Proposal: Alter ego nets for human augmentation

Dr. David Kupeev *

Abstract

A system for modeling human perception is proposed for development. The system is based on a new introduced algorithmic model where the perception is represented by two interacting iterative cycles, resembling respectively the forward and backward propagation executed at training convolution neural network.

The process of perception is modeled as a human's communication with the perceived object that functions like a neural network answering the user's requests ('forward' iterations). On the other hand, the perception includes the 'online training' of the network representing the perceived object ('backward' iterations). In this way perception by person of an apple is seen as a person's dialog with a network 'Apple', and an online learning of the network. We call this perception model the Alterego net.

The forward iterations reflect 'internal world' of a human. At the other hand the backward iterations yield the percept (internal representation) of the felt object. The interactionn of the two loops in the alter ego nets lead to creation of the percept that depends on the 'internal world'. In this way tuning the alteego net to a specific person or group of persons, will allow simulation of their perception, in particular generation of the content approximating the internal human's representation of the perceived objects. Thereby the Alterego nets is potentially a new human augmentation technology for various applications.

Contents

*kupeev@gmail.com,

1 Introduction

In this paper we model human perception of art objects, including paintings, symbolic images, mental images the person interacts with etc. We refer to them as ART objects. Implementation of our model will allow generation of the content approximating that perceived by humans. We will start with modeling perception of the ART objects as sequence of iterations. Then describe how the properties of the perceived objects are iteratively updated, in other words, how perceptrs of the objects are generated. These two types of iterations are lump together in the DuWheel perception scheme (Section 2.3). In section 2.4.3 we discuss the suggested implementation of this scheme. Tuning of the net to a specific person or a group of persons will allow generation of the

2 The DuWheel scheme

2.1 Perception of object as a sequence of forward iterations

We will model perception of the ART objects as iterations. Let us turn to Fig. 1, where hammer and sickle are depicted imagine the following 'dialog' between a person and the object. The person unconsciously generates a sequence of descriptions, reflecting its internal 'state'. These may be seen as unconscious to a certain extend thoughts of the person: 'street view', 'weather', ... We will call this the semantic stream associated with the person. The unconscious dialogue with the symbol occurs in such a way that the elements of this stream

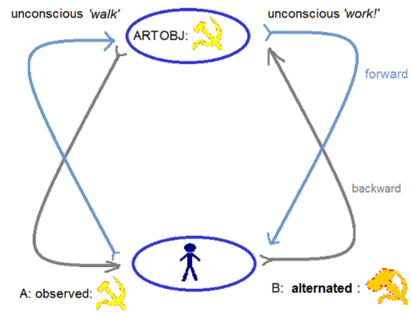

Figure 1: Example of du-wheel scheme: perception of an emblem is a sequence of [unconscious] iterations with the person. From this point of view, the *percept*,as the final result of perceiving, does not exist. Perceiving is essentially the non-stop iterations.

seem to be sent to the symbol, where they are compared with the words/notions associated with the ART object, yielding the 'answers' of the object, which are 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 an 'unconscious' term

$$x_1 = \text{'I wanna go walk'} \tag{1}$$

due to his aspiration. The term is compared with the words/notions properly associated with the object, and the object 'replies':

$$x_2 = \text{'You are going to collective work to help the motherland!'} \tag{2}$$

The x_2 is embedded to the sequence of words generated by the person, and the iterations continue. This iteration is illustrated in Fig. 4 (A).

As these iterations the perceived object is a 'constant' function: it receives input and outputs the response. By analogy with the deep learning notation we call these iterations forward. In the following section we consider how the properties of the perceived objects are changed, in other words, how actually the ART objects are constructed.

2.2 Alternation of the perceived object's properties at backward iterations

The object perception is not just iterations with the 'constant' ART object - sending and received the data from the object - but rather more complicated. It seems it includes in itself *alternation* of the perceived object. This resembles

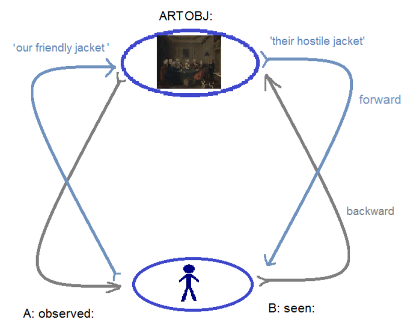

Figure 2: The illustration to DuWheel scheme. See Fig. 3.

