Dynamic Music Lessons on a Collaborative Score Annotation Platform

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***Abstract* - The recent progress in Information and Communication Technologies gave birth to advanced applications in the field of instrumental e-learning. However, most of these applications only propose a limited number of lessons on predetermined pieces, according to the vision of a single music expert. Thus, this article introduces a web platform to create music lessons dynamically and collaboratively, with the assistance of a semi-automatic score annotation module: @-MUSE. To do so, we first describe a new methodology to design such a platform: Sign Management. Then, we detail its general architecture as an Iterative Sign Base System based on a common practice in music learning: score annotation. Lastly, we give various algorithms to generate relevant annotations (explanations) on a score, based on the analysis of musical patterns difficulty.**

Keywords - e-learning; music; knowledge management; sign management; multimedia; annotation; semantic web; ontology; digital score; piano; human-computer interaction; logic; inference

I. Introduction

Information and Communication Technology for Education (ICTE) expanded rapidly these last years. Indeed more and more teachers resort to platforms such as Moodle or Blackboard to design their own online courses. While this trend is being confirmed in academic subjects such as mathematics and languages [7], it remains rare for know-how transmission and sharing, for instance in the field of music learning. Indeed, know-how transmission requires heavy multimedia usage and interaction to show the "correct gesture" and is thus complex to implement.

Some instrumental e-learning solutions exist in the form of offline tools, such as instructional DVDs (see the technical report of E-guitare [16]), or business software (Guitar Pro [17], Garage Band [18]). Nevertheless, getting a feedback is capital in know-how acquisition (is my gesture or fingering correct ?). But few applications try to implement a learner to teacher communication axis through video upload and commentaries on the web (see the FIGS [19] glosses system).

Still, the lessons provided by these platforms remain limited to a fixed list of pieces. Although a student can suggest a new title, the realization of a whole lesson on these platforms requires heavy installations and treatments (multi-angle video recording, 3D motion capture), as well as the intervention of multiple actors other than the teacher himself. While these methods produce high quality teaching material, the realization of a new course remains a complex and expensive process. In parallel, several teachers, for instance retired experts, wish to transmit their know-how in a simple way, without any constraint on the recording location and time and with minimal tool appropriation.

We thus introduce in this paper a complementary framework to rapidly create dynamic music lessons on new pieces with the assistance of a score annotation module.

This framework is implemented on a collaborative score annotation platform for music learning called @-MUSE (Annotation platform for MUSical Education). As described in [11], an online annotation system is chosen because it allows musicians to work with digital scores in a way similar to traditional lessons, where scores are a support for memory and information sharing. In addition, the digital transposition of this common practice enables to enrich it with multimedia incrustation, collaborative working and mobility. As such, its aim is also to constitute a scalable music playing knowledge base to collect and share tips and performances on all possible artistic works referenced on music data warehouse such as MusicBrainz.org [20], and which can evolve according to the learners' needs. This base is called ISBS (Iterative Sign Base System).

In this paper, we first introduce the methodology and principles of Sign Management that supports this platform. Then, we describe the general architecture of @-MUSE, based on Semantic Web concepts, in order to constitute a musical sign base (ISBS). To assist users into feeding and exploiting this base, we describe various methods to generate relevant annotations (i.e., explanations) on a score. Lastly, we conclude this work by detailing its principal perspectives: an adapted tactile interface and some serious gaming aspects.

II. Methodology : Sign Management

Sign Management deals with the management of know-how rather than knowledge. It manages live knowledge, i.e., subjective objects found in interpretations of real subjects on the scene (live performances) rather than objective entities found in publications (bookish knowledge). A Sign is a semiotic and dynamic object issued from a Subject and composed of three parts, Data, Information and Knowledge. All these subjective components communicate together to build a chain of sign-ifications that we want to capture.

