Revised Selected Papers

Accademia Musicale Studio Musica
Michele Della Ventura, *editor*

2020

Proceedings of the International Conference on New Music Concepts Inspired Education and New Computer Science Generation

Vol. 7

STUDIO MUSICA

Accademia Musicale Studio Musica

International Conference on New Music Concepts
Inspired Education and
New Computer Science Generation

Proceeding Book
Vol. 7

Accademia Musicale Studio Musica
Michele Della Ventura
Editor

Printed in Italy
First edition: March 2020

www.studiomusicatreviso.it
Accademia Musicale Studio Musica – Treviso (Italy)
ISBN: 978-88-944350-3-0

Preface

This volume of proceedings from the conference provides an opportunity for readers to engage with a selection of refereed papers that were presented during the International Conference on New Music Concepts, Inspired Education and New Computer Science Generation. The reader will sample here reports of research on topics ranging from a diverse set of disciplines, including mathematical models in music, computer science, learning and conceptual change; teaching strategies, e-learning and innovative learning, neuroscience, engineering and machine learning.

This conference intended to provide a platform for those researchers in music, education, computer science and educational technology to share experiences of effectively applying cutting-edge technologies to learning and to further spark brightening prospects. It is hoped that the findings of each work presented at the conference have enlightened relevant researchers or education practitioners to create more effective learning environments.

This year we received 57 papers from 19 countries worldwide. After a rigorous review process, 24 paper were accepted for presentation or poster display at the conference, yelling an acceptance rate of 42%. All the submissions were reviewed on the basis of their significance, novelty, technical quality, and practical impact.

The Conferece featured three keynote speakers: Prof. **Giuditta Alessandrini** (Università degli Studi Roma TRE, Italy), Prof. **Renee Timmers** (The University of Sheffield, UK) and Prof. **Axel Roebel** (IRCAM Paris, France).

I would like to thank the Organizing Committee for their efforts and time spent to ensure the success of the conference. I would also like to express my gratitude to the program Committee members for their timely and helpful reviews. Last but not least, I would like to thank all the authors for they contribution in maintaining a high-quality conference and I hope in your continued support in playing a significant role in the Innovative Technologies and Learning community in the future.

March 2020

Michele Della Ventura

Conference Chair

Michele Della Ventura, Accademia Musicale Studio Musica, Treviso, Italy

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Evaluation of Convolutional Neural Network and Four Typical Classification Techniques for Music Genres Classification

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Abstract. Classification of Music genres has increasing research interest due to the need of the multimedia websites categorization and user profiling. Music signals require many of preprocessing and features extraction operations. In this report, four typical classifiers have been used with 40 extracted features while CNN utilized to classify images that obtained from waveform and Spectrogram representations of music. The results showed that Random Forest classifier had the best performance with 71% validation accuracy.

Keywords: Music Genres, Convolution Neural Network, Random Forest, Decision Tree, Bayesian model, SVM.

1 Introduction

The increasing growth of the internet produces spreading millions of music tracks which make the organizing and categorizing those files an important need for more fast and efficient access. Music genres represent the conventional method for music categorization although some genres can be overlapped. This method is so popular in multimedia websites, digital media stores, and online radio stations. The need for classifying a new music track in a suitable genre and suggest the most related tracks for the users (profiling) increased the researchers interest for developing a music classification model based on machine learning techniques.

Classification is one of the major tasks of machine learning that aims to label data into previously defined categories, it generally has three main phases; the data is prepared to training process then machine learning techniques are applying for knowledge extraction and finally the results will be evaluated and processed in understandable for decision making. Data Preprocessing may include one or more from following operations: data sampling, feature extraction, most relevant features selection, discretization, and data transformation [1].

1.1 Audio Data Features

Basically, digital audio can be represented by a sequence of quantized pulses in time. The type of required information they are attempting to extract from the audio signal specifies the grouping audio features. In this work, three types of features are extracted; (1) Spectral Features (2) Mel-Frequency Cepstral Coeffcients (3) Pitch/Harmony Features [2].

