

Prevent Overfitting with Regularization



What is Overfitting?

- Overfitting happens when our model learns the training data too well.
- It memorizes noise and specific details instead of general patterns.
- This leads to poor performance on new, unseen data.
- The model fits the training data perfectly, but doesn't generalize.
- A model that is too complex can overfit.



Introducing Regularization

- Regularization is a technique to simplify a model.
- It adds a penalty to the model's complexity.
- This encourages the model to learn simpler, more general patterns.
- Essentially, it prevents the model from fitting the training data too closely.
- Regularization helps to avoid overfitting.



L1 Regularization

- L1 regularization (Lasso) adds a penalty proportional to the absolute value of the coefficients.
- It can drive some coefficients to exactly zero.
- This leads to feature selection – the model effectively ignores irrelevant features.
- Useful when you suspect many features are redundant.
- Regularization helps create more interpretable models.



L1 Regularization Effects

- **Sparse model:** Many coefficients are zero.
- **Feature selection:** Irrelevant features are ignored.
- **Simplified model:** Easier to understand and interpret.
- **Dimensionality reduction:** Reduces the number of features.
- **Can be computationally expensive** with large datasets.



L2 Regularization

- L2 regularization (Ridge) adds a penalty proportional to the square of the coefficients.
- It shrinks coefficients towards zero, but rarely sets them to zero.
- This prevents any single feature from having too much influence.
- Generally preferred when you have multicollinearity.
- Less prone to feature selection than L1.



L2 Regularization Effects

- **Coefficient shrinkage:** Coefficients are reduced.
- **Prevents overfitting:** Keeps complex models simpler.
- **Suitable for multicollinearity situations.**
- **Doesn't perform feature selection.**
- **Computationally efficient, even with large datasets.**



Combining Regularizations

- Sometimes, combining L1 and L2 regularization is beneficial.
- This is called Elastic Net regularization.
- It combines the features selection of L1 with the coefficient shrinkage of L2.
- Can be a powerful approach for complex datasets.
- Requires tuning of both penalty parameters.



Choosing the Right Approach

- The choice of regularization technique depends on your data and model.
- L1 is good for feature selection.
- L2 is good for preventing overfitting in the presence of multicollinearity.
- Experiment with different regularization strengths.
- Cross-validation is essential for tuning regularization parameters.



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Shoaib Akthar
@theshoaibakthar

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