

# Unsupervised Discovery of Novel Emphysema Subtypes

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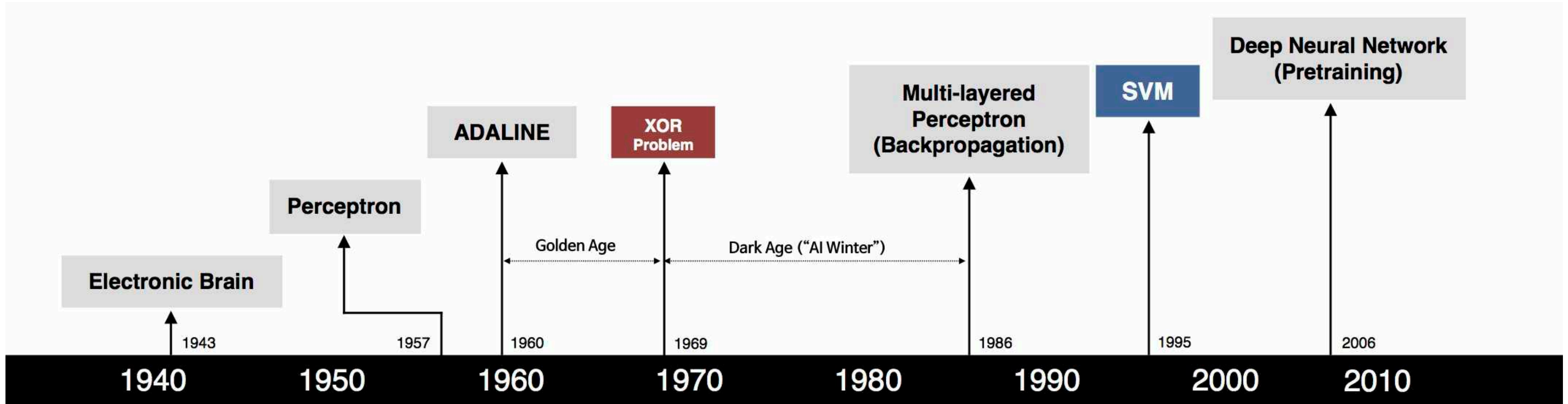
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Department of Radiology  
CUIMC

**Jie Yang** (Ph.D. Student, 2019)



# Historical Overview of AI: Timeline



S. McCulloch – W. Pitts



F. Rosenblatt



B. Widrow – M. Hoff



M. Minsky – S. Papert



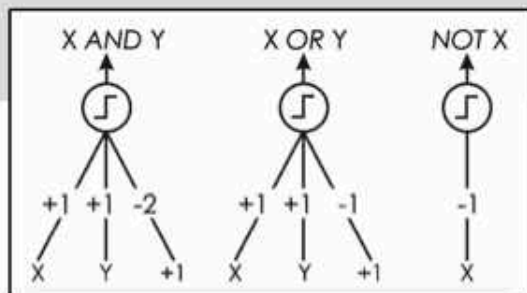
D. Rumelhart – G. Hinton – R. Williams



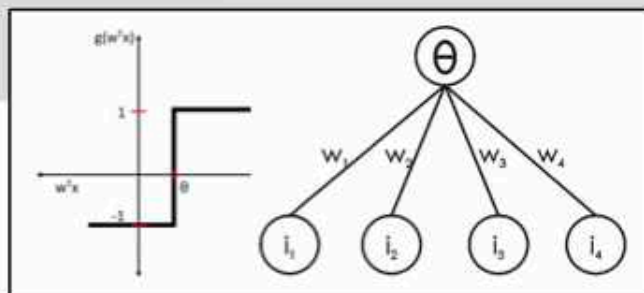
V. Vapnik – C. Cortes



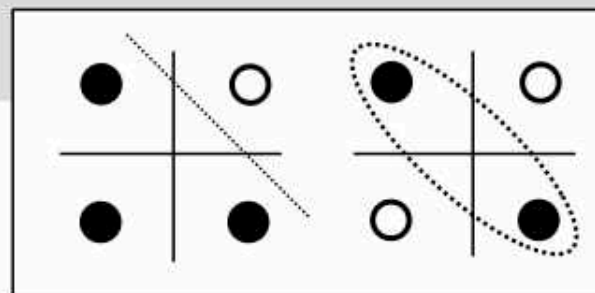
G. Hinton – S. Ruslan



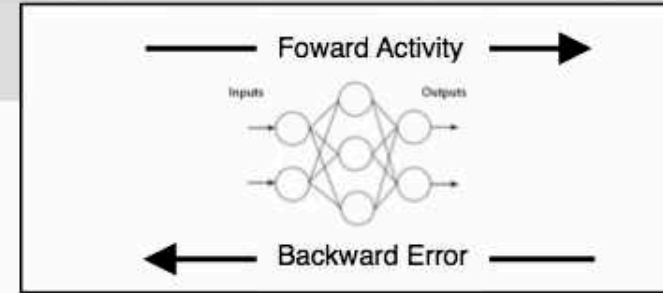
- Adjustable Weights
- Weights are not Learned



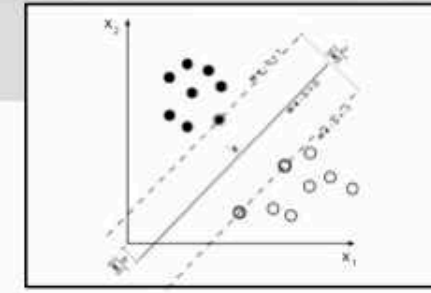
- Learnable Weights and Threshold



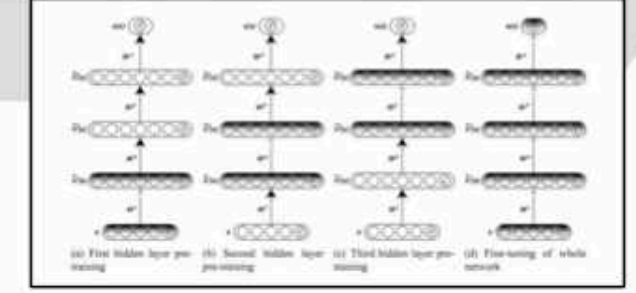
- XOR Problem



- Solution to nonlinearly separable problems
- Big computation, local optima and overfitting



- Limitations of learning prior knowledge
- Kernel function: Human Intervention



- Hierarchical feature Learning



# Machine Learning and AI

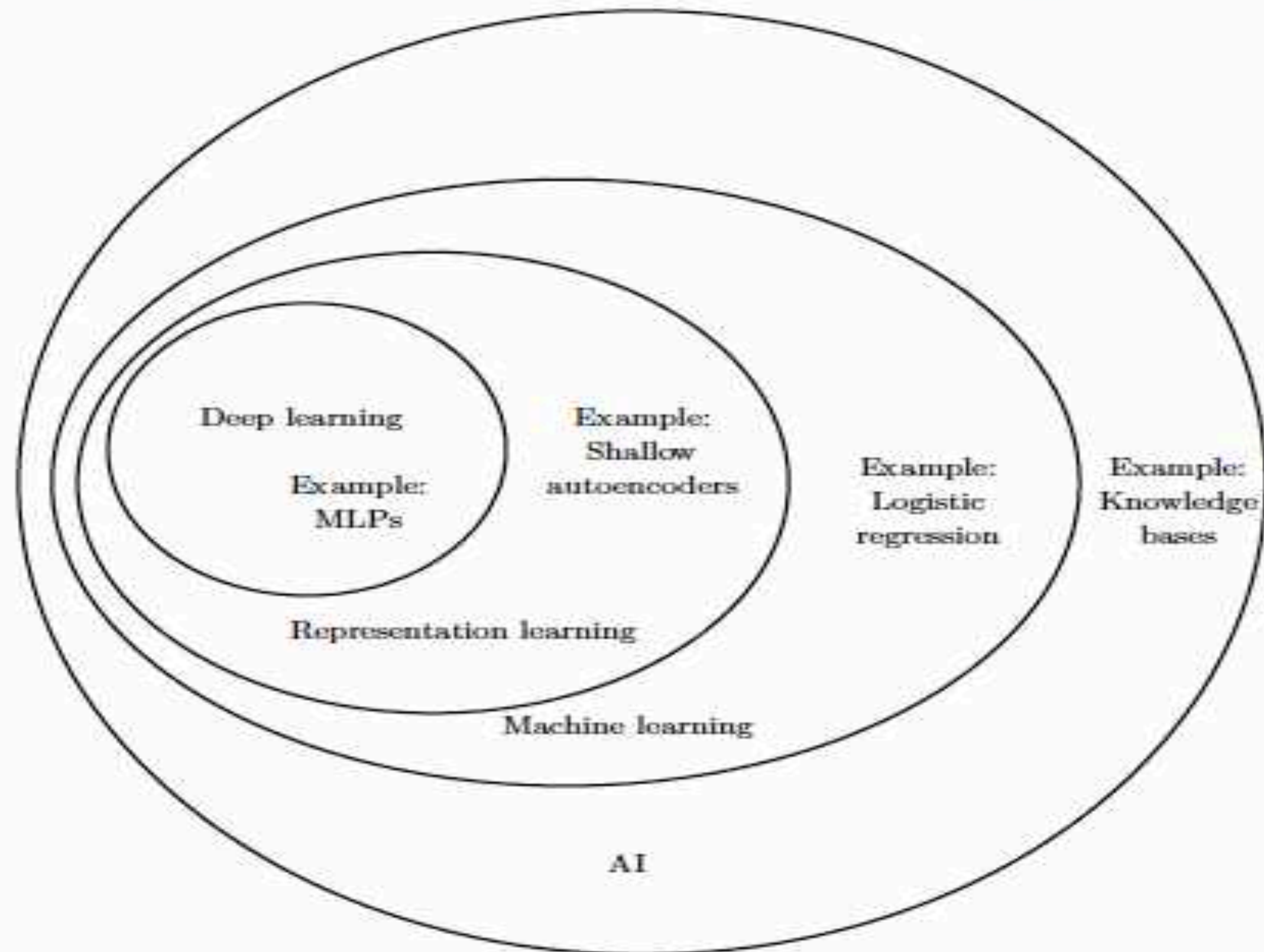


Figure 1.4



# Representations Matter

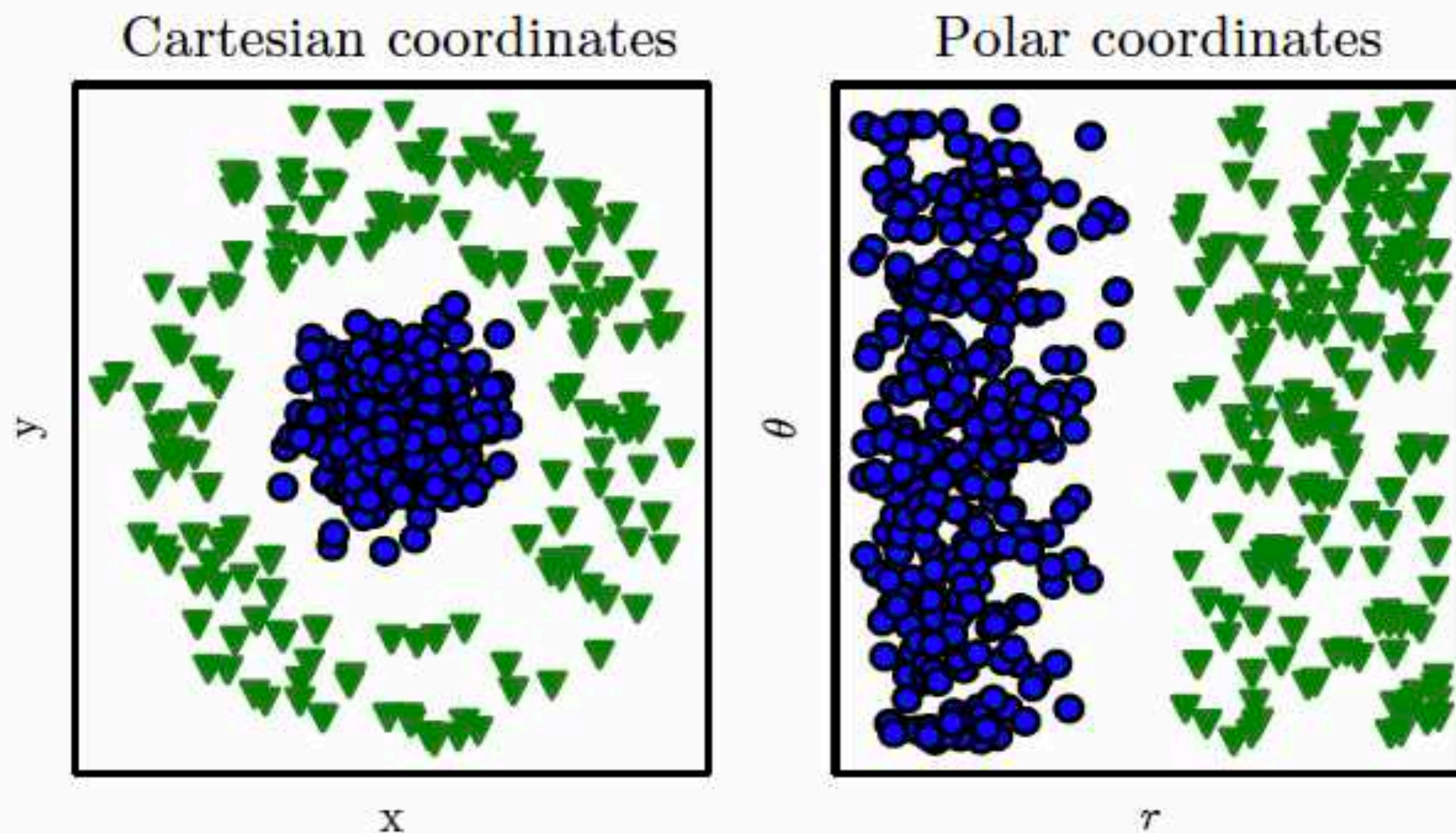
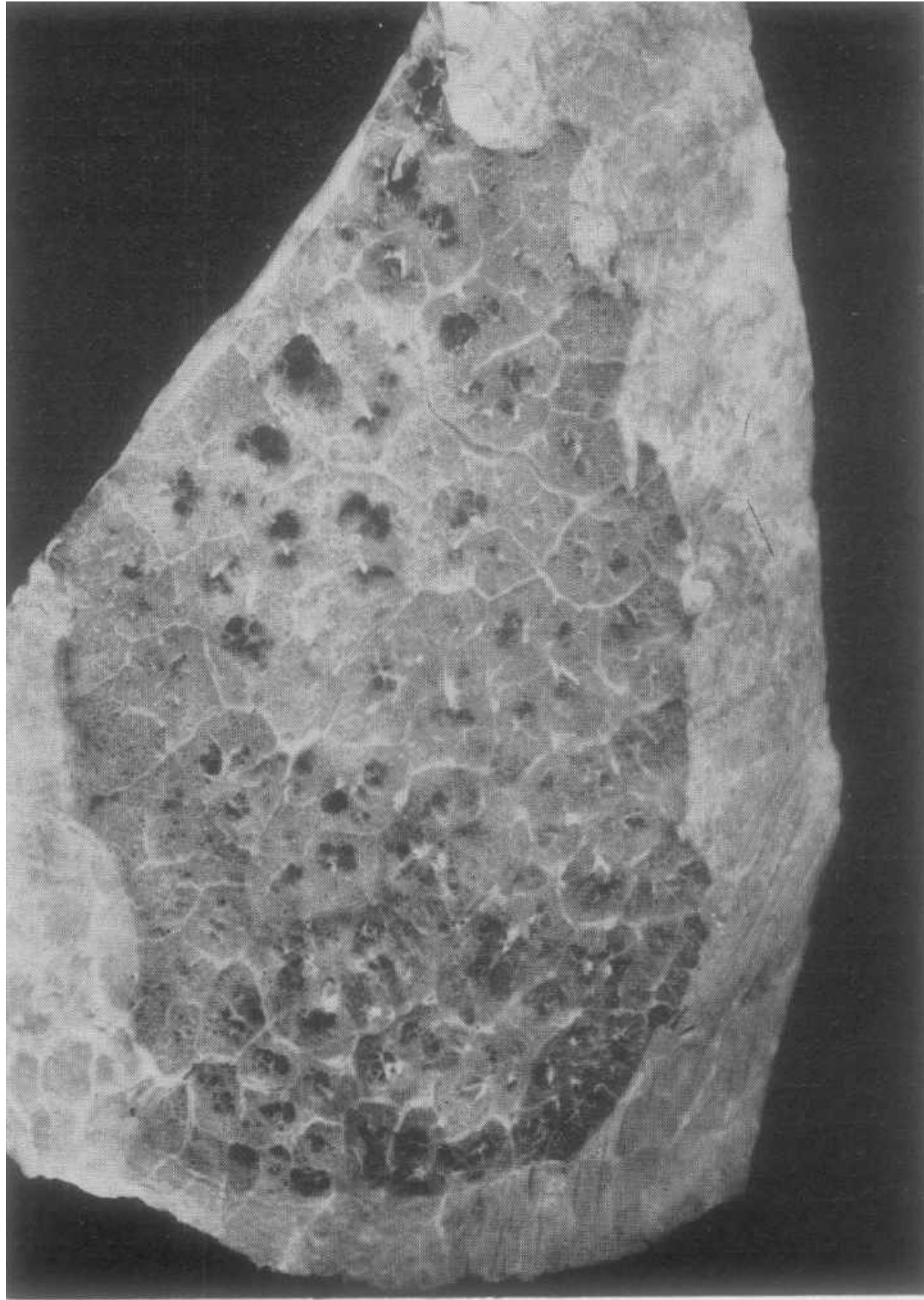


