Population Age classification based on subject's physiological responses

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Abstract

In this work we rely on physiological signals as honest indicator of people's instinctive behavior or emotions. Benefiting from the fact that these signals can be easily acquired from wearable devices, we here analyze the ability of these data to classify not only different human activities but also individuals' age. We consider Photoplethysmography (PPG) and Galvanic Skin Response (GSR) belonging to a dataset collected in a real laboratory environment at the University of Tokyo. In the experiment a population of Japanese young adults and a population of Japanese elderly people were involved and performed four different tasks: Reading, Comprehension, Audio Listening and Math Calculation. Four binary classifiers have been considered, one for each of the experiment tasks, to classify the population age. Different classification models have been tested (SVM, CART and XgBoost) with a LOSO validation strategy, obtaining classification accuracy between 69% and 78%. The task in which the two groups are most easily distinguishable is that of mathematical calculation. Finally, we also perform a multi-class classification considering age and tasks, for a total of six classes: Math Calculation, Reading and Audio Listening for each subject group (young adult and elderly), obtaining an overall good performance.

Keywords

Physiological Signals, Active Ageing, Photopletysmograpy, Galvanic Skin Response, Elettrodermal Activity, Machine Learning

1. Introduction

In daily life, the concept of the Internet of Things plays an increasingly important role [1]. The advance in communication and computing technologies, as well as the reduction in sensor and electronic component cost, led to the creation of interconnected systems where also everyday objects, such as mobile phones, actuators, appliances or smart devices, are capable of sending and receiving data over the network [2]. In this Smart Environment, the connected devices must be able to acquire knowledge, understand how to apply it and working collaboratively to make

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human life more comfortable [3]. In future scenarios, urban and home environments are destined to become increasingly linked to technological aspects, for example with the introduction of self-driving vehicles. In this context, thus, the analysis of the behaviors and emotions of people during their daily activities, interacting with the environment, may bring to the definition of systems able to receive feedback from users and consequently adapt. In particular, these systems may help to define environments more friendly to vulnerable citizens, such as the elderly and people with disabilities [4]. In urban environments, for example, technologies capable of receiving feedback from users could be involved in the definition of self-driving cars able to adapt their dynamic behaviours to the safety perception of different categories of pedestrians [5] or in the realization of traffic lights able to adapt their waiting time according to the presence or absence of people with impaired mobility.

To implement such systems, thus, an essential aspect consists in profiling and recognizing the categories of individuals with which these systems could interact. In this respect, the aging of the population is a relevant factor that should be taken into account. It has been observed that subjects of different ages react differently to particular stimuli both from emotional [6] and behavioral point of view [7] [8]. For instance, the elderly appear less reactive than young adults in response to audio and visual stimuli [9], as well as they appear slower in carrying out cognitive tasks as mouse pointing [10] or in driving ability [11]. In addition, also concerning walkability, the two populations appear different. In particular, in [7] it is reported how elderly tend to behave more cautiously when they have to face an obstacle, passing it only when they feel save.

For this reason, in a world where the average age of the population is destined to increase over the years [12, 13], the definition of systems capable of automatically recognizing the age of the users and behave consequently is becoming a primary issue. In this context, a fruitful research area concerns the use of person's physiological responses such as heartbeat (Photopletismography or Electrocardiography), sweat glands activity (Electrodermal Activity) or electrical activity on the scalp (Electroencephalography). These signals are not voluntary and uncontrolled responses of our Autonomous Nervous System (ANS) and can thus be considered as reliable and honest indicators of the subject's instinctive behavior or emotions. Besides, several studies underlined how these signals change with the increase of age. For example, in [14] it is shown how the shape of the Photoplethysmography (PPG) is affected by the subject's age. In particular, the PPG signals of elderly appear as more rounded and characterized by the disappearance of the dicrotic notch and the inflection point. Even concerning Electrodermal Activity (EDA) and Electroencephalography (EEG), age-related differences are reported. For example, from the analysis of EDA signal it emerges how, in general, some signal characteristics appear affected by the subject age with a lesser skin response in elderly with respect of young adults and middle-aged adults [15].

