This code is a Python program that provides a simple GUI interface for loading and analyzing CSV files. It uses various libraries for data visualization and machine learning, such as tkinter, pandas, plotly, and scikit-learn. Here is a detailed explanation of each line of code:

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* import tempfile
* import tkinter as tk
* import webbrowser
* from tkinter import filedialog
* from tkinter import ttk
* import pandas as pd
* import plotly.express as px
* import plotly.graph\_objs as go
* import plotly.io as pio
* from plotly.subplots import make\_subplots
* from sklearn.linear\_model import LinearRegression
* from sklearn.metrics import mean\_squared\_error, r2\_score
* from sklearn.model\_selection import train\_test\_split
* These lines import the necessary libraries for the program.
  + tempfile is used for creating temporary files,
  + tkinter is used for creating GUI interfaces,
  + webbrowser is used for opening HTML files in a web browser,
  + filedialog and .ttk are both used for creating file dialogs,
  + pandas is used for data manipulation,
  + plotly is used for data visualization, and,
  + scikit-learn is used for machine learning:
    - Specifically,
      * LinearRegression,
      * mean\_squared\_error,
      * r2\_score, and
      * train\_test\_split are ALL imported from scikit-learn.

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def open\_web\_view(html\_content):

with tempfile.NamedTemporaryFile(delete=False, suffix='.html') as f:

f.write(html\_content.encode())

f.flush()

webbrowser.open(f.name)

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* This function takes HTML content as input, creates a temporary HTML file using tempfile, writes the HTML content to the file, flushes the buffer to ensure that the content is written to the file, and then opens the HTML file in a web browser using webbrowser.
* This code defines a function called open\_web\_view that takes a string parameter html\_content.
  + The first line of the function uses the tempfile module to create a temporary file with a .html suffix and returns a file object.
  + This temporary file is created using the NamedTemporaryFile method. The delete parameter is set, so the file will not be automatically deleted when the program is finished executing.
    - The NamedTemporaryFile method is a function provided by the Python **tempfile** module that creates a temporary file securely.
      * This method creates a file that is deleted automatically when it is closed, and it guarantees that the file name will not conflict with other existing files on the system.
      * The NamedTemporaryFile method returns a file object that can be read from or written to the temporary file, just like any other file object.
    - The purpose of using the NamedTemporaryFile method is to provide temporary storage for data that does not need to be stored permanently or that is only required for a short time.
      * This method is often used when a program needs to store some intermediate results or data that is generated during the execution of the program, but that is not part of the final output.
      * For example, if a program needs to download a large file from the internet and process it, it may use a NamedTemporaryFile to store the downloaded file temporarily before parsing and processing it.
    - Using NamedTemporaryFile has several advantages over creating a regular file using open() or other file-related functions.
      * Firstly, the temporary file created by NamedTemporaryFile is guaranteed to have a unique name that does not conflict with existing files, reducing the risk of accidental file overwrites.
      * Secondly, the file is automatically deleted when closed, eliminating the need for explicit cleanup code.
      * Finally, NamedTemporaryFile provides a secure method for creating temporary files, as it sets appropriate file permissions and ensures that the file is not accessible by unauthorized users.
* The second line of the function writes the html\_content string to the temporary file using the write method, which is then encoded using the encode() method.
  + The encode() method is a function provided by Python's built-in str class, which converts a Unicode string to a byte string using a specified character encoding.
    - The encode() method takes a single parameter, specifies the character encoding, and returns a byte string representation of the Unicode string encoded in the specified encoding.
* When used for NamedTemporaryFile, the encode() method is typically used to convert a string that needs to be written to the temporary file from a Unicode string to a byte string.
  + Since files store data as sequences of bytes, the file’s contents must be converted to bytes before they can be written to the file.
* For example, suppose that a Python program needs to create a temporary file and write some text.
  + The program might create the temporary file using the NamedTemporaryFile method and then write the text to the file using the write() method of the file object.
  + However, since the write() method expects a byte string as input, any text that needs to be written to the file must first be encoded using the encode() method.
* Here's an example of how the encode() method can be used in conjunction with NamedTemporaryFile to write a string to a temporary file:

import tempfile

# Create a temporary file

with tempfile.NamedTemporaryFile(mode='w+', delete=True) as tmp\_file:

# Write a string to the file

string\_to\_write = "Hello, world!"

byte\_string\_to\_write = string\_to\_write.encode('utf-8')

tmp\_file.write(byte\_string\_to\_write)

# Read the contents of the file

tmp\_file.seek(0)

contents = tmp\_file.read()

print(contents)

