• conv $C = \left\{ \sum_{i=1}^k \theta_i \mathbf{x}_i \mid \mathbf{x}_i \in C, 0 \leq 0 \leq 1, 1^T 0 = 1 \right\}$		• conv C will be the sma	allest convex set that contains C
			set as long as C is also finite.
Affine hull: • aff $C = \{\sum_{i=1}^k \theta_i \mathbf{x}_i \mid \mathbf{x}_i \in C \text{ for } i = 1, \dots, k, 1^T 0 = 1\}$			affine set that contains C . vex set, θ_i is not restricted between 0 and 1
		• aff C will always be an	infinite set. If aff C contains the origin, it is also a subspace.
Conic hull: • $A = \left\{ \sum_{i=1}^{k} \theta_i \mathbf{x}_i \mid \mathbf{x}_i \in C, \theta_i > 0 \text{ for } i = 1, \dots, k \right\}$			convex conic that contains C . vex and affine sets, θ_i does not need to sum up 1.
Ray:			et that begins in \mathbf{x}_0 and extends infinitely in direction of \mathbf{v} . In other
Hyperplane:		• It is an infinite set \mathbb{R}^{n}	\mathbb{R}^n that divides the space into two halfspaces.
• $\mathcal{H} = \{ \mathbf{x} \mid \mathbf{a}^T \mathbf{x} = b \}$ • $\mathcal{H} = \{ \mathbf{x} \mid \mathbf{a}^T (\mathbf{x} - \mathbf{x}_0) = 0 \}$			ne set of vectors perpendicular to \mathbf{a} . It passes through the origin. Figin by \mathbf{x}_0 , which is any vector in \mathcal{H} .
• $\mathcal{H} = \mathbf{x}_0 + a^{\perp}$ Halfspaces:		• They are infinite sets	of the parts divided by \mathcal{H} .
• $\mathcal{H}_{-} = \{ \mathbf{x} \mid \mathbf{a}^{T} \mathbf{x} \le b \}$ • $\mathcal{H}_{+} = \{ \mathbf{x} \mid \mathbf{a}^{T} \mathbf{x} \ge b \}$		Sets (
Euclidean ball:		• $B(\mathbf{x}_c, r)$ is a finite set a	
• $B(\mathbf{x}_c, r) = \{\mathbf{x} \mid \mathbf{x} - \mathbf{x}_c _2 \le r\}$ • $B(\mathbf{x}_c, r) = \{\mathbf{x} \mid (\mathbf{x} - \mathbf{x}_c)^T (\mathbf{x} - \mathbf{x}_c) \le r\}$		 x_c is the center of the r is its radius. 	ball.
• $B(\mathbf{x}_c, r) = {\mathbf{x}_c + r \mathbf{u} \mid \mathbf{u} \le 1}$ Ellipsoid:		ullet E is a finite set as long	g as P is a finite matrix.
• $\mathcal{E} = \{ \mathbf{x} \mid (\mathbf{x} - \mathbf{x}_c)^T \mathbf{P}^{-1} (\mathbf{x} - \mathbf{x}_c) \le 1 \}$ • $\mathcal{E} = \{ \mathbf{x}_c + \mathbf{A} \mathbf{u} \mid \mathbf{u} \le 1 \}$, where $\mathbf{A} = \mathbf{P}^{1/2}$.			sitive definite, that is, $\mathbf{P} = \mathbf{P}^{T} > 0$.
		The lengths of the semA is invertible. When	i-axes are given by $\sqrt{\lambda_i}$. In it is not, we say that $\mathcal E$ is a degenerated ellipsoid (degenerated
Norm cone:		ellipsoids are also conv	
Norm cone: • $C = \{(x_1, x_2, \dots, x_n, t) \in \mathbb{R}^{n+1} \mid \mathbf{x} \in \mathbb{R}^n, \mathbf{x} _p \le t\} \subseteq \mathbb{R}^{n+1}$		• The cone norm increas	ses the dimension of \mathbf{x} in 1.
Proper cone: $K \subset \mathbb{R}^n$ is a proper cone when it has the followin	g properties	• The proper cone <i>K</i> is t	ne second-order cone, quadratic cone, Lorentz cone or ice-cream cone. used to define the generalized inequality (or partial ordering) in some
 K is a convex cone, i.e., αK ≡ K, α > 0. K is closed. 		$\bullet \ \mathbf{x} \leq \mathbf{y} \iff \mathbf{y} - \mathbf{x} \in K$	zed inequality, one must define both the proper cone K and the set S . for $\mathbf{x},\mathbf{y}\in S$ (generalized inequality)
 K is solid. K is pointed, i.e., -K ∩ K = {0}. 			K for $\mathbf{x}, \mathbf{y} \in S$ (strict generalized inequality). There K and S are understood from context and the subscript K is
			l $K = \mathbb{R}^n_+$ (the nonnegative orthant). In this case, $\mathbf{x} \leq \mathbf{y}$ means that
		matrices, S_+^n is the positive definite n	If $K = \mathcal{S}^n_+$ or $K = \mathcal{S}^n_{++}$, where \mathcal{S}^n denotes the set of symmetric $n \times n$ despace of the positive semidefinite matrices, and \mathcal{S}^n_{++} is the space of the natrices. \mathcal{S}^n_+ is a proper cone in \mathcal{S}^n (??). In this case, the generalized
		positive semidefindenote $X > 0$ and	means that $\mathbf{Y} - \mathbf{X}$ is a positive semidefinite matrix belonging to the ite cone \mathcal{S}^n_+ in the subspace of symmetric matrices \mathcal{S}^n . It is usual to $\mathbf{X} \succeq 0$ to mean than \mathbf{X} is a positive definite and semidefinite matrix,
		• Another common	the $0 \in \mathbb{R}^{n \times n}$ is a zero matrix. usage is when $S = \mathbb{R}^n$ and $K = 0 + c_n t^{n-1} \ge 0$, for $0 \le t \le 1$. In this case, $\mathbf{x} \le_K \mathbf{y}$ means that
		$x_1 + x_2t + \dots + x_nt^{n-1} \le$	$y_1 + y_2t + \dots + y_nt^{n-1}$. Ality has the following properties:
		▶ If $\mathbf{x} \leq_K \mathbf{y}$ and $\mathbf{y} \leq$	\mathbf{z}_{K} \mathbf{v} , then $\mathbf{x} + \mathbf{u} \leq_{k} \mathbf{y} + \mathbf{v}$ (preserve under addition). \mathbf{z}_{K} \mathbf{z} , then $\mathbf{x} \leq_{K} \mathbf{z}$ (transitivity).
		$\triangleright \mathbf{x} \leq_K \mathbf{x}$ (reflexivity	$\mathbf{x} \leq_K \mathbf{y}$ for $\alpha \geq 0$ (preserve under nonnegative scaling). \mathbf{y}). $\mathbf{x}_K \mathbf{x}$, then $\mathbf{x} = \mathbf{y}$ (antisymmetric).
		• It is called partial order	$\mathbf{x} = 1, 2, \ldots, \text{ and } \mathbf{x}_i \to \mathbf{x} \text{ and } \mathbf{y}_i \to \mathbf{y} \text{ as } i \to \infty, \text{ then } \mathbf{x} \leq_K \mathbf{y}.$ ring because $\mathbf{x} \not\succeq_K \mathbf{y}$ and $\mathbf{y} \not\succeq_K \mathbf{x}$ for many $\mathbf{x}, \mathbf{y} \in S$. When it happens,
		< and >).	the not comparable (this case does not happen in ordinary inequality, element of S with respect to the proper cone K if $\mathbf{x} \leq_K \mathbf{y}$, $\forall \mathbf{y} \in S$
		(for maximum, $\mathbf{x} \succeq_K \mathbf{y}$ where $\mathbf{x} + K$ denotes the is comparable with \mathbf{x} and $\mathbf{x} = \mathbf{x} + K$	$x, \forall y \in S$). It means that $S \subseteq x + K$ (for the maximum, $S \subseteq x - K$), the set K shifted from the origin by x . Note that any point in $K + x$ and is greater or equal to x in the generalized inequality mean. The
		set S does not necessary unique if it does.	rily have a minimum (maximum), but the minimum (maximum) is element of S with respect to the proper cone K if $\mathbf{y} \leq_K \mathbf{x}$ only when
		$\mathbf{y} = \mathbf{x}$ (for the maximal (for the maximal ($\mathbf{x} + \mathbf{A}$)	element of S with respect to the proper cone K if $\mathbf{y} \leq_K \mathbf{x}$ only when $\mathbf{y} \geq_K \mathbf{x}$ only when $\mathbf{y} = \mathbf{x}$). It means that $(\mathbf{x} - K) \cap S = \{\mathbf{x}\}$ for minimal $K \cap S = \{\mathbf{x}\}$, where $\mathbf{x} - K$ denotes the reflected set K shift by \mathbf{x} . Note is comparable with \mathbf{x} and is less than or equal to \mathbf{x} in the generalized
		inequality mean. The second when $K = \mathbb{R}_+$ and $S =$	set S can have many different minimal (maximal) elements. \mathbb{R} (ordinary inequality), the minimal is equal to the minimum and
		the maximal is equal t When we say that a s	
Dual cone:		nonincreasing scalar fu	nctions.
Dual cone: • $K^* = \{ \mathbf{y} \mid \mathbf{x}^T \mathbf{y} \ge 0, \ \forall \ \mathbf{x} \in K \}$		 • K* is a cone, and it is convex even when the original cone K is nonconvex. • K* has the following properties: ▶ K* is closed and convex. 	
		$ ightharpoonup K_1 \subseteq K_2 \text{ implies } I$	
		▶ If the closure of <i>I</i>	G is pointed then K^* has a nonempty interior. of the convex hull of K . Hence, if K is convex and closed, $K^{**} = K$.
Polyhedra:			or may not be an infinite set.