Finally, people's physiological signals are also involved in analysis related to compare young and elderly during specific tasks. In this context, the different behavior of the young and elderly during driving tasks has been studied through EEG signals [8]. This research shows how high drive performance is associated, in the elderly, with increased mental effort and fatigue while, in the young, with a higher focus on the task and lesser attention to distractors. In [16], instead, an emotion classification task involving two populations of different ages is reported. In this analysis, two physiological signals are taken into account: Galvanic Skin

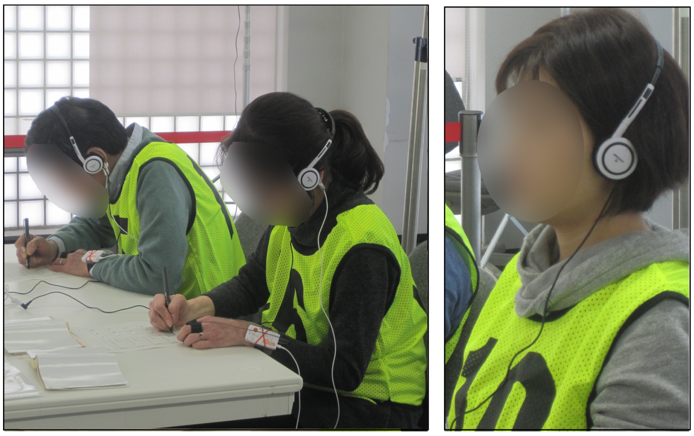

Figure 1: Example of signals acquisition: (Left) Math Calculation, (Right) relaxing audio listening

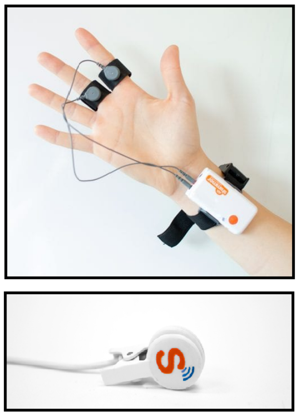

Figure 2: Sensors adopted

Response (GSR) and Heart-Beat Variability (HRV). In most of the studies presented, however, the physiological signals have been used to analyze the general individual's behaviour in a specific task (as driving) or to distinguish the emotion of different ageing people. Besides, rarely the physiological signals have been used in classification tasks to recognize people of different ages. Our study is developed in this context to automatically discriminate between young adults and the elderly while performing different tasks. To this end, starting from the dataset described in section 2, two types of analysis have been performed. In the first part of our study, we tested several binary classifiers in order to recognize the two populations while performing a specific cognitive activity. In the second part, instead, a multi-classification task has been carried out to define a classifier able to recognize both the age of the subject involved and the activity performed. In this work, different classifiers and feature sets have been tested. In particular, we focus our attention on the analysis of PPG and GSR signals. The preprocessing of these signals is reported in section 3 while the features extracted are described in section 4. In section 5, the classification settings and the results of the two analyses are presented and discussed. Finally, conclusions are drawn in section 6.

2. Experimental Protocol and Data Collection

All the analysis were performed on a dataset collected in a real laboratory environment at the University of Tokyo and already partially described in [17]. In the experiment, two different groups of subjects were involved: a population of young adults, composed of 16 Japanese master and PhD students, (average age = 24.7 years, standard deviation = 3.3, 4 women), and a population of Japanese elderly people (retired), 20 subjects, (average age of 65.15, standard deviation = 2.7, 10 women). All the subjects were healthy and no mental or heart diseases were reported.
All the participants performed the same tasks defined by the same experimental protocol, lasting about 30 minutes, and described below:

- *3 minutes* of **Subject's emotional profiling** carried out filling the STAI questionnaires [18].
- *6 minutes* of **Reading and Comprehension** tasks. Two different texts were proposed: a Fairy-tale ("The Wolf and the Seven Little Kids") and a philosophy text ("Kant's Critique of Pure Reason"). The subjects had 2 minutes to read each text and 1 minute to answer self assessment and Reading Comprehension questions.
- *15 minutes* of **Audio Listening and Math Calculation** tasks composed of six repetitions of a two steps sequence consisting of:

  1. *2 minutes* of audio listening in which the relaxation were induced by natural and real life sounds (Figure 1 right).
  2. *30 seconds* of mental arithmetic calculations like sums, subtractions and multiplications (Figure 1 left).

