AlteregoNets: a way to human augmentation

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Abstract

A person dependent network, called an AlterEgo net, is proposed for development. The networks are created per person. It receives at input an object descriptions and outputs a simulation of the internal person’s representation of the objects.

The network generates a textual stream resembling the narrative stream of consciousness depicting multitudinous thoughts and feelings related to a perceived object. In this way, the object is described not by a 'static' set of its properties, like a dictionary, but by the stream of words and word combinations referring to the object.

The network simulates a person’s dialogue with a representation of the object. It is based on an introduced algorithmic scheme, where perception is modeled by two interacting iterative cycles, reminding one respectively the forward and backward propagation executed at training convolution neural networks. The 'forward' iterations generate a stream representing the 'internal world' of a human. The 'backward' iterations generate a stream representing an internal representation of the object.

People perceive the world differently. Tuning AlterEgo nets to a specific person or group of persons, will allow simulation of their thoughts and feelings. Thereby these nets is potentially a new human augmentation technology for various applications.

Keywords: human augmentation; human perception; big data surveillance; natural language processing; deep learning;

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1 Introduction

Undoubtedly, modern computers perform arithmetical computations better than humans. Also, in recent years, the computers began to solve the problems of detection and classification in images in many hearings better than the man. Likewise, the topic of algoritic simulation of human perception of objects received some coverage in the research literature [12, 14, 20, 22]. However, to the best of our knowledge, to this day there have been no attempts to algoitmically generate the context that approximates what people perceive. This article is such an attempt.

Our goal is to enable computers to yield data which approximates internal human representations of perceived objects. These representation are the flows of thoughts [52] and emotions [40] related to an object, or groups of objects.

The objects are given to us in some modality, usually visual or textual. For example, the object depicted in Fig. 1 (A) is visual. One may assume that when the object is perceived, its certain representation acts ‘inside a person’. These representations can not be reproduced or operated directly. One may refer to them as the first level object representations. The percept [25] (ibid, (C)) may be considered as the mental image [24] of the object. It is naturally that the majority of scientific investigations of the mental image focus upon visual mental imagery [38]. This is what the person sees in a perceived image. On the other hand, we may consider the flow of thoughts [50] and feelings [40] related to the object. (In some sense one may see this as a flow of perceived object properties.) This is the internal human representation which we want to simulate.

One may consider the task of further representing the first level representations by tractable data, visual or textual, with which algorithms can operate. It may be viewed as constructing the second level object representations. It seems that natural representation of the percept is the image, and of the flow of
Figure 1: Relations between representations of perceived objects. (A): The image perceived by Don Quixote in the episode with windmills. (B): The flow of thoughts modeled in this paper. (C): The percept of the input image. (D), (E): The textual and image media representing the human representations. The flow of thoughts is naturally represented as a text, and the percept as an image. (D) depicts the representations constructed in this article. The dashed arrow (AB) denotes partial forming of the mental state bypassing the percept. For example, the feel of a color of a shoe may be obtained without forming the whole image of the shoe. Green dashed arrow (AD) denotes optional use of the tools for image annotations.
thoughts is the textual stream. In this paper we describe an algorithm for simulating flows of thoughts by textual streams, resembling the narrative stream of consciousness [51].

A key feature of our approach is that we represent the perceived object properties not just as static attributes associated with the object (e.g., an object may be 'large' or 'small'), but in dynamic fashion – as a textual stream. And it's not surprising. Indeed, at the first representation level, we may treat the human thoughts related to a perceived object as a kind of the 'general' flow of thoughts [50]. And the second level representation of this flow generated by our algorithm (Sect.2) may be seen as a particular case of the narrative stream of consciousness [51].

The objects whose perception is simulated in our paper are paintings, historical emblems the person may mentally interact with, social scenes, etc. We do not impose a formal criterion for selecting such objects, one may just note that the richer is the set of the notions which may be associated with the object, the more suitable is the object for simulating the process of its perception under our model.

We do not impose strict assumptions about the nature of the flow of the human thoughts and emotions we want to simulate (referred at Fig.1 (B)). Indeed, one may suggest that this flow may be roughly expressed by means of a natural language [57], but definitely this is not a natural language. On the other hand, our algorithm yields a stream of words and word combinations, similar to ibid (D). However, there is no contradiction – we represent the flow of some (unknown) modality by textual data.

