Machine Learning Spring 2025

Project 1 - Temperature Prediction Team: ST_ML2025_2

[30]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import re
import math
```

[31]:
```python
# Load the given datasets(located in the input folder)
train_df = pd.read_csv("./input/train_dataset.csv")
test_df = pd.read_csv("./input/test_dataset.csv")
station_info_df = pd.read_csv("./input/station_info.csv")
sample_submission_df = pd.read_csv("./input/submission_sample.csv")
```

Dataset 분석

주어진 데이터셋의 구성은 다음과 같다.

- `train_dataset.csv`: 동두천, 서울, 강화, 인천, 이천, 양평 관측소의 2019-2024년 데이터셋
- `test_dataset.csv`: 파주, 수원 관측소 데이터셋
- `station_info.csv`: 기상 관측소별 정보

[51]:
```python
train_df.sample(10)
```

[51]:

	id	station	station_name	date	cloud_cover_0	cloud_cover_1	\
5321	7509	112	인천	08-01	4.0	2.0	
11072	15451	203	이천	05-11	6.0	0.0	
9652	14031	202	양평	06-17	0.0	5.0	
2277	4465	108	서울	04-01	0.0	0.0	
212	212	98	동두천	08-01	2.0	9.0	
5186	7374	112	인천	03-19	10.0	6.0	
432	432	98	동두천	03-08	0.0	0.0	
3056	5244	108	서울	05-19	0.0	0.0	
11713	16092	203	이천	02-11	10.0	0.0	
6908	11287	201	강화	12-07	0.0	9.0	

	cloud_cover_10	cloud_cover_11	cloud_cover_12	cloud_cover_13	…	\
5321	8.0	6.0	7.0	6.0	…	
11072	0.0	0.0	0.0	0.0	…	
9652	0.0	0.0	0.0	0.0	…	
2277	0.0	0.0	1.0	2.0	…	
212	8.0	1.0	2.0	9.0	…	
5186	0.0	0.0	0.0	0.0	…	
432	0.0	0.0	0.0	0.0	…	
3056	0.0	0.0	0.0	0.0	…	
11713	4.0	7.0	0.0	0.0	…	
6908	3.0	7.0	8.0	6.0	…	

	wind_speed_23	wind_speed_3	wind_speed_4	wind_speed_5	wind_speed_6	\

5321	2.4	1.1	1.4	2.1	1.0
11072	1.4	0.9	0.4	0.4	0.3
9652	0.8	1.3	1.3	0.9	1.1
2277	1.8	0.6	0.8	1.2	0.9
212	0.3	0.1	0.9	1.2	0.5
5186	0.4	1.7	0.4	1.6	0.1
432	0.7	1.0	1.4	1.2	1.0
3056	1.1	0.3	0.0	1.8	1.6
11713	0.4	0.6	0.3	0.9	0.1
6908	0.0	0.9	0.0	1.1	0.8

	wind_speed_7	wind_speed_8	wind_speed_9	climatology_temp	target
5321	2.2	1.3	1.4	27.496429	-1.796429
11072	0.2	0.3	0.9	16.953571	3.346429
9652	0.3	1.0	1.0	22.250000	-1.750000
2277	1.1	2.3	3.2	12.312500	-5.612500
212	0.8	0.7	1.6	27.496429	0.303571
5186	1.9	2.2	3.4	6.646429	1.953571
432	1.1	0.1	0.6	5.733929	3.666071
3056	1.9	1.8	2.3	17.196429	1.503571
11713	0.7	0.4	0.3	1.498214	3.501786
6908	0.0	0.0	0.0	0.578571	-2.078571

[10 rows x 342 columns]

[33]:
```
train_df.describe()
```

[33]:

	id	station	cloud_cover_0	cloud_cover_1	\
count	13132.000000	13132.000000	12945.000000	12920.000000	
mean	9484.110493	153.980658	2.915798	3.022291	
std	5311.954253	48.183220	3.646779	3.652165	
min	0.000000	98.000000	0.000000	0.000000	
25%	5470.750000	108.000000	0.000000	0.000000	
50%	8753.500000	112.000000	0.000000	1.000000	
75%	14227.250000	202.000000	6.000000	6.000000	
max	17510.000000	203.000000	10.000000	10.000000	

	cloud_cover_10	cloud_cover_11	cloud_cover_12	cloud_cover_13	\
count	12916.000000	12926.000000	12931.000000	12926.000000	
mean	3.126742	3.092063	3.046400	3.035046	
std	3.659422	3.589739	3.512063	3.483002	
min	0.000000	0.000000	0.000000	0.000000	
25%	0.000000	0.000000	0.000000	0.000000	
50%	1.000000	1.000000	1.000000	1.000000	
75%	7.000000	7.000000	6.000000	6.000000	
max	10.000000	10.000000	10.000000	10.000000	

	cloud_cover_14	cloud_cover_15	…	wind_speed_23	wind_speed_3	\
count	12919.000000	12938.000000	…	13122.000000	13120.000000	
mean	2.992182	2.911115	…	-0.032754	-2.491814	
std	3.462070	3.440298	…	123.464434	195.197628	

