

Precise Relaxation for Motion Estimation

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Variational motion estimation

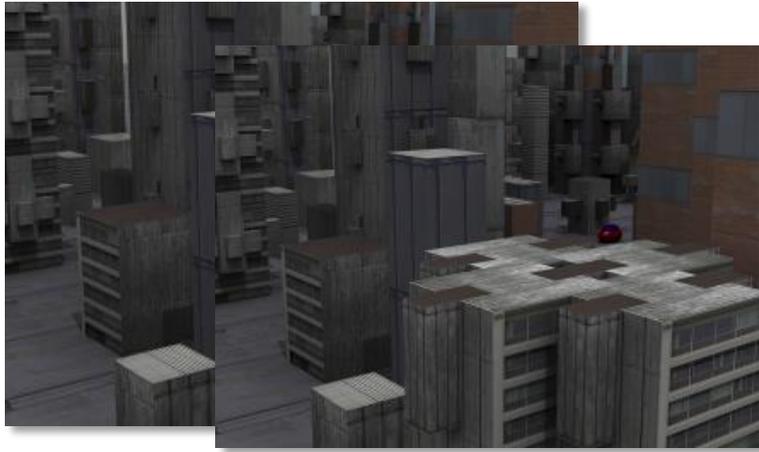


image sequence



optical flow/registration

$$\min_{u:\Omega\rightarrow\mathbb{R}^2} \int_{\Omega} D(I_{\sigma}^1(x), I_{\sigma}^2(x+u))dx + \lambda \int_{\Omega} d\|Du\|$$

u scalar (disparity, stereo) or vector field (optical flow, image registration)

Variational methods

We reconstruct the unknown data u from the measurements b by minimizing the energy

$$\min_u \{D(T(u); b) + R(u)\}$$

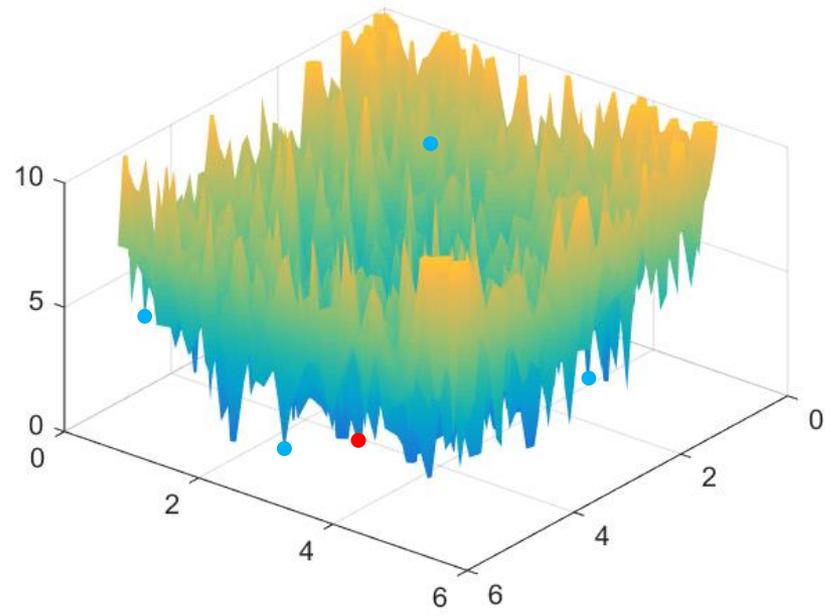
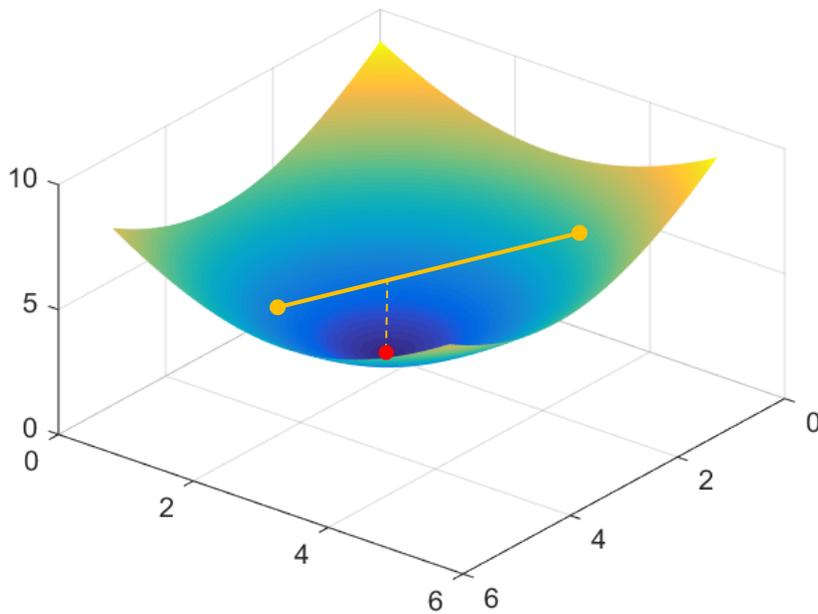
Intuitive (what do we want) and **modular** (reusable)

In practice: often

$$\min_{u:\Omega \rightarrow X} \int_{\Omega} \rho(x, u(x)) dx + \lambda \int_{\Omega} \sigma(\nabla u) dx$$

Convexity

Convexity assures that every **local minimizer** of the energy is also a **global minimizer**



Variational motion estimation

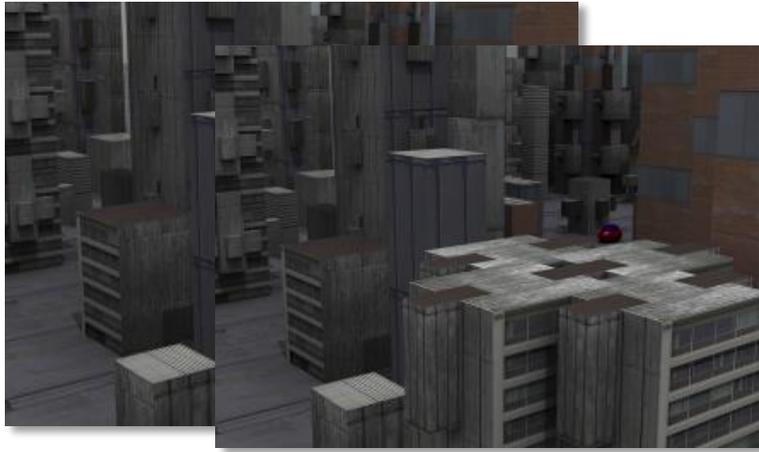


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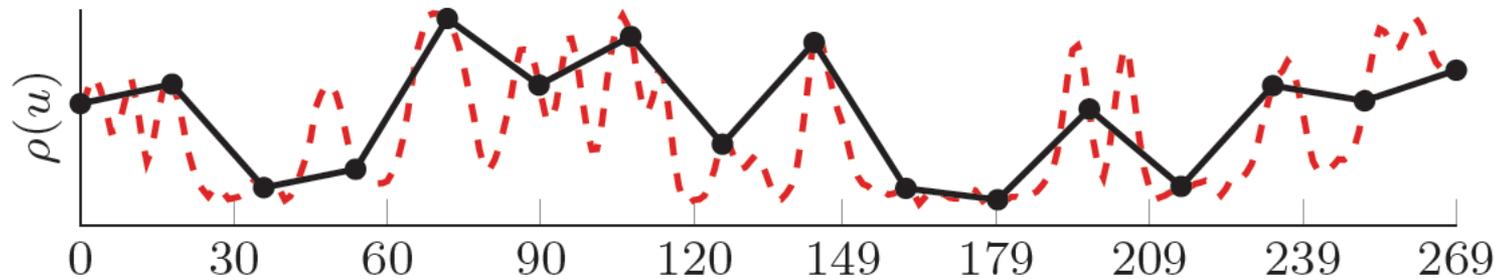
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Non-convexity

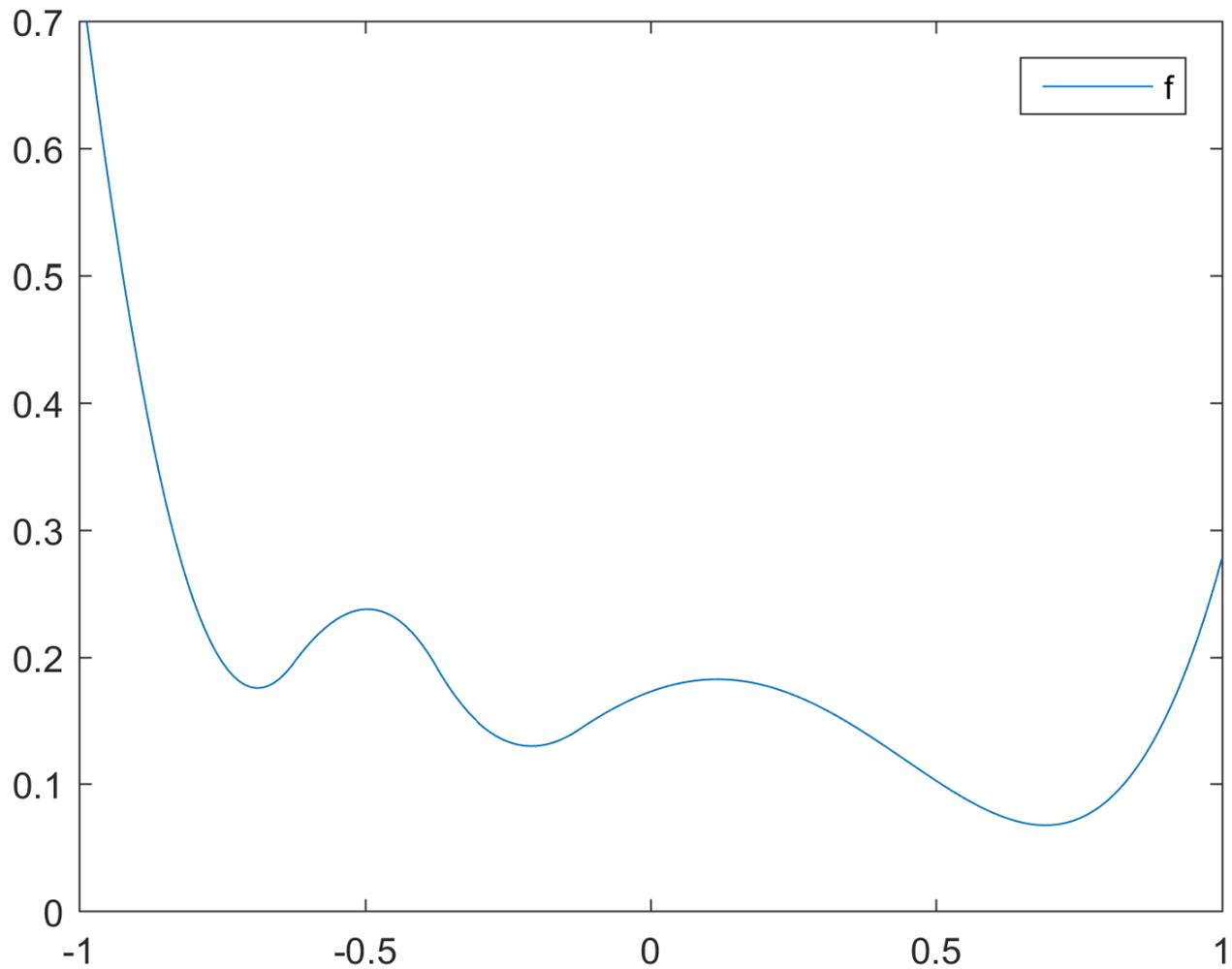
- Real-world disparity estimation/depth from stereo:



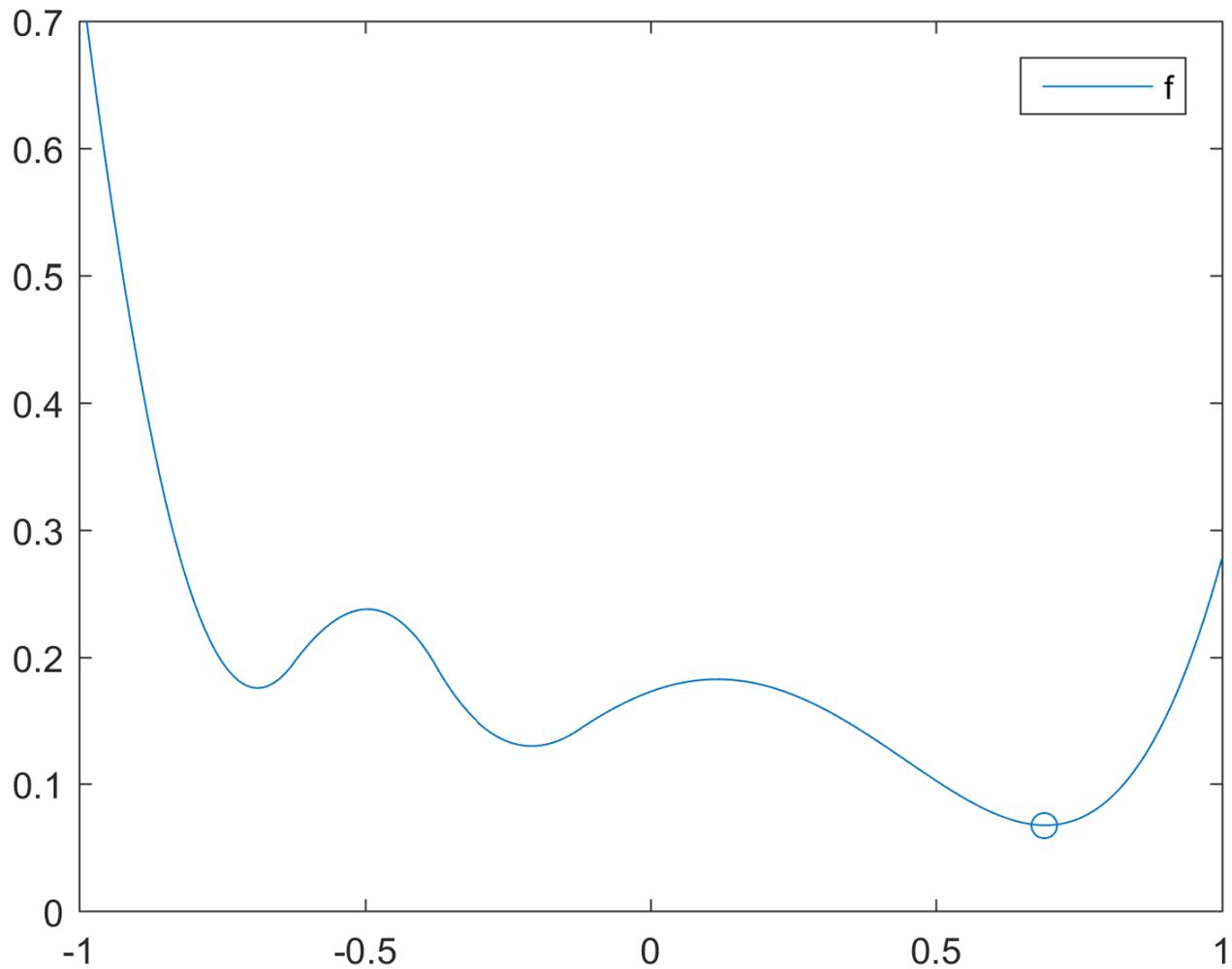
- Data-dependent nonconvexity at every point

Exact convex relaxation

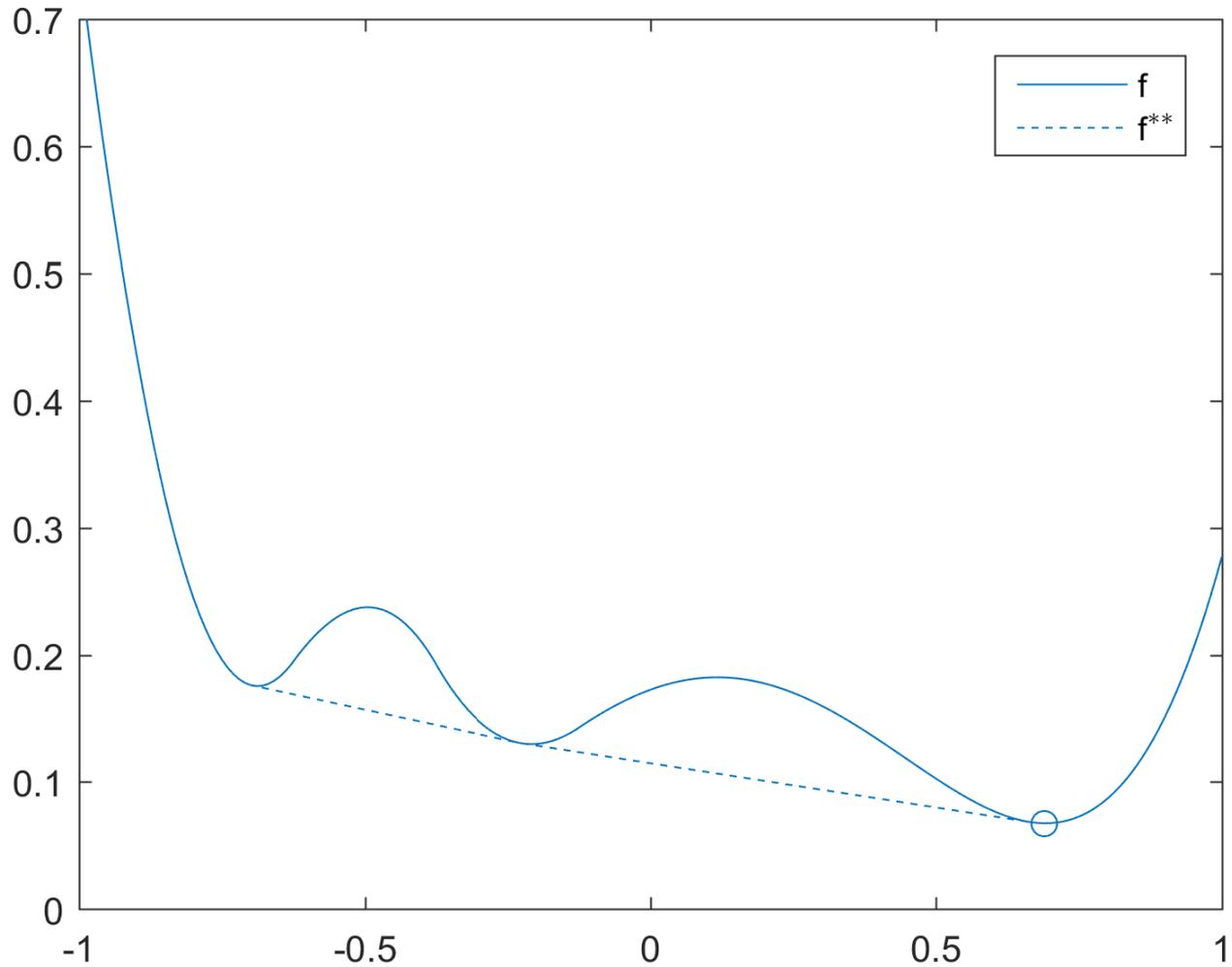
Exact convex relaxation



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Exact convex relaxation



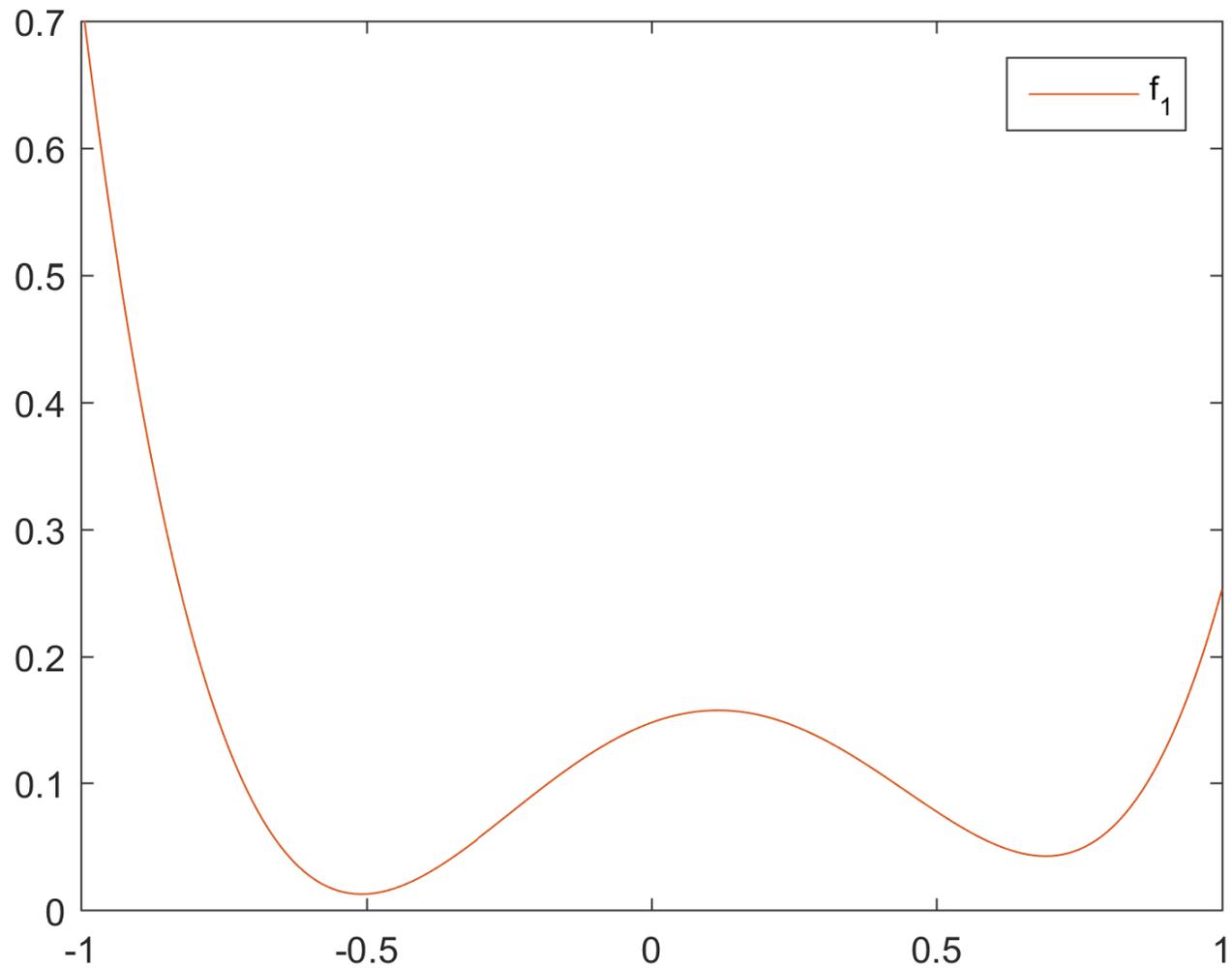
Drawback

This is generally as hard as
minimizing the original energy!

