

Supplementary information

Table 1 Functional Encoding Dictionary for data in Figure 5

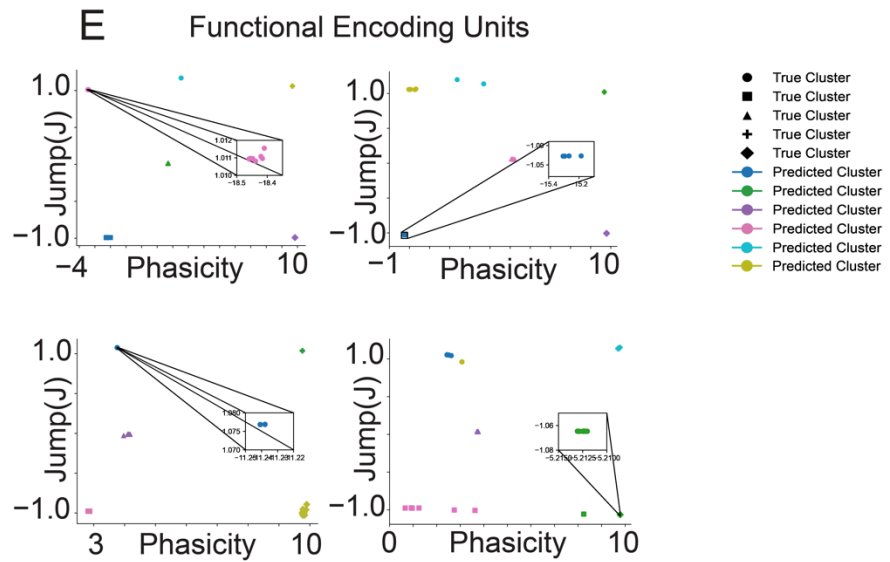
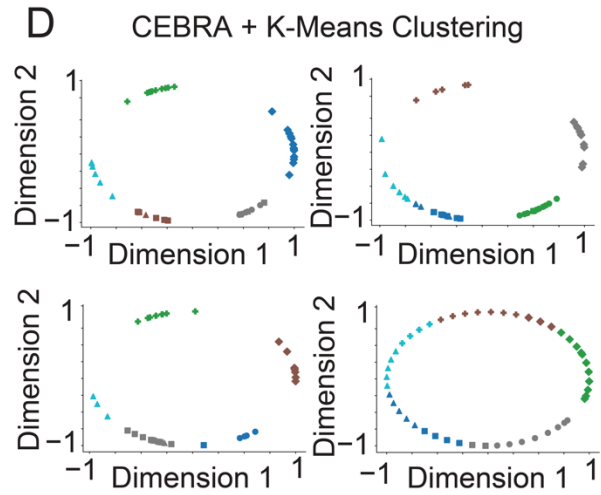
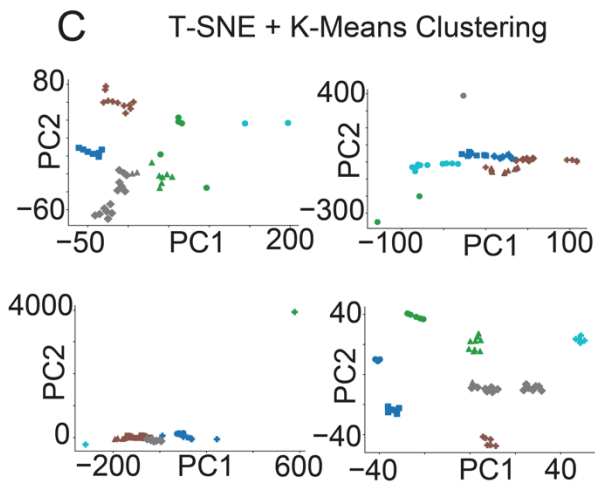
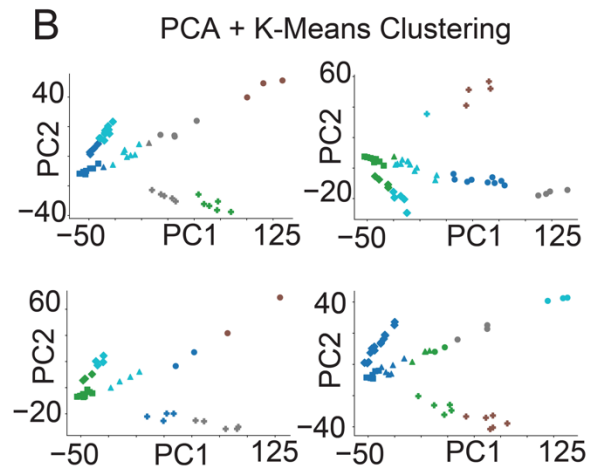
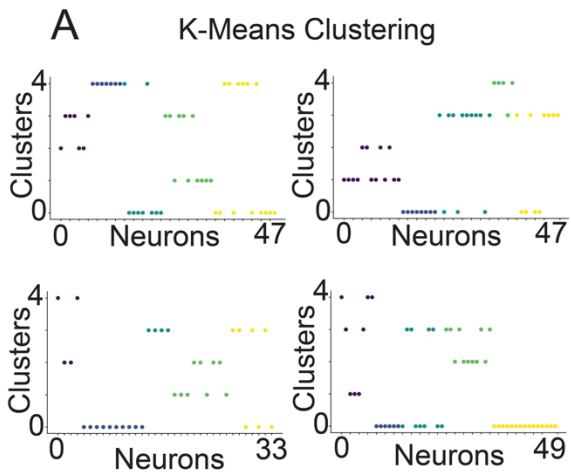
ACC									
social learning cue									
habituation							conditioning		
FEU	Jump	Phasicity	count (n=195)			jump	Phasicity	count (n=195)	
1	1.013753	9.874331	45			1	0.708874	9.267389	89
2	0.256558	0.544152	14			2	1.254519	9.952948	28
3	0.380936	9.887316	6			3	0.118707	5.706698	20
4	-0.178783	2.294918	16			4	-0.153754	9.562564	22
5	1.742927	9.671714	14			5	0.234562	8.000342	21
6	0.511013	8.512954	39			6	-0.722206	9.014569	12
7	0.036585	8.940191	27			7	2.396977	9.810637	2
8	-0.337037	0.514732	6			8	-2.566214	5.372104	1
9	-0.722206	9.014569	21						
10	-2.051888	8.544649	2						
11	0.485651	0.806981	5						
ACC									
control analysis									
habituation							conditioning		
FEU	Jump	Phasicity	count (n=195)			Jump	Phasicity	count (n=195)	
1	-0.100197	3.992866	69			1	-0.154046	1.878003	46
2	0.415732	0.449714	17			2	0.012521	4.616255	95
3	0.14902	0.180749	56			3	0.27781	5.170693	36
4	0.094573	9.836461	14			4	0.808602	8.957752	10
5	-0.255283	7.643664	13			5	-0.412457	2.676885	8
6	-0.722206	9.014569	14						
7	-0.479157	1.868132	9						
8	1.852387	5.133327	1						
9	1.851931	4.899814	1						
10	-2.525573	0.290565	1						

