

# Faster and still safe: Combining screening techniques and structured dictionaries to accelerate the Lasso



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**Accelerate the Lasso optimization**  
by combining two strategies :

- 1) Safe Screening Rules
- 2) Fast Structured Dictionaries

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01. Context (Lasso problem)
02. Fast Structured Dictionaries
03. Screening Rules
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# 01

## Context

# Lasso problem

The l1-regularized least squares.

$$\hat{\boldsymbol{\beta}} = \underset{\boldsymbol{\beta}}{\operatorname{argmin}} \underbrace{\frac{1}{2} \|\mathbf{X}\boldsymbol{\beta} - \mathbf{y}\|_2^2 + \lambda \|\boldsymbol{\beta}\|_1}_{P(\boldsymbol{\beta})}$$

Denoting :

- $\mathbf{y} \in \mathbb{R}^N$  the observation vector;
- $\mathbf{X} = [\mathbf{x}_1, \dots, \mathbf{x}_K] \in \mathbb{R}^{N \times K}$  the design matrix (or dictionary);
- $\boldsymbol{\beta} \in \mathbb{R}^K$  the sparse representation vector;
- $\lambda > 0$  parameter controlling the sparsity of the solution.

# Dual Lasso

Dual formulation of the Lasso problem :

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta} \in \Delta_{\mathbf{X}}}{\operatorname{argmax}} \underbrace{\frac{1}{2} \|\mathbf{y}\|_2^2 - \frac{\lambda^2}{2} \left\| \boldsymbol{\theta} - \frac{\mathbf{y}}{\lambda} \right\|_2^2}_{D(\boldsymbol{\theta})}$$

Denoting :

- $\boldsymbol{\theta} \in \mathbb{R}^N$  the dual variable;
- $\Delta_{\mathbf{X}} = \{\boldsymbol{\theta} \in \mathbb{R}^N : \|\mathbf{X}^T \boldsymbol{\theta}\|_{\infty} \leq 1\}$  the feasible set;

# Motivation

- **Iterative algorithms** are often used to solve the Lasso problem.
- Exemple : ISTA (Iterative Shrinkage-Thresholding Algorithm)

---

**while** not converged **do**

$$\beta_{t+1} \leftarrow \text{ST}_{\frac{\lambda}{L_t}} \left( \beta_t + \frac{1}{L_t} \mathbf{X}_t^T (\mathbf{y} - \mathbf{X}_t \beta_t) \right)$$

---

- Two **matrix-vector multiplications** at each iteration.

Quadratic complexity!

Can it be reduced?

# 02

## Fast Structured Dictionaries



# Structure $\Rightarrow$ Acceleration

## Accelerate matrix-vector multiplications



Constrain the dictionary matrix to have a certain type of structure.

Examples :

- Kronecker product
- Sparse factors
- Circulant factors
- (...)

# Structured Approximation

If the dictionary matrix  $\mathbf{X}$  is not structured, find a structured approximation  $\tilde{\mathbf{X}}$ .

$$\tilde{\mathbf{X}} = \mathbf{X} + \mathbf{E},$$

where  $\mathbf{E}$  is the approximation error matrix and  $\mathbf{e}_j$  is its  $j$ -th column.

# Algorithm (high level view)



1) Start Lasso optimization by using the structured  $\tilde{\mathbf{X}}$ , to take advantage of its reduced multiplication cost.

2) As the algorithm approaches the solution, switch back to the original dictionary  $\mathbf{X}$ .

---

**while** switching criterion not met **do**

$$\beta_{t+1} \leftarrow \text{ST}_{\frac{\lambda}{L_t}} \left( \beta_t + \frac{1}{L_t} \tilde{\mathbf{X}}_t^T (\mathbf{y} - \tilde{\mathbf{X}}_t \beta_t) \right)$$

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# 03

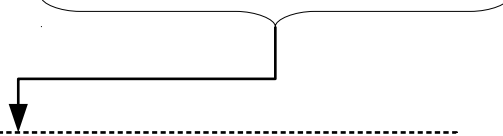
## Safe Screening Rules

# Safe Screening

- Rules for identifying inactive dictionary atoms, before solving the problem.

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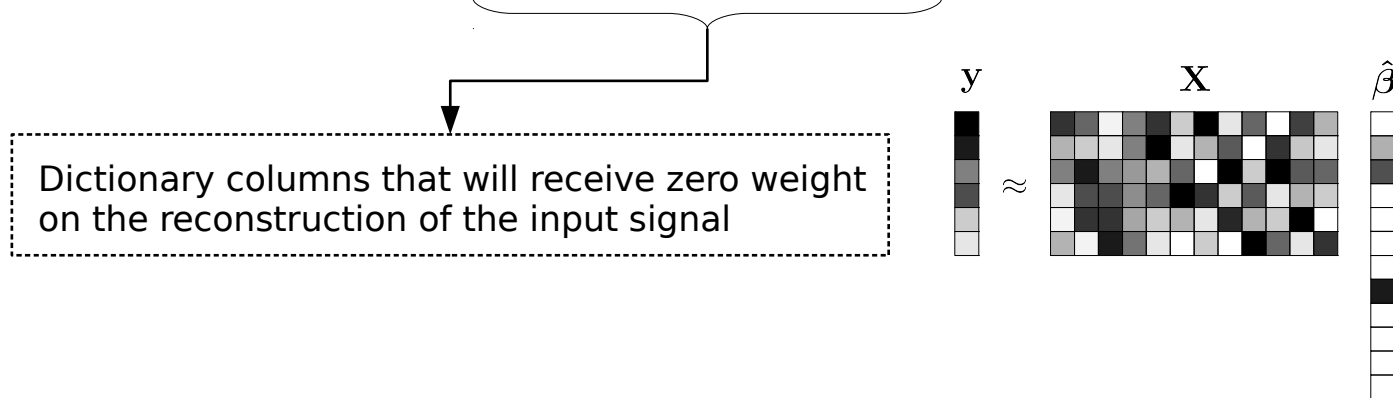
- Rules for identifying inactive dictionary atoms, before solving the problem.



Dictionary columns that will receive zero weight on the reconstruction of the input signal

# Safe Screening

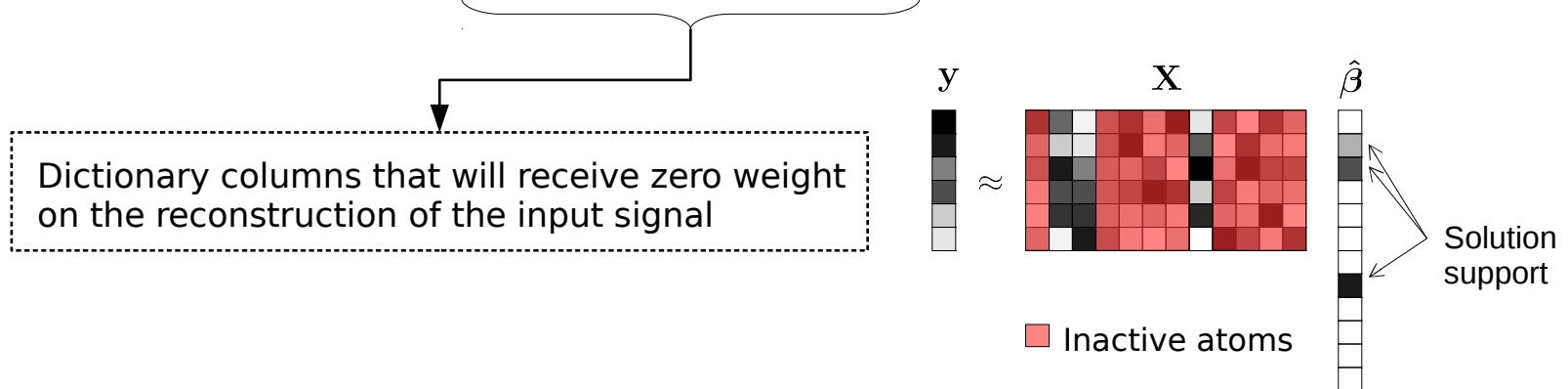
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# Safe Screening