Also, it may be noted that eventually our goal is not to approximate well the human perception. Indeed, the computer calculates not like humans, the computational models of visual recognition [27] differ from that by humans [37], etc. Hence our goal is defined as a rough computer modeling of certain mechanisms of human perception.

This underlines a 'target gap': on the one hand we want to simulate the perception as best as possible, and on the other we assume in advance that it can not be done perfectly. This raises the problem of validation of our simulation. What does a well-built simulation mean? For example, in the research on image classification [45], the quality of computer simulation is validated by the comparison with the 'ground truth' [26] – an a priori known true picture classification. But in our task the 'ground truth' is the internal human representation that we just want to simulate. Answering the above question, we expect that the actual verification of our approach may be mediated, as in the below example.

To generate the desired context, we introduce a machine model for human perception called the Alterego (AE) net. In the course of this article, we first describe the approach to creating a 'universal' AE network. Then we consider how, given a data stream associated with a specific person, or a group of persons, to tune up the universal AE net to this person or the group.

One may suggest various applications of these nets. Imagine, for example, a group of several thousand people, where for every person from the group there
exist an AE network associated with the person. Suppose that prior to a championship in a certain city the networks are fed data (pictures, text) associated with the sporting event. Than if any network generates a content semantically similar to "and then there were none" song (Agatha Christie), this serves as a 'red flag' signal for the respective person intentions.

The contributions of this paper are as follows:

- The AlterEgo net is created per person.
- It receives at input an object descriptions and produce at output a representation of the internal person representation of the object, referred as the first level object representations. The first level object representation is a flow of thoughts and feelings related to a perceived object.
- The BiWheel algorithm generates two interacting textual streams, similar to the narrative flow of consciousness.
- One of the above streams is comprised of the word combinations semantically related to a perceived object. The stream is a second level representation of the human object representation.
- This second level representation is a description of the object which is not just a set of object properties, but the text stream.

Our paper is organized as follows. We start Sect. 2 with modeling a flow of human thoughts and feelings by a sequence of iterations (Sect. 2.1). Then extend the model to incorporate alterations of the perceived properties of objects (Sect. 2.2) as iterations. These two types of iterations are lump together in an iterative scheme modeling human perception of objects (BiWheel scheme). An algorithmic implementation of the scheme is presented in Sect. 2.4. Further (Sect. 3.1), we describe how the introduced AE network is generalized to perception of several objects. Finally, we explain the personalization of the AE nets – tuning of the nets to a specific person or a group of persons, allowing generation of the representations reflecting their thought and felt contents, different for different humans (Sect. 3.2). Conclusions and description of the lateral research directions associated with the AE nets complete the paper.

2 The BiWheel scheme for modeling human object perception

In this section we describe our model of interactions of the flow of thoughts and feelings of a person with the mental images of the objects. The flow is modeled by textual streams resembling. The model is illustrated on the examples of an advertisement image, a historical emblem, and a social scene. We call the model the BiWheel scheme because it includes two interacting loops.
Figure 2: Illustration to BiWheel scheme (best viewed in color). The support and interleaving streams, are depicted respectively by green and yellow arrows.

(A): Perception of the advertisement image (Sect. 2.1).
(B): Perception of the historical emblem [53] (Sect. 2.1).
(C): Perception of the social scene shown at Fig. 3.

Brown arrows at (A), (B): the elements inserted to the PAS (resp. OAS) stream may be obtained using external tools for image annotations.
In Sect. 2.1, we describe a 'clockwise' loop comprising a first 'wheel' of the scheme. In Sect. 2.2, the scheme is extended to modeling perception of the objects with ambiguous meaning. This is done by supplementing the scheme with a 'counter-clockwise' loop (Sect. 2.2). An overview of the scheme is given in Sect. 2.3. In Sect. 2.4, we present the suggested algorithmic implementation of the BiWheel scheme.

2.1 Modeling a flow of human thoughts and feelings by a sequence of iterations

In this section we describe the first 'wheel' of the BiWheel scheme. We consider two examples. In the first one a person meets an advertisement image. In a second example a person meets a historical emblem, or refer to it in his thoughts.

Consider a person walking on a road. The person generates the flow of thoughts and feelings, reflecting its current mental state [58]. The flow’s elements at close temporal positions tend to be associated with each other [55].

