Structured sparse methods for matrix factorization

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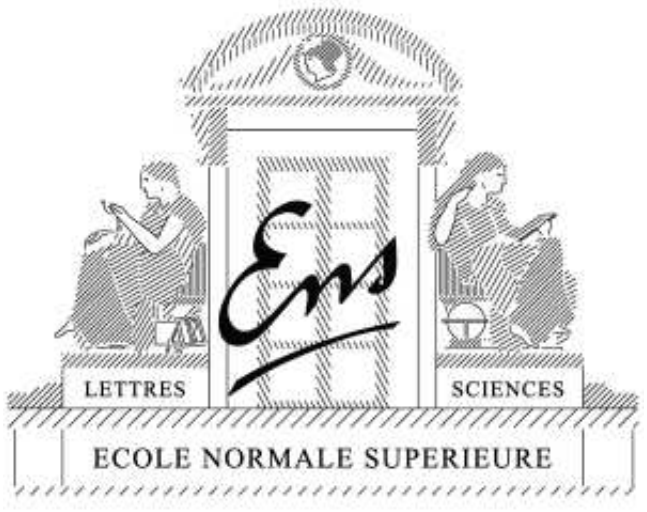

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Joint work with **R. Jenatton, J. Mairal, G. Obozinski**

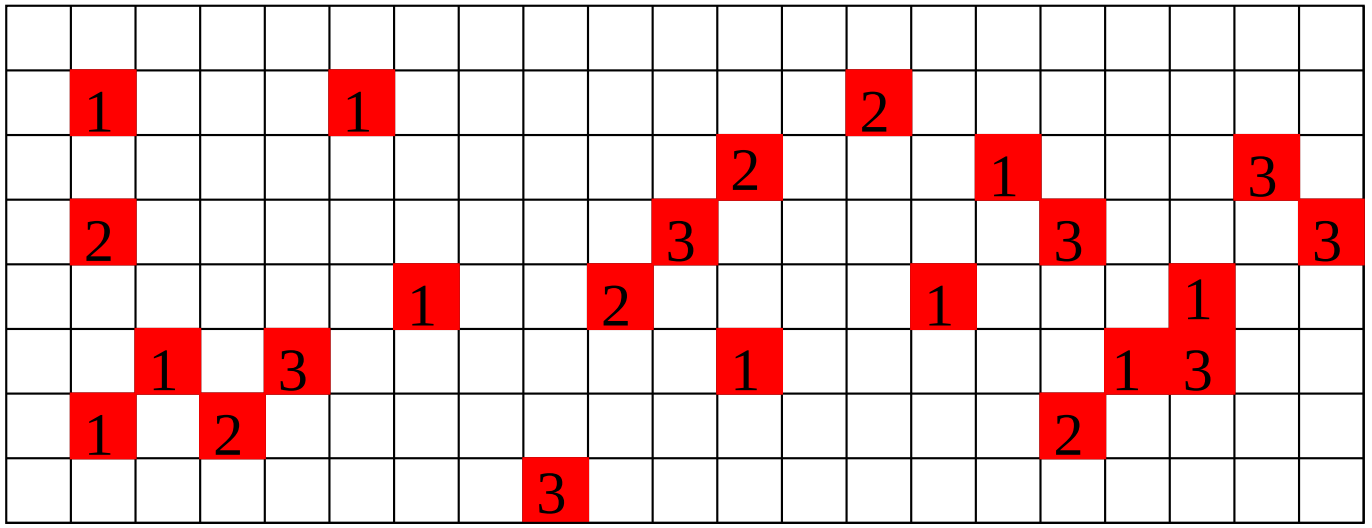
Structured sparse methods for matrix factorization

Outline

- **Learning problems on matrices**
- **Sparse methods for matrices**
  - Sparse principal component analysis
  - Dictionary learning
- **Structured sparse PCA**
  - Sparsity-inducing norms and overlapping groups
  - Structure on dictionary elements
  - Structure on decomposition coefficients

Learning on matrices - Collaborative filtering

- Given $n_{\mathcal{X}}$ "movies" $\mathbf{x} \in \mathcal{X}$ and $n_{\mathcal{Y}}$ "customers" $\mathbf{y} \in \mathcal{Y}$,
- Predict the "rating" $z(\mathbf{x}, \mathbf{y}) \in \mathcal{Z}$ of customer $\mathbf{y}$ for movie $\mathbf{x}$
- Training data: large $n_{\mathcal{X}} \times n_{\mathcal{Y}}$ incomplete matrix $\mathbf{Z}$ that describes the known ratings of some customers for some movies
- **Goal**: complete the matrix.

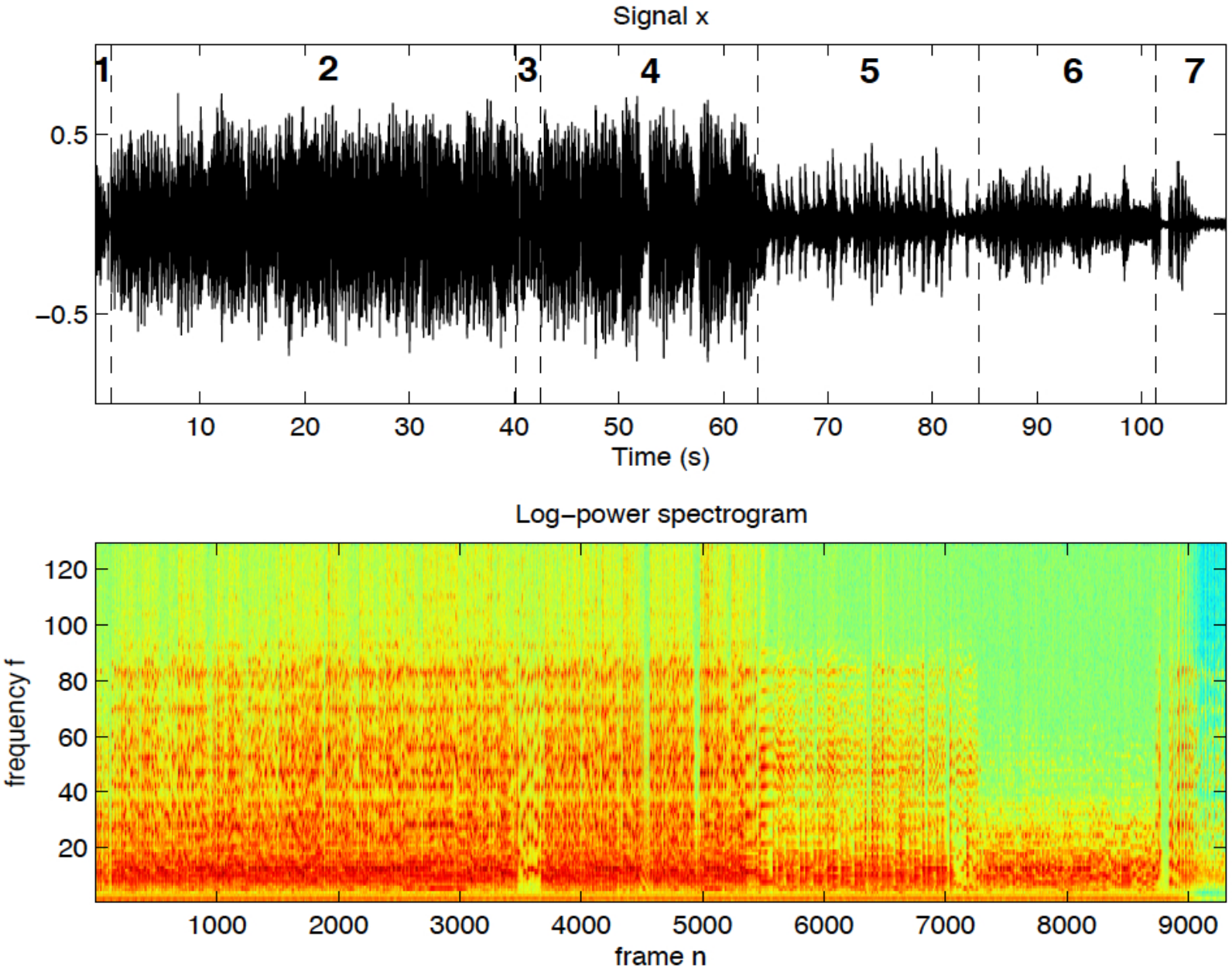


Learning on matrices - Image denoising

- Simultaneously denoise all patches of a given image
- Example from Mairal, Bach, Ponce, Sapiro, and Zisserman (2009c)

Learning on matrices - Source separation

- Single microphone (Benaroya et al., 2006; Févotte et al., 2009)

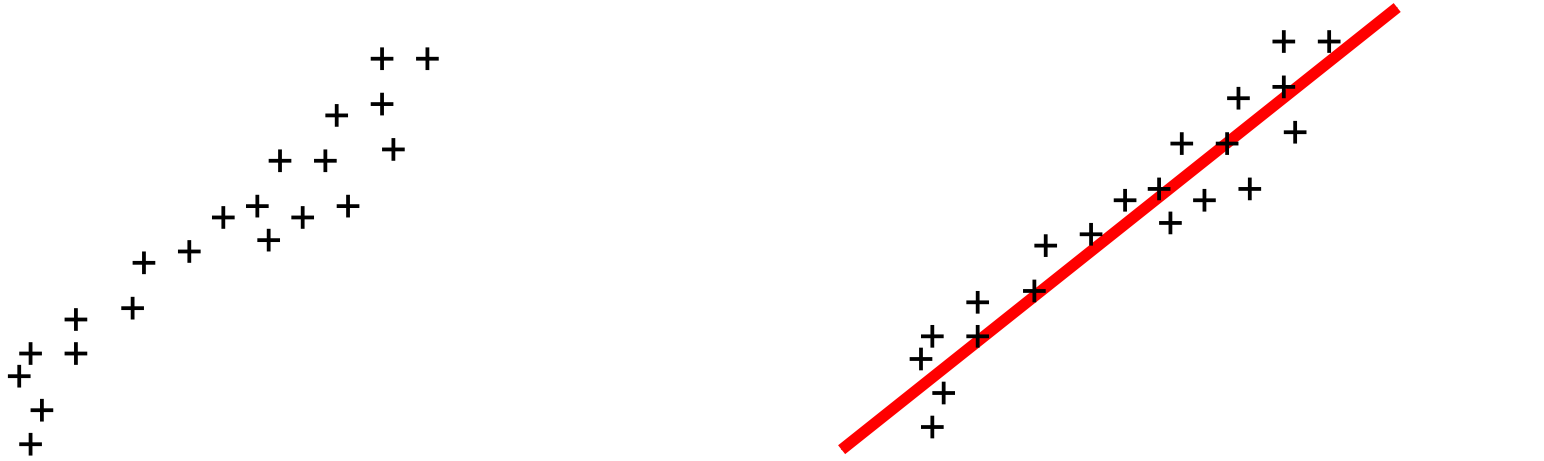


Learning on matrices - Multi-task learning

- k linear prediction tasks on same covariates $\mathbf{x} \in \mathbb{R}^p$
  - k weight vectors $\mathbf{w}_j \in \mathbb{R}^p$
  - Joint matrix of predictors $\mathbf{W} = (\mathbf{w}_1, \ldots, \mathbf{w}_k) \in \mathbb{R}^{p \times k}$
- Classical applications
  - Transfer learning
  - Multi-category classification (one task per class) (Amit et al., 2007)
- **Share parameters between tasks**
  - Joint variable or feature selection (Obozinski et al., 2009; Pontil et al., 2007)

Learning on matrices - Dimension reduction

- Given data matrix $\mathbf{X} = (\mathbf{x}_1^\top, \ldots, \mathbf{x}_n^\top) \in \mathbb{R}^{n \times p}$
  - **Principal component analysis**: $\boxed{\mathbf{x}_i \approx \mathbf{D}\boldsymbol{\alpha}_i}$

