

# Acoustics-specific Piano Velocity Estimation

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**Abstract**—Motivated by the state-of-art psychological research, we note that a piano performance transcribed with existing Automatic Music Transcription (AMT) methods cannot be successfully resynthesized without affecting the artistic content of the performance. This is due to 1) the different mappings between MIDI parameters used by different instruments, and 2) the fact that musicians adapt their way of playing to the surrounding acoustic environment. To face this issue, we propose a methodology to build acoustics-specific AMT systems that are able to model the adaptations that musicians apply to convey their interpretation. Specifically, we train models tailored for virtual instruments in a modular architecture that takes as input an audio recording and the relative aligned music score, and outputs the acoustics-specific velocities of each note. We test different model shapes and show that the proposed methodology generally outperforms the usual AMT pipeline which does not consider specificities of the instrument and of the acoustic environment. Interestingly, such a methodology is extensible in a straightforward way since only slight efforts are required to train models for the inference of other piano parameters, such as pedaling.

**Index Terms**—Music, Transcription, Music Information Processing, Neural Networks, Deep Learning, NMF

## I. INTRODUCTION

Automatic Music Transcription (AMT) consists in the analysis of music audio recordings to discover semantically meaningful events, such as notes, instruments and chords. In this work, we refer to those AMT methods that take as input an audio recording and output MIDI-like representations of the music performance. Two main methodologies for AMT exist, i.e. Non-negative Matrix Factorization (NMF) and Deep Learning (DL) (for a thorough review see [1]). During the last 4 years, DL has tremendously advanced the state-of-art of AMT, especially for piano music recordings [2]–[4]. Nonetheless, no attention has been placed on the influence of the instrument and environment acoustics on the AMT output.

Various evidence exist proving such influence [5]. Different research groups focused their efforts in the understanding of why and how music performers adapt their way of playing to the surrounding acoustics. Analyzed instruments include strings, wind instruments, and piano, while the major finding is that the adaptations applied by musicians influence the timbre, the amplitude dynamics, and the timing. Overall, psychologists agree in the identification of an “interior idea of the performance” that the musician adapts to the surrounding acoustic environment. A diagram of the phenomenon is shown in Fig. 1 while an overview of existing works and methodologies

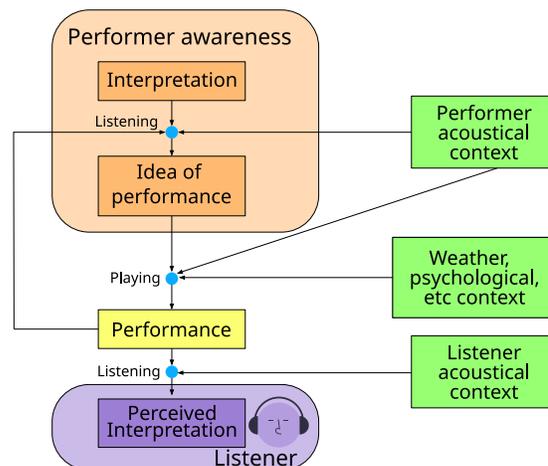


Figure 1. Diagram of the influence of the acoustic context on the performance as outlined in the related literature. First, the performer creates an interior representation of the performance that it wants to achieve (the “interpretation”). Then, based on the acoustic environment, the musician consciously adapts its idea of performance. Successively, based on the feedback from the acoustic environment, it adjusts the performance in a circular feedback. Other non-acoustic factors are included in the diagram to increase its generality. Finally, the listener itself understands the artistic intention based on the its own acoustic context.

is presented in [5]. However, all the existing studies are directed towards the understanding of the factors characterizing room acoustics. Conversely, they rarely consider the listener’s perception and never take into account indirect factors that can effectively change the acoustics of the instrument, such as temperature and humidity.