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Sign management is thus more central than Knowledge management for our purpose in instrumental music learning. Indeed, the musical signs to treat are made of emotional content (performances), technical symbols (scores) and tacit knowledge (rational and cultural know-how). Thus, a Sign is the interpretation of an object by a subject at a given time and place, composed of a form (Information), a content (Data) and a sense (Knowledge). The sign management process that we have created is made on a Creativity Platform for delivering an instrumental e-learning service [10][4][5]. It is founded on an imitation and explanation process for understanding gestures that produce a right and beautiful sound. The advantage for learners is that we are able to decompose the teacher's movement and understand the instructions that are behind the process of playing a piece of music. In fact, a lovely interpretation is made of a lot of technical and motivated details that the learner has to master, and the way we want to deliver this information is to show examples from experts through multimedia annotations indexed on the score. To do so, we introduce a new platform to design dynamic music lessons through multimedia annotations: @-MUSE.

III. @-MUSE GLOBAL ARCHITECTURE

As the aim of @-MUSE is to enable dynamic teaching and learning, it is capital that its architecture remains flexible. The usage of Semantic Web tools is thus an appropriate lead to allow the platform to benefit from a "networking effect". Indeed, a significant amount of scattered musical resources already exist on the web and can be relevant in the context of music lessons. These resources can be music metadata (MusicBrainz.org), digital scores (images, PDFs, MusicXML free or proprietary files available on Werner Icking Archive [21]), multimedia documents (recordings of video performances and lessons on YouTube [22] or eHow [23]) or simple textual comments. They constitute the different sign components listed in part II: data, information and knowledge. As many of these resources benefit from a Creative Commons License [24], they can be used in the context of a music lesson, complementary to high quality resources from a professional multimedia capture set [5]. Figure 1 exposes a comparison between traditional instrumental e-learning applications architecture and @-MUSE architecture. In the first case, lessons are defined in a static way. Each lesson correspond to a musical piece, with its associated resources : video, audio and image files synchronized together to form the lesson. While this system produces complete lessons, it cannot establish relations between two distinct resources or pieces, which is an essential point when learning music as a whole. In the second case, @-MUSE dynamically creates lessons by linking related resources and presenting them to the user in an adapted interface [11]. If a resource is not available (for instance, a logic representation of a score), the system still works with a temporary replacement (for instance a simple image representing the score) in the frame of a degraded mode. It can then point to any user the need to provide such resource to enable new functionalities on the platform. As more links are created between resources, different representations of the same piece can be proposed to learn

