Evolutionary Process Indicators for Active iGAs Applied to Weight Tuning in Unit Selection TTS Synthesis

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Lluís Formiga, Francesc Alías and Xavier Llorà

Media Technologies Research Group (GTM) - Universitat Ramon Llull.
C/Quatre Camins 2, 08022 Barcelona, Spain
{llformiga,falias}@salle.URL.edu

National Center for Supercomputing Applications (NCSA) - University of Illinois at Urbana-Champaign. 1205 W. Clark Street, Urbana IL 61801, USA
xllora@illinois.edu

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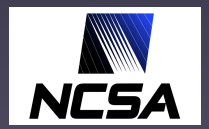

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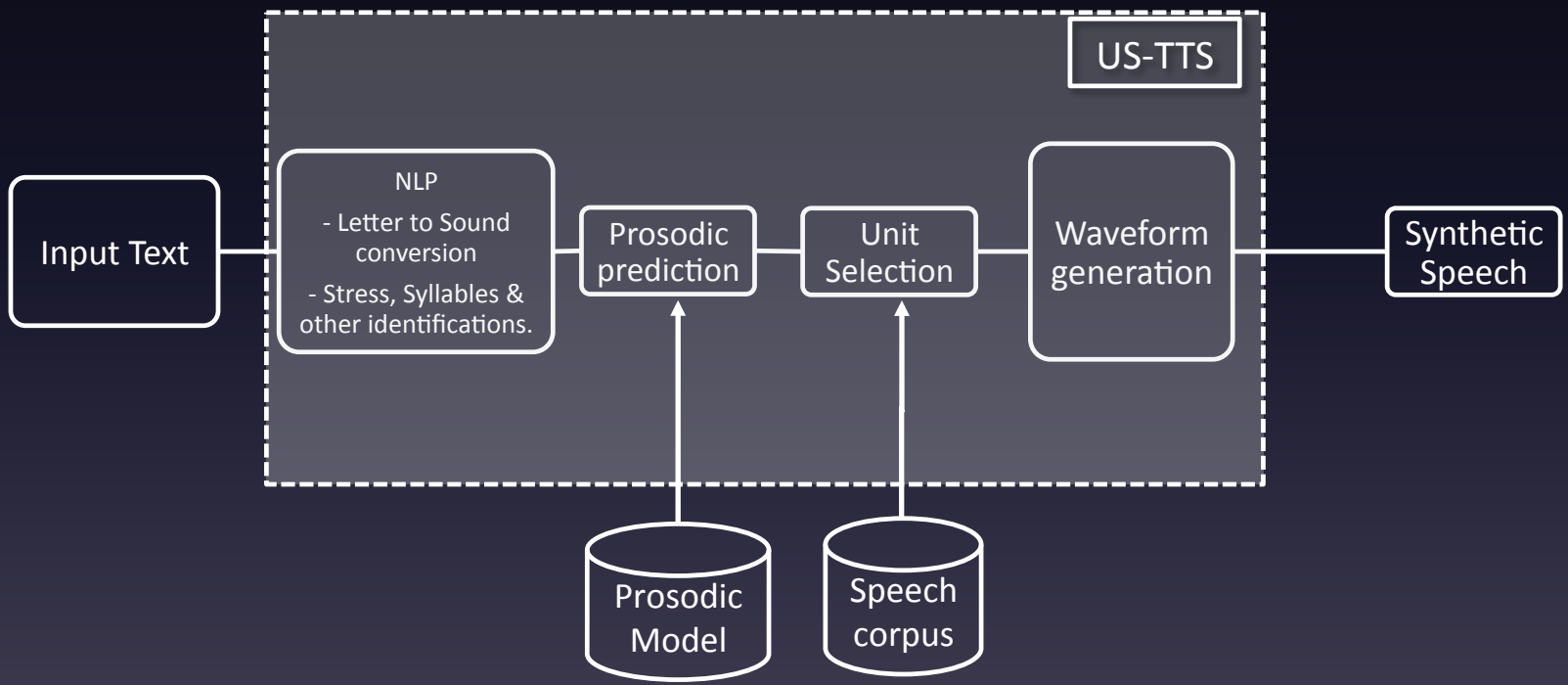

- Unit Selection TTS (US-TTS) approach retrieves the best set of speech units from a previously recorded speech database.

