Tuning Parameter Selection based on Validation-Error Descent

Abstract

In high-dimensional and/or non-parametric regression problems, regularization (or penalization) is used to control model complexity and induce desired structure. Each penalty has a weight parameter that indicates how strongly the structure corresponding to that penalty should be enforced. To date, for problems with $k = 2$ or more penalties, tuning these penalty parameters is a challenge. The current gold-standard of calculating validation error over a k-dimensional grid of parameter values quickly becomes computationally intractable as k increases. We propose tuning parameters by solving a continuous optimization problem over a validation set and updating the values using a descent-based approach. We show that our method is significantly more efficient than calculating validation error over an entire grid, and empirically achieves the same performance (on scenarios where a grid search could be performed). This descent-based approach enables us to test regularization problems with many penalty parameters, through which we discover new regularization methods with superior accuracy. We also include simulated experiments, and a data analysis, which illustrate the strength of this new method.

Keywords: regularization, high-dimensional regression, cross-validation, optimization

1 Introduction

Consider the usual regression framework with p features, $\boldsymbol{x}_i = (x_{i1}, \ldots, x_{ip})^\top$, and a response y_i measured on each of $i = 1, \ldots, n$ observations. Let $\boldsymbol{X}$ denote the $n \times p$ design matrix and $\boldsymbol{y}$ the response vector. Our goal here is to characterize the conditional relationship between $\boldsymbol{y}$ and $\boldsymbol{X}$. In simple low-dimensional problems this is often done by constructing an f in some pre-specified class $\mathcal{F}$ that minimizes a measure of discrepancy between $\boldsymbol{y}$ and $f(\boldsymbol{X})$. Generally, this discrepancy is quantified with some pre-specified loss, L. Often $\mathcal{F}$ will endow f with some simple form (e.g. a linear function). For ill-posed or high-dimensional problems ($p \gg n$), there can often be an infinite number of solutions that minimize the loss function L but have high generalization error. A common solution is to use regularization, or penalization, to select models with desirable properties, such as smoothness and sparsity.

In recent years, there has been much interest in combining regularization methods to produce models with multiple desired characteristics. Examples include the elastic net (Zou & Hastie 2003), which combines the lasso and ridge penalties, and the sparse group lasso (Simon et al. 2013), which combines the group lasso and lasso penalties. The general form of these regression problems is:

$$\hat{f}(\boldsymbol{\lambda}) = \arg\min_{f \in \mathcal{F}} L\left(\boldsymbol{y}, f(\boldsymbol{X})\right) + \sum_{i=1}^{J} \lambda_i P_i(f) \tag{1}$$

where $\{P_i\}_{i=1,\ldots,J}$ are the penalty functions and $\boldsymbol{\lambda} = (\lambda_1, \ldots, \lambda_J)^\top$ are the regularization parameters.

Regularization parameters control the degree of various facets of model complexity, such as the amount of sparsity or smoothness. Often, the goal is to set the parameters to minimize the fitted model's generalization error. One usually estimates this using a training/validation approach (or cross validation). There one fits a model on a training set $(\boldsymbol{X}_T, \boldsymbol{y}_T)$ and measures the model's error on a validation set $(\boldsymbol{X}_V, \boldsymbol{y}_V)$. The goal then is to choose penalty parameters $\boldsymbol{\lambda}$ that minimize the validation error, as formulated in the following optimization problem:

$$\begin{aligned} &\min_{\boldsymbol{\lambda} \in \Lambda} L\left(\boldsymbol{y}_V, \hat{f}(\boldsymbol{X}_V | \boldsymbol{\lambda})\right) \\ \text{s.t. } &\hat{f}(\cdot | \boldsymbol{\lambda}) = \arg\min_{f \in \mathcal{F}} L\left(\boldsymbol{y}_T, f(\boldsymbol{X}_T)\right) + \sum_{i=1}^{J} \lambda_i P_i(f) \end{aligned} \tag{2}$$

Here Λ is some set that $\boldsymbol{\lambda}$ are known to be in, which is often just $\mathbb{R}_+^J$.

The simplest approach to solving (2) is brute force: one fits models over a grid of parameter values and selects the model with the lowest validation error. As long as the grid is large and fine enough, this method of "grid search" will find a solution close to the global optimum. This approach is the current standard for choosing penalty parameters via training/validation. Unfortunately, it is computationally intractable in cases with more than two parameters since the runtime is exponential in the number of parameters. For certain special cases, there are more efficient ways of tuning the parameters (Golub et al. 1979), (Wood 2000), but there is no general solution to date.

In this paper, we propose leveraging the tools of optimization to solve (2). We give a gradient descent algorithm for minimizing the validation error over the penalty parameter space. In contrast to an exhaustive "grid search", this "descent-based" optimization makes use of the smoothness of our validation-error surface. (2) is generally not convex and thus we may not find the global minimum with a simple descent-based approach. However, in practice we find that simple descent gives competitive solutions.

In simulation studies we show that our descent-based optimization produces solutions with the same validation error as those from grid search. In addition, we find that our approach is highly efficient and can solve regressions with hundreds of penalty parameters. Finally, we use this method to analyze regularization methods that were previously computationally intractable. Through this, we discover that a variant of sparse group lasso with many more penalty parameters can significantly decrease error and produce more meaningful models.

Lorbert & Ramadge (2010) presented some related work on this topic. They solved linear regression problems by updating regression coefficients and regularization parameters using cyclical coordinate gradient descent. We take a more general approach that allows us to apply this descent-based optimization to a wide array of problems. We present examples in this paper that demonstrate the wide applicability of our method.

In Section 2, we describe descent-based optimization in detail and present an algorithm for solving it in example regressions. In Section 3, we show that our method achieves validation errors as low as those achieved by grid search. In Section 3, we explore variants of the example regression problems that have many more regularization parameters and demonstrate that

solving (2) is still computationally tractable. Finally, we present results on data predicting colitis status from gene expression in Section 5.

2 Descent-based Joint Optimization

2.1 Definition

In this manuscript we will restrict ourselves to classes $\mathcal{F} = \{f_{\boldsymbol{\theta}} | \boldsymbol{\theta} \in \Theta\}$, which, for a fixed sample size n, are in some finite dimensional space Θ. This is not a large restriction: the class of linear functions functions meets this requirement; as does any class of finite dimensional parametric functions. Even non-parametric methods generally either use a growing basis expansion (e.g. Polynomial regression, smoothing-splines, wavelet-based-regression, locally-adaptive regression splines (Tsybakov 2008), (Wahba 1981), (Donoho & Johnstone 1994), (Mammen et al. 1997)), or only evaluate the function at the observed data-points (eg. trend filtering, fused lasso, (Kim et al. 2009), (Tibshirani et al. 2005)). In these non-parametric problems, for any fixed n, $\mathcal{F}$ is representable as a finite dimensional class. We can therefore rewrite (1) in the following form:

$$\arg\min_{\boldsymbol{\theta} \in \Theta} L(\boldsymbol{y}, f_{\boldsymbol{\theta}}(\boldsymbol{X})) + \sum_{i=1}^{J} \lambda_i P_i(\boldsymbol{\theta}) \tag{3}$$

Suppose that we use a training/validation split to select penalty parameters $\boldsymbol{\lambda} = (\lambda_1, ..., \lambda_J)^\top$. Let the data be partitioned into a training set $(\boldsymbol{y}_T, \boldsymbol{X}_T)$ and validation set $(\boldsymbol{y}_V, \boldsymbol{X}_V)$. We can rewrite the joint optimization problem (2) over this finite-dimensional class as:

$$\begin{aligned} &\arg\min_{\boldsymbol{\lambda} \in \Lambda} L(\boldsymbol{y}_V, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})}(\boldsymbol{X}_V)) \\ &\text{s.t. } \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}) = \arg\min_{\boldsymbol{\theta} \in \Theta} L(\boldsymbol{y}_T, f_{\boldsymbol{\theta}}(\boldsymbol{X}_T)) + \sum_{i=1}^{J} \lambda_i P_i(\boldsymbol{\theta}) \end{aligned} \tag{4}$$

For the remainder of the manuscript we will assume that (3) for the training set is strictly convex in $\boldsymbol{\theta}$. This ensures that there is a unique $\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$ which perturbs continuously in $\boldsymbol{\lambda}$.

(4) is the explicit, though often unstated, criterion that training/validation methods attempt to minimize when choosing penalty parameters. The current standard is to minimize this using an exhaustive grid search. Grid-based methods solve the joint optimization

problem by fitting models over a J-dimensional grid in the penalty parameter space; so the computational runtime grows exponentially with the number of penalty parameters. While the approach is simple and powerful for a single penalty parameter, optimizing even moderate-dimensional functions (3+) via exhaustive grid search is inefficient (and quickly becomes completely intractable). In addition, (4) is generally a continuous, piecewise-smooth problem. An exhaustive search ignores information available from the smoothness of the surface.

We propose solving (4) by using the tools of smooth optimization. In particular we discuss iterative methods, based on walking in a descent direction until convergence to a local minimum. In the simple case where the criterion is differentiable with respect to the penalty parameters, it is straightforward to use gradient descent or some variant thereof. We show that, with some slight tweaks, gradient descent can be also applied in situations where the penalty is only differentiable in certain directions.

Figure 1 illustrates the difference between these two approaches. Grid search fits a model at every grid point, many of which are not close to the global (or local) minima. In contrast, descent-based methods incorporate information about the shape of the local neighborhood to choose an intelligent descent direction. It explores the space more efficiently since it avoids penalty parameter values unlikely to yield good models.

