Project Proposal: Semantic Classification of Point Cloud using Machine Learning

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Semantic Classification of Point Cloud using Machine Learning

Introduction

LiDAR. The term LiDAR stands is a combination of the terms, ‘Light’ and ‘Radar’ (James, 1963). Popularly it has come to be known as Light Detection and Ranging (US Department of Commerce, 2012). LiDAR is a remote sensing technique that is similar to radar but uses laser light instead. A device acts as the source through which rapidly fires the laser. This light travels towards the ground and reflects off surfaces such as buildings, trees, etc. The reflected light is gets redirected to the LiDAR sensor where its characteristics are captured. The time difference between the generation and reception is used to calculate the distance. This distance is later used to calculate the elevation. LiDAR helps in generating a three-dimensional structure of the target, which here is the surface of the Earth. It produces a fine grain representation and illuminates the surface characteristics.

Point Cloud. The collection of points representing a three-dimensional structure is called as a point cloud (FME Community, 2020). Every point is characterized by X, Y and Z attributes and may involve other attributes too. This point cloud is stored in LAS format.

Important Features of the Dataset

The LAS file can be converted to a CSV and some of the important features are as follows:

X, Y, Z. Three-dimensional coordinates representing the point in space. Z often denotes ‘elevation’.

Intensity. It quantifies the return strength of the laser beam. Typically, this is an integer that ranges between 1-256. The lower the number, the lesser the reflectivity. The higher the number, the higher the reflectivity (Geodetics Inc, 2019).

ReturnNumber. A laser pulse that has been sent out by the source can have a maximum of five returns. For example, as stated in (ArcGIS Desktop, n.d.), “The first return will be flagged as return number one, the second as return number two, and so on.”

NumberOfReturns. It quantifies the total number of returns for a given pulse (ArcGIS Desktop, n.d.).

Label. It is denoted with numeric integer code such that each integer represents an object that has reflected the laser pulse (ArcGIS Desktop, n.d.).

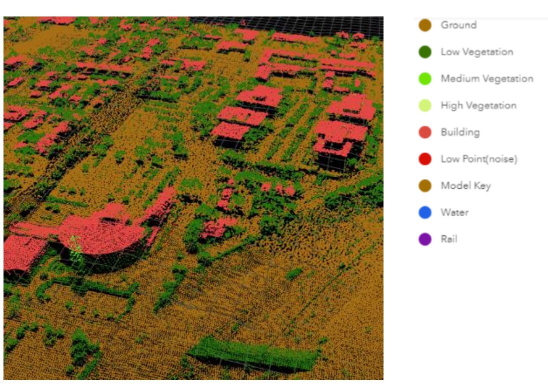

Figure 1. Example of LiDAR point cloud

Research/Practical Questions

The current research focuses on answering the below questions:

1. Can a Machine Learning model be developed to classify the point clouds into semantic classes?

2. How far are these models reliable? Can their reliability be quantified?

3. What are the most important features that affect the classification of the points in the point cloud?

Dataset

We have picked the Vaihingen dataset for our research. The Vaihingen dataset (International Society for Photogrammetry and Remote Sensing, n.d.) consists of a total of 1,165,598 points with a separate training set of 753,876 points and a testing set of 411,722 points. There are nine classes in the dataset including, powerline, low vegetation, impervious surfaces, fence/hedge, cars, roof, façade, tree, and shrub. However, due to hardware limitations, only 500,000 records were selected from the training set for the current project. These records were further split in the ratio of 80:20 to form the training and the test sets respectively. Hence, the number of records in our training set is 400,000 whereas the number of records in the test set is 100,000.

Figure 2 represents the number that denotes each class in the dataset. For example, a record with a value of 0 in the label column denotes that the LiDAR point belongs to the class ‘Powerline’.

Class/label	
0	Powerline
1	Low vegetation
2	Impervious surfaces
3	Car
4	Fence/Hedge
5	Roof
6	Facade
7	Shrub
8	Tree

Figure 2. Class/Label representation

Potential Stakeholders

The term stakeholder defines ‘a person with an interest or concern in something, especially a business’.