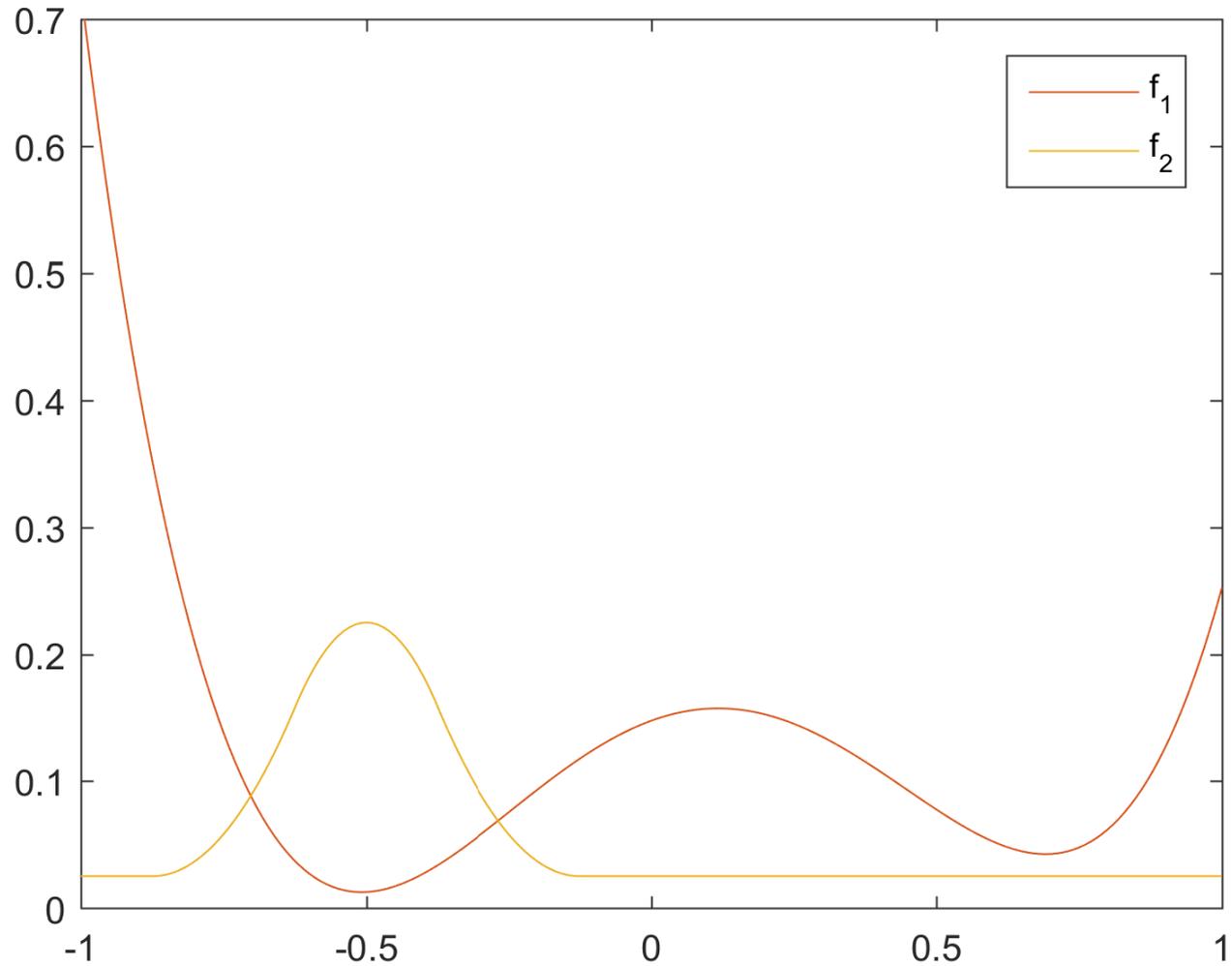
Objectives are often sums

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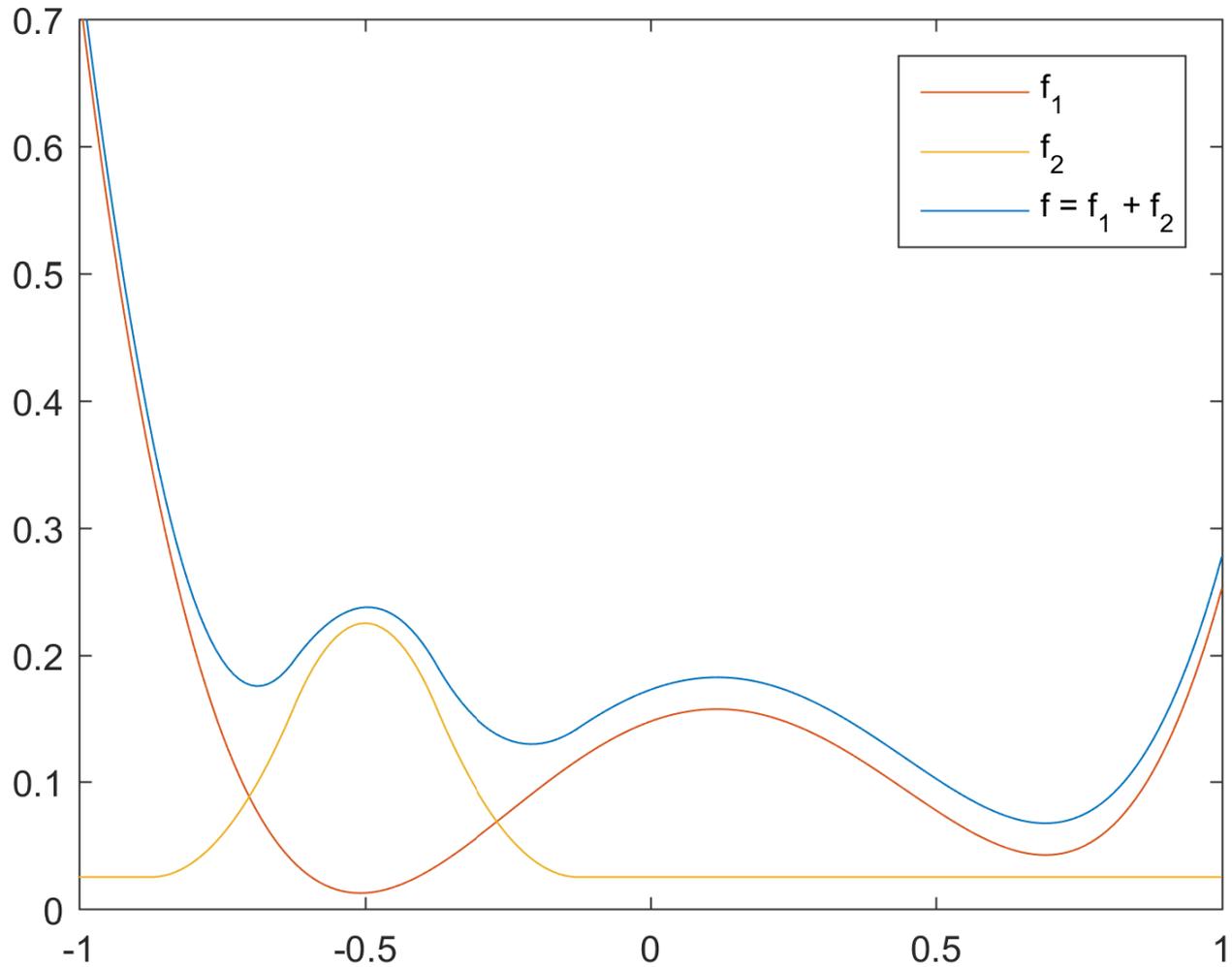
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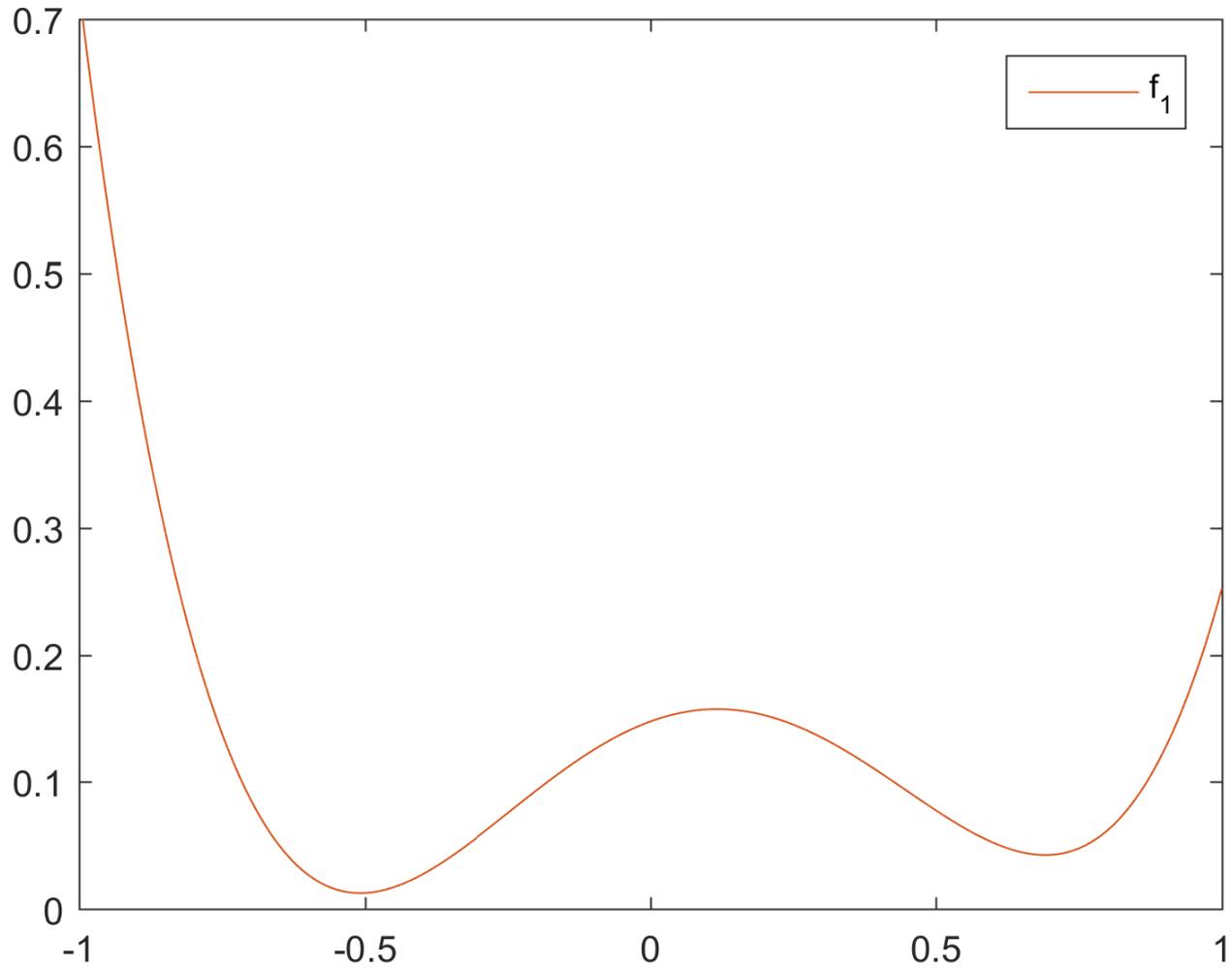


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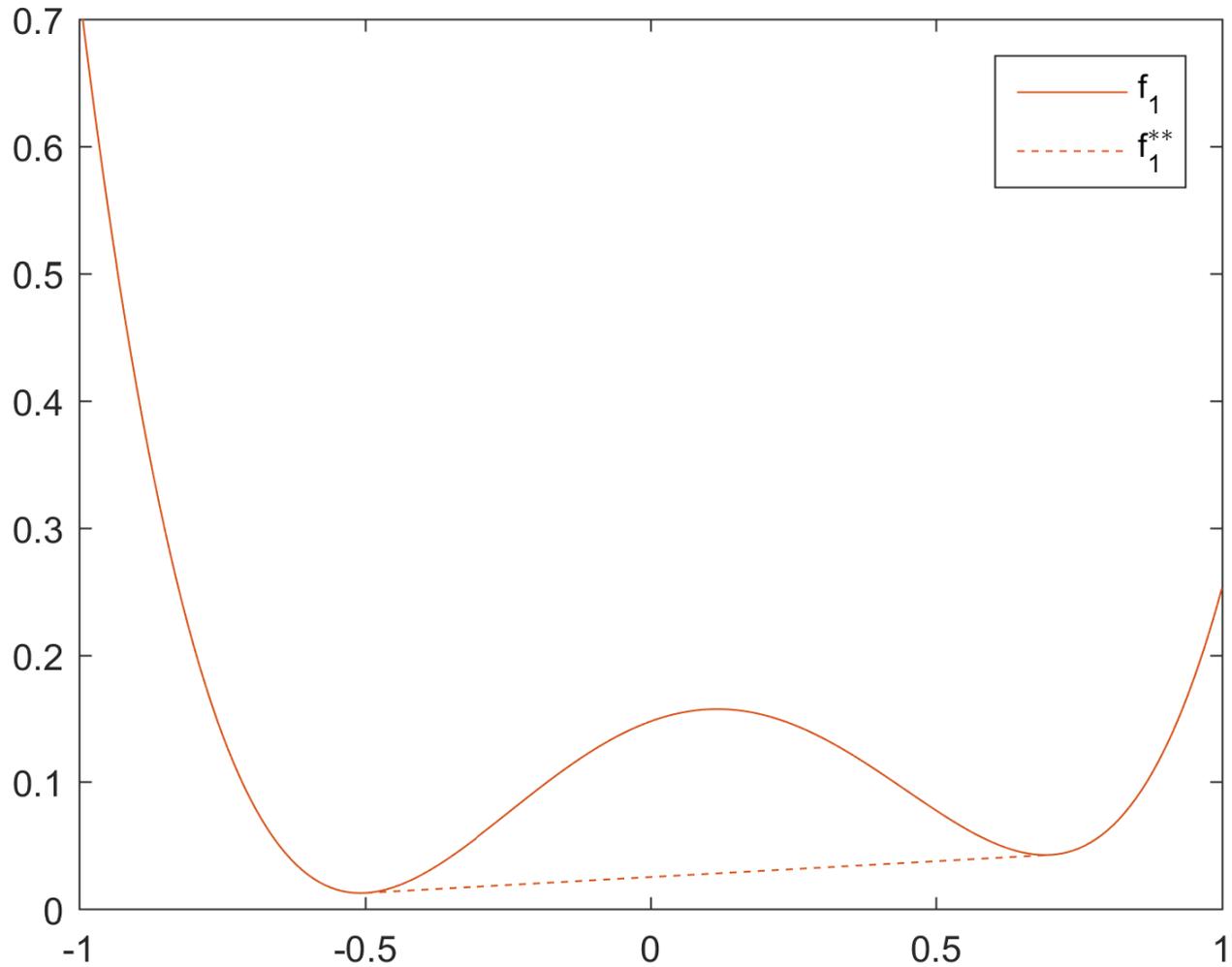