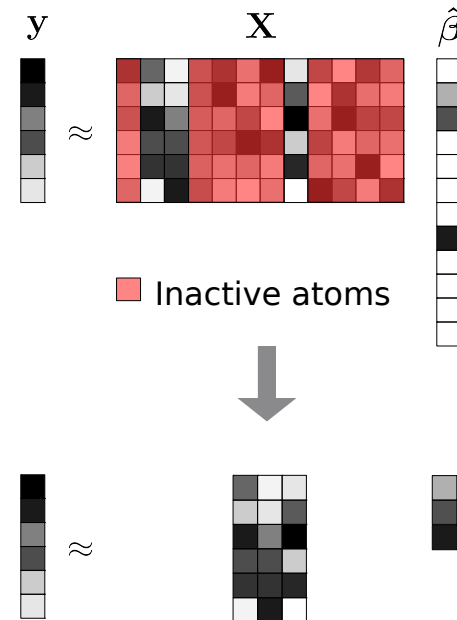
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# Safe Screening

- Rules for identifying inactive dictionary atoms, before solving the problem.

Dictionary columns that will receive zero weight on the reconstruction of the input signal



- We can eliminate such atoms.
- Zero risk of false eliminations!

# Screening Test

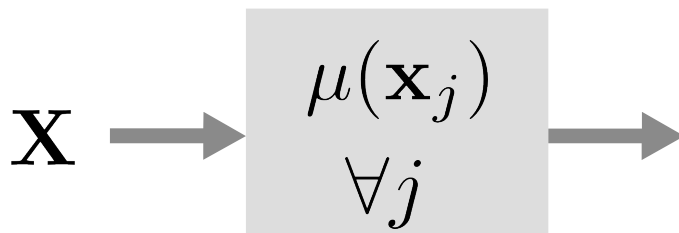
- Function  $\mu(\mathbf{x}_j)$  of the atom  $\mathbf{x}_j$

$$\mu(\mathbf{x}_j) < 1 \quad \Longrightarrow \quad \mathbf{x}_j \text{ is surely inactive.}$$

# Screening Test

- Function  $\mu(\mathbf{x}_j)$  of the atom  $\mathbf{x}_j$

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Rejection set:

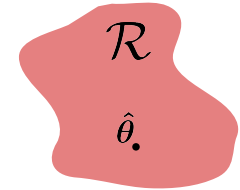
$$\mathcal{A}^c = \{j \in \{1, \dots, K\} : \mu(\mathbf{x}_j) < 1\}$$

Preserved set:

$$\mathcal{A} = \{j \in \{1, \dots, K\} : \mu(\mathbf{x}_j) \geq 1\}$$

# Screening Test – In practice

Given a region  $\mathcal{R}$  (**safe region**) which contains  $\hat{\theta}$ .

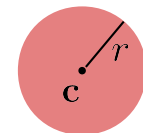


$$\mu_{\mathcal{R}}(\mathbf{x}_j) = \max_{\boldsymbol{\theta} \in \mathcal{R}} |\mathbf{x}_j^T \boldsymbol{\theta}|$$

## Sphere test

Safe region is a closed l2-ball with center  $\mathbf{c}$  and radius  $r$ :  $\mathcal{R} = B(\mathbf{c}, r)$

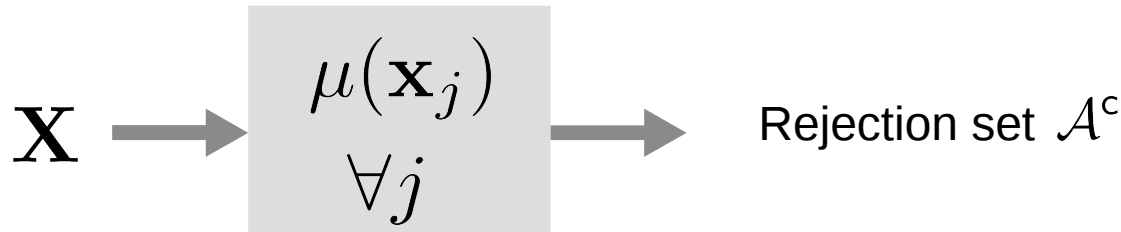
$$\mu_{B(\mathbf{c}, r)}(\mathbf{x}_j) = |\mathbf{x}_j^T \mathbf{c}| + r \|\mathbf{x}_j\|_2.$$



# 04

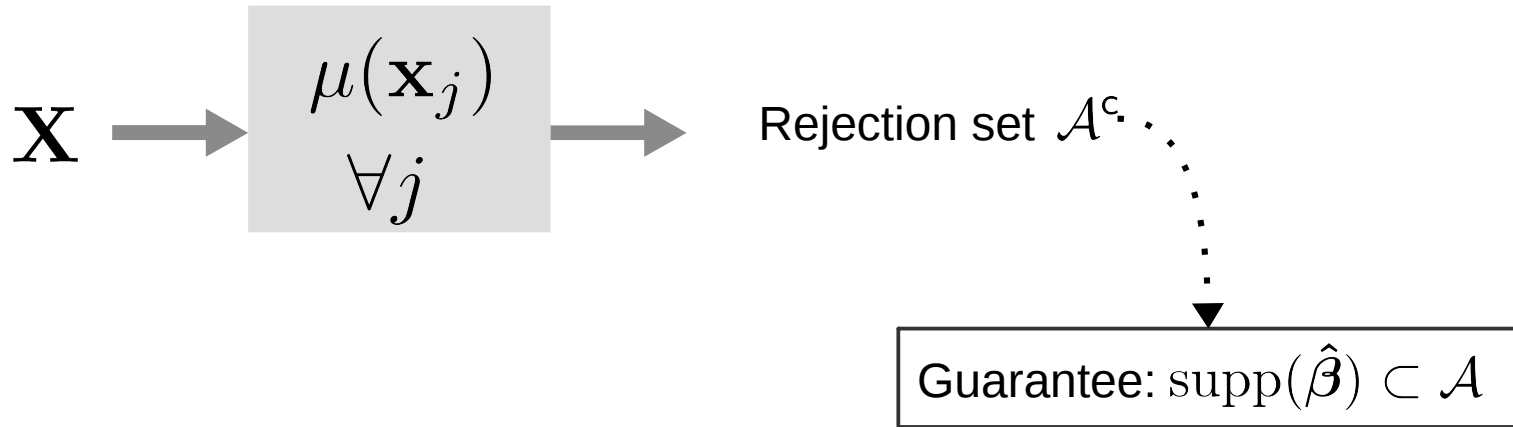
## Screening Rules with Approximate Dictionaries

$$\hat{\beta} = \operatorname{argmin}_{\beta} \frac{1}{2} \|\mathbf{X}\beta - \mathbf{y}\|_2^2 + \lambda \|\beta\|_1$$



