Finding Faults in Autistic and Software Active Inductive Learning

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Abstract

We analyze the cognitive learning skills of children with autism from the standpoint of active inductive learning. We start with the hyper-sensitivity which leads to the broken links between perceptions of different modalities, lack of adequate capability to perceive real world stimuli, which then leads to auto stimulation and autistic cognition. We draft a software active learning system which behaves in a similar way, going through the same cognitive steps. The commonalities in deficiencies of autistic and software active learning systems are analyzed. We hypothesize that the autistic learning system, starting with just a hyper-sensitivity feature without other deficiencies, can potentially evolve in a faulty inductive learning system, deviating stronger and stronger from a normally developed systems at each iteration of learning process. This paper confirms that the autistic cognitive process is plausible in terms of an abstract computational learning system.

Introduction

It is well known that sensory perception of children with autism is rather peculiar. Nevertheless, it is surprising how children with autism are so tolerant to the bright flash of light, loud sounds and noisy crowds. At the same time, a vast number of children with autism successfully ignore one kind of sensory stimulus and totally intolerable to the others.

Specialists experience difficulties carrying out rehabilitation sessions for children with autism. These children with unique but extremely selective memory refuse to memorize basic things. They can form simple and complex sequences from various subjects and action, but at the same time refuse to reproduce simple schemata suggested by their teachers. Also, they possess structural knowledge about a broad range of objects and observations of the real world; however they are unable to tackle causal links in real world, obvious for control children.

Most of times, the main issue of autistic rehabilitation of autistic children is establishing a "common language" between a child and a teacher. *A child with autism perceives the real world in a totally different way than a teacher.*

In this paper we describe an autistic learning mechanism from the computational learning standpoint. Autistic learning system is initially adequate but hyper-sensitive, and deviates stronger and stronger from both development of control children and adequate machine learning systems. Instead of collecting richer and richer stimuli of the real world, it learns to ignore them and substitute with auto stimulation. Attempting to recognize real stimuli, such learning system receives negative reward. We simulate such behavior computationally and explain how initial hyper-sensitivity leads to a number of limitations of learning system, inherent to autistic learning.

The learning paradigm in this paper is three-fold:

- We use *deterministic* learning model to avoid uncertainty features and maintain as simple model as possible;
- We use *inductive* learning to obey a clear cause-effect structure, following the traditional inductive schema. The commonality in stimuli is assumed to cause an effect (a target feature) which is a basis of learning framework being considered.
- Learning is *active*, since the system needs to select elements of training set by itself.
- Learning is *reward-based*, so each correct stimulus recognition problem solved is rewarded. Incoming stimulus are selected from the real world, and the learning

system itself chooses the best stimuli to recognize. We refer the reader to (Galitsky et al 2007) for the machine learning framework that is the closest to what we use to assess plausibility of our model of autistic development.

Fig. 1: Avoiding perception of the real world

Autistic way of active learning the real world

In this Section we express the observation about active learning of children with autism expressed from psychological and cognitive standpoint.

From hyper-sensitivity to broken multi-modality

In this work we hypothesize that a route cause of autistic cognition is hyper-sensitivity to input stimuli. Many studies of the dis-ontogenesis and the peculiarities of the development of children with autism confirm the hypothesis of hypersensitive perception at the earlier stages of ontogenesis. According this hypothesis, it becomes clear that the development of an adequate sensory system by an autistic child is impossible

In the efforts to protect themselves from stimuli which are too strong (Fig. 1), they develop a mechanism to filter out these strong stimuli (which are also more informative) and perceive weaker ones, less informative, but with a higher similarity with each other. Due to the hyper-sensitivity, a child with autism is over-selective to the stimuli of external world. As an example of such stimuli in visual space, let us consider recognition of (1) child's mother and (2) repetitive TV commercials. Since the perceived image of mother's face varies more significantly (facial expression, face position, condition of illumination) than the perceived image of repetitive TV commercials (which are essentially the same stimuli), the latter turns out to be a preferred type of stimulus which drives the development. At the same time, the former stimuli can be filtered out as being too strong (due to its variability and therefore higher recognition efforts). A partial case of stimuli with high similarity is repetitive stimuli, which go through the whole path of autistic development. All children select to use most repetitive stimuli as possible as the training set, however autistic children only select most repetitive stimuli and do not proceed beyond them. As a result of this initial problem, children with autism stop exploring human behavior and do not communicate properly with their mothers and other humans.

