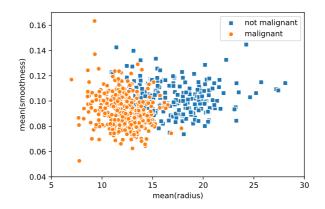
Preprocessing: Normalisation, scaling and categorical data

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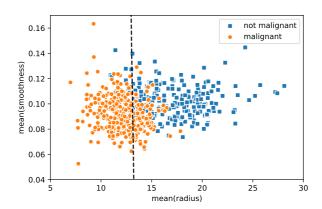
Feature normalisation example

Breast cancer data:1



Gradients on original data (for logistic regression):

Logistic regression on original data:



¹Data from the UCI Machine Learning Repository.

Feature normalisation

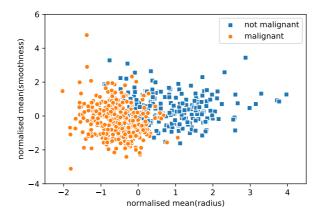
Standardise the means and variances of the data:

$$\tilde{x}_d^{(n)} = \frac{x_d^{(n)} - \hat{\mu}_d}{\hat{\sigma}_d}$$

where $\hat{\mu}_d$ and $\hat{\sigma}_d^2$ are, respectively, the sample mean and variance of the dth feature.

Feature normalisation example

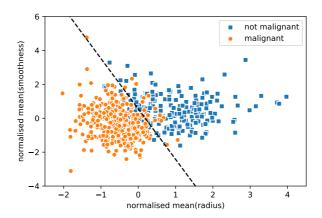
Normalised breast cancer data:



Gradients on normalised data (for logistic regression):

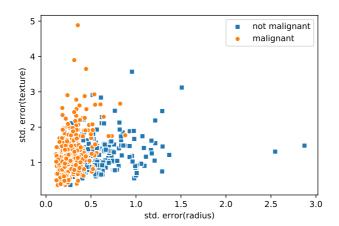
```
w_0 \quad w_1 \quad w_2 Iteration 1000 gradients: [ -0.525 9.179 2.472 ] Iteration 2000 gradients: [ -0.194 3.588 0.990 ] Iteration 3000 gradients: [ -0.096 1.752 0.486 ] Iteration 4000 gradients: [ -0.051 0.928 0.258 ]
```

Logistic regression on normalised data:

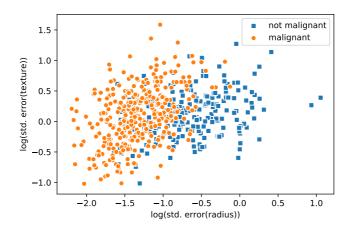


Log scaling example

Unnormalised breast cancer data:



Log-scaled breast cancer data:



Feature normalisation and scaling in practice

Feature normalisation and scaling are often a bit of an art.

You can develop an intuition as you play around with different models and optimisation algorithms.

Note: Always think about how you will apply your model to new unseen data.

Categorical output

In multiclass classification we have categorical output, i.e. $y \in \{1, 2, \dots, K\}$.

We can just save these target values explicitly. E.g. for softmax regression, you can write the loss as:

$$J(\mathbf{W}) = -\sum_{n=1}^{N} \sum_{k=1}^{K} \mathbb{I}\{y^{(n)} = k\} \log f_k(\mathbf{x}^{(n)}; \mathbf{W})$$

Alternatively, we can encode the target output using a one-hot vector:

$$\mathbf{y}^{(n)} = \begin{bmatrix} 0 & 0 & \dots & 0 & 1 & 0 & \dots & 0 \end{bmatrix}^{\mathsf{T}}$$

E.g. for softmax regression, you can write the loss as:

$$J(\mathbf{W}) = -\sum_{n=1}^{N} \sum_{k=1}^{K} y_k^{(n)} \log f_k(\mathbf{x}^{(n)}; \mathbf{W})$$

Note that these two formulations are mathematically exactly equivalent.

Categorical input

We might have inputs that are categorical (also called *discrete* or *qualitative* features).

E.g. someone's occupation might be student, lecturer or artist. How do we represent this?

One option is to create a new feature:

$$x = \begin{cases} 0 & \text{if student} \\ 1 & \text{if lecturer} \\ 2 & \text{if artist} \end{cases}$$

But this implies an ordering, which might not be true. E.g. in the above represtation, artist is closer to lecturer than to student.

Instead use one-hot vector (also called a $\emph{one-of-}K$ vector) to encode input:

Sometimes such a one-hot \mathbf{x} is called a *dummy variable*.

Videos covered in this note

- Preprocessing 1: Feature normalisation and scaling (14 min)
- Preprocessing 2: Categorical features and categorical output (9 min)

Reading

• ISLR 3.3.1