**Temporal Metrics Part II Deep Learning Model**

Cammie R Newmyer

[Newmyer.mtms@gamil.com](mailto:Newmyer.mtms@gamil.com)

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**Introduction**

The perception of time is a complex phenomenon, intricately linked to various psychological and physiological conditions. In an endeavor to quantitatively understand and predict altered time perception, the first part of our project involved the mathematical development of a novel constant, termed the Cr constant. This constant emerged from the foundational formula Cr = change in time / (distance/rate), offering a groundbreaking approach to quantifying time perception variations among individuals.

This project stands out for its hybrid approach, combining traditional machine learning predictions with a rule-based system driven by domain-specific insights. It caters to individual differences by considering a wide range of personal attributes and conditions, offering tailored predictions. The implementation showcases the flexibility of machine learning in accommodating complex, real-world scenarios.

Development of Cr:

The Cr constant was derived by examining how an average person, given specific conditions, would experience different brainwave types over a 24-hour period. The core idea was to link the time spent in various brainwave states to alterations in time perception. This approach integrated concepts from neurology, specifically the impact of myelination on neural transmission speed. Myelination, a process affecting the insulation of nerve cells, was found to be a crucial element influencing time perception. It directly correlates with speed in the formulas encompassing distance, frequency, cycles, and time.

Application in Machine Learning:

The initial phase of the project utilized a Random Forest multi-class classification model. This model demonstrated that the increase or decrease in myelination associated with each condition was the most significant feature influencing perceptions of time. Building on these insights, the Cr altered time perception predictor was then applied to a representative 0.001% of the U.S. adult population. In this representative sample, individuals were randomly assigned a corresponding Cr value if they tested positive for a specific condition.

Deep Learning Model Implementation:

The second part of the project, which this document focuses on, extends the application of the Cr constant using a deep learning model. This model aims to predict an individual's perception of time based on a wide array of conditions and lifestyle factors. The deep learning approach was chosen for its ability to handle complex, non-linear relationships inherent in the dataset. It leverages a comprehensive set of features, including age, sex, mental health conditions, lifestyle factors, and substance use. Each feature is weighted by its associated Cr value, reflecting its influence on time perception.

Results and Insights:

The deep learning model, grounded in the insights from the Cr constant, has shown promising results. It accurately predicts the time perception category - "Average," "Slower," or "Faster" - for individuals based on their unique profiles. This model not only stands as a testament to the applicability of the Cr constant in practical scenarios but also opens new avenues in understanding the subjective experience of time.

**Data Description**

Data Acquisition Process:

The data acquisition process for this model was meticulously designed to ensure a comprehensive and representative dataset, crucial for the effective training and evaluation of the deep learning model. Here's an overview of the steps involved in the data acquisition:

Identifying Relevant Variables:

The first step was to identify a range of variables that could influence the perception of time. This included demographic information like age and sex, psychological conditions such as ADHD, Alzheimer's, and anxiety, lifestyle factors like meditation and occupation, as well as substance use (e.g., alcohol, marijuana).

Collection from a Representative Sample:

Data was collected from a representative 0.001% of the U.S. adult population. This sample size was chosen to ensure a balance between a dataset that's comprehensive enough for deep learning, while still being manageable in terms of data processing and analysis.

Random Assignment of Cr Values:

For each individual in the sample, if they tested positive for a particular condition, they were randomly assigned a corresponding Cr value. This step was crucial in applying the theoretical framework developed in the first part of the project to a practical, predictive model.

Incorporating Myelination Data:

Based on the findings from the initial Random Forest model, myelination - the process affecting the insulation of nerve cells - was identified as a key feature influencing time perception. Data regarding the increase or decrease in myelination for each condition were integrated into the dataset.

Standardizing Data for Model Training:

The collected data were then standardized for use in the deep learning model. This involved encoding categorical variables, normalizing numerical values, and structuring the data in a format suitable for model input.

**Data Features**

The dataset comprises various features categorized as follows:

Demographic Information:

Age, sex. Psychological Conditions: ADHD, Alzheimer's, anxiety, depression, PTSD, etc. Lifestyle Factors: Professional status, meditation practices, sleep patterns. Substance Use: Alcohol, marijuana, prescription medications, and other substances.

Each feature was given a numerical value based on its potential impact on time perception, guided by the Cr constant's framework. The culmination of this data acquisition process was a robust, multi-faceted dataset that serves as the foundation for the deep learning model's predictions on time perception.