To ease exposition, we will assume throughout the remainder of the manuscript that $L\left(\boldsymbol{y}_V, f_{\boldsymbol{\theta}}(\boldsymbol{X}_V)\right)$ is differentiable in $\boldsymbol{\theta}$. This assumption is met if both 1) $f_{\boldsymbol{\theta}}(\boldsymbol{X}_V)$ is continuous as a function of $\boldsymbol{\theta}$; and 2) $L\left(\boldsymbol{y}_V, \cdot\right)$ is smooth. Examples include the squared-error, logistic, and poisson loss functions, though not the hinge loss.

2.2 Smooth Training Criterion

Let us denote the training criterion as follows

$$L_T\left(\boldsymbol{\theta}, \boldsymbol{\lambda}\right) \equiv L(\boldsymbol{y}_T, f_{\boldsymbol{\theta}}(\boldsymbol{X}_T)) + \sum_{i=1}^{J} \lambda_i P_i(\boldsymbol{\theta}) \tag{5}$$

First we consider the simple case where $L_T\left(\boldsymbol{\theta}, \boldsymbol{\lambda}\right)$ is smooth as a function of $(\boldsymbol{\theta}, \boldsymbol{\lambda})$. In this case, the validation loss is differentiable as a function of $\boldsymbol{\lambda}$. So we can directly apply gradient descent to solve (4), as described in Algorithm 1.

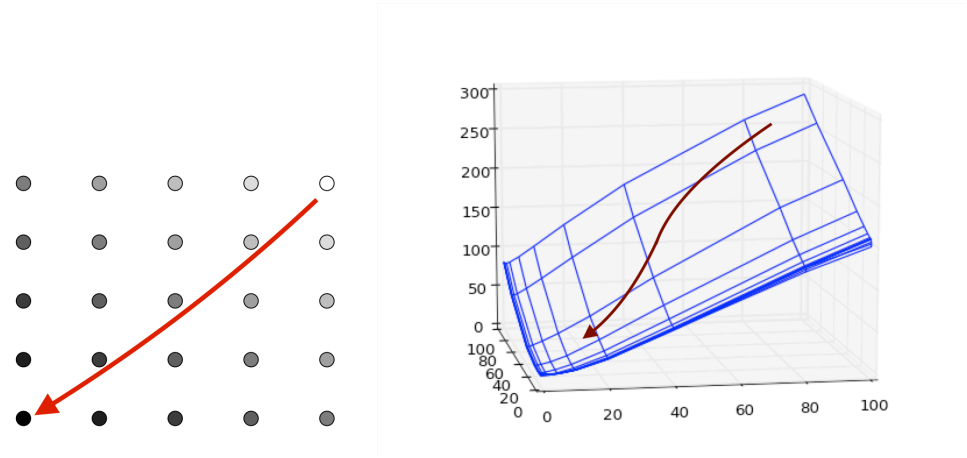


Figure 1: Left: A hypothetical grid of (λ_1, λ_2) points that an exhaustive grid search would fit models for. The darkness of each point indicates the validation cost; dark points mean lower cost. In this example, descent-based optimization would takes steps along the arrow, while a grid search would have to consider all grid points, many of which are obviously poor candidates. Right: The same example with validation loss now on the vertical axis.

Algorithm 1 Gradient Descent for Smooth Training Criterions

Initialize $\boldsymbol{\lambda}^{(0)}$.

for each iteration $k = 0, 1, ...$ until stopping criteria is reached **do**

Perform gradient step with step size $t^{(k)}$

$$\boldsymbol{\lambda}^{(k+1)} := \boldsymbol{\lambda}^{(k)} - t^{(k)} \nabla_{\boldsymbol{\lambda}} L\left(\boldsymbol{y}_V, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})}(\boldsymbol{X}_V)\right)\Big|_{\boldsymbol{\lambda}=\boldsymbol{\lambda}^{(k)}} \tag{6}$$

end for

There are a number of potential ways to choose the step-size $t^{(k)}$. Choice of step-size is discussed further in Section 2.5.

Calculating the Gradient: The gradient can be found using the chain rule:

$$\nabla_{\boldsymbol{\lambda}} L\left(\boldsymbol{y}_V, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})}(\boldsymbol{X}_V)\right) = \left[\frac{\partial}{\partial \boldsymbol{\theta}} L(\boldsymbol{y}_V, f_{\boldsymbol{\theta}}(\boldsymbol{X}_V))\Big|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})}\right]^{\top} \frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}) \tag{7}$$

The first term, $\frac{\partial}{\partial \boldsymbol{\theta}} L(\boldsymbol{y}_V, f_{\boldsymbol{\theta}}(\boldsymbol{X}_V))$, is problem specific, but generally straightforward to calculate. To calculate the second term, $\frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$, we note that $\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$ minimizes (5). Since (5) is smooth,

$$\nabla_\theta \left(L(\boldsymbol{y}_T, f_{\boldsymbol{\theta}}(\boldsymbol{X}_T)) + \sum_{i=1}^{J} \lambda_i P_i(\boldsymbol{\theta}) \right)\Bigg|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})} = \mathbf{0}. \tag{8}$$

Taking the derivative of both sides of (8) in $\boldsymbol{\lambda}$ and solving for $\frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$, we get:

$$\frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}) = - \left[\left[\nabla_\theta^2 \left(L\left(\boldsymbol{y}_T, f_{\boldsymbol{\theta}}(\boldsymbol{X}_T)\right) + \sum_{i=1}^{J} \lambda_i P_i(\boldsymbol{\theta}) \right) \right]^{-1} \nabla_{\boldsymbol{\theta}} P(\boldsymbol{\theta}) \right]\Bigg|_{\boldsymbol{\theta}=\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})} \tag{9}$$

where $\nabla_{\boldsymbol{\theta}} P(\boldsymbol{\theta})$ is the matrix with columns $\{\nabla_{\boldsymbol{\theta}} P_i(\boldsymbol{\theta})\}_{i=1:J}$.

We can plug (9) into (7) to get $\nabla_{\boldsymbol{\lambda}} L\left(\boldsymbol{y}_V, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})}(\boldsymbol{X}_V)\right)$. Note that because $\frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$ is defined in terms of $\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$, each gradient step requires minimizing the training criterion first. The updated version of Algorithm 1 with the specific gradient calculations is given in the Appendix.

2.3 Nonsmooth Training Criterion

When the penalized training criterion in the joint optimization problem is not smooth, gradient descent cannot be applied. Nonetheless, we find that in many problems, the solution $\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$ is smooth at almost every $\boldsymbol{\lambda}$ (eg. Lasso, Group Lasso, Trend Filtering); this means that we can indeed apply gradient descent in practice. In this section, we characterize these problems that are almost everywhere smooth. In addition, we provide a solution for deriving $\frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$ since calculating the gradient is a challenge in and of itself. This is then incorporated into an algorithm for tuning $\boldsymbol{\lambda}$ using gradient descent.

To characterize problems that are almost everywhere smooth, we begin with three definitions:

Definition 1. *The differentiable space of a real-valued function L at a point $\boldsymbol{\eta}$ in its domain is the set of vectors along which the directional derivative of L exists.*

$$\Omega^{L}(\boldsymbol{\eta}) = \left\{ \boldsymbol{u} \middle| \lim_{\epsilon \to 0} \frac{L(\boldsymbol{\eta} + \epsilon \boldsymbol{u}) - L(\boldsymbol{\eta})}{\epsilon} \text{ exists} \right\} \tag{10}$$

Definition 2. *S is a local optimality space for a convex function $L(\cdot, \boldsymbol{\lambda}_0)$ if there exists a neighborhood W containing $\boldsymbol{\lambda}_0$ such that for every $\boldsymbol{\lambda} \in W$,*

$$\arg\min_{\boldsymbol{\theta} \in \Theta} L(\boldsymbol{\theta}, \boldsymbol{\lambda}) = \arg\min_{\boldsymbol{\theta} \in S} L(\boldsymbol{\theta}, \boldsymbol{\lambda}) \tag{11}$$

Definition 3. *Let matrix $\boldsymbol{B} = [\boldsymbol{b}_1 \dots \boldsymbol{b}_p] \in \mathbb{R}^{n \times p}$ have orthonormal columns. Let f be a real-valued function over $\mathbb{R}^n$ and suppose its first and second directional derivatives of f with respect to the columns in $\boldsymbol{B}$ exist. The Gradient vector and Hessian matrix of f with respect to $\boldsymbol{B}$ are defined respectively as*

$$_{\boldsymbol{B}}\nabla f \in \mathbb{R}^p = \begin{pmatrix} \frac{\partial f}{\partial \boldsymbol{b}_1} \\ \frac{\partial f}{\partial \boldsymbol{b}_2} \\ \vdots \\ \frac{\partial f}{\partial \boldsymbol{b}_p} \end{pmatrix}; \quad _{\boldsymbol{B}}\nabla^2 f \in \mathbb{R}^{p \times p} = \begin{pmatrix} \frac{\partial^2 f}{\partial b_1^2} & \frac{\partial^2 f}{\partial b_1 \partial b_2} & \cdots & \frac{\partial^2 f}{\partial b_1 \partial b_p} \\ \frac{\partial^2 f}{\partial b_2 \partial b_1} & \frac{\partial^2 f}{\partial b_2^2} & \cdots & \frac{\partial^2 f}{\partial b_2 \partial b_p} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 f}{\partial b_p \partial b_1} & \frac{\partial^2 f}{\partial b_p \partial b_2} & \cdots & \frac{\partial^2 f}{\partial b_p^2} \end{pmatrix} \tag{12}$$

Using these definitions we can now give three conditions which together are sufficient for the differentiability of $L\left(\boldsymbol{y}_V, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})}(\boldsymbol{X}_V)\right)$ almost everywhere.

