```
import pandas as pd
import numpy as np
import random
import pylab as pl
import time
import datetime
from sklearn.feature_selection import RFECV

# for plotting
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
from scipy.stats import chi2_contingency
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from statsmodels.tsa.seasonal import seasonal_decompose
from lightgbm import LGBMRegressor
from xgboost import XGBRegressor
# scikit learning packages
from lightgbm import LGBMRegressor, early_stopping
from xgboost import XGBClassifier
from sklearn.model_selection import TimeSeriesSplit
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.feature_selection import RFE, SelectFromModel
from sklearn.neighbors import KNeighborsClassifier
from sklearn.dummy import DummyRegressor
from sklearn.model_selection import (
    train_test_split,
    cross_val_score,
    cross_val_predict,
    KFold,
    StratifiedKFold,
    GridSearchCV
)
from sklearn.ensemble import (
    RandomForestClassifier,
    RandomForestRegressor,
    GradientBoostingRegressor,
    GradientBoostingClassifier,
    AdaBoostClassifier,
    ExtraTreesClassifier,
    VotingClassifier,
    VotingRegressor
)
from sklearn.metrics import (
    confusion_matrix,
    accuracy_score,
    mean_absolute_error,
    mean_squared_error,
    r2_score,
    make_scorer,
    classification_report,
    roc_curve,
    auc
)
```

```python
from sklearn.preprocessing import (
    LabelEncoder,
    MinMaxScaler,
    StandardScaler,
    OneHotEncoder,
    PolynomialFeatures,
    scale
)
from sklearn.naive_bayes import GaussianNB, BernoulliNB, MultinomialNB
from sklearn.decomposition import PCA, FactorAnalysis
from sklearn.linear_model import (
    LinearRegression,
    Ridge,
    LogisticRegressionCV,
    LogisticRegression
)
from sklearn.svm import SVC
from sklearn import svm, metrics, tree
from sklearn.tree import DecisionTreeClassifier, DecisionTreeRegressor
from sklearn.multiclass import OneVsRestClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.neural_network import MLPClassifier
from sklearn.utils import resample, shuffle

from collections import Counter
from pandas.api.types import is_numeric_dtype
import holidays
import warnings
from scipy.stats.mstats import mquantiles
from scipy.stats import skew
warnings.filterwarnings("ignore")
cmap = sns.color_palette('Blues_r')


###################################
starting_time = time.perf_counter()
print('')
print('starting time: ', datetime.datetime.now().strftime("%H:%M:%S"))
print('')
###################################

### Read the file
df_raw = pd.read_excel(r"C:\Users\oslu.5\Desktop\ML test\ML_Absenteism.xlsx",sheet_name = 0)


##########
ending_time = time.perf_counter()
total_in_sec = ending_time-starting_time
print("Data time in sec")
print(total_in_sec)
print("Data uploaded")
```

```
starting time:  12:42:59



Data time in sec

72.5959234

Data uploaded
```

# 📊 Introduction to Our Columns and Their Data Types

The dataset contains **185,068 entries** with a total of **32 columns**. Below is the overview of the columns, their non-null counts, and data types:

### 🗂️ Data Types Summary:

- **datetime64[ns]**: 3 columns
- **float64**: 12 columns
- **int64**: 4 columns
- **object**: 13 columns

This structure helps us identify **missing values**, the **nature of each column**, and how we can handle the data effectively during preprocessing.

```
df_raw.info()
```

```
<class 'pandas.core.frame.DataFrame'>

RangeIndex: 185068 entries, 0 to 185067

Data columns (total 32 columns):

 #   Column          Non-Null Count   Dtype

---  ------          --------------   -----

 0   Date            185068 non-null  datetime64[ns]

 1   AssignedDep     185068 non-null  int64

 2   MU_Name         185068 non-null  object

 3   Country         184984 non-null  object

 4   Language        184477 non-null  object

 5   Location Type   132733 non-null  object

 6   Manager ID      171455 non-null  float64

 7   Role            183992 non-null  object

 8   dob             184411 non-null  datetime64[ns]

 9   sex             185068 non-null  object
```

# 📊 Dataset Overview

The dataset is part of the **Call Center Project**, selected for testing **predictive absenteeism models.** It spans the date range **2023-01-01 to 2025-01-23**, with data fetched from **Schedule**, a system used to track historical employee metrics.

Additional features such as **dob**, **sex**, **marital_status**, **hire_date**, **Is_Actual**, and **Is_Strike** have been introduced to enrich the dataset.

## 🔑 Key Features

### 📅 Date Columns:

- **Date**, **dob**, and **hire_date** provide chronological information essential for calculating:
  - Employee **tenure**
  - Employee **age**

### 🗂️ Categorical Data:

- Fields like:
  - **MU_Name** (Management Unit)
  - **Country**
  - **Language**
  - **Role**
  - **sex**

- **marital_status**

These describe **employee demographics** and **organizational roles.**

### 🔢 Numerical Data:

- Columns such as:
  - **AssignedDep**
  - **Contract Hours**
  - **Scheduled**
  - **Worked**
  - **Rest**
  - **Overtime**
  - **Absence**
  - **Sick**

  These capture **time-related work metrics** and serve as **features or targets** for absenteeism predictions.

### 🧮 Derived Features:

- New columns like:
  - **Is_Actual** *(Actual or Forecast)*
  - **Is_Strike** *(Strike day or not)*
  - Calculated fields:
    - **Age**
    - **Tenure_Company**
    - **Tenure_Department**

  These provide **deeper insights** for modeling.

## ❗ Missing Data

Significant missing values are found in the following columns:

- **Country**
- **Language**
- **Location Type**
- **Manager ID**
- **Role**
- **Contract Hours**

These require specific **imputation strategies** to handle missing data effectively.

## 🔍 Sample Insights

### 📅 Potential Predictive Features Include:

1. **Temporal Aspects:**

   - **Date**
   - **Shift_Starts**
   - **DayofWeek**
   - **Season**
2. **Employee Demographics:**

   - **dob**
   - **sex**
   - **marital_status**

3. **Work Metrics:**
    - **Scheduled**
    - **Worked**
    - **Overtime**
    - **Training**
    - **Vacation**
    - **Sick**
    - **Total_Lost**
    - **Absence**
    - **Early**
    - **Late**

## 🚀 Notable Enhancements

### ✨ Feature Additions:

- **Demographic Features:**
    - **dob**, **sex**, and **marital_status**
- **Derived Fields:**
    - **Age**
    - **Is_Holiday**
    - **Tenure_Department**

These enrich the dataset with **additional dimensions** for predictive analysis.

### 🔧 Imputation Strategies:

- **Missing Dates & Numeric Values:**
    - Filled using **forward/backward filling** and **averages**.
- **Group-level Imputation:**
    - Applied to columns like **Manager ID** for more accurate filling.

