

Машинное обучение и искусственный интеллект для решения научных и прикладных задач

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Industry 4.0



The term “Industry 4.0” is used to signify the beginning of the fourth industrial revolution – the previous three being mechanical production, mass production, and then the digital revolution. It could be argued that Industry 4.0 is simply an amalgamation of the three previous eras in manufacturing, but Industry 4.0 is poised to be much more impactful than that.

Industrial Internet of Things (IIoT), Automation, Artificial Intelligence, Big Data & Analytics, The Cloud, Cybersecurity, Simulations, Robotics, Smart manufacture, Mobile devices, Smart manufacture, etc.

Basis - machine learning

X — множество *объектов* (точнее, их информационных описаний)

Y — множество *ответов* (оценок, предсказаний или прогнозов)

$y: X \rightarrow Y$ — неизвестная зависимость (target function)

Дано:

$\{x_1, \dots, x_\ell\} \subset X$ — обучающая выборка (training sample)

$y_i = y(x_i)$, $i = 1, \dots, \ell$ — известные ответы

Найти:

$a: X \rightarrow Y$ — алгоритм, решающую функцию (decision function), приближающую y на всём множестве X

Весь курс машинного обучения — это конкретизация:

- как задаются объекты и какими могут быть ответы
- в каком смысле « a приближает y »
- как строить функцию a

Basis - machine learning

$f_j: X \rightarrow D_j, j = 1, \dots, n$ — признаки объектов (features)

Типы признаков:

- $D_j = \{0, 1\}$ — бинарный признак f_j
- $|D_j| < \infty$ — номинальный признак f_j
- $|D_j| < \infty, D_j$ упорядочено — порядковый признак f_j
- $D_j = \mathbb{R}$ — количественный признак f_j

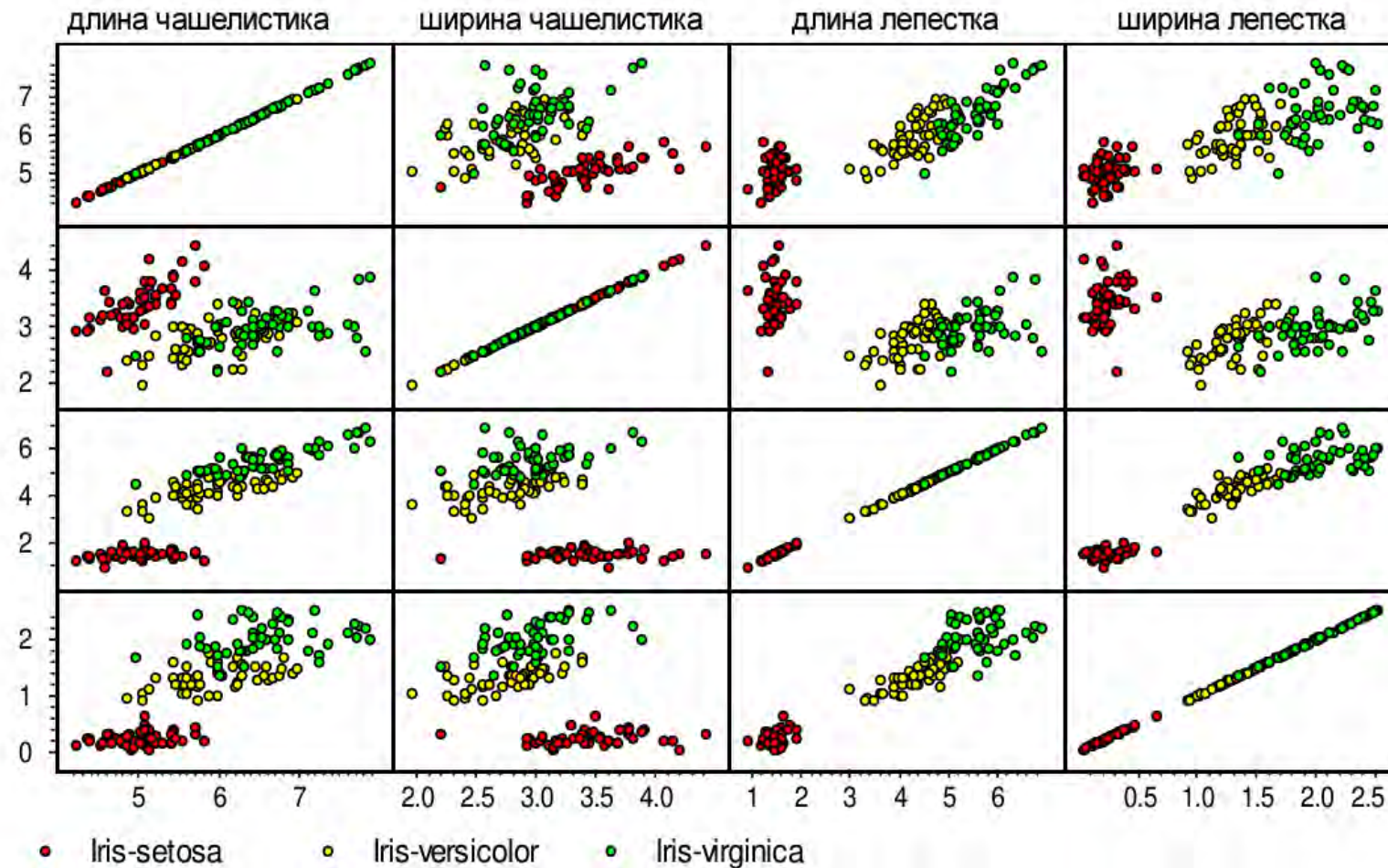
Вектор $(f_1(x), \dots, f_n(x))$ — признаковое описание объекта x

Матрица «объекты–признаки» (feature data)

$$F = \left\| f_j(x_i) \right\|_{\ell \times n} = \begin{pmatrix} f_1(x_1) & \dots & f_n(x_1) \\ \dots & \dots & \dots \\ f_1(x_\ell) & \dots & f_n(x_\ell) \end{pmatrix}$$

Basis - machine learning

$n = 4$ признака, $|Y| = 3$ класса, длина выборки $\ell = 150$.



Модель (predictive model) — параметрическое семейство функций

$$A = \{g(x, \theta) \mid \theta \in \Theta\},$$

где $g: X \times \Theta \rightarrow Y$ — фиксированная функция,
 Θ — множество допустимых значений параметра θ

Пример.

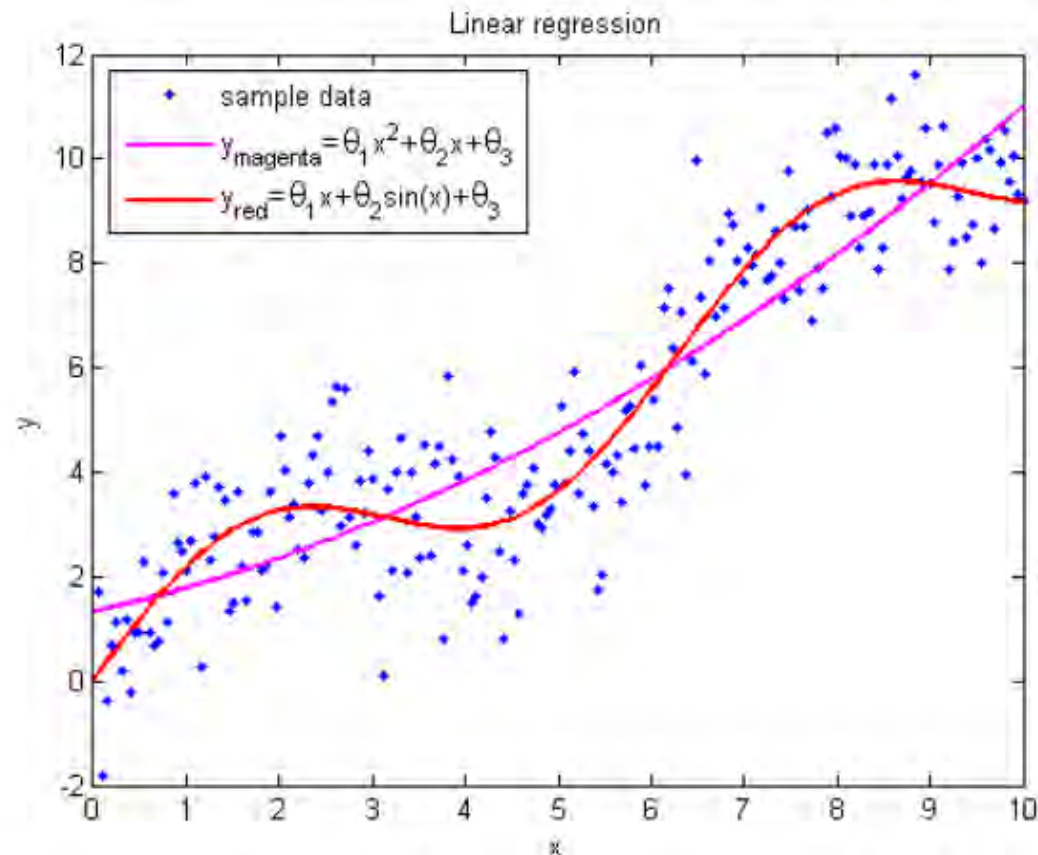
Линейная модель с вектором параметров $\theta = (\theta_1, \dots, \theta_n) \in \mathbb{R}^n$:

$$g(x, \theta) = \sum_{j=1}^n \theta_j f_j(x) \quad \text{— для регрессии и ранжирования, } Y = \mathbb{R}$$

$$g(x, \theta) = \text{sign} \sum_{j=1}^n \theta_j f_j(x) \quad \text{— для классификации, } Y = \{-1, +1\}$$

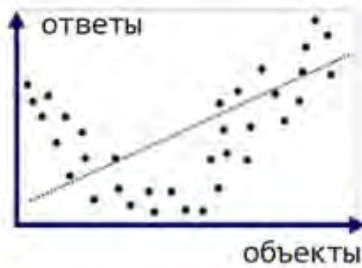
Basis - machine learning

$X = Y = \mathbb{R}$, $\ell = 200$, $n = 3$ признака: $\{x, x^2, 1\}$ или $\{x, \sin x, 1\}$

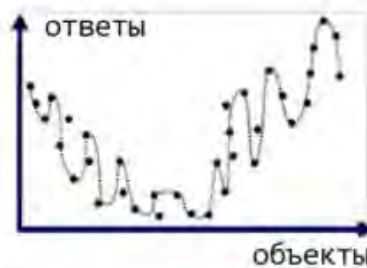
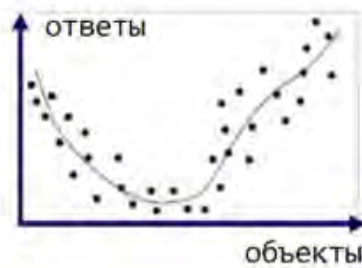


- генерация признаков (feature generation) обогащает модель
- на практике очень важно «правильно угадать модель»

Basis - machine learning

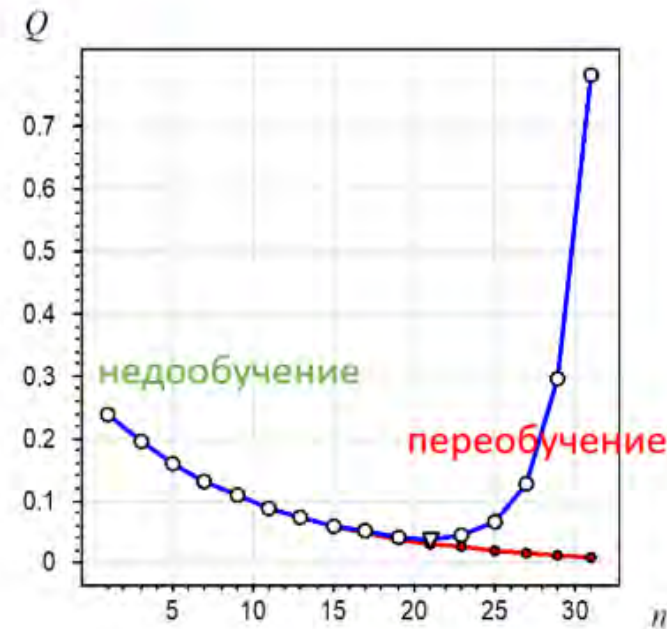


недообучение

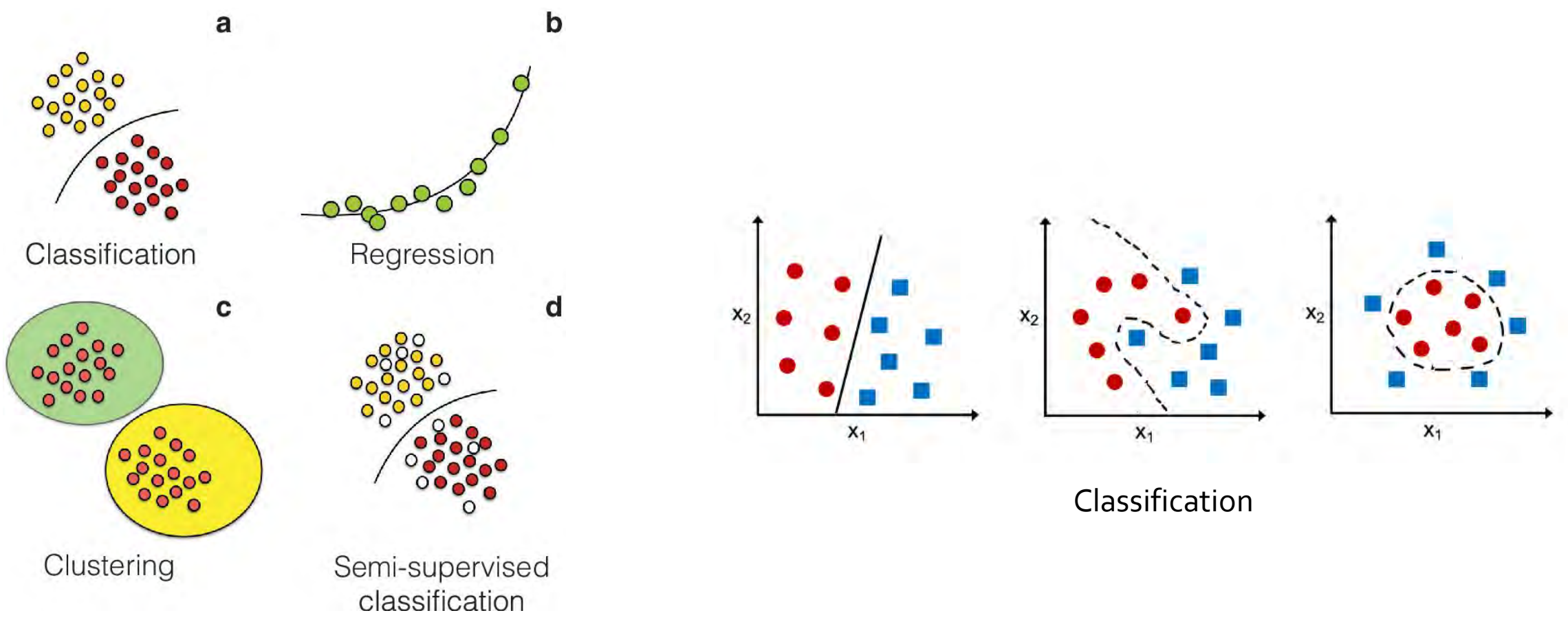


переобучение

- **Недообучение** (underfitting): модель слишком проста, недостаточное число параметров n
- **Переобучение** (overfitting): модель слишком сложна, избыточное число параметров n



Back to the machine learning





Воронцов Константин Вячеславович

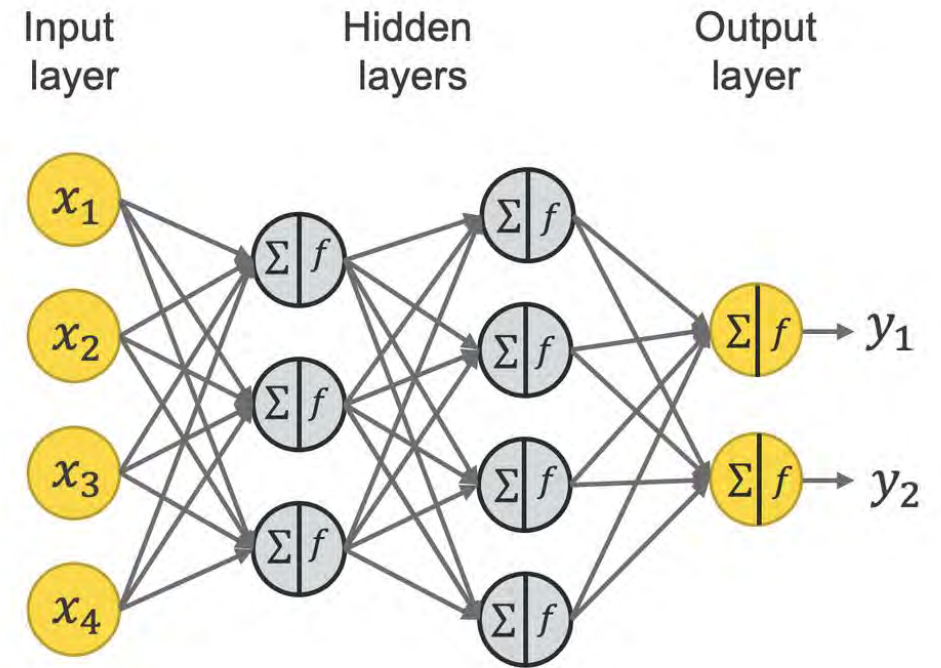
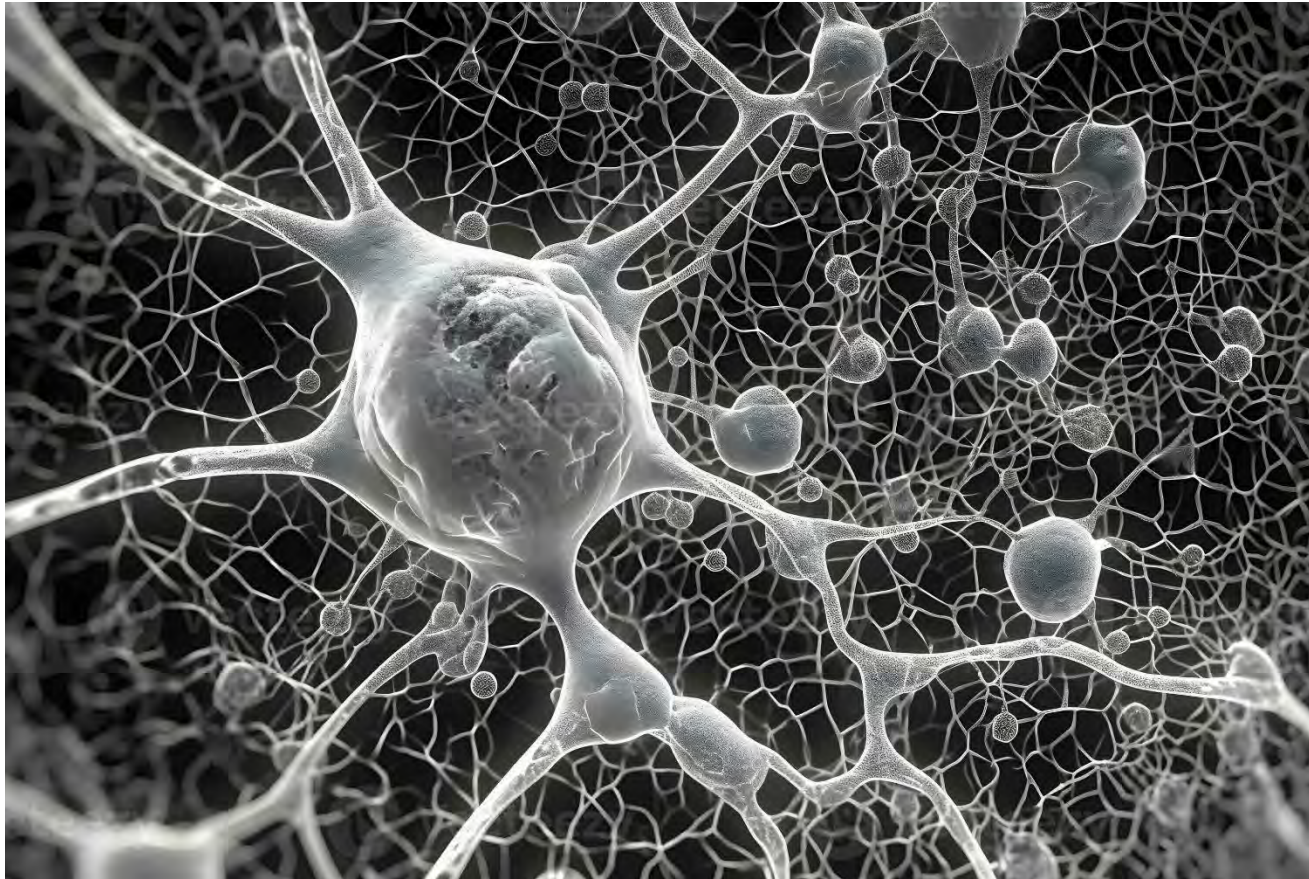
Зав. кафедрой **ММП**, профессор РАН, д.ф.-м.н.,
доцент **ММП**

Математические основы машинного обучения

<https://www.youtube.com/@MachineLearningIS>

Neural networks

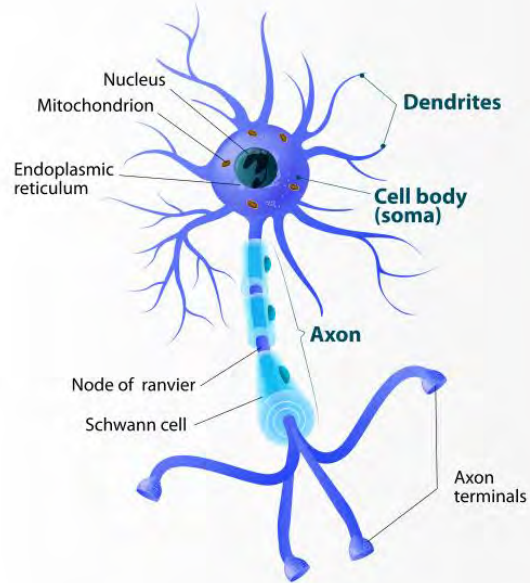
Neural networks are an example of a supervised learning algorithm and seek to approximate the function represented by your data



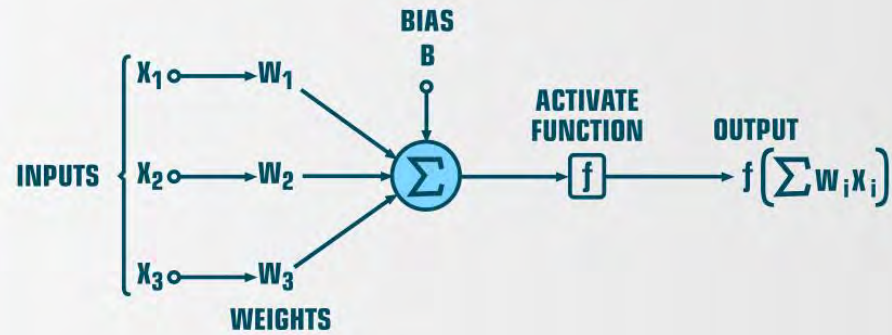
Farley and Wesley A. Clark were the first to simulate a Hebbian network in 1954 at MIT. They used computational machines, then called "calculators".

Neural networks

Structure of Typical Neuron



Structure of Artificial Neuron

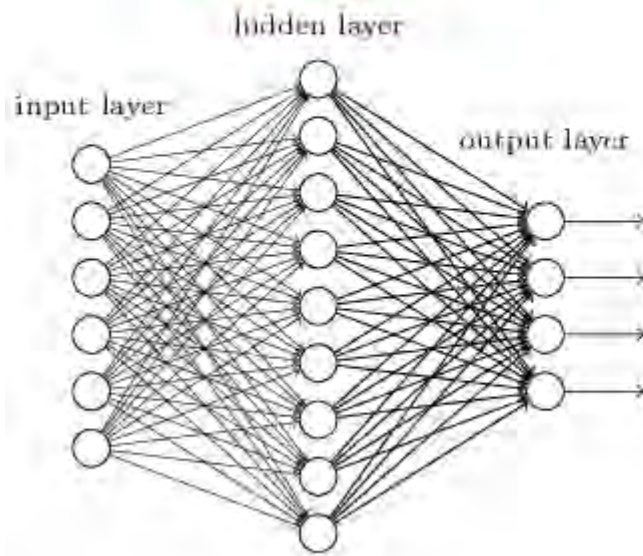


Neural Network Activation Functions: a small subset!

