



Cutting-Edge Techniques in Gaze Target Detection Through Computer Vision

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Why Gaze?



- A fundamental form of **non-verbal** communication
 - Reflects a person's **attention**, **intention**, and **emotional state**.
 - A “shy gaze” involves averted eye contact, often signaling **discomfort** or **self-consciousness**.
 - Crucial for understanding how **gestures** are interpreted and understood in **human interactions***.

*Beyan et al., Co-Located Human-Human Interaction Analysis using Nonverbal Cues: A Survey, ACM Computing Surveys, 2023

(Some) Applications of Automated Gaze Analysis



Mental Health
Monitoring: Autism



Driver Monitoring Systems:
Distraction Detection



Education and Learning:
Attention Analysis



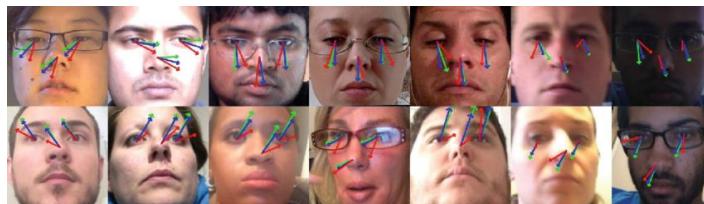
Human-Computer Interaction
Img. credit: geoGAZElab@ETH



Marketing and
Consumer Research

Gaze Analysis w/ Computer Vision

- Two tasks:
 - 1) **Gaze estimation:** Determines the direction of a person's gaze in 3D space, estimating horizontal and vertical angles, and the depth of focus.



Che et al., CVPR 2022

- 2) **Gaze target detection (gaze following):** Identifies the specific point or area a person is looking at in 2D/3D.



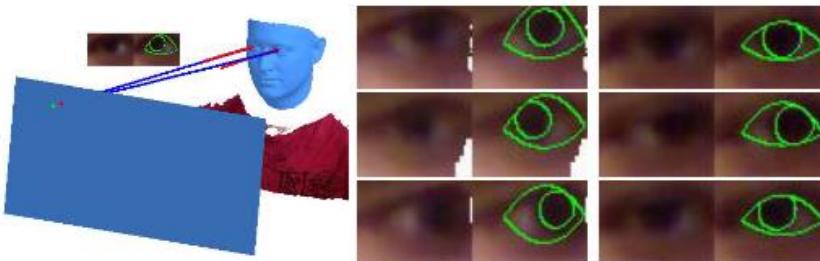
Tonini et al., ICCV 2023

Benefits & Differences

Gaze estimation

- Can be very accurate
- Applies to dedicated set-ups
 - May use simple geometric reasoning

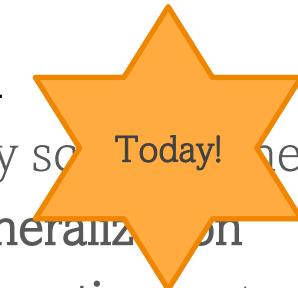
With respect to



Mora et al., CVPR 2014

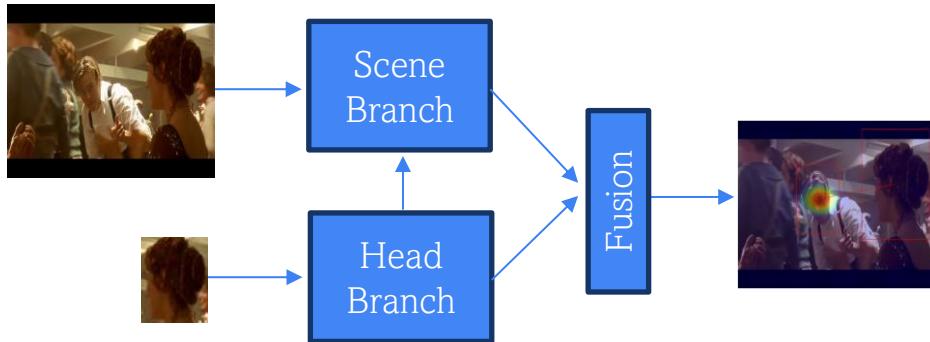
Gaze target detection

- Works on arbitrary images other than frontal images: **generalization**
- Results in **spatial location**, not only a direction
- Can determine the category of the target gaze: **semantic info**



Tonini et al., ICCV 2023

GTD Standard Approach



Recasens et al., NeurIPS 2015

Chong et al., ECCV 2018, CVPR 2020

Lian et al., ACCV 2018

Fang et al., CVPR 2021

Bao et al., CVPR 2022

Tonini et al., ICMI 2022

Qiaomu et al., WACV 2023.....

