Temporal Metrics

Quantifying Human Time Perception

Cammie Newmyer

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Project Objective

To introduce an innovative approach to understanding and quantifying human time perception, bridging the realms of neurology, physics, and psychology to offer new insights into a long-standing question: How do humans perceive the passage of time?

The way humans perceive time has far-reaching implications not only for individual subjective experiences but also for broader social and functional contexts. Our perception of time shapes our reactions, decisions, memories, and future anticipations. It influences our emotional state, the rhythm of our daily activities, and even our cultural narratives. From waiting for a bus to recollecting past experiences, our sense of time pervades every aspect of our lives. Thus, understanding it is pivotal for both enhancing personal well-being and addressing societal challenges.

A Novel Framework: The Distance = Rate x Time Paradigm in Time Perception

At first glance, the formula “distance = rate x time” seems exclusive to the physical realm, typically associated with motion. However, I postulate that it can be metaphorically applied to human time perception. Here, ‘distance’ doesn’t signify a physical journey but represents the cognitive journey our brains undertake in a 24-hour span, as they process myriad stimuli and experiences.

Building a Dataset and Applying Machine Learning

Question

How do humans perceive time and can this experience be quantified?

Research

For a complex and vastly studied concept like human time perception the development of ChatGPT 4.0 allows for rapid-fire research to inform dataset building decisions.

Build the Dataset

Gather information and prepare the raw data needed for the project. Design and feature engineer, clean, process and structure it into a usable dataset.

Explore the Data

Analyze and visualize the dataset to understand its characteristics, distributions and correlations.

Train a Model

Use the dataset to train a random forest machine learning model, tuning its hyperparameters for optimal performance.

Evaluate the Model

Test the trained model on holdout data to evaluate its accuracy, precision and other metrics.

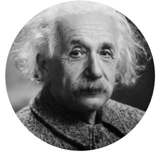
Human Time Perception Can't Be Quantified

Arthur "Skip" Lupia

- Human Communication Can't Be Quantified
- Yes it can
- Dr. Lupia applied Game Theory in order to quantify human communication
- Applications to World Peace: Juan Manuel Santos, Columbia
- See work "Uniformed"

Developing the Question

Relating the passage of time to known physical phenomena



Point #1

In Einstein's Theory of Special Relativity he postulates that the rate at which time passes depends on your frame of reference.

Point #2

Carlo Rovelli relates music to the passage of time. A song depends on the note that comes before and the note that comes after, just like time. "The Order of Time."

Point #3

Time is basically an illusion created by the mind to aid in our sense of temporal presence in the vast ocean of space. Without the neurons to create a virtual perception of the past and the future based on all our experiences, there is no actual existence of the past and the future. All that there is, is the present.— Abhijit Naskar

Point #4

Hawking identified three distinct “arrows of time”: a psychological arrow (underpinning our memories of the past and how we imagine the future), a thermodynamic arrow (the direction in which entropy increases), and a cosmological arrow (the direction in which the size of the universe increases).

Developing the Question

Relating the passage of time to known physical phenomena

Point #1

Time perception varies by age.

Point #2

Time perception varies by activity.

Point #3

Time perception is altered by physical conditions.

Point #4

Time perception is altered by mental conditions.

Point #5

Time perception is altered by pharmaceuticals.

Point #6

Time perception varies by person.

Point #7

Time perception varies by culture.

Point #8

Individuals can alter their perception of time.