Figure 1.1



# Emphysema



- Emphysema + COPD is 3<sup>rd</sup> leading cause of death in USA.
- Defined by loss of interalveolar septa
- Predicts mortality in patients with and without COPD



# Background

Computed tomography (CT) used to analyze lung structure:



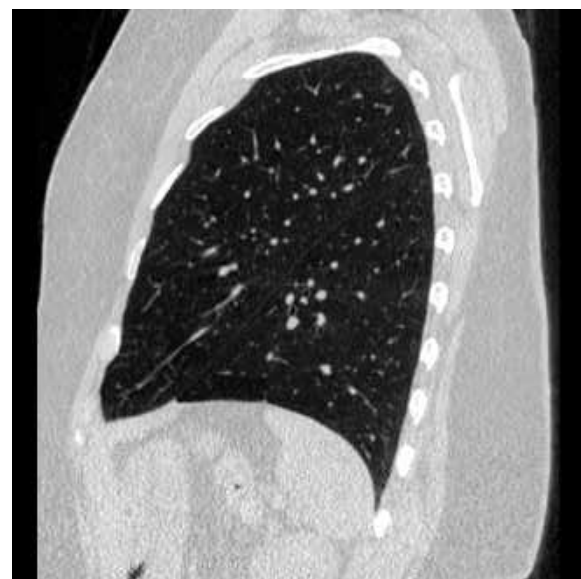
**Resolution =**  
 $0.5 \times 0.5 \times 0.75$  mm

**Matrix size =**  
 $512 \times 512 \times 500$  pixels

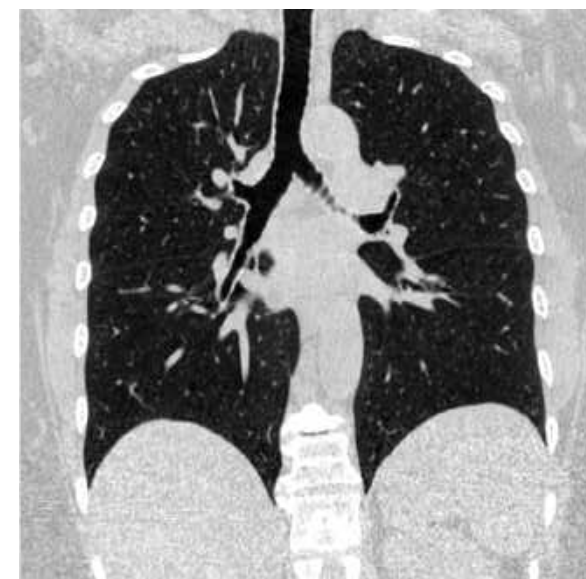
**Intensity range =**  
[-1024 1024] HU



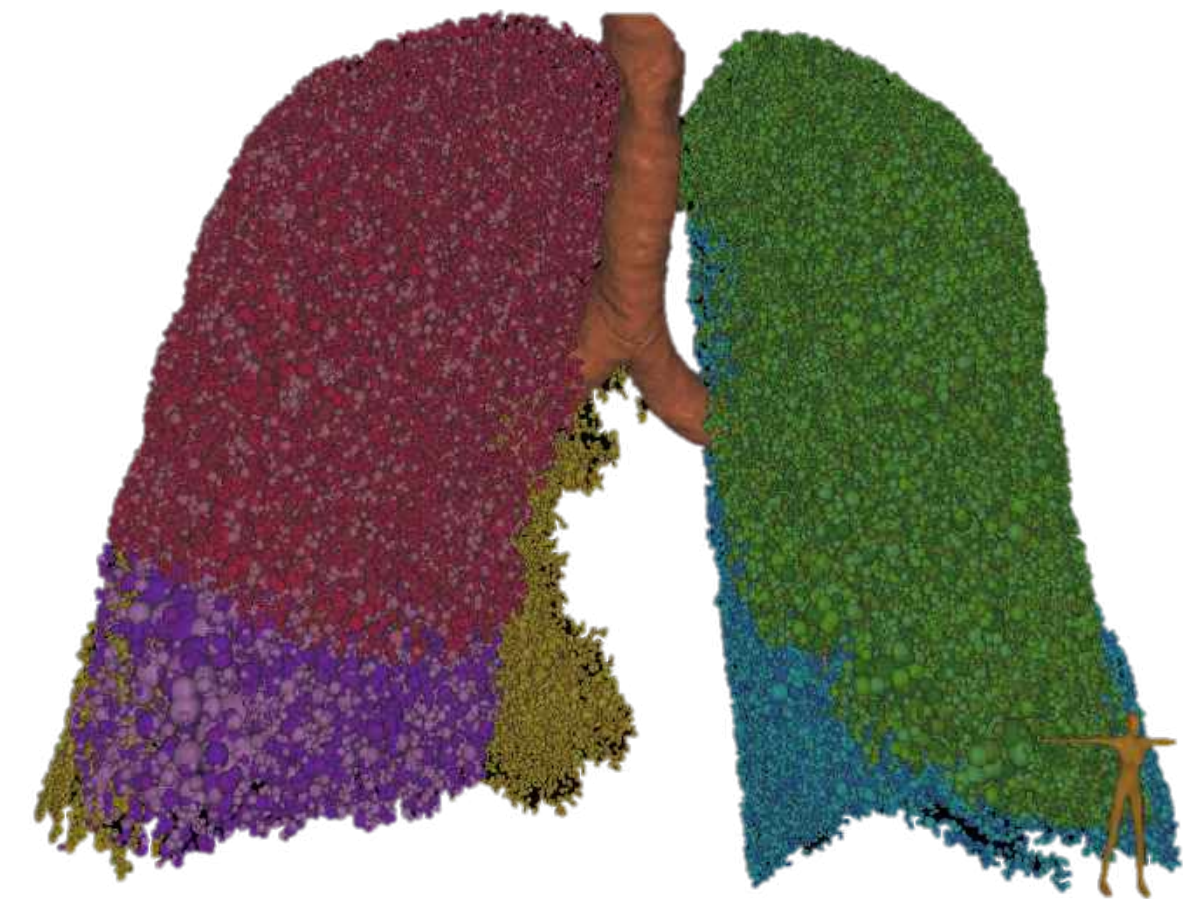
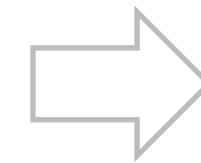
Axial



Sagittal



Coronal



**40 megavoxels of the lung:**

- Enable *in vivo* study of lung structure and disease patterns.



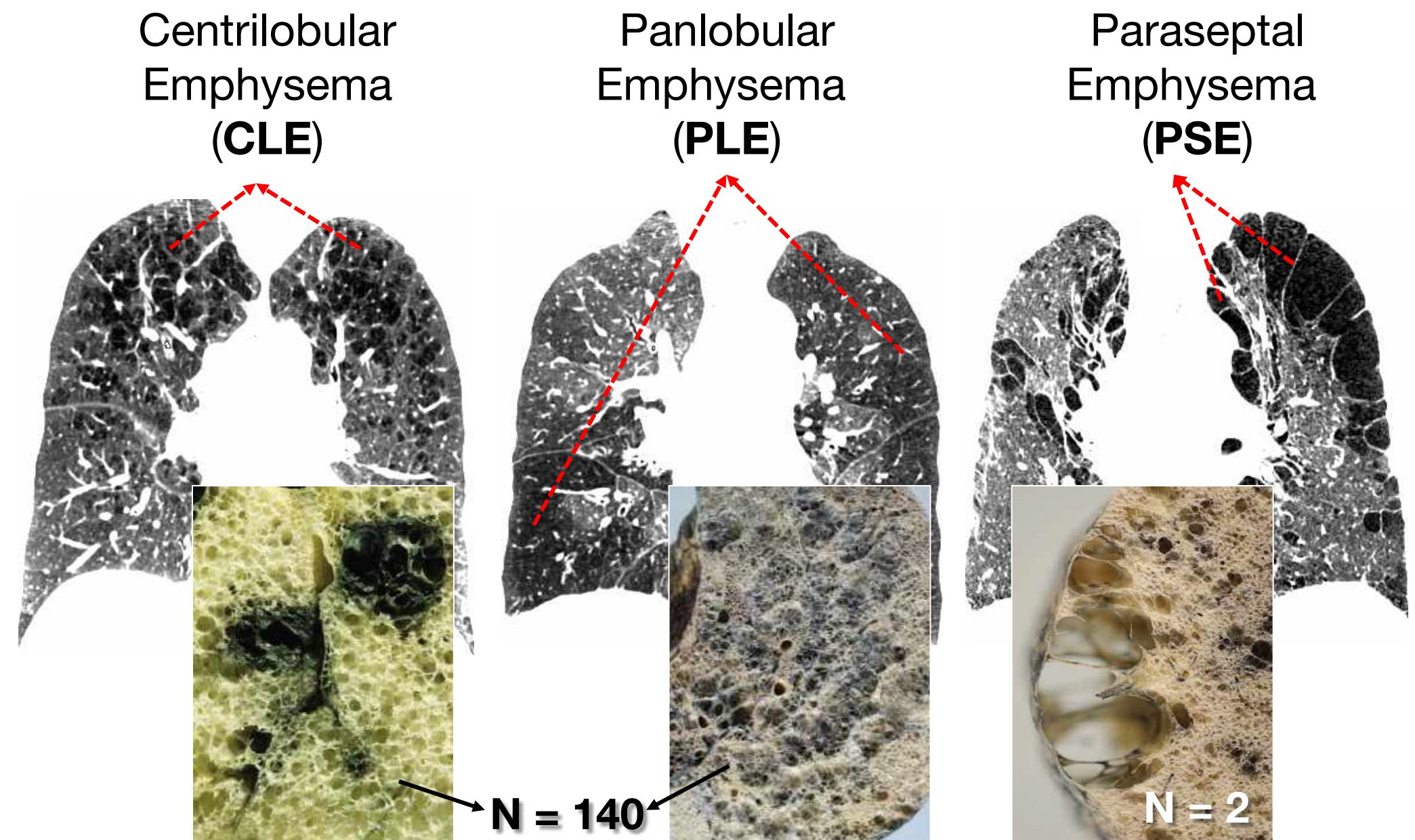
# Background

Lung texture learning to characterize emphysema subtypes:

## COPD and Emphysema

- ❑ Exact mechanism of developing COPD remains unknown;
- ❑ Three standard emphysema subtypes defined at autopsy <sup>[1]</sup>:
  - Limited inter-rater agreement.

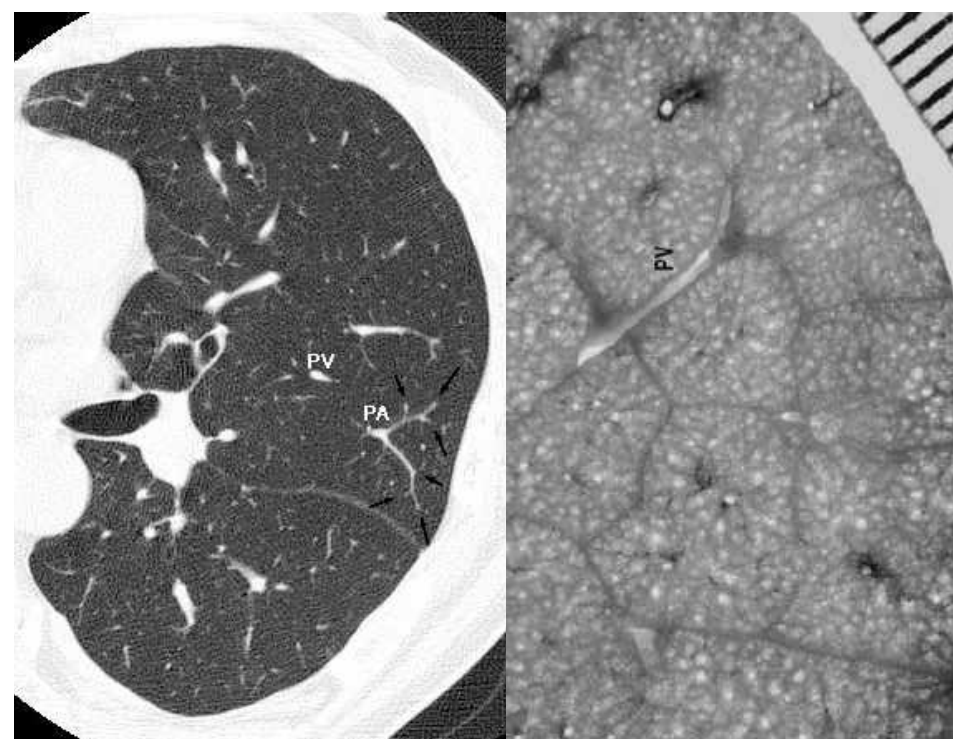
*Lung texture learning for emphysema subtyping can advance disease understanding*



