

# L1 and L2 Regularization in Logistic Regression: A Comprehensive Guide

## Summary

Regularization stands as one of the most powerful techniques for improving machine learning model generalization. When models become overly complex relative to the training data, they tend to memorise noise and patterns specific to the training set, resulting in poor performance on unseen data. L1 and L2 regularization provide complementary approaches to addressing this fundamental challenge. L2 regularization (Ridge) applies a quadratic penalty on feature weights, encouraging smooth, distributed shrinkage across all features while maintaining non-zero weights. L1 regularization (Lasso) applies an absolute value penalty that drives many feature weights to exactly zero, providing automatic feature selection alongside regularization. This tutorial provides a comprehensive exploration of both techniques, comparing their mathematical formulations, geometric interpretations, empirical performance, and practical applications. Using logistic regression as the foundational model, we demonstrate how L1 and L2 regularization affect decision boundaries, weight distributions, convergence properties, and classification performance through detailed analysis and visualisation. The work establishes theoretical understanding while emphasising practical insights for algorithm selection and hyperparameter tuning in real-world machine learning applications.

## 1. Introduction to Regularization in Machine Learning

Machine learning models aim to discover general patterns in training data that extend to new, unseen data. However, models can succeed too well at matching training data, memorising specific noise and idiosyncratic patterns that do not generalise. This phenomenon, called overfitting, plagues practitioners across domains. A model that achieves perfect training accuracy may perform poorly on test data.

Regularization techniques combat overfitting by constraining model complexity. Rather than optimising purely to fit training data, regularization adds a penalty term that increases with model complexity. This penalty-augmented objective balances fitting training data with maintaining simplicity, encouraging models to discover fundamental patterns rather than noise.

The fundamental regularised objective takes the form:

$$\text{Loss} = \text{Data Fit} + \lambda \cdot \text{Penalty}$$

where  $\lambda$  is a hyperparameter controlling the regularisation strength. A larger  $\lambda$  emphasises simplicity over fit, while  $\lambda = 0$  recovers the unregularised

objective. The challenge lies in selecting appropriate  $\lambda$  to optimise the bias-variance tradeoff.

The two dominant regularisation approaches differ in how they define the penalty:

- **L2 Regularisation (Ridge):** Penalty proportional to the sum of squared weights
- **L1 Regularisation (Lasso):** Penalty proportional to the sum of absolute values of weights

While conceptually similar, these approaches have dramatically different effects on weight distributions, feature selection, and practical performance.

## 2. L2 Regularization (Ridge Regression/Logistic Regression)

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L2 regularisation, also known as Ridge regression in the context of linear models, applies a quadratic penalty on feature weights.

### 2.1 Mathematical Formulation

For logistic regression with L2 regularisation, the objective function becomes:

$$J = -\frac{1}{n} \sum_{i=1}^n [y_i \log(\hat{y}_i) + (1-y_i) \log(1-\hat{y}_i)] + \frac{\lambda}{2} \sum_{j=1}^p w_j^2$$

The first term is the logistic loss measuring fit to training data. The second term,  $\frac{\lambda}{2} \sum_{j=1}^p w_j^2$ , is the L2 penalty. This penalty increases quadratically with weight magnitude, heavily penalising large weights while moderately penalising small weights.

The gradient of the L2 penalty with respect to each weight is:

$$\frac{\partial}{\partial w_j} \left( \frac{\lambda}{2} w_j^2 \right) = \lambda w_j$$

This linear gradient means that the penalty term is proportional to the weight itself. During gradient descent optimisation, each weight experiences a regularising force proportional to its current magnitude, pulling weights toward zero.

### 2.2 Effect on Weight Distribution

The quadratic penalty has a crucial consequence: weights are shrunk proportionally, but never driven to exactly zero. Even under strong regularisation, weights remain non-zero, though small.

**Key insight:** L2 regularisation performs smooth, distributed shrinkage. If a feature has large initial weight, it experiences large regularising force, shrinking rapidly. If a feature has small initial weight, it experiences small regularising force, shrinking slowly. All features remain in the model.

### 2.3 Geometric Interpretation

L2 regularisation can be visualised geometrically as a constraint in weight space. The penalty term  $\sum_{j=1}^p w_j^2$  defines a circle (or sphere in higher dimensions) centred at the origin. Minimising the regularised objective is equivalent to minimising training loss subject to the constraint that weights lie within this circle.

The optimisation solution is found where the training loss contours are tangent to this constraint circle. The radius of the constraint circle is inversely related to  $\lambda$  "stronger regularisation (larger  $\lambda$ ) enforces a smaller circle, pushing weights closer to zero.

