Foveating sensing with **KNN-convolutional neural networks** based on **isotropic cortical magnification**

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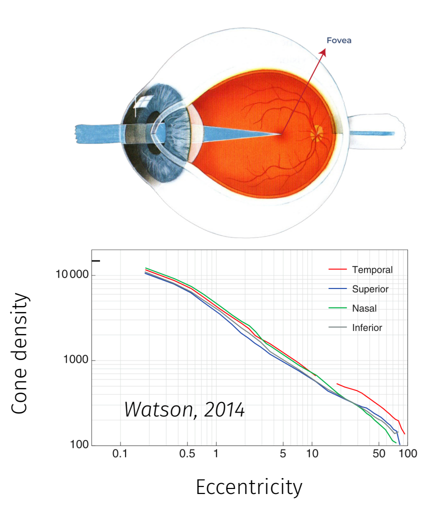
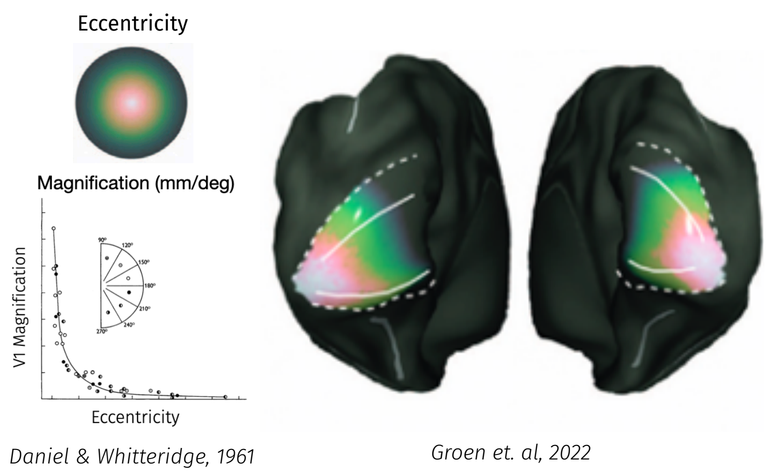
Introduction

Human vision is foveated



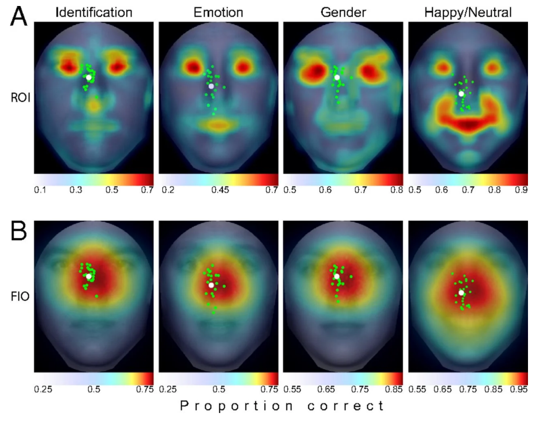
Foveation profoundly shapes cortical organization and visual cognition

Retinotopic organization & cortical magnification



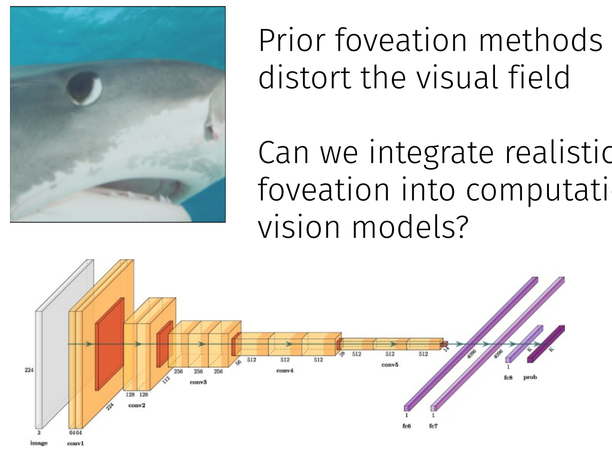
Daniel & Whitteridge, 1961 *Groen et. al, 2022*

