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

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

*Galassi Francesca, MCF, Empenn lab*

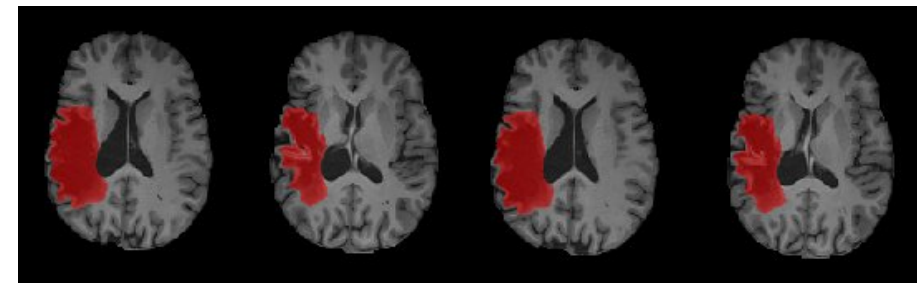
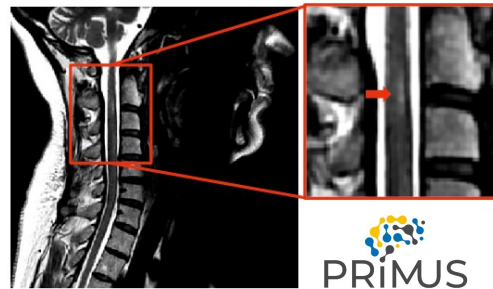
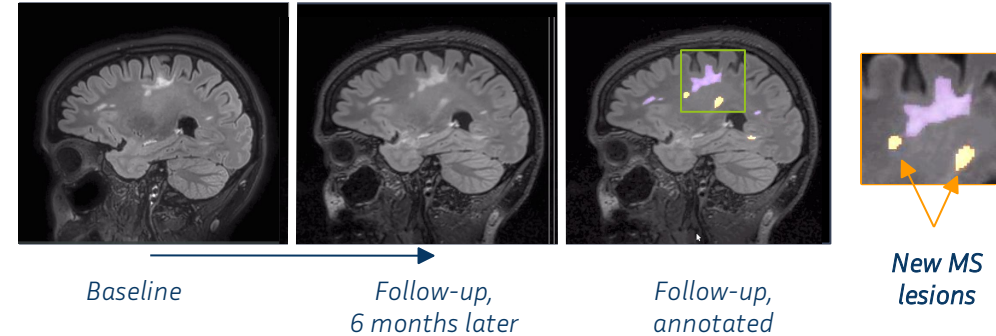
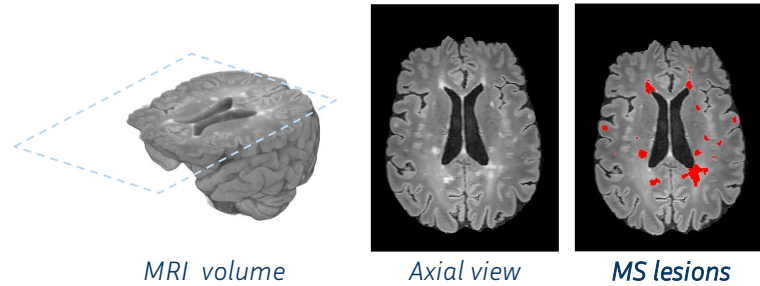
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*francesca.galassi@irisa.fr*



*Inria*

# Deep Learning in Medical Imaging



Stroke lesion

Hussein, B. R., Meurée, C., Gaubert, M., Masson, A., Kerbrat, A., Combès, B., & Galassi, F. (2023, April). A study on loss functions and decision thresholds for the segmentation of multiple sclerosis lesions on spinal cord MRI. In *2023 IEEE 20th International Symposium on Biomedical Imaging (ISBI)* (pp. 1-5). IEEE.