Inputs: Scene image + head crop + head location

Head Branch: processes the person's head to infer gaze direction

Scene Branch: processes the scene to capture saliency and the context.

Uses the head location information.

The attention mechanism by considering the head features.

Fusion: Combines information to predict the gaze heatmap.

GTD Standard Approach + What Else?

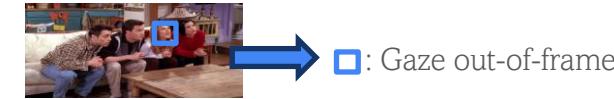
- Adjusting for **video processing**

(Chong et al., CVPR 2020)



- Adjusting to predict **out-of-frame** gaze detection

(Chong et al., CVPR2020)



- Injection **depth** information; improves the performance

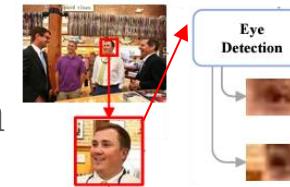
(Fang et al., CVPR 2021; Jin et al., 2022; Miao et al., WACV 2023; Tonini et al., ICMI 2022)



- Injecting **eye location**; improves

the performance by improving direction estimation

(Fang et al., CVPR 2021)



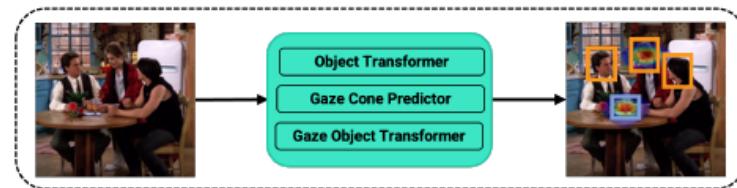
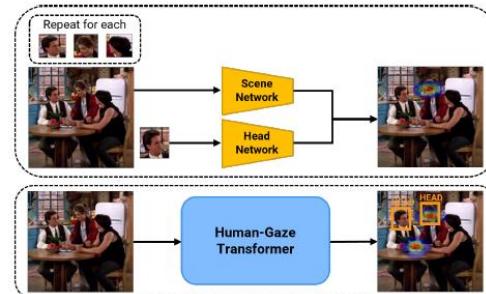
- Injecting **body pose**; is a good alternative (Fang et al., CVPR 2021;

Gupta et al., CVPRw 2022)



GTD Standard Approach: Disadvantages

- Single gaze target detection at a time, inefficient for multiple people
 - Tu et al., CVPR 2022; a transformer-based approach
- Not directly applicable to human-human or human-robot interaction analysis
 - Tonini et al., ICCV 2023; transformer-based approach, which also performs gazed-object classification and localization.
- Performs only in 2D & not privacy-preserving
 - Toaiari et al., ECCVw 2024; a pipeline preserving privacy (no head crops and blurred scene, pose-based) to predict the gaze location in both 2D and 3D.



This afternoon
@ T-CAP
workshop!



GTD Standard Approach & Extensions: Key Takeaways

- Multimodality matters!
 - Especially depth information, but also body pose and/or eye location
- Transformer-based methods are SOTA
- Most recent trend: exploring the zero-shot capabilities of **Vision-Language Models** (Gupta et al., CVPRw 2024)

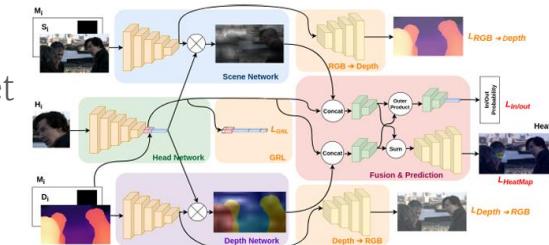
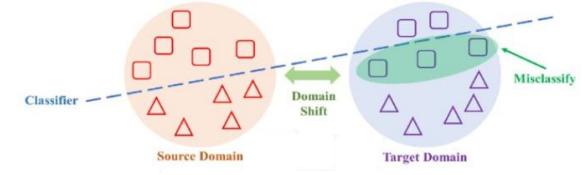
GTD Challenges

