

# Relational Learning between Multiple Pulmonary Nodules via Deep Set Attention Transformers

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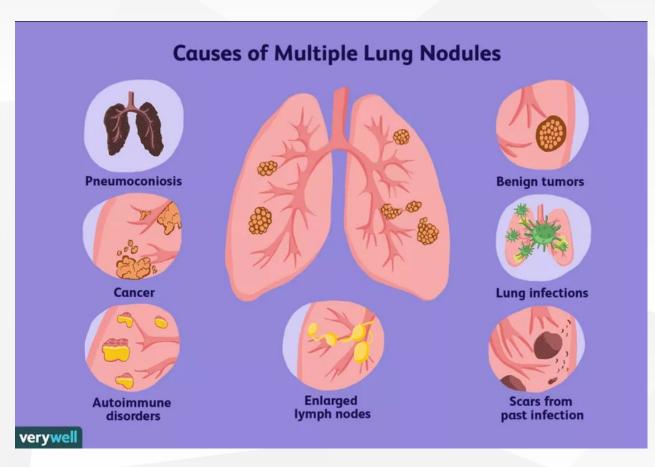








### Introduction



### Challenges:

1/ Diagnosis of multiple pulmonary nodules is **complex** 

2/ Previous methods use **solitary**-nodule approaches for **multiple** pulmonary nodules, *i.e.*, ignore the relations

#### Solutions:

**Relational learning** between multiple nodules via **Set Attention Transformers** 

Illustration by Jessica Olah, Verywell

https://www.verywellhealth.com/multiple-lung-nodules-causes-and-diagnosis-2249390





## **Methodology: Set Attention Transformers**



We propose **Set Attention Transformers (SATs)**, inspired from our previous study, **Point Attention Transformers** for point clouds:

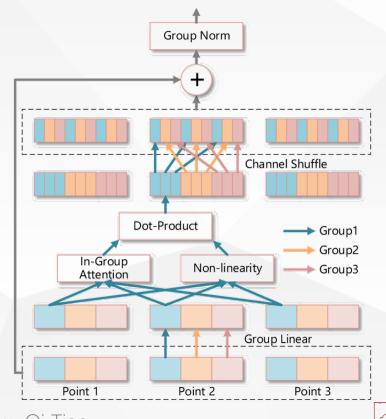
- Permutation-equivariant for sets
- Relational learning between set elements
- Parameter-efficient
- Group Shuffle Attention



#### Check our CVPR'19 study on point clouds

Modeling Point Clouds with Self-Attention and Gumbel Subset Sampling.

L\_\_\_\_Point
Jiancheng Yang, Qiang Zhang, Bingbing Ni, Linguo Li, Jinxian Liu, Mengdie Zhou, Qi Tian

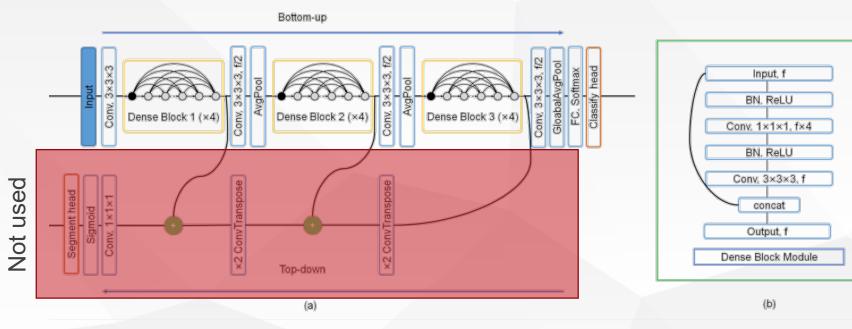




## Methodology: 3D DenseNet Backbone



We use a parameter-efficient 3D DenseNet for representation backbone, adapted from our previous study:





#### Check our Cancer Research study on tumor invasiveness

3D Deep Learning from CT Scans Predicts Tumor Invasiveness of Subcentimeter Pulmonary Adenocarcinomas.
Wei Zhao\*, Jiancheng Yang\*, Yingli Sun, et al. (\*equal contribution).



