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Using Error Level Analysis to remove Underspecification

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This presentation comes with a technical report and a GitHub repository. It presents the work of the author on a data competition.

- *The competition: https://challengedata.ens.fr/participants/challenges/95/*
- *The technical report: http://dx.doi.org/10.13140/RG.2.2.25127.21925*
- *The GitHub repository: https://github.com/DentanJeremie/age-underspecification.git*

Content

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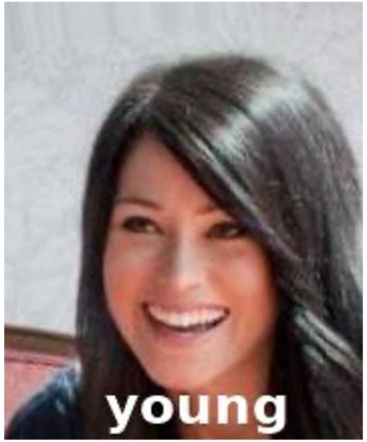
I- Introduction: The challenge

Huge distribution shift between the train and test set

The task: predict age from ambiguous data

Train

Train



AYTY

AYTO

AOTO

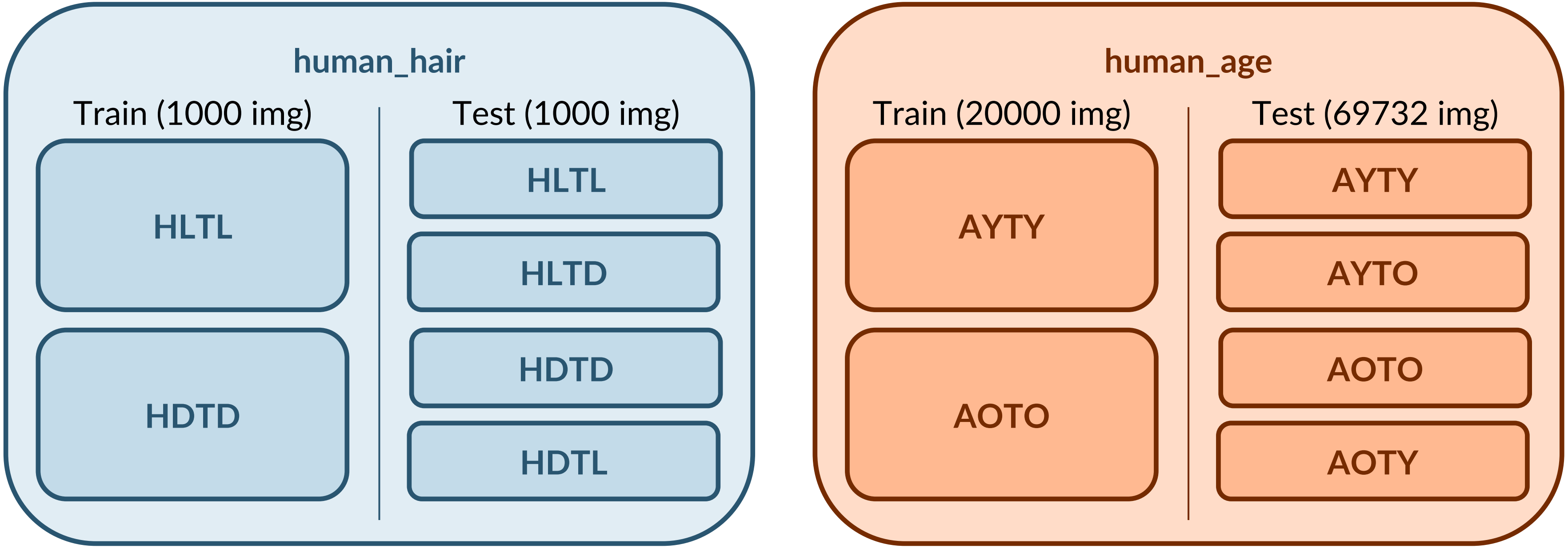
AOTY

Test

A=Age, T=text, Y=Young, O=Old

I- Introduction: The datasets

Two datasets: 2000 + 89732 JPEG-RGB images, size 178x218



HLTL, HDTD, HLTD, HDTL are que equivalent of AYTY, AOTO, AYTO, AOTY, replacing the Age by the Hair, and Old/Young by Light/Dark

I- Introduction: The rules

Some rules were there to make the challenge harder.

