

DATA

Artificial intelligence for support business processes

Marcin Hernes, Krzysztof Lutosławski, Agata Kozina

Artificial Intelligence in Research and Applications Seminar

Agenda

- Center for Intelligent Management Systems
- Analysis of users' opinions about products
- Default prediction in leasing companies
- Food demand prediction

Center for Intelligent Management Systems

Purpose

Realizing the effective activities related to the implementation of artificial intelligence in management information systems.

The main pillar of the activity is cooperation between the members of the Center as well as the economic and scientific environment.

Members - Universities

- Wrocław University of Economics - leader
- Wrocław University of Science and Technology
- University of Social Sciences in Łódź
- University of Management Personnel in Konin
- The Witelon State University of Applied Sciences in Legnica
- The International University of Logistics and Transport in Wrocław

Members - enterprises

- ZAP Rachunkowość sp. z o.o. – Ostrów Wielkopolski
- ZAP Robotyka sp. z o.o. – Ostrów Wielkopolski
- 4-Tune s.c. – Wrocław
- BI Technologies sp. z o.o. – Wrocław
- Divante S.A. – Wrocław
- Open Loyalty Sp. z o.o. - Wrocław
- ZAP Kooperacja sp. z o.o. – Ostrów Wielkopolski
- NOVASTER sp. z o.o. – Ostrów Wielkopolski
- Instytut 21 sp. z o.o. – Ostrów Wielkopolski
- Perspektywa sp. z o.o. – Ostrów Wielkopolski
- DI-RZ – Wrocław
- Unity S.A. - Wrocław

Projects

- **Towards a smart factory** - supporting business processes in production companies using artificial intelligence tools - financed under the Interekon project - the MINISTER OF HIGHER EDUCATION AND HIGHER EDUCATION program for 2019-2022" Regional Initiative of Excellence ".
- **Storage, distribution and tool management system 4.0**, - ZAP-Kooperacja.
- **Production design support systems in MAHLE company** - implemented by Instytut 21.

Projects

- **Development of an automatic repayment prediction for a leasing companies using artificial intelligence tools** (deep learning and cognitive technologies) - financed under the Lower Silesian Vouchers for Innovation.
- **GTM (Go-To-Market)** - The aim of the project is to develop a prototype of an IT tool that performs an automatic analysis of the behavior of the mobile applications' users , in the context of their retention, using deep learning tools.

Projects

- **Level 4.0 – Digital Innovation Hub** – supporting enterprises in implementation artificial intelligence, Internet of Things, cloud computing
- **Open Pay** - development of innovative digital loyalty payment cards (Blockchain and machine learning).

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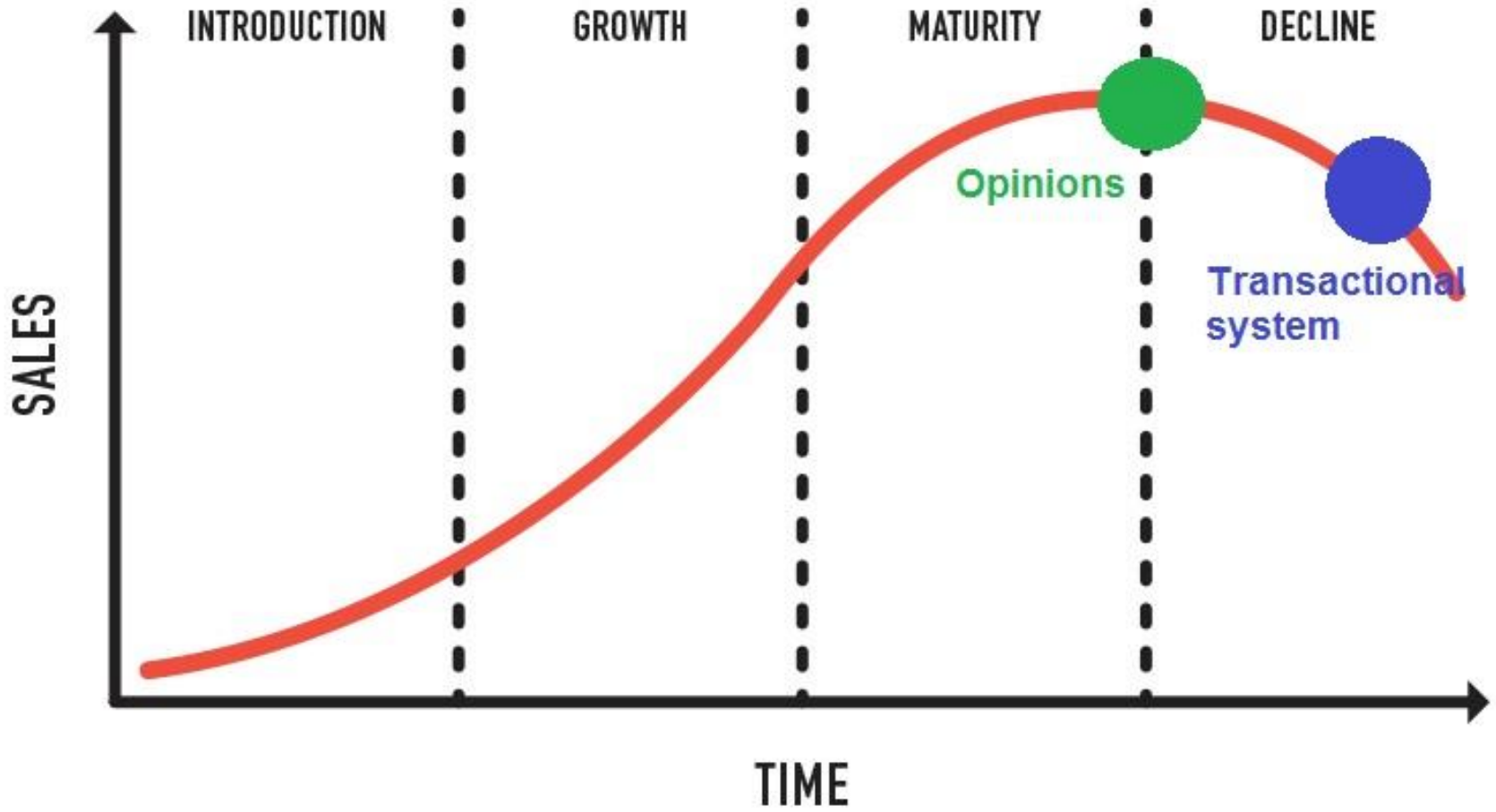
Analysis of users' opinions about products



