Predicting upcoming actions by observation: some facts, models and challenges

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May 21, 2014

Abstract

Predicting another person’s upcoming action to build an appropriate response is a regular occurrence in the domain of motor control. In this review we discuss conceptual and experimental approaches aiming at the neural basis of predicting and learning to predict upcoming movements by their observation.

Key words: Action anticipation, bayesian approach, statistical model selection, motor prediction

Short title: Predicting actions by observation

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1 Introduction

How does the brain predict an incoming movement? This requires an efficient coding of the movement features, including the context in which it occurs. As matter of fact, predicting movements in a variable environment is a fundamental aspect of skilled motor behavior (cf., for instance, [12], and [16]).
Prediction is essentially a statistical inference task. This is in part due to the noise associated to stimuli detection and processing as well as to the intrinsic stochasticity of the brain functioning. This is also due to the fact that predicting means choosing the next state of the upcoming movement given the knowledge of the past steps and of the inferred context. This choice is guided by an evaluation of the probabilities of the action’s possible outcomes.

Statistical inference requires a probabilistic model. This means a set of possible outcomes and a probability measure assigning a number between 0 and 1 to every event that can be expressed in this set of outcomes. In the case of motor prediction the brain must operate with a probabilistic model evolving in time, incorporating the past experience of the agent. This time evolution should allow to model the capacity of plastic change and adaptation found in motor systems, which is maintained throughout life by learning and learning-to-predict mechanisms.

This leads to a set of basic questions. First of all, how does the brain build the probabilistic models used to perform the statistical inference tasks required by motor prediction, and, more generally, to produce actions? How do these models evolve in time so as to incorporate former experiences and corresponding inference results? How should the model represent the network structure involved in the inference task? Discussing these questions from a neuromathematical point of view is the goal of the present text.

In Section 2 we present a set of experiments aiming at the neural basis of estimating upcoming actions performed by others. In Section 3 we briefly review how the bayesian perspective takes this experimental framework into account. In Section 4 we show that the bayesian approach is just an example of a more general framework, namely the statistical model selection approach. Finally, in a conclusion section, we briefly discuss new perspectives and challenges in modeling action prediction.
2 Predicting actions through observation: some neurophysiological evidence

Voluntary movements consist in transforming an action goal into a movement appropriate to a given context (review in [22]). In humans, this task is achieved by a widespread network of brain areas recruited both before and during action execution. A subset of these areas is also active whenever one observes, simulates or imagines an action, even without any explicit motor output (review in [11]). Within this framework, anticipating other agents’ motor behavior from the observation of their ongoing actions could lead to the recruitment of neural circuits similar to those enrolled in motor planning and execution. An extensive review of this field is outside the scope of this paper. Thus, we will herein briefly visit a set of experiments addressing such conjecture.

Kilner et al. (2004) investigated whether the readiness potential, traditionally described as an electrophysiological marker of motor preparation ([5], [21]), could also be detected whenever an observer expected an upcoming action to occur in a visual display [13]. The experiment consisted in randomly presenting videos depicting hands either in resting position or while grasping a glass. Before the beginning of the experiment, subjects were informed that each time the glass was green the actor would grab it, whereas whenever it was red, no action would be depicted on the display. Results showed a readiness potential in the green condition, that is, when both the nature and onset time of the upcoming action was predictable [13]. In contrast, no readiness potential was evoked in the red condition. These results suggested that the mere knowledge of a coming action automatically activates the motor system. The authors concluded that, besides being a marker of motor preparation, the readiness potential might also be regarded as a neural correlate of motor prediction [13].

In a very similar paradigm, Fontana et al. (2012) investigated the contribution of two key regions in anticipating upcoming actions performed by others [8]. The authors examined whether a readiness potential was generated in chronic stroke patients with focal lesions either in the parietal or the premotor cortex when they expected to observe an upcoming movement in a visual display. They found that the readiness potential was
preserved in the patients with premotor lesions but not in those with parietal lesions. These results suggested that the parietal cortex integrity is important in the capacity of estimating the occurrence of upcoming actions performed by others. As the parietal cortex is thought to create forward models of intended movements ([6], [3], [4]), the failure found in parietal patients in anticipating the onset of an observed action was interpreted as due to an impaired action prediction mechanism.

