[A4] Clustering and Feature Engineering

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1. 데이터셋 설명 (data point 개수, feature 개수)

(1) 세 종류의 레이블이 있고, data point의 개수는 210개, float 속성 feature 7개를 가지고 있습니다.

2. 다양한 데이터 전처리 방법 비교

(1) log(x+1) transform: 피처의 분포를 확인하여, 오른쪽으로 꼬리가 있는 0,3,5,6 피처에 대해 데이터 전처리 수행

(2) 정규화: 모든 피처에 Standard Scaling을 이용하여 데이터 전처리 수행

(3) Polynomial Features & Interactions: 7개의 피처에 degree=2 적용, 28개의 피처 생성

(4) PCA를 이용한 feature extraction: 전체 분산의 95%를 설명하는 주성분 이용

(5) Filter, Wrapper, Embedded Method를 이용한 feature selection: Filter에서는 mutual_info_classif와 f_classif를 사용하여 비교, Wrapper 에서는 logistic regression을 피처 선택시 사용, Embedded에서는 Lasso, Random Forest 이용해서 피처 선택 후 비교

3. 클러스터 개수에 따른 평가지표 추이 확인, Feature engineering의 활용에 따른 성능 개선 확인

(1) 클러스터 수를 2~7개일 때로 나누어 평가 진행, 피처 선택에서는 2~6개 사용

	K	ARI(raw data)	ARI(log transform)	ARI(Scaled)	ARI(Poly)	ARI(PCA)
0	2	0.4648	0.4815	0.4805	0.2351	0.4805
1	3	0.7168	0.6699	0.7860	0.3490	0.7631
2	4	0.5467	0.6197	0.6545	0.3290	0.6191
3	5	0.5600	0.4745	0.5227	0.3494	0.5999
4	6	0.4699	0.4389	0.4717	0.2816	0.4745
5	7	0.4658	0.4268	0.3874	0.2401	0.4443

	Clusters_K	Selected_Features	ARI(Filter1)	Clusters_K	Selected_Features	ARI(Filter2)
0	3	6	0.7039	3	6	0.7039
1	3	2	0.6595	3	2	0.6595
2	3	4	0.6562	3	5	0.6532
3	3	5	0.6532	3	4	0.6527
4	3	3	0.6364	3	3	0.6364
5	4	5	0.5709	4	4	0.6178

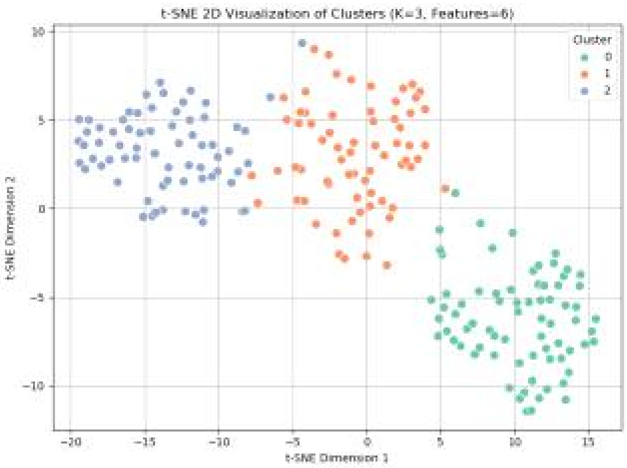
그림 1 2-(1) ~ 2-(4) 전처리 방법의 ARI 점수 그림 2 2-(5) 전처리 방법의 ARI 점수(Filter Method)

Clusters_K	Selected_Features	ARI(Wrapper)	Clusters_K	Selected_Features	ARI(Embedded1)	Clusters_K	Selected_Features	ARI(Embedded2)
3	6	0.7871	3	7	0.7860	3	4	0.6527
3	5	0.7109	3	6	0.7521	4	4	0.6178
4	5	0.6723	3	5	0.7412	2	4	0.5183
3	4	0.6723	3	5	0.7412	5	4	0.5127
4	6	0.6619	4	5	0.6699	6	4	0.4650
3	3	0.6085	4	5	0.6699	7	4	0.4158

그림 3 2-(5) 전처리 방법의 ARI 점수(Wrapper, Embedded Method)

최적의 결과는 Wrapper Method를 이용하고, 클러스터의 개수가 3개, 피처의 개수가 6개인 경우 ARI가 0.7871로 가장 높았습니다.

4. 2차원 시각화를 통한 최적의 클러스터링 결과 확인



5. 추가 성능 개선 및 적절한 클러스터링 성능평가를 위한 방안 논의

(1) 데이터셋과 피처에 대한 이해도를 높여, 파생 피처 생성을 통해 성능을 개선할 수 있습니다.

(2) KMeans 외 다른 군집화 알고리즘을 사용해 성능 개선을 논의할 수 있습니다.

(3) ARI 이외에도, Silhouette, Davies-Bouldin Index 등을 이용해 클러스터링 성능을 평가할 수 있습니다.

