Semi-Supervised Multi-Task Learning for Lung Cancer Diagnosis

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Outline

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  ○ Hypothesis
  ○ Proposal

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  ○ Multi-Task learning
  ○ Network architecture
  ○ Semi-Supervised learning

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Overview

● **Motivation**
  ○ CADs play a critical role in **early detection** and **diagnosis** of lung nodules.
  ○ CADs produce a lot of false positives (FP) and require a further FP reduction step.
  ○ **Shape and volume measurements** of abnormalities are important guidelines for early detection and diagnosis.

● **Hypothesis**
  ○ Joint learning of **false positive (FP) reduction** and **segmentation** can **improve** performance on **both tasks**.

● **Proposal**
  ○ a **3D deep multi-task CNN** to tackle **FP reduction** and **Segmentation**, **jointly**.
Multi-Task Learning (MTL)

MTL allows solving **multiple learning tasks** at the same time by optimizing **multiple loss functions** instead of one.

MTL can be **beneficial** in multiple senses:

- Generalization ability
- Highlighting underlying features
- Dealing with lack of data
Multi-Task Learning (MTL)

*Generalization ability*

A single model can be used to perform multiple tasks at the same time.

- The *inductive bias* acts as a *regularizer*.
  - Reduces the risk of *overfitting*.

- It will also help the model to *generalize to new tasks*.
  - Improves learning novel tasks as long as they are from the *same environment*. 
Multi-Task Learning (MTL)

**Highlighting underlying features**

- Some features $F$ are **easy to learn** for some task $B$,

- $F$ is **difficult to learn** for another task $A$,
  - $A$ interacts with the features in a more complex way.
  - Other features preventing the model's ability to learn $F$.

- MTL helps the model to learn this type of features
Multi-Task Learning (MTL)

Dealing with lack of data:

- Implicit data augmentation
  - All tasks are at least somewhat noisy.
  - Different tasks have different noise patterns.
  - A model that learns multiple tasks simultaneously is able to learn a more general representation.

- Attention focusing
  - For noisy tasks or limited and high-dimensional data, it can be difficult for a model to differentiate between relevant and irrelevant features.
  - MTL can help the model focus its attention on those features that are more relevant.
Semi-supervised learning

Algorithm 1: Semi-Supervised training algorithm

Input: labeled data: \((X_l, Y_l)\), unlabeled data: \(X_u\)

Train model \(f\) on \((X_l, Y_l)\)

for \(x\) in \(X_u\) do
  Predict on \(x \in X_u\)
  Add \((x, f(x))\) to labeled data
  Retrain model \(f\)
end

Return refined model \(f\);

\[
L(Y^{(n)}, f(X^{(n)}) = \sum_{i=1}^{k_n} -y_i \log(f(x_i)),
\]
Results

<table>
<thead>
<tr>
<th>Training strategy</th>
<th>DSC%</th>
<th>Sensitivity%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Single task</td>
<td>82%</td>
<td>88%</td>
</tr>
<tr>
<td>Multi task (manual GT)</td>
<td>86%</td>
<td>95%</td>
</tr>
<tr>
<td>Semi-Supervised multi task</td>
<td>91%</td>
<td>98%</td>
</tr>
</tbody>
</table>

Only 270 segmentation annotations
Results

<table>
<thead>
<tr>
<th>FPs/scan</th>
<th>0.125</th>
<th>0.25</th>
<th>0.5</th>
<th>1</th>
<th>2</th>
<th>4</th>
<th>8</th>
<th>Average</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sensitivity</td>
<td>0.773</td>
<td>0.870</td>
<td>0.924</td>
<td>0.941</td>
<td>0.962</td>
<td>0.980</td>
<td>0.986</td>
<td>0.919</td>
</tr>
</tbody>
</table>
Failure cases
Conclusion

**Multi-Task Learning:**

- Segmentation and FP reduction are auxiliary tasks sharing some underlying features and joint training improves the results for both tasks.

**Semi-Supervised learning**

- A semi-supervised approach can improve the results without the need for large number of labeled data in the training.
Thank you!