An evaluation of a neuron in the entorinal cortex for velocity encoding

Data Background

Extracellular neuronal activity in the hippocampus of rats were recorded during multiple sessions and in multiple environments while the rat performed tasks or moved freely[1]. Spike data was obtained with an electrode array rigged to provide recordings while allowing the rats to remain mobile though within contained areas.

The raw electrode stream was sampled at 20KHz, with the detected spike's timestamps and waveforms stored separated. The spikes where sorted into units using an open source set of tools, klastasuite[2].

Along with spike data, positional data was recording using a video camera and tracking LEDs at the animal's head and nose position; placed as to allow for easier and more accurate extraction. A timing LED was also present to synchronize spike timing with position data. The video, and position, sampling rate is 30hz[3].

All recordings, data extraction, and spike sorting occurred by original researchers prior to this analysis. The data was shared on a data-sharing server (http://crcns.org) funded by the Collaborative Research in Computational Neuroscience program.

Question

The selected subset of data is from the entorinal cortex, previously found to encode uniform, positional grids at various spatial phase, scaling, and orientation[4].

This project seeks to answer the question of whether or not a neuron in the entorinal cortex encodes the velocity of the animal as it moves around the recording box.

Findings

Figure 1 shows a single session as a movement plot of the rat within a recording box (180 cm by 180 cm rectangle). Note that the video camera's placement and the height of the rat above the 2 dimensional floor introduced projection issues, which skew the data[5]. This study ignores these distortions.

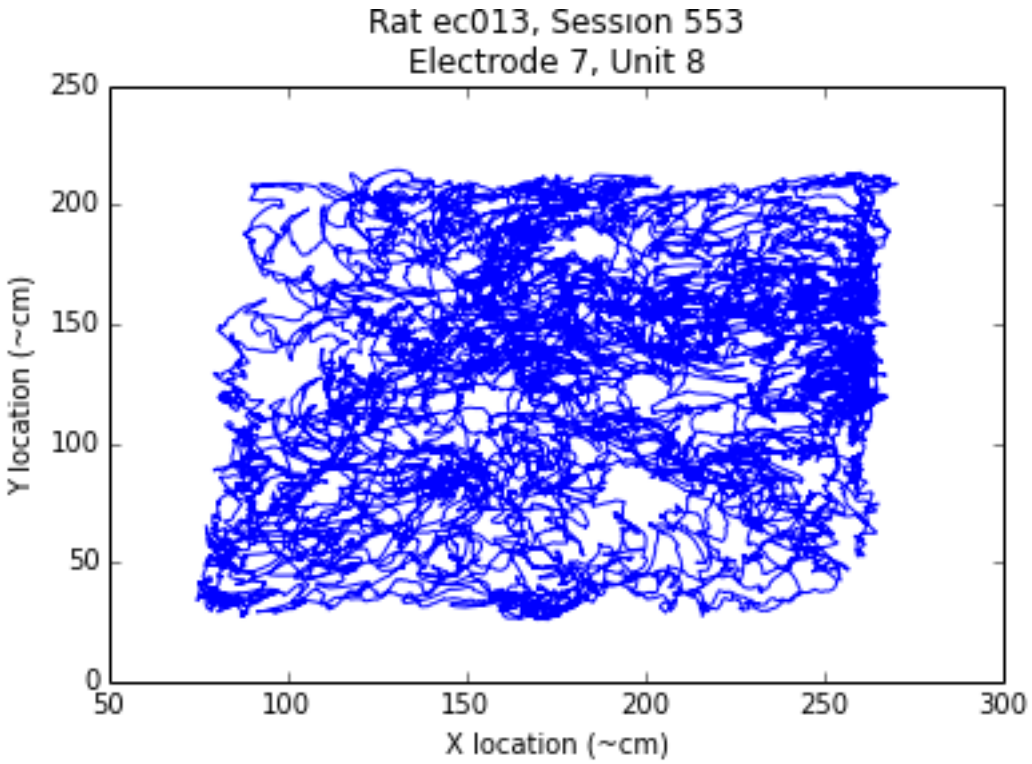

Figure 1) Animal EC013 moving within 'big square' environment during session 553. Session lasted 54 minutes and 21 seconds. Recording box is 180 cm squared. Projection distortion issues are clear.

