On the Potential of Machine Learning for Music Research

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Short running title: Machine Learning for Music Research

Abstract

This chapter argues that the branch of AI known as Machine Learning (ML) can make useful contributions to music research, if employed in a thoughtful way. After giving a brief introduction to machine learning and discussing some general methodological questions, the article presents an ongoing project by the author as an example of a substantial and highly non-trivial application of machine learning to a musical problem. The basic music-theoretic assumptions of the project are discussed, the general method is briefly described, and some exemplary results are presented to give the reader an appreciation of the kinds of benefits musicology may draw from such research.

Key words: Machine Learning, Music Research, Musical Expression, Expressive Performance

1 Introduction

The ability to *learn* is undoubtedly one of the central aspects, if not *the* defining criterion, of intelligence and intelligent behavior. While it is difficult to come up with a general and generally agreed definition of intelligence, it seems quite obvious that we would refuse to call something “intelligent” if it cannot adapt at all to changes in its environment, i.e., if it cannot learn. It is thus clear that Artificial Intelligence, as the scientific discipline that studies intelligence by means of computers, must also study the foundations and mechanisms of learning. The corresponding subarea within AI goes by the name of *Machine Learning (ML)* and has become one of the largest and most active research areas of AI. As in AI in general, research in machine learning covers a broad spectrum from mathematically oriented, very abstract learning models through cognitive theories and models of learning all the way to practical, ready-to-use generic algorithms. Recent years have seen a steady increase in practical applications of machine learning methods to industrial and commercial problems that involve tasks like classification, prediction and forecasting, or various kinds of data analysis.

Not surprisingly, there has also been some work in the intersection of machine learning and music. The problems tackled and strategies pursued are as diverse as the motivations and goals underlying these projects. In some cases, musical data are simply used as testbeds to test and demonstrate the abilities of some new learning algorithms. The results of such experiments are usually of little use to music theory or practice. But there are also projects with a more substantial musical side to them. Examples of such work include the extraction of typical patterns from masterworks that might constitute the building blocks of musical *style* (e.g., Cope, 1991, 1992), the development of practical musical tools like adaptive composition assistants (Courtot, 1992) or reactive instruments (Rowe, 1992), machine learning studies of historical performance data (Dovey, 1995; Widmer, 1995b), and more large-scale investigations that use learning algorithms as general methods for the empirical study of the conceptual basis of certain musical skills (Widmer, 1994, 1997).

Given this diversity of approaches and projects, it seems futile to try to give a comprehensive and coherent overview in a short article like this. Instead, this chapter will focus on a more specific question, namely, whether and how machine learning could make useful contributions to *music research* (as opposed to, e.g., practical applications like the development of adaptive instruments or interactive composition systems). To this end, we will first give a very cursory introduction to the field of machine learning, followed by a brief discussion of some general methodological questions that arise when one wants to apply machine learning methods to musical problems. The second part of the chapter will concentrate on a particular project by the author as an example of a substantial and highly non-trivial application of machine learning to a musical problem. The basic music-theoretic assumptions of the project will be discussed, the general method will be described (at a fairly abstract level), and some exemplary results will be shown that give the reader an appreciation of the kinds of results musicology may expect from such research.

2 A (Very) Brief Introduction to Machine Learning

Machine learning may be defined as the subfield of Artificial Intelligence that studies the phenomenon of learning, both by constructing formal theoretical models, and by developing operational algorithms and computer programs that can learn. Now what is learning, and how can it be modeled on a machine? On the face of it, learning is a very complex phenomenon, with many different manifestations. Definitions of learning that try to encompass all these different facets are by necessity very abstract. The following two definition attempts from the machine learning literature are interesting because they are both highly general, but stress very different aspects of learning:

> "Learning means behaving better as a result of experience." (Russell & Norvig, 1995, p.552).
>
> "Learning is constructing or modifying representations of what is being experienced." (Michalski, 1986, p.10)