This comprehensive overview provides a solid foundation for understanding the dataset and preparing it for **predictive modeling**. 📈

```
###################################
starting_time = time.perf_counter()
print('')
print('starting time: ', datetime.datetime.now().strftime("%H:%M:%S"))
print('')
###################################

df = df_raw.copy()

# -----------------------
# Drop Duplicates
# -----------------------
df = df.drop_duplicates(subset=['CCMS_ID','Date'], keep='first')

# -----------------------
# Handle Missing Age
# -----------------------
avg_dob = df['dob'].mean()
```

```python
avg_dh = df['hire_date'].mean()
# Fill missing dob with the average dob
df['hire_date'].fillna(avg_dh, inplace=True)

df['dob'].fillna(avg_dob, inplace=True)
df['Age'] = (df['Date'] - df['dob']).dt.days // 365

# ------------------------
# Identify columns with null, excluding 'dob'
# ------------------------
columns_with_null = df.columns[df.isna().any()].tolist()

print("Columns with missing values \n", columns_with_null)

# ------------------------
# Helper function to fill missing values for one column in one group
# ------------------------
def fill_missing_for_column(g, col):
    # If the column has no missing values in this group, do nothing
    if g[col].isna().sum() == 0:
        return g

    # Earliest date with a null in this column
    minnull = g.loc[g[col].isna(), 'Date'].min()

    # Earliest date with a non-null in this column
    minnotnull = g.loc[g[col].notna(), 'Date'].min()

    # Forward or backward fill based on minnull vs minnotnull
    if pd.notna(minnull) and pd.notna(minnotnull):
        if minnull > minnotnull:
            g[col] = g[col].bfill()
        else:
            g[col] = g[col].ffill()

    # Fill remaining null with 0 or 'Unknown'
    if is_numeric_dtype(g[col]):
        g[col] = g[col].fillna(0)
    else:
        g[col] = g[col].fillna('Unknown')

    return g

# ------------------------
# Apply per column and per group
# ------------------------
for col in columns_with_null:
    print(f"Handling missing values for {col}")
    df = (
        df
        .groupby('CCMS_ID', group_keys=False)
        .apply(lambda group: fill_missing_for_column(group, col))
    )

# Done.

conditions = [
    df['Role'].isin(['CSS', 'Operations Customer Expert I', 'Operations Customer Expert II']),
    df['Role'].isin(['Supervisor', 'Operations Supervisor', 'Flex Supervisor']),
    df['Role'].isin(['CCM', 'Operations Manager']),
```

```python
    df['Role'].isin(['ACM', 'Operations Assistant Manager']),
    df['Role'].str.contains('Flex QA Analyst|QA|Quality', case=False, na=False),
    df['Role'].str.contains('WFM', case=False, na=False),
    df['Role'] == 'Unknown'
]

choices = ['CSS', 'Supervisor', 'CCM', 'ACM', 'QA', 'WFM', 'Unknown']

# Apply the mapping logic
df['Role'] = np.select(conditions, choices, default='Unknown')



df['Country'] = df['Country'].str.replace('Unknown','Greece')

df = df.sort_values(by=['CCMS_ID','Date']).reset_index(drop=True)


df['Department_hire_date'] = df.groupby('CCMS_ID')['Date'].transform('min')
df['Tenure_Company'] = (df['Date'] - df['hire_date']).dt.total_seconds() / 3600
df['Tenure_Departmant'] = (df['Date'] - df['Department_hire_date']).dt.total_seconds() / 3600

df['Manager ID'] = df['Manager ID'].astype(int).astype(str)
df['Contract Hours'] = df['Contract Hours'].astype(int).astype(str)
df['AssignedDep'] = df['AssignedDep'].astype(int).astype(str)

df['Rest'] = df['Rest'].apply(lambda x: 0 if x < 0 else (100 if x > 100 else x))
## Bucketizer

def bucketizer(x):
    if x < 30:
        return 'NH'
    elif 30 <= x < 60:
        return '01mos'
    elif 60 <= x < 90:
        return '02mos'
    elif 90 <= x < 180:
        return '03mos'
    elif 180 <= x < 365:
        return '06Mos'
    elif 365 <= x < 730:
        return '1Year'
    elif 730 <= x < 1825:
        return '2-5Years'
    else:
        return '+5Year'
df['Tenure_Company'] = df['Tenure_Company'].apply(bucketizer)
df['Tenure_Departmant'] = df['Tenure_Departmant'].apply(bucketizer)

def age_bucketizer(x):
    if x < 25:
        return '18-25'
    elif 25 <= x < 30:
        return '25-30'
    elif 30 <= x < 35:
        return '30-35'
    elif 35 <= x < 40:
        return '35-40'
    elif 40 <= x < 45:
        return '40-45'
```

```python
    elif 45 <= x < 50:
        return '45-50'
    else:
        return '+50'
df['Age'] = df['Age'].apply(age_bucketizer)


# ## Drop columns
df = df.drop(columns=[ 'dob', 'hire_date', 'Department_hire_date'])

# Generate the dictionary by passing each unique country name to holidays.country_holidays
country_to_code = {}

for country in df['Country'].unique():
    try:
        iso_code = holidays.country_holidays(country=country).country
        country_to_code[country] = iso_code
    except Exception as e:
        print(f"Error for country: {country} - {e}")

# Function to check if a date is a holiday
def is_holiday(row):
    country_code = country_to_code.get(row['Country'])
    if country_code:
        try:
            country_holidays = holidays.country_holidays(country=country_code, years=row['Date'].year)
            return '1' if row['Date'] in country_holidays else '0'
        except Exception as e:
            print(f"Error checking holiday for {row['Country']} on {row['Date']}: {e}")
    return 0

# Apply the function to create the Is_Holiday column
df['Is_Holiday'] = df.apply(is_holiday, axis=1)

### Create extra Date columns

df['Year'] = df['Date'].dt.year
df['Month'] = df['Date'].dt.month
df['WeekofYear'] = df['Date'].dt.isocalendar().week
df['DayofMonth'] = df['Date'].dt.day
df['DayofWeek'] = df['Date'].dt.dayofweek
df['Season'] = (df['Date'].dt.month % 12 + 3) // 3

df['Total_Lost'] = df['Absence']
df['Absence'] = df['Total_Lost']-(df['Early']+df['Late'])
##########
ending_time = time.perf_counter()
total_in_sec = ending_time-starting_time
print("\n Data time in sec")
print(total_in_sec)
print("Data Cleaning Completed")
```

```
starting time:  12:44:12



Columns with missing values

 ['Country', 'Language', 'Location Type', 'Manager ID', 'Role', 'Contract Hours']

Handling missing values for Country

Handling missing values for Language

Handling missing values for Location Type

Handling missing values for Manager ID

Handling missing values for Role

Handling missing values for Contract Hours



 Data time in sec

51.457887

Data Cleaning Completed
```

# 📊 Cramér's V Analysis

### 🔍 What is Cramér's V?

Cramér's V is a **statistical measure** used to **quantify the strength of association** between two **categorical variables.** It is based on the **chi-squared statistic** and provides a **normalized value between 0 and 1:**

- **0** → Indicates **no association** between the variables.
- **1** → Indicates a **perfect association.**

Cramér's V is particularly useful for understanding relationships between **categorical features,** which **cannot be analyzed** using traditional correlation methods like **Pearson's correlation** (used for numerical data).

## 🤔 Why Implement Cramér's V in Analysis?

### 1️⃣ Feature Selection:

- Identify **strong associations** between **independent categorical features** and the **target variable** (e.g., **Absence** or **Sick**).
- Highlight **highly correlated categorical features** to **avoid redundancy** in the model.

### 2️⃣ Data Understanding:

- Reveal how variables like **Role, Language,** or **Country** interact with each other or with the **target feature.**
- Help decide whether features need **grouping, transformation,** or **encoding.**

### 3️⃣ Improving Model Interpretability:

- Selecting **meaningful features** ensures that **relationships identified by the model** are **relevant** and **interpretable** for stakeholders.

## ⚙️ Implementation in Analysis

### ✅ 1. Compute the Chi-Squared Statistic:

- A **contingency table** is created for the two categorical variables.
- The **chi-squared test** is performed on this table to measure **independence**.

### ✅ 2. Normalize the Chi-Squared Value:

Cramér's V is calculated as:

Where:

- **(\chi^2)** = Chi-squared statistic
- **N** = Total number of observations
- **k** = Minimum of the number of categories in the two variables

### ✅ 3. Use the Results:

- Variables with **high Cramér's V values** (e.g., **> 0.3**) show **strong associations** and are considered **impactful** for the analysis.
- Features with **low Cramér's V values** may have **weak or no association** and can potentially be **excluded**.

## 📊 Example Use Case in Predictive Absenteeism

In the **ML_Absenteeism** dataset:

- **Analyzing the relationship** between **Role** and **Absence** might reveal how certain **job roles** (e.g., **Supervisor** vs. **CSS**) **correlate with absenteeism rates.**
- Similarly, checking the **association between Country and Language** can help uncover if they are **highly redundant**, guiding decisions on **encoding** or **grouping**.

## 🚀 Why It Matters?

By implementing **Cramér's V**, we can:

- 🎯 **Reduce Dimensionality:**
  Avoid **multicollinearity** and **redundant features**, improving **model performance**.
- ⚡ **Improve Efficiency:**
  Focus on features with **meaningful associations**, simplifying **preprocessing** and reducing **computation time.**
- 📈 **Increase Accuracy:**
  Use the **most relevant categorical features**, enhancing the model's **predictive power**.

This method is a **powerful tool** for ensuring that our **predictive models** are both **efficient** and **accurate** when working with **categorical data.** ✅

# Cramér's V analysis for Categorical feature

```
# Define the column groups
cramers_v_cols = [
    'Is_Holiday', 'Year', 'Season', 'Month', 'WeekofYear', 'DayofMonth',
    'DayofWeek', 'AssignedDep', 'MU_Name', 'Country', 'Language', 'Location Type',
    'Manager ID', 'Role', 'sex', 'Age', 'marital_status', 'Tenure_Company',
    'Tenure_Departmant', 'c_excp', 'c_name_y','Is_Strike', 'Shift','Shift_Starts','Shift_Code', 'Contract
Hours'
]

columns_to_count = ['CCMS_ID']
columns_to_sum = ['Scheduled', 'Worked', 'Overtime', 'Training', 'Vacation', 'Sick','Total_Lost','Absence',
'Early', 'Late']
columns_to_mean = ['Rest', 'BreakLunch']

# Combine all necessary columns
crmcols = cramers_v_cols + columns_to_count + columns_to_sum + columns_to_mean
creamar_numeric = columns_to_count + columns_to_sum + columns_to_mean
dfg = df[df['Is_Actual']=='Actual'][crmcols]  # Ensure only relevant columns are selected

# Prepare the aggregation dictionary
agg_dict = {col: 'count' for col in columns_to_count}  # Count for CCMS_ID
agg_dict.update({col: 'sum' for col in columns_to_sum})  # Sum for numeric metrics
agg_dict.update({col: 'mean' for col in columns_to_mean})  # Mean for averages

# Group by cramers_v_cols and apply the aggregation
dfg = (
    df.groupby(cramers_v_cols)
    .agg(agg_dict)
    .reset_index()
)

# Ensure cramers_v_cols are treated as strings for consistency
for strcol in cramers_v_cols:
    dfg[strcol] = dfg[strcol].astype(str)

# Function to calculate Cramér's V
def cramers_v(x, y):
    confusion_matrix = pd.crosstab(x, y)
    chi2 = chi2_contingency(confusion_matrix)[0]
    n = confusion_matrix.sum().sum()
    phi2 = chi2 / n
    r, k = confusion_matrix.shape
    phi2corr = max(0, phi2 - ((k - 1) * (r - 1)) / (n - 1))
    rcorr = r - ((r - 1) ** 2) / (n - 1)
    kcorr = k - ((k - 1) ** 2) / (n - 1)
    return np.sqrt(phi2corr / min((kcorr - 1), (rcorr - 1)))

# Initialize an empty DataFrame to store the results
results = []

# Loop through each column in cramers_v_cols
for cat_col in cramers_v_cols:
    for num_col in creamar_numeric:
        try:
            # Calculate Cramér's V
            score = cramers_v(dfg[cat_col], dfg[num_col])
```

```
            results.append({
                'Categorical Feature': cat_col,
                'Numeric Feature': num_col,
                'Cramers_V': score
            })
        except Exception as e:
            # Handle cases where calculation fails
            results.append({
                'Categorical Feature': cat_col,
                'Numeric Feature': num_col,
                'Cramers_V': np.nan,
                'Error': str(e)
            })

# Convert results to DataFrame
df_cramers_v = pd.DataFrame(results)

# Add association categories
df_cramers_v['Association'] = pd.cut(
    df_cramers_v['Cramers_V'],
    bins=[-np.inf, 0, 0.2, 0.3, 0.5, np.inf],
    labels=['No association', 'Weak association', 'Moderate association',
            'Relatively strong association', 'Strong association']
)

df_cramers_v=df_cramers_v[df_cramers_v['Cramers_V'].isna()==False]
# Display the results
df_cramers_v=df_cramers_v.sort_values(by=['Cramers_V'],ascending=[False]).reset_index(drop=True)

df_cramers_v.head(30)
```