Figure 3: The image from Fig.2. [9]

backward propagation of training convolutional network, where the proper network parameters are updated. Accordingly we will keep this notation. Below we consider two examples of backward iterations. Along with forward iterations these comprise the DuWheel cycles considered in Section 2.3.

Consider again the forward loop in Fig. 1. What happens when the ART's output 'work!' come into contradiction with notions comprising the PAS stream of the person? In this case the person's attention will probably switch from this stream to the ART object itself. And the 'work!' will be started to be refereed as an attribute of the object. And the person may start a kind of reevaluating of the object with a 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" attribute.

Another example is shown in Figs. 2 reffig:FIG14C. Suppose we are summoned to a commission that should deal with our case, it is 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. Consider the

[1]this resembles some person's real experience at the oral entrance examination for Moscow

following forward iteration. There appears an 'unconscious' sequence of terms: '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. At some point in time, certain terms from the sequence are compared with the environment, – verified w.r.t. the (ART) image of the commission and initiate the response to the person (like 'walk' $\rightarrow$ 'work' above). This forward iteration is illustrated in Fig. 4 (A). In our scenario, 'this is a deeply friendly jacket' is sent to the ART object. And the obtained response may disagree with our sequence of terms, say, we obtain 'this jacket is not friendly to us at all' response.

At this moment the forward iterations are interrupted, and we switch to the backward iterations, which resemble the investigation of the properties of the ART image itself, initialized by consideration of the jacket related properties. We as if consider a sequence of terms similar to that of the forward iterations, but refereed to the ART object itself, eg.: 'jacket', 'commission', 'people', 'came against us', 'came for us', 'the jacket was just a trick', 'the jacket does not matter', 'they want to frighten us with their uniform', 'the hostile unity of their clothes', etc. The terms are depicted in Fig. 4 (B) in yellow.

Some descriptors are reevaluated, – we observe the object and reveal the new properties. For example, given an 'it is unknown whether the the jacket is friendly to us' discover 'non friendly jacket' property. This is shown in Fig. 4 (B), where the brown rectangles returned from the tool represent a new informative element added to the OAS stream.

This may lead to the change of the basic ART object properties, it is what may be called selective summarization - selection of small set of notions consistent with subsets of the stream[2]. For example ('non friendly jacket') and ('my predecessor has suffered from the commission') leads to 'non friendly commission for me' (shown as violet rectangle).

2.3 Comparison of dual loops.

The properties of the introduced DuWheel loops are summarized in Table 1.

University Faculty of Mechanics and Mathematics in the past

[2]This may be seen as a kind of compression.

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'[3]
Transformation:		conversion of observed (input) content to the seen (?)
Stream name:	general semantic stream = support + interleaving stream	object specific semantic stream = 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

Table 1: The dual loops: comparison

2.4 Implementation of DuWheel Scheme

In this section we describe the suggested algorithmic implementation of forward and backward iterations of the scheme. At forward iterations a dynamically changing set of internal human records is updated using the descriptors representing the perceived object. At backward iterations alternated are these descriptors. This proceeds using the third party tools, like convolutional neural networks, giving the information about the object.

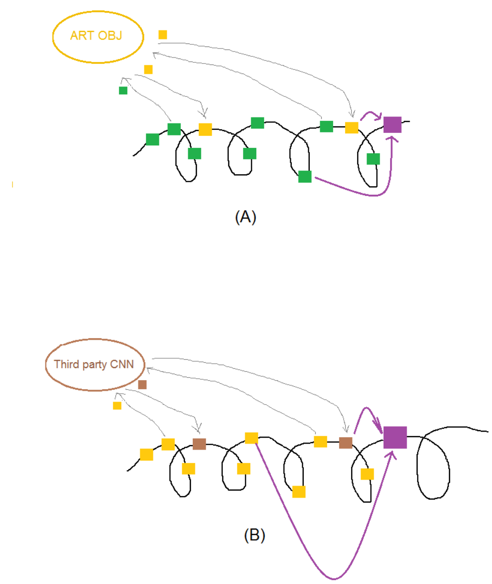

Figure 4: (A): PAS stream. The person description sequence terms are depicted as green rectangles and the elements returned from the ATR object are in yellow. (B): OAS stream. The ART object description sequence terms are depicted as yellow rectangles and the information about the ART objects elements (returned in the implementation of the OAS streamer by the third party tools) are in violet.

