Johns Hopkins
Whiting School of Engineering

Towards Annotation-Efficient Deep Learning for Computer-Aided Diagnosis

Label-Free Liver Tumor Segmentation

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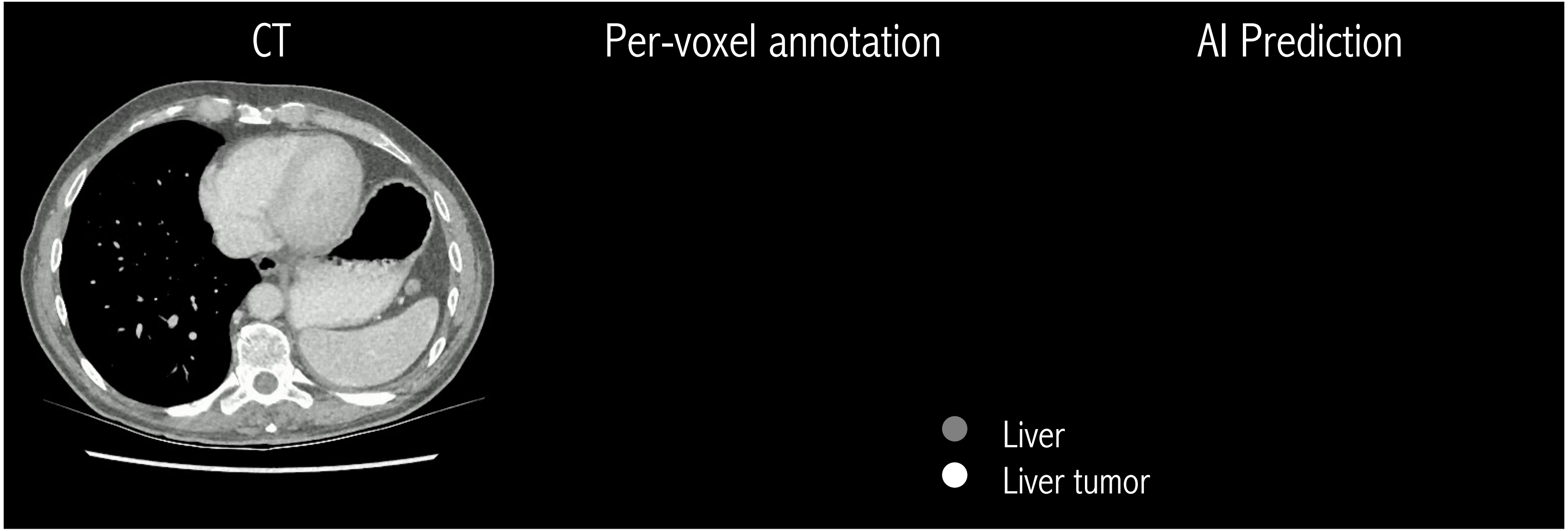
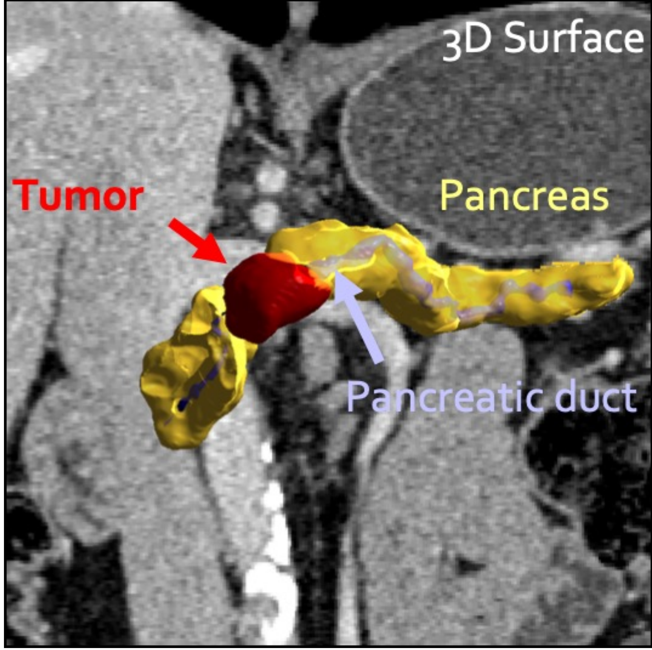
Goal: Detecting and Segmenting Cancer