Data Load

In [5]:
```
import pandas as pd

# 파일 경로 지정
file_path = r"C:\Users\준서\Desktop\준서\3-2\데과프\A4\seeds_dataset.txt"

# 공백 또는 탭을 구분자로 읽기
df = pd.read_csv(file_path, delim_whitespace=True, header=None)

# 컬럼 수 확인
print(df.shape)  # (행 수, 열 수)

# 앞부분 출력
print(df.head())

print(df.info())
```

```
(210, 8)
       0      1       2      3      4      5      6  7
0  15.26  14.84  0.8710  5.763  3.312  2.221  5.220  1
1  14.88  14.57  0.8811  5.554  3.333  1.018  4.956  1
2  14.29  14.09  0.9050  5.291  3.337  2.699  4.825  1
3  13.84  13.94  0.8955  5.324  3.379  2.259  4.805  1
4  16.14  14.99  0.9034  5.658  3.562  1.355  5.175  1
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 210 entries, 0 to 209
Data columns (total 8 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       210 non-null    float64
 1   1       210 non-null    float64
 2   2       210 non-null    float64
 3   3       210 non-null    float64
 4   4       210 non-null    float64
 5   5       210 non-null    float64
 6   6       210 non-null    float64
 7   7       210 non-null    int64  
dtypes: float64(7), int64(1)
memory usage: 13.3 KB
None
```

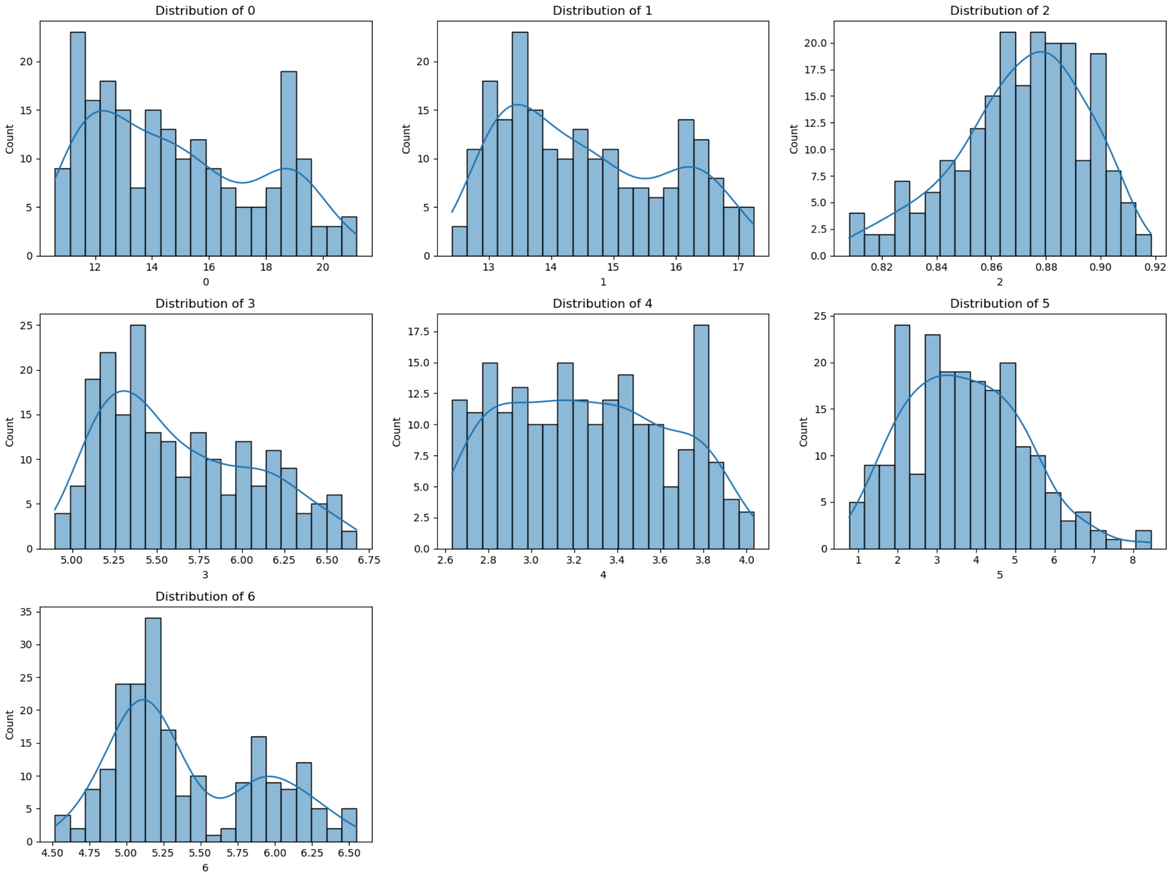
In [9]:
```
df_cluster = df.iloc[:,:-1]
print(df_cluster.info())
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 210 entries, 0 to 209
Data columns (total 7 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   0       210 non-null    float64
 1   1       210 non-null    float64
 2   2       210 non-null    float64
 3   3       210 non-null    float64
 4   4       210 non-null    float64
 5   5       210 non-null    float64
 6   6       210 non-null    float64
dtypes: float64(7)
memory usage: 11.6 KB
None
```

