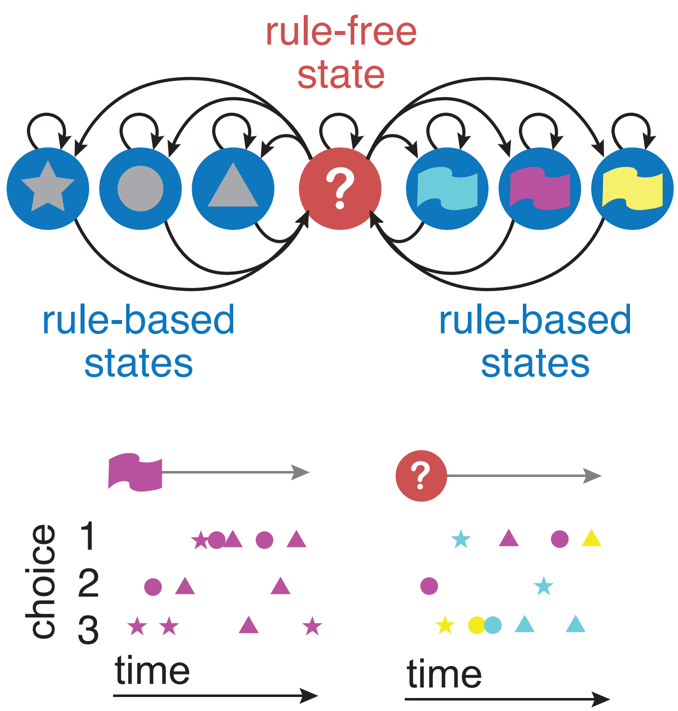
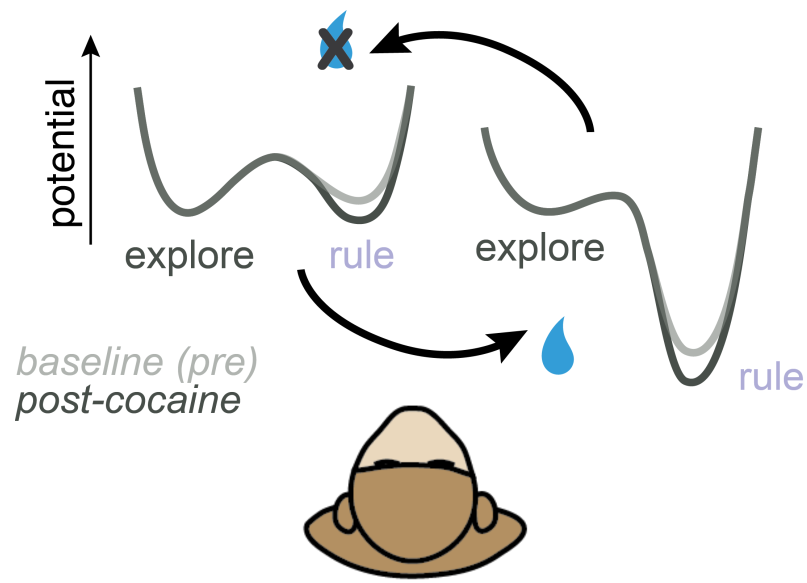
The energetics of strategy changes in the prefrontal cortex

Background

- Neural computations are energetically demanding. The brain is responsible for about 30% of our metabolic demand
- Spikes are especially costly (require a lot of ATP), so spiking computations are likely driving a lot of this demand.
- Cognitive flexibility is compromised when energy bioavailability is compromised.
- Perhaps this is because it takes a lot of energy to change our minds.
- But what are the energetic demands of flexibility and what does this look like neurally?

