The Costs and Benefits of Goal-Directed Attention in Deep Convolutional Neural Networks

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Abstract

Attention in machine learning is largely bottom-up, whereas people also deploy top-down, goal-directed attention. Motivated by neuroscience research, we evaluated a plug-and-play, top-down attention layer that is easily added to existing deep convolutional neural networks (DCNNs). In object recognition tasks, increasing top-down attention has benefits (increasing hit rates) and costs (increasing false alarm rates). At a moderate level, attention improves sensitivity (i.e., increases $d'$) at only a moderate increase in bias for tasks involving standard images, blended images, and natural adversarial images. These theoretical results suggest that top-down attention can effectively reconfigure general-purpose DCNNs to better suit the current task goal. We hope our results continue the fruitful dialog between neuroscience and machine learning.

1. Introduction

Attention-related approaches have met with great success in machine learning in key applications, such as machine translation (Vaswani et al., 2017) and image recognition (Hu et al., 2018). Although motivated by attention in living organisms, attention in machine learning often misses a critical component. Human attention is not just captured by the current bottom-up context (e.g., a word or an image) but can also be driven by the current top-down expectations or goals. Top-down attention is conspicuously absent in most deep convolutional neural networks (DCNN). Our work aims to bridge this gap by incorporating a simple plug-and-play component inspired by cognitive science research. We provide a theoretical analysis of the costs and benefits of our top-down attention mechanism that we hope lays the foundation for further developments.

Imagine looking for your apartment keys in the kitchen. At first, one might focus on features such as small and metallic. This attention focus could lead one to false alarm to a stray fork occluded by a chopping board, but should also increase the chances of finding one’s keys. To carry out this search task, the prefrontal cortex (PFC) exerts top-down biases on the visual cortex that favour the current goal, such as locating keys (Miller & Cohen, 2001). Top-down attention reconfigures bottom-up visual representations of the kitchen by highlighting task-relevant features while suppressing irrelevant features.

In this work, we focus on the costs and benefits of top-down attention. When searching for one’s keys, top-down attention benefits an agent by prioritising objects with key-like features, resulting in more efficient search. Top-down attention also exacts a cost—the key-like features of non-key objects are amplified, increasing the likelihood of a false alarm. For example, when albedo is highly attended, a person may mistake shiny objects for a key. On the other hand, without top-down attention is present, the search process may be inefficient. We hypothesise that the intensity of top-down attention will alter the bias and sensitivity of a model, which will determine whether top-down attention results in a net benefit for the agent. With the correct amount of top-down attention, a model may successfully balance the costs and benefits such that sensitivity ($d'$ in signal detection terms) is increased.

Psychologists and neuroscientists have developed models that include top-down attention to explain behavioural (Bar, 2006; Itti et al., 1998; Love et al., 2004; Miller & Cohen, 2001; Nosofsky, 1986; Plebanek & Sloutsky, 2017; Wolfe, 1994) and neuroimaging data (Ahlheim & Love, 2018; Mack et al., 2016; 2020). Algorithmically, top-down attention is often modelled as a set of weights that alters the importance of different psychological feature dimensions. Geometrically, one can think of attention weights as expanding and contracting the different feature dimensions of psychological space (Figure 1) (Kruschke, 1992; Love et al., 2004; Nosofsky, 1986).

Although the principles in these models are illuminating, the models are not directly applicable to deep learning as cognitive science researchers typically rely on low-dimensional, hand-coded stimulus representations, as opposed to photo-
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Figure 1. Attention alters the importance of feature dimensions. Four kitchen objects vary on two feature dimensions: albedo and size. In this example, albedo is the attended dimension (hence stretched) whereas attention to size is tuned down (hence compressed). Consequently, the key becomes more similar to the silver toaster than to the chopping board or salt shaker. Figure adapted from Nosofsky (1986).

Figure 2. Example stimuli from three categorisation problems. (Left) A standard image used in Experiment 1 from ImageNet’s Tabby Cat category (Deng et al., 2009). (Middle) A blended image used in Experiment 2 made by alpha-blending an image of a cat and an image of a dog. (Right) A natural adversarial image used in Experiment 3 of a dragonfly misclassified as banana by DenseNet-121 with high confidence (Hendrycks et al., 2019).