Cost Function on US-TTS

- The retrieval method [Hunt and Black, 1996] is a Viterbi algorithm cost minimization based on a global cost function (equations 1,2,3).

$$C_T^i = \sum_{j=0}^{param\_t} w_j^i \cdot SC_T^i \quad (1)$$

$$C_C^i = \sum_{j=0}^{param\_c} w_j^i \cdot SC_C^i \quad (2)$$

$$C^i = C_T^i + C_C^i \quad (3)$$

where, w_j^i refers to the weight for the weighted subcost SC, which values are in the range of [0,1], considering $\sum w_i = 1$.

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- Ongoing discussion on scientific community:
  - Using only linguistic or acoustic subcosts on C_T^i
  - Which are the best concatenation subcosts (spectral, LSF…)
  - Units all share same weight pattern or it depends on unit type (context, stress, phonetic specs. …)

Open Issues on Weight Tuning

- On cutting edge non-evolutionary perceptual approaches:
  - Unique solution for each specifity is assumed (Unimodal).
  - Monosyllabic words don't represent real case.
  - Complexity relegated to user: $\approx$ 5 files evaluated simultaneously.
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- *Main Goal:*
  i) Find suitable weight values without specific knowledge of the parameters involved in US.

  ii) Tuning method must deal to optimize different patterns.

aiGA-based weight tuning

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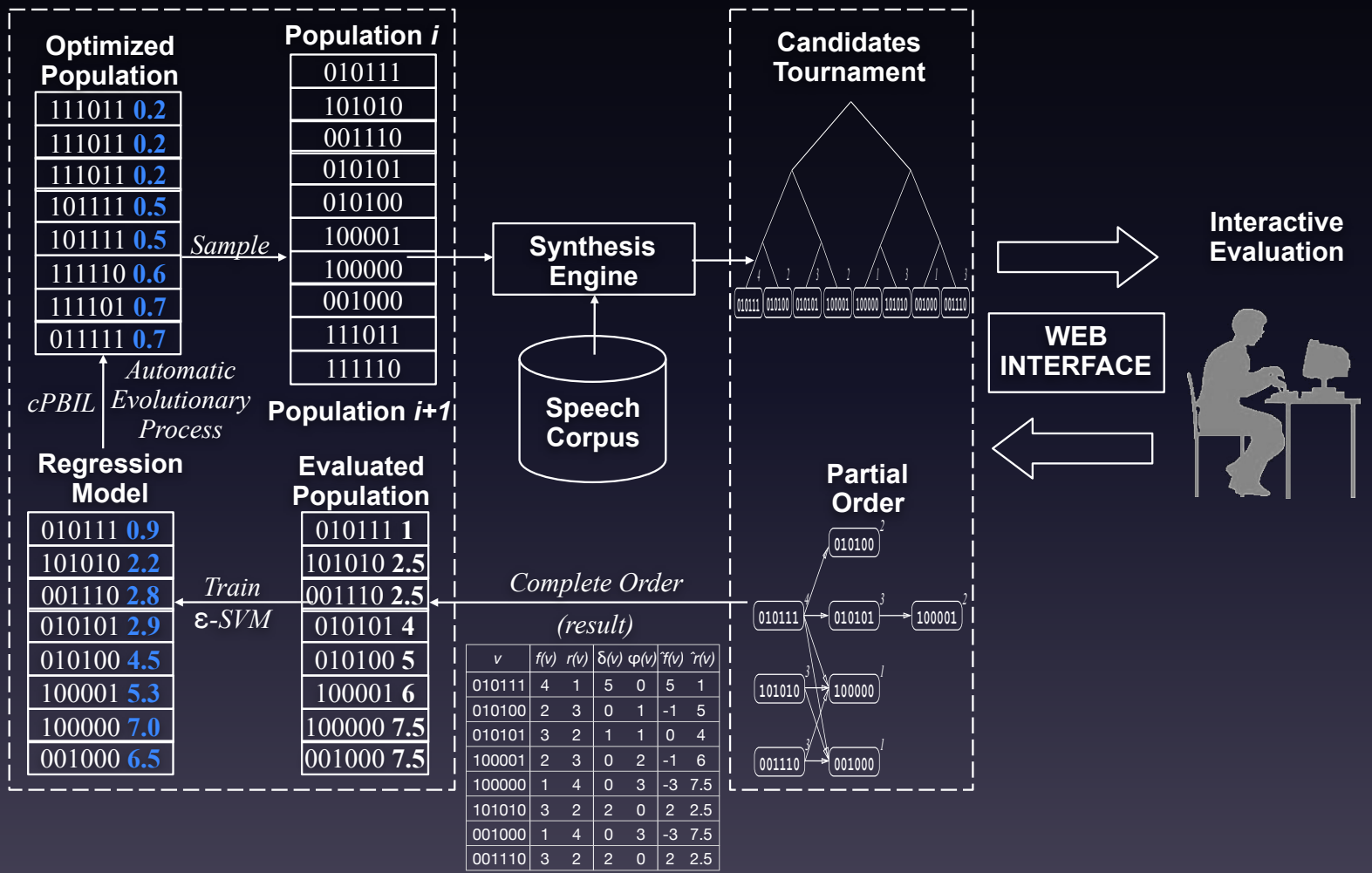
  - Surrogate Fitness heuristics based on Pareto's dominance [Coello-Coello, 1998, Deb et al., 2000]
  - Global ordering measure computed using two dominance measures:
    i) $\delta(v)$: Number of vertexes recursively departing from v
    ii) $\phi(v)$: Number of vertexes recursively arriving to v

