Physical Exercise Recommendation and Success Prediction Using Interconnected Recurrent Neural Networks

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ABSTRACT
Unhealthy behaviors, e.g., physical inactivity and unhealthful food choice, are the primary healthcare cost drivers in developed countries. Pervasive computational, sensing, and communication technology provided by smartphones and smartwatches have made it possible to support individuals in their everyday lives to develop healthier lifestyles. In this paper, we propose an exercise recommendation system that also predicts individual success rates. The system, consisting of two interconnected recurrent neural networks (RNNs), uses the history of workouts to recommend the next workout activity for each individual. The system then predicts the probability of successful completion of the predicted activity by the individual. The prediction accuracy of this interconnected-RNN model is assessed on previously published data from a four-week mobile health experiment and is shown to improve upon previous predictions from a computational cognitive model.

CCS CONCEPTS
• Information systems–Information retrieval–Retrieval tasks and goals–Recommender systems • Computing methodologies–Machine learning–Machine learning approaches–Neural networks • Computing methodologies–Artificial intelligence–Philosophical/theoretical foundations of artificial intelligence–Cognitive science

KEYWORDS
Recommendation System, Recurrent Neural Network, ACT-R, Deep Learning

1. Introduction
A major driver of healthcare costs in the U.S. and elsewhere are unhealthy behaviors such as physical inactivity, increased food intake, and unhealthful food choice [1, 2]. Behavioral and environmental health factors account for more deaths than genetics [1]. With the advent of pervasive computational, sensing, and communication technology, there is an opportunity to support individuals in their everyday lives to develop healthier lifestyles. For instance, the pervasive use of smartphones is a potential platform for the delivery of behavior-change methods at great economies of scale. Commercial systems such as noom aim to provide psychological support via mobile health (mHealth) systems. Research platforms, such as the Fittle+ system [3], have demonstrated the efficacy of translating known behavior-change techniques[4] into personal mHealth applications. Computational cognitive models have successfully simulated the day-by-day individual-level effects of such interventions in Fittle+ experiments [5, 6]. In this paper, we explore a related opportunity in the mHealth space: The application of machine learning to recommend specific health goals to specific individuals such that there is a high probability of achieving those goals.
Several psychological theories suggest that an ideal automated mHealth goal recommendation algorithm should modulate the perceived difficulty of goals for each individual. Behavior-change goals are typically defined to be...
specific and measurable. Specific means unambiguous descriptions of behavior (“drink five glasses of water”), and measurable means reasonably precise evaluation of success or failure. The perceived difficulty of a health goal depends on each individual’s history. Goal Setting Theory [7] predicts that goals need to be challenging enough to be motivating. The Social Cognition Theory of self-efficacy [8, 9] predicts that goals that are perceived as too difficult are unlikely to be attempted. Social Cognitive Theory also predicts that self-efficacy can be increased through a process whereby users succeed at progressively more difficult or complex goals over time (guided mastery). Greater levels of self-efficacy lead to greater likelihoods of achieving a goal. The Attributional Theory of Performance [10] proposes that the level of intended effort motivating a performance will increase with the difference between self-efficacy and the perceived difficulty of achieving a goal. Recommended behavior goals for individual users should be difficult enough to be motivating, but easy enough to be successfully achieved.

In this paper, we develop a novel algorithm to recommend exercise goals using data collected in a mHealth experiment [11]. Those data were also used to develop a computational cognitive model of self-efficacy [5]. The Konrad et al. [11] experiment contrasted different treatment conditions involving three different goal-scheduling algorithms, producing different patterns of daily goal success. We use these data to train a machine learning recommender technique that uses a combination of association rules and recurrent neural networks. The aim of this technique is to accurately recommend exercises for each individual on each day that have a high probability of being pursued and achieved.

The data we use comes from the Konrad et al. [11] mHealth experiment. The mHealth application was called DStress, and it was developed to provide coaching on exercise and meditation goals for adults seeking to reduce stress. The experiment took place over a 28-day period. Each week involved alternating Exercise days and Meditation Days, with one Rest Day at the end of the week. A total of 46 exercises were in the DStress library. These had been developed by three certified trainers on the development team, and all three trainers had provided difficulty ratings on the exercises. On each Exercise Day, each individual was assigned two sets of upper body, lower body, and circuit training exercises. The experiment compared three groups of adult participants: (1) a DStress-adaptive group (N = 19) who used the adaptive coaching system in which goal difficulties adjusted to the user based on past performance, (2) an Easy-fixed group (N = 24) in which the difficulty of daily goals increased at the same slow rate for all and (3) a Difficult-fixed group (N = 22) in which the goal difficulties increased at a greater rate. The participants in the DStress-adaptive group self-reported significantly lower stress levels compared to the Easy-fixed and Difficult-fixed groups. The algorithm used in the DStress-adaptive group was such that if a person successfully completed all exercises assigned for a day, the algorithm advanced them to the more difficult level. If they did not succeed at the exercise activities, then they were regressed to an easier level.