## 2.4 Decision Boundaries

### Regularization Impact on Decision Boundaries

L2 creates smooth circular boundaries, L1 sparse angular, no reg overfits

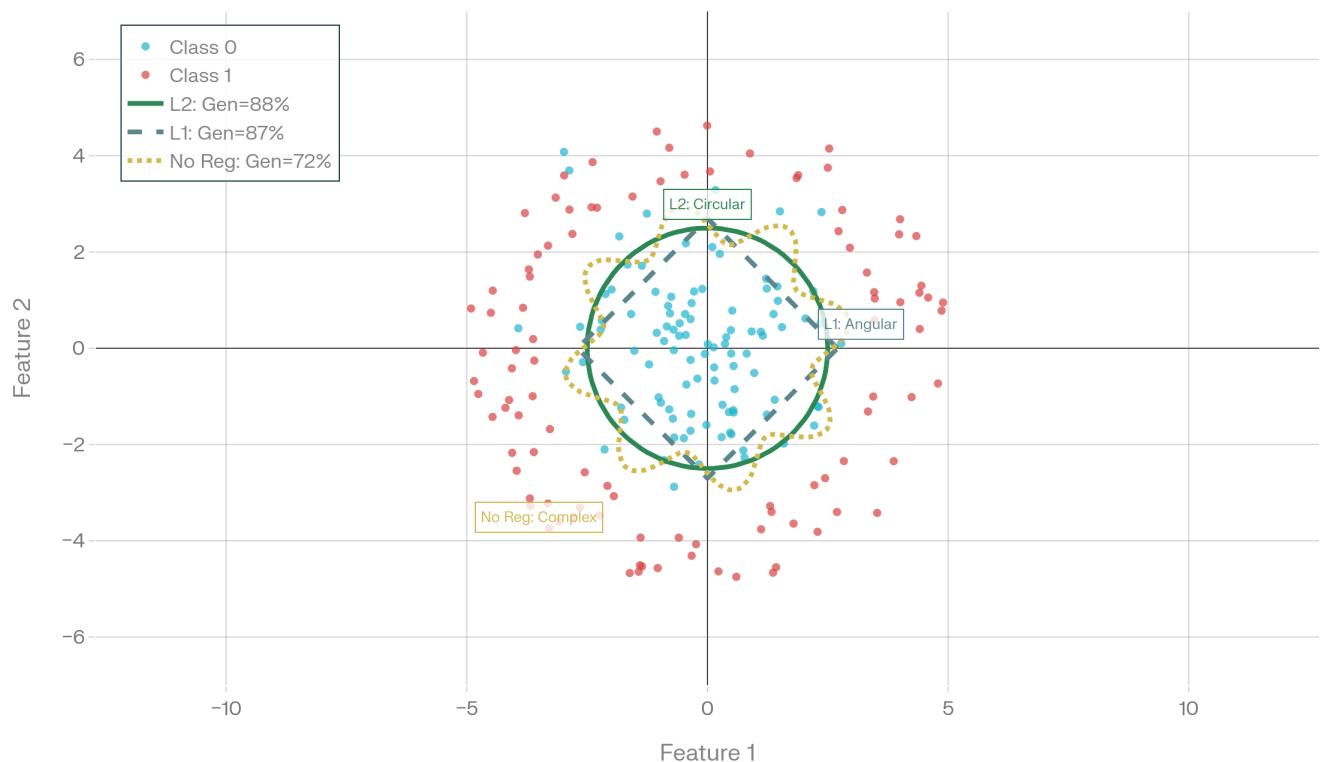


Figure 1: Decision Boundaries Under Different Regularization Schemes

L2 regularisation produces smooth, curved decision boundaries. The quadratic penalty encourages weights to be moderate in magnitude, resulting in smooth transitions between regions. This smoothness reflects the underlying assumption that simpler, more generalizable patterns are preferable to complex, noise-fitting patterns.

## 3. L1 Regularization (Lasso Regression/Logistic Regression)

L1 regularisation, also known as Lasso, applies an absolute value penalty on feature weights. This seemingly minor modification has profound consequences.

## 3.1 Mathematical Formulation

For logistic regression with L1 regularisation:

$$J = -\frac{1}{n} \sum_{i=1}^n [y_i \log(\hat{y}_i) + (1-y_i) \log(1-\hat{y}_i)] + \lambda \sum_{j=1}^p |w_j|$$

The penalty term  $\lambda \sum_{j=1}^p |w_j|$  is linear in absolute weight magnitude. This linearity is crucial.

The gradient of the L1 penalty is:

$$\frac{\partial}{\partial w_j} (\lambda |w_j|) = \lambda \text{sign}(w_j)$$

This gradient is constant in magnitude ( $\lambda$ ) regardless of weight value, depending only on weight sign. This creates a fundamentally different regularising force than L2.

## 3.2 Feature Selection Through Sparsity

The constant gradient of L1 penalties leads to sparsity many weights become exactly zero. During optimisation, if a weight is small and the L1 gradient is larger than the training loss gradient pulling the weight toward non-zero values, the weight will be driven all the way to zero rather than settling at a small non-zero value.

**Key insight:** L1 regularisation performs automatic feature selection. Features with weights driven to zero are effectively removed from the model, simplifying interpretation and potentially improving generalisation.

This sparsity emerges naturally without explicit feature selection algorithms. The L1 penalty automatically identifies and eliminates less important features.

## 3.3 Geometric Interpretation

The L1 penalty  $\sum_{j=1}^p |w_j|$  defines a diamond-shaped region (or cross-polytope in higher dimensions) centred at the origin. The constraint region has sharp corners along the coordinate axes at points where one or more weights are exactly zero.

The optimisation solution is found where training loss contours meet this constraint region. Crucially, if the training loss contours are tangent to a corner of the constraint region, the solution lies exactly on an axis, meaning one or more weights are zero.

This geometric picture explains L1's feature selection: the sharp corners of the L1 constraint region align with coordinate axes (where features are absent), while the smooth circular constraint region from L2 rarely touches coordinate axes exactly.