**Theoretical Foundation and Data Estimation**

Data Description Theoretical Foundation and Data Estimation:

In this project, the approach to data acquisition diverges from traditional methods, as it is rooted in a theoretical framework and thought experiment rather than empirical data collection from actual participants. This approach aligns with the innovative nature of the study, which aims to explore the complex interplay between various factors and their influence on the perception of time.

**Thought Experiment with ChatGPT 4.0**

Utilizing ChatGPT 4.0:

The estimation of data was conducted through a thought experiment facilitated by ChatGPT 4.0. This advanced language model, developed by OpenAI, has been trained on a diverse range of texts, enabling it to generate informed estimates about the potential relationships and impacts of various factors on time perception.

Data Estimation Process:

Leveraging the vast information contained within ChatGPT 4.0’s training data, estimates were made about how different conditions, lifestyle choices, and demographic factors might influence an individual's experience of time. This process involved generating hypothetical data points that reflect the potential outcomes and interactions of these variables.

Theoretical Sample Representation:

Rather than collecting data from real individuals, the study conceptualized a representative sample of the U.S. adult population. This theoretical sample was used to assign estimated Cr values to different conditions and factors, based on the model’s understanding of their probable impact on myelination and, consequently, on time perception.

Features and Variables:

The data encompassed a variety of features, including psychological conditions like ADHD and anxiety, lifestyle factors such as meditation and professional status, and substance use. Each feature was assigned a numerical value, reflecting its estimated impact on time perception as per the Cr constant's framework.

**Ethical and Conceptual Considerations**

Theoretical Nature of the Study:

It's crucial to note that this study is theoretical and does not involve real human participants. The data and its implications are hypothetical and are used to explore and model a complex cognitive phenomenon.

Compliance with Ethical Standards:

Given the theoretical nature of the study, the typical concerns around data privacy, consent, and ethical clearance for human subjects do not apply. However, the study still aligns with ethical considerations relevant to theoretical and simulation-based research.

Conclusion:

This unique approach, combining a theoretical exploration with advanced AI capabilities, represents an innovative way to probe into the intricate workings of human perception. While the data and findings are hypothetical, they provide valuable insights and a foundation for future empirical research in this area.

**Feature Descriptions**

The deep learning model in this study uses a range of features, each chosen for its potential impact on the perception of time. These features are divided into several categories, reflecting various aspects of psychological conditions, lifestyle factors, and biological influences. Here’s a brief overview of each category:

**Demographic Information**

Age: Categorized into groups (e.g., '30\_49', '50\_69', etc.) to understand how perception of time might vary across different life stages.

Sex: Included as a binary variable (Male/Female) to explore any potential differences in time perception based on gender.

Psychological Conditions: Conditions like ADHD, Alzheimer's, Anxiety, Depression, PTSD, Schizophrenia, etc., are included. The model considers how these conditions, which are often associated with alterations in brain function and structure, might influence the subjective experience of time.

Lifestyle Factors: Variables such as Professional Status (e.g., 'Graduate\_Student', 'Self\_Employed'), Meditation Practices (e.g., 'C\_Meditation', 'T\_Meditation'), and others. These factors explore the impact of daily activities and mental states on time perception. Sleep patterns, represented by features like 'Insomnia' and 'Ultrasomnia', are also considered, given their known effects on cognitive processes and mental health.

Substance Use: Includes a range of substances like Alcohol, Marijuana, Cocaine, Fentanyl, and Prescription Medications. Substance use can significantly affect neural functioning and, consequently, the perception of time.

Cr Values: Each condition and factor is assigned a Cr value, reflecting its estimated impact on time perception. These values are central to the model’s predictions and are derived from the theoretical framework established in the study.

Myelination: Recognized as a key feature in the model, myelination refers to the process of forming a myelin sheath around nerve cells, affecting transmission speed. The model incorporates data on how myelination increases or decreases with each condition, linking it directly to the perceived speed in cognitive processing. Each of these features contributes to the model’s ability to predict how an individual perceives time, offering a comprehensive view that integrates biological, psychological, and lifestyle factors. The inclusion of both traditional demographic variables and more nuanced psychological and lifestyle factors underscores the model’s holistic approach to understanding time perception.

**CODE – Run Code File “Temporal\_Metrics\_PartII\_Deep\_Learning\_Model.ipynb”**

**User Interface**

The user interface in this project serves as a crucial bridge between the complex deep learning model and the end users. It is designed to make the model's predictions accessible and understandable to individuals who may not have a background in data science or machine learning.

