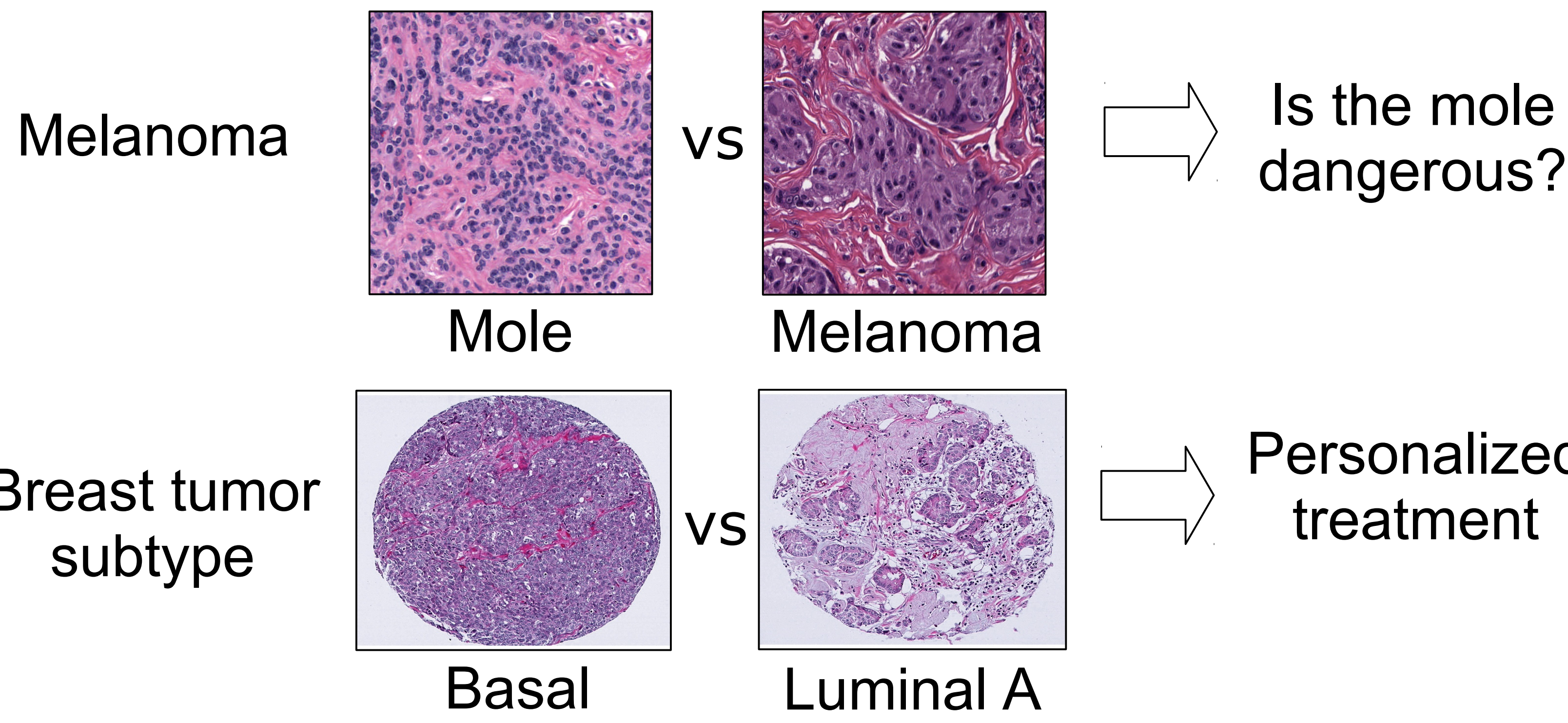# HIERARCHICAL TASK-DRIVEN FEATURE LEARNING FOR TUMOR HISTOLOGY

Heather D. Couture (heather@cs.unc.edu), J.S. Marron, Nancy E. Thomas, Charles M. Perou, Marc Niethammer – University of North Carolina

Problem Definition

Image classification:

Melanoma vs

Mole | Melanoma

⇒ Is the mole dangerous?

