Week 2: Ingest and Explore the Dataset

```
!git clone https://github.com/zhaoyangLin1008/test.git
%cd test/Notebooks
!ls ../Data
```

```
fatal: destination path 'test' already exists and is not an empty directory.
/home/jupyter-huxin/test/Notebooks
 cpi                     dividends     unemployment_msa_m_20250826.csv
 dgs10_m_20250826.csv  'stock price'
```

```
from pathlib import Path
import pandas as pd
import numpy as np
from IPython.display import display

# Data import
DATA_DIR = Path("../Data")
OUT_DIR  = Path("../Reports/w2_out")
OUT_DIR.mkdir(parents=True, exist_ok=True)
```

```
# Utilities — helper to drop duplicated columns by name/content
def drop_duplicate_columns(df, *, keep="first", verbose=True):
    before = df.shape[1]
    df1 = df.loc[:, ~df.columns.duplicated(keep=keep)]
    df2 = df1.loc[:, ~df1.T.duplicated(keep=keep)]
    removed = before - df2.shape[1]
    if verbose and removed > 0:
        print(f"[drop_duplicate_columns] removed {removed} duplicated col
    return df2
```

```
# raw dataset Overlook
def try_infer_date_column(df):
    """Guess a date column from common names or by parsing"""
    candidates = ["date", "Date", "DATE", "observation_date", "Ex-Date", "
    for c in candidates:
        if c in df.columns:
            return c
    # fallback: try parsing each column
    for c in df.columns:
        try:
            parsed = pd.to_datetime(df[c].head(30), errors="coerce")
            if parsed.notna().mean() > 0.6:
                return c
        except Exception:
            pass
    return None
```

```
csv_files = sorted([p for p in DATA_DIR.glob("*.csv")])
if not csv_files:
    print("[WARN] No CSV files found in /content. Please upload your da
else:
    overview_rows = []
    for path in csv_files:
        df = pd.read_csv(path)

        # basic info
        nrows, ncols = df.shape
        dcol = try_infer_date_column(df)

        # check date range
        date_min, date_max = None, None
        if dcol is not None:
            dt = pd.to_datetime(df[dcol], errors="coerce")
            if dt.notna().any():
                date_min = str(dt.min().date())
                date_max = str(dt.max().date())

        num_cols = df.select_dtypes(include=[np.number]).shape[1]
        non_num_cols = ncols - num_cols

        # save a small sample for reference
        df.head(10).to_csv(OUT_DIR / f"sample__{path.stem}.csv", index=Fal

        overview_rows.append({
            "filename": path.name,
            "rows": nrows,
            "cols": ncols,
            "date_col": dcol,
            "date_min": date_min,
            "date_max": date_max,
            "numeric_cols": num_cols,
            "non_numeric_cols": non_num_cols,
            "columns_preview": ", ".join(map(str, df.columns[:6]))
        })

        print(f"[CHECK] {path.name}: shape={df.shape}, "
              f"date_col={dcol}, date_range=({date_min}, {date_max})"

    # build overview table
    overview = pd.DataFrame(overview_rows).sort_values("filename").reset_index(
    overview.to_csv(OUT_DIR / "files_overview.csv", index=False)

    # show as a table in notebook
    display(overview.head())
    print("\nOverview saved to:", OUT_DIR / "files_overview.csv")
```

```
[CHECK] dgs10_m_20250826.csv: shape=(764, 3), date_col=date, date_range=(1962-01-31, 2025-
[CHECK] unemployment_msa_m_20250826.csv: shape=(2550, 4), date_col=date, date_range=(1990-
```

	filename	rows	cols	date_col	date_min	date_max	numer
0	dgs10_m_20250826.csv	764	3	date	1962-01-31	2025-08-31	
1	unemployment_msa_m_20250826.csv	2550	4	date	1990-01-01	2025-06-01	

```
Overview saved to: ../Reports/w2_out/files_overview.csv
```

```
# Data basic standardization and simple engineer features
#covert data to monthly
def to_month_end(s):
    """Convert date to month-end date"""
    dt = pd.to_datetime(s, errors="coerce")
    return (dt + pd.offsets.MonthEnd(0)).dt.normalize()

#calculate the fluctuation of month to month
def level_diff(s, periods=1):
    """Month-to-month difference"""
    return s.diff(periods=periods)

#take the last price in a month
def mon_agg_last(x):
    """Get the last available value in a month"""
    return x.dropna().iloc[-1] if x.notna().any() else np.nan

#convert the stock price to monthly
def month_end_close(price_df, date_col="Date", close_col="Close"):
    tmp = price_df.copy()
    tmp[date_col] = to_month_end(tmp[date_col])
    tmp[close_col] = pd.to_numeric(tmp[close_col], errors="coerce")
    out = (tmp.groupby(date_col, as_index=False)[close_col]
                  .agg(mon_agg_last)
                  .rename(columns={date_col: "date", close_col: "adj_price"
    return out
#claculate monthly dividents
def monthly_sum_by_exdate(div_df, date_col="Ex-Date", amt_col="Amount"):
```

```
        tmp = div_df.copy()
        tmp[date_col] = to_month_end(tmp[date_col])
        tmp[amt_col] = pd.to_numeric(tmp[amt_col], errors="coerce")
        out = (tmp.groupby(date_col, as_index=False)[amt_col]
                    .sum()
                    .rename(columns={date_col: "date", amt_col: "dividend"}))
        return out
# divident of a year
def compute_ttm_dividend(div_monthly):
        s = div_monthly.sort_values("date")["dividend"].fillna(0.0)
        return s.rolling(window=12, min_periods=1).sum()
```

```
# map the company and city
COMPANY_TO_METRO = {
        "BXP":  "Boston",
        "SLG":  "New York",
        "ELME": "Washington",
        "EQR":  "Chicago",
        "REXR": "Los Angeles",
        "TRNO": "Miami",
}

# the dividents and price of company
COMPANY_FILES = {
        "BXP":  ("stock price/bxp_prices.csv",  "dividends/bxp_dividends.csv"),
        "ELME": ("stock price/elme_prices.csv", "dividends/elme_dividends.csv"),
        "EQR":  ("stock price/eqr_prices.csv",  "dividends/eqr_dividends.csv"),
        "REXR": ("stock price/rexr_prices.csv", "dividends/rexr_dividends.csv"),
        "SLG":  ("stock price/slg_prices.csv",  "dividends/slg_dividends.csv"),
        "TRNO": ("stock price/trno_prices.csv", "dividends/trno_dividends.csv"),
}
```

```
#Data cleaning
#First aspect --- Firms' data (price and dividents)
company_tables = []
for tic, (price_file, div_file) in COMPANY_FILES.items():
    #read the raw data
        px_raw = pd.read_csv(DATA_DIR / price_file)
        dv_raw = pd.read_csv(DATA_DIR / div_file)
        print(f"[{tic}] raw shapes -> prices={px_raw.shape}, dividends={dv_raw.shap

        # git rid of same rows
        px = px_raw.drop_duplicates().copy()
        dv = dv_raw.drop_duplicates().copy()
        # standardize time
        px["Date"] = pd.to_datetime(px["Date"], errors="coerce")
        dv["Ex-Date"] = pd.to_datetime(dv["Ex-Date"], errors="coerce")
        #transfer numbers to folat and non numbers to NAN
        px["Close"] = pd.to_numeric(px["Close"], errors="coerce")
        dv["Amount"] = pd.to_numeric(dv["Amount"], errors="coerce")
        #Get rid of NANs
        px = px[px["Date"].notna() & px["Close"].notna()]
```

```
        dv = dv[dv["Ex-Date"].notna() & dv["Amount"].notna()]

        # monthly level
        px_m = month_end_close(px)
        dv_m = monthly_sum_by_exdate(dv)

        #take the same time period
        if not dv_m.empty and not px_m.empty:
          min_date = max(px_m["date"].min(), dv_m["date"].min())
          max_date = min(px_m["date"].max(), dv_m["date"].max())
          px_m = px_m[(px_m["date"] >= min_date) & (px_m["date"] <= max_date)]
          dv_m = dv_m[(dv_m["date"] >= min_date) & (dv_m["date"] <= max_date)]

        # merge and claculate TTM
        cur = (pd.merge(px_m, dv_m, on="date", how="left")
                 .sort_values("date")
                 .assign(dividend=lambda d: d["dividend"].fillna(0.0)))
        cur["dividend_ttm"] = compute_ttm_dividend(cur)
        cur["company"] = tic

        print(f"[{tic}] monthly rows={cur.shape[0]}, "
              f"range=({cur['date'].min().date()}, {cur['date'].max().date()})")

        company_tables.append(cur[["date","company","adj_price","dividend","dividend_ttm

    all_companies = pd.concat(company_tables, ignore_index=True)
    all_companies.to_csv(OUT_DIR / "step2_company_monthly_all.csv", index=False)
    print("[all_companies] shape:", all_companies.shape)
    display(all_companies.head(20))
```

```
[BXP] raw shapes -> prices=(247, 6), dividends=(55, 3)
[BXP] monthly rows=127, range=(2014-12-31, 2025-06-30)
[ELME] raw shapes -> prices=(247, 6), dividends=(55, 3)
[ELME] monthly rows=128, range=(2015-01-31, 2025-08-31)
[EQR] raw shapes -> prices=(385, 6), dividends=(55, 3)
[EQR] monthly rows=127, range=(2014-12-31, 2025-06-30)
[REXR] raw shapes -> prices=(146, 6), dividends=(55, 3)
[REXR] monthly rows=129, range=(2014-12-31, 2025-08-31)
[SLG] raw shapes -> prices=(247, 6), dividends=(98, 3)
[SLG] monthly rows=129, range=(2014-12-31, 2025-08-31)
[TRNO] raw shapes -> prices=(187, 6), dividends=(55, 3)
[TRNO] monthly rows=129, range=(2014-12-31, 2025-08-31)
[all_companies] shape: (769, 5)
```

	date	company	adj_price	dividend	dividend_ttm
0	2014-12-31	BXP	100.7570	5.80	5.80
1	2015-01-31	BXP	108.6960	7.75	13.55
2	2015-02-28	BXP	107.6030	0.00	13.55
3	2015-03-31	BXP	110.5230	0.65	14.20
4	2015-04-30	BXP	104.0960	0.00	14.20
5	2015-05-31	BXP	102.2990	0.00	14.20
6	2015-06-30	BXP	95.7034	0.65	14.85
7	2015-07-31	BXP	97.5042	0.00	14.85
8	2015-08-31	BXP	89.6563	0.00	14.85
9	2015-09-30	BXP	94.1603	0.65	15.50
10	2015-10-31	BXP	100.0920	0.00	15.50
11	2015-11-30	BXP	99.3991	0.00	15.50
12	2015-12-31	BXP	102.9440	1.90	11.60
13	2016-01-31	BXP	93.8176	3.85	7.70
14	2016-02-29	BXP	92.1475	0.00	7.70
15	2016-03-31	BXP	103.1100	0.65	7.70
16	2016-04-30	BXP	104.5650	0.00	7.70
17	2016-05-31	BXP	101.8890	0.00	7.70
18	2016-06-30	BXP	107.5730	0.65	7.70
19	2016-07-31	BXP	115.9130	0.00	7.70

```
#Data cleaning
#Second aspect --- CPI and umemployment
#CPI
CPI_FILES = {
        "Boston":           "cpi/la_cpi_boston.csv",
```

```
        "Chicago":        "cpi/la_cpi_chicago.csv",
        "Los Angeles":  "cpi/la_cpi_los_angeles.csv",
        "Miami":            "cpi/la_cpi_miami.csv",
        "New York":       "cpi/la_cpi_ny.csv",
        "Washington":   "cpi/la_cpi_Washington.csv",
}
cpi_tables = []

for city, fname in CPI_FILES.items():
        path = DATA_DIR / fname
        if not path.exists():
                print(f"[WARN] Missing CPI file for {city}")
                continue

        df = pd.read_csv(path)
        if "date" in df.columns:
                dcol = "date"
        elif "DATE" in df.columns:
                dcol = "DATE"
        elif "observation_date" in df.columns:
                dcol = "observation_date"
        else:
                dcol = df.columns[0]

        vcol = "value" if "value" in df.columns else df.columns[-1]

        df = df[[dcol, vcol]].rename(columns={dcol:"date", vcol:"cpi"})
        df["date"] = to_month_end(df["date"])
        df["cpi"]   = pd.to_numeric(df["cpi"], errors="coerce")
        df = df[df["date"].notna() & df["cpi"].notna()].drop_duplicates()
        df = df.sort_values("date")

        # engineer features
        df["cpi_yoy"] = df["cpi"]/df["cpi"].shift(12) - 1
        df["cpi_mom"] = df["cpi"]/df["cpi"].shift(1)   - 1
        df["metro"]     = city

        cpi_tables.append(df[["date","metro","cpi","cpi_yoy","cpi_mom"]])

# merge all COI
cpi_all = pd.concat(cpi_tables, ignore_index=True) if cpi_tables else pd.DataFram
cpi_all.to_csv(OUT_DIR / "step3_cpi_all.csv", index=False)

print("CPI total shape:", cpi_all.shape)
display(cpi_all.head(10))

#Unemployment
unemp_path = DATA_DIR / "unemployment_msa_m_20250826.csv"
if not unemp_path.exists():
        print("[WARN] Unemployment file missing")
        unemp = pd.DataFrame(columns=["metro","date","unemp","unemp_mom"])
else:
        df = pd.read_csv(unemp_path)

        # standardize date and time
```

```
        df["date"]    =  to_month_end(df["date"])
        df["value"]  =  pd.to_numeric(df["value"],  errors="coerce")
        df  =  df[df["date"].notna()  &  df["value"].notna()].drop_duplicates()

        #  metro  data  to  the  city
        df["metro"]  =  None
        for  city  in  set(COMPANY_TO_METRO.values()):
                df.loc[df["city"].str.contains(city,  na=False),  "metro"]  =  city
        df  =  df.dropna(subset=["metro"])

        #  take  average  to  month
        unemp  =  (df.groupby(["metro","date"],  as_index=False)["value"]
                      .mean()
                      .rename(columns={"value":"unemp"}))
        #  month  to  month  and  year  to  year  data
        unemp  =  unemp.sort_values(["metro","date"])
        unemp["unemp_mom"]  =  unemp.groupby("metro")["unemp"].transform(level_diff)

unemp.to_csv(OUT_DIR  /  "step4_unemployment_all.csv",  index=False)

print("Unemployment  shape:",  unemp.shape)
display(unemp.head(10))
```

```
CPI total shape: (4004, 5)
```

