



# Convergence Analysis of Monte Carlo Calibration of Financial Market Models

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Certain and Uncertain Processes

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# Fundamentals

Focus will be on calibration of European call options

## Definition 1 (European Call Option)

A **European call option** is the right to buy a predetermined underlying (e.g. stock) at a certain time  $T$  (maturity) for a certain price  $K$  (strike).



# Fundamentals

Focus will be on calibration of European call options

## Definition 1 (European Call Option)

A **European call option** is the right to buy a predetermined underlying (e.g. stock) at a certain time  $T$  (maturity) for a certain price  $K$  (strike).

## Definition 2 (Price of a Call Option)

The **price of a call option**  $C$  in  $t = 0$  can be calculated through

$$C = e^{-rT} E(\max(S_T - K, 0))$$

where  $r$  is the risk free rate and  $S_T$  the value of the underlying at future time  $T$ .



# Stochastic Differential Equation

L-dimensional system of stochastic differential equations (SDE):

$$dY_t(x) = a(x, Y_t(x))dt + b(x, Y_t(x))dW_t$$

where

$$x \in \mathbb{R}^P$$

vector of parameters

$$Y_t = [S_t, Y_t^1, \dots, Y_t^L] \in \mathbb{R}^L$$

Solution of SDE

$$W_t = (W_t^1, \dots, W_t^L) \in \mathbb{R}^L$$

Vector of Brownian motions

$$a : \mathbb{R}^P \times \mathbb{R}^L \rightarrow \mathbb{R}^L$$

$$a^l(x, Y_t(x))dt$$

$$b : \mathbb{R}^P \times \mathbb{R}^L \rightarrow \mathbb{R}^L \times \mathbb{R}^L$$

$$\sum_{\nu=1}^L b^{l,\nu}(x, Y_t(x))dW_t^\nu, l = 1, \dots, L$$



# Least Squares Problem

## Continuous Optimization Problem (True Problem)

$$\min_{x \in X} f(x) := \sum_{i=1}^I (C^i(x) - C_{\text{obs}}^i)^2$$

where  $C^i(x) = e^{-rT_i} E(\max(S_{T_i}(x) - K_i, 0))$

s.t.  $dY_t(x) = a(x, Y_t(x))dt + b(x, Y_t(x))dW_t, Y_0 > 0$

$X \subset \mathbb{R}^P$  convex and compact



# Least Squares Problem

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$X \subset \mathbb{R}^P$  convex and compact

## Discretized Optimization Problem (SAA Problem)

$$\min_{x \in X} f_{M, \Delta t, \epsilon} := \sum_{i=1}^I \left( C_{M, \Delta t, \epsilon}^i(x) - C_{\text{obs}}^i \right)^2$$

where  $C_{M, \Delta t, \epsilon}^i(x) := e^{-rT_i} \frac{1}{M} \sum_{m=1}^M \left( \pi_{\epsilon}(s_{N_i, \epsilon}^m(x) - K_i) \right)$

s.t.  $y_{n+1, \epsilon}^m(x) = y_{n, \epsilon}^m(x) + a_{\epsilon}(x, y_{n, \epsilon}^m(x))\Delta t_n + b_{\epsilon}(x, y_{n, \epsilon}^m(x))\Delta W_n^m$

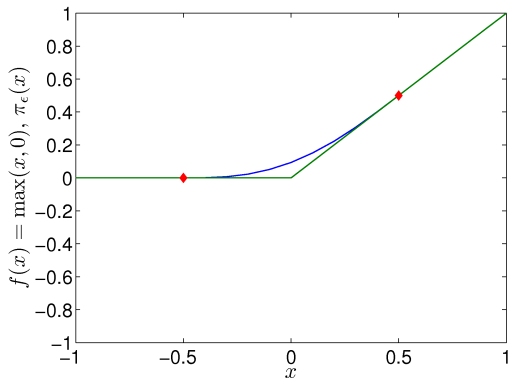


# Smoothing Non-differentiabilities

Consider Heston's Model:

$$dS_{t,\epsilon} = (r - \delta)S_{t,\epsilon}dt + \sqrt{v_{t,\epsilon}^+}S_{t,\epsilon}dW_t^1$$

$$dv_{t,\epsilon} = \kappa(\theta - v_{t,\epsilon}^+)dt + \sigma\sqrt{v_{t,\epsilon}^+}(\rho dW_t^1 + \sqrt{1 - \rho^2}dW_t^2)$$