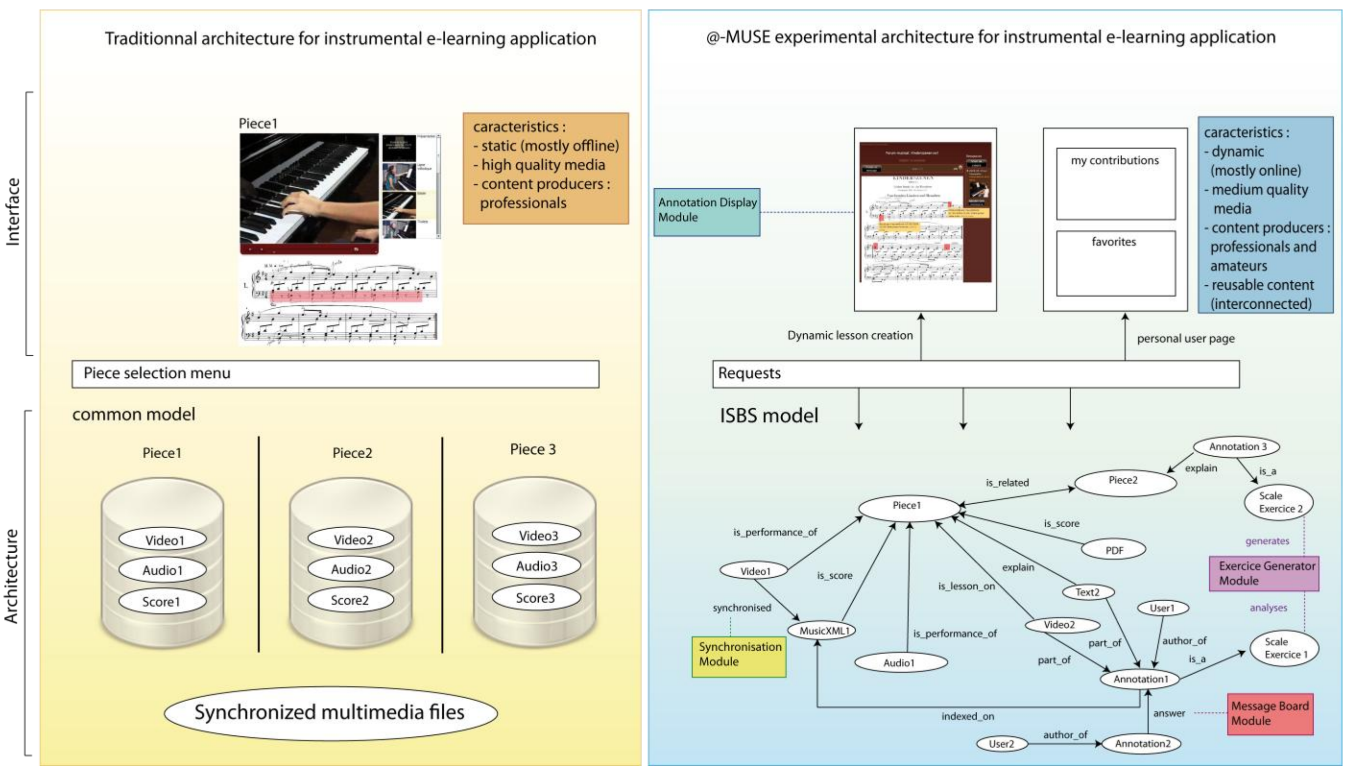


Figure 1. Architecture comparison between traditional instrumental e-learning application and @-MUSE

how to play it. Some links such as a time synchronization between two representations (i.e., a video performance and a logical description of the score) can be realized by specific independent modules (see Figure 1).

We have done previous work in [12] to propose an adapted ontology to link musical resources in an educational context using the Resource Description Framework (RDF [8]).

In the end, the association of these elements will allow the creation of an Iterative Sign Base System in the same vein as IKBS (Iterative Knowledge Base System [3]). The difference here lies in the manipulation of semiotic objects (signs), instead of conceptual ones (knowledge), as described in part II. The following chapter explains how new signs can be generated on this platform through semi-automatic score annotation, and thus participate in the enrichment of the sign base (ISBS) by demanding minimal efforts from the platform users.

IV. INFERENCE ON DIGITAL SCORES

ISBS is a sign base model designed to collect musical signs such as scores (model) and performances (cases), in order to explain and compare them. To realize such analysis in a semi-automatic way, we need to detect specific patterns within a score. This detection could be made directly on performances [14] but audio signal analysis algorithms are difficult to implement in a web application and may be unreliable in an educational context. That is why we rely on XML representations of a score. MusicXML [1] is an XML open source format to describe digital scores staff by staff, measure by measure, and lastly note by note (Figure 2).

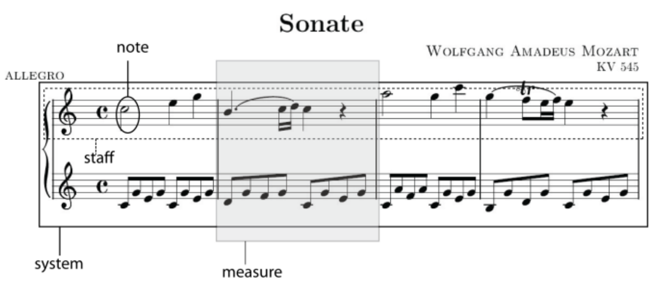


Figure 2. Score logical structure

In what follows, we review and propose different methods to extract various playing information from a piece metadata and structure.

We base these methods on how a pianist would address an unknown piece. As detailed in the descriptive model presented in [12], the musical work is first replaced in its context (composer, period, form). Then, its difficulty is evaluated, firstly globally, and then part by part, in order to determine what type of work can be made on this piece and where.

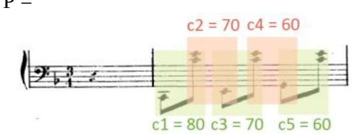
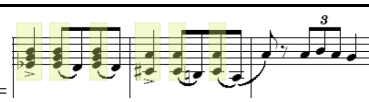
Thus, the first playing related information we display on a new piece is an approximation of its difficulty. In TABLE 1, we propose seven criteria affecting the level of a piece for piano and detail how they can be estimated from a MusicXML file. Globally, a piece difficulty depends on its tempo, its fingering, its required hand displacements, as well as its harmonic, rhythmic and polyphonic specificities. Of course, these various criteria affect each other in a complex manner. For example, hand displacement is strongly affected by fingering, as noted in TABLE 1.