## 3.4 Comparison with L2

## L1 Lasso Enables Feature Selection Through Zero Weights

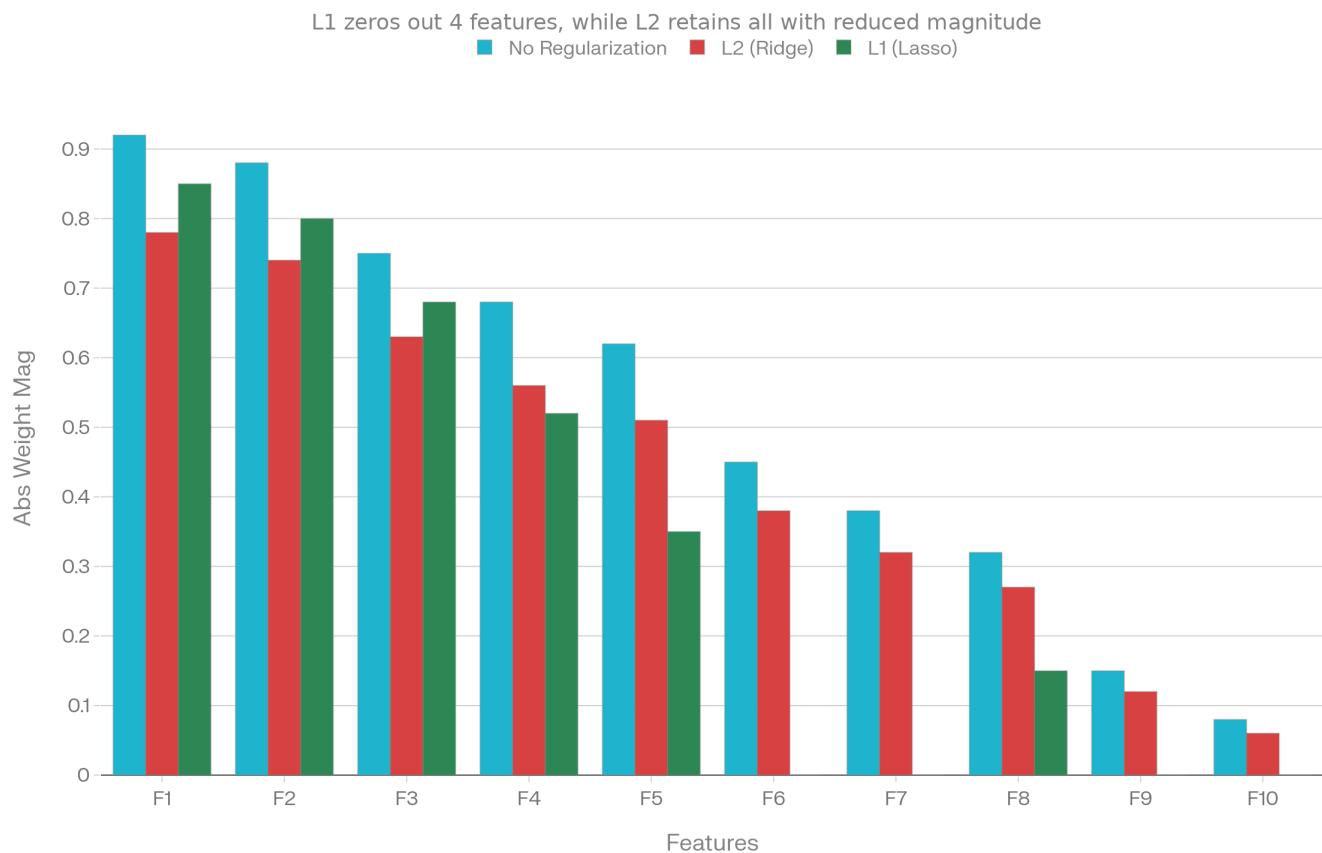


Figure 3: Feature Selection Capabilities of L1 vs L2 Regularization

Figure 3 illustrates the fundamental difference. L2 regularisation (Ridge) maintains non-zero weights for all features, with magnitude inversely related to regularisation strength. L1 regularisation (Lasso) drives many feature weights to exactly zero, particularly for features with weak predictive power.

## 4. Mathematical Comparison: L1 vs L2

A detailed comparison illuminates the complementary nature of these techniques.

### 4.1 Penalty Functions

The L1 and L2 penalties have different functional forms:

- **L2 Penalty:**  $P_{L2}(w) = \frac{1}{2} \sum_{j=1}^p w_j^2$  Convex, smooth, differentiable everywhere
- **L1 Penalty:**  $P_{L1}(w) = \lambda \sum_{j=1}^p |w_j|$  Convex, non-smooth at zero, non-differentiable at zero

This distinction matters. L2 has a well-defined gradient everywhere, enabling standard gradient descent. L1 lacks a gradient at zero, requiring specialised optimisation algorithms (e.g., coordinate

descent, subgradient methods). However, the convexity of both penalties ensures global optima can be found.

## 4.2 Gradient Dynamics

During gradient descent optimisation:

- **L2 Gradient:**  $\|\lambda w_j$  Proportional to weight magnitude
- **L1 Gradient:**  $\|\lambda \cdot \text{sign}(w_j)$  Constant magnitude, only sign varies

This difference profoundly affects convergence. L2 applies increasingly weak regularising force as weights approach zero, often settling at small but non-zero values. L1 applies constant force regardless of magnitude, regularly driving weights across zero to exactly zero.