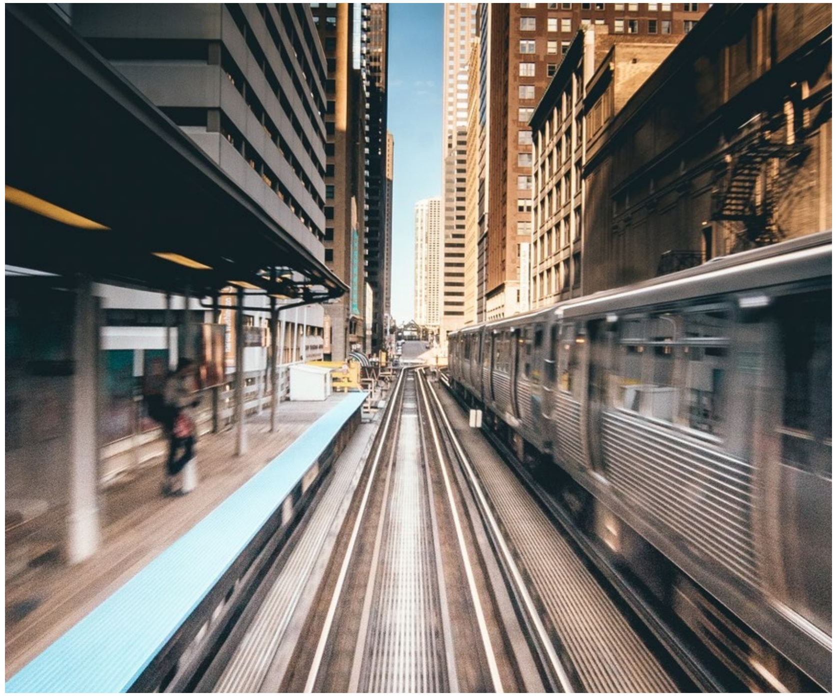
Connecting the Science

1. **Einstein's Theory of Special Relativity**: This theory introduced the idea that space and time are intertwined into a single continuum known as spacetime. The famous equation $E = mc^2$ and the concept of time dilation, where time can appear to move slower for an object moving close to the speed of light compared to one that is stationary, are central to this theory.
2. **Weber's Theory**: This refers to the idea in psychology and psychophysics that the just noticeable difference (JND) between two stimuli is proportional to the magnitude of the stimuli. The formula is: $\Delta I / I = k$, where ΔI is the JND, I is the initial intensity, and k is a constant.
3. **Brainwave Frequencies & Altered Time Perception**: Our discussion revolved around the theoretical representation of brainwave propagation in terms of distance, linking it to altered time perceptions in various states or disorders.

Connecting the Science

- **Relativity & Brainwaves**: Drawing a parallel with relativity, one could speculate that as brainwave frequencies (akin to velocities in relativity) change, the perception of time (akin to time dilation) might also change. An individual with faster (or altered) brainwave patterns might, in theory, perceive time differently than one with 'standard' patterns.
- **Weber's Theory & Time Perception**: Using Weber's principle, if the difference in time perception (or its intensity) reaches a certain threshold (ΔI), it becomes noticeable (k). The exact nature of this difference and its relation to brainwave frequency would be the challenging aspect to quantify.
- **Distance Formula & Brainwaves**: The formula $d = r * t$ where d is distance, r is rate (akin to our frequency or speed of brainwaves), and t is time can be likened to the theoretical distances we discussed based on brainwave frequencies. Alterations in frequency (rate)





Connecting the Science

1. Link brainwave frequencies to a relative 'velocity' akin to those in special relativity.
2. Factor in the 'distance' traveled by these waves in a given time using $d = r * t$.
3. Integrate Weber's Theory to identify when changes in this 'distance' or 'velocity' result in perceptually noticeable changes in time perception.

A potential speculative formula might look something like this:

$$\Delta t = k \times \left(\frac{d}{r}\right)$$

Where:

- Δt is the altered perception of time.
- k is a constant derived from Weber's theory.
- d is the 'distance' traveled by the brainwave.

START

Delta

Frequency 0.5 to 4 Hertz

Associated with deep sleep, infant wakefulness, certain brain disorders or injuries

Theta

Frequency of 4 to 8 Hertz

Associated with light sleep, deep meditation, old memory retrieval

Alpha

Frequency of 8 to 14 Hertz

Associated with relaxed alertness, mindfulness & meditation, transition between wakefulness and sleep

Low Beta

Frequency of 12 to 15 Hertz

Associated with conscious and active thought, alertness

Mid Beta

Frequency of 15 to 20 Hertz

Focused cognitive processing, alterness and vigilance

High Beta

Frequency of 20 to 30 Hertz

Complex or intense cognitive tasks, anxiety or restlessness, excitement or euphoria

Gamma

Frequency of 30 to 100 Hertz

Higher cognitive processing, perceptual awareness, epilepsy, migraines, schizophrenia, overstimulation

Mathematical Framework

<u>Distance</u>: The theoretical “distance” our brains travel is a cumulative representation of all brainwave activities in a typical day. This cognitive journey can vary significantly among individuals, especially when considering conditions or disorders that impact time perception.

<u>Rate</u>: This is characterized by the wavelengths and frequencies of standard brainwaves - delta, theta, alpha, low beta, mid beta, high beta, and gamma. Each type of wave represents different cognitive states and functions, from deep sleep to heightened alertness.

<u>Time</u>: Time, in this context, refers to the duration one experiences a particular brainwave activity within 24 hours.

