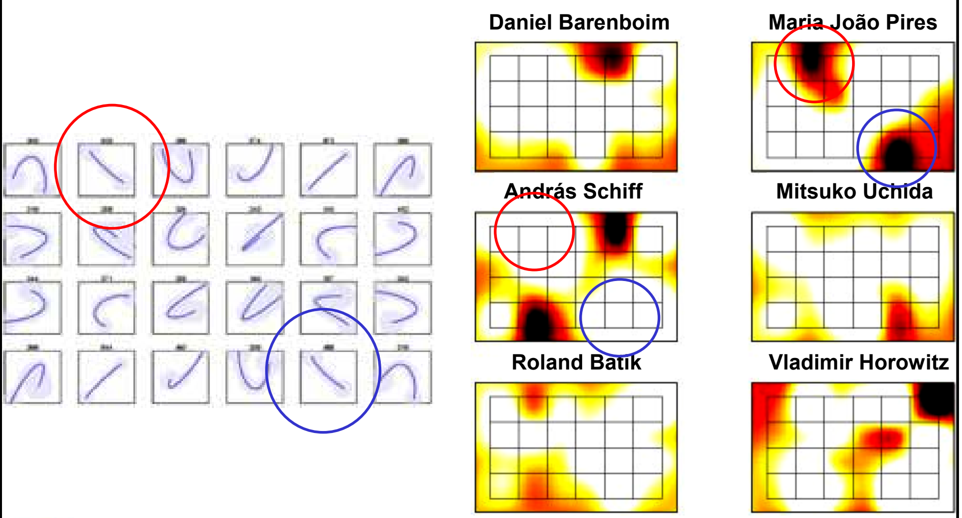
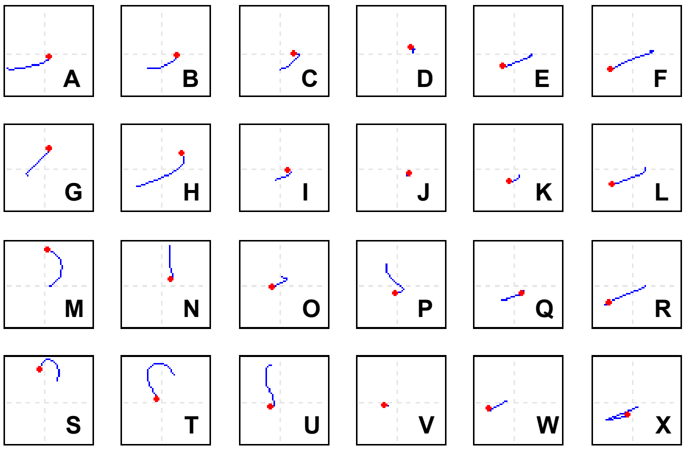



## PERFORMANCE ALPHABETS



## PERFORMANCE STRINGS

**F. Chopin, Ballade no. 3 op.47, $A^b$ major – Artur Rubinstein (1957)**

RPWWNEDHCGRPPVIQHIEDGGXPUSSQHECCQVLXSWVMNILHLGYTMQMBYTLGGCQGFNIQVCKJIQYTP
WLBXTKVIIEAFWQQMHRJIMHKWVKVSGXJKUJDRNLQSBXTCQYDQWBFHCYTBFSBXOAFVCXOCKYTQJ
KAFWUGPVJEKJKVHLGRPVEDFRPUECWJKUEKWJKVCKVJKQHEKPULQMMWSLHLQHIHEECMMRILRP
USMEDHCLRPUWJINCEDLGXSVSQVHEKWVNREDPUQVEDPVLHCXOFWNBCLBCNGGRPUMRSNMMHIIR
ILRPUMMMMMHIMMMLMNMHIWNMRNQYTVHLHCMQVNMIPUHECINQRNQYTGMHECMQVRNIPVNMEDPV
EDGRNQWSMRNLMJKVIPWSGQQRSHECMGQNQVJCINHIMQWSQWSLQVJECCCPUMIHIHLRNQWNQVP
VINLRJCYTBFSGFVEDQQXTLYTGXTGYTBXTAXTBXJCXOFWJKWSBPUEDNGXOKWJCXJLRHKWOKUJK
UUEKVIQNECECFPUMWWNLECMLLKVRQWJLGISVJNGFMMHDLMHIRNQVNQWSQRJIQSLXTLGXOFJIB
FQGXTCGWWQHKVHLRJINHKVHCMMMQUVHKVHIIHKRNQRNQXSPVDLMNLMMMMPVIHCXTGRSGXTQH
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LBFPPUHIRHPVIMHSWJIHCFWJDHCFWQVRXJGQNIQVMRNISQVIISJCHIQHCGILGCISNQWSLCXECHKU
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QVRNMRPVILEDQQRIMRNQHDLMQQMHMRSPUHIXSQHCHISQVJLFJCCCPUSQWVRSQHIMEKUQRSXJL
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RJKWOKUJKWOCRSVLQNMXORHEIMPVEKUJKVIQWOCKVLPWOGROQHIMMLXOCPJDFJDCGGXSGRN
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## DISCOVERING CHARACTERISTIC SUBSTRINGS