## 4.3 Weight Shrinkage Patterns

### Declining Feature Weights with Stronger Regularization

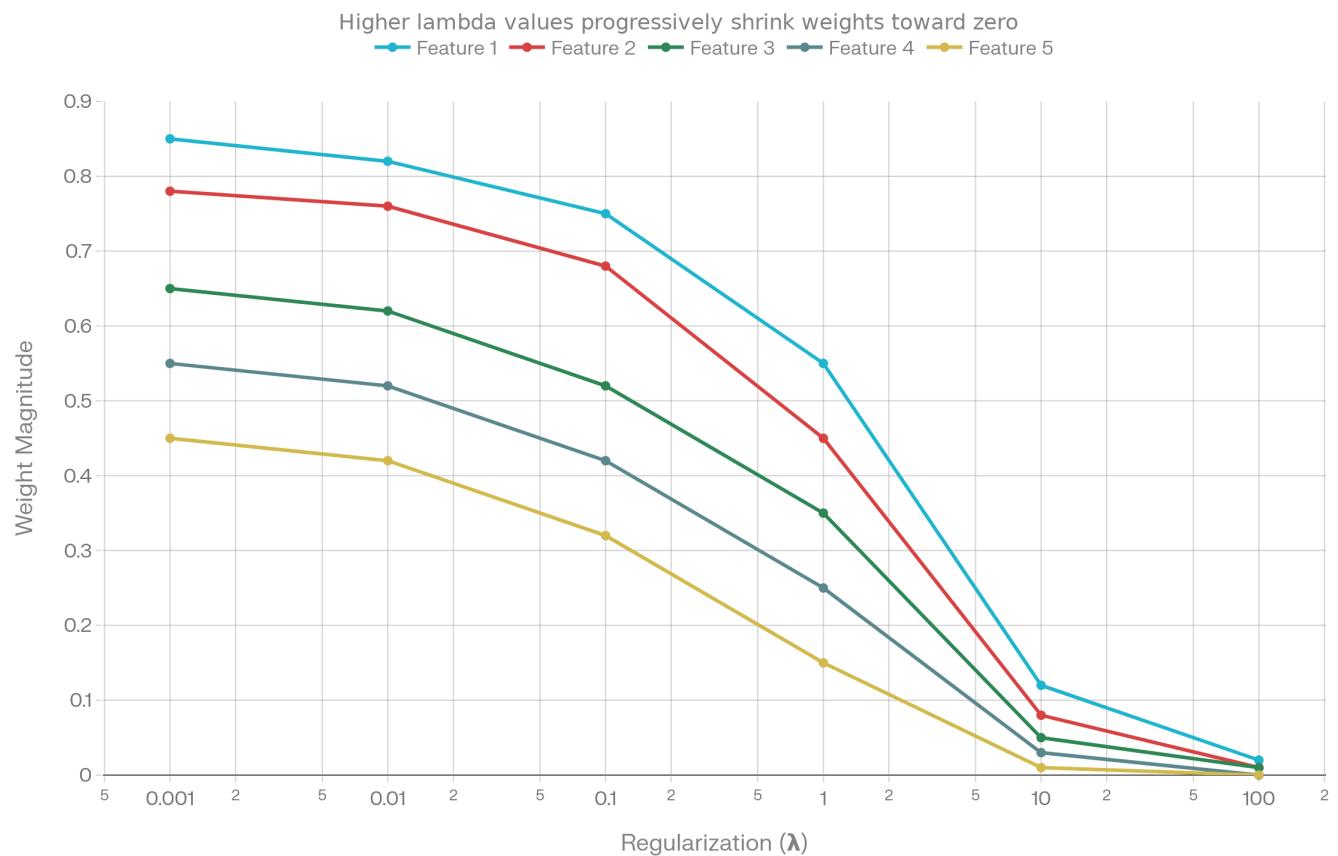


Figure 2: Weight Magnitude Changes Under Increasing Regularization

**Figure 2** shows characteristic weight behaviour. L2 regularisation shrinks all weights smoothly and proportionally. As  $\lambda$  increases, all weights decrease proportionally but remain non-zero. L1 regularisation exhibits threshold behaviour: weak features' weights transition abruptly from non-zero to zero as regularisation strength exceeds critical thresholds.