In [12]:

```python
import matplotlib.pyplot as plt
import seaborn as sns
feature_columns = df_cluster.columns

# 시각화 설정
plt.figure(figsize=(16, 12))
for idx, col in enumerate(feature_columns):
    plt.subplot(3, 3, idx + 1)
    sns.histplot(df[col], kde=True, bins=20)
    plt.title(f"Distribution of {col}")
    plt.xlabel(col)
    plt.ylabel("Count")

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

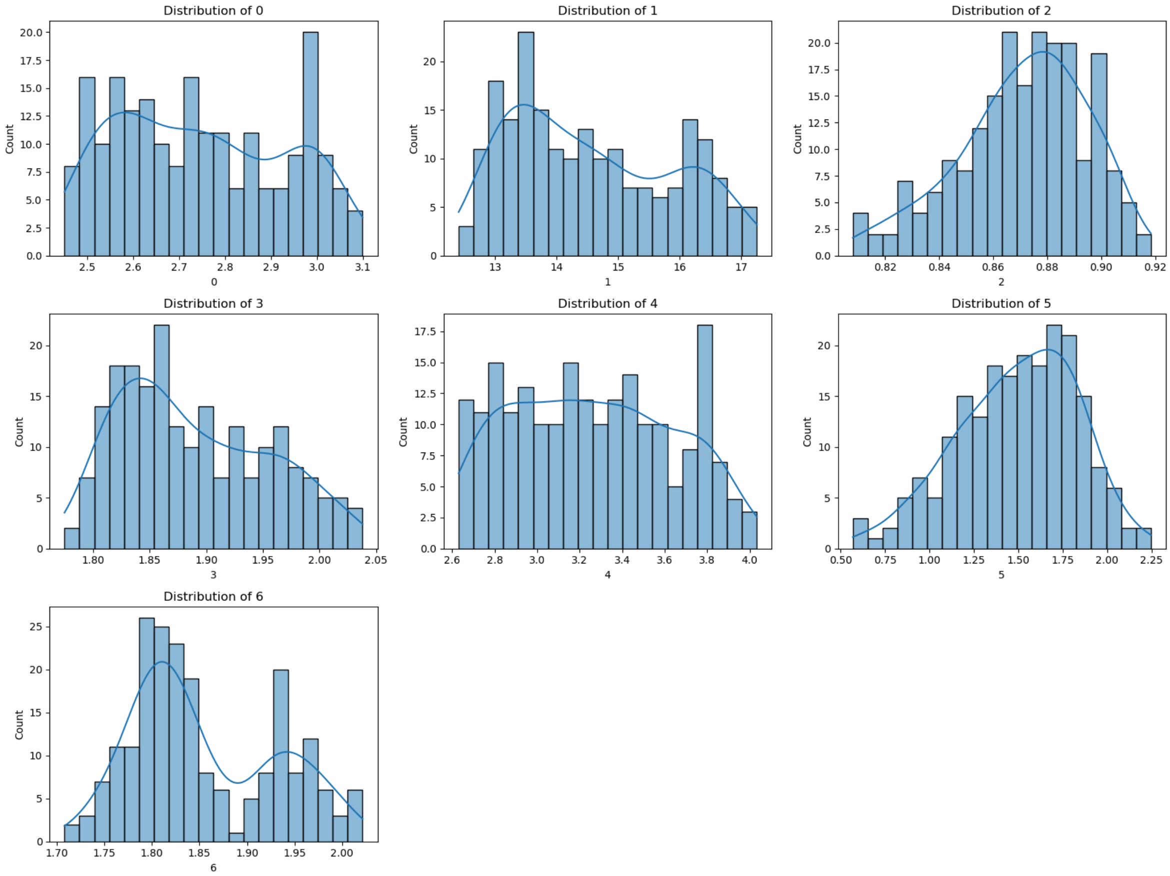
```
C:\anacon\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_n
a option is deprecated and will be removed in a future version. Convert inf value
s to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\anacon\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_n
a option is deprecated and will be removed in a future version. Convert inf value
s to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\anacon\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_n
a option is deprecated and will be removed in a future version. Convert inf value
s to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\anacon\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_n
a option is deprecated and will be removed in a future version. Convert inf value
s to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\anacon\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_n
a option is deprecated and will be removed in a future version. Convert inf value
s to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\anacon\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_n
a option is deprecated and will be removed in a future version. Convert inf value
s to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
C:\anacon\Lib\site-packages\seaborn\_oldcore.py:1119: FutureWarning: use_inf_as_n
a option is deprecated and will be removed in a future version. Convert inf value
s to NaN before operating instead.
  with pd.option_context('mode.use_inf_as_na', True):
```



Data Preprocessing

In [32]:
```
import warnings
warnings.filterwarnings('ignore')
```

In [33]:
```
import numpy as np

# 로그 변환 대상: 0, 3, 5, 6
df_log = df_cluster.copy()
for col in [0, 3, 5, 6]:
    df_log[col] = np.log1p(df_log[col])  # log(x + 1)

plt.figure(figsize=(16, 12))
for idx, col in enumerate(df_log.columns):
    plt.subplot(3, 3, idx + 1)
    sns.histplot(df_log[col], kde=True, bins=20)
    plt.title(f"Distribution of {col}")
    plt.xlabel(col)
    plt.ylabel("Count")

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



In [34]:
```
df_log
```

Out[34]:

	0	1	2	3	4	5	6
0	2.788708	14.84	0.8710	1.911467	3.312	1.169692	1.827770
1	2.765060	14.57	0.8811	1.880076	3.333	0.702107	1.784399
2	2.727199	14.09	0.9050	1.839120	3.337	1.308063	1.762159
3	2.697326	13.94	0.8955	1.844352	3.379	1.181420	1.758720
4	2.841415	14.99	0.9034	1.895819	3.562	0.856541	1.820509
...	...	...	...	...	...	...	...
205	2.579459	13.20	0.8783	1.814336	2.981	1.532773	1.769855
206	2.503892	12.88	0.8511	1.814825	2.795	1.672413	1.792259
207	2.653242	13.66	0.8883	1.830339	3.232	2.231626	1.801050
208	2.552565	13.21	0.8521	1.820509	2.836	1.525621	1.799066
209	2.587764	13.34	0.8684	1.831461	2.974	1.892660	1.802205

210 rows × 7 columns

In [35]:
```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform( df_log.iloc[:])
```

In [44]:
```
from sklearn.preprocessing import PolynomialFeatures

poly = PolynomialFeatures(degree=2, include_bias=False)
X_poly = poly.fit_transform(X_scaled)
```

In [47]:
```
from sklearn.decomposition import PCA

pca = PCA(n_components=0.95)  # 전체 분산의 95%를 설명하는 주성분만
X_pca = pca.fit_transform(X_scaled)
```

Training

Case1: without Data Preprocessing

In [23]:
```
import warnings
warnings.filterwarnings('ignore', category=UserWarning)
```

In [50]:
```
from sklearn.cluster import KMeans
from sklearn.metrics import adjusted_rand_score

X_raw = df_cluster.iloc[:]
y_true = df.iloc[:, -1]
k_values = range(2, 8)
ari_scores = []

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42,n_init='auto')
    y_pred = kmeans.fit_predict(X_raw)
    ari = adjusted_rand_score(y_true, y_pred)
    ari_scores.append({'K': k, 'ARI(raw data)': round(ari, 4)})

results_df1 = pd.DataFrame(ari_scores)
print(results_df1)
```

```
   K  ARI(raw data)
0  2         0.4648
1  3         0.7166
2  4         0.5467
3  5         0.5600
4  6         0.4699
5  7         0.4658
```

Case2: with Data Preprocessing (log transform for col 0,3,5,6)

In [51]:
```
#log변환 한 경우 training

X_log = df_log.iloc[:]
k_values = range(2, 8)
ari_scores = []

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42,n_init='auto')
    y_pred = kmeans.fit_predict(X_log)
    ari = adjusted_rand_score(y_true, y_pred)
    ari_scores.append({'K': k, 'ARI(log transform)': round(ari, 4)})

results_df2 = pd.DataFrame(ari_scores)
print(results_df2)
```

```
   K  ARI(log transform)
0  2              0.4815
1  3              0.6699
2  4              0.6197
3  5              0.4745
4  6              0.4389
5  7              0.4268
```

Case3: with Data Preprocessing (log transform for col 0,3,5,6 & Standard Scaling)

In [52]:
```
# scaling 한 경우 traing

k_values = range(2, 8)
ari_scores = []

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42,n_init='auto')
    y_pred = kmeans.fit_predict(X_scaled)
    ari = adjusted_rand_score(y_true, y_pred)
    ari_scores.append({'K': k, 'ARI(Scaled)': round(ari, 4)})

results_df3 = pd.DataFrame(ari_scores)
print(results_df3)
```

```
   K  ARI(Scaled)
0  2       0.4805
1  3       0.7860
2  4       0.6545
3  5       0.5227
4  6       0.4717
5  7       0.3874
```

Case4: with Data Preprocessing (log transform for col 0,3,5,6 & Standard Scaling & Polynomial features)

In [53]:
```
# Polynomial features

k_values = range(2, 8)
ari_scores = []

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42,n_init='auto')
    y_pred = kmeans.fit_predict(X_poly)
    ari = adjusted_rand_score(y_true, y_pred)
```

```
    ari_scores.append({'K': k, 'ARI(Poly)': round(ari, 4)})

results_df4 = pd.DataFrame(ari_scores)
print(results_df4)
```

```
   K  ARI(Poly)
0  2     0.2351
1  3     0.3490
2  4     0.3290
3  5     0.3494
4  6     0.2816
5  7     0.2401
```

Case5: with Data Preprocessing (log transform for col 0,3,5,6 & Standard Scaling & feature extraction)

In [79]:

```
# PCA 이용하여 feature extraction

k_values = range(2, 8)
ari_scores = []

for k in k_values:
    kmeans = KMeans(n_clusters=k, random_state=42,n_init='auto')
    y_pred = kmeans.fit_predict(X_pca)
    ari = adjusted_rand_score(y_true, y_pred)
    ari_scores.append({'K': k, 'ARI(PCA)': round(ari, 4)})

results_df = pd.DataFrame(ari_scores)
print(results_df5)
```

```
   K  ARI(PCA)
0  2    0.4805
1  3    0.7631
2  4    0.6191
3  5    0.5999
4  6    0.4745
5  7    0.4443
```

Case6: with Data Preprocessing (log transform for col 0,3,5,6 & Standard Scaling & Filter Method feature selection)

