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# Probabilistic Estimation of the Gaze Region of the Driver using Dense Classification

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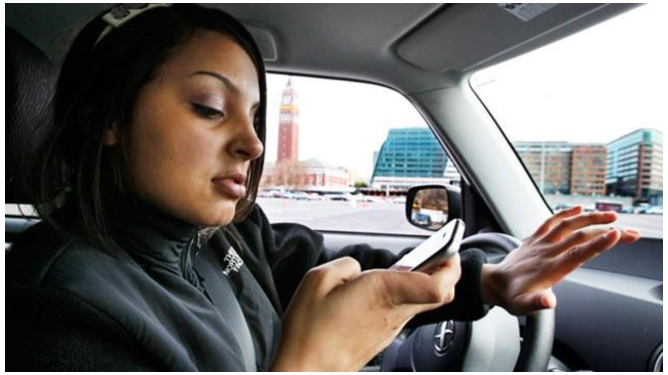
# Visual Attention

- **Drivers' Visual Attention**
  - Primary driving related task
    - Mirror checking actions [Li and Busso, 2016]
    - Lane change
    - Turns and cross sections
  - Secondary tasks
    - Mobile phones and in-vehicle entertainment unit
    - Co-passengers in the car
    - Billboards and other distractions from the environment
- **Gaze detection a challenging problem in car environment**
- **Often approximated by head pose**



Nanxiang Li and Carlos Busso, "Detecting drivers' mirror-checking actions and its application to maneuver and secondary task recognition," IEEE Transactions on Intelligent Transportation Systems 17 (4), 980-992.

# Related Work

- **Studying eyes-off-the-road [Liang and Lee, 2010]**
- **Predicting discrete gaze zones from the head pose [Vora et al., 2017]**
- **Relating driving actions to head pose**
  - Mirror checking actions [Li and Busso, 2016]
  - Lane change [ Doshi and Trivedi, 2012]


[Vora et al., 2017]


S. Vora, A. Rangesh, and M. M. Trivedi, "On generalizing driver gaze zone estimation using convolutional neural networks," in Intelligent Vehicles Symposium (IV), 2017 IEEE . Los Angeles, CA, USA: IEEE, June 2017, pp. 849–854.

Y. Liang and J. Lee, "Combining cognitive and visual distraction: Less than the sum of its parts," Accident Analysis & Prevention , vol. 42, no. 3, pp. 881–890, May 2010.

Nanxiang Li and Carlos Busso, "Detecting drivers' mirror-checking actions and its application to maneuver and secondary task recognition," IEEE Transactions on Intelligent Transportation Systems 17 (4), 980-992.

A. Doshi and M. Trivedi. Head and eye gaze dynamics during visual attention shifts in complex environments. Journal of vision, 2(12):1–16, February 2012.

# Motivations

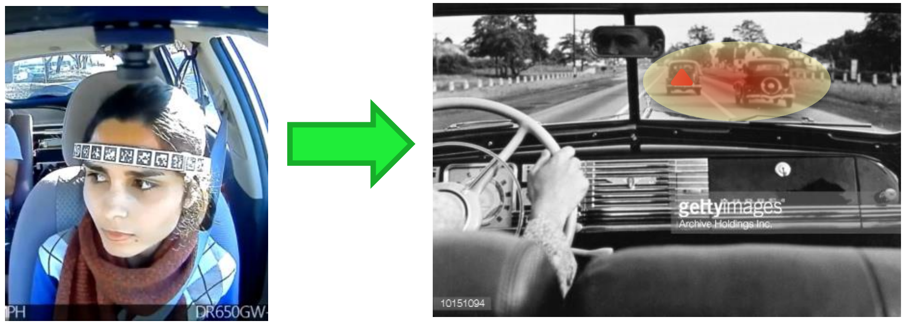
- **Head pose – Gaze relation not deterministic [Jha and Busso, 2016]**
  - The variability depends on the location of gaze
- **Probabilistic prediction of driver's visual attention from head pose**
  - Region of gaze provides important information about visual attention


Left mirror


Right mirror


Rear mirror

Visual Attention Estimation




S. Jha and C. Busso. Analyzing the relationship between head pose and gaze to model driver visual attention. In *International Conference on Intelligent Transportation Systems (ITSC 2016)*, pages 2157–2162, Rio de Janeiro, Brazil, November 2016.

