Towards Stress Detection in Real-Life Scenarios Using Wearable Sensors: Normalization Factor to Reduce Variability in Stress Physiology

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Abstract. Wearable physiological sensors offer possibilities for the development of continuous stress detection models. Such models need to address the inter-individual and intra-individual differences in stress physiology. In this paper we propose and evaluate a normalization factor, *Stress Response Factor* (*SRF*), to address such differences. *SRF* is computed using physiological features and the corresponding stress level at a reference point. The proposed normalization factor is evaluated in a dataset obtained from a free-living study with 10 participants, where each participant was monitored for 5 days during their working hours using different physiological sensors. We obtain an average reduction of mean squared error by up to 32% in models with *SRF* compared to the models without *SRF*.

Keywords: Stress detection · Wearable sensors · Physiology normalization · Machine learning

1 Introduction

Stress, in particular stress in the workplace, is a growing issue of concern worldwide. Recent studies provide evidence for this. In a survey conducted by the American Psychology Association [3], up to 60% of the Americans reported workplace as a significant source of their stress. Also in Europe, up to 25% of the workers have been found to be at the risk of health problems due to stress generated in the workplace [10]. It is important to develop an objective measure to reliably monitor stress in order to enable workplace stress management solutions. Wearable sensors are able to provide a sensing paradigm for continuous monitoring of stress-related physiological variables. Machine learning techniques can then be used to develop stress detection models which relate the physiological state to a stress level. However, it is challenging to build such models due to the variability in stress physiology. The changes in physiology, i.e., the physiological reaction, and the corresponding perception of stress, i.e., the psychological reaction, in response to a stressor, will depend upon various personal,

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contextual and psychological factors. These factors lead to differences in stress physiology across the individuals (inter-individual differences) and even within the same individual over time (intra-individual differences).

Most of the stress-related research studies are conducted in controlled laboratory conditions. As the duration of monitoring is short, only inter-individual differences have to be accounted for when developing the stress detection model. This, if addressed by the study, is generally done by normalizing the data from each individual by their baseline physiological response measured in the rest condition, at the start of the monitoring. However, controlled studies do not adequately represent the challenges of free-living conditions [25]. Further studies and validation of stress detection models in free-living conditions are required. In such free-living studies, the individuals need to be monitored for multiple days so as to capture various instances of responses to natural stressors which generally occur at a low frequency. Therefore, stress detection models for free-living conditions have to address the intra-individual differences also, in addition to the inter-individual differences in stress physiology.

The aim of our study is to investigate the development of machine learning models for stress detection in real-life conditions using wearable sensors. In this paper we show that machine learning models perform no better than a trivial model (a model with no learning capability) when differences in stress physiology are not accounted for. To address this, we propose normalization using $Stress\,Response\,Factor$ (SRF) which is computed with physiological features at a reference point scaled by the stress level for the corresponding period. Different reference points for the calculation of SRF are comparatively evaluated in this work. The proposed SRF leads to an improvement of up to 32% in the model performance, on an average across different machine learning models.

The paper is organized as follows. In Sect. 2, we outline previous works on stress detection using physiological sensors. This is followed by the discussion of stress physiology and the proposed $Stress\,Response\,Factor$ (SRF) for normalization in Sect. 3. In Sect. 4, we describe the dataset and the analysis method used for the evaluation. We present the experimental results in Sect. 5, followed by the discussion and conclusion in Sect. 6.