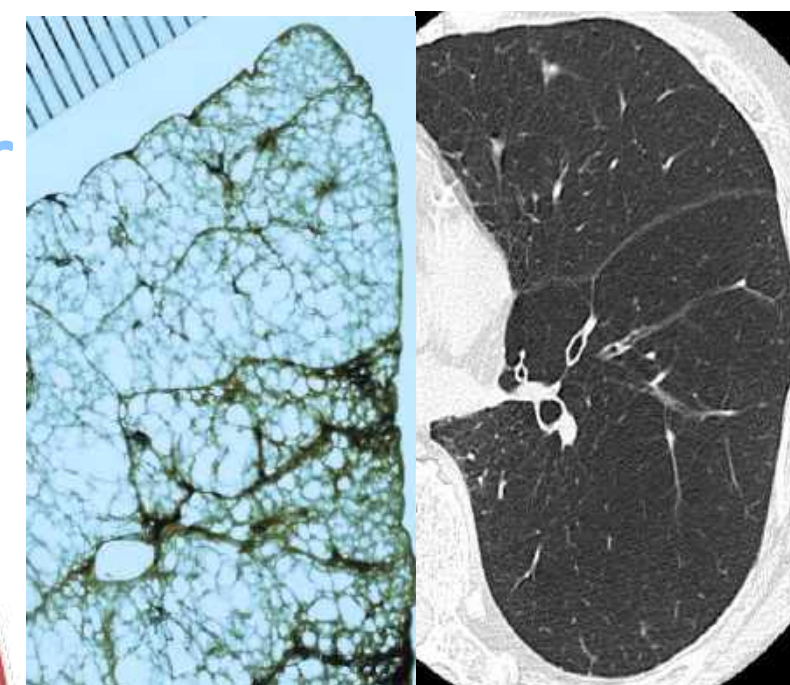
## Emphysema Subcategories



# Classic Emphysema Subtypes

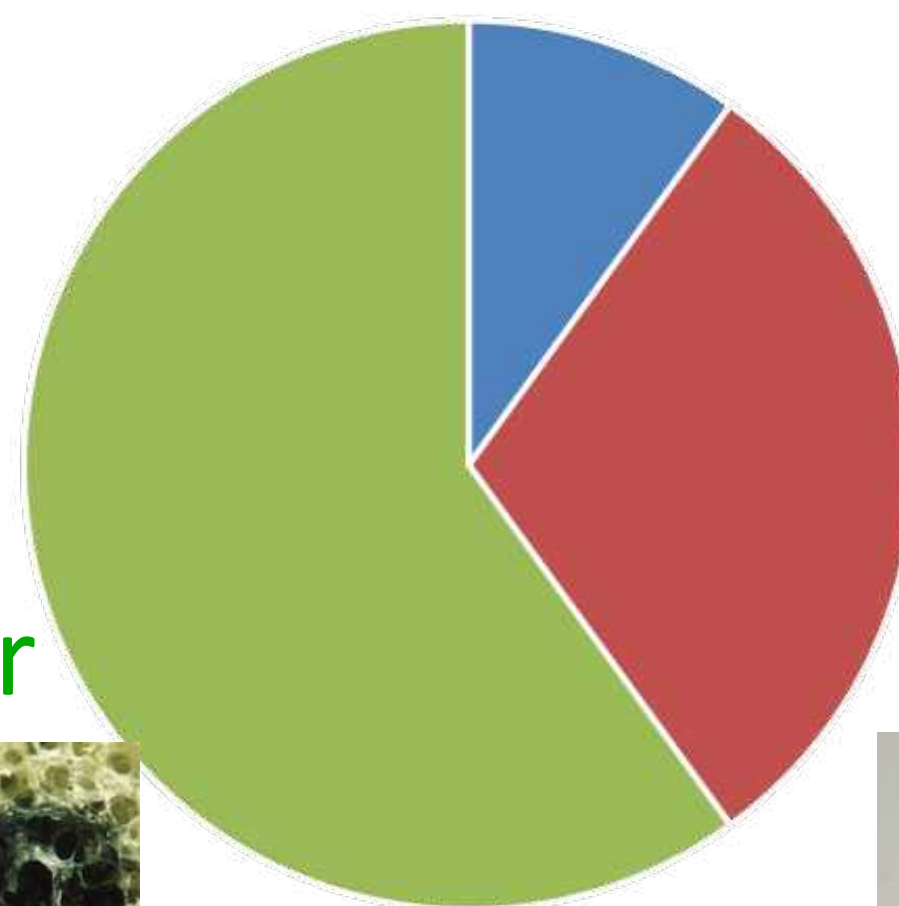
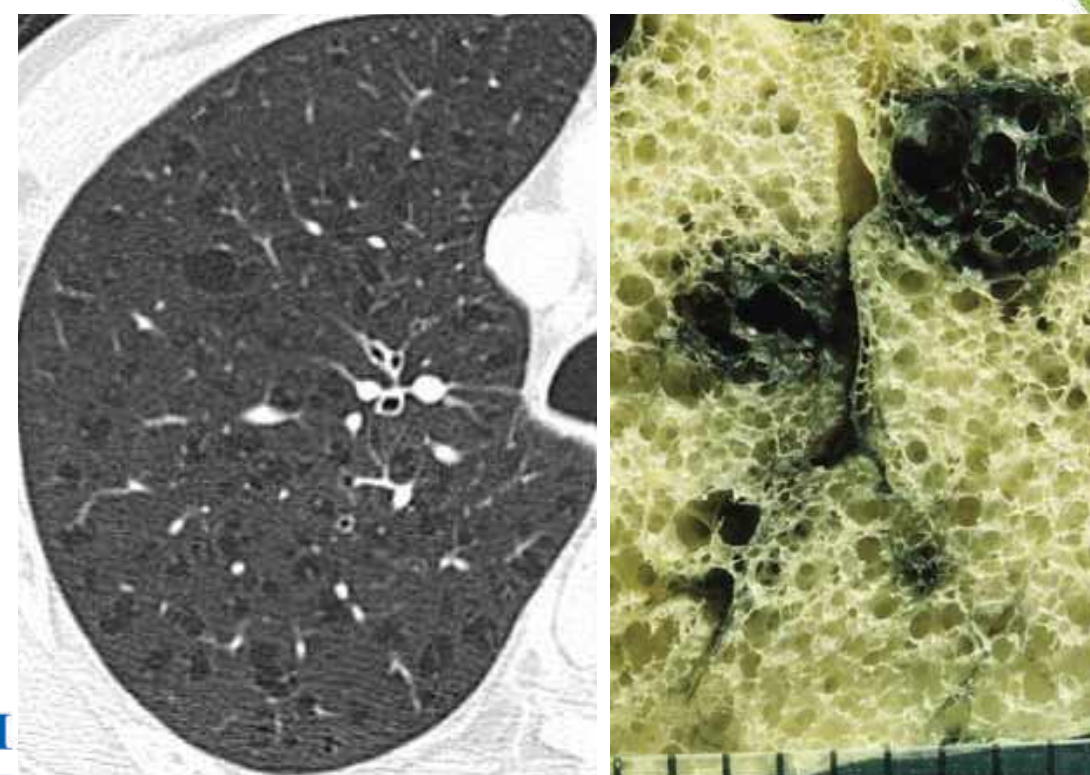


Panlobular



Paraseptal

Centrilobular





# Background

Aimed to tackle the problem of CT-based lung texture learning exploiting ***spatial localization***, using ***unsupervised*** / ***weakly-supervised*** learning.

***Aim 1:*** Develop an algorithm for **unsupervised** learning of **localized** texture patterns for **emphysema**.

***Aim 2:*** Label the discovered localized texture patterns on **large datasets** of **cardiac** CT scans.

***Aim 3:*** Examine possible correlations / hits with GWAS genomic information in MESA and SPIROMICS.



NIH R01-HL121270: **Novel Quantitative Emphysema Subtypes in MESA and SPIROMICS.**  
(PIs Dr. R.G. Barr, Dr. A.F. Laine)





# Hypothesis

- Unsupervised learning of spatial lung texture patterns on research CT scans will yield novel emphysema subtypes.
  - Reproducible
  - Distinct symptoms
  - Specific histology and genetic basis





# SPIROMICS and MESA

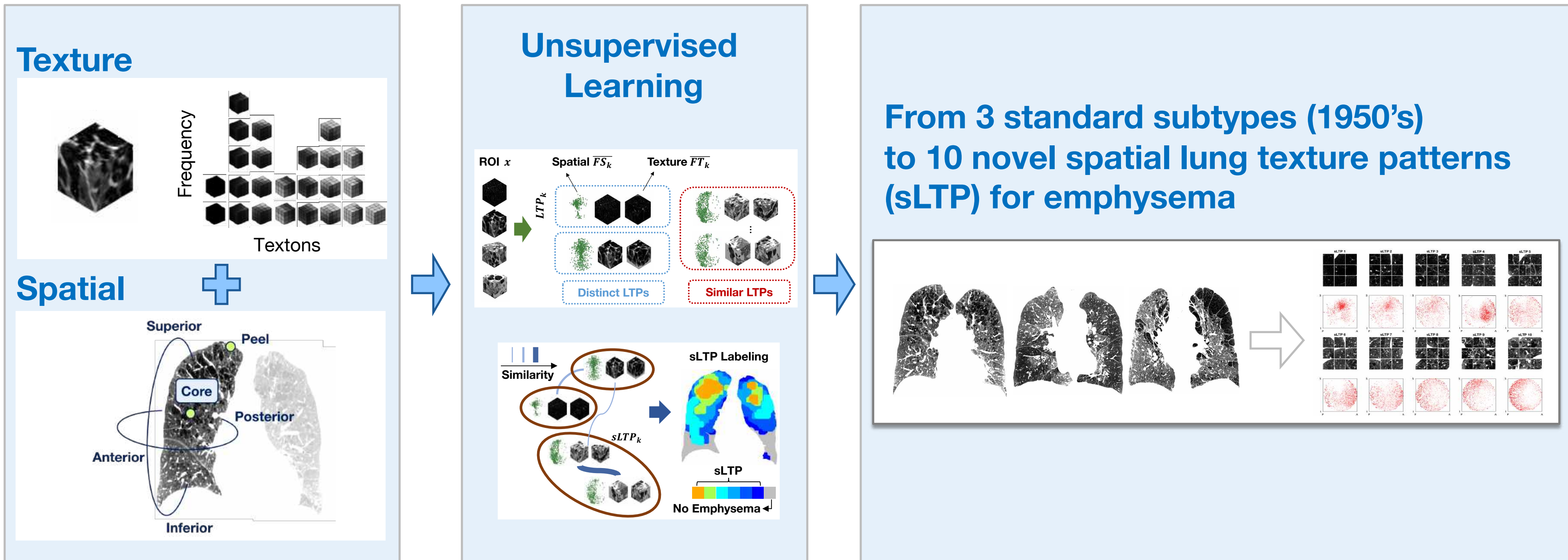


- ***SubPopulations and Intermediate Outcome Measures In COPD Study***
  - COPD case-control study
  - 2,983 participants with CT scans (~6,000 scans)
  - Whole genome sequencing, multi-omics
- ***Multi-Ethnic Study of Atherosclerosis Lung Study***
  - Population-based, prospective cohort study
  - 3,205 participants with full-lung CT scans (~50,000 scans)
  - Whole genome sequencing, multi-omics



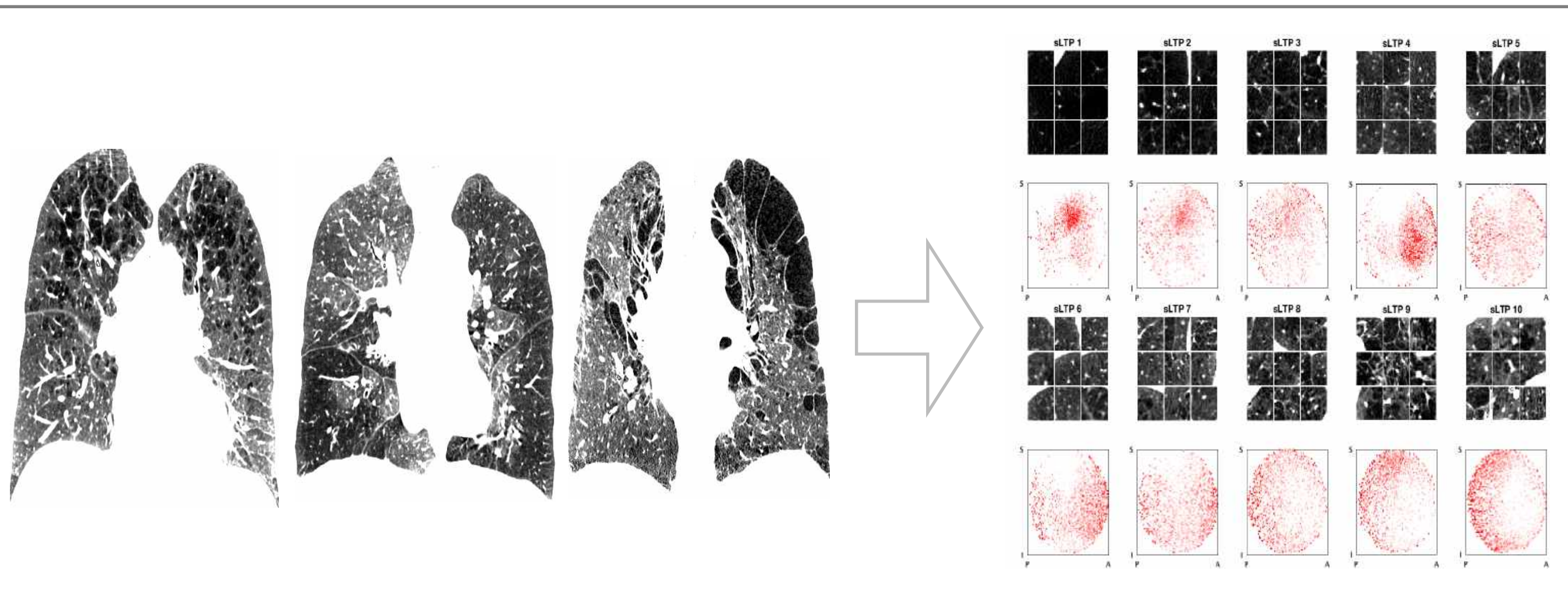
# Background: Processing Overview

- Unsupervised machine learning defined novel emphysema patterns on CT.





# Unsupervised Learning of Localized Texture Patterns for Pulmonary Emphysema



## Challenges

- Learning *localized texture* patterns in an *unsupervised* manner;
- *Homogeneity* vs. *redundancy* of the learned patterns.



## Summary of Findings:

- Applied a method to standardize *lung shape spatial mapping*;
- Developed a two-stage *unsupervised* framework combining *spatial and texture* information;
- Discovered emphysema patterns on *large COPD cohorts* with compelling clinical significance.

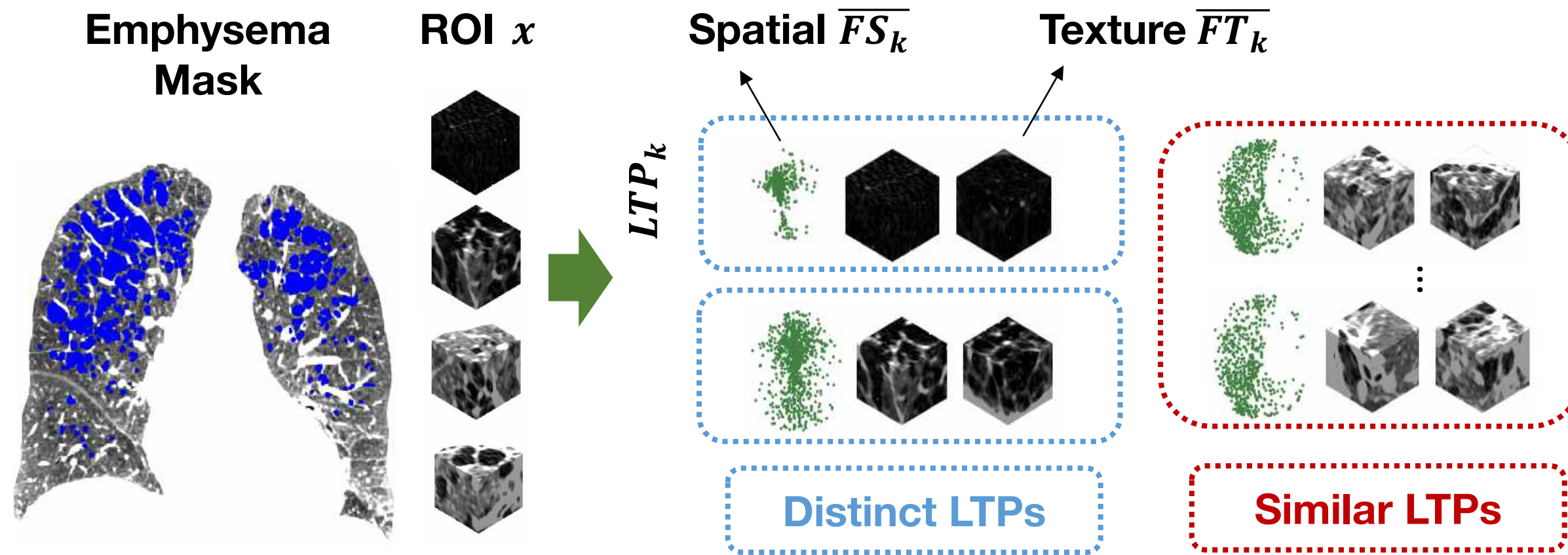
[1] **Jie Yang** et al., Unsupervised Machine Learning to Define Quantitative Subtypes of Pulmonary Emphysema on CT, **Science** (to submit in December 2018).

[2] **Jie Yang** et al., Unsupervised Discovery of Spatially-Informed Lung Texture Patterns for Pulmonary Emphysema: The MESA COPD Study. **MICCAI**, 2017.

