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3 Regression

3. (15 points) (a) Reggie heard about standardizing features for classification and thought they'd try it for regression, too. Reggie has a one-dimensional linear regression data set (so d=1) and so they decide to compute the transform

$$x_r^{(i)} = \frac{x^{(i)} - \mu(X)}{\mathrm{SD}(X)}$$

$$y_r^{(i)} = \frac{y^{(i)} - \mu(Y)}{\mathrm{SD}(Y)}$$

where $\mu(X)$ is the mean, or average, of the data values $x^{(i)}$ and SD(X) is the standard deviation. Then, they perform ordinary least squares regression using the $(x_r^{(i)}, y_r^{(i)})$ data points, and get the parameters θ and θ_0 .

Now they have to perform a transformation on θ and θ_0 to obtain the θ^* , θ_0^* that solve the original problem (that is, so that it will work correctly on the original $(x^{(i)}, y^{(i)})$ data). Write an expression for θ^* in terms of X, $\mu(X)$, SD(X), Y, $\mu(Y)$, SD(Y), θ and θ_0 .

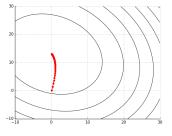
Name:	

(b) Reggie ran ridge regression using several different parameter settings, but scrambled the graphs! The dimension of the data is d=1, so there are two parameters, θ and θ_0 , which are the axes of the graphs. The contour lines indicate the value of the overall objective J, and the connected points indicate the trajectory of the (θ, θ_0) values during the process of gradient update. It always starts near (0,0), with θ plotted on the x axis and θ_0 on the y axis.

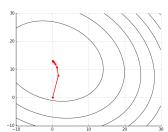
Which graph corresponds to which parameter settings?

• Step size: 0.05, 0.3, 0.7

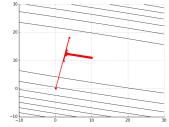
• lambda: 0.0, 1.0



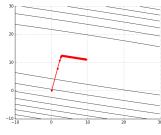
step size: _____lambda: _____



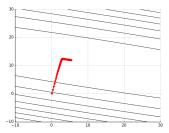
step size: _____lambda: _____



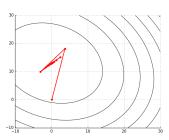
step size: _____lambda: _____



step size: _____lambda: _____



step size:_____lambda: _____



step size: _____lambda: _____

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valle.	

(c) We are considering formulating our machine-learning problem as an optimization problem with the following objective function

$$J(\theta) = \sum_{i=1}^{n} (\theta^{T} x^{(i)} - y^{(i)})^{2} + \lambda R(\theta) ,$$

but we are not sure what regularizer R to use. For each of the possible choices listed below, answer the questions.

i. $R(\theta) = \sum_{j=1}^{d} \theta_j$

Is this equivalent to ridge regression? () Yes () No Is this a reasonable choice for a regularizer? \bigcirc Yes \bigcirc No

ii. $R(\theta) = \sum_{j=1}^{d} |\theta_j|$ Is this equivalent to ridge regression? \bigcirc Yes \bigcirc No Is this a reasonable choice for a regularizer? O Yes O No

iii. $R(\theta) = \sum_{j=1}^d \theta_j^2$ Is this equivalent to ridge regression? \bigcirc Yes \bigcirc No Is this a reasonable choice for a regularizer? O Yes O No

iv. $R(\theta) = \sum_{j=1}^d \theta_j^3$ Is this equivalent to ridge regression? \bigcirc Yes \bigcirc No Is this a reasonable choice for a regularizer? O Yes O No

v. $R(\theta) = \theta^T \theta$

Is this equivalent to ridge regression? O Yes O No Is this a reasonable choice for a regularizer? O Yes O No