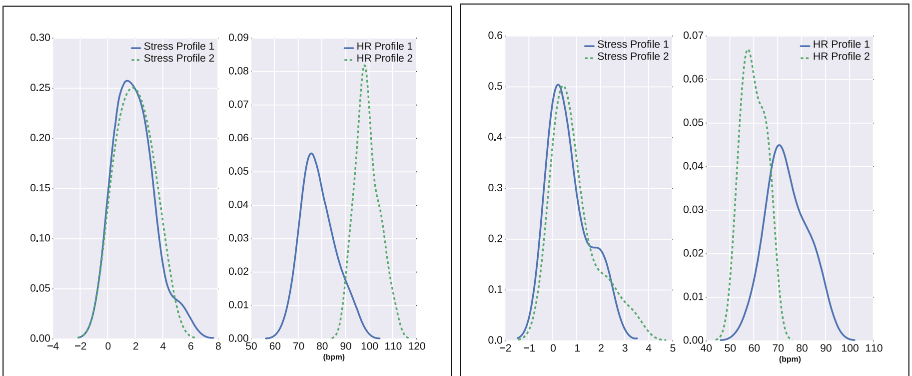
2 Previous Work

Stress detection based upon physiology has mostly been investigated in controlled studies [1,8,11,13,19,20,24,28]. Only few stress-related works have been conducted in free-living conditions. In [12], the authors studied stress detection in drivers. However, the study protocol was designed to create stressful conditions based upon the route driven, instead of having natural stressors. The authors of [18,26] investigated stress detection in free-living but do not address the model development and evaluation in subject-independent or day-independent settings. Therefore, the issue of intra-individual or inter-individual differences in stress physiology has not been investigated in either of those studies.

Some studies conducted in controlled conditions have acknowledged the presence of differences in stress physiology. In [8], the authors reported 20% reduction in classification accuracy, for a binary classification problem of detecting stress from non-stress state, with a between-subject model (affected by inter-individual differences) compared to a within-subject model (not affected by inter-individual differences). The authors in [17] noted that, within an individual, physiological data from the same day were clustered more cohesively in comparison to the data across the days, for a given affective state. They proposed various approaches to address the observed differences across the days, such as: include information about the day in the model, subtract the day-dependent baseline, or use features that are less influenced by the daily variability. In [21], the authors developed a stress detection model using heart rate variability features. They proposed to normalize the feature values with standardization and include the data from the baseline physiology for each subject, in order to account for the inter-individual differences. Authors in [19] addressed the inter-individual differences by developing a personalized model based upon the modification in the machine learning algorithm used to train the model. This is done by using the physiological data of the individual from the neutral state when no stressors are applied. Authors in [27] proposed to cluster the individuals based upon their baseline physiological features and develop cluster-specific stress detection model as the stress physiology is non-homogeneous across the individuals. In [11], the authors used subject's baseline physiological recordings to normalize the measured physiological data and suppress the inter-individual variability. This lead to an increment of up to 9% in the classification accuracy, for a binary classification problem of detecting stress from non-stress state. However, all these proposed methods for the correction of the differences in stress physiology cannot be translated directly to free-living studies. Majority of the solutions depend on the use of physiological baseline from the individual. The controlled studies, spanning few tens of minutes with an explicit baseline measurement phase in the protocol, facilitate the establishment of baseline physiology. Identification of such baseline is non-trivial in free-living studies where monitoring spans multiple days.

3 Stress Physiology and Normalization

Every individual has a different body physiology and varying responses to similar stressors. As an example, in Fig. 1a, stress profile (distribution of reported stress levels on a day) of two individuals is shown on the left-hand side. The stress profile of these individuals is similar, but their respective heart rate profile (distribution of the mean heart rate in the corresponding period) deviate significantly from each other (shown on the right-hand side). We have used mean heart rate as an example, it being one of the most commonly used features in stress detection models [12,20,21,25]. Individuals generally have differences in stress physiology. Physiological and psychological response to a stressor differ between the individuals due to a multitude of factors. Moreover, even within an individual, different physiological responses can be elicited for similar stressors (Fig. 1b). A stress detection model that works in real-life conditions should be able to account for these differences.



(a) Different individuals

(b) Same individual

Fig. 1. In the figure, distribution of stress level and heart rate (referred to as stress profile and HR profile respectively) measured over a day is shown. In (a), the profile for two individuals is shown. Even though they report similar stress profile on these days, their heart rate profile differs. In (b), profile of an individual on two different days is shown. As it can be seen from the figure, there can be physiological differences across the days for an individual, even though the reported stress is similar.

