Few-Shot Adaptive Gaze Estimation

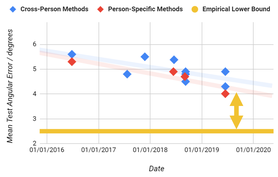
Seonwook Park[1,2]*, Shalini De Mello[1]*, Pavlo Molchanov[1], Umar Iqbal[1], Otmar Hilliges[2], Jan Kautz[1]

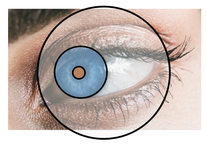
** The first two authors contributed equally.*

NVIDIA [1] · Advanced Interactive Technologies [2] · ETH zürich

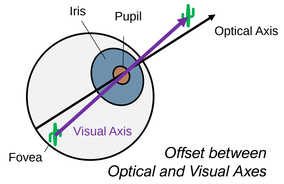
Motivation

- Large performance gap between empirical lower bound and state-of-the-art cross-person gaze estimation methods.
- We need to consider person-specific factors (below) while requiring as few calibration samples as possible.





Eyeball position and size



Offset between Optical and Visual Axes

Overview

REPRESENTATION LEARNING

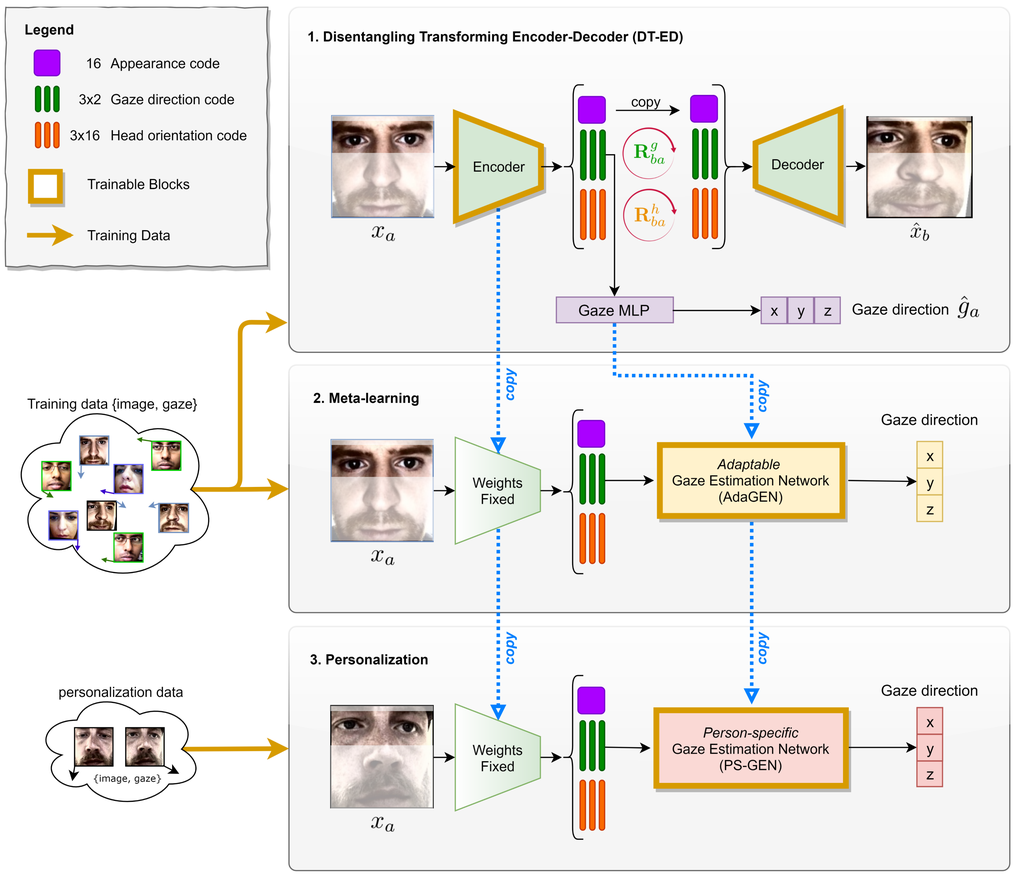
- Via a novel disentangling transforming encoder-decoder (DT-ED) architecture.
- Using novel loss terms for a) embedding consistency within a subject, (b) gaze estimation, and (c) image reconstruction with transformed gaze/head pose.
- The learned **gaze direction** and **head orientation** representations are:
  - Rotationally equivariant to eyeball / head rotation
  - Disentangled from head / eyeball rotations respectively
  - Compact & task-specific

META LEARNING

- We cast few-shot personalization as a meta-learning problem, where each person is a task in the meta-learning sense.
- We use MAML [Finn et al., ICML 2017] to yield a meta-learner (Adaptable Gaze Estimation Network - AdaGEN) via direct optimization of the within-person generalization error.
- We better leverage the subject-diversity of the large GazeCapture training set (993 subjects used in training).