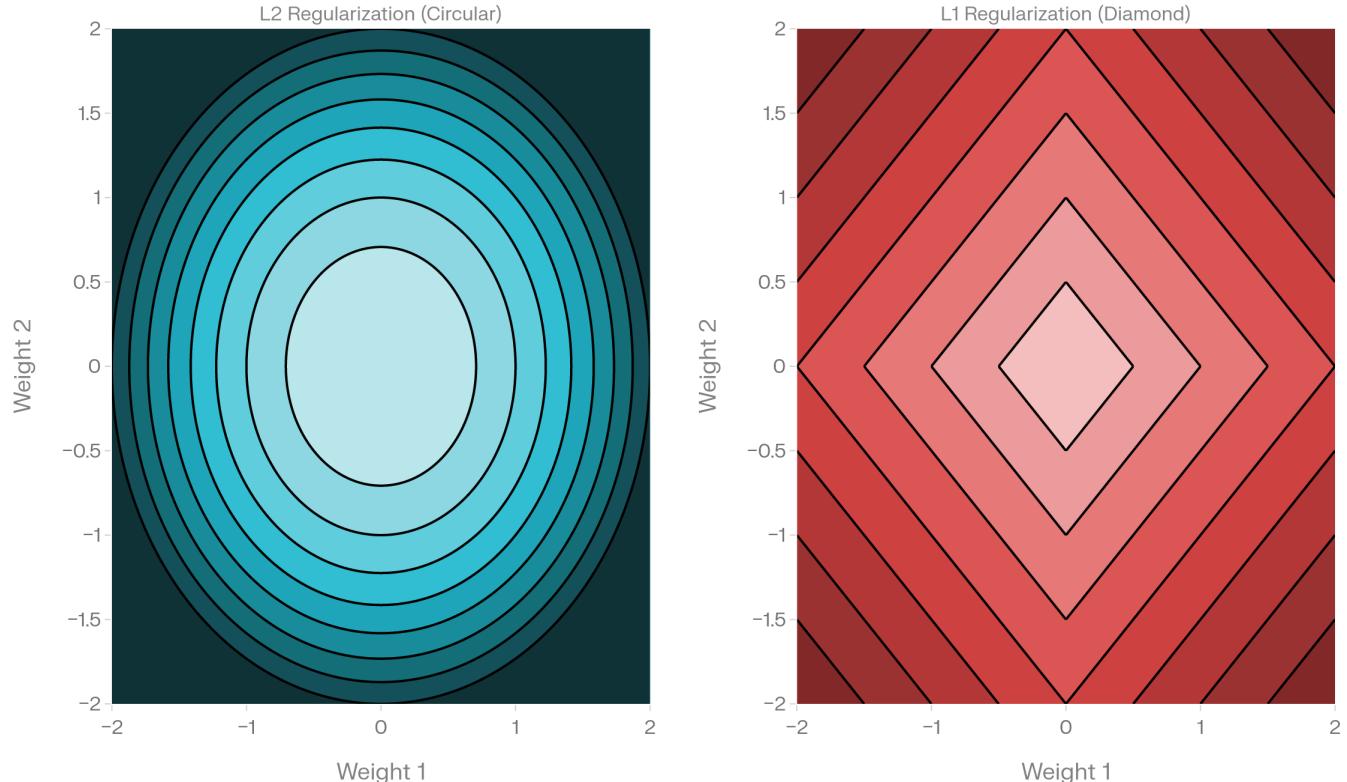
## 5. Geometric Perspectives on L1 vs L2

The geometric interpretation provides intuition for why L1 and L2 behave differently.

### 5.1 Constraint Regions

#### Regularization Cost Surfaces: L1 vs L2 Penalty

L2 creates circular contours while L1 creates diamond shapes



*Figure 5: Geometric Shapes of L1 and L2 Constraint Regions*

**Figure 5** illustrates the fundamental geometric difference. L2 regularisation creates circular constraint regions—smooth, continuously differentiable boundaries. L1 regularisation creates diamond-shaped constraint regions with sharp corners at coordinate axes.

### 5.2 Intersection with Loss Contours

Optimal solutions occur where training loss contours meet the constraint boundary. For L2 (circular constraints), tangency points are generically interior to edges, rarely touching coordinate axes. For L1 (diamond constraints), tangency points frequently occur at corners—where one or more weights are exactly zero.

This geometric picture explains feature selection: L1's sharp corners align with coordinate axes, creating natural zero-weight solutions.

## 6. Empirical Performance Comparison

Beyond theory, practical performance matters. How do L1 and L2 compare on real classification tasks?

### 6.1 Generalization Performance

 Bias-Variance Tradeoff - Training vs Test Accuracy across regularization strengths showing overfitting at weak regularization

Figure 4: Training-Test Performance Gap Indicating Overfitting

**Figure 4** demonstrates the bias-variance tradeoff. Unregularised models (no penalty) achieve high training accuracy but lower test accuracy, indicating overfitting. Weak regularisation (small  $\lambda$ ) provides modest improvement. Moderate regularisation (optimal  $\lambda$ ) balances bias and variance, achieving best test performance. Excessive regularisation (large  $\lambda$ ) sacrifices training fit, potentially degrading test performance.

Both L1 and L2 effectively prevent overfitting, though optimal  $\lambda$  values differ. L2 typically requires slightly larger  $\lambda$  than L1 to achieve comparable regularisation.