# Previous Work

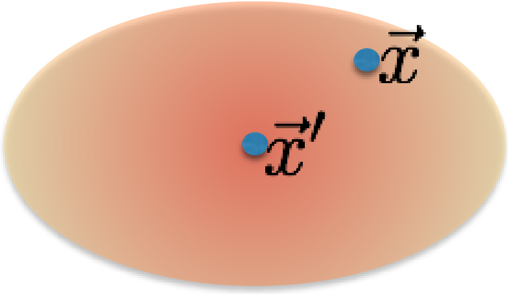


- **Predicting probability based gaze region based on the head pose on the head pose of the driver**
  - Example model using GPR [Jha_2017]

$$Y = \boxed{h(\vec{x})^T\beta} + \boxed{f(\vec{x})}$$

Deterministic component

Probabilistic component



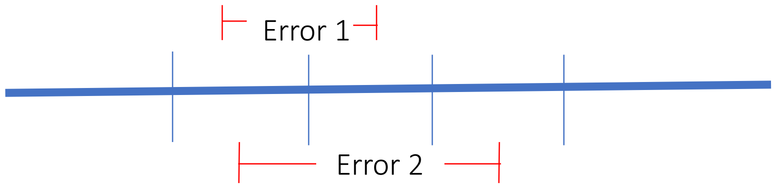

$$f(\vec{x}) \sim GP(0, K(\vec{x}, \vec{x}'))$$


- **Aim to design a more flexible model**
  - Non-parametric estimation of probability
  - Adaptable model with more control over the parameters

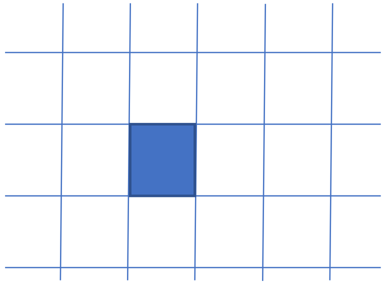
S. Jha and C. Busso, “Probabilistic estimation of the driver’s gaze from head orientation and position,” in IEEE International Conference on Intelligent Transportation (ITSC) , Yokohama, Japan, October 2017, pp. 1630–1635.

# Regression as Classification

- **Non-parametric probability estimation using softmax**
  - Softmax learns a probability distribution giving confidence value for each label
  - Better way of learning probability than GPR [VandenOord_2016]
- **Solving regression as a classification problem**
  - Class labels need to be ordered (error 1 < error 2)

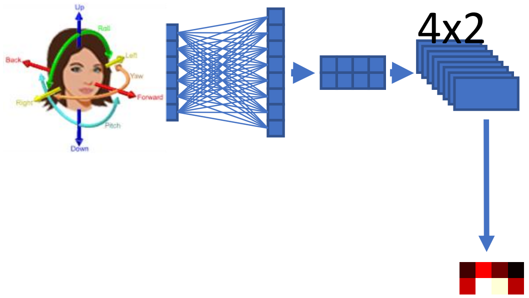



- **Implicit multitask learning with multidimensional features**
  - Classification in the grid of 2 variables
  - Problem becomes dense with $N^2$ classes for high resolution



