Modeling Attention with Neural Networks

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Abstract

This project explores the modeling of human visual attention using a convolutional neural network trained to predict saliency maps, heat maps that reflect where people are most likely to focus their gaze in an image. Using the publicly available SALICON-derived eye tracking data, the model learned spatial attention patterns with strong structural similarity to human fixations, achieving high SSIM scores (up to 0.92) on unseen images. These results support the idea that deep neural networks can approximate aspects of human perception, particularly bottom-up visual attention, and offer insight into how computational systems may simulate cognitive functions.

Keywords

Visual Attention, Saliency Prediction, Deep Learning, Cognitive Modeling, Perception, Cognitive Science

1 Introduction

Human visual attention is selective, guiding perception by focusing cognitive resources on specific regions of visual input. In this project, I built a neural network that predicts saliency maps, pixels-wise estimates of gaze likelihood, from raw images. This connects to cognitive science by modeling perceptual attention and evaluating how well artificial networks reflect human fixation behavior.

2 Dataset: SALICON

The SALICON (SALiency in CONtext) dataset was introduced in 2015 as part of the LSUN Challenge. It is a large-scale, publicly available dataset for saliency prediction tasks, derived from images in the Microsoft COCO dataset. Unlike traditional eye-tracking datasets that require specialized hardware, SALICON uses an innovative, less intrusive crowdsourcing method: participants indicate their focus points by moving a mouse cursor while viewing images, simulating gaze behavior.

Dataset summary:

- 10,000 training images
- 5,000 validation images
- 5,000 test images (ground truth withheld)
- All images sourced from the COCO 2014 dataset

The ground truth saliency maps are constructed by aggregating and blurring fixation points derived from multiple users' mouse trajectories. Each image's corresponding metadata is stored in MATLAB files containing raw gaze points, fixations, and resolution.

Shortcomings and limitations of dataset:

- Mouse-based attention is an approximation and may not perfectly match natural eye movements.
- Temporal dynamics and conscious goals of visual attention are not captured.
- The test set does not include gaze annotations, making full evaluation impossible on that subset.

Despite these limitations, SALICON is widely used due to its scale, accessibility, and non-intrusive data collection approach. It supports reproducible saliency research while avoiding the privacy and logistical concerns of hardware-based eye-tracking.

Rationale for selection. SALICON was chosen over alternatives such as ECSSD or PASCAL-S due to its openness, scale, and ease of use. Unlike smaller datasets, SALICON provides tens of thousands of annotated examples, which is more suitable for training deep neural networks. It is also freely accessible without restrictive licensing or specialized hardware requirements, making it ideal for academic and exploratory research. Its streamlined format and community support further contributed to its selection as the foundation for this project.

3 Model and Training

The model architecture is a U-Net-style convolutional network with a ResNet-50 backbone pretrained on ImageNet. The ResNet serves as the encoder, extracting hierarchical visual features at multiple spatial resolutions. These are passed to a decoder composed of upsampling layers and skip connections, which help reconstruct spatial details lost during downsampling. The final output is a 224×224 grayscale heatmap representing predicted saliency.

The network was trained using supervised learning with ground truth saliency maps derived from human gaze approximations. The final activation function is a sigmoid, ensuring outputs fall in the [0, 1] range.

Training configuration:

- Loss: Binary Cross Entropy (BCELoss)
- Optimizer: Adam
- Learning Rate: 1e-4
- Epochs: 15
- Batch Size: 16

4 Results

Training Overview. The model trained over 15 epochs, with loss decreasing from 0.0534 to 0.0262. The predicted saliency range increased from near-zero to a maximum of 0.86, indicating that the model became increasingly confident and expressive in highlighting regions of attention.

Quantitative Evaluation. Table 1 summarizes the performance on validation and test splits using four common saliency evaluation metrics: Mean Squared Error (MSE), Kullback-Leibler Divergence (KL), Structural Similarity Index (SSIM), and Pearson Correlation.

Table 1: Evaluation results on validation and test splits.

