CS786 research paper

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I am going for option 1, in class, we discussed odor guided choice task with rats. two odors signaled which response led to reward.third odor allowed free choice. result showed we must test possible task representation. but i think we can't assume animals follow task structure or path set by experiment.researchers design tasks to study animal learning. animals may not understand tasks as intended. this can lead to wrong conclusions.

abstract

so in my modeling paper, i implement 2 different RL model with diferent state representation of task. i tested how well they predicted trial by trial choice behavior for each animal. difference between 2 model is state representation (how learning generalized across odors).

in 4 state model i assume full generalization btw. forced choice & free choice trial.(valid respons on forced choice trial generalize to free-choice trials) also shared states exist btw them. this model shows generative structure of task.

in 6 state model, i assume no generalization between trial types. forced choice & free choice trials have separate states. states depend on both odor & action.

here is my idea : i'll fit free param.s for each model to choice data. use hierarchial bayesian inference with MCMC sampling. and model fits can be elevated using WAIC.

basically, tasks can be represented in many way. subject face same event but create unique representation. model discussed in class assume that subjects(animals) understand task as intended but it's not always true. animals can't be told task structure.

efficient representation will help generalize learning. animals may not generalize across odors. so using RL moel to analise trial by trial decisions for each rat looked like a good method to me.

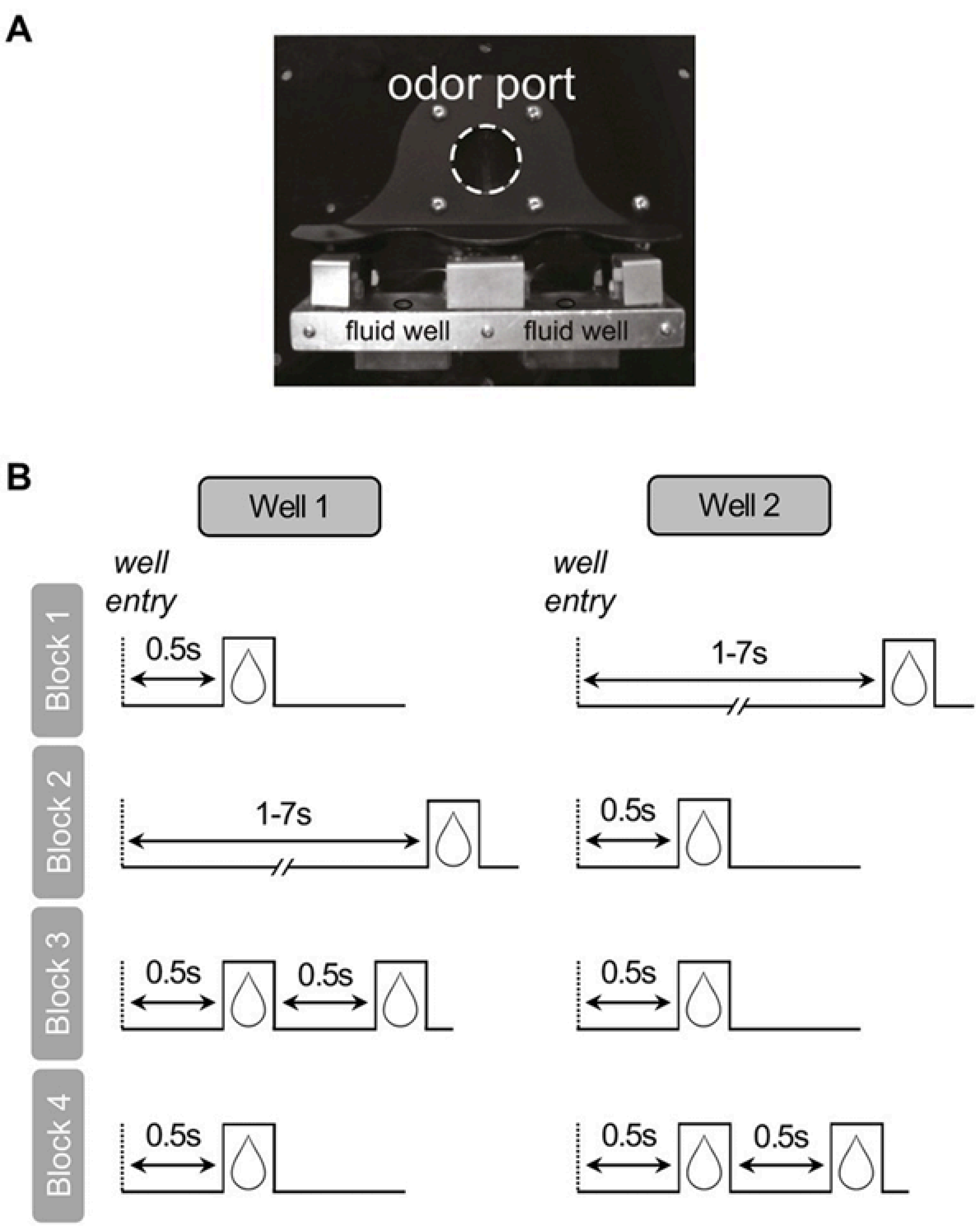
i have coded up simulation below(after text) for both model and compared their performance. result showed 6state model perform better. its WAIC score came out lower than 4 state model. result also showed rats' rely on simplified structure. simple structure allows generalization across trials. most rats did not develop this. rats did not use efficient task representation. they failed to generalize learning from forced to free choice trials, even after training.

intro

we often learn through observation not instruction. like, when choosing parking spot. first, we might check spots individually but over time, we notice certain areas are usually empty. this helps make faster decision next time we park. so we create state representation. it help us expect reward and decide action. when different situations lead to same result, seeing them as same makes task easier and speeds up learning.

but it's unclear how animals form state representation from experience. idk if animals learn in one situation and apply it to other?

intution from experiment



i read about experiment that tell how rat generalise lerned state representation in odor task. setup was like: rats smells before choosing 1 of 2 wells, each odor were suppose to signal which well had reward. 2 odor means forced choice trials with specific wells, & 3rd odor means free choic trial. reward delay and amount depended on well, not odor. one well gave a better reward each block. rewards changed between blocks (see in plots). if rats learned well, they would use forced choice trial to make better choice in free choice trial. they would adapt quickly when rewards changed.

here is code implementation to provide evidence that change proposed is reasonable

In [ ]:
```
import os
import sys
import pystan
import pickle
import numpy as np
import pandas as pd
import scipy as sp
from hashlib import md5
import seaborn as sns
from math import isnan
from math import isinf
from __future__ import division
import scipy.stats.kde as kde
from scipy.special import expit
from google.colab import drive
import matplotlib.pyplot as plt
from collections import OrderedDict

%matplotlib inline
```

In [ ]:
```
drive.mount('/content/drive')
```
```
Mounted at /content/drive
```

Parameters

```
In [ ]: sim_blocks = 4
        sim_trials = 16
        sim_sessions = 2
```

```
In [ ]: samples = 2000 # samples per chain
        warmup = 1500 # warmup samples
        chains = 4 # number of chains
        thin = 1 # period for saving samples
        n_jobs = 4 # cores
        n_blocks = 4 # blocks in experiment

        samplingInfo = dict(samples=samples, warmup=warmup, chains=chains, thin=thin, n_jobs=n_jobs)
```

i handle data with 3 differnet dataset

```
In [ ]: datasets = ['roesch2009', 'takahashi2016', 'burton2018']

        dataset2marker = {
            'roesch2009': '+',
            'takahashi2016': '.',
            'burton2018': 'x'
        }

        ratio_s = {
            'roesch2009': 4/3,
            'takahashi2016': 5/3,
            'burton2018': 1
        }

        dataset_labels = {
            'roesch2009': 'Roesch et al. (2009)',
            'takahashi2016': 'Takahashi et al. (2016)',
            'burton2018': 'Burton et al. (2018)'
        }

        dataset2rat = {
            'roesch2009': [1,2,3,4,5,6,7,8,9],
            'takahashi2016': [10,11,12,13,14,15,16],
            'burton2018': [17,18,19,20,21,22]
        }
```

```
In [ ]: rat2dataset = dict()
        for i in range(1,23):
            if 1 <= i <= 9:
                rat2dataset[i] = 'takahashi2016'
            elif 10 <= i <= 16:
                rat2dataset[i] = 'roesch2009'
            else:
                rat2dataset[i] = 'burton2018'

        ratOrder = np.array([10, 11, 12, 13, 14, 15, 16, 1, 2, 3, 4, 5, 6, 7, 8, 9, 17, 18, 19, 20, 21, 22]) - 1
```

params for 2 model i am implementing 6 state and 4 state

```
In [ ]: modelInfo = {
            'sixState_full': {
                'modelName': 'sixState_full',
                'parNames': ['beta','eta','gamma','sb','pers','lapse'],
                'Npars': 6,
                'parBounds': [[0,10], [0,1], [0,1], [-2,2], [-2,2], [0,1]]
            },
            'fourState_full': {
                'modelName': 'fourState_full',
                'parNames': ['beta','eta','gamma','sb','pers','lapse'],
                'Npars': 6,
                'parBounds': [[0,10], [0,1], [0,1], [-2,2], [-2,2], [0,1]]
            },
        }
```

helper func.

```
In [ ]: def phi_approx(x): # Phi_approx(x) = logit^{-1}(0.07056 x^3 + 1.5976 x)
            return expit(0.07056*(x**3) + 1.5976*x)
```

combined func. of above 2

```
In [ ]: def Parameter_processing(datasetName, modelName):
            data = pd.read_csv('/content/drive/My Drive/model_fits/' + datasetName + '_' + modelName + '_allSamples.csv')
            params = np.empty((modelInfo[modelName]['Npars']))
            for iPar, parName in enumerate(modelInfo[modelName]['parNames']):
                params[iPar] = data.loc[data['warmup']==0, 'params[' + str(iPar+1) + ']'].values.mean()

            #transforming  parameters
            params_trans = expit(0.07056*(params**3) + 1.5976*params)
            params_trans = params_trans[0]*10
            params_trans[4] = params_trans[4]*4-2
            params_trans[3] = params_trans[3]*4-2

            return params_trans
```

