Comparing Statistical and Neuroscientific Approaches to Perception

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Introduction

The physical world is full of data and information that humans can take in through their senses and interpret for themselves. Humans pick up stimuli from the world around them and through sensory transduction they convert this information into neural impulses. Perception is how living things represent and understand their physical environment, allowing them to interact with the world. An important aspect of perception is that it is unique to every organism. One example of this phenomenon is hearing a bird chirping in the distance. This experience may be slightly varied for each individual, because what the person is experiencing is not the actual event of acoustic energy, but their own representation of the physical event of the bird chirping - someone's perceptual experience may include the bird's varying pitches, while another person's experience may focus in on an aspect of the bird's melody. This highlights that perceptual experiences are only symbols of the physical word, also known as symbolic representations.

Understanding all facets of perception is of utmost importance to understanding and solving the puzzle of perception in humans. Perception is deeply rooted in philosophy, linguistics, neuroscience, and mathematics - to name a few. This paper will discuss statistical and neuroscientific approaches to solving the problem of perception. Both methods are direly needed to comprehend human perception from all angles and are significantly intertwined. This paper will discuss how the two approaches explain learning, information theory, preference for simplicity and how they all integrate mathematical and neurobiological concepts.

Neuroscientific Approach Overview

Neuroscience has an incredible influence on understanding perception. Biological events in the nervous system are the underpinnings of human perception. Human perception begins with incoming sensory information that provokes some change in neural activity in the brain, particularly in the cerebral cortex. The cerebral cortex plays one of the largest roles in neural stimulation for perception, memory, learning, and attention. After sensory information is manipulated by some neural processing in the cerebral cortex, some result occurs in the form of motor movement or representation of thought. Neural activity in the brain, indicated as brain states, causes perceptual experiences. It is important to realize that the only way living entities can experience the physical world is through sensory nerve fibers. Studying cases of sensory deprivation demonstrates how deprivation of senses can result in unwanted brain activity, causing hallucination of missing body parts for example. This reinforces that neurobiology is highly infused with perception, in that, the absence of sensory experiences can cause unwanted neural impulses that in turn cause painful hallucinations.

Cognitive neuroscience techniques are valuable while studying perception. Studying patients with certain damage to the brain can be instrumental to understanding structure/function relationships in perception. This usually takes the form of lesion studies. One technique to conduct this is transcranial magnetic resonance (TMS) which involves pulses of magnetic signals on the scalp of a subject that disrupt normal neural impulses of a specific brain area. This is a reversible way to create lesions. Additionally, brain scans like fMRI, PET, and MEG are effective ways to capture the brain at various stages of processing that contributes to perception. These techniques in addition to others like single cell recordings allow neuroscientists to detect and measure responses to perceptual activity.

Bayesian Approach Overview

One statistical approach that has and is being heavily explored and researched is the application of Bayesian Inference models to perception. When an image is casted on the retina it can be perceived as a myriad of different three-dimensional arrangements depending on light, color, texture and surface properties.The central question this approach attempts to answer is how perceptual systems are able to reliably decide which of the plausible arrangements is the configuration that is true of the world. In the following paragraphs, the Bayesian framework for perception will be discussed as well as applications to visual and auditory perception.

Conditional probability is central to the Bayesian framework. Conditional probability is the chance of an event A happening given that event B has already occurred (p(A | B)) - event A is conditional on event B. Reverend Thomas Bayes was the first to notice that p(A | B) and p(B | A) have similar mathematical properties and can be captured in terms of the inverse conditional probability. This became known as Bayes' Rule : $p(A \mid B) = (p(B \mid A) * p(A)) / p(B)$. Perception is subjective and grounded in uncertainty because given some visual input, there could be a large number of possible representations/ways to interpret the information. There is a large amount of uncertainty around which representation is accurate of the properties of the world. Bayesian inference creates a system to quantify which hypothesis about the world should be believed given the sensory data and prior knowledge. This uncertainty is projected onto a likelihood function that assigns probabilities to plausible hypotheses. The brain acts in synchrony with the likelihood principle, in that, the brain selects the hypothesis that is most likely to be true because all applicable data and information is included in it and being implicitly considered. Bayesian inference is a developed framework for choosing the most likely hypothesis based on prior knowledge and a likelihood function.

One aspect Bayesian and neuroscientific approaches have in common is that the retrieval of sensory information is the primary and most crucial step in perception. From a Bayesian perspective, without primary sensory input the likelihood function cannot be formed and without a continuous stream of sensory input the likelihood function cannot be updated to represent information more accurately. On the other hand, from a neurobiological perspective, without sensory data there is nothing for the brain to process. The neurobiological mechanisms are then superfluous. This may be a very simple observation, but one that is worth bringing up because it is fundamental to both approaches to perception.

Another way the brain is in harmony with this mathematical framework is that the human brain follows a generative model; as new data arrives, beliefs are updated to reflect new information so inferences are always made based on the most up to date belief distributions. This is known as Bayesian updating.

