

# CISC 271 Class 10

## Design Matrix and Standardized Data

Text Correspondence: ~

*Main Concepts:*

- *Design matrix: gathering data vectors*
- *Zero-mean data: difference from mean*
- *Standard score: multiple of standard deviation*
- *Standardized data: standard score of zero-mean data*

**Sample Problem, Data Analysis:** What is an effective way to prepare a set of data for linear analysis?

One guiding principle of this course can be caricatured as “see a set of vectors, gather them into a matrix”. A caution is that it is often unclear whether an information source, such as a scientific article or a fragment of code, is using the data as column vectors or as rows in a matrix. We must always read a source carefully to determine how the data is represented. For example, the textbook in this course – which is highly regarded – uses one convention whereas MATLAB – which is also highly regarded – uses a different convention.

Here, we will adopt the MATLAB convention. We will interpret the values of independent variables or dependent variables as *columns*, so each column has the same physical dimensions or other semantics. We will interpret a set of such variables as *observations*, so an observation or a “reading” is a matrix row that can have different semantics for each entry.

For example, historical data from Statistics Canada are available that describe basic body measurements such as: gender, weight, height, the ratio of the waist circumference to the hip circumference, and the sum of the measurements of flaps of skin. These measurements are available for multiple years and the age group of the subjects is also known. We might want to interpret these *anthropomorphic* measurements as independent variables, and interpret the age groups and the survey year as dependent variables. To reduce the problem to a single dependent variable, we might try to analyze each year separately. The dependent data could be given numerical labels such as those in Table 10.1.

For the first dependent value, which is ages 6 – 11, the actual mean values are provided in Table 10.2.

Table 10.1: Numerical codes for the dependent variable of age group.

<b>Ages</b>	<b>Code</b>
6 – 11	1
12 – 19	2
20 – 39	3
40 – 59	4
60 – 79	5

Table 10.2: Values of independent variables for Age Group #1. These are statistical means of a sample population that was measured in 2009.

<b>Variable</b>	<b>Value</b>
Gender	Female
Mass	33.15 kg
Height	135.28 cm
Hip circ.	73.3 cm
Waist/hip	0.82
Net skinfold	52.8 mm

In statistics, data analytics, and machine learning, the values of the independent variables are gathered into a data vector that we will write as  $\vec{x}_i$ . For example, we might write the values in Table 10.2 as the data vector

$$\vec{x}_1 = \begin{bmatrix} 33.15 \\ 135.28 \\ 73.3 \\ 0.82 \\ 52.8 \end{bmatrix}$$

There are two immediate problems that we have: how do we gather multiple data vectors into a matrix, and how can we manage the disparate ranges of the values of the data.

## 10.1 Data Matrix and Design Matrix

One common method of linear data analysis of a set of vectors is to use *regression*. Regression is a term from statistics for estimating relationship between a number of independent variables and, for this course, a single dependent variable. One such might be to try to find trends in a population.

A *linear model* for the data postulates that there is a linear relation between the independent data and the dependent data. In its simplest form, we might have four independent scalar values and two dependent values. Instead of stating two equations in two unknowns, we gather the independent data into a matrix  $A$  and the dependent data into a vector  $\vec{c}$ . The linear model for the data is

$$\begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} \approx \begin{bmatrix} c_1 \\ c_2 \end{bmatrix}$$

or  $A\vec{w} \approx \vec{c}$  (10.1)

In Equation 10.1, we will call the matrix  $A$  the *data matrix*. We can represent  $A$  in two ways: as columns, according to the variables, or as rows, according to the *observations*. We already write the  $j^{\text{th}}$  vector as  $\vec{a}_j$ . We will write the  $i^{\text{th}}$  observation as  $\underline{a}_i$ . The matrix  $A$  in Equation 10.1 can thus be written in two ways:

$$A = [\vec{a}_1 \quad \vec{a}_2] \tag{10.2}$$

$$= \begin{bmatrix} \underline{a}_1 \\ \underline{a}_2 \end{bmatrix} \tag{10.3}$$

We can think of the product  $A\vec{w}$  in Equation 10.1 in two ways. The first way of thinking is that the dependent vector  $\vec{c}$  is approximately a linear combination of the columns of  $A$  from Equation 10.2, which is

$$A\vec{w} = [\vec{a}_1 \quad \vec{a}_2] \begin{bmatrix} w_1 \\ w_2 \end{bmatrix} = w_1\vec{a}_1 + w_2\vec{a}_2 \tag{10.4}$$

The second way of thinking is that each dependent value  $c_i$  is approximately a linear combination of the corresponding observation in  $A$ , which is

$$\begin{aligned} \underline{a}_1\vec{w} &\approx c_1 \\ \underline{a}_2\vec{w} &\approx c_2 \end{aligned} \tag{10.5}$$

Mainly, we will use Equation 10.4 to inform us. We will call a linear equation that has the form of Equation 10.1 a *linear regression problem*. The weights  $w_j$  in the weight vector  $\vec{w}$  are the unknowns that we want to find.

We will assume that the observations  $\underline{a}_i$  in  $A$  either exactly determine or over-determine the weight vector  $\vec{w}$ . Mathematically, we will assume that the data matrix  $A$  is full rank, so  $\text{rank}(A) = n$ .

This matrix  $A$  is the data matrix, which addresses the first of our two problems. The second problem – how to manage the disparate ranges of values in data vectors – is addressed by using another concept from statistics.

A *design matrix* for a data matrix  $A$ , usually written as  $X$ , has two important statistical properties. The first property is that each column of the matrix  $X$  has an average value of 0, which is called a *zero-mean* column. The second property is that the standard deviation of the values of a column is 1. These two properties are used to *standardize* data for subsequent processing.

