

MACHINE LEARNING APPLIED TO THE ONE- AND TWO DIMENSIONAL ISING MODEL.

FYS-STK4155: PROJECT 2

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 github.com/mortele/FYS-STK4155

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Abstract

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INTRODUCTION

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trevor2009elements

THEORY

In the following we outline the theory of the present work. We consider logistic regression as a model for classification problems. Furthermore, neural networks are discussed both in the context of regression analysis and classification. The theoretical aspects of linear regression have been discussed in previous work and is not re-

peated here.

In contrast to the linear regression model, we can not find the optimal parameters of the logistic or neural network models analytically. Thus, we have to rely on numerical methods for optimization. In particular we will give a brief summary gradient descent methods.

Logistic regression

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Neural networks

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Gradient Descent

Almost every problem in machine learning and data science starts with a dataset X , a model $g(\theta)$, which is a function of the parameters θ and a cost function $C(X, g(\theta))$ that allows us to judge how well the model $g(\theta)$ explains the observations X . The model is fit by finding the values of θ that minimize the cost function. Ideally we would be able to solve for θ analytically, however this is not possible in general and we must use numerical methods to compute the minimum.

The method of steepest descent

The basic idea of gradient descent is that a function $F(\mathbf{x})$, $\mathbf{x} \equiv (x_1, \dots, x_n)$, decreases fastest if one goes from \mathbf{x} in the direction of the negative gradient $-\nabla F(\mathbf{x})$. It can be shown that if

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \gamma_k \nabla F(\mathbf{x}_k), \quad \gamma_k > 0 \quad (1)$$

for γ_k small enough, then $F(\mathbf{x}_{k+1}) \leq F(\mathbf{x}_k)$. This means that for a sufficiently small γ_k we are always moving towards smaller function values, i.e a minimum.

This observation is the basis of the method of steepest descent, which is also referred to as just gradient descent (GD). One starts with an initial guess \mathbf{x}_0 for a minimum of F and compute new approximations according to

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \gamma_k \nabla F(\mathbf{x}_k), \quad k \geq 0. \quad (2)$$

The parameter γ_k is often referred to as the step length or the learning rate in the context of ML.

Ideally the sequence $\{\mathbf{x}_k\}_{k=0}$ converges to a *global* minimum of the function F . In general we do not know if we are in a global or local minimum. In the special case when F is a *convex function*, all local minima are also global minima, so in this case gradient descent can converge to the global solution. The advantage of this scheme is that it is conceptually simple and straightforward to implement.

However the method in this form has some severe limitations:

- In machine learning we are often faced with non-convex high dimensional cost functions with many local minimum. Since GD is deterministic we will get stuck in a local minimum, if the method converges, unless we have a very good initial guess. This also implies that the scheme is sensitive to the chosen initial condition.
- Note that gradient is a function of $\mathbf{x} = (x_1, \dots, x_n)$ which makes it expensive to compute numerically.
- GD is sensitive to the choice of learning rate γ_k . This is due to the fact that we are only guaranteed that $F(\mathbf{x}_{k+1}) \leq F(\mathbf{x}_k)$ for *sufficiently* small γ_k . The problem is to determine an optimal learning rate. If the learning rate is chosen too small the method will take a long time to converge and if it is too large we can experience erratic behavior.

- Many of these shortcomings can be alleviated by introducing randomness. One such method is that of Stochastic Gradient Descent (SGD).

Stochastic Gradient Descent

Stochastic gradient descent (SGD) and variants thereof address some of the shortcomings of the Gradient descent method discussed above.

The underlying idea of SGD comes from the observation that the cost function, which we want to minimize, can almost always be written as a sum over n datapoints $\{\mathbf{x}_i\}_{i=1}^n$,

$$C(\theta) = \sum_{i=1}^n c_i(\mathbf{x}_i, \theta). \quad (3)$$

This in turn means that the gradient can be computed as a sum over i -gradients

$$\nabla_{\theta} C(\theta) = \sum_i^n \nabla_{\theta} c_i(\mathbf{x}_i, \theta). \quad (4)$$

Now, stochasticity/randomness is introduced by only taking the gradient on a subset of the data called minibatches. If there are n datapoints and the size of each minibatch is M , there will be n/M minibatches. We denote these minibatches by B_k where $k = 1, \dots, n/M$.

As an example, suppose we have 10 datapoints $(\mathbf{x}_1, \dots, \mathbf{x}_{10})$ and we choose to have $M = 5$ minibatches, then each minibatch contains two datapoints. In particular we have $B_1 = (\mathbf{x}_1, \mathbf{x}_2), \dots, B_5 = (\mathbf{x}_9, \mathbf{x}_{10})$. Note that if you choose $M = 1$ you have only a single batch with all datapoints and on the other extreme, you may choose $M = n$ resulting in a minibatch for each datapoint, i.e $B_k = \mathbf{x}_k$.

The idea is now to approximate the gradient by replacing the sum over all datapoints with a sum over the datapoints in one the minibatches picked at random in each gradient descent step

$$\begin{aligned} \nabla_{\theta} C(\theta) &= \sum_{i=1}^n \nabla_{\theta} c_i(\mathbf{x}_i, \theta) \\ &\rightarrow \sum_{i \in B_k}^n \nabla_{\theta} c_i(\mathbf{x}_i, \theta). \end{aligned} \quad (5)$$

Thus a gradient descent step now looks like

$$\theta_{j+1} = \theta_j - \gamma_j \sum_{i \in B_k}^n \nabla_{\theta} c_i(\mathbf{x}_i, \theta) \quad (6)$$

where k is picked at random with equal probability from the interval $[1, n/M]$. An iteration over the number of minibatches n/M is commonly referred to as an epoch. Thus it is typical to choose a number of epochs and for each epoch iterate over the number of minibatches.

Taking the gradient only on a subset of the data has two important benefits. First, it introduces randomness which decreases the chance that our optimization scheme gets stuck in a local minima. Second, if the size of the minibatches are small relative to the number of datapoints ($M < n$), the computation of the gradient is much cheaper since we sum over the datapoints in the k -th minibatch and not all n datapoints.

A natural question is when do we stop the search for a new minimum? One possibility is to compute the full gradient after a given number of epochs and check if the norm of the gradient is smaller than some threshold and stop if true. However, the condition that the gradient is zero is valid also for local minima, so this would only tell us that we are close to a local/global minimum. However, we could also evaluate the cost function at this point, store the result and continue the search. If the test kicks in at a later stage we can compare the values of the cost function and keep the θ that gave the lowest value.

Another approach is to let the step length γ_j depend on the number of epochs in such a way that it becomes very small after a reasonable time such that we do not move at all.

As an example, let $e = 0, 1, 2, 3, \dots$ denote the current epoch and let $t_0, t_1 > 0$ be two fixed numbers. Furthermore, let $t = e \cdot m + i$ where m is the number of minibatches and $i = 0, \dots, m - 1$. Then the function

$$\gamma_j(t; t_0, t_1) = \frac{t_0}{t + t_1} \quad (7)$$

goes to zero as the number of epochs gets large. I.e. we start with a step length $\gamma_j(0; t_0, t_1) = t_0/t_1$ which decays in "time" t .

In this way we can fix the number of epochs, compute θ and evaluate the cost function at the end. Repeating the computation will give a different result since the scheme is random by design. Then we pick the final θ that gives the lowest value of the cost function.

MODEL SYSTEMS

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The one-dimensional Ising model

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The two-dimensional Ising model

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RESULTS AND DISCUSSION

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Learning the one-dimensional Ising Hamiltonian

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Classifying phases of the two-dimensional Ising model

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CONCLUSION

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