Bayesian Speech Perception and Learning

This mathematical model can be applied to speech perception and visual perception. Speech perception involves taking in auditory and potentially visual stimuli to recognize phonetic categories of the speech, accents, and other properties of speech. Speech perception offers a unique situation where the listener cannot control the speaker's pace of speech; therefore, perceptual cues are unevenly distributed across the speech signal. This variability in the speech signal makes it difficult for the listener to absorb every perceptual cue making it a problem of inference and probability. Listeners must use their statistical knowledge about prior experience in familiar situations and generalize it to a new perceptual experience. For instance, when a listener interacts with a speaker with an accent, the listener will use past knowledge about speakers of similar accents to make the most of the new interaction. The ideal listener model addresses phonetic categorization with statistical inference, also known as a bayesian approach. Under Bayes' rule, the posterior probability of category (C) ci given observing some cue x can be written as follows:

$$p(C = c_i \mid x) = \frac{p(x \mid C = c_i)p(C = c_i)}{\sum_j p(x \mid C = c_j)p(C = c_j)}$$

For example, if the F2 locus is a cue for the phonetic contrast between /b/-/d/, the listener must infer how likely it is that the /b/ phonetic category was intended by the speaker given the F2 locus observation. This would be quantified by the following simplified equation:

$$p(b \mid F2\ locus) = p(F2\ locus \mid b) * p(b)$$

It is evident that in speech perception Bayes' rule sheds light onto three significant aspects of rational inference. First, It incorporates the prior probability, p(b), which specifies how likely a /b/ phonetic category is in the language. Second, it takes in account p(F2 locus | b), the probability of the F2 locus value given /b/ was the intended by the speaker. Lastly, all other hypotheses are implicitly encaptured in Bayes' rule since all probabilities of hypotheses add up to 1. These properties are significant because they explain how the human speech perception system, which is both reliable and quick, can be explained mathematically.

An important aspect of speech perception is that listeners do not have access to the true distribution of speech data but only their uncertain beliefs about the distribution based on observation. This relates to the extreme variance in speech that makes it difficult for the listener to grasp perceptual cues. In order to achieve a near flawless speech perception, listeners must adapt their beliefs and dispose of inaccurate beliefs. Incremental distributional learning integrates information about a new situation with prior knowledge and linguistic assumptions in order to achieve an adaptable speech perception system that facilitates implicit learning.

Neuroscientific Approach to Learning and Memory

Using a statistical approach, learning is described by belief updating and incremental distributional learning. The statistical likelihood function is updated as new experience drives new information. This novel data is incorporated into the likelihood function to be used for future experience and the person's belief distribution is expanded. Neuroscience approaches offer an enticing viewpoint to the matter of perceptual learning that shares some similarities to statistical viewpoints. Neuroscientists have studied the auditory cortex and found evidence that it is linked with learning and memory. The auditory cortex is located in the superior temporal gyrus in the temporal lobe. Contemporary neuroscience introduced the phenomenon of representational plasticity in the primary auditory cortex. Representational plasticity is a change in neural substrates in the brain to reflect learning and a stronger memory. An example of this is in a two tone discimination study. In this experiment, one tone, with a conditioned stimulus, resulted in a noxious sound while the second tone, with an absence of a conditioned stimulus, presented no sound. After conducting random trials, it was found that all subjects had developed discriminative conditioned associations. This was proved by a galvanic skin response for the conditioned stimulus tone. In fact, positron emission tomography (PET) scan showed changes in the regional cerebral blood flow in the tonotopic map in alignment to the specific tones in the experiment. The tonotopic map, a spatial representation of frequencies and sounds in the primary auditory cortex, changed in the specific region correlated with the conditioned stimulus tone, but not for the tone without the conditioned stimulus. An increase in tonotopic signal areas is a form of representational plasticity. This result is evidence for cortical plasticity and associative learning in the primary auditory cortex.

Comparing Neuroscientific and Bayesian Learning

This type of learning is the side effect of plasticity or actual neurobiological change in the brain. Whereas, the learning in statistical models is a byproduct of updating a nonphysical belief distribution. Although both of these approaches may seem different, they may be much more alike than it seems. After some sensory input triggers neural processing, that information is stored in long term memory for further use. This makes sense in the realm of both approaches because it confirms that for learning to occur new data must be stored and integrated into current processes either through neural plasticity or belief updating. Both approaches also capture the concept of implicit learning. Through the experience of listening to two tones, the subjects automatically made associations. This applies to all physical events - humans have been implicitly learning since existence, making implicit assumptions through experiences like denoting a high probability to seeing a car after hearing a horn.

An argument can be made that all auditory learning is perpetual learning. Perceptual learning occurs after associations between events are made. This causes changes in the auditory cortex and primary sensory cortices and increases sensory acuity. Perceptual learning is different from associative learning because it includes perceptual memory. Perceptual learning can be molded into a Bayesian framework too by assigning probabilities and creating a generative structure.

