Deep Learning in Medical Imaging: What’s Needed for Training Data?
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To cite this version:
Francesca Galassi. Deep Learning in Medical Imaging: What’s Needed for Training Data?.
Biogenoust days 2023, Oct 2023, Rennes (Campus Villejean), France. hal-04247143

HAL Id: hal-04247143
https://inria.hal.science/hal-04247143
Submitted on 18 Oct 2023

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Deep Learning in Medical Imaging: What's Needed for Training Data?

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Deep Learning in Medical Imaging


Good vs. bad

"Data, data everywhere and not a set to process."
Neil Lawrence
Data Quality

- Artifacts, noise, and corruption
- Considerations for robustness and quality control

Data Variety

- Training on homogenous data may not generalize well to heterogeneous test data.
- Consider adopting a versatile or narrowly focused approach.

Data Volume

- Traditional statistical rules don’t always fit the machine learning paradigm
- DL has mechanisms to determine whether more data could help
Data Volume

High bias

High variance: more data may help

Source of inspiration: Andrew NG machine learning course
Data Readiness

- Are data ready for a DL process?
- Consider using a framework to evaluate readiness

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Dataset shift

“Dataset shift is any situation in which the training and test data distributions disagree due to exogenous factors, e.g. dissimilar cohorts or inconsistent acquisition processes.”

Daniel C. Castro
Predictive Modeling

- Given an image $X$, train a model to predict some annotation $Y$

$$P(Y | X)$$

Assumptions:

- Availability of sufficient training data $(X, Y)$ – data volume
- Consistency in training and testing data distribution – data variety

Challenges in DL for medical imaging: *Data Scarcity & Data Mismatch*
Image and Annotation – *a causal perspective*

What is the **relationship** between image $X$ and annotation $Y$?

- **cause** $X$ → **effect** $Y$
- **causal**
- predict effect from cause

*Example*: MS Lesion segmentation

- $X$ - structural brain MRI scan
- $Y$ - manual segmentation masks

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Dataset Shift – data mismatch

- Training and test data distributions may disagree due to ...

Population shift

\[ Z : \text{unobserved true anatomy} \]

Acquisition shift

\[ X : \text{image} \]

Annotation shift

\[ Y : \text{annotation} \]

Domain Adaptation – a case study

- **Unsupervised DA** – *unlabeled target data accessible at training time*

```
\begin{align*}
\text{source} \ x^s_i & \rightarrow g : x \rightarrow z \\
\text{target} \ x^t_j & \rightarrow f : z \rightarrow y
\end{align*}
```

- **Optimization problem:**

```
\min_{\gamma, f, g} \sum_i L_s(\ y^s_i, f( g(x^s_i) )) + \sum_{ij} \gamma_{ij} \| g(x^s_i) - g(x^t_j) \|^2 + \beta L_t(\ y^t_j, f( g(x^t_j) ))
```

the coupling matrix

Annotation Shift – a case study

- Considerable inter- and intra-rater variability observed
- High precision and low sensitivity of individual experts

Key Takeaways

- Data quality, volume and variety matter

- Error analysis guides model improvements and data collection
  - A data readiness framework can help assessing data suitability for a DL process

- Dataset shifts arise from factors like population, acquisition, and annotation variations
  - Causal diagram can help describing the shift in the specific project

- Consider strategies for addressing these challenges, i.e., label noise reduction and domain adaptation