Homework 2

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Part 1. We will work through some details on the Hodrick-Prescott (HP) filter for smoothing time series data. Let $\mathbf{y} \in \mathbb{R}^n$ denote the values of a signal sampled at n time points. We assume the data has been generated from the model

$$\mathbf{y} = \boldsymbol{\theta} + \mathbf{e}$$

where $\mathbf{e} \in \mathbb{R}^n$ is a noise vector of i.i.d. zero mean Gaussian random variable and $\boldsymbol{\theta}$ is a smooth function, in the sense that its derivatives do not take on values that are "too big." The HP-filter seeks to recover a smooth $\boldsymbol{\theta}$ by minimizing a penalized negative log-likelihood:

$$\ell(\boldsymbol{\theta}) = \frac{1}{2}\|\mathbf{y} - \boldsymbol{\theta}\|_2^2 + \frac{\lambda}{2}\|\mathbf{D}_n^{(k)}\boldsymbol{\theta}\|_2^2,$$

where λ is a non-negative tuning parameter and $\mathbf{D}_n^{(k)}$ is the kth order differencing matrix for a signal of length n.

$$\mathbf{D}_n^{(1)} = \begin{pmatrix} -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ \vdots & & & & & \\ 0 & 0 & 0 & \cdots & -1 & 1 \end{pmatrix} \in \mathbb{R}^{n-1 \times n},$$

and $\mathbf{D}_n^{(k)} = \mathbf{D}_{n-k+1}^{(1)}\mathbf{D}_n^{(k-1)}$.

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1. Write the gradient and Hessian of $\ell(\boldsymbol{\theta})$.

Recall that for vectors a and b and matrix A

$$\frac{\partial a^T b}{\partial b} = a, \ \frac{\partial b^T A b}{\partial b} = (A + A^T)b$$

$$
\begin{aligned}
\ell(\theta) &= \frac{1}{2}\|\mathbf{y}-\boldsymbol{\theta}\|_2^2 + \frac{\lambda}{2}\|\mathbf{D}_n^{(k)}\boldsymbol{\theta}\|_2^2 \\
&= \frac{1}{2}(y-\theta)^T(y-\theta) - \frac{\lambda}{2}(\mathbf{D}_n^{(k)}\theta)^T(\mathbf{D}_n^{(k)}\theta)^T \\
&= \frac{1}{2}\Big[y^Ty - y^T\theta - \theta^Ty - \theta^T\theta\Big] + \frac{\lambda}{2}\theta^T(\mathbf{D}_n^{(k)})^T\mathbf{D}_n^{(k)}\theta \\
&= \frac{1}{2}\Big[y^Ty - y^T\theta - y^T\theta - \theta^T\theta\Big] + \frac{\lambda}{2}\theta^T(\mathbf{D}_n^{(k)})^T\mathbf{D}_n^{(k)}\theta && y^T\theta \text{ is a scalar}
\end{aligned}
$$

$$
\begin{aligned}
\nabla\ell(\theta) &= \frac{1}{2}(0-2y+2\theta) + \frac{\lambda}{2}\Big[(\mathbf{D}_n^{(k)})^T\mathbf{D}_n^{(k)} + ((\mathbf{D}_n^{(k)})^T\mathbf{D}_n^{(k)})^T\Big]\theta \\
&= -y + \theta + \lambda(\mathbf{D}_n^{(k)})^T\mathbf{D}_n^{(k)}\theta
\end{aligned}
$$

$$
\begin{aligned}
\nabla^2\ell(\theta) &= 0 + I + \lambda((\mathbf{D}_n^{(k)})^T\mathbf{D}_n^{(k)})^T \\
&= I + \lambda(\mathbf{D}_n^{(k)})^T\mathbf{D}_n^{(k)}
\end{aligned}
$$

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2. What is the computational complexity for a calculating the gradient and Hessian of $\ell(\boldsymbol{\theta})$? Be sure to take into account the sparsity in $\mathbf{D}_n^{(k)}$.

Recall that sparse matrix-vector multiplication scales with the number of nonzero elements in the sparse matrix. Similarly, sparse matrix-matrix multiplication scales in the number of rows times the number of nonzero elements.

Notice $\mathbf{D}_n^{(k)} \in \mathbb{R}^{(n-k)\times n}$ and have nk nonzero elements.

