Proposal: Alter ego nets for human augmentation (A draft)

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Abstract

We introduce an algorithmic model for human object perception. In this model the perceived object functions as a neural net that is answering the user's 'requests'. The perception is modeled by two interactive cycles, resembling the forward and backward propagations of CNN.

During the operation of this model , at 'forward' iterations, the 'internal human paradigm' is updated using the outputs returned by the net representing the perceived object. On the other hand, at 'backward' iterations, the net properties are alternated. We call this model the 'alterego' net.

People see the world differently. Even observing the same content. In other words, the 'seen' content differs from the observed, and, the 'seen' may be different for different people. Practical advantage of the alterego net is that it will allow one to simulate the content 'seen' at human perception.

Tuning the alter ego nets to a person or group of persons, will enable generation of the content representing the 'seen' by the subjects. Thus the alterego nets is actually a human augmentation allowing new applications, like simulation and analysis of the 'seen' by a person, generation of the book summaries 'per person', etc.

In my work on development the alterego nets I use my experience as a computer scientist and as a writer.

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1 The DuWheel Scheme

1.1 Perception of object as a sequence of iterations ('forward')

We consider images of art, symbolic images, mental images the person interacts with etc. We refer to them, without further specifying, the ART objects.

The perception of the ART objects is iterations, not just reading a value. Consider the example of (Figure 3), where hammer and sickle are depicted. The dialog between the person and the object may be schematized as follows. A person unconsciously generates a sequence of words (notions), reflecting its internal 'state'. These may be seen as unconscious to a certain extend thoughts of the person: 'street view', 'weather', ... We call this the general semantic steam associated with the person. The words are send to the ART object, compared with the words/notions associated with the ART object, yielding a word/notion output, that is sent back to the person. The inputs which are not relevant w.r.t. the ART object do not receive the response.

In out example, the person at some iteration step generates $x1$ = 'wanna going for a walk', due to, say, his aspiration. The $x1$ is compared with the words/notions properly associated with the object. And the object 'replies': $x2$ = 'You are going to collective work to help the motherland!' The $x2$ is embedding to the sequence of words generated by the person. Ans the iterations continue.

As these iterations the perceived object is a 'constant' function: receives input and outputs the response. By analogy with the deep learning notation we call these iterations forward.

In the next section we consider how the properties of the perceived objects are changed, in other words, how actually the ART objects are constructed

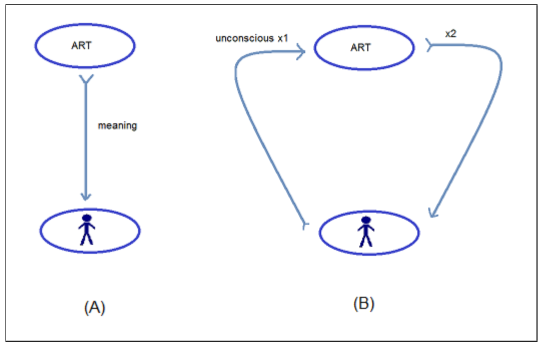

Figure 1: Art object is actually not a object (A) but a cyclic iteration with a person (B).

1.2 Perception of object with alternation of object properties ('forward/backward')

Actual object perseption is not iterations with the constant ATR object - sending and received the data the from the object - but something more compound. It seems to include in itself alternation of the perceived object. In this section we consider two examples, in the next describe the DuWheel scheme of the object updating perception. The operations under consideration resemble the 'forward' and 'backward' that of deep learning, thus we will use this notation.

Refer again to the 'forward' loop (Figure 3). What happens when the ART's output 'work!' come into collision with the person's expectations?

The subject of the person's attention became not internal experiences but the ART object *itself*. The 'work!' begins to be considered as an attribute of the object. The person as if starts reevaluating of the object with a new attribute And the whole set of the properties of ART is updated according to the new attribute. As the result, we may receive an updated ART object with new properties. For example with a new property "forced labor" replacing the old "free labor" property.