Method



v	f(v)	r(v)	δ(v)	φ(v)	f̂(v)	r̂(v)
010111	4	1	5	0	5	1
010100	2	3	0	1	-1	5
010101	3	2	1	1	0	4
100001	2	3	0	2	-1	6
100000	1	4	0	3	-3	7.5
101010	3	2	2	0	2	2.5
001000	1	4	0	3	-3	7.5
001110	3	2	2	0	2	2.5

Expanding the aiGAs: Evolutionary Process Indicators

- Reliability is a must on each kind of perceptual optimization.
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- On [Alías et al., 2006] we introduced the κ-measure:
  - *i*) Considers cycles in the graph model as contradictions (e.g $A > B$, $B > C$, $C > A$) causing a decrease of the consistency of the model.
  - *ii*) κ-measure is computed as within-cycle/all vertexes ratio.
  - *iii*) Allows discarding bad evolutions from the result extraction process

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- More indicators are needed for the following purposes:
  - *i*) Stop earlier the run due to noisy user evaluation (detect when he/she becomes fatigued/stucked): λ
  - *ii*) Discover convergence to unique/multiple solutions: ρ
  - *iii*) Ponder how user's agree with each other: τ

Certainty Ratio λ (1/2)

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- Defined as a within-cycle/all vertexes ratio.
- λ-measure also determines the effective test duration:
  - Once converged, all speech files seem indistinguishable to the evaluator
  - He/She tags them as equal, so no more building is required.
  - Direct consequences of low certainty ratio is a decrease on the ε-SVM regression accuracy.

