

PONTFELHŐ SZEGMENTÁLÁS MESTERSÉGES INTELLIGENCIA SEGÍTSÉGÉVEL

*Budapesti Műszaki és
Gazdaságtudományi Egyetem
Általános- és Felsőgeodézia Tanszék
Rédey szeminárium*

Előadó: Hrutka Bence Péter



BUDAPESTI MŰSZAKI
ÉS GAZDASÁGTUDOMÁNYI EGYETEM
Építőmérnöki Kar - építőmérnöki képzés 1782 óta

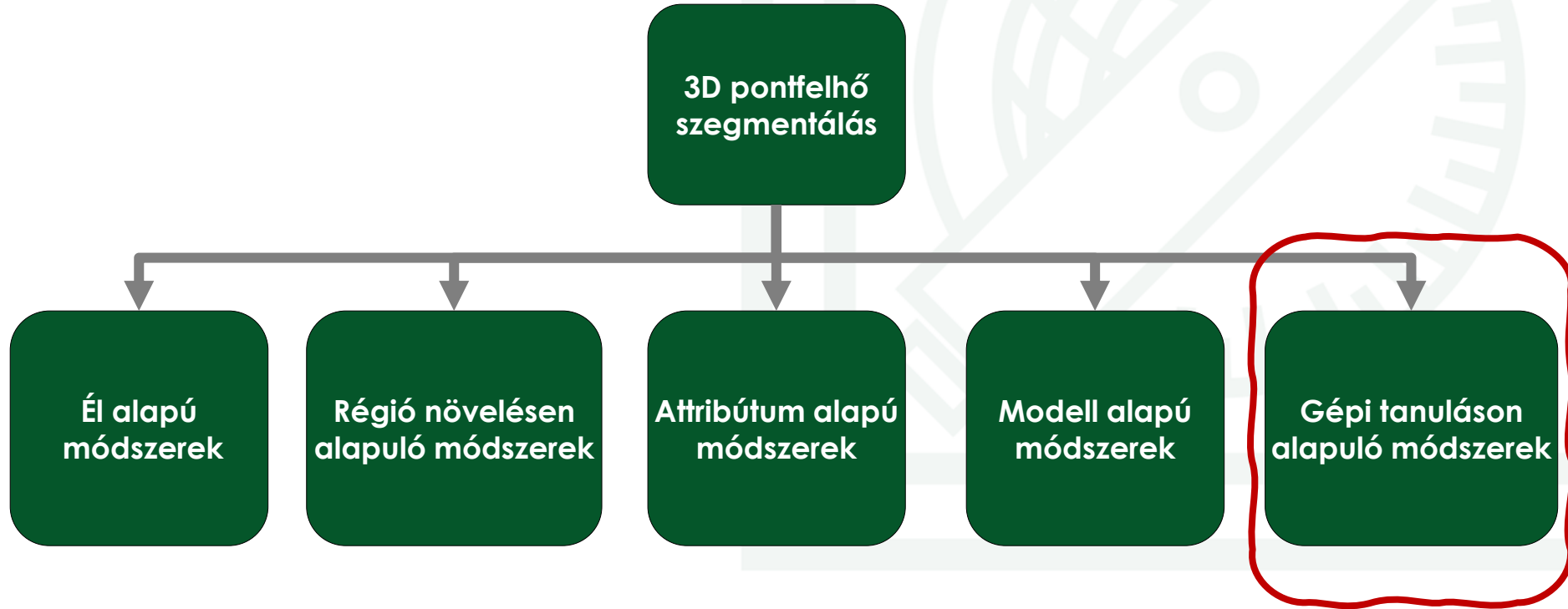
Általános és Felsőgeodézia Tanszék

2023.11.27.

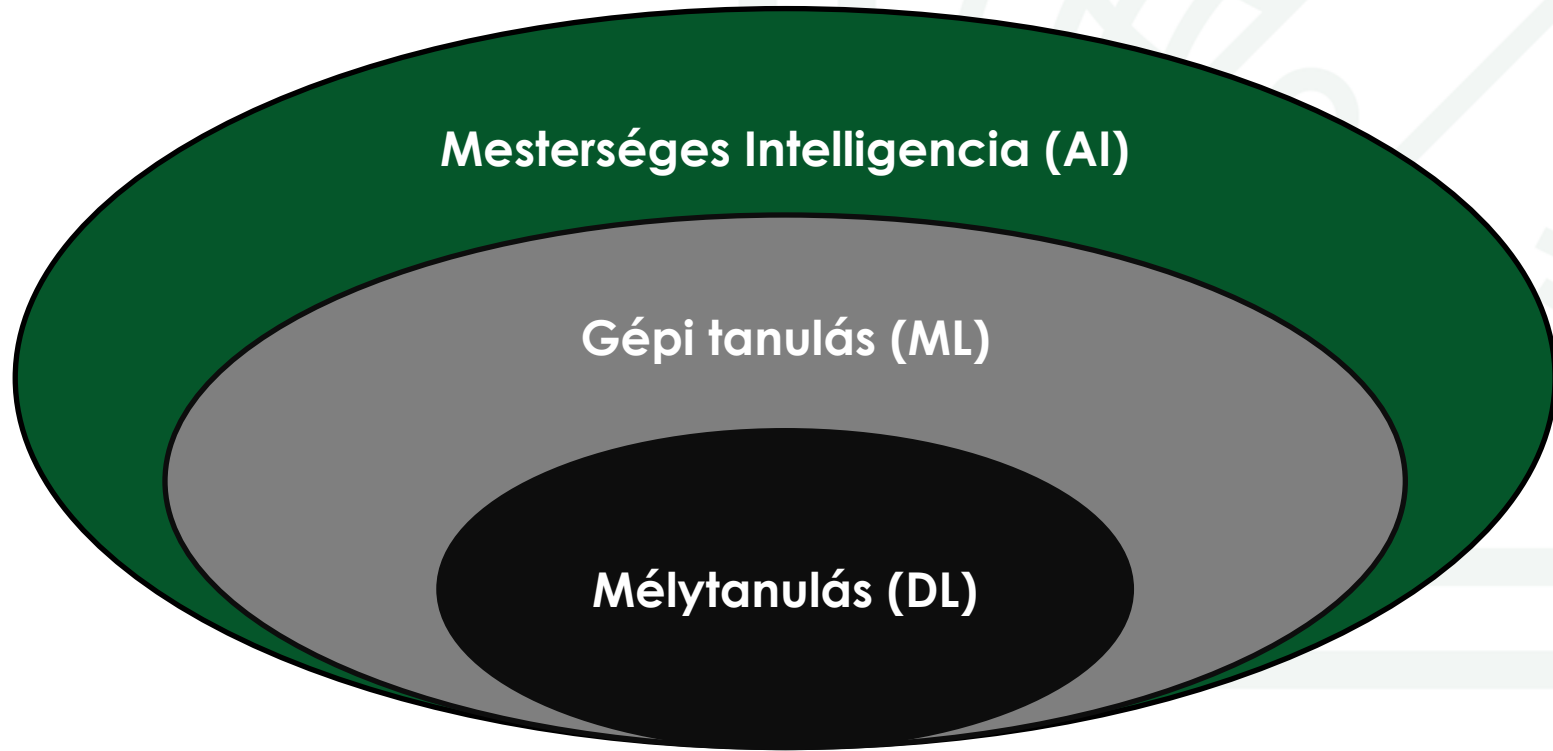
TARTALOM

- Bevezetés
- AI, ML és DL
- Pontfelhő jellemzők
- Gépi tanuláson alapuló feldolgozások
- Mélytanulás
- Összegzés