Optimized active eye movements



Peterson & Eckstein, 2012

Computer vision models lack mechanisms for realistic foveation

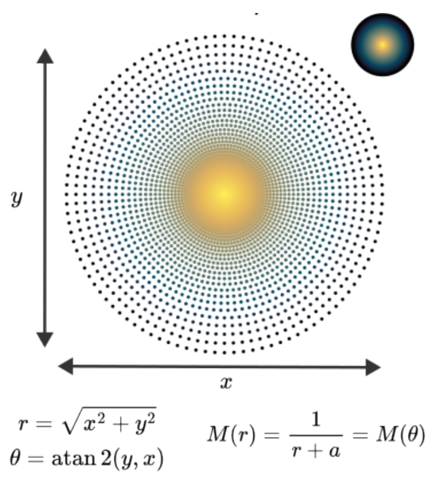


Prior foveation methods distort the visual field

Can we integrate realistic foveation into computational vision models?

Foveated sensing based on **isotropic cortical magnification**

Sampling in visual space

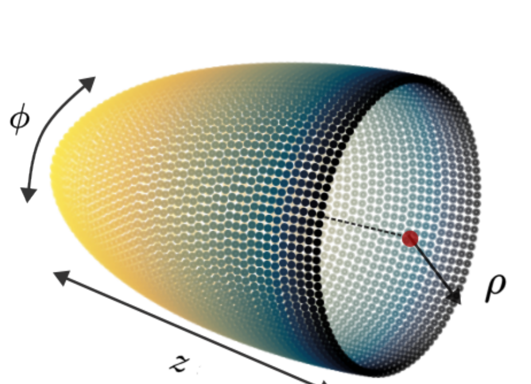


$r = \sqrt{x^2 + y^2}$ $\quad M(r) = \frac{1}{r+a} = M(\theta)$

$\theta = \text{atan}\,2(y, x)$

Sensor manifold

Rovamo & Virsu, 1984



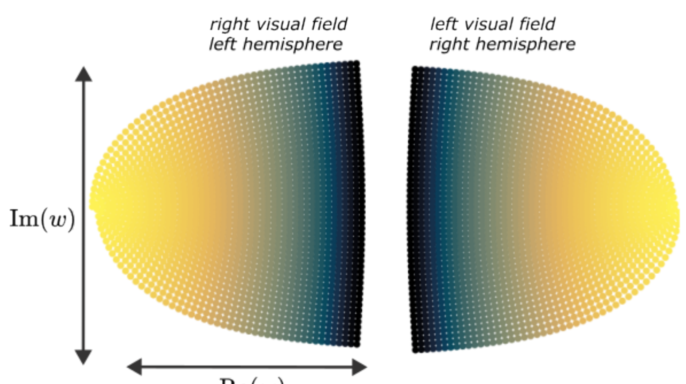
$\rho = M(r)\sin(r)$

$z = \int_0^w \left[M(r)^2 - (d\rho/dr)^2\right]^{0.5} dr$

$\phi = \theta$

Flat sensor manifold

(visualization only)

