Image Clustering by Source Camera via Sparse Representation

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CAMERA FINGERPRINT

- All cameras (CMOS, CCD, etc.) have an intrinsic pattern noise: FPN + PRNU
- PRNU properties: *robustness*, *stability*, *universality*.

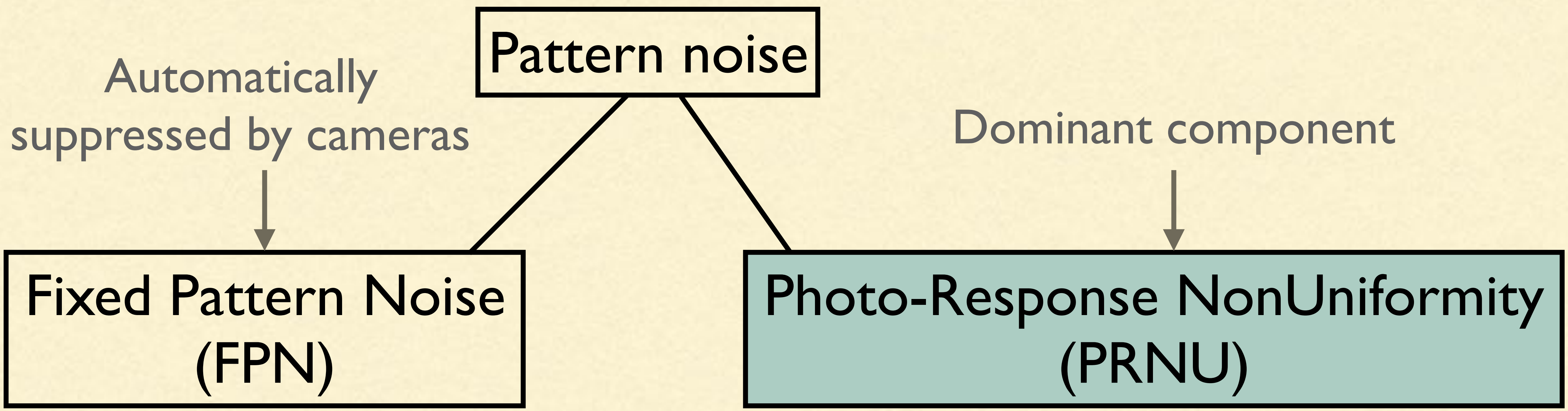

IMAGE CLUSTERING BY SOURCE CAMERA

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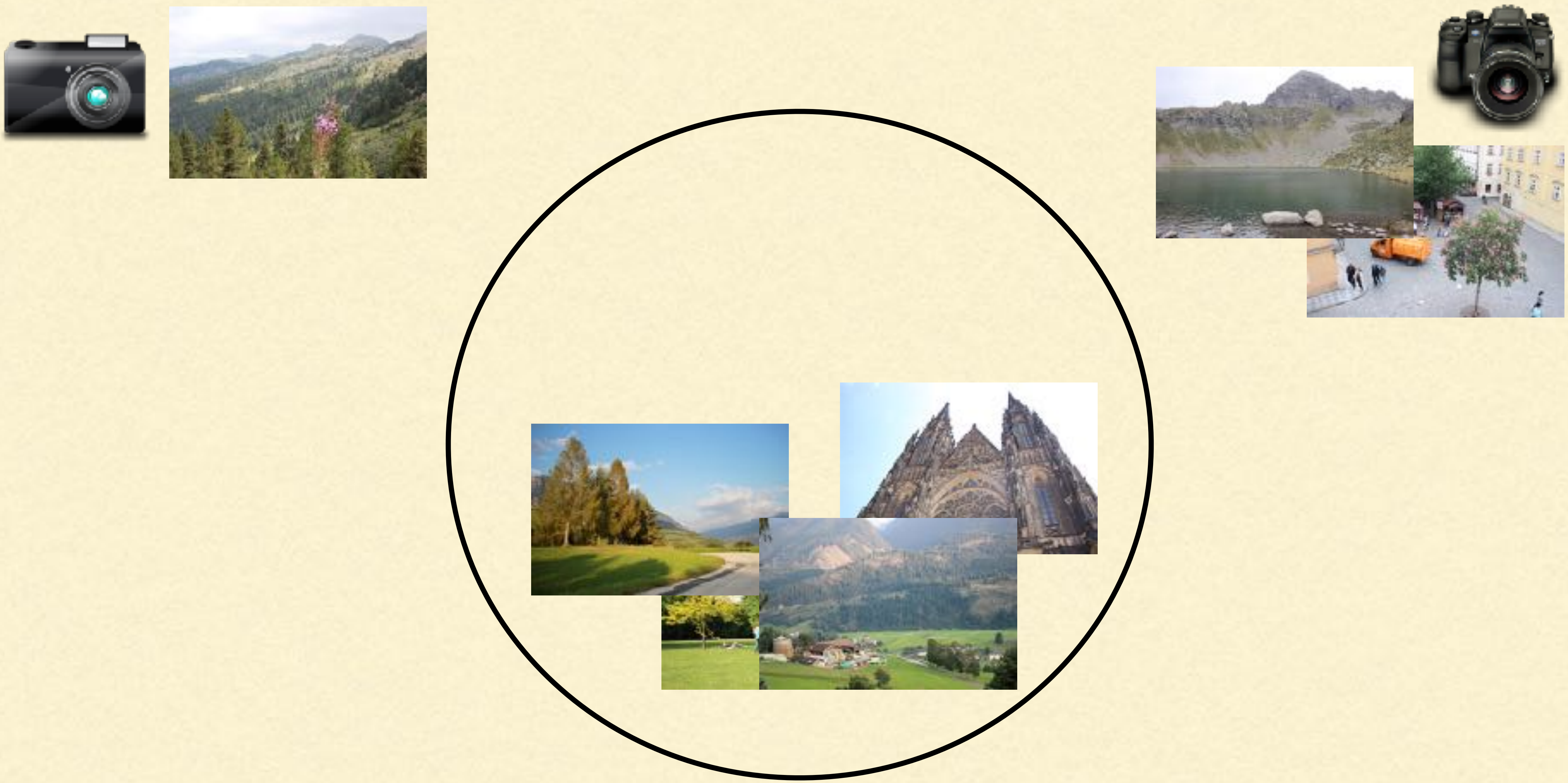
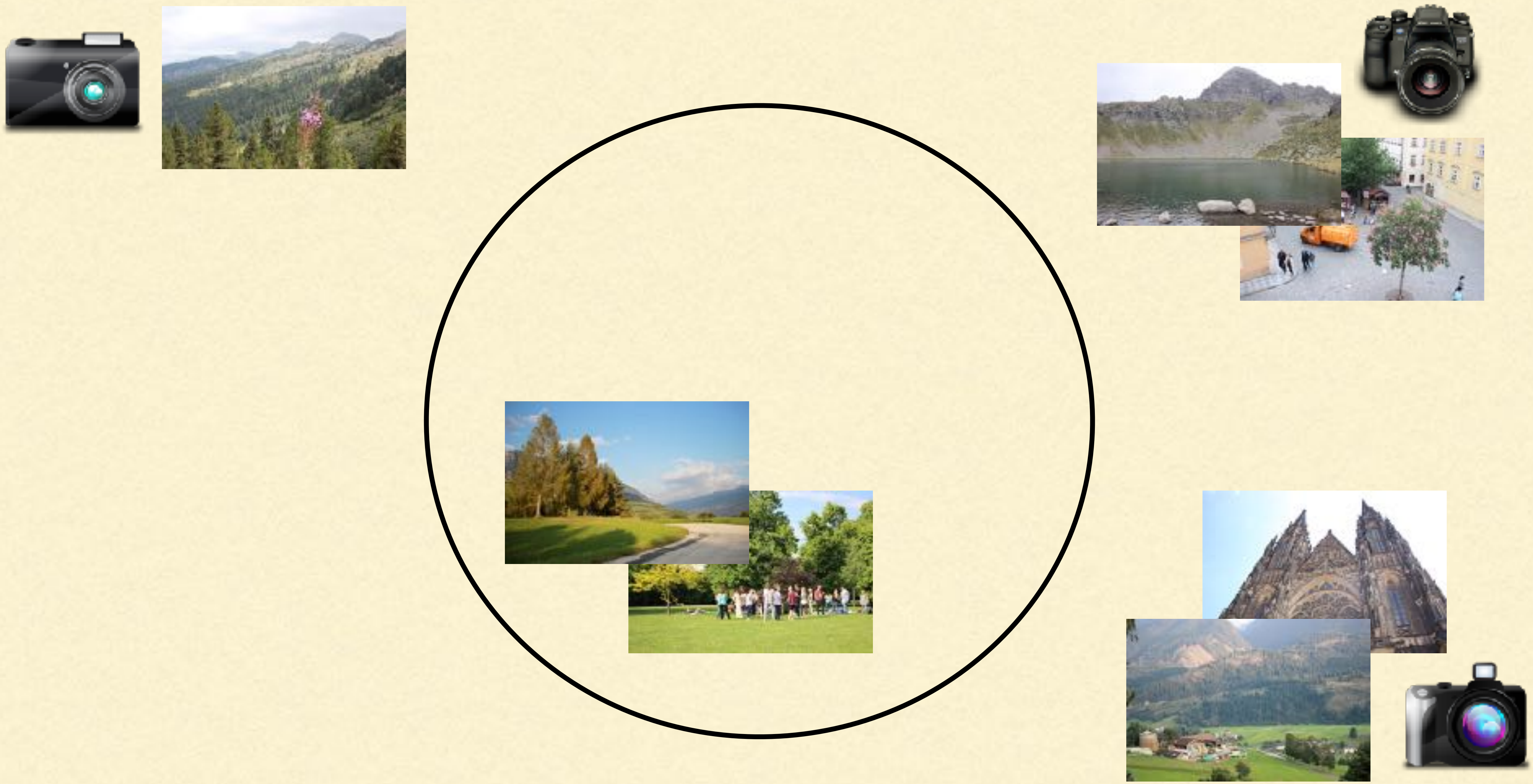