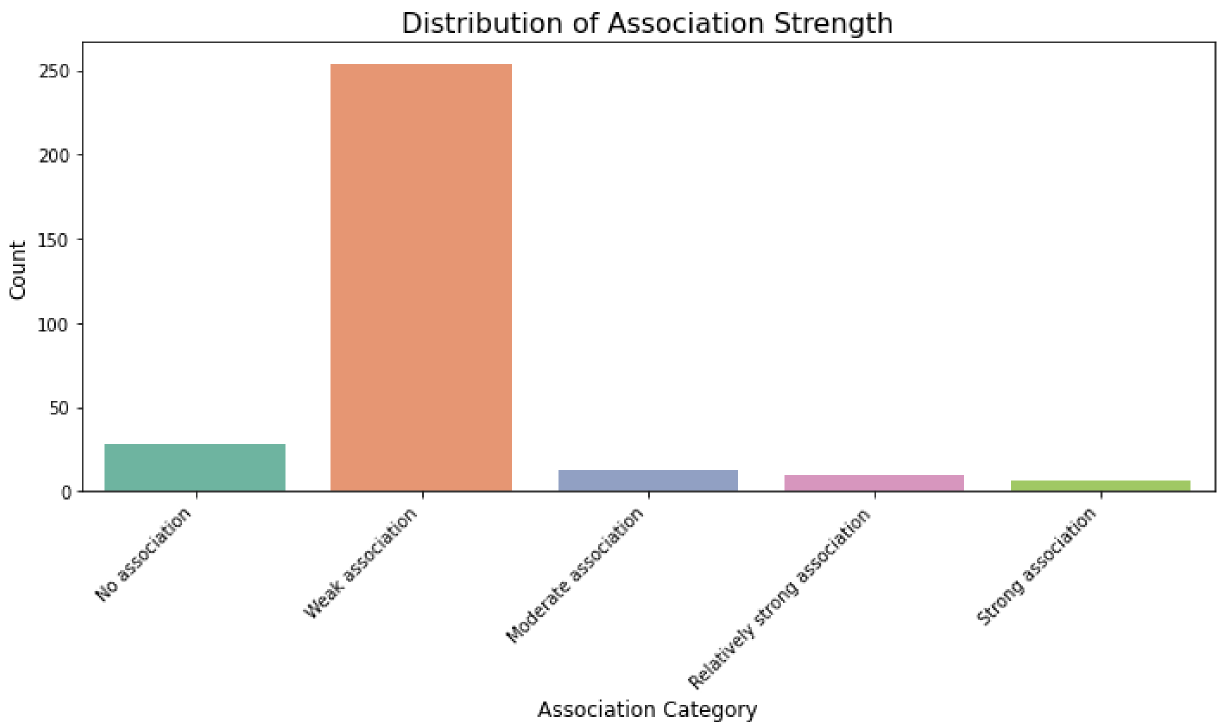
| | Categorical Feature | Numeric Feature | Cramers_V | Association |
|---|---|---|---|---|
| 0 | Shift | Overtime | 0.718001 | Strong association |
| 1 | c_excp | Rest | 0.706045 | Strong association |
| 2 | c_excp | Scheduled | 0.622988 | Strong association |
| 3 | c_excp | Worked | 0.595620 | Strong association |
| 4 | Contract Hours | Scheduled | 0.564758 | Strong association |
| 5 | Shift_Starts | Rest | 0.528850 | Strong association |
| 6 | Contract Hours | Worked | 0.506457 | Strong association |
| 7 | c_excp | BreakLunch | 0.484534 | Relatively strong association |
| 8 | Shift_Starts | Scheduled | 0.435912 | Relatively strong association |
| 9 | Shift_Starts | Worked | 0.413216 | Relatively strong association |
| 10 | Shift | Scheduled | 0.382836 | Relatively strong association |
| 11 | DayofWeek | Rest | 0.379165 | Relatively strong association |
| 12 | c_name_y | Vacation | 0.364851 | Relatively strong association |
| 13 | Contract Hours | Rest | 0.332065 | Relatively strong association |
| 14 | Contract Hours | BreakLunch | 0.327876 | Relatively strong association |
| 15 | Shift | Absence | 0.326476 | Relatively strong association |
| 16 | Shift_Starts | BreakLunch | 0.310433 | Relatively strong association |
| 17 | Shift_Code | Absence | 0.298289 | Moderate association |
| 18 | Shift | Sick | 0.295300 | Moderate association |
| 19 | Shift | Worked | 0.283563 | Moderate association |
| 20 | c_name_y | Sick | 0.280544 | Moderate association |
| 21 | Shift_Code | Sick | 0.276615 | Moderate association |
| 22 | Shift_Code | Scheduled | 0.244096 | Moderate association |
| 23 | DayofWeek | Scheduled | 0.217845 | Moderate association |
| 24 | c_name_y | Scheduled | 0.216853 | Moderate association |
| 25 | c_name_y | Absence | 0.214589 | Moderate association |
| 26 | c_name_y | Rest | 0.210777 | Moderate association |
| 27 | DayofWeek | Worked | 0.208389 | Moderate association |
| 28 | c_name_y | Total_Lost | 0.202159 | Moderate association |
| 29 | c_name_y | Worked | 0.200734 | Moderate association |

# Association Category

```
plt.figure(figsize=(10, 6))  # Increase figure width
sns.countplot(data=df_cramers_v, x="Association", palette="Set2")
plt.title("Distribution of Association Strength", fontsize=16)
plt.xlabel("Association Category", fontsize=12)
plt.ylabel("Count", fontsize=12)

# Rotate x-labels for better readability
plt.xticks(rotation=45, ha='right')
```

```python
plt.tight_layout()  # Ensure everything fits within the figure
plt.show()
```




# 📊 Observations on the Distribution of Association Strength

### 🔍 Key Observations

As observed from the **distribution chart**, the majority of our **categorical fields** exhibit a **weak association** with the **target KPIs**. While these associations primarily fall under the **"Weak" category**, it is still valuable to explore these relationships further.

### 💡 Why Weak Associations Matter

- **Hidden Insights:**
  Understanding the **dynamics** between **categorical** and **numerical fields** can **uncover hidden patterns** that may not be immediately obvious.
- **Model Interpretability:**
  Even weak associations can **improve the interpretability** of the model, providing **contextual understanding** for stakeholders.
- **Combined Impact:**
  **Weak associations** may hold **significant value** when combined with other variables, contributing to **interaction effects** that are critical in predictive modeling.

### 🚀 The Importance of In-Depth Analysis

- **Data Enrichment:**
  Analyzing these relationships helps identify **potential areas for data enrichment**, enabling the creation of **new features** that capture more nuanced behaviors.
- **Feature Engineering:**
  Insights gained can drive **feature engineering efforts**, such as:
  - **Grouping categories** with similar behaviors

- **Encoding strategies** for categorical variables
- **Interaction terms** for modeling complex relationships

### 📈 Impact on Model Performance

This effort can ultimately:

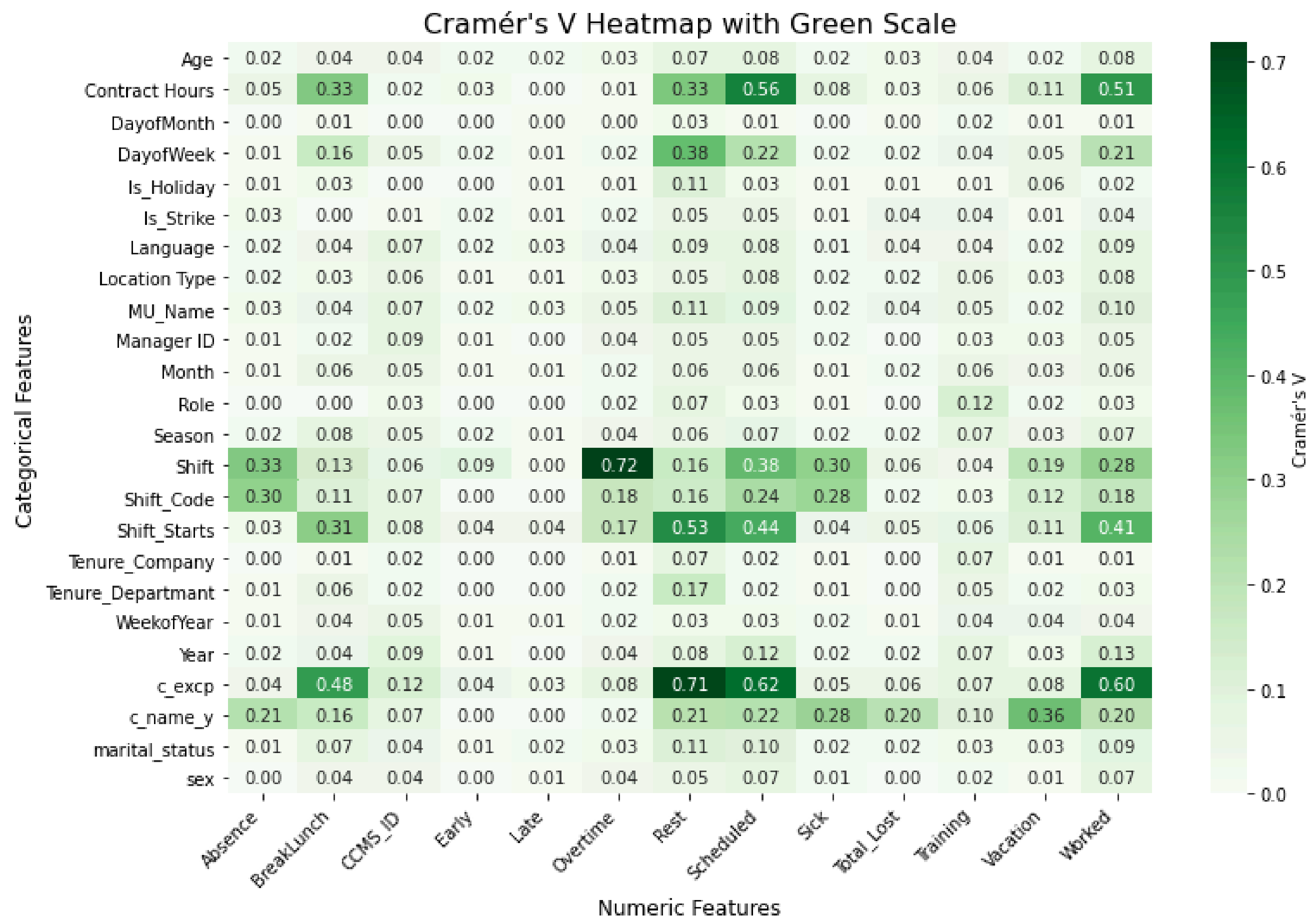
- **Enhance Predictive Power:**
  By capturing **subtle associations**, we can improve the **accuracy** of our predictions.
- **Improve Model Robustness:**
  Understanding all relationships, even weak ones, contributes to a **more resilient** model capable of handling diverse data scenarios.