- An example of CT scan, per-voxel annotations performed by radiologists, and AI predictions



Goal: Detecting and Segmenting Cancer



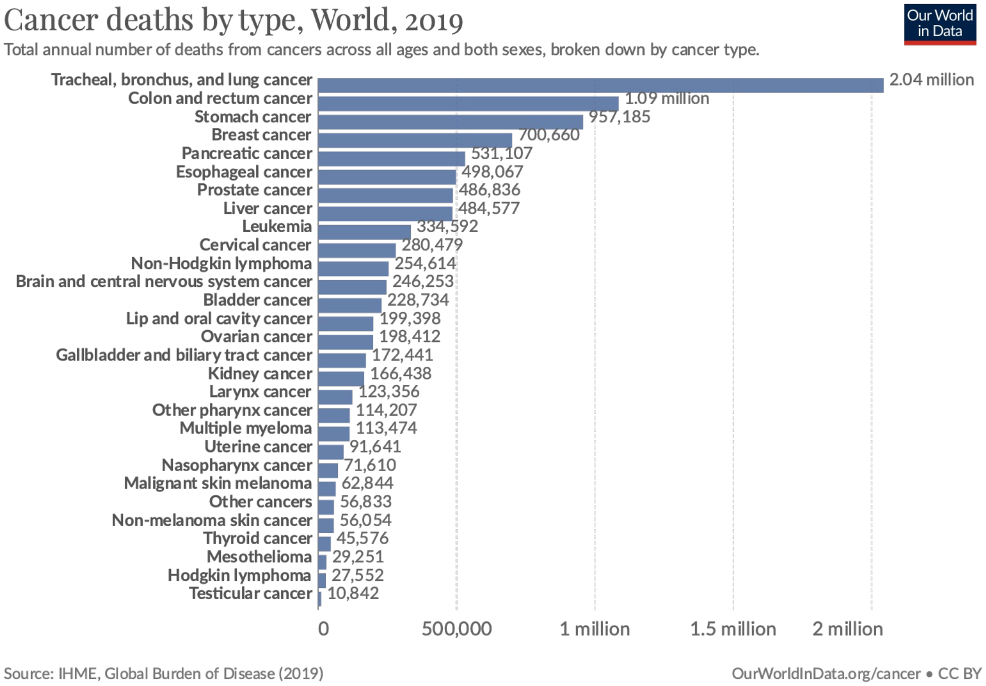
- Detailed per-voxel annotations are limited in public datasets
  - Colon tumors: 126 examples
  - Liver tumors: 131 examples
  - Pancreas tumors: 282 examples
  - Kidney tumors: 300 examples

- High-performance AI algorithms require large annotated data
  - Pancreas tumors: 5,038 examples in FELIX[1] ☛ Sensitivity = 97%, Specificity = 99%
  - This annotation took 15 human-year to create