IMAGE CLUSTERING BY SOURCE CAMERA



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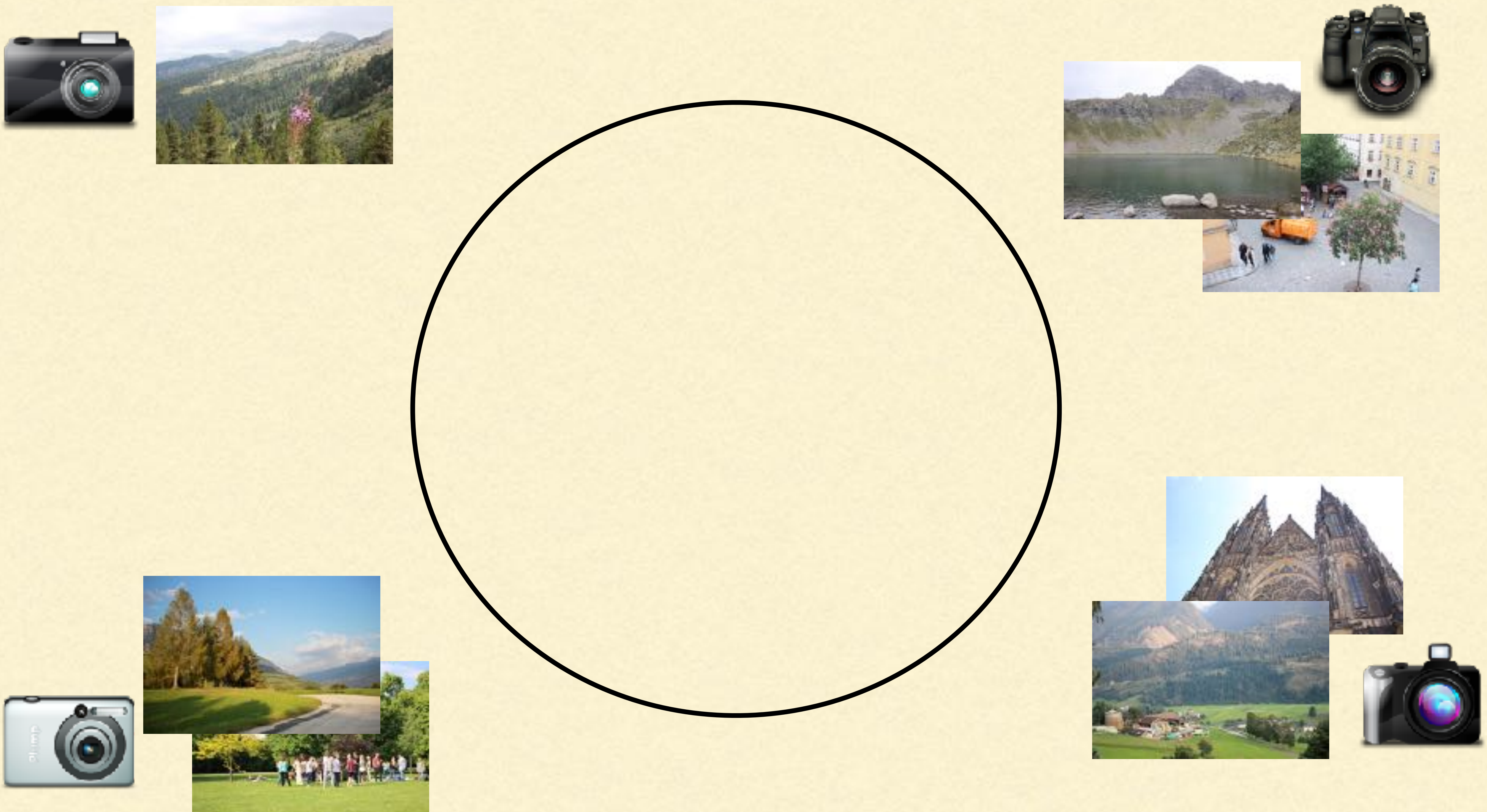


