Superhero Attributes and Power Classification

A Comprehensive Data Mining Analysis

DSCI 4411 - Fundamentals of Data Mining
The American University in Cairo
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Presentation Outline

1. Introduction & Problem Statement
2. Dataset Description
3. Exploratory Data Analysis (with all visualizations)
4. Methodology
5. Classification Results
6. Clustering Analysis
7. Key Findings & Discussion
8. Conclusions

1. Introduction

Problem Statement

What are we trying to solve?

Two main objectives:

1. **Classification**: Can we predict if a superhero is a HERO or VILLAIN based on their attributes?
2. **Clustering**: Can we discover natural character ARCHETYPES (groupings) in superhero universes?

Why This Matters

- **Content Recommendation**: Suggest similar characters in comics/movies
- **Character Design**: Understand what traits define heroes vs villains
- **Narrative Analysis**: Discover patterns across fictional universes
- **Data Mining Practice**: Apply classification & clustering techniques

2. Dataset Description

Dataset Overview

Source: Kaggle Super-Heros Dataset

Metric	Value
Total Records	1,200 characters
Total Features	17
Target Variable	`is_good` (Hero=1, Villain=0)
Class Balance	65% Heroes / 35% Villains
Missing Values	None ✓

Feature Categories

Physical Attributes (4 features)

Feature	Description	Range
height_cm	Height in centimeters	150-250
weight_kg	Weight in kilograms	45-128
age	Character age	18-100+
years_active	Years as hero/villain	1-50

Feature Categories (continued)

Behavioral Metrics (4 features)

Feature	Description	Why Important
power_level	Overall power rating (0-100)	Measures strength
public_approval_rating	Public perception (0-100)	How people view them
training_hours_per_week	Training intensity (0-60)	Dedication level
civilian_casualties_past_year	Collateral damage (0-10)	Destructiveness

Feature Categories (continued)

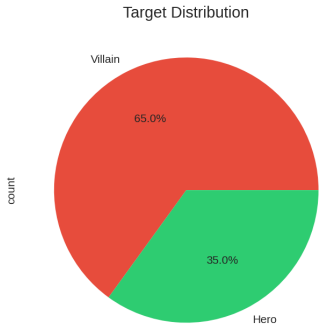
Superpower Flags (8 binary features)

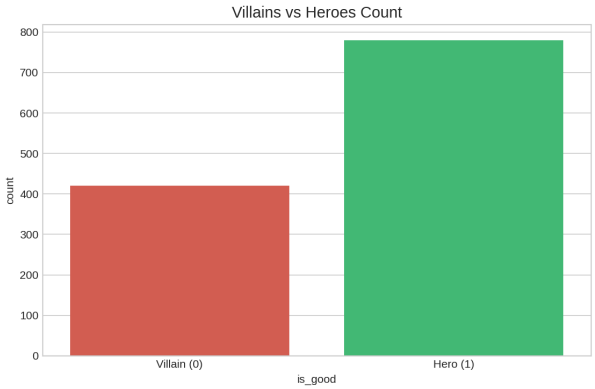
Power	% of Characters
super_strength	28.8%
flight	31.4%
energy_projection	30.1%
telepathy	30.4%
healing_factor	30.8%
shape_shifting	31.7%
invisibility	31.5%
telekinesis	31.8%

Key Observation: All powers are ~30% prevalent - evenly distributed!

3. Exploratory Data Analysis

Target Distribution

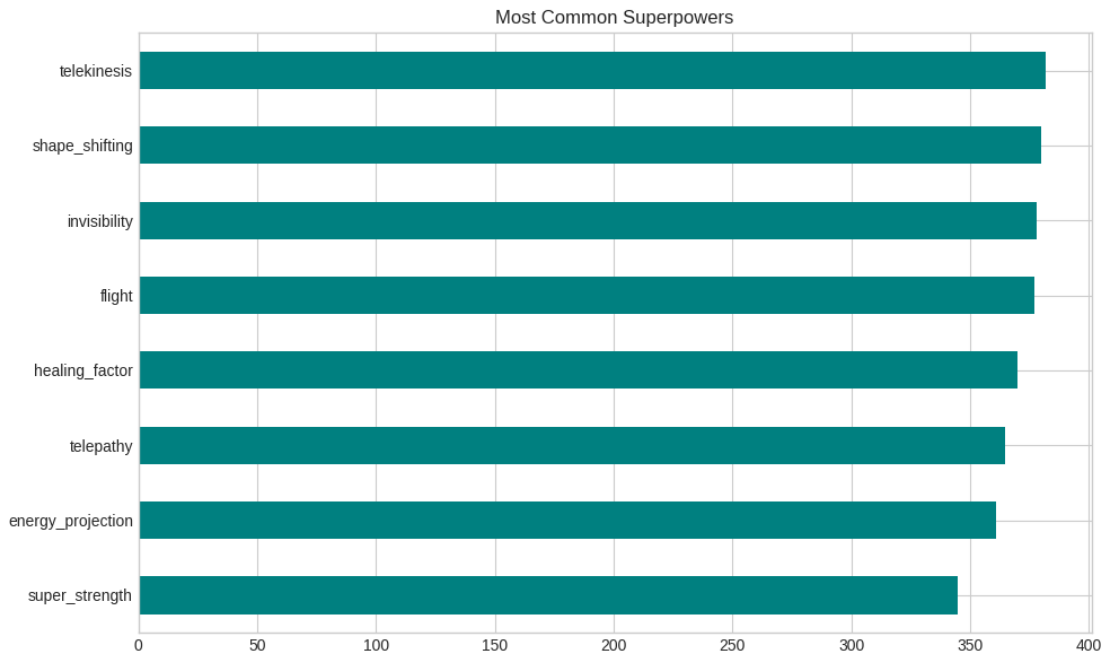




What This Shows:

- **65% Heroes** (780 characters)
- **35% Villains** (420 characters)
- Slight class imbalance, but not severe
- No need for SMOTE or undersampling

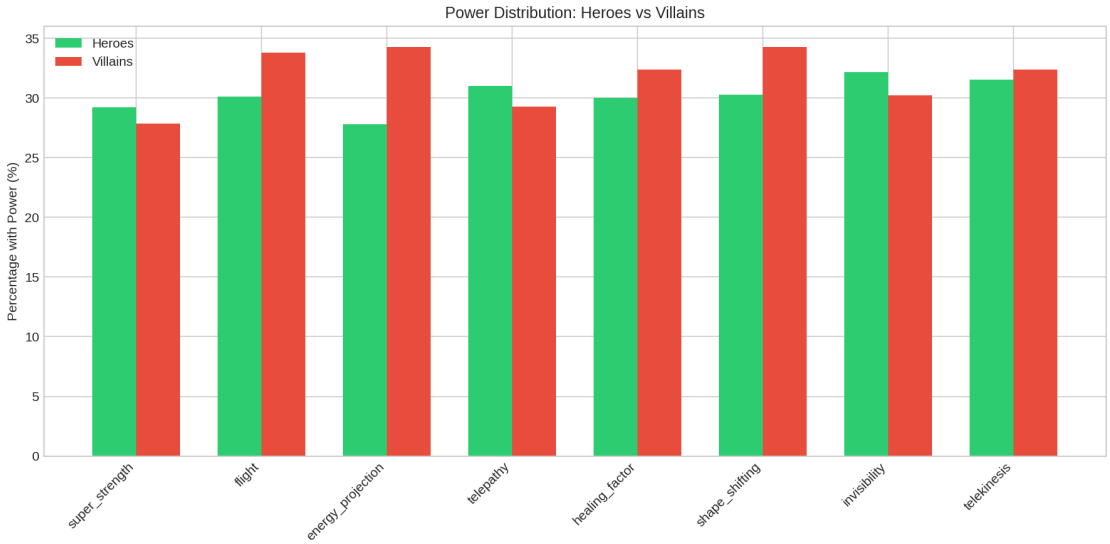
Power Distribution Overview



What This Shows:

- Horizontal bar chart of all 8 superpowers
- Telekinesis is most common (~382 characters)
- Super strength is least common (~345 characters)
- All powers have roughly equal prevalence