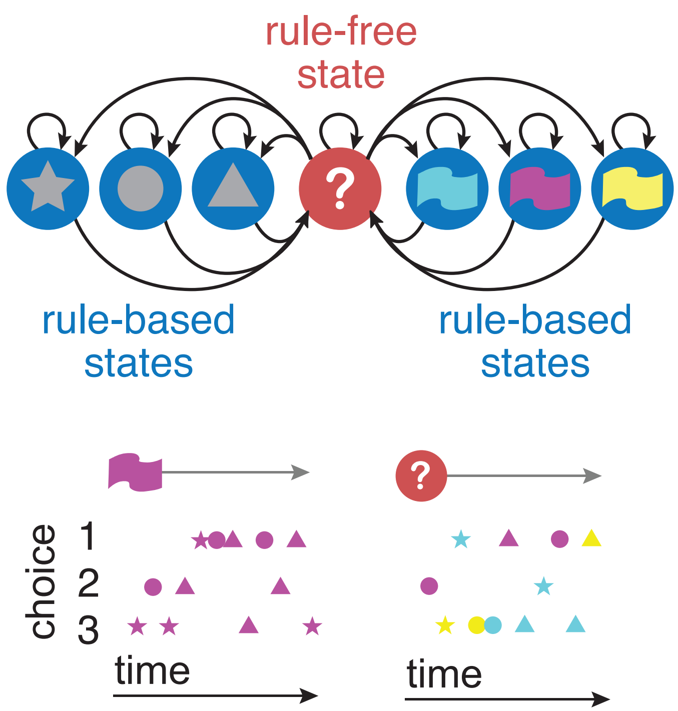
Prior work: Rules are energy minima

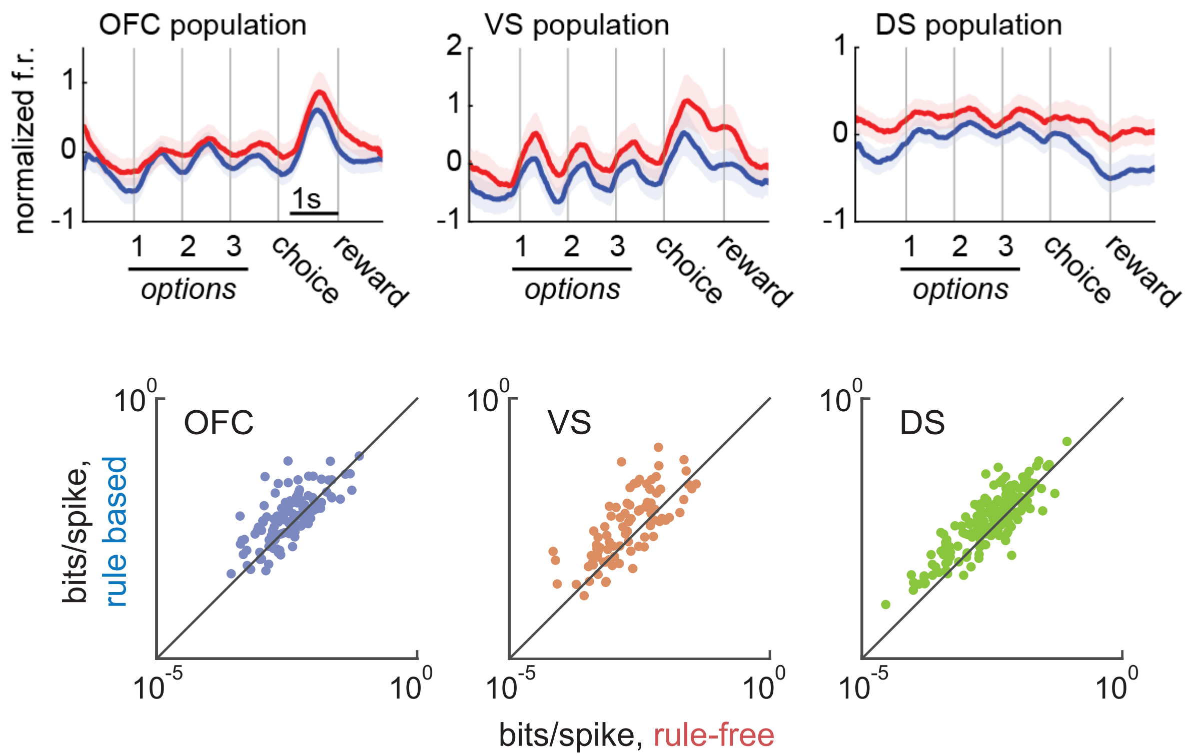




Ebitz, et al, *PLoS Comp Biology* 2019

Prior Work: Lower spike rates for rules



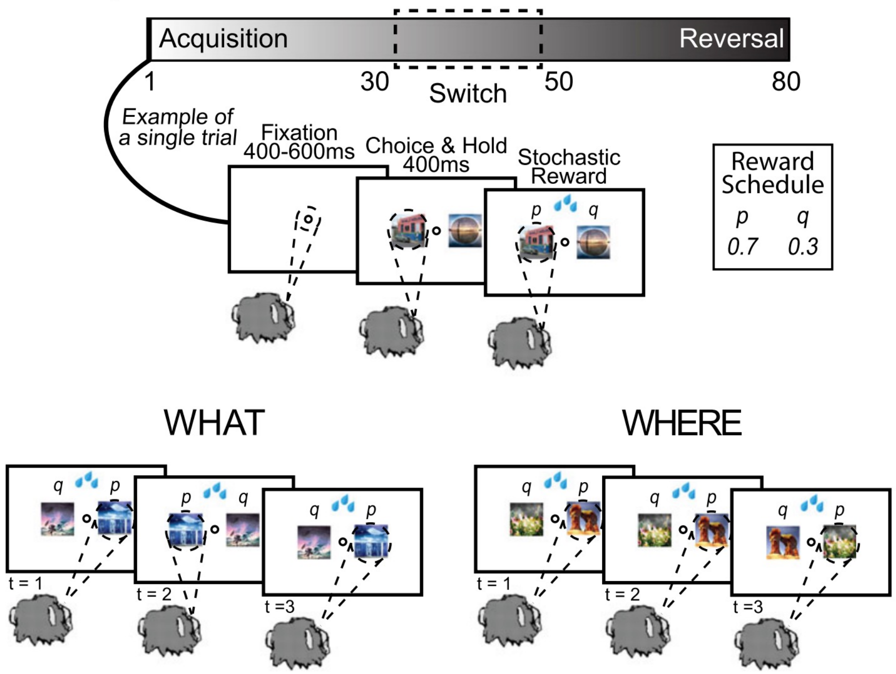


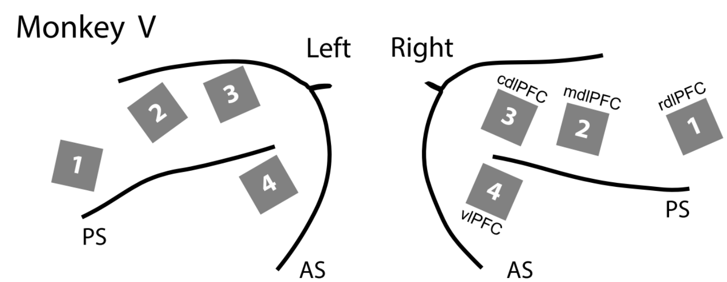
Ebitz, et al, *PLoS Biology* 2020

Next steps:

- We previously speculated that lower spike rates are due to computational efficiency of rules, which could be part of why we use them
- But this could also be a general purpose thing: energetically-demanding behavior (in the thermodynamic sense) could be rare because it has outsized **neuro-metabolic demands**
- So ....

Task design and dataset

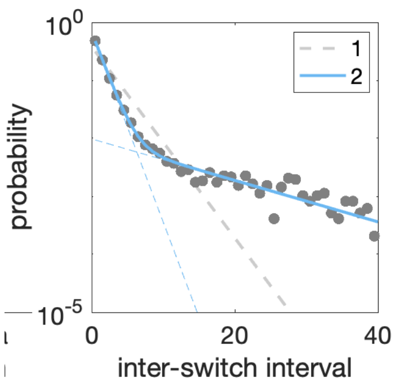


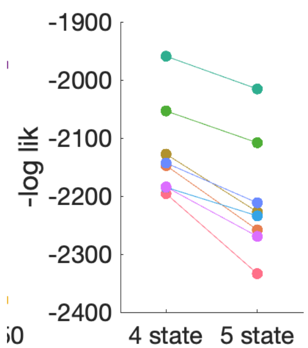


data: Bartolo & Averbeck, *Neuron* 2020;
Tang, Bartolo, Averbeck, *Nat Comms* 2021

x768 electrodes/monkey

Evidence for an explore state

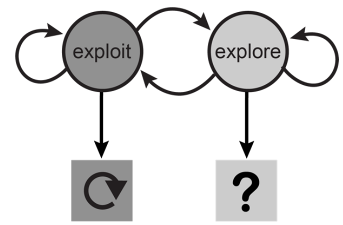


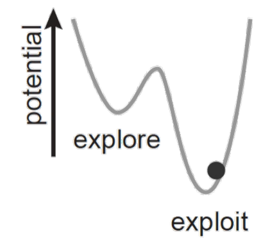


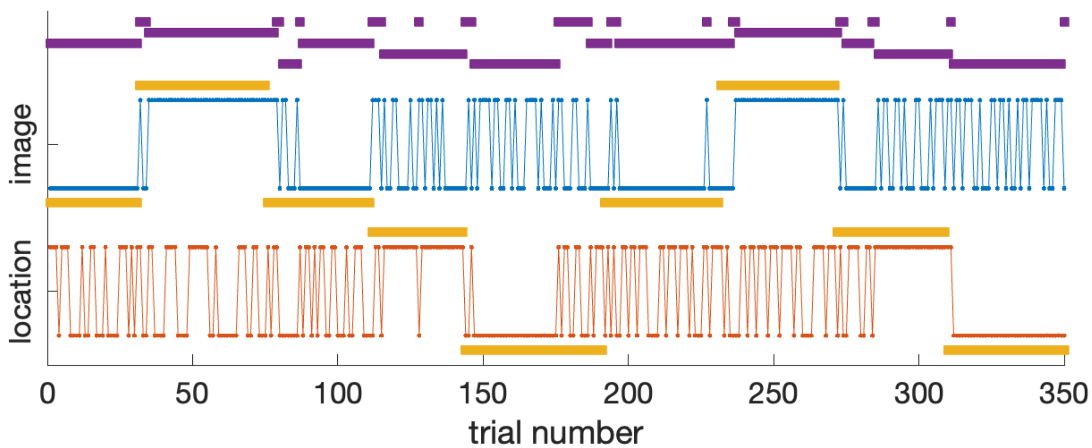

```
>> theta

theta =

    0.8031   10.3056    0.8846
    0.8287   11.6179    0.8890
    0.9088   12.3453    0.9009
    0.9755   15.4108    0.9054
    0.8573   13.9108    0.8802
    1.0175   13.7548    0.8934
    0.8588    8.7075    0.8341
    0.7897    8.4829    0.8289
```

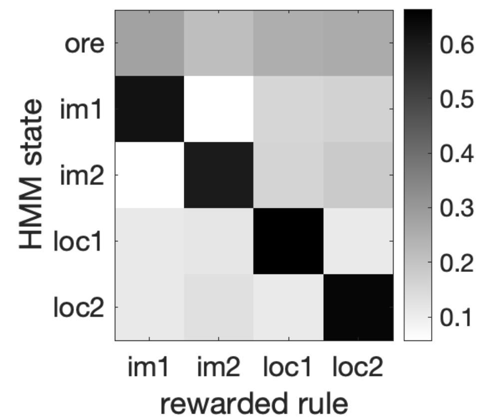
There are 2 switching time constants, but the short switches occur more frequently than would be expected if random decision making in 1 dimension only occurred during persistent decisions in another domain (compare 4 state and 5 state models)

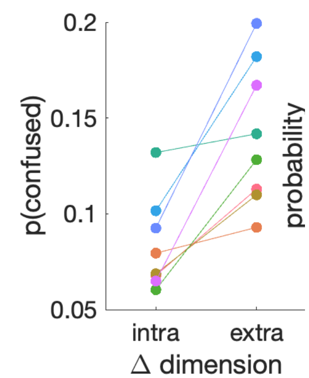
Hidden Markov model



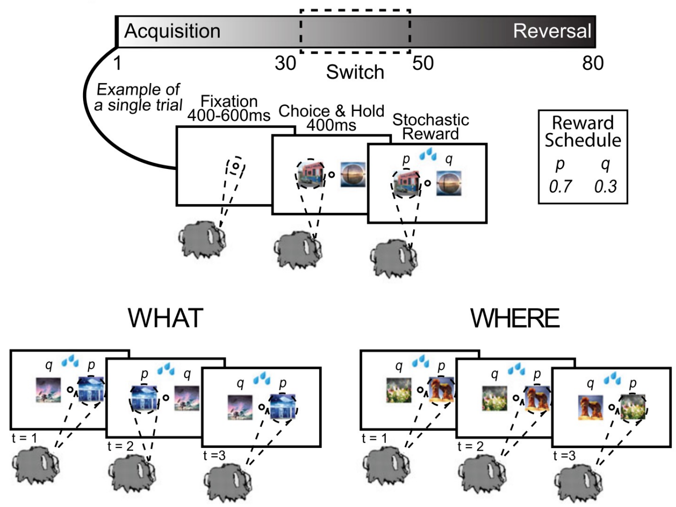


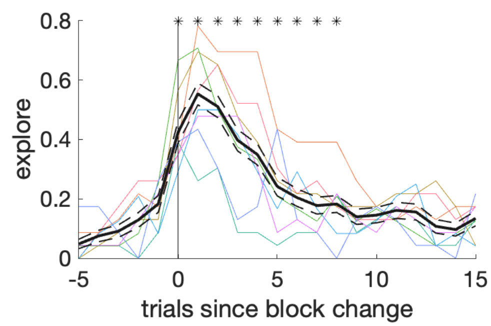


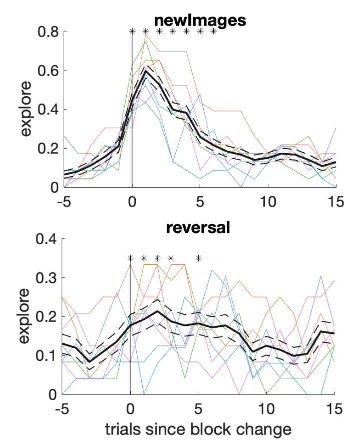


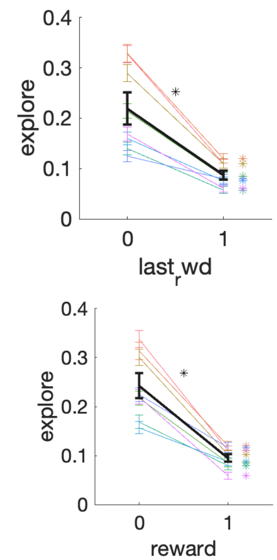


Some basic behavior





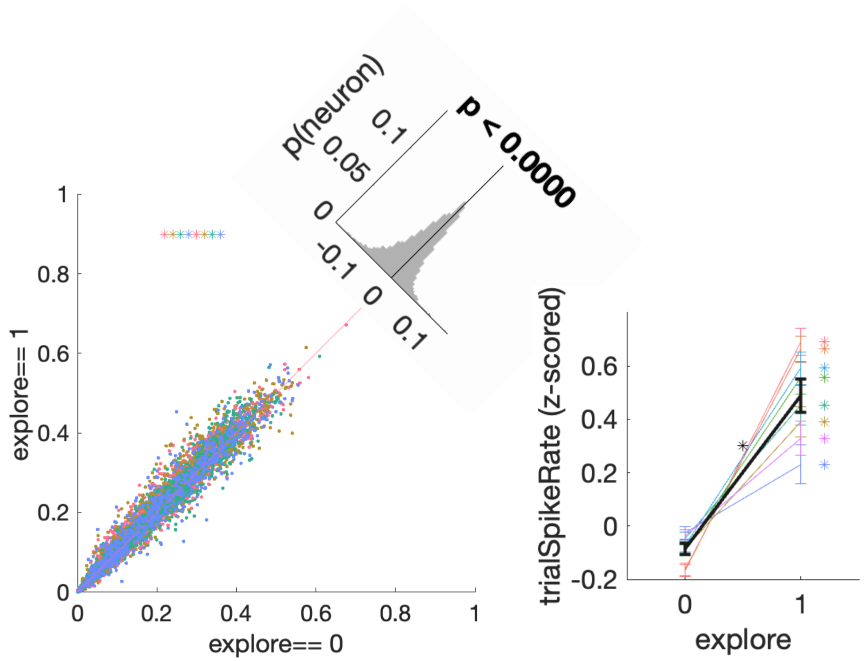


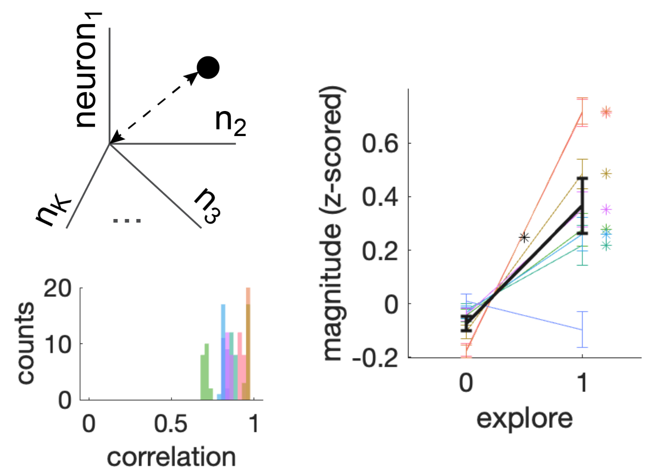


Neural data analyses

Spiking activity is *higher* during exploratory decisions.