<u>Incorporating Weber’s Time Constant and Myelination</u>:

The Weber time constant, derived by calculating the difference between the ‘distance’ covered by an average brain compared to those with altered time perception, offers a scalar measure of time perception variations. Furthermore, factoring in changes in myelination, which can influence the speed and efficiency of neural transmissions, adds depth to our understanding. An increase in myelination can speed up neural processes, possibly leading to altered time perception, while a decrease might have the opposite effect.ts into a long-standing question: How do humans perceive the passage of time?

Methodology

Data

My research began by tapping into the theoretical frameworks of neuroscience, psychology, and time perception. By leveraging these well-established theories, we constructed a foundational understanding u which more specific and nuanced data points could be built. Rapid Fire Questioning with AI ChatGPT-4: To deeper into the complexities of time perception, we engaged in extensive interactions with OpenAI's ChatC This state-of-the-art AI model, trained on vast amounts of data, provided us with nuanced insights and knowledge gaps in existing research.

Research

Why ChatGPT-4?

Access to Comprehensive Data: ChatGPT-4 has been trained on a multitude of research papers, articles, an databases. Its knowledge spans a wide array of fields, allowing us to extract valuable information on brain activity, associated tasks, and conditions influencing time perception. Efficient Interaction: Rapid-fire questioning with ChatGPT-4 ensured that the data acquisition process was both thorough and efficient. By posing sequential questions and building upon the AI's responses, I was able to derive detailed and interconnected insights within a short time frame. Dynamic Learning Approach: ChatGPT-4's ability to understand and respond contextually enabled a more organic, conversational approach to data gathering dynamic interaction often led to the revelation of unexpected but valuable insights.

Data Analysis

Brainwave Activity and Associated Tasks: With the data acquired, I charted out a comprehensive mapping different brainwave types (delta, theta, alpha, beta, gamma) against their associated cognitive tasks. This provided a clear picture of how various activities or states of being could influence time perception.

Alterations in Human Time Perception: Further, I analyzed the factors leading to alterations in time percep Data indicated a range of influences from biological (e.g., neurochemical changes, myelination variations) psychological (e.g., trauma, mindfulness practices).

Approach

By adopting this multifaceted approach, I aim to shed light on the intricate mosaic of human time percept Unveiling its mysteries could lead to therapeutic breakthroughs for disorders affecting time perception an offer everyone deeper insights into their own experiences of the world.

This methodology, which combined theoretical judgments with advanced AI-powered interactions, led to dataset on human time perception. By leveraging the power of ChatGPT-4 and its extensive training, we ha gathered insights that push the boundaries of existing knowledge and pave the way for future research in t intriguing field.

Feature Design

Description	Feature
Increase or decrease in myelin compared to average person (100% is average)	Myelin
Average speed associated with adequate myelination (75 meters per second)	Speed
Speed with myelination increase/decrease applied	Speed_M
Delta wavelength in meters = velocity divided by frequency	D_WL
Number of delta cycles = frequency x time	D_Cycle
Total delta distance (km) = wavelength x number of cycles	D_Dist
Time in hours per day spent in delta waves	D_Time
Average frequency of delta waves	D_Freq
Theta wavelength in meters = velocity divided by frequency	T_WL
Number of theta cycles = frequency x time	T_Cycle
Total theta distance (km) = wavelength x number of cycles	T_Dist
Time in hours per day spent in theta waves	T_Time
Average frequency of theta waves	T_Freq
Alpha wavelength in meters = velocity divided by frequency	A_WL
Number of alpha cycles = frequency x time	A_Cycle
Total alpha distance (km) = wavelength x number of cycles	A_Dist
Time in hours per day spent in alpha waves	A_Time
Average frequency of alpha waves	A_Freq
Low beta wavelength in meters = velocity divided by frequency	BL_WL
Number of low beta cycles = frequency x time	BL_Cycle
Total low beta distance (km) = wavelength x number of cycles	BL_Dist
Time in hours per day spent in low beta waves	BL_Time
Average frequency of low beta waves	BL_Freq
Mid beta wavelength in meters = velocity divided by frequency	BM_WL
Number of mid beta cycles = frequency x time	BM_Cycle
Total mid beta distance (km) = wavelength x number of cycles	BM_Dist
Time in hours per day spent in mid beta waves	BM_Time
Average frequency of mid beta waves	BM_Freq
High beta wavelength in meters = velocity divided by frequency	BH_WL
Number of high beta cycles = frequency x time	BH_Cycle
Total high beta distance (km) = wavelength x number of cycles	BH_Dist
Time in hours per day spent in high beta waves	BH_Time
Average frequency of high beta waves	BH_Freq
Gamma wavelength in meters = velocity divided by frequency	G_WL
Number of gamma cycles = frequency x time	G_Cycle
Total gamma distance (km) = wavelength x number of cycles	G_Dist
Time in hours per day spent in gamma waves	G_Time
Average frequency of gamma waves	G_Freq
24 hours	Total_Time
Cumulative distance in km	Total_Distance
Calculated percent increase/decrease based on average person total distance	Percent_Increase
Rate in km/hr	Total_Rate
Altered perception of time (Weber's constant)	Weber_k

