Modulation of early visual processing alleviates capacity limits in solving multiple tasks

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Abstract
In daily life situations, we have to perform multiple tasks given a visual stimulus, which requires task-relevant information to be transmitted through our visual system. When it is not possible to transmit all the possibly relevant information to higher layers, due to a bottleneck, task-based modulation of early visual processing might be necessary. In this work, we report how the effectiveness of modulating the early processing stage of an artificial neural network depends on the information bottleneck faced by the network. The bottleneck is quantified by the number of tasks the network has to perform and the neural capacity of the later stage of the network. The effectiveness is gauged by the performance on multiple object detection tasks, where the network is trained with a recent multi-task optimization scheme. By associating neural modulations with task-based switching of the state of the network and characterizing when such switching is helpful in early processing, our results provide a functional perspective towards understanding why task-based modulation of early neural processing might be observed in the primate visual cortex.²

Keywords: neural modulation, multi-task learning, early visual cortex, attention, perception, capacity limits

Introduction
Humans and other animals have to perform multiple tasks given a visual stimulus. For example, seeing a face, we may have to say whether it is happy or sad, or recognize its identity. For each of these tasks, a subset of all the features of the face are useful. In principle, it could be possible for a visual system to extract all of the features necessary to solve all possible tasks, and then select the relevant information from this rich representation downstream. However, as the number of tasks increases, a network with a limited capacity may not be able to extract all of the potentially relevant features (an information bottleneck is manifest), requiring the information that is extracted from the stimulus in the early processing stages to change according to the task. Several studies in neuroscience have found evidence for such task-dependent modulations of sensory processing in the primate visual system, including at the early levels (Carrasco, 2011; Maunsell & Treue, 2006; Gilbert & Li, 2013). For example, human neuroimaging studies have shown that attending to a stimulus could lead to an increase in the accuracy with which its task-relevant features could be decoded by a classifier in early visual areas (Jehee, Brady, & Tong, 2011), and neurophysiological experiments in non-human primates have shown that the stimulus selectivity of neurons in primary visual cortex was dependent on the task the monkeys had to perform (Gilbert & Li, 2013).

Despite the observation of such modulations of early visual processing, it is not clear whether they are causally necessary for performing better on the corresponding tasks. This question has been addressed by deploying biologically-inspired task-based modulations on computational models. Lindsay and Miller (2018) showed that task-based modulation deployed on multiple stages of a convolutional neural network improves performance on challenging object classification tasks. Other recent work (Thorat, van Gerven, & Peelen, 2018; Rosenfeld, Biparva, & Tsotsos, 2018) has also shown that task-based modulation of early visual processing aids in object detection and segmentation in addition to the task-based modulation of late processing. However, the conditions under which early modulation can be beneficial in performing multiple tasks have not been systematically investigated.

In the present work, we assessed the effectiveness of task-based modulation of early visual processing as a function of an information bottleneck in a neural network, quantified by the number of tasks the network had to execute and the neural capacity of the network. To do so, we trained networks to, given an image, provide an answer conditioned on the cued task. Every task required detecting the presence of the corresponding object in the image. The networks were trained according to a recent framework proposed in the field of continual learning (Cheung, Terekhov, Chen, Agrawal, & Olshausen, 2019), which helps them execute multiple tasks by switching their state given a task cue, in order to transmit relevant information through the network. In this work, to quantify the effectiveness of task-based modulation of early neural processing, we measured the increase in performance provided by modulating early neural processing in addition to modulating the late neural processing in the networks.

Methods
Task and system description
In a multi-task setting, object detection can be thought of as solving one of a set of possible binary classification (one object versus the rest) problems. Given an image and a task cue indicating the identity of the object to be detected, a network had to output if the object in the image matched the task cue.

We used MNIST (LeCun, Bottou, Bengio, & Haffner, 1998)
digits and their permutations as objects (Kirkpatrick et al., 2017). The original MNIST dataset has 28 × 28 px² images of 10 digits. Each permuted version consists of images of those 10 digits, whose pixels undergo a given permutation, creating 10 new objects. We varied the number of permutations used (10, 25, and 50) to modulate the number of tasks the networks had to perform (which are 10 times the number of permutations).

