OMNIMOUSE: SCALING PROPERTIES OF MULTI-MODAL, MULTI-TASK BRAIN MODELS ON 150B NEURAL TOKENS

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Paper under double-blind review

ABSTRACT

Scaling data and artificial neural networks has transformed AI, driving breakthroughs in language and vision. Whether similar principles apply to modeling brain activity remains unclear. Here we leveraged a dataset of 3.3 million neurons from the visual cortex of 78 mice across 323 sessions, totaling more than 150 billion neural tokens recorded during natural movies, images and parametric stimuli, and behavior. We train multi-modal, multi-task transformer models (1M–300M parameters) that support three regimes flexibly at test time: neural prediction (predicting neuronal responses from sensory input and behavior), behavioral decoding (predicting behavior from neural activity), neural forecasting (predicting future activity from current neural dynamics), or any combination of the three. We find that performance scales reliably with more data, but gains from increasing model size saturate – suggesting that current brain models are limited by data rather than compute. This inverts the standard AI scaling story: in language and computer vision, massive datasets make parameter scaling the primary driver of progress, whereas in brain modeling – even in the mouse visual cortex, a relatively simple and low-resolution system – models remain data-limited despite vast recordings. These findings highlight the need for richer stimuli, tasks, and larger-scale recordings to build brain foundation models. The observation of systematic scaling raises the possibility of phase transitions in neural modeling, where larger and richer datasets might unlock qualitatively new capabilities, paralleling the emergent properties seen in large language models.

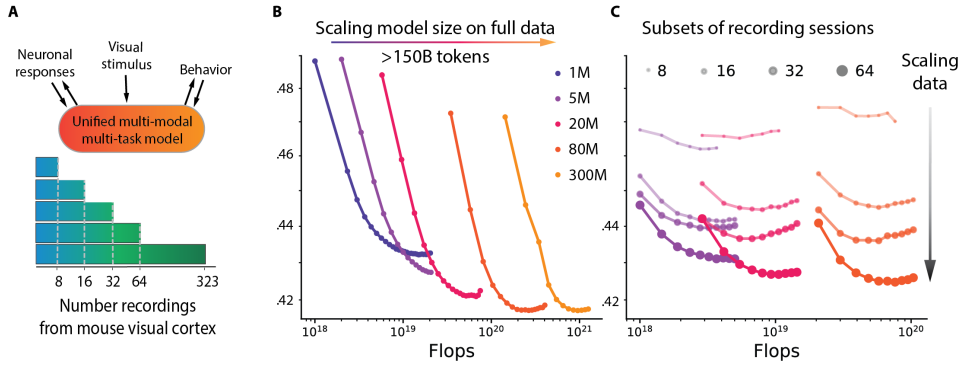

Figure 1: **A.** OmniMouse unifies neural prediction, behavior decoding, and forecasting tasks. **B.** Scaling model size on an 150+ billion neural tokens shows performance saturation, unlike language models. **C.** In contrast, scaling data consistently improves performance across all model sizes, suggesting that neural prediction is currently limited by data.

1 INTRODUCTION

Scaling models and data has driven recent progress in machine learning, with large language, vision, and multi-modal models showing consistent performance gains and enabling foundation models that unify tasks across domains. A natural question is whether models of the brain can also benefit from scaling. In the mouse visual cortex, large datasets (MICrONS Consortium et al., 2021; de Vries

et al., 2019; Angelaki et al., 2025) and standardized benchmarks (Willeke et al., 2022; Turishcheva et al., 2024) exist. Yet, compared with internet-scale corpora, the available datasets are much smaller, more fragmented, and less diverse. The neuroscience community has recently started to work towards foundational models for EEG (Chau et al., 2024; Chen et al., 2024; Cui et al., 2024; Jiang et al., 2024; Kostas et al., 2021; Yang et al., 2023; Thapa et al., 2024; Li et al., 2024), fMRI (Caro et al., 2023; Dong et al., 2024; Kan et al., 2022; Thomas et al., 2022; d'Ascoli et al., 2025), MEG (Csaky et al., 2024), and intracranial signals (Zhang et al., 2023; Wang et al., 2023). But single-neuron resolution, multi-modal foundation models are still missing.

Prior work in this direction focused on isolated modalities (Ye et al., 2023; Azabou et al., 2023), a single predictive task (Wang et al., 2025), lacked scalability across datasets (Ye & Pandarinath, 2021; Mi et al., 2023; Antoniades et al., 2024), or omitted stimulus and behavioral information (Jiang et al., 2025; Mi et al., 2023). These models do not capture the multi-modal and multi-task nature of neural computation. Hence, we cannot systematically study if there are benefits of scaling – a key hallmark of foundational models – in large-scale, single-neuron recordings.

In this work, we introduce OmniMouse, a multi-modal, multi-task architecture for modeling activity in the mouse visual cortex. OmniMouse integrates video stimuli, neuronal responses, and behavioral signals (running speed, eye movements and pupil size) into a single transformer framework. Unlike prior models restricted to a single modality, task or dataset, it supports diverse prediction tasks, including neural forecasting (predicting from past activity) , video-to-response prediction, and decoding behavior from neuronal activity. We train OmniMouse on the largest single-neuron dataset: 323 recordings from the visual cortex of 78 awake mice, with over 150 billion neuronal activity tokens. Mice were shown naturalistic movies, images, and parametric stimuli. The unprecedented scale of this dataset allows us to study how model and dataset size shape predictive performance and if the scaling improvements seen in language and vision extend to large-scale single-neuron recordings.

Our main findings and contributions are:

- **We propose a versatile multi-modal multi-task model**: OmniMouse handles both single-modality and multi-modal, supporting any combination of forecasting and stimulus-conditioned prediction across neurons, stimuli, time, and animals in a single model.
- We **demonstrate the benefits of scaling**: Larger models and datasets improve predictions, with OmniMouse surpassing specialized state-of-the-art models across all tasks.
- We find that performance plateaus beyond moderate model sizes, which suggests that predictive **accuracy may currently be constrained by data** rather than model size or compute.

2 Related work

Large-scale deep learning models for single-neuron predictions. Deep learning has advanced predictive modeling in neuroscience, particularly in vision (Cadieu et al., 2014; Batty et al., 2017; Klindt et al., 2017; McIntosh et al., 2016; Cadena et al., 2019; Kindel et al., 2019; Walker et al., 2019; Zhang et al., 2018; Ecker et al., 2018; Sinz et al., 2018; Burg et al., 2021; Cowley & Pillow, 2020). Early CNN-based approaches introduced shared feature cores with per-neuron readouts (Antolík et al., 2016; Klindt et al., 2017; McIntosh et al., 2016), later extended with temporal dynamics (Sinz et al., 2018) and more efficient readouts (Lurz et al., 2021). Building on these advances, Wang et al. (2025) trained a 13-mice CNN model and showed that "digital twins" can capture biological phenomena beyond their training data. With the shift to transformers, new variants have explored ViT cores (Li et al., 2023), hybrid convolution-attention designs (Lin et al., 2024; Pierzchlewicz et al., 2023), and spatial-transformer readouts (Saha et al., 2024), though most still omit video input.