  The audio tracks and the calculations proposed were the same for each subject but changed according to the iteration.

Between each couple of tasks, a period of resting time (**Baseline acquisition**) of about 1 minute was acquired.
During the whole experiment, the PPG and the GSR data of each participant were collected using the Shimmer3 GSR+ Unit [19], with a sampling frequency of 128 Hz. An example of the adopted sensors are showed in Figure 2.

3. Signal pre-processing

With the aim of remove acquisition artifacts and noise, both PPG and GSR signals have been pre-processed using a wavelet multiresolution denoising method similar to the one described in [20]. In particular, the PPG raw signal of each subject has been divided into frequency sub-bands using a Stationary Wavelet Transform (SWT) [21] with mother wavelet *Fejer-Korovkin22* [22] and four levels of decomposition. A Soft Thresholding has been then applied to the detail coefficients of each sub-band. The threshold adopted for this purpose was the Universal Threshold calculated by the formula $t_k = \sqrt{2log(N_j)}$, where N_j is the length of the jth wavelet coefficient [23].
Likewise, in literature, the use of wavelet-based denoising strategies, in particular those based on SWT, proved to be very efficient in removing noise from the GSR signal [24]. Therefore a multiresolution denoising strategy based on SWT has been also used to pre-process the GSR signals. In this second case, however, a Coiflet3 mother wavelet with 7 levels of decomposition has been employed for the decomposition. Besides, the threshold used in the Soft Thresholding was fixed and determined trying to yield minimum of the maximum mean square error over a given set of functions (Minimax thresholding method [25]).
Since in our study the SWT is implemented with the *algorithm a-trous* [26], a preliminary operation of replicate padding has been applied to both the analyzed signals in order to obtain a length divisible by 2^{level} [21]. In our study the value of "level" is different according to the signal considered: 4 in the case of PPG and 7 for GSR.

Table 1
Number of instances for each tasks before (first 4 columns) and after data augmentation (last 4 columns). First row young adult, second row elderly

	N° signals acquired				N°signal after data augmentation			
	Math Calculation	Audio Listening	Reading	Comprehension	Math Calculation	Audio Listening	Reading	Comprehension
Young	96	96	32	32	96	96	96	64
Elderly	120	120	40	40	120	120	120	80

In order to reduce both inter and intra subjects variability, the denoising task has been followed by a normalization phase. In case of PPG, a two-step normalization has been applied. Firstly, the amplitude of each signal has been normalized applying z-score operation. Then a subject's heartbeat normalization method is applied, considering the heart beat rate of the baseline. In the case of GSR signals, instead, only an amplitude normalization has been performed. In particular, a z-score normalization has been applied to the whole signal before splitting it into different experimental trails.
Once segmented, the number of instances for each task appeared unbalanced as shown in Table 1. In particular, there are less instances in the case of reading and comprehension tasks. Therefore, a data augmentation strategy has been applied in order to create more balanced groups. The signals related to reading task were divided in non-overlapping segments of 40 seconds while the Reading Comprehension signals were segmented into two parts of equal length. The last two columns of the Table 1 show the new cardinality after the data augmentation procedure.

4. Features Extracted

After the pre-processing, each of the resulting segments was analyzed in order to identify characteristics that can be significant in discriminating young subjects from elderly ones. For this purpose, seven time-domain features have been extracted from the PPG signal:

- Four statistical features (**Minimum**, **Maximum**, **Mean** and **Standard Deviation** of the signal);
- **Peak Rate**, representing the mean number of peaks per second;
- **Inter Beat Interval (IBI)**, representing the mean distance between two peaks in a row;
- **Root Mean Square of Successive Distance (RMSSD)** representing the variance of the distance between two peaks [27].