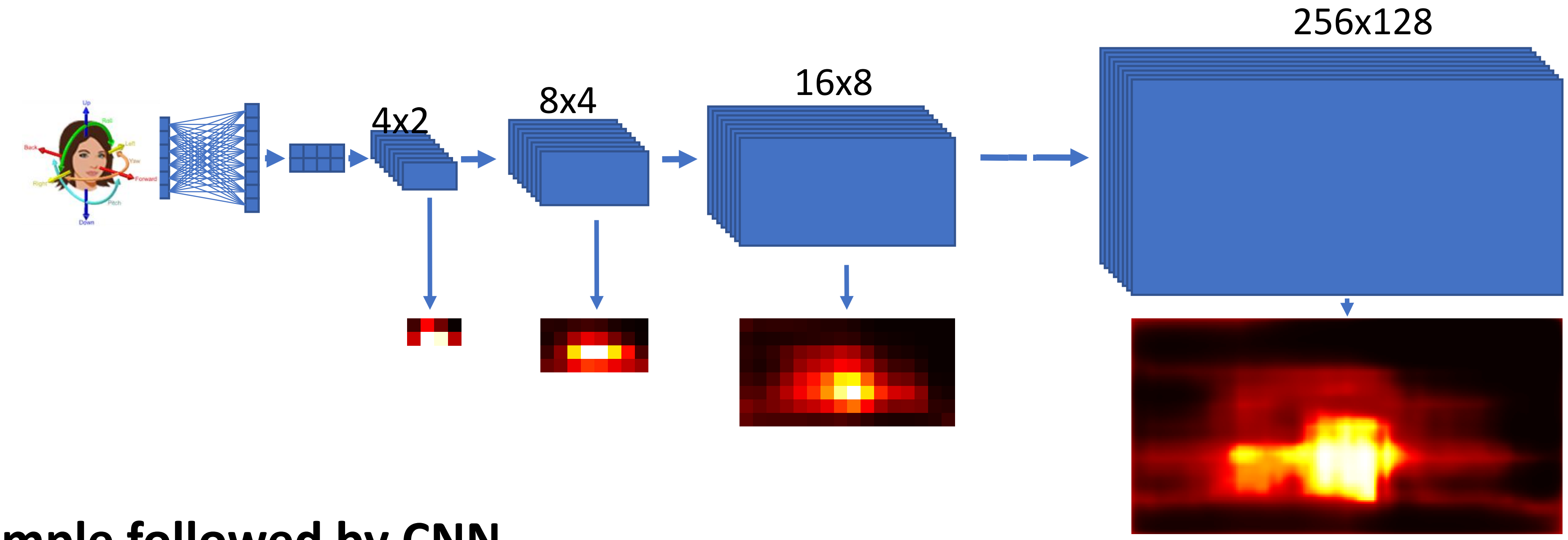
A. van den Oord, S. Dieleman, H. Zen, K. Simonyan, O. Vinyals, A. Graves, N. Kalchbrenner, A. Senior, and K. Kavukcuoglu, "Pixel recurrent neural networks," in Proceedings of the 33rd International Conference on International Conference on Machine Learning-Volume 48 . JMLR. org, 2016, pp. 1747–1756

# Model Architecture



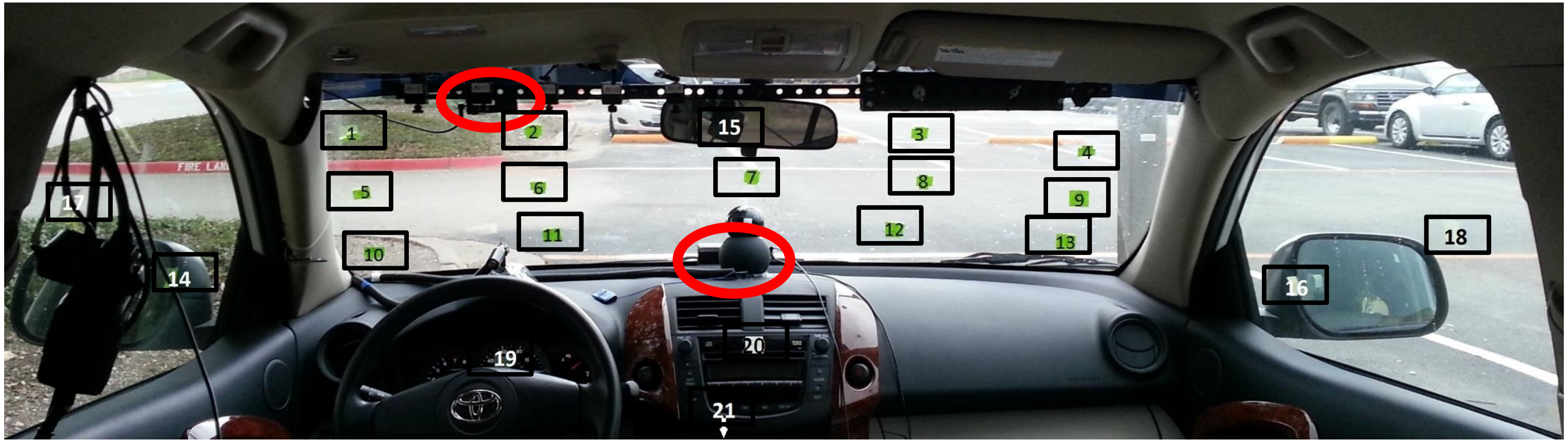

- **Input 6 degrees of head pose**
  - Head position (x,y,z)
  - Orientation (α,β,γ)
- **Fully connected layer followed by CNN**
  - Learn gaze representation in 4 x 2 discretized level

