Notes on Least Squares and Nearest Neighbors

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# Linear Models and Least Squares

The linear model is defined as:

Given a vector of inputs the output is predicted as:

(1)

where is the *intercept* or *bias*. Often, we include a unit constant ‘variable’ additionally in X and include the bias in the vector of the coefficients . Then we can rewrite (1) as :

(2)

where denotes a row vector or matrix transpose ( is a column vector).

Here we are modeling a single output so is a scalar; in general can be a -vector, in which case would be a matrix of coefficients. In the – dimensional input-output space, represents a hyperplane. If the constant is included in , then the hyperplane includes the origin and is a subspace; If not, it is an affine set cutting the -axis at the point . From now we assume that the intercept is included in .

Obviously, is a linear function over the -dimensional space and the gradient is a vector in input space that points in the steepest uphill direction.

Fitting the linear model to a set of training data

Popular method is least squares- we pick the coefficients to minimize the *residual sum of squares (RSS)* as:

(3)

is a quadratic function of the parameters, and hence its minimum always exists, but may not be unique. The solution can be written in matrix notation as:

(4)

where is an matrix with each row an input vector, and is an -vector of the outputs in the training set. Differentiating w.r.t. we get the *normal equations*:

(5)

If is non-singular, then the unique solution is given by:

(6)

and the fitted value at the -th input is .

## Insight in the Optimality of the Linear Regression with an Example

Let us look into a linear model in a classification context. The Figure 1 below shows a scatterplot of the training data.

The data is simulated. The output class variable has the values Blue or Orange and is represented as such on the scatterplot. There are 100 points in each of these two classes. The linear regression model was fit to these data, with the response coded as 0 for Blue and 1 for Orange. The fitted values are converted to a fitted class variable according to the rule

(7)

A graph of a linear regression

Description automatically generated with medium confidence

Figure 1: A classification example in two dimensions. The classes are coded as a binary variable (Blue = 0, Orange = 1), and then fit by linear regression.

The set of points in classified as Orange corresponds to depicted on the Figure 1 above. The two predicted classes are separated by the *decision boundary* , which is linear in this case. We notice that that there are misclassifications on both sides of the decision boundary.

Scenario 1: The training data in each class is generated from bivariate Gaussian distributions with uncorrelated components and different means.

Scenario 2: The training data in each class is generated from a mixture of 10 low-variance Gaussian distributions, with individual means themselves distributed as Gaussian.

*Note*: a mixture of Gaussians is usually described in terms of generative models. First, we generate a discrete variable that determines which of the component Gaussian to use, and then generate an observation from the chosen density.

With Scenario 1 it can be shown that a linear decision boundary is the best one can do, and that the Linear estimate is almost optimal. In the case of tightly clustered Gaussians (Scenario 2) the linear decision boundary is unlikely to be optimal. The optimal decision boundary is heavily nonlinear and disjoint and as such will be much more difficult to obtain.

# Nearest-Neighbor Methods

Nearest-neighbor methods use those observations in the training set closest in input space to to form . Specifically, the k-nearest neighbor fit for is defined as follows:

(8)

where is the neighborhood of defined by the closest points in the training sample. Closeness implies a metric, which for the moment we assume is Euclidean distance.

# References

[1] [The Elements of Statistical Learning; Data Mining, Inference, Prediction, Trevor Hastie, Robert Tibshirani, Jerome Friedman, Second Edition, 2017](https://github.com/dimitarpg13/statistical_learning_and_kernel_methods/blob/main/literature/books/EelementsOfStatisticalLearning_print12.pdf)

# Appendix

## Affine Space

### Informal discussion

Affine space is what is left from vector space after one has forgotten which point is the origin.

Imagine that there are two observers – observer *A* and observer *B*. Observer *A* knows the real origin, but Observer *B* believes that another point is the origin. Two vectors , and , are to be added. Observer *B* believes he has computed the distance but observer A knows better – B has actually computed .

Similarly, observers *A* and *B* may evaluate any linear combination of and or of any finite set of vectors and will generally get different answers. However, if the sum of the coefficients is unit then the observers will arrive at the same answer. Moreover, for any finite number of observers if the sum of the coefficients is unity each of them will come to the same answer.

Origin according to observer B

Origin according to observer A

*according to origin A*

*according to origin B*

according to origin A

*according to origin A*

Figure A.1: origins and vector computations from the perspectives of observer A (red) and observer B (blue)

In the example on Figure A.1 if observer *A* travels to and observer *B* travels using the same route then observer *A* will observe from his frame of reference the following path of observer *B* :

So under the condition all observers who have different frames of reference will describe the same point with the same linear combination despite the different origins. While only observer *A* on the earlier example knows the *linear structure* both observers *A* and *B* know the *affine structure* that is, the values of affine combinations defined as linear combinations in which the sum of the coefficients is unity.

**Definition** *Affine Space*

A set together with a vector space , and a transitive and free action of the additive group of on the set . The elements of the affine space are called points. The vector space is said to be associated with the affine space and its elements are called *translations,* or *free vectors*.

The action in affine space will be denoted as addition and it is a mapping having the following properties:

1) *Right identity*:

, where is the zero vector in

2) *Associativity*:

, (here the last is the addition in )

3) *Free and transitive action*:

, is a bijection

The first two properties are simply defining properties of a (right) group action. The third property characterizes free and transitive actions, and onto character coming from transitivity, and then the injective character follows from the action being free. Forth property follows from 1) and 2)

4) *Existence of one-to-one translations*

the mapping is a bijection

3) is often used in the following equivalent form :

5) *Subtraction*

denoted with such that