Optimizing piano practice with a utility-based scaffold

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Abstract

A typical part of learning to play the piano is the progression through a series of practice units that focus on individual dimensions of the skill, such as hand coordination, correct posture, or correct timing. Ideally, a focus on a particular practice method should be made in a way to maximize the learner’s progress in learning to play the piano. Because we each learn differently, and because there are many choices for possible piano practice tasks and methods, the set of practice tasks should be dynamically adapted to the human learner. However, having a human teacher guide individual practice is not always feasible since it is time consuming, expensive, and not always available. Instead, we suggest to optimize in the space of practice methods, the so-called practice modes. The proposed optimization process takes into account the skills of the individual learner and their history of learning. In this work we present a modeling framework to guide the human learner through the learning process by choosing practice modes that have the highest expected utility (i.e., improvement in piano playing skill). To this end, we propose a human learner utility model based on a Gaussian process, and exemplify the model training and its application for practice scaffolding on an example of simulated human learners.

1 Introduction

Learning to play sports or to play a musical instrument is not a trivial task, and normally we cannot learn these skills by simply observing an expert. Rather, they are learned with a help of a teacher who provides scaffolding. “Scaffolding is a reciprocal feedback process in which a more expert other (e.g., teacher, or peer with greater expertise) interacts with a less knowledgeable learner, with the goal of providing the kind of conceptual support that enables the learner, over time, to be able to work with the task, content, or idea independently” [18]. The main contribution of this work is a model of a scaffold that guides the human learner through the process of learning to play the piano by choosing the practice method that has the highest expected utility (i.e., improvement in piano playing skill). To this end, we propose a human learner utility model based on a Gaussian process, and exemplify the model training and its application for practice scaffolding on an example of a simulated human learner.

The mastery of the learner increases as they become more proficient with a growing mixture of abilities. Playing the piano is a typical complex combinatorial skill which builds upon gradual mastery of prerequisite skills [5]. Skilful performance requires a number of abilities, including being able to read notes, follow the speed, produce correct rhythmic structures, use a correct hand posture, and

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coordinate movements of both the hands and feet. In a band, an additional ability to coordinate with others adds to the challenge. A typical example of the scaffolding process is reducing the complexity of the task by reducing the degrees of freedom \cite{22}, and sometimes even by off-loading the rest onto something or somebody else \cite{15}. In piano practice, it is common to first practice with each hand individually. Here, the part of the non-practicing hand can be offloaded onto the computer. In the above example, a good level of mastery for both hands separately is necessary in order to be able to concentrate on the task of coordinating both hands. The focus on practicing one or several aspects or modes of the complex skill by reducing the complexity of the overall task accordingly is termed here **practice mode**. For the generation of practice modes, we need a set of procedures to simplify the target task for practice, to decompose it to a subset of modes. An example of this is a practice mode that targets improving timing in a particular piece of score \cite{2}, by substituting every note to one single pitch, such as middle C. This reduces the complexity of the task and enables the learner to just concentrate on timing correctness, instead of both timing and pitch correctness. Another practice mode that targets improvement in pitch correctness allows the learner to play as slowly as they want, waiting for the learner to play the next note for as long as they need before moving to the next note. This enables the learner to concentrate on pitch correctness only and not think about playing with correct timing. In general, a practice mode may need to specify both the target task adjustments (as in timing practice mode) as well as the method of practice organisation (such as waiting for the learner to play the correct note in pitch practice mode).

How to guide or even accelerate learning of multimodal skills such as playing the piano is an open research question. Although a large amount of research has been dedicated to the educational domain and towards creating intelligent human-in-the-loop tutoring systems \cite{9,11,16}, very little work exists for optimizing practice of motor tasks, such as piano playing. While research efforts focus mainly on analysis and rehabilitation of professional musicians \cite{8}, or the differences between the professional player and the novices \cite{3}, no recent work targeted scaffolding of learning for non-professional piano players.

Our long-term goal is to design a framework for intelligent tutoring with the human in the loop, to help the human learner (HL) stay engaged, get suitable challenges, and receive constructive feedback on their performance. In this work we propose a scaffolding framework consisting of a teacher-complementing model infrastructure and an experimental setting, both controlling the learning process. In particular, we train a Gaussian Process (GP) \cite{17} to represent the utility of practice modes, and illustrate the results in a simulated experiment. The final application performs an optimized selection of practice modes for a HL on one complexity level.