EXISTING CLUSTERING PIPELINE

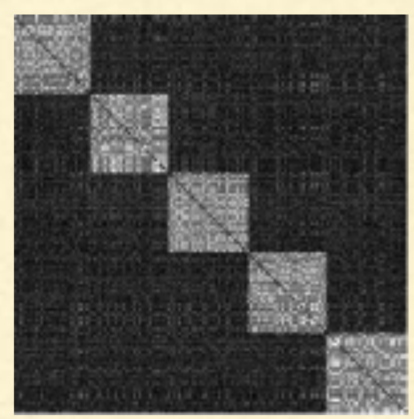
Camera fingerprint estimation → Correlation calculation → Clustering

$$W = I - \mathrm{filter}(I)$$

W : noise residual

$$\frac{\left(W^{(i)} - \overline{W^{(i)}}\mathbf{1}\mathbf{1}^T\right) \odot \left(W^{(j)} - \overline{W^{(j)}}\mathbf{1}\mathbf{1}^T\right)}{\left\|W^{(i)} - \overline{W^{(i)}}\mathbf{1}\mathbf{1}^T\right\| \left\|W^{(j)} - \overline{W^{(j)}}\mathbf{1}\mathbf{1}^T\right\|}$$

$\overline{W}$: arithmetic mean



Affinity matrix

Spectral clustering

Hierarchical clustering

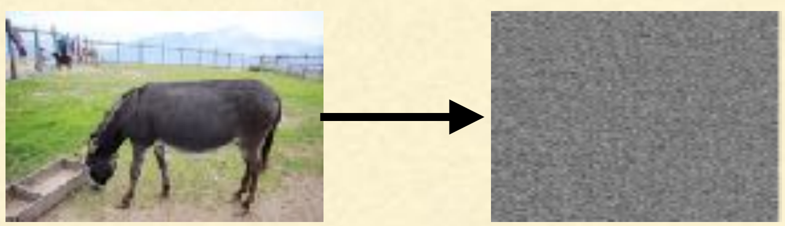
Markov Random Field

OUR CONTRIBUTION

Camera fingerprint estimation

Correlation calculation

Clustering



$$W = I - \mathrm{filter}(I)$$

W : noise residual

Sparse Representation Learning

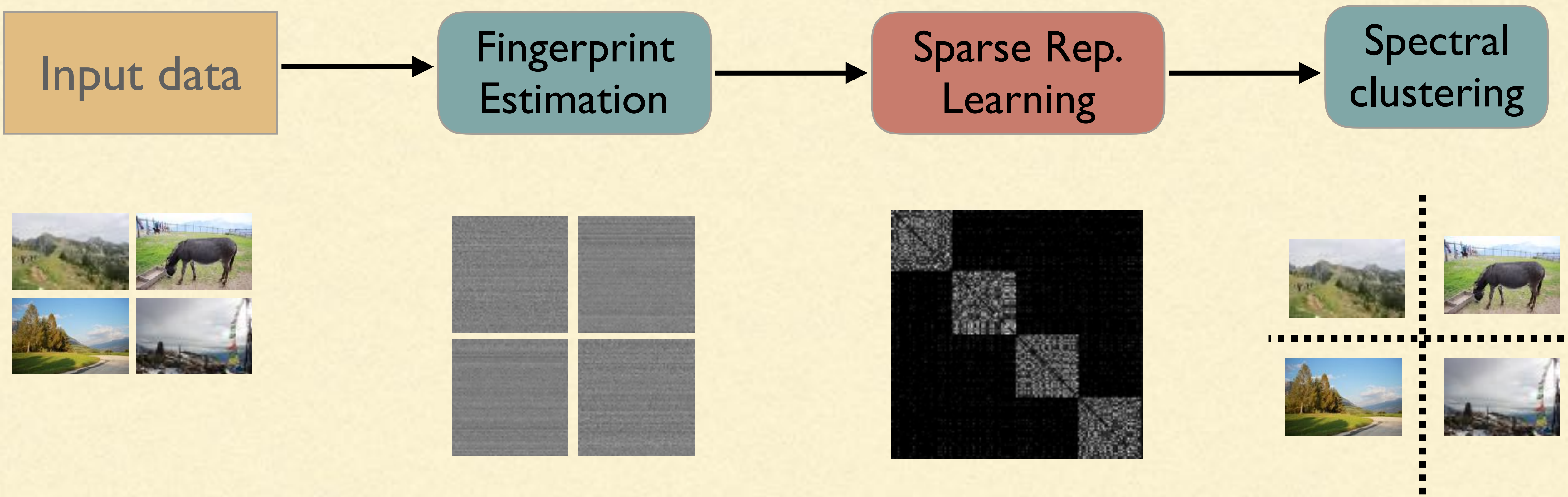
- Better represent relationship among data points in high dimensional space.
- Avoid pairwise correlation calculation.

