implementation_unsupervised

November 30, 2025

1 Unsupervised Learning: Implementation Notebook

This notebook explores the dataset without a target label, then applies K-Means to find groups. I kept the steps simple and clearly commented:

- Load features
- Quick EDA
- Scale numeric columns
- PCA for a 2D view
- K-Means clustering
- Silhouette score and a scatter plot

At the end, cluster labels and metrics are saved in `data/processed/`.

[1]:
```
# Clean imports for unsupervised workflow
# pandas/numpy for data manipulation; matplotlib/seaborn for visuals.
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
# scikit-learn tooling for scaling, dimensionality reduction, clustering, and
 ↪evaluation.
from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

# Local helper to load the feature-only dataset (no target labels).
from src.data_io import load_unsupervised_features

# Load the dataset. We'll explore and cluster its numeric structure.
unsup_df = load_unsupervised_features()
print("Shape:", unsup_df.shape)  # sanity check: rows × columns
# Peek at the first few rows to understand available columns.
unsup_df.head()
```

```
Shape: (2000, 18)
```

[1]:

```
   age  gender  daily_screen_time_hours  phone_usage_hours  \
0   51       0                      4.8                3.4
1   64       1                      3.9                3.5
2   41       2                     10.5                2.1
3   27       2                      8.8                0.0
4   55       1                      5.9                1.7

   laptop_usage_hours  tablet_usage_hours  tv_usage_hours  social_media_hours  \
0                 1.3                 1.6             1.6                 4.1
1                 1.8                 0.9             2.0                 2.7
2                 2.6                 0.7             2.2                 3.0
3                 0.0                 0.7             2.5                 3.3
4                 1.1                 1.5             1.6                 1.1

   work_related_hours  entertainment_hours  gaming_hours  \
0                 2.0                  1.0           1.7
1                 3.1                  1.0           1.5
2                 2.8                  4.1           1.7
3                 1.6                  1.3           0.4
4                 3.6                  0.8           0.8

   sleep_duration_hours  mood_rating  physical_activity_hours_per_week  \
0                   6.6            6                               0.7
1                   4.5            5                               4.3
2                   7.1            5                               3.1
3                   5.1           10                               0.0
4                   7.4            8                               3.0

   uses_wellness_apps  eats_healthy  caffeine_intake_mg_per_day  \
0                   1             1                       125.2
1                   0             1                       150.4
2                   0             0                       187.9
3                   0             1                        73.6
4                   1             1                       217.5

   mindfulness_minutes_per_day
0                          4.0
1                          6.5
2                          6.9
3                          4.8
4                          0.0
```

[2]:

```python
# Load configuration
from pathlib import Path
import yaml
# Optional config.yaml lets us tweak parameters (e.g., k, output paths) without
↪editing code.
```

```
config_path = Path('config.yaml')
config = {}
if config_path.exists():
    with open(config_path, 'r', encoding='utf-8') as f:
        # Safe-load; empty file yields {} so downstream lookups work.
        config = yaml.safe_load(f) or {}
# Echo the active config for transparency in the notebook.
config
```

[2]:

```
{'paths': {'supervised': 'data/raw/clean_supervised.csv',
  'unsupervised': 'data/raw/unsupervised_no_target.csv'},
 'supervised': {'target': 'mental_health_score',
  'test_size': 0.2,
  'random_state': 42},
 'unsupervised': {'use_numeric_only': True, 'random_state': 42, 'k': 3}}
```

1.1 Exploratory Data Analysis

[3]:

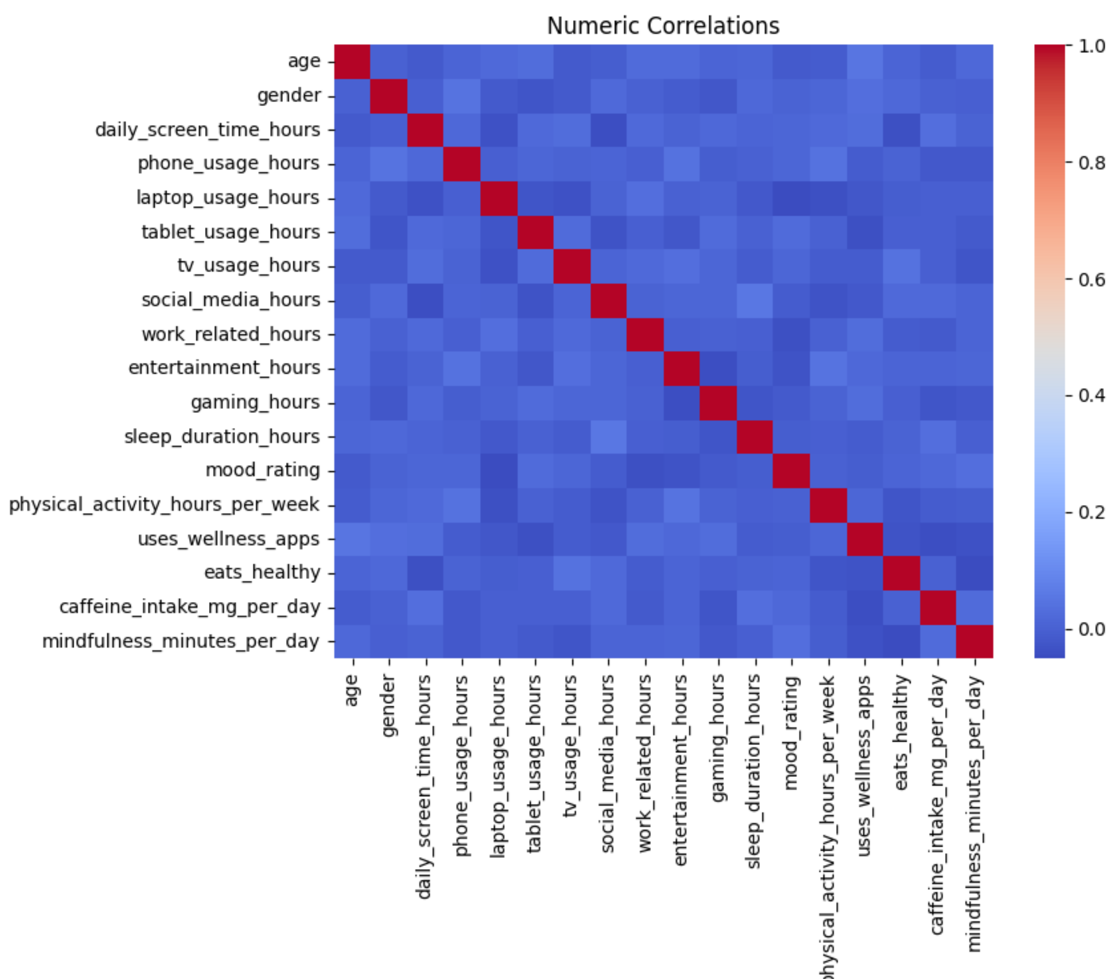
```
# Quick EDA
# Inspect dtypes and nulls to understand what preprocessing might be needed.
unsup_df.info()
# Summary stats for both numeric/categorical columns provide a fast overview.
display(unsup_df.describe(include='all'))
# Correlation heatmap helps spot collinear numeric features; only meaningful␣
↪with >1 numeric column.
if unsup_df.select_dtypes(include=np.number).shape[1] > 1:
    plt.figure(figsize=(8,6)); sns.heatmap(unsup_df.select_dtypes(include=np.
↪number).corr(), cmap='coolwarm'); plt.title('Numeric Correlations'); plt.
↪show()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2000 entries, 0 to 1999
Data columns (total 18 columns):
 #   Column                       Non-Null Count  Dtype
---  ------                       --------------  -----
 0   age                          2000 non-null   int64
 1   gender                       2000 non-null   int64
 2   daily_screen_time_hours      2000 non-null   float64
 3   phone_usage_hours            2000 non-null   float64
 4   laptop_usage_hours           2000 non-null   float64
 5   tablet_usage_hours           2000 non-null   float64
 6   tv_usage_hours               2000 non-null   float64
 7   social_media_hours           2000 non-null   float64
 8   work_related_hours           2000 non-null   float64
 9   entertainment_hours          2000 non-null   float64
 10  gaming_hours                 2000 non-null   float64
 11  sleep_duration_hours         2000 non-null   float64
 12  mood_rating                  2000 non-null   int64
```

```
 13  physical_activity_hours_per_week  2000 non-null   float64
 14  uses_wellness_apps                2000 non-null   int64
 15  eats_healthy                      2000 non-null   int64
 16  caffeine_intake_mg_per_day        2000 non-null   float64
 17  mindfulness_minutes_per_day       2000 non-null   float64
dtypes: float64(13), int64(5)
memory usage: 281.4 KB
               age     gender  daily_screen_time_hours  phone_usage_hours  \
count  2000.000000  2000.0000              2000.000000        2000.000000
mean     38.805500     0.6240                 6.025600           3.023700
