LibADMM: A Library of Alternating Direction Method of Multipliers for Compressed Sensing

Version 1.0

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https://github.com/canyilu/LibADMM

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TABLE 1: Applicability of the LibADMM package

Model	Problem		Function	Description and Reference
Sparse models	$\min_{\mathbf{x}}\ r(\mathbf{x})$ s.t. $\mathbf{A}\mathbf{x}=\mathbf{b}$	$r(\mathbf{x})=\Vert\mathbf{x}\Vert_1$	`l1`	ℓ_1 [14]
		$r(\mathbf{x})=\sum_{g\in\mathcal{G}}\Vert\mathbf{x}_g\Vert_2$	`groupl1`	Group Lasso [17]
		$r(\mathbf{x})=\Vert\mathbf{x}\Vert_1+\lambda_2\Vert\mathbf{x}\Vert_2^2$	`elasticnet`	Elastic net [19]
		$r(\mathbf{x})=\Vert\mathbf{x}\Vert_1+\lambda_2\sum_{i=2}^{p}\vert x_i-x_{i-1}\vert$	`fusedl1`	Fused Lasso [15]
		$r(\mathbf{x})=\Vert\mathbf{A}\mathrm{Diag}(\mathbf{x})\Vert_*$	`tracelasso`	Trace Lasso [12]
		$r(\mathbf{x})=\frac{1}{2}\Vert\mathbf{x}\Vert_{\text{ksp}}^2$	`ksupport`	k support norm [6]
	$\min_{\mathbf{x},\mathbf{e}}\ l(\mathbf{e})+\lambda r(\mathbf{x})$ s.t. $\mathbf{A}\mathbf{x}+\mathbf{e}=\mathbf{b}$	$l(\mathbf{e})=\Vert\mathbf{e}\Vert_1$ $l(\mathbf{e})=\frac{1}{2}\Vert\mathbf{e}\Vert_2^2$	`l1R`	Reg. ℓ_1
			`groupl1R`	Reg. Group Lasso
			`elasticnetR`	Reg. Elastic net
			`fusedl1R`	Reg. Fused Lasso
			`tracelassoR`	Reg. Trace Lasso
			`ksupportR`	Reg. k support norm
Low-rank matrix models	$\min_{\mathbf{L},\mathbf{S}}\ \Vert\mathbf{L}\Vert_*+\lambda l(\mathbf{S}),\ \text{s.t. } \mathbf{X}=\mathbf{L}+\mathbf{S}$		`rpca`	Robust PCA [2]
	$\min_{\mathbf{X}}\ \Vert\mathbf{X}\Vert_*,\ \text{s.t. } \mathcal{P}_\Omega(\mathbf{X})=\mathcal{P}_\Omega(\mathbf{M})$		`lrmc`	Low-rank matrix completion [1]
	$\min_{\mathbf{X},\mathbf{E}}\ \Vert\mathbf{X}\Vert_*+\lambda l(\mathbf{E}),\ \text{s.t. } \mathcal{P}_\Omega(\mathbf{X})+\mathbf{E}=\mathbf{M}$		`lrmcR`	Reg. Low-rank matrix completion
	$\min_{\mathbf{X},\mathbf{E}}\ \Vert\mathbf{X}\Vert_*+\lambda l(\mathbf{E}),\ \text{s.t. } \mathbf{A}=\mathbf{B}\mathbf{X}+\mathbf{E}$		`lrr`	Low-rank representation [8]
	$\min_{\mathbf{Z},\mathbf{L},\mathbf{E}}\ \Vert\mathbf{Z}\Vert_*+\Vert\mathbf{L}\Vert_*+\lambda l(\mathbf{E})$ s.t. $\mathbf{X}\mathbf{Z}+\mathbf{L}\mathbf{X}-\mathbf{X}=\mathbf{E}$		`latlrr`	Latent low-rank representation [9]
	$\min_{\mathbf{X},\mathbf{E}}\ \Vert\mathbf{X}\Vert_*+\lambda_1\Vert\mathbf{X}\Vert_1+\lambda_2 l(\mathbf{E})$ s.t. $\mathbf{A}=\mathbf{B}\mathbf{X}+\mathbf{E}$		`lrsr`	Low-rank and sparse representation [18]
	$\min_{\mathbf{L}_i,\mathbf{S}_i}\ \Vert\mathbf{L}\Vert_*+\lambda\sum_{i=1}^{m}\Vert\mathbf{S}_i\Vert_1,$ s.t. $\mathbf{X}_i=\mathbf{L}+\mathbf{S}_i,\ i=1,\cdots,m,\ \mathbf{L}\geq 0,\ \mathbf{L}\mathbf{1}=\mathbf{1}$		`rmsc`	Robust multi-view spectral clustering [16]