Potential stakeholders include:

Urban Planning agency: The classification and segmentation of a particular area can give insights into the surface characteristics of the Earth. You can use the data to perform land classification and identify its type, i.e., whether the land is commercial, open space, residential, etc. (Garnett et. al., 2018). This can help urban planning agencies plan various development/construction activities in that particular area.

Climate Change organizations: The geographical features such as the land cover can be calculated by this model. For example, icecaps can be surveyed with the help of LiDAR and the model will be able to classify them. We can observe the surface changes to understand the effect of climate change.

Department of transportation: Utah Department of Transportation has successfully used LiDAR data for updating the Highway Feature Inventory. Detecting bridges, curvelets, and maintaining them is another use-case (Utah Department of Transportation, 2017).

Construction companies: We can use this model to properly map the ground and identify things such as vegetation, buildings, etc. This helps the construction companies plan for the terrain (Commercial UAV News, 2018).

Real estate agencies: Real estate agents can map the existing assets, make a boundary and topographic surveys, high-rise inspections, etc. It removes the need for employing a person to physically navigate the area (Wolf Commercial Real Estate, 2020).

Department of Forestry: Some applications include quantification and measurement of ground elevation, Leaf Area, percentage cover, etc. The classification of vegetation is an important application related to this concept.

Policy Makers: Policymakers can look at different aspects related to different departments above, gain insights, and make policy reforms or laws accordingly.

Municipal Corporations: Changes in the urban environment, planning disaster management, mapping the city, identifying locations for city development, updating the locality maps are some of the areas that municipal corporations can take advantage of the current application (ACI USA, n.d.)

Importance of the Problems

Why is this problem/project important? How can it support various use-cases?

Below are some of the use-cases in addition to the examples mentioned above.

1. Precisely identify the changing landscape of an area. Example: Tracking climate change (icebergs, forest area), soil erosion, deforestation.

2. Helps in identifying any anomalous activity in an area. Example: We can find if any illegal constructions/settlements in a forest location.

3. Can track group movement (terrorists).

4. Can be used in Augmented Reality applications.

5. Can detect micro-topography that is hidden by vegetation which helps archeologists to understand the surface.

6. Urban Municipalities can know where things are and what are the changes that happened in the city.

7. City assessment department can use LIDAR to find out what are things building up in the public areas.

Design and Development of the project

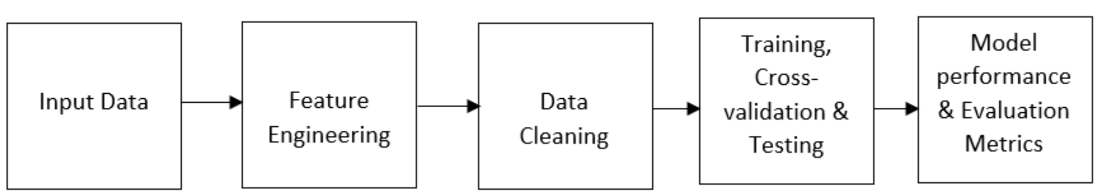

Figure 3. Theoretical/Conceptual model for the development of the project

Exploratory Data Analysis

To thoroughly understand the dataset and the relationships between the data columns, exploratory data analysis was carried out.

Barplot depicting the class distribution in the dataset: Figure 4 represents the class distribution in the dataset. It can be inferred that the highest number of records belong to the class ‘Impervious surfaces’ while the lowest number of records belong to the class ‘powerline’. The number of records belonging to the classes ‘Low Vegetation’ and ‘Impervious surfaces’ is close to each other. The records belonging to the classes ‘Shrub’, ‘Façade’, ‘Fence/Hedge’, ‘Car’ and ‘Powerline’ are very less when compared to the other classes.