std      14.929203     0.6464                 1.974123           1.449399
min      13.000000     0.0000                 0.000000           0.000000
25%      26.000000     0.0000                 4.700000           2.000000
50%      39.000000     1.0000                 6.000000           3.000000
75%      51.000000     1.0000                 7.325000           4.000000
max      64.000000     2.0000                13.300000           8.400000

       laptop_usage_hours  tablet_usage_hours  tv_usage_hours  \
count         2000.000000         2000.000000     2000.000000
mean             1.999950            0.995650        1.503700
std              0.997949            0.492714        0.959003
min              0.000000            0.000000        0.000000
25%              1.300000            0.600000        0.800000
50%              2.000000            1.000000        1.500000
75%              2.700000            1.300000        2.200000
max              5.600000            2.500000        4.700000

       social_media_hours  work_related_hours  entertainment_hours  \
count         2000.000000         2000.000000           2000.00000
mean             2.039200            2.010250              2.46735
std              1.133435            1.116111              1.23686
min              0.000000            0.000000              0.00000
25%              1.200000            1.200000              1.60000
50%              2.000000            2.000000              2.40000
75%              2.800000            2.800000              3.30000
max              5.800000            5.900000              6.80000

       gaming_hours  sleep_duration_hours  mood_rating  \
count     2000.0000           2000.000000  2000.000000
mean         1.2795              6.537550     5.591000
std          0.8945              1.203856     2.899814
min          0.0000              3.000000     1.000000
25%          0.6000              5.700000     3.000000
50%          1.2000              6.600000     6.000000
75%          1.9000              7.400000     8.000000
max          4.0000             10.000000    10.000000
```