Certainty Ratio λ (2/2)

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- Models may stuck earlier and become noisy and ambiguous.
- Stop-building point determined through λ-measure with a derivative averaging approach:

$$\begin{aligned} \Lambda &= \left[\lambda'_1, \ldots, \lambda'_t, \ldots, \lambda'_N\right], \quad \textit{where} \\ \lambda'_t &= \frac{\lambda(\mathcal{G}'^{t-1}) + \lambda(\mathcal{G}'^{t}) + \lambda(\mathcal{G}'^{t+1})}{3} \end{aligned}$$

$$sl_t = \lambda'_{t+1} - \lambda'_t, \forall t \in [1, \ldots, N-1]$$

$$t_{FINAL} = last(sl_t \geq 0)$$

where λ'_t is the averaged value $(\lambda_{t-1}, \lambda_t, \lambda_{t+1})$ of metric λ at iteration t. N is the total evaluations done by the user (45 in our case). Λ is the set of normalized λs and sl_t their derivative (slope).

Intra-user convergence ρ Inter-user correlation ratios τ

- *Intra-user* Convergence Ratio ρ
  - Measures convergence of the run either to a single solution or multiple solutions.
  - Final solution is obtained from best ranked individuals (aiGA has no replacement scheme).
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Inter-user Correlation Ratio τ

- Gives information about of the similarity of each perceptual test performed by different users.
- Analogously to ρ-measure, we consider best ranked individuals.
- 10% best solution of each run are compared through a correlation matrix, which is averaged to obtain the final indicator.

Evolutionary Process Indicators

- Formally presented by equations:

$$\kappa\left(\mathcal{G}'^{t}, \omega_{\kappa}\right) = 1 - \left(\frac{1}{|\mathcal{V}'^{t}|} \cdot \sum_{v \in \chi(\mathcal{G}'^{t})} \omega_{v}^{\kappa}\right)^{\alpha_{\kappa}} \qquad \rho\left(\mathcal{G}'^{t}\right) = \left(\frac{1}{|\mathcal{B}'^{t}|} \cdot \sum_{\substack{v \in \mathcal{B} \\ vv \in \{\mathcal{B} | vv \neq v\}}} corr(v, vv)\right)^{\alpha_{\rho}}$$

$$\lambda\left(\mathcal{G}'^{t}, \omega_{\lambda}\right) = 1 - \left(\frac{1}{|\mathcal{V}'^{t}|} \cdot \sum_{v \in \psi(\mathcal{G}'^{t})} \omega_{v}^{\lambda}\right)^{\alpha_{\lambda}} \qquad \tau\left(\mathcal{G}'^{t}\right) = \left(\frac{1}{|\mathcal{U}'^{t}|} \cdot \sum_{\substack{v \in \mathcal{U} \\ vv \in \{\mathcal{U} | vv \neq v\}}} corr(v, vv)\right)^{\alpha_{\tau}}$$

Applicability of indicators:

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- In [Llorà. et al., 2005] there were implemented two variants of extracting the final ranking table:

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- Longest Path approach may be seen as an elitist approach: Avoids bad convergences. (Only one vertex is extracted as the best)

- Both methods will be applied to our experiments and analyzed.

Experiments

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  - Bounding the maximum number of weights
- New corpus: From 15 minutes of Catalan to 1 hour of Spanish recorded speech.
- Subcosts expanded from 6 (acoustic) to 14 (acoustic / linguistic):
  i) Mismatches on Previous and Next Contexts of the unit, Part-Of-Speech, Position in utterance, Position in syllable, Position in word and Syllable Stress;
  ii) Target differences on half-phones durations, energy and pitch.
  iii) Energy, Mel-frequency cepstum and Pitch discontinuities at concatenation point.

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  - Assuring 3 users for each utterance
  - None of the users repeated the same 3 utterances set
  - Population size: 15 weight sets (individuals)([Llorà. et al., 2005]).
  - Maximum of 3 iterations [Alías et al., 2006]
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  - Number of different units to be selected (search depth)
- After a aiGA run a graph model of 37 vertexes (weight combinations) is obtained