2.4.1 Person Aligned Semantic Stream

The *Person Aligned Semantic Stream* (PAS) addresses a person itself, it may be seen as a 'stream of associations' of a person. The stream is a sequence of terms t_i describing the current person's 'internal environment', the terms at closer positions tend to be closer semantically. The PAS consists of the support and interleaving streams, depicted respectively by green and yellow elements in Fig.4 (A). The support stream consists of highly associated terms, for example 'they', 'they are kind to us', 'this city light is friendly to us' (Section 2.2). The interleaving stream is comprised of the responses obtained from the ART object at forward iterations. The responses may contradict ('walk' $\rightarrow$ 'work') or be in accordance with the support stream ('friendly jacket' in Section 2.2). After the responses are inserted to the PAS stream they operate as regular stream elements, yielding the associated terms.

2.4.2 Object Aligned Semantic Stream

An *Object Aligned Semantic Stream* (OAS) consists of the terms describing the properties of the ART object. Its structure is similar to that of the PAS. Like this, the OAS stream is comprised of the support and interleaving streams (depicted as green and yellow elements in Fig4 (B)). The former is a sequence of words (notions) related to the perceived object, like: 'stipe', 'mushroom', ... (Section 2.2). The latter consists of the third party's answers to the questions like: "is mushroom is somewhere in the image?", "which objects are in the image", "are the people of the image friendly to us?". The answers are given by the tools like CNN nets for localization and classification of the objects in the scene [6].

Similarly to the PAS, selective summarization acts at the OAS stream, resulting in updating the textual representation of the percept of the ART object (Sect. 2.2). This is depicted by violet squares in Fig. 4) (B) and as "alternated" object in Fig. 1.

2.4.3 Suggested implementations of the semantic streamers

Both the PAS and OAS streams may be constructed from the lumps of a text corpus texts. For the PAS we may assign to a person a small family

$$W = \{w_1, w_2, \ldots, w_I\} \tag{3}$$

of the words/short word combinations characterizing the current 'state' of the person. For example 'street', 'going along', 'the weather in the city', etc. We refer to these as the *generating elements* of the stream. Then we may form PAS as a sequence of the text lumps from the corpus, with small semantic distance between close elements, generated by the words from W:

$$PAS = < W > . \tag{4}$$

At Fig.4 (A) the stream is marked by green. Similarly, we may form the OAS stream generating the text lumps starting from the terms representing the perceived properties of the described object:

$$OAS = < \{v_1, v_2 \ldots, v_I\} > . \tag{5}$$

For example, if the described object is an apple,

$$OAS(\text{Apple}) = < \{\text{apple}, \text{green apple}, \text{fruit}, \text{fruit nutrition} \ldots\} > . \tag{6}$$

Up until this point the constructions of PAS and OAS are similar. The difference is in constructing the embedding responses (see Fig. 4). Construction of the responses from the ART object for the PAS stream proceeds in dictionary fashion. For example, $walk \to work$ may be constructed by enumeration in the OAS stream the lumps with the words w semantically close to 'walk' (entrance to the dictionary), and selecting there the words located closely to w (output of the dictionary). In the contrast, the embedding responses to OAS stream (violet boxes in Fig. 4 (B)) are obtained from the third part CNN, like [6], that work as a source of a new information for the whole DoWheel loop.

Another implementation of the PAS and OAS is possible. We may define a General Semantic Stream as a text sequence that statistically approximates the variety of possible textual descriptions of the person's 'environment'. This stream may be seen as a rather meaningless text with statistical properties reminiscent of human speech. In the simplest Markovian form, it may be implemented as a sequence of collocated words with the histogram of mutual word appearances close to mutual word probabilities in a text corpus. The sequence may be generated by a probablistic graph [2, 3], whose nodes are associated with the words, and the edges are assigned the probabilities of the word pairs appearances encountered in a text corpus. The collocations are calculated following [4]. Then the PAS (resp. OAS) stream may be constructed as realization of the GS containing the words/word combinations located closely [5] to w_i (resp v_i).

3 The Alterego nets

The Alterego nets model the human object perception and allow generation of the content approximating the *perceived* by the persons. The nets are based on the Duwheel scheme introduced in Section 2.

In this section we discuss the nature of the perceived content generated by Alterego nets, and outsketch their personalization.