We attempt to simulate the phenomenology of early development of autistic cognition as a choice of perception mode in the conditions of hyper-sensitive sensory system:

1) a child selects, or capable of, recognizing humans such as parents and relatives, which requires multimodal perception, classification of rather distinct images in a single pattern, and further emotional and mental development.

2) a child follows an "easier" way of perception, considering only very similar patterns coming as a sequence, such as TV commercials. Then this child is deprived of mental and emotional development due to his incapability to perceive humans and their mental attitudes (Nikolskaya et al 2000, Shpitsberg 2005, Galitsky 2013).

Notice that if a machine learning system is fed with very similar elements of the training set, it will have a problem of recognizing even very similar objects to the training ones. Moreover, it will be unable to recognize the ones with significant deviation from the elements of the training set, therefore the whole learning capability will be lacking. To be rewarded, such learning system would need to find input stimuli which are alike to be able to recognize them.

At the same time, to avoid unsuccessful recognitions, the learning system would need to do without complex stimuli, especially those requiting multiple modality signals to be recognized (visual, auditory, tactile; Giard & Peronnet 1999; Zmigrod & Hommel 2010, Fig. 2-3). Selectively blocking of a particular modality allows avoiding a stimulus which is too strong (for a machine learning system, too different to what has been in the training dataset). Hence we conclude that a hyper-sensitivity may lead to a condition where links between perception system for various modalities are not reinforced and therefore become dysfunctional at the next steps of autistic development.

Fig. 2: Visual and tactile multi-modal perception (Sunny World 2013)

Features of autistic development

It is amazing that the features of autistic behavior are also shared by children with other mental disorders such as cerebral palsy, Down syndrome and others. We suggest that in the case of failure in the processes and mechanisms of perception due to various reasons, a child forms an "autistic" model of adaptation to the real world as most efficient and less harmful for him. There is a necessity of adaptation to the conditions of life, changing under internal and internal forces. This adaptation, being the main driver of the behavior of a developing child, makes him revise his own behavior patterns to meet the only perceivable criterion: the feeling of satisfaction and comfort (safety).

Because autistic sensory and behavior control mechanisms does not fit the real world, children with autism experience failures after failures, forming their behavioral experience, unlike control children which are fairly successful at learning these control mechanism from real world. This is true for autism as well as other disorders, such as tonic regulation under cerebral palsy.

The only way of successful learning from the real world is permanent confirmation that the learned control patterns are adequate to the real world. The control patterns are further advanced and adjusted to changes in the real world if the learner feels a success of newly formed control patterns.

Under normal development, based on success in her own investigative experience, a child builds an adaptive model of behavior. This model is oriented to the consecutive investigation of the real world and successful adaptation. All behavioral forms target receiving various feeling of the real world, and as a result various forms of communication with this world develops, including speech. Also, the experience of social interaction is gained.

Under anomalous development, a child experiences a constant discomfort interacting with the real world. There many reasons for this: a child with autism cannot grab an object, mentally retarded child cannot understand what an adult wants from him, and a child with autism experiences discomfort from interaction with another person or an object from the real world. Such a child rebuilds his adaptation mechanisms so that feelings come from his internal world, not the real world. This child satisfies his natural desire in feelings by means of stimulus he forms himself. In this case he pleases himself by the successful feelings at the both tactile/sensory and intellectual levels. In the case of infantile type of mental development of children with cerebral palsy we encounter an extensive and saturated world of phantasies. This world of phantasies is intended to replace the negative sentiments associated with the perception of the real world. As a result, the behavior of such child becomes "autistic", the desire to receive feelings from the real world is replaced by the desire to receive feelings which are formed by this child "directly", without physical means. In this case the auto-stimulation of a child with autism, mental retardation and cerebral palsy can be similar. The purpose of auto-stimulation is to assure the comfort feelings in the conditions when the feelings from the real world are impossible (Fig. 3). Under such development scenario it is impossible to form an adequate adaptation system for the real world. We refer to this scenario as dis-ontogenesis; under this scenario the demand to develop communication skills is minimal down to the total lack of the necessity to communicate.

We suggest the anomaly occurs in the process of early formation if sensory system (before the age of 1,5–2 years), and afterwards, as a result of usage of the improperly formed sensory system, "sensory stereotype".

