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## Core Image Classification using Deep Features

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### Summary

A method for using deep neural networks to classify core images is presented. A pre-trained CNN is used to generate a hierarchy of deep convolutional features. A small amount of manually labeled examples is used along with the deep features to train a classification model. The resulting classification is accurate, and provides a rapid method of classifying an entire core.

### Introduction

This poster demonstrates a machine learning workflow for whole core image classification. There have been significant advances in the field of image classification in recent years due to rise of AI technologies like deep learning. Convolutional neural networks (CNNs) are a popular deep architecture for image classification and computer vision tasks (Krizhevsky et al. 2012). However, CNNs require an enormous amount of training data to achieve accurate results. Labeled databases such as ImageNet (Russakovsky et al. 2015) contain millions of classified images (of general objects) that have been used to train networks to a high degree of accuracy (Krizhevsky et al. 2012). There aren't currently geologic image databases of similar size. Here, we demonstrate that CNNs pre-trained on general image databases can be used to extract features from core images that can be used for geologic classification.

### Theory and/or Method

A typical core photograph is an RGB image has 3 features directly associated with each pixel location - the amount of red, green and blue light that comprise the color of the pixel. This is extremely local information, and classifying a pixel based on color features only neglects the spatial and textural context of a pixel. This is essential for accurate classification of core images that have similar colors appearing in many different contexts. Feature engineering can be applied to extract textural features that can be used to put individual pixels into a geologic context. This is largely a trial and error process that requires domain knowledge and is not generalizable to different types of images. During the training process, CNNs learn a hierarchy of discriminating features of increasing complexity. The first layers apply convolutional filters to the input image that are sensitive to simple features such as edges and corners. Later layers respond to successively more complex features, such as texture and shapes. Finally the last layers respond to complex image objects.



(as indicated in Figure 1). The output of these layers is concatenated into a vector for every pixel in the original image. This is the feature set used to classify the image.

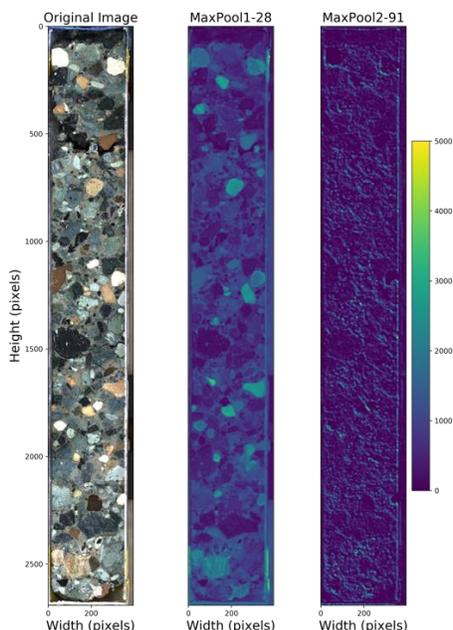
Training data is created by manually identifying representative pixels that belong to each of the geologic classes present in an image. For core images, this involves labeling a number of examples of each class of object present in the core. It is not required to completely label an image. The labeling can be sparse and performed at a isolated areas. For each labeled pixel, we extract the hypercolumns at that pixel location by concatenating the activations at the selected layers associated with that pixel.

Next, a random forest model from scikit-learn (Pedragosa et al. 2011) is trained on this data set. This is a robust machine learning model employed to gauge the effectiveness of using deep features to classify geologic images.

## Examples

To demonstrate the method, we use core images from IODP/ICDP Expedition 364 which recovered 829 meters of core from the peak ring of the Chicxulub impact structure (Hole M0077A). The interval between 617 to 747 [mBSF] is a melt bearing breccia, a fining upward sequence of rock clasts that were deposited in the crater in the hours and days after impact. This section presents a challenging classification task, due to the many different rock types (some of which have similar characteristics) and the different size scales of the clasts.

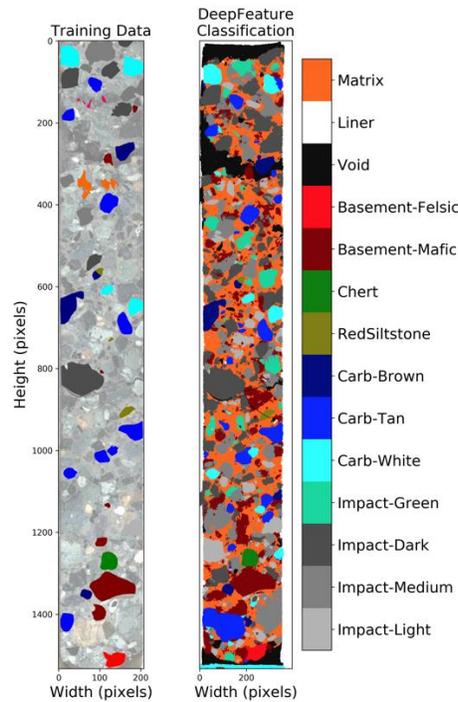
Figure 2 shows the image of core section 72-2, located 698.41 to 699.02 [mBSF]. The raw image is a 2693x369 [px] JPEG image with 3 color channels. This image is fed to a modified VGG-16 CNN that has been pre-trained on the ImageNet database. The fully connected portion of the CNN is ignored, as we are only interested in the intermediate activation layers. Figure 2 shows two feature maps that have been extracted from these layers, showing the response of the network to a specific convolutional filter, in this case MaxPool1-28 and MaxPool2-91. For this classification, we're using all the filters from MaxPool1 and MaxPool2.



**Figure 2:** Image of section 72-2, and example feature maps from the first two MaxPool layers.

A taxonomy of 14 classes was created to describe the variation of rock types in the interval. Representative clasts of each type were identified by manually labeling pixels, as shown in the left image in Figure 3. The hypercolumns (deep features) associated with each labeled pixel were extracted, and this data was used to train a random forest classifier. The classifier achieved an F1 score of 0.97 with 5% of the training data set aside for testing.

The results of the classification are shown in the right image of Figure 3. In general, the clasts are consistently classified, and are easily distinguished from adjacent clasts. The matrix/melt surrounding the clasts was accurately classified despite a relatively small amount of training data.



**Figure 3:** Training data used to classify section 72-2 (left), and classification results (right)

## Conclusions

We have demonstrated a workflow for classifying a complex core image using features extracted from a pre-trained CNN. We have shown the results for one core section; this classifier can be applied to all images in the entire core. The workflow was demonstrated using an exotic core with many different classes, but this approach is applicable to reservoir cores (both white light and UV images).

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