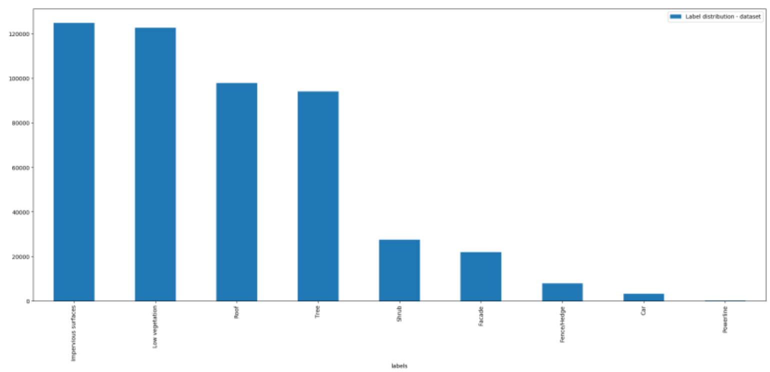

Figure 4. Distribution of classes in the dataset

Barplot of labels vs Mean Intensity values: Figure 5 represents a barplot where each value on the x-axis is the label and the y-axis is the measure of the mean intensity values. It can be inferred from the figure that the mean of intensities is the highest for ‘Fence/Hedge’, followed by ‘Low Vegetation’ and ‘Shrub’. The mean of intensities is the highest for ‘Fence/Hedge’, followed by ‘Low Vegetation’ and ‘Shrub’. Though the number of datapoints belonging to the class ‘Fence/Hedge’ is very less, their mean intensity is very high.

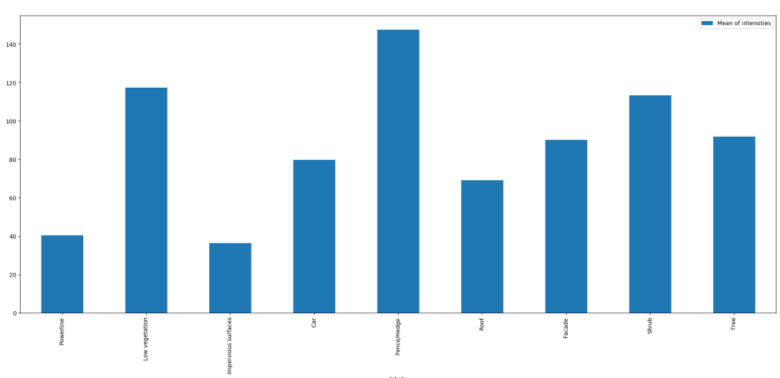

Figure 5. Barplot of Labels vs Mean Intensity values

Barplot of labels vs Mean Height (Z) values: Figure 6 represents a barplot in which the x-axis denotes the label and the y-axis denotes the mean of heights of points/records belonging to that label. It can be inferred that the mean height for the points belonging to the class ‘Powerline’ is the highest. The difference between the points belonging to the class ‘Roof’ and ‘Façade’ is very less and it is intuitive as high facades/buildings have high roofs. The difference between the mean height values for ‘Powerlines’ and ‘Tree’ is very less. This is also intuitive as Vaihingen city is an urban setting.

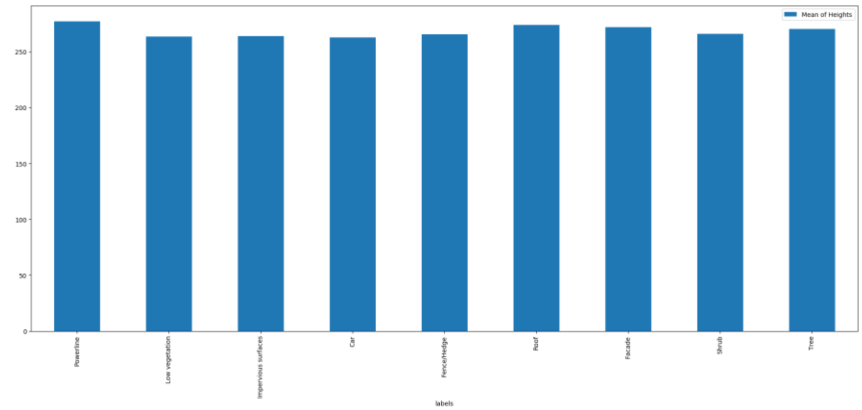

Figure 6. Barplot of Labels vs Mean Intensity values

Boxplot of Label vs Heights (Z): Figure 7 represents a boxplot in which the x-axis denotes the label and the y-axis denotes the Height (Z). It can be inferred from the figure that the classes ‘low vegetation’ (1), ‘impervious surfaces’ (2), and ‘car’ (3) have near to normal distribution. The class ‘tree’ (8) has a normal distribution. The highest variance can be observed in the class ‘Façade’ (6) while the lowest variance can be observed in the class ‘Powerline’.

