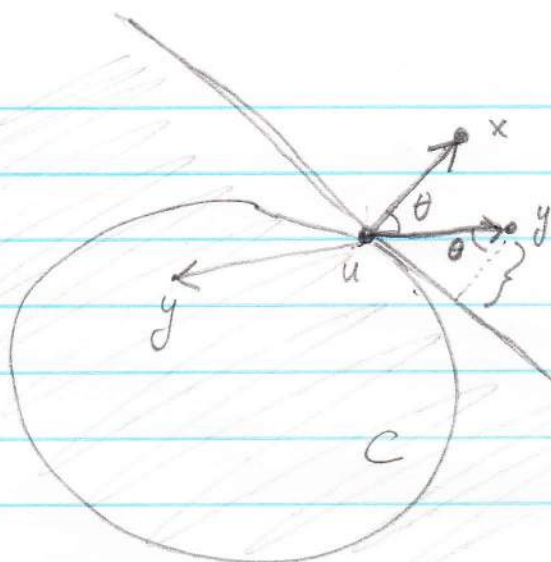




$$u = P_C(x)$$

$$\min_{u \in C} \frac{1}{2} \|u - x\|_2^2 = f(u)$$

$$\langle \nabla f(u), y - u \rangle \geq 0 \quad \text{all } y \in C$$

$$\langle u - x, y - u \rangle \geq 0 \quad \text{all } y \in C$$

$$C \subseteq H = \{y : \langle u - x, y - u \rangle \geq 0\}$$

Claim: for any y

$$\text{dist}(y, C) \geq \frac{(x - u)^T (y - u)}{\|x - u\|_2}$$

• $y \in H$: RHS is ≤ 0 , ✓

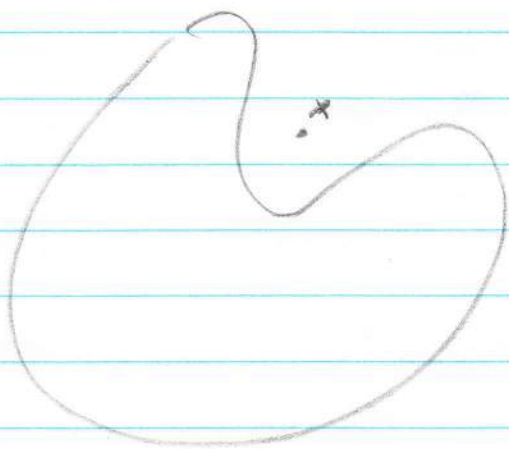
• $y \notin H$: $\frac{(x - u)^T (y - u)}{\|x - u\|_2} = \underbrace{\|x - u\|_2 \|y - u\|_2 \cos \theta}_{= \text{dist}(y, H)}$ ✓

$$\leq \text{dist}(y, C)$$

$$\underbrace{\text{dist}(y, C)}_{= f(y)} \geq \frac{(x - u)^T (y - x + x - u)}{\|x - u\|_2}$$

$$= \underbrace{\|x - u\|_2}_{= f(x)} + \underbrace{\frac{(x - u)^T (y - x)}{\|x - u\|_2}}_g$$

true for all y



$$t_k = \frac{1}{k}$$

$$f(x_{\text{best}}^{(k)}) - f^* \leq \frac{R^2 + G^2 \sum_{i=1}^k t_i^2}{2 \sum_{i=1}^k t_i}$$

$$R = \|x^{(0)} - x^*\|_2$$

Fixed: $t_k = t$

Bound is
$$\frac{R^2 + G^2 k t^2}{2 k t}$$

$$= \frac{R^2}{2 k t} + \frac{G^2 t}{2}$$

Diminishing:

$$\lim_{k \rightarrow \infty} f(x_{\text{best}}^{(k)}) - f^* \leq 0 + 0 = 0$$

Fixed: suppose want bound to be $\leq \epsilon$

make $\frac{R^2}{2 k t} \leq \frac{\epsilon}{2}$ and $\frac{G^2 t}{2} \leq \frac{\epsilon}{2}$

so $t = \frac{\epsilon}{G^2}$ and

$$h = \frac{R^2}{t\epsilon} = \frac{R^2 G^2}{\epsilon^2}$$

ie. convergence rate is $O(\frac{1}{\epsilon^2})$

compare to rate $O(\frac{1}{\epsilon})$ for grad desc.

$$\nabla \text{dist}(x, C_i) = \frac{x - P_{C_i}(x)}{\|x - P_{C_i}(x)\|_2}$$

$$f(x) = \max_{i=1 \dots m} f_i(x) = \max_{i=1 \dots m} \text{dist}(x, C_i)$$

$$\partial f(x) = \text{conv} \left(\bigcup_{\substack{i \text{ active,} \\ f_i(x) = f(x)}} \partial f_i(x) \right)$$

$$\partial f(x) = \text{conv} \left(\bigcup_{\substack{C_i \text{ is farthest} \\ \text{from } x}} \left\{ \frac{x - P_{C_i}(x)}{\|x - P_{C_i}(x)\|_2} \right\} \right)$$

repeat:

- find i such that C_i farthest from x
- take $g = \frac{x - P_{C_i}(x)}{\|x - P_{C_i}(x)\|_2}$
- $x^+ = x - t \cdot \frac{x - P_{C_i}(x)}{\|x - P_{C_i}(x)\|_2}$

take Polyak step size

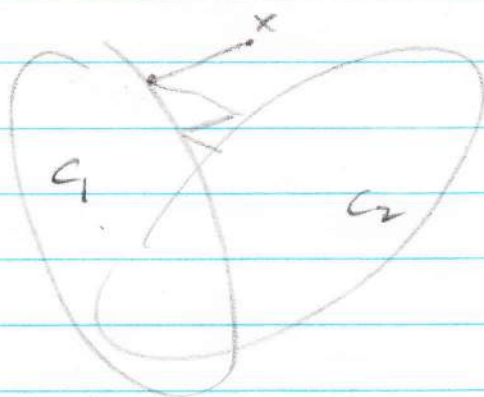
$$t = \frac{f(x) - f^*}{\|g\|_2^2}$$

$$= \frac{\|x - P_{C_1}(x)\|_2}{1} = 0$$

so

$$\begin{aligned} x^+ &= x - \frac{\|x - P_{C_1}(x)\|_2}{\|x - P_{C_1}(x)\|_2} (x - P_{C_1}(x)) \\ &= P_{C_1}(x) \end{aligned}$$

alternating projections algorithm



$$\sum_{i=1}^n (y_i - x_i^T \beta)$$

$f_i(\beta)$

$$\sum_{i=1}^n \left(-y_i x_i^T \beta + \log(1 + e^{-x_i^T \beta}) \right)$$

$f_i(\beta)$

$$f(x) = \sum_{i=1}^m f_i(x)$$

suppose f_i differentiable
cyclic rule, step size t

stochastic: $x_{k+m} = x_k - t \sum_{i=1}^m \nabla f_i(x_{k+i-1})$

batch: $x_{k+1} = x_k - t \sum_{i=1}^m \nabla f_i(x_k)$

$x_{k+m} = x_k - t \nabla f(x_k) + E$