Condition 1. *For almost every $\boldsymbol{\lambda}$, the differentiable space $\Omega^{L_T(\cdot,\boldsymbol{\lambda})}(\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}))$ is a local optimality space for $L_T(\cdot, \boldsymbol{\lambda})$.*

Condition 2. *For almost every $\boldsymbol{\lambda}$, $L_T(\cdot, \cdot)$ restricted to $\Omega^{L_T(\cdot,\cdot)}(\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}), \boldsymbol{\lambda})$ is twice continuously differentiable within some neighborhood of $\boldsymbol{\lambda}$.*

Condition 3. *For almost every $\boldsymbol{\lambda}$, there exists an orthonormal basis $\boldsymbol{B}$ of $\Omega^{L_T(\cdot,\boldsymbol{\lambda})}(\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}))$ such that the Hessian of $L_T(\cdot, \boldsymbol{\lambda})$ at $\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$ with respect to $\boldsymbol{B}$ is invertible.*

Note that if condition 3 is satisfied, the Hessian of $L_T(\cdot, \boldsymbol{\lambda})$ with respect to any orthonormal basis of $\Omega^{L_T(\cdot,\boldsymbol{\lambda})}(\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}))$ is invertible.

Putting all these conditions together, the following theorem establishes that the gradient exists almost everywhere and provides a recipe for calculating it.

Theorem 1. *Suppose our optimization problem is of the form in* (4)*, with* $L_T(\boldsymbol{\theta}, \boldsymbol{\lambda})$ *defined as in* (5)*.*

Suppose that $L\Big(\boldsymbol{y}_V, f_{\boldsymbol{\theta}}(\boldsymbol{X}_V)\Big)$ *is continuously differentiable in* $\boldsymbol{\theta}$*, and conditions* 1*,* 2*, and* 3*, defined above, hold.*

Then the validation loss $L(\boldsymbol{y_V}, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})}(\boldsymbol{X_V}))$ *is continuously differentiable with respect to* $\boldsymbol{\lambda}$ *for almost every* $\boldsymbol{\lambda}$*. Furthermore, the gradient of* $L(\boldsymbol{y_V}, f_{\hat{\theta}(\boldsymbol{\lambda})}(\boldsymbol{X_V}))$*, where it is defined, is*

$$\nabla_{\boldsymbol{\lambda}} L\left(\boldsymbol{y_V}, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})}(\boldsymbol{X_V})\right) = \left[\frac{\partial}{\partial \boldsymbol{\theta}} L(\boldsymbol{y_V}, f_{\boldsymbol{\theta}}(\boldsymbol{X_V}))\Big|_{\boldsymbol{\theta}=\tilde{\boldsymbol{\theta}}(\boldsymbol{\lambda})}\right]^{\top} \frac{\partial}{\partial \boldsymbol{\lambda}} \tilde{\boldsymbol{\theta}}(\boldsymbol{\lambda}) \tag{13}$$

where

$$\tilde{\boldsymbol{\theta}}(\boldsymbol{\lambda}) = \underset{\boldsymbol{\theta} \in \Omega^{L_T(\cdot,\boldsymbol{\lambda})}(\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}))}{\arg\min} L_T(\boldsymbol{\theta}, \boldsymbol{\lambda}) \tag{14}$$

We can therefore construct a gradient descent procedure based on the model parameter constraint in (14). At each iteration, let matrix $\boldsymbol{U}$ have orthonormal columns spanning the differentiable space $\Omega^{L_T(\cdot,\boldsymbol{\lambda})}(\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}))$. Since this space is also a local optimality space, it is sufficient to minimize the training criterion over the column space of $\boldsymbol{U}$. The joint optimization problem can be reformulated using $\boldsymbol{U}\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})$ as the model parameters instead:

$$\begin{aligned} &\min_{\boldsymbol{\lambda} \in \Lambda} L(\boldsymbol{y}_V, f_{\boldsymbol{U}\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})}(\boldsymbol{X}_V)) \\ &\text{s.t. } \hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) = \arg\min_{\boldsymbol{\beta}} L(\boldsymbol{y}_T, f_{\boldsymbol{U}\boldsymbol{\beta}}(\boldsymbol{X}_T)) + \sum_{i=1}^{J} \lambda_i P_i(\boldsymbol{U}\boldsymbol{\beta}) \end{aligned} \tag{15}$$

This locally equivalent problem now reduces to the simple case where the training criterion is smooth. As mentioned previously, implicit differentiation on the gradient condition then gives us $\frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})$, which gives us the value of interest

$$\frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}) = \boldsymbol{U} \frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) \tag{16}$$

Note that because the differentiable space is a local optimality space and is thus locally constant, we can treat $\boldsymbol{U}$ as a constant in the gradient derivations. Algorithm 2 provides the exact steps for tuning the regularization parameters.

Thus far, we have restricted our attention to joint optimization for training/validation splits. Refer to the Appendix for how to perform joint optimization for K-fold cross validation.

Algorithm 2 Joint Optimization with Gradient Descent

Initialize $\boldsymbol{\lambda}^{(0)}$.

for each iteration $k = 0, 1, ...$ until stopping criteria is reached **do**

Solve for $\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}^{(k)}) = \arg\min_{\theta\in\Theta} L_T(\boldsymbol{\theta}, \boldsymbol{\lambda}^{(k)})$.

Construct matrix $\boldsymbol{U}^{(k)}$, an orthonormal basis of $\Omega^{L_T(\cdot,\boldsymbol{\lambda})}\left(\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}^{(k)})\right)$.

Define the locally equivalent joint optimization problem

$$\begin{aligned} &\min_{\boldsymbol{\lambda}\in\Lambda} L(\boldsymbol{y}_V, f_{\boldsymbol{U}^{(k)}\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})}(\boldsymbol{X}_V)) \\ \text{s.t. } &\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) = \arg\min_{\boldsymbol{\beta}} L(\boldsymbol{y}_T, f_{\boldsymbol{U}^{(k)}\boldsymbol{\beta}}(\boldsymbol{X}_T)) + \sum_{i=1}^{J} \lambda_i P_i(\boldsymbol{U}^{(k)}\boldsymbol{\beta}) \end{aligned} \tag{17}$$

Calculate $\frac{\partial}{\partial\boldsymbol{\lambda}}\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})|_{\boldsymbol{\lambda}=\boldsymbol{\lambda}^{(k)}}$ where

$$\frac{\partial}{\partial\boldsymbol{\lambda}}\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) = -\left[{}_{\boldsymbol{U}^{(k)}}\nabla^2\left(L(\boldsymbol{y}_T, f_{\boldsymbol{U}^{(k)}\boldsymbol{\beta}}(\boldsymbol{X}_T)) + \sum_{i=1}^{J}\lambda_i P_i(\boldsymbol{U}^{(k)}\boldsymbol{\beta})\right)\Big|_{\boldsymbol{\beta}=\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})}\right]^{-1} {}_{\boldsymbol{U}^{(k)}}\nabla P(\boldsymbol{U}^{(k)}\boldsymbol{\beta})\Big|_{\boldsymbol{\beta}=\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})} \tag{18}$$

with ${}_{\boldsymbol{U}^{(k)}}\nabla^2$ and ${}_{\boldsymbol{U}^{(k)}}\nabla$ are as defined in (12).

Calculate the gradient $\nabla_{\boldsymbol{\lambda}} L(\boldsymbol{y}_{\boldsymbol{V}}, f_{\hat{\theta}(\boldsymbol{\lambda})}(\boldsymbol{X}_{\boldsymbol{V}}))|_{\boldsymbol{\lambda}=\boldsymbol{\lambda}^{(k)}}$ where

$$\nabla_{\boldsymbol{\lambda}} L\left(\boldsymbol{y}_{\boldsymbol{V}}, f_{\hat{\theta}(\boldsymbol{\lambda})}(\boldsymbol{X}_{\boldsymbol{V}})\right) = \left[\boldsymbol{U}^{(k)}\frac{\partial}{\partial\boldsymbol{\lambda}}\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})\right]^{\top}\left[{}_{\boldsymbol{U}^{(k)}}\nabla L\left(\boldsymbol{y}_{\boldsymbol{V}}, f_{\boldsymbol{U}^{(k)}\boldsymbol{\beta}}(\boldsymbol{X}_{\boldsymbol{V}})\right)\big|_{\boldsymbol{\beta}=\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})}\right] \tag{19}$$

Perform the gradient update with step size $t^{(k)}$

$$\boldsymbol{\lambda}^{(k+1)} := \boldsymbol{\lambda}^{(k)} - t^{(k)}\ \nabla_{\boldsymbol{\lambda}} L\left(\boldsymbol{y}_{\boldsymbol{V}}, f_{\hat{\theta}(\boldsymbol{\lambda})}(\boldsymbol{X}_{\boldsymbol{V}})\right)\Big|_{\boldsymbol{\lambda}=\boldsymbol{\lambda}^{(k)}}$$

end for

2.4 Examples

To better understand the proposed gradient descent procedure, we present example joint optimization problems and their corresponding gradient calculations. We start with ridge regression where the training criterion is smooth. Then we consider examples where the training criterions are nonsmooth, but $\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$ is smooth almost everywhere.