(a) **Spectral Features.** It related to **magnitude spectrum and** represents summarized information about energy distribution across frequency. An important feature from this type is the spectral centroid that considered as the gravity center the spectrum [2].
(b) **Mel-Frequency Cepstral Coeffcients (MFCCs).** are used widely in speech recognition and music analysis. Those Coefficients require three steps; the first is calculating Mel-scale filterbank using Fourier transformation, second step is to find the Log energy by calculating the logarithm of the magnitude of filterbank outputs. Finally, the dimensionality of the filterbank outputs is reduced using discrete cosine transform [2].
(c) **Pitch/Harmony Features.** it is related with underlying harmony of music piece and aim to find occurrence of specific musical pitches in a segment of music. It can be calculated by mapping and folding all the magnitude bins of a fast Fourier transform, and this process is called chroma or chromagram [3]

1.2 Audio Features Extraction

It aims to capture the higher-level information of underlying musical content by filtering the large amounts of raw data into more compact representations [music mining]. The representations of sound signals could have a separate notion of time and frequency. Many of common audio representation could be used for features extraction such as short-time Fourier transform and wavelets.

Short-time Fourier transform (STFT). produces elementary signals as a linear combination from an original signal to be in more understandable and manipulated form. It also is express the energy distribution of the signal in the time domain and frequency domain. The STFT is an adoption from a discrete Fourier transform (DFT) for providing localization in time [2].

Wavelet representation. is formed by using variable time-frequency resolution. It includes high precisely detection for low frequencies which are not placed in time very accurately. In the other hand, high frequencies have lower precisely detection and more accurate placing in time. The discrete wavelet transform has same number of coefficients of the original discrete signal [2].

1.3 Classification Techniques

The input of a classification task is a collection of data records. Each record is represented by a tuple (x, y), where x is the features set and y is the target of classification. The type of target attribute y detects the required technique; if values of y are binary, binary class classification techniques can be used, multi class classification is used if y has more than two categories. If values of y are continuous, regression techniques should be used for predictive task [1]. In this work, music genres contain more than two categories therefore it requires a multi class classification task. Four classification techniques are used in his work including Decision tree, Bayesian Model, SVM, and Random forest in addition to CNN classifier.

Decision Tree. DT is a simple data analysis tool which allows predicting, describing, or classifying a target. A decision tree represents by a flowchart-like tree structure, where every non-terminal node denotes a condition on an attribute, to split data records which have different characteristics. Each branch represents the result of that condition, and each leaf node (i.e. terminal node) holds a class label. The building of decision tree classifiers does not require any domain knowledge, and therefore is suitable for exploratory knowledge discovery [4].

Random Forest. is one of bagging ensemble classifiers that combine a set of single models; each one tries to solve the same original task for obtaining a better integrated model. Bagging combines the decisions of multiple trees by using voting concept for both binary class and multi-class predictive tasks. Random Forest can be discriminated from other bagging techniques by choosing random subsets from features. Random Forest uses randomness in two steps as follows: (i) choose data instances of for each single model (ii) choose a subset of features for each node. Random forest has two parameters; the number of trees and the number of features in a subset [4].

Bayesian Classifiers. is probabilistic model for performing classification tasks. In this classifier, the features (F1,F2,…,Fn) of each data record including the class label is considered as a random variables. The aim is to find the value of class Y that maximize the conditional probability P(C| F1, F2,…,Fn) [1].

Support Vector Machines. in this classifies, the margin among closest points of the classes is maximized for obtaining optimal separating hyper plane between them. SVMs are designed to deal with binary classification tasks, so for multi-class classification, it utilizes one-versus-one method in which all binary sub classifiers are fitted and finally the correct class is founded by using a voting mechanism [5].

Convolutional Neural Networks CNN. represents a neural network-based classification technique in which the input data is passed into a group of pairs contain convolutional and pooling layer. Output of the last layer considered as input into another group of fully connected layers that pass its output to a softmax layer. Choosing the suitable architecture of CNN has dependency on the type of classification problem, so the network may be built in different ways [6].

1.4 Related Works

In [7] a comparison was made among deep neural networks and set of typical learning models like SVM and logistic regression, music data was preprocessed using Spectrogram and MFCC and the best accuracy was 38.8%. Utilization of cepstral modulation spectrum is presented by [8] for building a deep neural network (DNN). GTZAN music dataset is used in this research and its result showed that the temporal features can obtain classification accuracy comparable or better than the spectral features.

