Welcome!

#pod-031

(Reviewed by: Deepak)

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Agenda

- **Day-#2**
  - Tutorial part 1 (Steps of modeling)
    - finding a phenomenon and a question to ask about it
    - understanding the state of the art
    - determining the basic ingredients
    - formulating specific, mathematically defined hypotheses
    - selecting the toolkit
  - Tutorial part 2 (Steps of modeling)
    - planning the model
    - implementing the model
    - completing the model
    - testing and evaluating the model
    - publishing models

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Moving average of a signal

In statistics, a **moving average** (**rolling average** or **running average**) is a type of finite impulse response filter, calculation to analyze data points by creating a series of averages of different subsets of the full data set.

Functionality:

1. Smooth out short-term fluctuations and highlight longer-term trends or cycles.
2. Denoising signals
3. Estimating signal velocities
4. Localization and tracking estimates of a moving source.

Ref: https://en.wikipedia.org/wiki/Moving_average
https://www.researchgate.net/publication/253623961_Seismic-array_signal_processing_for_moving_source_localization
https://www.sciencedirect.com/science/article/abs/pii/0146664X75900015

Processing Illusions: Relative motion

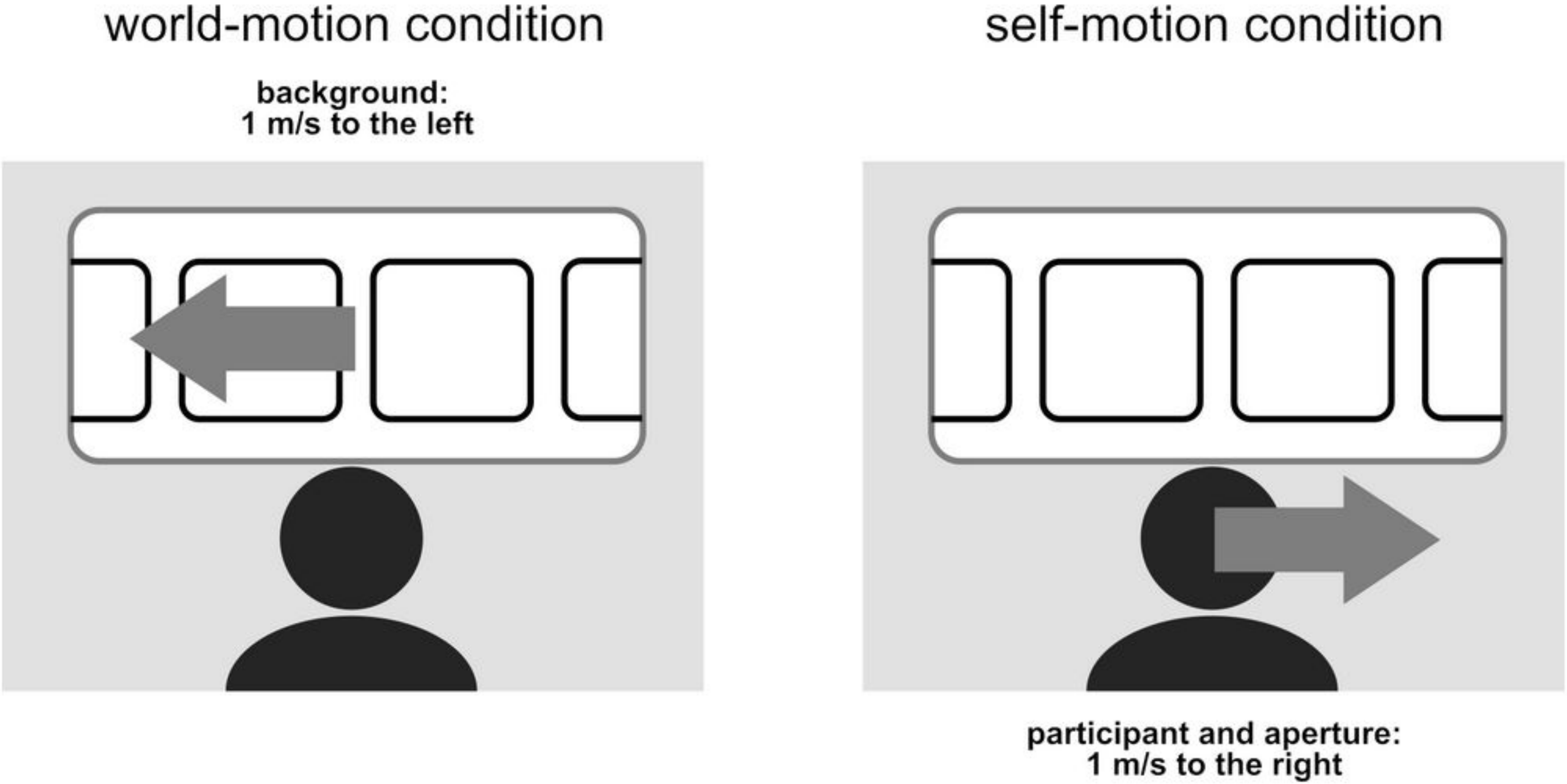
We sometimes perceive our own train to be moving and sometimes the other train (Remember: Never both at once!).

How come our perception is ambiguous even when relative motion perception is crucial for survival?

We as yet do not know the answer to the above question. But speculatively:
(a) Neural activity at earlier visual processing stages correlates with spontaneous perceptual fluctuations (gate keeping in visual awareness)

(b) Perceptual changes initiated by higher level processes by inference can stabilise bias or topple current interpretations

Ref: https://www.pnas.org/content/104/1/323

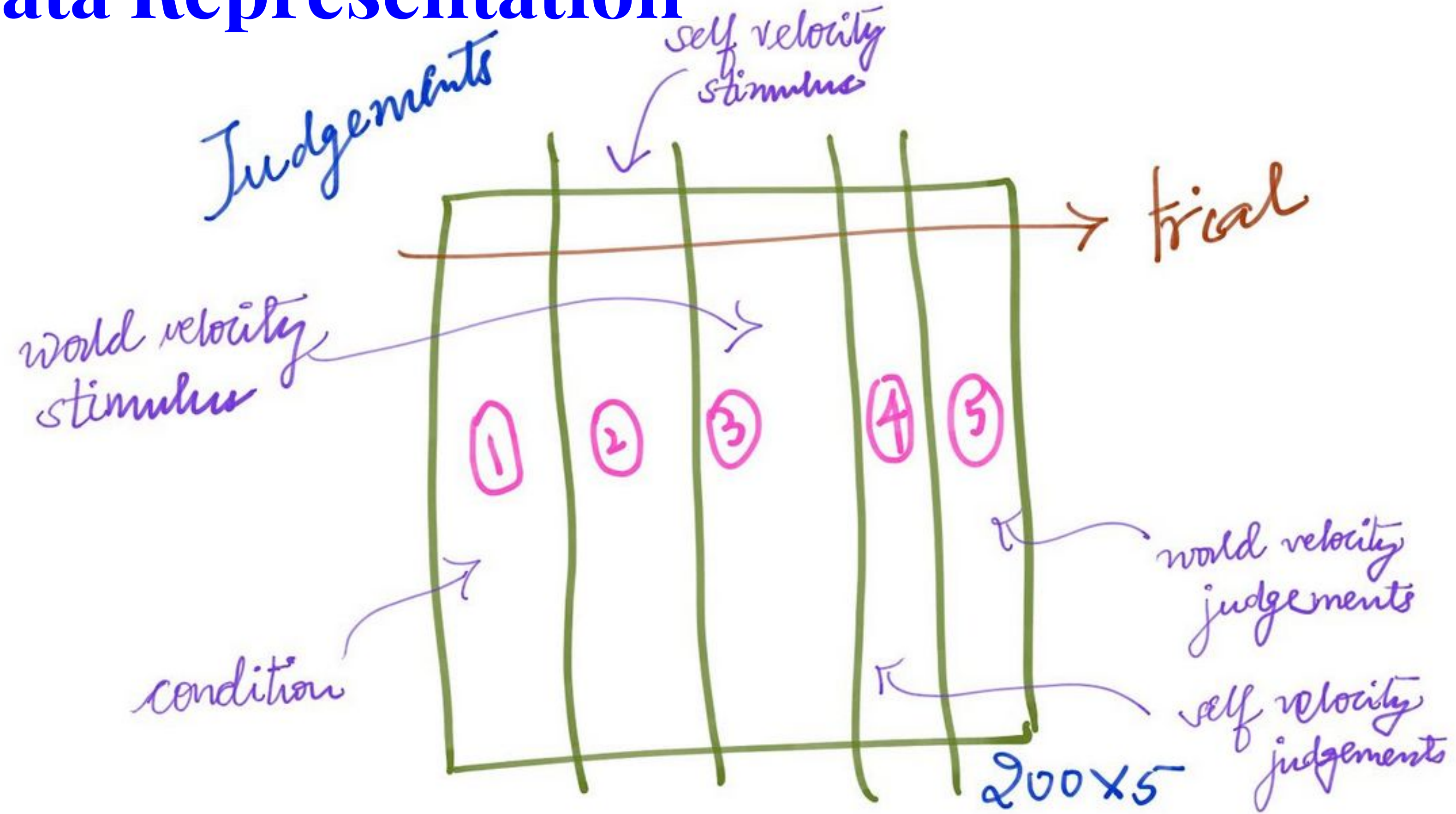

world-motion condition
background:
1 m/s to the left
self-motion condition
participant and aperture:
1 m/s to the right

Tutorial #1 Explanations

How?

- integration: get the vestibular signal in the same unit as the visual signal
- running average: accumulate evidence over some time, so that perception is stable
- decision if there was self motion (threshold)

Data Representation



Disambiguating self and world motion

Self motion perception: Visual/optic flow and vestibular/inner ear sensing

Optic flow: Moving image velocity on retina caused by self/world motion
Vestibular Signals: Relating to bodily self-movements and acceleration

The visual signal is ambiguous, it will be non-zero when there is either self-motion or world-motion. The vestibular signal is specific, it's only non-zero when there is self-motion.

How does it differ from your initial expectations? Why are there no data points in the middle?