	physical_activity_hours_per_week	uses_wellness_apps	eats_healthy	\
count	2000.000000	2000.000000	2000.000000	
mean	3.087150	0.387500	0.507500	
std	1.885258	0.487301	0.500069	
min	0.000000	0.000000	0.000000	
25%	1.600000	0.000000	0.000000	
50%	3.000000	0.000000	1.000000	
75%	4.400000	1.000000	1.000000	
max	9.700000	1.000000	1.000000	

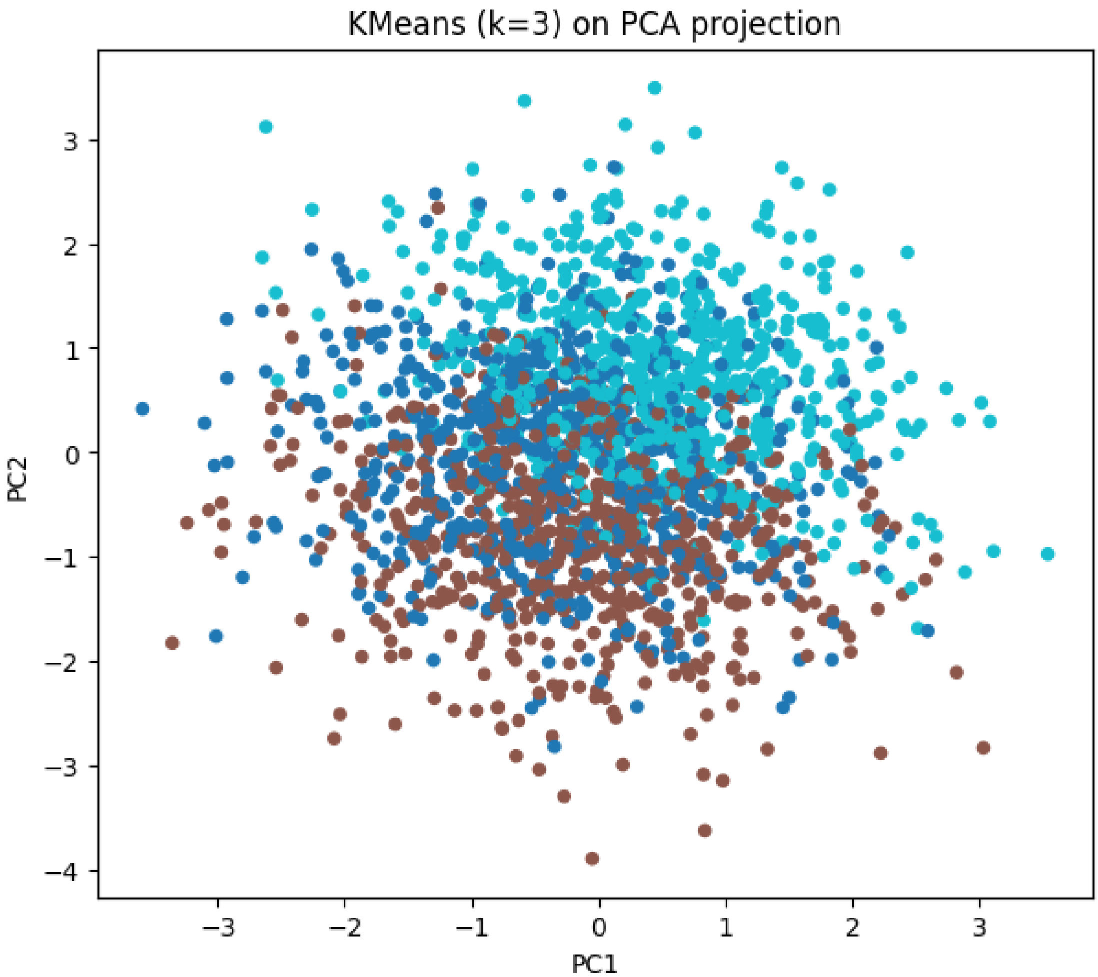
	caffeine_intake_mg_per_day	mindfulness_minutes_per_day
count	2000.00000	2000.000000
mean	148.07970	10.753750
std	48.86066	7.340269
min	0.80000	0.000000
25%	113.90000	4.900000
50%	147.45000	10.400000
75%	180.70000	15.800000
max	364.90000	36.400000



1.2 Scaling, PCA, and Clustering

[4]:
```
# Select numeric features (drop non-numeric)
# Unsupervised clustering typically needs numeric inputs; we focus on those.
num_df = unsup_df.select_dtypes(include=np.number).copy()
# Standardize features so PCA/KMeans aren't dominated by scale differences.
scaler = StandardScaler()
X_scaled = scaler.fit_transform(num_df)

# PCA to 2 components for visualization
# Reduces dimensionality; 2D projection lets us plot clusters even if original␣
↪data is high-dimensional.
pca = PCA(n_components=2, random_state=42)
X_pca = pca.fit_transform(X_scaled)
print('Explained variance:', pca.explained_variance_ratio_)

# KMeans clustering (k from config or 3)
# k is the number of clusters; we pull from config to keep it flexible.
k = int(config.get('unsupervised', {}).get('k', 3))
km = KMeans(n_clusters=k, n_init='auto', random_state=42)
labels = km.fit_predict(X_scaled)

# Silhouette score measures how well points fit within their clusters (higher␣
↪is better).
sil = silhouette_score(X_scaled, labels)
print('Silhouette score:', sil)

# Plot clusters in PCA space for an intuitive visual of separation.
plt.figure(figsize=(7,6))
plt.scatter(X_pca[:,0], X_pca[:,1], c=labels, cmap='tab10', s=20)
plt.title(f'KMeans (k={k}) on PCA projection')
plt.xlabel('PC1'); plt.ylabel('PC2'); plt.show()
```

```
Explained variance: [0.06426934 0.06384612]
Silhouette score: 0.03798480284443637
Silhouette score: 0.03798480284443637
```



The silhouette score is very low (~0.038), indicating weak or overlapping cluster structure. This means lifestyle behaviours in this dataset do not naturally separate into clear groups.

