CV_M9_L01

Logistic Regression Revisited

CS/DSA 5970: Machine Learning Practice

Logistic Regression Review

- Add a sigmoid non-linearity to the end of our linear model
- Sigmoid: output range from 0 to 1
  - Can interpret this as a probability
  - For classification, this can be the probability of being in the positive class
- Prior classification conversation:
  - Used the MSE cost function (mean squared differences between ground truth label and the probability)
  - Problematic because the derivative can become very flat

IPAD_M9_L01

- MSE cost function
- Derivative of MSE wrt a particular weight
  - Show that when output is close to 0 or 1, this derivative becomes zero
  - This is particularly a problem when we are incorrect in our answer: we want to move the coefficients associated with this decision, but we can't make much progress
  - This implies that we must wait a long time to find a solution
- Alternative: pick a new cost function that doesn't have this problem

CV_M9_L02

Log-Likelihood Cost Function

CS/DSA 5970: Machine Learning Practice

Parameter Selection for Likelihood Functions

From statistics:

- Given:
  - A set of samples drawn independently from a distribution
  - A form of distribution from which the samples are drawn (e.g., a Normal distribution)
- Find the "best" parameters that explain the set of samples
  - Typical approach: use a likelihood function

IPAD_M9_L02

- Likelihood function for a single sample (Normal dist)
- Likelihood function for a set of independent samples
- Take the log
- Mention that we can then compute mu and sigma

CV_M9_L03

Log-Likelihood For Classifiers

CS/DSA 5970: Machine Learning Practice

The UNIVERSITY of OKLAHOMA

Log-Likelihood Cost Function

- We can use a similar approach to talking about the “goodness” of a classifier
- The new twist: we now have two classes
  - The classifier should assign a high probability to the positive examples
  - And low probabilities to the negative examples

IPAD_M9_L03b

CV_M9_L04

Example: Logistic Regression

CS/DSA 5970: Machine Learning Practice

Example: Logistic Regression

- SGDClassifier with ‘log’ loss:
  - Logistic regression with log likelihood loss

  (we already played with this class)
- LogisticRegression class:
  - Also uses log likelihood loss
  - Different solver than SGDClassifier

Example: Logistic Regression

Both offer regularization

- L1, L2, Elastic (must pick solver appropriately)

- SGDClassifier with ‘log’ loss:
  - Regularization parameter: alpha
  - Increase value: more regularization
- LogisticRegression class:
  - Regularization parameter: C
  - Increase value: less regularization

Code demo

CV_M9_L05

Multiclass Case: Softmax

CS/DSA 5970: Machine Learning Practice

Softmax

Want to be able to handle K > 2 classes

- So far, the approach has been to create a set of binary classifiers and have them vote
- One vs all: need O(K) classifiers
- One vs one: need O(K^2) classifiers

Softmax

Approach:

- Learned function: output a score for each of K classes
- Use the softmax function to translate the scores into probabilities
- Output:
  - Can look at the probabilities directly
  - Or can pick the class with the highest probability as the predicted class

IPAD_M9_L05

CV_M9_L06

Example: Softmax

CS/DSA 5970: Machine Learning Practice

Example: Softmax

LogisticRegression class:

- Desired output can be an integer, with values encoding different classes
- Internally, the class performs one-hot encoding

Live demo