Indeed, among these seven criteria, fingering plays an important role. Several works present methods to automatically deduce fingering on a given musical extract for piano ([2][9][6]). Most of them are based on dynamic programming. All possible fingers combinations are generated and evaluated, thanks to cost functions. The latter are determined by kinematic considerations. Some functions, like in [6], even consider the player's hand size to adjust its results. Then, expensive (in term of effort) combinations are suppressed until only one remains, which will be displayed as the resulting fingering. While the result often differs from a fingering determined by a human professional, it remains largely playable and exploitable in the frame of an educational usage. However, few algorithms can process polyphonic extracts [6], and many other cases are ignored (i.e., left hand, finger substitutions, black and white keys alternation).

Even if more work is needed on this issue, the use of cost functions remain relevant as it is close from the process humans implicitly apply while working on a musical piece. That is why we extend this idea and create complementary criteria to design a piece difficulty analyzer for piano learning. For each criterion described in TABLE 1, a score is calculated in percentage. The piece difficulty rate is thus the average rate of each criterion. Furthermore, some weighting coefficients can be affected to each criterion to reflect the particularities of the player. For instance, pianists who are really at ease with polyrhythm would not consider it a relevant factor, thus affecting it a 10% weight.

However, we insist that the resulting difficulty rate should be interpreted with care and remains a simple approximation. As stated in [15], a pleasant performance is not a mere addition of criteria since it contains an important subjective part. Moreover, for the time being, the algorithms we propose remain bold and need some specific refinements which will be the object of a next paper. Indeed, some cost functions are applied measure by measure, while they should be applied phrase by phrase to remain coherent with the piece logic. Also, some of the parameters were determined after the practices of a small group of advanced pianists and need to be extended by working with a larger sample of musicians, including other instruments.

TABLE 1. PLAYING DIFFICULTY CRITERIA IN PIANO PRACTICE

Performance difficulty criterion	Musicological definitions	Cost function definition	Examples	MusicXML implementation
Playing speed	Tempo: speed or pace of a musical piece. May be indicated by a word (ex: allegro) or by a value in BPM (Beats Per Minute) Pulsation: reference value indicated in the tempo : 𝅝 = 1, 𝅗𝅥 = 2, ♩ = 4, ♪ = 8, 𝅘𝅥𝅯 = 16, etc.	Playing speed = tempo / (shortest note value in the piece) Unit: beats (time value)	P1: tempo = 120 ♪ Shortest value = 𝅘𝅥𝅯 P1 playing speed = 120*8/16 = 60 P2: tempo = 120 ♩ Shortest value = 𝅘𝅥𝅯 P2 playing speed = 120*4/16 = 30 Conclusion: Some parts in P2 are played faster than in P1. To be more accurate, it is possible to multiply the result by the proportion of notes of shortest value. Thus, if P1 contains 40% 𝅘𝅥𝅯, and P2 only 5%, then P1 is globally faster.	<note><type> elements Tempo attribute in <sound> element
Fingering	Fingering: choice of finger and hand position on various instruments. Different notations exist according to the instrument. (Ex: in piano: 1 = thumb, 2 = index finger, 3 = middle finger, etc.)	If m1, m2, ..., mn represent the measures of a given piece P, Fingering_difficulty(P) = ∑ (Fingering_cost(mi)>50) See [2][6][9][13] for more detail.	P =  Fingering_cost(m1) = 10 Fingering_cost(m2) = 0 Fingering_cost(m3) = 70 Fingering_difficulty(P) = 70	<measure> and <note> elements
Hand Displacement	Interval: pitch distance between two notes, in semitones. A hand displacement is considered difficult when two successive notes (or two chords) are spaced by at least 7 semitones, played by close fingers (on the same hand, distance < 4 fingers) at a high tempo. The displacement cost of an interval increases with its gap length. It also increases with polyphony.	If d1, d2, ..., dn represent n intervals verifying the conditions given in the previous description, in a piece P Displacement_difficulty(P) = ∑ Displacement_cost(di)	P =  Displacement_difficulty(P) = 340	Combined <note> elements where <pitch> gap ≥ 7. Associated fingering file.
Polyphony	Chord: aggregate of musical pitches sounded simultaneously.	Proportion of chords and chords sequences in the piece	P =  Chords_proportion(P) = 6/16 = 38%	<chord> element
Harmony	Tonality: system of music in which specific hierarchical pitch relationships are based on a key "center", or tonic. Various tonalities impose various sharps and flats as a key signature. The most basic ones (no alteration) are A minor and C major.	Proportion of altered notes	P =  Altered_notes_proportion(P) = 3/25 = 12%	<alter> and <accidental> elements
Irregular Rhythm	Polyrhythm: simultaneous sounding of two or more independent rhythms. Example : synchronizing a triplets over duplets	Proportion of remarkable polyrhythm patterns (Time reference = pulsation)	P =  Polyrhythm_proportion(P) = 4/4 = 100%	<time-modification> element
Length	The length of the piece in beats. NB: the number of pages cannot really reflect the length of a piece because of page setting parameters	Number of measures * number of beats per measure.	P =  Length(P) = 3*3 = 9	<beats> element of <time> element and <measure> elements

