Subgradient Descent

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Motivation and Review: Support Vector Machines

The Classification Problem

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- **Real-valued prediction function $f : \mathcal{X} \to \mathbf{R}$**

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- Intuitively, magnitude of the score represents the **confidence of our prediction**.

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- The value $f(x)$ is called the **score** for the input x.
- Intuitively, magnitude of the score represents the **confidence of our prediction**.
- Typical convention:

$$
\begin{aligned}
f(x) > 0 &\implies \text{Predict } 1 \\
f(x) < 0 &\implies \text{Predict } -1
\end{aligned}
$$

(But we can choose other thresholds...)

The Margin

- The **margin** (or **functional margin**) for predicted score $\hat{y}$ and true class $y \in \{-1, 1\}$ is $y\hat{y}$.

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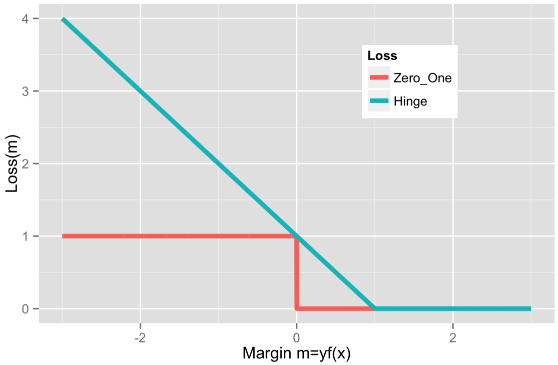
- The margin is a measure of how **correct** we are.
- We want to **maximize the margin**.

[Margin-Based] Classification Losses

SVM/Hinge loss: $\ell_{\text{Hinge}} = \max\{1-m, 0\} = (1-m)_+$



Not differentiable at $m = 1$. We have a "**margin error**" when $m < 1$.

[Soft Margin] Linear Support Vector Machine (No Intercept)

- Hypothesis space $\mathcal{F} = \left\{ f(x) = w^T x \mid w \in \mathbf{R}^d \right\}$.
- Loss $\ell(m) = \max(1, m)$
- ℓ_2 regularization

$$\min_{w \in \mathbf{R}^d} \sum_{i=1}^{n} \max\left(0, 1 - y_i w^T x_i\right) + \lambda \|w\|_2^2$$

SVM Optimization Problem (no intercept)

- SVM objective function:

$$J(w) = \frac{1}{n}\sum_{i=1}^{n} \max\left(0, 1 - y_i\left[w^T x_i\right]\right) + \lambda \|w\|^2.$$

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- Not differentiable... but let's think about gradient descent anyway.
- Derivative of hinge loss $\ell(m)=\max(0,1-m)$:

$$\ell'(m)=\begin{cases}0 & m>1\\ -1 & m<1\\ \text{undefined} & m=1\end{cases}$$

"Gradient" of SVM Objective

- We need gradient with respect to parameter vector $w \in \mathbf{R}^d$:

$$\nabla_w \ell\left(y_i w^T x_i\right)$$

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Gradient Descent on SVM Objective?

- The gradient of the SVM objective is

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when $y_i w^T x_i \neq 1$ for all i, and **otherwise is undefined**.

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- If we start with a random w, will we ever hit exactly $y_i w^T x_i = 1$?

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- If we start with a random w, will we ever hit exactly $y_i w^T x_i = 1$?
- If we did, could we perturb the step size by ε to miss such a point?
- Does it even make sense to check $y_i w^T x_i = 1$ with floating point numbers?

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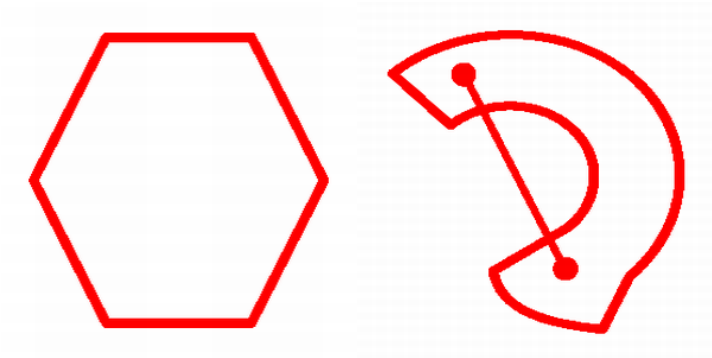
- If we blindly apply gradient descent from a random starting point
  - seems unlikely that we'll hit a point where the gradient is undefined.
- Still, doesn't mean that gradient descent will work if objective not differentiable!
- Theory of subgradients and subgradient descent will clear up any uncertainty.