The variability in stress physiology can be corrected by normalization. Let PV be the physiological feature vector representing the physiological state and l represent the stress level. An optimal normalization factor could be the value of PV, when l is at some fixed reference value. The variability of this factor encompasses the inconsistency in stress physiology. However, it is not possible to obtain such common reference point across the days and for different individuals in real-life conditions. The possible values for l on a given day for an individual are completely uncontrolled. Therefore, there is not one fixed value of l which is guaranteed to occur on each day for different individuals. We propose to obtain the reference point based upon some characteristic features in the stress physiology profile of the day and include scaling with the value of l in the normalization factor. This allows to compute a factor that accounts for the variability in the stress physiology, while l can have different values at the selected reference point. In this work, we empirically evaluate and compare different reference points that can be used to compute the normalization factor, using linear scaling by l. If PV^{ref} is the physiological feature vector and l^{ref} is the corresponding stress level at a given reference point, the factor for normalization, defined as $Stress\,Response\,Factor$ (SRF), is computed as:

$$SRF = PV^{ref}/(1 + l^{ref}) \tag{1}$$

where ref represents the selected reference point. Normalization with SRF computed for a particular day is able to factor the day's stress physiology profile in the model. This makes the stress physiology comparable over days and across individuals. We evaluate different reference points for computing *SRF* which are: (i). Ref_{minstr}: Minimum stressful period of the day (ii). Ref_{maxstr}: Maximum stressful period of the day (iii). Ref_{minhr}: The period of the day for which the heart rate is minimum (iv). Ref_{arbit}: An arbitrary period from the day.

These reference points have been chosen on the basis of insights from the research in stress and other application domains. Ref_{minstr} is the closest point of the day to a baseline rest phase, based upon the reported stress level as an evidence. As discussed earlier, baseline rest phase has been used to compute the normalization factor for stress detection model in many controlled studies. Ref_{maxstr} is the closest point of the day to a hypothetical maximum point in stress physiology. Normalization based upon maxima is commonly used in other applications like energy expenditure estimation [15]. Ref_{minhr} is the closest point of the day to a baseline rest phase based upon the physiological evidence, as lower heart rate is one of the indicator of a calm and resting state. Finally, Ref_{arbit} provides a comparison to establish the merit of using other reference points for computing *SRF*. A period from a given day is selected randomly as the reference point, from among the period for which the user reported their stress level.

4 Materials and Methods

4.1 Data Collection

Study Population: We evaluate our stress detection model using a dataset collected in free-living conditions [25]. A total of 10 healthy participants, 7 females and 3 males took part in the study. Mean age of the participants was 31.1 ± 11.9 years. All participants were researchers, typically sedentary during the work day. They were monitored continuously during their working hours for 5 days. The entire study protocol was communicated to each participant and they were asked to sign an informed consent form, before the start of the study. The participants were allowed to discontinue their participation in the study at any time, should they decide to do so for any reason.

Sensor Modalities: Wireless body area network developed within the Human++ program [7] was used for synchronous physiological signal acquisition from each participant. The system consisted a necklace-based device measuring ECG and 3D acceleration, a chest band for respiration monitoring, an EMG device measuring muscle activity at the upper trapezius muscle, and a wrist-band device measuring GSR, 3D acceleration, skin temperature, relative humidity, ambient temperature and ambient humidity. This system has been used before for physiological monitoring in various applications like energy expenditure estimation [2], emotion monitoring [7] etc. We refer to [25] for the details on the sensor setup used in the study. On the first day of the study, sensors were handed over to the participants and they were given instructions about its usage. On each day of the study, participants wore the sensors at the start of the day and took them off at the end of the working day. For the analysis in this paper, ECG, GSR, respiration and accelerometer signals (measured from the necklace-based device) are used. These signals were acquired at a sampling frequency of 256 Hz, 128 Hz, 256 Hz and 32 Hz respectively by the corresponding sensors.

Reference Stress Level: Various reference measures for the stress level were obtained from the participants. A smartphone, with an application to collect annotations every 30 min, was provided to each participant. The participants annotated their perceived stress level (for the past 30 min period and at the current moment) on a Visual Analog Scale (VAS), from 0 (not at all stressed) to 10 (totally stressed). Participants also provided annotations for their activities, postures, and food consumptions. Cortisol level, a bio-chemical marker of stress level, was also measured from the participants four times per day using saliva sampling equipment Salivettes (Sarstedt, Germany). Participants also filled in the Daily Stress Inventory [5] each day. For the analysis in this paper, only the self-reported perceived stress level has been used as the reference, it being the less intrusive probe into the stress level for free-living conditions.

4.2 Features Computation from Sensor Modalities

We use features that have been commonly used in other studies for stress detection [25]. The features are extracted from the 30 min window corresponding to the period for which the participant reported their stress levels. All the signals are processed without any sampling rate conversion.