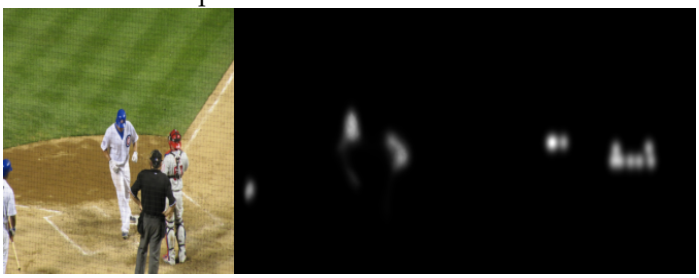
Split	MSE	KL Div.	SSIM	Pearson Corr.
Validation	0.0060	0.0042	0.8730	0.1446
Test	0.0017	0.0009	0.9204	0.0000*

*Pearson correlation on the test set is 0.0 due to the lack of ground truth gaze data.

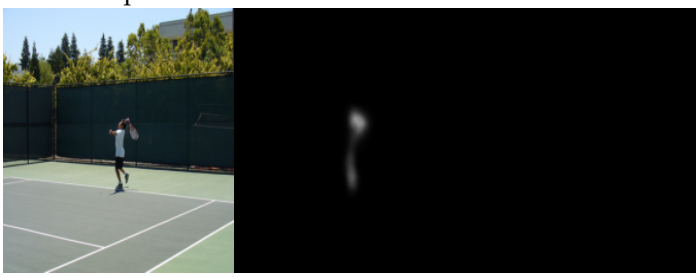
Interpretation. The model achieves strong structural similarity to human fixations on both validation and test sets, as indicated by SSIM values above 0.87. MSE and KL divergence are also low, suggesting that predictions align well with ground truth in both pixel intensity and distribution. The relatively low Pearson correlation on validation (0.1446) may be due to minor spatial shifts between predicted and true saliency peaks. On the test set, Pearson is 0.0 because no ground truth gaze data is available, predictions are evaluated without true reference, and the dummy ground truth maps used for placeholder evaluation yield undefined correlation.

Visual Examples.

Validation Example



Test Example



Left — the original input image, Middle — the model's predicted saliency map, Right — the human fixation ground truth.

In the validation example, the model accurately focuses attention on the batter and catcher, closely matching the human fixation map. The spatial distribution of predicted saliency highlights key players and aligns well with human perceptual bias.
In the test example, attention is strongly concentrated on the tennis player, particularly the head and upper body, consistent with natural viewing behavior. The prediction is confident and sharply defined, suggesting that the model has learned to identify action-relevant regions.
These visualizations illustrate the model's ability to produce interpretable, human-like saliency predictions across both validation and test images.

5 Discussion

Interpreting the Saliency Predictions. The visual examples show that the model learns human-like attention patterns directly from images. In the validation case, saliency is focused on task-relevant agents, the batter and catcher, suggesting the model has internalized attention biases common in human gaze behavior. Similarly, in the test example, strong attention is centered on the tennis player's upper body, particularly the face, aligning with well-documented human tendencies to fixate on faces and action cues.
This behavior reflects real-world perceptual biases: we are evolutionarily tuned to attend to people, faces, and objects in motion, a filtering mechanism that supports visual efficiency in complex scenes.

Bottom-Up Visual Processing. The model's architecture mirrors bottom-up perception, as covered in lecture and classic theories, where low-level features (edges, contrast, motion) are progressively integrated into meaningful patterns. Like the visual cortex, the convolutional layers act as feature detectors. Saliency predictions emerge without any contextual input, demonstrating that a substantial part of gaze behavior can be modeled from bottom-up cues alone. This aligns with the Feature Integration Theory of attention [2] and the idea that visual saliency is largely driven by early-stage perceptual mechanisms.

Selective Attention and Attenuation. The model's output represents a learned form of selective attention, elevating relevant visual regions while de-emphasizing background content. This mirrors the Attenuation Model of attention [3], in which unattended stimuli are weakened rather than fully suppressed. The network seems to apply this kind of filtering implicitly, learned through data rather than rule-based design. Reinforcing the potential of machine learning to approximate such cognitive mechanisms.

Cognitive Modeling Perspective. This project demonstrates how neural networks can serve as simplified models of perceptual processes. The network approximates bottom-up visual attention, showing that structured patterns of human gaze can be learned from image features alone. While not conscious or goal-driven, it captures key aspects of gaze behavior, supporting functionalist arguments that cognitive processes can be modeled by their inputs and outputs, even if the internal machinery differs.
Importantly, it also highlights the bottom-up vs. top-down divide emphasized in cognitive science: the model lacks context, memory, or task awareness. It responds only to the visual input in front of it, showing the power of bottom-up cues but also their limitations in capturing higher-level cognitive influences.

