Team Number :	apmcm24208620
Problem Chosen :	C

2024 APMCM summary sheet

Abstract

With the rapid growth of the global economy and increasing disposable incomes, the pet industry has emerged as a high-potential, fast-growing sector. This paper focuses on China's pet food industry, utilizing **time-series forecasting models** (**ARIMA**), **multiple linear regression models** (**MLR**), and **logistic growth models** to analyze the development trends of China's pet industry, global pet food market demand, China's production and export capacities, and the impact of international trade policy changes. Through quantitative analysis and data modeling, this research predicts the growth trajectory of China's pet industry over the next three years, reveals regional trends in the global market, and highlights China's rapid expansion in the global pet food sector. The findings also indicate that China's pet food exports are significantly impacted by international trade policies, particularly changes in U.S. tariff regulations. Furthermore, as the domestic market approaches saturation, the industry's growth will increasingly rely on the diversification of international markets and strategic policy adjustments. Despite the challenges posed by international trade policies, China's pet food industry has strong potential for sustainable growth through expansion into emerging markets and enhanced international collaboration.

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I. Introduction

1 .1 Background

With the continuous growth of the global economy and rising disposable incomes, pets have become increasingly significant as companions and family members. In recent years, the "pet economy" has emerged as a thriving industry, encompassing various sectors such as pet food, healthcare, accessories, and insurance. This high-potential, fast-growing industry has gained momentum worldwide, with China playing a key role in driving its expansion.

In China, the pet food sector has experienced explosive growth, driven by the rising number of pet cats and dogs and the evolving consumer mindset that prioritizes pet welfare. Pet food has become a significant portion of pet-related expenditures. Meanwhile, international markets for pet food are also expanding, with stable demand for premium products in high-income countries and robust growth potential in emerging markets and developing regions. As one of the leading pet food producers globally, China has steadily increased its production and exports, solidifying its role in the international market.

Despite these opportunities, challenges remain. Changes in international trade policies, such as tariff adjustments, could impact the competitiveness of Chinese pet food exports. Additionally, the balance between meeting the growing domestic demand for high-quality products and maintaining competitiveness in low- and mid-tier markets poses a challenge for the Chinese pet food sector.

1 .2 Problem Restatement

Problem 1

Development and Trends in China's Pet Industry:

Analyze the changes in China's pet industry over the past five years, focusing on the growth in the number of pet cats and dogs, and predict the industry's size and trends for the next three years.

Problem 2

Global Pet Food Market Demand:

Study the trends in pet food demand across major regions (e.g., North America, Europe, Asia) and predict global demand over the next three years, accounting for regional differences and growth potential.

Problem 3

Growth Potential of China's Pet Food Production and Exports:

Assess the growth capacity of China's pet food production and export volumes based on historical data and global market trends, evaluating its potential to meet international demand.

Problem 4

Impact of International Policies on China's Pet Food Sector:

Quantitatively analyze the effects of changes in international trade policies (e.g., tariffs) on China's pet food exports. Develop feasible strategies to ensure the sustainable growth of the Chinese pet food industry.

1 .3 Research Significance

The pet industry, as a rapidly growing sector within the global consumer economy, presents vast market opportunities and significant investment potential. This study aims to:

1. Forecast the future trends of China's and the global pet food industries, providing scientific insights for decision-makers.

2. Identify market opportunities and challenges, optimizing China's competitive strategies in the global pet food market.

3. Propose actionable strategies to address the impact of international trade policy changes, ensuring the stability and sustainability of China's pet food sector.

Grounded in data analysis and mathematical modeling, this research offers a comprehensive perspective on the future of the pet industry, benefiting both local and global stakeholders.

II. Analysis and Approach

2.1 Problem 1

The rapid growth of China’s pet industry is driven by the increasing number of pets (cats and dogs), as well as economic development (e.g., rising disposable income and consumer expenditure), social trends (e.g., urbanization, single households, and an aging population), and cultural phenomena (e.g., the "cat craze"). To predict the future growth of pet numbers, time series models such as ARIMA[1] are employed. Combined with multiple regression models to quantify the impact of socio-economic factors, these approaches provide a scientific basis for estimating the industry's growth over the next three years.

2.2 Problem 2

The growth in global pet food demand is influenced by regional pet populations, purchasing power (e.g., income levels, per capita expenditure), and market characteristics (e.g., the share of premium, mid-tier, and low-tier pet food) across different regions. To forecast global demand, both ARIMA and multiple regression models are employed. ARIMA is used to model the time series of pet food demand in key regions (e.g., North America, Europe, China) based on historical data. In addition, multiple regression models are applied to quantify the impact of economic factors, regional market characteristics, and pet populations on pet food demand. The combination of these two models allows for a more comprehensive forecast of global pet food demand, considering both time-dependent trends and socio-economic factors, providing a more accurate prediction for the next three years.

2.3 Problem 3

The development of China’s pet food industry is driven by growing domestic demand and the expansion of international markets. Historical data and global market trends are key to understanding production capacity and export growth. Logistic growth models are used to predict the gradual expansion of production, while multiple regression models analyze the relationships between production, global demand, and export values. These models provide insights into the potential for China's pet food production and export over the next three years.

2.4 Problem 4

Changes in international trade policies (e.g., tariffs) have a direct impact on the competitiveness of China's pet food exports. Scenario analysis is used to simulate the effects of varying tariff policies on export values. Combined with supply-demand balance models, this approach optimizes market strategies and develops plans for diversifying export markets and fostering international partnerships to ensure the sustainable growth of China's pet food industry.

III. Assumptions and Justifications

Assumptions1

This study assumes that all collected data are accurate, truthful, and reliably reflect the actual situation of the research subject.

Although this study assumes that the data are accurate and reliable, due to uncontrollable factors during the data collection process, there may be slight biases. Further research is required to verify this in more detail.

Assumptions2

Assuming that cats and dogs dominate the global pet population, and that the number of other types of pets is negligible, they can be disregarded in the analysis.

IV. Notations

Symbol	Description
dog_num	The number of pet dogs
cat_num	The number of pet cats
d_cost	Pet dog consumption
c_cost	Pet cat consumption
total_cost	Total pet consumption
pet_scal	Pet economy market size
d_per_cost	Single pet dog consumption
c_per_cost	Single pet cat consumption
PDI	Per capita disposable income
PCE	Per capita consumption expenditure
PN	Number of single-family households
PetsN	Total number of pets
PetsP	Number of pet households
UR	Urbanization rate
AR	Aging rate

Dog_ms	Dog market size
Cat_ms	Cat market size
Petsfood_ms	Pet food market size
PR	Pet food market share
Petsfood_Pr	Pet food prices
CN_dog_q	The quantity of pet dogs in China
CN_cat_q	The quantity of pet cats in China
CN_pet_q	The quantity of pet in China
Global_ms	Global pet market size
CN_Prodc	Total Value of China's Pet Food Production
CN_export	Total Value of China's Pet Food Exports
CN_ms	China pet market size
Dollars_rate	Dollar currency rate
Export_Rate	tariff

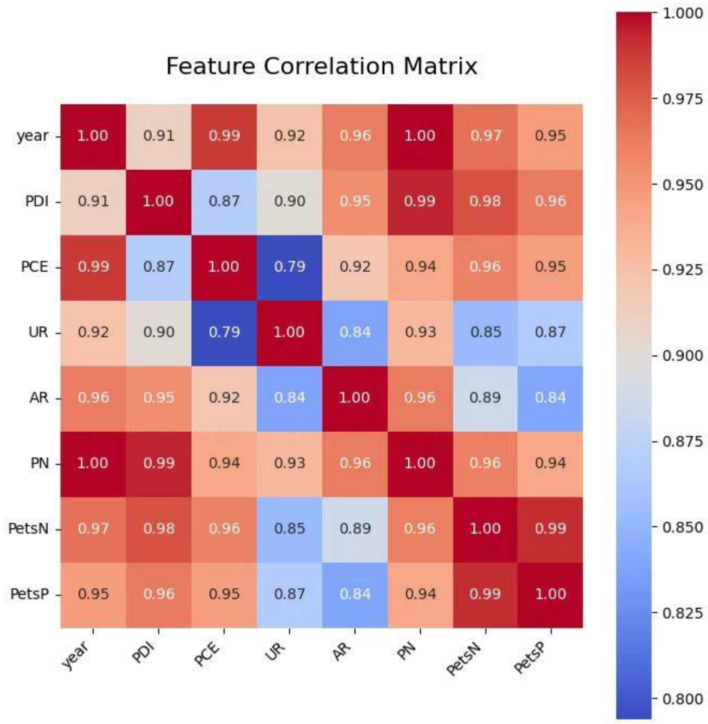
V. Question

5.1 Question 1: Model Construction and Solution

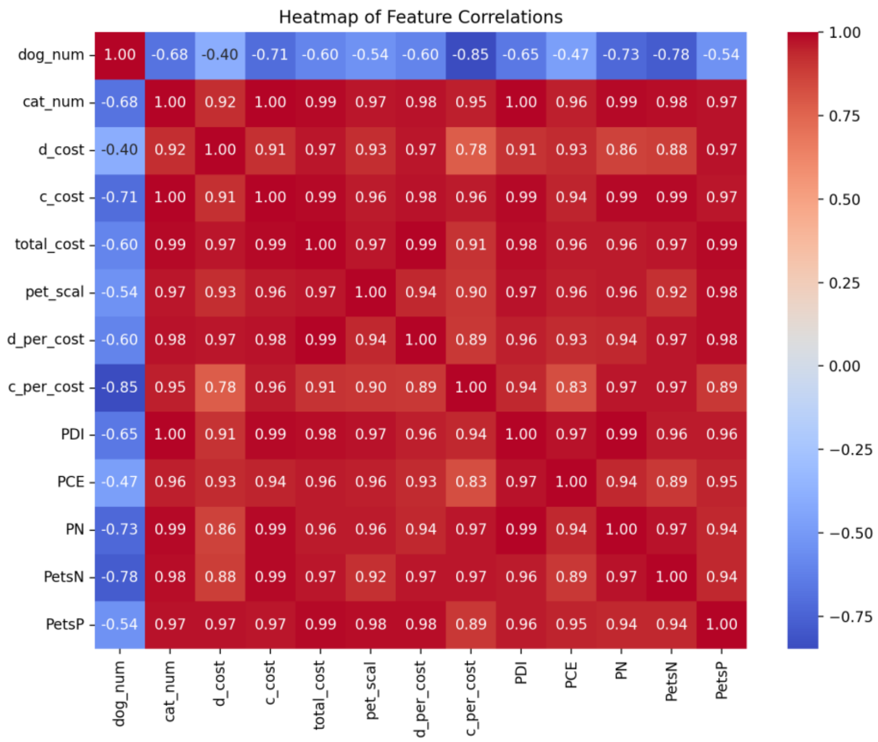
5.1.1 Data Preprocessing

In addition to the data provided in the problem, we have also gathered additional data on **Per capita disposable income, Per capita consumption expenditure, Urbanization rate, Aging rate, Number of single-family households, Total number of pets,** and **Number of pet households.** We performed a correlation analysis between these variables using a heatmap, and the results are shown in the figure below.

Based on the heatmap, it is observed that **Per capita disposable income, Per capita consumption expenditure, Number of single-family households,** and **Number of pet households** exhibit a relatively high correlation with the **Total number of pets**. In contrast, **the Urbanization rate** and **Aging rate** show a lower correlation with the **Total number of pets**. Therefore, we have selected **Per capita disposable income, Per capita consumption expenditure, Number of single-family households,** and **Number of pet households** as the primary reference factors for the analysis.



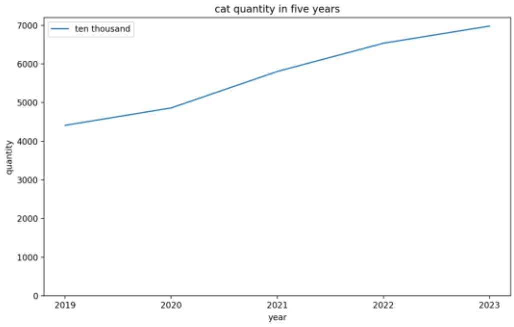
Considering the differences between cats and dogs, we have collected data related to both animals from the internet for a more targeted analysis. The following variables were replaced: "Indicates the number of pet dogs," "Total number of pet cats," "Pet dog consumption," "Pet cat consumption," "Total pet consumption," "Pet economy market size," "Single pet dog consumption," and "Single pet cat consumption," in place of the previously weaker correlated variables, namely "Urbanization rate" and "Aging rate." We then performed another correlation analysis using a heatmap on the updated data, which resulted in the following findings.