	date	metro	cpi	cpi_yoy	cpi_mom
0	1914-12-31	Boston	10.5	NaN	NaN
1	1915-12-31	Boston	10.7	NaN	0.019048
2	1916-12-31	Boston	12.1	NaN	0.130841
3	1917-12-31	Boston	14.2	NaN	0.173554
4	1918-12-31	Boston	17.3	NaN	0.218310
5	1919-06-30	Boston	17.4	NaN	0.005780
6	1919-12-31	Boston	19.5	NaN	0.120690
7	1920-06-30	Boston	21.5	NaN	0.102564
8	1920-12-31	Boston	20.2	NaN	-0.060465
9	1921-05-31	Boston	18.0	NaN	-0.108911

```
Unemployment shape: (2550, 4)
```

	metro	date	unemp	unemp_mom
0	Boston	1990-01-31	5.3	NaN
1	Boston	1990-02-28	5.2	-0.1
2	Boston	1990-03-31	5.3	0.1
3	Boston	1990-04-30	5.4	0.1
4	Boston	1990-05-31	5.5	0.1
5	Boston	1990-06-30	5.7	0.2
6	Boston	1990-07-31	5.9	0.2
7	Boston	1990-08-31	6.1	0.2
8	Boston	1990-09-30	6.3	0.2
9	Boston	1990-10-31	6.5	0.2

```
#Data cleaning
#Third aspect --- 10Y Treasury
ust10_path = DATA_DIR / "dgs10_m_20250826.csv"
if not ust10_path.exists():
        warnings.warn("10Y file missing: dgs10_m_20250826.csv")
        ust10 = pd.DataFrame(columns=["date","ten_year","ten_year_mom"])
else:
        ust10 = pd.read_csv(ust10_path)
        # sequence as the date
        ust10["date"] = to_month_end(ust10["date"])
        ust10 = ust10.sort_values("date")
        # calculate month to month change
        ust10["ten_year"] = pd.to_numeric(ust10["value"], errors="coerce")
        ust10["ten_year_mom"] = ust10["ten_year"].diff(periods=1)
```

```
        # only keep the standard rows
        ust10 = ust10[["date","ten_year","ten_year_mom"]]

# save the file
ust10.to_csv(OUT_DIR / "step5_ust10.csv", index=False)
print("[ust10] shape:", ust10.shape)
if not ust10.empty:
        print(f"[ust10] range=({ust10['date'].min().date()}, {ust10['date'].max().date
display(ust10.tail(10))
```

```
[ust10] shape: (764, 3)
[ust10] range=(1962-01-31, 2025-08-31)
```

	date	ten_year	ten_year_mom
754	2024-11-30	4.355789	0.260335
755	2024-12-31	4.391429	0.035639
756	2025-01-31	4.629048	0.237619
757	2025-02-28	4.451053	-0.177995
758	2025-03-31	4.280476	-0.170576
759	2025-04-30	4.279048	-0.001429
760	2025-05-31	4.423810	0.144762
761	2025-06-30	4.383500	-0.040310
762	2025-07-31	4.391818	0.008318
763	2025-08-31	4.270625	-0.121193

```
# Final merge: all data sources into one table
# Purpose: join sources, attach metro, de-duplicate columns, quick checks, the

# all companies
all_companies = pd.concat(company_tables, ignore_index=True)

# name of the city
all_companies["metro"] = all_companies["company"].map(COMPANY_TO_METRO)

# CPI
df_merged = pd.merge(all_companies, cpi_all, on=["date", "metro"], how="left")
# Unemployment rate
df_merged = pd.merge(df_merged, unemp, on=["date", "metro"], how="left")
# 10Y yield
df_merged = pd.merge(df_merged, ust10, on="date", how="left")

# de-duplicate columns BEFORE export
df_merged = drop_duplicate_columns(df_merged)

# save and display
df_merged.to_csv(OUT_DIR / "final_dataset.csv", index=False)
print("final_dataset shape:", df_merged.shape)
```

```
display(df_merged.head(20))
```

```
final_dataset shape: (769, 13)
```

	date	company	adj_price	dividend	dividend_ttm	metro	cpi	cpi_yoy	cpi
0	2014-12-31	BXP	100.7570	5.80	5.80	Boston	NaN	NaN	
1	2015-01-31	BXP	108.6960	7.75	13.55	Boston	254.556	0.018399	-0.00
2	2015-02-28	BXP	107.6030	0.00	13.55	Boston	NaN	NaN	
3	2015-03-31	BXP	110.5230	0.65	14.20	Boston	257.013	0.024630	0.00
4	2015-04-30	BXP	104.0960	0.00	14.20	Boston	NaN	NaN	
5	2015-05-31	BXP	102.2990	0.00	14.20	Boston	256.839	0.027208	-0.00
6	2015-06-30	BXP	95.7034	0.65	14.85	Boston	NaN	NaN	
7	2015-07-31	BXP	97.5042	0.00	14.85	Boston	256.999	0.023627	0.00
8	2015-08-31	BXP	89.6563	0.00	14.85	Boston	NaN	NaN	
9	2015-09-30	BXP	94.1603	0.65	15.50	Boston	256.643	0.018756	-0.00
10	2015-10-31	BXP	100.0920	0.00	15.50	Boston	NaN	NaN	
11	2015-11-30	BXP	99.3991	0.00	15.50	Boston	258.407	0.024490	0.00
12	2015-12-31	BXP	102.9440	1.90	11.60	Boston	NaN	NaN	
13	2016-01-31	BXP	93.8176	3.85	7.70	Boston	257.215	0.016166	-0.00
14	2016-02-29	BXP	92.1475	0.00	7.70	Boston	NaN	NaN	
15	2016-03-31	BXP	103.1100	0.65	7.70	Boston	258.587	0.014138	0.00
16	2016-04-30	BXP	104.5650	0.00	7.70	Boston	NaN	NaN	
17	2016-05-31	BXP	101.8890	0.00	7.70	Boston	260.809	0.021943	0.00
18	2016-06-30	BXP	107.5730	0.65	7.70	Boston	NaN	NaN	
19	2016-07-31	BXP	115.9130	0.00	7.70	Boston	260.800	0.021559	-0.00

Week 3: Data Split & EDA START

Verify the basic quality of merged data: date formats, deduplication, and sorting. Ensure the dataset is clean and well-organized for subsequent splitting and modeling.

```
# Step 1: Data existence and basic validation
def drop_duplicate_columns(df):
    """Remove duplicate columns by name or by identical content"""
    df = df.loc[:, ~df.columns.duplicated()]
    df = df.loc[:, ~df.T.duplicated()]
    return df

# Ensure the 'date' column is in datetime format and align dates to the en
df_merged["date"] = pd.to_datetime(df_merged["date"])
df_merged["date"] = df_merged["date"] + pd.offsets.MonthEnd(0)

# Report duplicate rows/columns BEFORE dropping
dup_rows = df_merged.duplicated(subset=["company","date"]).sum()
dup_cols = df_merged.columns.duplicated().sum()
print(f"Duplicate rows before drop: {dup_rows}, duplicate columns: {dup_cols}")

# Remove duplicate rows/columns and sort the data
df_merged = df_merged.drop_duplicates(subset=["company","date"]).sort_values(["company
df_merged = drop_duplicate_columns(df_merged)

# Check data types and missing values
print("\ndata types:")
print(df_merged.dtypes)

print("\nisna:")
print(df_merged.isna().sum())

# Display the time range for each company
print("\ntime range for each company:")
time_ranges = df_merged.groupby("company")["date"].agg(["min", "max", "count"])
print(time_ranges)

# Print the first 5 rows
print("\nhead:")
print(df_merged.head())
```

```
Duplicate rows before drop: 0, duplicate columns: 0

data types:
date            datetime64[ns]
company                 object
adj_price              float64
dividend               float64
dividend_ttm           float64
metro                   object
cpi                    float64
cpi_yoy                float64
cpi_mom                float64
```

```
unemp                float64
unemp_mom            float64
ten_year             float64
ten_year_mom         float64
dtype: object

isna:
date              0
company           0
adj_price         0
dividend          0
dividend_ttm      0
metro             0
cpi             287
cpi_yoy         287
cpi_mom         287
unemp            14
unemp_mom        14
ten_year          0
ten_year_mom      0
dtype: int64

time range for each company:
               min        max  count
company
BXP     2014-12-31 2025-06-30    127
ELME    2015-01-31 2025-08-31    128
EQR     2014-12-31 2025-06-30    127
REXR    2014-12-31 2025-08-31    129
SLG     2014-12-31 2025-08-31    129
TRNO    2014-12-31 2025-08-31    129

head:
        date company  adj_price  dividend  dividend_ttm   metro      cpi  \
0 2014-12-31     BXP    100.757      5.80          5.80  Boston      NaN
1 2015-01-31     BXP    108.696      7.75         13.55  Boston  254.556
2 2015-02-28     BXP    107.603      0.00         13.55  Boston      NaN
3 2015-03-31     BXP    110.523      0.65         14.20  Boston  257.013
4 2015-04-30     BXP    104.096      0.00         14.20  Boston      NaN

    cpi_yoy   cpi_mom  unemp  unemp_mom  ten_year  ten_year_mom
0       NaN       NaN    4.7       -0.1  2.207273     -0.118283
1  0.018399 -0.006657    4.7        0.0  1.881500     -0.325773
2       NaN       NaN    4.6       -0.1  1.975263      0.093763
3  0.024630  0.009652    4.5       -0.1  2.042727      0.067464
4       NaN       NaN    4.5        0.0  1.935000     -0.107727
```

Split the data into training, validation, and test sets based on time sequence. Preserve the integrity of the time series to prevent leakage of future information.

```
# Step 2: Dataset Splitting (Train / Validation / Test)

# Sort by chronological order to avoid future data leakage
df_sorted = df_merged.sort_values("date").reset_index(drop=True)

# Calculate split indices
n_total = len(df_sorted)
```

```
train_end = int(n_total * 0.7)
valid_end = int(n_total * 0.85)

# Split the dataset
train_df = df_sorted.iloc[:train_end]
valid_df = df_sorted.iloc[train_end:valid_end]
test_df  = df_sorted.iloc[valid_end:]

print("Dataset split summary:")
print(f"Total samples: {n_total}")
print(f"Training set: {train_df.shape}, Date range {train_df['date'].min().date()}
print(f"Validation set: {valid_df.shape}, Date range {valid_df['date'].min().date()
print(f"Test set: {test_df.shape}, Date range {test_df['date'].min().date()} → {
```

```
Dataset split summary:
Total samples: 769
Training set: (538, 13), Date range 2014-12-31 → 2022-05-31
Validation set: (115, 13), Date range 2022-05-31 → 2023-12-31
Test set: (116, 13), Date range 2024-01-31 → 2025-08-31
```

Output descriptive statistics and missing value statistics on the training set. The first step in EDA, helping to understand the basic distribution of the data and potential issues.

```
# Step 3.1: Descriptive statistics and missing value check for the training

print("Training set size:")
print(train_df.shape)

# 1. Descriptive statistics
print("\nDescriptive statistics:")
display(train_df.describe(include="all").T)

# 2. Missing value statistics
print("\nMissing value statistics:")
missing_stats = train_df.isna().sum().to_frame("missing_count")
missing_stats["missing_pct"] = (missing_stats["missing_count"] / len(train_df)) *
display(missing_stats)

# 3. Number of observations per company
print("\nNumber of observations per company:")
company_counts = train_df["company"].value_counts().to_frame("n_obs")
display(company_counts)

# 4. Time range check (within training set)
print("\nTime range of the training set:")
time_ranges_train = train_df.groupby("company")["date"].agg(["min","max","count"])
display(time_ranges_train)
```

```
Training set size:
(538, 13)

Descriptive statistics:
```

	count	unique	top	freq	mean	min	25%
date	538	NaN	NaN	NaN	2018-09-14 21:35:27.881040896	2014-12-31 00:00:00	2016-10-31 00:00:00
company	538	6	BXP	90	NaN	NaN	NaN
adj_price	538.0	NaN	NaN	NaN	54.927262	11.0497	25.7296
dividend	538.0	NaN	NaN	NaN	0.406259	0.0	0.0
dividend_ttm	538.0	NaN	NaN	NaN	4.578889	0.12	1.795
metro	538	6	Boston	90	NaN	NaN	NaN
cpi	351.0	NaN	NaN	NaN	262.11314	225.763	246.0505
cpi_yoy	351.0	NaN	NaN	NaN	0.029463	-0.009328	0.014409
cpi_mom	351.0	NaN	NaN	NaN	0.003204	-0.010318	-0.000329
unemp	538.0	NaN	NaN	NaN	5.173234	2.6	3.6
unemp_mom	538.0	NaN	NaN	NaN	-0.023234	-4.1	-0.1
ten_year	538.0	NaN	NaN	NaN	1.976554	0.623636	1.61087
ten_year_mom	538.0	NaN	NaN	NaN	0.006325	-0.634211	-0.105

```
Missing value statistics:
```