Another example is shown in Figure 10. Suppose we are summoned to a commission that should deal with our case, it known a priori the decision solution may not depend, but may highly depend on the commission's bias, for us or against. [1] The person does not know and hesitates. We start our considerations with forward iterations reflecting the current state of the person. The mental sequence appears: 'they', 'they are kind to us', 'this city light is friendly to us', 'look, they have the same jacket as we have', 'this is a deeply friendly jacket', etc. With some interval, elements of the sequence are verified (iterated) with the (ART) image of the commission and returned to the person (like 'walk' → 'work' above). This is illustrated at Figure 8 where the elements of

[1]this resembles some person's real experience at the oral entrance examination for MSU Faculty of Mechanics and Mathematics in the past

the mental sequence are depicted as green rectangles and the elements returned from the ATR object as blue. In our scenario, 'this is a deeply friendly jacket' is sent to the ART object. And suddenly we obtain the element that is not alligned with our sequence, say, we obtain 'we do not know whether the the jacket is friendly to us' reaction.

At this moment the forward iterations are interrupted, and we switch to the 'backward' iterations, where the object of our consideration become the ART image itself. One may tell the goal of the backward stage is alternation of the properties of the ART object itself. The alternation is induced by evaluation of 'jacketness' properties w.r.t. the ART object .

We begin reevaluating of the object with a new attribute 'the jacket toothy and hostile to us'. We consider a stream - sequence of words/notions refereed to the ART object. We call this the object specific semantic steam (OS3). This stream represents the properties of the ART object, similarly to how the general semantic stream represents the internal human's states.

Among them there are the elements associated with the 'jacket' notion. For example: 'commission', 'people', 'came against us', 'jacket', 'the jacket was just a trick', 'the jacket does not matter', 'they want to frighten us with their uniform', 'the hostile unity of their jackets', ... Some elements are verified versus the ART object using the third party tools like CNN nets for localization and classification of the objects in the scene. This is shown at Figure 9, where the brown rectangles returned from the tool represent new informative element added to the OS3 stream. For example, given an element 'we do not know whether the the jacket is friendly to us' the tool return 'non friendly jacket' element. Actual change of the ART object properties is in what may be called selective summarization - selection of small set of notions consistent with subsets of the stream. For example ('non friendly jacket') and ('my predecessor has suffered from the commission') leads to 'non friendly commission for me' (shown as violet rectangle).

1.3 Comparisionj of dualloops. Remarks on DuWheel scheme

The creation of ART objects proceeds according to the two cycle scheme (Figure 3)

- **duality of DuWheel scheme** The DuWheel scheme of Figure 3 is from the point of view of a person. We may see to this scheme as from the point of view of the ART object.
- **meaning of forward/backward computation** Ref to Figure 1. (B) is a generalization of (A) with empty input
- **meaning of forward/backward computation** Ref to Figure 1. The x2 of (B) may be conscious or unconscious
- **meaning of forward/backward computation** Ref to Figure 1. May we treat any object as iterative?

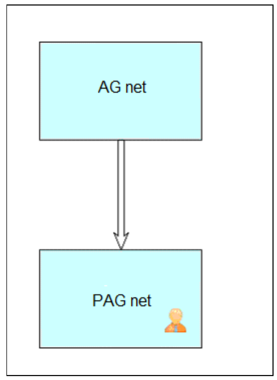

Figure 2: PAG Net

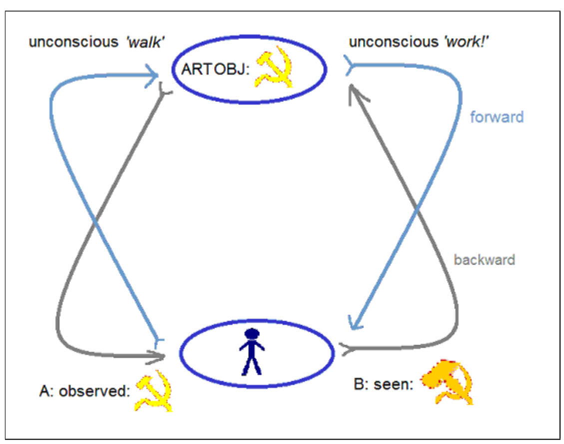

Figure 3: Example of du-wheel scheme: perception of an emblem as unconscious iterations with the person