• $\mathcal{P} = \left\{ \mathbf{x} \mid \mathbf{a}_{j}^{T} \mathbf{x} \leq b_{j}, j = 1, \dots, m, \mathbf{a}_{j}^{T} \mathbf{x} = d_{j}, j = 1, \dots, p \right\}$ • $\mathcal{P} = \left\{ \mathbf{x} \mid \mathbf{A} \mathbf{x} \leq \mathbf{b}, \mathbf{C} \mathbf{x} = \mathbf{d} \right\}, \text{ where } \mathbf{A} = \begin{bmatrix} \mathbf{a}_{1} & \mathbf{a}_{2} & \dots & \mathbf{a}_{m} \end{bmatrix}^{T} \text{ and } \mathbf{a}_{j} = \mathbf{a}_{j}, \mathbf{a}_{j} = \mathbf{a}_{j} = \mathbf{a}_{j}, \mathbf{a}_{j} = \mathbf{a}_{j}, \mathbf{a}_{j} = \mathbf{a}_{j}, \mathbf{a}_{j} = \mathbf{a}_{j}, \mathbf{a}_{j} = \mathbf{a}_{j} = \mathbf{a}_{j}, \mathbf{a}_{j} = a$	$\mathbf{d} \ \mathbf{C} = \begin{bmatrix} \mathbf{c}_1 & \mathbf{c}_2 & \dots & \mathbf{c}_m \end{bmatrix}^T$		It of the intersection of m halfspaces and p hyperplanes. es, lines, rays line segments, and halfspaces are all special cases of
[J		nt , $\mathbb{R}^n_+ = \{ \mathbf{x} \in \mathbb{R}^n \mid x_i \le 0 \text{ for } i = 1, \dots n \} = \{ \mathbf{x} \in \mathbb{R}^n \mid \mathbf{I}\mathbf{x} \succeq 0 \}$, is a spe-
Simplex: • $S = \text{conv } \{\mathbf{v}_m\}_{m=0}^k = \{\sum_{i=0}^k \theta_i \mathbf{v}_i \mid 0 \le \mathbf{\theta} \le 1, 1^T \mathbf{\theta} = 1\}$		• Simplexes are a subfar	
• $S = \{ \mathbf{x} \mid \mathbf{x} = \mathbf{v}_0 + \mathbf{V} \mathbf{\theta} \}$, where $\mathbf{V} = \begin{bmatrix} \mathbf{v}_1 - \mathbf{v}_0 & \dots & \mathbf{v}_n - \mathbf{v}_0 \end{bmatrix} \in \mathbb{R}$		 Also called k-dimensio The set {v_m}^k_{m=0} is a sindependent. 	nal Simplex in \mathbb{R}^n . affinely independent, which means $\{\mathbf v_1 - \mathbf v_0, \dots, \mathbf v_k - \mathbf v_0\}$ are linearly
• $S = \{ \mathbf{x} \mid \underbrace{\mathbf{A}_1 \mathbf{x} \leq \mathbf{A}_1 \mathbf{v}_0, 1^T \mathbf{A}_1 \mathbf{x} \leq 1 + 1^T \mathbf{A}_1 \mathbf{v}_0}_{\text{Linear inequalities in } x}, \underbrace{\mathbf{A}_2 \mathbf{x} = \mathbf{A}_2 \mathbf{v}_0}_{\text{Linear equalities in } x} \}$	(1 oryneura form), where $\mathbf{A} =$		tall matrix, i.e., $\operatorname{rank}(\mathbf{V}) = k$. All its column vectors are independent. t pseudoinverse.
$ \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \end{bmatrix} \text{ and } \mathbf{AV} = \begin{bmatrix} \mathbf{I}_{k \times k} \\ 0_{n-k \times n-k} \end{bmatrix} $ \alpha-sublevel set:		,	we) function, then sublevel sets of f are convexes (concaves) for any
• $C_{\alpha} = \{\mathbf{x} \in \text{dom}(f) \mid f(\mathbf{x}) \leq \alpha\}$ (regarding convexity), where • $C_{\alpha} = \{\mathbf{x} \in \text{dom}(f) \mid f(\mathbf{x}) \geq \alpha\}$ (regarding concavity), where		$\alpha \in \mathbb{R}$.	ie: a function can have all its sublevel set convex and not be a convex
		• $C_{\alpha} \subseteq \text{dom}(f)$	
Function Union: $C = A \cup B$	Convex (convex (convex is a second of the cases).	ncave)?	nvexity Comments
Intersection: $C = A \cap B$ Convex function: $f : \text{dom}(f) \to \mathbb{R}$	Yes, if A and B are convex set Yes.	S.	• Graphically, the line segment between $(\mathbf{x}, f(\mathbf{x}))$ and $(\mathbf{y}, f(\mathbf{y}))$ lies always above the graph f .
 f(θx + (1 - θ)y) ≤ θf(x) + (1 - θ)f(y), where 0 ≤ θ ≤ 1. dom (f) shall be a convex set to f be considered a convex function. 			 In terms of sets, a function is convex iff a line segment within dom (f), which is a convex set, gives an image set that is also
			 convex. dom f is convex iff all points for any line segment within dom (f) belong to it
			belong to it. • First-order condition: f is convex iff dom (f) is convex and $f(\mathbf{y}) \ge f(\mathbf{x}) + \nabla f(\mathbf{x})^{T}(\mathbf{y} - \mathbf{x}), \forall \mathbf{x}, \mathbf{y} \in \text{dom}(f), \mathbf{x} \ne \mathbf{y}, \text{ being } \nabla f(\mathbf{x}) \text{ the } \mathbf{y} = \mathbf{y}$
			gradient vector. This inequation says that the first-order Taylor approximation is a <i>underestimator</i> for convex functions. The first-order condition requires that f is differentiable.
			• If $\nabla f(\mathbf{x}) = 0$, then $f(\mathbf{y}) \geq f(\mathbf{x}), \forall \mathbf{y} \in \text{dom}(f)$ and \mathbf{x} is a global minimum.
			• Second-order condition: f is convex iff $dom(f)$ is convex and $\mathbf{H} \geq 0$, that is, the Hessian matrix \mathbf{H} is a positive semidefinite matrix. It means that the graphic of the curvature has a positive
			(upward) curvature at x . It is important to note that, if $\mathbf{H} > 0, \forall \mathbf{x} \in \text{dom}(f)$, then f is strictly convex. But is f is strictly convex, not necessarily that $\mathbf{H} > 0, \forall \mathbf{x} \in \text{dom}(f)$. Therefore,
Affine function $f: \mathbb{R}^n \to \mathbb{R}^m$	Yes, if the domain $S \subseteq \mathbb{R}^n$ is a $f(S) = \{f(\mathbf{x}) \mathbf{x} \in S\} \subseteq \mathbb{R}^m$ is a		strict convexity can only be partially characterized. • The affine function, $f(\mathbf{x}) = \mathbf{A}\mathbf{x} + \mathbf{b}$, is a broader category that encompasses the linear function, $f(\mathbf{x}) = \mathbf{A}\mathbf{x}$. The linear function
• $f(\mathbf{x}) = \mathbf{A}\mathbf{x} + \mathbf{b}$, where $\mathbf{A} \in \mathbb{R}^{m \times n}$, $\mathbf{b} \in \mathbb{R}^m$, $\mathbf{x} \in \mathbb{R}^n$	$J(\sim) - \{J(\mathbf{x}) \mathbf{x} \in \mathbf{S}\} \subseteq \mathbb{R}^m \text{ is a}$	JOHNOA.	encompasses the linear function, $f(\mathbf{x}) = \mathbf{A}\mathbf{x}$. The linear function has its origin fixed at 0 after the transformation, whereas the affine function does not necessarily have it (when not, this makes the affine function nonlinear). Graphically, we can think of an
			affine function as a linear transformation plus a shift from the origin of \mathbf{b} .
			• A special case of the linear function is when $\mathbf{A} = \mathbf{c}^{T}$. In this case, we have $f(\mathbf{x}) = \mathbf{c}^{T}\mathbf{x}$, which is the inner product between the vector \mathbf{c} and \mathbf{x} .
			 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B,
			 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved opti-
Exponential function $f: \mathbb{R} \to \mathbb{R}$	Yes.		 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization
Exponential function $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$	Yes. It depends on the matrix P :		 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved opti-
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$) .	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved opti-
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T\mathbf{P}\mathbf{x} + \mathbf{p}^T\mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and	It depends on the matrix P : • f is convex iff $P \ge 0$.		 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved opti-
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$	 It depends on the matrix P: f is convex iff P ≥ 0. f is strictly convex iff P > 0. f is concave iff P ≤ 0. f is strictly concave iff P < 	0.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved opti-
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$	 It depends on the matrix P: f is convex iff P ≥ 0. f is strictly convex iff P > 0. f is concave iff P ≤ 0. f is strictly concave iff P < 	0.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved opti-
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$	 It depends on the matrix P: f is convex iff P ≥ 0. f is strictly convex iff P > 0. f is concave iff P ≤ 0. f is strictly concave iff P < It depends on a f is convex iff a ≥ 1 or a ≤ 	0.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved opti-
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$	 It depends on the matrix P: f is convex iff P ≥ 0. f is strictly convex iff P > 0. f is concave iff P ≤ 0. f is strictly concave iff P < It depends on a f is convex iff a ≥ 1 or a ≤ f is concave iff 0 ≤ a ≤ 1. 	0.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved opti-
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on a . • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff f is concave if	0.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁+···+x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function:	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on a . • f is convex iff $a \ge 1$ or $a \le 0$. • f is convex iff f is concave if f is conca	0.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved opti-
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \leq 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \ \mathbf{x}\ _p$, where $p \in \mathbb{N}_{++}$.	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on P • f is convex iff P • f is convex iff P • f is convex iff P • f is concave iff P • f	0.	we have $f(\mathbf{x}) = \mathbf{c}^{T}\mathbf{x}$, which is the inner product between the vector \mathbf{c} and \mathbf{x} . • The inverse image of C , $f^{-1}(C) = \{\mathbf{x} \mid f(\mathbf{x}) \in C\}$, is also convex. • The linear matrix inequality (LMI), $\mathbf{A}(\mathbf{x}) = x_1 \mathbf{A}_1 + \dots + x_n \mathbf{A}_n \leq \mathbf{B}$, is a special case of affine function. In other words, $f(S) = \{\mathbf{x} \mid \mathbf{A}(\mathbf{x}) \leq \mathbf{B}\}$ is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. • When it is defined $f(x) _{x=0} = 0$, $\operatorname{dom}(f) = \mathbb{R}$.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on a . • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff f is concave if f	0.	we have $f(\mathbf{x}) = \mathbf{c}^{T}\mathbf{x}$, which is the inner product between the vector \mathbf{c} and \mathbf{x} . • The inverse image of C , $f^{-1}(C) = \{\mathbf{x} \mid f(\mathbf{x}) \in C\}$, is also convex. • The linear matrix inequality (LMI), $\mathbf{A}(\mathbf{x}) = x_1 \mathbf{A}_1 + \dots + x_n \mathbf{A}_n \leq \mathbf{B}$, is a special case of affine function. In other words, $f(S) = \{\mathbf{x} \mid \mathbf{A}(\mathbf{x}) \leq \mathbf{B}\}$ is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. • When it is defined $f(x) _{x=0} = 0$, $dom(f) = \mathbb{R}$.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on P • f is convex iff P • f is convex iff P • f is convex iff P • f is concave iff P • f	0 .	we have $f(\mathbf{x}) = \mathbf{c}^{T}\mathbf{x}$, which is the inner product between the vector \mathbf{c} and \mathbf{x} . • The inverse image of C , $f^{-1}(C) = \{\mathbf{x} \mid f(\mathbf{x}) \in C\}$, is also convex. • The linear matrix inequality (LMI), $\mathbf{A}(\mathbf{x}) = x_1 \mathbf{A}_1 + \dots + x_n \mathbf{A}_n \leq \mathbf{B}$, is a special case of affine function. In other words, $f(S) = \{\mathbf{x} \mid \mathbf{A}(\mathbf{x}) \leq \mathbf{B}\}$ is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. • When it is defined $f(x) _{x=0} = 0$, $dom(f) = \mathbb{R}$.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \leq 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \ \mathbf{x}\ _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{f_1(\mathbf{x}), \dots, f_n(\mathbf{x})\}$.	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on a . • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff f is concave if f is	0 .	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁+···+x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \leq 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \ \mathbf{x}\ _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{f_1(\mathbf{x}), \dots, f_n(\mathbf{x})\}$.	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on a . • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff f is f is concave iff f is f	0 .	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + · · · + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. It can be proved by triangular inequality. Its domain dom (f) = ∫_{i=1}ⁿ dom (f_i) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈ R}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{f_1(\mathbf{x}), \dots, f_n(\mathbf{x})\}$. Pointwise infimum: • $f(x) = \inf_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$.	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on a . • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff $0 \le 0$. Yes. Yes. Yes. Yes. Yes. Yes. Yes. Yes.	0. ex in x for each $y \in \mathcal{A}$.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + · · · + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. It can be proved by triangular inequality. Its domain dom (f) = ∫_{i=1}ⁿ dom (f_i) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the least value in the codomain of f that