A comparison between Convolutional Neural Networks CNN and Supported Vector Machine SVM is presented by [9] for Music Classification. The evaluation is performed using three different music datasets, and the results showed a significant performance of CNN with two datasets. [10] Proposed feature extraction method based on sparse FFT in addition to spectral analysis of audio signals. The results of this work led to signals dimensionality reduction and an improvement of computational time and accuracy is achieved.

In [11] the performance of CNN learning technique based on the images of the spectrogram of audio signal is compared with four typical classifiers which were trained base on hand-crafted features. The result of this work showed that CNN had better accuracy (64%) compared with Extreme Gradient Boosting XGB (59%) and other three typical classifiers, also the combination between CNN and XGB as an Ensemble Classifiers reached to (65%) accuracy.

2 Methodology

Classification of music genres in this work divides into two major independent parts; the first part includes extracting the important features from audio signals after applying Fast Fourier Transformation FFT, then four classification techniques (Decision Tree, Bayes Model, SVM, and Random Forest) are trained. The evaluation of classifiers performance is performed by five popular metrics (accuracy, precision, Recall, F-measure, and ROC).

The second part starts with represent the audio signal as an image using wave form representation and spectrogram representation. Images that produced by Wave form will converted to binary images while the RGB image that produced from spectrogram representation is split into three different images. CNN classification model is applied on the resulted images, and finally the performance is evaluated using validation accuracy. Fig.1 illustrates all the steps of methodology.

2.1 Shorter Form Features Analysis

The first step after gathering music data is to represent it in a shorter form. This will ensure getting the highest valuable information and reduce the required resources for

the classification process. This reduction can be performed by applying FFT on the audio signals; thereby the important features can be extracted.
For each feature (Chroma and spectral), mean and standard deviation are calculated to summarize the values of a music track in addition to 10 features from MFCCs. In the end of this step, each music track is converted to an instance with 40 features and class label value. These values represent the required dataset for applying classification techniques.
Four various classifiers utilize the resulted dataset that contain 40 features for training process; (1) Decision tree is generated by using Multi branch J48 algorithm. It produces a pruned decision tree based on information gain metric, and the part of the tree that don't reduce training error will be removed, (2) Bayesian classifier is build using a hill climbing as a search algorithm and estimate the conditional probability directly from data, (3) Support Vector classifier is build using SMO implementation in which all features are normalized and multi-class problems are handled using one versus one method, (4) Random forest is generated by choosing subset from features randomly for each iteration, also there is no limitation used for random tree depth. For performance evaluation, 10 cross-validation method is used to distribute data between training and testing process and five metrics is used (accuracy, precision, Recall, F-measure, and ROC).

2.2 Sound as an Image Analysis

Handling the sound signal as an image can facilitate the classification task by utilizing all image classification tools and techniques. Artificial Neural Networks and specially the Convolution Neural Networks have an interested performance for image classification, therefore for each music track, two images are created; the first by wave form and the other using spectrogram.
Wave Form Representation. The wave form resulted image has one color for representing waves in addition to white background color as can be seen in figure (2, a). Because the color of waves isn't meaningful, it can be converted to black color, then, the whole image can be represented as a binary image from 1 and 0 values.
Spectrogram Representation Color image with three channels (RGB) is resulted from Spectrogram and for more precise classification, each channel is separated as a single gray level image which contains s color values in range 0o 255. threshold is needed to covert gray level image to binary image and 128 is chosen in which every color value less than 128 will considered as 0 and every color value more than or equal 128 will considered as 1.
The resulted images from both representations feed into two separated CNNs with same architecture for both networks. It starts with four 2D convolution layers; each layer is represented by 2*2 array with Rectified Linear Unit as an activation function. Then, 2D max pooling layer with 2*2 pool size is added to the network for reducing the number of samples of the previous layer therefore the next operations will be minimized. Two Dense layers have been added to the architecture of CNN with a Flatten layer between them. The first Dense layer contains 8 neurons and uses Rectified Linear Unit as an

activation function. The second Dense layer uses softmax Unit as an activation function and represents the last layer, therefore it contains 10 neurons for 10 classes of music genres.

3 Implementation and Results

Music classification methodology is implemented using many of programming and data analysis tools. A standard music dataset is used also for this implementation.

3.1 Dataset Description

The evaluation of methodology requires testing its performance on real dataset; therefore, a popular dataset is chosen. GITZAN music dataset [12] contains 1000 data rows which distributed in equal among 10 music genres (100 data rows for each genre). It is used in many of music classification related works.