Model

first i convert data to dictionary

```
In [ ]: def data2dict(data):

            Ns = data['rat'].unique().size # N subjects
            Nt = data.shape[0] # total number of trials

            NSession = np.array([data.loc[data['rat']==rat,'session'].unique().size for rat in data['rat'].unique()]) #unique sessions
            NSessionTotal = np.sum(NSession)

            startSubject = np.concatenate(([1],data['rat'][1:].values!=data['rat'][:-1].values))
            startSession = np.concatenate(([1],data['session'][1:].values!=data['session'][:-1].values))
```

```
    block_index = data['block'].fillna(0).values.astype(int)

    # For  odor tasks
    odor = np.zeros(data.shape[0])
    odor[data['odor']=='left'] = 1
    odor[data['odor']=='right'] = 2
    odor[data['odor']=='free'] = 3
    odor = odor.astype(int)

    choice = data['choice'].fillna(0).values.astype(int)
    reward = data['rewardAmount'].fillna(0).values.astype(int)
    delay = data['rewardDelay'].fillna(0).values

    trialType = np.zeros(data.shape[0])
    trialType[data['trialType']=='valid'] = 1
    trialType[data['trialType']=='shortStay'] = -1
    trialType = trialType.astype(int)

    sessionType = np.zeros(data.shape[0])
    sessionType[data['sessionType']=='leftBetterFirst'] = 1
    sessionType[data['sessionType']=='rightBetterFirst'] = 2
    sessionType = sessionType.astype(int)
    return dict(Ns=Ns, Nt=Nt, NSession=NSession, NSessionTotal=NSessionTotal, odor=odor, choice=choice, reward=reward, delay=delay, trialType=trialType, sessionType=sessionType,
startSubject=startSubject, startSession=startSession, block_index=block_index)
```

func. for caching model

In [ ]:
```
def compile_model(filename, model_name=None, **kwargs):
    # Stan models for parameter defenition uploaded on drive
    with open(filename) as f:
        model_code = f.read()
        code_hash = md5(model_code.encode('ascii')).hexdigest()

        if model_name is None:
            cache_fn = 'cached-model-{}.pkl'.format(code_hash)
        else:
            cache_fn = 'cached-{}-{}.pkl'.format(model_name, code_hash)
        try:
            sm = pickle.load(open(cache_fn, 'rb'))
        except:
            sm = pystan.StanModel(model_code=model_code)
            with open(cache_fn, 'wb') as f:
                pickle.dump(sm, f)
        else:
            print("Using cached StanModel")
        return sm
```

compile: i use stan_utility for model definiton

i save cached model and reuse it if there is no change

In [ ]:
```
def fitModel(modelName, datasetName, dd=None, samplingInfo=None):

    stanFile = '/content/drive/My Drive/model_code_stan/' + modelName + '.stan'
    model = compile_model(stanFile)

    # fit model
    fit = model.sampling(data=dd, iter=samplingInfo['samples'], warmup=samplingInfo['warmup'], n_jobs=samplingInfo['n_jobs'], chains=samplingInfo['chains'], seed=0, init='rando
m')

    # save  fit to csv
    allSamples = fit.to_dataframe(permuted=False, inc_warmup=True)
    allSamples.to_csv('/content/drive/My Drive/model_fits/'+datasetName+'_'+modelName+'_allSamples.csv')

    return fit
```

In [ ]:
```
datasetName = 'data'
modelName = 'sixState_full'  # alternatively: 'fourState_full'

# import data
data = pd.read_csv('/content/drive/My Drive/' + datasetName + '.csv')
dd = data2dict(data)
```

In [ ]:
```
# fit model and save
fit = fitModel(modelName, datasetName, dd, samplingInfo)
```

```
INFO:pystan:COMPILING THE C++ CODE FOR MODEL anon_model_270956cc540b0fdc34127b71223c72da NOW.
```

Plot learning curve to see if changes i made are realistic

In [ ]:
```
def getFirstLastNTrials(N, sessionData, trialType, rewardType=None):
    first = sessionData.head(N).reset_index(drop=True).copy()
    last = sessionData.tail(N).reset_index(drop=True).copy()
    if rewardType is None:
        first.loc[(((first['odor']=='left')|(first['odor']=='right')) if trialType=='free' else first['odor']=='free'), 'correct'] = np.nan
        last.loc[((last['odor']=='left')|(last['odor']=='right') if trialType=='free' else last['odor']=='free'), 'correct'] = np.nan
    else:
        first.loc[((first['odor']=='left')|(first['odor']=='right') if trialType=='free' else first['odor']=='free') & (first['rewardType']==1 if rewardType == 'highR' else first
['rewardType']==2), 'correct'] = np.nan
        last.loc[((last['odor']=='left')|(last['odor']=='right') if trialType=='free' else last['odor']=='free') & (last['rewardType']==1 if rewardType == 'highR' else last['rewa
rdType']==2), 'correct'] = np.nan
    return (filltoNtrials(N, first['correct'].values, -1), filltoNtrials(N, last['correct'].values, 0))
```

In [ ]:
```
def filltoNtrials(N, tmp, loc):
    if loc == -1:
        if tmp.size<N:
            for i in range(N-tmp.size):
                tmp = np.append(tmp, np.nan)
    elif loc == 0:
        if tmp.size<N:
            for i in range(N-tmp.size):
                tmp = np.insert(tmp, 0, np.nan)
                np.append(tmp,[np.nan])
    return tmp
```

corect choice for free trial is based on block type (and thatss based on detected block change point. so detected point can be later than real change point)

In [ ]:
```
def plotLearningCurve(data, N=10, ifReturnCurveData=False, ifLegend=False):

    if ifReturnCurveData:
        curveData=dict()
        for trialType in ['forced','free']:
          for dataName in ['x','y','err']:
            curveData[(trialType, dataName)]=None
    else:
        # plot setting
        from IPython.display import set_matplotlib_formats
        set_matplotlib_formats('png', 'pdf')
        plt.rcParams.update({'font.family': 'arial'})
        lineWidth = 2
        fig, ax = plt.subplots(figsize=(10,3.5))

    # create x variable (trial index)
    trialIndices = []
    for i_block in range(n_blocks*2):
        if i_block == 0:
            start = 1
        else:
            start = trialIndices[-2] + (2 if i_block%2 else 1)
        trialIndices = np.concatenate((trialIndices, np.arange(start, start+N), [np.nan]))

    data['correctChoice'] = 1*(data['odor']=='left') + 2*(data['odor']=='right') + (data['odor']=='free')*(
            1*((data['blockType']=='short_long')|(data['blockType']=='big_small')) +
            2*((data['blockType']=='long_short')|(data['blockType']=='small_big')) )
    data['correct'] = (data['correctChoice'] == data['choice'])

    for trialType in ['forced','free']:
        learningCurves = []
        for iRat, rat in enumerate(data['rat'].unique()):
            learningCurve = []
            for i_block in np.arange(n_blocks)+1:
                sessions = data.loc[data['rat']==rat,'session'].unique()
                NSessions = sessions.shape[0]
                firstN = np.zeros((NSessions, N))
                lastN = np.zeros((NSessions, N))
                for iter_session in range(NSessions):
                    sessionData = data[(data['rat']==rat) & (data['block']==i_block) & (data['session']==sessions[iter_session]) & (data['trialType']=='valid')]
                    thisFirst, thisLast = getFirstLastNTrials(N, sessionData, trialType)
                    firstN[iter_session, :] = thisFirst
                    lastN[iter_session, :] = thisLast
                if NSessions > 1:
                    learningCurve.append(np.nanmean(firstN, axis=0))
                    learningCurve.append(np.nanmean(lastN, axis=0))
                else:
                    learningCurve.append(firstN[0, :])
                    learningCurve.append(lastN[0, :])
            learningCurves.append(np.concatenate([np.concatenate((curve,[np.nan])) for curve in learningCurve]))

        NValidRat = np.sum(~np.isnan(np.stack(learningCurves)), axis=0)
        y = np.nanmean(learningCurves, axis=0)
        err = np.nanstd(learningCurves, axis=0)/np.sqrt(NValidRat)
        if ifReturnCurveData:
            curveData[trialType, 'x'] = trialIndices
            curveData[trialType, 'y'] = y
            curveData[trialType, 'err'] = err
        else:
            ax.plot(trialIndices, y, 'r' if trialType=='forced' else 'b', label='Forced' if trialType=='forced' else 'Free', linewidth=lineWidth)
            ax.fill_between(trialIndices, y-err, y+err, color='r' if trialType=='forced' else 'b', alpha=0.3)

    if ifReturnCurveData:
        return curveData    #change return to print and remove else condition
    else:
        # plot  block switch points and general figure settings
        for blockChange in np.array([N*2+1, N*4+2, N*6+3])+0.5:
            ax.axvline(x=blockChange, linestyle='--', color='gray', linewidth=lineWidth)
        ax.set_ylim([0, 1])
        ax.set_xlim([0, N*8+4])
        ax.set_xlabel('Trial')
        ax.set_ylabel('Accuracy')
        ax.spines['top'].set_visible(False)
        ax.spines['right'].set_visible(False)
        ax.set_xticklabels('')
        ax.tick_params(axis='x', length=0)
        ax.set_xlabel('')
        ax.tick_params(axis='y', width=1.5, pad=5, direction='out')
        ax.set_yticks([0, 0.2, 0.4, 0.6, 0.8, 1])
        ax.set_yticklabels([0, 0.2, 0.4, 0.6, 0.8, 1], fontsize=20)
        ax.set_ylabel('Accuracy', fontsize=25)
        ax.yaxis.labelpad = 10
        ax.spines['left'].set_linewidth(1.5)
        ax.spines['bottom'].set_linewidth(1.5)
        if ifLegend:
            ax.legend(loc='lower right', frameon=False)
```