No manual annotation	→	• We need machine learning techniques
No other data	→	• We cannot scrap data to train an age classifier
No pretrained model, except the ones trained on ImageNet	→	• We cannot used pretrained age classifier • Difficult to use out-of-the box OCR, often pretrained

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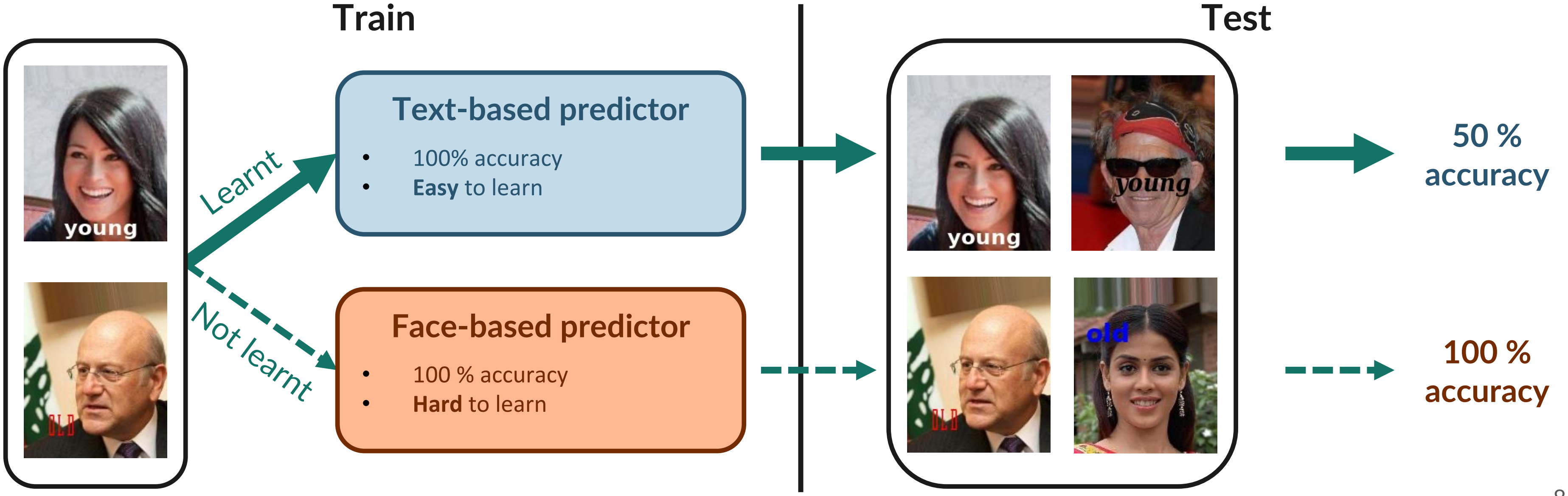
Ref: [2, 4, 5, 8, 19]

Synonym: ambiguity of the data

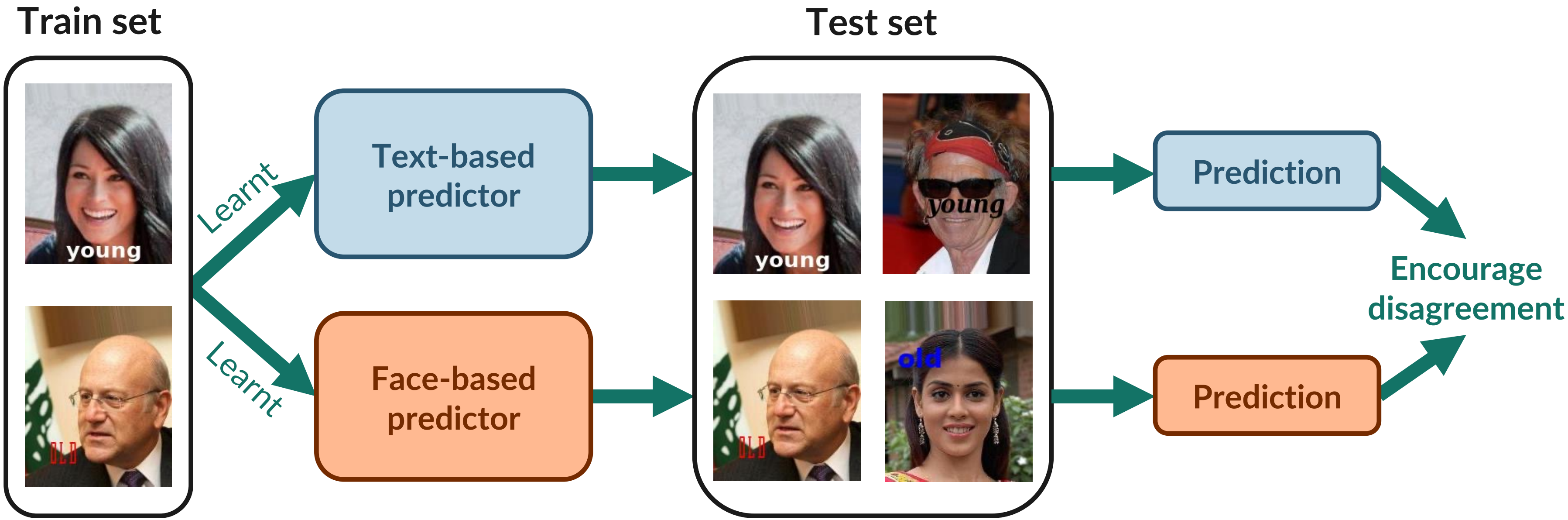
II- Underspecification: What is it?

During the training, the simplest predictor is learnt, however it is not always the one that have the best performance on the test set



II- Underspecification: One solution: DivDis

DivDis is an architecture that uses both the train and test set during the training, encouraging disagreement between the two predictors it learns.



