Lunit

Lunit's experience in data-driven medical imaging

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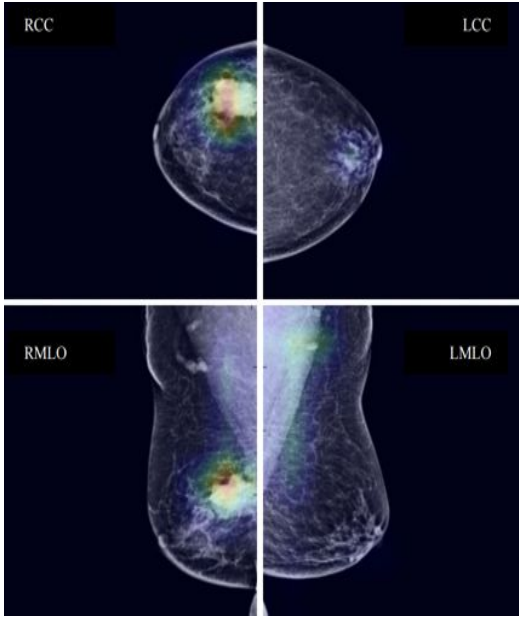
Lunit

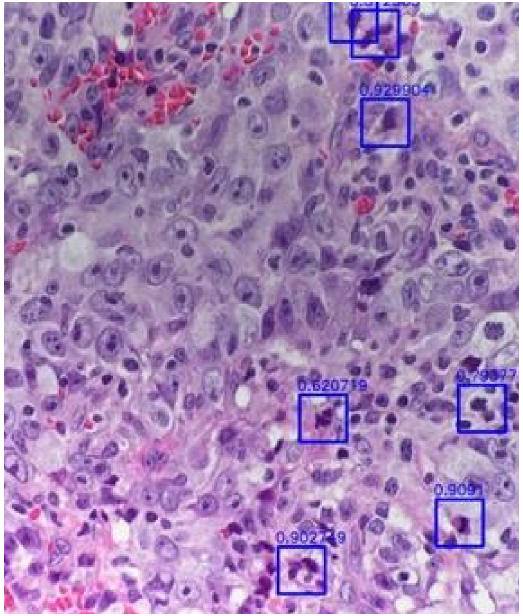
Lunit

Summary	Lunit develops data-driven imaging biomarker, a novel AI-powered medical image analysis technology that maximizes the diagnostic power of existing imaging modalities.		
Founded	Aug. 2013		
Funded	$5.2M		
Investors	Series AA	Sep. 2016 ~ $3.1M+	Intervest Mirae Asset Venture Investment
	Series A	Nov. 2015 $2M	SoftBank Ventures Korea Formation 8
	Seed	June. 2014 $100K	K-Cube Ventures
Members	30		
Office	Seoul, Korea (HQ)		

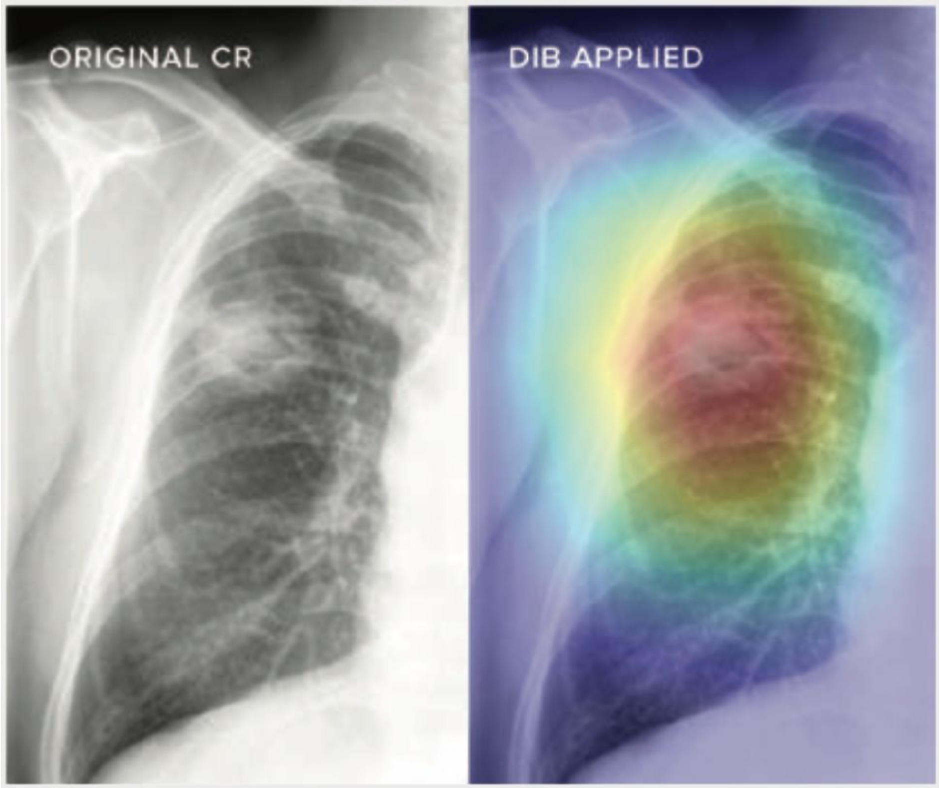
What we've focused

- Imaging modalities have a huge social impact!
  - Screening modalities where large population may benefit
  - Diagnosis modality where critical decisions occur





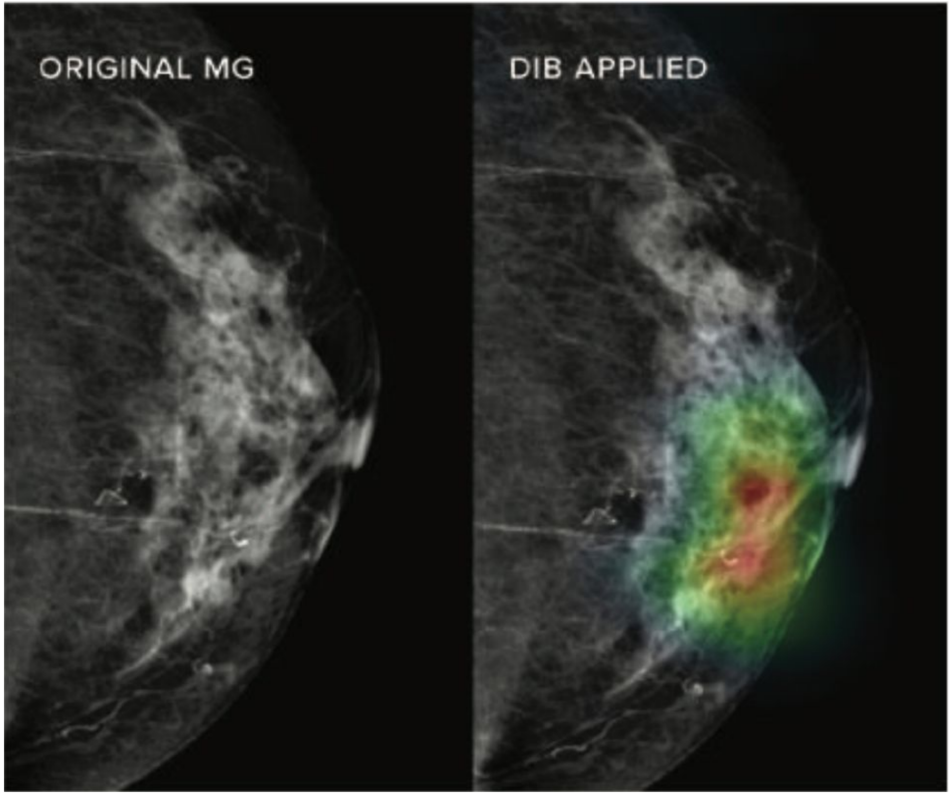
Chest radiography



- Detection of pulmonary nodules
- Detection of consolidation/focal lung disease
- Detection of diffuse lung disease
- Detection of heart diseases
- Detection of free air
- Detection of aortic diseases
- Detection of bony abnormalities