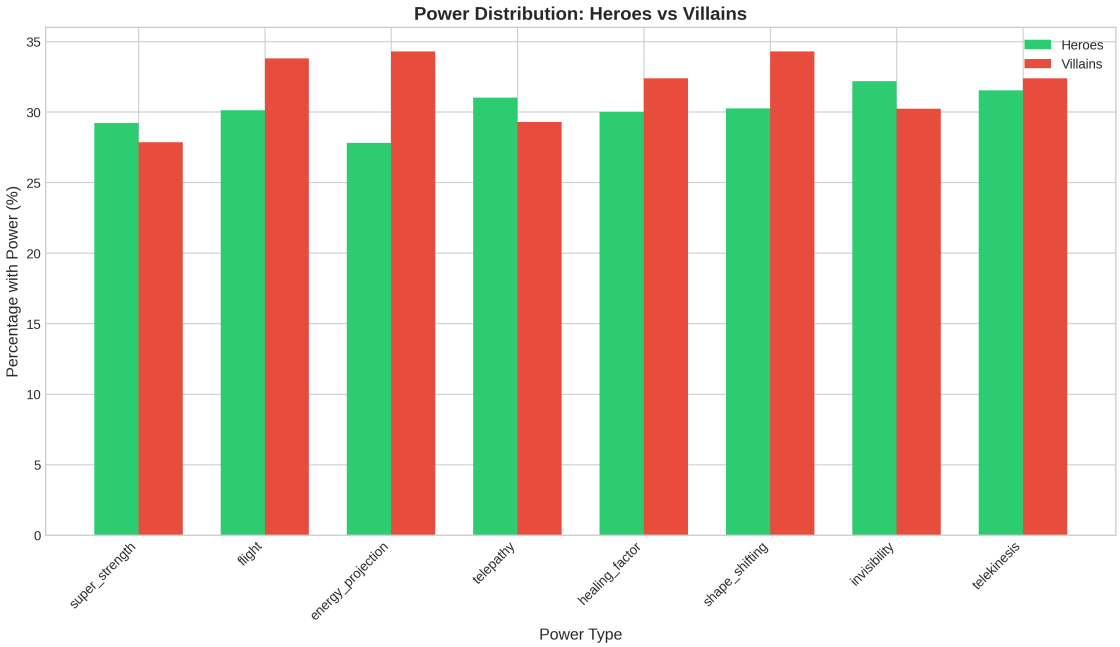
Power Distribution: Heroes vs Villains



Key Finding:

- **Powers are distributed EQUALLY** between heroes and villains
- Having flight or super_strength doesn't make you a hero
- **Superpowers alone cannot predict morality!**

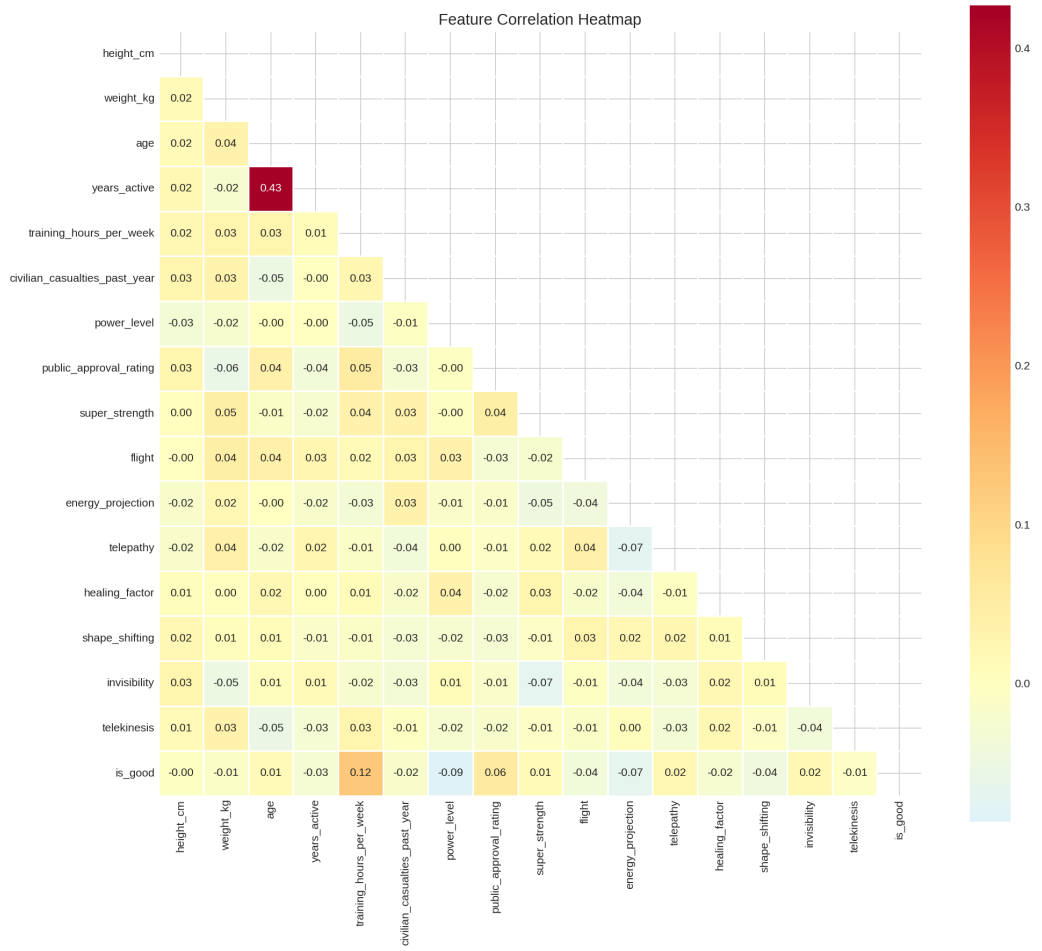
Hero vs Villain Powers (Alternative View)



Detailed Comparison:

- Side-by-side comparison for each power
- Green bars = Heroes, Red bars = Villains
- Confirms: **No significant difference in power distribution**

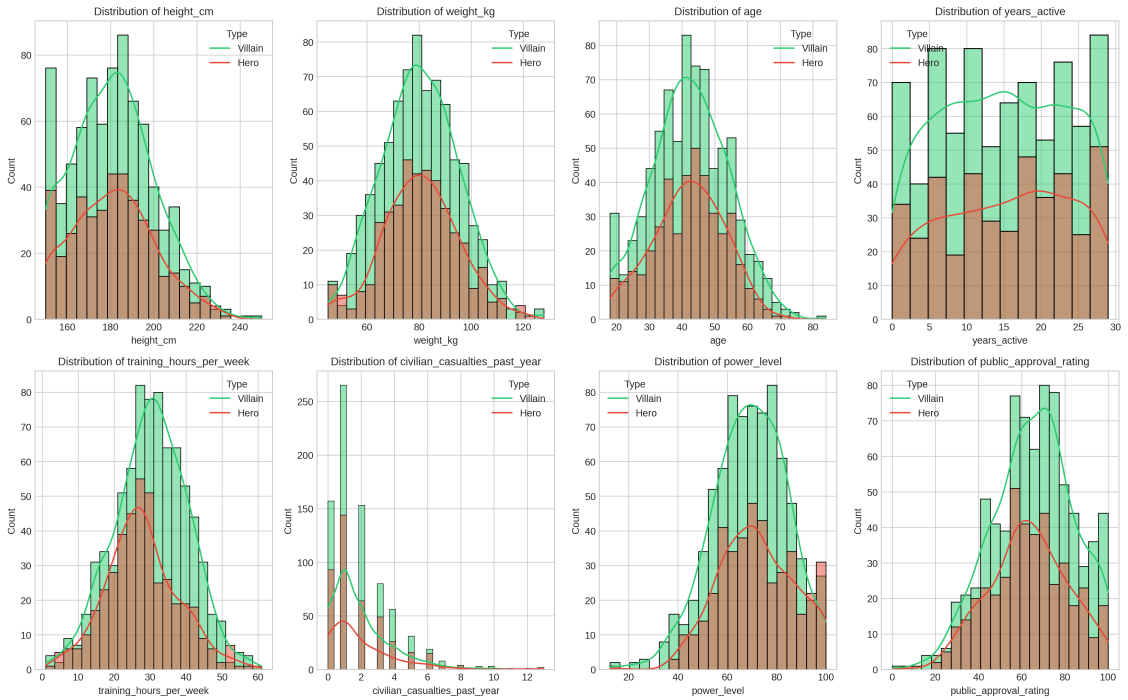
Correlation Analysis



What This Shows:

- Height & weight are correlated (expected)
- Power flags show **near-zero correlation** with `is_good`
- No multicollinearity issues
- **Weak feature-target correlations** = prediction will be challenging