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This algorithm also serves as a base for the next chain of information inference on the given piece. Indeed, it can be applied to identify difficult parts within the piece. By calculating the difficulty rate of each measure, we can display the remarkable parts, which rate exceeds a given threshold (determined by the player's level). The cause of its difficulty can then be deduced from the rates of each criterion (Figure 3). The application can then annotate the part accordingly, for instance by redirecting the learner to an adapted exercise.

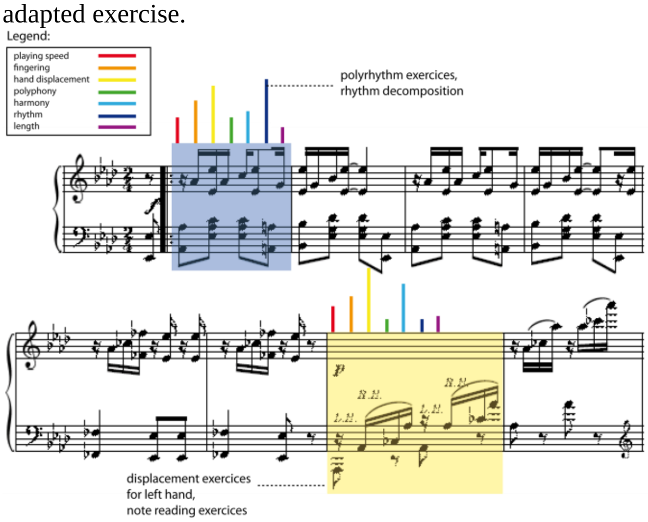

Figure 3. Difficulty analysis and recommendations on a digital score

In parallel to difficult parts, other remarkable structures can be identified within a piece. Indeed music learning relies a lot on the repetition of specific short patterns, with slight differences (for example the tone of a piece), which can be reused in various context, especially within the same genre (baroque, classical, jazz, etc). TABLE 2 gives some patterns examples.

TABLE 2. MUSICAL PATTERNS EXAMPLES

Pattern name	Example
Scale	
Arpeggio	
Trill	
Real sequence	

If long enough (and thus actually remarkable), each of these patterns can be detected as a note sequence within a MusicXML file. Then, corresponding exercises can be pointed to guide the learner. These exercises can be directly adapted from the considered pattern. For instance, in the case of an arpeggio, the latter will be extended to the whole keyboard and repeated part by part, by adding a new note every ten repetition. This process can easily be computed as suggested by Figure 4. Anytime, the annotation's owner and teachers can modify it in order to improve the given explanation with textual and video commentaries, symbols and tags. Users can also invalidate the generated annotation if considered as inappropriate. In this case, the motive for the suppression should be specified. This data will be later used to determine the reasoning error in order to improve the next generated annotations. This process will be detailed in an upcoming paper.