3.1 Generation of the representation of the percept

It is a good time now to clarify the notation. The perceived object (stimulus) is given to us in some modality, say, visual or textual (see Fig. 5). Following [11] we refer to the internal person representation of the perceived object as *percept*. We can not tell much about it, we even do not know its modality, but we may represent it by a certain media, for example, a visual image, or a text. In this paper we deal with textual medium - the OAS (Section 2.4.2) is textual representation of the percept.

People perceive the world differently. Even observing the same content. For example some people experience in the image of Fig. 5 (A) the percept that is represented verbally at Fig. 5 (C). And some people not. Like this, the percept, is being different from the observed, may be different for different people.

Whether our representation generated by the DuWheel scheme represents the percept well? We can say at least that it depends both on the perceived object and on the person. Indeed, this is the *object* describing content, because the OAS is generated per object. And this is *person* derived content because the OAS is the result of interaction with the PAS that reflects the internal world of the person

It is worth to note that the content generated by the Alterego described in this article is essentially the textual representation. For these nets, what is 'seen' in the image, is the text. In the image from Fig. 5 (A) the net's percept is the text from 5 (C) and not the image Fig. 5 (B).

Ability to approximate the perceived content is essential for human augmentation applications. The Alterego nets described in the next section are intended to provide such an approximation.

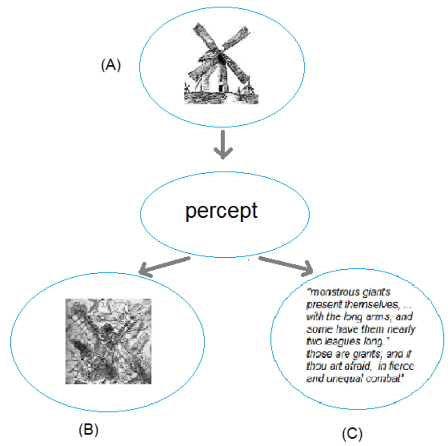

Figure 5: An Alterego net may simulate perception of Don Quixote in the episode with windmills. (A): an input image [8] (B): visual representation of the perceived image of giants [8] (C): textual representation of the perceived [7] The Alterego nets will be trained on the image pairs like (A,B) and (A,C)

Figure 6: (A)- observed image (B) - visualization of textual representation of the perceived object
An alternative approach (not 'deep dream') allow to obtain 'mushrum' within the image.

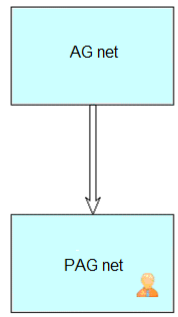

Figure 7: PAG Net

3.2 Implementation of Alterego nets

TBD: join pictures

The simplest Alterego net is DuWheel per object.

Multiobject DuWheel.

Tuning DuWheel. bu a person. By including to generated elements the conveyed information.

———————-

more TBD: join kartinki

in intro: ont thne other/at the other. give synionym: at the same time

———————

The main application of Alterego nets will be personalized Alterego nets considered below.

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

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 7

The AG nets will be trained so that their generated content will approximate the *perceived* 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.

In this way, tuning the alter ego nets to a specific person or group of persons (transfer learning), will enable generation of the content representing the percepts of the subjects. In such a way, the Alterego nets is actually a human augmentation. These will allow new applications, like analysis of the perceived human content, generation of the book summaries 'per person', etc.

4 Conclusions

TBD: reference to CG

We introduced the nets for generation of the *perceived* that is essentially the textual description of the input content. Enabling the Alterego nets the ability to generate the perceived image of the same modality as the input image, like the shown Fig. 5 (B) in the topic of the further research.

TO CONCLUSIONS: Generation of the 'seen' percept of the visual modality

5 Appendix

```
GSS->Person Aligned Semantic Streamer (PAS)
OAS3->Object Aligned Semantic Streamer (OAS)
General Semantic Streamer             (GS)
```

```
mu of percept:
    cho-to un-modal. To chto ne text, ne vis.
    no to cto predstavlyem by vis

    percept of internal states
    percept of the object


    no mu eto predstavlyem
        by text
        by vis

to chto my delaem v OAS:
    my predstavlyem [dinamicheskiy] percept
    by text representations
    =
    old: seen na perceived. "

    mozno li neformalno nazvat
    textual representation of the percept
    kotoruy textom ne yavlyaetsa:
    "TextualPercept"

chto takoe: visual repr
    to ze samoe kak textual

---------  OPEN ISSUE 1 ---------

chto takoe see v A smusle
    v sluchae input = image
    eto "VisualPercept"
    THAT IS EMBEDDED?
    THAT IS CLOASETO INPUT?

---------  OPEN ISSUE 2 ---------

iterations: videnno e/uvidennoe
```

Another example is a net whose input is a scene and the visual representation of the percept is the scene with the embedded image of the object that has been

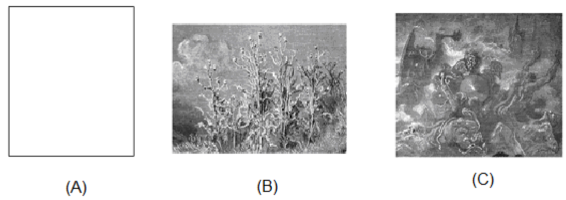

Figure 8: (B): observed [10] (C): seen [12]

recognized, (see Fig. 6). The OAS stream includes the summarization object 'mushrum' derived from 'stipe' (Section **??**).

The Alterego nets are different by:

- semantic level. The net with input 6 A and output 6 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.
- observed input may be empty/non empty. 8 (A) and Table 1.

5.1 Multi-subject Alterego nets

We have considered A one-subject Alterego nets.

Now 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.

5.2 Remarks on DuWheel scheme

- back to CNN. add the scheme to 'third party' cnn?
- **duality of DuWheel scheme** The DuWheel scheme of Fig. 1 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 Fig. 9. The (B) is a generalization of (A) with empty input
- **meaning of forward/backward computation** Ref to Fig. 9. The x_2 of (B) may be conscious or unconscious
- **meaning of forward/backward computation** Ref to Fig. 9. May we treat any object as iterative?
- In English: observed VS seen. The Russian allows better expression of this duality: vidennoe VS uvidennoe.

5.3 Further development of DuWheel scheme: estetically efficient samples

The DuWheel scheme which models human perception of aesthetically efficient samples.

TBD

5.4 Comparison with deep dream approach

TBD

5.5 OLD SCHEME: 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 Fig. 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.

5.5.1 Training the visual Alterego nets

For visual images the net is trained on pairs of Fig. 5 A, B. The trained net should given Fig. 8 A or B yield the image similar to Fig. 8 C.

5.5.2 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

5.6 NLP: hierarchy of creativity

The hierarchy of creativity is summarized in Table 2

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

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

5.7 Remarks

- The introduced model is related also to perception of situations, considered as a set of circumstances in which one finds oneself [1].

- **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 (DPAS→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 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 Fig. 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

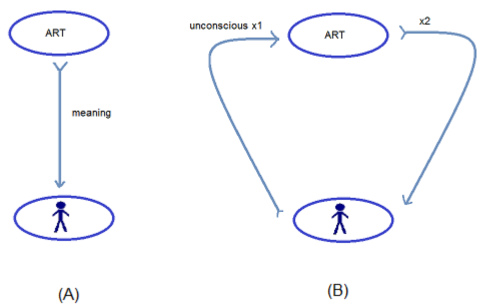

Figure 9: Art object is actually not a object (A) but a cyclic iteration with a person (B).

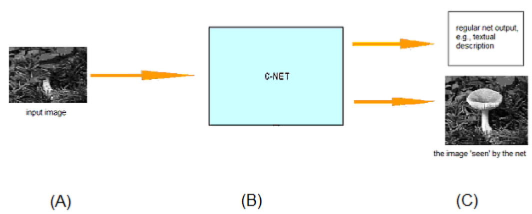

Figure 10: (B): observed (C): Alterego net

- **DU WHEEL as GAN**
- The mentioned third party CNN may be a part of 'close box' solution

References

[1] *https://en.oxforddictionaries.com/*

[2] Yoshua Bengio, Aaron Courville, Pascal Vincent, "Representation Learning: A Review and New Perspectives" *arXiv:1206.5538*

[3] Hao Wang, Dit-Yan Yeung "Towards Bayesian Deep Learning:A Survey" *arXiv:1604.01662*

[4] Bidyut Das "Extracting Collocations from Bengali Text Corpus" *Procedia Technology. Volume 4, 2012, Pages 325-329*