When one observes the behavior of a child with autism 2-3 year old, it is the second stage of the development process. At this second stage, a child tries to interact with the real world based on the anomalous sensory system built on the first stage. This first stage is primarily oriented at the protection of unknown stimulus and at finding familiar stimulus which can be understood.

Two factors lead to this: broken mechanism of interaction with the real world, and decrease of the threshold of affective discomfort caused by this interaction. In other words, the latter factor is connected with the increased sensitivity to sensory signals.

Control children learn to recognize objects of the real world correctly because:

1. improving the technique of focusing at an object, relying on the skills of ignorance of secondary, noisy information.
2. the coordination of sensory signals from various systems and the analysis of various properties of objects being recognized.

Under autistic development, since the majority of sensory signals is perceived as redundant, the child is forced to learn the process of ignoring, decreasing the volume of these signals. As a result, a child with autism learns to avoid the stimuli which are intended for him.

Fig. 3: Movement and perception of space in autistic development (Sunny World 2013)

Instead of systematic development and improvement of sensory systems in the direction of better understanding the real world, a child with autism develops a mechanism to ignore signals from the real world. At the same time, a child with autism develops his sensitivity of the signals which carry minimal sensory information. Instead of the frontal direction, which carries important stimuli, a child with autism perceives the peripheral visual and auditory signals. All bright and powerful stimuli are ignored: eye contacts are avoided, and a child is crying when petted. Sensory mechanisms are built in a way to perceive a minimum of sensory information and nevertheless represent somehow the real world. Hence the capability to merge different sensory systems (visual, auditory, kynestatic) is lacking, binocular vision and binaural auditory systems are not being developed.

Peripheral vision as a way to protect from overwhelming signals has always existed, even in medieval times. One of the examples can be a “puzzled look” of Mona Lisa of Leonardo da Vinci. We hypothesize that it is due to the fact that she uses peripheral vision. If one looks at the painting, it is visible that the face is oriented not along the pupils, but deviates from it. This is typical for people with autism.

If one looks at how an autistic child is tracking a hand of an adult ringing a bell, it is noticeable that this child either watches or hears, but does not do it simultaneously. A merge of sensory stimulus of a child with autism occurs only in the process of the formation of auto-stimulation. This process, being fairly intense, is intended to distract the child from the other stimulus of the real world.

In fact, the possibility to use a merged perception helps us interact with the external world successfully, building behavioral strategies capable of embedding us in this world. The feature of selectivity of perception, formed by a child with autism spontaneously, to decrease the intensity of the sensory input, leads to the lack of capability of perception of the real world and interaction with it.

Recent studies of autism also show a high capability of children with autism to ignore object in the domains they are not interested in. A child with autism concentrates on an object with high intensity and ignores background objects situated very near it. In case of control, such concentration decreases slowly as the objects are further away from the focus of attention.

One can hypothesize that to implement the mechanism of ignoring objects a child with autism develops and improves the fixation mechanisms. This mechanism achieves maximum annihilation of background objects by the property of the object she is being focused on. A child with autism selects less informative sensory features and directions in the real world as preferred, and at the same time develops the stimulus substitution mechanism, substituting unknown (as possibly dangerous) stimulus with the ones well known, his own (auto-stimulus). The mechanism of fixation plays the key role in this feature selection process.

Auto-stimulation can be of “reinforcing” as well as “substituting” natures, depending on how a child is focused on the feature selection process and his capability on combining stereotypical and arbitrary activities. Hence a child with autism stops at an “autistic” self-regulation mechanism as most adaptive for him.

In his further life, when the (intense) period of feature selections is over, a child continues to learn the real world with less intensity, relying on his specifically built sensory system. Peripheral sensory directions advance, and the real world is perceived by means of discreet signals, which are correlated neither within a single sensory mode nor synthesizing different signal modalities. Stereotypes occupy a key position in the sensory system of a child with autism, being "reinforcing" and "substituting". The substituting sensory signals almost completely replace the external ones, and reinforcing assure a stable self-perception, preventing to perceive real external stimuli.

Fig. 4: Visual and tactile auto-stimulation

Inductive Active Learning System

We present an active inductive learning system Jasmine (Galitsky et al 2007) that is based on a learning model called JSM-method of (Finn 1991, in honor of John Stuart Mill, the English philosopher who proposed schemes of inductive reasoning in the 19th century). JSM-method to be presented in this Section implements Mill's idea (Mill 1843) that similar effects are likely to follow common causes. It is a formalization of the framework we observed the learning process of children with autism in Section 2.