**Objective:**

find subsequences $<e_i,\ldots,e_j>$ in a set of sequences $\{S_1,\ldots,S_n\}$ of events that

- are frequent overall
- discriminate between different sequences/artists

**Method:**

- level-wise search for frequent item sets (Agrawal & Srikant, 1995; Mannila et al., 1995)
- combined with an information-theoretic heuristic for discrimination:

$$E(X_i) = \sum_j - n_{ij}/N_i \times \log_2 n_{ij}/N_i$$

Widmer et al., *AI Magazine* 24(3), 2003

## DISCOVERING CHARACTERISTIC SUBSTRINGS

**F. Chopin, Ballade no. 3 op.47, $A^{b}$ major – Artur Rubinstein (1957)**

RPWWNEDHCGRPPVIQHIEDGGXPUSSQHECCQVLXSWVMNILHLGYTMQMBYTLGGCQGFNIQVCKJIQYTP
WLBXTKVIIEAFWQQMHRJIMHKWVKVSGXJKUJDRNLQSBXTCQYDQWBFHCYTBFSBXOAFVCXOCKYTQJ
KAFWUGPVJEKJKVHLGRPVEDFRPUECWJKUEKWJKVCKVJKQHEKPULQMMWSLHLQHIHEECMMRILRP
USMEDHCLRPUWJINCEDLGXSVSQVHEKWVNREDPUQVEDPVLHCXOFWNBCLBCNGGRPUMRSNMMHIIR
ILRPUMMMMMHIMMMLMNMHIWNMRNQYTVHLHCMQVNMIPUHECINQRNQYTGMHECMQVRNIPVNMEDPV
EDGRNQWSMRNLMJKVIPWSGQQRSHECMGQNQVJCINHIMQWSQWSLQVJECCCPUMIHIHLRNQWNQVP
VINLRJCYTBFSGFVEDQQXTLYTGXTGYTBXTAXTBXJCXOFWJKWSBPUEDNGXOKWJCXJLRHKWOKUJK
UUEKVIQNECECFPUMWWNLECMLLKVRQWJLGISVJNGFMMHDLMHIRNQVNQWSQRJIQSLXTLGXOFJIB
FQGXTCGWWQHKVHLRJINHKVHCMMMQUVHKVHIIHKRNQRNQXSPVDLMNLMMMMPVIHCXTGRSGXTQH
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VDPVFVWJKUGXJKVRIRVCXJIWORIGHDPUROEDGMIMQQMHCIIMLPUVHIMHILHKWOQVNMRQQMHCR
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RJKWOKUJKWOCRSVLQNMXORHEIMPVEKUJKVIQWOCKVLPWOGROQHIMMLXOCPJDFJDCGGXSGRN
HEIGHQVMQVHKVLHDHPURNMMMRSHCMQVQVEIEKUQHIQVMHEPUQVILQHIRILMWSNHEIPUVIQVIISH
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HKJDPURIHIPVRNRNMSSHEDFWVXNRHINIHBAUWQQRNRNMHJPUIRJIECVBEKUJKUVNGQHDEKUEKU
XOGMHINQVJKUGLREDGFJDPUPUIRJIXJBAYTAXTBYTAF