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# Convergence

## True Problem

$$\min_{x \in X} f(x) := \sum_{i=1}^I (C^i(x) - C_{\text{obs}}^i)^2$$

## SAA Problem

$$\min_{x \in X} f_{M_k, \Delta t_k, \epsilon_k} := \sum_{i=1}^I (C_{M_k, \Delta t_k, \epsilon_k}^i(x) - C_{\text{obs}}^i)^2$$

Increase number of simulations:	$M_k \uparrow \infty$	} $x_k \in X$ solutions
Decrease discretization step size:	$\Delta t_k \downarrow 0$	
Decrease smoothing parameter:	$\epsilon_k \downarrow 0$	



# Convergence

## True Problem

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}  $x_k \in X$  solutions

$X$  compact  $\Rightarrow x_{k_l} \rightarrow x^*$  with  $x^*$  in  $X$ .



# Convergence

## True Problem

$$\min_{x \in X} f(x) := \sum_{i=1}^I (C^i(x) - C_{\text{obs}}^i)^2$$

## SAA Problem

$$\min_{x \in X} f_{M_k, \Delta t_k, \epsilon_k} := \sum_{i=1}^I (C_{M_k, \Delta t_k, \epsilon_k}^i(x) - C_{\text{obs}}^i)^2$$

Increase number of simulations:  $M_k \uparrow \infty$   
 Decrease discretization step size:  $\Delta t_k \downarrow 0$   
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}  $x_k \in X$  solutions

$X$  compact  $\Rightarrow x_{k_l} \rightarrow x^*$  with  $x^*$  in  $X$ .

## Question

$x^*$  solution of the true problem?



# Local Minima

$$\min_{x \in [-1;1]} f(x) \quad := \quad x^2$$

$$\min_{x \in [-1;1]} f_M(x) \quad := \quad x^2 - M^{-1} \sin(Mx^2)$$

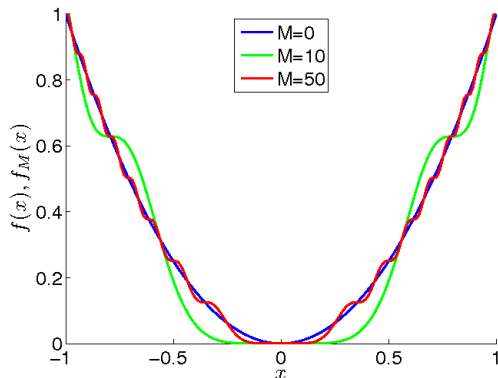


# Local Minima

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$$\min_{x \in [-1;1]} f_M(x) := x^2 - M^{-1} \sin(Mx^2)$$

**Local minima might lead to problems:**





# Literature Review

## True Problem:

$$\min_{x \in X} h(x) := E(H(x, \omega))$$

## SAA Problem

$$\min_{x \in X} h_M(x) := \frac{1}{M} \sum_{m=1}^M H(x, \omega_m)$$

- Shapiro (2000): Convergence if  $\min h(x)$  produces global minimum
- Rubinstein & Shapiro (1993): Convergence to a critical first order point under assumption that  $H(x, \omega)$  is dominated integrable and continuous
- Bastin *et al.* (2006): Additionally second order convergence even for stochastic constraints

⇒ Dependence on three error sources: Monte Carlo, discretization and smoothing!