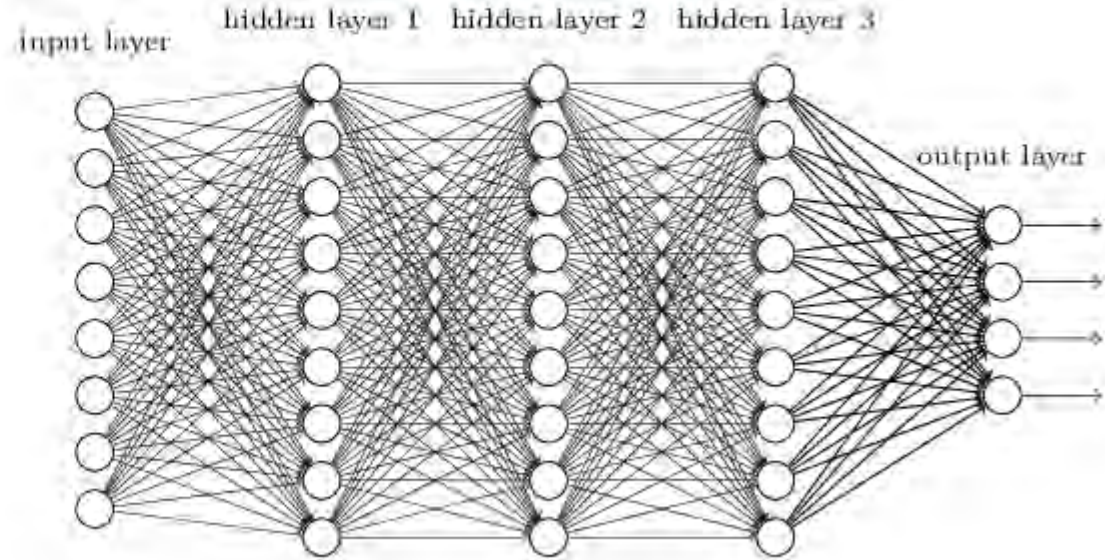
ReLU $\max(0, x)$	GELU $\frac{x}{2} \left(1 + \tanh \left(\sqrt{\frac{2}{\pi}} (x + ax^3) \right) \right)$	PReLU $\max(0, x)$
ELU $\begin{cases} x & \text{if } x > 0 \\ \alpha(x \exp x - 1) & \text{if } x < 0 \end{cases}$	Swish $\frac{x}{1 + \exp -x}$	SELU $\alpha(\max(0, x) + \min(0, \beta(\exp x - 1)))$
SoftPlus $\frac{1}{\beta} \log(1 + \exp(\beta x))$	Mish $x \tanh \left(\frac{1}{3} \log(1 + \exp(\beta x)) \right)$	RReLU $\begin{cases} x & \text{if } x \geq 0 \\ ax & \text{if } x < 0 \text{ with } a \sim \mathcal{R}(l, u) \end{cases}$
HardSwish $\begin{cases} 0 & \text{if } x < -3 \\ x & \text{if } x \geq 3 \\ x(x+3)/6 & \text{otherwise} \end{cases}$	Sigmoid $\frac{1}{1 + \exp(-x)}$	SoftSign $\frac{x}{1 + x }$
Tanh $\tanh(x)$	Hard tanh $\begin{cases} a & \text{if } x \geq a \\ b & \text{if } x \leq b \\ x & \text{otherwise} \end{cases}$	Hard Sigmoid $\begin{cases} 0 & \text{if } x \leq -3 \\ 1 & \text{if } x \geq 3 \\ x/6 + 1/2 & \text{otherwise} \end{cases}$
Tanh Shrink $x - \tanh(x)$	Soft Shrink $\begin{cases} x - \lambda & \text{if } x > \lambda \\ x + \lambda & \text{if } x < -\lambda \\ 0 & \text{otherwise} \end{cases}$	Hard Shrink $\begin{cases} x & \text{if } x > \lambda \\ x & \text{if } x < -\lambda \\ 0 & \text{otherwise} \end{cases}$

Deep neural networks

"Non-deep" feedforward neural network

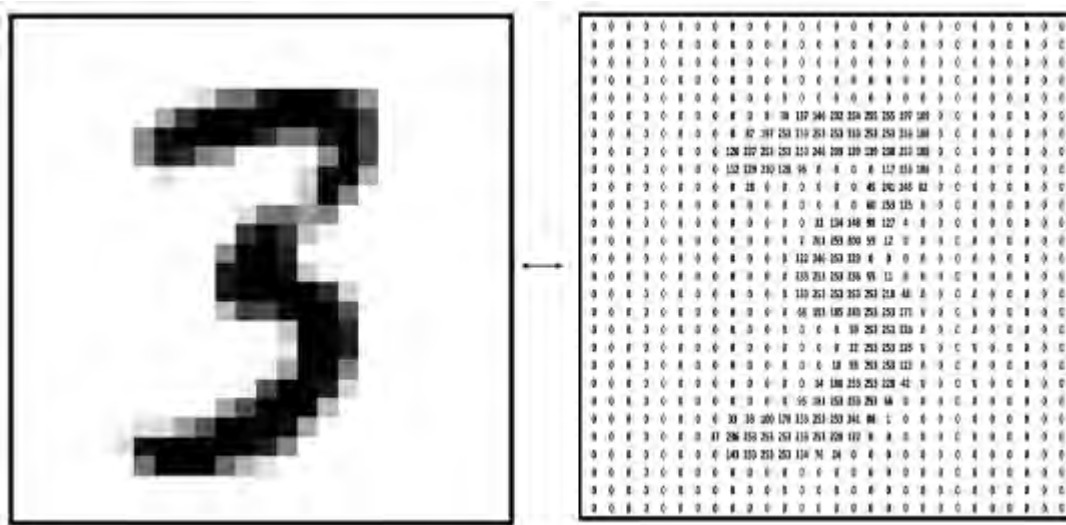


Deep neural network



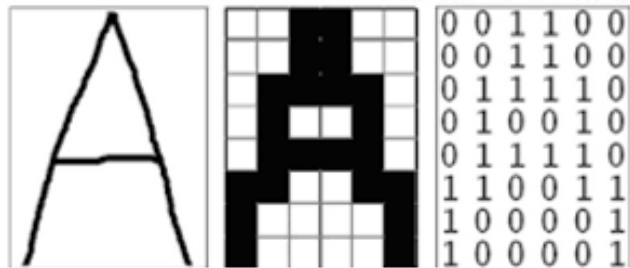
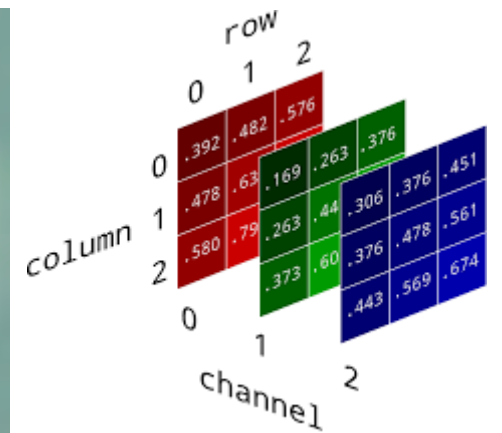
A neural network with multiple hidden layers and multiple nodes in each hidden layer is known as a **deep learning system** or a **deep neural network**. Deep learning is the development of deep learning algorithms that can be used to train and predict output from complex data.

What computer sees?



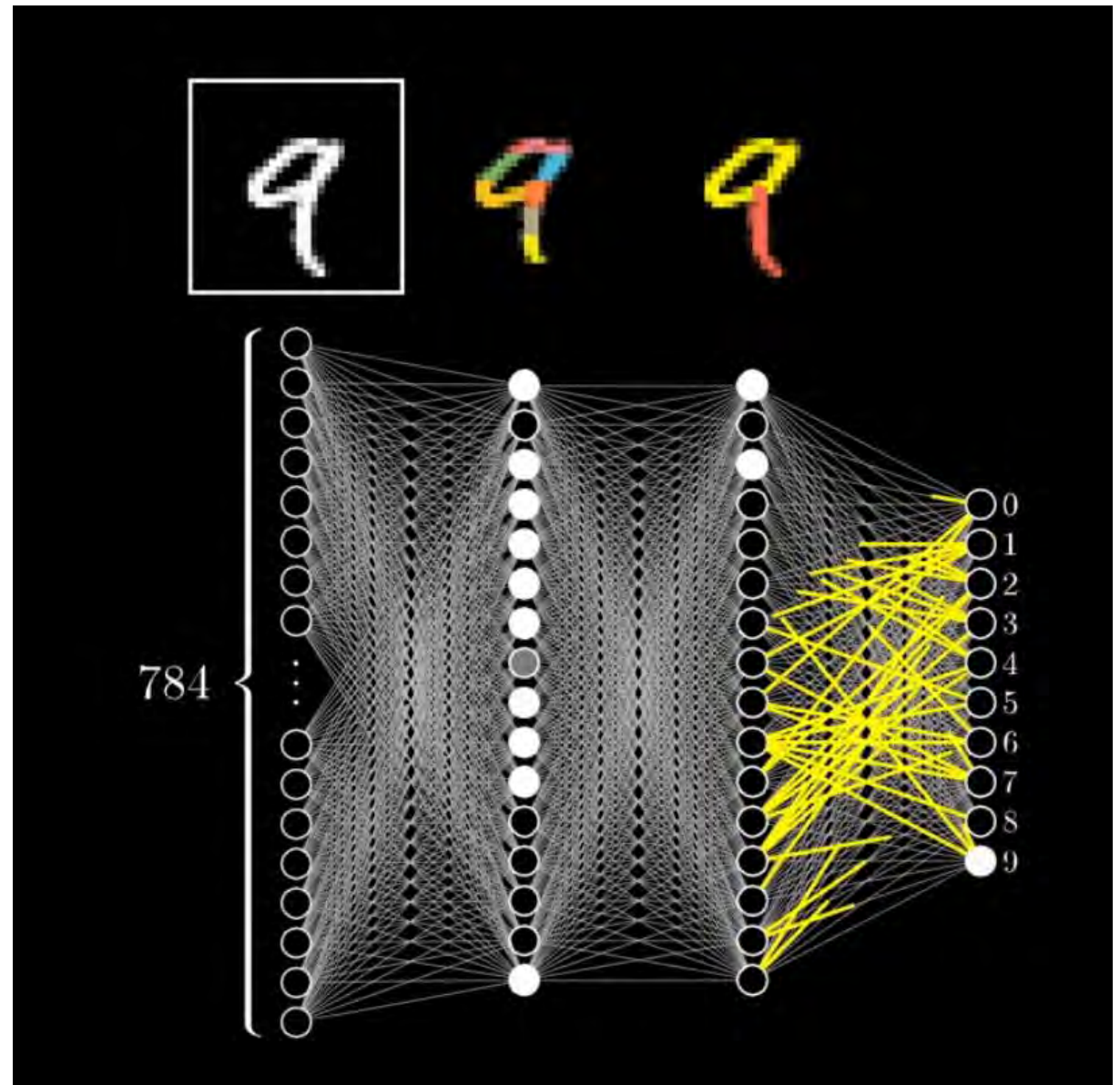
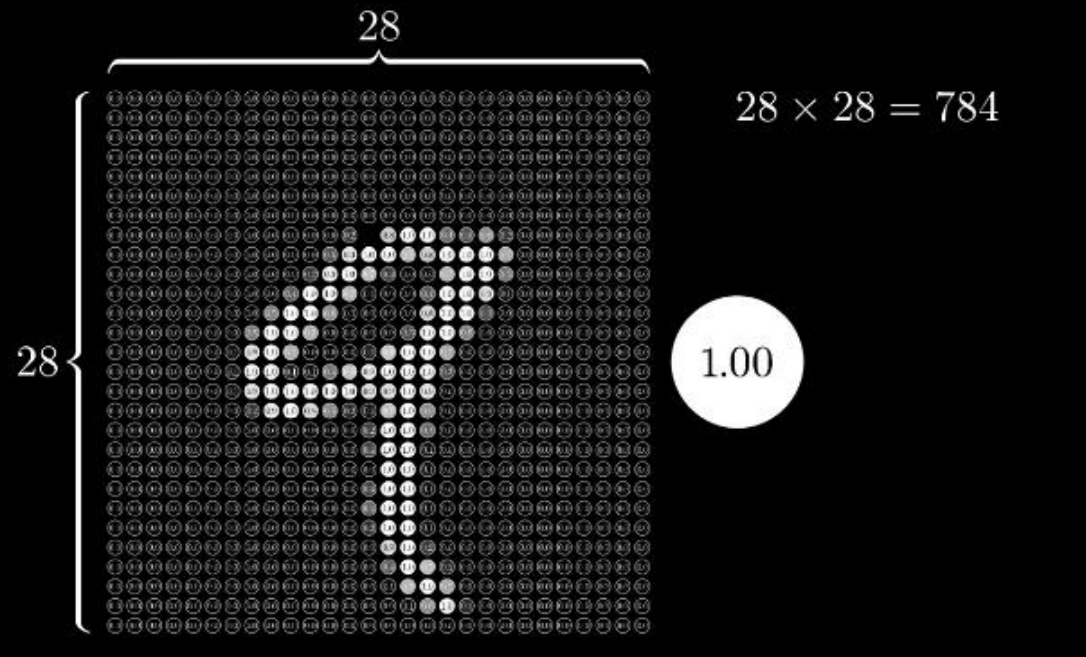
What we see

What a computer sees

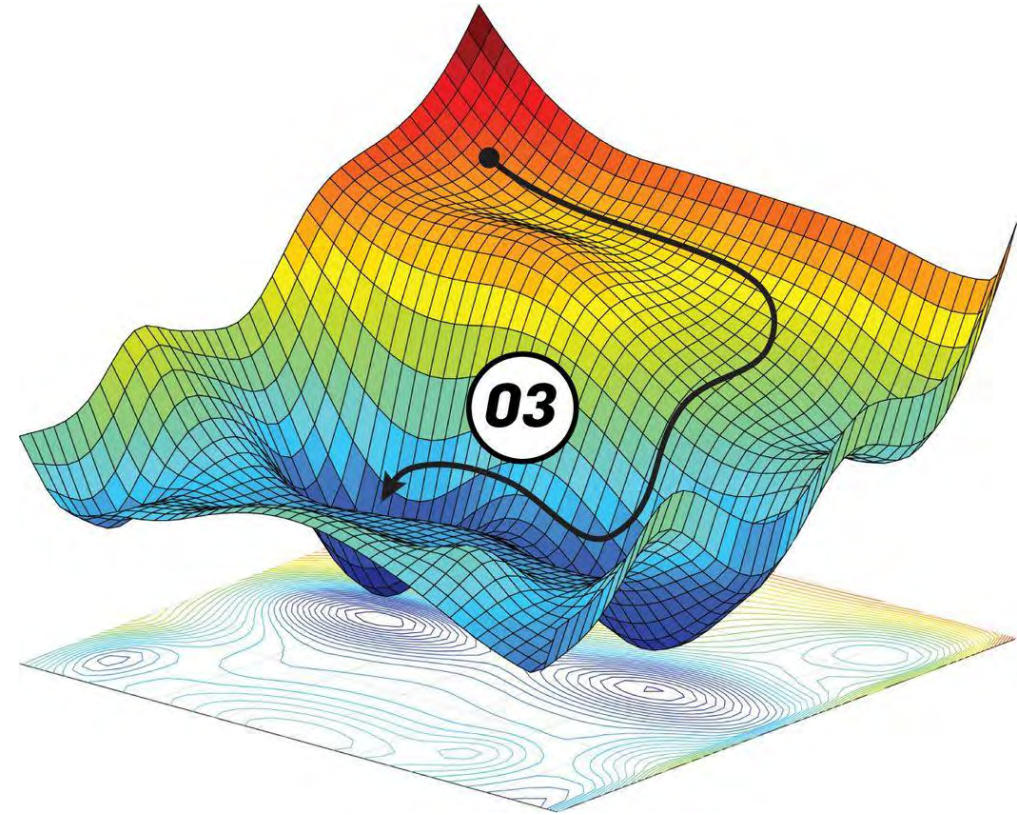
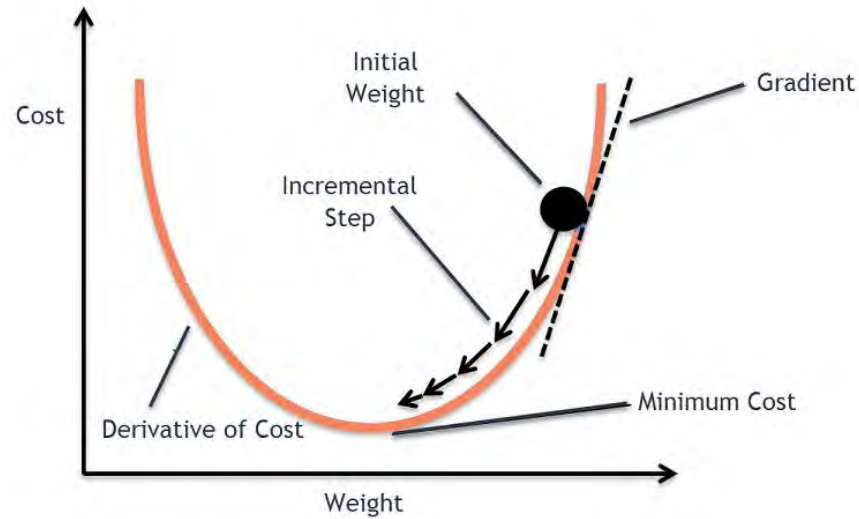


The image itself is a source of information.

Classification of handwritten digits

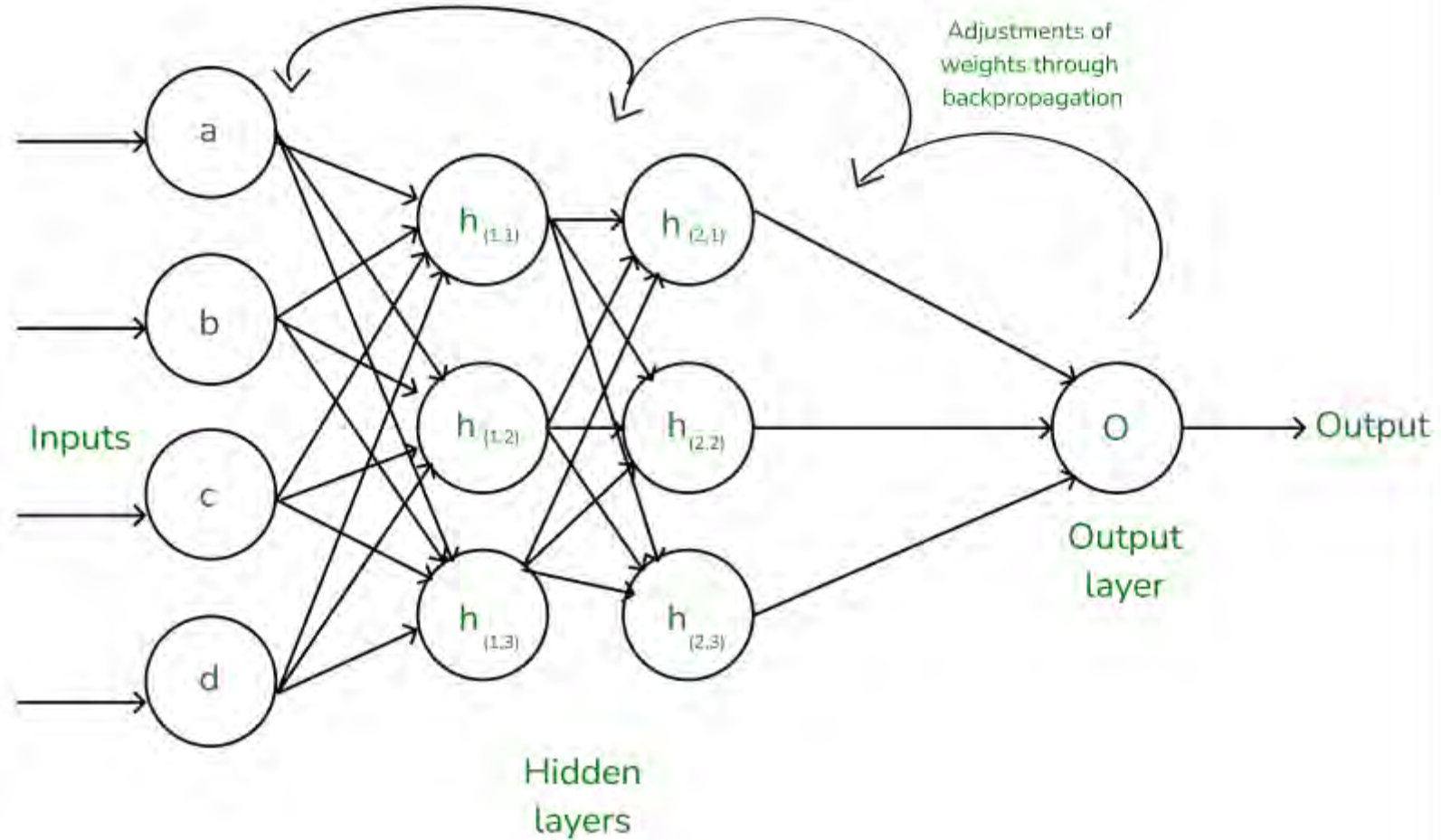


Basis - gradient descent



Gradient descent is an optimization algorithm which is commonly-used to train machine learning models and neural networks. It trains machine learning models by minimizing errors between predicted and actual results.

Basis - backpropagation

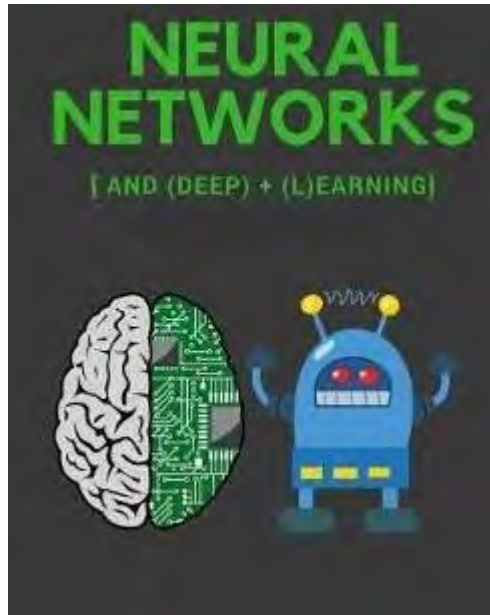


In machine learning, backpropagation is a gradient estimation method used to train neural network models. The gradient estimate is used by the optimization algorithm to compute the network parameter updates.



