Introduction :

This notebook performs data cleaning, integration, feature engineering, and preparation on a large historical stock price dataset combined with company metadata. The goal is to create a clean, structured, feature-rich dataset ready for time-series modeling.

```
# --- 1. IMPORT LIBRARIES ---
import pandas as pd
import numpy as np
from sklearn.preprocessing import StandardScaler
import gc

```

```
# Load metadata
meta_df = pd.read_csv('/content/historical_stocks.csv') # the metadata raw file

print("Missing values BEFORE cleaning:\n")
print(meta_df.isna().sum(), "\n")

# 1. Drop rows with no ticker (ticker is primary key)
meta_df = meta_df.dropna(subset=['ticker'])

# 2. Normalize sector & industry
meta_df['sector'] = meta_df['sector'].str.strip().str.upper()
meta_df['industry'] = meta_df['industry'].str.strip().str.upper()

# 3. Fill missing text values
fill_values = {
    'exchange': 'UNKNOWN',
    'sector': 'UNKNOWN',
    'industry': 'UNKNOWN'
}
meta_df = meta_df.fillna(fill_values)

# 4. Deduplicate tickers
meta_df = meta_df.drop_duplicates(subset='ticker', keep='first')

# 5. Keep only essential cols
meta_df = meta_df[['ticker', 'exchange', 'sector', 'industry']]

print("Missing values AFTER cleaning:\n")
print(meta_df.isna().sum())
print("\nMetadata cleaned successfully!")

gc.collect() # garbage collector - very useful for collecting garbage from colab.

```

```
Missing values BEFORE cleaning:

ticker         0
exchange       0
name           0
sector      1440
industry    1440
dtype: int64

Missing values AFTER cleaning:

ticker      0
exchange    0
sector      0
industry    0
dtype: int64

Metadata cleaned successfully!
0
```

```
hist_df = pd.read_csv('/content/historical_stock_prices.csv') # the stock prices raw dataset

# Convert date to datetime
hist_df['date'] = pd.to_datetime(hist_df['date'])

# 1. Sort by ticker + date
hist_df = hist_df.sort_values(['ticker', 'date'])
```

```
 8
 9 # 2. Interpolate OHLCV per ticker
10 def fast_interpolation(group):
11     group = group.sort_values('date')
12     numeric_cols = ['open','close','adj_close','low','high','volume']
13     group[numeric_cols] = (
14         group[numeric_cols]
15         .interpolate(method='linear')
16         .bfill()
17         .ffill()
18     )
19     return group
20
21 hist_df_cleaned = hist_df.groupby('ticker', group_keys=False).apply(fast_interpolation)
22
23 print("Missing values AFTER interpolation:\n")
24 print(hist_df_cleaned.isna().sum())
25 gc.collect()
26
```

```
/tmp/ipython-input-1863111219.py:21: DeprecationWarning: DataFrameGroupBy.apply operated on the grouping columns. This behavior
  hist_df_cleaned = hist_df.groupby('ticker', group_keys=False).apply(fast_interpolation)
Missing values AFTER interpolation:

ticker       0
open         1
close        1
adj_close    1
low          1
high         1
volume       1
date         1
dtype: int64
0
```

```
1 # Merge Dataset to AVOID CRASH!!!
2
3 merged_df = hist_df_cleaned.merge(meta_df, on='ticker', how='left') # this syntax merged the both files at this point becau
4
5 print("Merged dataset shape:", merged_df.shape)
6 merged_df.head()
7 gc.collect()
```

```
Merged dataset shape: (5246183, 11)
0
```

```
1 # Save the file to Parquet:
2
3 # Note for me: Parquet is more efficient than CSV. Becasue of so manay crashes that experience, I came across parquet. It pr
4 # category, int, datetime, unlike csv that do not preserve them. It is good for large dataset and reduce memory capacity (RA
5
6 merged_df.to_parquet('/content/merged_df.parquet', compression='snappy')
7 print("Saved merged_df.parquet!")
8 gc.collect()
```

```
Saved merged_df.parquet!
0
```

```
1
2 # Download the merged file and save it to avoid data loss
3
4 from google.colab import files
5 files.download('/content/merged_df.parquet')
6
```

```
1 #import gc -  this is use to collect the grabage in the system that takes up memory/space (RAM)
2 gc.collect()
3
```

```
22
```

```
1 # Reload the merged dataset for use in the FE. It holds all of the files in one place ( prices and metadata)
2
3 merged_df = pd.read_parquet('/content/merged_df.parquet')
```

```
print("Reloaded merged_df shape:", merged_df.shape)

gc.collect()