Masson, A., Le Bon, B., Kerbrat, A., Edan, G., Galassi, F., & Combes, B. (2021). A nnUnet implementation of new lesions segmentation from serial FLAIR images of MS patients. *MSSEG-2 challenge proceedings: Multiple sclerosis new lesions segmentation challenge using a data management and processing infrastructure*, 5. MICCAI MSSEG-2 Challenge.



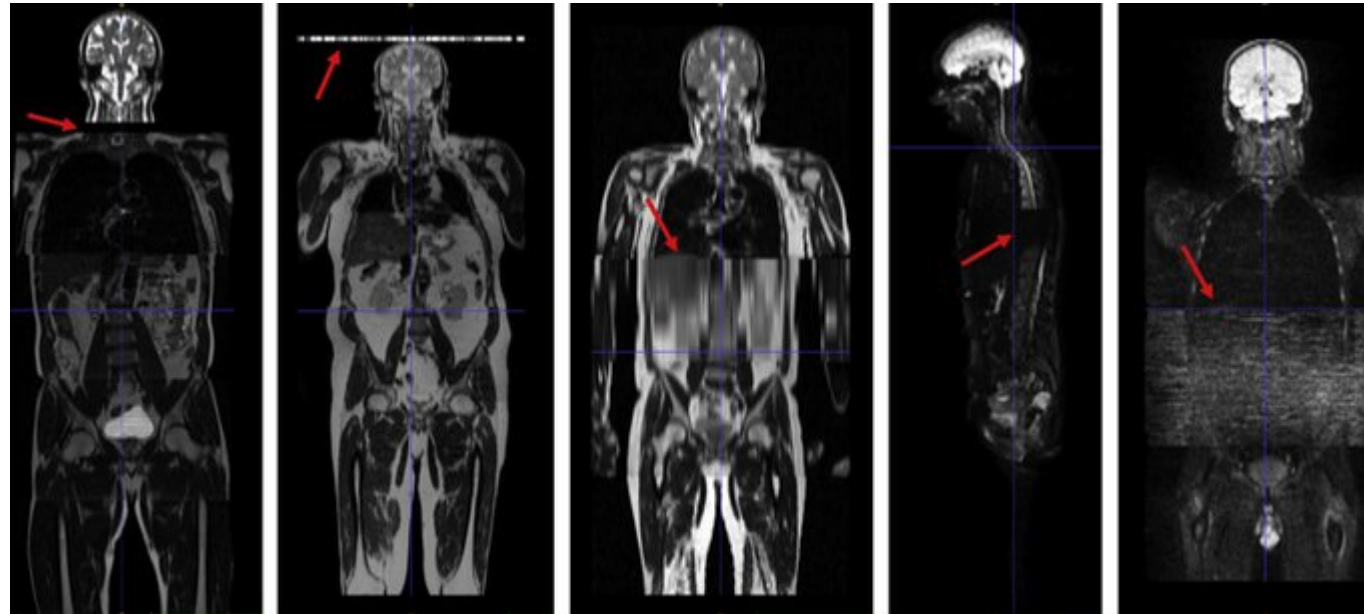
## Good vs. bad

*"Data, data everywhere and not a set to process."*

Neil Lawrence

# Data Quality

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



Lavdas, I., Glocker, B., Rueckert, D., Taylor, S. A., Aboagye, E. O., & Rockall, A. G. (2019). Machine learning in whole-body MRI: experiences and challenges from an applied study using multicentre data. *Clinical radiology*, 74(5), 346-356.