Using DCNNs as a starting point, we incorporate a simple top-down attention mechanism motivated by research in psychology and neuroscience (Miller & Cohen, 2001; Roe et al., 2012; Wolfe, 1994). Inspired by the role of the PFC, feature activations are modulated based on externally provided goal signals. The proposed extension differs from other attention strategies which lack a clear top-down component (e.g., Bahdanau et al. 2015; Hu et al. 2018). Upon receiving external expectation signals, a unique set of attention weights is learned so the resulting model becomes specialised for the current goal (e.g., a cat present in this image). Our attention mechanism is implemented as a single trainable layer inserted into a pre-trained DCNN, permitting plug-and-play use. We test our model on three (Figure 2) progressively challenging image classification tasks: standard ImageNet images (Deng et al., 2009), blended images, and natural adversarial images (Hendrycks et al., 2019). All three of our experiments found that both the costs and the benefits of attention increased as attention increased, and that there was a net benefit of attention at moderate levels.

2. Related Work

Attention in Neuroscience  Theories of attention in neuroscience make a distinction between bottom-up and top-down processes (Connor et al., 2004; Itti & Koch, 2001; Katsuki & Constantinidis, 2014). Bottom-up attention is captured solely by the stimulus, whereas top-down attention is determined by goals or expectations. Learning models in cognitive psychology successfully explain how people learn to selectively weight information sources to help achieve the learning goal (Nosofsky, 1986; Kruschke, 1992; Love et al., 2004). In these models, top-down attention is typically formalised as a single set of feature weights that are optimised for a particular categorisation task such that a unique set of feature weights are learned for each task. As shown in Figure 1, these models contort the similarity space to support the current learning goal, emphasising aspects of the stimuli that are useful for the current task. Although simple, these models capture human behaviour and how neural representations change with task goals (Mack et al., 2016). Amazingly, these models can capture individual differences in brain response when fit to human behaviour (Braunlich & Love, 2019; Mack et al., 2020), suggesting that these models are capturing nuances at both the behavioural and brain levels.

Unfortunately, most cognitive models rely on oversimplified stimulus representations based on the modeller’s intuitions. These models cannot develop rich feature representations. We aim to combine the positive qualities of cognitive models and DCNNs. Unlike cognitive models, DCNNs can develop rich representations of complex (e.g., photographic) stimuli. DCNNs are good candidate models to extend with a top-down attention mechanism as DCNNs already characterise aspects of the representational geometry of brain’s ventral visual stream (Schrimpf et al., 2018).

\[^1\] Code available at https://github.com/anonymous/dcnn_top_down_attention
Attention in Deep Learning  Attention approaches are gaining prominence in machine learning. We view self-attention as a form of bottom-up attention modulated by the current sequence of inputs rather than changes in top-down goals (Bahdanau et al., 2015; Chen et al., 2017; Vaswani et al., 2017; Xu et al., 2015). Self-attention is driven by the stimulus. For example, in machine translation, the contribution of each context word changes depending on the target word (Bahdanau et al., 2015; Vaswani et al., 2017). To provide another example, in image classification, filters are amplified or suppressed based on the input image (Hu et al., 2018). In contrast, our work learns top-down attention weights for different tasks. A second difference between our approach and self-attention is how attention weights are trained. Whereas self-attention is trained jointly with the rest of the network, we train the attention component separately from the rest of the network. Our attention mechanism is modular and designed to operate with any pre-trained DCNN. Unlike end-to-end fine-tuning which re-trains all parameters of a pre-trained DCNN for a new task (Yosinski et al., 2014), we only train the parameters associated with an attention layer. Our approach is motivated by the idea that prefrontal cortex (PFC) reconfigures existing networks to suit the current goal.

Although the notion of attention, particularly self-attention, is popular in deep learning (see Jetley et al. (2018) for a discussion), the distinction between bottom-up and top-down attention is rarely made (Bahdanau et al., 2015; Chen et al., 2017; Hu et al., 2018; Vaswani et al., 2017). We hope our work clarifies this distinction and is complementary to self-attention by addressing the neglected top-down component of attention.

