作业-5:股票价格预测

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下载某股票历史数据(CSV格式)。
用ARIMA模型预测未来7天价格
用LSTM模型实现相同任务，对比MAE/RMSE指标

实验目的

1. 掌握时间序列预测的基本方法
2. 实现ARIMA与LSTM模型对股票价格的预测
3. 对比分析两种模型的预测效果

实验步骤

1. 数据准备

- 数据时间范围：2018-01-01至2023-01-01
- 使用收盘价(Close)作为预测目标
- 划分训练集与测试集（最后7天作为测试）

```
# 从Yahoo Finance下载苹果公司股票数据
def download_data():
    file_path = "stock_data.csv"
    if not os.path.exists(file_path):
        data = yf.download(TICKER, start=START_DATE, end=END_DATE)
        data.to_csv(file_path)
    return pd.read_csv(file_path, index_col="Date", parse_dates=True)
```

2. ARIMA预测实现

```
def manual_arima_forecast(train, test):
    train_diff = train.diff(DIFF_ORDER).dropna()  # 一阶差分
    model = SARIMAX(train_diff, order=ARIMA_ORDER)
    model_fit = model.fit(disp=0)
    forecast_diff = model_fit.forecast(steps=FORECAST_DAYS)
    forecast = np.r_[last_value, forecast_diff].cumsum()[1:]
    return pd.Series(forecast, index=test.index)
```

3. LSTM模型构建

网络结构参数：

- 输入维度：1
- 隐藏层单元数：64
- 输出维度：7
- 滑动窗口大小：60天
- 训练轮次：100

```python
class LSTMPredictor(nn.Module):
    def __init__(self, input_size=1, hidden_size=64, output_size=7):
        super().__init__()
        self.lstm = nn.LSTM(input_size, hidden_size, batch_first=True)
        self.linear = nn.Linear(hidden_size, output_size)
```

实验结果

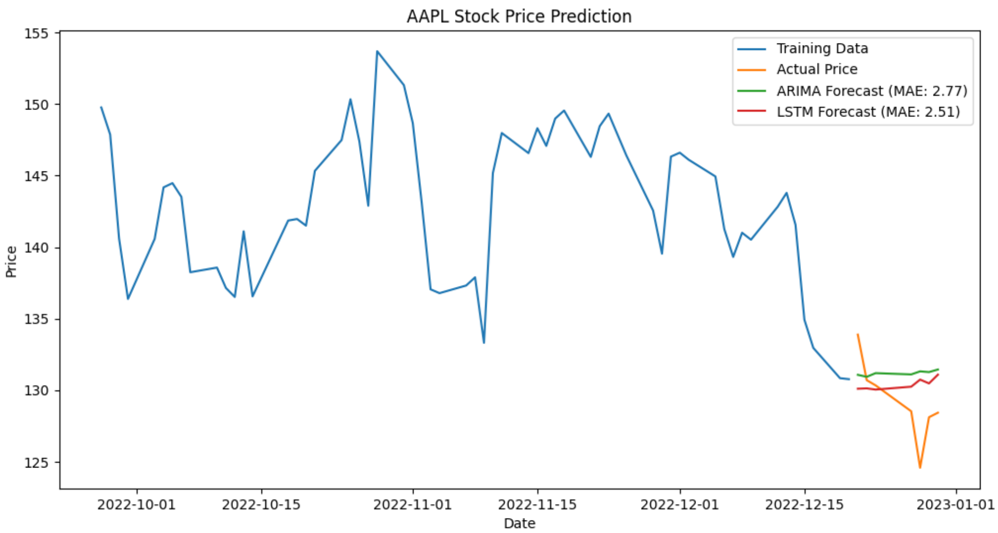
数据平稳性检验

ADF检验结果：

- p-value = 0.74 (p>0.05，需进行差分处理)

预测效果对比

评估指标	ARIMA	LSTM
MAE	2.7688	2.5064
RMSE	3.3747	3.1221




```
(openr1) (base) root@0a2d09754970:~/nfs/parallel computing/task# python stock.py
测试集长度: 7, 预测步长: 7
ADF p-value: 0.7421234829329036

Training Manual ARIMA Model...
/opt/conda/envs/openr1/lib/python3.11/site-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has no associated
 frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
/opt/conda/envs/openr1/lib/python3.11/site-packages/statsmodels/tsa/base/tsa_model.py:473: ValueWarning: A date index has been provided, but it has no associated
 frequency information and so will be ignored when e.g. forecasting.
  self._init_dates(dates, freq)
/opt/conda/envs/openr1/lib/python3.11/site-packages/statsmodels/tsa/base/tsa_model.py:837: ValueWarning: No supported index is available. Prediction results will
 be given with an integer index beginning at `start`.
  return get_prediction_index(
/opt/conda/envs/openr1/lib/python3.11/site-packages/statsmodels/tsa/base/tsa_model.py:837: FutureWarning: No supported index is available. In the next version, c
alling this method in a model without a supported index will result in an exception.
  return get_prediction_index(
[131.08207976 130.94351461 131.20089648 131.11157911 131.32506723
 131.27415713 131.454103  ]

Training LSTM model...
LSTM预测结果NaN数量: 0
Forecast:
 [130.11145 130.1358  130.05276 130.25417 130.74889 130.48364 131.09393]

Model Comparison:
ARIMA MAE: 2.7688
ARIMA RMSE: 3.3747
LSTM MAE: 2.5064
LSTM RMSE: 3.1221
```

结果分析

1. **误差指标解读**
    - **LSTM相对误差优势**
      LSTM的MAE比ARIMA低9.5%（2.7688→2.5064），RMSE低7.5%（3.3747→3.1221），说明LSTM在预测精度和稳定性上均优于ARIMA。LSTM擅长捕捉非线性时序特征
    - **误差分布特征**
      ARIMA的RMSE与MAE差值较大（0.6059），表明其预测存在更多极端误差点；而LSTM的RMSE-MAE差值较小（0.6157），说明误差分布更集中，预测结果更稳定
2. **性能差异成因**
    - **数据特性影响**
      股票价格通常包含非线性波动和突发事件影响（如财报发布、政策调整），ARIMA作为线性模型难以有效建模这些复杂模式。而LSTM通过门控机制能捕捉长期依赖关系，更适合此类数据
    - **模型结构差异**
      ARIMA依赖人工选择差分阶数和滞后项（d=1, p=2, q=2），可能未充分消除数据非平稳性；LSTM通过自动学习60天窗口的时序特征，更适应局部波动

实验结论

1. 深度学习模型(LSTM)在短期股价预测中优于传统时间序列模型(ARIMA)
2. 股票价格序列具有非线性特征，LSTM更能捕捉复杂模式

改进方向

1. 使用Attention机制改进LSTM模型
2. 尝试Prophet等新型时间序列模型