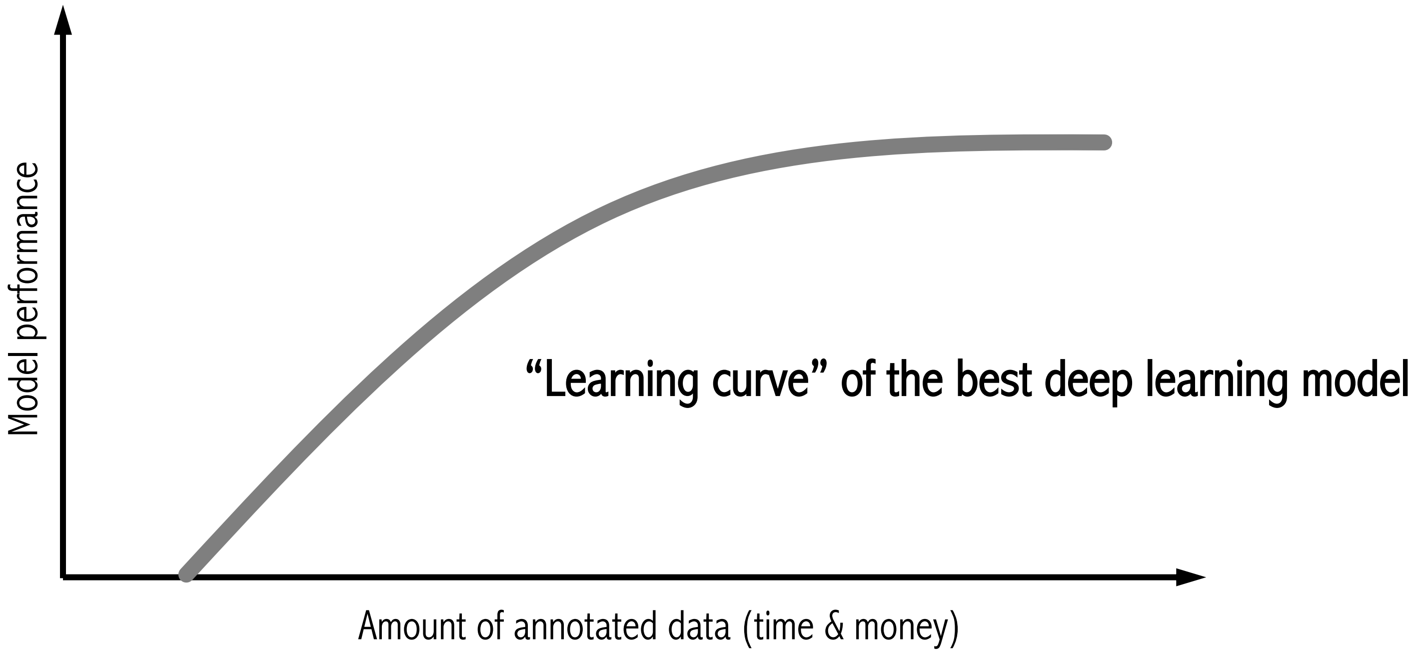
1. Xia, Y., Yu, Q., Chu, L., ... & Fishman, E. K. (2022). The FELIX Project: Deep Networks To Detect Pancreatic Neoplasms. medRxiv.

Goal: Detecting and Segmenting Cancers (Not Cancer)

