Unsupervised Machine Learning Workshop — Report

1 — Overview and objective

2 — Data ingestion and initial inspection

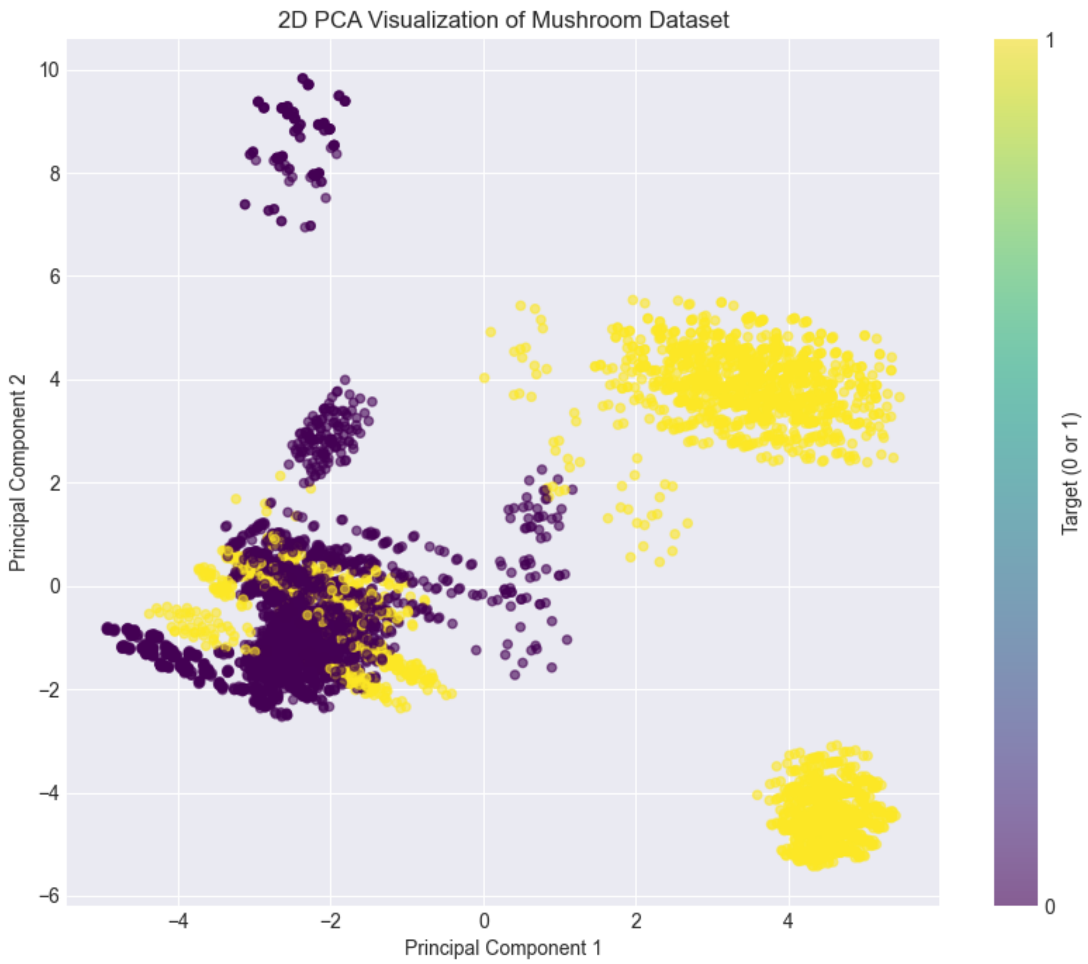
• File used: `data/raw/agaricus-lepiota.data` loaded with `pandas.read_csv()`.
• Initial checks: dataset shape, head/tail/sample, dtypes and memory usage were printed.
• Unique-values analysis produced a two-column summary (`Feature`, `N_Unique_Values`) and was saved to `results/reports/features_unique_values.csv`.
• Missing-value and null analysis was performed and saved to `results/reports/null_values_analysis.csv`.

3 — Advanced cleaning & preprocessing

• Missing value imputation: where appropriate (e.g., feature `e.1`), missing values were replaced using the mode.
• Constant features (single unique value) were dropped to reduce noise.
• One-hot encoding was applied to predictors using `pd.get_dummies()` to produce a fully numeric matrix for modeling; target `p` was label-encoded.
• Train/test split: a stratified split was used (test_size=0.33, random_state=42) to preserve class balance.