The Jasmine framework consists of features (communicative actions), objects (scenarios) and targets (features to be predicted: classes of scenarios). Within a first-order language, objects are atoms, features and effects (targets) are terms which include these atoms. For a target, there are four groups of objects with respect to the evidence they provide for this target: Positive – Negative – Inconsistent - Unknown.

An inference to obtain a target feature (satisfied or not) can be represented as one in a respective four-valued logic. The predictive machinery is based on building hypotheses, *target(S):- feature*$_1$*(S, ...), ...,feature*$_n$*(S, ...),* that separate behavioral scenarios *S*, where target is to be predicted. Desired separation is based on the similarity of objects in terms of features they satisfy. Usually, such similarity is domain-dependent. However, building the general framework of inductive-based prediction, we use the anti-unification of formulas that express the totality of features of the given and other objects (our features do not have to be unary predicates; they are expressed by arbitrary first- or second-order terms).

JSM-prediction is based on the notion of similarity between objects. Similarity between a pair of objects is a hypothetical object which obeys the common features of this pair of objects. In this work we choose anti-unification of formulas expressing features of the pair of objects to derive a formula for similarity sub-object (Finn 1991). Anti-unification, in the finite term case, was studied as the least upper bound operation in a lattice of terms.

Let us build a framework for predicting the target feature V of objects set by the formulas *X* expressing their features: *unknown(X, V)*. We are going to predict whether $V(x_1, ..., x_n)$ holds or not, where $x_1, ..., x_n$ are variables of formulas *X*.

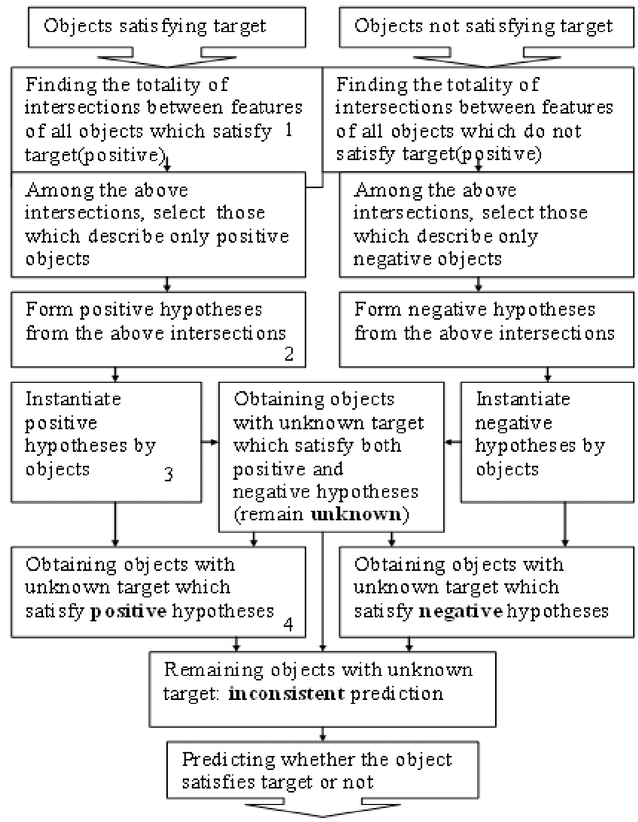

Fig. 5: A chart for a generalized active inductive learning procedure with positive and negative cases.

