

# Classification

November 13, 2024

```
[1]: try:
      # Cell 1: Import necessary libraries
      import os
      import glob
      import pandas as pd

      import matplotlib.pyplot as plt
      import seaborn as sns

      from sklearn.cluster import KMeans
      from kneed import KneeLocator
      from sklearn.metrics import silhouette_score

  except Exception as e:
      print(f"Error : {e}")
```

```
[2]: # Cell 2: Load the dataset
      # Find the CSV file in the Datasets directory
      data_path = '../Datasets/*.csv'
      file_list = glob.glob(data_path)

      for file in file_list:
          print(f"Found file: {file}")

      # Ensure there is exactly one file
      if len(file_list) == 1:
          # Load the dataset
          df = pd.read_csv(file_list[0])
          print(f"Loaded dataset: {file_list[0]}")
      else:
          raise FileNotFoundError("No CSV file found or multiple CSV files found in_
↪the Datasets directory.")
```

```
Found file: ../Datasets/Dataset.csv
Loaded dataset: ../Datasets/Dataset.csv
```

```
[3]: # Cell 3: Set the model saving path
destination = '../Models/'
os.makedirs(destination, exist_ok=True)
print(f"Model will be saved to: {destination}")
```

Model will be saved to: ../Models/

```
[4]: # Cell 4: Assign 'Unacceptable' to parts below threshold
clf_df = df.copy()
threshold_value = 1500

# Create 'Lifetime' column and set default to None
clf_df['Lifetime'] = None

# Assign 'Unacceptable' to rows where 'Lifespan' < threshold_value
clf_df.loc[clf_df['Lifespan'] < threshold_value, 'Lifetime'] = 'Unacceptable'

clf_df.head(10)
```

```
[4]:
```

	Lifespan	partType	microstructure	coolingRate	quenchTime	forgingTime	\
0	1469.17	Nozzle	equiGrain	13	3.84	6.47	
1	1793.64	Block	singleGrain	19	2.62	3.48	
2	700.60	Blade	equiGrain	28	0.76	1.34	
3	1082.10	Nozzle	colGrain	9	2.01	2.19	
4	1838.83	Blade	colGrain	16	4.13	3.87	
5	660.62	Valve	colGrain	28	4.45	3.82	
6	1835.46	Block	equiGrain	19	2.76	4.27	
7	1522.80	Block	equiGrain	16	1.48	9.61	
8	1347.72	Blade	equiGrain	21	1.41	4.17	
9	985.79	Valve	colGrain	10	3.75	6.82	

	HeatTreatTime	Nickel%	Iron%	Cobalt%	Chromium%	smallDefects	\
0	46.87	65.73	16.52	16.82	0.93	10	
1	44.70	54.22	35.38	6.14	4.26	19	
2	9.54	51.83	35.95	8.81	3.41	35	
3	20.29	57.03	23.33	16.86	2.78	0	
4	16.13	59.62	27.37	11.45	1.56	10	
5	18.11	50.30	33.30	12.45	3.95	21	
6	56.75	63.85	17.64	16.79	1.72	18	
7	51.37	52.75	37.10	9.05	1.10	21	
8	53.76	58.88	20.39	16.03	4.70	24	
9	23.47	66.75	14.48	18.14	0.63	0	

	largeDefects	sliverDefects	seedLocation	castType	Lifetime
0	0	0	Bottom	Die	Unacceptable
1	0	0	Bottom	Investment	None
2	3	0	Bottom	Investment	Unacceptable
3	1	0	Top	Continuous	Unacceptable

4	0	0	Top	Die	None
5	4	0	Top	Investment	Unacceptable
6	0	0	Bottom	Die	None
7	0	0	Bottom	Continuous	None
8	1	0	Bottom	Continuous	Unacceptable
9	0	0	Bottom	Die	Unacceptable

```
[5]: min_lifespan = clf_df['Lifespan'].min()
max_lifespan = clf_df['Lifespan'].max()

print(f"Minimum Lifespan: {min_lifespan}")
print(f"Maximum Lifespan: {max_lifespan}")
```