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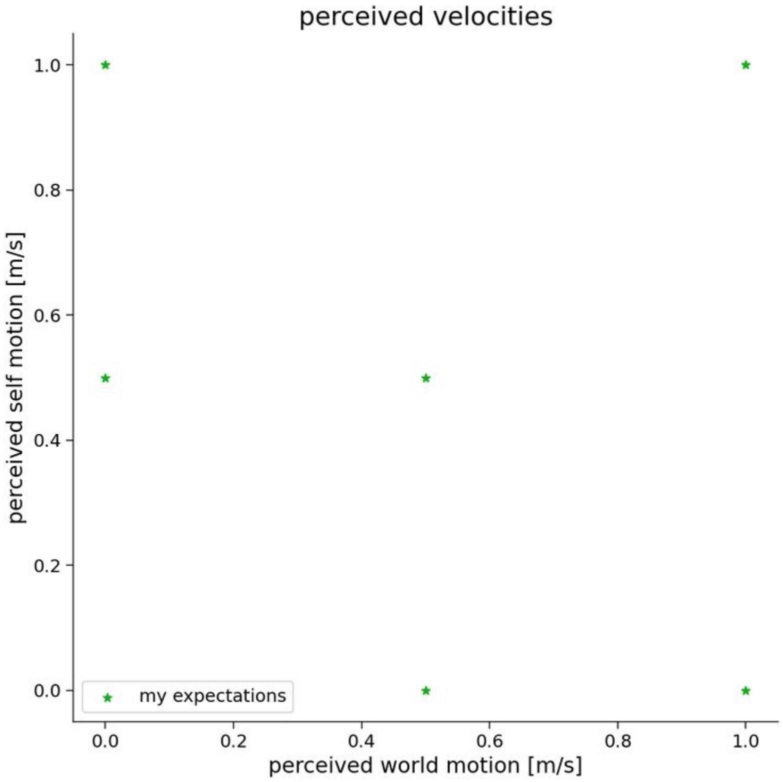
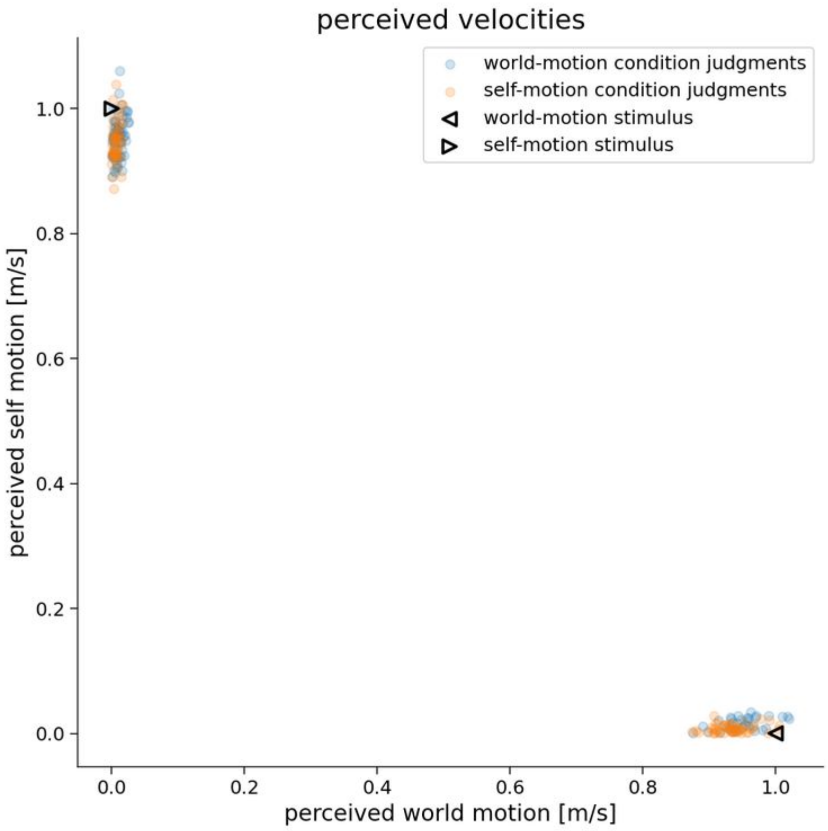
Intermittent points move towards extremes and form clusters: because data is now binarised (0: world motion and 1: self motion). Both of these are disjoint and do not occur simultaneously.



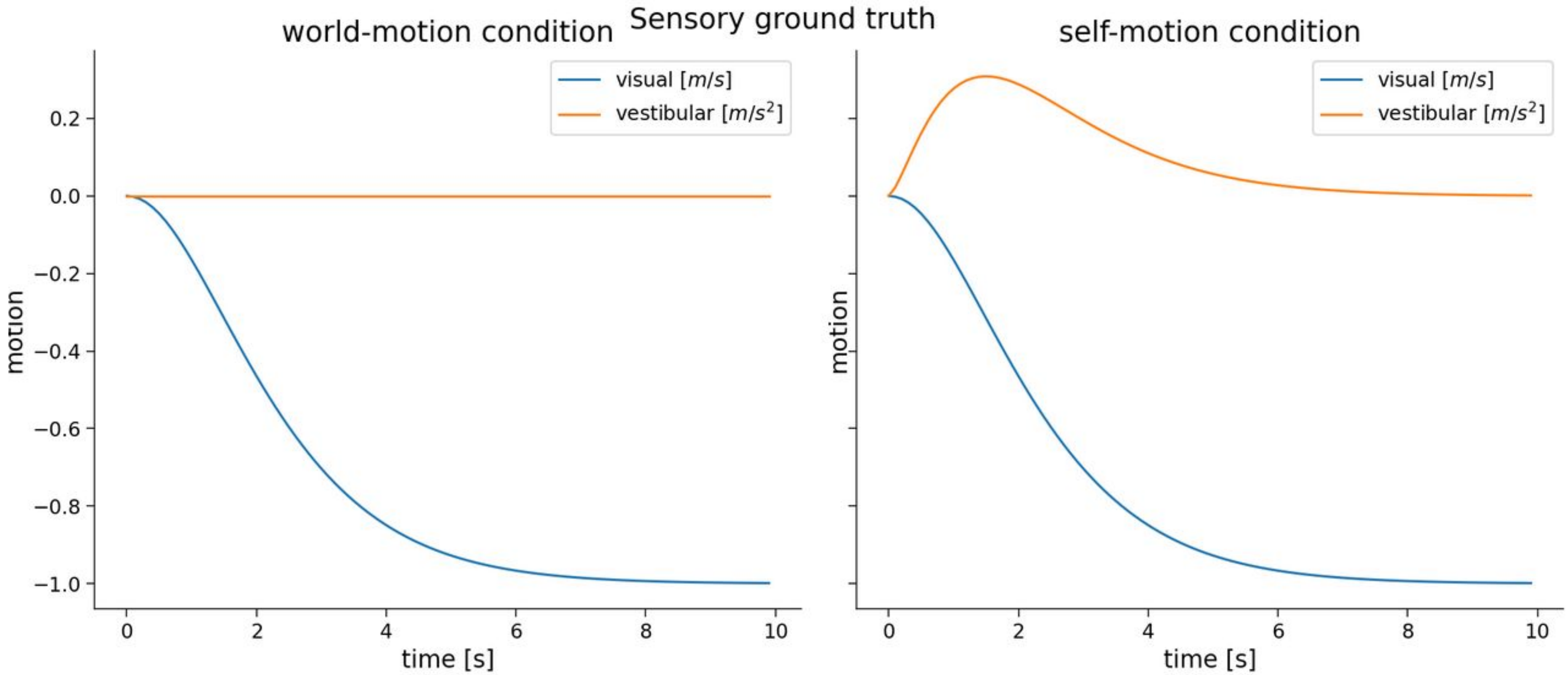


What does it mean that the some of the judgments from the world-motion condition are close to the self-motion stimulus and vice versa?

Judgements from the world motion condition close to the self motion stimulus could result from unreliability and imply noise and hence, result in illusionary behavior. However, both self-motion and world-motion conditions show both perceptions.

What aspects of the data require explanation?

If there are some ground truth values, we should be able to establish a relation between sensory signals and how they relate to ground truth. In principle, there should be enough information to disambiguate signals but noise in data could make analysis unreliable. How the ground truth should be obtained still needs explanation (We later average the integrated signal and threshold in order to solve this problem)


Sensory ground truth
world-motion condition
self-motion condition
visual [m/s]
vestibular [m/s²]
motion
time [s]
0.2
0.0
−0.2
−0.4
−0.6
−0.8
−1.0
0
2
4
6
8
10

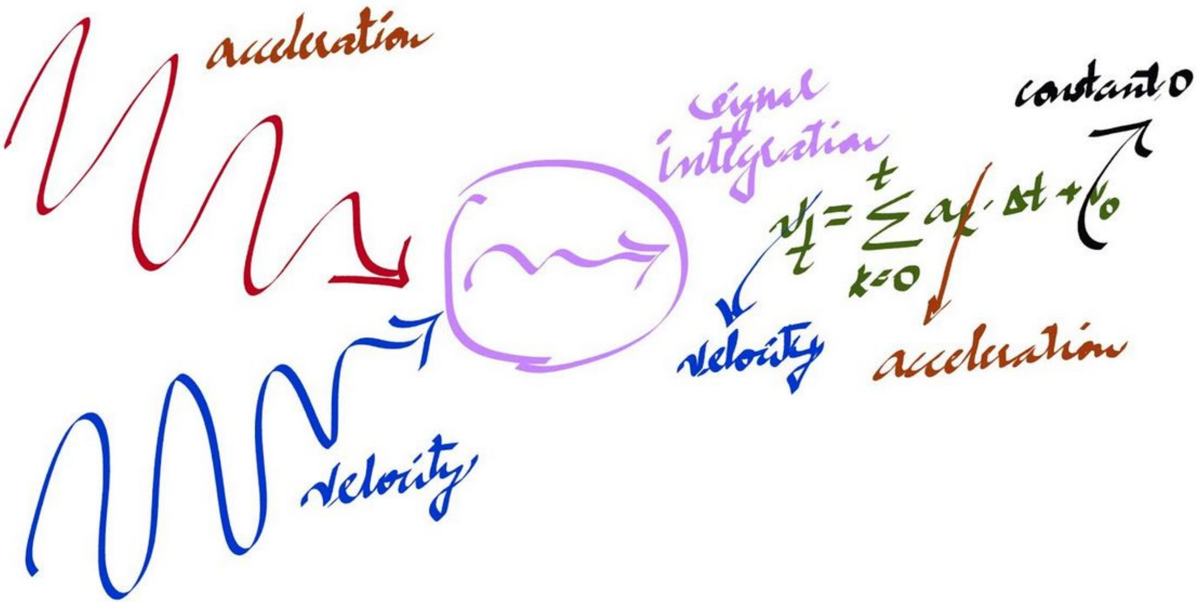
Self vs World motion: Visual, Vestibular signal processing

Visual signal behaviors are similar for self and world motion because the perception involves velocity and does not account for where (first person, second person) this velocity is perceived.