In many ways, our work is most similar to Lindsay & Miller (2018) in that they are informed by a neuroscience perspective and incorporate top-down attention into an existing DCNN. We depart by training attention weights through gradient descent to consider the costs and benefits of attention. We also consider 1000-way classification performance, rather than focusing exclusively on binary tasks.

3. Methods

In order to inject top-down attention into existing DCNN architectures, we introduce a simple network layer that is characterised by two training parameters: target class and attention intensity. The remainder of this section describes the attention layer, how a target class is defined, the interpretation of the different attention intensities, and how an attention model is trained.

Top-down Attention Layer  A top-down attention layer can be inserted between two arbitrary layers of a pre-trained DCNN. The shape of the attention layer is equal to the shape of its preceding layer. The attention layer is connected in a one-to-one fashion to the filters of preceding layer. These connections are referred to as attention weights and modulate the activations of the preceding layer.

In this work, we limit the flexibility of the attention layer by using a single weight to characterise all weights belonging to a particular filter (Figure 3), resulting in filter-wise attention weights. The attention weights are initialised to 1.0 and constrained to be between $[0, +\infty]$. During training, the attention weights are learned while the remaining network parameters are kept fixed, which we describe in more detail below.

Target Class  A target class $T$, is the set of all ImageNet classes that an attention network should focus on mastering. The remaining ImageNet classes are referred to as non-target classes. In general, a target class can be composed of multiple ImageNet classes. In this work, a target class is composed of a single ImageNet class. A different target class implies a different task.

Attention Intensity  The attention intensity ($\alpha \in [0, 1]$) determines the degree that the model should focus on mastering the target class at the expense of other non-target classes. Formally this is captured by weighting the contribution of each image to the loss term based on whether the
image belongs to the target class or a non-target class (see the Model Training section). In this work, we consider five different intensity levels (Table 1). When \( \alpha = 0 \), no preference is given to the target class and all classes are weighted equally. This intensity level exhibits no top-down attention and primarily acts as a control model. When \( \alpha = 0.5 \), each non-target class is half as important as the target class. When \( \alpha = 1 - \beta \) (where \( \beta = 1/999 \)), the summed weight of all the non-target classes is exactly equal to the weight of the target class. We refer to this intensity level as balanced attention. When \( \alpha = 1 - (\beta/1000) \), the summed weight of all the non-target classes is equal to 1/1000 of the weight of the target class. When \( \alpha = 1 \), the network focuses exclusively on mastering the target class and non-target classes make no contribution to the loss term.

Each level of intensity implies a trade-off between target and non-target performance. Weighting non-target classes by \( \alpha \) can be likened to training on an imbalanced dataset. When \( \alpha = 1 \), the learned attention weights will overfit to the target class given the absence of non-target classes. When \( \alpha = 1 - \beta \), a balance is struck between target and non-target classes. We expect that the largest net benefit will be achieved around this level.

In addition to overall performance, the level of intensity should influence the distribution of learned attention weights. We expect that higher intensity levels will result in a larger number of filters being turned off.

**Integration with VGG-16** In principle, the proposed top-down mechanism can be integrated into any DCNN. In this work, we use a pre-trained version of VGG-16 (Simonyan & Zisserman, 2015) as it is a well-known yet relatively simple architecture that has a high brain-score (Schrimpf et al., 2018). The attention layer is inserted after the fourth convolutional block of VGG-16.

**Model Training** The attention layer is trained using ImageNet-2012, the same dataset that was used to train the pre-trained network. A training set is created from the ImageNet-2012 training set by randomly sampling 90% of the images from each category. The remaining 10% of the images are used for validation. The ImageNet white-listed validation set is set aside as the test set. We use the Adam optimiser with initial a learning rate of 0.0003 and a batch size of 16. The training data are preprocessed and augmented according to Krizhevsky et al. (2012) and Simonyan & Zisserman (2015).

Given a target class \( T \) and an attention intensity \( \alpha \), the attention weights are trained on a 1,000-way classification problem, while keeping all other parameters fixed. The training objective is to minimise the standard multi-class cross-entropy loss (CE) over 1,000 classes. The contribution of each stimulus to the loss term is determined by whether it belongs to the target class. Stimuli that do no belong to the target class are weighted by \( \alpha \). For example when \( \alpha = 1 \) only stimuli belonging to the target class contribute to the loss term.