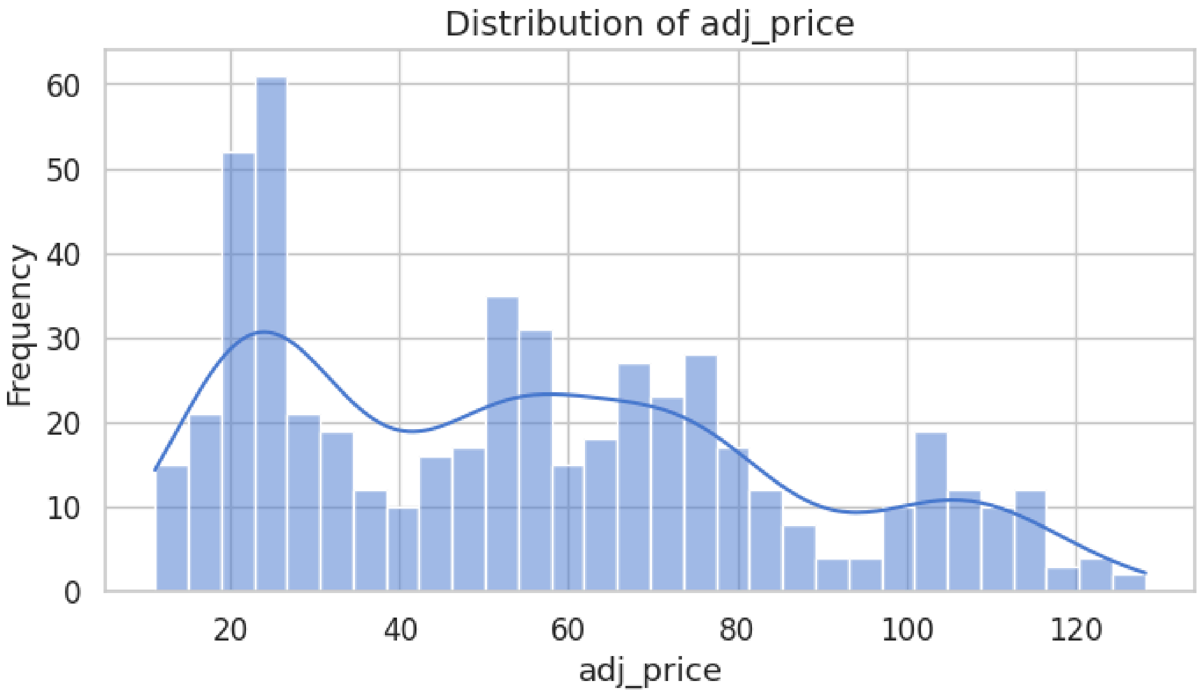
	missing_count	missing_pct
date	0	0.000000
company	0	0.000000
adj_price	0	0.000000
dividend	0	0.000000
dividend_ttm	0	0.000000
metro	0	0.000000
cpi	187	34.758364
cpi_yoy	187	34.758364
cpi_mom	187	34.758364
unemp	0	0.000000
unemp_mom	0	0.000000
ten_year	0	0.000000
ten_year_mom	0	0.000000

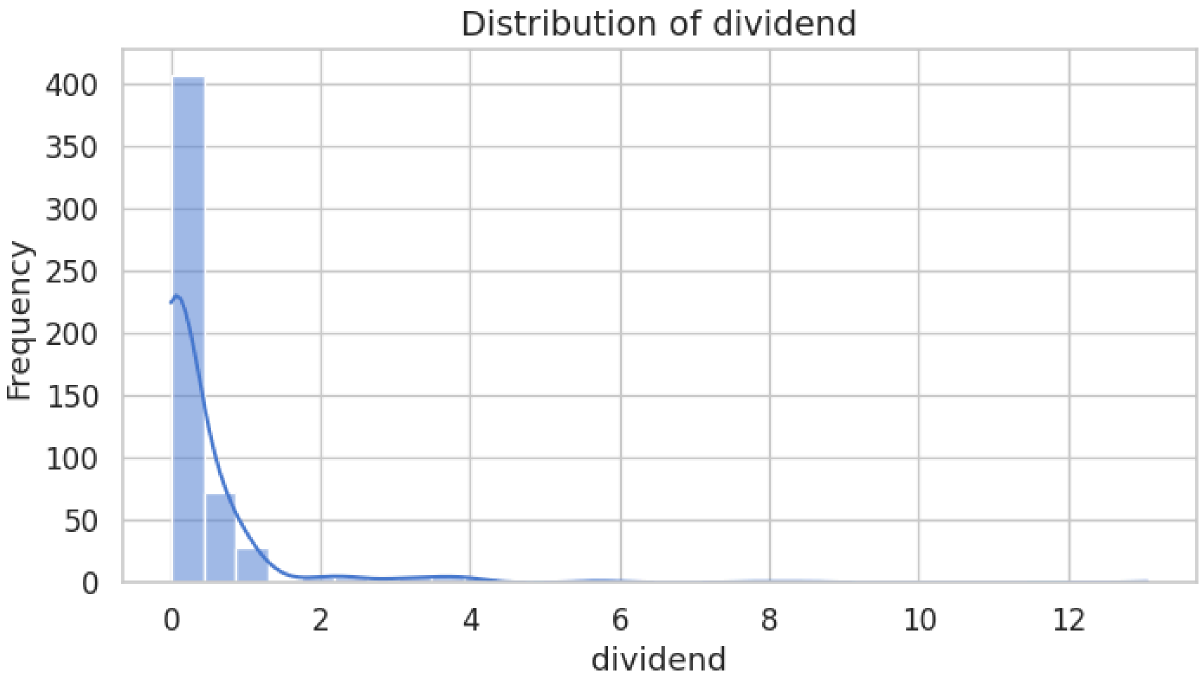
```
Number of observations per company:
        n_obs
company
  BXP     90
```

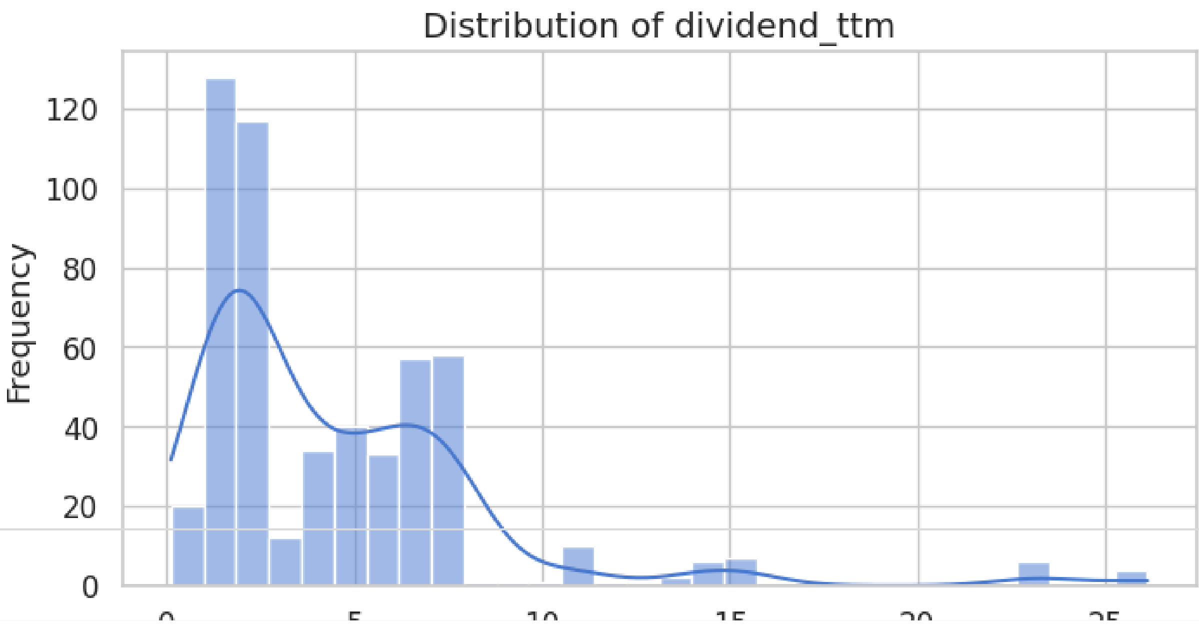
Plot histograms and grouped boxplots for numerical variables to examine distribution characteristics and differences across companies. Identify skewness, outliers, and variations between companies/regions.

```
# Step 3.2: Variable distribution visualization (Training set)

import matplotlib.pyplot as plt
import seaborn as sns

# Set plotting style
sns.set(style="whitegrid", palette="muted", font_scale=1.1)

# Select numerical features (excluding date and categorical variables)
num_cols = train_df.select_dtypes(include=["float64", "int64"]).columns

print("Numerical variables:", num_cols.tolist())

# 1. Histogram + KDE
for col in num_cols:
        plt.figure(figsize=(8, 4))
        sns.histplot(train_df[col].dropna(), bins=30, kde=True)
        plt.title(f"Distribution of {col}", fontsize=14)
        plt.xlabel(col)
        plt.ylabel("Frequency")
        plt.show()

# 2. Comparison across companies/regions (using CPI as an example)
plt.figure(figsize=(10, 5))
sns.boxplot(data=train_df, x="company", y="cpi")
plt.title("CPI distribution by company", fontsize=14)
plt.xticks(rotation=45)
plt.show()

plt.figure(figsize=(10, 5))
sns.boxplot(data=train_df, x="metro", y="unemp")
plt.title("Unemployment rate distribution by city", fontsize=14)
plt.show()
```

```
Numerical variables: ['adj_price', 'dividend', 'dividend_ttm', 'cpi', 'cpi_yoy', 'cpi_mc
```