# Goal: First Order Optimality

## Steps to be taken:

- 1 Pathwise Uniqueness of SDE
- 2 Uniform Convergence:

$$\lim_{k \rightarrow \infty} \sup_{x \in X} |f_{M_k, \Delta t_k, \epsilon_k}(x) - f(x)| = 0$$

$$\lim_{k \rightarrow \infty} \sup_{x \in X} \|\nabla f_{M_k, \Delta t_k, \epsilon_k}(x) - \nabla f(x)\| = 0$$

- 3 First Order Optimality Condition:

$$\nabla f(x^*)^T (x - x^*) \geq 0 \quad \forall x \in X$$



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# Pathwise Uniqueness under Lipschitz Continuity

## Theorem 3 (Kloeden & Platen)

*Under the assumptions that*

There exists a constant  $K_{\text{Lip}} > 0$  such that  $\forall t \in [0, T]$  and  $y \in \mathbb{R}^L$

$$|a(t, y) - a(t, z)| + |b(t, y) - b(t, z)| \leq K_{\text{Lip}}|y - z|$$

There exists a constant  $K_{\text{Grow}} > 0$  such that  $\forall t \in [0, T]$  and  $y \in \mathbb{R}^L$

$$|a(t, y)| + |b(t, y)| \leq K_{\text{Grow}}(1 + |y|)$$

*the stochastic differential equation*

$$dY_t = a(t, Y_t)dt + b(t, Y_t)dW_t, Y_0 \in (0, \infty).$$

*has a pathwise unique strong solution  $Y_t$  on  $[0, T]$ .*



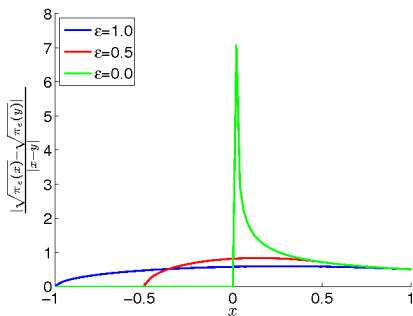
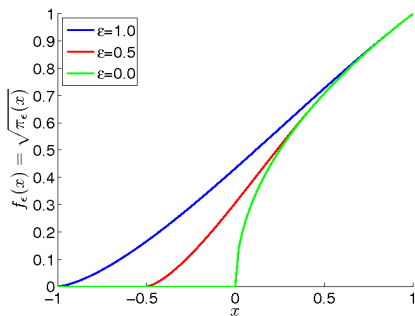
# Problem: Lipschitz Continuity

Consider Heston's model

$$dS_{t,\epsilon} = (r - \delta)S_{t,\epsilon}dt + \sqrt{\pi_\epsilon(v_{t,\epsilon})}S_{t,\epsilon}dW_t^1$$

$$dv_{t,\epsilon} = \kappa(\theta - \pi_\epsilon(v_{t,\epsilon}))dt + \sigma\sqrt{\pi_\epsilon(v_{t,\epsilon})}(\rho dW_t^1 + \sqrt{1 - \rho^2}dW_t^2)$$

Lipschitz continuity for  $\epsilon > 0$





# Yamada Condition

## Theorem 4

Let

$$dY_{t,\epsilon} = a_\epsilon(t, Y_{t,\epsilon})dt + b_\epsilon(t, Y_{t,\epsilon})dW_t.$$

with

$$a_\epsilon(t, Y_{t,\epsilon}) = (a_\epsilon^1(t, Y_{t,\epsilon}^1), \dots, a_\epsilon^L(t, Y_{t,\epsilon}^L))^T$$

$$b_\epsilon(t, Y_{t,\epsilon}) = \text{diag}(b_\epsilon^1(t, Y_{t,\epsilon}^1), \dots, b_\epsilon^L(t, Y_{t,\epsilon}^L))$$

If there exists a positive increasing function  $\beta : [0, \infty) \rightarrow [0, \infty)$  with

$$|b^i(t, x) - b^i(t, y)| \leq \beta(|x - y|) \quad \forall x, y \in \mathbb{R}, \quad i = 1, \dots, L$$

and

$$\int_0^\delta \beta^{-2}(z) dz = \infty.$$

with an arbitrarily small  $\delta > 0$  ...



## Yamada Condition (2)

... and a positive increasing concave function  $\alpha : [0, \infty) \rightarrow [0, \infty)$  such that

$$|a^i(t, x) - a^i(t, y)| \leq \alpha(|x - y|) \quad \forall x, y \in \mathbb{R}, \quad i = 1, \dots, L$$

with

$$\int_0^\delta \alpha^{-1}(z) dz = \infty.$$

with an arbitrarily small  $\delta > 0$ , the SDE has a pathwise unique solution.