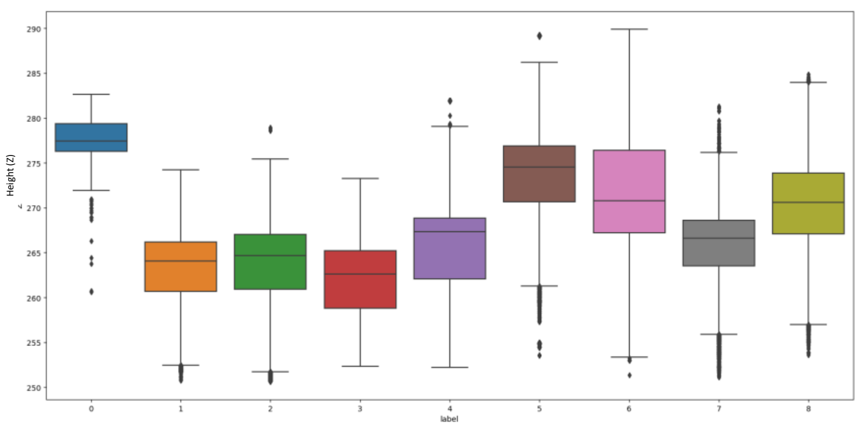

Figure 7. Boxplot of Label vs Heights (Z)

Boxplot of Label vs Sum of Eigen Values: Figure 8 represents a boxplot in which the x-axis represents the label and the y-axis represents the Sum of Eigen Values. The concept of Eigen Values will be introduced in the ‘Feature Engineering’ section of this paper. From figure 8, it can be inferred that the class ‘Impervious surfaces’ (2) has near to normal distribution and the classes ‘Car’ (3) and ‘Shrub’ (7) have a normal distribution. The highest variance is observed in ‘Low vegetation’ (1) while the minimum variance is observed in ‘Powerlines’ (0). Outliers can be observed in classes ‘Powerlines’ (0), ‘Façade’ (6), ‘Tree’ (8), and ‘Car’ (3).

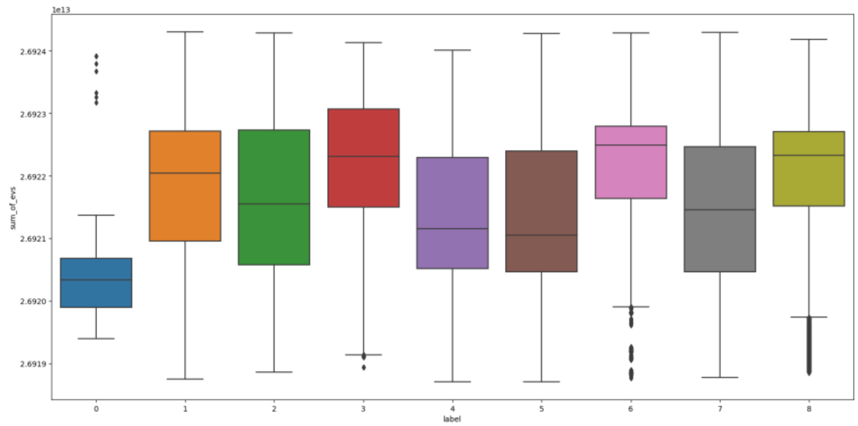

Figure 8. Boxplot of Label vs Sum of Eigen Values

Feature Engineering

The current problem is viewed from the perspective of geometry. Following the neighborhood approximation concept stated in Hackel et. al., for every record, we use the K-nearest neighbor search to identify the 3 closest neighbors to the current point from the whole point cloud. Since the search area is very large, KDTrees are employed for quick results. The covariance matrix between the three closest points is obtained and is used to generate the eigenvalues. Three eigenvalues would be generated for every point and they are denoted by λ1, λ2, and λ3. Following (Hackel et. al.), the below features were constructed.