For ease of notation, we will let $S_{\boldsymbol{\lambda}}$ denote the differentiable space of $L_T(\cdot, \boldsymbol{\lambda})$ at $\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$. All the example regressions satisfy the conditions in Theorem 1; details are included in the Appendix. Note that in some examples below, we add a ridge penalty with a fixed small coefficient $\epsilon > 0$ to ensure that the training criterion is strictly convex.

2.4.1 Ridge Regression

In ridge regression, the training criterion is smooth so applying gradient descent is straightforward. The joint optimization problem is

$$\begin{gathered} \min_{\lambda \in \mathbb{R}_+} \tfrac{1}{2}\|\boldsymbol{y}_V - \boldsymbol{X}_V \hat{\boldsymbol{\theta}}(\lambda)\|_2^2 \\ \text{where } \hat{\boldsymbol{\theta}}(\lambda) = \arg\min_{\boldsymbol{\theta}} \tfrac{1}{2}\|\boldsymbol{y}_T - \boldsymbol{X}_T \boldsymbol{\theta}\|_2^2 + \tfrac{1}{2}\lambda \|\boldsymbol{\theta}\|_2^2 \end{gathered} \tag{20}$$

The KKT conditions state that $\hat{\boldsymbol{\theta}}(\lambda)$ must satisfy

$$-\boldsymbol{X}_T^\top (\boldsymbol{y}_T - \boldsymbol{X}_T \hat{\boldsymbol{\theta}}(\lambda)) + \lambda \hat{\boldsymbol{\theta}}(\lambda) = 0 \tag{21}$$

The gradient of the validation loss can be easily derived by differentiating the above equation with respect to λ and then using the chain rule.

$$\nabla_{\boldsymbol{\lambda}} L(\boldsymbol{y_V}, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})}(\boldsymbol{X_V})) \;=\; (\boldsymbol{X}_V (\boldsymbol{X}_T^\top \boldsymbol{X}_T + \lambda \boldsymbol{I})^{-1} \hat{\boldsymbol{\theta}}(\lambda))^\top (\boldsymbol{y}_V - \boldsymbol{X}_V \hat{\boldsymbol{\theta}}(\lambda)) \tag{22}$$

2.4.2 Elastic Net

The elastic net (Zou & Hastie 2003), a linear combination of the lasso and ridge penalties, is an example of a regularization method that is not smooth. We are interested in choosing regularization parameters $\boldsymbol{\lambda} = (\lambda_1, \lambda_2)^\top$ using the following joint optimization problem:

$$\begin{gathered} \min_{\boldsymbol{\lambda} \in \mathbb{R}_+^2} \tfrac{1}{2}\|\boldsymbol{y}_V - \boldsymbol{X}_V \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})\|^2 \\ \text{s.t. } \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}) = \arg\min_{\boldsymbol{\theta}} \tfrac{1}{2}\|\boldsymbol{y}_T - \boldsymbol{X}_T \boldsymbol{\theta}\|^2 + \lambda_1 \|\boldsymbol{\theta}\|_1 + \tfrac{1}{2}\lambda_2 \|\boldsymbol{\theta}\|_2^2 \end{gathered} \tag{23}$$

Let the nonzero indices of $\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$ be denoted $I(\boldsymbol{\lambda}) = \{i|\hat{\theta}_i(\boldsymbol{\lambda}) \neq 0 \text{ for } i = 1, ..., p\}$ and let $\boldsymbol{I}_{I(\boldsymbol{\lambda})}$ be a submatrix of the identity matrix with columns $I(\boldsymbol{\lambda})$. Since $|\cdot|$ is not differentiable at zero, the directional derivatives of $||\boldsymbol{\theta}||_1$ only exist along directions spanned by the columns of $\boldsymbol{I}_{I(\boldsymbol{\lambda})}$. That is, the differentiable space at $\boldsymbol{\lambda}$ is $S_{\boldsymbol{\lambda}} = span(\boldsymbol{I}_{I(\boldsymbol{\lambda})})$.

Let $\boldsymbol{X}_{T,I(\boldsymbol{\lambda})} = \boldsymbol{X}_T \boldsymbol{I}_{I(\boldsymbol{\lambda})}$ and $\boldsymbol{X}_{V,I(\boldsymbol{\lambda})} = \boldsymbol{X}_V \boldsymbol{I}_{I(\boldsymbol{\lambda})}$. The locally equivalent joint optimization problem is

$$\begin{aligned} &\min_{\boldsymbol{\lambda} \in \mathbb{R}^2_+} \tfrac{1}{2} \|\boldsymbol{y}_V - \boldsymbol{X}_{V,I(\boldsymbol{\lambda})} \hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})\|^2 \\ \text{s.t. } &\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) = \arg\min_{\boldsymbol{\beta}} \tfrac{1}{2} \|\boldsymbol{y}_T - \boldsymbol{X}_{T,I(\boldsymbol{\lambda})} \boldsymbol{\beta}\|^2 + \lambda_1 \|\boldsymbol{\beta}\|_1 + \tfrac{1}{2} \lambda_2 \|\boldsymbol{\beta}\|_2^2 \end{aligned} \tag{24}$$

To calculate the gradient, we can apply (9) since the training criterion is now smooth

$$\frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) = \left(\boldsymbol{X}_{T,I(\boldsymbol{\lambda})}^\top \boldsymbol{X}_{T,I(\boldsymbol{\lambda})} + \lambda_2 \boldsymbol{I}\right)^{-1} \left[sgn\left(\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})\right) \quad \hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) \right] \tag{25}$$

Hence, the gradient of the validation loss with respect to $\boldsymbol{\lambda}$ is

$$\nabla_{\boldsymbol{\lambda}} L(\boldsymbol{y_V}, f_{\hat{\boldsymbol{\theta}}(\lambda)}(\boldsymbol{X_V})) = \left(\boldsymbol{X}_{V,I(\boldsymbol{\lambda})} \frac{\partial}{\partial \boldsymbol{\lambda}} \hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) \right)^\top \left(\boldsymbol{y}_V - \boldsymbol{X}_{V,I(\boldsymbol{\lambda})} \hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) \right) \tag{26}$$

2.4.3 Sparse Group Lasso

The sparse group lasso combines the $\|\cdot\|_2$ and $\|\cdot\|_1$ penalties, both of which are not smooth (Simon et al. 2013). This method is particularly well-suited for problems where features have a natural grouping, and only a few of the features from a few of the groups are thought to have an effect on response (e.g. genes in gene pathways).

The problem setup is as follows. Given M covariate groups, suppose $\boldsymbol{X}$ and $\boldsymbol{\theta}$ are partitioned into $\boldsymbol{X}^{(m)}$ and $\boldsymbol{\theta}^{(m)}$ for groups $m = 1, ..., M$. We are interested in finding the optimal regularization parameters $\boldsymbol{\lambda} = (\lambda_1, \lambda_2)^\top$. The joint optimization problem is formulated as follows.

$$\begin{aligned} &\min_{\boldsymbol{\lambda} \in \mathbb{R}^2_+} \tfrac{1}{2n} \left\| \boldsymbol{y}_V - \boldsymbol{X}_V \hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}) \right\|_2^2 \\ \text{s.t. } &\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}) = \arg\min_{\boldsymbol{\theta}} \tfrac{1}{2n} \|\boldsymbol{y}_T - \boldsymbol{X}_T \boldsymbol{\theta}\|_2^2 + \lambda_1 \sum_{m=1}^M \|\boldsymbol{\theta}^{(m)}\|_2 + \lambda_2 \|\boldsymbol{\theta}\|_1 + \tfrac{1}{2} \epsilon \|\boldsymbol{\theta}\|_2^2 \end{aligned} \tag{27}$$

Note the addition of a small, fixed ridge penalty to ensure strong convexity. As $\|\cdot\|_2$ (or $|\cdot|$) is not differentiable in any direction at $\mathbf{0}$ (or 0) and is differentiable in all directions elsewhere, it is straightforward to show that $S_{\boldsymbol{\lambda}} = span(\boldsymbol{I}_{I(\boldsymbol{\lambda})})$ where $I(\boldsymbol{\lambda}) = \{i|\hat{\theta}_i(\boldsymbol{\lambda}) \neq 0 \text{ for } i = 1, ..., p\}$ are the nonzero indices of $\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})$.