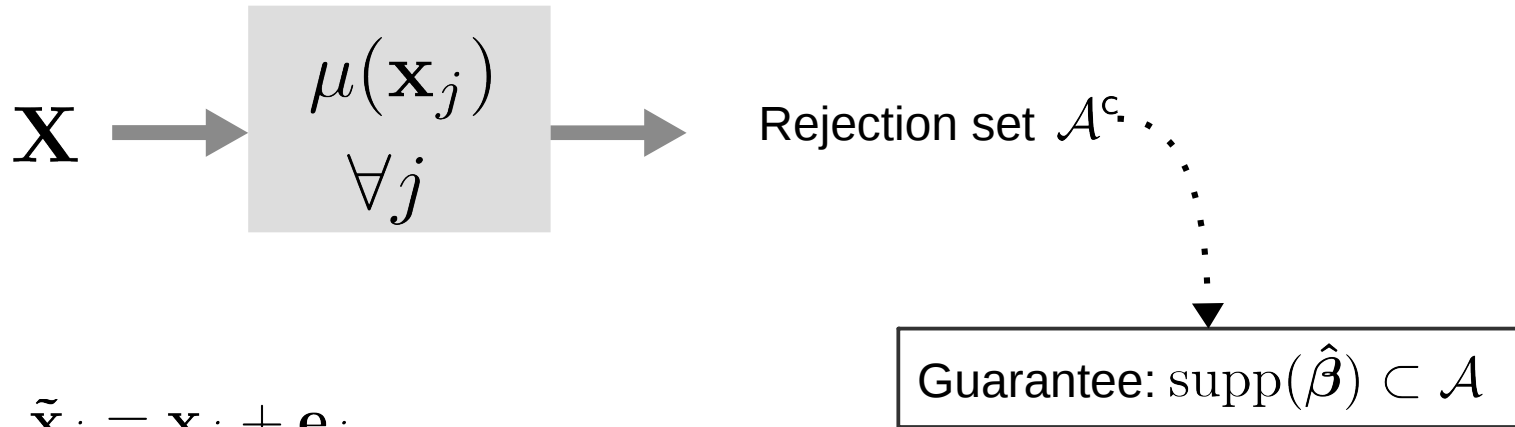
Guarantee:  $\operatorname{supp}(\hat{\beta}) \subset \mathcal{A}$

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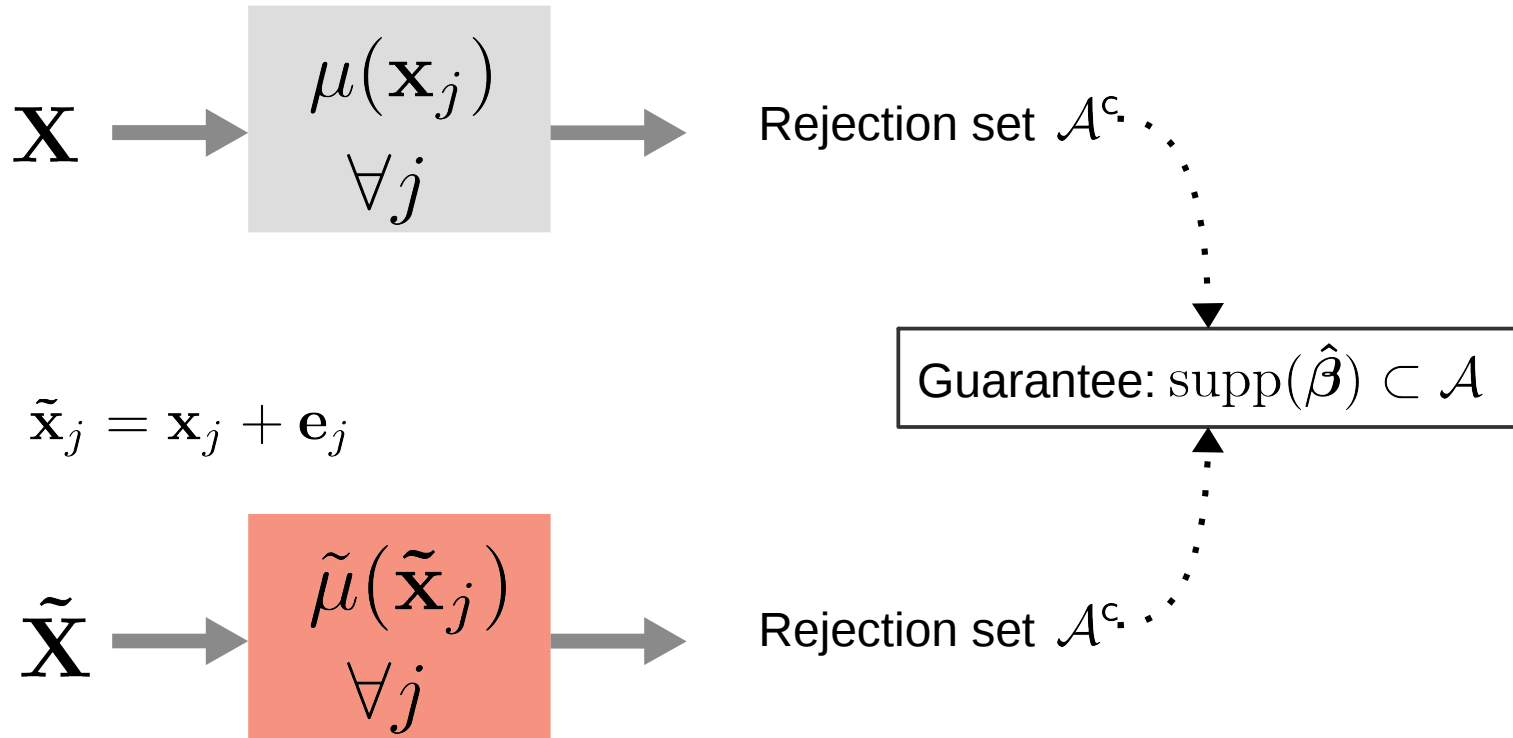




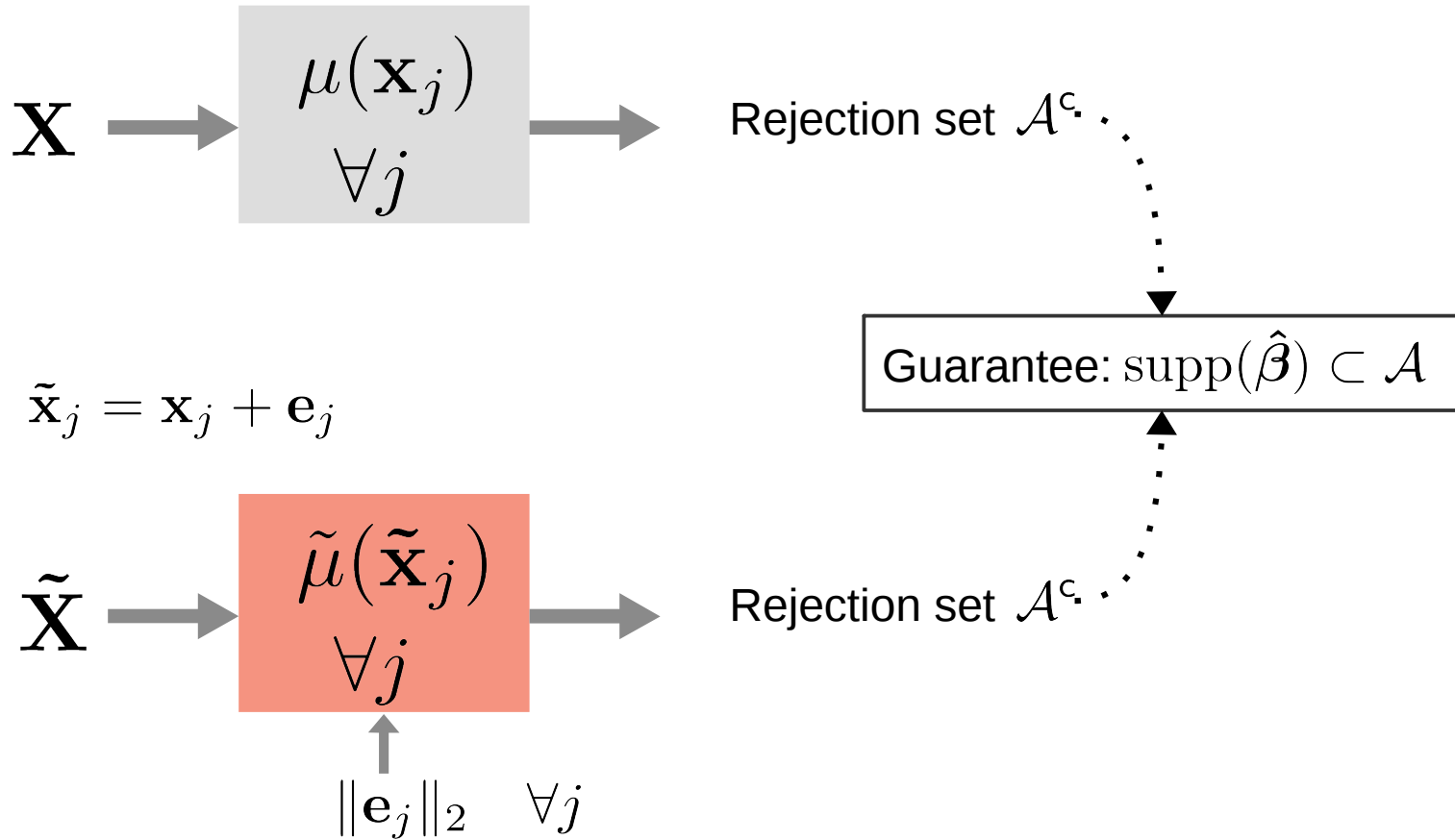
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# Extending sphere tests

