

# Spatially Aware Dictionary Learning and Coding for Fossil Pollen Identification



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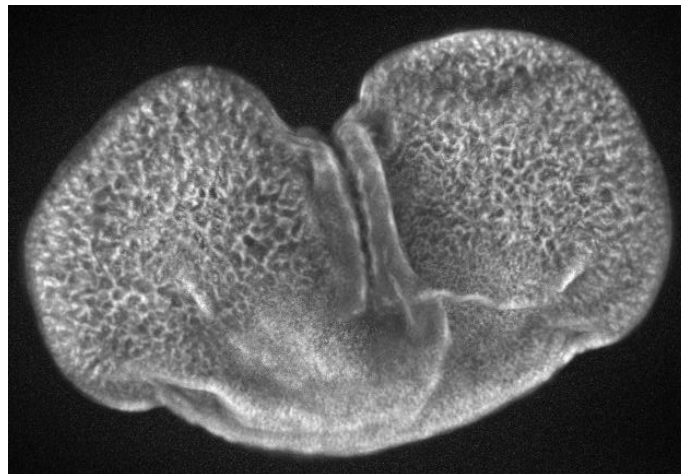
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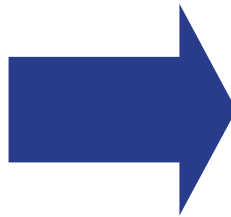
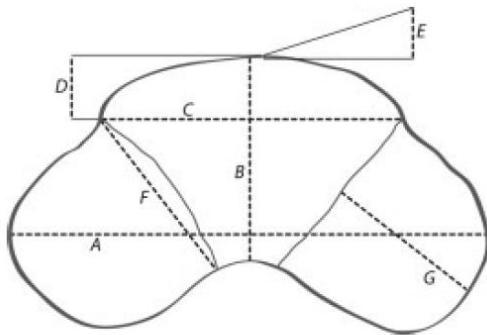
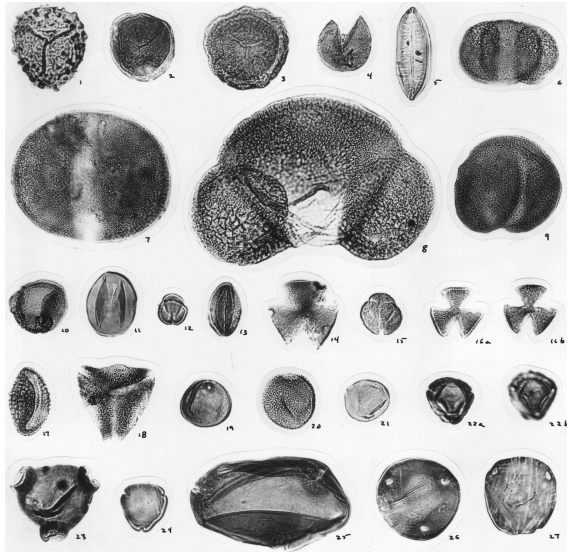
# Why do we care about identifying pollen?

- Pollen grains are ubiquitous and well preserved in the fossil record
- Identification of pollen samples allows for analysis of plant biodiversity and evolution, understanding history of long-term climate change, dating of rock strata, etc...



# Current identification is done “by eye”

Skilled experts train for years and make subtle distinctions between 100s of species.



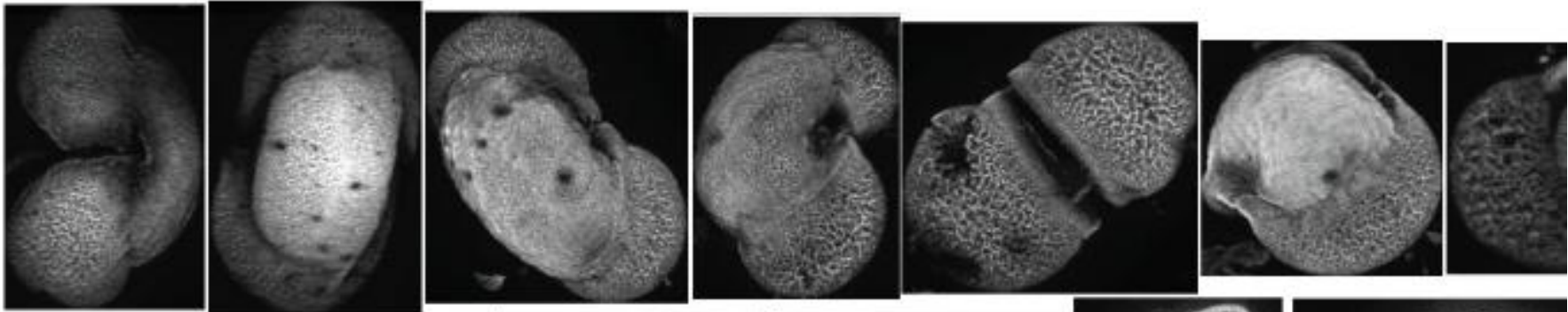
**Figure 1.** Sketch showing the measurements taken from specimens of *Picea* pollen in equatorial view (after Lindbladh *et al.*, 2002). Grain length (A), corpus height (B), corpus width (C), depth of saccus attachment (D), cap thickness (E), saccus width (F) and saccus height (G).