Transformers have also been applied to response-to-response modeling. The Neural Data Transformer (NDT) (Ye & Pandarinath, 2021) predicted spikes from spikes and behavior, later extended to multiple animals (Ye et al., 2023) and neuronal masking strategies (Zhang et al., 2024). While NDT projects all neurons together via linear layers, Quantformer (Calcagno et al., 2024), also a transformer-based forecaster, introduced neuron-specific tokens to handle any number of neurons. POYO (Azabou et al., 2023), a behavior-decoding model, added spike timing to similar tokens, removing the need for time-window binning, and its extension POYO+ (Azabou et al., 2025) also handled discrete classification tasks such as stimulus orientation. POCO (Duan et al., 2025) combined POYO and NDT tokenization to predict neuronal activity from history and other neurons, while

STDNT (Le & Shlizerman, 2022) explicitly modeled correlations but did not consistently outperform NDT. The aforementioned models ignore visual stimuli. To study the combined effect of both the 'brain state' and 'visual stimuli' on neuronal activity, Bashiri et al. (2021) used a CNN branch for processing static input stimuli and an additional flow-branch to model trial-to-trial correlations between neurons. For dynamic video stimuli, Schmidt et al. (2025) modeled a latent brain state probabilistically, using NDT-style response tokenization. Similarly, Neuroformer (Antoniades et al., 2024) used past activity and visual input but is limited to single sessions and cannot flexibly condition on subsets of neurons or response history. CEBRA (Schneider et al., 2023), a contrastive encoder, also mapped activity to behavior or stimuli, accounting for inter-neuron correlations.

The closest work to ours, outside of single-cell studies, is d'Ascoli et al. (2025). They built a multimodal fMRI predictor using concatenated video, text, and audio embeddings from pretrained backbones and used modality dropout and a subject-specific loss, but did not use other voxels as input.

General scaling laws in deep learning. Large-scale models in language and vision exhibit predictable improvements with scale, described by empirical "scaling laws". Kaplan et al. (2020) first showed that performance follows power-law trends in model size, dataset size, and compute. Hoffmann et al. (2022) refined this with "Chinchilla scaling", prescribing proportional growth of model and data size for optimal efficiency. Aghajanyan et al. (2023) adjusted scaling laws for models with large per-modality pre-trained tokenizers but newer lightweight tokenization ("early-fusion") approaches (Chameleon, 2024; Piergiovanni et al., 2024; Shukor et al., 2025) achieved stronger performance with fewer parameters. Hence, no universal framework for multi-modal scaling exists: Shukor et al. (2025) estimated power-law coefficients for early-fusion models but did not analyze cross-modal interactions. This gap is especially evident in scientific domains, where data are multimodal, complex, noisy, and limited. Examples such as AlphaFold3 (Abramson et al., 2024) suggest that systematic scaling of both models and datasets can drive major advances in AI for science.

Scaling neuroscience models. There is no consensus on whether classic machine learning scaling laws apply to single-neuron data. Jiang et al. (2025) questioned their applicability, analyzing the NDT-based model of Zhang et al. (2025), which predicted $\sim$30,000 spiking neurons across 74 sessions. Jiang et al. (2025) argued that cross-session variability – and thus implicit data heterogeneity – is crucial for scaling benefits, though it remains unclear if these results generalize to different mouse tasks or model architectures. Again using an NDT-based model but on EEG data, Ye et al. (2025) reported that scaling is constrained by data variability, which pretraining alone cannot fully overcome. Consistent with this view, POCO (Duan et al., 2025) used calcium imaging to show that longer recordings improve predictive performance, aligning with earlier results of Lurz et al. (2021). However, POCO included fewer than 90,000 neurons, mostly from zebrafish ($\sim$77,000). Neural saturation has also been observed: Gokce & Schrimpf (2024) found that behavioral alignment improves with model size, but neural alignment plateaus, with gains concentrated in higher-level visual areas. In contrast, Antonello et al. (2023) reported no such saturation when predicting language and audio fMRI responses, suggesting that scaling limits may depend on the modality and data regime. The largest single-cell response-to-behavior prediction model is POYO+ Azabou et al. (2025) with $\sim$100,000 neurons, which did not analyze scaling. Together, these findings highlight the need for large, multi-modal, single-neuron datasets to test how scaling laws manifest in systems neuroscience.

3 Large-scale single-neuron dataset

Data were collected from head-fixed mice running on a wheel while viewing visual stimuli consisting of both images and movies (Fig. 2). Neuronal activity was recorded alongside several behavioral variables: locomotion speed, pupil center positions (x and y), pupil diameter, and its temporal derivative. These behavioral signals are widely used as proxies for modulatory effects on neuronal responses (Niell & Stryker, 2010; Reimer et al., 2014).

Neuronal responses. We used a dataset of over 3 million single-unit neuronal recordings – an order of magnitude larger than the recently published Brain-Wide Map dataset (BWD, 621,733 neurons) (Angelaki et al., 2025). The dataset contains excitatory neurons' responses in visual cortex recorded via wide-field two-photon calcium imaging at 6–14 Hz in awake, head-fixed, behaving mice (Sofroniew et al., 2016), with spiking activity extracted by CAIMAN (Giovannucci et al., 2019), upsampled linearly to 30 Hz for all recordings.

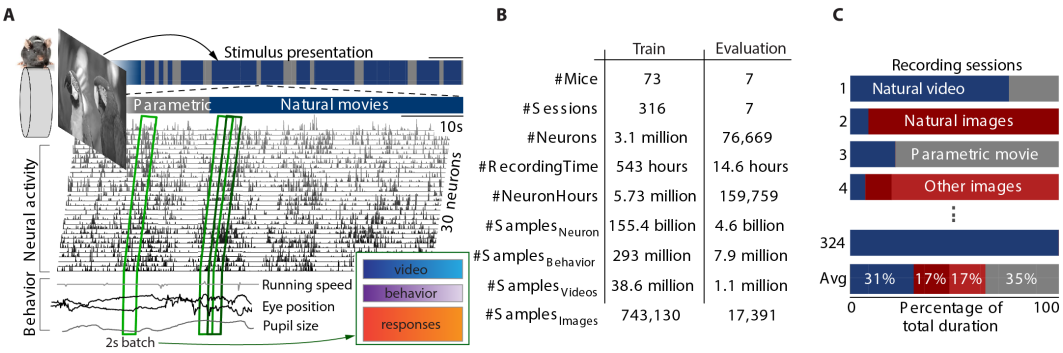

Figure 2: **Data**. **A**. Data were collected from head-fixed mice running on a wheel while viewing videos. Neuronal responses were recorded via calcium imaging, 4210 to 11284 neurons per session. Behavior variables include pupil center x and y positions, pupil dilation and its derivative and running speed. **B**. Dataset statistics. The total number of unique mice in our dataset is 78, since some mice had sessions in both train and evaluation sets. **C**. Different visual stimuli were presented across sessions, with stimulus types varying by session. The bottom row shows their overall distribution.

Visual stimuli. The mice were presented with naturalistic images sampled from ImageNet (Russakovsky et al., 2015) and videos sampled from cinematic movies and the Sports-1M dataset (Karpathy et al., 2014). In addition, they saw parametric stimuli such as static and drifting Gabors (Petkov & Subramanian, 2007), directional pink noise, flashing Gaussian dots, random dot kinematograms (Morrone et al., 2000), and model-generated stimuli (similar to Walker et al., 2019). All stimuli were shown at 30–60 Hz, with images presented for 500 ms and preceded by a 300–500 ms blank screen.

Data utilization. A key novelty is our ability to sample arbitrary 2-second windows from any point in the experiment, including inter-trial intervals and blank screens. We reconstruct the visual stimulus presented with millisecond precision throughout the entire recording, enabling continuous representation of the full experimental timeline. This dramatically increases training data by utilizing the complete recording duration rather than discrete trials.