The long-term use-case scenario that motivates the present work is an audio resynthesis application that allows musicians to achieve studio-quality music tracks by recording with cheap microphones and resynthesizing with high-quality virtual instruments, regardless of the acoustic environment of the source recording. The challenge is in the extraction of the artistic elements that constitute the expressive intention of the performance and in their re-rendering in a new known acoustic context – e.g. a virtual instrument. To this aim, in a previous work [6], we resynthesized the output of a state-of-art AMT model and the ground-truth MIDI in a new acoustic context, such as a high-quality piano virtual instrument. We found that the perceived artistic content of the original and of the new acoustic context was different for both the AMT model and the ground-truth MIDI data recorded on a sensorized-piano.

As in our previous work [6], we use a terminological distinc-

tion to identify two different levels of the performance. Namely, the term “performance” includes the set of physical events that constitute the act of playing; on the contrary, “interpretation” comprises the ideal performance that the musician wants to convey and that it adapts to the surrounding acoustic context – see Fig. 1. As it emerges from the current discussion, the performance depends on the acoustic environment where it happens, while the interpretation is independent from it. Such a distinction is discussed more in depth and studied from the perceptual perspective in [6].

The contribution of the present paper is the development of acoustics-specific models that are able to transfer the interpretation to a certain acoustic context by modeling the adaptations that musicians apply to convey their interior idea of performance. One previous work faced a similar problem, but tried to simulate the adaptation phenomenon applied by performers while knowing both the original and target context [7]. The proposed method, instead, is independent from the input context and can theoretically work using a recording taken in any acoustic context as input.

Towards more complete systems, the proposed approach focuses on the influence of the acoustic context on the piano velocity. The velocity is a MIDI parameter that controls the intensity with which a piano key is pressed. In the MIDI standard, the velocity is an integer value in  $[0, 127]$ , but there is no agreement on the mapping from this values to the physics of the instrument [8]. Consequently, the same velocity value does not sound the same in different virtual instruments nor actuated/sensorized pianos. However, the same applies to real-world pianos and rooms, because different piano/room combinations have different responses to the same physical stimulus. This is why musicians need to adapt their performance to different acoustic environments.

The proposed system aims at 1) transcribing MIDI data that successfully convey the interpretation content considering the target acoustic context, and 2) modeling the adaptations to the velocity that musicians put in place in different acoustic environments. We train a model to first extract the interpretation and then adapt it to each specific acoustic setting. The long-term goal is a system that can transcribe any piano recording in a way that can be resynthesized with one of the acoustic contexts seen during training.

We perform thorough tests with different DL models and demonstrate that acoustics-specifics strategies generally outperform the traditional non acoustics-specifics AMT systems. Targeting at full reproducibility of the conducted experiments, the implementation is available online<sup>1</sup>.

## II. EXPERIMENT OVERVIEW

One of the main datasets available for piano AMT is the Maestro dataset [2], containing 1276 audio recordings performed on a Yamaha Disklavier, a highly precise sensorized piano. The performances were recorded and for each audio, a precise MIDI recording is available. The whole datasets provides 7.04 millions of notes and 198.7 hours of music.

<sup>1</sup><https://limunimi.github.io/MIA/>

Instead of collecting a new ad-hoc dataset, we leverage existing datasets for piano AMT by resynthesizing various performances in multiple artificial acoustic contexts. In this setting, a certain MIDI sequence rendered in two different contexts without any adaptation generates two outcomes with different perceivable interpretations [6]. Thus, the same MIDI notes synthesized in different contexts without adaptation should be considered as generated from different interpretations, even if they have the same underlying MIDI data. Following this idea, we used the MIDI ground-truth data to resynthesize the Maestro dataset [2] in manifold artificial contexts.

We designed an ad-hoc AMT model for estimating the performance parameters. Since our aim is to understand whether the performance transcription error can be reduced by considering the acoustic context, we focus on performance parameter estimation in a controlled setting where note timings are known. In this work, we limit our analysis to velocity estimation, but the proposed method can be extended to new parameters.