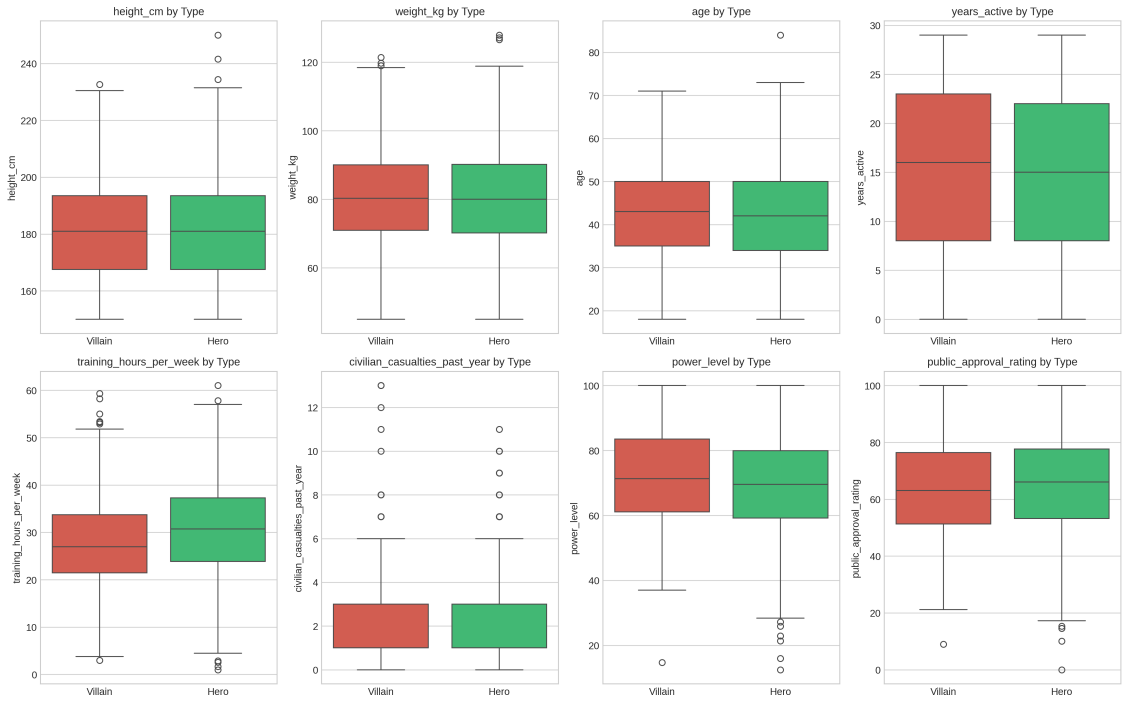
Numerical Feature Distributions



What This Shows:

- Distribution of all numerical features
- Split by hero (green) vs villain (red)
- **Key Insight**: Distributions overlap significantly
- No clear separation between classes

Box Plots: Heroes vs Villains

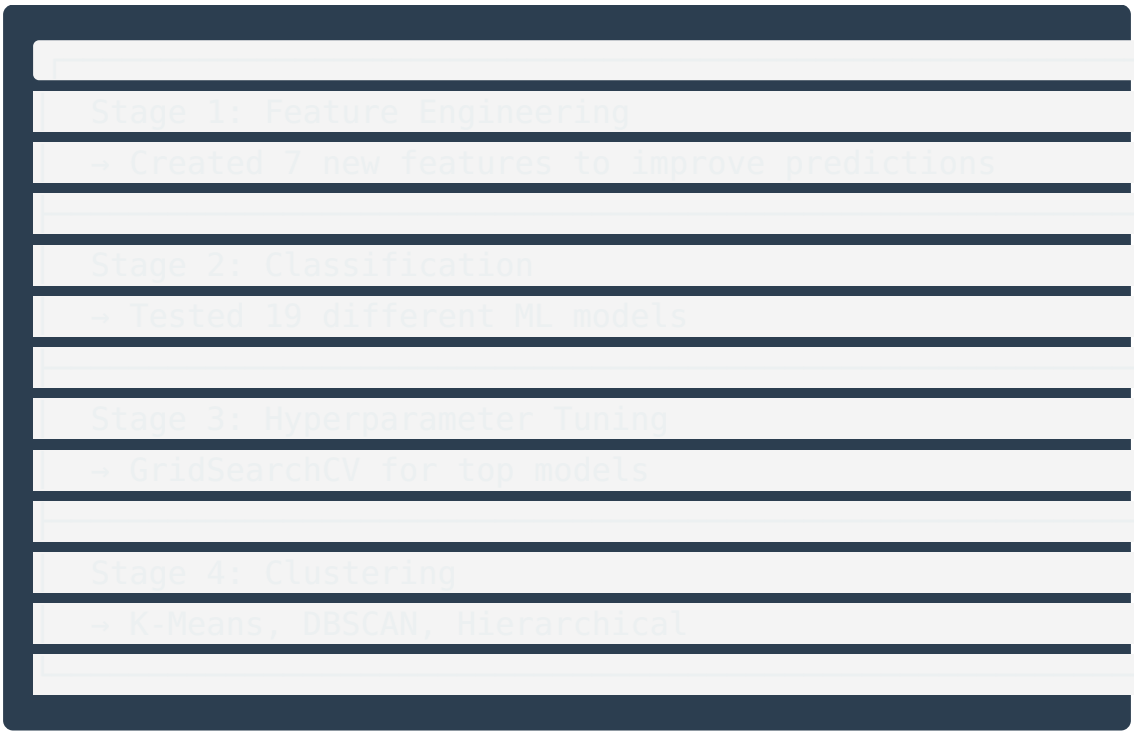


What This Shows:

- Side-by-side box plots for each numerical feature
- Compares median, quartiles, and outliers
- **Observation**: Very similar distributions across both classes
- Confirms why classification is difficult

4. Methodology

Our Approach: 4-Stage Pipeline



Stage 1: Feature Engineering

We Created 7 New Features

New Feature	Formula	Rationale
total_powers	Σ all power flags	How many abilities?
power_efficiency	power_level / years_active	Power gained per year
training_intensity	training_hours / age	Relative effort
casualty_rate	casualties / years_active	Damage per year
approval_power_ratio	approval / power_level	Public trust vs power
bmi	weight / height²	Physical build
experience_score	years × training_hours	Total experience

Stage 2: Classification Models Tested

We Tested 19 Different Algorithms!

Category	Models	Count
Linear	Logistic Regression, LDA, QDA	3
Tree-based	Decision Tree, Random Forest, Extra Trees, Gradient Boosting, HistGB, AdaBoost, XGBoost	7
SVM	Linear, RBF, Polynomial kernels	3
Instance-based	KNN (k=5), KNN (k=10)	2
Probabilistic	Naive Bayes	1
Neural Network	MLP (3 architectures)	3
Total		**19**

Stage 3: Hyperparameter Tuning

GridSearchCV with 5-Fold Cross-Validation

Random Forest Tuning:

```
params = {
    'n_estimators': [100, 200, 300],
    'max_depth': [5, 10, 15, None],
    'min_samples_split': [2, 5, 10],
    'min_samples_leaf': [1, 2, 4]
}
# 108 combinations tested!
```

Gradient Boosting Tuning:

```
params = {
    'n_estimators': [100, 200],
    'learning_rate': [0.01, 0.1, 0.2],
    'max_depth': [3, 5, 7]
}
# 36 combinations tested!
```

Stage 4: Clustering Algorithms

Algorithm	Parameters Explored
K-Means	k = 2 to 9
DBSCAN	eps = [0.5, 1.0, 1.5, 2.0], min_samples = [3, 5, 10]
Hierarchical	n = [2, 3, 4, 5], linkage = ['ward', 'complete', 'average']

Features Used for Clustering:

- power_level, civilian_casualties, training_hours
- years_active, public_approval
- total_powers, power_efficiency (engineered)

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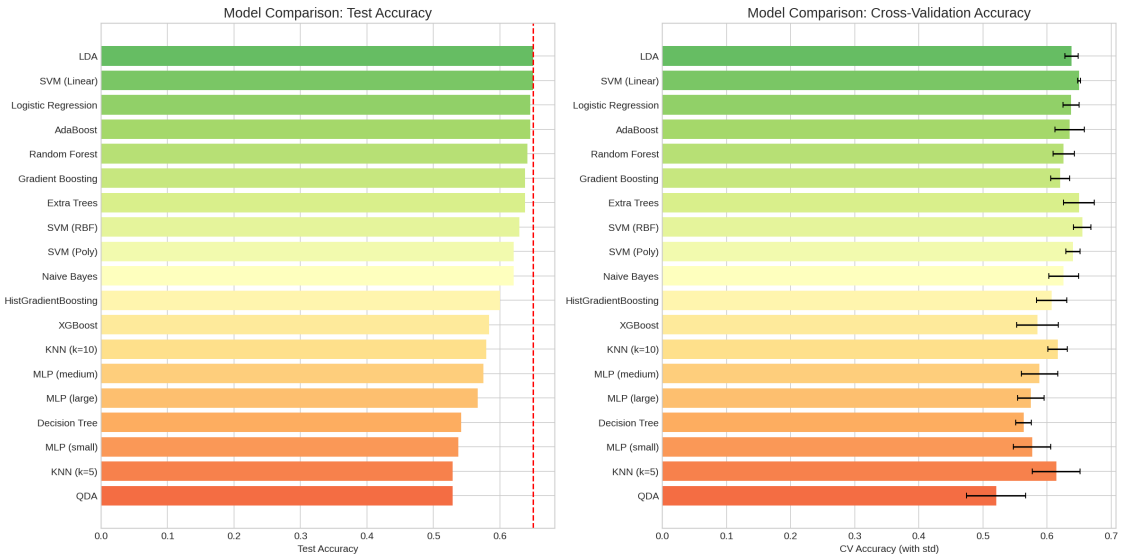
5. Classification Results