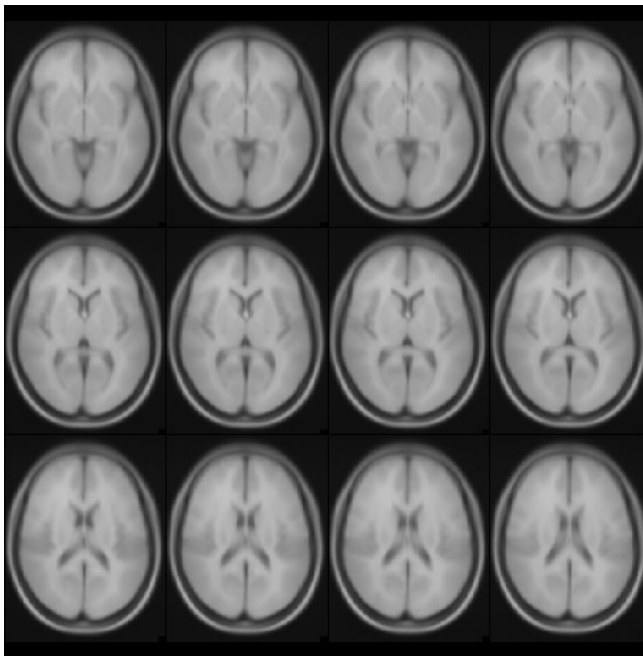


EMPENN

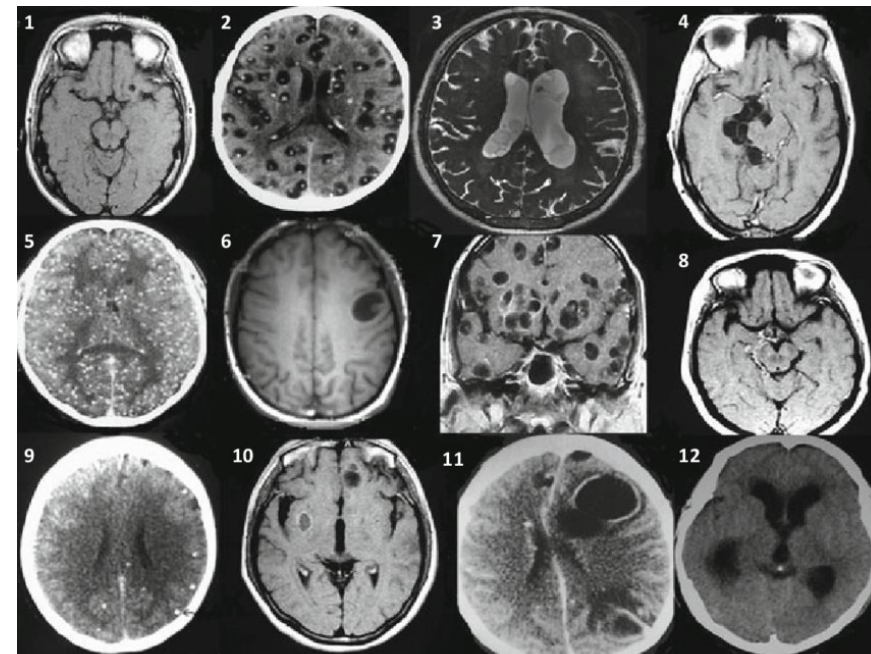
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# Data Variety

