7vsnqkizp

June 10, 2024

#Implementación del Modelo LSTM

Importación de bibliotecas:

Limpieza de Datos

```
[2]: def clean_data(data):
    data = data.dropna()
    return data
```

Normalización de las Variables

```
[3]: def normalize_data(data):
    scaler = MinMaxScaler()
    data_scaled = scaler.fit_transform(data)
    return pd.DataFrame(data_scaled, columns=data.columns), scaler
```

Selección de Variables utilizando diferentes métodos

```
[4]: def select_features(X, y, num_features):
    mutual_info = mutual_info_regression(X, y)
    k_best = SelectKBest(score_func=f_regression, k=num_features).fit(X, y)
    features = X.columns[k_best.get_support(indices=True)]
    return features.tolist()
```

Definición de la función para entrenar el modelo LSTM:

```
[5]: def train_lstm(X_train, y_train, input_shape):
```

```
Función para entrenar un modelo LSTM.
Parámetros:
X train (numpy array): Conjunto de datos de entrenamiento (características).
y_train (numpy array): Conjunto de datos de entrenamiento (objetivo).
input_shape (tuple): Forma de los datos de entrada.
Retorna:
model (Sequential): Modelo LSTM entrenado.
model = Sequential()
model.add(LSTM(units=50, return_sequences=True, input_shape=input_shape))
model.add(Dropout(0.2))
model.add(LSTM(units=50))
model.add(Dropout(0.2))
model.add(Dense(1))
model.compile(optimizer='adam', loss='mean_squared_error')
model.fit(X_train, y_train, epochs=500, batch_size=32, validation_split=0.2)
return model
```

Preparación de datos

```
[6]: # Cargar datos
     data = pd.read_csv('https://query1.finance.yahoo.com/v7/finance/download/FSM?
      →period1=1597123200&period2=1628659200&interval=1d&events=history&includeAdjustedClose=true
     # Mantener la columna de fechas para las gráficas
     dates = data['Date']
     data = data.drop(columns=['Date'])
     # Limpiar y Normalizar
     data = clean data(data)
     data, scaler = normalize_data(data)
     # Seleccionar Variables
     target_column = 'Close'
     num_features = 5  # Número de características a seleccionar
     selected_features = select_features(data.drop(columns=[target_column]),__
      →data[target_column], num_features)
     selected_features.append(target_column)
     data = data[selected_features]
     # Separar características y objetivo
     X = data.drop(columns=[target_column])
     y = data[target_column]
```

```
# Dividir los datos en conjuntos de entrenamiento y prueba
train_size = int(len(X) * 0.8)
X_train, X_test = X[:train_size], X[train_size:]
y_train, y_test = y[:train_size], y[train_size:]
dates_train, dates_test = dates[:train_size], dates[train_size:]
print(f'Características seleccionadas: {selected_features}')
```

Características seleccionadas: ['Open', 'High', 'Low', 'Adj Close', 'Volume', 'Close']

Preparación de los datos para LSTM:

```
[7]: # Los datos de entrenamiento y prueba se reestructuran en un formato 3D
→requerido por LSTM (samples, timesteps, features)

X_train_lstm = X_train.values.reshape((X_train.shape[0], 1, X_train.shape[1]))

X_test_lstm = X_test.values.reshape((X_test.shape[0], 1, X_test.shape[1]))
```