Formally, given a training image \( x_i \) and its true class label \( y_i \), the model outputs the probability for the true class \( p(x_i) \). The \( \alpha \)-weighted cross-entropy loss \( \text{loss}_i \) associated with image \( x_i \) can be expressed as:

\[
\text{loss}_i = \begin{cases} 
CE(y_i, p(x_i)), & \text{if } x_i \in T \\
(1 - \alpha)CE(y_i, p(x_i)), & \text{otherwise.}
\end{cases}
\]

Given that we train many attention models, it is computationally expensive to use the entire training set at each epoch. The computational cost is reduced by using a subset of the training set during each epoch. Each epoch uses all of the images belonging to the target class and a random 10% of the images from each non-target class. The non-target samples change every epoch. The non-target samples are up-weighted in the loss term to adjust for the imbalanced sampling. The end result is that interpretation of attention intensity is unaffected by the sub-sampling procedure.

Models are trained using a stopping criterion with a maximum of 5,000 training epochs. The early stopping criterion is based on the relative improvement in validation loss. Validation loss is computed using the \( \alpha \)-weighted cross-entropy (Equation 1) and all of images from the validation set. Relative improvement is computed between every other epoch. Training terminates when the relative improvement is less than 0.1% at two consecutive checks.

### 4. Experiments

The proposed top-down attention mechanism was evaluated using three experiments that used a shared training procedure. All experiments used the same set of trained models. One attention model was trained for each of the five attention intensities (Table 1) and each of 200 different target classes, yielding 1000 different attention models. Each target class corresponds to one of the classes defined in the natural adversarial dataset, a set of 200 classes which overlap with the ImageNet classes (Hendrycks et al., 2019).
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*Figure 4. Attention weight distributions for Experiment 1.* As attention intensity increased, attention weights became more extreme (i.e., the variance of weights increased). Furthermore, increasing attention resulted in more filters being turned off (i.e., the initial attention weight goes from 1 to 0).

*Figure 5. Main results from Experiment 1.* Top-down attention with varying degrees of intensity across all target classes were tested. As attention intensity increased, top-down attention had increasing benefits (higher model hit rates) as well as costs (higher model false alarm rates); With an increasing attention intensity, model sensitivity ($d'$) first increased and then decreased. Model was more biased towards making a false alarm (criterion decreased). A sweet spot for maximal net benefit of top-down attention was achieved with the highest model sensitivity ($\alpha = 1 - \beta$). At this intensity, attention on the target class was equal to the attention on non-target classes combined.

Each experiment tested the trained models using a different image classification problem. Experiment 1 used standard ImageNet images. Experiment 2 used blended images that are made from two alpha-blended standard images. Experiment 3 used natural adversarial images, taken from the natural adversarial dataset. Performance on each test problem was analysed using two distinct analyses. The first analysis examined how attention intensity affects the top-5 hit rate and top-5 false alarm rate. The second analysis used signal detection theory to evaluate any change in model sensitivity and criterion due to top-down attention (MacMillan, 2002). We expected a consistent pattern across all experiments such that increasing attention intensity would lead to higher benefits of top-down attention coupled with higher costs. The largest net benefit should be achieved when the target class and non-target classes are balanced ($\alpha = 1 - \beta$) or nearly balanced. We also expected that as attention intensity increases, more DCNN filters connected to the attention layer will be switched off (i.e., have an attention weight of 0).

### 4.1. Experiment 1: Standard Images

Standard images from ImageNet are the most straightforward tests can be used to analyse the costs and benefits of the proposed top-down mechanism under normal conditions.

**Testing Procedure** Each trained attention model was tested using an equal number of target and non-target test images. All target class images and a random sample of non-target class images were used during testing. Using an equal number of target and non-target class images facilitates signal detection analyses.
Results Consistent with our hypothesis about the costs and benefits of attention, one might expect attention weights to become more extreme as attention was increased. Indeed, the variance of the attention weights increased as attention intensity increased (Figure 4).

