AI-Rmonies of the Spheres

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Abstract. Thanks to the efforts and cooperation of the international community, nowadays it is possible to analyze astronomical data captured by the observatories and telescopes of major space agencies around the world from a personal computer. The development of virtual observatory technology (VO), and the standardization of the formats it uses, allow professional and amateur astronomers to access astronomical data and images through internet with relative ease. Immersed in this environment of global accessibility, this article presents an astronomical data-driven unsupervised music composition system based on *Deep Learning*, aimed at offering an automatic and objective review on the classical topic of the *Harmonies of the Spheres*. The system explores the MILES stellar library from the Spanish Virtual Observatory (SVO) using a variational autoencoder architecture to cross-match its stellar spectra via *Pitch-Class Set Theory* with a music score generated by a LSTM with attention neural network in the style of late-renaissance music.

Keywords: Deep Learning · LSTM · Sonification · Music · Astronomy.

1 Introduction

The Universe, understood not only as a source of inspiration but also as a source of musical harmony, has occupied the mind of mathematicians, musicians and astronomers from the times of ancient Greece. Updating this concept to the current available technology, the connection of different astronomical data streams with the generation and control of sound variables, opens a wide window of possibilities for Sound Design and Music Composition. This work explores the potential in the use of *Deep Learning* techniques to provide an unsupervised perspective of the classical concept of the *Music of the spheres*, focused around the figure of one of its biggest names, Johannes Kepler, and what was understood as music during the writing process of his treatment *Harmonices Mundi*, published in 1619, and containing his third law for planetary motion.

In summary, this work converts the almost 1000 stellar spectra of MILES stellar library from the Spanish Virtual Observatory (SVO) into a data base of "stellar chords", using a variational autoencoder architecture. These chords are cross-matched with the musical chords generated by a LSTM with attention neural network trained with over 1000 scores of music from the Italian composer Giovanni Pierluigi da Palestrina (1525-1594), considered one of the leading composers in Europe of late 16th-century. Finally, the spectral music composition driven by the style of Palestrina is generated with the "matched chords", that is, the musical chords present in the stellar chords library, or in a similar way, the stellar spectra auditory representations that fit the sounds of those times.

2 Concepts of interest

Exploring the intersections between Music and Astronomy using Artificial Intelligence requires a quick overview of the historical framework as well as some useful definitions before delving into the technical details of the research.

2.1 Brief History of astronomical harmonies

It seems agreed to mention Pythagoras (VI century BC) and his *Music of the spheres*, as the first work of practical and theoretical reference in the field of Music and Astronomy. According to the ethnomusicologist Mark Ballora, the demonstration carried out by the Pythagorean school on the mono-chord of the relationships between intervals of perfect fifths and the distances to the earth of the bodies that at that time were believed to orbit around it, can also be seen as the first evidence on astronomical data sonification [1]. This idea of relating musical intervals to the distances and orbital velocities of the planets transcends from antiquity to Renaissance from the hand of Plato and Aristotle. Regarding Plato, through two main sources: *The myth of Er* and *The passage of Timaeus*, both belonging to his ten-volume work *The Republic* [2]. Regarding Aristotle, through his clear description of the theory of the harmony of the spheres in *De caelo* 290 b12 and in 291a 8, in which he affirms that this concept is Pythagorean [3]. However, and despite the fact that little is known with certainty about the Pythagorean doctrines, authors specialized in Greek theories of the harmony of the spheres such as Von Jan (Jan, V. 1893, cited in [2], p.23), point out that the astronomical references of the Pythagorean school should be interpreted as simple analogies and not as an astronomical theory due to their limited knowledge on the subject

In the second century A.D., Ptolemy also outlined the concepts of harmonies of celestial bodies in his book *Harmonics*, describing them as mere rational connections obeying the general laws of motion. For Ptolemy, ordered movement, both in the stars and in music, follows certain patterns so that the study of these patterns in one field can help in the understanding of other fields [2].

The writings of Boethius (480-524 AD) on Aristotelian logic and the *Quadrivium*, had a very influential role in the dissemination of Pythagorean musical theories during the Middle Ages. Since the beginning of the sixth century, Arithmetic, Geometry, Astronomy and Music, understood as the science of numbers that describe sound, represented the four main fields of quantitative science.

The term *Quadrivium* was used to group these disciplines, considered as the four branches of Mathematics, capable of describing the knowledge of the natural world. Boethius established a tripartite classification of music -Mundane, Human and Instrumentalis-, which implied the acceptance of planetary relations with musical intervals from an apparently continuist position. *Mundane music*, referring to the harmony of the spheres of heaven, *Human music* dealing with the influence of music on the human soul and *Instrumentalis music*, what we currently know as music [2].

