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A neural circuit for flexible control of persistent behavioral states

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16 ABSTRACT

To adapt to their environments, animals must generate behaviors that are closely aligned 17 to a rapidly changing sensory world. However, behavioral states such as foraging or courtship 18 typically persist over long time scales to ensure proper execution. It remains unclear how neural 19 circuits generate persistent behavioral states while maintaining the flexibility to select among 20 alternative states when the sensory context changes. Here, we elucidate the functional 21 22 architecture of a neural circuit controlling the choice between roaming and dwelling states, which underlie exploration and exploitation during foraging in C. elegans. By imaging 23 ensemble-level neural activity in freely-moving animals, we identify stereotyped changes in 24 25 circuit activity corresponding to each behavioral state. Combining circuit-wide imaging with genetic analysis, we find that mutual inhibition between two antagonistic neuromodulatory 26 27 systems underlies the persistence and mutual exclusivity of the neural activity patterns observed in each state. Through machine learning analysis and circuit perturbations, we identify a sensory 28 processing neuron that can transmit information about food odors to both the roaming and 29 dwelling circuits and bias the animal towards different states in different sensory contexts, giving 30 rise to context-appropriate state transitions. Our findings reveal a potentially general circuit 31 32 architecture that enables flexible, sensory-driven control of persistent behavioral states.

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34 INTRODUCTION

The behavioral state of an animal—whether it is active, inactive, mating, or sleeping influences its perception of and response to the environment^{1–5}. In contrast to fast motor actions, behavioral states are often highly stable, lasting from minutes to hours. Despite this remarkable stability, animals can flexibly choose their behavioral state based on the sensory context and 39

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switch states when the context changes⁶⁻⁸. How the brain generates persistent behavioral states while maintaining the flexibility to select among alternative states is not well understood.

At the neural level, persistent behavioral states are often associated with stable patterns of 41 neural activity. For example, continuous activation of pCd neurons in male Drosophila underlies 42 persistent courtship and aggressive behaviors⁹. In addition, recent large-scale recordings of 43 neural activity have revealed that behavioral states such as sleep and active locomotion are 44 represented as stable, stereotyped activity patterns in neurons spanning multiple brain 45 regions^{5,6,10–13}. While the encoding of a behavioral state can be broadly distributed, the neurons 46 47 that control the onset and duration of a state are often a smaller subset of those that comprise the full circuit^{6,14}. To gain mechanistic insights into how persistent behavioral states are generated 48 and controlled, it will be critical to elucidate the functional interactions among key control 49 50 neurons and understand how they incorporate incoming sensory inputs that influence behavioral 51 states.

52 Past studies have proposed recurrent circuitry and neuromodulation as two central 53 mechanisms that contribute to the generation of persistent behavioral states. While theoretical 54 studies have shown that recurrent excitatory or inhibitory feedback can underlie stable firing patterns^{15–18}, direct experimental evidence linking recurrent circuitry with persistent activity 55 during minutes-long behavioral states remains scarce (the role of recurrent inhibition in fast 56 timescale switching is better established^{19,20}). Neuromodulators are known to control persistent 57 behaviors like sleep and wake states, as well as states of stress and hunger²¹⁻²⁴. However, our 58 59 understanding of how ongoing neuromodulator release in vivo promotes persistent circuit activity remains limited. In addition, it is unclear how dynamic sensory inputs interact with recurrent 60

circuitry and neuromodulation to elicit behavioral state transitions in a changing sensoryenvironment.

63 In this study, we investigate the neural circuit mechanisms that give rise to circuit-level activity patterns during persistent foraging states in C. elegans. While foraging on bacterial food, 64 C. elegans alternate between roaming states, characterized by high-speed forward movement and 65 occasional reorientations, and dwelling states, marked by slow forward and backward 66 movements^{25–28}. Each state can last up to tens of minutes and the transitions between states are 67 abrupt. The fraction of time an animal spends in each state is influenced by its satiety, ingestion 68 of bacterial food, and sensory cues such as odors^{25,26,29-31}. Consistent with the notion that these 69 70 states reflect an exploration-exploitation tradeoff, animals favor dwelling in food-rich environments and after starvation, but favor roaming in poor-quality food environments and after 71 aversive stimulation. 72

73 We and others previously found that serotonin (5-HT) and the neuropeptide pigment-74 dispersing factor (PDF) act as opposing neuromodulators that stabilize dwelling and roaming states, respectively^{31–35}. Serotonin acts through the serotonin-gated chloride channel MOD-1 to 75 promote dwelling, with a smaller contribution from the other serotonin receptors³³. PDF-1 and -2 76 neuropeptides act through a single PDF receptor, PDFR-1, to drive roaming³³. Cell-specific 77 genetic perturbations uncovered the neurons that produce and detect these neuromodulators to 78 control the stability of each behavioral state³³. However, these identified neurons are densely 79 80 interconnected with one another and with other neurons in the C. elegans connectome, making it infeasible to infer the core functional circuitry that shapes the roaming and dwelling states from 81 these previous genetic studies. Crucially, it remains unclear how 5-HT and PDF impact overall 82 circuit activity to promote persistent behavioral states. In addition, while it is known that the 83

sensory environment can influence roaming and dwelling, how sensory inputs converge onto this
core neuromodulatory circuit to influence behavioral states remains an open question.

To address these questions, we performed simultaneous calcium imaging of defined 86 neurons throughout the roaming-dwelling circuit in freely-moving animals. We identified 87 stereotyped, circuit activity patterns corresponding to each foraging state. By combining circuit 88 imaging with genetic perturbations, we identified a mutual inhibitory loop between the 89 90 serotonergic NSM neuron and the 5-HT and PDF target neurons. We found that this mutual inhibition is critical for the persistence and mutual exclusivity of the neural activity patterns 91 observed during roaming and dwelling. Furthermore, we found that the AIA sensory processing 92 93 neuron sends parallel outputs to both neuromodulatory systems and can bias the circuit towards either roaming or dwelling, depending on the overall sensory context. Together, these results 94 95 identify a functional circuit architecture that allows for flexible, sensory-driven control of 96 persistent behavioral states.

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98 **RESULTS**

99 Roaming and dwelling states are associated with stereotyped changes in circuit activity

To understand how roaming and dwelling states arise from circuit-level interactions between neurons, we sought to monitor the activity of neurons throughout the core roamingdwelling circuit in wild-type animals and additionally during perturbations that alter signaling among the neurons. We built a calcium imaging platform with a closed-loop tracking system that allows for simultaneous imaging of many neurons as animals freely move (Fig. 1A and Figure 1-Figure Supplement 1A-B)³⁶⁻³⁸. We generated a transgenic line where well-defined promoter 106 fragments were used to express GCaMP6m in a select group of 10 neurons (Fig. 1B; Figure 1-Figure Supplement 1C-D; Figure 1-Figure Supplement 2). These neurons were selected based on 107 their classification into at least one of the three following groups: (1) neurons expressing 5-HT, 108 PDF, or their target receptors MOD-1 or PDFR-1³³, (2) neurons that share dense synaptic 109 connections with those in group 1, and (3) premotor or motor neurons whose activities are 110 associated with locomotion^{20,39}. A small subset of neurons that had been implicated in roaming 111 and dwelling states were omitted from the multi-neuron GCaMP6m line because their cell bodies 112 were not located in the head (HSN, PVP³³). We performed circuit-level imaging (at a volume 113 rate of 2 Hz) of these transgenic animals as they foraged on uniformly-seeded bacterial lawns 114 (Fig. 1C and Fig. 1 – Figure Supplement 3). Imaging this defined subset of neurons allowed us to 115 leverage prior knowledge and easily determine the identity of each neuron in each recording, 116 117 thereby circumventing the challenge of determining neuronal identity in a densely-labeled brain.

While dwelling, animals move forwards at low speed and frequently display short, low-118 speed reversals. Roaming animals travel at high speed in forward runs that are punctuated by 119 long, high-speed reversals, which change the animal's heading direction. To determine how 120 121 neural activity in the roaming-dwelling circuit encodes locomotion parameters and/or behavioral states, we first examined whether each neuron's activity was associated with the animal's axial 122 123 velocity (i.e. velocity projected along the body axis), axial speed, movement direction (forward or reverse) or foraging state (roaming or dwelling; a Hidden Markov Model used to segment 124 125 roaming and dwelling states is described in the Methods; see also Fig. 1-Supplement 4). Six of 126 the ten recorded neurons displayed calcium levels that correlated with axial velocity and 127 movement direction (Fig. 1D-E; Fig. 1-Supplement 5A). Consistent with previous reports, we observed that the PDF-1-expressing neuron AVB and PDFR-1-expressing neurons AIY and RIB, 128

known to promote forward runs^{11,20,39–42}, exhibited increased activity during forward runs, while 129 the premotor neuron AVA, known to promote reversals^{11,20,42,43}, exhibited heightened activity 130 during reversals. A partially overlapping group of neurons, including the serotonergic neuron 131 NSM, displayed activity that co-varied with animal speed (Fig. 1-Supplement 5A). Moreover, we 132 found that nine of the ten recorded neurons exhibited changes in activity as animals transitioned 133 between roaming and dwelling states (Fig. 1D-E). Interestingly, almost all neurons whose 134 activity correlated with axial velocity and/or movement direction, in particular AVB, AIY, RIB, 135 and AVA, exhibited reduced activity during dwelling, compared to roaming (overall and/or 136 137 surrounding moments of state transitions; Fig. 1D-E). This observation is consistent with the known roles of these neurons in driving locomotion, insofar as locomotion is reduced during 138 dwelling. These effects can also be clearly detected when comparing the joint activity 139 distributions of forward- and reverse-active neurons during roaming versus dwelling (Fig. 1-140 Supplement 6). In contrast, the serotonergic neuron NSM was more active during dwelling. 141 Together, these data reveal that changes in the roaming/dwelling state of the animal are 142 accompanied by changes in the activities of multiple neurons, including NSM and a set of 143 neurons that have previously been shown to control forward and reverse locomotion. 144

The encoding of locomotion and behavioral state across many neurons suggests a circuitlevel representation of the animal's behavior. To test whether the dominant modes of activity in the circuit were associated with the animal's behavior, we performed Principal Component Analysis (PCA) using the activity profiles of all the recorded neurons. Indeed, the top two principal components (PC1 and PC2), which together explained 44% of the total variance, exhibited clear behavioral correlates (Fig. 1F-G). Neural activity along PC1 was coupled to the animal's forward and reverse locomotion (Fig. 1F), while activity along PC2 was coupled to the 152 animal's axial speed and foraging state (Fig. 1G). PC1 consisted of positive contributions from forward-run-active neurons (e.g. AVB, AIY, RIB, and RME), a negative contribution from the 153 reversal-active neuron AVA, and almost no contribution from the serotonergic neuron NSM (Fig. 154 1-Supplement 7). These results provide a clear match to our single-neuron analyses above and 155 suggest that PC1 primarily encodes movement direction. In contrast, PC2 consisted of a strong 156 157 positive contribution from NSM, which is active at low speeds, and negative contributions from both forward-run- and reversal-active neurons (Fig. 1-Supplement 7). These results are also 158 consistent with our single neuron analyses and suggest that PC2, which primarily encodes 159 160 dwelling, is associated with elevated NSM activity and decreased activity in the forward-runand reversal-active neurons. These results indicate that the main modes of dynamics in this 161 circuit are associated with the animal's movement direction and foraging state. 162

Finally, to test whether neural activity in the roaming-dwelling circuit was sufficient to 163 accurately predict behavior, we trained statistical models to predict animal velocity and 164 behavioral state from neural activity (Fig. 1H-I; Fig. 1-Supplement 8). A nonlinear regression 165 model was able to predict animal velocity from concurrent neural activity data with a high 166 degree of accuracy (Fig. 1H). This observation provides a rough match to a previous study⁴⁴ and 167 is consistent with the known roles of several of these neurons in controlling velocity^{11,19,20,39,42,43}. 168 169 In addition, a logistic regression model trained to predict the roaming and dwelling state achieved over 95% accuracy when using activity from all 10 neurons, and exhibited 170 171 classification accuracy significantly above baseline when using data from only NSM or the 172 roaming-active neurons AIY, RIB, and AVB (Fig. 11). Thus, ongoing neural activity in the 173 roaming-dwelling circuit can predict the animal's locomotion and foraging state. This robust mapping between circuit activity and behavior raised the possibility that stable activation of oneor more neurons in this circuit might underlie persistent roaming and dwelling states.