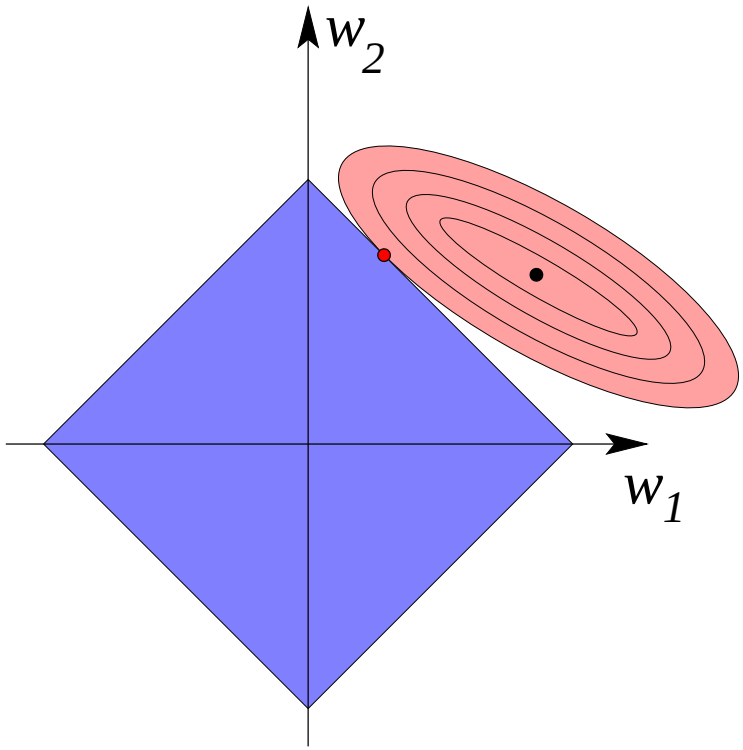


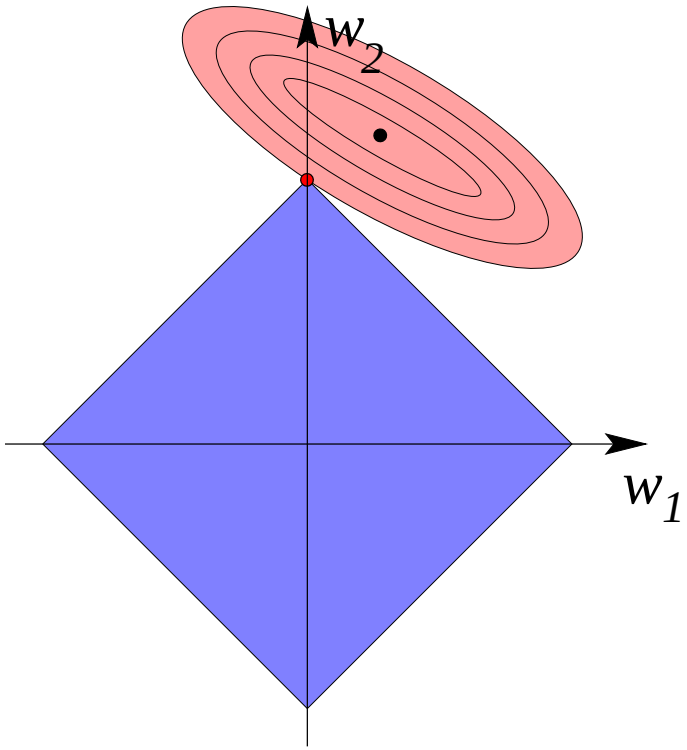
  - **K-means**: $\boxed{\mathbf{x}_i \approx \mathbf{d}_k \Rightarrow \mathbf{X} = \mathbf{DA}}$

Sparsity in machine learning

- **Assumption**: $\mathbf{y} = \mathbf{w}^\top \mathbf{x} + \varepsilon$, with $\mathbf{w} \in \mathbb{R}^p$ sparse
  - Proxy for interpretability
  - Allow high-dimensional inference: $\boxed{\log p = O(n)}$

- **Sparsity and convexity** (ℓ_1-norm regularization): $\boxed{\min_{\mathbf{w} \in \mathbb{R}^p} L(\mathbf{w}) + \|\mathbf{w}\|_1}$

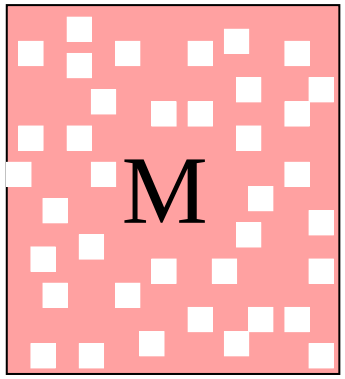




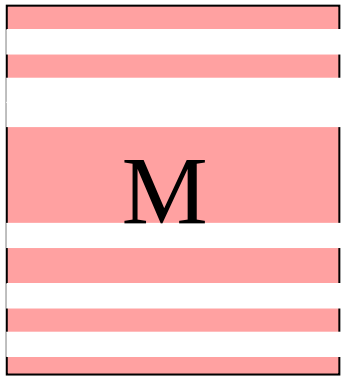
Two types of sparsity for matrices $\mathbf{M} \in \mathbb{R}^{n \times p}$

I - Directly on the elements of $\mathbf{M}$

- Many zero elements: $\mathbf{M}_{ij} = 0$

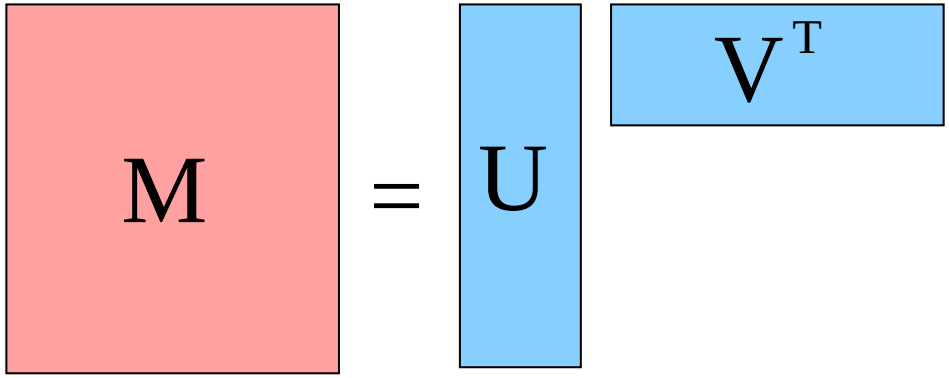


- Many zero rows (or columns): $(\mathbf{M}_{i1}, \ldots, \mathbf{M}_{ip}) = 0$

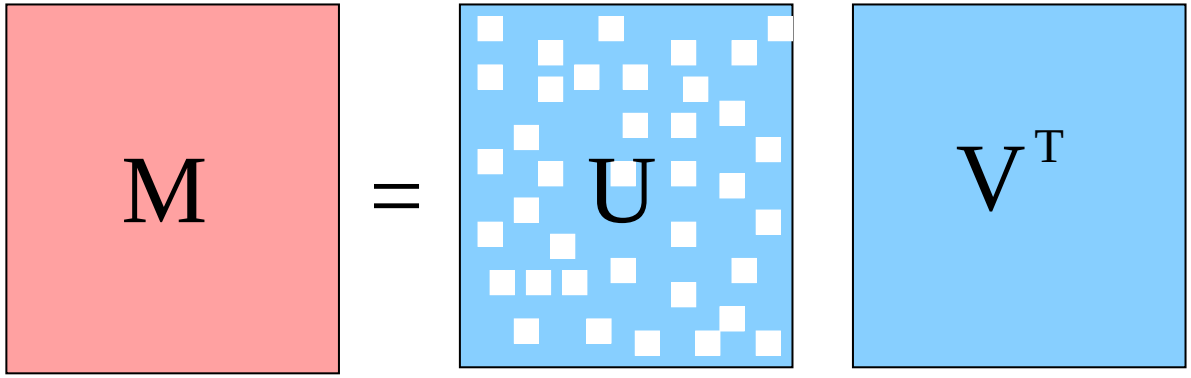


Two types of sparsity for matrices $\mathbf{M} \in \mathbb{R}^{n \times p}$
II - Through a factorization of $\mathbf{M} = \mathbf{U}\mathbf{V}^\top$

- Matrix $\mathbf{M} = \mathbf{U}\mathbf{V}^\top$, $\mathbf{U} \in \mathbb{R}^{n \times k}$ and $\mathbf{V} \in \mathbb{R}^{p \times k}$
- **Low rank**: m small



- **Sparse decomposition**: $\mathbf{U}$ sparse



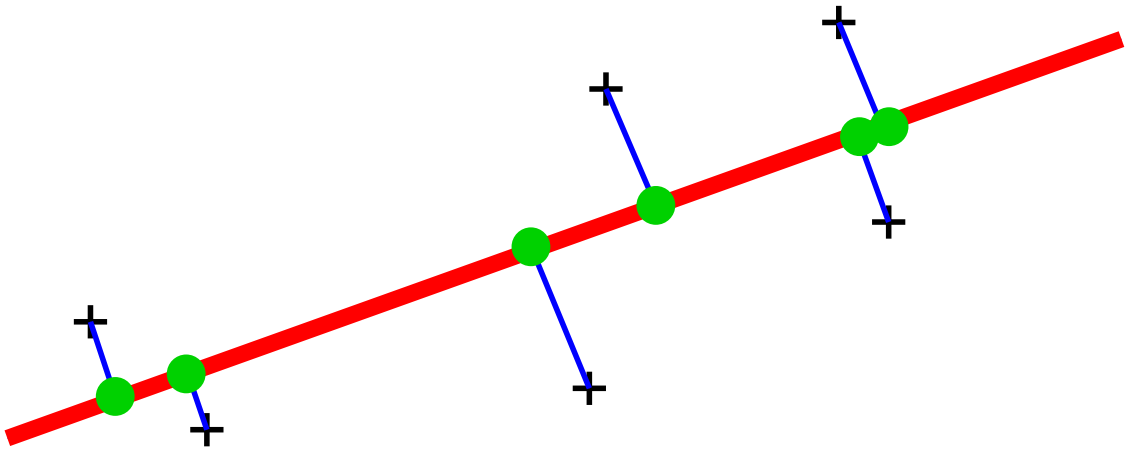
Structured (sparse) matrix factorizations

- Matrix $\mathbf{M} = \mathbf{U}\mathbf{V}^\top$, $\mathbf{U} \in \mathbb{R}^{n \times k}$ and $\mathbf{V} \in \mathbb{R}^{p \times k}$
- **Structure on $\mathbf{U}$ and/or $\mathbf{V}$**
  - Low-rank: $\mathbf{U}$ and $\mathbf{V}$ have few columns
  - Dictionary learning / sparse PCA: $\mathbf{U}$ has many zeros
  - Clustering (k-means): $\mathbf{U} \in \{0,1\}^{n \times m}$, $\mathbf{U}\mathbf{1} = \mathbf{1}$
  - Pointwise positivity: non negative matrix factorization (NMF)
  - Specific patterns of zeros
  - Low-rank + sparse (Candès et al., 2009)
  - etc.
- **Many applications**
- **Many open questions**: algorithms, identifiability, evaluation

Sparse principal component analysis

- Given data $\mathbf{X} = (\mathbf{x}_1^\top, \ldots, \mathbf{x}_n^\top) \in \mathbb{R}^{p \times n}$, two views of PCA:
  - **Analysis view**: find the projection $\mathbf{d} \in \mathbb{R}^p$ of maximum variance (with deflation to obtain more components)
  - **Synthesis view**: find the basis $\mathbf{d}_1, \ldots, \mathbf{d}_k$ such that all $\mathbf{x}_i$ have low reconstruction error when decomposed on this basis

- For regular PCA, the two views are equivalent



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- For regular PCA, the two views are equivalent
- **Sparse (and/or non-negative) extensions**
  - Interpretability
  - High-dimensional inference
  - Two views are differents
  - For analysis view, see d'Aspremont, Bach, and El Ghaoui (2008)

Sparse principal component analysis
Synthesis view

- Find $\mathbf{d}_1, \ldots, \mathbf{d}_k \in \mathbb{R}^p$ **sparse** so that

$$\sum_{i=1}^{n} \min_{\boldsymbol{\alpha}_i \in \mathbb{R}^m} \left\| \mathbf{x}_i - \sum_{j=1}^{k} (\boldsymbol{\alpha}_i)_j \mathbf{d}_j \right\|_2^2 = \sum_{i=1}^{n} \min_{\boldsymbol{\alpha}_i \in \mathbb{R}^m} \left\| \mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i \right\|_2^2 \text{ is small}$$

  - Look for $\mathbf{A} = (\boldsymbol{\alpha}_1, \ldots, \boldsymbol{\alpha}_n) \in \mathbb{R}^{k \times n}$ and $\mathbf{D} = (\mathbf{d}_1, \ldots, \mathbf{d}_k) \in \mathbb{R}^{p \times k}$ such that $\mathbf{D}$ is sparse and $\|\mathbf{X} - \mathbf{D}\mathbf{A}\|_F^2$ is small

Sparse principal component analysis
Synthesis view

- Find $\mathbf{d}_1, \ldots, \mathbf{d}_k \in \mathbb{R}^p$ **sparse** so that

$$\sum_{i=1}^{n} \min_{\boldsymbol{\alpha}_i \in \mathbb{R}^m} \left\| \mathbf{x}_i - \sum_{j=1}^{k} (\boldsymbol{\alpha}_i)_j \mathbf{d}_j \right\|_2^2 = \sum_{i=1}^{n} \min_{\boldsymbol{\alpha}_i \in \mathbb{R}^m} \|\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i\|_2^2 \text{ is small}$$

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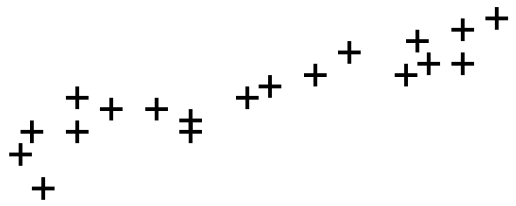
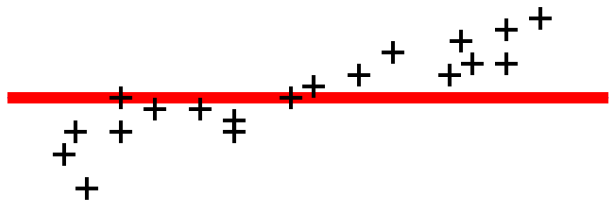
- Sparse formulation (Witten et al., 2009; Bach et al., 2008)
  - Penalize/constrain $\mathbf{d}_j$ by the ℓ_1-norm for sparsity
  - Penalize/constrain $\boldsymbol{\alpha}_i$ by the ℓ_2-norm to avoid trivial solutions

$$\min_{\mathbf{D},\mathbf{A}} \sum_{i=1}^{n} \|\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i\|_2^2 + \lambda \sum_{j=1}^{k} \|\mathbf{d}_j\|_1 \text{ s.t. } \forall i, \|\boldsymbol{\alpha}_i\|_2 \leqslant 1$$