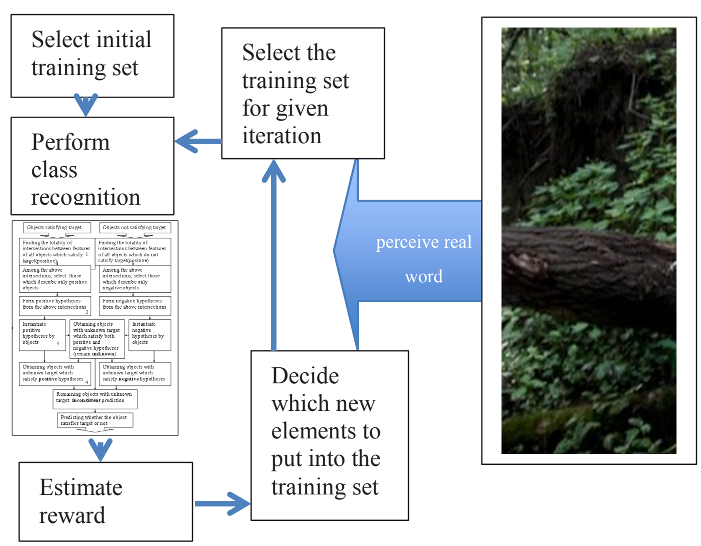

Fig. 6: Active learning loop

We start with the raw data, positive and negative examples, *rawPos(X, V)* and *rawNeg(X, V),* for the target *V*, where *X* range over formulas expressing features of objects (Fig. 5). We form the totality of intersections for these examples (positive ones, *U*, that satisfy *iPos(U,V),* and negative ones, *W*, that satisfy *iNeg(W,V)*, not shown). Notice the correspondence between the steps in formula numbers and components of the chart Fig. 5.

iPos(U, V):- rawPos(X1, V), rawPos(X2, V), X1\=X2, similar(X1, X2, U), U\=[ ].

(1) *iPos(U, V):- iPos(U1, V), rawPos(X1, V), similar(X1, U1, U), U\=[ ].*

Above are the recursive definitions of the intersections. As the logic program clauses which actually construct the lattice for the totality of intersections for positive and negative examples, we introduce the third argument to accumulate the currently obtained intersections (the negative case is analogous):

iPos(U, V):- iPos(U, V, _).

iPos(U, V, Accums):- rawPos(X1, V), rawPos(X2, V), X1\=X2, similar(X1, X2, U), Accums=[X1, X2], U\=[ ].

iPos(U, V, AccumsX1):- iPos(U1, V, Accums), !, rawPos(X1, V), not member(X1, Accums), similar(X1, U1, U), U\=[ ], append(Accums, [X1], AccumsX1).

To obtain the actual positive posHyp and negative negHyp hypotheses from the intersections derived above, we filter out the inconsistent hypotheses which belong to both positive and negative intersections *inconsHyp(U, V):*

inconsHyp(U, V):- iPos(U, V), iNeg(U, V).

(2) *posHyp(U, V):-iPos(U, V), not inconsHyp(U, V).*

negHyp(U, V):-iNeg(U, V), not inconsHyp(U, V).

Here *U* is the formula expressing the features of objects. It serves as a body of clauses for hypotheses *V :- U*.

The following clauses deliver the totality of objects so that the features expressed by the hypotheses are included in the features of these objects. We derive positive and negative hypotheses *reprObjectsPos(X, V)* and *reprObjectsNeg(X, V)* where *X* is instantiated with objects where *V* is positive and negative respectively. The last clause (with the head *reprObjectsIncons(X, V)*) implements the search for the objects to be predicted so that the features expressed by both the positive and negative hypotheses are included in the features of these objects.

reprObjectsPos(X, V):-
rawPos(X, V), posHyp(U, V), similar(X, U, U).

(3) *reprObjectsNeg (X, V):-*
rawNeg(X, V), negHyp(U, V), similar(X, U, U).

reprObjectsIncons(X, V):-unknown(X,V), posHyp(U1, V), negHyp(U2, V), similar(X, U1, U1), similar(X, U2, U2).

Finally, we approach the clauses for prediction. Two clauses above (top and middle) do not participate in prediction directly; their role is to indicate which objects deliver what kind of prediction. For the objects with unknown targets, the system predicts that they either satisfy these targets, do not satisfy these targets, or that the fact of satisfaction is inconsistent with the raw facts. To deliver V, a positive hypothesis has to be found so that a set of features *X* of an object has to include the features expressed by this hypothesis and *X* is not from *reprObjectsIncons(X, V).* To deliver ┐*V*, a negative hypothesis has to be found so that a set of features X of an object has to include the features expressed by this hypothesis and *X* is not from *reprObjectsIncons(X, V*). No prediction can be made for the objects with features expressed by X from the third clause, *predictIncons(X,V).*

(4) *predictPos(X,V):- unknown(X, V), posHyp(U, V), similar(X, U,U), not reprObjectsIncons(X, V).*

predictNeg(X,V):- unknown(X, V), negHyp(U, V), similar(X, U,U), not reprObjectsIncons(X, V).

predictIncons(X,V):- unknown(X, V), not predictPos(X, V), not predictNeg(X, V), not reprObjectsIncons(X, V).