176

177 Persistent NSM activation and associated circuit activity changes correspond to the

178 dwelling state

Among the neurons recorded, the serotonergic neuron NSM was unique in that its 179 180 persistent activation was closely aligned to the dwelling state (Fig. 1D-E; Fig. 1-Supplement 5). 181 NSM activity was increased during dwelling as compared to roaming, resulting in a negative correlation with animal speed, which differs across the two states (Fig. 2A). However, NSM 182 183 activity was not correlated with speed within the roaming state and it was not associated with 184 movement direction during any state (Fig. 2A, Fig. 1D-E). An increase in NSM activity 185 consistently preceded dwelling, with an average latency of 23 seconds (Fig. 2B-C). Dwelling states frequently ended with a decrease in NSM activity, though with a more variable latency 186 187 (Fig. 2C and Fig. 2-Supplement 1A). Across wild-type animals, the durations of individual 188 dwelling states were positively correlated with the durations of co-occurring bouts of NSM activity, which both typically lasted many minutes (Fig. 2D). Together, these observations 189 indicate that NSM displays persistent dwelling state-associated neural activity. 190

Since previous work showed that optogenetic NSM activation can drive animals into dwelling states^{31,33}, our observation that NSM is persistently active during dwelling raised the possibility that NSM activation may play an important role in organizing the circuit-wide activity changes that accompany dwelling. To further explore this possibility, we examined how circuit activity evolved in PC space during periods of NSM activation (Fig. 2E-F). NSM activity serves as a major component of PC2 and is only weakly represented on PC1 (Fig. 1-Supplement 7). As 197 a result, high and low NSM activity segregates well along PC2, but not PC1 (Fig. 2E; Figure 2-Figure Supplement 1B). By aligning circuit activity to the onset of NSM activity bouts and 198 projecting the activity in PC space, we found that NSM activation often began when circuit 199 200 activity was in the region of the PC space with high PC1 activity and low PC2 activity, typical of forward locomotion during roaming (Fig. 2F, compare with Fig. 1F). As NSM became active, 201 circuit activity rose rapidly along PC2 and stayed within the positive half of PC2 (a region 202 typically associated with low speed and dwelling; see Fig. 1F-G). Afterwards, circuit activity 203 slowly traveled towards low values of both PC1 and PC2 (a region typically associated with 204 205 reversals; see Fig. 1F). This observation suggests that the persistent activation of NSM during dwelling is associated with stereotyped changes in overall circuit dynamics. To test whether 206 NSM activation was sufficient to drive these changes in circuit dynamics, we stimulated NSM 207 208 using the red-shifted opsin Chrimson while imaging circuit activity. Indeed, optogenetic stimulation of NSM (performed at a low all-trans-retinal (ATR) concentration to avoid 209 background activation; see Methods) inhibited the activity of the roaming-active neurons AVB, 210 AIY, and RIB and led to a decrease in animal speed (Fig. 2G). These effects were largely 211 abolished in mutants lacking the 5-HT-gated chloride channel mod-1 (Fig. 2 - Figure 212 Supplement 1C), consistent with previous reports that the mod-1 receptor is critical for 5-HT-213 induced locomotion changes³³⁻³⁵. Taken together, these results indicate that NSM activation is 214 associated with and can drive, at least in part, stereotyped changes in circuit activity 215 216 characteristic of the dwelling state.

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218 Persistent activity in serotonergic NSM neurons requires feedback from its target neurons

219 that express the MOD-1 serotonin receptor

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220 Our analyses of wild-type circuit dynamics revealed that stereotyped changes in circuit activity are associated with the roaming and dwelling states. We next examined how these neural 221 dynamics are influenced by neuromodulatory connections embedded in the circuit. Although the 222 223 5-HT and PDF systems are known to act in opposition to regulate roaming and dwelling behaviors³³, it is not known how these neuromodulators impact circuit dynamics. To address this 224 question, we imaged neural activity in mutants deficient in 5-HT signaling, PDF signaling, or 225 both (Fig. 3 and 4). Mutants that disrupt 5-HT signaling, such as those lacking a key enzyme for 226 serotonin biosynthesis (tph-1) or a 5-HT-gated chloride channel (mod-1), exhibited a decrease in 227 time spent in the dwelling state (Fig. 3A-B, Fig. 3-Supplement 1, Fig. 3-Supplement 2), 228 consistent with previous results³³. In wild-type animals, NSM activity was strongly associated 229 with reduced speed, but this relationship was attenuated in *tph-1* and *mod-1* mutants (Fig. 3C). 230 231 Surprisingly, we also found that the durations of the NSM activity bouts, which were minuteslong in wild type animals, were dramatically shortened in these mutants (Fig. 3D). This resulted 232 in a significant decrease in the fraction of time that NSM is active in the mutants (Fig. 3E). These 233 results indicate that 5-HT signaling is required to sustain the activity of the serotonergic neuron 234 NSM. Because MOD-1 is an inhibitory 5-HT-gated chloride channel, the mod-1-expressing 235 236 neurons are relieved from inhibition by 5-HT in mod-1 mutants. Thus, the decrease in NSM 237 activity in these mutants suggests an inhibitory role for the mod-1-expressing neurons in regulating NSM activity. Previous work has shown that mod-1 functions in the neurons AIY, RIF, 238 and ASI to promote dwelling³³ (Fig. 1B). Since none of these neurons directly synapse onto 239 240 NSM, they must functionally inhibit NSM through a polysynaptic route or via the release of a 241 neuromodulator. To directly test whether activation of these neurons inhibits NSM, we activated 242 the *mod-1*-expressing neurons with Chrimson while recording NSM activity. We delivered the

optogenetic stimuli specifically when NSM activity was high and observed a sustained inhibition
of NSM activity throughout the stimulation (Fig. 3F). Together, these results indicate that the
serotonergic NSM neuron promotes its own activity via mutual inhibition with neurons
expressing the inhibitory 5-HT receptor MOD-1 (Fig. 3G).

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PDF receptor-expressing neurons inhibit NSM to promote mutual exclusivity between NSM and AVB

250 We next examined the impact of PDF signaling on circuit dynamics by imaging animals carrying a null mutation in the PDF receptor gene pdfr-1 (Fig. 4A and Fig. 4-Supplement 1A). In 251 252 wild-type animals, the serotonergic neuron NSM and the PDF-1-producing neuron AVB 253 exhibited a mutually exclusive activity pattern, wherein NSM activity was high and AVB 254 activity was low during dwelling, while NSM activity was low and AVB was dynamically active 255 during roaming (Fig. 4C; here we define "mutual exclusivity" to be a lack of concurrent high 256 activity in NSM and AVB; see Methods and Figure 4 – Figure Supplement 2A for thresholding 257 approach to segment low versus high activity). This mutual exclusivity was strongly disrupted in 258 pdfr-1 mutants (Fig. 4C-D). In addition, an analysis of graded AVB activity changes during periods of NSM activation confirmed that the overall decrease in AVB activity during periods of 259 260 high NSM activity was disrupted in *pdfr-1* mutants (Fig. 4-Supplement 2). In these mutant 261 animals, the two neurons were frequently co-active, giving rise to a positive correlation between the activities of the two neurons (Fig. 4D and Figure 4-Figure Supplement 3). Positive 262 263 correlations also appeared between NSM and other roaming-active neurons, including the pdfr-1expressing neurons AIY and RIB (Figure 4-Figure Supplement 3). This increased co-activity of 264 NSM and AVB was observed when using multiple distinct GCaMP normalization methods and 265

266 when sampling from matched speed distributions in wild-type and mutant animals (Fig. 4 -Figure Supplement 4). We observed that *pdfr-1* animals frequently moved at speeds mid-way 267 between those typically seen for roaming and dwelling states in wild-type animals (Figure 4-268 Figure Supplement 5A-B; this observation prompted us to not perform roaming-dwelling state 269 calls on the pdfr-1 mutant). One likely explanation for this behavioral phenotype is that ectopic 270 271 co-activation of NSM and the roaming-active neurons results in mixed behavioral outputs that differ from either roaming or dwelling. These findings indicate that PDF signaling is required for 272 273 the neural circuit to maintain mutual exclusivity between NSM and the locomotion-controlling 274 neurons that are active during roaming.

275 In contrast to the tph-1 animals, NSM activity bouts in pdfr-1 mutants were more persistent than they were in wild-type animals (Fig. 4E-F). This result suggests that PDF 276 277 signaling plays an important role in suppressing NSM activity. Consistent with this interpretation, 278 constitutive activation of PDFR-1 signaling, via expression of the hyperactive PDFR-1 effector 279 ACY-1(P260S) in the *pdfr-1*-expressing neurons, strongly inhibited NSM activity (Fig. 4B; Fig. 4E-F; Fig. 4-Supplement 4B). In addition, optogenetic activation of the *pdf-1*-expressing neurons 280 led to an acute and robust inhibition of NSM (Fig. 4G; Fig. 4-Supplement 5C). Together, these 281 282 findings indicate that PDF signaling is necessary and sufficient to keep NSM inactive during 283 roaming, a key requirement for generating the opposing roaming and dwelling states.

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PDFR-1 neurons act downstream of MOD-1 neurons to inhibit NSM activity and promote roaming

To probe whether the MOD-1- and PDFR-1-expressing neurons act in the same pathway to impact NSM activity, we performed epistasis analysis by examining *tph-1;pdfr-1* double mutants. Similar to the *pdfr-1* single mutants, these animals exhibited prolonged bouts of NSM activation, an increased probability of NSM being active, and a near two-fold increase in the probability of co-activation between NSM and AVB (Fig. 4C-F). At the behavioral level, *tph-1;pdfr-1* animals spent over a third of their time moving at intermediate speeds, similar to the *pdfr-1* animals (Figure 4-Figure Supplement 5A-B). Together, these results suggest that *pdfr-1* functions downstream of *tph-1* to control NSM activity and locomotion.

It has been shown that 5-HT targets the mod-1-expressing neurons to inhibit roaming 295 while *pdfr-1* functions in multiple *pdfr-1*-expressing neurons, including RIM, AIY, RIA, and 296 RIB, to promote roaming^{31,45}. To test whether *mod-1*-expressing neurons and *pdfr-1*-expressing 297 298 neurons act in the same neuronal pathway to control foraging states, we optogenetically activated 299 *mod-1*-expressing neurons in either wild-type animals or pdfr-1 mutants. We found that 300 optogenetic activation of the *mod-1*-expressing neurons, which triggered high-speed locomotion 301 in wild-type animals, failed to do so in *pdfr-1* mutants (Fig. 4H). These results indicate that the *pdfr-1*-expressing neurons act downstream of the *mod-1*-expressing neurons to promote roaming 302 (Fig. 4I), consistent with the epistasis analysis described above. Altogether, these results indicate 303 that the mutually inhibitory interaction between NSM and the neurons that express the MOD-1 304 305 and PDFR-1 receptors is necessary to stabilize the opposing neural activity and behavioral 306 patterns underlying roaming and dwelling.

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308 A CNN classifier reveals stereotyped circuit dynamics that precede roaming-to-dwelling 309 transitions

Based on the *C. elegans* connectome⁴⁶ and previous studies^{39,42,47–49}, many of the MOD-1- and PDFR-1-expressing neurons receive dense inputs from sensory neurons and are functionally involved in sensorimotor behaviors (Fig. 1B). Therefore, the functional circuit architecture revealed through our calcium imaging analyses raised the possibility that incoming sensory inputs that act on the MOD-1- and PDFR-1-expressing neurons might influence the transitions between roaming and dwelling. One prediction of this hypothesis is that these neurons that receive sensory inputs may display stereotyped activity patterns prior to state transitions.

To test the above hypothesis, we sought to predict state transitions from the circuit-wide 317 318 activity patterns that precede them. Our calcium imaging results showed that the onset of NSM activity reliably coincided with the onset of dwelling states (Fig. 2B and C). We thus focused on 319 uncovering potential circuit elements that function upstream of NSM to drive the roaming-to-320 321 dwelling transition. We adopted a supervised machine learning approach by training a Convolutional Neural Network (CNN) classifier to predict NSM activation using the preceding 322 323 multi-dimensional activity profile from all other neurons imaged (Figure 5A-B and Figure 5-324 Figure Supplement 1; see Methods). We chose the CNN classifier because of its flexible architecture, which can model complex nonlinear relationships between the input and output 325 variables and detect multiple relevant activity patterns via the same network^{50–52}. Successfully 326 trained networks achieved over 70% test accuracy, equaling or exceeding other supervised 327 328 learning methods (Figure 5-Figure Supplement 2A). This result indicates that stereotyped circuit 329 activity patterns frequently precede NSM activation.

We examined the parameters of the trained networks to define the activity patterns that were being used to make successful predictions about upcoming NSM activation. Successfully trained networks consistently employed a convolutional filter where the largest positive weights were associated with the sensory processing neuron AIA and the largest negative weights were linked to RIB and AVA, which promote forward and reverse movement, respectively (Fig. 5B). 335 These weights suggest that NSM activation is most likely to occur following increased activity in AIA and decreased activity in RIB and AVA. Withholding AIA, RIB, and AVA from the 336 training data abolished the predictive power of the trained network, while withholding AIA 337 activity alone also led to a significant reduction in test accuracy (Fig. 5B and Figure 5-Figure 338 Supplement 2B). Moreover, networks trained on the activities of only AIA, RIB, and AVA 339 340 performed nearly as well as those trained on all the neurons (Figure 5-Figure Supplement 2B). Training a CNN classifier to directly predict dwelling state onset from all of the neurons except 341 342 NSM led to a similar convolutional filter; including NSM in the training data yielded a classifier 343 that predicts dwelling state onset solely using NSM activity (Figure 5-Figure Supplement 3A). These observations suggest that the combined activities of AIA, RIB, and AVA can frequently 344 345 predict the onset of NSM activity, which is strongly associated with roaming-to-dwelling state transitions. 346

Utilizing this same approach, we also trained CNN classifiers to predict the termination of NSM activity bouts and the onsets of roaming states (Figure 5-Figure Supplement 3B-C). The resulting convolutional kernels displayed strong positive weight on AVB and RIB. Strong negative weight on NSM was also a feature of the convolutional kernel predicting roaming state onset. These results are consistent with the mutual inhibitory loop described above and suggest that activation of the AVB and other roaming-active neurons, concurrent with NSM inactivation, predicts dwelling-to-roaming transitions.