# Challenge: Automating species-level identification

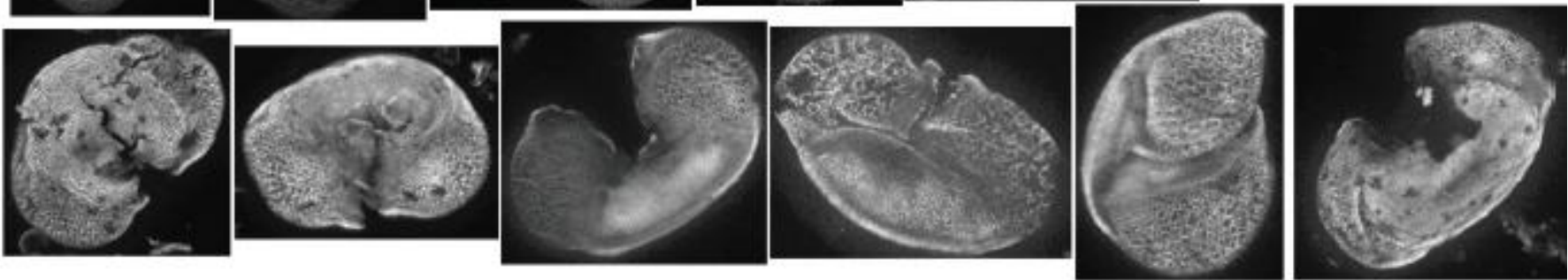
Distinguish pollen from three different species of spruce tree

- Large within-class variation
- Small between-class differences in shape and texture

