Analysis and Modeling of Neural Ensemble Rehearsal During Sleep Using Logistic Regression and Shallow Neural Networks

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Abstract

Significant work has been carried out to elucidate the mechanisms of memory. One route of investigation has aimed to determine the role of sleep in learning. Specifically, slow wave sleep (SWS) has been identified to improve consolidation of hippocampus-dependent memory. Using a session from the pfc-6 dataset from crcns.org collected by Peyrache et al. (2009), this analysis sought to determine the role of neuronal ensemble rehearsal during SWS in memory consolidation of a behavioral contingency task. Logistic regression models and shallow neural networks were trained on frequency-domain neural spike data from the behavior epoch to predict whether an animal behaved correctly in the task. Then, neural spike data from the same rat during SWS directly before (pre-SWS) and directly after (post-SWS) the behavior epoch was inputted into the models to determine similarity of firing patterns to the behavior session. Model training failed to converge, predicting that the animal had behaved correctly on 100% of the activation patterns in behavioral train data, behavioral test data, pre-SWS data, and post-SWS. While this analysis remains inconclusive, the approach developed may be worthwhile for future work in this field.

Keywords: Sleep, Learning, Computational Modeling, Neural Patterns, Logistic Regression, Shallow Neural Network

Introduction

Despite sleep constituting a large portion of the human lifetime, little is known of its biological significance. Sleep studies often lack the interactive behavioral component necessary to understand memory consolidation and resulting learned behavior. The subjective and complex nature of sleep makes data collection of its quality and ramifications difficult, leading to a reliance on the physiological components and processes of the brain to fill in the gaps of knowledge that surround sleep and behavior. However, the physiological data alone cannot define the neurological function of sleep unless supplemented with behavioral data. Though the prospect of studying sleep can be daunting, understanding the effects of said sleep on behavior would inform our understanding of both the cognitive and neurophysiological aspects of the human brain, one of which is learning.

Overall, memory formation is a highly complicated process, but one important aspect is sleep. Memory is generally divided into three stages: (1) Acquisition, (2) Consolidation, and (3) Retrieval. Each of these stages play an important role in memory longevity. In acquisition, encoding is the first stage that begins the minute animals are subject to training in a behavioral model. Next, consolidation is the stage where the short term memory is consolidated into a longer term memory and can take several hours. Lastly, retrieval refers to the moment when the memory is recalled. It is also significant to mention that sleep deprivation can impact memory processing and affect the outcome of brain plasticity (Havekes et al, 2015). Sleep is generally divided into two large divisions, rapid eye movement (REM) and non-REM (NREM). REM sleep entails a brain state which is produced by highly complex neural circuitry that among other things activates the cerebral cortex. This circuitry has been found to regularly be part of the consolidation process in both procedural and declarative memories (Boyce et al, 2017).

Slow wave sleep (SWS), which often occurs in the first half of the night, is a deep form of the NREM components of sleep. In a study conducted in humans, they found that SWS is particularly relevant in the discussion of memory consolidation and found that it may play an active role in memory processing and is likely the result of the reactivation of certain neural regions that are needed for learning (Chambers, 2017). Another mechanism that has been hypothesized is the mechanism of memory consolidation related to hippocampal sharp wave ripples (SPW-Rs). These ripples are high frequency oscillations that most commonly occur during SWS are thought to participate in memory reactivation in the hippocampus. The generation of the waves allows for the necessary labile memory transfer for hippocampal memories to a more permanent neocortical storage (Muehlroth et al, 2020).