Proof: Yamada (1971)



## Yamada Condition (3)

Reconsider Heston's model

$$dS_{t,\epsilon} = (r - \delta)S_{t,\epsilon}dt + \sqrt{\pi_\epsilon(v_{t,\epsilon})}S_{t,\epsilon}dW_t^1$$

$$dv_{t,\epsilon} = \kappa(\theta - \pi_\epsilon(v_{t,\epsilon}))dt + \sigma\sqrt{\pi_\epsilon(v_{t,\epsilon})}(\rho dW_t^1 + \sqrt{1 - \rho^2}dW_t^2)$$

The drift is Lipschitz continuous:

$$|a^i(t, x) - a^i(t, y)| \leq K_{\text{Lip}}|x - y| \quad \forall x, y \in \mathbb{R}, \quad i = 1, 2$$

and the diffusion is Hölder continuous:

$$|b^i(t, x) - b^i(t, y)| \leq \sqrt{|x - y|} \quad \forall x, y \in \mathbb{R}, \quad i = 1, 2$$

with

$$\int_0^\delta \frac{1}{K_{\text{Lip}}z} dz = \infty; \quad \int_0^\delta \frac{1}{z} dz = \infty.$$



## Problem: Independent components required

Heston's model:

$$\begin{aligned}dS_{t,\epsilon} &= (r - \delta)S_{t,\epsilon}dt + \sqrt{\pi_\epsilon(v_{t,\epsilon})}S_{t,\epsilon}dW_t^1 \\dv_{t,\epsilon} &= \kappa(\theta - \pi_\epsilon(v_{t,\epsilon}))dt + \sigma\sqrt{\pi_\epsilon(v_{t,\epsilon})}dW_t^2\end{aligned}$$



## Problem: Independent components required

Heston's model:

$$\begin{aligned}dS_{t,\epsilon} &= (r - \delta)S_{t,\epsilon}dt + \sqrt{\pi_\epsilon(v_{t,\epsilon})}S_{t,\epsilon}dW_t^1 \\dv_{t,\epsilon} &= \kappa(\theta - \pi_\epsilon(v_{t,\epsilon}))dt + \sigma\sqrt{\pi_\epsilon(v_{t,\epsilon})}dW_t^2\end{aligned}$$

Solution:

- Process  $v_{t,\epsilon}$  has pathwise unique solution following Yamada's Theorem
- Insert this unique solution in process  $S_{t,\epsilon}$
- Process  $S_{t,\epsilon}$  has pathwise unique solution following Yamada's Theorem

⇒ Pathwise unique solution via Yamada's Theorem



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# Convergence of the Problem

Reconsider:

$$|f_{M,\Delta t,\epsilon}(x) - f(x)| \leq |f_{M,\Delta t,\epsilon}(x) - f_{\Delta t,\epsilon}(x)| \quad (1)$$

$$+ |f_{\Delta t,\epsilon}(x) - f_{\epsilon}(x)| \quad (2)$$

$$+ |f_{\epsilon}(x) - f(x)| \quad (3)$$



# Convergence of the Problem

Reconsider:

$$|f_{M,\Delta t,\epsilon}(x) - f(x)| \leq |f_{M,\Delta t,\epsilon}(x) - f_{\Delta t,\epsilon}(x)| \quad (1)$$

$$+ |f_{\Delta t,\epsilon}(x) - f_{\epsilon}(x)| \quad (2)$$

$$+ |f_{\epsilon}(x) - f(x)| \quad (3)$$

## Assumption:

There exists a constant  $K_{\text{Grow}} > 0$  such that  $\forall t \in [0, T]$  and  $y \in \mathbb{R}^L$

$$\|a_{\epsilon}(t, y)\| + \|b_{\epsilon}(t, y)\| \leq K_{\text{Grow}}(1 + \|y\|).$$