Table 1: The dual loops: comparision

Activity:	'forward': calulation of the values of the function	'backward': alternation of the function itself
Direction:	clockwise	counter-clockwise
Updated object:	The person's states	The whole ART object:
Examples of the processed objects:	walk $\rightarrow$ work	mill $\rightarrow$ giant; friendly commission $\rightarrow$ hostile commission
Examples of the processed objects at creation of ART object:		'sea' $\rightarrow$ 'Black sea, orating, nears me, resolute, And thunders by my headboard, loud and rough' [2]
Transformation:		conversion of observed (input) content to the seen
Streamer name:	general semantic streamer = support + interleaving stream	object specific semantic streamer = support + interleaving stream
Support stream	a sequence of associations for a person's paradigm	a sequence of associations object properties
Interleaving stream	responses from the object to the support stream	responses from the 3-rd party net to the support stream
Associated terms:	inhale, passive	exhale, active

- In English: observed VS seen. The Russian allows better expression of this duality: vidennoe VS uvidennoe.
- zrimattery

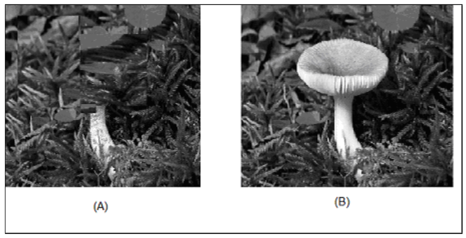

Figure 4: (A)- observed image (B) - seen image: contains the objects 'seen' in the observed object

In the NLP modeling of the backward iteration (section 1.2 the 'seen' is obtained as summarization object 'mushrum' derived from 'stipe'. An alternative approach (not 'deep dream') allow to obtain 'mushrum' within the image.

1.3.1 Difference from deep dream approach

2 The alterego nets

People see the world differently. Even observing the same content. Like this, the 'seen' content is being different from the observed, and, the 'seen' is different for different people.

I propose to create the nets that, given an input content, output the content 'seen' by the net in the input. We call these 'alterego' nets.

I propose to create a new type neural nets. The nets are trained to perceive an input content and expose an output that may be regarded as the content 'seen by the net' in the input.

We call such nets the alterego nets.

One example of alterego nets is a net whose input to the net is a scene, and the seen output is the scene with the embedded image of the sought object, that the net has 'seen' in the input (Figure 2,A,B)

Another example of the 'seen' content is textual representation of the input as shown in 4

Another example of the 'seen' content is textual representation of the input as shown in 5

Tuning the alter ego nets to a person or group of persons (personalization)will allow generation of the content representing that 'seen' by a person or group of persons.

The main application of alterego nets will be personalized alterego nets considered below. The alterego nets are different by:

- semantic level. The net with input 4 A and output 4 1 B is of low level. The net with input 5 A and output 5 B is of high level.
- domain modality. Image domains may be high o low semantic levels. Language domains are of high level.

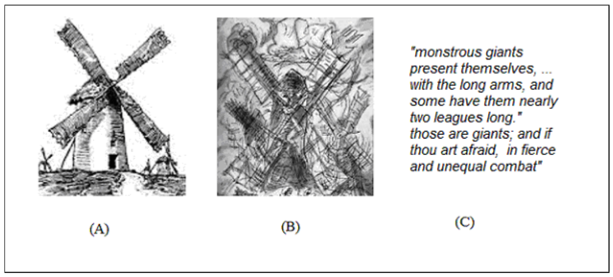

Figure 5: An alterego net may simulate perception of Don Quixote in the episode with windmills. (A): an input image [1] (B): the perceived image of giants [1] (C): textual content 'seen' by Don Quixote [2]. The alterego nets will be trained on the image pairs like (A,B) and (A,C)