```
min         0.000000      0.000000  ...  -9999.000000  -9999.000000
25%         0.000000      0.000000  ...      0.600000      0.400000
50%         1.000000      1.000000  ...      1.200000      1.000000
75%         6.000000      6.000000  ...      2.100000      1.900000
max        10.000000     10.000000  ...     10.700000     11.300000

       wind_speed_4  wind_speed_5  wind_speed_6  wind_speed_7  wind_speed_8  \
count  13116.000000  13112.000000  13119.000000  13120.000000  13125.000000
mean      -0.234637     -1.011882     -4.068389     -7.119787    -10.073272
std      123.489868    151.258218    230.949420    289.453706    337.895538
min    -9999.000000  -9999.000000  -9999.000000  -9999.000000  -9999.000000
25%        0.400000      0.400000      0.400000      0.400000      0.500000
50%        0.900000      0.900000      0.900000      0.900000      1.000000
75%        1.900000      1.800000      1.800000      1.800000      2.000000
max        9.500000     10.600000     12.400000     11.100000     11.300000

       wind_speed_9  climatology_temp        target
count  13127.000000      13132.000000  13132.000000
mean      -9.119029         12.658557      0.221979
std      326.432094         10.023504      2.960544
min    -9999.000000         -4.487500    -12.864286
25%        0.700000          3.292857     -1.643052
50%        1.300000         12.842857      0.157143
75%        2.200000         22.271429      2.045536
max        9.400000         28.455357     11.778571

[8 rows x 340 columns]
```

[34]:
```python
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 13132 entries, 0 to 13131
Columns: 342 entries, id to target
dtypes: float64(338), int64(2), object(2)
memory usage: 34.3+ MB
```

Feature 분석

Feature 분류 및 설명

[35]:
```python
def search_time_based_feature_names(df):
    "각 시간별로 구성된 feature들(e.g. 'cloud_cover_0', 'cloud_cover_1' ...)에 대해␣
 ↪각각의 고유한 이름(e.g. 'cloud_cover')을 찾는다."

    time_based_features_pattern = re.compile(r"^(.*)_(\d{1,2})$")
    searched_time_based_feature_names = set()

    for column in df.columns:
        match = time_based_features_pattern.match(column)
        if match:
            feature_name, hour = match.groups()
            hour = int(hour)
```

```
            searched_time_based_feature_names.add(feature_name)

    return searched_time_based_feature_names

time_based_feature_names = search_time_based_feature_names(train_df)