During the fifteenth century, humanists such as Coluccio Salutati or musicians such as Johannes Tinctoris rejected the idea of the existence of worldly or Mundane music, while music theorists such as Franchino Gaffurio claimed that it could only be heard by true virtuous people.

At the end of the sixteenth century, in an attempt to describe music in its entirety, Gioseffo Zarlino published the treatise *Istitutioni harmoniche* (1558), which extended the Pythagorean harmonic theory, and was the frame of reference for the musical theory of that time.

Far from the mysticism of the ancient Greeks, Ptolemy's approaches together with the discoveries of the empirical bases of the musical consonances of Vizenzo Galilei -father of Galileo- in his *Dialogo della musica antica, et della moderna* (1581), would inspire the work *Harmonices Mundi*, in which Johannes Kepler exposes how the planets move describing an elliptical orbit around the sun. The book was published in 1619, and it is considered the masterpiece of the interdisciplinary musical-astronomical thought. In *Book V* of this treatise, Kepler translated the parameters of motion and distance of the planets of the solar system into musical intervals, something that apparently led him to formulate the equation that allowed him to lay the foundations of astronomy. Analyzing his work as a model of planetary sonification, Kepler used the distances of aphelion and perihelion to obtain the relationships of musical intervals, matching angular velocities with frequencies and anticipating the identification of the concepts of frequency and height of a sound, made by Mersenne in his law of *L'harmonie universelle* [4]. In Kepler's own words, '*Astronomy and Music are various nationalities of the common homeland, Geometry*' (Kepler, 1619, quoted in [5]).

2.2 Sonification and Data-Driven Music

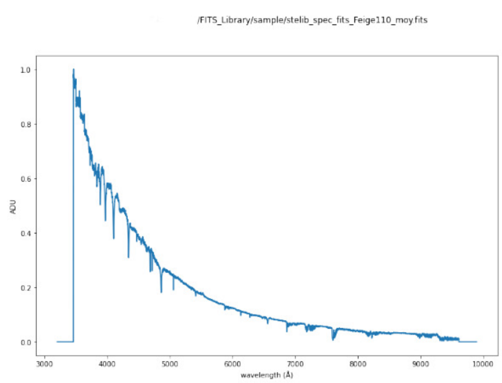
As defined by Herman [6], 'a technique that uses data as input, and generates sound signals (eventually response to optional additional excitation or triggering), may be called sonification, if and only if (C1) The sound reflects objective properties or relationships in the input data. (C2) The transformation is systematic. This means that there is a precise definition provided of how the data (and optional interactions) cause the sound to change. (C3) The sonification is reproducible: given the same data and identical interactions (or triggers) the resulting sound has to be structurally identical. (C4) The system can intentionally be used with different data, and also be used in repetition with the same data'.

Trying to maintain the accuracy of this definition in the use of terminology, we should also remark the main differences between Sonification and Data-

Driven Music. Understanding Musification as the musical representation of data and according to Scaletti [7], 'perhaps the most important distinction between sonification and music is the difference in intent. The goal and purpose of data sonification is to aid in understanding, exploring, interpreting, communicating, and reasoning about a phenomenon, an experiment, or a model, whereas in sound art, the goal is to make an audience think by creating a flow of experience for them'. In this sense, the methods here described for unsupervised generation of music and scores should be considered under the Data-Driven Music paradigm, although the auditory exploration of stellar catalogs based on *Deep Learning* is also being used by the authors in scientific oriented approaches.

2.3 Stellar spectra

Commonly used in star classification, a stellar spectrum is a two-dimensional graphical representation of the flux variations of the brightness of a star as a function of wavelength. It contains information used in the characterization of stars as, for instance, their effective temperature, luminosity and chemical composition. The *MK* system and the *OBAFGKM* temperature sequence of spectral types of stars are based in the detailed analysis of the absorption and emission lines revealed in these curves [8].

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CD1_1   =      1.0000000000000 /
LTM1_1  =                   1.
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WAT1_001= 'wtype=linear label=Wavelength units=Angstroms
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Fig. 1. Stellar spectra (left) and *FITS* file header fragment (right) of *Feige 110* star. STELIB library, Spanish Virtual Observatory (SVO) [9].

Stellar spectra are common data products publicly available in the standard *Flexible Image Transport System (FITS)* [10] files, that also provide identification metadata -as shown in *Figure 1*-, including the name of the object, its position marked by right ascension and declination, the physical units, length and resolution of the axis, the date, and the instrument or mission of the observation. All the information about this kind of data can be found in documents like the *Kepler Data Characteristics Handbook* [11] and the *MAST Kepler Archive Manual* [12, 13].