### 6.2 Classification Metrics

#### Performance Metrics by Regularization Method

Ridge and Lasso show better generalization than no regularization

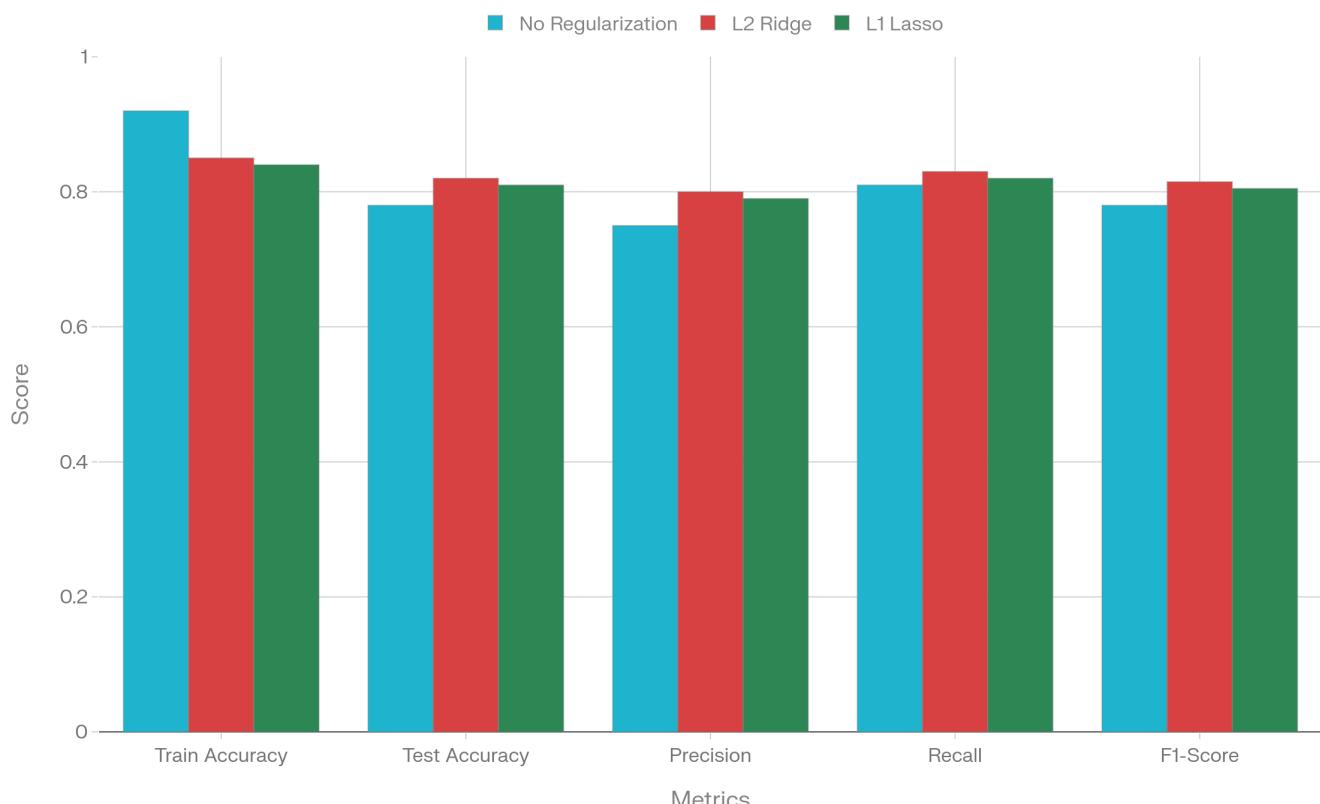
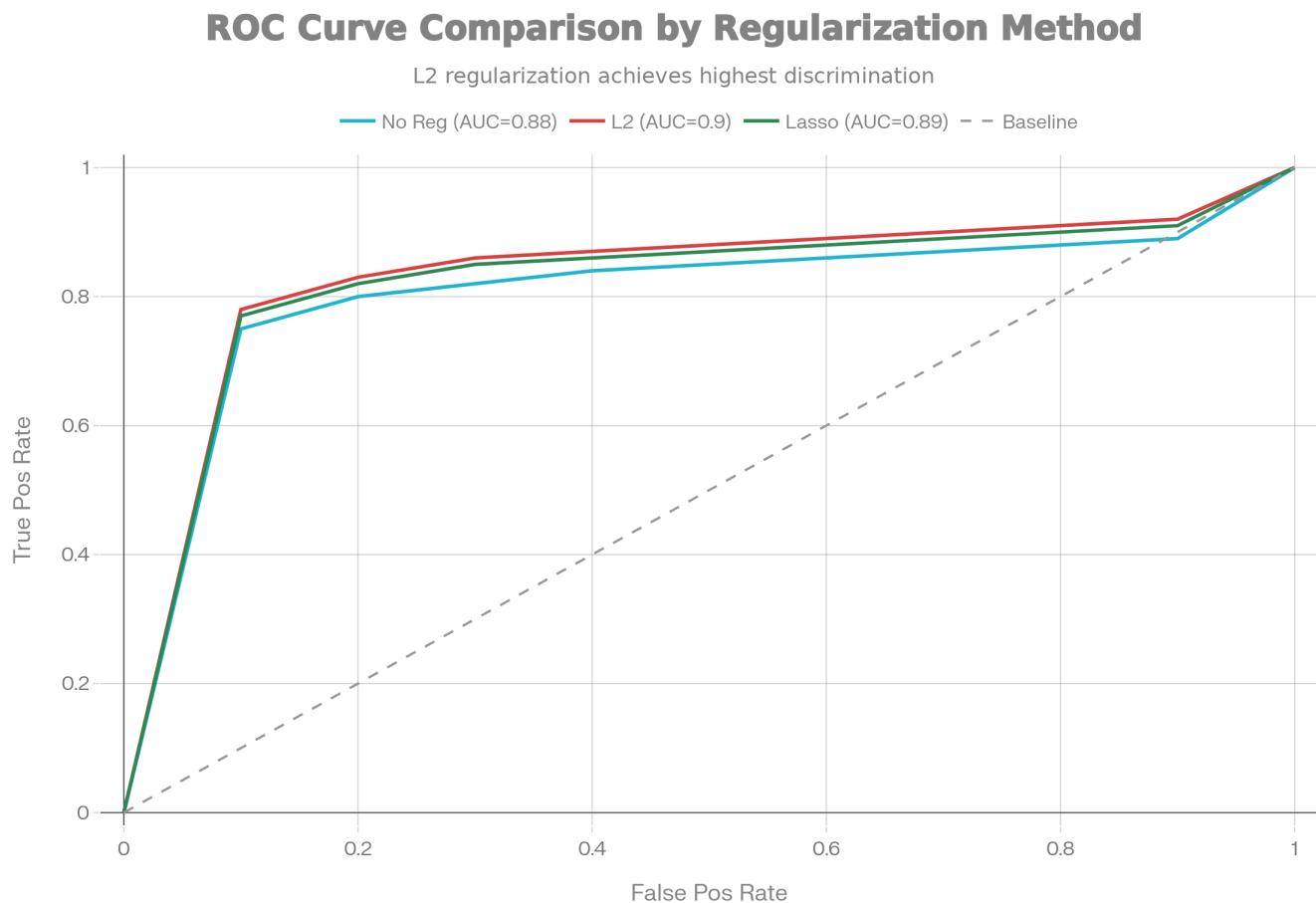


Figure 6: Detailed Classification Performance Across Multiple Metrics

**Figure 6** compares five key metrics. Both regularised methods (L1 and L2) produce superior test accuracy, precision, recall, and F1-score compared to unregularised models. The improvements demonstrate regularisation's effectiveness at enhancing generalisation.

