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December 4, 2024

Question 1 - LSTM Autoencoder You are required to build an LSTM Autoencoder to detect anomalies in a time series dataset. The dataset contains daily temperature readings from a weather station over the course of a few years. Your task is to: 1. Load the dataset: The dataset will contain a single column temperature and a date column. 2. Preprocess the data: Normalize the temperature data and split it into training and testing sets. 3. Build an LSTM Autoencoder: o The encoder should reduce the input dimensions to a latent representation. o The decoder should reconstruct the input from the latent representation. 4. Train the model: Train the autoencoder on the training data and evaluate the reconstruction error on the test set. 5. Anomaly Detection: Use the reconstruction error to detect anomalies. Define a threshold for the reconstruction error, and identify days where the temperature is considered anomalous. 6. Visualize the results: Plot the original temperature data and highlight the detected anomalies.

1. Load the weather_data.csv - Dataset and Parse the Date column as datetime and ensure the Temperature column is numeric.

[54]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import MinMaxScaler
from sklearn.model_selection import train_test_split
from tensorflow.keras.layers import Input, LSTM, RepeatVector, Dense
from tensorflow.keras.models import Model
```

[55]:
```
def load_data(filepath='/content/weather_data.csv'):
    df = pd.read_csv(filepath)
    df['date'] = pd.to_datetime(df['date'])
    return df.set_index('date')
```

2. Exploratory Data Analysis

[56]:
```
df.tail()
```

[56]:

	date	temperature
2552	2020-12-27	10.598482
2553	2020-12-28	9.876287
2554	2020-12-29	9.265936
2555	2020-12-30	9.986115
2556	2020-12-31	8.419751

[57]:
```python
df.describe()
```

[57]:
```
       temperature
count  2557.000000
mean     10.017472
std       0.923047
min       3.337291
25%       9.335195
50%      10.031778
75%      10.681384
max      15.587945
```

[58]:
```python
df.head()
```

[58]:
```
         date  temperature
0  2014-01-01    10.248357
1  2014-01-02     9.950428
2  2014-01-03    10.362958
3  2014-01-04    10.820167
4  2014-01-05     9.961091
```

[59]:
```python
df.isnull().sum()
```

[59]:
```
date           0
temperature    0
dtype: int64
```

[73]:
```python
def perform_eda(df):

    plt.figure(figsize=(15, 12))

    # Time Series Plot
    plt.subplot(3, 1, 1)
    plt.plot(df.index, df['temperature'])
    plt.title('Temperature Time Series')
    plt.xlabel('Date')
    plt.ylabel('Temperature')

    # Distribution Plot
    plt.subplot(3, 1, 2)
    sns.histplot(df['temperature'], bins=30, kde=True)
    plt.title('Temperature Distribution')

    # Monthly Box Plot
    plt.subplot(3, 1, 3)
    df['month'] = df.index.month
    sns.boxplot(x='month', y='temperature', data=df)
```

```
    plt.title('Monthly Temperature Distribution')

    plt.tight_layout()
    plt.show()

    # Print basic statistics
    print("\nBasic Statistics:")
    print(df['temperature'].describe())
```

3. Model Implementation

[61]:
```
def create_sequences(data, seq_length=7):
    return np.array([data[i:i+seq_length] for i in␣
↪range(len(data)-seq_length+1)])
```

Create the AutoEncoder

[70]:
```
def build_autoencoder(seq_length=7):
    # Encoder
    inputs = Input(shape=(seq_length, 1))
    encoded = LSTM(32, activation='relu')(inputs)

    # Decoder
    decoded = RepeatVector(seq_length)(encoded)
    decoded = LSTM(32, activation='relu', return_sequences=True)(decoded)
    decoded = Dense(1)(decoded)