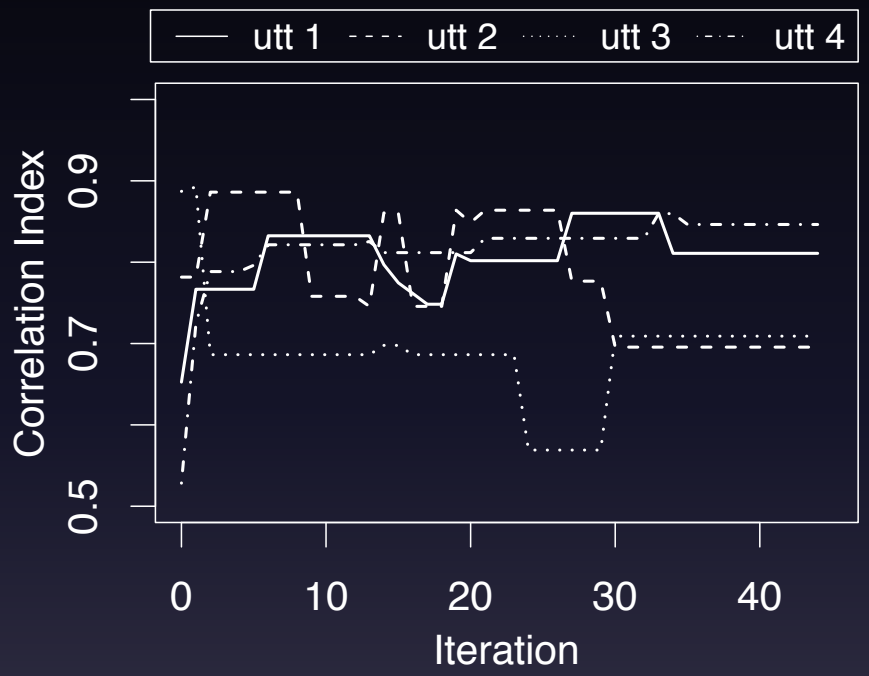
Indicators at work (1/2)

(a) *Evolution of consistency measure for an specific test utterance*

(b) *Evolution of certainty measure for an specific test utterance*

Indicators at work (2/2)

(c) *Evolution of intra-user convergence for an specific test utterance (longest path method)*



(d) *Evolution of inter-user correlation through four different test utterances (longest path method)*

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- Weight value differs depending on unit specification
- Utterance to unit mapping:
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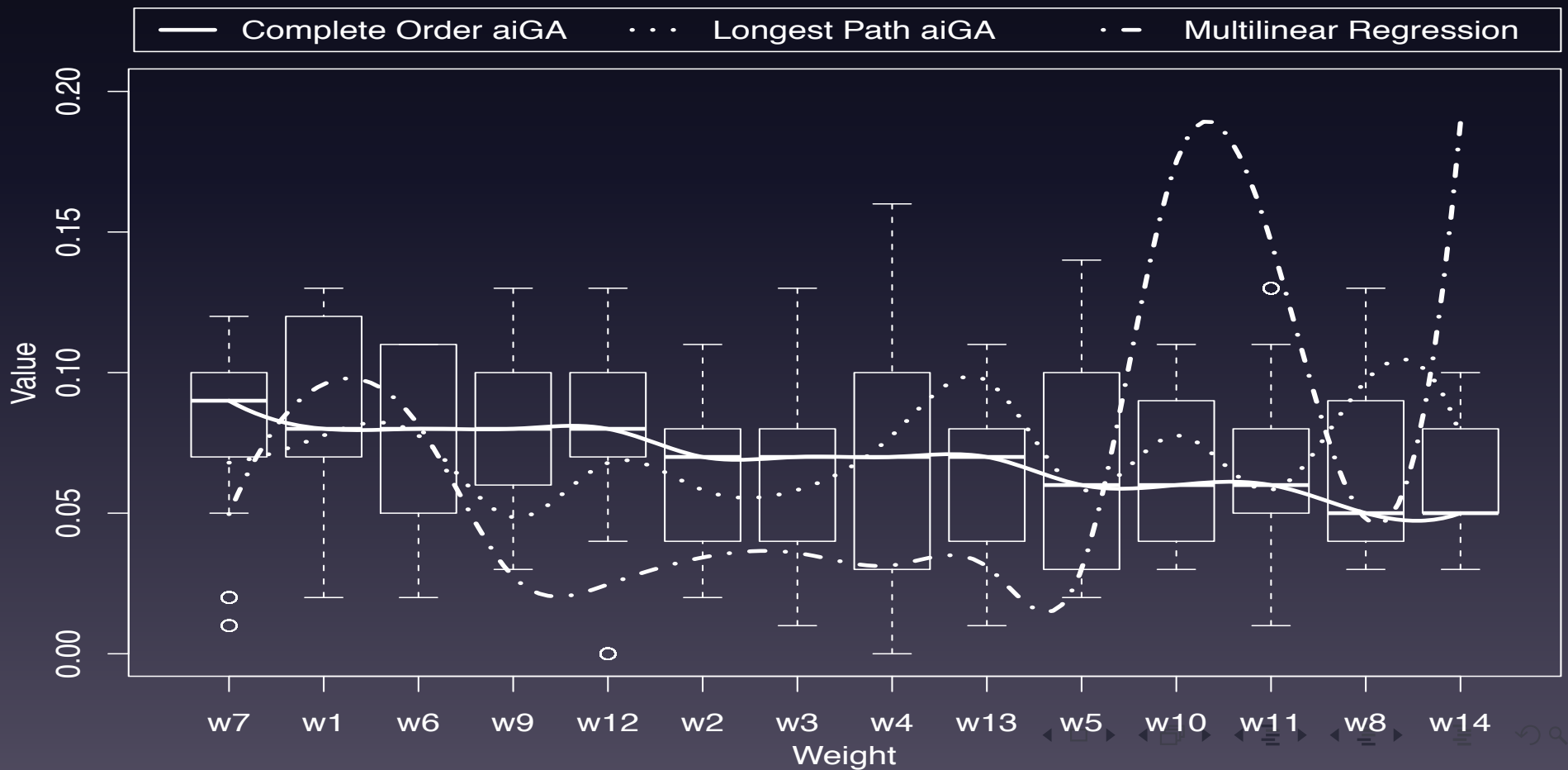
Weights behaviour