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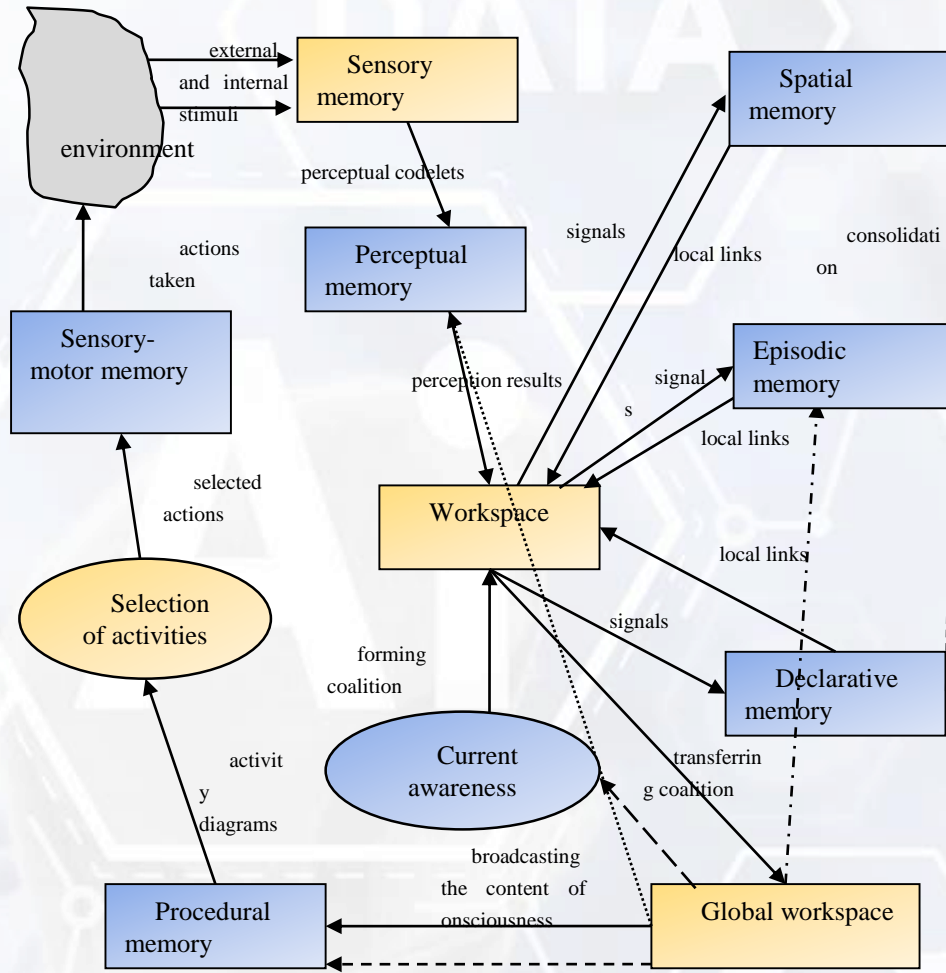
PRODUCT LIFECYCLE