ECG: We compute different features from the ECG signal based upon the R-peaks detected using the Pan-Tompkins algorithm [14]. The features extracted are: i. mean heart rate (mhr) ii. standard deviation of R-R peak intervals (sdnn) iii. root mean of sum of squared difference of consecutive R-R peak intervals (rmssd) iv. low frequency component of the spectrum of R-R peak intervals (lf): power in the 0.04 Hz–0.15 Hz band v. high frequency component of the spectrum of R-R peak intervals (hf): power in the 0.15 Hz–0.4 Hz band vi. ratio of LF to HF (lfhf) vii. percentage of R-R peak intervals that are greater than 50 ms (pnn50) viii. approximate entropy of R-R peak intervals (apen) ix. poincare plot based features. As suggested in [23], we extract the following features from the poincare plot: sd1 (length of the major axis), sd2 (length of the minor axis), sd1/sd2 (ratio of the axes).

GSR: The features extracted from the measured GSR signal are: i. skin conductance level (scl) ii. signal power of the skin conductance (scp) iii. skin conductance response rate (scrr) iv. signal power in the second order difference of the skin conductance (scdiff2).

Respiration: We extract respiration rate (resprate), the number of respiration cycles per minute, as a feature from the respiration signal.

Accelerometer: We extract the magnitude of motion (mom) feature from the measured 3-D accelerometer signal. This is computed as the mean of the magnitude of the 3-D motion vector, $mom = \frac{1}{N}\sum_{i=1}^{N} \sqrt{accx_i{}^2 + accy_i{}^2 + accz_i{}^2}$.

4.3 Data Analysis

We use regression models for the prediction of the stress level using physiological features, as the reported stress levels are in a continuous scale. *Random Forest (Rforest)* [6] for regression, *Lasso* [22], *Support Vector Regression (SVR)* [9] with epsilon-insensitive loss function, and *k-Nearest Neighbours (k-NN)* have been used in our analysis.

4.4 Evaluation Method and Metrics

We use leave-one-participant-out cross-validation to evaluate the performance of the models, using mean squared error (mse) as the performance metric. A trivial regression model is evaluated to obtain a baseline against which the performance of other regression models is compared. A trivial regression model is defined as a model which provides the mean of the labels for the data in the training set, as the constant prediction output. Unlike classification problems, where baseline performance can be established with the class prior (e.g. 50% accuracy on a balanced binary classification problem), no such prior-based baseline can be established for regression problems. The performance of a trivial model helps to establish an alternate baseline. Using mse or rmse (root mean squared error) as a model evaluation metric to compare with the baseline from a trivial or other regression models has been used in other studies [4,16].

SRF is used for normalization in a model by scaling all sample points from the day with the factor. The reference point used to compute *SRF* is excluded from the analysis for all the models. Thus each model, regardless of its usage of *SRF*, is evaluated with the same training and test set for comparison. We also compare other standard normalization methods, namely a min-max scaler (scales the data between 0 and 1) and a standard-scaler (removes the mean and scales the data to have a unit variance) applied to the data from each day.

The effect of *SRF* on model performance is summarized with the within-model and over-baseline gain. If mse_{model} is the mse obtained from a model when no normalization is used, $mse_{model\,SRF}$ is the mse obtained from the model when *SRF* is used for normalization, and $mse_{trivial}$ is the mse obtained from a trivial regression model, then the within-model gain is defined as: $\frac{mse_{model} - mse_{model\,SRF}}{mse_{model}} * 100$ and over-baseline gain is defined as: $\frac{mse_{trivial} - mse_{model\,SRF}}{mse_{trivial}} * 100$.

We tune the parameters of regression models with cross-validation within the training set. For *Rforest*, the number of estimators ($\{101, 201, 301\}$) and the maximum number of features ($\{sqrt(total\,number\,of\,features), log2(total\,number\,of\,features)\}$) to be used for the split of decision trees are tuned. In *Lasso*, α (the regularization parameter) is tuned automatically with iterative fitting. For SVR, we use a RBF kernel and tune ϵ ($\{i/10\}_{i=1}^{10}$), γ ($\{2^i\}_{i=-8}^{8}$) and C($\{2^i\}_{i=-8}^{8}$). In the k-NN model, the number of neighbors k ($\{3, 5, 7, 9, 11\}$), weights ($\{uniform, distance\}$) and distance-metric ($\{'euclidean', 'manhattan', 'chebyshev'\}$) are tuned.