Given that AIA, RIB, and AVA activities could predict the onset of NSM activity and dwelling states, we next examined how the activities of these neurons changed during transitions from roaming to dwelling (Fig. 5C-G). During roaming, AIA activity was positively correlated with that of forward run-promoting neurons, such as RIB, and negatively correlated with the

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358 reversal-promoting neuron AVA. Within 30 seconds of NSM activation, AIA often exhibited a further increase in activity, while RIB and AVA activity stayed at similar levels or decreased. As 359 360 NSM activity rose and the animal entered the dwelling state, RIB and AVA activity declined sharply while AIA became correlated with NSM. AIA then declined to baseline over the 361 following minutes. Thus, AIA activity co-varies with the forward-active neurons during roaming 362 363 and with NSM at the onset of dwelling. This native activity pattern is consistent with the convolutional kernel from the CNN classifier, where heightened activity of AIA relative to the 364 locomotion-promoting neurons RIB and AVA predicts NSM activation. Together, these results 365 reveal a stereotyped, multi-neuron activity pattern that predicts NSM activation. 366

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368 AIA activation can elicit both roaming and dwelling states

369 Because AIA activity co-varied with both roaming- and dwelling-active neurons and was 370 required for the prediction of NSM activation, we hypothesized that AIA might play an active 371 role in controlling the transitions between roaming and dwelling. To test this, we optogenetically 372 activated AIA in foraging animals exposed to uniform lawns of bacterial food (Fig. 6A-B). 373 Behavioral responses to AIA activation depended on the state of the animal at the time that AIA was activated. Roaming animals exhibited a rapid and transient decrease in speed upon AIA 374 375 activation, while dwelling animals showed a gradual increase in speed upon AIA activation (Fig. 376 6A-B). These results indicate that optogenetic activation of AIA can affect state transitions on two different time scales: triggering the roaming-to-dwelling transition within a few seconds and 377 378 promoting entry into the roaming state upon tens of seconds of continued activation.

To determine if AIA promotes behavioral switching by modulating 5-HT- or PDFreleasing neurons, we optogenetically activated AIA in mutants defective in 5-HT or PDF

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381 signaling (tph-1 and pdfr-1 animals, Fig. 6A-B). For the tph-1 mutant, animals that were roaming pre-stimulation no longer displayed rapid entry into dwelling and showed a higher probability of 382 staying in the roaming state later into the stimulation. tph-1 animals that were dwelling pre-383 stimulation displayed a higher probability of entering roaming compared to control animals. 384 These results suggest that *tph-1* is critical for the effect of AIA activation on triggering entry into 385 386 dwelling and for preventing AIA-induced entry into the roaming state. In contrast, AIA activation in *pdfr-1* mutants that were dwelling pre-stimulation failed to promote transitions into 387 roaming. Roaming states in these mutants were too infrequent and brief to warrant meaningful 388 389 analysis of AIA activation during that state. Together, these results suggest that AIA promotes dwelling via 5-HT signaling and promotes roaming via PDF signaling. 390

Previous work has characterized neuronal cell types in mammals that exhibit similar trial-391 by-trial variation where optogenetic activation can elicit opposing behavioral effects^{24,53}. In some 392 393 of these previous examples, stimulation intensity influenced the behavioral outcome of the optogenetic activation. Thus, we examined whether stimulation intensity influenced the ability of 394 AIA to promote roaming or dwelling. Indeed, AIA activation at lower light intensities primarily 395 elicited roaming-to-dwelling transitions, while activation at higher intensities elicited dwelling-396 397 to-roaming transitions (Fig. 6C). Because the AIA-induced slowing response and speeding 398 response depend on different neuromodulatory systems and can be elicited independently at different light intensities, these results are suggestive that AIA provides independent outputs to 399 400 the PDF and 5-HT systems to control roaming and dwelling states, respectively (Fig. 6D).

401

402 AIA can promote either roaming or dwelling, depending on the sensory context

Based on the C. elegans connectome^{54,55}, AIA receives the majority of its synaptic inputs 403 (~80%) from chemosensory neurons (Figure 6-Figure Supplement 1), many of which detect 404 temporal changes in the concentrations of olfactory and gustatory cues^{56–58}. Previous work has 405 406 shown that AIA is activated by an increase in the concentration of attractive odorants present in bacterial food^{57,59}. In the absence of food, AIA promotes forward runs when animals detect 407 increases in attractive odors⁵⁷. AIA sends synaptic output to multiple neurons in the sensorimotor 408 pathway, including several mod-1- and pdfr-1-expressing neurons, though its role in roaming and 409 dwelling behaviors has not been examined. 410

Based on AIA's established role in sensory processing and our observations that AIA can 411 412 drive both roaming- and dwelling-like behaviors, we hypothesized that AIA promotes either roaming or dwelling, depending on the sensory cues in the environment. To test this hypothesis, 413 we examined the foraging behaviors of wild-type animals in different sensory contexts, and 414 415 compared them to animals in which AIA had been silenced (AIA::unc-103gf). Given that AIA responds to food odors, we developed a patch foraging assay in which animals placed on a sparse 416 food patch can navigate a food odor gradient to approach an adjacent dense food patch (Fig. 7A). 417 This assay is notably different from standard chemotaxis assays, where animals are not in contact 418 419 with any food source and therefore do not display roaming or dwelling behaviors. We also 420 examined AIA's impact on roaming and dwelling in the absence of an olfactory gradient by performing a second assay where wild-type or AIA-silenced animals were presented with 421 422 uniform-density bacterial food (Fig. 7F).

In the patch foraging assay, wild-type animals exhibited directed motion towards the dense food patch and alternated between roaming and dwelling as they approached it (Fig. 7A, bottom). Compared to control plates without the dense food patch, animals in the patch foraging 426 assay spent more time in the roaming state (Fig. 7B), and biased their movement towards the dense food patch as they roamed (Figure 7-Figure Supplement 1A). Animals preferentially 427 switched from roaming to dwelling when their direction of motion (measured as heading bias; 428 429 Fig. 7C) began to deviate away from the dense food patch (Fig. 7D). Because the animal's heading direction impacts the change in odor concentration that it experiences, these results 430 431 indicate that dynamic changes in the concentration of food odors influences the transition rates between roaming and dwelling. Consistent this interpretation, we found that chemosensation-432 defective *tax-4* mutants⁶⁰ subjected to the patch foraging assay failed to exhibit elevated roaming 433 434 and failed to couple the roaming-to-dwelling transition with their direction of motion (Fig. 7B and D). 435

We next asked whether AIA was necessary for the sensory-induced modulation of roaming and dwelling states in the patch foraging assay. We found that AIA-silenced animals (*AIA::unc-103gf*) exhibited an overall decrease in roaming compared to wild-type animals and did not selectively enter dwelling states when their movement direction deviated away from the dense food patch (Fig. 7E and Figure 7-Figure Supplement 1B). These results indicate that AIA is necessary for animals to display elevated roaming in the presence of a food odor gradient and for animals to couple their movement direction with roaming-to-dwelling transitions.

We also examined the roles of 5-HT and PDF in the patch foraging assay. We found that *pdfr-1* mutants failed to increase their roaming in the odor gradient but still displayed some coupling of the roaming-to-dwelling transition to their direction of motion (Figure 7-Figure Supplement 1C-D). In contrast, *tph-1* mutants displayed increased time in the roaming state but did not couple the roaming-to-dwelling transition to their direction of motion (Figure 7-Figure Supplement 1C-D). 449 Lastly, to examine the role of AIA in controlling roaming and dwelling in the absence of a strong sensory gradient, we compared the behavior of wild-type and AIA-silenced animals in 450 environments with uniformly-seeded bacterial food. We tested two different bacterial densities 451 (Fig. 7F). In both cases, AIA-silenced animals displayed a significant decrease in the fraction of 452 time spent dwelling (Fig. 7F). These results suggest that AIA functions to promote the dwelling 453 454 state in a constant sensory environment. This contrasts sharply with the role of AIA in promoting roaming in the presence of a strong sensory gradient (Fig. 7E). Taken together, these results 455 456 indicate that AIA can promote either roaming or dwelling, depending on the overall sensory 457 environment.

458

459 **DISCUSSION**

Our findings reveal the functional architecture of a neural circuit that generates persistent 460 461 behavioral states. Circuit-wide calcium imaging during roaming and dwelling identified several 462 neurons whose activities differ between the two states, most notably the serotonergic NSM 463 neuron that displays long bouts of activity during dwelling and inactivity during roaming. By 464 combining circuit imaging with genetic perturbations, we found that mutual inhibition between 465 the serotonergic NSM neuron and the 5-HT and PDF target neurons promotes the stability and 466 mutual exclusivity of the neural activity patterns observed during roaming and dwelling. Furthermore, we found that the AIA sensory processing neuron that responds to food odors sends 467 468 parallel outputs to both neuromodulatory systems and biases the network towards different states 469 in different sensory contexts. This circuit architecture allows C. elegans to exhibit persistent roaming and dwelling states, while flexibly switching between them depending on the sensorycontext.

472

473

Neural circuit mechanisms that generate persistent behavioral states

The recordings in this study provide new insights into how neural activity changes as 474 475 animals switch between stable, alternative behavioral states. Previous work had shown that 5-HT and PDF were critical for dwelling and roaming behaviors³³, but how they impact circuit activity 476 was not known. We found that NSM displayed long bouts of activity during dwelling and was 477 478 inactive during roaming. In addition, several neurons that were previously shown to drive forward and reverse movement^{11,19,20,39,42,43}, including the PDF-producing neuron AVB, were 479 more active during roaming than they were during dwelling. However, whereas NSM displayed 480 long bouts of persistent activity during dwelling, the locomotion neurons displayed fast timescale 481 dynamics associated with forward and reverse movements during roaming, matching their 482 483 previously described roles in controlling locomotion. *tph-1* mutants that lack 5-HT had an imbalance in the winner-take-all dynamics of this circuit, such that NSM activity was less 484 persistent. pdfr-1 mutants that lack PDF signaling displayed ectopic co-activation of NSM 485 486 neurons along with AVB and other roaming-active neurons, as well as exaggerated persistence in NSM. These results suggest that neuromodulation is critical to establish the overall structure of 487 circuit-level activity. Our data also suggest that there is mutual inhibition between NSM and the 488 489 neurons that express MOD-1 (an inhibitory 5-HT receptor) and PDFR-1. The MOD-1- and 490 PDFR-1-expressing neurons, which are more active during roaming, synapse onto the PDFproducing neuron AVB that is also more active during roaming, suggesting that they excite 491

492 AVB. Thus, although NSM and AVB display mutually exclusive high activity states and produce 493 opposing neuromodulators, they do not have direct connections with one another, as is typical in 494 a flip-flop switch. Instead, they coordinate their activities by both interacting with the same 495 network of neurons that expresses the 5-HT and PDF receptors. This architecture might allow for 496 more flexible regulation of behavioral state switching.

The circuit states that correspond to roaming and dwelling differ in several respects. 497 498 Dwelling states are characterized by persistent activity in serotonergic NSM neurons and reduced activity in several, but not all, locomotion-associated neurons. NSM activation always occurred 499 within seconds of dwelling state onset and persisted for minutes, though NSM inactivation in 500 501 some cases occurred one or two minutes from roaming state onsets. It is unclear whether this variable time lag involves the perdurance of 5-HT in extracellular space or other effects. 502 503 Previous work has identified sub-modes of dwelling where animals display distinct subsets of postures⁶¹, but our datasets here, which lack detailed posture information, did not permitted us to 504 identify neural correlates of these sub-modes. Roaming states are characterized by fast 505 fluctuations in the activities of neurons that have previously been shown to drive forward (AVB, 506 AIY, RIB) and reverse (AVA) movement^{11,19,20,39,42,43}. We did not identify a neuron that is 507 persistently active throughout roaming in a manner analogous to NSM activation during 508 509 dwelling. While it is possible that such a neuron may exist (and that we did not record it in our study), it is also possible that the roaming state might be the "default" state of the C. elegans 510 network and thus does not require devoted, persistently-active neurons to specify the state. 511 512 Consistent with this possibility, circuit dynamics similar to roaming are observed in the absence of food and even in immobilized animals^{11,37,38}. The correlational structure of neural activity also 513 514 differs between roaming and dwelling. For example, the sensory processing neuron AIA is active

515 in both states, but is coupled to NSM during dwelling, and to the forward-active neurons (AVB, 516 AIY, RIB) during roaming. Neurons that can affiliate to different networks and switch their 517 affiliations over time have also been observed in the stomatogastric ganglion and other 518 systems⁶². The correlational changes that we observe here might allow for state-dependent 519 sensory processing.