- GTD models trained on one dataset often struggle to **generalize** to new datasets in **zero-shot** settings.
 - Performance drop up to 30% in AUC (Tonini et al., ICMI 2022).
- **Unsupervised domain adaptation** can be a solution to some extent, but the gap with fine-tuning is still noticeable (Tonini et al., ICMI 2022). → In practice, we perhaps need labelled data to be used for training
- Labelling gaze data: highly tedious and time-consuming

“Labor times ranging from ten seconds to one minute for every second of gaze data”

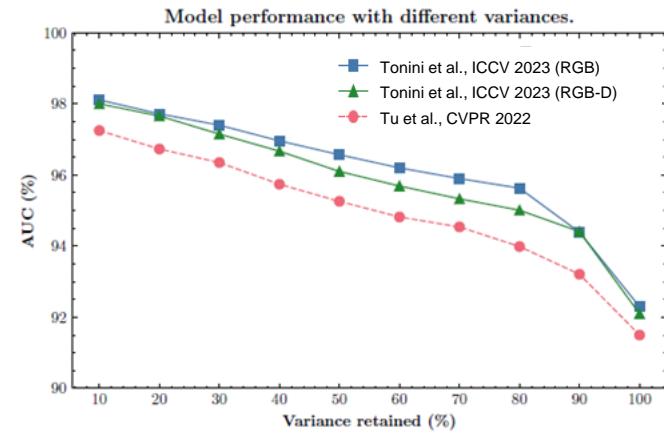
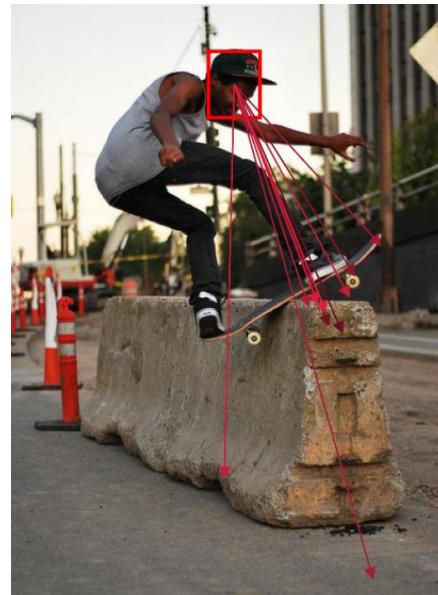
-- Agtzidis, et al., 2020; Gutiérrez et al., 2018

“An experienced human annotator may require two to more than ten times the duration of a video to accurately label the gaze” -- Erel et al., 2023



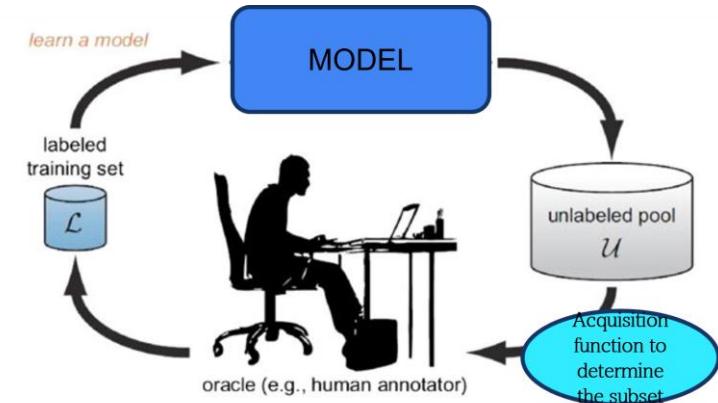
GTD Challenges

- Low annotation reliability due to subjectivity, causing inconsistencies in labelling the same image.