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{f_1(\mathbf{x}), \dots, f_n(\mathbf{x})\}$. Pointwise infimum: • $f(x) = \inf_{y \in \mathcal{A}} g(x, y)$.	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on a . • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff f is f is concave iff f is f is concave iff f is f is f is concave iff f is f	o. o. ex in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. It can be proved by triangular inequality. Its domain dom (f) = ∫_{t=1}ⁿ dom (f_t) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{f_1(\mathbf{x}), \dots, f_n(\mathbf{x})\}$. Pointwise infimum: • $f(x) = \inf_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$.	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on a . • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff $0 \le 0$. Yes. Yes. Yes. Yes. Yes. Yes. Yes. Yes.	o. o. ex in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ +···+x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. Its domain dom (f) = ∫_{i=1}ⁿ dom (f_i) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈ R}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ R, sinf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈ R}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ R, sinf g(x, y) < ∞}. In terms of epigraphs, the pointwise supremum of the infinite set
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \leq 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \ \mathbf{x}\ _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{f_1(\mathbf{x}), \dots, f_n(\mathbf{x})\}$. Pointwise infimum: • $f(x) = \sup_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$.	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. • f is convex iff $a \ge 1$ or $a \le 0$. • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff f is convex if f is convex in f is convex in f is convex in f if f is convex in f if f is convex in f in f is convex in f in f in f in f is convex in f	o. o. ex in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁+···+x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. Its domain dom (f) = ∫_{i=1}ⁿ dom (f_i) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈ A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sup g(x, y) < ∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈ A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sup g(x, y) < ∞}. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sup g(x, y) < ∞}.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \ \mathbf{x}\ _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(\mathbf{x}), \dots, f_n(\mathbf{x})\}$. Pointwise infimum: • $f(x) = \sup_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \sup_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$.	 It depends on the matrix P: f is convex iff P ≥ 0. f is strictly convex iff P > 0. f is concave iff P ≤ 0. f is concave iff P < It depends on a f is convex iff a ≥ 1 or a ≤ f is concave iff 0 ≤ a ≤ 1. Yes. Yes. Yes. Yes. Yes. Yes. Not in most of the cases. Not in most of the cases. 	o. o. ex in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. Its domain dom (f) = \(\begin{align*} \text{dom} \text{dom} \(\text{dom} \) (f_i) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, \text{inf} \(g(x, y) \) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, \text{sup} \(g(x, y) \) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, \text{sup} \(g(x, y) \) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, \text{sup} \(g(x, y) \) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, \text{sup} \(g(x, y) \) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, \text{sup} \(g(x, y) \) _{y∈A}. The value f(x) will be the least value in the codomain of the infinite set of lunctions g(x, y) _{y∈A}. Corresponds to the intersection of the following epigraphs: epi f = \(\hat{y} \) _{y∈A}. Or expensional to t
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f: \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f: \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \leq 1$. Logarithm function: $f: \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \ \mathbf{x}\ _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(\mathbf{x}), \dots, f_n(\mathbf{x})\}$. Pointwise infimum: • $f(x) = \sup_{\mathbf{y} \in \mathcal{R}} g(x, \mathbf{y})$. Minimum function: $f: \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. • f is convex iff $a \ge 1$ or $a \le 0$. • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff f is convex if f is convex in f is convex in f is convex in f if f is convex in f if f is convex in f in f is convex in f in f in f in f is convex in f	o. o. ex in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ···· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. It can be proved by triangular inequality. Its domain dom (f) = ∩ dom (f_i) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sup g(x, y) < ∞}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sup g(x, y) < ∞}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \mathbf{x} ^p$, where $p \leq 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \ \mathbf{x}\ _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{f_1(\mathbf{x}), \dots, f_n(\mathbf{x})\}$. Pointwise supremum: • $f(x) = \sup_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \sup_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$. Committee $f(\mathbf{x}) = \sup_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \sup_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$. Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$	 It depends on the matrix P: f is convex iff P ≥ 0. f is strictly convex iff P > 0. f is concave iff P ≤ 0. f is concave iff P < It depends on a f is convex iff a ≥ 1 or a ≤ f is concave iff 0 ≤ a ≤ 1. Yes. Yes. Yes. Yes. Yes. Yes. Not in most of the cases. Not in most of the cases. 	o. o. ex in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. Its domain dom (f) = ∫_{i=1}ⁿ dom (f_i) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sin g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sin g(x, y) √∞ A, y∈A (x, y) √∞ A, y∈A (
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \leq 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \ x\ _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \sup_{y \in \mathcal{A}} g(x, y)$. Pointwise supremum: • $f(x) = \sup_{y \in \mathcal{A}} g(x, y)$. Cosume-exp function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log (e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log (e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log (e^{x_1} + \dots + e^{x_n})$ Log-determinant function $f : \mathbb{S}^n \to \mathbb{R}$	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on a . • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff $0 \le a \le 1$. Yes. Yes. Yes. Yes. Yes. One of is convex in f is convex in f in f in f in f is convex in f	o. o. ex in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. Its domain dom (f) = ∫_{i=1}ⁿ dom (f_i) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sin g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sin g(x, y) √∞ A, y∈A (x, y) √∞ A, y∈A (
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T P x + p^T x + r \in \mathbb{R}$, where $x, p \in \mathbb{R}^n, P \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \ x\ _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \sup_{y \in \mathcal{R}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{y \in \mathcal{R}} g(x, y)$. Commence of $f(x) = \sup_{y \in \mathcal{R}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log (e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log (e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log (e^{x_1} + \dots + e^{x_n})$	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is convex iff $P \le 0$. • f is convex iff $P \le 0$. It depends on $P \le 0$. • f is convex iff $P \ge 0$. • f is convex iff $P \ge 0$. • f is convex iff $P \ge 0$. Yes. Yes. Yes. Yes. Yes. Yes. Yes. Yes. Not in most of the cases. Yes. Yes. Yes.	0. O. Example 1 in x for each $y \in \mathcal{A}$. Cave in x for each $y \in \mathcal{A}$.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. Its domain dom (f) = f dom (f₁) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈3}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈3}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) < ∞}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y∈3} corresponds to the intersection of the following epigraphs: epi f = ∩ epi g(·, y) In the composition function, since max {x₁,,x_n} ≤ f(x) ≤ max {x₁,,x_n} + log n X is positive semidefinite, i.e., X > 0 ∴ X ∈ Sⁿ₊₊. The composition function allows us to see a large class of functions
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \leq 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwooki distance, p -norm function, or l_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \ \mathbf{x}\ _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max\{f_1(\mathbf{x}), \dots, f_n(\mathbf{x})\}$. Pointwise infimum: • $f(x) = \inf_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \sup_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$. Log-sum-exp function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \log (e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \log (e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \log \mathbf{x} $	 It depends on the matrix P: f is convex iff P ≥ 0. f is strictly convex iff P > 0. f is concave iff P ≤ 0. f is concave iff P ≤ 1. It depends on a f is convex iff a ≥ 1 or a ≤ f is concave iff 0 ≤ a ≤ 1. Yes. 	oving statements hold for \mathbb{R} and \mathbb{R} and \mathbb{R} are each $y \in \mathcal{A}$. The example of \mathbb{R} and \mathbb{R} and \mathbb{R} are each \mathbb{R} and \mathbb{R} are eac	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁x₁ + ··· + x_nA_n ⊆ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. Its domain dom (f) = ∫_{i=1}ⁿ dom (f_i) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) < ∞}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y∈A} corresponds to the intersection of the following epigraphs: epi f = ∫ epi g(x, y) This function is interpreted as the approximation of the maximum element function, since max {x₁, , x_n} ≤ f(x) ≤ max {x₁, , x_n} + log n X is positive semidefinite, i.e., X > 0 X ∈ Sⁿ_{x+}.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \mathbf{x} ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_{+} \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max \{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \inf_{\mathbf{y} \in \mathcal{A}} f(x, \mathbf{y})$. Pointwise supremum: • $f(x) = \sup_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{\mathbf{y} \in \mathcal{A}} g(x, \mathbf{y})$. Commodition of $f(x) = \sup_{\mathbf{y} \in \mathcal{A}} f(x, \mathbf{y})$. Pointwise supremum: • $f(x) = \sup_{\mathbf{y} \in \mathcal{A}} f(x, \mathbf{y})$. Commodition of $f(x) = \sup_{\mathbf{y} \in \mathcal{A}} f(x, \mathbf{y})$. Commodition of $f(x) = \sup_{\mathbf{y} \in \mathcal{A}} f(x, \mathbf{y})$. Composite function $f(x) = h \cdot g(x) = h(g(x))$, where:	It depends on the matrix P : • f is convex iff $P \ge 0$. • f is strictly convex iff $P > 0$. • f is concave iff $P \le 0$. • f is concave iff $P \le 0$. • f is strictly concave iff $P < 0$. It depends on a • f is convex iff $a \ge 1$ or $a \le 0$. • f is concave iff $0 \le a \le 1$. Yes. Only if f is convex if f is convex if f is convex if f is convex if f is convex. In f is convex if f is convex i	owing statements hold for \mathbb{R} and $g: \mathbb{R}^n \to \mathbb{R}$: ave in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$.	 we have f(x) = e^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ····+x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = (x A(x) ≤ B) is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. Its domain dom (f) = f dom (f_t) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈ N}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈ N}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > ∞}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y∈ N} corresponds to the intersection of the following epigraphs: epi f = corresponds to the intersection of the following epigraphs: epi f = corresponds to the intersection of the maximum clowing time function allows us to see a large class of functions as convex (or concave). X is positive semidefinite, i.e., X > 0 ∴ X ∈ S