We may represent this flow as a sequence of words and short word combinations with semantic meaning [60], like:

\[ \text{PAS} = \text{'street view', 'weather', 'cold', ...} \]  

(1)

We call such sequence a Person Aligned Semantic stream (PAS). By some analogy with universal algebra operations [18], we call the stream elements the terms. Since the PAS represents the flow of thoughts and feelings, the terms at closer positions tend to be closer semantically.

Now suppose that during the walk the man meets an advertisement image of Coca Cola (Fig. 2 (A)) which may influence his flow of thoughts and feelings. Let us ask whether there exist a linkage between the encountered image and the man’s thoughts and feelings, prior to the act of image perception? The answer is yes since the advertising targets the basic psychological needs [6], in other
words, the advertising is virtually answering requests that already exist in the modeled flow of thoughts. For example, among the human’s thoughts there may exist the represented in the PAS as:

\[ x_1 = \text{'I wanna drink'} \in PAS \]  

The \( x_1 \) may be considered as a request virtually sending to the image (Fig. 2(A)). Among the notions associated with the image content there exist

\[ x_2 = \text{'Drink'}, \]  

semantically related to \( x_1 \).

Transition \( x_1 \to x_2 \) is illustrated at Fig. 2 (A): we submit to the object representation (the notions associated with the object) an input, and obtain the response depending on the properties of the representation. This resembles the forward step in in training convolutional neural networks \[64\], which is basically the calculation of the network value for a given input. Respectively, we refer to such transitions as forward iterations.

Forward iterations are comprised of ’sending’ terms of the PAS stream to the object, comparing them with the concepts \[39\] associated with the object, and generating the ’answers’, sending back to the stream. (The requests which are not relevant to the object do not yield the responses.) The iterations may be seen as a ’dialogue’ between a PAS stream and an object.

\(^1\)It is worth to note a certain duality \[9\]: like the person’s consciousness before the act of perceiving the image contains ’requests’ terms associated with the image (like \( x_1 \)), so the image ‘contains’ the terms, which may be associated with the user’s request (like \( x_2 \)). This is a precondition of the interaction between a person and an image.
Figure 5: (Best viewed in color.) (A): The PAS stream. The elements of the support substream are depicted in green, of the interleaving stream in yellow. (B): The OAS stream. The elements of the support substream are depicted in yellow, of the interleaving stream in brown. Optionally, the elements of the interleaving streams may be obtained by using annotation tools. (A) and (B): In the both PAS and OAS streams the elements obtained by using selective summarization are depicted in violet.

The PAS can be seen now as comprised of the support and interleaving streams, as illustrated in Fig.5 (A). The support stream consists of the terms, related to the person, like $x_1$ in Eq.2 and sent as requests to the object. The interleaving stream consists of the terms related to the object, like $x_2$ of Eq.3 sending as responses to the PAS. By their meaning, the responses may conform to the support stream (as in the above example), or contradict it (as we will see in Sect.2.2). After the responses having been inserted to the PAS, they operate as regular stream elements, yielding the associated PAS terms.
In our second example we show how the forward iterations model perception of historical emblems. Let us consider Fig. 2 (B), where hammer and sickle are depicted. As in the above example, consider a man walking on a road. Let us imagine the following ‘dialog’ between the PAS stream and the set of the concepts associated with the emblem.

In the PAS stream (Eq. 1), at some iteration step, is generated a term

$$x_1 = \text{‘I wanna go walk’}. \quad (4)$$

Similarly to the above example, the term is compared with the ones associated with the emblem. There may be found a term

$$x_2 = \text{‘You are going to collective work to help the motherland!’} \quad (5)$$

semantically related to $x_1$, depicted with green dashed lines in Fig. 2 (B). As in the example with the advertisement image, $x_2$ may be inserted to the PAS, and the forward iterations will continue. On the other hand, the $x_2$ may fire a contradiction signal with the PAS (like neuron 56) and thus not be inserted to the stream. This option is considered in the next section.

In the examples considered in this section the perceived object ‘operates’ like a function: it receives an input term $x_1$ and returns the response. In the following section we consider how alterations of perceived properties of objects may be modeled.