In [96]:

```
from sklearn.feature_selection import SelectKBest, mutual_info_classif
from itertools import product

k_range = range(2, 8)        # 클러스터 수: 2~7
feature_range = range(2, 7)  # 선택 피처 수: 2~6

results = []
for k, n_features in product(k_range, feature_range):
    # 피처 선택
    selector = SelectKBest(mutual_info_classif, k=n_features)
    X_selected = selector.fit_transform(X_scaled, y_true)

    kmeans = KMeans(n_clusters=k, random_state=42, n_init='auto')
    y_pred = kmeans.fit_predict(X_selected)

    # ARI 평가
    ari = adjusted_rand_score(y_true, y_pred)
    results.append({
```

```
        'Clusters_K': k,
        'Selected_Features': n_features,
        'ARI(Filter1)': round(ari, 4)
    })

# 5. 결과 정렬 및 상위 5개 출력
results_df6 = pd.DataFrame(results).sort_values(by='ARI(Filter1)', ascending=Fal


# 6. 출력
print("KMeans Results with Feature Selection(mutual_info_classif):")
print(results_df6)
```

```
KMeans Results with Feature Selection(mutual_info_classif):
    Clusters_K  Selected_Features  ARI(Filter1)
9            3                  6        0.7039
5            3                  2        0.6595
7            3                  4        0.6562
8            3                  5        0.6532
6            3                  3        0.6364
13           4                  5        0.5709
12           4                  4        0.5504
18           5                  5        0.5455
14           4                  6        0.5180
3            2                  5        0.4912
4            2                  6        0.4858
11           4                  3        0.4850
1            2                  3        0.4797
10           4                  2        0.4765
0            2                  2        0.4720
17           5                  4        0.4708
2            2                  4        0.4683
16           5                  3        0.4544
23           6                  5        0.4527
15           5                  2        0.4523
24           6                  6        0.4358
19           5                  6        0.4347
21           6                  3        0.4161
20           6                  2        0.4096
28           7                  5        0.3994
22           6                  4        0.3855
26           7                  3        0.3800
25           7                  2        0.3773
29           7                  6        0.3479
27           7                  4        0.3470
```

Case6-(2): with Data Preprocessing (log transform for col 0,3,5,6 & Standard Scaling & Filter Method feature selection)

In [97]:
```
from sklearn.feature_selection import SelectKBest, f_classif
from itertools import product

k_range = range(2, 8)        # 클러스터 수: 2~7
feature_range = range(2, 7)  # 선택 피처 수: 2~6

results = []
for k, n_features in product(k_range, feature_range):
    # 피처 선택
    selector = SelectKBest(f_classif, k=n_features)
    X_selected = selector.fit_transform(X_scaled, y_true)
```

```
    # KMeans
    kmeans = KMeans(n_clusters=k, random_state=42, n_init='auto')
    y_pred = kmeans.fit_predict(X_selected)

    # ARI 평가
    ari = adjusted_rand_score(y_true, y_pred)
    results.append({
        'Clusters_K': k,
        'Selected_Features': n_features,
        'ARI(Filter2)': round(ari, 4)
    })

# 5. 결과 정렬 및 상위 5개 출력
results_df62 = pd.DataFrame(results).sort_values(by='ARI(Filter2)', ascending=Fa


# 6. 출력
print("KMeans Results with Feature Selection(f_classif):")
print(results_df62)
```

```
KMeans Results with Feature Selection(f_classif):
    Clusters_K  Selected_Features  ARI(Filter2)
9            3                  6        0.7039
5            3                  2        0.6595
8            3                  5        0.6532
7            3                  4        0.6527
6            3                  3        0.6364
12           4                  4        0.6178
13           4                  5        0.5709
18           5                  5        0.5455
2            2                  4        0.5183
14           4                  6        0.5180
17           5                  4        0.5127
3            2                  5        0.4912
4            2                  6        0.4858
11           4                  3        0.4850
1            2                  3        0.4797
10           4                  2        0.4765
0            2                  2        0.4720
22           6                  4        0.4650
16           5                  3        0.4544
23           6                  5        0.4527
15           5                  2        0.4523
24           6                  6        0.4358
19           5                  6        0.4347
21           6                  3        0.4161
27           7                  4        0.4158
20           6                  2        0.4096
28           7                  5        0.3994
26           7                  3        0.3800
25           7                  2        0.3773
29           7                  6        0.3479
```

Case7: with Data Preprocessing (log transform for col 0,3,5,6 & Standard Scaling & Wrapper Method feature selection)

In [98]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.feature_selection import SequentialFeatureSelector
from itertools import product
```

```
k_range = range(2, 8)        # 클러스터 수: 2~7
feature_range = range(2, 7)  # 선택 피처 수: 2~6

results = []
for k, n_features in product(k_range, feature_range):
    estimator = LogisticRegression()
    sfs = SequentialFeatureSelector(estimator, n_features_to_select=n_features,
    sfs.fit(X_scaled, y_true)

    X_wrapper = sfs.transform(X_scaled)

    kmeans = KMeans(n_clusters=k, random_state=42, n_init='auto')
    y_pred = kmeans.fit_predict(X_wrapper)

    # ARI 평가
    ari = adjusted_rand_score(y_true, y_pred)
    results.append({
        'Clusters_K': k,
        'Selected_Features': n_features,
        'ARI(Wrapper)': round(ari, 4)
    })

