precipitate the change within the laboratory environment.

Get on a Project
Pick one new project to work on using the new language. Solving concrete problems will force students and PI alike to learn skills directly relevant to their research. Ideally, this project will build on a real strength of the new language that demonstrates its added utility compared with the prior language. Python, for example, has unparalleled offerings for machine learning (scikit-learn, tensorflow, pytorch and keras, among others). Advanced statistical modeling and data visualization both have remarkable solutions implemented in R. The idea is to start getting the reward for the change as early as possible, allowing you to stay motivated to move forwards.

Divide and Conquer
If the laboratory has an extensive code base written with the old scientific stack, a transition period is unavoidable. Gradually start using the new language for small projects and slowly transition some functionalities from the legacy code base. You may be surprised to discover that large portions of the legacy code base have drop-in replacements in the new language, which may even be of better quality and wider functionality.

Contribute to Open-Source Software
Open-source communities offer a unique learning experience for coding, such as the development teams behind nilearn (https://nilearn.github.io/), nipype (https://nipy.readthedocs.io), MNE (https://martinos.org/mne/), and DIPY (http://nipy.org/dipy/). These communities welcome new contributors and have established guidelines to help them get onboard. There are also initiatives such as ‘hacktoberfest’ and dedicated scientific workshops such as brainhack (www.brainhack.org; for neuroscientists) and the NCBI hackathons (https://biohackathons.github.io/) for bioinformatics where new contributors can often get in-person support to get started. Even if new contributors simply work on improving the documentation or adding new tests, the contributor may receive extensive feedback on their code, and will also have to look into an established code base adhering to some of the best development practices. For these reasons, the learning benefits of contributing to open-source software cannot be overstated.

With the advent of ever-more-complex analyses and ever-growing datasets, staying on top of one’s software stack is a core challenge for every scientist. We hope that this article can provide a helpful resource for researchers at any career stage who are looking to switch their primary programming language or scientific software.

Acknowledgments
We thank everyone who participated in the discussion on the initial Twitter thread. Figure 1 uses several openly available vector graphics downloaded from freepik.com.

A deeply challenging and popular question concerns what information is preserved during processing of invisible stimuli. Can an invisible stimulus reach processing stages commonly attributed to high-level semantic or cognitive processing? Continuous flash suppression (CFS) is a perceptual suppression technique that provides a means to test this question because it allows for keeping stimuli invisible for considerably more time than traditional suppression methods. Over the past 15 years, a substantive literature has accumulated and parts of this literature suggest that high-level processing of unseen stimuli as integrated, semantic entities can indeed occur. This notion of integrated high-level processing was recently challenged by highlighting that interocular suppression, the putative mechanism underlying CFS, likely relies on representations of fractionated stimuli early in visual cortex [1,2]. That is, interocular competition acts on the low-level features that are the consequence of stimulus fractionation in early visual processing.

Sklar et al. [3] do not challenge the premises on which our arguments rest, yet instead argue that a selective review of the literature can indeed lead to our ‘pessimistic’ fractionation account. They cite several findings consolidating their point that there is sufficient evidence for high-level processing.
despite stimulus fractionation. In principle, we do not disagree with the examples of high-level processing that are presented. Indeed, considered together they paint a positive and convincing picture. However, any particular selection of findings necessarily biases one’s reading of the literature, in either direction.

We argue that not all published CFS studies should be weighted equally when debating whether high-level processing occurs under CFS. We outline three criteria we consider crucial to assess a study’s evidential weight. None of the studies Sklar et al. [3] cite pass these three criteria. Therefore, we consider their examples to be unsatisfactory to claim high-level processing during CFS.

(i) Breaking CFS Findings Are Insufficient to Claim Unconscious Processing
Many studies Sklar et al. present as evidence for high-level processing are breaking CFS studies (where the time for an invisible stimulus to overcome CFS is used as a measure for unconscious processing). An aspect that is rarely highlighted in this discussion on high-level processing during CFS is that it is currently debated whether this paradigm can provide evidence for unconscious processing at all [4,5]. Nevertheless, even if it is considered to be a valid tool, very few studies show high-level unconscious processing if the proper controls are included [6]. Indeed, we consider the dissociation approach where an implicit processing measure is contrasted with an explicit awareness measure to be the stronger, more valid approach to claim genuine unconscious processing (see [7] for an example).

(ii) Findings That Have Not Yet Been Subject to Replication Should Be Judged with Caution
The CFS literature is riddled with so-called ‘one-off’ findings. As publication bias is still thriving, it is difficult to judge the evidential value of these findings, even if a published study consists of a set of multiple experiments, where each experiment is the logical next step based on the results of the previous experiment. Thus, to judge the evidence for high-level unconscious processing, findings that have been the subject of a replication study should be given much more weight compared to other findings. As a clear example of high-level processing during CFS, Sklar et al. highlight a study where expressions of unseen faces influence the perception of visible, neutral faces [8]. However, the same lab has now called into question the unconscious nature of this effect [9]. More generally, most studies claiming high-level unconscious visual processing that have been the target for replication fail to replicate [10].