# Model Architecture



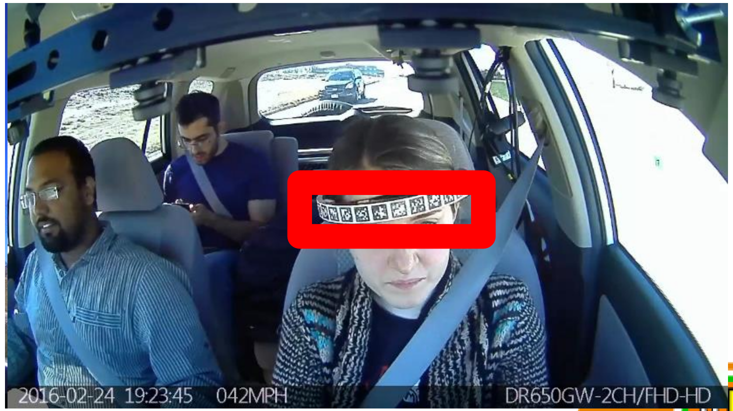

- **Upsample followed by CNN**
  - Learn the gaze representation at 8x4 discretization
- **Repeat to get incrementally higher resolution**
  - Train at each resolution
- **Softmax activation at the output layers to obtain probability maps that sum to 1**

# Data for the study



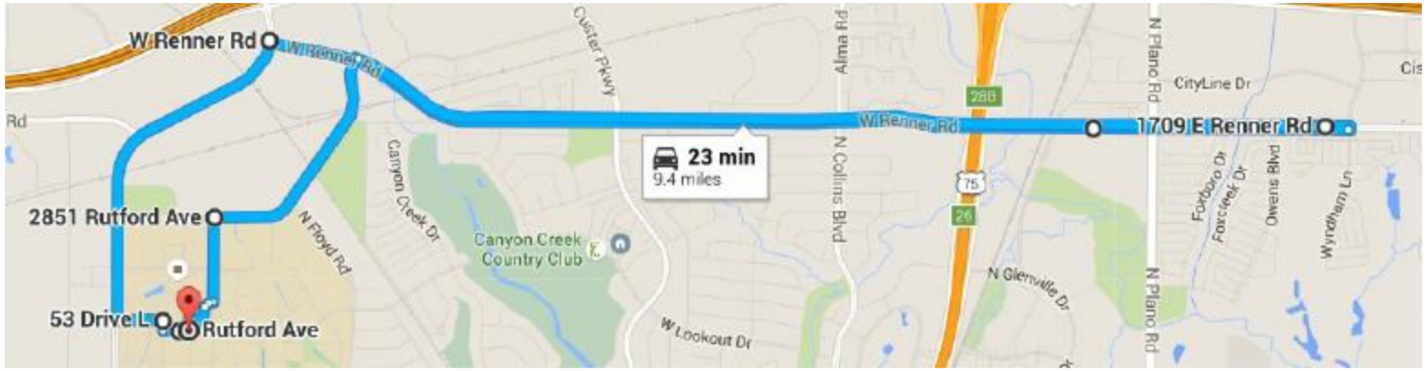

- Camera-1 → Face
- Camera-2 → Road
- Markers on the windshield
- Use Apriltags for tracking head movement

- **Ask subjects to look at each point multiple times at random**



# Ground truth gaze data during Naturalistic Driving

- Collected when the subject is driving the car
- Subject asked to look at points
- Data collected in a straight road with minimum maneuvering task
- Data collected with 16 subjects (10 males 6 females)