# 5. 결과 정렬 및 출력
results_df7 = pd.DataFrame(results).sort_values(by='ARI(Wrapper)', ascending=Fal


# 6. 출력
print("KMeans Results with Feature Selection(Wrapper):")
print(results_df7)
```

```
KMeans Results with Feature Selection(Wrapper):
    Clusters_K  Selected_Features  ARI(Wrapper)
9            3                  6        0.7871
8            3                  5        0.7109
13           4                  5        0.6723
7            3                  4        0.6723
14           4                  6        0.6619
6            3                  3        0.6085
18           5                  5        0.5689
5            3                  2        0.5522
17           5                  4        0.5288
15           5                  2        0.5283
12           4                  4        0.5280
16           5                  3        0.5116
19           5                  6        0.5115
0            2                  2        0.5087
1            2                  3        0.5027
2            2                  4        0.5027
3            2                  5        0.4912
4            2                  6        0.4858
23           6                  5        0.4759
24           6                  6        0.4694
11           4                  3        0.4630
21           6                  3        0.4615
22           6                  4        0.4408
29           7                  6        0.4405
26           7                  3        0.4304
20           6                  2        0.4294
10           4                  2        0.4232
27           7                  4        0.4151
25           7                  2        0.4099
28           7                  5        0.3893
```

Case8: with Data Preprocessing (log transform for col 0,3,5,6 & Standard Scaling & Embedded Method feature selection)

In [92]:
```
#Lasso 기반 피처 선택

from sklearn.linear_model import Lasso
from sklearn.feature_selection import SelectFromModel

k_range = range(2, 8)                  # 클러스터 수: 2 ~ 7
alpha_values = [0.001, 0.005, 0.01, 0.05, 0.1]  # Lasso alpha 값

results = []
for k, alpha in product(k_range, alpha_values):
    lasso = Lasso(alpha=alpha)
    model = lasso.fit(X_scaled, y_true)

    selector = SelectFromModel(model, prefit=True)
    X_embedded = selector.transform(X_scaled)

    if X_embedded.shape[1] == 0:
        continue

    kmeans = KMeans(n_clusters=k, random_state=42, n_init='auto')
    y_pred = kmeans.fit_predict(X_embedded)

    # ARI 평가
```

```
    ari = adjusted_rand_score(y_true, y_pred)
    results.append({
        'Clusters_K': k,
        'Lasso_Alpha': alpha,
        'Selected_Features': X_embedded.shape[1],
        'ARI(Embedded1)': round(ari, 4)
    })

# 5. 결과 정렬 및 출력
results_df8 = pd.DataFrame(results).sort_values(by='ARI(Embedded1)', ascending=F


# 6. 출력
print("KMeans Results with Feature Selection(Embedded,Lasso):")
print(results_df8)
```

```
KMeans Results with Feature Selection(Embedded,Lasso):
    Clusters_K  Lasso_Alpha  Selected_Features  ARI(Embedded1)
5            3        0.001                  7          0.7860
6            3        0.005                  6          0.7521
8            3        0.050                  5          0.7412
7            3        0.010                  5          0.7412
13           4        0.050                  5          0.6699
12           4        0.010                  5          0.6699
10           4        0.001                  7          0.6545
11           4        0.005                  6          0.6261
9            3        0.100                  3          0.5712
18           5        0.050                  5          0.5705
17           5        0.010                  5          0.5705
16           5        0.005                  6          0.5662
14           4        0.100                  3          0.5353
15           5        0.001                  7          0.5227
3            2        0.050                  5          0.4858
2            2        0.010                  5          0.4858
1            2        0.005                  6          0.4838
0            2        0.001                  7          0.4805
20           6        0.001                  7          0.4717
21           6        0.005                  6          0.4671
22           6        0.010                  5          0.4611
23           6        0.050                  5          0.4611
19           5        0.100                  3          0.4501
4            2        0.100                  3          0.4399
26           7        0.005                  6          0.4199
27           7        0.010                  5          0.4068
28           7        0.050                  5          0.4068
25           7        0.001                  7          0.3874
29           7        0.100                  3          0.3534
24           6        0.100                  3          0.3505
```

Case8-2: with Data Preprocessing (log transform for col 0,3,5,6 & Standard Scaling & Embedded Method feature selection)

In [93]:

```
#Random Forest 기반 피처 선택

from sklearn.ensemble import RandomForestClassifier
from sklearn.feature_selection import SelectFromModel

k_range = range(2, 8)                    # 클러스터 수: 2 ~ 7

results = []
```

```
for k in k_range:
    rf = RandomForestClassifier(random_state=42)
    rf.fit(X_scaled, y_true)

    selector = SelectFromModel(rf, threshold="median")
    X_selected = selector.transform(X_scaled)

    if X_selected.shape[1] == 0:
        continue
    kmeans = KMeans(n_clusters=k, random_state=42, n_init='auto')
    y_pred = kmeans.fit_predict(X_selected)

    ari = adjusted_rand_score(y_true, y_pred)
    results.append({
        "Clusters_K": k,
        "Selected_Features": X_selected.shape[1],
        "ARI(Embedded2)": round(ari, 4)
    })