Both the hit rate and false alarm rate of the attention model increased as attention intensity increased (Figure 5). Model sensitivity (d') peaked near the balanced value of \( \alpha = 1 - \beta \). Sensitivity difference across five attention intensities were significant, \( F(4, 995) = 1285.4, p < .001 \). The attention model with \( \alpha = 1 - \beta \) had the highest sensitivity among sampled attention intensities and the difference to the second highest sensitivity (\( \alpha = 0.5 \)) was significant, \( t(199) = 10.1, p < .001 \). The model criterion monotonically decreased as \( \alpha \) increased (Figure 5).

Discussion The results from Experiment 1 were consistent with our predictions in regards to the costs and benefits of attention. As attention intensity increased, attention weights became more extreme. Correspondingly, hits and false alarms both increased with increasing attention intensity. Sensitivity peaked near a moderate attention intensity that successfully balanced these benefits and costs. As expected, a sweet spot of attention intensity was shown around \( \alpha = 1 - \beta \) from the sensitivity analysis when target and non-target classes were balanced. Decreasing model criterion suggests that as attention intensity increased, the model was more biased in favour of a target class response, which was more likely to result in a false alarm. Results on standard images demonstrated initial success of the proposed mechanism. Harder images with degraded features were used in Experiment 2 to further our understanding of the top-down attentional mechanism.

4.2. Experiment 2: Blended Images

Psychophysicists often use challenging visual tasks to probe important properties of the human visual system (Yi et al., 2004). This experiment extended Lindsay & Miller (2018), which also used blended images to tax a top-down attentional mechanism. Blended images are harder tests for the model in that when two images are merged into one, features become overlaid and degraded.

Testing Procedure This experiment used the same attention models from Experiment 1, only the testing procedure differed. Blended images were created from the test set used in Experiment 1 (Figure 6) by combining images from two classes (e.g., Japanese Spaniel and Tabby Cat). For this study, hits were defined as detecting the target class for which attention was deployed (e.g., responding Japanese Spaniel with Japanese Spaniel attention weights) and false alarms were responding according to the attention weights of a third class not present in the image (e.g., responding Dragonfly with Dragonfly attention weights).

Results As attention intensity became stronger, the model hit rate and false alarm rate both increased. The sensitivity of the attention model increased at first and then decreased after balanced attention (\( \alpha = 1 - \beta \)). The overall sensitivity difference across the five levels of intensity was significant, \( F(4, 198995) = 10311.3, p < .001 \). The highest net benefit was achieved when there was a moderate level of attention (\( \alpha = 1 - \beta \)) and was significantly higher than the next highest sensitivity (\( \alpha = 0.5 \)), \( t(39799) = 150.4, p < .001 \). Additionally, model criterion dropped as attention intensity grew.

Discussion Classifying blended images is a more difficult problem than classifying standard images because the features of one class are superimposed on the features of another class. The difficulty of this experiment can be seen by comparing the results between the current experiment and Experiment 1 when no top-down attention was present (\( \alpha = 0 \)). The current experiment had a much lower baseline hit rate. It is a stronger demonstration that the proposed top-down mechanism was effective in selectively processing stimulus features in a task-specific manner. There is a consistent pattern to the previous experiment that increasing attention intensity improved the hit rate and false alarm rate, which suggests a clear trade-off between costs and benefits of attention. Consistent with our hypothesis that the largest net benefit was achieved when target and non-target classes were balanced (\( \alpha = 1 - \beta \)). As target and non-target classes becoming more imbalanced (increased \( \alpha \)), model criterion decreased, which indicates the model became more biased towards making a target class prediction over any test images.

4.3. Experiment 3: Natural Adversarial Images

The final experiment uses natural adversarial images to evaluate the efficacy of top-down attention. The natural adversarial images are composed of 200 classes of real-world, unmanipulated images collected from the Internet (Hendrycks et al., 2019). The classes have been intentionally selected to overlap with 200 classes from ImageNet. The images exploit DCNNs’ vulnerabilities such as colour.
and texture biases to drastically reduce their performance (Guest & Love, 2019; Hu et al., 2018). Although adversarial attacks have been heavily studied (Goodfellow et al., 2015; Nguyen et al., 2015; Song et al., 2018), these works use synthetic or unrealistic images that are carefully designed to defeat advanced DCNNs. Natural adversarial images offer an opportunity to test the proposed model with stimuli that humans would plausibly encounter in the environment.

