2D Project — Mathematical Modelling
Illuminating Engagement: Machine Learning Optimizes Lighting For Enhanced User Experience

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EXECUTIVE SUMMARY

Lighting conditions play a crucial role in influencing user engagement levels. However, the existing lighting control systems (at our site) often utilize generic, one-size-fits-all approaches, failing to account for the nuances of individual user preferences and environmental factors. This project tackles this challenge by leveraging a data-driven approach, aiming to develop an intelligent system capable of accurately predicting user engagement levels based on prevailing lighting conditions. The ultimate goal is to enable strategic lighting adjustment and optimization, maximizing user engagement through customized lighting setups.

Several key assumptions underpin the proposed solution. First, the collected data on lighting conditions (light intensity, colour temperature, and ambient noise levels) and user engagement metrics must be representative of the target user population and environment. Second, the data must be free from significant errors, outliers, and biases that could skew the analysis. Furthermore, it is assumed that the multilayer perceptron (MLP) neural network architecture can effectively model the complex, nonlinear relationships between the independent lighting variables and the dependent user engagement variable. Additionally, it is assumed that the network architecture, hyperparameters, and training process have been optimized to achieve robust and accurate predictions, and that the trained model can generalize well to new, unseen data, providing reliable predictions for enhancing user experiences.

The chosen solution method employs an MLP neural network model with an input layer, two hidden layers (first layer within 10 neurons and second layer within 5 neurons) and an output layer. The model learns a nonlinear mapping function, parametrized by weight matrices and bias vectors, to map the input features (light intensity, colour temperature, and noise level) to the target user engagement level. The model parameters are optimized using a mean squared error loss function and gradient-based optimization methods, such as forward-propagation and stochastic gradient descent. Once trained, this MLP model can make predictions on new, unseen data by forward-propagating the input features through the network to obtain the estimated user engagement levels.

The trained MLP model achieved promising results on both the training round (Mean Squared Error : 0.015, R^2 : 0.828) and testing round (Mean Squared Error : 0.016, R^2 : 0.825) of datasets, demonstrating its ability to capture the intricate relationships between lighting conditions and user engagement levels. Various visualizations, including 3D plots, contour plots, and partial dependence plots, were generated to assess the model's performance and interpretability. These visualizations provide insights into the model's predictions and the influence of individual input features on the predicted engagement levels.

The proposed MLP model exhibits several strengths, including the ability to model complex, nonlinear relationships, a flexible and adaptive architecture facilitated by multiple hidden layers and nonlinear activation functions, and a data-driven approach that uncovers insights directly from the collected dataset. However, a key weakness is the model's dependence on the quality and representativeness of the collected data, as well as the potential for overfitting or poor generalization if not properly regularized or trained with diverse data. Future improvements could involve exploring ensemble methods by combining multiple MLP models, implementing advanced regularization techniques, tuning hyperparameters through techniques like grid search or Bayesian optimization, collecting more real-world data across diverse lighting scenarios and user demographics, and comparing the MLP's performance against other model architectures like decision trees or gradient boosting machines to identify the most comprehensive and scalable approach.