# 결과 정렬 및 출력
results_df82 = pd.DataFrame(results).sort_values(by='ARI(Embedded2)', ascending=


# 6. 출력
print("KMeans Results with Feature Selection(Embedded,RF):")
print(results_df82)
```

```
KMeans Results with Feature Selection(Embedded,RF):
   Clusters_K  Selected_Features  ARI(Embedded2)
1           3                  4          0.6527
2           4                  4          0.6178
0           2                  4          0.5183
3           5                  4          0.5127
4           6                  4          0.4650
5           7                  4          0.4158
```

Evaluation & 2D visualization

In [81]:
```
df_merged = results_df1.merge(results_df2, on='K') \
                       .merge(results_df3, on='K') \
                       .merge(results_df4, on='K') \
                       .merge(results_df5, on='K')

# 보기 좋게 출력
print("Merged ARI Scores by K:")
display(df_merged)
```

```
Merged ARI Scores by K:
```

	K	ARI(raw data)	ARI(log transform)	ARI(Scaled)	ARI(Poly)	ARI(PCA)
0	2	0.4648	0.4815	0.4805	0.2351	0.4805
1	3	0.7166	0.6699	0.7860	0.3490	0.7631
2	4	0.5467	0.6197	0.6545	0.3290	0.6191
3	5	0.5600	0.4745	0.5227	0.3494	0.5999
4	6	0.4699	0.4389	0.4717	0.2816	0.4745
5	7	0.4658	0.4268	0.3874	0.2401	0.4443

In [100…

```
# 각 결과에서 상위 5개 행 추출 및 인덱스 통일
top5_filter1 = results_df6[['Clusters_K', 'Selected_Features', 'ARI(Filter1)']].
top5_filter2 = results_df62[['Clusters_K', 'Selected_Features', 'ARI(Filter2)']]
top5_wrapper = results_df7[['Clusters_K', 'Selected_Features', 'ARI(Wrapper)']].
top5_Embedded1 = results_df8[['Clusters_K', 'Selected_Features', 'ARI(Embedded1)
top5_Embedded2 = results_df82[['Clusters_K', 'Selected_Features', 'ARI(Embedded2

# 가로로 병합
summary_top6 = pd.concat([top5_filter1, top5_filter2, top5_wrapper,top5_Embedded

# 결과 출력
print("Top 6 Results per Feature Selection Method")
display(summary_top6)
```

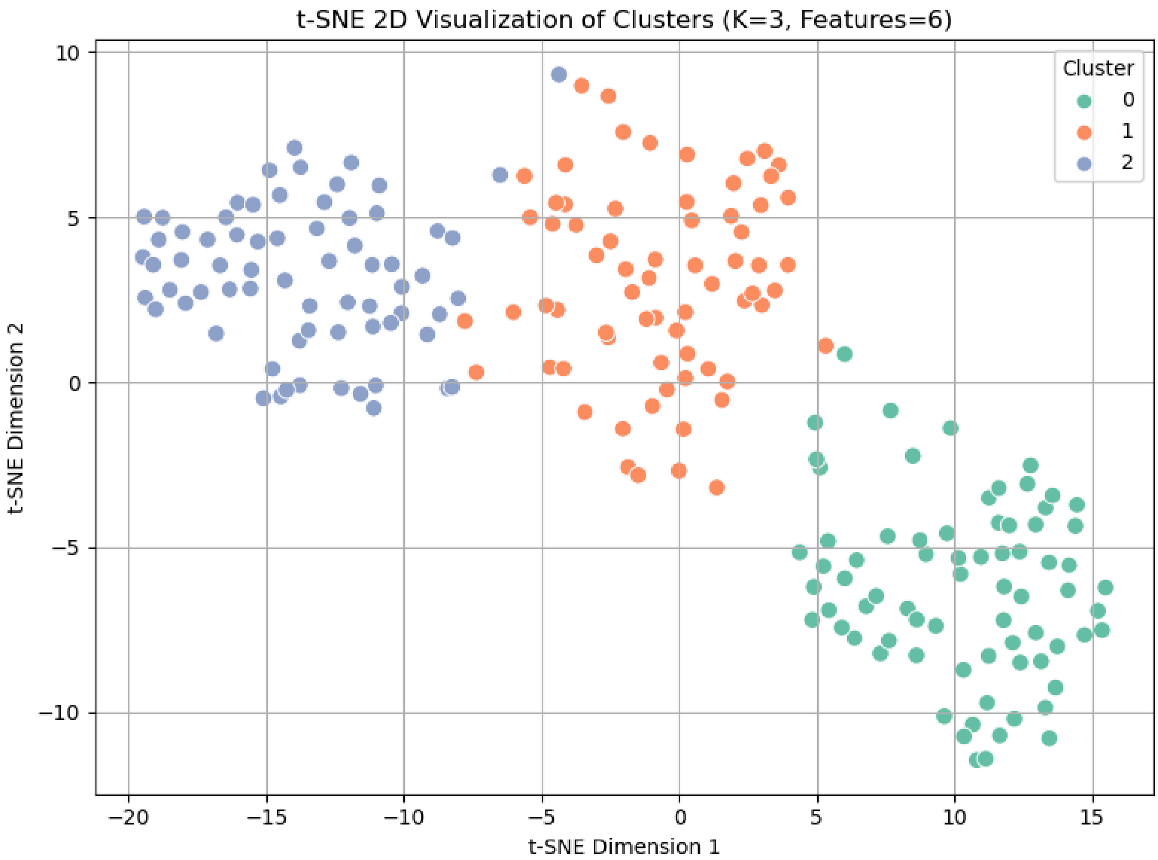
```
Top 6 Results per Feature Selection Method
```

	Clusters_K	Selected_Features	ARI(Filter1)	Clusters_K	Selected_Features	ARI(Filter2)
0	3	6	0.7039	3	6	0.7039
1	3	2	0.6595	3	2	0.6595
2	3	4	0.6562	3	5	0.6532
3	3	5	0.6532	3	4	0.6527
4	3	3	0.6364	3	3	0.6364
5	4	5	0.5709	4	4	0.6178

In [72]:

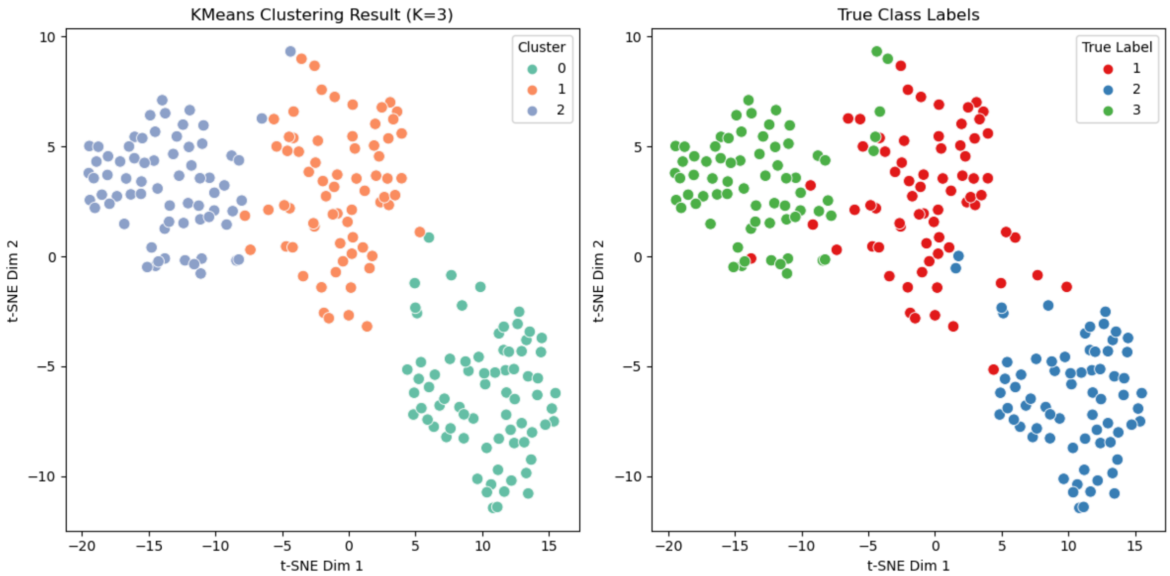
```
from sklearn.manifold import TSNE

