Optimization Assignment 1

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2.1 Example Optimization Trajectories

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3.1 Gradient Descent

3.1.1 Objective Function Definition and Gradient Derivation

$$L = \sum_i (y_{\text{data}} - y_{\text{model}})^2 \tag{1}$$

$$L = \sum_i (y_i - x_1 + x_2 e^{x_4 t_i} + x_3 e^{x_5 t_i})^2 \tag{2}$$

We can now derive the gradient.

$$\nabla L = \nabla \left(\sum_i (y_i - x_1 + x_2 e^{x_4 t_i} + x_3 e^{x_5 t_i})^2 \right) \tag{3}$$

$$\nabla L = \sum_i \left(\nabla \left((y_i - x_1 + x_2 e^{x_4 t_i} + x_3 e^{x_5 t_i})^2 \right) \right) \tag{4}$$

$$\nabla L = \sum_i \left(2(y_i - x_1 + x_2 e^{x_4 t_i} + x_3 e^{x_5 t_i}) \cdot \nabla(y_i - x_1 + x_2 e^{x_4 t_i} + x_3 e^{x_5 t_i}) \right) \tag{5}$$

$$\nabla L = \sum_i \left(2(y_i - x_1 + x_2 e^{x_4 t_i} + x_3 e^{x_5 t_i}) \cdot \nabla(x_1 + x_2 e^{x_4 t_i} + x_3 e^{x_5 t_i}) \right) \tag{6}$$

$$\nabla(x_1 + x_2 e^{x_4 t_i} + x_3 e^{x_5 t_i}) = \begin{bmatrix} 1 \\ e^{x_4 t_i} \\ e^{x_5 t_i} \\ x_2 t_i e^{x_4 t_i} \\ x_3 t_i e^{x_5 t_i} \end{bmatrix} \tag{7}$$

3.2 Hooke-Jeeves

3.3 (EXTRA) Automatic Differentiation Gradient Descent

4 Q4. (Graduate Student)

Let V be the vector space of polynomial functions from $\mathbb{R} \to \mathbb{R}$ which have degree less than or equal to 2.

That is, for all $a, b, c \in \mathbb{R}$ the following polynomial $p(x)$ is in V

$$p(x) = a + bx + cx^2$$

4.1 Proving B_1 and B_1 are both a basis of V

4.1.1 Proof: B_1 is Linearly Independent

- Implication of only way to get 0 vector.

4.1.2 Proof: B_1 spans V

- Show all $v \in V$ can be represented in basis

4.1.3 Proof: B_2 is Linearly Independent

4.1.4 Proof: B_2 spans V

4.2 Transformation between B_1 and B_2

4.3 D Derivative Operator

4.3.1 Proof: D is linear

4.3.2 Matrix Representation of D in the bases B_1 and B_2

5 Q5. (Graduate Student)

5.1 x in full $\mathbb{R}^3$ standard basis

5.2 Coordinates of x in B_X

5.3 Coordinates of y in B_Y using L ($c_y = Lc_x$)

5.4 y in full $\mathbb{R}^4$ standard basis

6 Q6. (Graduate Student)

6.1 Df derivation

Let $f : \mathbb{R}^4 \to \mathbb{R}$ be defined as $f(x) = \|Ax - b\| + \lambda\|Cx\| + \gamma\|Eb\|$ where $A, C, E \in \mathbb{R}^{4\times4}$, $x, b \in \mathbb{R}^4$ and $\lambda, \gamma \in \mathbb{R}$.

Let D denote the differential operator.

$$
\begin{aligned}
Df(x) &= D\left(\|Ax-b\| + \lambda\|Cx\| + \gamma\|Eb\|\right) \\
&= D\left(\|Ax-b\|\right) + \lambda D\left(\|Cx\|\right) + \gamma D\left(\|Eb\|\right) && \text{[using linearity of D]} \\
&= D\left(\|Ax-b\|\right) + \lambda D\left(\|Cx\|\right) + 0 \\
&= D\left(\|Ax-b\|\right) + \lambda D\left(\|Cx\|\right) \\
&= \frac{(Ax-b)^T A}{\|Ax-b\|} + \lambda \frac{(Cx)^T C}{\|Cx\|} && \text{[using derivations from next sections]}
\end{aligned}
$$

The full derivation of $D\left(\|Ax-b\|\right)$ and $D\left(\|Cx\|\right)$ can be found in the following sections.

6.2 $D\left(\|Cx\|\right)$ Derivation

$$
\begin{aligned}
D\left(\|Cx\|\right) &= D\left(\sqrt{(Cx)^T(Cx)}\right) \\
&= D\left(\left((Cx)^T(Cx)\right)^{\frac{1}{2}}\right) \\
&= \frac{1}{2}\left((Cx)^T(Cx)\right)^{\frac{-1}{2}} D\left((Cx)^T(Cx)\right) && \text{[using Chain Rule]} \\
&= \frac{1}{2\sqrt{(Cx)^T(Cx)}} D\left((Cx)^T(Cx)\right) \\
&= \frac{1}{2\|Cx\|} D\left((Cx)^T(Cx)\right) \\
&= \frac{\left((Cx)^T D(Cx)\right) + \left((Cx)^T D(Cx)\right)}{2\|Cx\|} && \text{[using Product Rule]} \\
&= \frac{2\left((Cx)^T D(Cx)\right)}{2\|Cx\|} \\
&= \frac{(Cx)^T C}{\|Cx\|}
\end{aligned}
$$

6.3 $D\left(\|Ax-b\|\right)$ Derivation

$$
\begin{aligned}
D\left(\|Ax-b\|\right) &= D\left(\sqrt{(Ax-b)^T(Ax-b)}\right) \\
&= D\left(\left((Ax-b)^T(Ax-b)\right)^{\frac{1}{2}}\right) \\
&= \frac{1}{2}\left((Ax-b)^T(Ax-b)\right)^{\frac{-1}{2}} D\left((Ax-b)^T(Ax-b)\right) \quad \text{[using Chain Rule]} \\
&= \frac{1}{2\sqrt{(Ax-b)^T(Ax-b)}} D\left((Ax-b)^T(Ax-b)\right) \\
&= \frac{1}{2\|Ax-b\|} D\left((Ax-b)^T(Ax-b)\right) \\
&= \frac{\left((Ax-b)^T D(Ax-b)\right) + \left((Ax-b)^T D(Ax-b)\right)}{2\|Ax-b\|} \quad \text{[using Product Rule]} \\
&= \frac{2(Ax-b)^T D(Ax-b)}{2\|Ax-b\|} \\
&= \frac{2(Ax-b)^T A}{2\|Ax-b\|} \\
&= \frac{(Ax-b)^T A}{\|Ax-b\|}
\end{aligned}
$$

A Source Code

A.1 All Optimization Algorithms (A1Module.jl)

A.2 Plot Generation Script (makeplots.jl)

A.3 (EXTRA) Automatic Differentiation for Gradient