In [ ]:
```python
plotLearningCurve(data=data, N=10,ifLegend=False)
plotLearningCurve(data=data, N=30, ifLegend=False)
```

```
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:47: RuntimeWarning: Mean of empty slice
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:46: RuntimeWarning: Mean of empty slice
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:54: RuntimeWarning: Mean of empty slice
/usr/local/lib/python3.7/dist-packages/numpy/lib/nanfunctions.py:1671: RuntimeWarning: Degrees of freedom <= 0 for slice.
  keepdims=keepdims)
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:46: RuntimeWarning: Mean of empty slice
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:47: RuntimeWarning: Mean of empty slice
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:54: RuntimeWarning: Mean of empty slice
/usr/local/lib/python3.7/dist-packages/numpy/lib/nanfunctions.py:1671: RuntimeWarning: Degrees of freedom <= 0 for slice.
  keepdims=keepdims)
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:47: RuntimeWarning: Mean of empty slice
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/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:54: RuntimeWarning: Mean of empty slice
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  keepdims=keepdims)
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:46: RuntimeWarning: Mean of empty slice
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:47: RuntimeWarning: Mean of empty slice
/usr/local/lib/python3.7/dist-packages/ipykernel_launcher.py:54: RuntimeWarning: Mean of empty slice
/usr/local/lib/python3.7/dist-packages/numpy/lib/nanfunctions.py:1671: RuntimeWarning: Degrees of freedom <= 0 for slice.
  keepdims=keepdims)
WARNING:matplotlib.font_manager:findfont: Font family ['arial'] not found. Falling back to DejaVu Sans.
WARNING:matplotlib.font_manager:findfont: Font family ['arial'] not found. Falling back to DejaVu Sans.
```
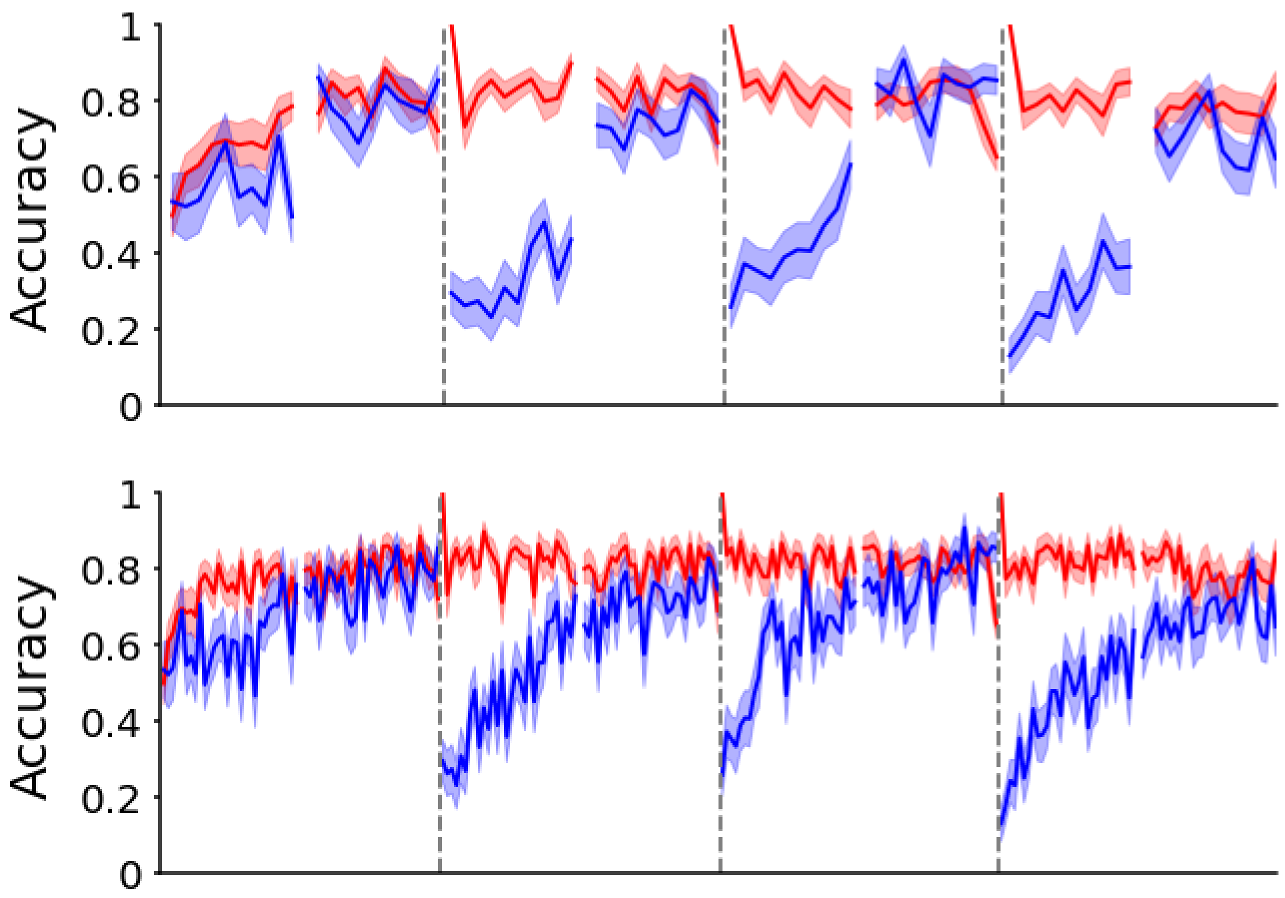



observe

track accuracy in forced-choice (red) and free-choice (blue) trials. I align curves to block-switch points shown as gray dashed lines. include first 10 trial and last 10 trial of each block.

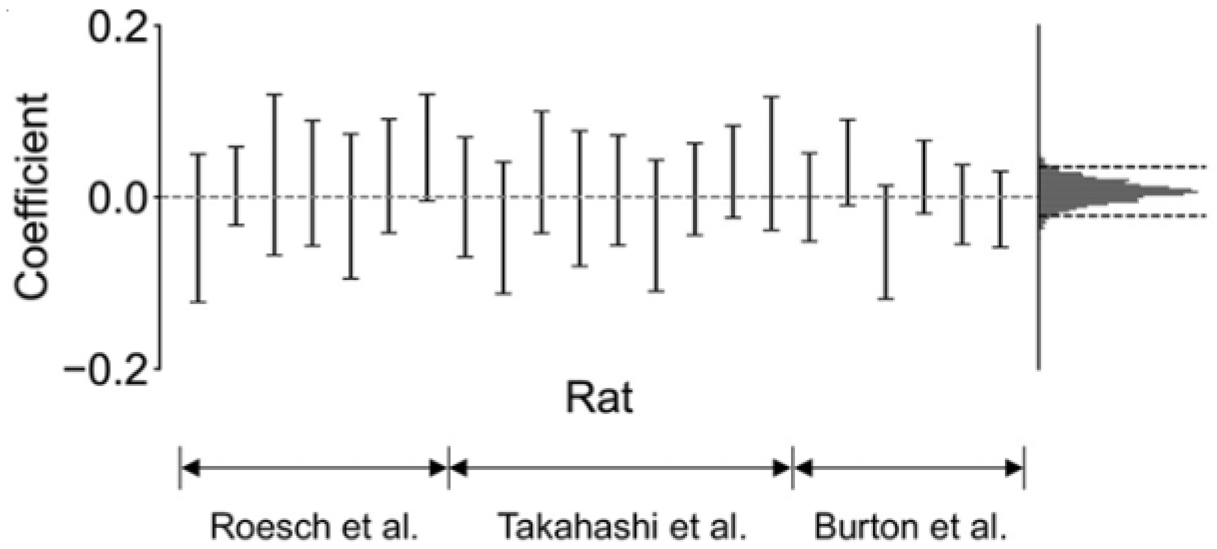
in forced-choice trials, I count how often rewarded well is chosen. In free-choice trials, I count how often better option (shorter delay or larger reward) is chosen.

block-switch points mark changes in trial condn.s. I use these to see how performance adjusts before and after changes.