3.2 Frameworks and Tools

The implementation of music classification methodology included utilizing a wide and various range of tools. Two different environments are used to this task; the first one was on a pc with windows 10 operating system, Core i5 1.8 GHz processer, and 4 Gigabytes of RAM). The second environment was an AWS Amazon server with Windows server 2016 operating system, 8 vCpu Xeon 2.5 GHz, 32 Gigabytes RAM).
Python [13] programming language with many of its libraries alongside with Weka [14] are used. Anaconda [15] with Spider editor is chosen as the programming framework in both environments. For reading the music data from files, Librosa [16] library is used. It is also used for features extraction in the first environment and for representing the music as wave form and spectrogram in the second environment.
Applying FFT in the first environment is performed using Scipy [17] python library. OpenCV library package is used for generating the binary images from wave form images and for splitting RGB images of spectrogram representation. Tenserflow [18] and Keras [19] are used together for applying CNN classification technique on the images that resulted from both wave form and spectrogram representations. Figure (2) illustrate all the steps of the implementation of music classification methodology.

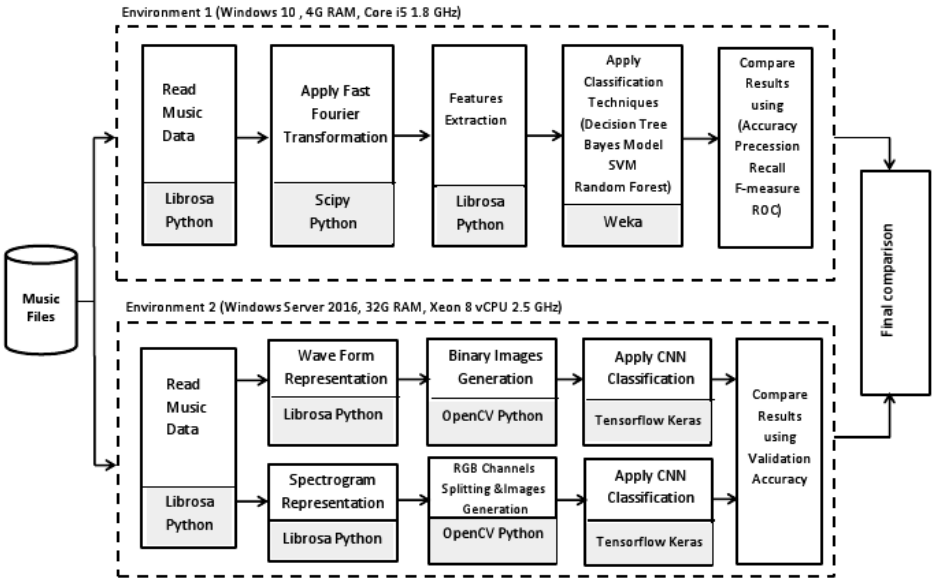

Fig. 1. Block Diagram of Music Classification Methodology and Implementation.

3.3 Results

Many experiments are performed to validate the performance of the methodology based on GITZAN dataset. In shorter form features analysis, after applying FFT on the music data, 10 chroma and spectral features are extracted. Mean and slandered deviation are used for each feature to construct 20 features, in addition to 20 MFCCs features, we get 40 features and the class label as shown in Table I.

TABLE I. DESCRIPTION OF DATASET FEATURES EXTRACTED USING LIBOSA PYTHON LIBRARY.

Feature Name	Feature Description	Feature Name	Feature Description
F1-F2	mean and standard deviation (STD) of Chroma shift	F31-F32	mean and STD of Roof mean square error
F3-F4	mean and STD of Spectral centroid	F33-F34	mean and STD of Spectral contrast
F5-F6	mean and STD of Spectral bandwidth	F35-F36	mean and STD of Spectral flatness
F7-F8	mean and STD of Rolloff mean	F37-F38	mean and STD of Chroma cqt
F9-F10	mean and STD of Zero crossing rate	F39-F40	Chroma Energy Normalized: mean & STD
F11-F30	Mfcc1 - Mfcc20	Music Genre	Class Label

In the first experiment, we use only mean to obtain 30 features, and we made a comparison between the performance of the four classifiers with and without using FFT before features extraction. Five metrics are used in this comparison, and the results in Table II

showed that the performance of all classifiers is better without applying FFT. The best classification is achieved by Random forest with 0.69 accuracy.
In the second experiment, the full set of 40 features is used, and the performance of all classifiers is improved. Accuracy of Random forest reached to 0.71 after 220 iterations as shown in Table III and Fig.2.