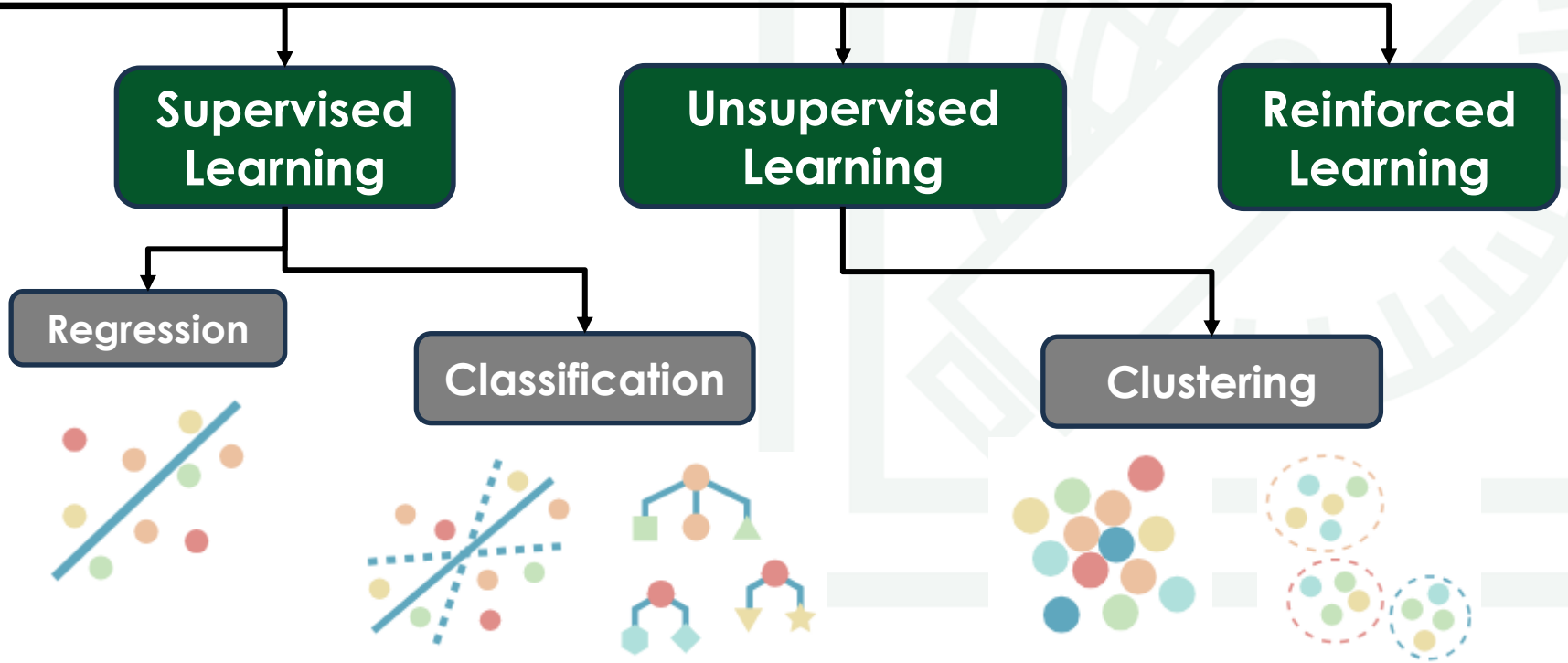
SZEGMENTÁLÁS



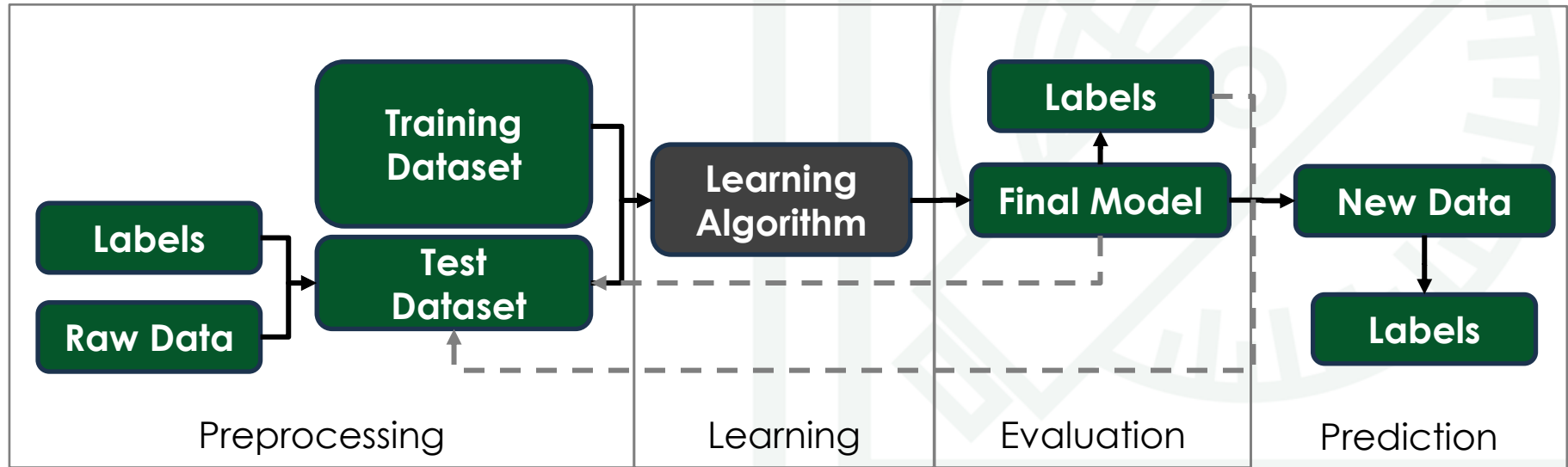
MESTERSÉGES INTELLIGENCIA



MACHINE LEARNING



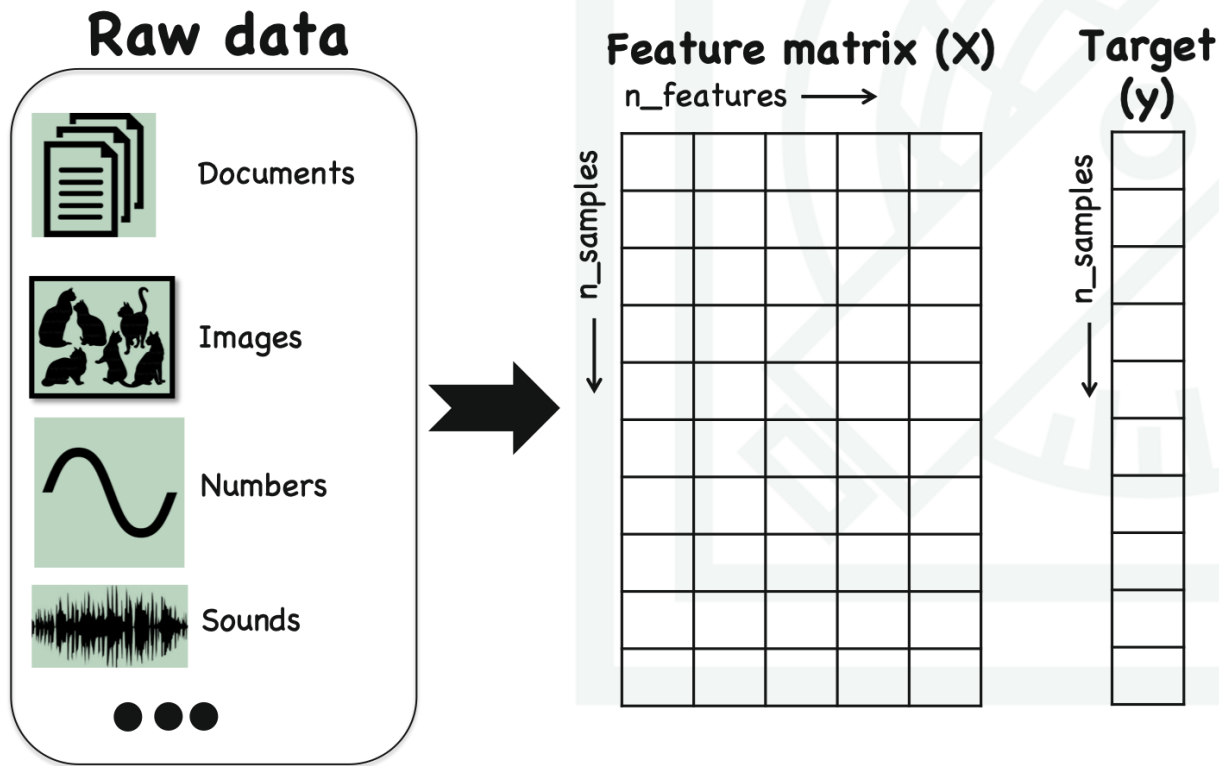
MACHINE LEARNING



*Feature Extraction and Scaling,
Sampling*

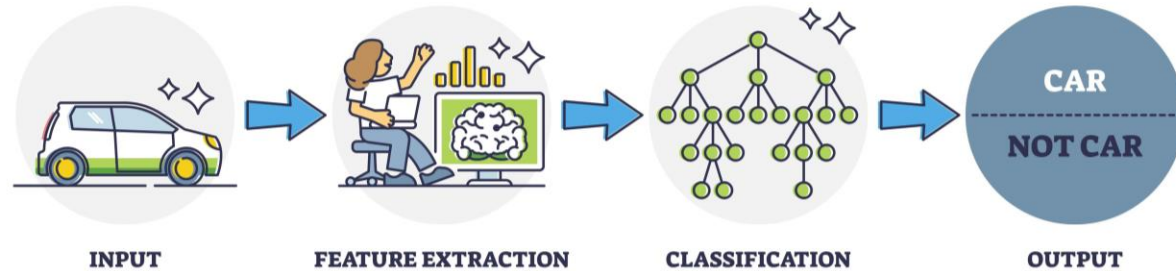
*Model Selection,
Performance Metrics,
Hyperparameter
Optimization*

MIT TAKAR AZ AZ ELŐKÉSZÍTÉS?

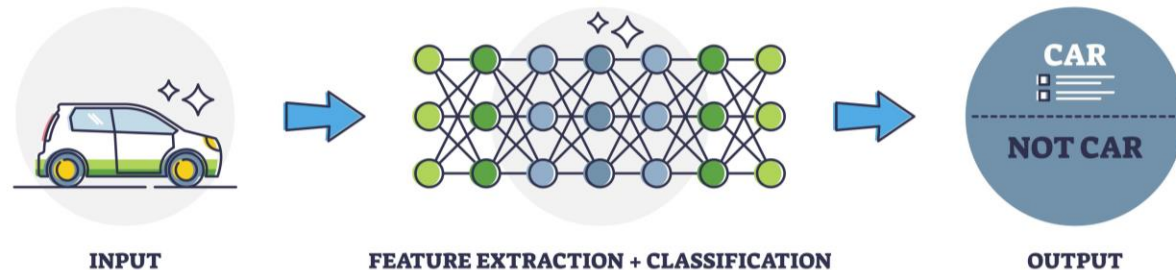


MACHINE LEARNING VS. DEEP LEARNING

MACHINE LEARNING



DEEP LEARNING



Forrás: <https://www.turing.com/kb/ultimate-battle-between-deep-learning-and-machine-learning>

PONTFELHŐ JELLEMZŐK

- Geometriai jellemzők
 - *Koordináták*
 - *Pontsűrűség*
 - *Görbület*
- Spektrális jellemzők
 - *RGB*
 - *Intenzitás*
- Sajátértékeken alapuló jellemzők

Geometric features

Local neighborhood radius 0.050000

Roughness

- ☐ Roughness
- ☐ Up direction
 - X=0.00 Y=0.00 Z=1.00

Curvature

- ☐ Mean
- ☐ Gaussian
- ☐ Normal change rate

Density

- ☐ Number of neighbors
- ☐ Surface density
- ☐ Volume density

Moment

- ☐ 1st order moment

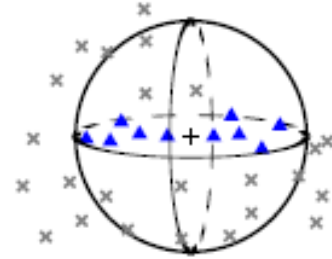
Features

- ☐ Sum of eigenvalues
- ☐ Ominvariance
- ☐ Eigenentropy
- ☐ Anisotropy
- ☐ Planarity
- ☐ Linearity
- ☐ PCA1
- ☐ PCA2
- ☐ Surface variation
- ☐ Sphericity
- ☐ Verticality
- ☐ 1st eigenvalue
- ☐ 2nd eigenvalue
- ☐ 3rd eigenvalue

Feng - Guo 2018.

SAJÁTÉRTÉKEKEN ALAPULÓ JELLEMZŐK

- A pont és környezete
 - „ R ” sugár
- Ponthalmazra
 - Voxel



$$\mathbf{A} = \begin{bmatrix} x_1 - \bar{x} & y_1 - \bar{y} & z_1 - \bar{z} \\ \vdots & \vdots & \vdots \\ x_m - \bar{x} & y_m - \bar{y} & z_m - \bar{z} \end{bmatrix}$$

Mayr et al. 2017.

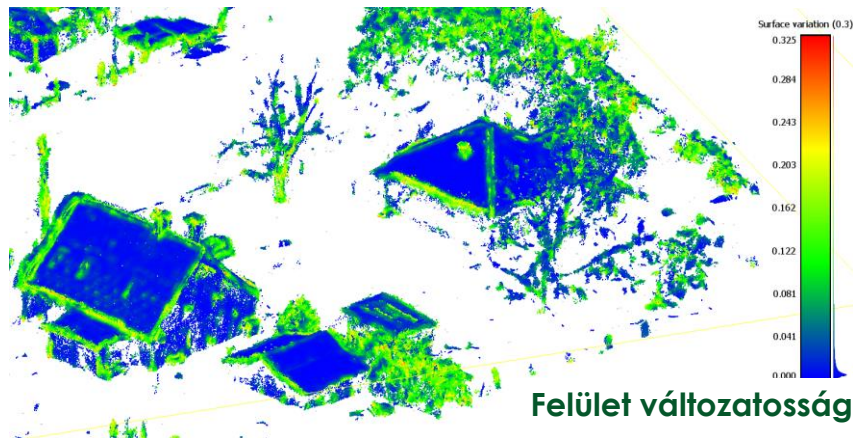
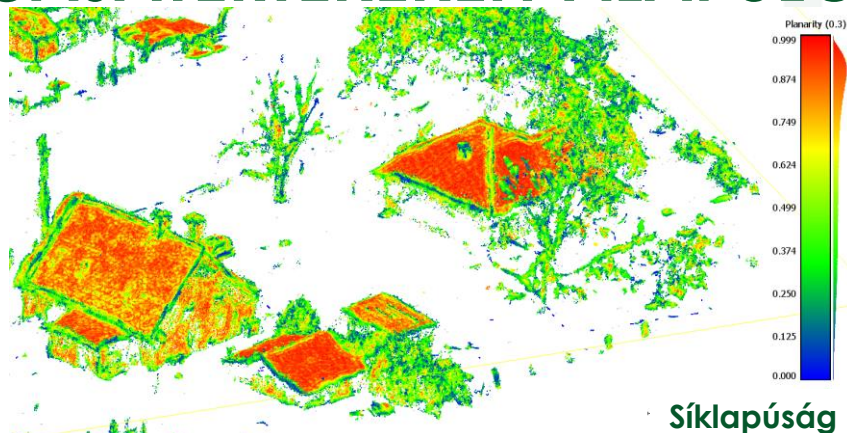
SAJÁTÉRTÉKEKEN ALAPULÓ JELLEMZŐK

- Kovariancia mtx.
 - Sajátértékek
 - $\lambda_1 \geq \lambda_2 \geq \lambda_3$

$$Q = \mathbf{A}^T \mathbf{A} = \begin{bmatrix} \sum_{i=1}^m (x_i - \bar{x})^2 & \sum_{i=1}^m (x_i - \bar{x})(y_i - \bar{y}) & \sum_{i=1}^m (x_i - \bar{x})(z_i - \bar{z}) \\ \sum_{i=1}^m (x_i - \bar{x})(y_i - \bar{y}) & \sum_{i=1}^m (y_i - \bar{y})^2 & \sum_{i=1}^m (y_i - \bar{y})(z_i - \bar{z}) \\ \sum_{i=1}^m (x_i - \bar{x})(z_i - \bar{z}) & \sum_{i=1}^m (y_i - \bar{y})(z_i - \bar{z}) & \sum_{i=1}^m (z_i - \bar{z})^2 \end{bmatrix}$$

Mayr et al. 2017.

SAJÁTÉRTÉKEKEN ALAPULÓ JELLEMZŐK



Sajátértékeken alapuló jellemzők	Meghatározás
Omnivariancia (omnivariance)	$\sqrt[3]{\lambda_1 \cdot \lambda_2 \cdot \lambda_3}$
Anizotrópia (anisotropy)	$\frac{(\lambda_1 - \lambda_3)}{\lambda_1}$
Síklapúság (planarity)	$\frac{(\lambda_2 - \lambda_3)}{\lambda_1}$
Felület változatosság (surface variation)	$\frac{\lambda_3}{(\lambda_1 + \lambda_2 + \lambda_3)}$
Gömbszerűség (sphericity)	$\frac{\lambda_3}{\lambda_1}$

FELÜGYELT GÉPI TANULÁS

KIINDULÁS

- Korábbi szegmentálás
- Tető vagy növényzet?