520

521 Sensory control of roaming and dwelling states

Previous work showed that chemosensory neurons regulate roaming and dwelling 522 523 behaviors: mutants that are broadly defective in chemosensation display excessive dwelling, while mutants that are defective in olfactory adaptation display excessive roaming²⁶. However, 524 525 the neural circuitry linking sensory neurons to roaming and dwelling had not been characterized. Using a machine learning-based approach, we identified AIA as a pivotal neuron for roaming-526 527 dwelling control. AIA receives synaptic inputs from almost all chemosensory neurons in the C. elegans connectome and displays robust responses to appetitive food odors^{57,59}. We observed 528 apparently spontaneous AIA dynamics in freely foraging animals, which could reflect responses 529 to small changes in the sensory environment or feedback from other neurons. Here we found that 530 531 AIA provides dual outputs to both the dwelling-active NSM neuron and the roaming-active neurons. Three lines of evidence support this interpretation: (1) native AIA activity correlates 532 with NSM during dwelling and with forward-active neurons during roaming, (2) optogenetic 533 534 activation of AIA can drive behaviors typical of both states, and (3) AIA silencing strongly alters roaming and dwelling states, but has different effects in different sensory contexts: AIA is 535 necessary for roaming while animals navigate up food odor gradients, but is necessary for 536

dwelling while animals are in uniform feeding environments. Thus, AIA is required to couple thesensory environment to roaming and dwelling states.

The dual output of AIA onto both roaming and dwelling circuits is an unusual aspect of 539 the circuit architecture uncovered here. However, similar functional architectures, where a 540 common input drives competing circuit modules, have been suggested to underlie behavior 541 selection in other nervous systems^{1,24,63}. One possible function of this motif in the roaming-542 543 dwelling circuit is that it might allow both the roaming- and dwelling-active neurons to be latently activated when the animal is exposed to food odors detected by AIA. AIA-transmitted 544 information about food odors could then be contextualized by other sensory cues that feed into 545 546 this circuit. For example, NSM is not directly activated by food odors, but instead is directly activated by the ingestion of bacteria via its sensory dendrite in the alimentary canal³¹. Thus, 547 when animals detect an increase in food odors that is accompanied by increased ingestion, this 548 might promote dual AIA and NSM activation to drive robust dwelling states. In contrast, when 549 animals detect an increase in food odors that is not accompanied by increased ingestion, this 550 might activate AIA and the other side of the mutual inhibitory loop, biasing the animal towards 551 roaming. This flexible architecture could therefore allow animals to make adaptive foraging 552 decisions that reflect their integrated detection of food odors, food ingestion, and other salient 553 554 sensory cues.

555

556 Mutual inhibition as a network motif for generating opposing activity states

Long-standing theoretical work^{64–67} and recent experimental evidence^{65,68} has highlighted 557 the role of recurrent circuitry in driving persistent neural activity. In particular, mutual inhibition 558 has long been proposed to underlie opposing cognitive states⁶⁹⁻⁷². Recent modeling and 559 560 experimental studies of the locomotion circuit of C. elegans has shown that fast timescale behavioral changes involve stochastic switching of flip-flop circuits, and nested oscillatory 561 dynamics that depend on the ongoing state of these circuits^{19,20,73}. Our results here suggest that a 562 neural circuit with mutual inhibition mediated by neuromodulatory signals can generate 563 behavioral switching over a much longer timescale, giving rise to persistent behavioral states that 564 can be flexibly generated depending on the demands of the sensory environment. 565

566

Key Resources Table				
Reagent type (species) or resource	Designati on	Source or referen ce	Identifiers	Additional information
strain, strain background (<i>C. elegans</i>)	N2	CGC	ID_Flavell Database: N2	Wild-type Bristol N2
strain, strain background (<i>C. elegans</i>)	SWF90	This study	ID_Flavell Database: SWF90	flvEx46[[tph-1::GCaMP6m, mod-1::GCaMP6m, sto- 3::GCaMP6m, glr- 3::GCaMP6m, odr- 2b::GCaMP6m, gcy- 28.d::GCaMP6m, lgc- 55(short)::GCaMP6m, nmr- 1::GCaMP6m, tph- 1::wrmScarlett, mod- 1::wrmScarlett, nmr- 1::wrmScarlett, sto- 3::wrmScarlett]; lite-1(ce314), gur-3(ok2245)].

567 MATERIALS AND METHODS

				See: Figure 1.
strain, strain background (<i>C. elegans</i>)	SWF113	This study	ID_Flavell Database: SWF113	flvls1[tph-1::GCaMP6m, mod- 1::GCaMP6m, sto- 3::GCaMP6m, glr- 3::GCaMP6m, odr- 2b::GCaMP6m, gcy- 28.d::GCaMP6m, lgc- 55(short)::GCaMP6m, nmr- 1::GCaMP6m, tph- 1::wrmScarlett, mod- 1::wrmScarlett, mod- 1::wrmScarlett, sto- 3::wrmScarlett, sto- 3::wrmScarlett]; lite-1(ce314), gur-3(ok2245). See: Figures 1-5, Figure 1 – Figure Supplements 1-8, Figure 2 – Figure Supplement 1, Figure 3 – Figure Supplement 1, Figure 4 – Figure Supplements 2-5, Figure 5 – Figure Supplements 1-3.
strain, strain background (<i>C. elegans</i>)	SWF186	This study	ID_Flavell Database: SWF186	flvIs1; lite-1(ce314); gur-3 (ok2245); mod-1(ok103). See: Figures 3-4, Figure 3 – Figure Supplements 1-2, Figure 4 – Figure Supplements 4-5.
strain, strain background (<i>C. elegans</i>)	SWF124	This study	ID_Flavell Database: SWF124	flvIs1; lite-1(ce314); gur-3 (ok2245); pdfr-1(ok3425) See: Figure 4, Figure 4 – Figure Supplements 1-5.
strain, strain background (<i>C. elegans</i>)	SWF263	This study	ID_Flavell Database: SWF263	flvls1; lite-1(ce314); gur-3 (ok2245); flvEx129[pdfr-1::acy- 1gf, elt-2::nGFP]. See: Figure 4, Figure 4 – Figure Supplements 1-5.
strain, strain background (<i>C. elegans</i>)	SWF125	This study	ID_Flavell Database: SWF125	flvEx46; lite-1(ce314); gur-3 (ok2245); tph1(mg280); pdfr- 1(ok3425).

				See: Figures 3-4, Figure 3 – Figure Supplements 1-2, Figure 4 – Figure Supplements 2-5
strain, strain background (<i>C. elegans</i>)	SWF168	This study	ID_Flavell Database: SWF168	flvls1; lite-1(ce314); gur-3 (ok2245); flvEx86[tph- 1(short)::chrimson, elt- 2::nGFP].
				See: Figure 2, Figure 2 – Figure Supplement 1, Figure 4 – Figure Supplement 5.
strain, strain background (<i>C. elegans</i>)	SWF801	This study	ID_Flavell Database: SWF801	flvls1; lite-1(ce314); gur- 3(ok2245); mod-1(ok103); flvEx86[tph-1(short)::chrimson, elt-2::nGFP].
				See: Figure 2 – Figure Supplement 1.
strain, strain background (<i>C. elegans</i>)	CX14684	This study	ID_Flavell Database: CX14684	pdfr-1(ok3425); kyls580[mod- 1::nCre, myo-2::mCherry]; kyEx4816[ttx-3::ChR2(C128S)- GFP, odr-2b::inv[ChR2-sl2- GFP], myo-3::mCherry].
				See: Figure 4.
strain, strain background (<i>C. elegans</i>)	SWF194	This study	ID_Flavell Database: SWF194	flvls1; lite-1(ce314); gur-3 (ok2245); flvEx98[gcy- 28.d::Chrimson, elt-2::nGFP].
				See Figure 6.
strain, strain background (<i>C. elegans</i>)	SWF216	This study	ID_Flavell Database: SWF216	flvls1; lite-1(ce314); gur-3 (ok2245);tph-1(mg280); flvEx98[gcy-28.d::Chrimson, elt-2::nGFP].
				See Figure 6.
strain, strain background (<i>C. elegans</i>)	SWF326	This study	ID_Flavell Database: SWF326	flvls1; lite-1(ce314); gur-3 (ok2245); pdfr-1(ok3425); flvEx98[gcy-28.d::Chrimson, elt-2::nGFP].
				See Figure 6.

strain, strain background (<i>C. elegans</i>)	CX14597	Larsch et al, 2015	ID_Flavell Database: CX14597	kyEx4745[gcy-28.d::unc- 103gf::sl2-mCherry, elt- 2::mCherry]. See Figure 7, Figure 7 – Figure Supplement 1.
strain, strain background (<i>C. elegans</i>)	CX13078	This study	ID_Flavell Database: CX13078	<i>tax-4(p678) [5x backcrossed to N2].</i> See Figure 7, Figure 7 – Figure Supplement 1.
strain, strain background (<i>C. elegans</i>)	CX14295	Flavell et al, 2013	ID_Flavell Database: CX14295	<i>pdfr-1(ok3425).</i> See: Figure 7 – Figure Supplement 1.
strain, strain background (<i>C. elegans</i>)	MT15434	CGC	ID_Flavell Database: MT15434	<i>tph-1(mg280).</i> See: Figure 7 – Figure Supplement 1.
strain, strain background (<i>C. elegans</i>)	SWF392	This study	ID_Flavell Database: SWF392	lite-1(ce314); gur-3(ok2245); flvEx148[gcy-28.d::Chrimson, myo-3::mCherry]. See Figure 6.
strain, strain background (<i>C. elegans</i>)	SWF167	This study	ID_Flavell Database: SWF167	flvls1; lite-1(ce314), gur- 3(ok2245); flvEx85[pdf- 1::Chrimson, elt-2::nGFP]. See: Figure 4, Figure 4 – Figure Supplement 5.
strain, strain background (<i>C. elegans</i>)	SWF166	This study	ID_Flavell Database: SWF166	flvIs1; lite-1(ce314), gur- 3(ok2245); flvEx84[mod- 1::Chrimson, elt-2::nGFP]. See: Figure 3, Figure 4 – Figure Supplement 5.
software, algorithm	MATLAB	MathW orks (www. mathw orks.co m)	RRID:SCR _001622	v2019a

software, algorithm	NIS Elements	Nikon (www. nikonin strume nts.co m/prod ucts/so ftware)	RRID:SCR _014329	v5.02.00
software, algorithm	Streampix	Norpix(www.n orpix.c om/pro ducts/s treamp ix/strea mpix.p hp)	RRID:SCR _015773	v7.0

568

569 Growth conditions and handling

570 Nematode culture was conducted using standard methods⁷⁴. Populations were maintained 571 on NGM agar plates with *E. coli* OP50 bacteria. Wild-type was *C. elegans* Bristol strain N2. For 572 genetic crosses, all genotypes were confirmed using PCR. Transgenic animals were generated by 573 injecting DNA clones plus fluorescent co-injection marker into gonads of young adult 574 hermaphrodites. One day old hermaphrodites were used for all assays. All assays were conducted 575 at room temperature (~22°C).

576

577 Construction and characterization of multi-neuron GCaMP strain

To generate a transgenic strain expressing GCaMP6m in a specific subset of neurons involved in roaming and dwelling, we first generated pilot strains where one or two plasmids were injected at a time to optimized DNA concentrations. This also allowed us to determine the precise GCaMP6m and/or Scarlett expression pattern from each promoter. We then injected these plasmids as a mixture into *lite-1;gur-3* double mutants, which are resistant to blue light delivered during calcium imaging. We selected a line for use that had normal behavioral parameters and showed relatively balanced expression of GCaMP6m and Scarlett in the target cells (SWF90). To obtain more consistent expression, the transgene was integrated by UV to generate *flvIs1* (SWF113). The integrated strain was outcrossed 4 times.

587

588 Microscope Design and Assembly

Overview. The tracking microscope design was inspired and based off previously described systems^{36–38}, with several modifications aimed at reducing motion artifacts and extending the duration of calcium imaging, so that long-lasting behavioral states could be examined. As illustrated in Figure 1-Figure Supplement 1, two separate light paths, below and above the specimen, were built onto a Ti-E inverted microscope (Nikon).

594 High-magnification light path for GCaMP imaging. The light path used to image GCaMP6m and Scarlett at single cell resolution is an Andor spinning disk confocal system. 595 Light supplied from a 150mW 488nm laser and a 50mW 560nm laser passes through a 5000rpm 596 597 Yokogawa CSU-X1 spinning disk unit with a Borealis upgrade (with a dual-camera configuration). A 40x/1.15NA CFI Apo LWD Lambda water immersion objective (Nikon) with 598 a P-726 PIFOC objective piezo (PI) was used to image the volume of the worm's head. A custom 599 quad dichroic mirror directed light emitted from the specimen to two separate Andor Zyla 4.2 600 USB3 cameras, which had in-line emission filters (525/50, and 625/90). Data was collected at 601 602 2x2 binning in a 512x512 region of interest in the center of the field of view.