To calculate the gradient, we define the locally equivalent joint optimization problem, using the same notational shorthand $\boldsymbol{X}_{T,I(\boldsymbol{\lambda})}$ and $\boldsymbol{X}_{V,I(\boldsymbol{\lambda})}$:

$$\begin{aligned} &\min_{\boldsymbol{\lambda}\in\mathbb{R}_+^2} \tfrac{1}{2n}\left\|\boldsymbol{y}_V - \boldsymbol{X}_{V,I(\boldsymbol{\lambda})}\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})\right\|_2^2 \\ \text{s.t. } &\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) = \arg\min_{\boldsymbol{\beta}} \tfrac{1}{2n}\left\|\boldsymbol{y}_T - \boldsymbol{X}_{T,I(\boldsymbol{\lambda})}\boldsymbol{\beta}\right\|_2^2 + \lambda_1 \sum_{m=1}^{M} \|\boldsymbol{\beta}^{(m)}\|_2 + \lambda_2\|\boldsymbol{\beta}\|_1 + \tfrac{1}{2}\epsilon\|\boldsymbol{\beta}\|_2^2 \end{aligned} \tag{28}$$

From (9) and the chain rule, we get that the gradient of the validation loss is:

$$\nabla_{\boldsymbol{\lambda}} L(\boldsymbol{y_V}, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda})}(\boldsymbol{X_V})) = -\frac{1}{n}\left(\boldsymbol{X}_{V,I(\boldsymbol{\lambda})}\frac{\partial}{\partial\boldsymbol{\lambda}}\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})\right)^{\top}\left(\boldsymbol{y}_V - \boldsymbol{X}_{V,I(\boldsymbol{\lambda})}\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})\right) \tag{29}$$

where

$$\frac{\partial}{\partial\boldsymbol{\lambda}}\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) = \left(\frac{1}{n}\boldsymbol{X}_{T,I(\boldsymbol{\lambda})}^{\top}\boldsymbol{X}_{T,I(\boldsymbol{\lambda})} + \lambda_1\boldsymbol{B}(\boldsymbol{\lambda}) + \epsilon\boldsymbol{I}_p\right)^{-1}\begin{bmatrix}\begin{bmatrix}\frac{\hat{\boldsymbol{\beta}}^{(1)}(\boldsymbol{\lambda})}{||\hat{\boldsymbol{\beta}}^{(1)}(\boldsymbol{\lambda})||_2}\\ \dots \\ \frac{\hat{\boldsymbol{\beta}}^{(M)}(\boldsymbol{\lambda})}{||\hat{\boldsymbol{\beta}}^{(M)}(\boldsymbol{\lambda})||_2}\end{bmatrix} & sgn(\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}))\end{bmatrix} \tag{30}$$

2.4.4 Generalized Lasso

The generalized lasso (Roth 2004) penalizes the ℓ_1 norm of the coefficients $\boldsymbol{\theta}$ weighted by some matrix $\boldsymbol{D}$. Depending on the choice of $\boldsymbol{D}$, the generalized lasso induces different structural constraints on the regression coefficients. Special cases include the fused lasso, trend filtering, and wavelet smoothing (Tibshirani et al. 2005), (Kim et al. 2009), (Donoho & Johnstone 1994).

To tune the regularization parameter λ, we formulate the generalized lasso as a joint optimization problem:

$$\begin{aligned} &\min_{\lambda\in\mathbb{R}_+} \tfrac{1}{2}\|\boldsymbol{y}_V - \boldsymbol{X}_V\hat{\boldsymbol{\theta}}(\lambda)\|^2 \\ \text{s.t. } &\hat{\boldsymbol{\theta}}(\lambda) = \arg\min_{\boldsymbol{\theta}\in\mathbb{R}^p} \tfrac{1}{2}\|\boldsymbol{y}_T - \boldsymbol{X}_T\boldsymbol{\theta}\|^2 + \lambda\|\boldsymbol{D}\boldsymbol{\theta}\|_1 + \tfrac{1}{2}\epsilon\|\boldsymbol{\theta}\|_2^2 \end{aligned} \tag{31}$$

Let $I(\lambda)$ denote the indices of the zero elements of $\boldsymbol{D}\hat{\boldsymbol{\theta}}(\lambda)$:

$$I(\lambda) = \left\{i|(\boldsymbol{D}\hat{\boldsymbol{\theta}}(\lambda))_i = 0 \text{ for } i = 1, ..., p\right\} \tag{32}$$

Since $\|\boldsymbol{D}\boldsymbol{\theta}\|_1$ is differentiable in θ only along directions where the current zero elements of $\boldsymbol{D}\boldsymbol{\theta}$ remain zero, the differentiable space S_λ is the null space of $\boldsymbol{I}_{I(\lambda)}^{\top}\boldsymbol{D}$, denoted $\mathcal{N}(\boldsymbol{I}_{I(\lambda)}^{\top}\boldsymbol{D})$. Let $\boldsymbol{U}_\lambda$ be an orthonormal basis for $\mathcal{N}(\boldsymbol{I}_{I(\lambda)}^{\top}\boldsymbol{D})$.

Now we show the gradient calculations. Following Algorithm 2, we first define the locally equivalent joint optimization problem:

$$\begin{aligned} &\min_{\lambda\in\mathbb{R}_+} \tfrac{1}{2}\|\boldsymbol{y}_V - \boldsymbol{X}_V\boldsymbol{U}_\lambda\hat{\boldsymbol{\beta}}(\lambda)\|^2 \\ \text{s.t. } &\hat{\boldsymbol{\beta}}(\lambda) = \arg\min_{\boldsymbol{\beta}} \tfrac{1}{2}\|\boldsymbol{y}_T - \boldsymbol{X}_T\boldsymbol{U}_\lambda\boldsymbol{\beta}\|^2 + \lambda\|\boldsymbol{D}\boldsymbol{U}_\lambda\boldsymbol{\beta}\|_1 + \tfrac{1}{2}\epsilon\|\boldsymbol{U}_\lambda\boldsymbol{\beta}\|_2^2 \end{aligned} \tag{33}$$

Implicit differentiation with respect to λ of the gradient condition for $\hat{\boldsymbol{\beta}}(\lambda)$ gives us

$$\frac{\partial}{\partial\lambda}\hat{\boldsymbol{\beta}}(\lambda) = -(\boldsymbol{U}_\lambda^\top\boldsymbol{X}_T^\top\boldsymbol{X}_T\boldsymbol{U}_\lambda + \epsilon\boldsymbol{U}_\lambda)^{-1}\boldsymbol{U}_\lambda^\top\boldsymbol{D}^\top sgn(\boldsymbol{D}\boldsymbol{U}_\lambda\hat{\boldsymbol{\beta}}(\lambda)) \tag{34}$$

The chain rule then gives the gradient of the validation loss with respect to λ:

$$\nabla_\lambda L(\boldsymbol{y_V}, f_{\hat{\boldsymbol{\theta}}(\lambda)}(\boldsymbol{X_V})) = -\left(\boldsymbol{X}_V\boldsymbol{U}_\lambda\frac{\partial}{\partial\lambda}\hat{\boldsymbol{\beta}}(\lambda)\right)^\top\left(\boldsymbol{y}_V - \boldsymbol{X}_V\boldsymbol{U}_\lambda\hat{\boldsymbol{\beta}}(\lambda)\right) \tag{35}$$

2.4.5 Additive Partially Linear Models

Finally, consider an additive partially linear model (APLM) for response y given covariates $\boldsymbol{x} \in \mathbb{R}^p$ and $\boldsymbol{z} \in \mathbb{R}^q$. For this example of semi-parametric regression, we assume that y is the sum of p univariate functions and a linear function:

$$y = \sum_{i=1}^{p} f_i(x_i) + \boldsymbol{\beta}^\top\boldsymbol{z} + \epsilon \tag{36}$$

As before, we fit the model using least squares. In addition, we induce smoothness in the estimates $\hat{\boldsymbol{\theta}}^{(i)} \in \mathbb{R}^n$ for f_i by penalizing the second-order differences and we induce sparsity in $\hat{\boldsymbol{\beta}}$ by adding a lasso penalty.

To formalize our optimization problem we give a bit of notation. Let $\boldsymbol{Z}_T \in \mathbb{R}^{|T|\times q}, \boldsymbol{Z}_V \in \mathbb{R}^{|V|\times q}$ be the linear covariates from the training and validation sets. Let $\boldsymbol{X} \in \mathbb{R}^{n\times p}$ be the design matrix for the nonlinear covariates where the first $|T|$ observations are from the training set and the last $|V|$ observations are from the validation set. Let $\boldsymbol{I}_T$ and $\boldsymbol{I}_V$ be matrices such that $X_T = I_T X$ and $X_V = I_V X$. We combine the validation and training nonlinear covariates into one design matrix since we use the training data to fit estimates for f_i at the validation points.

The joint optimization problem is

$$\begin{aligned} &\min_{\boldsymbol{\lambda}\in\mathbb{R}_+^{p+1}} \tfrac{1}{2}\left\|\boldsymbol{y}_V - \boldsymbol{Z}_V\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}) - \boldsymbol{I}_V\textstyle\sum_{i=1}^p\hat{\boldsymbol{\theta}}^{(i)}(\boldsymbol{\lambda})\right\|_2^2 \\ \text{s.t. } &\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda}), \hat{\boldsymbol{\theta}}^{(i)}(\boldsymbol{\lambda}) = \arg\min_{\boldsymbol{\beta},\boldsymbol{\theta}} \tfrac{1}{2}\left\|\boldsymbol{y}_T - \boldsymbol{Z}_T\boldsymbol{\beta} - \boldsymbol{I}_T\textstyle\sum_{i=1}^p\boldsymbol{\theta}^{(i)}\right\|_2^2 + \lambda_0\|\boldsymbol{\beta}\|_1 \\ &\quad + \tfrac{1}{2}\textstyle\sum_{i=1}^p\lambda_i\left\|\boldsymbol{D}_{\boldsymbol{x}_i}^{(2)}\boldsymbol{\theta}^{(i)}\right\|_2^2 + \tfrac{1}{2}\epsilon\left(\|\boldsymbol{\beta}\|_2^2 + \textstyle\sum_{i=1}^p\|\boldsymbol{\theta}^{(i)}\|_2^2\right) \end{aligned} \tag{37}$$

The matrix $\boldsymbol{D}^{(2)}_{\boldsymbol{x}_i}$ gives the second-order differences between the nonparametric estimates of f_i for unevenly-spaced inputs. Construction of $\boldsymbol{D}^{(2)}_{\boldsymbol{x}_i}$ is given in the Appendix. Note that we have presented an extremely general form on the training criterion, where there are separate λ_i for $\left\|\boldsymbol{D}^{(2)}_{\boldsymbol{x}_i}\boldsymbol{\theta}^{(i)}\right\|_2^2$. In practice, one would pool λ_i since tuning more than 2 penalty parameters is difficult.