Breast tumor subtype vs

Basal | Luminal A

⇒ Personalized treatment

Applications:
• Diagnosis – differentiate between benign and malignant lesions
• Prognosis – identify dangerous tumors
• Subtyping – complement recent methods that target treatment based on molecular analysis

Goal: improve predictions by using automated image analysis
• Faster
• More repeatable
• Capture properties that pathologists cannot

Method: learn dictionary of patch-based features by sparse coding to describe tumor tissue and predict class
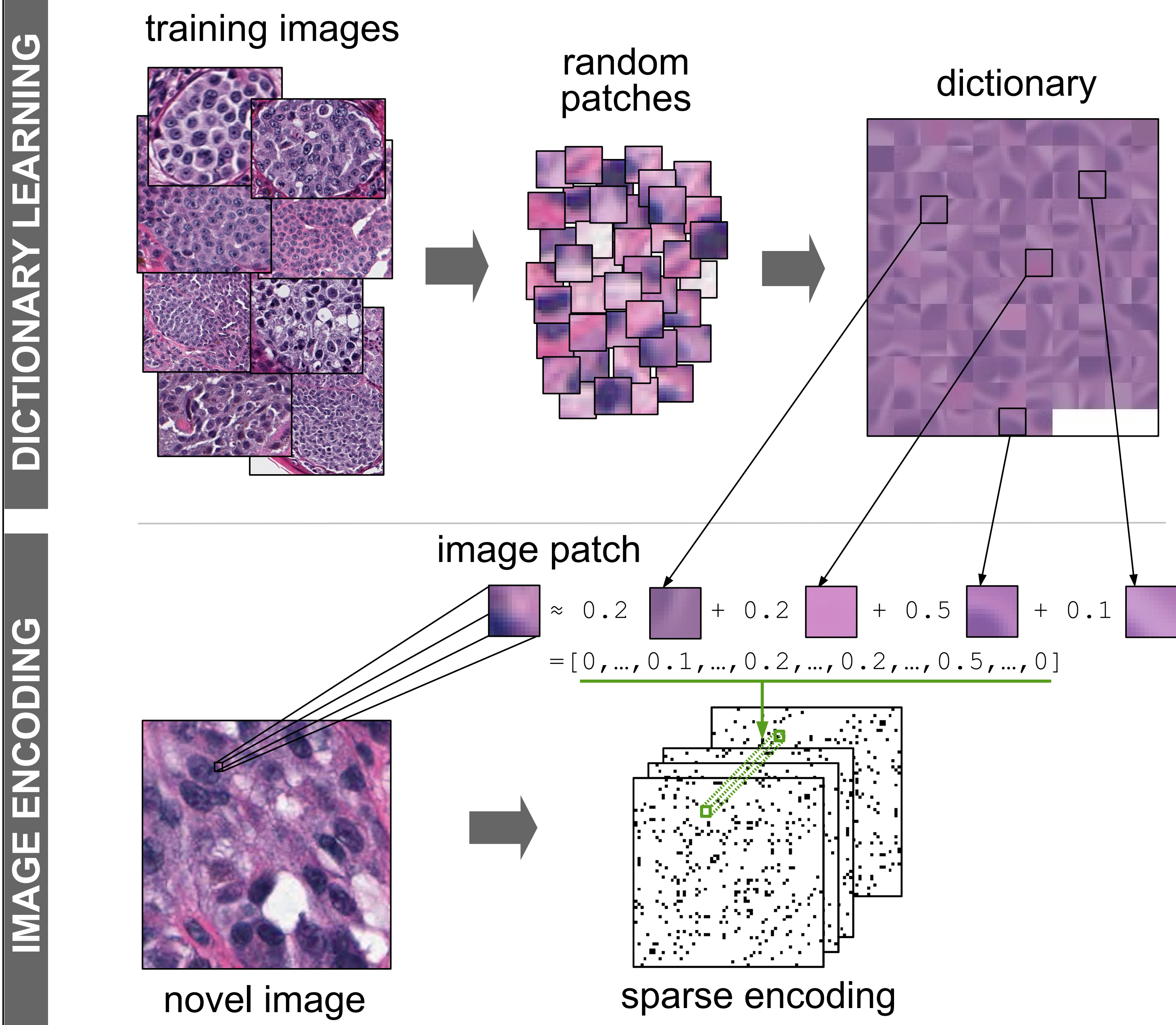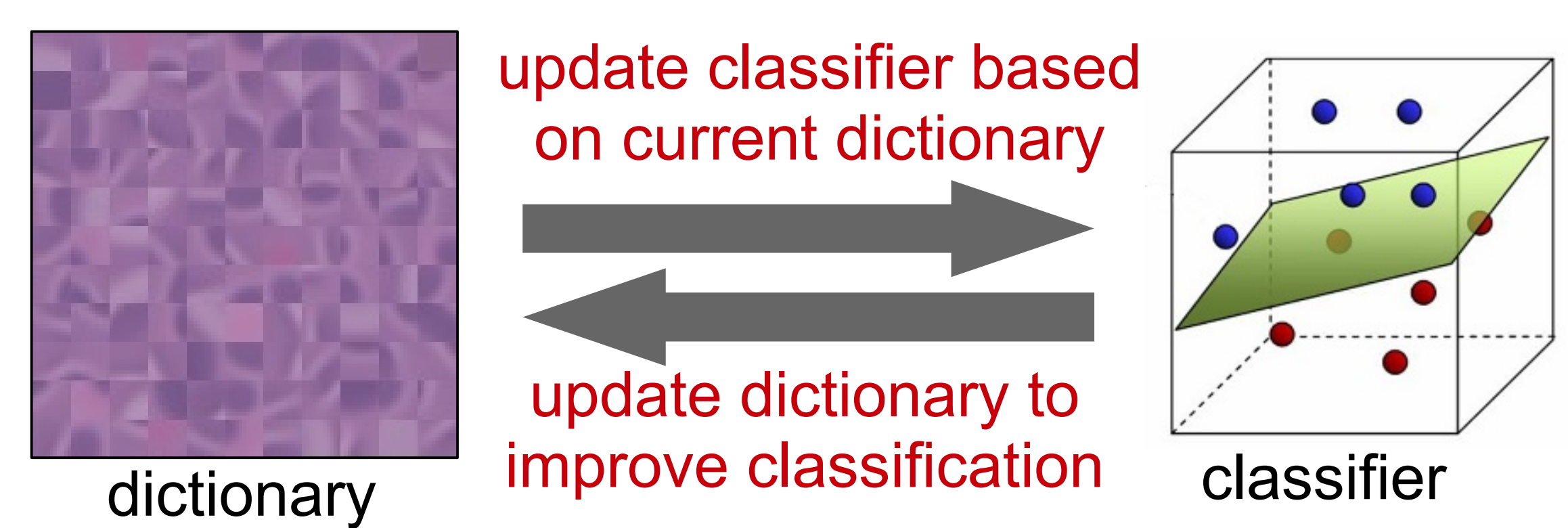
Contributions:
1) Discover subtle differences between classes with task-driven dictionary learning
2) Capture local and architectural structure with a hierarchical model
3) Provide insight into sample classification with visualizations