Latent space walk by rotating **gaze direction** and **head orientation** embeddings

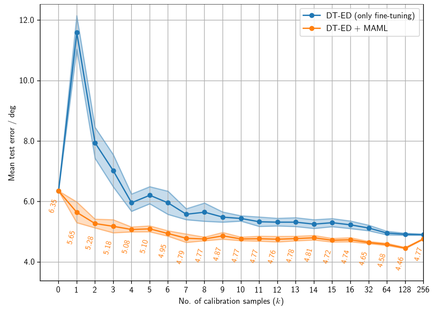
Our FAZE Framework



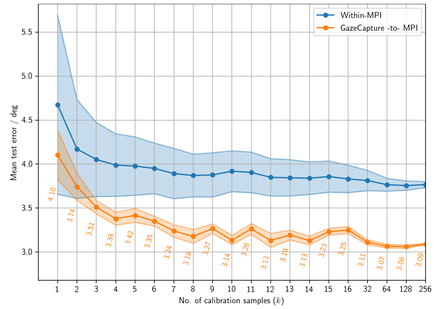
Results

(evaluated on MPIIFaceGaze [Zhang et al., CVPRW 2017], see paper for results on GazeCapture [Krafka et al. CVPR 2016])

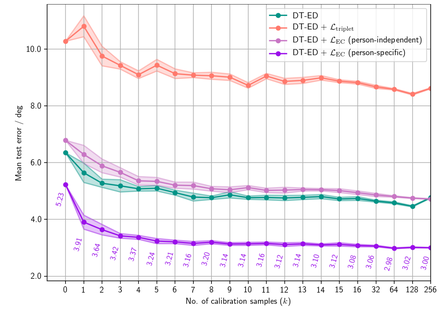
MAML is better than naïve few-shot fine-tuning and does not suffer from over-fitting



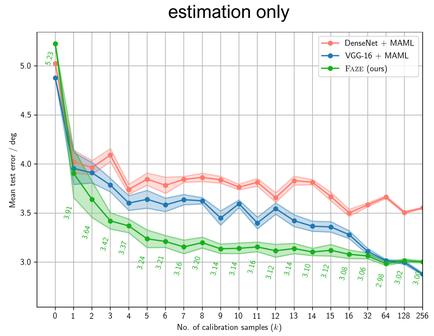
MAML and DT-ED benefit with more training subjects (993 in GazeCapture vs 15 in MPIIGaze)



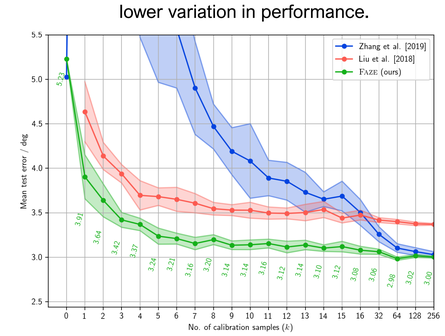
Within-person consistency is important. Maximizing between-person differences is not beneficial.



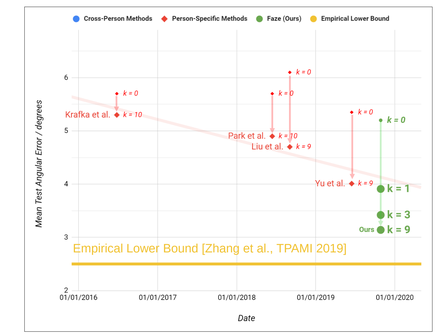
We do better than MAML applied to CNN features where the CNNs are trained directly for gaze estimation only



We out-perform state-of-the-art person-specific methods consistently and over all *k* values with lower variation in performance.



Overall, we show greater improvement compared to all prior art, and out-perform [Yu et al., CVPR 2019] even with 1 calibration sample.



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Source Code

github.com/NVLabs/few_shot_gaze

Conclusions

- Our DT-ED learns a compact, rotation-equivariant representation of gaze.
- Learning a Few-Shot learner yields better performance than naive fine-tuning or hand-designed personalization functions.
- FAZE can apply to other personalization problems such as gesture recognition and affective state estimation.