### 2.2 Modeling alterations of perceived object’s properties

When we look at advertising images, their meaning is unequivocal – they rarely have ambiguous interpretation. For many others perceived objects it is not so. For example, historical emblems may have quite different meanings. For instance, the ‘Hammer and sickle’ symbol of the former Soviet Union was associated by some people with the ideas of freedom, and on the other hand, by other people, their negation. Another example of objects that allow different interpretations are social scenes and situations estimated by persons. The meaning of such objects may be altered during the perception process.
In this section we extend the PAS model of Sect. 2.1 – it will simulate also alterations of perceived properties of objects during the perception act. This is done by adding the second iteration loop to the BiWheel model. The model extension will be illustrated on the examples of a historical emblem and a social scene.

Let us consider a sequence of semantically related terms associated with a perceived object. We call it the Object Aligned Semantic (OAS) stream. This stream consists of the terms describing perceived properties of the object. Actually we have dealt with this stream in the previous section, this is the stream where from the terms $x_2$ were selected. For example, for the image from Fig. 4 (A) the OAS may consist of the terms like

$$\text{OAS } = \text{‘red’, ‘Coca Cola’, ‘drink’, ‘star’, ‘rays’,...} \quad (6)$$

It may be regarded as a stream of annotations of the advertising image.

Let us turn again to the second example from the previous section. What will happen if the ideas associated with the emblem come in collision with the human thoughts and feeling? Then likely the person’s thoughts will be switched to the object itself, leading to rethinking its properties. As a result the meaning of the object for that person may be alternated.

In our model this is represented as firing collision between the object representation’s response ($x_2$ Eq. 5) and the notions comprising the PAS stream of the person. It leads to switching the data processing to the OAS stream, and starting enumeration of the terms semantically close to $x_2$. This might lead to a change in the semantic meanings (currently) associated with the object.

Our next example is illustrated by Fig. 2 (C) and related to estimation of social scenes. Suppose a person is summoned to a commission (illustrated at Fig. 3), which will make a decision regarding him, and it is known in advance that the decision may be biased, for the person or against. The person does not know the bias and hesitates.

As in Sect. 2.1 we model the person’s flow of thoughts as a PAS stream of terms, say:

$$\text{PAS } = \text{‘they’, ‘they are kind to us’, ‘this city light is friendly to us’, ‘they’, ‘they are kind to us’, ‘this city light is friendly to us’, ‘look, they have the same jacket as we have’, ‘this is a deeply friendly jacket’,...} \quad (7)$$

Similarly to the above example (Eq. 6), we model the mental image of the environment (commission) by an OAS stream:

$$\text{OAS } = \text{‘jacket’, ‘commission’, ‘people’, ‘came against us’, ‘came for us’, ‘does not matter’,...} \quad (8)$$

2The example was developed basing on some person’s experience at the oral entrance examination for Moscow University Faculty of Mechanics and Mathematics in the past.
At some point in time, terms $x_1$ from the PAS are compared with the environment – verified w.r.t. the mental image of the commission and initiate the responses $x_2$. The obtained response may contradict to the PAS stream, e.g., for $x_1 = \text{‘this is a deeply friendly jacket’}$, the $x_2 = \text{‘this jacket is not friendly to us at all’}$. At this moment the forward iterations are interrupted, and our simulation process is switched to enumeration of the properties of the commission, starting with $x_2$. The iterations yield a new portion of an OAS stream, like:

\[
\text{OAS} = \ldots \text{‘this jacket is not friendly to us at all’, ‘jacket’, ‘commission’, ‘people’, ‘came against us’, ‘came for us’, ‘the jacket does not matter’, ‘they want to frighten us with their uniform’, ‘the hostile unity of their ‘clothes’}, \ldots
\]

(9)

In the both above examples, the elements $x_2$ from the OAS serve as magnets attracting the person’s attention, influencing formation of subsequent OAS elements. Accordingly, these elements may be seen as forming an interleaving stream to the support (proper) OAS. In this way, similarly to the PAS, the OAS stream is comprised of the support and interleaving streams.

If we interpret obtaining the ‘answers’ $x_2$ from the OAS stream to $x_1$ as a calculation of the value of an OAS ‘function’ at $x_1$, then generation of the new terms of Eq. 9 may be treated as updating the function parameters. This resembles the backpropagation step in training convolutional neural networks [64], where the network parameters are updated. We keep this notation for the whole iteration loop (Figs. 2 (B), (C)) together with the forward iteration notation (Sect. 2.1).