4 OmniMouse architecture

Tokenization. We sample 2-second chunks of multi-modal data: video frames $\mathbf{V} \in \mathbb{R}^{h \times w \times 1 \times 60}$, neural calcium traces $\mathbf{X} \in \mathbb{R}^{P \times 60}$ for population P, and behavioral traces $\mathbf{B} \in \mathbb{R}^{5 \times 40}$ (running speed, pupil xy-position / size / size derivative). Alongside the chunk, we sample a masking configuration for each modality.

For *video*, the sampled mask defines a starting frame v_0 and the length of visible frames v_c such that $v_0 + v_c \leq 60$, $v_c \in [10, 20, 30, 40, 50, 60]$. The resulting sequence $\mathbf{V}_{v_0:v_0+v_c}$ is encoded through a lightweight, randomly-initialized Hiera vision transformer (Ryali et al., 2023), followed by a linear projection to our model dimension, d_M, producing spatiotemporal embeddings $\widetilde{\mathbf{V}} \in \mathbb{R}^{h' * w' * v'_c \times d_M}$, where h', w', and v'_c result from the stride of the Hiera module.

Table 1: **Scaling variants of OmniMouse.** L: multi-modal transformer layers; d_m: model dimension; h: number of attention heads; d_e: dimensions of all embeddings; p_L: multi-modal transformer layer parameters; p_M: model parameters (excluding neuronal embeddings); p_N: all neuronal, session, and animal parameters; p_T: total parameters; S: sequence length.

Model	L	d_m	h	d_e	p_L	p_M	p_N	p_T	S
OmniMouse-1M	2	256	4	256	1.7M	6M	779M	885M	4096
OmniMouse-5M	6	256	8	256	5.1M	10.4M	779M	891M	4096
OmniMouse-20M	6	512	8	256	19.1M	29.1M	779M	810M	4096
OmniMouse-80M	12	768	12	256	88M	115M	779M	894M	4096
OmniMouse-300M	24	1024	16	256	308M	348M	779M	1.1B	4096

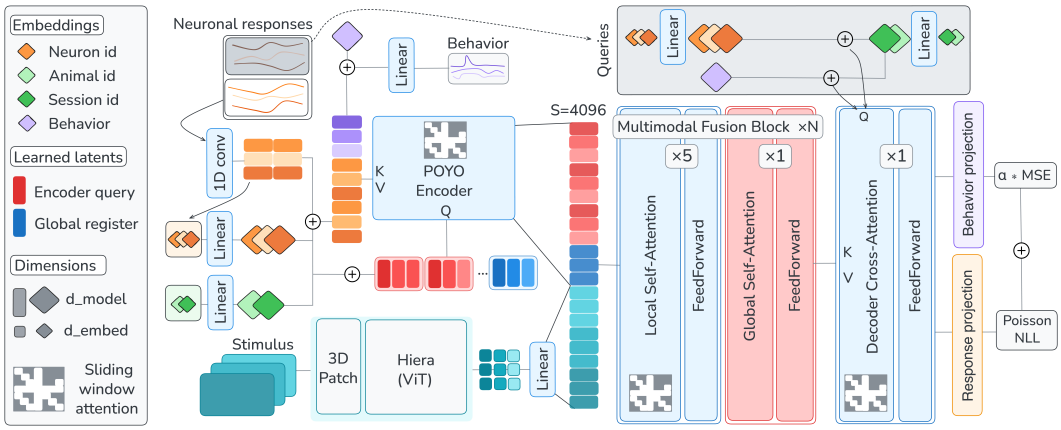

Figure 3: **Model architecture.** We tokenize the visual stimuli with a Hiera encoder, behavior via a shared linear projection with specific embeddings, and responses following POYO+ (Azabou et al., 2025). All tookens are concatenated and processed by transformer blocks, with behavior and responses decoded through cross-attention.

For *neural responses*, during training we randomly sample $S = 4096$ neurons from population P. From these we select $P_{target} = 3072$ neurons whose final second of activity serves as our prediction target. From the remaining data, we collect activity sequences of each neuron's *unmasked* samples. For OmniMouse, we developed a novel and a flexible neural activity masking scheme that allows for any combination of input masks, down to single-neuron single-sample precision (Fig. 5). The scheme defines a *population prefix* — activity from the population before the last 30 samples — and a *population context* — activity from neurons not being predicted, possibly overlapping in time with the prediction targets. To avoid inflated scores from upsampling artifacts, a gap of at least 0.17 seconds (5 samples) was enforced between the *prefix* and the prediction target. To tokenize the unmasked activity, we apply a strided 1D-convolution to each neuron's sequence and concatenate the outputs, creating a unified sequence of activity embeddings, $\widetilde{\mathbf{X}} \in \mathbb{R}^{S*T \times d_M}$, where T is the number of strides per neuron sequence. Following POYO (Azabou et al., 2023), we add learned identity embeddings for each neuron, session, and animal to the activity features. We use a smaller dimension, d_e, for these embeddings and up-project to d_M in order to reduce the number of parameters learned per-neuron.

For *behavior*, we either fully mask or fully unmask the input. When unmasked, we use a shared linear to project the traces along the temporal dimension and add learned channel-specific embeddings (as well as the session/animal embeddings), yielding $\widetilde{\mathbf{B}} \in \mathbb{R}^{5 \times d_M}$, for 5 behavior channels.

Each token also maintains its timestamp for positional encoding in the input sequence.

Model architecture. After tokenization, we concatenate activity and behavior, $[\widetilde{\mathbf{X}}, \widetilde{\mathbf{B}}]$, and encode using cross-attention with a repeated set of learned latents (Azabou et al., 2023), $\mathbf{Z} \in \mathbb{R}^{M*N \times d_M}$, ($M$ unique latents and N repeats, each repeat with a unique timestamp evenly spaced across the context window), generally reducing the number of input tokens by ~ 10. Within the cross-attention block, we implement *local sliding-window attention*, where latent features only attend to response / behavior features within a fixed temporal window. We also append $g = 256$ "global registers" (Darcet et al., 2023) , $\mathbf{G} \in \mathbb{R}^{g \times d_M}$ which always attend to the entire sequence.

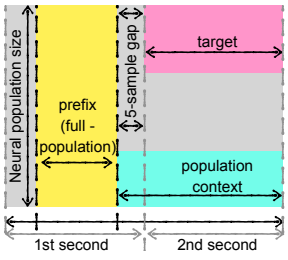

Figure 4: **Neuronal response masking.** We introduce a flexible scheme that supports arbitrary input masks, down to single-neuron, single-sample, and single-frame precision.

Then we concatenate the cross-attention output and video features, $[\widetilde{\mathbf{Z}}, \widetilde{\mathbf{V}}]$, and pass the sequence to a series of L multi-modal transformer layers (Tab. 1). We interleave local attention (with a sliding-window mask), and global attention blocks at a ratio of $5:1$ (Fig. 3).