Limitations and Cognitive Implications. Although effective at predicting static saliency, the model has several cognitive limitations. It does not model temporal dynamics, how attention shifts over time, nor can it incorporate task goals, prior knowledge, or emotional relevance. These are key components of top-down attention and are essential for modeling real human cognition.

As such, the model captures the selection aspect of attention well but lacks the capacity-limited, flexible resource allocation described in more complete theories. It is a strong computational analogy for early visual processing, but still far from capturing the full spectrum of human attention.

6 Limitations and Future Directions

While this project successfully demonstrates that neural networks can model bottom-up visual attention, there are several notable limitations to the approach:

1. Limited Ground Truth and Evaluation.
The SALICON dataset, while large and open, relies on mouse-tracking as a proxy for eye-tracking, which may not perfectly represent natural gaze behavior. Furthermore, the lack of ground truth annotations in the test set prevents a comprehensive quantitative evaluation on unseen data.

2. Absence of Top-Down Attention.
The current model is trained solely on bottom-up visual features and does not incorporate any top-down influences such as task demands, prior knowledge, or goals. Human attention is strongly shaped by these factors, as discussed in class, but they are not represented in the model.

3. Static Images Only.
The model predicts saliency for single static images and does not account for temporal dynamics of attention—how gaze shifts over time, or how attention is influenced by motion, change, or scene transitions.

4. Interpretability and Biological Plausibility.
While convolutional neural networks provide useful predictions, their internal representations remain difficult to interpret in biological or psychological terms. The model's "attention" is learned implicitly and may not correspond to explicit psychological mechanisms or neural processes.

5. Generalization and Overfitting.
With a powerful model and a relatively fixed dataset, there is always a risk of overfitting to particular image features or dataset biases. Although strong SSIM scores were achieved, real-world generalization to novel domains or image types remains an open question.

Future Directions.
Addressing these shortcomings could involve integrating top-down cues (such as image captions or task information), employing true eye-tracking data, modeling temporal attention, or exploring more interpretable architectures (such as attention-based neural models). Expanding the evaluation to more diverse or ecologically valid datasets would also strengthen the cognitive relevance of the findings.

7 Code Walkthrough

The project is implemented in Python using PyTorch and follows a modular structure that separates data processing, model architecture, and training logic.

1. dataset.py
This script defines a custom PyTorch `Dataset` class for SALICON. It loads images and corresponding saliency maps from disk, processes fixation data from MATLAB files, and generates smooth ground truth heatmaps using Gaussian filtering. It returns image/map pairs resized and normalized for input into the network.

2. model.py
This file defines the neural network architecture. The encoder uses a ResNet-50 backbone pretrained on ImageNet to extract multi-scale visual features. The decoder upsamples these features using a U-Net-style architecture with skip connections. The final layer applies a sigmoid activation to produce a grayscale saliency map.

3. main.py
This is the central training and evaluation script. It handles:

- Model initialization and optimizer setup
- Data loading for training, validation, and test splits
- Training loop with loss tracking and prediction range monitoring
- Metric computation (MSE, SSIM, KL Divergence, Pearson correlation)
- Saving visual outputs and plotting results

The script also includes logic to resume training from a saved model or skip training if a checkpoint is already available.

4. Output and Visualization
During evaluation, example predictions are saved as side-by-side images showing the input, predicted saliency map, and ground truth (if available). Training curves and prediction range plots are also saved as figures to support analysis in the report.

This modular design makes the code easy to follow and extend; for example, by swapping in a different backbone, adding a new loss function, or adapting it to another saliency dataset.

8 Conclusion.

In total, the model provides a compelling approximation of early visual attention, illustrating how perceptual saliency can emerge from learned feature hierarchies. It aligns well with theories of bottom-up processing and selective attention, but also highlights the gap between current machine learning models and full cognitive flexibility. This project serves as both a functional implementation and a theoretical exploration of how artificial systems can begin to replicate, and eventually extend, the mechanisms underlying human perception.

References

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