3 Unsupervised auditory exploration of stellar catalogs

Providing an additional auditory dimension -understood as a complementary way of exploration- to the current graphical display systems for the virtual observation and analysis of astronomical data, opens up endless opportunities to be used in both, research and creative processes. The development of user-oriented tools focused on this dual role also represent a field of undoubted application for improving the accessibility of stellar catalogs, spectra and light curve databases for blind and visual impaired (BVI) users.

3.1 Autoencoders

Deep Learning is a subset of *Machine Learning* in which multilayered neural networks learn from a representative set of population data. Inside this category, *autoencoders* represent one of the unsupervised learning algorithms used to identify relationships within data.

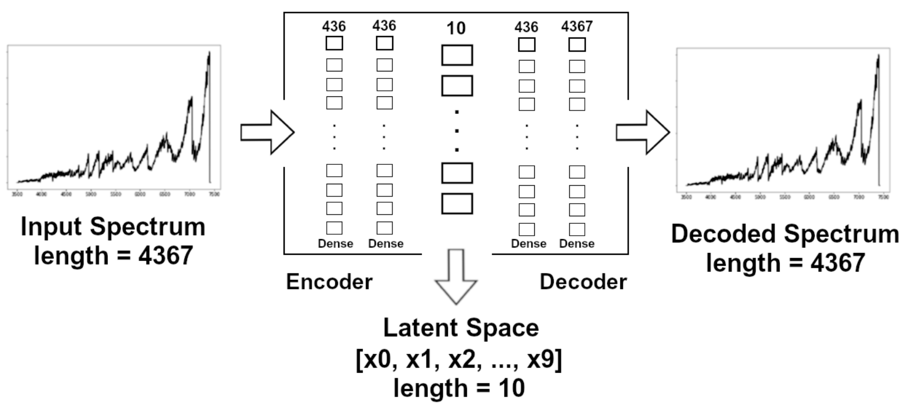

Fig. 2. Illustration of an autoencoder structure applied to stellar spectra input data. For the reduction of the 4367 values of each spectrum into a 10 axes latent space tensor, the encoder uses two hidden layers with 2,099,350 parameters. For the reconstruction of the decoded spectrum, the decoder uses two hidden layers with 1,913,175 parameters.

As defined by Goodfellow et al. [14] *'an autoencoder is a neural network that is trained to attempt to copy its input to its output'*. It is composed of two modules, an *encoder* and a *decoder*. Both are feed-forward neural networks with a variable number of hidden layers. *Figure 2*, presents an example of this architecture in which the *encoder* takes the input and compresses it to a lower-dimensional representation called the *latent space*. From this compressed representation, the *decoder* attempts to reconstruct the original input. The model is designed to be unable to learn to copy perfectly, being forced to prioritize which aspects of the input should be copied. This restriction makes the architecture to learn useful properties of the input data. *Figure 3* shows the deviation between original and decoded spectra measured by the R^2 coefficient, which provides a value between 0 and 1 that represents the variance of the decoded output related to the variance of the original spectrum.

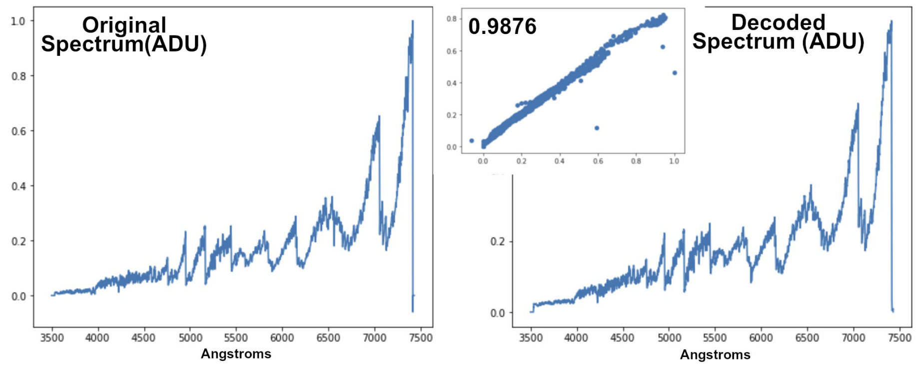

Fig. 3. Example using a 4D variational autoencoder. Original spectrum (left), deviation with R^2= 0.9876 (center), and decoded output (right) for HD 017491 star with coordinates RA:02:47:55.90 and DEC:-12:27:38.16. MILES spectral library (SVO).

On the other hand, *'variational autoencoders have the added constraint that the encoded representation, the latent variables, follow some prior probability distribution. Usually, a Gaussian distribution is chosen for its generality'* [15]. In this approach, the encoder develops a conditional mean and standard deviation re-parameterized by an epsilon term -distributed normally-, to build the distribution of latent variables. In addition to the reconstruction loss function, *variational autoencoders* incorporate a *KL* loss function to maintain the shape of the latent distribution close to the normal. This feature is known as *manifold learning* or *representation learning* and provides a simple way of generating new realistic inputs by sampling the normal distribution of the latent space and decoding those values to obtain a synthetic output.