# Method

Unsupervised learning of localized texture patterns for pulmonary emphysema

## 2 Learning Stage 1: ➤ Augmented Lung Texture Patterns (LTPs)



$FT_x / FS_x$  = texture / spatial feature of ROI  $x$

$\overline{FT_k} / \overline{FS_k}$  = texture / spatial centroid of  $LTP_k$

Iteratively update ROI assignment  $\Lambda_k^{(t)}$  of  $LTP_k$ , by **minimizing a dedicated cost function** <sup>[1]</sup>:

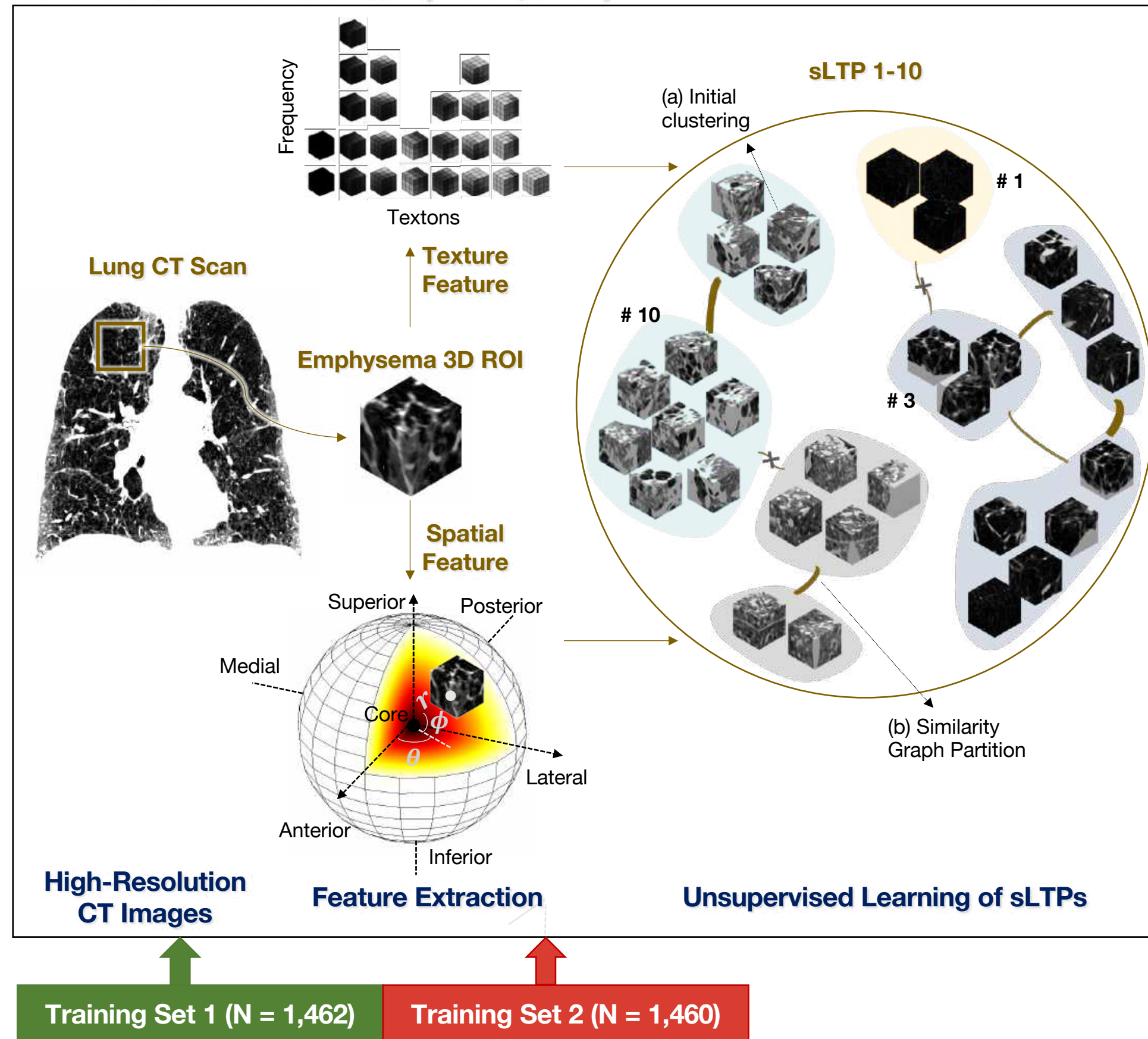
$$\begin{aligned}
 & \chi^2 \left( FT_x, \overline{FT_k^{(t-1)}} \right) && \text{Texture distance} \\
 & + \\
 & \omega \cdot W \cdot \left\| FS_x, \overline{FS_k^{(t-1)}} \right\|_2^2 && \text{Spatial regularization} \\
 & + \\
 & \gamma \cdot \mathbb{I} \left( \chi^2 \left( FT_x, \overline{FT_k^{(t-1)}} \right) > thresh_{\chi^2} \right) && \text{Texture penalty}
 \end{aligned}$$



# Learning Pipeline and Results in SPIROMICS and MESA Lung Study

Unsupervised learning of localized texture patterns for pulmonary emphysema

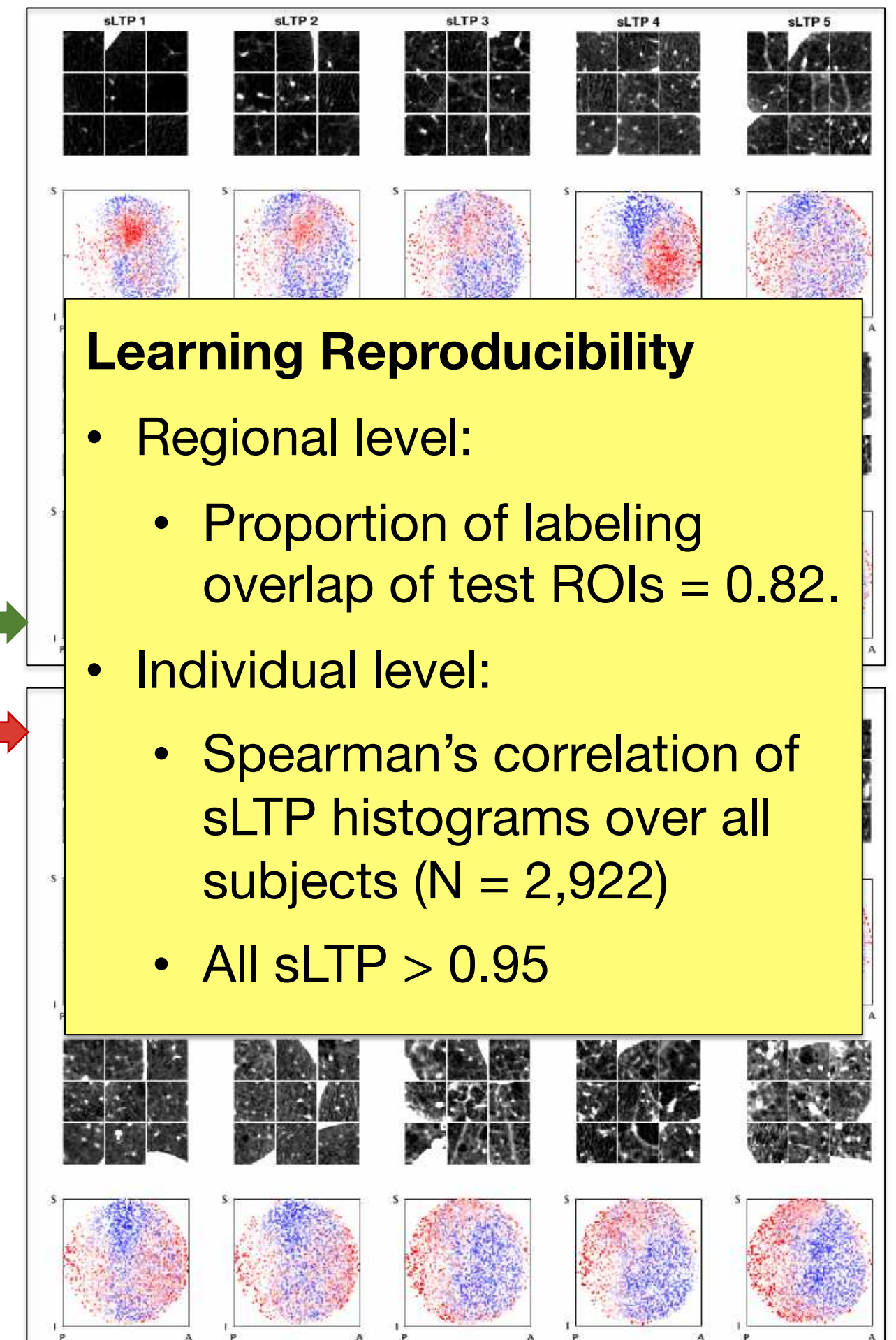
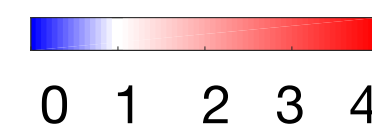
**DATA: SPIROMICS (N=2,922)**



Training Set 1  
(N = 1,462)

Training Set 2  
(N = 1,460)

Spatial density

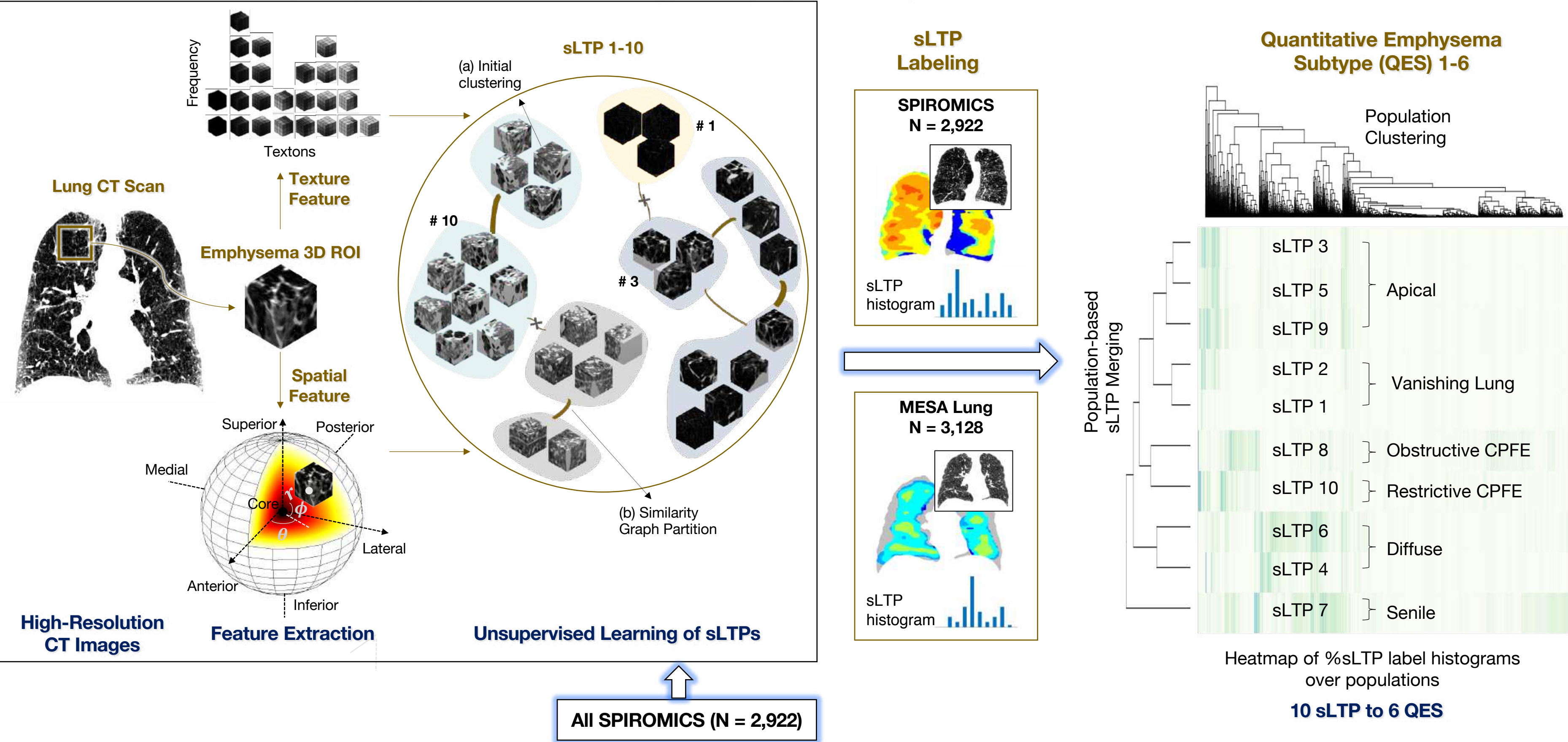




# Learning Pipeline and Results in SPIROMICS and MESA Lung Study

Unsupervised learning of localized texture patterns for pulmonary emphysema

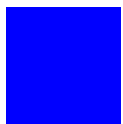
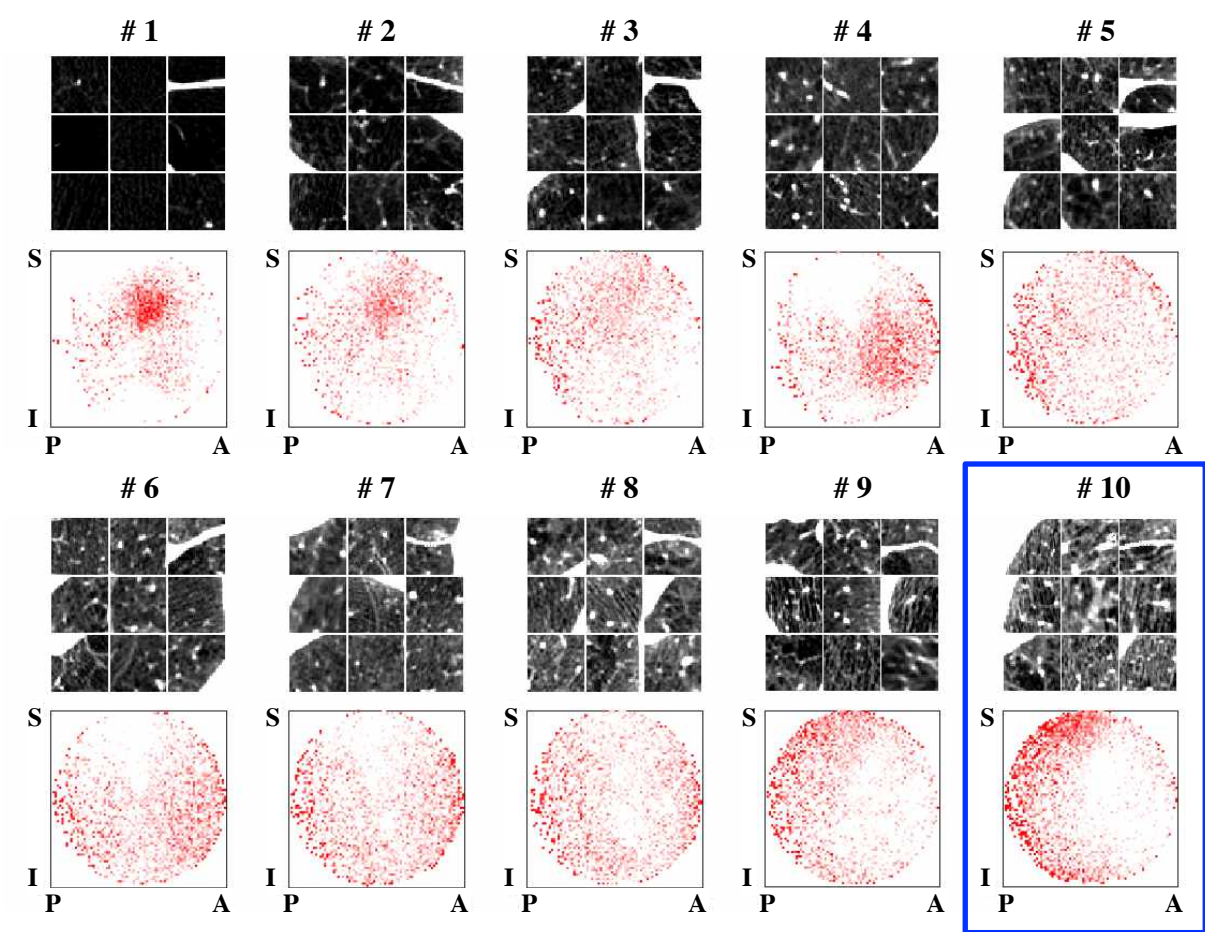
**DATA: SPIROMICS (N=2,922) and MESA Lung Study (N=3,128)**





# Experimental Results in SPIROMICS and MESA Lung Study

Unsupervised learning of localized texture patterns for pulmonary emphysema



**Restrictive CPFE**



Associated with  
Dyspnea  
Hypoxemia at rest  
Desaturation on exertion  
↓↓6MWT  
Exacerbations

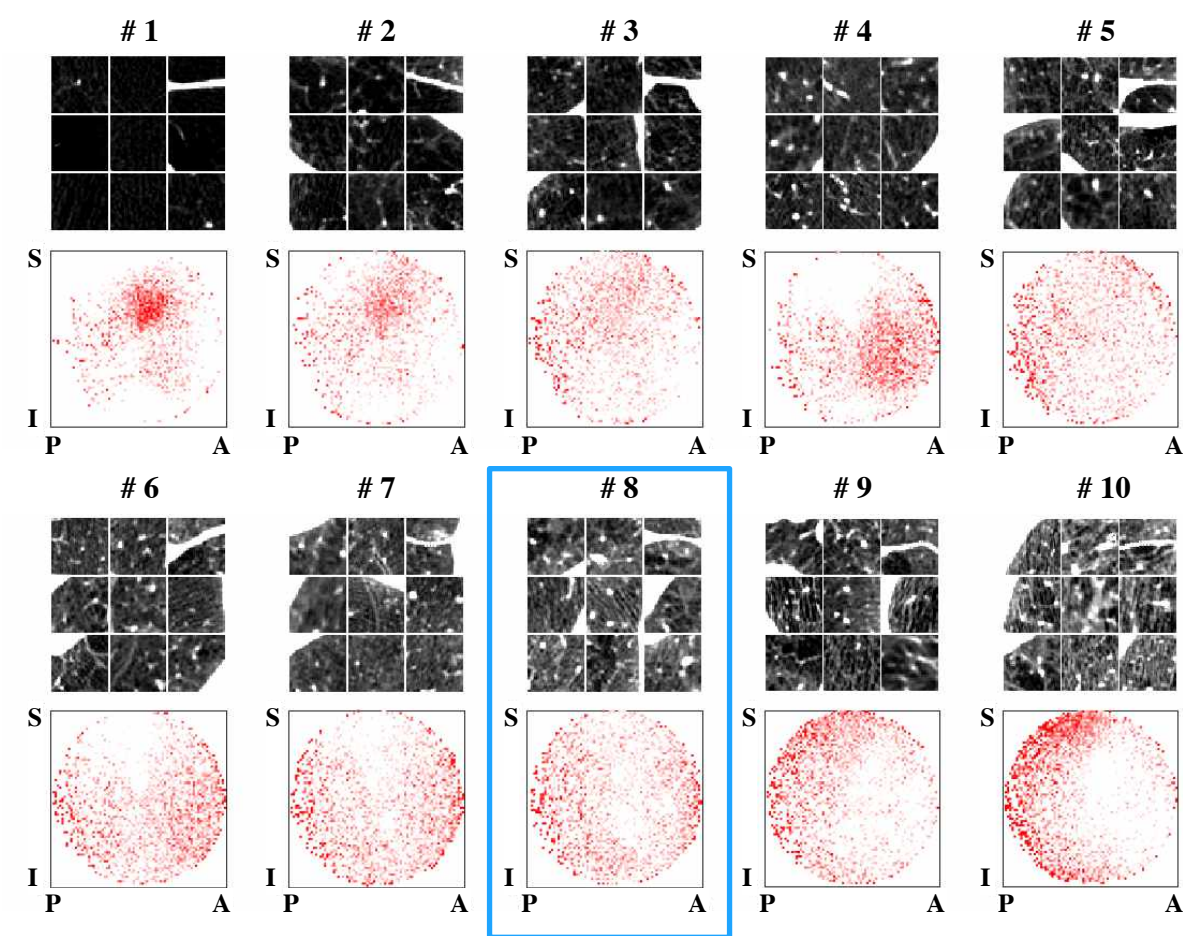
↓ FEV<sub>1</sub>  
FVC  
FEV<sub>1</sub>/FVC  
↓↓ TLV on CT

Adjusted for age, sex, race/ethnicity, height, weight, smoking status, pack-years, COPD, scanner manufacturer, FEV1, other QES.

