Inductive logic programming applied for knowledge representation in computer music

Programação lógica indutiva aplicada para representação do conhecimento em música computacional

DOI:10.34115/basrv5n4-009

Recebimento dos originais: 06/06/2021
Aceitação para publicação: 15/07/2021

Clenio B. Gonçalves Junior
Master and PhD student in Computer Science
Federal Institute of Education, Science and Technology of São Paulo (IFSP)
Federal University of São Carlos (UFSCar)
Rod. Prefeito Quintino de Lima, 2100 - São Roque/SP - Brazil
clenio@ifsp.edu.br

Murillo Rodrigo Petrucelli Homem
PhD in Computer Science
Federal University of São Carlos (UFSCar)
Department of Computer Science
Rod. Washington Luís, km 235 - São Carlos/SP - Brazil
murillo@dc.ufscar.br

ABSTRACT

In Computer Music, the knowledge representation process is an essential element for the development of systems. Methods have been applied to provide the computer with the ability to generate conclusions based on previously established experience and definitions. In this sense, Inductive Logic Programming presents itself as a research field that incorporates concepts of Logic Programming and Machine Learning, its declarative character allows musical knowledge to be presented to non-specialist users in a naturally understandable way. The present work performs a systematic review based on approaches that use Inductive Logic Programming in the representation of musical knowledge. Questions that these studies seek to address were raised, as well as identifying characteristic aspects related to their application.

keywords: Computer Music, Inductive Logic Programming, Knowledge Representation, Artificial Intelligence, Machine Learning.

RESUMO

Na Computer Music, o processo de representação do conhecimento é um elemento essencial para o desenvolvimento de sistemas. Métodos têm sido aplicados para fornecer ao computador a capacidade de gerar conclusões baseadas em experiências e definições previamente estabelecidas. Neste sentido, a Programação Lógica Indutiva se apresenta como um campo de pesquisa que incorpora conceitos de Programação Lógica e Aprendizagem de Máquina, seu caráter declarativo permite que o conhecimento musical seja apresentado a usuários não-especialistas de forma naturalmente compreensível. O presente trabalho realiza uma revisão sistemática baseada em abordagens que utilizam a Programação Lógica Indutiva na representação do conhecimento musical. Foram levantadas questões que estes estudos procuram abordar, assim como identificados aspectos característicos relacionados à sua aplicação.

Palavras-Chave: Música computacional, Programação Lógica Indutiva, Representação do Conhecimento, Inteligência Artificial

1 INTRODUCTION

The field of Computer Music has stood out over time, among other factors, for its multidisciplinary characteristic (MILETTO et al., 2004). Studies carried out in this area have provided assistance in understanding concepts involving human-computer interaction, programming paradigms, cognitive processes, etc. The area of Artificial Intelligence, in particular, concentrates a great variety of works that maintain a close relationship and whose affinity dates back several decades ago (FERNÁNDEZ; VICO, 2013; MINSKY, 1981; WIGGINS, 2000; DELGADO, 2011; ROADS, 1985).

Closely linked to the symbolic approach in artificial intelligence, there is the concept of knowledge representation. This research field deals with information modeling elements, so that the computer has the ability to efficiently generate logical conclusions, enabling the execution of complex activities that involve elements such as reasoning and creativity. The definition of an adequate tool for knowledge representation is essential for the development of an artificial intelligence system to be successful (ALVARO; MIRANDA; BARROS, 2005).

Thus, the modeling of the knowledge representation structure is of paramount importance in computer music activities (RAMIREZ; HAZAN, 2005), and the processes involving such activity should compose the first phase in the development of a system (BALABAN, 1996). More specifically, declarative modeling, through First Order Logic, is an important method. Both its descriptive structure and the application mechanisms raise particularly interesting questions (WHALLEY, 2005). This model presents a natural formalism for the definition of musical components, allowing inferences to be made on a previously defined musical basis, in addition to providing the discovery of new structural patterns.

In this context, Inductive Logic Programming (ILP) presents itself as a growing field of research that combines the concepts of Logic Programming and Machine Learning (MORALES; MORALES, 1995). ILP is based on first-order logic, which gives it a declarative character, this allows the result of the processing generated by a system to be presented to non-specialist users in a simple and intuitive way (DIXON; MAUCH; ANGLADE, 2011).