Sparse PCA vs. dictionary learning

- **Sparse PCA**: $\mathbf{x}_i \approx \mathbf{D}\boldsymbol{\alpha}_i$, $\mathbf{D}$ sparse

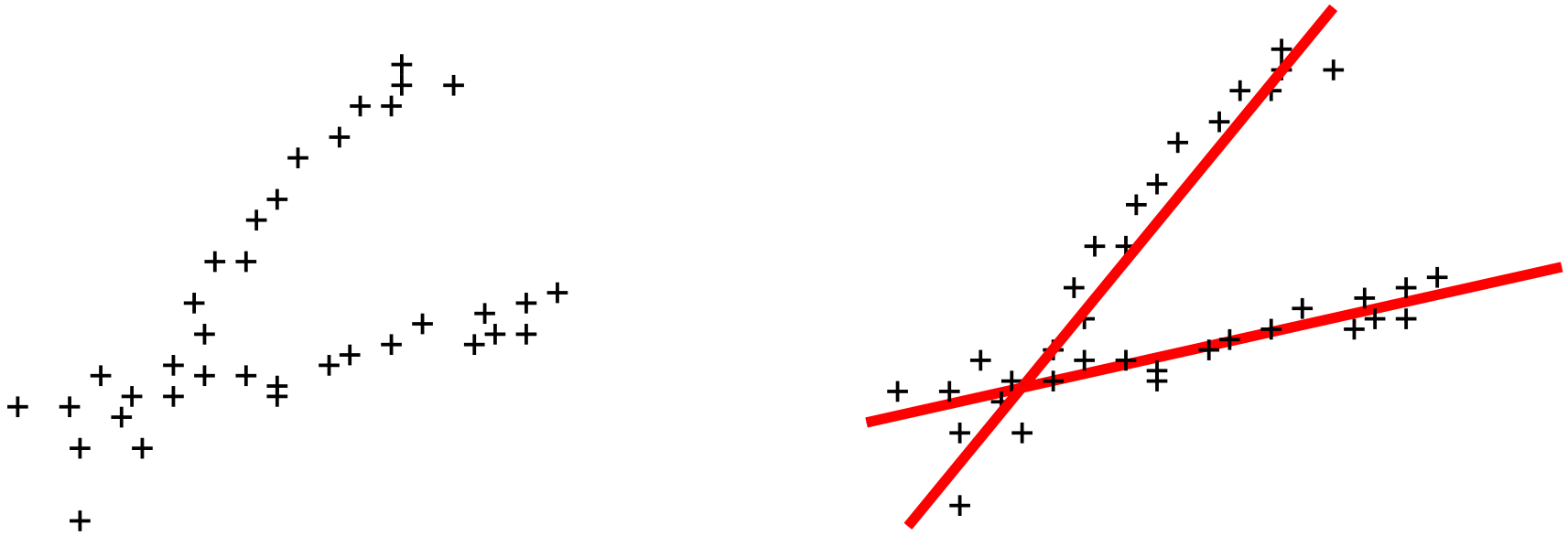




Sparse PCA vs. dictionary learning

- **Sparse PCA**: $\mathbf{x}_i \approx \mathbf{D}\boldsymbol{\alpha}_i$, $\mathbf{D}$ sparse

- **Dictionary learning**: $\mathbf{x}_i \approx \mathbf{D}\boldsymbol{\alpha}_i$, $\boldsymbol{\alpha}_i$ sparse



Structured matrix factorizations (Bach et al., 2008)

$$\min_{\mathbf{D},\mathbf{A}} \sum_{i=1}^{n} \|\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i\|_2^2 + \lambda \sum_{j=1}^{k} \|\mathbf{d}_j\|_\star \text{ s.t. } \forall i, \|\boldsymbol{\alpha}_i\|_\bullet \leqslant 1$$

$$\min_{\mathbf{D},\mathbf{A}} \sum_{i=1}^{n} \|\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i\|_2^2 + \lambda \sum_{i=1}^{n} \|\boldsymbol{\alpha}_i\|_\bullet \text{ s.t. } \forall j, \|\mathbf{d}_j\|_\star \leqslant 1$$

- Optimization by alternating minimization (non-convex)
- $\boldsymbol{\alpha}_i$ decomposition coefficients (or "code"), $\mathbf{d}_j$ dictionary elements
- Two related/equivalent problems:
  - **Sparse PCA = sparse dictionary** (ℓ_1-norm on $\mathbf{d}_j$)
  - **Dictionary learning = sparse decompositions** (ℓ_1-norm on $\boldsymbol{\alpha}_i$) (Olshausen and Field, 1997; Elad and Aharon, 2006; Lee et al., 2007)

Dictionary learning for image denoising

$$\underbrace{\mathbf{x}}_{\text{measurements}} = \underbrace{\mathbf{y}}_{\text{original image}} + \underbrace{\varepsilon}_{\text{noise}}$$

Dictionary learning for image denoising

- **Solving the denoising problem** (Elad and Aharon, 2006)
  - Extract all overlapping 8×8 patches $\mathbf{x}_i \in \mathbb{R}^{64}$
  - Form the matrix $\mathbf{X} = (\mathbf{x}_1^\top, \ldots, \mathbf{x}_n^\top) \in \mathbb{R}^{n \times 64}$
  - Solve a matrix factorization problem:

$$\min_{\mathbf{D},\mathbf{A}} ||\mathbf{X} - \mathbf{D}\mathbf{A}||_F^2 = \min_{\mathbf{D},\mathbf{A}} \sum_{i=1}^{n} ||\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i||_2^2$$

    where $\mathbf{A}$ is **sparse**, and $\mathbf{D}$ is the **dictionary**
  - Each patch is decomposed into $\mathbf{x}_i = \mathbf{D}\boldsymbol{\alpha}_i$
  - Average the reconstruction $\mathbf{D}\boldsymbol{\alpha}_i$ of each patch $\mathbf{x}_i$ to reconstruct a full-sized image

- The number of patches n is large ($=$ number of pixels)

Online optimization for dictionary learning

$$\min_{\mathbf{A}\in\mathbb{R}^{k\times n},\mathbf{D}\in\mathcal{D}} \sum_{i=1}^{n} \left\{ ||\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i||_2^2 + \lambda ||\boldsymbol{\alpha}_i||_1 \right\}$$

$$\mathcal{D} \triangleq \{\mathbf{D} \in \mathbb{R}^{p\times k} \text{ s.t. } \forall j = 1,\ldots,k, \quad ||\mathbf{d}_j||_2 \leqslant 1\}.$$

- Classical optimization alternates between $\mathbf{D}$ and $\mathbf{A}$.
- Good results, but very slow !

Online optimization for dictionary learning

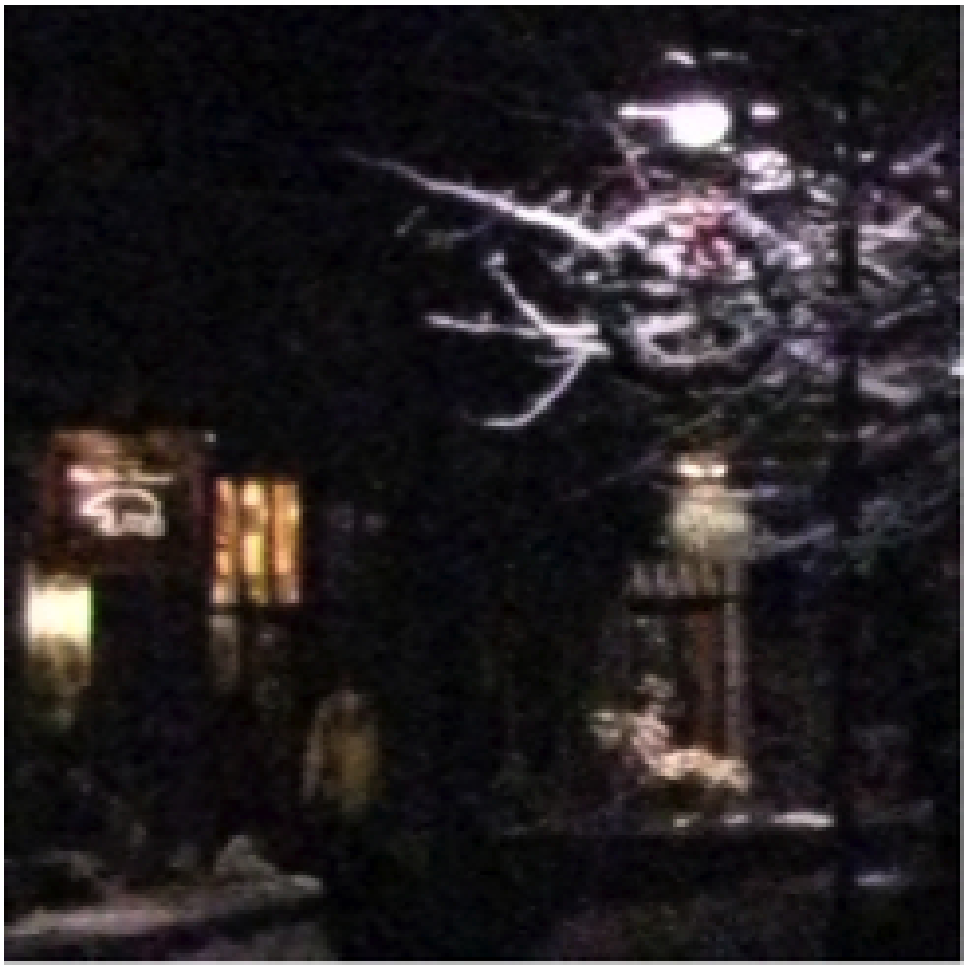
$$\min_{\mathbf{D}\in\mathcal{D}} \sum_{i=1}^{n} \min_{\boldsymbol{\alpha}_i} \left\{ ||\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i||_2^2 + \lambda ||\boldsymbol{\alpha}_i||_1 \right\}$$

$$\mathcal{D} \triangleq \{\mathbf{D} \in \mathbb{R}^{p\times k} \text{ s.t. } \forall j = 1,\ldots,k, \quad ||\mathbf{d}_j||_2 \leqslant 1\}.$$

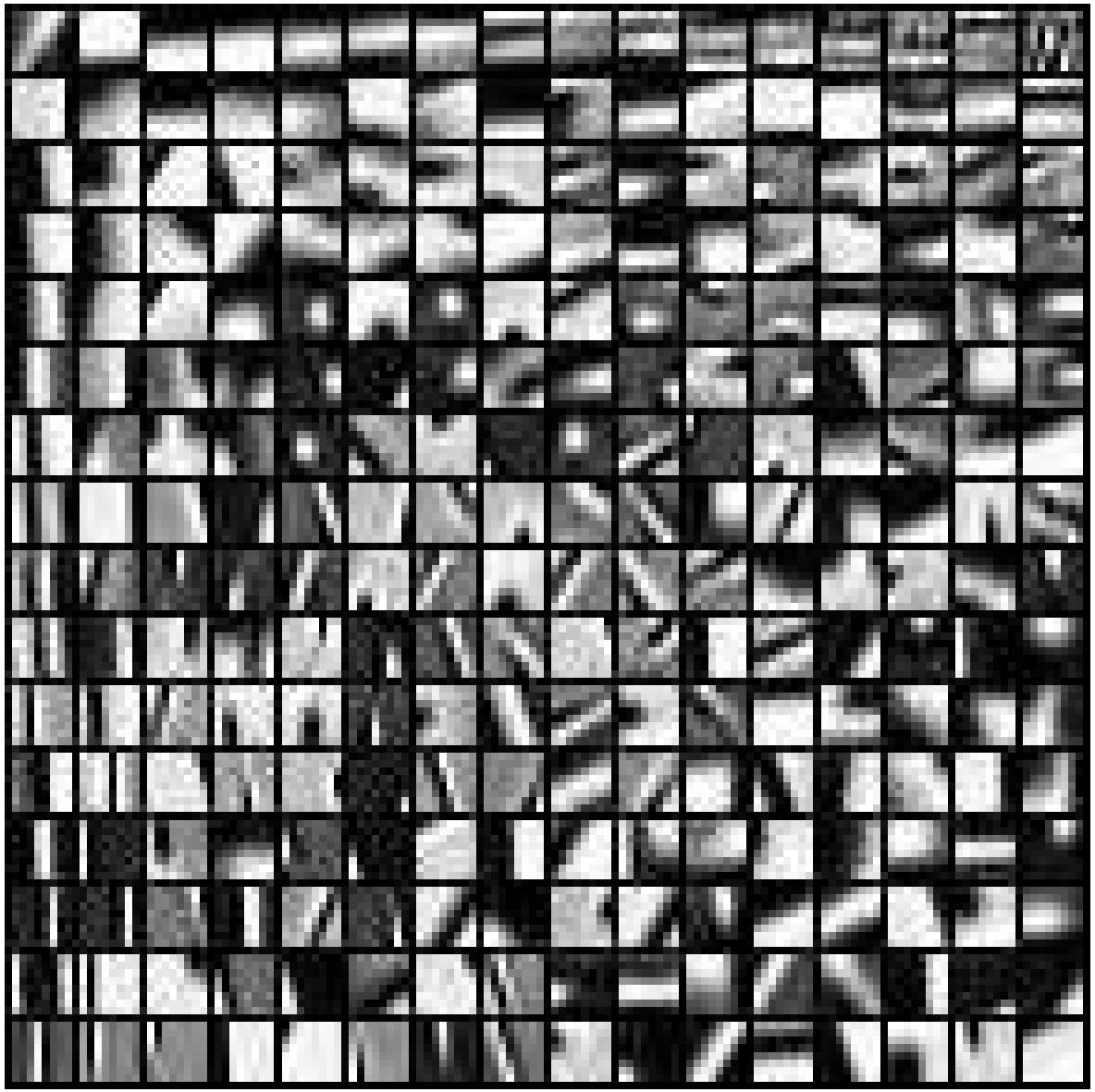
- Classical optimization alternates between $\mathbf{D}$ and $\mathbf{A}$.
- Good results, but very slow !
- **Online learning** (Mairal, Bach, Ponce, and Sapiro, 2009a) can
  - handle potentially infinite datasets
  - adapt to dynamic training sets
  - online code (`http://www.di.ens.fr/willow/SPAMS/`)

Denoising result
(Mairal, Bach, Ponce, Sapiro, and Zisserman, 2009c)

Denoising result
(Mairal, Bach, Ponce, Sapiro, and Zisserman, 2009c)



What does the dictionary $\mathbf{D}$ look like?