Separate exact relaxation

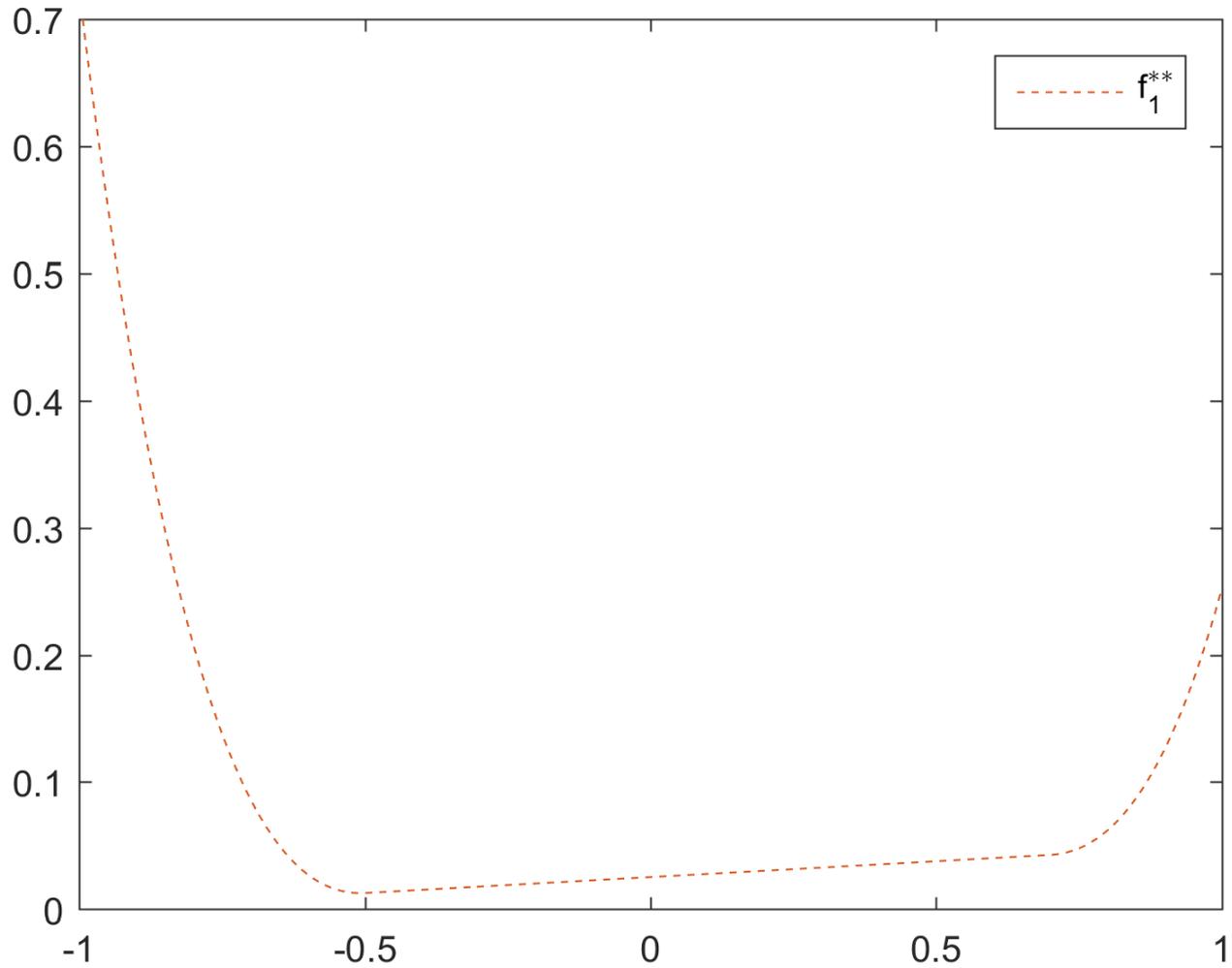
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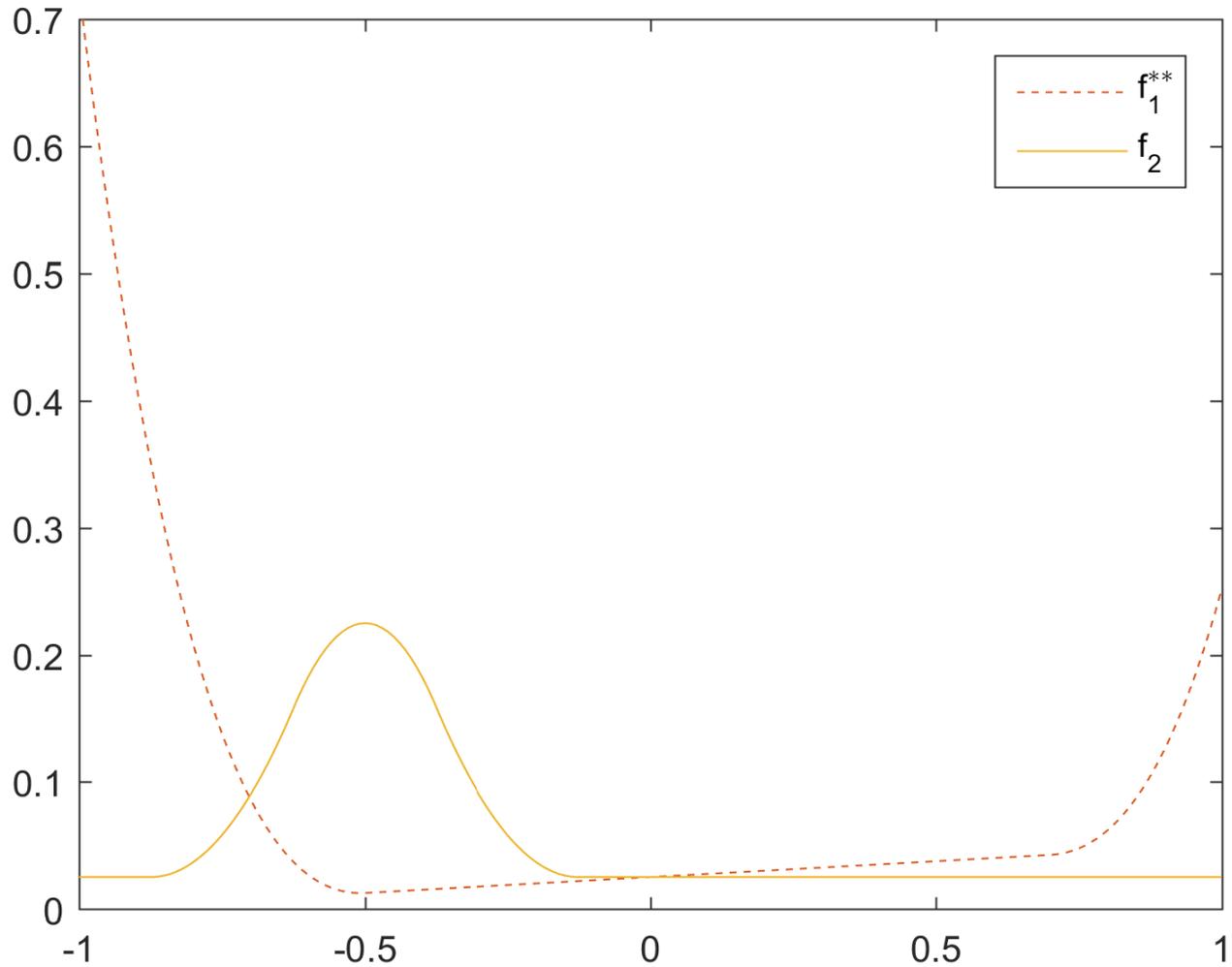
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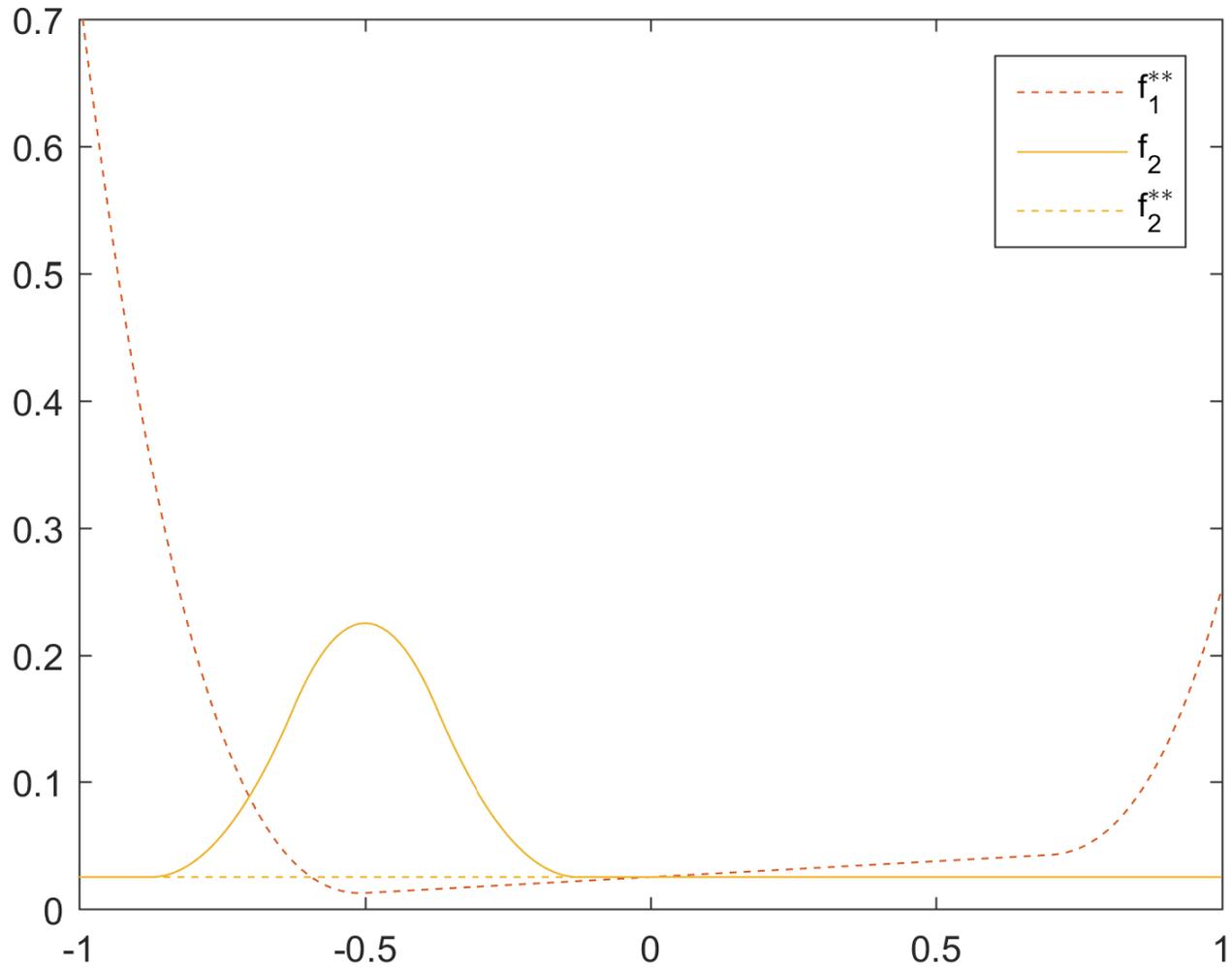
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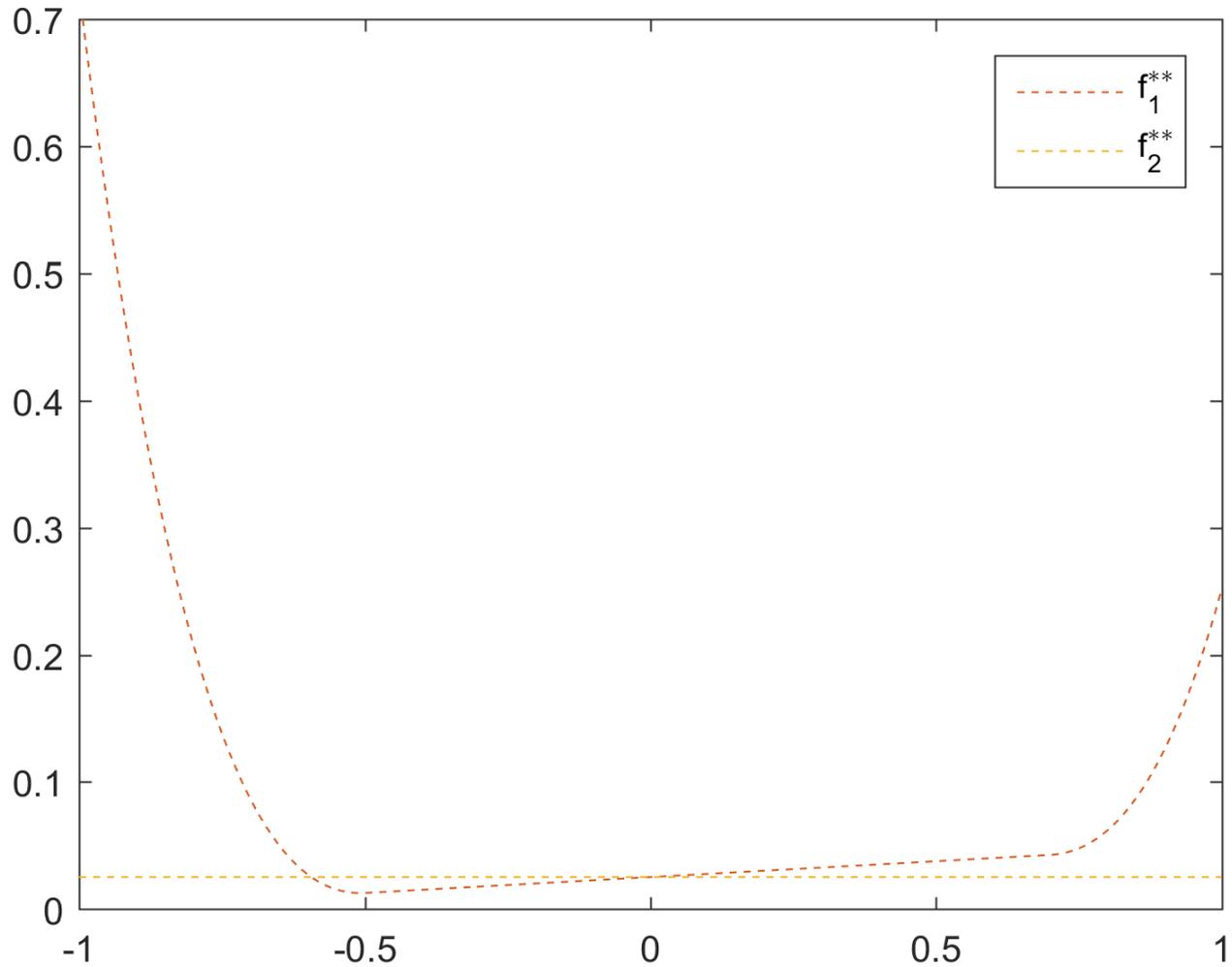
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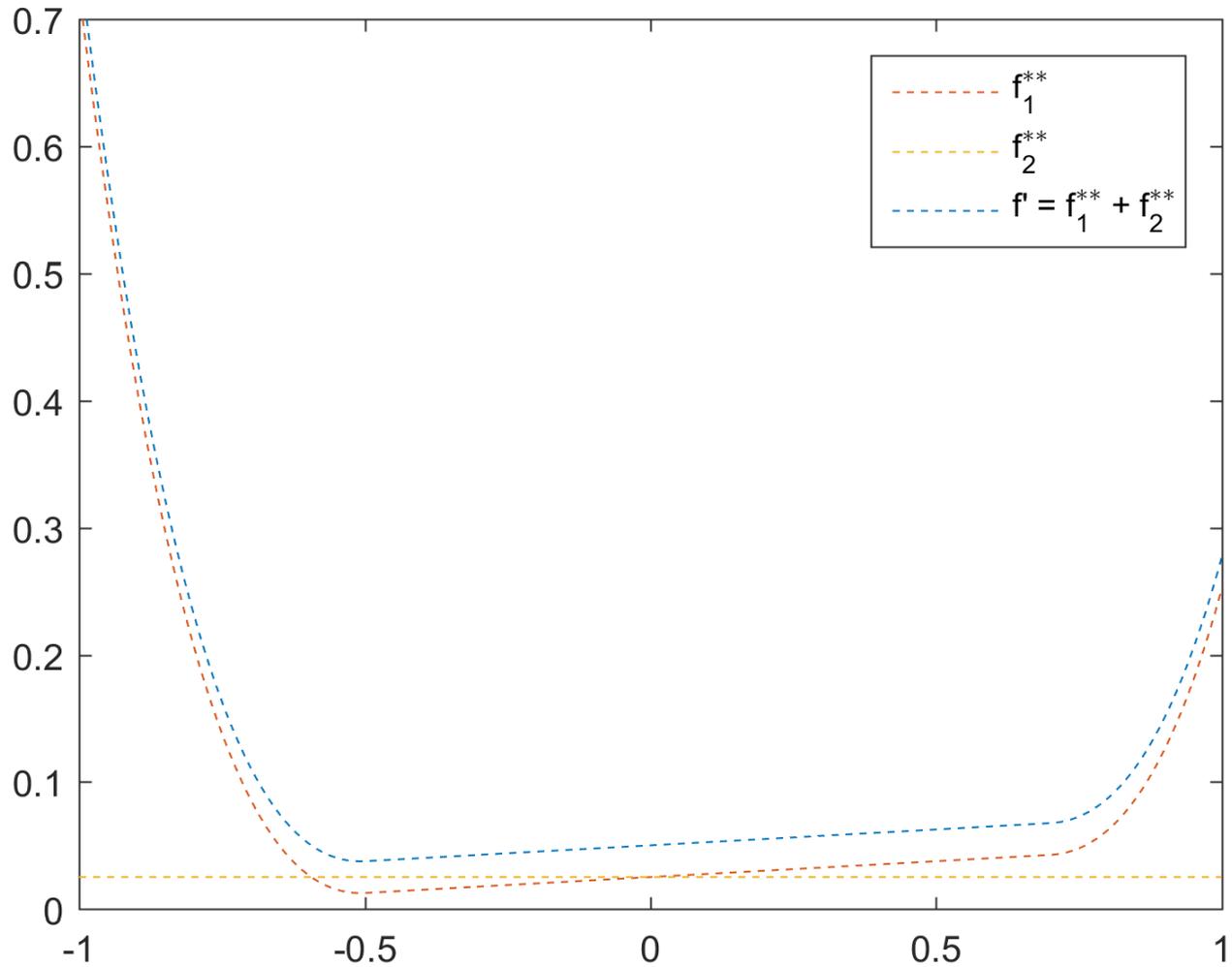
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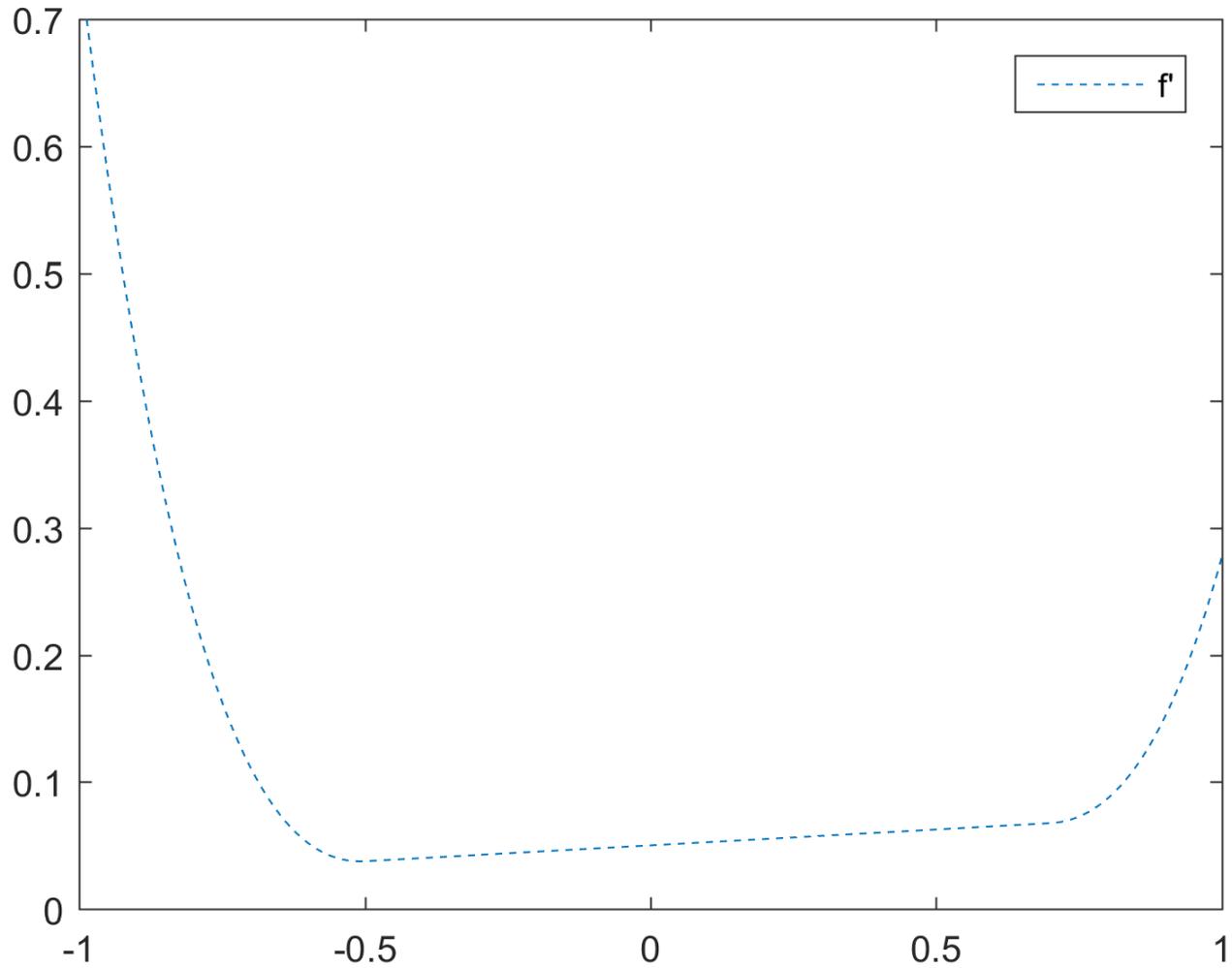
Separate exact relaxation



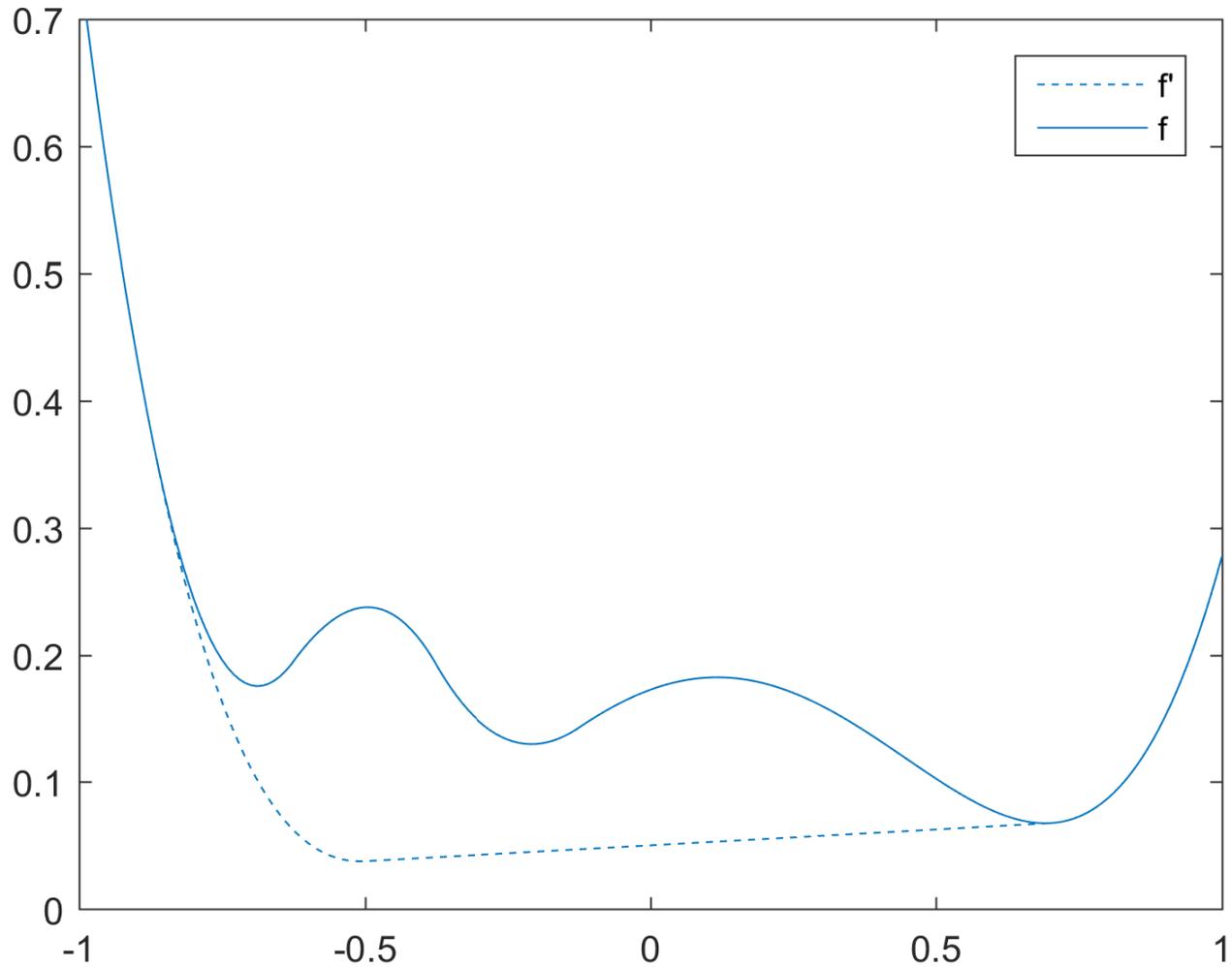
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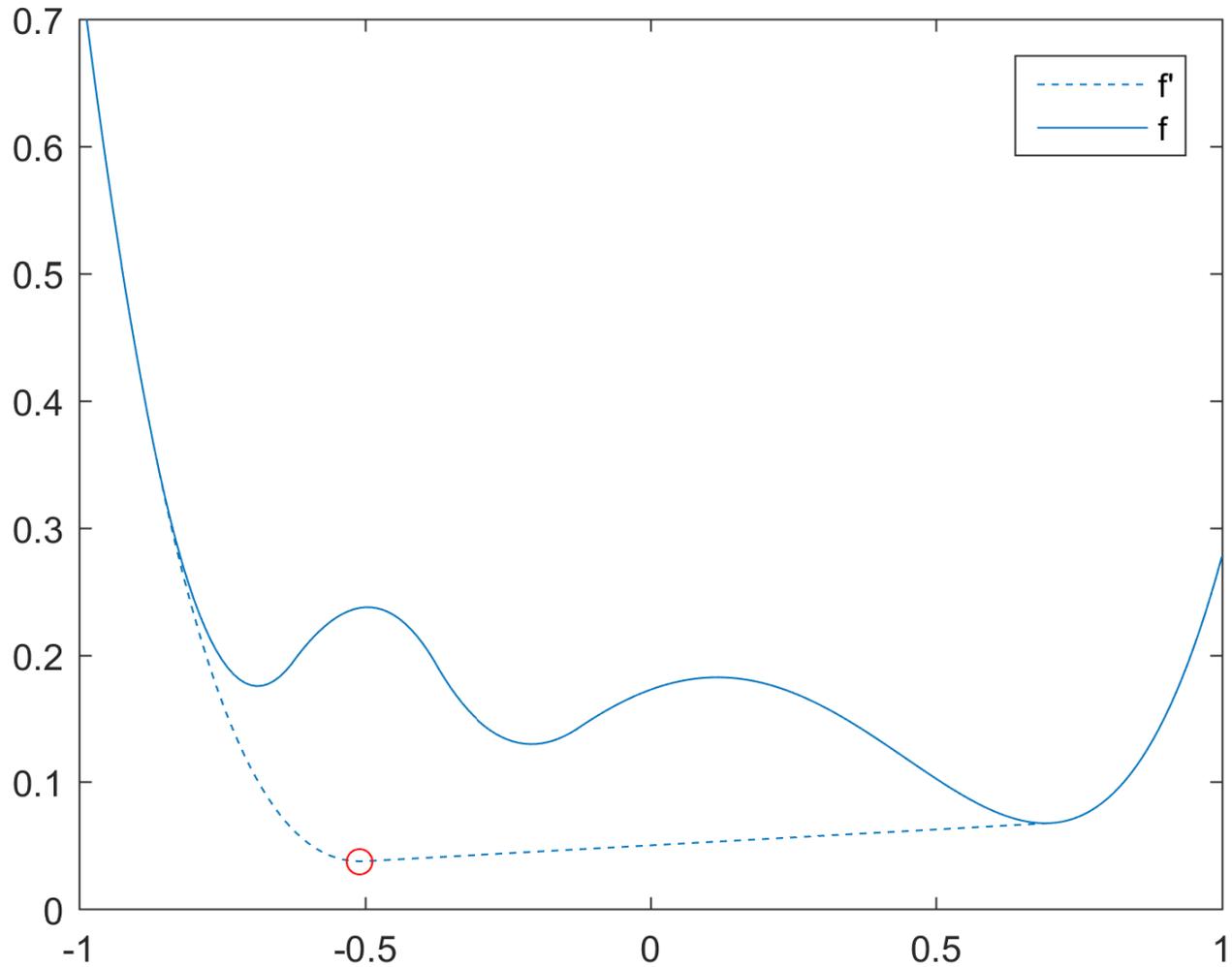
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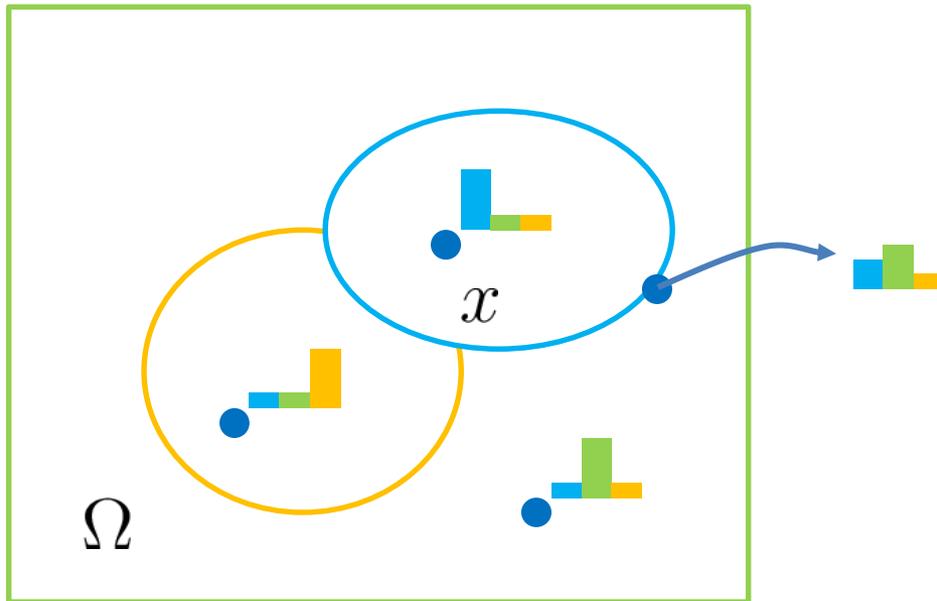
Separate exact relaxation



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Lifting



Hard decisions are replaced by soft “probabilities”

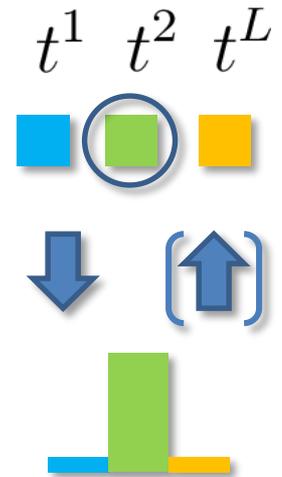
Lifting

We extend the problem

$$\min_{u': \Omega \rightarrow X} f'(u')$$

to the probability measures:

$$\min_{u: \Omega \rightarrow \mathcal{P}(X)} f(u)$$



The new energy f should agree with f' on Dirac measures, and not create artificial minimizers.