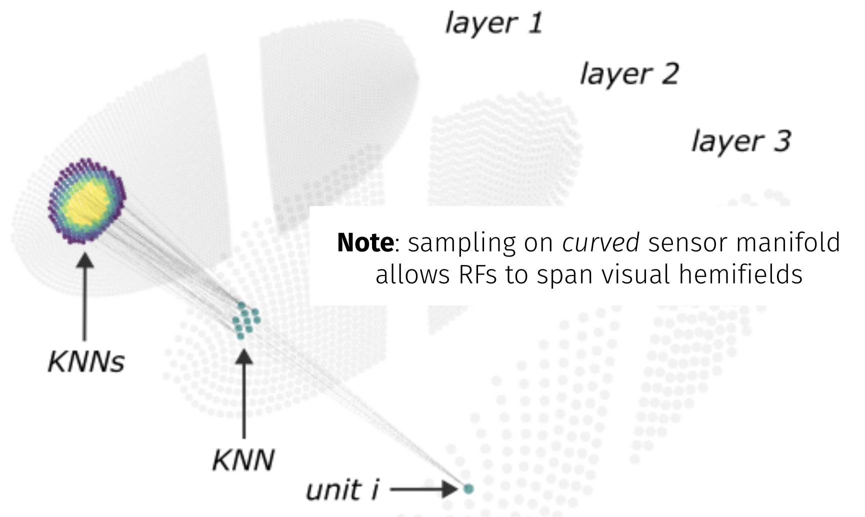


Note: *this is the famous Schwartz (1980) model*

$z = x + iy$

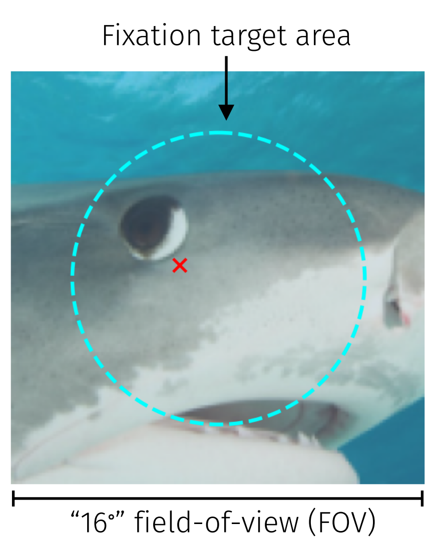
$w = \log(z + a)$

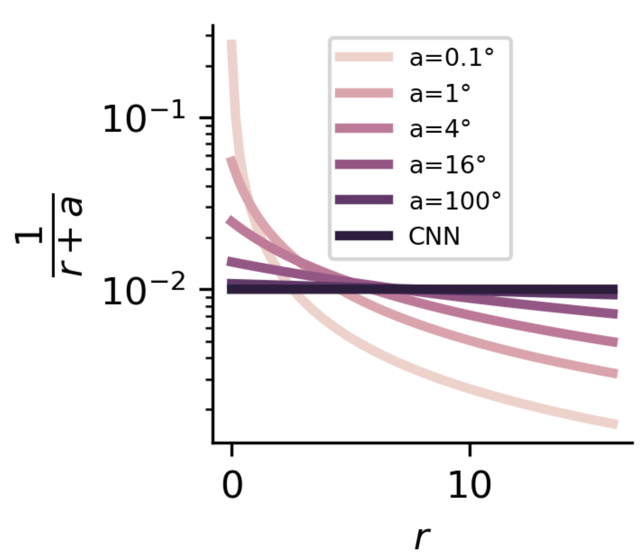
K-Nearest-Neighbor ConvNets (KNN-CNNs)