- Assessment of normal vs. abnormal
- Tentative differential diagnosis

Mammography



- Detection of significant breast lesions
- Assessment of BI-RADS category
- Assessment of breast density
- Assessment of overall cancer probability

- Prediction of “masking” probability and quantitative recommendation of further examinations (ex. DBT, USG, MRI)
- Prediction of LN microinvasion/metastasis

Digital pathology

- Digital era of pathology is coming
- Pathologists can read digitized slides rather than looking slides through microscopy

FDA News Release

FDA allows marketing of first whole slide imaging system for digital pathology

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For Immediate Release April 12, 2017

Release

The U.S. Food and Drug Administration today permitted marketing of the Philips IntelliSite Pathology Solution (PIPS), the first whole slide imaging (WSI) system that allows for review and interpretation of digital surgical pathology slides prepared from biopsied tissue. This is the first time the FDA has permitted the marketing of a WSI system for these purposes.

“The system enables pathologists to read tissue slides digitally in order to make diagnoses, rather than looking directly at a tissue sample mounted on a glass slide under a conventional light microscope,” said Alberto Gutierrez, Ph.D., Director of the Office of In Vitro Diagnostics and Radiological Health in the FDA’s Center for Devices and Radiological Health. “Because the system digitizes slides that would otherwise be stored in physical files, it also provides a streamlined slide storage and retrieval system that may ultimately help make critical health information available to pathologists, other health care professionals and patients faster.”

https://www.fda.gov/NewsEvents/Newsroom/PressAnnouncements/ucm552742.htm

Where We Are

Diagnostic features

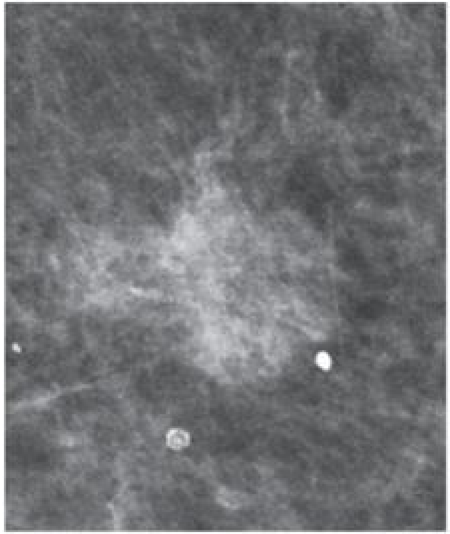


Figure 8 – SHAPE: IRREGULAR. Mass with primarily indistinct and partially spiculated margin. Core biopsy: invasive ductal carcinoma.

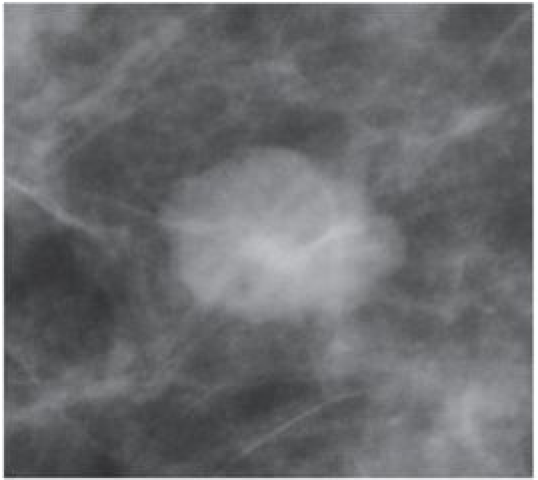


Figure 18 – MARGIN: MICROLOBULATED. Irregular mass with MICROLOBULATED margin. Note that although almost the entire margin is well defined (mass almost completely surrounded by fatty tissue), the depiction of numerous short-cycle undulations should prompt classification of the margin as microlobulated (more worrisome) rather than circumscribed. Core biopsy: invasive ductal carcinoma.

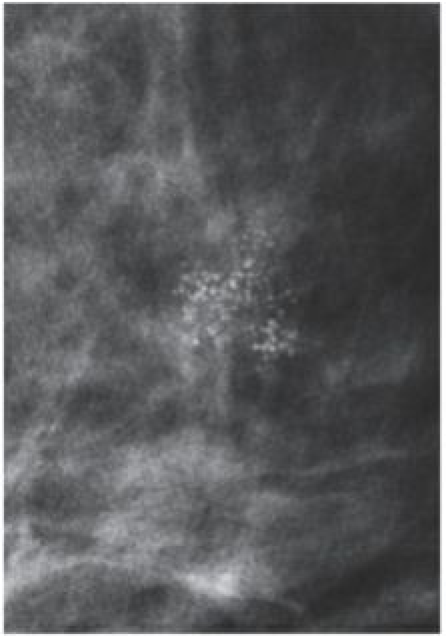
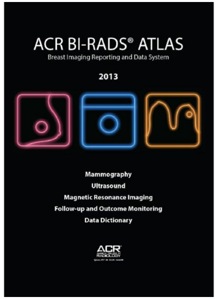
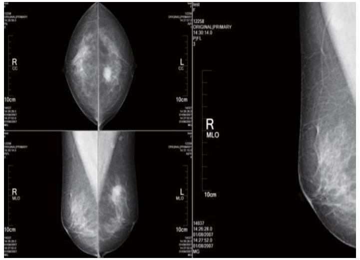


Figure 101 – DISTRIBUTION: GROUPED. GROUPED amorphous calcifications. Core biopsy: ductal carcinoma in situ.

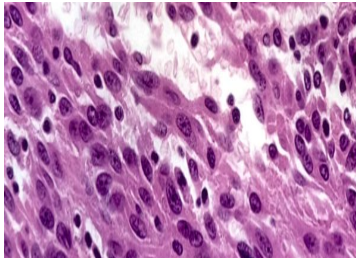


Where we are



32% of cancers are missed in mammography screening.

“Breast Cancer Screening.”, Medscape, 2015
http://emedicine.medscape.com/article/1945498-overview



25% disagreement among pathologists interpreting breast biopsy specimens.

“Diagnostic Concordance Among Pathologists Interpreting Breast Biopsy Specimens”, JAMA, 2015
http://jama.jamanetwork.com/article.aspx?articleid=2203798

Lack of tool for **quantitative differential diagnosis** of chest x-ray.