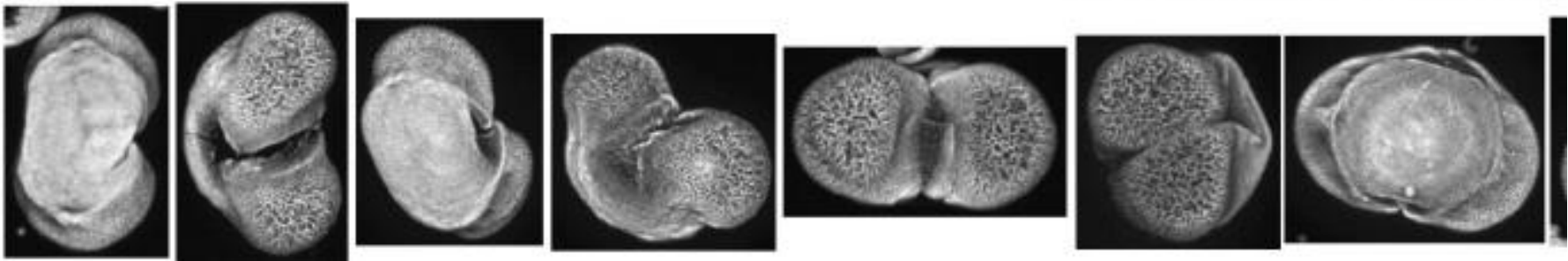
*P. critchfieldii*



*P. glauca*



*P. mariana*

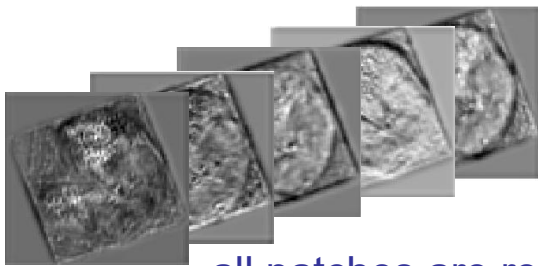
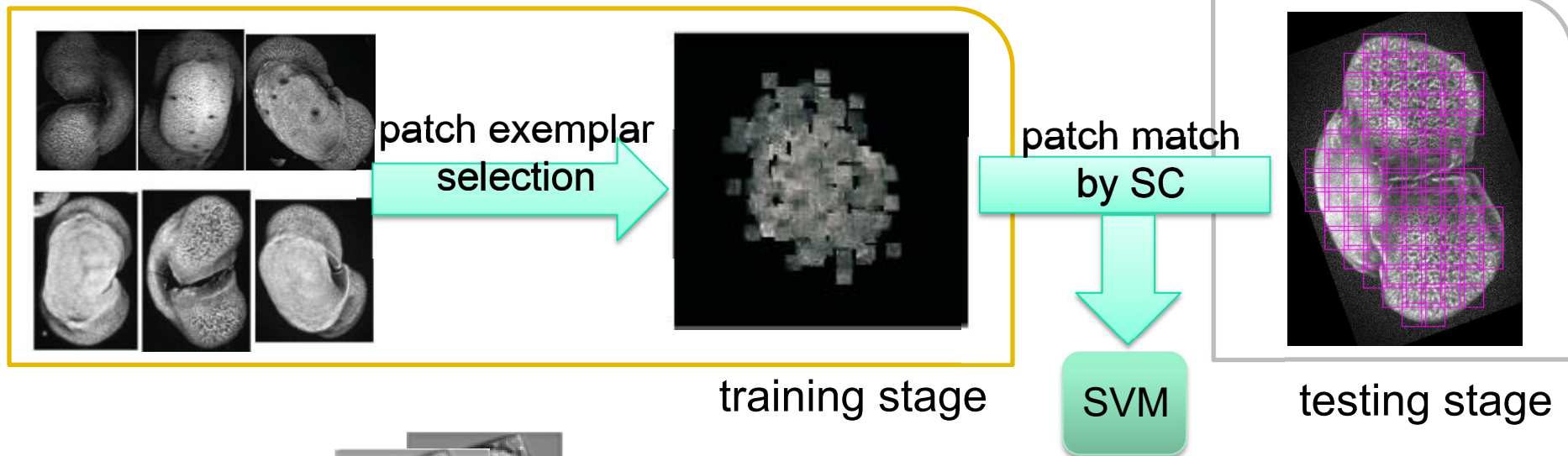




# Our methodology

## Identification by patch-match sparse coding

- Code appearance of test image using sparse combinations of patches from labeled training examples
- Classify using SVM based on code activations

