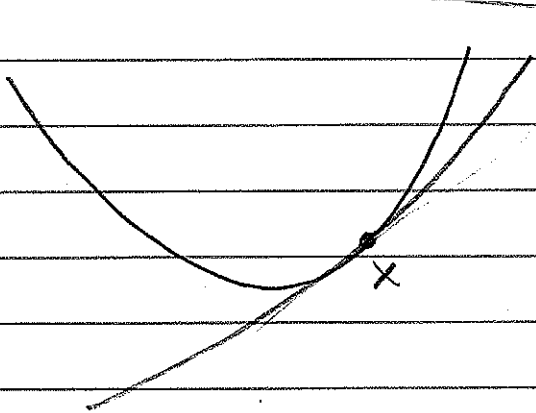
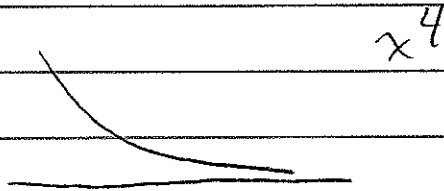


$f''(x) > 0$  strict convexity  
 $f''(x) \geq m$

$e^{-x}$



$$\hat{f}(y) \approx \boxed{f(x) + \nabla f(x)^T (y-x)} + \boxed{\frac{1}{2\epsilon} \|y-x\|_2^2}$$

usual:  $\frac{1}{2} (y-x)^T \nabla^2 f(x) (y-x)$

gradient descent  
chooses update

$$x^+ = \underset{y}{\operatorname{argmin}} \hat{f}(y)$$

$$= \underset{y}{\operatorname{argmin}} f(x) + \nabla f(x)^T (y-x) + \frac{1}{2\epsilon} \|y-x\|_2^2$$

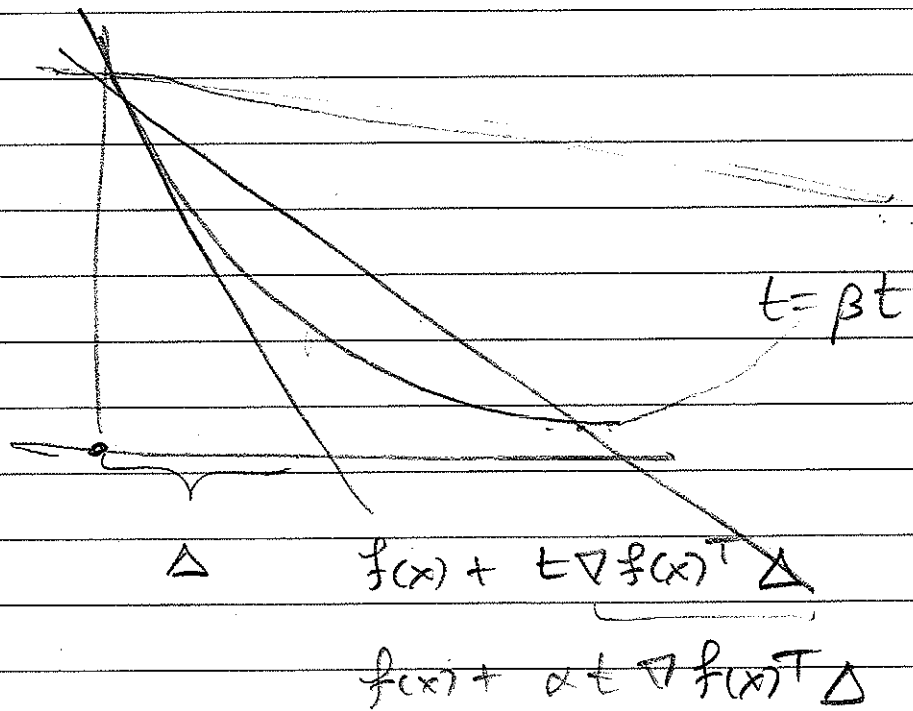
$$f(u) = au^2 + bu + c, \quad -b/2a$$

$$f(u) = u^T A u + b^T u + c, \quad -\frac{1}{2} A^{-1} b$$

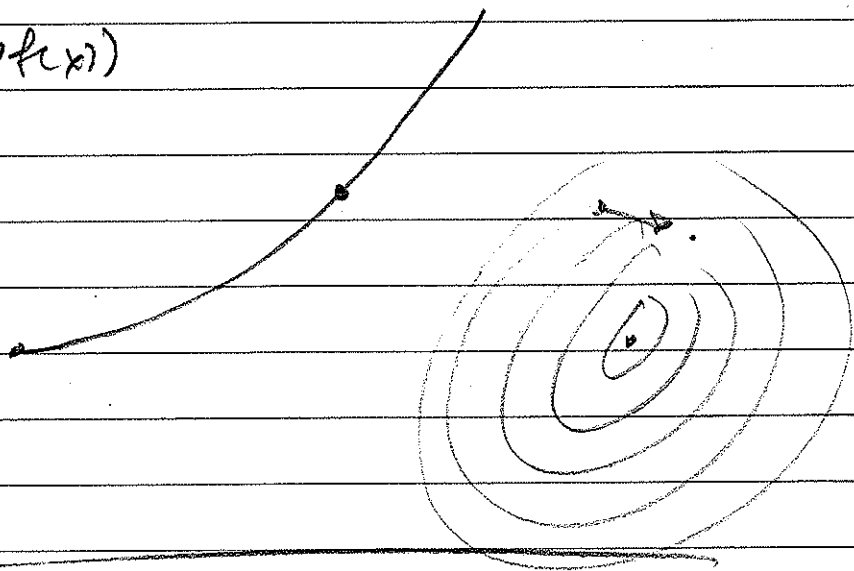
$$= \frac{1}{2\epsilon} y^T y + (\nabla f(x) - \frac{1}{\epsilon} x)^T y + \text{const.}$$

minimizer

$$\underline{x^+ = x - \epsilon \nabla f(x)}$$



$$g(s) = f(x - s \nabla f(x))$$



$f$  to within  $\epsilon$

$$|f(x^{(k)}) - f(x^*)| \leq \frac{C}{k} = \epsilon$$

$$O(1/k)$$

$$k = \frac{C}{\epsilon}$$

$$O(1/\epsilon)$$