Entrenamiento del modelo LSTM:

```
[8]: # Entrenamos el modelo LSTM usando los datos de entrenamiento reestructurados lstm_model = train_lstm(X_train_lstm, y_train, (1, X_train.shape[1]))
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Epoch 1/500
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val_loss: 1.1036e-04
Epoch 436/500
9.1791e-05
Epoch 437/500
1.1104e-04
Epoch 438/500
1.2496e-04
Epoch 439/500
3.9110e-05
Epoch 440/500
9.7210e-05
Epoch 441/500
```

```
8.6851e-05
Epoch 442/500
4.7905e-05
Epoch 443/500
4.4892e-05
Epoch 444/500
1.8664e-04
Epoch 445/500
val_loss: 7.8578e-05
Epoch 446/500
8.8549e-05
Epoch 447/500
1.0328e-04
Epoch 448/500
2.1879e-04
Epoch 449/500
5.0996e-05
Epoch 450/500
1.7394e-04
Epoch 451/500
2.2234e-04
Epoch 452/500
val loss: 9.8510e-05
Epoch 453/500
9.5854e-05
Epoch 454/500
2.6327e-04
Epoch 455/500
val_loss: 8.4269e-05
Epoch 456/500
1.3061e-04
Epoch 457/500
```

```
9.4579e-05
Epoch 458/500
1.3939e-04
Epoch 459/500
1.0607e-04
Epoch 460/500
1.3245e-04
Epoch 461/500
1.0167e-04
Epoch 462/500
9.6944e-05
Epoch 463/500
6.6236e-05
Epoch 464/500
val_loss: 1.5552e-04
Epoch 465/500
5.8215e-05
Epoch 466/500
val_loss: 1.2450e-04
Epoch 467/500
2.0872e-04
Epoch 468/500
6.4797e-05
Epoch 469/500
9.2896e-05
Epoch 470/500
val_loss: 1.3583e-04
Epoch 471/500
1.1004e-04
Epoch 472/500
5.0771e-05
Epoch 473/500
```

```
6.9127e-05
Epoch 474/500
3.2355e-04
Epoch 475/500
5.9108e-05
Epoch 476/500
val_loss: 5.2941e-05
Epoch 477/500
val_loss: 6.3423e-05
Epoch 478/500
val_loss: 1.0178e-04
Epoch 479/500
1.0830e-04
Epoch 480/500
5.7170e-05
Epoch 481/500
6.3400e-05
Epoch 482/500
val_loss: 4.4178e-05
Epoch 483/500
val_loss: 5.4542e-05
Epoch 484/500
8.0816e-05
Epoch 485/500
4.3282e-05
Epoch 486/500
5.9225e-05
Epoch 487/500
2.4141e-04
Epoch 488/500
8.3615e-05
Epoch 489/500
```

```
4.8538e-05
  Epoch 490/500
  3.2798e-04
  Epoch 491/500
  5.6893e-05
  Epoch 492/500
  5/5 [=========== ] - Os 14ms/step - loss: 9.4746e-04 -
  val_loss: 5.8685e-05
  Epoch 493/500
  5/5 [============ ] - Os 18ms/step - loss: 0.0010 - val_loss:
  8.7827e-05
  Epoch 494/500
  7.8305e-05
  Epoch 495/500
  val loss: 2.3932e-04
  Epoch 496/500
  6.3198e-05
  Epoch 497/500
  val_loss: 5.4453e-05
  Epoch 498/500
  val_loss: 7.9729e-05
  Epoch 499/500
  4.4347e-05
  Epoch 500/500
  val loss: 5.7166e-05
  Predicciones con el modelo LSTM:
[9]: # Generamos predicciones sobre los datos de prueba usando el modelo LSTM_
   \hookrightarrowentrenado
   lstm_predictions = pd.Series(lstm_model.predict(X_test_lstm).flatten(),__
   →index=X_test.index)
  2/2 [======= ] - 1s 9ms/step
  Cálculo de métricas de validación:
[10]: # Calculamos el MAPE (Mean Absolute Percentage Error) para evaluar la precisiónu
   \hookrightarrow del modelo
```

```
mape_lstm = mean_absolute_percentage_error(y_test, lstm_predictions)
# Calculamos el RMSE (Root Mean Squared Error) para evaluar el error del modelo
rmse_lstm = np.sqrt(mean_squared_error(y_test, lstm_predictions))
# Imprimimos las métricas de validación
print(f'MAPE LSTM: {mape_lstm}')
print(f'RMSE LSTM: {rmse_lstm}')
```

MAPE LSTM: 15383864263620.277 RMSE LSTM: 0.04525085860789593