In realizing an extensible AMT method, we use the perfectly aligned MIDI files recorded by the Disklavier which are available in the Maestro dataset to inform the transcription process. In a real-world scenario, a precise alignment of a score can be obtained using the Audio-to-score method presented in the last year MMSP conference [9]. We applied Non-negative Matrix Factorization (NMF) [10] to perform a source-separation of each single key of the piano and then analyzed the spectrogram representation of each source-separated note. Namely, we compute the MFCCs characterizing timbral aspects that are connected to the note velocity due to the piano acoustics [11] and are independent of the non-linear amplitude distortions of the microphones [12], [13]. Then, we employ a Convolutional Neural Network (CNN) model to infer the velocity of each note.

The CNN model is split in two parts as follows:

- 1) the “encoder”, which infers the interpretation by taking as input the note-separated spectrogram with size  $13 \times 30$  and one channel, where 13 is the number of MFCCs and 30 is the number of considered time frames;
- 2) the “performer”, which adapts the interpretation to the target acoustic context by taking the latent output of the encoder and computing the velocity in the target context.

Let us observe a typical workflow for two MIDI files and two acoustic contexts:

- 1) the two MIDI files are synthesized using respectively two acoustic settings  $X_0$  and  $X_1$ , generating two audio waveforms  $A_0$  and  $A_1$ ;
- 2) all the notes are extracted from  $A_0$  and  $A_1$  using the NMF algorithm;
- 3) each note spectrogram  $n_{0i}$  from  $A_0$  is processed by the encoder producing a latent representation  $L_{0i}$ ; that is also true for each note  $n_{1i}$  from  $A_1$ , that generates a latent representation  $L_{1i}$ ; if the underlying MIDI velocity for  $n_{0k}$  and  $n_{1h}$  was the same, their spectrogram will be different, as well as their interpretation data, that we model with the latent representation  $L_{0k}$  and  $L_{1h}$ ; this is mainly because the resynthesis did not adapt the velocity to  $X_0$  and  $X_1$ ;

- 4) each latent representation is then processed by the performer, which infers the original velocity value, i.e. the same value for  $n_{0k}$  and  $n_{1h}$ .

Furthermore, we considered various strategies for acoustics-specificity. More specifically:

- 1) the performer can be the same for every context, i.e. context-independent, or it can be context-specific, meaning that in the model there is a different performer for each context;
- 2) since  $L_{0k} \neq L_{1h}$ , the latent space found by the encoder should still include the information required for identifying the input context; as such, it is interesting to understand if enforcing this property facilitates the learning process.

The implementation of the first variable consists in building one performer per context or one performer for every context. As regards to the second variable, we add an additional branch to the model to classify the target context based on the encoder output; this branch works as a learnable loss function that separates the latent space according to the input context.

We compared the 4 different strategies resulting by the combinations of the above-mentioned 2 boolean variables, i.e.

- **Single-w/o**: one single performer and no context classification – this case corresponds to non acoustics-specific AMT;
- **Multiple-w/o**: one performer per context without using a context classifier;
- **Single-with**: one single performer with context classifier;
- **Multiple-with**: one performer per context and context classification.

Since we aim at showing that knowing the target context is beneficial regardless the approximation error, we repeat the experiments with various types of function. More precisely, we define a set of hyper-parameters that determine the shape of the neural network model and then perform a grid-search to explore how the error changes when different model structures are used for the estimation.

All four strategies were tested for each point in the hyper-parameter space, resulting in a highly computationally demanding experiment. We thoroughly tested 36 different model shapes, each with 4 different training strategies, summing up to 144 trained models.

### III. DATASET

This section describes the data creation process facilitating the proposed experiment.

#### A. Resynthesis

We designed an experiment based on the resynthesis of existing datasets. To this end, we developed `pycarla`<sup>2</sup>, a Python module that leverages the excellent `Carla`<sup>3</sup> plugin host to synthesize MIDI messages both in real-time and offline using

<sup>2</sup><https://web.archive.org/web/20211213132835/https://pypi.org/project/pycarla/>

<sup>3</sup><https://web.archive.org/web/20211205195725/https://kx.studio/Applications:Carla>

Table I

SUMMARY OF THE MAIN CHARACTERISTICS OF THE 6 PRESETS USED FOR RESYNTHESIZING THE MAESTRO [14] DATASET.