🔑 **Conclusion:**
While weak associations may seem insignificant at first glance, their **combined influence** and **contextual importance** can play a crucial role in **optimizing predictive models**. Therefore, a **comprehensive analysis** is essential for achieving the best results.

# Cramér's V Heatmap

```
# Pivot the data for heatmap
heatmap_data = df_cramers_v.pivot("Categorical Feature", "Numeric Feature", "Cramers_V")

# Plot the heatmap with the green color scale
plt.figure(figsize=(12, 8))
sns.heatmap(
    heatmap_data,
    annot=True,
    fmt=".2f",
    cmap="Greens",  # Lighter to darker green colormap
    cbar_kws={'label': "Cramér's V"}
)
plt.title("Cramér's V Heatmap with Green Scale", fontsize=16)
plt.xlabel("Numeric Features", fontsize=12)
plt.ylabel("Categorical Features", fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.show()
```




```
df_cramers_v= df_cramers_v[(df_cramers_v['Cramers_V']>=0.3)
                          &(df_cramers_v['Numeric Feature']!='Rest')]
Association_Features = list(df_cramers_v['Categorical Feature'].unique())
```

# 🚀 Feature Selection Based on Association Analysis

### 📊 Key Findings from the Analysis

From our analysis, we have identified that **most of the categorical features exhibit little to no association** with **Total_Lost**.

To **improve model efficiency** and **focus on features with meaningful contributions**, we will:

- ❌ **Exclude** non-associated categorical features from the model.
- ✅ **Retain** categorical features with reasonable associations, as identified in the `Association_Features` variable.

### 🎯 Retained Features

### ✅ Features with Strong Associations:

- The categorical features listed in the `Association_Features` variable show a **reasonable level of association** with **Total_Lost.**
- These features will be **retained** to ensure the model captures important **patterns** related to absenteeism.

### 📋 Operationally Relevant Features:

In addition to the association-based features, we will also include **essential categorical features** such as:

- **MU_Name** (Management Unit)
- **Language**
- Other **operationally relevant attributes** that are critical for maintaining key **business requirements**.

## 🚀 Why This Approach?

- **Optimized Model Performance:**
  By excluding irrelevant features, we reduce **noise** and improve the model's **predictive power**.
- **Improved Efficiency:**
  A **leaner feature set** means faster **training times** and **reduced computational costs**.
- **Enhanced Interpretability:**
  Focusing on features with **clear associations** makes the model's predictions more **understandable** and **actionable** for stakeholders.
- **Business Relevance:**
  Including operationally important features ensures the model aligns with **real-world business needs**.

💡 **Conclusion:**
By refining our feature set in this manner, we aim to **optimize the model's performance** while maintaining a **comprehensive understanding** of the data. This balanced approach supports both **technical efficiency** and **business relevance**.

```
print(Association_Features)
df_cramers_v
```

```
['Shift', 'c_excp', 'Contract Hours', 'Shift_Starts', 'c_name_y']
```

| | Categorical Feature | Numeric Feature | Cramers_V | Association |
|---|---|---|---|---|
| 0 | Shift | Overtime | 0.718001 | Strong association |
| 2 | c_excp | Scheduled | 0.622988 | Strong association |
| 3 | c_excp | Worked | 0.595620 | Strong association |
| 4 | Contract Hours | Scheduled | 0.564758 | Strong association |
| 6 | Contract Hours | Worked | 0.506457 | Strong association |
| 7 | c_excp | BreakLunch | 0.484534 | Relatively strong association |
| 8 | Shift_Starts | Scheduled | 0.435912 | Relatively strong association |
| 9 | Shift_Starts | Worked | 0.413216 | Relatively strong association |
| 10 | Shift | Scheduled | 0.382836 | Relatively strong association |
| 12 | c_name_y | Vacation | 0.364851 | Relatively strong association |
| 14 | Contract Hours | BreakLunch | 0.327876 | Relatively strong association |
| 15 | Shift | Absence | 0.326476 | Relatively strong association |
| 16 | Shift_Starts | BreakLunch | 0.310433 | Relatively strong association |

# Cramér's V Bar Plots

```
# List of unique categorical features
unique_categorical_features = df_cramers_v['Categorical Feature'].unique()
```

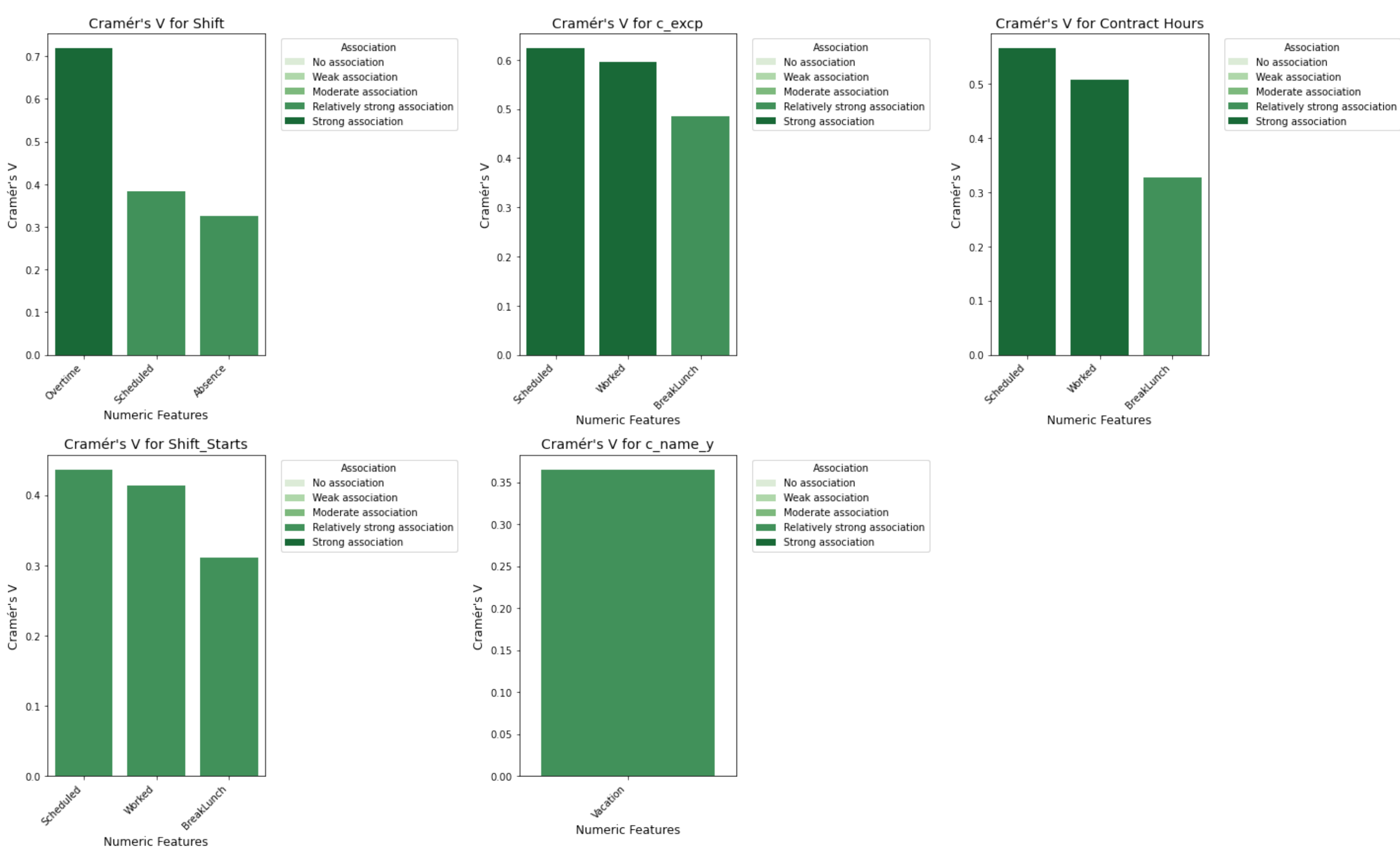
```
# Set the number of rows and columns for the subplots
num_features = len(unique_categorical_features)
cols = 3  # Number of plots per row
rows = (num_features + cols - 1) // cols  # Calculate required rows

# Set the figure size
plt.figure(figsize=(20, rows * 6))

# Iterate through each categorical feature and create a bar plot
for i, feature in enumerate(unique_categorical_features):
    filtered_data = df_cramers_v[df_cramers_v['Categorical Feature'] == feature]

    plt.subplot(rows, cols, i + 1)
    sns.barplot(
        data=filtered_data,
        x="Numeric Feature",
        y="Cramers_V",
        hue="Association",
        dodge=False,
        palette="Greens"  # Lighter to darker green
    )
    plt.title(f"Cramér's V for {feature}", fontsize=14)
    plt.xlabel("Numeric Features", fontsize=12)
    plt.ylabel("Cramér's V", fontsize=12)
    plt.xticks(rotation=45, ha='right')
    plt.legend(title="Association", bbox_to_anchor=(1.05, 1), loc='upper left')

# Adjust layout and show the plot
plt.tight_layout()
plt.show()
```



# 📊 Refining Feature Selection Based on Association Strength

### 🔍 Key Observations

After filtering for only the following levels of association:

- **Moderate Association**
- **Relatively Strong Association**
- **Strong Association**

...and **excluding the rest of the numerical values**, we observed that:

- ✅ Only **five categorical features** showed a **moderate or higher association** with our **numerical KPIs**.
- ❌ However, **almost none of these features demonstrated a direct impact** on **absenteeism**.