There is relatively little computational support for the connection between sleep and learning and our study aims to fill this gap. Intuition informs that memory consolidation happens after learned behavior. Our model seeks to find the new links between learning and replay in the hippocampus and medial prefrontal cortex are primarily seen as: the occurrence of replay in the transient episodes corresponding to the activation of distinct cell assemblies, coinciding hippocampal sharp wave events and neocortical interactions, and the neural activity patterns emerging only after the acquisition. Our algorithm uses logistic regression and shallow neural networks to compare pre-behavioral SWS (pre-SWS) and post-behavioral sleep (post-SWS) neural patterns to neural patterns during the behavioral period itself, which allows for further understanding of memory rehearsal during sleep in learning. Our models use neural data from the behavioral period to predict behavior in sleep periods. We hypothesized that, if rehearsal is in fact occurring, our model should predict post-SWS activation patterns as correct more often than pre-SWS activation patterns; i.e., that post-SWS activation patterns more closely mimic activation patterns during the behavioral task than do pre-SWS patterns.

Methods

The pfc-6 dataset from Collaborative Research in Computational Neuroscience (http://crcns.org/data-sets/pfc/pfc-6) was used for this analysis. Spike data was collected from 31 neurons in rat prefrontal cortex by Peyrache et al. (2009) during a behavioral contingency task (BEH), as well as during rest periods before (PRE) and after (POST) the behavioral task. A total of 86 sessions across 4 rats were conducted.

Behavioral Task

A novel behavioral contingency task based on the Wisconsin card sorting task in humans was used for this experiment. Rats were placed in one arm of a Y-maze, in which each of the 3 arms was an experimenter-controlled light and an experimenter-controlled reward mechanism. Animals were administered a reward upon entering a specific arm, determined by the current rule. This rule was either cue-guided (go to illuminated arm or go to dark arm) or spatially-guided (go to left arm or go to right arm). Upon achieving 10 consecutive correct trials or only 1 error over 12 consecutive trials, the rat was considered to have learned the rule, and the rule was changed with no further cue to the animal. If the rat did not learn a rule in one session, the same rule carried over to the next session.

Dataset

The data used in this study was collected by Peyrache et al. (2009) and is available as pfc-6 at crcns.org. The authors provide 86 sessions (consisting of PRE, BEH, POST) split across 4 rats. For each session, the dataset includes 7 files: *(1) Spike Data* (n by 2) records the time in milliseconds of each spike during the entire session (i.e., PRE, BEH, and POST) and the identity of the neuron which spiked (1-31). Sample frequency for spike data was 10,000Hz. *(2) Behavior* (n by 6) includes information about each trial of the behavioral contingency task in that session: trial start time (ms), end time (ms), trial rule, behavior correctness, which arm the animal entered (left or right), and light position (left or right) (see section *Behavioral Task*). *(3) Cell Type* (31 by 2) includes classification of each of 31 neurons as pyramidal, interneuron, or unknown by spike waveform shape per Benchenane et al (2010). *(4) Wake* (1 by 2) includes start and end timepoints of behavior epoch. *(5) Pre-SWS* (n by 2) includes start and end timepoints of SWS in PRE. *(6) Post-SWS* (n by 2) includes start and end timepoints of SWS in POST. *(7) Position* (n by 3) describes (x, y) position over time (ms).

Data Recoding & Preprocessing

One of the 86 total sessions (ID 201222) was chosen for analysis. Only one rule ("illuminated arm") occurred throughout this session, and the animal learned the rule. For BEH, neural spike data during behavior trials was recoded into the frequency domain by counting the number of spikes in consecutive 100ms bins for each neuron. A final column ("correct") indicated whether the animal went to the correct (illuminated) arm of the Y-maze in the trial from which this bin was taken. Each of these (31+1)x1 vectors was appended into one dataframe, forming the recoded dataset for the behavior epoch. Similar neural data binning was conducted for SWS periods in pre-behavior and post-behavior rest epochs, respectively. Peyrache et al. (2009) describe the criteria for SWS, based on frequencies of neural firing.