sum_of_evs: This feature denotes the sum of the eigenvalues.

$$\text{sum\_of\_evs} = \lambda 1 + \lambda 2 + \lambda 3$$

omnivariance: As describes the distribution of points in a 3D space in the neighborhood.

$$\text{omnivariance} = (\lambda 1 \cdot \lambda 2 \cdot \lambda 3)1/3$$

Eigenentropy: It is a logarithmic measure of the rate of transfer of information with respect to eigenvalues.

$$\text{eigenentropy} = -\sum_{i=1}^{3} \lambda i \ln (\lambda i)$$

Surface Variation: The below formula measures the variation in the surface using eigenvalues.

$$\text{Surface Variation} = \lambda 3 / (\lambda 1 + \lambda 2 + \lambda 3)$$

Planarity, Linearity, Anisotropy, and **Sphericity** are calculated as mentioned in Hackel et. al.,

$$\text{Planarity} = (\lambda_2 - \lambda_3)/ \lambda_1$$
$$\text{Linearity} = (\lambda_1 - \lambda_2)/ \lambda_1$$
$$\text{Anisotropy} = (\lambda_1 - \lambda_3)/ \lambda_1$$
$$\text{Sphericity} = \lambda_3 / \lambda_1$$

local_vertical_range: The word local refers to the 3 nearest points for a given point in the dataset. The local vertical range is the difference between the maximum and the maximum heights in the perspective of 'local' as stated.

Similarly, we define '**local_height_below'** as the difference between the height of the point and the local minimum height and '**local_height_above'** as the difference between the local maximum height and the height of the point.

local_avg_height is the average of the heights of the points in the locality.

local_average_above_or_below is the distance between the height of the current point from the local_average_height.

There are also certain features defined in the 'global' perspective. By global, we consider the total dataset. '**global_height_below**' is the difference between the height of the point and the global minimum height whereas the '**global_height_above'** is the difference between the global maximum height and the height of the point.

Data Cleaning

NaN, -inf, and inf values are generated due to various reasons during the process of feature engineering. All such values are replaced with a zero. There are also certain complex numbers generated during the process and only the real part of the complex numbers are taken into account disregarding the imaginary part.

The final dataset consists of 26 features. A snapshot of the subset of the dataset is shown in figure 9.