Inpainting a 12-Mpixel photograph

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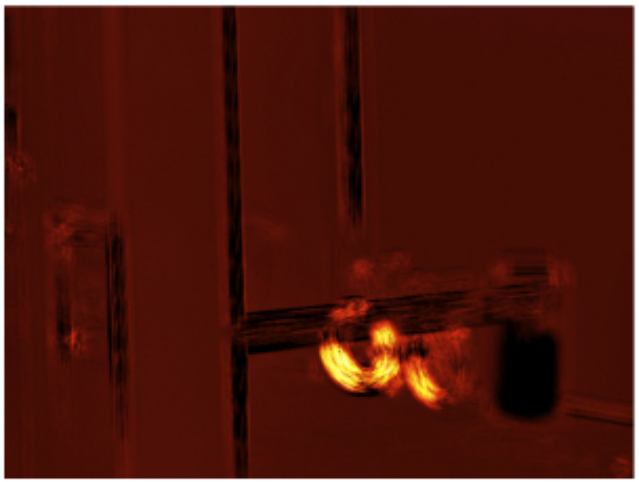
Alternative usages of dictionary learning

Computer vision

- Use the "code" α as representation of observations for subsequent processing (Raina et al., 2007; Yang et al., 2009)
- **Adapt dictionary elements to specific tasks** (Mairal, Bach, Ponce, Sapiro, and Zisserman, 2009b)
  - Discriminative training for weakly supervised pixel classification (Mairal, Bach, Ponce, Sapiro, and Zisserman, 2008)


Structured sparse methods for matrix factorization

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  - Dictionary learning
- **Structured sparse PCA**
  - Sparsity-inducing norms and overlapping groups
  - Structure on dictionary elements
  - Structure on decomposition coefficients

Sparsity-inducing norms

$$\min_{\boldsymbol{\alpha} \in \mathbb{R}^p} \overbrace{f(\boldsymbol{\alpha})}^{\text{data fitting term}} + \lambda \underbrace{\psi(\boldsymbol{\alpha})}_{\text{sparsity-inducing norm}}$$

- Regularizing by a sparsity-inducing norm ψ
- Most popular choice for ψ
  - ℓ_1-norm: $\|\boldsymbol{\alpha}\|_1 = \sum_{j=1}^{p} |\boldsymbol{\alpha}_j|$
  - Lasso (Tibshirani, 1996), basis pursuit (Chen et al., 2001)
  - ℓ_1-norm only encodes cardinality
- **Structured sparsity**
  - Certain patterns are favored
  - Improvement of interpretability and prediction performance

Sparsity-inducing norms

- **Another popular choice for ψ:**
  - The ℓ_1-ℓ_2 norm,

$$\sum_{G \in \mathbf{F}} \|\boldsymbol{\alpha}_G\|_2 = \sum_{G \in \mathbf{F}} \Big(\sum_{j \in G} \boldsymbol{\alpha}_j^2 \Big)^{1/2}, \text{ with } \mathbf{F} \text{ a partition of } \{1, \ldots, p\}$$

  - The ℓ_1-ℓ_2 norm sets to zero groups of non-overlapping variables (as opposed to single variables for the ℓ_1 -norm)
  - For the square loss, group Lasso (Yuan and Lin, 2006)

Sparsity-inducing norms

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  - The ℓ_1-ℓ_2 norm sets to zero groups of non-overlapping variables (as opposed to single variables for the ℓ_1 -norm)
  - For the square loss, group Lasso (Yuan and Lin, 2006)

- However, the ℓ_1-ℓ_2 norm encodes **fixed/static prior information**, requires to know in advance how to group the variables

- What happens if the set of groups $\mathbf{F}$ is not a partition anymore?

Structured Sparsity (Jenatton, Audibert, and Bach, 2009a)

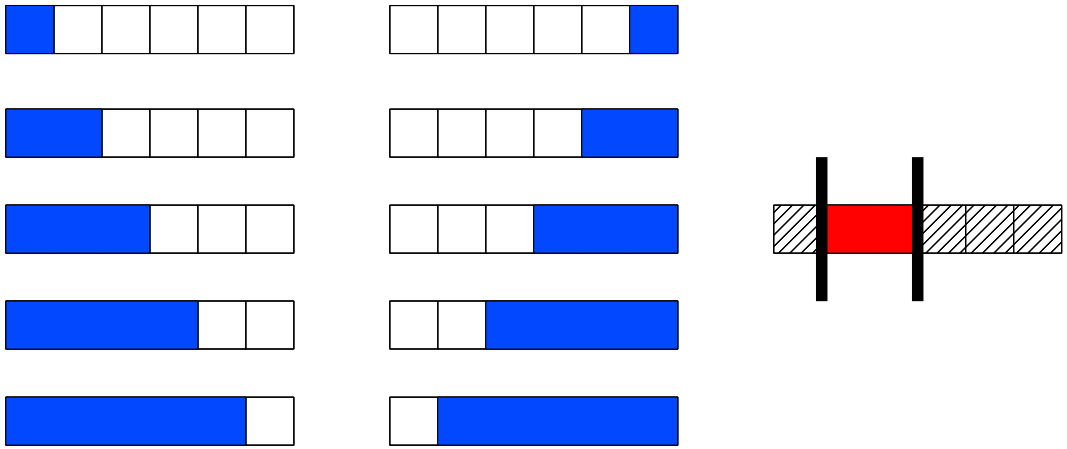
- When penalizing by the ℓ_1-ℓ_2 norm,

$$\sum_{G \in \mathbf{F}} \|\boldsymbol{\alpha}_G\|_2 = \sum_{G \in \mathbf{F}} \Big(\sum_{j \in G} \boldsymbol{\alpha}_j^2 \Big)^{1/2}$$

  - The ℓ_1 norm induces sparsity at the group level:
    - Some $\boldsymbol{\alpha}_G$'s are set to zero
  - Inside the groups, the ℓ_2 norm does not promote sparsity

Examples of set of groups $\mathbf{F}$

- Selection of contiguous patterns on a sequence, $p = 6$



  - $\mathbf{F}$ is the set of blue groups
  - Any union of blue groups set to zero leads to the selection of a contiguous pattern

Structured Sparsity (Jenatton, Audibert, and Bach, 2009a)

- When penalizing by the ℓ_1-ℓ_2 norm,

$$\sum_{G \in \mathbf{F}} \|\boldsymbol{\alpha}_G\|_2 = \sum_{G \in \mathbf{F}} \Big(\sum_{j \in G} \boldsymbol{\alpha}_j^2 \Big)^{1/2}$$

  - The ℓ_1 norm induces sparsity at the group level:
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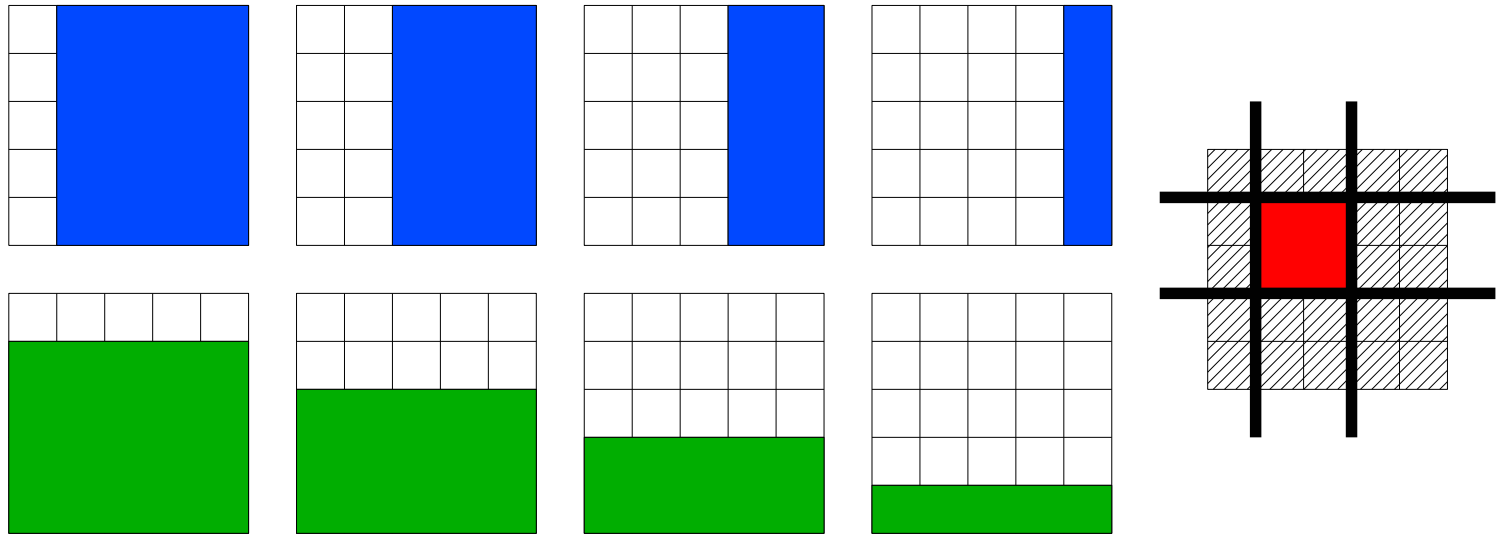
- Intuitively, the zero pattern of w is given by

$$\{j \in \{1, \ldots, p\};\ \boldsymbol{\alpha}_j = 0\} = \bigcup_{G \in \mathbf{F}'} G \quad \text{for some } \mathbf{F}' \subseteq \mathbf{F}$$

This intuition is actually true and can be formalized

Examples of set of groups $\mathbf{F}$

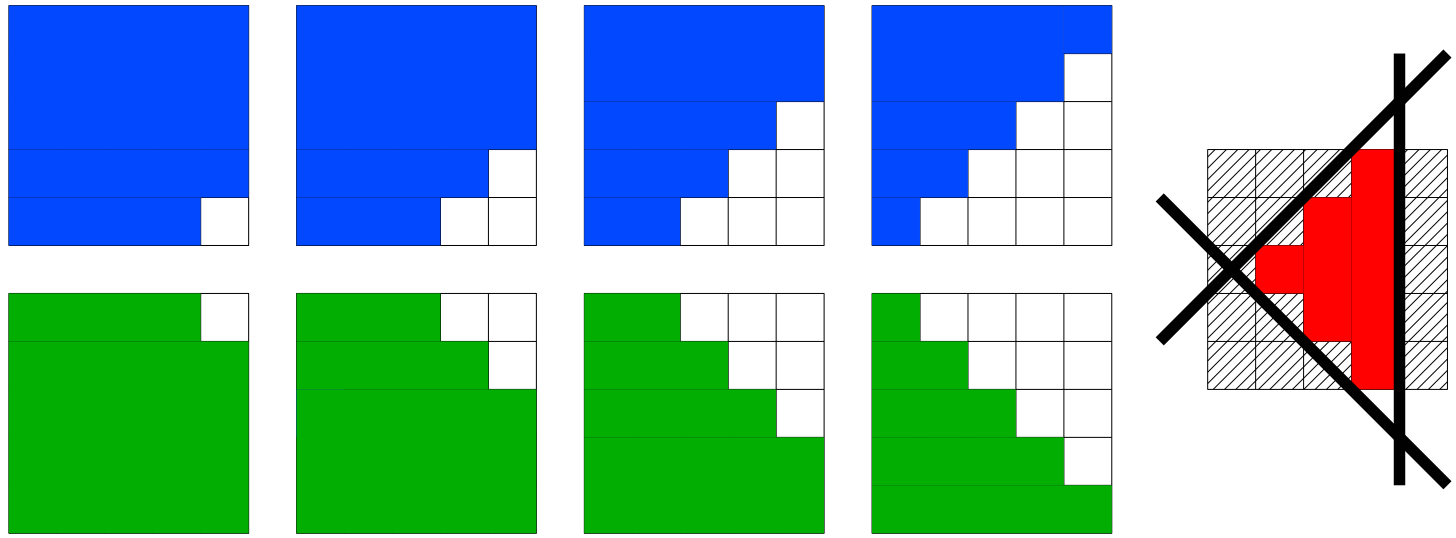
- Selection of rectangles on a 2-D grids, $p = 25$



  - $\mathbf{F}$ is the set of blue/green groups (with their not displayed complements)
  - Any union of blue/green groups set to zero leads to the selection of a rectangle

Examples of set of groups $\mathbf{F}$

- Selection of diamond-shaped patterns on a 2-D grids, $p = 25$.



