OLS

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***Abstract*—Implementation of linear regression using the closed form and the gradient descent solutions. Incorporate the ridge regularization from scratch and used the lasso implementation from scikit-learn [1].**

I. Introduction

This demo file is intended to serve as a "starter file" for IEEE conference papers produced under LaTeX using IEEEtran.cls version 1.8a and later. I wish you the best of success.

II. Implementation of OLS

$$Y = X\beta + \epsilon \tag{1}$$

A. Closed Form

With the traditional assumption of $X^T\epsilon = 0$ [**?**], i.e. that the error is uncorrelated with the matrix X, it is easy to solve for the weights, the resulting equation is given by

$$\begin{aligned} Y &= X\beta + \epsilon && (2)\\ X^TY &= X^TX\beta + X^T\epsilon && (3)\\ \hat{\beta} &= (X^TX)^{-1}X^TY && (4)\\ & && (5) \end{aligned}$$

B. Gradient Descent

It is computationally inefficient to invert large matrices such as the one provided for this exercise. It is more efficient to minimize the sum of squares $SSR(\beta) = \sum_{i=1}^{n}(Y - X\beta)^2$. We need to take the derivative to

$$\frac{\partial SSR(\beta)}{\partial \beta} = -2X^T(Y - X\beta) \tag{6}$$

cite Joelle's slides lecture 2

if $i \geq maxval$ **then**
  $i \leftarrow 0$
else
  if $i + k \leq maxval$ **then**
    $i \leftarrow i + k$
  end if
end if

C. Lasso and Ridge Regularization

To be able to generalize well to new data, we want to avoid over fitting. To do so we will penalize extreme weights for our β

Talk about Occam's razor

if $i \geq maxval$ **then**
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else
  if $i + k \leq maxval$ **then**
    $i \leftarrow i + k$
  end if
end if

III. Results

IV. Complementary Dataset

V. Conclusion

The conclusion goes here.

Acknowledgment

The authors would like to thank...

References

[1] F. Pedregosa, G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay, "Scikit-learn: Machine learning in Python," *Journal of Machine Learning Research*, vol. 12, pp. 2825–2830, 2011.