Due to the fact that our application should be suitable to scaffold a real human learner, a case in which data acquisition is costly, we pursue a modeling approach with a GP that enables us to model data with very few samples. GPs provide not only the approximation in the functional space but also can represent the uncertainty about the estimate at a particular point, which is a useful property for both data-acquisition and scaffolding. Following previous work \cite{14}, we build on the assumption of a static tree-like curriculum (described in more detail in Section 3.1). In \cite{14} the authors propose to use the so-called actionable features to dynamically react to the learner’s needs. An actionable feature encodes an intervention, e.g., that the learner needs more practice on a corresponding prerequisite skill before moving up the curriculum tree. In this work we extend the concept of actionable features as described in \cite{14} to practice modes (see Section 2 for a more detailed description). This new concept can be illustrated particularly well on an example of piano learning domain. Here we can track far more information characterizing performance of the learner and the amount of improvement, in comparison to typical educational applications that in some cases only output whether the question has been answered correctly or not. Due to a clear multimodal structure of the piano playing task, the practice modes can be derived from the task automatically based on expert advice for a wide range of pieces invariant to the complexity level. This is different to the educational applications, where new actionable features might be necessarily on new complexity levels. In this work we introduce the basic modeling infrastructure needed to optimize practice mode selection for a piano playing scaffold, and the simulated learner environment that provides us with insights about how to shape future human learner studies.
Figure 1: (Left:) The envisioned intelligent tutoring setup consisting of a GUI displaying a music score, a keyboard and a practice mode specified by guidance with an exoskeleton Dexmo. (Right:) an example of a practice mode implemented through guidance with Dexmo. During this practice mode, Dexmo generates a sequence of force impulses corresponding to the structure of the score, and moves the corresponding fingers of the human learner (HL) according to the start and end of the note.

2 Components and Notation

- **Tasks** \( \tau \). Mathematically, a single task is denoted \( \tau \in \mathbb{R}^N \). A task is defined as a vector that represents a set of \( N \) task attributes (playback speed in beats per minute, number of notes, rhythmic complexity, volume, number of hands, etc.) Task attributes may also specify the performance method or goal, such as focus on correct timing and pitch, etc. We differentiate between a target task \( \tau_{\text{target}} \) (coll. “parent task”) and a set of corresponding practice modes \( \tau_M \) that are derived from the target task by using a subset \( M \subseteq \{1, \ldots, N\} \) of target task attributes. A practice mode is then represented by an \( N \)-dimensional vector with irrelevant task attributes zeroed out; we normalize the relevant task attributes to values \( > 0 \). Importantly, all tasks and all practice modes have the same dimensionality.

Example: let \( \tau_{\text{target}} \) be a task, which is characterised by a full set of task attributes. The performance of the target task is tracked in both hands w.r.t. pitch, timing, and posture correctness. We generate a practice mode by selecting attribute values, e.g. \( (\tau_1, \ldots, \tau_k) \) that correspond to practising aspects of the target task such as pitch correctness separately for each hand, clapping instead of playing to improve timing, or being guided by an exoskeleton to improve fingering (see Figure 1).

- **Task set** \( \mathcal{T} \). We denote a (finite) set of tasks as \( \mathcal{T} \). We specify a partition of the task set \( \mathcal{T} = \bigcup \mathcal{T}_c \) into subsets of different complexity levels, denoted by \( c \) (using prior knowledge from, e.g., a textbook or app).

- **Task distributions** \( p \). We denote a task distribution as \( p_{\phi}^T \), with support over the tasks in the set \( \mathcal{T} \) and parameterised by \( \phi \). (E.g., \( p \) could be Gaussian and \( \phi \) the mean and variance of that Gaussian). We can sample individual tasks from this distribution, \( \tau \sim p_{\phi}^T \). Each complexity level \( c \) is characterised by its own distribution over the task-subset, denoted \( p_{\phi}^{T_c} \).

- **Music score generator** \( G \). \( G \) is a mapping of task attributes to a corresponding score \( G : \tau \rightarrow s \), where \( s \) is a music score (which is a sheet of notes the student has to play). The music score generator generates scores for both full tasks, or the practice modes according to the attributes specified by \( \tau \).

For example, it could use attributes such as number of active hands (left, right, both), number of active fingers (1-5), rhythmic complexity (usage of half, quarter notes, etc.) or the note range (e.g. C through G, just the natural (white) keys, an octave, the whole scale) to either select a piece from a database or to construct it randomly to satisfy the above-mentioned constraints. An example of a randomly generated task for one hand in the range of a whole octave is illustrated in Figure 7 (Appendix A.2). Randomly generating practice tasks allows

\[^{\text{2}}\text{by “score” we mean the music score.}\]
us to produce a wide range of practice opportunities that can be individually tuned to the skill level of the HL and whose complexity may increase in a fine-grained manner. The underlying data structure is visualized in Appendix A.1.