### ⚠️ Implications of the Findings

- **Limited Direct Impact:**
  While these features may show statistical associations with other numerical KPIs, they **do not directly influence absenteeism**, which is the core focus of our predictive model.
- **Potential Indirect Effects:**
  Despite the lack of a direct impact, some features might still play an **indirect role** through interactions with other variables. Hence, further analysis may be warranted in specific cases.
- **Feature Re-evaluation:**
  This finding prompts us to **re-evaluate the importance** of certain features, ensuring that we prioritize variables with **actual predictive power** for absenteeism.

### 🚀 Next Steps

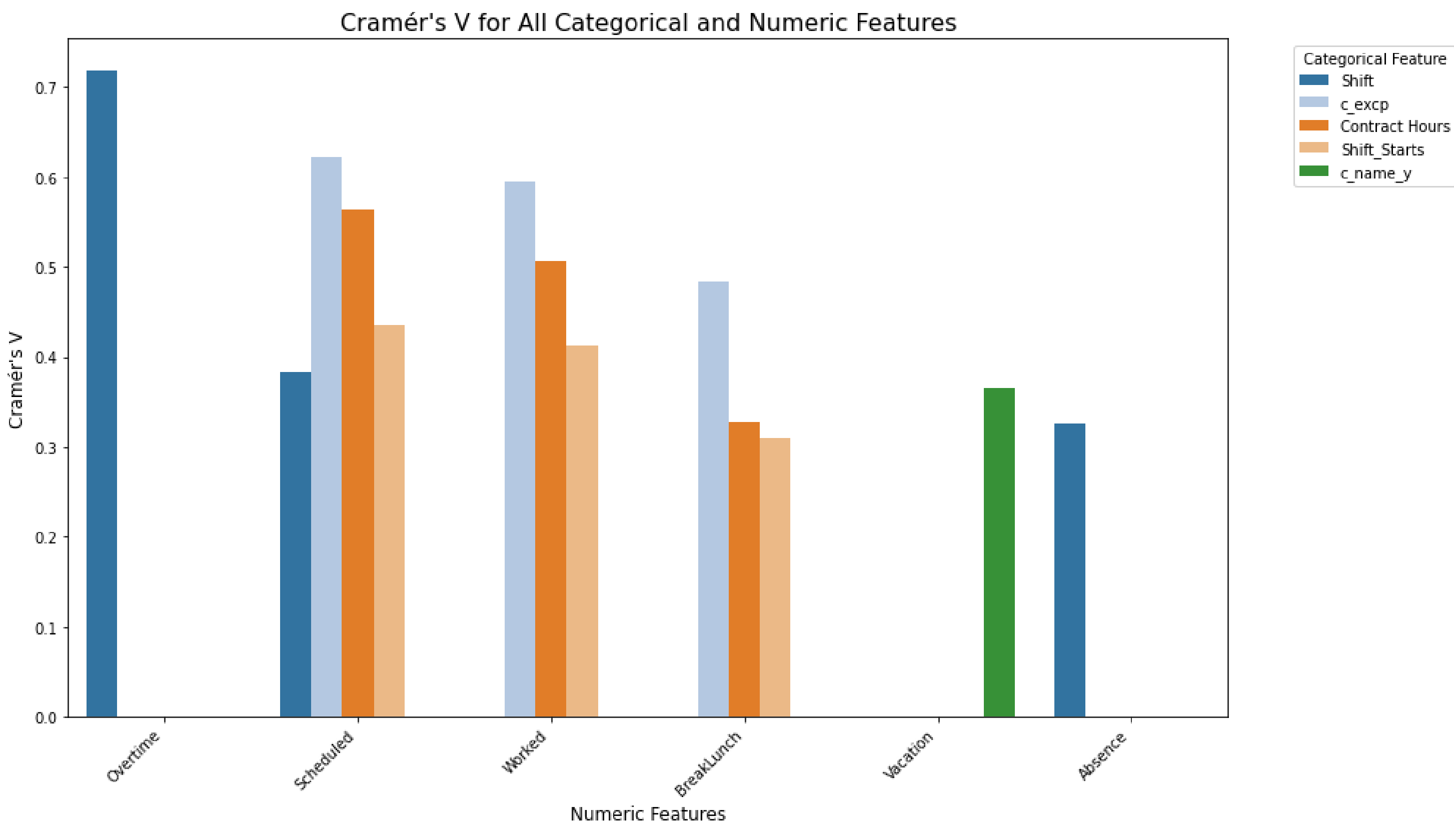
1. **Exclude Non-Impactful Features:**
   - Remove categorical features that lack a **direct association** with absenteeism to **enhance model efficiency**.
2. **Focus on Impactful Variables:**
   - Retain features with **clear, measurable impacts** on absenteeism.
3. **Explore Interactions:**
   - For features with **moderate associations**, consider exploring **interaction effects** with other variables to uncover **hidden patterns**.

💡 **Conclusion:**
This process ensures that our model remains **focused, efficient**, and **aligned** with the goal of accurately predicting absenteeism while avoiding the inclusion of **irrelevant features**.

# Grouped Bar Plot for All Categorical Features

```
# Grouped bar plot for all categorical features
plt.figure(figsize=(14, 8))
sns.barplot(data=df_cramers_v, x="Numeric Feature", y="Cramers_V", hue="Categorical Feature", dodge=True,
palette="tab20")
```

```python
plt.title("Cramér's V for All Categorical and Numeric Features", fontsize=16)
plt.xlabel("Numeric Features", fontsize=12)
plt.ylabel("Cramér's V", fontsize=12)
plt.xticks(rotation=45, ha='right')
plt.legend(title="Categorical Feature", bbox_to_anchor=(1.05, 1), loc='upper left')
plt.tight_layout()
plt.show()
```




# 📊 Pearson and Spearman Correlation Coefficients

### 🔍 Overview and Why They're Important

When analyzing data for **predictive modeling**, **Pearson** and **Spearman correlation coefficients** are used to evaluate the relationships between **numerical features.**

Here's a breakdown of their purpose, differences, and why they are vital in data analysis:

### 📈 Pearson Correlation Coefficient

#### ✅ 1. What It Measures:

- Pearson's correlation coefficient (**r**) quantifies the **linear relationship** between two continuous variables.
- It ranges from:
  - **-1** → Perfect **negative** linear relationship
  - **0** → **No** linear relationship
  - **1** → Perfect **positive** linear relationship

### ⚡ 2. Use Case:

- Ideal for **numerical data** that has a **linear relationship**.
- **Example in Absenteeism Dataset:**
  - Exploring the correlation between **Scheduled** and **Worked** hours.

### 💡 3. Why It's Used:

- Identifies **highly correlated numerical features**, which may cause **multicollinearity** and reduce model performance.
- Helps decide which features to **retain** or **drop** during feature engineering.

## 📊 Spearman Correlation Coefficient

### ✅ 1. What It Measures:

- Spearman's correlation coefficient (**ρ**) measures the **rank-order relationship** between two variables.
- Unlike Pearson, it does **NOT assume linearity** but focuses on **monotonic relationships** (increasing or decreasing trends).
- Also ranges from **-1** to **1**.

### ⚡ 2. Use Case:

- Useful for numerical data with **non-linear but monotonic relationships**.
- **Example in Absenteeism Dataset:**
  - **Age vs. Absence:** Older employees might have more sick days, but the relationship could be **nonlinear**.
  - **Tenure_Company vs. Sick:** Employees with longer tenures may show **varying trends** in absenteeism.

### 💡 3. Why It's Used:

- Detects **monotonic relationships** that Pearson might miss, especially in **non-linear datasets**.
- Provides insights that can improve **feature engineering** and **transformation decisions**.

## 🚀 Why Both Analyses Are Important

In the context of **absenteeism modeling**:

### 🎯 1. Feature Selection:

- Identifies **redundant features**.
  - E.g., if **Scheduled** and **Worked** are highly correlated, one can be **dropped**.

### 🔄 2. Data Transformation:

- **Spearman** may highlight the need for **non-linear transformations** (e.g., **log**, **square root**) to better capture relationships.

### ⚠️ 3. Multicollinearity Check:

- Highly correlated features can cause **instability** in linear models (e.g., **Ridge Regression**).
  Identifying these relationships is **crucial**.

## 📊 How We Are Performing Our Analysis

#### ✅ 1. Calculate Correlation Matrices:

- **Pearson correlation** → Identifies **linear** relationships.
- **Spearman correlation** → Captures **non-linear but monotonic** relationships.

#### 🎨 2. Visualize Results:

- **Heatmaps** are created to provide a **visual overview** of correlation coefficients, making it easier to identify **strong relationships.**

#### 📏 3. Set Thresholds:

- We set thresholds (e.g., **|0.7|** for **high correlations**) to flag strongly correlated variables.

#### 📊 4. Feature Selection:

- **Review** features with high correlations.
- **Drop redundant** features to reduce **multicollinearity** and improve **model performance.**

#### ⚙️ 5. Choosing the Correlation Method:

- **Pearson:** For **linear relationships**, like **Scheduled vs. Overtime.**
- **Spearman:** For **non-linear but monotonic trends**, like **Age vs. Absence.**

### 🚀 Why This Approach?

- **Comprehensive Analysis:**
  Captures both **linear** and **monotonic** relationships for a **complete understanding**.
- **Improved Model Performance:**
  Removing **redundant features** reduces **noise** and **multicollinearity**.
- **Efficient Feature Set:**
  Focuses on **meaningful features** that contribute to **predictive power**.