Machine Learning Approach

The utilization of **Random Forest** models in this research project stems from their inherent advantages in addressing the complexities of our multiclass classification problem. Random Forest models offer a robust and insightful approach to gaining a deeper understanding of the factors influencing classification accuracy. Their applicability was chosen based on the recognition that they provide a unique opportunity to unravel the importance of specific features, thereby informing subsequent feature selection and engineering efforts for the development of a deep learning neural network (NN) model.

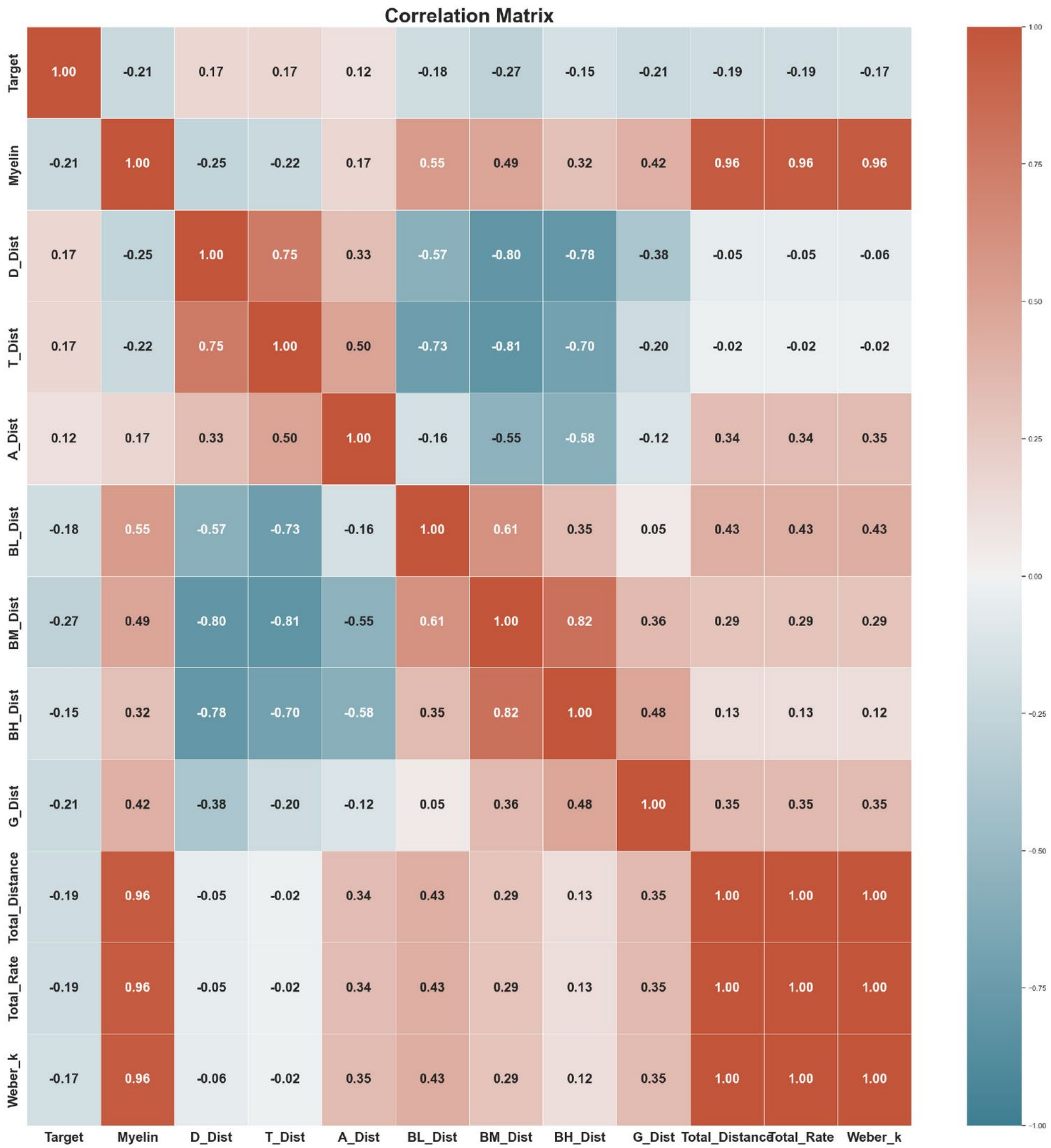
Another compelling reason for embracing Random Forest models is their transparency in interpreting complex datasets. This transparency facilitates a clear comprehension of feature interactions and their contributions to overall accuracy. Beyond interpretability, these models serve as effective benchmarking tools, allowing for the establishment of performance baselines that aid in assessing the value of more intricate deep learning models. Moreover, their adeptness at handling class imbalances, often encountered in multiclass classification tasks, adds to their appeal, equipping us with the expertise needed to address real-world data scenarios effectively.