To decode neuronal activity and behavior, we again use cross-attention, using fused multi-modal features as keys K and values V (Fig. 3). Query construction mirrors the input construction: for samples in the response prediction

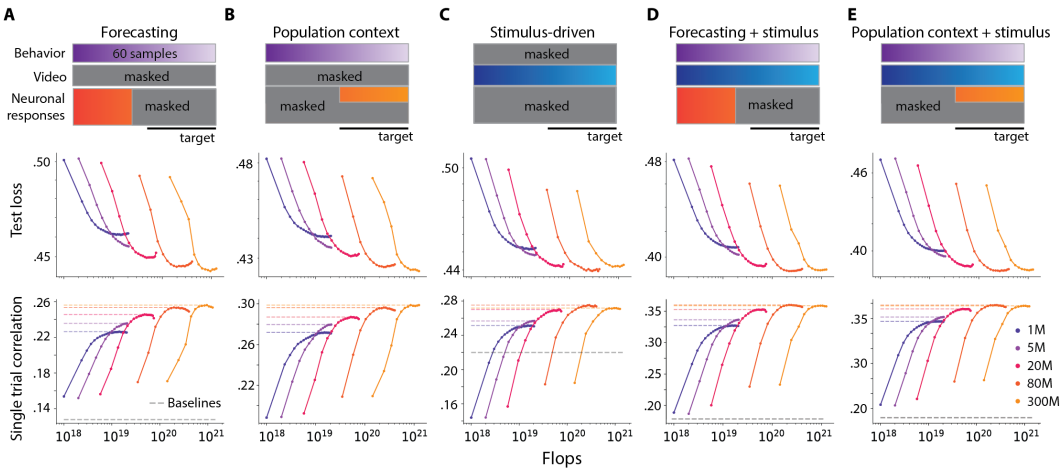

Figure 5: **Task-specific performance gains with model scaling.** Top row: masking schema. Middle row: Test loss. Bottom row: single-trial correlation on seven SENSORIUM 2022 & 2023 mice. Both loss and correlations are computed on the final test split for natural video. **A**. Forecasting, prefix = 25 samples. **B**. Population context, context = 256 neurons. **C**. Stimulus-driven. **D**. Stimulus-conditioned forecasting, prefix = 25 samples. **E**. Stimulus-conditioned population context, context = 256 neurons.

target, we create a sequence of embeddings using the same learned neuron, animal, and session identity embeddings, with only the activity embedding left out. Each query also maintains a timestamp indicating the position of target sample to be decoded. Similarly, to decode each channel of behavior we use the same channel embeddings used for the behavior input. Note, during training behavior is always masked in the input if it is also a prediction target. Finally, the outputs of the decoder cross-attention block for each modality are routed to modality-specific linear readouts, projecting from d_M back to the original dimensionality. All attentions use RoPE (Su et al., 2024) to encode relative timing between features, both within and across modalities, as well as recent best practices including: RMSNorm pre-normalization layers, query-key normalization, and gated SiLU feed-forward networks (Shazeer, 2020; OLMo et al., 2024; Yang et al., 2025; Biderman et al., 2023).

Training. We trained our model to predict both neuronal responses and behavioral traces, using Poisson loss (averaged across neurons) for neural encoding and mean squared error (MSE) loss for behavior decoding. We used 119 masking configurations App. C.4.1) during training, varying which modalities were fully or partially masked as well as the amount and duration of neuronal context. To balance the two objectives, the behavioral loss is down-weighted by a factor of 0.1 so that its scale matches the magnitude of the Poisson loss. For our scaling experiments, we trained models on either the complete dataset of 323 sessions or constructed collections (8, 16, 32, 64 sessions) to study data scaling effects. These nested collections were designed so that larger collections always contained all sessions from smaller ones, ensuring consistent evaluation (see below for evaluation details). We followed Hu et al. (2024); Wen et al. (2024); Hägele et al. (2024) and trained our model with warmup followed by a constant learning rate for at least 250k steps, corresponding to 500B tokens. We then restart training from intermediate checkpoints every 20k steps, and use inverse square root learning rate decay for 10k steps.

5 Unified evaluation framework

All scaling experiments use a standardized evaluation protocol on the same mice to ensure fair comparison across models, baselines, and conditions. We chose seven mice (*evaluation mice*) comprised of five publicly available datasets from SENSORIUM 2023 and two test mice from SENSORIUM 2022. For all analyses, we use the held-out set provided by these datasets. We evaluate five regimes of response prediction (Fig. 5) as well as behavior decoding (Fig. 6):

Forecasting conditions predictions on the past activity of the entire population and 40 frames of behavior. We always predict the last second (30 samples) within each two-second batch, using the first 25 frames of the batch as context. Since NDT-based models (Ye & Pandarinath, 2021) dominate

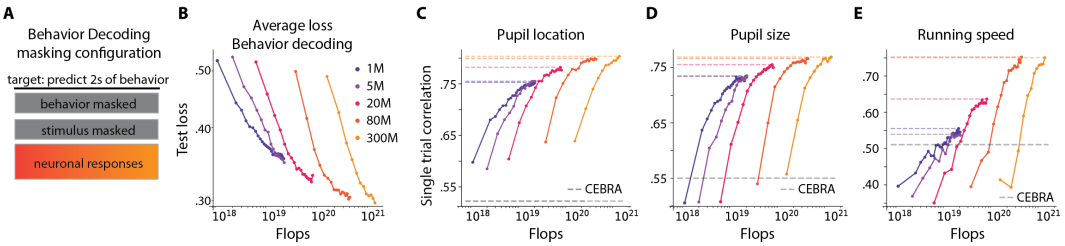

Figure 6: **Behavior decoding scales with model size.** **A**. Masking for behavior decoding. **B**. Decoding loss averaged over all behavioral variables. **C**. Pupil center: correlations computed separately for x and y, then averaged. **D**. Pupil size and its derivative: correlations trace, then averaged. **E**. Running speed: correlation with ground truth.

in the forecasting literature, we use IBL (Zhang et al., 2024), a variant of NDT trained with multiple masking strategies similar to ours, as a baseline.

Population context conditions predictions on $N = 256$ other simultaneously recorded neurons and 40 frames of behavior. As in the forecasting regime, we predict the last second of each batch and evaluate performance on this interval. This setting assesses how much of the trial-to-trial variability can be explained by simultaneously recorded neurons.

Stimulus-driven conditions predictions on two seconds of video and predicts activity for all neurons in the batch. We provide two seconds of input and evaluate predictions on the final second of neural activity. SENSORIUM 2023 (Turishcheva et al., 2024) establishes a strong baseline for this setting.

Stimulus-conditioned forecasting is identical to forecasting, except that the full 2 seconds of video are also provided as input. We used Schmidt et al. (2025) as a baseline model, which also conditions on neurons, video and behavior.

Stimulus-conditioned population context is identical to population context, except that the full 2 seconds of video are also provided as input. Again, Schmidt et al. (2025) was used as a baseline.

Behavior prediction conditions on the activity of all neurons (without video) and simultaneously predicts all behavioral traces (i. e. pupil size, pupil location and running speed). CEBRA (Schneider et al., 2023) is used as a baseline for this regime.

We train all state-of-the-art baselines on the collection of eight mice, used in our smallest data-scaling experiment (Fig. 7) to reduce computational cost. Implementation details and hyperparameters for each baseline are provided in App. C. Consistent with SENSORIUM 2022/2023 competitions, we use single-trial correlation as an evaluation metric. Additionally we evaluate our model on the SENSORIUM 2023 competition test set, which allows direct comparison against the state of the art model of predicting mouse visual cortex responses from video stimuli. We use OmniMouse-80M, freeze the entire model, and train only the neuron and animal embeddings using the released training data of five mice provided by the competition.

Table 2: **OmniMouse is state of the art on all tasks.** Correlations were computed across all neurons, except in population context tasks, which used a held-out 50%. For all mice we used final test set, with in-domain (natural stimuli) split for SENSORIUM 2023 mice. Forecasting used 25 frames; population masking 256 neurons.

