CS 581 – ADVANCED ARTIFICIAL INTELLIGENCE

TOPIC: LOGISTIC REGRESSION





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LOGISTIC REGRESSION

LOGISTIC REGRESSION

- Learns P(Y|X) directly, without going through P(X|Y) and P(Y)
- Assumes P(Y|X) follows the logistic function

$$P(Y = false \mid X_1, X_2, \dots, X_n) = \frac{1}{1 + e^{w_0 + \sum_{i=1}^n w_i X_i}}$$

$$P(Y = true \mid X_1, X_2, \dots, X_n) = \frac{e^{w_0 + \sum_{i=1}^n w_i X_i}}{1 + e^{w_0 + \sum_{i=1}^n w_i X_i}}$$

• Learning: estimate the weights $w_0, w_1, ..., w_n$

Learning – Parameter Estimation

Maximize (conditional) log-likelihood

$$W \leftarrow \operatorname{argmax}_{W} \prod P(Y[d] \mid X[d])$$

$$W \leftarrow \underset{W}{\operatorname{argmax}} \sum \ln P(Y[d] \mid \boldsymbol{X}[d])$$

4

TAKE DERIVATIVE OF CLL WRT W

• See OneNote

OPTIMIZATION

- No closed-form solution for W
- One solution: gradient ascent
- Good news: log-likelihood for logistic regression is concave

GRADIENT OPTIMIZATION

MOTIVATION

- Maximize / minimize a function f(x)
- Typical approach
 - Take gradient of f(x) wrt x and set it to 0
 - That is, solve $\nabla f(x) = 0$
- What if there is no analytical solution to $\nabla f(x) = 0$?
- One approach is gradient ascent (for maximization of f) and gradient descent (for minimization of f)

GRADIENT ASCENT

- Using the Taylor expansion, a function f(x) can be approximated at around a as
 - $f(x) \approx f(a) + \nabla f(a) * (x a)$

GRADIENT ASCENT

- Find maximum of f(x) where there is no closed form solution
- Start with some initial guess x_0
- While change is not much
 - $x_{i+1} = x_i + \eta * \nabla f(x_i)$
- η is called the learning rate and it is a user specified parameter

LET'S SEE A SIMPLE EXAMPLE

- Maximize $f(x) = -2x^2 + 8x + 10$
- Note that $\nabla f(x) = 0$ has a closed from solution for this example. We'll use this simple example just for illustration purposes

LOGISTIC REGRESSION GRADIENT EXAMPLE

See Jupyter Notebook

REGULARIZATION

REGULARIZATION

- Prefer smaller weights
 - Why?

L_2 REGULARIZATION

- Objective function
 - $W \leftarrow \underset{W}{\operatorname{argmax}} \left(\sum \ln P(Y[d] \mid X[d]) \frac{\lambda}{2} ||W||^2 \right)$
 - Trade-off between fit to the data vs model complexity
- Assuming *n* features
 - $W \leftarrow \underset{W}{\operatorname{argmax}} \left(\sum \ln P(Y[d] \mid X[d]) \frac{\lambda}{2} \sum_{i=1}^{n} w_i^2 \right)$
- Take derivate of the objective function with respect to w_i .
 - See OneNote

L_2 Regularization & Bayesian Estimation

- Unregularized version corresponds to maximum likelihood estimate of the parameters
- Bayesian means we put a prior on what we do not know. Remember $p(\theta)$, $p(\theta|D)$, P(X|D).
- In this case, we put a prior on w. That is, we have a prior distribution p(w).
- L₂ regularization corresponds to
 - p(w) is a Gaussian distribution with zero mean and variance related to $1/\lambda$, and
 - Taking the maximum of the posterior

L_1 REGULARIZATION

- Instead of a quadratic penalty, absolute value is used
- Assuming *n* features
 - $W \leftarrow \underset{W}{\operatorname{argmax}}(\sum \ln P(Y[d] \mid X[d] \beta \sum_{i=1}^{n} |w_i|)$
- In the Bayesian case, p(w) is assumed to be not a Gaussian distribution but instead a Laplace distribution

L_2 VS L_1

- \circ L_2 forces the large weights to get closer to zero and places an emphasis on the large weights
 - Even though the weights get closer to zero, they are often not zero
- \circ L_1 also penalizes large weights but the emphasis is not necessarily on the large weights
 - Some of the weights become zero
 - Leads to sparser representation

CATEGORICAL FEATURES

- Logistic regression's parameters are feature weights
 - Hence, features need to have values that can be multiplied by a weight
- What if you have a binary feature?
 - Two choices: 0/1, or -1/+1.
- What if you have a categorical features that has more than two possible values, such as R, G, B?
 - Incorrect way: R=1, G=2, B=3. Why?
 - How should we handle these features?

REFERENCES

- http://www.cs.cmu.edu/~tom/mlbook/NBayesLog
 Reg.pdf
- https://scikit-learn.org/stable/modules/linear_model.html#logis-tic-regression