Potts '52; Boykov et al. '98, '01; Kleinberg, Tardos '01
Zach et al. '08; Lellmann, Becker, Schnörr '09; Chambolle, Cremers, Pock '11; Yuan, Bae, Tai, Boykov '10
Young measures: Young '37; Currents: Schwartz '51; de Rahm '55; Federer '69
Paired calibrations: Brakke '91; Alberti, Bouchitté, Dal Maso '01

Linear relaxation

- Lifting + relaxation using the biconjugate:

$$\int_{\Omega} \rho(u(x)) dx \rightsquigarrow \int_{\Omega} \boldsymbol{\rho}^{**}(u(x)) dx$$

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- Linear relaxation (*1-sparse* solutions):

$$\boldsymbol{\rho}(z) = \begin{cases} \rho(t^i), & z = e^i, \quad i \in \{1, \dots, L\}, \\ +\infty, & \text{otherwise.} \end{cases}$$

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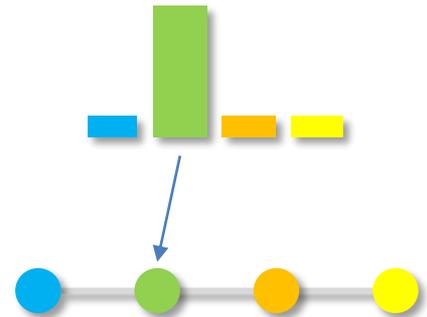
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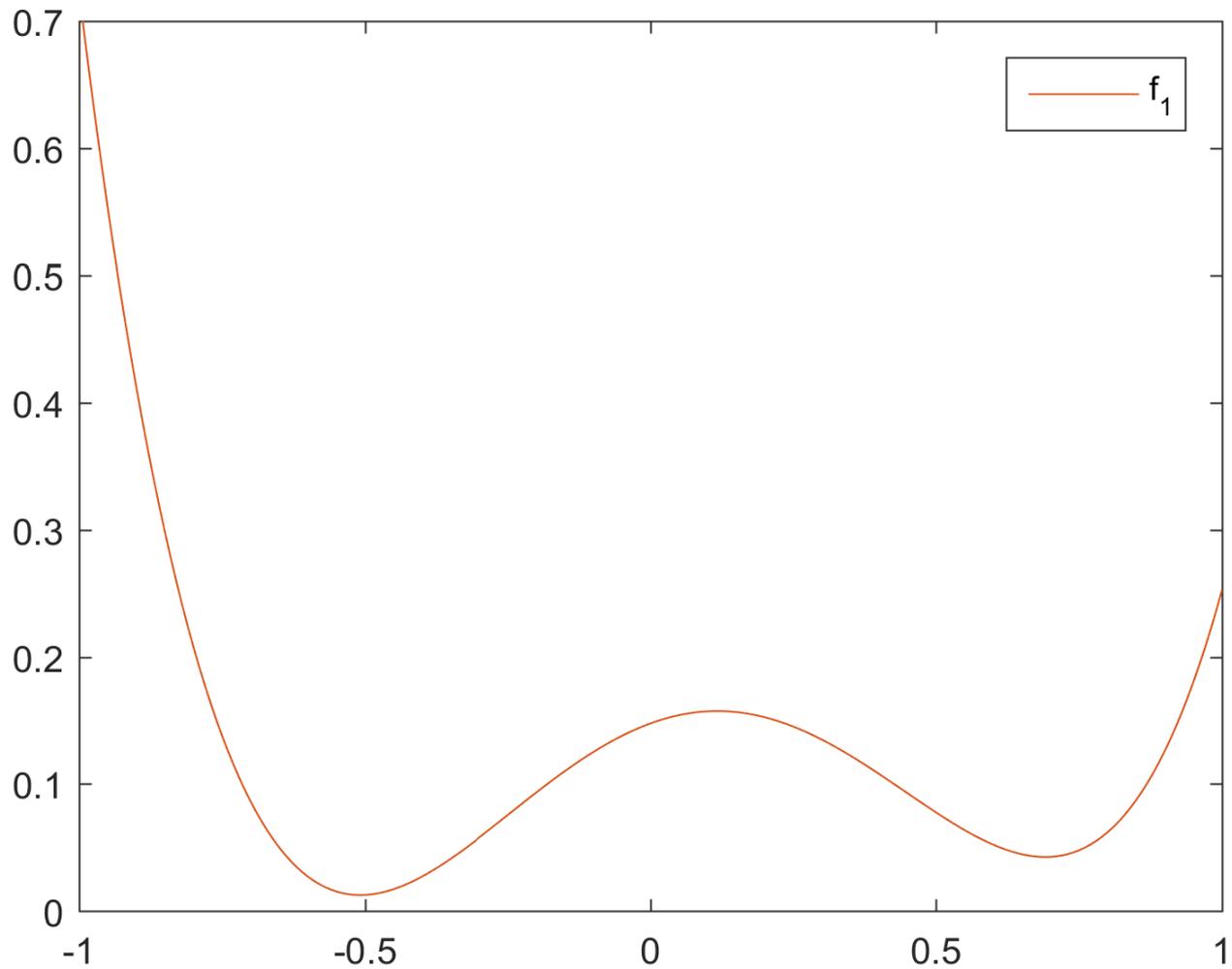
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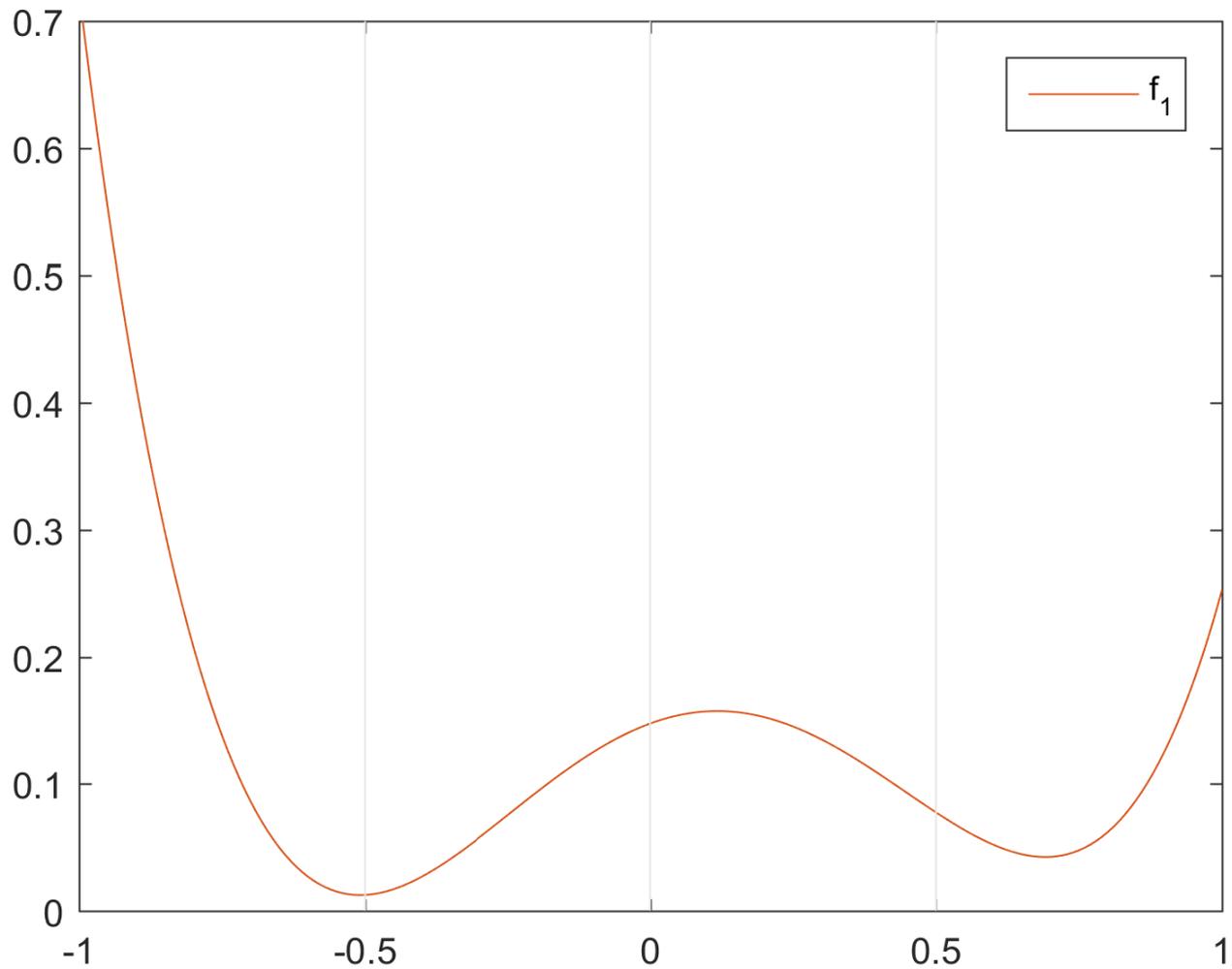
$$\min_{u \in \text{BV}(\Omega, \mathcal{P}(X))} f(u) := \int_{\Omega} \langle u(x), s(x) \rangle dx + \int_{\Omega} d\Psi(Du)$$

Lifting + linear relaxation

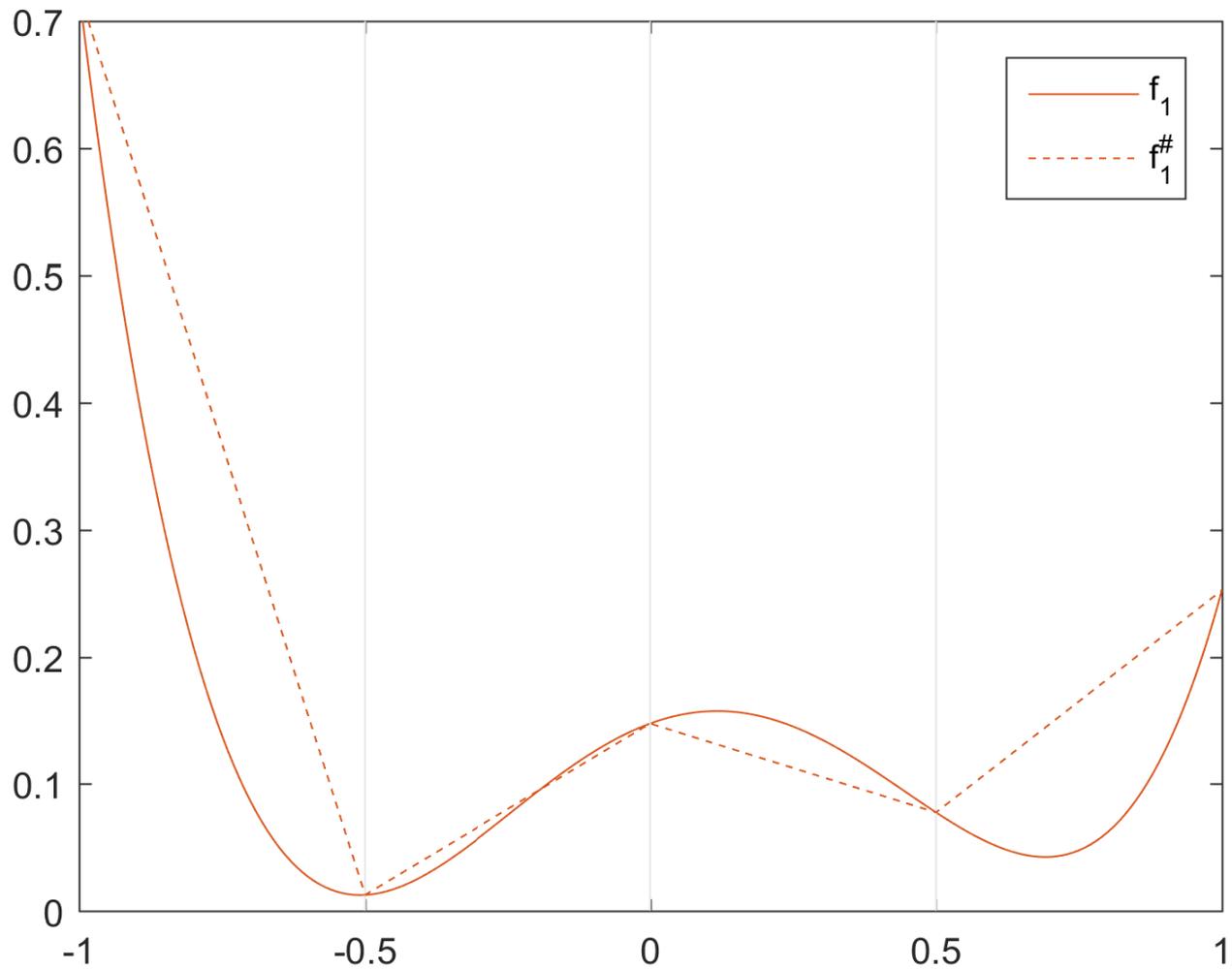
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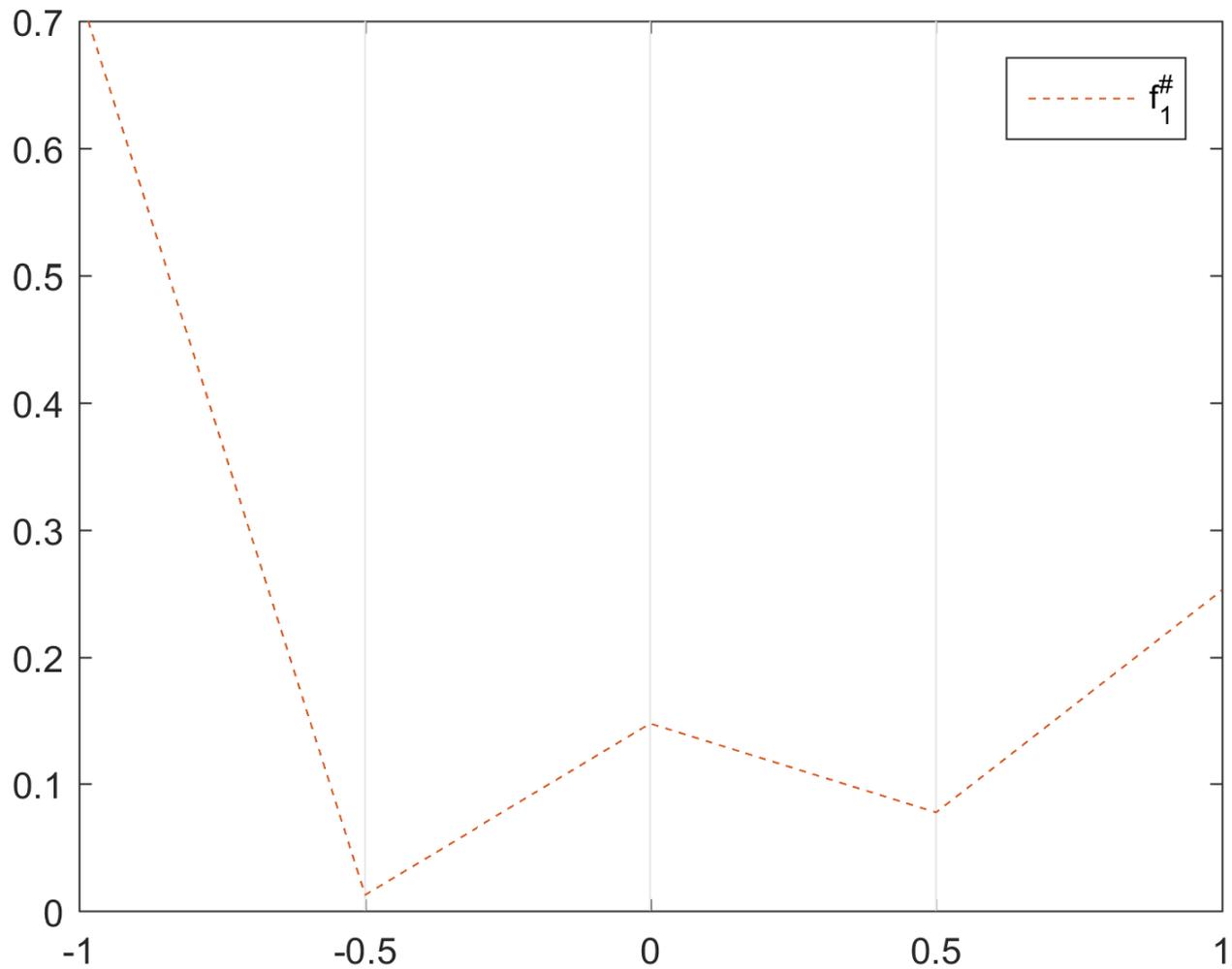
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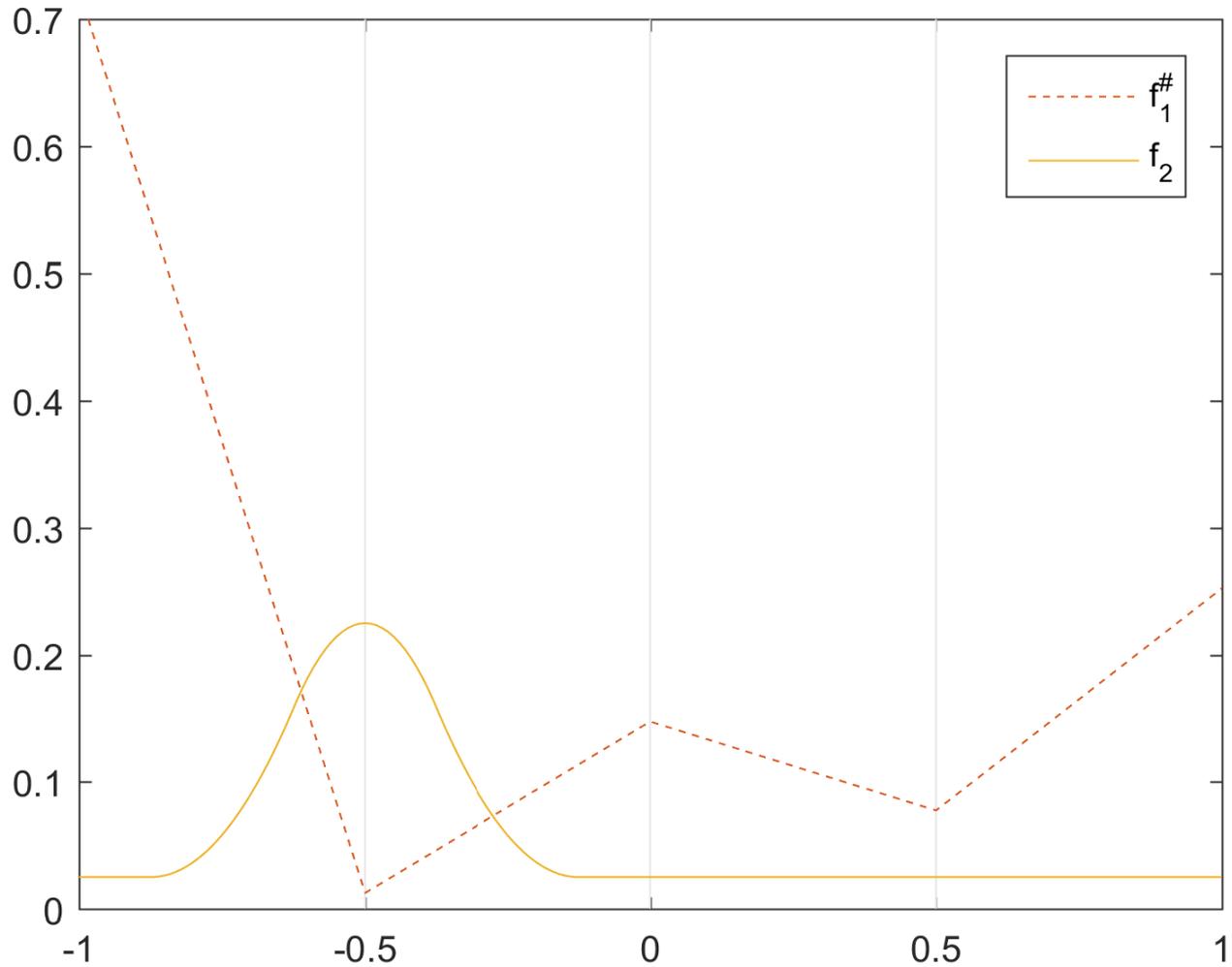
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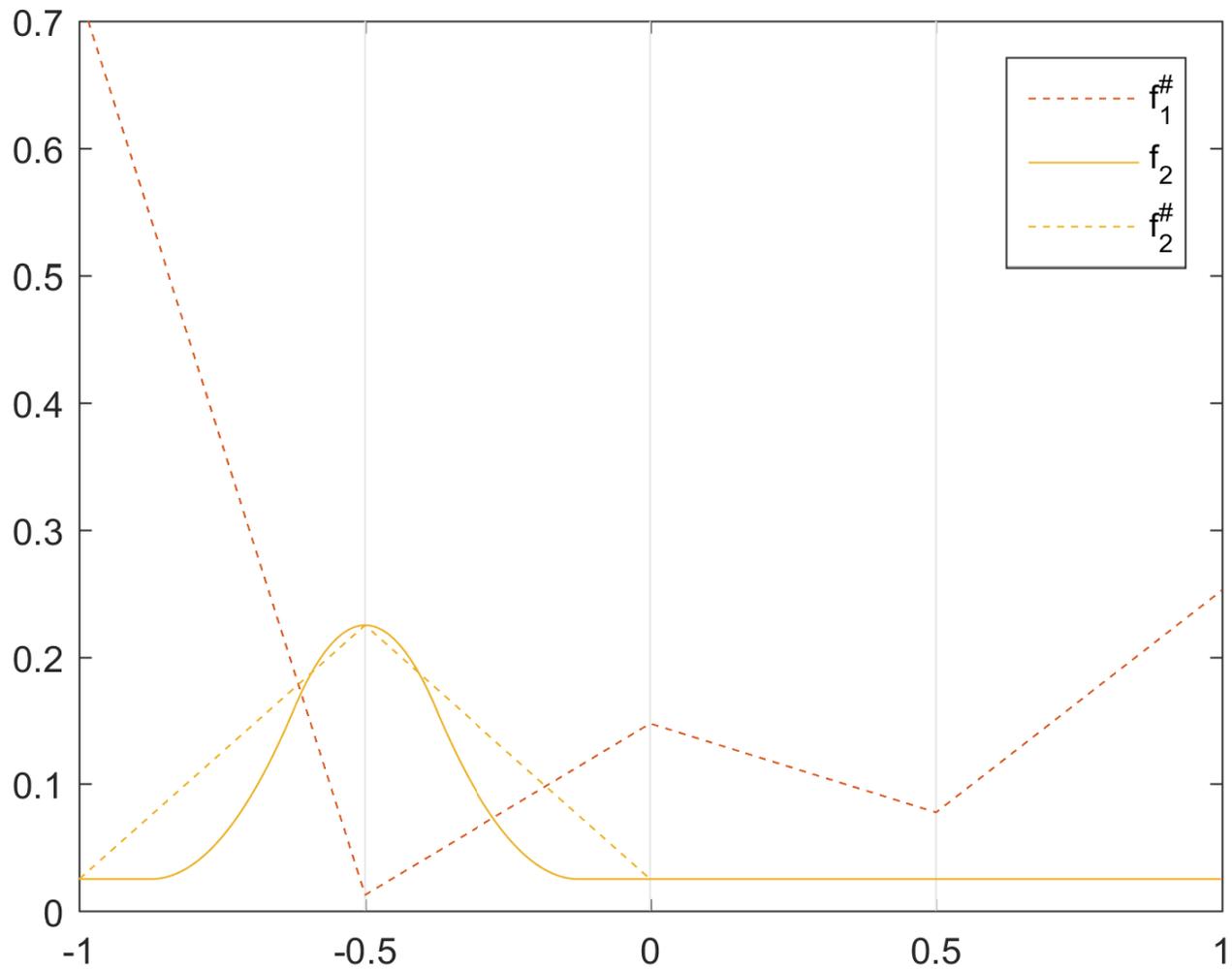
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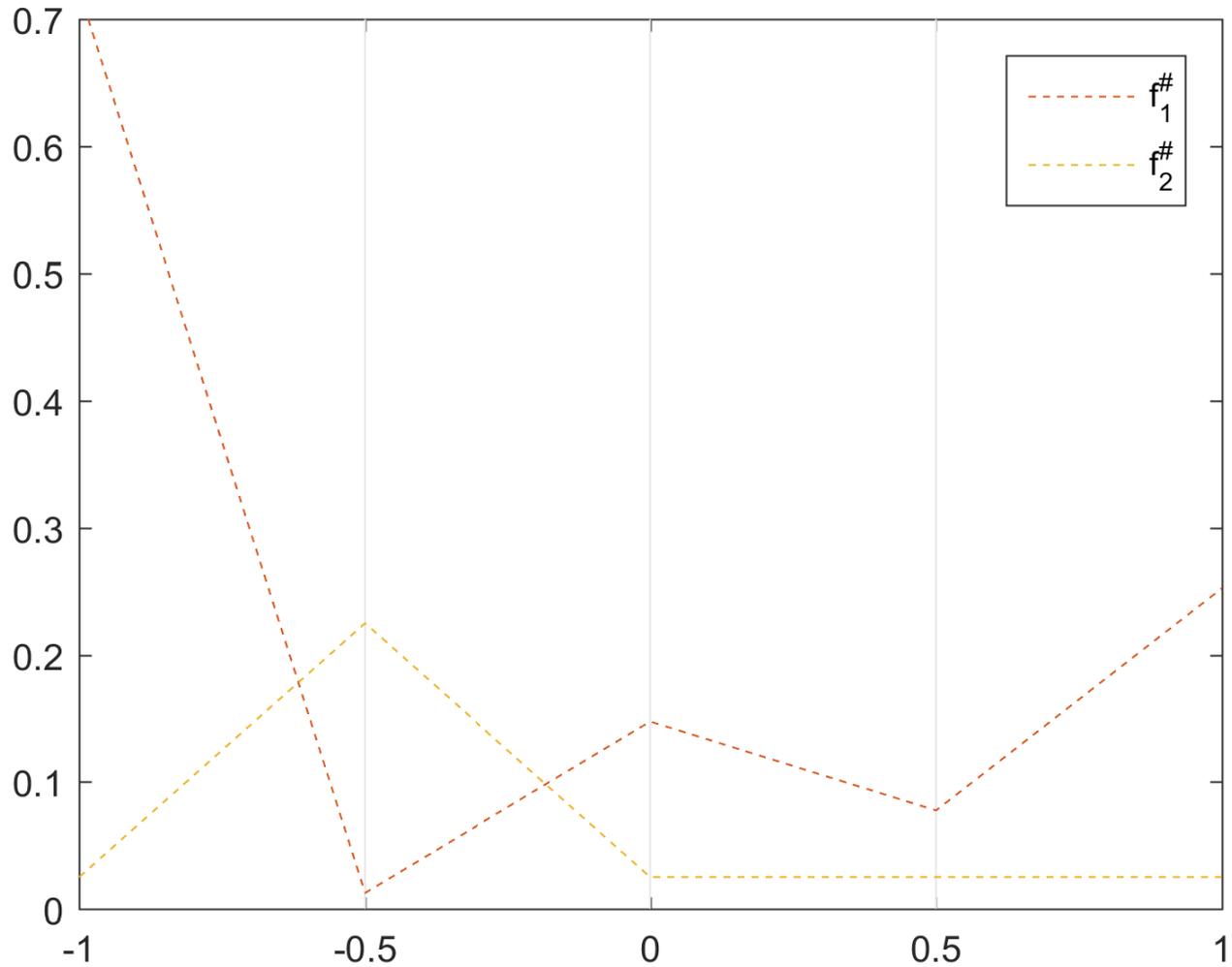
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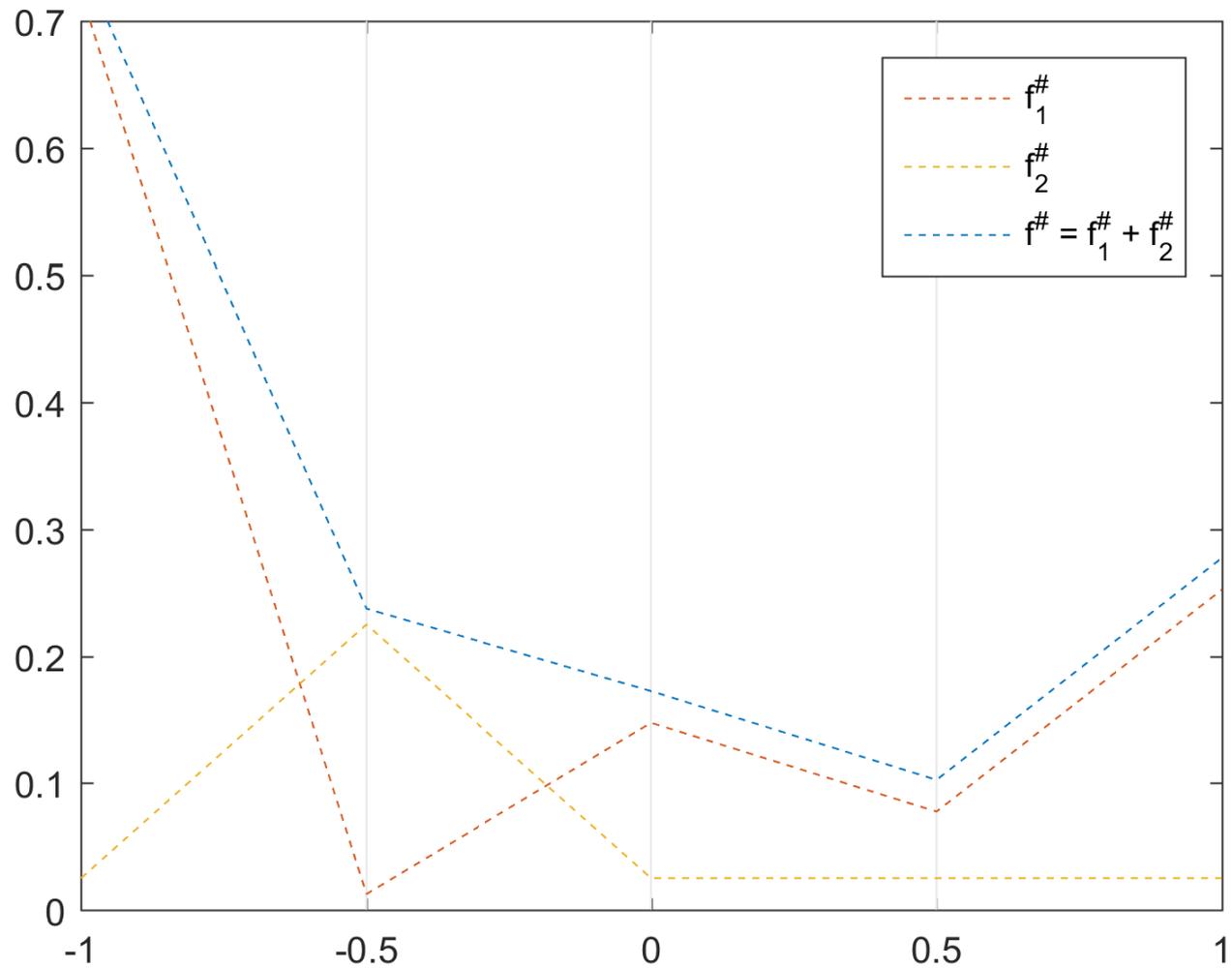
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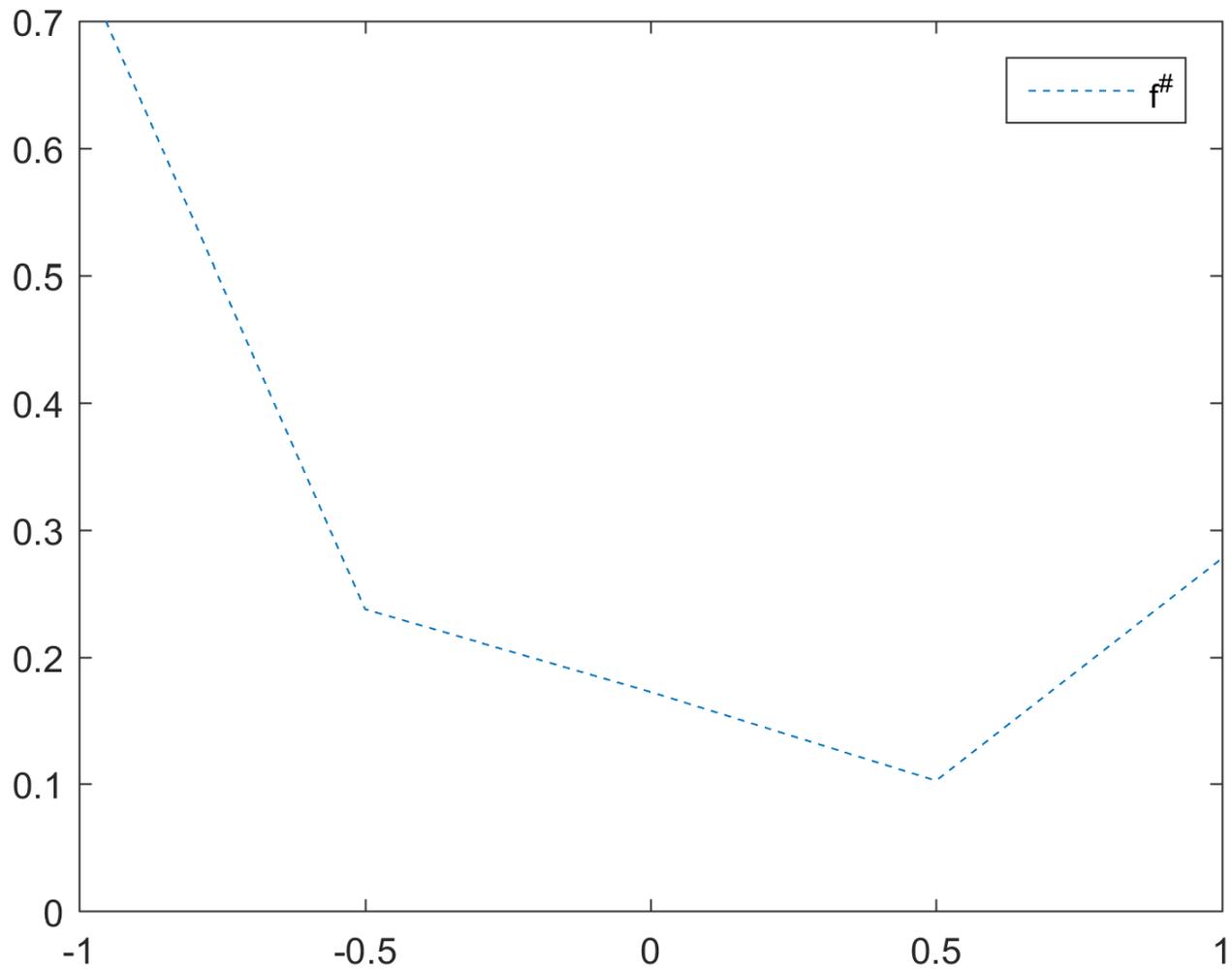
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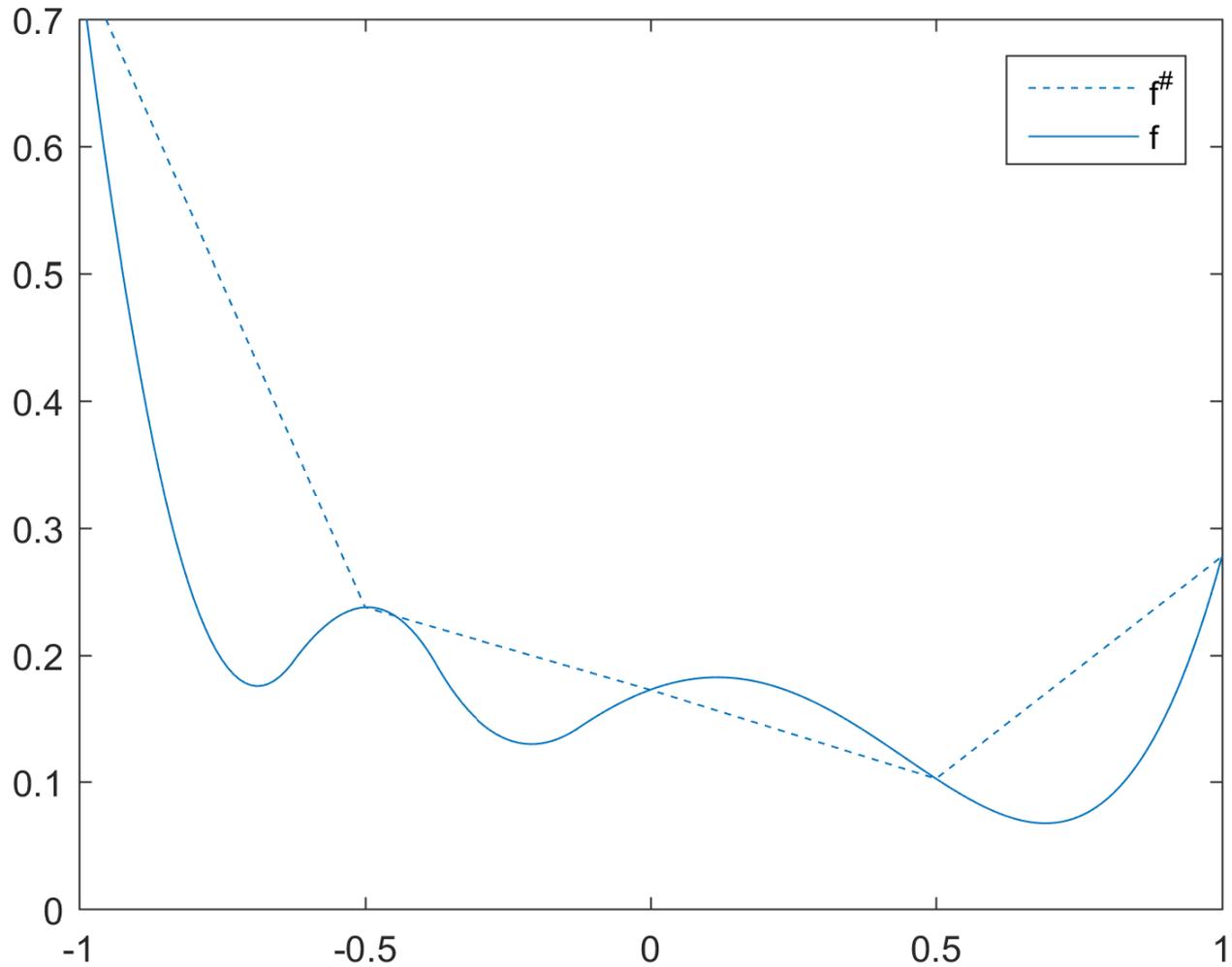
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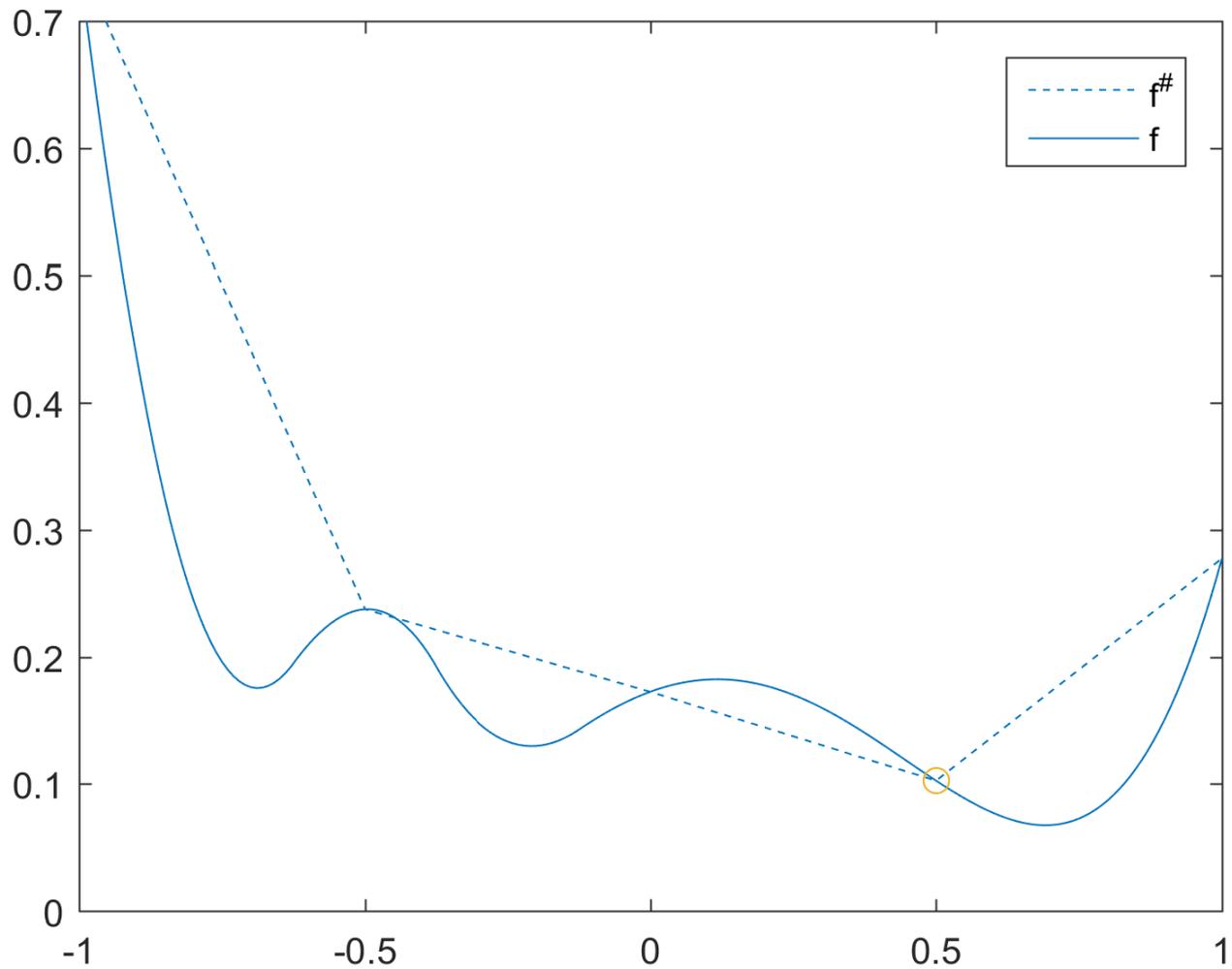
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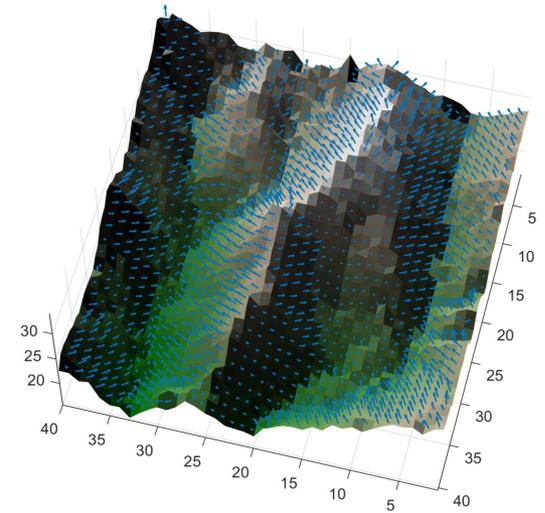
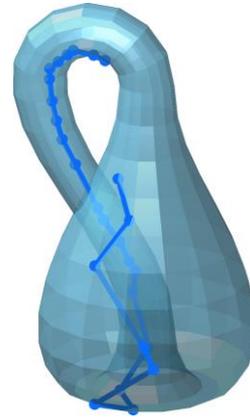