Spectral clustering

Hierarchical clustering

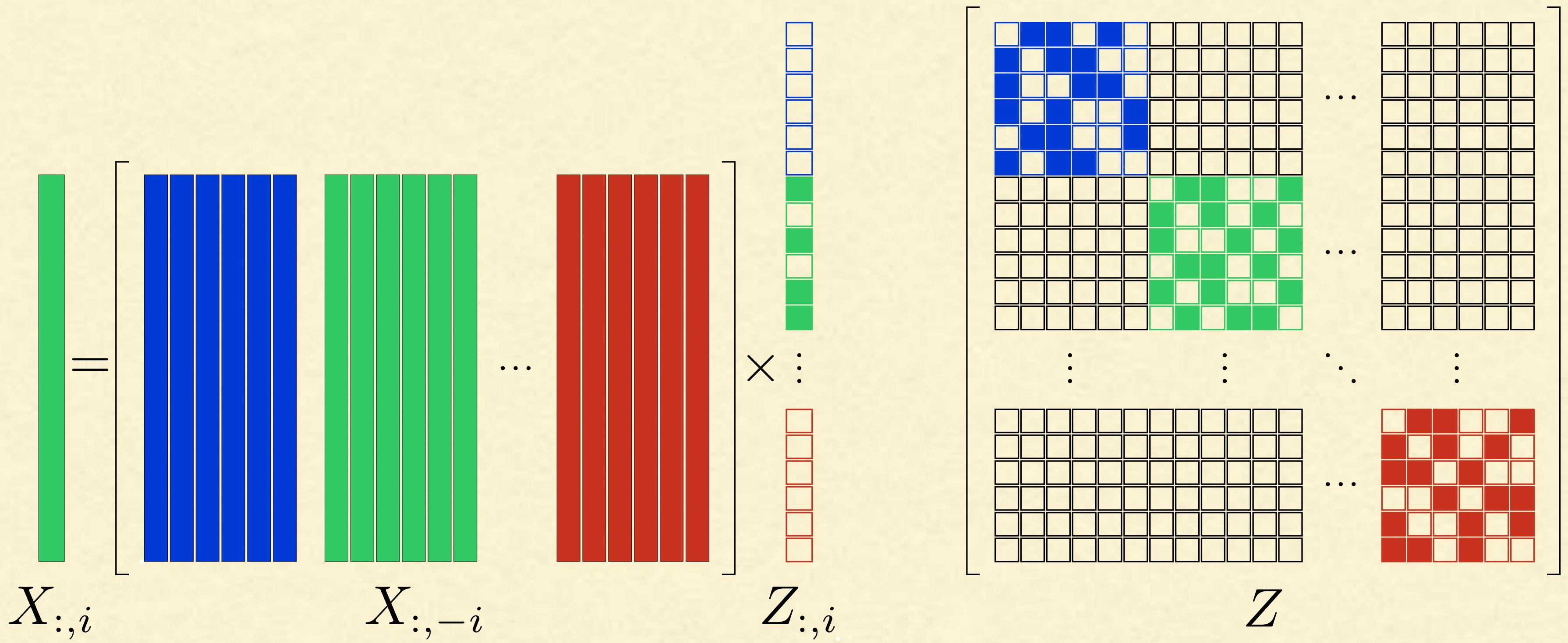
Markov Random Field

OVERALL SCHEMA

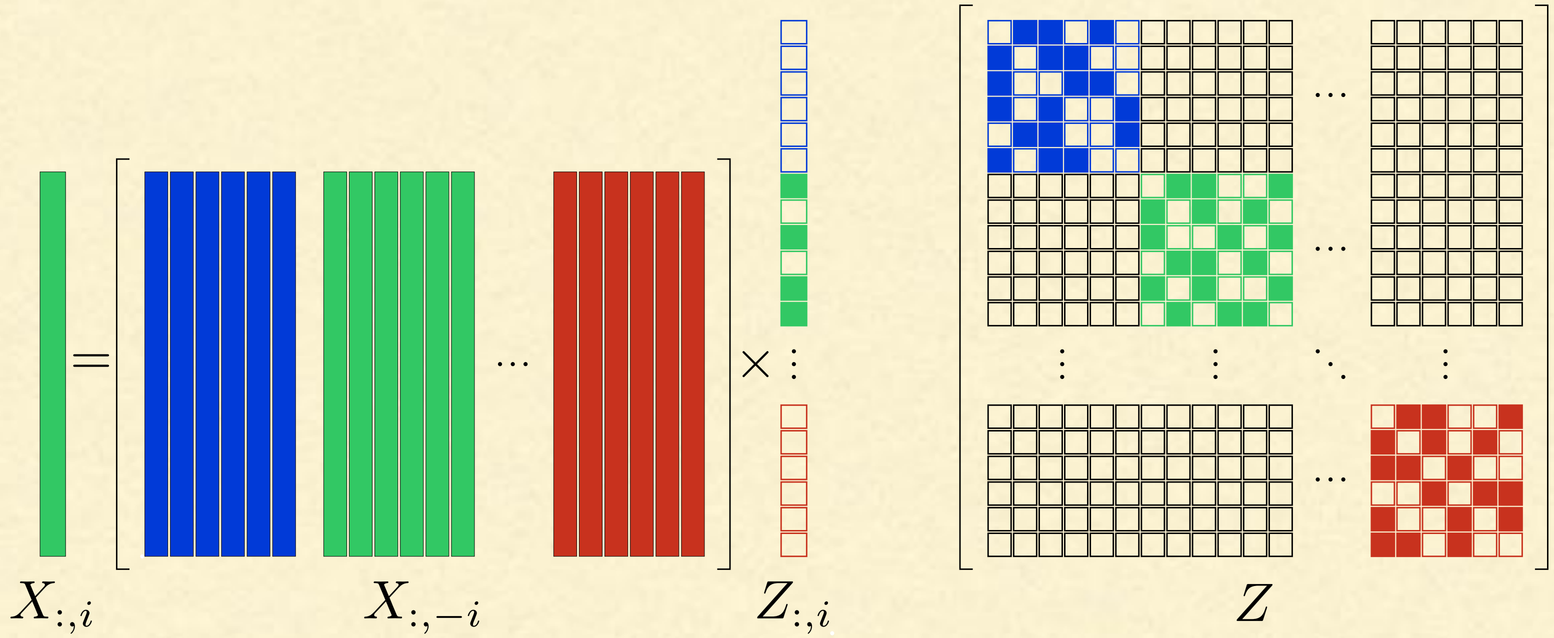


SPARSE REPRESENTATION LEARNING

- Sparse Subspace Clustering (SSC) was proposed by [E. Elhamifar et al. 2009] and theoretically analyzed in [E. Elhamifar et al. 2013].
- Each data point can be expressed as the linear combination of a proper basis.
- If the input data sufficiently fulfilled the underlying subspaces, the data matrix itself can be used as the subspace basis.