Learning Intelligent Distribution Agent

Prof. S. Franklin

Cognitive Computing Research Group

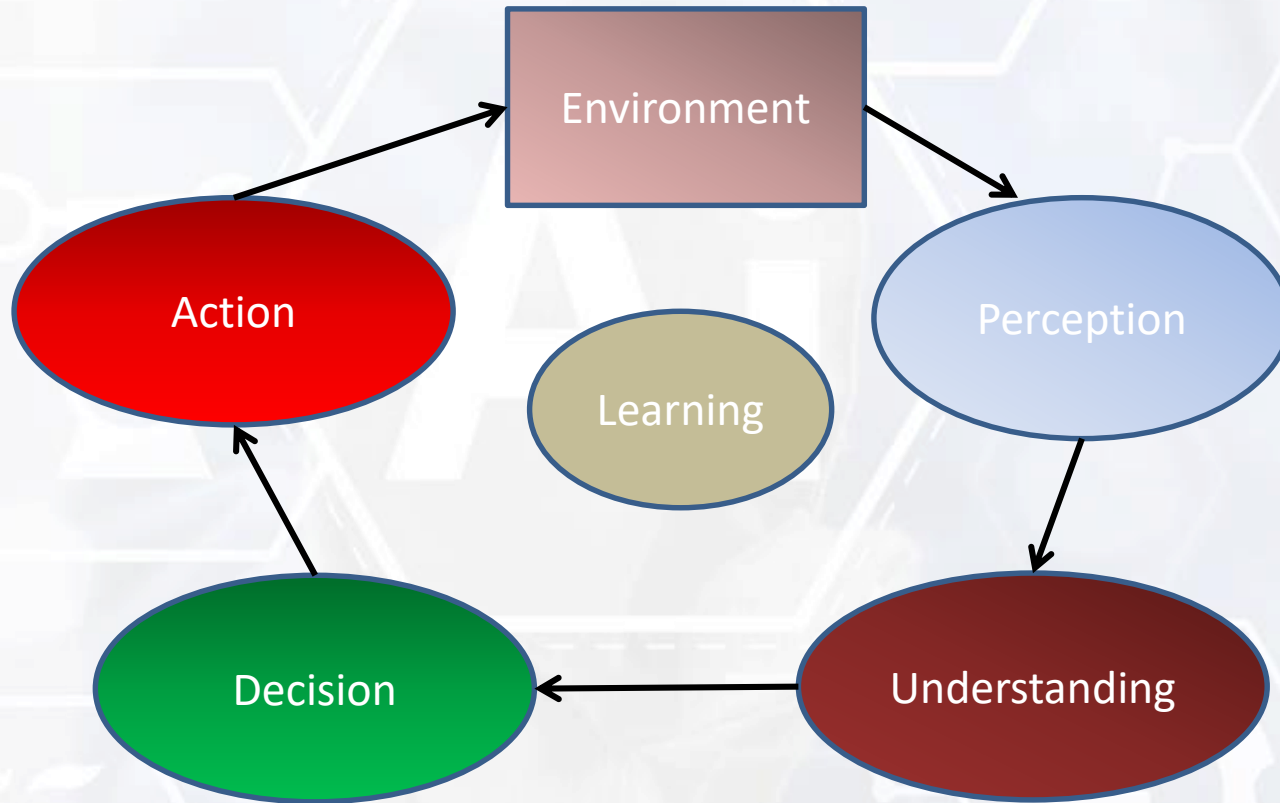


The key:

- the order of steps
- perceptual learning
- procedural learning
- episodic learning
- conscious learning

- memory modules
- long-term content
- process modules
- long-term content
- short-term content

Cognitive cycle



LIDA Framework

File Panels Help

Start / Pause Paused Current tick: 1118 Step mode 0 Run ticks

CSM Global Workspace Procedural Memory Action Selection

PAM Table PAM Graph Activation Chart Perceptual Buffer

Refresh Relax

None

planZdolnosci Parent zamowienie zamowienie Parent planProdukcji

CSM Global Workspace Procedural Memory Action Selection

PAM Table PAM Graph Activation Chart

Refresh

Scheme Lab...	ID	Current Activ...	Base-level A...	Context	Action
if zamowieni...	0	0,0000	0,0100	zamowienie[...	action.planuj

Logging Running Tasks Task Queue Configuration Files

Refresh

Task ID	Activation	Status	Description	Next sched...
6	0,0000	RUNNING	Neighborh...	1120
5	0,0000	RUNNING	Neighborh...	1120
0	0,0000	CANCELED	StartTrigge...	1
7	0,0000	RUNNING	Neighborh...	1120
2	0,0000	RUNNING	SensoryMe...	5
1	0,0000	RUNNING	BehaviorN...	1119
3	0,0000	RUNNING	Dokument...	3
4	0,0000	RUNNING	UpdateCs...	1120

Objectives

- determining the overall polarity of an opinion, i.e. determining whether the opinion is positive or negative,
- extraction of product features,
- determining the polarity of opinions about individual product characteristics

Agent operating environment

- The agent's operating environment is a set of text documents containing opinions,
- The source of these documents are the resources of the Internet network (opinions can be found on the websites of online stores, forums or dedicated portals).

Information Extraction and Text Mining Step 1

- On the basis of the training set (a set of opinions about a specific product), a semantic network is created in the perceptual memory, containing concepts (related to the product) and connections between them.
- Perceptual memory also stores synonyms and different variations of words. In the perceptual memory of the LIDA agent, concepts are represented by nodes, and associations by links.

Information Extraction and Text Mining Step 2

- Individual opinions are transferred one by one to the sensory memory (containing strings).

Information extraction and text mining

Step 3

- Opinion analysis is performed by codelets, i.e. programs (implemented in the Java programming language classes) that search the text according to criteria specified by configuration parameters, the value of which can be indicated by the user.

The example of codelets configuration

```
<task name=„positive_opinion">  
  <tasktype> CodeletObjectDetector </tasktype>  
  <param name="object" type="string">recommend</param>  
  <param name="noobject" type="string">not</param>  
  <param name="distance" type="int">1</param>  
  <param name="node" type="string"> positive_opinion </param>  
</task>
```

```
<task name=„negative_opinion">  
  <tasktype>CodeletObjectDetector</tasktype>  
  <param name="object" type="string">recommend,not</param>  
  <param name="distance" type="int">1</param>  
  <param name="node" type="string"> negative_opinion </param>  
</task>
```

The example of codelets programming

```
public double detect() {  
    if (noobj.equals("")){  
        for (int j=0; j<obj1.length;j++) {  
            for(int i =0; i < temp.length ; i++){  
                if(temp[i].equals(obj1[j])){  
                    acto++;  
                }  
            }  
        }  
        if (acto==obj1.length){  
            activation=1.0;  
        }  
    }  
    else  
    {
```

```
        for (int j=0; j<obj1.length;j++)  
        {  
            for(int i =0; i < temp.length ; i++){  
                if(temp[i].equals(obj1[j])){  
                    actno ++; }  
            }  
            for (int j=0; j<noobj1.length;j++)  
            {  
                for(int i =0; i < temp.length ; i++){  
                    if(temp[i].equals(noobj1[j])){  
                        actno++;  
                    }  
                }  
            }  
            if ((acto==obj1.length) && (actno==0))  
            {  
                activation=1.0;  
            }  
        }  
        return activation;  
    }  
}
```

