

## Comparison of Cross-Validation Approaches

	Validation Set Approach	LOOCV (Leave One Out Cross Validation)	PRESS (Predicted Residual Sum of Squares)	K-Fold Cross Validation
<b>Bias</b>	<b>High.</b> Since it only uses a subset of data for training, it tends to overestimate the test error	<b>Low.</b> It uses $n - 1$ observations for training, which is almost the entire data set, leading to a nearly unbiased estimate	<b>Low.</b> Functionally equivalent to LOOCV for linear models; it uses almost all data for each calculation.	Intermediate. Usually, $k = 5$ or $k = 10$ provides a balance between the high bias of the validation set and the low bias of LOOCV
<b>Variance</b>	<b>High.</b> The result can change significantly depending on exactly which observations end up in the training vs testing (validation) set	<b>High.</b> Because the $n$ training sets are highly similar (correlated), the outputs of each fold are also correlated, leading to higher variance in the mean	<b>High.</b> Inherits the variance characteristics of LOOCV because it is a specific implementation of it	<b>Intermediate.</b> Offers a “sweet spot” with lower variance than LOOCV because the training sets are less overlapping.
<b>Computational Cost</b>	<b>Lowest.</b> The model is only trained <b>once</b>	<b>Highest.</b> Requires fitting the model $n$ times (where $n$ is the number of observations)	<b>Low (for linear models).</b> Can be calculated using a single model fit using a specific mathematical formula ( $h_i$ leverage values)	<b>Medium.</b> Requires fitting the model $k$ times (usually 5 or 10)
<b>Consistency</b>	<b>Inconsistent.</b> Results vary with different random splits	<b>Consistent.</b> Will always produce the same result for the same dataset because there is no random sampling ( <b>deterministic</b> )	<b>Consistent.</b> Like LOOCV, it is <b>deterministic</b> for a given data set	<b>Variable.</b> Results can change slightly depending on how the “folds” are randomly assigned

## Comparison of Linear vs. Nonlinear Models

	Linear (Simple) Model	Nonlinear (Flexible) Model
<b>Bias</b>	<b>High:</b> these models make stronger assumptions and are more likely to have higher bias as they may be too simple to capture the true relationship	<b>Low:</b> These models are more flexible, allowing them to capture complex patterns and reduce the error introduced by simple approximations
<b>Variance</b>	<b>Low:</b> Simple models are stable; the estimated functions are less likely to change significantly with a different training dataset.	<b>High:</b> Flexible models are highly sensitive to the specific training data used, which can lead to significant changes in the model with different data sets
<b>Training MSE</b>	<b>Higher:</b> because they are less flexible, they cannot fit the training data points as closely as a complex model	<b>Lower:</b> highly flexible models (like degree 10 polynomials) will always have a training MSE less than or equal to a linear model
<b>Test MSE</b>	<b>Lower if the relationship is simple:</b> it generalizes better when the true relationship is close to linear	<b>Lower if the relationship is complex:</b> it performs better if it captures real nonlinear patterns, but becomes higher if the model overfits
<b>Irreducible Error</b>	<b>Fixed:</b> represents the noise ( $\epsilon$ ) in the data, which can NOT be reduced regardless of the model chosen.	

- **Reducible Error:** This consists of the squared Bias and the Variance. As you move from a linear model to a nonlinear model (increasing flexibility), bias generally decreases while variance generally increases.
- **Overfitting:** This occurs when a nonlinear model has extremely **low training MSE** but **high test MSE** because it has captured the irreducible noise in the training data rather than just the underlying pattern.
- **Underfitting:** This occurs when a linear model is used for a complex relationship, resulting in **high training MSE** and **high test MSE** due to high bias.

	Training Set Correlation	Effect of Variance
<b>LOOCV</b>	<b>Very High:</b> each of the $n$ training sets is nearly identical, sharing $n - 2$ observations	<b>Higher Variance:</b> because the outputs of the $n$ models are highly correlated, the mean of those outputs has higher variance than if they were independent
<b>k-fold</b>	<b>Lower:</b> the training sets have less overlap compared to LOOCV	<b>Lower Variance:</b> since the models are less correlated with each other, the average of their performance is more stable

```
> summary(model)
```

Call:

```
lm(formula = satisf ~ age + severe + anxiety, data = patient)
```

Residuals:

Min	1Q	Median	3Q	Max
-18.3524	-6.4230	0.5196	8.3715	17.1601

Coefficients:  $\hat{\beta}$   $SE(\hat{\beta})$

	Estimate	Std. Error	t value	Pr(> t )
(Intercept)	158.4913	18.1259	8.744	5.26e-11 ***
age	-1.1416	0.2148	-5.315	3.81e-06 ***
severe	-0.4420	0.4920	-0.898	0.3741
anxiety	-13.4702	7.0997	-1.897	0.0647 .

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