# 📊 Generating New Numerical Measures to Enrich the Dataset

To enhance the dataset's **predictive capabilities**, we generate new **numerical measures** based on **rolling calculations** and **aggregations**. These measures capture **trends** and **patterns** over time, providing insights into **employee behavior** and **absenteeism.**

### 🔄 Steps to Generate New Measures

#### ✅ 1. Identify Relevant Features:

- Focus on features with potential associations with absenteeism:
  - **DayofWeek, c_excp (exceptions), Shift_Starts, Contract Hours**
    (Referred to as `Association_Features`).

#### 🔍 2. Filter Dataset:

- Focus on rows where `Is_Actual` = `'Actual'` for **reliable data.**
- Sort by **Date** to ensure **chronological accuracy** for rolling calculations.

### 🗓️ 3. Define Rolling Windows:

- Capture trends over different time periods:
  - **1 Month (1M):** Immediate past trends (**30 days**).
  - **3 Months (3M):** Medium-term trends (**90 days**).
  - **6 Months (6M):** Long-term trends (**180 days**).

### 📊 4. Perform Rolling Calculations:

- **Rolling Sum:** For features like **Scheduled, Worked, Overtime,** and **Absence.**
- **Rolling Average:** For features like **Rest** and **BreakLunch.**

### ⚖️ 5. Average of Rolling Sums:

- Compute the **average** across all rolling windows to capture **cumulative behavior patterns.**

### 📊 6. Aggregation:

- Group data by key **association features** (e.g., **DayofWeek, Shift_Starts**).
- Apply aggregation functions:
  - **Count:** For unique IDs (e.g., **CCMS_ID**).
  - **Sum:** For cumulative metrics (e.g., **Absence, Late**).
  - **Mean:** For averages (e.g., **Rest, BreakLunch**).

## 🚀 Why We Perform This Analysis

### 🔍 1. Enhanced Insights:

- Reveals **trends and anomalies** that static metrics might miss.
- Identifies patterns tied to specific conditions like **Shift_Starts** or **DayofWeek.**

### 📈 2. Improved Predictive Power:

- Captures **lagged effects** and **time-dependent patterns,** improving **model accuracy.**

### 🧠 3. Feature Enrichment:

- Adds features like **rolling sums** and **averages** to account for **cumulative behavior.**

### ⚡ 4. Efficient Feature Engineering:

- **Automates** the generation of rolling metrics, streamlining the **data preparation process.**

## 📊 How These Measures Are Evaluated

- **Correlation Analysis:**
  Newly generated features are evaluated using **Pearson** and **Spearman correlation coefficients** against the **target variable (Absence).**
- **Feature Importance:**
  During **model training,** feature importance scores help determine whether these measures **contribute significantly** to predictions.

💡 **Conclusion:**
This approach ensures that we capture **meaningful patterns** and **enhance predictive performance** while maintaining an **efficient** and **interpretable** model.

# Pearson and Spearman correlation coefficients

```
#Pearson and Spearman correlation coefficients between numeric variables and the target variable



##  Association_Features
## ['DayofWeek', 'c_excp', 'c_name_y', 'Shift', 'Shift_Starts', 'Shift_Code', 'Contract Hours']
Association_Features = ['DayofWeek', 'c_excp','Shift_Starts', 'Contract Hours']

dfc = df[df['Is_Actual']=='Actual'].sort_values(by='Date').reset_index(drop=True)
## Rolling Values
rolling_windows = {
    '1M': 30,         # Last 1 months
    '3M': 90,        # Last 3 months (approx 6x7)
    '6M': 180         # Last 6 months (approx 3x30)
}

columns_to_total =
['Scheduled','Worked','Overtime','Training','Vacation','Sick','Total_Lost','Absence','Early','Late']
columns_to_avg = ['Rest', 'BreakLunch']

# Perform rolling calculations for each CCMS_ID
for window_label, window_size in rolling_windows.items():
    # Rolling sum
    for col in columns_to_total:
        dfc[f'{col}_RollingSum_{window_label}'] = (
            dfc.groupby('CCMS_ID')[col]
            .rolling(window=window_size, min_periods=1)
            .sum()
            .reset_index(level=0, drop=True)
            .round(2)
        )

    # Rolling average
    for col in columns_to_avg:
        dfc[f'{col}_RollingAvg_{window_label}'] = (
            dfc.groupby('CCMS_ID')[col]
            .rolling(window=window_size, min_periods=1)
            .mean()
            .reset_index(level=0, drop=True)
            .round(2)
        )

# Add AVGofRollingSum columns
avg_rolling_sum_cols = [col for col in dfc.columns if 'RollingSum' in col]
for col in avg_rolling_sum_cols:
    dfc[f'AVGof{col}'] = (
        dfc.groupby('CCMS_ID')[col]
        .transform('mean')
        .round(2)
    )
```

```python
# Update columns for aggregation
corr_cols = ['Date']+Association_Features
columns_to_count = ['CCMS_ID']
columns_to_sum = ['Scheduled',
'Worked','Overtime','Training','Vacation','Sick','Total_Lost','Absence','Early', 'Late']
columns_to_sum += [col for col in dfc.columns if 'Sum_' in col]
columns_to_mean = ['Rest', 'BreakLunch']
columns_to_mean += [col for col in dfc.columns if 'Avg_' in col or 'AVGofRollingSum' in col]

cooefcols = corr_cols + columns_to_count + columns_to_sum + columns_to_mean

# Prepare the aggregation dictionary
agg_dict = {col: 'count' for col in columns_to_count}  # Count for CCMS_ID
agg_dict.update({col: 'sum' for col in columns_to_sum})  # Sum for numeric metrics
agg_dict.update({col: 'mean' for col in columns_to_mean})  # Mean for averages

# Group by corr_cols and apply the aggregation
dfc = (
    dfc.groupby(Association_Features)
    .agg(agg_dict)
    .reset_index()
)

# Ensure categorical columns are treated as strings for consistency
for strcol in Association_Features:
    dfc[strcol] = dfc[strcol].astype(str)

# del dfc['Date']


# Define the function to dynamically select the better correlation method
def calculate_correlation(dfc, target_column='Total_Lost', feature_filter=None, rolling_only=False):
    """
    Calculates Pearson and Spearman correlations between features and a target variable,
    dynamically selecting the better method based on overall results.
    """
    # Filter columns
    if rolling_only:
        selected_features = [col for col in dfc.columns if 'Rolling' in col and col != target_column]
    elif feature_filter:
        selected_features = [col for col in feature_filter if col in dfc.columns and col != target_column]
    else:
        selected_features = [col for col in dfc.columns if col != target_column]

    # Check if selected_features is valid
    if not selected_features:
        raise ValueError("No valid features found for correlation calculation.")

    # Calculate Pearson and Spearman correlations
    pearson_corr = dfc[selected_features + [target_column]].corr(method='pearson')[target_column]
    spearman_corr = dfc[selected_features + [target_column]].corr(method='spearman')[target_column]

    # Create DataFrames
    pearson_corr_df = pd.DataFrame({'Feature': pearson_corr.index, 'Pearson_Corr': pearson_corr.values})
    spearman_corr_df = pd.DataFrame({'Feature': spearman_corr.index, 'Spearman_Corr': spearman_corr.values})

    # Calculate absolute values
    pearson_corr_df['Abs_Pearson_Corr'] = pearson_corr_df['Pearson_Corr'].abs()
    spearman_corr_df['Abs_Spearman_Corr'] = spearman_corr_df['Spearman_Corr'].abs()
```

```python
    # Merge and calculate average correlation
    df_corr = pearson_corr_df.merge(spearman_corr_df, on='Feature', how='left')
    count_pearson_better = (df_corr['Abs_Pearson_Corr'] > df_corr['Abs_Spearman_Corr']).sum()
    count_spearman_better = (df_corr['Abs_Spearman_Corr'] > df_corr['Abs_Pearson_Corr']).sum()

    # Dynamically choose the better correlation
    if 0.4 <= count_pearson_better / len(df_corr) <= 0.6:
        print('Using average of Pearson and Spearman due to close performance.')
        df_corr['Corr'] = (df_corr['Pearson_Corr'] + df_corr['Spearman_Corr']) / 2
        df_corr['Abs_Corr'] = (df_corr['Abs_Pearson_Corr'] + df_corr['Abs_Spearman_Corr']) / 2
        df_corr['Method_Used'] = 'Average'
    elif count_pearson_better > count_spearman_better:
        print('Using Pearson correlation as it performed better.')
        df_corr['Corr'] = df_corr['Pearson_Corr']
        df_corr['Abs_Corr'] = df_corr['Abs_Pearson_Corr']
        df_corr['Method_Used'] = 'Pearson'
    else:
        print('Using Spearman correlation as it performed better.')
        df_corr['Corr'] = df_corr['Spearman_Corr']
        df_corr['Abs_Corr'] = df_corr['Abs_Spearman_Corr']
        df_corr['Method_Used'] = 'Spearman'

    return df_corr[['Feature', 'Corr', 'Abs_Corr', 'Method_Used']].sort_values(by='Abs_Corr',
ascending=False).reset_index(drop=True)

# Add correlation strength mapping
def map_corr_strength(abs_corr):
    if abs_corr < 0.1:
        return 'No Association'
    elif abs_corr < 0.3:
        return 'Weak Association'
    elif abs_corr < 0.5:
        return 'Moderate Association'
    elif abs_corr < 0.7:
        return 'Strong Association'
    else:
        return 'Very Strong Association'

# Example usage
df_corr = calculate_correlation(dfc)
df_corr['Corr_Strength'] = df_corr['Abs_Corr'].apply(map_corr_strength)
```