In the GSR, two types of signal components are usually taken into account during the feature extraction procedure: the *Phasic component*, related to rapid changes in skin conduction (Skin Conductance Responses) due to external stimuli or spontaneous responses, and the *Tonic* *component* related, instead, to the slow change in the signal and representative of the general arousal or stress level. In our analysis, features from both phasic and tonic components were considered. To this aim, the GSR signals were first decomposed into these two components applying the Cvx algorithm [28]. Different time domain features have been extracted, according to the signal component, as listed below:

- *Signal not decomposed*: four statistical features (**Maximum**, **Minimum**, **Mean** and **Standard Deviation** of the signal)
- *Phasic Component*: seven statistical and peak related features:
  - **Maximum** and **Minimum**
  - **Peak Rate**, representing the mean number of peaks per second
  - **Peak Area** and **Peak Area per Second**, representing respectively the mean area under the peaks and the mean area under peaks evaluated per second.
  - **Peak Height** representing the mean height of the peak detected on the phasic component.
  - **Rise Time** (or also Onset-to-Peak Time) defined as the mean number of samples from the onset of the skin conductance response to the top of the peak.[29, 30]
- *Tonic Component*: the **Regression Coefficient** has been considered as representative of the signal slope.

Finally, the features have been normalized by z-scoring before using them as input to classifiers.

5. Results and discussion

5.1. Classification Setting

In order to determine if it is possible to recognize signals acquired from young adults with respect to signals acquired from elderly, four binary classification tasks have been performed, one for each activity in the dataset (reading, comprehension, math calculations and audio listening). For each task, the signals collected on young adults define the instances of the first class while the signals collected on elderly subjects characterize the elements of the second class. In addition, in all the experiments performed, three well-known classifiers have been involved: *Classification and Regression Tree (Cart)*[31], *Support Vector Machine (SVM)*[32] and gradient boosted decision trees algorithm implemented as *XgBoost*[33]. In the case of SVM, three different kernel have been tested: linear (*SVM-Linear*), gaussian (*SVM-Gauss*) and polynomial cubic (*SVM-Cubic*) kernel. It is important to underline that all the selected classifiers perform in general well even in the case of moderately unbalanced classes[34, 35]. This makes their use suitable in our datasets.
Finally, a *Leave-One-Subject-Out* procedure has been applied to evaluate the performance of the trained classifiers. In this method, during each iteration, all the signals of one subject were used as test set while the signals of the remaining subjects were used to train the model. Several evaluation metrics including accuracy, F1-score and the weighted F1-score [36] have been computed to evaluate the performance of the different classification tasks. In particular,

the weighted F1-score (W-F1) is computed as the weighted mean of per-class F1 scores on the base of the following formula:

$$W\text{-}F1 = \sum_{j=1}^{m} \frac{N_c}{N_{tot}} * F1_j \tag{1}$$

where m is the number of classes considered (here 2), N_c is the number of elements in class "c", N_{tot} is the total number of elements analyzed and $F1_j$ is the F1-score for the jth-class.

5.2. Classification Results

Four different binary classifications, one for each activity, have been performed to recognizing young adults' signals from elderly ones. The classification performance obtained are summarized in Tables 2a (Reading), 2b (Comprehension), 2c (Math Calculation) and 2d (Audio Listening). The performance metrics (accuracy, F1-score and weighted F1-score) are reported, considering five classification models and varying the set of features used (PPG, GSR or joining PPG and GSR). To reduce bias in the results, a Leave One Subject Out (LOSO) strategy has been adopted for all the classifiers.