Testing Procedure The same attention models were used, only the testing procedure differed. Each model was tested using an equal number of target and non-target images from the natural adversarial dataset. The same analyses were carried out on the test results.

Results The same pattern of results was observed (Figure 8) as in Experiments 1 and 2. Increasing the attention intensity led to greater benefits (e.g., higher hit rate) and costs (e.g., higher false alarm rate). As in the previous studies, model sensitivity peaked for a moderate value of attention intensity. Model criterion decreased (biasing toward the target class) as intensity increased. The difference across models’ sensitivities was significant, $F(4, 995) = 115.1, p < .001$. Model sensitivity was the greatest when $\alpha = 1 - (\beta/1000)$, which was significantly higher than $\alpha = 1 - \beta$, $t(199) = 3.5, p < .001$.

Discussion Like the previous two experiments, the proposed top-down mechanism achieved higher hit rates with higher false alarm rates as attention intensity increased. The optimal model sensitivity was found when attention intensity was $\alpha = 1 - (\beta/1000)$, which was near the point where target and non-target classes are in balance. Model criterion shared the same pattern to previous studies, which suggests it was shifting to favor the target class responding as attention intensity becoming more extreme. There is a clear trade-off between costs and benefits of attention at different intensity levels. Unlike blended images, natural adversarial images exploit DCNNs’ biases towards colour, texture and background cues. Although the top-down attention mechanism did not tackle these issues directly, the simple approach substantially improved performance.

5. General Discussion

Motivated by research in neuroscience, we set out to test whether top-down attention could be successfully incorporated into pre-trained DCNNs for object recognition as a plug-and-play additional layer. The theoretical idea evaluated was that top-down expectations (not driven by recent inputs) could reconfigure the existing network to specialise for the current task. In humans and non-human primates, this type of attention is thought to rely on top-down influences from prefrontal cortex.

Rather than aim for a deployable system, we instead evaluated some general hypotheses about how top-down attention should impact network performance. We predicted that as attention intensity (a hyperparameter in our model) increased that both the costs and benefits of attention should increase. We evaluated this hypothesis across three computational experiments, involving either standard images, blended images, or natural adversarial images. The basic prediction was that both the costs and benefits of attention should in-
Increase as attention intensity increases. We also predicted that there should be a sweet spot at moderate attention intensity where these benefits and costs would successfully balance.

All predictions held across all studies. We evaluated network performance in signal detection terms. Benefits, measured in terms of hit rate (e.g., responding Tabby Cat with Tabby Cat attention weights when a Tabby Cat is present), increased with increasing attention intensity. Likewise, costs, measured in terms of false alarm rate (e.g., responding Tabby Cat with Tabby Cat attention weights when a Tabby Cat is not present), increased with increasing attention intensity. Overall benefits, measured in terms of sensitivity (i.e., $d'$), peaked for moderate levels of attention. We predicted the location of this peak as it was for an attention intensity setting that effectively balanced the importance of target and non-target items when training the attention weights. Bias toward the target category also increased with increasing attention intensity. Much like people, the network had a propensity to see what it expected.

Top-down attention appeared to reconfigure the network to specialise it for detecting the target class, much like how top-down attention reconfigures the human visual system when searching for a particular target (e.g., one’s keys). Consistent with this notion, increasing attention intensity had the effect of increasing the variance of attention weights, which reweight filter response, and turning off filters not relevant for detecting the target class (see Figure 4). One possible view is that the pre-trained DCNN effectively contains numerous subnetworks, many of which are not relevant to the current task and add unhelpful noise to the network response.

Attention weighting could help by silencing irrelevant aspects of the network and amplifying relevant aspects.

We set out to evaluate basic theoretical principles by evaluating attention weights trained for specific target classes. Although that satisfied our aims, successful systems may instead generalise across attention sets. For example, knowing what is relevant to attend when searching for a cat should overlap more with what is relevant when searching for a dog than for a truck. One solution is for the top-down signal itself to be a trained network that configures the attention weights for the current task goal. Such networks could also be endowed with the capability to search for conjunctions and disjunctions of target classes. We hope our results provide a foundation for such future work.