Convexity and Sublevel Sets

Convex Sets

Definition

A set C is **convex** if the line segment between any two points in C lies in C.

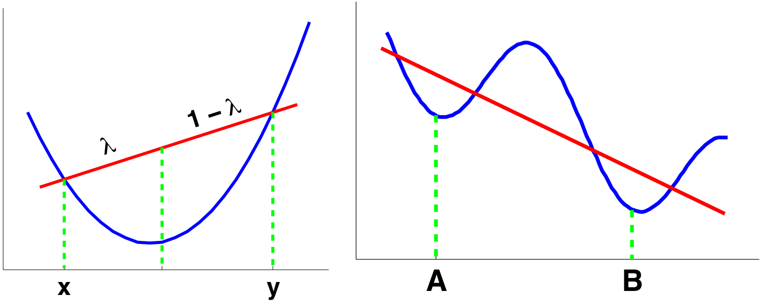


KPM Fig. 7.4

Convex and Concave Functions

Definition

A function $f : \mathbf{R}^d \to \mathbf{R}$ is **convex** if the line segment connecting any two points on the graph of f lies above the graph. f is **concave** if $-f$ is convex.



KPM Fig. 7.5

Examples of Convex Functions on $\mathbf{R}$

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- $x \mapsto e^{ax}$ is convex on $\mathbf{R}$ for all $a \in \mathbf{R}$
- Every norm on $\mathbf{R}^n$ is convex (e.g. $\|x\|_1$ and $\|x\|_2$)
- Max: $(x_1, \ldots, x_n) \mapsto \max\{x_1 \ldots, x_n\}$ is convex on $\mathbf{R}^n$

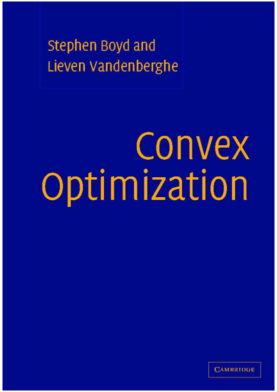
Simple Composition Rules

Examples

- If g is convex, and $Ax+b$ is an affine mapping, then $g(Ax+b)$ is convex.
- If g is convex then $\exp g(x)$ is convex.
- If g is convex and nonnegative and $p \geqslant 1$ then $g(x)^p$ is convex.
- If g is concave and positive then $\log g(x)$ is concave
- If g is concave and positive then $1/g(x)$ is convex.

Main Reference for Convex Optimization

- Boyd and Vandenberghe (2004)
  - Very clearly written, but has a ton of detail for a first pass.
  - See the Extreme Abridgement of Boyd and Vandenberghe.



Convex Optimization Problem: Standard Form

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$$\begin{array}{ll} \text{minimize} & f_0(x) \\ \text{subject to} & f_i(x) \leqslant 0, \;\; i = 1, \ldots, m \end{array}$$

where $f_0, \ldots, f_m$ are convex functions.

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where $f_0, \ldots, f_m$ are convex functions.

Question: Is the $\leqslant$ in the constraint just a convention? Could we also have used $\geqslant$ or $=$?

Level Sets and Sublevel Sets

Let $f : \mathbf{R}^d \to \mathbf{R}$ be a function. Then we have the following definitions:

Definition

A **level set** or **contour line** for the value c is the set of points $x \in \mathbf{R}^d$ for which $f(x) = c$.

