Spatial Learning and Overfitting in Visual Recognition and Route Planning Tasks

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Keywords: Spatial Cognition, Navigation, Machine Learning, Overfitting, Retraining.

Abstract: Spatial data recognition, navigation based on localized visual clues and ability to identify significant elements in the environment and build routes is formed as a result of general spatial learning and then adjusted to a specific location. Modern artificial intelligence (AI) — from visual processing applications to autonomous vehicles—also includes this capability. However, excessive learning can lead to overfitting, which significantly reduces the efficiency of spatial actions. In this work we describe typical algorithms for navigation, spatial learning in pigeon flights, and remote sensing recognition in neural networks. We consider learning algorithms based on significant topological elements, and suggest possible methods to expand learning opportunities and reduce the impact of erroneous settings. Our calculation results show how overfitting affects navigation behaviour and visual recognition. Result of this work provides direction for the future development of new algorithms that optimize the efficiency of spatial learning.

1 INTRODUCTION

Spatial behavior is determined by the internal settings, goals, and expectations of subjects and by the external world as well as by ways of obtaining additional information about the external environment. The ability to solve spatial problems is used directly in everyday life and affects global processes of settlement and migration.

Animals solve their spatial tasks reflexively, without a detailed study of topological relationships; they directly relate their observations, actions, and results to the physical capabilities of their bodies and the available environment. Humans have an opportunity to apply both their natural skills and digital technologies to solve localized problems in spatial structures (Freksa *et al.* 2017). An application of artificial intelligence (AI) complements the possibilities of spatial perception and navigation of humans and animals and builds a new level for discoveries and achievements in geography (Galvani, Zaleshina, and Zaleshin 2021).

Detailed skills for terrain orientation are acquired through spatial learning. There are different ways to evaluate the effectiveness of spatial actions. In practice, it can be summarized into two main indicators - how many wanted objects of spatial search are found and reached, and how much time and material resources are spent. Additionally, for AI often calculates a percentage of correct finds in relation to all finds, and a percentage of found objects in relation to all objects. This work compares spatial perception and navigation behavior for animals (using the example of pigeons), and for artificial neural networks (using the example of recognizing basic urban landmarks). Particular attention is paid to the issues of overfitting and underfitting. It is emphasized that learning increases speed and minimizes costs of wayfinding, but at the same time, overfitting and lack of updates to the applied patterns lead to systematic repeated errors, leading to a large number of false results during actions.

The materials of this work can be useful in various topics related to the formation of spatial cognition and navigational behavior algorithms.

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2 BACKGROUND

2.1 Spatial Learning Algorithms

The ability to perceive and recognize spatial data and use this data during movement is innate in both animals and humans. Now this need is being built into various AI applications, from programs for remote sensing recognition to autonomous vehicles. For both living organisms and AI, learning can be two types: independent learning and learning with a teacher.

Spatial learning serves to optimize expenditures of time, effort, and resources. At the same time, the costs of the path are non-linearly related to the quantity and quality of the result obtained. In addition, material resources can be replenished along the way. Typical learning flowchart is shown in Figure 1.
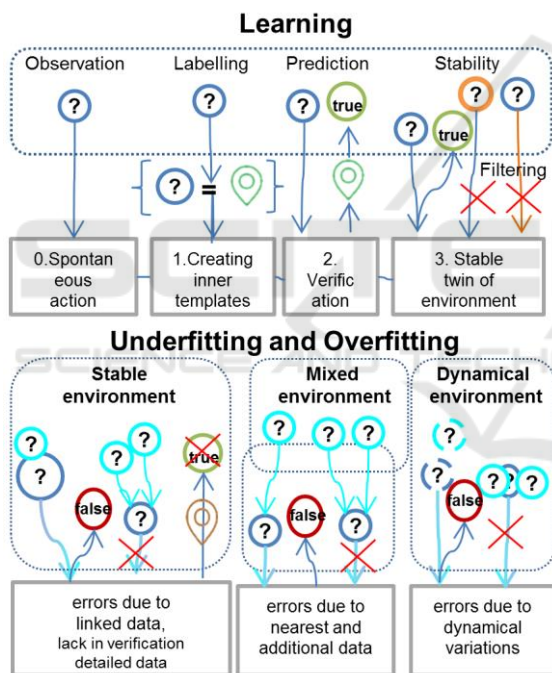

Figure 1: Learning stages and typical underfitting and overfitting problems.