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \inf_{y \in \mathcal{A}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{y \in \mathcal{A}} g(x, y)$. Commetric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(x)$ Log-determinant function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P ≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 1. It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. Yes. Yes. Yes. Yes. Yes. Yes. It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes.	owing statements hold for f and f and f are each f and f and f are each f are each f and f are each f are each f and f are each f are each f and f are each f are each f and f are each f and f are each f and f are each f are each f and f are each f are each f and f are each f are each f and f are each f and f are each f and f are each f are each f and f are each f are each f and f are each f and f are each f and f are each f are each f and f are each f are each f and f are each f and f are each f are each f are each f are each f a	 we have f(x) = e^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ···· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) is a special case of affine function. In other words, f(S) is a low set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. It can be proved by triangular inequality. It can be proved by triangular inequality. For each value of x, we have an infinite set of points g(x, y) _{y \in \mathcal{H}}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ \mathcal{H}, \sinf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y ∈ \mathcal{H}}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ \mathcal{H}, \sinf g(x, y) _{y ∈ \mathcal{H}}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ \mathcal{H}, \sinf g(x, y) _{y ∈ \mathcal{H}}. Sinf g(x, y) _{y ∈ \mathcal{H}}. Sinf g(x, y) _{y ∈ \mathcal{H}}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y ∈ \mathcal{H}} = \cap \text{epi g(x)}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y ∈ \mathcal{H}} = \cap \text{epi g(x)}. This function is interpreted as the approximation of the maximum element function, since max {x_1,, x_n} ≤ f(x) ≤ \maxhcal{H}. The composition function allows us to see a large class of functions as convex (or concave), the remarkable ones are: If g is concave and for g(y) ∈ \maxhcal{H}, then f(x) = h(g(x)) = lf(g(x)) is conevex. If
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \inf_{y \in \mathcal{A}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{y \in \mathcal{A}} g(x, y)$. Commetric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(x)$ Log-determinant function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P ≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 1. It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes.	o.	 we have f(x) = e^xx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ··· + x_nA_n ≤ B, is a special case of affine function. In other words, f(S) = {x A(x) ≤ B}, is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimially. When it is defined f(x) _{x=0} = 0, dom (f) = ℝ. It can be proved by triangular inequality. Its domain dom (f) = ∫ dom (f) is also convex. for each value of x, we have an infinite set of points g(x, y) _{y ∈ A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y ∈ A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sup g(x, y) < ∞}. For each value of x, we have an infinite set of points g(x, y) _{y ∈ A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sup g(x, y) < ∞}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y ∈ A} corresponds to the intersection of the following epigraphs: epi f = ∫ epi g(x, y) This function is interpreted as the approximation of the maximum element function, since max {x₁,,x_n} ≤ f(x) ≤ max {x₁,,x_n} + log n This function is interpreted as the approximation of the maximum element function, since max {x₁,,x_n} ≤ f(x) ≤ max {x₁,,x_n} + log n The composition, the remarkable ones are: If g is convex then f(x) = h(g(x)) = exp g(x) is convex. If g is convex and dom (g) ⊆ ℝ₊₊, then f(x) = h(g(x)) = g^p(x) is convex, wher
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \inf_{y \in \mathcal{A}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{y \in \mathcal{A}} g(x, y)$. Commetric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(x)$ Log-determinant function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P ≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is trictly concave iff P < It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes.	oving statements hold for \mathbb{R} and $g:\mathbb{R}^n \to \mathbb{R}$. cave in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$. cave, \tilde{h} is nonincreasing, is case, dom (h) is either acave, \tilde{h} is nonincreasing, oving statements hold for h and h is nonincreasing, oving statements hold for h and h is nonincreasing, oving statements hold for h and h is nonincreasing, oving statements hold for h and h is nonincreasing, oving statements hold for h and h is nonincreasing, oving statements hold for h and h is nonincreasing, oving statements hold for h and h is nonincreasing, over	 we have f(x) = c¹x, which is the inner product between the vector e and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ···· + x_nA_n ≤ B_i is a special case of affine function. In other words, f(3) = (x₁ A(x) ≤ B) is a convex set if 3 is convex. Many optimization problems can be formulated as LMI problems and solved optimally. Its domain dom (f) = ⁿ/_{i=1} dom (f_i) is also convex. It can be proved by triangular inequality. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ Ā, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ Ā, sing g(x, y) > ∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ Ā, sing g(x, y) < ∞}. In terms of epigraphs: epi f =
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \inf_{y \in \mathcal{A}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{y \in \mathcal{A}} g(x, y)$. Commetric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(x)$ Log-determinant function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1. It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is co	owing statements hold for $\rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}$: avex in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$. cave, \tilde{h} is nonincreasing, is case, dom (h) is either acave, \tilde{h} is nonincreasing, in cave, \tilde{h} is nonincreasing, is case, dom (h) is either acave, \tilde{h} is nonincreasing, in cave, \tilde{h} is nonincreasing, \tilde{h} is	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. It is a special case of affine function. In other words, f(s) = {x A(x) ≤ B} is a convex set if s is convex. Many optimization problems can be formulated as LMI problems and solved optimally. It is can be proved by triangular inequality. For each value of x, we have an infinite set of points g(x, y) _{y∈SI}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈SI}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sing g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈SI}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sing g(x, y) > ∞}. In terms of epigraphs, the greatest value in the intersection of the following epigraphs: epi f = ∩ epi g(x, y) In terms of epigraphs, the greatest value in the codomain of the maximum element function, since max {x₁,,x_n} ≤ f(x) ≤ max {x₁,,x_n} + log n The composition function allows us to see a large class of functions as convex (or concave). For scale composition, the remarkable ones are: If g is concave then f(x) = h(g(x)) = exp g(x) is convex. If g is convex then f(x) = h(g(x)) = exp g(x) is convex. If g is convex then f(x) = h(g(x)) = -log (-g(x)) is convex.
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = x _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \inf_{y \in \mathcal{A}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{y \in \mathcal{A}} g(x, y)$. Commetric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(x)$ Log-determinant function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}^k$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P ≥ 0. • f is convex iff P ≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is convex iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is convex function for the cases. Yes. Yes. Yes. Yes. Yes. • f is convex in x if g is convex in	owing statements hold for $\rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}$: nex in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$. cave, \tilde{h} is nondecreasing, in case, \tilde{h} is nondecreasing, neave, \tilde{h} is nondecreasing, owing statements hold for $\tilde{h} \rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}^k$. owing statements hold for $\tilde{h} \rightarrow \mathbb{R}$ and $\tilde{h} \rightarrow \mathbb{R}$.	 we have f(x) = c^Tx, which is the inner product between the vector e and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The linear matrix inequality (LMI), A(x) = x₁A₁ + ···· + x_nA_n ≤ B, is a special case of affine function. In other words, f(x) = {x A(x) ≤ B} is a convex set if 3 is convex. Many optimization problems can be formulated as LMI problems and solved optimally. Its domain dom (f) = f₁ dom (f₁) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y \in A}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y \in A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y \in A}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sup g(x, y) < ∞}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y \in A} corresponds to the intersection of the following epigraphs: epi f = ∩ epi g(·, y) This function is interpreted as the approximation of the maximum element function, since max {x₁,,x_n} ≤ f(x) ≤ max {x₁,,x_n} + log n The composition function allows us to see a large class of functions as convex (or concave). For scale composition, the remarkable ones are: If g is convex then f(x) = h(y ≤ x) = xy g(x) is convex. If g is convex and dom (g) ⊆ k_n, then f(x) = h(g(x)) = log g(x) is convex. If g is convex and dom (g) ⊆ k_n, then f(x) = h(g(x)) = g^p(x) is g(x) = xy g(x) is convex. If g is convex and dom (g
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = x _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \inf_{y \in \mathcal{A}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{y \in \mathcal{A}} g(x, y)$. Commetric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(x)$ Log-determinant function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}^k$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P ≥ 0. • f is strictly concave iff P > 0. • f is concave iff P ≤ 0. • f is strictly concave iff P < It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. Ye	owing statements hold for \mathbb{A} . The each \mathbb{A} is nondecreasing, incave, \tilde{h} is nondecreasing in where	 we have f(x) = c^Tx, which is the inner product between the vector e and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. [x] A(x) ≤ B} is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimization problems can be formulated as LMI problems and solved optimization problems can be proved by triangular inequality. It can be proved by triangular inequality. For each value of x, we have an infinite set of points g(x, y) _{y \in R}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ R, sinf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y \in R}. The value f(x) will be the lesst value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ R, sup g(x, y) < ∞}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y \in R} corresponds to the intersection of the following epigraphs: epi f = ∫ epi g(x, y) This function is interpreted as the approximation of the maximum element function, since max (s₁,, s_n) ≤ f(x) ≤ max (s₁,, s_n) + logn The composition function allows us to see a large class of functions as convex (or concave). For scale composition, the remarkable ones are: If g is concex and dom (g) ⊆ R₊, then f(x) = h(g(x)) = log (g) is conceve and dom (g) ⊆ R₊, then f(x) = h(g(x)) = log (g) is conceve. If g(x) is concave and dom (g) ⊆ R₊, then f(x) = h o g is convex, where dom (f) = {x g(x) s R₊, then f(x) = h o g is convex, where dom (f) = R₊ R₊ R₊ R₊ R₊ R