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*If $f : \mathbf{R}^d \to \mathbf{R}$ is **convex**, then the **sublevel sets are convex**.*

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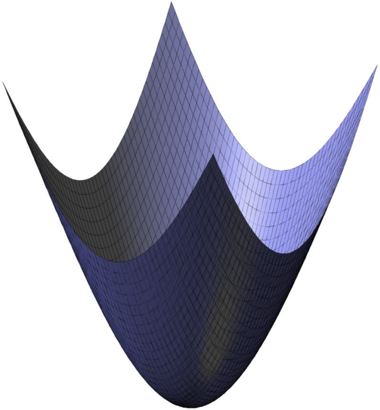
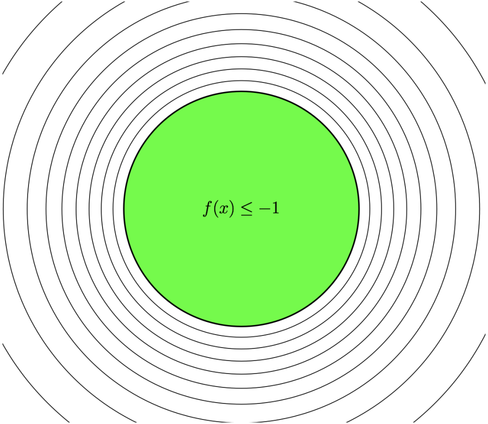
(Proof straight from definitions.)

Convex Function



Plot courtesy of Brett Bernstein.

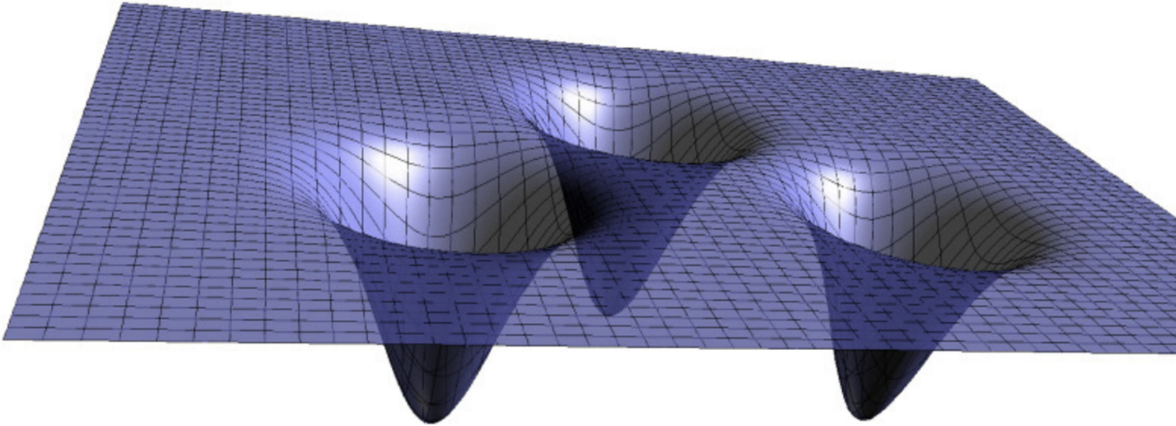
Contour Plot Convex Function: Sublevel Set



Is the sublevel set $\{x \mid f(x) \leqslant 1\}$ convex?

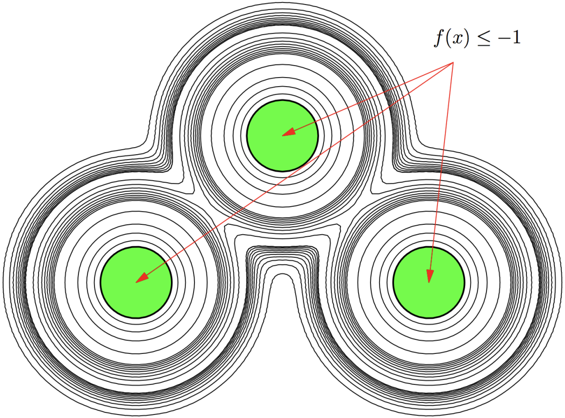
Plot courtesy of Brett Bernstein.

Nonconvex Function



Plot courtesy of Brett Bernstein.