Algorithms, once formed during training, can be repeated for a long time, but this time is limited. First, the environment can be modified, e.g., due to climate change. Second, a repeated action can be a reason of outside changes, e.g., if the sheep eat and trample all the grass in the pasture. Third, learning errors can have a cumulative effect due to filters or due to repetition.

Another problem that occurs during learning is overfitting. In the case of a stable environment, trained algorithms usually work. Overfitting occurs when a trained algorithm is able to process a limited set of data in too much detail, it processes well in fixed sets of samples, but is unable to generalize the processing to new situations. In fact, novelty is contraindicated for it. This needs to be eliminated by retraining on new samples, unlocking the rigidity of the predefined classification (Bashir *et al.* 2020). Additionally, in reinforcement learning, the novelty of an event can strengthen a motivated response to it (Siddique *et al.* 2017), which partially facilitates efforts to get rid of existing incorrect algorithms.

Overfitting and underfitting can greatly affect learning outcomes: data can be misinterpreted or misclassified, relevant data can be filtered out. Underfitting often results from misinterpretation of noise or confusion in scales. Some of the noise can be removed at the preprocessing stage using the decision tree method (Alharbi 2024) or by segmenting spatial data according to the scale.

2.2 Typical Spatial Tasks

- **Bird Flights: Homing and Foraging**

In flight, birds focus their attention on the main elements of the environment: long roads and rivers, or well-observed objects. Blaser *et al.* (Blaser *et al.* 2013) describe how pigeons' mental map helps them find a route to home or to feeding site based on their current location. Detailed training in fixed route flight can be done with a teacher, while flying in a flock, or while following a leader. Flight consistency in a flock of pigeons often depends on the flying experience and/or age of the individual birds and the ability of the flock leader to set the direction of flight (Santos *et al.* 2014).

The difference in the length of the flight paths of a bird making its first flight and a bird that has undergone training can differ several times over the distance A trained pigeon does not need to make a choice every time where to fly, and its route is optimally shortened.

Both in the case of the first flight and in the case of failure to find the original target, the pigeons begin to survey around the starting point or predicted POI, over distances comparable to their usual flights. Schaffner *et al.* (Schiffner *et al.* 2018) studied the difference between surveying trajectories of pigeons at the moment of departure from the site and subsequent directed flight to the target. The authors suggested that complex perception of external information in pigeons slows down their flight speed, but at the same time allows the birds to more steadily and efficiently adhere to the target direction.

▪ **AI: Machine Learning and Unlearning**

In remote sensing recognition tasks, including for navigation, the priority is to identify key objects - roads, buildings, vegetation. Depending on data sources, quality, and specificity for a particular area, recognition results of trained neural networks have different quality. U-Net (Benedetti, Femminella, and Reali 2022) or DeepLabV3 (Wang *et al.* 2022) are often used to recognize remote sensing images. Such neural networks often have difficulty eliminating noise interference, such as shadows from trees, when recognizing buildings or roads. Well-chosen segmentation labeling algorithm (Lee *et al.* 2022) helps to optimize neural networks.

Machine learning models can adapt to variability in the data they process, although this often requires pre-training or retraining. In primary sequential training, the observed data sets are used to fit the model, assuming that the predicted features are constant over time. Retraining requires the ability to collect new data and compare the recognition results of incoming data with predicted ones (Dietterich 2002). Active learning algorithm improves the model quality by checking of data labeling and label dispersion (Bengar, Raducanu, and van de Weijer 2021). Adversarial learning methods are limited in data generalization and give unreliable results after overfitting (Zhao, Alwidian, and Mahmoud 2022).

Machine unlearning is used to partially eliminate incorrect settings, while preserving the neural network model's ability to recognize the necessary data. When unlearning significant indicators that need to be forgotten and those that need to be remembered are determined (Foster, Schoepf, and Brintrup 2024).

Hopkins *et al.* (Hopkins *et al.* 2024) propose a model-independent solution based on the ability to generalize properties across sets of different classes. Kim *et al.* (Kim, Kim, and Bengio 2021) associate each branch of models with a visual concept and further manage the resulting set using the attention module. Processing first calculates the content, which is then returned to a pixel space containing the subject area and style.