- *How can we deal with many other types of tumors?*

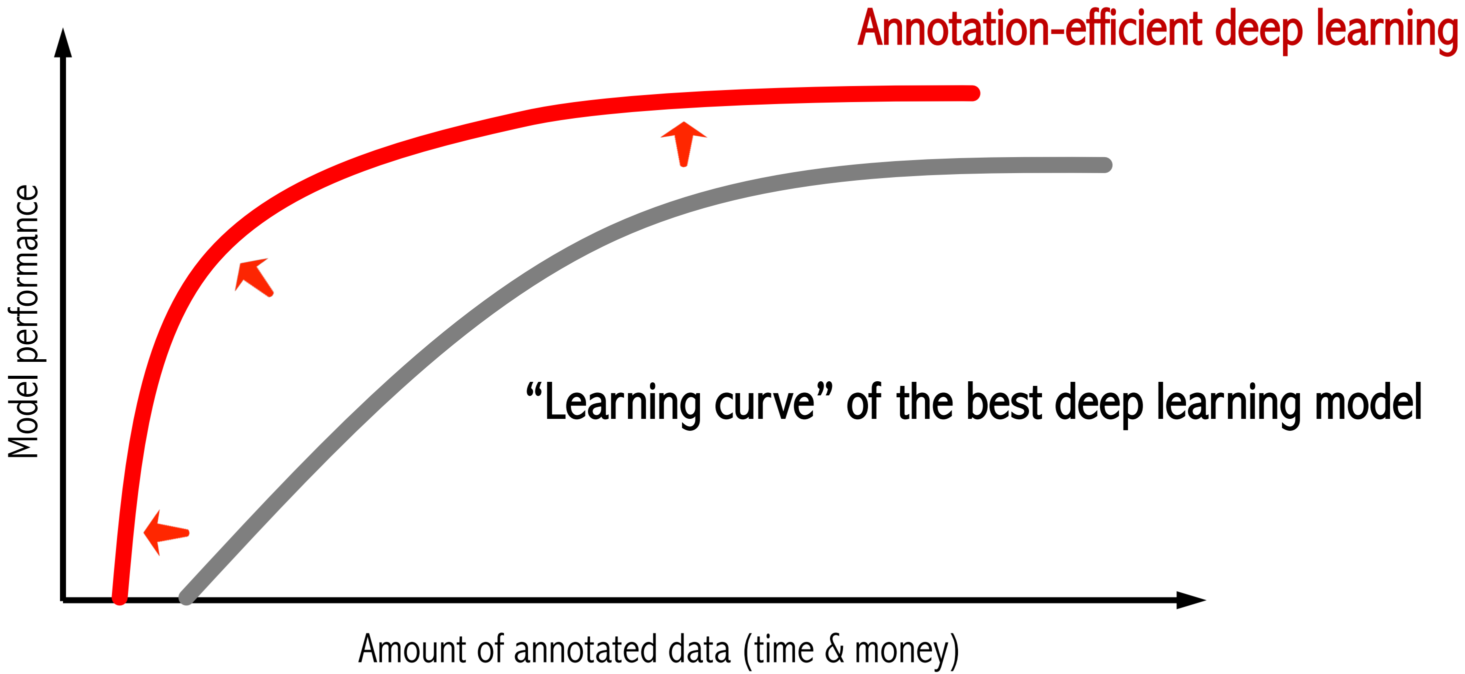


Towards Annotation-Efficient Deep Learning



1. Zhou, Z. (2021). Towards annotation-efficient deep learning for computer-aided diagnosis (Doctoral dissertation, Arizona State University).

Towards Annotation-Efficient Deep Learning



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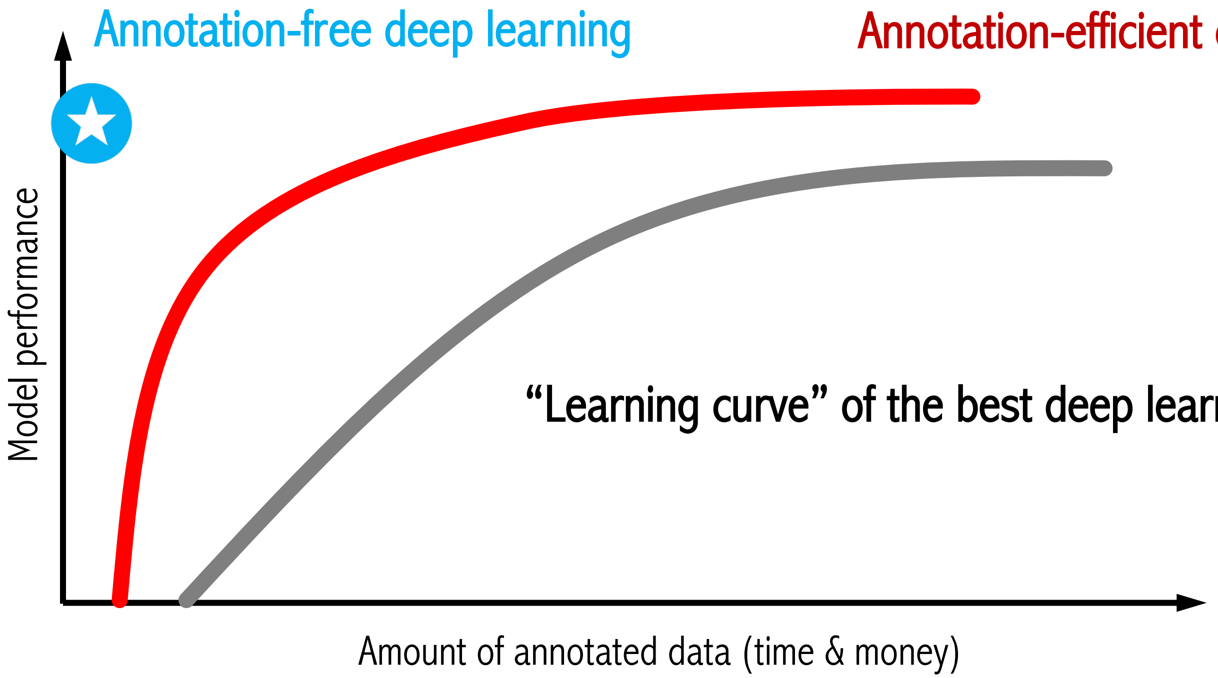
Towards Annotation-Free Deep Learning