X	Y	Z	lambda1	lambda2	lambda3	sum_of_e	omnivaria	eigenotro	anisotropy	planarity	linearity	surface_v	sphericity	local_vert	local_heig	local_heig	global_he	global_he	local_avg_	local_aver	extracted_	extracted_	Intensity	return_nu	number_o	label
496849	5419404	265.46	2.7E+13	0.02165	0.00189	2.7E+13	1032.01	-8.3E+14	1	7.34E-16	1	5.1E+10	7.01E-17	0.05	0.04	0.01	14.86	24.45	265.45	-0.01	14.86	24.45	19	1	1	1
496849	5419404	265.43	0	2.7E+13	-1.05E-10	2.7E+13	0	0	0	0	0	-2836.24	0	0.01	0.01	0	14.83	24.48	265.423	-0.00667	14.83	24.48	24	1	1	1
496849	5419404	265.4	0	2.7E+13	0	2.7E+13	0	0	0	0	0	0	0	0.04	0.02	0.02	14.8	24.51	265.4	5.68E-14	14.8	24.51	31	1	1	1
496849	5419405	265.36	0	2.7E+13	-0.00138	2.7E+13	0	0	0	0	0	-3.7E+10	0	0.02	0	0.02	14.76	24.55	265.37	0.01	14.76	24.55	33	1	1	1
496849	5419406	265.3	2.7E+13	-0.00187	0.00166	2.7E+13	0	0	1	-1.31E-16	1	4.5E+10	6.16E-17	0.07	0	0.07	14.7	24.61	265.337	0.03667	14.7	24.61	44	1	1	1
496849	5419405	265.34	0.00391	2.7E+13	0	2.7E+13	0	0	1	6.9E+15	-6.9E+15	0	0	0.07	0.04	0.03	14.74	24.57	265.337	-0.00333	14.74	24.57	50	1	1	1
496849	5419405	265.37	2.7E+13	0.00045	0.01611	2.7E+13	578.667	-8.3E+14	1	-5.82E-16	1	4.3E+11	5.98E-16	0.01	0	0.01	14.77	24.54	265.373	0.00333	14.77	24.54	34	1	1	1
496849	5419405	265.38	2.7E+13	-0.00204	0.01397	2.7E+13	0	0	1	-5.95E-16	1	3.8E+11	5.19E-16	0.01	0.01	0	14.78	24.53	265.377	-0.00333	14.78	24.53	39	1	1	1
496849	5419404	265.41	2.7E+13	0.00118	0.01808	2.7E+13	830.118	-8.3E+14	1	-6.28E-16	1	4.9E+11	6.72E-16	0.04	0.03	0.01	14.81	24.5	265.403	-0.00667	14.81	24.5	35	1	1	1
496849	5419404	265.46	2.7E+13	-0.00207	0.02321	2.7E+13	0	0	1	-9.39E-16	1	6.2E+11	8.62E-16	0.04	0.03	0.01	14.86	24.45	265.453	-0.00667	14.86	24.45	44	1	1	1
496849	5419404	265.47	2.7E+13	-0.00079	0.02419	2.7E+13	0	0	1	-9.28E-16	1	6.5E+11	8.98E-16	0.01	0.01	0	14.87	24.44	265.463	-0.00667	14.87	24.44	46	1	1	1
496850	5419403	269.44	2.7E+13	0.00087	0.0845	2.7E+13	1256.17	-8.3E+14	1	-3.11E-15	1	2.3E+12	3.14E-15	0.89	0	0.89	18.84	20.47	269.78	0.34	18.84	20.47	35	1	2	8
496850	5419404	265.38	0	2.7E+13	0.01105	2.7E+13	0	0	0	0	0	3E+11	0	0.03	0	0.03	14.78	24.53	265.393	0.01333	14.78	24.53	8	2	2	1
496850	5419403	273.71	2.7E+13	0.0903	-0.00184	2.7E+13	0	0	1	3.42E-15	1	-5E+10	-6.85E-17	0.98	0	0.98	23.11	16.2	274.057	0.34667	23.11	16.2	90	1	1	8
496850	5419403	274.75	2.7E+13	-0.00121	0.02402	2.7E+13	0	0	1	-9.37E-16	1	6.5E+11	8.92E-16	0.12	0.06	0.06	24.15	15.16	274.75	0	24.15	15.16	51	1	2	8
496850	5419406	265.21	2.7E+13	0.00101	0.16175	2.7E+13	1637.85	-8.3E+14	1	-5.97E-15	1	4.4E+12	6.01E-15	0.09	0	0.09	14.61	24.7	265.243	0.03333	14.61	24.7	2	2	2	1
496850	5419404	274.73	2.7E+13	-0.00109	0.00247	2.7E+13	0	0	1	-1.32E-16	1	6.7E+10	9.18E-17	0.04	0.02	0.02	24.13	15.18	274.73	0	24.13	15.18	102	1	1	8

Figure 9. Snapshot of the dataset after feature engineering and data cleaning

Training, Cross-validation, and Testing

The training set consists of 400,000 records. The test set consists of 100,000 records. With respect to the Machine Learning model, Random Forest was chosen as it generally produces good results because of the ensemble approach. A RandomizedSearchCV was used to pick the best metrics for the random forest classifier after performing 3-fold cross-validation. Only the training set was used for finding the best hyperparameters. Figure 10 represents the set of hyperparameters from which the best one will be chosen depending on the performance.

```
RandomizedSearchCV(cv=3, error_score='raise-deprecating',
                   estimator=RandomForestClassifier(bootstrap=True,
                                                    class_weight=None,
                                                    criterion='gini',
                                                    max_depth=None,
                                                    max_features='auto',
                                                    max_leaf_nodes=None,
                                                    min_impurity_decrease=0.0,
                                                    min_impurity_split=None,
                                                    min_samples_leaf=1,
                                                    min_samples_split=2,
                                                    min_weight_fraction_leaf=0.0,
                                                    n_estimators='warn',
                                                    n_jobs=None,
                                                    oob_sc...
                                                    random_state=None,
                                                    verbose=0,
                                                    warm_start=False),
                   iid='warn', n_iter=100, n_jobs=-1,
                   param_distributions={'bootstrap': [True],
                                        'max_depth': [10, 20, 30, 40, 50, 60,
                                                      70, 80, 90, 100, 110,
                                                      None],
                                        'max_features': ['auto'],
                                        'n_estimators': [200, 400, 600, 800,
                                                         1000, 1200, 1400, 1600,
                                                         1800, 2000]},
                   pre_dispatch='2*n_jobs', random_state=42, refit=True,
                   return_train_score=False, scoring=None, verbose=2)
```

