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Constructing 3-D Ground Ice Map Using Deep Learning on Regional Borehole Data

Background

The thawing of sub-surface ice affects neighborhood ecosystems and infrastructures. Knowing where ice exists underground is crucial, but borehole measurements are expensive. Given regional borehole data, a neural network is trained to predict the existence of ground ice in a 3D grid.

Method

Input
known parameters
•Depth, Longitude, latitude, +?
•Land surface raster data

Model
deep learning architecture
•Multilayer-Perceptron
•Feature-wise Linear Modulation

Output
prediction of ground ice characteristics
- Amount of visible ice
- Frozenness
- Material

Borehole data set

Inuvik-Tuktoyaktuk Highway

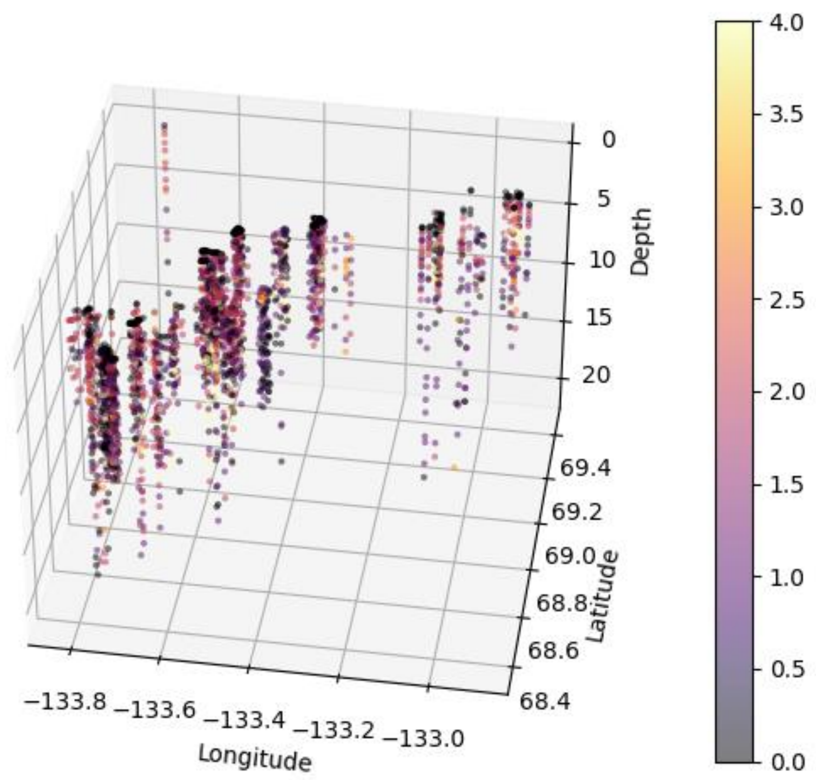

Figure 1: Visualization of locations of borehole data set, where colour indicates the amount of visible ice recorded

This dataset records parameters including **amount of visible ice, frozenness, materials**, etc. It is **fine in resolution** spatially and in depth: most boreholes reach at least 5m depth, and most of neighbouring boreholes are located 100m apart

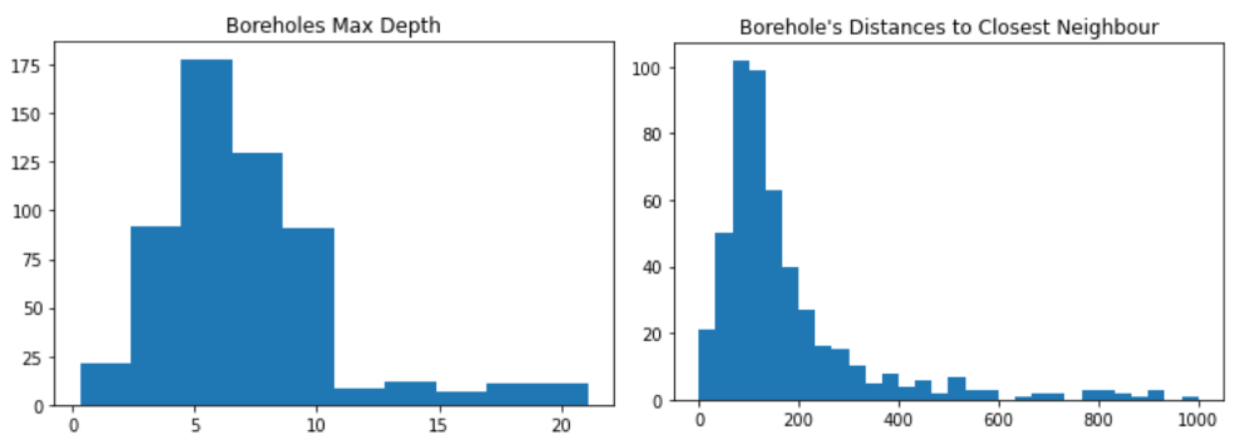

Figure 2,3: Histograms of maximum depth and neighbouring distances of boreholes

Train on borehole data only

Using a regular deep learning model

Training a regular deep-learning model like MLP (multilayer perceptron) on the **borehole data alone** produces 3D grid maps which predict characteristics such as amount of visible ice.