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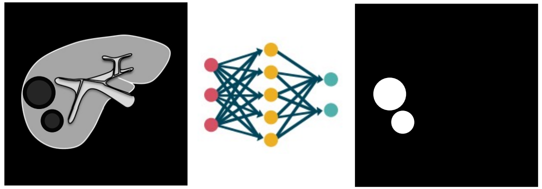
Goal: Detecting and Segmenting Cancers (Not Cancer)

- *How can we deal with many other types of tumors?*

- Three perspectives
- I. Exploiting existing public datasets and their partial annotation
- II. Investigating the power of weak annotation (e.g., circle, box, scribble, tag)
- III. Exploring the potential of ultra-weak annotation (e.g., radiology report and synthetic tumors)

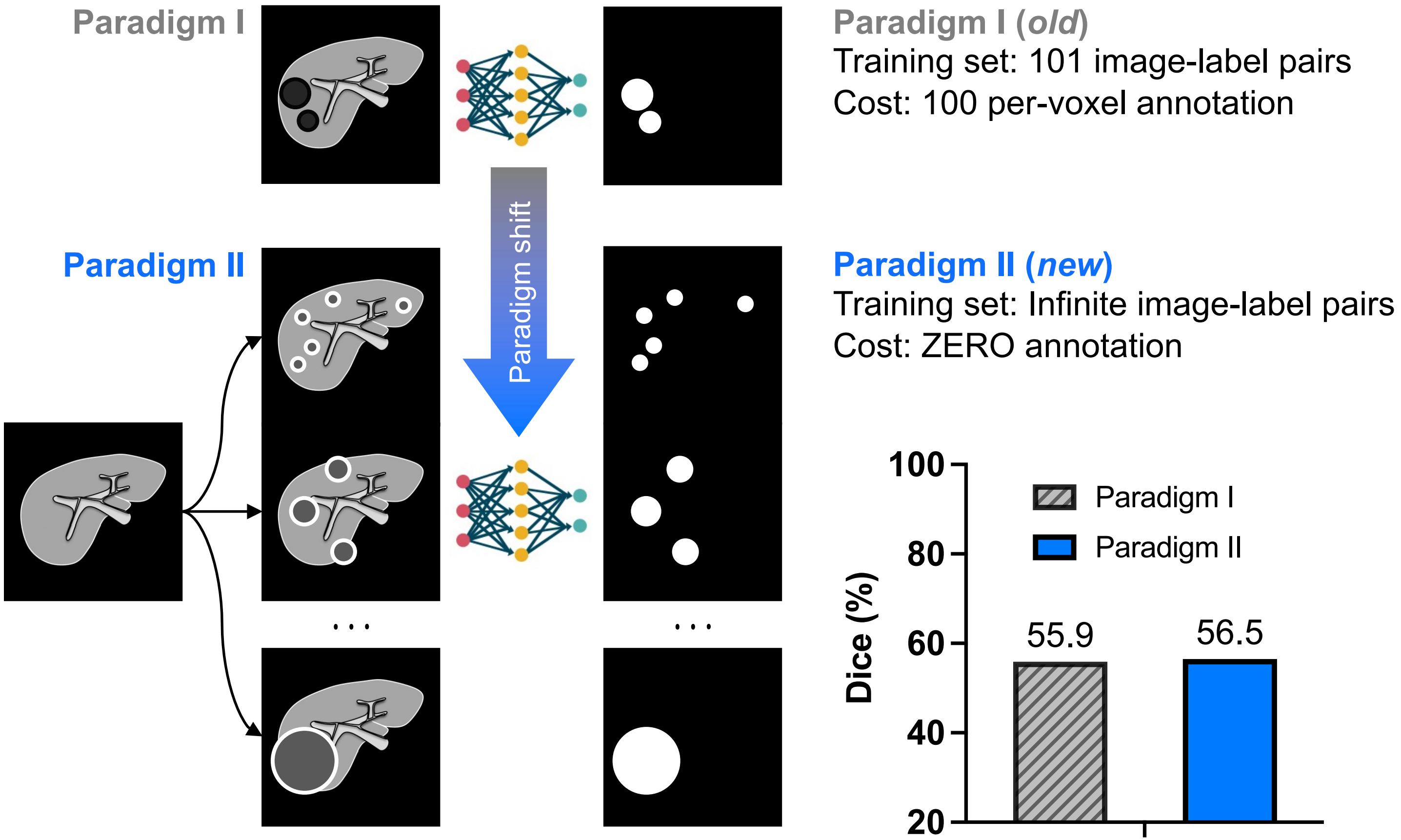
Paradigm I



Paradigm I (*old*)