2.3 Route Planning

▪ **Aggregation of Route Planning Information.**

The rapid development of digital technologies contributes to a significant increase in the volume of collection and processing of spatial and temporal route data. Depending on the structure, route data can be divided into explicit entities directly related to observation and implicit additions with weak spatiotemporal continuity (Kong *et al.* 2018).

The availability of route points with known attributes serves as the basis for creating a route through such natural objects that have been located close to each other for a long time and usually have similar or dependent components that determine their structure and content. To a lesser extent, this applies to artificial objects. Tobler's first law (Tobler 1970) assumes the dependence of some attributes of objects that are close to each other.

Unlike static orientation elements, dynamic elements are not constant in their properties over time. Natural objects can change their visual properties depending on the time of day and season. Artificial objects can change their other attributes without changing visually over time: public facilities (museums, cafes, shops, etc.) have opening hours; public transport runs on a schedule, possibly, with long breaks.

In an unfamiliar environment, a person searches for previously encountered objects and signs to recognize other ones. The uncertainty generated by a little-known situation results in an attempt to orientate and search for fragments of previously encountered elements (Tversky and Kahneman 1974). The variety of identification and interpolation options leads to the creation of both copies and complementary extensions of existing fragments. Like puzzles, such identified fragments do not always form a recognizable whole. Fragments that are not combined into blocks collectively make up a potentially usable pool. The search allows for identifying suitable fragments and supplements thereto. Missing points can be added based on the available parts of other objects, when points with known attributes transfer their properties onto fragments or whole areas, as is the case in kriging.

Points with known attributes can also serve as reference points. Reference points have stable locations, but their locations can change over time. A set of reference points forms a system of spatiotemporal relations that can be used for orientation along a route. Reference points with known attributes make it possible to create generalized coordinate systems based on their spatial positions or on non-numeric indicators. The complex nature of reference points allows them to be used as a tool for operations with objects and attributes, and as a framework for spatial positioning. The relative positions of points and objects form the structural code of the track points. With small changes, the structural code may remain the same, with significant changes in the data set of the environment; a new structural code is formed from some stable or repetitive components/elements of the environment.

The lines of short routes, if possible, run as straight as possible, especially if they are also in the line of sight. If the line of sight of the short route endpoint is obscured by visual obstructions, the route may deviate greatly from the straight line and detour along the visible road section.

▪ **Fragmentation of Observed Data.**

The environment, including both artificial and natural signs, is often underrepresented, contradictory, and ambiguous; the boundaries, color, and texture are not perceived clearly. The composition of objects selected by a person changes over time, and when the same objects are selected again, their fragments are added and removed, and new combinations of fragments are generated (LaPointe, Lupianez, and Milliken 2013). In the observed environment, fragments are selected that belong to one or several objects, for example, not the road sign itself but some part thereof, being jointly selected and even combined with the adjacent lawn.

The success of the configuration options, fragmentation, and recombination of blocks and structural code can be determined by the statistics of contradictions between a single found element and the correspondence among the existing several elemental options found exactly according to the specified parameters. Attribute transferring allows to smooth out corners and to make modest changes and additions, and filling large voids in the data approximately (Ge *et al.* 2021a, 2021b).

When overfitting, trained topics overwhelm untrained topics by searching the environment for previously encountered objects, phenomena, and events. But potentially there is a transfer of attributes from the known to the unknown. A list of objects or fragments can create thematic non-overlapping layers in a location that form new structures, this gradually leads to changes in fields from the attribute table where the transfer of attributes changes, for example, color from green to red, and a car to a tractor in the same field. Versions of assembly of layers are possible. In such cases, a block combining elements into a common or a consolidated block of mixed elements or fragments from one or different sources can be combined into a common whole with other parts.

▪ **Multiscale Spatial Code.**

The nature of spatial perception can be described in terms of topological entities, with visual form primitives serving as key geometric invariants (Chen 2005). A multiscale spatial code is also present in the brain, which allows external stimuli to be represented with varying degrees of refinement, both in generalization and in detail (Bellmund *et al.* 2018).

In problems of detecting visual changes, researchers have shown that objects embedded in a contextually heterogeneous scene tend to be detected faster than objects embedded in a contextually homogeneous scene. consisting of types of objects and their probable location (LaPointe, Lupianez, and Milliken 2013). The relative positions of points, fragments, and objects form the structural code of the route. The structural code is determined by the relative location of commensurate objects and, in general, does not change when objects are replaced with their counterparts. Searching for objects with the same attributes results in finding objects with the same structural code.

The structure of a composite block of fragments is a set of fragments and links between them. Such a structural code of a composite block can be transferred from one block to another. The structural code for a set of objects is determined by the presence or absence of boundaries adjacent to each other or to the "background." The structural code can change when fragment blocks move relative to each other. After a search for additional data in a collection of fragments and blocks, an incomplete object can be supplemented with missing data.

The structural code, like a route description, can be used as a geometrical relative location of a set of objects and as an invariant for describing motion. Object attributes and structure codes often become similar if they have been neighbors for a long time. The difference between the existing and predicted fragments can be calculated at the same location.

Tobler (Tobler 1970) assumes the dependence of some attributes of objects that are close to each other. Neighboring artificial objects may have a similar structural code. If a group of objects is located in the same area, attributes of objects are useful for restoring the missing attributes of another object from the same class. If objects of the same class are located in sight, missing attributes can be added based on the available attributes of other objects.

Search operations make it possible to find intermediate points along a route. With redundant but varied options, the lack of information is compensated by additions found during the search.

▪ **Signs and Dynamic Elements Along a Route.**

In choosing a route, the goal is usually not a single endpoint of interest but to obtain a variety of "vacation" impressions, which is achieved by selecting the entire set of points to visit—both final and intermediate. Some of these POIs chosen by a traveler may relate to their favorite hobby (places for sports activities, cultural attractions, etc.), some POIs are directly related to everyday needs, and some are

explicitly aimed at gaining new experiences (see Figure 2).

Figure 2: Route signs in Stein am Rhein.

A sign is a material object or a pointer, which is identified by many people in the environment, but can have different imaginative content for any person. However, for standard logistics tasks, identically perceived signs are used. When exchanging data, a sign usually represents a small amount of data and is spatially localized. Signs along a route replace the immediate appearance of a predicted event or external information.

Points of interest often serve as bookmarks and reference points in navigational applications. These are required for a variety of cases of access to information sources. Similar data from the external world with supplements in the form of search results restore the same initial conditions for collecting and processing information. Being small in volume, POIs allow quick recovery of information with the relevant set of parameters, which was prepared earlier. Such POIs often continue to be observed for a long time, maintaining the sample selection stability when searching.

Orientation information has the property of maneuverability. When included in the current data set together with other observed data, its fragments, links, attributes, and structural codes are transferred. Incoming data is modified by adding extra-large fragments or reference points or by filling in missing data using fragments. Expanding the currently collected data using a search is also possible when accessing extended data, with orientation information acting as an instance of some class, or if there are dependent or identical parts in the observed or found elements.

▪ **Choosing with Insufficient Information**

If there is no fixed endpoint, the route can be very tortuous. When fixing the start and end points of a route, its intermediate points are movable and depend on the selection and external events. According to some signs, that are known and equally understood by many people, it is possible to determine the type and intensity of traffic at certain hours in a certain direction.

Uncertainty in choosing a route can occur when there is a lack or excess of information, or when it is impossible to determine the importance of the observed data. Choosing between two insignificant options or avoiding a choice may be based on intermediate surveying, or affected by external influence, or accompanied by withdrawal from the situation. Failure to pay attention to any POIs when changing the thematic setting may be a result of fatigue or overfitting.

Untrained – a deviating path taking into account POIs, trained by teacher – the most well-trodden paths – mostly based on the decisions of others, taking into account the variations and, trained without teacher – shortest paths.

Let the path consist of four parts: 1) planned activities, 2) relaxation with inactive rest without almost external events, c) visually attractive contemplation or observation without temporary haste for what is interesting and d) active spontaneous entertainment here and now.

▪ **Unexpected Events or New Road Signs**

For some, perhaps a long, time synchronicity is displayed in different structures and processes that start at the same time. The synchronicity of objects can be either temporal, as for a series of objects, or spatial, as for a set of objects that are selected by a person simultaneously (Ort and Olivers 2020). Even if the geometric distance is fixed, due to weather and other unexpected factors, traveling time from one city to another may be variable (Neumann 2017). Short-distance travel is associated with risk, when this movement is carried out to link initially unrelated segments of the route path that are close to each other in the task of quick transition. It is worth noting that often many short sections of the route can only be traversed on foot.