print(len(time_based_feature_names))
print(time_based_feature_names)
```

```
14
{'sea_level_pressure', 'wind_direction', 'local_pressure', 'dew_point', 'precipitation',
'sunshine_duration', 'snow_depth', 'vapor_pressure', 'cloud_cover', 'visibility',
'wind_speed', 'surface_temp', 'humidity', 'min_cloud_height'}
```

[36]:
```
categorical_features = [col for col in train_df.columns if train_df[col].dtype ==␣
↪'object' or train_df[col].dtype.name == 'category']
```

[37]:
```
categorical_features
```

[37]:
```
['station_name', 'date']
```

train dataset에 있는 feature를 특성에 따라 다음과 같은 카테고리별로 정리하였다.

1. Data 식별
    - `id`: 순서(identical)
    - `station`: 지상관측소 번호(98: "동두천", 201: "강화" 등)
    - `station_name`: 지상관측소 이름("동두천", "서울", "강화" 등)
    - `date`: 날짜(월-일 형식, 1월 29일은 "01-29"로 표기)
2. 구름 관련 feature
    - `cloud_cover_[0-23]`: 증하층운량(10분위, 0~10)
    - `min_cloud_height_[0-23]`: 시간별 최저운고(100m 단위)
3. 온도 관련 feature
    - `dew_point_[0-23]`: 시간별 이슬점 온도(°C)
    - `surface_temp_[0-23]`: 시간별 지면온도(°C)
    - `climatology_temp`: 해당 날짜의 평균 기온(°C) (7년 동안 평균)
4. 습도 관련 feature
    - `humidity_[0-23]`: 시간별 습도(%)
    - `vapor_pressure_[0-23]`: 시간별 증기압(hPa)
    - `percipitation_[0-23]`: 시간별 강수량(mm)
    - `snow_depth_[0-23]`: 시간별 적설(cm)
5. 기압 관련 feature
    - `local_pressure_[0-23]`: 시간별 현지기압(hPa)
    - `sea_level_pressure_[0-23]`: 시간별 해면기압(hPa)
6. 가시성 관련 feature
    - `visibility_[0-23]`: 시간별 시정(10m 단위)
    - `sunshine_duration_[0-23]`: 시간별 일조(hr)
7. 바람 관련 feature
    - `wind_speed_[0-23]`: 시간별 풍속(m/s)
    - `wind_direction_[0-23]`: 시간별 풍향(도 단위)
8. target feature
    - `target`: 시간별 기온(°C, 다음날 평균 기온(°C)에서 `climatology_temp`를 뺀 값)

결측치 패턴

1. -9999: 관측소 기계에서 감지한 결측치 또는 이상치
2. NaN:
   - sunshine_duration: 야간 시간대(0, 1, 2, 3, 4, 5, 22, 23시), 즉 해가 없는 시간대
   - snow_depth: 눈이 오지 않은 경우
   - precipitation: 비가 오지 않은 경우

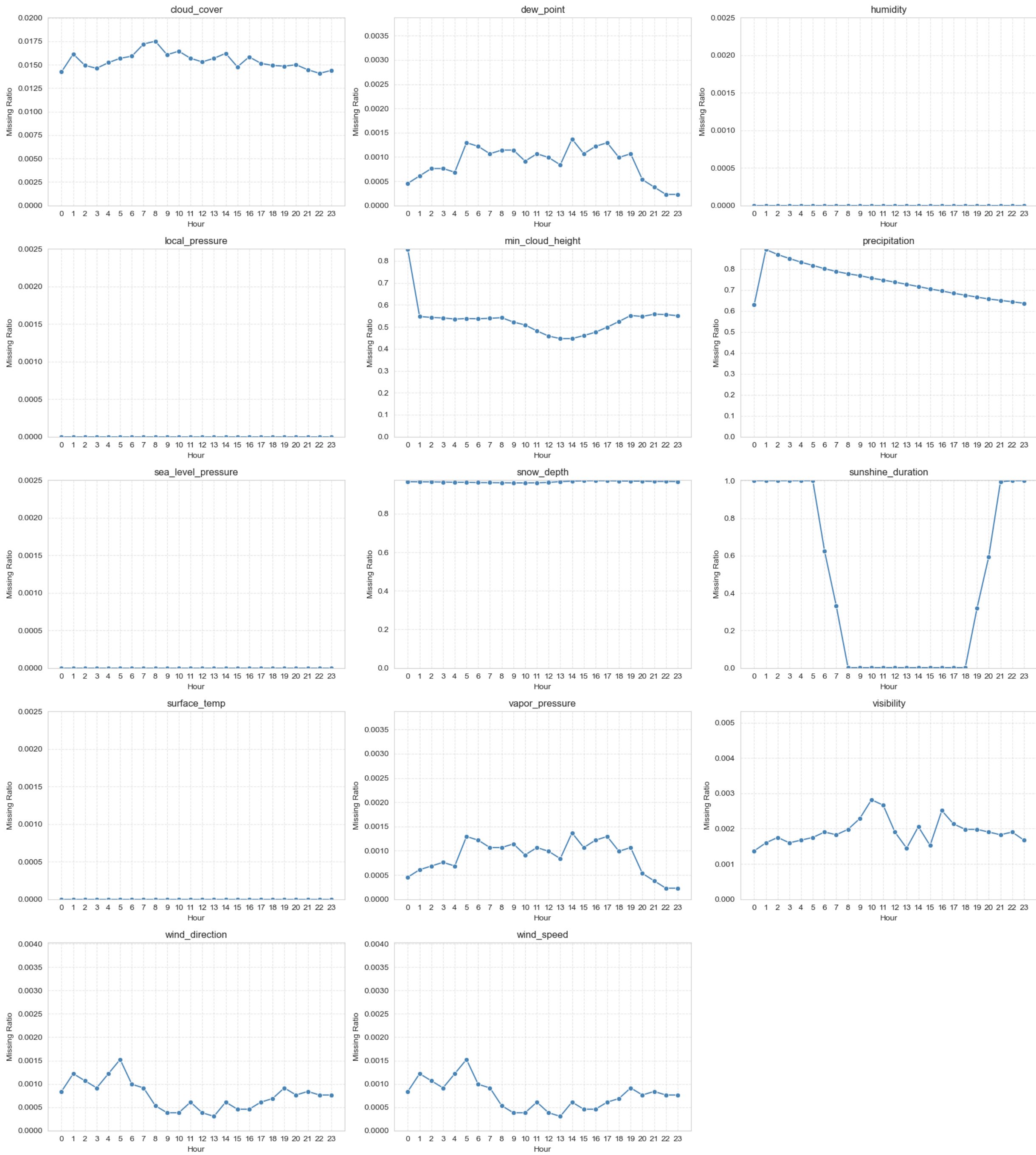
결측치 식별

Time-based feature에 대한 결측치

시간대별 결측률 분석

[38]:
```python
def analyze_time_based_features_missing_by_hour(ax, df, base_name):
    hour_missing = {}