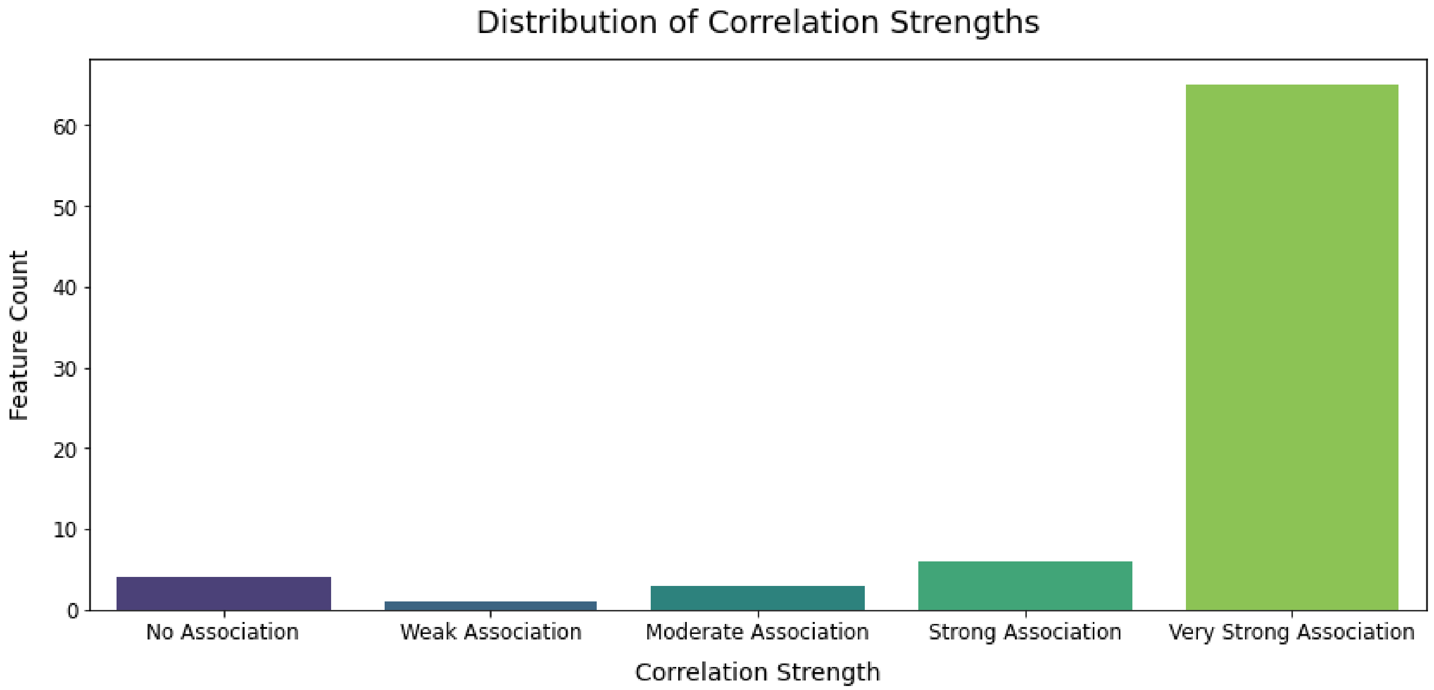
```
Using Spearman correlation as it performed better.
```

```python
# Bar plot for distribution of correlation strength
plt.figure(figsize=(12, 6))
sns.countplot(
    data=df_corr,
    x='Corr_Strength',
    palette='viridis',
    order=['No Association', 'Weak Association', 'Moderate Association', 'Strong Association', 'Very Strong
Association']
)

# Customize plot aesthetics
plt.title("Distribution of Correlation Strengths", fontsize=18, pad=15)
plt.xlabel("Correlation Strength", fontsize=14, labelpad=10)
```

```python
plt.ylabel("Feature Count", fontsize=14, labelpad=10)
plt.xticks(fontsize=12)
plt.yticks(fontsize=12)

# Display the plot
plt.tight_layout(pad=2)
plt.show()
```




```python
# Define the replacement values to remove
replace_terms = [
    '_RollingSum_1M',
    '_RollingAvg_1M',
    '_RollingSum_3M',
    '_RollingAvg_3M',
    '_RollingSum_6M',
    '_RollingAvg_6M',
    'AVGof'
]
# Replace the values in the 'Feature' column and create a new 'KPI' column
df_corr['KPI'] = df_corr['Feature']
for term in replace_terms:
    df_corr['KPI'] = df_corr['KPI'].str.replace(term, '', regex=False)
High_corr_Features = df_corr[(df_corr['Abs_Corr']>=0.5)&
(df_corr['Feature']!=df_corr['KPI'])].reset_index(drop=True)
Low_corr_Features = df_corr[(df_corr['Abs_Corr']<0.5)&
(df_corr['Feature']!=df_corr['KPI'])].reset_index(drop=True)
```

```python
print(f"Number  of {df_corr[df_corr['Abs_Corr']>=0.5].shape[0]} Feature showed Strong or Higher
Correlation")

df_corr[df_corr['Abs_Corr']>=0.5].head(20)
```

```
Number  of 71 Feature showed Strong or Higher Correlation
```

| | Feature | Corr | Abs_Corr | Method_Used | Corr_Strength | KPI |
|---|---|---|---|---|---|---|
| 0 | Total_Lost | 1.000000 | 1.000000 | Spearman | Very Strong Association | Total_Lost |
| 1 | Scheduled | 0.885439 | 0.885439 | Spearman | Very Strong Association | Scheduled |
| 2 | Worked | 0.869834 | 0.869834 | Spearman | Very Strong Association | Worked |
| 3 | Absence | 0.856232 | 0.856232 | Spearman | Very Strong Association | Absence |
| 4 | Early | 0.855741 | 0.855741 | Spearman | Very Strong Association | Early |
| 5 | Sick | 0.812157 | 0.812157 | Spearman | Very Strong Association | Sick |
| 6 | Total_Lost_RollingSum_1M | 0.781225 | 0.781225 | Spearman | Very Strong Association | Total_Lost |
| 7 | Training_RollingSum_6M | 0.779647 | 0.779647 | Spearman | Very Strong Association | Training |
| 8 | AVGofTotal_Lost_RollingSum_6M | 0.778188 | 0.778188 | Spearman | Very Strong Association | Total_Lost |
| 9 | AVGofTotal_Lost_RollingSum_3M | 0.778133 | 0.778133 | Spearman | Very Strong Association | Total_Lost |
| 10 | AVGofTotal_Lost_RollingSum_1M | 0.776697 | 0.776697 | Spearman | Very Strong Association | Total_Lost |
| 11 | AVGofTraining_RollingSum_3M | 0.773080 | 0.773080 | Spearman | Very Strong Association | Training |
| 12 | AVGofTraining_RollingSum_1M | 0.772678 | 0.772678 | Spearman | Very Strong Association | Training |
| 13 | Total_Lost_RollingSum_3M | 0.771894 | 0.771894 | Spearman | Very Strong Association | Total_Lost |
| 14 | AVGofEarly_RollingSum_1M | 0.771461 | 0.771461 | Spearman | Very Strong Association | Early |
| 15 | AVGofTraining_RollingSum_6M | 0.770800 | 0.770800 | Spearman | Very Strong Association | Training |
| 16 | Total_Lost_RollingSum_6M | 0.769146 | 0.769146 | Spearman | Very Strong Association | Total_Lost |
| 17 | AVGofEarly_RollingSum_3M | 0.767777 | 0.767777 | Spearman | Very Strong Association | Early |
| 18 | AVGofEarly_RollingSum_6M | 0.765994 | 0.765994 | Spearman | Very Strong Association | Early |
| 19 | Scheduled_RollingSum_6M | 0.765175 | 0.765175 | Spearman | Very Strong Association | Scheduled |

```python
print(f"Number  of {df_corr[df_corr['Abs_Corr']<0.5].shape[0]} Feature showed Moderate or lower
Correlation")
df_corr[df_corr['Abs_Corr']<0.5].head(10)
```

```
Number  of 8 Feature showed Moderate or lower Correlation
```

| | Feature | Corr | Abs_Corr | Method_Used | Corr_Strength | KPI |
|---|---|---|---|---|---|---|
| 71 | BreakLunch_RollingAvg_6M | 0.371747 | 0.371747 | Spearman | Moderate Association | BreakLunch |
| 72 | BreakLunch | 0.360294 | 0.360294 | Spearman | Moderate Association | BreakLunch |
| 73 | BreakLunch_RollingAvg_3M | 0.307598 | 0.307598 | Spearman | Moderate Association | BreakLunch |
| 74 | BreakLunch_RollingAvg_1M | 0.251018 | 0.251018 | Spearman | Weak Association | BreakLunch |
| 75 | Rest | -0.085667 | 0.085667 | Spearman | No Association | Rest |
| 76 | Rest_RollingAvg_6M | -0.042318 | 0.042318 | Spearman | No Association | Rest |
| 77 | Rest_RollingAvg_3M | -0.024464 | 0.024464 | Spearman | No Association | Rest |
| 78 | Rest_RollingAvg_1M | -0.023723 | 0.023723 | Spearman | No Association | Rest |

# 📊 Insights from Correlation Analysis

## 🔍 Key Observations

As observed from the **table above** and the **heatmap below**:

- **Rest** and **BreakLunch**, two of our numerical variables, exhibit only **moderate or weak associations** with **Total Lost**.
- However, key variables such as:
  - **Absence**
  - **Early**
  - **Late**

    Show **relatively strong correlations** and play a **significant role** in explaining variations in **Total Lost**.

## 📈 Handling Variables for Future Predictions

Since **Absence**, **Early**, and **Late** will **NOT** be available in the **prediction dataset** for future dates, we must rely on their:

- **Rolling Measures:**
  - **Early (Rolling)**
  - **Late (Rolling)**
  - **Absence (Rolling)**
  - **Worked (Rolling)**

Additionally, the **Scheduled** value can be **directly utilized** as it will be **available for future days**.

## 🚫 Excluding Low-Impact Variables

From our correlation analysis, we identified that variables such as:

- **Rest before Shift**
- **BreakLunch**
- **Vacation**
- **Worked Overtime**

  ...and their respective **rolling calculations** offer **limited predictive value** due to their **weak correlations**.