* In this example, the encode() method converts the string\_to\_write variable to a byte string using the UTF-8 character encoding.
  + The resulting byte\_string\_to\_write variable is then passed to the write() method of the temporary file object, which writes the byte string to the temporary file.
  + Finally, the file’s contents are read back using the read() method of the file object, and the result is printed to the console.
* The flush() method is then called to ensure that the data is written to the file and is available to read.
* Finally, the function calls webbrowser.open(f.name), which opens the temporary file in the default web browser of the user's system.
  + The f.name attribute returns the file name of the temporary file, which is used as the URL to open in the browser

def load\_dataset(file\_path):

df = pd.read\_csv(file\_path)

return df

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* This function takes a file path as input, reads the CSV file using pandas, and returns a pandas DataFrame object.
* This is a Python function called load\_dataset that takes one parameter called file\_path.
  + The purpose of this function is to load a dataset that is stored in a CSV file and return it as a pandas DataFrame.
* def load\_dataset(file\_path):
  + This line defines a new function called load\_dataset that takes one argument, file\_path.
    - The load\_dataset() function is not a built-in Python function but is a custom function defined in this Python application wed in data analysis and machine learning.
    - The function loads a dataset from a file located at the specified path.
      * In machine learning and data analysis, a dataset is typically a collection of data used for training a model or performing statistical analysis.
      * A dataset can come from various sources, including structured files like CSV, Excel, or JSON files, or nstructured sources like text files or databases.
      * The file\_path parameter in load\_dataset() is used to specify the file’s location containing the dataset to be loaded.
        + This parameter is usually a string containing the file’s path, including the file name and extension.
        + The exact format of the file\_path parameter may depend on the file format of the dataset, as different file formats may have different requirements for the file path.
      * The load\_dataset() function is responsible for reading the file specified by file\_path and creating a data structure that represents the file's contents as a dataset.
        + The exact implementation of load\_dataset() may depend on the file format of the dataset, as different file formats may require different methods for reading the file and processing the data.

For example, if the dataset is stored in a CSV file, the load\_dataset() function may use the built-in csv module in Python to read the file and create a pandas DataFrame object to represent the dataset.

Alternatively, if the dataset is stored in an Excel file, the load\_dataset() function may use a third-party library like openpyxl or xlrd to read the file and create a pandas DataFrame object.

* In summary, the load\_dataset() function is a custom function defined in a Python script or module used for loading a dataset from a file, and the file\_path parameter is used to specify the location of the file containing the dataset to be loaded. The exact implementation of load\_dataset() may depend on the file format of the dataset, and may use built-in Python modules or third-party libraries to read the file and create a data structure that represents the dataset.
* df = pd.read\_csv(file\_path):
  + This line loads the CSV file located at file\_path using the read\_csv function provided by the pandas library.
  + The resulting DataFrame is stored in the variable df.
* return df:
  + This line returns the DataFrame that was loaded from the CSV file. The DataFrame can be used for further analysis, processing or visualization.
* Overall, this function is a simple utility that can be used to load CSV files into a pandas DataFrame.
  + The returned DataFrame can then be used for various purposes, such as machine learning, data exploration, or visualization.

def train\_model(X\_train, y\_train):

model = LinearRegression()

model.fit(X\_train, y\_train)

return model

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* This is a function that takes training data (X\_train and y\_train) as input, creates a LinearRegression model using scikit-learn, trains the model using the training data, and returns the trained model.
  + The purpose of this function is to train a linear regression model on the training data and return the trained model.

**Understanding Linear Regression in Python:**

* Linear regression is a statistical technique used to establish a relationship between a dependent variable (often denoted as "y") and one or more independent variables (often denoted as "x1", "x2", ..., "xn").
  + The goal of linear regression is to find the best-fit line that represents the relationship between the variables.

The regression equation for a linear regression model can be written as:

y = b0 + b1x1 + b2x2 + ... + bn\*xn

* where b0, b1, b2, ..., bn are the coefficients that determine the slope and intercept of the regression line.
  + The independent variables, x1, x2, ..., xn, are the predictor variables, and the dependent variable, y, is the variable we are trying to predict.
* The coefficients, b0, b1, b2, ..., bn, represent the parameters of the model, which describe the relationship between the independent variables and the dependent variable.
  + The coefficient b0 represents the intercept of the regression line, and the coefficients b1, b2, ..., bn represent the slopes of the regression line with respect to the independent variables x1, x2, ..., xn.
* The goal of linear regression is to find the values of the coefficients, b0, b1, b2, ..., bn, that best fit the data.
  + To do this, the model is trained on a dataset containing pairs of input and output values.
  + The model then calculates the predicted values of the dependent variable, y, using the regression equation.
  + These predicted values are then compared to the actual values of y in the dataset, and the sum of the squared differences between the predicted values and the actual values is calculated.
* The model then adjusts the values of the coefficients, b0, b1, b2, ..., bn, in an iterative process to minimize the sum of the squared differences between the predicted and actual values of y.
  + This process is known as "***minimizing the mean squared error***," and it is achieved through a technique called "***least squares optimization***."
    - "Minimizing the mean squared error" is the process of finding the best-fit line for a linear regression model, which is achieved through a technique called "least squares optimization".
    - In simple terms, "mean squared error" (MSE) is a measure of how well the model fits the data.
      * It is calculated as the average of the squared differences between the predicted values of the dependent variable (y) and the actual values of the dependent variable in the dataset.
      * The MSE can be thought of as a measure of the distance between the regression line and the actual data points.
    - The goal of linear regression is to find the values of the coefficients that minimize the MSE, which means finding the line that is closest to the actual data points.
      * This is achieved through a technique called "least squares optimization," which involves minimizing the sum of the squared differences between the predicted and actual values of the dependent variable.
    - The "least squares optimization" technique involves using calculus to find the values of the coefficients that minimize the MSE.
      * Specifically, the coefficients that minimize the MSE are found by taking the partial derivatives of the MSE with respect to each of the coefficients, setting them equal to zero, and solving the resulting system of equations.
      * This process gives us the values of the coefficients that minimize the MSE and provide the best-fit line for the model.
    - Once the coefficients have been determined, the linear regression model can be used to make predictions on new input data.
      * The model calculates the predicted value of the dependent variable (y) using the regression equation, which incorporates the values of the independent variables (x1, x2, ..., xn) and the coefficients (b0, b1, b2, ..., bn).
  + Therefore, "minimizing the mean squared error" is the process of finding the best-fit line for a linear regression model, which is achieved through a technique called "least squares optimization". The technique involves minimizing the sum of the squared differences between the predicted and actual values of the dependent variable, using calculus to find the values of the coefficients that minimize the MSE, and using the resulting coefficients to make predictions on new input data.
* Once the model has been trained and the values of the coefficients have been determined, the model can be used to make predictions on new input data.
  + The model uses the regression equation to calculate the predicted value of the dependent variable, y, based on the values of the independent variables, x1, x2, ..., xn.
* Linear regression is a statistical technique used to establish a relationship between a dependent variable and one or more independent variables. The model's parameters are the coefficients of the regression equation, which describe the relationship between the independent variables and the dependent variable.
* The goal of linear regression is to find the values of the coefficients that minimize the sum of the squared differences between the predicted values and the actual values of the dependent variable in the dataset.
* Once the model has been trained, it can be used to make predictions on new input data.
* **Linear regression** is a type of supervised machine learning algorithm used to model the relationship between one or more independent variables (also called features or predictors) and a dependent variable (also called the response or target variable).
  + What is **supervised machine learning**, though?
    - Supervised machine learning is a type of machine learning in which a model is trained on a labeled dataset. In supervised learning, the input data is already labeled with the correct output, which is used to train the model to make predictions on new, unseen data.
    - The process of supervised machine learning can be broken down into the following steps:
      * **Data collection**:
        + The first step in supervised machine learning is to collect a labeled dataset. This dataset typically consists of input data (features or attributes) and the corresponding output data (labels or targets).
        + The input data can be in various forms, such as images, text, or numerical data.
      * **Data preprocessing**:
        + Once the data is collected, it needs to be preprocessed to prepare it for training.
        + This step typically involves cleaning the data, handling missing values, and transforming the data into a format that can be fed into the machine learning algorithm.
      * **Model selection**:
        + The next step is to choose an appropriate machine learning algorithm to train the model.
        + The choice of algorithm depends on the type of problem being solved, the size and complexity of the dataset, and other factors such as the computational resources available.
      * **Training the model**:
        + In supervised machine learning, the model is trained on the labeled dataset.
        + During training, the model learns to map the input data to the correct output data by adjusting its parameters (weights and biases) using an optimization algorithm that minimizes a loss function.
      * **Model evaluation**:
        + Once the model is trained, it needs to be evaluated on a separate dataset that was not used during training.
        + This step is important to ensure that the model is not overfitting to the training data and can generalize well to new, unseen data.
      * **Model tuning**:
        + Based on the evaluation results, the model may need to be tuned or adjusted to improve its performance.
        + This could involve tweaking the model parameters, changing the algorithm, or adjusting the preprocessing steps.
      * **Prediction**:
        + Finally, the trained and tuned model can be used to make predictions on new, unseen data.
        + This involves feeding the input data into the model and getting a predicted output.
    - Supervised machine learning is a type of machine learning in which a model is trained on a labeled dataset. The process involves data collection, data preprocessing, model selection, training the model, model evaluation, model tuning, and prediction. The goal is to build a model that can accurately predict the output for new, unseen input data.
* In Python, the LinearRegression class in the sklearn.linear\_model module provides an implementation of linear regression that can be used to fit a linear model to a dataset.
* The **LinearRegression** class uses the method of least squares to estimate the parameters of the linear model that best fit the data.
* The model’s parameters are the coefficients of the regression equation, which describe the relationship between the independent variables and the dependent variable.