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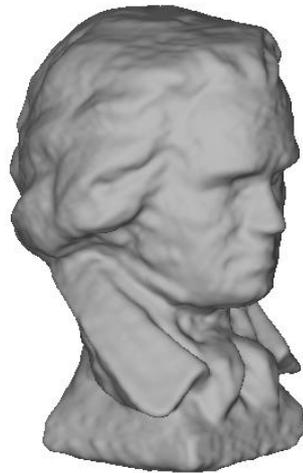




RGB-depth segmentation
(Diebold et al., SSVM '15)

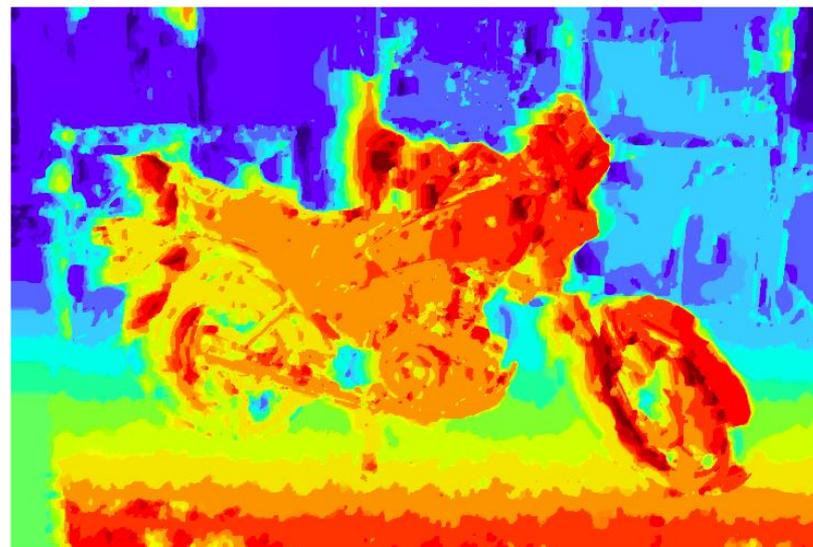


Restoring manifold-valued data
(Cremers, Strelakowski '12,
Lellmann et al., ICCV'13)
related: Weinmann, Demart, Storath'14;
Bergman et al.'14



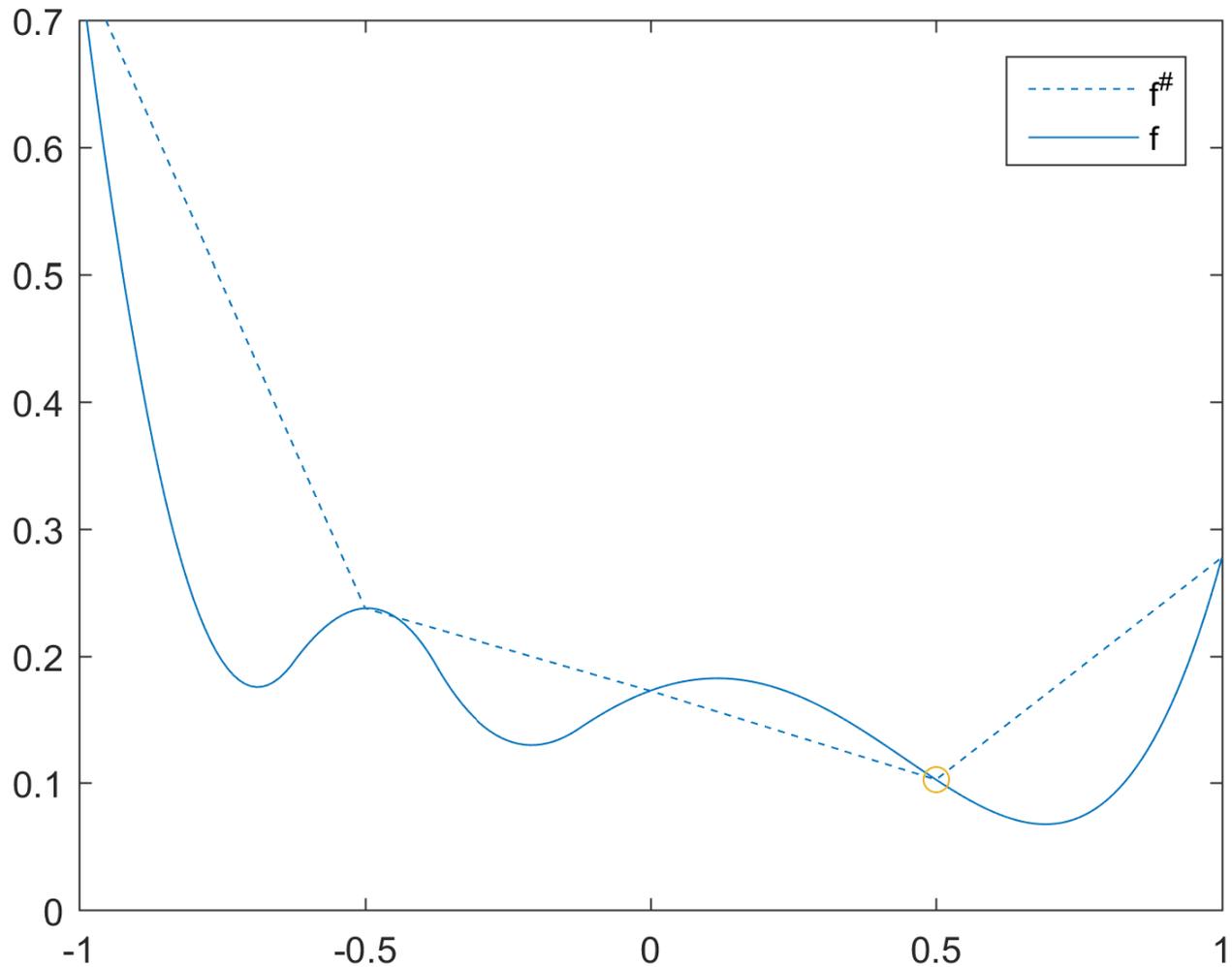
3D reconstruction
(Kolev et al., Int. J. Comp. Vis. '09)

Label bias



The solution tends strongly towards the chosen labels!