Neural Networks and Deep Learning 2019

Michael Nielsen

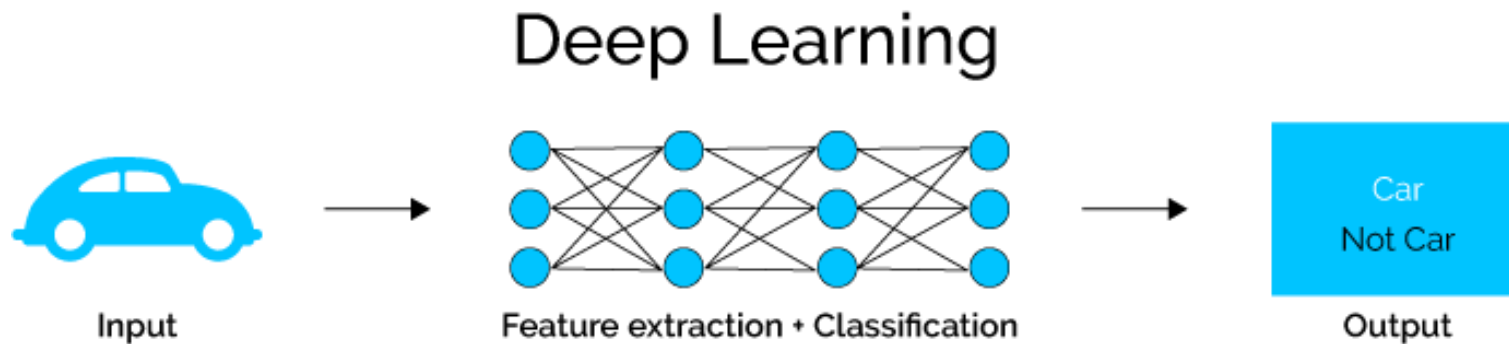
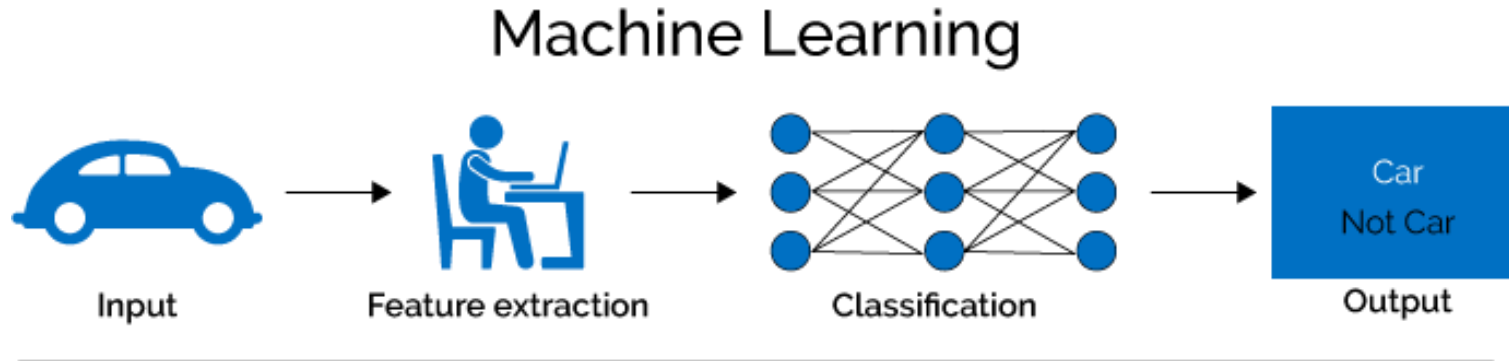


<http://neuralnetworksanddeeplearning.com/index.html>

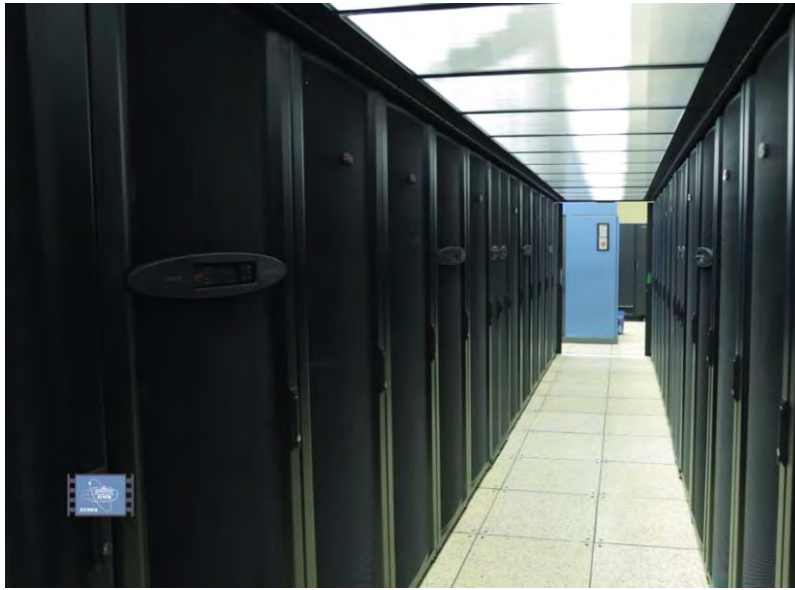
ML vs. Deep Learning

Deep learning (DL) is a machine learning subfield that uses multiple layers for learning data representations

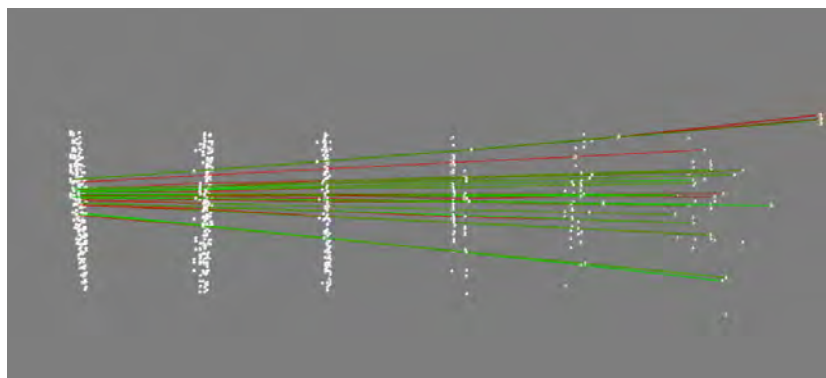
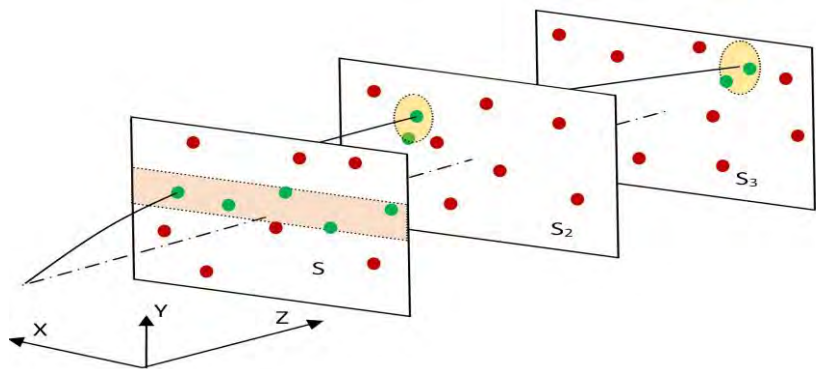
DL is exceptionally effective at learning patterns



HybriLIT & SUPERCOMPUTER "Govorun"

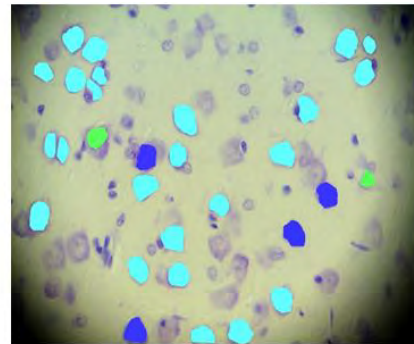
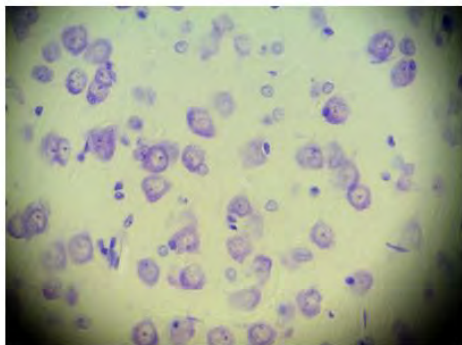


Использование нейросетей для трекинга в ФВЭ

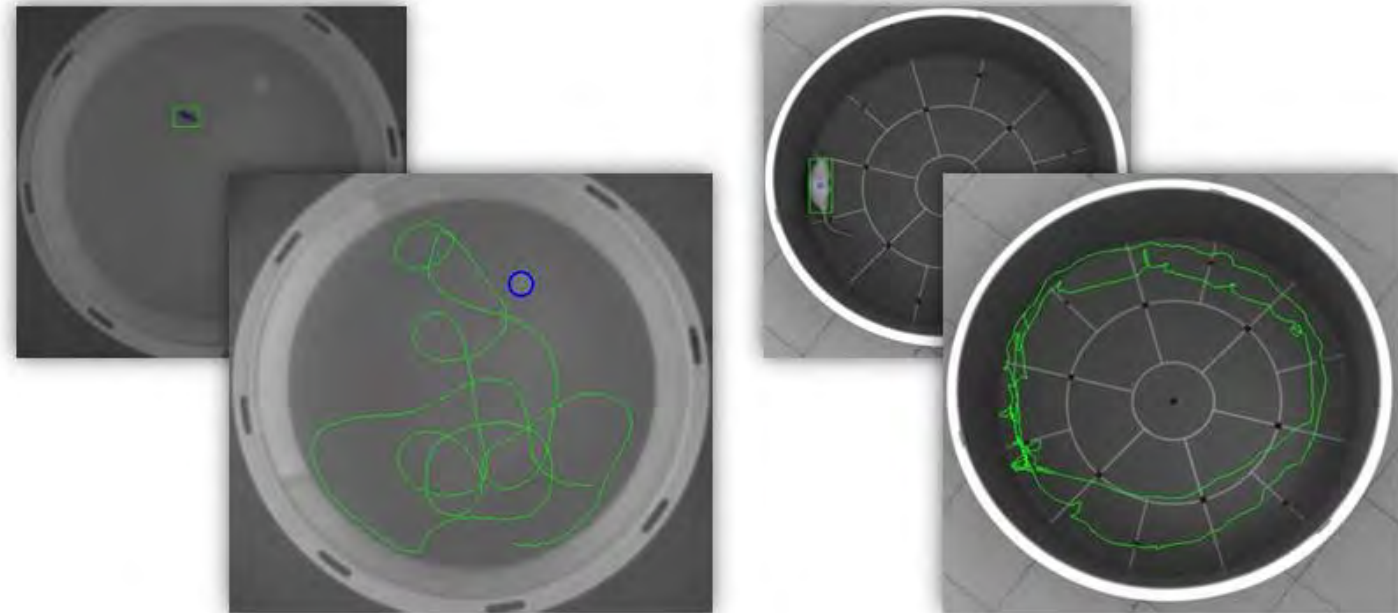


проф. Г. А. Ососков – следующая лекция

Radiation biology tasks



МОРФОЛОГИЧЕСКИЙ АНАЛИЗ



ПОВЕДЕНЧЕСКИЙ АНАЛИЗ

Контроль загрязнения тяжелыми металлами

Environmental Concerns

The environmental problems like global warming, acid rain, air pollution, urban sprawl, waste disposal, ozone layer depletion, water pollution, climate change and many more affect every human, animal, and nation on this planet.

Over the last few decades, the exploitation of our planet and the degradation of our environment has gone up at an alarming rate. As our actions have been not in favor of protecting this planet, we have seen natural disasters striking us more often in the form of flash floods, earthquakes, blizzards, tsunamis, and cyclones.



Air pollution

Air pollution has a significant **negative impact** on the various components of ecosystems, **human health**, and ultimately, causes significant **economic damage**.

More than nine out of 10 of the world's population – 92% – lives in places where **air pollution exceeds safe limits**, according to research from the World Health Organization (WHO).



There are regional and international **environment control programs**. They use different techniques and tools but as a result, they all want to understand **what is the current situation** and how it will evolve.

Approaches



Generally, studies are based on the data obtained at the sampling sites in manual or automatic mode. The collected material is analyzed using various techniques in the field or in special laboratories. Air quality (AQ) monitoring stations provide information about regulatory air pollutants such as gaseous pollutants, PM, but rarely about heavy metals. To get detailed information samples should be processed in laboratories.

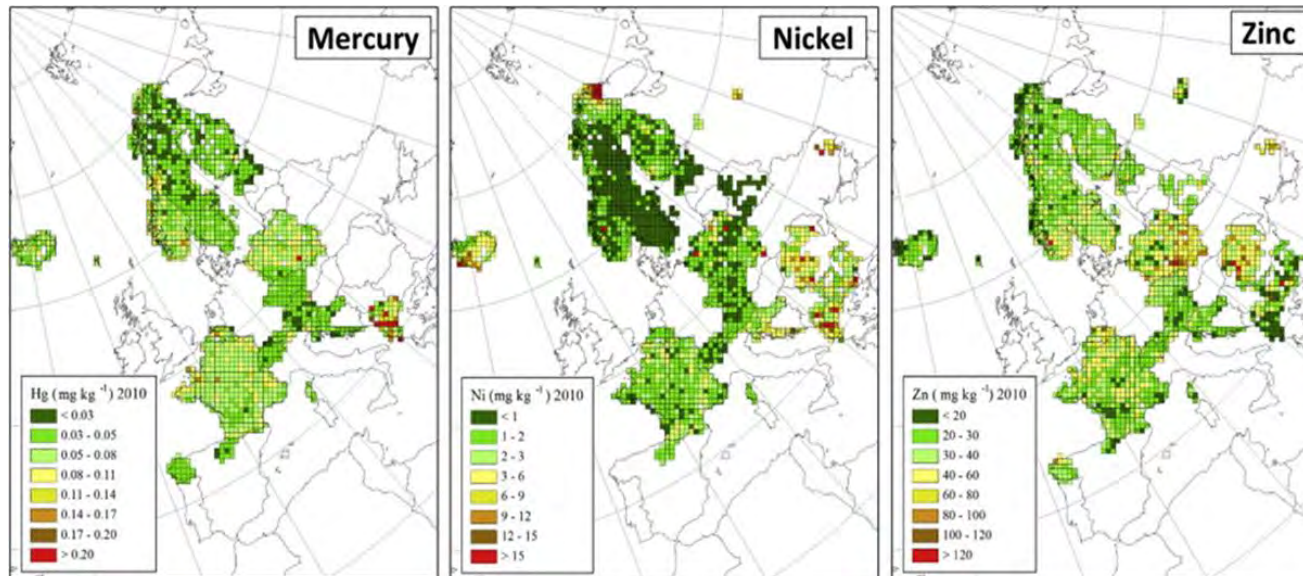
After collection the data are aggregated and interpreted, and quite often the results are ambiguous and require the involvement of experts.

The level of automation and adoption of information technology in environmental monitoring programs is constantly increasing, although it lags far behind areas where the use of modern technology can lead to rapid economic impact.

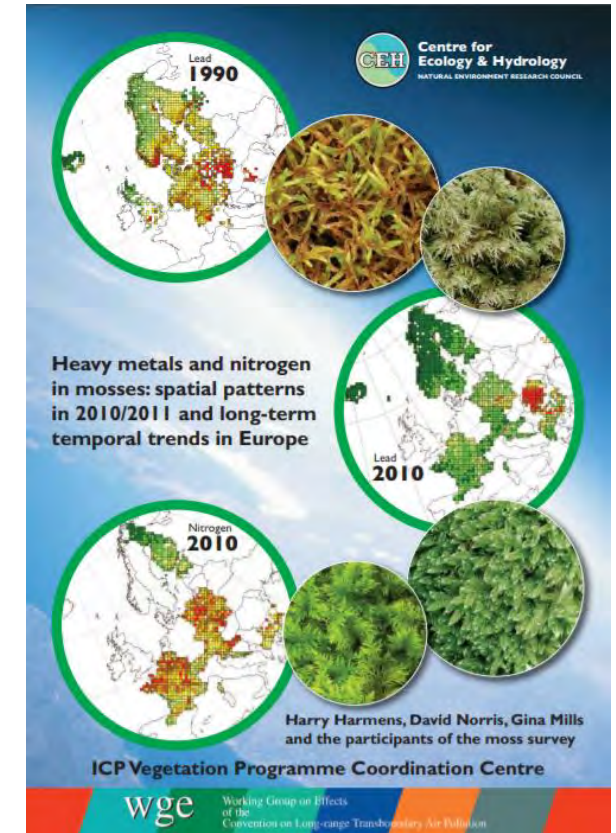


ICP Vegetation

The aim of the **UNECE International Cooperative Program (ICP) Vegetation** in the framework of the United Nations Convention on Long-Range Transboundary Air Pollution is to **identify the main polluted areas of Europe**, produce regional maps and further develop the understanding of the long-range transboundary pollution. Atmospheric deposition study of heavy metals, nitrogen, persistent organic compounds (POPs) and radionuclides is based on the analysis of naturally growing mosses through moss surveys carried out **every 5 years**. The program is realized in **43 countries of Europe and Asia**. Mosses are collected at thousands of sites



Examples of distribution maps in Atlas 2010



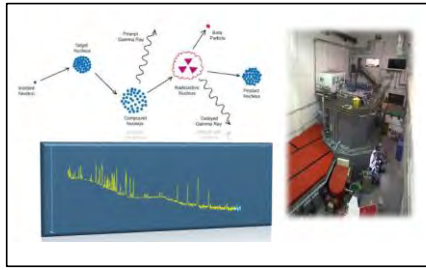
Since 2014 the JINR Frank Laboratory of Neutron Physics sector of neutron activation analysis is the **coordinator of the ICP Vegetation program**

The platform

Samples collection



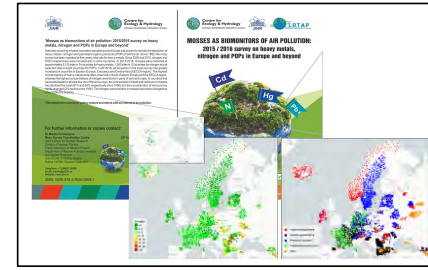
Samples analysis



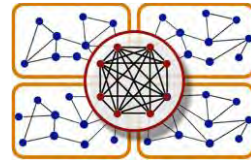
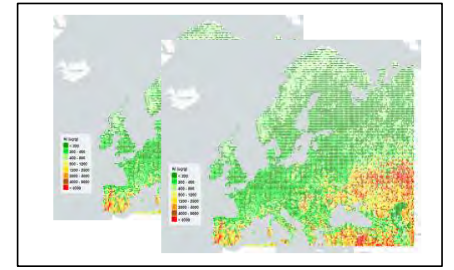
Data analysis



Data presentation



Prediction/Controle



Tensorflow
Keras



Microservices



Google Earth Engine



HybriLIT



Since the launch of the first version of the platform, a mobile application has been developed to simplify the process of collecting and verifying data, deep learning models for image classification and pollution prediction based on remote sensing data, various functional blocks implemented in a microservice architecture to automate a number of operational tasks, and the analytical capabilities of the system are also expanded.



'Mosses as biomonitors of air pollution: 2015/2016 survey on heavy metals, nitrogen and POPs in Europe and beyond'

Naturally-occurring mosses have been sampled across Europe and beyond to monitor the deposition of heavy metals, nitrogen and persistent organic pollutants (POPs) from the air. Since 1990, the moss survey has been repeated at five-yearly intervals for heavy metals. Since 2005 and 2010, nitrogen and POPs respectively were included too in some countries. In 2015/2016, mosses were collected at approximately 5,100 sites in 34 countries for heavy metals, 1,500 sites in 12 countries for nitrogen and at selected sites in eight countries for POPs. In 2015/16, participation in the moss survey has greatly increased in countries in Eastern Europe, Caucasus and Central Asia (EECCA region). The highest concentrations of heavy metals were often observed in South-Eastern Europe and the EECCA region, whereas the highest concentrations of nitrogen were found in parts of central Europe. In countries that have participated in at least four out of the six surveys, the concentration of lead and cadmium in mosses has declined the most (81% and 64% respectively since 1990) and the concentration of mercury has hardly changed (2% decline since 1995). The nitrogen concentration in mosses has hardly changed too since 2005 (5% decline).

This report is for scientists, policy makers and others with an interest in air pollution.

For further information or copies contact:

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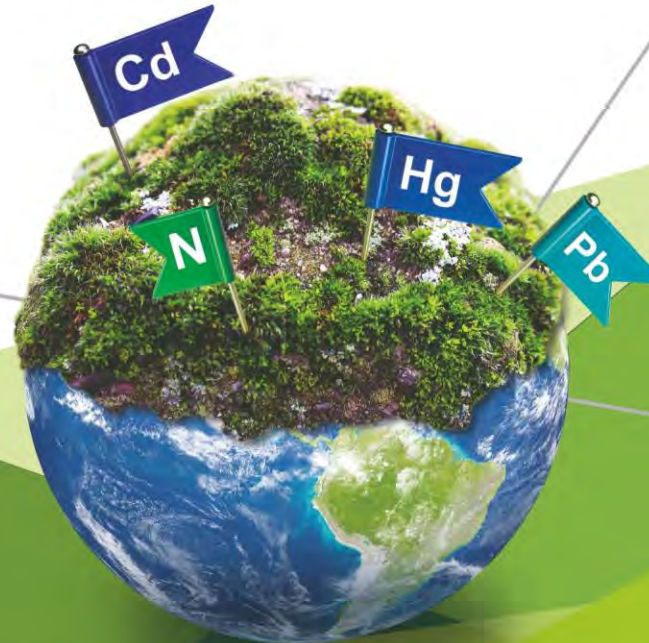
ISBN: ISBN 978-5-9530-0508-1

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MOSSES AS BIOMONITORS OF AIR POLLUTION: 2015 / 2016 survey on heavy metals, nitrogen and POPs in Europe and beyond

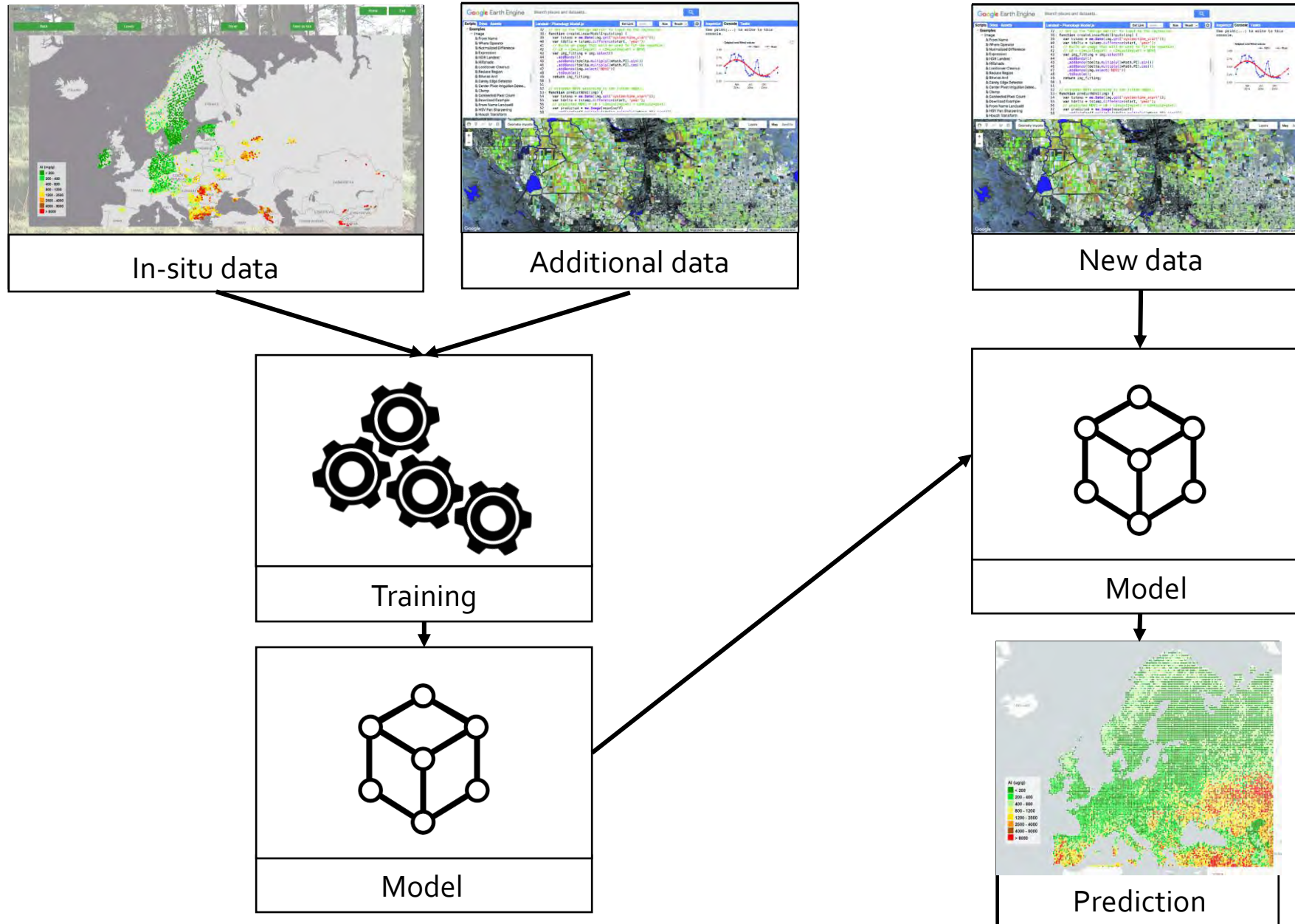


Marina Frontasyeva, Harry Harmens, Alexander Uzhinskiy
and the participants of the moss survey



The project, designed to automate typical operations with data and the creation of regional maps, absorbed more and more new approaches and technologies and now it may be classified as intelligent platforms.

Machine learning (Supervised learning)



Satellite programs



The Earth Engine Data Catalog



Landsat & Sentinel 1, 2
10-30m, weekly



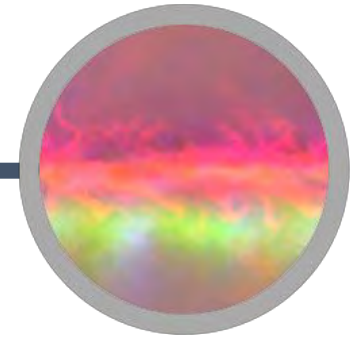
MODIS
250m daily



Vector Data
WDPA, Tiger



**Terrain &
Land Cover**



Weather & Climate
NOAA NCEP, OMI, ...

... and upload your own vectors and rasters

> 200 public datasets

> 5 million images

> 4000 new images every day

> 80 petabytes of data

Reducer in action

The screenshot displays the Google Earth Engine web interface. The top navigation bar includes the Google Earth Engine logo, a search bar, and user profile icons. The left sidebar shows a file explorer with folders like 'tutorial' and 'Writer'. The main editor area contains a JavaScript script for a tutorial, with the following code:

```
38  
39 // Display the results.  
40 Map.addLayer(composite, {bands: ['SR_B4', 'SR_B3', 'SR_B2'], min: 0, max: 0.3});  
41  
42 var region = ee.Geometry.Rectangle(37.16, 56.73, 37.17, 56.735);  
43 Map.addLayer(region, {'color': 'red'});  
44  
45 var mean = composite.reduceRegion({  
46   reducer: ee.Reducer.mean(),  
47   geometry: region,  
48   scale: 30  
49 });
```

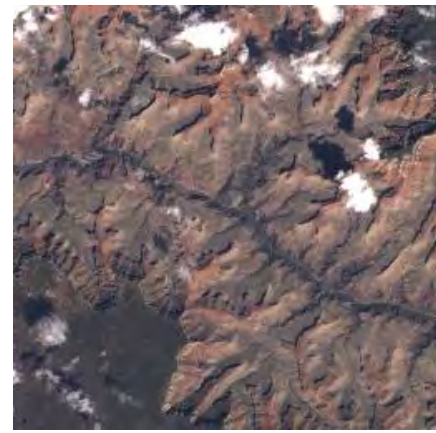
The Inspector panel on the right shows the output of the script, displaying an object with 19 properties:

```
Object (19 properties) JSON  
QA_PIXEL: 21824  
QA_RADSAT: 0  
SR_B1: 0.029713583044238552  
SR_B2: 0.03616107042660685  
SR_B3: 0.060925221691503134  
SR_B4: 0.05429918944533672  
SR_B5: 0.24582152299513438  
SR_B6: 0.14452542855088027  
SR_B7: 0.09044999080735738
```

The main map area shows a satellite view of a landscape with a red square highlighting a specific region. The bottom of the interface includes a Google logo, keyboard shortcuts, copyright information (© 2022 Google), a scale bar (1 km), and a link to the terms of use.