- **Performance error** $\rho(\tau) \in \mathbb{R}^K$. The performance error of a human learner on a task $\tau$ evaluated w.r.t. a $K$-element set of attributes and denoted by $\rho(\tau)$. Performance error can be evaluated w.r.t. pitch correctness, timing correctness, correctness of hand posture, pressure, fingering, volume, etc. We here assume for simplification that we can evaluate the performance error level for each attribute with a single scalar value (if this is a restriction, we can always split an attribute into several "subattributes", one for each required performance error dimension).

- **Human learner**: We assume that each HL $h_a : \tau \rightarrow \rho_\tau$ has a set of attributes $a \in \mathbb{R}^T$ characterizing their personal talents, strengths and weaknesses. In Section 4 we differentiate between three simplified HL groups defined by their performance error dynamics w.r.t. timing and pitch.

- **Task utility function** $g$: For a given task $\tau$ we have a set of practice modes $\tau_m \in \tau_M$, where $M \subseteq \{1, \ldots, N\}$ is a subset of attribute indices of the task. The Gaussian process represents the following utility function of selecting a practice mode for the human learner:

$$g_a : \tau_m \rightarrow u_\tau,$$

where the utility $u_\tau$ of the practice mode $\tau_m$ for reducing performance error of $\tau$ is approximated by the error delta after one practice with $\tau_m$:

$$u_\tau = \rho_{\text{pre}}(\tau_m) - \rho_{\text{post}}(\tau_m).$$

Such approximation is necessary due to the fact that it might be impossible for a HL to initially play the target task without performing multiple practice modes first. In this case, we cannot initially let HLS perform the target task directly.

- **Scaffold** $S$: takes predictions of the task utility function as an input and selects the practice mode with the highest utility. Building upon the definition of scaffolding, in future work we will extend $S$ to increase or decrease the task complexity according to the progress of the HL.

Figure 2a exemplifies main stages of one loop iteration describing the reciprocal interaction between the human learner and the scaffold.

### 3 Practice Infrastructure for the Human Learner

In this section, we first outline the individual parts of the practice infrastructure for the human learner, and then focus our attention on the parts that can be optimized.

#### 3.1 Practice Infrastructure Components

Building upon previous work on intelligent tutoring systems (e.g. [14]), as well as the theory of scaffolding coming from the educational psychology [18], we assume that the practice infrastructure consists of two main parts: 1) a static curriculum represented by a tree-like structure of prerequisite skills, and 2) a scaffold whose role is, based on the utility function $g$ and a target task $\tau_{\text{target}}$, to dynamically select practice modes for the HL depending on their estimated utility.

On the one hand, a static curriculum is a learning plan anchored in music-theory, with the human learner being gradually introduced to tasks with increasing complexity. Examples are tonal keys of increasing number of sharps (C major, G major, D major), moving from playing single notes, then intervals, then chords, moving from playing adjacent notes to extending the spatial distance between the keys, moving from simple time signatures such as 4/4, to 3/4 to more difficult ones such as 5/4, etc. On the other hand, the scaffold is the interactive component that takes the learner’s skill level and their individual practice utility into account to pick the most useful practice modes on-the-fly. Figure 2b illustrates both components: the interactive (bottom) and the static (top), respectively. The top row shows an example for a curriculum consisting of two complexity levels. On the complexity level $c = 0$ there are tasks to practice for one hand only. On the level $c = 1$ the generated task
For a target task and a practice mode specification, the music score generator $G$ produces a piece of score. In this case the practice mode with the highest utility targets improvement of pitch. The error of the learner is evaluated and is employed for the update of the utility function.

Figure 2: Practice infrastructure for the human learner.
case we do not want any covariance between each category, which could be realized by using a high scaled one-hot encoding, or since the covariance between points is zero regardless, embed them in a single dimension by placing them sufficiently far apart.