Lifting + linear relaxation



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- New: Precise relaxation (*2-sparse!*)

$$\boldsymbol{\rho}(z) = \begin{cases} \rho((1 - \alpha)t^i + \alpha t^{i+1}), & z = (1 - \alpha)e^i + \alpha e^{i+1}, \\ +\infty, & \text{otherwise.} \end{cases}$$

- Linear programs: solution lies on vertex.
- Here: solution between two vertices

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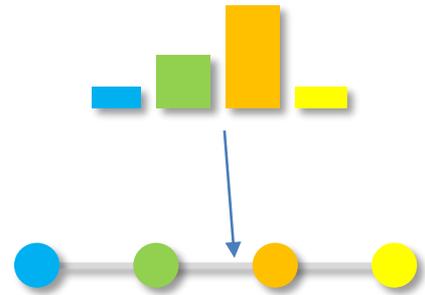
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Relaxing the regularizer

Proposition 4. *The convex envelope of (15) is*

$$\Phi^{**}(g) = \sup_{q \in \mathcal{K}} \langle q, g \rangle, \quad (17)$$

where $\mathcal{K} \subset \mathbb{R}^{k \times d}$ is given as:

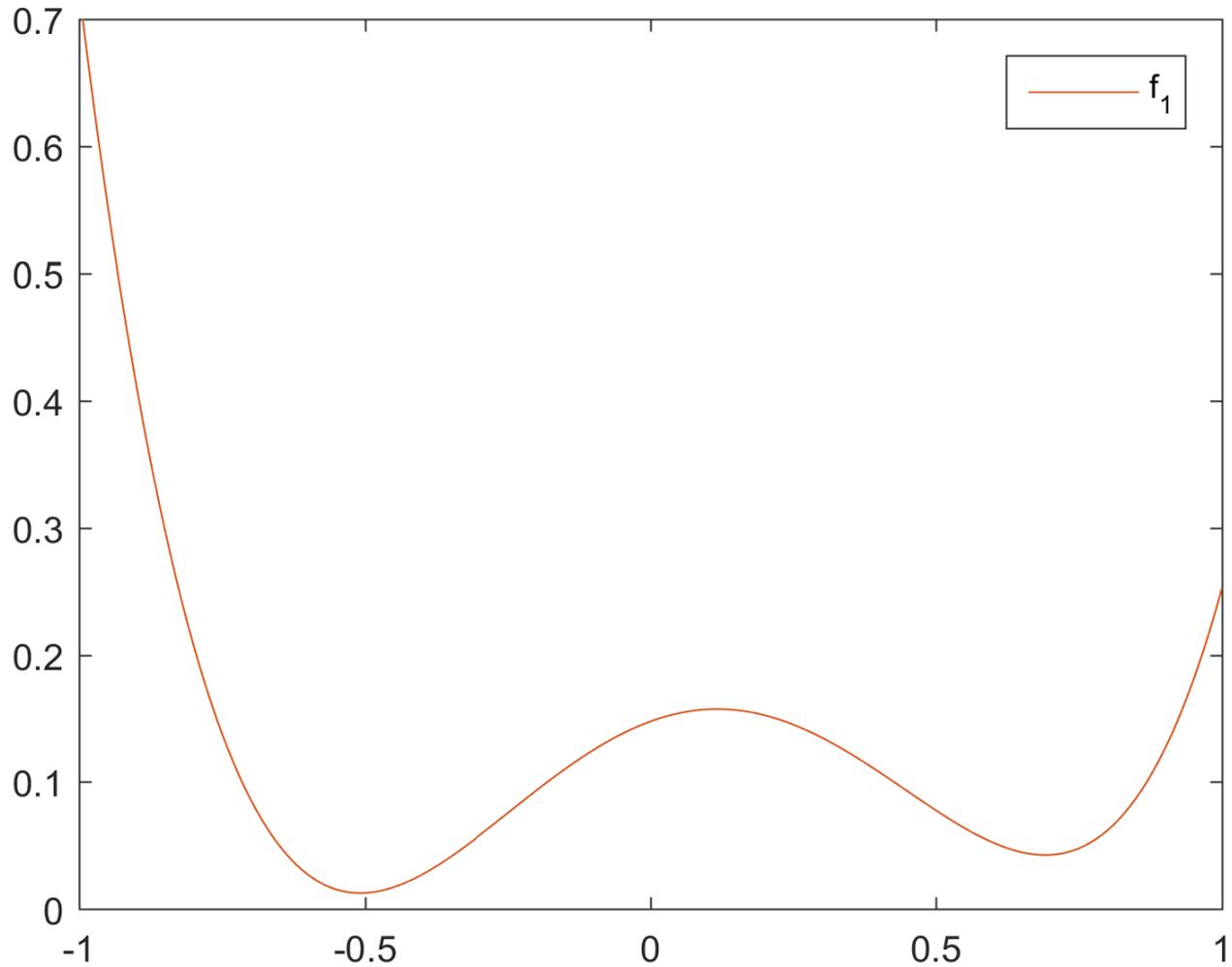
$$\mathcal{K} = \left\{ q \in \mathbb{R}^{k \times d} \mid \begin{aligned} & \left| q^T (\mathbf{1}_i^\alpha - \mathbf{1}_j^\beta) \right|_2 \leq \left| \gamma_i^\alpha - \gamma_j^\beta \right|, \\ & \forall 1 \leq i \leq j \leq k, \forall \alpha, \beta \in [0, 1] \end{aligned} \right\}. \quad (18)$$

Proposition 5. *In case the labels are ordered, i.e., $\gamma_1 < \gamma_2 < \dots < \gamma_L$, then the constraint set \mathcal{K} from Eq. (36) is equal to*

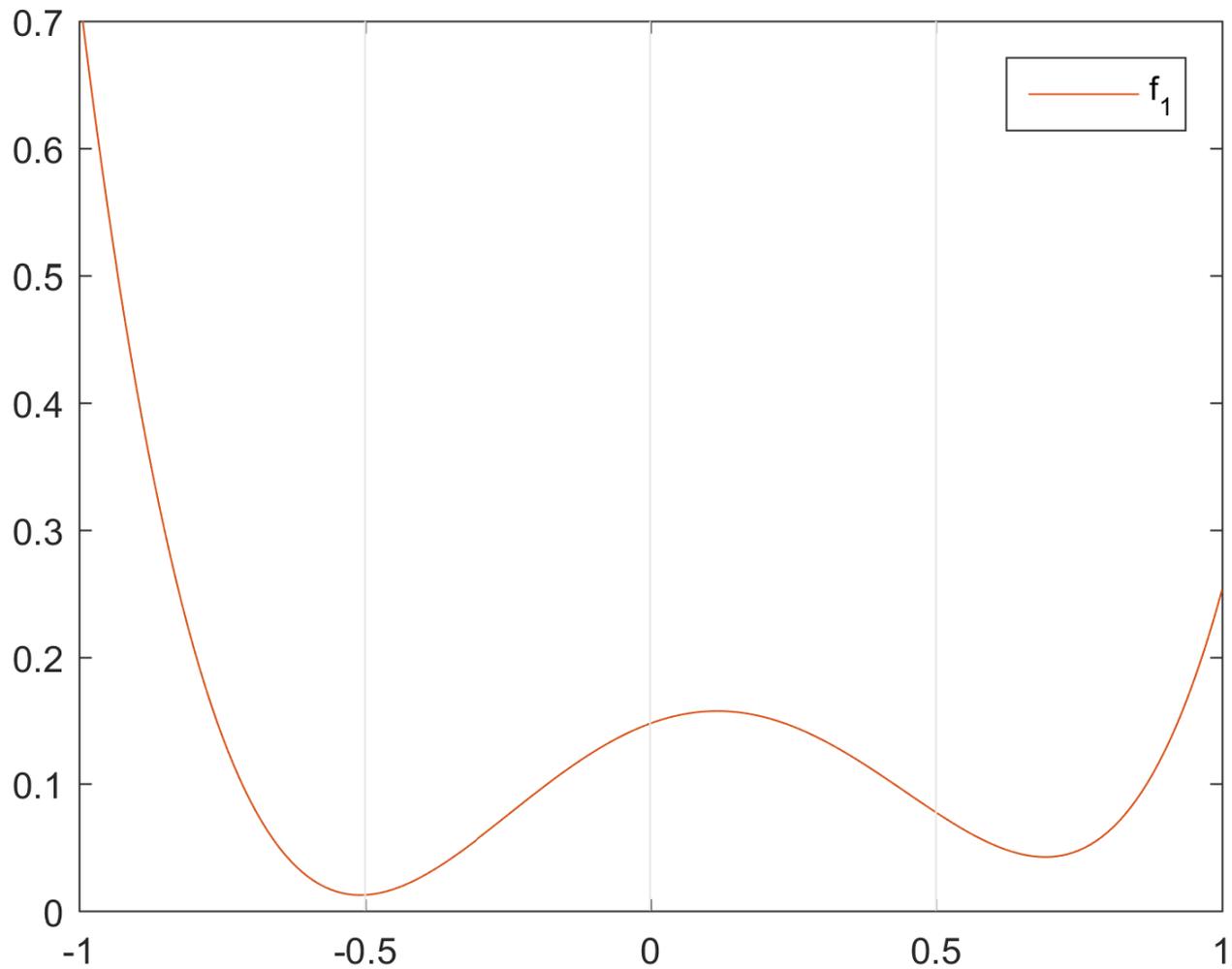
$$\mathcal{K} = \{ q \in \mathbb{R}^{k \times d} \mid \|q_i\|_2 \leq \gamma_{i+1} - \gamma_i, \forall i \}. \quad (19)$$

