

Homework 1 - Applied Machine Learning

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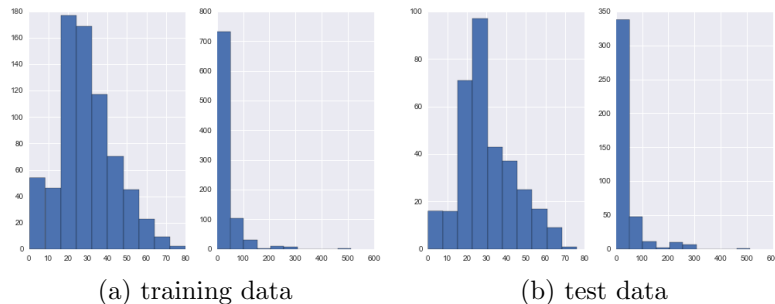


Figure 1: Age (left) and fare (right) distributions

2. Titanic Disaster

For this assignment, we competed in the Titanic dataset challenge on Kaggle. Our goal was to train a logistic regression classifier that uses passenger data, such as age and gender, to predict who survived.

It turns out that the `scikit-learn` package contains a `LogisticRegression` model that we can use for this very purpose. Before we can train such a model, however, we need to clean the data provided by Kaggle, fill in missing values, and select a combination of features for the model to examine.

Preparation of the training and test data occurs within `munge_data()` in the attached code. For the logistic regression training and predicting to work, input data must be numeric, so much of our preparation involves mapping categorical data (i.e. `Sex` and `Port of Embarkation`) to numeric values (`Sex_enum` and `Embarked_enum`).

Next, we fill in missing data - in particular, `Age` and `Fare` - with a dummy value derived from the rest of the dataset. To determine the best dummy values, it is helpful to examine the attached histograms in Figure 1. We see that the distributions of ages and fares are both very skewed, so a median value might be more appropriate than a mean. One sophisticated approach, borrowed from Kaggle's "Getting Started With Python II" guide, is to use the median fare/age for a given gender and passenger's socioeconomic status, which will hopefully better represent typical passengers.

A couple of features in the dataset were ignored, namely `Ticket` and `Cabin`. The difficulty of mapping these categorical values presumably would outweigh any benefit. Additionally, the values for `Cabin` were largely incomplete.

Following the Kaggle article, we constructed two new features from the

2644	new	JianxinDuan	0.75598	3	Fri, 11 Sep 2015 21:22:20 (-1.4h)
2645	new	Sam Raudabaugh	0.75598	3	Sun, 13 Sep 2015 19:30:29 (-1.6h)
2646	new	OlgaSergeyevna	0.75598	3	Sun, 13 Sep 2015 19:17:01

Figure 2: Kaggle result for Titanic challenge

dataset: `FamilySize`, obtained simply by adding together the number of siblings, spouses, parents and children aboard, and `Age*Class`, obtained by multiplying age by the passenger’s socioeconomic status (1 for upper class, 2 for middle class, 3 for lower class), since both older and lower class passengers had a lower likelihood of survival.

At each decision step, we test the usefulness of a combination of features with a 10 fold cross-validation technique, which uses the code from Michael Wilber’s lecture working with the `cross_validation` module in `scikit-learn` as a starting point. Using `FamilySize` and `Age*Class` in place of `Age` both produced higher cross-validation scores.

We also experimented with pulling out the titles of each passenger’s name and categorizing them in different ways. The first strategy was a binary approach with only pedestrian and non-pedestrian titles, while the second strategy used 5 title types: pedestrian, honorary, academic, military, or religious. The latter approach resulted in higher cross-validation scores, but neither approach affected the Kaggle test score. For reference, the attached code makes use of the second strategy, defined in `get_title_type()`.

Finally, we ran our solution on the test dataset, submitting the results to Kaggle. We received a score of 0.75598 as shown in Figure 2. For future improvements, experimenting with another model, such as a random forest classifier, is recommended.

Written 1. Variance of a sum

Show $\text{var}[X+Y] = \text{var}[X] + \text{var}[Y] + 2\text{cov}[X,Y]$.

$$\text{var}[X + Y] = \text{cov}[X + Y, X + Y]$$

By definition of covariance:

$$\text{var}[X + Y] = E[(X + Y)(X + Y)] - E[X + Y]E[X + Y]$$

$$\text{var}[X + Y] = E[(X^2 + 2XY + Y^2] - (E[X] + E[Y])(E[X] + E[Y])$$

$$\text{var}[X + Y] = E[X^2] - E[X]E[X] + E[Y^2] - E[Y]E[Y] + E[XY] - E[X]E[Y] + E[XY] - E[X]E[Y]$$

$$\text{var}[X + Y] = \text{cov}[X, X] + \text{cov}[Y, Y] + \text{cov}[X, Y] + \text{cov}[X, Y]$$

$$\text{var}[X + Y] = \text{var}[X] + \text{var}[Y] + 2\text{cov}[X, Y]$$

Written 2. Bayes rule for medical diagnosis

Let D refer to the event that you have the disease, and TP refer to the event that you tested positive. Then:

$$P(D|TP) = \frac{P(D)P(TP|D)}{P(TP)}$$

Given $P(D) = 0.0001$ and $P(TP|D) = 0.99$, we only need to derive $P(TP)$.

$$P(TP) = P(TP|D)P(D) + P(TP|D')P(D')$$

Finally, with $P(TP|D') = 0.01$ and $P(D') = 0.9999$:

$$P(D|TP) = \frac{P(D)P(TP|D)}{P(TP|D)P(D) + P(TP|D')P(D')} = \frac{0.0001*0.99}{0.99*0.0001 + 0.01*0.9999} = 0.0098$$

Written 3a. Derivative of sigmoid function

$$\text{Given } \sigma(a) = \frac{1}{1+e^{-a}} = (1 + e^{-a})^{-1}$$

$$\frac{d\sigma(a)}{da} = -(1 + e^{-a})^{-2} * -e^{-a}$$

$$\frac{d\sigma(a)}{da} = \frac{e^{-a}}{(1+e^{-a})^2}$$

$$\frac{d\sigma(a)}{da} = \frac{1}{1+e^{-a}} \left(\frac{e^{-a}}{1+e^{-a}} \right)$$

$$\frac{d\sigma(a)}{da} = \frac{1}{1+e^{-a}} \left(\frac{1+e^{-a}}{1+e^{-a}} - \frac{1}{1+e^{-a}} \right)$$

$$\frac{d\sigma(a)}{da} = \sigma(a) (1 - \sigma(a))$$