Prediction task	**Baseline**	**Baseline score ↑**	**OmniMouse-300M (ours) ↑**
Forecasting	IBL (Zhang et al., 2024)	0.12	**0.26**
Forecasting + stimulus	Latent Model (Schmidt et al., 2025)	0.18	**0.36**
Stimulus driven	Sensorium 2023 Baseline (Turishcheva et al., 2024)	0.23	**0.28**
Population context	*N.A.*	✗	**0.30**
Population context + stimulus	Latent Model (Schmidt et al., 2025)	0.16	**0.37**
Behavior decoding:			
Pupil location	CEBRA (Schneider et al., 2023)	0.52	**0.81**
Pupil size	CEBRA (Schneider et al., 2023)	0.55	**0.76**
Running speed	CEBRA (Schneider et al., 2023)	0.51	**0.75**
Stimulus driven (attentive probe):			
Sensorium 2023 competition	DwiseNeuro (Turishcheva et al., 2024)	0.30	**0.34**

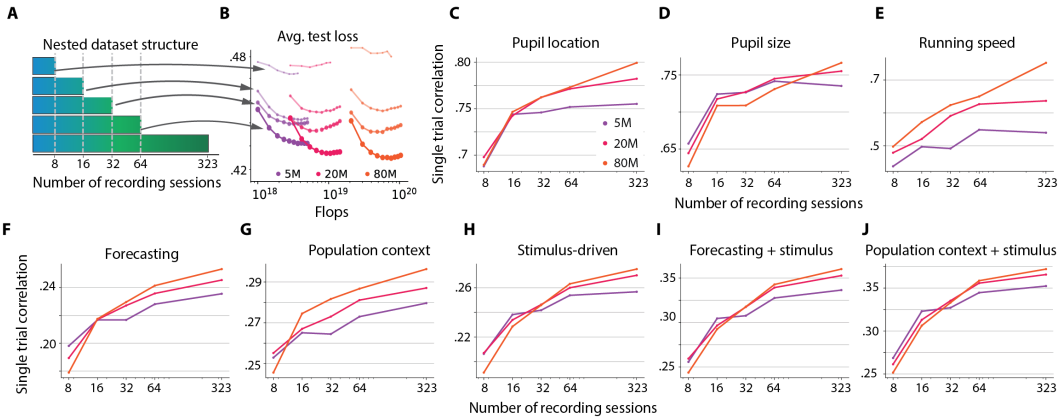

Figure 7: **Scaling data improves model performance.** **A**. Nested datasets structure. **B**. Test loss for different model and data sizes, averaged across all response prediction tasks. **C-K**. Performance improvements when scaling dataset from 8 to 323 sessions: **C**. Pupil center location. **D**. Pupil size and rate of pupil change. **E**. Running speed. **F**. Forecasting, prefix = 25 samples. **J**. Population context, context = 256 neurons. **H**. Stimulus-driven. **I**. Stimulus-conditioned forecasting, prefix = 25 samples. **K**. Stimulus-conditioned population context, context = 256 neurons.

6 Results: The benefits of scaling

Current neuronal-predictive models are not compute- or parameter-limited. Because collecting neuronal data is costly, we first asked if existing models are already limited by compute or parameters, or if more data would still improve performance. To answer this question, we trained models on all 323 sessions while scaling width and depth as in Tab. 1. We evaluated five neuronal response masking strategies (Fig. 5, top row): two based on response dynamics (forecasting and population context), two analogous variants that additionally condition on video (video-conditioned forecasting and video-conditioned population context), and one stimulus-driven strategy (video & behavior). For each strategy, models ranged from 1M to 300M parameters, and we tracked both test loss and single-trial correlation as a function of total compute (model FLOPs, excluding FLOPS of neuron-specific parameters). Performance improved across all neuronal prediction tasks as model size increased up to 80M parameters (Fig. 5). Beyond this point, gains were minimal, as loss curves saturated or overfit, indicating that current models are data-limited rather than compute- or parameter-limited.

OmniMouse-300M achieves state-of-the-art performance across all tasks. Our large-scale model outperforms all baselines across six evaluation regimes for both response and behavior prediction (Tab. 2). We establish new state-of-the-art results in stimulus-driven response prediction and achieve the highest score to date on the Sensorium 2023 competition (Tab. 2)—remarkably, with OmniMouse frozen and only neuron-specific parameters trained.

Behavior prediction shows the most promising scaling dynamics on the available data. To characterize the scaling of behavior prediction, we used the same models and evaluated their ability to predict pupil location, pupil size, and running speed from neuronal activity only (Fig. 6). Across all three settings, performance improved smoothly with compute budget, reminiscent of classic scaling-law behavior. Larger models consistently achieved higher single-trial correlations, albeit with an indication of saturation at the largest scale tested. Note, though, that training was stopped to avoid overfitting for the response prediction task. The models had not yet fully converged for the behavior prediction task and longer training could have improved performance further even on the largest model. OmniMouse not only matches, but surpasses the performance of all strong baselines such as CEBRA, particularly for running speed prediction, where correlation improves by over 0.15% relative to the baseline. These results show that behavioral prediction continues to improve with model scaling and may benefit from further increases in capacity.

Scaling dataset size improves performance. To study how dataset size affects performance, we trained three model sizes – 5M, 20M, and 80M – on nested collections of 8, 16, 32, 64, and 323 sessions such that the larger collections are supersets of the smaller ones (Fig. 7A). For evaluation, we test the model on the same held-out test set of the same seven mice that were contained in all collections (Fig. 7C–J). In all cases, performance improved with the number of sessions, exhibiting

predictable data-scaling trends. Larger models consistently benefited more from additional data. The larger models required a minimum size of the training set to outperform the smaller models and the performance gap widened as the dataset increased in size. Behavior decoding benefited the most from data scaling (Fig. 7C–E), showing no saturation and large performance differences between 5M and 80M models. For responses, the strongest gains were observed for tasks that included video input (Fig. 7C–E), where the 80M models continued to improve even beyond 100 sessions, suggesting that they remained data-limited rather than capacity-limited. The *forecasting* and *population context* showed bigger benefits from scaling of both data and model sizes. The gaps between 20M and 80M models (Fig. 7A, B) increased faster compared to the tasks with video input, which could indicate a lack of diversity of the visual stimuli in our dataset. Overall, these results highlight that scaling both model size and data quantity is synergistic and necessary to approach peak predictive performance.

OmniMouse enables systematic evaluation of how neuronal context shapes predictive performance. Lastly, we assessed the model's generalization by testing on masking conditions not seen during training, varying neuronal history duration (10–25 frames) and population context size (16–2048 neurons). Performance scaled smoothly with additional context demonstrating that OmniMouse learns generalizable representations that enables systematic analyses of contextual contributions to neural variability (see Fig. S1, and App. A).

7 Discussion

In this work we introduce OmniMouse, a multi-modal, multi-task foundation model of mouse visual cortex that integrates neural activity, video, and behavior across animals. A single model achieves state-of-the-art performance on diverse tasks – predicting neural responses from visual stimuli, forecasting activity and decoding behavior. Trained on the largest neural dataset to date (3.3M neurons, 78 mice, 323 sessions), OmniMouse enables systematic study of scaling in brain models.

Our motivation for studying scaling laws is practical: if brain models are to become foundation models for neuroscience, it is essential to ask whether current data can sustain scaling. Despite using naturalistic movies and images, we find that performance saturates with model size, suggesting data – not compute – as the limiting factor. Even in the relatively simple mouse visual system, richer tasks, more varied stimuli, and larger-scale recordings are needed to support continued scaling. At the same time, relatively sparse sampling already yields strong models: with 60,000 neurons from just eight mice, predictive accuracy is high, likely due to redundancy in neural codes. Additional gains from larger datasets appear modest, paralleling language and vision models – yet in those domains, such small improvements have triggered phase transitions to qualitatively new abilities. By analogy, richer neuroscience data may similarly unlock new capabilities in brain models, revealing deeper principles of neural computation.

Limitations. Our work has several limitations. First, OmniMouse parameters scale linearly with the number of neurons, as it learns per-neuron embeddings. This makes training computationally prohibitively expensive may limit scaling to even larger datasets. Second, large-scale transformers remain difficult to interpret, and like deep learning models, they are prone to optimization issues and overparameterization, which constrain the biological insights that can be drawn. Furthermore, the behavioral data present in our data is limited to spontaneous activity and it is thus unclear if this approach can transfer to more complex behaviors.

Future work. Future work could extend to stimulus decoding (Benchetrit et al., 2023; Bauer et al., 2024; Zhu et al., 2025) and more precise study of training dynamics of modality interactions and multi-task learning to improve the masking recipe. Beyond calcium imaging in mouse visual cortex, models could integrate other data types such as electrophysiological recordings, diverse animal species, and more multi-modal stimuli such as audio. Alternatively, one could test generalization of the existing model across new tasks, stimuli, and species via (semi) closed-loop in-silico experiments (Ustyuzhaninov et al., 2022; Li et al., 2025), potentially finding biological insights about neuronal functional properties as in Walker et al. (2019); Li et al. (2025). Finally, jointly modeling visual input, neuronal responses, and behavior enables analysis of spontaneous and evoked activity (Stringer et al., 2019), revealing how brain state shapes sensory processing and core principles of computation.

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A Supplemental results

OmniMouse enables systematic evaluation of how neuronal context shapes predictive performance. We evaluated OmniMouse on conditions not seen during training, systematically varying neuronal history duration (10-25 samples) and population context size (16-2048 neurons) for population context tasks. Performance scaled smoothly with context availability across all conditions Fig. S1. When video was available, performance plateaued more quickly for forecasting but continued to improve for population context, suggesting that nearby neurons carry complementary information beyond visual input. These systematic evaluations demonstrate that OmniMouse has learned generalizable representations of neural variability, enabling quantitative assessment of how different sources of context—temporal history contribute to explaining variability in neural responses.

Furthermore, we hypothesized that harder tasks might benefit more from scaling, as shown for large language models (Minaee et al., 2024; Naveed et al., 2025). To test this, we varied the neuronal history duration (*full-population prefix* $\in [10, 15, 20, 25]$) for forecasting tasks and context size (*context* $\in [16, 32, ..., 1024, 2048]$) for population context tasks, where shorter contexts represent harder tasks. We also compared performance with and without 2 seconds of video input. Fig. S1 confirms our hypothesis: performance improves consistently as context grows, hence, bigger context indicates easier task. Non-video conditioned regimes scale more steeply, likely due to lower baselines. For forecasting, they never match video-conditioned models, since video provides temporal information unavailable at prediction. For population context, however, sufficient neural responses recover enough information to match video performance. However, contrary to LLMs, in our case scaling does not preferentially benefit harder tasks: across all tasks, curves for different model sizes remain parallel. If harder tasks gained more, larger models (20–80M) would show bigger advantages over smaller ones (1–5M) at minimal context.

B Relation to other neuroscience scaling.

This is the first study to systematically scale both model and data size using only neuro-data, yet our findings align with prior neuro-scaling work. Consistent with Gokce & Schrimpf (2024), behavior prediction improves with larger models, and the greater gains from joint model–data scaling on non-video tasks (Fig. 7A,B) support claims from Jiang et al. (2025); Ye et al. (2025) that data heterogeneity limits scaling: our visual stimuli include many repeats, while neural responses vary with latent brain state and noise even when the visual stimuli is same.

C Baselines

To establish baseline comparisons while managing computational costs, we train state-of-the-art baseline models on the smallest nested dataset containing eight mice (the seven evaluation mice plus one additional training mouse). This approach ensures that all methods are compared under identical conditions while keeping baseline training tractable. We train all baselines on 8 recordings

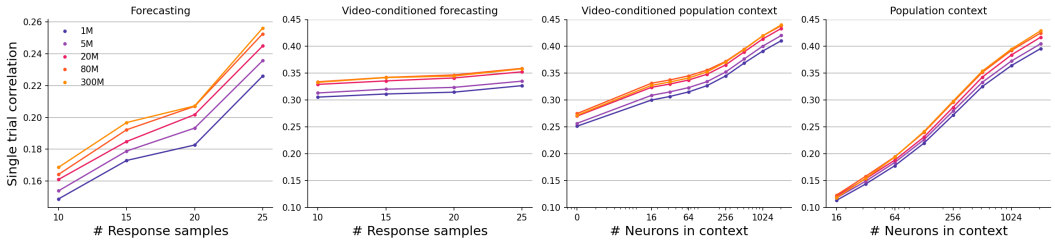

Figure S1: **Using the models capabilities to investigate context lengths for forecasting and population context tasks. A**. Forecasting with a change of prefix length. **B**. Same change of forecasting context as **A**, but with video. **C**. Performance improvements in addition to video with population context. # neurons in context = 0 means the normal "sensorium" task, i.e. video & behavior. Will be added as an arrow to the panels. Context increases from 0-16-...-2048. **D**. Population context only, 16 - 2048 neurons

from 8 unique mice – 5 fully released mice from the sensorium 2023 competition (keeping the original train-validation-test splits), 2 mice from the sensorium 2022 competition that were used for the test split. session from the MiCRONs collection. The same 8 mice were used in the smallest scaling experiment.

C.1 CEBRA

CEBRA explanation: We perform dimensionality reduction on neural activity using InfoNCE contrastive learning, where positive and negative pairs are defined by auxiliary variables such as time or behavior. When the auxiliary variable is discrete, for example a left or right wheel turn, we select positives uniformly from all samples with the same label. When the variable is continuous, such as running speed or pupil direction, we choose a random point within a time window around the sample and then find the closest match in the dataset using either Euclidean or cosine distance; this sample becomes the positive pair, which adds diversity and prevents repeatedly selecting the same example. Negative pairs are sampled randomly. For decoding, we encode neural responses, find the nearest latent vectors for responses in the training set, and return their associated behavioral variables as predictions.

Model hyperparameters: We trained a joint model for 8 mice, using a batch size of 512 and learning rate of $3 \cdot 10^{-4}$. The network contained 256 hidden units and produced 128-dimensional outputs (both doubled relative to the Allen example `https://cebra.ai/docs/demo_notebooks/Demo_Allen.html`). Training ran for up to 50,000 iterations with cosine distance as the loss metric. The model used a temperature of 1, time-delta conditioning to enable behavior mode, and time offsets of 5. As CEBRA requires same frequencies between responses and behavior, both were resamples to 20 Hz, in order to compute correlation on the same predictions as for the OmniMouse. Please note that downsampling from 30 Hz responses is not reducing any information as responses were upsampled from 6-16 Hz to 30 Hz and the upsampling is done with nearest-neighbor interpolation.