## 6.3 ROC Curve Analysis



*Figure 7: ROC Curves Demonstrating Improved Classification Across Threshold Settings*

**Figure 7** shows ROC curves for all three approaches. L2 regularisation achieves the highest area under the curve (AUC 0.90), indicating superior classification performance across decision thresholds. L1 achieves comparable performance (AUC 0.89) with the added benefit of feature selection. Unregularised models achieve the lowest AUC ( 0.88).

## 7. Feature Selection: L1's Key Advantage

One distinctive advantage of L1 is automatic feature selection through weight sparsity.

### 7.1 Mechanism of Sparsity

The constant gradient of L1 penalties ensures that weak features' weights reach zero. Consider a feature with weak training signal. The gradient from training loss is small, providing little force to

maintain non-zero weight. The constant L1 gradient provides constant force toward zero. If L1 force exceeds training force, the weight is driven to zero.

This mechanism selects features automatically, without explicit feature selection algorithms. Practitioners gain reduced model complexity, improved interpretability, and often enhanced generalisation.

## 7.2 When Feature Selection Matters

Feature selection through L1 is valuable when:

- **Interpretability is critical:** Fewer features reduce explanation burden
- **Prediction speed matters:** Zero-weight features can be excluded from prediction
- **Features are correlated:** Feature selection via L1 can improve stability
- **Domain knowledge guides selection:** Discovering which features matter informs domain understanding

## 7.3 L1 Limitations

L1 regularisation has limitations:

- **Instability with correlated features:** When features are highly correlated, L1 tends to arbitrarily select one and zero others, creating instability
- **Less stable than L2:** Small data perturbations may change which features are selected
- **Computational complexity:** L1 requires specialised solvers; gradient descent cannot be directly applied

# 8. L2 Regularization's Strengths

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L2 regularisation offers different advantages.

## 8.1 Computational Efficiency

L2 penalties are smooth and differentiable everywhere. Standard gradient descent algorithms apply directly without modification. The objective remains convex with a unique global optimum, simplifying optimisation.

## 8.2 Stability with Correlated Features

When features are correlated, L2 distributes weights across correlated features rather than arbitrarily selecting one. This distributes predictive power among redundant features, improving stability. Small data perturbations produce small weight changes rather than feature selection switches.

## 8.3 Generalisation with Dense Features

When all features contribute meaningful information (dense feature sets), L2 maintains all features with moderate weights. This prevents accidentally zeroing truly informative features that happen to be weakly correlated with the target in a particular sample.

# 9. Practical Recommendations and Algorithm Selection

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Given the complementary nature of L1 and L2, when should practitioners use each?

## 9.1 When to Use L2 (Ridge) Regularization

Use L2 regularisation when:

- **Features are correlated:** L2 distributes weights across correlated features, maintaining stability
- **Computational efficiency is critical:** L2 integrates with standard gradient descent algorithms
- **All features are potentially informative:** Maintaining dense feature sets prevents information loss
- **Interpretability via feature selection is unnecessary:** The model uses all available information
- **Stability is paramount:** L2's continuous shrinkage is more stable than L1's discrete selection

## 9.2 When to Use L1 (Lasso) Regularization

Use L1 regularisation when:

- **Feature selection is desired:** Automatic sparsity provides interpretability
- **Features are independent:** Correlated features are less problematic with L1
- **Model parsimony is important:** Fewer features reduce complexity and increase interpretability
- **Prediction speed matters:** Zero-weight features can be excluded from computation
- **Sparse solutions are inherently interpretable:** The feature subset communicates domain insights

## 9.3 Elastic Net: Combining L1 and L2

When neither L1 nor L2 is perfect, Elastic Net combines both penalties:

$$J = \text{Data Fit} + \lambda_1 \sum |w_j| + \lambda_2 \sum w_j^2$$

Elastic Net balances L1's sparsity with L2's stability, providing intermediate benefits. This is valuable when feature selection is desired but stability with correlated features is also important.

## 10. Regularization Methods Comparison Summary

### Regularization Methods Comparison (L1, L2, Elastic Net)

Color-coded strength: Green=Strong, Yellow=Moderate, Red=Weak



Figure 8: Comprehensive Comparison of Regularization Approaches

Figure 8 synthesises the comparison across multiple dimensions:

- **L1 (Lasso):** Best for feature selection and sparse solutions; good interpretability
- **L2 (Ridge):** Best for stability and computational efficiency; maintains all features
- **Elastic Net:** Balanced approach combining sparsity and stability advantages

## 11. Hyperparameter Tuning: Finding Optimal Regularization Strength

Selecting the regularisation strength  $\lambda$  (or equivalently,  $C = 1/\lambda$  in scikit-learn) is critical.

