# maths

The purpose here is to derive mathematically the expected performance of a decoder on prestimulus data in a ordered sequence of stimuli such as implemented in Demarchi et al. 2019.

## Under null hypothesis

We assume the null hypothesis is true: there is only sensory but no predictive/anticipatory activity.

Let p be the probability the decoder finds the correct input. We assume  $p_A = p_B = p_C = p_D$ , i.e. the decoder performs equally on all stimuli types. p is the sensitivity of the classifier.

Based on the transition matrix of the ordered sequence in Demarchi et al. 2019, we consider the following pairs of consecutive stimuli and their occurrence rates:

$S_{-1}$	$S_0$	occurrence rate
A	A	0.25
В	A	0
$\mathbf{C}$	A	0
D	A	0.75

#### **Equiprobable errors**

We further assume that when the classifier fails, it might return any other class with equal probability, i.e.

$$\forall Y \neq X, p(Y|X) = \frac{1-p}{3}$$

#### Testing on $S_{-1}$

Then for any  $S_0$ , the probability that a decoder tested on  $S_{-1}$  finds the identity of  $S_0$  in the ordered sequence is:

$$p(Y = S_0|X = S_0) = \frac{1}{4}p(S_0|S_{-1} = S_0) + \frac{3}{4}p(S_0|S_{-1} \neq S_0) = \frac{1}{4}p + \frac{3}{4}\frac{1-p}{3} = \frac{1}{4}p(S_0|S_{-1} \neq S_0) = \frac{1}{4}p + \frac{3}{4}\frac{1-p}{3} = \frac{1}{4}p(S_0|S_{-1} \neq S_0) = \frac{1}{4}p + \frac{3}{4}\frac{1-p}{3} = \frac{1}{4}p + \frac{3}{4$$

In conclusion, under the assumption of equiprobable errors, the performance of the decoder tested on the previous trial is **at chance level**.

### Testing on $S_{-2}$

We can extend the same reasoning to testing on  $S_{-2}$ :

$$p(Y=S_0|X=S_0) = \frac{1}{16}p(S_0|S_{-2}=S_0) + \frac{15}{16}p(S_0|S_{-2} \neq S_0) = \frac{1}{16}p + \frac{5}{16}\frac{1-p}{3} = \frac{5-4p}{16}$$

Considering that  $p > \frac{1}{4}$ , the latter quantity is necessarily smaller than  $\frac{1}{4}$ , i.e. the decoder performs below chance level.

#### Non-equiprobable misses

In practice, we might expect pairs of stimuli to be more often confounded if they are physically close:

A complete confounding matrix can be obtained at any latency from training and testing on random sequences. Here, for convenience, we parametrize the 3 possible error rates as having a geometric relationship:

$$p(B|A) = kp(C|A) = k^2p(D|A)$$

where k > 1

We can extend this logic to all others X and  $p(Y \neq X|X)$ , with the additional constraint that:

$$\sum_{Y \neq X} p(Y|X) = 1 - p$$

An example of a plausible confounding matrix with p = 0.35 (based on fig.2a in Demarchi et al. 2019) and k = 2:

However, this confusion matrix is not plausible as we end up with some error rates being larger than the true positive rate (.372 vs. .35). Let us try with k = 1.5:

Using this 35+3.08 confusion matrix and the transition matrix, we can now calculate the probability that a decoder tested on  $S_{-1}$  finds the identity of  $S_0$  in the ordered sequence:

$$p(Y=S_0|X=S_0) = \sum_{x \in X} p(Y=x|x) = \frac{1}{4}((\frac{1}{4}p + \frac{3}{4}.137) + 3(\frac{1}{4}p + \frac{3}{4}.244)) = \frac{1}{4}p + \frac{3*.137 + 9*.244}{16} = .2504$$

While the accuracy is now **above chance level**, it remains largely under the accuracy reported by Demarchi et al. 2019 (fig. 3) which is between .255 and .26.

The unbalance can be made a little more dramatic with k = 1.7: Let us try with k = 1.5:

But even under the unfavourable conditions, the accuracy is still only .204.