Shaded regions show variability, standard error of mean (s.e.m.) across animals.

Behavioral Patterns

from above graph, i can say rats learned to choose well with better reward on free choice trials. they kept high accuracy on forced choice trials . to check if rats used knowledge from forced choice trials for free choice trials, use hierarchical logistic regression. i looked if free choice performance improved after correct forced choice trials.



analysis showed no generalization. at both group and individual levels, high posterior density interval (HDI) of coeff.s overlapped with zero. this showed little transfer of learning between trial types. adding a trial index did not change results.

- **accuracy trends:**
  rats did well in forced-choice trials and learned quickly, but they struggled more with free-choice trials
- **trial type segregation:**
  difference in learning speeds between forced-choice and free-choice trials shows that rats didn't generalize between two types of tasks.

simulation

In [ ]:
```python
models = ['sixState_full', 'fourState_full']
dir_simu = '/content/drive/My Drive/model_simulation/'
datasetName = 'data'
```

simulation params.

In [ ]:
```python
NSessions = 100000
NTrials = 57
w4List = [0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1]
```

In [ ]:
```python
def get_params(datasetName, modelName):
    allSamples = pd.read_csv('/content/drive/My Drive/model_fits/' + datasetName + '_' + modelName + '_allSamples.csv')
    mu_pr = np.empty((modelInfo[modelName]['Npars']))
    for iPar, parName in enumerate(modelInfo[modelName]['parNames']):
        mu_pr[iPar] = allSamples.loc[allSamples['warmup']==0, 'mu_pr[' + str(iPar+1) + ']'].values.mean()
    pars = transform_params(modelName, mu_pr)
    return pars
```

In [ ]:
```
def transform_params(modelName, mu_pr):
    pars = phi_approx(mu_pr);
    pars[0] = pars[0] * 10;  # beta
    pars[3] = pars[3] * 4 - 2;
    pars[4] = pars[4] * 4 - 2;
    return pars
```

simulated task

I used simulations to study how different task representations affect behavior. I focused on controls balance btw different representations. when (w_4 = 1), learning was faster, and rats used forced-choice trials to help with free-choice decisions. However, accuracy improvement was small compared to model with (w_4 = 0), where no generalization occurred.

In [ ]:
```
def get_TrialConditionCode(choice, bType):
    if choice == 1:
        if bType == 'big_small':
            return 1
        elif bType == 'small_big':
            return 3
        elif bType == 'short_long':
            return 5
        elif bType == 'long_short':
            return 7
    else:
        if bType == 'big_small':
            return 4
        elif bType == 'small_big':
            return 2
        elif bType == 'short_long':
            return 8
        elif bType == 'long_short':
            return 6
    return -1
```

generate odor sequences

In [ ]:
```
def generate_odorSeq():
    odorSeq = []
    while len(odorSeq) < sim_trials:
        newSeq = [1]*8 + [2]*8 + [3]*7
        np.random.shuffle(newSeq)
        newSeq = list(newSeq)
        if not (([1, 1, 1] in newSeq) or ([2, 2, 2] in newSeq) or ([3, 3, 3] in newSeq)):
            odorSeq = odorSeq + newSeq

    return odorSeq
```

In [ ]:
```
def sixState_full_sim(params, iRat=1):
    beta, eta, gamma, sb, pers, lapse = params[0], params[1], params[2], params[3], params[4], params[5]
    # initialization
    odorchoice2state = np.array([[1,4],[3,2],[1,2]])
    sessionList, sessionTypeList, trialList, blockList, blockTypeList, odorList, choiceList, rewardAmountList, rewardDelayList, trialTypeList, trialCondCodeList, trialCondList
[[] for _ in range(12)]

    for iSession in range(sim_sessions):
        # session info
        sessionType = np.random.choice(['leftBetterFirst', 'rightBetterFirst'])
        if sessionType == 'leftBetterFirst':
            blockTypeSeq = ['short_long', 'long_short', 'big_small', 'small_big']
        else:
            blockTypeSeq = ['long_short', 'short_long', 'small_big', 'big_small']

        # at   start of a new session, reset Q values and  erseveration term
        Q = np.zeros((3, 2));
        preChoice = 0;
        perseveration = np.zeros(2);

        for iBlock in range(sim_blocks):
            blockType = blockTypeSeq[iBlock]
            longDelay = 0
            freeChoices = []

            odorSeq = generate_odorSeq()

            iOdor = 0
            for iTrial in range(sim_trials):

                # trial info
                odor = odorSeq[iOdor]

                # decision variable of left and right choices
                if preChoice > 0:  # not  irst choice of a session
                    perseveration[preChoice-1] = pers;
                    perseveration[2-preChoice] = 0;

                DVLeft = Q[odor-1, 0] + perseveration[0]
                DVRight = Q[odor-1, 1] + sb + perseveration[1]

                # simulate choice
                pLeft = (1 - lapse) * 1 / (1 + np.exp(- beta * (DVLeft - DVRight))) + lapse/2
                choice = 2 - (np.random.random() < pLeft)
                if odor == 3:
                    freeChoices.append(choice)

                # simulate reward
                ifReward = (odor == choice) + (odor == 3)
                if ifReward:
                    # reward amount
                    if (blockType in ['short_long', 'long_short']) or (blockType == 'small_big' and choice == 1) or (blockType == 'big_small' and choice == 2):
                        reward = 1
                    else:
                        reward = 2
                    # reward delay
                    if (blockType == 'long_short' and choice == 1) or (blockType == 'short_long' and choice == 2): # if choosing   long reward side
                        longDelay = longDelay + 1
                        if longDelay > 7:
                            longDelay = 7
                        delay = longDelay
                    else:
                        delay = 0.5
                    # trial condition code
                    trialCondCode = get_TrialConditionCode(choice, blockType)

                    # discounted reward
                    rewardPerceived = reward * np.power(gamma, delay)
                else:
                    reward = 0
                    delay = np.nan
                    trialCondCode = np.nan
                    rewardPerceived = 0

                # in timing blocks, reduce longDelay by 1s if chosen less than 8 times in   last 10 free choice trials, to a minimum of 3s
                if (blockType in ['short_long', 'long_short']) and (longDelay > 3):
                    choiceLong = 1 if blockType == 'long_short' else 2
                    if (len(freeChoices) >= 10) and (len(np.where(np.array(freeChoices[-10:]) == choiceLong)[0]) < 8):
                        longDelay = longDelay - 1

                delta = rewardPerceived - Q[odor-1, choice-1]
                Q[odor-1, choice-1] += eta * delta

                # update  revious choice
                preChoice = choice;

                # record data
                sessionList.append(iSession+1)
                sessionTypeList.append(sessionType)
                trialList.append(iTrial+1)
                blockList.append(iBlock+1)
                blockTypeList.append(blockType)
                odorList.append('left' if odor==1 else ('right' if odor==2 else 'free'))
                choiceList.append(choice)
                rewardAmountList.append(reward)
                rewardDelayList.append(delay)
                trialTypeList.append('valid')
                trialCondCodeList.append(trialCondCode)

                # proceed to  ext trial
                if not ((odor < 3) and (choice != odor)): # if correct forced choice or any free choice
                    iOdor += 1

    trialCondMapping = ['big_left','big_right','small_left','small_right','short_left','short_right','long_left','long_right']
    trialCondList = [np.nan if np.isnan(trialCondCode) else trialCondMapping[trialCondCode - 1] for trialCondCode in trialCondCodeList]
    dataset = ['simulation'] * len(sessionList)
    rat = [iRat] * len(sessionList)
    data = pd.DataFrame(list(zip(dataset, rat, sessionList, sessionTypeList, trialList, blockList, blockTypeList, odorList, choiceList, rewardAmountList, rewardDelayList, trialTy
peList, trialCondCodeList, trialCondList)), columns=['dataset', 'rat', 'session', 'sessionType', 'trial', 'block', 'blockType', 'odor', 'choice', 'rewardAmount', 'rewardDelay',
'trialType', 'trialCondCode', 'trialCond'])

    return data
```