3.2 Sequential *Chordification* of MILES stellar library

One of the most interesting possibilities offered by the application of autoencoders to the sonification and musification of astronomical data, is the improvement of the accessibility of stellar spectra catalogs and databases for blind and visual impaired (BVI) scientists. This section describes a method for the conversion of stellar spectra into music chords to provide an auditory sequential representation of the curves from the MILES stellar spectra library [16], developed by the Spanish Virtual Observatory.

In this approach, a four-dimensional variational autoencoder is used. *Figure 4* shows the structure of its encoder. For each spectrum, the four-values tensor generated by the encoder is translated into a four-notes musical chord. This musical structure was chosen in reference to the value of the tetra-chord as the unit of the harmonic system in ancient Greece [17], with the intention of generating complex but not-overwhelming sounds. Each latent value is multiplied by 1000 to bring it to the audible range, and approximated to the closest note's fundamental frequency of the chromatic scale. The duration of each chord is calculated using a self-weighting mechanism that sums the values of the latent vector, generating longest chords from the vectors with the highest values. An excerpt of a Sci-Fi style representation of MILES stellar library from the Spanish Virtual Observatory can be found at: https://vimeo.com/764757244

```
In [18]: encoder.summary()

Model: "encoder"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 encoder_input (InputLayer)     [(None, 4367)]       0           []

 dense (Dense)                  (None, 545)          2380560     ['encoder_input[0][0]']

 dense_1 (Dense)                (None, 68)           37128       ['dense[0][0]']

 dense_2 (Dense)                (None, 68)           4692        ['dense_1[0][0]']

 dense_3 (Dense)                (None, 68)           4692        ['dense_2[0][0]']

 z_mean (Dense)                 (None, 4)            276         ['dense_3[0][0]']

 z_log_var (Dense)              (None, 4)            276         ['dense_3[0][0]']

 sampling (Sampling)            (None, 4)            0           ['z_mean[0][0]',
                                                                  'z_log_var[0][0]']

==================================================================================================
Total params: 2,427,624
Trainable params: 2,427,624
Non-trainable params: 0
__________________________________________________________________________________________________
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Fig. 4. Architecture of the variational encoder used to extract latent features from each stellar spectrum of the MILES library (SVO).

3.3 Pipeline and technical details for the musification of 4D stellar spectra latent space

Developed in *Jupyter notebook* [18], the proposed pipeline for the generation of stellar spectra latent space uses *astropy* [19], *numpy* [20] and *matplotlib* [21] libraries to allow the analysis of each stellar spectrum and to reduce it to a 4 dimensional latent space representation by a variational autoencoder. The encoder that generates each latent vector trying to mimic each stellar spectrum uses 4 *dense* layers and trains 2,427,624 parameters during 100 epochs. The neural network has been implemented using *tensorflow 2* [22] and, as shown in *figure 5*, its results are promising despite the simplicity of the network and the small number of curves used for the training (899). R^2 analysis values for the test and train sets are respectively 0.8472 and 0.8468 (variance weighted). The spectra set has been balanced through the repetition of the only three O type spectra included in the MILES library, increasing the total number of curves to 1124 spectra. The R^2 analysis values for the imbalanced set, using directly the 985 spectra of the library, were 0.8369 and 0.7978 (variance weighted). Finally, the Python music analysis library *music 21* [23] is used to generate a score with the sequence of chords that is rendered using the open software *MuseScore3* [24].

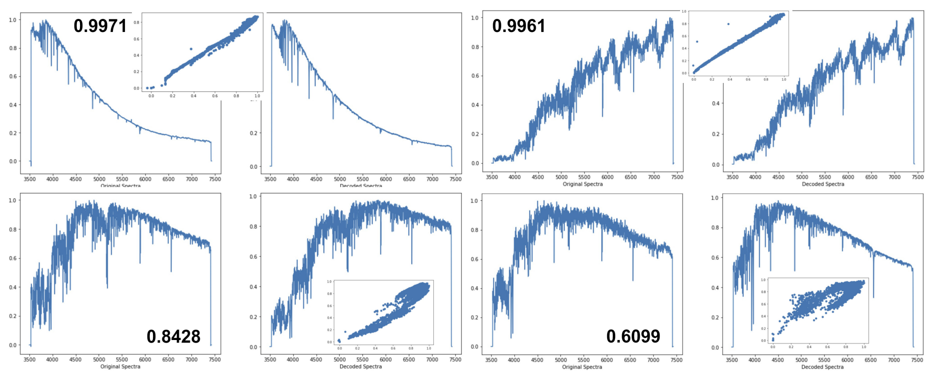

Fig. 5. Four examples generated by the 4D variational autoencoder over the MILES stellar spectra library (SVO). Original spectrum, deviation with R^2 results, and decoded output for HD 057061 (up-left), HD 095578 (up-right), HD 026965 (down-left), and M71 K169 (down-right).

3.4 OBAFGKM evaluation

Spectral classification has traditionally been done by comparing unknown stellar spectra with those of known standard stars. Most current classification methods, including automation and artificial neural network pattern recognition, are based on the *Morgan-Keenan* (*MK*) spectral classification system and make use of the seven classical *OBAFGKM* types of stars, with O representing the hottest and M representing the cooler ones.