# Convergence of Smoothed and Discretized SDE

## Theorem 5

Consider the SDE

$$dY_{t,\epsilon} = a_\epsilon(t, Y_{t,\epsilon})dt + b_\epsilon(t, Y_{t,\epsilon})dW_t.$$

and the continuously interpolated process

$$y_{t,\epsilon} = Y_0 + \int_0^t a_\epsilon(x, y_{\tau(s),\epsilon})ds + \int_0^t b_\epsilon(x, y_{\tau(s),\epsilon})dW_s$$

where  $\tau(s) = n, \forall s \in [\tau_n, \tau_{n+1})$  and  $n = 0, \dots, N - 1$ . Assuming that the growth condition holds and the SDE has a pathwise unique solution it holds

$$\lim_{\Delta t \rightarrow 0} \sup_{x \in X} E \left( |y_{t,\epsilon} - Y_{T,\epsilon}|^2 \right) = 0.$$

Proof: Kaneko & Nakao (1988)



# Convergence of Smoothed SDE

## Theorem 6

Assume that the growth condition and the pathwise uniqueness holds for a solution of

$$dY_t = a(t, Y_t)dt + b(t, Y_t)dW_t$$

and let  $Y_{t,\epsilon}$  be a solution of

$$dY_{t,\epsilon} = a_\epsilon(t, Y_{t,\epsilon})dt + b_\epsilon(t, Y_{t,\epsilon})dW_t.$$

If  $a_\epsilon$  and  $b_\epsilon$  converge uniformly to  $a$  and  $b$  for  $\epsilon \rightarrow 0$ , i.e.

$$\lim_{\epsilon \rightarrow 0} \sup_{t \in [0, T]} \sup_{x \in X} (|a_\epsilon(t, x) - a(t, x)| + \|b_\epsilon(t, x) - b(t, x)\|) = 0.$$

where  $\|\cdot\|$  is a matrix norm, it holds

$$\lim_{\epsilon \rightarrow 0} \sup_{x \in X} E \left( |Y_{t,\epsilon} - Y_t|^2 \right) = 0.$$

Proof: Kaneko & Nakao (1988)



# Dominated Integrability & Continuity

## Lemma 7

*Assume that the families  $\{\pi(S_T(x, \omega) - K), x \in X\}$  are dominated by a  $Q$ -integrable function  $\bar{P}(\omega)$ . Then there exist  $\bar{\Delta t} > 0$  and  $\bar{\epsilon} > 0$  such that  $\{\pi_\epsilon(s_{N,\epsilon}(x, \omega) - K), x \in X\}$  is dominated by a  $Q$ -integrable function for all  $\Delta t \in [0, \bar{\Delta t}]$  and  $\epsilon \in [0, \bar{\epsilon}]$ .*

## Lemma 8

*If the functions  $\pi(S_T(\cdot, \omega) - K)$  are continuous on  $X$  for  $Q$  almost every  $\omega$ , the functions  $\pi_\epsilon(s_{N,\epsilon}(x, \omega) - K)$  are continuous on  $X$  for  $0 < \Delta t < \infty$  and  $0 < \epsilon < \infty$ .*



# Uniform Convergence

## Theorem 9

Assume that the families  $\{\pi(S_T(x, \omega) - K), x \in X\}$  are dominated by a  $Q$ -integrable function  $\bar{P}(\omega)$  and furthermore the functions  $\pi(S_T(\cdot, \omega) - K)$  are continuous on  $X$  for  $Q$  almost every  $\omega$ . If additionally  $X$  is compact, then  $f(x)$  is continuous on  $X$ . Furthermore  $f_{M, \Delta t, \epsilon}$  converges uniformly to  $f$  on  $X$ , i.e. for given sequences  $(M_k)_k \subset \mathbb{N}$ ,  $(\Delta t_k)_k \subset \mathbb{R}_+$  and  $(\epsilon_k)_k \subset \mathbb{R}_+$  satisfying  $M_k \uparrow \infty$ ,  $\Delta t_k \downarrow 0$ ,  $\epsilon_k \downarrow 0$  it holds

$$\lim_{k \rightarrow \infty} \sup_{x \in X} |f_{M_k, \Delta t_k, \epsilon_k}(x) - f(x)| = 0.$$

Note that the same can be shown for the gradients!