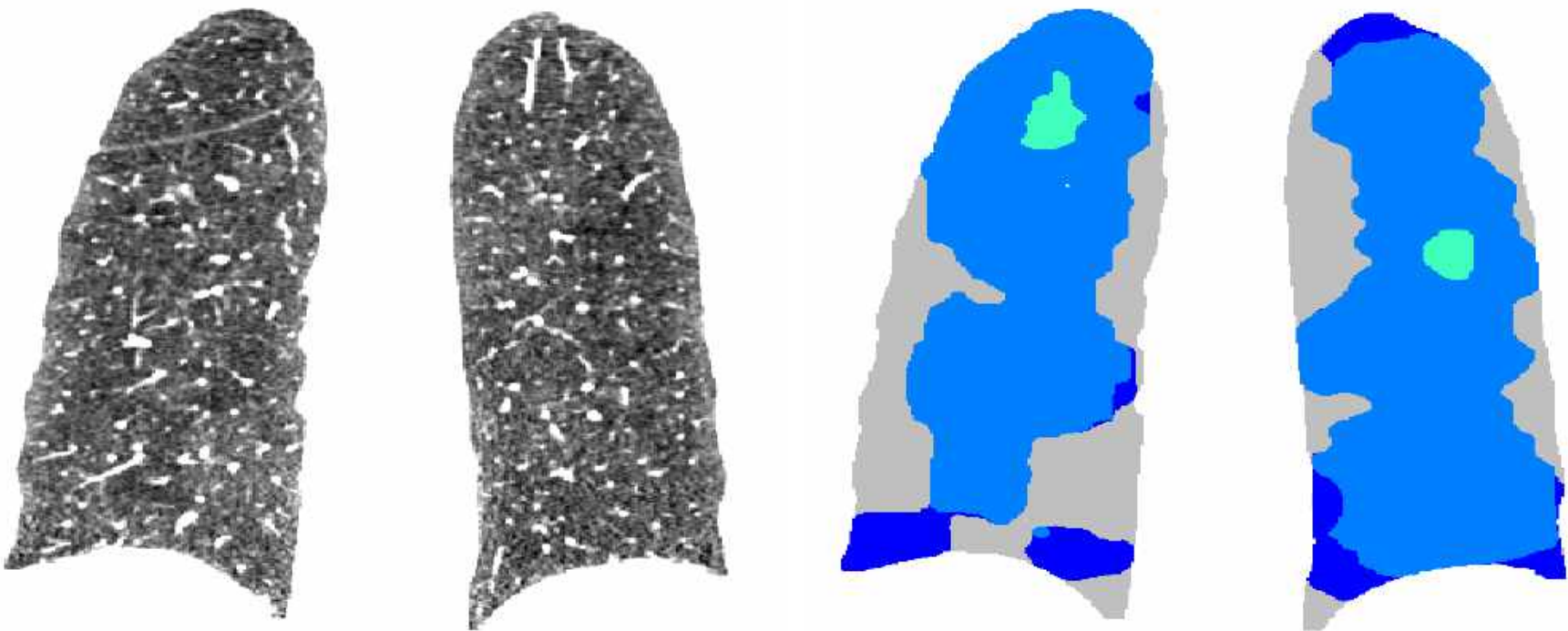


# Experimental Results in SPIROMICS and MESA Lung Study

Unsupervised learning of localized texture patterns for pulmonary emphysema



 **Obstructive CPFE**



Associated with

Desaturation on exertion

- ↓ FEV<sub>1</sub>
- ↓ FVC
- ↓ FEV<sub>1</sub>/FVC
- ↑ TLV on CT

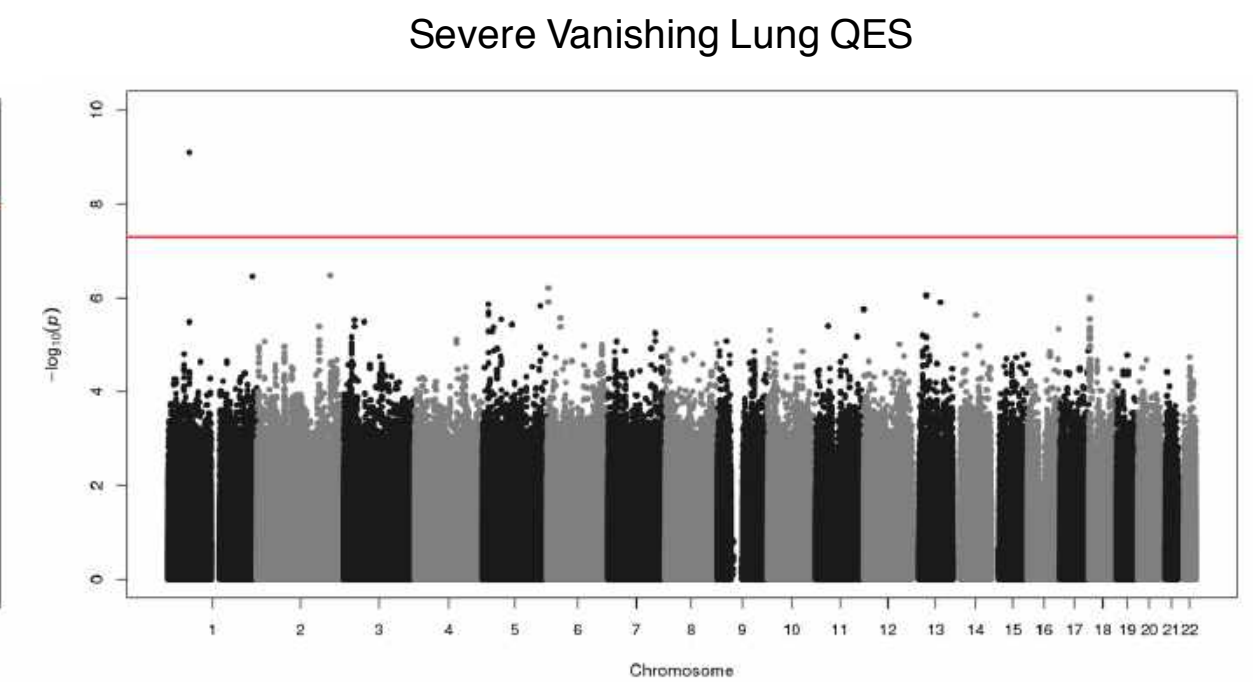
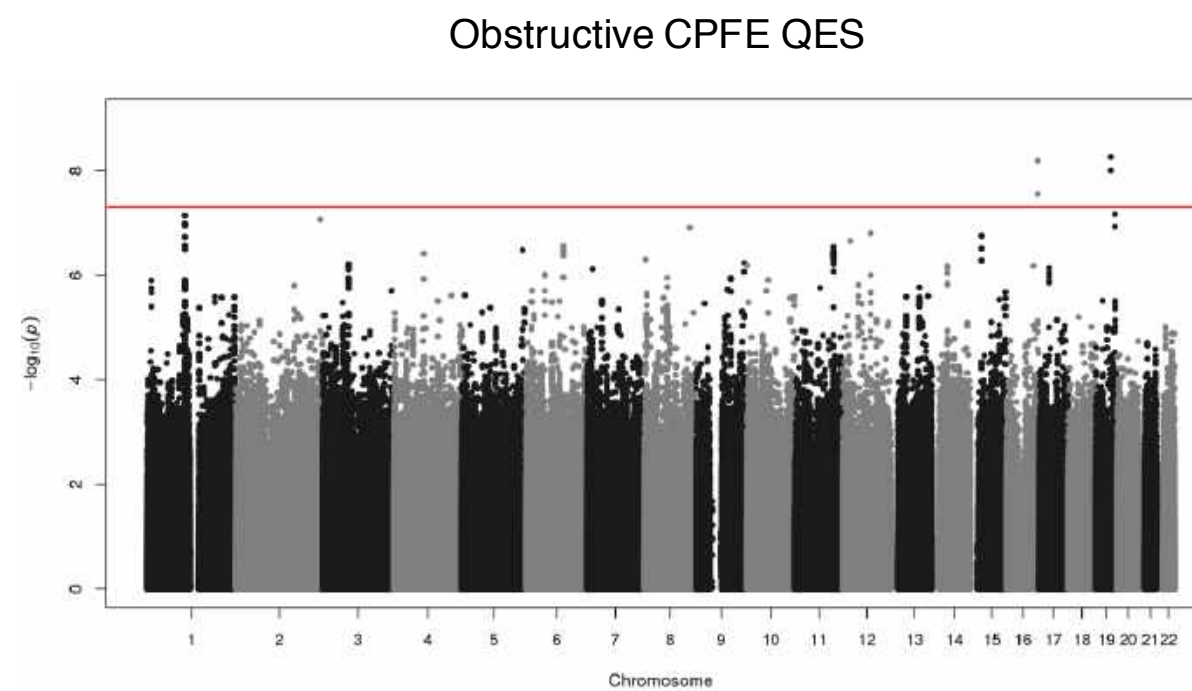
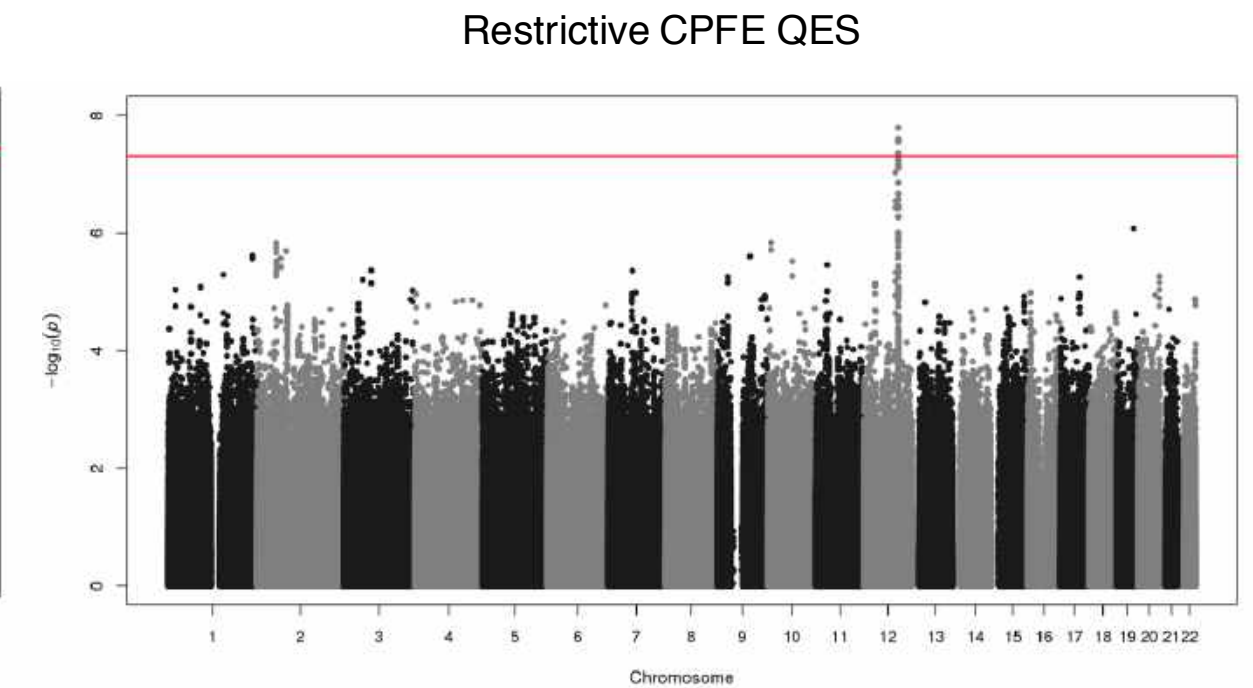
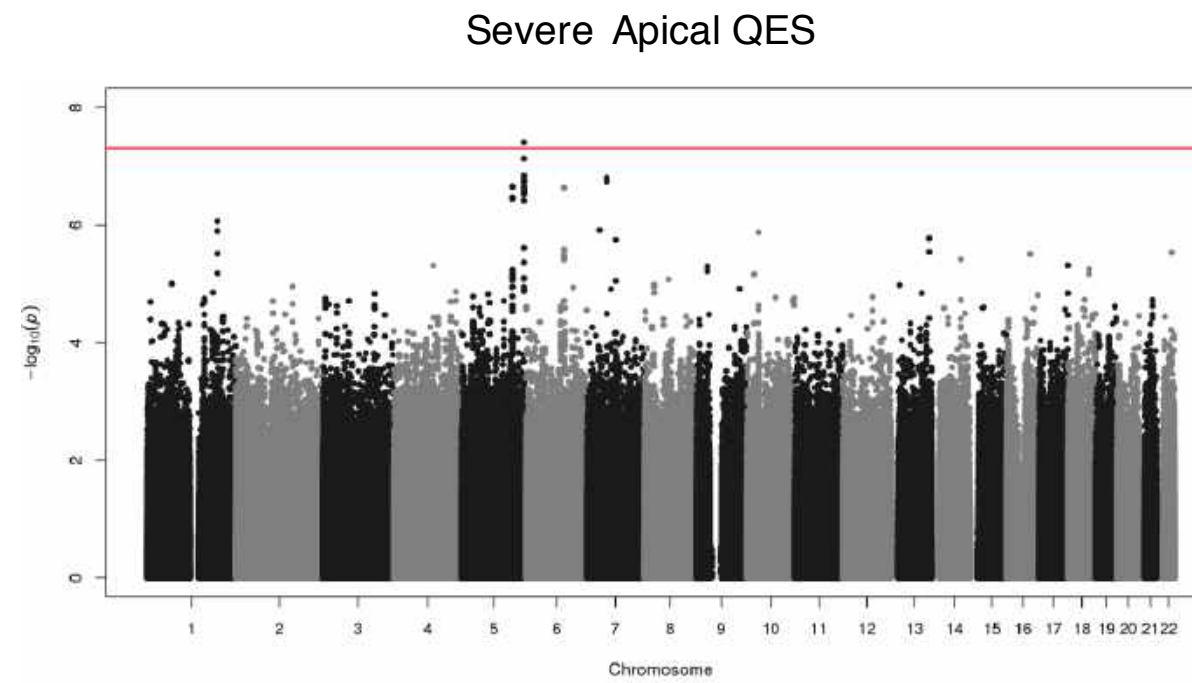
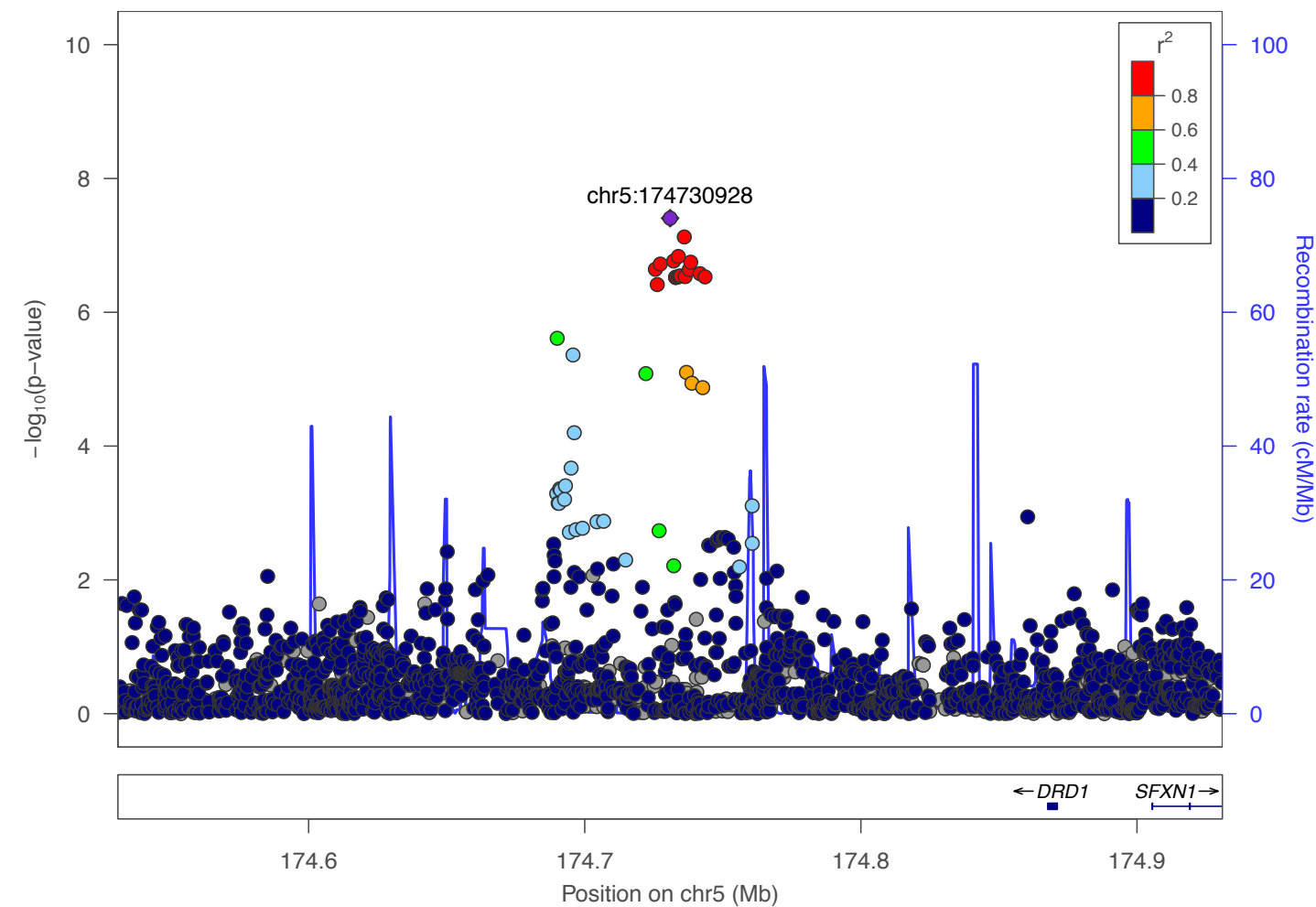
Adjusted for age, sex, race/ethnicity, height, weight, smoking status, pack-years, COPD, scanner manufacturer, FEV1, other QES.