ELŐKÉSZÍTÉS

- Manuális címkézés



Tető

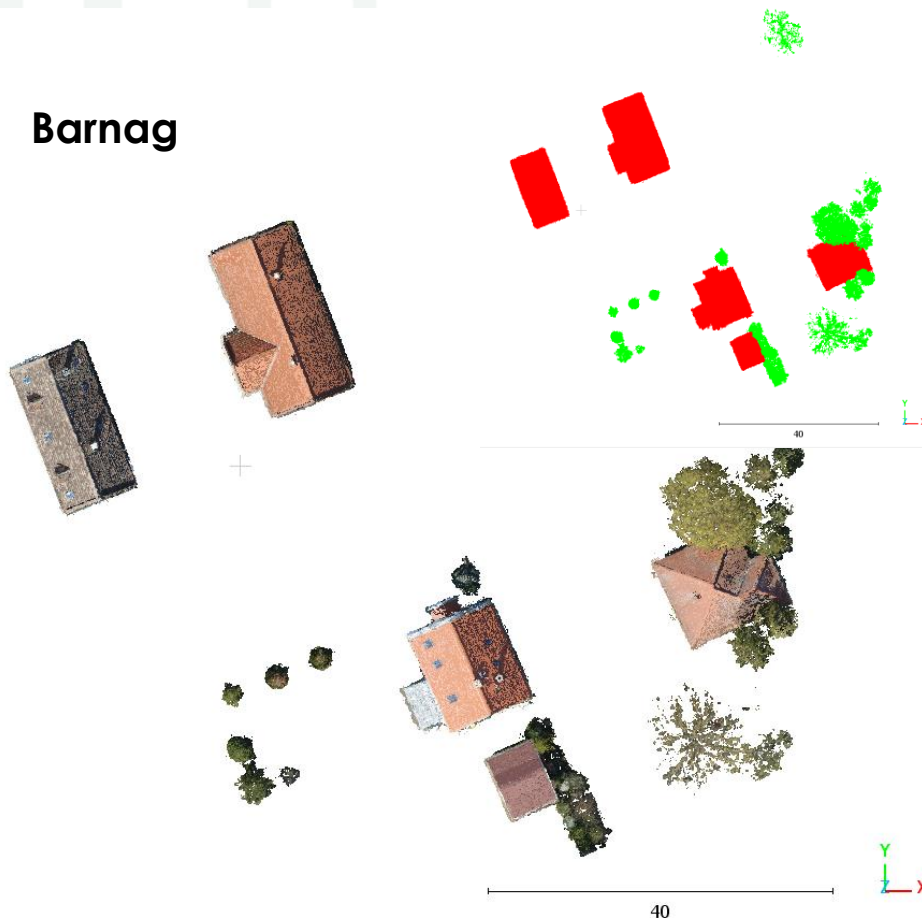
- 1 175 660 db



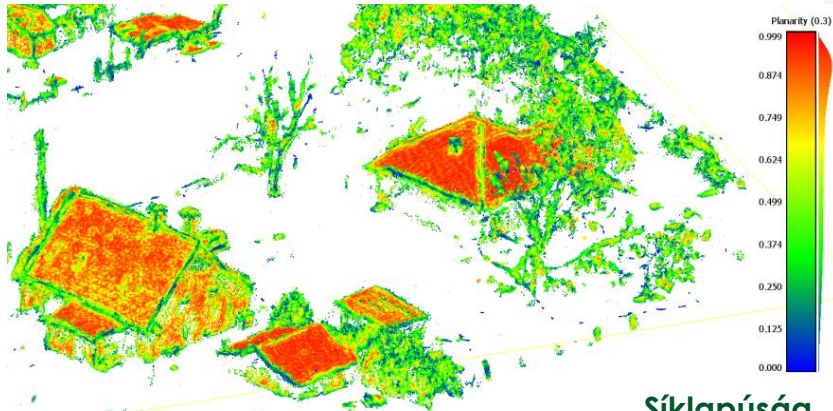
Növényzet

- 306 057 db

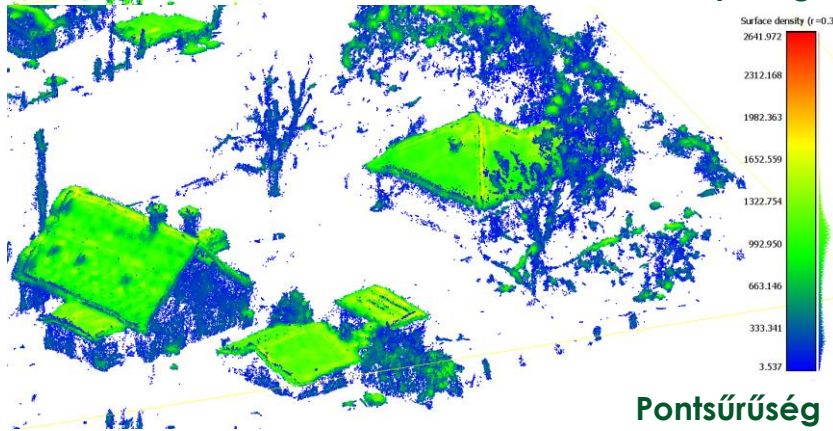
Barnag



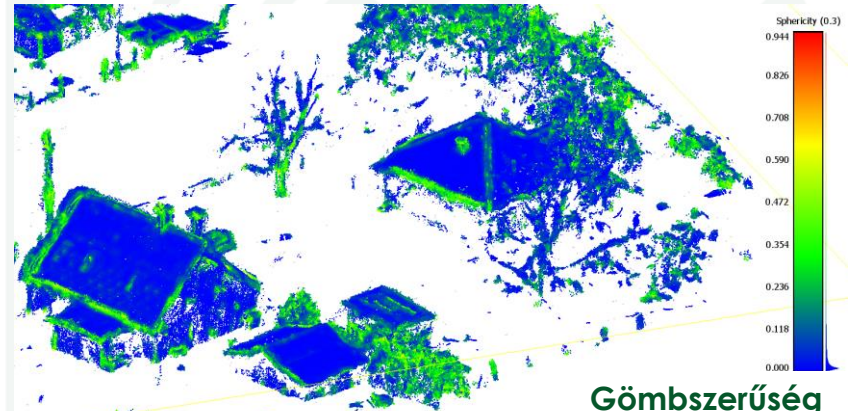
JELLEMZŐK



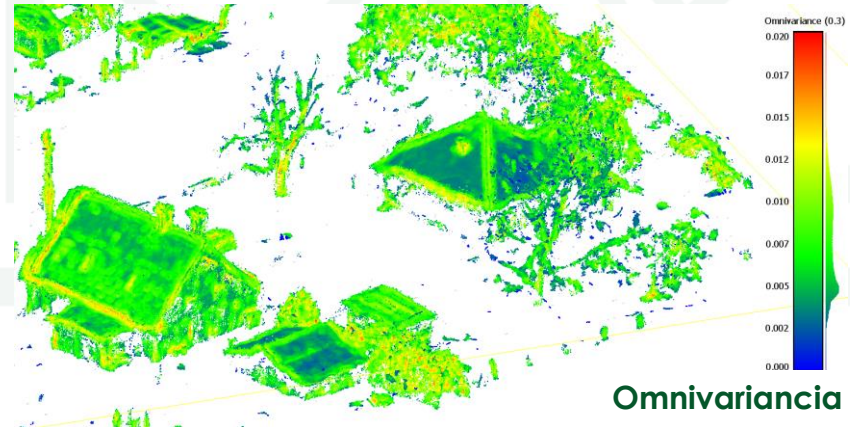
Síklapúság



Pontsűrűség



Gömbszerűség



Omnivariancia

VÁLASZTOTT ALGORITMUSOK

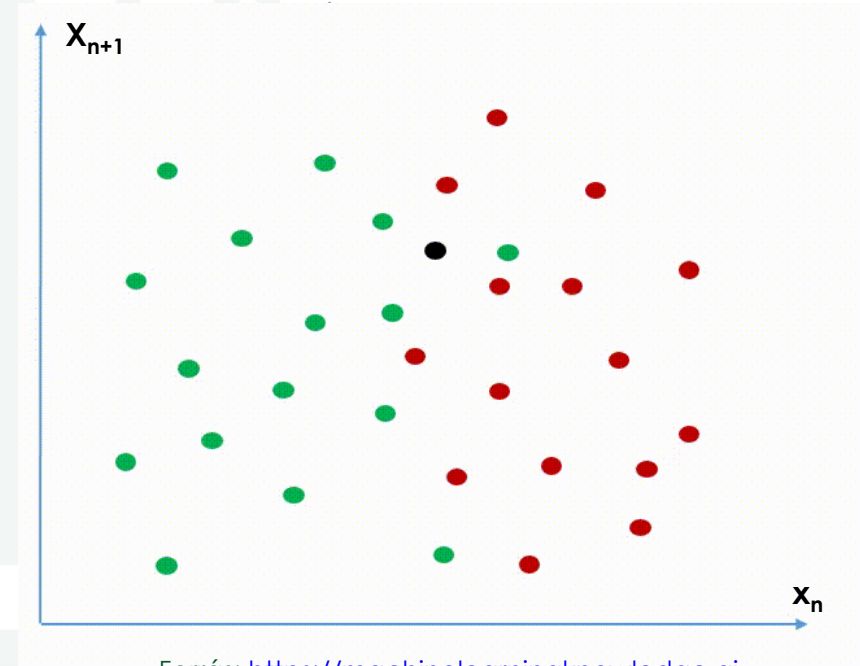


- K-Nearest Neighbors
- Random Forest Classifier
- Multi-Layer Perceptron

The screenshot shows the scikit-learn website. The header has the scikit-learn logo and navigation links: Install, User Guide, API, Examples, Community, and More. Below the header, the main banner features the text 'scikit-learn' and 'Machine Learning in Python'. There are three buttons: 'Getting Started', 'Release Highlights for 1.3', and 'GitHub'. To the right of the banner, a list of features is displayed: 'Simple and efficient tools for predictive data analysis', 'Accessible to everybody, and reusable in various contexts', 'Built on NumPy, SciPy, and matplotlib', and 'Open source, commercially usable - BSD license'. Below the banner, there are three columns: 'Classification' (describing identifying categories), 'Regression' (describing predicting continuous values), and 'Clustering' (describing automatic grouping). Each column lists applications and algorithms.

K-NEAREST NEIGHBORS - KNN

- Nincs igazi tanítás
- Jellemzők tárolása
- Új pont
- „k” legközelebbi szomszéd
 - *Távolság?*
- Szavazás

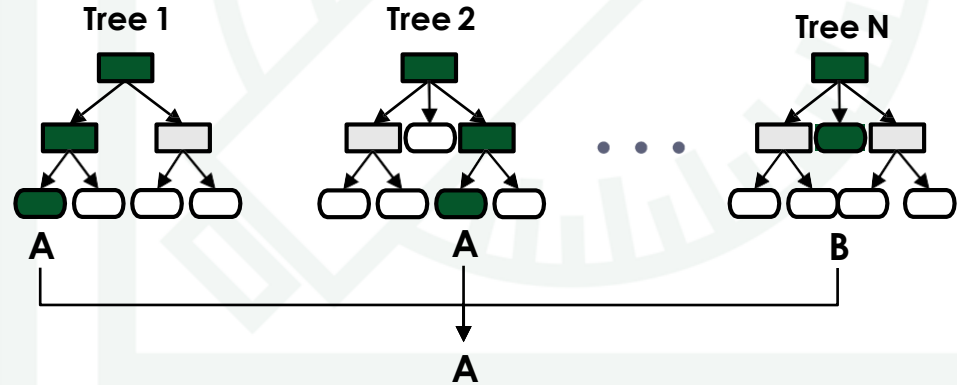


Forrás: <https://machinelearningknowledge.ai>

Awange et al. 2020; Bonaccorso 2018.

RANDOM FOREST CLASSIFIER - RFC

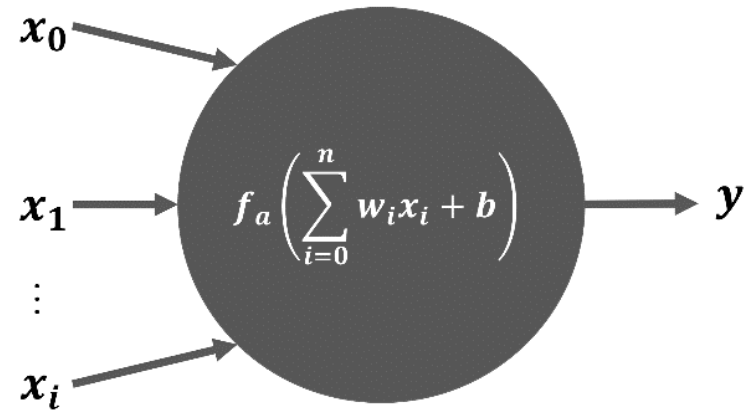
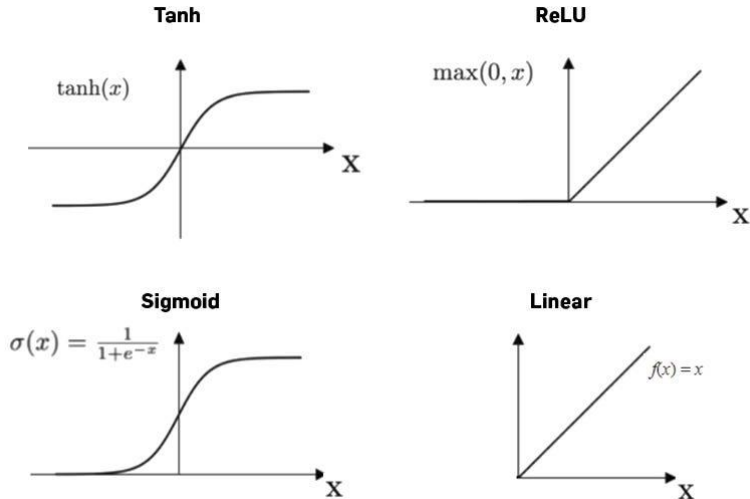
- Alapja: döntési fa
- „N” darabot készít
 - *Különböző adatok*
 - *Különböző jellemzők*
- Szavazás



Awange et al. 2020; Bonaccorso 2018.