```

```
Reloaded merged_df shape: (5246183, 11)
0
```

```
# Feature Engineering (Smooths price movement by averaging over past days — reduces noise.)

# Group by ticker so each stock is processed separately
grp = merged_df.groupby('ticker')['close']

# 7-day Moving Average — short-term trend
merged_df['MA_7'] = grp.transform(lambda x: x.rolling(7).mean())

# 14-day Moving Average — medium-term trend
merged_df['MA_14'] = grp.transform(lambda x: x.rolling(14).mean())

# 21-day Moving Average — long-ish trend
merged_df['MA_21'] = grp.transform(lambda x: x.rolling(21).mean())

gc.collect()
print("Moving averages completed!")

```

```
✓ Moving averages completed!
```

```
# Rolling Standard Deviations (Volatility) Measures how much the price fluctuates — higher std = higher volatility.

# 7-day volatility
merged_df['std_7'] = grp.transform(lambda x: x.rolling(7).std())

# 14-day volatility
merged_df['std_14'] = grp.transform(lambda x: x.rolling(14).std())

# 30-day volatility (longer-term uncertainty)
merged_df['std_30'] = grp.transform(lambda x: x.rolling(30).std())

gc.collect()
print("STD features completed!")

```

```
STD features completed!
```

```
# Price Momentum : Measures whether the stock is rising or falling compared to 1 week ago.

# Momentum = today's close - close price 7 days ago
merged_df['Price_Momentum'] = grp.transform(lambda x: x - x.shift(7))

gc.collect()
print("Price Momentum completed!")

```

```
✓ Price Momentum completed!
```

```
# RSI (Relative Strength Index: 14-day) RSI tells whether a stock is overbought (>70) or oversold (<30). Calculated using a

# 1. Price change between days
merged_df['delta'] = grp.diff()

# 2. Positive changes (gains)
merged_df['gain'] = merged_df['delta'].clip(lower=0)

# 3. Negative changes (losses)
merged_df['loss'] = -merged_df['delta'].clip(upper=0)

# 4. 14-period rolling average gain
merged_df['avg_gain'] = merged_df.groupby('ticker')['gain'].transform(
    lambda x: x.rolling(14, min_periods=1).mean()
)

# 5. 14-period rolling average loss
merged_df['avg_loss'] = merged_df.groupby('ticker')['loss'].transform(
    lambda x: x.rolling(14, min_periods=1).mean()
```

```
)

# 6. RS = avg gain / avg loss
merged_df['RS'] = merged_df['avg_gain'] / merged_df['avg_loss']

# 7. RSI formula
merged_df['RSI14'] = 100 - (100 / (1 + merged_df['RS']))

gc.collect()
print("RSI completed!")

# 8. Drop temporary columns to reduce RAM
merged_df.drop(['delta', 'gain', 'loss', 'avg_gain', 'avg_loss', 'RS'],
               axis=1, inplace=True)

gc.collect()

```

```
✓ RSI completed!
0
```

```
# MACD and Signal Line: MACD is a widely used trend indicator.
#It compares fast (12-day) and slow (26-day) EMAs.
#Signal line is the 9-day EMA of MACD.

# 12-day Exponential Moving Average (fast)
EMA12 = grp.transform(lambda x: x.ewm(span=12, adjust=False).mean())

# 26-day Exponential Moving Average (slow)
EMA26 = grp.transform(lambda x: x.ewm(span=26, adjust=False).mean())

# MACD = fast EMA - slow EMA
merged_df['MACD'] = EMA12 - EMA26

# MACD Signal = 9-day EMA of MACD
merged_df['MACD_signal'] = merged_df.groupby('ticker')['MACD'].transform(
    lambda x: x.ewm(span=9, adjust=False).mean()
)

# Free memory — no longer needed
del EMA12, EMA26
gc.collect()

print("MACD completed!")