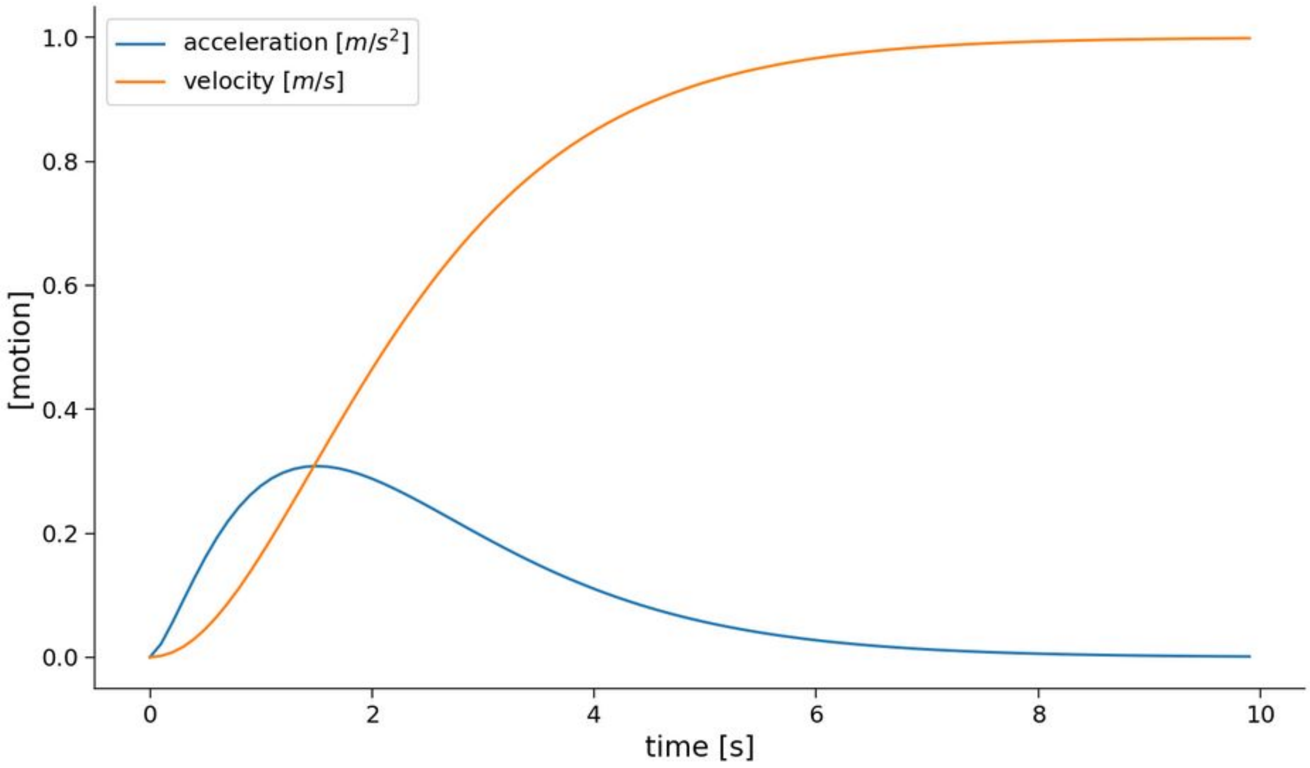
Inference: In world motion, personally experienced vestibular motion/acceleration is 0. And in self motion, acceleration is experienced first hand and is as mapped.

Signal integration

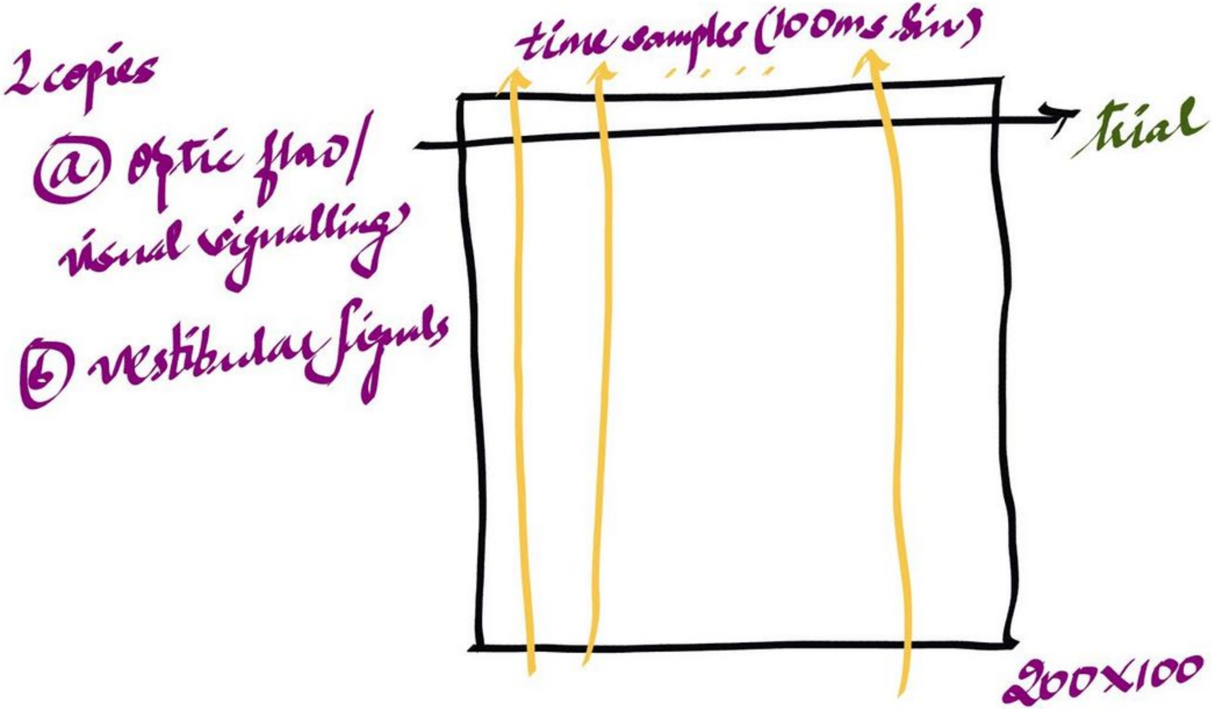
To understand how the vestibular *acceleration* signal could underlie the perception of self-motion *velocity*, we assume the brain integrates the signal. This also allows comparing the vestibular signal to the visual signal, by getting them in the same units.



Integrated Signal: Velocity vs acceleration



Data Representation of sensory signals



Is this what you expected?

We might have expected less noisy signals; With respect to data representation: Instead of two matrices, an alternative data representation could include one matrix of 400x100 where the first 200 trials relate to optic flow while the next two hundred refer to the vestibular signals. (Note: Space complexity is similar)

In which of the two signals should we be able to see a difference between the conditions?

Vestibular signals show an evident difference between conditions.

Can we compare the the visual and vestibular motion signals when they're in different units?

Integration helps bring the signals into a single unit and hence, can be compared.

Can we use the data as it is to differentiate between the conditions?

Analysing trends across these conditions (rate of change) using the given data might help differentiate between self and world motions.

Comparing sensory data to true signals

How quickly do sensory signals change?

Sampling rate is 10 Hz.

How quickly does perception change?

10 seconds, perception at one end.

Decoding Illusions: Relative motion

How can we re-adjust our ambiguous perception? How does the brain differentiate the two conditions?

(a) Using cues:

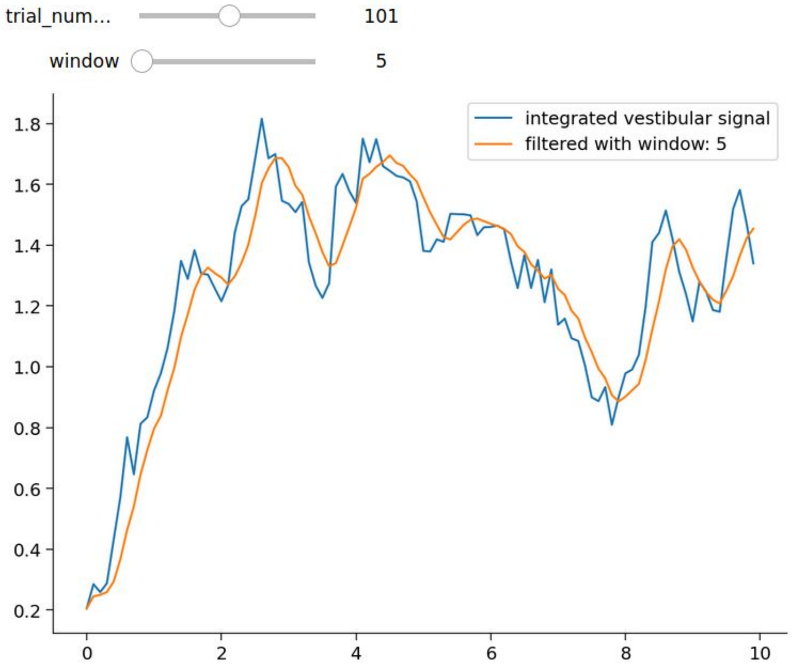
   (i) Exogenous cues, such as other environmental motion, and

   (ii) Endogenous cues, such as our own actions, or previously learned experiences

Ref: https://www.frontiersin.org/articles/10.3389/fpsyg.2015.00902/full

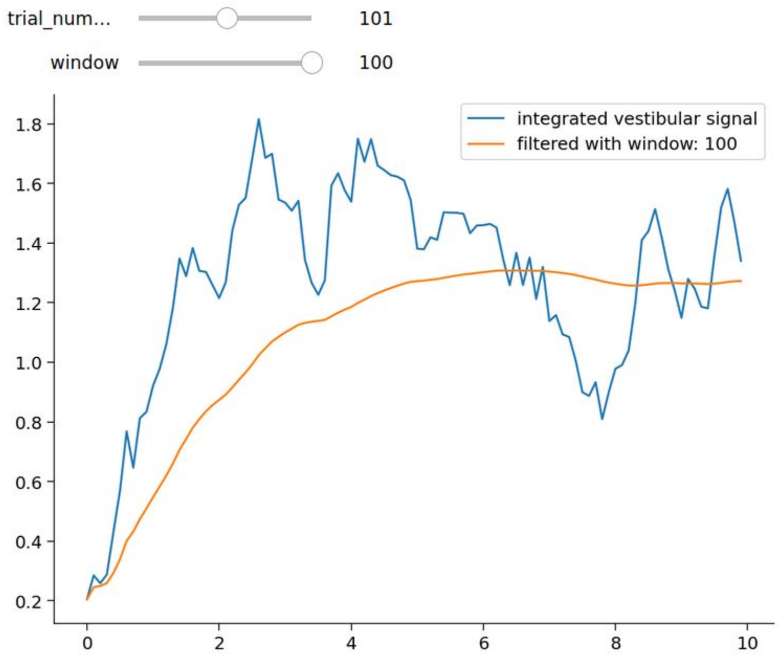
Effect of averaging window size

One vestibular signal integrated to get a velocity estimate for self motion, and then filtering with minimum window size



Effect of averaging window size

One vestibular signal integrated to get a velocity estimate for self motion, and then filtering with maximum window size



Why does increasing the window size shift the curves?

The effect of the window size on the data is as follows:
Smaller window size : increased sensitivity to changes in the underlying process from which we sample.
Larger window size : decreased noise due to small sample size
Which explains shifting curves

How do the filtered estimates differ from the true signal?

Data variations range from being merely "noise" to more meaningful indications of true temporal changes in the underlying activity. Filtered estimates are more robust to noise as opposed to true signal.

Often, "ball-park" estimates based on common sense will be adequate. In some cases, it will be worthwhile to experiment with different window sizes, as doing so may give you more insight into the underlying mechanism(s).

Thresholding self motion vestibular signal

To determine if there's a self motion or not, compare the integrated, filtered (accumulated) vestibular signals with a threshold.