Unexpected events, obstacles or new road signs can significantly change both the route itself and the set of intermediate points of interest. A small gap in the planned route that arises due to a lack of information regarding objects along the route is closed under the assumption of the similarity of these unknown objects with previously encountered ones.

Often, difficulties arise when opting for a particular route; besides, natural and artificial obstacles can affect the already planned path in the most unpredictable ways. In such cases, where a person is not able to generate a route model due to unpredictable events or a mismatch with expectations, they can always simplify the choice model to a series of one-time choices (existing "here and now"); however, in each new moment, the person will again need to make next choice.

In addition to the existing "points of interest" on a map of the area, a traveler can find new "points of

attraction" that unexpectedly invite attention. They can become intermediate points on the route.

The scale of the planned route determines the features of its formation. When optimizing a route, considering points of interest, one can draw an isoline, connecting points with the same levels of interest. For more flexibility in working with data, one can use a dynamic segmentation of events along the route. During the formation of the preliminary route, it is assumed that both a choice has been made and a class of objects to be approached has been selected or the routes are offered to all known objects within acceptable limits. During the search, objects located in the vicinity of the route track can supplement the set of criteria for route selection. A not-fixed route endpoint increases the significance of pointers located near the starting point.

The presence of a distinguishable choice between two options does not imply the presence of a predisposition to one of them. In this situation, preparation is required for the solution: surveying in situation with clarification of route details, external interference to the situation, outside signs, and so on. An important reason for the change or complete cancellation of a route may be the discrepancy between expected and real events.

3 MATERIALS AND METHODS

3.1 Materials

▪ Pigeon Flights

Spatial processing of GPS pigeon tracks was performed based on data on bird flights in flocks over the combined terrain, published in open repositories: Dryad Digital Repository https://datadryad.org/resource/doi:10.5 061/dryad.f9n8t, where flocks flew near the seashore and Movebank Data Repository https://doi.org/10.5441/001/1.33159h1), where flocks flew near the foothills. The distance between the points of departure and destination was about 10 km. The distance in the coordinate sequence of pigeon GPS tracks was about 3-6 meters. Measurements of coordinates were taken 4–5 times per second. The number of pigeons in each flock was 4-8 birds.

▪ Remote Sensing Data

Spatial remote sensing data were obtained from open sources, such as Sentinel2 data hub (https://www.sentinel-hub.com).

3.2 Processing Steps and Metrics

When analyzing the movement trajectories of birds, our processing consisted of the following steps:
- Creating a new project in QGIS (http://qgis.org) and uploading data about trajectories and terrain;
- Identification of local key objects based on remote sensing data, including selection of contours of significant extended objects;
- Object recognition using neural networks;
- Calculation of the main indicators of tracks for different degrees of learning;
- Calculation of track metrics.

When analyzing remote sensing data, we accomplished data recognition in different versions of networks:
- Non-specialized in remote sensing recognition, but able to recognize images of a different type,
- Trained for remote sensing recognition,
- Trained, but with modified recognition parameters - conditionally untrained.

Calculation of recognition metrics F1-Score_obj (Lipton, Elkan, and Naryanaswamy 2014). To calculate the F1-Score values, we used sklearn.metrics module from open source machine learning library Scikit-learn (https://scikit-learn.org/stable/modules/generated/sklearn.metrics.f1_score.html).

3.3 Applications

Spatial analysis was performed using QGIS applications Extracts contour lines and Heatmap, and LF Tools (https://github.com/LEOXINGU/lftools/wiki/LF-Tools-for-QGIS).

The recognized remote sensing materials was obtained using Mapflow AI platform (https://github.com/Geoalert/mapflow-qgis, http://mapflow.ai), which provides geoinformation pipelines for recognizing objects based on remote sensing data, such as buildings, roads, fields, forests, etc. using various neural network models. To improve the quality of recognition, settings are specified for pre- and post-processing of the results. Such settings provide a fitting variation in recognition depending on sources (aerial/satellite) and specifics of the recognized classes (density of buildings, urban or forest vegetation, etc.). Mapflow's recognition capabilities can be used even to segment trees by crown type and houses by height (see Figure 3).