## 10.2 Standardized Data or Z Score

In regression – especially for methods that are developed from a statistical point of view – it is usual practice to use *standard* or standardized data. These are data that have a mean of zero and a variance of one. Historically, the concept seems to have been suggested, at around 1900, by Karl Pearson when he introduced the concept of a probability “ellipsoid”, in which data were scored by their number of standard deviations from the mean in each relevant direction.

We can derive a standardization transformation for a single vector  $\vec{a} \in \mathbb{R}^m$  and then generalize to a matrix of data. Previously, we defined the mean of a vector  $\vec{a}$  as

$$\bar{a} \stackrel{\text{def}}{=} \frac{1}{m} \sum_{i=1}^m a_i \quad (10.6)$$

For a matrix  $A$ , we will define the mean as a “row” matrix, which is called a *1-form*. The entries of the mean 1-form are the means of the columns. We will define the mean of a matrix  $A$ , which is a generalization of Definition 10.6, as

$$\bar{A} \stackrel{\text{def}}{=} [\bar{a}_1 \quad \bar{a}_2 \quad \cdots \quad \bar{a}_n] \quad (10.7)$$

Statistically, the variance of a set of data has two definitions: the *sample* variance and the *population* variance. Here, we will use the sample variance; we will be cautious because other writings and code may explicitly or implicitly use the population variance.

For a vector  $\vec{a}$ , the sample variance is the sum of the squares of the entries of the vector divided by one less than the size of the vector. Using the conventional statistical symbol  $\sigma^2$ , we will define

the sample variance of a vector as

$$\sigma_{\vec{a}}^2 \stackrel{\text{def}}{=} \frac{1}{m-1} \sum_{i=1}^m (a_i - \bar{a})^2 = \frac{\|\vec{a} - \vec{1}\bar{a}\|^2}{m-1} \quad (10.8)$$

We will define the standard-deviation of a matrix  $A$  as a diagonal matrix  $D$ . The  $j^{\text{th}}$  diagonal entry of  $D$  is the sample standard deviation of the  $j^{\text{th}}$  column of  $A$ . The definition of the sample variance of a matrix  $A$ , using Definition 10.8, is

$$D_A \stackrel{\text{def}}{=} \begin{bmatrix} \sigma_{\vec{a}_1} & & & \\ & \sigma_{\vec{a}_2} & & \\ & & \ddots & \\ & & & \sigma_{\vec{a}_n} \end{bmatrix} \quad (10.9)$$

We can use these definitions to concisely state how we will standardize data. Suppose that we are given a regression problem with a matrix of independent data  $A$  and a vector of dependent data  $\vec{c}$ , that is to be approximated as

$$A\vec{w} \approx \vec{c} \quad (10.10)$$

We want to convert Equation 10.10 to a standardized form, which implies that we seek:

- A design matrix  $X$  with columns that are zero-mean and unit variance
- A vector of dependent data  $\vec{y}$  with zero mean and unit variance
- A linear model of the data that is

$$X\vec{u} = \vec{y} \quad (10.11)$$

For the independent data in  $A$ , we must subtract the mean of  $A$  from  $A$  and scale the difference to have a sample variance of one. We must likewise modify the dependent data in  $C$ . These operations can be expressed as

$$\begin{aligned} X &= [A - [\vec{1}\bar{A}]]D_A^{-1} \\ \vec{y} &= [\vec{c} - [\vec{1}\bar{c}]]D_{\vec{c}}^{-1} \end{aligned} \quad (10.12)$$

**Observation: Equation 10.10 and Equation 10.11 solve different problems**

We can explore some effects of using zero-mean data by considering a problem where the sample variances are one, that is, where  $D_A = I$  and  $D_{\vec{c}} = 1$ . For any such unit-variance problem, we would estimate a solution of Equation 10.11 to be the vector  $\hat{u}$ . We would then estimate the

dependent data, which are in the vector  $\vec{c}$  of Equation 10.10, from the zero-mean independent data in the matrix  $X$  as

$$\hat{c} = X\hat{u} + [\vec{1}\bar{y}] \quad (10.13)$$

In general, the solution  $\hat{u}$  of Equation 10.11 is *not* the same as a solution  $\hat{w}$  of Equation 10.10.

Methods that are derived from the statistical point of view generally try to find solutions that are based on standard data, as stated in Equation 10.11. In particular, we generally want to avoid problems where a constant offset term is stated. We can see that the transformation in Equation 10.12 will produce a division by zero when any column of  $A$  is a constant value, because we would be trying to invert a scaling matrix that refers to the variance of the zero vector  $\vec{0}$ .

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Extra Notes

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### Extra Notes: Example of a Standardized Data Vector

Consider the vector  $\vec{a} = \begin{bmatrix} 15 \\ 17 \\ 31 \\ 19 \\ 3 \end{bmatrix}$

The mean value of  $\vec{a}$  is 17, so the zero-mean vector is  $\vec{m} = \begin{bmatrix} -2 \\ 0 \\ 14 \\ 2 \\ -14 \end{bmatrix}$

The variance of  $\vec{a}$  is the sum of the squares of the entries of  $\vec{m}$ , divided by  $(5 - 1) = 4$ , so  $\sigma^2 = 100$  and  $\sigma = 10$ .

The standardization of  $\vec{a}$  is  $\vec{m}$  divided by  $\sigma = 10$ , which is  $\vec{x} = \begin{bmatrix} -0.2 \\ 0.0 \\ 1.4 \\ 0.2 \\ -1.40 \end{bmatrix}$

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End of Extra Notes

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