Minimum Lifespan: 417.99  
Maximum Lifespan: 2134.53

```
[6]: # Cell 5: Prepare data for clustering
# Data to be clustered (Lifespan >= threshold_value)
acceptable_df = clf_df[clf_df['Lifespan'] >= threshold_value].copy()
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[7]: # Cell 6: Select 'Lifespan' feature for clustering
X_acceptable = acceptable_df[['Lifespan']]
```

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[8]: # Cell 7: Perform K-Means clustering
# Ensure there is enough data to cluster
if len(acceptable_df) > 1:
    # Initialize a list to store inertia values
    max_k = min(10, len(acceptable_df))
    k_values = range(1, max_k)

    inertia = []

    # Calculate inertia for each k
    for k in k_values:
        kmeans = KMeans(n_clusters=k, random_state=42)
        kmeans.fit(X_acceptable)
        inertia.append(kmeans.inertia_)

    # Dynamically determine the elbow point using KneeLocator
    kneedle = KneeLocator(k_values, inertia, curve='convex',
        direction='decreasing')
    elbow_k = kneedle.elbow

    # If elbow_k is None, default to 3
    if elbow_k is None:
        elbow_k = 3

    # Ensure elbow_k is not greater than max_k
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elbow_k = min(elbow_k, max_k - 1)

# Perform KMeans clustering with elbow_k clusters
kmeans = KMeans(n_clusters=elbow_k, random_state=42)
acceptable_df['cluster'] = kmeans.fit_predict(X_acceptable)

# Compute mean 'Lifespan' per cluster
cluster_means = acceptable_df.groupby('cluster')['Lifespan'].mean()

# Sort clusters by mean lifespan
cluster_order = cluster_means.sort_values().index.tolist()

# Define desired labels
desired_labels = ['Fair', 'Good', 'Excellent']

labels = []
for i in range(elbow_k):
    if i < len(desired_labels):
        labels.append(desired_labels[i])
    else:
        # For additional clusters, create labels based on lifespan ranges
        cluster_idx = cluster_order[i]
        min_life = acceptable_df[acceptable_df['cluster'] ==
↳cluster_idx]['Lifespan'].min()
        max_life = acceptable_df[acceptable_df['cluster'] ==
↳cluster_idx]['Lifespan'].max()
        labels.append(f'{min_life:.2f}--{max_life:.2f}')

# Create mapping from cluster index to label
cluster_to_label = dict(zip(cluster_order, labels))

# Map labels to 'Lifetime' column
acceptable_df['Lifetime'] = acceptable_df['cluster'].map(cluster_to_label)

# Update 'Lifetime' column in clf_df
clf_df.loc[acceptable_df.index, 'Lifetime'] = acceptable_df['Lifetime']

# Drop 'cluster' column if not needed
acceptable_df.drop(columns=['cluster'], inplace=True)
else:
    print("Not enough data to perform clustering on acceptable parts.")

```

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[9]: # Plotting the Elbow Method with all indicators
plt.figure(figsize=(10, 6))
# Plot line segments with different colors
plt.plot(k_values[:elbow_k], inertia[:elbow_k], 'bo-', label="Decreasing Phase")

```

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plt.plot(k_values[elbow_k - 1:], inertia[elbow_k - 1:], 'go-', label="Slow
↳Decrease Phase")