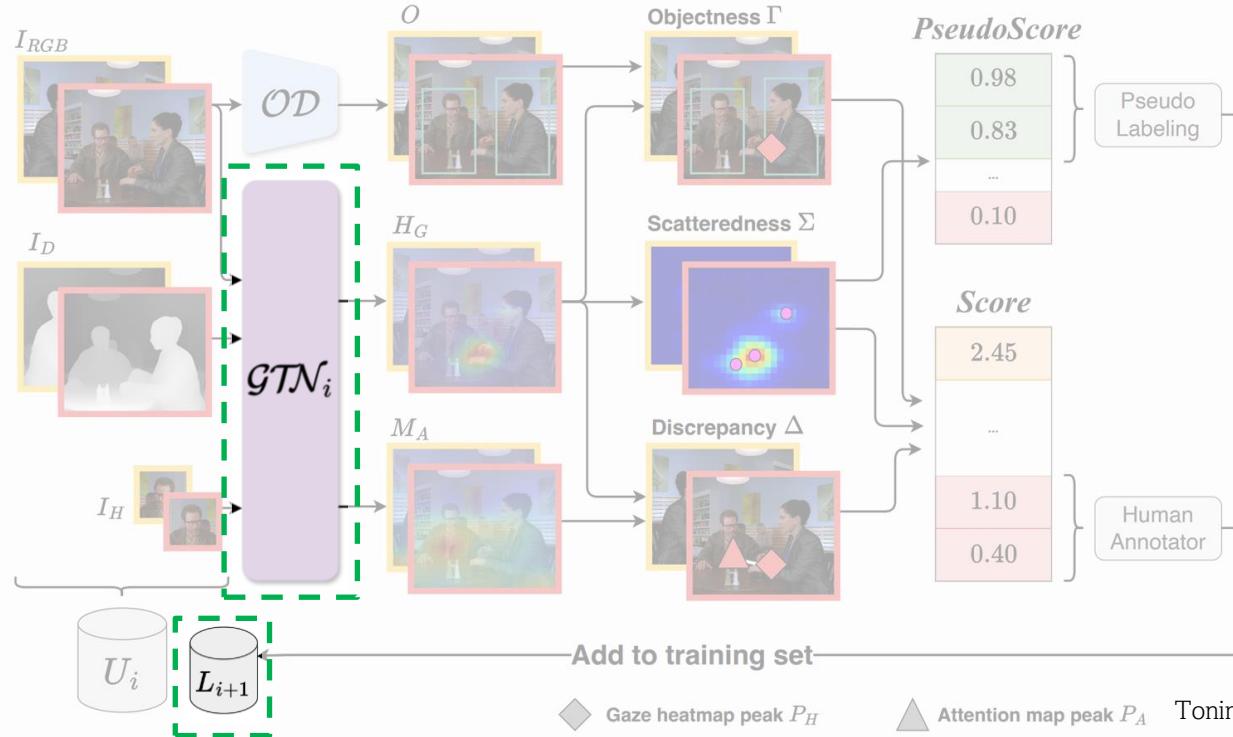
Research Question & Approach

- Can we reduce reliance on labelled training data for gaze detection without sacrificing performance?
- Given a gaze target detection network,
 - Aim: to **effectively select a subset** of the data that optimizes model training.
- Our Solution: based on **Active Learning**
 - Among a large pool of unlabelled data, choose those that are the most informative to be labelled.
 - Iterative approach.
 - Most informative is defined by an acquisition function.