Suppose a safe sphere  $B(\mathbf{c}, r)$  given.

**Sphere test :** 
$$\mu_{B(\mathbf{c}, r)}(\mathbf{x}_j) = |\mathbf{x}_j^T \mathbf{c}| + r \|\mathbf{x}_j\|_2.$$

A certain « **security margin** » must be added to account for the atom approximation error.

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A certain « **security margin** » must be added to account for the atom approximation error.

**Sphere test with approximate dictionary :**

$$\tilde{\mu}_{B(\mathbf{c}, r)}(\tilde{\mathbf{x}}_j) = |\tilde{\mathbf{x}}_j^T \mathbf{c}| + \|\mathbf{e}_j\|_2 \|\mathbf{c}\|_2 + r \|\mathbf{x}_j\|_2.$$

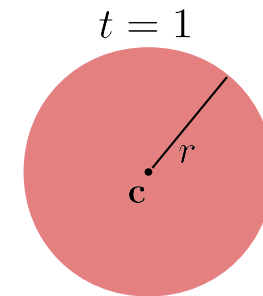
# Obtaining a safe sphere

## GAP safe sphere :

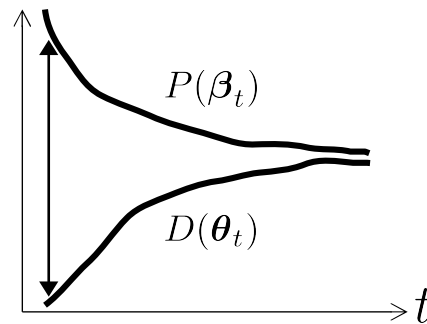
Given a primal-dual estimation  $(\beta_t, \theta_t)$  at iteration  $t$ .

$$\mathbf{c} = \theta_t$$

$$r = \frac{1}{\lambda} \sqrt{2G(\beta_t, \theta_t)}$$



with  $G(\beta_t, \theta_t) = P(\beta_t) - D(\theta_t)$  the duality gap at iteration  $t$ .



# Obtaining a safe sphere

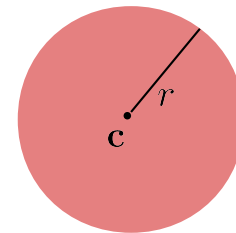
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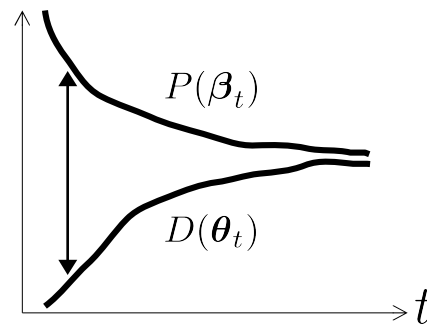
$$\mathbf{c} = \theta_t$$

$$r = \frac{1}{\lambda} \sqrt{2G(\beta_t, \theta_t)}$$

$t = 2$



with  $G(\beta_t, \theta_t) = P(\beta_t) - D(\theta_t)$  the duality gap at iteration  $t$ .



# Obtaining a safe sphere

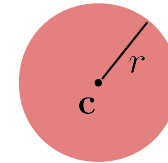
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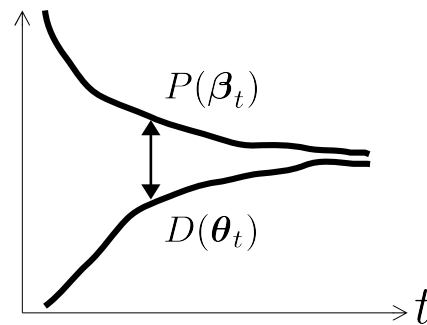
$$\mathbf{c} = \theta_t$$

$$r = \frac{1}{\lambda} \sqrt{2G(\beta_t, \theta_t)}$$

$t = 6$



with  $G(\beta_t, \theta_t) = P(\beta_t) - D(\theta_t)$  the duality gap at iteration  $t$ .





# Obtaining a safe sphere

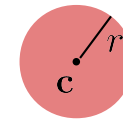
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Given a primal-dual estimation  $(\beta_t, \theta_t)$  at iteration  $t$ .

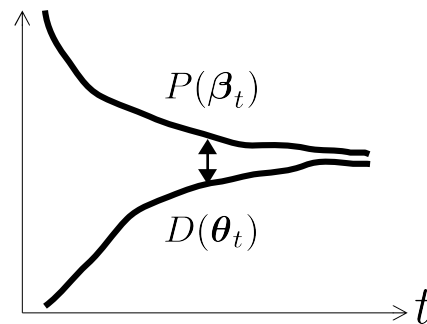
$$\mathbf{c} = \theta_t$$

$$t = 10$$

$$r = \frac{1}{\lambda} \sqrt{2G(\beta_t, \theta_t)}$$



with  $G(\beta_t, \theta_t) = P(\beta_t) - D(\theta_t)$  the duality gap at iteration  $t$ .



# Obtaining a safe sphere

## GAP safe sphere:

Given a primal-dual estimation  $(\beta_t, \theta_t)$  at iteration  $t$ .

$$\mathbf{c} = \theta_t$$

$$r = \frac{1}{\lambda} \sqrt{2G(\beta_t, \theta_t)}$$

## GAP safe sphere with approximate dictionary:

$G(\beta_t, \theta_t)$  cannot be calculated, since  $P(\beta_t) = \frac{1}{2} \|\mathbf{X}\beta_t - \mathbf{y}\|_2^2 + \lambda \|\beta_t\|_1$  depends on  $\mathbf{X}$ .