[5] Bidyut Das Vivian Tsang , Suzanne Stevenson, "Calculating Semantic Distance between Word Sense Probability Distributions" *Proceedings of the*

Figure 11:

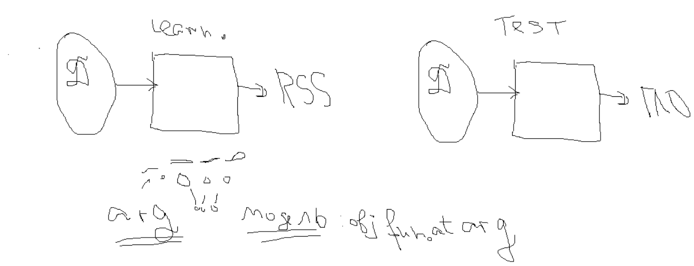

Figure 12:

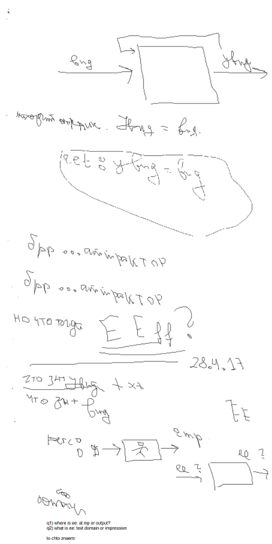

Figure 13:

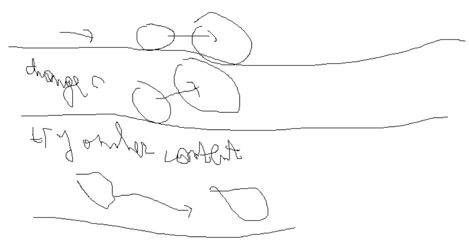

Figure 14:

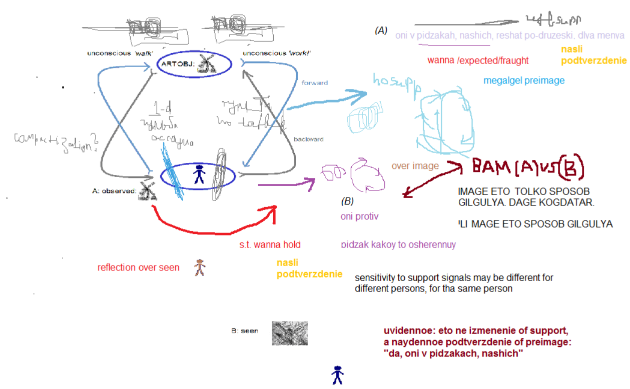

Figure 15:

Eighth Conference on Computational Natural Language Learning, CoNLL-2004, pp. 81–88

[6] Ren, Shaoqing; He, Kaiming; Girshick, Ross; Sun, Jian, "Faster R-CNN: Towards Real-Time Object Detection with Region Proposal Networks" 2015arXiv150601497R

[7] from http://www.online-literature.com/cervantes/don_quixote/12/

[8] a modified image from https://www.google.com/search?as_st=y&tbm=isch&as_q=don+quixote+and+the+windmills&as_epq=&as_oq=&as_eq=&cr=&as_sitesearch=&safe=images&tbs=sur:fmc

[9] https://www.google.com/imgres?imgurl=https%3A%2F%2Fupload.wikimedia.org%2Fwikipedia%2Fcommons%2F8%2F8b%2FJoseph_Highmore_-_A_Club_of_Gentlemen_-_Google_Art_Project.jpg&imgrefurl=https%3A%2F%2Fcommons.wikimedia.org%2Fwiki%2FFile%3AJoseph_Highmore_-_A_Club_of_Gentlemen_-_Google_Art_Project.jpg&docid=6hrc1_yH3pwV1M&tbnid=GTTUFz5Ug8ZxsM%3A&vet=1&w=5941&h=4757&safe=images&bih=639&biw=1265&ved=0ahUKEwif27uX98vZAhUJElAKHRzFBsYQ__EBCAM&iact=c&ictx=1
Licensing: This photographic reproduction is considered to be in the public domain in the United States. In other jurisdictions, re-use of this content may be restricted.

[10] The modified image from https://commons.wikimedia.org/wiki/File:Don_Quixote_4.jpg

[11] https://en.wikipedia.org/wiki/Perception

[12] The modified image from https://commons.wikimedia.org/wiki/File:Don_Quixote_2.jpg