With the intention of evaluating the application of the four-dimensional variational autoencoder on stellar spectra feature extraction, a test with the samples of each type of star listed in *table 1* has been done. Analyzing the results presented in *figure 6*, despite the fact that the autoencoder generates an O type spectrum for the *O7Ia* input, which suggests that it has learned to differentiate this type of star with the only three replicated samples, this type of star presents the poorest response. The resulting OBAFGKM chord sequence can be heard at: https://vimeo.com/770510584.

The O spectral class was originally defined by the presence of absorption and sometimes emission lines of the He II at blue-violet wavelengths. The study of B stars led to the discovery and mapping of the spiral structure of the Milky

Table 1. Stellar spectra samples used for the *OBAFGKM* evaluation. Summarizing the Morgan-Keenan (MK) luminosity classes, Ia and Ib correspond to luminous supergiants, II to bright giants, III are normal giants, IV are subgiants, V corresponds to main sequence dwarf stars, VI to subdwarfs and D to white dwarfs. The number allow scaling each type from 0 (the hottest) to 9 (the coolest).

Type of star	R^2	Name	RA(J2000)	DEC(J2000)	Library	Reference
O7Ia	0.988	HD 057060	07:18:40.38	-24:33:31.32	MILES	[25–27]
B5V	0.879	HD 003369	00:36:52.80	33:43:09.48	MILES	[25–27]
A0V	0.979	HD 031295	04:54:53.69	10:09:02.88	MILES	[26–28]
F1V	0.948	HD 222451	23:40:40.56	36:43:14.88	MILES	[25–27]
G1V	0.977	HD 114606	13:11:21.36	09:37:33.49	MILES	[26, 27]
K0V	0.972	HD 233832	11:26:05.52	50:22:32.88	MILES	[25–27]
M1V	0.949	HD 036395	05:31:27.41	-03:40:37.99	MILES	[25–27]

Way. This class was originally defined for those stars showing lines of HeI in the absence of HeII in the blue-violet. *A*-stars are characterized by the disappearance of lines of HeI and often present chemical peculiarities. An *F*-type star presents an atmosphere in which important physical changes occur. The sun is an example of *G*-type star, characterized by their abundance of spectral features. *G*- and *K*-types are the most likely stars to have habitable planets around them while *M*-type stars are the most numerous of all classes [8].

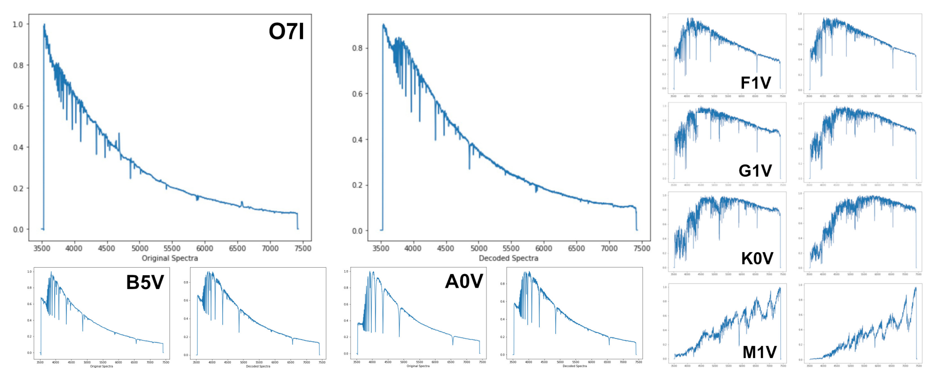

Fig. 6. Results for seven samples of the *OBAFGKM* types of stars. Original spectrum (left) and 4D variational autoencoder decoded output (right) for HD 057060, HD 003369, HD 031295, HD 222451, HD 114606, HD 233832, and HD036395.

3.5 Synthetic stellar spectra from musical chords

To close the circle of this review on the interdisciplinary possibilities involving stellar catalog exploration, variational autoencoders and music generation, some synthetic spectra can be created by sampling the latent space of the model with user defined chord inputs. *Figure 7* shows an example of this approach that could be used in artistic contexts to generate synthetic stellar spectra with a piano keyboard.

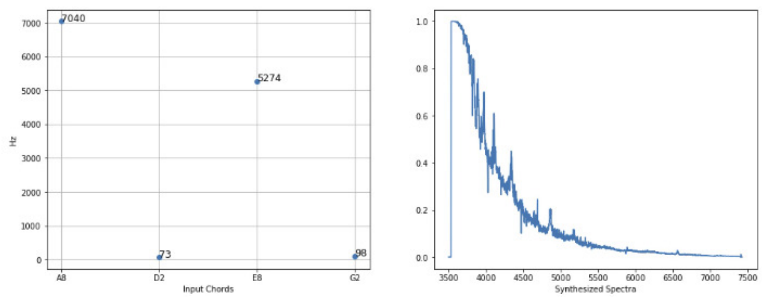

Fig. 7. Generation of synthetic stellar spectra from user defined chords. Input: *A8*, *D2*, *E8*, *G2*. Worth mentioning the appearance of several synthetic absorption lines.

4 Unsupervised music composition system based on *Deep Learning*

With the double intention of exploring the possibilities of *deep music* generation from astronomical data, and providing an unsupervised and objective approach to Kepler's ideas of the music of the spheres, this paper offers some experiments realized with VAE-LSTM with attention neural networks trained with music corpus by Josquin Des Prez, Orlando di Lasso and Giovanni Pierluigi da Palestrina, as representative renaissance composers that could had inspired Kepler's musical thoughts.

4.1 RNN, LSTM networks and *attention* mechanism

'A recurrent neural network (RNN) is a neural network specialized for processing a sequence of values' that *'can also process sequences of variable length'* through parameter sharing across the model. First described by Rumelhart et al.(1986a) [29], and specially useful in *sequence to sequence* models, it *'shares the same weights across several time steps'* so that *'each member of the output is produced using the same update rule applied to the previous outputs. This recurrent formulation results in the sharing of parameters through a very deep computational graph.'* [14]

Long short-term memory (LSTM) architectures, first presented by Graves et al. (2013) [30], are built on gated RNN to resolve the problem of vanishing and exploding gradients, appearing when RNNs try to learn long-term dependencies [31], through the introduction of context-dependent weighted self-loops.

They propagate information through long sequences and allow previous outputs to be used as inputs along the hidden layers. LSTM networks improve the capacity to learn possible relationships between features over time and allow the maintenance in memory of relevant features from input data.

An additional *attention* mechanism, introduced on machine translation by Bahdanau et al. (2014) [32], can be incorporated to improve the management of long-term dependencies. This approach makes use of the most relevant parts of the input sequence by a weighted combination of the encoded input vectors to get focused *'at each time step on some specific elements of the input sequence'*. [15]