  – It is possible to extend such settings to 3-D space, or more complex topologies

Relationship between $\mathbf{F}$ and Zero Patterns (Jenatton, Audibert, and Bach, 2009a)

- $\mathbf{F} \rightarrow$ **Zero patterns**:
  - by generating the union-closure of $\mathbf{F}$
- **Zero patterns** $\rightarrow \mathbf{F}$:
  - Design groups $\mathbf{F}$ from any **union-closed set** of **zero** patterns
  - Design groups $\mathbf{F}$ from any **intersection-closed set** of **non-zero** patterns

Related work on structured sparsity

- Specific hierarchical structure (Zhao et al., 2009; Bach, 2008)
- Union-closed (as opposed to intersection-closed) family of nonzero patterns (Jacob, Obozinski, and Vert, 2009)
- Nonconvex penalties based on information-theoretic criteria with greedy optimization (Baraniuk et al., 2008; Huang et al., 2009)
- Link with submodular functions (Bach, 2010)
  - Acting on supports or level sets

Sparse structured PCA (Jenatton, Obozinski, and Bach, 2009b)

- Learning **sparse and structured dictionary elements**:

$$\min_{\substack{\mathbf{A}\in\mathbb{R}^{k\times n}\\ \mathbf{D}\in\mathbb{R}^{p\times k}}} \sum_{i=1}^{n} \|\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i\|_2^2 + \lambda \sum_{j=1}^{p} \psi(\mathbf{d}_j) \text{ s.t. } \forall i,\ \|\boldsymbol{\alpha}_i\|_2 \leq 1$$

- Structure of the dictionary elements determined by the choice of overlapping groups $\mathbf{F}$ (and thus ψ)

- Efficient learning procedures through "η-tricks"
  - Reweighted ℓ_2: $\displaystyle\sum_{G\in\mathbf{F}} \|\mathbf{y}_G\|_2 = \min_{\eta_G\geqslant 0, G\in\mathbf{F}} \frac{1}{2} \sum_{G\in\mathbf{F}} \left\{ \frac{\|\mathbf{y}_G\|_2^2}{\eta_G} + \eta_G \right\}$

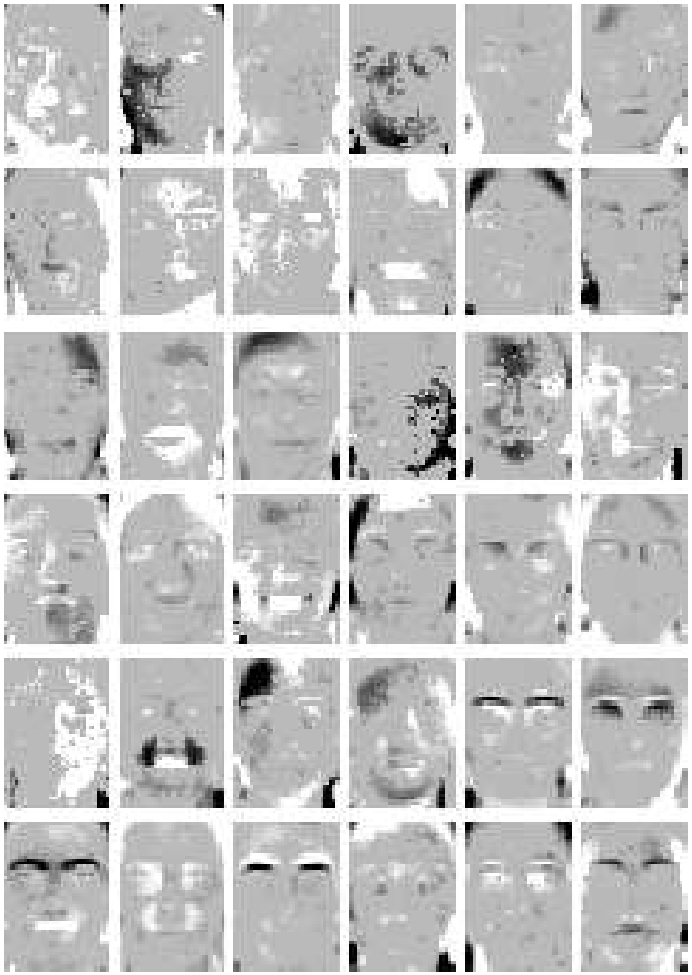
Application to face databases

raw data

(unstructured) NMF

- NMF obtains partially local features

Application to face databases

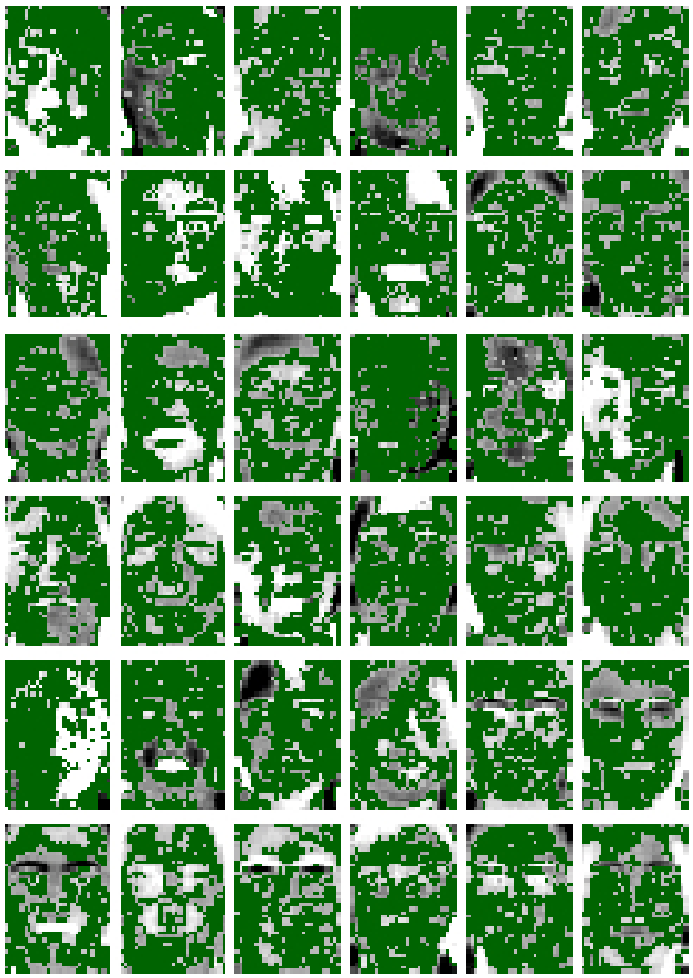


(unstructured) sparse PCA

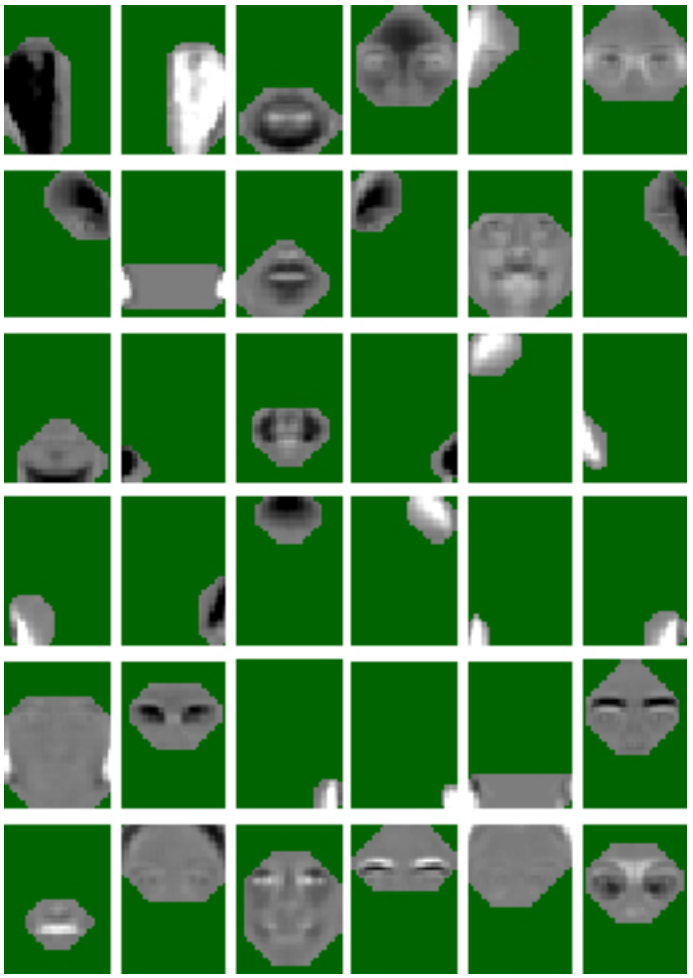
Structured sparse PCA

- Enforce selection of convex nonzero patterns $\Rightarrow$ robustness to occlusion

Application to face databases



(unstructured) sparse PCA

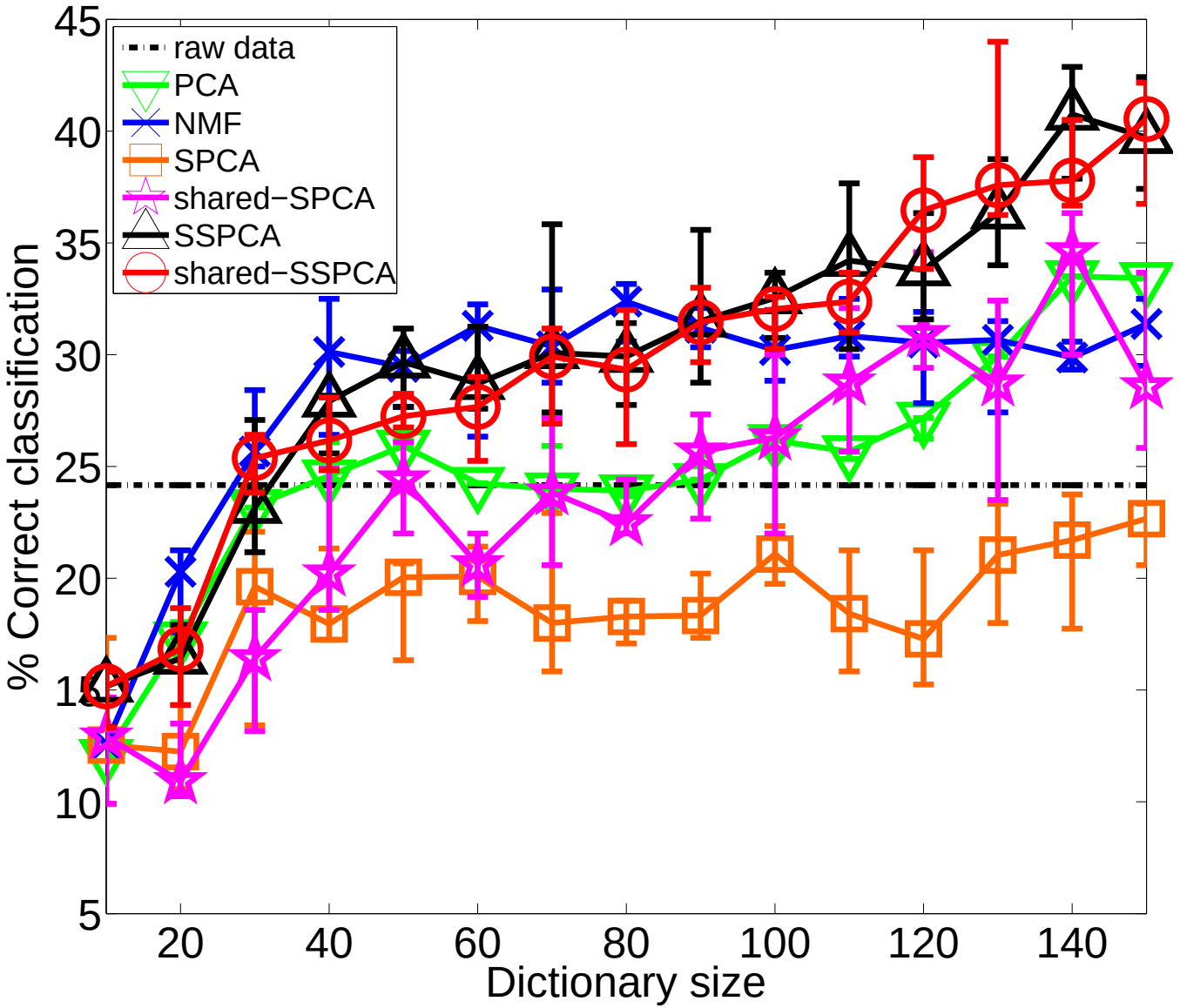


Structured sparse PCA

- Enforce selection of convex nonzero patterns $\Rightarrow$ robustness to occlusion

Application to face databases

- Quantitative performance evaluation on classification task



Dictionary learning vs. sparse structured PCA
Exchange roles of $\mathbf{D}$ and $\mathbf{A}$

- Sparse structured PCA (sparse and structured dictionary elements):