We would expect this to show up as a change in magnitude at the population level





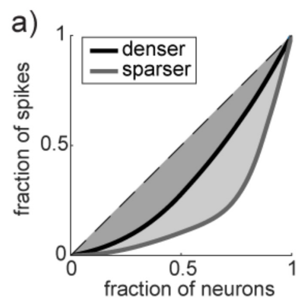
not due to last reward:

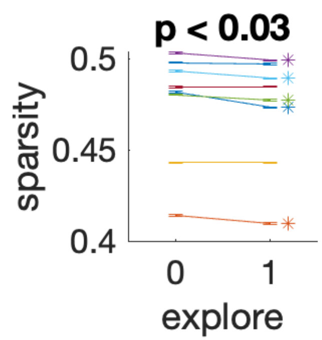
```
'trialSpikeRate
  last rwd, main effect = -0.38, p = 0.0000
  explore, main effect = 0.30, p = 0.0000
  explore, main effect = -0.05, p = 0.0641'
```

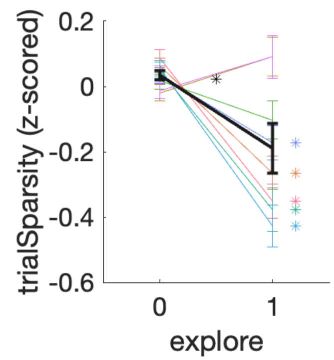
```
'magnitude
  last rwd, main effect = -0.16, p = 0.0000
  explore, main effect = 0.09, p = 0.0000
  explore, main effect = -0.01, p = 0.6729'
```

Spiking activity is also *denser* during exploratory decisions.

would be nice to illustrate an example session for the sparsity; this is a cartoon



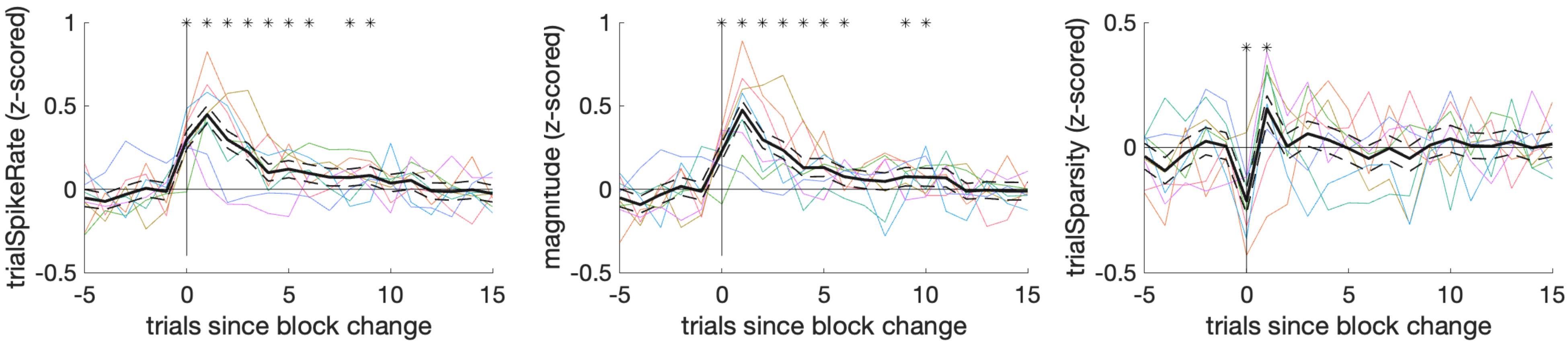




not due to last reward:

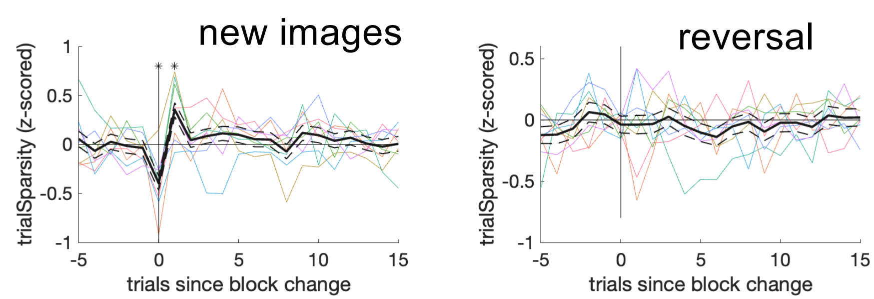
```
'trialSparsity
  last rwd, main effect = 0.18, p = 0.0000
  explore, main effect = -0.06, p = 0.0000
  explore, main effect = -0.02, p = 0.4432'
```

The increase in spike count and density, aligned to block changes

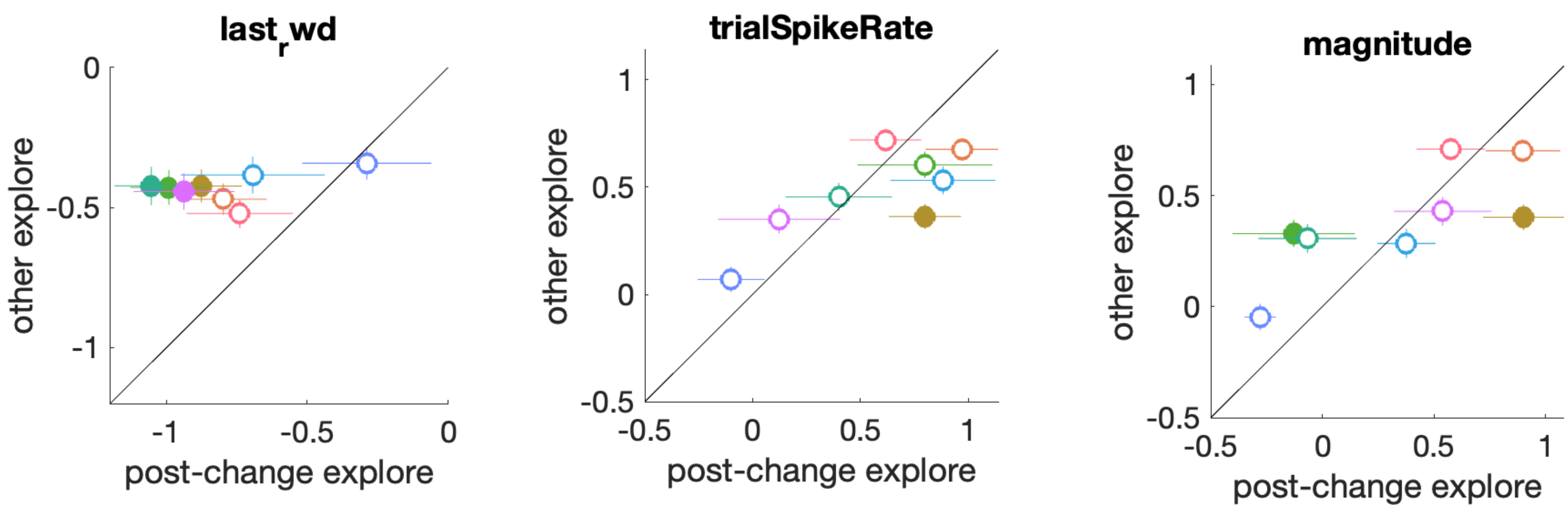


need to show the new images/reversal distinction for the spike rate and magnitude

- makes the point that those are more similar

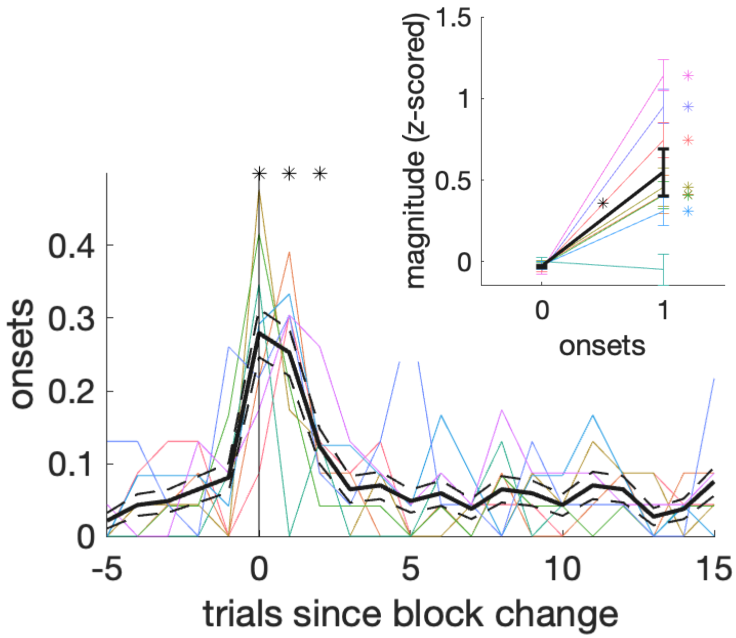


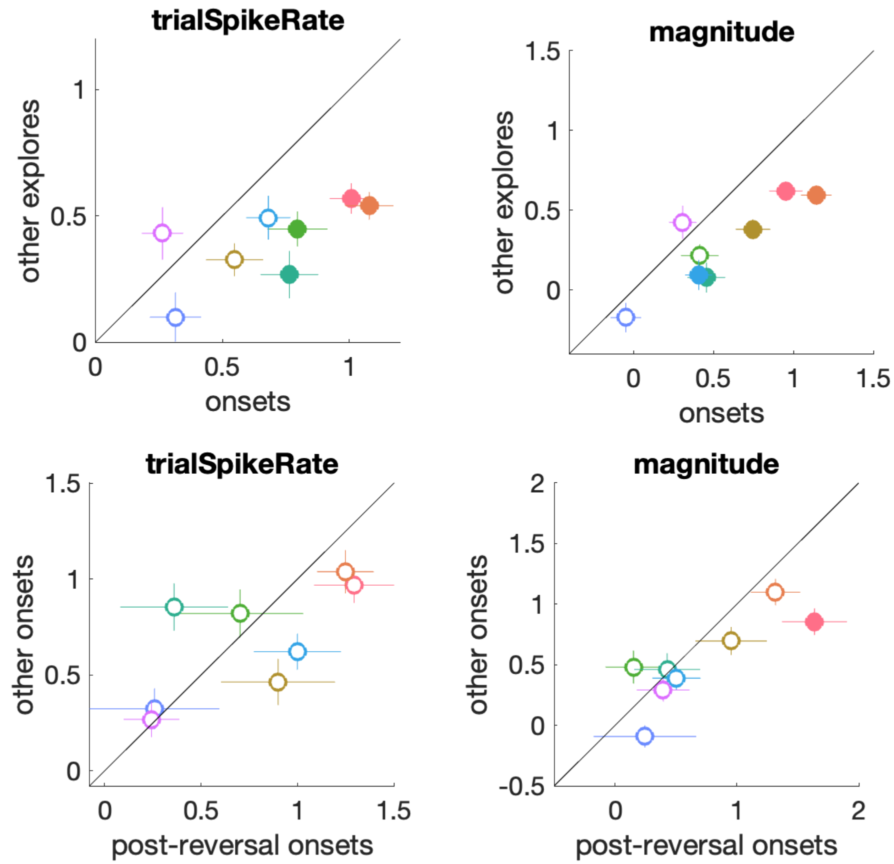
The increase in spike rate / magnitude is present on all explore choices, not just after reversal



these are w/in 5 trials of the change pt

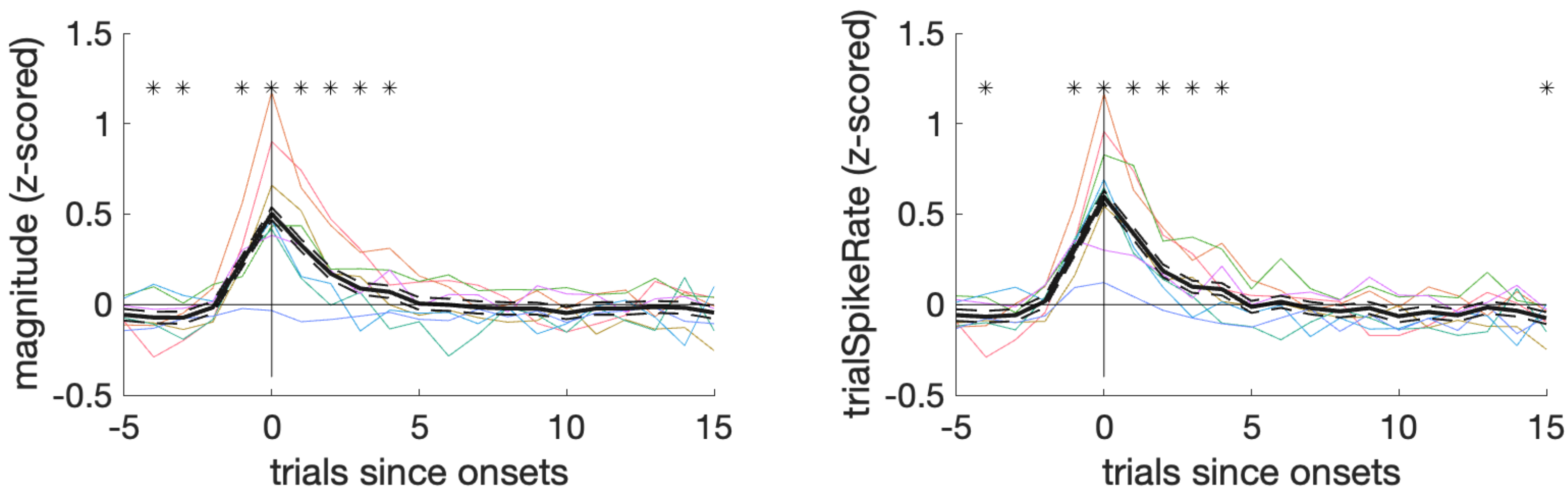
Onsets, not reversals, are driving the increase in magnitude and avg. firing rate,