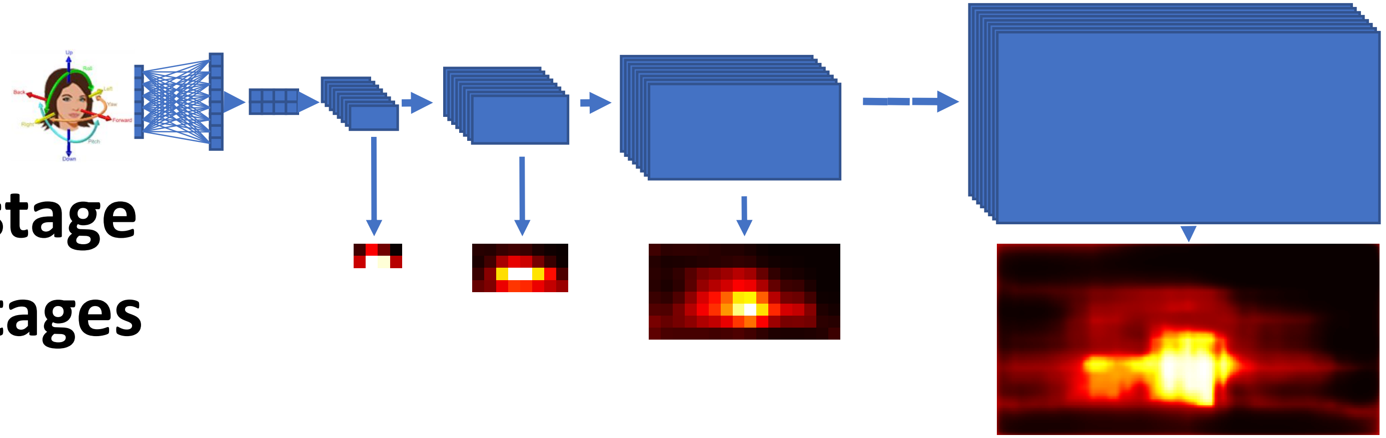

# AprilTags for Head Pose Estimation

- **Head pose estimation challenging in driving environment**
- **Avoid the error in head pose estimation to affect the performance of the model**
- **AprilTags [Olson, 2011]**
  - 2D barcodes that can be robustly detected in an image
- **Headband designed with 17 AprilTags**
- **Useful for robust detection of head pose across conditions**

Olson, Edwin. "AprilTag: A robust and flexible visual fiducial system." *Robotics and Automation (ICRA), 2011 IEEE International Conference on*. IEEE, 2011.