Subset Correlation Matrix

The decision to make a subset of data for exploratory data analysis and visualizations was due to the relationships of the dataset which relied on mathematical formulas applied from one feature to the next.

The Target Field is slightly negatively correlated with BM_Dist which stands for the theoretical distance traveled by the subject in the mid-beta wave state.

Colinearity can be viewed in the features Total_Distance, Total_Rate, and Weber_k. This is not surprising as these features are closely related by the distance = rate * time formula along with the Weber constant application to the data.



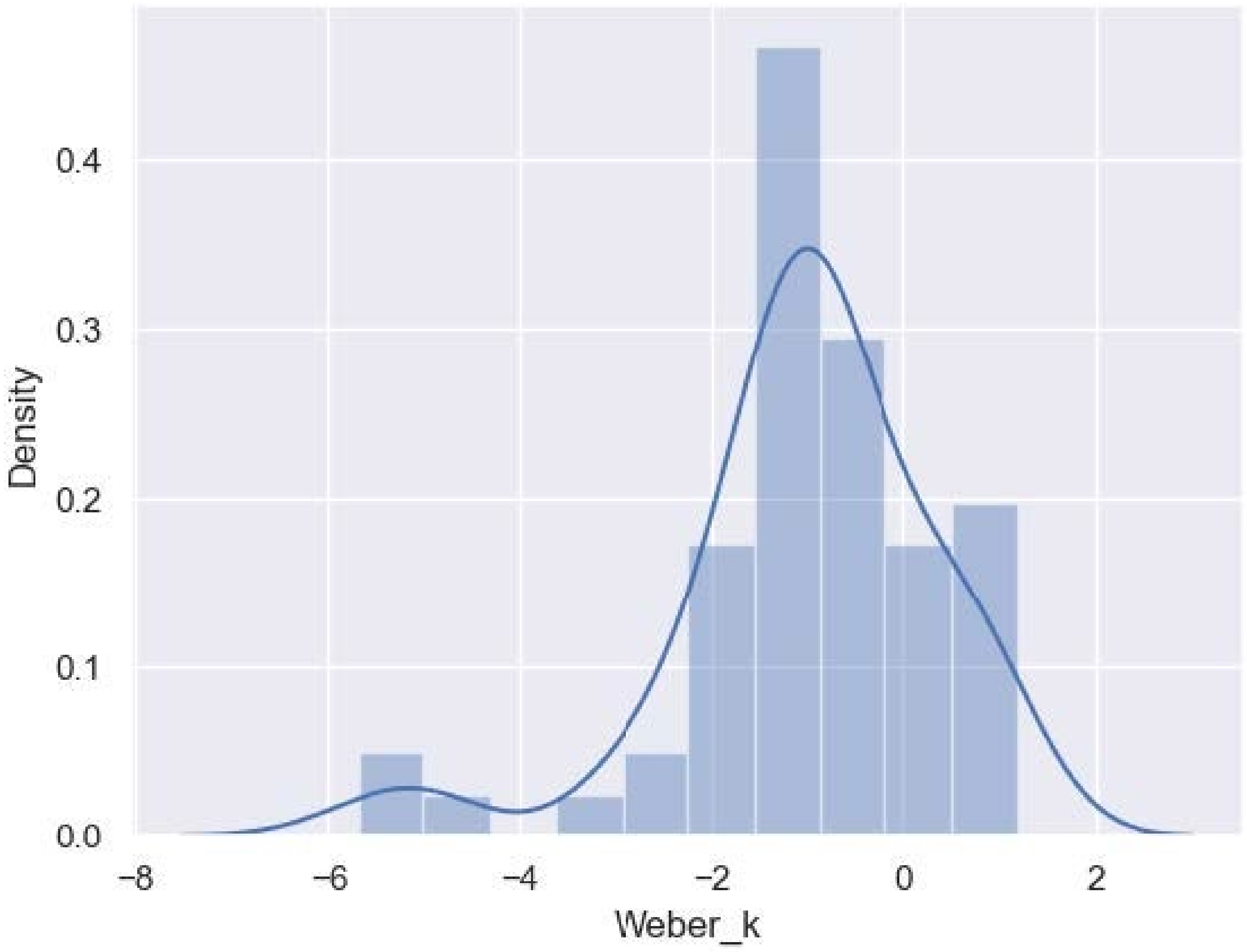
Weber_k Distribution

