Classification of LEGO parts using Topological features

Jiayue Xu and Srishti Saha

Problem Statement

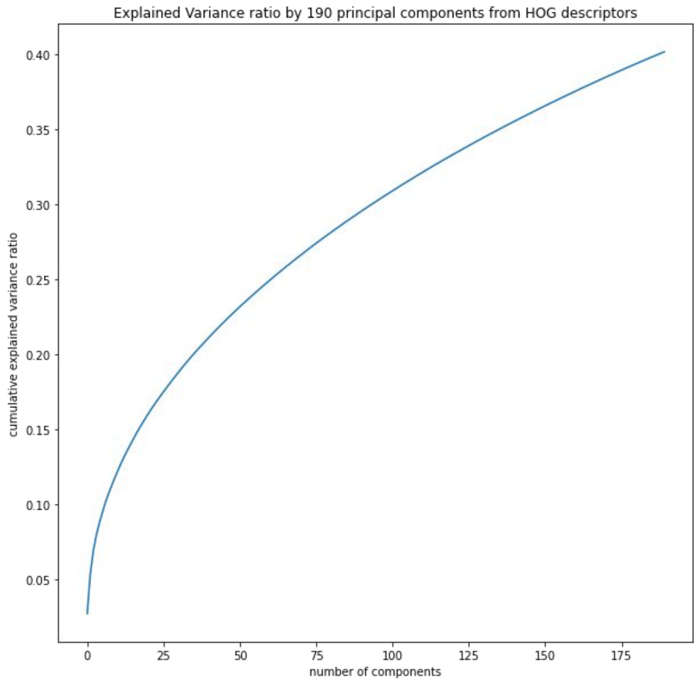
- **Objective**: Image classification of LEGO parts by extracting topological features from 3D drawings of LEGO parts.
- **Motivation**: In the manufacturing space, 3D mechanical drawings are widely used for a variety of applications like:
  - checking for anomalies in model consistency,
  - checking for flaws in produced models,
  - categorizing products into classes for inventory and supply purposes etc.
- The aim of the project is to create a prototype of how topological features can be used to train a classification algorithm for these LEGO parts
- We will also investigate if the addition of topological features adds any significant amount of information over and above the normal features

Data Set

- Source: https://rebrickable.com/downloads/
- It consists of the LEGO Parts/Sets/Colors and Inventories of every official LEGO set in the Rebrickable database.
- The raw data source has 12 csv files with parts information and more than 80,000 PNG images of official LEGO parts of different colors.
- We filtered and prepared the dataset for appropriate parts to do our analysis.
- Each LEGO part is identified by a unique part number and has been assigned a part category on the basis of its use and function.

Feature Extraction (Conventional Features)

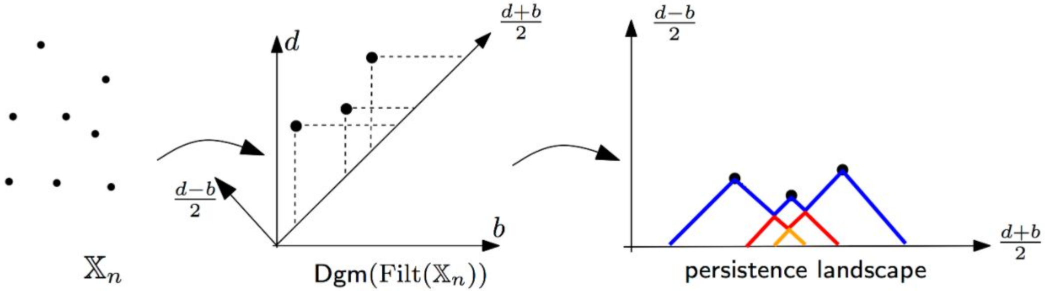
- Edge Detection
  - Canny Edge Detection
- Texture features[1]-
  - **Means of image**
  - **Standard Deviations of Image**
  - Shannon Entropy (information content) of image
- **Corner Detection using Shi-Tomasi transformation**
  - Improvement on the previously used Harris Corner Detection
- SATO tubeness
- **Orientation (direction) and gradient (magnitude) of edges:**
  - **HOG (Histogram of Oriented Gradients) feature descriptor**
  - **Derived 10 principal components (using incremental PCA) from ~148840 feature descriptors per image** (in the interest of time and computational resources- can extract more)



[1] Matsuyama, E.; Takahashi, N., Watanabe, H., Tsai Du-Yih A Method of Using Information Entropy of an Image as an Effective Feature for Computer-Aided Diagnostic Applications, 2016

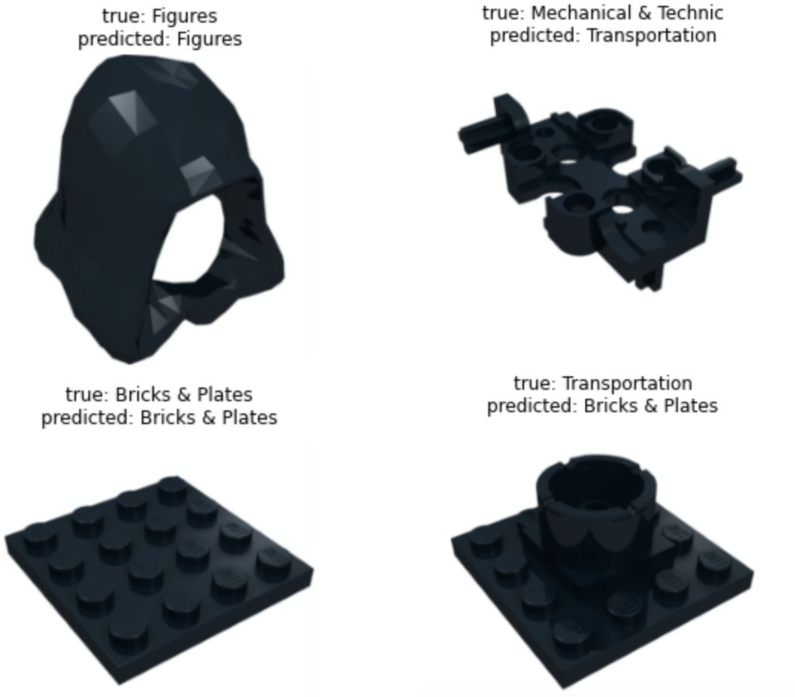
Feature Extraction: Topological Features