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = x _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \inf_{y \in \mathcal{A}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{y \in \mathcal{A}} g(x, y)$. Commetric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(x)$ Log-determinant function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}^k$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P ≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is strictly concave iff P < It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is convex in d is concave in x if g is convex in the concave in x if g is convex in the concave in x if g is convex in the concave in x if g is convex in the concave in x if g is convex in the concave in x if g is convex in the concave in x if g is convex in the concave in x if g is convex in the concave in x if g is convex in x if x is x if x if x if x if x if x if	owing statements hold for \mathbb{R} and \mathbb{R} is nondecreasing, is case, dom (h) is either each \tilde{h} is nondecreasing, is case, dom (h) is either each, \tilde{h} is nondecreasing, is case, dom (h) is either each, \tilde{h} is nondecreasing, is case, dom (h) is either each, \tilde{h} is nondecreasing, is case, dom (h) is either each, \tilde{h} is nondecreasing, each, \tilde{h} is nondecreasing, each, \tilde{h} is nondecreasing in each \tilde{h} is nonde	 we have f(x) = c¹x, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse matrix inequality (IAII), A(x) = x, A₁ + ···· + x₁A₁ ≤ B, is a special case of affine function. In other words, f(x) = (x A(x) ≤ B) is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. Its domain dom (f) = ∫₁ dom (f₁) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y ∈ X}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ X, \(\text{inf} g(x, y) > -∞ \). For each value of x, we have an infinite set of points g(x, y) _{y ∈ X}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ X, \(\text{sing} g(x, y) > -∞ \). For each value of x, we have an infinite set of points g(x, y) _{y ∈ X}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ X, \(\text{sing} g(x, y) < ∞ \). In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y ∈ X} corresponds to the intersection of the following epigraphs: epi f = 0, \(\text{cip} \) cip g(x). This function is interpreted as the approximation of the maximum element function, since max(x₁,,x_n) ≤ f(x) ≤ max(x₁,,x_n) + log n The composition function, since max(x₁,,x_n) ≤ f(x) ≤ max(x₁,,x_n) + log n The g(x) = Ax + b is an affine function, then f(x) = h(g(x)) = log g(x) is convex. If g is convex and om (g) ⊆ R_n, then f(x) = h(g(x)) = reg(x) is convex. If g is convex there g ≥ 1. If g
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^a$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = x _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \inf_{y \in \mathcal{A}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{y \in \mathcal{A}} g(x, y)$. Commetric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(x)$ Log-determinant function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}^k$ • $f(x) = h \circ g : \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P ≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is strictly concave iff P < It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes.	owing statements hold for $\rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}$: ave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$.	 we have f(x) = c^Tx, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The inverse matrix inequality (LMI), A(x) = x₁A₁ + ····+x₁A₂ ≤ B₁ is a special case of affine function. In other words, A(x) = {x A(x) ≤ B} is a pocal case of affine function. A(x) ≤ B) is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. Its domain dom (f) = f₁ dom (f₁) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y∈Z}. The value f(x) will be the greatest value in the codomain of f that is set than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sing g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y∈Z}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sing g(x, y) < ∞}. for each value of x, we have an infinite set of points g(x, y) _{y∈Z}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sing g(x, y) < ∞}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y∈Z}, corresponds to the intersection of the following epigraphs: epi f = (1, e) eig g(x). This function is interpreted as the approximation of the maximum element function, since max (x₁,,x_n) ≤ f(x) ≤ max (x₁,,x_n) + log n This function is interpreted as the approximation of the maximum element function, since max (x₁,,x_n) ≤ f(x) ≤ max (x₁,,x_n) + log n The composition, the remarkable ones are: If g is convex then f(x) = h(g(x)) = cxp(x) is convex. If g is convex and dom (g) ⊆ E_{n+}, then f(x) =
• $f(x) = e^{nx} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \in \mathbb{N}$. Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \in \mathbb{N}$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_{+} \to \mathbb{R}$ • $f(x) = x \log x$ Minkwoski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = x \log_p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max_i f_i(x), \dots, f_n(x)$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max_i f_i(x), \dots, f_n(x)$. Pointwise supremum: • $f(x) = \sup_{y \in \mathbb{R}} g(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \min_i f_i(x), \dots, f_n(x)$. Log-sum-exp function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log_i (e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log_i \mathbb{R}^n$	It depends on the matrix P: • f is convex iff P ≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is strictly concave iff P < It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is convex in x if g is convex in the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex. In the convex in x if g is convex	owing statements hold for $\rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}$: next in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$. cave in x for each $y \in \mathcal{A}$. cave, \tilde{h} is nondecreasing, and \tilde{h} is nondecreasing and \tilde{h} is nondecreasin	 we have f(x) = c¹x, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse matrix inequality (IAII), A(x) = x, A₁ + ···· + x₁A₁ ≤ B, is a special case of affine function. In other words, f(x) = (x A(x) ≤ B) is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. Its domain dom (f) = ∫₁ dom (f₁) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y ∈ X}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ X, \(\text{inf} g(x, y) > -∞ \). For each value of x, we have an infinite set of points g(x, y) _{y ∈ X}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ X, \(\text{sing} g(x, y) > -∞ \). For each value of x, we have an infinite set of points g(x, y) _{y ∈ X}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ X, \(\text{sing} g(x, y) < ∞ \). In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{y ∈ X} corresponds to the intersection of the following epigraphs: epi f = 0, \(\text{cip} \) cip g(x). This function is interpreted as the approximation of the maximum element function, since max(x₁,,x_n) ≤ f(x) ≤ max(x₁,,x_n) + log n The composition function, since max(x₁,,x_n) ≤ f(x) ≤ max(x₁,,x_n) + log n The g(x) = Ax + b is an affine function, then f(x) = h(g(x)) = log g(x) is convex. If g is convex and om (g) ⊆ R_n, then f(x) = h(g(x)) = reg(x) is convex. If g is convex there g ≥ 1. If g
• $f(x) = e^{nx} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(x) = x^a$ Power function $f: \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = \mathbf{x} ^p$, where $p \leq 1$. Logarithm function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Minkwaski distance, p -norm function, or l_p norm function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \mathbf{x} _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{x_1, \dots, x_n\}$. Pointwise maximum (maximum function): $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max\{f_1(x), \dots, f_n(x)\}$. Pointwise infimum: • $f(x) = \sup_{y \in \mathcal{X}} g(x, y)$. Minimum function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{y \in \mathcal{X}} g(x, y)$. Contains a supremum: • $f(x) = \sup_{y \in \mathcal{X}} g(x, y)$. Dog-sum-exp function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \mathbb{R}^n \to \mathbb{R}^n$ • $f(x) = \log \mathbf{X} $ Composite function $f = h \circ g: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbf{X} $ $f(x) = \mathbb{R}^n \to \mathbb{R}^n$ • $f(x) = $	It depends on the matrix P: • f is convex iff P ≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is rictly concave iff P < It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. Ye	owing statements hold for $\Rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \to \mathbb{R}$: and $g: \mathbb{R}^n \to \mathbb{R}^n$: and	 we have f(x) = c²x, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. In can be proved by triangular inequality. It can be proved by triangular inequality. It can be proved by triangular inequality. It can be proved by triangular inequality. For each value of x, we have an infinite set of points g(x, y) _{x > 0}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inst g(x, y) > -∞ }. For each value of x, we have an infinite set of points g(x, y) _{x > 0}. The value f(x) will be the less value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sup g(x, y) < ∞ }. In terms of epigraphs, the pointwise supremum of ten infinite set of functions g(x, y) _{x > 0}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{x > 0}. This function is interpreted as the approximation of the maximum element function, since max {x₁,,x_n} ≤ f(x) ≤ max {x₁,,x_n} + log n This function is interpreted as the approximation of the maximum element function, since max {x₁,,x_n} ≤ f(x) ≤ max {x₁,,x_n} + log n The composition function allows us to see a large class of functions as convex (or oposition, the remarkable ones are: If g is convex then f(x) = h(g(x)) = ep g(x) is convex. If g is convex then f(x) = h(g(x)) = ep g(x) is convex. If g is convex then f(x) = h(g(x)) = -log (-g(x)) is convex. If g is convex then f(x) = h(g(x)) = -log (-g(x)) is convex. where g ≥ 1. If g(x) is convex. F h o g is a convex function. For a c P