Instead, we use a modified primal  $\tilde{P}(\beta_t) = \frac{1}{2} \|\tilde{\mathbf{X}}\beta_t - \mathbf{y}\|_2^2 + \lambda \|\beta_t\|_1$

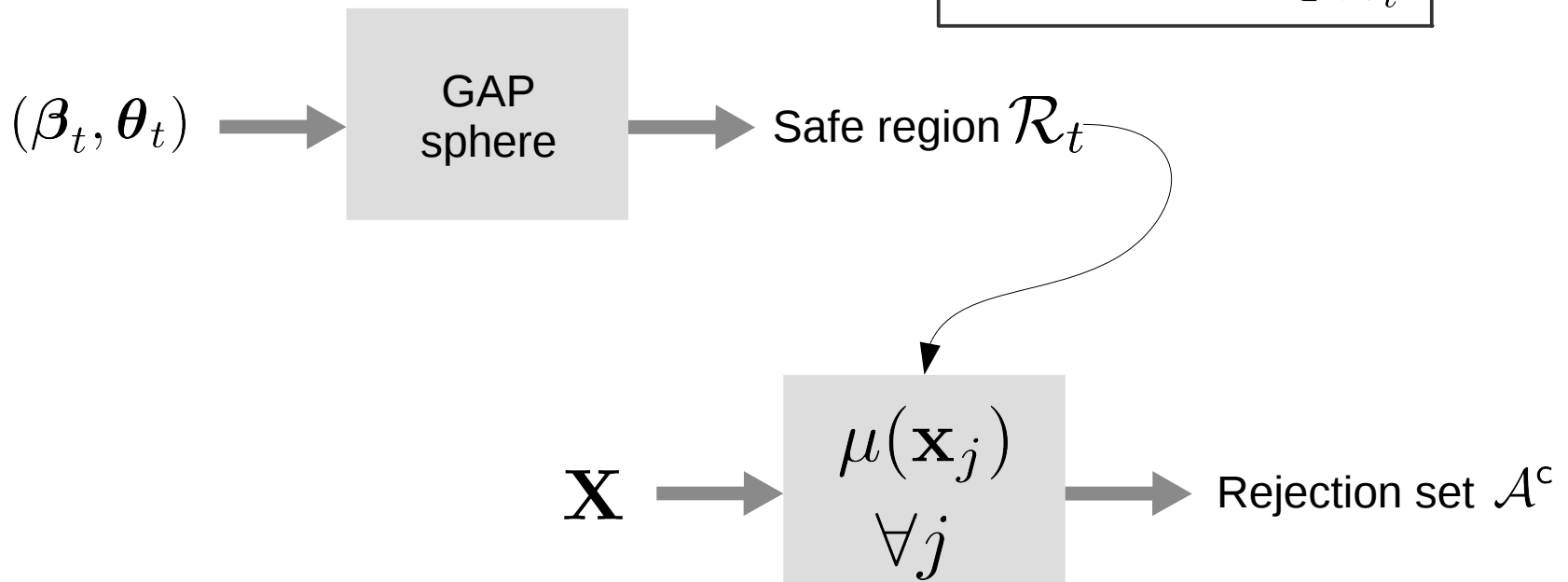
$$\tilde{\mathbf{c}} = \tilde{\theta}_t$$

$$\tilde{r} = \frac{1}{\lambda} \sqrt{2\tilde{G}(\beta_t, \tilde{\theta}_t) + 2\delta'}$$

with  $\delta' = \|\tilde{\rho}_t\|_2 \|\mathbf{E}\| \|\beta_t\|_2 + \frac{1}{2} \|\mathbf{E}\|^2 \|\beta_t\|_2^2$

# Dynamic screening

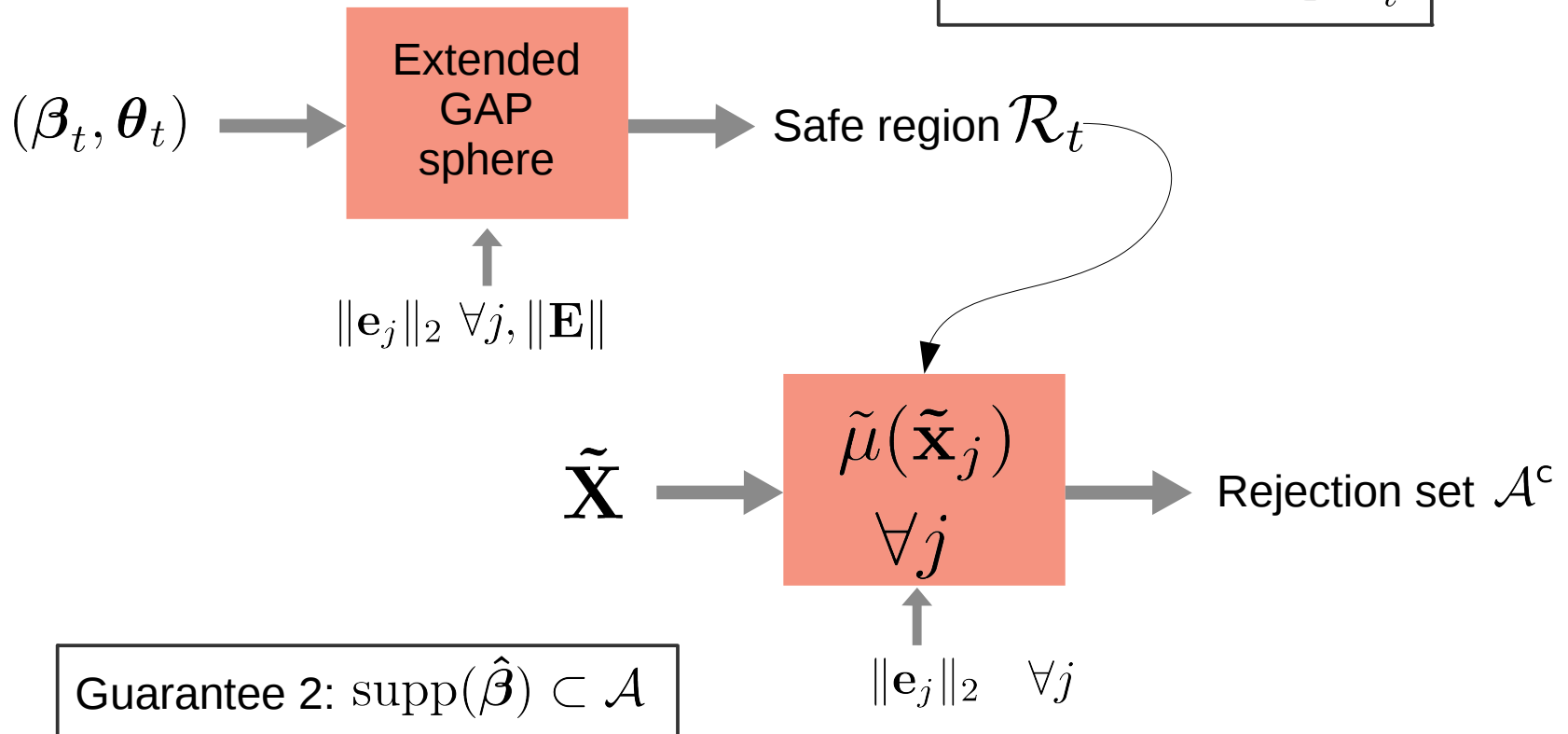
Guarantee 1:  $\hat{\theta} \in \mathcal{R}_t$