While Russell and Norvig stress the improvement of (problem solving) *behavior* as the main goal of learning, Michalski's definition suggests that we view learning as the acquisition of *knowledge* about the world (again based on experience or observation). Both of these views have counterparts in the world of actual machine learning research. Among the research directions that explicitly focus on behavior improvement we find areas like *speedup learning* (Minton, 1988), *reinforcement learning* (Kaelbling, 1994), or *genetic algorithms* (De Jong, 1988). On the other hand, learning as the extraction of knowledge from observations or data has been and continues to be the dominant paradigm in machine learning research. Algorithms are being developed that induce knowledge in a variety of forms, like classification and prediction rules (Clark & Niblett, 1989; Quinlan, 1990), decision trees (Quinlan, 1986, 1993), or logic programs (Lavrac & Dzeroski, 1994). This knowledge-centered view of learning has recently received another boost by the birth and rapidly growing practical success of the (arguably) new fields of *knowledge discovery in databases* and *data mining* (Fayyad et al., 1996). For an excellent introduction to and overview of the field of machine learning, we refer the reader to (Mitchell, 1997)

Despite the apparent diversity of approaches and sub-fields, however, all learning methods and algorithms must ultimately rely on the same fundamental mechanism: learning means drawing general conclusions from specific observations or experiences, and that, in essence, means performing *inductive generalization*. Machine learning algorithms may differ in the representation languages and formalisms used, in the search stragies applied, and in what kind of learning scenario they assume (e.g., 'one-shot' or incremental learning, the presence or absence of a teacher, etc.), but ultimately learning reduces to the search for generalizations that are consistent with the given observations (i.e., the given data). We feel that it is important to stress this, as non-specialists of machine learning are easily confused by the apparent multiplicity of methods.

The general problem of inductive generalization is that as a form of reasoning it is inherently uncertain. The larger the collection of data that a learner can rely on, the smaller the risk of making incorrect generalizations, but the risk is always there. On the other hand, the potential benefit of inductive generalization is that, by inducing general rules from complex data, it may lead to the discovery of new knowledge. That is why we think machine learning can also be of use for empirical music research, as we will try to show in the following sections.

3 Machine Learning for Music Research

Machine learning methods have proven useful in many real-world applications that involve general tasks like classification, prediction, forecasting, and the extraction of patterns and regularities from data. In some cases, learning systems have actually led to new discoveries in scientific domains like biochemistry (Muggleton et al., 1992) or astronomy (JPL, 1995).

One can easily imagine similar uses of machine learning both in music practice and in music research. The practice of both traditional (tonal) and contemporary music could benefit from the flexibility and adaptivity afforded by learning capabilities. Examples of systems that are in development or might be conceivable are reactive instruments or artificial performers that interact with human performers or conductors (Rowe, 1992), adaptive music editing or composition systems (Courtot, 1992), trainable optical notation recognition systems (Fujinaga et al., 1989), or computer systems that help composers and performers in manipulating complex musical information, especially in the context of contemporary computer-based music. An example of the latter is the automatic classification and characterization, in terms of high-level, intuitive terms, of complex sound information (Miranda, 1995; Rolland & Pachet, 1995). Of course, all of these tasks are extremely complex; a lot of research is still required to arrive at robust, useful adaptive systems, but the practical possibilities and implications are exciting.

The same holds for (empirical) music research (where *empirical music research* is used here to mean all forms of musicological investigations that are based primarily on the study of corpora of existing data, be it compositions, transcriptions of jazz improvisations, performance data, or any other kind of records of musical activities). Here, it is especially the data analysis and knowledge discovery capabilities of machine learning methods that hold promise. The role of such methods would be to assist the human analyst in finding patterns and regularities in collections of real data that may help in understanding and explaining some musical phenomenon or the foundations of some musical skill. An example of such a use of machine learning is described in the following section.

Finally, another potential role of machine learning models, which we will not discuss here, is that they may serve as a direct inspiration for cognitively plausible models of musical skills, as in the case of (Marsden, 1989).