TABLE II. EVALUATION OF FOUR CLASSIFICATION TECHNIQUES WITH AND WITHOUT USING FFT FOR AUDIO SIGNAL BASED ON FIVE METRICS AND 30 EXTRACTED FEATURES.

	Accuracy		Precision		Recall		F-Measure		ROC Area	
	With FFT	Without FFT	With FFT	Without FFT	With FFT	Without FFT	With FFT	Without FFT	With FFT	Without FFT
DT	0.190	0.491	-	0.492	0.190	0.491	-	0.491	0.641	0.741
Bayesian	0.387	0.452	0.372	0.432	0.387	0.452	0.369	0.425	0.787	0.865
SVM	0.416	0.641	0.423	0.637	0.416	0.641	0.414	0.636	0.804	0.902
Random forest	0.474	0.692	0.458	0.689	0.474	0.692	0.464	0.689	0.850	0.936

TABLE III. EVALUATION OF FOUR CLASSIFICATION TECHNIQUES WITH AND WITHOUT USING FFT FOR AUDIO SIGNAL BASED ON FIVE METRICS AND 40 EXTRACTED FEATURES.

	Accuracy		Precision		Recall		F-Measure		ROC Area	
	With FFT	Without FFT	With FFT	Without FFT	With FFT	Without FFT	With FFT	Without FFT	With FFT	Without FFT
DT	0.429	0.522	0.424	0.522	0.429	0.522	0.426	0.520	0.702	0.754
Bayesian	0.440	0.506	0.421	0.492	0.440	0.506	0.419	0.489	0.832	0.888
SVM	0.514	0.700	0.504	0.702	0.514	0.700	0.498	0.697	0.851	0.926
Random forest	0.558	0.713	0.544	0.711	0.558	0.713	0.546	0.709	0.896	0.949

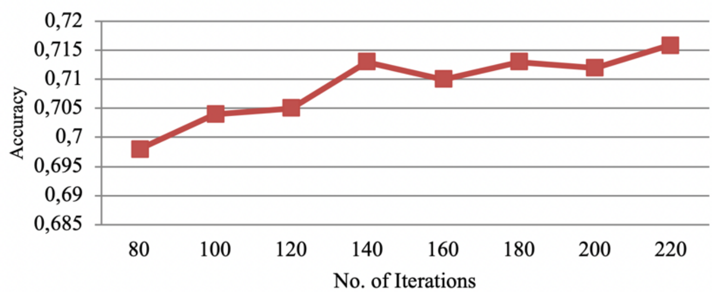

Fig. 2. Accuracy of Random Forest Classifier with variable number of iterations.

From Confusion Matrix of Random Forest Classifier in Table IV we can recognize different classification accuracy for music genres. The best result reached to 89 instances classified correctly in classical genre while with rock genre only 41 instances classified correctly.

TABLE IV. CONFUSION MATRIX OF RANDOM FOREST CLASSIFIER.

blues	classical	country	disco	hiphop	jazz	metal	pop	reggae	rock	Genre
83	0	2	1	1	3	5	0	2	3	blues
0	89	5	1	0	3	0	0	1	1	classical
2	0	68	4	0	11	1	3	4	7	country
6	0	3	68	9	1	3	1	3	6	disco
2	0	0	7	63	0	6	4	17	1	hiphop
1	6	5	3	0	79	1	2	3	0	jazz
3	0	0	2	6	1	84	0	0	4	metal
0	0	5	3	3	3	0	80	5	1	pop
2	1	6	6	11	2	0	6	61	5	reggae
7	0	12	15	1	3	6	5	10	41	rock

Another two experiments are performed for two representations of music signals as an image, one using waveform and the other using spectrogram. CNN classifier which explained in section 2.2 is applied on waveform images (figure 3.a illustrates waveform of Blues Music track), 700 images are used for training and 300 for validation through 16 iterations. Training accuracy reached to the best value 1 (in 0-1 range) after 10 iterations while the best validation accuracy has been obtained 0.45 in iteration 11as shown in Fig.3.

