

# Lecture #4: Model Selection

CS 109A, STAT 121A, AC 209A: Data Science

Pavlos Protopapas    Kevin Rader



# Lecture Outline

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Review

Model Selection: Overview

Stepwise Variable Selection

Cross Validation

Applications of Model Selection

## Review

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# Multiple Linear and Polynomial Regression

Last time, we saw that we can build a linear model for multiple predictors,  $\{X_1, \dots, X_J\}$ ,

$$y = \beta_0 + \beta_1 x_1 + \dots + \beta_J x_J + \epsilon.$$

Using vector notation,

$$\mathbf{Y} = \begin{pmatrix} y_1 \\ \vdots \\ y_y \end{pmatrix}, \quad \mathbf{X} = \begin{pmatrix} 1 & x_{1,1} & \dots & x_{1,J} \\ 1 & x_{2,1} & \dots & x_{2,J} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n,1} & \dots & x_{n,J} \end{pmatrix}, \quad \boldsymbol{\beta} = \begin{pmatrix} \beta_0 \\ \beta_1 \\ \vdots \\ \beta_J \end{pmatrix},$$

We can express the regression coefficients as

$$\hat{\boldsymbol{\beta}} = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \operatorname{MSE}(\boldsymbol{\beta}) = (\mathbf{X}^\top \mathbf{X})^{-1} \mathbf{X}^\top \mathbf{Y}.$$

# Multiple Linear and Polynomial Regression

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We also saw that there are many ways to generalize multiple linear regression:

- ▶ Multiple linear regression with interaction terms,  $x_i x_j x_k$  etc.
- ▶ Polynomial regression

$$y = \beta_0 + \beta_1 x + \dots + \beta_M x^M + \epsilon.$$

- ▶ Polynomial regression with multiple predictors and interaction terms.

In each case, we treat each polynomial term  $x_j^m$  or interaction term  $x_i x_j x_k$  as an unique predictor and perform multiple linear regression.

# Selecting Significant Predictors

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When modeling with multiple predictors, we are interested in which predictor or sets of predictors have a significant effect on the response.

Significance of predictors can be measured in multiple ways:

► **Hypothesis testing:**

- Subsets of predictors with higher  $F$ -stats higher than 1 may be significant.
- Individual predictors with  $p$ -values smaller than established threshold (e.g. 0.05) may be significant.

► **Evaluating model fitness:**

- Subsets of predictors with higher model  $R^2$  should be more significant.
- Subsets of predictors with lower model AIC or BIC should be more significant.

## Model Selection: Overview

# Overfitting: Another Motivation for Model Selection

Finding subsets of significant predictors is an important for model interpretation. But there is another strong reason to model using the smaller set of significant predictors: to avoid overfitting.

## Definition

**Overfitting** is the phenomenon where in the model is unnecessarily complex, in the sense that portions of the model captures the random noise in the observation, rather than the relationship between predictor(s) and response.

Overfitting causes the model to lose predictive power on new data.



# An Example

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# Causes of Overfitting

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As we saw, overfitting can happen when

- ▶ there are too many predictors:
  - the feature space has high dimensionality
  - the polynomial degree is too high
  - too many cross terms are considered
- ▶ the coefficients values are too extreme

A sign of overfitting may be a high training  $R^2$  or low  $MSE$  and unexpectedly poor testing performance.

**Note:** There is no 100% accurate test for overfitting and there is not a 100% effective way to prevent it. Rather, we may use multiple techniques in combination to prevent overfitting and various methods to detect it.

# Model Selection

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**Model selection** is the application of a principled method to determine the complexity of the model, e.g. choosing a subset of predictors, choosing the degree of the polynomial model etc.

Model selection typically consists of the following steps:

1. split the training set into two subsets: training and **validation**
2. multiple models (e.g. polynomial models with different degrees) are fitted on the training set; each model is evaluated on the validation set
3. the model with the best validation performance is selected
4. the selected model is evaluated one last time on the testing set

## Stepwise Variable Selection

## Exhaustive Selection

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To find the optimal subset of predictors for modeling a response variable, we can

- ▶ compute all possible subsets of  $\{X_1, \dots, X_J\}$ ,
- ▶ evaluate all the models constructed from the subsets of  $\{X_1, \dots, X_J\}$ ,
- ▶ find the model that optimizes some metric.

While straightforward, **exhaustive selection** is computationally infeasible, since  $\{X_1, \dots, X_J\}$  has  $2^J$  number of possible subsets.

Instead, we will consider methods that iteratively build the optimal set of predictors.

# Variable Selection: Forward

In **forward selection**, we find an ‘optimal’ set of predictors by iterative building up our set.

1. Start with the empty set  $P_0$ , construct the null model  $M_0$ .
2. For  $k = 1, \dots, J$ :
  - 2.1 Let  $M_{k-1}$  be the model constructed from the best set of  $k - 1$  predictors,  $P_{k-1}$ .
  - 2.2 Select the predictor  $X_{n_k}$ , not in  $P_{k-1}$ , so that the model constructed from  $P_k = X_{n_k} \cup P_{k-1}$  optimizes a fixed metric (this can be  $p$ -value,  $F$ -stat; validation MSE,  $R^2$ ; or AIC/BIC on training set).
  - 2.3 Let  $M_k$  denote the model constructed from the optimal  $P_k$ .
3. Select the model  $M$  amongst  $\{M_0, M_1, \dots, M_J\}$  that optimizes a fixed metric (this can be validation MSE,  $R^2$ ; or AIC/BIC on training set).
4. Evaluate the final model  $M$  on the testing set.

