Evaluating a Learning Algorithm

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Contents

I. Evaluating a Hypothesis

- Someway to improve our algorithm:
  - Getting more training examples
  - Trying smaller sets of features
  - Trying additional features
  - Trying polynomial features
  - Increasing or decreasing

After doing the mentioned solution, we can move on to evaluate our new hypothesis.

A hypothesis might have low error for training set but inaccurate in real situation (overfitting). Thus, to evaluate it, we divide the training set to 2 sets: a training set and a test set. Training set ~ 70% and the test set ~30%.

The new procedure using these two sets is: 1. Learn Θ and minimize $J_{train}(\Theta)$ using the training set 2. Compute the test set error $J_{test}(\Theta)$

The test set error

1. For linear regression: $J_{test}(\Theta) = \frac{1}{2m_{test}} \sum_{i=1}^{m_{test}} (h_\Theta(x_{test}^{(i)}) - y_{test}^{(i)})^2$
2. For classification ~ Misclassification error (aka 0/1 misclassification error):

$$err(h_\Theta(x), y) = 1 : if\ h_\Theta(x) >= 0.5\ and\ y = 0\ or\ h_\Theta(x) < 0.5\ and\ y = 1$$

$$err(h_\Theta(x), y) = 0 : otherwise$$

This gives us a binary 0 or 1 error result. The average test error for the test set is:

$$Test\_Error = \frac{1}{m_{test}} \sum_{i=1}^{m_{test}} err(h_\Theta(x_{test}^{(i)}, y_{test}^{(i)}))$$