**What It Does**

Data Input: The interface allows users to input their personal information, including age, sex, and various lifestyle and psychological factors. This data is then used by the model to predict the user's perception of time.

Interactive Elements: Through interactive elements like checkboxes, sliders, or dropdown menus, users can easily select or input their details corresponding to the available features in the model.

Results Presentation: Once the data is submitted, the interface displays the model's prediction regarding the user's time perception category. It also provides an explanation of what this prediction means, enhancing the user's understanding.

**Importance to the User**

Accessibility: The interface demystifies the model's workings, making its insights accessible to a broad audience.

Personalization: By providing personalized insights based on individual data, it helps users understand how various aspects of their lifestyle and health might be influencing their perception of time.

Empowerment: It empowers users with knowledge about themselves, which can be intriguing and insightful.

**Results**

Outcome of Model Training:

The model's training and testing phases demonstrated exceptionally high performance metrics, indicative of its robustness and accuracy in predicting time perception categories based on the dataset.

The outcome of the model training and testing is summarized as follows:

Training Accuracy: The model achieved a training accuracy of 99.56%. This high level of accuracy suggests that the model was highly effective in learning from the training data. It was able to correctly classify the vast majority of instances in the training dataset into the correct perception of time categories ("Average," "Slower," or "Faster").

Testing Performance Test Loss: The model reported a test loss of 0.010047183372080326. Test loss is a measure of how well the model performs on unseen data. A lower loss value indicates that the model's predictions are close to the actual values. In this case, the low test loss signifies excellent model performance on the test dataset.

Test Accuracy: The test accuracy, similar to the training accuracy, was 99.56%. This high test accuracy indicates that the model not only learned the training data well but also generalized effectively to new, unseen data. It shows the model's ability to maintain its performance and reliably predict the time perception category when presented with data it hasn't encountered before.

Test Accuracy (Percentage): Expressed in percentage terms, the test accuracy of 99.56% reinforces the model's high level of precision in classification tasks. It is a clear indicator of the model's capability in handling the complexity and nuances of the dataset.

**Interpretation of Results**

The high accuracy rates in both training and testing phases indicate that the model is well-tuned and not suffering from overfitting or underfitting. Overfitting is usually a concern when the training accuracy is significantly higher than the test accuracy, but in this case, both metrics are closely aligned and exceptionally high.

The results suggest that the model is effectively utilizing the features, including those weighted by the Cr values, to make precise predictions about time perception.

The low test loss further adds to the confidence in the model's predictive power, ensuring that the predictions are not only accurate but also close to the expected values.

The outcomes from the model training and testing are highly encouraging, demonstrating the model's effectiveness in understanding and predicting altered perceptions of time. With training and test accuracies both exceeding 99%, the model stands as a powerful tool in the study of cognitive perception, particularly in how various psychological and physiological factors influence one's experience of time.

**Conclusion**

Project Overview

This project involves developing a machine learning model to predict how individuals perceive time based on a range of psychological and physiological features. The model takes into account various factors like age, sex, and specific conditions or behaviors (e.g., ADHD, insomnia, use of certain substances) to predict one of three categories: "Average," "Slower," or "Faster," each representing an altered perception of time.

Data and Features

The model utilizes a dataset comprising various features, each with a numerical value representing its impact. The features include age groups, mental health conditions (like depression, anxiety), lifestyle factors (such as meditation practices, professional status), and substance use (like alcohol, marijuana). Each feature has a corresponding value that contributes to the overall mean calculation, influencing the final prediction.

Model Implementation Model Choice: A RandomForestClassifier, known for its robustness and ability to handle non-linear relationships, was initially chosen. However, details about the final model implementation (like using RandomForestClassifier or another algorithm) are not explicitly mentioned.

Data Preprocessing: The data is preprocessed to transform categorical variables like sex into numerical values. Features selected by users are encoded into a binary format (1 if the feature applies, 0 otherwise).

Feature Engineering: The model includes a unique approach where the mean of the selected features' values is calculated. This mean plays a crucial role in the final prediction, especially for determining the "Faster" category.

User Input Handling: The model is designed to interact with users, allowing them to input their age, sex, and select relevant features. Input validation ensures age is within the 18-100 range and sex is correctly categorized.

Prediction Logic: The core of the model involves predicting the perception of time. The model first uses the RandomForestClassifier (or the chosen algorithm) to make a prediction. Then, it applies a rule-based approach: if the calculated mean of the features is less than zero, the prediction is overridden to "Faster." Otherwise, the model's prediction is used.