# Variable Selection: Backward

In **backward selection**, we find an ‘optimal’ set of predictors by iterative eliminating predictors.

1. Start with all the predictors  $P_J$ , construct the full model  $M_J$ .
2. For  $k = 1, \dots, J$ :
  - 2.1 Let  $M_k$  be the model constructed from the best set of  $k - 1$  predictors,  $P_k$ .
  - 2.2 Select the predictor  $X_{n_k}$  in  $P_k$  so that the model constructed from  $P_{k-1} = P_k - \{X_{n_k}\}$  optimizes a fixed metric (this can be  $p$ -value,  $F$ -stat; validation MSE,  $R^2$ ; or AIC/BIC on training set).
  - 2.3 Let  $M_{k-1}$  denote the model constructed from the optimal  $P_{k-1}$ .
3. Select the model  $M$  amongst  $\{M_0, M_1, \dots, M_J\}$  that optimizes a fixed metric (this can be validation MSE,  $R^2$ ; or AIC/BIC on training set).
4. Evaluate the final model  $M$  on the testing set.

# An Example

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## Cross Validation

## Cross Validation: Motivation

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Using a single validation set to select amongst multiple models can be problematic - there is the possibility of overfitting to the validation set.

One solution to the problems raised by using a single validation set is to evaluate each model multiple validation sets and average the validation performance.

One can randomly split the training set into training and validation multiple times, but randomly creating these sets can create the scenario where important features of the data never appear in our random draws.

# Leave-One-Out

Given a data set  $\{\mathbf{X}_1, \dots, \mathbf{X}_n\}$ , where each  $\mathbf{X}_i = (x_{i,1}, \dots, x_{i,J})$  contains  $J$  number of features.

To ensure that every observation in the dataset is included in at least one training set and at least one validation set, we create training/validation splits using the **leave one out** method:

- ▶ validation set:  $\{\mathbf{X}_i\}$
- ▶ training set:  $\mathbf{X}_{-i} := \{\mathbf{X}_1, \dots, \mathbf{X}_{i-1}, \mathbf{X}_{i+1}, \dots, \mathbf{X}_n\}$

for  $i = 1, \dots, n$ . We fit the model on each training set, denoted  $\hat{f}_{\mathbf{X}_{-i}}$ , and evaluate it on the corresponding validation set,  $\hat{f}_{\mathbf{X}_{-i}}(\mathbf{X}_i)$ . The **cross validation score** is the performance of the model averaged across all validation sets:

$$CV(\text{Model}) = \frac{1}{n} L \left( \hat{f}_{\mathbf{X}_{-i}}(\mathbf{X}_i) \right),$$

where  $L$  is a loss function.

# K-Fold Cross Validation

Rather than creating  $n$  number of training/validation splits, each time leaving one data point for the validation set, we can include more data in the validation set using **K-fold validation**:

- ▶ split the data into  $K$  uniformly sized chunks,  $\{C_1, \dots, C_K\}$
- ▶ we create  $K$  number of training/validation splits, using one of the  $K$  chunks for validation and the rest for training.

We fit the model on each training set, denoted  $\hat{f}_{C_{-i}}$ , and evaluate it on the corresponding validation set,  $\hat{f}_{C_{-i}}(C_i)$ . The **cross validation score** is the performance of the model averaged across all validation sets:

$$CV(\text{Model}) = \frac{1}{n} L \left( \hat{f}_{C_{-i}}(C_i) \right),$$

where  $L$  is a loss function.

## Applications of Model Selection

## Predictor Selection: Cross Validation

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Rather than choosing a subset of significant predictors using stepwise selection, we can use  $K$ -fold cross validation:

- ▶ create a collection of different subsets of the predictors
- ▶ for each subset of predictors, compute the cross validation score for the model created using only that subset
- ▶ select the subset (and the corresponding model) with the best cross validation score
- ▶ evaluate the model one last time on the test set

## Degree Selection: Stepwise

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We can frame the problem of degree selection for polynomial models as a predictor selection problem: which of the predictors  $\{x, x^2, \dots, x^M\}$  should we select for modeling?

We can apply stepwise selection to determine the optimal subset of predictors.

## Degree Selection: Cross Validation

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We can also select the degree of a polynomial model using  $K$ -fold cross validation.

- ▶ consider a number of different degrees
- ▶ for each degree, compute the cross validation score for a polynomial model of that degree
- ▶ select the degree, and the corresponding model, with the best cross validation score
- ▶ evaluate the model one last time on the test set



## kNN Revisited

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Recall our first simple, intuitive, non-parametric model for regression - the kNN model. We saw that it is vitally important to select an appropriate  $k$  for the data.

If the  $k$  is too small then the model is very sensitive to noise (since a new prediction is based on very few observed neighbors), and if the  $k$  is too large, the model tends towards making constant predictions.

A principled way to choose  $k$  is through  $K$ -fold cross validation.

# A Simple Example

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# Bibliography

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