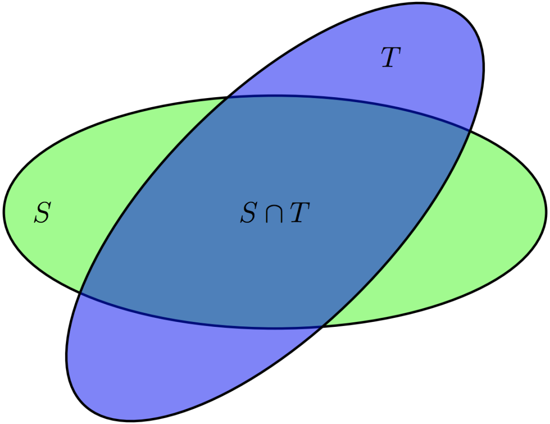
Contour Plot Nonconvex Function: Sublevel Set



Is the sublevel set $\{x \mid f(x) \leqslant 1\}$ convex?

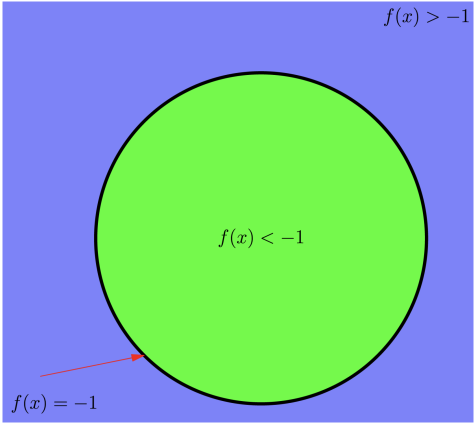
Plot courtesy of Brett Bernstein.

Fact: Intersection of Convex Sets is Convex



Plot courtesy of Brett Bernstein.

Level and Superlevel Sets



Level sets and superlevel sets of convex functions are **not** generally convex.

Plot courtesy of Brett Bernstein.

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where $f_0, \ldots, f_m$ are convex functions.

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- What can we say about each constraint set $\{x \mid f_i(x) \leqslant 0\}$?

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- What can we say about each constraint set $\{x \mid f_i(x) \leqslant 0\}$? (convex)
- What can we say about the feasible set $\{x \mid f_i(x) \leqslant 0, \, i = 1, \ldots, m\}$?

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Convex Optimization Problem: Implicit Form

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An alternative "generic" convex optimization problem.

Convex and Differentiable Functions

First-Order Approximation

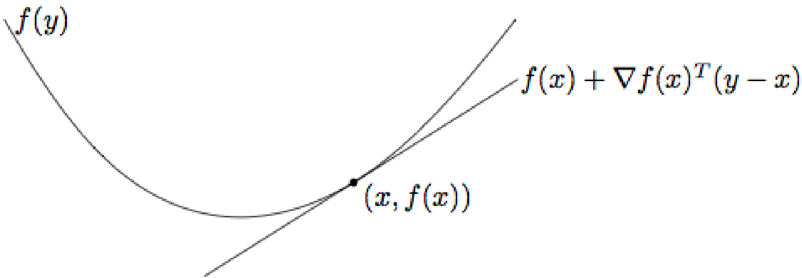
- Suppose $f : \mathbf{R}^d \to \mathbf{R}$ is **differentiable.**
- Predict $f(y)$ given $f(x)$ and $\nabla f(x)$?

Boyd & Vandenberghe Fig. 3.2

First-Order Approximation

- Suppose $f : \mathbf{R}^d \to \mathbf{R}$ is **differentiable.**
- Predict $f(y)$ given $f(x)$ and $\nabla f(x)$?
- Linear (i.e. "**first order**") approximation:

$$f(y) \approx f(x) + \nabla f(x)^T (y - x)$$



Boyd & Vandenberghe Fig. 3.2

First-Order Condition for Convex, Differentiable Function

- Suppose $f : \mathbf{R}^d \to \mathbf{R}$ is **convex** and **differentiable.**
- Then for any $x, y \in \mathbf{R}^d$

$$f(y) \geqslant f(x) + \nabla f(x)^T (y - x)$$

Figure from Boyd & Vandenberghe Fig. 3.2; Proof in Section 3.1.3

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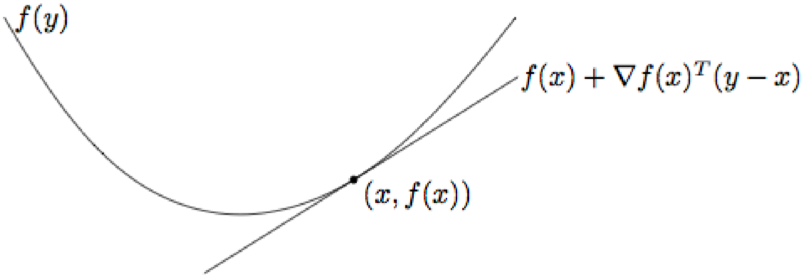
- The linear approximation to f at x is a **global underestimator** of f:



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Corollary

If $\nabla f(x) = 0$ then x is a global minimizer of f.