Specifically, the regression equation can be written as:

y = b0 + b1\*x1 + b2\*x2 + ... + bn\*xn

* + where y is the dependent variable, x1, x2, ..., xn are the independent variables, and b0, b1, b2, ..., bn are the coefficients that determine the slope and intercept of the regression line.
* The goal of linear regression is to find the values of b0, b1, b2, ..., bn that minimize the sum of the squared differences between the predicted values of y and the actual values of y in the dataset.
* To use the LinearRegression class in Python, the first step is to create an instance of the class:
  + from sklearn.linear\_model import LinearRegression:

model = LinearRegression()

* + Once an instance of the LinearRegression class has been created, the fit() method can be used to fit the linear model to a dataset.
    - The fit() method takes two parameters: the independent variables (as a 2D array or matrix) and the dependent variable (as a 1D array or vector).
* For example, to fit a linear model to a dataset with two independent variables (x1 and x2) and one dependent variable (y), the following code could be used:
  + import numpy as np
  + from sklearn.linear\_model import LinearRegression
* # Create a dataset with two independent variables and one dependent variable

X = np.array([[1, 2], [3, 4], [5, 6], [7, 8]])

y = np.array([5, 10, 15, 20])

* # Create an instance of the LinearRegression class and fit the model to the data

model = LinearRegression()

model.fit(X, y)

* After the fit() method has been called, the coef\_ attribute of the LinearRegression object contains the coefficients of the regression equation, and the intercept\_attribute contains the intercept:

print(model.coef\_) # [2.5, 2.5]

print(model.intercept\_) # 0.0

* The coefficients indicate how much the dependent variable (y) is expected to change for a one-unit increase in each independent variable (x1 and x2), while holding all other independent variables constant.

* In this example, the coefficients are both 2.5, which means that the expected change in y is 2.5 for a one-unit increase in either x1 or x2, holding the other variable constant.
  + The intercept is 0.0, which means that the regression line passes through the origin.
* Once the model has been fit to the data, the predict() method can be used to make predictions for new values of the independent variables.

* For example, to make a prediction for a new observation with x1=10 and x2=12, the following code could be used:

X\_new = np.array([[10, 12]])

y\_pred = model.predict(X\_new)

print(y\_pred) # [32.5]

``

* This predicts that for a new observation with x1=10 and x2=12, the model predicts a value of y=32.5.
* In this way, the LinearRegression class in Python provides a way to fit a linear model to a dataset and use the model to make predictions for new observations.
* Linear regression is a widely used technique in machine learning and data science, and the LinearRegression class in Python provides a simple and flexible way to implement linear regression models.
* The LinearRegression class provides several additional methods that can be used to analyze and evaluate the performance of the linear regression model.

