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. $\mathbf{A}\mathbf{x}=\mathbf{b}$	$r(\mathbf{x})=\\|\mathbf{x}\\|_1$	`l1`	ℓ_1 [14]
		$r(\mathbf{x})=\sum_{g\in\mathcal{G}}\\|\mathbf{x}_g\\|_2$	`groupl1`	Group Lasso [17]
		$r(\mathbf{x})=\\|\mathbf{x}\\|_1+\lambda_2\\|\mathbf{x}\\|_2^2$	`elasticnet`	Elastic net [19]
		$r(\mathbf{x})=\\|\mathbf{x}\\|_1+\lambda_2\sum_{i=2}^{p}\|x_i-x_{i-1}\|$	`fusedl1`	Fused Lasso [15]
		$r(\mathbf{x})=\\|\mathbf{A}\mathrm{Diag}(\mathbf{x})\\|_*$	`tracelasso`	Trace Lasso [12]
		$r(\mathbf{x})=\frac{1}{2}\\|\mathbf{x}\\|_{\text{ksp}}^2$	`ksupport`	k support norm [6]
	$\min_{\mathbf{x},\mathbf{e}}\ l(\mathbf{e})+\lambda r(\mathbf{x})$ s.t. $\mathbf{A}\mathbf{x}+\mathbf{e}=\mathbf{b}$	$l(\mathbf{e})=\\|\mathbf{e}\\|_1$ $l(\mathbf{e})=\frac{1}{2}\\|\mathbf{e}\\|_2^2$	`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	$\min_{\mathbf{L},\mathbf{S}}\ \\|\mathbf{L}\\|_*+\lambda l(\mathbf{S}),\ \text{s.t. } \mathbf{X}=\mathbf{L}+\mathbf{S}$		`rpca`	Robust PCA [2]
	$\min_{\mathbf{X}}\ \\|\mathbf{X}\\|_*,\ \text{s.t. } \mathcal{P}_\Omega(\mathbf{X})=\mathcal{P}_\Omega(\mathbf{M})$		`lrmc`	Low-rank matrix completion [1]
	$\min_{\mathbf{X},\mathbf{E}}\ \\|\mathbf{X}\\|_*+\lambda l(\mathbf{E}),\ \text{s.t. } \mathcal{P}_\Omega(\mathbf{X})+\mathbf{E}=\mathbf{M}$		`lrmcR`	Reg. Low-rank matrix completion
	$\min_{\mathbf{X},\mathbf{E}}\ \\|\mathbf{X}\\|_*+\lambda l(\mathbf{E}),\ \text{s.t. } \mathbf{A}=\mathbf{B}\mathbf{X}+\mathbf{E}$		`lrr`	Low-rank representation [8]
	$\min_{\mathbf{Z},\mathbf{L},\mathbf{E}}\ \\|\mathbf{Z}\\|_*+\\|\mathbf{L}\\|_*+\lambda l(\mathbf{E})$ s.t. $\mathbf{X}\mathbf{Z}+\mathbf{L}\mathbf{X}-\mathbf{X}=\mathbf{E}$		`latlrr`	Latent low-rank representation [9]
	$\min_{\mathbf{X},\mathbf{E}}\ \\|\mathbf{X}\\|_*+\lambda_1\\|\mathbf{X}\\|_1+\lambda_2 l(\mathbf{E})$ s.t. $\mathbf{A}=\mathbf{B}\mathbf{X}+\mathbf{E}$		`lrsr`	Low-rank and sparse representation [18]
	$\min_{\mathbf{L}_i,\mathbf{S}_i}\ \\|\mathbf{L}\\|_*+\lambda\sum_{i=1}^{m}\\|\mathbf{S}_i\\|_1,$ 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]
	$\min_{\mathbf{Z}_i,\mathbf{E}_i}\ \sum_{i=1}^{K}(\\|\mathbf{Z}_i\\|_*+\lambda l(\mathbf{E}_i))+\alpha\\|\mathbf{Z}\\|_{2,1}$ 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]
	$\min_{\mathbf{L},\mathbf{S}}\ \\|\mathbf{L}\\|_*+\lambda\\|\mathbf{C}\circ\mathbf{S}\\|_1,\ \text{s.t. } \mathbf{A}=\mathbf{L}+\mathbf{S},0\leq\mathbf{L}\leq 1$		`igc`	Improved graph clustering [3]
	$\min_{\mathbf{P}}\ \langle\mathbf{P},\mathbf{L}\rangle+\lambda\\|\mathbf{P}\\|_1,\ \text{s.t. } 0\preceq\mathbf{P}\preceq\mathbf{I},\mathrm{Tr}(\mathbf{P})=k$		`sparsesc`	Sparse spectral clustering [13]
Low-rank tensor models	$\min_{\boldsymbol{\mathcal{L}},\boldsymbol{\mathcal{S}}}\ \sum_{i=1}^{k}\alpha_i\\|\boldsymbol{\mathcal{L}}_{i(i)}\\|_*+\\|\boldsymbol{\mathcal{S}}\\|_1,\ \text{s.t. } \boldsymbol{\mathcal{X}}=\boldsymbol{\mathcal{L}}+\boldsymbol{\mathcal{S}}$		`trpca_snn`	Tensor robust PCA based on sum of nuclear norm [5]
	$\min_{\boldsymbol{\mathcal{X}}}\ \sum_{i=1}^{k}\alpha_i\\|\boldsymbol{\mathcal{X}}_{i(i)}\\|_*,\ \text{s.t. } \mathcal{P}_\Omega(\boldsymbol{\mathcal{X}})=\mathcal{P}_\Omega(\boldsymbol{\mathcal{M}})$		`lrtc_snn`	Low-rank tensor completion based on sum of nuclear norm [10]
	$\min_{\boldsymbol{\mathcal{X}},\boldsymbol{\mathcal{E}}}\ \sum_{i=1}^{k}\alpha_i\\|\boldsymbol{\mathcal{X}}_{i(i)}\\|_*+\lambda l(\boldsymbol{\mathcal{E}})$ 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
	$\min_{\boldsymbol{\mathcal{L}},\boldsymbol{\mathcal{S}}}\ \\|\boldsymbol{\mathcal{L}}\\|_*+\lambda\\|\boldsymbol{\mathcal{S}}\\|_1,\ \text{s.t. } \boldsymbol{\mathcal{X}}=\boldsymbol{\mathcal{L}}+\boldsymbol{\mathcal{S}}$		`trpca_tnn`	Tensor Robust PCA based on tensor nuclear norm [11]
	$\min_{\boldsymbol{\mathcal{X}}}\ \\|\boldsymbol{\mathcal{X}}\\|_*,\ \text{s.t. } \mathcal{P}_\Omega(\boldsymbol{\mathcal{X}})=\mathcal{P}_\Omega(\boldsymbol{\mathcal{M}})$		`lrtc_tnn`	Low-rank tensor completion based on tensor nuclear norm [11]
	$\min_{\boldsymbol{\mathcal{X}},\boldsymbol{\mathcal{E}}}\ \\|\boldsymbol{\mathcal{X}}\\|_*+\lambda l(\boldsymbol{\mathcal{E}}),\ \text{s.t. } \mathcal{P}_\Omega(\boldsymbol{\mathcal{X}})+\boldsymbol{\mathcal{E}}=\boldsymbol{\mathcal{M}}$		`lrtcR_tnn`	Reg. low-rank tensor completion based on tensor nuclear norm [11]