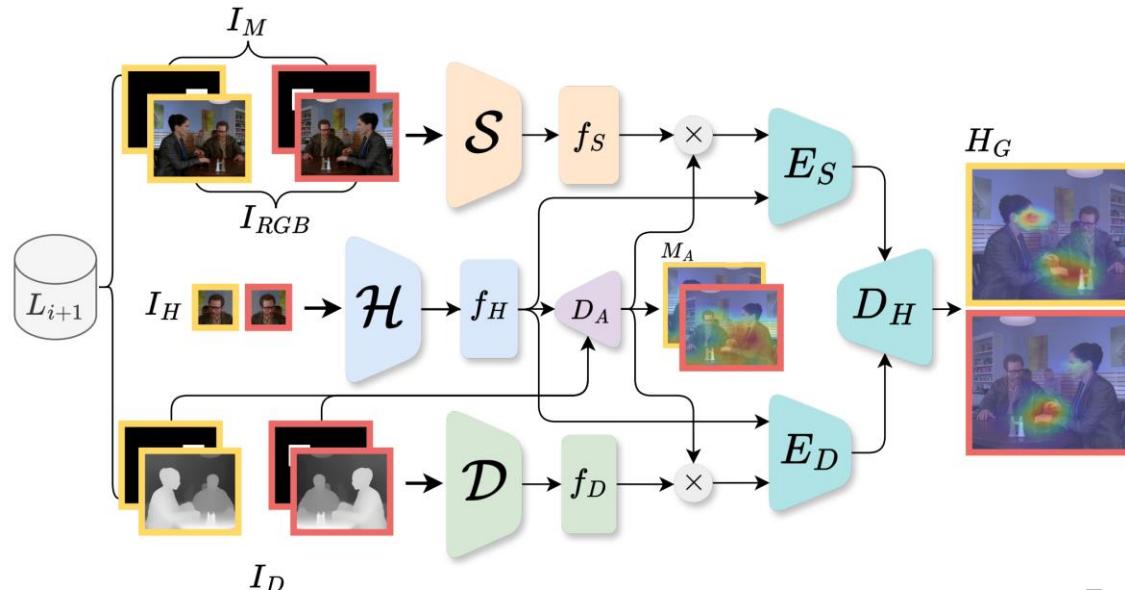
Our pipeline – Pre-training the gaze model on random data

Train a gaze target detection model on a **small random subset** of labelled samples L and obtain predictions for unlabelled samples U .



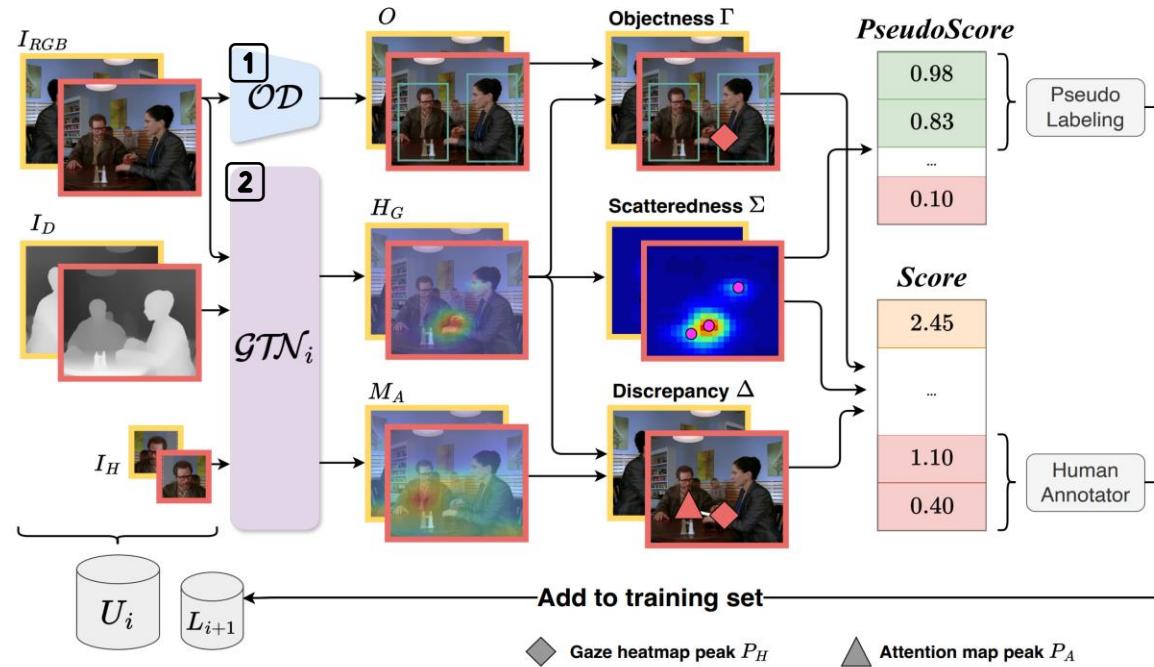
Training the Gaze Target Detection model

Follows standard recipe of GTD training. To alleviate prediction inconsistency, we perform **strong augmentations** and perform self-supervised learning among augmentations and the **original image**.