COPD death



# Unsupervised Learning of Localized Texture Patterns for Pulmonary Emphysema

- **GWAS results :** \*
  - 5 genetic variants for four QES
  - Apical QES: DRD1



\* University of Virginia

# Summary

## Unsupervised learning of localized texture patterns for pulmonary emphysema

- ❑ Novel **unsupervised learning** of emphysema patterns on CT:
  - A standardized lung shape **spatial mapping**;
  - A **two-stage** learning framework.
- ❑ Applied on large COPD and controls yielded:
  - 10 **highly-reproducible** sLTPs;
  - Six quantitative emphysema subtypes, associated independently with distinct **symptoms, lung function changes** and **mortality**.
- ❑ Enables:
  - **Novel definitions** of emphysema subtypes;
  - CT-based **emphysema-specific signatures (biomarkers)** of the lungs;
  - May facilitate future study for understanding COPD and emphysema, and the design of personalized / gene / drug therapies.

### Other Evaluations:

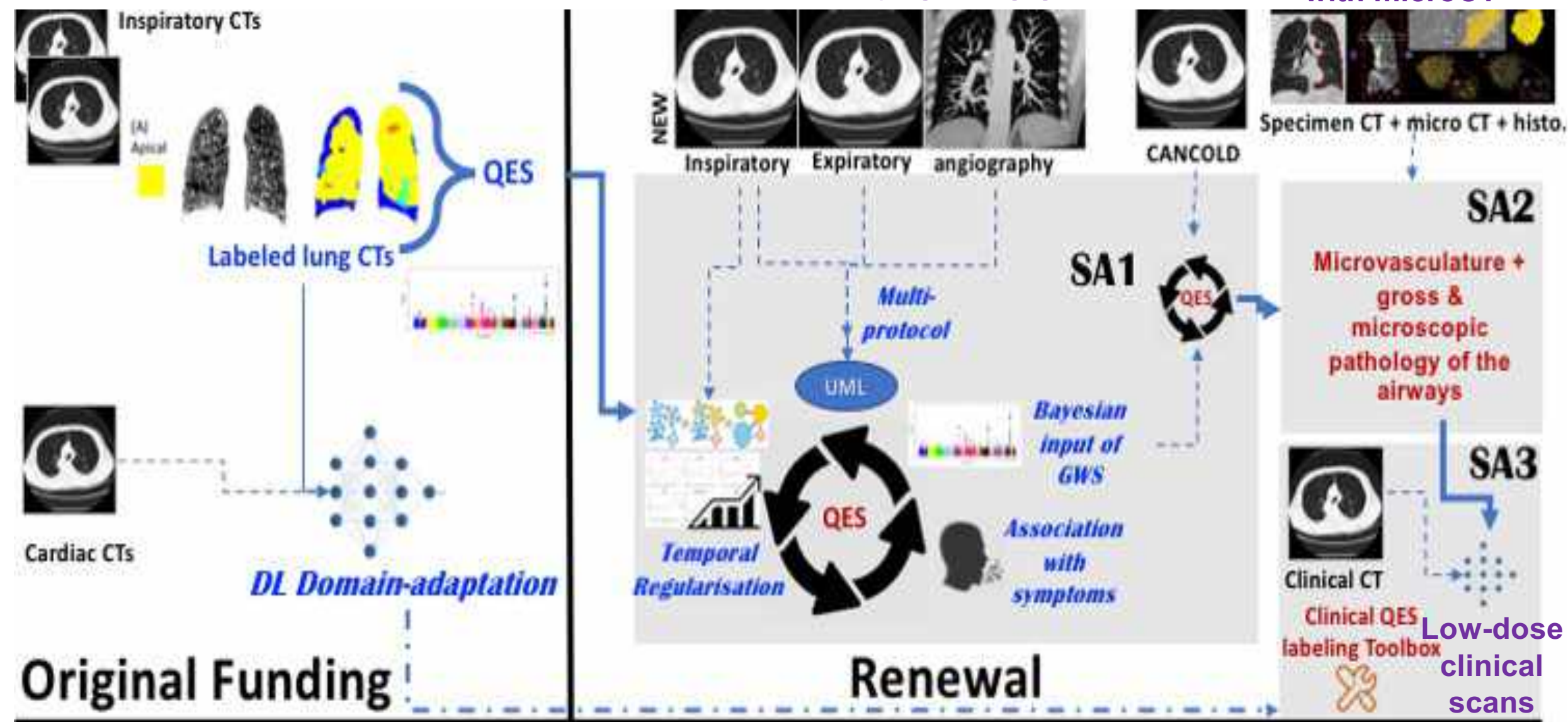
- GWAS; 3 “hits” reproducible
- Extensive evaluation of sLTP reproducibility in MESA COPD (N = 317);
- Linking sLTP and standard emphysema subtypes in MESA COPD (N=317).



# What's next?

- Deep & Molecular QES

## MESA Exam 6 & CANCEL



- Quantitative airway tree subtyping



Role of variants in COPD?

28

\* COVID-19 vasculature

# Acknowledgements

## Collaborators

Elsa D. Angelini, Ph.D.

R. Graham Barr, M.D., Ph.D.

## Heffner Biomedical Imaging Lab

Jie Yang (Ph.D. Student, 2019)

Xinyang Feng (Ph.D. student, 2019)

Yrjö Häme (Ph.D. student)

Yu Gan (Post-doc)

Thomas Vetterli (M.Sc. Intern)

## Additional Collaborators

Columbia University Medical Center:

Pallavi P. Balte, Ph.D.

John H.M. Austin, M.D.

Benjamin M. Smith, M.D.

Yifei Sun, Ph.D.

Wei Shen, M.D.

Iowa University:

Eric A. Hoffman, Ph.D.

University of Virginia:

Ani Manichaikul, Ph.D.

**And the MESA, SPIROMICS Investigators!**



# Heffner Biomedical Imaging Laboratory



<https://hbil.bme.columbia.edu>



# Thank you!



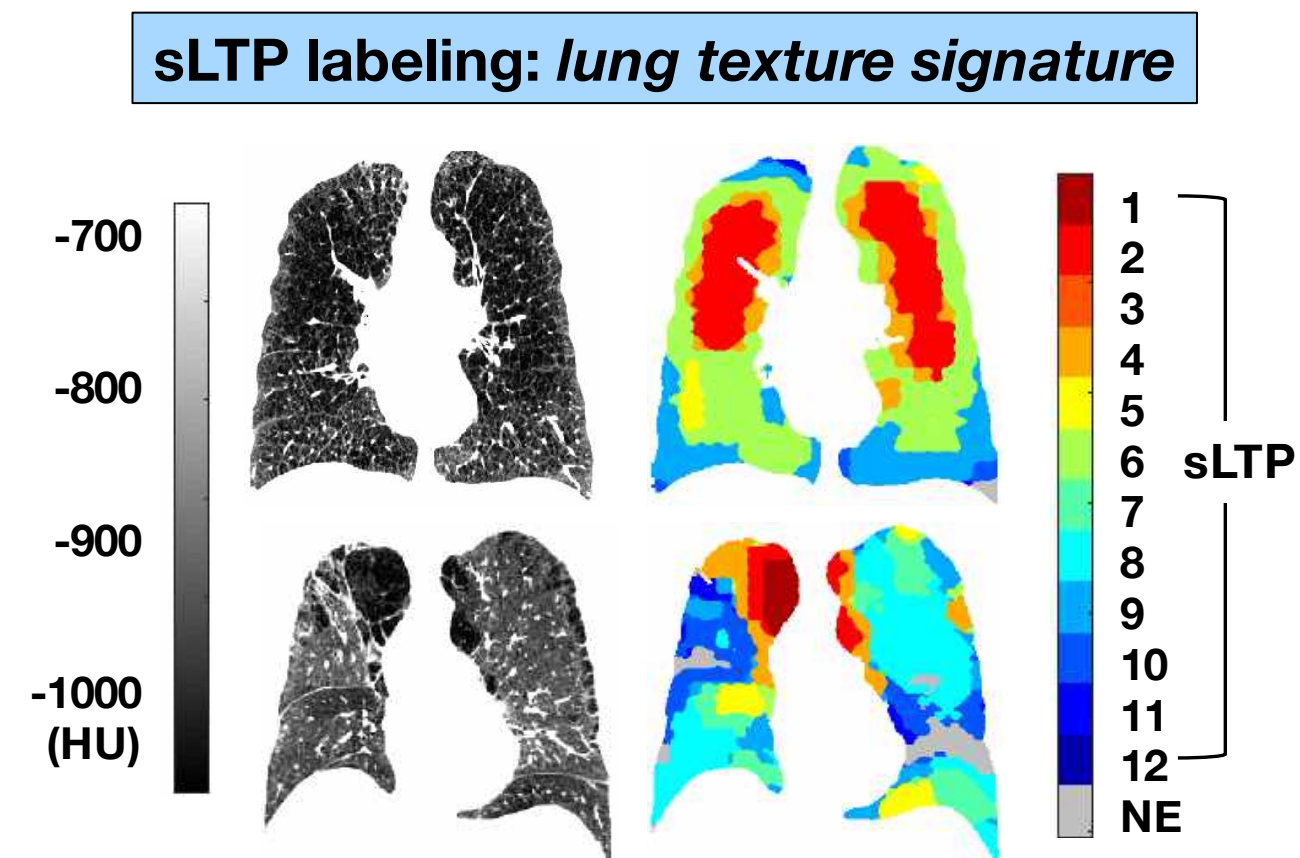


# Extra Slides

# Unsupervised Learning of Localized Texture Patterns for Pulmonary Emphysema

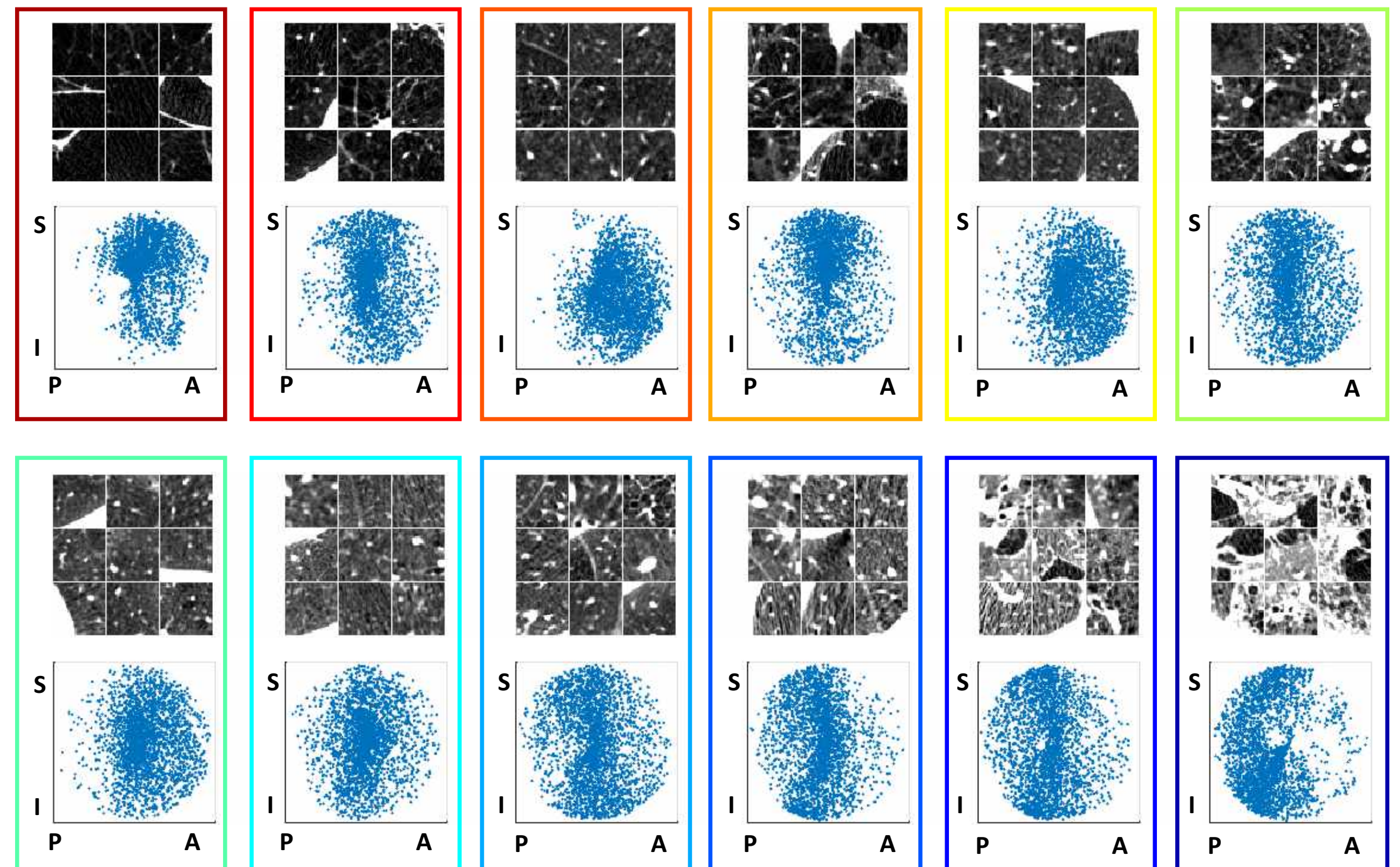
- Learn sLTPs in MESA COPD study:

- N = 317 full-lung CT scans.