Guarantee 2:  $\text{supp}(\hat{\beta}) \subset \mathcal{A}$

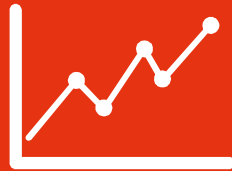
# Extended dynamic screening

Guarantee 1:  $\hat{\theta} \in \mathcal{R}_t$





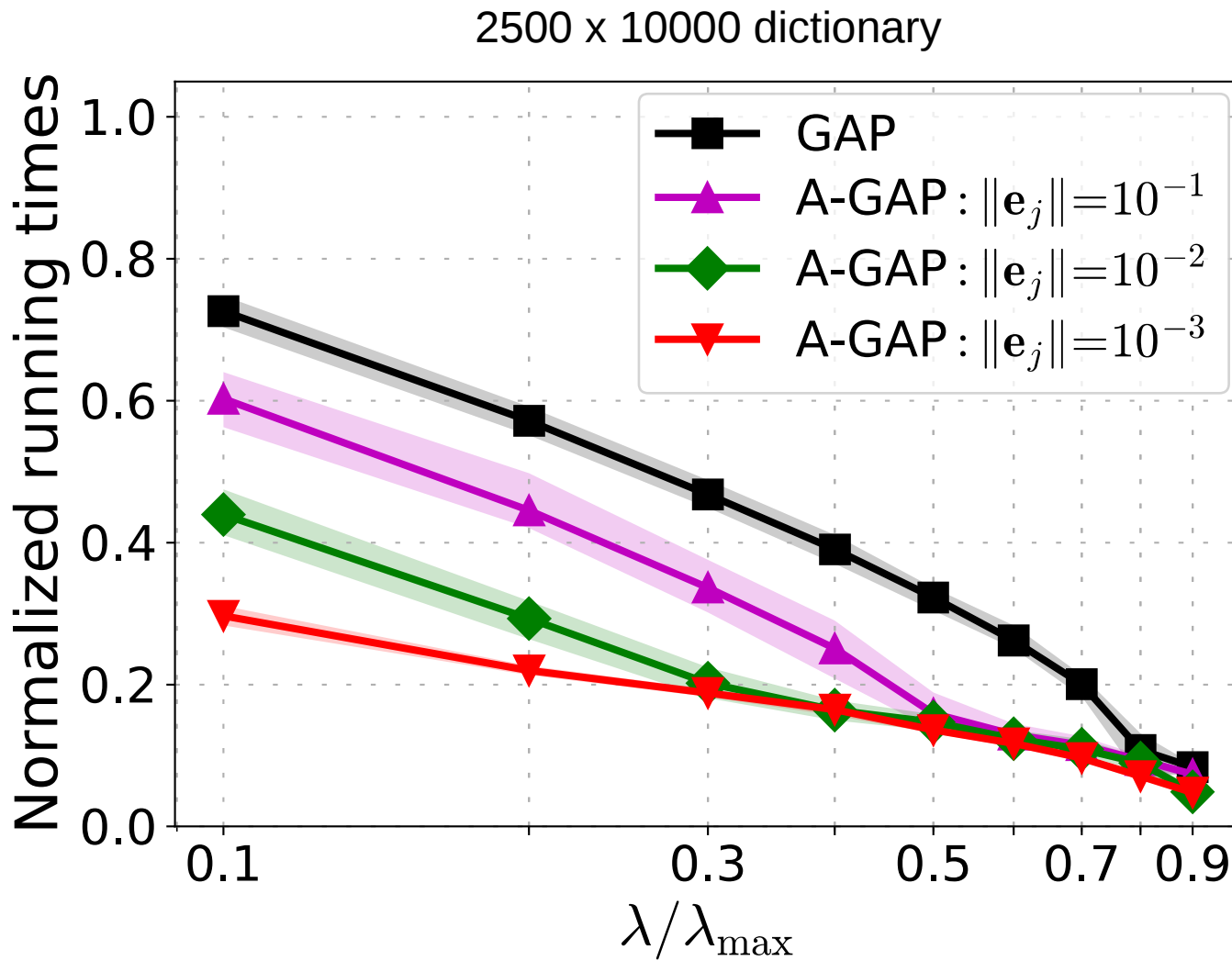
We now have safe screening rules that manipulate an approximate dictionary.



But, what's the impact of the numerous security margins? Is it still worth it?

# 05

## Results



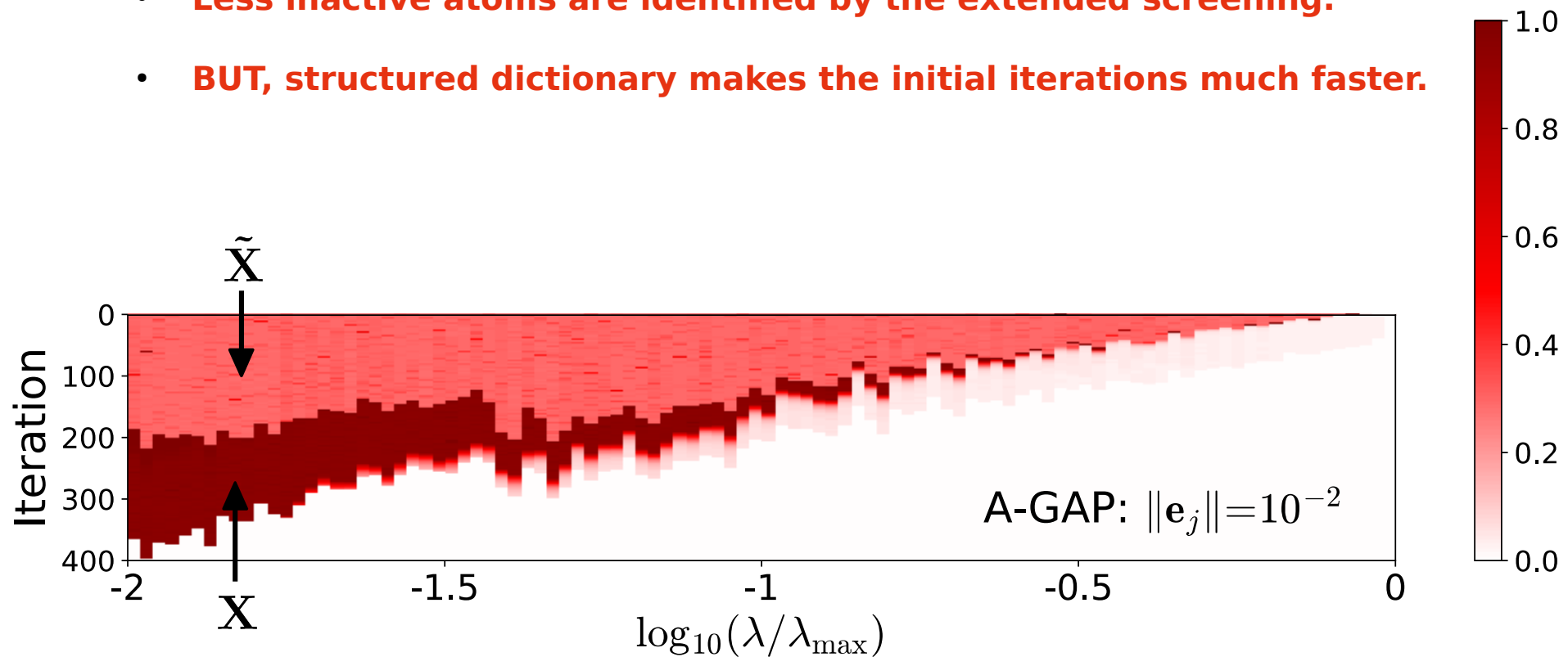
# Running times per iteration

- **Less inactive atoms are identified by the extended screening.**
- **BUT, structured dictionary makes the initial iterations much faster.**