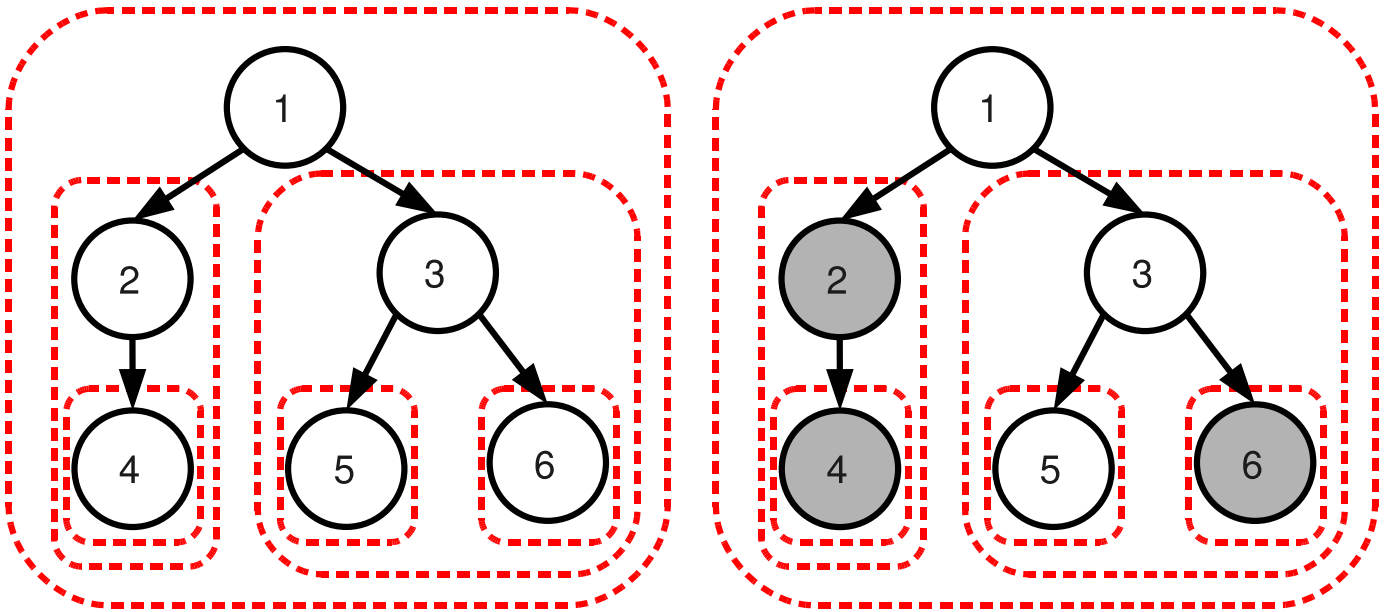
$$\min_{\substack{\mathbf{A}\in\mathbb{R}^{k\times n}\\ \mathbf{D}\in\mathbb{R}^{p\times k}}} \sum_{i=1}^{n} \|\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i\|_2^2 + \lambda \sum_{j=1}^{k} \psi(\mathbf{d}_j) \text{ s.t. } \forall i,\ \|\boldsymbol{\alpha}_i\|_2 \leq 1.$$

- Dictionary learning with structured sparsity for $\boldsymbol{\alpha}$:

$$\min_{\substack{\mathbf{A}\in\mathbb{R}^{k\times n}\\ \mathbf{D}\in\mathbb{R}^{p\times k}}} \sum_{i=1}^{n} \|\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i\|_2^2 + \lambda \psi(\boldsymbol{\alpha}_i) \text{ s.t. } \forall j,\ \|\mathbf{d}_j\|_2 \leq 1.$$

Hierarchical dictionary learning (Jenatton, Mairal, Obozinski, and Bach, 2010)

- Structure on codes $\boldsymbol{\alpha}$ (not on dictionary $\mathbf{D}$)
- Hierarchical penalization: $\psi(\boldsymbol{\alpha}) = \sum_{G \in \mathbf{F}} \|\boldsymbol{\alpha}_G\|_2$ where groups G in $\mathbf{F}$ are equal to set of descendants of some nodes in a tree



- Variable selected after its ancestors (Zhao et al., 2009; Bach, 2008)

Hierarchical dictionary learning
Efficient optimization

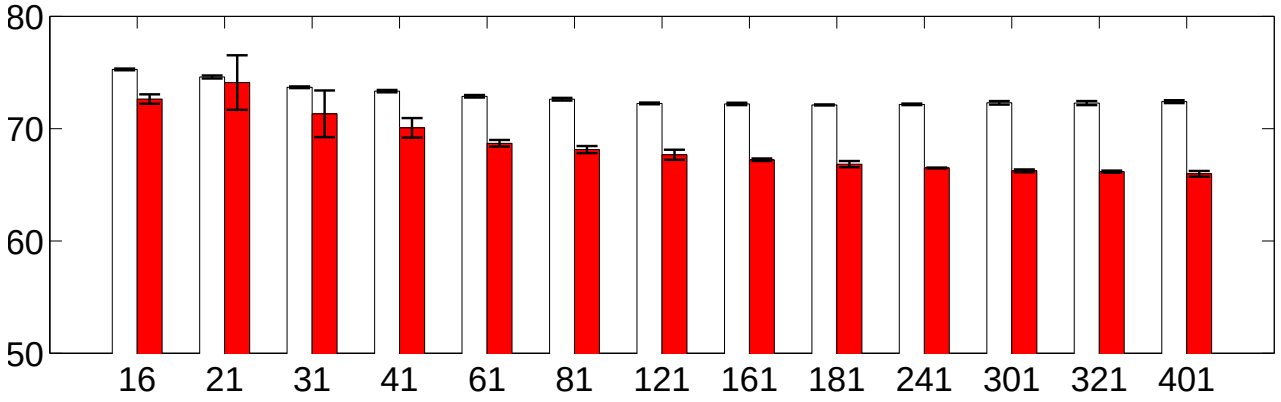
$$\min_{\substack{\mathbf{A}\in\mathbb{R}^{k\times n}\\ \mathbf{D}\in\mathbb{R}^{p\times k}}} \sum_{i=1}^{n} \|\mathbf{x}_i - \mathbf{D}\boldsymbol{\alpha}_i\|_2^2 + \lambda\psi(\boldsymbol{\alpha}_i) \text{ s.t. } \forall j,\ \|\mathbf{d}_j\|_2 \leq 1.$$

- Minimization with respect to $\boldsymbol{\alpha}_i$: regularized least-squares
  - Many algorithms dedicated to the ℓ_1-norm $\psi(\boldsymbol{\alpha}) = \|\boldsymbol{\alpha}\|_1$
- Proximal methods : first-order methods with optimal convergence rate (Nesterov, 2007; Beck and Teboulle, 2009)
  - Requires solving many times $\min_{\boldsymbol{\alpha}\in\mathbb{R}^p} \frac{1}{2}\|\mathbf{y} - \boldsymbol{\alpha}\|_2^2 + \lambda\psi(\boldsymbol{\alpha})$
- Tree-structured regularization : **Efficient linear time algorithm based on primal-dual decomposition** (Jenatton et al., 2010)

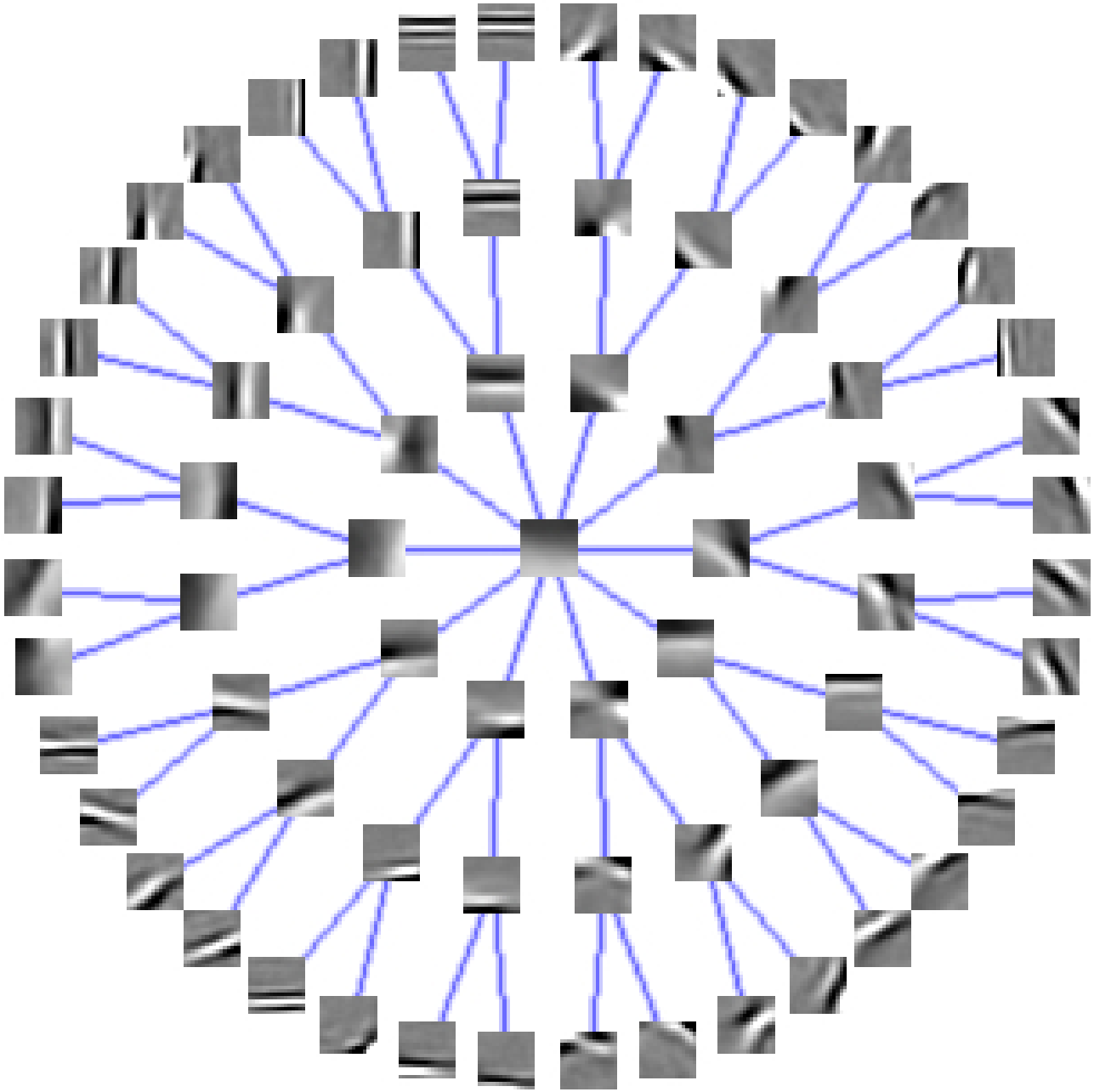
Hierarchical dictionary learning
Application to image denoising

- Reconstruction of 100,000 8×8 natural images patches
  - Remove randomly subsampled pixels
  - Reconstruct with matrix factorization and structured sparsity

noise	50 %	60 %	70 %	80 %	90 %
flat	19.3 ± 0.1	26.8 ± 0.1	36.7 ± 0.1	50.6 ± 0.0	72.1 ± 0.0
tree	18.6 ± 0.1	25.7 ± 0.1	35.0 ± 0.1	48.0 ± 0.0	65.9 ± 0.3



Application to image denoising - Dictionary tree



Hierarchical dictionary learning
Modelling of text corpora

- Each document is modelled through word counts
- Low-rank matrix factorization of word-document matrix
- Probabilistic topic models (Blei et al., 2003)
  - Similar structures based on non parametric Bayesian methods (Blei et al., 2004)
  - **Can we achieve similar performance with simple matrix factorization formulation?**