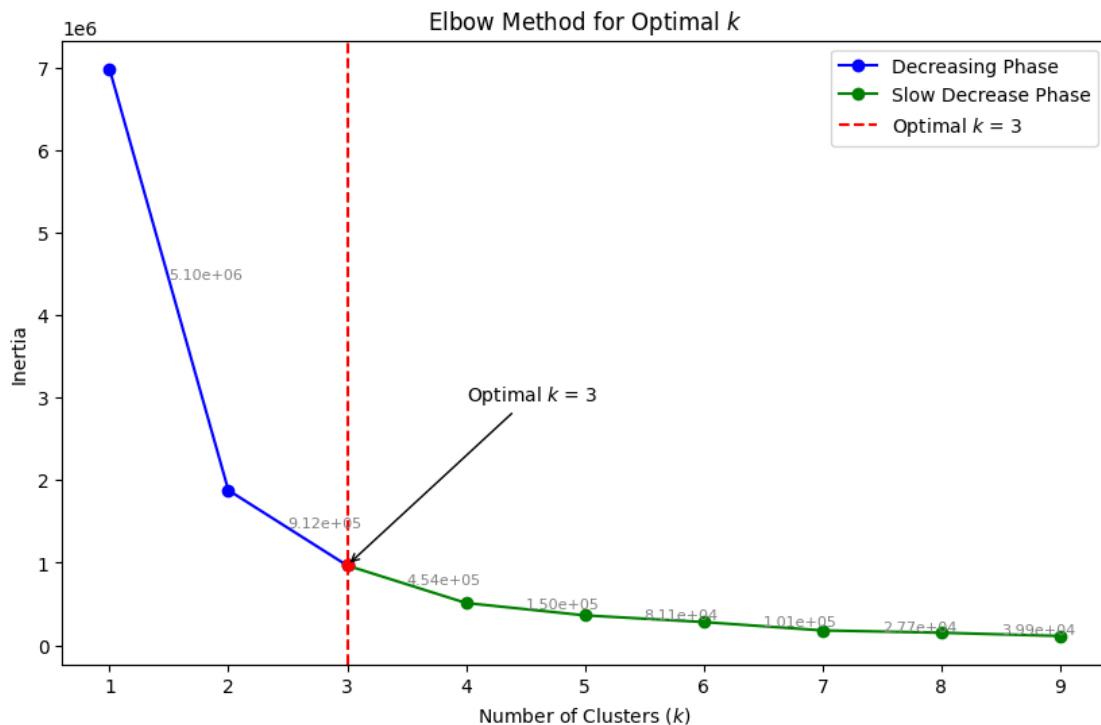
# Vertical line at elbow
plt.axvline(x=elbow_k, linestyle='--', color='r', label=f'Optimal $k$ =
↳{elbow_k}')

# Highlight the elbow point with a red marker and annotation
plt.plot(elbow_k, inertia[elbow_k - 1], 'ro') # red point at elbow
plt.annotate(f"Optimal $k$ = {elbow_k}", xy=(elbow_k, inertia[elbow_k - 1]),
            xytext=(elbow_k + 1, inertia[elbow_k - 1] + 0.2e7),
            arrowprops=dict(facecolor='black', arrowstyle="→"))

# Annotate each segment with inertia differences
for i in range(1, len(k_values)):
    plt.annotate(f"{inertia[i-1] - inertia[i]:.2e}",
                (k_values[i] - 0.5, (inertia[i-1] + inertia[i]) / 2),
                fontsize=8, color='gray')