In forming the OAS streams there may occur what may be called selective summarization – selection of a small set of the terms consistent with the stream. For example, ‘non friendly jacket’ and ‘my predecessor has suffered from the commission’ appeared in the OAS of Eq. 9 may lead to a new term ‘non friendly commission for me’ (Fig. 5 (B)). This may be seen as a kind of compression of the OAS. Similar summarization may act on the PAS stream.

It is interesting to note that forming the PAS and OAS streams resembles exploring the YouTube [42] engine. Indeed, each stream looks like a sequence of annotations displayed by the engine after a user has picked a video. We explore this similarity in Sect. 2.4.

In the latter two sections we have studied the forward and backward loops comprising the BiWheel algorithm. In the next section we overview the whole scheme.

2.3 Overview of BiWheel scheme. Received and perceived.

Generation of the PAS and OAS streams is based on the following principles:

1. In each stream the generated terms tend to be semantically close to recently generated terms of the stream.
Figure 6: (A)–(E): Sequential forming the PAS and OAS streams by BiWheel scheme. The added elements are denoted by dots. (A), (B), (C): new element are added to the PAS stream are semantically related to the previous PAS elements. (C): The new element is semantically related to the terms from the OAS (considered as the element from the interleaving stream). (D), (E), (F): new elements are added to the OAS stream are semantically related to the previous OAS elements. (E): The new element is semantically related to the terms from the PAS (considered as the element from the interleaving stream). (F): The new element is obtained from the annotation tool (considered as the element from the interleaving stream).

2. Periodically, the generated terms of each stream tend to be semantically related to terms of the opposite stream.

3. Some terms of the OAS stream may be input from external annotations tools.

One may summarize the work of the BiWheel scheme as follows (Fig. 6):

1. PAS is a stream of mutually associated terms representing the alternated mental state of a person.

2. OAS is a stream of mutually associated terms representing the alternated perceived properties of the object.

3. Current elements of the PAS stream are compared with the semantically related current OAS elements, the latter are sent to the PAS as the OAS responses.

4. These responses are embedded to the PAS stream, or (if contradict to PAS) invoke a reestimation of the object properties.
5. The reestimation proceeds as adding to the OAS new terms associated with the responses, or adding the object’s descriptions from annotation tools.

6. The summarization is optionally performed on both the streams.

Let us note that each of the generated streams may include term repetitions. It is worth to mention that the interaction between the PAS and OAS streams is non symmetric. As we saw above, at forward iterations, elements of OAS are embedded to PAS and start to participate in forming the stream (arrow 3 in Fig. 7). In contrast to this, at backward iterations, no new elements are embedded to the OAS stream. Namely, at the start of a backward iteration, the elements of OAS that have invoked switching from the forward to backward iteration, are beginning to form continuation of the stream (ibid, arrow 2). Together with annotations from external tools (ibid, arrow 1), the asymmetry indicates the transfer of a new ‘information’ from outside the streams to the OAS, and then to the PAS stream.

The OAS stream is constructed in such a way 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 depends on interactions with the PAS stream, which reflects the internal world of the person. But how the OAS stream approximates the perceived content (Fig. 1(D), (E))?
An OAS stream starts to be generated being not dependent on the person (Eq. 8): these streams built for different persons may begin with the same terms. Furthermore, the elements of the OAS stream embedded to the PAS (Sect. 2.1) may be interpreted as perceived object properties. These may be seen as the OAS terms the person associates with the current PAS terms. Although their selection depends on the person, it does not affect the OAS stream. Furthermore, the interleaving OAS stream is comprised of the OAS terms which have switched the person’s attention, and so convey a person’s ‘imprint’. Thus the interleaving stream may be seen as consisting of the perceived object properties in a strong sense. Furthermore, the interleaving stream influences the whole OAS stream.

In this way the OAS stream is a representation of the ‘thought & felt’ content of the person, whereas the interleaving substream may be considered as representing this content in a strict sense.

It is interesting to note that the work of the scheme is reminiscent of training the neural network [49]. Indeed, the former is comprised of iterations that may be referred as forward and backward (Sects. 2.1, 2.2). Thus, our modeling of human perception may be considered as reinforcement learning [28] of the network associated with the perceived object. For example, perception by a person of an apple is modeled as the person’s dialog with a network ‘Apple’, accompanying with a simultaneous training of the network.