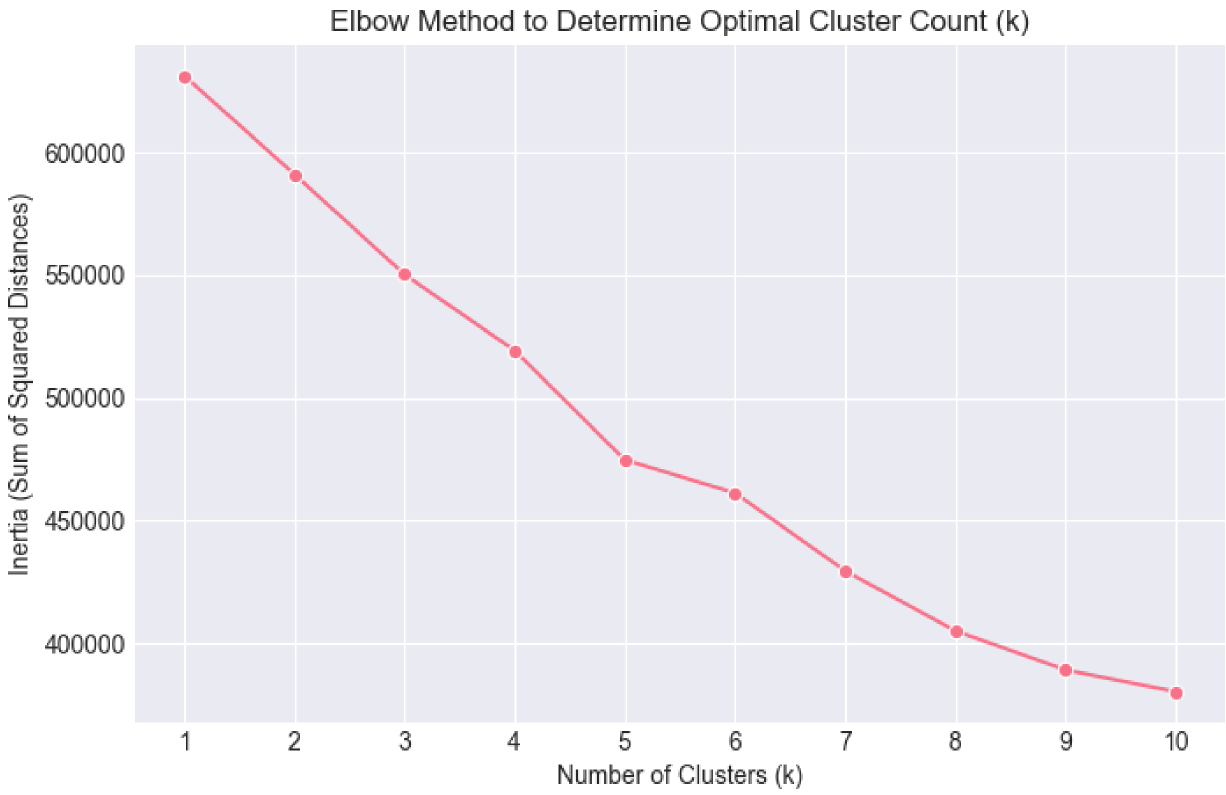
4 — Dimensionality reduction (PCA) and visualization

• PCA was used to visualize data in 2D and to evaluate how many components are required to retain variance.
• 2-component visualization retained a small fraction of variance (notebook reports ~2.24% for the first two components). The explained variance for the 2 components was printed alongside a scatter visualization saved to `results/figures/pca_target_plot.png`.
• A full PCA run determined ~109 components were needed to retain ~95% of variance (i.e., original feature space of ~116 variables reduced to 109 components for ~95% variance retention). This indicates the original features are largely non-redundant.



5 — Clustering and unsupervised analysis

• K-Means clustering was evaluated using the elbow method (inertia across k=1..10). The elbow plot is saved to `results/figures/kmeans_elbow_method.png`.
• KMeans with K=2 was trained on PCA-reduced data for visualization and comparison with the target variable; cluster-target distribution plots are saved to `results/figures/kmeans_target_distribution.png` and `results/figures/pca_kmeans_clusters.png`.



6 — Supervised modeling & ensemble methods

• A Random Forest classifier was trained on the standardized features and evaluated on the held-out test set. The notebook reports a test accuracy of 1.0000 (100% accuracy) for the Random Forest (RandomForestClassifier with 100 trees, random_state=42).
• To test dimensionality reduction effects, Random Forest was retrained on PCA-reduced data (109 components) and the test accuracy recomputed. Training time and accuracy for the reduced-space model were printed and compared.

7 — Reproducible outputs

• `results/reports/features_unique_values.csv`
• `results/reports/null_values_analysis.csv`
• `results/reports/unique_values_analysis.csv`
• `results/reports/dataset_summary.csv`
• `results/figures/pca_target_plot.png`
• `results/figures/cardinality_analysis.png`
• `results/figures/kmeans_elbow_method.png`
• `results/figures/kmeans_target_distribution.png`
• `results/figures/pca_kmeans_clusters.png`

8 — Competency checklist (mapping)

• ■ Use and management of .csv format — dataset read from CSV; multiple result CSVs written to `results/reports/`.
• ■ Data cleaning and preprocessing — missing-value imputation, removal of constant features, and feature-wise inspection implemented.
• ■ Data visualization (Seaborn, Matplotlib, Plotly) — visualizations saved and used for EDA and model diagnostics.
• ■ Detailed exploratory data analysis (EDA) — head/tail/sample, dtype and memory checks, unique-value summaries, cardinality analysis.
• ■ Preprocessing techniques — Label Encoding (target), One-Hot Encoding (predictors), StandardScaler for scaling before PCA and modeling.
• ■ Advanced cleaning — mode imputation for missing entries, flagging/removal of low-information features.
• ■ Dimensionality reduction — PCA used for 2D visualization and to determine component counts for variance retention; t-SNE may be applied as an optional visualization.
• ■ Variable selection — constant/near-constant features removed; low-information features flagged.
• ■ Recognize unsupervised case — KMeans clustering applied and evaluated as an unsupervised approach.
• ■ Apply clustering models — elbow method and KMeans training implemented and visualized.
• ■ Identify regression/classification — target `p` encoded and classification pipeline used where appropriate.
• ■ Train/test split — stratified split used to create training and testing sets.
• ■ Use of ensemble models — RandomForest implemented; pipeline supports GradientBoosting/AdaBoost and other ensembles.

Competency: Apply machine learning algorithms according to the problem