1. Apply a moving average filter, and take the last value of each trial's vestibular signal as an estimate of self-motion velocity.
2. Transfer the estimates of self-motion velocity into binary (0,1) decisions by comparing them to a threshold. (0 - no self motion, 1 - self motion)
3. We sort these decisions separately for conditions of real world-motion vs. real self-motion to determine 'classification' accuracy.
4. To understand how the threshold impacts classification accuracy, we do 1-3 for a range of thresholds.

Determine threshold self motion vestibular signal

We calculate proportion self motion for both conditions and the overall proportions for correct classifications. The classification steps 1-3 above are further combined, for a variable threshold. This will allow us to find the threshold that produces the most accurate classification of self-motion.

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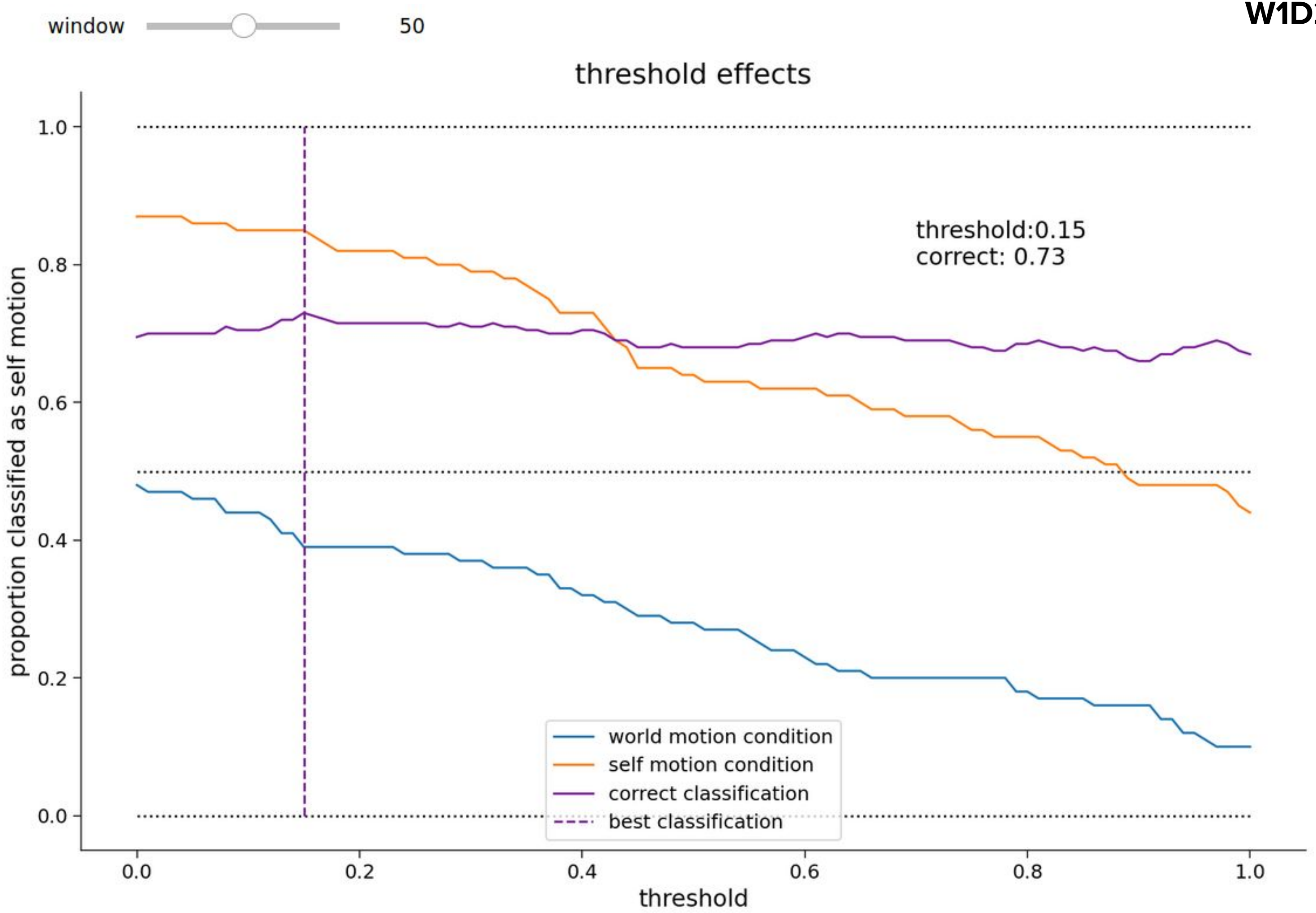

window
50
threshold effects
threshold:0.15
correct: 0.73
proportion classified as self motion
threshold
1.0
0.8
0.6
0.4
0.2
0.0
0.0
0.2
0.4
0.6
0.8
1.0
world motion condition
self motion condition
correct classification
best classification

Effects of thresholding

Ideally, in the self-motion condition (orange line) we should always detect self motion, and never in the world-motion condition (blue line). This doesn't happen, regardless of the settings we pick. However, we can pick a threshold that gives the highest proportion correctly classified trials, which depends on the window size, but is between 0.2 and 0.4. We'll pick the optimal threshold for a window size of 100 (the full signal) which is at 0.33.

Sensory Signals

ⓐ Optic flow

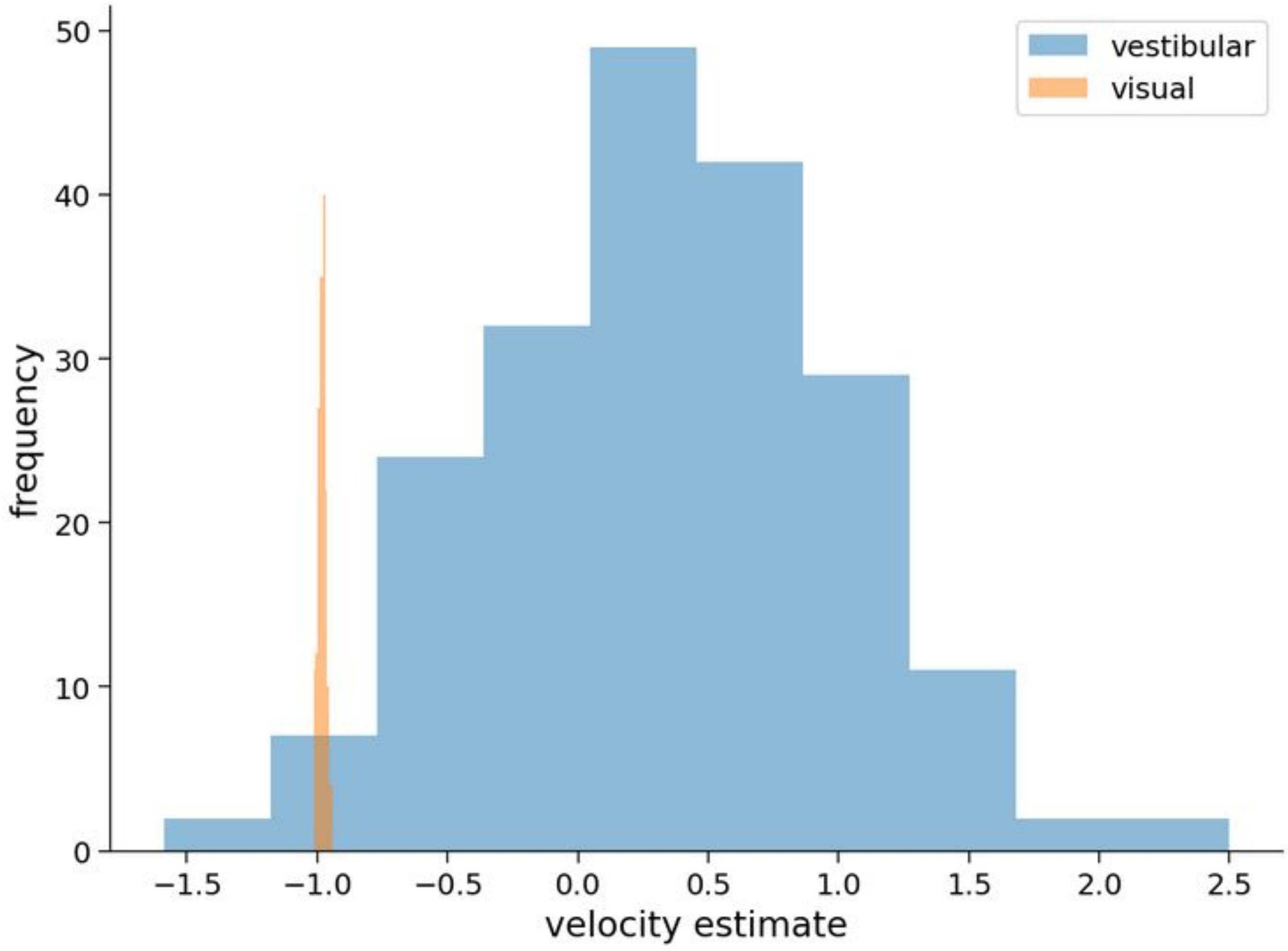
$S_{visual} = w_v - s_v + noise$

(both world/self motion drive visual motion)

ⓑ vestibular signals

$S_{vestibular} = s_v + noise$

(vestibular signals are driven only by self motion,
ambiguous when noisy)



vestibular
visual
frequency
velocity estimate
50
40
30
20
10
0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0
2.5

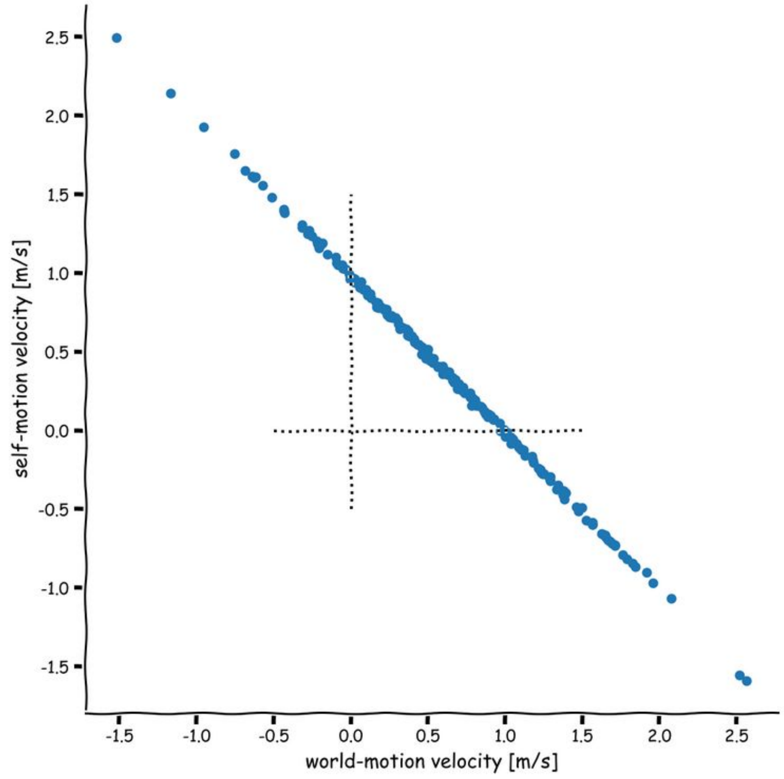
Noisy Vestibular Signals

Vestibular signals are noisier than visual signals. Possibly because information from multiple modalities yields more certain estimates than compared to the noisy estimate of a standalone modality.