“Difficulties in the Interpretation of Chest Radiography”, Comparative Interpretation of CT and Standard Radiography of the Chest, Springer, 2010
http://link.springer.com/chapter/10.1007%2F978-3-540-79942-9_2

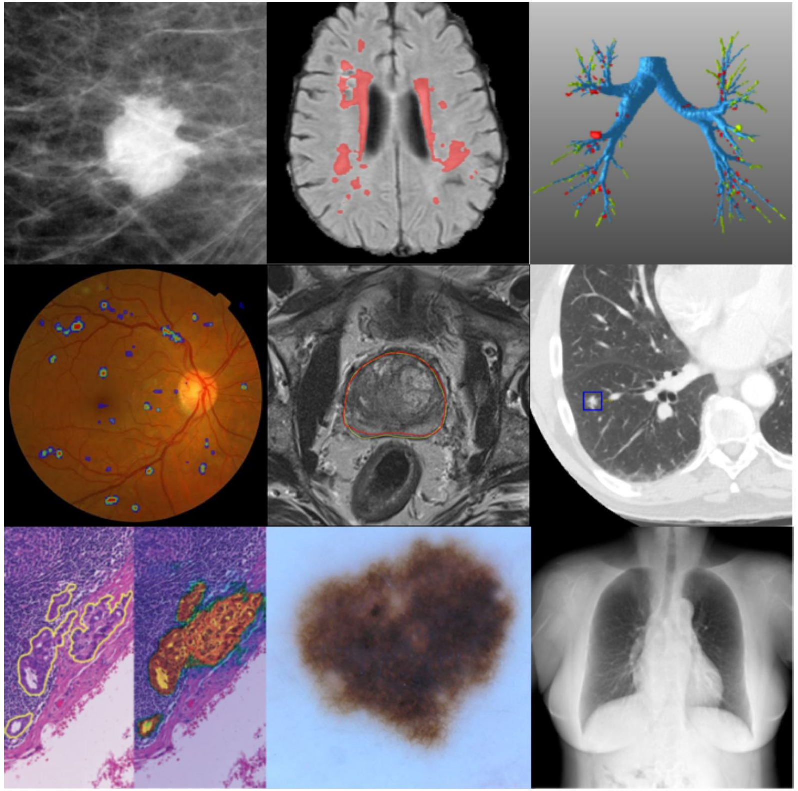
Where we are going

https://www.youtube.com/watch?v=2HMPRXstSvQ

"They should stop training radiologists now. It's just completely obvious within five years deep learning is going to do better than radiologists. .... It might be ten years."

- G. Hinton

Medical imaging applications



- Mammographic mass classification
- Segmentation lesions in the brain
- Leak detection in airway tree segmentation
- Diabetic retinopathy classification
- Prostate segmentation
- Nodule classification
- Breast cancer metastases detection in lymph nodes
- Skin lesion classification
- Bone suppression in chest x-rays

Applications in which deep learning has achieved state-of-the-art results

Litjens, G. et al. (2017), “A survey on deep learning in medical image analysis”, arXiv:1702.05747v2

Model Development

Model development process

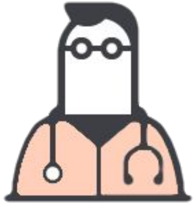
Data acquisition

Data preparation

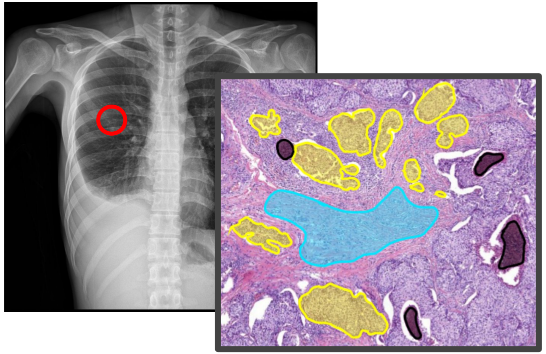
Training

Equipments

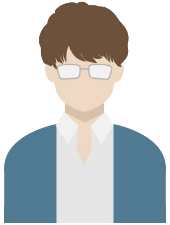
Storage



Doctors



Annotation tool

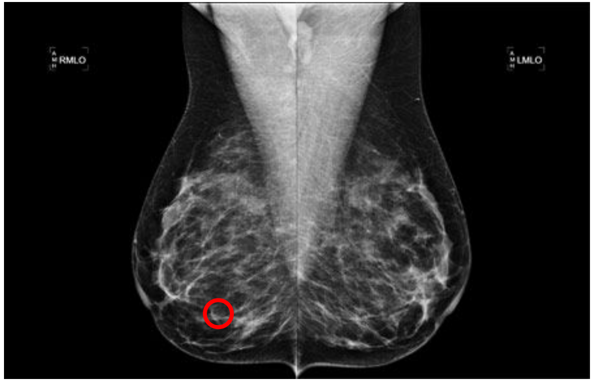


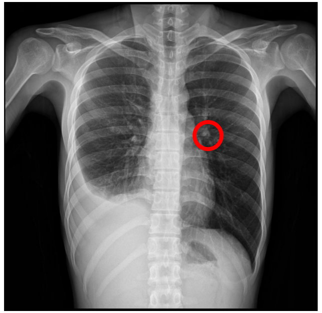
Engineer

Computing Machine

Medical images and neural networks

- There are unique characteristics of medical image data!
  - high resolution compared to natural images
  - relatively small ROIs





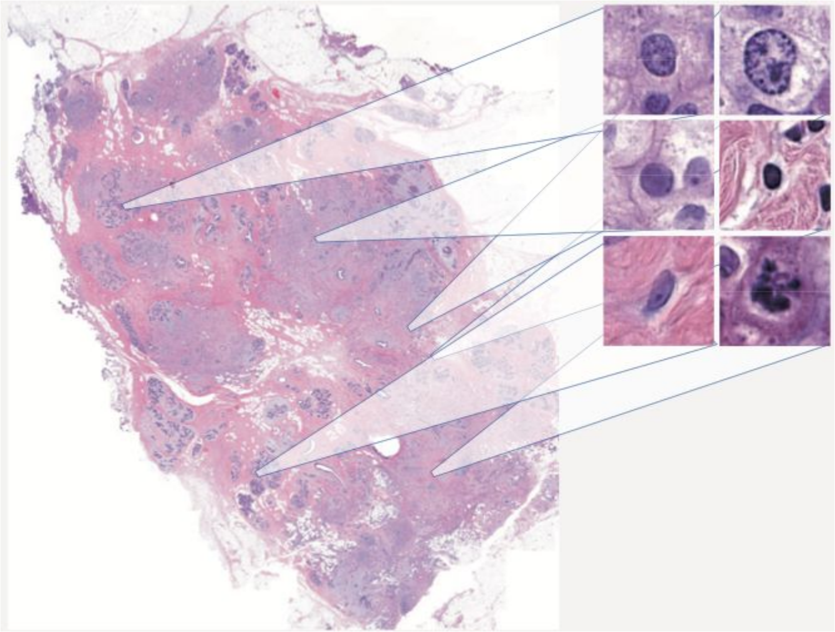
  - **noisy labels**
  - **difficult to have large-scale training dataset and supervisions**

Our Experience

How to get clean data?