• $f(x) = e^{nx} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x^n$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \leq 1$. Logarithm function: $f : \mathbb{R}_{++} \to \mathbb{R}$ • $f(x) = x p$, where $p \leq 1$. Logarithm function: $f : \mathbb{R}_{+} \to \mathbb{R}$ • $f(x) = x p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = x p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max_i f_1(x), \dots, f_n(x)$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max_i f_1(x), \dots, f_n(x)$. Pointwise infimum: • $f(x) = \min_i f_2(x, y)$. Minimum function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \min_i f_1(x), \dots, f_n(x)$. Log-sum-exp function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \min_i f_1(x), \dots, f_n(x)$. Log-sum-exp function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = (\Pi_{i=1}^n x_i)^{1/n}$ Log-determinant function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is trictly concave iff P < 0. • f is concave iff P ≤ 0. • f is convex iff a≥ 1 or a≤ • f is convex iff a≥ 1 or a≤ • f is concave iff 0 ≤ a ≤ 1. Yes. Yes. Yes. Yes. Yes. Yes. Yes. Yes. • f is convex in x if g is convex in the following formulation for the cases. Yes. Yes. Yes. Yes. Yes. • f is convex in x if g is convex in the following formulation for fix the following formulation	owing statements hold for \mathbb{R} and $g:\mathbb{R}^n\to\mathbb{R}$. The cave in x for each $y\in\mathcal{A}$. The cave, h is nonincreasing, the cave, h is nonincreasing that h is a set of convex, h is nonincreasing that h is a set of convex, h is nonincreasing that h is nonincrea	 we have f(x) = c²x, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. In can be proved by triangular inequality. It can be proved by triangular inequality. It can be proved by triangular inequality. It can be proved by triangular inequality. For each value of x, we have an infinite set of points g(x, y) _{x > 0}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, inst g(x, y) > -∞ }. For each value of x, we have an infinite set of points g(x, y) _{x > 0}. The value f(x) will be the less value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, sup g(x, y) < ∞ }. In terms of epigraphs, the pointwise supremum of ten infinite set of functions g(x, y) _{x > 0}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{x > 0}. This function is interpreted as the approximation of the maximum element function, since max {x₁,,x_n} ≤ f(x) ≤ max {x₁,,x_n} + log n This function is interpreted as the approximation of the maximum element function, since max {x₁,,x_n} ≤ f(x) ≤ max {x₁,,x_n} + log n The composition function allows us to see a large class of functions as convex (or oposition, the remarkable ones are: If g is convex then f(x) = h(g(x)) = ep g(x) is convex. If g is convex then f(x) = h(g(x)) = ep g(x) is convex. If g is convex then f(x) = h(g(x)) = -log (-g(x)) is convex. If g is convex then f(x) = h(g(x)) = -log (-g(x)) is convex. where g ≥ 1. If g(x) is convex. F h o g is a convex function. For a c P
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(x) = x^a$ Power function $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \mathbf{x} ^p$, where $p \leq 1$. Logarithm function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \mathbf{x} \mathbf{g}$, where $p \in \mathbb{N}_+$. Minkwoold distance, p -norm function, or l_p norm function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} \mathbf{g}$, where $p \in \mathbb{N}_+$. Maximum element: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max \{f_1(\mathbf{x}, \dots, f_n(\mathbf{x})\}$. Pointwise maximum (maximum function): $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \max \{f_1(\mathbf{x}, \dots, f_n(\mathbf{x})\}$. Pointwise infimum: • $f(\mathbf{x}) = \min_{y \in \mathcal{X}} f(\mathbf{x}, y)$. Pointwise supremum: • $f(\mathbf{x}) = \sup_{y \in \mathcal{X}} g(\mathbf{x}, y)$. Minimum function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \sup_{y \in \mathcal{X}} g(\mathbf{x}, y)$. Log-sum-exp function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \log(e^{a_1} + \dots + e^{a_n})$ Geometric mean function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \log(\mathbf{x})$ Composite function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \log(\mathbf{x})$ Composite function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \log(\mathbf{x})$ • $f(\mathbf{x}) = (\mathbf{x} \in \text{dom}(g) \mid g(\mathbf{x}) \in \text{dom}(h))$.	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is strictly concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is strictly concave iff P < It depends on a • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. Not in most of the cases. Yes. Y	owing statements hold for $\Rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \to \mathbb{R}$: and $g: $	 we have f(x) = c²x, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = {x f(x) ∈ C}, is also convex. The kinear matrix integrably (LMI), k(x) ∈ X, is also convex. The kinear matrix invegably (LMI), k(x) = x, k(x) + ·····*x, k ≤ B; is a special case of affine function. In other words, f(S) = (x k(x) ≤ B); is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimially. It can be proved by triangular inequality. It can be proved by triangular inequality. For each value of x, we have an infinite set of points g(x, y) _{y∈X}. The value f(t) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ X, \(\pi_{x} \) \ \ \frac{x}{x} \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \ \
• $f(x) = e^{nx} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f : \mathbb{R}_{+n} \to \mathbb{R}$ • $f(x) = x^n$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = x ^p$, where $p \leq 1$. Logarithm function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Minikveski distance, p -norm function, or t_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \mathbb{R}^n _p$, where $p \in \mathbb{N}_{++}$. Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max(x_1, \dots, x_n)$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max(f_1(x), \dots, f_n(x))$. Pointwise infimum: • $f(x) = \min(f_1(x), \dots, f_n(x))$. Pointwise supremum: • $f(x) = \min(f_1(x), \dots, f_n(x))$. Log-sum-exp function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \inf(f_1(x), \dots, f_n(x))$. Log-sum-exp function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log \mathbb{R}^n _{-\infty} = \mathbb{R}^n$ • $f(x) = \log \mathbb{R}^n _{-\infty} = \mathbb$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P> 0. • f is trictly concave iff P < 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. Ye	over \hat{h} is nonincreasing, is case, \hat{h} is nonincreasing in \hat{h} and \hat{h} is nonincreasing in \hat{h} in \hat{h} in \hat{h} is a set of increasing in \hat{h} i	 we have f(x) = c²x, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. It is a special case of affine interior. (x f(x) ≤ B) is a convex set if 3 is convex. Many optimization problems can be formulated as LMI problems and solved optimidly. It can be proved by triangular inequality. It can be proved by triangular inequality. For each value of x, we have an infinite set of points g(x, y) _{x, x, x} = 1 than be f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ R, sign f(x, y) > -∞s}. For each value of x, we have an infinite set of points g(x, y) _{x, x, x} = 1 the value f(x) will be the inset value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ R, sign f(x, y) < ∞s}. In terms of epigraphs, the pointwise supremum of the infinite set of functions g(x, y) _{x, y, y} corresponds to the intersection of the following epigraphs: epi f = f(x) g(x) g(x, y). This function is interpreted as the approximation of the maximum element function, since max (x₁,,x_n) ≤ f(x) ≤ max (x₁,,x_n) + log x The composition function allows us to see a large class of functions as correct (or concave). The size concave and dom (g) ⊆ E_x, then f(x) = h(g(x)) = log (x) is convex. If g is concave and dom (g) ⊆ E_x, then f(x) = h(g(x)) = log (x) is convex. If g is concave and dom (g) ⊆ E_x, then f(x) = h(g(x)) = log (x) is convex. If g is convex then g(x) = log (x) = log (x) is convex. If g is convex then g(x) = log (x) = log (x) is convex. If g is convex then g(x) = log (x) = log (x) is convex.
• $f(x) = e^{nx} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n$, $\mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \mathbf{x}^n$ Power of absolute value: $f: \mathbb{R} \to \mathbb{R}$ • $f(x) = \mathbf{x} ^n$, where $p \leq 1$. Logarithm function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ $f(x) = \log x$ Pointwise infimum: • $f(x) = \max_i f_{i_1}(x_1, \dots, f_n(x))$. Pointwise maximum (maximum function): $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max_i f_{i_1}(x_1, \dots, f_n(x))$. Pointwise supremun: • $f(x) = \sup_{y \in \mathcal{I}} g(x, y)$. Minimum function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \min_i f_{i_1}(x_1, \dots, f_n(x))$. Log-sum-exp function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ $f(x) = \log x$ Composite function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ • $f(x) = \log x$ Nonnegative weighted sum: $f: \dim(f) \to \mathbb{R}$ • $f(x) = \log x$ Perspective function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ • $f(x) = \log x$ Nonnegative maximum $f(x) \to \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ Perspective function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) \to \mathbb{R}^n \to \mathbb{R}^n \to \mathbb{R}$ • $f(x) \to \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is strictly concave iff P < 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is convex in the following form of the cases. Yes.	over \hat{h} is nonincreasing, is case, \hat{h} is nonincreasing in \hat{h} and \hat{h} is nonincreasing in \hat{h} in \hat{h} in \hat{h} in \hat{h} in \hat{h} is a set of increasing in \hat{h} in	 we have f(x) = c*x, which is the inner product between the vector c and x. The inverse image of C, f^1(C) = (x f(x) ∈ C), is also convex. The finear matrix megability (LMI), A(x) ∈ X, h. + · · · *x, A₀ ≤ B, is a special case of afflite function. In other words, f(S) = (x A(x) ≤ B) is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimizing. Its domain dom f(f) = f⁰/1 dom (f) is also convex. For each value of x, we have an infinite set of points g(x, y) _{y=2x}. The value f(S) will be the groutest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, larg (x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y=2x}. The value f(x) will be the grout value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, larg (x, y) < ∞}. In terms of epigraphs, the pointwise suprenum of the infinite set of functions g(x, y) _{y=2x} the points g(x, y) _{y=2x} the function is given to function, since max {x_1,, x_n} ≤ f(x) ≤ max {x_1,, x_n} + log x The composition function allows us to see a large class of functions as convex (or concave). For scale composition, the remarkable once are: If g is convex than f(x) = h(g(x)) = exp (g(x)) is convex. If g is convex and dom (g) ⊆ R₊₊, then f(x) = h(g(x)) = log (g(x)) = log (x) is convex. If g is convex and dom (g) ⊆ R₊₊, then f(x) = h(g(x)) = log (x) is convex, where y ∈ R⁰ is g(x) = log (x) is convex. If g is convex than f(x) = h(g(x)) = log (-g(x)) is convex. If g is convex than f(x) = h(g(x)) = log (-g(x)) is convex. where dom (g) = x, then f h(x) = h(g(x)) = exp (x) is convex. If g is convex than f(x) = h(g(x)) = log (-g(x)) is convex. For vector apax+is n, we attend the following the after a pig is convex where dom (g) = x,