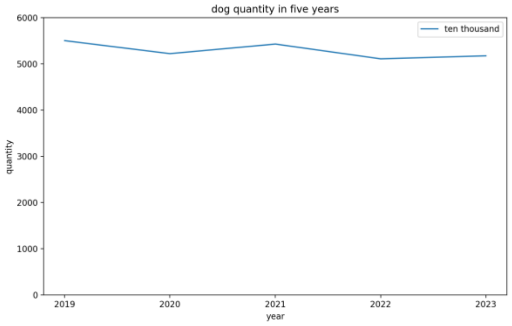


It is evident that there is a strong correlation among the variables, and therefore, they have been selected as the key factors for consideration in this analysis.

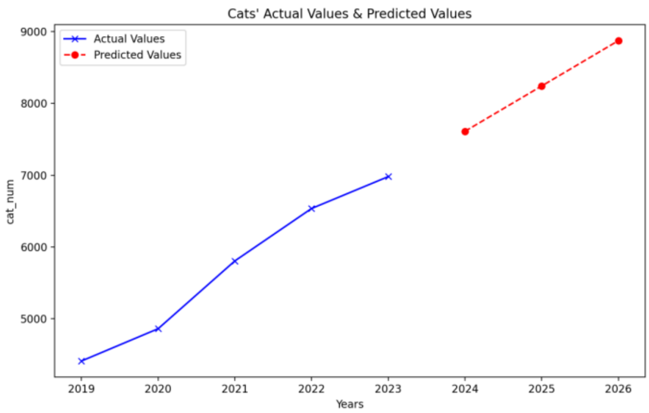
5.1.2 The ARIMA model is used to predict the development of China's pet industry in the next three years.

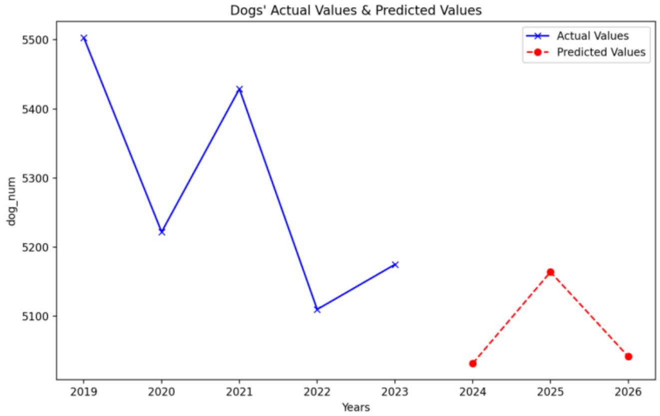
First, the given five years of data are plotted as a line chart, as shown below.

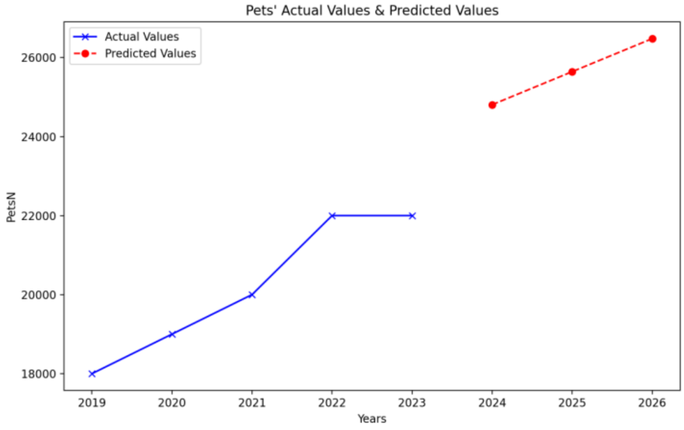




It can be observed that the number of cats in China's pet industry shows an increasing trend, while the number of dogs generally exhibits a decreasing trend, along with periodic fluctuations. Additionally, as shown in the analysis above, both variables are strongly correlated with time. Therefore, the time series forecasting model ARIMA is selected to predict the number of cats, dogs, and the total number of pets in China over the next three years. The results are shown below:





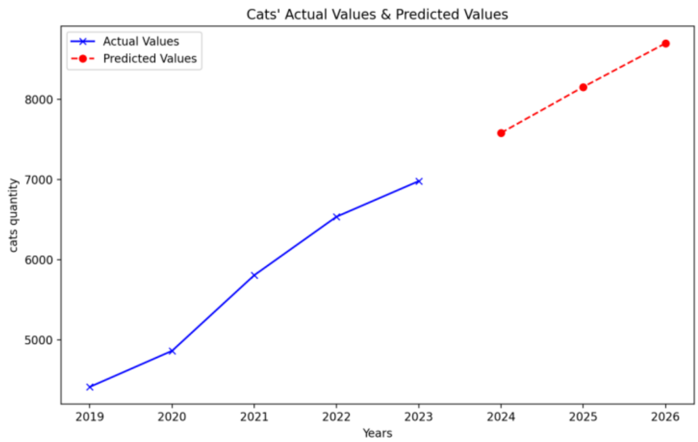


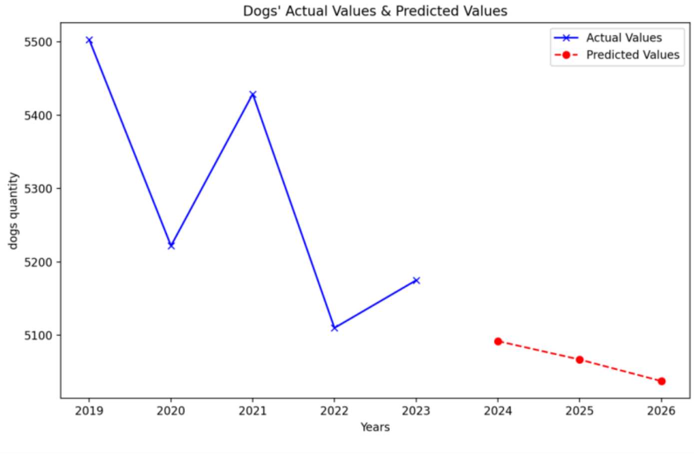
The predicted values are as follows:

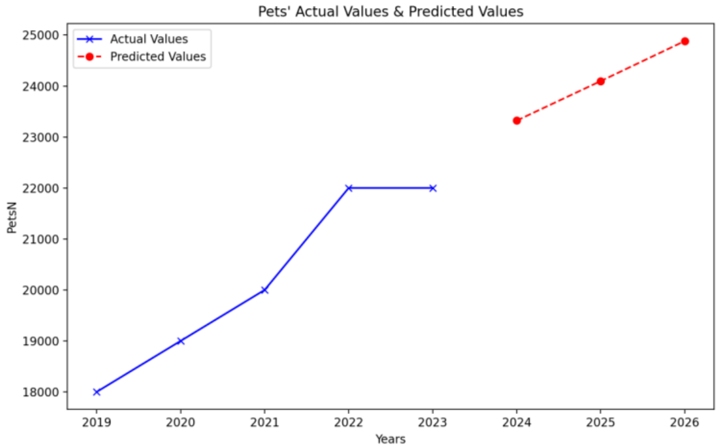
	Cat(ten thousand head)	Dog(ten thousand head)	Pet(ten thousand head)
2024	7611.012385	5031.843053	24806.313626
2025	8241.977955	5164.146316	25642.545844
2026	8872.896714	5041.873847	26478.696662

5.1.3 Using MLR to predict the development of China's pet industry in the next three years.

Considering that the number of pets may be influenced by multiple factors, and based on the heatmap analysis above, it is evident that several variables are strongly correlated with the number of pets. Therefore, the MLR[2] (Multiple Linear Regression) model is selected to incorporate multiple factors for predicting the number of pets. The results are as follows:







The predicted values are as follows:

	Cat(ten thousand head)	Dog(ten thousand head)	Pet(ten thousand head)
2024	7581.11724689	5091.98483266	23320.83780417
2025	8154.93729267	5066.92009736	24096.07799108
2026	8699.13459705	5037.48750359	24880.70416177

5.1.4 Comparison of the predictions made using ARIMA and MLR is presented below.

The ARIMA model was used to predict the trend of pet numbers over time based solely on historical data. It is well-suited for capturing time-dependent patterns, especially for data with trends and seasonality. On the other hand, the Multiple Linear Regression (MLR) model incorporated socio-economic factors, such as Per capita disposable income, Per capita consumption expenditure, and Number of single-family households, to explain and predict changes in pet numbers. By combining external influencing variables, MLR aims to provide a more comprehensive prediction.

To evaluate the accuracy of the two models, we computed the Mean Squared Error (MSE) and R^2 values using the available data for the years 2019–2023. The results are as follows:

MLR	Cat	Dog	Pet
MSE	1303.53	10044.80	61178.29
R^2	1.00	-17.19	0.97

ARIMA	Cat	Dog	Pet
MSE	955194.68	40471.65	8525716.01
R^2	-18.38	-37.32	-13.25

From the above analysis, it can be concluded that the MLR model performs better in predicting future data, indicating that it can explain more of the variability and reflects the impact of external driving factors on the number of pets.

While ARIMA provides a reliable trend-based prediction, it does not account for external factors such as income growth or changes in household structure. In contrast, MLR incorporates these socio-economic drivers, making its predictions more dynamic and reflective of real-world changes. The slight differences in predicted values arise from ARIMA's reliance on time-dependent patterns versus MLR's dependence on external variables.

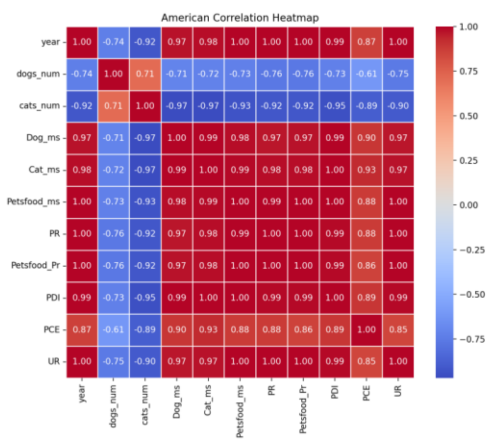
Considering the scope of the problem and the availability of socio-economic data, we recommend using MLR as the primary model while leveraging ARIMA for trend validation.

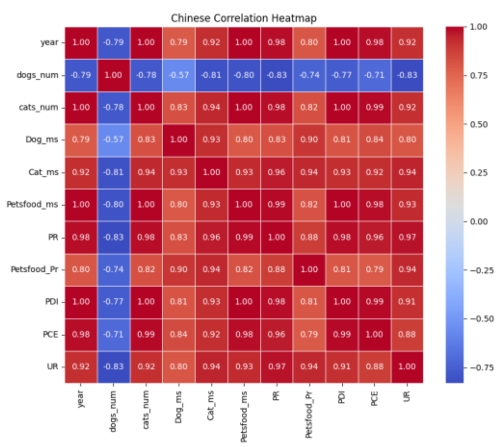
5.2 Question 2: Model Construction and Solution

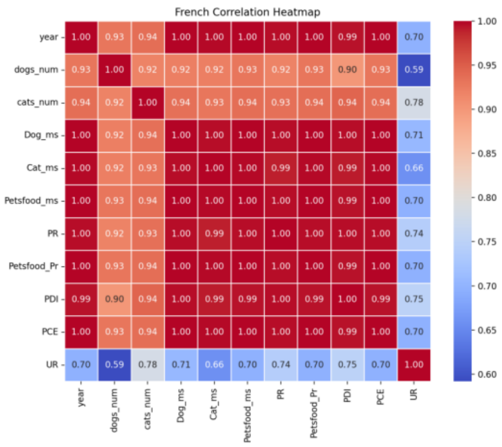
5.2.1 Data Preprocessing

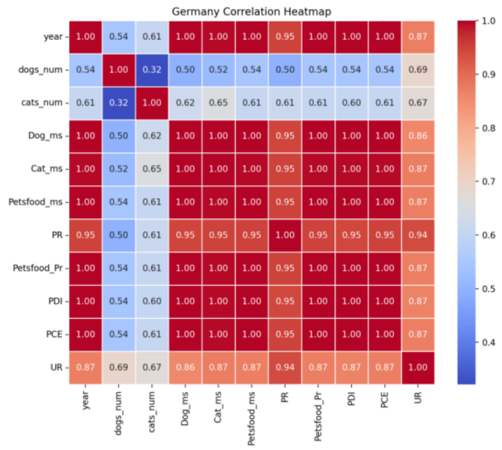
In recent years, the pet industry in overseas markets, such as Europe and North America, has experienced rapid growth, leading to an increase in global demand for pet food. According to research, the pet food markets in North America, Europe, and Asia dominate the global landscape. Therefore, we primarily investigate data related to the pet food industries in the United States, Brazil, France, Germany, China, and Japan. The key factors considered include the number of dogs, the number of cats, the market size for dogs, the market size for cats, the pet food market size, the market share of pet food, pet food prices, per capita disposable income, per capita consumption levels, and urbanization rates.