2. Related Work

Recommendation systems have been used in online shopping for several years. The goal of recommendation systems is to recommend products that suit the consumers’ tastes. Traditional recommendation systems have been used collaborative filters to suggest products similar to those the consumers have purchased. With the advancements in deep learning algorithms, several studies have proposed deep learning-based recommendation systems [12]. In [12], a multi-stack recurrent neural network (RNN) architecture is used to develop a recommendation system to suggest businesses in Yelp based on their reviews. Wu et al. [13] used an RNN with long-short term memories (LSTM) to predict future behavioral trajectories. A few studies have proposed exercise recommendation systems [14, 15]. Sami et al. [14] used several independent variables to recommends various sports such as swimming using collaborative approaches. Ni et al. [16] developed an LSTM-based model called FitRec for estimating a user’s heart rate profile over candidate activities and then predicting activities on that basis. The model was tested against 250 thousand workout records with associated sensor measurements including heart rate.

3. Proposed Algorithm

Our proposed method is an innovative architecture of two inter-connected RNNs that takes exercise embedding and exogenous data as the input and recommends exercise activity and its probability of successful completion in the output.
3.1. Exercise Embedding

Similar to symbolic data samples such as words in NLP, the exercise names must be embedded onto a vector space to obtain their vector representations. Word2vec is the most well-known word embedding set of algorithms. The two main methods of word2vec are: skip-gram and CBOW [17]. In this paper, we use SkipGram to find the vector representation of exercise names. Word2vec methods embed words that appear together in one sentence close together in the vector space representation. The sequence of exercises performed by one individual in the training dataset is considered as one sentence for the word2vec algorithm. The challenge with sequences of exercises for different individuals is that people with the same exercises on the first day may choose different exercises on the second day. For example, in Figure 1, individuals who have received the recommended exercises “Two Leg Hip Bridge on Floor” and “Pushups off Wall” selected different exercises such as Crunches and Deadbug afterward. This causes an inaccurate exercise prediction because three words “Two Leg Hip Bridge on Floor”, “Pushups off Wall”, and Crunches do not appear frequently together instead other variants such as “Two Leg Hip Bridge on Floor”, “Pushups off Wall”, and “Deadbug” appears in other sequences. To mitigate this problem, we propose to embed the set of exercises that come as descendants close to each other in the vector representation space.

To find the set of exercises that appear together—e.g., {Crunches, Deadbug, Dumbbell Kneeling Row, Kneeling Plank, Marching in Place, Modified Burpee No Jump, Pushups on Bar, Standing Knee Lifts, Static Lunge With Wall} in Figure 1—an association analysis algorithm is applied to the dataset [18]. Association analysis discovers interesting relationships in large data, and represent them as association rules or set of frequent items. Figure 1 shows an example of association rules extracted from an exercise dataset.

After extracting association rules, the set of all exercises appear as consequences of a sequence of exercises that are considered as one sentence for the word2vec algorithm. The reason for choosing the set of consequences as a sentence is that these exercises appear interchangeably so they should be embedded close to each other in the vector representation space.

Figure 1. Set of exercises with the same antecedent exercises within a window.

3.2. Exercise and Its Success Probability Prediction

Our goal is to recommend an exercise to an individual based on their previous exercises and their success rate. This problem is formulated as a time series and success rate prediction. Let’s assume that we represent the vector representation of the $i$th exercise with $v_i \in \mathbb{R}^N$, where $N$ is the dimension of the vector representation. For each individual, we have a sequence of training dataset $\{(v_{i1}, x_{i1}, p_{i1}), (v_{i2}, x_{i2}, p_{i2}), \ldots, (v_{iK}, x_{iK}, p_{iK})\}$, where $K$ is the total length of the sequence, $p_i$ is the indication of successful completion of the exercise with values $\{0, 1\}$, and $x_i \in \mathbb{R}^J$ is the $J$-dimensional exogenous data of the $i$th exercise. The exogenous data are the additional information that we have about each exercise, such as its difficulty level and the body parts involved in the exercise. The successful completion of an exercise depends on various factors, including the previous exercises an individual has received, as well as
information about the exercise. For example, the probability of successful completion of the exercise depends on its difficulty, the body part it targets, and the similar information of previous exercises.