The best performance for each task is obtained using both GSR and PPG features. In particular, the best of all results has been observed in the Math Calculation task, where an accuracy of 78% has been reached using a SVM with a linear kernel. In this case, the two classes (young and elderly) are well discriminable with F1-score values greater than 70%. On the other hand, the two populations are less distinguishable in the case of audio listening. In this case, XgBoost with features concatenated from both signals allowed to reach an accuracy of 69%. Considering the classification performance that can be reached using only one of the two physiological signals, the PPG seems in general to be more useful in discriminating the two populations. In fact, in almost all the studies carried out, features related to the subjects heartbeat outperformed the results generated using features related to skin conductance. Moreover, we recall that all the PPG signals were normalized not only with respect to the amplitude but also with respect to subject's heartbeat during baseline. This procedure reduces the inter-subject heterogeneity making the signals subject-independent. Finally, another general consideration regards the classifiers that allowed to reach the best performances. In all the conducted experiments, the highest accuracy has been achieved using XgBoost or SVM with Linear Kernel while the worst performances have been obtained using CART with accuracies around 55%. The results described so far have shown, in general, positive performance in recognizing young adults from elderly when a given task is analyzed. To discriminate not only the population group with respect to age but also the task performed, a multi-class classification analysis has been carried out. In this latter, six classes have been considered: three activities (Math Calculation, Reading and Audio Listening) for the two population groups. The Comprehension task has been excluded by the analysis due to its limited number of instances compared to the others. To train the different classifiers, the features extracted from both the types of physiological signals have been employed as suggested by the analyses of the binary classifiers.

In Table 3 the results of this multi-class analysis are summarized. As in binary classification, the best performance has been reached using the SVM with Linear kernel. This model allowed to reach an accuracy of 62%, outperforming the accuracy of the other classifiers.

Furthermore, in order to better understand the misclassification errors, an in-depth analysis of the confusion matrix has been performed. From this matrix, shown in Table 4, it emerges that the classes that are better recognized are those related to Math Calculation, while on the opposite the lower performances are obtained in the Audio listening tasks. In case of misclassification, the algorithm tends to well classify the task performed but to misunderstand the population group.

Table 2
Performance of the binary classifiers in discriminating Young adults (Yng) from Elderly (Eld) in the different tasks analyzed, varying the feature set and adopting a LOSO validation strategy. Three performance metrics are reported: accuracy, F1-score (F1) and Weighted F1-score (W-F1). In each table, the accuracies in bold represent the best performances achieved for each feature set considered, while in red is highlighted the best accuracy at all.

(a) Binary classifiers performance for the *Reading Task*

	PPG Features				**GSR Features**				**PPG and GSR Features**			
Classifier	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*
SVM - Linear	63%	0,53	0,69	62%	63%	0,54	0,70	63%	**75%**	0,71	0,77	**74%**
SVM - Cubic	64%	0,59	0,68	64%	58%	0,53	0,62	58%	64%	0,62	0,66	64%
SVM - Gauss	66%	0,61	0,70	66%	62%	0,54	0,68	62%	72%	0,67	0,76	72%
Cart	56%	0,54	0,59	57%	59%	0,52	0,64	59%	65%	0,60	0,69	65%
XgBoost	**70%**	0,68	0,71	**70%**	**65%**	0,59	0,69	**65%**	71%	0,68	0,74	71%

(b) Binary classifiers performance for the *Comprehension Task*

	PPG Features				**GSR Features**				**PPG and GSR Features**			
Classifier	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*
SVM - Linear	69%	0,55	0,76	67%	**66%**	0,63	0,69	**66%**	69%	0,67	0,72	70%
SVM - Cubic	62%	0,60	0,64	62%	58%	0,53	0,61	58%	61%	0,56	0,65	61%
SVM - Gauss	65%	0,41	0,75	60%	65%	0,59	0,70	65%	61%	0,56	0,65	61%
Cart	59%	0,56	0,62	59%	63%	0,57	0,67	62%	58%	0,52	0,63	58%
XgBoost	**67%**	0,64	0,70	**67%**	61%	0,55	0,66	61%	**74%**	0,69	0,77	**74%**

(c) Binary classifiers performance for the *Math Calculation Task*

	PPG Features				**GSR Features**				**PPG and GSR Features**			
Classifier	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*
SVM - Linear	**74%**	0,68	0,78	**73%**	64%	0,59	0,68	64%	**78%**	0,75	0,81	**78%**
SVM - Cubic	70%	0,68	0,72	70%	**66%**	0,61	0,70	**66%**	69%	0,64	0,72	68%
SVM - Gauss	71%	0,65	0,75	71%	62%	0,55	0,67	62%	71%	0,68	0,74	71%
Cart	73%	0,68	0,76	73%	54%	0,49	0,59	54%	67%	0,63	0,70	67%
XgBoost	72%	0,69	0,75	72%	59%	0,50	0,65	58%	70%	0,67	0,73	70%