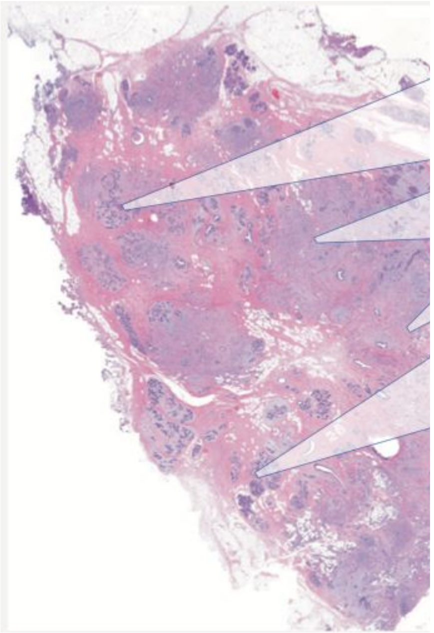
Ambiguity of labels

- Mitosis detection task



Ambiguity of labels

- Mitosis detection task

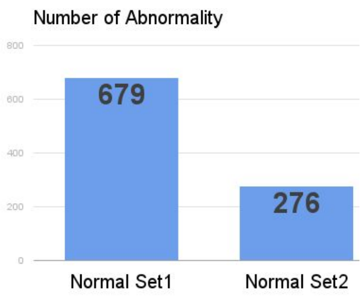


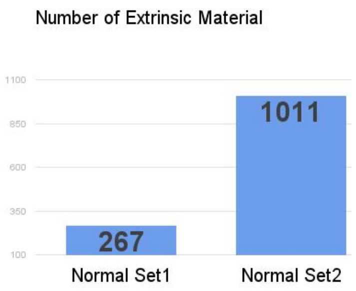
ID	Outlined area (mm^2)	Number of annotated objects by observer 1	Number of annotated objects by observer 2	Number of HPFs in the challenge data set	Number of ground truth mitotic figures
Training data set					
1	20	60	188	39	73
2	36	51	32	28	37
3	41	13	46	16	18
4	24	178	338	61	224
5	20	5	8	10	6
6	43	104	89	61	96
7	22	55	140	43	68
8	21	2	5	10	3
9	58	0	12	10	2
10	26	0	4	10	0
11	20	5	25	13	15
12	41	9	5	10	8

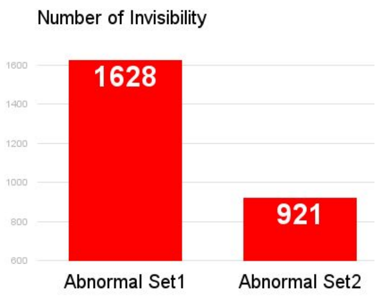
Veta, M. et al. (2014), “Assessment of algorithms for mitosis detection in breast cancer histopathology images, arXiv:1411.5825

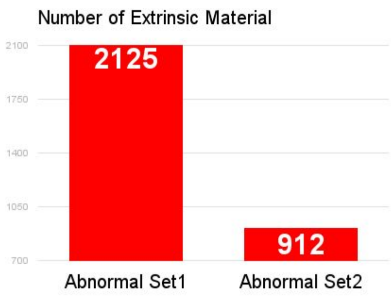
Ambiguity of labels

- Labeling on chest X-rays (CXRs)
  - randomly split dataset into two groups
  - assign each group to a radiologist







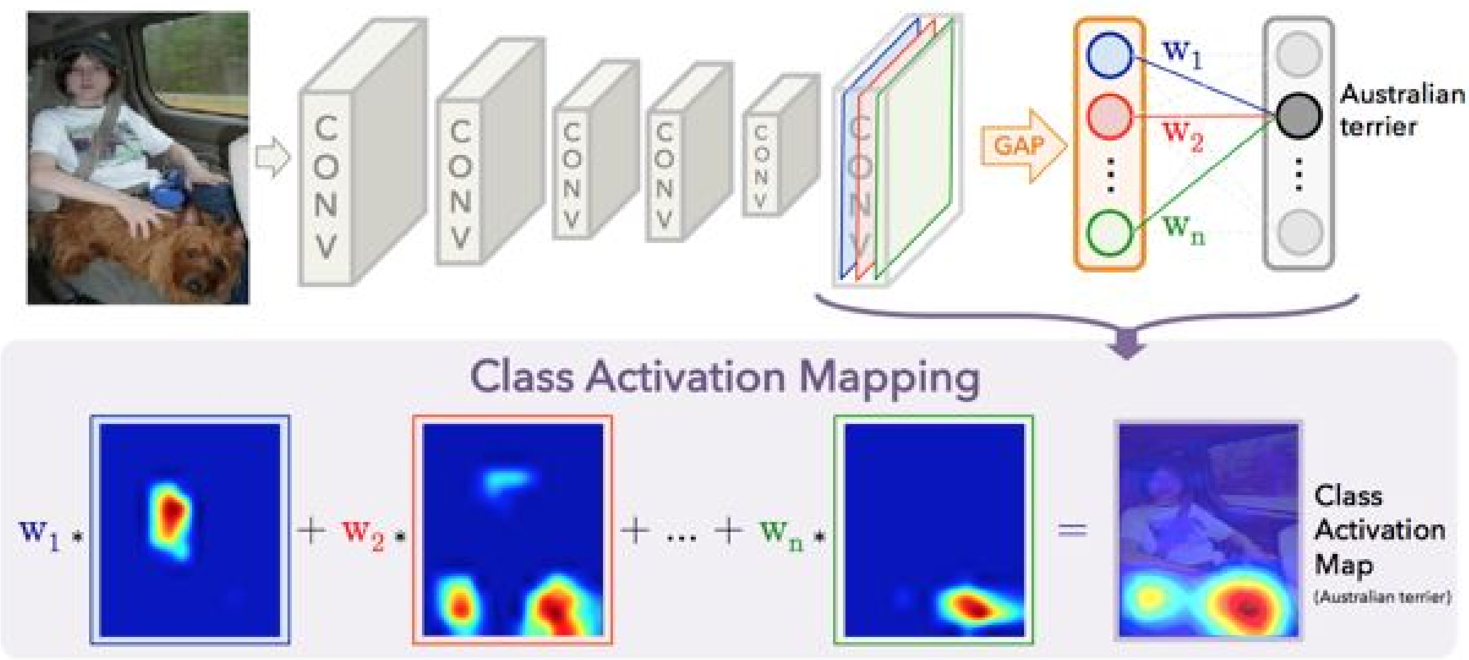


- **Even CXRs, a high degree of inter-reader variability can be observed.**
- **We should have the ground-truth labels!**

How to get large-scale data?