MULTI-LAYER PERCEPTRON - MLP

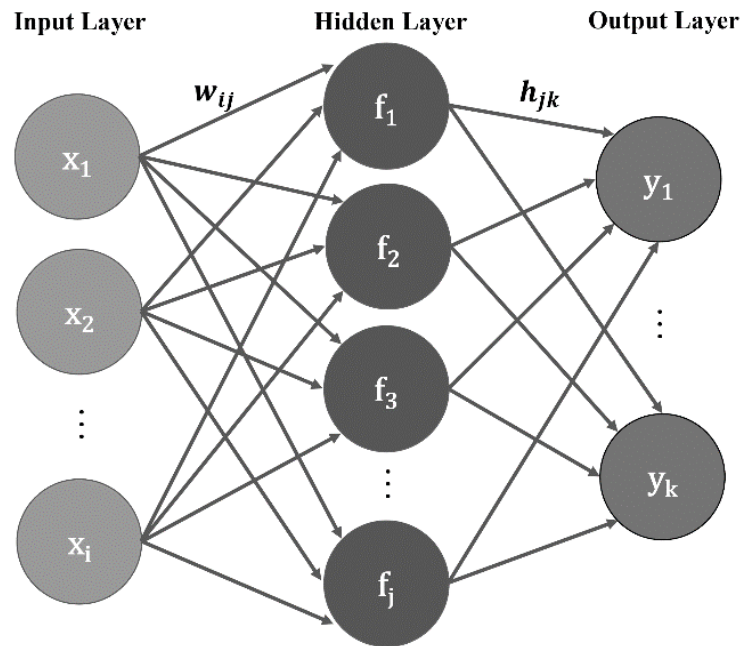
- Alapja: neuron
- Aktivációs függvény (f_a)



Awange et al. 2020; Bonaccorso 2018.

MULTI-LAYER PERCEPTRON - MLP

- Több réteg
 - *Bemeneti*
 - *Rejtett*
 - *Kimeneti*
- Tanítás: súlyok, eltolások meghatározása
- Célfüggvény (L) minimalizálás



$$L = \frac{1}{n} \sum_{i=1}^n (y_i^{\text{Predicted}} - y_i^{\text{Target}})^2$$

Awange et al. 2020; Bonaccorso 2018.

MULTI-LAYER PERCEPTRON

- Célfüggvény változása az egyes súlyokra
 - *Parciális deriváltak számítása*
 - *Hibavisszaterjesztés (backpropagation)*
- Tanulás: hálózat súlyainak változása → Véletlen gradiens csökkentés (SGD)
 - η – tanulási sebesség (learning rate)

$$\frac{\partial L}{\partial w_{ij}} : \frac{\partial L}{\partial h_{jk}}$$

$$\begin{cases} h_{jk}^{(t+1)} = h_{jk}^{(t)} - \eta \frac{\partial L}{\partial h_{jk}} \\ w_{ij}^{(t+1)} = w_{ij}^{(t)} - \eta \frac{\partial L}{\partial w_{ij}} \end{cases}$$

ÖSSZEHASONLÍTÁS

- Accuracy
- Confusion Matrix
 - True Positive (TP)
 - True Negative (TN)
 - False Positive (FP)
 - False Negative (FN)
- Recall
- Precision
- F1-score

$$Accuracy = \frac{N_{correct\ pred.}}{N_{total\ pred.}}$$

Confusion mtx.		True	
		Positive	Negative
Predicted	Positive	TP	FP
	Negative	FN	TN

$$Recall = \frac{TP}{TP+FN}$$

$$Precision = \frac{TP}{TP+FP}$$

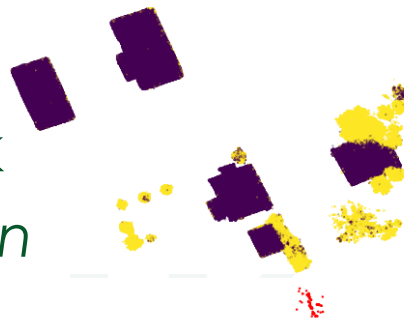
$$F1-score = \frac{2 \cdot Precision \cdot Recall}{Precision + Recall}$$

Awange et al. 2020; Bonaccorso 2018.

ÖSSZEHASONLÍTÁS

- ~150 MB (.las) adat
 - *Jellemzőkkel együtt*
- Hasonló eredmények
 - *300 ezer teszt adaton*
- Modell méretek:
 - *kNN: 120 MB*
 - *RFC: 295 MB*
 - ***MLP: 12 KB***

Osztályozás
eredménye



Eltérések



kNN
Model accuracy score: 0.99

	precision	recall	f1-score
Roofs	1.00	0.99	0.99
Vegetation	0.97	0.99	0.98

RFC
Model accuracy score: 0.98

	precision	recall	f1-score
Roofs	0.99	0.99	0.99
Vegetation	0.95	0.96	0.95

MLP
Model accuracy score: 0.97

	precision	recall	f1-score
Roofs	0.98	0.99	0.98
Vegetation	0.94	0.94	0.94

VÁLASZTÁS: MULTI-LAYER PERCEPTRON

TANÍTÓ ADATOK

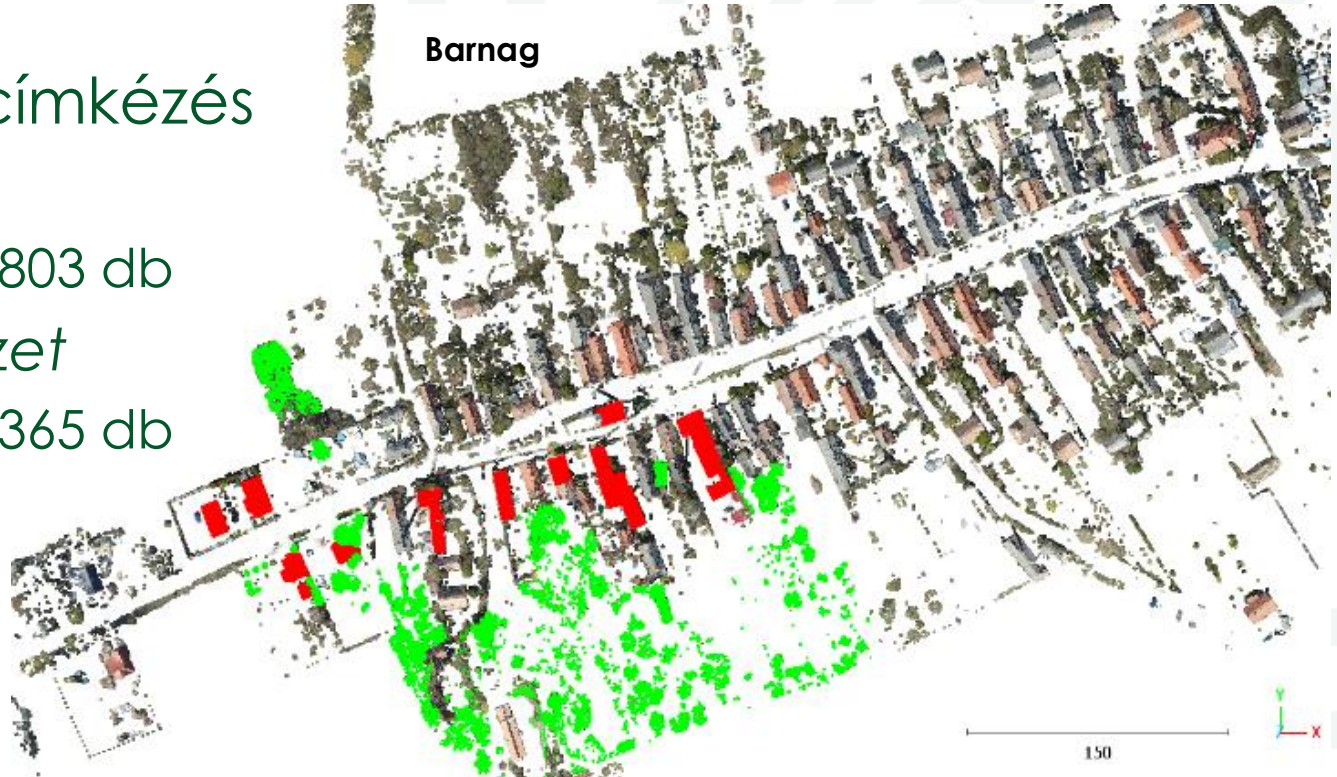
- Manuális címkézés

■ *Tető*

- 2 688 803 db

■ *Növényzet*

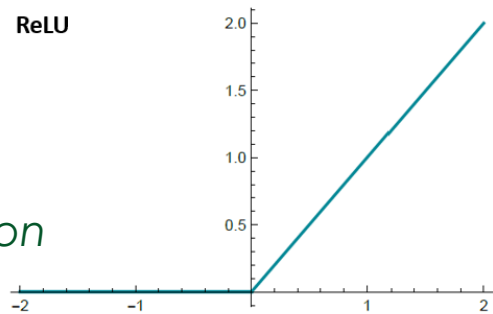
- 1 519 365 db



TANÍTÁS, MODELL ELŐÁLLÍTÁS

- Multi-Layer Perceptron modell
 - Rectified Linear Unit (ReLU)
 - Bemeneti réteg: 12 db
 - Rejtett réteg: 1 db → 15 db neuron
 - Kimeneti réteg: 2 db
 - Adaptive Moment Estimation (ADAM)
 - Learning rate: 0.001
- Mennyire „jó” a modell?
 - Accuracy: 97,4%
 - Precision: 98% (t); 96%(v)
 - Recall: 98% (t); 97% (v)
 - F1-score: 98% (t); 96% (v)

ReLU



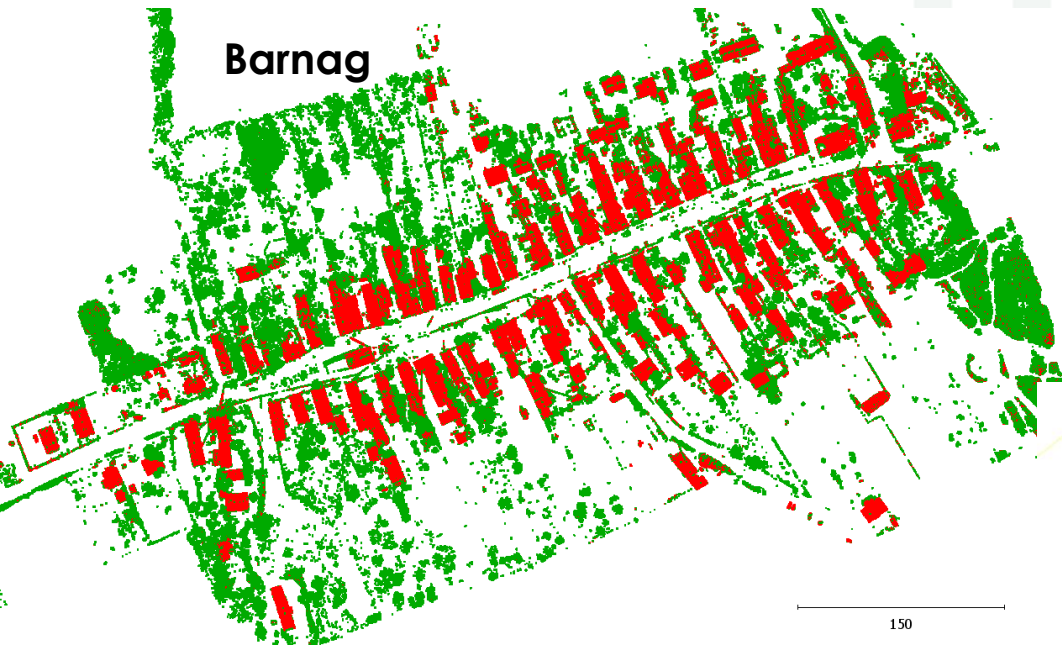
		Predicted label	
		Roofs	Vegetation
True label	Roofs	655160 62.3%	16640 1.6%
	Vegetation	11221 1.1%	369021 35.1%

Features
Relative height
RGB values
Omnivariance
Anisotropy
Planarity
Surface variation
Sphericity
Number of neighbors
Surface density
Normal change rate