4 Simulated Experimental Setting

Algorithm 1: Pseudocode of the error and utility calculation

Input: HL-model (performer), noise_var, bpm, note_range, practice_mode
Result: utility

1. initial_error.timing = ϵ * \frac{bpm}{10}
   \epsilon \sim \mathcal{N}(1, \text{noise}_\text{var}^2)

2. initial_error.pitch = ϵ *
   \begin{cases} 0.5 & \text{if note_range} = 0 \\ 1.5 & \text{if note_range} = 1 \\ 3 & \text{if note_range} = 2 \end{cases}
   \epsilon \sim \mathcal{N}(1, \text{noise}_\text{var}^2)

3. error_pre = initial_error.copy()
4. if performer == bad_pitch then
   5. error_pre.pitch = initial_error.pitch \times 1.75
5. end
6. if performer == bad_timing then
6. if performer == bad_timing then
5. error_pre.timing = initial_error.timing \times 1.5
6. end
7. end
8. if practice_mode == improve_pitch then
6. if practice_mode == improve_pitch then
5. error_post.pitch = error_pre.pitch \times 0.5
7. end
8. end
9. utility = error_pre.timing - error_post.timing + error_pre.pitch - error_post.pitch
10. utility *= ϵ
    \epsilon \sim \mathcal{N}(1, \text{noise}_\text{var}^2)
11. utility -= mean_utility
    (\text{mean}_\text{utility} \text{ is a predefined constant})
12. return utility

In order to test the practice infrastructure without performing trials with HLs, similar to [14] we build a simulated experimental setting consisting of the following building blocks:

1. The Gaussian process representing the utility function: for a set of task parameters, including a specification of the practice mode, it approximates the corresponding utility. The mode with the highest expected utility then gets selected.

2. Two simulated practice modes denoted by IMP_TIMING and IMP_PITCH that model optimal practice that improves timing and pitch correctness, respectively.

3. A two-dimensional task specification consisting of target playback speed denoted by beats per minute (bpm) and three categories for the range of notes that are employed for task generation, with bpm ∈ \{50, \ldots, 200\} and note-range ∈ \{0, 1, 2\}. Note range parameter exemplifies a categorical input attribute, and will in future determine the number and placement of notes employed for the music score generation. All generated tasks specified by (bpm, note-range) tuples are located on the complexity level c = 0.

4. Three simulated groups of HLs, \(h_1 - h_3\), characterized by different error dynamics (see Algorithm[1]). \(h_1\) has difficulties playing the right pitch, \(h_2\) has difficulties with the timing, while \(h_3\) features no such error amplification (balanced case). As a coarse model of the learning effect of the practice mode we simply assume that working through a practice mode reduces the associated error measure by some fixed percentage, e.g. 50%. The utility of a practice mode is then defined by the decrease of error in the post-practice-mode performance (see Algorithm[1]). The scaling factors chosen in lines 5 and 8 of the algorithm are designed to generate different optimal ground truth practice mode policies for each HL group (discussed in more detail below).
The experiments showed that leaving the bpm input-value not normalized leads to very little improvement of the model with the increasing number of training iterations. Learning is much faster with normalized inputs (therefore we use an empirically estimated \( \frac{bpm}{10} \)). We subtract a mean utility from the calculated utility value to better fit the GP model assumption (zero mean function \( m(\cdot) \)).

**Algorithm 2:** Pseudo code of the GP training.

**Input:** The learner\_performance\_error and calc\_utility functions

**Result:** The policy of the trained GP

```
1 c = 0
2 GP = GP()
3 for _ in num_iter do
4     tp = random_task_parameters()
5     error_pre = learner_performance_error(tp)
6     practice_mode = GP.get_practice_mode(c, tp)
7     error_post = learner_performance_error(tp, practice_mode)
8     utility = calc_utility(error_pre, error_post)
9     GP.add_data_point(c, tp, practice_mode, utility)
10 end
```

Therefore, practice by a HL from a group \( h_a \) contributes one datapoint for the training of the Gaussian utility predictor model \( g_a \). This datapoint has as its input elements \( (bpm, note_range, practice\_mode\_type) \). The target output in the datapoint is the actual utility value inferred from the training result. Our goal is to check how well the Gaussian model can capture this setting from few datapoints.

To be able to evaluate the quality of our model, we need to compare the GP-based policy with an optimal policy. Using the simple model assumptions outlined in above points 1.-4. we can calculate the ground truth for the optimal policy that specifies the best practice mode to suggest for each combination of task parameters (see Figure 3).