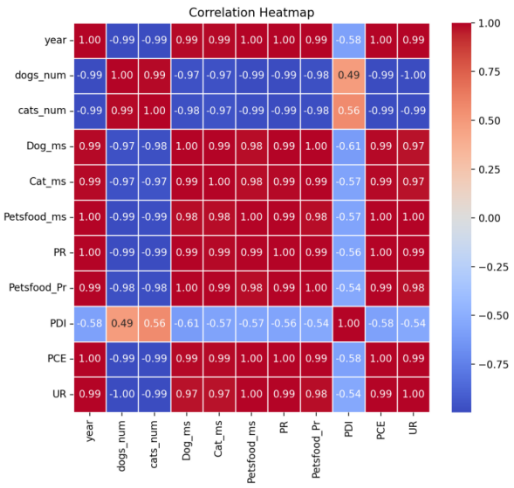
Given the presence of multiple influencing factors and based on the performance of the model used in Question 1, we opted to use Multiple Linear Regression (MLR) as the predictive model for Question 2. A heatmap correlation analysis was conducted for the relevant data from each country, and the results are as follows:

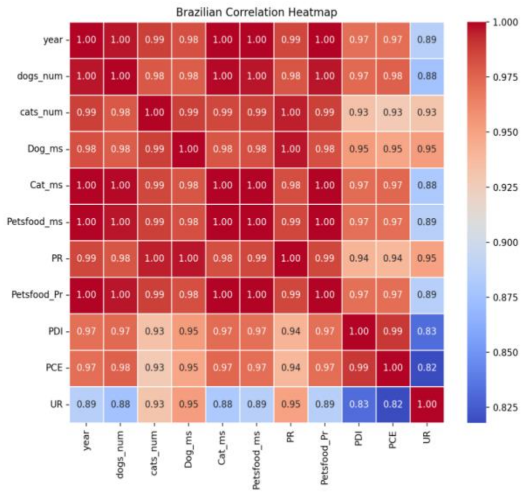






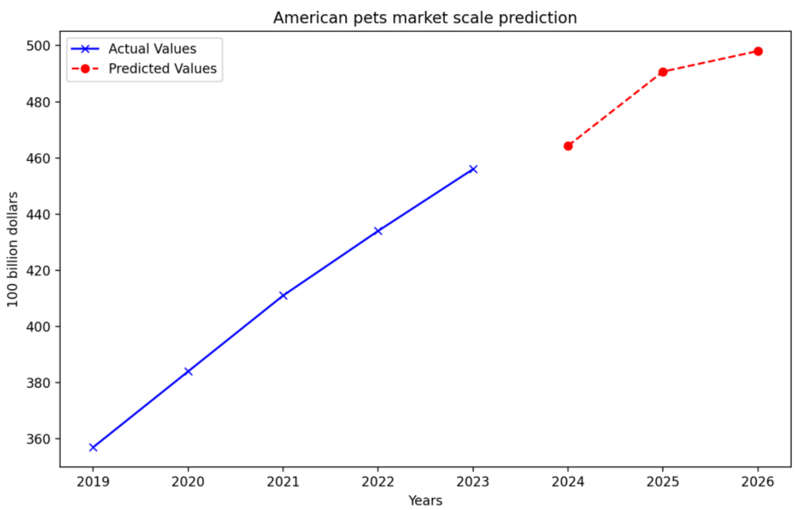


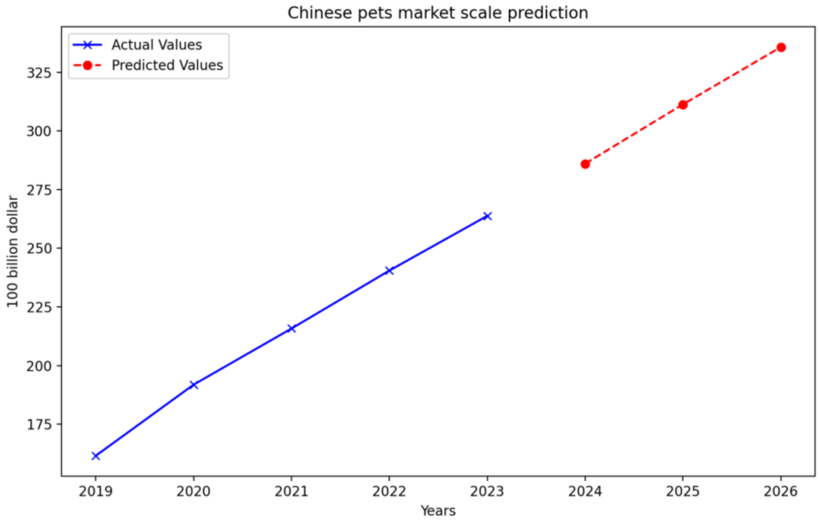


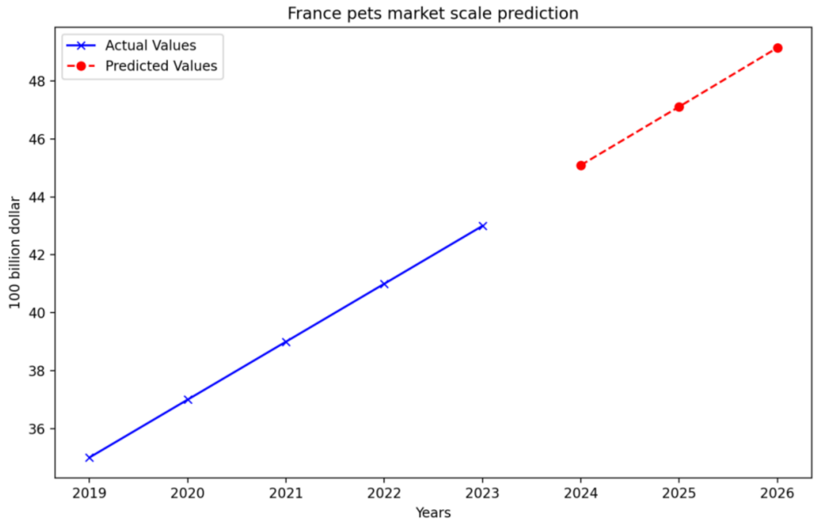


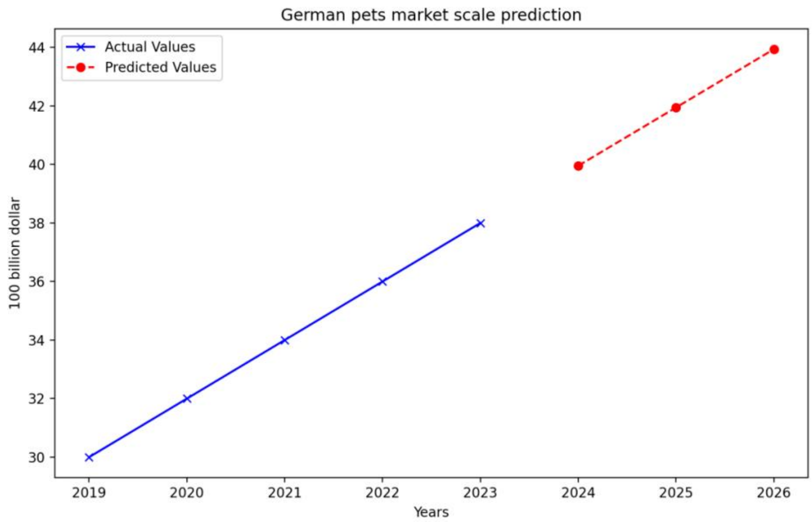
5.2.2 The Multiple Linear Regression (MLR) model is employed to predict the pet food market size for each country.

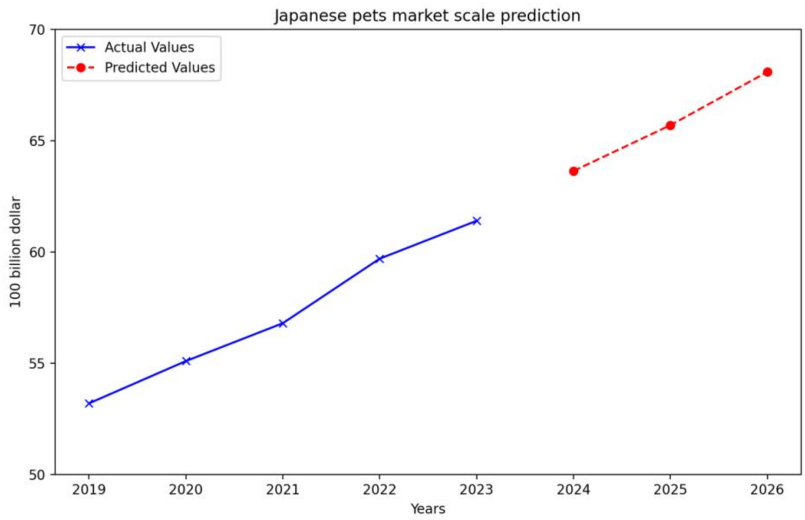
For each country, heatmap correlation analyses were performed to identify the variables most strongly correlated with pet food market size. These selected variables were used as features in the MLR model to predict the pet food market size for the next three years. The prediction results are as follows:

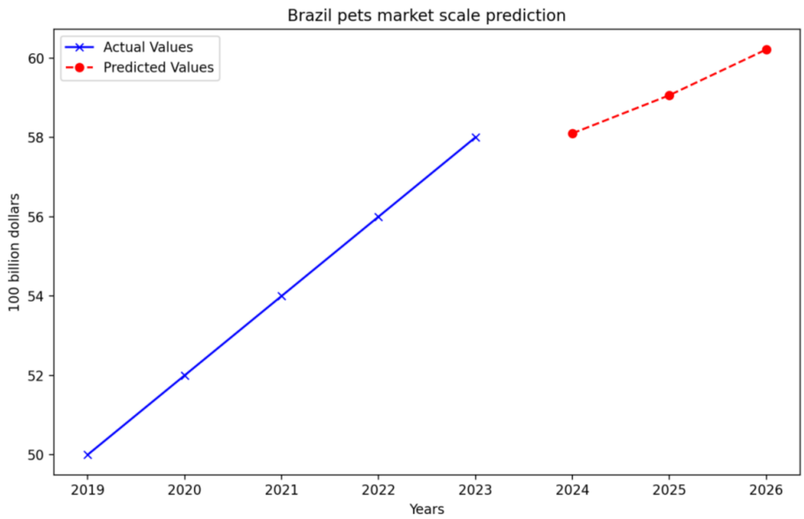



Chinese pets market scale prediction
Actual Values
Predicted Values
100 billion dollar
Years


France pets market scale prediction
Actual Values
Predicted Values
100 billion dollar
Years


German pets market scale prediction
Actual Values
Predicted Values
100 billion dollar
Years