best_k = 3
best_n_features = 6

estimator = LogisticRegression()
sfs = SequentialFeatureSelector(estimator, n_features_to_select=best_n_features,
sfs.fit(X_scaled, y_true)
X_selected = sfs.transform(X_scaled)

kmeans = KMeans(n_clusters=best_k, random_state=42, n_init='auto')
clusters = kmeans.fit_predict(X_selected)

# t-SNE로 2D 시각화
tsne = TSNE(n_components=2, random_state=42, perplexity=30)
X_tsne = tsne.fit_transform(X_selected)
```

```
# 결과 시각화
plt.figure(figsize=(8, 6))
sns.scatterplot(x=X_tsne[:, 0], y=X_tsne[:, 1], hue=clusters, palette='Set2', s=
plt.title(f"t-SNE 2D Visualization of Clusters (K={best_k}, Features={best_n_fea
plt.xlabel("t-SNE Dimension 1")
plt.ylabel("t-SNE Dimension 2")
plt.legend(title="Cluster")
plt.grid(True)
plt.tight_layout()
plt.show()
```



In [77]:

```
plt.figure(figsize=(12, 6))

# (1) KMeans 클러스터링 결과
plt.subplot(1, 2, 1)
sns.scatterplot(x=X_tsne[:, 0], y=X_tsne[:, 1], hue=clusters, palette='Set2', s=
plt.title(f"KMeans Clustering Result (K={best_k})")
plt.xlabel("t-SNE Dim 1")
plt.ylabel("t-SNE Dim 2")
plt.legend(title="Cluster")

# (2) 실제 클래스 라벨
plt.subplot(1, 2, 2)
sns.scatterplot(x=X_tsne[:, 0], y=X_tsne[:, 1], hue=y_true, palette='Set1', s=70
plt.title("True Class Labels")
plt.xlabel("t-SNE Dim 1")
plt.ylabel("t-SNE Dim 2")
plt.legend(title="True Label")

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


KMeans Clustering Result (K=3)
Cluster
0
1
2
t-SNE Dim 1
t-SNE Dim 2
True Class Labels
True Label
1
2
3
t-SNE Dim 1
t-SNE Dim 2

In [ ]:

In [ ]:

In [ ]: