Learning-related modulation of rule representation in primate prefrontal cortex ensembles

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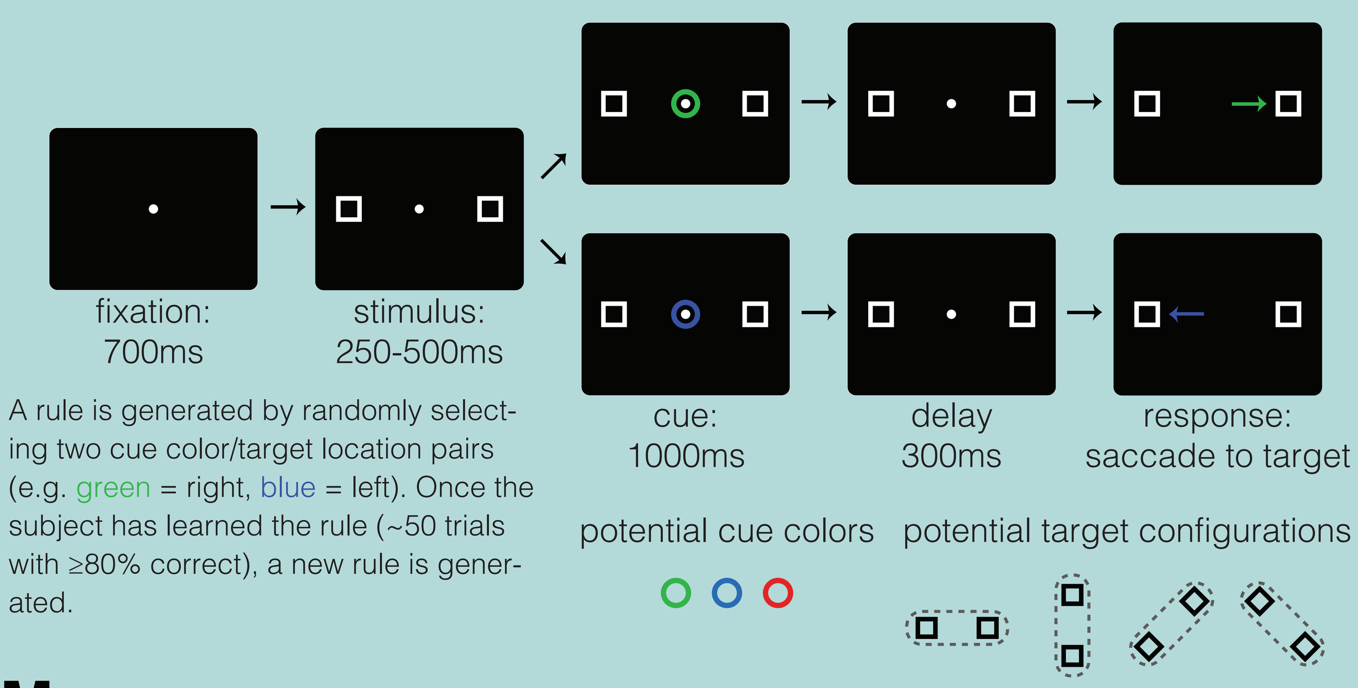
Introduction

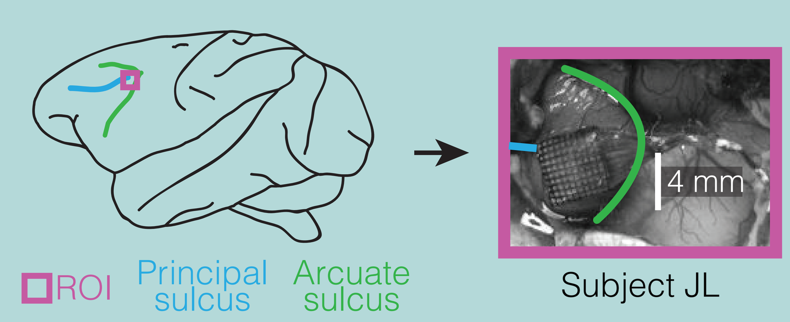
The lateral prefrontal cortex (LPFC) is necessary for learning associations between arbitrary pairs of stimuli and responses. Lesions to LPFC area 8a severely impair the ability of macaques to learn associations between more than one stimulus-response pair simultaneously (Petrides, 1987; referred to as conditional associative learning–CAL). Saccade direction selectivity in single LPFC neurons has also been shown to emerge earlier in a trial as macaques learn the associations between objects and saccade directions (Asaad et al.,1998). However, the ensemble-level mechanisms of CAL in LPFC are poorly understood. The need to average neuronal activity across multiple instances of learning in single neuron recordings can mask underlying dynamics in the neural activity, obscuring the relationship between neuronal activity and behavior. We predict that trial-to-trial variability in the learning curve will be reflected in the ensemble state.

Conditional associative learning (CAL) task



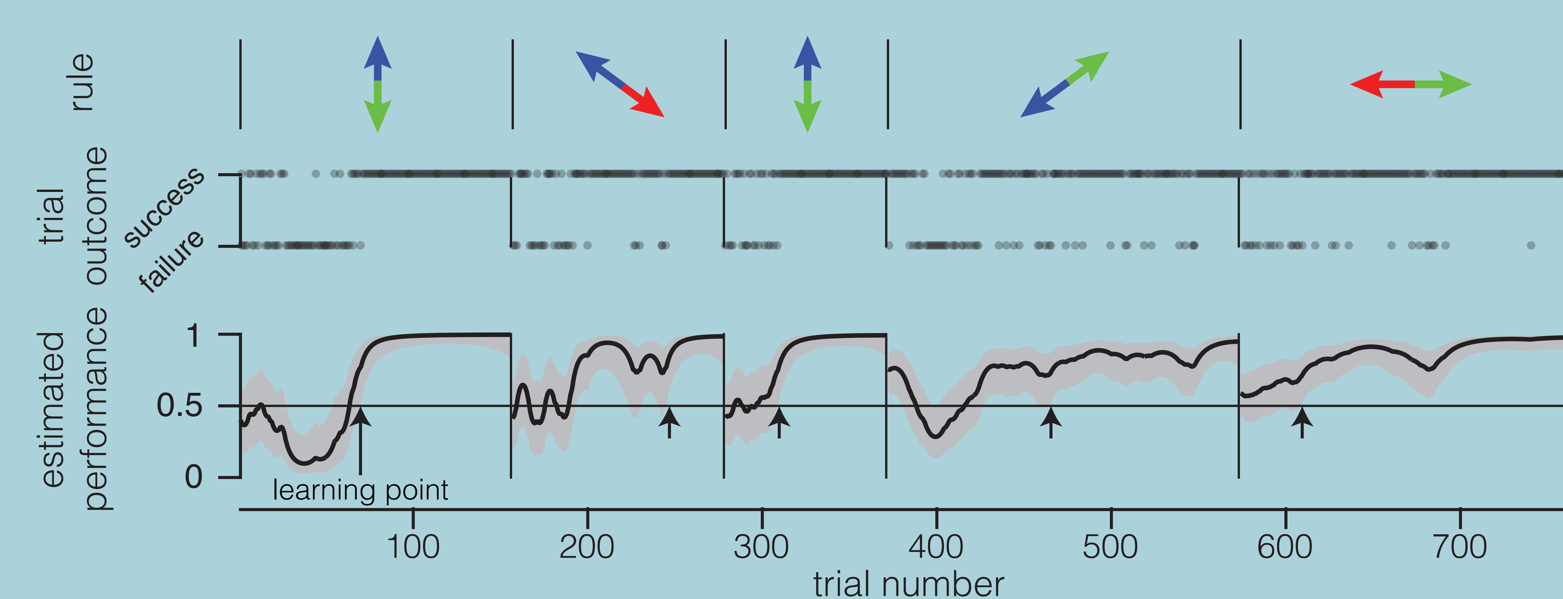
A rule is generated by randomly selecting two cue color/target location pairs (e.g. green = right, blue = left). Once the subject has learned the rule (~50 trials with ≥80% correct), a new rule is generated.

Multielectrode array recording



Two *Macaca fascicularis* were implantated with 96-electrode microarrays (Blackrock Microsystems, Utah) in LPFC area 8a. We recorded neuronal ensemble activity across dozens of recording sessions. The data presented here are from a six recording sessions of 40-70 units each.

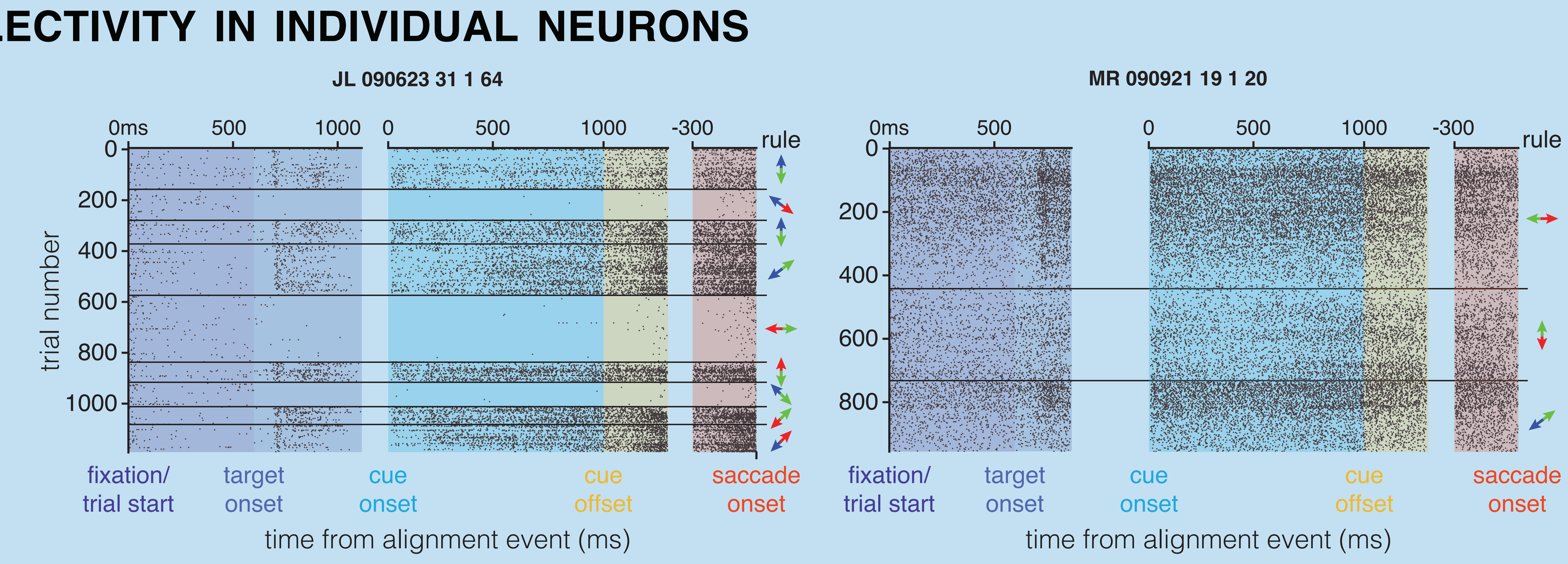
Quantifying performance and behavior

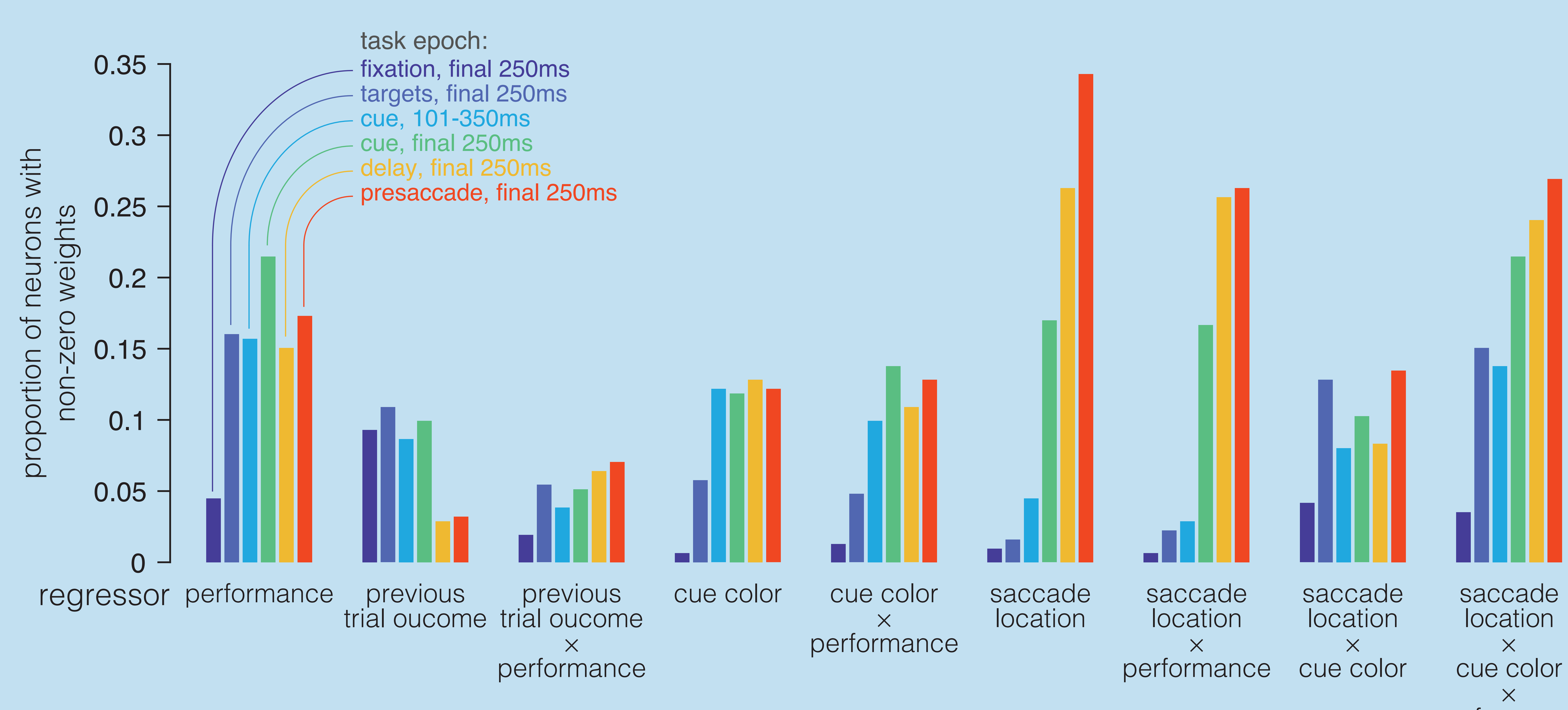


A subject's performance for five example rule blocks from a single session. The rule is displayed in the top row (e.g. blue = top, green = bottom). Trial outcomes are displayed in the middle row. The bottom row shows a continuous estimate of the animal's performance (i.e. learning curve), estimated as in Smith et al. (2004) *J. Neuro.* The 95% confidence interval (shaded grey region) can be used to determine the first trial in which the animal's performance was significantly above chance.

Diverse selectivity in individual neurons

Rasters for two example neurons from two different subjects. Rasters are separated into three parts based on the alignment point: fixation initiation (left), cue onset (center), or saccade onset (right). Background color indicates task epoch. Horizontal lines delineate different rule blocks. Note the changes in firing rate both within and across rule blocks.



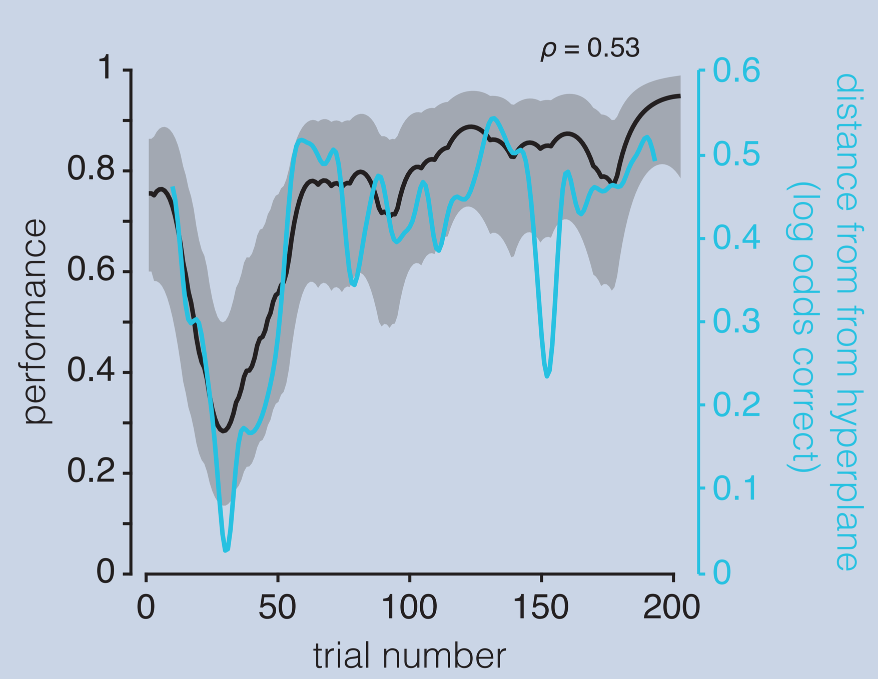


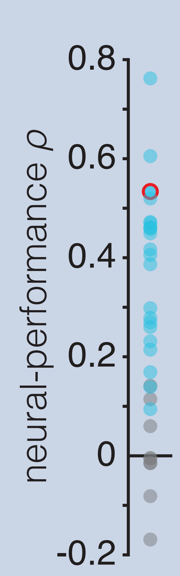
Diverse task selectivity in individual units. A GLM was fitted to each unit in order to predcit its firing rate from task features and across different task epochs. A separate model was fitted to firing rates from each task epoch (task epochs denoted by color), and different predictors are labeled on the x-axis. Predictor weights were L1-regularized (lasso) to promote sparsity. The proportion of units with non-zero weights for each predictor is shown on the y-axis. n = 312 units.

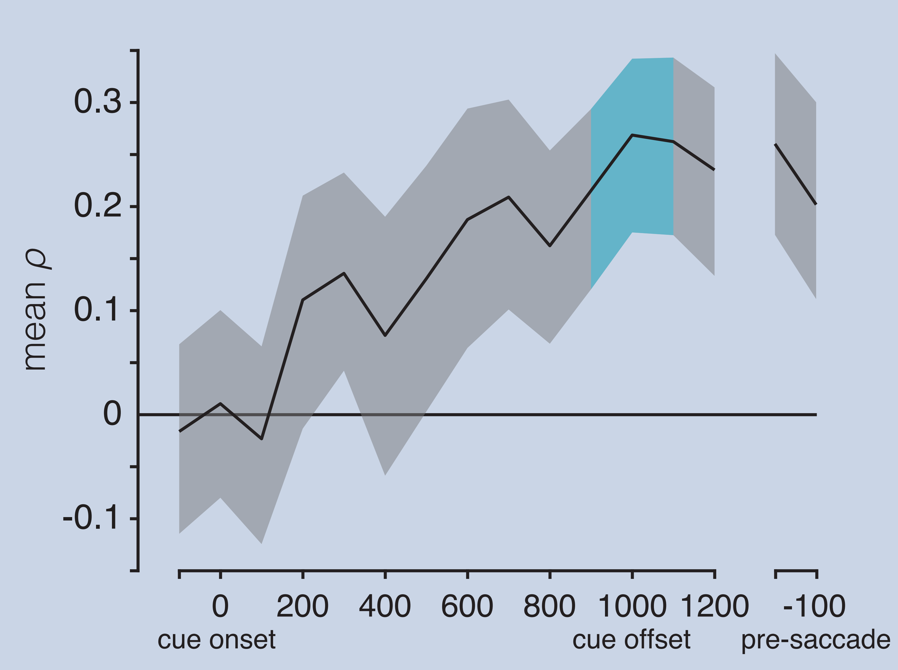
Learning modulates choice coding

A logistic regression model was fitted to each rule block to predict the subject's response. The models were fitted to the ensemble firing rates averaged over the final 200ms of the delay epoch. The models were then used to project the ensemble firing rates for each trial (right y-axis, blue). We then computed the Spearman correlation between the projections and the behavioral performance. Note that a negative distance indicates log odds in favor of an incorrect classification. Logistic regression projections were smoothed with gaussian kernel of SD = 3 trials.

Left: Results for an example rule block. Right: Results across all 31 rule blocks.