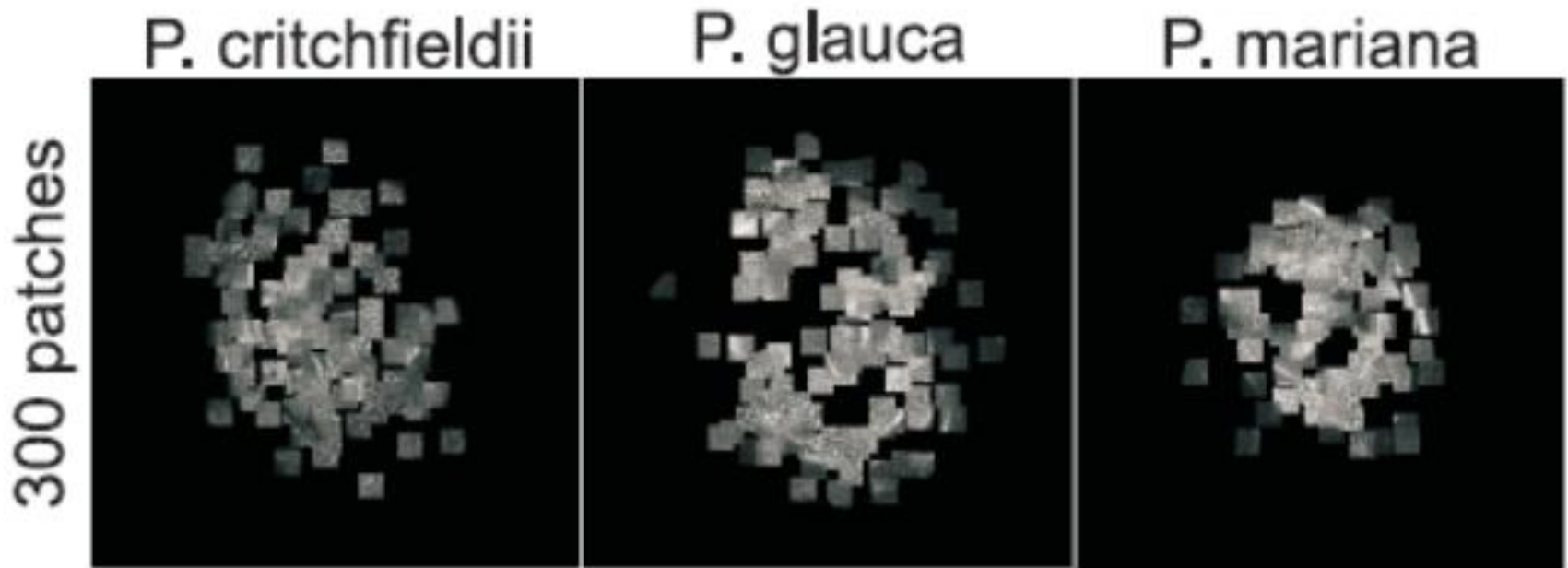


all patches are represented by CNN  
features at hidden layers

# Our contribution

## Identification by patch-match sparse coding

1. Automatic patch exemplar selection (dictionary learning)  
based on discriminative and generative criteria

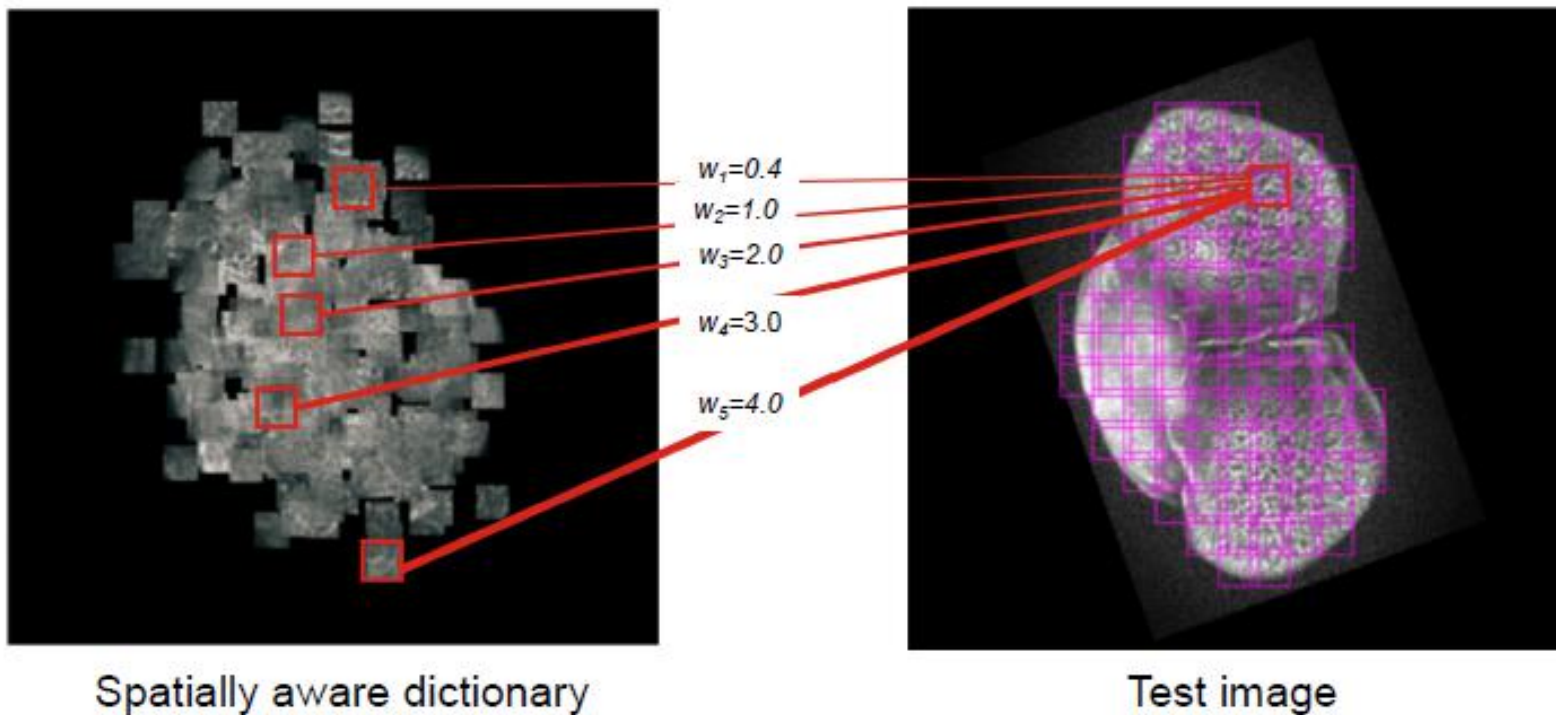


Automatically selected patches

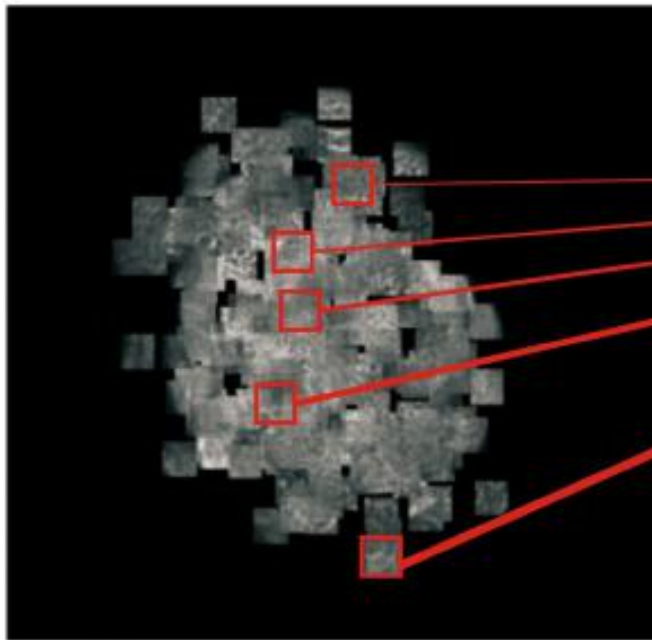
# Our contribution

## Identification by patch-match sparse coding

1. Automatic patch exemplar selection
2. Spatially-aware sparse coding (SACO)
  - penalize dictionary elements from distant spatial locations



# Spatially aware coding (SACO)



Spatially aware dictionary