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# First Order Optimality Condition

## Theorem 10

Assume that the families  $\{\pi(S_T(x, \omega) - K), x \in X\}$  and  $\{\frac{\partial}{\partial x_p} \pi(S_T(\cdot, \omega) - K), x \in X\}$ ,  $i = 1, \dots, I$  are dominated by a  $Q$ -integrable function  $\bar{P}(\omega)$  and furthermore the functions  $\pi(S_T(\cdot, \omega) - K)$  and  $\frac{\partial}{\partial x_p} \pi(S_T(\cdot, \omega) - K)$ ,  $i = 1, \dots, I$  are continuous on  $X$  for  $Q$  almost every  $\omega$  and additionally that  $X$  is compact. Further let  $(M_k)_k \subset \mathbb{N}_+$ ,  $(\Delta t_k)_k \subset \mathbb{R}_+$ ,  $(\epsilon_k)_k \subset \mathbb{R}_+$  and  $(\gamma_k)_k \subset \mathbb{R}_+$  with  $M_k \uparrow \infty$ ,  $\Delta t_k \downarrow 0$ ,  $\epsilon_k \downarrow 0$  and  $\gamma_k \downarrow 0$  be given sequences and assume that  $(x_k)_{k \in \mathbb{N}} \subset X$  is a sequence of points satisfying

$$\nabla f(x_k)^T (x - x_k) \geq -\gamma_k \quad \forall x \in X.$$

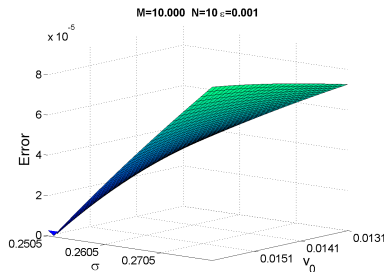
Then every limit point  $x^* \in X$  of  $(x_k)_k$  almost surely satisfies the first order optimality condition

$$\nabla f(x^*)^T (x - x^*) \geq 0 \quad \forall x \in X.$$



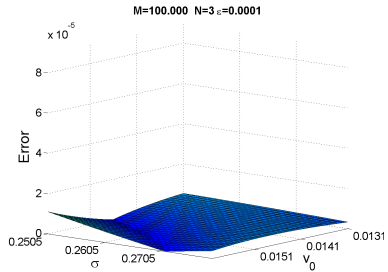
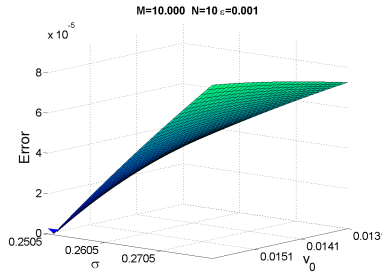


# Convergence: Graphical Illustration



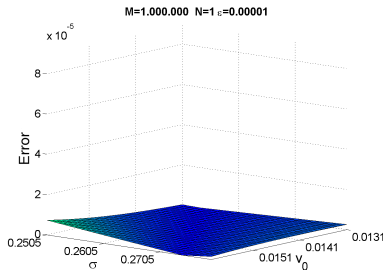
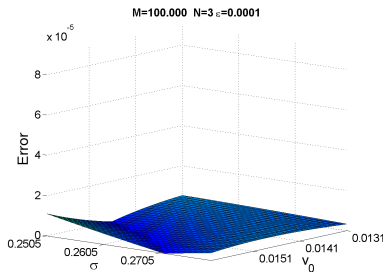
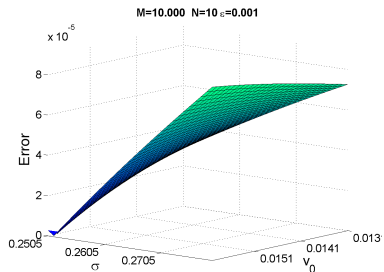


# Convergence: Graphical Illustration





# Convergence: Graphical Illustration





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# Conclusions

- Set up calibration problem
- Discretized via Monte Carlo, Euler-Maruyama and smoothing
- Pathwise Uniqueness for resulting SDE under Yamada Condition
- Uniform convergence of objectives under unrestrictive assumptions
- First order optimality condition satisfied for limit point  $x^*$



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