Unsupervised Dictionary Learning

Model image patches as sparse linear combinations of dictionary elements

DICTIONARY LEARNING

training images → random patches → dictionary

IMAGE ENCODING

image patch ≈ 0.2 ☐ $+ 0.2$ ☐ $+ 0.5$ ☐ $+ 0.1$ ☐
$= [0, \dots, 0.1, \dots, 0.2, \dots, 0.2, \dots, 0.5, \dots, 0]$

novel image → sparse encoding

Task-Driven Dictionary Learning

Tune dictionary to classification task

dictionary — update classifier based on current dictionary / update dictionary to improve classification — classifier
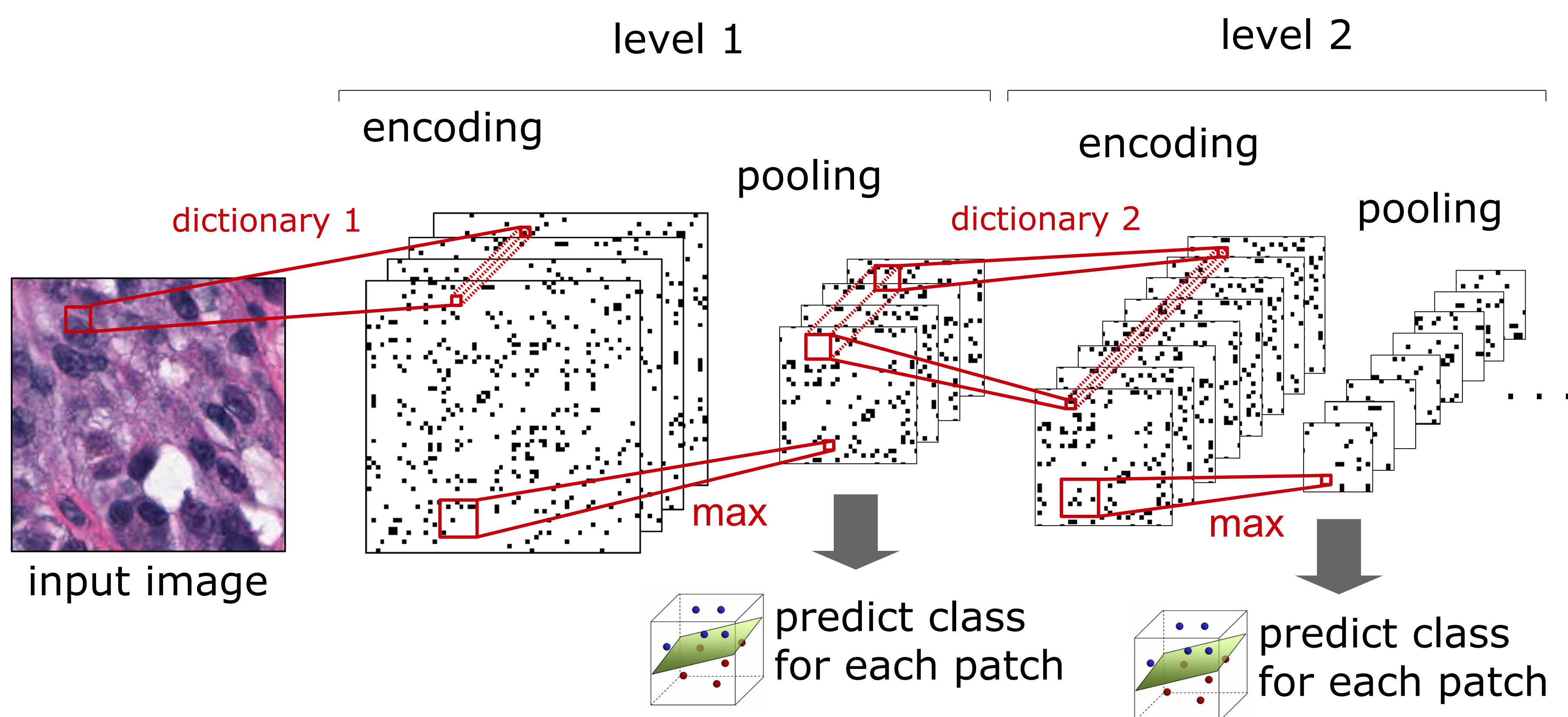
Approach: minimize logistic loss by updating classifier and dictionary using stochastic gradient descent

Algorithm:
Initialize dictionary with unsupervised dictionary learning
Initialize classifier with logistic regression on set of patches
Repeat until convergence:
• Select random images patches
• Compute sparse encodings
• Update classifier with gradient descent step
• Update dictionary with gradient descent step