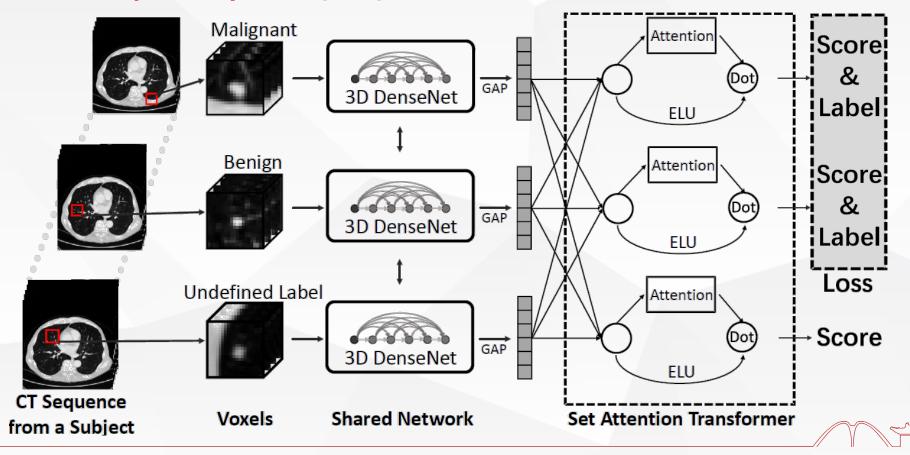


## Methodology: NoduleSATs



Combining 3D DenseNet backbone with the proposed Set Attention

Transformers (SATs), we proposed end-to-end NoduleSATs:





## **Experiments: Lung Nodule Detection**



Dataset	Method	Average FROC (CPM)
LUNA16 [10]	2D-CNN [11] 3D-CNN [12] 3D DenseNet NoduleSAT	$0.790$ $0.908^{2}$ $0.884$ $0.916$
Tianchi VAL	3D DenseNet NoduleSAT	0.677 <b>0.716</b>

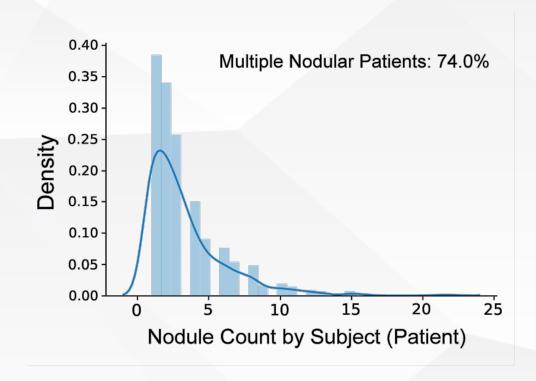
1/ LUNA16 False Positive Reduction: 888 subjects with 1186 nodules, totally 754,975 candidates, 10-fold cross validation.

2/ Tianchi Lung Nodule Detection: 800 subjects with 1,224 nodules, 5,531 candidates on the training set, 1,515 candidates on the validation set.



## **Experiments: Malignancy Classification**





93.5 93.17 93 2175 92.48 92.5 92 91.5 91.62 1183 91.5 91 90.5 90 Nodule SAT 3D DenseNet Nodule SAT w. masked loss Models

# Data Samples ——AUC

94

(a) Nodule Count Distribution

(b) Model Performance

LIDC-IDRI: one of the largest public available lung cancer screening databases

Patients in LIDC-IDRI dataset have 1 - 23 nodules

527 malignant + 656 benign + 992 undefined-label



## Conclusion



- We propose a Set Attention Transformer (SAT), to explicitly learn relational information between multiple pulmonary nodules from a same subject.
- Integrated with a 3D DenseNet, the proposed end-to-end trainable NoduleSAT encourages the model to learn top-down relations from bottom-up inter-nodule nodule-level representations.
- We empirically prove the benefit of relation learning between multiple pulmonary nodules.



## Thanks for Listening