Singular Value Decomposition

For behavior-epoch data A_B, we have singular value decomposition (SVD)

$$A_B = U_B \cdot \Sigma \cdot V'$$

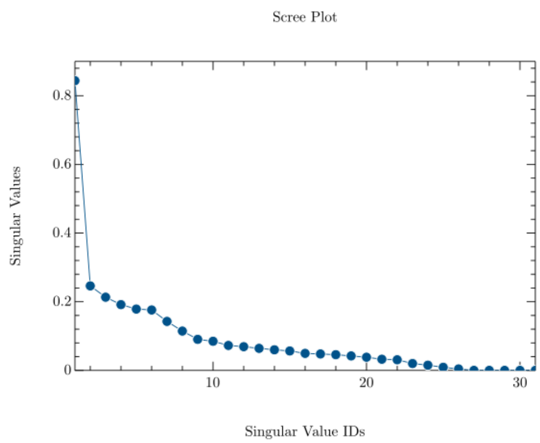
We want to express sleep epoch data A_S (either pre or post) in terms of an orthonormal basis of the row space, the columns of *V'*. These are linearly independent "activation patterns" of the 31 neurons. Thus, we take

$$U_S = A_S \cdot (V')^{-1} \cdot \Sigma^{-1} = A_S \cdot V \cdot \Sigma^{-1}$$

We then pick the first *n* singular values by keeping only the first *n* columns of U_B and U_S. The relative weights of each singular value are shown in Figure 1; 6 singular values were kept. We trained our models on some of the rows of U_B, then tested on the remainder of U_B. Then, we applied the model to $U_{S\text{-}PRE}$ and $U_{S\text{-}POST}$ and compared predictive performance.

Figure 1

Singular Value Decomposition Scree Plot



Note. Scree plot displaying relative weight of each singular value in decomposition of data during behavior epoch. The first 6 singular values were selected.

Models & Training

Four total models were trained for this project: simple logistic regression and shallow neural network on raw recoded data and singular value decomposed data, respectively. For each model, the features were neural activation, and target was correctness. Each model was trained on 80% of the BEH data, then tested on the training data, on the 20% of novel behavior data. Then, neural data collected during each PRE and POST, respectively, were inputted into this model to determine the predictive capabilities of this model on each epoch.

Model Evaluation

The accuracy scores were calculated for all four models, as well as the percent of the trials that were predicted as ‘correct’. Three-fold cross validation training, using grid search, was conducted to determine the best hyperparameters for the models using both types of data. The hyperparameters we searched for were the solver, regularization parameter (c), and maximum iterations for the logical regression, and solver, hidden layer sizes and maximum iterations for the shallow neural network. This search gave us the best hyperparameters for each model, which we then used to create the best models. Classification reports were then made for each of the best models, and include precision, recall, f1, support, and accuracy values for each of those models.

Results

The recoded dataset had 2202, 5621, and 3871 rows for the behavior, pre-behavior sleep, and post-behavior sleep, respectively. For the singular value decomposition, 6 singular values were chosen based on the leveling-off point of the Scree Plot (Figure 1). The first five rows of the recoded behavior data are shown in Table 1 and the first five rows of the singular value decomposition behavior data is given in Table 2. The first five rows of the pre- and post-behavior sleep data sets for both the recoded and singular value decomposition data sets can be found in Tables S1-S4.

Table 1

Recoded Behavior Data

	NEURON ID							
Bin time start (ms)	**1**	**2**	**3**	**4**	…	**29**	**30**	**31**	**correct**
2046699.6	0	1	0	0		0	0	0	1
2046799.6	0	0	0	0		0	0	0	1
2046899.6	0	0	0	0		0	0	0	1
2046999.6	0	0	0	0		0	0	0	1
2047099.6	0	2	0	0		0	0	0	1

Note. This table shows the first five rows of the behavior recoded data set. The time bins in the left column increase in 100 millisecond intervals. The data points for each neuron ID represent the number of times the neuron fired during that time bin. In the rightmost column, a 1 indicates that the animal went to the correct arm of the Y-maze in the trial from which this bin was taken, and a 0 indicates the rat did not.