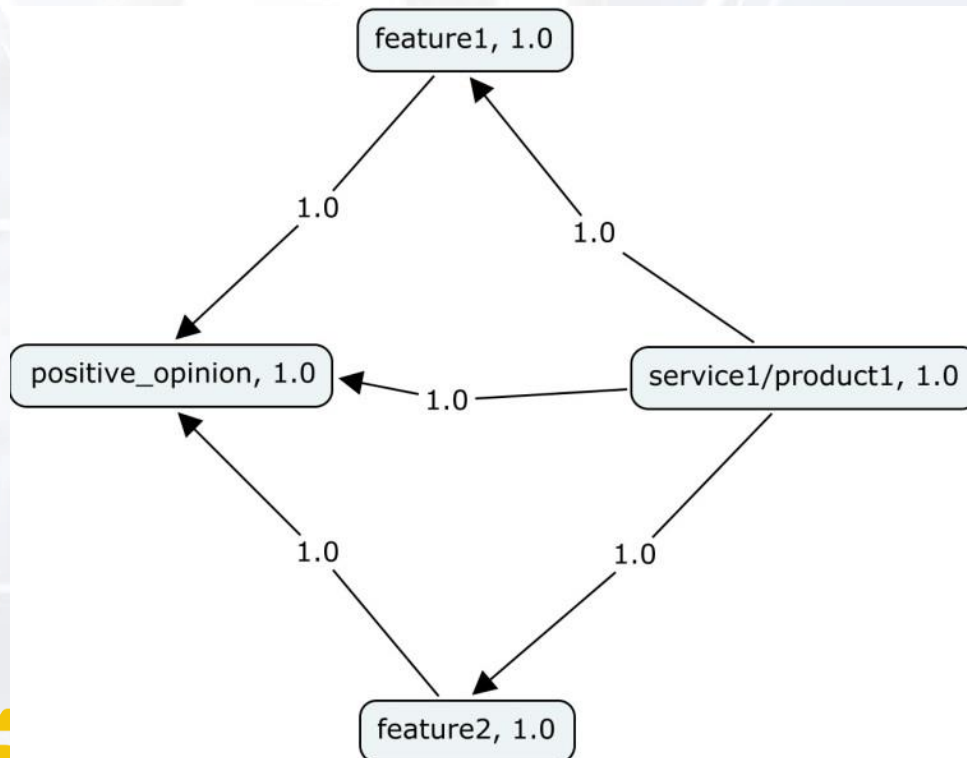
Information extraction and text mining

Step 4

- The results of the analysis, in the form of a semantic network, are transferred to the workspace

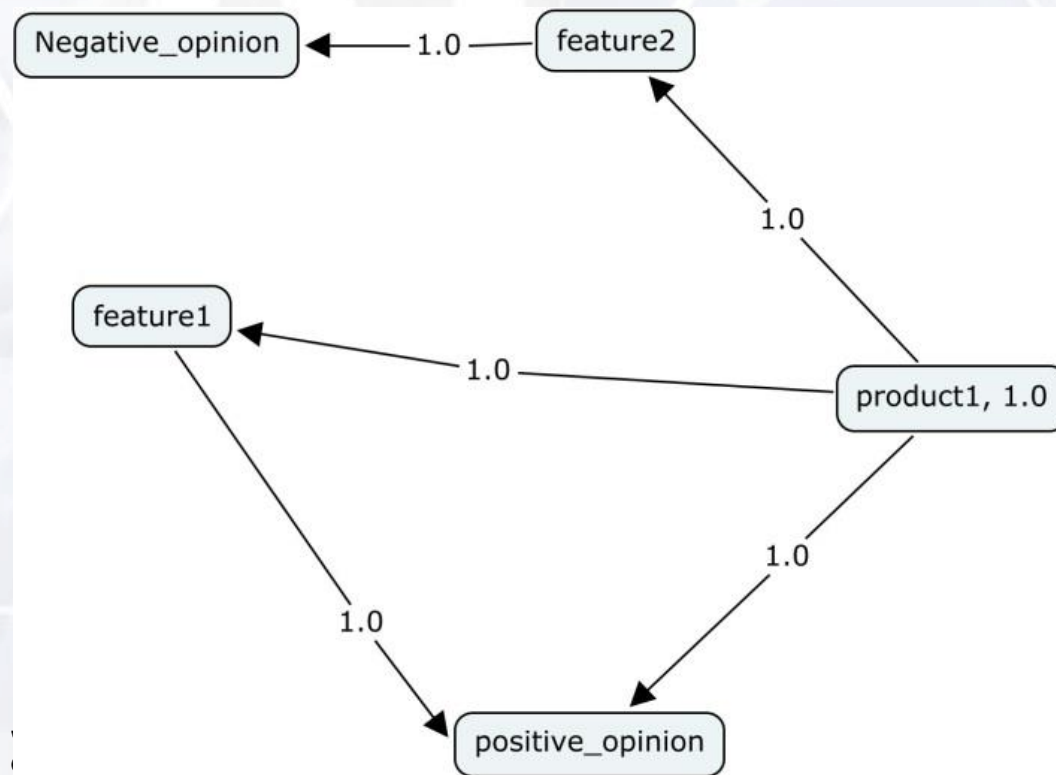
The example of results of analysis

- Positive opinion and positive features: „I recommend it, feature1 and feature2 are good”.