Google Earth Engine

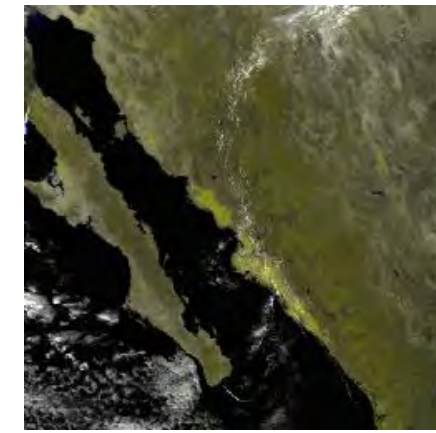
There are more than **100 satellite programs** and modeled datasets. Google Earth Engine has **JavaScript online editor** to create and verify code and **python API** to communicate with user's applications.



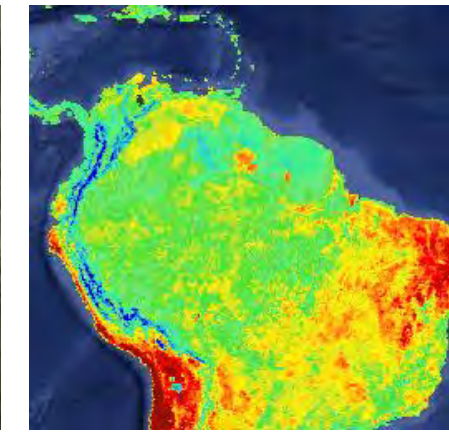
Landsat (15-30m Resolution)



Modis (250-500m Resolution)

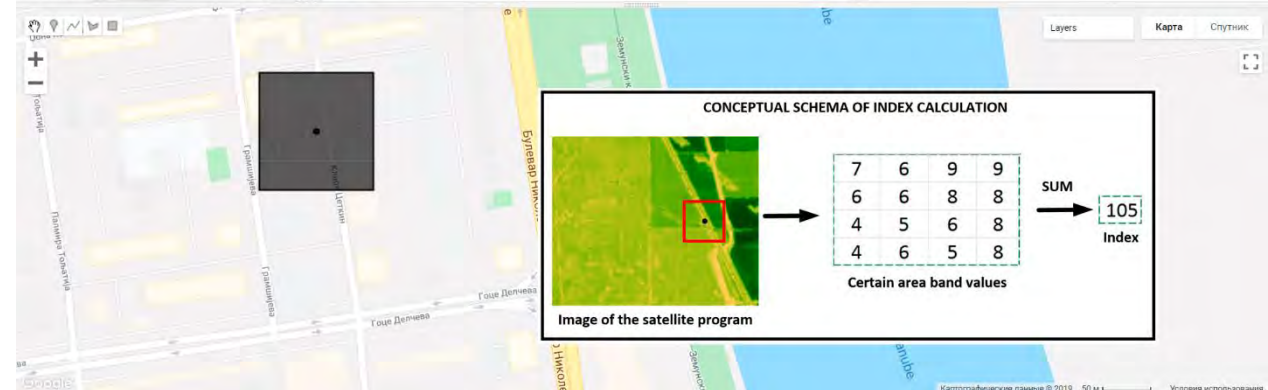


Sentinel (250-500m Resolution)



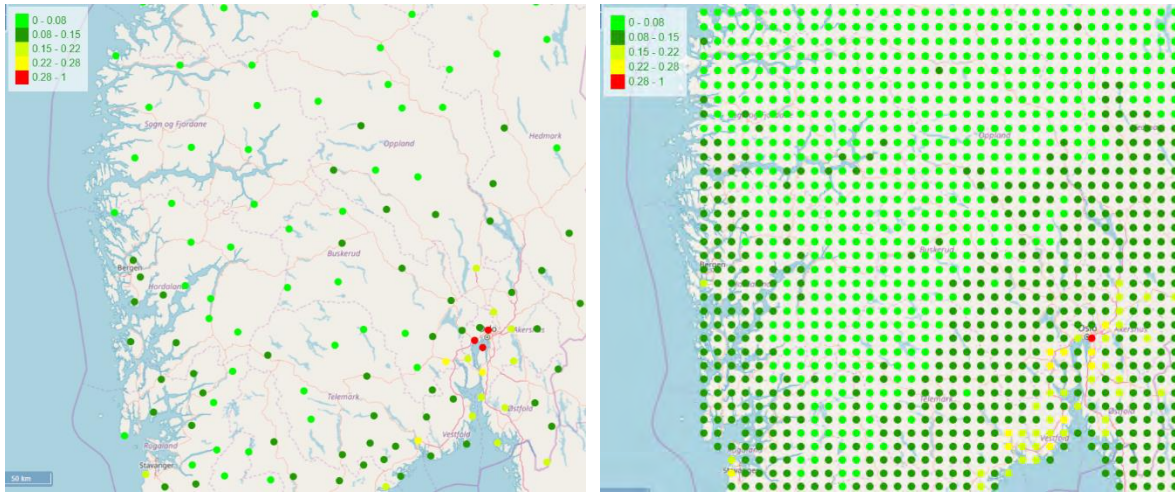
The MOD11A2 V6 average 8-day land surface temperature (LST) in a 1200 x 1200 kilometer grid.

```
13 var point = ee.Geometry.Point(20.415833, 44.832778);
14 Map.addLayer(point);
15
16 var collection = ee.ImageCollection('LANDSAT/LC8_L1T')
17   .filterDate('2013-06-15', '2013-08-15')
18   .filterBounds(point)
19   .sort('CLOUD_COVER', true);
20
21 var median = collection.median();
22
23 // Get a dictionary of means in the region. Keys are bandnames.
24 var mean = median.reduceRegion({
25   reducer: ee.Reducer.mean(),
26   geometry: region,
27   scale: 30
28 });
29
30 print(mean);
31
```



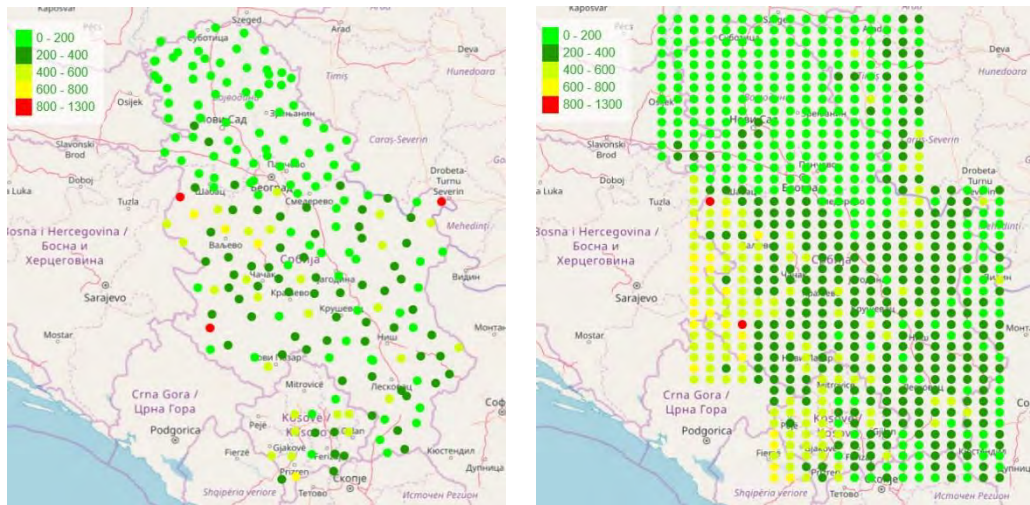
Specify program and time-period to get a collection of images, for example, program – “MODIS/oo6/MOD09A1” from 2013-06-15 to 2013-08-15 (the period relevant for in situ biomonitoring). Then, define the analyzed area, for example, a square kilometer, with center at the coordinates where sampling was performed. During the satellite data collection, under the bands (channels) of the median image, we execute some mathematical functions (max, min, median, etc.) and get the numerical values.

Results on the regional level

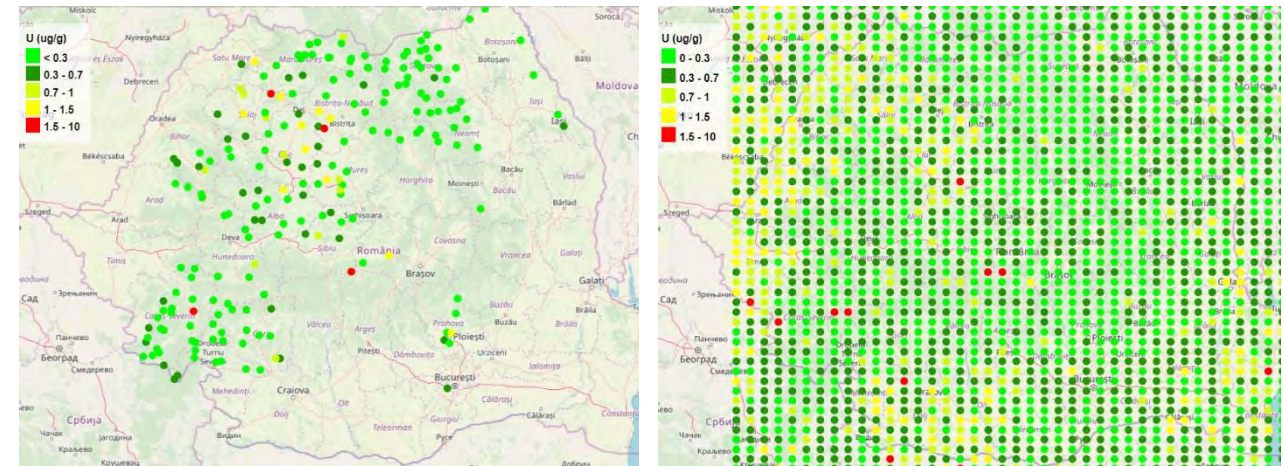


Sb at Norway. Left – real life, right - prediction

Candidates for modeling:
Al, As, Cr, Cu Fe, Mn, Ni, Pb, V, Sb, U ...



Mn at Serbia. Left – real life, right - prediction



U at Romania. Left – real life, right - prediction

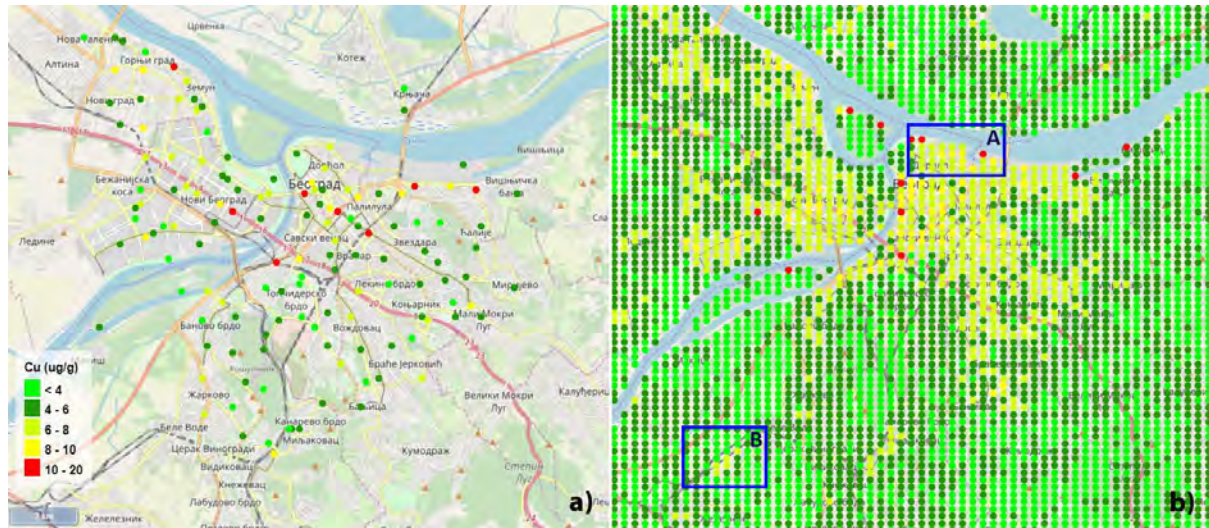


Figure 3. Concentration of Cu in the summer of 2013 (Belgrade): a) real measurements, and b) prediction values; area A represents central part of Old Belgrade with permanently high traffic flow; area B represents a large railway terminal

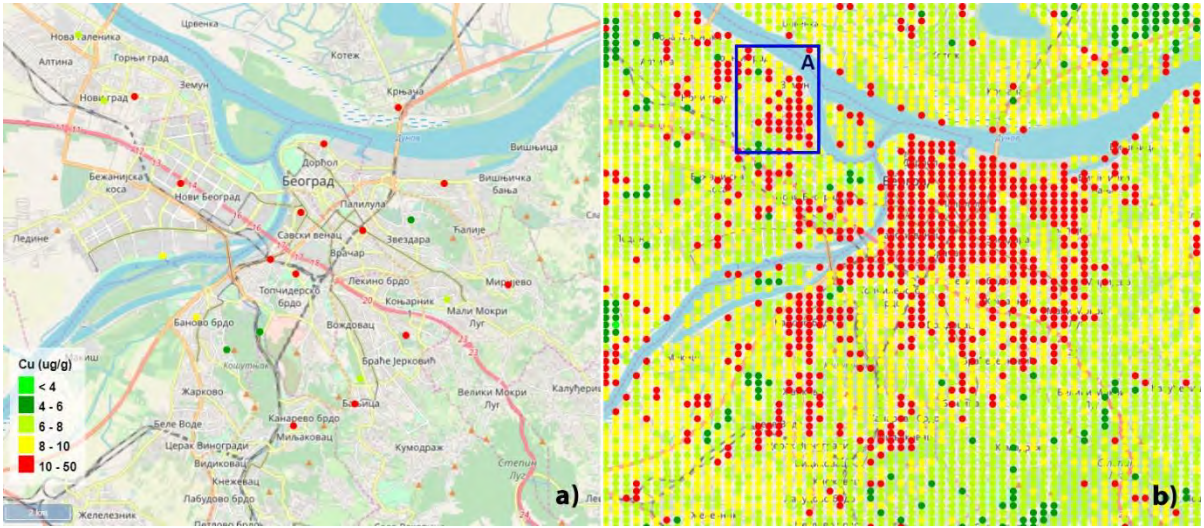


Figure 4. Concentration of Cu in the winter season 2013/2014 (Belgrade): a) real measurements, and b) prediction values; area A represents an old city core highly polluted in winter season

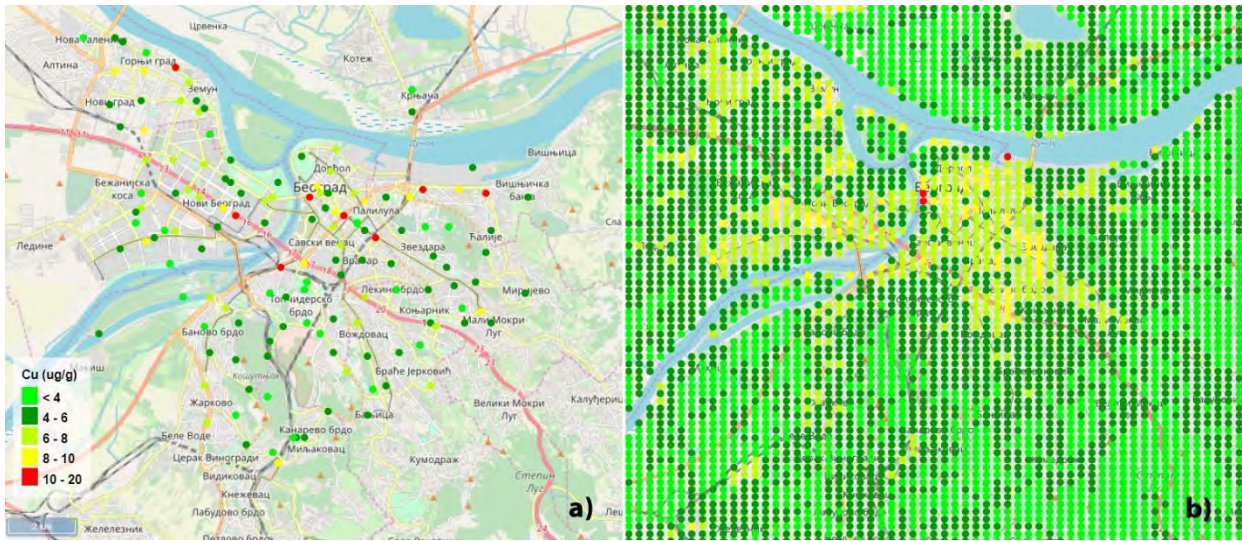
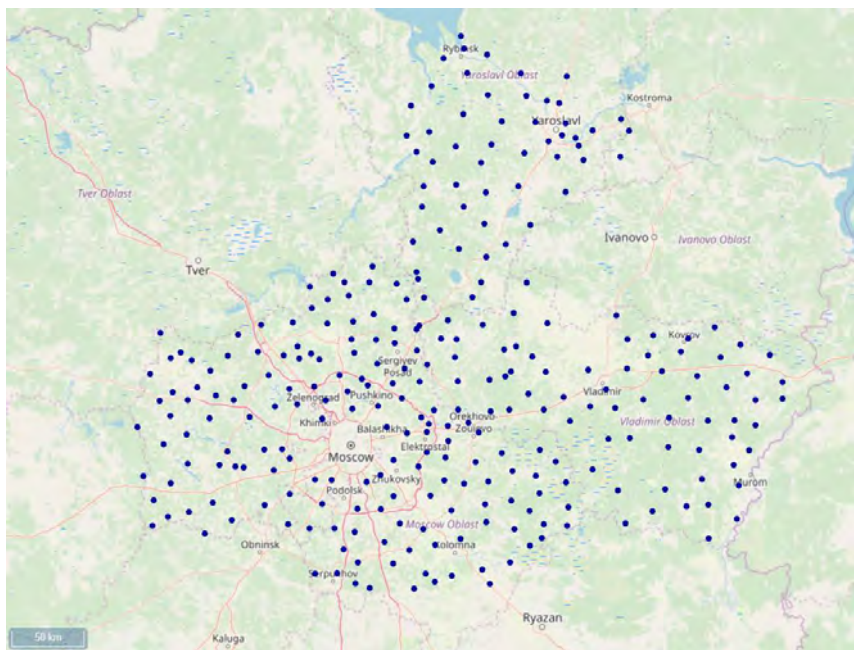


Figure 5. Concentration of Cu in Belgrade: a) biomonitored measurements in the summer of 2013, and b) prediction for 2018

Prediction of air pollution by potentially toxic elements over urban area by combining satellite imagery, Moss Biomonitored Data and Machine Learning
 A. Uzhinskiy,
 M. Anitch Urorevice, M. Frontasyeva, Ciencia e Tecnica Vitivinicola Journal, ISSN:2416-3953, 12, 35, 2020

Machine learning and neural networks



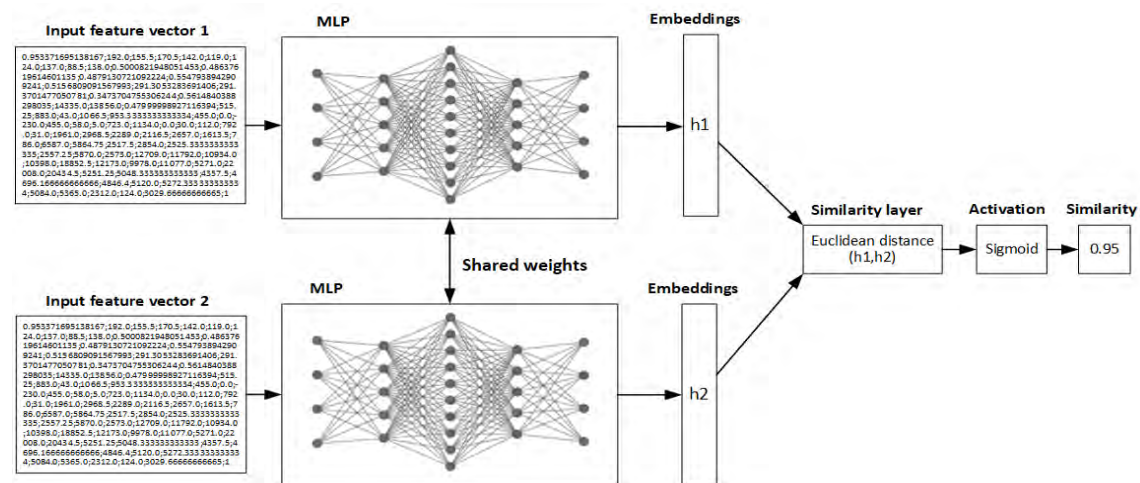
We use the information on 73, 53, and 156 samples from the Vladimir, Yaroslavl, and Moscow regions gathered in 2018 - 2019.

The indices are gathered based on data from 13 programs for 281 sampling sites, and their linkage with the concentration of 18 heavy metals is verified. Altogether 9 HMs, i.e., Al, Fe, Sb, Na, Sc, Sm, Tb, Th, and U, look very prospective for modeling.

We examine three approaches: Gradient Boosting, Multilayer perceptron, and Siamese network.

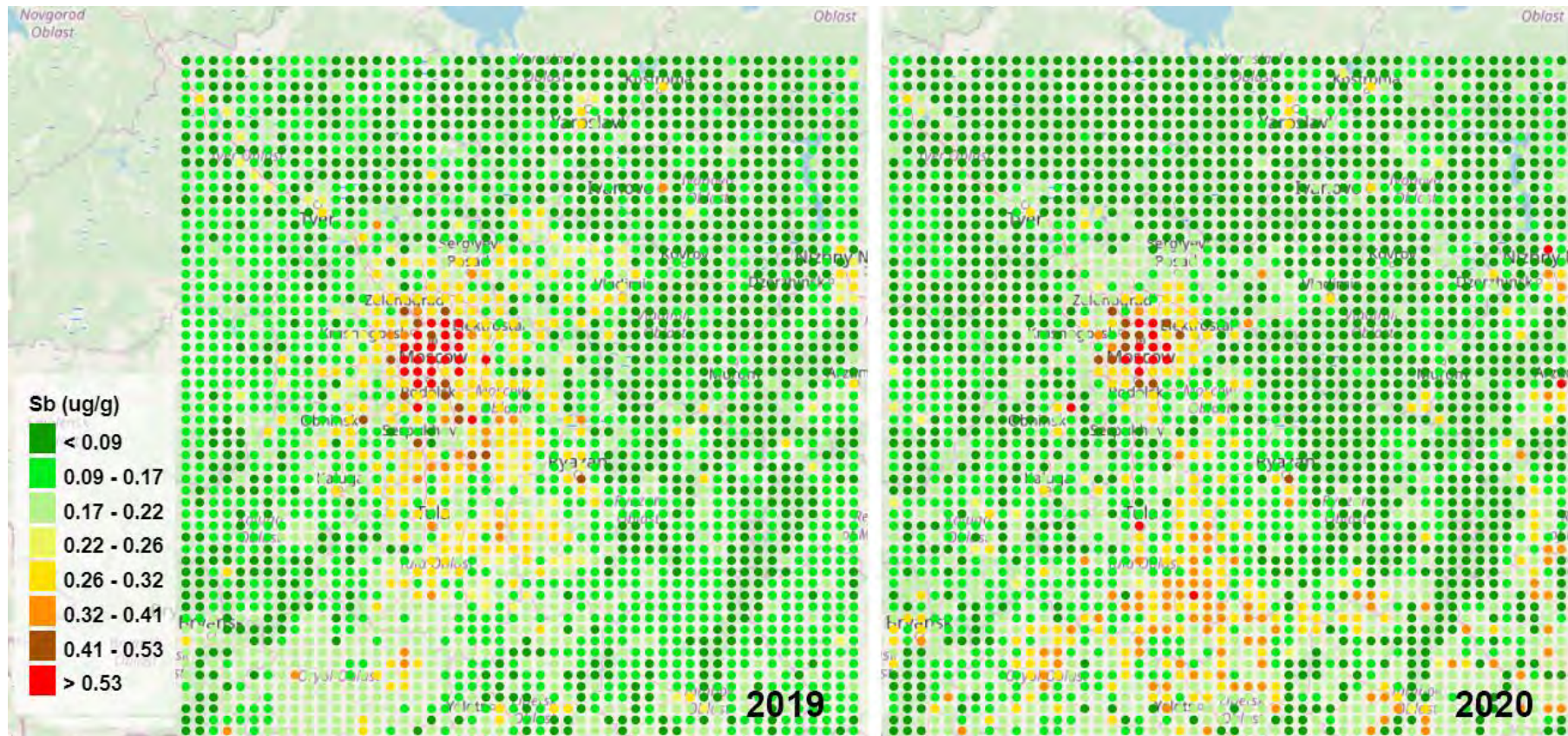
	Al		Fe		Sb	
	Acc si	Acc ai	Acc si	Acc ai	Acc si	Acc ai
GB	0.91	0.92	0.92	0.93	0.94	0.94
MLP	0.89	0.91	0.92	0.92	0.89	0.92
SNN	0.92	0.93	0.93	0.93	0.93	0.94

Table 2. Mean accuracy of the models. GB is gradient boosting. MLP is the multilayer perceptron. SNN is the Siamese neural network. Acc Si is the accuracy on the selected indices. Acc Ai is the accuracy on all indices.



