Identifying Metastatic Cancer through Deep Learning

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CS 230
Winter 2019

MOTIVATION
- With over 2 million new cases in 2018, breast cancer is the second most commonly occurring cancer in the world.
- Metastatic involvement of lymph nodes is a key prognostic characteristic of breast cancer.
- Progression is poorer when cancer has spread to the lymph nodes; pathologists take exceptional care when examining and diagnosing lymph nodes.
- The diagnostic procedure is tedious and time-consuming even for experienced pathologists.

DATA
- Subset of the PatchCamelyon (P-Cam) benchmark.
- Consists of 200/320 color images (96 x 96 pixels) extracted from histopathological scans of lymph node sections.
- Each image is annotated with a binary label indicating presence of metastatic tissue.
- A positive label means that at least one pixel of tumor tissue in the center 32 x 32 pixel region of the image.
- 172/226/226 Split: 80% Train/10% Dev/10% Test

MODEL
- A ConvNet with 4-Convolutional and 4-Fully Connected layers trained with the Adam optimizer.
- Built with PyTorch, an open-source ML library.
- Trained on a Microsoft Azure Deep Learning V12.

PREDICTING METHODOLOGY AND EXPERIMENTS

- **Hyperparameter Tuning**
  - We trained our model with different sets of hyperparameters to optimize accuracy.

<table>
<thead>
<tr>
<th>Batch Size</th>
<th>Train Accuracy</th>
<th>Dev Accuracy</th>
<th>Test Accuracy</th>
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<tbody>
<tr>
<td>16</td>
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- **Gray-scale Input**
  - Explored the possibility of augmenting the data set by converting the training images to gray-scale.
  - Removed the bias arising due to different training techniques used at different labs.
  - Unfortunately, did not generalize better than model based on color input.

- **Error Analysis**
  - **Saliency Maps**:
    - From final convolutional layer with the center 32 x 32 pixels patches highlighted.
    - Comparing True Positive vs. False Negatives
  - **Comparing True Negatives vs. False Positives

- **Comparing True Negatives vs. False Positives

RESULTS AND DISCUSSIONS
- Final model (hybrid) achieved an accuracy of 97.2%.
- Replacing ResNet with SEUNet (scaled exponential linear units) in our model yield negative results.
- The optimal learning rate does not need to be a magnitude of 0.1.
- A lack of expertise in the subject area made the error analysis especially challenging.
- PyTorch is a good framework for beginners.

FUTURE WORK
- Use transfer learning from an existing pre-trained model like AlexNet or VGG16.
- Try out other activation functions like Exponential Linear Unit (ELU).
- Progressive re-sizing (start by training the model on the 32 x 32 pixel center of each image and then move to the full image later).
- Apply our pre-trained model to other cancer-related problems using transfer learning (One possible use is for the Camelyon-16 tasks of tumor detection and Whole-Slide Imaging diagnosis).

REFERENCES

https://youtu.be/XPsdZpcMlk