The properties of the BiWheel loops are summarized below in Table 2 in informal fashion.
Table 2 Informal properties of the dual loops: comparison.

| Activity: | Forward | Backward |
|-----------|---------|----------|
| The notation associated: | internal, inhale, passive, atomistic | external, exhale, active, holistic |
| Direction: | Clockwise | Counter-clockwise |
| Stream name: | Person Aligned Stream = support + interleaving stream | Object Aligned Stream = support + interleaving stream |
| Support stream: | A sequence of associations yielded by the person’s paradigm | A sequence of associations yielded by the object’s representation of a human |
| Interleaving stream: | Responses from the object to the support stream based on associations of the terms | Insertions to the support stream based on associations of the terms, or obtained using from the external annotation tools |
| Interpretation of the interleaving stream: | The ‘thought & felt by the object’ | The ‘thought & by the person’ |

2.4 Implementation of BiWheel Scheme

Below we describe the suggested simplest algorithmic implementation of the scheme. It simulates a perception of an ‘average’ person, located in an environment $ENV$ of an object $OBJ$.

Both the PAS and OAS streams are comprised of the terms of a text corpus. We initialize the PAS to a small family

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

of the words and short word combinations describing the environment $ENV$ of a person. For example ‘street’, ‘going along’, ‘the weather in the city’, etc. We refer to those terms as the generating elements of the stream. Our goal is to generate the PAS (Eq. 12) subjected to the following conditions:

- Environmental condition: terms $w_i$ are semantically close to the terms from $W$;
• Continuity condition: terms $w_i$ tend to be close to recently generated terms \( \{ w_i \mid i_0 < i \} \).

We denote the PAS stream generated subjected to these conditions by:

\[ PAS = \langle \overline{W} \rangle. \tag{11} \]

The stream is constructed as a sequence of terms

\[ PAS = w_1, w_2, \ldots, \tag{12} \]

in such a way that at every step \( i \) a new term \( w_i \) is generated subjected to the environmental condition with probability \( p \), and to the continuity condition with probability \( 1 - p \), where \( p \) is a predefined probability value. In the former case \( w_i \) is constructed to be similar to at least one term from \( \overline{W} \). In the latter, it is constructed to be similar to the term, randomly selected (with probability proportional to \( \lambda \) weight assignment) from the set of recently generated terms (Algorithm 1). In both the cases, \( w_i \) is selected to be semantically similar to a certain term \( w' \in \{ w_j \mid j < i \} \), referred further as attractor.

Given an attractor \( w' \), construction of \( w_i \) may proceed by retrieval terms from text corpora and selection those semantically close to \( w' \). For example, to treat the attractor as a document and map it to a set of documents with semantically similar content using semantic hashing [29]. Then one may perform an exhaustive search of n-grams [61] in the retrieved documents, and select the terms semantically similar to the attractor [5].

Let us notice that the generation of the PAS stream (Eq. 12) resembles retrieval operations using the YouTube [42] engine, where a user randomly searches the items related to the input terms \( \overline{W} \). Indeed, fulfillment of the environmental condition is similar to queering the engine with terms from \( \overline{W} \) and assigning \( w_i \) the annotation of a video \( vid \) randomly selected from the list of retrieved videos. Respectively, fulfillment of the continuity condition is similar to selecting \( vid \), and assigning to a \( w_i \) the annotation of a randomly selected video from the YouTube suggestion list [13]. In such a way the PAS stream could be generated using deep neural networks, like the YouTube recommendations algorithm [4].

Likewise to PAS, we initialize the OAS stream to a family of terms describing the properties of the input object \( OBJ \):

\[ \overline{V} = \{ v_1, v_2, \ldots, v_I \}. \tag{13} \]

For example, if the described object is an apple, then

\[ \overline{V}(\text{Apple}) = \{ \text{apple, green apple, fruit, fruit nutrition} \ldots \}. \tag{14} \]

Similarly to PAS, we may generate the OAS subjective to the environmental (proximity of the generated terms \( v_i \) to \( \overline{V} \) ) and continuity conditions, denote it as:
Algorithm 1 The simplest AE net

**input**: environment \( ENV \), perceived object \( OBJ \)

**output**: OAS stream

1. Initialization:
   - Generate the starting portion \( P \) of PAS stream, \( P = \overline{W} \), following Eq. 10.
   - Generate the starting portion \( O \) of OAS stream, \( O = \overline{V} \), following Eq. 13.