V. CONCLUSION AND PERSPECTIVES

In this paper, we proposed a methodology (Sign Management), a model (Iterative Sign Base System) and some inference methods to build an instrumental e-learning platform called @-MUSE. This platform allows teachers and learners to create music lessons dynamically with the assistance of a semi-automatic pieces annotator. These lessons can evolve according to the users' needs by submitting contextual exercises to them, in the form of multimedia annotations. These exercises are generated from the original score based on the identification of remarkable patterns and their playability. Users can then give their point of view on the generated annotations but also add new ones, thanks to a dedicated symbols library as well as a multimedia capture module. The more knowledge is created on the platform, the more detailed will be the lessons, thanks to the emerging network effect resulting from the semantic linking of the various resources.

Different perspectives are also considered for this work, including the addition of tactile functionalities, as well as some serious gaming aspects. For instance, an interface adapted to tablet PC would allow to use our platform directly in front of the instrument, guaranteeing an experience close to a traditional music lesson. The collaborative aspects of such a platform also need to be studied to approach music learning under an entertaining angle, for instance by proposing specific group performances (Global Sessions [25]) and game features. Indeed, as implied by our platform's name, learning music should first and foremost be a pleasure.

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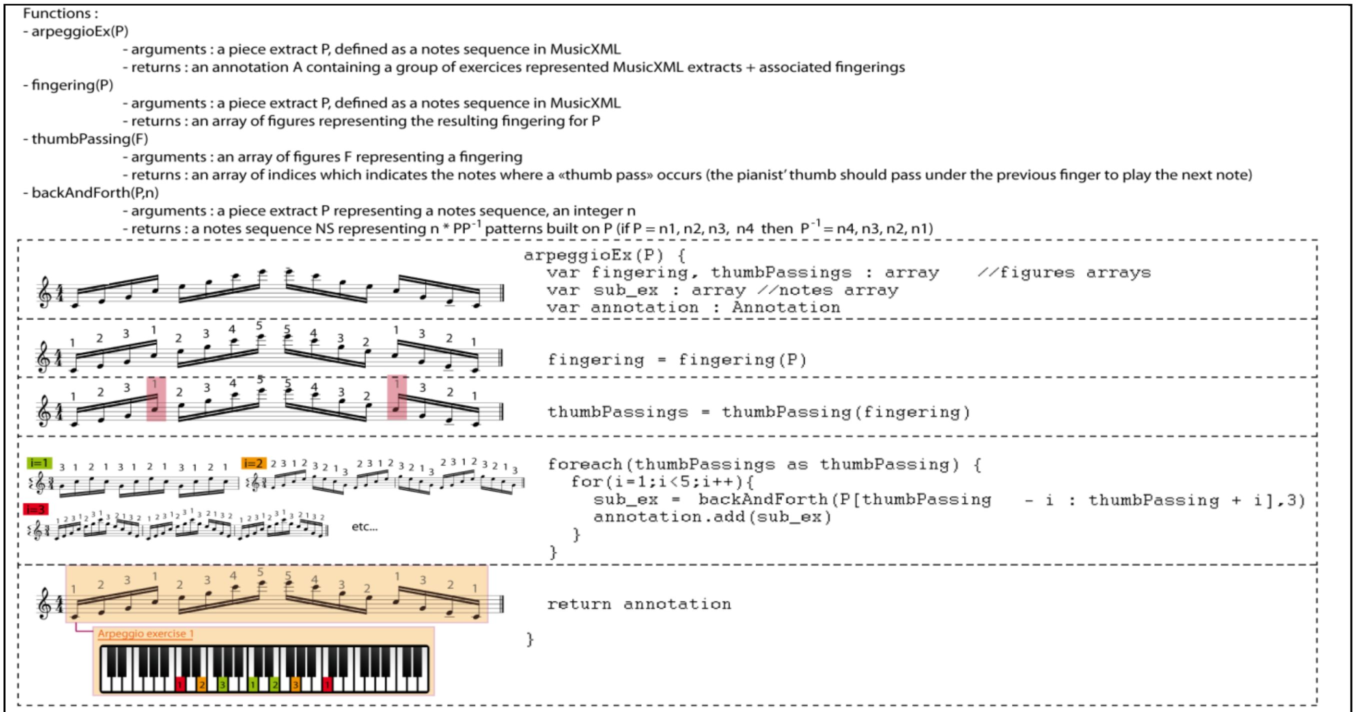

Figure 4. Pseudocode algorithm generating progressive arpeggio exercises

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