	$\min_{\mathbf{Z}_i,\mathbf{E}_i}\ \sum_{i=1}^{K}(\Vert\mathbf{Z}_i\Vert_*+\lambda l(\mathbf{E}_i))+\alpha\Vert\mathbf{Z}\Vert_{2,1}$ s.t. $\mathbf{X}_i=\mathbf{X}_i\mathbf{Z}_i+\mathbf{E}_i,\ i=1,\cdots,K$		`mlap`	Multi-task low-rank affinity pursuit [4]
	$\min_{\mathbf{L},\mathbf{S}}\ \Vert\mathbf{L}\Vert_*+\lambda\Vert\mathbf{C}\circ\mathbf{S}\Vert_1,\ \text{s.t. } \mathbf{A}=\mathbf{L}+\mathbf{S}, 0\leq\mathbf{L}\leq 1$		`igc`	Improved graph clustering [3]
	$\min_{\mathbf{P}}\ \langle\mathbf{P},\mathbf{L}\rangle+\lambda\Vert\mathbf{P}\Vert_1,\ \text{s.t. } 0\preceq\mathbf{P}\preceq\mathbf{I},\ \mathrm{Tr}(\mathbf{P})=k$		`sparsesc`	Sparse spectral clustering [13]
Low-rank tensor models	$\min_{\boldsymbol{\mathcal{L}},\boldsymbol{\mathcal{S}}}\ \sum_{i=1}^{k}\alpha_i\Vert\boldsymbol{\mathcal{L}}_{i(i)}\Vert_*+\Vert\boldsymbol{\mathcal{S}}\Vert_1,\ \text{s.t. } \boldsymbol{\mathcal{X}}=\boldsymbol{\mathcal{L}}+\boldsymbol{\mathcal{S}}$		`trpca_snn`	Tensor robust PCA based on sum of nuclear norm [5]
	$\min_{\boldsymbol{\mathcal{X}}}\ \sum_{i=1}^{k}\alpha_i\Vert\boldsymbol{\mathcal{X}}_{i(i)}\Vert_*,\ \text{s.t. } \mathcal{P}_\Omega(\boldsymbol{\mathcal{X}})=\mathcal{P}_\Omega(\boldsymbol{\mathcal{M}})$		`lrtc_snn`	Low-rank tensor completion based on sum of nuclear norm [10]
	$\min_{\boldsymbol{\mathcal{X}},\boldsymbol{\mathcal{E}}}\ \sum_{i=1}^{k}\alpha_i\Vert\boldsymbol{\mathcal{X}}_{i(i)}\Vert_*+\lambda l(\boldsymbol{\mathcal{E}})$ s.t. $\mathcal{P}_\Omega(\boldsymbol{\mathcal{X}})+\boldsymbol{\mathcal{E}}=\boldsymbol{\mathcal{M}}$		`lrtcR_snn`	Reg. low-tank tensor completion based on sum of nuclear norm
	$\min_{\boldsymbol{\mathcal{L}},\boldsymbol{\mathcal{S}}}\ \Vert\boldsymbol{\mathcal{L}}\Vert_*+\lambda\Vert\boldsymbol{\mathcal{S}}\Vert_1,\ \text{s.t. } \boldsymbol{\mathcal{X}}=\boldsymbol{\mathcal{L}}+\boldsymbol{\mathcal{S}}$		`trpca_tnn`	Tensor Robust PCA based on tensor nuclear norm [11]
	$\min_{\boldsymbol{\mathcal{X}}}\ \Vert\boldsymbol{\mathcal{X}}\Vert_*,\ \text{s.t. } \mathcal{P}_\Omega(\boldsymbol{\mathcal{X}})=\mathcal{P}_\Omega(\boldsymbol{\mathcal{M}})$		`lrtc_tnn`	Low-rank tensor completion based on tensor nuclear norm [11]
	$\min_{\boldsymbol{\mathcal{X}},\boldsymbol{\mathcal{E}}}\ \Vert\boldsymbol{\mathcal{X}}\Vert_*+\lambda l(\boldsymbol{\mathcal{E}}),\ \text{s.t. } \mathcal{P}_\Omega(\boldsymbol{\mathcal{X}})+\boldsymbol{\mathcal{E}}=\boldsymbol{\mathcal{M}}$		`lrtcR_tnn`	Reg. low-rank tensor completion based on tensor nuclear norm [11]

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