In another line of evidence, Aglioti et al. (2008) applied transcranial magnetic stimulation in the primary motor cortex to investigate the dynamics of action anticipation and its underlying neural correlates in professional basketball players [2]. The participants were exposed to videos presenting basketball players performing correct (IN) and incorrect (OUT) free shots. The results showed an increased motor evoked potential response in hand muscles of elite athletes (but not in novices nor in basketball expert observers) for the OUT shots. This indicates that high levels of motor expertise are linked to the fine-tuning of specific anticipatory resonance mechanisms. Furthermore, these results strongly suggested that these anticipatory mechanisms are dependent on a previous motoric experience [2]. Taken together, this set of results indicates that the ability to anticipate upcoming movements performed by other agents (or else, anticipating their outcomes) draws on brain areas enrolled in motor control ([13], [2]), certainly involves prior learning ([2], [10], [18]) and seems to depend on the parietal cortex’s integrity [8].

Now the question is how does the brain process actions being performed by other agents to anticipate/predict upcoming movements. The bayesian framework has been suggested as a possible approach to model the way the brain chooses a most likely outcome, using both its past experience and the new online information provided by external stimuli (cf., for instance, [15], [14], [7] and [17]). In the next session this framework will be briefly presented.

3 The bayesian approach

The brain operates in the presence of incomplete evidence. It must assign patterns to observed actions, either to react in an appropriate way, or just to give meaningful interpretations to observed scenes. The incomplete evidence is provided by sensory information.
Using this incomplete and noisy information, the brain must make predictions about the state of the world.

To express this situation mathematically we must define a probabilistic model. The first component of the probabilistic model is the set $\Omega$ of possible outcomes. The set $\Omega$ is traditionally called the sample space. In the present case $\Omega$ is a set of ordered pairs. The first element of the pair is the hidden variable, say $s$, expressing a state of the world that it is not directly observed. The second element of the pair, say $x$, is the available observed information about this hidden variable provided the sensory stimuli. Therefore, if we call $\mathcal{S}$ the set of hidden variables and $\mathcal{X}$ the set of observed variables, we have that the sample space $\Omega$ is the cartesian product of $\mathcal{S}$ and $\mathcal{X}$

$$\Omega = \mathcal{S} \times \mathcal{X}.$$

The second ingredient of a probabilistic model is a probability measure $\mathbb{P}$ associated to the sample space. In the bayesian framework this probability measure is defined as a mixture of measures. More precisely, $\mathbb{P}$ is defined as a weighted combination of conditional probabilities on $\mathcal{X}$, with weights defined through a distribution on the set of hidden variables $\mathcal{S}$. If we assume that the sets of hidden and observed variables are countable sets, then this can be expressed as follows. For any element $x \in \mathcal{X}$, we have

$$\mathbb{P}(x) = \sum_{s \in \mathcal{S}} \mathbb{P}(x | s) \mathbb{P}(s).$$

(1)

The above formula was written assuming that the sets $\mathcal{S}$ and $\mathcal{X}$ are finite or at most countable. However, usually motor control data assumes real or even function values. In this case, and in general, whenever the sets $\mathcal{S}$ and $\mathcal{X}$ are not countable, the sum in formula (1) must be replaced by an integral and $\mathbb{P}(x | s)$, interpreted as a density function.

The distribution on $\mathcal{S}$ which defines the weights in formula (1) is called the a priori distribution. The a priori distribution contains the previous information about the statistical distribution of the states of the world available before the experience producing the observed variables takes place. The conditional probability $\mathbb{P}(x | s)$ tells how likely it is to get the observable value $x$, given that the hidden state of the world is $s$.