Through inductive logic programming, new musical knowledge can be generated automatically from the derivation of structures and rules expressed in the form of Horn clauses. A series of models have been proposed in works involving concepts such as counterpoint, performative expressiveness, harmonic representation, modal inference, among others. Additionally, ILP has been applied as an efficient resource for knowledge representation regarding the characterization of musical genres and styles (POMPE; KOONONENKO; MAKSE, 1996; NUMAO; TAKAGI; NAKAMURA, 2002; ANGLADE et al., 2010; DIXON ; MAUCH; ANGLADE, 2011; PEREZ; RAMIREZ; KERSTEN, 2008).

Several systems that implement logical induction have been used in specific musical applications, such as Aleph (SRINIVASAN, 2007), TILDE (BLOCKEEL, 1999) and PAL (MORALES, 1994). Such systems carry out the inductive process using languages like Prolog. Furthermore, cognitive theories have been applied in musical analysis, such as Narmor (SAKHARE; HANCHATE, 2014), aiming at understanding melodic structures.

Thus, the importance of conducting a survey is highlighted, considering approaches that apply ILP in the process of representing musical knowledge. This should investigate criteria and practices adopted, as well as the use of computational resources, as well as concepts involved in the field of Musicology. Such activity should provide evidence-based subsidies that lead to the design of guidelines in the elaboration of related works (KEELE, 2007).

This present work is an extension of GONÇALVES JR; HOMEM (2015), presenting a systematic literature review based on approaches that apply Inductive Logic Programming in the process of musical knowledge representation. The rest of the article is organized as follows: Section 2 describes the methodology used. Section 3 presents and analyzes the results related to the research questions. Section 4 concludes the paper, outlining the main conclusions reached.

2 METHODOLOGY

In order to carry out a survey of works that address the representation of musical knowledge through Inductive Logic Programming, a systematic literature review was prepared. The research methodology was applied according to criteria and recommendations presented in KITCHENHAM (2009). Two questions were raised to serve as a guideline for the work:

Q1: What architecture is proposed for the representation of musical knowledge?

Q2: How does the approach apply computational resources linked to ILP?

Thus, we sought to find approaches that enable the study of the technique in question. The steps taken to select the jobs are described below.

2.1 SEARCH STRATEGY

The search was carried out based on publications of academic papers, articles in scientific journals and participation in conferences. The following query bases were used:

- Academic Search Premier
- ACM Digital Library
- Cambridge Journals Online
- Computers and Applied Sciences
- Oxford Journals
- Computer and Information Systems
- SpringerLink
- Web of Science
- ScienceDirect
- SCOPUS
- IEEE Xplore
- Google Scholar

Regarding the research strategy, the work was based on the English and Portuguese languages. The main terms were listed according to the issues raised. The activities were carried out along the same lines as the approaches presented in (TOMAS, 2013; KHURUM; GORSCHEK, 2009; ABDALLA; DAMASCENO; NAKAGAWA, 2015; CHEN; BABAR; ALI, 2009). Only works carried out from 1990 onwards were considered, due to the fact that in that year the formalism of the First Order Inductive Logic (FOIL) was introduced (QUINLAN, 1990).

2.2 SEARCH STRINGS

Two initial expressions were taken as the basis for the search, emphasizing the musical element and inductive logic programming. Both were applied in conjunction with components aimed at representing knowledge. Next, equivalent literal expressions were added and pronunciation derivations added. The key elements for selection were joined by the "AND" operator and the alternative variations were connected by the "OR" operator. Thus, considering the two languages in question, the following search strings were created:

1. ("knowledge representation" AND musi*) OR ("musi* representation" AND knowledge) OR ("musi* knowledge" AND representation) OR (knowledge AND representation AND "computer musi*")
2. ("representacao de conhecimento" AND musi*) OR ("representacao musi*" AND conhecimento) OR ("conhecimento musi*" AND representacao) OR (conhecimento AND representacao AND "computacao musical")
3. "inductive logic programming" AND knowledge AND representation
4. "programação lógica indutiva" AND conhecimento AND representação