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Corollary

If $\nabla f(x) = 0$ then x is a global minimizer of f.

For convex functions, **local information gives global information.**

Subgradients

Subgradients

Definition

A vector $g \in \mathbf{R}^d$ is a **subgradient** of $f : \mathbf{R}^d \to \mathbf{R}$ at x if for all z,

$$f(z) \geqslant f(x) + g^T(z - x).$$

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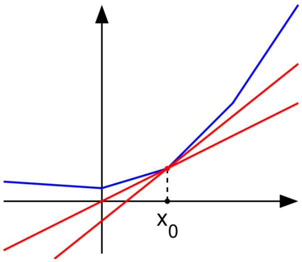

Blue is a graph of $f(x)$.

Each red line $x \mapsto f(x_0) + g^T(x - x_0)$ is a global lower bound on $f(x)$.

Subdifferential

Definitions

- f is **subdifferentiable** at x if $\exists$ at least one subgradient at x.
- The set of all subgradients at x is called the **subdifferential:** $\partial f(x)$

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Basic Facts

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- $\partial f(x) = \emptyset \implies f$ is not convex.

Globla Optimality Condition

Definition

A vector $g \in \mathbf{R}^n$ is a **subgradient** of $f : \mathbf{R}^d \to \mathbf{R}$ at x if for all z,

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Corollary

If $0 \in \partial f(x)$, then x is a ***global minimizer*** *of f.*

Subdifferential of Absolute Value

- Consider $f(x) = |x|$

Boyd EE364b: Subgradients Slides

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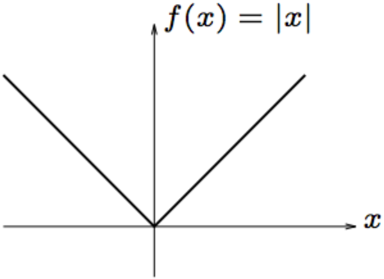

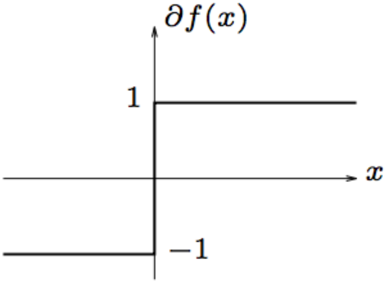

- Plot on right shows $\{(x, g) \mid x \in \mathbf{R},\ g \in \partial f(x)\}$

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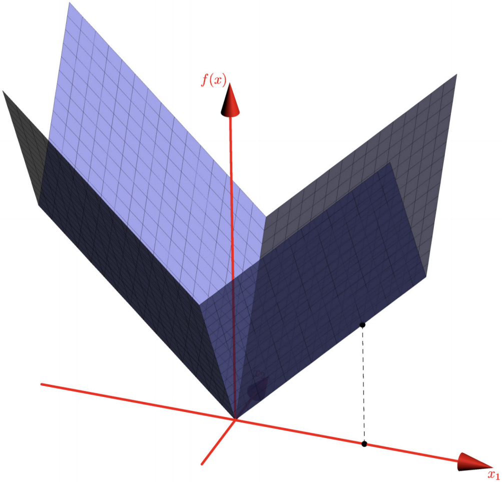
$f(x_1, x_2) = |x_1| + 2|x_2|$



Plot courtesy of Brett Bernstein.

