Our framework contains three key components:
- Segmenter, discriminator, and the oracle

**Initial Training**
We initialize segmenter and discriminator with CBIS-DDSM data.

**Active Learning Loop**
- The segmenter predicts labels, and the discriminator predicts how good they are.
- We choose images to show to the oracle based on the scores, and receive feedback.
- We employ an automated oracle system that can approve a label as correct, or provide ground-truth labels.
- With the feedback, retrain the segmenter and discriminator.

### Active learning
Intentionally choose which subset of data to label, with the idea that some labels are more informative for training. Iteratively query a user for labeling.

### Segmenter:
X-ray picture of the breast

**UNet**: Deep-learning architecture (UNet) we use to label mass lesions. We use nnUNet, an adaptive UNet implementation.

**Discriminator**: Convolutional neural network (VGG11) we train that assigns a score (0 to 1) on the accuracy of labels produced by segmenter.

**Oracle**: Expert who approves/validates labels.

**CBIS-DDSM data**: Curated Breast Imaging Subset of Digital Database for Screening Mammography, used for initial training.

**In-house data**: 1136 images from 484 patients who received mammograms at Duke University Health Systems between 2008 and 2018.

---

**Key Takeaway**
- Active learning can help create mammogram datasets more efficiently and economically.
- Querying oracle with **best** labels led to a dataset of 824 good labels with avg 312 aided by segmenter, comparable to **random**.
- **best** produces good labels at a faster rate.
- Querying with **worst** labels led more quickly to better segmenter model performance.

**Next Step**: Improve discriminator accuracy

---

**Currently, the method with most efficient labeling reduces required expert input by 37.9%.

### References