Before turning to the details of a project where machine learning is actually applied to the study of musical data, it seems worthwhile to briefly discuss a few general methodological issues that arise in any investigation of this kind:

Problem complexity: To make a project both feasible and interesting, it is crucial to choose an object of study of appropriate complexity. Unconstrained tasks like learning to compose good symphonies are clearly too complex. On the other hand, the kinds of artificial musical 'micro-worlds' that have been and still are quite popular in many machine learning experiments (like the almost ubiquitous first-species counterpoint — see, e.g., Pompe & Kononenko, 1996; Morales & Morales, 1995; Widmer, 1992) are too trivial to produce any results of interest to musicology. The phenomenon to be studied should be complex and realistic enough to be interesting, but also constrained and circumscribed well enough so that (most of) the relevant influencing factors can actually be captured. Expressive music performance seems to be a suitable candidate (see next section); another positive example is the improvisation of jazz bass lines, given the harmonic grid (Ramalho, 1996).

Real data: By the same token, if the learning experiments are to produce new knowledge and insight into musical phenomena, it is essential that the data collected for analysis be unbiased and from 'realistic' sources (e.g., not produced by the experimenter him/herself). In the study to be described in the following, the acquisition of 'real-world' data turned out to be a serious problem. Preliminary experiments used sample data produced by the author himself, which, to a certain degree, compromised the generality of the experimental results. It was only recently that we managed to obtain real data (though still an insufficient amount) for unbiased experiments.

Music-theoretic assumptions: The two key factors that influence the outcome of learning experiments are the input data (examples) given to the learner, and the representation language in which the learning system can represent its hypotheses. As both of these factors are (mostly) under control of the experiment designer, they must be regarded as potential sources of *bias*. That is why it is crucial that the experimenter be very conscious of, and explicit about, any assumptions that guide his/her choice of training data and choice of representation language. In particular, any musicological assumptions that influenced these choices (e.g., which factors are explicitly represented in the system because they are assumed to be common knowledge, which aspects are considered irrelevant or negligible and are thus omitted, etc.) must be made explicit, as they also determine what conclusions may legitimately be drawn from the results of the experiments.

Representation and abstraction level: A specific instance of the above, important enough to be noted explicitly, is the abstraction level chosen for the description of the training data and the learner's representation language (see also Smaill & Wiggins, this volume). For instance, are notes or tones assumed to be atomic units, or does the representation also include acoustic factors at lower levels? The abstraction level chosen implicitly represents a number of fundamental assumptions about the phenomenon under study, and it should be made clear on what grounds this decision was made, and what impact that has on the interpretation of the results.

All these considerations should be kept in mind when designing empirical experiments with machine learning algorithms, and the project to be described in the following must also be judged in this light.

4 An Example Project: Learning Expressive Performance

In this section, we describe one specific ongoing research project as an example of a highly non-trivial application of machine learning to a complex musical phenomenon. Experimental results achieved so far, though only preliminary, hint at the kinds of results musicology could expect from machine learning applications of this kind.

4.1 Problem and assumptions

The phenomenon being studied is *expressive music performance*, specifically, *dynamics* and *rubato* (or *expressive timing*). We are developing computer programs that learn general expression rules from examples of human performances. To be more precise, input to the learner are *melodies* of musical pieces (i.e., sequences of notes), along with actual *performances* of these melodies by some human performer. Performances are represented as tempo and loudness curves associated with the melody, and the learner's task is to learn when and how to apply dynamics (*crescendo* vs. *decrescendo*) and tempo (*accelerando* vs. *ritardando*) variations to given melodies. The learned rules should then allow the system to play new pieces more or less expressively.

Our approach is guided by several important assumptions, which are worth being stated explicitly:

Assumption 1: One important role of expressive interpretation is the communication of an understanding of musical structure, from the performer to the listener (see, e.g., Sundberg et al., 1991). Expression serves to emphasize structure. Consequently, we may assume that expression becomes partly explainable if we know the relevant structural dimensions and how they are perceived by human listeners.