ID	Velocity Map	Reverb	Instrument
0	Linear	Jazz Studio	Steinway B Prelude
1	Logarithmic	Jazz Studio	Steinway B Prelude
2	Logarithmic	Cathedral	Steinway B Prelude
3	Linear	Jazz Studio	Grotrian Cabaret
4	Logarithmic	Jazz Studio	Grotrian Cabaret
5	Logarithmic	Cathedral	Grotrian Cabaret

the major audio plugin formats – such as VST, AU, LV2, LADSPA, DSSI, SF2, SFZ.

We used 6 different presets for the physically modeled virtual piano by Pianoteq, kindly provided for research purposes by Modartt<sup>4</sup>. Table I summarize the main characteristics of each preset.

#### B. Clustering

The source dataset was Maestro [14] and was used as provided by ASMD library [15]. The Maestro dataset was selected using the ASMD Python API; then, *train*, *validation*, and *test* splits were partitioned in 6 different subsets, each associated to one of the presets in Table I, sampled so that they were equally distributed across the dataset. Similarly to stratified sampling, 6 sets were generated by unifying subsets associated to the same preset, so that each set was still split in *train*, *validation*, and *test* sets. Each generated set was resynthesized and saved to a new ASMD definition file.

Since each set consisted of only 1/6 of the whole dataset, a uniform random sampling would have not grasped the underlying distribution. Thus, we developed an ad-hoc method to obtain equal-sized subsets maintaining a similar underlying distribution as the parent set. To this aim, we extracted features from the MIDI data and clustered them.

The 6 new subsets in each split were chosen as follows. First, one split at a time among the already defined *train*, *validation*, and *test* was selected. Supposing that the chosen split has cardinality  $K$ ,  $C$  clusters were created with  $C = \lfloor K/6 + 1 \rfloor$  and a target cardinality  $t = 6$  was set. Then, a redistribution policy is applied to the points of the clusters: for each cluster with cardinality  $< t$  – a “poor” cluster – we look for the point nearest to that cluster’s centroid and belonging to a cluster with cardinality  $> t$  – a rich cluster – and move that point to the poorer cluster. The redistribution stops when all clusters have cardinality  $\geq t$ . Since the redistribution algorithm moves points from rich clusters to the poor ones, we named it “Robin Hood” redistribution policy. Having obtained  $C$  clusters each with 6 samples, we partitioned the chosen split in 6 subsets as follows:

- 1) we randomized the order of subsets and clusters
- 2) we selected one point from each cluster using a random uniform distribution and assigned it to one of the 6 subsets
- 3) we did the same for the other 5 subsets
- 4) we restarted from point 2 until every point is assigned to a cluster.

<sup>4</sup><https://web.archive.org/web/20211112075858/https://www.modartt.com/>

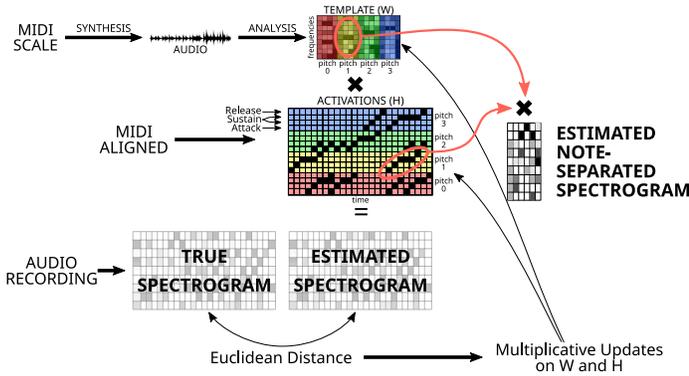


Figure 2. The entire NMF workflow. First, the initial template and activation matrices are computed. Then, the Euclidean distance between the estimated and the true spectrograms is used to multiplicatively update both the template and the activation matrix. Finally, only the relevant part of the template and activations are used for estimating the note-separated spectrogram. For simplicity, 4 columns are used to represent each note while during the experiments, we considered 30.

Details about the clustering procedures and the features selected are provided in the accompanying website.