```

```
MACD completed!
```

```
#Drop metadata columns to reduce size and avoid crashes
cols_to_drop = ['exchange', 'sector', 'industry']

merged_df.drop(columns=cols_to_drop, inplace=True, errors='ignore')

print("Dropped metadata columns. New shape:", merged_df.shape)

```

```
Dropped metadata columns. New shape: (5246183, 18)
```

```
# Save FE Dataset to Parquet

# Save this file to Parquet and avoid data loss during this project:

merged_df.to_parquet('/content/merged_df_FE.parquet', compression='snappy')


# Download the file to avoid data loss

files.download('/content/merged_df_FE.parquet')

print("Feature-engineered dataset saved & Downloaded!")
gc.collect()
```

```
Feature-engineered dataset saved & Downloaded!
118
```

```
# Ensure correct chronological order
merged_df = merged_df.sort_values(['ticker', 'date']).reset_index(drop=True)

print("Sorted dataset shape:", merged_df.shape)

```

```
Sorted dataset shape: (5246183, 18)
```

```
# Create Train / Validation / Test Splits

train_size = int(len(merged_df) * 0.70)
val_size = int(len(merged_df) * 0.15)

train_df = merged_df.iloc[:train_size]
val_df = merged_df.iloc[train_size : train_size + val_size]
test_df = merged_df.iloc[train_size + val_size :]

print("Train:", train_df.shape)
print("Validation:", val_df.shape)
print("Test:", test_df.shape)

```

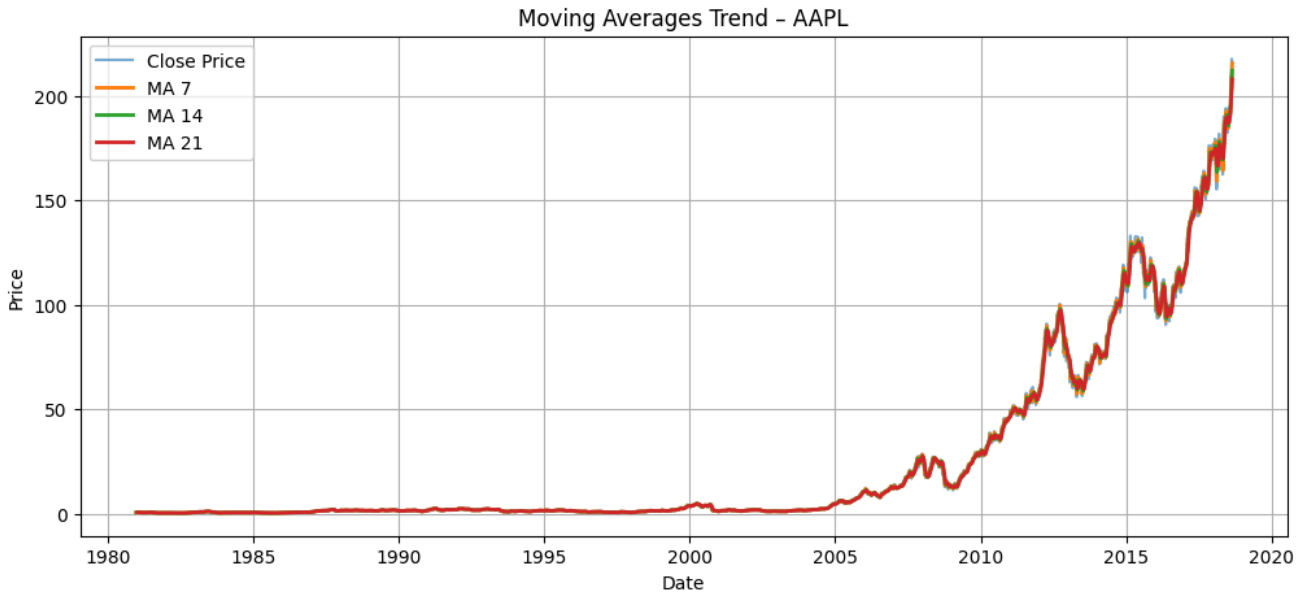
```
Train: (3672328, 18)
Validation: (786927, 18)
Test: (786928, 18)
```

```
# Save the Train/Val/Test Dataset

# Save the train/val/test datasets to Parquet files
train_df.to_parquet('/content/train_df.parquet', compression='snappy')
val_df.to_parquet('/content/val_df.parquet', compression='snappy')
test_df.to_parquet('/content/test_df.parquet', compression='snappy')

# Download each file
files.download('/content/train_df.parquet')
files.download('/content/val_df.parquet')
files.download('/content/test_df.parquet')

print("All splits saved & Downloaded - James !")