2.3 STUDY SELECTION

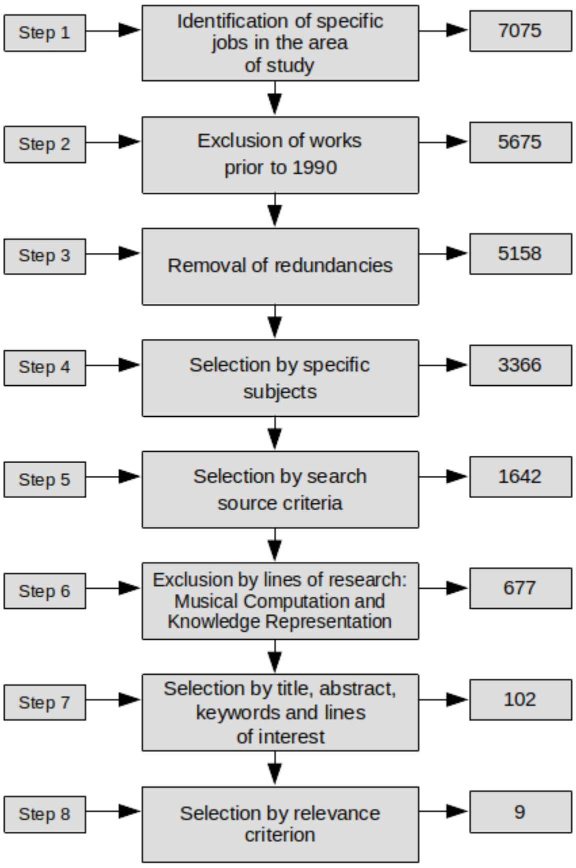
For the selection of studies, filters were applied in order to highlight the most important studies according to the proposed purpose. For an adequate refinement of relevant topics, the search was directed more specifically to the following subjects:

> Artificial intelligence, Expert systems, Automatic composer, Algorithmic composition, Music representation, Logic programming, Answer set programming, Prolog, Logical language, Automatic composition, Constraint programming, Declarative languages, Declarative system, Knowledge-based system.

Figure 1 shows the criteria used in the elaboration of the filters, as well as the number of works selected at each stage.

From an initial quantity of 7075 works, the number of 9 works to be studied was reached. The difference between these values is explained in KITCHENHAM (2009). Table 1 presents the approaches, each one received a numerical identification and a name formed by the first two words of the title.

Figure 1: Steps in the search strategy.



3 RESULTS AND ANALYSIS

Continuing the research and screening processes, the 9 selected approaches were analyzed from the point of view of the components relevant to the review. Fundamental elements as well as characteristic features were identified according to the basic questions. The following is a discussion of the approaches taken in relation to these issues. Considering the interrelationship between the raised components, some aspects will be analyzed along with their description.

3.1 WHICH ARCHITECTURE IS PROPOSED FOR THE REPRESENTATION OF MUSICAL KNOWLEDGE?

When dealing with elements related to musical representation through the computer, components such as symbolic notation, file formats, encoding resources, programming techniques and data abstraction have been applied at the information processing level. Additionally, the work involving musical knowledge representation addresses aspects related to programming paradigms and components linked to formal logics, in addition to efficient search and decision-making methods.

Table 1: List of reviewed studies.

ID	APPROACH	TITLE	REFERENCE
1	SymbolicRepresentation	Symbolic Representation of Chords for Rule-Based Evaluation of Tonal Progressions	Chong and Ding, 2014
2	ImprovingMusic	Improving Music Genre Classification Using Automatically Induced Harmony Rules	Anglade et al., 2010
3	ProbabilisticLogic	Probabilistic and Logic-Based Modelling of Harmony	Dixon et al., 2011
4	ApplicationILP	Application of ILP in a musical database: learning to compose the two-voice counterpoint	Pompe et al., 1996
5	LearningMusical	Learning Musical Rules	Morales and Morales, 1995
6	ExpressiveConcatenative	Expressive Concatenative Synthesis by Reusing Samples from Real Performances Recordings	Maestre et al., 2009
7	ConstructiveAdaptive	Constructive Adaptive User Interfaces - Composing Music Based on Human Feelings	Numao et al., 2002
8	ModelingMoods	Modeling Moods in Violin Performances	Perez et al., 2008
9	ModelingExpressive	Modeling Expressive Music Performance in Jazz	Ramirez and Hazan, 2005

SymbolicRepresentation (CHONG; DING, 2014) uses a rules-based system to incorporate the knowledge applied in the musical information interpretation process. The rules are formulated based on considerations such as displacement of the fundamental, movement of the bass and factors related to the conduction of the main voice. In order to model the movement of the harmonic field, the grammatical structure is represented by rules of current western musical theory. In contrast to traditional "if-then-else" algorithms, a decision tree structure is adopted, which allows for more efficient results.

