First-order methods
Convexity

10-725 Optimization
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Administrivia

- HW1 out, due 9/20
  - in class, at ***beginning*** of class—no skipping lecture to keep working on it ;-)
  - if you use late days, hand in to course assistant before 1:30PM on due date + k days
- Reminder: think about project teams and project proposals (due 9/25)

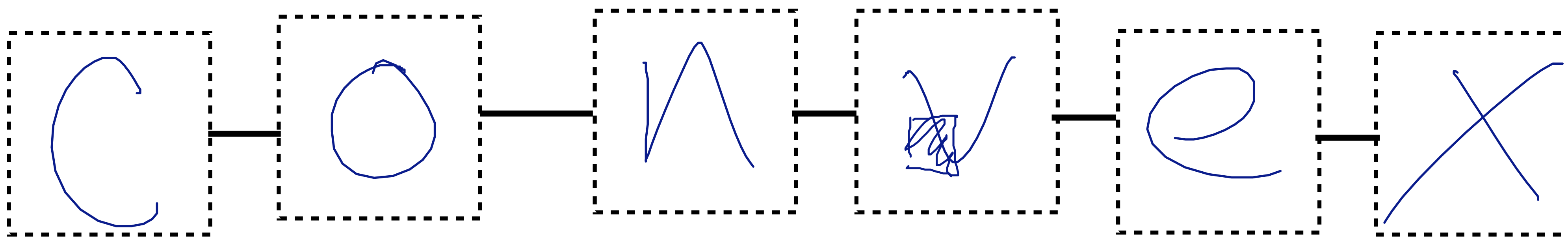
Review

- Convex sets
  - primal (convex hull) vs. dual (intersect hyperplanes)
  - supporting, separating hyperplanes
  - operations that preserve convexity
    - affine fn; perspective
  - open/closed/compact

Review

- Convex functions
  - epigraph
  - domain
  - sublevel sets; quasiconvexity
  - first order, 2nd order conditions
  - operations that preserve convexity
    - perspective; minimization over one argument

Ex: structured classifier



x_i pixels of char i

y_i a ... z

$\varphi_j(x_i)$ feature of a char

$\psi_{ijk}(x_i, y_i)$ $\quad \phi_j(x_i)\,\delta(y_i = k)$ ← w_{ijk}

$\chi_{ikl}(y_i, y_{i+1})$ $\quad \delta(y_i = k)\,\delta(y_{i+1} = l)$ ← v_{ikl}

$L(x,y;v,w) = \sum_{ijk} \psi_{ijk} w_{ijk} + \sum_{ikl} \chi_{ikl}(y_i, y_{i+1})\, v_{ikl}$

Classifier: $y = \arg\max_y L(x,y;v,w)$

Learning structured classifier

- Get it right if: $L(x, y; v, w) > L(x, y', v, w) \quad \forall y' \neq y$
- So, want: $L(x, y; v, w) \geq \max_{y'} \left(L(x, y'; v, w) + \pi(y, y') \right)$
- Where $\pi(y,y') = \{$ $0 \quad y = y'$; $>0 \quad y \neq y'$
- RHS: convex in v, w
- RHS – LHS: convex
- Train: lots of pairs (x^t,y^t) $\min_{v,w} \sum_t (RHS^t - LHS^t)$