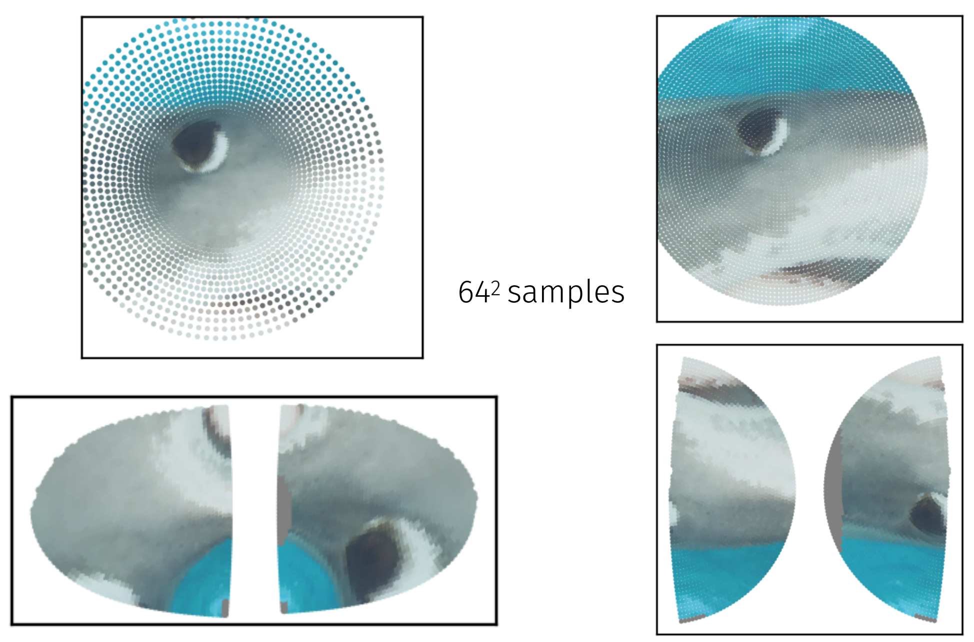


Note: sampling on *curved* sensor manifold allows RFs to span visual hemifields

Result 2: strong performance in foveated networks

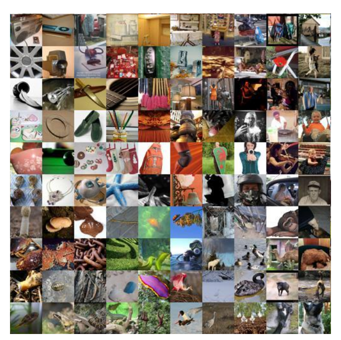


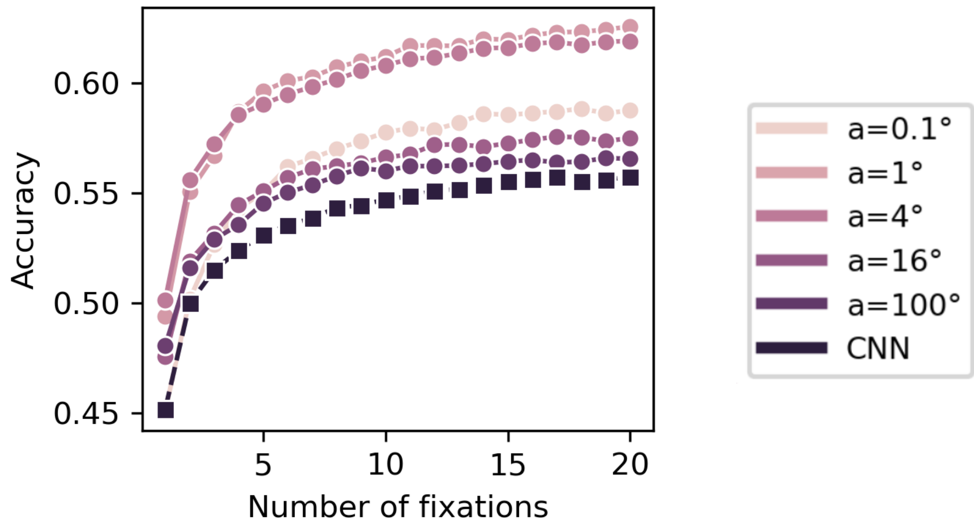




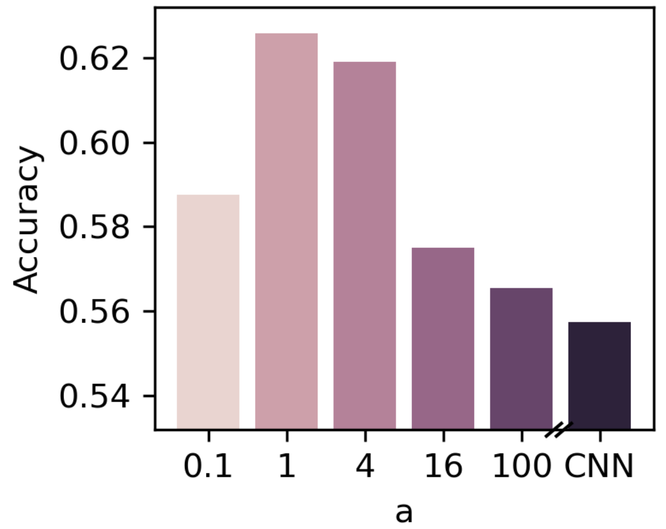
Performance increases with multiple fixations