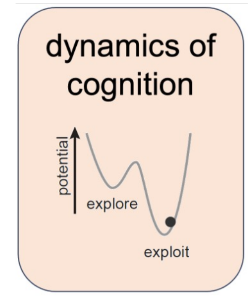


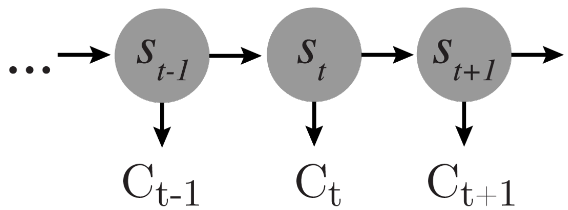
not related to reversals,
just related to the behavioral change

neural measures aligned to onsets



Measuring cognitive dynamics





Boltzman distribution

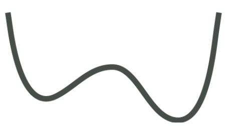
$$E_j - E_i \propto \ln\left(\frac{p_i}{p_j}\right)$$

Arrhenius equation

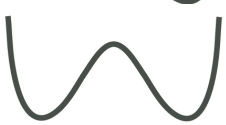
$$E_a \propto -\ln\left(\frac{r_{ij}}{C}\right)$$

$$T = \begin{bmatrix} .7 & .3 \\ .3 & .7 \end{bmatrix}$$

$$T = \begin{bmatrix} .7 & .3 \\ .1 & .9 \end{bmatrix}$$



$$T = \begin{bmatrix} .9 & .1 \\ .1 & .9 \end{bmatrix}$$

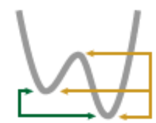


transition matrix

emissions

$$T : s_t \mapsto s_{t+1}$$

$$E : s_i \mapsto C$$

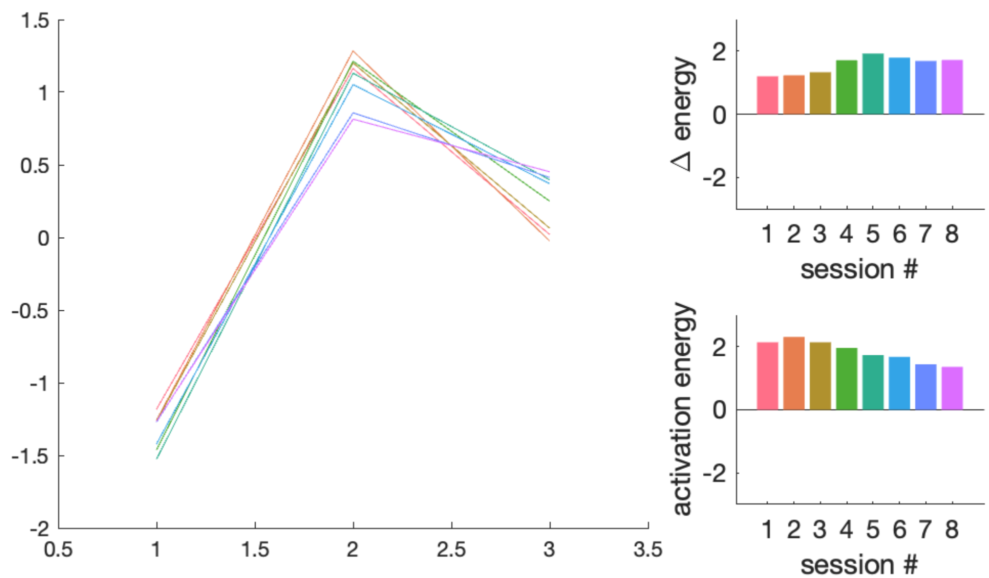


$$T = \begin{bmatrix} P_{ore \to ore} & 1 - P_{ore \to ore} \\ 1 - P_{oit \to oit} & P_{oit \to oit} \end{bmatrix}$$

Ebitz, et al., *PLoS Comp Bio* 2018;
Chen, et al., *Elife* 2021

Ebitz, Albarran & Moore, *Neuron* 2018;
Chen, Knep, Han, Ebitz & Grissom, *Elife* 2021

Bump graphs work in this dataset



Explore is deeper than exploit, consistently

Session-by-session variability in activation energy (barrier height) predicts the neural costs at onset