MODELL ALKALMAZÁSA

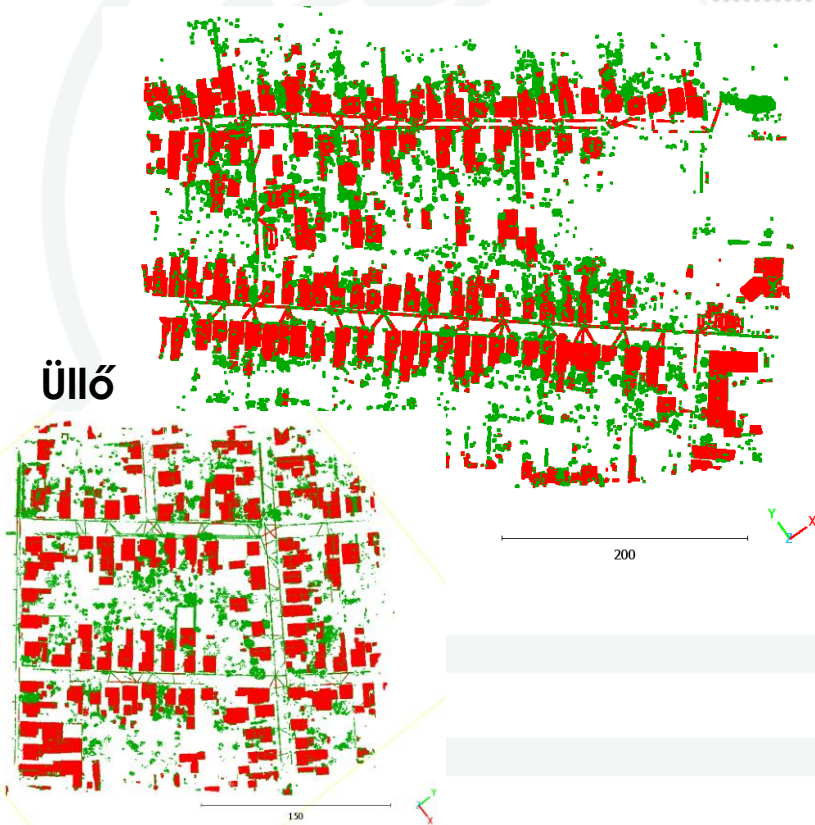


Barnag

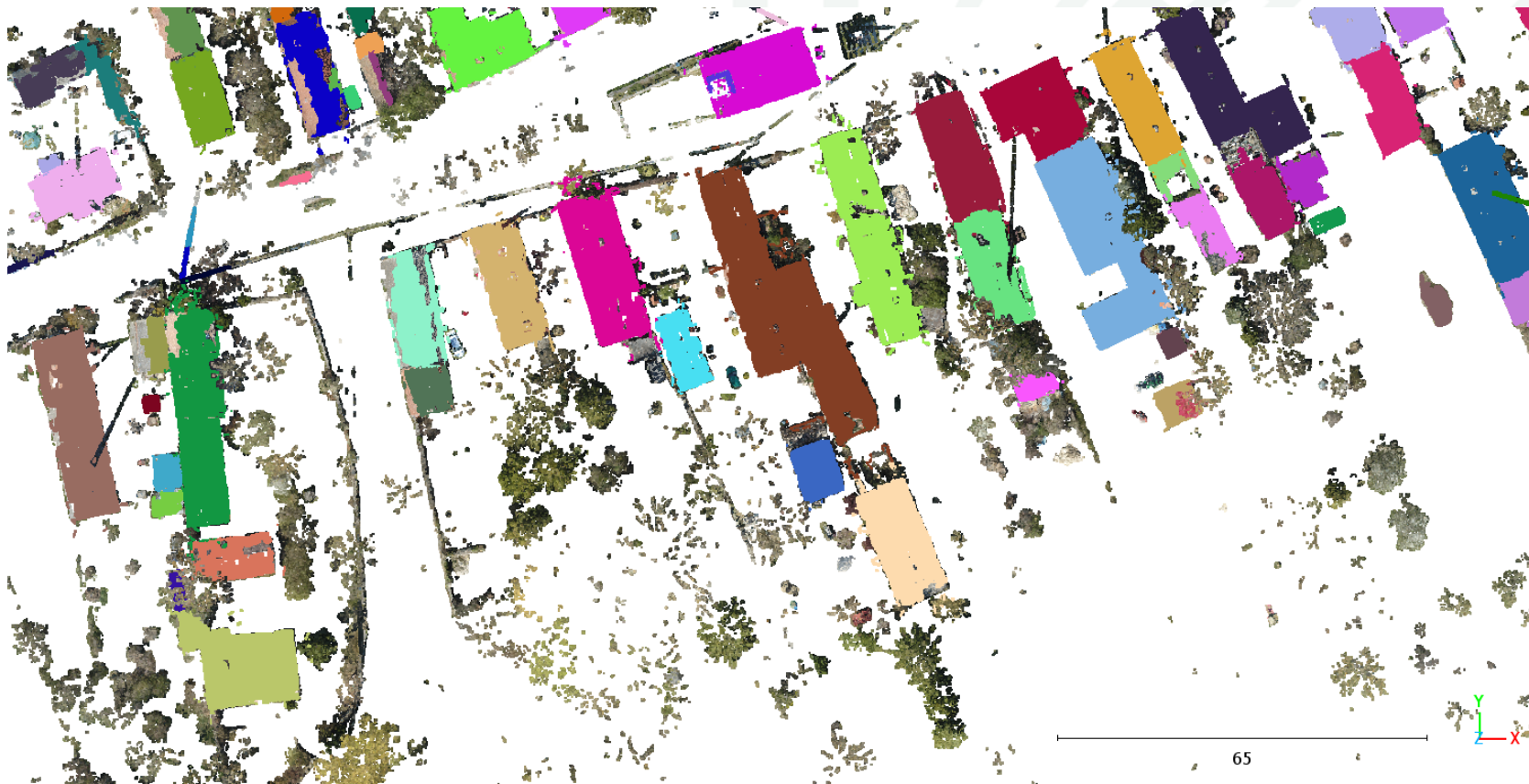


Sződ

Üllő



ÉRDELMÉNYEK KÖZELEBBRŐL



ÉRDELMÉNYEK KÖZELEBBRŐL



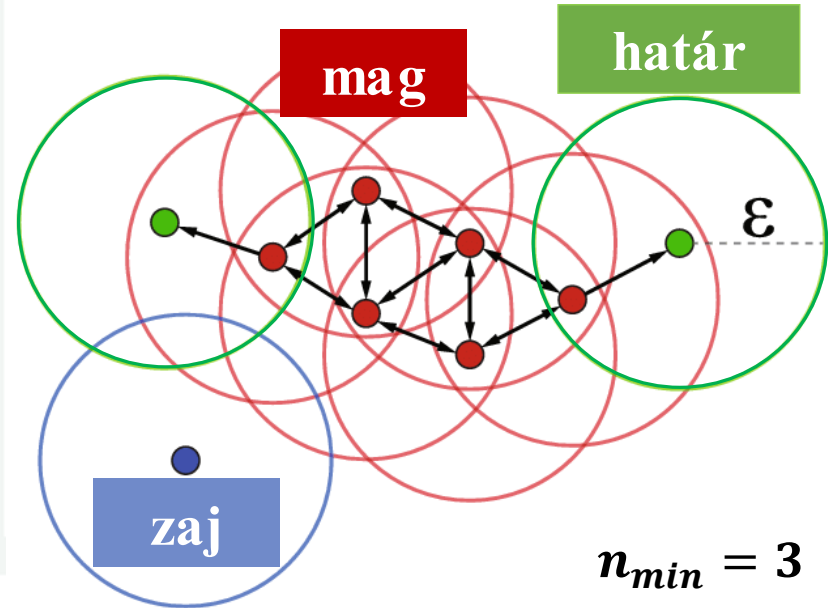
FELÜGYELET NÉLKÜLI GÉPI TANULÁS

DBSCAN

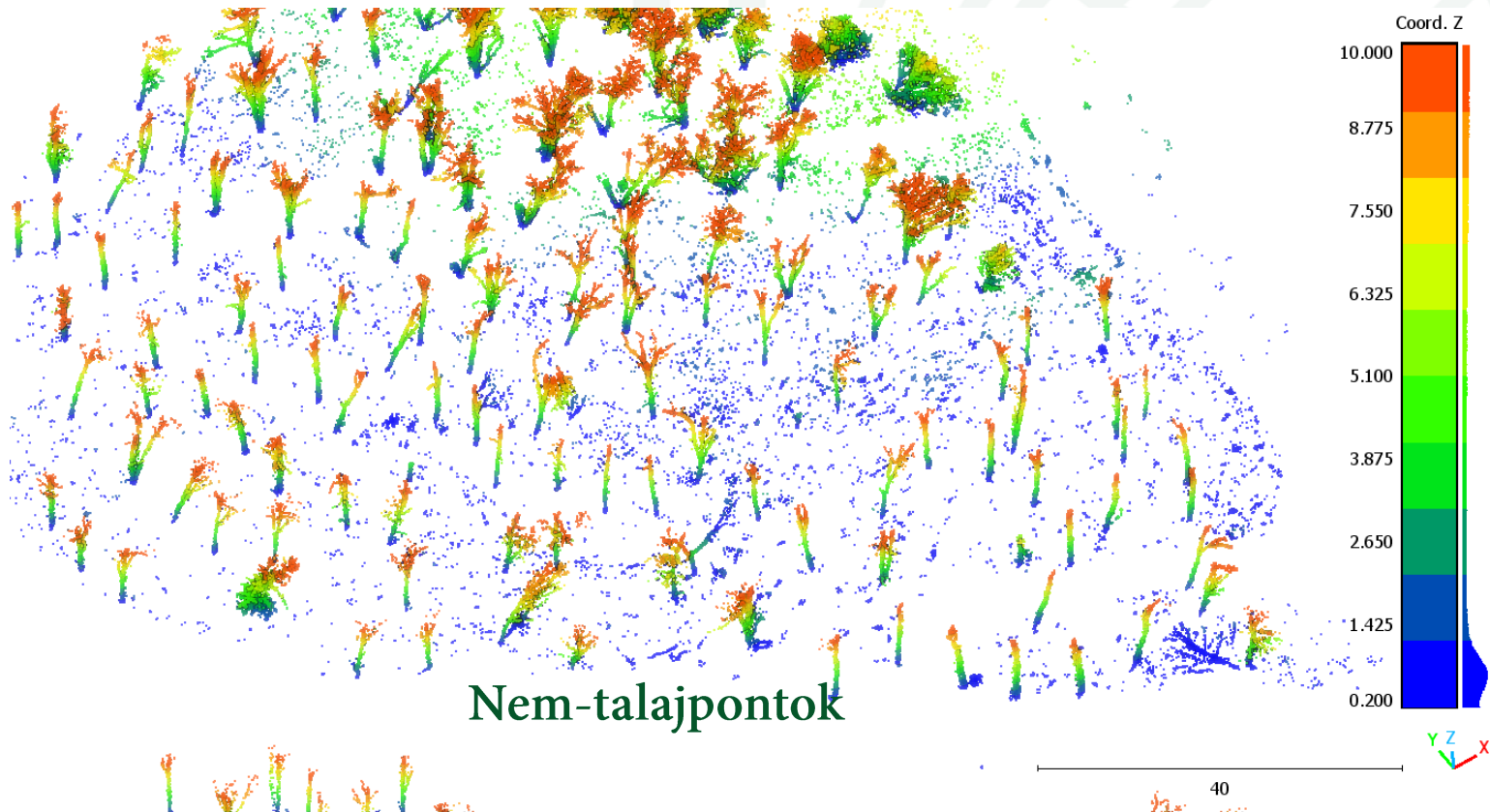
- Density-Based Spatial Clustering of Applications with Noise
- Pontsűrűség alapján
- 2 paraméter:
 - ε – sugár
 - n_{min} = min. pontszám

$$N(d(\bar{x}_i, \bar{x}_j) \leq \varepsilon) \geq n_{min}$$

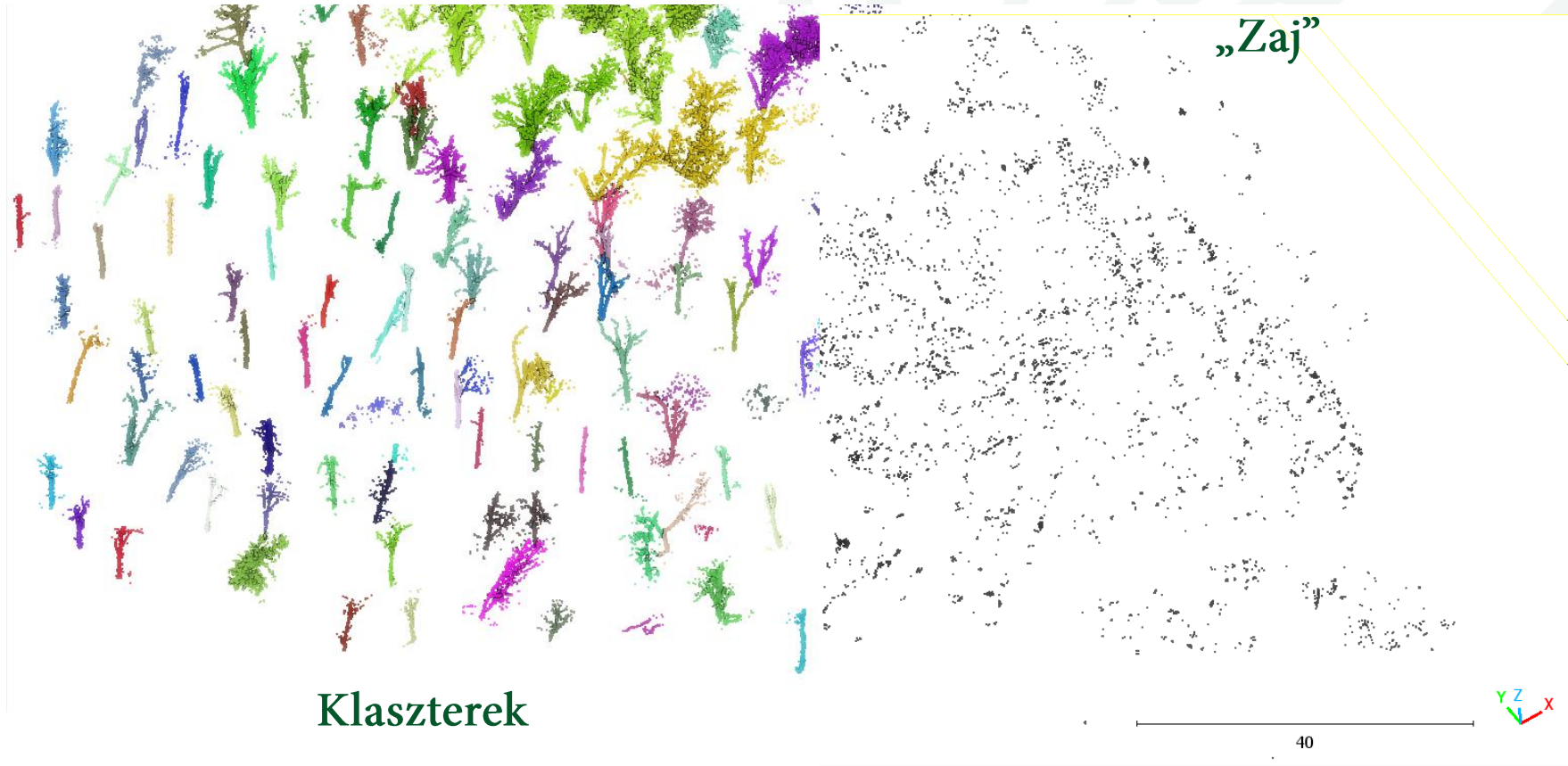
$$d(\bar{x}_i, \bar{x}_j) \leq \varepsilon$$