C.2 Universal Spike Transalator

Universal Spike Translator explaination: The Universal Spike Translator Zhang et al. (2024) performs a self-supervised modeling approach called multi-task-masking (MtM). The model alternates between masking out and reconstructing neural activity across different time steps and neurons. It uses a learnable token that provides the model with context about the specific masking scheme that is being applied during training, allowing for "mode switching" at test time for different downstream tasks. During training, the masking schemes are sampled randomly which are: **(1) Neuron masking:** Randomly masks individual neurons and reconstructs their activity using the unmasked neurons as context. **(2) Causal masking:** Masks future time steps and predicts them using the past steps as context.

Model hyperparameters: We used the default hyperparameters from "ndt1_stitching_prompting" and "ssl_session_trainer" configs from `https://github.com/colehurwitz/IBL_MtM_model`. Please note that compared to our forecasting settings, IBL does not take behavior as model input.

C.3 Latent dynamic model

Latent dynamic model explanation: This is a probabilistic model that predicts the joint distribution of neuronal responses from naturalistic video stimuli and stimulus-independent latent factors. Specifically, the model predicts time-varying neuronal response using a Zero-Inflated-Gamma (ZIG) distribution to model the distribution of neuronal responses conditioned on the stimulus and the latent factor. This is a modification of the deterministic factorized 3D convolutional core and a Gaussian readout, where we have an additional encoder that takes a subset of neurons as input to derive a latent variable. This latent variable is then combined with the transformed visual input to predict the activity of other neurons in the session. The model is trained by maximizing the Evidence Lower Bound (ELBO) of $p_{ZIG}(y|x)$ via variational inference.

Model hyperparameters: For both SENSORIUM 2023 baseline and Schmidt et al. (2025) baseline we used the default hyperparameters from Schmidt et al. (2025): 3 layer core with both spatial and temporal kernel = 11 in the first layer and 5 on the layer two and three. For more details see App.C from Schmidt et al. (2025). All data modalities were upsampled to 30 Hz as both SENSORIUM 2023

baseline and Schmidt et al. (2025) latent model require all modalities to have the same frequencies. Both SENSORIUM 2023 baseline and Schmidt et al. (2025) latent model predict 42 samples from a 60-frame video input, we always used only last 30 frames for evaluation, to make it consistent with OmniMouse, who was trained to predict 30 samples. Please note that OmniMouse suppost flexible size of predictions, while SENSORIUM 2023 baseline and Schmidt et al. (2025) latent model cannot do it.

C.4 Implementation details

C.4.1 Masking strategies used during training

Mask	Behavior	Video (last frames visible)	Visible Neurons	Context (from → to)	Prefix (from → to)	Predicted Behavior
1–3	✓	0	[64, 256, 1024]	0 → 60	—	
4	✗	0	4096	0 → 60	—	✓
5–7	✗	0	[64, 256, 1024]	0 → 60	—	✓
8–19	✓	0	[64, 256, 1024, 4096]	—	[0, 10, 15] → 25	
20–28	✓	0	[64, 256, 1024]	25 → 60	[0, 10, 15] → 25	
29–37	✗	0	[64, 256, 1024]	25 → 60	[0, 10, 15] → 25	✓
38–40	✓	10	[64, 256, 1024]	10 → 60	—	
41–52	✓	10	[64, 256, 1024, 4096]	—	[0, 10, 15] → 25	
53–58	✓	10	[64, 256, 1024, 4096]	25 → 60	[10, 15] → 25	
59–61	✓	20	[64, 256, 1024]	20 → 60	—	
62–73	✓	20	[64, 256, 1024, 4096]	—	[0, 10, 15] → 25	
74–79	✓	20	[64, 256, 1024]	25 → 50	[10, 15] → 25	
80–82	✓	20	[64, 256, 1024]	30 → 60	—	
83–94	✓	30	[64, 256, 1024, 4096]	—	[0, 10, 15] → 25	
95–100	✓	30	[64, 256, 1024]	25 → 40	[10, 15] → 25	
101–103	✓	40	[64, 256, 1024]	30 → 50	—	
104–111	✓	40	[64, 256, 1024, 4096]	—	[10, 15] → 25	
112–114	✓	50	[64, 256, 1024]	30 → 40	—	
115–118	✓	50	[64, 256, 1024, 4096]	—	10 → 20	
119	✓	60	—	—	—	

Table 3: **Summary of training mask configurations**. In each batch all behavior traces for the whole 2 seconds were either given as input or predicted. For each batch 4096 neurons were randomly sampled from N neurons per mouse and last second (30 responses) for 3072 neurons of these 4096 the activity was predicted.

C.4.2 Nested scaling dataset construction

The nested dataset was constructed such that for the 7 mice we conducted evaluation on - 3 mice we had repeated sessions, such that the number of repeats grew proportionally to the dataset growth, and 4 other mice had a single session. As session-per-mice distribution is highly skewed, the other sessions were samples randomly.

C.5 Distribution of sessions per mouse

D Neurophysiological experiments

Model evaluation was performed on neurophysiological data from Sensorium 2022 ((Willeke et al., 2022), Mouse 1 and 2, evaluation animals for Sensorium and Sensorium Plus tracks) and Sensorium 2023 ((Turishcheva et al., 2024), all animals). Model training was performed on historical data, including data from MICrONS Consortium (2025), Wang et al. (2025), Ding et al. (2025b), Ding et al. (2025a), Fahey et al. (2019), Willeke et al. (2022),Turishcheva et al. (2024), but also included data not previously published.

All procedures were approved by the Institutional Animal Care and Use Committee of Baylor College of Medicine. Seventy-eight mice (Mus musculus, 32 females, 46 males, P50–155 on day of

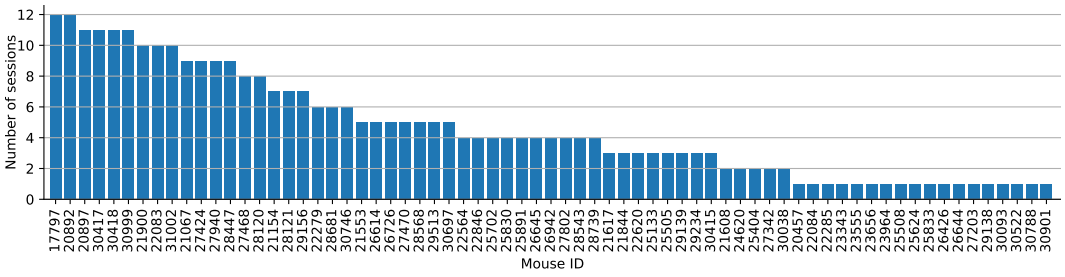

Figure S2: **Distribution of 316 sessions across 69 mice.** More than 100 sessions come from first 10 mice.

first scan) expressing GCaMP6s in excitatory neurons via Slc17a7-Cre and Ai162 transgenic lines (recommended and generously shared by Hongkui Zeng at Allen Institute for Brain Science; Jackson Labs stock 023527 and 031562, respectively) were anesthetized and a 4 mm craniotomy was made over the visual cortex of the right hemisphere as described previously (Reimer et al., 2014; Froudarakis et al., 2014). In two of the seventy-six animals, GCaMP6s was additionally expressed in inhibitory neurons via DLX5-CreER (Jackson Labs stock 010705), following treatment with tamoxifen (orogastric gavage of tamoxifen (Sigma Aldritch T5648) dissolved in corn oil (Sigma Aldritch C8267) at 15 mg/mL, 200 mg/kg body weight, two doses two days apart, second dose >= 13 days before the first included scan).

