

# CHALLENGES AND STRATEGIES FOR DEVELOPING ROBUST AI APPLICATIONS IN ONCOLOGY

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### Image assessments of cancer lesions are the basis of evaluating treatment response

- Measurements are made on images
- Recorded as a separate process (spreadsheet, dictated report, etc)
- Disconnected from the image(s)

| Lesion ID | Description/Location  | SI  | SI  | SI  | SI  | SI  | SI  |
|-----------|-----------------------|-----|-----|-----|-----|-----|-----|
| 1         | near mass             | 1.8 | 1.5 | 1.5 | 1.5 | 1.5 | 1.5 |
| 2         | near mass             | 2.7 | 2.7 | 2.7 | 2.7 | 2.7 | 2.7 |
| 3         | near mass             | +   | +   | +   | +   | +   | +   |
| 4         | 13 basal lesion       | +   | +   | +   | +   | +   | +   |
| 5         | 16th rib lesion       | +   | +   | +   | +   | +   | +   |
| 6         | Left pleural effusion | +   | +   | +   | +   | +   | +   |
| 7         | near mass             | +   | +   | +   | +   | +   | +   |

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### Lesion measurements are basis of patient response and cohort treatment efficacy

**Sum of Maximum Lesion Diameters Over Time**

**Best Change in Lesion Diameters**

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### Problem: Inter-reader variation: Sufficiency of information in 167 imaging studies and reports

| No of Observations  | Baseline (55) | Follow-up (112) |
|---------------------|---------------|-----------------|
| <b>Report</b>       |               |                 |
| Lesion Described    | 39 (71%)      | 43 (38%)        |
| Longest Diameter    | 30 (55%)      | 31 (28%)        |
| <b>Image Markup</b> |               |                 |
| Lesion Identified   | 40 (73%)      | 78 (70%)        |
| Longest Diameter    | 27 (50%)      | 29 (26%)        |

Radiologist not aware of measurable disease being tracked by oncologists

| Number of CT Scans             | Baseline (13) | Follow-up (29) | Total (42) |
|--------------------------------|---------------|----------------|------------|
| Sufficient to Calculate RECIST | 54%           | 14%            | 26%        |
| Sum of Longest Diameters       |               |                |            |

Levy MA, Rubin DL. Tool support to enable evaluation of the clinical response to treatment. AMIA Annu Symp Proc. 2008:399-403. Copyright © Daniel Rubin 2017

### Opportunities for AI in cancer imaging

- Lesion detection
- Lesion segmentation
- Diagnosis
- Treatment selection
- Response assessment
- Clinical prediction (of treatment response or future disease)

**Critical for Drug Evaluation**

**Active research area**

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### Detection and segmentation: General fully connected networks

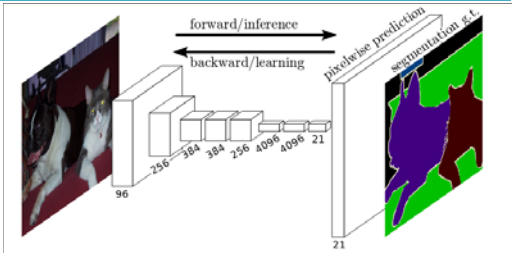


Figure 1. Fully convolutional networks can efficiently learn to make dense predictions for **per-pixel** tasks like semantic segmentation.

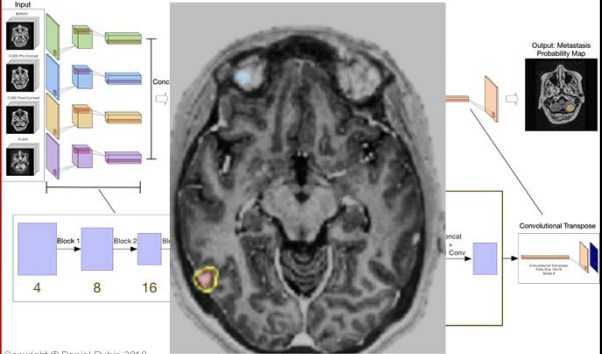
**Detection/segmentation are pixel-based classification tasks**