Subgradients of $f(x_1, x_2) = |x_1| + 2|x_2|$

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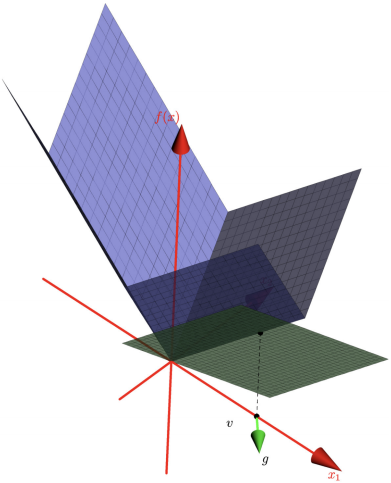
- First coordinate of subgradient must be 1, from $|x_1|$ part (at $x_1 = 3$).
- Second coordinate of subgradient can be anything in $[-2, 2]$.
- So graph of $h(x_1, x_2) = f(3, 0) + g^T(x_1 - 3, x_2 - 0)$ is a global underestimate of $f(x_1, x_2)$, for any $g = (g_1, g_2)$, where $g_1 = 1$ and $g_2 \in [-2, 2]$.

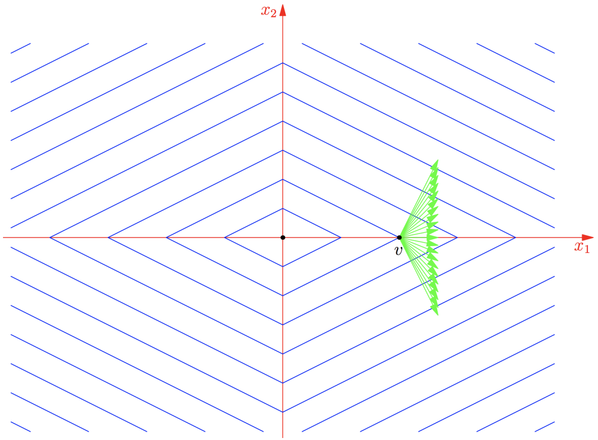
Underestimating Hyperplane to $f(x_1, x_2) = |x_1| + 2|x_2|$



Plot courtesy of Brett Bernstein.

Subdifferential on Contour Plot

$$\partial f(3,0) = \{(1,b)^T \mid b \in [-2,2]\}$$



Contour plot of $f(x_1, x_2) = |x_1| + 2|x_2|$, with set of subgradients at $(3,0)$. .

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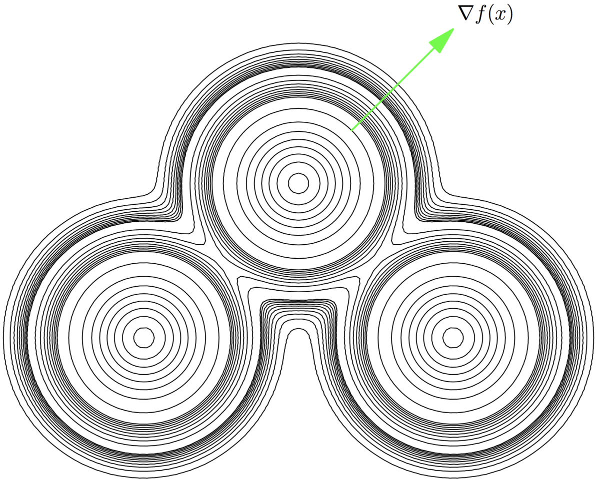
- Proof sketch in notes.

Gradient orthogonal to sublevel sets



Plot courtesy of Brett Bernstein.

Contour Lines and Subgradients

Let $f: \mathbf{R}^d \to \mathbf{R}$ have a subgradient g at x_0.

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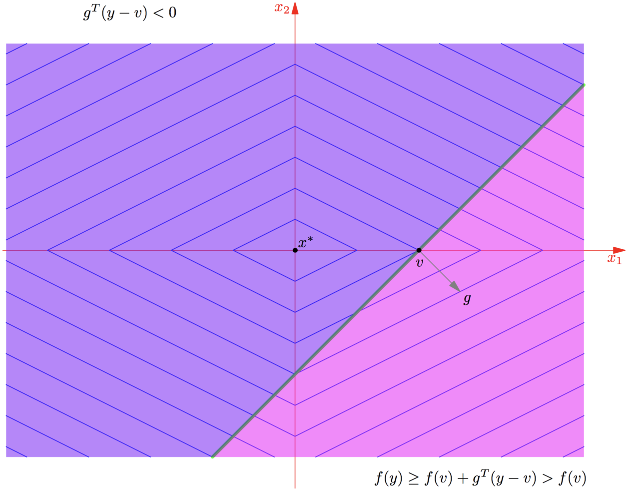
  - So y is not in the level set S.
- $\therefore$ All elements of S must be on H or on the $-g$ side of H.