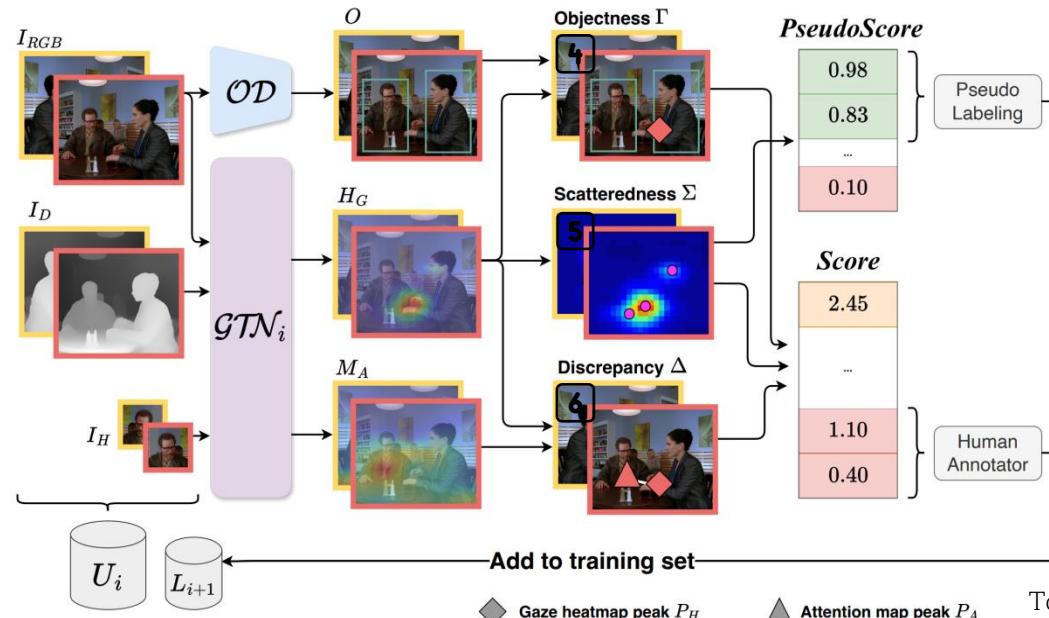
Our pipeline - Active Learning for Gaze Target Detection

- 1 Detect objects in the image.
- 2 Extract a gaze heatmap and attention map of the scene.



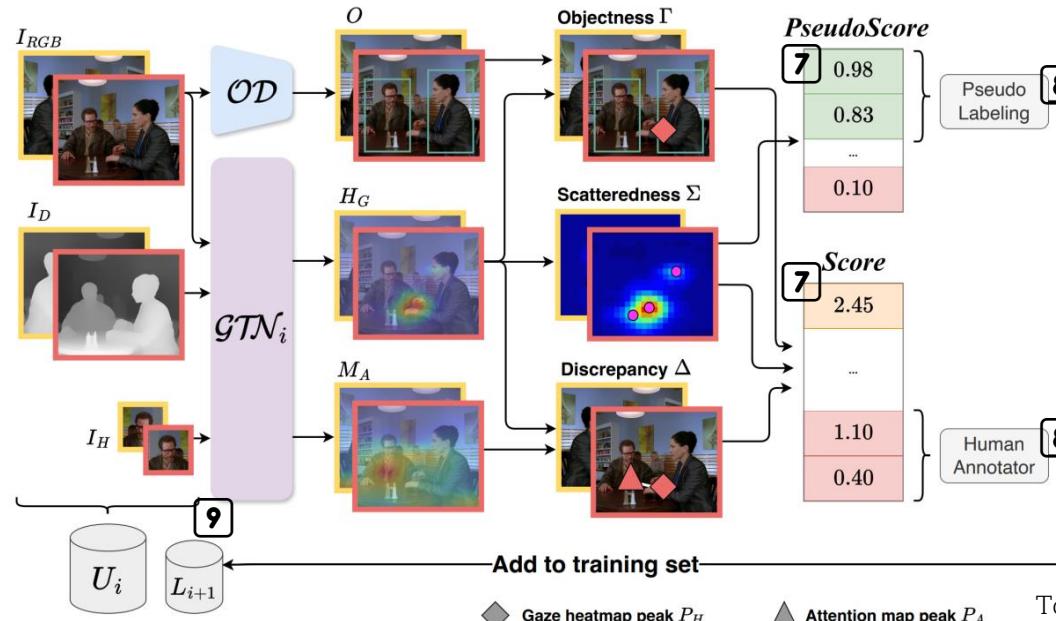
Our pipeline – AL Acquisition Function

- 4 Objectness score: penalize predictions centred on foreground objects.
- 5 Scatteredness score: penalize sparse activation of the network output corresponding to prediction uncertainty
- 6 Discrepancy score: penalize differences in network predictions among attention map (M_A) and gaze heatmap (H_G).