    cols = [col for col in df.columns if col.startswith(base_name + "_")]

    for col in cols:
        try:
            hour = int(col.split("_")[-1])
            missing_ratio = df[col].isnull().mean()
            hour_missing[hour] = missing_ratio
        except ValueError:
            continue

    hours = sorted(hour_missing.keys())
    missing_values = [hour_missing[h] for h in hours]

    sns.lineplot(x=hours, y=missing_values, marker="o", ax=ax, color="steelblue")
    ax.set_title(f"{base_name}")
    ax.set_xlabel("Hour")
    ax.set_ylabel("Missing Ratio")
    ax.set_xticks(hours)
    ax.set_ylim(0, max(missing_values) + 0.0025)
    ax.grid(True, linestyle="--", alpha=0.5)
```

[39]:
```python
num_features = len(time_based_feature_names)
n_cols = 3
n_rows = math.ceil(num_features / n_cols)

fig, axes = plt.subplots(n_rows, n_cols, figsize=(n_cols * 6, n_rows * 4))
axes = axes.flatten()

for i, feature in enumerate(sorted(time_based_feature_names)):
    analyze_time_based_features_missing_by_hour(axes[i], train_df, feature)

for j in range(i + 1, len(axes)):
    fig.delaxes(axes[j])

plt.tight_layout()
plt.show()
```

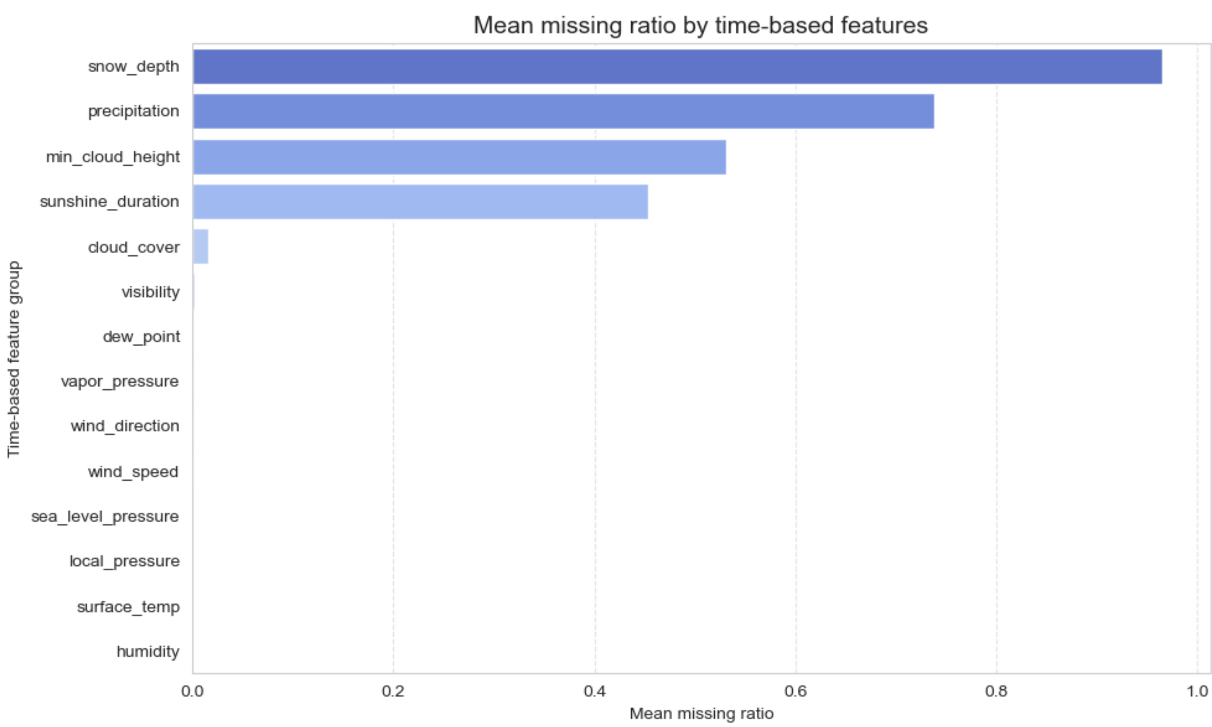


Time-based feature 종류별 평균 결측치 비율

[40]:
```python
def analyze_missing_values_by_time_groups(df, time_based_feature_names):
    group_missing_summary = []