In [ ]:

```
def fourState_full_sim(params, iRat=1):
    beta, eta, gamma, sb, pers, lapse = params[0], params[1], params[2], params[3], params[4], params[5]
    # initialization
    odorchoice2state = np.array([[1,4],[3,2],[1,2]])
    sessionList, sessionTypeList, trialList, blockList, blockTypeList, odorList, choiceList, rewardAmountList, rewardDelayList, trialTypeList, trialCondCodeList, trialCondList
[[] for _ in range(12)]

    for iSession in range(sim_sessions):
        # session info
        sessionType = np.random.choice(['leftBetterFirst', 'rightBetterFirst'])
        if sessionType == 'leftBetterFirst':
            blockTypeSeq = ['short_long', 'long_short', 'big_small', 'small_big']
        else:
            blockTypeSeq = ['long_short', 'short_long', 'small_big', 'big_small']

        # at  tart of a new session, reset Q values and th erseveration term
        Q = np.zeros(4);
        preChoice = 0;
        perseveration = np.zeros(2);

        for iBlock in range(sim_blocks):
            blockType = blockTypeSeq[iBlock]
            longDelay = 0
            freeChoices = []

            odorSeq = generate_odorSeq()

            iOdor = 0
            for iTrial in range(sim_trials):

                # trial info
                odor = odorSeq[iOdor]

                # decision variable of left and right choices
                if preChoice > 0:  # not  irst choice of a session
                    perseveration[preChoice-1] = pers;
                    perseveration[2-preChoice] = 0;

                DVLeft = Q[odorchoice2state[odor-1,0]-1] + perseveration[0]
                DVRight = Q[odorchoice2state[odor-1,1]-1] + sb + perseveration[1]

                # simulate choice
                pLeft = (1 - lapse) * 1 / (1 + np.exp(- beta * (DVLeft - DVRight))) + lapse/2
                choice = 2 - (np.random.random() < pLeft)
                if odor == 3:
                    freeChoices.append(choice)

                # simulate reward
                ifReward = (odor == choice) + (odor == 3)
                if ifReward:
                    # reward amount
                    if (blockType in ['short_long', 'long_short']) or (blockType == 'small_big' and choice == 1) or (blockType == 'big_small' and choice == 2):
                        reward = 1
                    else:
                        reward = 2
                    # reward delay
                    if (blockType == 'long_short' and choice == 1) or (blockType == 'short_long' and choice == 2): # if choosing  ong reward side
                        longDelay = longDelay + 1
                        if longDelay > 7:
                            longDelay = 7
                        delay = longDelay
                    else:
                        delay = 0.5
                    # trial condition code
                    trialCondCode = get_TrialConditionCode(choice, blockType)

                    # discounted reward
                    rewardPerceived = reward * np.power(gamma, delay)
                else:
                    reward = 0
                    delay = np.nan
                    trialCondCode = np.nan
                    rewardPerceived = 0

                # in timing blocks, reduce longDelay by 1s if chosen less than 8 times in  ast 10 free choice trials, to a minimum of 3s
                if (blockType in ['short_long', 'long_short']) and (longDelay > 3):
                    choiceLong = 1 if blockType == 'long_short' else 2
                    if (len(freeChoices) >= 10) and (len(np.where(np.array(freeChoices[-10:]) == choiceLong)[0]) < 8):
                        longDelay = longDelay - 1

                delta = rewardPerceived - Q[odorchoice2state[odor-1, choice-1] - 1]
                Q[odorchoice2state[odor-1, choice-1] - 1] += eta * delta

                # update   previous choice
                preChoice = choice;

                # record data
                sessionList.append(iSession+1)
                sessionTypeList.append(sessionType)
                trialList.append(iTrial+1)
                blockList.append(iBlock+1)
                blockTypeList.append(blockType)
                odorList.append('left' if odor==1 else ('right' if odor==2 else 'free'))
                choiceList.append(choice)
                rewardAmountList.append(reward)
                rewardDelayList.append(delay)
                trialTypeList.append('valid')
                trialCondCodeList.append(trialCondCode)

                # proceed to   next trial
                if not ((odor < 3) and (choice != odor)): # if correct forced choice or any free choice
                    iOdor += 1

    trialCondMapping = ['big_left','big_right','small_left','small_right','short_left','short_right','long_left','long_right']
    trialCondList = [np.nan if np.isnan(trialCondCode) else trialCondMapping[trialCondCode - 1] for trialCondCode in trialCondCodeList]
    dataset = ['simulation'] * len(sessionList)
    rat = [iRat] * len(sessionList)
    data = pd.DataFrame(list(zip(dataset, rat, sessionList, sessionTypeList, trialList, blockList, blockTypeList, odorList, choiceList, rewardAmountList, rewardDelayList, trialTy
peList, trialCondCodeList, trialCondList)), columns=['dataset', 'rat', 'session', 'sessionType', 'trial', 'block', 'blockType', 'odor', 'choice', 'rewardAmount', 'rewardDelay',
'trialType', 'trialCondCode', 'trialCond'])

    return data
```

Model Fitting

I used Bayesian analysis in PyStan, running 4 MCMC chains with 2000 iterations.

simulation was using params set to posterior means. simulation included block transition & reward adjustments.

```
In [ ]: def get_simulated_data(varName, modelName, w4=None, NSessions=10000, run_simulation=False):

    fileName = dir_simu + modelName + '_' + datasetName + '_groupMean' + (('_w4' + str(w4)) if w4 is not None else '') + '_NSessions' + str(NSessions) + '_NTrials' + str(NTrials)
+ '_' + varName + '.pickle'

    if varName == 'curveData':
        curveData = None

    if run_simulation:
        # set parameter values
        params = get_params(datasetName, modelName)
        if w4 is not None:
            params[1] = w4
        # run simulation
        if modelName=='sixState_full':
          dataSimu = sixState_full_sim(params)
        elif modelName=='fourState_full':
          dataSimu = fourState_full_sim(params)
        if varName == 'avgR':
            # calculate average reward
            value = dataSimu['rewardAmount'].mean()
        elif varName == 'curveData':
            # prepare data for plotting learning curve
            value = plotLearningCurve(dataSimu, N=10, ifReturnCurveData=True)
        # save results
        pickle.dump(value, open(fileName, 'wb'))
    else:
        # load results
        value = pickle.load(open(fileName, 'rb'))

    return value
```

split-half analysis by comparing task representation from first and second halves of training, I noticed ,some rat showed increase in generalization with experience. In later sessions, some rat rely more on 4 state model. so, generalization takes time to develop. even it didn't improve their performance.

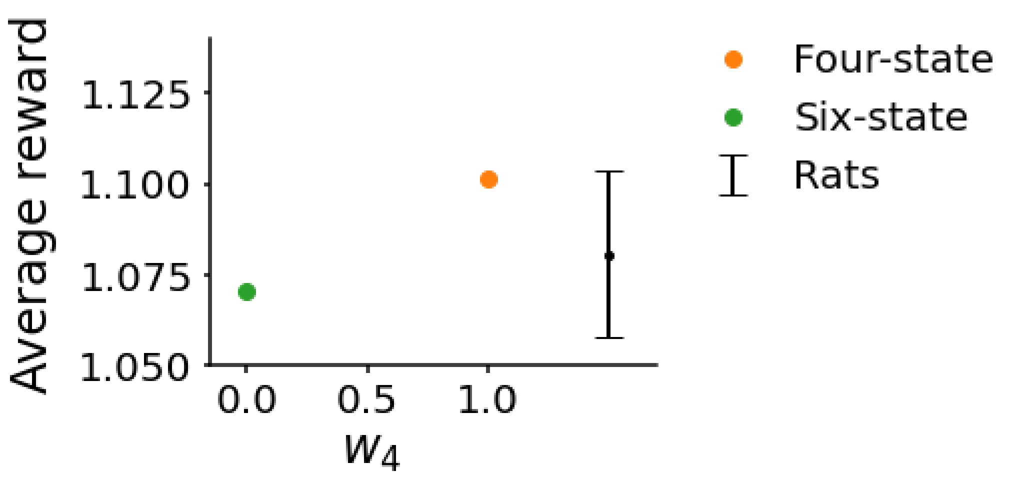
more complex representation didn't offer much benefit in task.