Figure 2 shows a plot of the rat's velocity over time. The mean velocity is 11.01 cm/second.

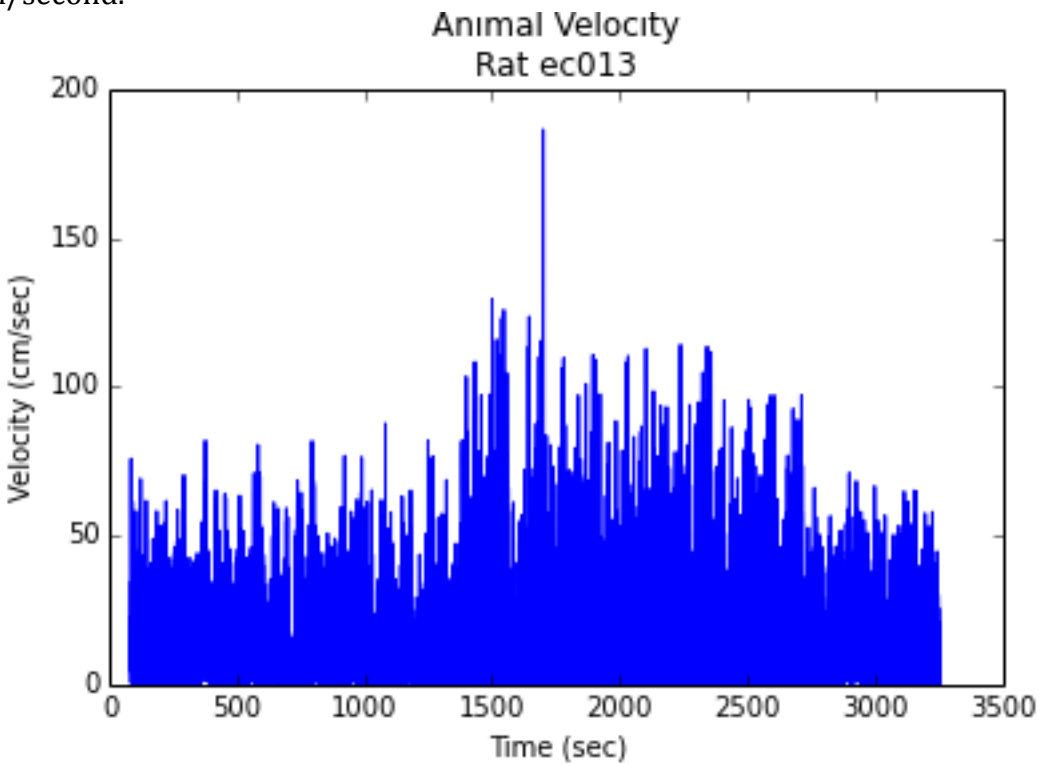

Figure 2 Velocity over time. Not all of the position and spike data from the beginning and end of the session are present.

To see if a neuron is sensitive to velocity, velocity in this study is considered a 'stimulus', as if the animal's velocity information has been processed in another region of the brain and that information has funneled its way to this neuron.

Choosing a recording session with a large amount of sample velocity data should produce a data distribution that is well formed.

Figure 3 shows the animal's velocity as a histogram; note that the distribution appears smooth.