## DISCOVERING CHARACTERISTIC SUBSTRINGS

**F. Chopin, Ballade no. 3 op.47, $A^{b}$ major – Artur Rubinstein (1957)**

RPWWNEDHCGRPPVIQHIEDGGXPUSSQHECCQVLXSWVMNILHLGYTMQMBYTLGGCQGFNIQVCKJIQYTP
WLBXTKVIIEAFW**QQMH**RJIMHKWVKVSGXJKUJDRNLQSBXTCQYDQWBFHCYTBFSBXOAFVCXOCKYTQJ
KAFWUGPVJEKJKVHLGRPVEDFRPUECWJKUEKWJKVCKVJKQHEKPULQMMWSLHLQHIHEECMMRILRP
USMEDHCLRPUWJINCEDLGXSVSQVHEKWVNREDPUQVEDPVLHCXOFWNBCLBCNGGRPUMRSNMMHIIR
ILRPUMMMMMHIMMMLMNMHIWNMRNQYTVHLHCMQVNMIPUHECINQRNQYTGMHECMQVRNIPVNMEDPV
EDGRNQWSMRNLMJKVIPWSGQQRSHECMGQNQVJCINHIMQWSQWSLQVJECCCPUMIHIHLRNQWNQVP
VINLRJCYTBFSGFVEDQQXTLYTGXTGYTBXTAXTBXJCXOFWJKWSBPUEDNGXOKWJCXJLRHKWOKUJK
UUEKVIQNECECFPUMWWNLECMLLKVRQWJLGISVJNGFMMHDLMHIRNQVNQWSQRJIQSLXTLGXOFJIB
FQGXTCGWWQHKVHLRJINHKVHCMMMQUVHKVHIIHKRNQRNQXSPVDLMNLMMMMPVIHCXTGRSGXTQH
ICIQVMMLMQUVILRQIMLMHLMHIMNHEIKVQNPUSQEDIEKUJIPULMHIXEDUWPUQMMNEDSHINPUECRJI
LBFPPUHIRHPVIMHSWJIHCFWJDHCFWQVRXJGQNIQVMRNISQVIISJCHIQHCGILGCISNQWSLCXECHKU
VDPVFVWJKUGXJKVRIRVCXJIWORIGHDPUROEDGMIM**QQMH**CIIMLPUVHIMHILHKWOQVNMR**QQMH**CR
QVRNMRPVILEDQQRIMRNQHDLM**QQMH**MRSPUHIXSQHCHISQVJLFJCCCPUSQWVRSQHIMEKUQRSXJL
BCQHKVMQVQWNRSHIXSHKHIHCLLHKVQUVSVMJIQXSRIMQVGFNQHIGXSQWJKVNCXOGXTLHIGXOG
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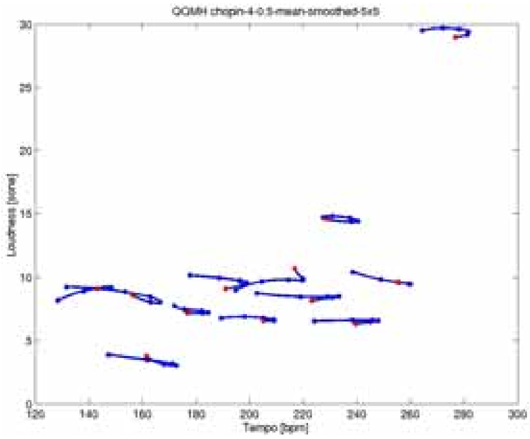
HEIGHQVMQVHKVLHDHPURNMMMRSHCMQVQVEIEKUQHIQVMHEPUQVILQHIRILMWSNHEIPUVIQVIISH
LHKUQVEDEKUMINQMIEDPUPVIQRJIMHIQWVQHLRSXSHDILCEDPUSQWSMXSRNEKUSWJIBFOCXOIPU
DQPHDSQHIINQVMIHIXOCECWPUXOBXWOFJOFUWOCLRQHEPUDOGQQHKVLRJDQVMQHINQHINCKU
HKJDPURIHIPVRNRNMSSHEDFWVXNRHINIHBAUWQQRNRNMHJPUIRJIECVBEKUJKUVNGQHDEKUEKU
XOGMHINQVJKUGLREDGFJDPUPUIRJIXJBAYTAXTBYTAF