Hierarchy of Features

level 1
encoding — pooling
dictionary 1
level 2
encoding — pooling
dictionary 2

input image

max → predict class for each patch
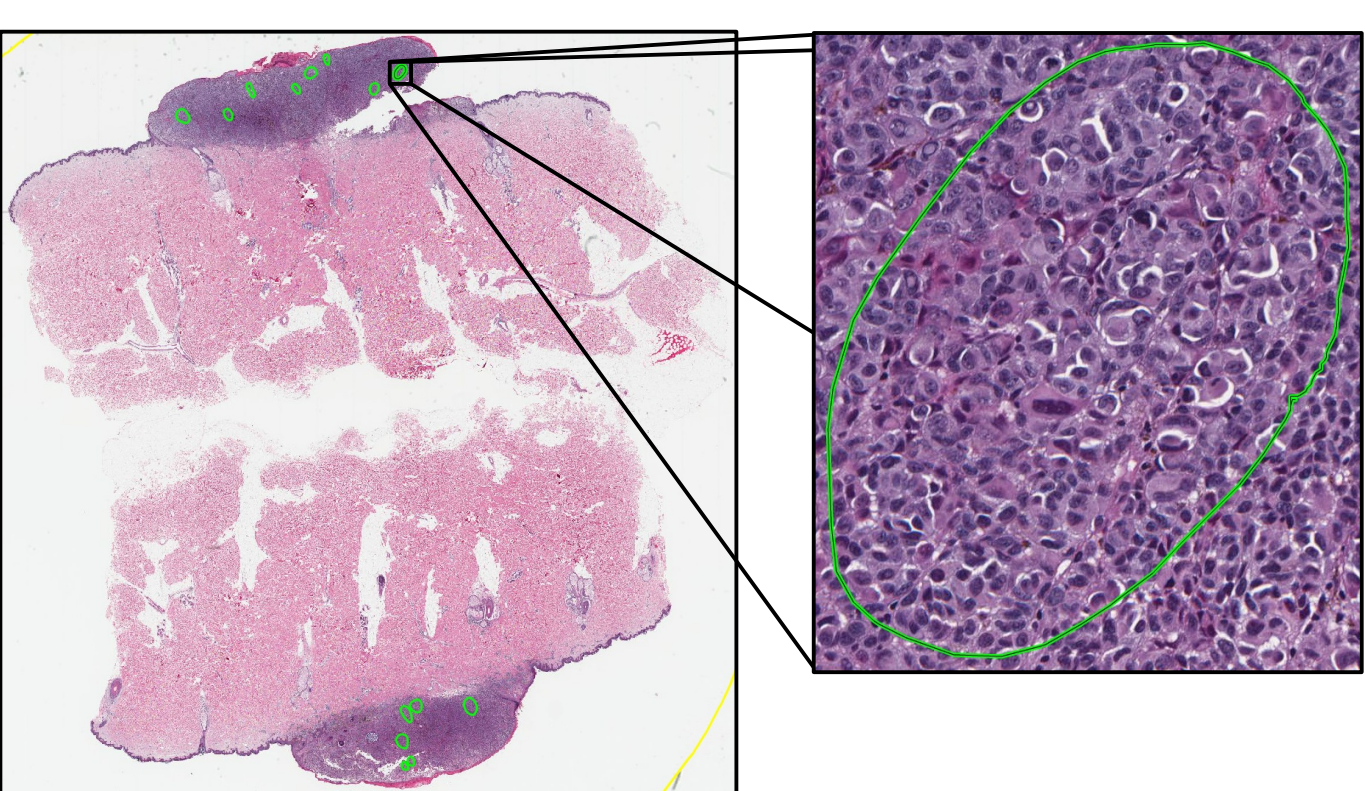max → predict class for each patch

To capture structures at different scales:
Form hierarchy by alternating encoding and max pooling
• Local translation invariance
• Downsizes representation to capture larger-scale properties on next level