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



MNI atlas



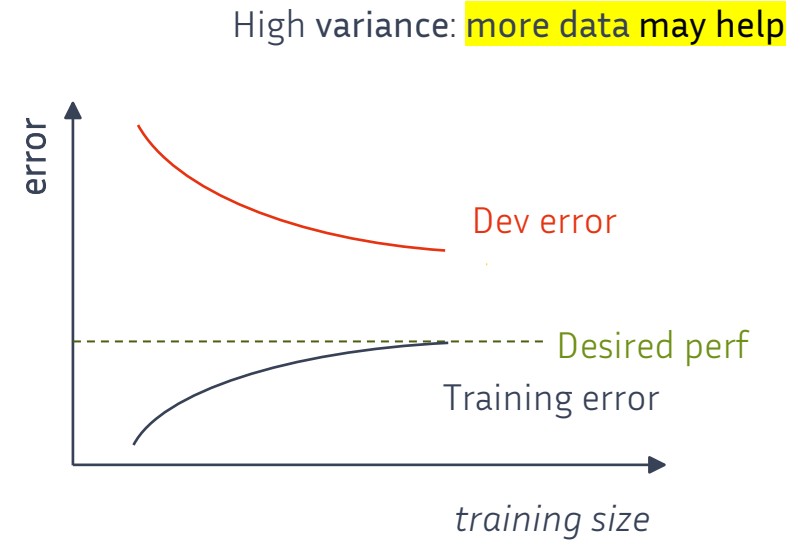
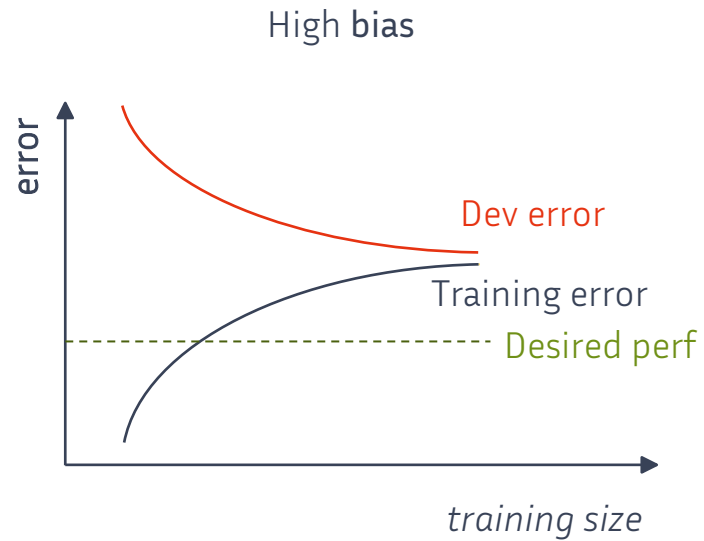
# Data Volume