2. Controller:
   - perform Step 3, Step 4, Step 3, Step 4 . . .

3. Forward iteration:
   3.1. Form a new portion \( P \) of PAS stream, generating the elements \( w_i \)
       semantically close to \( \overline{W} \) and to the element with larger weight \( \lambda \)
       After the portion generation, assign weights \( \lambda(w_i) = 1 \), to the recently generated elements, normalize distribution \( \lambda \) to unit sum.
   3.2. For PAS elements of \( P \) find a set \( S \subseteq O \) of semantically related elements in OAS, preferring the elements with larger weight \( \mu \).
       3.2.1. Construct \( S_1 \subseteq S \), consisting of elements semantically similar to the PAS elements.
           Form interleaving portion to PAS: add the terms from \( S_1 \) to the PAS with weights \( \lambda = 1 \), normalize distribution \( \lambda \) to unit sum.
       3.2.2. Construct \( S_2 \subseteq S \), consisting of elements semantically contradicting the PAS elements.
           Form interleaving portion to OAS: add \( S_2 \) to the OAS with weight \( \mu = 1 \), normalize distribution \( \mu \) to unit sum.
   3.3. Return to the controller block.

4. Backward iteration:
   4.1. Form a new portion \( O \) of OAS stream, generating the elements \( v_j \)
       semantically close to \( \overline{V} \) and to the element with larger weight \( \mu \)
       After the portion generation, assign weights \( \mu(w_i) = 1 \), to the recently generated elements, normalize distribution \( \mu \) to unit sum.
   4.2. Optional step. Add new elements to the OAS using the annotation tools. After the portion generation, assign weights \( \mu(w_i) = 1 \), to the recently generated elements, normalize distribution \( \mu \) to unit sum.
   4.3. Return to the controller block.
The work of our BiWherel scheme is summarized in Algorithm\[1]\.
Over the course of the algorithm running, the set of the terms $S$ in Step.\[3.2\] is constructed by enumeration of the pairs of terms
\[
L = \{ (t_1, t_2) \mid t_1 \in P, t_2 \in O \},
\]
selecting the set of $L_1 \subset L$ of semantically related pairs of the terms, and calculation of projection
\[
S = \{ t_1 \mid (t_1, t_2) \in L_1 \}.
\]
The $S_2 \subseteq S$ in Step.\[3.2.2\] is constructed by selecting $L_2 \subset L_1$ consisting of semantically contradicting terms $(t_1, t_2) \in L_1$, following projection calculation:
\[
S_2 = \{ t_1 \mid (t_1, t_2) \in L_2 \}.
\]
Our description of the BiWheels scheme given in (Sect.2) may cause the question: why AE is called the net? The AE implementation considered in this section answers this question. Indeed, the AE is implemented using a kit of NLP instruments which, in their turn, are naturally implemented using the deep learning tools. Therefore, the AE may be seen as a compound deep learning net.

The networks AE considered up to this point are limited by two main factors: networks model the perception of one object and do not imitate human perception in a person-dependent fashion. In the next section, we extend the BiWheel model to overcome these limitations.

3 AE nets for simulation of human perception

In the previous sections we described the simplest AE net which consists of a single BiWheel scheme. The net models perception of a single object. In this section we introduce the Multiobject AE nets allowing to model perception of several objects. We also discuss how Multiobject AE nets may be tuned for modeling perception of different persons.

3.1 Multiobject AE nets

Multiobject AE net is generalization of the BiWheel scheme for simulating perception of several objects. Given a BiWheel scheme and a family of a new objects the Multiobject AE is constructed by incorporation to the scheme the OAS loops, representing the objects. As the result, the PAS stream of the new net is receiving the interleaving embedments from several OAS streams. This is illustrated at Fig.8

One may notice that our implementation of the simplest AE net (Sect.2.4) is easily generalized to the multiobject format. The Multiobject AE may be
implemented in multithread fashion, one thread per object, in such a way that every thread is responsible for forming the OAS stream for the respective object.