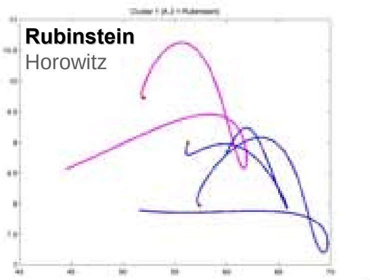
## DISCOVERING CHARACTERISTIC PATTERNS

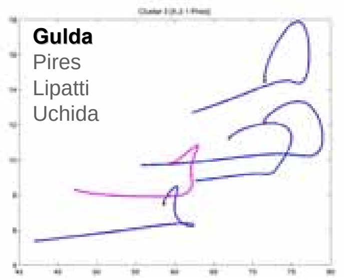
**Arthur Rubinstein plays Chopin …**

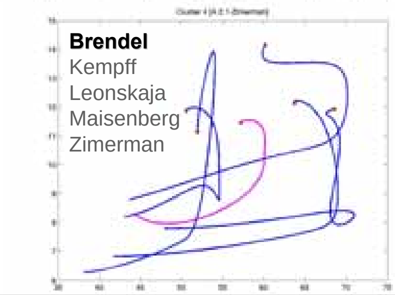



## CHARACTERISTIC MUSICAL BEHAVIOURS

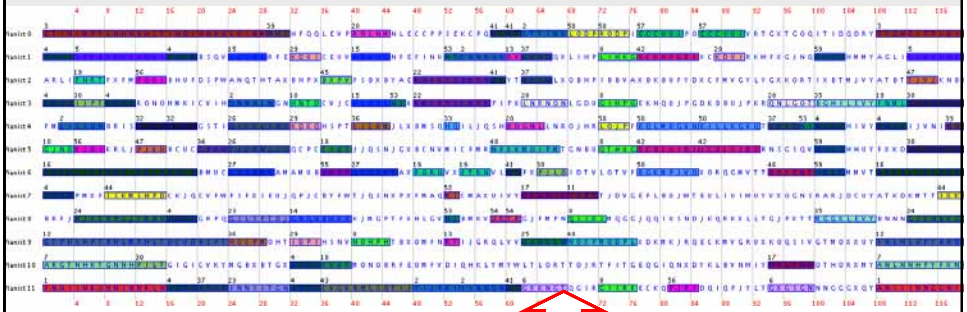
**Franz Schubert, Impromptu D.899/3, G$^b$ major**



## QUANTIFYING STYLISTIC CONSISTENCY



**Structural analysis of piece:**

| Position number | 0 | 4 | 8 | 12 | 16 | 20 | 24 | 29 | 32 | 36 | 40 | [illegible] | 48 | 52 | 54 | 58 | 60 | 62 | 68 | 72 | 77 | 85 | 94 | 100 | 104 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Measure number | 1 | 3 | 5 | 7 | 9 | 11 | 13 | 15 | 17 | 19 | 21 | 23 | 25 | 27 | 28 | 30 | 31 | 32 | 35 | 37 | 39 | 43 | 48 | 51 | 53 |
| Form section | A | | | | B | | | | B | | | | C | | | | | D | | | E | | D' | | |
| Subsection | a | b | a | c | d | d | e | f | d | d | e | f | g | h | g | h | h | i | j | j | k | k | i | j | l |
| Duration (positions) | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 3 | 4 | 4 | 5 | 3 | 4 | 2 | 4 | 2 | 2 | 6 | 4 | 5 | 8 | 9 | 6 | 4 | 4 |