Subgradient of $f(x_1, x_2) = |x_1| + 2|x_2|$



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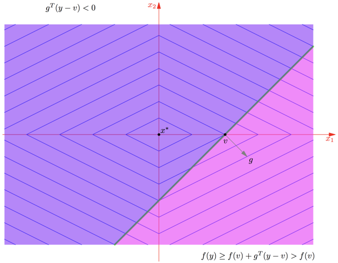

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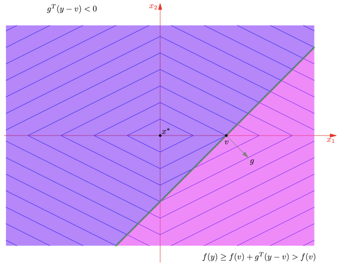

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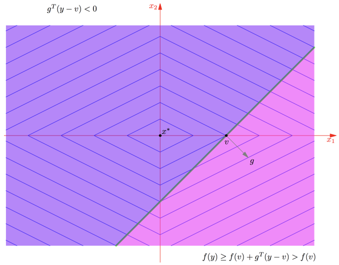

- Points on g side of H have larger f-values than $f(x_0)$. (from proof)
- But points on $-g$ side may **not** have smaller f-values.
- So $-g$ may **not** be a descent direction. (shown in figure)

Plot courtesy of Brett Bernstein.

Subgradient Descent

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- Suppose f is convex, and we start optimizing at x_0.
- Repeat
  - Step in a negative subgradient direction:

$$x = x_0 - tg,$$

    where $t > 0$ is the step size and $g \in \partial f(x_0)$.

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$-g$ not a descent direction – can this work?

Subgradient Gets Us Closer To Minimizer

Theorem

Suppose f is convex.

- *Let $x = x_0 - tg$, for $g \in \partial f(x_0)$.*
- *Let z be any point for which $f(z) < f(x_0)$.*
- *Then for small enough $t > 0$,*

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- Apply this with $z = x^* \in \arg\min_x f(x)$.

$\Longrightarrow$ **Negative subgradient step gets us closer to minimizer.**

Subgradient Gets Us Closer To Minimizer (Proof)

- Let $x = x_0 - tg$, for $g \in \partial f(x_0)$ and $t > 0$.
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$$\|x - z\|_2^2 = \|x_0 - tg - z\|_2^2$$

Based on Boyd EE364b: Subgradients Slides

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- Consider $-2t[f(x_0) - f(z)] + t^2\|g\|_2^2$.
  - It's a convex quadratic (facing upwards).
  - Has zeros at $t = 0$ and $t = 2(f(x_0) - f(z))/\|g\|_2^2 > 0$.
  - Therefore, it's negative for any

$$t \in \left(0, \frac{2(f(x_0) - f(z))}{\|g\|_2^2}\right).$$

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Convergence Theorem for Fixed Step Size

Assume $f : \mathbf{R}^n \to \mathbf{R}$ is convex and

- f is Lipschitz continuous with constant $G > 0$:

$$|f(x) - f(y)| \leqslant G\|x - y\| \text{ for all } x, y$$

Theorem

For fixed step size t, subgradient method satisfies:

$$\lim_{k \to \infty} f(x_{best}^{(k)}) \leqslant f(x^*) + G^2 t/2$$

Based on https://www.cs.cmu.edu/~ggordon/10725-F12/slides/06-sg-method.pdf

Convergence Theorems for Decreasing Step Sizes

Assume $f : \mathbf{R}^n \to \mathbf{R}$ is convex and

- f is Lipschitz continuous with constant $G > 0$:

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Theorem

For step size respecting Robbins-Monro conditions,

$$\lim_{k \to \infty} f(x_{best}^{(k)}) = f(x^*)$$

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