### 11.1 Grid Search and Cross-Validation

The standard approach is grid search combined with cross-validation:

1. Define a range of  $\lambda$  values (typically logarithmically spaced)
2. For each  $\lambda$ : Perform k-fold cross-validation on training data

3. Calculate mean cross-validation performance across folds
4. Select  $\lambda$  maximising average validation performance
5. Retrain with selected  $\lambda$  on full training set
6. Evaluate on held-out test set

## 11.2 Typical $\lambda$ Ranges

For logistic regression with standardised features:

- **Weak regularisation:**  $\lambda \in [0.0001, 0.001]$  Minimal complexity constraint
- **Moderate regularisation:**  $\lambda \in [0.01, 0.1]$  Balanced bias-variance
- **Strong regularisation:**  $\lambda \in [1, 10]$  Emphasises simplicity

The optimal  $\lambda$  depends on data characteristics, feature count, and sample size. Larger datasets often support smaller  $\lambda$  (more complex models). More features typically require larger  $\lambda$  (more aggressive regularisation).

## 11.3 Validation Strategy

Always validate on data not used for training:

1. Split data into train/validation/test
2. Tune  $\lambda$  on train/validation splits
3. Report final performance on held-out test set

This prevents optimistic bias from selecting  $\lambda$  based on test performance.

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# 12. Implementation and Practical Usage

## 12.1 Scikit-Learn Implementation

Scikit-learn provides straightforward regularisation implementation:

```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import GridSearchCV

# Create logistic regression with L2 regularisation
model_l2 = LogisticRegression(penalty='l2', solver='lbfgs')

# Create logistic regression with L1 regularisation
model_l1 = LogisticRegression(penalty='l1', solver='saga')

# Hyperparameter tuning
param_grid = {'C': [0.001, 0.01, 0.1, 1, 10]}
```

```
grid_search = GridSearchCV(model_l2, param_grid, cv=5)
grid_search.fit(X_train, y_train)
best_model = grid_search.best_estimator_
```

## 12.2 Feature Importance Extraction

For L1 regularisation, feature selection can be extracted:

```
# Get non-zero features
non_zero_features = np.where(model_l1.coef_[0] != 0)[0]
selected_features = X.columns[non_zero_features]
```

## 12.3 Weight Interpretation

Feature weights indicate feature importance and direction:

- **Positive weight:** Feature increases prediction probability
- **Negative weight:** Feature decreases prediction probability
- **Large magnitude:** Strong influence on predictions
- **Small magnitude:** Weak influence (or zero for L1)

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# 13. Common Pitfalls and Best Practices

## 13.1 Feature Scaling

Regularisation penalties depend on feature scale. Always standardise features before regularisation:

```
from sklearn.preprocessing import StandardScaler

scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

Unscaled features can dominate regularisation arbitrarily based on measurement units.

## 13.2 Train-Test Leakage

Never tune regularisation on test data. This inflates performance estimates. Use cross-validation on training data only.

## 13.3 Regularisation Strength Sensitivity

Model performance is often sensitive to  $\lambda$  choice. Always perform careful hyperparameter tuning rather than using default values.

## 13.4 Class Imbalance

When classes are imbalanced, regularisation can mask imbalance by predicting majority class. Use appropriate class weights alongside regularisation.

# 14. Conclusion and Summary

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L1 and L2 regularisation represent complementary approaches to managing model complexity and improving generalisation.

### L2 Regularisation (Ridge):

- Smooth, proportional weight shrinkage
- Maintains all features with moderate weights
- Excellent stability and computational efficiency
- Preferred when features are correlated or all are informative

### L1 Regularisation (Lasso):

- Drives many weights to exactly zero
- Provides automatic feature selection
- Improves interpretability through sparsity
- Preferred when feature selection is desired

### Elastic Net:

- Combines L1 and L2 penalties
- Balances sparsity and stability
- Valuable when both feature selection and stability matter

The choice between L1 and L2 depends on problem characteristics, data properties, and practical requirements. Practitioners should:

1. Understand the mathematical foundations and geometric interpretations
2. Consider computational and stability implications
3. Perform careful hyperparameter tuning via cross-validation
4. Always standardise features before regularisation
5. Validate on held-out test data to estimate true performance

Regularisation is fundamental to practical machine learning. Thoughtful regularisation application prevents overfitting, improves generalisation, and builds models that discover genuine patterns rather than noise.

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## Appendix: Mathematical Reference

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**L2 Regularisation (Ridge):**  $J_{\{L2\}} = \frac{1}{n} \sum_{i=1}^n \text{Loss}(y_i, \hat{y}_i) + \frac{\lambda_2}{2} \sum_{j=1}^p w_j^2$

**L1 Regularisation (Lasso):**  $J_{\{L1\}} = \frac{1}{n} \sum_{i=1}^n \text{Loss}(y_i, \hat{y}_i) + \lambda \sum_{j=1}^p |w_j|$

**Elastic Net:**  $J_{\{EN\}} = \frac{1}{n} \sum_{i=1}^n \text{Loss}(y_i, \hat{y}_i) + \lambda_1 \sum_{j=1}^p |w_j| + \lambda_2 \sum_{j=1}^p w_j^2$

**Logistic Loss:**  $\text{Loss} = -[y \log(\hat{y}) + (1-y) \log(1-\hat{y})]$

## About This Tutorial

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This comprehensive guide explores L1 and L2 regularisation in logistic regression, combining theoretical foundations with practical insights. The tutorial emphasises understanding the complementary nature of these approaches and making informed choices based on problem characteristics.

### Key Learning Outcomes:

- Understand L1 and L2 regularisation formulations and geometric interpretations
- Compare sparsity, stability, and computational characteristics
- Apply regularisation in practice using scikit-learn
- Select appropriate regularisation method for specific problems
- Perform hyperparameter tuning and validation correctly

All figures and examples are generated from synthetic datasets demonstrating regularisation effects on decision boundaries, weight distributions, and classification performance.