Neurologically, molecular mechanism measures of how vestibular afferent sensors work or population neural activity in early vestibular pathway could help.

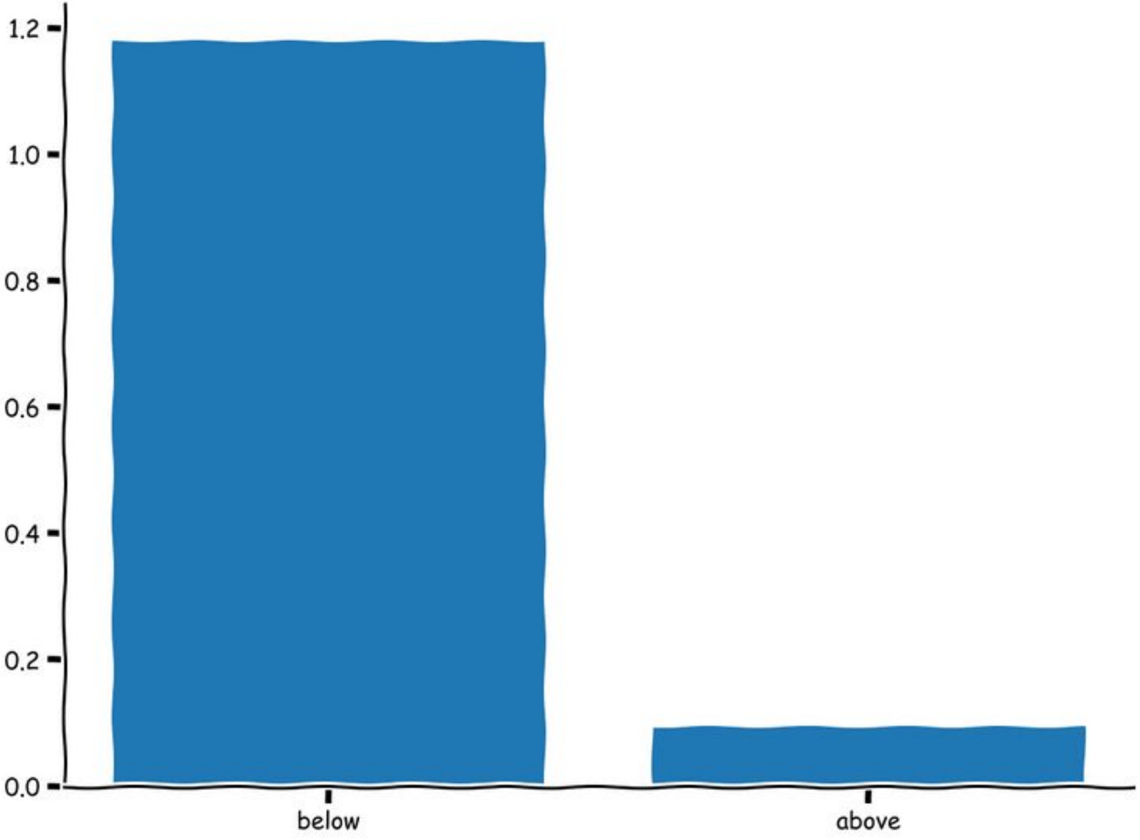
Ref: https://journals.plos.org/plosone/article?id=10.1371/journal.pone.0124573

Relationship between estimates



Inverse proportion: When there's much self motion, perceived world motion is less. When there's much of world motion, self motion in less. In between lies the zone of ambiguity.

Splitting to: above and below threshold

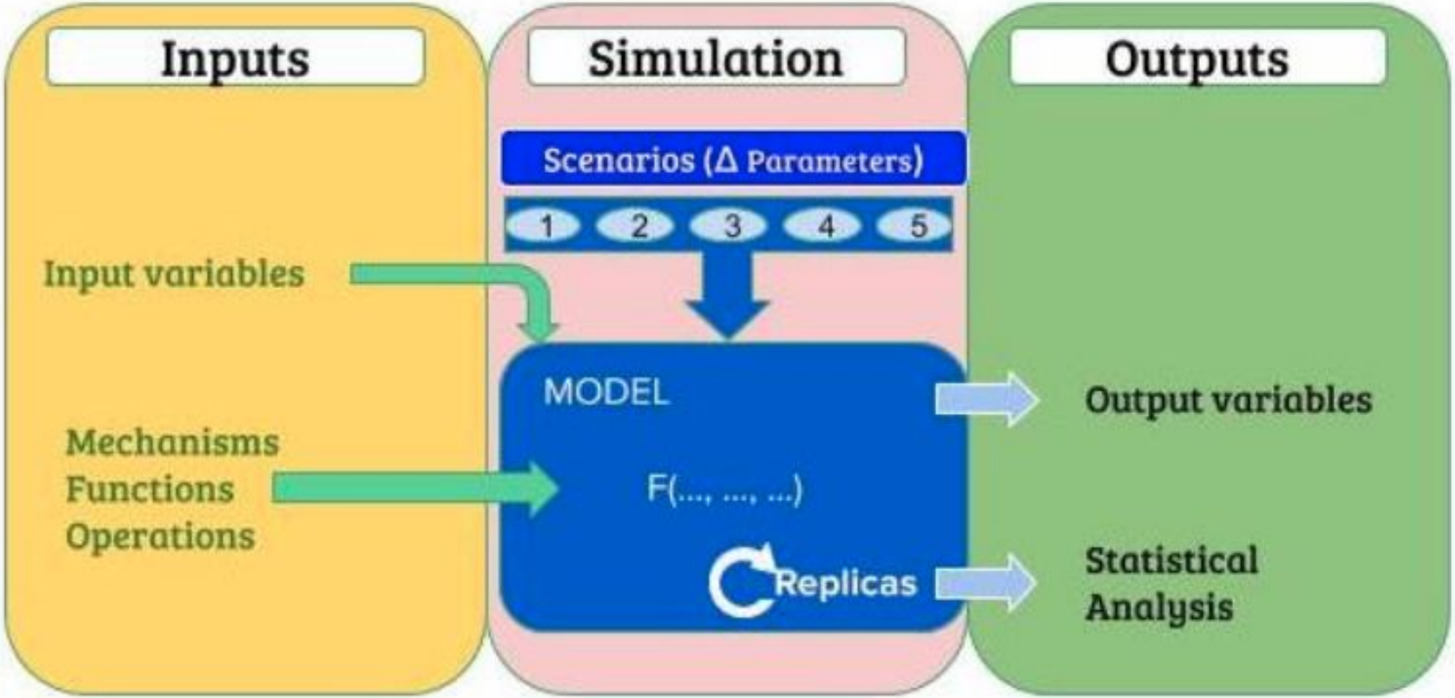


Simulation models

Simulation modeling is the process of creating and analyzing a digital prototype of a physical model to predict its performance in the real world. Simulation modeling is used to help designers and engineers understand whether, under what conditions, and in which ways a part could fail and what loads it can withstand.

Ref: https://en.wikipedia.org/wiki/Simulation_modeling

Structure of simulation models



Hypothesis

Illusory self motion occurs when vestibular noise >> actual signal which occurs possibly because integrated/filtered vestibular signals with low signal to noise level ratios (SNR) don't provide accurate self-motion information (may not pass self motion detection threshold).

Deciding a toolkit

It's useful to ask the following questions:

- What types of mechanisms (causes, processes, systems) will you need to consider in your model?
- What aspects of the data and ingredients are *essential* which are clearly *irrelevant*, and which can be abstracted over.

Ref: https://en.wikipedia.org/wiki/Simulation_modeling

Deciding a toolkit

Toolkits are sets of mathematical functions/ theories and computational methods! They're mostly used if you want to simulate or model mechanisms, causes or relationships at different levels of resolutions. There's an intimate relationship between toolkit needed and the question asked.

In our case here, statistics, population codings, dimensionality reduction, single-neuron model with detailed synaptic descriptions could work.

Brain's integration system: study of neural signals of input and output coding from related areas simulated with single-neuron biophysics/neural networks

Ref: https://en.wikipedia.org/wiki/Simulation_modeling

Designing for illusions

In case of train: Behavioral reports (like we have now) but for different window sizes.

Mathematical model simulations: General linear models

Ref: https://en.wikipedia.org/wiki/Simulation_modeling

Results and Takeaways

We found that the model could capture the illusion but also predicted intermediate perceptions, between world- and self-motion. This was due to the simple fact that visual signals and integrated vestibular acceleration add up linearly (with opposite sign) to produce optic flow. However, the model still made many mistakes and only reached about 70% accuracy.

Ref: https://en.wikipedia.org/wiki/Simulation_modeling

Reading

Blohm G, Kording KP, Schrater PR (2020). *A How-to-Model Guide for Neuroscience* eNeuro, 7(1) ENEURO.0352-19.2019.
https://doi.org/10.1523/ENEURO.0352-19.2019

Dokka K, Park H, Jansen M, DeAngelis GC, Angelaki DE (2019). *Causal inference accounts for heading perception in the presence of object motion*. PNAS, 116(18):9060-9065. https://doi.org/10.1073/pnas.1820373116