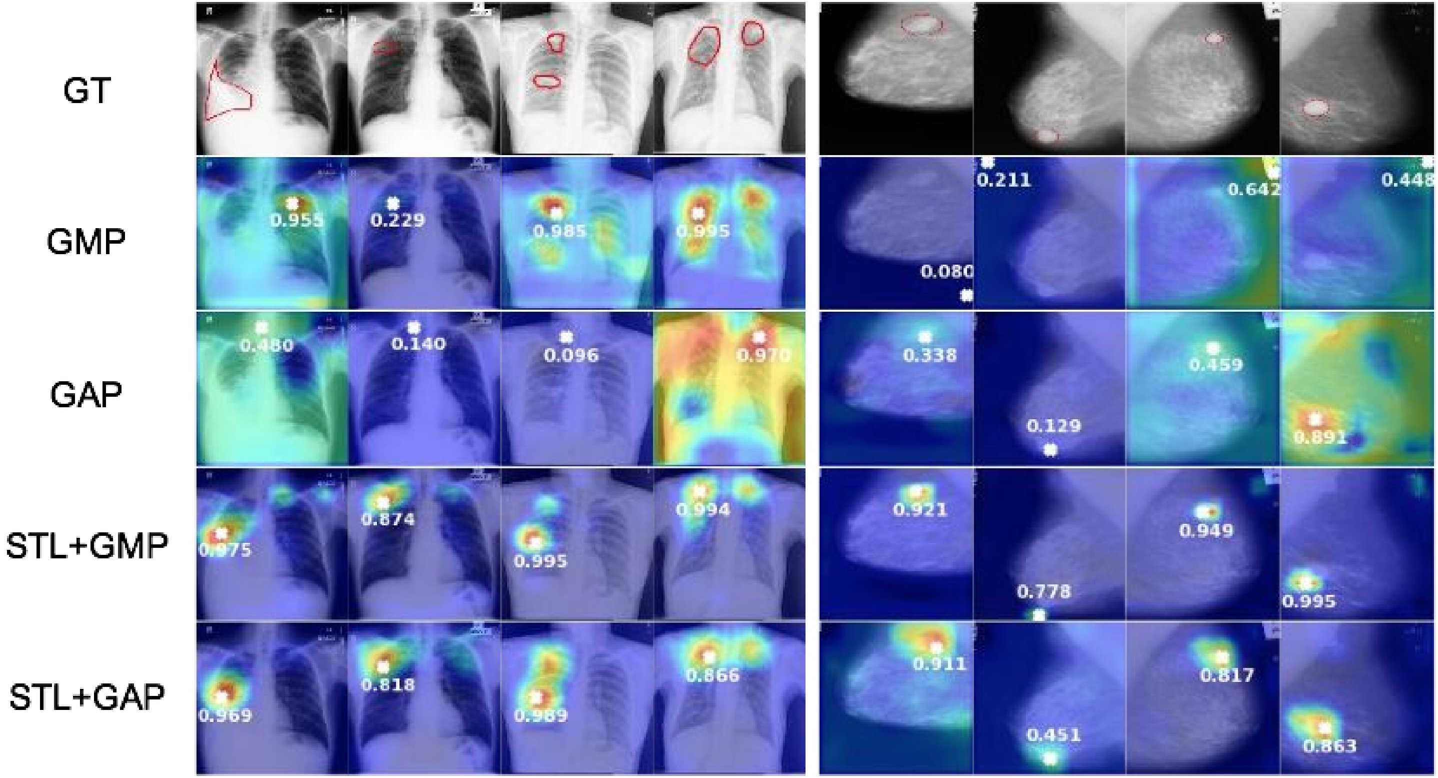
Weakly supervised approach

- We want to detect lesions without any location information!



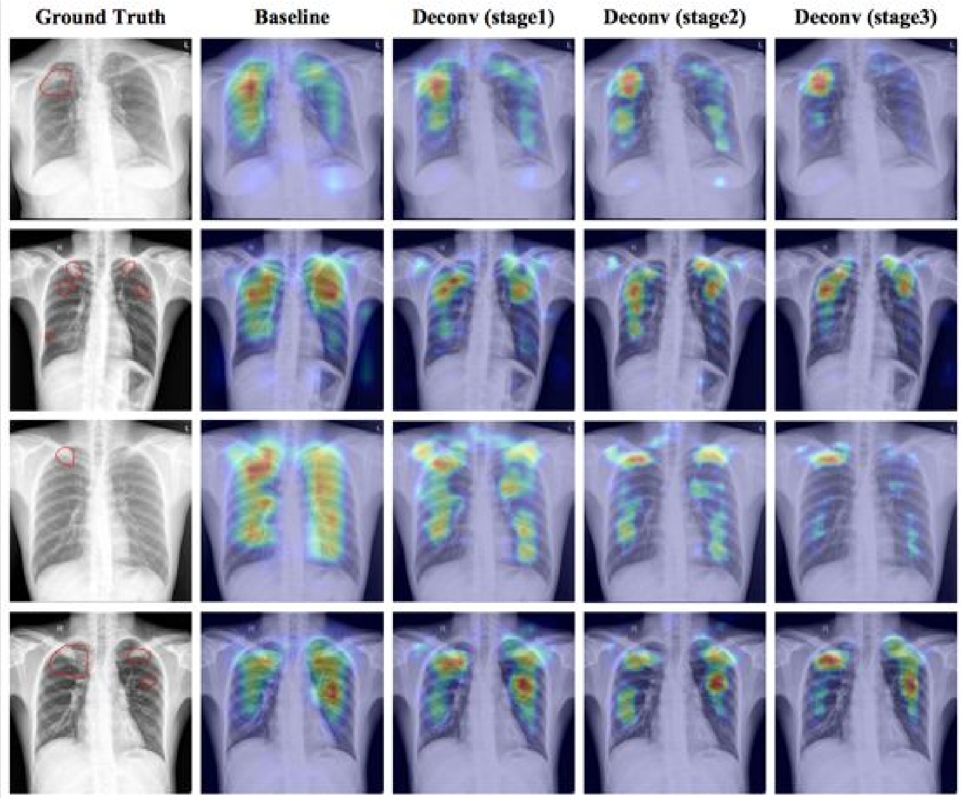
Zhou, B. et al. (2015), “Learning deep features for discriminative localization”, CVPR

Weakly supervised approach!!



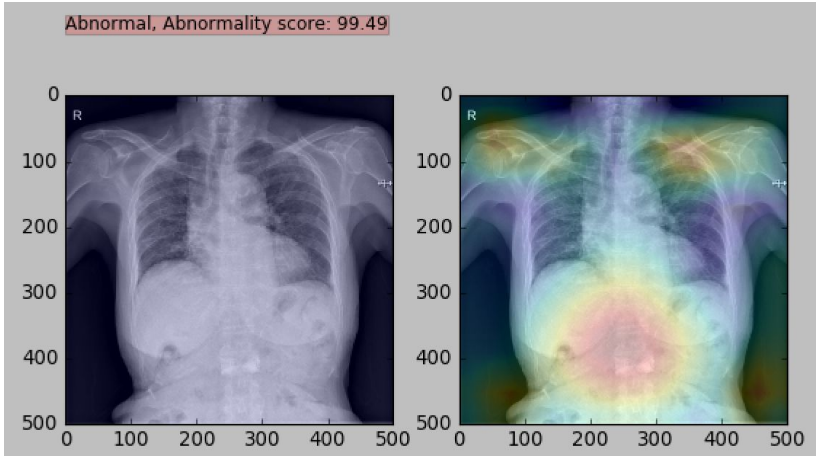
Hwang, S. and Kim, H.-E. (2016), “Self-transfer learning for weakly supervised lesion localization”, MICCAI