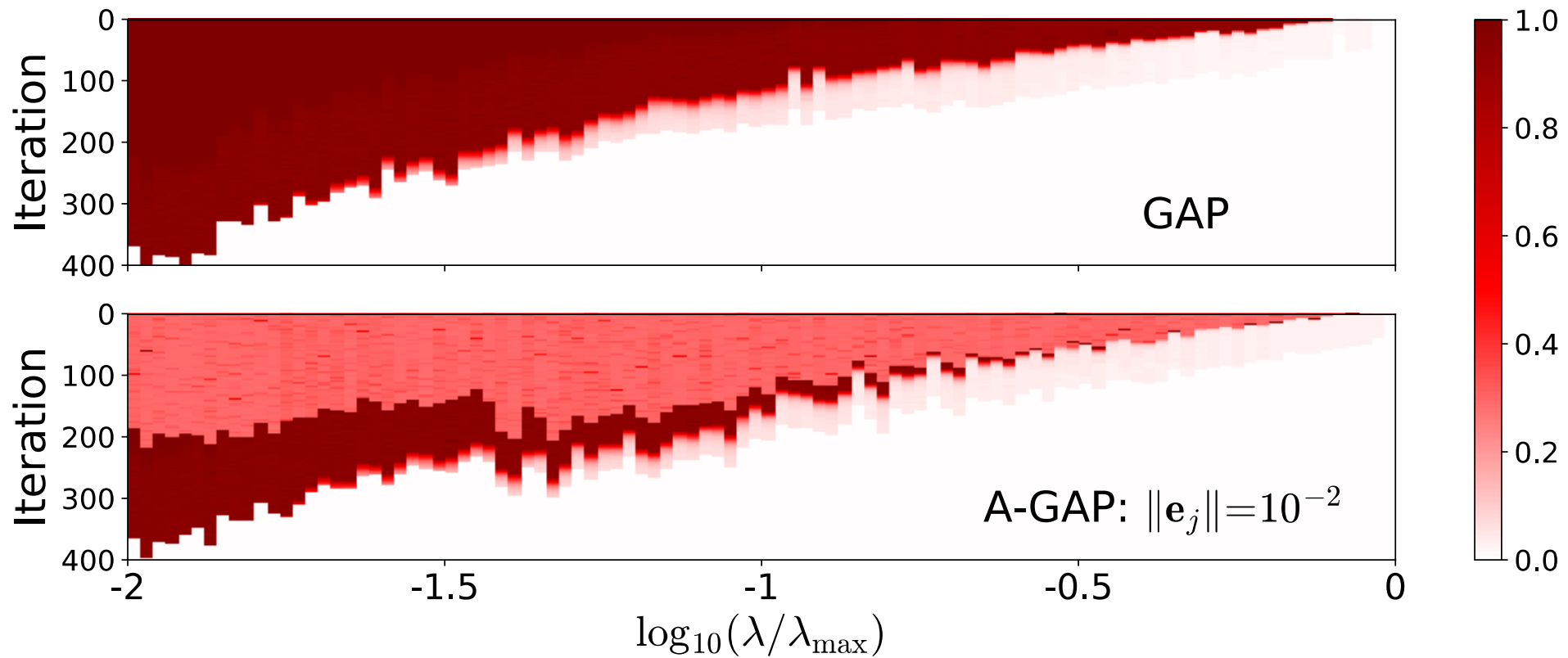


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# Running times per iteration



# 06

## Conclusion

# Conclusion

- The proposed approach combines screening rules and fast approximate dictionaries.
- It reduces even further the execution time w.r.t screening rules alone.

## Potential extensions

- Other region types (e.g. domes)
- Other problems than Lasso (e.g. Group-Lasso, Regularized Logistic Regression)

# Thank you!

Questions?

Contact me: [cassio.fraga-dantas@inria.fr](mailto:cassio.fraga-dantas@inria.fr)



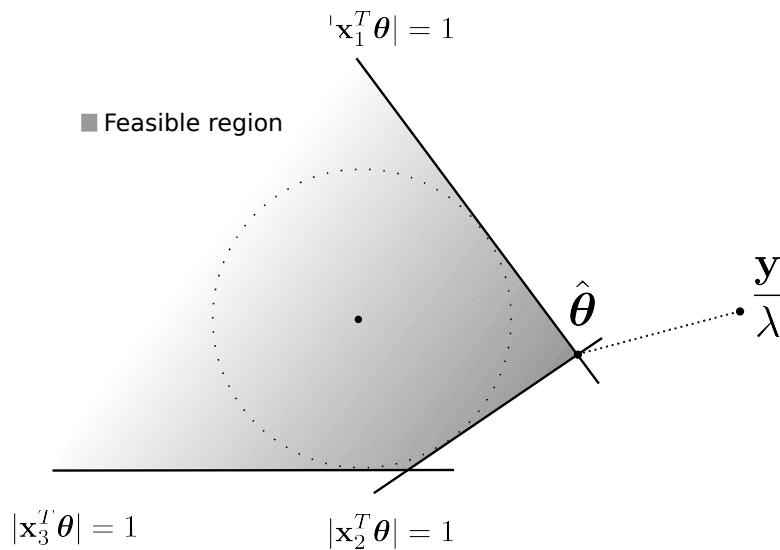


# Screening test – Details

Dual formulation of the Lasso problem :

$$\hat{\boldsymbol{\theta}} = \underset{\boldsymbol{\theta}}{\operatorname{argmax}} \frac{1}{2} \|\mathbf{y}\|_2^2 - \frac{\lambda^2}{2} \left\| \boldsymbol{\theta} - \frac{\mathbf{y}}{\lambda} \right\|_2^2$$

$$\text{s.t.} \quad \|\mathbf{X}^T \boldsymbol{\theta}\|_\infty \leq 1.$$



Projection problem !

At the dual solution  $\hat{\boldsymbol{\theta}}$ :

- Constraints on  $\mathbf{x}_1$  and  $\mathbf{x}_2$  are active, i.e.

$$|\mathbf{x}_1^T \hat{\boldsymbol{\theta}}| = 1, \quad |\mathbf{x}_2^T \hat{\boldsymbol{\theta}}| = 1$$


- Constraints on  $\mathbf{x}_3$  is inactive, i.e.

$$|\mathbf{x}_3^T \hat{\boldsymbol{\theta}}| < 1$$

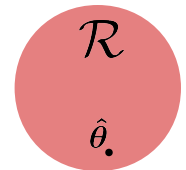


# Screening test – Details

- Every dictionary atom for which  $|\mathbf{x}_j^T \hat{\boldsymbol{\theta}}| < 1$  is **inactive**.
- Then, simply calculate  $|\mathbf{x}_j^T \hat{\boldsymbol{\theta}}|$  for all  $j$  and discard all atoms for which the result is smaller than 1.

 Dual solution  $\hat{\boldsymbol{\theta}}$  is not known.

 Identify a region  $\mathcal{R}$  (**safe region**) which contains  $\hat{\boldsymbol{\theta}}$ .



Sufficient condition :  $\forall \boldsymbol{\theta} \in \mathcal{R}, |\mathbf{x}_j^T \boldsymbol{\theta}| < 1 \implies \mathbf{x}_j$  is inactive



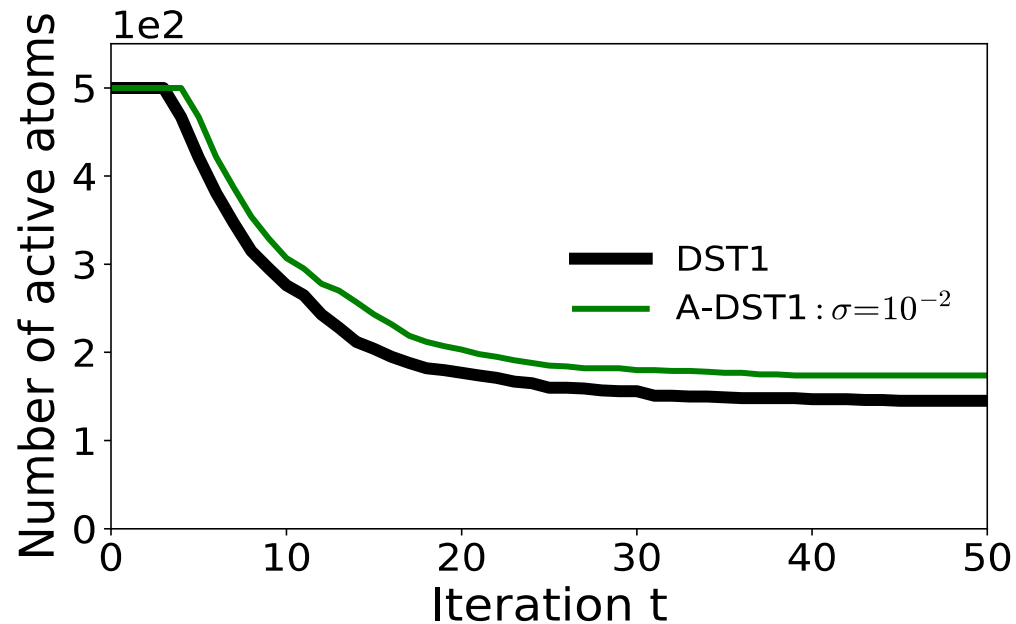
# Switching criterion

Reasons to switch back from  $\tilde{\mathbf{X}}$  to  $\mathbf{X}$ :