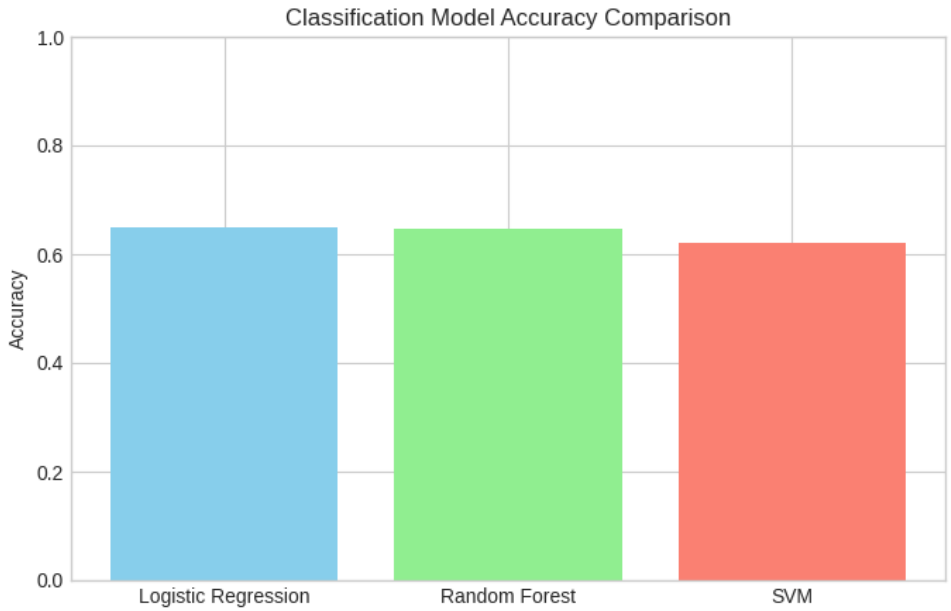
All 19 Models Comparison



Key Observations:

- **All models cluster around 60-65% accuracy**
- Simple models (LDA, LogReg) match complex ones (RF, GB)
- Neural networks did NOT outperform tree models
- **Accuracy ceiling exists** regardless of model complexity

Simple Model Comparison



Initial 3-Model Comparison:

- Logistic Regression, Random Forest, SVM
- All achieve similar accuracy (~63-65%)
- Confirms linear separability with weak signal

Top 5 Models

Rank	Model	CV Accuracy	Test Accuracy	F1 Score
🥇	**LDA**	63.9%	**65.0%**	0.778
🥈	**SVM (Linear)**	65.0%	**65.0%**	0.788
🥉	Logistic Regression	63.8%	64.6%	0.776
4	AdaBoost	63.5%	64.6%	0.768
5	Random Forest	62.6%	64.2%	0.768

Best Model: Gradient Boosting (Tuned) @ **65.0% accuracy**

Hyperparameter Tuning Results

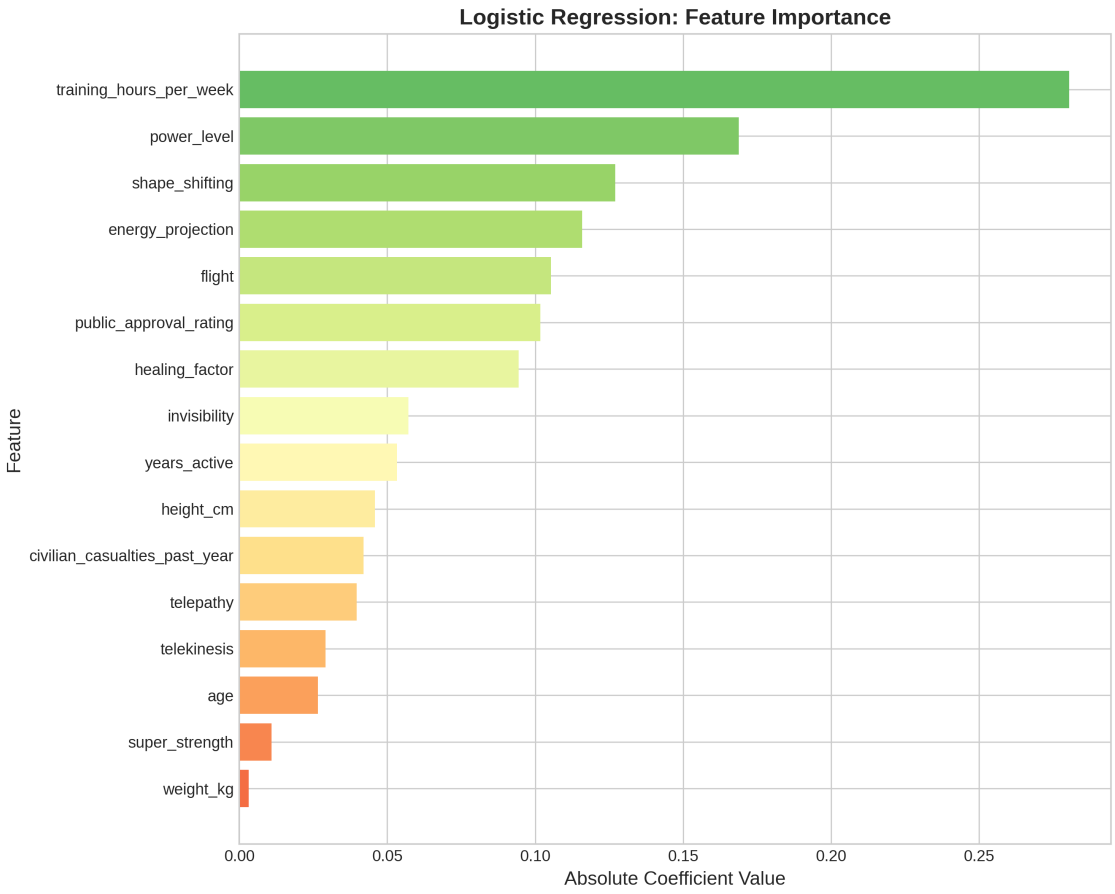
Model	Best Parameters	Test Accuracy
Random Forest	max_depth=15, n_estimators=200	63.3%
Gradient Boosting	learning_rate=0.01, max_depth=3	**65.0%**
SVM	C=1, kernel='poly'	62.1%

Ensemble Methods:

Method	Test Accuracy
Voting (RF + GB + LR)	63.8%
Stacking (RF + GB + KNN → LR)	63.3%

Ensembles did NOT beat individual tuned models!