The example of results of analysis

- Positive opinion, negative feature: „I recommend it, feature1 is good, but feature2 is not good”



Information extraction and text mining

Step 5

- The situational model is transferred to the global workspace and the following action schemes are automatically selected from the procedural memory: "saving the opinion analysis results to the database" (noSQL database - analysis results - semantic network - are saved in XML format) and "loading another opinion to sensory memory ". It is also possible to select the action "statistical analysis", as a result of which the agent also indicates the product features that are most desired by customers.

Research experiment- assumptions

- The opinions on TV sets on the websites of online stores, portals that enable price comparisons and internet forums were analyzed.
- A shallow text analysis was performed.
- Number of opinions analyzed: 300. This limitation is due to the fact that each opinion had to be analyzed manually, which is a time-consuming process.

Research experiment- assumptions

- For the purposes of this experiment, 13 TV features were analyzed: brand, type, price, color, appearance, matrix type (LCD, LED, plasma), power consumption, screen size, resolution, sound parameters, Wi-Fi technology, internet browser, connectors (e.g. HDMI, USB, EURO, CI).

Research experiment- assumptions

- It was assumed that if the opinion does not contain information about the polarity of a given feature, then the polarity of this feature is identical to the polarity of the opinion (for example, when analyzing the opinion "I recommend this TV set, only the sound is weak", the polarity of the opinion was defined as positive, the polarity of the feature "sound" as negative, the polarity of the other features as positive).
- The polish language opinions have been analyzed.

Research experiment- assumptions

- The following measures have been used:
 - ✓ Accuracy,
 - ✓ Precision,
 - ✓ Recall,
 - ✓ F1 measure.

Research experiment – the manner of conducting

- The database contains 300 randomly selected opinions read from the websites of stores offering RTV equipment, price comparison websites and internet forums.
- The manual annotation of opinions has been performed.

Research experiment – the manner of conducting

- A training set was created containing 30% randomly selected opinions, on the basis of which codelets were parameterized (learning with the teacher).
- These opinions were also grouped according to the degree of difficulty (four groups - group 1 - polarity of opinions and features easy to define, group 4 - polarity of opinions and features difficult to define) of recognizing their polarity and the polarity of the features of televisions characterized in these opinions.
- Measurements of the correctness of the results of the analysis were calculated for individual groups of the degree of difficulty.

Group	Przykładowa treść opinii
1	I recommend (not recommend), good (not good)
2	<p>I recommend,</p> <p>advantages:</p> <ul style="list-style-type: none">- high quality- price- meets expectations- appearance <p>disadvantages:</p> <ul style="list-style-type: none">- poor sound quality <p>I have this TV for about a month and I think that it is really great, first of all clean and smooth picture (...) I judge the operation of voice commands on the downside</p>
3	<p>The TV is ok, the only thing that annoys me. it's a frame, it has a beautiful thin frame everywhere in the photos, and after turning it on, it turns out that the screen is reduced by an additional approx. 7mm, which significantly spoils the effect for me. Overall tv worth recommending</p>
4	<p>I bought this TV for my mom. Previously, she had a 3.5-year-old Panasonic that got muddled or hung on digital channels (problem with the MPEG decoder) - hence the replacement. Unfortunately, not only me, but also my mother, noticed that the image on Samsung does not reach Panasonic's heels, even despite the calibration. I spit on my chin that I did not add and bought the Panasonic, because I was a bit disappointed with it. But on this Samsung model even more</p>

Research experiment – the manner of conducting

- The next step was to load each opinion from the test set one by one into the sensory memory, for the agent to analyze these opinions and save the results in a database.
- The measures of correctness of the automatic analysis results were calculated in the last step.

Research experiment - results

Group	Measure	Polarity of opinion	Cechy												
			Brand	Type	Price	Color	Appearance	Matrix type	Power consumption	screen size	Resolution	Sound	Wi-Fi	Browse r	Connec tions
1	Accuracy	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697
	Precision	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697	0,9697
	Recall	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000	1,0000
	F1	0,9846	0,9846	0,9846	0,9846	0,9846	0,9846	0,9846	0,9846	0,9846	0,9846	0,9846	0,9846	0,9846	0,9846
2	Accuracy	1,0000	1,0000	1,0000	1,0000	1,0000	0,8462	0,9615	1,0000	0,9615	1,0000	0,8077	0,8462	0,8846	0,8462
	Precision	1,0000	1,0000	1,0000	1,0000	1,0000	0,8750	1,0000	0,8750	0,9600	0,9600	0,8750	1,0000	0,8750	0,8261
	Recall	1,0000	1,0000	1,0000	1,0000	1,0000	0,9545	0,9615	0,9545	0,9600	0,9600	0,9545	0,9615	0,9545	0,9048
	F1	1,0000	1,0000	1,0000	1,0000	1,0000	0,9130	0,9804	0,9130	0,9600	0,9600	0,9130	0,9804	0,9130	0,8636
3	Accuracy	1,0000	1,0000	1,0000	1,0000	1,0000	0,8571	0,8571	0,9643	0,8571	0,8929	0,8929	0,8929	0,9286	0,7273
	Precision	1,0000	1,0000	1,0000	0,9600	0,9600	0,7727	0,9600	0,9600	0,9200	0,9200	0,6522	0,6522	0,7727	0,7727
	Recall	1,0000	1,0000	1,0000	0,9600	0,9600	0,7391	0,9600	0,9600	0,8846	0,8846	0,6818	0,6818	0,7391	0,7391
	F1	1,0000	1,0000	1,0000	0,9600	0,9600	0,7556	0,9600	0,9600	0,9020	0,9020	0,6667	0,6667	0,7556	0,7556
4	Accuracy	0,8462	0,7692	0,8462	0,8462	0,8462	0,7692	0,8462	0,8462	0,8462	0,8462	0,8462	0,8462	0,7692	0,6923
	Precision	0,9231	0,5556	0,5556	0,7778	0,7500	0,5556	0,7778	0,7500	0,7778	0,7778	0,5556	0,7500	0,7500	0,7500
	Recall	1,0000	0,5556	0,5556	0,6364	0,9000	0,5556	0,6364	0,9000	0,6364	0,6364	0,5556	0,9000	0,9000	0,9000
	F1	0,9600	0,5556	0,5556	0,7000	0,8182	0,5556	0,7000	0,8182	0,7000	0,7000	0,5556	0,8182	0,8182	0,8182
Average	Accuracy	0,9540	0,9347	0,9540	0,9540	0,9540	0,8606	0,9086	0,9450	0,9086	0,9272	0,8791	0,8887	0,8880	0,8089
	Precision	0,9732	0,8813	0,8813	0,9269	0,9199	0,7932	0,9269	0,8887	0,9069	0,9069	0,7631	0,8430	0,8419	0,8296
	Recall	1,0000	0,8889	0,8889	0,8991	0,9650	0,8123	0,8895	0,9536	0,8702	0,8702	0,7980	0,8858	0,8984	0,8860
	F1	0,9862	0,8850	0,8850	0,9112	0,9407	0,8022	0,9063	0,9190	0,8866	0,8866	0,7800	0,8625	0,8678	0,8555

