Who Is The Killer?

Piraeus Vice Pattern Recognition Project

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Outline

Project Overview

Objective

Identify the most likely killer for each crime incident in the “Piraeus Vice” dataset using machine learning techniques.

Supervised Methods:

- Gaussian Bayes Classifier
- Linear Classifier
- SVM (RBF kernel)
- Multi-Layer Perceptron

Unsupervised:

- PCA for visualization
- k-means clustering

Dataset Overview

- **Total incidents:** 4,800 crime cases
- **Target:** 8 killers (multiclass classification)
- **Split:** TRAIN / VAL / TEST (predefined)

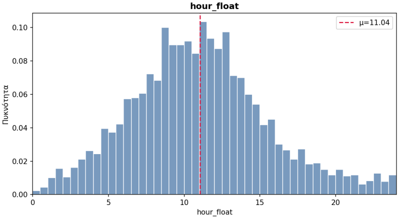
Continuous Features (8):

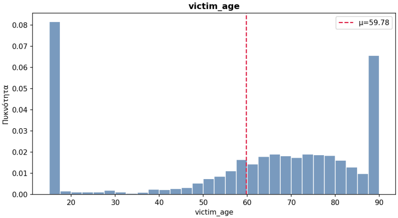
- hour_float
- latitude, longitude
- victim_age
- temp_c, humidity
- dist_precinct_km
- pop_density

Categorical Features (4):

- weapon_code
- scene_type
- weather
- vic_gender

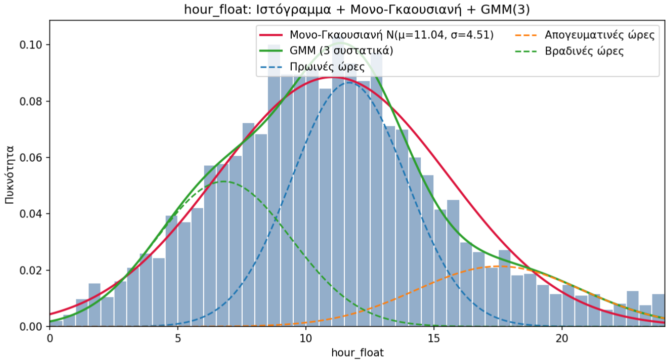
Q1: Key Variable Distributions





- **hour_float:** Peak incidents during daytime (unexpected)
- **victim_age:** Bimodal — very young or very old (vulnerable groups)

Q1: Gaussian Mixture vs Single Gaussian



Key Insight

Single Gaussian inadequate — GMM (3 components) captures multiple time-of-day patterns better.

Q2: Maximum Likelihood Estimation

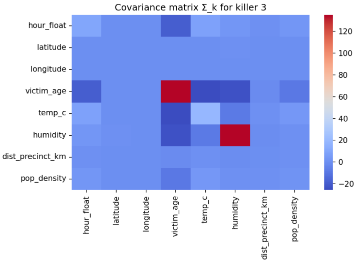
Approach

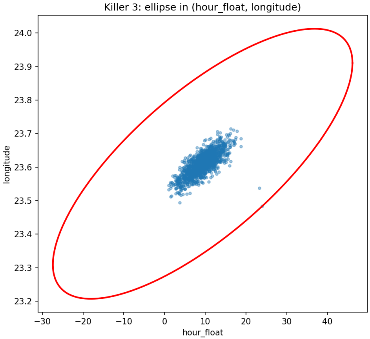
For each killer k, estimate mean μ_k and covariance Σ_k of continuous features using MLE on TRAIN split.

Assumption: Each killer's feature vector follows a multivariate Gaussian distribution:

$$p(\mathbf{x}|k) = \mathcal{N}(\mathbf{x}; \mu_k, \Sigma_k)$$

Q2: Covariance Heatmaps & Ellipses





- Each killer exhibits distinct spatial-temporal patterns
- 2D ellipses show hour_float vs longitude distributions

Q3: Multiclass Gaussian Bayes Classifier

Method

Use MLE parameters from Q2 to build a Bayesian classifier:

$$\hat{k} = \arg\max_{k} \; p(k|\mathbf{x}) \propto p(\mathbf{x}|k) \cdot p(k)$$

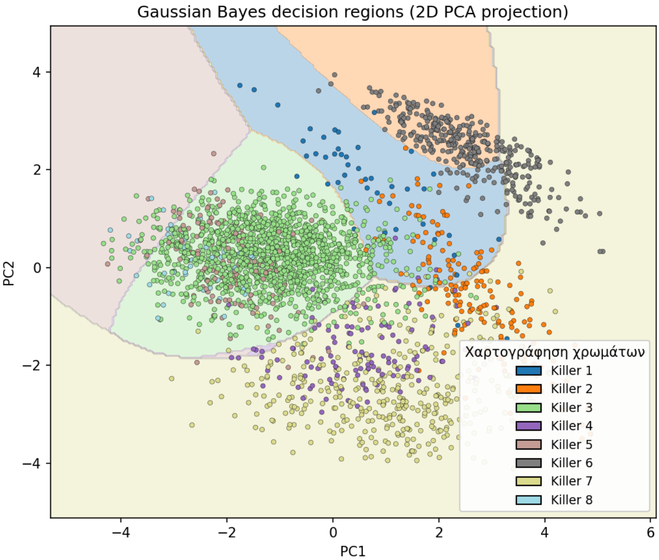
Results:

- TRAIN Acc: **89%**
- VAL Acc: **90%**

Observations:

- Confusion matrix mostly diagonal
- Killers 3, 6, 7 dominate

Q3: Decision Regions (PCA Projection)



Q4: Linear Classifier

Approach

Discriminative multiclass classification using all 12 features (8 continuous + 4 categorical via one-hot encoding).

Results:

- TRAIN Acc: **77%**
- VAL Acc: **78%**

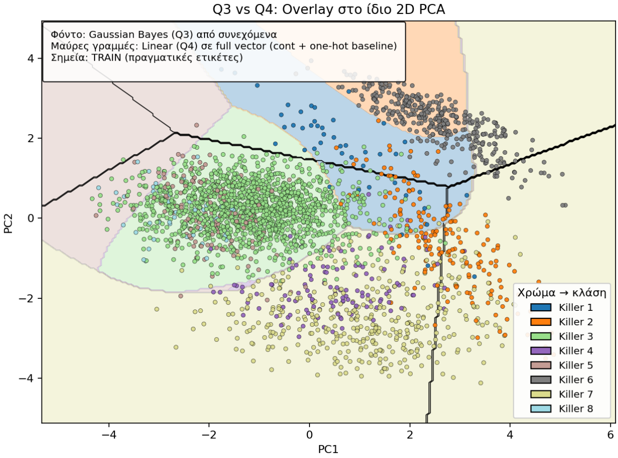
Analysis:

- Lower than Bayes (90%)
- Linear boundaries too restrictive

Limitation

Cannot capture nonlinear killer patterns in feature space.

Q4: Linear Decision Boundaries



Linear boundaries (straight lines) fail to separate complex killer profiles.

Q5: SVM with RBF Kernel

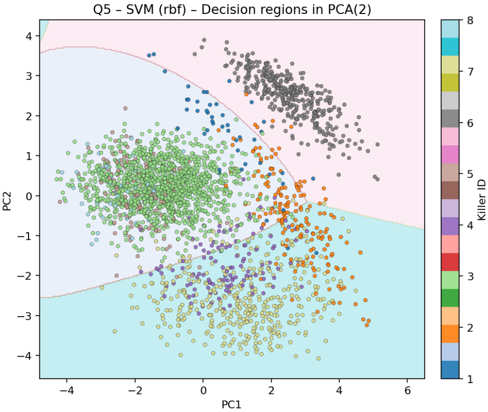
Configuration

- **Kernel:** RBF (allows nonlinear boundaries)
- **Strategy:** One-vs-Rest (8 binary classifiers)
- **Tuning:** Grid search over $C \in \{0.3, 1, 3\}$ and $\gamma \in \{\text{scale}, 0.1, 0.03\}$

Performance

VAL Accuracy: 94% — Best performance so far!

Q5: SVM Decision Regions & Support Vectors



Nonlinear boundaries effectively capture killer-specific patterns.

Q6: Neural Network (MLP)

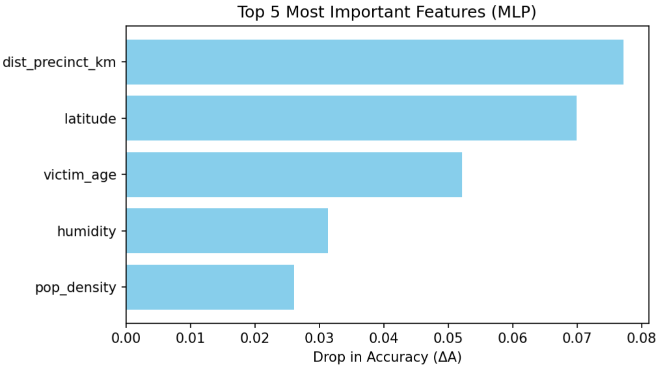
Architecture

- **Hidden layers:** 2 layers (64, 32 neurons)
- **Activation:** ReLU
- **Optimizer:** Adam
- **Regularization:** Early stopping

Performance

VAL Accuracy: 94% — Matches SVM performance!