| Position number | 108 | 112 | 116 | 120 | 124 | 128 | 132 | 137 | 140 | 145 | 146 | 150 | 152 | 154 | 158 | 160 | 162 | 164 | 166 | 168 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Measure number | 55 | 57 | 59 | 61 | 63 | 65 | 67 | 69 | 71 | 73 | 74 | 76 | 77 | 78 | 80 | 81 | 82 | 83 | 84 | 85 |
| Form section | A | | | | B' | | | | | | C | | | | | | | | | |
| Subsection | a | b | a | c | d | d | e | f | e | f | j | m | n | j | m | n | n | n | o | o |
| Duration (positions) | 4 | 4 | 4 | 4 | 4 | 4 | 5 | 3 | 5 | 1 | 4 | 2 | 2 | 4 | 2 | 2 | 2 | 2 | 2 | 4 |

## QUANTIFYING STYLISTIC CONSISTENCY

**Ranking pianists according to how similarly they play similar passages (Material: F. Schubert, Impromptu D.899 no.3, $G^b$ major)**

| Rank | Recall | Precision | F-measure | St. dev F-m | Pianist |
|---|---|---|---|---|---|
| 1 | **0.613** | 0.725 | **0.336** | 0.000 | Barenboim |
| 2 | 0.538 | 0.765 | 0.368 | 0.091 | Horowitz |
| 3 | 0.478 | 0.717 | 0.427 | 0.049 | Lipatti |
| 4 | 0.408 | **0.803** | 0.460 | 0.029 | Maisenberg |
| 5 | 0.440 | 0.666 | 0.472 | 0.023 | **Leonskaja** |
| 6 | 0.459 | 0.606 | 0.478 | 0.084 | Kempff |
| 7 | 0.361 | 0.636 | 0.540 | 0.042 | Uchida |
| 8 | 0.380 | 0.539 | 0.555 | 0.044 | Brendel |
| 9 | 0.366 | 0.535 | 0.567 | 0.044 | Rubinstein |
| 10 | 0.338 | 0.505 | 0.597 | 0.093 | Pires |
| 11 | 0.308 | 0.340 | 0.678 | 0.050 | Zimerman |
| 12 | 0.172 | 0.390 | 0.761 | 0.075 | Gulda |

* Madsen & Widmer, *IJAIT 2006*

## STUDY 2: AUTOMATIC PERFORMER IDENTIFICATION

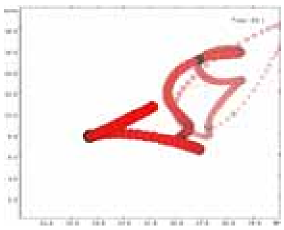
Daniel Barenboim?

Glenn Gould?

Maria João Pires?

András Schiff?

## STUDY 2: AUTOMATIC PERFORMER IDENTIFICATION



CDSRWHGSNMBDSOMEXOQVWOQ
QHHSRQVPHJFATGFFUVPLDTPNME
CDOVTOMECDSPFXPOFAVHDTPNF
EVHHDXTPMARIFFUHHGIEEARWTTL
JEEEARQDNIBDSQIETPPMCDTOMA
WOFVTNMHHDNRRVPHHDUQIFEUT
PLXTORQIEBXTORQIECDHFVTOFAR
BDXPKFURMHDTTPDTPJARRQWLG
FCTPNMEURQIIBDJCGRQIEFFEDTT
OMEIFFAVTTP..................

Daniel Barenboim?

Glenn Gould?

Maria João Pires?

András Schiff?

## STUDY 2: AUTOMATIC PERFORMER IDENTIFICATION

**Classification of performance strings with string kernels and support vector machines**

| Pair | Classifier 2 | [%] |
|---|---|---|
| Gould-Barenboim | 21 | 87.5 |
| Barenboim-Batik | 22 | 91.7 |
| Pires-Barenboim | 18 | 75.0 |
| Pires-Batik | 22 | 91.7 |
| Pires-Gould | 23 | 95.8 |
| Schiff-Barenboim | 19 | 79.2 |
| Schiff-Batik | 23 | 95.8 |
| Schiff-Gould | 18 | 75.0 |
| Schiff-Pires | 23 | 95.8 |
| Uchida-Barenboim | 15 | 62.5 |
| Uchida-Batik | 17 | 70.8 |
| Uchida-Gould | 19 | 79.2 |
| Uchida-Pires | 19 | 79.2 |
| Uchida-Schiff | 18 | 75.0 |
| | | 81.9 |