Our top-down filter-based attention is distinct from work in spatial attention, though it could be related. For example, an attentional spotlight could move to areas of an image most responsible for driving top-down attention-weighted filters’ responses. Likewise, our work could be extended to characterise the interplay of bottom-up saliency driven attentional capture with top-down goal-directed attention.

Neuroscience and machine learning have been enjoying a virtuous cycle in which advances in one field spurs advances in the other. For example, DCNNs were loosely inspired from the structure of the ventral visual stream and in turn have proven useful in understanding neuroscience data from these same brain regions. We hope that our work hastens this virtuous cycle by begetting more useful machine learning models that in turn inform our understanding of the brain.
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References

Ahlheim, C. and Love, B. C. Estimating the functional dimensionality of neural representations. *NeuroImage*, 179:51–62, 10 2018. ISSN 10959572. doi: 10.1016/j.neuroimage.2018.06.015.

Bahdanau, D., Cho, K., and Bengio, Y. Neural Machine Translation by Jointly Learning to Align and Translate. In *ICLR*, 2015. URL http://arxiv.org/abs/1409.0475.

Bar, M. A Cortical Mechanism for Triggering Top-Down Facilitation in Visual Object Recognition. *Journal of Cognitive Neuroscience*, 15(4):600–609, 2006.

Braunlich, K. and Love, B. C. Occipitotemporal representations reflect individual differences in conceptual knowledge. *Journal of Experimental Psychology: General*, 148(7):1192–1203, 7 2019. ISSN 00963445. doi: 10.1037/xge0000501.

Chen, L., Zhang, H., Xiao, J., Nie, L., Shao, J., Liu, W., and Chua, T. S. SCA-CNN: Spatial and channel-wise attention in convolutional networks for image captioning. In *Proceedings - 30th IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2017*, volume 2017-January, pp. 6298–6306. Institute of Electrical and Electronics Engineers Inc., 11 2017. ISBN 9781538604571. doi: 10.1109/CVPR.2017.667.

Connor, C. E., Egeth, H. E., and Yantis, S. Visual attention: Bottom-up versus top-down, 10 2004. ISSN 09609822.

Deng, J., Dong, W., Socher, R., Li, L.-J., Li, K., and Fei-Fei, L. ImageNet: A Large-Scale Hierarchical Image Database. In *CVPR*. IEEE, 2009. ISBN 9781424439913.

Goodfellow, I. J., Shlens, J., and Szegedy, C. Explaining and Harnessing Adversarial Examples. In *International Conference on Learning Representations*, 2015. URL http://arxiv.org/abs/1412.6572.

Guest, O. and Love, B. C. Levels of Representation in a Deep Learning Model of Categorization. *bioRxiv*, pp. 626374, 5 2019. doi: 10.1101/626374.

Hendrycks, D., Zhao, K., Basart, S., Steinhardt, J., and Song, D. Natural Adversarial Examples. In *ICML*, 2019. URL http://arxiv.org/abs/1907.07174.

Hu, J., Shen, L., and Sun, G. Squeeze-and-Excitation Networks. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pp. 7132–7141. IEEE Computer Society, 12 2018. ISBN 9781538664209. doi: 10.1109/CVPR.2018.00745.

Itti, L. and Koch, C. Computational modelling of visual attention. *Nature Reviews Neuroscience*, 2(3):194–203, 2001. ISSN 14710048. doi: 10.1038/35058500.

Itti, L., Koch, C., and Niebur, E. Short Papers A Model of Saliency-Based Visual Attention for Rapid Scene Analysis. *IEEE TRANSACTIONS ON PATTERN ANALYSIS AND MACHINE INTELLIGENCE*, 20(11), 1998.

Jetley, S., Lord, N. A., Lee, N., and Torr, P. H. S. Learn To Pay Attention. In *ICLR*, 2018. URL http://arxiv.org/abs/1804.02391.

Katsuki, F. and Constantinidis, C. Bottom-up and top-down attention: Different processes and overlapping neural systems, 10 2014. ISSN 10894098.

Krizhevsky, A., Sutskever, I., and Hinton, G. E. ImageNet classification with deep convolutional neural networks. In *Advances in Neural Information Processing Systems*, volume 2, pp. 1097–1105, 2012. ISBN 9781627480031.