Siamese network architecture

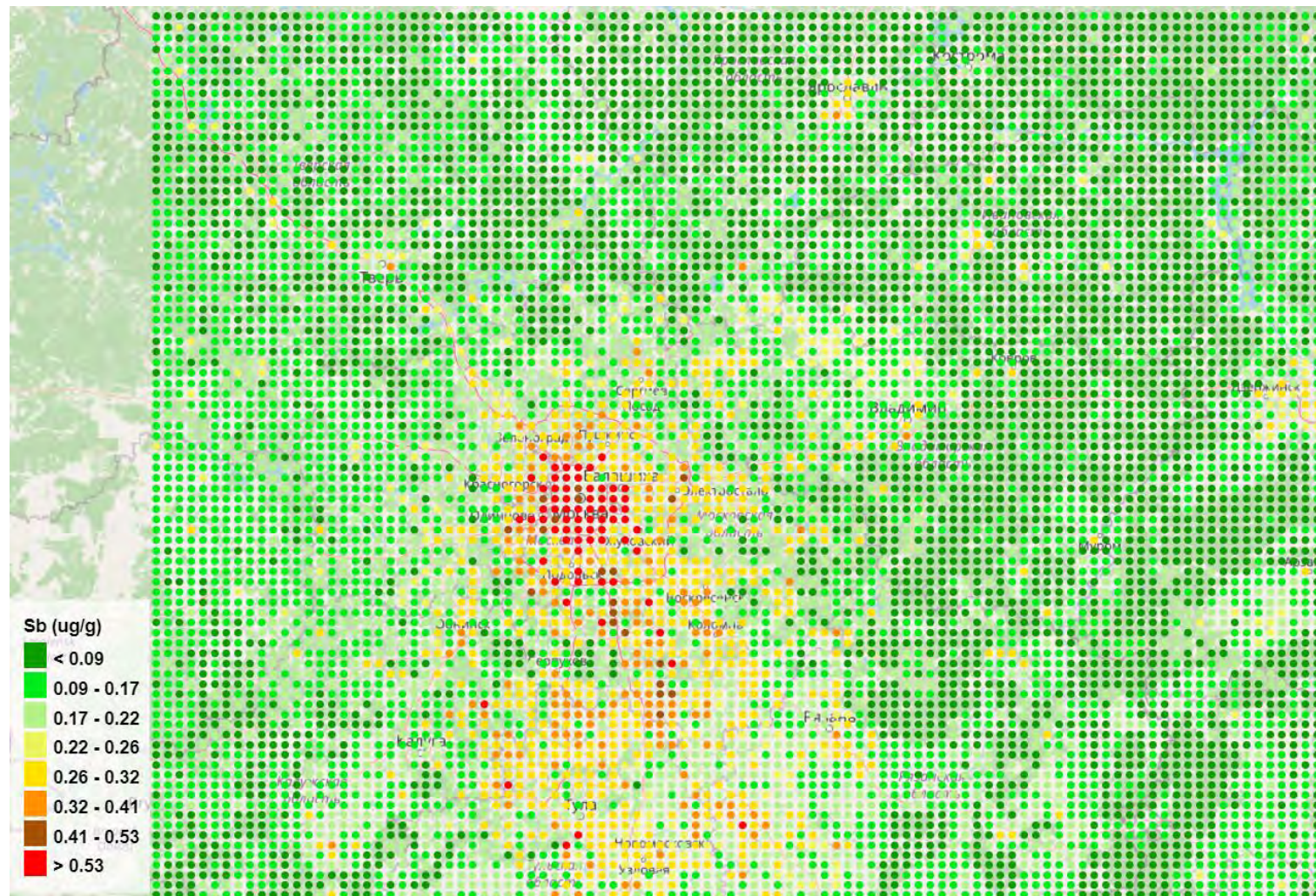
Results (2019 – 2020)



Sb contamination prediction for 2019 (left) and 2020 (right)

The lockdown in Russia that lasted for approximately 1.5 months imposed different limitations. Most of the limitations restricted the movement activities of the population. According to the official statistics, industrial production in Russia decreased by 2.9% from the past, by the end of 2020.

Results (High spatial resolution)



High spatial resolution of the SNN model prediction of Sb contamination

Moscow is a thickly populated city, and the population is increasing at a fast pace. Published information reveals, there are about 12.5 million habitants in Moscow. Therefore the Sb contamination level there is bound to be very high.

The map also reveals clusters of hot spots in large cities, such as Tula, Kaluga, Vladimir, Tver, Nizhny Novgorod, Yaroslavl, etc. It is also seen that from Sergiyev Posad to the north direction, the contamination level is rather low, except Yaroslavl, where the working oil refinery is located.

The Tula region stands out on the map. There is a multitude of industrial enterprises located in the region, i.e., chemical, metallurgical, and machine-building, besides several large thermal power plants. Huge transport nodes and federal freeways are seen, rather clearly, on the map.

Uzhinskiy A.; Vergel K.; Central Russia heavy metal contamination model based on satellite imagery and machine learning, *Computer Optics* 2023; 47(1): 137-151. DOI: 10.18287/2412-6179-CO-1149.

В настоящее время ведутся исследования в области прогнозирования загрязнения почвы в долинах Нила (Египет)

Alternative projects

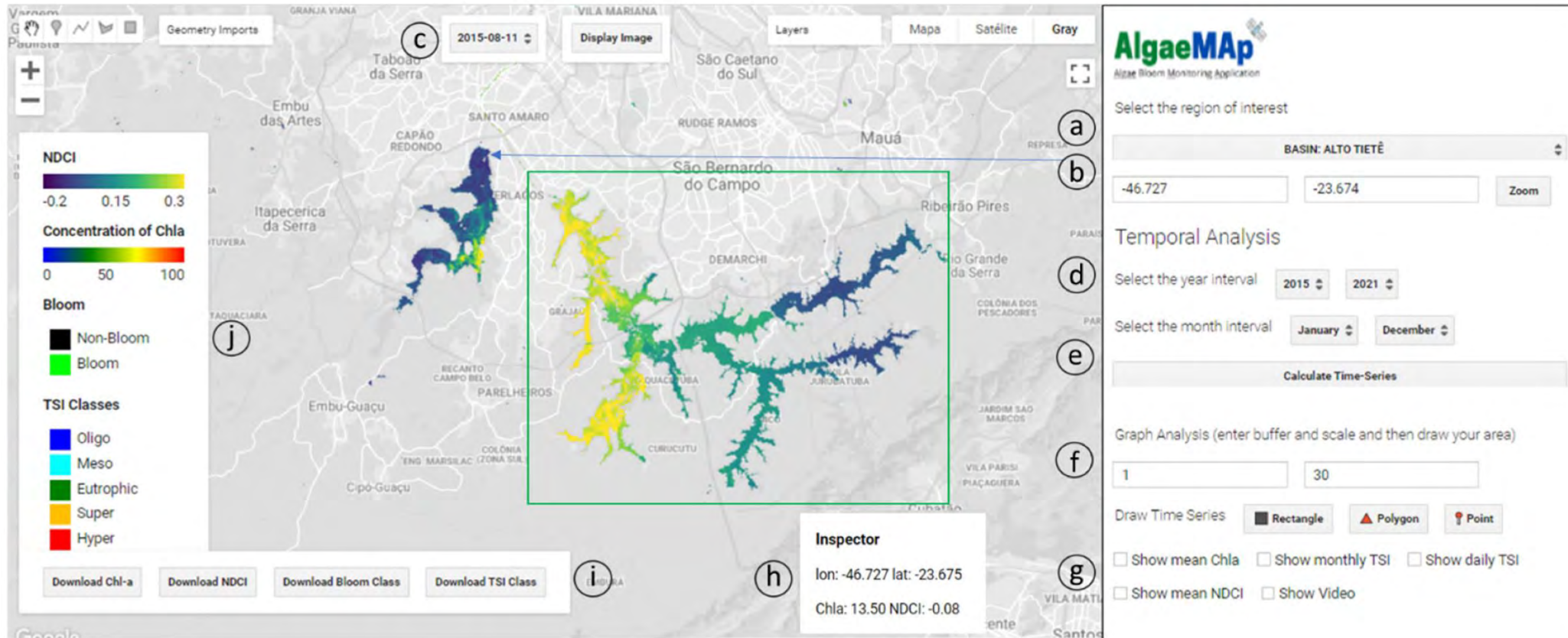
Trends.Earth

Through this project, we will develop a cloud-based platform dedicated to mapping land degradation which identifies potential land restoration opportunities at national to regional scale, allowing communities to prioritize areas to protect, manage, and restore in order to achieve land degradation neutrality.



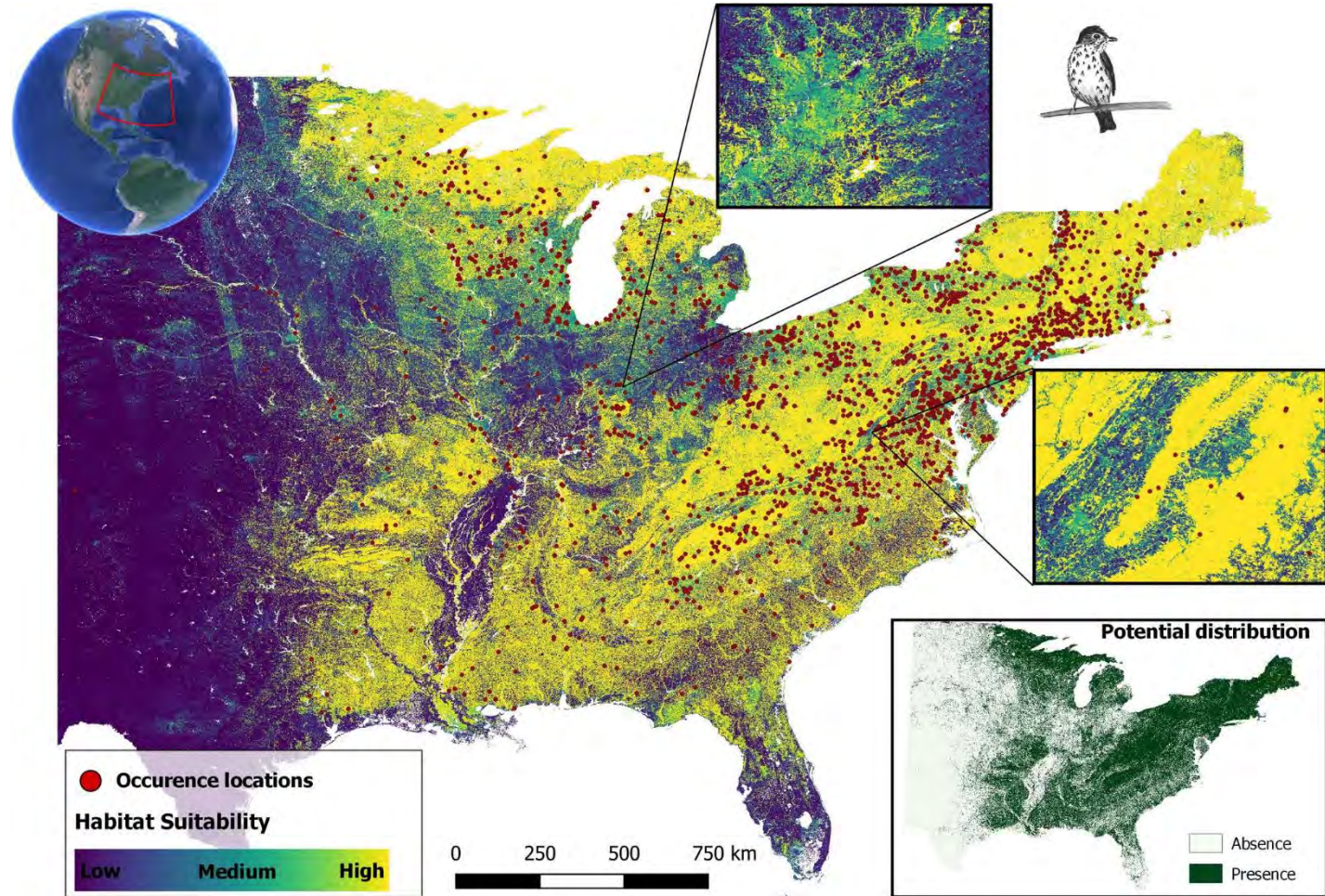
Alert System for Algal Bloom

Algae blooms occur when certain kinds of algae grow very quickly, forming patches, or "blooms," in the water. These blooms can be indicators of water degradation and emit powerful toxins that can endanger human and animal health.



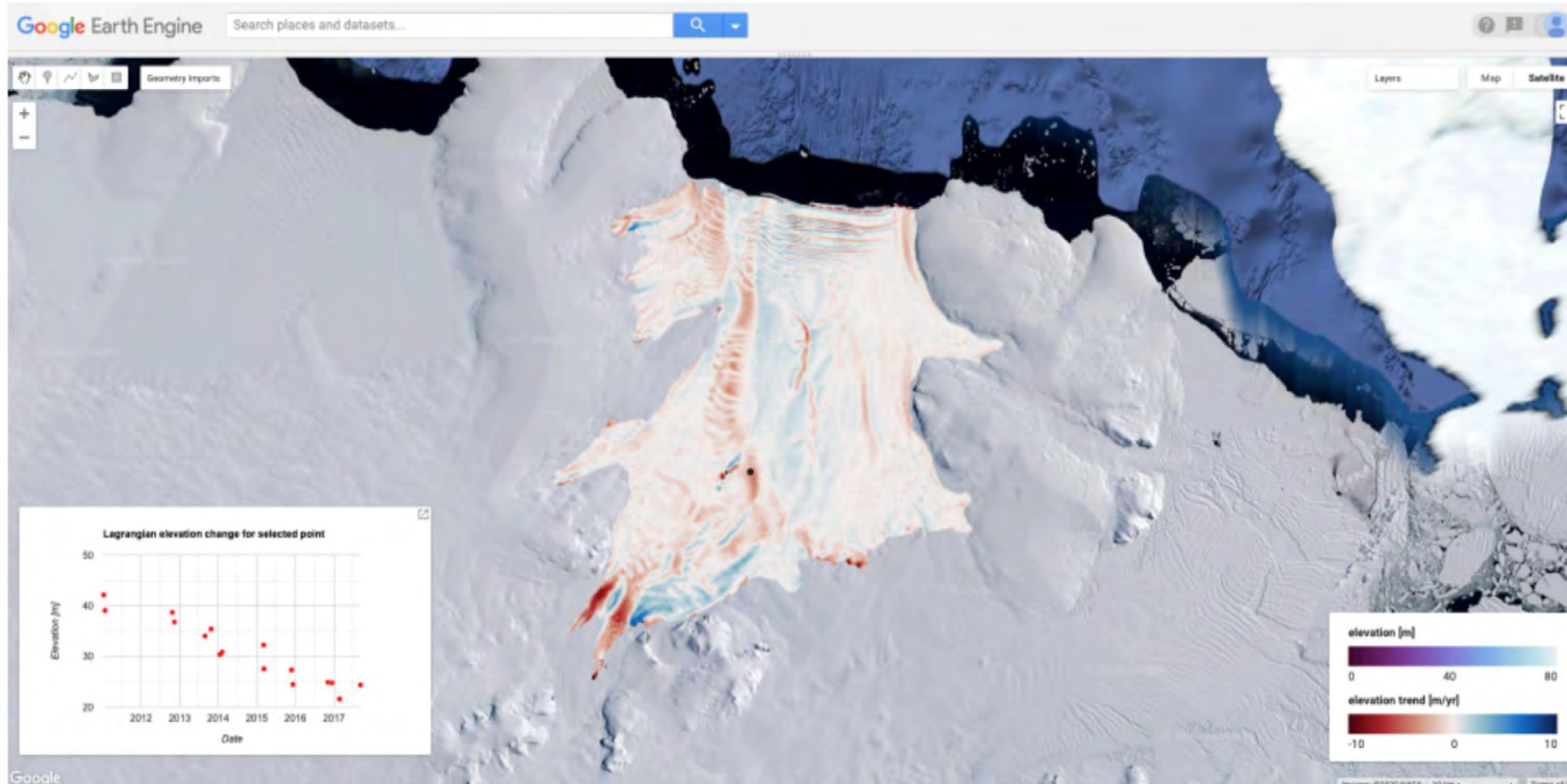
Essential Biodiversity Variables - ScaleUp

We implemented a workflow for species distribution modelling in GEE that includes importing species occurrence data into the GEE platform, selecting and preparing predictor variables, and performing model fitting with spatial or temporal split-block cross-validation techniques.



GEE-interface for analyzing basal melt over Dotson ice shelf

A platform to analyze and demonstrate the use of satellite data over Antarctic ice shelves. This will allow insight in the surface, subsurface and basal conditions of these ice shelves, which are major sources of uncertainty in future sea level projections from Antarctica.



Supporting water and disaster risk management in Mozambique

The project HydroPC focused on co-development and application of innovative data technologies and comprehensive training of beneficiaries to support water and disaster risk management in Mozambique.



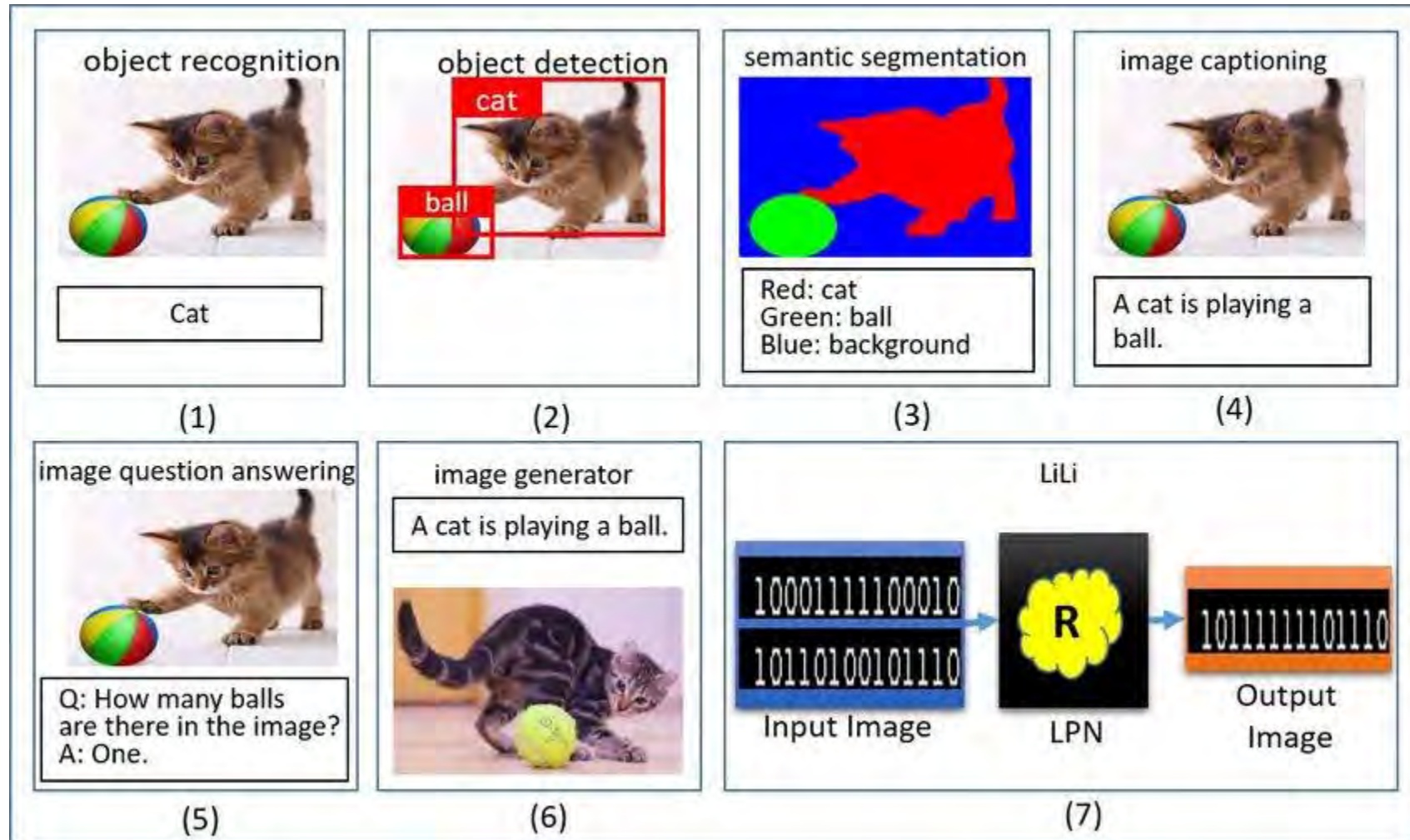
Что можете сделать вы?

- Проект по контролю за качеством воздуха с использованием открытых данных с метео-станций
- Проект по контролю состояния водных ресурсов
- Проект по отслеживанию изменений (леса, реки, использование земельных ресурсов и т.д.)
- Ваш вариант ...

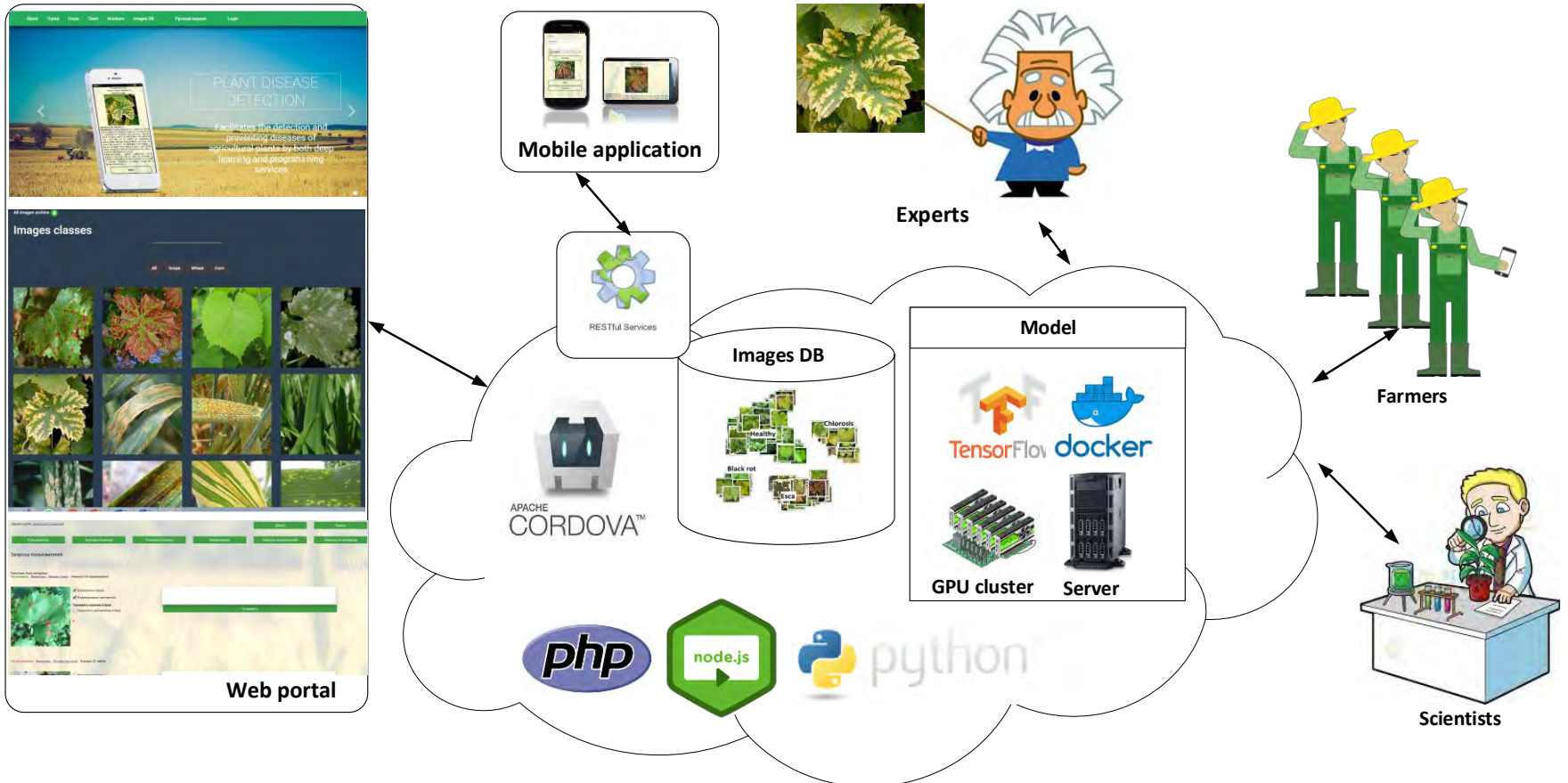
Использование нейросетей в задачах сельского хозяйства



Tasks



Palnts disease detection platform



PDDP consists of a set of interconnected services and tools developed, deployed and hosted with the help of the JINR cloud infrastructure. Our web-portal (pdd.jinr.ru – old. Doctorp.org - new), was developed with the Node.js and PHP. It provides not only a web-interface but also the API for third-party services. We have the Pytorch model in the Docker realized as a Tensorflow serving. The model can work at the virtual server, or at a GPU cluster. We have a mobile App for Android that was developed using the Flutter, so we could build it for iOS, and Windows.