Hence, these variables will be **excluded from the model**.

## 🎯 Refining the Feature Set

We will focus on **numerical features** that:

- Provide **meaningful insights**
- Contribute to **improving the model's ability** to explain variations in **Absence**

This selective approach helps in:

- ✅ **Enhancing Model Accuracy:**
  By focusing on impactful variables, we improve the model's **predictive power**.
- ✅ **Improving Interpretability:**
  A leaner feature set ensures that the model remains **easy to understand** and **explain** to stakeholders.

💡 **Conclusion:**
By refining our feature set in this way, we aim to **enhance the model's accuracy** and **interpretability**, ensuring that **only impactful variables** are used for predicting **future Total Lost trends**.

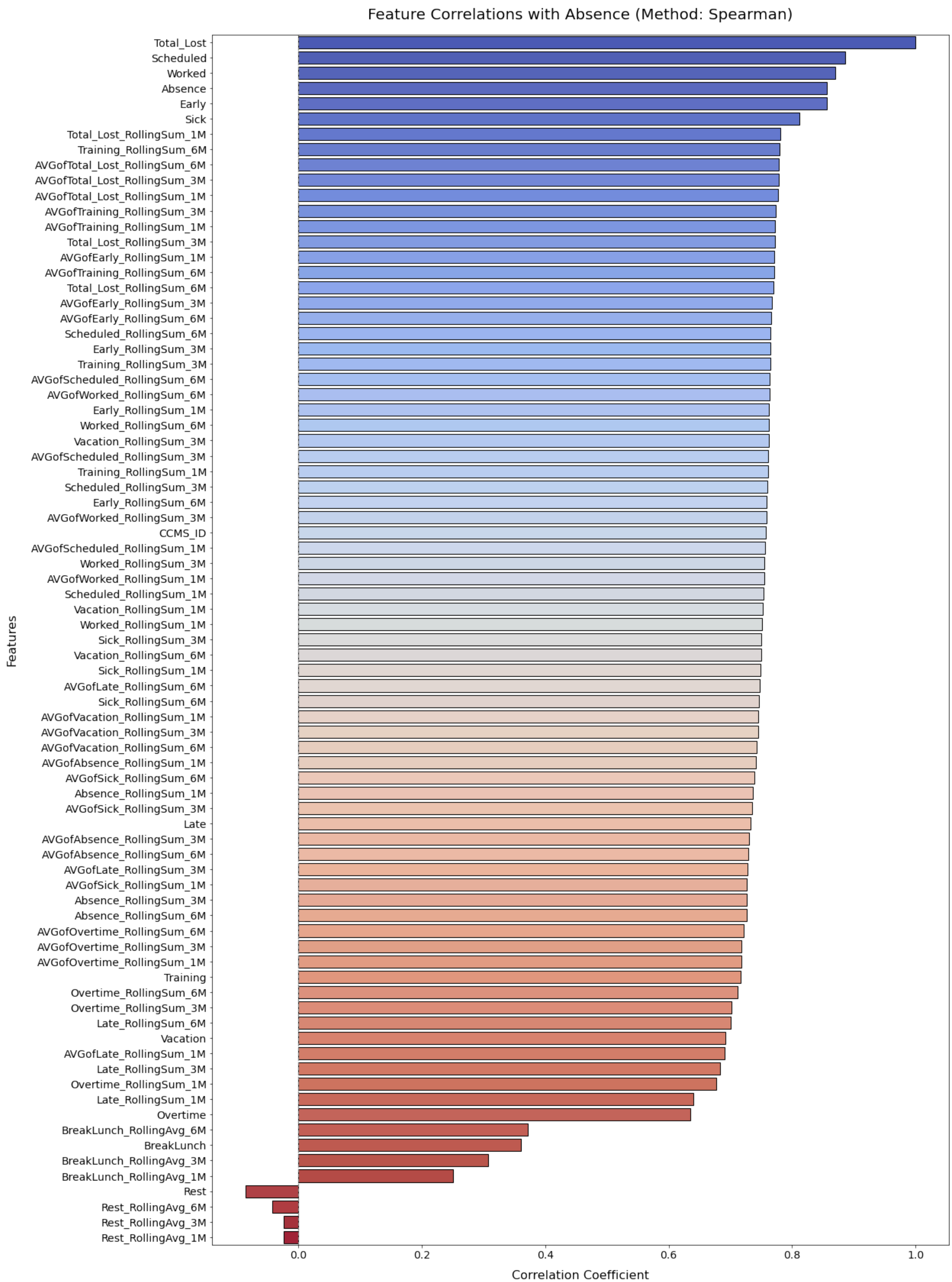
```
# Determine the correlation method used
method_used = df_corr['Method_Used'].iloc[0]  # Assuming all rows use the same method

# Adjusted bar plot for correlation values with increased features
plt.figure(figsize=(18, 24))  # Increased height and width for better visibility
sns.barplot(
    data=df_corr,
    x='Corr',
    y='Feature',
    palette='coolwarm',
    edgecolor='black'
)

# Customize plot aesthetics
plt.title(f"Feature Correlations with Absence (Method: {method_used})", fontsize=20, pad=20)  # Add method
to title
plt.xlabel("Correlation Coefficient", fontsize=16, labelpad=12)  # Add padding to the x-label
plt.ylabel("Features", fontsize=16, labelpad=18)  # Add padding to the y-label
plt.xticks(fontsize=14)
plt.yticks(fontsize=14)

# Highlight neutral correlation (0 line)
plt.axvline(x=0, color='gray', linestyle='--', linewidth=1.2)

# Adjust layout for better spacing
plt.tight_layout(pad=3)
plt.show()
```




```
groupbycols = ['Date',
```

```
 'Year',
 'Season',
 'Month',
 'WeekofYear',
 'DayofMonth',
 'DayofWeek',
 'Is_Strike']
df['Is_Holiday'] = df['Is_Holiday'].astype(int)
df_grouped = df[df['Is_Actual']=='Actual'].groupby(groupbycols,as_index=False).agg(
                                          Is_Holiday=('Is_Holiday',np.mean)
                                         ,HC=('CCMS_ID','size')
                                         ,Scheduled =('Scheduled',np.sum)
                                         ,Worked =('Worked',np.sum)
                                         ,Overtime =('Overtime',np.sum)
                                         ,Training =('Training',np.sum)
                                         ,Vacation =('Vacation',np.sum)
                                         ,BreakLunch =('BreakLunch',np.sum)
                                         ,Sick =('Sick',np.sum)
                                         ,Total_Lost =('Total_Lost',np.sum)
                                         ,Absence =('Absence',np.sum)
                                         ,Early =('Early',np.sum)
                                         ,Late =('Late',np.sum)
                                         ).reset_index(drop=True)
df['Is_Holiday'] = df['Is_Holiday'].astype(str)
df_grouped['Date'] = pd.to_datetime(df_grouped['Date'])

df_grouped.describe().T
```

| | count | mean | std | min | 25% | 50% | 75% | max |
|---|---|---|---|---|---|---|---|---|
| **Year** | 754.0 | 2023.546419 | 0.556115 | 2023.0 | 2023.0000 | 2024.000 | 2024.0000 | 2025.00 |
| **Season** | 754.0 | 2.456233 | 1.128559 | 1.0 | 1.0000 | 2.000 | 3.0000 | 4.00 |
| **Month** | 754.0 | 6.351459 | 3.529023 | 1.0 | 3.0000 | 6.000 | 9.0000 | 12.00 |
| **WeekofYear** | 754.0 | 25.732095 | 15.410793 | 1.0 | 12.0000 | 26.000 | 39.0000 | 52.00 |
| **DayofMonth** | 754.0 | 15.624668 | 8.775099 | 1.0 | 8.0000 | 16.000 | 23.0000 | 31.00 |
| **DayofWeek** | 754.0 | 2.996021 | 2.002319 | 0.0 | 1.0000 | 3.000 | 5.0000 | 6.00 |
| **Is_Strike** | 754.0 | 0.011936 | 0.108672 | 0.0 | 0.0000 | 0.000 | 0.0000 | 1.00 |
| **Is_Holiday** | 754.0 | 0.034483 | 0.182587 | 0.0 | 0.0000 | 0.000 | 0.0000 | 1.00 |
| **HC** | 754.0 | 235.380637 | 18.009432 | 210.0 | 221.0000 | 228.000 | 246.7500 | 279.00 |
| **Scheduled** | 754.0 | 1220.447825 | 539.286838 | 8.0 | 750.2500 | 1442.245 | 1581.0350 | 2034.00 |
| **Worked** | 754.0 | 1189.366817 | 526.883080 | 8.0 | 726.3900 | 1390.125 | 1542.8325 | 2034.00 |
| **Overtime** | 754.0 | 13.458793 | 11.191562 | 0.0 | 4.0000 | 11.500 | 20.5000 | 60.50 |
| **Training** | 754.0 | 35.580981 | 47.734699 | 0.0 | 0.0000 | 16.000 | 54.2500 | 235.93 |
| **Vacation** | 754.0 | 70.967175 | 78.653269 | 0.0 | 8.0000 | 56.000 | 104.0000 | 544.00 |
| **BreakLunch** | 754.0 | 92.611459 | 49.990662 | 0.0 | 49.3125 | 116.070 | 130.5000 | 175.00 |
| **Sick** | 754.0 | 21.733422 | 18.752084 | 0.0 | 8.0000 | 16.000 | 32.0000 | 104.00 |
| **Total_Lost** | 754.0 | 22.806379 | 19.979378 | 0.0 | 7.0000 | 19.440 | 34.0000 | 107.75 |
| **Absence** | 754.0 | 13.770491 | 14.883175 | 0.0 | 0.0000 | 8.000 | 22.0000 | 88.00 |
| **Early** | 754.0 | 7.041340 | 8.497761 | 0.0 | 0.0000 | 4.500 | 10.7500 | 60.50 |
| **Late** | 754.0 | 1.994549 | 2.446302 | 0.0 | 0.0000 | 1.110 | 3.1175 | 16.75 |