1.3 Save Artifacts

[5]:
```
# Save labels and metrics
from pathlib import Path
import json
# Persist outputs so we can reference them outside the notebook (e.g., in␣
↪slides).
processed_dir = Path(config.get('paths', {}).get('processed', 'data/processed'))
processed_dir.mkdir(parents=True, exist_ok=True)
labels_path = processed_dir / 'unsupervised_kmeans_labels.csv'
metrics_path = processed_dir / 'unsupervised_metrics.json'

# Save cluster assignments as a single-column CSV; easy to join back later.
```

```
out = pd.DataFrame({'cluster': labels})
out.to_csv(labels_path, index=False)
# Record the configuration-derived k and the silhouette score for reporting.
with open(metrics_path, 'w', encoding='utf-8') as f:
    json.dump({'k': int(config.get('unsupervised', {}).get('k', 3)),␣
↪'silhouette': float(sil)}, f, indent=2)
# Return both paths for quick confirmation.
labels_path, metrics_path
```

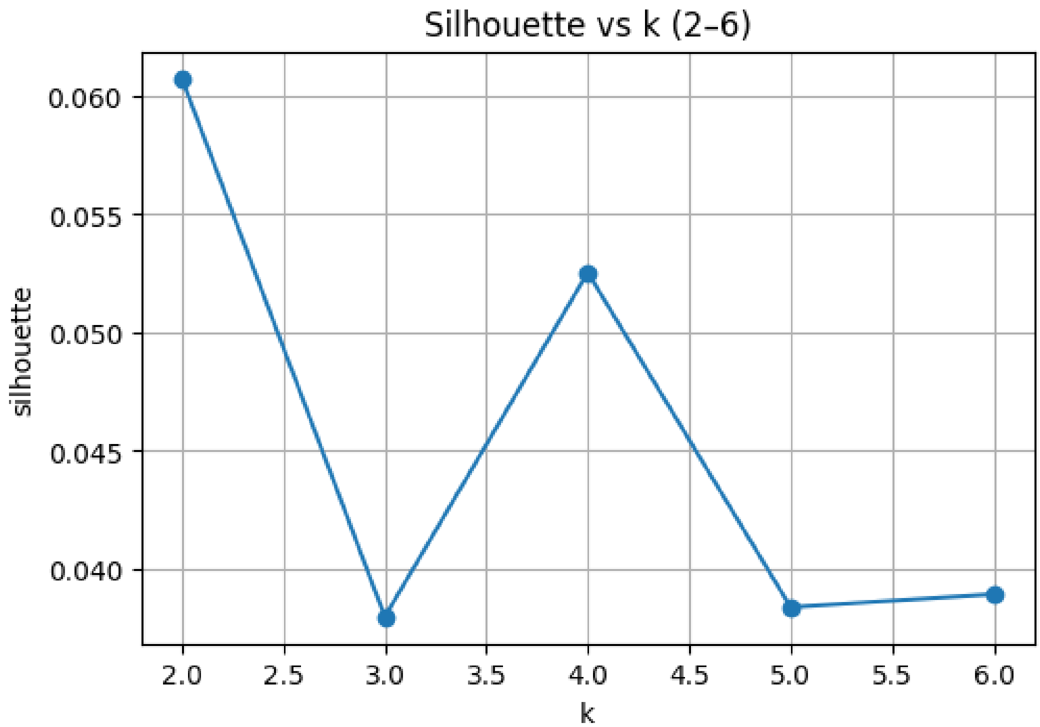
[5]:
```
(WindowsPath('data/processed/unsupervised_kmeans_labels.csv'),
 WindowsPath('data/processed/unsupervised_metrics.json'))
```

1.3.1 K selection via silhouette (2–6)

We test a few k values and report silhouette scores. A low score means clusters overlap and the separation is weak.