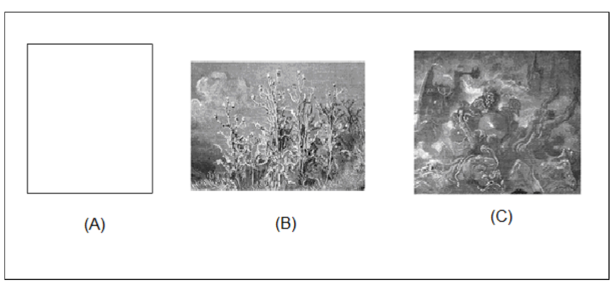

Figure 6: (B): observed (C): seen

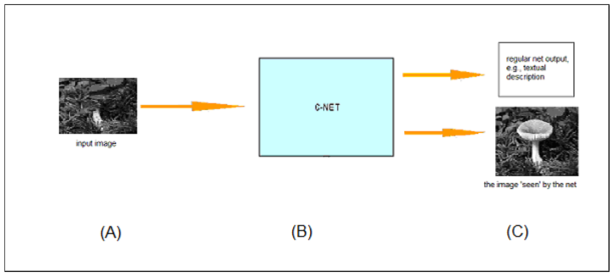

Figure 7: (B): observed (C): alterego net

- observed input may be empty/non empty. 6 (A) and Table 1.

2.1 A one-subject Alterego net

In this section we deal with technical issues and outsketch the suggested implementation of the alterego nets.

2.1.1 general semantic streamer

The *general semantic streamer* (GSS) approximates 'stream of consciousness' of a person that includes the responses obtained from the ART object. One may tell the GSS addresses a person itself.

The GSS is a sequence of words (notions) w_i representing the person's current state, the notions at closer positions are associated in a greater degree. The GSS is comprised of the support and interleaving stream. The former consists of highly associated notions, for example 'they', 'they are kind to us', 'this city light is friendly to us' (Section 1.2). The association may be implemented as dictionary [3]. The answers received from the ART object form an interleaved stream consisting of elements inserted to the support stream. The elements are read from the ART object as described in section 1.1. These may contadict ('walk' *rightarrow* 'work') or be in accordance with the support stream ('friendly jacket'). After insertion they operates as a support stream yielding associated notions.Reference to Figure 8.

2.1.2 Object specific semantic streamer (OS3)

An object specific semantic streamer (OS3) is a stream of words (notions) describing the properties of the ART object. It's stucture is similar to that of GSS. Th OS3 is comprised of the support stream interleaved with the answers about the ART objects obtained from the third party CNN nets. The support stream a sequence of words (notions) related to the perceived object, e.g. 'stipe', 'mushrum', ... (Section 1.2). The elements of the stream may be built using the

[3] it seems literature texts like James Joyce's are suitable

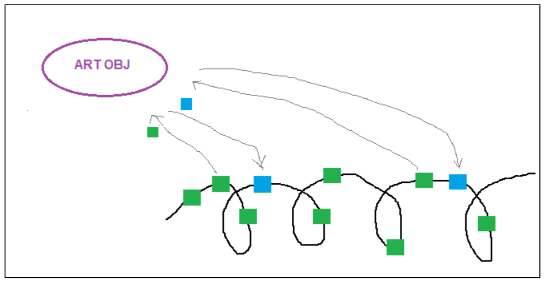

Figure 8: GSS streameR is comprised of support (green) and interleaving (blue) streams

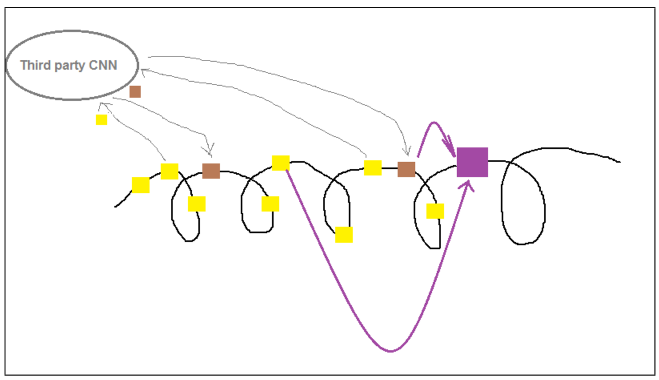

Figure 9: OS3 streamer

dictionaries. The intreleaving stream consists of the third perty answers like: "is mushrum is somwhere in the image?", "which objects are in the image", "are the people of the image friendly to us?". The difference between support streams of OS3 and GSS is in what one may call selective summarization: selection of small set of notions consistent with subsets of the stream. [4]. For example ('non friendly jacket') and ('my predeccor suffred from the comission') leads to 'non friendly comission'. Selective summarization results in updating of the ART object and is the "seen" content of the ART object . It is depicted by violet square at Figure 9 and as "seen" object in Figure 3.

? what is object: oseph of notions aor explicti dictuonary

[] Simulation of perception: duwheel iteration betw

streamer associated with a

Duwheel interaction between GSS and

Consider a simplest situation: given is a set S of words representing some subjects, eg S='movie', 'Paganini', 'Uruguay'...

Run duwheels schemes for the notions.

[4]This may be seen as a kind of compression

2.2 Personalized alterego nets

An alterego net may be fine tuned for a given person concerning the content input/output of the person. We call this the personalization of the alterego net. This may be done for a group of of persons also. Reference to 2

The AG nets will be trained so that their perceived content will approximate that of the respective person. In this way, the alterego nets will allow tight modeling and classification of the respective human's perception. Thus the AG nets as an technological advance w.r.t. 'static' person's profile.

These may be learned analysis of user feedbacks.

3 Appendix

3.0.1 Further development of DuWheel scheme: estetically efficient samples

The nets will be trained using the introduced DuWheel scheme which models human perception of aesthetically efficient samples.

3.1 Training the alterego nets

Training/Testing example is a pair (observed, seen). Alterego nets will be trained on content pairs as (A,B) or (A,C) of Figure 5. Visual and textt data are different in that the textual alterego net may be trained at very small (eg one) number of examples. For visual data .... to 'blind inpainting'. For textual data the interpretation model is a graph that reflects relations (interactions) between the meanings of words, sounds (probably, also, and letters) comprising aesthetically efficient patterns **??**. The model may be tuned on at a single example like the shown in 2.

3.1.1 Training the visual alterego nets

For visual images the net is trained on pairs of Figure 5 A, B. The trained net should given Figure 6 A or B yield the image similar to Figure 6 C.

3.1.2 OLD SCHEME: Training the textual alterego nets

One may explain this effect as follows. These short phrase include a few mutually interacting meanings, the interaction affects the human. The meanings exists at several levels. At low level, interacted are the meanings associated with the letters. At high level, interact the meanings of the words. It is worth to emphasize the low meanings interact with these of high level. The process is similar to perception of visual forms, where detected low level primitives (edges) are interacted with detected high level ones , and the whole process is simultaneously bottom-up and top-down.

Humans learn EE at very small number of examples. For example, a new tuple may be output given one EE example (imitation of an input text, Table

2). We may train a alterego net in similar fashion using model of EE with free parameters. The model describes relations between the elements of different semanic levels. The parameters may be trained given very small number of 'positive' examples. Learning the model parameters resembles learning the NN layers coefficients. [Similarity score for candidates is determined by inexact graph ismorpism.???]

For NLP images the alterego net is the net whose input is fixed and is a dictionary of English words. The output is a series of EE triplets. The net will be trained to 'tell' new EE triplets. Collections of high-level literature texts will be used in the training