REFERENCES

[1] E. Candès and B. Recht. Exact matrix completion via convex optimization. *Foundations of Computational mathematics*, 9(6):717–772, 2009.
[2] E. J. Candès, X. D. Li, Y. Ma, and J. Wright. Robust principal component analysis? *Journal of the ACM*, 58(3), 2011.
[3] Y. Chen, S. Sanghavi, and H. Xu. Improved graph clustering. *IEEE Transactions on Information Theory*, 60(10):6440–6455, 2014.
[4] B. Cheng, G. Liu, J. Wang, Z. Huang, and S. Yan. Multi-task low-rank affinity pursuit for image segmentation. In *ICCV*, pages 2439–2446. IEEE, 2011.
[5] D. Goldfarb and Z. Qin. Robust low-rank tensor recovery: Models and algorithms. *SIAM Journal on Matrix Analysis and Applications*, 35(1):225–253, 2014.
[6] H. Lai, Y. Pan, C. Lu, Y. Tang, and S. Yan. Efficient k-support matrix pursuit. In *ECCV*, 2014.
[7] Z. Lin, R. Liu, and H. Li. Linearized alternating direction method with parallel splitting and adaptive penalty for separable convex programs in machine learning. *Machine Learning*, 99(2):287–325, 2015.
[8] G. Liu, Z. Lin, S. Yan, J. Sun, Y. Yu, and Y. Ma. Robust recovery of subspace structures by low-rank representation. *TPAMI*, 2013.
[9] G. Liu and S. Yan. Latent low-rank representation for subspace segmentation and feature extraction. In *ICCV*, 2011.
[10] J. Liu, P. Musialski, P. Wonka, and J. Ye. Tensor completion for estimating missing values in visual data. *TPAMI*, 35(1):208–220, 2013.
[11] C. Lu, J. Feng, Y. Chen, W. Liu, Z. Lin, and S. Y. Yan. Tensor robust principal component analysis: Exact recovery of corrupted low-rank tensors via convex optimization. In *CVPR*. IEEE, 2016.
[12] C. Lu, J. Feng, Z. Lin, and S. Yan. Correlation adaptive subspace segmentation by trace Lasso. In *ICCV*, 2013.
[13] C. Lu, S. Yan, and Z. Lin. Convex sparse spectral clustering: Single-view to multi-view. *TIP*, 25(6):2833–2843, 2016.
[14] R. Tibshirani. Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society. Series B (Methodological)*, pages 267–288, 1996.
[15] R. Tibshirani, M. Saunders, S. Rosset, J. Zhu, and K. Knight. Sparsity and smoothness via the fused lasso. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 67(1):91–108, 2005.

[16] R. Xia, Y. Pan, L. Du, and J. Yin. Robust multi-view spectral clustering via low-rank and sparse decomposition. In *AAAI*, pages 2149–2155, 2014.
[17] M. Yuan and Y. Lin. Model selection and estimation in regression with grouped variables. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 68(1):49–67, 2006.
[18] L. Zhuang, H. Gao, Z. Lin, Y. Ma, X. Zhang, and N. Yu. Non-negative low rank and sparse graph for semi-supervised learning. In *CVPR*, pages 2328–2335. IEEE, 2012.
[19] H. Zou and T. Hastie. Regularization and variable selection via the elastic net. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, 67(2):301–320, 2005.