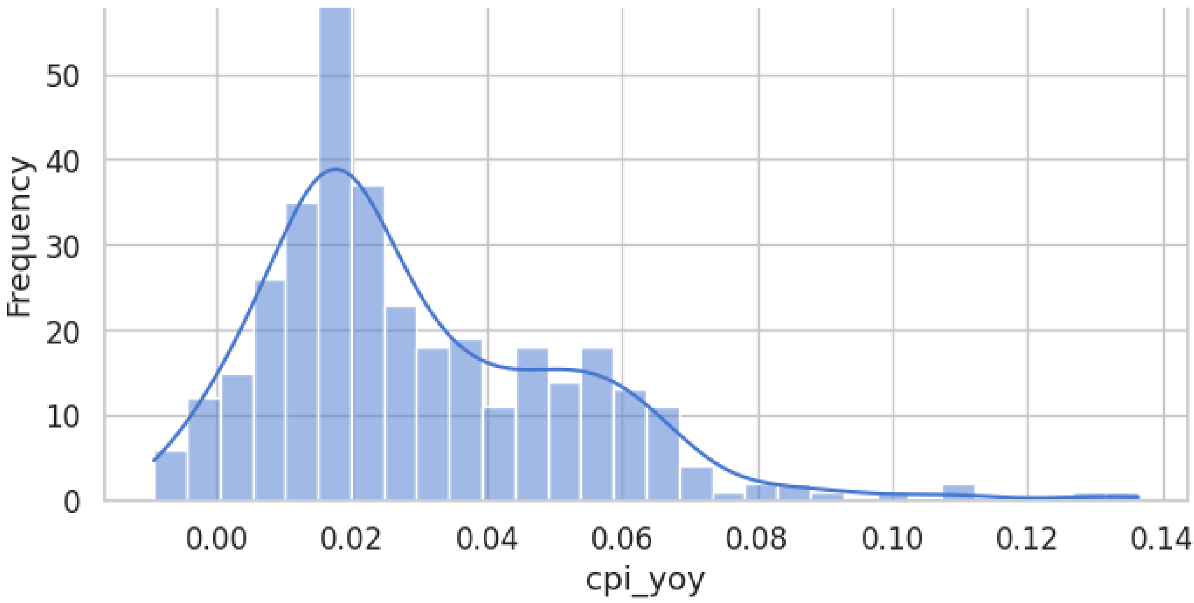


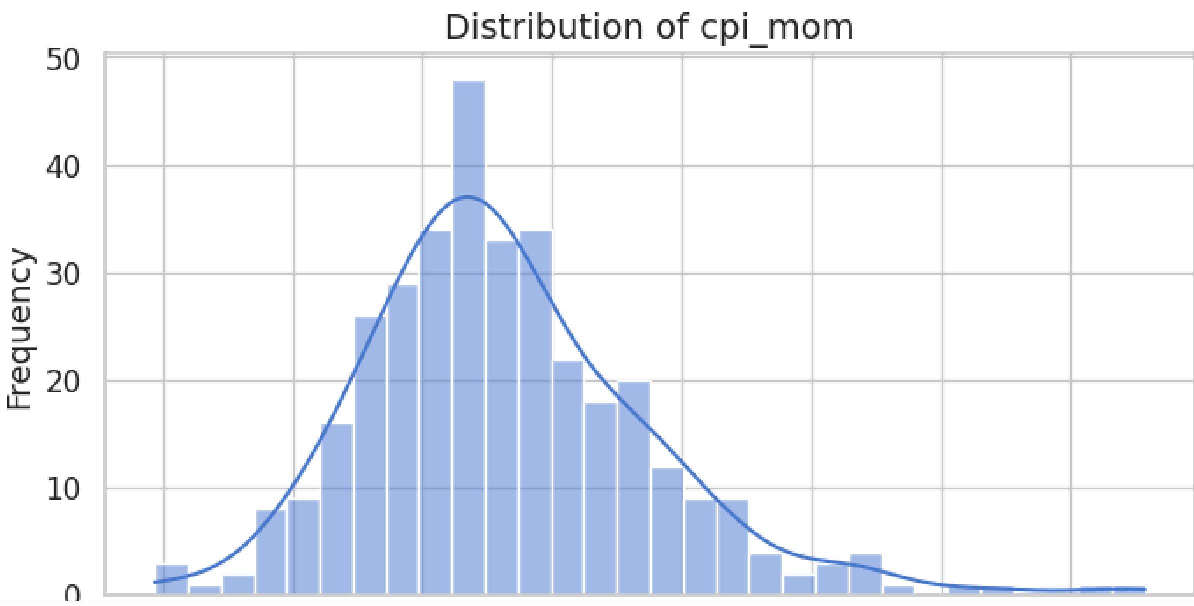




Calculate the correlation between numerical variables and plot a heatmap. Explore linear relationships among variables to determine if multicollinearity exists.

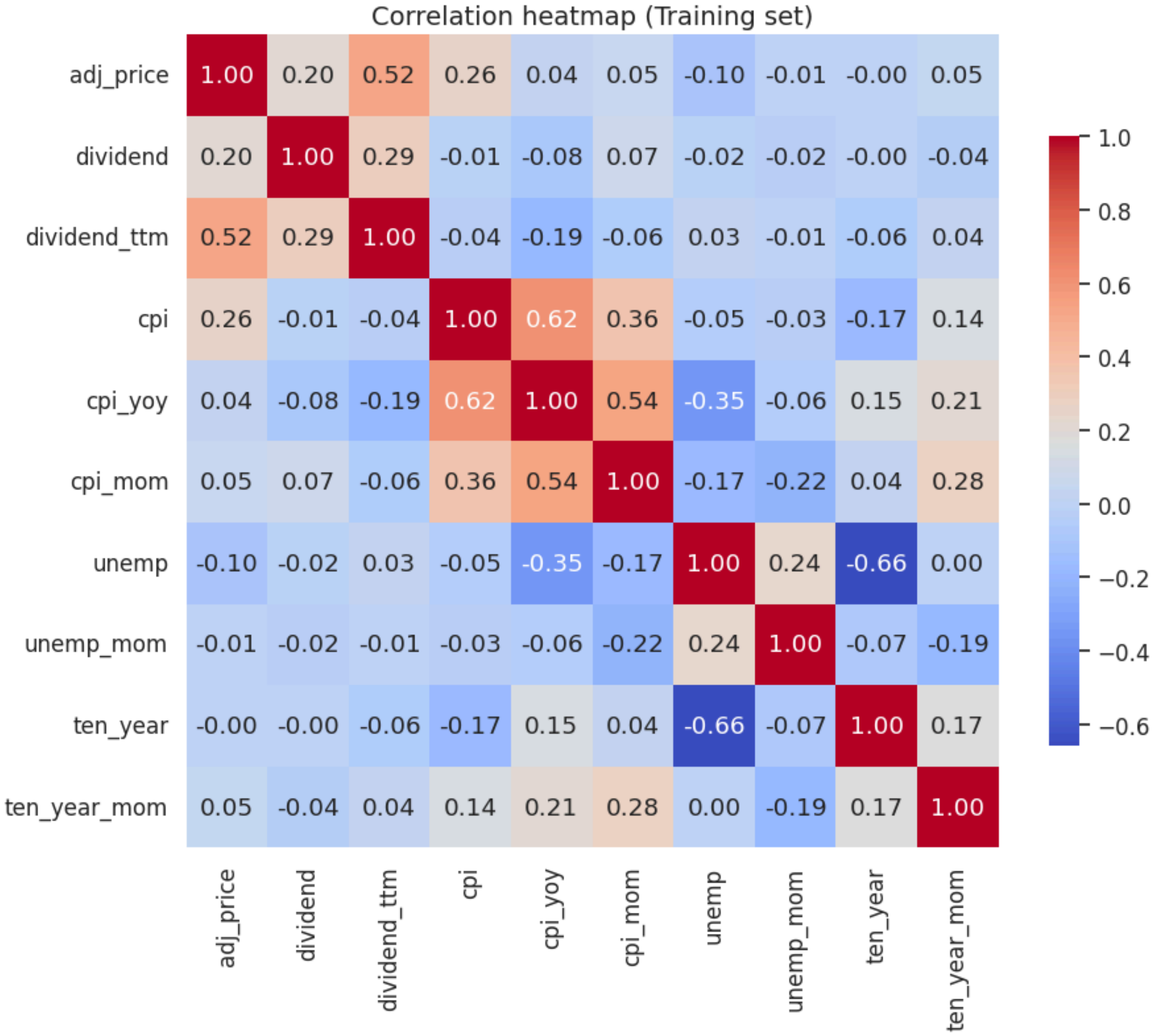
```
# Step 3.3: Correlation analysis (Training set)

# Select only numerical features
num_cols = train_df.select_dtypes(include=["float64", "int64"]).columns

# Compute Pearson correlation coefficients
corr_matrix = train_df[num_cols].corr(method="pearson")

print("Correlation matrix of numerical variables:")
display(corr_matrix)

# Visualize as a heatmap
plt.figure(figsize=(10, 8))
sns.heatmap(corr_matrix, annot=True, fmt=".2f", cmap="coolwarm", square=True, cbar_
plt.title("Correlation heatmap (Training set)", fontsize=14)
plt.show()
```





```
Correlation matrix of numerical variables:
```

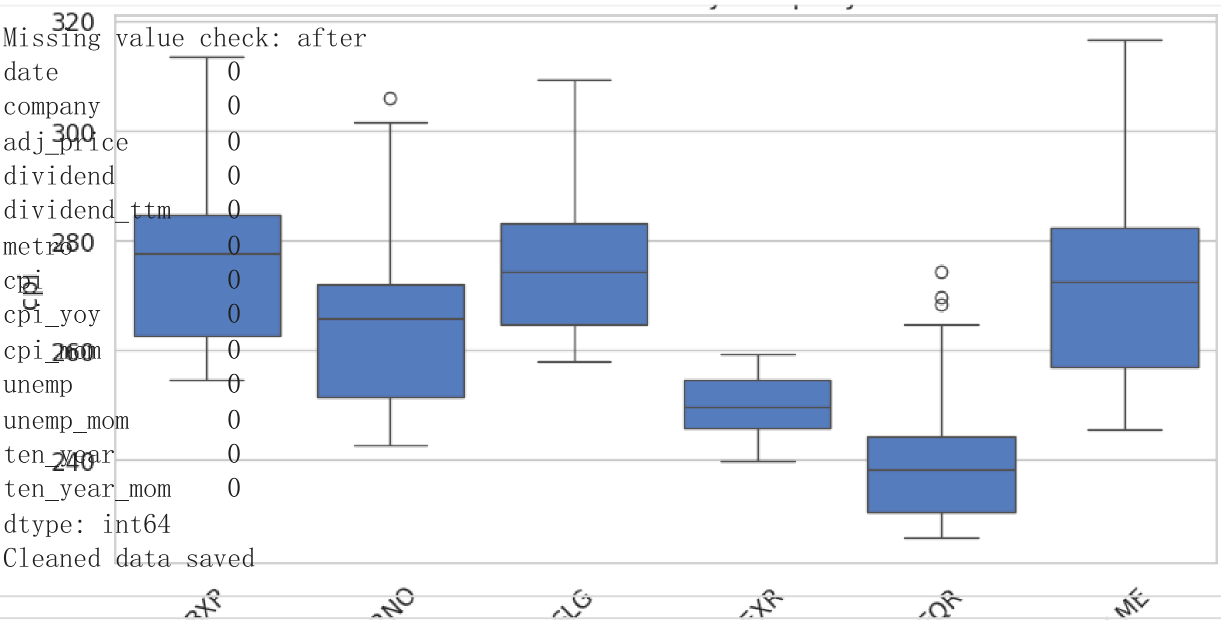
	adj_price	dividend	dividend_ttm	cpi	cpi_yoy	cpi_mom	
adj_price	1.000000	0.196598	0.524375	0.262500	0.038913	0.052025	-0.
dividend	0.196598	1.000000	0.287565	-0.012953	-0.083534	0.074500	-0.
dividend_ttm	0.524375	0.287565	1.000000	-0.035349	-0.185490	-0.059667	0.
cpi	0.262500	-0.012953	-0.035349	1.000000	0.616430	0.362379	-0.
cpi_yoy	0.038913	-0.083534	-0.185490	0.616430	1.000000	0.535181	-0.
cpi_mom	0.052025	0.074500	-0.059667	0.362379	0.535181	1.000000	-0.
unemp	-0.102272	-0.017832	0.031208	-0.048867	-0.348630	-0.173192	1.
unemp_mom	-0.010750	-0.020127	-0.006864	-0.034361	-0.056443	-0.219157	0.
ten_year	-0.002515	-0.004540	-0.059679	-0.168095	0.148846	0.038487	-0.
ten_year_mom	0.045657	-0.041438	0.038203	0.139841	0.206491	0.280047	0.