Table 2

Singular Value Decomposition Behavior Data

Singular Values						
x1	x2	x3	x4	x5	x6	correct
-0.0179	0.0371	-0.0180	-0.0093	-0.0147	0.0127	1
-0.0088	0.0172	0.0149	0.0026	-0.0001	0.0163	1
-0.0229	0.0187	-0.0238	-0.0085	-0.0054	0.0252	1
-0.0208	-0.0103	0.0086	-0.0113	-0.0056	0.0091	1
-0.0207	-0.0067	0.0247	-0.0014	-0.0340	0.0233	1

Note. This table shows the first five rows of the behavior singular value decomposition data set.

The rows give the first six singular values of each time bin, corresponding to the activation pattern. In the rightmost column, a 1 indicates that the animal went to the correct arm of the Y-maze in the trial from which this bin was taken, and a 0 indicates the rat did not.

The accuracy scores for all four models are given in Table 3, as well as the ‘correct’ predictions for the train, test, pre-behavior, and post-behavior sets for all four models. Both models had a train accuracy of 0.6491 and a test accuracy of 0.6236 for the recode data and a train accuracy of 0.6366 and a test accuracy of 0.6735 for the singular value decomposition data. All four models predicted 1 for all the trials, meaning they predicted 100% (1.000) correct trials for the train, test, pre-behavior sleep, and post-behavior sleep. Figure 2 gives the confusion matrix for the ‘best model’. In this case, the confusion matrices for all four models were identical. As shown on the right side of the confusion matrix, the models predicted a value of 1 for both trials with a true value of 1 and a true value of 0. This indicates that the models had all true positives and false positives, and no true negatives or false negatives.

Table 3

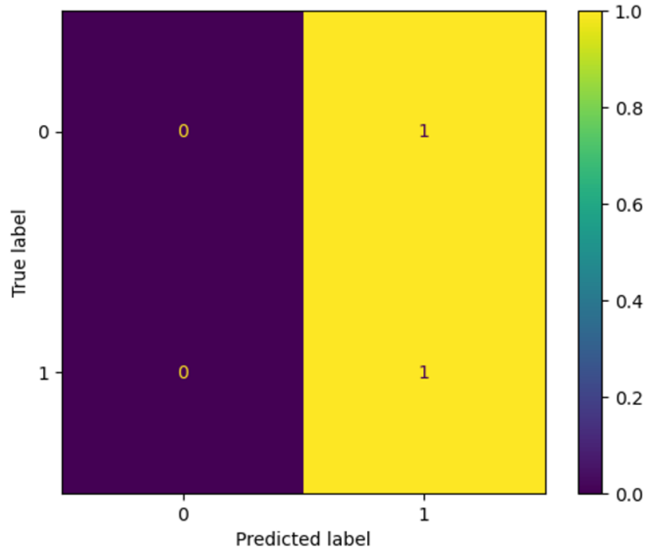
Accuracy Scores

	Train Accuracy	Test Accuracy	Train 'Correct' Prediction	Test 'Correct' Prediction	Pre-Behavior 'Correct' Prediction	Post-Behavior 'Correct' Prediction
Logistic Regression w/ Recode	0.6491	0.6236	1.000	1.000	1.000	1.000
Shallow Neural Network w/ Recode	0.6491	0.6236	1.000	1.000	1.000	1.000
Logistic Regression w/ SVD	0.6366	0.6735	1.000	1.000	1.000	1.000
Shallow Neural Network w/ SVD	0.6366	0.6735	1.000	1.000	1.000	1.000

Note. This table gives the accuracy scores for both the logistic regression and shallow neural network with the recode and singular value decomposition (SVD) data. Train accuracy is performance of the model on the training data. Test accuracy is performance of the model on test data. The 'Correct' Prediction columns indicate the models' predictions for the number of correct trials (a prediction of 1) with a value of 1.000 indicating a prediction of 100% correct trials.