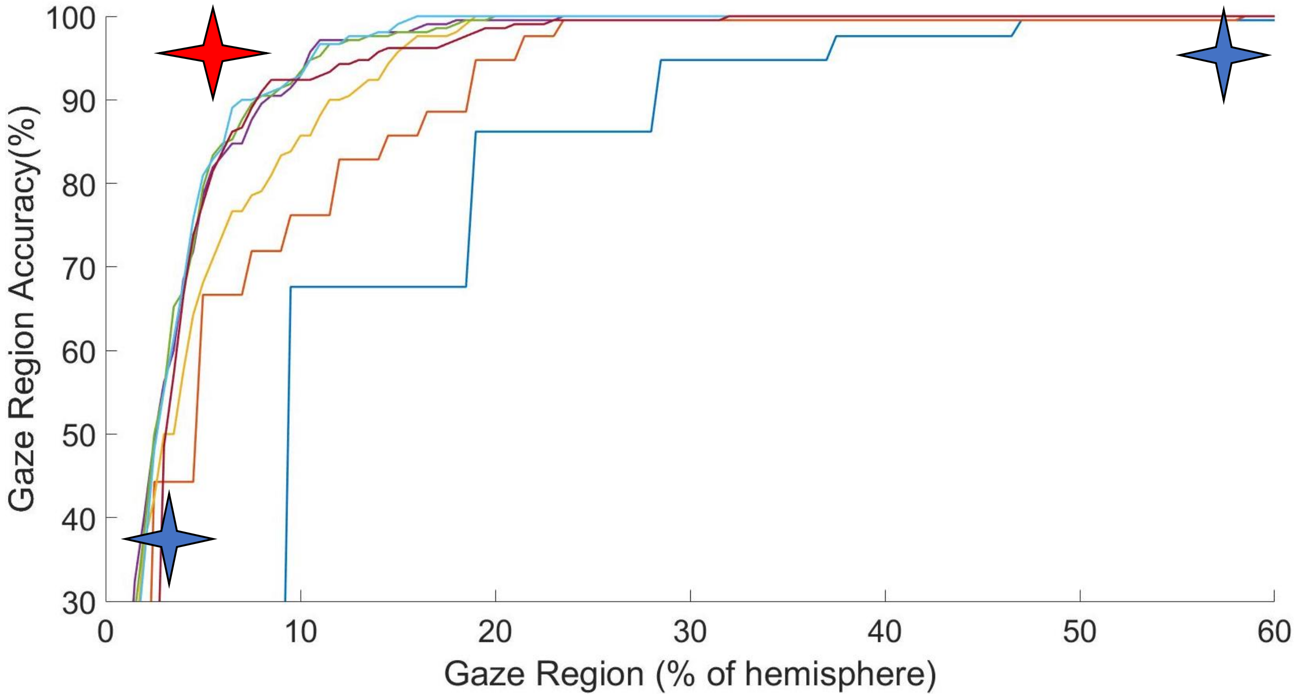
# Implementation of the Proposed Model

- Keras on top of tensorflow to learn the model
- Final output is obtained at 256 x 128 (7 stages)
- Entire network trained at each stage
- Learning rate lowered at later stages with more number of epochs
  - $10^{-2}$ for first 5 stages, 200 epochs
  - $10^{-3}$ for last 2 stages, 500 epochs
- Driver independent partition
  - 14 subjects for training
  - 1 subject for validation
  - 1 subject for test