[http://www.cv-foundation.org/openaccess/content\\_cvpr\\_2015/papers/Lang\\_Fully\\_Convolutional\\_Networks\\_2015\\_CVPR\\_paper.pdf](http://www.cv-foundation.org/openaccess/content_cvpr_2015/papers/Lang_Fully_Convolutional_Networks_2015_CVPR_paper.pdf)

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### Example automated segmentation

Yellow Outline = Expert Segmentation



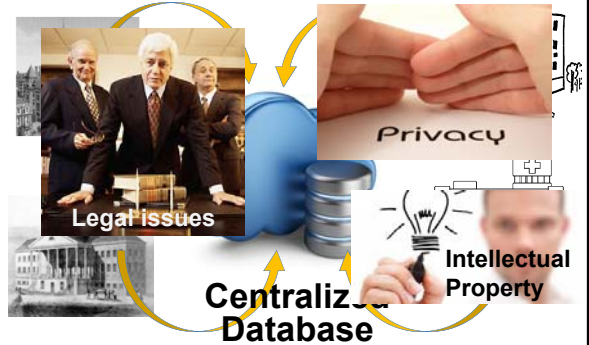
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### There are challenges to building robust AI models

- Data among institutions varies
  - Geographic variations in patient populations
  - Differences in imaging parameters
  - Differences in vendor equipment
- Robust AI models require **large amounts of labeled training data** in order to **generalize**
- Difficult/costly to acquire large amounts of data
- There are tremendous amounts of historical data across institutions that could be leveraged

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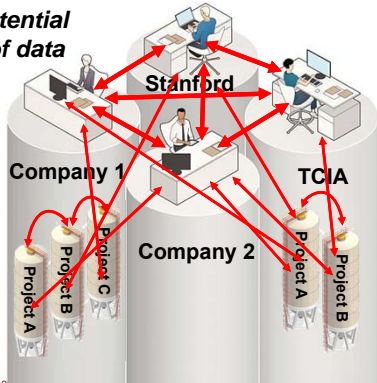
### Acquiring data from multiple sites is challenging



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### AI development (and data) is siloed

**Limited potential for reuse of data**

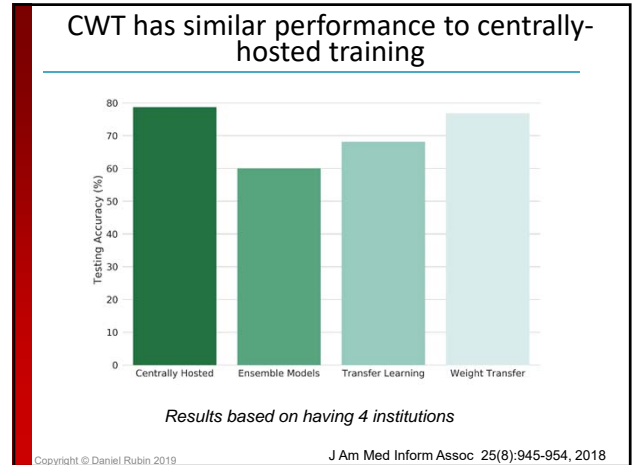
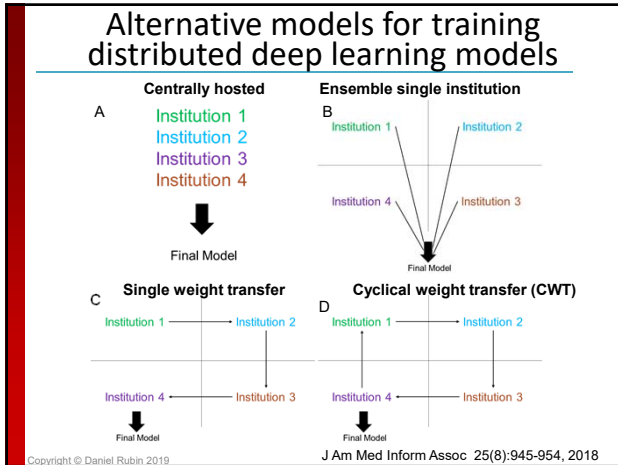