Two main categories of rules are implemented. The first defines constraints in order to direct the focus of the inference process to specific sets of harmonic progressions. Thus, if there is a need to distinguish between chromatic and diatonic chords, you can create a rule that all chords in a progression must belong to the same key. The second category carries out harmonic considerations on the conduction of the main voice. In this case, a set of rules can be implemented to ensure proper handling of cadential chord resolutions.

The ImprovingMusic approach (ANGLADE et al., 2010) is focused on identifying music styles and genres. Harmonic progressions are handled using the sequential description of chords. Low-level audio descriptors are combined with a machine learning tool, which enables classification based on cadences. The sequences serve as a basis for training and are obtained inductively from automatic transcriptions.

In this way, it is possible to obtain a satisfactory performance in the classification of musical genres. A set of attributes is used in defining the representative parameters.

This set involves elements such as time and dynamics, in addition to the sound spectrum and pitch descriptors. Musical excerpts are represented by lists that incorporate the chords they contain. Genres are represented by sets of snippets. For each genre, we seek to find harmonic rules that describe characteristic sequences in chords present in the stored songs. These harmonic rules constitute a Context-Free Grammar.

Table 2: Structural elements in knowledge representation.

	1	2	3	4	5	6	7	8	9
Uses the MIDI standard			■			■	■		■
Performs analog data collection								■	■
Performs pre-processing		■							■
Performs additive synthesis						■			
Basic structure: melody						■			■
Basic structure: counterpoint				■	■				
Basic structure: harmony	■	■	■						
Integrated Technique: Genetic Algorithms							■		
Integrated Technique: Data Mining									■
Integrated technique: Stochastic processes			■						
Integrated Technique: Logical Constraints	■				■				
Polyphonic texture representation						■			

Only harmonic characteristics belonging to known genres are considered in this model. Thus, chords with purely ornamental purposes and sequences not characteristic of the styles maintained are disregarded. In this formalism, chords are represented by letters of the alphabet and labeled using cipher notation. Chord properties are described using logical predicates that return true or false values. Integrating to the inductive mechanism, some structural elements were used in the approaches. Such components were applied in order to compose the specific knowledge representation model. Table 2 presents these elements.

ProbabilisticLogic (DIXON; MAUCH; ANGLADE, 2011) presents two approaches aimed at harmonic modeling: probabilistic and logic. With this, it is possible to obtain both the category of musical knowledge, as well as the reasoning used by a musician when performing a similar task. Chords are transcribed from audio recordings. The system performs high-level musical context modeling. In this model, elements such as chords, clefs, metric positioning, bass note, chromatic characteristics and repetition structures are integrated in a Bayasian system.

The system produces the content of a master staff that contains a symbolic sequence representing chords. Each symbol includes key variations and modulations over time. In addition, he focuses on the logical description of harmonic sequences in order to characterize musical styles and particular genres. Harmonic relations are represented through the formalism of first-order logic. The approach is based on representations by decision trees, used to classify unvisited samples or provide suggestions regarding database characteristics.

ApplicationILP (POMPE; KOONONENKO; MAKSE, 1996) developed a tool with the purpose of carrying out the knowledge discovery process in a database with tens of thousands of instances. The system was implemented in such a way that the induction of a hypothesis is treated as an optimization problem. This approach is aimed at dealing with the problem involving the composition of the two-part counterpoint.

The application of machine learning techniques proved to be adequate for this subdomain of tonal music, which has imprecise characteristics, involving unconventional and demanding aspects from the point of view of accuracy. Two target predicates were used to represent prior knowledge from the universe of musical constants. Additionally, both positive and negative instances were trained, with the purpose of applying induction through rules.

LearningMusical (MORALES; MORALES, 1995) uses first-order logic to express counterpoint rules, allowing relations between musical states to be described in a compact and understandable way. The system performs the analysis from a finite set of well-established rules. The learning of rules is implemented through the PAL system (MORALES, 1994). This environment is powered by a subset of Horn clauses.

These clauses contain stored knowledge from two sources: samples and prior information, being in both cases expressed declaratively. PAL incorporates counterpoint rules and uses them in music analysis and note generation according to the *cantus firmus* conventions. In this way, a sequence of individual notes is used as the basis for applying the counterpoint rules. With this, new notes are generated according to the established harmonic restrictions. Through the PAL system, constraints can be used as guidelines in the search for hypotheses, both in the immediate context and in a more extensive way.