The pseudocode of the GP training is shown in Algorithm 2. In each iteration, random task parameters get generated within their respective bounds. We then let our HL-model “play” the task and get the pre-practice error. This is a multi-dimensional error with its timing dimension determined by the tempo (bpm) and the pitch dimension determined by the value of the note-range parameter. These errors are increased according to the selected HL-model \( h_1, h_2 \) or \( h_3 \), respectively. We then use the utility predicted by the GP to select the best practice mode for the generated task parameters and calculate the second error, using the same HL-model. Here we assume that it “practiced” with the selected mode (see lines 11-15 of the Algorithm 1). We then calculate the utility of this practice by comparing the two errors (pre- and post-practice) and add the new data point to our GP model. We apply noise to the difficulty of the task parameters as well as the final utility to account for the variability of learners in the respective group, differences within the set of randomly generated tasks within the complexity level, as well as the variance in performance of the learner depending on factors such as focus, fatigue, etc.

## 5 Results

We train the GP by iterating the above algorithm (see Algorithm 2). For implementation we have used gpyopt library [4]. Figure 4 illustrates convergence of the training process for three different groups of HLs. Each plot illustrates results for different types of noise added to the calculated utility function. We evaluate the learning progress of our model (depicted on the \( y \)-axis) based on the policy-loss (see Equation 3) calculated based on our prior knowledge of the ground truth policy. We calculate loss that, for a given task-parameter tuple, describes the missed utility of selecting a certain practice mode (zero if the optimal mode is selected) as follows: \( \text{loss} = u_{\text{optimal}} - u_{\text{selected}} \) and \( \text{loss}_{\text{max}} = u_{\text{optimal}} - u_{\text{non-optimal}} \). This can be applied to the whole policy by summing over all considered parameter combinations and dividing by the total possible loss. For \( T = \{(\text{bpm, note_range})|\text{bpm} \in \{50,\ldots,200\}, \text{note_range} \in \{0,1,2\} \} \) we define the policy-loss as follows:

\[
\text{policy-loss} = \frac{\sum_T \text{loss}}{\text{median loss}_{\text{max}} \times |T|}.
\]
Figure 3: Optimal ground truth practice mode policy for each considered task-parameter combination and each HL group. Three subfigures correspond to three HL group: bad pitch (left), a balanced error (middle), bad timing (right). Different types of error dynamic determine HL-specific ground truth utility for each parameter combination, and, finally, result in a different practice modes being optimal in each one of the three HL groups. Color yellow depicts an optimal selection of IMP_PITCH practice mode, and color purple corresponds to IMP_TIMING practice mode.
Figure 4: The convergence towards the optimal policy for each of the HLs with their respective weaknesses. Each combination was run 27 times, average and standard deviation are shown.

Figure 5: Visualization of the internal states of two GPs after 20 data-points each. Mean and standard deviation for both practice modes are shown for each process. The left GP had no noise applied to its data and learned the optimal policy (for the balanced learner) and dependencies (timing utility based only on bpm; pitch utility on note-range). The right GP had noise with a standard deviation of 0.5 applied during the creation of its input data. It fails to cleanly make out the true utilities and dependencies, and its resulting policy-loss is 16%. Each policy is the \( \text{argmax} \) of the two practice-mode means.

Adding noise into the system, equally applied to the initial difficulty of the task, as well as the utility of a practice mode, leads to slower convergence towards the optimal policy, as can be seen in Figure 4. It is nevertheless clear that learning takes place and no overfitting artifacts appear. Figure 5 gives more insight into how the noise hinders the regression towards the true utilities. Figure 5 visualizes the trained GPs with and without noise added to the utility of the practice mode.
6 Discussion

In this work we have introduced the concept of practice modes and presented our approach to scaffolding the learner by dynamic practice mode selection, designed to optimize learner’s progress in learning how to play piano. On an example including a large set of simulated tasks on a single complexity level, two simulated practice modes and three groups of human learners, we have illustrated the functionality of a utility-based scaffolding infrastructure. One future work direction will be to perform a study with real human learners with the goal to verify the efficacy of our approach. Another will consist of integrating Hidden Markov Model (HMM)-based methods as described in [14] to determine when or whether to move the human learner up and down the curriculum tree, i.e. from one complexity level to another to better model longer-term learning processes.

We believe that the proposed approach to scaffolding, illustrated on the specific domain of piano practice, may be extended to other motor tasks, including sports and rehabilitation, where complex skills also need to be learned. There is mixed evidence in the field of motor learning as to whether learning a complex skill is better performed on the task as a whole, or whether and how it is better to divide the task into parts and learn these parts individually before combining them [12,21]. The question that is asked in these studies is whether the learning of the parts performed individually transfers effectively to the situation when the parts are combined. A very general approach to both task and practice mode definition, which enables us to define a practice mode by any combination of the “parent task” attributes, will give us a strong formal framework to address the open research questions of whether and how to optimally learn (“part” vs. “whole” practice) for each individual learner. The combination of an individually optimized training program on one complexity level, combined with appropriately moving between complexity levels (as described above) may provide beneficial features from both part and whole learning including the optimal time for switching complexity levels.