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### Overcoming barriers to data sharing

- Bring the **model to the data** instead of bring the data (centralized) to the model
- **Distributed computation** of training deep learning models (“distributed learning”)

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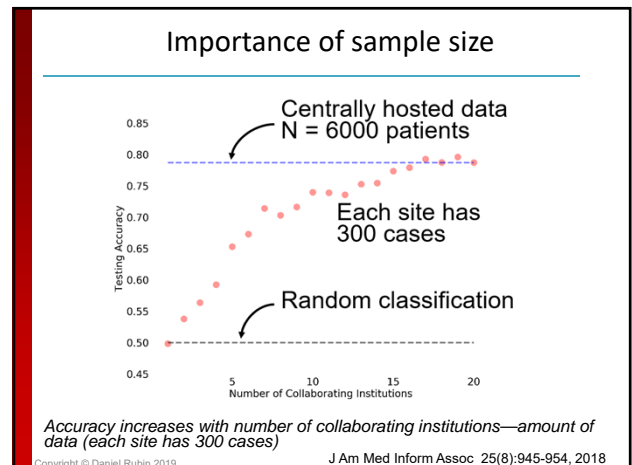
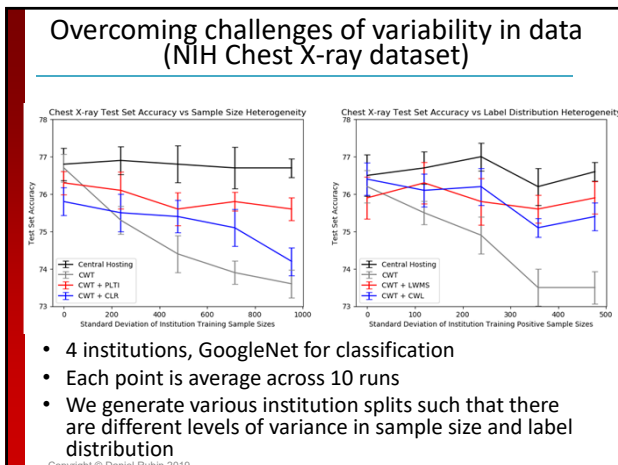
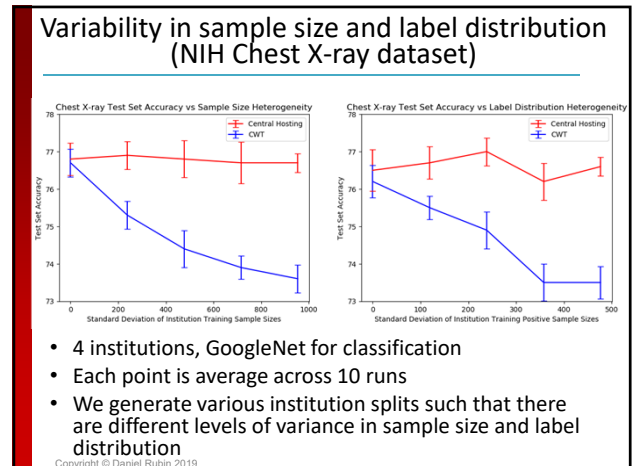


### Challenges to making distributed learning work

**Distributed model performance may be inferior to centrally hosted performance**

- **Heterogeneity in data** across institutions
  - Different patient populations (sample sizes, label distribution)
  - Differences in manifestation of disease
  - Different scanning hardware/parameters
  - Differences in image resolution
  - Differences in image quality
- Differences in **computing hardware** (GPU/CPU) among institutions
- Differences in **network bandwidth** among institutions

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## The future: A collaborative AI ecosystem

- Each site specifies a dataset they wish to make available for building AI
- “Pop-up” collaborations to build AI models using distributed learning
- Full control over data and data use



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## Summary

- We need AI in cancer imaging to reduce **variations in assessment of lesions**
- Key AI methods are automated **lesion detection** and **segmentation**
- Building robust AI models requires much data
- Data from multiple institutions can be leveraged through distributed learning
  - Heterogeneities among sites is a challenge
  - Optimizations in distributed computational approaches can overcome challenges

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*Thank you.*

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