DBSCAN ALKALMAZÁSA



DBSCAN ALKALMAZÁSA



ÉGYÉB ELÉRHETŐ MEGOLDÁSOK

SAJÁTÉRTÉKEKEN ALAPULÓ JELLEMZŐK EGYÉB ALKALMAZÁSA



SAJÁTÉRTÉKEKEN ALAPULÓ JELLEMZŐK EGYÉB ALKALMAZÁSA

Geometric features



Local neighborhood radius

Roughness

- ☐ Roughness
- ☐ Up direction

X=0.00 Y=0.00 Z=1.00

Curvature

- ☐ Mean
- ☐ Gaussian
- ☐ Normal change rate

Density

- ☐ Number of neighbors
- ☐ Surface density
- ☐ Volume density

Moment

- ☐ 1st order moment

Features

- ☐ Sum of eigenvalues
- ☐ Ominvariance
- ☐ Eigenentropy
- ☐ Anisotropy
- ☐ Planarity
- ☐ Linearity
- ☐ PCA1
- ☐ PCA2
- ☐ Surface variation
- ☐ Sphericity
- ☐ Verticality
- ☐ 1st eigenvalue
- ☐ 2nd eigenvalue
- ☐ 3rd eigenvalue

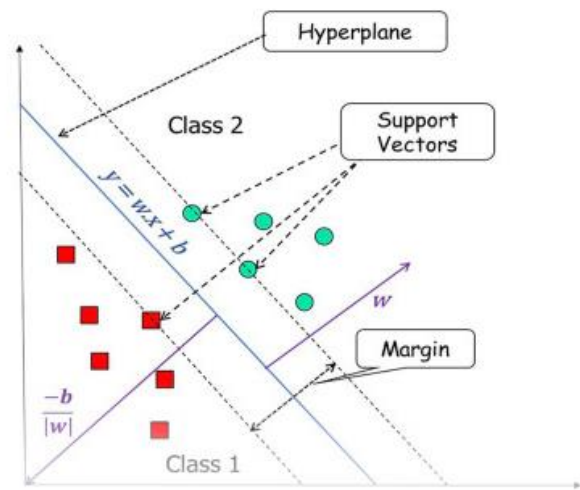
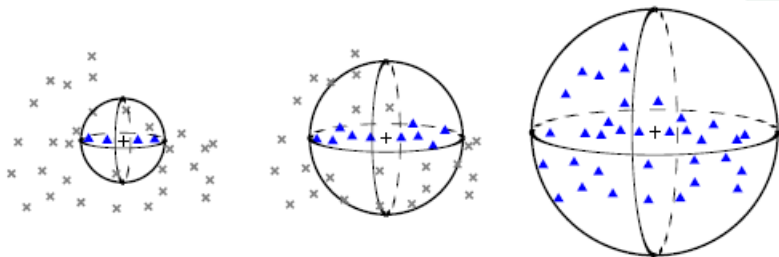
50



SAJÁTÉRTÉKEKEN ALAPULÓ JELLEMZŐK EGYÉB ALKALMAZÁSA



- CAractérisation de NUages de Points
- Pontok osztályozása
- Support Vector Machine (SVM)
 - *Sajátértékeken alapuló jellemzők*
 - *Különböző sugár*

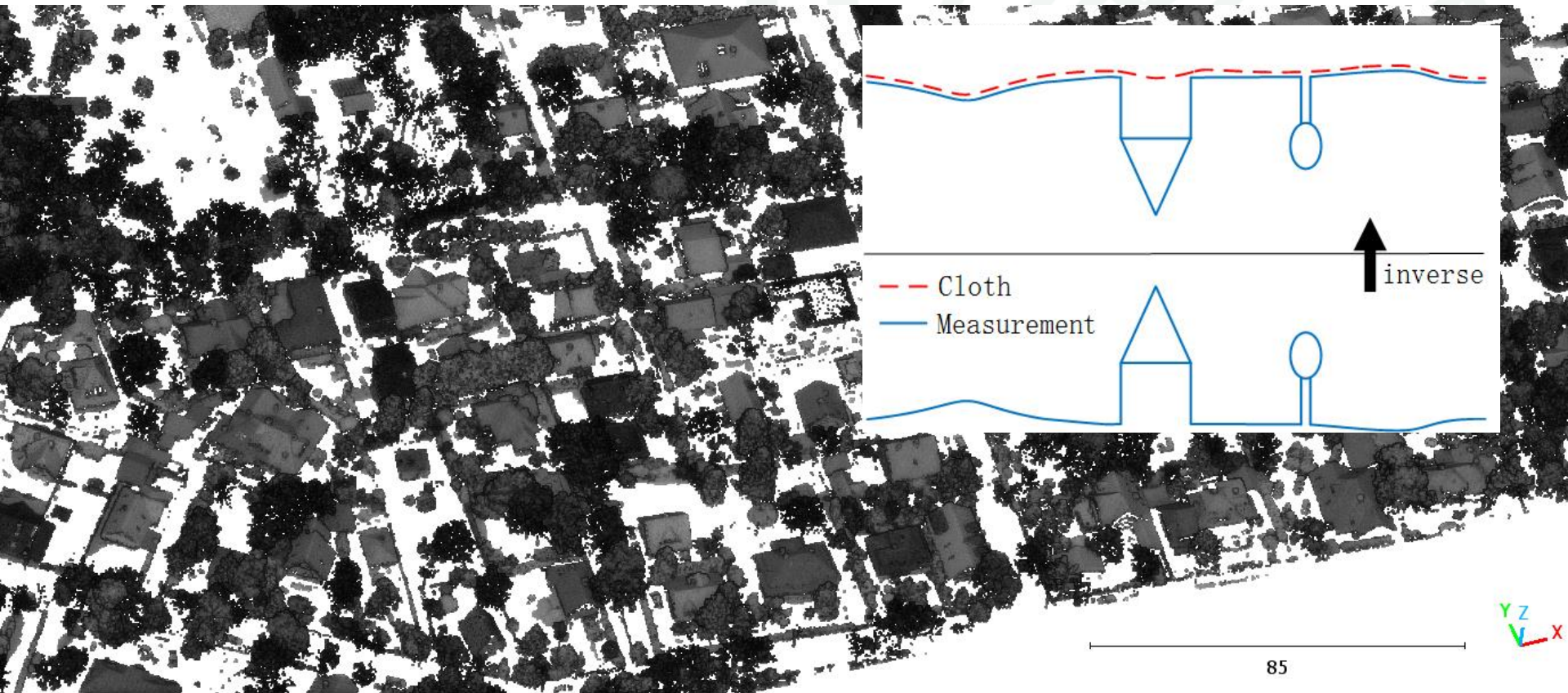


Brodu - Lague 2016.

CANUPO - GYAKORLATBAN



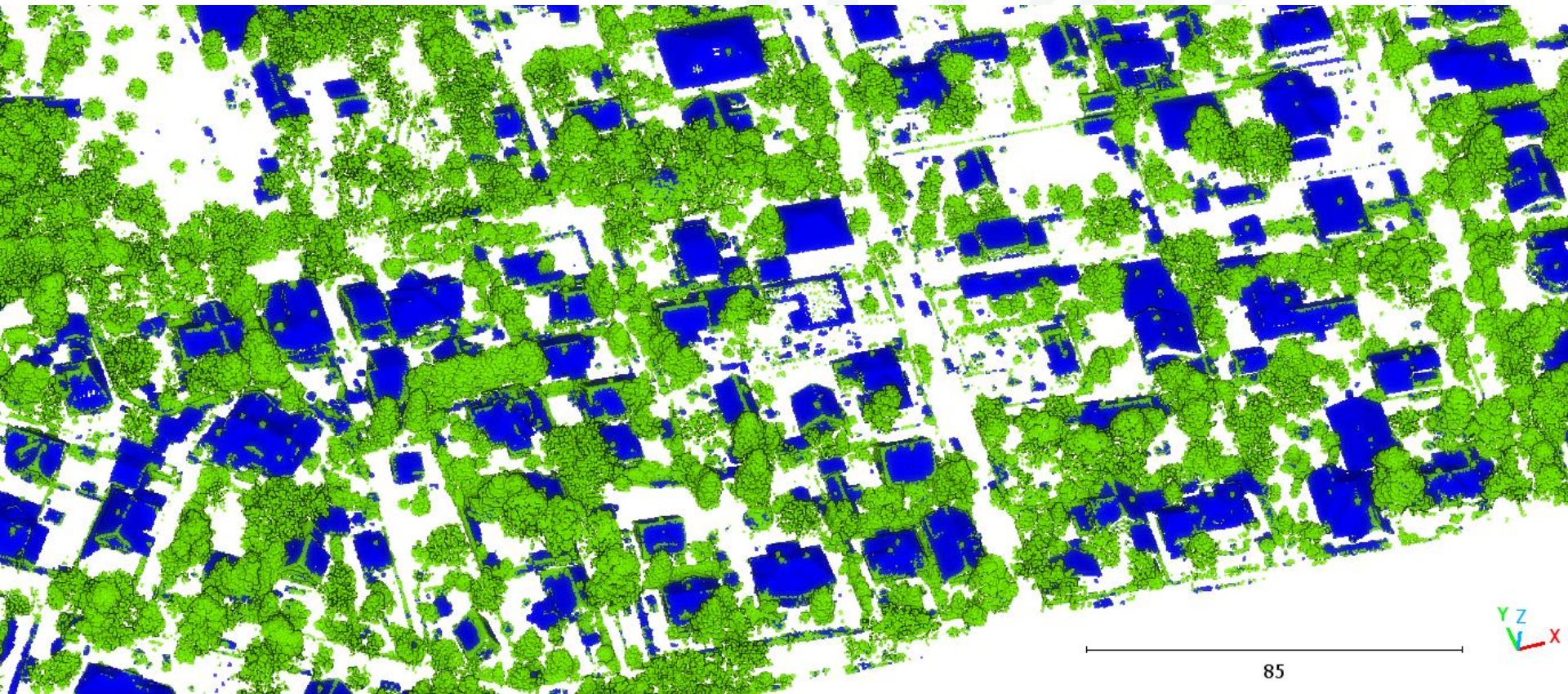
CANUPO - ELŐKÉSZÍTÉS



CANUPO - TANÍTÁS

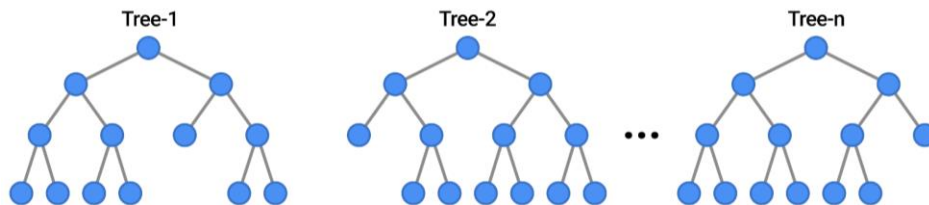


CANUPO - FELHASZNÁLÁS



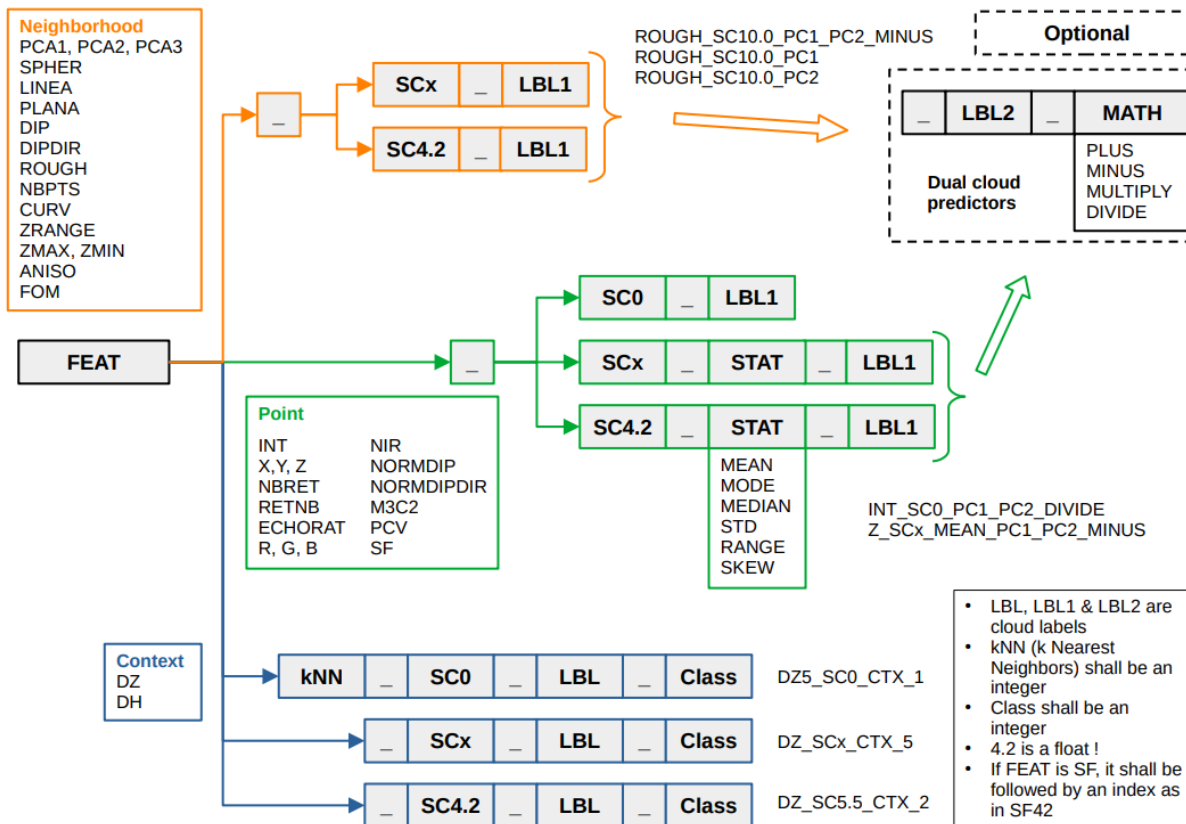
3DMASC

- 3D point classification with Multiple Attributes, Multiple Scales, and Multiple Clouds
- CloudCompare (2.13.beta)
- Osztályozás
- Random Forest Classifier



Letard et al. 2023.