Table 2 Functional Encoding Dictionary for data in Figure 6

ACC						
habituation						
FEU	Jump	Phasicity	count (n=195)	photoidentified %	excited network %	inhibited network %
1	1.013753	9.874331	45	35.7	21.4	6.6
2	0.256558	0.544152	14	7.1	14.3	6.6
3	0.380936	9.887316	6	7.1	14.3	
4	-0.178783	2.294918	16		3.6	20
5	1.742927	9.671714	14	7.1	17.9	
6	0.511013	8.512954	39	14.3	17.9	26.7
7	0.036585	8.940191	27	14.3	7.1	
8	-0.337037	0.514732	6			13.3
9	-0.722206	9.014569	21	14.3		26.7
10	-2.051888	8.544649	2			
11	0.485651	0.806981	5		3.5	
ACC						
conditioning						
FEU	Jump	Phasicity	count (n=195)	photoidentified %	excited network %	inhibited network %
1	0.708874	9.267389	89	64.3	71.4	40
2	1.254519	9.952948	28	14.3	10.7	
3	0.118707	5.706698	20		7.1	
4	-0.153754	9.562564	22	14.3	3.6	26.6
5	0.234562	8.000342	21		3.6	20
6	-0.722206	9.014569	12	7.1		13.3
7	2.396977	9.810637	2		3.6	
8	-2.566214	5.372104	1			

Table 3 Functional Encoding Dictionary for data in Figure 7

ACC face				ACC object			
FEU	Jump	Phasicity	count (n=236)	FEU	Jump	Phasicity	count (n=184)
1	-0.015117	0.171617	172	1	0.019435	3.489979	156
2	0.213257	5.90104	18	2	-1.836143	8.44577	2
3	-0.162247	7.371203	18	3	-0.24348	4.779605	15
4	-0.233201	6.88877	23	4	0.232237	3.772021	7
5	0.130502	2.9514	5	5	-0.747206	7.171842	1
				6	0.351108	8.117762	3
BLA face				BLA object			
FEU	Jump	Phasicity	count (n=537)	FEU	Jump	Phasicity	count (n=393)
1	0.074587	1.003158	91	1	-0.050213	5.800307	63
2	-0.01666	0.904745	225	2	-0.004533	0.676951	88
3	0.023357	7.41292	63	3	-0.129041	3.837597	52
4	-0.169746	9.043318	35	4	0.063474	0.886419	72
5	-0.20652	2.821232	25	5	0.108349	7.725325	56
6	0.166382	5.056808	38	6	-1.534201	4.325586	4
7	0.024505	4.674267	51	7	-0.027084	6.219159	29
8	0.419689	9.682577	6	8	-0.13327	9.843607	29
9	0.176288	7.079611	1				
10	1.23387	1.581351	2				
dmPFC face				dmPFC object			
FEU	Jump	Phasicity	count (n=187)	FEU	Jump	Phasicity	count (n=139)
1	-0.017626	2.024209	108	1	0.242413	9.723268	6
2	-0.092583	1.096741	19	2	0.021292	6.405596	103
3	-0.096001	8.671568	3	3	-0.258845	7.160438	29
4	0.109218	1.214583	22	4	-0.455267	0.312573	1
5	0.053151	8.77568	26				
6	0.004324	8.82068	9				
OFC face				OFC object			
FEU	Jump	Phasicity	count (n=241)	FEU	Jump	Phasicity	count (n=195)
1	-0.238121	9.936711	10	1	-0.044021	8.474085	57
2	0.047788	7.135459	76	2	0.008295	3.102671	51
3	-0.01392	3.259947	68	3	0.118643	4.917292	15
4	-0.097605	5.022757	38	4	0.086658	5.138108	26
5	-0.066333	7.810266	49	5	-0.081089	2.374053	45
				6	-1.451036	0.653735	1



Supplemental Figure 1

FEU pipeline, on average clusters simulated data more accurately than other methods

We apply the 5 techniques to cluster 5 simulated datasets into ensembles. Across the 5 experiments (experiment 1 is shown in Figure 3), the FEU pipeline obtains the best average performance. This is evident in the visualizations of these clusters.