In this example, the lasso is the only penalty which is not everywhere differentiable. Let the nonzero indices of $\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})$ be denoted $I(\boldsymbol{\lambda}) = \{i|\hat{\beta}_i(\boldsymbol{\lambda}) \neq 0 \text{ for } i = 1, ..., p\}$. The differentiable space is then $S_{\boldsymbol{\lambda}} = \boldsymbol{C}(\boldsymbol{I}_{I(\boldsymbol{\lambda})}) \oplus \mathbb{R}^{n\times p}$.

We now calculate the gradient of the validation loss. Given $I(\boldsymbol{\lambda})$, the nonzero set of $\hat{\boldsymbol{\beta}}(\boldsymbol{\lambda})$, the locally equivalent joint optimization problem as

$$\begin{aligned} &\min_{\boldsymbol{\lambda}\in\mathbb{R}^2_+} \tfrac{1}{2}\left\|\boldsymbol{y}_V - \boldsymbol{X}_{V,I(\boldsymbol{\lambda})}\hat{\boldsymbol{\eta}}(\boldsymbol{\lambda}) - \boldsymbol{I}_V\textstyle\sum_{i=1}^p \hat{\boldsymbol{\theta}}^{(i)}(\boldsymbol{\lambda})\right\|_2^2 \\ \text{s.t. } &\hat{\boldsymbol{\eta}}(\boldsymbol{\lambda}), \hat{\boldsymbol{\theta}}^{(i)}(\boldsymbol{\lambda}) = \arg\min_{\boldsymbol{\eta},\boldsymbol{\theta}} \tfrac{1}{2}\left\|\boldsymbol{y}_T - \boldsymbol{X}_{T,I(\boldsymbol{\lambda})}\boldsymbol{\eta} - \boldsymbol{I}_T\textstyle\sum_{i=1}^p \boldsymbol{\theta}^{(i)}\right\|_2^2 \\ &+\lambda_0\|\boldsymbol{\eta}\|_1 + \tfrac{1}{2}\textstyle\sum_{i=1}^p \lambda_i\|\boldsymbol{D}(\boldsymbol{z})\boldsymbol{\theta}^{(i)}\|_2^2 + \tfrac{1}{2}\epsilon\left(\|\boldsymbol{\eta}\|_2^2 + \textstyle\sum_{i=1}^p \|\boldsymbol{\theta}^{(i)}\|_2^2\right) \end{aligned} \tag{38}$$

We follow the same steps as before to calculate the gradient. The gradient is then

$$\nabla_{\lambda_j} L_V(\boldsymbol{\lambda}) = -\left(\boldsymbol{X}_{V,I(\boldsymbol{\lambda})}\frac{\partial}{\partial\lambda_j}\hat{\boldsymbol{\eta}}(\boldsymbol{\lambda}) + \boldsymbol{I}_V\sum_{i=1}^p \frac{\partial}{\partial\lambda_j}\hat{\boldsymbol{\theta}}^{(i)}(\boldsymbol{\lambda})\right)^\top \left(\boldsymbol{y}_V - \boldsymbol{X}_{V,I(\boldsymbol{\lambda})}\hat{\boldsymbol{\eta}}(\boldsymbol{\lambda}) - \boldsymbol{I}_V\sum_{i=1}^p \hat{\boldsymbol{\theta}}^{(i)}(\boldsymbol{\lambda})\right)$$

where

$$\begin{bmatrix} \frac{\partial}{\partial\boldsymbol{\lambda}}\hat{\boldsymbol{\eta}}(\boldsymbol{\lambda}) \\ \frac{\partial}{\partial\boldsymbol{\lambda}}\hat{\boldsymbol{\theta}}^{(1)}(\boldsymbol{\lambda}) \\ ... \\ \frac{\partial}{\partial\boldsymbol{\lambda}}\hat{\boldsymbol{\theta}}^{(p)}(\boldsymbol{\lambda}) \end{bmatrix} = \begin{bmatrix} \frac{\partial}{\partial\boldsymbol{\lambda}_0}\hat{\boldsymbol{\eta}}(\boldsymbol{\lambda}) & ... & \frac{\partial}{\partial\boldsymbol{\lambda}_p}\hat{\boldsymbol{\eta}}(\boldsymbol{\lambda}) \\ \frac{\partial}{\partial\boldsymbol{\lambda}_0}\hat{\boldsymbol{\theta}}^{(1)}(\boldsymbol{\lambda}) & ... & \frac{\partial}{\partial\boldsymbol{\lambda}_p}\hat{\boldsymbol{\theta}}^{(1)}(\boldsymbol{\lambda}) \\ ... & ... & ... \\ \frac{\partial}{\partial\boldsymbol{\lambda}_0}\hat{\boldsymbol{\theta}}^{(p)}(\boldsymbol{\lambda}) & ... & \frac{\partial}{\partial\boldsymbol{\lambda}_p}\hat{\boldsymbol{\theta}}^{(p)}(\boldsymbol{\lambda}) \end{bmatrix} = H^{-1}\begin{bmatrix} sgn\left(\hat{\boldsymbol{\eta}}(\boldsymbol{\lambda})\right) & \boldsymbol{0} & ... & \boldsymbol{0} \\ \boldsymbol{0} & D^T_{x_1}D_{x_1}\hat{\boldsymbol{\theta}}^{(1)}(\boldsymbol{\lambda}) & ... & \boldsymbol{0} \\ ... & ... & ... & ... \\ \boldsymbol{0} & \boldsymbol{0} & ... & D^T_{x_p}D_{x_p}\hat{\boldsymbol{\theta}}^{(p)}(\boldsymbol{\lambda}) \end{bmatrix} \tag{39}$$

The hideous matrix H is given in the appendix.

2.5 Gradient Descent Details

Here we discuss choice of step size and our convergence criterion.

There are many possible choices for our step size sequence $\{t^{(k)}\}$. Popular choices for convex problems are discussed in Boyd & Vandenberghe (2004). We chose a backtracking

line search as discussed in Chapter 9. In our examples initial step size was between 0.5 and 1 and we backtrack with parameters $\alpha = 0.01$ and $\beta \in [0.01, 0.1]$. Details of backtracking line search are given in the Appendix. During gradient descent, it is possible that the step size will result in a negative regularization parameter; we reject any step that would set a regularization parameter to below a minimum threshold of $1e$-10.

Our convergence criterion is based on the change in our validation loss between iterates. More specifically, we stop our algorithm when

$$L\left(\boldsymbol{y}_V, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}^{(k+1)})}(\boldsymbol{X}_V)\right) - L\left(\boldsymbol{y}_V, f_{\hat{\boldsymbol{\theta}}(\boldsymbol{\lambda}^{(k)})}(\boldsymbol{X}_V)\right) \leq \delta$$

for some prespecified tolerance δ. For the results in this manuscript we use $\delta = 1e$-5.

2.6 Accelerated Gradient Descent

We also use a modification of Algorithm 2 based on the work of Nesterov (1983). For smooth convex problems, these "accelerated" algorithms have faster worst-case convergence than gradient descent (while maintaining the same per-iteration complexity). In practice, these accelerated algorithms often vastly improve performance. In particular, we follow the recipe from O'Donoghue & Candes (2013) which performs adaptive restarts whenever the function value increases. As before, we choose step size using backtracking. We present the exact details in Algorithm 3 included in the Appendix.

3 Results: regressions with two penalty parameters

We ran two simulation studies for this paper. The purpose of this first set of simulations is to compare the performance and efficiency of grid-based and descent-based joint optimization across different regularization methods, namely the elastic net, sparse group lasso, and APLM.

The regularization parameters were tuned over a training/validation split. We implemented descent-based joint optimization using two different methods: gradient descent and accelerated gradient descent with adaptive restarts. For both grid search and descent-based joint optimization we fit the model over the training set using the splitting conic solver (SCS) in CVXPY (Diamond & Boyd 2016). We describe the simulation settings below, followed by a discussion of the results.

3.1 Elastic net

We generated thirty datasets, each consisting of 80 training and 20 validation observations with 250 predictors. The $\boldsymbol{x}_i$ were marginally distributed $N(\boldsymbol{0}, \boldsymbol{I})$ with $cor(x_{ij}, x_{ik}) = 0.5^{|j-k|}$. The response vector $\boldsymbol{y}$ was generated by

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \sigma\boldsymbol{\epsilon} \tag{40}$$

where

$$\boldsymbol{\beta} = (\underbrace{1, ..., 1}_{\text{size } 15}, \underbrace{0, ..., 0}_{\text{size } 235}) \tag{41}$$

and $\boldsymbol{\epsilon} \sim N(\boldsymbol{0}, \boldsymbol{I})$. σ was chosen such that the signal to noise ratio is 2.

Both descent-based methods were initialized at (0.01, 0.01) and (10, 10). Grid search was performed over a 10×10 grid from $1e$-5 to four times the largest eigenvalue of $\boldsymbol{X}_T^\top \boldsymbol{X}_T$.