* Here are some of the most commonly used methods:
  + score(X, y):
    - Computes the coefficient of determination (R-squared) of the linear regression model.
    - R-squared is a statistical measure that represents the proportion of the variance in the dependent variable that is explained by the independent variables.
  + The score() method takes the independent variables (as a 2D array or matrix) and the dependent variable (as a 1D array or vector) as input parameters.
  + predict(X):
    - Computes the predicted values of the dependent variable (y) for a given set of independent variables (X).
    - The predict() method takes the independent variables (as a 2D array or matrix) as input parameters.
  + residues\_:
    - Returns the sum of squared residuals (SSR), which is a measure of the difference between the predicted values of the dependent variable and the actual values in the dataset.
  + intercept\_:
    - Returns the intercept (b0) of the regression equation.
  + coef\_:
    - Returns the coefficients (b1, b2, ..., bn) of the regression equation.
  + get\_params():
    - Returns a dictionary containing the parameters of the linear regression model.
  + set\_params(\*\*params):
    - Sets the parameters of the linear regression model using a dictionary of parameter values.
* In addition to these methods, the LinearRegression class also supports regularization techniques like L1 and L2 regularization, which can be used to prevent overfitting and improve the generalization of the model.
* Regularization can be enabled by setting the alpha parameter of the LinearRegression class to a non-zero value.
* Overall, the LinearRegression class in Python provides a flexible and powerful way to perform linear regression modeling and analysis. Its simplicity and ease of use make it a popular choice for beginners in machine learning and data science.
* In addition to the basic linear regression model, there are several variations of linear regression that can be implemented using the LinearRegression class in Python.
  + Here are some of the most commonly used variations:
    - **Multiple Linear Regression**:
      * This is the most basic form of linear regression and involves modeling the relationship between one dependent variable and multiple independent variables.
    - **Polynomial Regression**:
      * This is a form of linear regression that involves fitting a polynomial equation to the data instead of a straight line.
        + This allows for more complex relationships between the independent and dependent variables to be modeled.
    - **Ridge Regression**:
      * This is a form of linear regression that uses L2 regularization to prevent overfitting of the model.
      * Ridge regression works by adding a penalty term to the sum of squared errors in the objective function of the linear regression model.
    - **Lasso Regression**:
      * This is a form of linear regression that uses L1 regularization to prevent overfitting of the model.
      * Lasso regression works by adding a penalty term to the absolute value of the coefficients in the objective function of the linear regression model.
    - **Elastic Net Regression**:
      * This is a form of linear regression that combines the L1 and L2 regularization techniques to prevent overfitting of the model.
      * Elastic net regression works by adding a penalty term that is a linear combination of the L1 and L2 penalty terms to the objective function of the linear regression model.
    - The LinearRegression class in Python provides a way to implement all of these variations of linear regression using the same basic interface.
    - To use one of these variations, you simply need to create an instance of the LinearRegression class and set the appropriate parameters, such as the degree of the polynomial equation for polynomial regression or the alpha value for Ridge, Lasso, or Elastic Net regression.
* Overall, the LinearRegression class in Python provides a powerful and flexible way to perform linear regression modeling and analysis, with support for several variations of the basic linear regression model. Its ease of use and integration with other Python libraries like NumPy and pandas make it a popular choice for machine learning and data science projects.
* def train\_model(X\_train, y\_train):
  + This line defines a new function called train\_model that takes two arguments, X\_train and y\_train.
* model = LinearRegression():
  + This line creates an instance of the LinearRegression class from the scikit-learn library.
  + This class provides a linear regression model that can be used for regression analysis.
* model.fit(X\_train, y\_train):
  + This line trains the linear regression model on the training data.
  + The fit method takes two arguments, X\_train and y\_train, which are the features and labels of the training data, respectively.
  + The model is trained to learn a linear relationship between the features and labels.
* return model:
  + This line returns the trained linear regression model.
  + The trained model can be used to make predictions on new data or for further analysis, such as feature importance analysis or model comparison.
* Overall, this function is a simple utility that can be used to train a linear regression model on training data. The returned model can be used to predict new data or for further analysis. Linear regression is a widely used machine learning algorithm for regression tasks, such as predicting the price of a house given its features.

def evaluate\_model(model, X\_test, y\_test):

y\_pred = model.predict(X\_test)

mse = mean\_squared\_error(y\_test, y\_pred)

r2 = r2\_score(y\_test, y\_pred)

return mse, r2

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* This is a function that takes a trained model (model), testing data (X\_test and y\_test), and evaluates the performance of the model using mean squared error (mean\_squared\_error) and R2 score (r2\_score) from scikit-learn.
  + It returns both the mean squared error and R2 score.
* The purpose of this function is to evaluate the performance of a machine learning model on a test dataset and return two performance metrics, mean squared error and R-squared.
* def evaluate\_model(model, X\_test, y\_test):
  + This line defines a new function called evaluate\_model that takes three arguments, model, X\_test, and y\_test.
* y\_pred = model.predict(X\_test):
  + This line uses the trained model to make predictions on the test data X\_test.
  + The predicted values are stored in the variable y\_pred.
* mse = mean\_squared\_error(y\_test, y\_pred):
  + This line calculates the mean squared error (MSE) between the true values y\_test and the predicted values y\_pred.
  + The mean squared error is a common metric used to evaluate regression models.
  + It measures the average squared difference between the predicted and true values.
* r2 = r2\_score(y\_test, y\_pred):
  + This line calculates the R-squared (R2) coefficient between the true values y\_test and the predicted values y\_pred.
  + The R-squared coefficient is a common metric used to evaluate regression models.
  + It measures the proportion of variance in the dependent variable that is predictable from the independent variable(s).
* return mse, r2
  + This line returns two performance metrics, mean squared error and R-squared, as a tuple.
* Overall, this function is a simple utility that can be used to evaluate the performance of a machine learning model on a test dataset. The function calculates two common regression metrics, mean squared error and R-squared, which can be used to compare the performance of different models or to fine-tune hyperparameters. The returned metrics can be used to get an idea of how well the model is performing on new data.

def plot\_charts(df):

fig\_pie = px.pie(df, names=df.columns[-1], title='Pie Chart of Target Variable')

fig\_scatter = px.scatter\_matrix(df, dimensions=df.columns[:-1], color=df.columns[-1],

title='Scatter Matrix of Features')

X = df.iloc[:, :-1]

y = df.iloc[:, -1]