Hierarchical dictionary learning
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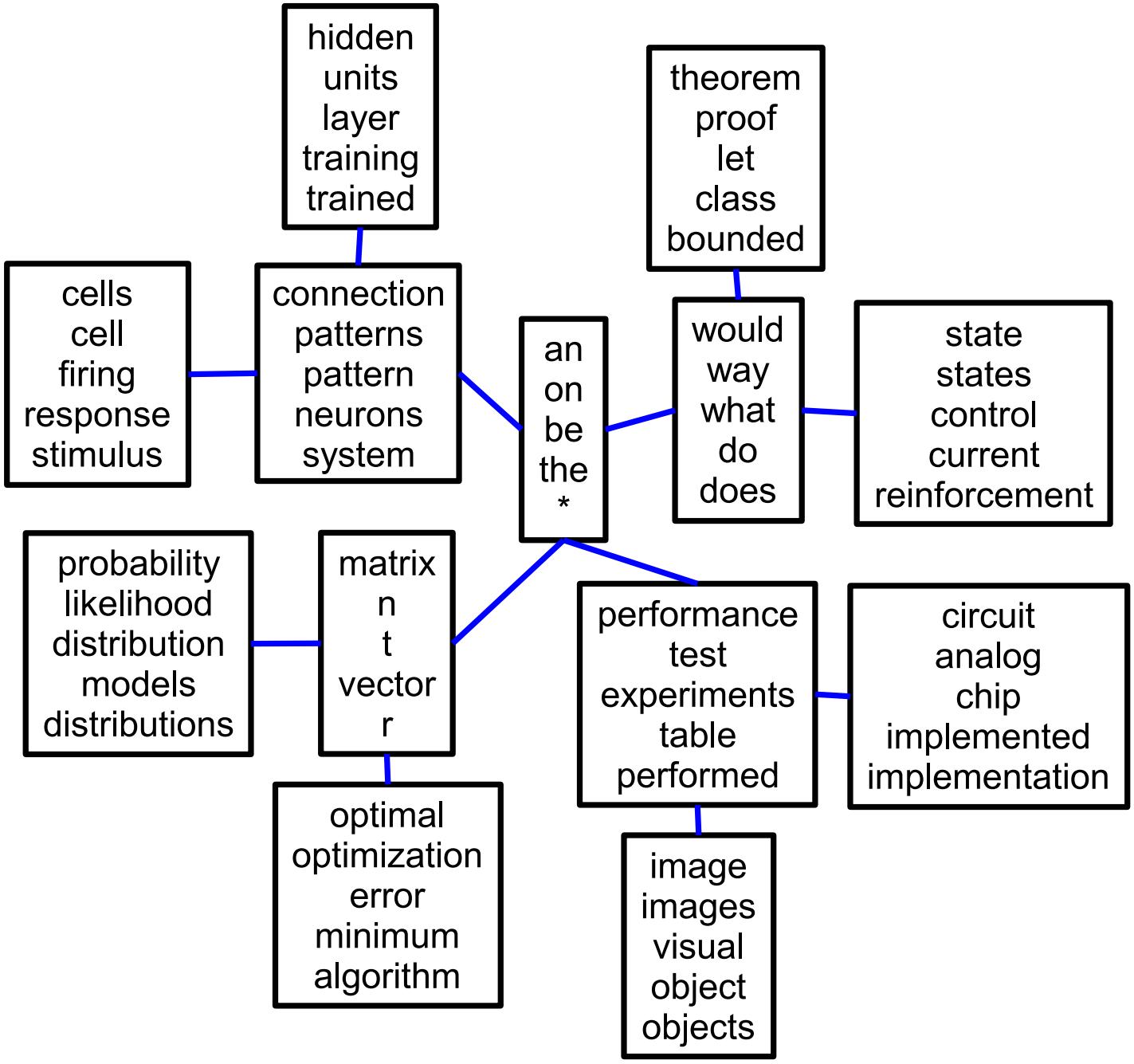
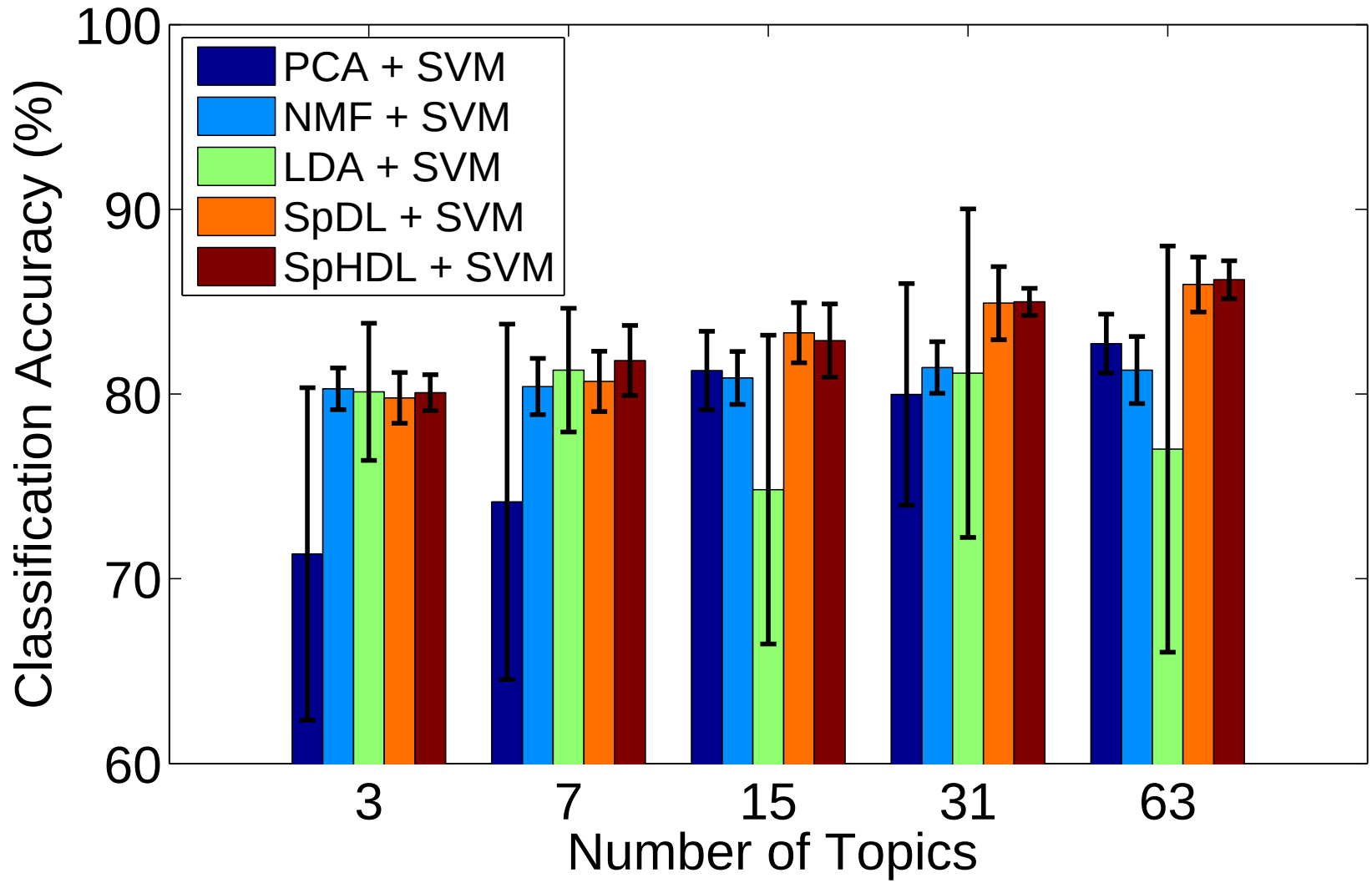
  - **Can we achieve similar performance with simple matrix factorization formulation?**
- Experiments:
  - Qualitative: NIPS abstracts (1714 documents, 8274 words)
  - Quantitative: newsgroup articles (1425 documents, 13312 words)

Modelling of text corpora - Dictionary tree



Modelling of text corpora

- Comparison on predicting newsgroup article subjects:



Topic models, NMF and matrix factorization

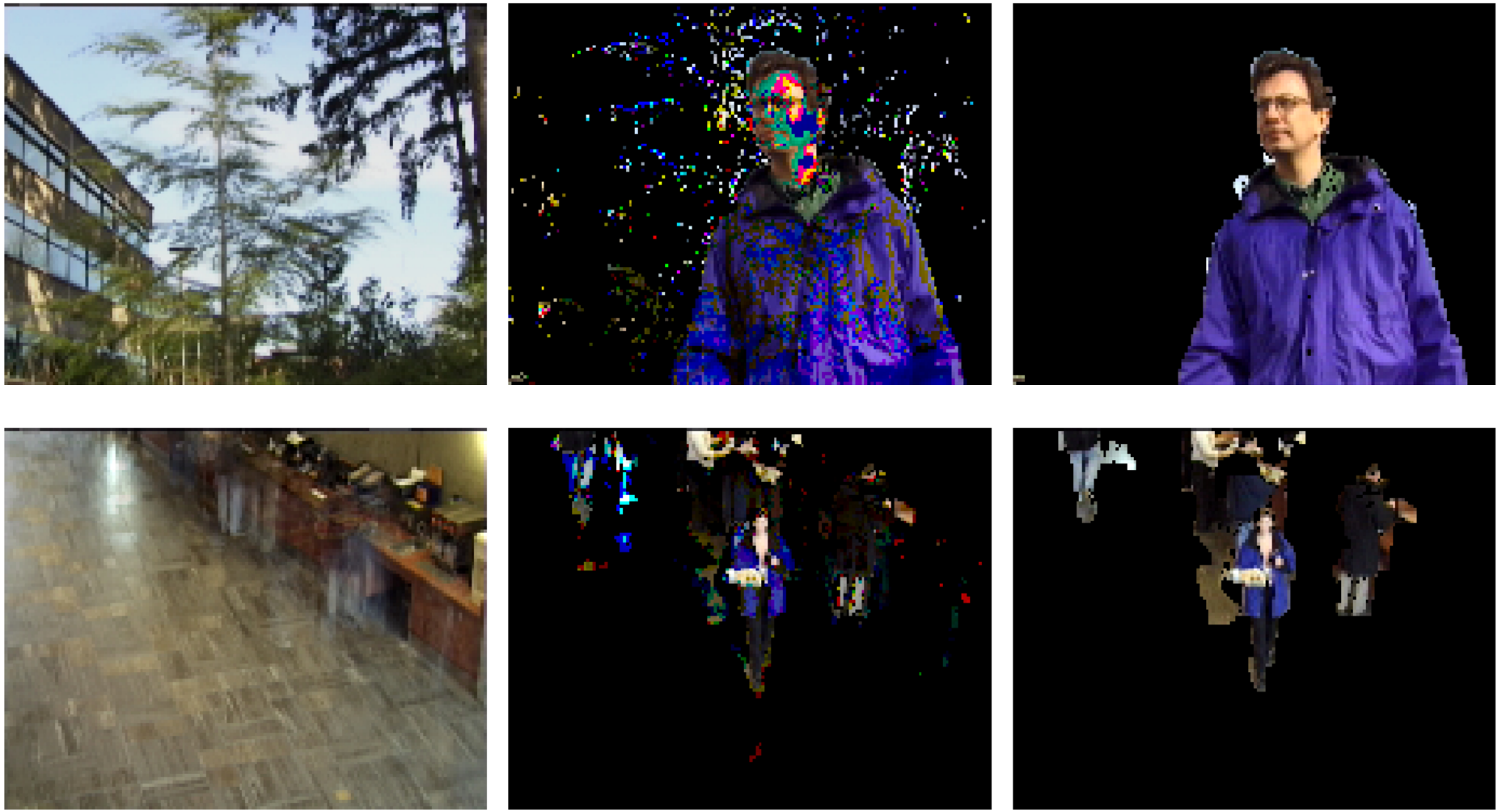
- **Three different views on the same problem**
  - Interesting parallels to be made
  - Common problems to be solved
- **Structure on dictionary/decomposition coefficients** with adapted priors, e.g., nested Chinese restaurant processes (Blei et al., 2004)
- **Learning hyperparameters from data**
- **Identifiability and interpretation/evaluation of results**
- **Discriminative tasks** (Blei and McAuliffe, 2008; Lacoste-Julien et al., 2008; Mairal et al., 2009b)
- **Optimization and local minima**

Conclusion

- **Structured matrix factorization has many applications**
  - Machine learning
  - Image/signal processing, audio/music (Lefèvre et al., 2011)
  - Extensions to other tasks

Application to background subtraction (Mairal, Jenatton, Obozinski, and Bach, 2010)

Background | ℓ_1-norm | Structured norm



Ongoing Work - Digital Zooming

Digital Zooming (Couzinie-Devy et al., 2010)