3.2 Sparse group lasso

We generated thirty datasets, each consisting of 60 training and 15 validation observations with 1500 covariates. The predictors X were generated from a standard normal distribution. The response $\boldsymbol{y}$ was generated by

$$\boldsymbol{y} = \sum_{j=1}^{3} \boldsymbol{X}^{(j)}\boldsymbol{\beta}^{(j)} + \sigma\boldsymbol{\epsilon} \tag{42}$$

where $\boldsymbol{\beta}^{(j)} = (1, 2, 3, 4, 5, 0, ..., 0)$ for $j = 1, 2, 3$ and $\boldsymbol{\epsilon} \sim N(\boldsymbol{0}, \boldsymbol{I})$. σ was chosen such that the signal to noise ratio was 2. For the sparse group lasso, we used $M = 150$ covariate groups with 10 covariates each.

Both descent-based methods were initialized at (0.01, 0.01), (1, 1), and (100, 100). Grid search was performed over a 10×10 grid from $1e$-5 to $\max(\{||\boldsymbol{X}^{(j)T}\boldsymbol{y}||_2\}_{j=1,...,m})$.

3.3 Additive partially linear models

We generated thirty datasets, each consisting of 100 training and 25 validation observations with 20 linear predictors and one nonlinear predictor. Linear predictors were generated such

that the first two groups of three features were highly correlated and the rest of the features were generated from a standard normal distribution:

$$\begin{aligned} x_{ij} &= Z_1 + \delta_{ij} \text{ for } j = 1, 2, 3 \\ x_{ij} &= Z_2 + \delta_{ij} \text{ for } j = 4, 5, 6 \\ x_{ij} &\sim N(0, 1) \text{ for } j = 7, ..., 20 \end{aligned} \tag{43}$$

where $Z_1 \sim N(0, 1)$, $Z_2 \sim N(0, 1)$, and $\delta_{ij} \sim N(0, \frac{1}{16})$. Nonlinear predictors $\boldsymbol{z}$ were independently drawn the standard uniform distribution. The response $\boldsymbol{y}$ was generated by

$$\boldsymbol{y} = \boldsymbol{X}\boldsymbol{\beta} + \kappa g(\boldsymbol{z}) + \sigma\boldsymbol{\epsilon} \tag{44}$$

where $\boldsymbol{\beta} = (1, 1, 1, 1, 1, 1, 0, ..., 0)$ and $g(\boldsymbol{z}) = (2 - \boldsymbol{z})\sin(20\boldsymbol{z}^4)$. Constants κ and σ were chosen such that the linear to nonlinear ratio $\frac{||\boldsymbol{X}\boldsymbol{\beta}||_2}{||g(\boldsymbol{z})||_2}$ was 2 and the signal to noise ratio was 2.

Both descent-based methods were initialized at $\lambda_1 = \lambda_2 = 10^i$ for $i = -2, -1, 0, 1$. Grid search was performed over a 10×10 grid from $1e$-6 to 10.

3.4 Discussion of results

As shown in Table 1, the descent-based joint optimization and grid search have the same average performance in all three regression examples. In regards to computational time, descent-based joint optimization is only slightly faster than grid search. So for regressions with one or two regularization parameters, the two methods have the same performance and do not differ much in terms of runtime.

4 Results: regressions with $k \geq 2$ penalty parameters

In this second simulation study we tested descent-based joint optimization on regressions with more than two regularization parameters. We compared the performance of the fitted models from regressions with $k > 2$ penalty terms to that from regressions with $k \leq 2$ penalty terms.

We experimented with generalizations of the simple regressions from the previous section. For the sparse group lasso, we tried an "un-pooled" version in which each covariate group

Elastic Net		
	Validation Error	Runtime (sec)
Grid Search	0.34 (0.003)	10.74
Gradient Descent	0.34 (0.003)	4.43
Nesterov's Gradient Descent	0.34 (0.003)	2.28
Sparse Group Lasso		
	Validation Error	Runtime (sec)
Grid Search	1.36 (0.09)	161.29
Gradient Descent	1.36 (0.09)	71.34
Nesterov's Gradient Descent	1.36 (0.10)	67.10
APLM		
	Validation Error	Runtime (sec)
Grid Search	1.31 (0.05)	27.82
Gradient Descent	1.31 (0.05)	16.04
Nesterov's Gradient Descent	1.31 (0.05)	12.09

Table 1: Validation error comparisons for simulation studies in Section 3. Variance is provided in parentheses.

has its own regularization parameter. For the additive partial linear model example, we added a ridge penalty as a third regularization term. In addition, we consider a completely nonparametric additive model with three univariate functions, a special case of APLMs. (Joint optimization formulations and gradient derivations for these generalized regression models are in the Appendix.)

Our results show that the models from the generalized regressions achieved lower test error and tuning their regularization parameters using gradient descent was computationally tractable, even in cases with over a hundred regularization parameters.

4.1 Un-pooled sparse group lasso

We first generalize sparse group lasso by replacing the group lasso penalty parameter with individual penalty parameters for each covariate group. This "un-pooled" version of sparse group lasso is defined as follows:

$$\frac{1}{2n} \|\boldsymbol{y}_T - \boldsymbol{X}_T\boldsymbol{\theta}\|_2^2 + \sum_{m=1}^{M} \lambda_1^{(m)} \|\boldsymbol{\theta}^{(m)}\|_2 + \lambda_2 \|\boldsymbol{\theta}\|_1 \tag{45}$$

This version increases the number of penalty parameters from two to $M + 1$, where M is the number of groups. The additional flexibility allows setting covariate and covariate group effects to zero by different thresholds. Hence un-pooled sparse group lasso may be better at modeling covariate groups with very different distributions.

We ran three experiments with different numbers of covariate groups M and total covariates p, as given in Table 2. The simulation settings were similar to the simulation settings and grid search procedure in Section 3.2. A separate test set of 200 observations was generated each run. For gradient descent, the $M + 1$ regularization parameters were initialized at $1e\text{-}4 \times \mathbf{1}^\top$, $1e\text{-}3 \times \mathbf{1}^\top$, and $1e\text{-}2 \times \mathbf{1}^\top$.

Model performance was assessed using three metrics: test error, β error (defined as $\|\boldsymbol{\beta} - \hat{\boldsymbol{\beta}}\|_2^2$), and the percentage of nonzero coefficients correctly identified among all the true nonzero coefficients. The results show that un-pooled sparse group lasso tuned using gradient descent performed better by all metrics.

Gradient descent was significantly faster in all three settings. In fact, the runtimes for gradient descent did not grow as the number of regularization parameters increased.

n=60, p=300, g=3, M=30				
	β Error	% Correct Nonzero β	Test Error	Runtime (sec)
SGL	1.13	10.70	0.04	15.81
Un-pooled SGL	0.18	23.79	0.01	5.62
n=60, p=1500, g=3, M=50				
	β Error	% Correct Nonzero β	Test Error	Runtime (sec)
SGL	7.79	9.63	0.28	148.64
Un-pooled SGL	4.00	17.79	0.14	88.78
n=60, p=1500, g=3, M=150				
	β Error	% Correct Nonzero β	Test Error	Runtime (sec)
SGL	2.20	10.69	0.080	162.14
Un-pooled SGL	0.06	15.34	0.002	48.63

Table 2: Comparison of models from un-pooled sparse group lasso and sparse group lasso (SGL), tuned using gradient descent and grid search, respectively.

4.2 Additive partially linear model with three penalties

Now consider generalizing the APLM criterion in (37) by using the elastic net instead of the lasso penalty, as follows:

$$\frac{1}{2}\left\|\boldsymbol{y}_T - \boldsymbol{X}_T\boldsymbol{\beta} - \boldsymbol{I}_T\boldsymbol{\theta}\right\|_2^2 + \lambda_1\|\boldsymbol{\beta}\|_1 + \frac{1}{2}\lambda_2\|\boldsymbol{\beta}\|_2^2 + \frac{1}{2}\lambda_3\|\boldsymbol{D}(\boldsymbol{z})\boldsymbol{\theta}\|_2^2 \tag{46}$$

Since the elastic net tends to perform better when some of the predictors are correlated, we hypothesize that this generalized APLM is well-suited for cases where the linear predictors are correlated. We can test this since descent-based joint optimization makes tuning the regularization parameters computationally tractable.

We used the same simulation settings as those in Section 3.3. A separate test set of 200 observations was generated each run. Gradient descent was initialized at $\boldsymbol{\lambda} = 10^i \times \mathbf{1}_3^\top$ for $i = -4, ..., 1$. We experimented with three nonlinear functions $g : \mathbb{R} \mapsto \mathbb{R}$ of varying levels of smoothness, as given in Table 3.

In addition to comparing models based on their test error, we measured the error of the fitted linear effects and the nonparametric estimates. These correspond to the β error ($||\boldsymbol{\beta} - \hat{\boldsymbol{\beta}}||_2^2$) and θ error ($||g(\boldsymbol{z}) - \boldsymbol{\theta}||_2^2$), respectively.

The results show that the generalized APLM criterion performed better by all three metrics. The linear model fits improved the most, which supports our hypothesis. Surprisingly, the estimation of the nonlinear components also improved slightly, even though the penalty term for the nonparametric estimates was not modified.

The runtime for tuning the three-parameter regularization problem was slightly longer than tuning the original two-parameter problem with grid search. Nonetheless, the runtime remained reasonable.