3.2 NLP: hierarchy of creativity

3.3 Remarks

- **learninngh at small number of examples** Another application of IP nets is that these will may allow creation of highly personalized user content (adversarial, news, summarization).
- **learninngh at small number of examples** Uchitsya eto ne kopirovat. Dle EE ya mogu buold similar (DPS→GLO). Ya postroil sililar. Ya mogu tak ze similat to obuchoy kakrtinke. Ponyatie similarity drugoe VS EE object is a net. Kogdauchimsya. DElaem TL.(TL et postroenie simil net) Possibility to learn machine at very small number of examples is property of textual data. OBJECTION!: ee paintings
- **terms:** rotam, dual circular flow,Pentium dual rotam, dual circular stream,dual circular flow, circuit, round, cycle,dual chart, dual wheel
- **Question** The alterego net is the creation of ART object? Or the alterego net is the of ART object?
- **Question** The alterego net is the creation of ART object? May ART obj be the internet?
- **IDEA** IDEYA. TO CHTO VOOBSHE EVERY USER IS NET.
- **Question** Ok, every user is net. Chto dast seen conent¿? nu,mozem access it, ispolzovat dlya klassifikatcii. Dali Lozky/ Kak vidit lozku. Kakuyu chochet. Kupit ne kupit,
- **Question** chto izvlech is du schemu krome EE construction? Answered. See thge next item below
- **Question** Kak du scheem svazane s AE net? Otvet:Dobavlyaem loops dlya vsech vozmoznuch objects
- **Question:Why the alterego net simulating person (P) is better then profile information associated with (P)?** chto izvlech is du

Table 2: hierarchy of creativity. Machine given learning example, the machine is able to produce evaluation example.

Level	Learning Example		Evaluation example		Remark	
	Observed	Seen	Observed	Seen		
0	–	Rain Steam speed	–	rain steam speed	repetition	
1	–	rain steam speed	–	gypsum summer faint	imitation	
1	–	the mountains of the far shore swimming in a sunset haze	–	Half-drunk switchman in a red semaphore cap	Creative imitation of specific text	Vladimir Nabokov
2	–	Large text collection	–	Half-drunk switchman in a red semaphore cap	Creative imitation of non-specified text	
3	–	Large text collection	–	Two roads diverged in a wood and I - I took the one less traveled by, and that has made all the difference.	Creation of a new text.	Robert Frost

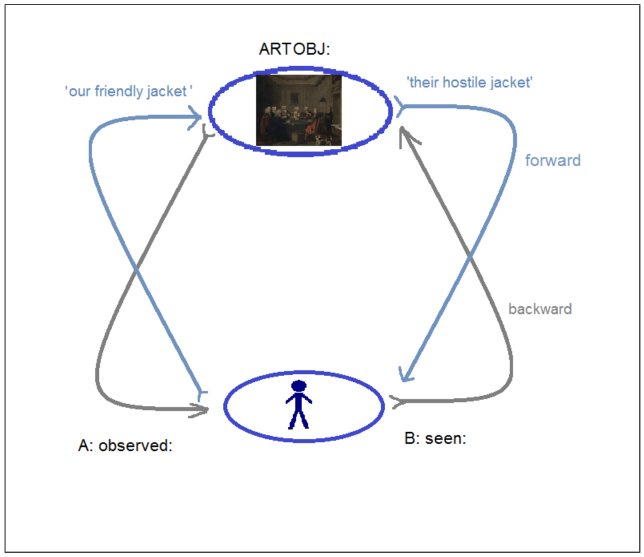

Figure 10: Raw scheme

schemu krome EE construction? Answered. See thge next item below The alterego net exposes approximation to the internal world of P, that should be much more powerful then the profile. Contextually, the output of alterego nets is highly associative/intelligent media .... //why better that plain text?//

1)mozet sami po sebe budut silnee: transfer from intelligence accumulated in the trextsa 2)bolee polnaya simultion of a person. mshiva napevaet kva kva kva. Mozno observe associativnue relations nu current content

- **Difference from summarization** The texts like shown Figure 5 (C) differ from text summarizations of the image (D). The (C) resembles but is not summarization of (A). Also, the (B) resembles but is not (A).
- Difference from deep dream
- DU WHEEL SIMULATES HUMAN PERCEPTION
- **DU WHEEL as GAN**
- The mentioned third party CNN may be a part of 'close box' solution

References

[1] At Figure 10 the 'A Club of Gentlemen by Joseph Highmore' is used as an illustration