*How much data do you need? - Clinician*

*How much data do you have? - DL Researcher*

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

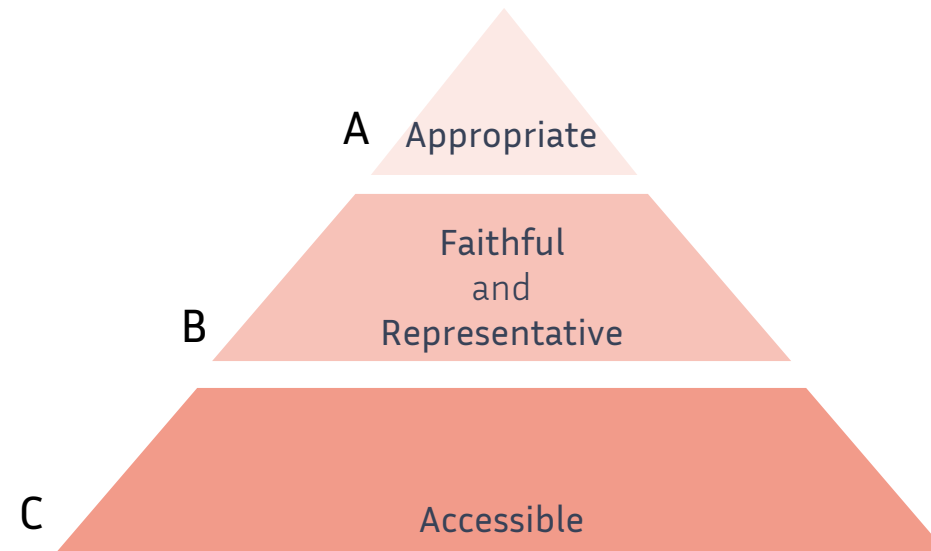
# Data Volume





# Data Readiness

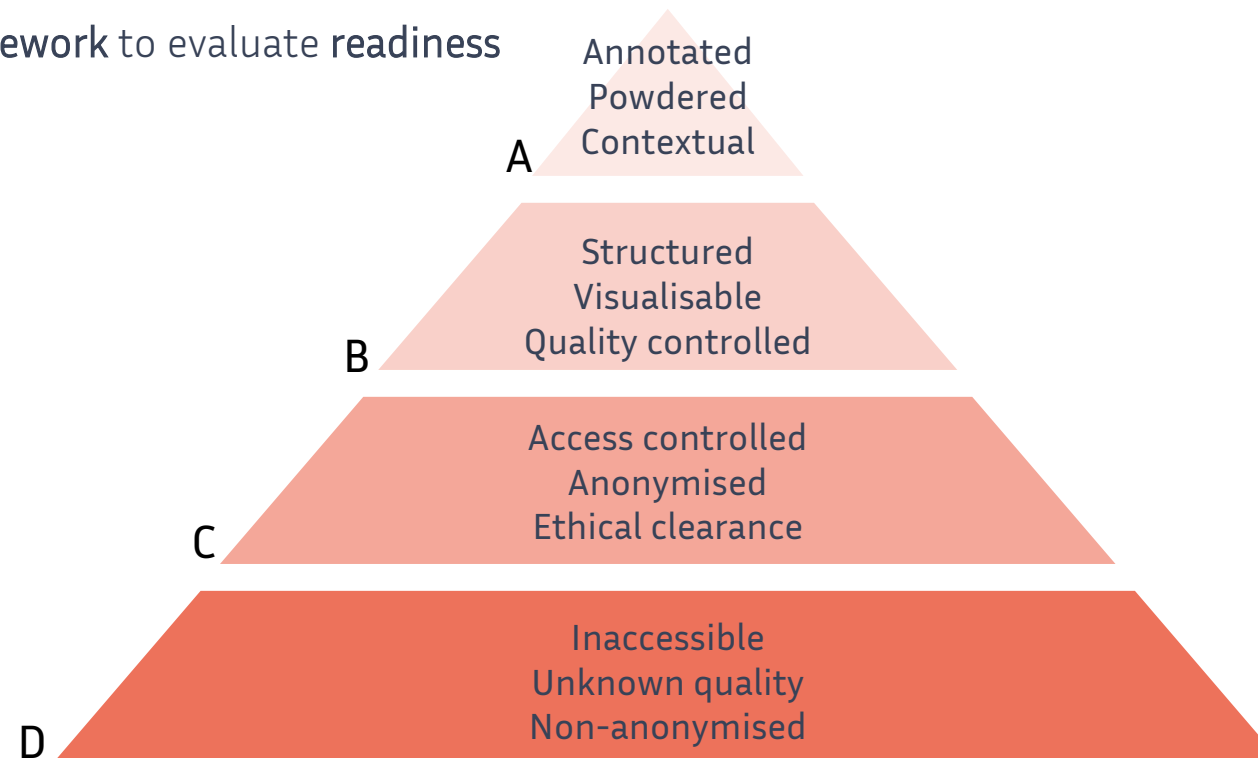
- Are data **ready** for a DL process?
- Consider using a **framework** to evaluate **readiness**



Lawrence, N. D. (2017). Data readiness levels. *arXiv preprint arXiv:1705.02245*.

# Data Readiness

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



Harvey, H., & Glocker, B. (2019). *A standardised approach for preparing imaging data for machine learning tasks in radiology*. Artificial intelligence in medical imaging: opportunities, applications and risks, 61-72.

# 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*

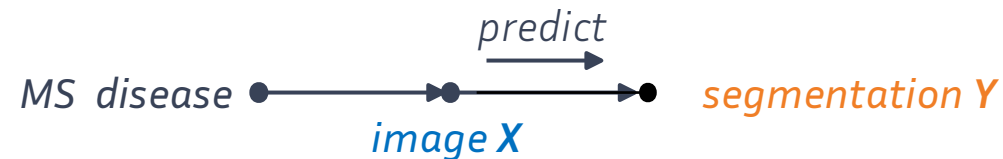
What is the relationship between image  $X$  and annotation  $Y$ ?