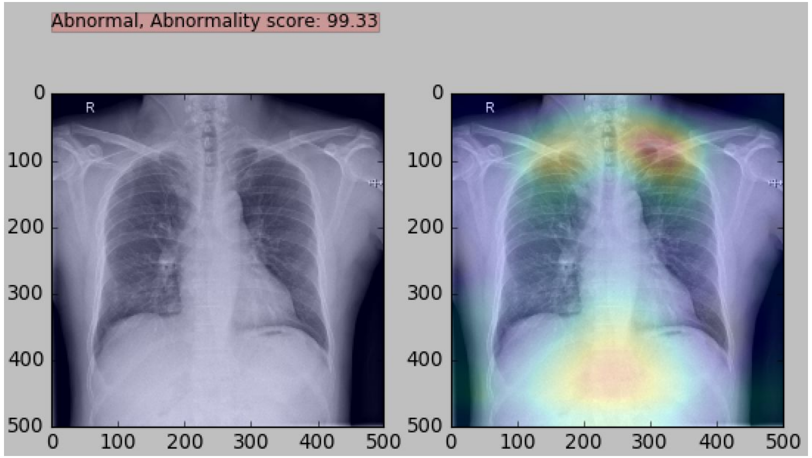
Weakly supervised approach!!!!



Kim, H.-E. and Hwang, S. (2016), “Deconvolutional feature stacking for weakly-supervised semantic segmentation”, arXiv:1602.04984v3

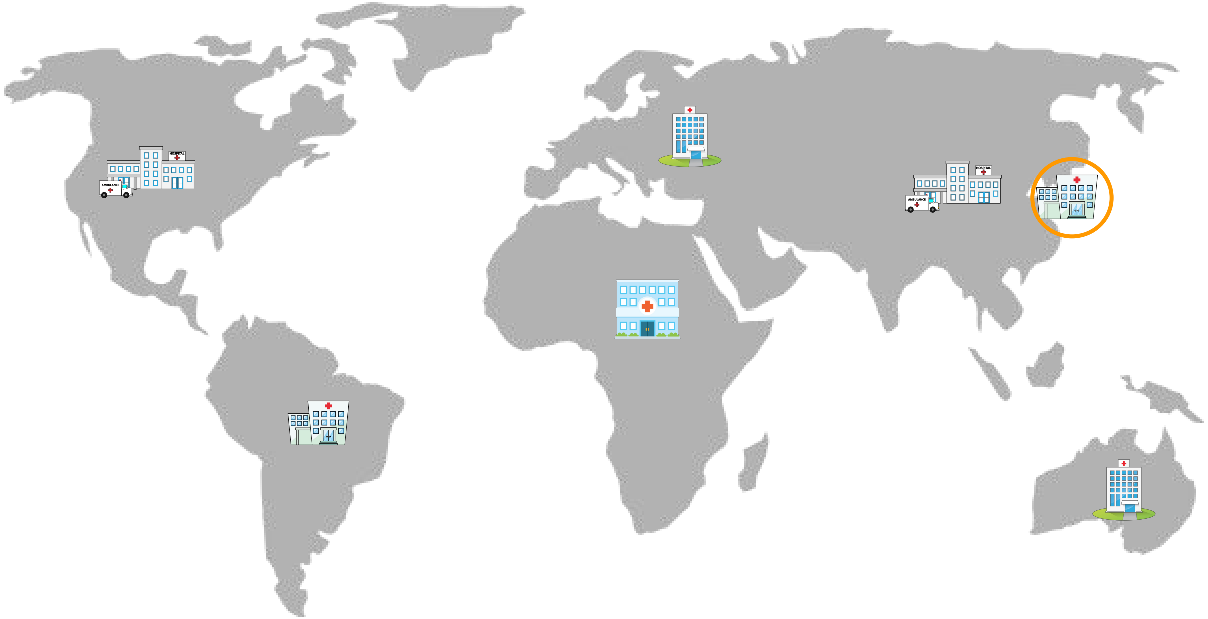
Weakly supervised approach?





- Why did this happen?
  - There are some hidden biases!
  - We need an unprecedented amount of data to resolve this!

Sample VS Population



Our dataset is NOT unbiased, representative, random sample!

Biased algorithm?

Google AI chief claims biased algorithms are a big danger

BY KEN HANLY OCT 7, 2017 IN TECHNOLOGY LISTEN | PRINT

http://www.digitaljournal.com/tech-and-science/technology/google-ai-chief-claims-biased-not-killer-robots-are-big-danger/article/504460

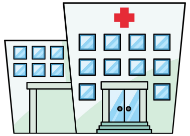
Why Healthcare Must Beware of Bunk Data

Jack Murtha
OCTOBER 12, 2017

http://www.hcanews.com/news/why-healthcare-must-beware-of-bunk-data

- “The real safety question is that if we give these systems biased data, they will be biased”
- We should be carefully looking for hidden biases in our training data.
- A study group should reflect the larger population in question.
- Biased data produce skewed results.

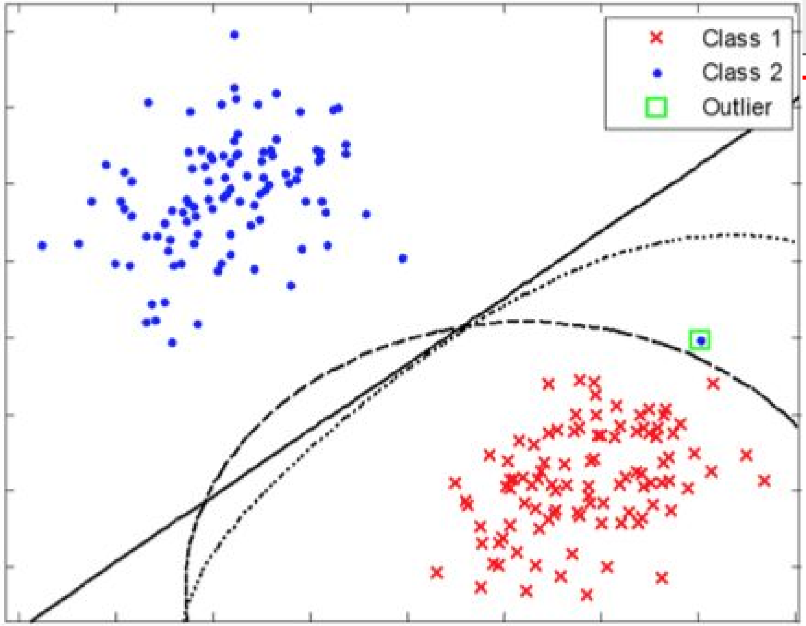
Which dataset is important?