Kruschke, J. K. ALCOVE: A Connectionist Model of Human Category Learning. *Psychological Review*, 99(1):22–44, 1992.

Lindsay, G. W. and Miller, K. D. How biological attention mechanisms improve task performance in a large-scale visual system model. *eLife*, 7, 10 2018. ISSN 2050084X. doi: 10.7554/eLife.38105.

Love, B. C., Medin, D. L., and Gureckis, T. M. SUSTAIN: A Network Model of Category Learning. *Psychological Review*, 111(2):309–332, 4 2004. ISSN 0033295X. doi: 10.1037/0033-295X.111.2.309.

Mack, M. L., Love, B. C., and Preston, A. R. Dynamic updating of hippocampal object representations reflects new conceptual knowledge. *Proceedings of the National Academy of Sciences of the United States of America*, 113(46):13203–13208, 11 2016. ISSN 10916490. doi: 10.1073/pnas.1614048113.

Mack, M. L., Preston, A. R., and Love, B. C. Ventromedial prefrontal cortex compression during concept learning. *Nature Communications*, 11(1), 12 2020. ISSN 20411723. doi: 10.1038/s41467-019-13930-8.

MacMillan, N. A. Signal Detection Theory. In *Stevens’ Handbook of Experimental Psychology*. John Wiley & Sons, Inc., Hoboken, NJ, USA, 7 2002. doi: 10.1002/0471214426pas0402. URL http://doi.wiley.com/10.1002/0471214426pas0402.
Miller, E. K. and Cohen, J. D. An Integrative Theory of Prefrontal Cortex Function. *Annual Review of Neuroscience, 24*(1):167–202, 3 2001. ISSN 0147-006X. doi: 10.1146/annurev.neuro.24.1.167.

Nguyen, A., Yosinski, J., and Clune, J. Deep neural networks are easily fooled: High confidence predictions for unrecognizable images. In *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, volume 07-12-June-2015, pp. 427–436. IEEE Computer Society. 10 2015. ISBN 9781467369640. doi: 10.1109/CVPR.2015.7298640.

Nosofsky, R. M. Attention, similarity, and the identification-categorization relationship. *Journal of Experimental Psychology: General, 115*(1):39–57, 1986. ISSN 0096-3445. doi: 10.1037/0096-3445.115.1.39.

Plebanek, D. J. and Sloutsky, V. M. Costs of Selective Attention: When Children Notice What Adults Miss. *Psychological Science, 28*(6):723–732, 6 2017. ISSN 14679280. doi: 10.1177/0956797617693005.

Roe, A. W., Chelazzi, L., Connor, C. E., Conway, B. R., Fujita, I., Gallant, J. L., Lu, H., and Vanduffel, W. Toward a Unified Theory of Visual Area V4, 4 2012. ISSN 08966273.

Schrimpf, M., Kubilius, J., Hong, H., Majaj, N. J., Rajalingham, R., Issa, E. B., Kar, K., Bashivan, P., Prescott-Roy, J., Schmidt, K., Yamins, D. L. K., and DiCarlo, J. J. Brain-Score: Which Artificial Neural Network for Object Recognition is most Brain-Like? *bioRxiv*, 2018. doi: 10.1101/407007. URL http://dx.doi.org/10.1101/407007.

Simonyan, K. and Zisserman, A. Very Deep Convolutional Networks for Large-Scale Image Recognition. In Yoshua Bengio and Yann LeCun (ed.), *International Conference on Learning Representations, 2015*. URL http://arxiv.org/abs/1409.1556.

Song, Y., Kushman, N., Shu, R., and Ermon, S. Constructing unrestricted adversarial examples with generative models. In *Advances in Neural Information Processing Systems*, volume 2018-December, pp. 8312–8323. Neural information processing systems foundation, 2018.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, L., and Polosukhin, I. Attention is all you need. In *Advances in Neural Information Processing Systems*, volume 2017-December, pp. 5999–6009. Neural information processing systems foundation, 2017.

Wolfe, J. M. Guided Search 2.0 A revised model of visual search. *Psychonomic Bulletin & Review, 1*(2):202–238, 6 1994. ISSN 10699384. doi: 10.3758/BF03200774.