*cause*  $X$   $\longrightarrow$   $Y$  *effect*  
*causal*  
*predict effect from cause*

*Example:* MS Lesion segmentation

$X$  - structural brain MRI scan

$Y$  - manual segmentation masks



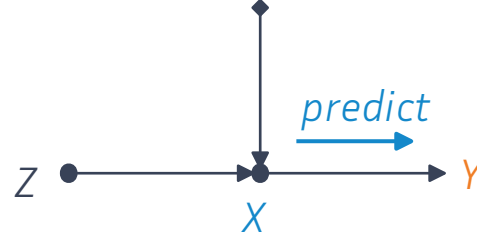
# Dataset Shift – *data mismatch*

❖ Training and test data distributions may **disagree** due to ...

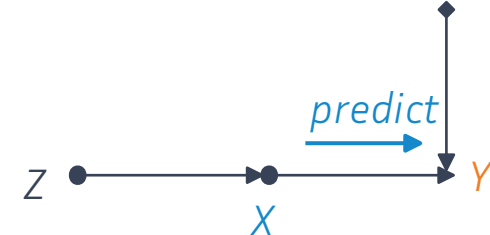
*Population shift*



*Acquisition shift*



*Annotation shift*



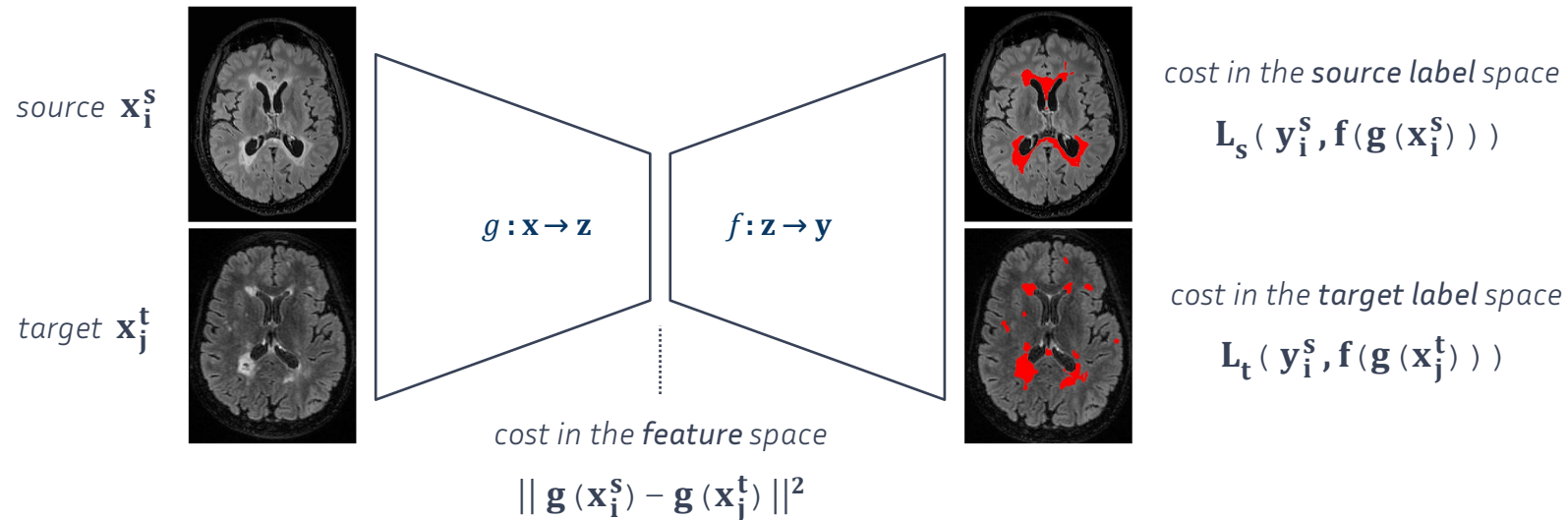
Z: unobserved true anatomy