This paper used two interconnected RNNs for exercise recommendation and success rate prediction. Figure 2 shows the architecture of the proposed inter-connected RNNs. The first RNN is trained to predict the next exercise according to the history of exercises. The RNN network will be trained on the sequence \( \{v_1, v_2, ..., v_K\} \). The network will predict \( v_i \) based on \( \{v_{i-w}, v_{i-w-1}, ..., v_{i-1}\} \), where \( w \) is the window length. We examined the sequence dependency of the training data using statistical time series methods, e.g., autocorrelation, to select the appropriate window length. We propose to use RNNs if the temporal dependency is small—such as our dataset and to use RNNs with LSTM units when the temporal dependencies are long. Since there is no long-term dependency among the sequence of our exercise data, we have selected a two-layer RNN with \( N \) nodes for this purpose. The cost function selected to predict the next exercise is mean square error (MSE).

![Figure 2: The architecture of RNN for predicting exercises and their probability of success.](image)

The second RNN architecture is designed to predict the probability of the recommended exercise. The architecture is inspired by ARMAX model. The probability of success depends on the predicted exercise as well as previous exercises. The probability of success is also affected by exogenous data. We use a two-layer RNN architecture with \( N + J \) nodes. The network gets the exogenous data of each predicted exercise as well as the latent representation of exercises from the hidden layer of the first RNN. The second RNN learns to predict \( P(p_i|v_{i-w}, v_{i-w-1}, ..., v_{i-1}) \). The below equation represents the proposed model in the form of time series analysis.

\[
p_i = f_0(\rho \hat{t}_i) + f_1 \left( \sum_{j=i-w}^{i-1} \alpha_{j-i+w} p_j \right) + f_2 \left( \sum_{j=i-w}^{i-1} \beta_{j-i+w} \tau_j \right) + f_3 \left( \sum_{j=i-w}^{i} \gamma_{j-i+w} x_j \right)
\]

where \( f_5 \) are nonlinear functions—ReLu and Sigmoid, \( \alpha_j, \beta_j, \gamma_j \) are weights that will be learned from the training data, \( \tau_j \) is the latent representations of \( v_j \) obtained from the hidden layer of the first RNN, \( \hat{t}_i \) is the latent presentation of the predicted exercise, and \( \rho \) is its coefficients to be learned from the training data. The cost function used for training the second RNN is the binary cross-entropy.

4. Experimental Results

4.1. Data

This paper uses DSTRESS dataset, collected through a mobile application. DStress[11] is a web- and mobile-based system that provides automated coaching on exercise and meditation goals aimed at reducing perceived stress. As discussed above, An experimental evaluation of this app [11] took place over 28 days with interleaved Exercise Days with Meditation Days and one Rest Day per week. The experiment compared three groups of adult participants: (1) a DStress-adaptive group who used the adaptive coaching system in which goal difficulties adjusted to the user based on past performance, (2) an Easy-fixed group in which the difficulty of daily goals increased at the same slow rate for
all and (3) a Difficult-fixed group in which the goal difficulties increased at a greater rate. The participants in the DStress-adaptive group self-reported lower stress levels compared to the Easy-fixed and Difficult-fixed groups. The DStress-adaptive group reported a higher level of activity completions than the other two groups (Figure 3) even though they were performing more difficult exercises than the Easy-fixed group. This increased ability to tackle more difficult goals is consistent with a build-up in self-efficacy. The individual-level day-by-day success rate data have been modelled [5] using the ACT-R neurocognitive architecture [3, 6]. ACT-R is a computational architecture for simulating and understanding human learning and cognition. The ACT-R simulations were used to predict each individual’s success in performing each assigned exercise in the 28-day DSTRESS dataset, and we compare our RNN-based approach to the ACT-R model-fits below.

![Figure 3](image)

**Figure 3** - Summary data from the DStress experiment [11]: the mean rate of participants successfully completing assigned exercises per session over 28 days (3 times per week).

There were 72 participants in this study. Participants were assigned different exercises of differing difficulty levels depending on experimental condition and personal history. After each exercise, participants indicated whether they have finished the exercise successfully or not. The exercise difficulty levels were rated by three experts. Moreover, the dataset includes lag (days since last successful performance of the exercise) and frequency (cumulative successful performances of the exercise) information for each exercise. Each participant performed 36 exercises.

### 4.2. Experiment Setup

We have used the k-folding approach for training and testing our algorithm, where \( k \) is 72. At each time, we leave out one participant from the training and train the architecture on the remaining 71 participants’ data. Then, we evaluate our algorithm on one test participant. The statistical analysis of the exercise time series has determined the length of the window equal to \( w = 3 \). This means that the temporal dependencies among the exercises is at most three-time steps. This has created 2650 sequences of length 3. The exercises are embedded onto a space of dimension \( N = 20 \) using word2vec algorithm. The exogenous variables are Lag, Frequency, and Difficulty Level \( (K = 3) \). The adaptive learning optimization algorithm “Adam” is used to train the RNN modules [19] (Kingma & Ba). The learning rate is \( lr = 0.01 \).