Plants doctor

толстянка
суккулент лаванда манго
петунья кустус
фикус помидоры клубника
барбарис спатифиллум огурцы
морковь папоротник кукуруза
виноград хризантема смородина
хамедорея орхидея лавр розмарин
герника бегония алоказия декабрист
свекла антуриум фиалка
базилек астра хлорофитум
авокадо манго гортензия заманкулькас бархатцы
капуста перец маранта розы пионы
маниока сансевиерия герань картофель георгины
петрушка алоэ диффенбахия
вишня фикус традесканция
гибискус драцена хлопок
фиалка

Доктор для растений в вашем телефоне



Диагностика по фото

Сфотографируйте или загрузите с устройства

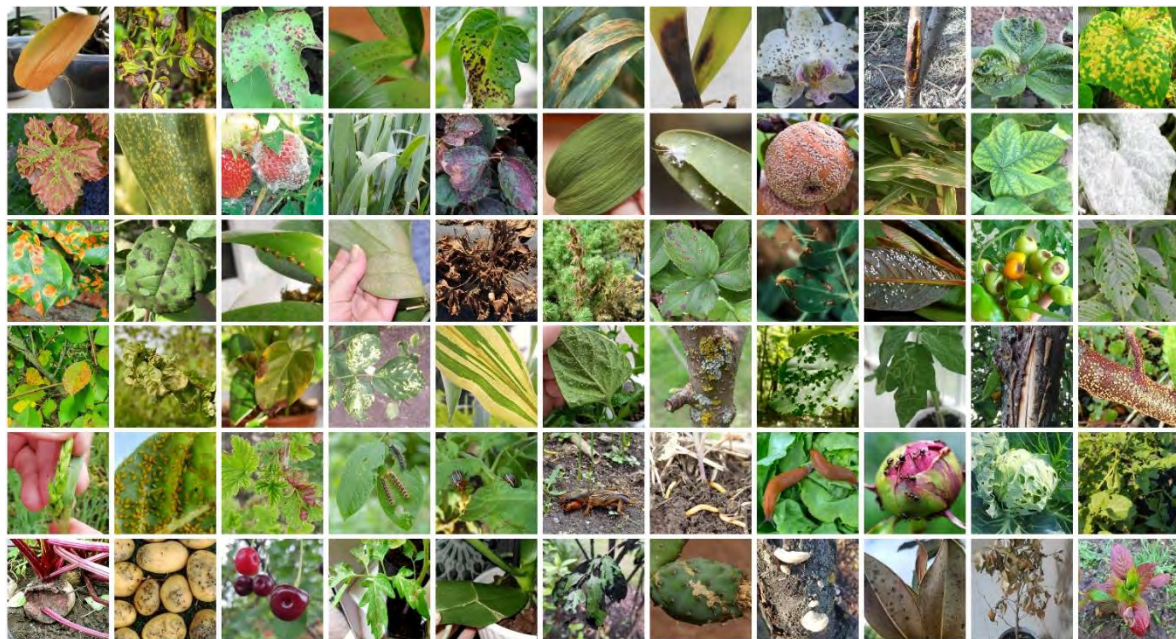


Выберите наиболее подходящий вариант



Лечение

Получите советы и рекомендации от лучших агрономов



```

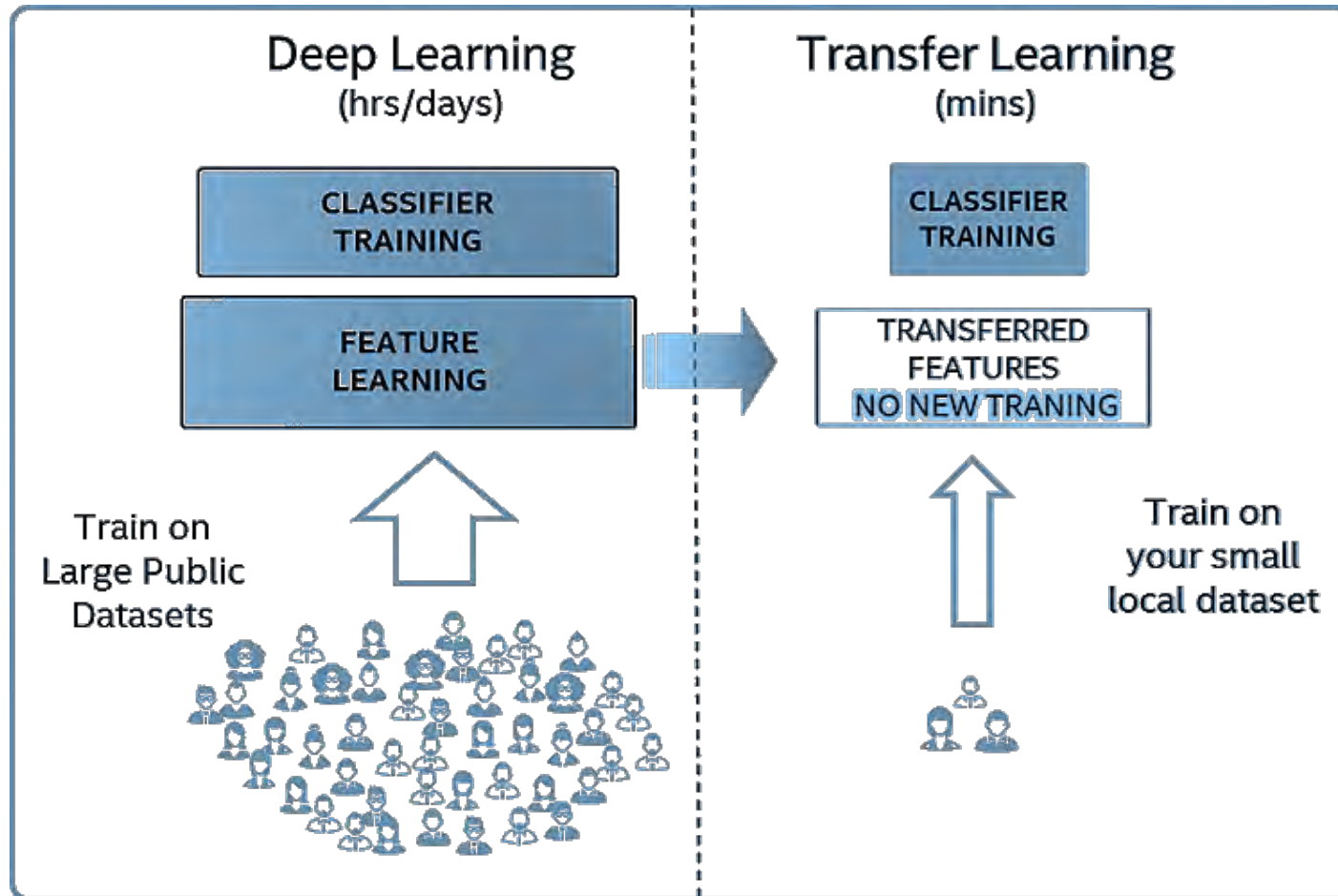
{
  "error": 0,
  "general_predictions": [
    { ... },
    { ... },
    { ... }
  ],
  "custom_predictions": [
    { ... },
    {
      "type": "розы",
      "prediction": [
        {
          "name": "Мозаика",
          "sample": "http://usrbb.ru/botainika/diseases/xmv1.jpg",
          "description": "<p>Это наиболее распространенное заболевание вирусного типа. Узнать его очень просто - листья покрываются хлоротичными пятнами и узорами, которые могут перейти в прожилковый хлороз. Листья деформируются (узколистность, курчавость, морщинистость) и постепенно опадают. Рост побегов замедляется, и они не вызревают. Побеги, которые больны, вырезают. При дальнейшем распространении болезни растение уничтожают"
        }
      ]
    }
  ]
}

```



Basis

HOW TO LEARN IF LACK OF DATA TRANSFER LEARNING



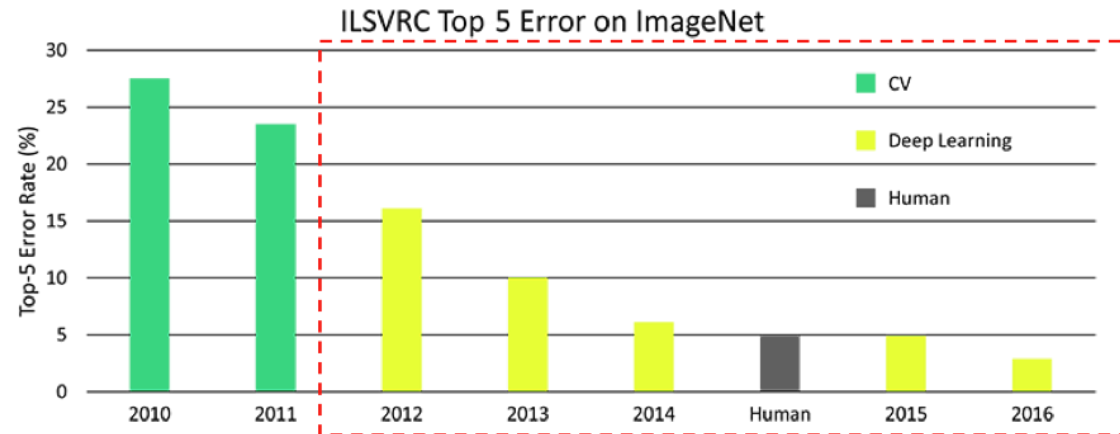
- FIND A DEEP NEURAL NETWORK PRETRAINED ON A BIG DATASET
- Replace the classification layer with a layer appropriate for your task
- Finetune the new classifier on specific data
- Voila! Use the new model for inference

ImageNet

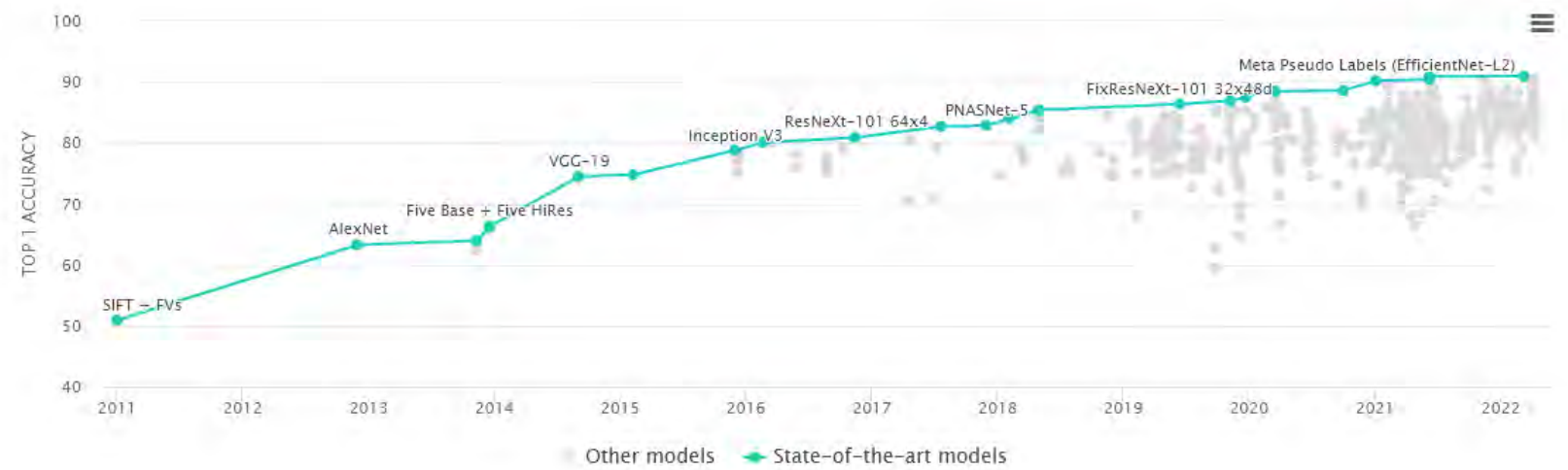
This dataset spans 1000 object classes and contains 1,281,167 training images, 50,000 validation images and 100,000 test images.

Since 2010 the dataset is used in the ImageNet Large Scale Visual Recognition Challenge (ILSVRC), a benchmark in image classification and object detection.





The introduction of Deep Learning techniques drove performance on image categorization from 30% error rates in 2010, down to <2% in 2017



One-shot / Few-shot Learning:

Few-shot learning (FSL) is a branch of supervised machine learning, focused on learning from limited number of examples¹

Inspired by human/animal ability to rapidly generalize from few examples.

Typical scenarios¹:

- Learning for rare cases – when obtaining labelled data is hard or impossible
- Reducing data gathering effort and computational cost

Variations:

- (<50, e.g. 5,10)-shot learning: General case, where only few examples are given
- 1-shot learning: Extreme case, where only one data example is given (e.g. 1 image per class)
- 0-shot learning: Instead of image, we have description of new class
- 'Less than 1'-shot learning²: N classes, M examples, $M < N$, use soft-labels

Why does it work?

In ML, experience is gained by fitting data.

In FSL we also have prior knowledge¹. Two training phases:

1. Gain prior knowledge by fitting large amount of examples that are similar to goal task
2. Gain experience on small dataset for goal task.



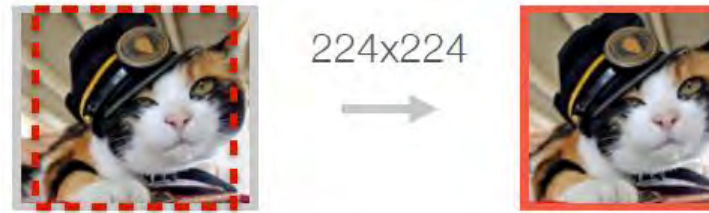
Autoaugmentation

Random Search learner This learner is a purely randomised searcher.

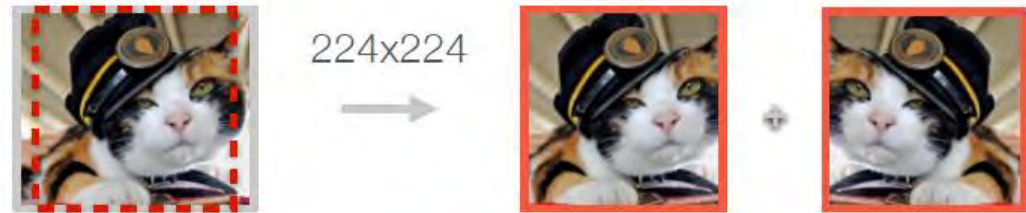
The genetic learner has similar elements to the Random Search learner, but uses information from previous sub-policies when generating new ones to more efficiently search for optimal augmentation parameters.

GRU with PPO updating Agent (`gru learner.py`) An GRU controller was used, which output a policy in the form of a length 10 sequence of vectors, each vector representing a operation. The GRU controller was updated using proxima policy optimization(PPO), using the accuracy of the child network as the reward value. In the context of the PPO update, which was developed in the reinforcement learning literature, the subpolicies are the 'actions' of RL agent.

a. No augmentation (= 1 image)



b. Flip augmentation (= 2 images)

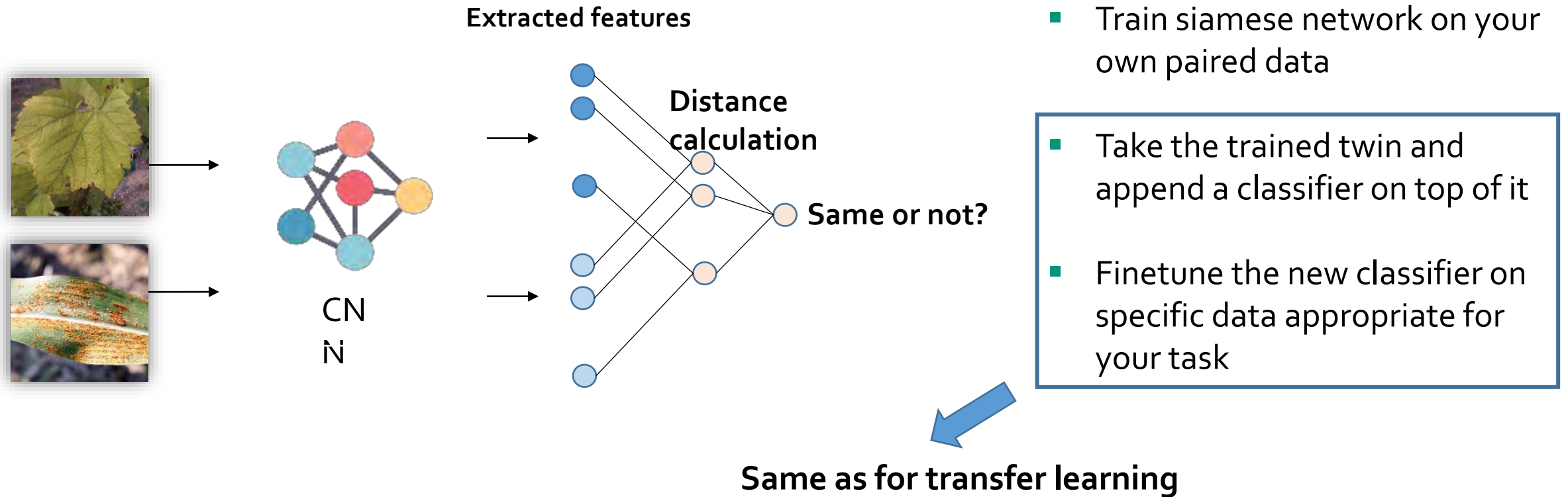


c. Crop+Flip augmentation (= 10 images)

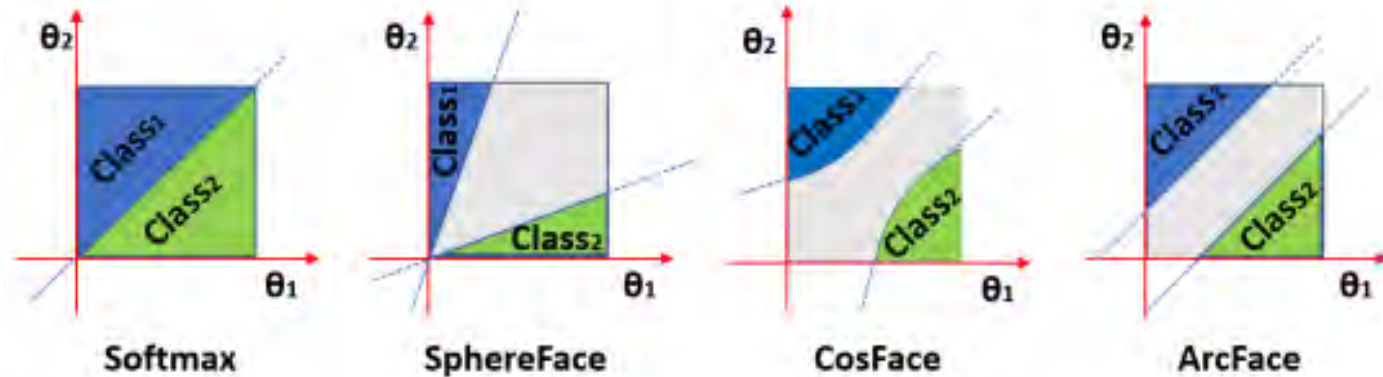


How to learn if lack of data - Siamese Networks

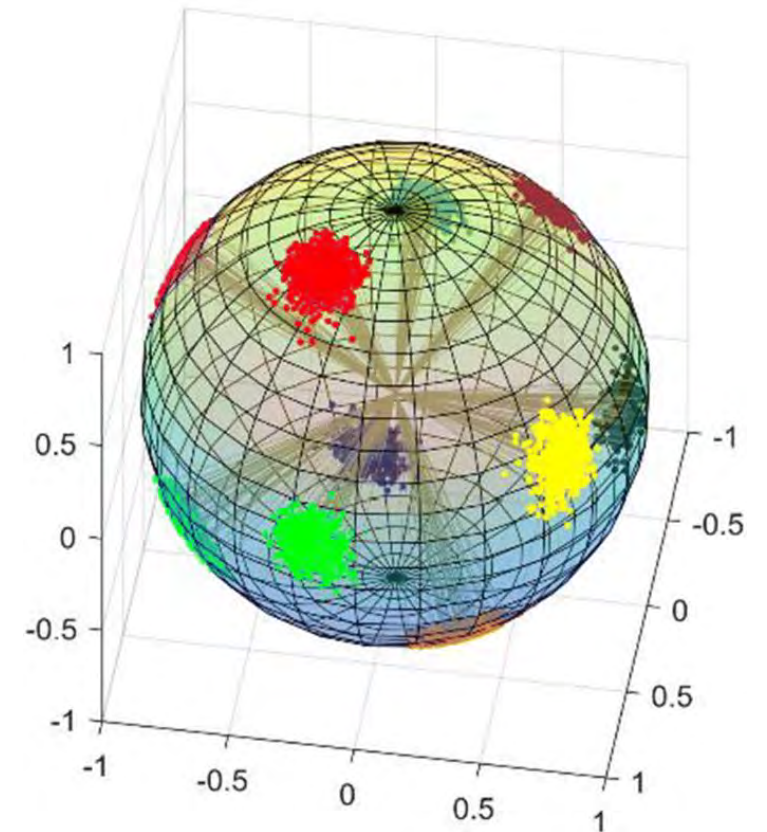
Siamese networks is a part of **one-shot learning** approach. One shot-learning aims to learn information about object categories from one, or only a few, training samples/images



Geometrical loss functions: arcface spherface cosface



ArcFace, or **Additive Angular Margin Loss**, is a loss function used in face recognition tasks. The [softmax](#) is traditionally used in these tasks. However, the softmax loss function does not explicitly optimise the feature embedding to enforce higher similarity for intraclass samples and diversity for inter-class samples, which results in a performance gap for deep face recognition under large intra-class appearance variations.



Stage 2 – Validation of the generalization abilities (400 images)

Custom datasets of real-life images are utilized, comprising over 4,000 samples across 68 classes of plant diseases, pests, and their effects.

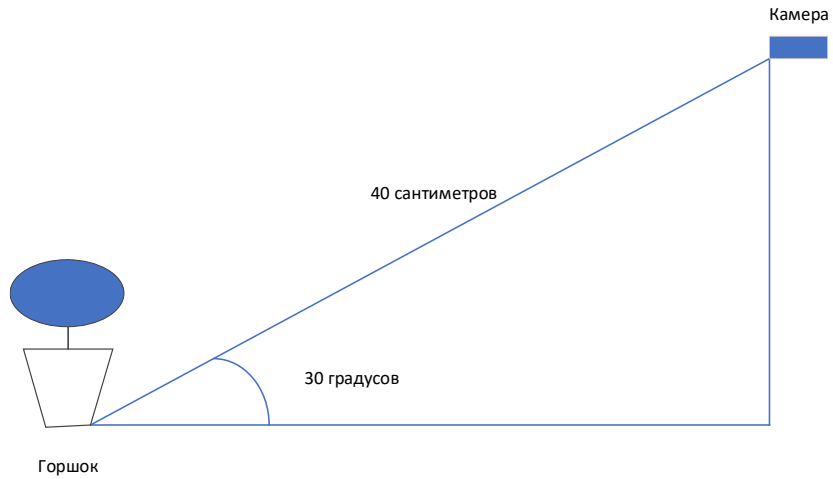
Table presents the evaluation results of models on a dataset consisting of 400 hard-case images. Additionally, to illustrate the advantages of few-shot learning methods over Transfer Learning methods, the accuracy of networks using ImageNet weights with the same classification architecture, referred to as “Vanilla TL,” was also evaluated.



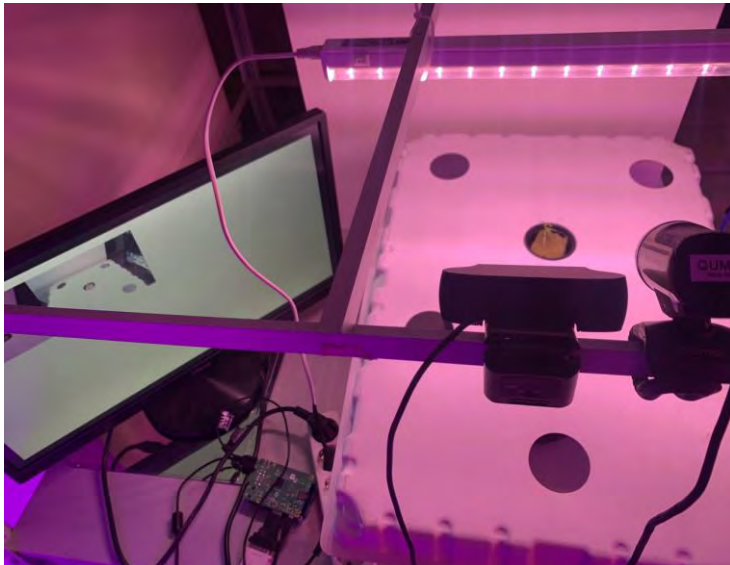
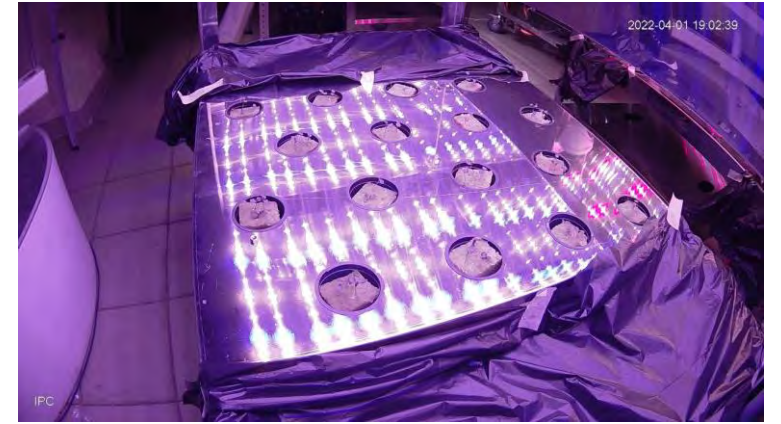
	ConvNeXt_small (191.7 Mb)		EfficientNet_B3 (47.2 Mb)		MobileNetV2 (13.6 Mb)		ResNeXt50_32X4D (95.8 Mb)	
	Vanilla	Norm	Vanilla	Norm	Vanilla	Norm	Vanilla	Norm
Contrastive	44%	46.4%	43.4%	46.2%	38.4%	40%	37.6%	43%
Triplet	58.2%	58.6%	54.4%	53.4%	39.4%	40.2%	47.4%	51.8%
Quadruple	58.6%	62.4%	55%	53.4%	40.6%	40.6%	50.4%	51.6%
SphereFace	72.2%	75.8%	57.6%	62%	45.8%	43.4%	53.4%	55.2%
CosFace	71.2%	73.6%	56.8%	59.8%	43.6%	43.8%	52.6%	49.6%
ArcFace	70%	67.8%	55%	57.2%	40.6%	41.2%	51.6%	49.6%
Vanilla TL	43.2%		37%		32%		38.6%	

Plant state tracking

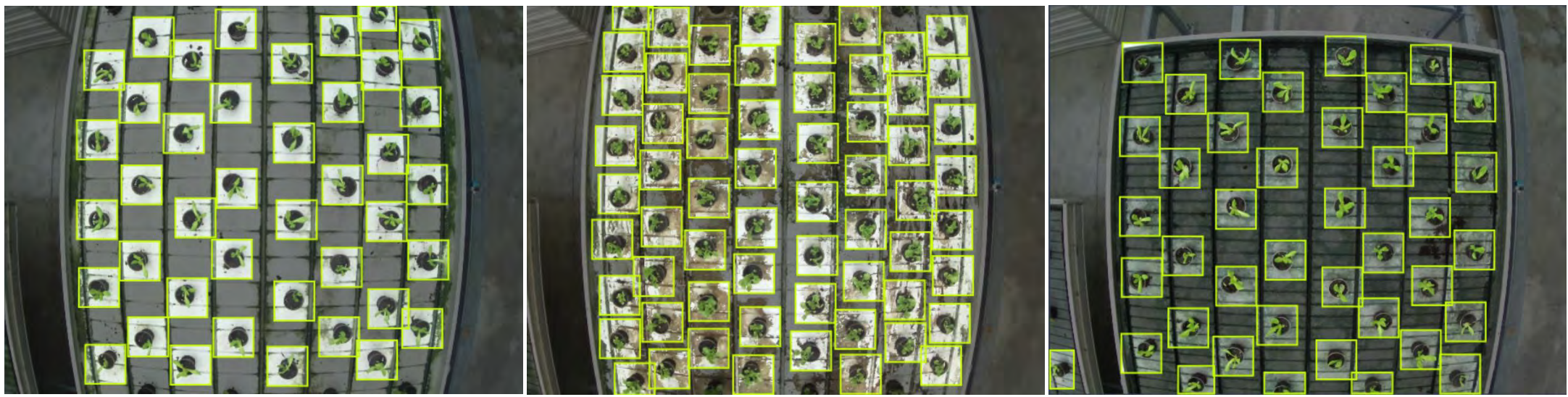
Joint project with the Temiryazev Academy within the framework of the project World-class Scientific Center "Agrotechnologies of the Future"



- Classification of the degree of development of the plant.
- Determination of the weight group of the plant.



Salads classification



Object detection – 1 class
Classification – 6 classes

Accuracy > 99%

Тестировалась на различных моделях семейств YOLO V5, YOLO V7, YOLO V8, YOLO NAS

1я модель 92 изображения, 200 объектов

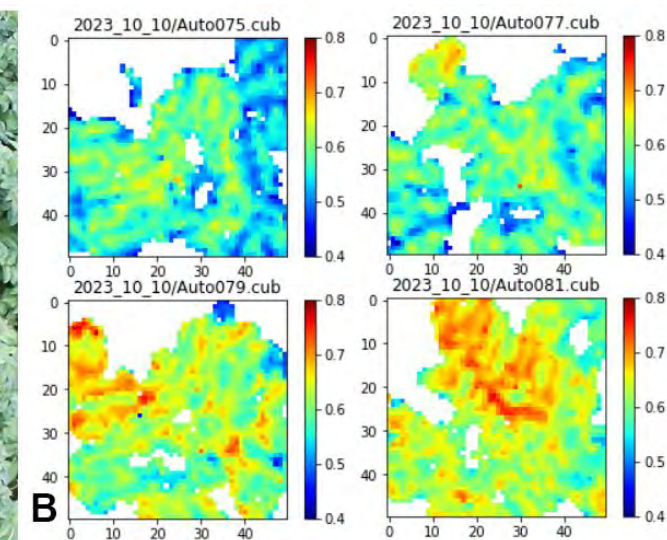
2я модель 92 изображения из нового сезона, 170 объектов

3я модель (объединенная 1я и 2я)

Модель	Precision	Recall	mAP50
V1	0.685	0.417	0.516
V2	0.635	0.531	0.586
V3	0.728	0.588	0.631

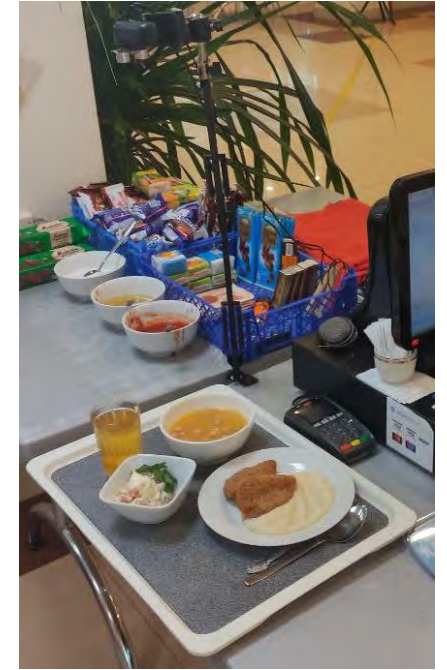
1я модель 124 изображения, 194 объектов

	Precision	Recall	mAP50
V1	0.827	0.567	0.703



Set of images

Data collection was carried out in automatic mode using raspberry pi 4, a digital camera with manual focus, and sonar.



A set of images in 5 days:



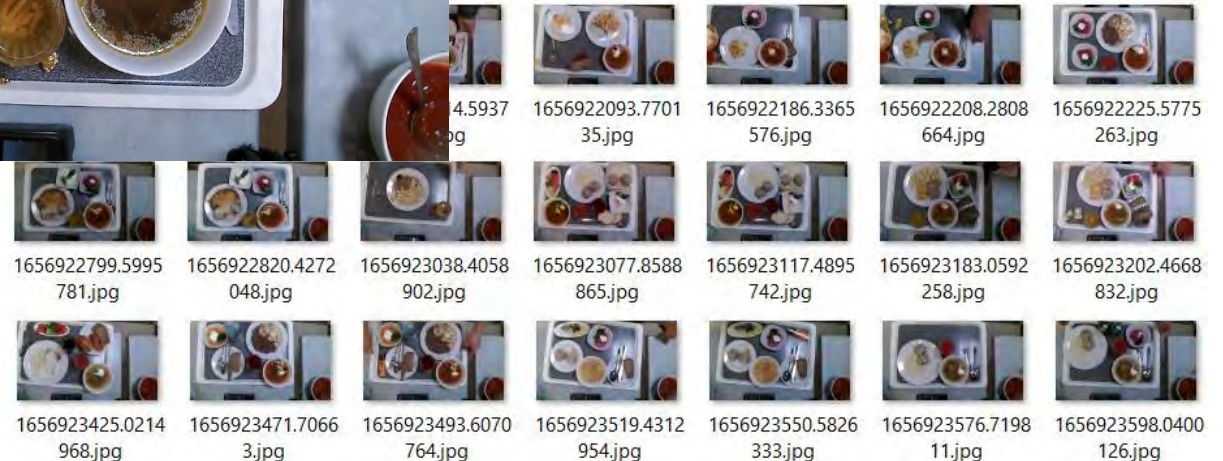
446 images



More than 150 different classes of objects

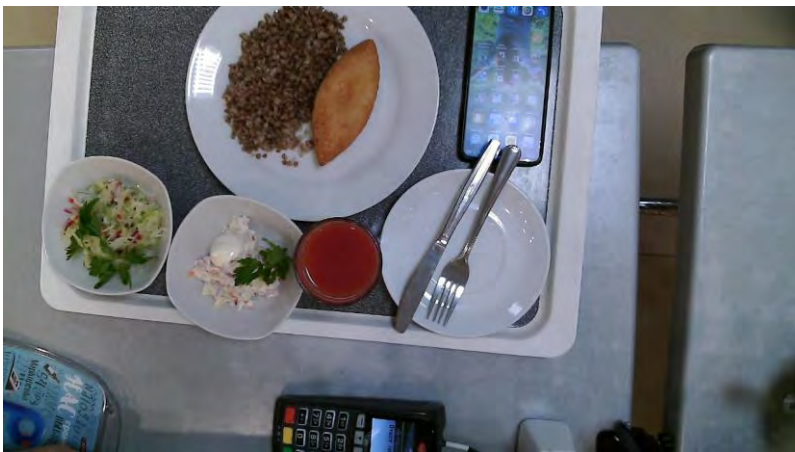


Dining room LIT JINR

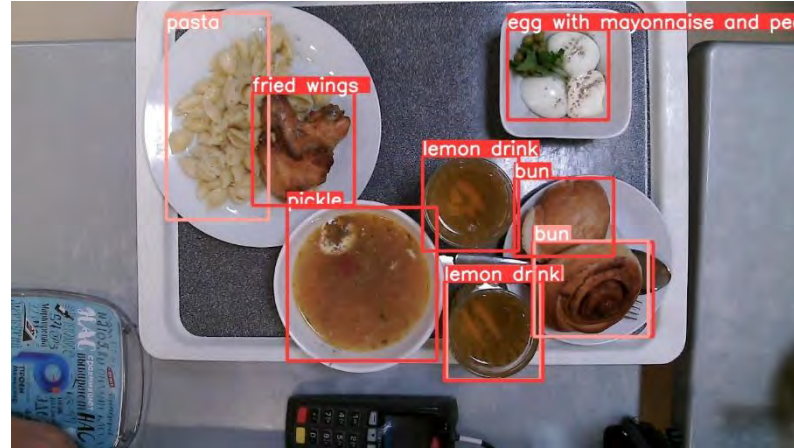


Examples

Input images



Output images



Processing



Что можете сделать вы?

- Исследование различных подходов к расширению обучающей выборки
- Использование Generative adversarial networks (GANs) для расширения базы изображений
- Оценка эффективности различных object detection подходов на различных задачах
- Использование методов классификации и детекции для решения прикладных задач в различных областях
- Ваш вариант ...





Russian greenhouse market
> 30 big complexes
> 1300 hectares
> 1300 thousand tons of vegetables
cucumbers — 48%
tomatoes - 46%
salads, greens, etc. - 6%



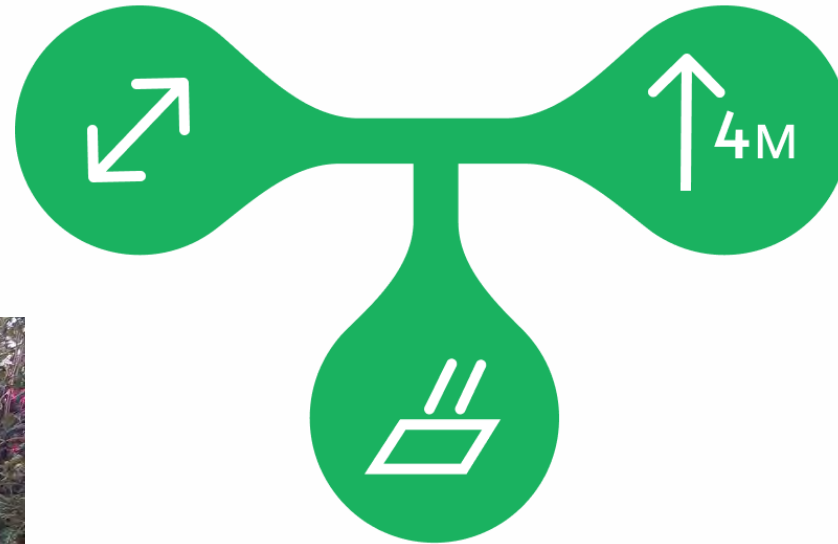
Greenhouse complexes

Greenhouse complexes play a pivotal role in year-round production of various crops. A crucial challenge in greenhouse operations involves early pest detection and precise localization on leaves. Additionally, tasks like plant accounting, yield estimation, and environmental control at different locations are of paramount importance.



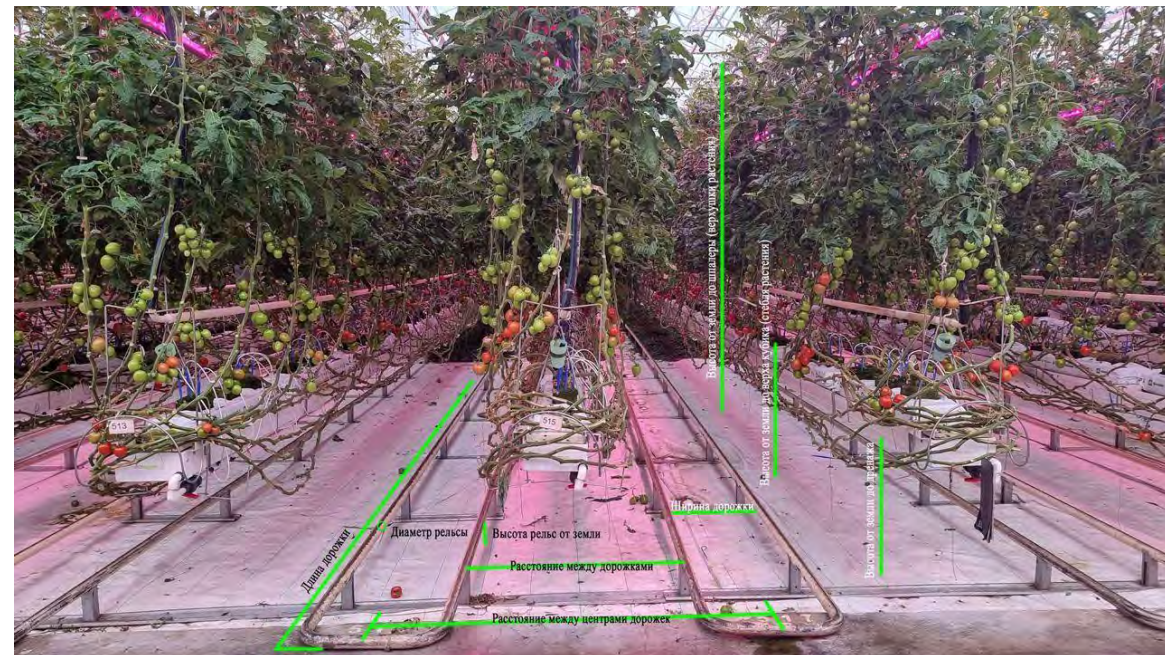
Issues

Greenhouse dimensions

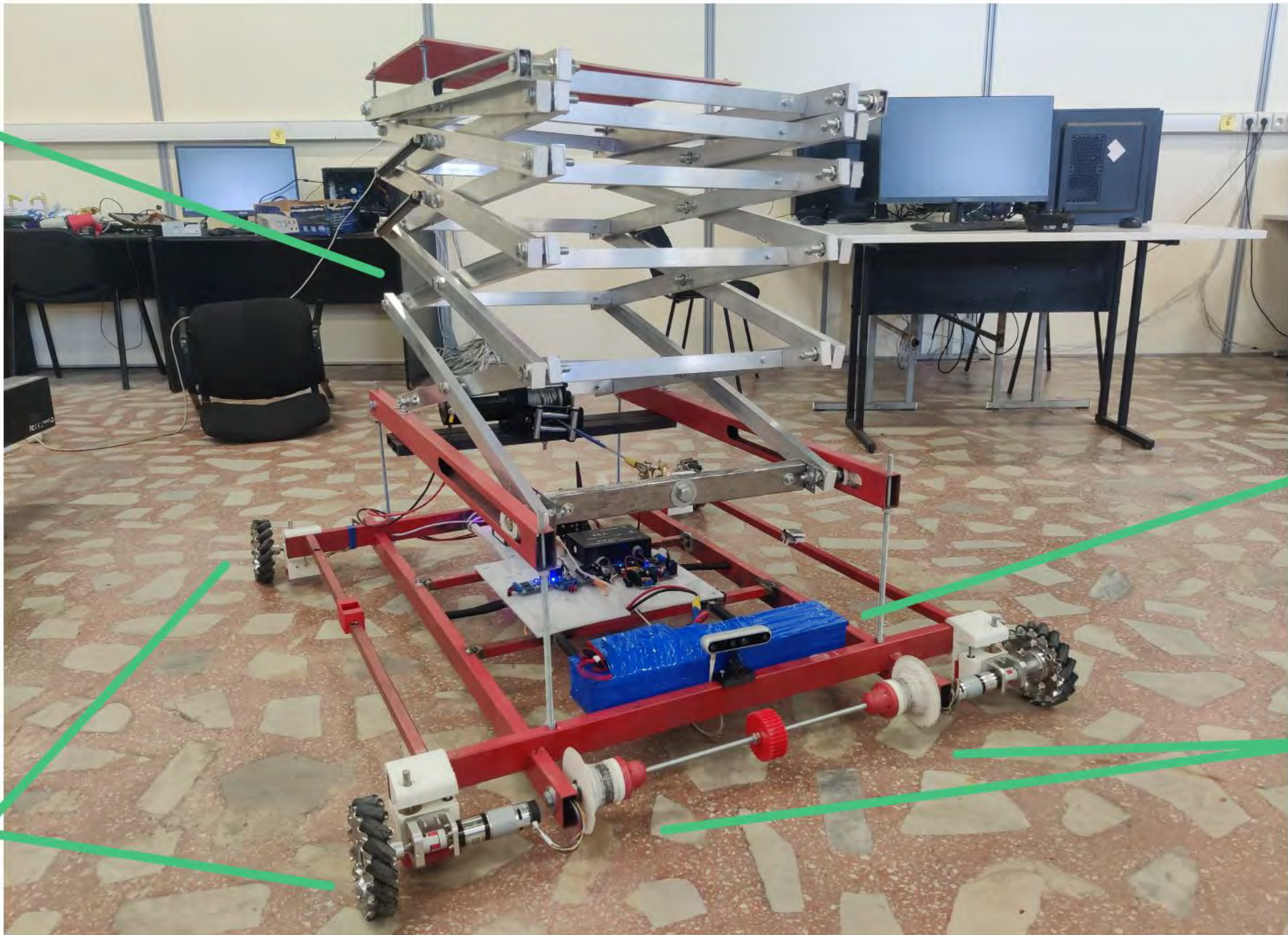
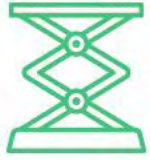


Diverse tasks at high altitude

Two methods of movement - rails and concrete platform



Robot



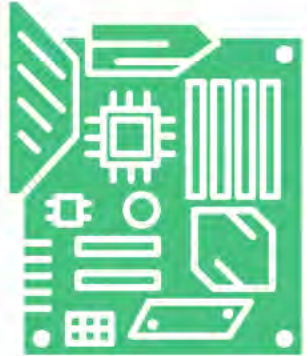
Control system



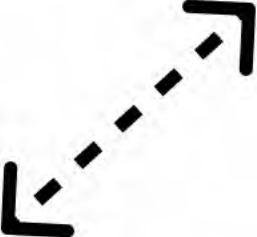
sensors



Arduino Mega



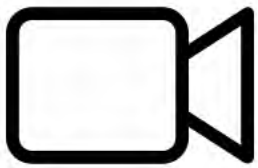
ROS



server



lidars



cameras



motors



Navigation



QR codes

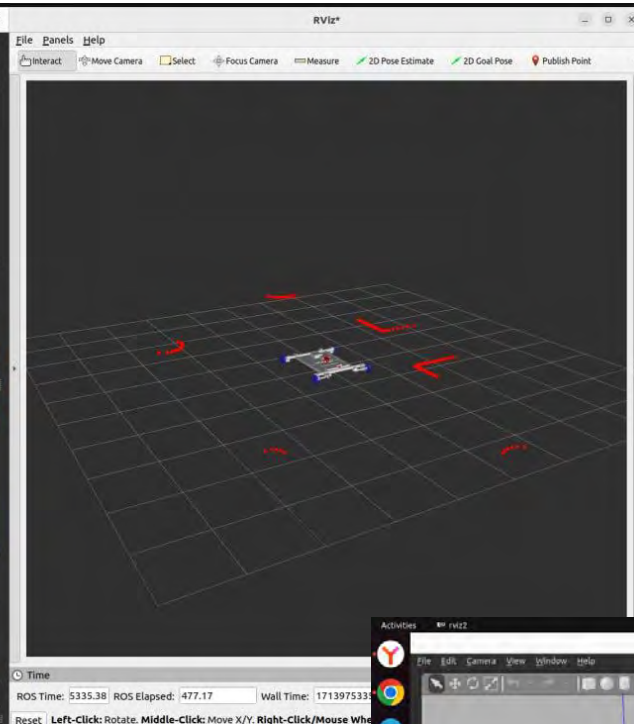
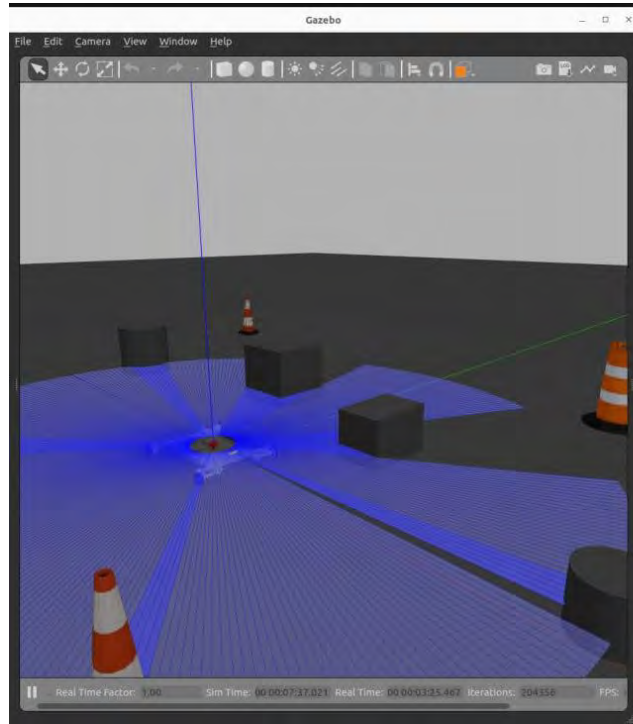


Point cloud

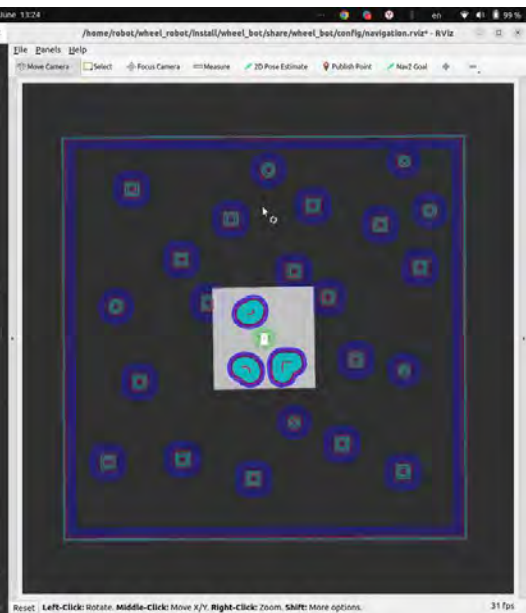
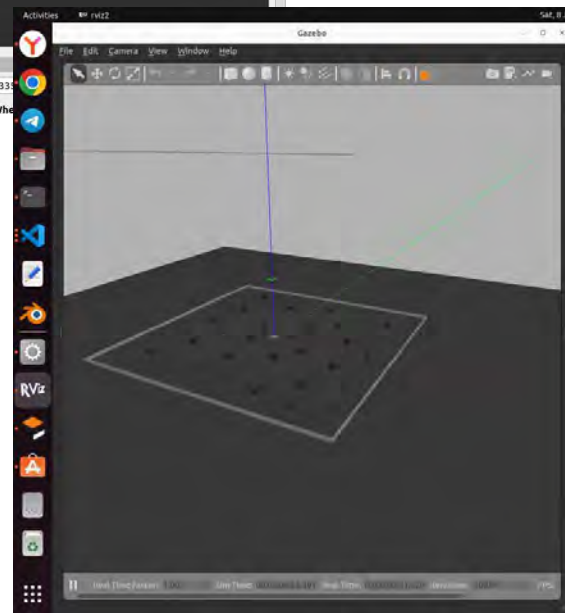
IMU
Odometry



Lidars



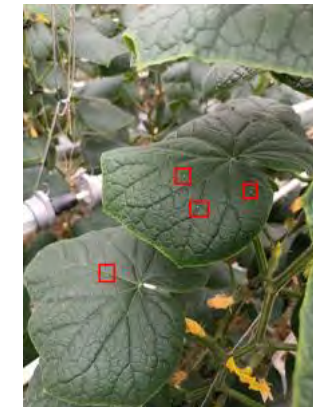
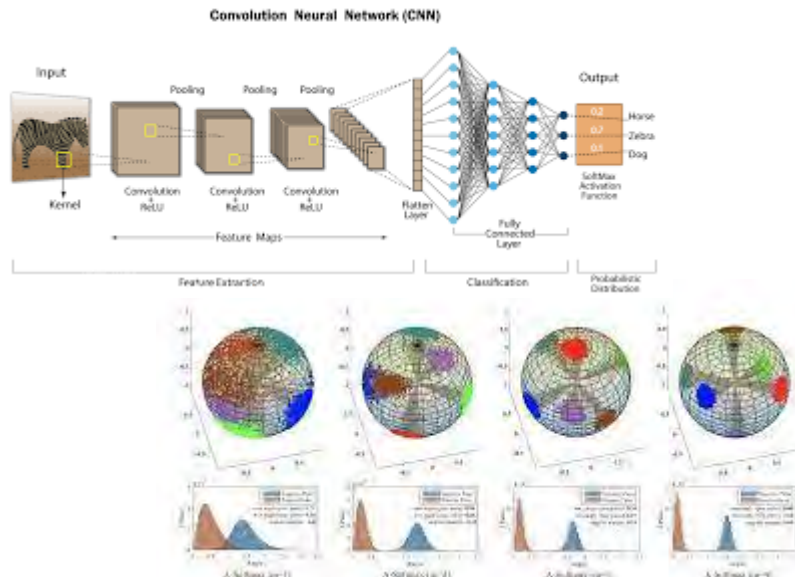
ROS2