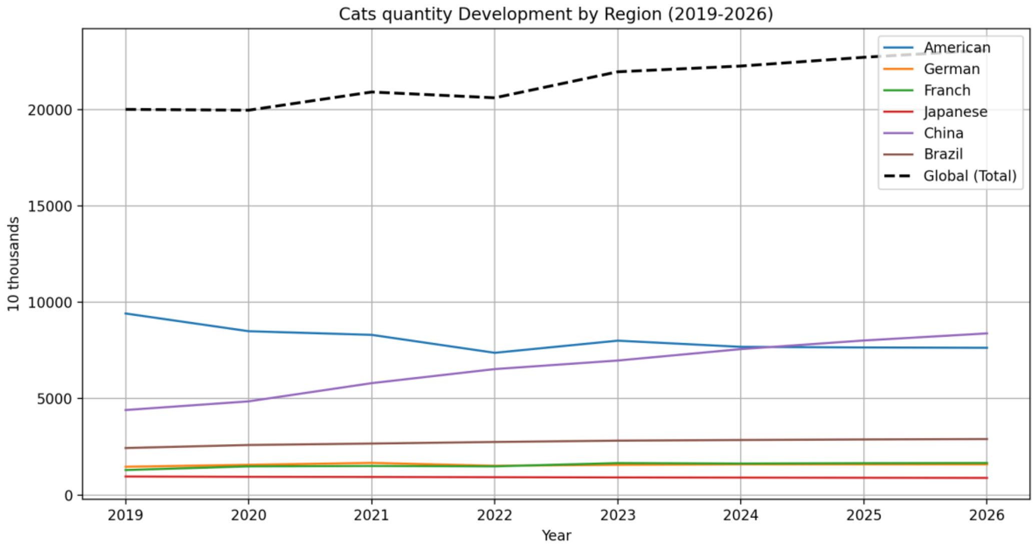


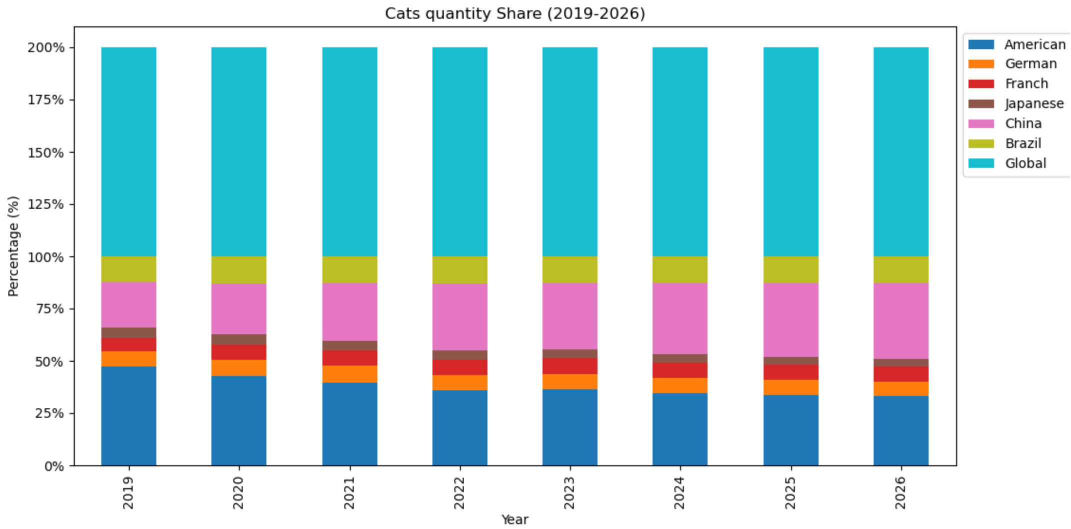
The predicted results are as follows:

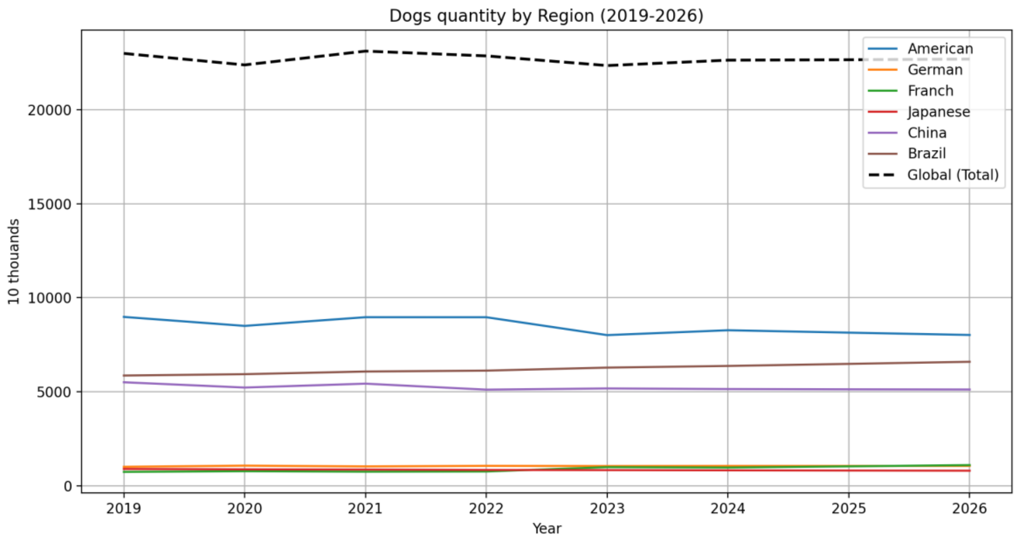
year	American (100 billion dollars)	German (100 billion dollars)	Franch (100 billion dollars)	China (100 billion dollars)	Brazil (100 billion dollars)	Japan (100 billion dollars)
2024	464.3097	39.95336	45.09633	286.0237	58.09957	63.63976
2025	490.7397	41.94467	47.11519	311.3347	59.06028	65.69419
2026	498.0538	43.93574	49.15098	335.6917	60.21357	68.08602

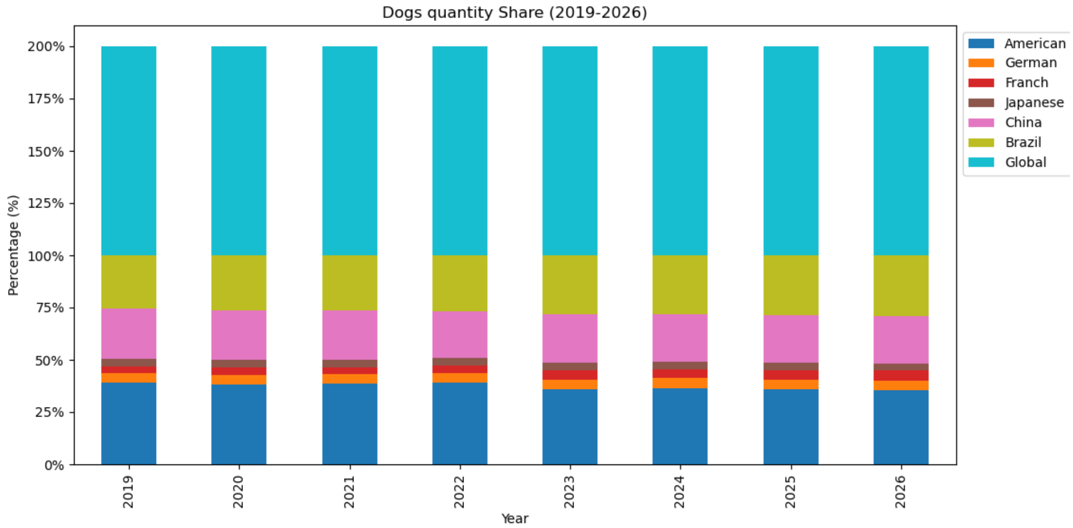
5.2.3 Forecast for Global Pet Food Market Demand Over the Next Three Years

We analyzed and predicted the development trends of the global dog and cat populations over the next three years (2024-2026), as well as the market share of each country's dog and cat populations globally. The predicted results are as follows:


Cats quantity Development by Region (2019-2026)
American
German
Franch
Japanese
China
Brazil
Global (Total)
10 thousands
Year


Cats quantity Share (2019-2026)
American
German
Franch
Japanese
China
Brazil
Global
Percentage (%)
Year


Dogs quantity by Region (2019-2026)
American
German
Franch
Japanese
China
Brazil
Global (Total)
10 thouands
Year



Based on the predictions from the models, the following graphs and analysis are presented:

a. Global Cat Population Trends

a) Overall Trend:

Globally, the number of cats is showing a steady increase.

Predictions suggest that the number of cats will continue to rise over the next three years, reflecting the growing popularity of pet cats and increasing willingness to raise them.

b) Regional Performance:

- United States: While the number of cats remains high, it shows a slight decline, indicating that the U.S. market may be nearing saturation.
- China: Exhibits significant growth and is one of the fastest-growing regions in terms of cat population, likely due to the rapid development of pet-raising culture in China.
- Other Regions: Countries such as France, Germany, and Japan show limited growth, possibly because their markets have reached a stable state.

c) Future Prediction:

The global cat population will continue to grow over the next three years, with market potential primarily concentrated in emerging markets (such as China and Brazil).

d) Industry Impact:

Demand for cat-related products (e.g., cat food, litter, and toys) is expected to rise.

Emerging markets, particularly in Asia and South America, are likely to become the growth hubs for the industry.

b. Global Dog Population Trends

a) Overall Trend:

Globally, the number of dogs remains relatively stable, although some regions show a slight decline.

The forecast for the next three years suggests that the dog population may either decline slightly or remain stable.

b) Regional Performance:

- United States: The dog population remains stable with a slight decline, which may reflect market maturity and changes in household structure (e.g., increased diversification in pet types).
- China: The dog population has slightly decreased, possibly due to policy restrictions (e.g., pet ownership laws) and the influence of urbanization.
- Brazil: As a large dog-owning market, the dog population remains stable, supported by cultural habits.
- Other Countries: In Japan and some European countries, growth is limited, indicating market saturation.

c) Future Prediction:

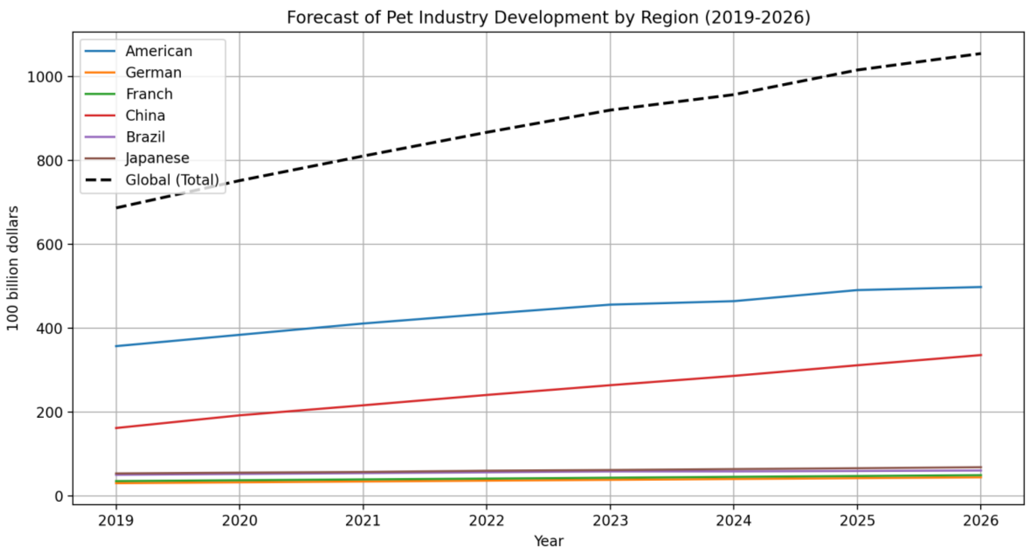
The global dog population is not expected to change significantly in the short term, although it may be influenced by urbanization and shifts in pet type preferences.

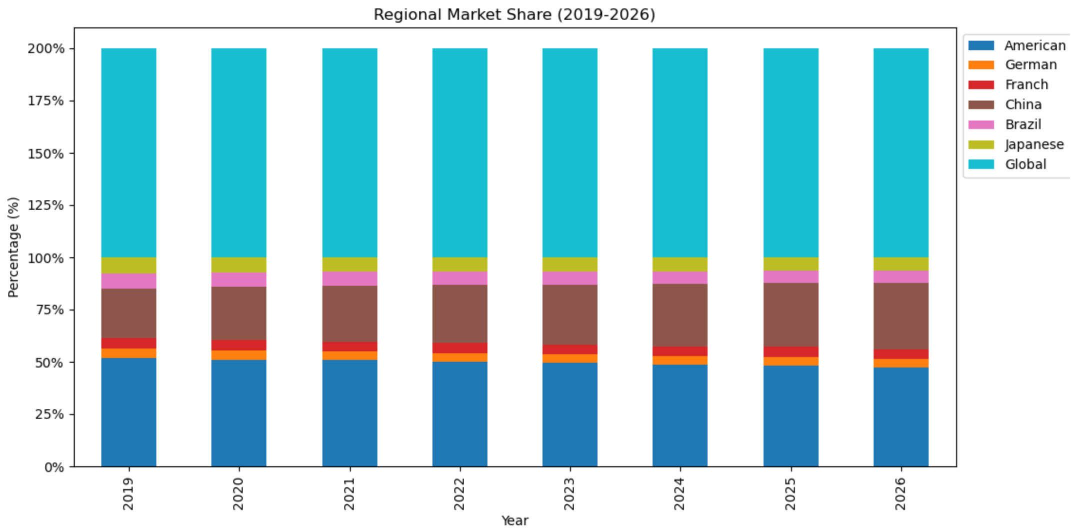
d) Industry Impact:

The dog-related product market will remain stable, though new demand growth may be limited.