Low-magnification light path for closed-loop tracking. A second light path positioned above the animal collected data for closed-loop tracking. Light supplied from a Sola SE2 365 Light Engine (Lumencor) passed through a DSRed (49005, Chroma) filter set and a 10x/0.3NA air objective to excite Scarlett in the head of the worm. Red light emitted from the specimen passed through the filter set to an acA2000-340km Basler CMOS camera. Data was collected at 100 Hz.

609 Synchronized control of camera exposures and illumination light sources. The Andor Zyla cameras used for calcium imaging were run in rolling shutter mode. A trigger signal was 610 611 generated by one of the two cameras whenever the camera shutter is fully open (~2 ms per exposure). This trigger signal served as a master control that synchronized several devices 612 (Figure 1-Figure Supplement 1B). First, it was used to drive the 488nm and 560nm lasers, such 613 614 that illumination is only provided when the full field of view is open. Second, the same trigger signal was used controlled the movement of the objective piezo, such that fast piezo movement 615 616 occurs largely outside the window of laser illumination. Lastly, this signal was used to time the green LED used by the closed-loop tracking system. The LED was turned on only when the 617 calcium imaging cameras were not actively acquiring images (i.e. outside the window when the 618 619 rolling shutter is fully open) and when the lasers were off. Together, these approaches minimize photo-bleaching, photo-toxicity, and motion artifacts induced by movable parts of the 620 621 microscope.

622 **Closed-loop tracking software.** A custom C/C++ software was used to process 623 incoming frames from the tracking camera and to instruct the movement of a motorized stage 624 (96S107-N3-LE2, Ludl; with a MAC6000 controller) to keep the head region of the animal at the 625 center in the field of view. This software was adapted from Nguyen et al. with two key modifications: First, at each control cycle, the future velocity of the stage was calculated to match the predicted future velocity of the animal (i.e. predictive control as opposed to proportional control employed in previous study). Specifically,

$$v_{stage}(t+1) = v_{animal}(t) + \frac{(v_{animal}(t) - v_{animal}(t-1))}{\Delta t}$$

where $v_{stage}(t)$ is the instantaneous velocity of the stage and $v_{animal}(t)$ the instantaneous velocity of the animal. The latter was estimated as described below (see **Estimation of instantaneous animal location and velocity**). The right side of the formula was found empirically to be sufficient for predicting future animal velocity. The second modification was that we used the motion of the head region of the animal to extrapolate the locomotory state of the animal. This approach results in a loss of postural information, but circumvents the need for a third light path for imaging the full body of the animal.

Optogenetic stimulation during calcium imaging. For experiments where we activated Chrimson while performing circuit-wide imaging, L4 animals were picked to plates with 1 uM ATR (or not, in the case of -ATR controls) for overnight growth. They were then subjected to our standard calcium imaging methods described above, except the 561nm laser light to image Scarlett in neurons was omitted due to concerns of cross-activation of Chrimson. For optogenetic stimulation, an overhead spotlight LED (Mightex 617nm Type-H) directed towards the sample was illuminated for 30s at a time. Animals were stimulated 1-3 times each.

643

644 **Behavioral Assays**

645 Patch foraging assay. For the patch foraging assays, we used 24.5cm x 24.5cm NGM plates. Plates were uniformly seeded with sparse OP50 bacteria (OD 0.5 diluted 300x), and one 646 half of the plate was seeded with dense bacteria (OD 0.5 concentrated 20x). The border between 647 the sparse and dense food was always sharp and typically very straight. Plates were left overnight 648 at room temperature. The following day, one-day-old adult animals were picked to the sparse 649 side of the food plate, approximately 1.5 cm from the dense food patch. Video recordings were 650 started immediately, though for all analyses the first 20 min of data (equilibration time) was not 651 analyzed. Videos were recorded at 3 fps using Streampix 7.0, a JAI SP-20000M-USB3 CMOS 652 653 cameras (41mm, 5120x3840, Mono) with a Nikon Micro-NIKKOR 55mm f/2.8 lens. Backlighting was achieved using a white panel LED (Metaphase Technologies Inc. White 654 Metastandard 10" X 25", 24VDC). Assay plates were placed on glass 3" above LEDs to avoid 655 656 heat transfer to plates. Videos were processed using custom Matlab scripts, which included a step to manually confirm the exact frame of dense food patch encounter for each animal. 657 Segmentation of behavior into roaming and dwelling was conducted as previously described 658 (Flavell et al, 2013). 659

Foraging at different food densities. To examine animal behavior in uniform environments with different food densities, we seeded NGM plates (either circular 10 cm or 24.5x24.5cm) with different densities of food. For the experiments in Fig. 7, low-density was OP50 bacteria at OD 0.5 diluted 300x; high-density was OD 0.5 concentrated 20X. Plates grew overnight at room temperature. The following day, one-day-old adult animals were picked to these plates and allowed to equilibrate for 45 mins, after which video recordings began. Videos were recorded and analyzed as described above.

667	Optogenetic stimulation during foraging behavior. For optogenetic stimulation of
668	free-behaving animals, we picked one-day-old adult animals (grown on 50uM ATR the night
669	before) to NGM plates seeded with 300X diluted OD 0.5. Animals were permitted to equilibrate
670	for 45 min, after which videos were recorded using the setup described above. In these videos,
671	light for optogenetic stimulation was delivered using a 625nm Mightex BioLED at 30 uW/mm ² .
672	Patterned light illumination was achieved using custom Matlab scripts, which were coupled to a
673	DAQ board (USB-6001, National Instruments) and BioLED Light Source Control Module
674	(Mightex). Videos were analyzed as described above.

675

676 Data Analysis for Calcium Imaging

677 Semi-automated image segmentation to obtain neuron outlines. All image analyses 678 were performed on maximum intensity projections of the collected z-stacks, since the neurons were well separated along the x-y axes. We used data from the side of the animal (left or right) 679 680 that was closest to the microscope objective, due to better optical quality of these data. First, 681 feature points and feature point descriptors were extracted for each frame of the calcium imaging video. Next, an N-by-N similarity matrix (N = number of frames in a video) was generated 682 where each entry equals the number of matched feature points between a pair of frames. The 683 columns of this matrix were clustered using hierarchical clustering. Around 30 frames (typically 684 685 1-2% of frames from a video) were chosen across the largest 15 clusters. These frames were then 686 segmented manually. The user was asked to outline the region for interest (ROI) around each neuronal structure of interest (axonal segment for the AIY neurons; soma for all other neurons). 687 After manual segmentation, the automatic segmentation software looped through each of the 688

35
689 remaining frames. For each unsegmented frame (target frame), a best match (reference frame) was found among the segmented frames based on the similarity matrix. Then, geometrical 690 transformation matrices were estimated using the locations of the matched feature points. The 691 estimated transformation was then applied to the boundary vertices of each ROI in the reference 692 frame to yield the estimated boundary of the same region in the target frame. Once done, the 693 694 target frames with their automatically computed ROIs were included into the pool of segmented frames and could serve as a reference frame for the remaining unsegmented frames. This 695 696 procedure was repeated iteratively through the rest of the video.

Calcium signal extraction and pre-processing. The fluorescent signal from each 697 698 neuron in a given frame was calculated as the median of the brightest 100 pixels within the ROI 699 (or all pixels if the size of the ROI was smaller than 100 pixels) of that neuron. This approach 700 was adopted to render the estimation of calcium signal insensitive to the exact segmentation 701 boundary of the neuron, which could inadvertently contain background pixels. This was done for 702 both the green and the red channels. The following pre-processing steps were then applied to the 703 time-series signals from both channels: 1) To reduce spurious noise, a sliding median filter with 704 a window size of 5 frames were applied to the time series (Figure 1-Figure Supplement 2D). 2) 705 To correct for the decay in fluorescent signal due to photobleaching, an exponential function was 706 first fit to the time series. Next, the estimated exponential was normalized by its initial value and divided away from the denoised time series (Figure 1-Figure Supplement 2E). 3) To control for 707 708 fluctuations in fluorescent signal due to the movement of the animal, we calculated the 709 ratiometric signal. Specifically, the denoised and bleach-corrected time series from the green 710 channel was divided by that from the red channel. 4) Lastly, to control for the variations in the 711 dynamic range of the calcium signal due to variations in the expression of the fluorescent

indicators, we normalized the ratio-metric signal such that the 1st percentile of the signal takes a 712 value of 0 while the 99th percentile takes the value of 1. To control for cases where a given 713 neuron never became active in a given recording (e.g. NSM in *pdfr-1::acy-1gf* animals), 714 exceptions were made if a neuron's peak activity in a given recording was less than 10% of the 715 average across all recordings. In this case, the original $\Delta R/R_0$ value was used without 716 normalization. Apart from this exception, the normalized ratio-metric signal was used for 717 718 subsequent data analyses, except where indicated. These data processing steps (dividing by 719 mScarlett; normalizing to a 0-1 scale) did not change the distributions of GCaMP intensity 720 values (Figure 1-Figure Supplement 2H).

721 Estimation of instantaneous animal location and velocity. The instantaneous location 722 of the animal $\begin{bmatrix} x_a \\ y_a \end{bmatrix}$ was calculated based on the following formula:

$$\begin{bmatrix} x_a \\ y_a \end{bmatrix} = \begin{bmatrix} x_s \\ y_s \end{bmatrix} + r * \begin{bmatrix} \cos\theta & -\sin\theta \\ \sin\theta & \cos\theta \end{bmatrix} \cdot \begin{bmatrix} x_c \\ y_c \end{bmatrix}$$

where $\begin{bmatrix} x_s \\ y_s \end{bmatrix}$ is the instantaneous location of the microscope stage, $\begin{bmatrix} x_c \\ y_c \end{bmatrix}$ is the position of the head region of the animal as seen on the frame captured by the tracking camera, θ is the rotation angle between the field of view of the tracking microscope and the sensor of the tracking camera, and ris the pixel size of the frames taken through the tracking camera. The velocity of the animal was calculated by dividing the displacement vector of the animal between adjacent time points by the duration of the time interval.

Classification of roaming and dwelling states. Previous methods to segment roaming
 and dwelling defined these states based on the speed and angular speed of animal movement
 measured over 10s time windows (Ben Arous et al, 2009; Flavell et al, 2013). These prior

732 datasets were recorded on multi-worm trackers with lower resolution than that of our confocal microscope. High-amplitude angular speed measurements from the low-resolution trackers 733 primarily reflected paused movement and/or low-speed forward/backward movement. Under 734 high-resolution confocal recordings, angular speed was measured with greater precision and, 735 thus, displayed a different profile, in part reflecting body oscillations. Therefore, we utilized a 736 737 slightly different approach to segment roaming and dwelling from our confocal recordings: (i) we computed the median and variance of animal speed using a sliding window of 20 seconds, 738 739 which transformed the 1-dimensional speed data into two dimensions (Fig. 1 - Figure 740 Supplement 4A). We then (ii) fit a Hidden Markov Model with Gaussian mixture emissions to this two-dimensional dataset. This yielded a model with three Gaussian components and two 741 hidden states. The two hidden states successfully captured periods of persistent fast and slow 742 movements, which we define as roaming and dwelling, respectively (Figure 1 and Figure 1-743 Figure Supplement 3). Roaming and dwelling segmentation of multi-worm tracking data (Fig. 6-744 7) was performed using previous methods (Flavell et al, 2013) and is described above. 745

Aligning calcium imaging data with behavioral data. As described in the Microscope Design and Assembly section, the trigger signal for the confocal laser was simultaneously sent to the computer controlling the tracking microscope. This computer thereby stores two sets of time stamps, one for the laser illumination sequence and the other for the behavioral tracking video. Since the internal clock is the same, we can interpolate both the calcium activity data and the behavioral data onto the same time axis. Specifically, we interpolated both the calcium activity and behavior time series to obtain a common sampling frequency of 2 Hz.

Principal component analysis (PCA). An *N-by-M* data matrix was assembled with the rows representing neuron identity (N = 10) and the columns time points. Data across different

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755 recording sessions were concatenated together along the time dimension. PCA was performed by 756 first subtracting the mean from each row and then applying singular value decomposition to the matrix. We chose this method over the previously described approach of performing PCA on the 757 time derivatives of the calcium signals¹¹. We found that applying PCA on the time derivatives 758 did not yield PCs with intuitive behavioral correlates when applied to our data. This may have 759 760 resulted from the higher sensitivity of the time derivatives to measurement noise in these freelymoving animals or from our recordings consisting of a different subset of neurons, compared to 761 previous studies. 762

763 **Cross-correlation in neural activity.** To estimate the time-lagged similarity between the 764 activity of two neurons for a given genotype, the cross-correlation function (XCF) was first 765 calculated individually for each data set of that genotype and then averaged. Bootstrapping was 766 done to obtain confidence intervals on the mean. To examine the functional coupling between 767 two neurons over time, average XCFs were calculated for data from a series of 60 second time windows spanning from 90 seconds before NSM activation to 90 seconds after. For each time 768 769 window, the point with the largest absolute value along the average XCF was identified. The 770 mean and 95% CI values of these extrema points were concatenated chronologically to generate 771 plots.