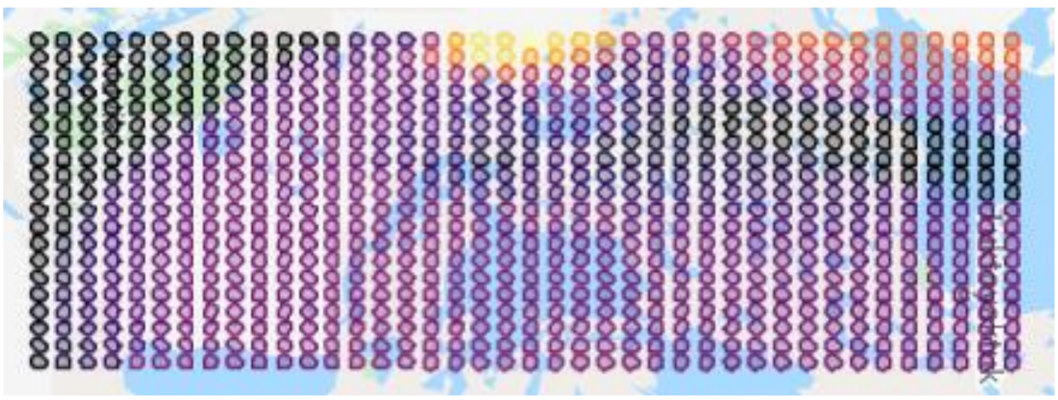

Figure 4: Flattened visualization of 3D map predicted by MLP model, where colour indicates amount of visible ice

Train with additional data

Incorporate surface image data

When the neural network has more information to learn from, such as land surface data, the hope is that it finds **correlations between surface and sub-surfaces characteristics**, hence improving prediction accuracy. The FiLM technique can be applied on any neural network to allow training on more than one type of data.

borehole	depth	frozen	cryostructures
0170-1-10	0.15	0	
0170-1-10	0.85	1	
0170-1-10	1.9	1	Nf
0170-1-10	5.4	1	Nf
0170-1-12	1.2	1	Nf
0170-1-12	3.95	1	Nf
0170-1-12	6.1	1	Nf
0170-1-17	0.3	0	
0170-1-17	1.45	1	
0170-1-17	3.45	1	

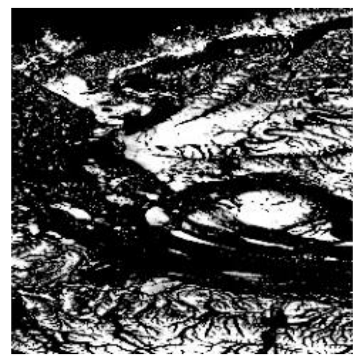

Figure 5, 6: Borehole tabular data and land surface raster data

FiLM method

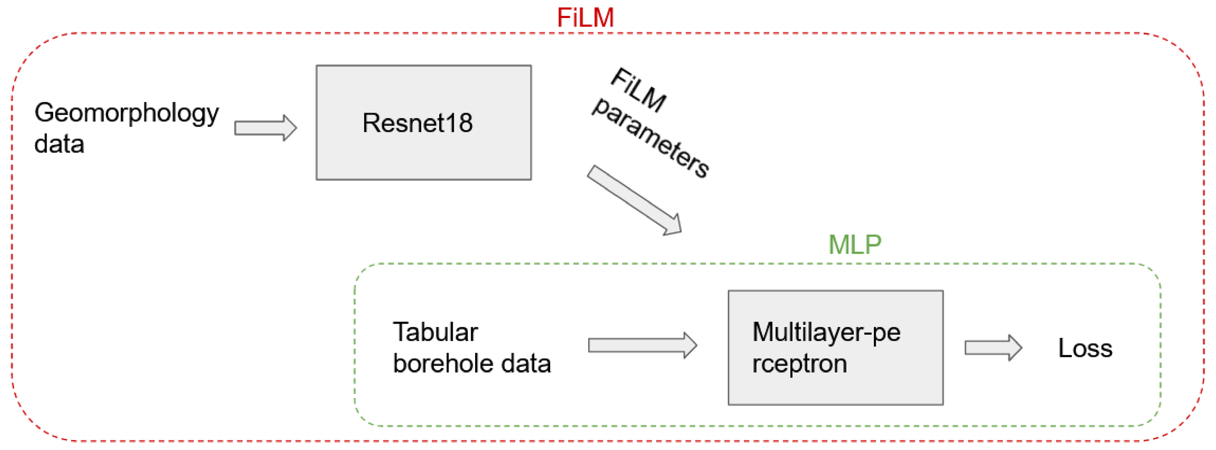

Figure 7: FiLM architecture

FiLM (feature-wise linear modulation) **adds a branch** to an existing neural network, where each branch ingests a type of data, and both branches are backpropagated and trained simultaneously.

Challenge of choosing datasets

The FiLM method has been verified on cifar10 test data. However, when the two types of data do not match in terms of resolution, as the borehole data has finer resolution than many land surface maps, the FiLM network may not find correlation to learn from.

Statistical investigations such as **independent component analysis (ICA)** reveal there exists little correlation between the current raster data and borehole data. High correlation revealed by ICA would be a powerful reference guide for choosing training data in the future.

Figure 8, 9: ICA results from borehole data vs from land surface data

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