ImageNet-100



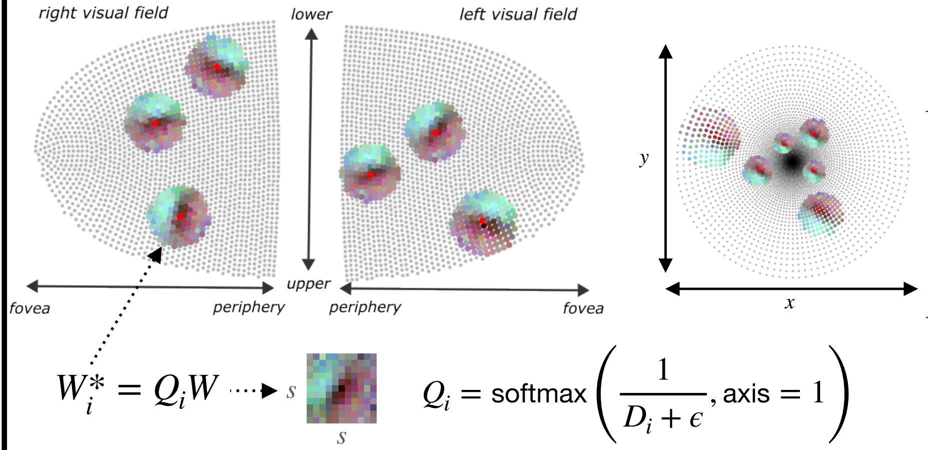


Optimal performance for strong-intermediate foveation



Result 1: foveated model accounts for biological receptive field properties

Receptive fields (RFs) are uniform circular samples on sensor manifold



$W^*_i = Q_i W$ $\quad Q_i = \text{softmax}\left(\frac{1}{D_i + \epsilon}, \text{axis} = 1\right)$

W^*_i: weight in ith neighborhood

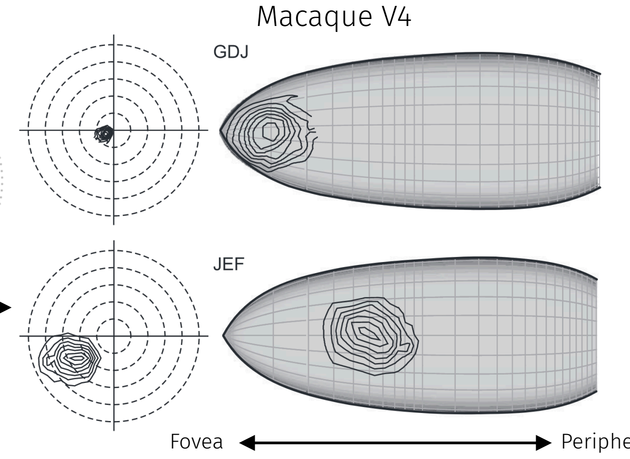
W: reference kernel

Q_i: mapping matrix

D_i: distance from normalized neighborhood coords to reference coords

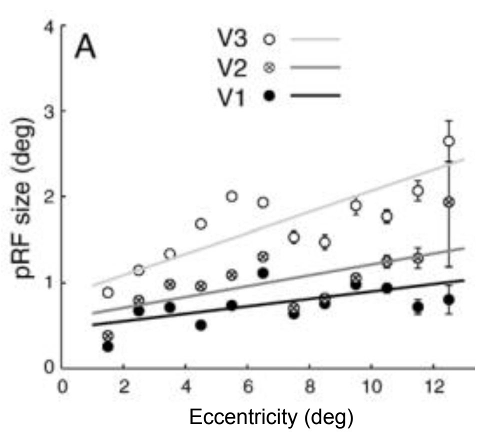
Visual RF size increases with eccentricity and hierarchical level