In certain regions (e.g., China and the U.S.), consumers may prefer smaller dog breeds or other types of pets, driving further segmentation within the industry.

Since the surveyed regions dominate the global pet food market, the total global pet food demand forecast was obtained by summing the predicted values for each region. The total demand and the market share of each country are as follows:





The predicted results are as follows:

year	Global(100 billion dollars)
2024	957.122408
2025	1015.888776
2026	1055.131883

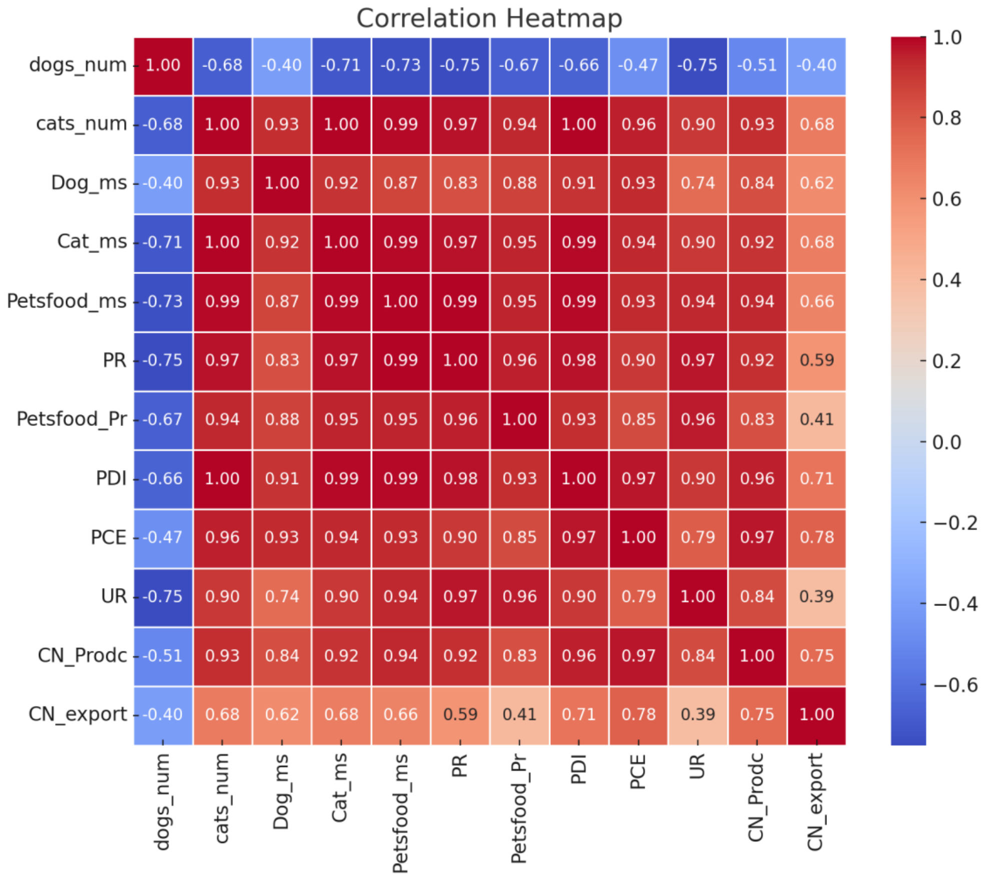
5.3 Question 3: Model Construction and Solution

5.3.1 Data Preprocessing

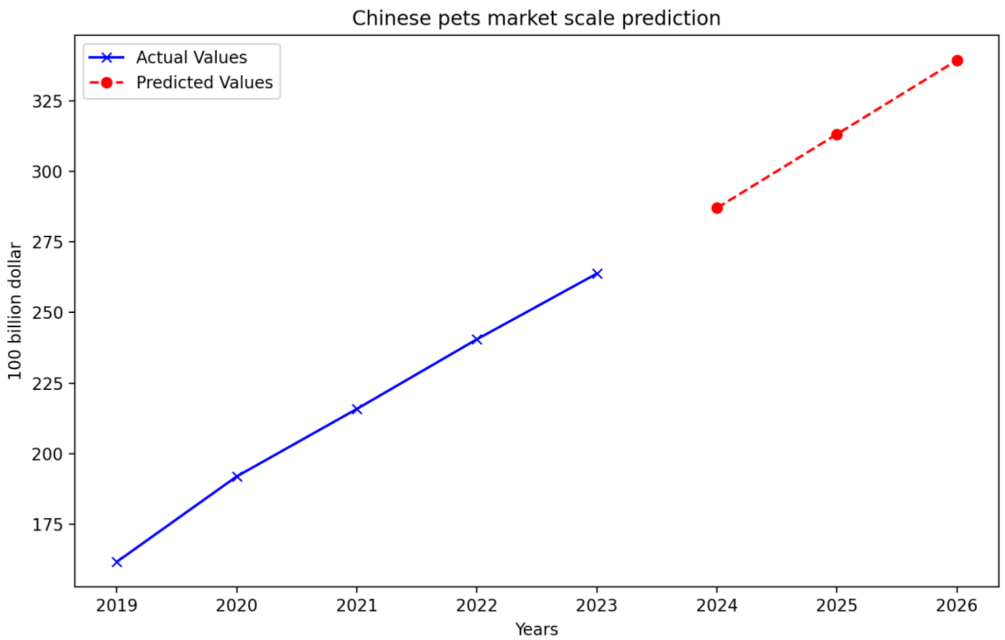
In this question, we combine the data from Questions 1 and 2, along with the production and export data of pet food in China provided in the problem, to analyze the development of the pet food industry in China and predict the global demand for pet food over the next three years.

5.3.2 The analysis of the development of the pet food industry in China.

Based on the second question, the data on pet food production and export value in China is added. A correlation heatmap is used to analyze the relationship between various factors and the pet food industry in China, resulting in the following outcomes:



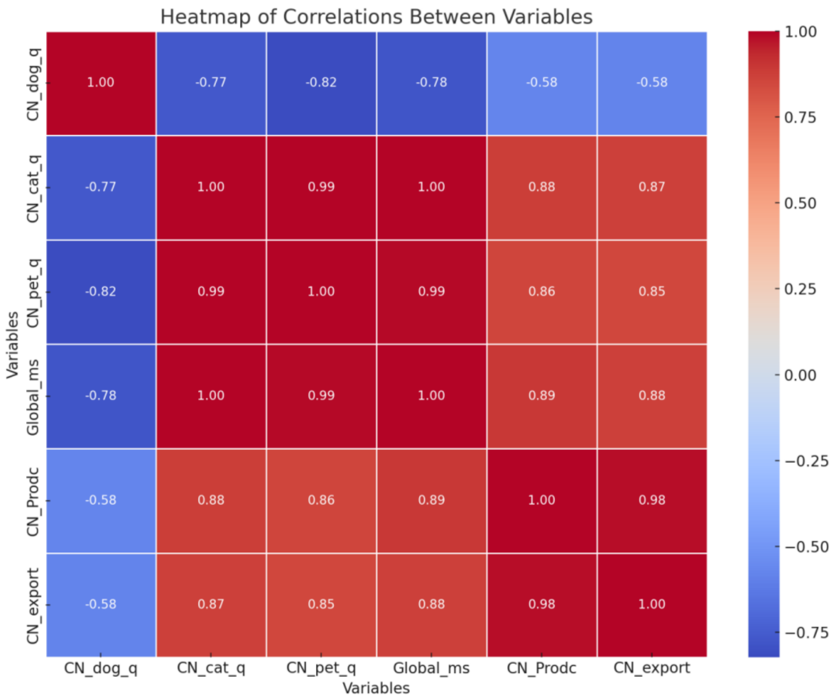
Based on the heatmap correlation analysis, factors with a strong correlation to the Chinese pet food market were selected. Using the MLR model, we analyzed the development of the Chinese pet food market over the past five years and predicted its growth over the next three years. The results obtained from the MLR model analysis are as follows:



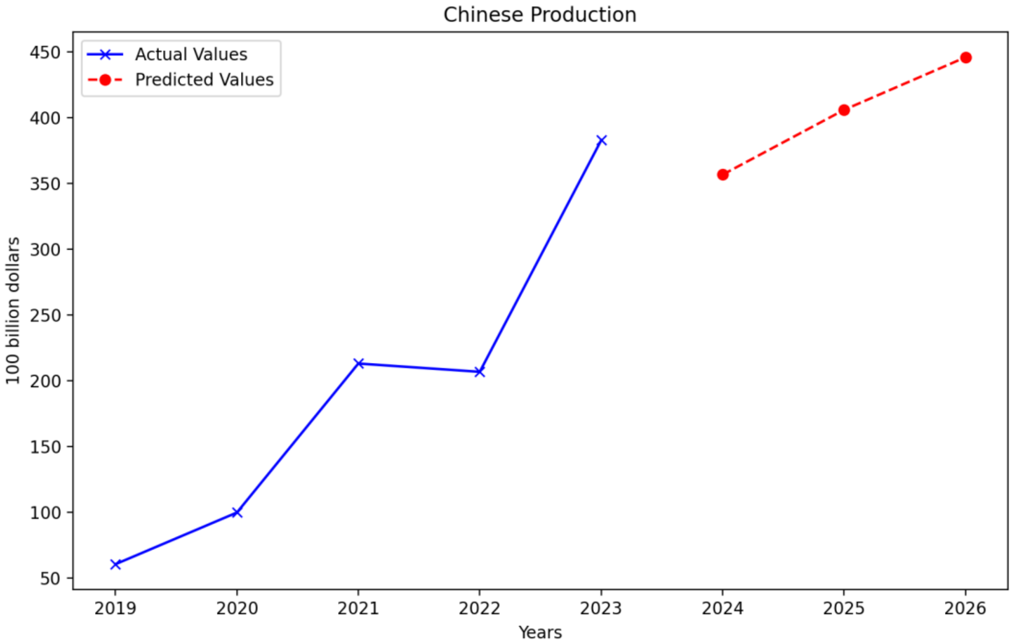
It can be observed that the pet food industry in China has shown a growth trend over the past five years and is expected to continue this upward trend in the future.

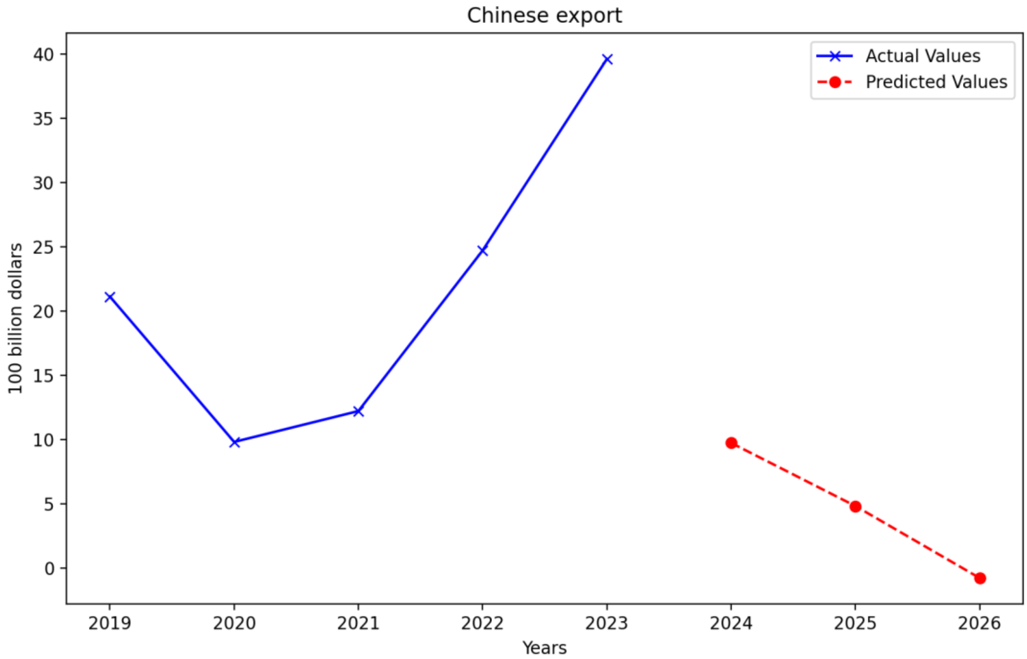
5.3.3 Using Multiple Linear Regression (MLR) to predict the production value and export value of China's pet food industry.