Conclusions

- Based on the results of the opinion analysis, decisions can be made regarding, inter alia, planning the production (or sale) of products with such characteristics that have been identified in customer reviews as positive

Conclusions

- Using the LIDA architecture allow for automatic decision making and realization
- The LIDA is the approach for Artificial General Intelligence
- The main limitation is low level of technology readiness level

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Default prediction in leasing companies



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Motivation

- Nowadays default prediction is also performed using the machine learning methods.
- This problem is very often analyzed by researches, but mainly products offered by banks are considered.

Motivation

- However the approaches for default prediction related to banks' products most often do not achieve good performance in the case of leasing products.
- It can be put stressed, the subject of leasing is mainly a fixed asset, such, as a machine or a car. Thus additional attributes of fixed asset should be used for developing the method for default of leasing contracts.

Objective

- Develop and comparing the machine learning methods for increase the level of the default of leasing contracts prediction.
- We focus mainly on Random Forest Classifier, AdaBoostClassifier, GradientBoostingClassifier and Deep Neural Networks

Data description and processing

- Input data comes from both internal sources (databases of information systems of an organization) and external ones (databases of financial supervision institutions).
- Additionally, the input vector consists of specific attributes related to the leasing contract (such as fixed asset features).
- The dataset consists of approximately 4,500 cases described by 424 variables (17 of them are text type).
- Two data sets were modeled: a test sample and a learning sample.

Results

Random Forest Classifier

	Precision	Recall
Non-Default	71,9%	76,6%
Default	75,0%	70,1%

Gradient Boosting Classifier

	Precision	Recall
Non-Default	75,2%	71,9%
Default	73,1%	76,3%

AdaBoost Classifier

	Precision	Recall
Non-Default	76,1%	70,9%
Default	72,8%	77,7%

Deep neural network

	Precision	Recall
Non-Default	79,1%	69,7%
Default	72,9%	81,6%

Conclusions

- The results of experiments allow us to draw the conclusion that the precision of prediction of defaults is from 72,8% to 75% (the highest precision has been achieved by random forest classifier)
- The precision of non-default prediction, in turn, is from 71,9% to 79,1% (the highest precision has been achieved by deep neural network)

Conclusions

- The use of automatic forecast models reduces the probability of a situation in which borrowers (lessees) will cease to pay their liabilities resulting from the concluded loan (lease) agreements.
- From the point of view of economic usefulness, the presented tool contributes to reducing the probability of losses caused by the suspension of default of liabilities by clients of a wide range of financial institutions

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Food demand prediction



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Motivation

- The sustainable development issues are mainly related to food loss and waste have been drawing much attention in recent years
- Food and Agriculture Organization of the United Nations estimates that up to one-third of food produced globally, amounting to 1,3 billion tons of food per year, is lost and wasted