(iii) More Parsimonious Explanations of the Findings Should Be Exhausted before Claiming High-Level Processing
A canonical case of invoking a more parsimonious explanation for a CFS finding is showing that low-level stimulus confounds or statistical artifacts due to post hoc data sorting explain the results. Sklar et al. present studies on certain emotional expressions having preferential access to awareness as examples of high-level unconscious processing. However, it has been shown that low-level stimulus differences between these expressions explain these results [11]. Relatedly, Stein et al. [12] showed that facial dominance, and trustworthy-related differences in suppression times, can be explained by physical differences between stimuli in the eye region, as differences in suppression durations between dominance or trustworthy conditions were still observed with cropped versions of these faces for which observers could no longer rate the dominance or trustworthiness.

We believe passing these three criteria is critical for claiming genuine high-level unconscious processing. Despite their subjective nature, they provide a useful benchmark to evaluate the literature in its proper context. Their application will facilitate a constructive discussion regarding the state of the literature. We hope this will ultimately enable a consensus view on high-level processing under CFS, providing solid groundwork on which future studies can be built.
Letter
High Action Values Occur Near Our Body

Jean-Paul Noel¹ and Andrea Serino²,*

In a recent Opinion article Bufacchi and Iannetti (2018) [1] claim that peripersonal space (PPS) – the space immediately adjacent to one’s body – is widely considered to be ‘a single entity, with binary in-or-out boundary, and mostly dependent on stimulus proximity to the body’. In counterpoint, the authors argue that PPS should not be conceived as an area of space demarked by a strong boundary but instead as ‘fields’ computing ‘contact-related behavioral relevance’ [1]. They argue that this conceptualization (i) allows PPS measures to change gradually with distance, (ii) reflects the fact that there are many different PPS measures showing different response profiles, and (iii) explains the functional significance of the values composing PPS. Regarding this last point, they suggest that ‘[t]here is no reason to think that . . . stimulus proximity is more important to PPS measures than any of the other factors they are sensitive to’. We fully agree with (i) and (ii); PPS should be conceived as a gradient and as plurality of representations [2]. Contrarily, we argue that, although PPS can be conceived as a ‘value field’, and this definition indeed allows disparate neural networks (e.g., reward systems) to interact with the PPS network, ‘value’ for PPS neurons is nevertheless defined by proximity to the body and is encoded by a specific population of multisensory neurons.

Bufacchi and Iannetti (2018) [1] argue that, because a whole host of phenomena (e.g., tool-use, personality traits) modulate the size and shape of PPS, when indexing PPS we are in fact measuring the value of performing a particular action, given the structure of our environment and our action possibilities. This argument is appealing in that it places PPS within the perception-to-action continuum [3], in line with the location of PPS neurons within sensorimotor frontoparietal networks [4]. Further, because ‘values’ are the measure of interest, this theory reinforces the fact that PPS-related processing can occur in areas beyond frontoparietal networks, such as in prefrontal and limbic areas. This framework beyond classic sensorimotor loops helps to clarify how, for instance, the perceived moral quality of a conspecific [5] or idiosyncratic phobias [6,7] can modulate PPS. Lastly, the theory provides clear leverage on open questions within the field, specifically from the perspective of developmental psychology and computational modeling. Namely, if one ascribes the PPS literature to ‘value’ computation, we would need to suppose that PPS is matured over development as a consequence of reinforcement learning.

Taking the reinforcement learning perspective further, however, leads to the conclusion that, in principle and given enough time, PPS values (most of them close to zero) will exist for all space and time coordinates. For example, there is a particular value in my taking action today for a potential consequence in 10 years. This possibility, however, refers back to the earlier neurophysiological literature (e.g., [8,9]) which is notorious because it holds that particular actions – those that are most relevant because of spatiotemporal proximity – are directly mapped onto specific neurons. Even though a larger neural network, including reward centers, may be involved in computing the value of executing any possible action at all possible positions in space and time, the matter of the fact is that there are specific multisensory neurons that encode potential contact and action possibilities in near space and time [10,11]. Thus, although Bufacchi and Iannetti [1] provide an appealing functional view, from a neurobiological standpoint it is simply the case that neurons with explicit proximity tuning – via spatially overlapping, body part-centered, multisensory receptive fields – have been described [8,9]. Likely, these neurons exist because the physical laws of our environment are such that objects move gradually across space/time and do not jump instantaneously across these dimensions. Further, tactile receptive fields are anchored on our body, we can only manipulate and physically interact with objects near us, and damage to our bodies implies direct physical contact. Thus, the value of performing a goal-directed action or avoiding a threat is by necessity higher in close spatiotemporal proximity. In turn, as Bufacchi and Iannetti [1] propose, it is possible that values associated with particular actions are computed in a distributed manner, but it seems equally true that high values are encoded explicitly in PPS neurons and that the defining characteristic of these neurons is the fact that they encode proximity. In other words, we propose that value functions across the entirety of space and time may be approximated/estimated in a distributed manner – the only way this is feasible, given the computational burden. Importantly, these values only cross a certain threshold, leading to potential defensive or goal-directed behavior, when a stimulus is in close spatiotemporal proximity – because they are explicitly hard-coded in PPS neurons. This hard