Let's start with the Hessian.

$$
\nabla^2\ell(\theta) = \underbrace{I + \lambda\overbrace{\underbrace{(\mathbf{D}_n^{(k)})^T\mathbf{D}_n^{(k)}}_{\mathcal{O}(n(nk))}}^{\mathcal{O}(n^2)}}_{\mathcal{O}(n)}
$$

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3. Prove that $\ell(\boldsymbol{\theta})$ is strongly convex.

We will use the condition

$$
\nabla^2 f(x) \succeq mI
$$

which means that $\nabla^2 f(x) - mI$ is positive semidefinite for $m > 0$. If we take $m = 1$ then

$$
\nabla^2 f(x) - mI = I - \lambda(\mathbf{D}_n^{(k)})^T\mathbf{D}_n^{(k)} - I = \lambda(\mathbf{D}_n^{(k)})^T\mathbf{D}_n^{(k)}.
$$

Notice that $\lambda > 0$ and since we have a matrix multiplied by its transpose, we know that this is always positive semidefinite. Thus, we have strong convexity.

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4. Prove that $\ell(\boldsymbol{\theta})$ is L-Lipschitz differentiable with $L = 1 + \lambda \|\mathbf{D}_n^{(k)}\|_{\text{op}}^2$.

Recall that for matrices $||\cdot||_2 = ||\cdot||_{op}$. Thus,

$$||\nabla^2 \ell(\boldsymbol{\theta})||_2 = ||\nabla^2 \ell(\boldsymbol{\theta})||_{op} \leq L$$

We can proceed with the triangle inequality.

$$\begin{aligned}
||\nabla^2 \ell(\boldsymbol{\theta})||_{op} &= ||I + \lambda(\mathbf{D}_n^{(k)})^T \mathbf{D}_n^{(k)}||_{op} && \\
&\leq ||I||_{op} + ||\lambda(\mathbf{D}_n^{(k)})^T \mathbf{D}_n^{(k)}|| && \text{Triangle Inequality} \\
&= 1 + \lambda||(\mathbf{D}_n^{(k)})^T \mathbf{D}_n^{(k)}||_{op} && \\
&\leq 1 + \lambda||(\mathbf{D}_n^{(k)})^T||_{op}||\mathbf{D}_n^{(k)}||_{op} && \text{Cauchy-Schwartz} \\
& 1 + \lambda||\mathbf{D}_n^{(k)}||_{op} && ||A^T||_{op} = ||A||_{op}
\end{aligned}$$

Thus, take $L = 1 + \lambda||\mathbf{D}_n^{(k)}||_{op}$.

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5. Prove that $\ell(\boldsymbol{\theta})$ has a unique global minimizer for all $\lambda \geq 0$.

One condition to have a unique global minimizer is that a function is both strongly convex and coercive. From 3. we have strong convexity. Notice that all of the norms in $\ell(\boldsymbol{\theta})$ are squared. This means that all of the terms will be positive. As $||\theta||$ increases, so will these norms will all go to infinity as $||\theta|| \to \infty$. Thus, we have coercivity. Thus we have the sufficient conditions to say that $\ell(\boldsymbol{\theta})$ has a unique global minimizer.

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Part 2. Gradient Descent

You will next add an implementation of gradient descent to your R package. Your function will include using both a fixed step-size as well as one chosen by backtracking.

Please complete the following steps.

Step 0: Make an R package entitled "unityidST790".

Step 1: Write a function "gradient_step."

```r
#' Gradient Step
#'
#' @param gradf handle to function that returns gradient of objective function
#' @param x current parameter estimate
#' @param t step-size
#' @export
gradient_step <- function(gradf, x, t) {

}
```

Your function should return $\mathbf{x}^+ = \mathbf{x} - t\nabla f(\mathbf{x})$.

Step 2: Write a function "gradient_descent_fixed." Your algorithm can stop iterating once the relative change in the objective function drops below `tol`.

```r
#' Gradient Descent (Fixed Step-Size)
#'
#' @param fx handle to function that returns objective function values
#' @param gradf handle to function that returns gradient of objective function
#' @param x0 initial parameter estimate
#' @param t step-size
#' @param max_iter maximum number of iterations
#' @param tol convergence tolerance
#' @export
gradient_descent_fixed <- function(fx, gradf, x0, t, max_iter=1e2, tol=1e-3) {

}
```

Your function should return

- The final iterate value
- The objective function values
- The 2-norm of the gradient values
- The relative change in the function values
- The relative change in the iterate values

Step 3: Write a function "backtrack."

```r
#' Backtracking
#'
#' @param fx handle to function that returns objective function values
#' @param x current parameter estimate
#' @param t current step-size
#' @param df the value of the gradient of objective function evaluated at the current x
#' @param alpha the backtracking parameter
#' @param beta the decrementing multiplier
```

```r
#' @export
backtrack <- function(fx, x, t, df, alpha=0.5, beta=0.9) {

}
```

Your function should return the selected step-size.