The use of automated techniques for individualizing motor learning as used in this study has significant potential [20] for improving learner outcomes. As different learners show different learning curves, the individual customization of motor training can ensure that each learner receives an appropriate next exercise to maximize the amount of learning taking place in a given amount of time. Additionally, maintaining appropriate difficulty levels seems to be an important factor in determining intrinsic motivation for a task [12]. Further, our learning infrastructure can be extended for measuring the effect of factors such as augmented feedback [13] and reward [1] on motor learning at an individual level, and for determining the optimal presentation of feedback and reward for improving motor learning. The interaction of feedback, reward and individually optimized learning tasks may lead to further enhancement of the motor learning process.

6.1 Limitations

Currently our GP maps to a single output dimension: utility; defined as the sum of improvements across all error aspects. This procedure is reasonable for our simulated experiments, where the hyperparameters were chosen to lead to three different policies in the end (see Figure 5). In the real world, the error differences come in different modalities (e.g. seconds, half-notes off pitch) and it will not be sufficient to simply add them together. It is difficult to compare different expected improvement aspects and weigh them against one another. One solution would be to bin the improvements per aspect, for example a one second timing improvement over 7 bars, into categories like no improvement, slight improvement, improvement, large improvement. These bins could be defined by semi-experts, describing the magnitude of improvement between two real world data-samples. Determining an intuitive weighting algorithm based on such bins should be more feasible.

The current approach does not address the question of the number of repetitions necessary to master the task specified by the practice mode. Finding an optimal number of repetitions is an interesting extension of this work which can be achieved in a similar way to [14] by tracking “not mastered/engaged”, “not mastered/not engaged” and “mastered” states during practice. We define an optimal practice schedule as one that maximizes engagement, which is likely to results in a higher persistence of the human learner.

In the beginning of human learner experiments, very few data points exist, and therefore a robust utility estimation for a new human learner is not possible without their own GP training. This needs to be approached by gathering more data from different human learners, and allocating them to a growing set of groups according to their attributes. Once sufficient data has been acquired, a new
learner could be allocated to their own group by a dynamic adjustment procedure, evaluating their individual attributes. Furthermore, we will explore the idea of forming a meta-model based on multiple human learners, which then during practice adjusts to the individual learner’s needs. This feature is in general necessary due to the fact that the learner may change their attributes as they practice over long periods of time. Over short periods of time, the learning progress of a HL may be accounted for by an extension of the GP to learning non-stationary system dynamics, such as described in [19].

Another possible improvement may be made to the music score generation. Although it is advantageous to be completely automated for an input of task attributes specific to a given complexity level, it produces random note combinations which may not be very motivating for the HLs. For the experiments with real HLs, we will use wave function collapse [7] to generate pieces that are different to known tunes, but through a slight similarity with the original may be more pleasant to the learners. Another option that will enable us to create music scores with a similarity to the known original tune is to additionally anchor them in the harmonic progression of the original. An adherence to basic musical rules would guarantee a sufficiently musical outcome. e.g. formulaic cadences, and overall note distributions that reflect established tonal hierarchies [10].

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A Appendix

A.1 Music Score Generation for Tasks and Practice Modes

Music scores are generated by e.g. sampling from ranges defined by task parameters like note range. Music scores generated for practice modes in some cases need to be adapted to the practice mode, e.g. in order to improve timing, every note in the score is changed to one single value such as middle C to allow the learner to concentrate on timing only, and not mind the pitch (see Figure 6).

A.2 GUI

Figure 7 shows an example of a task presented to the HL in real setting (which is part of future work).
Figure 6: Overview of the underlying data structures. Every task starts with TaskParameters which then get passed into a generator to render a TaskData object which includes the score (represented by the notes in Notes Left, Notes Right). This process is probabilistic and thus a large number of scores/TaskData objects can be generated from the same TaskParameters. Applying a PracticeMode to a TaskData object produces a new TaskData object with e.g. adapted notes. A TargetTask is an overarching construct that includes the TaskData of the main task, as well as the practice mode variations of said data.

Figure 7: Left: an example of a score piece randomly generated by the music score generator based on the specified task parameters, which is presented to a study participant via GUI. Both the notes as well as the fingering can be generated automatically (see [6]). Right: a simple error visualization.