

Classification of Skin Cancer Images using Topological Data Analysis

MTG 7396: Topological Data Analysis – Gainesville, Florida

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Overview of Presentation

Classification of Skin Cancer Images using Topological Data Analysis

- 1. Introduction
 - 1.1 Data Set: Skin Cancer MNIST HAM10000
- 2. Data Preprocessing Pipeline
 - 2.1 Sampling Points from Skin Cancer Images
 - 2.2 Topological Data Analysis
- 3. Data Visualization and Classification
 - 3.1 Principal Component Analysis
 - 3.2 Support Vector Machines
 - 3.3 Deep Neural Network
- 4. Conclusion



Data Set: Skin Cancer MNIST HAM10000

- Consists of 10015 dermatoscopic images on various locations of body
- Includes representatives from primary diagnostic categories of pigmented lesions:
 - MEL: Melanoma
 - NV: Melanocytic nevi
 - AKIEC: Actinic keratoses and Intraepithelial Carcinoma / Bowen's disease
 - BCC: Basal cell carcinoma
 - BKL: Benign keratosis-like lesions (solar lentigines / seborrheic keratoses and lichenplanus like keratoses)
 - DF: Dermatofibroma
 - VASC: Vascular lesions (angiomas, angiokeratomas, pyogenic granulomas and hemorrhage)

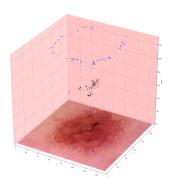


Sampling Points from Skin Cancer Images

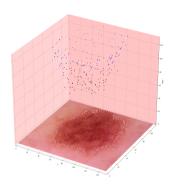
- Detected boundary of largest skin cancer region in image
 - Used cv2.findContours from the OpenCV library in Python to detect boundary
 - Uniformly sampled 100 points from boundary
- Used thresholding to isolate skin cancer region within image
 - Used cv2.threshold from the OpenCV library in Python
- Implemented various methods for sampling pixels after thresholding
 - Simple: 100 darkest / 100 lightest pixels using grayscale, RGB, or HSV image format
 - Cluster: Cluster pixels by intensity using sklearn.cluster.KMeans then sample darkest and lightest points from each cluster using grayscale, RGB, or HSV image format
- Used 80 images: Sampled points from 40 images in each class (NV, MEL)



Sampling Points from Skin Cancer Images



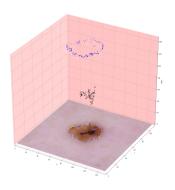
Grayscale Simple Sampling Method



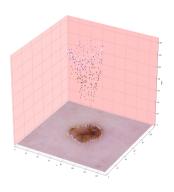
Grayscale Cluster Sampling Method

NV Image: Boundary (white), 100 lightest (blue), and 100 darkest (black) pixels

Sampling Points from Skin Cancer Images



Grayscale Simple Sampling Method



Grayscale Cluster Sampling Method

MEL Image: Boundary (white), 100 lightest (blue), and 100 darkest (black) pixels

Computing Death Vectors and Persistence Landscapes

- Computed persistence landscapes and death vectors with RStudio TDA package
 - For each image, we used the sampled 100 boundary points and 100 darkest points from the simple sampling method for a total of 200 points per image
 - Used Vietoris-Rips complex in TDA pipeline
- After processing the sampled data in R, for each image we had:
 - One death vector of length 199
 - One persistence landscape vector of length 30100



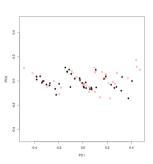


Figure 1: Projection of Death Vectors onto two leading PCA basis vectors

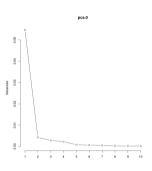


Figure 2: Variance in direction of first ten basis vectors from PCA

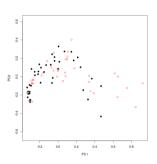


Figure 1: Projection of Pers. Landscapes onto two leading PCA basis vectors

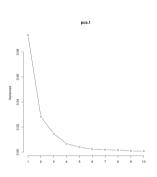
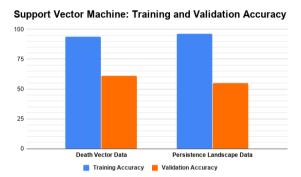


Figure 2: Variance in direction of first ten basis vectors from PCA

Support Vector Machine Classification



- Used R package ksvm with Gaussian radial basis function kernel
 - Data does not appear to be lineary separable based on the principal component analysis



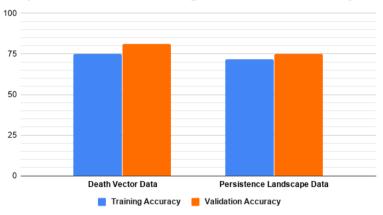
Deep Neural Network (DNN) Classification

- Used Python packages TensorFlow and Keras to model and train DNNs
- Used Google Colab with GPU accelerator to reduce training time of DNNs
- Death Vector DNN:
 - 2 hidden layers, ReLU activation, batch normalization, dropout layers
 - Total of 167,506 trainable parameters
 - Trained for 120 epochs using Adam optimizer with batch size of 5
- Persistence Landscape DNN:
 - 1 hidden layer, ReLU activation, batch normalization, dropout layers
 - Total of 3,015,503 trainable parameters
 - Trained for 150 epochs using Adam optimizer with batch size of 8



Deep Neural Network (DNN) Classification

Deep Neural Network: Training and Validation Accuracy





Conclusion and Future Work

- Successfully modeled and trained classifier for MEL and NV images that does not suffer from overfitting
- Future work includes:
 - Update sampling method to capture slightly more of internal skin cancer structure
 - Streamline pipeline so sampling, TDA, and DNN classification can be done in Python
 - Sample points from more images and more classes in HAM10000 data set
 - Model and train DNN for multiclass classification



Thank you for your attention. Any questions?