3DMASC – MEGADHATÓ JELLEMZŐK



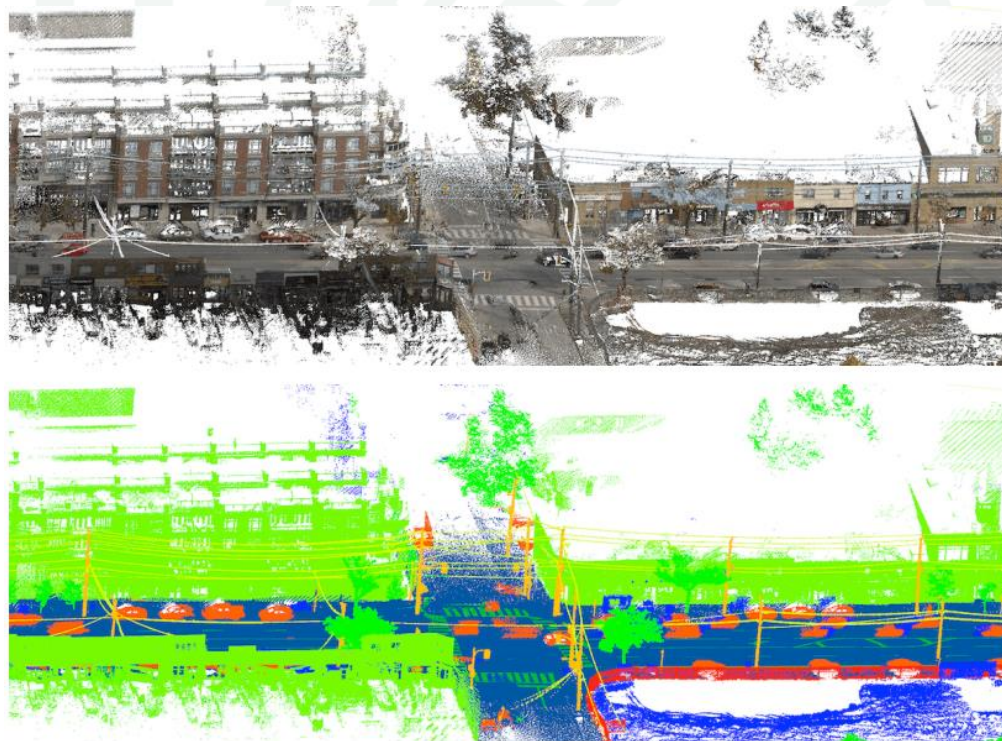
Letard et al. 2023.

3DMASC – ADATOK A TANÍTÁSHOZ



- Toronto 3D

-  Road (label 1)
-  Road marking (label 2)
-  Natural (label 3)
-  Building (label 4)
-  Utility line (label 5)
-  Pole (label 6)
-  Car (label 7)
-  Fence (label 8)
-  Unclassified (label 0)



Tan et al. 2020.

3DMASC – TANÍTÁS



NAMES

cloud: PC1=

CORE POINTS

core_points: PC1

SCALES

scales: 0.25;0.5;1

FEATURES

feature: Z_SC0.5_STD_PC1

feature: DIP_SCx_PC1

feature: ROUGH_SCx_PC1

feature: ANISO_SCx_PC1

feature: SPHER_SCx_PC1

feature: LINEA_SCx_PC1

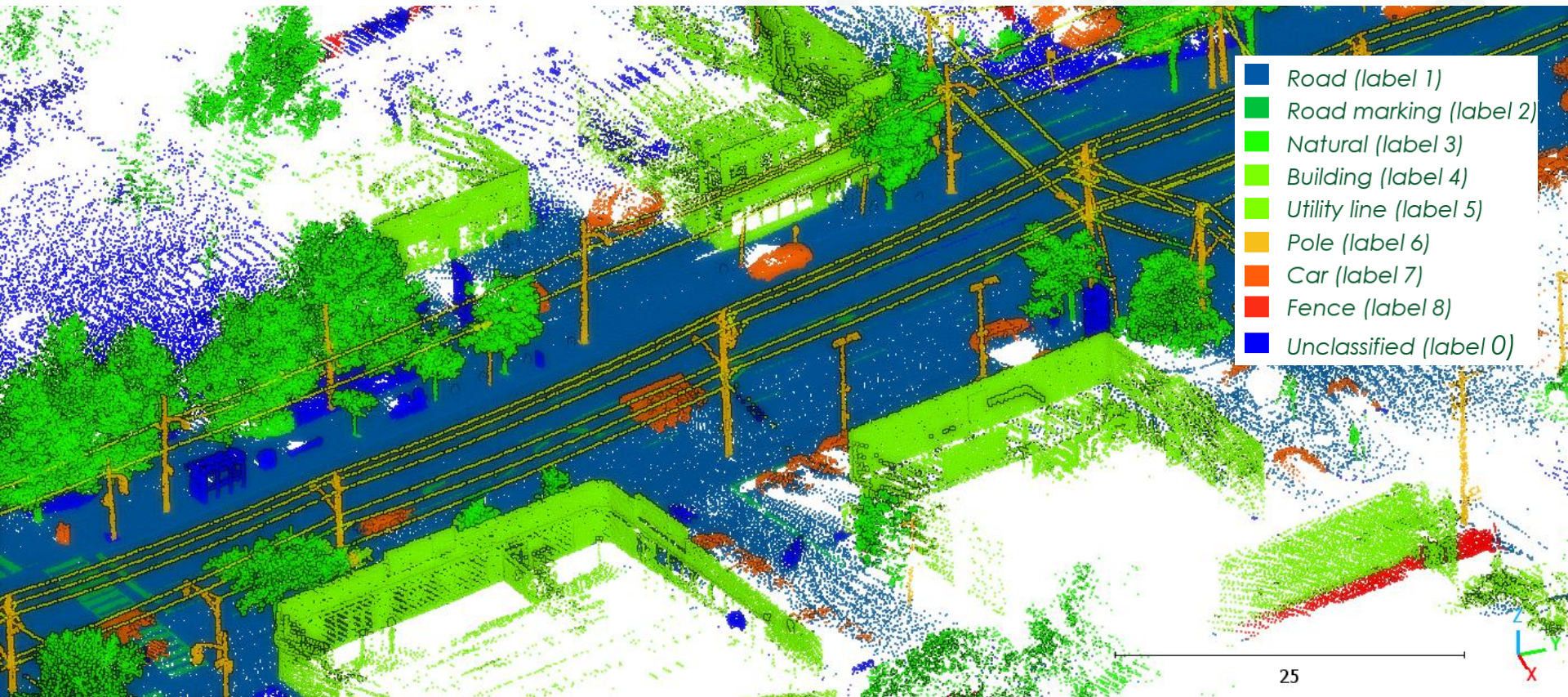
feature: PLANA_SCx_PC1

- Road (label 1)
- Road marking (label 2)
- Natural (label 3)
- Building (label 4)
- Utility line (label 5)
- Pole (label 6)
- Car (label 7)
- Fence (label 8)
- Unclassified (label 0)

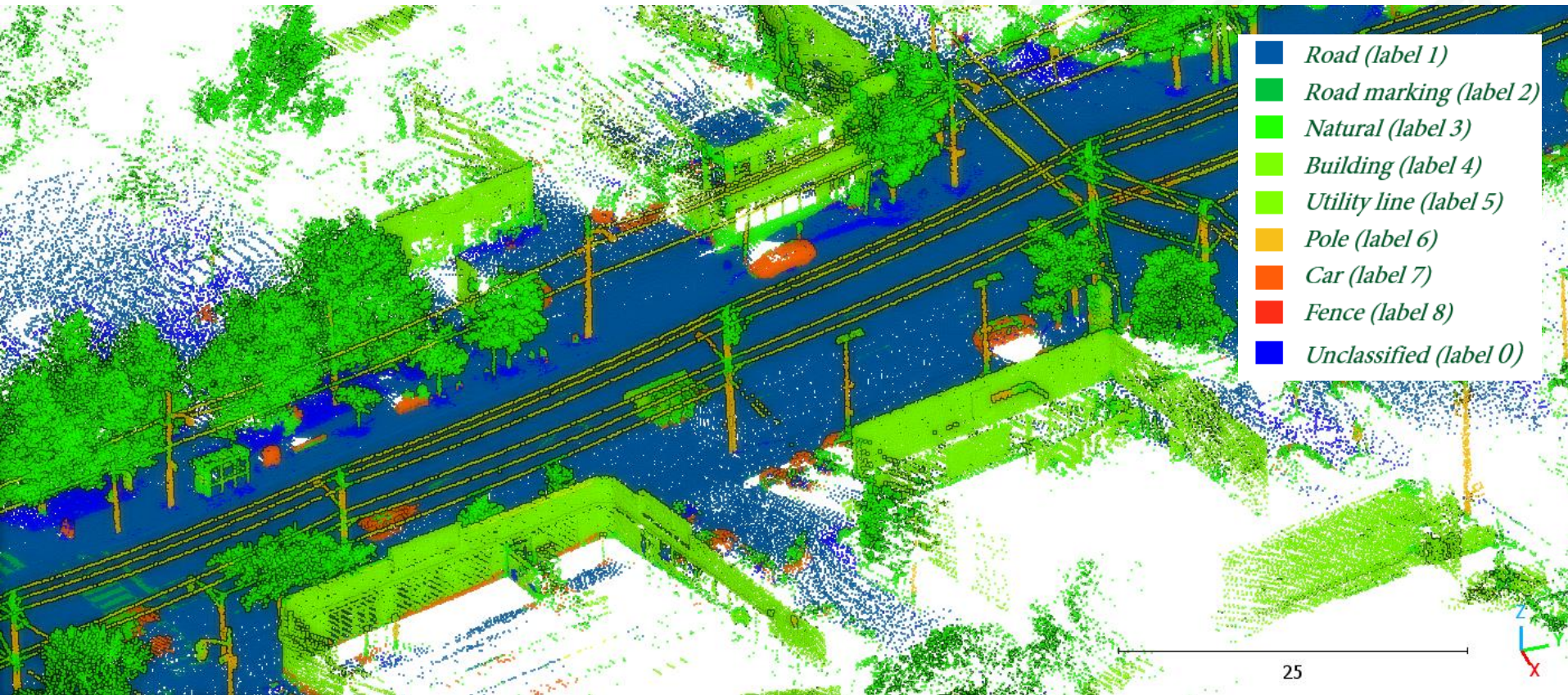
CC Form

		Predicted											
		0	1	2	3	4	5	6	7	8	Precision	Recall	F1-score
Real	0	19873	636	0	1899	128	0	8	78	0	0.94	0.88	0.91
	1	487	80002	245	310	41	4	7	229	4	0.96	0.98	0.97
	2	0	1492	2516	0	0	0	0	4	0	0.91	0.63	0.74
	3	411	525	0	113754	1076	17	19	65	0	0.93	0.98	0.95
	4	218	168	0	5705	28986	2	7	36	0	0.95	0.83	0.88
	5	0	0	0	206	27	2292	14	1	0	0.99	0.9	0.94
	6	43	11	0	382	114	11	1700	6	0	0.97	0.75	0.84
	7	37	325	0	454	20	0	3	7620	0	0.95	0.9	0.92
	8	8	7	0	99	101	0	2	20	228	0.98	0.49	0.65
Overall accuracy 0.94												3dmasc_20231108_16h13 / 1	