    model = Model(inputs, decoded)
    model.compile(optimizer='adam', loss='mse')
    return model
```

Train The AutoEncoder Model

[72]:
```
def train_model(model, X_train, X_test):
    history = model.fit(
        X_train, X_train,
        epochs=50,
        batch_size=32,
        validation_data=(X_test, X_test),
        verbose=1
    )
    return history
```

4. Results Analysis and Visualization

[81]:
```
def analyze_results(model, df, test_data, test_sequences, scaler):
    """Analyze and visualize results"""
    # Get predictions and errors
```

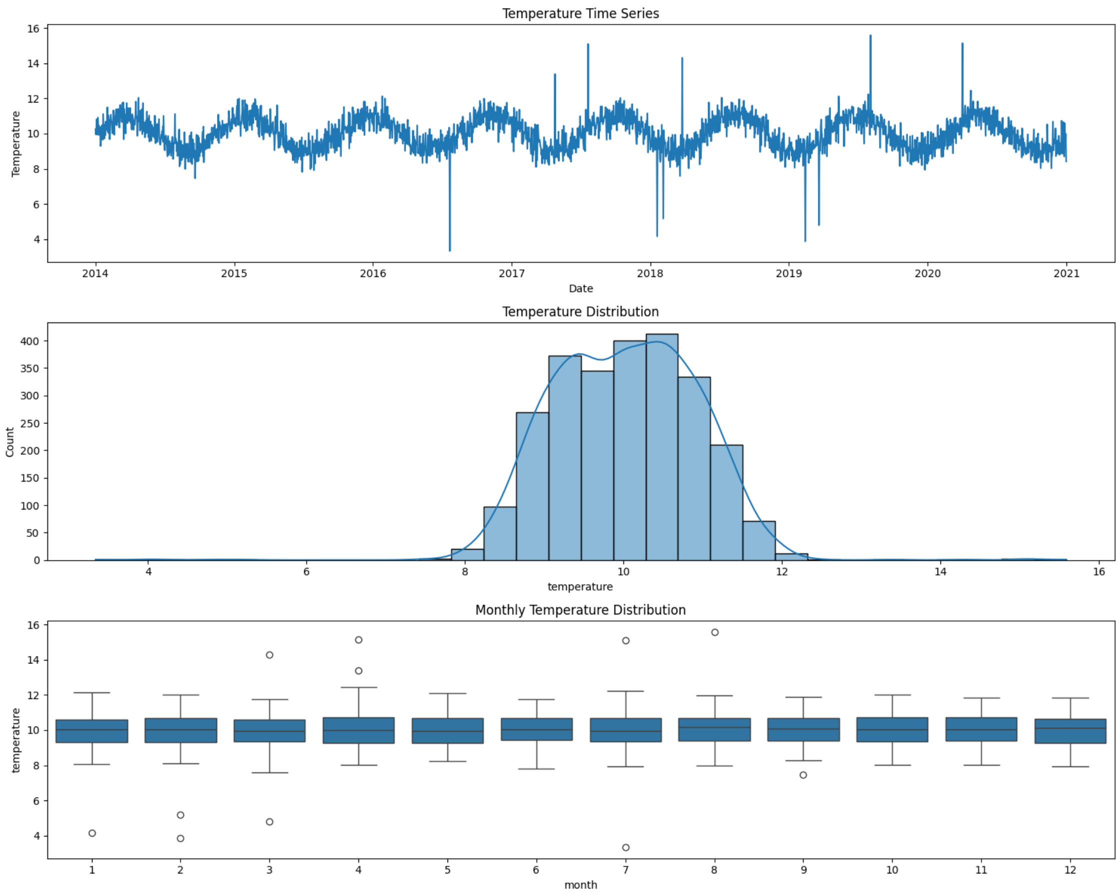
```
    predictions = model.predict(test_sequences)
    mse = np.mean(np.square(test_sequences - predictions), axis=(1,2))
    threshold = np.mean(mse) + 2 * np.std(mse)
    anomalies = mse > threshold

    # Plot results
    plt.figure(figsize=(15, 10))

    plt.subplot(2, 1, 1)
    plt.plot(test_data.index, scaler.inverse_transform(test_data),␣
 ↪label='Original')
    anomaly_points = test_data[anomalies]
    plt.scatter(anomaly_points.index,
                scaler.inverse_transform(anomaly_points),
                color='red', label='Anomaly')
    plt.title('Temperature Data with Detected Anomalies')
    plt.legend()


    plt.subplot(2, 1, 2)
    plt.plot(mse, label='Reconstruction Error')
    plt.axhline(y=threshold, color='r', linestyle='--', label='Threshold')
    plt.title('Reconstruction Error and Threshold')
    plt.legend()

    plt.tight_layout()
    plt.show()



    #Insights
    print("\nAnalysis Insights:")
    print(f"Total anomalies detected: {sum(anomalies)}")
    print(f"Anomaly percentage: {(sum(anomalies)/len(anomalies))*100:.2f}%")

    return anomalies, mse, threshold
```

5. Main Funtion Executions

[84]:
```
import pandas as pd
from sklearn.preprocessing import MinMaxScaler

def main():
    df = load_data()