Assumption 2: Some knowledge about the human perception of musical structure can be described explicitly and encoded in a computer program in operational form. In particular, the music theories of Lerdahl & Jackendoff (1983) and Narmour (1977) postulate a variety of musical structures that are musically and cognitively plausible and may thus serve as useful basic knowledge for a learning program.

Assumption 3: The level of symbolic notes (as opposed to, e.g., the level of sound spectra) is a reasonable abstraction level; it allows for effective learning from example performances while not hiding too much relevant detail. (This should not be misconstrued as claiming cognitive plausibility for this abstraction level. What we claim is *musical plausibility*, i.e., that most of those aspects of the music itself that influence an expressive performance (e.g., grouping structure) are above that level.)

The *hypotheses* to be tested are whether expressive principles can be learned at all by a machine, and whether the addition of musical 'knowledge' (i.e., knowledge about musical structure) does indeed help the learning process. In the following, we briefly describe two systems that were developed and implemented to test these hypotheses.

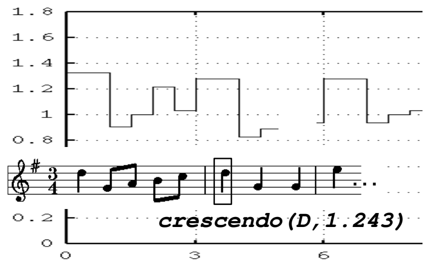

Figure 1: Training example for note-level learner.

4.2 Approach I: Learning expression at the note level

In a first system, described in detail in (Widmer, 1995a), we took a rather straightforward approach. Every note in a given example performance is interpreted as a training example (see Figure 1), i.e., an example of either *crescendo* or *decrescendo* in the dynamics dimension, and an example of either *accelerando* or *ritardando* in the tempo dimension. The computer's task is to learn general decision rules for *crescendo*, *decrescendo*, etc.

In addition, the learning system is equipped with an explicit *qualitative model of musical knowledge* that is meant to represent some basic aspects of structural hearing as they might be relevant to expressive performance; it serves as a kind of simple 'musical ear' to the learning program, allowing it to interpret the example performances in a more structured way. The model cannot be discussed in detail here, the interested reader is referred to (Widmer, 1995a). Essentially, it comprises a set of analysis routines that perform an analysis of the example melodies and identify musical structures along various dimensions; the analysis is based on selected parts of Lerdahl and Jackendoff's (1983) theory of tonal music and—very remotely—Narmour's (1977) *Implication-Realization Model*.

The qualitative model is used by the learning program to enrich the description of the training examples (the individual notes in a given melody) with additional descriptors that explicitly describe the various roles a note plays in the structural analysis. That allows the learning algorithm to refer to higher-level musical concepts that may be more adequate in forming hypotheses about expressive performance. The learning algorithm itself had to be specially developed for this purpose. It is called IBL-SMART and is described in detail in the machine learning literature (Widmer, 1993).

Experiments with relatively simple types of music (e.g., minuets by J.S.Bach) showed that the learning system performed significantly better — both in terms of the quality of the expressive performances it produced and in terms of the comprehensibility of the learned rules — when it was equipped with the qualitative knowledge model than when it had to learn purely from examples. These results testify to the importance of a basic understanding of musical structure for learning expression rules. We return to this point in section 4.5 below.

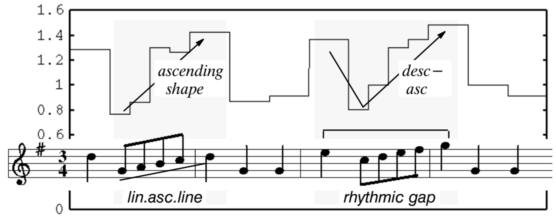

Figure 2: Training example for structure-level learner.

4.3 Approach II: Learning expression at the structure level

Despite some encouraging results with the first approach, it became clear eventually that the note level is not really appropriate. For one thing, though the performances produced by the system were in large part musically sensible, they lacked a certain smoothness and a sense of both local and global form. Second, it is psychologically implausible that performers think and decide on a purely local level in terms of single notes; rather, they tend to comprehend music in terms of higher-level abstract forms like phrases etc. And finally, as observed, e.g., by Sloboda (1985), expression is a *multi-level* phenomenon: expressive shapes, like musical structures, appear at multiple levels. Local expression patterns may be embedded within larger patterns (e.g., shaping of ornaments within an overall crescendo). A sensible formalization of musical expression should reflect this fact.