correlations between parameters I found that rats who used partial generalization strategies applied them consistently across sessions, shown by correlations between their generalization rates and weights for four-state representation.

```
In [ ]: run_simulation = True

avgR = dict.fromkeys(['rat'+str(rat) for rat in ratList] + models + ['w4'+str(w4) for w4 in w4List])

# all models
for modelName in models:
    avgR[modelName] = get_simulated_data('avgR', modelName, None, NSessions, run_simulation)

# animals
for rat in ratList:
    avgR['rat'+str(rat)] = dataValid.loc[dataValid['rat'] == rat, 'rewardAmount'].mean()
```

```
In [ ]: from IPython.display import set_matplotlib_formats
set_matplotlib_formats('png', 'pdf')

lineWidth = 2
fontsize = 24
labelsize = 20
ylim=[1.05, 1.14]

fig, ax = plt.subplots(figsize=(4,3))

# simulation
ax.plot(1, avgR['fourState_full'], 'o', color='C1', linewidth=lineWidth, markersize=8, label='Four-state')
ax.plot(0, avgR['sixState_full'], 'o', color='C2', linewidth=lineWidth, markersize=8, label='Six-state')

from matplotlib.colors import ListedColormap, BoundaryNorm
from matplotlib.collections import LineCollection

N = 256
vals = np.ones((N, 2))
vals[:, 0] = np.linspace(44/256, 255/256, N)
vals[:, 1] = np.linspace(160/256, 127/256, N)

cmap = ListedColormap(vals)

# animals
avgR_rat = np.array([avgR['rat'+str(rat)] for rat in ratList])
ax.errorbar(x=1.5, y=np.mean(avgR_rat), yerr=np.std(avgR_rat)/np.sqrt(len(ratList)), linestyle='', color='k', capsize=7, linewidth=lineWidth, label='Rats')
ax.plot(1.5, np.mean(avgR_rat), '.', color='k', markersize=8)

ax.set_xlabel('$w_4$          ', fontsize=fontsize)
ax.set_ylabel('Average reward', fontsize=fontsize, labelpad=10)
ax.tick_params(axis='both', width=1.5, pad=5, direction='out', labelsize=labelsize)
ax.spines['top'].set_visible(False)
ax.spines['right'].set_visible(False)
ax.spines['left'].set_linewidth(1.5)
ax.spines['bottom'].set_linewidth(1.5)
ax.set(xlim=[-0.15,1.7], ylim=ylim)
ax.set(xticks=[0,0.5,1])

ax.legend(frameon=False, fontsize=labelsize, handletextpad=0.5, bbox_to_anchor=(1, 1.1))

plt.show()
```

```
WARNING:matplotlib.font_manager:findfont: Font family ['arial'] not found. Falling back to DejaVu Sans.
```



observe

4state model (w_4 = 1) learns faster in each block, reaches higher asymptotic accuracy than 6 state model (w_4 = 0).

Compare model

RL model Comparisons

to see how much rats generalize, i built RL models with different state representations. i checked how well these models predicted rats' choices trial by trial. model assume rats learned left and right actions for each odor through trial and error, with some noise in their decisions. models differed in how they represented task:

four-state model: assume full generalization btw forced choice trial and free choice response, sharing state across trial types. this structure showed underlying task design.

six-state model: assumed no generalization, with separate states for each odor and action combination.

i fitted these model to rats choice using hierarchical bayesian inference with mcmc sampling.

samples is datafram with sample of params & dd is data dictionary

i extract parameter (beta, eta, gamma) by doing : #samples * #subjects and then get likelihood of all data

For 6 state

In [ ]:
```
def sixState_full_predict(samples, dd):

    beta = np.array(samples.loc[:, ['beta['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])
    eta = np.array(samples.loc[:, ['eta['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])
    gamma =  np.array(samples.loc[:, ['gamma['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])
    sb =  np.array(samples.loc[:, ['sb['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])
    pers =  np.array(samples.loc[:, ['pers['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])
    lapse =  np.array(samples.loc[:, ['lapse['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])

    NSamples = samples.shape[0]

    likelihood = np.empty((NSamples, dd['Nt'])) * np.nan
    currentSubject = -1;
    currentSession = -1;

    for tr in np.arange(dd['Nt']):
        if dd['startSubject'][tr]>0: # if this is  start of a new subject
            currentSubject += 1;
        if dd['startSession'][tr]>0: # if this is  start of a new session
            currentSession += 1;
            # reset Q values and  perseveration term
            Q = np.zeros((NSamples, 3, 2));
            preChoice = 0;
            perseveration = np.zeros((NSamples, 2));
        if dd['trialType'][tr] != 0: # valid trials or early exit trials (trials with choices)
            if preChoice > 0:  # not  first choice of a session
                perseveration[:, preChoice-1] = pers[:, currentSubject];
                perseveration[:, 2-preChoice] = 0;
            # likelihood of observed choice
            DVLeft = Q[:, dd['odor'][tr]-1, 0] + perseveration[:, 0]
            DVRight = Q[:, dd['odor'][tr]-1, 1] + sb[:, currentSubject] + perseveration[:, 1]
            pLeft = (1 - lapse[:, currentSubject]) * 1 / (1 + np.exp(- beta[:, currentSubject] * (DVLeft - DVRight))) + lapse[:, currentSubject]/2
            likelihood[:, tr] = pLeft if dd['choice'][tr] == 1 else (1-pLeft)
            # calculate reward prediction error
            delta = dd['reward'][tr] * np.power(gamma[:, currentSubject], dd['delay'][tr]) - Q[:, dd['odor'][tr]-1, dd['choice'][tr]-1];
            # update Q values
            Q[:, dd['odor'][tr]-1, dd['choice'][tr]-1] += eta[:, currentSubject] * delta;
            # update  previous choice
            preChoice = dd['choice'][tr];

    return likelihood
```

for 4 state

In [ ]:
```
def fourState_full_predict(samples, dd):

    beta = np.array(samples.loc[:, ['beta['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])
    eta = np.array(samples.loc[:, ['eta['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])
    gamma =  np.array(samples.loc[:, ['gamma['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])
    sb =  np.array(samples.loc[:, ['sb['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])
    pers =  np.array(samples.loc[:, ['pers['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])
    lapse =  np.array(samples.loc[:, ['lapse['+str(iSub+1)+']' for iSub in np.arange(dd['Ns'])]])

    NSamples = samples.shape[0]

    odorchoice2state = np.array([[1,4],[3,2],[1,2]])

    likelihood = np.empty((NSamples, dd['Nt'])) * np.nan
    currentSubject = -1;
    currentSession = -1;

    # likelihood of all  data
    for tr in np.arange(dd['Nt']):
        if dd['startSubject'][tr]>0: # if this is  start of a new subject
            currentSubject += 1;
        if dd['startSession'][tr]>0: # if this is  start of a new session
            currentSession += 1;
            # reset Q values and  perseveration term
            Q = np.zeros((NSamples, 4));
            preChoice = 0;
            perseveration = np.zeros((NSamples, 2));
        if dd['trialType'][tr] != 0: # valid trials or early exit trials (trials with choices)
            if preChoice > 0:  # not  first choice of a session
                perseveration[:, preChoice-1] = pers[:, currentSubject];
                perseveration[:, 2-preChoice] = 0;
            # likelihood of observed choice
            DVLeft = Q[:, odorchoice2state[dd['odor'][tr]-1,0] -1] + perseveration[:, 0]
            DVRight = Q[:, odorchoice2state[dd['odor'][tr]-1,1] -1] + sb[:, currentSubject] + perseveration[:, 1]
            pLeft = (1 - lapse[:, currentSubject]) * 1 / (1 + np.exp(- beta[:, currentSubject] * (DVLeft - DVRight))) + lapse[:, currentSubject]/2
            likelihood[:, tr] = pLeft if dd['choice'][tr] == 1 else (1-pLeft)
            # calculate reward prediction error
            delta = dd['reward'][tr] * np.power(gamma[:, currentSubject], dd['delay'][tr]) - Q[:, odorchoice2state[dd['odor'][tr]-1, dd['choice'][tr]-1] - 1 ];
            # update Q values
            Q[:, odorchoice2state[dd['odor'][tr]-1, dd['choice'][tr]-1] - 1 ] += eta[:, currentSubject] * delta;
            # update  previous choice
            preChoice = dd['choice'][tr];

    return likelihood
```

predictions

In [ ]:
```
modelPredictions = {
    'sixState_full': sixState_full_predict,
    'fourState_full': fourState_full_predict,
}
```

In [ ]:
```
def func_WAIC(likelihood, typeCorrection=2):

    # likelihood: #samples * #trials
    lppd = np.sum(np.log(np.mean(likelihood, axis=0)))
    if typeCorrection == 1:
        pWAIC = 2 * np.sum( np.log(np.mean(likelihood, axis=0)) - np.mean(np.log(likelihood), axis=0) )
    else:
        pWAIC = np.sum(np.var(np.log(likelihood), axis=0, ddof=1))
    return - 2 * lppd + 2 * pWAIC
```

