# CO367: Nonlinear Optimization Lecture 8, Thursday Jan. 31, 2013. 

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## Definition: $f: D \rightarrow \mathbb{R}, D \subset \mathbb{R}^{n}$ open convex set

$f$ is a convex function iff
(1) (0-order: secant lines lie above the graph)

$$
f(\lambda x+(1-\lambda) y) \leq \lambda f(x)+(1-\lambda) f(y), \forall 0 \leq \lambda \leq 1, \forall x, y \in D
$$

## iff

(2) (l-order: tangent planes lie below the graph)

$$
\nabla f(x)^{T}(y-x) \leq f(y)-f(x), \forall x, y \in D
$$

iff
(3) (II-order: Hessians are psd (curvature) )

$$
\nabla^{2} f(x) \succeq 0, \forall x \in D \quad(\mathrm{psd})
$$

## Epigraph

## Definition:

As above, let $f: D \rightarrow \mathbb{R}, D \subset \mathbb{R}^{n}$ open convex set. Then the epigraph of $f$ is

$$
\mathrm{epi}(f)=\left\{(x, r) \in \mathbb{R}^{n} \times \mathbb{R}: x \in D, f(x) \leq r\right\}
$$

## Theorem

Let $f: D \rightarrow \mathbb{R}, D \subset \mathbb{R}^{n}$ open convex set. Then $f$ is a convex function if, and only if, epi $(f)$ is a convex set.

The proof is immediate from the 0-order characterization, i.e., from the fact that the secant lines lie above the graph.

## Convex Function Preserving Operations

Let $h: \mathbb{R} \rightarrow \mathbb{R}, g: \mathbb{R}^{n} \rightarrow \mathbb{R}$ and the composition (domains/ differentiability appropriately defined/assumed). And define the composition

$$
f(x)=h(g(x))
$$

Then the second derivative

$$
f^{\prime \prime}(x)=h^{\prime \prime}(g(x)) g^{\prime}(x)^{2}+h^{\prime}(g(x)) g^{\prime \prime}(x)
$$

## is convex if either condition holds:

(1) $h$ is convex and nondecreasing and $g$ is convex
(2) $h$ is convex and nonincreasing and $g$ is concave

## Examples of Composite Convex Functions

(1) $g$ convex implies $\exp (g(x))$ is convex
(2) $g$ convex, nonnegative, $p \geq 1$ implies $(g(x))^{p}$ is convex
(3) $g$ convex, implies $-\log (-g(x))$ is convex on $\{x: g(x)<0\}$.

## Further Convexity Preserving Operations

(1) set of convex functions on suitable convex domain $D \subseteq \mathbb{R}^{n}$ forms a convex cone, i.e., closed under addition and nonneg. scalar multipl.: $g(x):=\sum_{i=1}^{k} \lambda_{i} f_{i}(x), \lambda_{i} \geq 0, \forall i$ (proof: e.g. use 2nd-order Hessian characterization)
(2) $g(x):=\sup _{i \in I}\left\{f_{i}(x)\right\}$ (proof: use the epigraph characterization and intersection of epigraphs)

Applications of sup:
(1) $\lambda_{\max }(A)=\max _{\|x\|=1} x^{\top} A x$ (largest eigenvalue)
(2) $g(x):=\sup _{y \in C}\|x-y\|$ (distance to furthest point in $C$ )

## AGM

## Arithmetic-Geometric Mean Inequality

Consider max $\left\{\sqrt[n]{\prod_{i=1}^{n} x_{i}}: \frac{1}{n} \sum_{i=1}^{n} x_{i}=1\right\}$. We can take logs and scale without changing the optimal $x$ to get

$$
\max \left\{\sum_{i=1}^{n} \log x_{i}: \sum_{i=1}^{n} x_{i}=1\right\} .
$$

We can use Lagrange multipliers (one multiplier) to get the Lagrangian $L(x, \lambda)=\sum_{i=1}^{n} \log x_{i}+\lambda\left(1-\sum_{i=1}^{n} x_{i}\right)$. and

$$
0=\nabla L(x, \lambda)=\left(\left(1 / x_{i}\right)-\lambda\right),
$$

i.e., all $x_{i}$ are equal. The optimal solution for $\sum_{i=1}^{n} x_{i}=1$ is $x_{i}=\frac{1}{n}$. Therefore

$$
\mathrm{GM}=\sqrt[n]{\prod_{i=1}^{n} x_{i}}=\frac{1}{n}=\frac{1}{n} \sum_{i=1}^{n} x_{i}=A M
$$

at the maximum for the GM. Conclusion: $\mathrm{GM} \leq \mathrm{AM}$ with equality if, and only if all $x_{i}$ are equal.

## Other Inequalities

Similarly: generalized AGM and other inequalities, e.g., Cauchy-Schwartz and Holder inequalities, can be proved this way.

## Applications of AGM

Problem: Find the open rectangular box with a fixed surface area $S_{0}$ that has the largest volume.

## Solution

$$
\begin{aligned}
S_{0} & =x_{1} x_{2}+2 x_{1} x_{3}+2 x_{2} x_{3} \\
& =3\left(\frac{x_{1} x_{2}+2 x_{1} x_{3}+2 x_{2} x_{3}}{3}\right) \\
& \geq 3\left(\left(x_{1} x_{2}\right)^{1 / 3}\left(2 x_{1} x_{3}\right)^{1 / 3}\left(2 x_{2} x_{3}\right)^{1 / 3}\right) \\
& =3(4)^{1 / 3}\left(x_{1}^{2} x_{2}^{2} x_{3}^{2}\right)^{1 / 3} \\
& =3(4)^{1 / 3} V^{2 / 3}
\end{aligned}
$$

and $V$ is max when $x_{1} x_{2}=2 x_{1} x_{3}=2 x_{2} x_{3}=S_{0} / 3$. Yields $x_{1}=x_{2}=\sqrt{\frac{S_{0}}{3}}$ and $x_{3}=\frac{1}{2} \frac{S_{0}}{3}$

## Thanks for your attention!

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