To illustrate these notions consider the case of a duel, in which a swordsman faces an armed opponent. In this case, predicting the motion of the opponent’s sword is really
a matter of life or death. The observable variable is the one given by the observation
of the motion of the opponent’s sword. This observation is noisy and contains a certain
amount of imprecision. Previous knowledge of fencing techniques tells the swordsman
how to interpret the hidden intentions of his opponent. Even better if he has previous
knowledge of his opponent’s style. All this previous knowledge is embodied in the a priori
distribution. The prediction of the hidden goal of the opponent is made by evaluating
the possible goals of the opponent, taking into account the observable movement of the
opponent and evaluating these possibilities using as weights the a priori knowledge of his
opponent’s style.

Formally this is done using formula (1) and the definition of conditional probability

\[ P(s \mid x) = \frac{P(s)}{P(x)} P(x \mid s). \]  

Equation (2) is the famous Bayes formula. It shows that the best prediction about the
hidden state of the world, given the observable evidence \( x \), is the state \( s \) which maximizes
\( P(s)P(x \mid s) \).

This shows how the available evidence is evaluated using the previous knowledge con-
tained in the a priori distribution. Given the empirical evidence \( x \), the distribution \( P(\cdot \mid x) \)
on the set of hidden states of the world \( S \) is called the a posteriori distribution. It encap-
sulates our new knowledge about the probability distribution of the hidden states of the
world, taking into account the new empirical evidence provided by \( x \).

At this point it is interesting to make a comparison between the bayesian approach to
statistics and the classical frequentist point of view. In the classical frequentist approach to
statistics, the parameters of the unknown probability measure are estimated using the Law
of Large Numbers, and the Central Limit Theorem is used to obtain confidence intervals or
regions for these estimations. The Law of Large Numbers and the Central Limit Theorem
are asymptotical results. They hold when the sample size diverges to infinity. In other
terms, the quality of the estimation increases with the size of the sample.

An estimation based on an asymptotical result is not what the swordsman really needs.
He cannot wait until he has a large sample of movements of his opponent to estimate
what is the goal purchased by his opponent sword in his first and maybe final attack. He
must defend himself immediately. That is what makes the bayesian approach much more attractive to him.

In the bayesian approach the estimation is done immediately. The swordsman uses his previous knowledge of his opponent’s style and fencing techniques as weights to evaluate what is his opponent’s most likely goal, given the empirical evidence contained in the visible data $x$.

Both the swordsman and the brain must make decisions in real time, without waiting until a large sample of evidence is available. This does not mean that the accumulated past experience is not taken into account. Actually, every time new empirical evidence arrives, we update our knowledge about the probability distribution on the set $S$ of the states of the world. The previous a priori distribution is replaced by the a posteriori distribution obtained using the visible variable provided experimentally. This a posteriori distribution becomes the new a priori distribution, and so on.

To exemplify, let us now rephrase Kilner et al (2004) and Fontana et al (2012) in bayesian terms ([13], [8]). In this case, the set of states of the world $S$ has two elements: action $a$ and no action $n$. The set of observable variables $X$ also has two elements: green condition $g$ and red condition $r$.

The a priori distribution implicitly considered in Kilner et al (2004) and Fontana et al (2012) assigns equal probabilities $1/2$ and $1/2$ to each state of the world. In bayesian terminology, an a priori distribution which assigns equal probabilities to all the states of the world is called non informative.

Finally, the conditional probabilities $\mathbb{P}(\cdot \mid a)$ and $\mathbb{P}(\cdot \mid n)$ are degenerated, in the sense that each one of them assigns probabilities 1 or 0 to each one of the observable variables, namely

$$\mathbb{P}(g \mid a) = 1 \text{ and } \mathbb{P}(r \mid a) = 0$$

and

$$\mathbb{P}(g \mid n) = 0 \text{ and } \mathbb{P}(r \mid n) = 1.$$
hand, given that the state of world is no action, the probability of having the red condition is 1 and probability of having the green condition is 0.