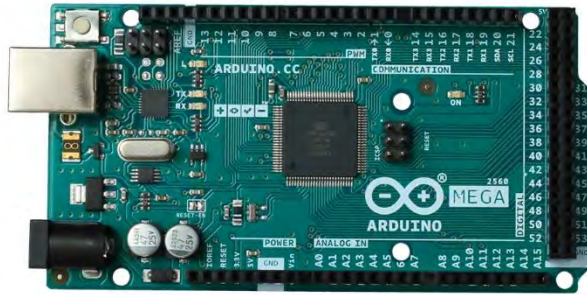


YOLO

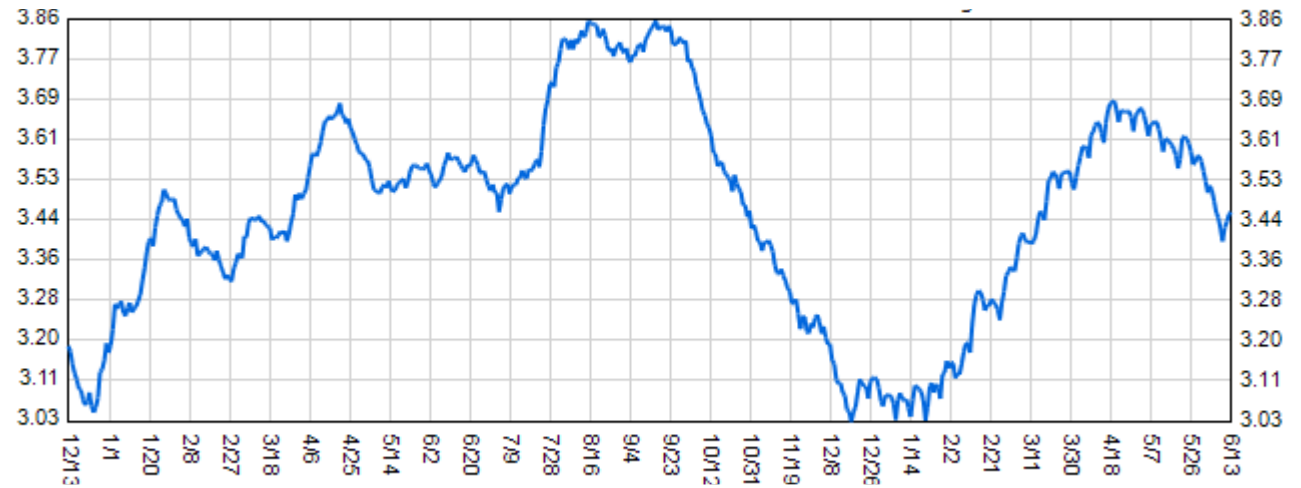
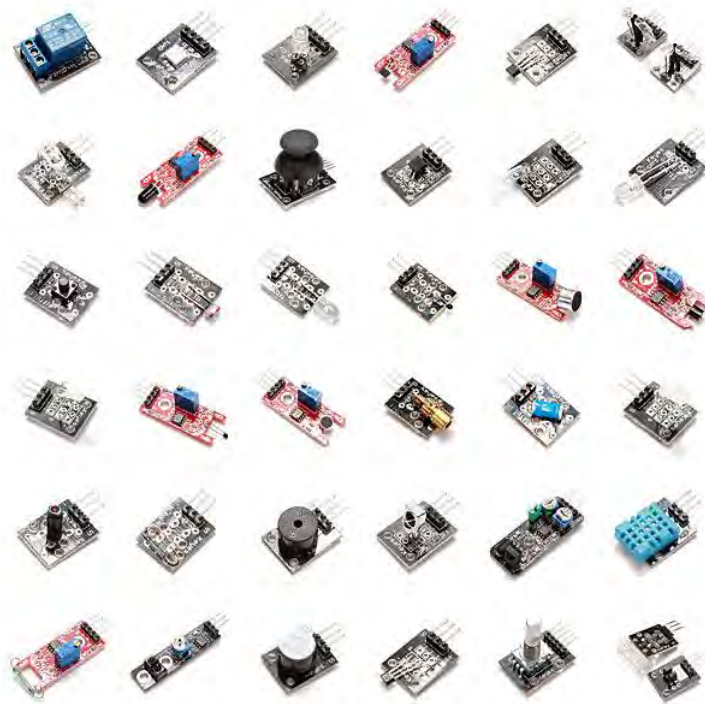
8, 9, 10



Uzhinskiy, A.; Ososkov, G.; Goncharov, P.; Nechaevskiy, A.; Smetanin, A.
 Oshot learning with triplet loss for vegetation classification tasks. *Comput. Opt.* 2021, 45, 608–614.



Sensors:
Temperature,
Humidity,
Light,
Carbon dioxide, Nitrous
oxide, Hydrogen,
Hydrocarbon gases, etc

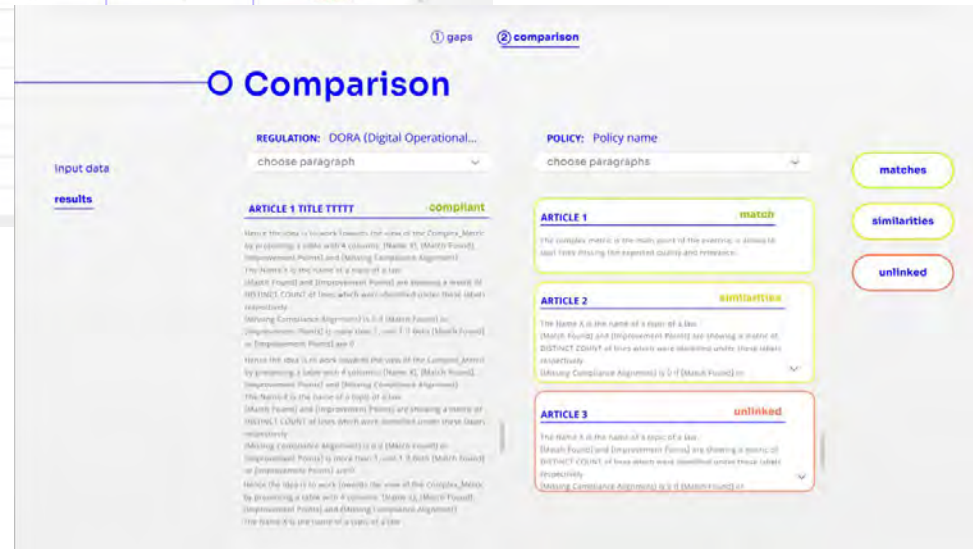
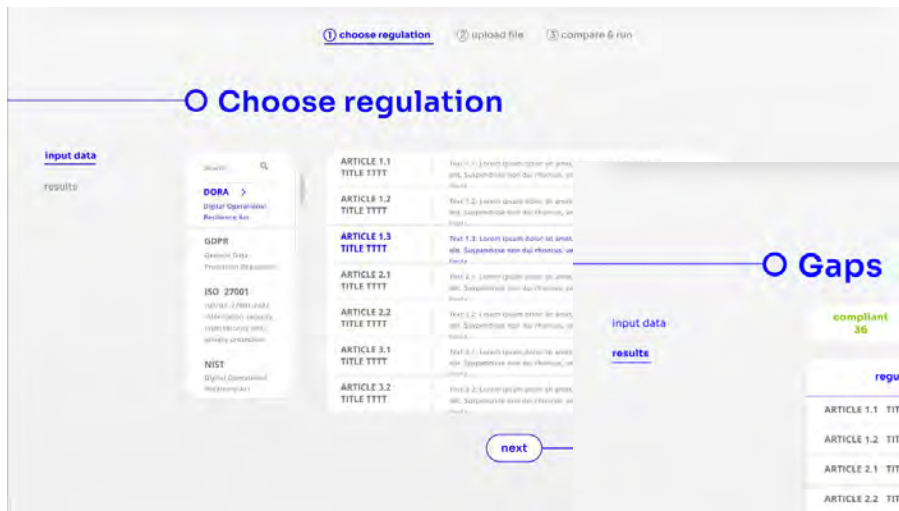


Что можете сделать вы?

- Широкий спектр различных задач в области робототехники - навигация, локализация, картографирование, движение
- Оценка эффективности различных object detection подходов для отслеживания болезней и вредителей в тепличных комплексах
- Интеграция датчиков для измерения различных параметров среды в тепличных комплексах
- Ваш вариант

Анализ похожести текстов

Сравниваем по частям текст внутренней документации компании с законами или стандартами и находим какие части закона/стандарта схожи с регламентами компании. Те части закона, которые никак не отражены во внутренней документации, являются потенциальными уязвимостями при проверке со стороны аудитора и их необходимо описать в регламентах компании.



В текущей версии реализовано через векторизацию **TF-IDF**. Идет сравнение параграфов текста, предложений внутри параграфов и их комбинаций

Что можете сделать вы?

- Исследование альтернативных подходов к решению задачи:
 - сплит-модели
 - кросс-энкодеры типа MonoBERT
 - LLM + LLaMa3 и Mixtral
 - ваш вариант ...

Спасибо за внимание!

email: auzhiskiy@jinr.ru
<https://t.me/bigzmey>

Additional information

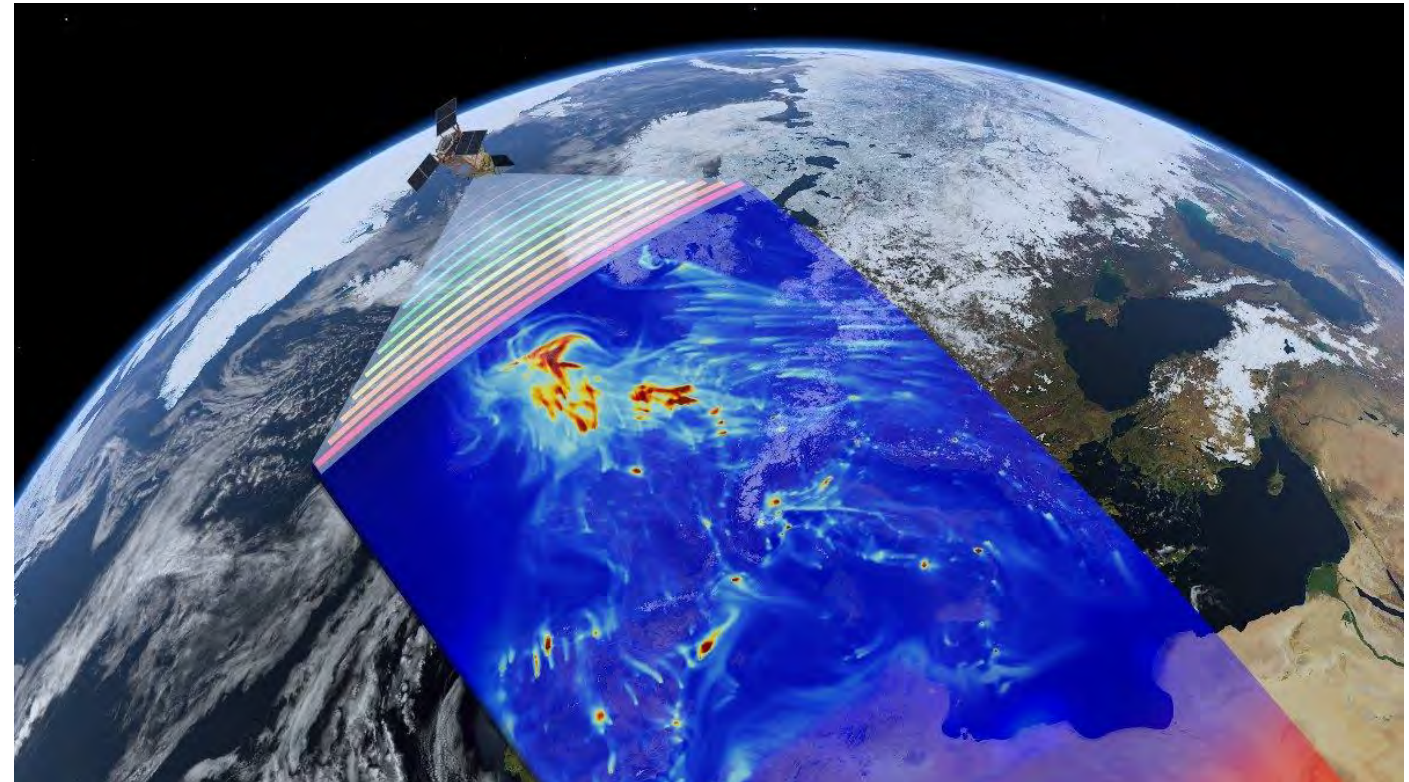
Коммерческие спутниковые программы

Sentinel-5

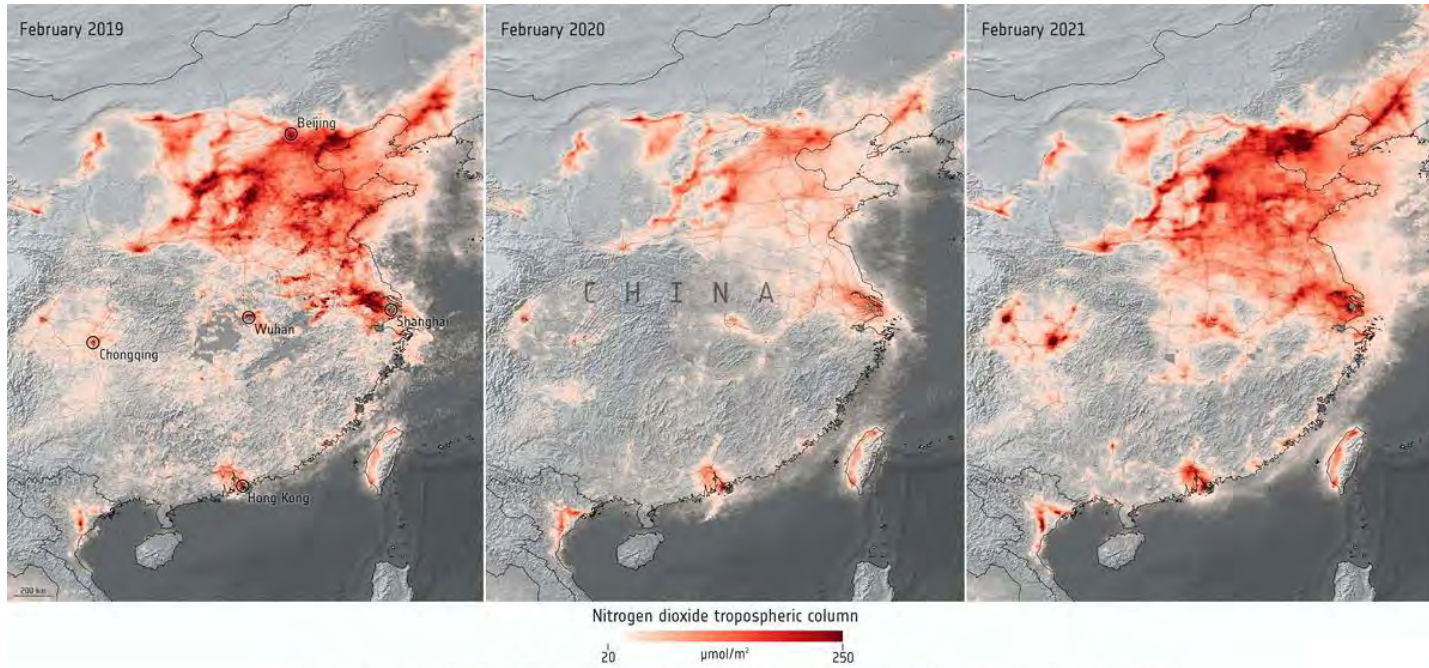


Sentinel-5 is focused on air quality and composition-climate interaction with the main data products being O_3 , NO_2 , SO_2 , HCHO, CHOCHO and aerosols. Additionally Sentinel-5 will also deliver quality parameters for CO , CH_4 , and stratospheric O_3 with daily global coverage for climate, air quality, and ozone/surface UV applications.

The Sentinel-5 mission is part of the European Earth Observation Programme "Copernicus" which is coordinated and managed by the European Commission (EC). The space component of the Copernicus observation infrastructure is developed under the aegis of the European Space Agency (ESA).



Sentinel-5

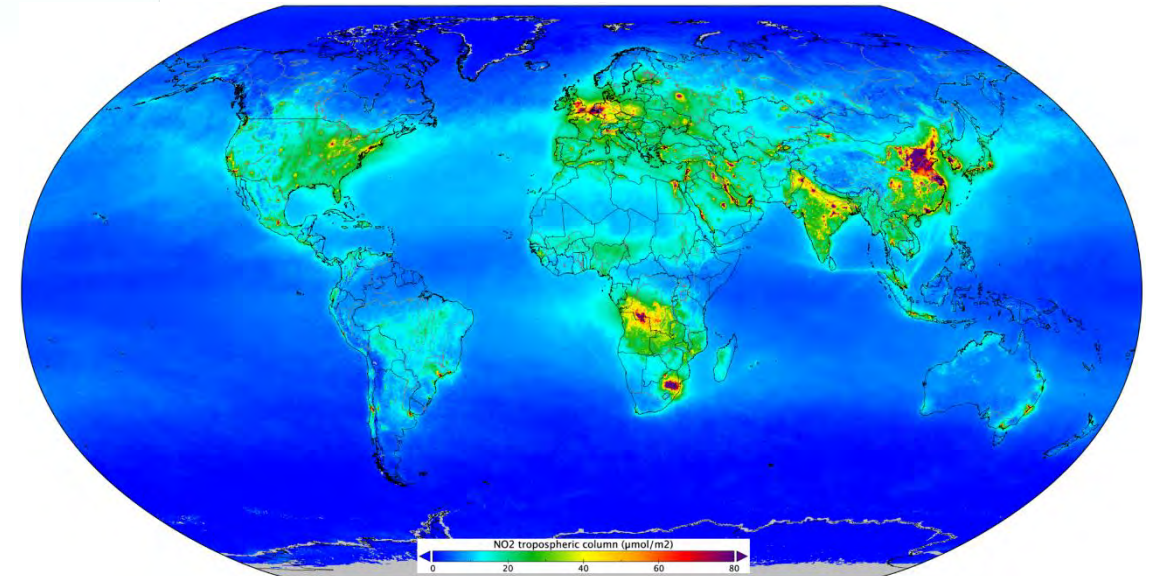


contains modified Copernicus Sentinel data (2019-21), processed by ESA

Resolution ~ 1114 m,
Orbital cycle 16 days.

Sentinel 7 (CO2M - Copernicus Anthropogenic
Carbon Dioxide Monitoring) 2025 - 2026

The Sentinel-5 mission consists of high resolution spectrometer system operating in the ultraviolet to shortwave infrared range with 7 different spectral bands: UV-1 (270-300nm), UV-2 (300-370nm), VIS (370-500nm), NIR-1 (685-710nm), NIR-2 (745-773nm), SWIR-1 (1590-1675nm) and SWIR-3 (2305-2385nm).



Nitrogen dioxide worldwide 12/03/2019



Formula 1 Miami Grand Prix

2019

Daily, less than 3m resolution, 4 spectral channels





PlanetScope
Always-on Monitoring

~200
Satellites

3.7 m (3.0 NIIRS)
GSD

8
Spectral Bands

Not required
Tasking



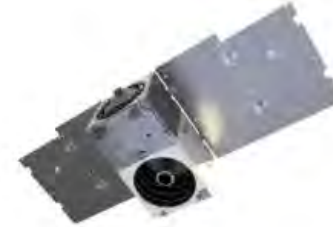
SkySat
High-Resolution Tasking

21
Satellites

0.5 m (4.0-5.0 NIIRS)
GSD

RGB, Pan and NIR
Spectral Bands

Sub-daily
Tasking



Pelican
Very High Resolution

~32
Satellites

0.3 m (>5.5 NIIRS at-nadir)
GSD

7
Spectral Bands

Up to 12 revisits/day
Tasking

Now



Hyperspectral
Broad Spectral Range

2
Satellites

30 m
GSD

400-2500nm
(5nm spacing)
Spectral Bands

Tasking Required
Tasking



1999
~ 3 days, 3m resolution, 3
spectral channels

ON ORBIT

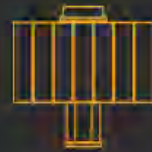


WORLDVIEW-1

- Electro-Optical
- 50 cm resolution
- <5.0 m CE90

[Download datasheet](#)

From 2007
~ 2 days
1 spectral channel



GEOEYE-1

- Electro-Optical
- 41 cm resolution
- <5.0 m CE90

[Download datasheet](#)

From 2008
< 2 day
5 spectral channels



WORLDVIEW-2

- Electro-Optical
- 41 cm resolution
- <5.0 m CE90

[Download datasheet](#)

From 2009
~ 1.2 day
9 spectral channels



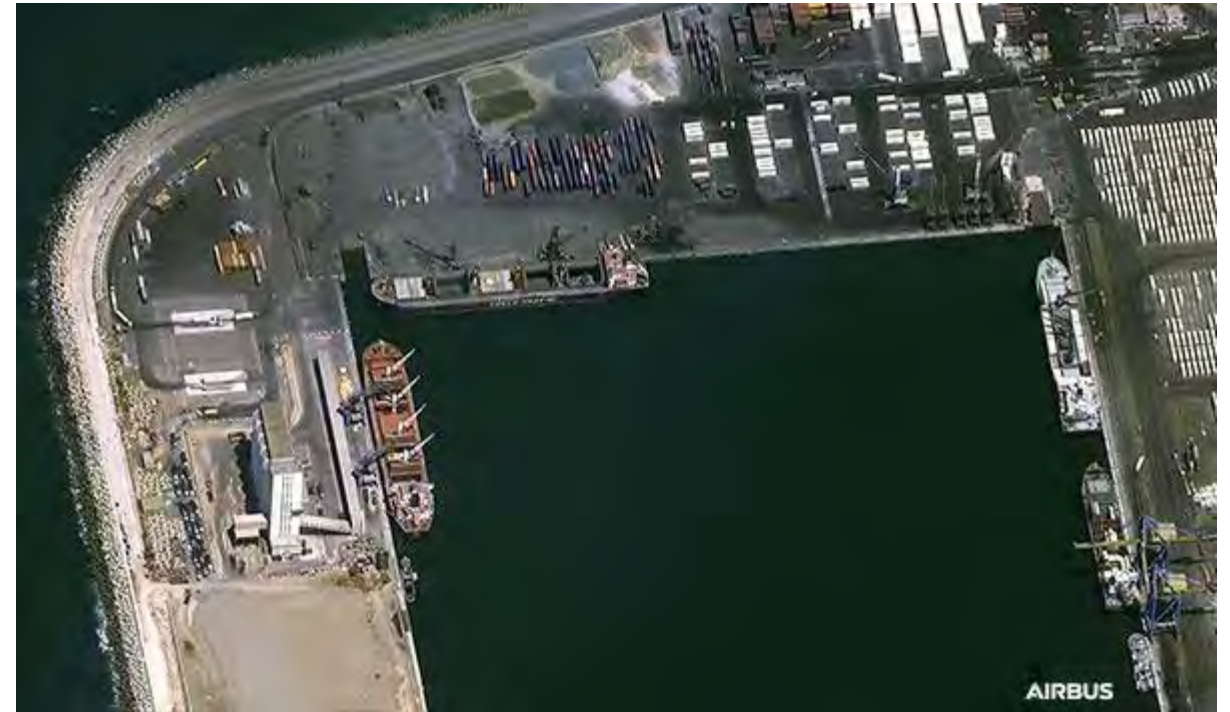
WORLDVIEW-3

- Electro-Optical
- 31 cm resolution
- <5.0 m CE90

[Download datasheet](#)

From 2014
< 1 day
29 spectral channels

Commercial programs - Airbus



Commercial programs - Airbus

Pléiades Neo
📷 30 cm
Revisit capacity
Daily, anywhere.
Daily acquisition capacity:
1,000,000 km²

Pléiades 1A/1B
📷 50 cm
Revisit capacity
Daily, anywhere
Daily acquisition capacity:
700,000 km²

Vision-1
📷 90 cm
Revisit capacity:
Daily to 8 days, anywhere,
depending on latitude and
partner satellites
Daily acquisition capacity:
20,000 km²

SPOT 6
📷 1.5 m
Revisit capacity
Daily, anywhere
Daily acquisition capacity:
3,000,000 km²

RADAR Constellation
📷 From 25cm to 40 m
Revisit capacity
Daily for most latitudes
Daily acquisition capacity:
5,400,000 km²

DMC Constellation
📷 from 12 to 24 m
Revisit 3-5 days anywhere
Daily acquisition capacity:
10,000,000 km²