

forecast tourist inflows. It also visualizes results with Seaborn.

import streamlit as st

```
import pandas as pd
import numpy as np
  from sklearn.model_selection import train_test_split
  from sklearn.ensemble import RandomForestRegressor
  import seaborn as sos
  import matplotlib.pyplot as plt
  # Load dataset
  @st.cache
  def load_data():
 url = "https://ppl-ai-file-upload.s3.amazonaws.com/web/direct-
files/21882887/3ff946c2-cd56-49a6-86db-
67592c1cc761/thailand_domestic_tourism.csv"
       data = pd.read_csv(url)
       data['travel_date'] = pd.to_datetime(data['travel_date'])
data['month'] = data['travel_date'].dt.month
       return data
  data = load data()
  st.sidebar.header("User Input Parameters")
 province = st.sidebar.selectbox("Select Province",
data['province_eng'].unique())
  month = st.sidebar.slider("Select Month (1-12)", 1, 12, 1)
  # Filter data by province
province_data = data[data['province_eng'] == province]
  # Prepare features and target variable
X = province_data[['month', 'no_tourist_foreign', 'no_tourist_thai']]
  y = province_data['no_tourist_all']
  # Train-test split
%_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2,
random_state=42)
  model = RandomForestRegressor(n estimators=100, random state=42)
  model.fit(X_train, y_train)
  # Predict and evaluate the model
  y_pred = model.predict(X_test)
  mse = mean_squared_error(y_test, y_pred)
st.write(f"Model Mean Squared Error: {mse:.2f}")
  # Forecast for user-selected month
forecast_input = pd.DataFrame({'month': [month], 'no_tourist_foreign':
 [X['no_tourist_foreign'].mean()],
 [X['no_tourist_thai'].mean()]})
  forecast = model.predict(forecast_input)[0]
st.write(f"Predicted Tourist Inflow for {province} in Month {month}:
 {forecast:.0f}")
  # Visualization: Actual vs Predicted
  st.subheader("Actual vs Predicted Tourist Inflows")
fig, ax = plt.subplots()
  ax.set_ylabel("Predicted")

ax.set_ylabel("Predicted")
  ax.set_title("Actual vs Predicted Tourist Inflows")
  st.pyplot(fig)
# Visualization: monthly lourist frends
st.subhead(f'Monthly Tourist Trends for {province}")
monthly_trends = province_data.groupby('month')
['no_tourist_all'].mean().reset_index()
fig2, ax2 = plt.subplots()
sns.lineplot(data=monthly_trends, x='month', y='no_tourist_all',
 marker='o', ax=ax2)
ax2.set_title(f"Monthly Trends for {province}")
ax2.set_xlabel("Month")
  ax2.set_ylabel("Average Tourists")
st.pyplot(fig2)
Key Features:
  1. Data Loading and Preprocessing:

    The dataset is loaded from a CSV file and preprocessed to extract features like

            `month`.
 2. Model Training:
       * A `RandomForestRegressor` is trained to predict total tourist inflows based on
 3. User Interaction:
```

. Users select a province and month to forecast tourist inflows interactively.

## 4. Visualizations:

- Scatter plot of actual vs predicted values.
- . Line chart showing monthly trends for the selected province.

- 1. Save the code in a file named 'app.py'.
- 2. Install required libraries: 'streamlit', 'pandas', 'numpy', 'scikit-learn', 'seaborn',
- 3. Run the app using the command: 'streamlit run app.py'.

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RandomForestRegressor is an excellent choice for this predictive modeling task for

- 1. Handling Non-Linear Relationships: Random forests can capture complex, non-linear relationships between features and the target variable, which is likely the case with tourism data that may have intricate patterns.
- 2. Feature Importance: The model provides feature importance scores, allowing us to understand which factors (e.g., month, foreign tourists, Thai tourists) have the most significant impact on total tourist numbers.
- 3. Robustness to Outliers: Random forests are less sensitive to outliers compared to linear models, making them suitable for tourism data that may contain extreme values due to events or seasonal fluctuations.
- 4. Ensemble Learning: As an ensemble method, random forests combine multiple decision trees, reducing overfitting and improving generalization to new data.
- 5. Handling Mixed Data Types: The model can work well with both numerical and categorical features, which is useful for incorporating various types of tourism-related data.
- 6. No Assumption of Normality: Unlike some statistical methods, random forests do not assume a normal distribution of the target variable, making them flexible for different data distributions.
- 7. Parallelization: Random forests can be easily parallelized, allowing for faster training on large datasets, which is beneficial when working with extensive historical tourism

By using RandomForestRegressor, we can create a robust predictive model that captures the complexities of tourism patterns and provides valuable insights for forecasting tourist