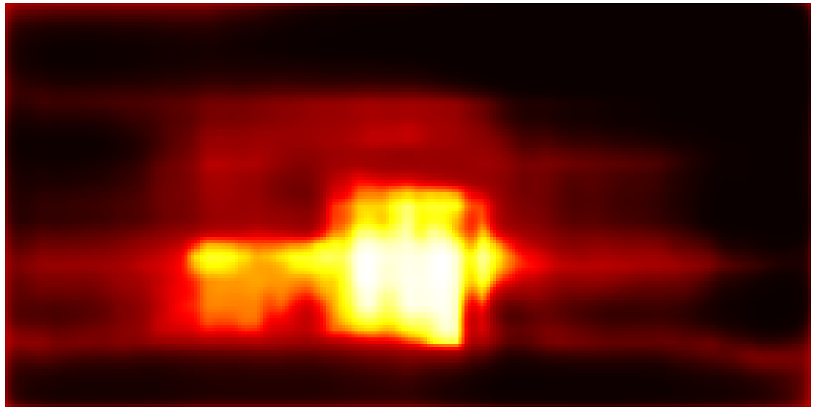


# Results of Experimental Evaluation

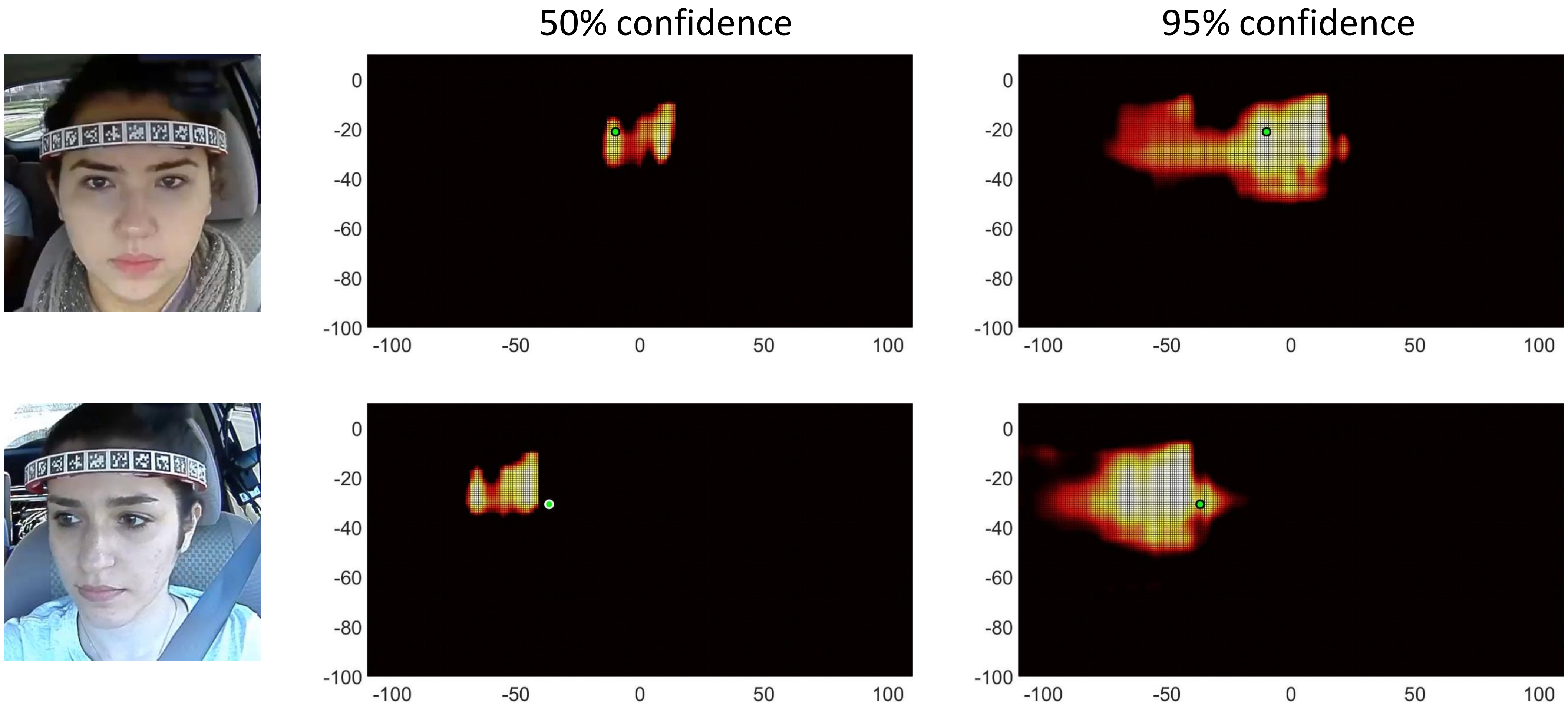
- **Accuracy versus resolution**
  - Area represented as a portion of the hemisphere in front of the driver
  - Study the performance at different stages
  - As we increase resolution the precision increases