• $f(x) = e^{nx} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n$, $\mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ Power function $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \mathbf{x}^n$ Power of absolute value: $f: \mathbb{R} \to \mathbb{R}$ • $f(x) = \mathbf{x} ^n$, where $p \leq 1$. Logarithm function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ $f(x) = \log x$ Pointwise infimum: • $f(x) = \max_i f_{i_1}(x_1, \dots, f_n(x))$. Pointwise maximum (maximum function): $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max_i f_{i_1}(x_1, \dots, f_n(x))$. Pointwise supremun: • $f(x) = \sup_{y \in \mathcal{I}} g(x, y)$. Minimum function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \min_i f_{i_1}(x_1, \dots, f_n(x))$. Log-sum-exp function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log(e^{x_1} + \dots + e^{x_n})$ Geometric mean function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ $f(x) = \log x$ Composite function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ • $f(x) = \log x$ Nonnegative weighted sum: $f: \dim(f) \to \mathbb{R}$ • $f(x) = \log x$ Perspective function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ • $f(x) = \log x$ Nonnegative maximum $f(x) \to \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \log x$ Perspective function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) \to \mathbb{R}^n \to \mathbb{R}^n \to \mathbb{R}$ • $f(x) \to \mathbb{R}^n \to \mathbb{R}$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is strictly concave iff P < 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is convex in the following form of the cases. Yes.	over \hat{h} is nonincreasing, is case, \hat{h} is nonincreasing in \hat{h} and \hat{h} is nonincreasing in \hat{h} in \hat{h} in \hat{h} in \hat{h} in \hat{h} is a set of increasing in \hat{h} in	 we have f(x) = c*x, which is the inner product between the vector c and x. The linear matrix inequality (LMI), A(y) ∈ C), is also convex. The linear matrix inequality (LMI), A(y) = x A₁ + · · · · x_{AA} ≤ B₁ is a special case of affitic function. is a special case of affitic function. in (A(x) ≤ B) is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimally. Its domain dom (f) = n of the function of the function in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A₁, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y,y,z}. The value f(x) will be the less value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A₁, inf g(x, y) > -∞}. For each value of x, we have an infinite set of points g(x, y) _{y,y,z}. The value f(x) will be the less value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A₁, sup g(x, y) < ∞}. In terms of epigraphs, the pointwise approximation of the following epigraphs: cpi f = n of function g(x, y) _{x,y} corresponds to the intersection of the following epigraphs: cpi f = n of g(x) = n of g(x) = n of function g(x, y) _{x,y} corresponds to the intersection of the maximum determs function, since max (x₁, x_p) ≠ log y X is positive semidefinite, i.e., X > 0 X ∈ S_n^n. The composition function allows us to see a large class of functions as convex (or concave). if y is convex then f (x) = h(y(x)) = cop g(x) is convex. if y is convex then f (x) = h(y(x)) = cop g(x) is convex. if y is convex then f (x) = h(y(x)) = cop g(x) is convex. if y is convex then f (x) = h(y(x)) = log (-g(x)) is convex. if y is convex then f (x) = h(y(x)) = log (-g(x)) is convex. if y is
• $f(\mathbf{x}) = e^{\mathbf{x}\mathbf{x}} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = e^{\mathbf{x}^n} \mathbf{P} \times \mathbf{P}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbb{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(\mathbf{x}) = e^{\mathbf{x}^n} \mathbf{P} \times \mathbf{P}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbb{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x}^n$ • $f(\mathbf{x}$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is strictly concave iff P < 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is convex in the following form of the cases. Yes.	owing statements hold for $\rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}$: ave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. The cave in x for each $y \in \mathcal{A}$ is nonincreasing, and the cave, h is nonincreasing and h is a vector-vector function, where the cave, h is nonincreasing and h is nonincreasing.	 we have f(x) = c² x, which is the inner product between the vector c and x. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. The inverse image of C, f⁻¹(C) = (x f(x) ∈ C), is also convex. It is a special sear of allien intuition. In other words, f(S) = (x A(x) ≤ B) is a convex set if S is convex. Many optimization problems can be formulated as LMI problems and solved optimolly. Its domain dom (f) = f/1 dom (f) is also convex. For each value of x, we have an infinite set of points g(x, y) _{x ∈ X}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, \(\limet{A}\) int g(x, y) > ∞se}. for each value of x, we have an infinite set of points g(x, y) _{x ∈ X}. The value f(x) will be the least value in the codomain of f that is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, \(\limet{A}\) int g(x, y) < ∞e}. for each value of x, we have an infinite set of points g(x, y) _{x ∈ X}. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, \(\limet{A}\) in probability is greater than or equal this set. dom (f) = {x (x, y) ∈ dom (g) ∀ y ∈ A, \(\limet{A}\) in probability (f) is convex. for terms of epigraphs, the pointwise supermum of the infinite set of functions g(x, y) _{x ∈ X} corresponds to the intersection of the following epigraphs: epi f - (e) g(x) = (e) g(x) =
• $f(\mathbf{x}) = e^{\mathbf{x} \mathbf{x}} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = e^{\mathbf{x}} \mathbf{P} \mathbf{x} + p^{T} \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n$, $\mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(\mathbf{x}) = x^n$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} ^n$, where $p \in \mathbb{N}$. • $f(\mathbf{x}) = \mathbf{x} ^n$, where $p \in \mathbb{N}$. Logarithm function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} \log \mathbf{x}$ Negative entropy function: $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} \log \mathbf{x}$ Minkwoods distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} \log \mathbf{x}$ • $f(\mathbf{x}) = \mathbf{x} \log \mathbf{x}$ Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x}, \mathbf{x})$. Pointwise maximum (maximum function): $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x}, \mathbf{x})$. Pointwise supremum: • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x}, \mathbf{x})$. Pointwise supremum: • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x}, \mathbf{x})$. Dogsum-exp function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x})$. $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x})$. • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x})$. • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x})$. Pointwise supremum: • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x}, \mathbf{x})$. • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x}, \mathbf{x})$. Pointwise supremum: • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x}, \mathbf{x})$. Pointwise supremum: • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x}, \mathbf{x})$. Pointwise supremum: • $f(\mathbf{x}) = \mathbf{x} \otimes f(\mathbf{x})$. • $f(\mathbf{x}) = \mathbf{x} $	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is x if	owing statements hold for $\rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}$: ave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. The cave in x for each $y \in \mathcal{A}$ is nonincreasing, and the cave, h is nonincreasing and h is a vector-vector function, where the cave, h is nonincreasing and h is nonincreasing.	 we have f(x) = e¹x, which is the inner product between the vector c and x. The forcer wait's improving (x, f(x) e x), is also convex. The forcer wait's improving (x, f(x) e x), a, a, a + · · · · · · · · · · · · · · · · · ·
• $f(\mathbf{x}) = e^{\mathbf{x}\mathbf{x}} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = e^{\mathbf{x}^n} \mathbf{P} \times \mathbf{P}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbb{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(\mathbf{x}) = e^{\mathbf{x}^n} \mathbf{P} \times \mathbf{P}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbb{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x}^n$ • $f(\mathbf{x}$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is x if	owing statements hold for $\rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}$: ave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. The cave in x for each $y \in \mathcal{A}$ is nonincreasing, and the cave, h is nonincreasing and h is a vector-vector function, where the cave, h is nonincreasing and h is nonincreasing.	 we have f(x) = e¹x, which is the lamer product between the vector and x. The inverse image of C, f⁻¹(C) = (x f(x) f(x) e C), is also convex. The linear notices invessediby (LMV), a(x) = x₁a, 1 + · · · x₁a, ≤ B; a special case of after familian. In other words, f(x) = y₁ = x₁a, ≤ B; a superior case of after familian. In other words, f(x) = problems can be formulated as LMI problems and solved optimally. It can be proved by triangular inequality. Its domain dom (f) = \(\frac{\hat{\cap{\text{const}}}{\text{const}} \) dom (f) is also convex. For each value of x, we have an infinite set of points g(x, y) _{x > x_1} = \text{The value f(x)} \) will be the greatest value in the codomain of f that is fees than or equal this set. dom (f) = \{x \{ (x, y) \) c dom (g) \(\frac{\text{const}}{\text{const}} \) and f(x) in the feet in the codomain of f that is greater than or equal this set. dom (f) = \{x \{ (x, y) \} \) c dom (g) \(\frac{\text{const}}{\text{const}} \) (x \(\frac{\text{const}}{const
• $f(x) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^n + p^Tx + p \in \mathbb{R}$, where $x, p \in \mathbb{R}^n$, $p \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(x) = x^n$ Power function $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x ^n$, where $p \in \mathbb{R}$. • $f(x) = x ^n$, where $p \in \mathbb{R}$. • $f(x) = a x^n$, where $p \in \mathbb{R}$. • $f(x) = a x^n$ Negative entropy function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = a x_0$, where $p \in \mathbb{N}_+$. Maximum chrunct: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = a x_0$, where $p \in \mathbb{N}_{++}$. Maximum chrunct: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = a x_0 + f(x)$,, $f_n(x)$. Pointwise maximum function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = a x_0 + f(x)$,, $f_n(x)$. Pointwise maximum: • $f(x) = a x_0 + f(x)$,, $f_n(x)$. Pointwise supremum: • $f(x) = a x_0 + f(x)$,, $f_n(x)$. Log-sum-exp function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = a x_0 + f(x)$,, $f_n(x)$. Log-determinant function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = a x_0 + f(x)$, $f(x) = a x_0 + f(x)$, where: • $g: \mathbb{R}^n \to \mathbb{R}$. • $f(x) = a x_0 + f(x)$, $f(x) = a x_0 + f(x)$, where: • $g: \mathbb{R}^n \to \mathbb{R}$. • $f(x) = a x_0 + f(x)$, $f(x) = a x_0 + f(x)$, where: • $g: \mathbb{R}^n \to \mathbb{R}$. • $f(x) = a x_0 + f(x)$, $f(x) = a x_0 + f(x)$, where: • $g: \mathbb{R}^n \to \mathbb{R}$. • $f(x) = a x_0 + f(x)$, where $x \in \mathbb{R}^n$, $f(x) = f(x)$, where: • $g: \mathbb{R}^n \to \mathbb{R}^n$. Is an after function $g^{n+1} = g^{n+1} = g^{n+1}$. • $f(x) = g^{n+1} = g^{$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is x if	owing statements hold for $\rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}$: ave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. The cave in x for each $y \in \mathcal{A}$ is nonincreasing, and the cave, h is nonincreasing and h is a vector-vector function, where the cave, h is nonincreasing and h is nonincreasing.	 we have f(x) = e¹x, which is the inner product between the vector and x. The income image of C, f⁻(C) = (x f(x) x x x x x x x x x
