In any case, we know from Proposition 51.2 and Proposition 51.3 that the minimum set of f is convex, and closed iff f is closed.

Subdifferentials provide the first criterion for deciding whether a vector  $x \in \mathbb{R}^n$  belongs to the minimum set of f. Indeed, the very definition of a subgradient says that  $x \in \mathbb{R}^n$  belongs to the minimum set of f iff  $0 \in \partial f(x)$ . Using Proposition 51.16, we obtain the following result.

**Proposition 51.34.** Let f be a proper convex function over  $\mathbb{R}^n$ . A vector  $x \in \mathbb{R}^n$  belongs to the minimum set of f iff

$$0 \in \partial f(x)$$

iff f(x) is finite and

$$f'(x;y) \ge 0$$
 for all  $y \in \mathbb{R}^n$ .

Of course, if f is differentiable at x, then  $\partial f(x) = {\nabla f_x}$ , and we obtain the well-known condition  $\nabla f_x = 0$ .

There are many ways of expressing the conditions of Proposition 51.34, and the minimum set of f can even be characterized in terms of the conjugate function  $f^*$ . The notion of direction of recession plays a key role.

**Definition 51.20.** Let  $f: \mathbb{R}^n \to \mathbb{R} \cup \{+\infty\}$  be any function. A direction of recession of f is any non-zero vector  $u \in \mathbb{R}^n$  such that for every  $x \in \text{dom}(f)$ , the function  $\lambda \mapsto f(x + \lambda u)$  is nonincreasing (this means that for all  $\lambda_1, \lambda_2 \in \mathbb{R}$ , if  $\lambda_1 < \lambda_2$ , then  $x + \lambda_1 u \in \text{dom}(f)$ ,  $x + \lambda_2 u \in \text{dom}(f)$ , and  $f(x + \lambda_2 u) \leq f(x + \lambda_1 u)$ .

**Example 51.12.** Consider the function  $f: \mathbb{R}^2 \to \mathbb{R}$  given by  $f(x,y) = 2x + y^2$ . Since

$$f(x + \lambda u, y + \lambda v) = 2(x + \lambda u) + (y + \lambda v)^{2} = 2x + y^{2} + 2(u + yv)\lambda + v^{2}\lambda^{2},$$

if  $v \neq 0$ , we see that the above quadratic function of  $\lambda$  increases for  $\lambda \geq -(u+yv)/v^2$ . If v = 0, then the function  $\lambda \mapsto 2x + y^2 + 2u\lambda$  decreases to  $-\infty$  when  $\lambda$  goes to  $+\infty$  if u < 0, so all vectors (-u, 0) with u > 0 are directions of recession. See Figure 51.25.

The function  $f(x,y) = 2x + x^2 + y^2$  does not have any direction of recession, because

$$f(x + \lambda u, y + \lambda v) = 2x + x^2 + y^2 + 2(u + ux + yv)\lambda + (u^2 + v^2)\lambda^2,$$

and since  $(u,v) \neq (0,0)$ , we have  $u^2 + v^2 > 0$ , so as a function of  $\lambda$ , the above quadratic function increases for  $\lambda \geq -(u+ux+yv)/(u^2+v^2)$ . See Figure 51.25.

In fact, the above example is typical. For any symmetric positive definite  $n \times n$  matrix A and any vector  $b \in \mathbb{R}^n$ , the quadratic strictly convex function q given by  $q(x) = x^{\top}Ax + b^{\top}x$  has no directions of recession. For any  $u \in \mathbb{R}^n$ , with  $u \neq 0$ , we have

$$q(x + \lambda u) = (x + \lambda u)^{\top} A(x + \lambda u) + b^{\top} (x + \lambda u)$$
$$= x^{\top} A x + b^{\top} x + (2x^{\top} A u + b^{\top} u) \lambda + (u^{\top} A u) \lambda^{2}.$$