The Weber_k feature is a result of feature engineering which takes into consideration the work by Ernst Heinrich Weber in 1834.

The Weber-Fechner law, or Weber's law is a principle in experimental psychology proposed by Ernst Weber. It states that the just-noticeable difference between two stimuli is proportional to the magnitude of the stimuli.

In the context of time perception, applying Weber's law would mean that our ability to distinguish between two durations would be based on a ratio or proportion rather than a fixed quantity.

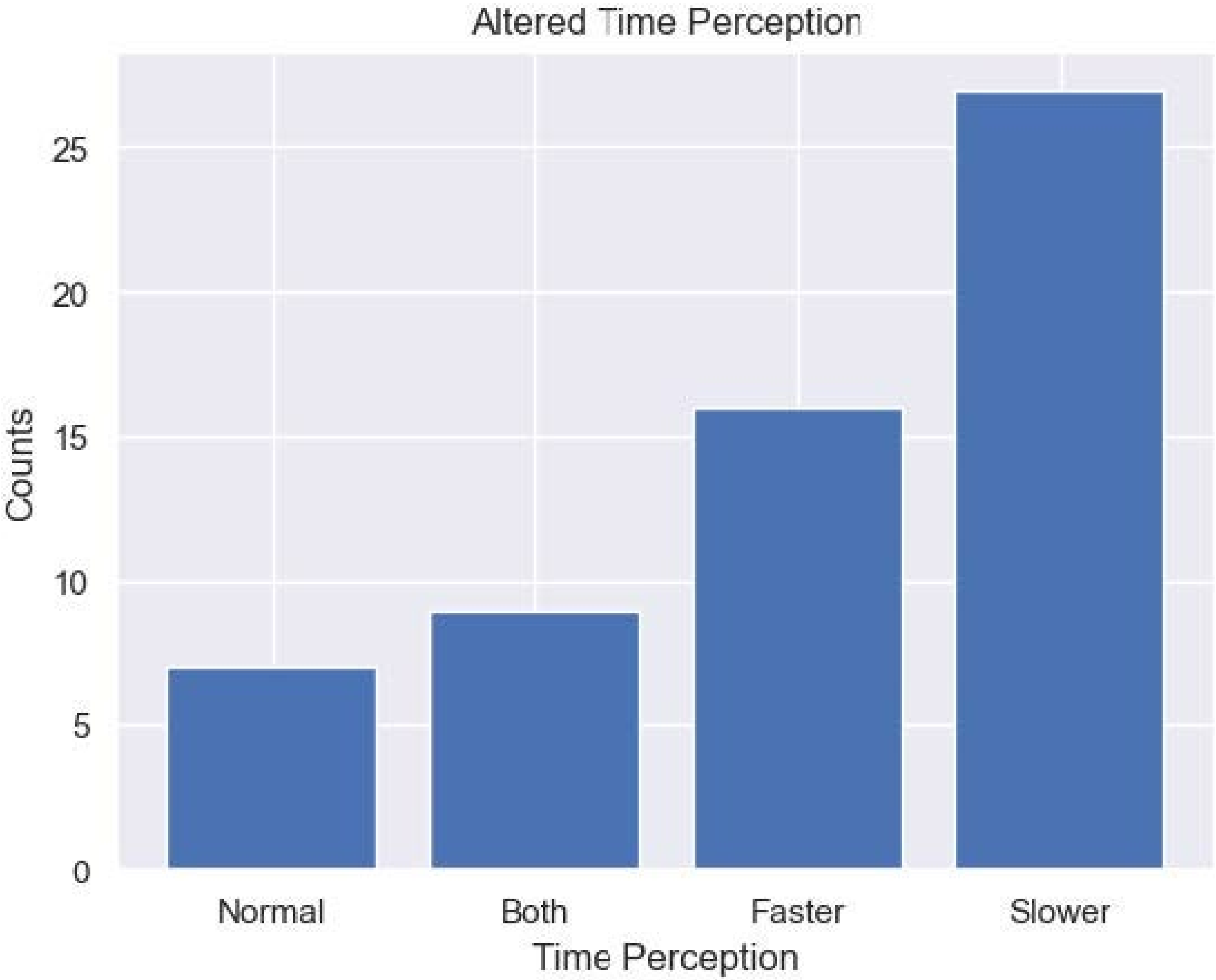
This graph illustrates that there is a larger distribution of conditions where time is being perceived as slower than average.