We considered a multilayer perceptron with rectified linear units (ReLU), which had one hidden layer between the input (image) and the binary output. The number of neurons in the hidden layer were variable (32, 64, and 128) and determined the neural capacity of the late stage of the network.

**Task-based modulation and its function**

Modelling biological neurons as perceptrons (Rosenblatt, 1957), task-based modulations have been shown to affect the effective biases and gains of the neurons (Maunsell & Treue, 2006; Boynton, 2009; Ling, Liu, & Carrasco, 2009). The nature of modulation - which neurons to modulate and how - is under debate (Boynton, 2009; Thorat et al., 2018). We adapted these findings by introducing task-based modulation into our networks via the biases of the perceptrons and the gains of their ReLU activation functions. The modulations were then trained end-to-end with the rest of the network.

Given a particular task, the task cue is a one-hot encoding of the relevant object. Task-based modulation is mediated through bias and gain modulation in the following manner.

\[
x_n = [W_n(g_{n-1} \circ x_{n-1}) + b_n]_+ \\
g_n = G_n c, \quad b_n = B_n c
\]

where the transformation between layers \( n - 1 \) and \( n \) \((L_{n-1} \rightarrow L_n)\) is modulated by changing the slope of the ReLU activation function \((g_n, g_{n-1})\) in \( L_{n-1} \) and the bias \((b_n)\) to the perceptrons in \( L_n \); \( x_n \) are the pre-gain activations of the perceptrons in \( L_n \), \( W_n \) is the task-independent transformation matrix between \( L_{n-1} \) and \( L_n \), \( G_n \) and \( B_n \) map the task cue \( c \) (one-hot encoding of the relevant object \( k \)) to the gain and bias modulations of the perceptrons in \( L_n \) respectively, and \( \circ \) refers to element-wise multiplication.

Given a task \( k \), modulating the gains of the pre-synaptic perceptrons (in \( L_{n-1} \)) and the biases of the post-synaptic perceptrons (in \( L_n \)) transforms the information transformation between \( L_{n-1} \) and \( L_n \). This allows for the transmission of information required to perform task \( k \), while ignoring the information required to perform the other tasks, as formalized in Cheung et al. (2019). This transformation can also be thought of as the network switching its state to selectively transmit task-relevant information downstream (see Figure 1). The conditions - the nature of these modulations and the neural capacity of the network - under which the network can switch between a given number of tasks, are preliminarily described in Cheung et al. (2019).

Here, for every relevant layer \( L_n \), \( W_n \), \( B_n \), and \( G_n \) were jointly learned for the given number of tasks.

**Evaluation metric and expected trends**

The effectiveness of early neural modulation was quantified by the average absolute increase in detection performance across all the tasks when modulations were implemented on both the transformations \( L_1 \rightarrow L_2 \) and \( L_2 \rightarrow L_3 \). We considered adaptive stochastic gradient descent with backpropagation through the ADAM optimizer (Kingma & Ba, 2014) with the default settings in TensorFlow (v1.4.0) and \( \alpha = 10^{-3} \). We used a batch size of 100. Half of each batch contained randomly selected images of randomly selected tasks where the cued object was present, and half where the cued object was not present. These images were taken from the MNIST training set and its corresponding permutations. The images were augmented by adding small translations and some noise. We trained each network with \( 10^7 \) such batches. The relevant metrics discussed in the previous section are computed at the end of training over a batch of size \( 10^5 \) created from the MNIST test set and its corresponding permutations.

![Figure 1: The effect of bias and gain modulation on the transformations in the network. Modulating the gains and biases on the transforms is functionally equivalent to switching the transformation being performed to one suited for the relevant task. Such an example of switching is visualized in the figure. Given a task cue corresponding to object \( k \), corresponding gain and bias modulations are applied, which results in the \( L_{n-1} \rightarrow L_n \) transformation being switched into one that transmits feature information required to detect the presence or absence of object \( k \).](image)
We first analyzed the detection performance of the network with only $L_2 \rightarrow L_3$ modulation. The network performance as a function of the number of neurons in $L_2$ and the number of detection tasks the network had to perform is shown in Figure 2 (red circles). The network performance increased with an increase in the number of neurons in $L_2$, as the neural capacity increased. The performance decreased with an increase in the number of tasks to be performed, as the representational capacity of the network for any one task was reduced. A network with as little as 32 neurons in its hidden layer was able to switch between as many as 500 detection tasks, while keeping the average detection performance across all the tasks as high as 87%, thus replicating the success of the multi-task learning framework proposed by Cheung et al. (2019).