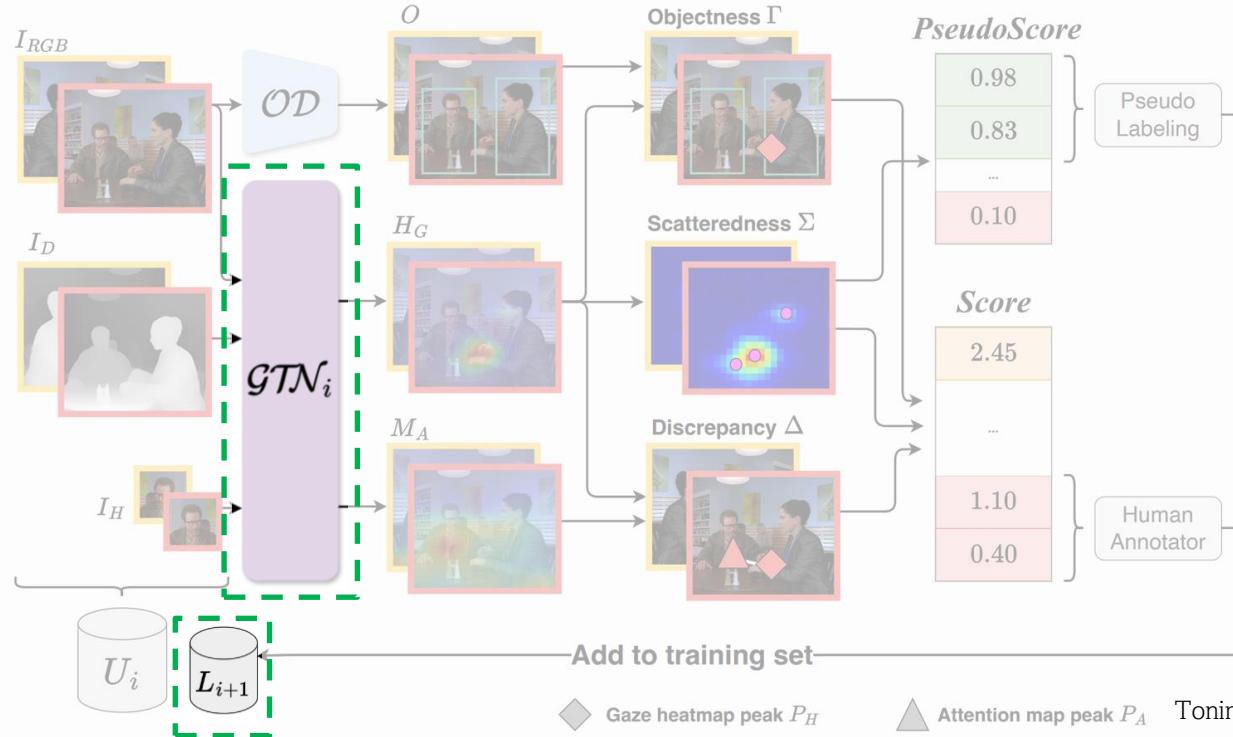
Our pipeline - Active Learning for Gaze Target Detection

- 7 The score and pseudo score are calculated.
- 8 Oracle annotates the most informative samples, while those with high pseudo scores are pseudo labelled.
- 9 The newly labelled data are added to the training pool and used for the next AL cycle.