The ExpressiveConcatenative model (MAESTRE et al., 2009) performs expressive synthesis through the acquisition of knowledge obtained from audio recordings. From these recordings, samples of punctual notes are carefully concatenated, forming melodies with a body directed to their execution. The system seeks to produce an audio sequence from the analysis of scores. For this, it uses an inductive performance model, which is integrated with a database generated from real executions.

The approach applies the idea of using the same database in the main steps of the process. In this way, both in the introduction of the performance model and in the sound concatenation of the samples, the same knowledge base is manipulated. Thus, a connection is established during the synthesis process between the sound of the instrument being played and the characteristics modeled from this execution.

ConstructiveAdaptive (NUMAO; TAKAGI; NAKAMURA, 2002) deals with musical structures capable of causing characteristic human feelings. A system for automatic arrangement and composition was built, which generates musical pieces with the ability to produce specific feelings in a person. Initially, the system collects feelings from musical works.

Based on this information, musical structures are extracted that will serve as a basis for the production of feelings. With regard to musical generation, the system is directed towards two possibilities: making arrangements in pre-existing music and creating new compositions automatically. In both cases, the result produced has the capacity to produce previously determined feelings in an individual.

The approach of ModelingMoods (PEREZ; RAMIREZ; KERSTEN, 2008) is focused on the instrumental aspect of works performed on the violin. The system stores expressive patterns that are acquired automatically. Performs the modeling of interpretive aspects such as variations in time, dynamics and height. In addition, the model receives information related to gesture control, with emphasis on the direction of the arc and positioning of the fingers.

The system is based on four types of performative moods: Sadness, Happiness, Fear and Anger. There are two expressive characteristics analyzed: time and a set of note-level descriptors. These descriptors comprise qualities related to attack, duration, energy, bow direction and string being plucked. Both the note sequences and the expressiveness variations in the performance are defined in a structured way through first-order logic predicates. There are two groups of predicates to describe the musical context of each note and expressive variations.

Predicates for musical context define information about intrinsic properties of notes, including duration and metric position. They also store your predecessor and subsequent notes, as well as the length and direction of the intervals. Expressive variation predicates define the length factor of a note with respect to its duration on the staff.

Additionally, they have the ability to incorporate the change point in the direction of the bow, the string the note is played on, and the energy level in the performance.

In ModelingExpressive (RAMIREZ; HAZAN, 2005) the approach aims to investigate musical performance in Jazz melodies. Uses machine learning techniques to extract regular movements and performance patterns. Therefore, classification and regression methods are applied to databases obtained from real jazzy executions. Considering the regression methods, predictive precision is sought to generate good solutions from the point of view of accuracy. In the case of classification, its use is intended to provide an understandable description regarding the system's predictions. Regression-based models are introduced with the aim of implementing transformations that enable characteristic performances. The classification models are used to enable the understanding of the principles and criteria regarding the execution of musical excerpts.

3.2 HOW DOES THE APPROACH APPLY THE COMPUTATIONAL RESOURCES LINKED TO ILP?

The computational resources used involve mechanisms for logical induction, pre-processing tools, programming languages, theoretical conceptualization for perception and melodic cognition. Initially, the logical inference mechanism TILDE (Top-down Induction of Logical Decision Trees), (BLOCKEEL, 1999) is based on first-order logic and applies induction through decision trees. Its functionality is considered an extension to the C4.5 algorithm (SALZBERG, 1994), which instead of testing attribute values in nodes of a tree, tests logical predicates (MAESTRE et al., 2009). In this model, each tree addresses a specific classification problem.

In ImprovingMusic, rules describing harmonic patterns from a given genre can coexist with rules from other genres in the same tree. ProbabilisticLogic performs the description of chords in terms of their root note, scale degree, and interval categories between successive notes. The use of TILDE in ExpressiveConcatenative provides advantages in the sense of obtaining propositional decision trees with efficiency and pruning techniques, in addition to the use of first-order logic and the possibility of including prior knowledge in the learning process. ModelingMoods performs structured data mining through the inductive approach, applying the top-down algorithm to decision trees. The computational resources and tools used in each approach are presented in Table 3**.**

Table 3: Computational resources linked to ILP

	1	2	3	4	5	6	7	8	9
Aleph		■	■						■
C4.5									■
SFOIL				■					
Narmour						■		■	■
SMSTools									■
TILDE		■	■			■		■	
Pal					■				
JBoss Drools	■								
Induction from Prolog		■	■		■		■	■	■
Uses WEKA									■
Uses additional training base		■	■			■	■	■	■

The inductive logic programming system Aleph (A Learning Engine for Proposing Hypotheses), (SRINIVASAN, 2007) was developed with the purpose of exploring ideas expressed by Horn clauses with high representational capacity. Written in Prolog, it allows the description of complex expressions, simultaneously incorporating the acquired knowledge, with the ability to choose the order of generation of rules, change in the evaluation and search functions (CONCEIÇÃO, 2008).

