### Group lasso with Overlap and Graph Lasso

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#### Lasso

Well known that regularizing a learning problem by  $\ell_1$ -norm induces sparse solutions (Tibshirani, 1996, Chen *et al.*, 1998).



# Sparsity-inducing norms

#### Group lasso

If groups of covariates are likely to be selected together, the  $\ell_1/\ell_2$ -norm induces sparse solutions at the group level (Yuan & Lin, 2006).



# Biological markers for cancer





Predict metastasis, identify few predictive genes.

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Overlapping group lasso

### Gene selection

• X is the expression matrix of p genes for n tumors.



- Learning with a ℓ<sub>1</sub>-penalty favors a linear classifier w ∈ ℝ<sup>p</sup> involving few genes.
- Remark : may only select one of several correlated genes.
- After this selection, people often try to find enriched *functional groups*.

- We have prior information under the form of groups of genes with functional meaning (*e.g.* pathways).
- We would like to favor directly w involving few groups
  - Better interpretability.
  - Correlated genes typically in the same group, hence selected together.
  - Robustness to spurious gene selection.
- Group lasso originally proposed for disjoint groups.
- For overlapping groups,  $\Omega_{group}(w) = \sum_{g \in \mathcal{G}} \|w_g\|_2$  is still a norm and has been considered for :
  - Hierarchical variable selection (Zhao et al. 2006, Bach 2008).
  - Structured sparsity (Jenatton *et al.* 2009).

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#### Issue of using the group-lasso

- $\Omega_{group}(w) = \sum_{g} \|w_{g}\|_{2}$  sets groups to 0.
- One variable is selected ⇔ all the groups to which it belongs are selected.



 $\begin{array}{c} G_{1} \\ \Rightarrow \\ \|w_{g_{1}}\|_{2} = \|w_{g_{3}}\|_{2} = 0 \end{array} \begin{array}{c} 0 \\ G_{2} \\ G_{3} \end{array}$ 

election of conta

Removal of *any* group containing a gene  $\Rightarrow$  the weight of the gene is 0.

IGF selection  $\Rightarrow$  selection of unwanted groups

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### Overlap norm

Introduce latent variables  $v_g$ :

$$\begin{cases} \min_{w,v} \mathcal{L}(w) + \lambda \sum_{g \in \mathcal{G}} \|v_g\|_2 \\ w = \sum_{g \in \mathcal{G}} v_g \\ \operatorname{supp}(v_g) \subseteq g. \end{cases}$$



#### Properties

- Resulting support is a *union* of groups in  $\mathcal{G}$ .
- Possible to select one variable without selecting all the groups containing it.
- Setting one  $v_g$  to 0 doesn't necessarily set to 0 all its variables in w.

#### Overlap norm

$$\begin{cases} \min_{w,v} L(w) + \lambda \sum_{g \in \mathcal{G}} \|v_g\|_2 \\ w = \sum_{g \in \mathcal{G}} v_g \\ \operatorname{supp}(v_g) \subseteq g. \end{cases} = \min_{w} L(w) + \lambda \Omega_{overlap}(w)$$

$$\stackrel{h}{\Omega_{overlap}(w)} \stackrel{\Delta}{=} \begin{cases} \min_{v} \sum_{g \in \mathcal{G}} \|v_g\|_2 \\ w = \sum_{g \in \mathcal{G}} v_g \\ \operatorname{supp}(v_g) \subseteq g. \end{cases}$$
(\*)

#### Property

wit

- $\Omega_{overlap}(w)$  is a norm of w.
- Ω<sub>overlap</sub>(.) associates to w a specific (not necessarily unique) decomposition (v<sub>g</sub>)<sub>g∈G</sub> which is the argmin of (\*).