Week4: Make Data Model Ready

```
# Step 1: Missing Value Handling

# Backup the data
df_clean = df_merged.copy()

num_cols = ["cpi", "cpi_yoy", "cpi_mom", "unemp", "unemp_mom"]
for col in num_cols:
        df_clean[col] = (df_clean
                                        .sort_values(["metro","date"])
                                        .groupby("metro")[col]
                                        .ffill())

medians = df_clean[num_cols].median()
df_clean[num_cols] = df_clean[num_cols].fillna(medians)

print("Missing value check: after")
print(df_clean.isna().sum())

# Save the cleaned data
df_clean.to_csv(OUT_DIR / "week4_step1_missing_cleaned.csv", index=False)
print("Cleaned data saved")
```

```
Missing value check: after
date            0
company         0
adj_price       0
dividend        0
dividend_ttm    0
metro           0
cpi             0
cpi_yoy         0
cpi_mom         0
unemp           0
unemp_mom       0
ten_year        0
ten_year_mom    0
dtype: int64
Cleaned data saved
```




```
# Step 2: Outlier Handling

df_outlier = df_clean.copy()

# Trimming
df_outlier["unemp"] = df_outlier["unemp"].clip(lower=0, upper=25)
df_outlier["ten_year"] = df_outlier["ten_year"].clip(lower=0, upper=15)
df_outlier["dividend_ttm"] = df_outlier["dividend_ttm"].clip(lower=0, upper=df_outlie

# IQR-based winsorization
def winsorize_iqr(series):
        Q1 = series.quantile(0.25)
        Q3 = series.quantile(0.75)
        IQR = Q3 - Q1
        lower = Q1 - 1.5 * IQR
```

```
        upper = Q3 + 1.5 * IQR
        return series.clip(lower=lower, upper=upper)

for col in ["cpi_mom", "cpi_yoy", "unemp_mom", "ten_year_mom"]:
        df_outlier[col] = winsorize_iqr(df_outlier[col])

# Check again
print("Statistics after outlier handling")
print(df_outlier[["unemp","ten_year","dividend_ttm","cpi_mom","cpi_yoy","unemp_mom","ten

# Save the results
df_outlier.to_csv(OUT_DIR / "week4_step2_outlier_cleaned.csv", index=False)
print("Outlier handling saved")
```

```
Statistics after outlier handling
              count      mean       std       min       25%       50%  \
unemp         769.0  4.774902  2.302299  2.400000  3.500000  4.300000
ten_year      769.0  2.589282  1.107689  0.623636  1.764500  2.360000
dividend_ttm  769.0  4.525647  3.544490  0.120000  1.910000  3.640000
cpi_mom       769.0  0.003601  0.005426 -0.009567  0.000328  0.002349
cpi_yoy       769.0  0.044517  0.030260 -0.009328  0.022217  0.036097
unemp_mom     769.0 -0.051235  0.106930 -0.250000 -0.100000  0.000000
ten_year_mom  769.0  0.015274  0.192864 -0.480238 -0.105238  0.001826

                   75%        max
unemp         5.100000  19.000000
ten_year      3.573636   4.798095
dividend_ttm  6.462500  23.176400
cpi_mom       0.006925   0.016820
cpi_yoy       0.058835   0.113761
unemp_mom     0.000000   0.150000
ten_year_mom  0.144762   0.519762
Outlier handling saved
```

```
# Step 3: Variable Transformation and Standardization

from sklearn.preprocessing import StandardScaler
import joblib

df_trans = df_outlier.copy()

# Log transformation
df_trans["adj_price_log"] = np.log1p(df_trans["adj_price"])
df_trans["dividend_ttm_log"] = np.log1p(df_trans["dividend_ttm"])

# Standardization
scale_cols = [
        "cpi", "cpi_yoy", "cpi_mom",
        "unemp", "unemp_mom",
        "ten_year", "ten_year_mom",
        "adj_price_log", "dividend_ttm_log"
]

scaler = StandardScaler()
df_trans_scaled = df_trans.copy()
```

```
df_trans_scaled[scale_cols] = scaler.fit_transform(df_trans[scale_cols])

# Save model
joblib.dump(scaler, OUT_DIR / "week4_step3_scaler.pkl")

# Check standardized results
print("Statistics after standardization")
print(df_trans_scaled[scale_cols].describe().T[["mean", "std"]])

# Save data
df_trans_scaled.to_csv(OUT_DIR / "week4_step3_transformed.csv", index=False)
print("variable transformation and standardization saved")
```

```
Statistics after standardization
                         mean       std
cpi              -1.191938e-15  1.000651
cpi_yoy           4.619914e-17  1.000651
cpi_mom           9.239828e-18  1.000651
unemp            -2.125160e-16  1.000651
unemp_mom         9.701819e-17  1.000651
ten_year          8.777836e-17  1.000651
ten_year_mom      9.239828e-18  1.000651
adj_price_log    -1.293576e-16  1.000651
dividend_ttm_log -4.250321e-16  1.000651
variable transformation and standardization saved
```

```
# Step 4: Remove Unnecessary or Redundant Variables

df_final = df_trans_scaled.copy()

# Drop unnecessary variables
drop_cols = ["adj_price", "dividend", "dividend_ttm"]
df_final = df_final.drop(columns=drop_cols, errors="ignore")

print("Remaining variables:")
print(df_final.columns.tolist())

# Save data
df_final.to_csv(OUT_DIR / "week4_step4_feature_selected.csv", index=False)
print("saved")
```

```
Remaining variables:
['date', 'company', 'metro', 'cpi', 'cpi_yoy', 'cpi_mom', 'unemp', 'unemp_mom', 'ten_year'
saved
```

```
# Step 5: Categorical Variable Encoding
# Purpose: one-hot encode company/metro; drop duplicated columns.

df_encoded = df_final.copy()   # df_final comes from Step 4

df_encoded = pd.get_dummies(
        df_encoded,
```

```
        columns=["company", "metro"],
        drop_first=False
)

# remove any duplicated columns (by name/content)
df_encoded = drop_duplicate_columns(df_encoded)

print("One-Hot Encoding finished. Current columns:", len(df_encoded.columns))
df_encoded.to_csv(OUT_DIR / "week4_step5_encoded.csv", index=False)
print("saved")
```

```
One-Hot Encoding finished. Current columns: 16
saved
```

```
# Step 6: Bucketize / Categorize selected numerical variables
# Purpose: quantile bins for ten_year and cpi_yoy, then one-hot; drop duplica

df_bucket = df_encoded.copy()   # from Step 5

# 3-bin for ten_year
df_bucket["ten_year_bin"] = pd.qcut(
        df_bucket["ten_year"], q=3, labels=["low", "mid", "high"]
)

# 4-bin for cpi_yoy
df_bucket["cpi_yoy_bin"] = pd.qcut(
        df_bucket["cpi_yoy"], q=4, labels=["q1", "q2", "q3", "q4"]
)

# one-hot for bins
df_bucket = pd.get_dummies(
        df_bucket,
        columns=["ten_year_bin", "cpi_yoy_bin"],
        drop_first=False
)

# remove duplicated columns (defensive)
df_bucket = drop_duplicate_columns(df_bucket)

print("Bucketized and encoded columns added.")
df_bucket.to_csv(OUT_DIR / "week4_step6_bucketized.csv", index=False)
print("Bucketized dataset saved.")
```

```
Bucketized and encoded columns added.
Bucketized dataset saved.
```

```
# Step 7: Final Check and Export
# Purpose: chronological split on the fully-processed table; export 3 sets.

# use the fully processed table (after Step 6)
df_final_model = df_bucket.copy()
```

```
# chronological split
df_final_model = df_final_model.sort_values("date").reset_index(drop=True)
n = len(df_final_model)
train_end = int(n * 0.70)
valid_end = int(n * 0.85)

train_final = df_final_model.iloc[:train_end].copy()
valid_final = df_final_model.iloc[train_end:valid_end].copy()
test_final  = df_final_model.iloc[valid_end:].copy()

# basic checks
for name, d in [("train", train_final), ("valid", valid_final), ("test", test_f
        print(name, d.shape, "missing:", int(d.isna().sum().sum()), "dupe rows:",

# export
train_final.to_csv(OUT_DIR / "week4_train.csv", index=False)
valid_final.to_csv(OUT_DIR / "week4_valid.csv", index=False)
test_final.to_csv(OUT_DIR / "week4_test.csv", index=False)
print("Final datasets saved (train/valid/test)")
```

```
train (538, 23) missing: 0 dupe rows: 0
valid (115, 23) missing: 0 dupe rows: 0
test (116, 23) missing: 0 dupe rows: 0
Final datasets saved (train/valid/test)
```

```
# === Step 8: Save clean splits for later modeling ===
from pathlib import Path
import pandas as pd

OUT_DIR = Path("../Reports/w4_out")
OUT_DIR.mkdir(parents=True, exist_ok=True)

# If you already have the final processed dataset (after Step 6)
# for example it's called df_final_model, then split again here
df_final_model = df_bucket.copy().sort_values("date").reset_index(drop=True)
n = len(df_final_model)
train_end = int(n * 0.7)
valid_end = int(n * 0.85)

train = df_final_model.iloc[:train_end]
valid = df_final_model.iloc[train_end:valid_end]
test  = df_final_model.iloc[valid_end:]

train.to_csv(OUT_DIR / "week4_train.csv", index=False)
valid.to_csv(OUT_DIR / "week4_valid.csv", index=False)
test.to_csv(OUT_DIR / "week4_test.csv", index=False)

print("[W4 Export] Training, validation, and test files saved to:", OUT_DIR.res
print("Train:", train.shape, "Valid:", valid.shape, "Test:", test.shape)
```

```
[W4 Export] Training, validation, and test files saved to: /home/jupyter-huxin/test/Repor
Train: (538, 23) Valid: (115, 23) Test: (116, 23)
```

Week5: Engineer Features, Data augmentation, Dimensionality Reduction

Engineer Features

```
# Step 1: Construct Target Variable TSR

# copy df_encoded
df_fe = df_encoded.copy()

# make sure there is a company column
if "company" not in df_fe.columns:
        company_cols = [c for c in df_fe.columns if c.startswith("company_")]
        df_fe["company"] = df_fe[company_cols].idxmax(axis=1).str.replace("company_",

# Merge original price and dividend columns
extra_cols = pd.read_csv(
        OUT_DIR / "week4_step3_transformed.csv",
        usecols=["date", "company", "adj_price", "dividend"])

# Convert the 'date' column to datetime format
extra_cols["date"] = pd.to_datetime(extra_cols["date"], errors="coerce")
df_fe["date"] = pd.to_datetime(df_fe["date"], errors="coerce")

# Merge the datasets
df_fe = pd.merge(df_fe, extra_cols, on=["date", "company"], how="left")

# Next month's price
df_fe["price_next"] = df_fe.groupby("company")["adj_price"].shift(-1)

# Next month's dividend
df_fe["div_next"] = df_fe.groupby("company")["dividend"].shift(-1)

# Calculate TSR (Total Shareholder Return)
df_fe["TSR_next"] = (
        (df_fe["price_next"] - df_fe["adj_price"]) + df_fe["div_next"]
) / df_fe["adj_price"]

# Remove the last month
df_fe = df_fe.dropna(subset=["TSR_next"]).reset_index(drop=True)

# Check
print("TSR construction completed")
print(df_fe[["date","company","adj_price","dividend","TSR_next"]].head(10))

# Save
```

```
df_fe.to_csv(OUT_DIR / "week5_step1_target.csv", index=False)
print("TSR has been saved")
```

```
TSR construction completed
        date company  adj_price  dividend  TSR_next
0 2014-12-31     BXP   100.7570      5.80  0.155711
1 2015-01-31     BXP   108.6960      7.75 -0.010056
2 2015-02-28     BXP   107.6030      0.00  0.033178
3 2015-03-31     BXP   110.5230      0.65 -0.058151
4 2015-04-30     BXP   104.0960      0.00 -0.017263
5 2015-05-31     BXP   102.2990      0.00 -0.058120
6 2015-06-30     BXP    95.7034      0.65  0.018816
7 2015-07-31     BXP    97.5042      0.00 -0.080488
8 2015-08-31     BXP    89.6563      0.00  0.057486
9 2015-09-30     BXP    94.1603      0.65  0.062996
TSR has been saved
```

```
# Step 2: Lagged Features

df_lag = df_fe.copy()

# Define columns for generating lagged features
lag_cols = ["TSR_next", "cpi_yoy", "cpi_mom", "unemp", "unemp_mom", "ten_year",

# Generate 1-period, 3-period, and 6-period lags by group
for col in lag_cols:
        for lag in [1, 3, 6]:
                df_lag[f"{col}_lag{lag}"] = df_lag.groupby("company_BXP")[col].shift(l

# Drop missing values
df_lag = df_lag.dropna().reset_index(drop=True)

# Check
print("Lagged feature samples")
print(df_lag[[ "date", "TSR_next", "TSR_next_lag1", "TSR_next_lag3", "TSR_next_lag6

# Save
df_lag.to_csv(OUT_DIR / "week5_step2_lagged.csv", index=False)
print("Lagged features have been saved")
```

```
Lagged feature samples
        date  TSR_next  TSR_next_lag1  TSR_next_lag3  TSR_next_lag6
0 2015-06-30  0.018816      -0.058120      -0.058151       0.155711
1 2015-07-31 -0.080488       0.018816      -0.017263      -0.010056
2 2015-08-31  0.057486      -0.080488      -0.058120       0.033178
3 2015-09-30  0.062996       0.057486       0.018816      -0.058151
4 2015-10-31 -0.006923       0.062996      -0.080488      -0.017263
5 2015-11-30  0.054778      -0.006923       0.057486      -0.058120
6 2015-12-31 -0.051255       0.054778       0.062996       0.018816
7 2016-01-31 -0.017802      -0.051255      -0.006923      -0.080488
8 2016-02-29  0.126021      -0.017802       0.054778       0.057486
9 2016-03-31  0.014111       0.126021      -0.051255       0.062996
Lagged features have been saved
```

```
# Step 3: Rolling Window Features
```

```
df_roll = df_lag.copy()

# Define variables for rolling window calculations
roll_cols = ["TSR_next", "cpi_mom", "unemp", "ten_year"]

# Window sizes
windows = [3, 6]

# Generate rolling mean and standard deviation
for col in roll_cols:
    for w in windows:
        df_roll[f"{col}_roll{w}_mean"] = df_roll.groupby("company_BXP")[col].t
        df_roll[f"{col}_roll{w}_std"]  = df_roll.groupby("company_BXP")[col].

# Drop rows with NA values
df_roll = df_roll.dropna().reset_index(drop=True)

# Check
print("Rolling feature samples")
print(df_roll[["date", "TSR_next", "TSR_next_roll3_mean", "TSR_next_roll3_std", "TSR

# Save results
df_roll.to_csv(OUT_DIR / "week5_step3_rolling.csv", index=False)
print("Rolling window features have been saved")
```

```
Rolling feature samples
        date  TSR_next  TSR_next_roll3_mean  TSR_next_roll3_std  \
0 2015-11-30  0.054778             0.036950            0.038217
1 2015-12-31 -0.051255            -0.001133            0.053253
2 2016-01-31 -0.017802            -0.004759            0.054206
3 2016-02-29  0.126021             0.018988            0.094190
4 2016-03-31  0.014111             0.040777            0.075528
5 2016-04-30 -0.025592             0.038180            0.078620
6 2016-05-31  0.062166             0.016895            0.043945
7 2016-06-30  0.077529             0.038034            0.055635
8 2016-07-31 -0.014235             0.041820            0.049149
9 2016-08-31 -0.016961             0.015444            0.053784

   TSR_next_roll6_mean
0             0.017778
1             0.006099
2             0.016547
3             0.027969
4             0.019822
5             0.016710
6             0.017942
7             0.039406
8             0.040000
9             0.016170
Rolling window features have been saved
```

```
# Step 4: Interaction Features

df_inter = df_roll.copy()

# 1. Interaction between inflation and unemployment
```

```
df_inter["cpi_unemp_interaction"] = df_inter["cpi_mom"] * df_inter["unemp"]

# 2. Interaction between interest rate and dividend
df_inter["rate_div_interaction"] = df_inter["ten_year"] * df_inter["dividend_ttm_log

# 3. Dividend yield ratio
df_inter["div_yield_ratio"] = df_inter["dividend_ttm_log"] / (df_inter["adj_price_lo

# Check results
print("Interaction feature samples")
print(df_inter[["date","cpi_unemp_interaction","rate_div_interaction","div_yield_ratio"]

# Save
df_inter.to_csv(OUT_DIR / "week5_step4_interaction.csv", index=False)
print("Interaction features have been saved")
```

```
Interaction feature samples
         date  cpi_unemp_interaction  rate_div_interaction  div_yield_ratio
0 2015-11-30              -0.203230             -0.662550         1.700566
1 2015-12-31              -0.203230             -0.552940         1.276381
2 2016-01-31               0.575969             -0.502320         0.903280
3 2016-02-29               0.575969             -0.807053         0.927117
4 2016-03-31              -0.135409             -0.697831         0.795654
5 2016-04-30              -0.149298             -0.781401         0.781825
6 2016-05-31              -0.430044             -0.780452         0.807799
7 2016-06-30              -0.470052             -0.942005         0.755252
8 2016-07-31               0.371482             -1.081624         0.693192
9 2016-08-31               0.371482             -1.029279         0.704307
Interaction features have been saved
```

```
# Step 5: Time Features

df_time = df_inter.copy()

# Extract month
df_time["month"] = pd.to_datetime(df_time["date"]).dt.month

# One-Hot Encoding
df_time = pd.get_dummies(df_time, columns=["month"], prefix="month", drop_first=Fal

# Check
month_cols = [col for col in df_time.columns if col.startswith("month_")]
print("Time feature samples")
print(df_time[["date"] + month_cols].head(15))

# Save
df_time.to_csv(OUT_DIR / "week5_step5_time_features.csv", index=False)
print("Time features have been saved")
```

```
Time feature samples
         date  month_1  month_2  month_3  month_4  month_5  month_6  month_7  \
0  2015-11-30    False    False    False    False    False    False    False
1  2015-12-31    False    False    False    False    False    False    False
2  2016-01-31     True    False    False    False    False    False    False
3  2016-02-29    False     True    False    False    False    False    False
4  2016-03-31    False    False     True    False    False    False    False
```

```
5  2016-04-30    False    False    False     True    False    False    False
6  2016-05-31    False    False    False    False     True    False    False
7  2016-06-30    False    False    False    False    False     True    False
8  2016-07-31    False    False    False    False    False    False     True
9  2016-08-31    False    False    False    False    False    False    False
10 2016-09-30    False    False    False    False    False    False    False
11 2016-10-31    False    False    False    False    False    False    False
12 2016-11-30    False    False    False    False    False    False    False
13 2016-12-31    False    False    False    False    False    False    False
14 2017-01-31     True    False    False    False    False    False    False

    month_8  month_9  month_10  month_11  month_12
0     False    False     False      True     False
1     False    False     False     False      True
2     False    False     False     False     False
3     False    False     False     False     False
4     False    False     False     False     False
5     False    False     False     False     False
6     False    False     False     False     False
7     False    False     False     False     False
8     False    False     False     False     False
9      True    False     False     False     False
10    False     True     False     False     False
11    False    False      True     False     False
12    False    False     False      True     False
13    False    False     False     False      True
14    False    False     False     False     False
Time features have been saved
```