```
In [35]: model.summary()

Model: "model"
__________________________________________________________________________________________________
 Layer (type)                   Output Shape         Param #     Connected to
==================================================================================================
 input_1 (InputLayer)           [(None, None)]       0           []

 input_2 (InputLayer)           [(None, None)]       0           []

 embedding (Embedding)          (None, None, 128)    1649152     ['input_1[0][0]']

 embedding_1 (Embedding)        (None, None, 128)    1920        ['input_2[0][0]']

 concatenate (Concatenate)      (None, None, 256)    0           ['embedding[0][0]',
                                                                  'embedding_1[0][0]']

 lstm (LSTM)                    (None, None, 128)    197120      ['concatenate[0][0]']

 lstm_1 (LSTM)                  (None, None, 128)    131584      ['lstm[0][0]']

 dense (Dense)                  (None, None, 1)      129         ['lstm_1[0][0]']

 reshape (Reshape)              (None, None)         0           ['dense[0][0]']

 activation (Activation)        (None, None)         0           ['reshape[0][0]']

 repeat_vector (RepeatVector)   (None, 128, None)    0           ['activation[0][0]']

 permute (Permute)              (None, None, 128)    0           ['repeat_vector[0][0]']

 multiply (Multiply)            (None, None, 128)    0           ['lstm_1[0][0]',
                                                                  'permute[0][0]']

 lambda (Lambda)                (None, 128)          0           ['multiply[0][0]']

 pitch (Dense)                  (None, 12884)        1662036     ['lambda[0][0]']

 duration (Dense)               (None, 15)           1935        ['lambda[0][0]']

==================================================================================================
Total params: 3,643,876
Trainable params: 3,643,876
Non-trainable params: 0
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Fig. 8. Network structure of the dual LSTM with attention architecture used to generate the unsupervised music compositions described in sections *4.2* and *4.3*.