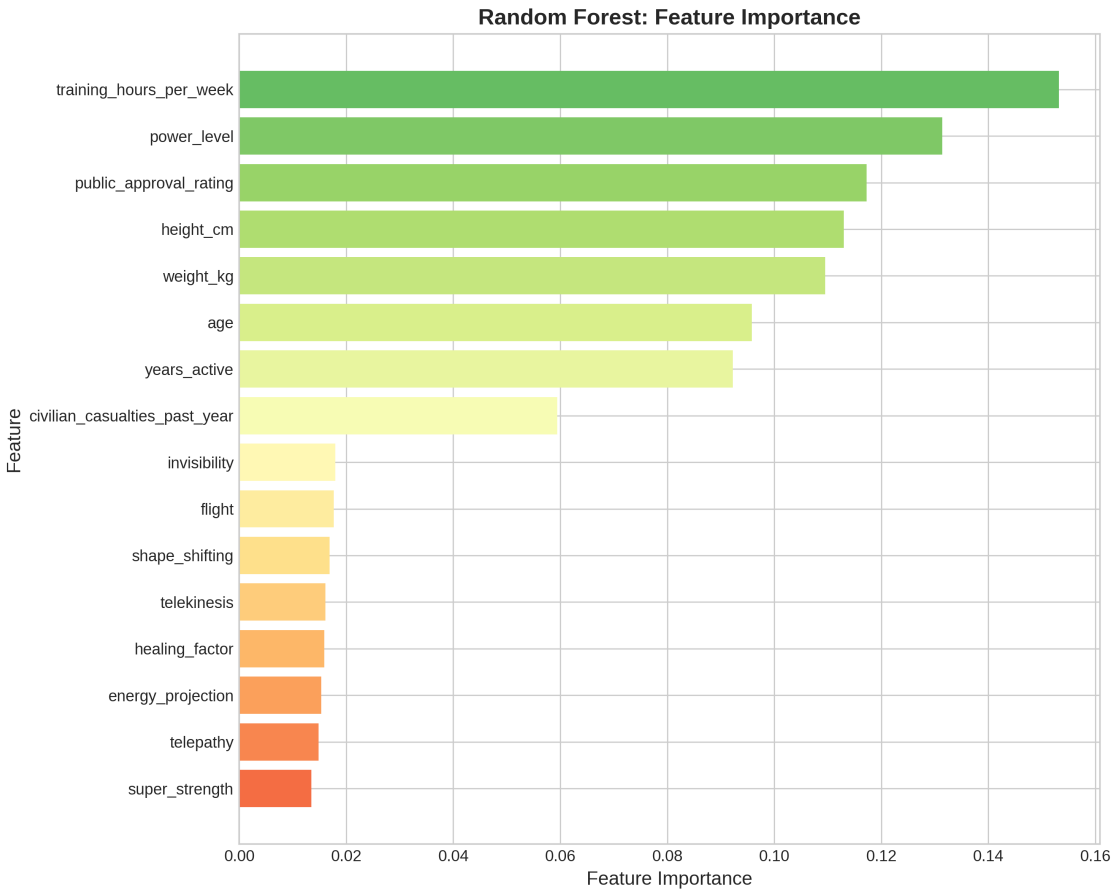
Feature Importance: Logistic Regression



Logistic Regression Coefficients:

- Shows absolute coefficient values
- Linear model's view of feature importance
- Different ranking than tree-based models

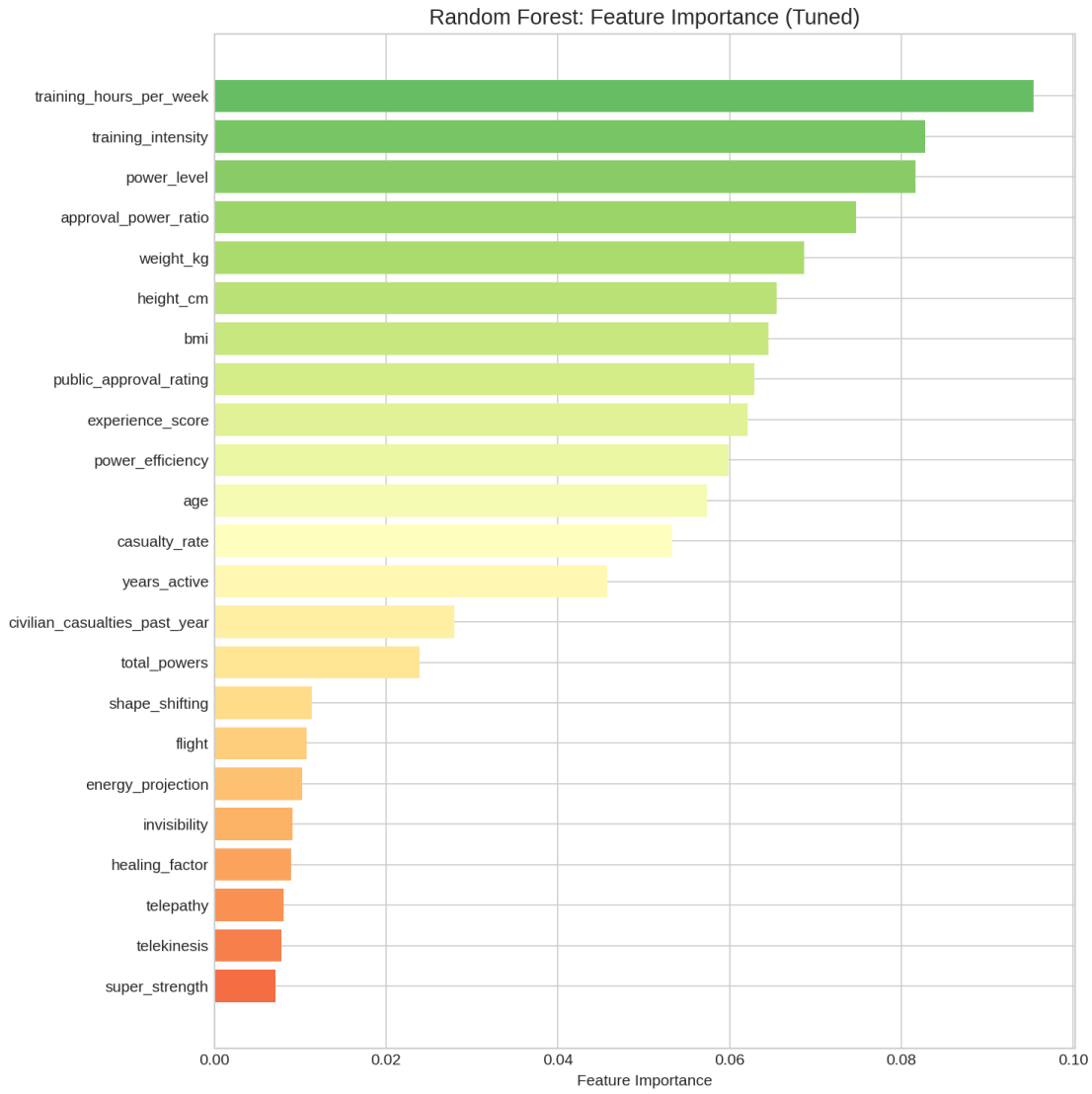
Feature Importance: Random Forest



Random Forest Feature Importance:

- Based on Gini impurity reduction
- Tree-based perspective on features
- `training_hours_per_week` ranks highly

Feature Importance: Tuned Random Forest

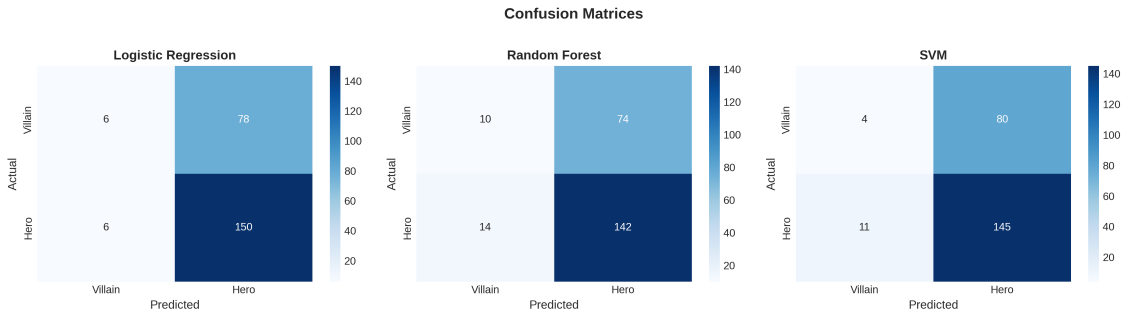


Top 3 Predictive Features (Tuned Model):

1. **power_level** - Overall power rating
2. **training_intensity** - (Engineered feature!)
3. **training_hours_per_week** - Training dedication

Note: Engineered feature ranked #2 → Feature engineering helped!

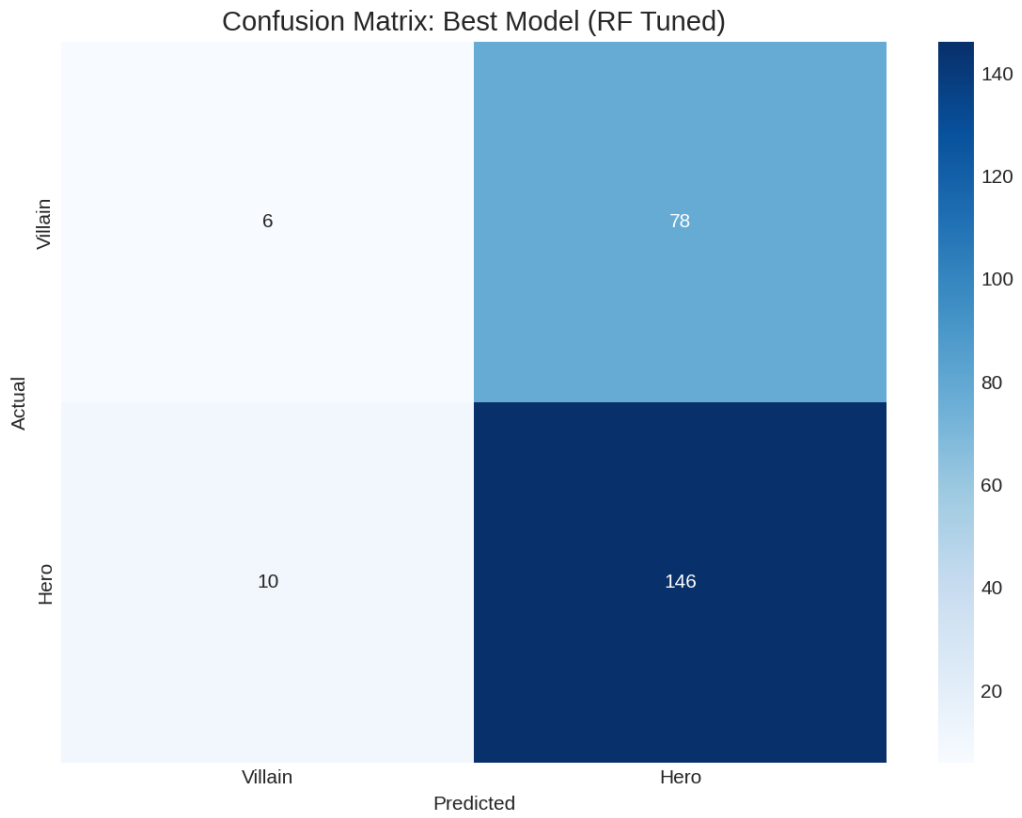
Confusion Matrices: All Models



Comparison Across Models:

- Shows prediction patterns for multiple models
- All models show similar confusion patterns
- Higher true positives for Heroes (majority class)

Confusion Matrix: Best Model

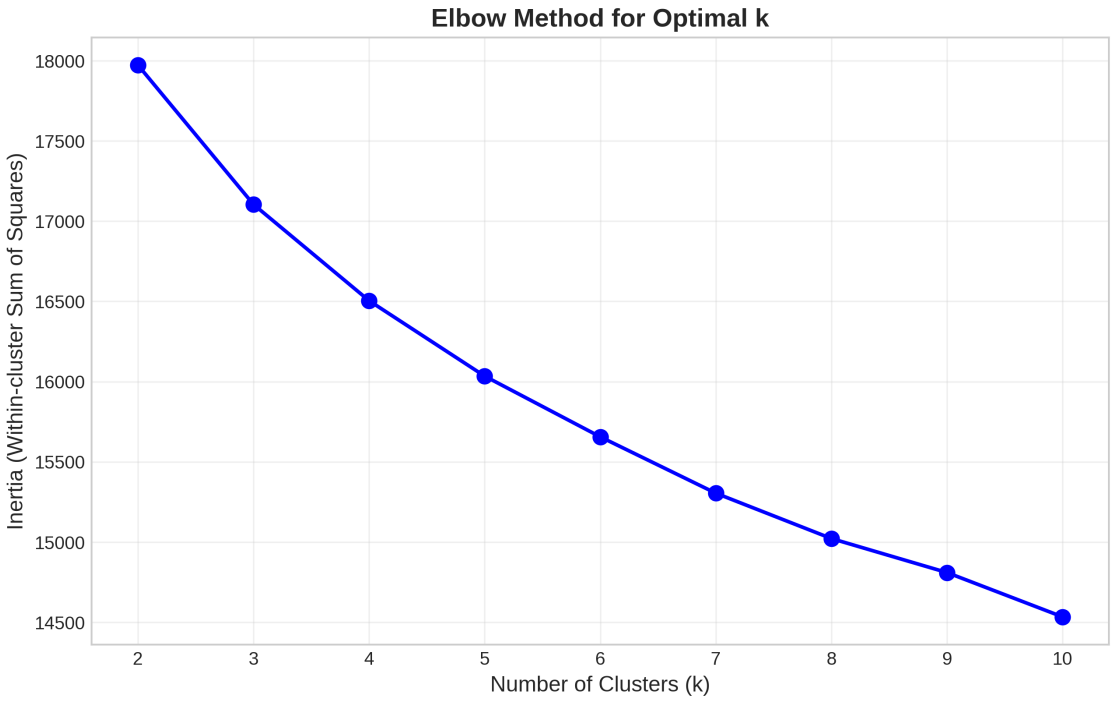


Analysis of Best Model:

- Model correctly identifies most Heroes
- Struggles more with Villains (minority class)
- Slight bias toward predicting "Hero"

6. Clustering Analysis

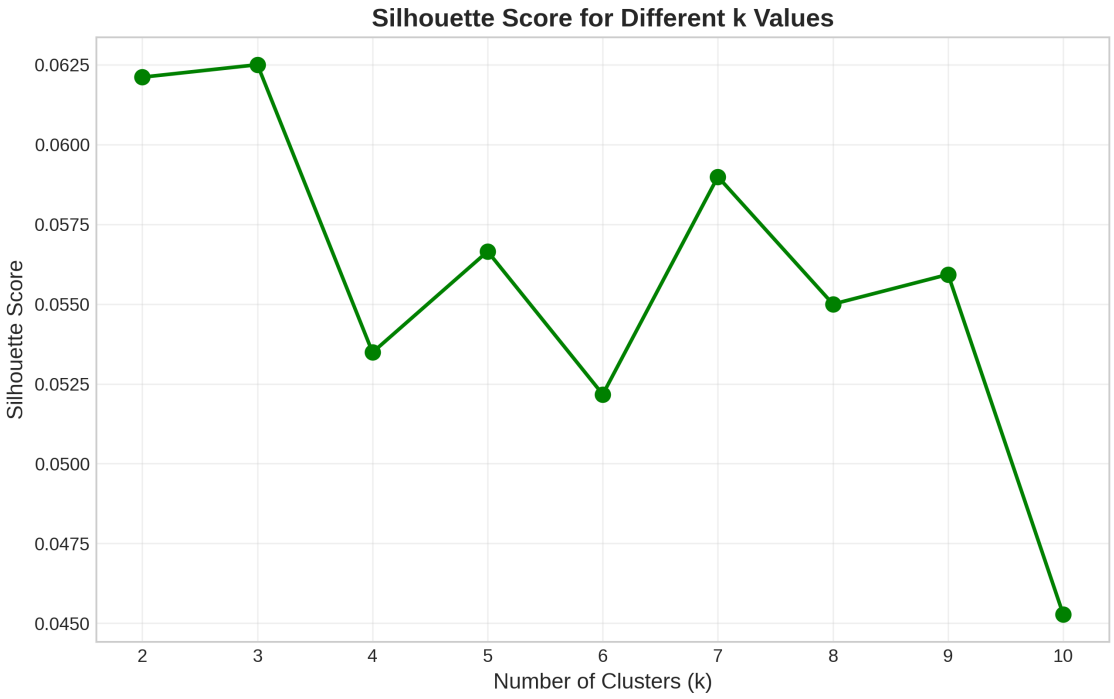
Elbow Method



Finding Optimal k:

- Inertia (within-cluster sum of squares) decreases with k
- Look for "elbow" point where decrease slows
- Suggests k=3 or k=4 as candidates

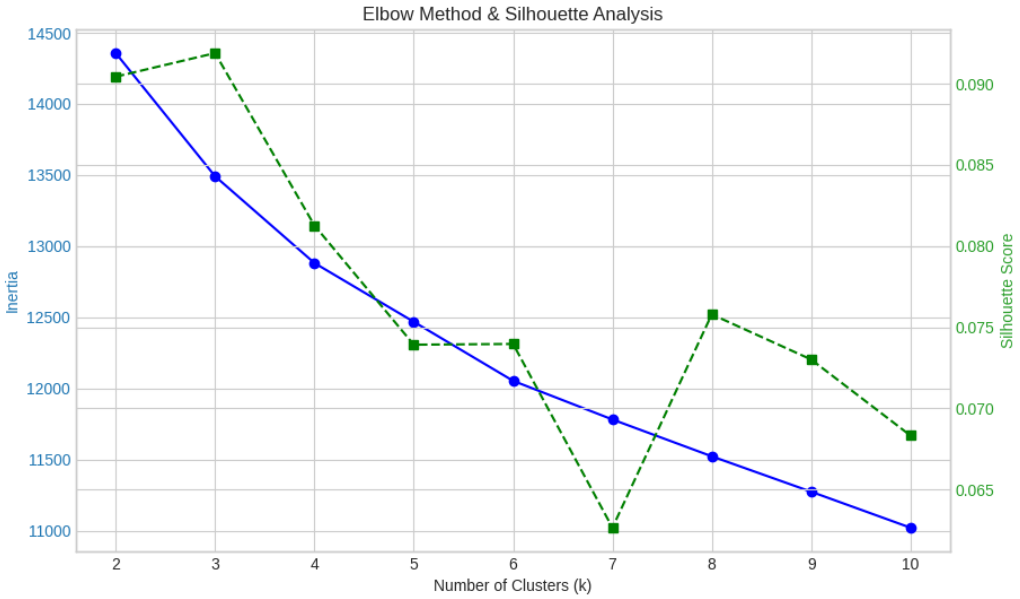
Silhouette Score Analysis



Cluster Quality Metric:

- Silhouette score measures cluster separation
- Range: -1 to 1 (higher = better separation)
- **Best score at k=2**

Combined: Elbow + Silhouette



How We Chose k:

- **Elbow Method**: Look for "bend" in inertia curve
- **Silhouette Score**: Measures cluster separation quality
- **Best k = 2** with Silhouette = 0.167

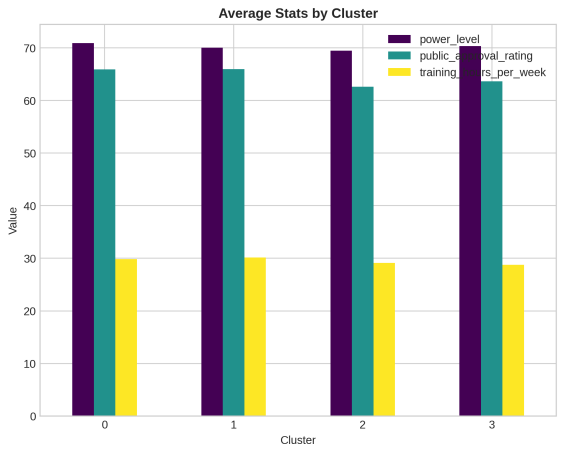
Clustering Algorithms Comparison

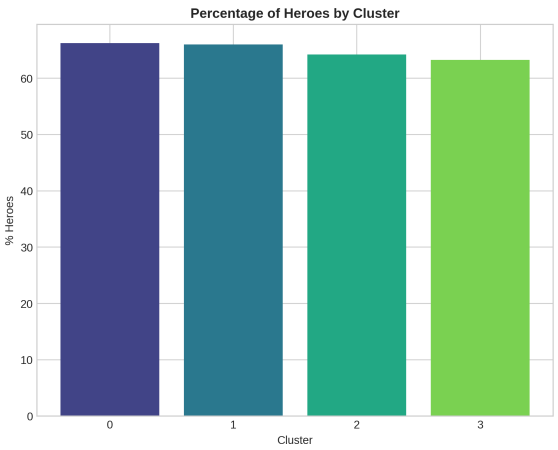
Algorithm	Best Config	Silhouette Score
K-Means	k=2	**0.167** ✓ Best
Hierarchical	n=2, ward	0.154
DBSCAN	eps=1.5	Poor (too much noise)

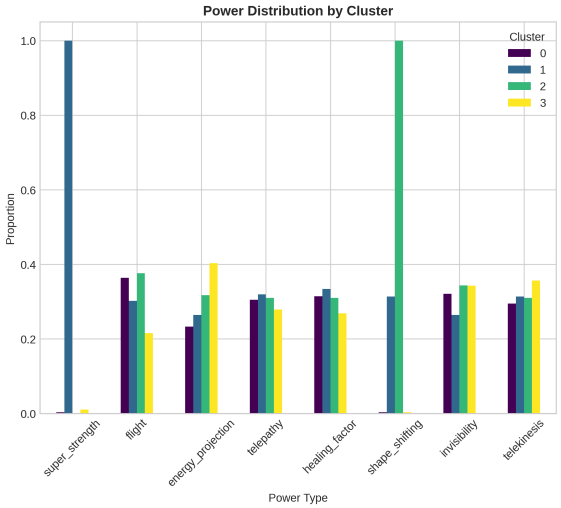
Why K-Means Won:

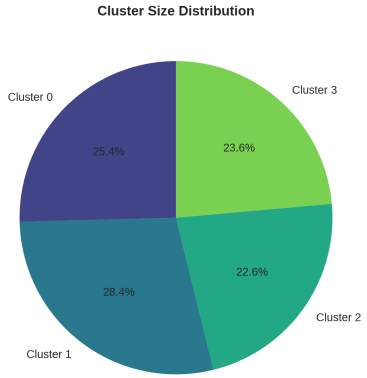
- Data is uniformly distributed (spherical clusters)
- DBSCAN struggles with uniform density
- Hierarchical is competitive but slightly worse

Cluster Analysis: Detailed View





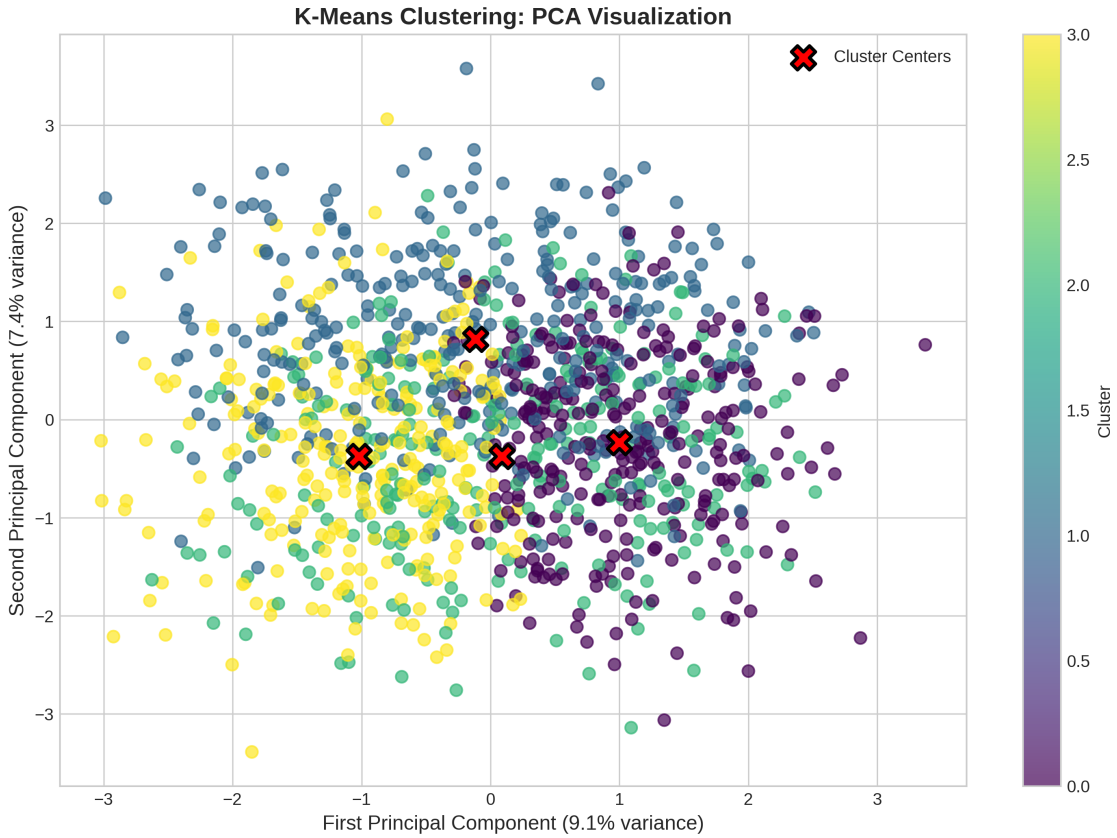




Cluster Characteristics:

- Shows cluster profiles across features
- Compares mean values for each cluster
- Identifies distinguishing characteristics