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## Equivalent formulation

#### Regular group-lasso in latent variable space

$$\begin{cases} \min_{w,v} L(Xw) + \lambda \sum_{g} \|v_{g}\|_{2} \\ w = \sum_{g} v_{g} \\ \operatorname{supp}(v_{g}) \subseteq g. \end{cases} = \min_{\tilde{v}} L(\tilde{X}\tilde{v}) + \lambda \sum_{g} \|\tilde{v}_{g}\|_{2} \end{cases}$$



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# Overlap and group unity balls



Balls for  $\Omega_{\text{group}}^{\mathcal{G}}(\cdot)$  (middle) and  $\Omega_{\text{overlap}}^{\mathcal{G}}(\cdot)$  (right) for the groups  $\mathcal{G} = \{\{1,2\},\{2,3\}\}$  where  $w_2$  is represented as the vertical coordinate. Left : group-lasso ( $\mathcal{G} = \{\{1,2\},\{3\}\}$ ), for comparison.

### Consistency in group support

- Let  $\bar{w}$  be the true parameter vector.
- Assume that there exists a unique decomposition  $\bar{v}_g$  such that  $\bar{w} = \sum_g \bar{v}_g$  and  $\Omega^{\mathcal{G}}_{\text{overlap}}(\bar{w}) = \sum \|\bar{v}_g\|_2$ .
- Consider the regularized empirical risk minimization problem  $L(w) + \lambda \Omega^{\mathcal{G}}_{\text{overlap}}(w).$

Then

- under appropriate mutual incoherence conditions on X,
- as  $n \to \infty$ ,
- with very high probability,

the optimal solution  $\hat{w}$  admits a unique decomposition  $(\hat{v}_g)_{g\in\mathcal{G}}$  such that

 $\{g\in \mathcal{G}|\hat{v}_g\neq 0\}=\{g\in \mathcal{G}|\bar{v}_g\neq 0\}.$ 

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# Graph lasso

#### Graph lasso

• Other types of biological priors can be represented as graphs (protein interaction, gene regulation...).



- In that case, it is reasonable to expect that relevant genes form connected components in such a graph.
- Moreover, these components might be used as groups of potential drug targets and uncover biological processes relevant for metastasis.

### Graph lasso

• Consider groups that are subgraphs whose union would give such connected components (*e.g.*, edges *E*).



• 
$$\Omega_{\text{graph}}(w) = \min_{v \in \mathcal{V}_E} \sum_{e \in E} \|v_e\|$$
 s.t.  $\sum_{e \in E} v_e = w$ ,  $\text{supp}(v_e) = e$ .

### Results

#### Synthetic data : overlapping groups

- 10 groups of 10 variables with 2 variables of overlap between two successive groups : $\{1, \ldots, 10\}, \{9, \ldots, 18\}, \ldots, \{73, \ldots, 82\}.$
- Support : union of 4th and 5th groups.
- Learn from 100 training points.



Frequency of selection of each variable with the lasso (left) and  $\Omega^{\mathcal{G}}_{overlap}(.)$  (middle), comparison of the RMSE of both methods (right).

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Overlapping group lasso

### Results

#### Breast cancer data

- Gene expression data for 8,141 genes in 295 breast cancer tumors.
- Canonical pathways from MSigDB containing 639 groups of genes, 637 of which involve genes from our study.

Method	$\ell_1$	$\Omega^{\mathcal{G}}_{overlap}\left(. ight)$
Error	$0.38\pm0.04$	$0.36\pm0.03$
♯ path.	148, 58, 183	6, 5, 78
Prop. path.	0.32, 0.14, 0.41	0.01, 0.01, 0.17

Graph on the genes.

Method	$\ell_1$	$\Omega_{graph}(.)$
Error	$0.39\pm0.04$	$0.36\pm0.01$
Av. size c.c.	1.1, 1, 1.0	1.3, 1.4, 1.2

#### Summary

- Generalization of the group-lasso penalty leading to sparsity patterns which are *unions* of overlapping groups.
- Helps to recover sparse connected patterns in a graph.
- Group-consistency conditions.
- Encouraging results on breast cancer data.