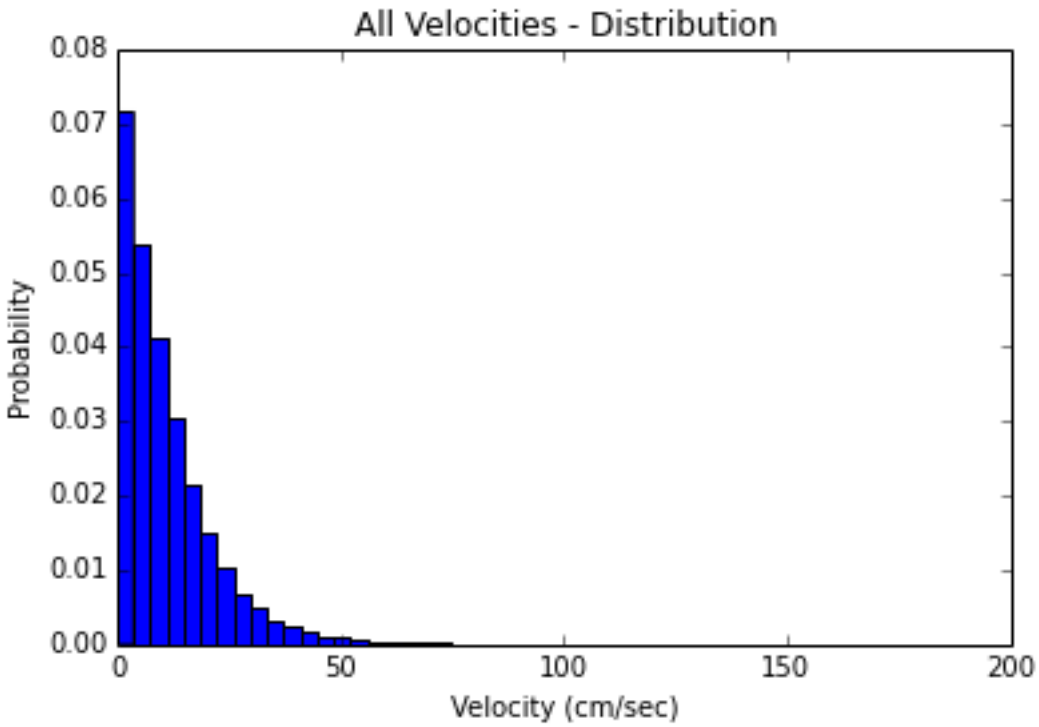

Figure 3 All velocities from the recording session are included.

Mean velocity is 11.3 cm/sec, variance 127.18.

This brings up a **stumbling block** for my project, as I was unable to categorize and justify the type of distribution the data appears to fit. By guessing that the distribution is an exponential distribution, and then plotting a q-q plot[6] with my data against a sample data set with the same mean and standard deviation, I obtained the graph in Figure 4.