SPARSE REPRESENTATION LEARNING



- For each, $X_{:,i}$ we want to learn its corresponding sparse representation $Z_{:,i}$ by solving ℓ_1-**regularized least squares**.

$$Z_{:,i} = \underset{z}{\operatorname{argmin}} \quad \underbrace{\gamma \|z\|_1}_{\text{Sparsity}} + \underbrace{\|X_{:,-i} z - X_{:,i}\|_2^2}_{\text{Reconstruction error}}$$

SOLVING ℓ_1-REGULARIZED LEAST SQUARES

- The objective function is non-smooth due to ℓ_1 norm.
- The dimensionality of data is high, off-the-shelf optimization tools, e.g., CVX, cannot manage.

Alternating Direction Method of Multiplier (ADMM) [Boyd. 2011]

- Decouple non-differentiable term and differentiable term.

$$Z_{:,i} = \underset{z}{\operatorname{argmin}} \quad \gamma\|v\|_1 + \|X_{:,-i}z - X_{:,i}\|_2^2 \quad \text{s.t.} \quad v = z$$

- At each iteration:
  - Keep v fixed and update z by an analytical solution.
  - Keep z fixed and update v by soft thresholding.

ESTIMATING NUMBER OF CLUSTERS

- **Step 1**: Generate the affinity matrix and its corresponding normalized Laplacian matrix

$$H = |Z| + |Z^T|$$

$$L = I - D^{-1/2} H D^{-1/2} \quad \text{where} \quad D_{i,i} = \sum_{j}^{N} H_{i,j}$$

- **Step 2**: Estimate the number of clusters $\hat{K}$ using eigengap heuristic

$$\hat{K} = \underset{K}{\text{argmax}} \quad \lambda_{K+1} - \lambda_K,$$

$$\text{where} \quad \lambda_1, \cdots, \lambda_N \quad \text{are non decreasing eigenvalues of L}$$

ESTIMATING REGULARIZATION PARAMETER

$$Z_{:,i} = \underset{z}{\operatorname{argmin}} \quad \underbrace{\gamma\|v\|_1}_{\text{Sparsity}} + \underbrace{\|X_{:,-i}z - X_{:,i}\|_2^2}_{\text{Reconstruction error}} \quad \text{s.t.} \quad v = z$$

- The regularization parameter γ controls the tradeoff between the sparseness of solutions and the reconstruction errors.
  - Too dense solutions result in merged clusters.
  - Too sparse solutions result in many small clusters.

On a development set, select γ minimizing Normalized Cuts and maximizing eigengap.

EXPERIMENTAL SETUP

- Images from **Dresden** [T. Gloe et al. 2010] and **RAISE** [D.-T. D.-Nguyen et al. 2015] are used to generate 5 datasets.

Name	From	#models	#cameras	#images/camera	Total
D_1	RAISE	3	3	50	150
D_2	Dresden	10	10	100	1000
D_3	RAISE	3	3	50,75,100	225
D_4	Dresden	10	10	40, 60, 80, 100	660
D_{ev}	Dresden	5	5	100	500

D_1, D_2 are symmetric; D_3, D_4 are asymmetric; D_{ev} is used as the development set

EXPERIMENTAL SETUP

- Evaluation metric:
  - F1-score.
  - The ratio of number of discovered clusters K_p to the number of ground-truth clusters K_g.
- Comparison to SoA:
  - **MRF**: Markov Random Field (*Li et al. 2010*).
  - **MSC**: Multiclass Spectral Clustering (*Liu et al. 2010*).
  - **SCNcuts**: Spectral Clustering with

    Normalized Cut criterion (*Amerini et al. 2014*).
  - **HC**: Hierarchical Clustering (*Villalba et al. 2015*).
  - **LS**: Large-Scale method (*Lin et. al. 2017*).