- Methods compared: Methods compared: MLR/ aiGA (complete order/longest path)
- Patterns represent general behaviour through all units.



Experiments

- The proposed aiGA indicators are computed comparing longest path and complete order approaches (10 win / 2 tied / 4 lose), obtaining:

Test id	$\bar{\kappa}$	$\bar{\lambda}$	Complete Order		Longest Path	
			$\bar{\rho}$	$\bar{\tau}$	$\bar{\rho}$	$\bar{\tau}$
1	1	0.74	0.67	0.74	1	*0.81*
2	0.93	0.79	0.64	0.74	1	*0.77*
3	1	0.73	0.71	*0.71*	1	*0.71*
4	1	0.74	0.69	0.76	1	*0.85*
5	1	0.6	0.61	*0.78*	1	0.75
6	1	0.88	0.65	*0.78*	1	*0.78*
7	1	0.62	0.53	*0.72*	1	0.66
8	0.95	0.66	0.63	0.78	1	*0.80*
9	1	0.75	0.69	0.79	1	*0.86*
10	1	0.76	0.67	0.79	1	*0.87*
11	1	0.6	0.61	0.75	1	*0.82*
12	1	0.6	0.50	*0.71*	1	0.68
13	1	0.75	0.60	*0.71*	1	0.69
14	1	0.77	0.69	0.74	1	*0.76*
15	1	0.47	0.61	0.80	1	*0.95*
16	1	0.53	0.72	0.73	1	*0.82*

Results analysis

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- aiGA is capable of combining acoustic and linguistic formulations on the cost function.
- Linguistics weights gain importance on subjective evolution. Otherwise on MLR (automatic regression) they achieve lower values.