Figure 10. List of possible parameters to choose from for the Random Forest Model.

Based on the results obtained in cross-validation, the final set of hyper-parameters chosen **include n_estimators: 1000, max_features: auto, max_depth: 90, and bootstrap: True** while the other parameters are set to default.

With the selected hyper-parameters, 5-fold cross-validation was performed to know the performance of the model on different distributions of the train set. In each fold, the model was trained on 4-folds and was tested on the fifth fold. The size of each fold is 80,000 records. The mean of Precision, Recall, F1-score, and Accuracy for the five folds is depicted in figure 11.

Class/label		Precision	Recall	F1-score	Accuracy
0	Powerline	0.738	0.408	0.526	0.948
1	Low vegetation	0.926	0.958	0.94	
2	Impervious surfaces	0.96	0.97	0.97	
3	Car	0.934	0.586	0.722	
4	Fence/Hedge	0.906	0.782	0.84	
5	Roof	0.98	0.99	0.984	
6	Facade	0.946	0.798	0.864	
7	Shrub	0.832	0.794	0.81	
8	Tree	0.95	0.96	0.965	

Figure 11. Mean cross-validation metrics of the model on 5-fold cross-validation.

Since the model showed good performance, the same hyper-parameters were used to train the model on the whole dataset and then applied to the test set. Figure 12 shows the performance of the trained Random Forest model on the test set.

Class/label		Precision	Recall	F1-score	Support	Accuracy
0	Powerline	0.88	0.40	0.55	52	0.95
1	Low vegetation	0.93	0.96	0.95	24497	
2	Impervious surfaces	0.97	0.98	0.97	24951	
3	Car	0.95	0.62	0.75	660	
4	Fence/Hedge	0.91	0.81	0.86	1510	
5	Roof	0.98	0.99	0.99	19540	
6	Facade	0.94	0.82	0.88	4446	
7	Shrub	0.85	0.82	0.83	5537	
8	Tree	0.96	0.96	0.96	18808	

Figure 12. Performance of trained Random Forest model on the test set

Feature Importance:

The importance of each feature in the classification is determined by the Random Forest model. Figure 13 shows the feature importance of predictors. The top 6 predictors in determining the class are Intensity, X, Y, sum_of_evs, local_avg_height, and local_vertical_range.

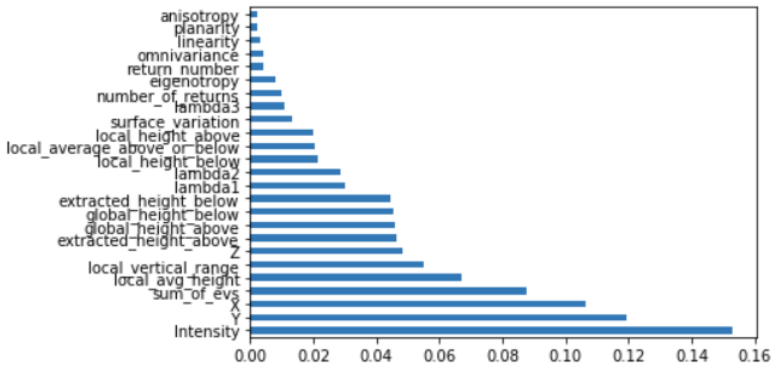

Figure 13. Feature Importance of predictors extracted from the Random Forest model.