The first clause above will serve as an entry point to predict (choose) an effect of given features from the generated list of possible effects that can be obtained for the current state. The clause below is an entry point to Jasmine being integrated into an active learning system.

predict_effect_by_learning(EffectToBePredicted,S):-
findAllPossibleEffects (S, As),
loadRequiredSamples(As),
member(EffectToBePredicted, As), predictPos(X, EffectToBePredicted), !, X\=[ ].

Predicate *loadRequiredSamples(As)* above forms the training dataset in an active way, depending on the current recognition results (Fig 6).

If for a given dataset a prediction is inconsistent, it is worth eliminating the cases from the dataset which deliver this inconsistency. Conversely, if there is an insufficient number of positive or negative cases, additional ones are included in the dataset by their active selection. A number of iterations may be required to obtain a prediction, however the iteration procedure is deterministic: the source of inconsistency / insufficient data cases are explicitly indicated at the step where predicates *reprObjectsPos* and *reprObjectsNeg* introduced above are satisfied.

Faulty active learning scenarios in the real world

Hypersensitivity of the learning system can be viewed as a high number of features which are mutually correlated, and therefore redundant. The learning algorithm itself can reasonably tackle such situation of overfitting (Cawley and Talbot 2010), but the active learning would be selecting training objects which would not adequately cover the real world, and therefore its proper recognition will not be occur. To keep being awarded for recognition, the system will at some point stop collecting training objects from external world and start using the existing ones, which is essentially an auto-stimulation (Fig. 4).

If the initial training set includes the objects that are very similar |*U*| is almost the same as |*X1*| and |*X2*| in (1), then learning without automated choice of training set elements can still be adequate, but the active learning does not. It would keep selecting the objects of the real world which are very similar to what the training set already has, to be better rewarded for the current recognition results (Fig. 6).

It turns out that the active inductive learning algorithm presented in the previous section 3 can malfunction in a way which would display the behavior presented in the section 2 of the paper. Once we introduce faulty training set elements due to hypersensitivity, initially the system develops normally and behaves normally. Faulty rules do not cause peculiar behavior of small children, but the active learning scenarios start to deviate. As a result, such forms of autistic behavior as auto-stimulation and a lack of coherence between the perceptions of the features of various types (perception modalities) occur.

Another acquired feature of the faulty active learning system is inability to distinguish important features of the external world (those bringing higher reward) and unimportant ones. In terms of the reward, the faulty active learning system reaches local maximum by means of keep feeding the learning system with the stimuli which have already been recognized. The necessity to transition through the state with lower reward prevents the autistic learning system from evolving to a state where recognizing important features of the external world become possible.

A typical default system of active inductive learning (Mitchell 1997) does not display such faulty behavior, if the training sets (the environment the system conducts its learning) are randomized. However, once we have hyper-sensitivity, which in computational terms is an overfitting for the initial set of training data, the autistic learning system extends this initial training set in a faulty manner. So the consecutive behavioral rules, formed from the adequate data of the real world but selected based on faulty rules, are also faulty. After a number of such iterations, having the adequate training environment and just a small subset of initial faulty training elements, the autistic active inductive learning system forms the majority of inadequate rules which totally misrepresents the external world and applies inappropriate behavior patterns to it. As a result we observe the unnatural behavior and malfunctioning perception outlined in Section 2.

Conclusions

In our earlier studies we built a number of models for autistic reasoning, from the mental world (Galitsky 2002, Galitsky & Shpitsberg 2006) to defaults (Galitsky & Peterson 2005). We also proposed a rehabilitation strategy to cure various forms of autistic reasoning (Galitsky 2003, Galitsky 2013). In this study we attempt to design a plausible machine learning system which shows two forms of behavior, when operating in an active mode of auto selecting the elements of the training set:

1) normal mode, where new features from the real world form the training dataset and form the basis for its proper recognition
2) autistic faulty mode, where the active learning evolves to the set of irrelevant features and although the learning sessions occur, the system is not capable of recognizing the real world.

Hence given the operational learning system, once it becomes hyper-sensitive in an active learning mode, it displays the number of features inherent to autistic cognition:

- Broken multi-modal links
- Auto-stimulation
- Blocking the strong stimuli of the real world
- Distinguishing important from unimportant features.

We proposed a concrete design of a machine learning system reproducing the phenomenology of the studies of children with early autism. In our future studies we will attempt to form the methodology of rehabilitation of autistic cognition, based on the model built in this paper.

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