Validation Stage (1/2)

- 10 different sentences synthesized with:
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- Results compared using a 5 point CMOS across 13 users.
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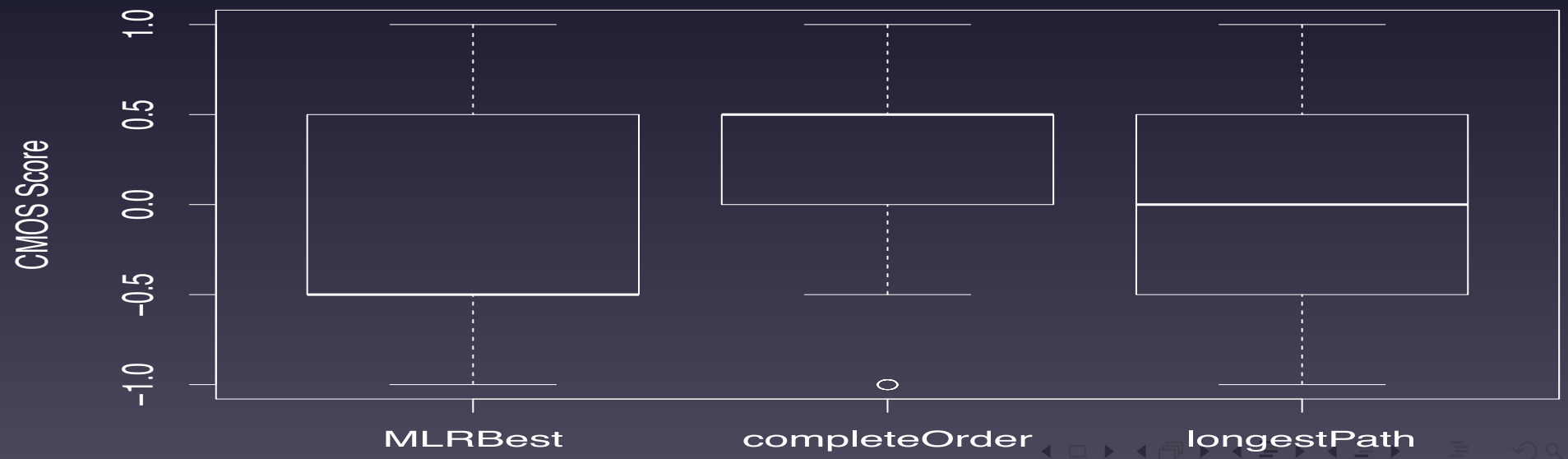

Validation Stage (2/2)

- complete-order-aiGA > MLR / $p = 1.7 \cdot 10^{-5}$
- longest-path-aiGA > MLR / $p = 0.024$
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- MLR method (not perceptual) is perceived as the worst one.

- Better correlation/convergence indicators don't infer better results
- Diversity is preferred on building the final ranking of the graph despite being noisy and confusing (not elitist)

Conclusions (1/2)

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- New process indicators implemented beyond consistency measure κ in order to assess aiGA behavior across the run.
  - λ certainty ratio
  - ρ intra-user convergence ratio
  - τ inter-user correlation ratio
- Results validated by CMOS including baseline MLR.
- Validation stage states complete-order-aiGA as the best approach.

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- aiGA-based tuning method is capable of simultaneously tuning 14 weights
- In contrast to MLR, aiGA obtains reliable information over the linguistic/acoustic discussion without flattering linguistic weights (discrete) to zero values.

Conclusions (2/2)

- Counterintuitively, longest-path-aiGA approach does not yield to the best results even though adopting better correlation and convergence ratios.
- Informal polls on [Llorà. et al., 2005] showed that the longest path method tended to be tedious and repetitive.
- aiGA-based tuning method is capable of simultaneously tuning 14 weights
- In contrast to MLR, aiGA obtains reliable information over the linguistic/acoustic discussion without flattering linguistic weights (discrete) to zero values.
- Technical expertise of the evaluation users is not mandatory for conducting the tuning process

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Lluís Formiga and Francesc Alías
Media Technologies Group
Enginyeria la Salle
Ramon Llull University
{llformiga,falias}@salle.URL.edu

Xavier Llorà
NCSA
Univ. Illinois Urbana Champaign
xllora@illinois.edu

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