(d) Binary classifiers performance for the *Audio Task*

	PPG Features				**GSR Features**				**PPG and GSR Features**			
Classifier	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*	*Accuracy*	*Yng F1*	*Eld F1*	*W-F1*
SVM - Linear	60%	0,44	0,69	58%	**67%**	0,60	0,72	**67%**	65%	0,59	0,69	65%
SVM - Cubic	64%	0,62	0,65	64%	58%	0,51	0,63	58%	64%	0,58	0,69	64%
SVM - Gauss	56%	0,39	0,66	54%	59%	0,49	0,66	58%	65%	0,59	0,69	65%
Cart	50%	0,46	0,52	50%	57%	0,54	0,61	58%	62%	0,55	0,66	61%
XgBoost	**67%**	0,64	0,69	**67%**	61%	0,53	0,67	61%	**69%**	0,63	0,74	**69%**

Table 3
Performance of the multi-class recognition task obtained concatenating PPG and GSR features and adopting a LOSO validation strategy. Six classes are considered corresponding to three tasks: Math Calculation (MC), Reading (READ) and Audio Listening (AUDIO)) and two population groups: Young Adult (Y) and Elderly (E)). The classifiers involved in the different analyses are reported on the rows. The metrics used to evaluate the performance are accuracy, F1-score (F1) and Weighted F1-score (W-F1)).

PPG and GSR Features								
Classifier	*Accuracy*	*MC_Y F1*	*READ_Y F1*	*AUDIO_Y F1*	*MC_E F1*	*READ_E F1*	*AUDIO_E F1*	*W-F1*
SVM - Linear	**62%**	0,62	0,46	0,55	0,73	0,72	0,59	**62%**
SVM - Cubic	58%	0,56	0,52	0,56	0,67	0,63	0,55	59%
SVM - Gauss	57%	0,50	0,50	0,51	0,63	0,68	0,58	57%
Cart	49%	0,46	0,35	0,37	0,61	0,65	0,47	49%
XgBoost	58%	0,60	0,43	0,49	0,67	0,70	0,57	58%

Table 4
Confusion Matrix of SVM classifier with Linear kernel for Multi-class recognition task. Six classes are considered, one for each couple of Cognitive Load Task (Math Calculation (MC), Reading (READ) and Audio Listening (AUDIO)) and subject aging (Young Adult (Y) and Elderly (E)). The values in bold are the main diagonal elements and represent the cases where the class predicted by the classifier and true class agree.

		Predicted Class					
		MC_Y	READ_Y	AUDIO_Y	MC_E	READ_E	AUDIO_E
True class	MC_Y	**56%**	7%	3%	19%	10%	4%
	READ_Y	4%	**46%**	2%	5%	26%	17%
	AUDIO_Y	0%	6%	**50%**	0%	4%	40%
	MC_E	14%	7%	1%	**71%**	1%	7%
	READ_E	2%	15%	2%	3%	**76%**	3%
	AUDIO_E	2%	12%	18%	2%	2%	**66%**

6. Conclusion

In their daily life, people are subjected to different stimuli that could affect their behavior and emotions. In particular, the age of a person seems a relevant factor in the definition of how an individual responds to specific stimuli. In this paper different binary and multi-class classification tasks have proved that physiological signals permit to well discriminate between young adults and elderly, while performing different actions. PPG seems in general to be more useful in all the classification tasks, however the best results are achieved considering both PPG and GSR. These results, together with the increasing availability and reliability of wearable devices, are promising in the perspective of the definition of systems that, interacting with subjects, can recognize their emotions and behaviors as well as their age group, and consequently adapt. Concerning this topic, several factors like different cultural aspects or daily habits could be taken into account in future analysis to create systems able to interact with the largest possible number of heterogeneous users. Furthermore, the age of the individuals could be also used as an additional input variable, together with other parameters like the subject's health, lifestyle or nutritional habits, in the definition of accurate measures of "physiological age" that could be used by industrial designers and product developers to guide their work in the development of appropriate technology able to provide efficient and personalized assistance to individuals of different ages and needed.

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