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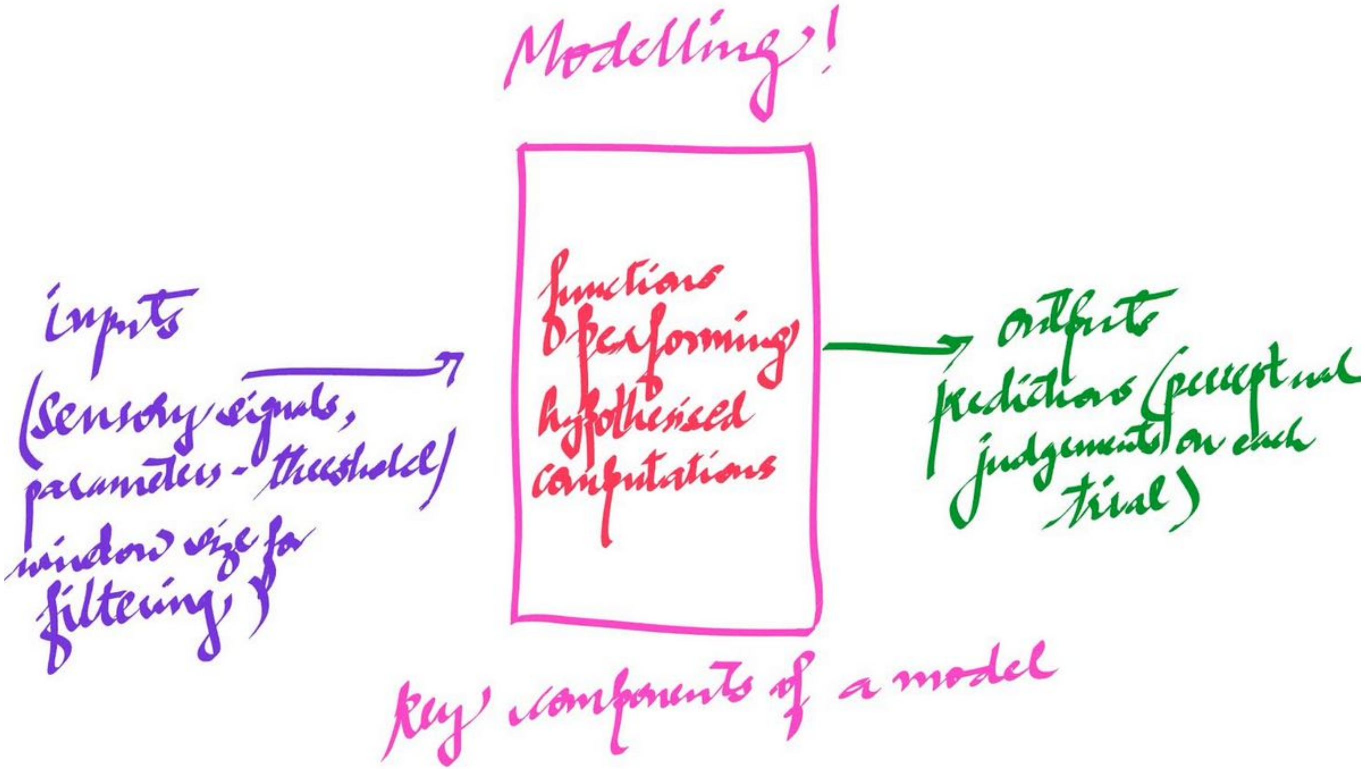
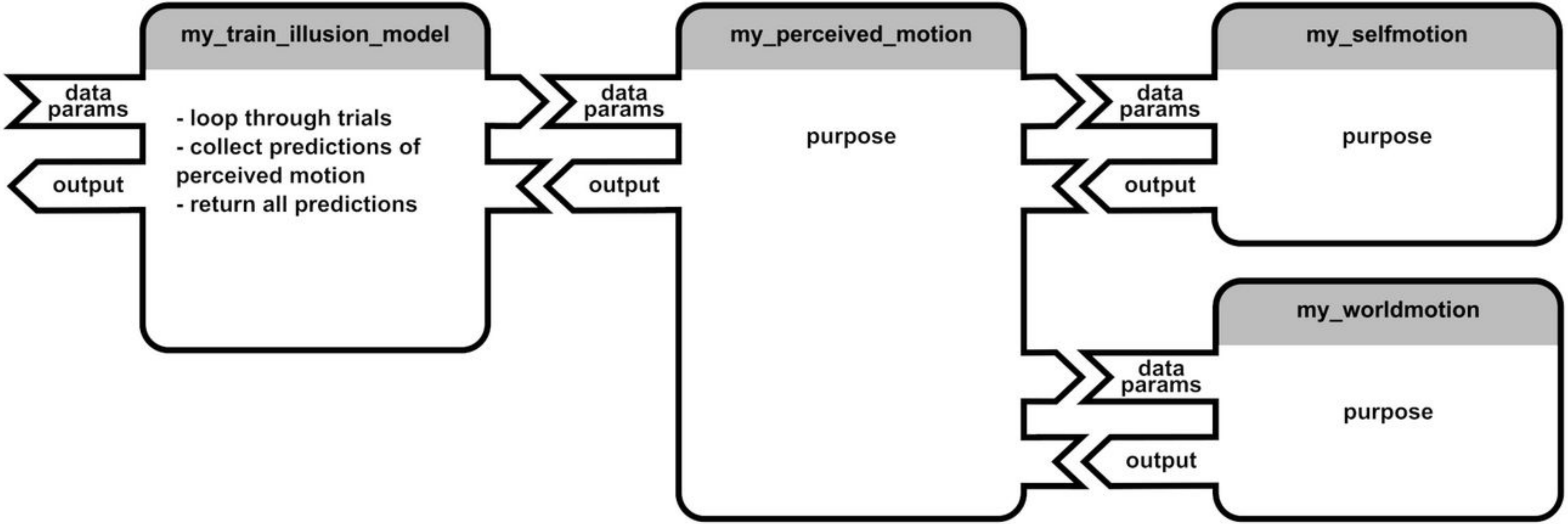
Seno T, Fukuda H (2012). *Stimulus Meanings Alter Illusory Self-Motion (Vection) - Experimental Examination of the Train Illusion*. Seeing Perceiving, 25(6):631-45. https://doi.org/10.1163/18784763-00002394

Tutorial #2
Explanations

Key modelling components



Planning the model



Formulate purpose of self motion function

what (sensory) data is necessary?

input : {

optic_flow : [ ] $N \times M$

no of trials

no of signal samples!

vestibular : [ ] $N \times M$

}

what parameters does the function need, if any?

params: {

threshold : <float>,

filterwindows: [s_{visual}, s_{vest}], → strength of filtering

integrate: True/false, → whether to integrate vestibular signals

function : filtering function, → np.mean() default

samplingrate : no of samples per second in sensory data → 10 default

}

which operations will be performed on the input?

Operations on input:

sanitisation (setting defaults) → loop through trials (estimate parameters)

⇓

integrate vestibular signals

running window function

compare output to threshold

what is the output?

Output : {

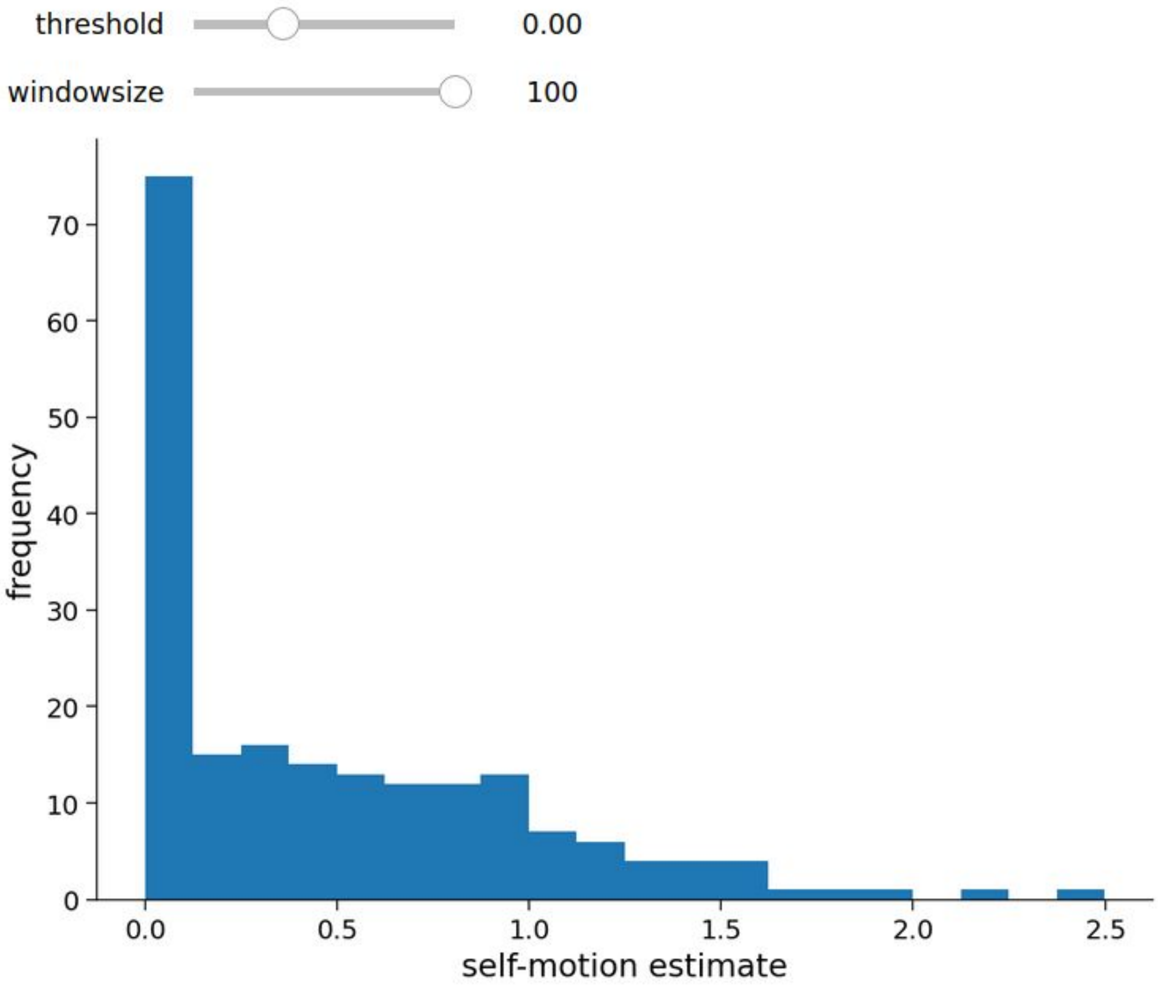
Self motion : $[\quad]_{N\times1}$

with predictions of motion

World motion : $[\quad]_{N\times1}$

}

Distribution of Self-motion Estimates



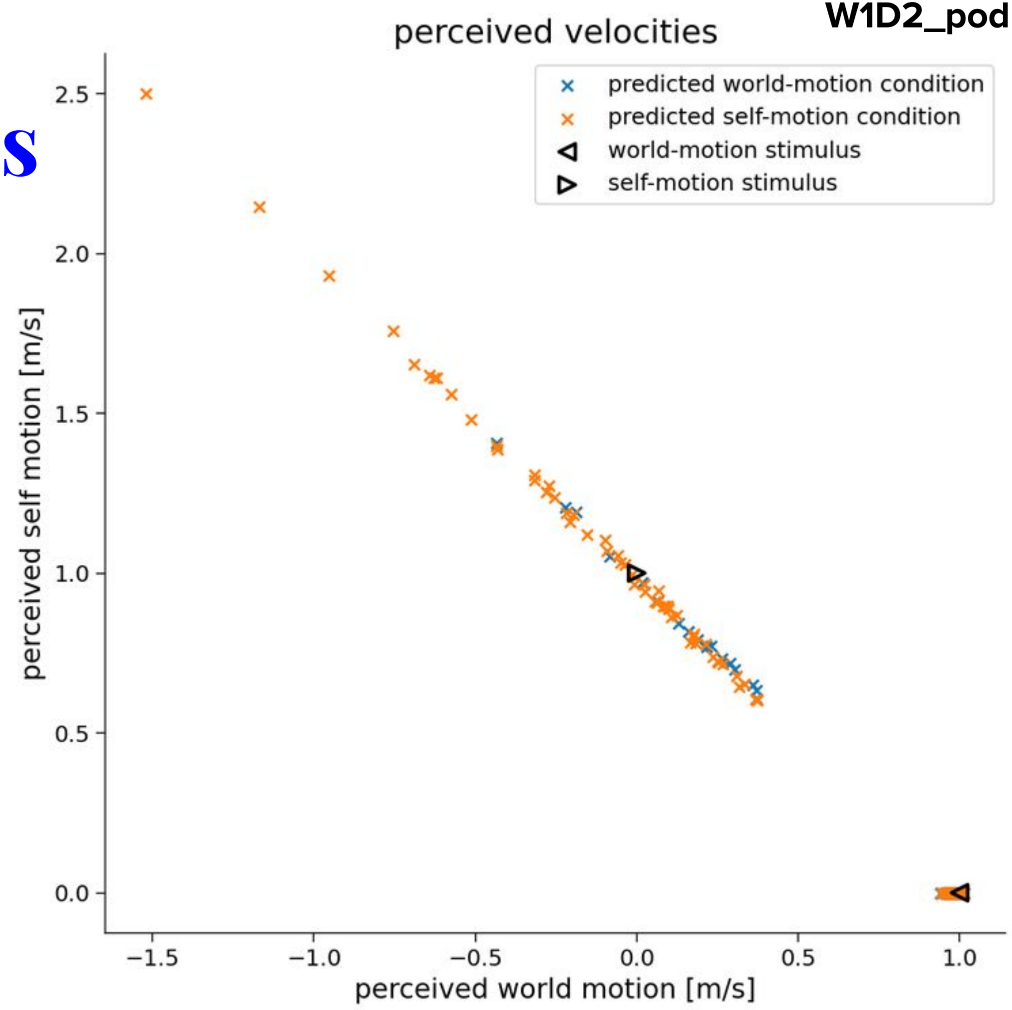
Model Completion

Goal: Make sure the model can speak to the hypothesis. Eliminate all the parameters that do not speak to the hypothesis.