#### Future works

- Comparison with  $\Omega_{group}$  when both retrieve the same class of patterns (*e.g.* graphs).
- Weighted penalty (group sizes, overlap sizes).
- More general consistency conditions.

#### **Dual formulation**

$$\Omega_{overlap}(w) = \begin{cases} \inf_{v} \sum_{g} \|v_{g}\|_{2} \\ w = \sum_{g} v_{g} \\ \sup p(v_{g}) \subseteq g. \end{cases} = \begin{cases} \sup_{\alpha} \alpha^{\top} w \\ \forall g, \|\alpha_{g}\|_{2} \leq 1 \\ \forall g, \|\alpha_{g}\|_{2} \leq 1 \end{cases}$$
(1)

A vector α ∈ ℝ<sup>p</sup> is a solution of (1) if and only if there exists
 v = (v<sub>g</sub>)<sub>g∈G</sub> ∈ V(w) such that :

$$\forall g \in \mathcal{G}, \text{ if } v_g \neq 0, \ \alpha_g = rac{v_g}{\|v_g\|} \text{ else } \|\alpha_g\| \leq 1$$
 (2)

• Conversely, a  $\mathcal{G}$ -tuple of vectors  $\mathbf{v} = (v_g)_{g \in \mathcal{G}} \in \mathcal{V}_{\mathcal{G}}$  such that  $w = \sum_g v_g$  is a solution to (1) if and only if there exists a vector  $\alpha \in \mathbb{R}^p$  such that (2) holds.

#### Consistency

If we assume that

$$(H1) \qquad \Sigma := \frac{1}{n} X^\top X \succ 0$$

**2** (H2) There exists a neighborhood of  $\bar{w}$  in which the decomposition in v is unique,

then

$$\forall g \in \mathcal{G}_2, \ \left\| \Sigma_{gJ_1} \Sigma_{J_1J_1}^{-1} \alpha_{J_1}(\bar{w}) \right\| \le 1 \tag{C1}$$

$$\forall g \in \mathcal{G}_2, \ \|\boldsymbol{\Sigma}_{gJ_1}\boldsymbol{\Sigma}_{J_1J_1}^{-1}\boldsymbol{\alpha}_{J_1}(\bar{w})\| < 1 \tag{C2}$$

are respectively necessary and sufficient for the minimization of

$$\min_{w \in \mathbb{R}^{p}} R(w) + \lambda \Omega_{\text{overlap}}^{\mathcal{G}}(w) , \qquad (3)$$

to estimate consistently the group-support of  $\bar{w}$ .

### Consistency : Remark

• Consistency conditions for  $\Omega_{overlap}^{\mathcal{G}}(.)$  :

$$\forall g \in \mathcal{G}_2, \ \|\boldsymbol{\Sigma}_{gJ_1}\boldsymbol{\Sigma}_{J_1J_1}^{-1}\boldsymbol{\alpha}_{J_1}(\bar{w})\| \le 1$$
(C1)

$$\forall g \in \mathcal{G}_2, \ \|\boldsymbol{\Sigma}_{gJ_1}\boldsymbol{\Sigma}_{J_1J_1}^{-1}\boldsymbol{\alpha}_{J_1}(\bar{w})\| < 1 \tag{C2}$$

• Consistency conditions for group-lasso (Bach et al., 2008) :

$$\forall g \in \mathcal{G}_2, \ \|\Sigma_{gJ_1} \Sigma_{J_1J_1}^{-1} \mathsf{Diag}(1/\|ar{w}_{J_1,i}\|_2)_i ar{w}_{J_1}\| \le 1$$
 (C1)

$$orall g \in \mathcal{G}_2, \ \| \Sigma_{gJ_1} \Sigma_{J_1J_1}^{-1} \mathsf{Diag}(1/\|ar w_{J_1,i}\|_2)_i ar w_{J_1} \| < 1$$
 (C2)

- No closed form for  $\alpha(\bar{w})$  in the general case.
- If there is no overlap, we recover the group-lasso result.