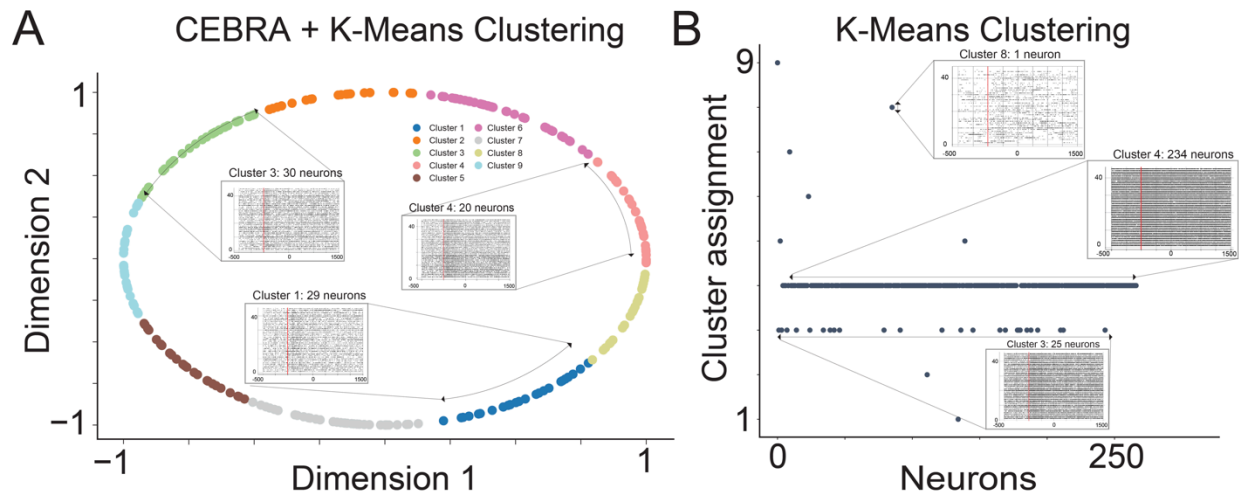
A. We applied K-Means to cluster simulated neuron spike data. Data points correspond to individual neurons; the y-axis 'Clusters' denotes each neuron's cluster assignments determined by K-Means, with colors indicating the neurons' true clusters. Perfect clustering is achieved when neurons within the same predicted cluster share identical colors, reflecting accurate alignment with their true cluster.

B. We performed dimensionality reduction on the simulated neuron spike data with PCA and clustered the resulting principal components with K-Means. Data points correspond to individual neurons; data point shape denotes the ground truth cluster assignment, while colors denote the predicted clusters. Perfect clustering is achieved when data points in clusters have the same color and shape.

C. We conducted dimensionality reduction on the simulated neuronal spike data using T-SNE, followed by clustering the derived principal components with K-Means. Each data point represents an individual neuron, with the shape of the data point indicating the neuron's actual cluster assignment and colors representing the predicted clusters. Perfect clustering is achieved when data points in clusters have the same color and shape.

D. We performed dimensionality reduction on the simulated neuronal spike data utilizing CEBRA and subsequently clustered the resultant components with K-Means. Each data point signifies an individual neuron; data point shape denotes the ground truth cluster assignment, while colors denote the predicted clusters. Perfect clustering is achieved when data points in clusters have the same color and shape.

E. FED representation of the simulated neuron spike data. We use FEU analysis to cluster the simulated neuron spike data. Perfect clustering is achieved when data points in each cluster have the same color and shape. Callout to show overlapping data points in a cluster.