Target Counts (Altered Time Perception)

The Target variable in this study is an Altered Perception of Time. Specifically whether a disorder or condition is associa with average time perception, time is perceived faster, time perceived slower, or a condition where both alterations are possible.

Analyzed Conditions: ADHD, Aging 18-29, Aging 30-49, Aging 50-69, Aging 70-89, Aging 90+, Alcohol, Alzheimer's Disease, Anxiety, Autism Type 1, Autism Type 2, Average, Bipolar Depressive, Bipolar Manic, Brain Damage, Brain Lesions, Caffeine, Chronic Pail disorder, Cocaine, Concentration Meditation, Depression (MDD), Dissociative Disorders, Elite Athlete, Emregency Event, Epilepsy, Fentanyl, Flow State, Graduate Student, Heroin, High IQ, Insomnia, Ketamione, Learrning Problems, Low IQ, LSD, Marijuana, MDMA (Ecstasy Methamphetamine, Migraine, Morphine, MS, Musician, Nicotine, Oxycodone, Parkinson's Disease, Percription Antidepressants, Perscription Sleep Aids, Perscription Stimulants, Psilocybin, Psychosis, PTSD, Savant Type 1, Sava Type 2, Schizophrenia, Severe Cognitive Disability, Stress, TE Tibetyan Meditation, Transcendental Meditation.



Model Accuracy

	Accuracy	Feature Importance 1	Feature Importance 2	Feature Importance 3
Decision Tree	55.56%	BM_Dist	BL_Dist	Total_Distance
Random Forest (1)	61.11%	BM_Dist	BL_Dist	Weber_k
Random Forest (2)	50.00%	BH_Dist	BM_Dist	G_Dist
Random Forest (3)	50.00%	BM_Dist	BL_Dist	Weber_k
Random Forest (4)	55.56%	BM_Dist	BL_Dist	Myelin
Random Forest (5)	50.00%	BM_Dist	BL_Dist	BH_Dist
Random Forest (6)	50.00%	BH_Dist	T_Dist	BM_Dist
Random Forest (Full-1)	66.67%	BM_Dist	BL_Dist	Percent_Increase
Random Forest (Full-2)	38.89%	T_Cycle	BH_Cycle	D_Cycle
Random Forest (Full-3)	75.00%	BM_Dist	BL_Dist	Weber_k

BM_Dist is the feature with the greatest importance in evaluating all models. BM_Dist is the theoretical distance travelled in a day in mid beta waves which is associated with calm cognitive tasks and productivity.

Model 1 (Subset)

Before performing the Random Forest Models, I ran a Decision Tree Model to get a visualization of possible connections among the features.

Most Accurate Model

```python
# Initialize RandomForestClassifier
clf = RandomForestClassifier(random_state=42)

# Define the parameter grid
param_grid = {
    'n_estimators': [300, 500, 800],
    'max_depth': [None, 20, 40, 60],
    'min_samples_split': [2, 4, 6],
    'min_samples_leaf': [1, 2, 3],
    'max_features': ['sqrt', 'log2']
}

# Initialize GridSearchCV
grid_search = GridSearchCV(clf, param_grid, cv=10, verbose=2, n_jobs=-1)

# Fit GridSearchCV to the training data
grid_search.fit(X_train, y_train)

# Get the best estimator
best_clf = grid_search.best_estimator_

# Predict on the test data
y_pred = best_clf.predict(X_test)

print("Best Parameters:", grid_search.best_params_)
```

Hyperparameters:

Number of Estimators (n_estimators): This defines how many trees I have in my forest. After the grid search, the optimal number fell among the given choices of 300, 500, or 800 trees.