Two RNNs are interconnected, so the inference is performed at the same time. However, we will describe their evaluations separately. Two approaches are selected for evaluating the first RNN—exercise prediction—because the first RNN gets its input from and gives its output to Word2Vec. Thus, we evaluate the RNN accuracy on the training and test data using MSE (mean square error). We also compare the top5 predicted exercises with the list of co-embedded exercises. Because several exercises appear together as consequences of a given sequence, if our proposed algorithm predicts any of the consequences, we call it a success. We explained how we co-embed these consequences together using Word2Vec approach in §3.1. We use the same approach to find the co-embedded list of exercises. If the co-embedded list and the top5 predicted list have common names, we consider it as a true positive (TP). If there is no overlap, it is a false negative (FN). We use this approach to calculate the precision and recall for the first RNN. Figure 4 shows the test accuracy of the first RNN for predicting the next exercise. Figure 4a shows the histogram of
the test accuracy of the exercise name prediction for subject $i$ when subject $i$ is left out during the training. To calculate the accuracy, we have left out subject $i$ and trained the model on the remaining subjects. Then, the test accuracy of exercise prediction is calculated for subject $i$ as described above with top5 prediction. In Figure 4a, the accuracy of exercise prediction is on average %80. The accuracy includes the prediction of exercise vector representations and the exercise prediction names from the predicted vector representations. Figure 4b shows the histogram of the mean square error (MSE) for the same experiment. MSE is computed between the activity embedding $v_i$ and the predicted vector representation $\hat{v}_i$. In Figure 4b, the MSE values are in the order of $1e^{-05}$ that shows the great performance of the trained RNN for predicting the test data.

![Figure 4- (a) The histogram of the test accuracy of exercise name prediction for subject $i$ when subject $i$ is left out during the training; (b) The histogram of the test accuracy of exercise vector representation prediction for subject $i$ when subject $i$ is left out during the training. The accuracy is calculated using MSE between $v_i$ and $\hat{v}_i$.](image)

The second RNN predicts the probability of success for predicted exercises. We use precision to evaluate the performance of the second RNN. Figure 5 shows the histogram of the precision values for the same experiment described above—leaving out subject $i$ during the training. Figure 5b shows the Brier score of the prediction of the probability of success using RNN and ACT-R models for subject $i$ when subject $i$ is left out during the training. Overall, the RNN model is more accurate in the prediction, except for five subjects.

Note that the training in all models—both RNNs—are performed on all subjects except for the test subject. Thus, the trained models are able to predict activities for each subject without any personalization. After a certain time and collecting enough data for each subject, we will be able to fine-tune the proposed algorithm for each subject and improve the performance significantly.

![Figure 5- (a) The histogram of the precision values for the success prediction using the second RNN model for subject $i$ when subject $i$ is left out during the training; (b) The Brier score for predicting the probability for success using RNN and ACT-R models.](image)
5. Conclusion
The dual-RNN system for recommending workout exercises along with predicting individual success rates achieves high accuracy for individuals from whom we do not have any training data. We validated this achievement by training the proposed model on a set of users and testing on a new set of test users. Even though our time series analysis of the workout data showed short-term dependency, RNN with LSTM units can be deployed for datasets with long term interdependencies.

Similar to many existing recommendation systems, our algorithm suffers when the number of users is small or when the systems are deployed without any prior history of the user. This issue of predictive accuracy is especially problematic in domains where there is a significant downside to making prediction errors. mHealth and behavioral medicine in general are surely examples of such domains. One would not want an algorithm to repeatedly recommend exercises that a person would not or could not perform. The user would likely abandon the app altogether, and the algorithm would never collect enough data to improve. This problem can, of course, be remedied by using hand-crafted recommendation algorithms (such as the DStress example), or digital platforms that use human-to-human counselling as part of the bootstrapping process.

Another approach might involve combinations of explanatory computational models such as ACT-R and machine learning approaches such as the dual-RNN system presented here. With a small amount of engineering and zero parameter estimation, ACT-R was able to predict individual-level exercise success rates “out of the box.” Such models can provide initial predictive capabilities and explanations of the psychological mechanisms in play[5]. As even small datasets, from small numbers of participants are collected, we can see that machine learning approaches can overtake the predictive accuracy of those initial psychological models. As more data are collected, one can imagine that patterns learned by machine learning could be used to refine and expand the explanatory mechanisms embodied in the computational cognitive architecture, thus improving both prediction and explanation in tandem.

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