Using now Bayes formula (2), we now compute the a posteriori probability and obviously they are also degenerated. Namely

\[ P(a | g) = 1 \text{ and } P(n | r) = 0 \]

and

\[ P(a | r) = 0 \text{ and } P(n | n) = 1 \].

In other terms, in this experimental setup, the action is predicted with probability 1, whenever the observed variable was the green condition, and the state of no action is predicted with probability 1, given that the observed variable was the red condition.

This results in a situation where, after several repetitions per condition, a measurable parameter (the readiness potential) was extracted from the brain signal in the green condition but not in the red condition. This was taken as an evidence that the readiness potential would be a marker of predictive coding [13]. In the case of parietal patients this predictive mechanism would be supposedly dysfunctional. This is coherent with the experimental result which shows no marker of motor preparation to incoming movements performed by other agents (i.e, the green condition) for this group of patients [8].

There is a practical reason to work with events which have probability either 0 or 1. The reason is the difficulty to identify evoked potentials trial by trial. As a matter of fact, the experiments presented above use a large number of perfectly synchronized trials to extract a readiness potential from the otherwise noisy EEG signals. In these cases the analysis strategy consists in making an average of the signals obtained in the repetitions so as to eliminate the fluctuations of the EEG signal. Therefore, with this approach, only events which occur with probability 1 or 0 will be extracted from the experimental data. To get evidence of the occurrence of events with a probability strictly between 0 and 1, one should be able to identify the evoked response in a trial by trial basis. This requires new signal processing procedures as the ones proposed, for instance, by [19] or by [1].

Now a more general question is: how to infer from this or any other electrophysiological data the mechanisms by which the brain builds such estimates. Any attempt to model the
brain’s inference activity must be able to describe the way this inference machine evolves in time and incorporates previous experiences. This issue will be discussed in the next section.

The bayesian predictive solution described above is an example of a more general framework. Namely, given a sample of observable variables, how to assign a model for the source producing this data. In statistical terms this is called statistical model selection. This suggests a new paradigm not only for motor learning and prediction, but more generally to describe the way the brain encodes and processes information.

4 Modeling the brain activity using statistical model selection

In Aglioti et al. (2008), the corticospinal excitability of hand muscles was modulated in elite basketball players whenever an OUT shot was about to occur [2]. This was taken as an evidence that the motor system was estimating the result of the shot beforehand. Such effect was absent both in trained observers and in novice players, suggesting that the learning and retrieval of such motor representations is crucial to bring forth the brain activity corresponding to the next upcoming movement in the context of observation.

This experiment can be rephrased as a statistical model selection procedure performed throughout time. The observer encodes in a suitable way each successive step of the action being performed by the player in the movie. Each step is encoded by a symbol summarizing the main features of the observed action. This translates the movie into a symbolic chain. This chain is intrinsically random, in other terms, the movie is encoded as a realization of a stochastic chain. Acting as a statistician the brain uses the information provided by the successive steps of the movie to identify in an adaptive way the probabilistic structure of the stochastic chain producing the sample. And then it uses the transition probabilities identified in this way to predict the successive steps of the action.

Let us state this in a more formal way. Denote by $A$ the set of all symbols used to encode each step of the observed action. To simplify, we assume that the set $A$ is finite. For each $n = 1, 2, \ldots$, let $X_n$ denote the symbol belonging to the set $A$ which was used to
encode the $n^{th}$ step of the action.

The sequence of symbols

$$X_1, X_2, X_3, \ldots,$$

produced in this way can be interpreted as a realization of a stochastic chain, which is a mathematical term to denote a discrete time evolution affected by chance. The question is which stochastic chain should be used to fit in an economic way the observed symbolic chain. This is precisely the goal of a statistical model selection procedure.

Model selection involves the choice of a class of candidate models and the choice of a procedure to select a member of this class, given the data. Stochastic chains with memory of variable length are good candidates to represent in an economic way random stationary sources producing sequences of symbols.