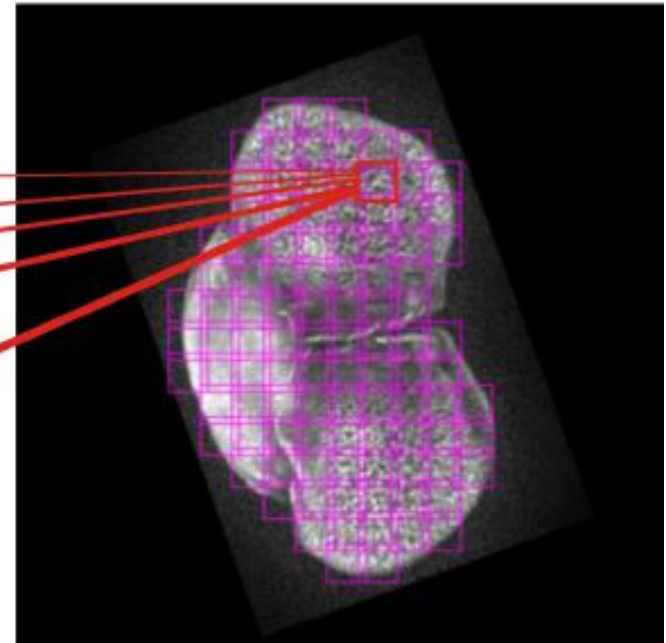
$w_1=0.4$

$w_2=1.0$

$w_3=2.0$

$w_4=3.0$

$w_5=4.0$



Test image

$$\underset{\mathbf{a}}{\operatorname{argmin}} \left\| \mathbf{x} - \mathbf{D}\mathbf{a} \right\|_2^2 + \lambda_1 \left\| \operatorname{diag}(\mathbf{w})\mathbf{a} \right\|_1$$

Spatial weights

Exemplar patches (dictionary)

Test patch



## Good classification performance

Represent patch using CNN feature extractor (VGG19)

Global average pooling of sparse codes + linear SVM

SRC	VGG19+SVM	FV+SVM	SACO-I	SACO-II
62.04	65.11	61.46	83.21	86.13

Substantially outperforms standard CNN and Fisher-vector based approaches!

# Thank you!



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