Figure 3: Segmentation of trees by their crown types.

4 RESULTS

4.1 Analysis of Pigeon Flights

During the calculations, comparisons were made for untrained, trained and overfitting cases of bird flights, and it was found how pigeons fly without turning off the path, depending on the types of flight and degree of training.

Calculations were made for middle distance tracks, where all distances between the points of departure and destination of the flock of pigeons were about 10 km. In GPS measurements were taken 4–5 times per second, distances between points of pigeon GPS tracks was about 3-6 meters. The number of pigeons in each group was 4-8 birds.

The following indicators were calculated:

- Straightness index (ratio of flight length in target direction to total flight length);
- Flight around newly found POIs (percentage of cases of flying over the buffer zone of the flight to explore new POIs).
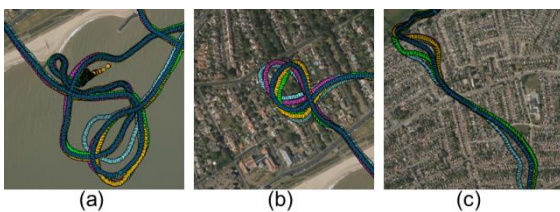

Figure 4: Typical flights: (a) Surveying flight; (b) Trained flight; (c) Trained flight.

Typical pigeon flights are shown in the Figure 4.

The calculation took into account the pigeon's level of training, in accordance with the number of flights performed along a given route. It was believed that the 1st-3rd flight is an untrained or surveying pigeon; the 3rd–7th flight is a trained pigeon; above the 7th flight is an overfitting pigeon.

The calculated results of pigeons' flight efficiency for surveying flights (the bird does not yet know the way), trained flights (the bird knows the way, but is distracted by external factors), and overfitting flights (the bird flies as directed as possible towards its target) are shown in the Table 1.

Table 1: Pigeon's flight efficiency.

Evaluation	Surveying flights	Trained flights	Overfitting flights
Straightness index	0.09	0.64	0.89
Flight around POIs	64 %	27%	11%

4.2 Efficiency of Neural Networks

Examples of building recognition by untrained, trained, and overfitting neural networks (NN) are shown in the Figure 5. It is noticeable that the untrained neural network tries to find buildings based on any minimal features, the trained neural network detects buildings with high efficiency, and the overfitting neural network correctly recognizes buildings in images of a familiar type but at the same time makes a large number of errors on unfamiliar textures.
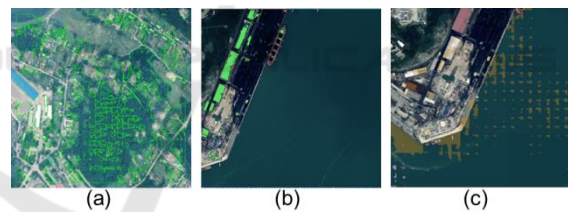

Figure 5: Buildings recognition: (a) untrained NN; (b) trained NN (c) overfitting NN.

The calculated results of F1-Score are shown in the Table 2.

Table 2: Untrained, trained, and overfitting NN.

Evaluation	Untrained NN	Trained NN	Overfitting NN
Number of training samples (1 x 1 km^2)	3	9	17
Recognized objects in training samples	265	854	1430
F1-score	0.17	0.87	0.52

5 CONCLUSIONS

Spatial learning in perception and navigation are essential skills in a changing environment. Both in AI and in nature, there is a problem of "overfitting" when a bird accustomed to the same route fails to notice new places to forage, or an artificial neural network begins to detect buildings in the ripples of the ocean. The "challenge" of overfitting makes it difficult to obtain new information and to find optimal solutions. Special attention is paid to the problems of overfitting when detailed adherence to previously acquired behavioral patterns leads to a decrease in efficiency and the accumulation of systematic errors. Additionally, due to overfitting, the ability to make optimal decisions in the presence of significant changes in the environment is reduced.

Our work systematizes general issues related to spatial data processing. We examine the problem of learning and retraining in spatial cognition and navigational behavior in categories: birds' navigation behavior and remote sensing recognition with neural networks and demonstrates techniques for solving the problem of overfitting. It can be helpful in various industry applications, including tracking changes in animal migrations in conditions of climate change, creating smart interactive tourist routes and adapting infrastructure for tourism, and preparing new neural network models for recognizing spatial data.

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