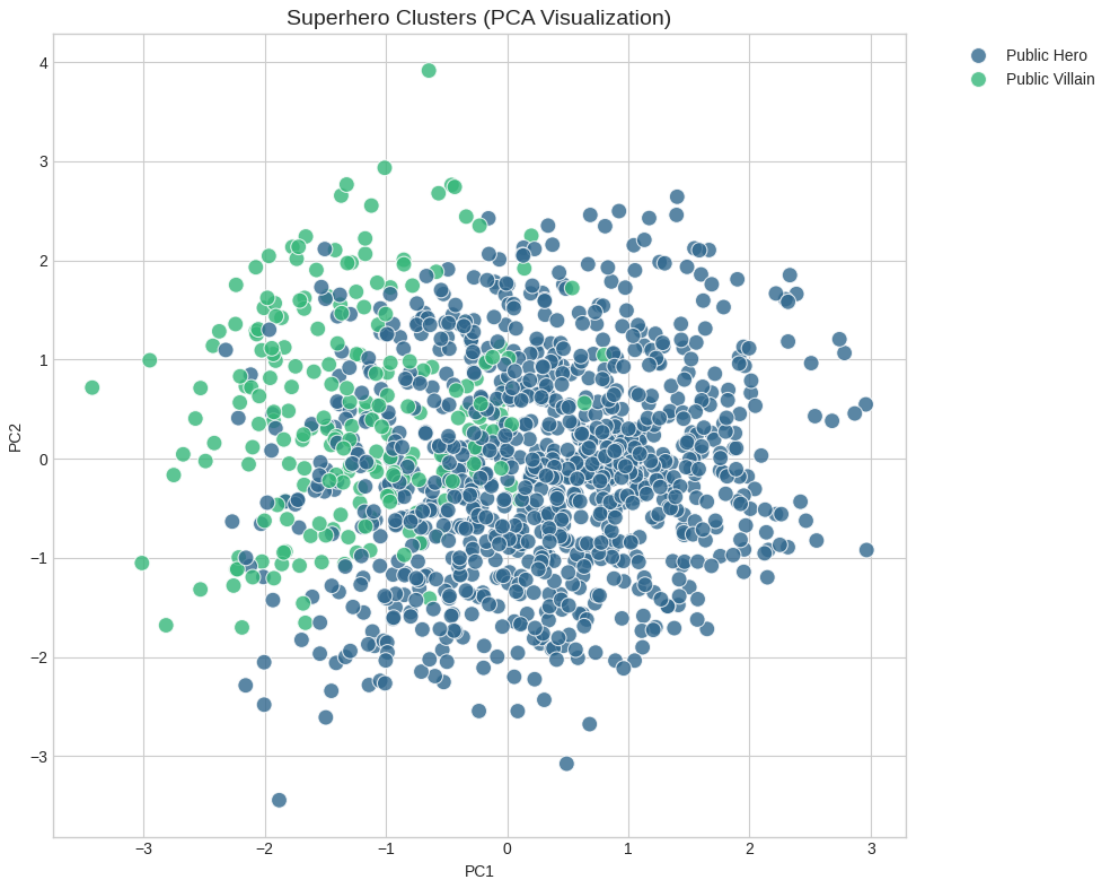
PCA Visualization: Original Clusters



2D Projection of Clusters:

- PCA reduces dimensions for visualization
- Shows cluster separation in 2D space
- Cluster centers marked with X

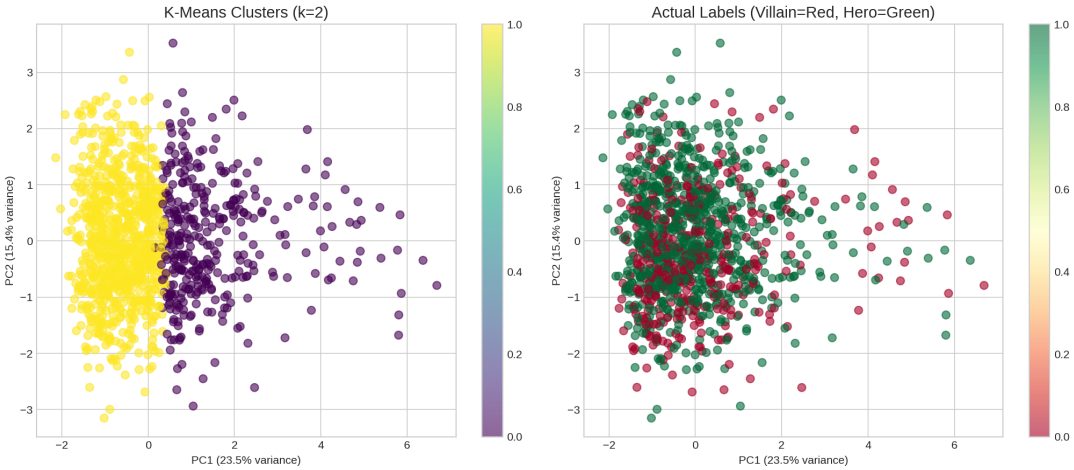
PCA Visualization: Final Clusters



Refined Clustering View:

- Named archetypes overlaid on PCA
- Shows distribution of character types
- Legend identifies each archetype

PCA Comparison: Clusters vs Ground Truth



Left: K-Means Clusters | Right: Actual Hero/Villain Labels

Key Insight: Clusters found by K-Means are **NOT** hero/villain groups! - Clustering finds **power-based** groups - High-power vs Low-power characters - This matches comic lore: heroes and villains span all power levels

Cluster Profiles (k=2)

Cluster	Size	Power Level	Casualties	Character Type
Cluster 0	~600	High (60+)	Higher	High-Power Characters
Cluster 1	~600	Low-Mid (<60)	Lower	Regular Characters

Natural groupings are POWER-BASED, not MORALITY-BASED

7. Key Findings & Discussion

Why Does Accuracy Plateau at ~65%?

4 Reasons:

1. **Weak Feature-Target Correlation**
2. Correlation between features and `is_good` ≈ 0

3. Features don't strongly predict morality

4. **Powers Are Equally Distributed**

5. Heroes and villains have the same superpowers
6. No power is exclusive to heroes or villains

Why Does Accuracy Plateau at ~65%? (continued)

1. **Missing Narrative Features**
2. Real hero/villain distinction depends on:
    - Origin story ("bitten by spider" vs "fell into acid")
    - Motivations (save people vs revenge)
    - Team affiliations (Avengers vs Hydra)
3. None of these are in our dataset!
4. **Possible Synthetic Data**
5. Dataset may be artificially generated
6. Random assignment of labels explains weak signal

Feature Engineering Impact

Did Our 7 Engineered Features Help?

Feature	Importance Rank
training_intensity	**#2** ✓
power_efficiency	Top 10
total_powers	Top 10

Yes! But overall improvement was only ~1-2% accuracy

The dataset's fundamental limitations cannot be overcome with engineering.

Clustering Insights

What We Learned:

1. **Data splits by POWER, not MORALITY**
2. High-power group vs Low-power group
3. Not hero group vs villain group
4. **This Makes Sense in Comics!**
5. Superman (hero) and Darkseid (villain) are both high-power
6. Hawkeye (hero) and Crossbones (villain) are both low-power
7. Power level ≠ Moral alignment

8. Conclusions

Summary of Results

Classification:

- Tested **19 models** → Best accuracy: **65%**
- Simple linear models work as well as complex ensembles
- Top features: power_level, training_intensity, training_hours

Clustering:

- **K-Means (k=2)** found the best clusters
- Clusters are **power-based**, not hero/villain-based
- Silhouette score: 0.167 (moderate separation)

Key Takeaways

Finding	Implication
🎯 Accuracy ceiling at 65%	Dataset lacks predictive signal
⚡ Powers don't define morality	Villains and heroes share same abilities
📊 Behavioral features matter most	power_level, training are key
🔍 Natural clusters are power-based	Not hero/villain groups
🧪 Feature engineering helped	But couldn't break the ceiling

Limitations

1. **Dataset may be synthetic**
2. Random label assignment explains weak patterns
3. **Missing key features**
4. No text descriptions, origin stories, affiliations
5. **Binary labels too simplistic**
6. Real characters have moral complexity (anti-heroes)

Future Work

1. **Acquire richer data**
2. Character descriptions, origin stories
3. Team affiliations, universe data
4. **Multi-class classification**
5. Predict alignment spectrum (Lawful Good → Chaotic Evil)
6. **Graph analysis**
7. Model character relationships & interactions
8. **NLP on text**
9. Use character bios for prediction

Technical Details

Tools & Technologies Used

Category	Tools
Language	Python 3.10
Data Processing	pandas, numpy
ML Models	scikit-learn, XGBoost
Visualization	matplotlib, seaborn
Environment	Jupyter Notebook
Version Control	Git, GitHub

Code & Outputs

File Structure:

GitHub Repository:

https://github.com/elbarbary/superhero-classification

Complete Figure Gallery (22 Figures)

Exploratory Data Analysis:

Figure	Description
target_distribution.png	Class balance (65% heroes, 35% villains)
power_distribution.png	Frequency of each superpower
power_comparison.png	Powers split by hero/villain
hero_villain_powers.png	Detailed hero vs villain power comparison
correlation_heatmap.png	Feature correlations
numerical_distributions.png	Histograms of all numerical features
boxplots_comparison.png	Box plots comparing classes

Complete Figure Gallery (continued)

Classification Results:

Figure	Description
model_comparison.png	Initial 3-model comparison
model_comparison_all.png	All 19 models ranked
lr_feature_importance.png	Logistic Regression coefficients
rf_feature_importance.png	Random Forest importance
feature_importance_tuned.png	Tuned RF importance
confusion_matrices.png	Multiple model confusion matrices
confusion_matrix_best.png	Best model confusion matrix

Complete Figure Gallery (continued)

Clustering Analysis:

Figure	Description
elbow_method.png	K-Means inertia curve
silhouette_scores.png	Silhouette scores for different k
elbow_silhouette.png	Combined elbow + silhouette
cluster_analysis.png	Cluster characteristic profiles
clustering_pca.png	PCA visualization with clusters
cluster_pca_final.png	Final named archetypes
clustering_pca_comparison.png	Clusters vs ground truth

Thank You!

Questions?

Contact & Resources

GitHub: https://github.com/elbarbary/superhero-classification

Dataset: https://www.kaggle.com/datasets/kenil1719/super-heros

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