II- Underspecification: Discussion on DivDis

DivDis is hard to apply in real life, because we need an expert to understand where the ambiguity comes from and how to characterize it.

Challenges with the architecture:

- Need to be sure there is a distribution shift between two datasets
- Need to choose which predictor to deploy on real data

→ Requires an expert to **understand** the ambiguity and **characterize it**

Approach 1

- Use the DivDis architecture
- Characterize the ambiguity *a posteriori*
- Choose one of the two predictor

Approach 2

- Characterize the ambiguity *a priori*
- Remove it
- Train a single predictor

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Ref: [12] (DivDis) ; [6] (ImageNet) ; [9] (ResNet)

III- First approach: DivDis with a pretrained head

To adapt the DivDis architecture to our problem, we wanted to pretrain one of the two heads to read the text on the images.

human_hair + human_age

4-label classification

- ResNet50 architecture
- Frozen backbone
- 20% images for validation
- Data replication to have balanced dataset, with: (1) Gaussian noise (2) Rolling color channels (3) Reverting lightness

Merging the two datasets, the text was supposed to be no longer correlated with the image

This did not work well on the unlabeled image, so we abandoned this approach

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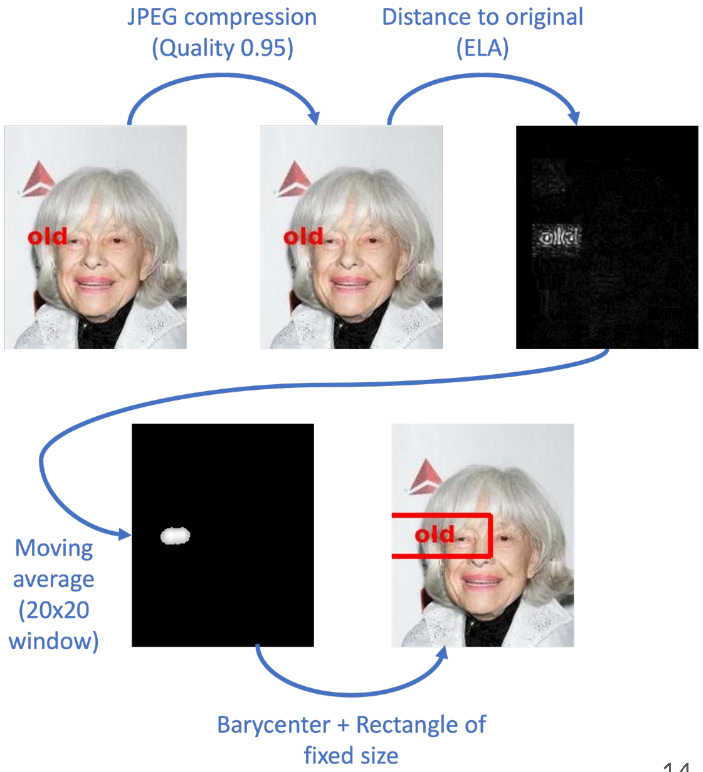
III- Second approach: Removing the text

We adapted a forensic technique called Error Level Analysis (ELA) to remove the text from the image, with perfectly worked in 91% of the cases.

Some examples of detections:

- Image 1 and 2: correct detection, as in 91% of cases. The detection was difficult: presence of another text in the image or low contrast.
- Image 3 and 4: partially incorrect detection or fully incorrect detection, as respectively in 4% and 5% of cases.

The accuracy rates are manually evaluated using 200 random images.

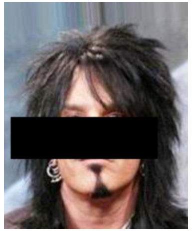


Ref: [10, 20] (Age classification pipelines) ; [9, 22] (ResNet50, VGG19) ; [11] (Adam)

III- Second approach: Training the classifier

After having removed the text, we trained a binary classifier, leading to a final accuracy of 73% (vs. 64% for the DivDis baseline).

data



Binary classification

- ResNet50 and VGG19 architectures
- Adam Optimizer
- Binary cross-entropy
- 20% images for validation
- Gradual unfreezing across 13 epochs
- Early stopping and memorization of the best validation accuracy
- Data replication with gaussian noise

Some metrics:

- 73% accuracy on test set (vs. 64% for the DivDis baseline).
- CPU for text removal: Intel Xeon W-1290P 3.70GHz, 20 virtual cores: 455sec, i.e. about 10sec/img/proc
- GPU for age prediction: NVIDIA GeForce RTX 3090 24Go: 760sec/epoch, i.e. about 2h45 total training time per model

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IV- Conclusion

- We have tried **two different approaches** to fight the ambiguity of the data at hand
- Removing the ambiguity ***a priori*** does not require more domain knowledge than doing it ***a posteriori*** as with DivDis
- We showed that simple **forensic techniques** can prove to be very efficient to detect some patterns to remove the ambiguity
- We obtained a satisfying **final accuracy of 73%** (vs. 64% for the DivDis baseline)

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