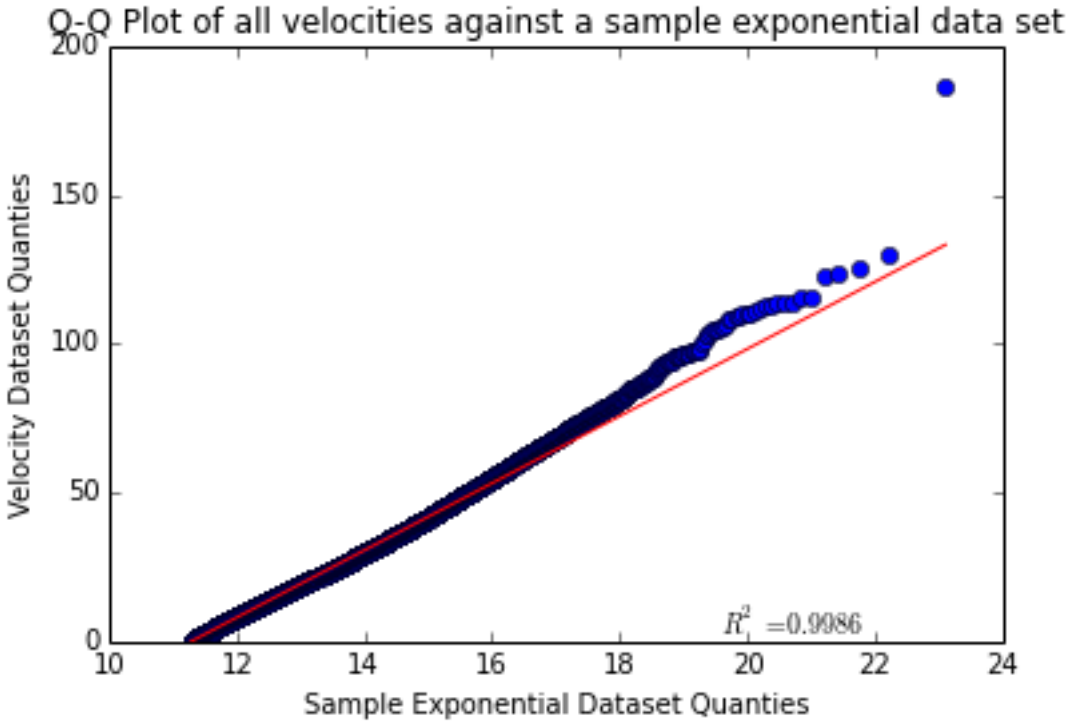

Figure 4 Q-Q Plot

It seems reasonable based on the closeness of my distribution to the sample exponential distribution that I can assume that the velocity dataset conforms to an exponential distribution. The study continues under this assumption, the important part is that the data is well formed and has a meaningful mean and standard deviation.

When correlated with neuron activity, this distribution would either stay the same or change, depending on whether or not the neuron is encoding for the animal's velocity. Comparing the distributions should allow for a reasonable finding (either positive or null).

Instead of looking at the entire dataset, if one where to randomly select a large enough subset of the velocities, and plot the subset's distribution, this new distribution would have the same mean and variance as the whole data set. An example in Figure 5.

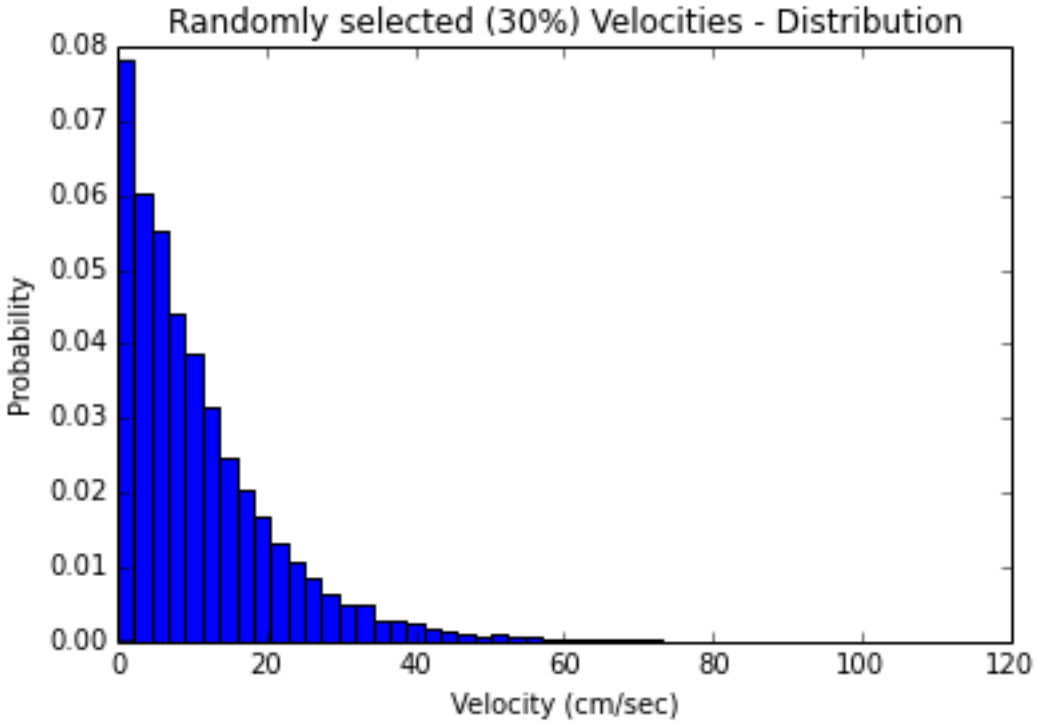

Figure 5 Randomly selected 30% of the velocity samples from the recording session.

Mean 11.4 cm/sec, variance 131.2.

If one were to select a subset of the velocities, but bias the select criteria so that, say higher velocities are more likely to be selected, then this new distribution would also be similar to the whole, however, have a different mean and variance. See Figure 6.