In all evaluations, data in the training set is scaled with a min-max scaler to restrict the feature space between 0 and 1 and these scaling parameters are also propagated for scaling data in the test set. All tests for significance are evaluated with a paired t-test at a significance level of 0.05.

5 Experimental Results

In our evaluation setting, the training and test set, on an average, consist of 630 samples and 70 samples respectively. In Fig. 2, the evaluation results for different regression models with and without normalization are shown. Significant reduction in mse is obtained with our proposed normalization method. The model performances for *SRF* computed with different reference points are shown in Fig. 3.

We proposed to compute *SRF* based upon the reference point from each day. This is compared with the model performance when a single *SRF* is computed per participant with an assumption that there is no variability in stress physiology within an individual. Two different methods for computing a single *SRF* per participant are evaluated. The first method pools all the data of a participant from across the multiple days together, establishes a single reference point in the pooled data and computes *SRF* based upon this reference point. The second method computes *SRF* from the reference point in the first day.

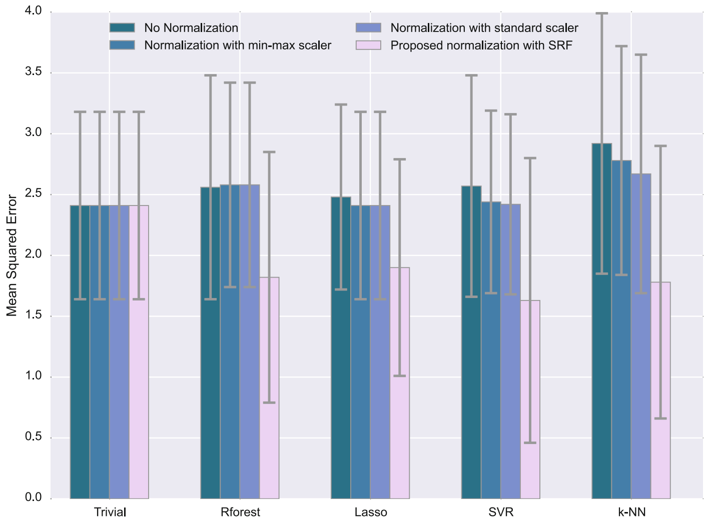


Fig. 2. mse obtained for different regression models evaluated in leave-one-participant-out setting. The performance of models without normalization and with different normalization methods is compared. The model performance for the normalization with *SRF* is reported with the reference point considered at the minimum stressful period of the day (Ref_{minstr}).

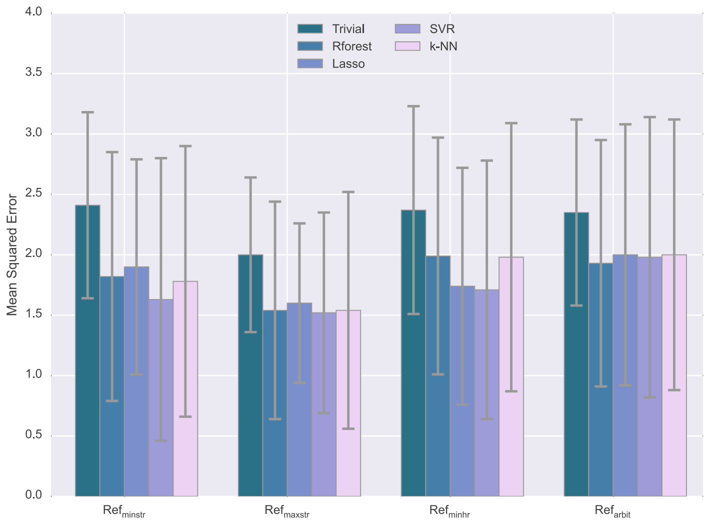


Fig. 3. Performance of the models with normalization factor computed from different reference points. For Ref$_{arbit}$, the average performance from 8 runs is reported.