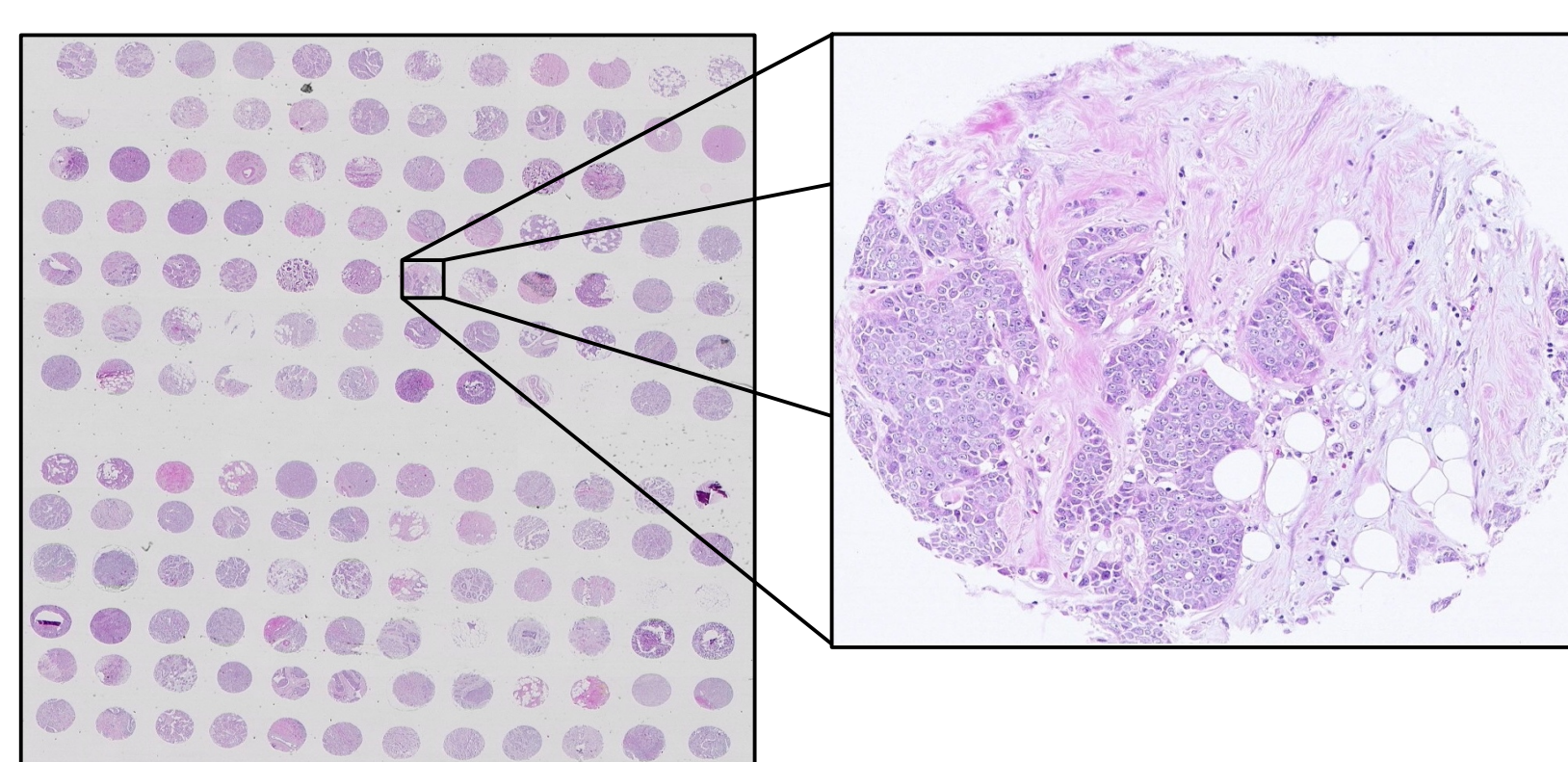Classify images by applying task-driven patch classifier and taking mean across image

Results

Melanoma vs. mole

whole slide

31 benign nevi, 21 melanoma

Breast tumor subtype

tissue microarray

43 Basal, 42 Luminal A

Interpreting classification models:
Apply classifier to patches within image to determine which regions are contributing to the predicted class

Patch-level Classification Accuracy

	Melanoma vs. mole		Breast tumor subtype Basal vs. Luminal A	
	Unsupervised dictionary	Task-driven dictionary	Unsupervised dictionary	Task-driven dictionary
Level 1	55.2%	**59.0%**	50.7%	**52.0%**
Level 2	59.8%	**63.9%**	56.4%	**58.0%**
Level 3	59.0%	**70.0%**	51.1%	**54.6%**

Patient-level Classification Accuracy

	Melanoma vs. mole		Breast tumor subtype Basal vs. Luminal A	
	Unsupervised dictionary	Task-driven dictionary	Unsupervised dictionary	Task-driven dictionary
Level 1	**65.5%**	53.6%	**61.5%**	59.3%
Level 2	82.9%	**84.4%**	**64.9%**	64.6%
Level 3	84.5%	**88.5%**	**70.1%**	62.1%

Level | Unsupervised dictionary | Task-driven dictionary

1
2
3

Original image (melanoma)

Melanoma ⟶ Mole