• $f(x) = e^{gx} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = ax^T \mathbf{P} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n$, $\mathbf{p} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(x) = ax^n$ Power function $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = x^n$ • $f(x) = x ^n$, where $p \leq 1$. Logarithm function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(x) = \log x$ Minkwooki distance, p -norm function, or I_p norm function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = x p$, where $p \in \mathbb{N}_+$. Maximum element: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max_{x \in \mathbb{R}} f(x), \dots, f_p(x)$. Pointwise infimum: • $f(x) = \max_{x \in \mathbb{R}} f(x, y)$. Pointwise supremum: • $f(x) = \sup_{x \in \mathbb{R}} g(x, y)$. $f(x) = \sup_{x \in \mathbb{R}} g(x, y)$. Minimum function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \sup_{x \in \mathbb{R}} g(x, y)$. • $f(x) = \sup_{x \in \mathbb{R}} g(x, y)$. Minimum function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \lim_{x \in \mathbb{R}} f(x)$. $f(x) = \lim_{x \in \mathbb{R}} f(x)$. $f(x) = \lim_{x \in \mathbb{R}} f(x)$. Integral function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \lim_{x \in \mathbb{R}} f(x)$. $f(x) = \lim_{x \in \mathbb{R}} f(x)$. where: • $f(x) = \lim_{x \in \mathbb{R}} f(x)$. $f(x) = \lim_{x \in \mathbb{R}}$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is x if	owing statements hold for $\rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \rightarrow \mathbb{R}$: ave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. The cave in x for each $y \in \mathcal{A}$ is nonincreasing, and the cave, h is nonincreasing and h is a vector-vector function, where the cave, h is nonincreasing and h is nonincreasing.	 where f(x) = (x, which is the linear product between the vector and x. The inverse image of C, g⁻¹(C) = (x f(x) e(x), is also convex. The linear was air sequelly (LMI), (x(x) = x, x, x + who + x, x, x ≤ B). The linear was air sequelly (LMI), (x(x) = x, x, x + who + x, x, x ≤ B). The linear was air sequelly (LMI), (x(x) = x, x, x + x, x ≤ B). If can be proved by triangular inequality. If can be proved by triangular inequality. If it domain dom (f) = ∫(1 dom (f)) is also convex. For each value of x, we have an infinite set of points g(x, y) _{x,y,y}. The value f(x) will be the greatest value in the codomain of f that is less than or equal this set. dom (f) = {x (x,y) ∈ dom (g) ∀ y ∈ X, linf g(x,y) > -∞}. For each value of x, we have an infinite set of points g(x,y) _{x,y,y}. The value f(x) will be the most value in the codomain of f that is gener than or equal this set. dom (f) = {x (x,y) ∈ dom (g) ∀ y ∈ X, linf g(x,y) > -∞}. For each value of x, we have an infinite set of points g(x,y) _{x,y,y}. a for the codomain of x = x in the codomain of the following epigraphs: qui f = ∫(1) qi g(x). In terms of epigraphs, the pointwise expressum of the infinite set of functions g(x) _{x,y,y}. a for the codomain of the following epigraphs: qui f = ∫(1) qi g(x). The composition function allows us to see a large class of functions as convex (or concave). If g is connect and dom (g) ∈ R_x, then f(x) = b(g(x)) = g(x) in max(x₁,x_k) + bg g Y is g is concerve and dom (g) ∈ R_x, then f(x) = b(g(x)) = g(x) in max(x₁,x_k) + bg g If g is convex then f(x) = b(g(x)) = b(g(x)) = g(x) in max(x₁,x_k) + bg g If g is convex then f(x) = f(x) + f(x) + f(x) + f(x) = f(x) + f(x) +
• $f(\mathbf{x}) = e^{a\mathbf{x}} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^T \mathbf{P} \mathbf{x} + p^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n$, $\mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}^n$ Power of absolute value: $f: \mathbb{R} \to \mathbb{R}$ • $f(\mathbf{x}) = b\mathbf{x}^n$ Power of absolute value: $f: \mathbb{R} \to \mathbb{R}$ • $f(\mathbf{x}) = b\mathbf{x}^n$ Power of absolute value: $f: \mathbb{R} \to \mathbb{R}$ • $f(\mathbf{x}) = b\mathbf{x}^n$ Negative actropy function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(\mathbf{x}) = b\mathbf{x}$ Negative currency function: $f: \mathbb{R}_+ \to \mathbb{R}$ • $f(\mathbf{x}) = b\mathbf{x}$ Minkwooki distance, p -norm function, or I_p norm function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}(f_1(\mathbf{x}), \dots, f_n(\mathbf{x}))$. Pointwise maximum (maximum function): $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{x}(f_1(\mathbf{x}), \dots, f_n(\mathbf{x}))$. Pointwise infimum: • $f(\mathbf{x}) = a\mathbf{x}(f_1(\mathbf{x}), \dots, f_n(\mathbf{x}))$. Pointwise supremum: • $f(\mathbf{x}) = a\mathbf{x}(f_1(\mathbf{x}), \dots, f_n(\mathbf{x}))$. Log-sum-exp function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = b\mathbf{y}(f_1(\mathbf{x}), \dots, f_n(\mathbf{x}))$. Log-sum-exp function: $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = a\mathbf{y}(f_1(\mathbf{x}), \dots, f_n(\mathbf{x}))$. Log-determinant function $f: \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = (a\mathbf{y}, \mathbf{x})$ • $f(\mathbf{x}) = (a\mathbf{y}, \mathbf{x}$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is x if	over a statement shold for \mathbb{R} and $g: \mathbb{R}^n \to \mathbb{R}$: and $g: \mathbb{R}^n \to \mathbb{R}$ is nondecreasing, and $g: \mathbb{R}^n \to \mathbb{R}^n$ is nondecreasing, and $g: \mathbb{R}^n \to \mathbb{R}^n$ is nondecreasing, and $g: \mathbb{R}^n \to \mathbb{R}^n$ is nondecreasing in decay, \tilde{h} is nondecreasing in decay, \tilde	 we have \$(x) = e^{-x}x, which is the linear product between the vector and \$x\$. The inverse image of \$C, f^{-1}(C) = x f(x) ∈ C, s a decrease convex, and the production of the production problems can be formulated as LMI problems and solved optimally. Its domain dom \$(f) = \begin{align*} \tilde{\phi} \text{ domain dom \$(f) = \begin{align*} \tilde{\phi} \text{ domain dom \$(f) = \begin{align*} \tilde{\phi} \text{ dom \$(f)\$ is also convex.} \end{align*} For each value of \$x\$, we have an infinite set of points \$g(x, y) _{x,y,y}\$. The value \$f(x)\$ will be the greatest value in the codomain of \$f\$ that is greater than or equal this set. dom \$(f) = \begin{align*} \x f \text{ dom \$(g) \text{ y \in \$\mathcal{H}\$, and the infinite set of functions \$g(x, y) _{x,y,y}\$ corresponds to the intersection of the following epigenples \$g(x, y) \in \text{ dom \$(f) = \begin{align*} \x f \text{ dom \$(f) \text{ y \in \$\text{ dom }(f) \text{ production of the following epigenples \$g(x, y) \in \text{ dom \$(f) = \begin{align*} \x f \text{ production of the following epigenples \$g(x, y) \in \text{ dom \$(f) = \begin{align*} \x f \text{ production of the following epigenples \$g(x, y) \in \text{ dom \$(f) = \begin{align*} \x f \text{ dom \$(f) = \begin{align*} \x f \text{ production of the following epigenples \$g(x) \text{ for \$(g) = \begin{align*} \x f \text{ production of the following epigenples \$g(x) \text{ for \$(g) = \begin{align*} \x f \text{ production of the following epigenples \$g(x) \text{ for \$(g) = \begin{align*} \x f \text{ for \$(g) = \begin{align*} \x f \text{ for \$(g) = \begin{align*} \x f for \$(g) = \begin{al
• $f(\mathbf{x}) = e^{ax} \in \mathbb{R}$, where $a \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x}^T \mathbf{P} \mathbf{x} + \mathbf{p}^T \mathbf{x} + r \in \mathbb{R}$, where $\mathbf{x}, \mathbf{p} \in \mathbb{R}^n, \mathbf{P} \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x}^n$ Power function $f : \mathbb{R}_+ \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{x}^n$ Fower of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{k} \mathbf{r}^n$, where $p \leq \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{r}^n$, where $p \leq \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{r}^n$, where $p \in \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{r}^n$, where $p \in \mathbb{R}_+$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{r}^n$, where $p \in \mathbb{N}_+$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{r}^n$, where $p \in \mathbb{N}_+$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $p \in \mathbb{N}_+$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $p \in \mathbb{N}_+$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $p \in \mathbb{N}_+$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, $f(\mathbf{x})$,, $f_{\mathbf{x}}(\mathbf{x})$. Pointwise infimum: • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, $f(\mathbf{x})$,, $f_{\mathbf{x}}(\mathbf{x})$. Pointwise supremum: • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, $f(\mathbf{x})$,, $f_{\mathbf{x}}(\mathbf{x})$. Integral function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, $f(\mathbf{x})$,, $f_{\mathbf{x}}(\mathbf{x})$. Log-sum-exp function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n$, $f(\mathbf{x}) = \mathbf{k}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}^n$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $, where $\mathbf{x} \in \mathbb{R}^n \to \mathbb{R}^n$. • $f(\mathbf{x}) = \mathbf{k} \mathbf{x} $ is an eliment of $f(\mathbf{x}$	It depends on the matrix P: • f is convex iff P≥ 0. • f is strictly convex iff P> 0. • f is concave iff P≤ 0. • f is concave iff P≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is concave iff 0 ≤ a ≤ 1. Yes. • f is convex in x if g is convex for and g is convex. In the (-∞, a) or (-∞, a). • f is convex if h is i	owing statements hold for $\Rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \to \mathbb{R}$: avec in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. The proof of x is nondecreasing, it case, x is nondecreasing in the proof of x is a set of convex of x is nondecreasing in the proof of x is nondecreasing.	 when y(x) = (*x, which is the loner produce between the vester and x.* The inverse image of C, y* (*C) = (x) f(x) = C), is also convex. The inverse image of C, the lone (*x) f(x) = x, x,
• $f(x) = e^{\alpha x} \in \mathbb{R}$, where $\alpha \in \mathbb{R}$ Quadratic function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \alpha x^2 \operatorname{Px} + p^4 x + r \in \mathbb{R}$, where $x, p \in \mathbb{R}^n, P \in \mathbb{R}^{n \times n}$, and $a, b \in \mathbb{R}$ • $f(x) = a^{n}$ Power of absolute value: $f : \mathbb{R} \to \mathbb{R}$ • $f(x) = \ln^p$, where $p \le 1$. Logarithm function: $f : \mathbb{R}_n \to \mathbb{R}$ • $f(x) = \log x$ Negative entropy function: $f : \mathbb{R}_n \to \mathbb{R}$ • $f(x) = \log x$ Minkweski distance, p -norm function, or I_p norm function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \ \mathbf{x}\ _{f}$, where $p \in \mathbb{N}_{t+1}$ Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \ \mathbf{x}\ _{f}$, where $p \in \mathbb{N}_{t+1}$ Maximum element: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max_{x \in \mathcal{X}} f(x_1, \dots, f_n(x))$. Pointwise maximum (maximum function); $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \max_{x \in \mathcal{X}} f(x_1, \dots, f_n(x))$. Pointwise supremum: • $f(x) = \min_{x \in \mathcal{X}} f(x_1, \dots, f_n(x))$. Log-sum-exp function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \min_{x \in \mathcal{X}} f(x_1, \dots, f_n(x))$. Log-sum-exp function: $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \lim_{x \to \infty} f(x_1, \dots, f_n(x))$. Log-determinant function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \lim_{x \to \infty} f(x_1, \dots, f_n(x))$ by where $f(x_1, x_2, \dots, x_n) = f(x_1, \dots, f_n(x))$ by $f(x_1, \dots, f_n(x)) = f(x_1, \dots, f_n(x))$. Projective function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \int x^2 f(x_1, \dots, f_n(x)) = f(x_1, \dots, f_n(x))$. Projective function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \int x^2 f(x_1, \dots, f_n(x)) = f(x_1, \dots, f_n(x))$. Projective function $f : \mathbb{R}^n \to \mathbb{R}$ • $f(x) = \int x^2 f(x_1, \dots, f_n(x)) = f(x_1, \dots, x_n)$. Projective function $f : \mathbb{R}^n \to \mathbb{R}^n$ • $f(x) = \int x^2 f(x_1, \dots, x_n) = f(x_1, \dots, x_n)$. Projective function $f : \mathbb{R}^n \to \mathbb{R}^n$ • $f(x) = \int x^2 f(x_1, \dots, x_n) = f(x_1, \dots, x_n)$. Projective function $f : \mathbb{R}^n \to \mathbb{R}^n$ • $f(x) = \int x^2 f(x_1, \dots, x_n) = f(x_1, \dots, x_n)$. Projective function $f : \mathbb{R}^n \to \mathbb{R}^n$ • $f(x) = \int x^2 f(x_1, \dots, x_n) = f(x_1, \dots, x_n)$.	It depends on the matrix P: • f is convex iff P ≥ 0. • f is strictly convex iff P > 0. • f is concave iff P ≤ 0. • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1 or a ≤ • f is convex iff a ≥ 1. Yes. Ye	owing statements hold for $\Rightarrow \mathbb{R}$ and $g: \mathbb{R}^n \to \mathbb{R}$: avec in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. Eave in x for each $y \in \mathcal{A}$. The proof of x is nondecreasing, it case, x is nondecreasing in the proof of x is a set of convex of x is nondecreasing in the proof of x is nondecreasing.	 we have f(x) = e¹x, with is the linear product between the vector and x. The inverse image of C, f¹(C) = {x} f(x) ∈ C), is also convex. The inverse image of C, f¹(C) = {x} f(x) = C), is also convex. If he does not foreign degrade (1, 10), x(x) = x, x, x = x, x ≤ R is a special case of affine function. In other words, f(x) = (x A(x) = 8) is a convex set f(x) is convex. If y x x x x x x x x x