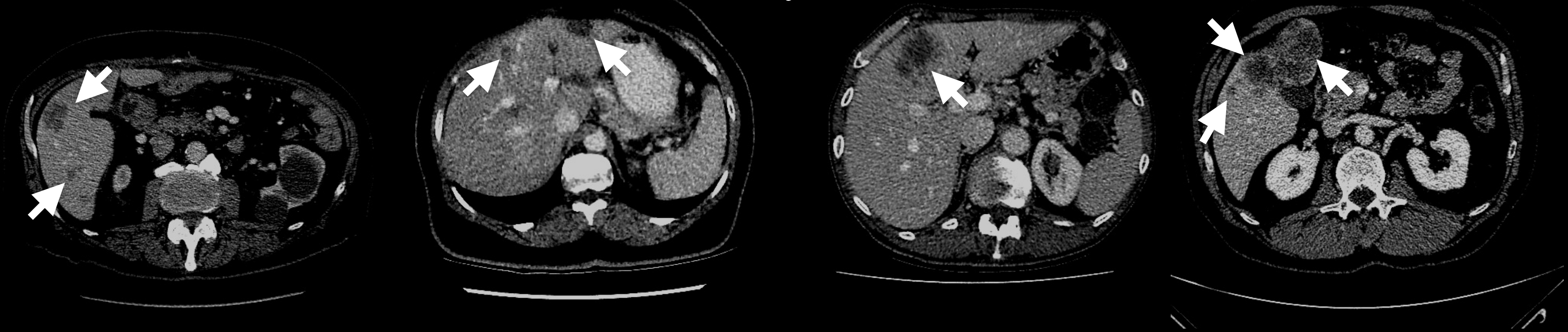
Training set: 101 image-label pairs

Cost: 100 per-voxel annotation


Paradigm I
Paradigm shift
Paradigm II
. . .
. . .
Paradigm I (old)
Training set: 101 image-label pairs
Cost: 100 per-voxel annotation
Paradigm II (new)
Training set: Infinite image-label pairs
Cost: ZERO annotation
Dice (%)
100
80
60
40
20
Paradigm I
Paradigm II
55.9
56.5

Medical professionals with over 6-year experience cannot tell which are real and which are synthetic tumor with an accuracy of 20% (lower than random guess)

Can you?



Training AI on synthetic tumors performs almost as well as training it on real tumors.

CT

AI prediction
trained on real tumors
with per-voxel annotation

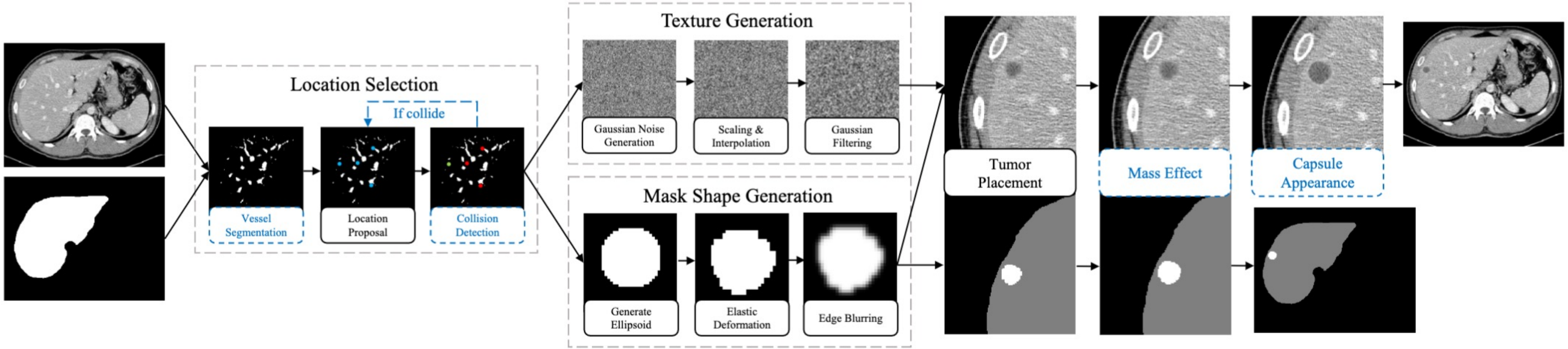
AI prediction
trained on synthetic tumors
with no annotation

Liver
Liver tumor

1. Hu, Q., Xiao, J., Chen, Y., ... & Zhou, Z. (2022). "Synthetic Tumors Make AI Segment Tumors Better." Medical Imaging Meets NeurIPS, 2022.