    for base_name in time_based_feature_names:
        cols = [col for col in df.columns if col.startswith(base_name + "_")]
        if not cols:
            continue
        missing_ratio = df[cols].isnull().mean().mean()  # 각 시간대의 평균 결측률
        group_missing_summary.append((base_name, missing_ratio))
```

```
    summary_df = pd.DataFrame(group_missing_summary, columns=["feature_group",␣
↪"mean_missing_ratio"])
    summary_df = summary_df.sort_values(by="mean_missing_ratio", ascending=False).
↪reset_index(drop=True)
    return summary_df
```

[41]:
```
group_missing_ratio = analyze_missing_values_by_time_groups(train_df,␣
↪time_based_feature_names)

plt.figure(figsize=(10, 6))
sns.barplot(
    data=group_missing_ratio,
    x="mean_missing_ratio",
    y="feature_group",
    hue="feature_group",
    palette="coolwarm",
)
plt.title("Mean missing ratio by time-based features", fontsize=14)
plt.xlabel("Mean missing ratio")
plt.ylabel("Time-based feature group")
plt.grid(axis='x', linestyle='--', alpha=0.5)
plt.tight_layout()
plt.show()
```



EDA & Feature Engineering

결측치 처리

결측치 처리 방법

1. -9999는 NaN으로 처리
2. `snow_depth`, `precipitation`, `min_cloud_height`, `sunshine_duration`과 같이 결측치 비율이 높은 feature 처리 논의…
3. `sunshine_duration`이 야간에 결측치 -> 0으로 처리

[42]:
```python
def handle_missing_values(df):
    # 1. -9999를 NaN으로 변환
    df = df.replace(-9999, np.nan)

    # 2. 시간대별 특징에 맞게 처리
    night_hours = [0, 1, 2, 3, 4, 5, 22, 23]
    day_hours = [h for h in range(6, 22) if h not in night_hours]

    # 2.1. sunshine_duration
    # 2.1.1. 밤 시간대
    for hour in night_hours:
        col = f'sunshine_duration_{hour}'
        if col in df.columns:
            df[col] = df[col].fillna(0)

    # 2.1.2. 낮 시간대
    for hour in day_hours:
        col = f'sunshine_duration_{hour}'
        if col in df.columns:
            df[col] = df.groupby('station')[col].transform(lambda x: x.fillna(x.
↪mean()))
            # 낮시간대에 측정소 문제로 NaN이 있을 경우, global mean으로 대체함
            df[col] = df[col].fillna(df[col].mean())

    # 2.2. snow_depth
    # 눈이 오지 않는 계절에는 0으로 대체하고, 눈이 오는 계절에는 그룹별 평균으로␣
↪대체
    month_series = df['date'].str.split('-').str[0].astype(int)
    winter_mask = month_series.isin([12, 1, 2])

    for hour in range(24):
        col = f'snow_depth_{hour}'
        if col in df.columns:
            # 겨울철
            df.loc[winter_mask, col] = df.loc[winter_mask].groupby('station')[col].
↪transform(
                lambda x: x.fillna(x.mean()))

