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

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Abstract

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.

We 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.

Personalization of alter ego nets will allow generation of the content that approximates the seen by a person or group of persons.

This will be actually a kind of human augmentation that allow new applications, like creation of highly personalized content, estimation of human's preferences, etc

In my work on creation of alterego nets targeting NLP, I will explore my experience as a computer scientist and as a poet.

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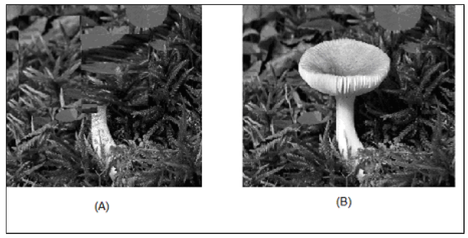

Figure 1: (A)- observed image (B) - seen image: contains the objects 'seen' in the observed object

1 Introduction

2 The alterego nets

2.1 Definition. Examples

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 1

Another example of the 'seen' content is textual representation of the input as shown in 4.4

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 1 A and output 1 1 B is of low level. The net with input 4.4 A and output 4.4 B is of high level.

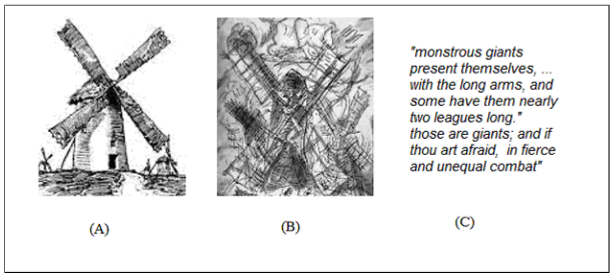

Figure 2: An alterego net may simulate perception of Don Quixote in the episode with windmills. (A): an input image [1] (B): the perceived image of giants [1] (C): textual content 'seen' by Don Quixote [2]. The alterego nets will be trained on the image pairs like (A,B) and (A,C)

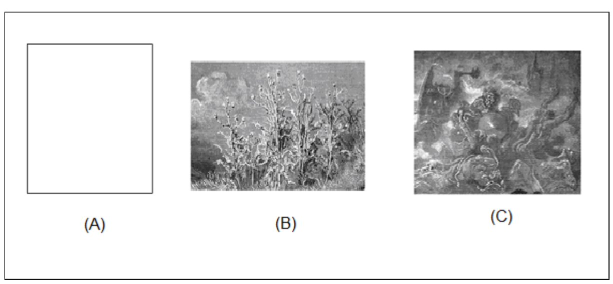

Figure 3: (B): observed (C): seen

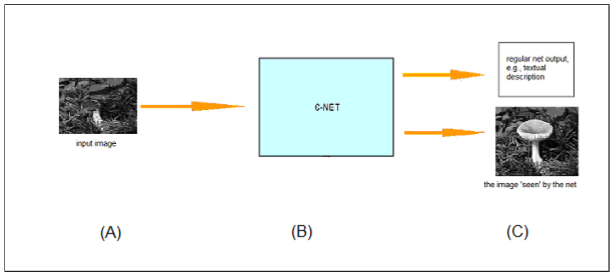

Figure 4: (B): observed (C): alterego net

- domain modality. Image domains may be high o low semantic levels. Language domains are of high level.
- observed input may be empty/non empty. 3 (A) and Table 1.

2.2 Object as Net. The Dual Wheel.

('forward'/'backward': ATR object is a net//perception of ATR object is learning a net The Dual Wheel

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

Consider images of art, symbolic images, etc. We call them, without further specifying, ATR objects. Perception of ATR objects is an iteration, not just reading a value.

Reference to (Figure 6), where hammer and sickle are depicted. The are exist various scenarios of human perception of the symbol.

Many scenarios of perception of the symbol may be seen as 'unconscious' dialog between the person and the object, proceeding as follows.

A person generates an 1-d sequence of words/notions, reflecting its internal 'state'. These may be seen as are 'partially unconscious' thoughts of the person: 'street view, I, weather, ...' These words are send to the ATR object as input, and compared with the words/notions associated with the ART object, yielding a word/notion output, that is sent back to the person.

Some inputs are not relevant w.r.t. the ATR object, they do not receive a response.

In out example, the person in some step refers to the words x1 = 'I am going for a walk', due to, say, the word reflects some internal person's aspiration.

And 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!'

Ans the iterations continue.

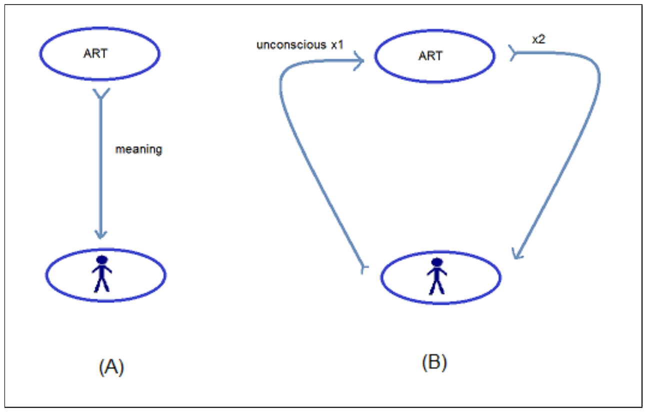

Figure 5: Art object is actually not a object (A) but a cyclic iteration with a person (B).

As these iterations the perceived object is 'constant' working as a 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 updated, i.e. the how actually the ATR objects are constructed

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

At object updating perception updated are not only the parameters sending and received from the object, but also the object itself. In this section we consider some eamples, in tne next we describe the duwheel scheme of the object updating perception.

The iterations resemble 'forward' and 'backward' steps of deep learning, accordingly we shall retain the notation

Consider the following examples.

Refer again to the 'forward' loop (Figure 6). What happens when the ART output 'work!' come into collision with the person's expectations? The *ARTO becames a subject* of the our attention. First, the 'work!' begins to be considered as an attribute ARTO (reflection?). We seem to start reevaluating of the objects. The subject of our thoughts is already not internal experiences, but the ATP object itself. Then the set of perceived properties of ATRO is updated according to the new attribute. One may expect we receive a less friendly set.

Another example is shown in (Figure **??**). Suppose we are summoned to a commission that deals with our case, the decision highly depends on the commission's bias, for us or against. We dont know and hesitate. 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 inreval, element of the seuqunce are alligned (iterated) with [the percived image of] comission. And sudenly the element is not verifgied, conversely, we observe 'this is a deeply friendly jacket', but obtain 'the is jacket toothy and hostile to us'. At this moment the fprward iterations are interrupted, and we we procced aith the 'backward' iterations, where the object of our consideration is the comission image itself. We sart with the pair [the image of the comission, 'hostile jacket']. At this itaretion we consider accociations with the object. [comission, people, came against us, jacket, the jacket was just a trick, the jacket does not matter, tghey want to frighten us with their uniform, the hostile unity of their jadckets, ...] these are alligned with our observation. More comcat attribure set

2.2.3 The duwheel scheme

The creation of ART objects proceeds according to the two cycle scheme (Figure 6)

	'forward': calulation of the values of the function	'backward': alternation of the function itself
Direction:	clockwise	counter-clockwise
Associated notion:	inhale	exhale
Updated object:	Element	The whole ART object:
Examples of the processed objects at passive perception:	walk → work	mill → giant; friendly commission → hostile commission
Examples of the processed objects at creation of ART object:		'more' → 'more chernoe vitiystvuya shumit
transformation:		conversion of observed (input) content to the seen

2.2.4 Remarks on duwheel scheme

- **duality of ducircle scheme** The ducircle scheme of Figure 6 is from the point of view of a person. We may see to this scheme as from the point of view of the ATR object.
- **meaning of forward/backward computation** Ref to Figure 5. (B) is a generalization of (A) with empty input
- **meaning of forward/backward computation** Ref to Figure 5. The x2 of (B) may be conscious or unconscious

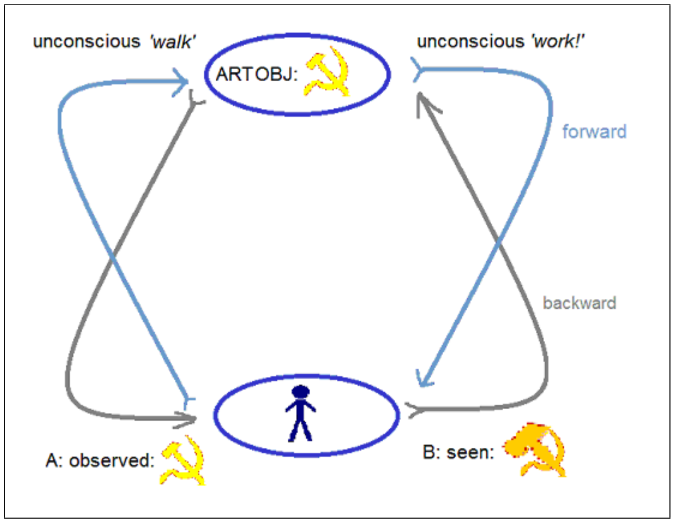

Figure 6: Example of du-wheel scheme: modeling perception of an emblem

- **meaning of forward/backward computation** Ref to Figure 5. May we treat any object as iterative?
- In English: observed VS seen. The Russian allows better expression of this duality: videnoe VS uvidennoe.
- zrimattery

2.2.5 Difference from deep dream approach

3 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 **??**

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.

4 Appendix

4.1 The alterego nets for a natural language content

4.1.1 Further development of duwheel scheme: estetically efficient samples

4.2 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 4.4. 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 esthetically efficient patterns **??**. The model may be tuned on at a single example like the shown in 1.

4.2.1 Training the visual alterego nets

For visual images the net is trained on pairs of Figure 4.4 A, B. The trained net should given Figure 3 A or B yield the image similar to Figure 3 C.

4.2.2 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 1). 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

4.3 NLP: hierarchy of creativity

4.4 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, circle,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 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

Table 1: 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

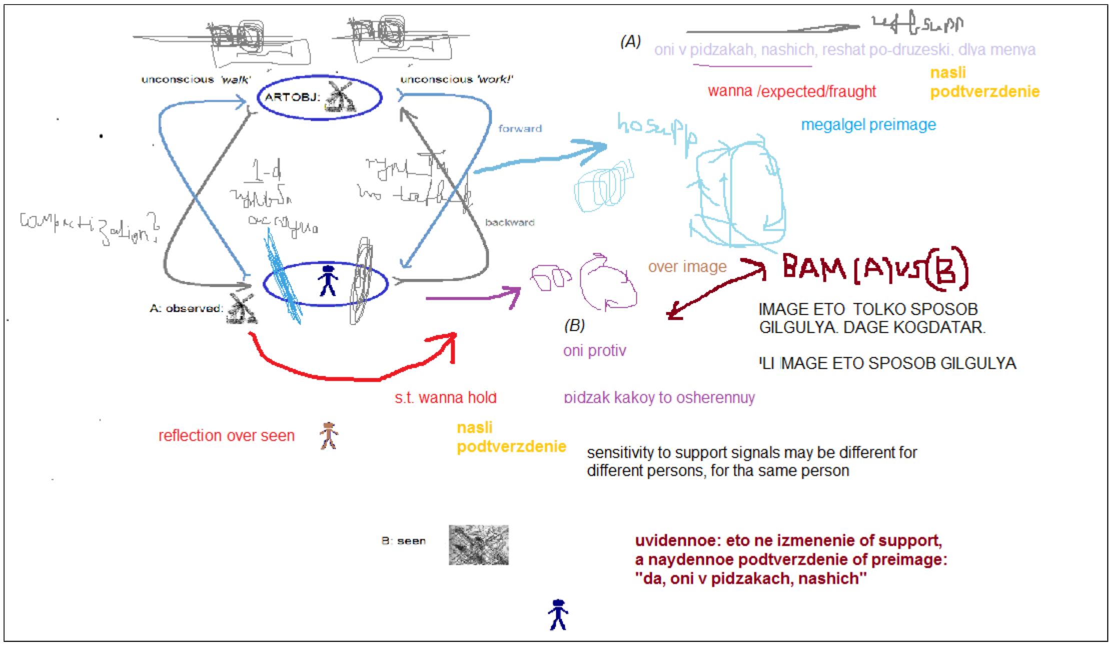

Figure 7: Raw scheme

- **Difference from summarization** The texts like shown Figure (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**

References

[1] At (Figure **??**) the 'A Club of Gentlemen by Joseph Highmore' is used as an illustration