    # 1. Perform EDA
    print("Performing Exploratory Data Analysis...")
```

```python
    perform_eda(df)

    # 2. Preprocess data
    scaler = MinMaxScaler()
    scaled_data = scaler.fit_transform(df[['temperature']])

    # Create sequences
    seq_length = 7
    sequences = create_sequences(scaled_data)

    # Split data
    train_size = int(len(sequences) * 0.8)
    X_train = sequences[:train_size]
    X_test = sequences[train_size:]
    test_data = pd.DataFrame(
        scaled_data.flatten()[train_size + seq_length - 1:],
        index=df.index[train_size + seq_length - 1:],
        columns=['temperature']
    )

    # 3. Build and train model
    print("\nTraining LSTM Autoencoder...")
    model = build_autoencoder(seq_length)
    history = train_model(model, X_train, X_test)

    # 4. Analyze results
    print("\nAnalyzing Results...")
    anomalies, mse, threshold = analyze_results(model, df, test_data, X_test,␣
 ↪scaler)

    return model, history, anomalies

if __name__ == "__main__":
    model, history, anomalies = main()
```

```
Performing Exploratory Data Analysis…
```



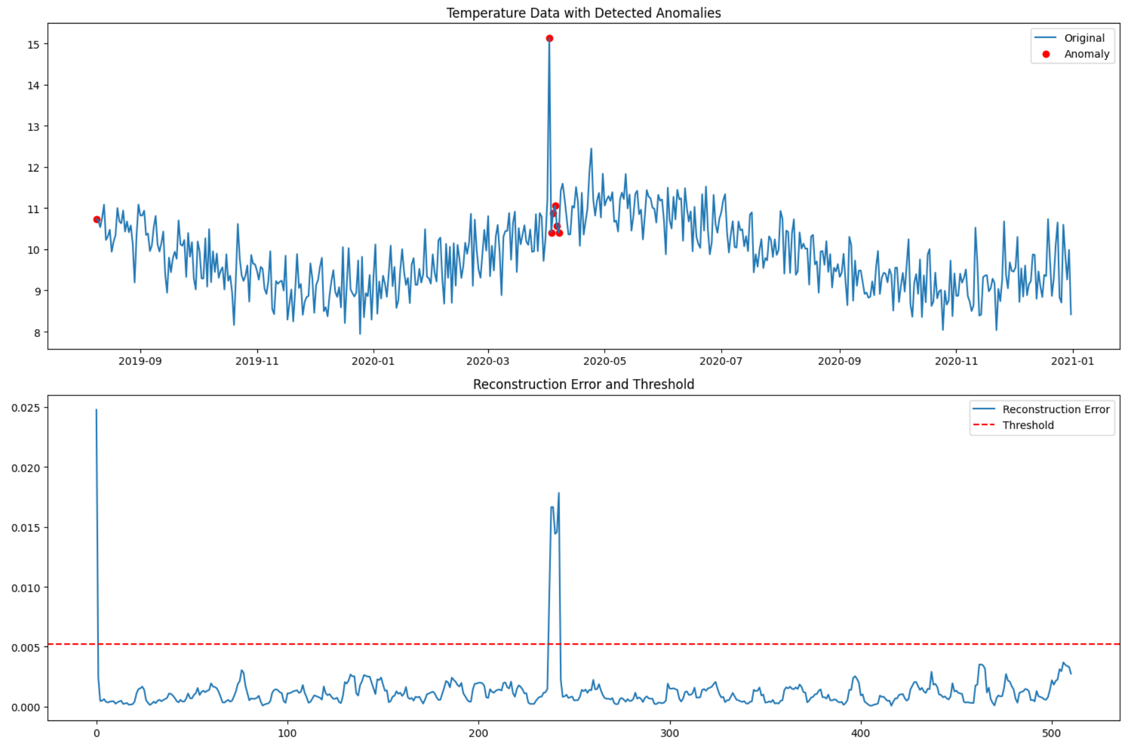

```
Basic Statistics:
count    2557.000000
mean       10.017472
std         0.923047
min         3.337291
25%         9.335195
50%        10.031778
75%        10.681384
max        15.587945
Name: temperature, dtype: float64

Training LSTM Autoencoder…
Epoch 1/50
64/64              4s 20ms/step -
loss: 0.1744 - val_loss: 0.0212
Epoch 2/50
64/64              1s 20ms/step -
loss: 0.0149 - val_loss: 0.0049
```