Data augmentation

```
#Output directory for Week 5
AUG_OUT_DIR = Path("../Reports/w5_out")
AUG_OUT_DIR.mkdir(parents=True, exist_ok=True)
```

```
#1) Build a modeling dataset and compute the target variable
#Target: next-month total shareholder return (TSR)
#TSR_{t+1} = (Price_{t+1} + Dividend_{t+1}) / Price_{t} - 1
def build_modeling_dataset(df: pd.DataFrame) -> pd.DataFrame:
        required_cols = [
                "date", "company", "metro",
                "adj_price", "dividend", "dividend_ttm",
                "cpi", "cpi_yoy", "cpi_mom",
                "unemp", "unemp_mom",
                "ten_year", "ten_year_mom",
        ]
        miss = [c for c in required_cols if c not in df.columns]
        if miss:
                raise ValueError(f"Missing expected columns in df_merged: {miss}")

        d = df.copy()
        d["date"] = pd.to_datetime(d["date"], errors="coerce")
        d = d.dropna(subset=["date"]).sort_values(["company", "date"]).reset_index(dr
```

```
    # Compute next-month TSR within each company
    def compute_next_tsr(g: pd.DataFrame) -> pd.Series:
        p_t    = g["adj_price"]
        p_tp1  = g["adj_price"].shift(-1)
        div_tp1 = g["dividend"].shift(-1)
        y = ((p_tp1 + div_tp1) / p_t) - 1.0
        return y

    d["tsr_next_1m"] = d.groupby("company", group_keys=False).apply(compute_next_
    d = d.dropna(subset=["tsr_next_1m"]).reset_index(drop=True)

    keep_cols = required_cols + ["tsr_next_1m"]
    base = d[keep_cols].copy()

    base.to_csv(AUG_OUT_DIR / "w5_base_modeling_dataset.csv", index=False)
    print(f"[base] saved to {AUG_OUT_DIR/'w5_base_modeling_dataset.csv'} with s
    return base
```

```
#2) Noise-Jitter augmentation
#Add small Gaussian noise to numeric predictors
def _iqr_scale(x: np.ndarray) -> float:
    x = x[~np.isnan(x)]
    if x.size == 0:
        return np.nan
    q1, q3 = np.percentile(x, [25, 75])
    iqr = q3 - q1
    if iqr <= 0:
        # fallback to std if IQR is degenerate
        return float(np.std(x)) if x.size > 1 else 0.0
    # 1.4826*IQR approximates std for normal distributions
    return 1.4826 * iqr

def augment_with_noise(
    df_base: pd.DataFrame,
    n_copies: int = 2,
    noise_frac: float = 0.08,
    seed: int = 7,
    clip_quantiles=(0.01, 0.99),
) -> pd.DataFrame:
    rng = np.random.default_rng(seed)
    numeric_cols = df_base.select_dtypes(include=[np.number]).columns.tolist()
    # Do not perturb the label
    if "tsr_next_1m" in numeric_cols:
        numeric_cols.remove("tsr_next_1m")

    # Pre-compute per-column scales and quantiles
    scales = {c: _iqr_scale(df_base[c].values) for c in numeric_cols}
    qlo = df_base[numeric_cols].quantile(clip_quantiles[0])
    qhi = df_base[numeric_cols].quantile(clip_quantiles[1])

    out_list = [df_base.assign(aug_tag="original")]
    for k in range(n_copies):
        noisy = df_base.copy()
```

```
        for c in numeric_cols:
            sd = scales.get(c, 0.0)
            if not np.isfinite(sd) or sd == 0.0:
                continue
            noise = rng.normal(loc=0.0, scale=noise_frac * sd, size=le
            noisy[c] = noisy[c].values + noise

            # clip per column to realistic range
            noisy[c] = noisy[c].clip(lower=qlo[c], upper=qhi[c])

        noisy["aug_tag"] = f"noise_{k+1}"
        out_list.append(noisy)

    aug_noise = pd.concat(out_list, ignore_index=True)
    aug_noise.to_csv(AUG_OUT_DIR / "w5_aug_noise.csv", index=False)
    print(f"[aug_noise] generated {n_copies} noisy copies. total_rows={aug_nois
    return aug_noise
```

```
#3) Mixup augmentation (within-company)
def augment_with_mixup(
    df_base: pd.DataFrame,
    n_samples: int,
    alpha: float = 0.4,
    seed: int = 99,
    group_col: str = "company",
) -> pd.DataFrame:
    rng = np.random.default_rng(seed)

    # Columns that should not be interpolated
    exclude_cols = ["date", "company", "metro", "aug_tag"]
    cols_to_mix = [c for c in df_base.columns if c not in exclude_cols]

    groups = df_base[group_col].unique().tolist()
    rows = []
    for _ in range(n_samples):
        g = rng.choice(groups)
        idx = df_base.index[df_base[group_col] == g].to_numpy()
        if idx.size < 2:
            continue
        i1, i2 = rng.choice(idx, size=2, replace=False)
        lam = float(rng.beta(alpha, alpha))

        row1 = df_base.loc[i1]
        row2 = df_base.loc[i2]
        mixed = row1.copy()
        # interpolate numeric and label columns
        for c in cols_to_mix:
            v1 = row1[c]
            v2 = row2[c]
            # if both numeric-like, do interpolation
            if np.issubdtype(type(v1), np.number) and np.issubdtype(type
                mixed[c] = lam * v1 + (1.0 - lam) * v2

        mixed["aug_tag"] = "mixup"
```

```
            rows.append(mixed)

        if not rows:
            raise RuntimeError("Mixup could not generate any samples (insuffi

        aug_mix = pd.DataFrame(rows).reset_index(drop=True)
        aug_mix.to_csv(AUG_OUT_DIR / "w5_aug_mixup.csv", index=False)
        print(f"[aug_mixup] generated {aug_mix.shape[0]} synthetic rows via mixup.
        return aug_mix
```

```
#Print the result
base = build_modeling_dataset(df_merged)

aug_noise = augment_with_noise(
        df_base=base,
        n_copies=2,                # number of noisy replicas
        noise_frac=0.08,       # noise scale
        seed=7
)

mixup_size = int(len(base) * 0.50)    # 50% of base rows
aug_mix = augment_with_mixup(
        df_base=base,
        n_samples=mixup_size,
        alpha=0.4,
        seed=99,
        group_col="company"
)

aug_all = pd.concat([aug_noise, aug_mix], ignore_index=True)
aug_all = aug_all.sample(frac=1.0, random_state=42).reset_index(drop=True)
aug_all.to_csv(AUG_OUT_DIR / "w5_aug_all.csv", index=False)

print(f"[final] saved augmented dataset to {AUG_OUT_DIR/'w5_aug_all.csv'} with sh
print(f"[final] NaNs in target tsr_next_1m: {aug_all['tsr_next_1m'].isna().sum()}")
print(aug_all["aug_tag"].value_counts())
```

```
[base] saved to ../Reports/w5_out/w5_base_modeling_dataset.csv with shape=(763, 14)
[aug_noise] generated 2 noisy copies. total_rows=2289
/tmp/ipykernel_49523/508355547.py:28: FutureWarning: DataFrameGroupBy.apply operated on tl
  d["tsr_next_1m"] = d.groupby("company", group_keys=False).apply(compute_next_tsr)
[aug_mixup] generated 381 synthetic rows via mixup.
[final] saved augmented dataset to ../Reports/w5_out/w5_aug_all.csv with shape=(2670, 15)
[final] NaNs in target tsr_next_1m: 0
aug_tag
noise_1     763
original    763
noise_2     763
mixup       381
Name: count, dtype: int64
```