Figure 2

Confusion Matrix



Note. This figure is the confusion matrix that was generated for both models with both the SVD and recode data. The 'True Label' axis represents what the actual target is, and the 'Predicted Label' axis is what the model predicts the target is. The yellow portion of the figure shows that the models are predicting a '1' target for each trial.

Three-fold cross validated training for the recode data using grid search revealed the regularization parameter (c) of 0.01 as the best hyperparameter for the logistic regression. For the shallow neural network, the best hyperparameters were as follows: hidden layer size of 20, 100 maximum iterations, and the 'sgd' solver. For the singular value decomposition, the best hyperparameters were c=0.01 and the 'newton-cg' solver for the logical regression, and hidden layer size of (1,5,10), 10,000 maximum iterations and the 'lbfgs' solver for the shallow neural network. Performance evaluation for the models using the singular value decomposition data is presented in Table 4. The precision for the models with both train and test data were 0.00 for the 0 target and 1.00 for the 1 target. Recall was 0.00 for the 0 target as well, and for the 1 target recall was 0.64 for the train data and 0.67 for the test data in both the logistic regression and shallow neural network models. The f1 scores for the 0 target was 0.00 for both models with both the train and test data. The 1 target had an average f1 value of 0.79 for both models with both train and test data. The performance evaluation for the models using the recoded data is given in Table S5 and were not significantly different to the singular value decomposition scores.

Table 4

Performance Evaluation for Singular Value Decomposition Data

		PRECISION	RECALL	F1	SUPPORT
LOGISTIC REGRESSION W/ TRAIN DATA	0	0.00	0.00	0.00	0
	1	1.00	0.64	0.78	1761
	Accuracy			0.64	1761
	Macro Average	0.50	0.32	0.39	1761
	Weighted Average	1.00	0.64	0.78	1761
LOGISTIC REGRESSION W/ TEST DATA	0	0.00	0.00	0.00	0
	1	1.00	0.67	0.80	441
	Accuracy			0.67	441
	Macro Average	0.50	0.34	0.40	441

	Weighted Average	1.00	0.67	0.80	441
SHALLOW NEURAL NETWORK W/ TRAIN DATA	0	0.00	0.00	0.00	0
	1	1.00	0.64	0.78	1761
	Accuracy			0.64	1761
	Macro Average	0.50	0.32	0.39	1761
	Weighted Average	1.00	0.64	0.78	1761
SHALLOW NEURAL NETWORK W/ TEST DATA	0	0.00	0.00	0.00	0
	1	1.00	0.67	0.80	441
	Accuracy			0.67	441
	Macro Average	0.50	0.34	0.40	441
	Weighted Average	1.00	0.67	0.80	441
		PRECISION	**RECALL**	**F1**	**SUPPORT**

Note. This table includes the model performance evaluation results using the singular value decomposition. The evaluations are given for each model with both the test and train data, as indicated by the leftmost column. The precision, recall, f1, and support are calculated for the targets (0 and 1) accuracy, macro average and weighted average.

Discussion

Learning-related changes in neural activity over brief time scales have been described in both the prefrontal cortex and hippocampus, but the effects of these changes on subsequent sleep activity have not been fully studied. In our model, we created logistic regressions and shallow neural networks using both recoded data and singular value decomposition data. These models were trained and used to predict correctness of behavior in a novel contingency task, and subsequently to predict pre-behavioral and post-behavioral slow wave sleep. The purpose of doing so is to understand if memory rehearsal occurs during slow wave sleep after learning trials. If true, then our models would have similar predictions for the behavioral and post-behavioral sleep data. After training all four types of models and searching for the best hyperparameters, the behavioral, pre- and post-behavioral data were inputted, and all four models consistently predicted 100% 'correct' trials, which does not reflect the actual data; as evidenced by the recode behavioral data and singular value decomposition data, the rats were not getting the trials correct all the time. The accuracy of these models was relatively low as well, ranging from 0.62 to 0.67, and this was true for both the basic models and the 'best' models created with grid search. Given, since the models almost always predicted every value as correct, this is simply the percent of the dataset which was "correct" trials in the first place. Due to the limitations of our models, our results were inconclusive in determining the validity of our hypothesis. Possibly this was a limitation of the data selected: correct and incorrect trials may have been temporally close enough that there is no significant difference in activation patterns between the two. Future work might address this with the addition of non-session data; e.g., while the rat is learning a different rule. Less likely, but possible, is that the hyperparameters for our models could be better tuned to provide better performance.