Bayesian Visual Perception

The Bayesian approach also applies to visual perception. Visual perception is a tricky area because shadows, lights, texture, and three-dimensional subspace factors can play a role in deceiving humans of the true properties of the physical world. Contour integration is one problem within visual perception. Physical contours can take a wide variety of forms in a subspace. The angle between two edges offers insight into which competing hypothesis is true of the world. Mathematically, edges that are closer to being collinear are assigned higher probabilities.The estimation of motions can be an ambiguous situation because objects are moving in space at different velocities. Similar to speech signals, a sequence of image data showing motion can be extremely ambiguous and can elicit multiple interpretations depending on how the person perceives the velocities. Looking at this situation from a Bayesian perspective, a single most-probable interpretation of the physical world can be achieved. First, there must be a prior knowledge addressing which velocities are more likely to be true. Second, there must be a likelihood function to fit current visual data to possible hypotheses. This kind of approach addresses visual illusions with smaller probabilities, indicating they are less likely to be true and instituting a system of rational inference.

Bayesian Models and Simplicity Principle

Bayesian models also assign lower probabilities to complex models, enforcing a preference for simpler models. The probabilities or priors are assigned this way due to the nature of statistics; because complex models have more options and they must add up to 1, each option therefore has to take on a smaller probability. The concept that rational agents prefer simpler models is called the simplicity principle which entails that the brain detects the simplest hypothesis. Bayes' rule captures the simplicity principle just from the nature of statistical inference. The simplicity principle however is derived from the concept of heuristics. Perceptual neuroscientists have found evidence that the brain is actually a "bag of tricks" and individual heuristics or hacks are used for the brain's computations. Although this is an ongoing debate in cognitive science, it proves that the human brain's mechanisms and processes are inclined towards a Bayesian approach. Whether it is through heuristics or a mathematical model, the brain is biased towards the simplest hypothesis, which is a property of Bayesian inference. This is an instance of how statistical and biological approaches intertwine in a way. Furthermore, this illustrates that Bayesian models coincides with biological tendencies. Moreover, Considering the fact that natural selection drives organisms to continuously adapt to optimal conditions, the Bayesian theory should be in synchrony with Evolution. If this notion is further abstracted, the claim can be made that the Bayesian proposition is well suited for the brain, as reflected by human behavior, and by the process of evolution it should be supported in perceptual neuroscience.

Problem of Perceptual Organization

Another problem of visual perception is perceptual organization. Perceptual organization deals with how to group components of visual information such as objects and contours. This is different from statistically estimating the probability of something being true in the physical world because it is solely about how humans choose to perceptually organize visual images. For instance, when looking at 8 dots on a page, do humans perceive it as 8 single dots, 2 groups of 4 dots, or 4 groups of 2 dots? Do humans perceive the configuration vertically or horizontally? This is a question of perceptual organization and can be solved by a bayesian likelihood function and prior knowledge. The fact that perceptual organization is even a conundrum humans encounter suggests that the human brain is biased towards being rational. The problem of perceptual organization has always been one of effective configuration of objects in a mental subspace. The human brain has a tendency to want to perceive things quickly and in the simplest way possible. This again reveals the overlap between statistical methods and neuroscientific features of perception.

Neuroscience and Statistics as Related to Information Theory

Perceptual neuroscience and perceptual statistics are both intrinsically related to information theory. Neuroscience is grounded in mathematics. The brain as a whole is described as computational machinery that processes sensory information. This is different from simply responding to sensory information because the word processing inherently refers to a computational process. This is also key to the information processing theory; the brain takes in selective information, processes it, and then stores it into long term memory for future use.

Likewise, perceptual statistics is tied to information theory because hypotheses with higher complexity are given lower probabilities - a key feature of information theory and a key component to Bayesian perception. In information theory, Shannon-Fano encoding found that the minimum expected code length is the most optimal proposition. It also claimed that code length of a proposition A is proportional to the negative log probability of A - smaller values indicating a higher likelihood. In the Bayesian framework, the maximum posterior probability (MAP) is also correlated with the negative log probability of A. It is evident the process of the brain as a sensory information processor and the similarity of probability features of Bayesian perception are both integrated with information theory. This is another similarity both domains of perception have in common in different ways.

Conclusion

This paper has explored two dimensions of human perceptions and has discussed comparisons of both approaches. One fundamental commonality between both domains is that both the statistical framework and the neurobiological hardware cannot perform their tasks without the input of sensory data. Next, the two approaches to learning were shown as contrasting. Learning in a Bayesian theory refers to belief updating and incremental distributional learning while learning in a neuroscientific sense means representational plasticity in the brain. Both perspectives also show bias towards simplicity and rationality as most optimal. Lastly, information theory is applicable to both Bayesian perceptual models and the neuroscience of human perception.