Training

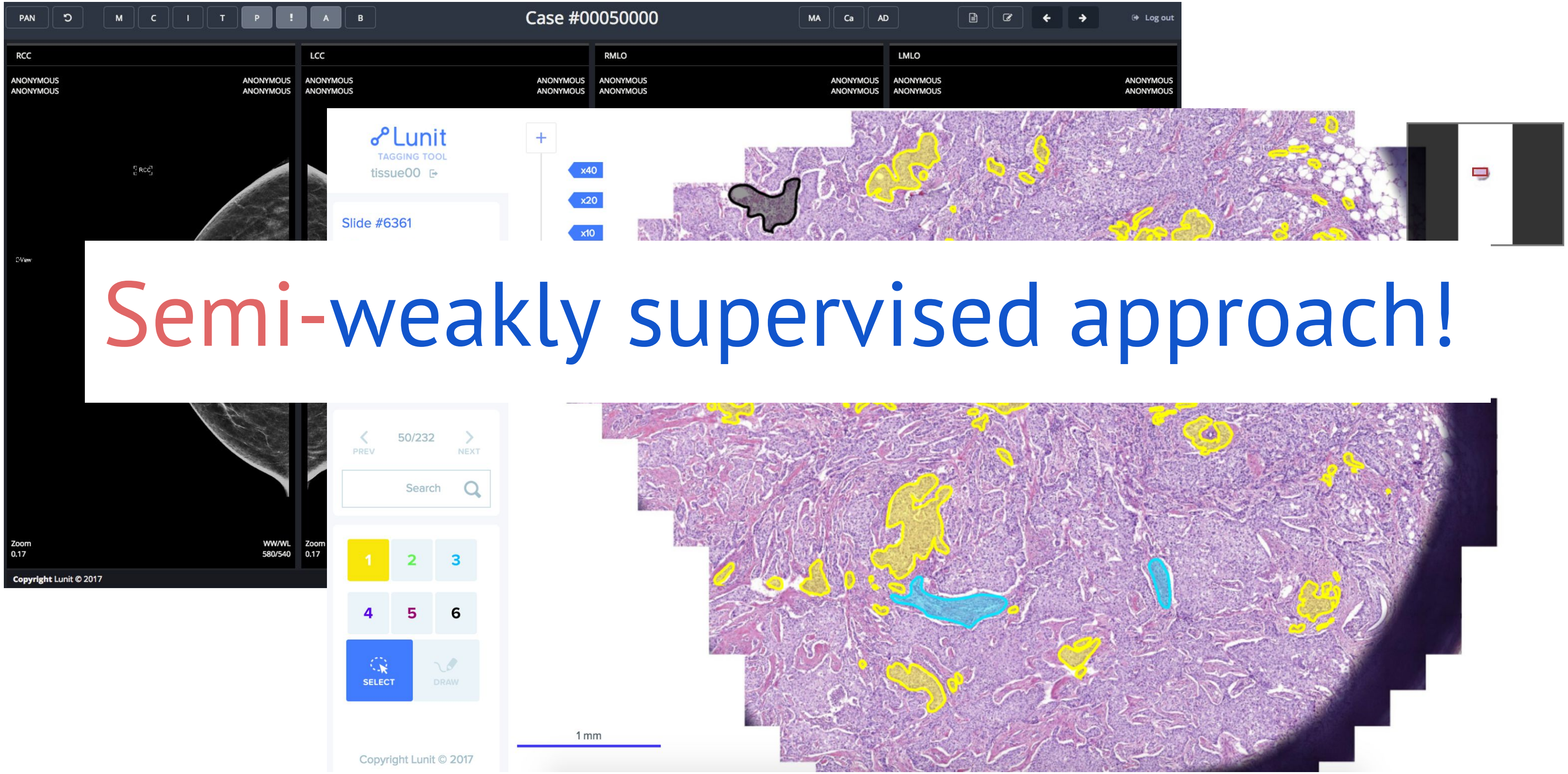
Validation

Test



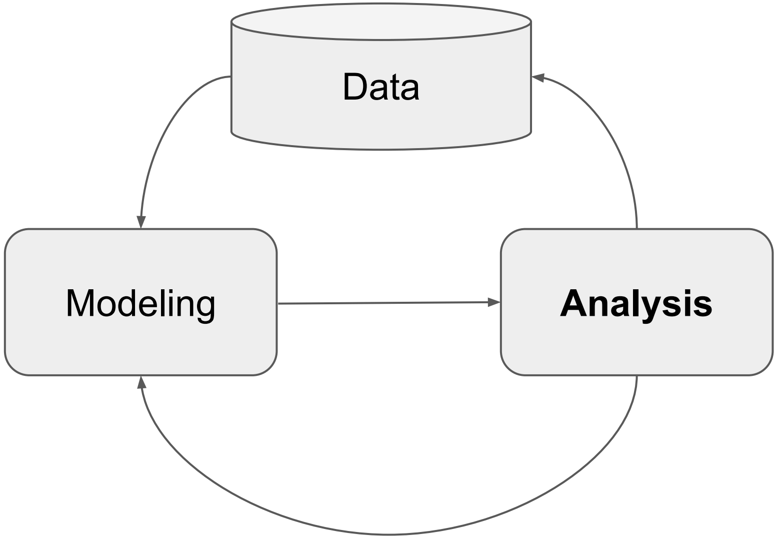
- Validation set defines the target space of our model.
- Training set? at least, we can try to resolve them!

So?



Semi-weakly supervised approach!