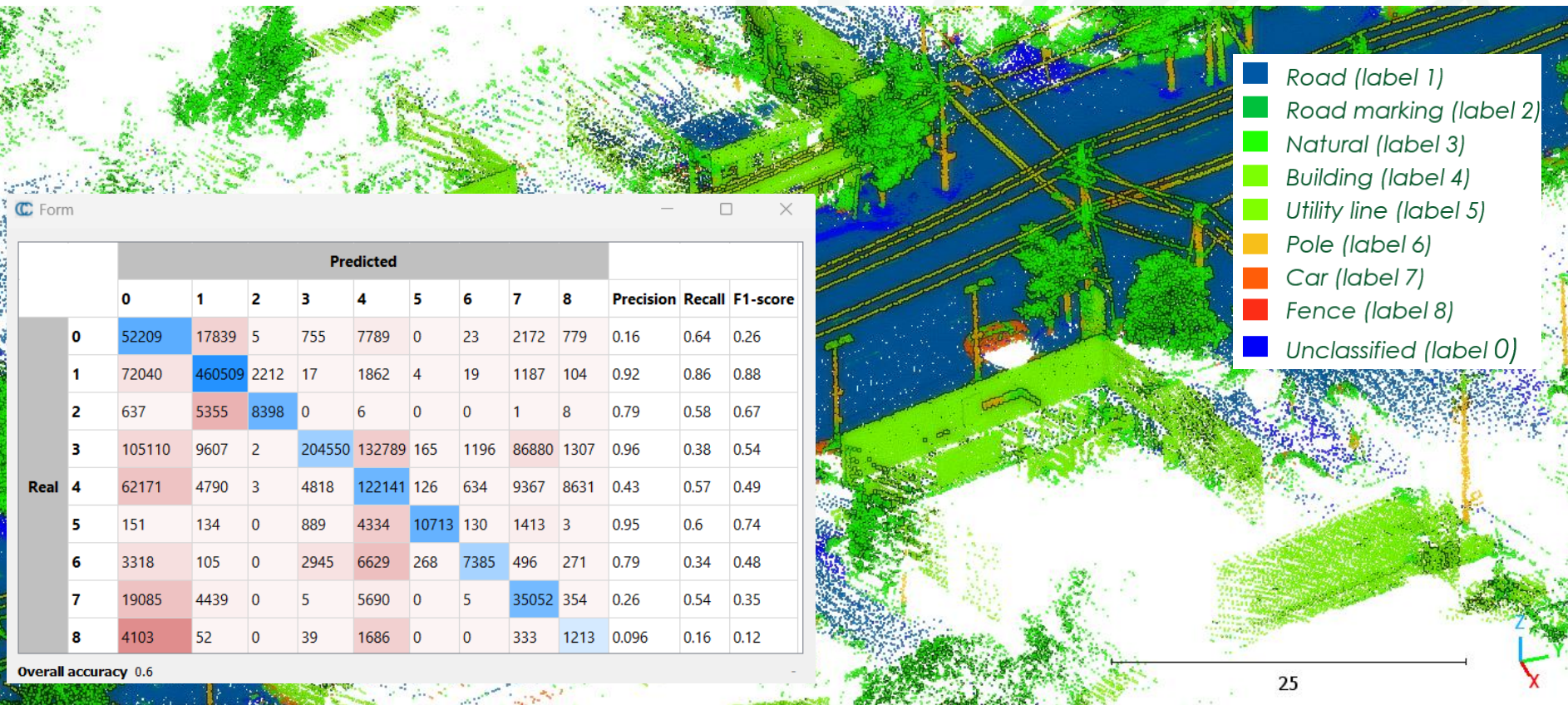
3DMASC - EREDMÉNYEK



3DMASC - EREDMÉNYEK

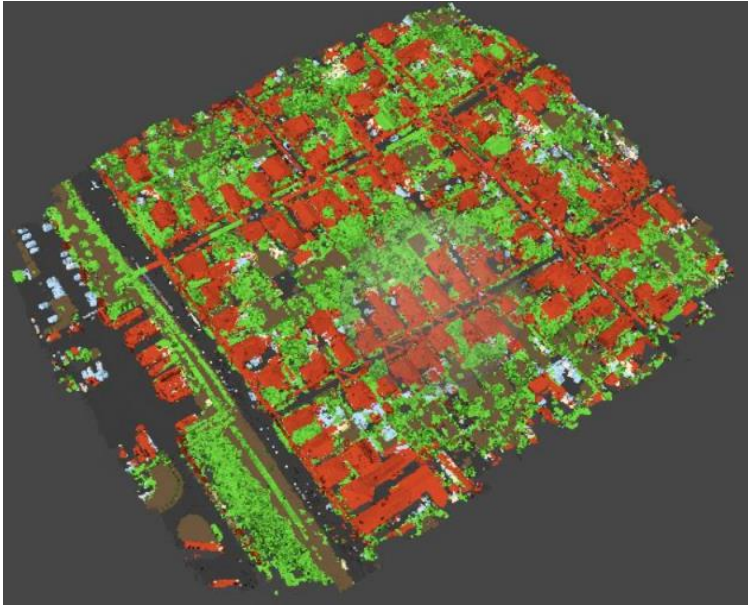


3DMASC - EREDMÉNYEK

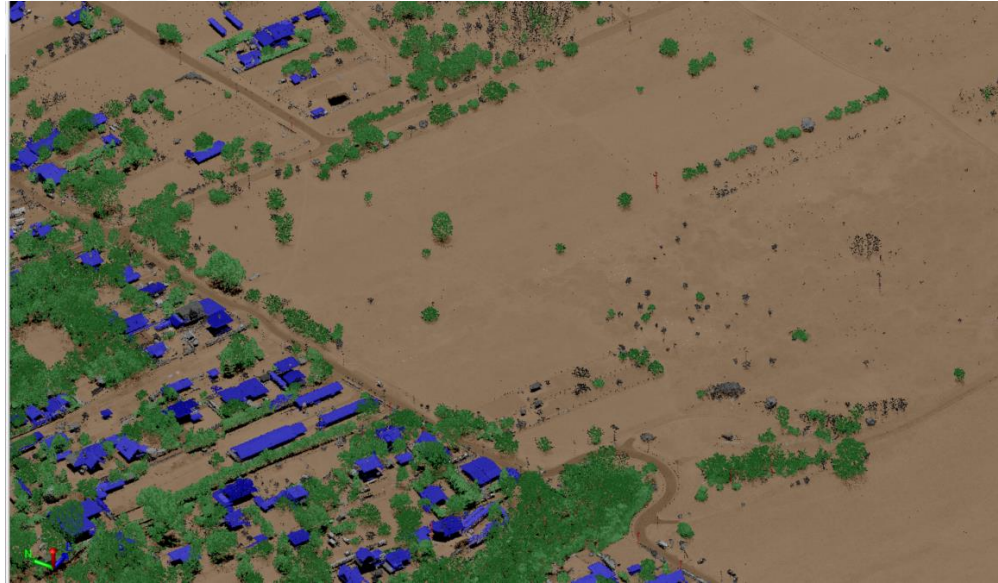


OSZTÁLYOZÁS KERESKEDELMI SZOFTVEREKBEN

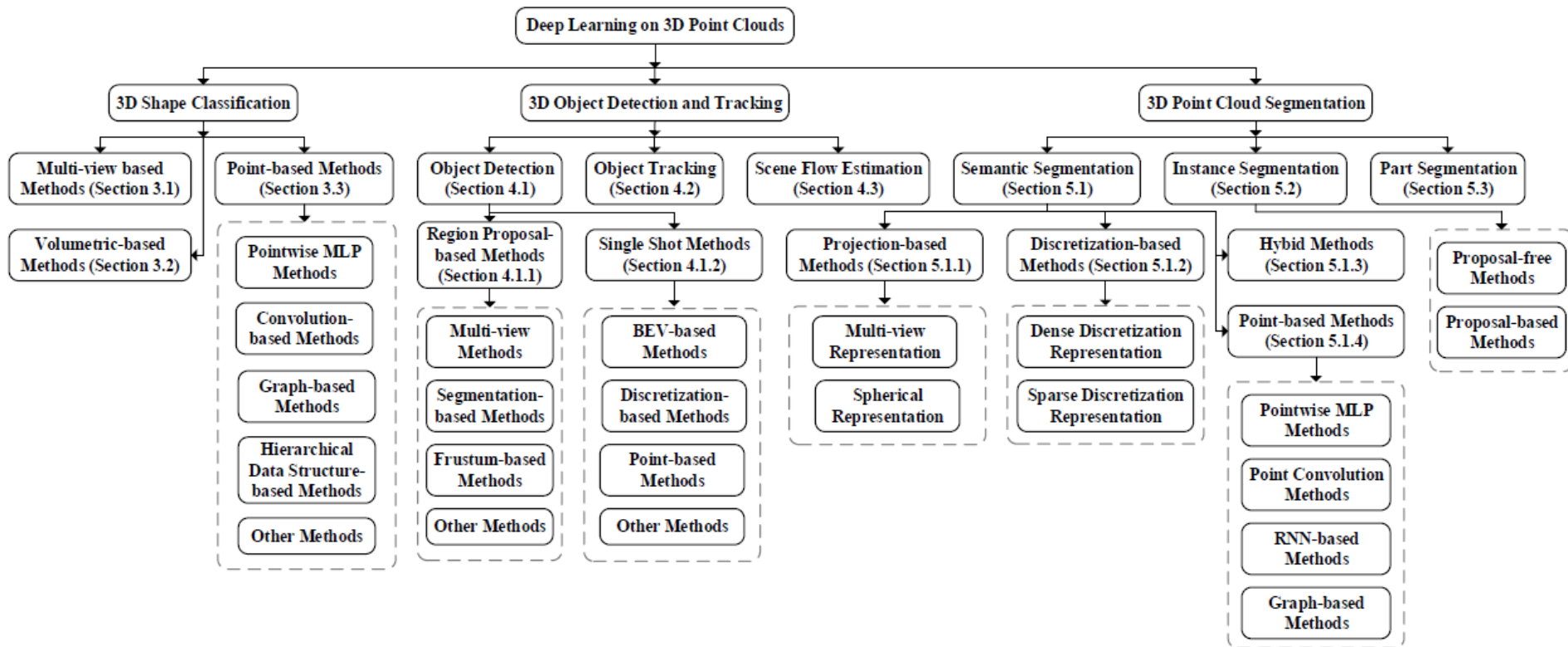
Agisoft Metashape



Trimble Business Center



MÉLYTANULÁS



Guo et al. 2020.



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Datasets

8,818 machine learning datasets

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Point cloud

Images 2503

Texts 2382

Videos 812

Audio 371

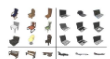
Filter by Task

Semantic Segmentation 13

3D Object Detection 12

3D Semantic 11

96 dataset results for **Point cloud**



ShapeNet

ShapeNet is a large scale repository for 3D CAD models developed by researchers from Stanford University, Princeton University and the Toyota Technological Institute at Chicago, US...

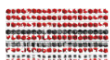
1,494 PAPERS • 11 BENCHMARKS



nuScenes

The nuScenes dataset is a large-scale autonomous driving dataset. The dataset has 3D bounding boxes for 1000 scenes collected in Boston and Singapore. Each scene is 20 seconds...

1,233 PAPERS • 17 BENCHMARKS



ModelNet

The ModelNet40 dataset contains synthetic object point clouds. As the most widely used benchmark for point cloud analysis, ModelNet40 is popular because of its various categories...

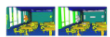
1,143 PAPERS • 16 BENCHMARKS



SUN RGB-D

The SUN RGBD dataset contains 10335 real RGB-D images of room scenes. Each RGB image has a corresponding depth and segmentation map. As many as 700 object categories are labeled...

379 PAPERS • 13 BENCHMARKS

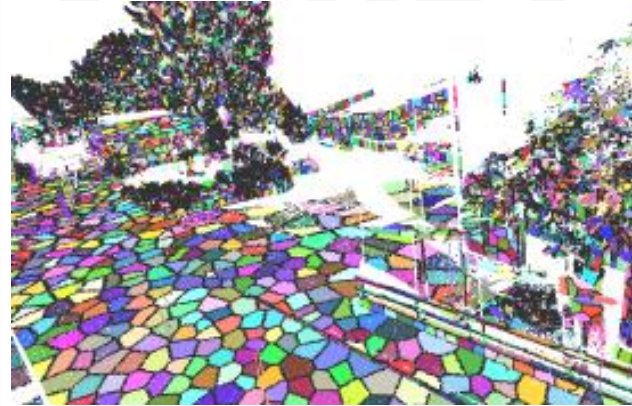


S3DIS (Stanford 3D Indoor Scene Dataset (S3DIS))

The Stanford 3D Indoor Scene Dataset (S3DIS) dataset contains 6 large-scale indoor areas with 3D point cloud data and 2D depth maps.

ÖSSZEGZÉS

- Gépi tanulás
- Pontfelhő szegmentálás
- Módszerek
- További tervek
 - *Gépi tanulás*
 - Pont vagy ponthalmaz
 - Deep Learning
 - $LOD1 \rightarrow LOD2$

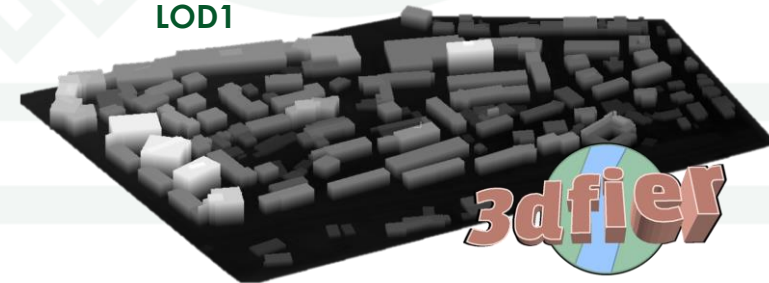


TensorFlow



Keras

LOD1



Forrás: Bátori Boglárka TDK dolgozata



KÖSZÖNÖM A FIGYELMET!

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