            # 겨울 X -> 0으로 대체
            df.loc[~winter_mask, col] = df.loc[~winter_mask][col].fillna(0)

            # 겨울철에도 NaN이 남아있을 경우, global mean으로 대체
```

```
            df[col] = df[col].fillna(df[col].mean())


    # 2.3. percipitation
    # 지역별(측정소별) persistency가 존재할 것이므로, forward / back fill 사용(임시)
    for hour in range(24):
        col = f'precipitation_{hour}'
        if col in df.columns:
            df[col] = df.groupby('station')[col].transform(lambda x: x.ffill())
            df[col] = df.groupby('station')[col].transform(lambda x: x.bfill())
            df[col] = df[col].fillna(0) # 비 안오는 날은 0으로

    # 2.4. min_cloud_height
    # outlier 영향을 줄이기 위해 median 사용함
    for hour in range(24):
        col = f'min_cloud_height_{hour}'
        if col in df.columns:
            df[col] = df.groupby('station')[col].transform(lambda x: x.fillna(x.
↪median()))
            df[col] = df[col].fillna(df[col].median())

    # 3. 나머지 feature 처리
    remaining_time_based_features = [
        'cloud_cover', 'dew_point', 'humidity', 'local_pressure',
        'sea_level_pressure', 'surface_temp', 'vapor_pressure',
        'visibility', 'wind_direction', 'wind_speed'
    ]

    for feature in remaining_time_based_features:
        for hour in range(24):
            col = f'{feature}_{hour}'
            if col in df.columns and df[col].isna().any():
                # station별 평균으로 대체
                df[col] = df.groupby('station')[col].transform(lambda x: x.fillna(x.
↪mean()))
                # 남은 결측치는 global mean으로
                df[col] = df[col].fillna(df[col].mean())

    return df
```

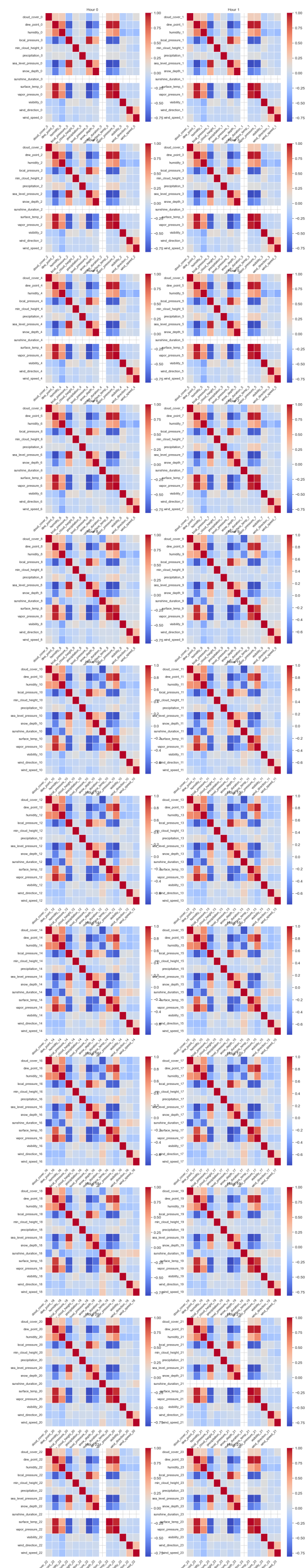
[43]:
```
print("결측치 처리 전 train_df 결측치 개수")
print(train_df.isnull().sum().sum())

train_df = handle_missing_values(train_df)

print("결측치 처리 후 train_df 결측치 개수")
print(train_df.isnull().sum().sum())
```

```
결측치 처리 전 train_df 결측치 개수
853979
결측치 처리 후 train_df 결측치 개수
0
```

Time-based features간 상관관계

[45]:
```
hourly_corr = {}

for hour in range(24):
    cols = [col for col in train_df.columns if col.endswith(f"_{hour}")]
    if cols:
        df_hour = train_df[cols]
        hourly_corr[hour] = df_hour.corr()

n_rows, n_cols = 12, 2
fig, axes = plt.subplots(n_rows, n_cols, figsize=(n_cols * 6, n_rows * 6))
axes = axes.flatten()