Result Analysis:

From figure 12, it can be inferred that the class 'Roof' has the highest recorded metrics. The records with classes 'Tree' and 'Impervious surfaces' were also predicted very well by the model. The F1-scores for 'Powerline' and 'Car' is less when compared to the other classes and this can be attributed to the imbalanced class distribution. From figure 4, it can be observed that the number of records belonging to the classes 'Car' and 'Powerline' are very few.

After analyzing the misclassified records, it was found that the majority of the records whose actual class were 'Powerlines' were predicted as 'Roofs'. 60.3% of the labels that were wrongly predicted as 'Low vegetation' actually belong to the 'Impervious surfaces' class. Additionally, 90.4% of the misclassified records for the class, 'Impervious surfaces' fall into the 'Low vegetation' class. This means that the characteristics of the classes 'Impervious surfaces' and 'Low vegetation' are very similar.

It is also intuitive that 42.4% of the records misclassified as 'Low vegetation' have their actual class as 'Car'. Majority of the records misclassified as 'Façade' actually belong to 'Roof'. This can be because of the mean height of points belonging to the class 'Façade' and 'Roof' being very similar as observed in exploratory data analysis. The majority of the records whose actual class is 'Shrubs' were predicted as 'Low Vegetation'. The records whose actual class is 'Trees' were predicted as 'Low vegetation', 'Roof' Façade' and 'Shrubs'. This can be due to their height variability.

Limitations and Challenges

Class imbalance: Imbalanced class distribution in the dataset is observed. This causes the model to find patterns related to one class more effectively than the other. Eventually, this affects prediction.

Data size: LiDAR data is common of very large size typically in hundreds of thousands. This causes problems in model fitting and scaling. We sampled 500,000 records out of 753,876 of the original training set and further divided them to train and test sets.

Training time: Since the number of records and values are very large, the training time is also very high. In our case, the cross-validation process itself takes more than 1.5 hrs on a PC with 16GB RAM, i7 processor.

Hardware and Memory: The hardware requirements for processing and modeling LiDAR data are very high. Future deployment into a production environment demands sophisticated equipment.

Extensive model development: Due to large data size and hardware constraints, it requires a lot of time and resources to train and test extensive Machine Learning models on the dataset.

Answers to research questions:

1. Can a Machine Learning model be developed to classify the point clouds into semantic classes?

Ans: Yes. It is possible to build ML models with high prediction power. We have demonstrated the Random Forest model in this project.

2. Can a Machine Learning model be developed to classify the point clouds into semantic classes?

Ans: The Precision, Recall, Accuracy, and F1-scores are the measures that can be used to quantify the performance of the models. We have observed reliable metrics for all the classes in the dataset.

3. Can a Machine Learning model be developed to classify the point clouds into semantic classes?

Ans: The top 6 important features affecting the classification in the point cloud are Intensity, Y, X, Sum of Eigen Values, Local Average Height, and Local Vertical Range.

Helpful for future Data Scientists

The exploratory data analysis that we provided helps greatly in analyzing the misclassified records. The hand-designed features characterize the 3D coordinates/LiDAR points. The feature importance extracted provides information on the features to concentrate on for classification. The trained model may be used to check if it works in similar cities/neighborhoods. This saves a lot of time, effort, and resources involved in the training, development, and testing of the new models. The results analysis section gives details on similar and dissimilar classes. Additional features can be designed to characterize the differences between such similar classes to improve classification metrics.

How is the current topic connected to S&CC related issues?

In addition to the use-cases that we have discussed previously, we answer this question by looking at three aspects.

How can city managers or policy-makers benefit from the new ideas?

This modeling approach can help policymakers perform object/structural detection from simple point cloud data obtained from LiDAR. It can also help in precisely identify the changing landscape of an area. It can be extremely helpful in the town planning and development of a city.

How the key ideas of the paper are related to S&CC topics practically?

The features are either hand-built/automatically extracted that can provide information over the characteristics of different objects/surfaces in the point cloud. Further, their importance can also be quantified.

How can the techniques or concepts used in the project help solve S&CC problems?

The trained model can be used to classify objects in the new point cloud which is provided as an input.

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