New: lifting + precise relaxation

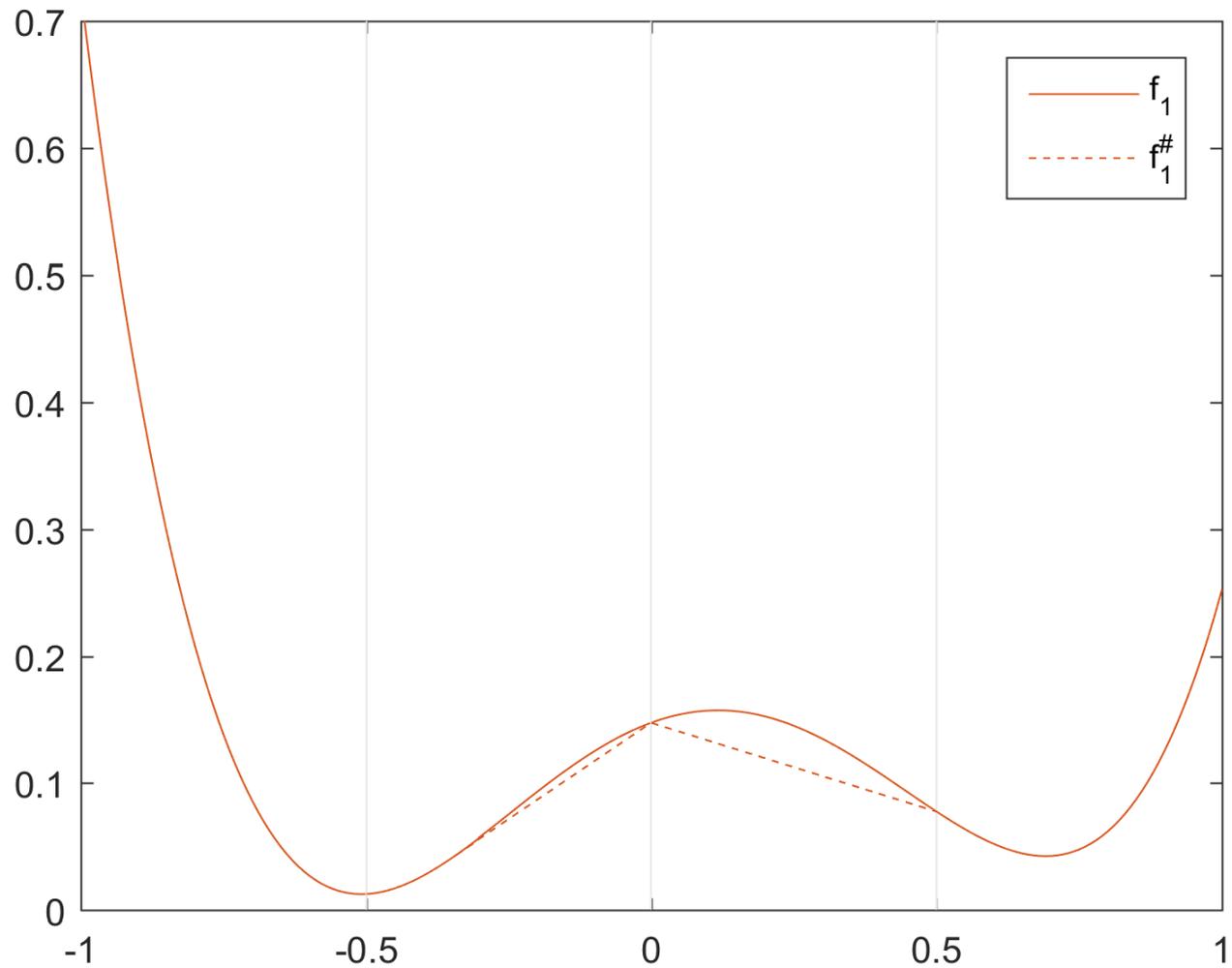
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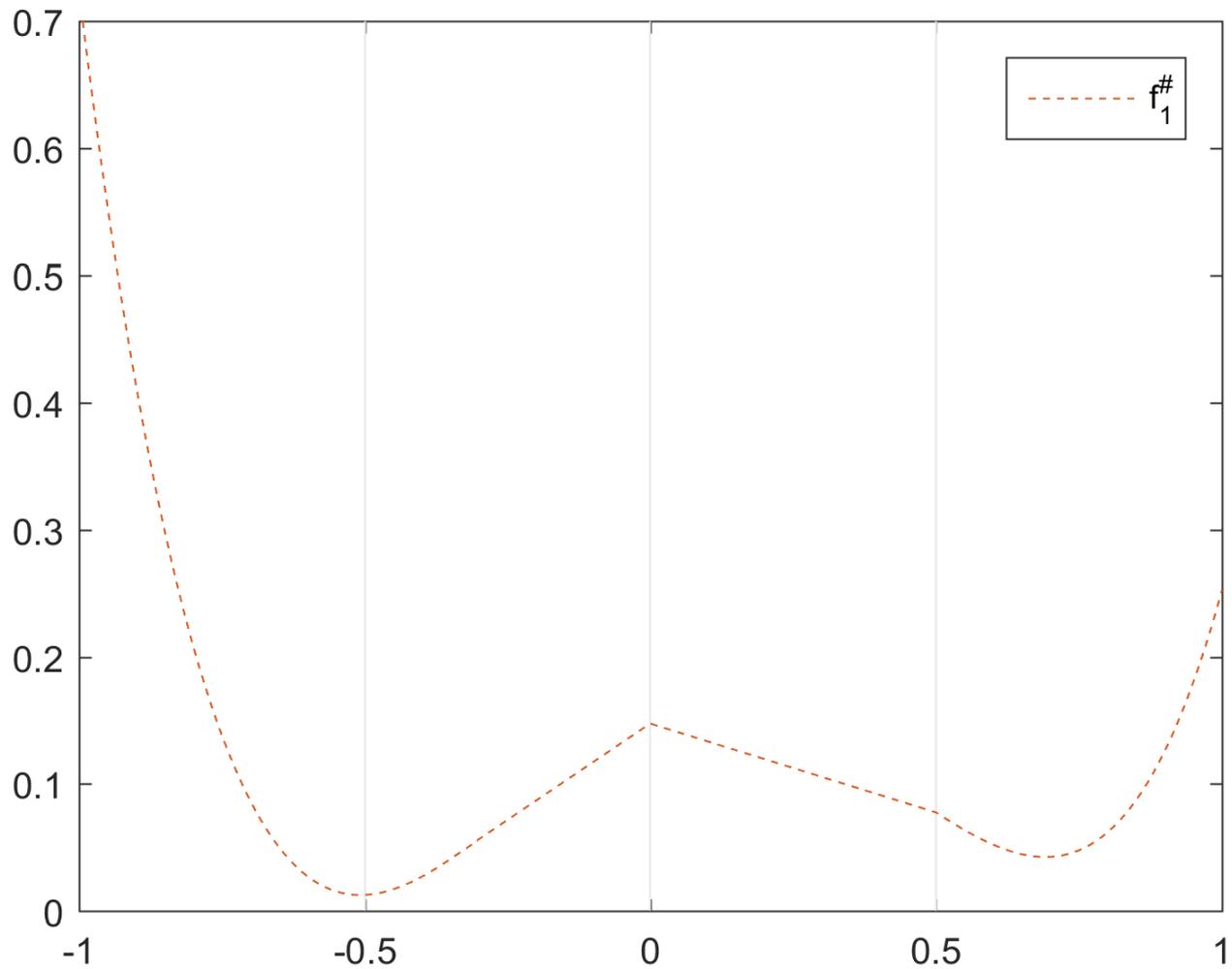
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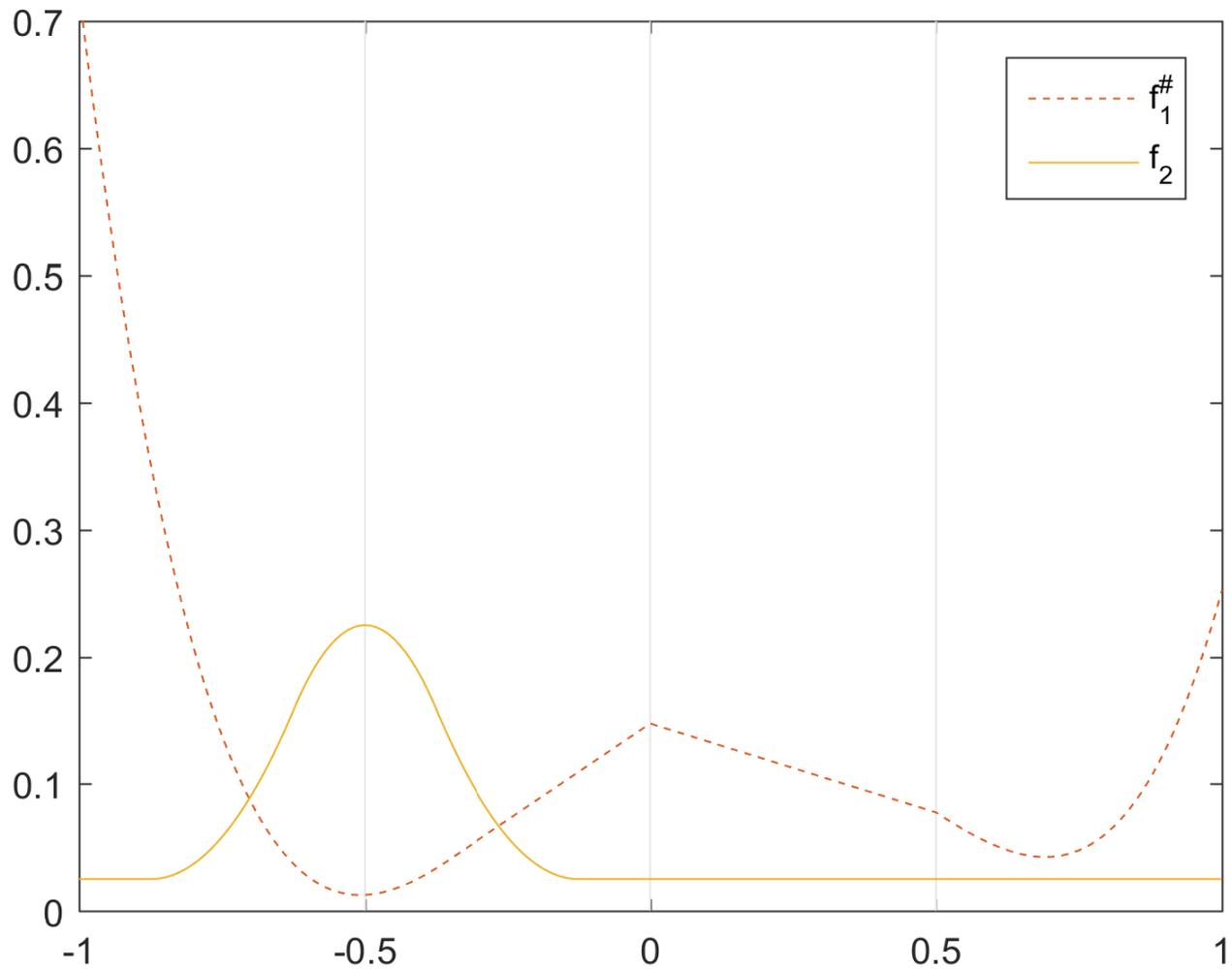
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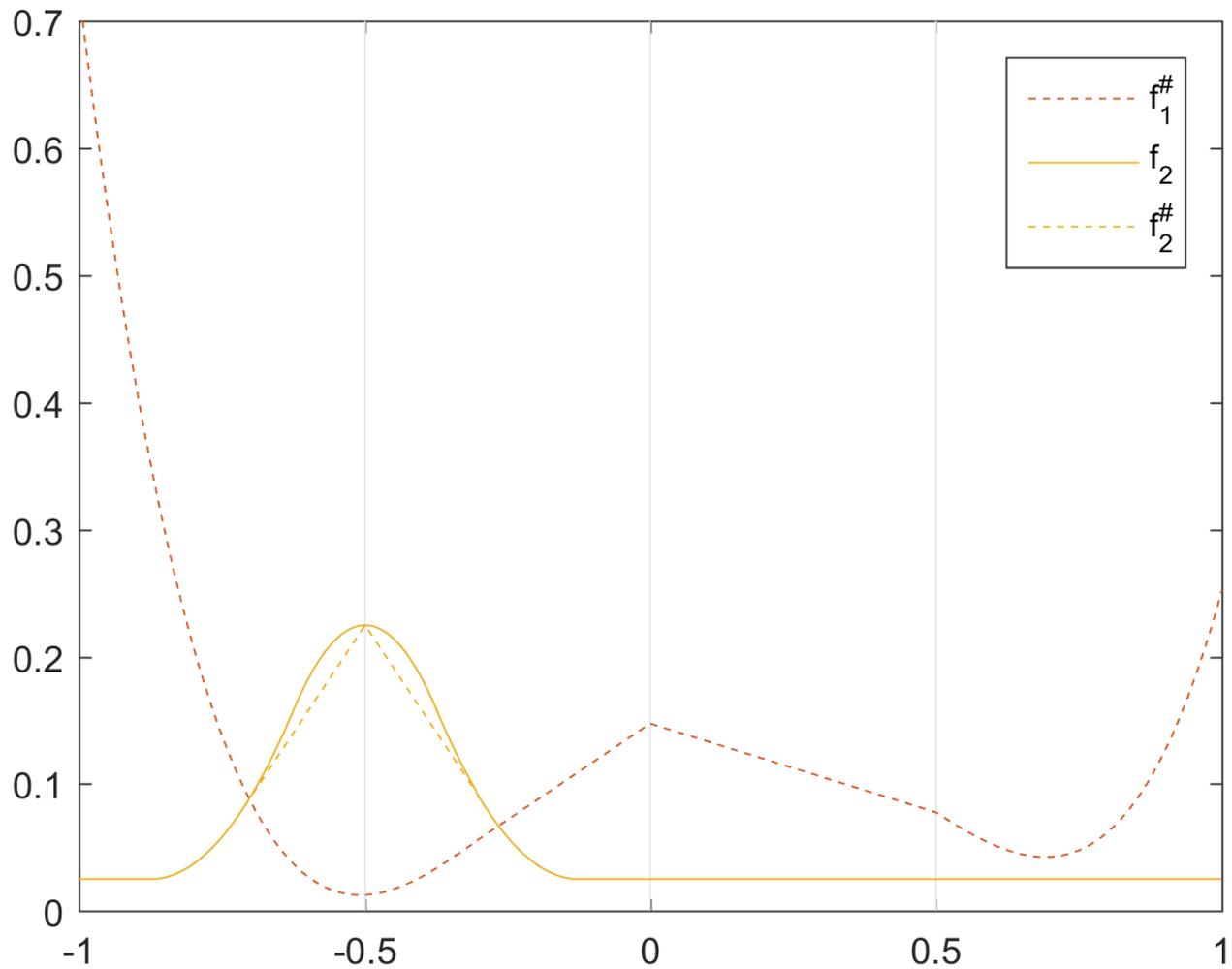
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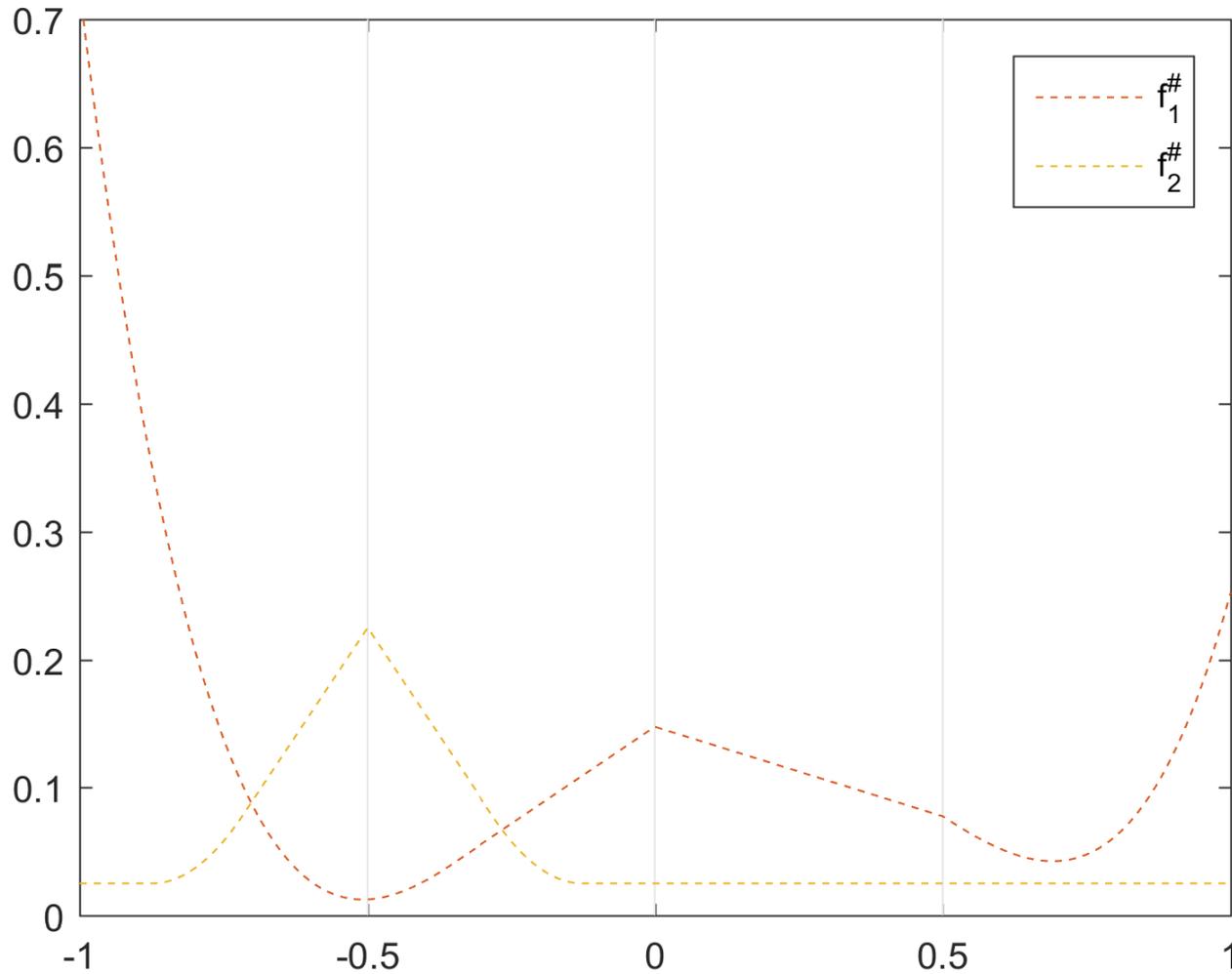
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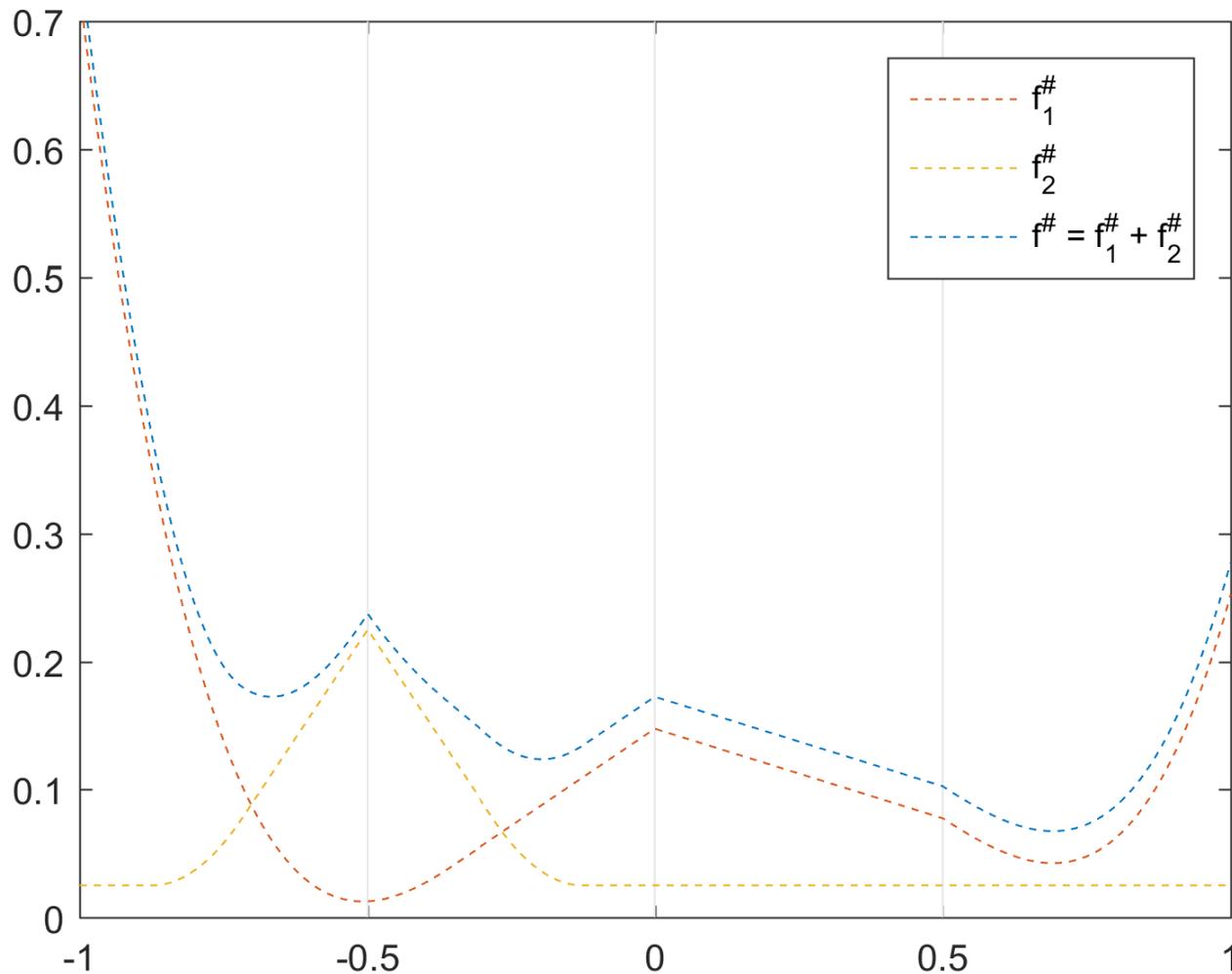
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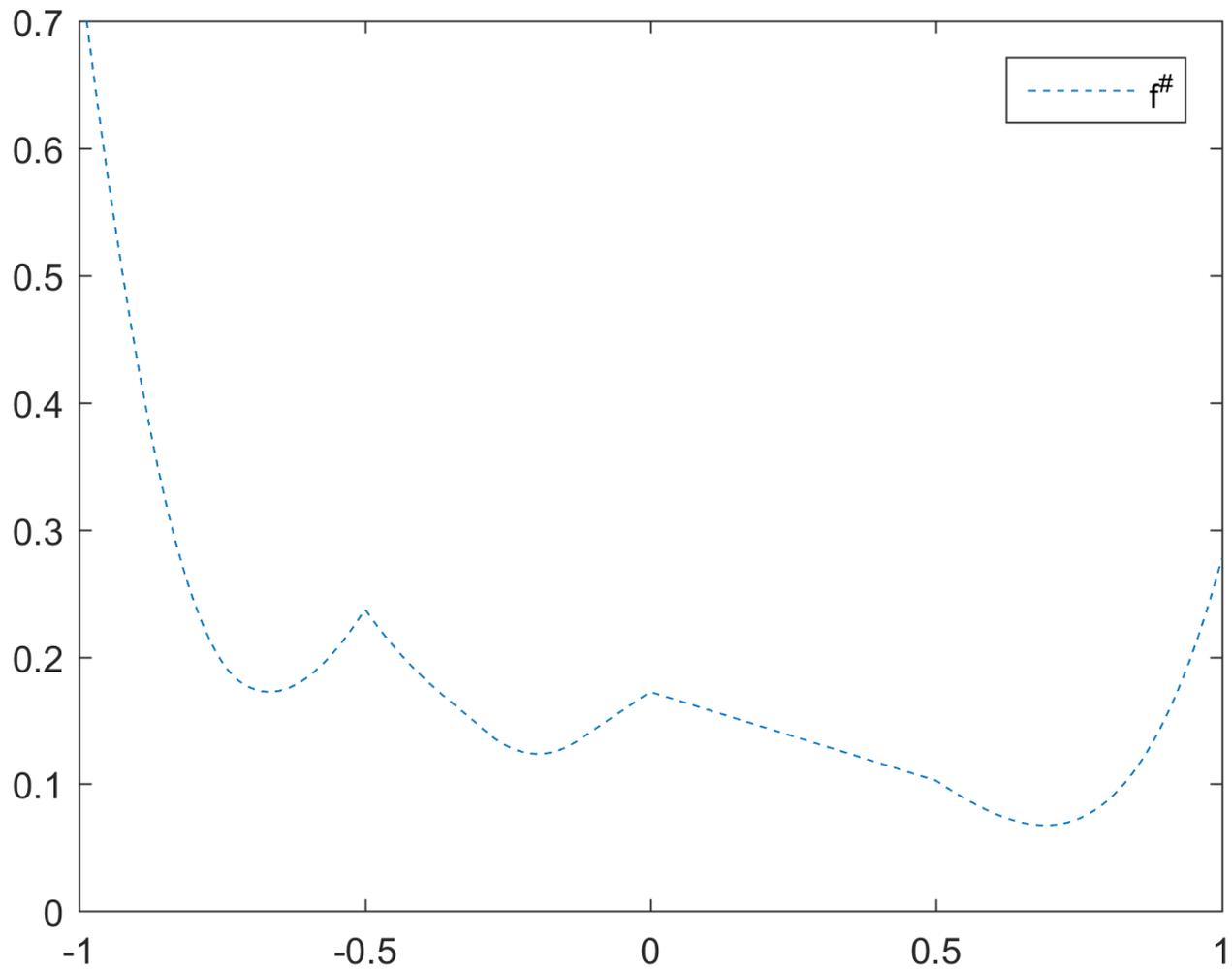
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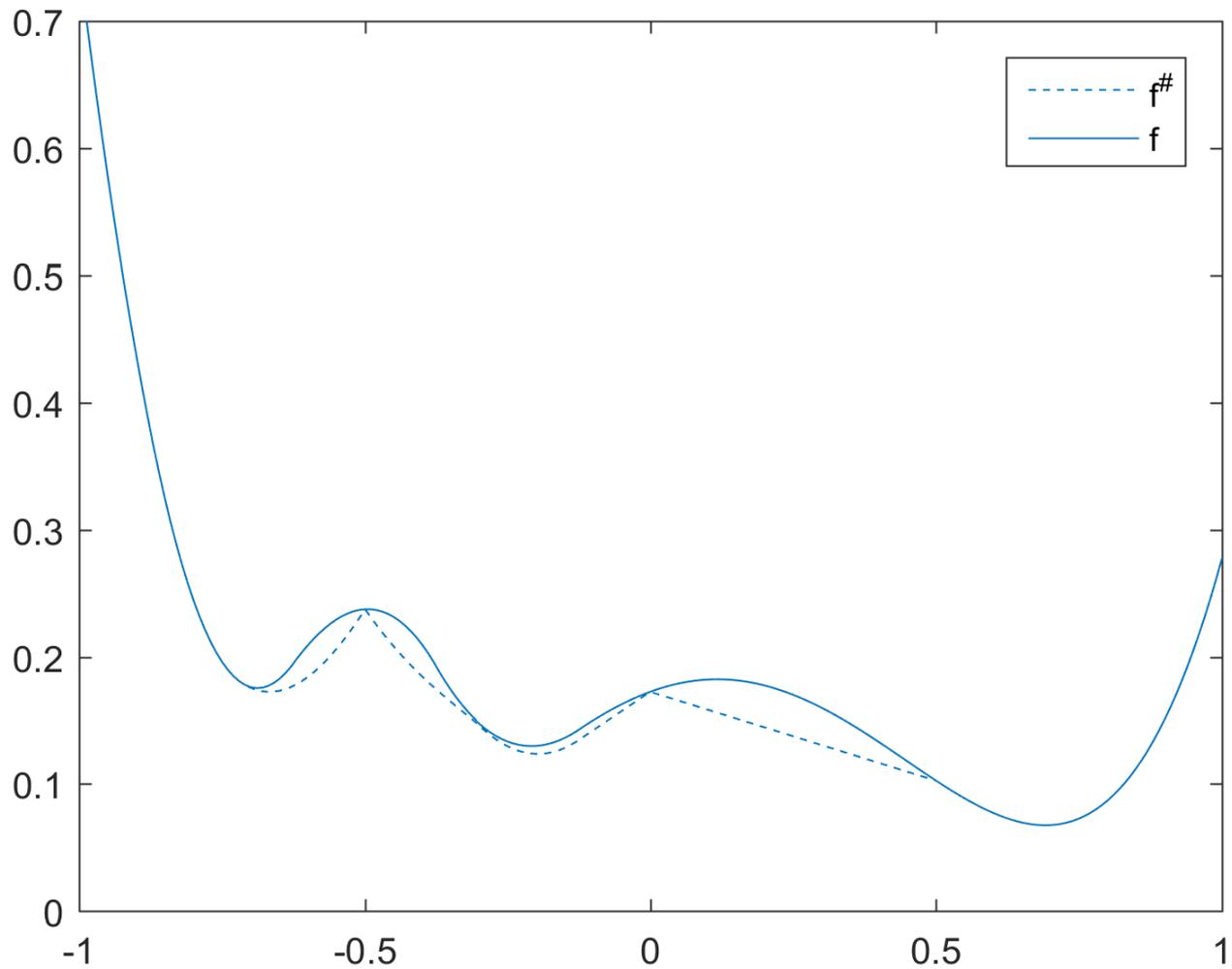
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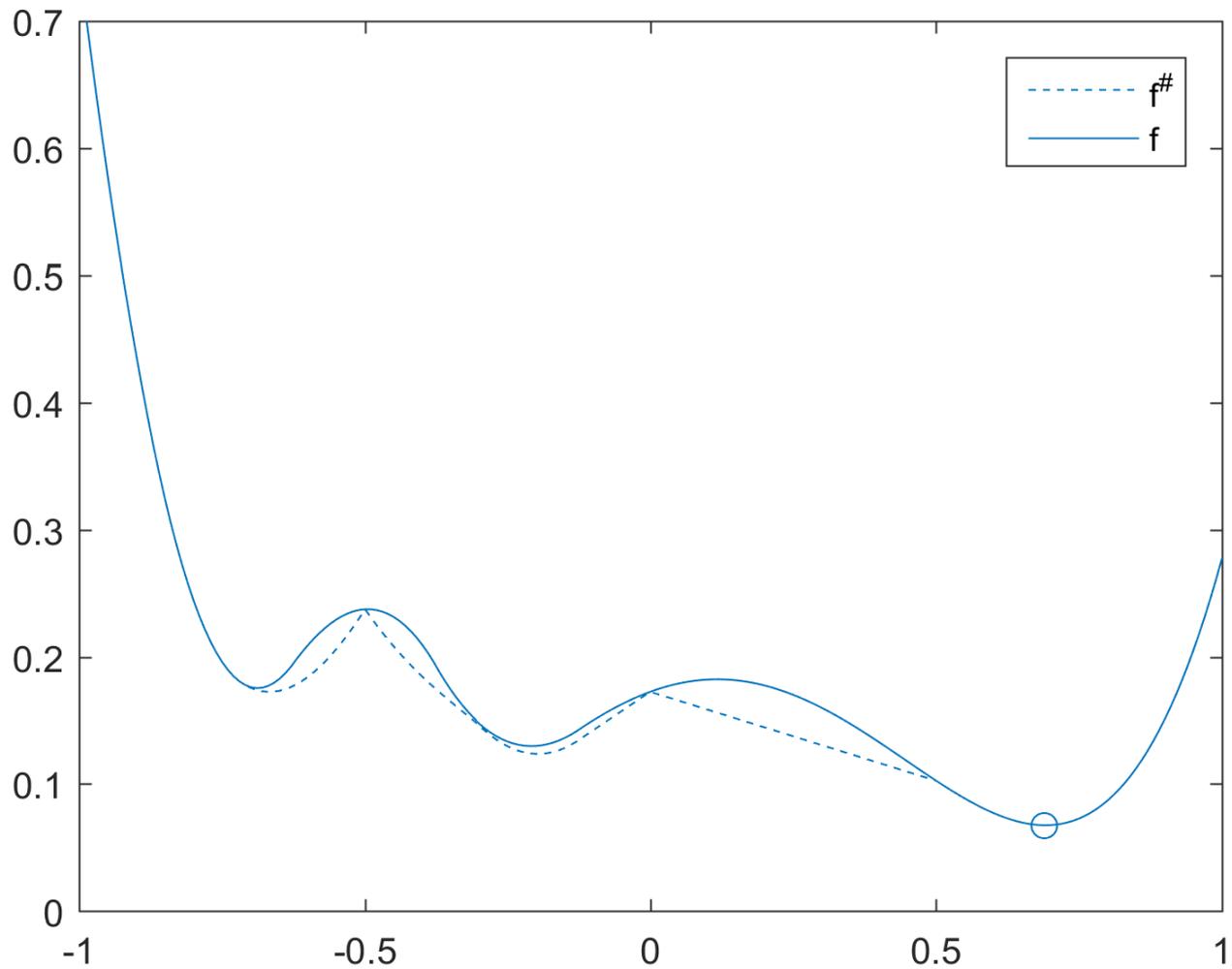
New: lifting + precise relaxation



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Results – disparity estimation

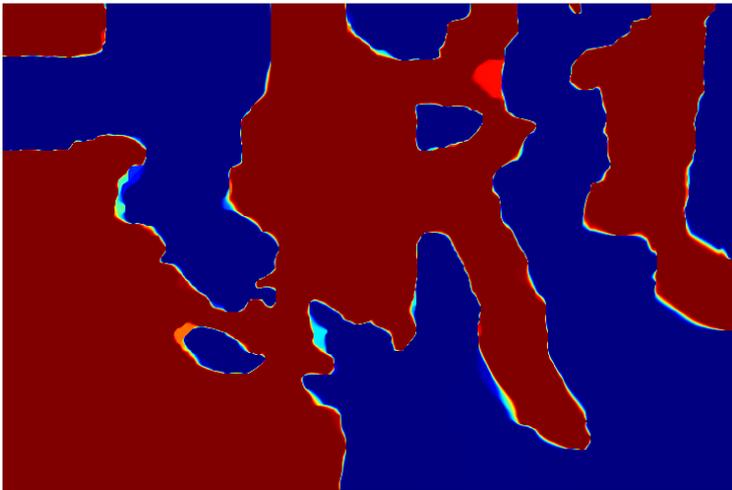


Results – disparity estimation



linear lifting

$$L = 2$$

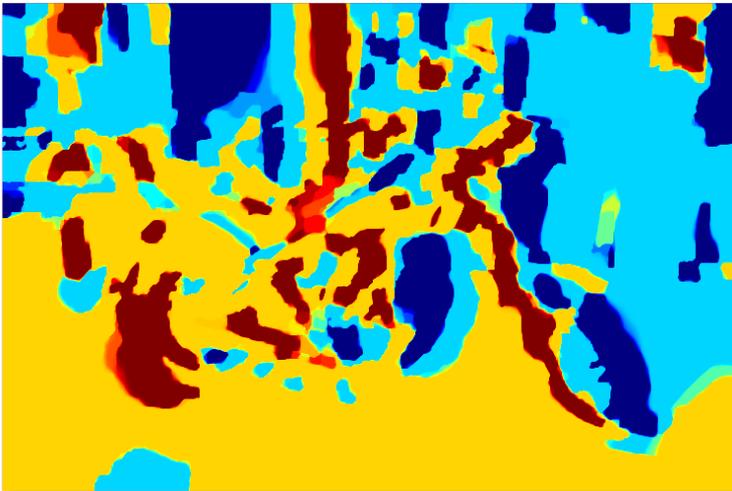


Results – disparity estimation



linear lifting

$$L = 4$$

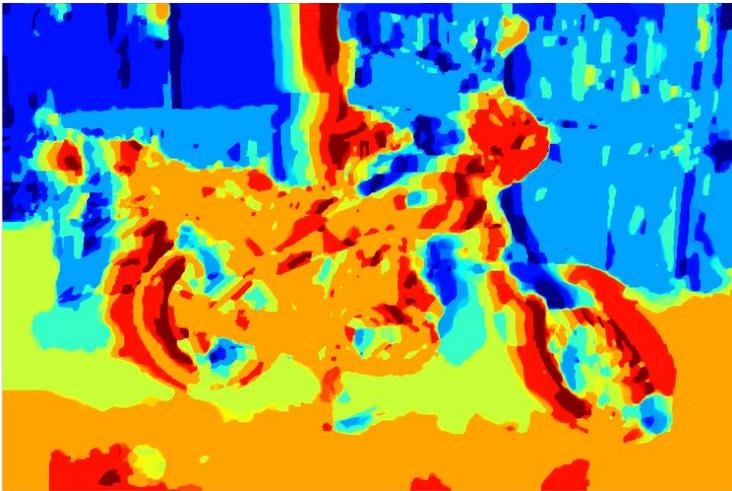


Results – disparity estimation



linear lifting

$$L = 8$$

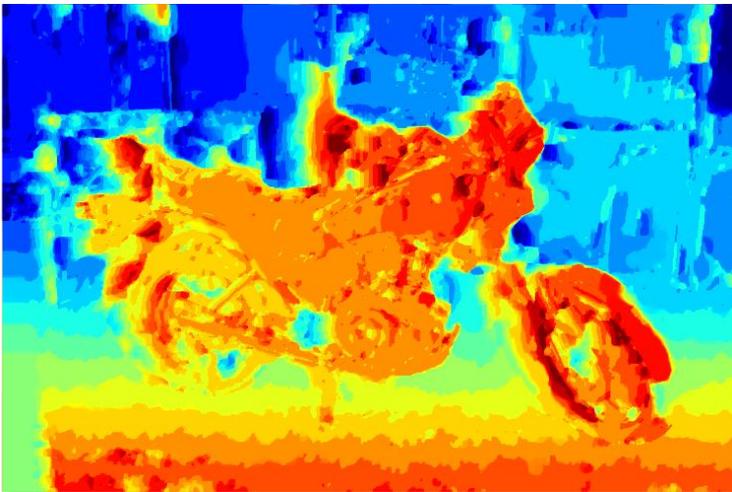


Results – disparity estimation



linear lifting

$L = 16$

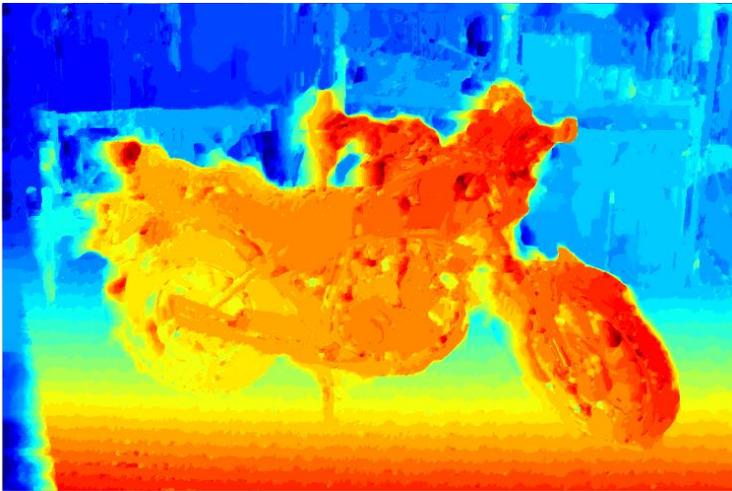


Results – disparity estimation



linear lifting

$$L = 32$$



Results – disparity estimation

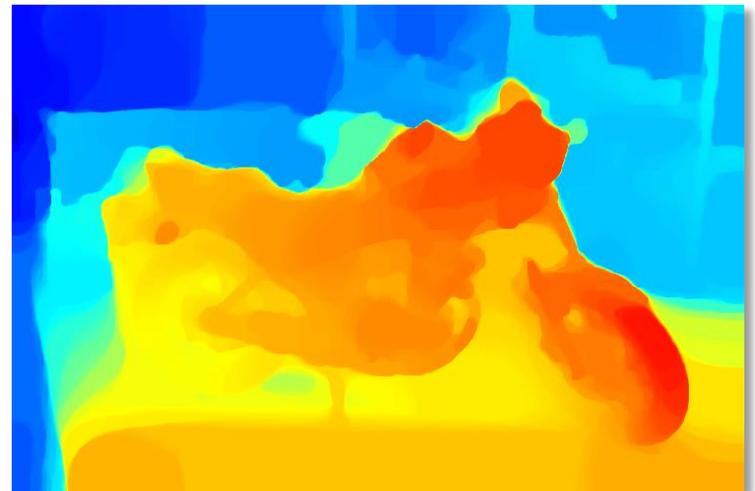
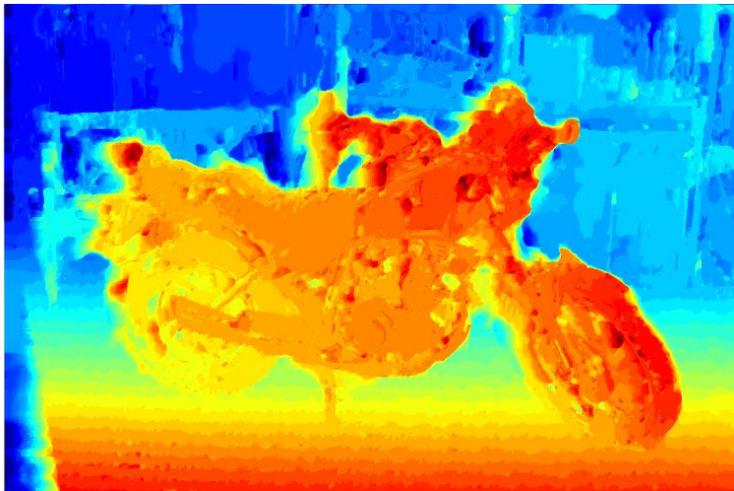
linear lifting