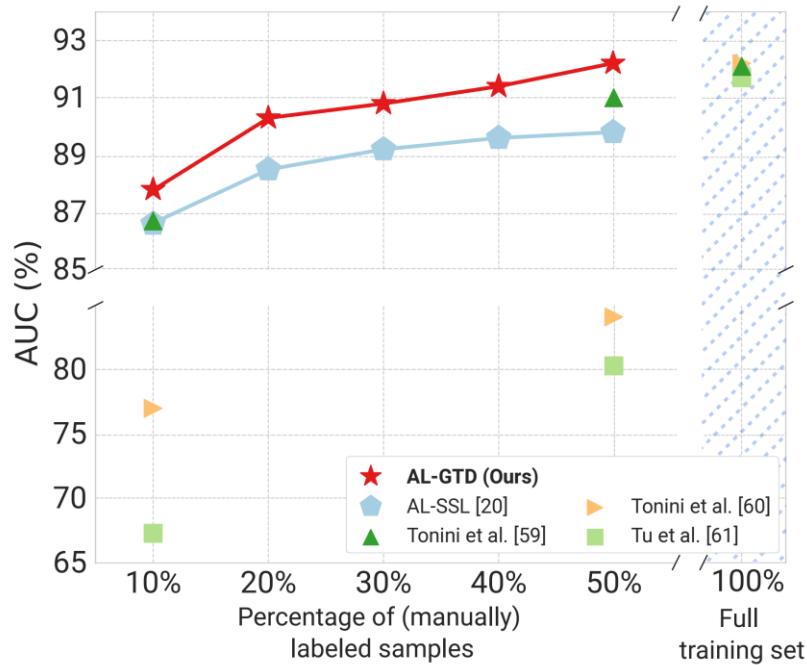


Our pipeline – Training the gaze model on new labeled data

(Re-)Train a gaze target detection method on a small random subset + newly labelled data and obtain predictions for unlabelled samples U .



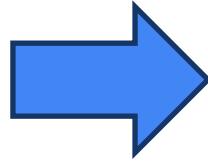
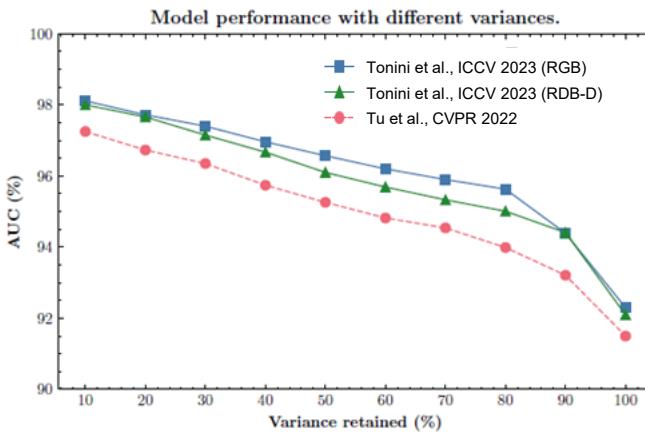
Results



Our proposal achieves SOTA AUC performance with just **40-50%** of the usual training data and is competitive w.r.t. the current best-performing models even when trained on a mere 10-20% of the full training dataset.

Results

- Is the model suitable for complex scenes?
- Complex: the gaze points whose annotation has low reliability (high variance)

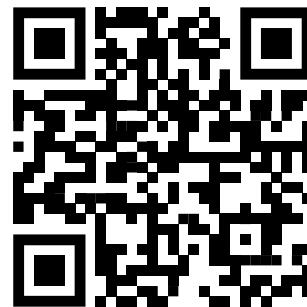


	Performance difference among complex and simple scenes			
Variance	5%	10%	50%	100%
10%	5.79%	5.92%	6.32%	5.79%
50%	8.74%	8.47%	9.44%	9.87%

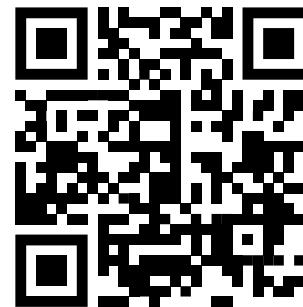
No significant performance drop (AUC) on complex scenes with 5%, 10%, 50%, or 100% training data.

For further analysis

- Comparison with other Active Learning methods
- Comparison with several SOTA gaze target detector
- Ablation study
-



Code



Paper

The GAZE Team!



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THANK YOU!



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Slides with references can be found on my website!

I am hiring!

If you're interested in joining my team, feel free to connect ☺



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