4.3 Nonparametric Additive Models

Finally, we consider the special case of APLMs where a completely nonparametric model is used for y. That is, we suppose that y is the sum of p univariate functions f_i, where each is penalized separately with parameter λ_i. This model is particularly useful when the functions have varying levels of smoothness. Ideally, λ_i is large for f_i with nearly constant first-order derivatives and small for f_i with drastically changing first-order derivatives.

$g(z) = 4z^3 - z^2 + 2z$				
	β Error	θ Error	Test Error	Runtime (sec)
APLM 2	0.59	3.35	3.78	35.48
APLM 3	0.38	2.96	3.73	43.44
$g(z) = \sin(5z) + \sin(15(z-3))$				
	β Error	θ Error	Test Error	Runtime (sec)
APLM 2	0.51	3.76	3.90	37.04
APLM 3	0.34	3.73	3.79	45.95
$g(z) = (2-z)\sin(20z^4)$				
	β Error	θ Error	Test Error	Runtime (sec)
APLM 2	0.58	4.91	4.13	40.75
APLM 3	0.41	4.85	4.08	54.63

Table 3: Comparison of the performance of APLM with three penalties (APLM 3) and that with two penalties (APLM 2). The regularization parameters were tuned using gradient descent and grid search, respectively.

	Validation Error	Test Error	Runtime (sec)
Gradient Descent	33.97 (1.31)	38.17 (1.61)	97.15
Grid Search	38.93 (1.57)	42.84 (1.88)	23.70

Table 4: Comparison of the performance of additive model with three penalty parameters tuned by gradient descent and that with one penalty parameter tuned by grid search. Standard errors are given in parentheses.

The simulation settings are as follows. We generated thirty datasets, each with 180 training, 60 validation, and 60 test observations with $p = 3$ covariates. Each set of covariates $\boldsymbol{x}_i$ was a random permutation of values $\delta_i - 15 + 0.1j$ for $j = 1, ..., 300$ where the random variable $\delta_i \sim \mathcal{U}(0, 0.1)$ jitters the start position. The functions are

$$\begin{aligned} f_1(x_1) &= 9\sin(2x_1) \\ f_2(x_2) &= x_2 \\ f_3(x_3) &= 6\cos(1.25x_3) + 6\sin(0.5x_3 + 0.5) \end{aligned} \tag{47}$$

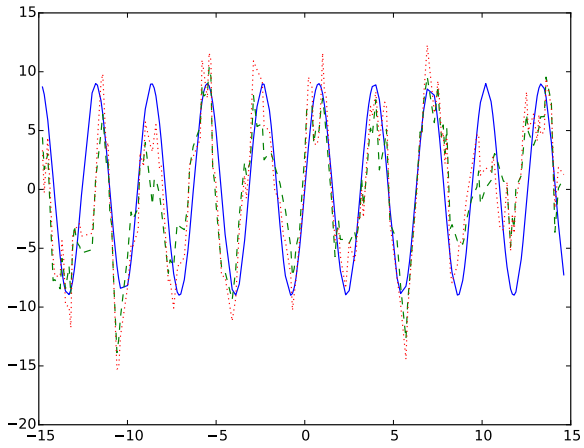
The response y was generated from the model

$$y = \sum_{i=1}^{3} f_i(x_i) + \sigma\epsilon \tag{48}$$

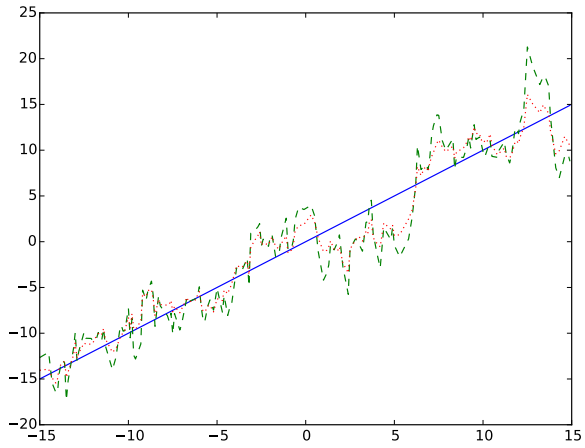
where $\epsilon \sim N(0, 1)$ and σ was chosen such that the signal to noise ratio was 2.

As a baseline, we consider the joint optimization problem with one penalty parameter and tune λ by performing grid search over 10 log-spaced values from 1e-3 to 50. Gradient descent was initialized at $\lambda_1 = \lambda_2 = \lambda_3 = 1$. The inner optimization problem for the training set was solved using ECOS (Domahidi et al. 2013).

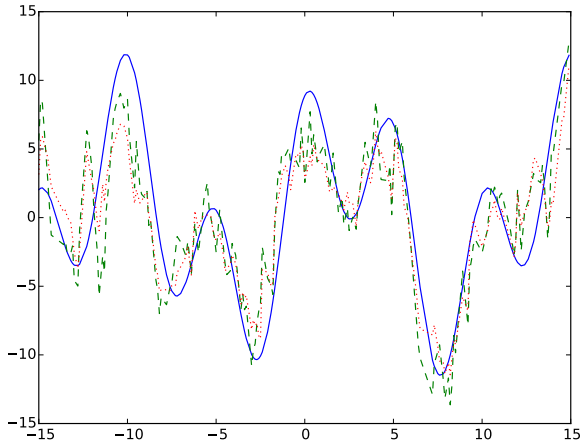
As seen in Table 4, the additive model with three penalty parameters has significantly lower validation error compared to one with a single penalty parameter, which is expected given the larger model space. Furthermore, the additive model with three penalty parameters achieved significantly lower test error. In Figure 2, we provide example estimates given by the model with one penalty parameter vs. three penalty parameters. As seen in the figures, the latter produces estimates with less variation for f_2 and more variation for f_1 and f_3,



(a) f_1



(b) f_2



(c) f_3

Figure 2: Example estimates $\hat{\boldsymbol{\theta}}_1, \hat{\boldsymbol{\theta}}_2, \hat{\boldsymbol{\theta}}_3$ for the test set: Left - Grid search, Right - Gradient descent. The solid lines are the true values of the test observations, the dotted lines are the estimates from the model with three penalty parameters, and the dashed lines are the estimates from the model with one penalty parameter.

which is exactly what we would hope for. In fact, gradient descent consistently determined that f_2 was the smoothest function; for 27 of the thirty runs, $\hat{\lambda}_2$ was larger than $\hat{\lambda}_1$ and $\hat{\lambda}_3$.

The runtime for tuning the additive model with three penalty parameters using gradient descent was slower than grid search, but still within a reasonable range. Gradient descent is certainly much faster than performing a three-dimensional grid search for this problem.

5 Application to Biological Data

Finally, we tested descent-based joint optimization in a real data example. More specifically, we considered the problem of finding predictive genes from gene pathways for Crohn's Disease and Ulcerative Colitis. Simon et al. (2013) addressed this problem using the sparse group lasso; we now compare this against applying the un-pooled sparse group lasso, where the regularization parameters were tuned using gradient descent.

Our dataset is from a colitis study of 127 total patients, 85 with colitis (59 crohn's patients + 26 ulcerative colitis patients) and 42 healthy controls (Burczynski et al. 2006). Expression data was measured for 22,283 genes on affymetrix U133A microarrays. We grouped the genes according to the 326 C1 positional gene sets from MSigDb v5.0 (Subramanian et al. 2005) and discarded the 2358 genes not found in the gene set.

We randomly shuffled the data and used the first 50 observations for the training set and the remaining 77 for the test set. Five-fold cross validation was used to fit models. To tune the penalty parameters in un-pooled sparse group lasso, we initialized gradient descent at $0.5 \times \mathbf{1}^\top$. For sparse group lasso, we tuned the penalty parameters over a 5×5 grid $1e$-4 to 5.

Table 5 presents the average results from repeating this process ten times. Un-pooled sparse group lasso achieved a slightly higher classification rate than sparse group lasso. Interestingly, un-pooled sparse group lasso found solutions that were significantly more sparse than sparse group lasso; on average, un-pooled sparse group lasso identified 9 genesets whereas sparse group lasso identified 38. These results suggest that un-pooling the penalty parameters in sparse group lasso could potentially improve interpretability.

In regards to runtime, we find that descent-based joint optimization for un-pooled sparse group lasso was computationally tractable, even though it required tuning 327 regularization

	% Correct	Num. Genesets	Num. Genes	Runtime (sec)
SGL	82.47 (0.7)	38.4 (671.2)	207.0 (22206.2)	2722.4
Un-pooled SGL	84.29 (0.3)	8.9 (1.9)	83.9 (664.5)	2298.5

Table 5: Comparison of predictive genes and genesets of Ulcerative Colitis found by un-pooled sparse group lasso and sparse group lasso (SGL). The variance is given in parenthesis.

parameters. In fact, it was slightly faster than grid-based joint optimization for sparse group lasso.

6 Discussion

In this paper, we proposed finding the optimal regularization parameters by treating it as an optimization problem over the regularization parameter space. We have proven that a descent-based approach can be used for regression problems in which the penalties are smooth almost everywhere and present a general algorithm for performing a modified gradient descent.

Empirically, we find that models fit by descent-based joint optimization have similar accuracy to those from grid search. Furthermore, the scalability of this approach allows us to test new regression problems with multiple penalties. In particular, we found that an un-pooled variant of sparse group lasso showed promising results. More research should be done to explore this new regularization method.

Future work could include finding other classes of regularization methods that are suitable for descent-based joint optimization and implementing descent-based joint optimization with more sophisticated optimization methods.

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