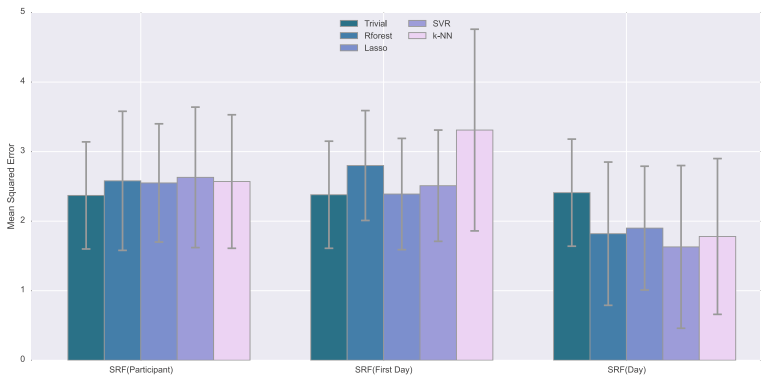


Fig. 4. Performance of the models with a single *SRF* per participant by pooling data of the participant from all the days: RF(participant), a single *SRF* per participant based upon the reference point obtained from the first day: RF(first day) and a *SRF* for each day of the monitoring: RF(day). The results are reported with Ref$_{minstr}$ as the considered reference point.

The comparison result is shown in Fig. 4. An improvement in the model performance is obtained only when *SRF* is computed for each day per participant. In Table 1, we report the obtained improvement in the model performance due to *SRF*, using within-model and over-baseline gain metrics.

Table 1. Within-model gain and over-baseline gain (defined in Sect. 4.4) for different models and reference points. For Ref_{arbit}, average gain obtained from 8 runs is reported.

	Within-model gain (%)					*Over-baseline gain (%)*				
	Rforest	*Lasso*	*SVR*	*k-NN*	*Average*	*Rforest*	*Lasso*	*SVR*	*k-NN*	*Average*
Ref_{minstr}	28.90	23.38	36.57	39.04	**31.97**	24.4	21.16	32.36	26.14	**26.01**
Ref_{maxstr}	24.50	21.10	28.97	35.02	27.39	23.00	20.00	24.00	23.00	22.50
Ref_{minhr}	20.71	28.97	32.41	30.76	28.21	16.03	26.58	27.84	16.45	21.73
Ref_{arbit}	22.40	18.03	22.35	28.05	22.70	17.87	14.89	15.74	14.89	15.85

6 Discussion and Conclusion

Without normalization, stress detection model performs no better than a trivial model (Fig. 2). This result highlights the discussed differences in stress physiology, over time and across the individuals. The relation between physiological features and stress level cannot be modelled well because this relation is not comparable across the days and individuals. With min-max scaler and standard scaler to normalize the data from each day, still no improvement in the model performance is obtained. The use of *SRF* for normalization leads to a significant improvement in the model performance. This is because *SRF* helps to include some characterization of the stress-physiology profile of the day into the model, thus making stress physiology comparable across the days and individuals. The characterization obtained from any of the reference point in the day improves the model performance (Fig. 3). Using within-model and over-baseline gain metrics as the comparison criteria, Ref_{minstr} gives the best performance in our evaluation setting (Table 1). The results shown in Fig. 4 depict that the *SRF* needs to be computed for each day, highlighting the presence of intra-individual differences across days. Stress detection in free-living requires periodic identification of the normalization factor to account for the temporal variations in stress physiology.

One limitation of the proposed *SRF* is that the normalization factor is dependent upon the availability of labeled data points. Normalization factor which can be derived directly from the features, without the need of corresponding label, would be desirable for deployment scenarios. For future work, it would be interesting to investigate the temporal characteristics of the features at different label-independent reference points or ranges (e.g. during morning period) for such normalization factor. Nonetheless, the analysis presented here makes first step towards robust stress detection models in free-living conditions identifying the differences in stress physiology as one of the key challenges for such models.

To conclude, stress physiology shows variability due to the effects of different personal and temporal factors. A stress detection model needs to account for the differences stemming from these factors. The *Stress Response Factor* (*SRF*) proposed in this paper helps in addressing these differences by characterizing the stress physiology profile of the day into the model. We were able to validate its contribution to the stress detection model, using a dataset collected in free-living conditions. It is desirable to further investigate and validate stress detection models with a study involving long-term monitoring of a larger number of individuals.

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