# Set plot labels and title
plt.xlabel(f'Number of Clusters ($k$)')
plt.ylabel('Inertia')
plt.title(f'Elbow Method for Optimal $k$')
plt.legend()
plt.show()

```

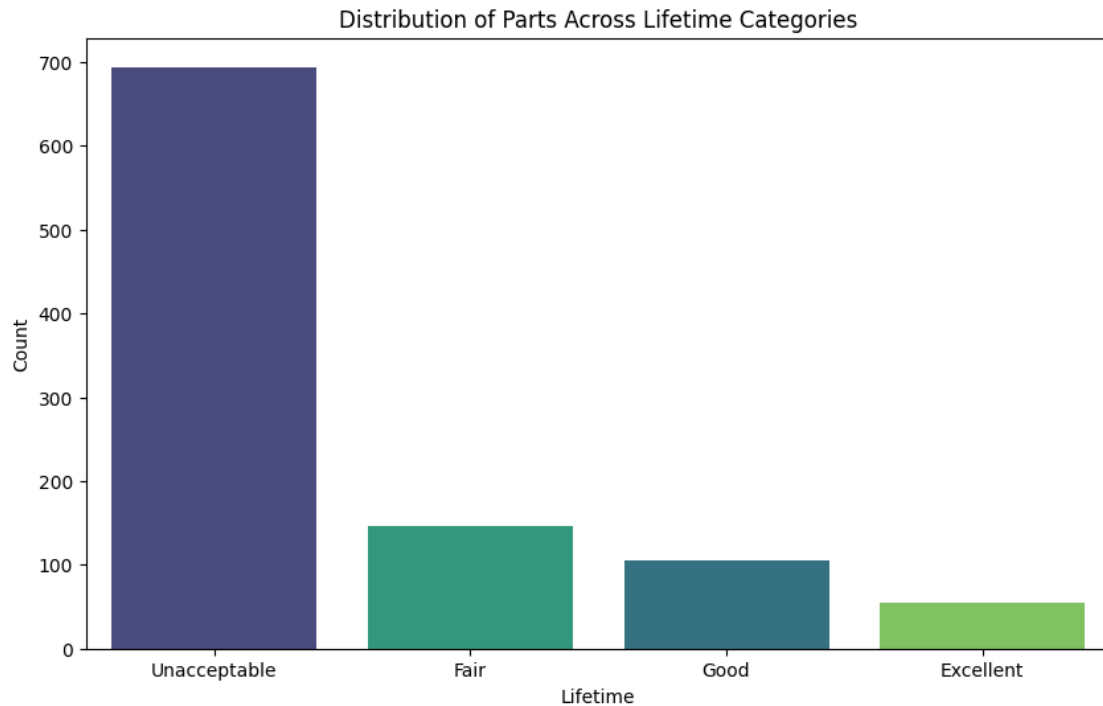


```
[10]: # Cell 8: Display the cluster ranges
# Group the data by 'Lifetime' and aggregate to find the min and max Lifespan
↳for each group
cluster_ranges = clf_df.groupby('Lifetime')['Lifespan'].agg(['min', 'max']).
↳sort_values(by='min').reset_index()

# Display the sorted DataFrame
display(cluster_ranges)
```

	Lifetime	min	max
0	Unacceptable	417.99	1499.31
1	Fair	1501.76	1661.54
2	Good	1666.64	1850.75
3	Excellent	1854.50	2134.53

```
[11]: # Cell 9: Visualize the distribution of parts across Lifetime categories
plt.figure(figsize=(10, 6))
sns.countplot(
    x='Lifetime',
    data=clf_df,
    hue='Lifetime',
    order=cluster_ranges['Lifetime'].unique(),
    palette='viridis',
    dodge=False,
    legend=False
)
plt.xlabel('Lifetime')
plt.ylabel('Count')
plt.title('Distribution of Parts Across Lifetime Categories')
plt.show()
```



```
[12]: # Cell 10: Calculate the silhouette score
if len(acceptable_df['Lifetime'].unique()) > 1:
    # Map Lifetime labels back to cluster numbers for silhouette score
    label_to_cluster = {v: k for k, v in cluster_to_label.items()}
    acceptable_clusters = acceptable_df['Lifetime'].map(label_to_cluster)
    silhouette_avg = silhouette_score(X_acceptable, acceptable_clusters)
    print(f'Silhouette Score for k={elbow_k}: {silhouette_avg:.2f}')
else:
    print("Cannot compute silhouette score with only one cluster.")
```

Silhouette Score for k=3: 0.58

```
[13]: clf_df.head(10)
```

```
[13]:   Lifespan partType microstructure coolingRate quenchTime forgeTime \
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2     700.60    Blade    equiGrain        28         0.76         1.34
3    1082.10   Nozzle    colGrain         9         2.01         2.19
4    1838.83    Blade    colGrain        16         4.13         3.87
5     660.62    Valve    colGrain        28         4.45         3.82
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3	1	0	Top	Continuous	Unacceptable
4	0	0	Top	Die	Good
5	4	0	Top	Investment	Unacceptable
6	0	0	Bottom	Die	Good
7	0	0	Bottom	Continuous	Fair
8	1	0	Bottom	Continuous	Unacceptable
9	0	0	Bottom	Die	Unacceptable