In ProbabilisticLogic, these concepts are applied to find a minimum set of rules that is capable of describing the totality of positive samples and a minimum number of negative samples. These rules cover all 4-chord sequences, with each sequence being dealt with only once. ModelingExpressive uses its standard set manipulation algorithm to build individual hypotheses. In this way, Aleph uses the first unvisited positive sample as a seed for the search and covers the clause space according to a previously defined length constraint.

Namour is a theory for perception and cognition of melodies applied to music analysis. It helps to understand both the melodic meaning and the knowledge involved in its creation (SAKHARE; HANCHATE, 2014). ExpressiveConcatenative uses the implication/realization model of this theory, where each note belongs to a Namour structure. ModelingMoods uses the Namour context, where specific groups are defined with which a note maintains a membership relationship. ModelingExpressive makes extensive use of this concept, incorporating information about previous and successor notes, as well as intrinsic properties of intervals.

ModelingExpressive uses SMSTools (SALAMON, 2013) to perform preprocessing, creating a high-level description of audio recordings. It also generates an expressive sound according to transformations obtained by machine learning. This approach uses the C4.5 algorithm (SALZBERG, 1994) to obtain a set of classification rules directly from the generated decision tree. The rules mechanism applied in SymbolicRepresentation is based on JBoss Drools (LEY; JACOBS, 2011) which allows the operation according to pre-defined lines of development.

This mechanism uses the Rete algorithm (LIU; GU; XUE, 2010) to perform pattern matching. LearningMusical is based on the PAL system (MORALES, 1994) for logical learning. This system is used in the counterpoint analysis process to perform transition rules learning. Such rules are expressed in the form of Horn clauses from pairs of musical states (sets of notes), in addition to representing general purpose musical knowledge.

The FOIL system (QUINLAN, 1990) is an initial step towards obtaining efficient tools to deal with real world problems. It is considered a milestone in the field of ILP (POMPE; KOONONENKO; MAKSE, 1996; PATEL; OZA, 2014; KOSTER; SABATER-MIR; SCHORLEMMER, 2011). ApplicationILP uses the SFOIL (Stochastic FOIL) algorithm, this algorithm combines the efficiency of FOIL with the implementation of a stochastic search strategy. This approach uses an extensional representation of experiences, based on target predicates. Such representation enabled the knowledge discovery process in a database superior to 10,000 instances.

3.3 DISCUSSION

Some additional factors were raised from the directions applied by the approaches. Regarding the Musicology components discussed, the characterization of genre and style, applied to expressive performance, automatic composition and instrumentation, stand out. With regard to experiments and tests, considerations were made about computational complexity, benchmarks and accuracy evaluation, among others. Table 4 presents the elements discussed in relation to both concepts in Musicology and experiments and tests. Regarding the logical rules representation system, the use of the Prolog language is considered, whose importance stems from its strongly declarative aspect. The Prolog unification mechanism - whose inference process has imperative characteristics (GUIMARAES, 2015) - is activated in the background, due to the logical induction algorithms applied to it. In this sense, the Aleph and TILDE tools stand out. Both perform logical induction on Prolog predicates. The Narmor theory also stands out as an important descriptive resource.

Through this modeling, melodies can be expressed by lists of superimposed structures (Narmour sequences). The concept of Namour context allows the convenient representation of groupings, where one can express both the notion of successor notes and membership in specific groups.

Table 4: Musicology, experiments and tests.