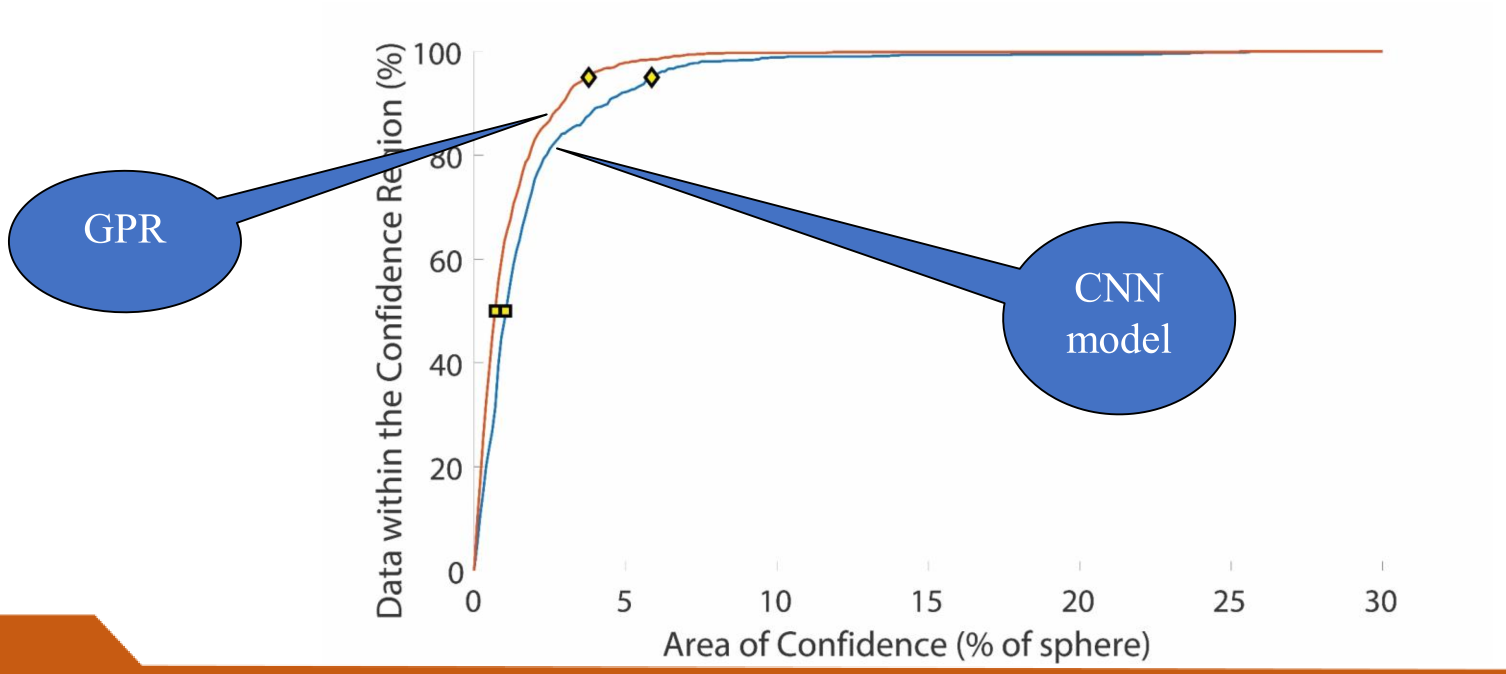
# Prediction of visual attention



# Prediction of visual attention

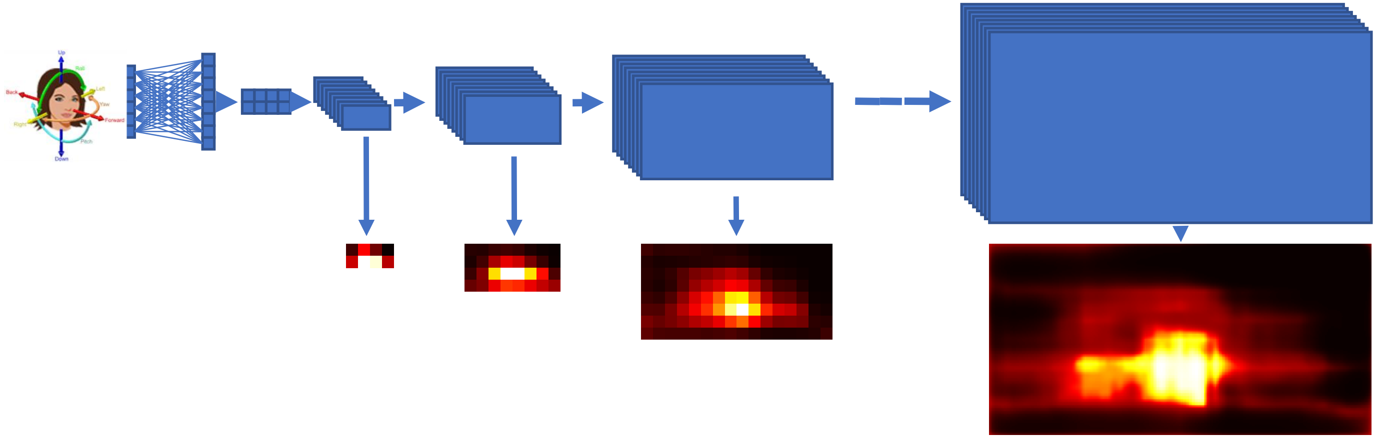
# Comparison with GPR

- **Performance of basic architecture slightly worse compared to GPR**
- **Possible improvements**
  - Deeper architecture in each upsampling
  - Cost sensitive loss functions
  - Continuous and more exhaustive gaze data (as opposed to limited discrete points in the space)



# Conclusions and future work

- Deep learning framework to learn the probability distribution of gaze from head pose
- Incrementally learn higher resolution
- Incorporate information from the eye to increase accuracy



# Thank You

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