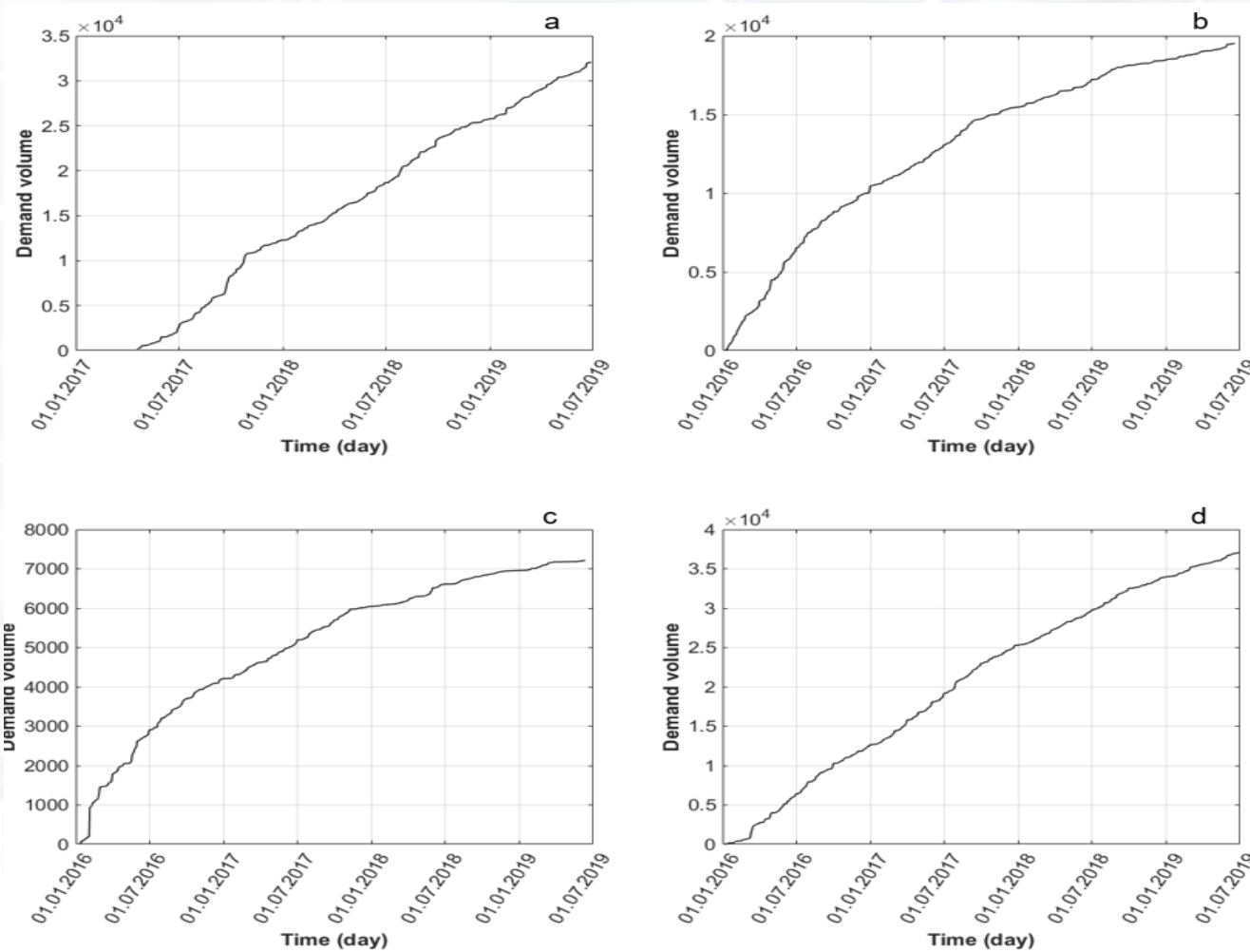
Motivation and objective

- One of the manner of food waste reduction is food demand prediction
- The aim of the research is to develop the models for food demand prediction based on the Nonlinear Autoregressive Exogenous Neural Network

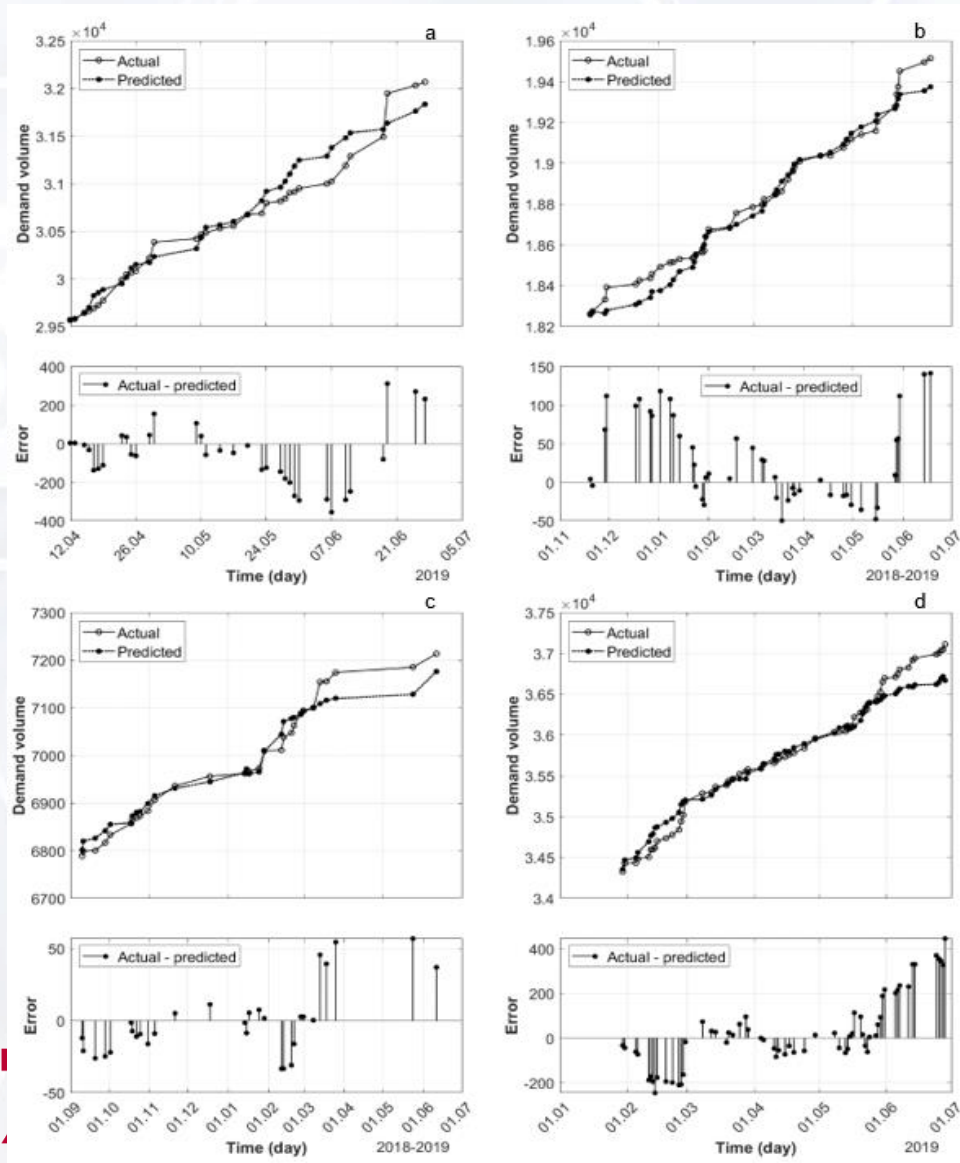
Data description of four selected products