[6]:
```
# Silhouette sweep for k=2..6
# We try several k values to see how cluster cohesion/separation changes.
import pandas as pd
from sklearn.metrics import silhouette_score
scores = []
for k_try in range(2, 7):
    km_try = KMeans(n_clusters=k_try, n_init='auto', random_state=42)
    lbl = km_try.fit_predict(X_scaled)
    s = silhouette_score(X_scaled, lbl)
    scores.append({'k': k_try, 'silhouette': float(s)})
# Show a tidy table for quick comparison.
sil_df = pd.DataFrame(scores)
display(sil_df)

# Line plot provides an at-a-glance trend across k.
plt.figure(figsize=(6,4))
plt.plot(sil_df['k'], sil_df['silhouette'], marker='o')
plt.title('Silhouette vs k (2-6)')
plt.xlabel('k')
plt.ylabel('silhouette')
plt.grid(True)
plt.show()
```

	k	silhouette
0	2	0.060755
1	3	0.037985
2	4	0.052541
3	5	0.038384
4	6	0.038933



1.3.2 Cluster interpretation

We join cluster labels back to the original data and compute simple per-cluster means. If the example columns are present, we show those; otherwise we fall back to a few numeric columns.

[7]:
```
# Join labels, compute per-cluster means, and print a readable summary
# Attach the computed cluster labels to the original dataframe for␣
↪interpretation.
unsup_df_with_cluster = unsup_df.copy()
unsup_df_with_cluster['cluster'] = labels

# Prefer these columns if present; else fallback to top 3 numeric columns.
preferred = ['daily_screen_time_hours', 'sleep_duration_hours', 'mood_rating']
available = [c for c in preferred if c in unsup_df_with_cluster.columns]
if not available:
    num_cols = unsup_df_with_cluster.select_dtypes(include=np.number).columns.
↪tolist()
    # Avoid including the 'cluster' column in the mean calculation.
    available = [c for c in num_cols if c != 'cluster'][:3]

print('Columns used for interpretation:', available)
# Cluster-wise means give a quick snapshot of typical values per cluster.
```

```
cluster_means = unsup_df_with_cluster.groupby('cluster')[available].mean().
↪round(2)
display(cluster_means)

# Simple textual summary vs overall mean: which features are relatively higher/
↪lower per cluster.
overall = unsup_df_with_cluster[available].mean()
print('\nQuick interpretation (relative to overall mean):')
for cl in sorted(unsup_df_with_cluster['cluster'].unique()):
    deltas = (cluster_means.loc[cl] - overall)
    deltas_sorted = deltas.sort_values()
    low = deltas_sorted.index[:1].tolist()  # lowest feature relative to overall
    high = deltas_sorted.index[-1:].tolist()  # highest feature relative to␣
↪overall
    print(f"- Cluster {cl}: higher {high}; lower {low}")
```

```
Columns used for interpretation: ['daily_screen_time_hours',
'sleep_duration_hours', 'mood_rating']
```

cluster	daily_screen_time_hours	sleep_duration_hours	mood_rating
0	6.32	6.65	5.86
1	5.71	6.16	3.73
2	6.05	6.79	7.15

```
Quick interpretation (relative to overall mean):
- Cluster 0: higher ['daily_screen_time_hours']; lower ['sleep_duration_hours']
- Cluster 1: higher ['daily_screen_time_hours']; lower ['mood_rating']
- Cluster 2: higher ['mood_rating']; lower ['daily_screen_time_hours']
```

1.4 Cluster Summaries

1.4.1 Cluster 0

- Slightly higher screen time
- Slightly less sleep
- Mood around the overall average

Summary: Heavier screen use, a bit less sleep, average mood.

1.4.2 Cluster 1

- Lower mood (~3.7 vs ~5.6 overall)
- Sleep and screen time slightly lower than Cluster 0

Summary: Lower mood scores with otherwise average sleep and screen habits.

1.4.3 Cluster 2

- Higher mood (~7.1)

- Sleep slightly above average
- Screen time slightly below Cluster 0

Summary: Higher mood and slightly more sleep; somewhat lighter screen use.

Note: Silhouette scores are very low, so boundaries between clusters are fuzzy. Treat these as weak tendencies, not distinct groups.