The last experiment was with 3000 Spectrogram images that resulted from splitting the three channels of RGB images, Fig 4.b, Fig 4.c, Fig 4.d, and Fig 4.e illustrate Spectrogram images of music signals before and after channels splitting. 2100 images are used to training CNN classifier; the remaining images are used for validation. Five iterations are used in this experiment; the best training accuracy was 0.974 while best validation accuracy was 0.505 as shown in Fig5.

The comparison among all the five classifiers that used in this work showed that Random Forest had best performance followed by SVM as shown in Fig.6.

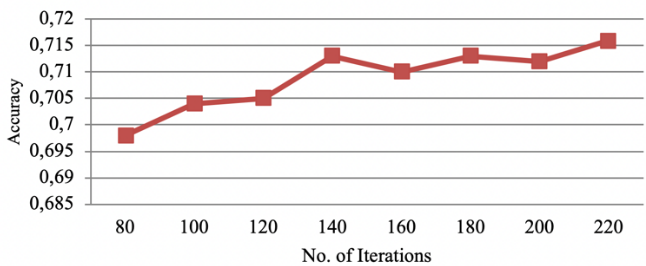

Fig.3. CNN Validation Accuracy for three different sizes of waveform images.

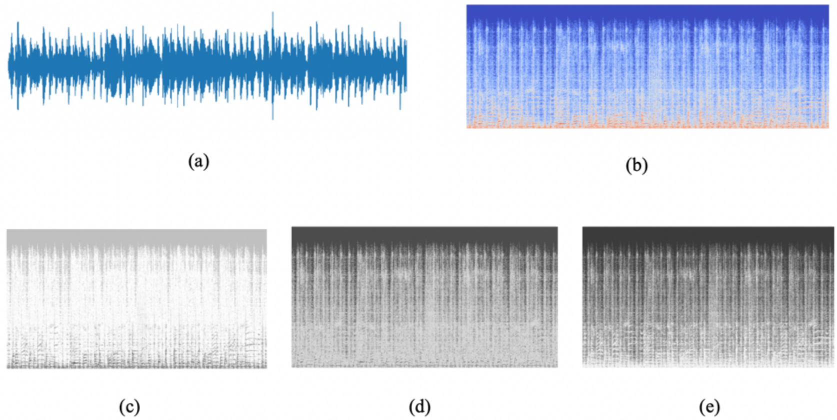

Fig.4. Blues Music track representation in (a) wave form (b) Spectrogram as three channels image (c,d,e) Spectrogram as three images for three channels.

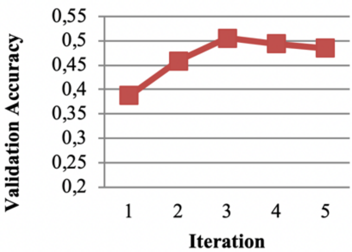

Fig. 5. CNN validation accuracy for Spectrogram images.

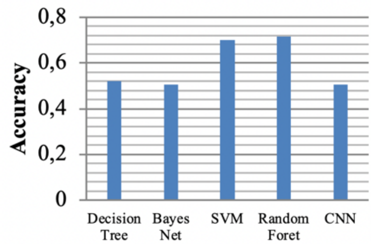

Fig. 6. Comparison of validation accuracy among five classifiers.

4 Conclusion

Music data as a part from the digital content need to be classified and genre of music can represents a target of this classification. This work aims to compare the performance of typical classifiers that trained on 40 audio extracted features with CNN classifier which trained on images that obtained from waveform and Spectrogram representations of music. From the results we can conclude that the performance of all four classifiers is improved by increasing number of extracted features. The performance of CNN is enhanced by increasing number of trained data rows. The limitation of the available resources led to simplify CNN architecture in which the validation accuracy didn't exceed 50% although the training accuracy reached to 100%. Also, increasing the resolution of images had a preferred impact on CNN results. Finally, Random Forest had best accuracy 71% followed by SVM classifier with 70%.

5 Acknowledgment

The project has been supported by the European Union, co-financed by the European Social Fund (EFOP-3.6.3-VEKOP-16-2017-00002).

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Michele Della Ventura, editor

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ISBN: 978-88-944350-3-0

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