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

model = train\_model(X\_train, y\_train)

mse = evaluate\_model(model, X\_test, y\_test)

mse\_var.set(f"MSE: {mse:.2f}")

r2\_var.set(f"R2 Score: {r2:.2f}")

fig\_regression = make\_subplots(rows=1, cols=X.shape[1], subplot\_titles=X.columns)

for idx, col in enumerate(X.columns):

fig\_regression.add\_trace(go.Scatter(x=X[col], y=y, mode='markers', name=col, showlegend=False), row=1, col=idx + 1)

X\_reg = X[[col]]

model\_reg = train\_model(X\_reg, y)

y\_reg = model\_reg.predict(X\_reg)

fig\_regression.add\_trace(go.Scatter(x=X[col], y=y\_reg, mode='lines', name=f"{col}\_reg", showlegend=False), row=1, col=idx + 1)

fig\_regression.update\_layout(title\_text='Linear Regression Plots', showlegend=False)

fig\_histograms = make\_subplots(rows=1, cols=X.shape[1], subplot\_titles=X.columns)

for idx, col in enumerate(X.columns):

fig\_histograms.add\_trace(go.Histogram(x=X[col], name=col), row=1, col=idx + 1)

fig\_histograms.update\_layout(title\_text='Histograms')

open\_web\_view(pio.to\_html(fig\_pie, full\_html=False))

open\_web\_view(pio.to\_html(fig\_scatter, full\_html=False))

open\_web\_view(pio.to\_html(fig\_regression, full\_html=False))

open\_web\_view(pio.to\_html(fig\_histograms, full\_html=False))

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Description automatically generated



* This function takes a pandas DataFrame (df) as input, creates various plots using plotly, trains a LinearRegression model using train\_test\_split from scikit-learn, evaluates the model using evaluate\_model, and then displays the plots and evaluation metrics in the web browser using open\_web\_view.
* Specifically, it creates a pie chart (fig\_pie) and scatter matrix (fig\_scatter) using plotly.express, creates regression plots (fig\_regression) and histograms (fig\_histograms) using plotly.subplots and go.Scatter and go.Histogram from plotly.graph\_objs.
* It then updates the layouts of the regression and histogram plots and finally, calls open\_web\_view to display all the figures in the web browser.
* def plot\_charts(df):
  + This line defines a new function called plot\_charts that takes one argument, df, which is a pandas DataFrame containing the dataset.
* fig\_pie = px.pie(df, names=df.columns[-1], title='Pie Chart of Target Variable'):
  + This line creates a pie chart using the px.pie function from the Plotly Express library.
  + The chart shows the distribution of the target variable, which is assumed to be in the last column of the dataset. The chart is stored in the variable fig\_pie.
* fig\_scatter = px.scatter\_matrix(df, dimensions=df.columns[:-1], color=df.columns[-1],
* title='Scatter Matrix of Features'):
  + This line creates a scatter matrix plot using the px.scatter\_matrix function from the Plotly Express library.
  + The plot shows the pairwise relationships between the features in the dataset. The color of the points is determined by the target variable, which is assumed to be in the last column of the dataset.
  + The plot is stored in the variable fig\_scatter.
* X = df.iloc[:, :-1]

y = df.iloc[:, -1]

X\_train, X\_test, y\_train, y\_test = train\_test\_split(X, y, test\_size=0.2, random\_state=42)

model = train\_model(X\_train, y\_train)

mse = evaluate\_model(model, X\_test, y\_test)

mse\_var.set(f"MSE: {mse:.2f}")

r2\_var.set(f"R2 Score: {r2:.2f}"):

* + These lines split the dataset into training and testing sets, train a linear regression model on the training set, and evaluate the model on the testing set.
  + The training set consists of all the features in the dataset except for the last column, which is assumed to be the target variable.
  + The testing set consists of 20% of the data.
  + The train\_model and evaluate\_model functions are called to train and evaluate the model.
  + The mean squared error (MSE) and R-squared (R2) are computed and stored in mse variable.
    - The MSE and R2 values are set to variables mse\_var and r2\_var respectively, which are later used to display these values on the GUI.
* fig\_regression = make\_subplots(rows=1, cols=X.shape[1], subplot\_titles=X.columns):
  + This line creates a subplot using the make\_subplots function from the Plotly library.
    - The subplot consists of a row of charts, one for each feature in the dataset. The subplot is stored in the variable fig\_regression.
* for idx, col in enumerate(X.columns)

fig\_regression.add\_trace(go.Scatter(x=X[col], y=y, mode='markers', name=col, showlegend=False), row=1, col=idx + 1)

X\_reg = X[[col]]

model\_reg = train\_model(X\_reg, y)

y\_reg = model\_reg.predict(X\_reg)

fig\_regression.add\_trace(go.Scatter(x=X[col], y=y\_reg, mode='lines', name=f"{col}\_reg", showlegend=False), row=1, col=idx + 1):