To assess the dependence of the effectiveness of task-based modulation of early neural processing ($L_1 \rightarrow L_2$) on the bottleneck in the network, we analyzed the boost in average detection performance when task-based modulation of $L_1 \rightarrow L_2$ was deployed in addition to task-based modulation of $L_2 \rightarrow L_3$, as a function of the number of neurons in $L_2$ and the number of detection tasks the network had to perform. The resulting boosts are shown in Figure 2 ($\Delta_1$ quantification). The performance boost increased as the number of neurons in $L_2$ decreased, and as the number of tasks the network has to perform increased. This confirms the hypothesis that task-based modulation of early neural processing is essential when an information bottleneck exists in a subsequent processing stage.

**The contribution of bias and gain modulation**

Gain, but not so much bias, modulation of neural responses has been observed in experiments investigating feature-based attention in the monkey/human brain (Maunsell & Treue, 2006; Boynton, 2009). We assessed how the two contributed to the overall modulation of the transformations in the network.

We selectively turned off the bias or gain modulation for all the variants of the network that were trained. The average detection performance decreased by $43.0 \pm 2.0\%$ when gain modulation was turned off, and by $3.9 \pm 0.9\%$ when bias modulation was turned off, suggesting that in our framework, when jointly deployed, gain modulation is more important than bias modulation in switching the state of the network to be able to perform the desired task well.

We also trained a network with 32 neurons in $L_2$, on 25 permutations of MNIST, with gain-only or bias-only modulations of both the $L_1 \rightarrow L_2$ and $L_2 \rightarrow L_3$ transformations. When the gain and bias modulations were jointly trained, the network performance was 94.7%. With gain-only modulation, the performance was 94.8%, and with bias-only modulation the performance was 90.9%. As the performance when only bias modulation was deployed was much higher than chance (50%), we can conclude that bias modulation alone can also lead to efficient task-switching. When the bias and gain modulations are jointly trained, gain might take over as it multiplicatively impacts responses, and therefore has higher gradients during training, as opposed to the additive impact of bias.

### Results

To further investigate the relevance of our findings to biological visual systems, in follow-up work we intend to deploy our modulation scheme on architectures that bear more similarity to the primate visual hierarchy, such as deep convolutional networks (Kriegeskorte, 2015), datasets of naturalistic images.
such as ImageNet (Russakovsky et al., 2015), and general naturalistic tasks such as visual question answering (Agrawal et al., 2017). This will allow us to assess whether the functional advantage provided by early modulation holds true in a more realistic scenario, and whether the resulting modulation schemes resemble those observed in the early visual areas of the primate brain.

Finally, a key aspect of our approach is the fact that the network is constantly operating in a task-dependent manner. Most previous approaches to task-dependent modulation have assumed the presence of an underlying task-free representation on which the modulation operates (for example, in the case of Lindsay and Miller (2018) this corresponds to a network pre-trained on object recognition). Providing the network with task cues during the training phase, on the other hand, has been used in the field of continual learning (Cheung et al., 2019; Masse, Grant, & Freedman, 2018; Yang, Joglekar, Song, Newsome, & Wang, 2019), and according to one influential theory in neuroscience, the interplay between sparse, context-specific information encoded by the hippocampus and shared structural information in the neocortex is crucial for learning new tasks without overwriting previous ones (Kumaran, Hassabis, & McClelland, 2016). To our knowledge, the question of how the task-based modulations observed in visual cortex might be learned has not been explicitly addressed in previous literature. On the one hand, it is possible that a context-free representation is learned first, possibly through unsupervised learning, and then modulated upon. On the other, learning of representations and task modulations might interact at all stages, allowing the representations to be optimized for the type of modulations they are subject to. Whether one scheme or the other constitutes a better explanation for the modulations observed in biological visual systems is an important direction for future research.

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