Considering that the pet food industry in China is influenced by multiple factors, and there are certain correlations between these factors, Multiple Linear Regression (MLR) is selected to predict the production value and export value of China's pet food industry over the next three years. First, a correlation heatmap between the variables is plotted as follows:



Based on the results of the correlation heatmap, factors with a strong correlation to the production value and export value of China's pet food industry are selected as features. Multiple Linear Regression (MLR) is then used to predict the production and export values of China's pet food industry for the next three years. The results are as follows:

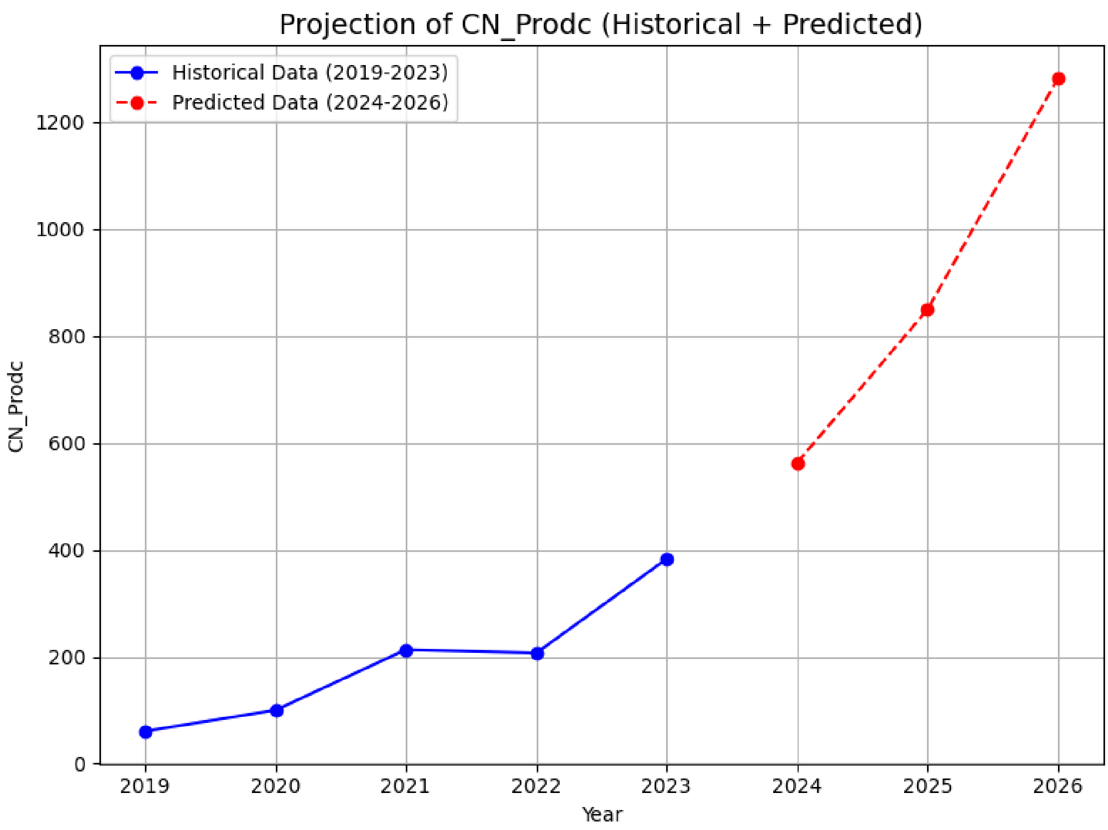


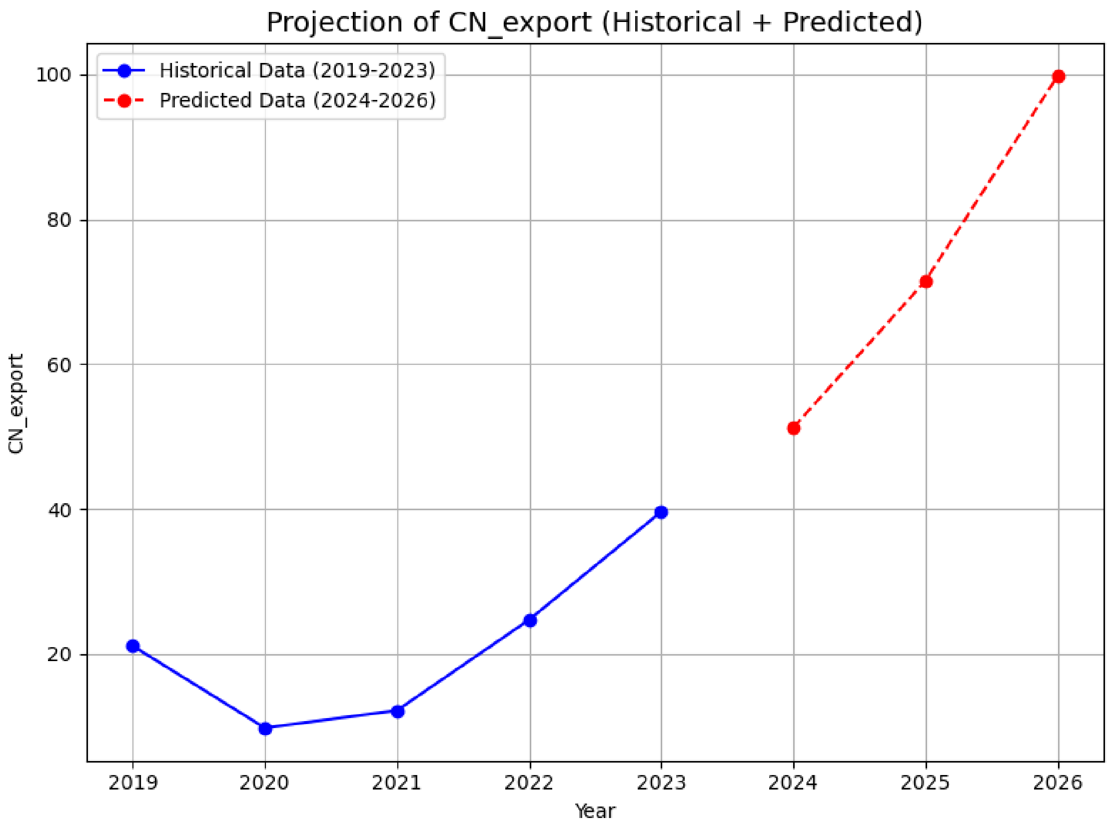


The predicted values obtained are as follows:

year	Production(100 billion dollars)	Export(100 billion dollars)
2024	356.44693504	9.72142637
2025	405.68654879	4.81092374
2026	445.65477395	-0.79064116

It was observed that the predicted export value of China's pet food industry decreases annually from 2024 to 2026 and turns negative by 2026. Upon further analysis, this anomaly can be attributed to a significant decline in export value between 2019 and 2020, as shown in Appendix 3, which had a substantial impact on the model parameters. Consequently, the predicted value for 2026 resulted in an unreasonable outcome. Therefore, without considering policy factors, and recognizing that the overall trend of the Chinese pet food industry exhibits growth over time, influenced by various factors such as the market, we have decided to use the Logistic Growth Model[3] to make a revised prediction of the production and export values for China's pet food industry. The updated prediction results are as follows:





The predicted values obtained are as follows:

year	Production(100 billion dollars)	Export(100 billion dollars)
2024	562.5199599668122	51.20388604295047
2025	848.989296258607	71.45031034879881
2026	1281.345911683736	99.70232923558311

In summary, we found that using the Logistic Growth Model to predict the production and export values of China's pet food market is more reasonable when policy factors are excluded. In contrast, the predictions generated by the MLR model showed significant deviations, likely due to the substantial influence of policy factors on the production and export values of the pet food market in China. Therefore, in the absence of policy considerations, we ultimately choose the predictions from the Logistic Growth Model as the final results.

5.4 Question 4: Model Construction and Solution

5.4.1 Data Preprocessing

Building on the analysis in Question 3, we further quantified the impact of international taxation policies. As revealed in Question 2, the United States holds a significant share of the global pet market. Therefore, we primarily focus on the U.S. tariff policies toward China. In contrast, since the European Union's tariff policies toward China remained relatively stable from 2019 to 2023, the influence of EU tariffs is excluded from consideration.

The analysis focuses on the impact of U.S. policies on China's pet market. According to investigations, during 2019–2020, the U.S.-China trade war led to a significant increase in U.S. tariffs on Chinese goods, resulting in a sharp short-term decline in China's export volume. Based on relevant data, it is evident that tariffs have a substantial effect on China's domestic market. Additionally, the U.S. dollar exchange rate also influences global economic trade to some extent, and thus it is included in the scope of consideration.

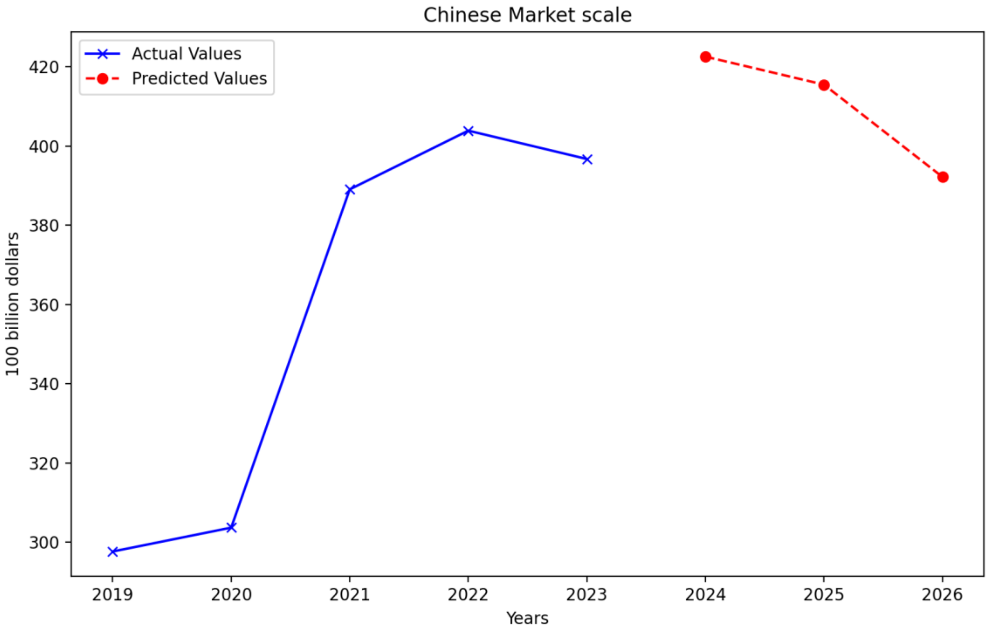
Subsequently, building on the solutions to the first three questions, an in-depth analysis and calculation of global pet market demand trends and the development trajectory of China's pet food market have been conducted. These aspects are intricately linked to the future development of China's pet food industry, warranting further discussion regarding their combined impact on its future growth.

5.4.2 The future development of China's pet food industry over the next three years is predicted using the Logistic model.

Firstly, considering the high correlation of various variables with time, the Logistic model was applied to predict each variable as well as the market size of China's pet food industry. The prediction results are presented in Question 3.

5.4.3 The future development of China's pet food industry over the next three years is predicted using the Multiple Linear Regression (MLR) model.

