Structured Sparsity

- group testing & compressed sensing
- a norm that induces structured sparsity

(arxiv.org/abs/1110.0413 Obozinski, G., Jacob, L., & Vert, J.-P., October 2011)

> Mittagsseminar 2011 / 11 / 10 Martin Jaggi

Sparse Solutions to underdetermined Linear Systems

b = Ax $b \in \mathbb{R}^m \\ x \in \mathbb{R}^d \qquad m \ll d$

 $\|x\|_0 \le k$

 $b \in \mathbb{R}^m \\ x \in \mathbb{R}^d \qquad m \ll d$

 $||x||_0 \le k$

Group Testing

Dorfman, R. (1943). **The Detection of Defective Members of Large Populations**. Annals of Mathematical Statistics



Kainkaryam et al. (2010). pooIMC: Smart pooling of mRNA samples in microarray experiments. *BMC Bioinformatics*

Coding theory interpretation: A is the parity check matrix of a linear code

 $b \in \mathbb{R}^m \\ x \in \mathbb{R}^d \qquad m \ll d$

Group Testing





 $\|x\|_0 \le k$

Compressed sensing



Theorem

$$m = O(k \, \log d)$$
 is enough.

k-sparse signals are recovered by taking the solution of smallest $\,\ell_1$ -norm

Donoho, D. L. (2006). Compressed sensing. IEEE Transactions on Information Theory

(3400 citations)

Candes, E. J., & Tao, T. (2005). Decoding by Linear Programming. IEEE Transactions on Information Theory (1200 citations)

$$\min_{x} \|Ax - b\|^2 + \lambda \|x\|_0$$

$$\begin{array}{c}
\operatorname{easy} \ell_{1} \\
\min_{x} \|Ax - b\|^{2} + \lambda \|x\|_{1}
\end{array}$$

Santosa and Symes (1983)

Phase transition

$$b \in \mathbb{R}^{m}$$

$$x \in \mathbb{R}^{d} \qquad m \ll d$$

$$\|x\|_{0} \le k$$

$$\begin{array}{c} \operatorname{hard} \ell_{0} \\ \min_{x} \|Ax - b\|^{2} + \lambda \|x\|_{0} \end{array}$$

$$easy \ell_1$$
$$\min_x \|Ax - b\|^2 + \lambda \|x\|_1$$



Exceeds The Number Of Observations. PhD thesis. stanford.edu.



How to solve
$$\lim_{x} ||Ax - b||^2 + \lambda ||x||_1$$
 in practice?

Linear Program
$$\min_{\substack{x \\ s.t.}} \|x\|_1 \\ s.t. \quad Ax - b = 0$$

Frank-Wolfe (Sparse Greedy)

$$\begin{array}{l} \min_{x} & \|Ax - b\|^2 \\ s.t. & \|x\|_1 \leq t \end{array}$$



Single Pixel Camera



Duarte et al. Single-Pixel Imaging via Compressive Sampling. IEEE Signal Processing Magazine

Computer Vision

Background Subtraction



Candes, E. J. et al. (2011). Robust principal component analysis Journal of the ACM

 $\min_{X} \|B - X\|_* + \lambda \|X\|_1$

A Structured Norm

Obozinski, G., Jacob, L., & Vert, J.-P. (October 2011). Group Lasso with Overlaps: the Latent Group Lasso approach. *arXiv stat.ML*.

$${\mathcal G}$$
 is a collection of subsets $\,g\subseteq [d]$ $igsquare$ $igsquare$ $igsquare$ $igsquare$ $g=[d]$

 $\bigcup_{g \in \mathcal{G}} g =$

$$\begin{aligned} \|x\|_{1} &:= \min_{(v^{i})} \quad \sum_{i \in [d]} |v^{i}| \\ s.t. \quad x &= \sum_{i \in [d]} v^{i} \\ supp(v^{i}) &= \{i\} \end{aligned}$$

$$\begin{aligned} \|x\|_{\mathcal{G}} &:= \min_{(v^g)} \quad \sum_{g \in \mathcal{G}} \|v^g\|_g \\ s.t. \quad x &= \sum_{g \in \mathcal{G}} v^g \\ supp(v^g) &\subseteq g \end{aligned}$$





A Structured Norm

Obozinski, G., Jacob, L., & Vert, J.-P. (October 2011). Group Lasso with Overlaps: the Latent Group Lasso approach. *arXiv stat.ML*.

$${\mathcal G}$$
 is a collection of subsets $\,g\subseteq [d]\,$

 $\bigcup_{g \in \mathcal{G}} g = [a]$

$$\begin{aligned} \|x\|_{1} &:= \min_{(v^{i})} \quad \sum_{i \in [d]} |v^{i}| \\ s.t. \quad x &= \sum_{i \in [d]} v^{i} \\ supp(v^{i}) &= \{i\} \end{aligned}$$

$$\begin{aligned} \|x\|_{\mathcal{G}} &:= \min_{(v^g)} \quad \sum_{g \in \mathcal{G}} \|v^g\|_g \\ s.t. \quad x &= \sum_{g \in \mathcal{G}} v^g \\ supp(v^g) \subseteq g \end{aligned}$$





Optimizing with the Structured Norm

$$\min_{x} f(x) + \lambda \|x\|_{\mathcal{G}}$$

Frank-Wolfe (Sparse Greedy) $\min_{x} f(x)\\ s.t. \quad \|x\|_{\mathcal{G}} \leq t$

 $\|x\|_{\mathcal{G}} := \min_{(v^g)} \quad \sum_{g \in \mathcal{G}} \|v^g\|_g$ s.t. $x = \sum_{g \in \mathcal{G}} v^g$





Relation to Set-Cover

$${\mathcal G}$$
 is a collection of subsets $\,g\subseteq [d]\,$ $\bigcup_{g\in {\mathcal G}}g=[d]\,$

$$\|x\|_{1} := \min_{(v^{i})} \sum_{i \in [d]} |v^{i}|$$

s.t. $x = \sum_{i \in [d]} v^{i}$
 $supp(v^{i}) = \{i\}$

$$\begin{aligned} \|x\|_{\mathcal{G}} &:= \min_{(v^g)} \quad \sum_{g \in \mathcal{G}} \|v^g\|_g \\ s.t. \quad x &= \sum_{g \in \mathcal{G}} v^g \\ supp(v^g) \subseteq g \end{aligned}$$

$$\begin{aligned} \|x\|_{\mathcal{G}-\text{set}} &:= \min_{(v^g)} \quad \sum_{g \in \mathcal{G}} \mathbf{1}_{v^g \neq 0} \\ s.t. \quad x = \sum_{g \in \mathcal{G}} v^g \\ \sup_{supp(v^g) \subseteq g} \end{aligned}$$

$$\|x\|_{0} := \min_{(v^{i})} \sum_{i \in [d]} \mathbf{1}_{v^{i} \neq 0}$$

s.t. $x = \sum_{i \in [d]} v^{i}$
 $supp(v^{i}) = \{i\}$

Open Questions



- More applications (related to set-cover?)
- Phase transition phenomenon when applied to the combinatorial set-cover?
- Is it the "closest" convex function to set-cover?