Product ID	Observations		Min	Max	Mean	SD	Kolmogorov-Smirnov test: exponential distribution, $\alpha=0.01$			
	Date	n					p-value	K-S stat.	c-value	H
492	19.04.2017-27.06.2019	339	10	820	94.5	103.4	0.0020	0.1003	0.0879	1
1272	05.01.2016-18.06.2019	451	-23	298	43.3	42.0	0.0772	0.0597	0.0762	0
1325	11.01.2016-11.06.2019	296	0	700	24.4	45.8	0.1168	0.0687	0.0940	0
1347	05.01.2016-28.06.2019	617	-44	410	60.1	61.5	0.0947	0.0494	0.0652	0

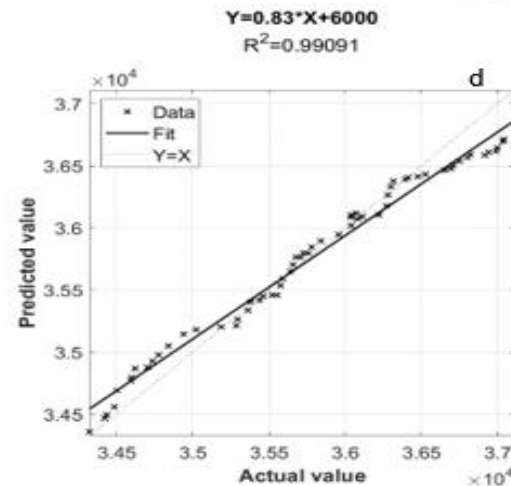
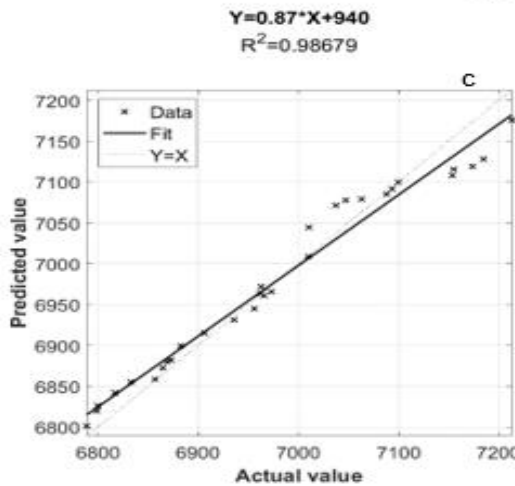
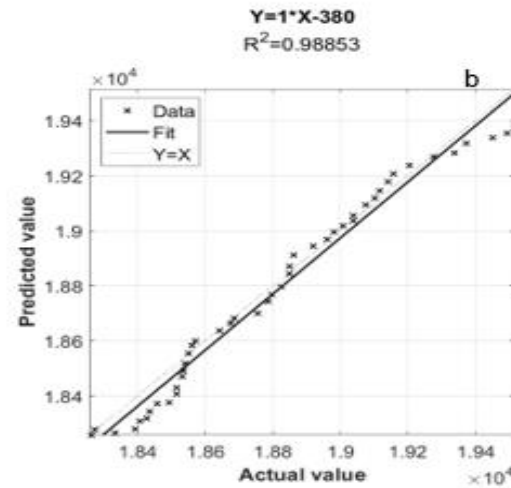
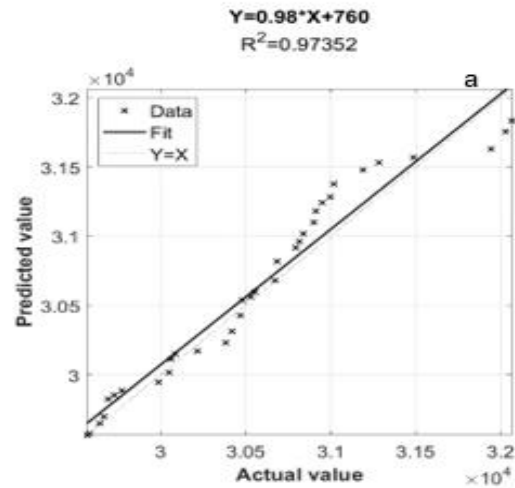
Variation in demand volume for four selected food products



Demand volume prediction with error prediction at the high ratio



Comparison between actual values and NARX neural network model predictions at the high ratio



Conclusions

- Hybrid concept, consisting in a combination of the NARX with neural networks, was successfully implemented to predict demand data for food products
- However, depending on the type of product, its prediction performance slightly differed. The results of the R2 measure ranged from 97% to 99% depending on particular products

Conclusions

- The developed approach can lead to reducing food waste
- The main limitation of the developed models is the lack of possibility of analysing small data sets.

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Thank you very much for attention!

Contact:

**Center for Intelligent Management Systems
Wroclaw University of Economics and Business–**

www.imscenter.pl

dr hab. inż. Marcin Hernes, prof. UEW – chair
marcin.hernes@ue.wroc.pl