Our model supports the importance of computational modeling as a whole, especially when compared to other models. Our data was drawn from Peyrache et al. (2009), who used ANOVA two-way data analysis and pairwise cell activity correlation matrices to draw their conclusions. They posit that neural patterns that occurred during the behavioral phase also occurred during sleep. This corresponds with the 2017 data from Chambers that deduced that slow-wave sleep is in fact playing an active role in the memory consolidation process. Understanding the results and limitations of our model suggests that, should the model be revisited, better conclusions can be drawn. The modeling process described above, along with its shortcomings, proposes the need for more specific models and further analysis. The results from Peyrache et al (2009), Chambers (2017), and other similar papers bolsters the links between sleep and memory consolidation, so it is unlikely that computational models such as ours will completely oppose this notion. Instead, they will only further the analysis of physiological data and its relation to learned behavior.

In studying any sophisticated system such as memory consolidation, it is valuable to use a variety of models to understand it and evaluate it, including computational analysis. A huge portion of our lives is spent sleeping, which is limited in our ability to behaviorally analyze it and how it affects memory. Computationally modeling this data is useful for learning, research, and possible clinical implications in the future. In this experiment, modeling provides a valuable insight to changes in neural firing patterns from rule-based learning maze tests, to memory consolidation during slow wave sleep. This in turn helps us to evaluate the nature of memory consolidation between the hippocampus and neocortex, specifically the medial prefrontal cortex Peyrache et al. (2009). After hippocampal sharp wave/ripple complexes, this is when cortico-hippocampal exchange gets enhanced Peyrache et al. (2009). The models and data support that it is a rehearsal of neuronal ensembles that take place between the mPFC and hippocampus during slow wave sleep that is responsible for memory consolidation (Chambers, 2017). The model provides an objective determination that it is the previously acquired information from the rule-based maze test that is being replayed, demonstrating a mechanism of learning. The possible clinical implications of this can vary from sleep disorders to learning and memory conditions. These models could be used as a baseline to collect data on humans in order for early detection of Alzheimer's disease or other conditions or diseases that affect sleep or learning and memory. Future studies that this experiment inspires are different models other than shallow learning, shallow neural networks, and logistical regression. Because the patterns appeared after rule acquisition, we know the patterns resemble learning. We can therefore reasonably conclude that succession in the completion of rule-based maze-tests is because of learning. This is exemplified in how influential it was on what patterns occurred and what gets replayed and exchanged by the hippocampus and cortex during slow wave sleep. This data, represented with these models, provides a unique method of analysis which gives us a more complete depiction of memory consolidation.

Sleep and learning are both complex processes and likely complex models are needed to further analyze any physiological data. Our data and algorithm was not sufficient to accurately model and reflect the processes of learning and sleep. Further development of these models, or a different algorithm altogether may prove more successful. Overall, our results further emphasize the need for continued modeling of sleep and other neurological processes.

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Methods	Ciro Randazzo
Results	Sabrina Hallal
Introduction/Literature Review	Ashna Adhikari, Malavika Ramaswamy
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Appendix

Table S1

Recoded Pre-Behavior Data

	NEURON ID						
Bin time start (ms)	**1**	**2**	**3**	**4**	**…**	**29**	**30**	**31**
565997.3	0	0	1	0		0	0	0
566097.3	0	0	0	0		0	0	0
566197.3	0	0	0	1		0	0	0
566297.3	0	0	0	1		0	0	0
566397.3	1	0	1	1		0	0	0

Note. This table shows the first five rows of the pre-behavior sleep recoded data set. The time bins in the left column increase in 100 millisecond intervals. The data points for each neuron ID represent the number of times the neuron fired during that time bin.