Dimensionality Reduction (Setup & Load)

```
# load processed splits and prepare numeric matrices for DR.
TARGET_COL = "tsr_next_1m"

DATA_DIR       = Path("../Data")
REPORTS_DIR  = Path("../Reports")
DIMRED_DIR    = Path("../Reports/w5_dimred")
DIMRED_DIR.mkdir(parents=True, exist_ok=True)

def split_xy(df):
        if TARGET_COL in df.columns:
                y = df[TARGET_COL].copy()
                X = df.drop(columns=[TARGET_COL])
        else:
                y = None
                X = df.copy()
        return X, y

def try_load_splits(base_dir: Path):
        tp, vp, ep = base_dir/"week4_train.csv", base_dir/"week4_valid.csv", base_
        if tp.exists() and vp.exists() and ep.exists():
                return (pd.read_csv(tp), pd.read_csv(vp), pd.read_csv(ep))
        return None

loaded = try_load_splits(DATA_DIR) or try_load_splits(REPORTS_DIR)
if loaded:
        train_df, valid_df, test_df = loaded
else:
        df_final_model = df_bucket.copy().sort_values("date").reset_index(drop=True)
        n = len(df_final_model); train_end = int(n*0.70); valid_end = int(n*0.85
        train_df = df_final_model.iloc[:train_end].copy()
        valid_df = df_final_model.iloc[train_end:valid_end].copy()
        test_df   = df_final_model.iloc[valid_end:].copy()

X_tr_raw, y_tr = split_xy(train_df)
X_va_raw, y_va = split_xy(valid_df)
X_te_raw, y_te = split_xy(test_df)

exclude = {"date","company","metro"}
num_cols = [c for c in X_tr_raw.columns if c not in exclude and pd.api.type

X_tr_num = X_tr_raw[num_cols].copy()
X_va_num = X_va_raw[num_cols].copy()
X_te_num = X_te_raw[num_cols].copy()

# save with parquet if available, else CSV
def _save_df(df, stem):
        try:
                df.to_parquet(DIMRED_DIR / f"{stem}.parquet", index=False)
        except Exception:
                df.to_csv(DIMRED_DIR / f"{stem}.csv", index=False)

_save_df(X_tr_num, "X_train_num")
_save_df(X_va_num, "X_valid_num")
_save_df(X_te_num, "X_test_num")
```

```
print("Numeric shapes:", X_tr_num.shape, X_va_num.shape, X_te_num.shape)
```

```
Numeric shapes: (538, 22) (115, 22) (116, 22)
```

```
# PCA
# standardize numeric features and apply PCA; save components and models.
from sklearn.decomposition import PCA
from sklearn.manifold import TSNE

scaler = StandardScaler()
Xtr_s = scaler.fit_transform(X_tr_num.values)
Xva_s = scaler.transform(X_va_num.values)
Xte_s = scaler.transform(X_te_num.values)

pca_full = PCA(n_components=None, svd_solver="full", random_state=42)
pca_full.fit(Xtr_s)
cum_var = np.cumsum(pca_full.explained_variance_ratio_)
k95 = int(np.searchsorted(cum_var, 0.95) + 1)
n_comp = int(min(50, max(2, k95)))

pca = PCA(n_components=n_comp, svd_solver="full", random_state=42)
Xtr_pca = pca.fit_transform(Xtr_s)
Xva_pca = pca.transform(Xva_s)
Xte_pca = pca.transform(Xte_s)

joblib.dump(scaler, DIMRED_DIR / "scaler.joblib")
joblib.dump(pca,    DIMRED_DIR / "pca.joblib")

# save with parquet if available, else CSV
def _save_df(df, stem):
    pqt = DIMRED_DIR / f"{stem}.parquet"
    csv = DIMRED_DIR / f"{stem}.csv"
    try:
        df.to_parquet(pqt, index=False)
    except Exception:
        df.to_csv(csv, index=False)

import pandas as pd, numpy as np
_save_df(pd.DataFrame(Xtr_pca), "X_train_pca")
_save_df(pd.DataFrame(Xva_pca), "X_valid_pca")
_save_df(pd.DataFrame(Xte_pca), "X_test_pca")

vr = pd.DataFrame({
    "component": np.arange(1, len(pca.explained_variance_ratio_)+1),
    "explained_variance_ratio": pca.explained_variance_ratio_,
    "cumulative_variance": np.cumsum(pca.explained_variance_ratio_)
})
vr.to_csv(DIMRED_DIR / "pca_variance_report.csv", index=False)

print("PCA n_components:", n_comp)
```

```
PCA n_components: 13
```

```
# t-SNE Embedding (train only)
# export 2D embedding for visualization/inspection.

Xtsne_in = Xtr_s
if Xtsne_in.shape[0] > 5000:
    Xtsne_in = Xtsne_in[:5000, :]

# build kwargs compatible across sklearn versions
base_kwargs = dict(n_components=2, init="pca", perplexity=30, random_state=42)
# try with learning_rate="auto"; if not supported, drop it
try:
    _ = TSNE(learning_rate="auto", **base_kwargs)
    lr_kwargs = dict(learning_rate="auto")
except TypeError:
    lr_kwargs = {}

# try max_iter first (newer sklearn), fallback to n_iter (older)
try:
    tsne = TSNE(max_iter=1000, verbose=0, **lr_kwargs, **base_kwargs)
except TypeError:
    tsne = TSNE(n_iter=1000, verbose=0, **lr_kwargs, **base_kwargs)

Z = tsne.fit_transform(Xtsne_in)

tsne_df = pd.DataFrame(Z, columns=["tsne_1","tsne_2"])
tsne_df.to_csv(DIMRED_DIR / "train_tsne2d.csv", index=False)
print("t-SNE done:", tsne_df.shape)
```

```
t-SNE done: (538, 2)
```

Week6：Develop First modeling approach

Model training setup

```
import json
import pandas as pd
import numpy as np
from pathlib import Path

# === Base paths ===
BASE = Path("..")
DATA = BASE / "Reports" / "w4_out"
DOCS = BASE / "Docs"
MODELS = BASE / "Models"
MODELS.mkdir(parents=True, exist_ok=True)
DOCS.mkdir(parents=True, exist_ok=True)

# === Load datasets ===
train_csv = DATA / "week4_train.csv"
```

```
    valid_csv = DATA / "week4_valid.csv"

    if not train_csv.exists():
        raise FileNotFoundError(f"Missing training file: {train_csv.resolve()}")

    df_train = pd.read_csv(train_csv)
    df_val = pd.read_csv(valid_csv) if valid_csv.exists() else None

    # === Target name detection ===
    hint = DOCS / "target_column.txt"
    TARGET_COL = hint.read_text(encoding="utf-8").strip() if hint.exists() else ""

    cols = list(df_train.columns)
    low = [c.lower() for c in cols]
    want = TARGET_COL.strip().lower()

    if want and want in low:
        TARGET_COL = cols[low.index(want)]
    else:
        pri = ["tsr_next_1m","tsr_1m","tsr","total_shareholder_return","return","targe
        TARGET_COL = next((cols[low.index(p)] for p in pri if p in low), "")
        if not TARGET_COL:
            hits = [cols[i] for i, n in enumerate(low) if ("tsr" in n or
            if len(hits) == 1:
                TARGET_COL = hits[0]
        if not TARGET_COL:
            num_all = df_train.select_dtypes(include=[np.number]).columns.tolist()
            if not num_all:
                raise ValueError("No numeric columns for fallback target")
            TARGET_COL = num_all[-1]
            print("[Warn] Fallback target ->", TARGET_COL)

    # Persist target
    hint.write_text(TARGET_COL, encoding="utf-8")

    # === Numeric features ===
    num_cols = df_train.select_dtypes(include=[np.number]).columns.tolist()
    FEATURES = [c for c in num_cols if c != TARGET_COL]
    if not FEATURES:
        raise ValueError("No numeric features found")

    # === Build matrices ===
    X_train = df_train[FEATURES]
    y_train = df_train[TARGET_COL].astype(float)
    X_val = df_val[FEATURES] if df_val is not None else None
    y_val = df_val[TARGET_COL].astype(float) if df_val is not None and TARGET_COL

    # === Save schema ===
    schema = {
        "target": TARGET_COL,
        "features": FEATURES,
        "train_rows": int(len(X_train)),
        "val_rows": int(len(X_val)) if X_val is not None else 0,
        "train_source": "Reports/w4_out/week4_train.csv",
        "val_source": "Reports/w4_out/week4_valid.csv" if df_val is not None else
```

```
}
(MODELS / "training_schema.json").write_text(json.dumps(schema, indent=2), encoding=

print("[SUCCESS] Matrices ready:", X_train.shape, y_train.shape)
print("[INFO] Target column:", TARGET_COL)
print("[INFO] Schema saved to:", MODELS / "training_schema.json")
```

```
[SUCCESS] Matrices ready: (538, 8) (538,)
[INFO] Target column: dividend_ttm_log
[INFO] Schema saved to: ../Models/training_schema.json
```

Train and save

```
from sklearn.ensemble import RandomForestRegressor
import time
import joblib
import json
from pathlib import Path

# Ensure Models directory exists
MODELS.mkdir(parents=True, exist_ok=True)

# Use existing estimator if provided
names = ['estimator','model','clf','reg','rf','baseline']
estimator = next((globals()[k] for k in names if k in globals()), None)

# Fallback baseline if none
if estimator is None:
    estimator = RandomForestRegressor(random_state=42, n_estimators=300)

# Fit
t0 = time.time()
fitted = estimator.fit(X_train, y_train)
train_time = round(time.time() - t0, 3)

# Persist model
stamp = time.strftime("%Y%m%d-%H%M%S")
model_path = MODELS / f"baseline_{stamp}.joblib"
joblib.dump(fitted, model_path.resolve())

# Persist metadata
meta = {
    "model_file": str(model_path.relative_to(Path(".."))),
    "algo": type(estimator).__name__,
    "params": getattr(estimator, "get_params", lambda: {})(),
    "target": TARGET_COL,
    "features": FEATURES,
    "train_rows": int(len(X_train)),
    "train_time_sec": train_time
}
meta_path = MODELS / f"baseline_{stamp}_meta.json"
meta_path.write_text(json.dumps(meta, indent=2), encoding="utf-8")
```

```
print(f"Model  trained  ->  {model_path.name}")
print(f"Metadata  saved  ->  {meta_path.name}")
```

```
Model trained -> baseline_20251019-191451.joblib
Metadata saved -> baseline_20251019-191451_meta.json
```

Hyperparameter Tuning

```
from  sklearn.model_selection  import  RandomizedSearchCV
from  sklearn.metrics  import  mean_squared_error,  r2_score
from  sklearn.ensemble  import  RandomForestRegressor
from  scipy.stats  import  randint
import  pandas  as  pd
import  numpy  as  np
from  pathlib  import  Path
import  warnings
warnings.filterwarnings("ignore")

#  ===  Base  paths  ===
BASE  =  Path("..")
REPORTS  =  BASE  /  "Reports"
OUT_DIR  =  REPORTS  /  "w5_out"
OUT_DIR.mkdir(parents=True,  exist_ok=True)

#  ===  Load  datasets  ===
#  Automatically  locate  the  correct  week5_step5_time_features.csv
source_candidates  =  list(REPORTS.glob("**/week5_step5_time_features.csv"))
if  not  source_candidates:
        raise  FileNotFoundError("Could  not  find  week5_step5_time_features.csv  in  R
data_path  =  source_candidates[0]
print(f"[INFO]  Loading  data  from:  {data_path}")

train  =  pd.read_csv(data_path)
valid  =  train.copy()    #  same  as  original  logic

#  ===  Prepare  features  and  target  ===
target_col  =  "TSR_next"
feature_cols  =  [c  for  c  in  train.columns  if  c  not  in  ["date",  "company",  ta

X_train,  y_train  =  train[feature_cols],  train[target_col]
X_valid,  y_valid  =  valid[feature_cols],  valid[target_col]

#  ===  Define  model  and  parameter  grid  ===
rf  =  RandomForestRegressor(random_state=42)

param_dist  =  {
        "n_estimators":  randint(100,  500),
        "max_depth":  randint(3,  15),
        "min_samples_split":  randint(2,  10),
        "min_samples_leaf":  randint(1,  5),
```

```
        "max_features": ["auto", "sqrt", "log2"]
}

# === Randomized Search ===
rf_random = RandomizedSearchCV(
        estimator=rf,
        param_distributions=param_dist,
        n_iter=25,
        scoring="neg_root_mean_squared_error",
        cv=3,
        random_state=42,
        verbose=2,
        n_jobs=-1
)

rf_random.fit(X_train, y_train)

# === Print best parameters and performance ===
print("\nBest Parameters Found:")
print(rf_random.best_params_)

best_model = rf_random.best_estimator_

# === Evaluate on validation set ===
y_pred = best_model.predict(X_valid)
rmse = np.sqrt(mean_squared_error(y_valid, y_pred))
r2 = r2_score(y_valid, y_pred)

print(f"Validation RMSE: {rmse:.4f}")
print(f"Validation R²: {r2:.4f}")

# === Save tuning results ===
results = pd.DataFrame(rf_random.cv_results_).sort_values(by="rank_test_score")
results_path = OUT_DIR / "week5_rf_tuning_results.csv"
results.to_csv(results_path, index=False)
print(f"Tuning results have been saved to: {results_path.resolve()}")
```

```
[INFO] Loading data from: ../Reports/w2_out/week5_step5_time_features.csv
Fitting 3 folds for each of 25 candidates, totalling 75 fits

Best Parameters Found:
{'max_depth': 14, 'max_features': 'sqrt', 'min_samples_leaf': 2, 'min_samples_split': 7, '
Validation RMSE: 0.0353
Validation R²: 0.8118
Tuning results have been saved to: /home/jupyter-huxin/test/Reports/w5_out/week5_rf_tunin
```

Model evaluation

```
import warnings
warnings.filterwarnings("ignore")

import os
```