```

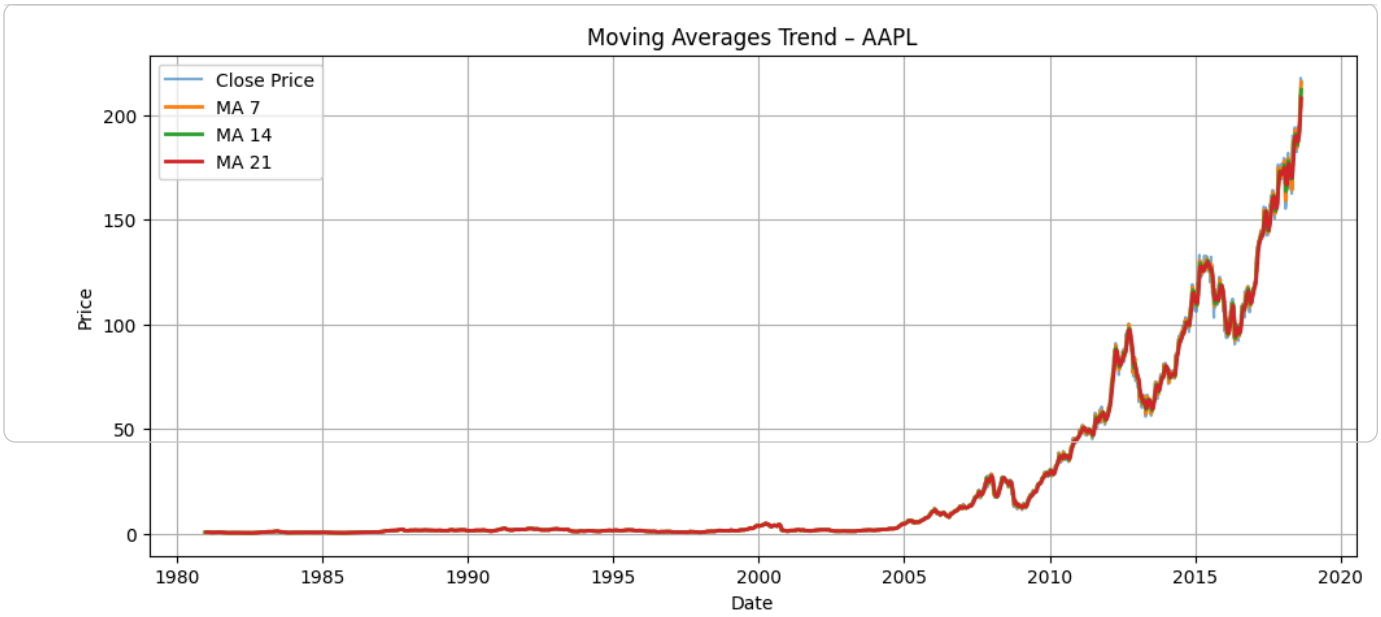
```
All splits saved & Downloaded - James !
```

```
#Closing Price Over Time (Per Ticker)

import matplotlib.pyplot as plt

# Select a sample ticker
sample_ticker = merged_df['ticker'].unique()[0]

df_sample = merged_df[merged_df['ticker'] == sample_ticker]

plt.figure(figsize=(12,5))
plt.plot(df_sample['date'], df_sample['close'])
plt.title(f"Closing Price Over Time – {sample_ticker}")
plt.xlabel("Date")
plt.ylabel("Close Price")
plt.grid(True)
plt.show()

```


```
# Moving Averages Overlay Chart (Trend Detection)

plt.figure(figsize=(12,5))
plt.plot(df_sample['date'], df_sample['close'], label='Close Price', alpha=0.6)
plt.plot(df_sample['date'], df_sample['MA_7'], label='MA 7', linewidth=2)
plt.plot(df_sample['date'], df_sample['MA_14'], label='MA 14', linewidth=2)
plt.plot(df_sample['date'], df_sample['MA_21'], label='MA 21', linewidth=2)

plt.title(f"Moving Averages Trend – {sample_ticker}")
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend()
plt.grid(True)
plt.show()

```




```
# Moving Averages Overlay Chart (Trend Detection)

plt.figure(figsize=(12,5))
plt.plot(df_sample['date'], df_sample['close'], label='Close Price', alpha=0.6)
plt.plot(df_sample['date'], df_sample['MA_7'], label='MA 7', linewidth=2)
plt.plot(df_sample['date'], df_sample['MA_14'], label='MA 14', linewidth=2)
plt.plot(df_sample['date'], df_sample['MA_21'], label='MA 21', linewidth=2)

plt.title(f"Moving Averages Trend – {sample_ticker}")
plt.xlabel("Date")
plt.ylabel("Price")
plt.legend()
plt.grid(True)
plt.show()

```


Moving Averages Trend – AAPL
Close Price
MA 7
MA 14
MA 21
Price
Date
0
50
100
150
200
1980
1985
1990
1995
2000
2005
2010
2015
2020