COMP 414/514: Optimization – Algorithms, Complexity and Approximations

Overview

- In the last lecture, we:
 - Introduced some notions on convex optimization
 - Studied how such global assumptions affect the performance of gradient descent and what we can say about its convergence rate

- In this lecture, we will:
 - Solely focus on an important variant in convex optimization, the Frank-Wolfe algorithm

Thus far:

 $\min_{x} f(x)$

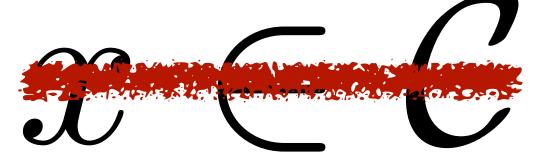
s.t. $x \in C$

Thus far:

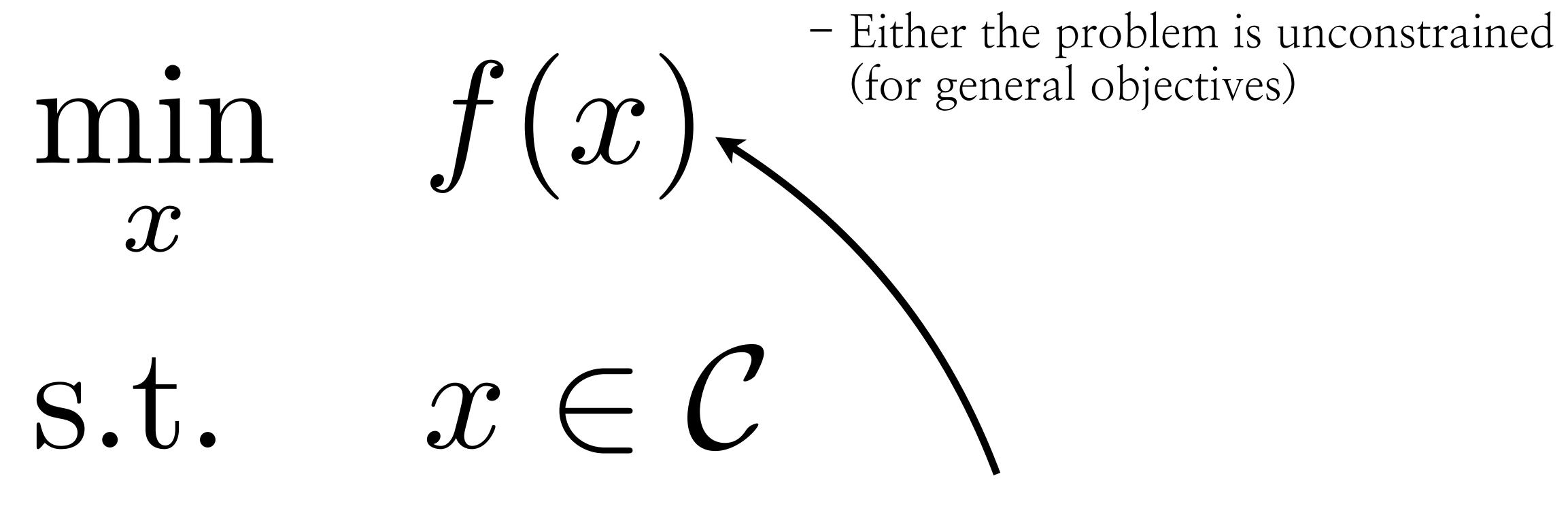
$$\min_{x} f(x)$$

- Either the problem is unconstrained (for general objectives)

S.t.



Thus far:



 Or the problem is constrained (but the analysis assumes convex objective)

$$\min_{x} f(x)$$

s.t. $x \in C$

f(x) — Designed for convex optimization (originally)

s.t.
$$x \in C$$

f(x)

S.t.

- Designed for convex optimization (originally)
- Its purpose is to handle constraints in a more efficient way (while remaining convex)

f(x)

s.t.

 $x \in C$

- Designed for convex optimization (originally)
- Its purpose is to handle constraints in a more efficient way (while remaining convex)
- We will see that, compared to convex projected gradient descent, we can achieve practical acceleration, without losing theoretical guarantees

Whiteboard

Conclusion

- We have introduced the notion of convexity

- We studied some of the merits of convex optimization

Conclusion

- We have introduced the notion of convexity
- We studied some of the merits of convex optimization

Next lecture

- We will consider an important variant for convex optimization for large-scale computing: Frank-Wolfe (conditional gradient) algorithm