```
Epoch 3/50
64/64              2s 9ms/step - loss:
0.0038 - val_loss: 0.0018
Epoch 4/50
64/64              1s 8ms/step - loss:
0.0021 - val_loss: 0.0017
Epoch 5/50
64/64              1s 9ms/step - loss:
0.0020 - val_loss: 0.0017
Epoch 6/50
64/64              1s 9ms/step - loss:
0.0020 - val_loss: 0.0017
Epoch 7/50
64/64              1s 9ms/step - loss:
0.0020 - val_loss: 0.0017
Epoch 8/50
64/64              1s 9ms/step - loss:
0.0020 - val_loss: 0.0017
Epoch 9/50
64/64              1s 9ms/step - loss:
0.0020 - val_loss: 0.0017
Epoch 10/50
64/64              1s 9ms/step - loss:
0.0019 - val_loss: 0.0017
Epoch 11/50
64/64              1s 9ms/step - loss:
0.0019 - val_loss: 0.0016
Epoch 12/50
64/64              1s 8ms/step - loss:
0.0019 - val_loss: 0.0016
Epoch 13/50
64/64              1s 9ms/step - loss:
0.0019 - val_loss: 0.0016
Epoch 14/50
64/64              1s 9ms/step - loss:
0.0019 - val_loss: 0.0016
Epoch 15/50
64/64              1s 8ms/step - loss:
0.0019 - val_loss: 0.0016
Epoch 16/50
64/64              1s 9ms/step - loss:
0.0019 - val_loss: 0.0016
Epoch 17/50
64/64              1s 8ms/step - loss:
0.0019 - val_loss: 0.0016
Epoch 18/50
64/64              1s 9ms/step - loss:
0.0019 - val_loss: 0.0016
```

```
Epoch 19/50
64/64            1s 12ms/step -
loss: 0.0019 - val_loss: 0.0016
Epoch 20/50
64/64            1s 14ms/step -
loss: 0.0019 - val_loss: 0.0016
Epoch 21/50
64/64            1s 14ms/step -
loss: 0.0018 - val_loss: 0.0016
Epoch 22/50
64/64            1s 14ms/step -
loss: 0.0018 - val_loss: 0.0016
Epoch 23/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0016
Epoch 24/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0016
Epoch 25/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0016
Epoch 26/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0016
Epoch 27/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0016
Epoch 28/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0016
Epoch 29/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0016
Epoch 30/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0016
Epoch 31/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0016
Epoch 32/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0016
Epoch 33/50
64/64            1s 9ms/step - loss:
0.0018 - val_loss: 0.0015
Epoch 34/50
64/64            1s 10ms/step -
loss: 0.0017 - val_loss: 0.0015
```

```
Epoch 35/50
64/64            1s 8ms/step - loss:
0.0017 - val_loss: 0.0015
Epoch 36/50
64/64            1s 9ms/step - loss:
0.0017 - val_loss: 0.0015
Epoch 37/50
64/64            1s 9ms/step - loss:
0.0017 - val_loss: 0.0015
Epoch 38/50
64/64            1s 11ms/step -
loss: 0.0017 - val_loss: 0.0015
Epoch 39/50
64/64            1s 14ms/step -
loss: 0.0017 - val_loss: 0.0015
Epoch 40/50
64/64            1s 13ms/step -
loss: 0.0017 - val_loss: 0.0014
Epoch 41/50
64/64            1s 8ms/step - loss:
0.0017 - val_loss: 0.0014
Epoch 42/50
64/64            1s 9ms/step - loss:
0.0017 - val_loss: 0.0014
Epoch 43/50
64/64            1s 9ms/step - loss:
0.0016 - val_loss: 0.0014
Epoch 44/50
64/64            1s 8ms/step - loss:
0.0016 - val_loss: 0.0014
Epoch 45/50
64/64            1s 9ms/step - loss:
0.0016 - val_loss: 0.0014
Epoch 46/50
64/64            1s 8ms/step - loss:
0.0016 - val_loss: 0.0013
Epoch 47/50
64/64            1s 9ms/step - loss:
0.0016 - val_loss: 0.0013
Epoch 48/50
64/64            1s 8ms/step - loss:
0.0015 - val_loss: 0.0013
Epoch 49/50
64/64            1s 9ms/step - loss:
0.0015 - val_loss: 0.0013
Epoch 50/50
64/64            1s 9ms/step - loss:
0.0015 - val_loss: 0.0013
```

```
Analyzing Results…
16/16              1s 23ms/step
```




```
Analysis Insights:
Total anomalies detected: 7
Anomaly percentage: 1.37%
```