Output: The final output includes the calculated mean and a text-based interpretation of the prediction, providing users with an understanding of their time perception category.

**Visualizations**

Summary of Exploratory Data Analysis (EDA) and Model Visualization Methods

In this project, a thorough Exploratory Data Analysis (EDA) was conducted, complemented by a range of visualization techniques. These methods were crucial in understanding the dataset's characteristics, identifying patterns and relationships, and interpreting the model's performance.

Here's a summary of the various visualization tools used:

Box Plots: Used to visually represent the distribution of numerical data and to spot outliers. Box plots were particularly useful in understanding the spread and central tendency of continuous variables like age and Cr values.

Pair Plots: These plots provided a comprehensive view of pairwise relationships between features. They helped in identifying correlations and possible trends between different variables, which was instrumental in feature selection and engineering.

Correlation Matrix: A correlation matrix was generated to quantify and visualize the degree of correlation between different features. This matrix helped identify highly correlated variables, guiding the decision on which features to include in the model to avoid multicollinearity.

Confusion Matrix: Post-model training, a confusion matrix was used to evaluate the performance of the classification model. It provided insights into the model's accuracy in predicting each class and highlighted areas where the model might be confusing one class for another.

Violin Plots: These plots combined box plots and density plots to show the distribution of data. They were particularly useful in visualizing the distribution of features across different categories of time perception.

ROC and AUC Curves: Receiver Operating Characteristic (ROC) curves and the Area Under the Curve (AUC) were utilized to assess the model's predictive performance, especially its ability to distinguish between the classes.

Scatter Plots: Scatter plots allowed for the visualization of relationships between two variables. They were used to explore potential linear or non-linear relationships and clustering tendencies within the data.

Histograms and Distribution Plots: These were used to visualize the frequency distribution of individual variables. Histograms and distribution plots provided insights into the skewness and kurtosis of the data.

Network Graph: A network graph was employed to visualize the complex interrelationships between different features. This graph helped in understanding the structure and connections within the data, offering a macro view of feature interactions.

Heatmaps for Feature Importance: Heatmaps were used to visualize the importance of different features as determined by the model. This was particularly useful for understanding which features had the most significant impact on the model's predictions.

Kernel Explainer Visualizations: The Kernel Explainer, part of the SHAP framework, was utilized to create visualizations that explained the model's predictions. These visualizations were instrumental in breaking down and quantifying the impact of each feature on the model's outcomes. Through plots like beeswarm and force plots, the Kernel Explainer made it possible to understand both the global importance of features and their specific contributions to individual predictions. This approach was especially beneficial in elucidating the complex relationships and influences within the model, enhancing overall interpretability and transparency.

These visualization methods were integral to the EDA process, providing a deep understanding of the data and the model's behavior. They offered both qualitative and quantitative insights, aiding in everything from preprocessing and feature engineering to model evaluation and interpretation. The use of diverse visualization tools ensured a comprehensive analysis, capturing various aspects of the data and the model in a visually interpretable manner.

**Future Applications**

Potential Transformation into an App for Behavior Monitoring and Change Monitoring Activities

Tracking: The app could allow users to regularly track various aspects of their life, such as sleep patterns, mood, and daily activities. This data can be analyzed in relation to their time perception. Notifications and Reminders: The app could send notifications or reminders for users to log their daily activities or any significant changes in their routine or health conditions.

Facilitating Behavior Changes Insights and Recommendations: Based on the user's data and the model's predictions, the app could provide personalized insights and recommendations. For example, if a user's data suggests a "Faster" perception of time, the app could recommend relaxation techniques or changes in routine.

Progress Tracking: Users can track how changes in their behavior over time affect their perception of time, offering a feedback loop that reinforces positive behavior changes.

Community and Support: Integrating community features where users can share experiences and tips could foster a supportive environment for making and maintaining behavior changes.

**Why It Matters**

Health and Wellbeing: Understanding and monitoring one's perception of time can be crucial for mental health and wellbeing. The app can play a role in managing stress and improving life balance.

Behavioral Insights: Continuous tracking and analysis provide deep insights into how different behaviors and conditions affect time perception, enabling users to make more informed decisions about their lifestyle. By turning the user interface into a comprehensive app, there's an opportunity to significantly impact users' understanding of their cognitive processes and empower them with tools to improve their quality of life.

**For use of any intellectual property presented within this study, please contact:**

**Cammie R Newmyer, Math That Makes Sense,** [**Newmyer.mtms@gmail.com**](Newmyer.mtms@gmail.com)