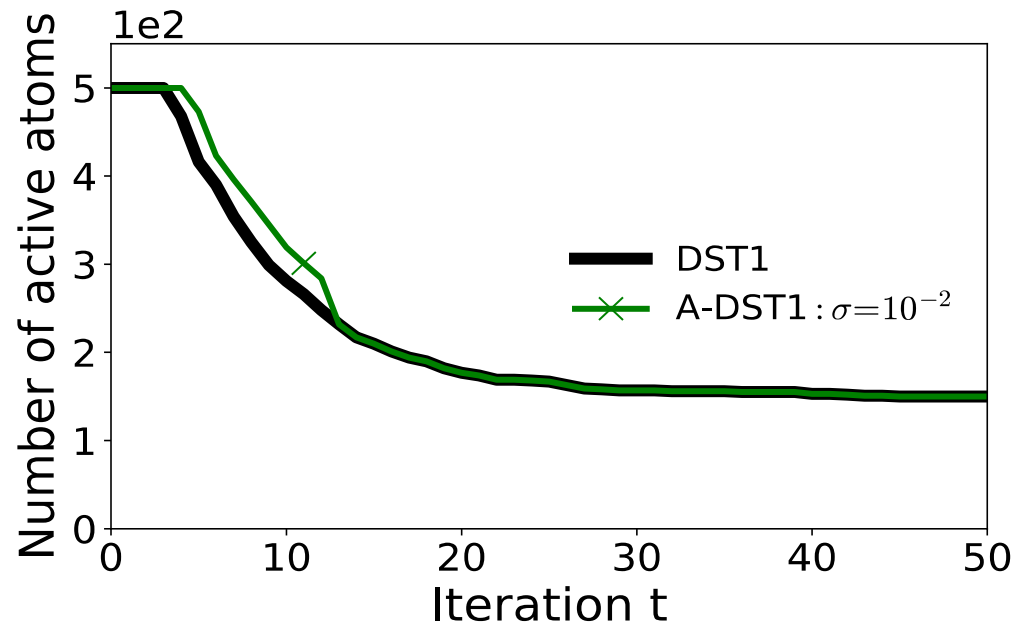
- **Convergence:** to avoid converging to the solution of the approximate problem.
  - The higher the approximation error, the sooner we need to switch.
- **Screening ratio:** the number of active atoms may become so small that the use of  $\tilde{\mathbf{X}}$  does not pay off anymore.

# Comparison

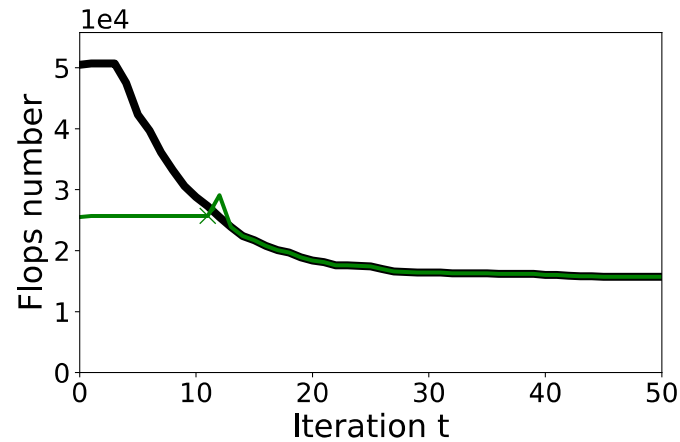
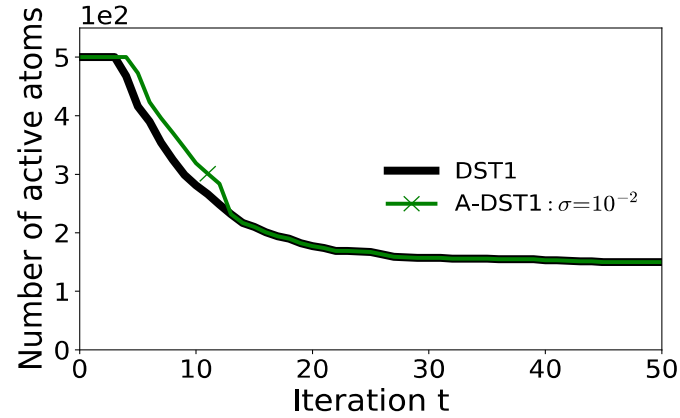
**Less inactive atoms are identified by the extended screening.**



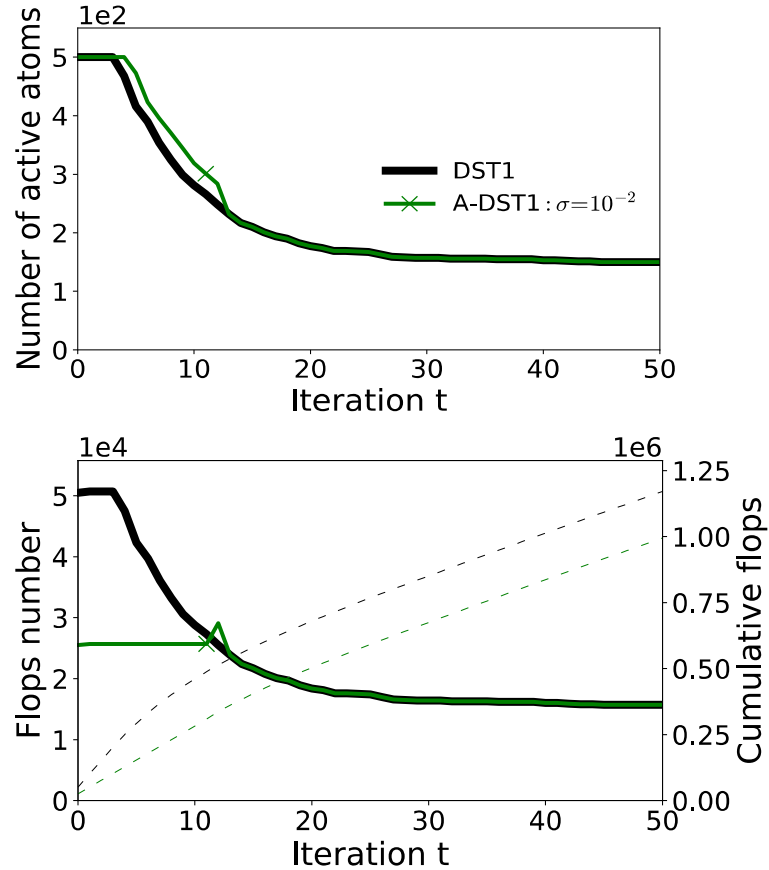
# Switching criterion



# Complexity reduction



# Complexity reduction



# Impact of the Approximation Error