#### IV. NOTE-SEPARATION

NMF has largely been used for score-informed AMT [6], [12], [16], [17] and our application is mainly based on the existing literature. Using NMF, a target non-negative matrix  $S$  can be approximated with the multiplication between a non-negative template matrix  $W$  and a non-negative activation matrix  $H$ . When applied to audio,  $S$  is usually a time-frequency representation of the audio recording,  $W$  is the template matrix representing each audio source, and  $H$  represents the instants in which each source is active. As such, the rows of  $W$  represent frequency bins, the columns of  $W$  and the rows of  $H$  refer to sound sources, and the columns of  $H$  are time frames. The  $W$  and  $H$  matrices are first initialized with some initial values and then updated until some loss function comparing  $S$  and  $W \times H$  is minimized. Similarly to previous works [6], [12], we build an initial template matrix by analyzing a MIDI file synthesized with a further virtual instrument and containing all the 88 piano keys playing with different velocities and duration. We initialize the activation matrix using pianoroll-based information from the aligned MIDI file and proceed to minimize the euclidean distance. The proposed method for NMF is shown in figure 2 and more details are provided in the accompanying website.

Once the NMF algorithm is finished, we use the original perfectly aligned activation matrix to select the region of a note in  $H$  and  $W$  to obtain its approximated spectrogram separated from the rest of the recording. We consider the first 30 frames (690 ms) of each note, padding with 0 if the note is shorter. We finally compute the first 13 MFCC features in each column of the spectrogram using Essentia.

#### V. NEURAL NETWORK MODELS

For every function estimation, we use Convolutional Neural Networks (CNN) with skip connections similarly to

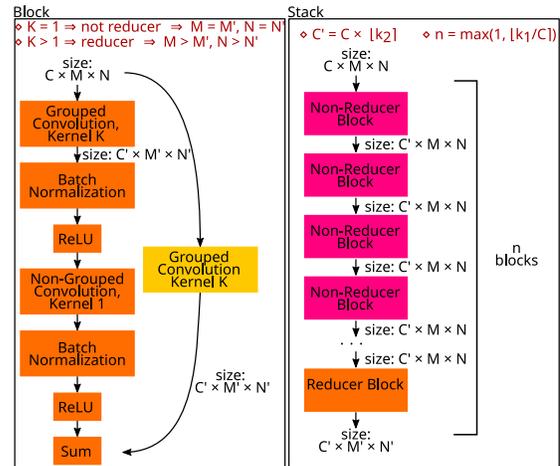


Figure 3. Architecture of the Residual blocks and stacks networks used in this work.  $\lfloor \cdot \rfloor$  denotes the rounding operation.

ResNet [18]. A schematic representation of the proposed model building blocks is shown in Figure 3.

In ResNet, a building block is defined so that the output can have the same size as the input (“not reducer” block) or can be reduced (“reducer” block); in both cases, the output of each block is summed to the input to prevent the vanishing gradients phenomenon and other degradation problems connected with the increase of the network complexity [18]. Since they can maintain the output size equal to the input, a virtually infinite number of blocks can be put one after the other, and multiple stacks of blocks can be concatenated to create arbitrarily large and complex networks without depending on the input size.

In the proposed model, each block consists of the following elements:

- a grouped convolutional layer with kernel size  $K$ ; if the block is a not-reducer, a padding is used;
- a batch-normalization layer;
- a ReLU non-linear activation;
- a non-grouped convolutional layer with kernel size 1 – corresponding to a linear combination of each data entry across channels;
- another batch-normalization layer;
- a final ReLU activation.

Furthermore, each block sums its output to the input processed with a grouped convolutional layer having kernel size 1 if the block is a not reducer and  $K$  otherwise. Figure 3 better depicts the building of a single block.

Multiple blocks can be put one after the other forming a stack. In each stack, the first block changes the number of channels, while the rest keeps it constant. Moreover, all blocks in a stack are not reducers except the last one. As such, each stack can increase or decrease the number of channels in the data representation and at the same time it decreases the size of the data with only one convolution. Figure 3 represents a stack.