Chains with memory of variable length appear in Rissanen’s paper called *A universal data compression system* ([20]). His idea was to model a string of symbols as a realization of a stochastic chain where the length of the memory needed to predict the next symbol is not fixed, but it is a function of the string of the past symbols.

It turns out that in many data sets consisting of the strings of symbols, the length of the relevant portion of the past is not fixed, on the contrary it depends on the past. Rissanen’s ingenious idea was to construct a stochastic model that generalizes this notion of relevant portion of the past to any kind of symbolic strings. This obviously includes symbolic chains obtained by encoding the successive steps of the action being performed by a basketball player and any other kind of action.

In ([20]) Rissanen called context the relevant part of the past. The law of the stochastic chain is defined by the set of all contexts and an associated family of transition probabilities which gives the probability of the next symbol, given a context. The set of contexts expresses in a precise and economic way the structural dependencies present in the data.

Besides the choice of a class of candidate models, model selection also requires the choice of a procedure to select a member of the class of candidate models. For the class of chains with memory of variable length this issue has been addressed by an increasing number of papers, starting with [20] who introduced the so-called Algorithm Context. For a recent result on this area and a more extensive bibliography we refer the reader to [9].
The Algorithm Context works in an adaptive way. It estimates at each step the length
of the context associated to the string of symbols observed until that time step, as well
as the associated transition probability. In other terms, the Algorithm Contexts checks
at each step how much of the past information present in the observed chain is relevant
to predict the next step. It gives as an output the shortest suffix of the past symbols
obtained in this way as a candidate context. This procedure is done in real time and when
the sample is big enough, the algorithm identifies in a precise way each one of the contexts
characterizing the chain producing the sample.

It is tempting to conjecture that the adaptive procedure performed by the Algorithm
Context mimics in some sense the statistical procedure performed by the brain when it
selects in real time a model for the action being performed by another agent. And if this
picture is correct, then the model for the observed action, in other terms, the neural code
assigned to the action, can be described as a set of contexts and a family of associated
transition probabilities.

5 Challenges and perspectives

Statistical model selection in suitable classes of stochastic chains should be a major notion
in neuroscience modeling. Research in motor control and prediction would particularly
benefit from modeling actions as realisations of stochastic chains. Within this framework,
the prediction of the next steps would be performed throught time, in an adaptive way,
by assigning more and more effective models based on a statistical procedure strongly
reminiscent of the Algorithm Context. Such approach might likely allow inferring about
the mechanisms by which the brain predicts upcoming actions.

Implementing this point of view requires the introduction of new classes of stochastic
systems describing the time evolution of neural networks in simple and economic way.
These models must be simple enough to be analysed in a mathematically rigourous way.
At the same time, these models must display some of the important qualitative features
of these networks. This combination of simple models with complex and realistic behavior
is essential to make progress in the understanding of the brain activity. An example of a
simple mathematical model of this type was recently introduced in Galves and Löcherbach
(2013)([?]). The development of these new classes of stochastic systems is a challenge for mathematicians.

In parallel, the development of this new statistical model selection paradigm requires the invention of new procedures allowing to challenge this paradigm from an experimental point of view. What kind of experimental evidence would reject the assumption that the brain learns and interpret the world by performing a model selection procedure? To the best of our knowledge, neuroscience is still not able to describe how the brain could possibly perform statistical analyses. Making progress in this direction is a major challenge for neuroscientists.

Acknowledgments

This work is part of CAPES/Nuffic project 038/12, USP project Mathematics, computation, language and the brain and was done as an activity of FAPESP’s Research, Innovation and Dissemination Center for Neuromathematics-NeuroMat (FAPESP grant 2011/51350-6). CDV and AG are partially supported by CNPq fellowships (303247/2011-8 and 309501/2011-3 respectively) and CNPq grants (480108/2012-9 and 478537/2012-3 respectively). CDV is also supported by FAPERJ (grant E26/110.526/2012). CDV thanks Numec-USP and AG thanks INDC for hospitality.

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