Strict convexity; strong convexity

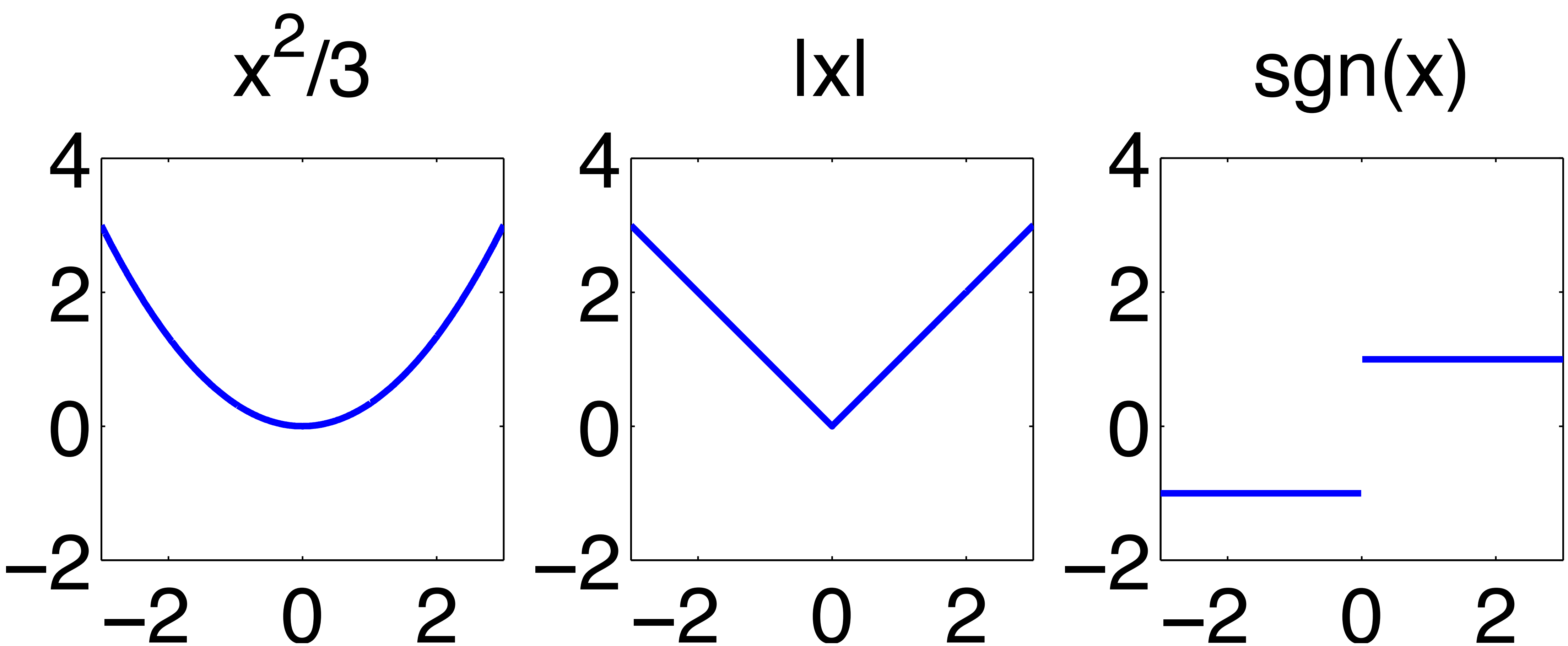
- Strictly convex:
  -
- k-strongly convex:
  -

Extended reals

- Suppose dom f $\subset R^n$
- Define g(x) = {
- f convex   g convex
  - f(tx+(1-t)y) ≤ tf(x) + (1-t)f(y)
  - g(tx+(1-t)y) ≤ tg(x) + (1-t)g(y)
  - cases:

Lipschitz

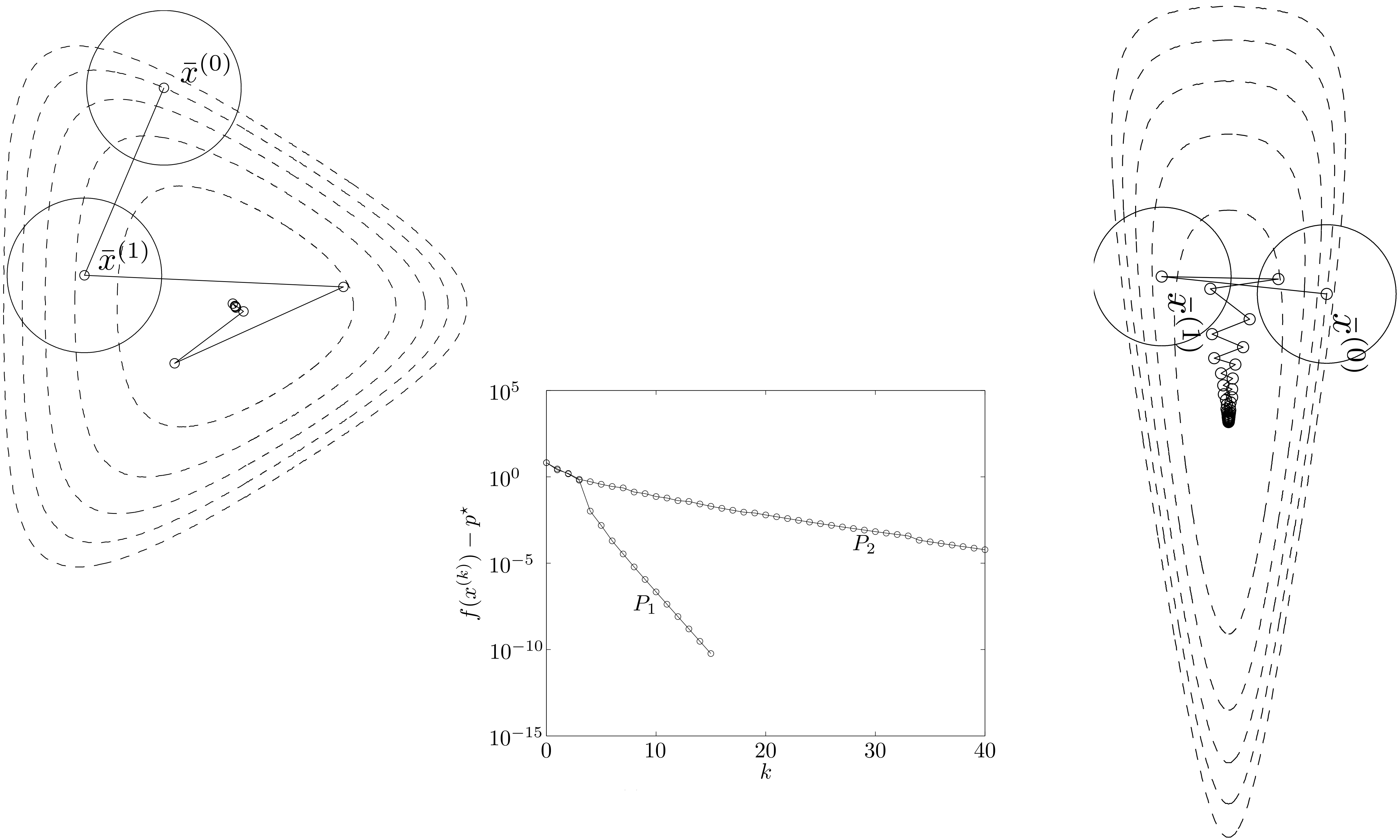
- Function f(x) is Lipschitz (in norm ||x||) if:
  -



Back to gradient descent

- Suppose f(x) is convex, $\nabla f(x)$ exists
- Iterations to get to accuracy $\epsilon(f(x_0) - f(x^*))$: if
  - f Lipschitz: $O(1/\epsilon^2)$
  - ∇f Lipschitz: $O(1/\epsilon)$
  - f strongly convex: $O(\ln(1/\epsilon))$
- Constant in O(…): ***conditioning*** of f

Conditioning



Extensions

- Subgradient descent
- Prox operator (e.g., $g_t = \arg\min_g \|g\|_p^2 + \nabla f \cdot g$)
- FISTA, mirror descent, conjugate gradient
- Nesterov's smoothing
- Line search (BV sec 9.2)
- Stochastic GD (when $f(x) = E(f_i(x) \mid i \sim P)$)
  - sample one i on each iter, use $\nabla f_i(x)$
  - or, minibatches: sample a few i's, use mean $\nabla f_i(x)$

Comparison: stochastic GD

- Iteration bounds for stochastic GD
  - f Lipschitz: $O(1/\epsilon^2)$ *(worse const, same O() as GD)*
  - f strongly convex: $O(\ln(1/\epsilon)/\epsilon)$ *(much worse)*
- f Lipschitz: stochastic GD often wins big
- Even if f strongly convex:
  - plain GD: each iter O(N), #iters $O(\ln(1/\epsilon))$
  - stochastic: each iter O(1), #iters $O(\ln(1/\epsilon)/\epsilon)$
  - stochastic can win if lots of data, loose tolerance
  - could make sense to throw data away, use full GD