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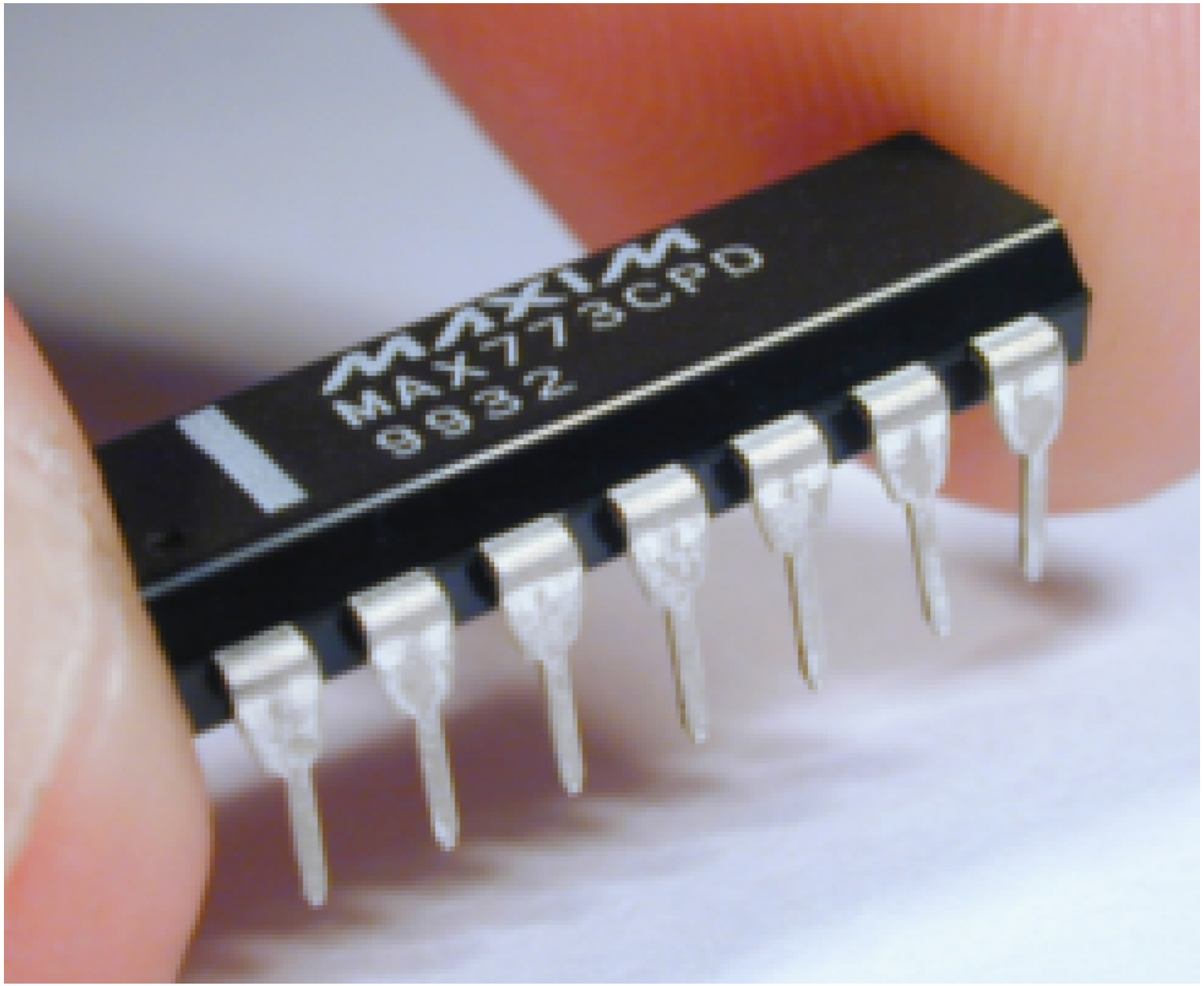
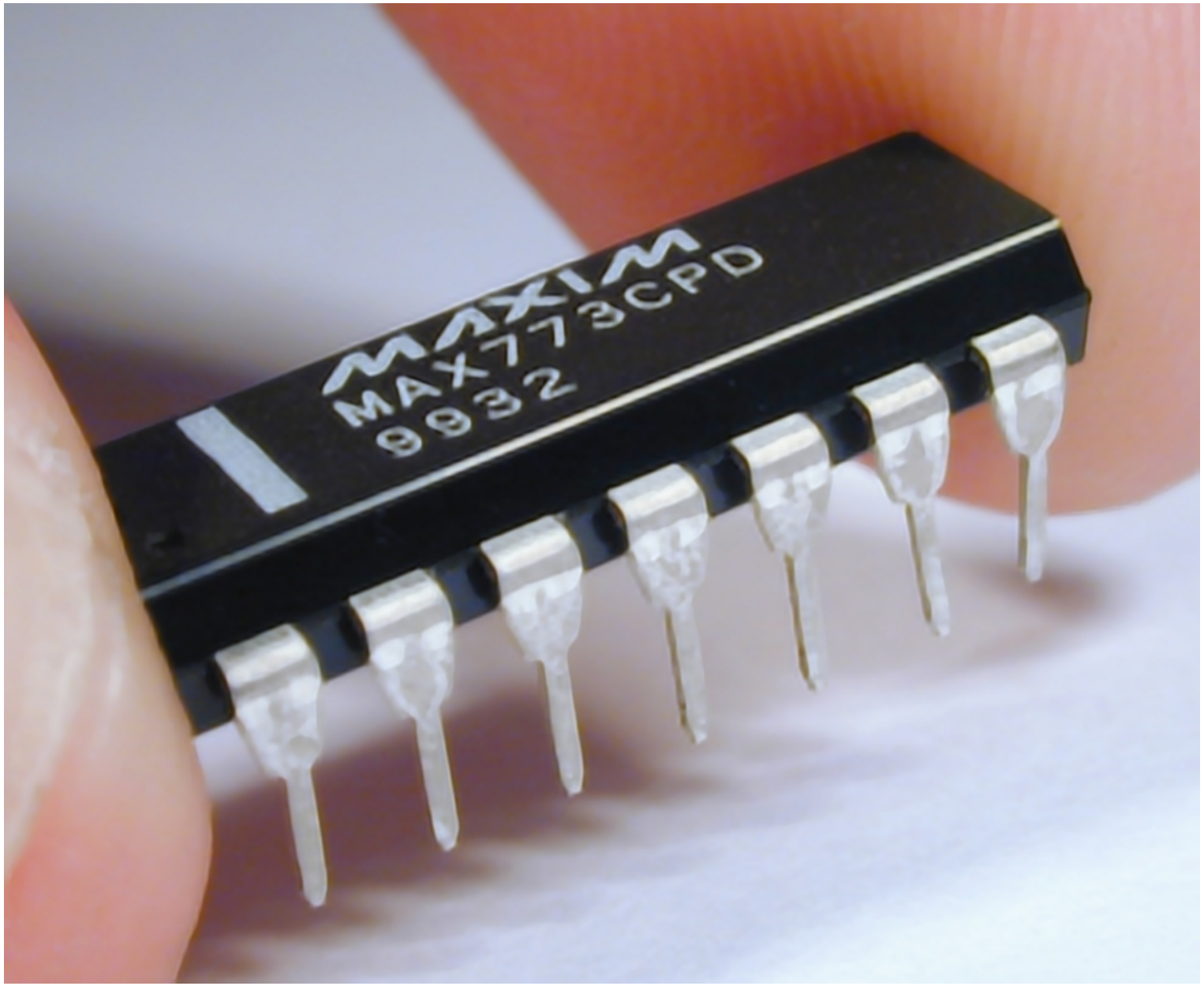
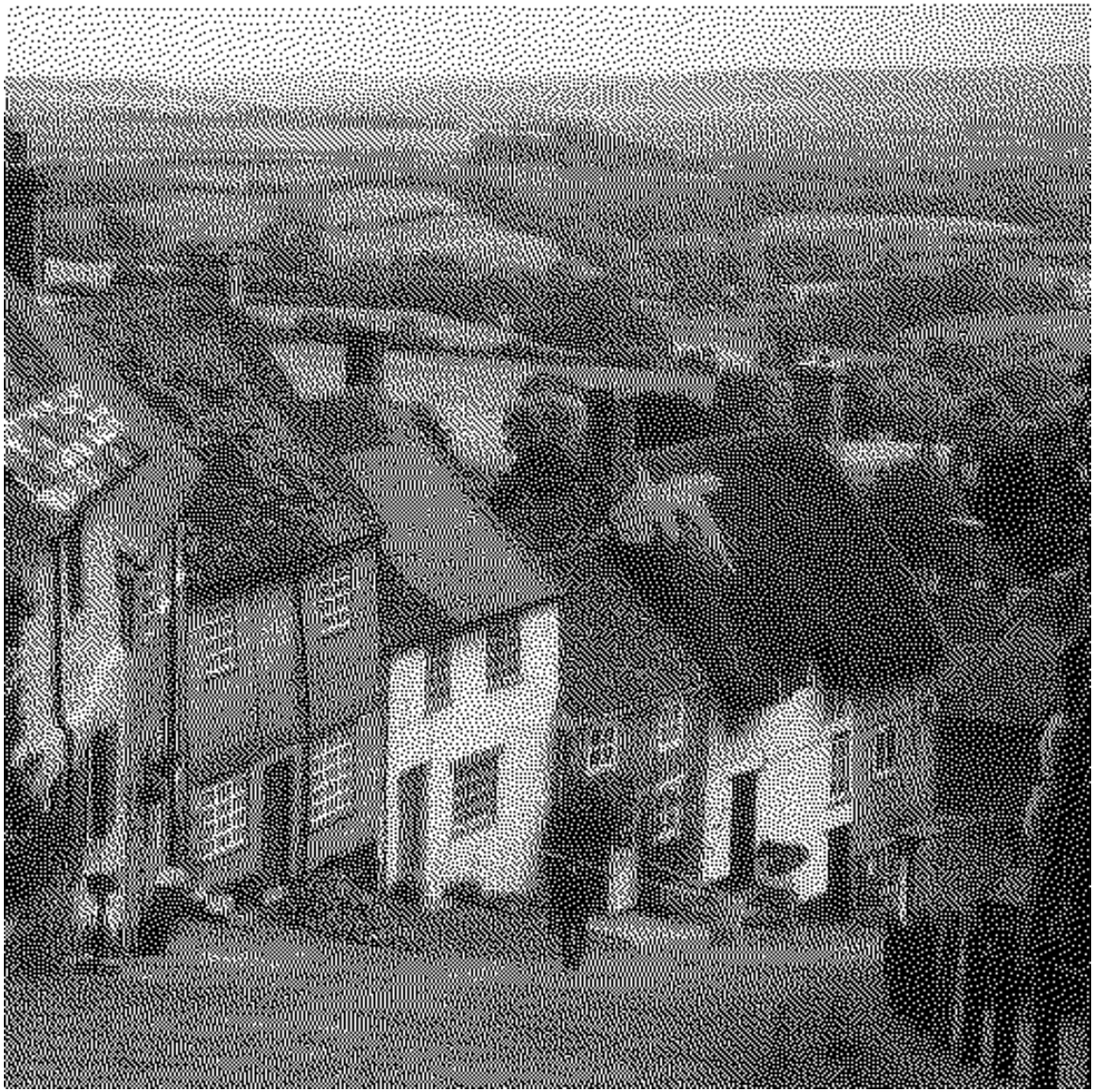


Digital Zooming (Couzinie-Devy et al., 2010)

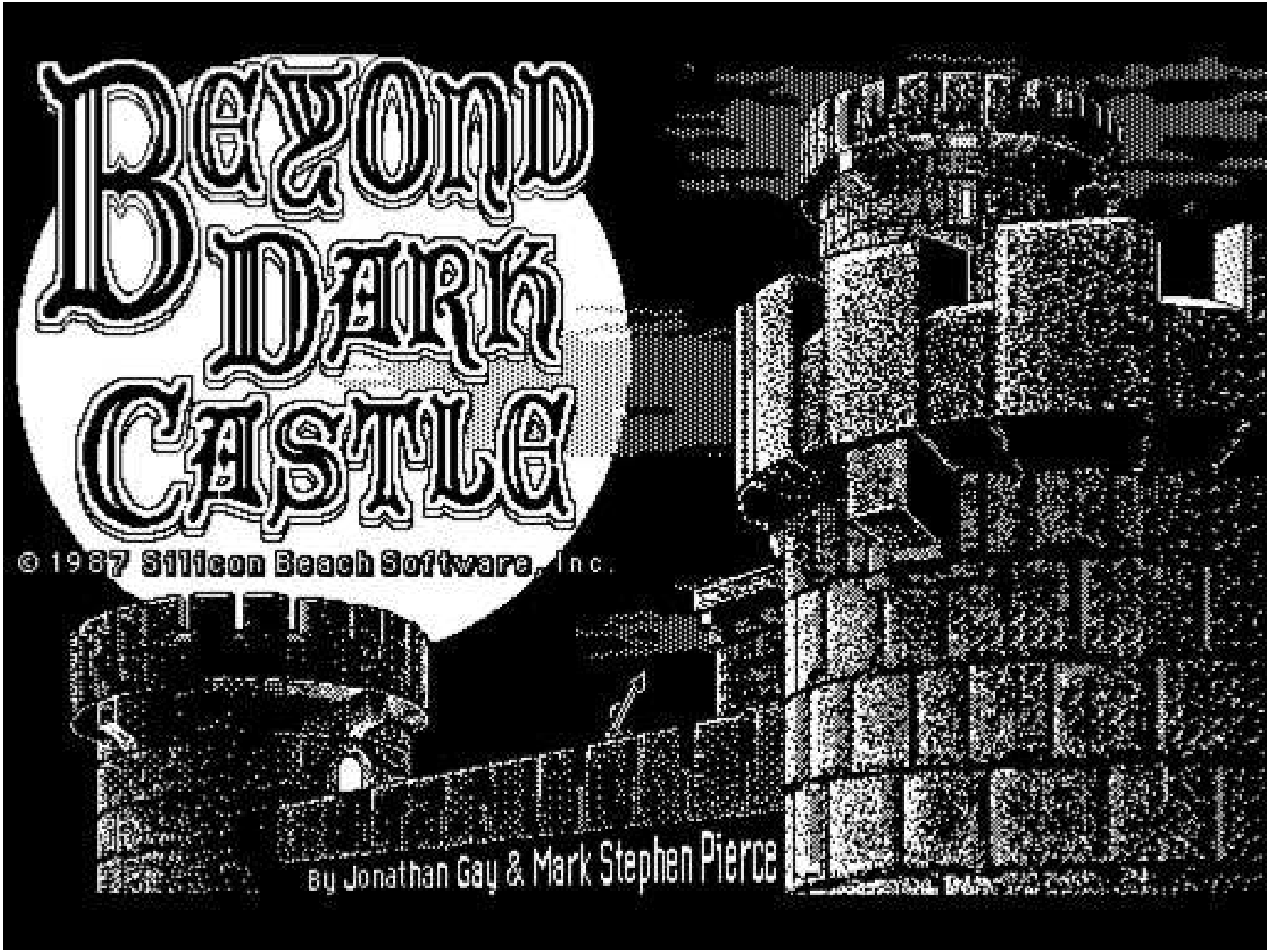


Ongoing Work - Task-driven dictionaries inverse half-toning (Mairal et al., 2010)



Ongoing Work - Task-driven dictionaries inverse half-toning (Mairal et al., 2010)

Ongoing Work - Inverse half-toning



Ongoing Work - Inverse half-toning

Ongoing Work - Inverse half-toning

Ongoing Work - Inverse half-toning

Conclusion

- **Structured matrix factorization has many applications**
  - Machine learning
  - Image/signal processing, audio/music (Lefèvre et al., 2011)
  - Extensions to other tasks
- **Algorithmic issues**
  - Large datasets
  - Structured sparsity and convex optimization
  - Link with submodular functions (Bach, 2010)
- **Theoretical issues**
  - Identifiability of structures and features
  - Improved predictive performance
  - Other approaches to sparsity and structure

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