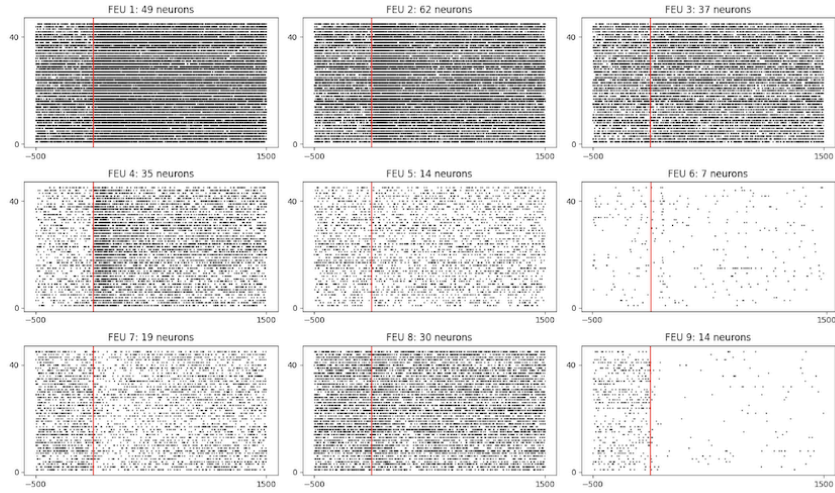
Supplemental Figure 2

Alternative methods do not efficiently capture ensembles in real trial data

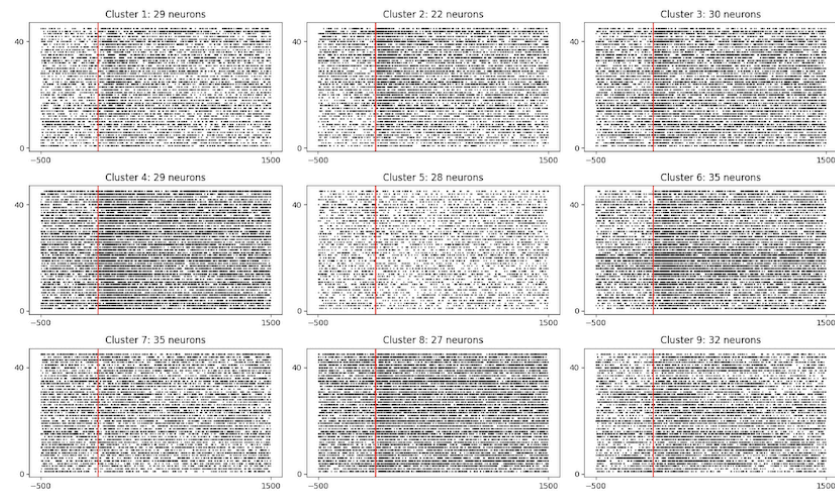
A. We use CEBRA to perform dimensionality reduction and K-Means to cluster the neural spike data from the rodent social learning tasks.

B. We use K-Means to cluster neural spike data from the rodent social learning experiment.

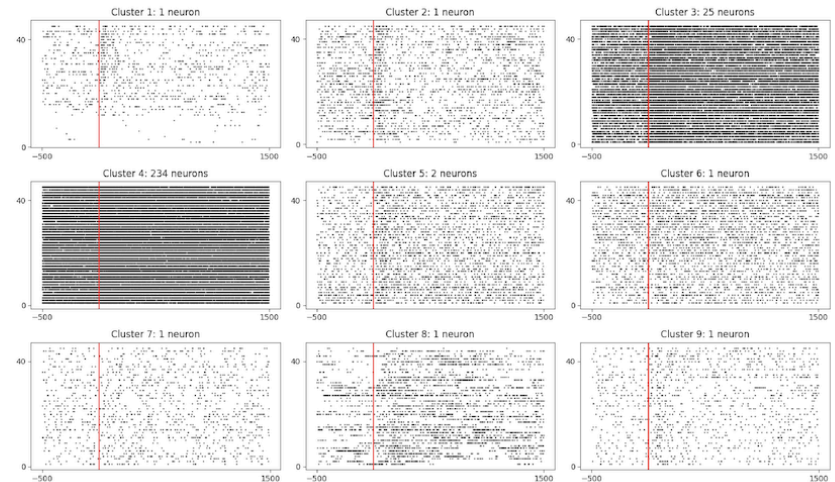
A Ensembles by Functional Encoding Units Pipeline



B Ensembles by Cebra + K-Means Clustering



C Ensembles by K-Means Clustering



Supplemental Figure 3

Alternative methods do not efficiently capture ensembles in real trial data

A. Ensembles found by the FEU pipeline.

B. Ensembles predicted by the CEBRA + K-Means approach of clustering demonstrated limited interpretability.

C. Ensemble predicted by the K-Means clustering technique shows a significant lack of substantive coherence.