In order to control the complexity of the network, we designed a family of CNNs that vary the ratio between the

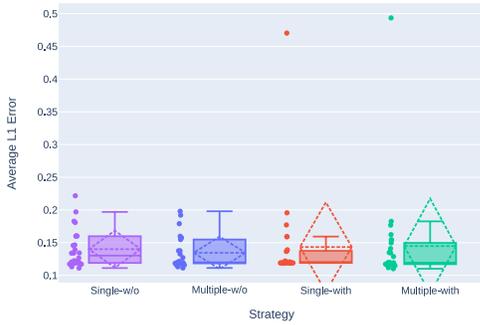


Figure 4. Comparison between the 4 proposed strategies. **Single-w/o** strategy corresponds to the traditional non acoustics-specific transcription function. The dotted rhombus represents average and standard deviation. The continuous line represents the median and box-plot.

number of blocks and the number of channels in each stack based on two parameters  $k_1$  and  $k_2$ . By setting  $k_1$  and  $k_2$ , one may find Residual CNNs that approximate various types of functions. Specifically,  $k_1$  is inversely proportional to  $k_2$  while  $k_1$  is related to the number of blocks and  $k_2$  is connected with the number of channels – see Fig. 3. In our experiments, we manually found that  $k_1 = 4$  comprises an effective parameter and observed the way the models perform when  $k_2$  changes. Following this algorithm, multiple stacks were concatenated until the output size has at least one dimension  $< k_0$ , where  $k_0$  is the kernel size, which is fixed across the stacks.

We use multiple of such CNNs in each model to estimate encoder and performer functions and an additional one for the context classifier. After the stacks, a further convolutional layer followed by batch normalization and ReLU is added aiming at reducing the data size to 1 and at compressing all existing information into the channel dimension; in the performer and context classifier, this last block also takes care of reducing the number of channels to the expected output dimension, i.e. 1 for the velocity and 6 for the context classifier. Finally, we apply a linear transformation using a grouped convolution and activation block with kernel size 1; the last activation is a ReLU in the encoder, a Sigmoid in the performers, and a SoftMax in the context classifier.

The considered hyper-parameters were 4:

- 1) the kernel size in the encoder (values: 3, 5)
- 2) the kernel size in the performer (values: 3, 5)
- 3) the  $k_2$  parameter in the encoder (values: 1, 2, 3)
- 4) the  $k_2$  parameter in the performer (values: 1, 2, 4)

The acoustic context classifier branch is built with the same performer kernel; however, due to the higher computational complexity needed for classifying 6 labels,  $\{k_1, k_2\}$  were multiplied by 1.25 – i.e.  $k_1 = 5$  and  $\lfloor k_2 \rfloor \in \{1, 3, 5\}$ .

## VI. TRAINING

The training datasets include 7.1 millions of music notes. Since the experiment includes the training of more than 100 models, to make the problem computationally accessible, we use only 0.1% of the available data with a batch size of 10, resulting in 703 batches (7030 notes). Subsampling was performed with a uniform distribution and was repeated on all

Table II

WIN ANALYSIS. THE TABLE MUST BE READ AS: “STRATEGY AT ROW  $x$  IS BETTER THAN STRATEGY AT COLUMN  $y$  IN  $n$  HYPER-PARAMETER CONFIGURATIONS”

	Single-w/o	Multiple-w/o	Single-with	Multiple-with	All
Single-w/o	-	2	12	3	1
Multiple-w/o	24	-	19	11	11
Single-with	14	7	-	6	5
Multiple-with	23	12	20	-	12

6 contexts and splits (train, validation, and test sets). Overall, the training set is made of 566 batches, the validation counted 63 batches, and the test set is composed of 74 batches.

Training is performed using Adadelta [19] optimizer with initial learning rate set according to an existing algorithm designed to find its optimal value based on repeated small experiments with increasing learning rates [20]. When the algorithm fails, the initial learning rate is automatically set to 1e-5. The loss function for the performers is the L1 error, while for the context classifier we use the Cross-Entropy loss. When the context classifier is used, we treat the problem from a multi-task perspective. For this reason, we sum the two losses and use the recently proposed RotoGrad algorithm [21] to stabilize the gradients. Moreover, when using multiple performers, to speed up the training process, we load data so that each batch contains notes related to only one context at a time and we cycle across contexts so that all of them are equally represented. However, this strategy leads to unstable losses both in training and in validation, making it hard to understand when the model is actually overfitting. As such, we imposed an early-stop procedure with a patience of 20 by observing the Exponential Moving Average of the validation loss on a window of 15 epochs.