Classification of NSM activity states. We first computed the local median and variance
of NSM activity using a sliding window of 20 seconds. This transformed the 1-dimensional
activity data into 2 dimensions (Figure 1 – Figure Supplement 4B). We then fit a Hidden Markov
Model with Gaussian mixture emissions to this 2-dimensional dataset. This yielded a model with
3 Gaussian components and 2 hidden states. As the average NSM activity under these two

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hidden states differed significantly, we interpreted these hidden states as states of high and lowNSM activity.

General Linear Model to predict animal speed from calcium activity. The model
performs linear regression on a set of linear and nonlinear terms derived from the instantaneous
calcium activity of individual neurons. These include an intercept term, linear and squared terms
of each neuron's activity, and all pairwise products of neural activity across all 10 neurons
measured. The model then computes a linear fit of these predictor variables to the concurrent
speed of the animal using QR decomposition.

Logistic regression to predict foraging state from calcium activity. Logistic regression was performed using the instantaneous activity of all or a subset of the 10 neurons to predict the concurrent foraging state (i.e. roaming or dwelling). Model parameters was regularized through the elastic net algorithm, which implements a combination of L^1 and L^2 normalization.

Segmentation of NSM and AVB activities via thresholding. For analyses in Fig. 4, we
segmented NSM and AVB activities into high versus low values. The threshold values for
defining the high versus low values were determined using the Otsu method. This was
implemented using the "multithresh" function in MATLAB (with the source data set to the wild
type activity of NSM or AVB, and the parameter N set to 1). Thresholds determined from wildtype animals were uniformly applied to all genotypes.

Convolutional neural network (CNN) classifier. The classifier was implemented using
the Deep Learning Toolbox in MATLAB. The architecture of the network consists of a single
convolutional layer with a single channel of two 9-by-3 convolutional kernels with no padding,
followed by a Rectified Linear Unit (ReLu) layer, a fully connected layer with two neurons, a

800 two-way softmax layer and a classification output layer. The last layer is specifically required for the Matlab implementation and computes the cross-entropy loss. We used two 9-by-3 801 convolutional kernels to allow for the possibility that two separate activity patterns might be 802 803 necessary for accurate predictions, though in reality only one convolutional kernel had informative values (the other was typically comprised of values close to zero). Calcium activity 804 805 from all neurons imaged, except for the 5-HT neuron NSM, were used for training, validation and testing. To specifically predict the transition from roaming to dwelling, only data during 806 807 roaming were used to predict the onset of NSM activity. For each wild-type data set, calcium 808 activity during each roaming state was first down-sampled by averaging data from time bins of 809 various widths (7.5-50s, see Fig. 5 – Figure Supplement 1) starting from immediately prior to the onset of a dwelling state and going back in time to the beginning of the roaming state. The 30-810 811 second bin width was selected after a systematic examination of how well CNNs performed 812 when trying a range of different bin widths and total numbers of bins (Fig. 5 - Figure Supplement 1). Each data point in the down-sampled data was assigned a label of 1 or 0: 1 if it is 813 immediately prior to an episode of NSM activation, and 0 otherwise. Positive and negative 814 815 samples were balanced by weighting the prediction error of each sample by the number of 816 samples in that class. The positive and negative sample groups were each partitioned at random 817 into the training, validation, and test sets at an 8:1:1 relative ratio. This random partition was repeated 200 times. For each data partition, network training was performed 10 times with 818 819 random initial conditions, using Stochastic Gradient Descent with Moment (SGDM) with the following hyper-parameters: 820

Hyper-parameter name	Value
Initial Learning Rate	0.09
L2 Regularization Rate	0.0001
Learning Rate Drop Factor	0.1

Learning Rate Drop Period	10
Momentum	0.9
Validation Frequency	30
Max number of epochs	150

821

822 To identify convolutional kernels that consistently contribute to classifier accuracy, convolutional kernels from networks that achieved greater than 50% test accuracy were recorded 823 824 and k-means clustering was performed. Within each cluster, the distribution of weights at each 825 kernel location was used to extract a confidence interval for the mean value of that kernel element. Elements of the kernel with mean values significantly different from 0 were taken to 826 827 indicate important neural activity profiles for predicting NSM activation. Since each kernel element maps to the activity of a given neuron at a particular time window, the preferred sign of 828 a kernel element would suggest whether a neuron is preferentially active (when the preferred 829 sign is positive) or inactive (when the preferred sign is negative) at that time window. 830 Feature selection was performed to identify key neurons whose activity critically 831 832 contribute to classification accuracy. To generate the results in Fig. 5B, data from a chosen 833 neuron was removed from the 9-neuron data set, and the resulting partial data set was used to train CNNs following the procedure described above. To generate the results in Figure 5-Figure 834 835 Supplement 2B, two types of partial data sets were used. In the first category, data from 6 out of 836 9 neurons were used for training. We tested all possible 9-choose-6 neuron combinations. In

second category, we tested using data from only RIB, AIA, and AVA for network training.

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839 Data Analysis for Behavioral Assays

Extraction of locomotory parameters. Animal trajectories were first extracted using
 custom software described previously ³¹. Speed and angular speed were calculated for all time
 points of each trajectory, and then averaged over 10 second intervals.

Identification of roaming and dwelling states. Roaming and dwelling states were
identified as previously described³³. Briefly, the speed and angular speed measured for each
animal at each time point was assigned into one of two clusters. This allowed each animal
trajectory to be converted into a binary sequence. A two-state HMM was fit to these binary
sequences to estimate the transition and emission probabilities. This was done separately for each
genotype under each experimental condition.

849 Calculation of heading bias. The instantaneous heading bias c(t) was defined as:

$$c(t) = \frac{(\boldsymbol{v} \cdot \boldsymbol{g})}{(\|\boldsymbol{v}\| \times \|\boldsymbol{g}\|)}$$

where v is the instantaneous velocity of the animal, and g is the unit vector that points from the animal's current location to the nearest point on the boundary between the sparse food patch and the dense food patch. Here, g is used as the proxy for the gradient of olfactory cues at the animal's current location. Equivalently, c(t) is the cosine of the angle between the animal's instantaneous direction of motion and the direction of the chemotactic gradient at its current location.

856 Statistical Analysis

857 Comparison of sample means. The Wilcoxon ranksum test was applied pair-wise to
858 obtain the raw p-values. When multiple comparisons were done for the same type of experiment
859 (e.g. comparing the fraction of animal roaming during the patch foraging assay for different

genotypes), the Benjamini-Hochberg correction was used to control the false discovery rate. A
corrected p-value less than 0.05 was considered significant.

Bootstrap confidence intervals. Bootstrapping was performed by sampling with
replacement *N* times from the original data distribution (*N* equals the size of the original
distribution). This procedure was repeated 1000 times and the test statistic of interest (e.g. the
sample mean) was calculated each time on the bootstrapped data. The 5th and 95th percentiles of
the calculated values then constitute the lower and upper bounds of the 95% confidence interval.

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868 DECLARATION OF INTERESTS

869 The authors have no competing interests to declare.

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1036 FIGURE LEGENDS

1037 Figure 1. Circuit-wide calcium imaging reveals a stable, low-dimensional neural representation of foraging states. (A) (Top) Movement trajectory of a C. elegans animal 1038 foraging on bacterial food under the tracking microscope. Red and black dots mark the beginning 1039 1040 and end of the trajectory, respectively. Orange indicates that the animal was in the roaming state, while blue indicates the animal was in dwelling state. (Bottom) The speed of the animal during 1041 the same period. (B) Putative neural circuit that mediates the sensory control of the roaming and 1042 dwelling states, based on the C. elegans connectome⁴⁶ and genetic analyses from a previous 1043 study³³. Each C. elegans neuron has a three-letter name. Blue highlights indicate sites of 1044 serotonin signaling and orange highlights indicate sites of PDF signaling. Gray arrows are 1045 synapses from the *C. elegans* connectome. The thickness of these arrows indicate the number of 1046 synapses at a given connection. Dotted blue and orange arrows indicate neuromodulatory 1047 1048 connections from Flavell et al., 2013. (C) Example dataset from multi-neuron calcium imaging in a free-moving wild-type animal. The calcium activity of each neuron is shown in black. The 1049 green-red heat map in the background indicates axial velocity of the animal, and the behavioral 1050 state of the animal is shown on top. GCaMP6m data were divided by co-expressed mScarlett 1051 fluorescence levels and normalized to a 0-1 scale, based on the 1st and 99th percentiles of the 1052 1053 neuron's signal (see Methods). (D) Event-triggered averages of individual neuron activity aligned to transitions between roaming ("R") and dwelling ("D") (left column), or transitions 1054 between forward runs ("F") and reversals ("RV") (right column). Data are shown as means and 1055 1056 95% confidence interval (95% CI). (E) Histograms of individual neuron's activity during 1057 roaming (orange), dwelling (blue), forward runs (green), or reversals (red). Note that shifts of distributions to the right indicate increased neural activity. (F) Simultaneously recorded activity 1058 of the 10 neurons projected onto the space spanned by the 1st and 2nd principal components (i.e. 1059

1060 PC1 and PC2). Individual data points are colored according to the ongoing axial velocity. Histograms above and to the right of the scatterplot indicate distribution of PC1 and PC2 values 1061 1062 for 3 ranges of axial velocity (v): $v \le -0.0165$ mm/s (red), -0.0165 mm/s $< v \le 0.0165$ mm/s (gray), $v \ge 0.0165$ mm/s (green). (G) Projection of neural activity in principal component space, 1063 1064 colored by the ongoing foraging state. Histograms show distributions of PC1 or PC2 values conditioned on the foraging state. H) Comparison of measured velocity (x-axis) to the velocity 1065 1066 predicted by a General Linear Model that was trained from the neural data (y-axis). The density 1067 of datapoints in this space is represented as a two-dimensional histogram. I) Average Receiver 1068 Operating Curves from logistic regression models trained to predict foraging states using 1069 ongoing neural activity data from all 10 neurons or subsets of neurons (see Supplemental 1070 Methods for details). Dotted line indicates level expected by chance. Data in D-H are from the same set of wild-type animals (N=17). *p<0.05, **p<0.01, ***p<0.001, ****p<0.0001, 1071 1072 Wilcoxon rank-sum test.

1073

1074 Figure 2. Persistent NSM activity is associated with the dwelling state. (A) Joint distribution 1075 of NSM activity and the concurrent axial velocity during the dwelling (left column) or the 1076 roaming (right column) state. Histograms on top show marginal distributions of NSM activity 1077 during dwelling (left) or roaming (right). Histogram to the right show marginal distributions of 1078 axial velocity during dwelling (blue) or roaming (orange) states. (B) NSM activity aligned to the 1079 onset of dwelling states. (Top) Average NSM activity around the onset of dwelling states. 1080 (Bottom) Heat map of NSM activity around individual instances of roaming-to-dwelling 1081 transitions. Dotted black line denotes the onsets of dwelling states. Black ticks on the heat map 1082 mark the onset of an NSM activity bout. (C) Left: latencies of roaming-to-dwelling transitions

1083 relative to the closest onset of an NSM activity bout. Right: latencies of dwelling-to-roaming transitions relative to the closest offset of an NSM activity bout. NSM activity bouts are defined 1084 1085 through Gaussian Mixture Clustering (see Methods for details). (D) Scatterplot of the durations of individual dwelling states and the durations of their coinciding NSM activity bouts. (E) 1086 Projection of neural activity in principal component space, colored by concurrent NSM activity. 1087 1088 Histograms show distributions of NSM activity along both axes. (F) Average circuit activity 1089 dynamics in principal component space aligned to the onset of NSM activation. Each colored 1090 arrow represents average activity dynamics over a 15 second interval. Color indicates ongoing 1091 NSM activity. Faint lines show bootstrap samples of the average dynamics. (G) Event triggered averages of individual neuron activity and animal speed aligned to the optogenetic activation of 1092 1093 NSM. Red and green traces represent data from animals raised on all-trans retinal (ATR) (N = 61094 animals), while gray traces represent data from control animals raised without ATR (N = 41095 animals). Light red patch indicates the time window in which the red light is turned on. 1096 Comparisons are made between 1 second before the onset of the red light stimulation and 18 seconds into the stimulation. Data are shown as means and 95% C.I.s **p<0.01, ***p<0.001, 1097 *****p<0.0001, Wilcoxon rank-sum test with Benjamini-Hochberg (BH) correction. 1098

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Figure 3. Serotonin signaling promotes persistent activation of serotonergic NSM neurons via a mutual inhibitory circuit. (A-B) Example circuit-wide calcium imaging datasets from *tph-1* (A) and *mod-1* (B) mutant animals, shown as in Fig. 1C. (C) Association of NSM activity and axial speed in the indicated genotypes. Data are shown as probability density plots. (D) Duration of NSM activity bouts for the indicated genotypes. Data points represent individual NSM activity bouts and violin plots show distributions across animals of the same genotype. 1106 Blue "+" marks the median of each distribution. (E) Probability of NSM being active in wild type animals and serotonin mutants. Data points represent individual animals and violin plots 1107 show distributions across animals of the same genotype. Blue "+" marks the median of each 1108 distribution. For (D-E), N = 17, 10, and 8 animals for WT, *tph-1*, and *mod-1*, respectively. (F) 1109 Event triggered averages of NSM activity and animal speed aligned to the optogenetic activation 1110 1111 of *mod-1* expressing neurons. Red and green traces represent data from animals raised on all-1112 trans retinal (ATR) (N = 7 animals), while gray traces represent data from control animals raised 1113 without ATR (N = 4 animals). Data are shown as means and 95% C.I.s. Light red patch indicates 1114 the time window in which the red light is turned on. For NSM calcium activity, the comparison is made between 1 second before the onset of the red light stimulation and 30 seconds into the 1115 1116 stimulation. For animal speed, the comparisons is made between 1 second before the onset of the red light stimulation and 60 seconds into the stimulation. (G) Circuit schematic based on results 1117 from the *tph-1* and *mod-1* mutants, showing cross inhibition between the NSM and the MOD-1 1118 expressing neurons. For (D-F), **p<0.01, ***p<0.001, ****p<0.0001, Wilcoxon rank-sum test 1119 with Benjamini-Hochberg (BH) correction. 1120