X: image

Y: annotation

# Domain Adaptation – a case study

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

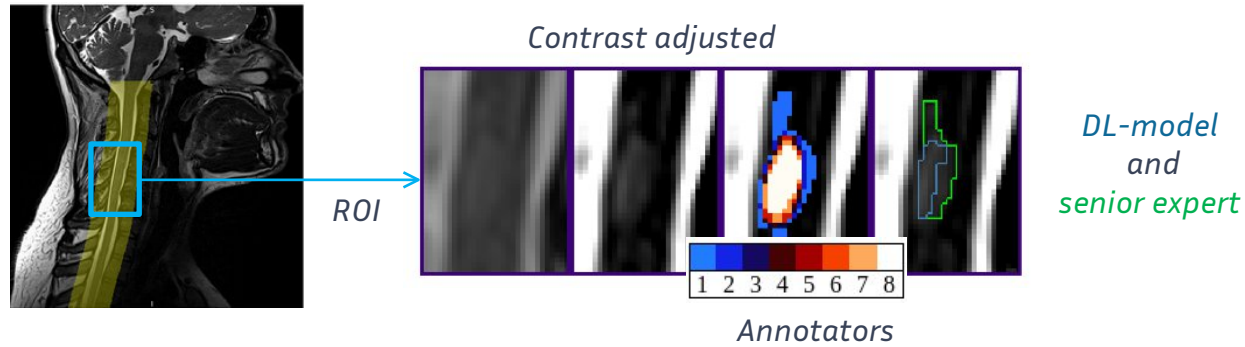


- Optimization problem:

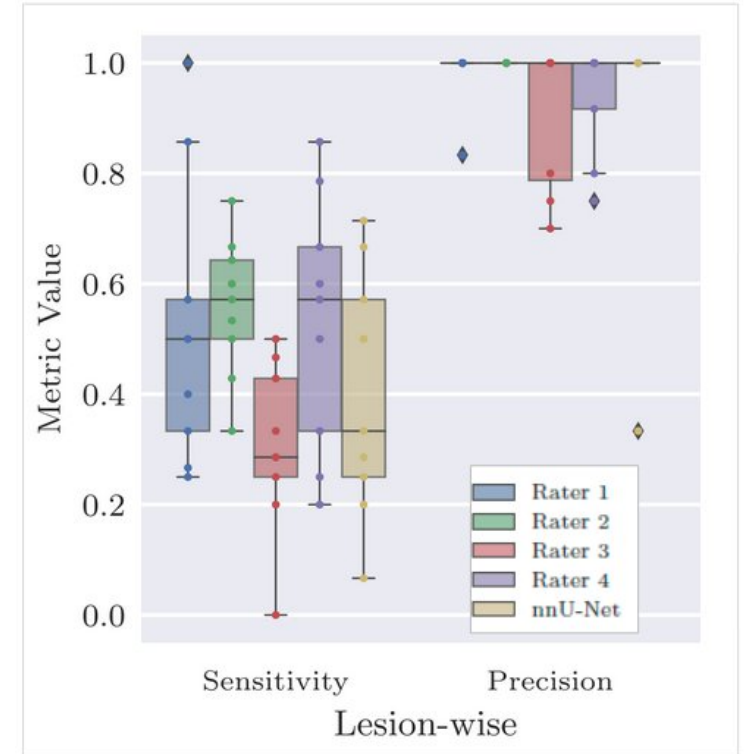
$$\min_{\gamma, f, g} \sum_i L_s(\mathbf{y}_i^s, f(\mathbf{g}(\mathbf{x}_i^s))) + \sum_{i,j} \gamma_{i,j} (\alpha \|\mathbf{g}(\mathbf{x}_i^s) - \mathbf{g}(\mathbf{x}_j^t)\|^2 + \beta L_t(\mathbf{y}_i^s, f(\mathbf{g}(\mathbf{x}_j^t))))$$

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