III. Exploring the potential of ultra-weak annotation

- https://github.com/MrGiovanni/SyntheticTumors



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Goal: Detecting and Segmenting Cancer

- We plan to generate synthetic tumors in many more organs
- In the future, annotations are still needed, but these annotations will be only used for evaluation
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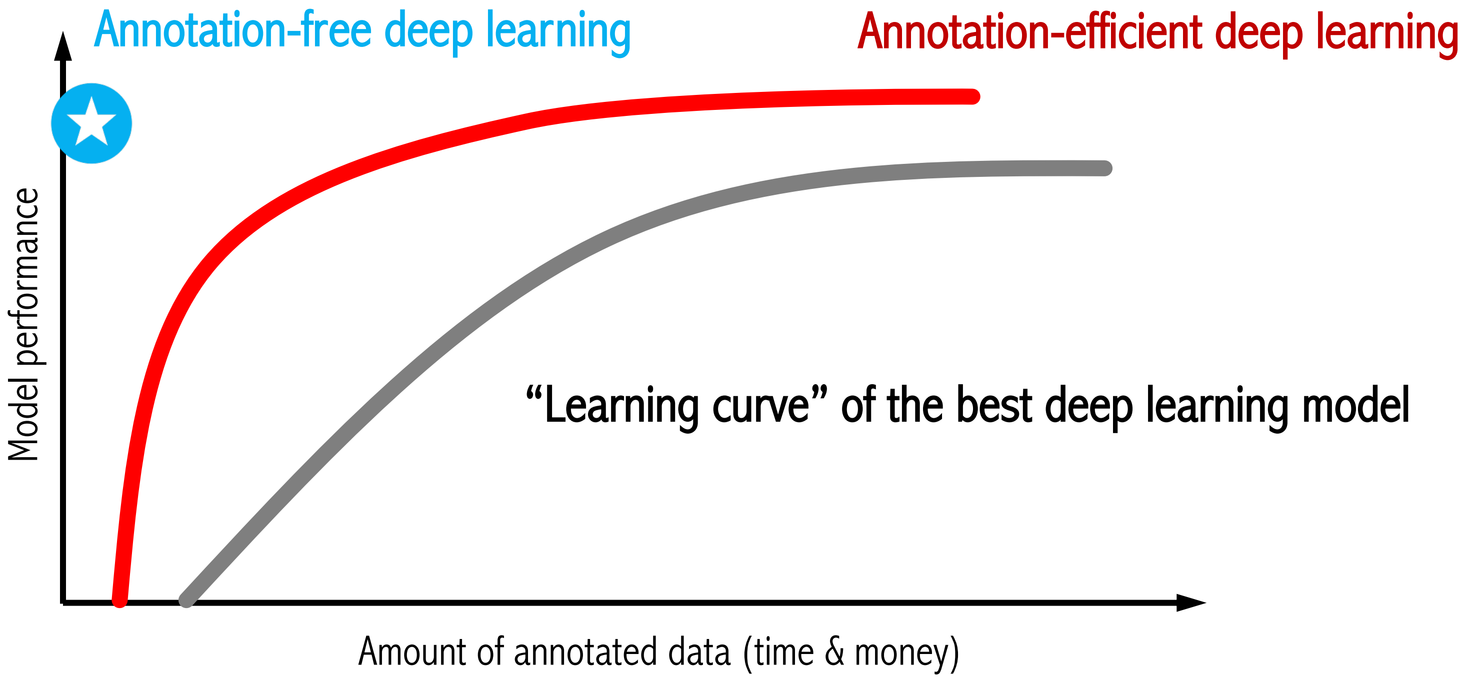
Towards Annotation-Efficient *(-Free)* Deep Learning



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