3.2 Personalization of AE nets

The AE nets considered so far do not deal with a person specific information and accordingly model perception of an 'average' human. Tuning to the specific person may be done incorporation to the input environment of the scheme (Sect. 2.4) the person specific information. Given a person $H$ and a set of terms $T(H)$ representing this information (this may be referred as the set of person specific features terms), we may add $T(H)$ to the generating set of the PAS stream (Eq. 11):

$$PAS_H = < W \cup T_H > .$$

(19)

The $T_H$ may be constructed as a verbal description of the person, e.g.,

$$T_H = \{ 'age: 35 – 50', \text{movie:"Call Me by Your Name"} \},$$

(20)

or be retrieved from the content environment associated with the the person, like the search engine queries. This is illustrated at Fig. 9. In a similar fashion, the personalization may be performed for a group of of persons.

4 Conclusions and lateral research directions

In this paper we introduced a scheme for modeling internal human representation of perceived objects. The scheme is based on two pivots. First is the idea that ability to dialog characterizes a human [15]. Second, the inference, inspired by recent advances in NLP, like Word2Vec, claiming that iterations may be more important than their non-iterative counterparts [10]. We simulate the object perception as iterative dialog between the persons. We believe that this simulation may be more powerful than descriptions comprised of the 'static' information.
The scheme generates the data approximating the internal human content. This allows to suggest numerous scenarios for its application. For example, given conglomeration of persons, one may associate with every person of the conglomeration an AE net, and train the nets using the observations associated with the persons. Then for a certain input object, for example, an advertisement image, the trained nets generate the content approximating how the people perceive the object. This may be used for construction of the input objects that are desirable by the persons, in per person fashion. In another scenario, the AE nets associated with every person from a given conglomeration are used for search of the people with a specified characteristic of their perceived content. An example of such application has been considered in the introduction. In a third scenario, the AE nets may be generalized to simulate communication between the contents perceived by different people. In such a way one may model a crowd perception.

There are exist additional directions of the research of AE. The first is related to modeling the perceived visual content. The AE nets described in this paper model the human thought content by textual stream. It may be desirable given a perceived object (Fig. 1(A)), to model the mental image (Fig. 1(C)) by digital image (ibid (E)), i.e., to model the ‘seen’ instead of the ‘thought’. It is worth to note that from the point of view of the artificial intelligence research, modeling the ‘seen’ is not bound to simulation of the human perception. Indeed, it may be desirable to enable the neural network trained to seek the mushrooms in the photographs, given the image shown Fig. 10(A), to yield the output similar to that of ibid (B). This may resemble the Deep Dream approach, but in contrast to the latter, the sought image should be obtained at the output end of the AE network, and not at the end of the input image. This is the topic of our current research.  

\[3\] Of course, such social measurements can only be carried out under control provided with social mechanisms.
Figure 10: Whether we may train a neural network to seek the mushrooms in the photographs, and given an input image (A) \[70\], to yield the image similar to (B) \[69\]?

Another lateral direction of the AE research is their use for the human content creation, for example, automatic poetry generation \[8\]. We outline this approach in Appendix A.

We believe that AE networks will find applications beyond the described in this article.

The image and text data from \[65\] – \[73\] were used in the preparation.

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A Use of BiWheel scheme for the automatic generation of the art content

It seems very likely that the BiWheel scheme may be used also for simulation of the art content creation, for example, automatic poetry generation \[8\]. Let us show how the scheme is related to the perception of the existing poetic texts. Consider the following example. A human may obtain aesthetic impression while reading a piece of poetry describing the sea (e.g., \[59\]), if suddenly feels that the sea’s noise referred in the poem resembles the physical rhythm of the text read. The ”sea’s noise” may be seen as elements of the PAS stream (Sect. 2.1) representing the human flow of thoughts generated while perceiving the poem. The rhythm of the text may be associated with the subsequence of the OAS stream (Sect. 2.2) describing perceived physical properties of the text (along with visual text appearance). Receiving the impression of resemblance mentioned above, may be seen as firing similarity signal between the PAS and OAS streams. In such a way, the peaks of aesthetic impression correspond to the pairs of semantically similar elements in these streams (depicted in Fig. 6 by blue segments). Analogously, our model may describe perception of aesthetically efficient texts of small length, like ”Rain, Steam and Speed” of J. M. W.
Turner [62], or presented in [19]. It seems therefore that our scheme may be used in similar fashion as generative model for the art content creation.

Probably, similar mechanism may be used also for automatic generation of the simplest mathematical propositions, for example, from the groups theory [17].

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