Detecting working patterns from online workers and predicting task completion

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Background of the problem:

As digital platforms become integral to remote work, they generate extensive behavioral data. Analyzing this data is essential for enhancing productivity and managing resources efficiently. This project aims to address the challenge of predicting how long tasks will take to complete by examining user activities, including platform interactions, browser events, and task categories.

Project Objective:

- To identify patterns in user behavior through data analysis.
- To forecast task completion times accurately using machine learning techniques.
- To deliver practical insights that can aid in boosting productivity and guiding decision-making in remote work settings.

Methodological Paradigm:

Methodology: Regression Analysis

Models: Random Forest Regressor and XGBoost

Supporting rationale for the selected methodological paradigm:

- Regression analysis was selected due to its effectiveness in predicting continuous outcomes such as task completion durations.
- Random Forest was chosen for its capability to process both categorical and numerical data types effectively.
- XGBoost was chosen to address the limitations of Random Forest by offering better management
 of high-dimensional data, capturing complex patterns, and minimizing overfitting through
 regularization methods.

Summary of the dataset:

Unit of analysis: Individual user activities within crowd work platforms - each row represents a single action like loading a page, starting a task, or communicating within the platform.

Observations in the dataset: The dataset has 3,496,373 observations in total.

Unique Observations:

• Unique Users: 119

• Unique URLs visited: 255,518

• Unique Platforms: 5

Unique Task Subtypes: 29Unique Browser Events: 18Unique Type Values: 10

Time Period Covered: The 'time' column indicates all data was collected in May 2020.

Summary of Data Cleaning:

Percentage of Samples with Missing Data: The dataset has a total of 3,496,373 observations, the percentage of missing data in the user column is approximately: 0.0075 %. This indicates a negligible amount of missing data.

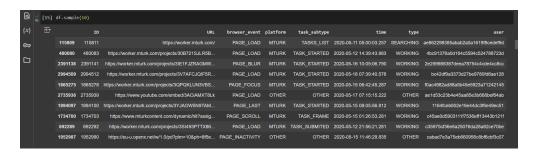
The data cleaning steps performed include:

- **Assigning Column Names:** Initially, the dataset lacked column names, so names were assigned based on the provided data dictionary.
- **Data Type Conversion:** The *time* column, originally in milliseconds, was converted to a datetime format using *pd.to_datetime* for better temporal analysis.
- **Handling Missing Values:** The *user* column had 264 missing entries. Further exploration or consultation was considered to determine their impact.
- Removing Irrelevant Columns: Extraneous columns (extra and skip) were removed as per the data dictionary to streamline analysis.
- Ensuring Consistency: Checked and resolved inconsistencies in data formats and types across the dataset.

Before Data Cleaning:



After Data Cleaning:



Handling of Missing Data:

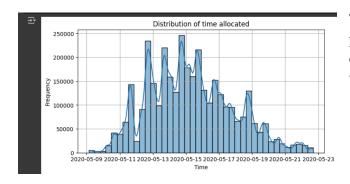
Missing values in categorical variables were replaced with a placeholder value ('Unknown').

• Numerical features with missing values were imputed using median values to maintain data integrity.

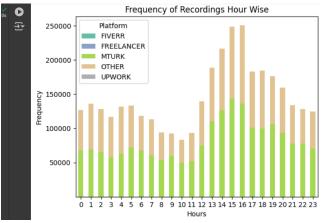
Outcome Variable Summary:

The outcome variable is the task completion time, measured in hours. It represents the duration required to finish tasks based on user behavior data, including platform usage, browser events, and task types. Predicting this variable helps in understanding productivity patterns and optimizing task management.

Outcomes of Appropriate Visualization technique:

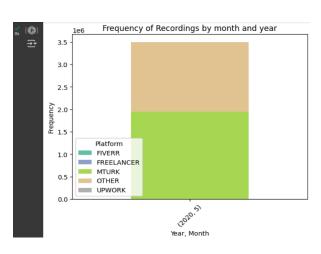


The visualization highlights May 15, 2020, as a peak in time allocation and user activity. Users engaged more frequently and spent more time on the platform that day than on others.



understand platform dynamics.

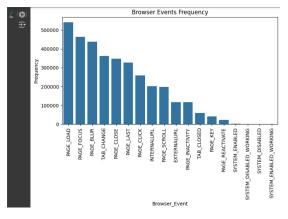
The second visualization represents the hourly distribution of user activity across different platforms, with a strong emphasis on MTurk and similar platforms. Distinct peaks at certain hours indicate periods of increased user engagement. This pattern suggests that users tend to prefer accessing these platforms at specific times, likely influenced by task availability, user schedules, or platform popularity. Analyzing these trends can help platform administrators and researchers determine optimal periods for task releases, improve user engagement strategies, and better



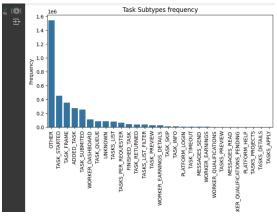
The third visualization showcases a high concentration of recorded activities solely within May 2020, with the majority of interactions occurring on two main platforms: MTurk and other similar platforms.

Key Predictors:

Based on our dataset analysis, we identify browser_event and platform as key predictors and they are structured.

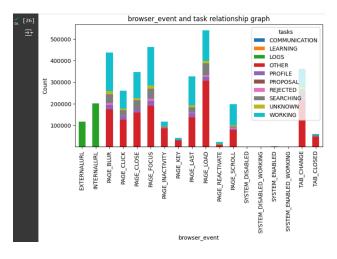


Browser Event: This captures the type of user interaction with the browser, which can influence task outcomes. For instance, a PAGE_LOAD event may signify the initiation of a new task, whereas a PAGE_BLUR event could indicate user distraction or a break. Examining the frequency and sequence of these interactions can help predict user behavior and task completion patterns.



Task Subtype: This refers to the specific type of task a user is engaged in, each requiring varying levels of time, effort, and skill. For instance, a TASK_STARTED event may suggest prolonged user engagement, while a TASK_RETURNED event could indicate difficulty in completing the task. Analyzing the frequency and sequence of these task subtypes can help predict user performance and task outcomes.

Relationship between browser_event and task_subtype:



Relationship between browser_event and task: PAGE_LOAD, PAGE_FOCUS, and PAGE_CLOSE indicate engagement, linking to WORKING and COMMUNICATION, while PAGE_INACTIVITY and PAGE_BLUR suggest disengagement, aligning with REJECTED and SEARCHING. Their sequence helps predict task outcomes.