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Figure 4. PDF signaling is required for mutual exclusivity between circuit states and acts downstream of the 5-HT target neurons in the mutual inhibitory circuit. (A) Example circuit-wide calcium imaging dataset from *pdfr-1* mutants lacking PDF neuropeptide signaling, shown as in Fig. 1C. No roaming/dwelling ethogram is shown for *pdfr-1* animals due to changes in their speed distribution that implicate altered or new behavioral states (see Figure 4-Figure Supplement 4A-B). (B) Example circuit-wide calcium imaging dataset from transgenic animals expressing the hyperactive PDFR-1 effector ACY-1(P260S) specifically in *pdfr-1* expressing

neurons. For NSM, the un-normalized $\Delta R/R_0$ is shown since the $\Delta R/R_0$ values never exceeded 1129 1130 10% of the average peak NSM activity wild-type animals. (C) Scatterplots of NSM and AVB 1131 activity in *pdfr-1* mutants, transgenic *pdfr-1::acy-1(P260S)gf* animals, and *tph-1; pdfr-1* double mutants. Data points are colored by the instantaneous speed of the animal. Color scale was 1132 1133 chosen so that blue colors correspond to speeds typical of the dwelling state, orange correspond 1134 to speeds typical of the roaming states, while gray colors indicate speeds in-between the former. Dotted lines show the threshold values for NSM and AVB activity used for defining "co-activity" 1135 1136 (determined using the Otsu method; see Methods). Insets show the density of data points in each of the quadrants defined by these threshold activity levels. (D) Probability of NSM and AVB 1137 being co-active for genotypes shown in (C). ***p<0.001; ****p<0.0001, bootstrap estimates of 1138 1139 the mean with BH correction. (E) Duration of NSM activity bouts for the indicated genotypes. 1140 Data points corresponds to individual NSM activity bouts. Each violin plot represent data from animals of the same genotype. "+" denotes the median of each distribution. (F) Probability of 1141 1142 NSM being active in wild-type and mutant animals. Data points corresponds to individual NSM activity bouts. Each violin plot represent data from animals of the same genotype. "+" denotes 1143 1144 the median of each distribution. For (C-F), N = 17, 10, 8, 11, 9 and 8 animals for WT, *tph-1*, and 1145 mod-1, pdfr-1, pdfr-1::acy-1gf, and tph-1;pdfr-1 animals. (G) Event triggered averages of NSM 1146 activity and animal speed aligned to the optogenetic activation of pdf-1 expressing neurons. Red 1147 and green traces represent data from animals raised on all-trans retinal (ATR) (N = 5 animals), 1148 while gray traces represent data from control animals raised without ATR (N = 4 animals). Data 1149 are shown as means and 95% C.I.s. For NSM calcium activity and animal speed, comparisons 1150 are made between 1 second before the onset of the red light stimulation and 30 seconds into the 1151 stimulation. (H) Speed of wild-type and *pdfr-1* mutant animals in response to optogenetic

activation of the MOD-1 expressing neurons (red shading). Average speeds during the window spanned by the black line were compared between animals of the two genotypes. (I) Circuit schematic summarizing results shown in (C-H): the PDFR-1 expressing neurons act downstream of the MOD-1 expressing neurons to inhibit the 5-HT neuron NSM. Black arrows indicate anatomical connections based on the *C. elegans* connectome⁵⁵. For (D- H), **p<0.01, ***p<0.001, ****p<0.0001, Wilcoxon rank-sum test with BH correction.

1158

1159 Figure 5. A CNN classifier identifies circuit activity patterns predictive of roaming-todwelling state transitions. (A) Schematic illustrating the architecture of the Convolutional 1160 Neural Network (CNN) trained to predict NSM activation events. (B) Left: a common 1161 1162 convolutional kernel found across successfully trained CNNs. Only weights that are significantly different from zero are colored. Right: Feature selection results. Each black bar depicts the 1163 1164 average area under the curve for the Receiver Operating Characteristic curve (AUC-ROC) from 1165 networks trained using data with one neuron held out at a time. The identity of the held-out neuron is indicated to the far left. The gray stripe in the background denotes the 95% CI of the 1166 AUC-ROC from networks trained using data from all 9 neurons. Error bars are 95% CI of the 1167 mean. **p<0.01, bootstrap estimate of the mean with BH correction. (C) Example activity traces 1168 1169 from NSM, AVB, and the three neurons with significant weights in the convolutional kernel. 1170 Activity traces were taken during roaming (left), dwelling (right) and roaming-to-dwelling 1171 transition. (D) Scatterplots of simultaneously measured neural activity of the indicated pairs of 1172 neurons. Orange data points are taken during roaming states at least 1 minute before the onset of 1173 the next dwelling states and before NSM becomes active. Green data points are taken within 1 minute before the onset of dwelling states. Along the x- and the y- axes are marginal probability 1174

1175 distributions of the data points shown in the scatterplots. (E) Scatterplots of simultaneously measured neural activities of AIA and NSM. Orange data points are taken within 1 minute before 1176 the onset of the next dwelling states and before NSM becomes active. Blue data points are taken 1177 1178 within 30 seconds after the onset of dwelling states. Along the x- and the y- axes are marginal probability distributions of the data points shown in the scatterplots. (F) Average cross-1179 1180 correlation functions between the indicated pairs of neurons during roaming (orange, data taken from 100-70 seconds before the onset of the next dwelling state), roaming-to-dwelling transition 1181 1182 (green, data taken from 30-0 second before the NSM activation event prior to the onset of the 1183 next dwelling state), or dwelling (blue, data taken from 10-40 seconds after dwelling onset). Error bars are standard error of the mean. Arrowheads denote the point of maximum in absolute 1184 1185 magnitude of the cross-correlation function. (G) Average cross-correlation coefficients computed at peak points indicated in (F). For (B, D-G), N = 17 WT animals. For (D-E and G), *p<0.05, 1186 **p<0.01, ****p<0.0001, Wilcoxon rank-sum test with BH correction. 1187

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1189 Figure 6. The AIA sensory processing neuron can drive behavioral state switching. (A) Average locomotion speed before, during, and after AIA::Chrimson activation for wild-type 1190 (left), tph-1 (middle), and pdfr-1 (right) animals. Animals were grouped by whether they were 1191 roaming (orange) or dwelling (blue) prior to AIA stimulation. Pink patches in the background 1192 1193 denote the one-minute stimulation window. Gray lines indicate no-all-trans-retinal (no-ATR) 1194 controls. N=1032 wild-type animals were compared to N=370 no-ATR controls. N= 927 tph-1mutants were compared to N = 284 no-ATR control. N= 383 pdfr-1 mutants were compared to N 1195 1196 = 237 no-ATR controls. Note that roaming in pdfr-1 animals was too rare and brief to be included for analysis on AIA-induced slowing. Orange and blue arrowheads denote time points 1197

1198 used for analyses in (B). Error bars are 95% CI of the mean. (B) Fraction of animals in the 1199 roaming state at different phases of AIA::Chrimson stimulation. Top: Among animals that were roaming pre-stimulation, the fraction of them that were roaming after 4 seconds or 40 seconds 1200 1201 from the onset of AIA stimulation. Bottom: Among animals that were dwelling pre-stimulation, the fraction of them that were roaming after 20 seconds or 40 seconds from the onset of AIA 1202 1203 stimulation. Same analyses were performed for wild-type (left), tph-1 (middle), and pdfr-1 (right) animals. See panel (A) for full traces. (C) AIA-induced changes in roaming and dwelling at 1204 1205 different optogenetic stimulation intensities. For (B-C), error bars are 95% CI of the mean and 1206 ****p<0.0001, Wilcoxon rank-sum test. (D) Functional architecture of the circuit controlling the roaming and dwelling states, based on results from Figures 2-5. 1207

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Figure 7. The AIA sensory processing neuron can promote either roaming or dwelling, 1209 depending on the sensory context. (A) Top: Cartoon depicting the patch foraging behavioral 1210 1211 assay. Horizontal bar with gradient signifies the food odor gradient emanating from the dense food patch. Bottom: example trajectories of two animals from a patch foraging assay. Color scale 1212 indicates speed, with orange corresponding to roaming-like speeds and blue dwelling-like speeds. 1213 1214 Red dots denote the starting points of the animals. (B) Average fraction of animals roaming on 1215 the sparse food patch in the patch foraging assay. Comparisons are made between wild-type 1216 animals in the patch foraging assay (n=288), wild-type animals assayed on uniform sparse food with no dense patch around (n=194), and *tax-4* animals in the patch foraging assay (n=81). (C) 1217 Schematic depicting how heading bias is calculated. (D) Event-triggered averages showing 1218 1219 average heading bias of animals for two minutes prior to transitions into dwelling states. 1220 Experimental conditions are depicted with same color scheme as in (B). Data are shown as

means \pm SEM. The average heading bias within two time windows, one from 60-50 seconds 1221 1222 prior to dwelling onset, the other from 20-10 seconds prior to dwelling onset, were compared. (E) 1223 Left: Average fraction of animals roaming on sparse food in the patch foraging assay in wild-1224 type (black) versus AIA silenced (AIA::unc-103gf) animals (green). Right: Heading bias of 1225 AIA-silenced animals (green) two minutes prior to the transition into the dwelling state. n=197. Wild type data (black with gray error bar) are shown for comparison. (F) Left: schematic of 1226 1227 behavioral assays in uniformly-seeded food environments. Right: Average fractions of animals 1228 roaming for wild-type (black bars) and AIA-silenced (green bars) animals exposed to two 1229 different densities of uniformly-distributed sparse food. For all calculations on fraction of animals roaming, error bars are 95% CI of the mean. For all calculations of heading bias, error 1230 1231 bars are SEM. For all comparisons, **p<0.01, ****p<0.0001, Wilcoxon rank sum test with BH 1232 correction.

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1234 SUPPLEMENTARY FIGURE LEGENDS

1235 Figure 1 – Figure Supplement 1. Design and calibration of the spinning-disk confocal tracking scope. (A) Design of the microscope. Orange and green shaded boxes indicate the 1236 confocal and behavioral tracking parts of the microscope, respectively. An example image from 1237 1238 the behavior tracking camera is shown, with the worm outlined in white. mScarlett-expressing 1239 neurons can be robustly detected in the animal's head. (B) To minimize photo-bleaching, 1240 movement artifacts, and animal disturbance, the laser illumination of animals was timed to 1241 camera exposure and objective piezo movement during volume acquisition, as is illustrated. The 1242 tracking LED was also only illuminated in between GCaMP/mScarlett volume acquisitions, so as to prevent cross-talk between the upper and lower microscope paths. Laser illumination 1243

permitted animal tracking during volume acquisition. (C) A sample volume captured by the confocal microscope. Neurons expressing the GCaMP6m and the mScarlett fluorescent proteins are annotated. For AIY, the neurite is labeled. (D) Semi-automated segmentation of neuron boundaries using the SURF algorithm. For a subset of frames in a video, the neuron boundaries are manually outlined. Then, the boundaries are propagated from one frame to others, based on image transformations that are defined by matching SURF features across frames.

1250

1251 Figure 1 – Figure Supplement 2. Calibration of behavioral tracking accuracy and the effect of motion on calcium imaging data. (A) Example trajectory of an animal recorded under the 1252 tracking confocal microscope. (B) An image of this animal's head region captured through the 1253 1254 behavior tracking camera. Bright pixels correspond to neurons expressing the mScarlett transgene. (C) Probability distribution of the location of the head region as seen through the 1255 behavior tracking camera across all of the frames of the recording shown in (A). All scale bars in 1256 1257 (A-C) represent 0.1 mm. (D-F) Extraction of calcium activity from dual-channel fluorescent intensities from a representative neuron. (D) Time series of red (emission wavelength 603-1258 678nm) and green (emission wavelength 502-538nm) fluorescent intensities were first denoised 1259 1260 by median filtering. (E) Next, photobleaching over time was corrected by fitting and then 1261 normalizing away an exponential decay function. (F) Finally, the time series data from the green 1262 channels was divided by that from the red channel. The resulting time series was normalized to a relative scale of 0 to 1, with 0 corresponding to the 1st percentile and 1 to the 99th percentile of 1263 ratiometric values. (G) Range of variation normalized by mean calculated for the bleach-1264 1265 corrected red and green fluorescent intensities. Histograms were computed for aggregate data 1266 from all videos used in this study. Curved lines overlaying the red and green histograms (color matched) are mixture of Gaussian models fit to the corresponding histogram. (H) Distributions of fluorescence measurements are not perturbed by data processing. Probability distribution functions for the activity of three example neurons after various stages of data pre-processing: (top) cell-specific fluorescent signals from the green channel after denoising, bleach correction and baseline subtraction; (middle) ratiometric values computed by dividing signals from the green channel with those from the red channel; (bottom) normalized $\Delta R/R_0$ values computed by remapping the 1st and 99th percentiles of the distribution to 0 and 1.