Macaque V4



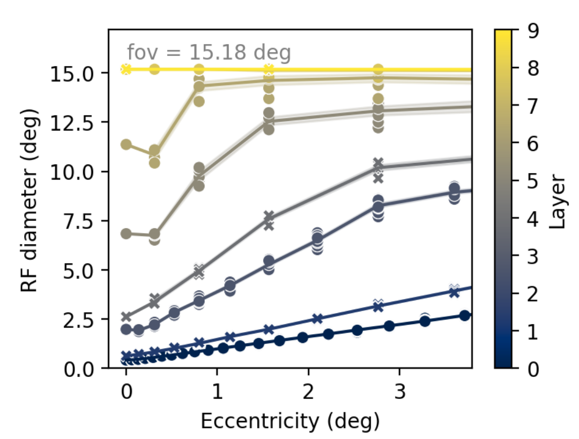
Motter, 2009

Human V1-V3



Dumoulin & Wandell, 2008

Model



Existing grid-like foveated sensors warp receptive fields

$M(r) = \frac{1}{r+a}$ $\quad n_r = n_\theta$

$w = \log(r + a)$

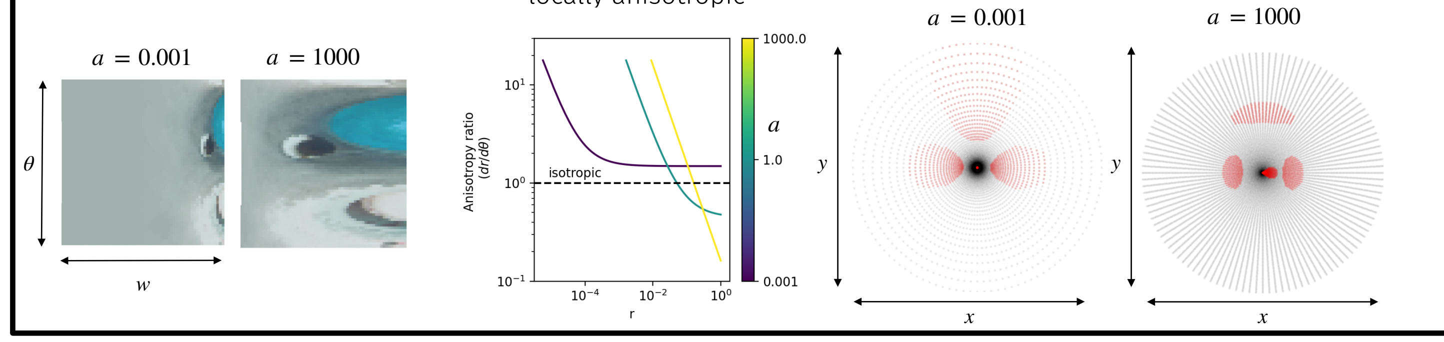
(grid-like simplification of Schwartz (1980) model)

Log-polar image foveation

e.g. Jérémie et. al, 2024

Sampling is locally anisotropic

Eccentricity-dependent RF aspect ratios



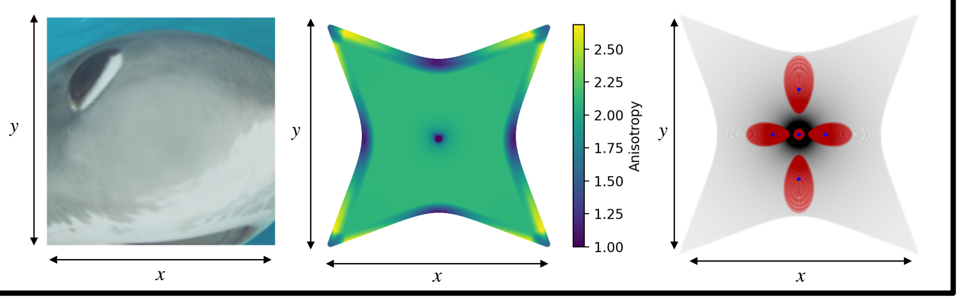
Warped cartesian foveation

e.g. Wang et. al, 2021; see also Da Costa et. al, 2024

Foveated cartesian image

Sampling is locally anisotropic

Eccentricity-dependent RF shapes



Conclusions

Human vision is **foveated** — non-uniform sampling is mapped to a uniform layout in V1 via **isotropic cortical magnification**

We integrate foveation into computational models with a **magnification function,** appropriate **sensor manifold,** and **KNN-CNN architecture**

This leads to **biologically-plausible receptive field** properties, and **strong performance**

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