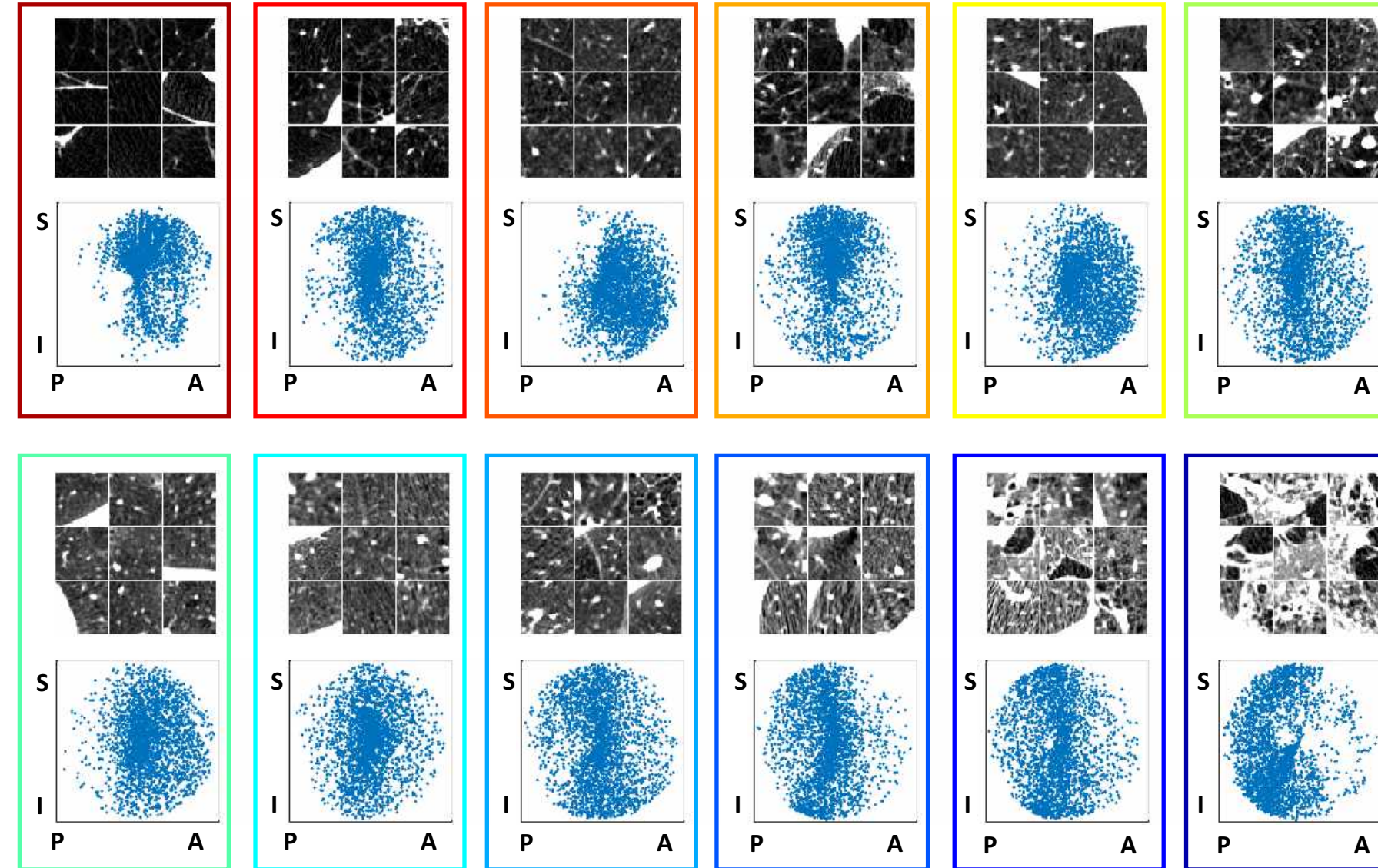
12 sLTPs discovered, ordered by average intensity

- Training ROI:  $\%emph > 1\%$





# Unsupervised Learning of Localized Texture Patterns for Pulmonary Emphysema



Global label

sLTP histogram

$$H_g = [\%CLE, \%PLE, \%PSE, \%NE] = [P(L(x) = C_1), \dots, P(L(x) = C_4)]$$

$$H_p = [\%sLTP_1, \dots, \%sLTP_{12}, \%NE] = [P(F(x) = p_1), \dots, P(F(x) = p_{13})]$$

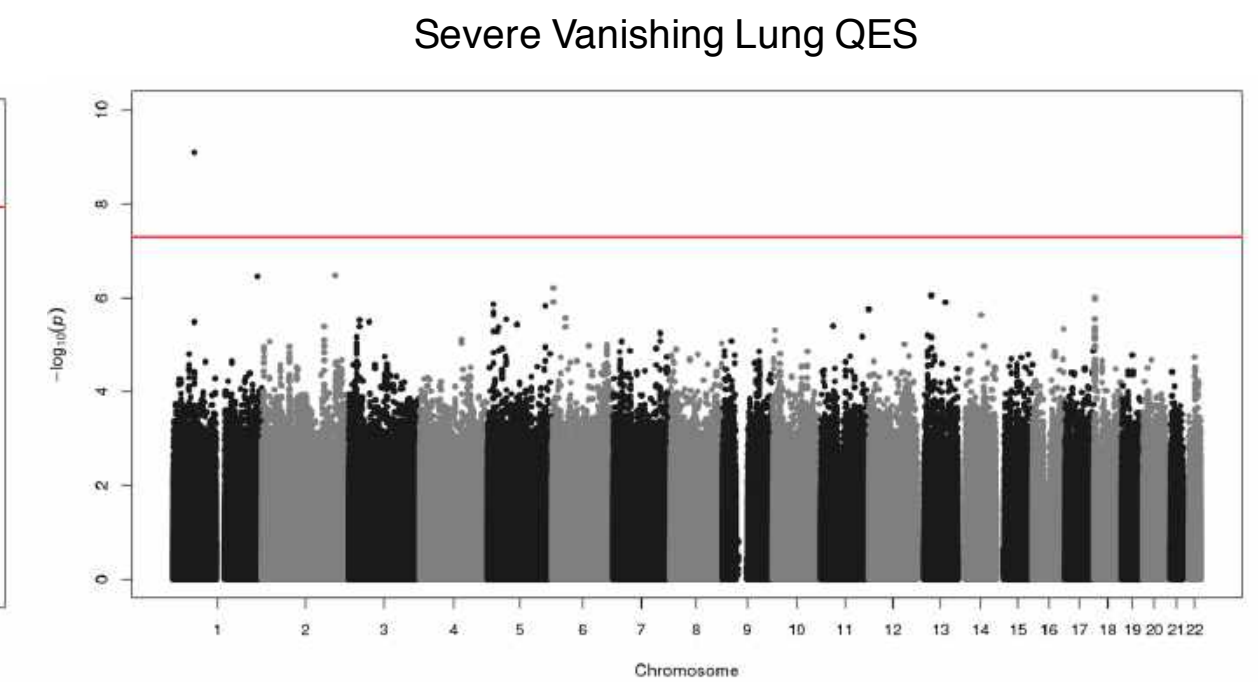
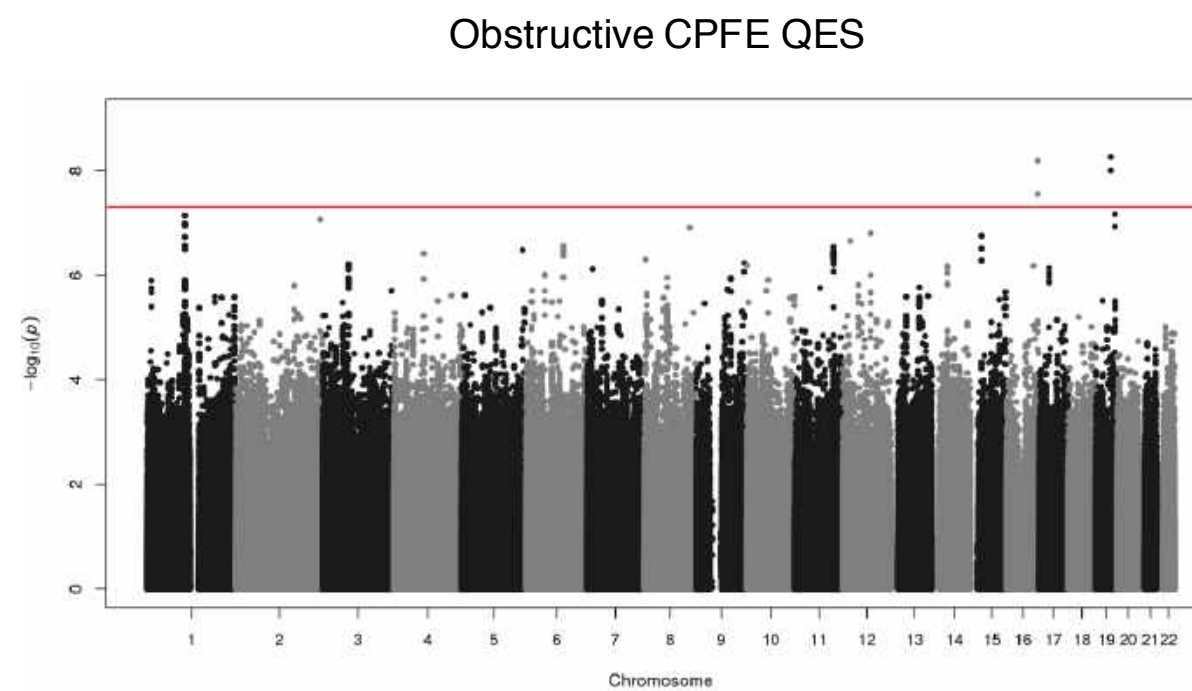
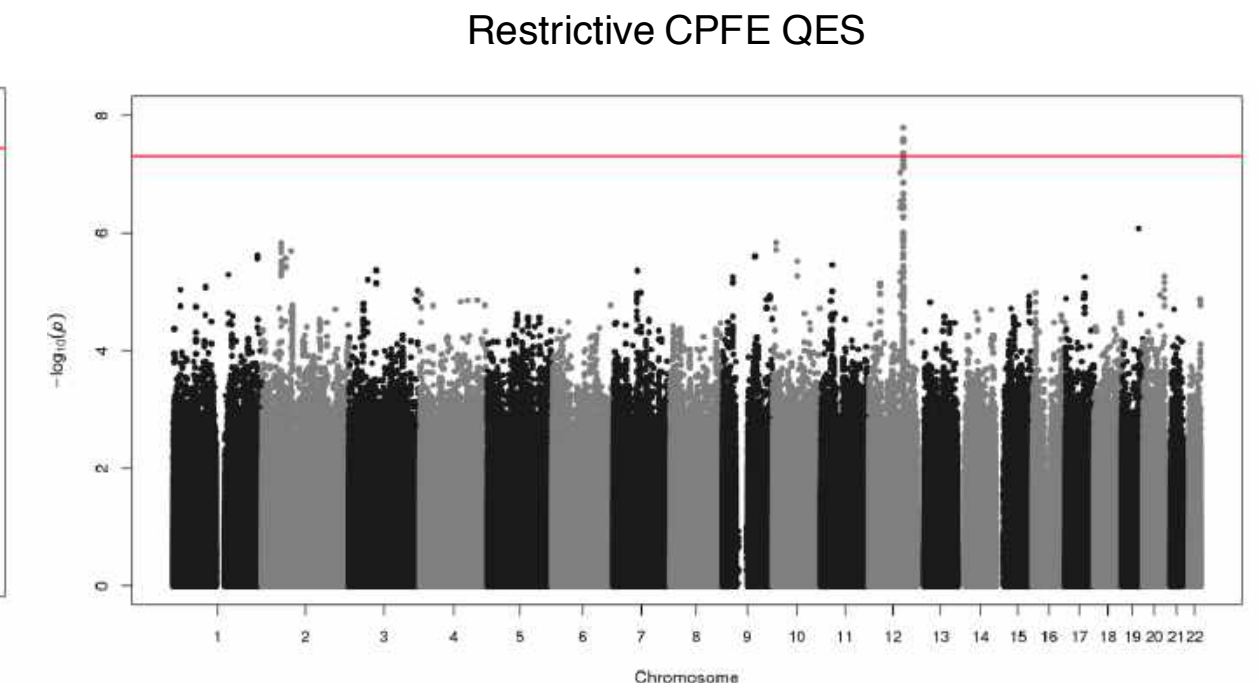
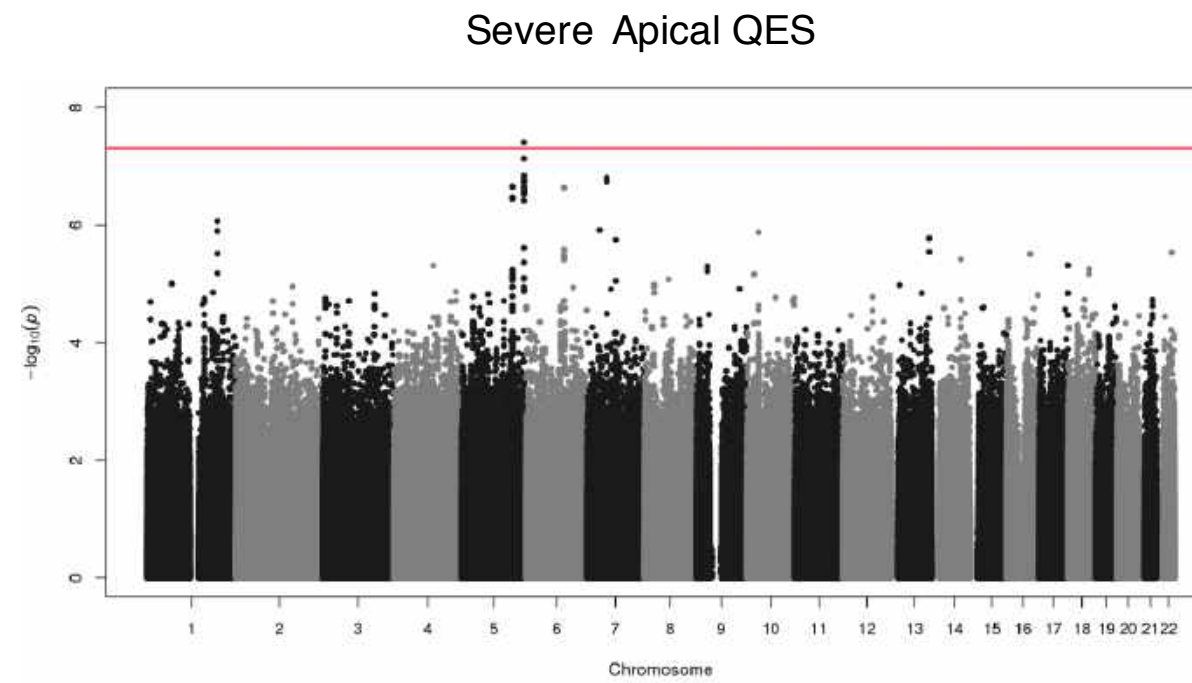
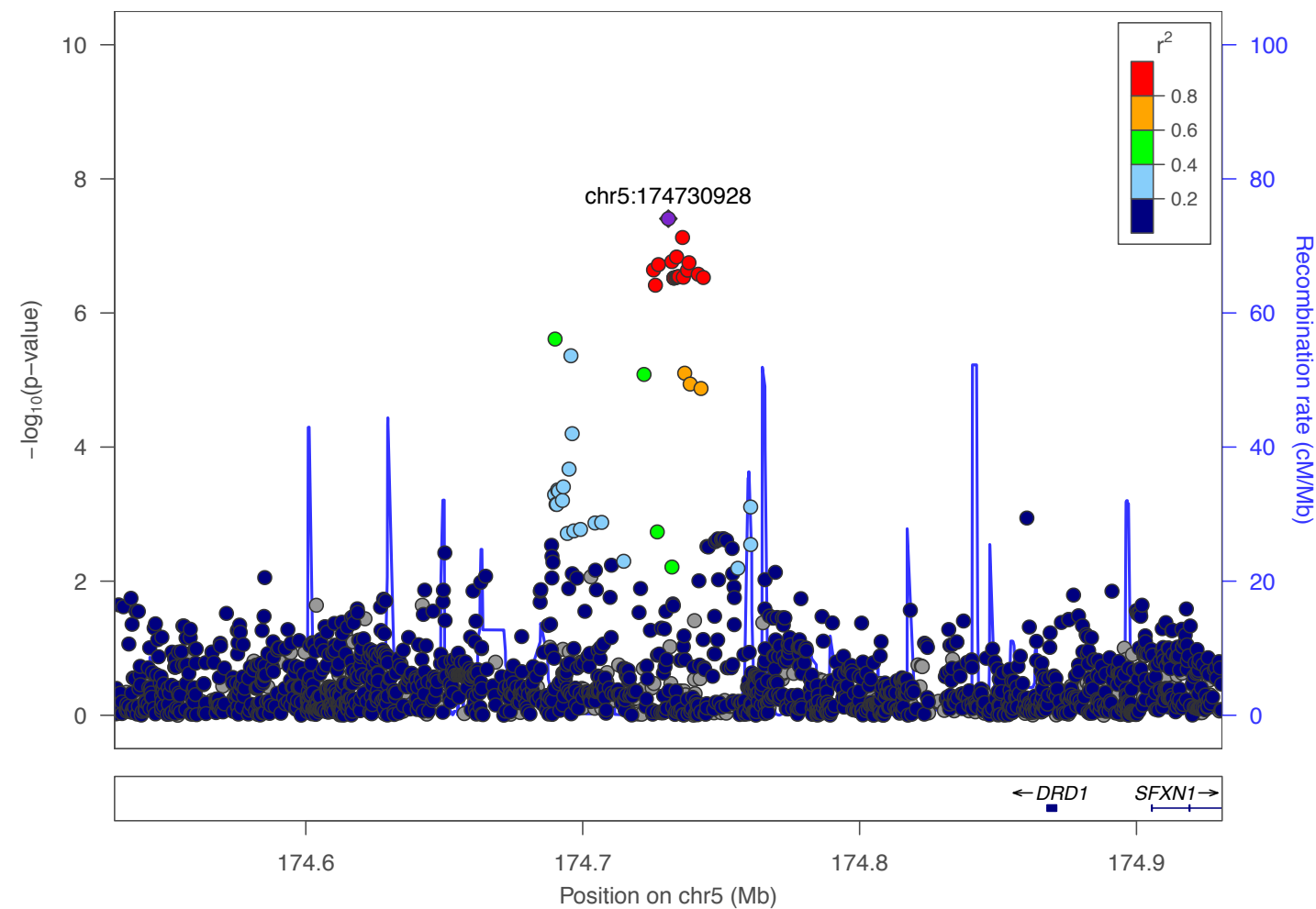
$$P(L(x) = C_i) = \sum_{k=1}^{13} P(L(x) = C_i | P(F(x) = p_k)) P(F(x) = p_k)$$