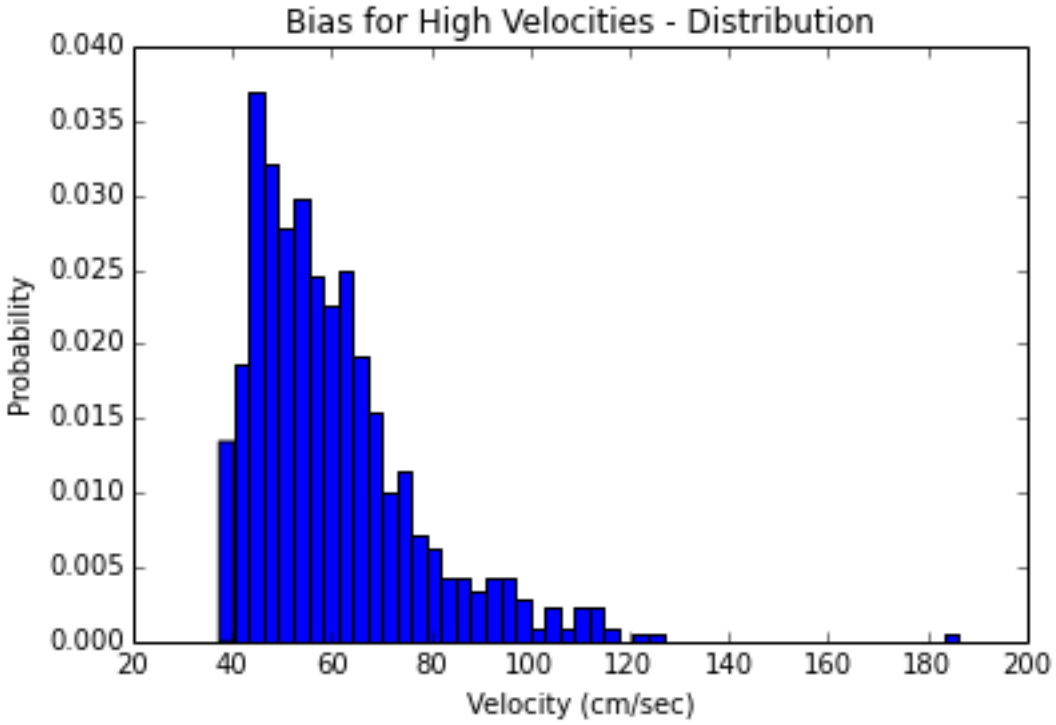

Figure 6 Selected subset of velocities in the recording session. Higher velocities are more likely to have been included, see the programing trick described after the results section.

Mean 55.02 cm/sec, variance 279.7.

Using the firing events of a neuron as the selector, and so pulling out all the corresponding velocities from the dataset when a spike occurs, we can get a subset of the data and plot its distribution.

If the neuron has little or no sensitivity to velocity, and so the firing events are more or less random as it pertains to the animal's velocity, then the new selected subset's distribution will have the same mean and variance as the whole data set.

If the neuron is encoding for velocity, then the new selected distribution will still be similar; however, will have a different mean and variance as the whole data set.

Results

Figure 7 shows a histogram of a subset of velocities that where selected during $1/30^{th}$ of second intervals that corresponded to the neuron firing.