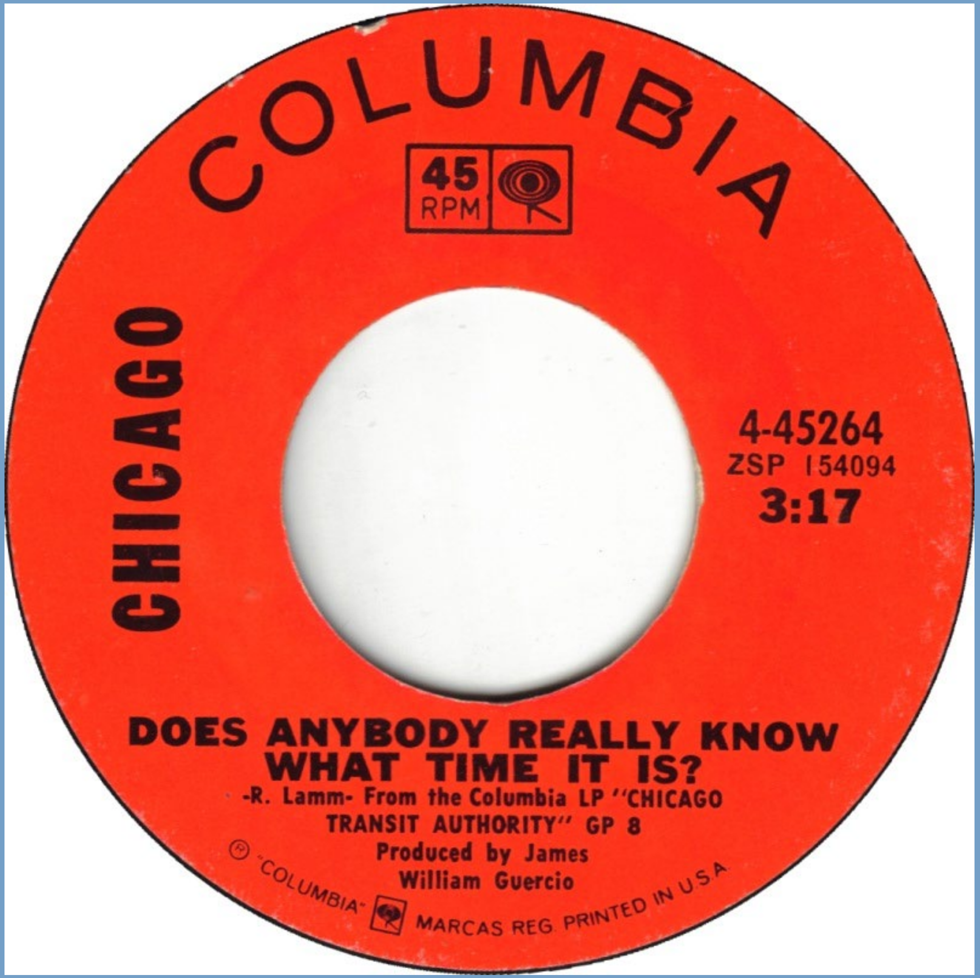
Maximum Depth (max_depth): This parameter determines how deep each tree can grow. The choices I had considered were letting the tree grow without restriction (None), or limiting its growth to a depth of 20, 40, or 60.

Minimum Samples for Split (min_samples_split): This is the minimum number of samples required to split a node further. My model used one of the pre-specified numbers: 2, 4, or 6.

Minimum Samples at Leaf (min_samples_leaf): This specifies the least number of samples I want at each leaf node of the trees. From the grid search, the best model chose either 1, 2, or 3 as its optimal number.

Maximum Features (max_features): This determines the number of features the algorithm should consider when deciding the best split. The model found its best performance with either the square root ('sqrt') or the logarithm base 2 ('log2') of the total number of features.

After the grid search was completed, the exact values for each of these hyperparameters were displayed using grid_search.best_params_, pinpointing the optimal configuration for my Random Forest model. This best-performing model was then used to make predictions on my test data.



Temporal Metrics

The song "Does Anybody Really Know What Time It Is?" by Chicago Transit Authority was released in 1970. The lyrics ponder the passage of time and our efforts to measure and understand it.

Here is a link to the song:

Does Anybody Really Know What Time It Is?