1274

1275 Figure 1 – Figure Supplement 3. Additional examples of multi-neuron calcium activity
1276 traces in freely-moving wild-type animals. Data are shown as in Fig. 1C

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1278 Figure 1 – Figure Supplement 4. Gaussian Mixture Models (GMM) for analyzing animal 1279 speed and NSM calcium activity. (A) GMM fit to the joint distribution of the normalized animal speed and the log-transformed variance of the normalized speed. Regions encircled by the 1280 white lines are centered on and encompass 50% of the probability mass of each of the 3 1281 Gaussians that compose of the GMM. (B) GMM fit to the joint distribution of the normalized 1282 NSM calcium activity and the log-transformed variance of it. Regions encircled by the white 1283 1284 lines are centered on and encompass 50% of the probability mass of each of the 4 Gaussians that compose the GMM. 1285

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Figure 1 – Figure Supplement 5. Encoding of behavioral parameters by the calcium activity
 of individual neurons. (A) Joint distribution of individual neuron's activity versus axial velocity

1289 (left column) or speed (right column). Colored dots indicate the Spearman's correlation coefficient between neural activity and the locomotory parameters for all wild-type data or 1290 conditioned on the animal's movement direction. Green and red color indicates positive or 1291 negative correlation respectively, while the size the dot indicates the magnitude of the correlation 1292 coefficient. Insignificant correlations are represented with a small black dot. (B) Average 1293 1294 autocorrelation function for the activity of each neuron across wild-type animals. The average autocorrelation function for animal speed is shown in green for comparison. N=17 wild-type 1295 1296 animals, same dataset as in Fig. 1.

1297

Figure 1 – Figure Supplement 6. Differences in RIB and AVA joint activity during roaming
compared to dwelling. (A) Joint distributions of AVA and RIB activity during dwelling and
roaming in wild-type animals. (B) Quantification of data from panel (A). Distribution of AVA
activity, conditioned on RIB activity being low, during roaming versus dwelling. **p<0.01,
Wilcoxon rank-sum test.

1303

Figure 1 – Figure Supplement 7. Relationships between specific neurons and the principal
components. (A) Loadings of individual neurons on to PCs 1-4. (B) Projection of neural activity
in principal component space, colored by the concurrent activity of each of the 10 neurons. N=17
WT animals, same dataset as in Fig. 1.

1308

Figure 1 – Figure Supplement 8. Examples showing the prediction of locomotion
 parameters using circuit activity. Prediction of foraging state (top ethograms) and axial

velocity (middle traces) from the simultaneous activity of the 10 neurons shown in Fig. 1. Model
predictions were plotted side-by-side with measured data for comparison. Activity traces of
NSM and AVA were plotted to illustrate the multi-neuron activity data used for prediction.

1314

Figure 2 – Figure Supplement 1. Further analysis of NSM activity. (A) NSM activity aligned 1315 to the onset of roaming states. (Top) Average NSM activity around the onset of roaming states. 1316 (Bottom) Heat map of NSM activity around instances of dwelling-to-roaming transition. Same 1317 color scale as in (D). Dotted black line denotes the onset of roaming states. Black ticks on the 1318 heat map mark the offset of an NSM activity bout. (B) Event-triggered averages centered on 1319 NSM activation (left) and termination (right) events. Data are from 17 WT animals and are 1320 1321 shown as mean and 95% CI. PC4 is shown as an example to illustrate that dynamics beyond the first two principle components also change around the time of NSM activation. (C) Event 1322 triggered averages of individual neuron activity and animal speed aligned to the optogenetic 1323 1324 activation of NSM for the indicated genotypes and experimental conditions. Light red patch indicates the time window in which the red light is turned on. Comparisons are made between 1 1325 second before the onset of the red light stimulation and 22 seconds into the stimulation. N=4-5 1326 1327 animals per condition, with an average of 3 independent stimulation events (minutes apart) per 1328 animal. Wild-type control animals were recorded in parallel to *mod-1* mutants. Data are shown as means and 95% C.I.s *p<0.05, **p<0.01, ***p<0.001, ****p<0.0001, Wilcoxon rank-sum test 1329 1330 with Benjamini-Hochberg (BH) correction.

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Figure 3 – Figure Supplement 1. Further analysis of NSM activity. (A) Fraction of time animals spent roaming versus dwelling for wild-type (WT), *tph-1*, and *mod-1* animals. Data points represent individual animals and violin plots show distributions across animals of the same genotype. Blue "+" marks the median of each distribution. N = 17, 10, and 8 animals for WT, *tph-1*, and *mod-1*, respectively. **p<0.01, ***p<0.001, ****p<0.0001, Wilcoxon rank-sum test with Benjamini-Hochberg (BH) correction.

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Figure 3 – Figure Supplement 2. Additional examples of multi-neuron calcium activity
traces in free-moving serotonin mutants. Data are shown as in Fig. 1C

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Figure 4 – Figure Supplement 1. Additional examples of multi-neuron calcium activity
traces in free-moving serotonin mutants. Data are shown as in Fig. 1C.

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Figure 4 - Figure Supplement 2. Further analysis of NSM-AVB co-activity. (A) Joint 1345 distribution of NSM and AVB activity during roaming and dwelling. (B) Data from the indicated 1346 genotypes, showing the probability of AVB activity exceeding a range of different threshold 1347 values, while NSM activity is high. Note that in WT (black) there is a rapid decrease in P(AVB 1348 1349 high | NSM high) as the threshold for calling AVB high is increased. This reflects a low incidence of high AVB activity during high NSM activity, which is attenuated in *pdfr-1* mutants. 1350 Error bars show boostrapped 95% confidence intervals p<0.05, empirical bootstrap test versus 1351 1352 wild-type.

1353

Figure 4 – Figure Supplement 3. Correlations between neurons in wild-type and mutant animals. (A-D) Pairwise correlation coefficients among neurons in the roaming-dwelling circuit. Same color scale (lower right) is used to represent correlation coefficients. Boxes outline the neurons known to promote forward runs (green) and reversals (magenta), as well as the correlations of NSM and other neurons (yellow). N = 17, 10, 8, 11, and 8 animals for WT, *tph-1*, and *mod-1*, *pdfr-1*, and *tph-1;pdfr-1* animals.

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Figure 4 – Figure Supplement 4. Joint activity of NSM and AVB in serotonin and PDF 1361 1362 signaling mutants. (A) Joint distribution of NSM and AVB activity, without normalizing to a 0-1363 1 scale, for movement speeds below (top row) or above (bottom row) a speed of 0.03 mm/s. (B-C) Probability of NSM and AVB being coactive for wild-type and mutant animals moving below 1364 (B) or above (C) 0.03mm/s, quantified without using the 0-1 normalization method. (D-E) 1365 1366 Distributions of NSM (D) and AVB (E) activity, without normalizing to a 0-1 scale, across wildtype and mutant animals. N = 17, 10, 8, 11, and 8 animals for WT, tph-1, and mod-1, pdfr-1, and 1367 tph-1;pdfr-1 animals. ***p<0.001, ****p<0.0001, Wilcoxon rank-sum test with Benjamini-1368 Hochberg (BH) correction. 1369

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Figure 4 – Figure Supplement 5. Analyses of circuit dynamics and foraging behavior in serotonin and PDF signaling mutants. (A) Distributions of axial speed in wild-type animals and various 5-HT and PDF signaling mutants. Top panel shows speed distributions specific to the dwelling (blue) or the roaming (orange) states. Dotted blue and orange lines indicate the

1375 median speeds for the dwelling and roaming states, respectively. Shaded region defines the intermediate speed range used for the analysis in panel B. (B) Fraction of time animals moved at 1376 speeds intermediate between typical dwelling and roaming speeds for wild-type and mutant 1377 animals. The range of intermediate speeds is defined by the shaded region shown in panel B. 1378 Data are shown as mean and standard error. N = 17, 10, 8, 11, 9 and 8 animals for WT, tph-1, 1379 and mod-1, pdfr-1, pdfr-1::acy-1gf and tph-1;pdfr-1 animals. ***p<0.001, ****p<0.0001, 1380 Wilcoxon rank-sum test with Benjamini-Hochberg (BH) correction. (C) Distributions of axial 1381 1382 speed during spontaneous locomotion in transgenic animals used for optogenetic experiments in 1383 Figs. 2G, 3F, and 4G grown on (solid line) or off (dotted line) ATR. *p<0.05, **p<0.01, ****p<0.0001, comparison of bootstrap distributions with BH correction. 1384

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Figure 5 – Figure Supplement 1. Parameter selection for the CNN model. 1386 (A) Convolutional kernels from CNN models trained to predict NSM activation using neural activity 1387 history of different time span and diverse temporal resolution. Kernels in the same row are 1388 trained neural activity history that span similar durations prior to NSM activation; kernels in the 1389 same column are trained with activity data of identical temporal resolution. Each kernel 1390 corresponds to a boot-strapped average across training episodes. Only kernel weights 1391 1392 significantly different from zero are represented by a blue-red color scale spanning from -1 to 1 1393 (lower right). See Supplemental Methods for further details on model specification and training. (B) Average test accuracy of the model types presented in (A). Only models with a test accuracy 1394 1395 greater than 0.5 (i.e. better than random guess) are included. The CNN architecture that uses 1396 input data span of 90 seconds at 30 second resolution was chosen for its simplicity and accuracy and used for further analysis in Fig. 5 and Fig. 5-S2. All models were trained using the same WTdata as in Fig. 5.

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Figure 5 – Figure Supplement 2. Evaluation of CNN classifier performance. (A) AUC-ROC
of the CNN classifiers trained on authentic data compared to those trained on scrambled data and
to the performance of two other common types of classifiers. Data are shown as mean and 95%
CI from 200 training sessions. (B) AUC-ROC of CNN classifiers trained on data withholding
different neuron triplets from the full data set, or with data from only the RIB, AIA, and AVA
neurons. Gray band indicates the 95% CI of the accuracy of CNN classifiers trained on the full
data set, as shown in A.

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Figure 5 – Figure Supplement 3. Convolutional kernels trained to predict transitions in 1408 1409 foraging state or NSM activity. (A) Average convolutional kernels from CNN models trained to predict dwelling state onset using data from all neurons except (left panel) or including (right 1410 panel) NSM. Only kernel weights significantly different from zero are represented by a blue-red 1411 1412 color scale spanning from -1 to 1. (B) Average convolutional kernels from CNN models trained to predict roaming state onset using data from all neurons except (left panel) or including (right 1413 panel) NSM, presented similarly as in (A). (C) Average convolutional kernel from CNN models 1414 trained to predict the offset of NSM activity bouts. All models were trained using the same WT 1415 1416 data as in Fig. 5.

1417

Figure 6 – Figure Supplement 1. Connectivity of the AIA interneuron. Synaptic inputs and outputs of the AIA neuron. Data are from the *C. elegans* connectome. Bilaterally symmetric pairs of neurons (e.g. AIAL and AIAR) were merged here for display purposes. Connections supported by only one single synapse were not included. Note the dense synaptic inputs onto AIA from chemosensory neurons.

1423

Figure 7 – Figure Supplement 1. Food-directed navigation in patch foraging assays. (A) 1424 Heading bias during roaming versus dwelling in the patch foraging assay (dark bars) and control 1425 sparse food plates (light bars), shown separate for roaming and dwelling. (B) Heading bias 1426 during roaming for animals of the indicated genotypes. (C) Average fractions of animals roaming 1427 1428 on the sparse food patch for pdfr-1 (blue) and tph-1 (orange) mutant animals during the patch 1429 foraging assay. (D) Heading bias two minutes prior to the transition into the dwelling state for *pdfr-1* (blue) and *tph-1* (orange) mutant animals. n=99 for *pdfr-1* and n=212 for *tph-1* animals. 1430 1431 Wild type data (black with gray error bar) are shown for comparison. All error bars are 95% CI of the mean. ***p<0.001, ****p<0.0001, Wilcoxon rank sum test. 1432

1433



Figure 1



Figure 2




Figure 4



Figure 5







D

В



С





Figure 1 – Figure Supplement 1



Figure 1 – Figure Supplement 2



Roam









Figure 1 – Figure Supplement 3





Figure 1 – Figure Supplement 5

50



Α





Figure 1 – Figure Supplement 7





Figure 2 – Figure Supplement 1







Figure 4 – Figure Supplement 1





D





С





tph-1; pdfr-1



Figure 4 – Figure Supplement 3



Figure 4 – Figure Supplement 4



Figure 4 – Figure Supplement 5

Temporal resolution (s)



0.8



Figure 5 – Figure Supplement 1





В





С



Figure 5 – Figure Supplement 3