	1	2	3	4	5	6	7	8	9
ELEMENTS OF MUSICOLOGY									
Style characterization			■						
Genre characterization		■	■						
Audio related analysis						■			
Melody/Harmony Analysis		■	■						■
Tonal functions	■					■	■		
Diatonic degrees	■	■							
Score representation							■	■	
Modal system					■				
Interactive processing	■		■						
Focus on expressive performance						■	■	■	■
Focus on automatic composition				■	■		■		
Focus on instrumentation						■		■	
Educational purpose	■								
EXPERIMENTS AND TESTS									
Computational complexity considerations		■				■			
Study by empirical processes		■							
Evaluation by musicians and non-musicians				■					
Performs benchmark			■	■		■	■		■
Performs beta test	■	■						■	
Performs complete tests		■		■				■	
Accuracy analysis		■	■			■		■	■

4 CONCLUSION

This present work allows the evaluation of works that perform the representation of musical knowledge through Inductive Logic Programming. The research methodology was described in the second section and the results were analyzed in the third section according to the research questions. A number of characteristics addressed by the works were identified, so that the review provides a view covering fundamental components in the representation of musical knowledge.

Regarding the architecture for knowledge representation, the fundamental importance of 3 elements was observed: declarative programming language, mechanism for implementing logical induction and integrated technique for knowledge acquisition. In this sense, the Prolog language stands out for its expressive characteristic, which, combined with an induction mechanism such as Aleph or TILDE, enables high representational capacity, in addition to simplicity in presenting such knowledge.

The methods involving genetic algorithms, logical constraints and data mining had analogous application by the approaches studied in relation to knowledge acquisition. It can be seen that the works analyzed are in different stages of validation. As is typical in this field, few considerations have been developed regarding computational complexity. Benchmark tests and accuracy evaluations were carried out, however, there was no study regarding targeting specific audiences, both lay and specialized. Similarly, no evaluations were performed from the point of view of human-computer interaction. In future studies, it is important to raise criteria aimed at a better understanding of such aspects.

REFERENCES

ABDALLA, G.; DAMASCENO, C. D. N.; NAKAGAWA, E. Y. A systematic literature review on systems-of-systems knowledge representation. 2015.

ALVARO, J. L.; MIRANDA, E. R.; BARROS, B. Ev: Multilevel music knowlegde representation and programming. SBCM, Belo Horizonte, Brazil, 2005.

ANGLADE, A. et al. Improving music genre classification using automatically induced harmony rules. Journal of New Music Research, Taylor & Francis, v. 39, n. 4, p. 349–361, 2010.

BALABAN, M. The music structures approach in knowledge representation for. Computer Music Journal. Citeseer, v. 20, n. 2, p. 96–111, 1996.

BLOCKEEL, H. Top-down induction of first order logical decision trees. Aicommunications, Ios press, v. 12, n. 1-2, p. 119–120, 1999.

CHEN, L.; BABAR, M. A.; ALI, N. Variability management in software product lines: a systematic review. In: CARNEGIE MELLON UNIVERSITY. Proceedings of the 13th International Software Product Line Conference. [S.l.], 2009. p. 81–90.

CHONG, E. K. M.; DING, Q. Symbolic representation of chords for rule-based evaluation of tonal progressions. 2014.

CONCEIÇÃO, J. P. D. The aleph system made easy. Integrated Master in Electrical and Computers Engineering, Faculdade de Engenharia da Universidade do Porto, 2008.

DELGADO, M.; FAJARDO, W.; MOLINA-SOLANA, M. A state of the art on computational music performance. Expert Systems with Applications, Elsevier, v. 38, n. 1, p. 155–160, 2011.

DIXON, S.; MAUCH, M.; ANGLADE, A. Probabilistic and logic-based modelling of harmony. In: Exploring Music Contents. [S.l.]: Springer, 2011. p. 1–19.

FERNÁNDEZ, J. D.; VICO, F. Ai methods in algorithmic composition: A comprehensive survey. Journal of Artificial Intelligence Research, p. 513–582, 2013.

GONÇALVES JR, C. B.; HOMEM, M. R. P. Representação de conhecimento musical e programação lógica indutiva - uma revisão sistemática. 15º Simpósio Brasileiro de ComputaçãO Musical – SBCM. NUCOM, 2015, pp. 138–141.

GUIMARAES, J. O. Programming languages paradigms. In: . [S.l.]: UFSCar Sorocaba, 2015. p. 96–114.

KEELE, S. Guidelines for performing systematic literature reviews in software engineering. In: Technical report, Ver. 2.3 EBSE Technical Report. EBSE. 2007.

KHURUM, M.; GORSCHEK, T. A systematic review of domain analysis solutions for product lines. Journal of Systems and Software. Elsevier, v. 82, n. 12, p. 1982–2003, 2009.

KITCHENHAM, B. et al. Systematic literature reviews in software engineering. Information and software technology, Elsevier, v. 51, n. 1, p. 7–15, 2009.