## VII. RESULTS

The results we obtained are shown in Figure 4 and 5. We computed the average L1 error for velocity estimation in each tested hyper-parameter set, discarding those configurations that generated models exceeding GPU or even CPU RAM or that returned invalid losses. Overall, we considered 26 hyper-parameter sets corresponding to 104 runs. Moreover, to reduce the computational burden, we stopped each training at the 40th epoch, in case the training procedure was not terminated by the early-stopping criterion.

For evaluating the statistical significance of the results in Figure 4, we applied the Shapiro-Wilk normality test to each strategy distribution and then Kruskal-Wallis and Wilcoxon signed-rank test for post-hoc analysis. We found that all analyzed distributions rejected the null hypothesis of normality tests with  $p < 4e-3$ , meaning that the distributions are not normal. We found no significant difference according to the omnibus Kruskal-Wallis test ( $p = 1.74e-1$ ). However, we also computed the Wilcoxon p-values using the Bonferroni-Holm correction and found a statistically significant difference with confidence of 95% only between Multiple-w/o and Single-w/o, Multiple-with and Single-w/o. Note that the  $p > 0.05$

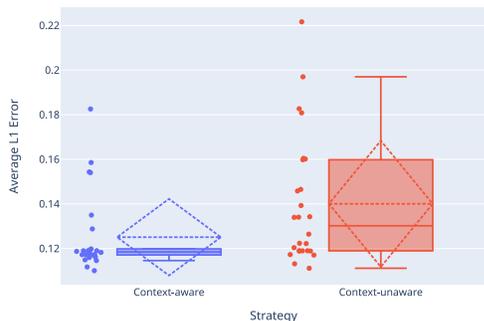


Figure 5. Comparison between the best acoustics-specific strategy and the traditional non acoustics-specific transcription in each hyper-parameter point. The dotted rhombus represents average and standard deviation. The continuous line represents the median and box-plot.

found with the Kruskal-Wallis test is coherent with the pairwise significance found using the corrected Wilcoxon test [22], [23]. Given the statistical analysis, we argue that  $R > 0$  for the Multiple-with and Multiple-w/o strategies. To further assess such conclusions, we also computed the number of hyper-parameter sets won by each strategy. Table II shows this analysis and highlights how in only 1 configuration the best training strategy was Single-w/o.

However, no optimal strategy was found. Indeed, considering Multiple-w/o, Single-with, and Multiple-with, there is no agreement about which one is the most effective method. To obtain a deeper understanding of the problem, we tried to check what would happen in case an oracle could indicate the optimal strategy depending on the model shape. Results were highly statistically significant ( $p = 6e-5$ ) and showed far improved results when one of the proposed acoustics-specific strategy was used – see Figure 5. This result highlights how, in theory, the benefit coming from acoustics-specific AMT can be definitely larger than 0.

## VIII. CONCLUSIONS

In this paper, we proposed an extensible framework to deepen the understanding of acoustic factors on music performance analysis from the perspective of AMT.

We extensively evaluated 4 different strategies for velocity estimation of single notes. We demonstrated that considering acoustics-specific strategies consistently improves model performance. However, no acoustics-specific strategy was found to outperform the rest; it was shown that they complement each other.

Future works could also estimate non-MIDI parameters that are relevant for the timbre realization of pianists [11]. Another attractive addition would be the note offset precise inference based on the hammer second and third impulsive sound; given the low accuracy of the note offset inference in state-of-the-art AMT models, such an addition could be useful for precisely defining the performer interpretation. A third addition could be performer-specific adaptation functions, as suggested in previous experiments [24]. Finally, an important parameter that we plan to focus in next works is the pedaling level estimation.

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