In [ ]:
```
def func_WAIC_comparison(likelihood1, likelihood2, typeCorrection=2):

    # likelihood1/2: #samples * #trials
    # take model 1 as baseline
    Ntrials = likelihood1.shape[1]

    lppd1_trial = np.log(np.mean(likelihood1, axis=0))
    lppd2_trial = np.log(np.mean(likelihood2, axis=0))
    if typeCorrection == 1:
        pWAIC1_trial = 2 * ( np.log(np.mean(likelihood1, axis=0)) - np.mean(np.log(likelihood1), axis=0) )
        pWAIC2_trial = 2 * ( np.log(np.mean(likelihood2, axis=0)) - np.mean(np.log(likelihood2), axis=0) )
    else:
        pWAIC1_trial = np.var(np.log(likelihood1), axis=0, ddof=1)
        pWAIC2_trial = np.var(np.log(likelihood2), axis=0, ddof=1)

    waic1_trial = - 2 * lppd1_trial + 2 * pWAIC1_trial
    waic2_trial = - 2 * lppd2_trial + 2 * pWAIC2_trial

    waic_diff = np.sum(waic2_trial - waic1_trial)
    waic_diff_se = np.sqrt(Ntrials * np.var(waic2_trial - waic1_trial))

    return waic_diff, waic_diff_se, waic_diff/Ntrials, waic_diff_se/Ntrials,
```

In [ ]:
```
def calculate_likelihood(datasetName, data, baselineModel, modelList):

    # import data
    dd = data2dict(data)

    # get  likelihood for  baseline model
    allSamples_baseline = pd.read_csv('/content/drive/My Drive/model_fits/'+datasetName+'_'+baselineModel+'_allSamples.csv')
    parSamples_baseline = allSamples_baseline.loc[allSamples_baseline['warmup']==0, [col for col in allSamples_baseline if np.sum([col.startswith(parName+'[') for parName in mode
lInfo[baselineModel]['parNames']])>0]]
    likelihood_baseline = modelPredictions[baselineModel](parSamples_baseline, dd)

    # calculate waic difference
    waicDiff, waicDiff_se = [dict.fromkeys(modelList) for i in range(2)]
    waicDiff_rat_perTrial, waicDiff_rat_perTrial_se = [pd.DataFrame() for i in range(2)]

    for model in modelList:
        allSamples = pd.read_csv('/content/drive/My Drive/model_fits/'+datasetName+'_'+model+'_allSamples.csv')
        parSamples = allSamples.loc[allSamples['warmup']==0, [col for col in allSamples if np.sum([col.startswith(parName+'[') for parName in modelInfo[model]['parNames']])>0]]
        likelihood = modelPredictions[model](parSamples, dd)

        # for  entire group
        waicDiff[model], waicDiff_se[model], _, _ = func_WAIC_comparison(likelihood_baseline, likelihood, typeCorrection=2)

        # for each individual animal
        for rat in data['rat'].unique():
            _, _, diff_perTrial, se_perTrial = func_WAIC_comparison(likelihood_baseline[:, data['rat'] == rat], likelihood[:, data['rat'] == rat])
            waicDiff_rat_perTrial.loc[rat, model] = diff_perTrial
            waicDiff_rat_perTrial_se.loc[rat, model] = se_perTrial

    metrics_group = pd.DataFrame(data=[waicDiff, waicDiff_se], index=['waicDiff','waicDiff_se'])
    waicDiff_rat_perTrial = waicDiff_rat_perTrial.reset_index().rename(columns={'index':'rat'})
    waicDiff_rat_perTrial_se = waicDiff_rat_perTrial_se.reset_index().rename(columns={'index':'rat'})

    return metrics_group, waicDiff_rat_perTrial, waicDiff_rat_perTrial_se
```

WAIC Comparison

WAIC measures model fit. Lower WAIC is better. It includes a penalty for complexity.

$$\text{WAIC} = -2\left(\sum_{i=1}^{N}\log p(y_i|\theta^*) - \text{penalty term}\right)$$

$$\text{penalty term} = \sum_{i=1}^{N}\left(\text{variance of}\log p(y_i|\theta^*)\right)$$

- **N** is no. of observations in data.
- $$p(y_i|\theta^*)$$
  is the likelihood estimate for the (i)-th observation based on model parameters (\theta^).
- first part calculates log-likelihood for each data point.
- **penalty term** is added to adjust for model complexity, to prevent overfitting.

$$\hat{p}(\text{data})$$

is likelihood of data

$$\hat{p}(\text{model})$$

is number of model parameters.

WAIC Difference

difference between models is:

$$\Delta\text{WAIC} = -2\left(\sum_{i=1}^{n}\left[\log\left(\hat{p}_1(y_i \mid \theta_i)\right) - \log\left(\hat{p}_2(y_i \mid \theta_i)\right)\right]\right)$$

$$+2\left(\text{tr}\left(\text{Cov}\left(\hat{\theta}_i^1\right)\right) - \text{tr}\left(\text{Cov}\left(\hat{\theta}_i^2\right)\right)\right)$$

If

$$\Delta\text{WAIC} > 0,$$

then model 2 is better. else model 1 is better.

Summed Across Trials

WAIC is summed across all trials and animals to provide overall model fit.

Error Bars

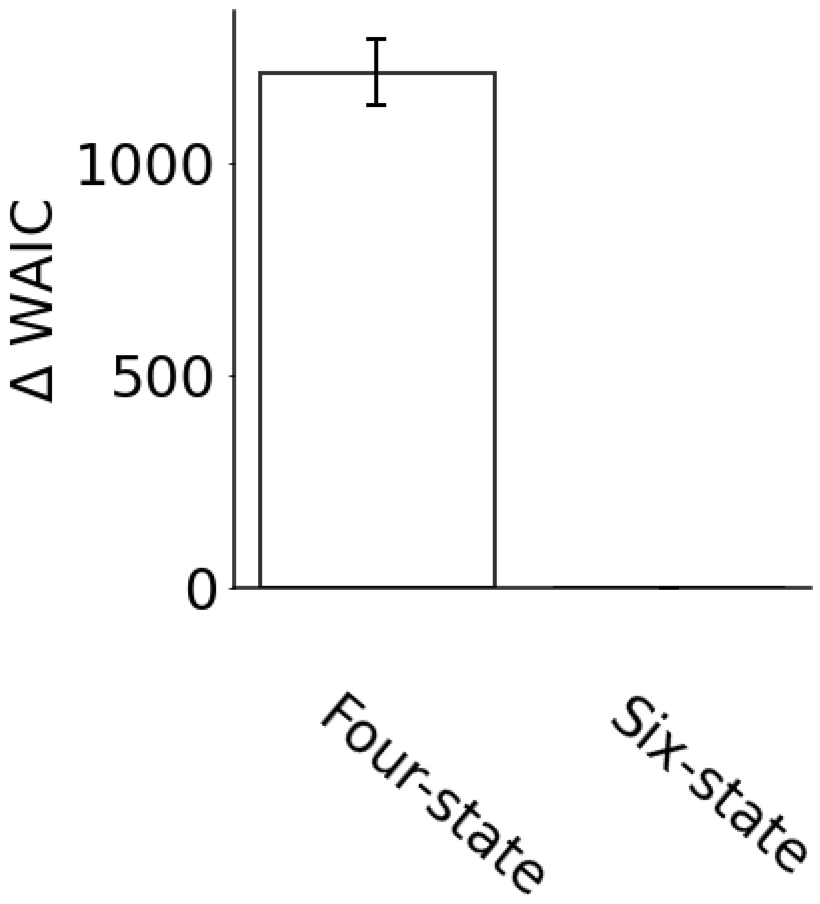
Error bars show variability in WAIC difference. Smaller error bars = more consistency. Larger error bars = more uncertainty.

In [ ]:

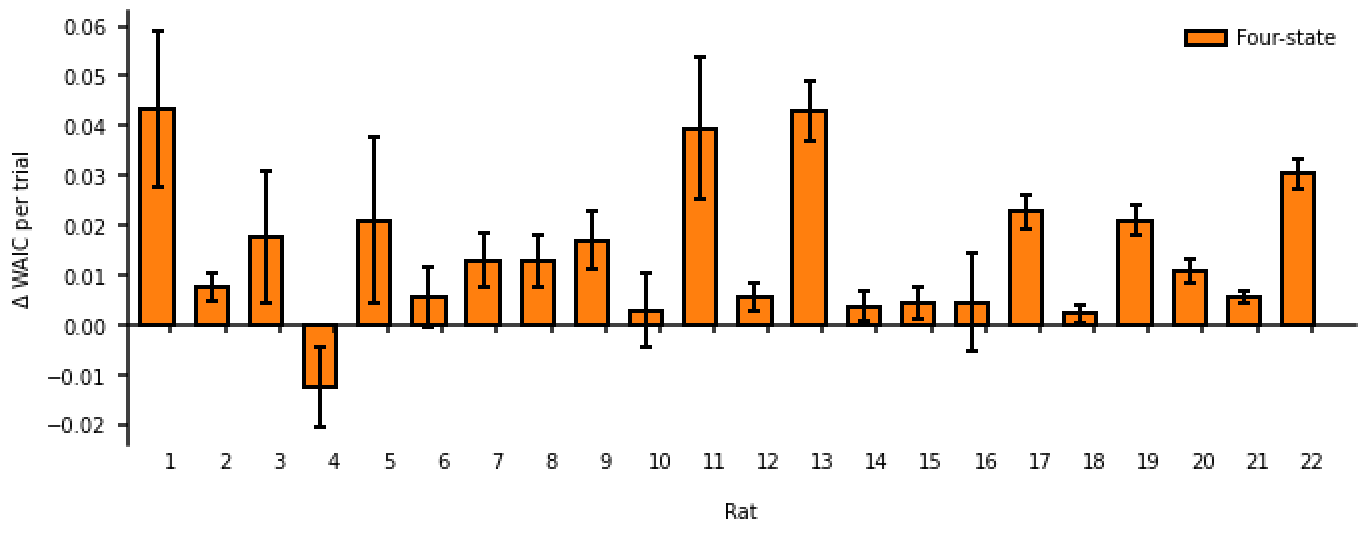
```
modelList = ['fourState_full', 'sixState_full']
baselineModel = 'sixState_full'
modelNames = {
    'sixState_full': 'Six-state',
    'fourState_full': 'Four-state',
    }

# Calculate WAIC difference from model fits ( following cell may take a few minutes to run)

metrics_group, waicDiff_rat_perTrial, waicDiff_rat_perTrial_se = calculate_likelihood(datasetName, data, baselineModel, modelList)

# Model comparison (WAIC) figure

colors_group = {
    'sixState_full':'w',
    'fourState_full':'w'
}

colors_individual = {
    'sixState_full': 'C2',
    'fourState_full': 'C1'
}

# for  entire group
fig, ax = plt.subplots(figsize=(4,4))
display(metrics_group[modelList])

iM = 0
for model in modelList:
    ax.bar(x=iM, height=metrics_group.loc['waicDiff', model], alpha=0.8, edgecolor='k', lineWidth=2, color=colors_group[model])
    ax.errorbar(x=iM, y=metrics_group.loc['waicDiff', model], yerr=metrics_group.loc['waicDiff_se', model], ecolor='k', fmt='None', capsize=5, label=None, elinewidth=2, markeredg
ewidth=2)
    iM += 1
ax.set_xticks(np.arange(len(modelList))-0.25)
ax.set_xlabel('', fontsize=28)
ax.set_ylabel(r'$\Delta$ WAIC', fontsize=28)
ax.tick_params(axis='both', pad=5, labelsize=28)
ax.tick_params(axis='x', length=0)
sns.despine()
ax.spines['bottom'].set_position('zero')
ax.spines['bottom'].set_linewidth(1.5)
ax.spines['left'].set_linewidth(1.5)
ax.tick_params(axis='x', pad=50)
ax.set_xticklabels([modelNames[model] for model in modelList], rotation=-40, horizontalalignment='left')
fig.subplots_adjust(left=0, bottom=0, right=1, top=1)
plt.show()


# per animal
fig, ax = plt.subplots(figsize=(5.5*(len(modelList)),4))
NRats = data['rat'].unique().size
x = np.arange(NRats)+1
deltax = np.linspace(0,1,len(modelList)-1)*0.5-0.25 #[-0.3, 0, 0.3]
barwidth = 0.2*3/(len(modelList)-1)
iM = 0
for model in modelList:
    waicDiff = waicDiff_rat_perTrial[model].values
    waicDiff_se = waicDiff_rat_perTrial_se[model].values
    if 'sixState' not in model:
        ax.bar(x+deltax[iM], height=[waicDiff[r] for r in ratOrder], width=barwidth, edgecolor='k', align='center', lineWidth=2, color=colors_individual[model], label=modelNames
[model])
        ax.errorbar(x=x+deltax[iM], y=[waicDiff[r] for r in ratOrder], yerr=[waicDiff_se[r] for r in ratOrder], ecolor='k', fmt='None', capsize=3, label='', elinewidth=2, markere
dgewidth=2)
        iM += 1
ax.set_xticks(x)
ax.set_xlabel('Rat')
ax.set_ylabel(r'$\Delta$ WAIC per trial')
ax.spines['bottom'].set_position('zero')
sns.despine()
ax.xaxis.labelpad = 15
ax.tick_params(axis='x', width=1.5, pad=15)
ax.tick_params(axis='x', pad=60)
ax.tick_params(axis='y', width=1.5, length=5, pad=5)
ax.spines['bottom'].set_linewidth(1.5)
ax.spines['left'].set_linewidth(1.5)
ax.set(xlim=[0.2, NRats+0.8])
ax.legend(frameon=False, handletextpad=0.5, bbox_to_anchor=(1, 1))
plt.show()
```

	fourState_full	sixState_full
waicDiff	1211.398557	0.0
waicDiff_se	78.425047	0.0

```
WARNING:matplotlib.font_manager:findfont: Font family ['arial'] not found. Falling back to DejaVu Sans.
```




```
WARNING:matplotlib.font_manager:findfont: Font family ['arial'] not found. Falling back to DejaVu Sans.
```



comparison result

above plot is of WAIC difference btw 4 & 6state model for dataset (summed across all trials from all animals).

in above graph lower values indicate better model fits. error bars represent standard errors across samples.

individual difference in generalization

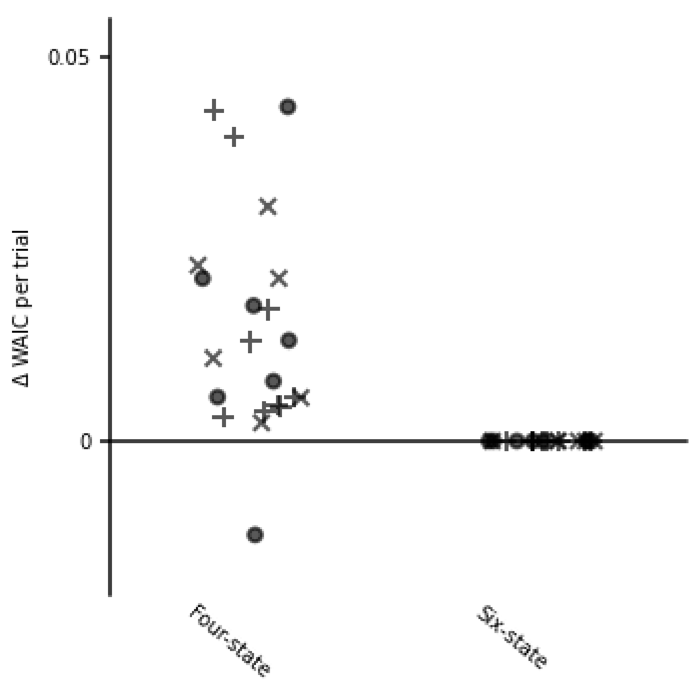
not all rats acted same way.most rats were better explained by six-state model, some showed generalization. we can see that by negative WAIC difference, indicating some generalization occurred. there was variability in how rats used models. experience or genetics, maybe the reason for generalized but i am not sure. some rats had high weight (w_4) for 4state model, showing high generalization. but had bad rewards, so generalization had limited practical benefit.

most rats didn't adopt more efficient task representation. they learned forced choice and free choice trials separately, with minimal generalization.

cognitive resource allocation: 6 state model required less mental effort because it kept odor cues and responses separate. 4state model was more complex, so rats might have avoided it to save energy. (it might be a reason but still not sure)

Scatter plot for individual delta WAIC per trial

In [ ]:
```python
waicdiff = pd.melt(waicDiff_rat_perTrial, id_vars=['rat'], value_vars=modelList, var_name='model', value_name='waicDiff_rat_perTrial')
fig, ax = plt.subplots(figsize=(4,4))
for dataset in datasets:
    sns.stripplot(x='model', y='waicDiff_rat_perTrial', data=waicdiff[waicdiff['rat'].isin(dataset2rat[dataset])], linewidth=2,
                  ax=ax, jitter=0.2, color='black', alpha=.65, size=8*ratio_s[dataset], marker=dataset2marker[dataset], label=dataset_labels[dataset])
sns.despine()
ax.spines['bottom'].set_linewidth(1.5)
ax.spines['left'].set_linewidth(1.5)
ax.spines['bottom'].set_position('zero')
ax.tick_params(axis='x', length=0, width=1.5, pad=80)
ax.tick_params(axis='y', width=1.5, length=5, pad=5)
ax.set_xticks(np.arange(len(modelList))-0.25)
ax.set(yticks=[0, 0.05],yticklabels=[0,0.05])
ax.set_ylim([-0.02,0.055])
ax.set_xticklabels([modelNames[model] for model in modelList], rotation=-40, horizontalalignment='left')
ax.set_xlabel('')
ax.set_ylabel(r'$\Delta$ WAIC per trial')
fig.subplots_adjust(left=0, bottom=0, right=1, top=1)
plt.show()
```



I show individual differences in average WAIC per trial. Each marker represents one animal. Different markers represent different datasets.

model performance

4-state model assumed learned values for left and right actions are same for both trial types. this makes learning faster by using same reward.

6-state model treats each trial type separately. each odor leads to a different state, causing separate learning for each action. this is less efficient but matches how most rats behaved.

so 4 state is simpler and uses shared learning, while 6state model matches rat's behaviour.

6 state model performed best, with lower WAIC scores (1211 ± 78 units). (WAIC difference: -134 ± 24), so rats didn't use a shared representation for forced choice and free choice trial.