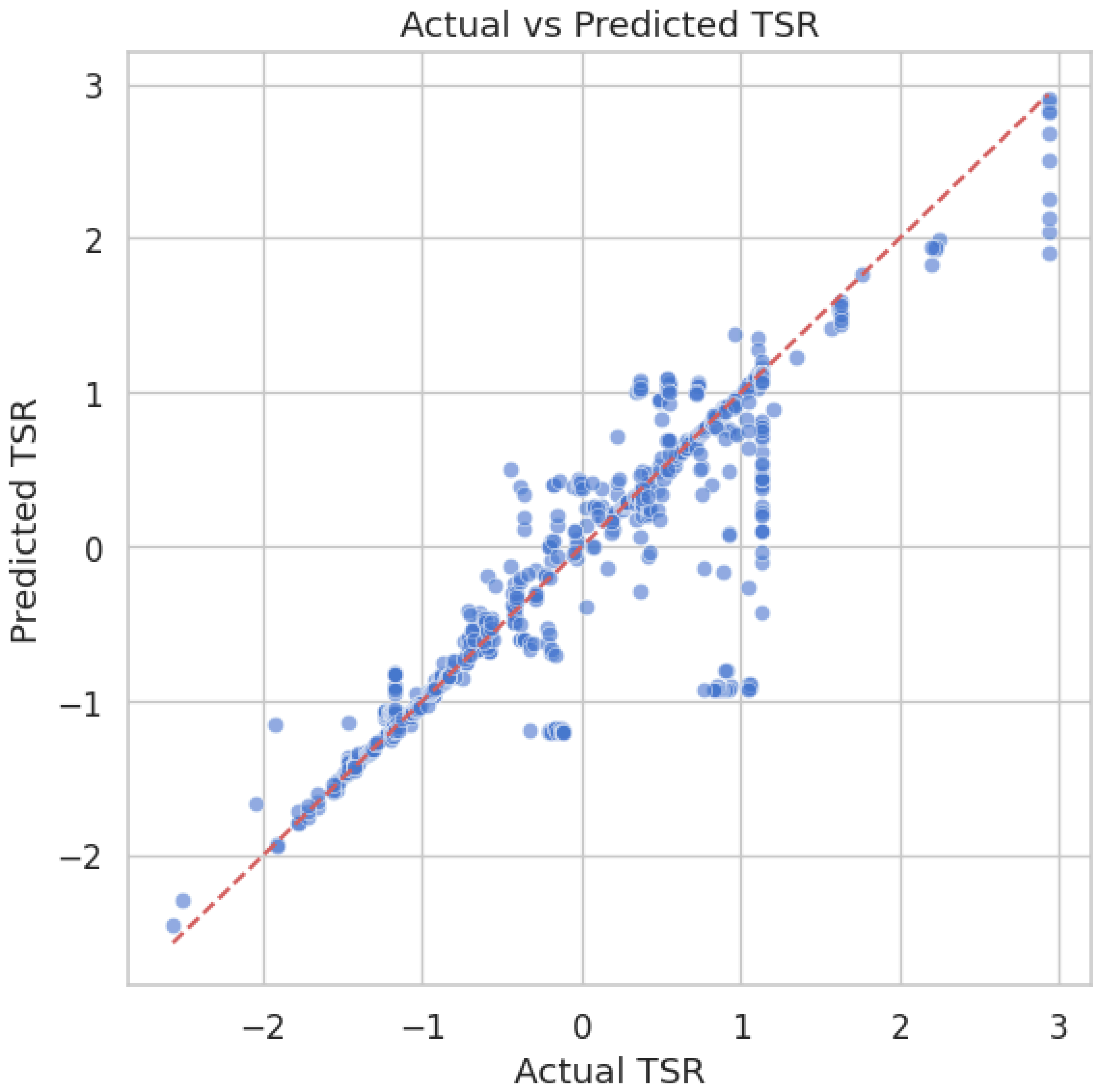
```
os.environ["PYTHONWARNINGS"] = "ignore"
os.environ["TF_CPP_MIN_LOG_LEVEL"] = "3"
os.environ["JOBLIB_TEMP_FOLDER"] = "/tmp"
os.environ["LOKY_MAX_CPU_COUNT"] = "1"

import numpy as np
import pandas as pd
import joblib, json
from pathlib import Path
from sklearn.metrics import mean_squared_error, mean_absolute_error, r2_score, mea

BASE = Path("..")
REPORTS = BASE / "Reports"
MODELS = BASE / "Models"

candidate_paths = [
        REPORTS / "w5_out" / "week5_step5_time_features.csv",
        REPORTS / "w2_out" / "week5_step5_time_features.csv"
]
data_path = next((p for p in candidate_paths if p.exists()), None)
if data_path is None:
        raise FileNotFoundError("Could not find week5_step5_time_features.csv")

df = pd.read_csv(data_path)

model_candidates = list(MODELS.glob("baseline_*.joblib"))
if not model_candidates:
        raise FileNotFoundError("No trained model found")
model_path = sorted(model_candidates)[-1]
model = joblib.load(model_path)

schema_path = MODELS / "training_schema.json"
if not schema_path.exists():
        raise FileNotFoundError("training_schema.json not found")
with open(schema_path, "r", encoding="utf-8") as f:
        schema = json.load(f)

feature_cols = schema["features"]
target_col = schema["target"]

X = df.reindex(columns=feature_cols, fill_value=0)
y_true = df[target_col] if target_col in df.columns else None
y_pred = model.predict(X)

def adjusted_r2(r2, n, k):
        return 1 - ((1 - r2) * (n - 1) / (n - k - 1)) if n > k + 1

if y_true is not None:
        n, k = X.shape
        mse = mean_squared_error(y_true, y_pred)
        rmse = np.sqrt(mse)
        mae = mean_absolute_error(y_true, y_pred)
        mape = mean_absolute_percentage_error(y_true, y_pred)
        r2 = r2_score(y_true, y_pred)
        adj_r2 = adjusted_r2(r2, n, k)
```

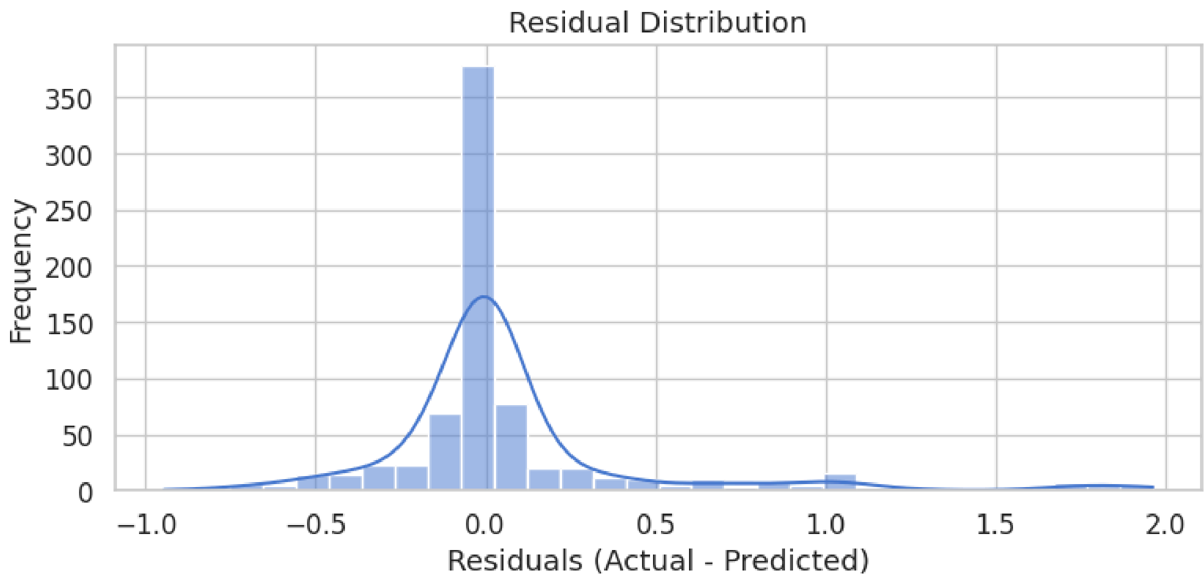
```
        print(f"MSE:  {mse:.4f}")
        print(f"RMSE:  {rmse:.4f}")
        print(f"MAE:  {mae:.4f}")
        print(f"MAPE:  {mape:.4f}")
        print(f"R2:  {r2:.4f}")
        print(f"Adjusted  R2:  {adj_r2:.4f}")

        metrics  =  {
                "MSE":  mse,
                "RMSE":  rmse,
                "MAE":  mae,
                "MAPE":  mape,
                "R2":  r2,
                "Adj_R2":  adj_r2,
                "n_samples":  n,
                "n_features":  k
        }
        out_dir  =  REPORTS  /  "w5_out"
        out_dir.mkdir(parents=True,  exist_ok=True)
        (out_dir  /  "week5_model_metrics.json").write_text(json.dumps(metrics,  indent=
else:
        print("Target  column  not  found  in  evaluation  dataset.")
```

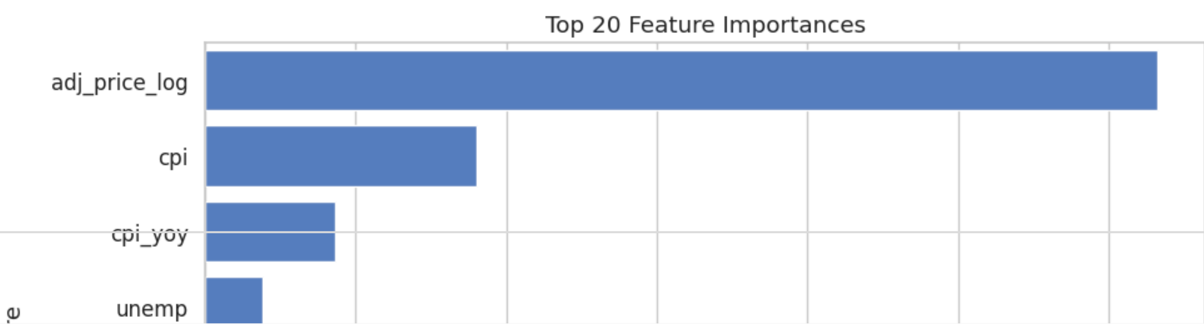
```
MSE: 0.1688
RMSE: 0.4109
MAE: 0.1988
MAPE: 0.8849
R2: 0.8220
Adjusted R2: 0.8200
```

```
#visualization
BASE  =  Path("..")
REPORTS  =  BASE  /  "Reports"
MODELS  =  BASE  /  "Models"
OUT  =  REPORTS  /  "w5_out"
OUT.mkdir(parents=True,  exist_ok=True)

#  ===  Plot  1:  Actual  vs  Predicted  ===
plt.figure(figsize=(6,6))
sns.scatterplot(x=y_true,  y=y_pred,  alpha=0.6)
plt.plot([y_true.min(),  y_true.max()],  [y_true.min(),  y_true.max()],  "r--")
plt.title("Actual  vs  Predicted  TSR")
plt.xlabel("Actual  TSR")
plt.ylabel("Predicted  TSR")
plt.tight_layout()
plt.savefig(OUT  /  "plot_actual_vs_pred.png",  dpi=300)
plt.show()

#  ===  Plot  2:  Residual  Distribution  ===
residuals  =  y_true  -  y_pred
plt.figure(figsize=(8,4))
sns.histplot(residuals,  bins=30,  kde=True)
```

```
plt.title("Residual Distribution")
plt.xlabel("Residuals (Actual - Predicted)")
plt.ylabel("Frequency")
plt.tight_layout()
plt.savefig(OUT / "plot_residuals.png", dpi=300)
plt.show()

# === Plot 3: Feature Importance (if supported) ===
if hasattr(model, "feature_importances_"):
    fi = pd.DataFrame({"feature": feature_cols, "importance": model.feature_imp
                   .sort_values("importance", ascending=False)
    plt.figure(figsize=(10,6))
    sns.barplot(x="importance", y="feature", data=fi.head(20))
    plt.title("Top 20 Feature Importances")
    plt.tight_layout()
    plt.savefig(OUT / "plot_feature_importance.png", dpi=300)
    plt.show()
    fi.to_csv(OUT / "feature_importance.csv", index=False)
    print("Feature importance saved.")
else:
    print("Model does not provide feature_importances_.")
```


Actual vs Predicted TSR
Predicted TSR
Actual TSR
3
2
1
0
−1
−2
−2
−1
0
1
2
3


Residual Distribution
Frequency
350
300
250
200
150
100
50
0
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
Residuals (Actual - Predicted)


Top 20 Feature Importances
adj_price_log
cpi
cpi_yoy
unemp

Week7-LLM model training


```
# target column
if "target_col" not in globals() or target_col not in train_df.columns:
    _feats = set(feature_cols) if "feature_cols" in globals() else set()
    _cands = [
        c for c in train_df.columns
        if c not in _feats and pd.api.types.is_numeric_dtype(train_df[c])
    ]
    if not _cands:
        raise ValueError("set target_col to a numeric column")
    target_col = _cands[0]

# drop null target
_train = train_df.dropna(subset=[target_col])

# infer task type
_vals = _train[target_col].astype(float).unique()
task = "classification" if set(_vals).issubset({0.0, 1.0}) else "regression"

# rebuild feature_cols from current data
_exclude_names = {target_col, "company", "ticker", "date", "id", "ts_code"}
_exclude_sub = ["next", "label", "target"]
feature_cols = []
for _c in _train.columns:
    if _c in _exclude_names:
        continue
    _lc = _c.lower()
    if any(s in _lc for s in _exclude_sub):
        continue
    if pd.api.types.is_numeric_dtype(_train[_c]):
        feature_cols.append(_c)
if not feature_cols:
    raise ValueError("no usable features in train_df")

# small helper
def _kv(row, cols):
    # row to key value text
    out = []
    for c in cols:
        v = row[c]
        if isinstance(v, float):
            out.append(f"{c}={v:.4f}")
        else:
            out.append(f"{c}={v}")
    return "; ".join(out)

# build few shot lines
shots = 10
_samp = _train.sample(n=min(shots, len(_train)), random_state=42)
_lines = []
_idx = []
for i, r in _samp.iterrows():
```

```
    if task == "classification":
        _y = str(int(r[target_col]))
    else:
        _y = f"{float(r[target_col]):.6f}"
    _x = _kv(r, feature_cols)
    _lines.append(f"Example: {_x} -> Label: {_y}")
    _idx.append(i)
fewshot_text = "\n".join(_lines)

# header and template
if task == "classification":
    head = (
        "Task: Predict the binary label. "
        "Output 0 or 1 only."
    )
else:
    head = (
        "Task: Predict a real valued target. "
        "Output a single number."
    )
template = (
    f"{head}\n"
    f"{fewshot_text}\n"
    "Now predict the label for the following samples.\n"
    "For each sample return only the final value."
)

# model object
llm_model = {
    "type": "llm_fewshot",
    "task": task,
    "shots": int(shots),
    "temperature": 0.0,
    "model_name": None,
    "feature_cols": list(feature_cols),
    "target_col": target_col,
    "prompt_template": template,
    "fewshot_index": _idx
}

print("LLM prompt model ready")
print(f"task={task}")
print(f"shots={shots}")
```