for hour in range(24):
    ax = axes[hour]
    if hour in hourly_corr:
        sns.heatmap(hourly_corr[hour], annot=False, fmt=".2f", cmap="coolwarm",
                    cbar=True, linewidths=0.5, ax=ax)
        ax.set_title(f"Hour {hour}", fontsize=10)
        ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right', fontsize=8)
        ax.set_yticklabels(ax.get_yticklabels(), rotation=0, fontsize=8)
    else:
        ax.set_title(f"Hour {hour}\n(No Data)", fontsize=10)
        ax.axis('off')

plt.suptitle("Time-based Features: Correlation by Hour", fontsize=16)
plt.show()
```

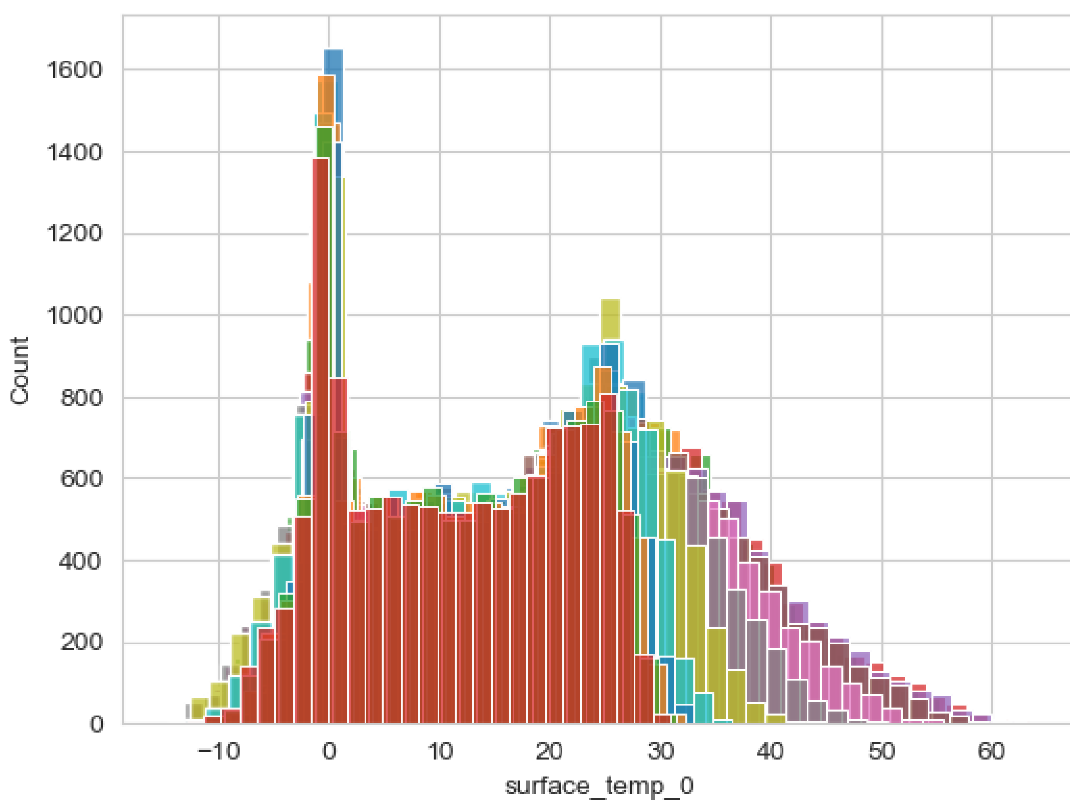
Time-based Features: Correlation by Hour



[ ]:

Histogram of Surface temps

[47]:
```
surface_temps = ["surface_temp_" + str(n) for n in range(24)]



n_rows, n_cols = 8, 3
fig, axes = plt.subplots(n_rows, n_cols, figsize=(n_cols * 6, n_rows * 6))
axes = axes.flatten()

for hour in range(24):
    ax = axes[hour]
    if hour in surface_temps:
        sns.histplot()
        ax.set_title(f"Hour {hour}", fontsize=10)
        ax.set_xticklabels(ax.get_xticklabels(), rotation=45, ha='right', fontsize=8)
        ax.set_yticklabels(ax.get_yticklabels(), rotation=0, fontsize=8)
    else:
        ax.set_title(f"Hour {hour}\n(No Data)", fontsize=10)
        ax.axis('off')

plt.suptitle("Time-based Features: Correlation by Hour", fontsize=16)
plt.show()
```



[ ]:

```

```