* Saunders, Hardoon, Shawe-Taylor & Widmer, *Proc. ECML'2004*

## STUDY 3: STYLE IMITATION

* A. Tobudic & G. Widmer,
"Learning to Play Like the Great Pianists", *Proc. IJCAI 2005*

| | | compared with | | | | | |
|---|---|---|---|---|---|---|---|
| | learned from | DB | RB | GG | MP | AS | MU |
| Barenboim | DB | **.44** | .21 | .26 | .34 | .38 | .28 |
| | | **.44** | .27 | .26 | .32 | .31 | .31 |
| Batik | RB | .21 | **.32** | .09 | .19 | .19 | .17 |
| | | .28 | **.42** | .20 | .22 | .30 | .27 |
| Gould | GG | .25 | .09 | **.36** | .19 | .21 | .22 |
| | | .25 | .18 | **.32** | .23 | .29 | .28 |
| Pires | MP | .33 | .19 | .19 | **.39** | .33 | .28 |
| | | .31 | .23 | .27 | **.38** | .28 | .34 |
| Schiff | AS | .36 | .17 | .20 | .31 | **.40** | .26 |
| | | .32 | .29 | .28 | .25 | **.41** | .32 |
| Uchida | MU | .27 | .18 | .21 | .28 | .26 | **.38** |
| | | .34 | .30 | .32 | .36 | .37 | **.50** |

## INSIGHTS (2)

- Visualisation helps to understand differences in performance
- There are systematic differences between great artists that machines can pick up
- Some characteristic patterns can be discovered, but their statistical (and *musical!* ) significance is difficult to establish

## A NEW PROJECT

Computational Performance Style Analysis
from Audio Recordings
(2007 – 2010)

funded by the Austrian National Science Foundation

FWF Der Wissenschaftsfonds.

## STARTING POINT:
## A NEW SOURCE OF PEFORMANCE DATA

**Nikita Magaloff**
* 1912 (St. Petersburg)
† 1992 (Vevey)

Recorded almost complete solo piano works by Frederic Chopin on a Bösendorfer computer-monitored piano (1989)

**Bösendorfer SE 290**

## THE DATA

Nocturnes op. 9, 15, 27, 32, 37, 48, 55, 62
Mazurkas op. 6, 7, 17, 24, 30, 33, 41, 50, 56, 59, 63
Polonaises op. 26, 40, 44, 53, 61
Waltzes op. 34, 42, 64
Etudes op. 10, 25
Scherzi op. 31, 39, 54
Impromptus op. 29, 36, 51
Ballades op. 38, 47, 51
Sonatas op. 4, 35, 58
+ miscellaneous piano works (e.g., Fantaisie F minor, op.49)

---

*9:04:23 hours total playing time*
*301.679 played notes*
*1,5 million sustain pedal events*

## RESOURCES

Magaloff

audio recordings (complete Chopin)

MIDI / Bösendorfer (complete Chopin)

scores in kern or MIDI format

*direct time index*

*score-performance matching*

detailed information about expressive „deviations“

**MATCH**

## RESOURCES

Magaloff

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*direct time index*

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detailed information about expressive „deviations“

**MATCH**

Other famous pianists:

manually annotated (beats) by Mazurka team

## RESEARCH QUESTIONS

**Research on music (audio) analysis:**

- more precise extraction of performance details from audio recordings
- better matching and annotation
- quantification of achievable accuracy

**Research in machine learning:**

- interpretable probabilistic models

**Music-related research:**

- detailed studies on specific performance aspects (ritardando, pedalling, ornaments, …)
- intra-performer stylistic consistency
- inter-performer differences

## CONCLUSIONS

**AI / Machine Learning can help in analysing large amounts of empirical data, but you still need to**

- pose the right questions
- provide appropriate data representations
- interpret the results in a musical context

=> need input and help from musicology