KOSTER, A.; SABATER-MIR, J.; SCHORLEMMER, M. Trust alignment: a sine qua non of open multi-agent systems. In: On the Move to Meaningful Internet Systems: OTM 2011. [S.l.]: Springer, 2011. p. 182–199.

LEY, E. D.; JACOBS, D. Rules-based analysis with jboss drools: adding intelligence to automation. Proceedings of ICALEPCS 2011, p. 790–793, 2011.

LIU, D.; GU, T.; XUE, J.-P. Rule engine based on improvement rete algorithm. In: IEEE. Apperceiving Computing and Intelligence Analysis (ICACIA), 2010 International Conference on. [S.l.], 2010. p. 346–349.

MAESTRE, E. et al. Expressive concatenative synthesis by reusing samples from real performance recordings. Computer Music Journal, MIT Press, v. 33, n. 4, p. 23–42, 2009.
MILETTO, E. M. et al. Introdução a computação musical. In: CBComp xCongresso Brasileiro de Computação, 4., Itajaí, 2004. "Anais...". Itajaí, SC - Brasil, ISSN 1677-2822. [S.l.: s.n.], 2004. p. 883–902. ISSN 1677-2822.

MINSKY, M. Music, mind, and meaning. Computer Music Journal, JSTOR, p. 28–44, 1981.

MORALES, E. Learning patterns for playing strategies. International Computer Chess Association Journal, Citeseer, v. 17, n. 1, p. 15–26, 1994.

MORALES, E.; MORALES, R. Learning musical rules. In: CITESEER. Proceedings of the International Joint Conference on Artificial Inteligence. [S.l.], 1995.

NUMAO, M.; TAKAGI, S.; NAKAMURA, K. Constructive adaptive user interfaces-composing music based on human feelings. In: Menlo Park, CA; Cambridge, MA; London; AAAI PRESS; MIT PRESS; 1999. Proceedings of the National Conference on Artificial Intelligence. [S.l.], 2002. p. 193–198.

PATEL, J.; OZA, B. A. Survey on graph pattern mining approach. In: IJEDR. International Journal of Engineering Development and Research. [S.l.], 2014. v. 2, n. 1.

PEREZ, A.; RAMIREZ, R.; KERSTEN, S. Modeling moods in violin performances. In: UniversitatsverlagG Der Tu, SMC 08: 5th Sound and Music Computing Conference: Sound in Space-Space in Sound, July 31st-August 3rd, 2008, Berlin, Germany: Proceedings. [S.l.], 2008. p. 30.

POMPE, U.; KONONENKO, I.; MAKSE, T. An application of ilp in a musical database: Learning to compose the two-voice counterpoint. Citeseer, 1996.

QUINLAN, J. R. Learning logical definitions from relations. Machine learning, Springer, v. 5, n. 3, p. 239–266, 1990.

RAMIREZ, R.; HAZAN, A. Modeling expressive music performance in jazz. In: FLAIRS Conference. [S.l.: s.n.], 2005. p. 86–91.

ROADS, C. Research in music and artificial intelligence. ACM Computing Surveys (CSUR), ACM, v. 17, n. 2, p. 163–190, 1985.

SAKHARE, Y. N.; HANCHATE, M. D. Comparative study of musical performance by machine learning. International Journal on Recent and Innovation Trends in Computing and Communication, ISSN 2321-8169, v. 2, n. 2, p. 347–352, 2014. ISSN 2321-8169.

SALAMON, J. Melody extraction from polyphonic music signals. Tese (Doutorado) — Ph. D. thesis, Department of Information and Communication Technologies Universitat Pompeu Fabra, Barcelona, Spain, 2013.

SALZBERG, S. C4.5: Programs for machine learning. Morgan kaufmann publishers, inc., 1993. Machine Learning, ISSN 0885-6125, Kluwer Academic Publishers, v. 16, n. 3, p. 235–240, 1994. ISSN 0885-6125.

SRINIVASAN, A. The Aleph manual: version 4 and above. 2007.

TOMAS, G. H. et al. Smart cities architectures-a systematic review. In: ICEIS (2). [S.l.: s.n.], 2013. p. 410–417.

WHALLEY, I. International computer music conference 2004: Papers. In: Proceedings International Computer Music Conference, Miami, ICMA Press. [S.l.]: JSTOR, 2005.

WIGGINS, G. A.; SMAILL, A. Musical Knowledge: what can Artificial Intelligence bring to the musician? 2000.