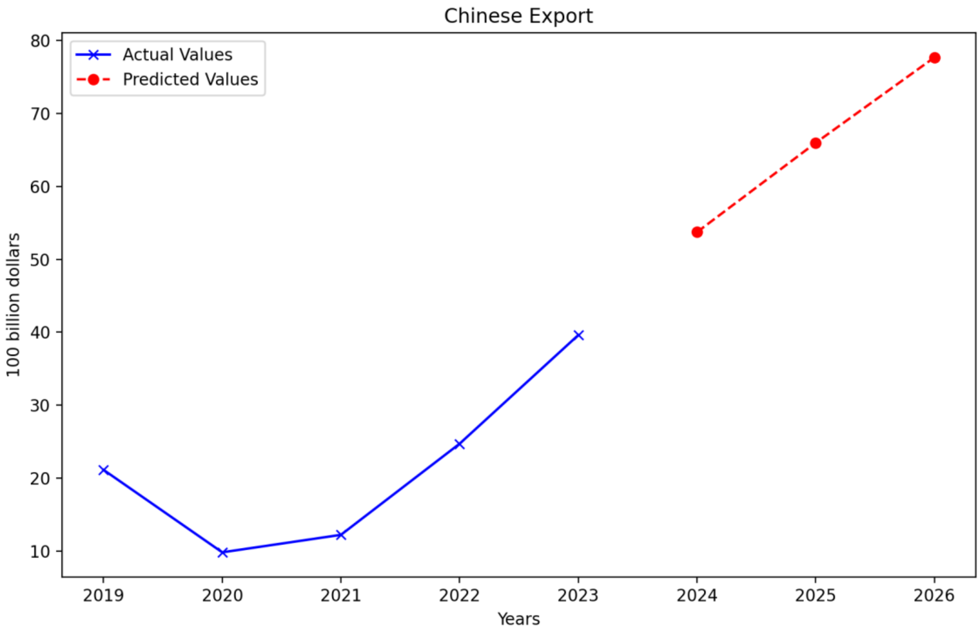
Considering that China's pet food industry is influenced by multiple factors, including international trade and economic policies, the Multiple Linear Regression (MLR) model was chosen to predict the future trends in the industry's market size. The prediction results are as follows:



As shown in the figure, the domestic market size of China's pet food industry is expected to reach saturation in the coming years, with a potential decline within a certain range.

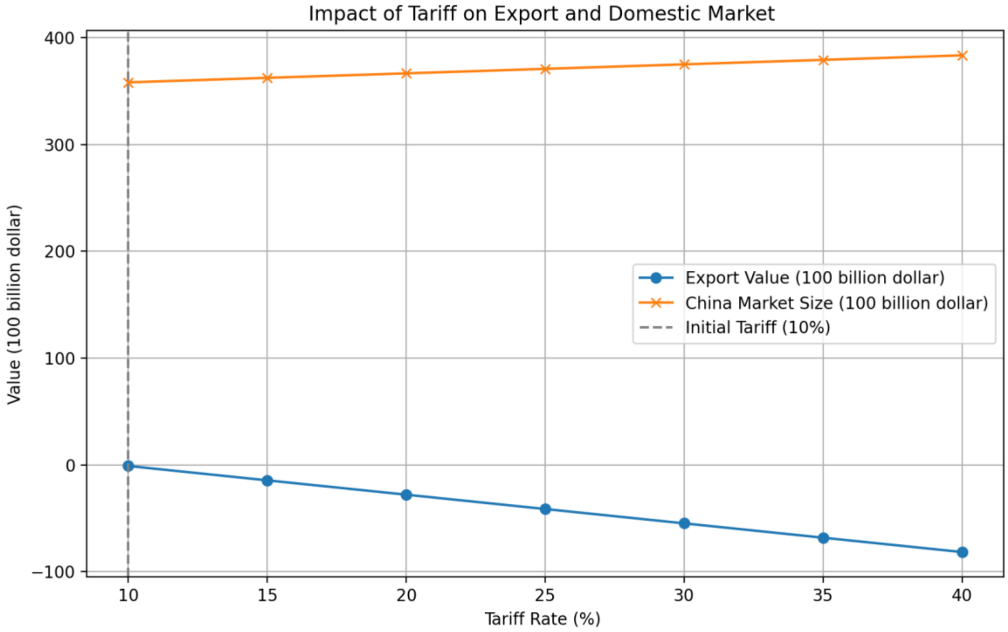
According to research, for every 1% increase in export tariffs, domestic market sales increase by 0.235%.[4] Therefore, an elasticity model is established, taking into account the substitution effect in the domestic market. The elasticity coefficient of domestic sales with respect to tariffs is set at 0.235%. Based on this, an MLR (Multiple Linear Regression) model is constructed.

The following analysis focuses on incorporating various factors to develop the MLR model, predicting and discussing its impact on the export volume of China's pet food industry. The prediction results are as follows:



As illustrated in the figure, the export volume of China's pet food market is projected to show an upward trend in the future, aligning with the time-based forecast results. Furthermore, this growth trend better matches the demands of the international market. Comparing these results with the predictions in Question 3, which excluded policy factors, reveals that policy factors have a significant impact on China's pet food industry.

On this basis, an MLR (Multiple Linear Regression) model is developed to analyze the impact of tariff changes on China's pet market size and export volume. The analysis is as follows:



The figure indicates that as tariffs increase, export volumes decline significantly, highlighting the substantial negative impact of tariffs on exports. Meanwhile, the domestic market size shows a growth trend, though at a slower rate, which is insufficient to offset the negative impact caused by the decline in export volumes.

In conclusion, based on the analysis of China’s pet food industry[5], the following strategies are proposed to promote its sustainable development:

a. Diversified Market Expansion: Explore emerging markets such as Southeast Asia, Latin America, and Africa to reduce dependence on a single market and mitigate trade risks.

b. Monitoring International Trade Policies: Closely track changes in tariff policies in major markets like the U.S. and Europe to adjust export strategies promptly and navigate trade barriers effectively.

c. Strengthening International Collaboration and Exchange: Actively participate in international industry exhibitions and forums to understand global market trends, learn from advanced practices, and expand cooperation opportunities.

By implementing these strategies, China’s pet food industry can achieve sustainable growth in the face of complex international trade environments.

VI. References

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[2] Aziz A ,Anwar M M .Assessing the Level of Urban Sustainability in the Capital of Pakistan: A Social Analysis Applied through Multiple Linear Regression[J].Sustainability,2024,16(7):

[3] Mishra N ,Ashok S ,Tandon D .Predicting Financial Distress in the Indian Banking Sector: A Comparative Study Between the Logistic Regression, LDA and ANN Models[J].Global Business Review,2024,25(6):1540-1558.

[4] Chen B ,Guo D ,Li Y , et al.How U.S. tariffs impact China's domestic sourcing: Evidence from firm-to-firm transactions[J].Journal of International Money and Finance,2025,150103216-103216.

[5] CBD Pet Market Demand, Growth, Opportunities and Analysis Of Top Key Player Forecast To 2030[J].M2 Presswire,2021,

VII. Appendix

Appendix I: Using the MLR Model to Predict the Development of China's Pet Industry for the Next Three Years and Visualization:

```
import sys
import io
sys.stdout = io.TextIOWrapper(sys.stdout.buffer, encoding='utf-8')
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import seaborn as sns

def load_data(filepath):
    df = pd.read_csv(filepath)
    return df

def preview_data(df):
    print("First five lines in dataset:")
    print(df.head())
    print("\nData description:")
    print(df.describe())
    print("\nMissing values:")
    print(df.isnull().sum())

def preprocess_data(df, feature_columns, target_column):
    X = df[feature_columns].values
    y = df[target_column].values
    return X, y

def split_data(X, y, test_size=3/8, random_state=42):
    return train_test_split(X, y, test_size=test_size, random_state=random_state)
```

```
def train_model(X_train, y_train):
    model = LinearRegression()
    model.fit(X_train, y_train)
    return model

def print_model_coefficients(model, feature_columns):
    for feature, coef in zip(feature_columns, model.coef_):
        print(f"{feature}: {coef:.2f}")

def predict(model, X_test):
    return model.predict(X_test)

def evaluate_model(y_test, y_pred):
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    print(f"Mean Squared Error (MSE): {mse:.2f}")
    print(f"R-squared (R²): {r2:.2f}")

def visualize_predictions(y,y_pred):
    plt.figure(figsize=(10, 6))
    years = [2024,2025,2026]
    year=[2019,2020,2021,2022,2023]
    #plt.plot(range(len(y)), y, label="actuall Values", marker='o')
    plt.plot(year, y, label="Actual Values", color="blue", marker='x')
    plt.plot(years, y_pred, label="Predicted Values", color="red",marker='o',linestyle="-
-")
    plt.title('Actual Values & Predicted Values')
    plt.xlabel('Years')
    plt.ylabel('PetsN')
    year=np.append(year, years)
    plt.xticks(year)
    plt.legend()
    plt.show()
```

```
if __name__ == "__main__":
    filepath = 'Quiz_1\Pest_quantity_MLR\total_num_2.csv'
    df = load_data(filepath)

    preview_data(df)

    feature_columns = ['PDI', 'PCE', 'PN', 'PetsP']
    target_column = 'PetsN'

    X, y = preprocess_data(df, feature_columns, target_column)
    z=X[5:]
    X=X[:5]
    y=y[:5]

    X_train, X_test, y_train, y_test = split_data(X, y)

    model = train_model(X_train, y_train)

    print_model_coefficients(model, feature_columns)

    y_pred = predict(model, z)
    print(y_pred)

visualize_predictions(y,y_pred)
```

Appendix II: Predicting the Future Three Years of China's Pet Market Data Using the ARIMA Time Series Model and Visualization:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
from statsmodels.tsa.arima.model import ARIMA
from statsmodels.tsa.stattools import adfuller
```

```
from statsmodels.graphics.tsaplots import plot_acf, plot_pacf
from matplotlib.ticker import MaxNLocator

def load_data(filepath):
    df = pd.read_csv(filepath, parse_dates=['year'], index_col='year')
    df.index = pd.to_datetime(df.index, format='%Y')

    return df

def visualize_data(df, column):

    plt.figure(figsize=(10, 6))
    plt.plot(df[column], label='ten thousand')

    ax = plt.gca()
    ax.xaxis.set_major_locator(mdates.YearLocator())
    ax.xaxis.set_major_formatter(mdates.DateFormatter('%Y'))

    plt.title('dog quantity in five years')
    plt.xlabel('year')
    plt.ylabel('quantity')
    plt.legend()



    plt.show()

def check_stationarity(data):

    result = adfuller(data)
    print('ADF Statistic:', result[0])
    print('p-value:', result[1])
    print('Critical Values:', result[4])
    if result[1] < 0.05:
        print("True")
```

```
    else:
        print("False,will done")

def difference_data(data, lag=1):

    return data.diff(periods=lag).dropna()

def plot_acf_pacf(data):

    fig, axes = plt.subplots(1, 2, figsize=(16, 6))
    plot_acf(data, ax=axes[0], lags=1)
    plot_pacf(data, ax=axes[1], lags=1)
    axes[0].set_title('Autocorrelation (ACF)')
    axes[1].set_title('Partial Autocorrelation (PACF)')
    plt.show()

def fit_arima(data, order):
    model = ARIMA(data, order=order)
    fitted_model = model.fit()
    print(fitted_model.summary())
    return fitted_model
def forecast_arima(model, steps):
    forecast = model.forecast(steps=steps)
    return forecast

if __name__ == "__main__":
    filepath = 'Quiz_1/pets_quantity_ARIMA/total_num_2.csv'
    df = load_data(filepath)



    column = 'PetsN'
    visualize_data(df, column)
```

```
        check_stationarity(df[column])



        diff_data = difference_data(df[column])
        visualize_data(pd.DataFrame(diff_data, columns=['Differenced Data']), 'Differenced
Data')
        check_stationarity(diff_data)



        plot_acf_pacf(diff_data)



        p, d, q = 1, 1, 1
        model = fit_arima(df[column], order=(p, d, q))

        forecast = forecast_arima(model, steps=3)
    print("forecast:", forecast)
```

Appendix III: Using MLR to Predict the Pet Industry Figures for Different Regions:

```
import sys
import io
sys.stdout = io.TextIOWrapper(sys.stdout.buffer, encoding='utf-8')
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import seaborn as sns

def load_data(filepath):
    df = pd.read_csv(filepath)
    return df
```

```
def preview_data(df):
    print("First five lines in dataset:")
    print(df.head())
    print("\nData description:")
    print(df.describe())
    print("\nMissing values:")
    print(df.isnull().sum())

def preprocess_data(df, feature_columns, target_column):
    X = df[feature_columns].values
    y = df[target_column].values
    return X, y

def split_data(X, y, test_size=3/8, random_state=42):
    return train_test_split(X, y, test_size=test_size, random_state=random_state)

def train_model(X_train, y_train):
    model = LinearRegression()
    model.fit(X_train, y_train)
    return model

def print_model_coefficients(model, feature_columns):
    for feature, coef in zip(feature_columns, model.coef_):
        print(f"{feature}: {coef:.2f}")

def predict(model, X_test):
    return model.predict(X_test)

def evaluate_model(y_test, y_pred):
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    print(f"Mean Squared Error (MSE): {mse:.2f}")

def visualize_predictions(y,y_pred):
```

```
    plt.figure(figsize=(10, 6))
    years = [2024,2025,2026]
    year=[2019,2020,2021,2022,2023]
    #plt.plot(range(len(y)), y, label="actuall Values", marker='o')
    plt.plot(year, y, label="Actual Values", color="blue", marker='x')
    plt.plot(years, y_pred, label="Predicted Values", color="red",marker='o',linestyle="-
-")
    plt.title('American pets market scale prediction')
    plt.xlabel('Years')
    plt.ylabel('100 billion dollars')
    year=np.append(year, years)
    plt.xticks(year)
    plt.legend()
    plt.show()

if __name__ == "__main__":
    filepath = 'Quiz_2\American\American_train_data.csv'
    df = load_data(filepath)

    preview_data(df)

    feature_columns = ['Dog_ms', 'PR', 'Cat_ms','PDI','UR']
    target_column = 'Petsfood_ms'

    X, y = preprocess_data(df, feature_columns, target_column)
    z=X[5:]
    X=X[:5]
    y=y[:5]

    X_train, X_test, y_train, y_test = split_data(X, y)

    model = train_model(X_train, y_train)

    print_model_coefficients(model, feature_columns)
```

```
    y_pred = predict(model, z)
    print(y_pred)

    visualize_predictions(y,y_pred)
```

Appendix IV: Calculating Global Total and Regional Market Shares with Visualization:

```
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.ticker import PercentFormatter

regions = ['American', 'German', 'Franch', 'China', 'Brazil','Japanese']
forecast_years = [2019, 2020, 2021, 2022, 2023, 2024, 2025, 2026]

df = pd.read_csv('Quiz_2\Global\ms\World_ms_train_data.csv', parse_dates=['year'], index_col='year')
df.index = pd.to_datetime(df.index, format='%Y')
#df = pd.DataFrame(region_data, index=forecast_years)
df['Global'] = df.sum(axis=1)

print(df['Global'])

plt.figure(figsize=(12, 6))
for region in regions:
    plt.plot(forecast_years, df[region], label=region)

plt.plot(forecast_years, df['Global'], label='Global (Total)', linestyle='--', color='black', linewidth=2)
plt.title('Forecast of Pet Industry Development by Region (2019-2026)')
plt.xlabel('Year')
plt.ylabel('100 billion dollars')
plt.xticks(forecast_years)
plt.legend()
plt.grid(True)
```

```
plt.show()

region_percentage = df.div(df['Global'], axis=0) * 100



region_percentage['year'] = [2019,2020,2021,2022,2023,2024, 2025, 2026]
region_percentage.plot(x='year', kind='bar', stacked=True, figsize=(12, 6),
colormap='tab10')
plt.title('Regional Market Share (2019-2026)')
plt.xlabel('Year')
plt.ylabel('Percentage (%)')
plt.gca().yaxis.set_major_formatter(PercentFormatter())
plt.legend(loc='upper left', bbox_to_anchor=(1.0, 1.0))
plt.show()
```

Appendix V: Using the Logistic Model to Predict Export Volume and Visualization

```
import numpy as np
from scipy.optimize import curve_fit
import matplotlib.pyplot as plt
import pandas as pd
import os

def logistic_growth(x, K, P0, r):
    return K / (1 + ((K - P0) / P0) * np.exp(-r * x))

file_path = 'Quiz_3/history_data.csv'
data = pd.read_csv(file_path)
print(data.head())

years = data['year']
x = (years - years.min()).values
future_years_count = 3
future_years = np.arange(years.max() + 1, years.max() + future_years_count + 1)
```

```
    predictions = {}
    parameters = {}

    for column in data.columns[1:]:
        y = data[column].values
        try:

            popt, _ = curve_fit(logistic_growth, x, y, maxfev=10000, bounds=(0, [np.inf,
np.inf, 1]))
            parameters[column] = popt



            future_x = np.arange(len(x), len(x) + future_years_count)
            future_values = logistic_growth(future_x, *popt)
            predictions[column] = future_values
        except RuntimeError:

            predictions[column] = ["Model fit failed"] * future_years_count

    future_predictions_df = pd.DataFrame(predictions, index=future_years)
    future_predictions_df.index.name = 'year'

    full_data = pd.concat([data.set_index('year'), future_predictions_df])

    for column in data.columns[1:]:
        plt.figure(figsize=(8, 6))



        plt.plot(data['year'], data[column], marker='o', label='Historical Data (2019-2023)',
color='blue')

        if column in predictions:
                plt.plot(future_years, predictions[column], marker='o', linestyle='--',
label='Predicted Data (2024-2026)', color='red')
```

```
    plt.title(f"Projection of {column} (Historical + Predicted)", fontsize=14)
    plt.xlabel("Year")
    plt.ylabel(column)
    plt.legend()
    plt.grid(True)
    plt.tight_layout()
    plt.show()

    print(predictions[column])
```

Appendix VI: Using MLR to Predict Export Volume and Visualization:

```
import sys
import io
sys.stdout = io.TextIOWrapper(sys.stdout.buffer, encoding='utf-8')
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import seaborn as sns

def load_data(filepath):
    df = pd.read_csv(filepath)
    return df

def preview_data(df):
    print("First five lines in dataset:")
    print(df.head())
    print("\nData description:")
    print(df.describe())
    print("\nMissing values:")
    print(df.isnull().sum())
```

```
def preprocess_data(df, feature_columns, target_column):
    X = df[feature_columns].values
    y = df[target_column].values
    return X, y

def split_data(X, y, test_size=3/8, random_state=42):
    return train_test_split(X, y, test_size=test_size, random_state=random_state)

def train_model(X_train, y_train):
    model = LinearRegression()
    model.fit(X_train, y_train)
    return model

def print_model_coefficients(model, feature_columns):
    for feature, coef in zip(feature_columns, model.coef_):
        print(f"{feature}: {coef:.2f}")

def predict(model, X_test):
    return model.predict(X_test)

def evaluate_model(y_test, y_pred):
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    print(f"Mean Squared Error (MSE): {mse:.2f}")
    print(f"R-squared (R2): {r2:.2f}")

def visualize_predictions(y,y_pred):
    plt.figure(figsize=(10, 6))
    years = [2024,2025,2026]
    year=[2019,2020,2021,2022,2023]
    #plt.plot(range(len(y)), y, label="actuall Values", marker='o')
    plt.plot(year, y, label="Actual Values", color="blue", marker='x')
    plt.plot(years, y_pred, label="Predicted Values", color="red",marker='o',linestyle="-
```

```
-")
        plt.title('Chinese Production')
        plt.xlabel('Years')
        plt.ylabel('100 billion dollars')
        year=np.append(year, years)
        plt.xticks(year)
        plt.legend()
        plt.show()

    if __name__ == "__main__":
        filepath = 'Quiz_3/future_data.csv'
        df = load_data(filepath)

        preview_data(df)

        feature_columns = ['CN_dog_q', 'CN_cat_q', 'CN_pet_q','Global_ms']
        target_column = 'CN_Prodc'

        X, y = preprocess_data(df, feature_columns, target_column)
        z=X[5:]
        X=X[:5]
        y=y[:5]

        X_train, X_test, y_train, y_test = split_data(X, y)

        model = train_model(X_train, y_train)

        print_model_coefficients(model, feature_columns)

        y_pred = predict(model, z)
        print(y_pred)

        visualize_predictions(y,y_pred)
```

Appendix VII: Using MLR and Elasticity Coefficients to Quantify the Impact of Tariff Policies on Regression Parameters and Visualization:

```
import numpy as np
from scipy.optimize import curve_fit
import matplotlib.pyplot as plt
import pandas as pd

# Load the dataset to understand its structure
file_path = 'Quiz_4\data_4.csv'
data = pd.read_csv(file_path)

# Display the first few rows of the dataset for initial inspection
data.head()

# Logistic growth model function
def logistic_growth(x, K, P0, r):
    return K / (1 + ((K - P0) / P0) * np.exp(-r * x))

# Preparing the data for modeling
years = data['year']
x = (years - years.min()).values   # Normalizing years to start from 0
future_years = np.arange(years.max() + 1, years.max() + 4)   # Next three years

predictions = {}
parameters = {}

# Predicting each column using logistic growth model
for column in data.columns[1:]:   # Exclude 'year'
    y = data[column].values

    # Fit logistic model
    try:
        popt, _ = curve_fit(logistic_growth, x, y, maxfev=10000, bounds=(0, [np.inf, np.inf, 1]))
```

```
            parameters[column] = popt

            # Predict future values
            future_x = np.arange(len(x), len(x) + 3)   # Future years relative to x
            future_values = logistic_growth(future_x, *popt)
            predictions[column] = future_values
        except RuntimeError:
            predictions[column] = ["Model fit failed"] * 3

    # Create a DataFrame for predictions
    future_predictions_df = pd.DataFrame(predictions, index=future_years)
    future_predictions_df.index.name = 'year'

    # Combine past data and predictions
    full_data = pd.concat([data.set_index('year'), future_predictions_df])

    # Plotting predictions
    for column in data.columns[1:]:
        plt.figure()
        plt.plot(full_data.index, full_data[column], marker='o', label='Actual + Predicted')
        plt.title(f"Projection of {column}")
        plt.xlabel("Year")
        plt.ylabel(column)
        plt.legend()
        plt.grid(True)
        plt.show()

    # Save the full dataset including predictions to a CSV file
    output_path = 'Quiz_4/future_data.csv'
    full_data.to_csv(output_path)
```

Appendix VIII: Predicting the Future Development of China's Pet Food Industry for the Next Three Years Using MLR:

```
    import sys
```

```
import io
sys.stdout = io.TextIOWrapper(sys.stdout.buffer, encoding='utf-8')
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.linear_model import LinearRegression
from sklearn.metrics import mean_squared_error, r2_score
import seaborn as sns

def load_data(filepath):
    df = pd.read_csv(filepath)
    return df

def preview_data(df):
    print("First five lines in dataset:")
    print(df.head())
    print("\nData description:")
    print(df.describe())
    print("\nMissing values:")
    print(df.isnull().sum())

def preprocess_data(df, feature_columns, target_column):
    X = df[feature_columns].values
    y = df[target_column].values
    return X, y

def split_data(X, y, test_size=3/8, random_state=42):
    return train_test_split(X, y, test_size=test_size, random_state=random_state)

def train_model(X_train, y_train):
    model = LinearRegression()
    model.fit(X_train, y_train)
    return model
```

```
def print_model_coefficients(model, feature_columns):

    for feature, coef in zip(feature_columns, model.coef_):
        print(f"{feature}: {coef:.2f}")

def predict(model, X_test):
    return model.predict(X_test)

def evaluate_model(y_test, y_pred):
    mse = mean_squared_error(y_test, y_pred)
    r2 = r2_score(y_test, y_pred)
    print(f"Mean Squared Error (MSE): {mse:.2f}")


def visualize_predictions(y,y_pred):
    plt.figure(figsize=(10, 6))
    years = [2024,2025,2026]
    year=[2019,2020,2021,2022,2023]
    #plt.plot(range(len(y)), y, label="actuall Values", marker='o')
    plt.plot(year, y, label="Actual Values", color="blue", marker='x')
    plt.plot(years, y_pred, label="Predicted Values", color="red",marker='o',linestyle="-
-")
    plt.title('Chinese Export')
    plt.xlabel('Years')
    plt.ylabel('100 billion dollars')
    year=np.append(year, years)
    plt.xticks(year)
    plt.legend()
    plt.show()

if __name__ == "__main__":
    filepath = 'Quiz_4/future_data.csv'
    df = load_data(filepath)
```

```
preview_data(df)

feature_columns = ['Global_ms','Dollars_rate','Export_Rate','CN_ms']
target_column = 'CN_export'

X, y = preprocess_data(df, feature_columns, target_column)
z=X[5:]
X=X[:5]
y=y[:5]

X_train, X_test, y_train, y_test = split_data(X, y)

model = train_model(X_train, y_train)

print_model_coefficients(model, feature_columns)

y_pred = predict(model, z)
print(y_pred)

visualize_predictions(y,y_pred)
```