Mice were head-mounted above a cylindrical treadmill and calcium imaging was performed using Chameleon Ti-Sapphire laser (Coherent) tuned to 920 nm and a large field of view mesoscope (Sofroniew et al., 2016) equipped with a custom objective (excitation NA 0.6, collection NA 1.0, 21 mm focal length). Laser power after the objective was increased exponentially as a function of depth from the surface according to:

$$P = P_0 \times e^{(z/L_z)} \tag{1}$$

Here P is the laser power used at target depth z, P0 is the power used at the surface (typically not exceeding 25 mW), and L_z is the depth constant (160-220 µm). The greatest laser output of ca. 112 mW was used at approximately 400-500 µm from the surface.

The craniotomy window was leveled with regards to the objective with six degrees of freedom. Pixel-wise responses from an ROI spanning the cortical window (1.7-4 mm diameter FOV, >0.2 px/µm, superficial cortex, >2.47 Hz) to drifting bar stimuli were used to generate a sign map for delineating visual areas (Garrett et al., 2014). In some but not all cases where the imaging field of view spanned multiple areas, area boundaries on the sign map were manually annotated. Imaging FOV of varying dimensions were targeted to lie within the boundaries of visual cortex, and may span between primary visual cortex and surrounding higher visual areas depending on the scan design.

Scan dimensions typically fell into one of three categories. Local field of view scans contained multiple imaging planes at different depths (10-13 planes, most commonly with 5 µm z spacing but ranging between 3 and 45 µm z spacing), with each plane spanning 600-630 × 600-630 µm (240-252 × 240-252 pixels, 0.4 px/µm resolution), acquired most commonly at 7.98 Hz (range 4.34-8.31 Hz). Large field of view scans contained single imaging planes at a single depth, with each plane scanning 1.5 - 3 mm diameter (0.33 - 0.4 px/um resolution), acquired at between 6.5 - 12.4 Hz. In between are scans containing multiple imaging planes at different depths (2-5 planes, with variable interplane spacing between 5 and 150 µm), with each plane spanning approximately 0.8-1.2 mm diameter (0.4-0.6 px/µm resolution), acquired at between 6.3 and 9.6 Hz. Scans with multiple planes, especially at high sampling densities (ex. 5 µm z spacing), have a high likelihood of multiple segmented traces emerging from multiple planes intersecting with the soma of a single neuron in a single scan. Multiple scans were also often collected from the same animal, and as a result single biological neurons may be recorded across multiple scans.

Movie of the animal's eye and face was captured throughout the experiment. A hot mirror (Thorlabs FM02) positioned between the animal's left eye and the stimulus monitor was used to reflect an IR image onto a camera (Genie Nano C1920M, Teledyne Dalsa) without obscuring the visual stimulus.

The position of the mirror and camera were manually calibrated per session and focused on the pupil. Field of view was manually cropped for each session to contain the left eye in its entirety, although across different experiments the field of view may have additionally contained more or less of the face, centered or not centered on the eye, or characterized the pupil at different resolutions. Video was captured at ca. 20 Hz. Frame times were time stamped in the behavioral clock for alignment to the stimulus and scan frame times. Video was compressed using Labview's MJPEG codec with quality constant of 600 and stored in an AVI file.

Light diffusing from the laser during scanning through the pupil was used to capture pupil diameter and eye movements. A DeepLabCut model (Mathis et al., 2018) was trained as previously described (Turishcheva et al., 2024) on 17 manually labeled samples from 11 animals to label each frame of the compressed eye video (intraframe only H.264 compression, CRF:17) with 8 eyelid points and 8 pupil points at cardinal and intercardinal positions. Pupil points with likelihood >0.9 were fit with the smallest enclosing circle, and the radius and center of this circle was extracted. Frames with < 3 pupil points with likelihood >0.9, or producing a circle fit with outlier > 5.5 standard deviations from the mean in any of the three parameters (center x, center y, radius) were discarded. Gaps in behavior were replaced by linear interpolations over the whole session, if there were more than 2 frames with gaps, then the video is removed.

The mouse was head-restrained during imaging but could walk on a treadmill. Rostro-caudal treadmill movement was measured using a rotary optical encoder (Accu-Coder 15T-01SF-2000NV1ROC-F03-S1) with a resolution of 8000 pulses per revolution, and was recorded at approx. 50-100 Hz in order to extract locomotion velocity.

Visual stimuli were presented with Psychtoolbox 3 in MATLAB (Brainard & Vision, 1997; Kleiner et al., 2007; Pelli, 1997) to the left eye with a 31.8 $\times$ 56.5 cm (height $\times$ width) monitor (ASUS PB258Q) with a resolution of 1080$\times$1920 pixels positioned 15 cm away from the eye. When the monitor is centered on and perpendicular to the surface of the eye at the closest point, this corresponds to a visual angle of 3.8 °/cm at the nearest point and 0.7 °/cm at the most remote corner of the monitor. As the craniotomy coverslip placement during surgery and the resulting mouse positioning relative to the objective is optimized for imaging quality and stability, uncontrolled variance in animal skull position relative to the washer used for head-mounting was compensated with tailored monitor positioning on a six dimensional monitor arm. The pitch of the monitor was kept in the vertical position for all animals, while the roll was visually matched to the roll of the animal's head beneath the headbar by the experimenter. In order to optimize the translational monitor position for centered visual cortex stimulation with respect to the imaging field of view, we used a dot stimulus with a bright background (maximum pixel intensity) and a single dark square dot (minimum pixel intensity). Dot locations were randomly ordered from a grid tiling a portion of the screen, either a 10 $\times$ 10 grid tiling a central square (approx. 90° width and height, 10 repeats per location, 200-300 ms presentation at each location), or a 5 $\times$ 8 grid tiling the majority of the monitor (approx. 93° height and 119° width, 20 repeats per location, 200 ms presentation at each location). The final monitor position for each animal was chosen in order to center the population receptive field of the scan field ROI on the monitor, with the yaw of the monitor visually matched to be perpendicular to and 15 cm from the nearest surface of the eye at that position.

A photodiode (TAOS TSL253) was sealed to the top left corner of the monitor, and the voltage was recorded at 10 kHz and timestamped on the behavior clock (MasterClock PCIe-OSC-HSO-2 card). Simultaneous measurement with a luminance meter (LS-100 Konica Minolta) perpendicular to and targeting the center of the monitor was used to generate a lookup table for linear interpolation between photodiode voltage and monitor luminance in cd/m² for 16 equidistant values from 0-255, and one baseline value with the monitor unpowered.

At the beginning of each experimental session, we collected photodiode voltage for 52 full-screen pixel values from 0 to 255 for one second trials. The mean photodiode voltage for each trial V_{pd} was fit as a function of the pixel intensity V_{in}:

$$V_{pd} = B + A \times V_{in}^{\gamma} \tag{2}$$

in order to estimate the γ value of the monitor ($\approx 1.50 - 1.76$). All stimuli were shown with no γ correction.

During the stimulus presentation, sequence information was encoded in a 3 level signal according to the binary encoding of the flip number assigned in-order. This signal underwent a sine convolution, allowing for local peak detection to recover the binary signal. A linear fit was applied to the trial timestamps in the behavioral and stimulus clocks, and the offset of that fit was applied to the data to align the two clocks, allowing linear interpolation between them. The mean photodiode voltage of the sequence encoding signal at pixel values 0 and 255 was used to estimate the luminance range of the monitor during the stimulus, with typical maximum values of approx. 10-12 cd/m².