* + These lines create scatter plots for each feature in the dataset using the go.Scatter function from the Plotly library.
  + For each feature, two plots are created.
    - The first plot is a scatter plot of the feature values versus the target variable.
    - The second plot is a line plot of the linear regression fit for the feature. The regression line is trained using only the feature and target variable.
* The plots are added to the subplot fig\_regression using the add\_trace method.
* fig\_regression.update\_layout(title\_text='Linear Regression Plots', showlegend=False):
  + This line updates the layout of the fig\_regression subplot by setting the title to "Linear Regression Plots" and hiding the legend.
* fig\_histograms = make\_subplots(rows=1, cols=X.shape[1], subplot\_titles=X.columns):
  + This line creates another subplot using the make\_subplots function from the Plotly library.
  + The subplot consists of a row of histograms, one for each feature in the dataset. The subplot is stored in the variable fig\_histograms.
* for idx, col in enumerate(X.columns)
* fig\_histograms.add\_trace(go.Histogram(x=X[col], name=col), row=1, col=idx + 1):
  + These lines create histograms for each feature in the dataset using the go.Histogram function from the Plotly library.
  + The plots are added to the subplot fig\_histograms using the add\_trace method.
* fig\_histograms.update\_layout(title\_text='Histograms'):
  + This line updates the layout of the fig\_histograms subplot by setting the title to "Histograms".
* open\_web\_view(pio.to\_html(fig\_pie, full\_html=False))

open\_web\_view(pio.to\_html(fig\_scatter, full\_html=False))

open\_web\_view(pio.to\_html(fig\_regression, full\_html=False))

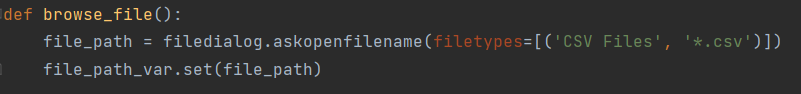
open\_web\_view(pio.to\_html(fig\_histograms, full\_html=False)):

* + These lines display the plots in a web view using the open\_web\_view function.
  + The pio.to\_html function is used to convert the plots to HTML code, which is then displayed in the web view.
  + Four plots are displayed: the pie chart, the scatter matrix, the linear regression plots, and the histograms.
* Overall, this function is a utility that can be used to visualize the given dataset using various charts and plots. It uses several libraries such as Plotly, Pandas, and scikit-learn to create and display the charts. The function is intended to be used in a GUI application or Jupyter notebook to provide an interactive way to explore and analyze the dataset.

def browse\_file():

file\_path = filedialog.askopenfilename(filetypes=[('CSV Files', '\*.csv')])

file\_path\_var.set(file\_path)



* This is a function that is called when the user clicks the "Browse" button.
  + It opens a file dialog using filedialog from tkinter and returns the file path of the selected CSV file.
  + The file path is then set as the value of the file\_path\_var variable.

def analyze\_data():

file\_path = file\_path\_var.get()

df = load\_dataset(file\_path)

plot\_charts(df)

Text

Description automatically generated

* This is a function that is called when the user clicks the "Analyze" button.
* It gets the file path from the file\_path\_var variable, loads the CSV file using load\_dataset, and then calls plot\_charts to create and display the plots.
  + It retrieves the file path from a variable named file\_path\_var using the .get() method of that variable.
    - It assumes that file\_path\_var is a tkinter StringVar object, or a similar object that has a .get() method.
  + It loads a dataset from the file located at the file path retrieved in step 1, using a function called load\_dataset().
    - The function load\_dataset() could be defined elsewhere in the code, but it is not shown here.
    - The load\_dataset() function likely reads the file and returns a pandas DataFrame, which is stored in a variable called df.
  + It calls another function named plot\_charts() and passes the DataFrame df as an argument.
    - This function presumably creates one or more visualizations (charts) based on the data in the DataFrame.
* The analyze\_data() function specifically handles the first two steps of this process, while delegating the charting responsibilities to a separate function.

root = tk.Tk()

root.title("Data Analysis")

file\_path\_var = tk.StringVar()

mse\_var = tk.StringVar()

r2\_var = tk.StringVar()

ttk.Label(root, text="Select CSV file:").grid(column=0, row=0)

ttk.Entry(root, textvariable=file\_path\_var, width=50).grid

(column=1, row=0)

ttk.Button(root, text="Browse", command=browse\_file).grid(column=2, row=0)

ttk.Button(root, text="Analyze", command=analyze\_data).grid(column=1, row=1)

ttk.Label(root, textvariable=mse\_var).grid(column=1, row=2)

ttk.Label(root, textvariable=r2\_var).grid(column=1, row=3)

Text

Description automatically generated

* mse\_explanation = “MSE (Mean Squared Error) measures the average squared difference between predicted and actual values. Lower values indicate better model performance."
* r2\_explanation = "R2 Score represents the proportion of the variance in the dependent variable that is predictable from the independent variable(s). It ranges from 0 to 1, with higher values indicating better model performance."