Q6: Feature Importance (Permutation)



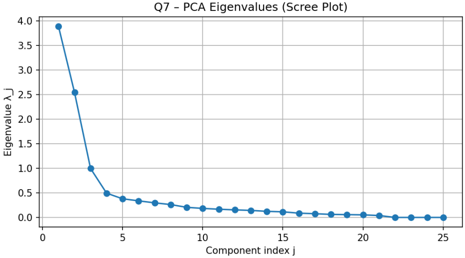
Top 5 Features:

1. dist_precinct_km ($\Delta A = 0.07$)
2. latitude ($\Delta A = 0.06$)
3. victim_age ($\Delta A = 0.05$)
4. humidity ($\Delta A = 0.03$)
5. pop_density ($\Delta A = 0.02$)

Q7: PCA for Dimensionality Reduction

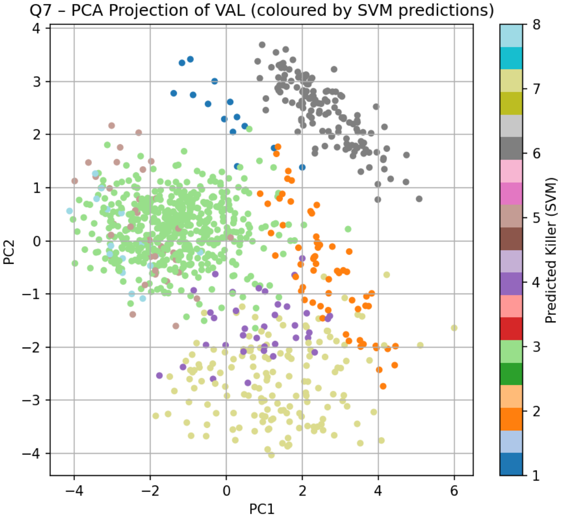
Purpose

- Visualize high-dimensional data in 2D
- Reduce noise and computational cost
- Preserve maximum variance



First few components capture most variance.

Q7: PC1–PC2 Scatter (Colored by Killer)



Q8: Unsupervised k-means in PCA Space

Approach

- Apply PCA (5 components) on TRAIN
- Run k-means with $k = 8$ (number of killers)
- Map clusters to killers via majority voting
- Evaluate on VAL

Result

Lower accuracy than supervised methods.
Natural clusters in feature space do not perfectly align with killer identities.

Q8: Interpretation

- k-means finds geometric clusters, not class labels
- Supervised methods leverage labeled data more effectively
- Useful for exploratory analysis, not final prediction

Key Takeaway

When labels are available, supervised learning outperforms unsupervised clustering for classification tasks.

Performance Comparison

Table: VAL Accuracy across all models

Model	**VAL Accuracy**
SVM (RBF kernel)	**94.8%**
MLP (2 hidden layers)	**94.4%**
Gaussian Bayes	90.5%
Linear Classifier	78.2%
PCA + k-means	Lower

Ranking: SVM $\approx$ MLP $>$ Bayes $>$ Linear $>$ k-means

Visual Insights Summary

Exploratory:

- GMM better than single Gaussian
- Victims: vulnerable age groups
- Spatial clustering around centers

Decision Boundaries:

- Gaussian: curved, smooth
- Linear: straight, restrictive
- SVM/MLP: complex, accurate

Most Important Features

Geographic (lat/long), victim info (age, gender), scene conditions (weather, type), weapon type.

Key Findings

1. **Nonlinear models excel:** SVM and MLP achieve 94% accuracy
2. **Feature importance:** Geographic + victim characteristics dominate
3. **Gaussian assumption works:** Bayes classifier at 90% is strong baseline
4. **Linear limits:** Only 78% — insufficient for complex patterns
5. **Unsupervised falls short:** k-means cannot match supervised performance

Main Contributions

What We Did

- Comprehensive comparison of 5 methods (generative, discriminative, nonlinear, unsupervised)
- Proper preprocessing pipeline (standardization, one-hot encoding)
- No data leakage (fit on TRAIN, apply to VAL/TEST)
- Systematic hyperparameter tuning
- Rich visualizations (heatmaps, ellipses, decision boundaries, PCA)

Limitations & Future Work

Limitations

- Limited to provided features (no time series, network analysis)
- Imbalanced classes (killers 3, 6, 7 dominate)
- No ensemble methods explored

Future Directions

- Ensemble models (voting, stacking)
- Deep learning (CNN, attention mechanisms)
- External data (social networks, historical patterns)
- Explainability (SHAP, LIME)

Thank You!

Questions?

Who Is The Killer? — Piraeus Vice

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