Step 4: Write a function "gradient_descent_backtrack" that performs gradient descent using backtracking. Your algorithm can stop iterating once the relative change in the objective function drops below `tol`.

```r
#' Gradient Descent (Backtracking Step-Size)
#'
#' @param fx handle to function that returns objective function values
#' @param gradf handle to function that returns gradient of objective function
#' @param x0 initial parameter estimate
#' @param max_iter maximum number of iterations
#' @param tol convergence tolerance
#' @export
gradient_descent_backtrack <- function(fx, gradf, x0, max_iter=1e2, tol=1e-3) {

}
```

Your function should return

- The final iterate value
- The objective function values
- The 2-norm of the gradient values
- The relative change in the function values
- The relative change in the iterate values

Step 5: Write a function "gradient_descent" that is a wrapper function for "gradient_descent_fixed" and "gradient_descent_backtrack." The default should be to use the backtracking.

```r
#' Gradient Descent
#'
#' @param fx handle to function that returns objective function values
#' @param gradf handle to function that returns gradient of objective function
#' @param x0 initial parameter estimate
#' @param t step-size
#' @param max_iter maximum number of iterations
#' @param tol convergence tolerance
#' @export
gradient_descent <- function(fx, gradf, x0, t=NULL, max_iter=1e2, tol=1e-3) {

}
```

Your function should return

- The final iterate value
- The objective function values
- The 2-norm of the gradient values
- The relative change in the function values
- The relative change in the iterate values

Step 6: Write a function to compute the kth order differencing matrix $\mathbf{D}_n^{(k)}$. Use the Matrix package by adding it to the dependency list in the DESCRIPTION file. Among other things, the Matrix package provides efficient storage and mulitplication for sparse matrices.

```
#' Compute kth order differencing matrix
#'
#' @param k order of the differencing matrix
#' @param n Number of time points
#' @export
myGetDkn <- function(k, n) {

}
```

Step 7: Write functions 'fx_hp' and 'gradf_hp' to perform HP-filtering.

```
#' Objective Function for HP-filtering
#'
#' @param y response
#' @param theta regression coefficient vector
#' @param Dkn sparse differencing matrix
#' @param lambda regularization parameter
#' @export
fx_hp <- function(y, theta, Dkn, lambda=0) {

}

#' Gradient for HP-filtering
#'
#' @param y response
#' @param theta regression coefficient vector
#' @param Dkn sparse differencing matrix
#' @param lambda regularization parameter
#' @export
gradf_hp <- function(y, theta, Dkn, lambda=0) {

}
```

Step 8: Perform HP-filtering (with $\lambda = 100$) on the following data example using the fixed step-size. Use your answers to Part 1 to choose an appropriate fixed step-size. Try using $\mathbf{0}$ and $\mathbf{y}$ as initial values for $\boldsymbol{\theta}$. Plot the difference $\ell(\boldsymbol{\theta}_m) - \ell(\boldsymbol{\theta}_{1000})$ versus the iteration m. Comment on the shape of the plot given what you know about the iteration complexity of gradient descent with a fixed step size.

```
set.seed(12345)
n <- 1e2
x <- seq(0, 5, length.out=n)
y <- sin(pi*x) + x + 0.5*rnorm(n)
```

- Also plot the noisy data, as points, and smoothed estimates, as a line.

Step 9: Perform HP-filtering (with $\lambda = 100$) on the simulated data above using backtracking. Try using $\mathbf{0}$ and $\mathbf{y}$ as initial values for $\boldsymbol{\theta}$. Plot the difference $\ell(\boldsymbol{\theta}_m) - \ell(\boldsymbol{\theta}_{1000})$ versus the iteration m. Comment on the shape of the plot given what you know about the iteration complexity of gradient descent with backtracking.

Step 10: Use your code above to smooth some interesting time series data. For example, you might use the tseries R package on CRAN (see the function **get.hist.quote**) to download historical financial data for the daily closing prices of Apple stock over the past two years. Try at least 3 different λ values - different enough to generate noticably different smoothed estimates - and at least two differencing matrix orders, e.g. $\mathbf{D}^{(2)}$

and $\mathbf{D}^{(3)}$. For all six λ and differencing matrices combinations, plot the noisy data, as points, and smoothed estimates, as a line.