Once we have a working model, we can keep improving it, but at some point we need to decide that it is finished. Once we have a model that displays the properties of a system we are interested in, it should be possible to say something about our hypothesis and question. Keeping the model simple makes it easier to understand the phenomenon and answer the research question. Here that means that our model should have illusory perception, and perhaps make similar judgments to those of the participants (behavioral studies), but not much more.

Model predictions Of motion Estimates

However, the main observation should be that there are illusions: the blue and red data points are mixed in each of the two clusters of data points. This mean the model can help us understand the phenomenon.



How does the distribution of data points compare to the plot in TD 1.2 or in TD 7.1?

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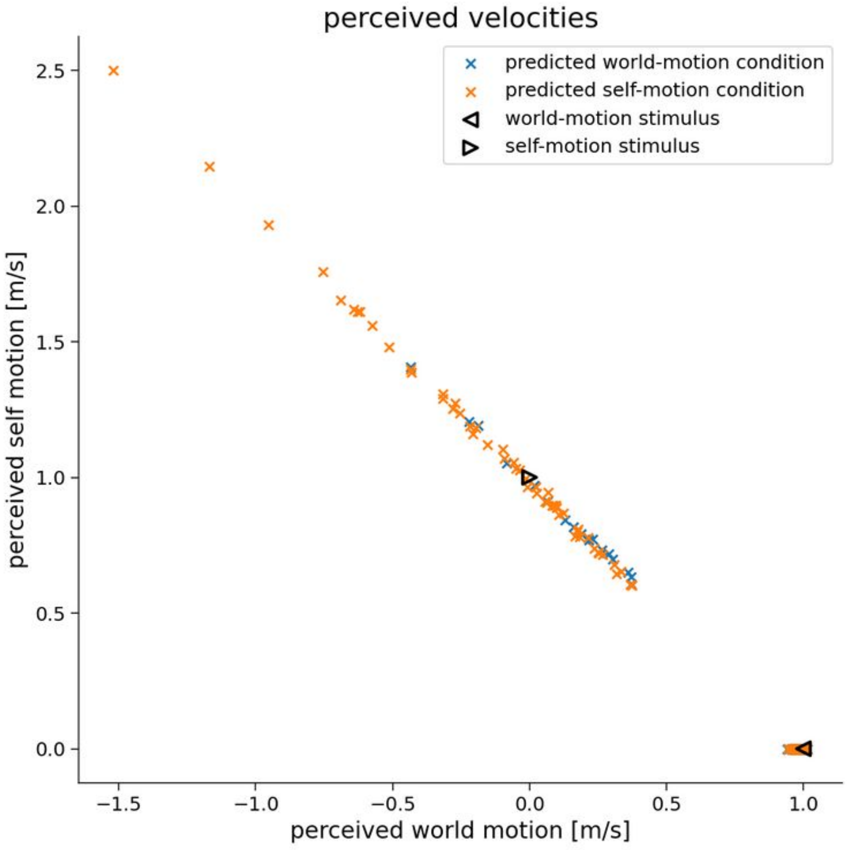
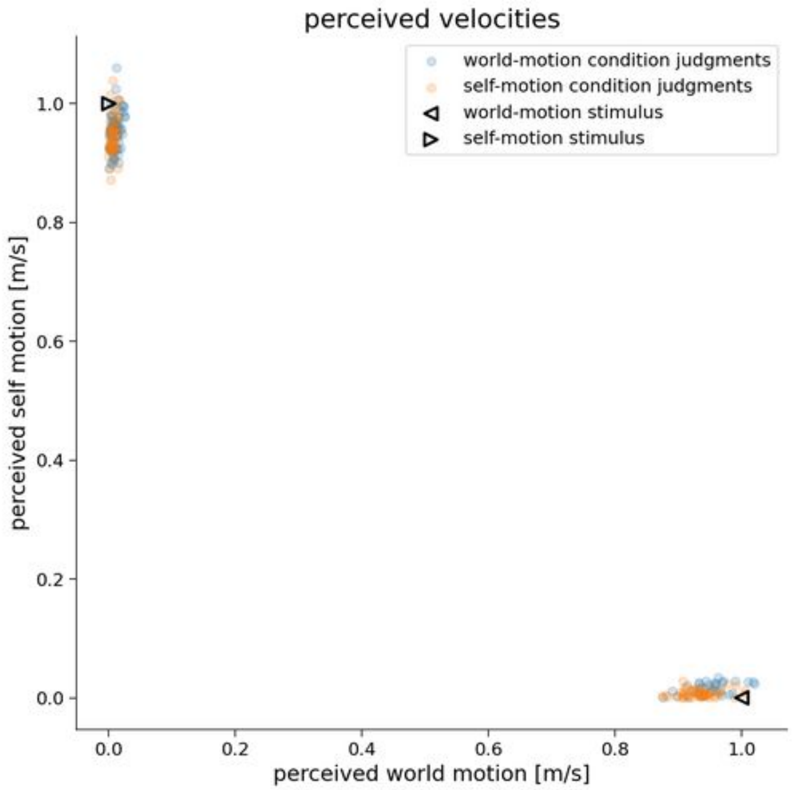
In prior plots (1.2 and 7.1), the data settled at the extremes where as here, the data displays an inverse trend where the mixture of conditions illustrates illusions;





Did you expect to see this?
The idea is to model the illusionary behavior effectively. But the presence of external noise hinders performance.

Where do the model's predicted judgments for each of the two conditions fall?
The predicted judgements fall on the inverse trend line (influence of noise is as shown).

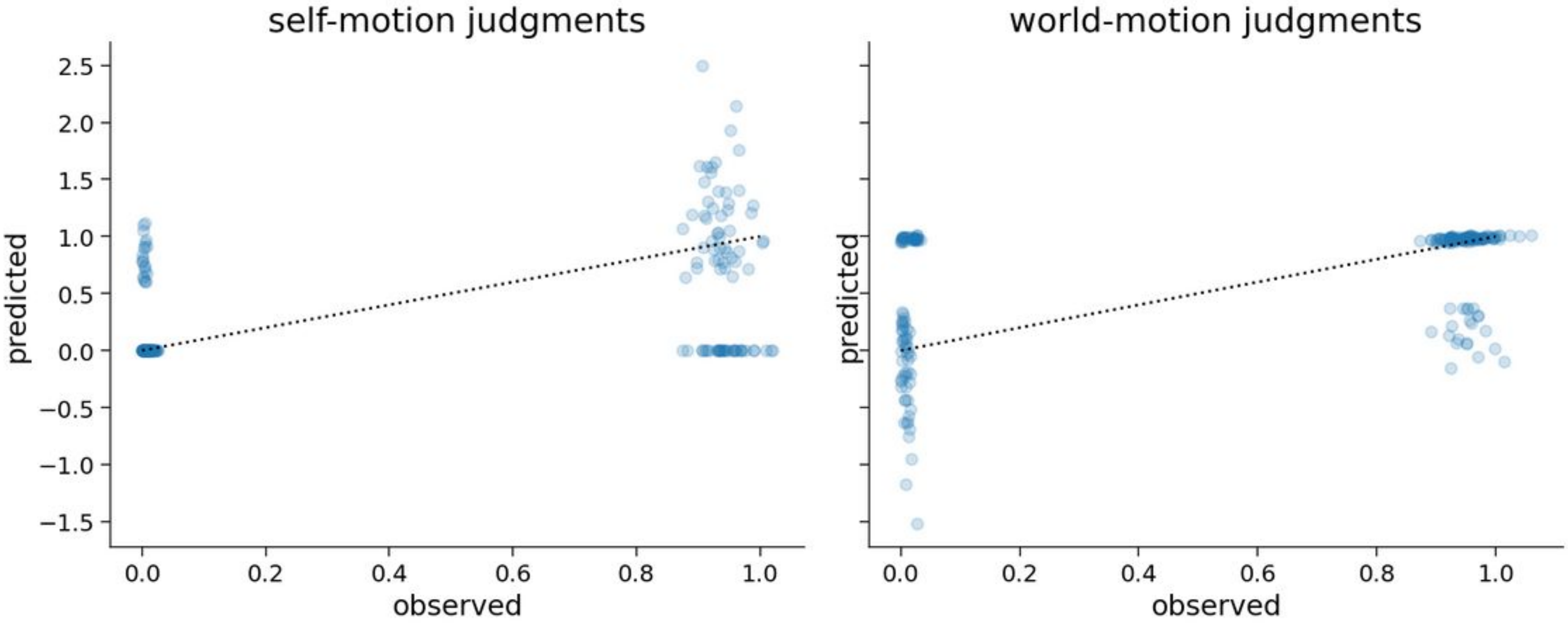
How does this compare to the behavioral data?
This compares to the behavioural data as follows:
(a) Captured data is noisy than in biological systems possibly.
(b) This data could lead to illusions that stimuli perception occurs simultaneously but in reality don't.

Model Evaluation

Goal: Once we have finished the model, we need a description of how good it is. The question and goals we set in micro-tutorial 1 and 4 help here. There are multiple ways to evaluate a model. Aside from the obvious fact that we want to get insight into the phenomenon that is not directly accessible without the model, we always want to quantify how well the model agrees with the data.

Quantify model quality with R^2

Predictions over data



When model predictions are correct, the red points in the figure should lie along the identity line (a dotted black line here). Points off the identity line represent model prediction errors. While in each plot we see two clusters of dots that are fairly close to the identity line, there are also two clusters that are not. For the trials that those points represent, the model has an illusion while the participants don't or vice versa.