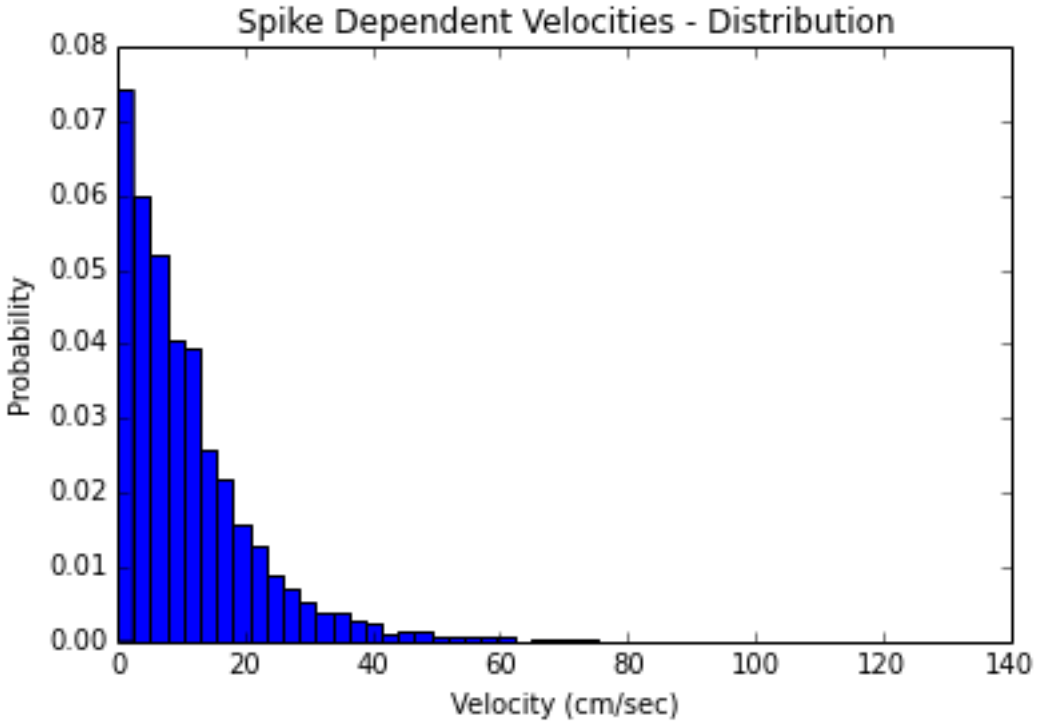

Figure 7 Mean 11.31, variance 129.81.

The mean and variance of this spike dependent velocity distribution is 11.21 cm/sec and 129.81 respectively.

It is clear that the distribution follows the original whole distribution; the neuron exhibits no bias towards high or low velocities.

Programming Trick

In order to select a subset of velocities with a higher change of selection for higher velocities, the following code was used.

```
In [149]: all_velocities = np.arange(0,10)

In [150]: all_velocities
Out[150]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [151]: rnd_vel = np.random.rand(all_velocities.shape[0]) * all_velocities

In [152]: rnd_vel
Out[152]:
array([ 0.        ,  0.35417812,  1.6981407 ,  2.94177069,  1.34656581,
        1.00307766,  0.90322221,  5.13199583,  7.50704486,  3.108211  ])

In [153]: bias_vel = all_velocities[rnd_vel > (rnd_vel.max() * 0.3)]

In [154]: bias_vel
Out[154]: array([3, 7, 8, 9])
```

For the example, all_velocities is set to a arange(0,10).
First the entire set of velocities were multiplied by a random factor. (In 151).

```
rnd_vel = np.random.rand(all_velocities.shape[0]) * all_velocities
```

Next, biased velocities were selected by filtering elements in the all_velocities array that do not correspond with rnd_vel elements that are less then a threshold (In 153).

```
bias_vel = all_velocities[rnd_vel > (rnd_vel.max() * 0.3)]
```

See that the final array (Out 154) contains higher velocities but doesn't strictly exclude low velocities or always include high velocities.

Follow-up Analysis

Further studies could hone the analysis and come to a stronger conclusion about this particular neuron and many more neurons in the cortex.

For instance, the animal's position could be rectified to offset some of the distortions induced by the angle of the camera.

Also, the distributions could be quantified and compared to each other in a more mathematically rigorous way. First the data could be fit to an appropriate curve, then the curve's mean and variance could be quantified, and then estimated mean and variance could be compared across the different graphs.

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[1] Mizuseki, K., Sirota, A., Pastalkova, E., Diba, K., Buzsáki, G. (2013)

[2] http://klusta-team.github.io
[3] http://crcns.org/files/data/hc3/crcns-hc3-data-description.pdf
[4] doi:10.4249/scholarpedia.3394
[5] http://crcns.org/forum/using-datasets/502885984
[6] http://en.wikipedia.org/wiki/Q%E2%80%93Q_plot