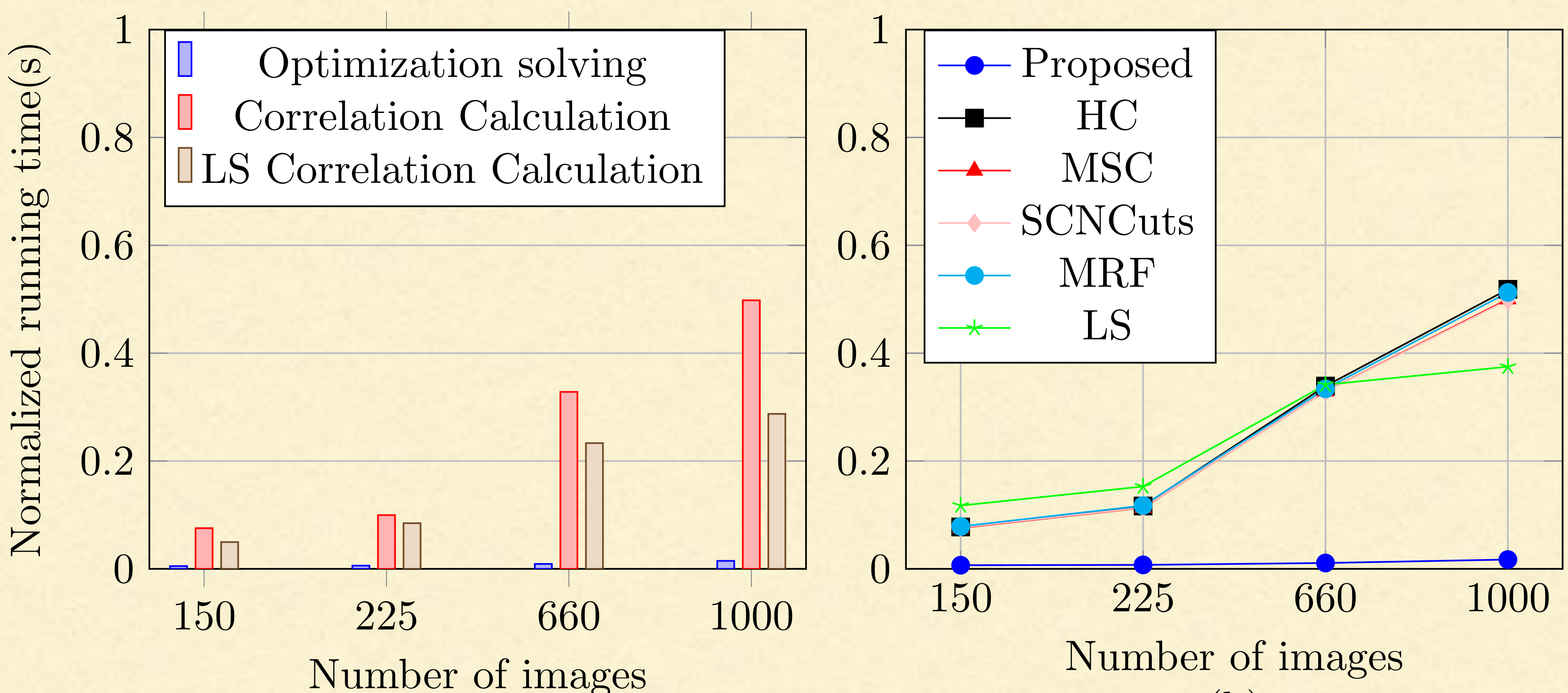
EXPERIMENTAL RESULTS

- Clustering results on symmetric datasets D_1, D_2 and asymmetric dataset D_3, D_4.

Method	D_1		D_2		D_3		D_4	
	F1	K_P/K_G	F1	K_P/K_G	F1	K_P/K_G	F1	K_P/K_G
HC	0.75	28/3	0.62	48/10	0.82	39/3	0.64	25/10
MSC	0.98	5/3	0.80	21.7/10	0.92	5.5/3	0.74	12.7/10
SCNCuts	**0.99**	**3/3**	0.32	2/10	**0.98**	3/3	0.44	4/10
MRF	0.82	9.6/3	0.81	24/10	0.88	10/3	0.50	21/10
LS	0.93	5/3	**0.91**	12/10	0.97	3/3	0.89	13/10
Proposed	0.97	**3/3**	**0.91**	**11/10**	0.97	**3/3**	**0.90**	**11/10**

EXPERIMENTAL RESULTS

- Running time comparison to SoA methods.
  - Normalized correlation calculation: built-in function `corr2`



(a) (b)

CONCLUSION

- A complete clustering framework for image clustering by source camera.
    - Learn sparse representations of camera fingerprints by solving ℓ_1-regularized least squares.
    - Estimate number of clusters (cameras).
    - Without the need to set regularization parameter.
    - Outperform SoA methods.

FUTURE WORK

- Validate the framework on cameras of the same model.
- Extend the framework to deal with large-scale datasets.
- Make the software publicly available.

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THANK YOU!!!

Q&A