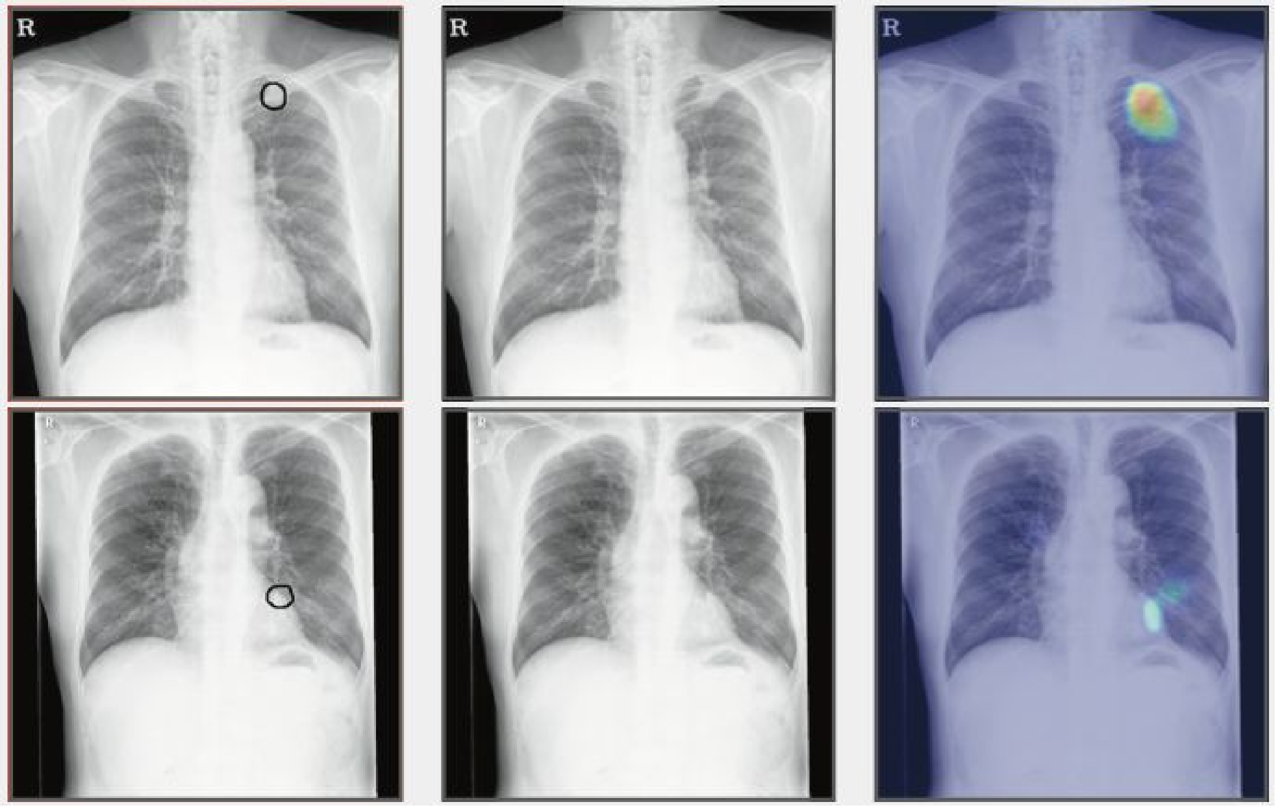
Revisited: Product development process



- Construct initial dataset
- Train model
- Evaluate model
- **Analyze evaluation result**
  - **no matter the result is good or bad**
- **Improve model**
  - **get additional data**
  - **develop algorithms**

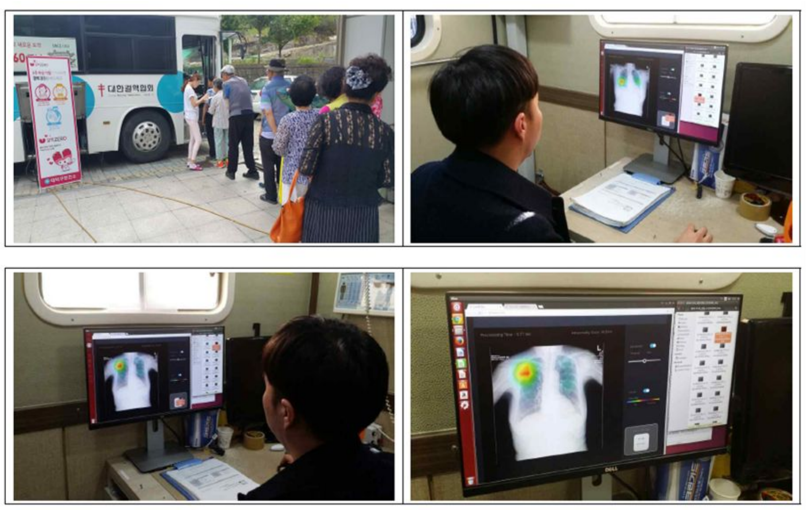
Lunit INSIGHT

Clinical study on chest radiography (2017, RSNA)



Establishing actual user cases

Korea National Tuberculosis Association

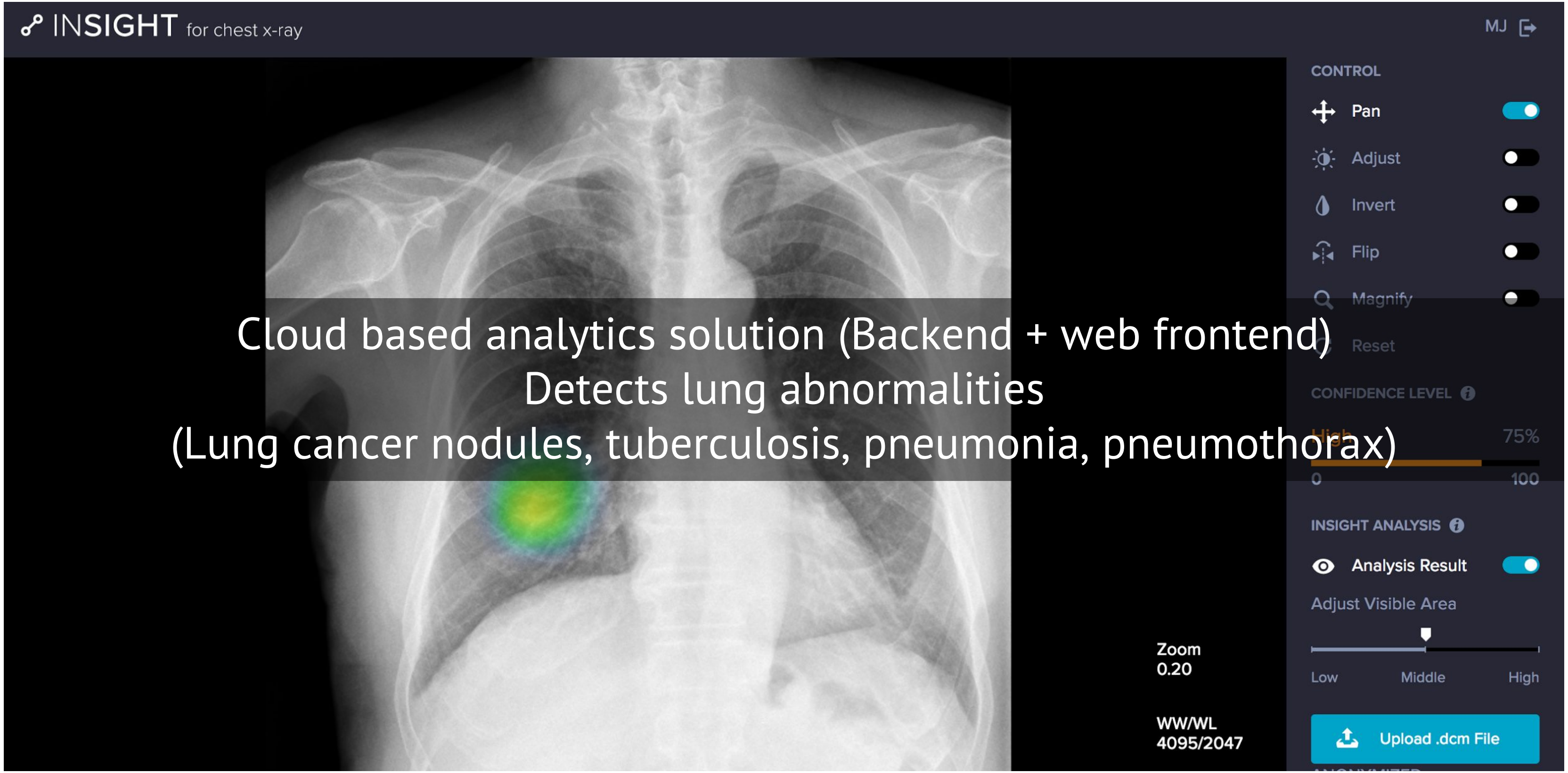


- Integration of Lunit Insight in national tuberculosis screening systems
- Benefit: 2-stop clinic → 1-stop clinic

The Armed Forces Medical Command

- Cooperation with Republic of Korea Army in applying Lunit Insight in battalions without adequate medical support

Lunit Insight



Cloud based analytics solution (Backend + web frontend)
Detects lung abnormalities
(Lung cancer nodules, tuberculosis, pneumonia, pneumothorax)

Thank you!

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