4.2 Generative composition using dual LSTM with attention networks

Some controversy has been found about the influence of most relevant composers of early seventeenth century in Kepler's work. For Ball (2009) *'Kepler's musical world embraced the polyphonic opulence of Palestrina and Monteverdi'* [33] while Pesic (2005) affirms that *'he (Kepler) accepts Zarlino's system and refers only to Lasso and Artusi, never to Monteverdi'* [34]. Anyway, seems clear that although he didn't include any explicit mention in his treatment, Kepler could had been interested in what we know today as the Franco-Flemish school, especially focused on the music of Orlando di Lasso, and more specifically on his *In me transierunt* motet *'as approaching the ideal, unwritten celestial motet'* fitting his thoughts [34]. Inspired by this references, several generative composition experiments have been done using music examples of the sixteenth century to train and test a LSTM with attention network based on one of the implementations described in Babcock and Bali(2021) [35]. The network, represented in *figure 8*, learns pitch and duration from each chord of the data set thanks to a dual-input dual-output architecture. Attending some technical details, its implementation uses *Tensorflow 2* and *Keras*, and includes a temperature-based sampling strategy after feeding the notes into the prediction function.

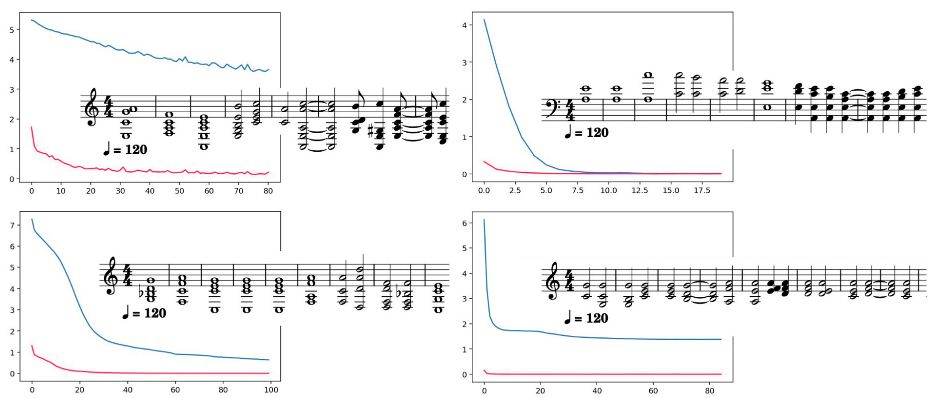

Fig. 9. Resulting scores and *Loss* function for pitch (blue) and durations (red) of four experiments with different training sets: one single Lasso's motet (up-left), the same piece repeated 100 times (up-right), 50 music pieces from Des Prez and Lasso (down-left) and 1318 pieces from Palestrina (down-right). Note how the Pitch Loss function reflects an unexpected fast learning rate for Palestrina's corpus (the biggest), probably motivated by the composer's intrinsic musical characteristics.

Figure 9 summarizes the experiments carried out. The up-left score is the result of testing the behavior of the network when trained with a single MIDI file. The 203 chords and 7 different note durations of Lasso's *In me transierunt* motet were used to train a 382,803 parameters network but, as expected, the results are only useful as starting point, providing a final pitch loss error of 3.6543 after 81 epochs. The up-right score was generated with an augmented corpus, repeating the motet 100 times. Worth mentioning how the network is able to mimic the piece after less than 10 epochs. The final pitch loss is 0.0118 after 20 epochs. The down-left experiment used 50 musical pieces, 25 by Josquin Des Prez and 25 by Orlando di Lassso. 3,245 "Chords" and 46 different durations that clearly increased the learning ability of the system, in this case, with 1,174,620 trainable parameters. After 100 epochs, the final pitch loss was 0.6431. The down-right score results from training the 3,643,876 parameters of the network with 12,884 "chords" and 15 different durations extracted from 1,318 pieces by Giovanni Pierluigi da Palestrina. Final pitch loss of 0.8879 after 41 epochs.

4.3 *Pitch Class Set Theory* cross-match

The last step in this approach to generate music from starlight is to cross-match the musical chords obtained with the neural network described in the previous section with those "stellar chords" obtained in sections *3.2* and *3.3* by an autoencoder exploring the MILES library, and generate a final score with the positive matched chords, which durations are function of their own summed latent space values. This cross-matching process is hold by the *Pitch Class Set Theory*, which provides one of the most used methods for reducing and labeling musical information [37]. *Figure 10* provides a representation of the architecture.