We will use a straightforward, quantitative measure of how good the model is:

"R-squared", which can take values between 0 and 1, and expresses how much variance is explained by the relationship between two variables (model's predictions and actual judgments). It is also called coefficient of determination, and is calculated as the square of the correlation coefficient (r or ρ).

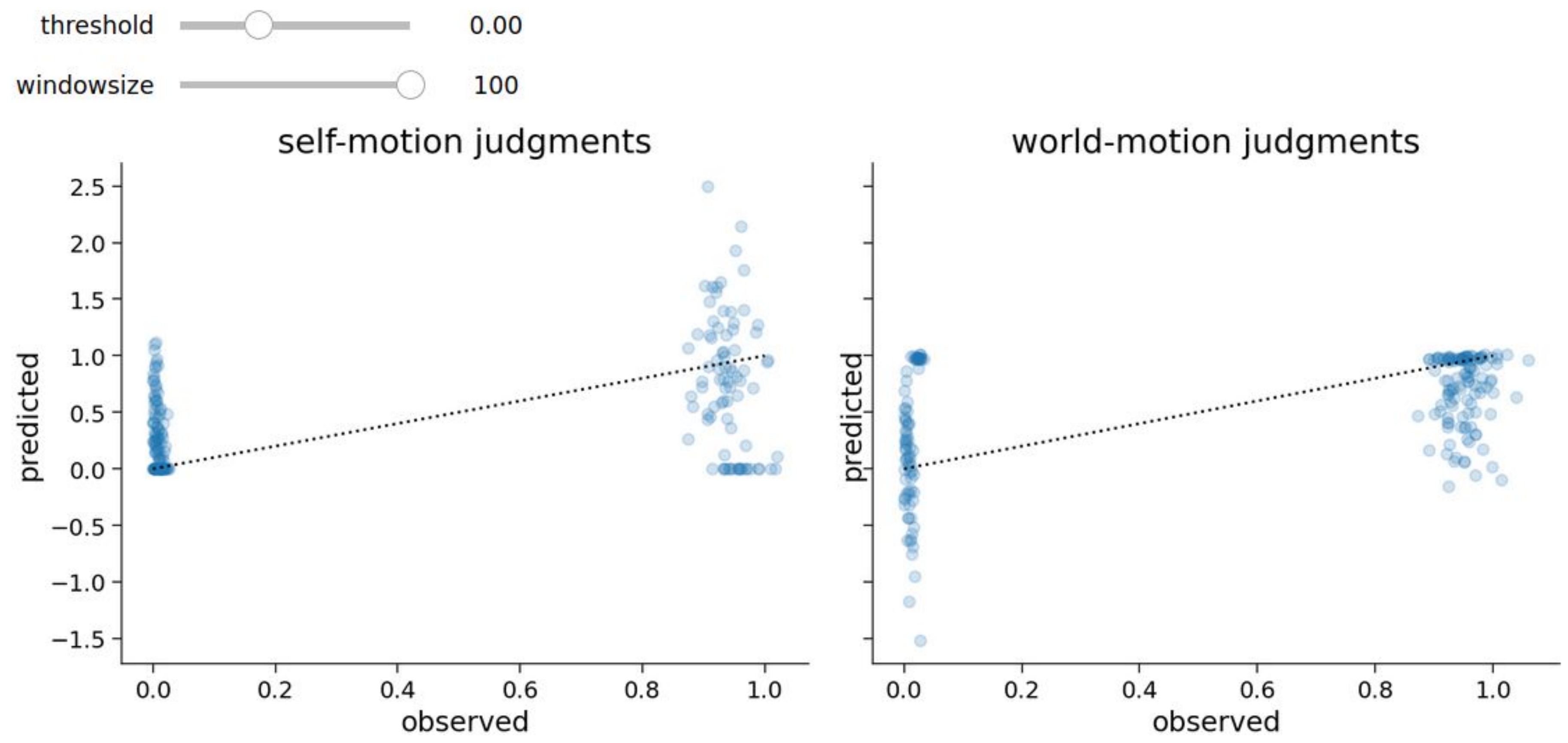
conditions -> judgments R^2: 0.032

predictions -> judgments R^2: 0.256

These *R^2*'s express how well the experimental conditions explain the participants judgments and how well the models predicted judgments explain the participants judgments.

Perhaps the *R^2* values don't seem very impressive, but the judgments produced by the participants are explained by the model's predictions better than by the actual conditions. In other words: in a certain percentage of cases the model tends to have the same illusions as the participants.

Model Optimisation




```
predictions -> judgments R^2: 0.223
```

While the model still predicts velocity judgments better than the conditions (i.e. the model predicts illusions in somewhat similar cases), the R^2 values are a little worse than those of the simpler model. What's really going on is that the same set of points that were model prediction errors in the previous model are also errors here. All we have done is reduce the spread.

Interpret the model's meaning

Here's what you should have learned from model the train illusion:

1. A noisy, vestibular, acceleration signal can give rise to illusory motion.
2. However, disambiguating the optic flow by adding the vestibular signal simply adds a lot of noise. This is not a plausible thing for the brain to do.
3. Our other hypothesis - credit assignment - is more qualitatively correct, but our simulations were not able to match the frequency of the illusion on a trial-by-trial basis.

- **What is the phenomena**? Here summarize the part of the phenomena which your model addresses.
- **What is the key scientific question?**: Clearly articulate the question which your model tries to answer.
- **What was our hypothesis?**: Explain the key relationships which we relied on to simulate the phenomena.
- **How did your model work?** Give an overview of the model, it's main components, and how the model works. '
- **What did we find? Did the model work?** Explain the key outcomes of your model evaluation.
- **What can we conclude?** Conclude as much as you can *with reference to the hypothesis*, within the limits of the model.
- **What did you learn? What is left to be learned?** Briefly argue the plausibility of the approach and what you think is *essential* that may have been left out

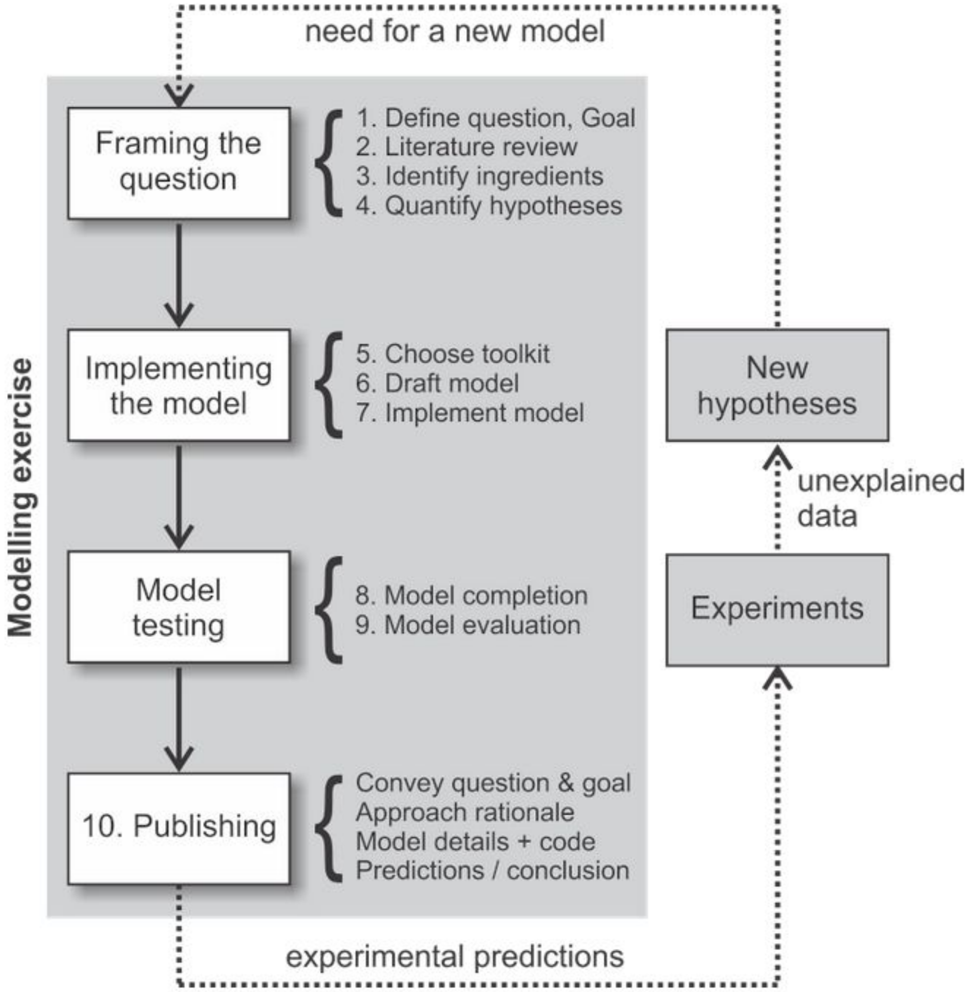
Introduction: Steps 1 & 2 (maybe 3)

Methods: Steps 3-7, 9

Results: Steps 8 & 9, going back to 1, 2 & 4

In addition, you should provide a visualization of the model, and upload the code implementing the model and the data it was trained and tested on to a repository (e.g. GitHub and OSF).

The audience for all of this should be experimentalists, as they are the ones who can test predictions made by your your model and collect new data. This way your models can impact future experiments, and that future data can then be modeled (see modeling process schematic). Remember your audience - it is *always* hard to clearly convey the main points of your work to others, especially if your audience doesn't necessarily create computational models themselves.


need for a new model
Modelling exercise
Framing the question
1. Define question, Goal
2. Literature review
3. Identify ingredients
4. Quantify hypotheses
Implementing the model
5. Choose toolkit
6. Draft model
7. Implement model
Model testing
8. Model completion
9. Model evaluation
10. Publishing
Convey question & goal
Approach rationale
Model details + code
Predictions / conclusion
New hypotheses
unexplained data
Experiments
experimental predictions

Suggestion

For every modeling project, a very good exercise in this is to ***first*** write a short, 100-word abstract of the project plan and expected impact, like the summary you wrote. This forces focussing on the main points: describing the relevance, question, model, answer and what it all means very succinctly. This allows you to decide to do this project or not **before you commit time writing code for no good purpose**. Notice that this is really what we've walked you through carefully in this tutorial! :)

Readings

Blohm G, Kording KP, Schrater PR (2020). *A How-to-Model Guide for Neuroscience* eNeuro, 7(1). https://doi.org/10.1523/ENEURO.0352-19.2019

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Summary

Summary

- define a phenomenon and formulate a question (step 1)
- collect information the state-of-the-art on the topic (step 2)
- determine the basic ingredients (step 3), and use these to formulate a specific mathematically defined hypothesis (step 4), and
- choose the most appropriate modeling approach (i.e., toolkit) for phenomenon/background information/hypothesis (step 5)
- identify the key components of the model, and examine how they work together (step 6)
- implement the model (step 7), and complete it (step 8)
- test and evaluate model (step 9), and finally
- publish model in order to increase its visibility amongst peers.