Table S2

Recoded Post-Behavior Data

	NEURON ID							
Bin time start	**1**	**2**	**3**	**4**	**…**	**29**	**30**	**31**
5357368.0	0	1	0	1		0	0	0
5357468.0	1	0	0	1		0	0	0
5357568.0	0	1	1	0		0	0	0
5357668.0	0	0	1	0		0	0	0

5357768.0	0	0	0	0	0	0	0

Note. This table shows the first five rows of the post-behavior sleep recoded data set. The time bins in the left column increase in 100 millisecond intervals. The data points for each neuron ID represent the number of times the neuron fired during that time bin.

Table S3

Singular Value Decomposition Pre-Behavior Sleep Data

Singular Values

x1	**x2**	**x3**	**x4**	**x5**	**x6**
-0.0129	0.0273	-0.0104	-0.0105	-0.0184	0.0119
-0.0060	0.0124	0.0050	0.0087	-0.0011	0.0117
-0.0095	0.0118	0.0158	0.0194	-0.0140	0.0282
-0.0123	0.0430	-0.0126	0.0022	-0.0086	0.0073
-0.0062	-0.0005	0.0079	0.0309	0.0052	0.0233

Note. This table shows the first five rows of the pre-behavior sleep singular value decomposition data set. The rows give the first six singular values of each time bin, corresponding to the activation pattern.

Table S4

Singular Value Decomposition Post-Behavior Sleep Data

Singular Values

x1	x2	x3	x4	x5	x6
-0.0104	-0.0121	0.0064	0.0024	-0.0084	0.0270
-0.0088	-0.0195	0.0292	0.0416	-0.0032	0.0457
-0.0138	0.0069	0.0190	0.0117	-0.0071	0.0362
-0.0195	0.0119	-0.0185	0.0061	-0.0196	0.0154
-0.0088	0.0045	0.0213	0.0113	-0.0123	0.0135

Note. This table shows the first five rows of the post-behavior sleep singular value decomposition data set. The rows give the first six singular values of each time bin, corresponding to the activation pattern.

Table S5

Performance Evaluation for Recode Data

		PRECISION	RECALL	F1	SUPPORT
LOGISTIC REGRESSION W/ TRAIN DATA	0	0.00	0.00	0.00	0
	1	1.00	0.65	0.79	1753
	Accuracy			0.65	1761
	Macro Average	0.50	0.32	0.39	1761
	Weighted Average	1.00	0.65	0.79	1761
LOGISTIC REGRESSION W/ TEST DATA	0	0.00	0.00	0.00	0
	1	1.00	0.62	0.77	441
	Accuracy			0.62	441

	Macro Average	0.50	0.31	0.38	441
	Weighted Average	1.00	0.62	0.77	441
SHALLOW NEURAL NETWORK W/ TRAIN DATA	0	0	0	0	0
	1	1.00	0.65	0.79	1761
	Accuracy			0.65	1761
	Macro Average	0.50	0.32	0.39	1761
	Weighted Average	1.00	0.65	0.79	1761
SHALLOW NEURAL NETWORK W/ TEST DATA	0	0	0	0	0
	1	1.00	0.62	0.77	441
	Accuracy			0.62	441
	Macro Average	0.50	0.31	0.38	441
	Weighted Average	1.00	0.62	0.77	441

Note. This table includes the model performance evaluation results using the recoded data. The evaluations are given for each model with both the test and train data, as indicated by the leftmost column. The precision, recall, f1, and support are calculated for the targets (0 and 1) accuracy, macro average and weighted average.