Consequently, we have developed a new approach that abandons the note level and tries to learn expression rules directly at the level of musical structures. As these structures are of widely varying scope — some comprising only a few notes, others spanning several measures — the system learns to apply expression at multiple levels at once.

The essence of the approach is an *abstraction strategy* that transforms the training examples and the entire learning problem to a musically plausible abstraction level. Given the 'raw' training examples as above (a melody as a sequence of notes along with dynamics and tempo curves), the system again first performs a structural analysis of the given melody. It then tries to find prototypical *shapes* in the dynamics and tempo curves that can be directly associated with the structures found. Figure 2 illustrates this step for the dynamics curve associated with the beginning of a Bach minuet (the curve is derived from a performance by the author). We look at two of the many structures found by the structural analysis: the ascending melodic line in measures 1–2 is associated with the shape `ascending`, as the curve shows a clear ascending (*crescendo*) tendency in this part of the recording. And the 'rhythmic gap fill' pattern in measures 3–4 has been played with a `desc_asc` (*decrescendo – crescendo*) shape.

The results of this transformation are thus pairs <*musical structure, expressive shape*>, and these are passed to the learning algorithm as training examples. Applying the algorithm IBL-SMART to these transformed examples yields a set of expression rules that determine, given a particular musical structure in some new piece, what kind of expressive shape should be applied to the entire structure. Generally, this abstraction approach is a more or less direct translation of our belief that many expression decisions are tightly linked to high-level structural aspects of the piece being played, and our expectation was that it would lead to improved learning results by

Figure 3: Chopin Waltz op.64, C$\sharp$ minor, as played by learner (*tempo*).

allowing the learner to recognize and represent expression patterns at the appropriate abstraction level.

4.4 Musical results

The two learning systems just described have been tested on music of various styles, from simple Baroque pieces (Bach minuets) to Chopin waltzes, Schubert songs, and also swing and bebop tunes. In all these cases, the training performances for the learner were played by the author himself, on an electronic MIDI keyboard. Of course, that is problematic from the perspective of experimental methodology, but it could not be done otherwise at the time, due to the difficulty of obtaining 'real' machine-readable performance data.

It is impossible to try to give a representative overview of the results here. Figure 3 shows just one representative example, namely, the *tempo curve* of the system's performance of part of a Chopin waltz after learning (at the structure level) from five excerpts from other Chopin waltzes, performed by the author. The curve plots local tempo, i.e., the higher the curve, the faster the tempo at the respective point.

This example demonstrates both positive and negative effects. Overall, the performance seems musically sensible and shows clear structure at various levels. At the macro level (see arrows above the graph), for instance, we recognize a general accelerando over the first four bars, then a pronounced slowing down towards the G$\sharp$ at the beginning of measure 7, which is explicitly marked for emphasis by a $>$ mark in the score. (Note that such expression marks are not visible to the learning system!) At lower level, we notice a quite consistent phrasing of the individual measures. On the other hand, there are also mistakes, such as the "spike" of high tempo associated with the third note in measure 4, and generally the fact that in absolute terms, the tempo variations are too extreme. Still, the performance is reasonable, and this and other examples (see, e.g., Widmer, 1996b) suggest that approach II — learning at the abstraction level of musical structures — produces performances of much higher quality than rules learned and formulated at the note level.

More recently, this has also been confirmed in experiments with "real" data, i.e., pieces not played by the author himself. In an investigation based on (the tempo curves of) performances of Robert Schumann's *Träumerei* by over 20 famous pianists (Repp, 1992), the beneficial effect of knowledge about musical structure on the learnability of expression patterns was demonstrated both in qualitative (Widmer, 1995b) and quantitative (Widmer, 1996b) terms.