This code uses the Tkinter library to create a GUI (Graphical User Interface) window that provides options for data analysis.

* Here is a step-by-step explanation of what the code does:
  + The first line creates a new instance of the Tk class from the Tkinter library, which represents the main window of the GUI.
  + The second line sets the title of the window to "Data Analysis".
  + The next three lines create three StringVar variables, which are special variables in Tkinter that can store string values and can be used to update labels, entry fields, and other widgets dynamically.
  + The next line creates a label widget using the ttk.Label class, which displays the text "Select CSV file:" on the GUI window.
    - The grid method of this widget is used to position it in the first row and first column of the grid layout of the window
  + The next line creates an entry widget using the ttk.Entry class, which allows the user to enter text.
    - The textvariable option of this widget is set to file\_path\_var, so that the value entered by the user will be stored in this variable.
    - The grid method of this widget is used to position it in the first row and second column of the grid layout of the window.
  + The next line creates a button widget using the ttk.Button class, which displays the text "Browse" and executes a function called browse\_file when clicked.
    - The command option of this widget is set to browse\_file, which means that the browse\_file function will be called when the button is clicked.
    - The grid method of this widget is used to position it in the first row and third column of the grid layout of the window.
  + The next line creates another button widget using the ttk.Button class, which displays the text "Analyze" and executes a function called analyze\_data when clicked.
    - The command option of this widget is set to analyze\_data, which means that the analyze\_data function will be called when the button is clicked.
    - The grid method of this widget is used to position it in the second row and second column of the grid layout of the window.
  + The next line creates a label widget using the ttk.Label class, which displays the value of mse\_var on the GUI window.
    - The grid method of this widget is used to position it in the third row and second column of the grid layout of the window.
  + The next line creates another label widget using the ttk.Label class, which displays the value of r2\_var on the GUI window.
    - The grid method of this widget is used to position it in the fourth row and second column of the grid layout of the window.
  + Overall, this code creates a GUI window that allows the user to select a CSV file, analyze the data in the file, and display the results of the analysis on the window.
    - The browse\_file and analyze\_data functions are not defined in this code, but they are likely defined elsewhere in the program to handle the file selection and data analysis tasks.

ttk.Label(root, text=mse\_explanation, wraplength=400).grid(column=1, row=4)

ttk.Label(root, text=r2\_explanation, wraplength=400).grid(column=1, row=5)

root.mainloop()

Text

Description automatically generated

* These lines create the GUI interface using tkinter and ttk.
  + It creates a window with the title "Data Analysis" (root.title), and adds various widgets to the window using ttk.Label, ttk.Entry, ttk.Button, and ttk.Label.
    - Specifically, it creates a label for selecting the CSV file (ttk.Label), an entry box for displaying the file path (ttk.Entry), buttons for browsing the file and analyzing the data (ttk.Button), labels for displaying the evaluation metrics (ttk.Label).
    - It then sets the values of the mse\_explanation and r2\_explanation variables, which contain explanations of the evaluation metrics.
    - Finally, it enters the event loop using root.mainloop(), which waits for the user to interact with the GUI.
* This code adds two more label widgets to the GUI window created by the previous code. Here is a step-by-step explanation of what the code does:
  + The first line creates a new ttk.Label widget and assigns it to a variable.
    - This label widget is used to display an explanation of the "mean squared error" (MSE) metric used in data analysis.
    - The text option of the widget is set to mse\_explanation, which presumably contains a string explaining what the MSE is and how it is calculated.
    - The wraplength option specifies the maximum width of the label widget in pixels before the text wraps to a new line.
    - The grid method of the widget is used to position it in the fifth row and second column of the grid layout of the window.
  + The second line creates another ttk.Label widget and assigns it to a variable.
    - This label widget is used to display an explanation of the "coefficient of determination" (R²) metric used in data analysis.
    - The text option of the widget is set to r2\_explanation, which presumably contains a string explaining what the R² is and how it is calculated.
    - The wraplength option specifies the maximum width of the label widget in pixels before the text wraps to a new line.
    - The grid method of the widget is used to position it in the sixth row and second column of the grid layout of the window.
  + The last line starts the Tkinter event loop using the mainloop() method of the root object.
    - This method listens for user events, such as button clicks or keyboard input, and updates the GUI window accordingly.
    - It runs until the user closes the window or the program is terminated in some other way.
* Overall, this code adds two more label widgets to the GUI window created by the previous code, which provide additional information about the metrics used in data analysis. The wraplength option is used to ensure that the text fits within the label widgets without overflowing, and the grid method is used to position the widgets in the appropriate rows and columns of the window. Finally, the mainloop() method is called to start the Tkinter event loop and allow the user to interact with the window.