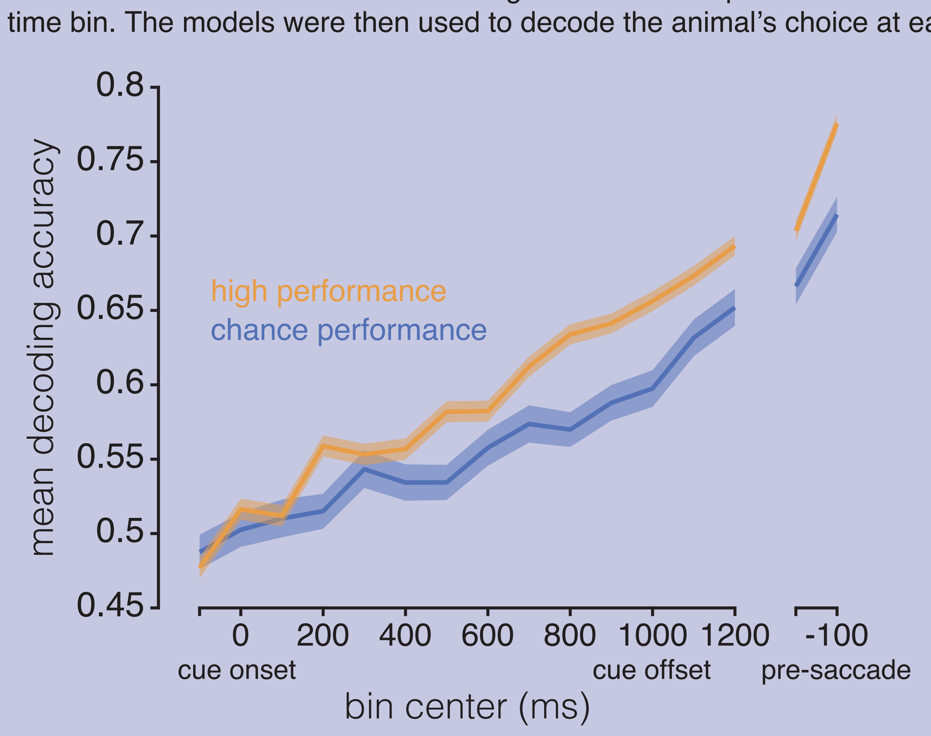




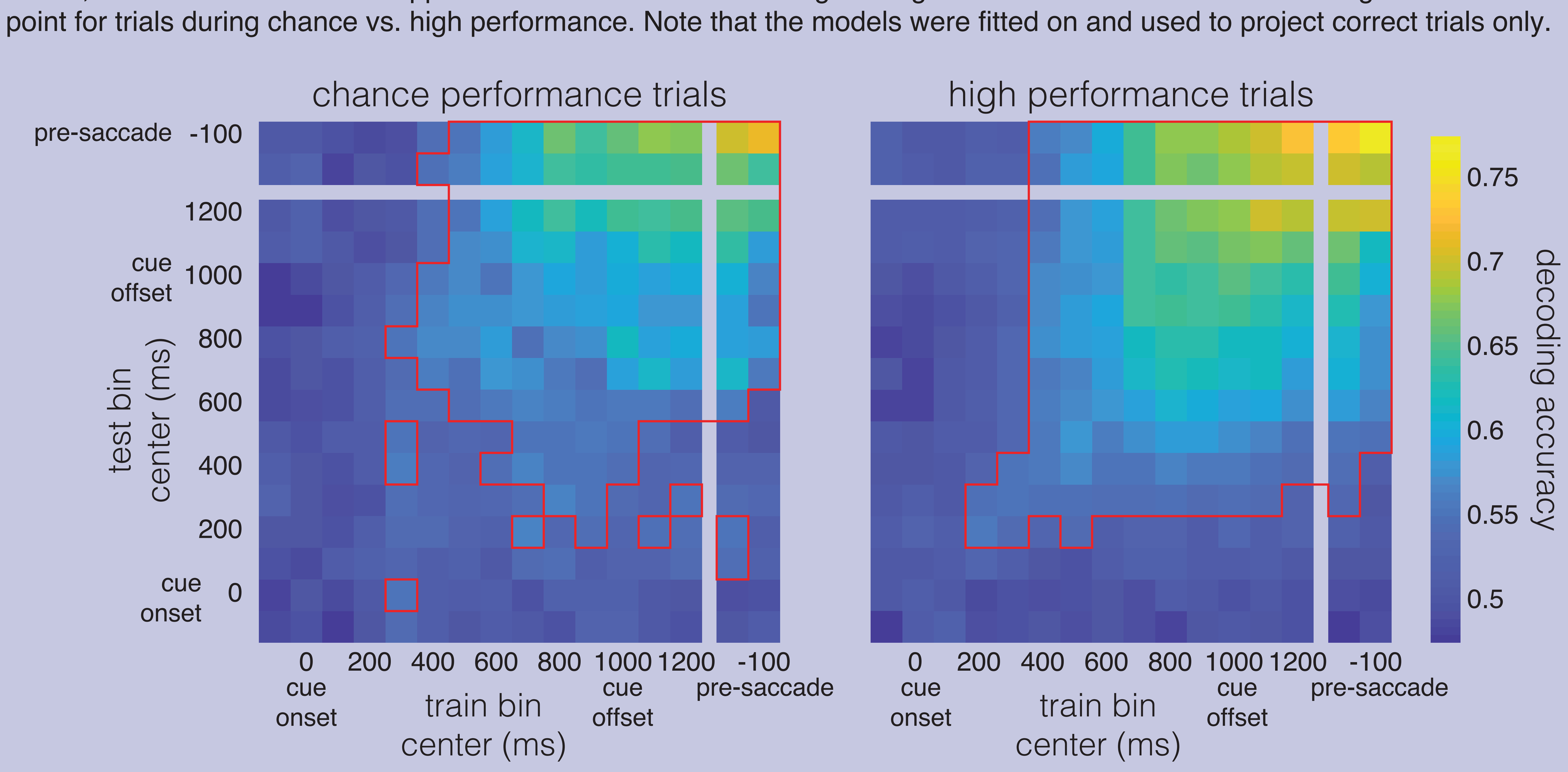
Left: Time course of projection-performance correlation. A 200ms bin was stepped at 100ms intervals to compute the ensemble firing rates across the time course of each individual trial, and the procedure from A was repeated at each time point. Shaded region = 95% confidence interval. n = 31 rule blocks. Blue region indicates time bin used for previous examples.

Learning accelerates and temporally-stabilizes choice representation

For the 40 consecutive trials with the highest behavioral performance in each rule block, a 200ms window was stepped at 100ms intervals and a logistic regression model was fitted to the firing rates in each time bin. The models were then used to decode the animal's choice at each time point for trials during chance vs. high performance. Note that the models were fitted on and used to project correct trials only.



Shaded region = S.E.M.



Cross-temporal decoding analysis. The red circumscribed regions indicate train/test bins in which the 95% confidence intervals of classification accuracy exceed chance.

Conclusions

LPFC area 8a neurons exhibit diverse selectivity across features and time during a rule-learning task.

Learning-related fluctuations in behavioral performance correlate with the strength of saccade choice representation in LPFC neuronal ensembles

Choice information in single trials accumulates more rapidly after learning.

Learning stabilizes the ensemble code for choice across time within single trials.

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