4.5 General results

Beyond a set of new computer-generated expressive performances with more or less interesting characteristics (and some are really surprisingly good), we believe that the project has produced more general results that might be of interest to musicology. Let us discuss some of these in more detail:

Empirical confirmation of musical assumptions: Taken together, the musical results from our various experiments indicate that some principles of expressive performance are indeed learnable, at least to a certain extent. In addition, the results also confirm the validity of the assumptions that guided the project (see section 4.1 above). In particular, they provide strong empirical evidence for the essential role of knowledge about musical structure perception. The improvement brought about by providing the learning algorithms with such knowledge has been shown convincingly, both in qualitative and in quantitative terms (Widmer, 1995a, 1996b).

Adequacy of underlying music theories: By the same token, the fact that the learners' music-structural vocabulary is based (though rather loosely, in Narmour's case) on the music theories by Lerdahl & Jackendoff (1983) and Narmour (1977) and that the systems make extensive use of these music-theoretic terms in formulating their hypotheses provides a certain empirical evidence for the adequacy and usefulness of these theories — at least for the relevance of the structural concepts we borrowed from them.

Interpretability of learned rules: One advantage of using a *symbolic* learning algorithm like IBL-SMART is that the learned rules can be analyzed and interpreted (as opposed to, e.g., neural networks, which are more or less opaque). The possibility of discovering novel, meaningful patterns and regularities via learning was one of the explicit motivations for this research. While we cannot report spectacular novel discoveries at this point, it is interesting and testifies to the potential of the learning approach that our learners did re-discover (variants of) some expression rules that were postulated earlier by other researchers. In (Widmer, 1995a, 1995b) several rules, found by learning from actual performances, are described that turned out to be variants of rules described in (Sundberg et al., 1983; Friberg, 1995). This is a highly motivating result and points the way to further, more focused investigations.

Varying relevance of different structural dimensions: At a more fine-grained level, an analysis of the learned rules can give a more detailed picture of which structural features of the music seem most relevant to 'explaining' given expressive performances. For instance, an analysis of this kind in the domain of Bach minuets (Widmer, 1995a) revealed that rhythmic and metrical characteristics (like metrical strength and duration of notes) seem to be very important, as do certain melodic and rhythmic patterns derived from Narmour's theory, while (perhaps surprisingly) grouping and phrase structure turn out to play a lesser role in the rules learned. A different picture emerges when rules learned from Schubert songs are analyzed. Studies of this kind could thus contribute to more general investigations into musical styles.

Identification of stylistic differences: A related question is whether machine learning systems could actually learn (and characterize, through the learned rules) aspects of personal performance style. A comparative experiment with performances of the same piece by Vladimir Horowitz and by a group of advanced piano students (Widmer, 1996a) gave slight indications that some style-specific patterns might be picked up by the learner, but we could not find intelligible differences in the learned rules that could be interpreted as really characterizing aspects of personal style. What we can realistically expect from machine learning algorithms is that they extract general, common performance patters; the fine artistic details are certainly beyond their reach.

All in all, it is results like these that lead us to believe that machine learning has something to offer to empirical musicology. Of course, the experiments are still very limited, especially given that we do not have access to extensive collections of real performance data. Also, the systems as currently implemented suffer from a number of technical limitations, and we had to make many simplifying assumptions that may detract from the generality and musical plausibility of the results. But the project continues, and other researchers are invited to join this enterprise.

5 Conclusion

In summary, this chapter has argued that machine learning, as a field that develops operational learning methods, may make useful contributions both to music practice and music research. For the case of music research, we hope to have demonstrated this with a specific research project that, despite all its limitations, at least hints at the kinds of benefits musicology could reap from such projects. We have also discussed at some length certain methodological issues that must be considered if such projects are to yield useful and reliable results. It must be said that much of the work currently going on in the area of machine learning and music is still rather *ad hoc* and not well co-ordinated. With this article, we hope to have shown to a wider audience that this is an exciting and promising research area, and we hope that the field will continue to grow, to the benefit of not only music research and music practice but also Artificial Intelligence itself.

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