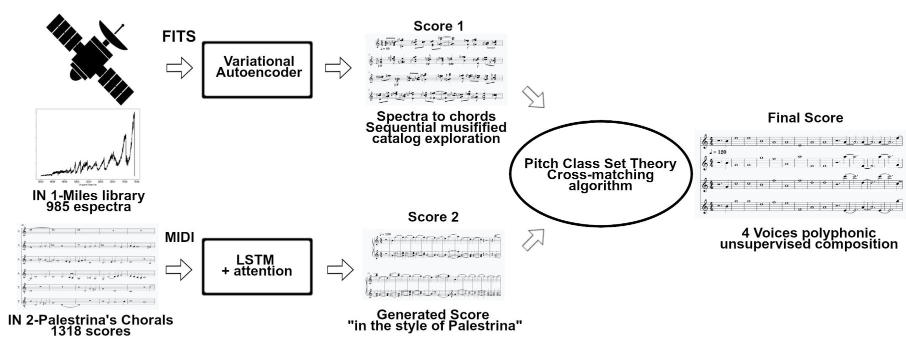

Fig. 10. Four voices astronomical data-driven unsupervised composition system based on *Deep Learning*. Block diagram of the complete VAE-LSTM with attention and *Pitch Class Set Theory* cross-match architecture.

According to the establishments of the theory, a *pitch class A*, is a group of all registers corresponding to that note with octave equivalence, *A0, A2, A4*, etc, and without distinguishing enharmonic equivalences like *A3 sharp* and *B3 flat*. Translating those classes into numbers, with *0* corresponding to *C*, and *11* corresponding to *B*, each generated chord is reduced to a single code that allows their comparison for finding positive matches between corpus. In this way, the chord *G4-E5-C5-G5* corresponds to the code *047*, as an example of a chord which is present in both generated stellar and musical chord scores, and corresponds to HD 049933 star with coordinates RA: 06:50:49.8309, DEC: -00:32:27.1675. This comparison is implemented using the *Chord.orderedPitchClassesString* method from *Music 21* library. The resulting durations are forked and reduced to only 4 different figures -*whole*, *half*, *quarter* and *eight*- to maintain a slow cadence in the music that allows the synchronization with the graphical representation of the source star, in a multimodal exploration inspired mood. At the end of the process, the score is also generated using the *Music 21* library. Final musical results are rendered with commercial DAW software for best audio quality.

A synchronization of the generated music and score, with the images of each source star, and its spectrum for the Lasso-Des Prez corpus in an electroacoustic style render, is available at: https://vimeo.com/770493178.

A similar representation showing the results with the Palestrina corpus for flute, violin and piano can be found at: https://vimeo.com/746620075.

Finally, in order to obtain more general results, an experiment to train the network with the MAESTRO data set [36] has been conducted. This corpus offers about 200 hours of virtuous piano performances by several composers from the 17th to the 20th century. A total of 82,231 unique notes and 118 different durations have been used to train the 21,492,526 parameters of the network during 525 epochs, four and a half hours using high performance GPU processing. The next video shows the resulting composition obtained when feeding the model with the notes and durations of Lasso's *In me transierunt* motet. https://vimeo.com/794718061.

4.4 Conclusion and prospective

Assuming that *'for a sonification to represent information meaningfully, the information must be part of the experience of the representation'* Worrall [38], the unsupervised generation of scores from astronomical data has been proved as an effective way of composition that could be applied in the creation of original soundtracks for films and audiovisual content and, at the same time, having the potential of representing stellar information through sound. The method here described generates completely original pieces that could also be interpreted as an empirical and automated review of the classical *Harmonies of the Spheres* theories, framed in the context of Renaissance Music and Johannes Kepler's musical interests. This approach should be understood as a tribute to one of the most important pioneers of the concept that traces a new line of development for multimodal analysis and comparison of astronomical data through sound.

Thanks to the highly deterministic characteristics of renaissance music, it is possible to analyze the behavior of *Machine Learning* algorithms trained with renaissance music corpus through sound, which could also make this approach useful for neural network auditory monitoring, a branch of Sonification that could be more deeply explored and expanded. The creation of a big MIDI corpus of the Franco-Flemish school inspired by the MAESTRO concept is being considered, to generalize the model and potential results.

In the short term, additional efforts will be addressed to the search of interesting scientific case studies, and to the design of new experiments using selected corpus in both fields, Music and Astronomy. The collaboration and feedback between experts, as well as the evaluation of the results by specialized and non-specialized users, constitutes one of the main axis of future development in this field of research.

The highly interdisciplinary space in which this work is framed, and the polyhedral nature of its results, provide a wide field of resources aimed at using the

Music-Astronomy binomial on science communication, outreach, and engagement, while improving the accessibility of astronomical catalogs and databases for blind and visual impaired users.

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All MIDI files used in the experiments have been downloaded from *music21* and *Musescore* open libraries.

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