$$L = 32$$



precise lifting

$$L = 2$$



Results – disparity estimation

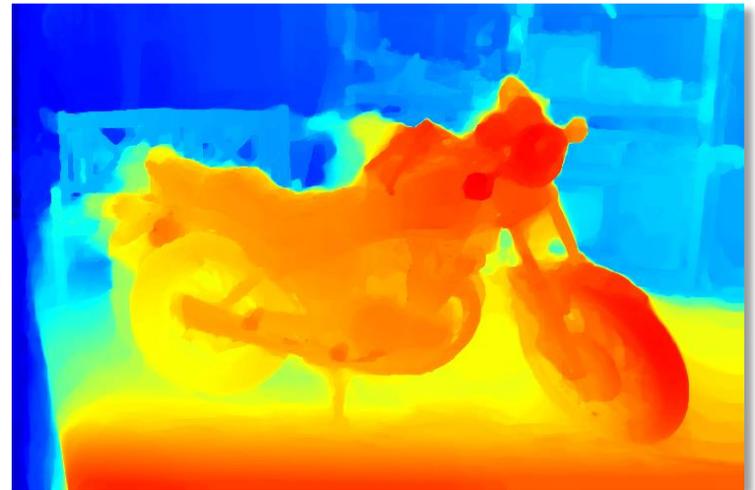
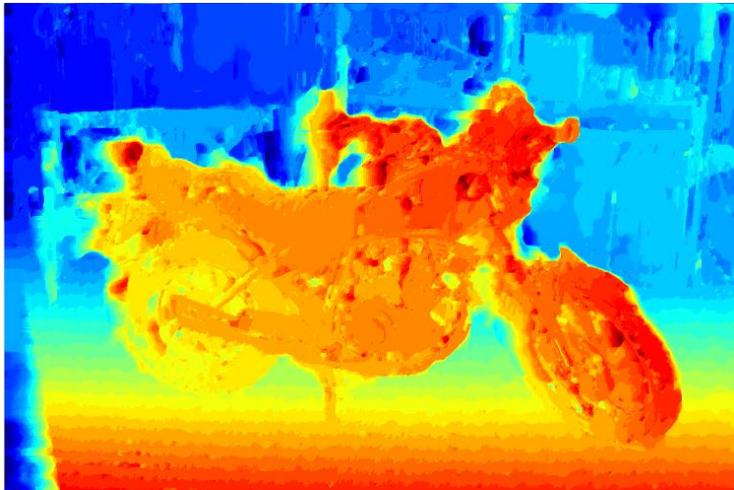


linear lifting

$$L = 32$$

precise lifting

$$L = 4$$



Results – disparity estimation

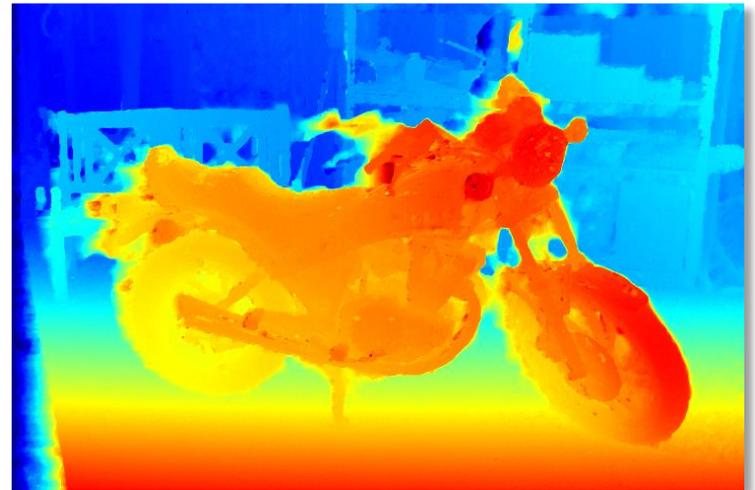
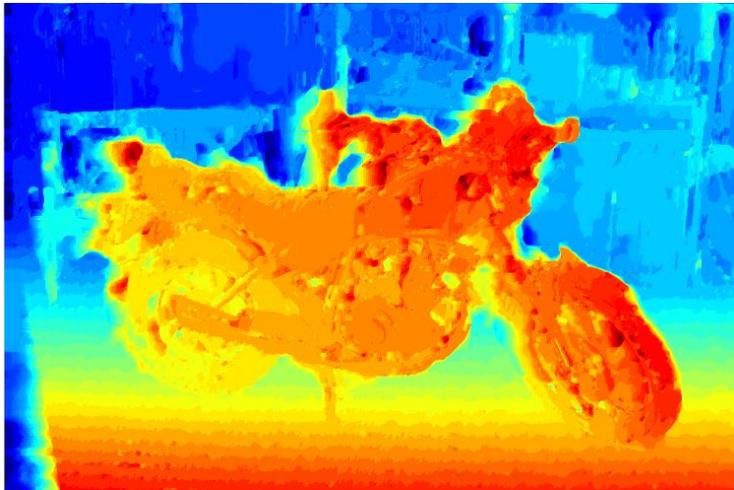


linear lifting

$$L = 32$$

precise lifting

$$L = 8$$



Results – disparity estimation

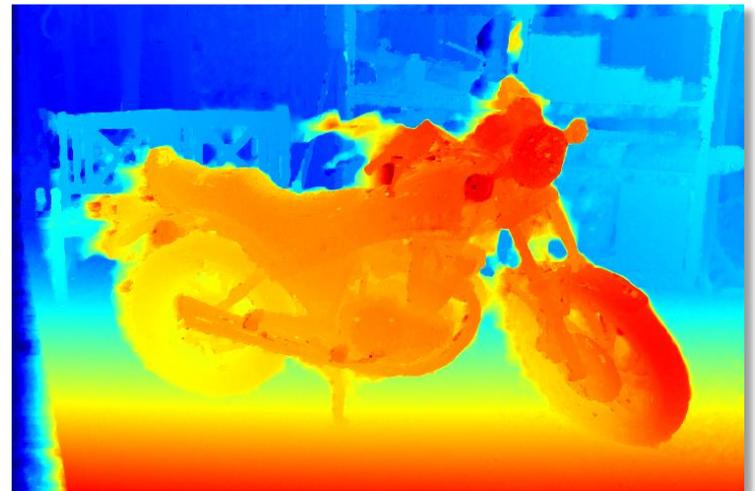
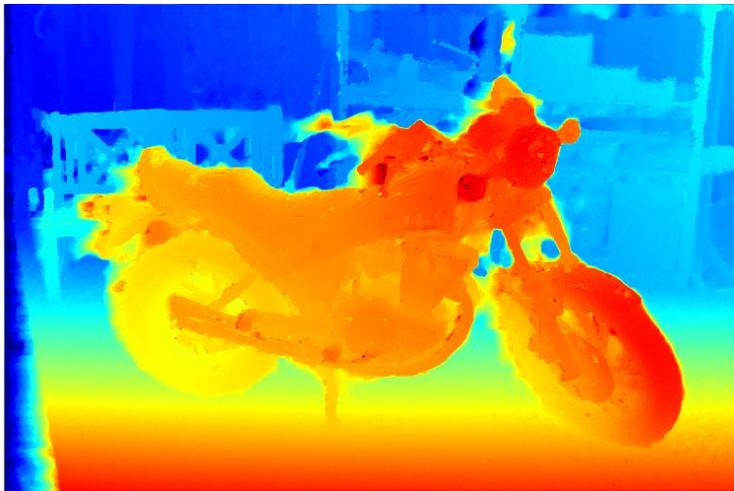


linear lifting

$$L = 270$$

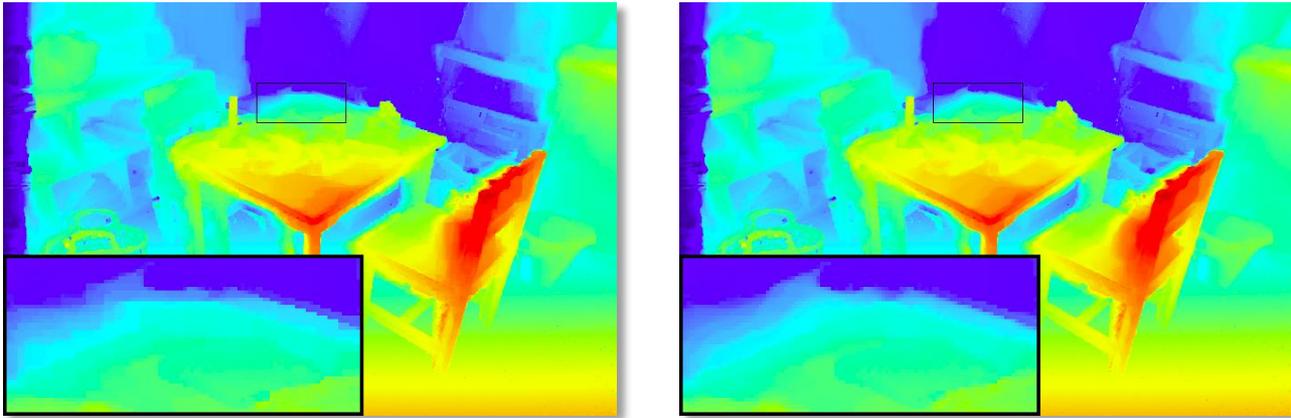
precise lifting

$$L = 8$$

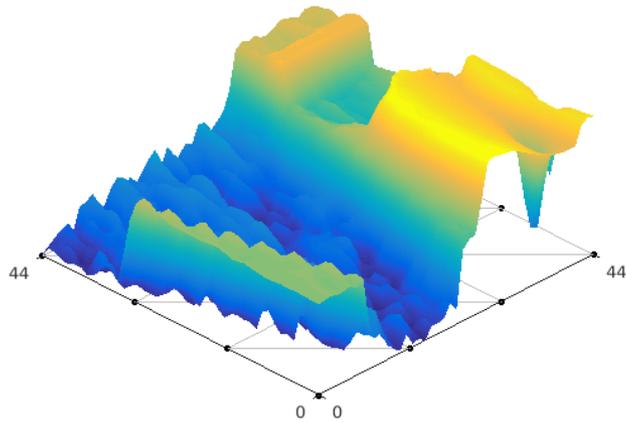


Related work

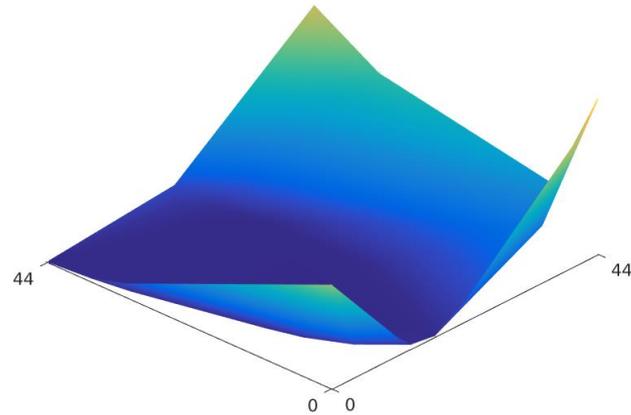
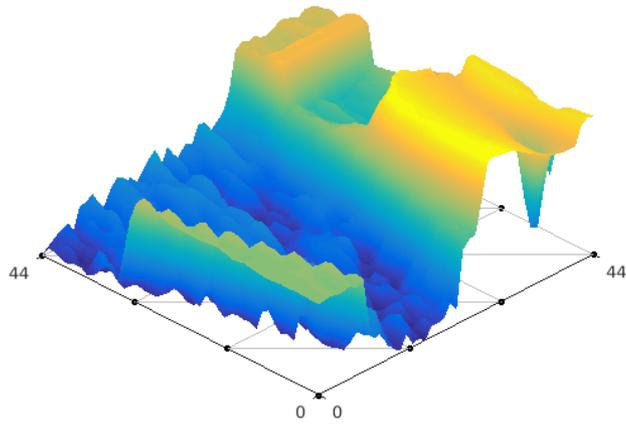
- Zach, Kohli'12; Zach'13; Fix, Agarwal'14
 - piecewise convex
 - different relaxation
 - MRF-based – not isotropic yet



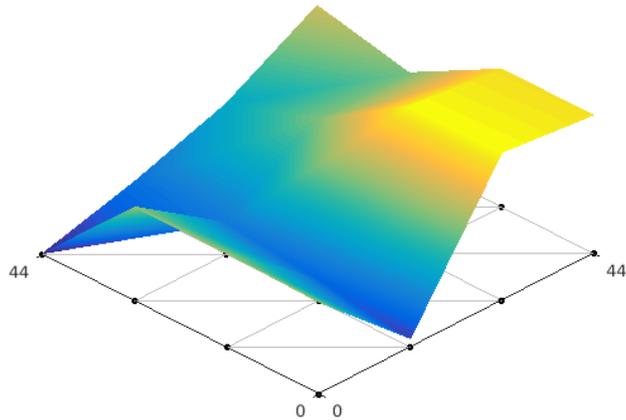
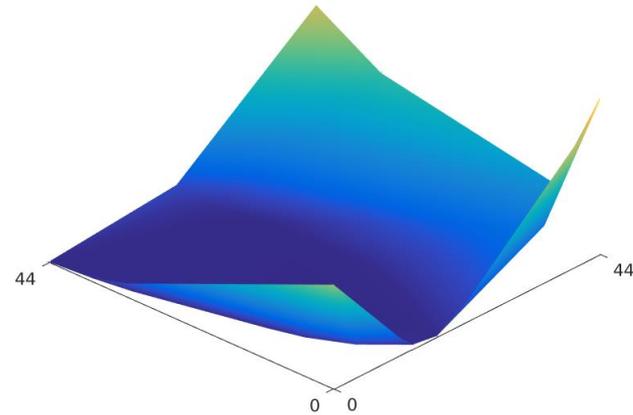
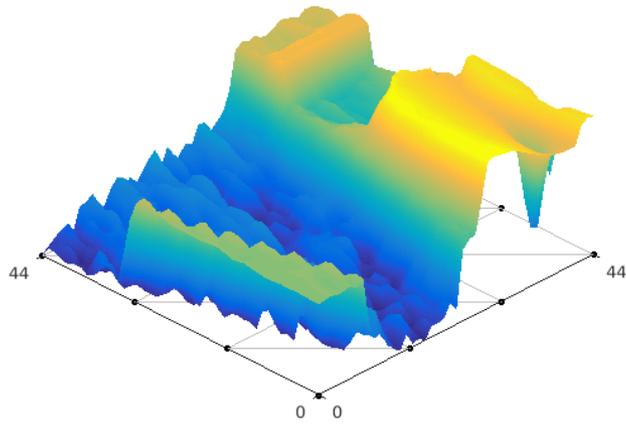
Outlook – multiple dimensions



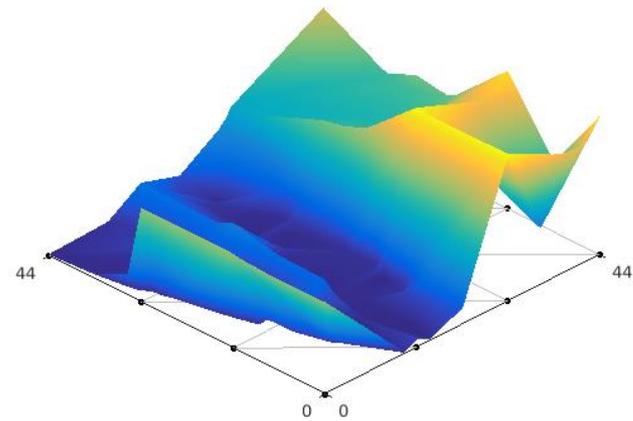
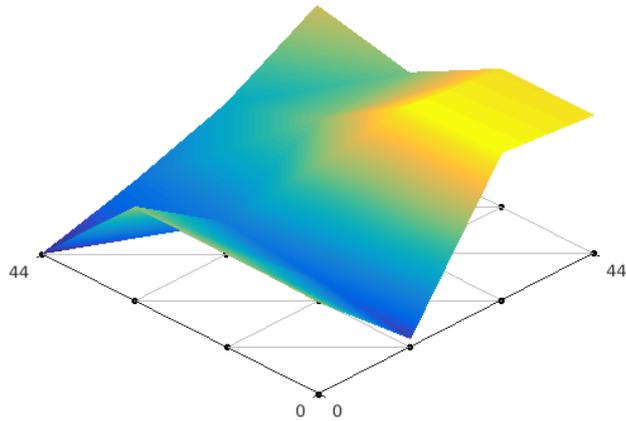
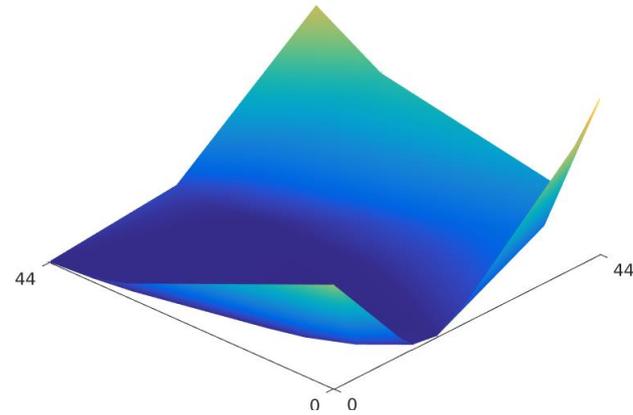
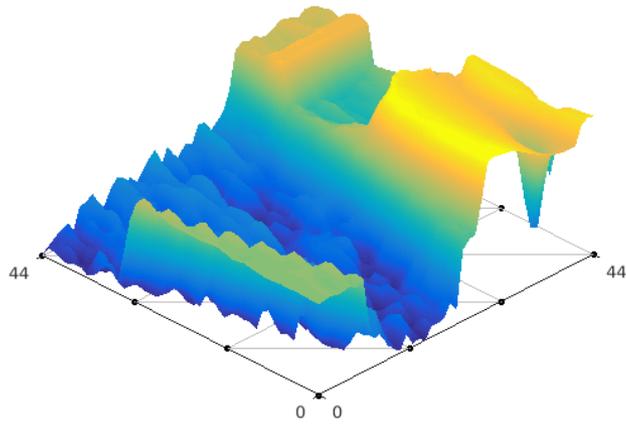
Outlook – multiple dimensions



Outlook – multiple dimensions



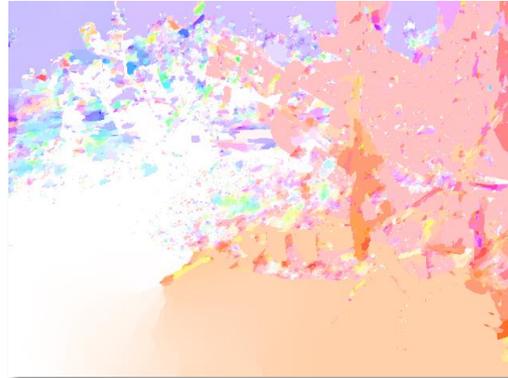
Outlook – multiple dimensions



Large displacement optical flow



input sequence
(Middlebury)



LP-style relaxation (L. et al.'13)
7x7, 5.2GB, 33min, aep 2.65



ours, 2x2 labels
0.63GB, 17min, aep 1.28



ground truth



product spaces (Goldluecke et al.'13),
28x28, 9.3GB, 60min, aep 1.39

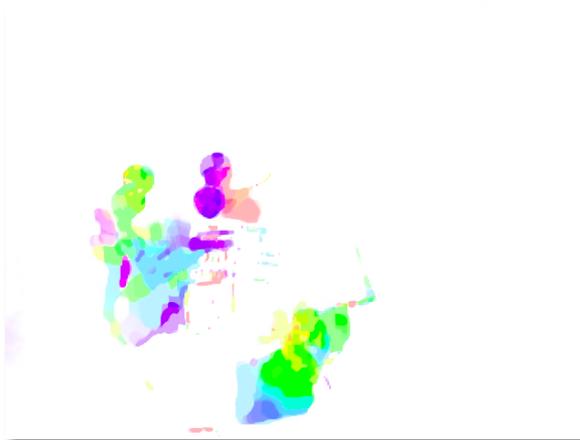


ours, 6x6 labels
10.1GB, 56min, aep 0.9

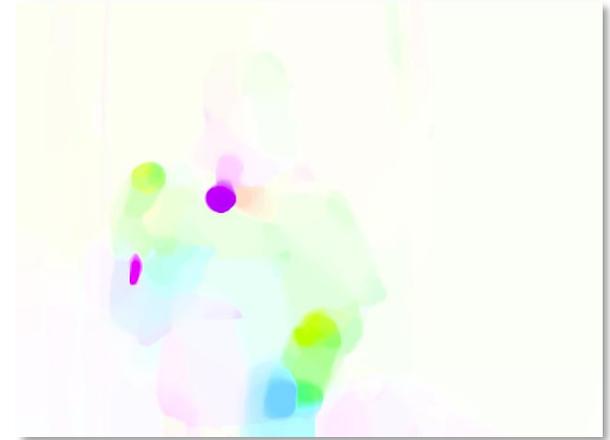
Large displacement optical flow



input sequence



MRF-based, 81x81 labels



ours, 4 labels

References:

- T. Möllenhoff, E. Laude, M. Möller, J. Lellmann, D. Cremers: *Sublabel-Accurate Relaxation of Nonconvex Energies*. arXiv Tech. Rep., 2015
- E. Laude, T. Möllenhoff, M. Möller, J. Lellmann, D. Cremers: *Sublabel-Accurate Convex Relaxation of Vectorial Multilabel Energies*. arXiv Tech. Rep., 2016

Take-home

- Goal: global minimizer of nonconvex energies
- Lift into larger space
- Relax piecewise convex
- Much smaller problems, often 2-4 labels enough

Relaxation Methods in Variational Image Processing

Jan Lellmann, Emanuel Laude, Thomas Moellenhoff,
Daniel Cremers, Michael Moeller, Evgeny Strekalovskiy

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