$$H_g = H_p A$$

$$A_{k,i} = P(L(x) = C_i | F(x) = p_k)$$

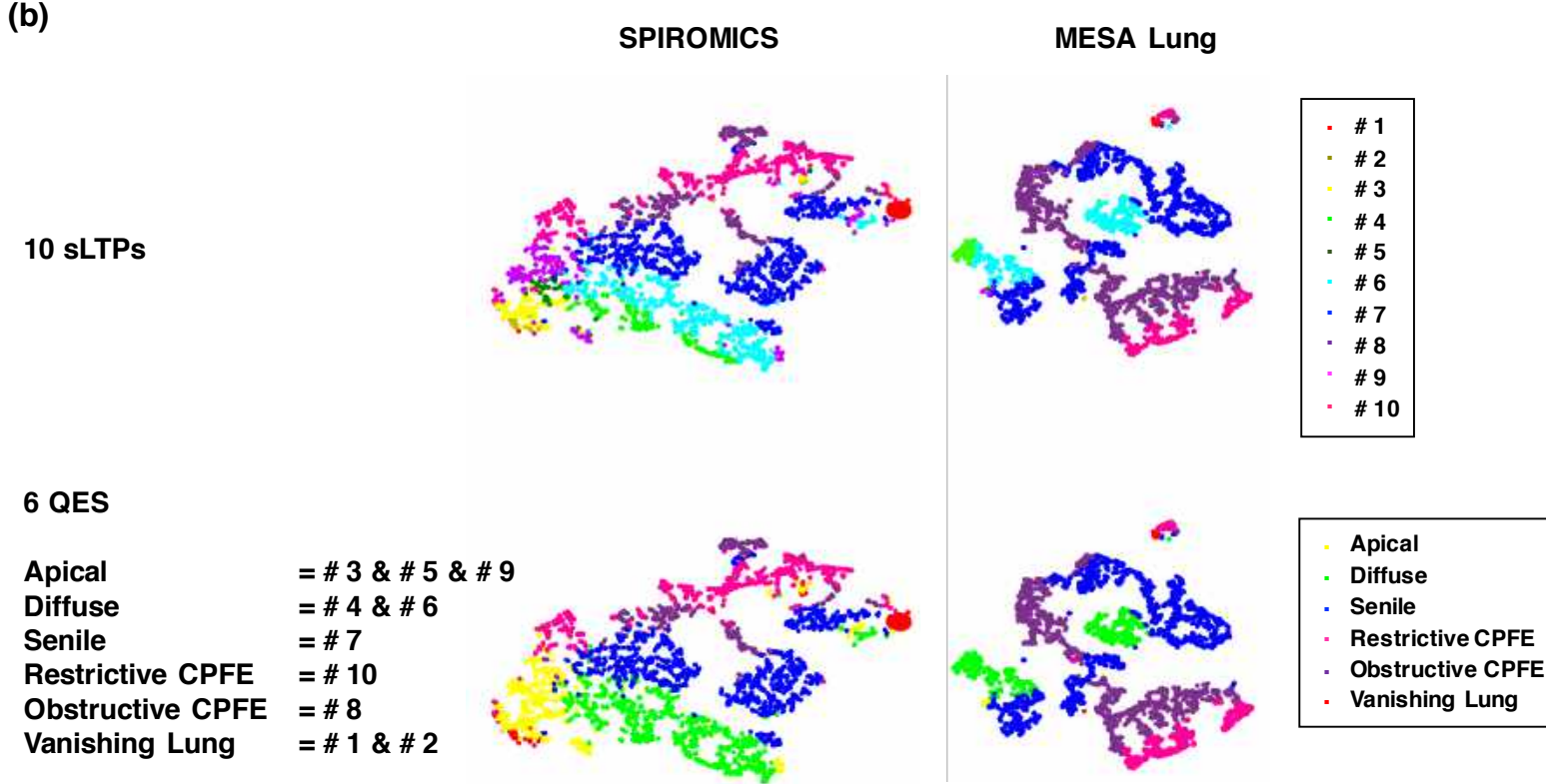
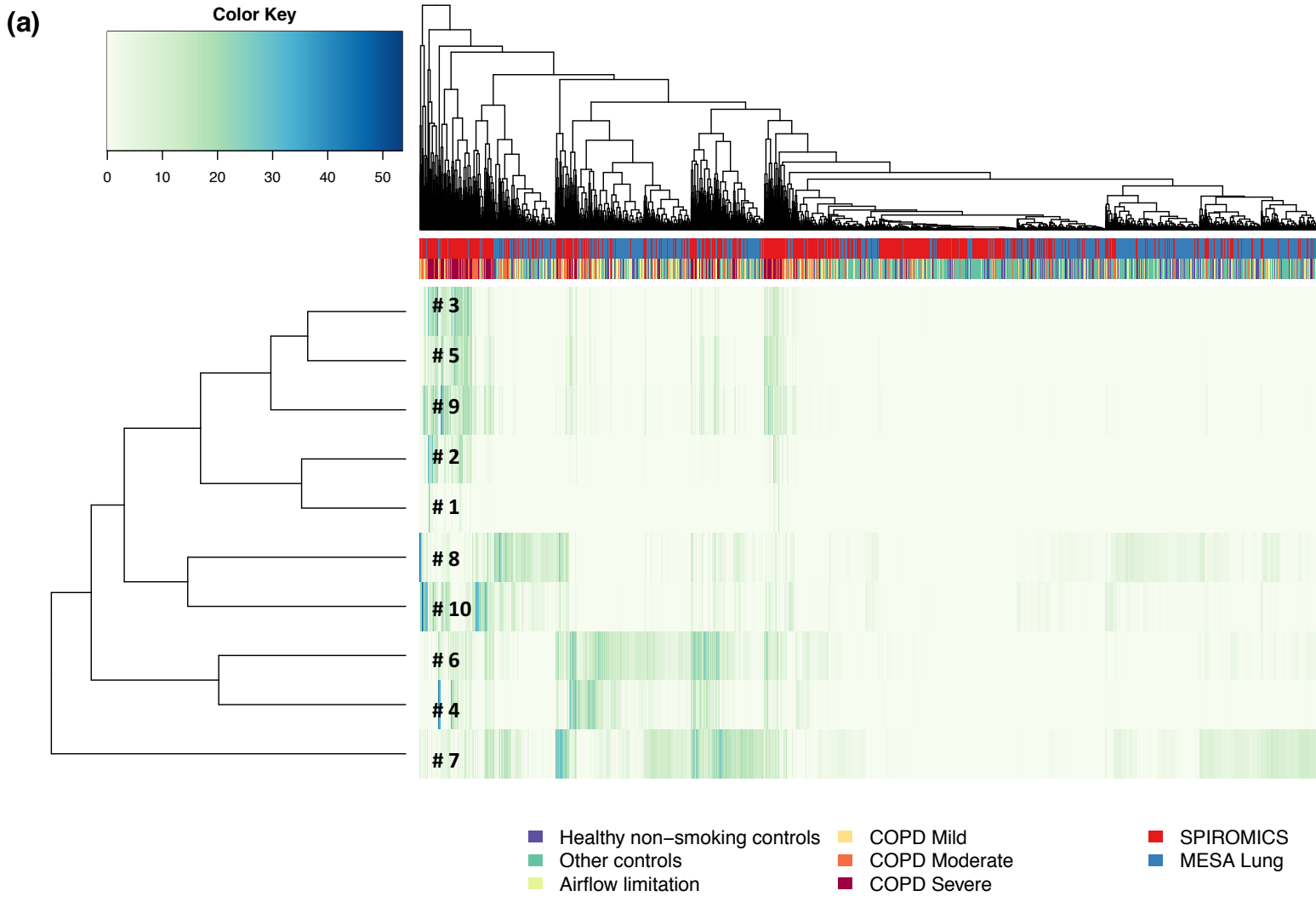
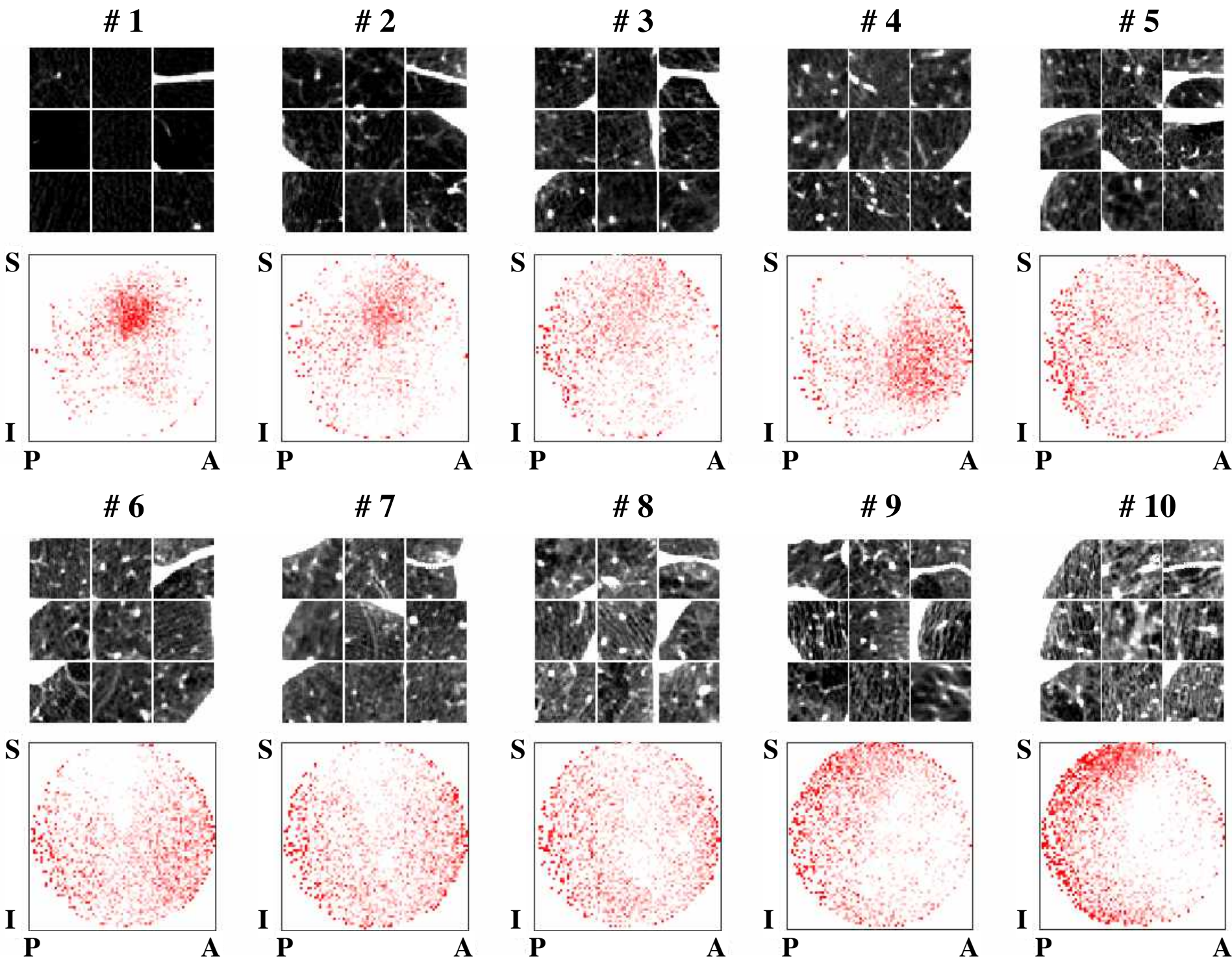
# Unsupervised Learning of Localized Texture Patterns for Pulmonary Emphysema

- **GWAS results:**
  - 5 genetic variants for four QES
  - Apical QES: DRD1



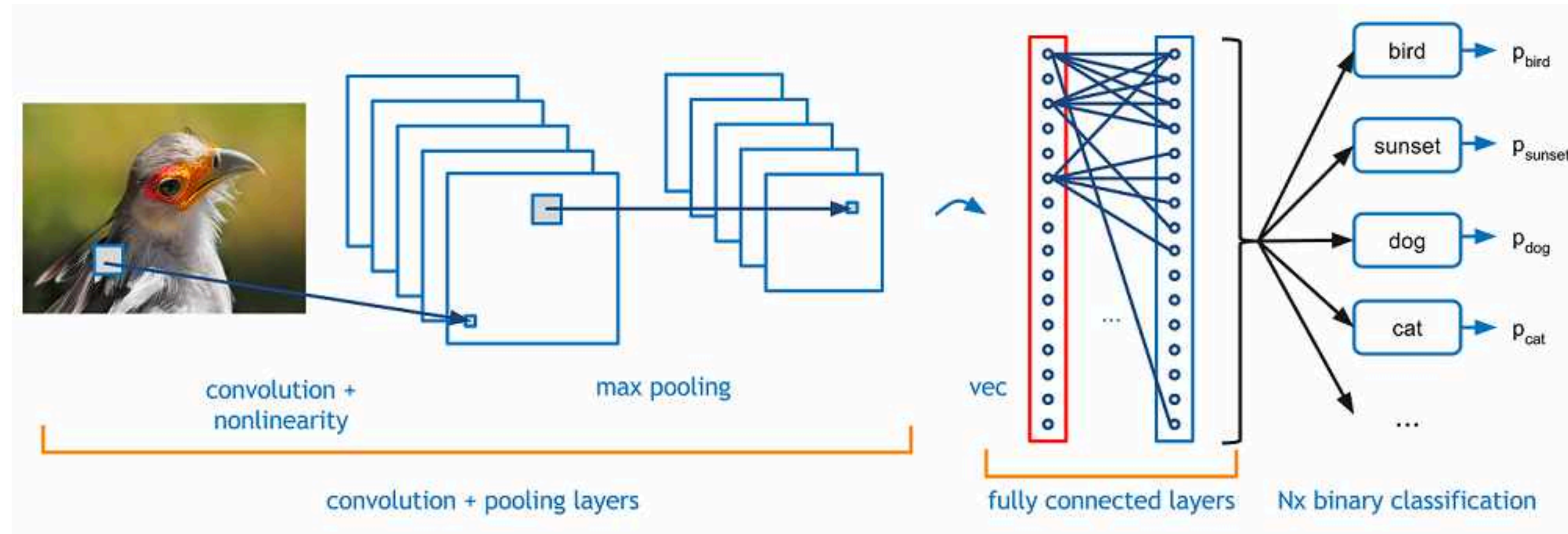


# Unsupervised Learning of Localized Texture Patterns for Pulmonary Emphysema





# CNN Background



$h_i^l$  =  $i$ -th feature map in layer  $l$

$h_k^{l-1}$  =  $k$ -th feature map in layer  $l - 1$

$$h_i^l = \sigma \cdot \left( \sum_k h_k^{l-1} * W_{ki}^l + b_i^l \right)$$

$$h^l = \sigma \cdot \left( \sum_k h_k^{l-1} W^l + b_l \right)$$

$h^l$  = feature vector  $\in \mathbb{R}^Q$  in layer  $l$

$h^{l-1}$  = feature vector  $\in \mathbb{R}^P$  in layer  $l-1$