- Scalar Persistence Diagrams features:
  - **Persistence Entropy**: Given a persistence diagrams consisting of birth-death-dimension triples [b, d, q], sub-diagrams corresponding to distinct homology dimensions are considered separately, and their respective persistence entropies are calculated as the (base e) entropies of the collections of differences (d - b), normalized by the sum of all such differences. [Source: https://giotto-ai.github.io/gtda-docs/0.2.2/modules/generated/diagrams/features/gtda.diagrams.PersistenceEntropy.html]
  - **Amplitude:** Amplitudes of persistence diagrams
- **Persistence Landscapes (WIP)**



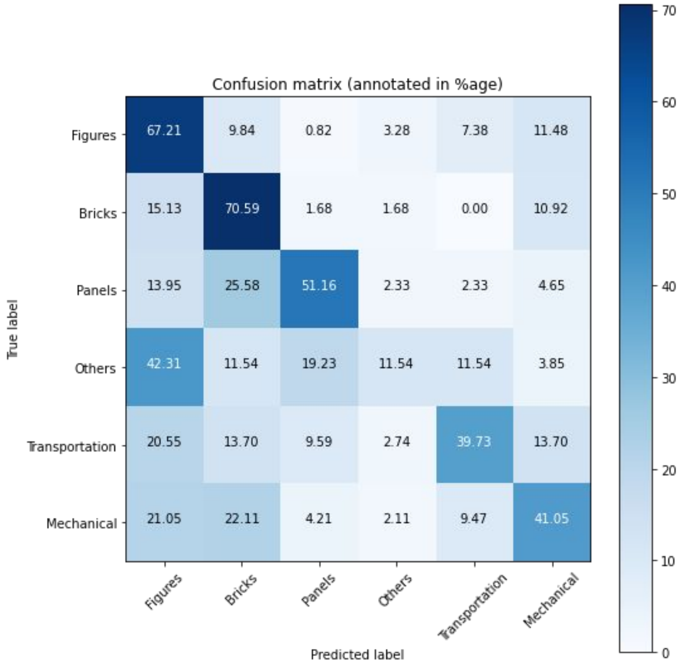
Source: http://bertrand.michel.perso.math.cnrs.fr/Enseignements/TDA/Tuto-Part4.html

Learning Algorithm (Baseline NN)



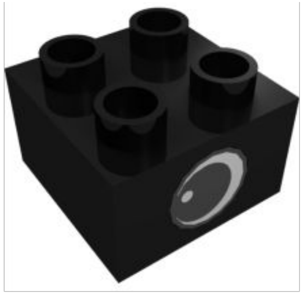
- Using *just the base images as an input* to a Neural Network, transfer learning of ResNet-50 architecture
- **validation-set accuracy of 77.20%**.
- For *example*: The base model was able to correctly classify a part from the 'Figures' category and 'Bricks and Plates' category.
- However, it could not identify parts from the mechanical category and transportation category.
- This might be because these parts have high similarity to the parts from the predicted class.

Learning Algorithm (Light GBM)



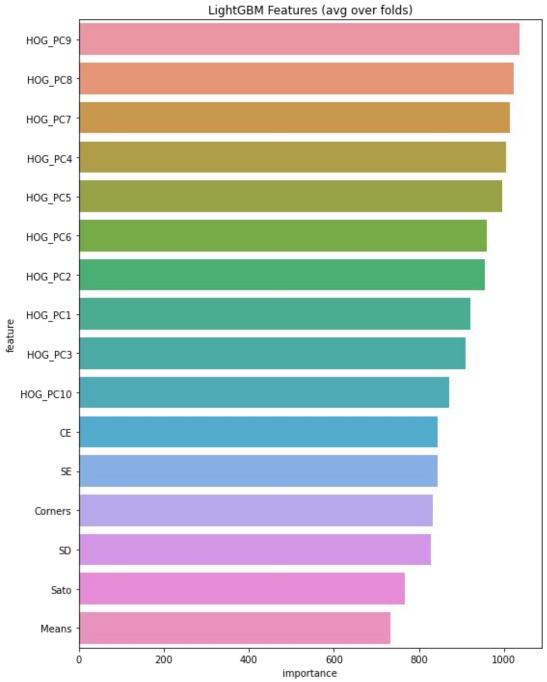
- Light Gradient Boosting Algorithm, using only conventional geometrical features
- Used 10-fold cross-validation for hyper-parameter tuning
- **Validation-set accuracy of 65.3%** (error rate: 0.347)
- **Test-set accuracy of 54%** (on completely unobserved data)

True: Bricks
Predicted: Bricks



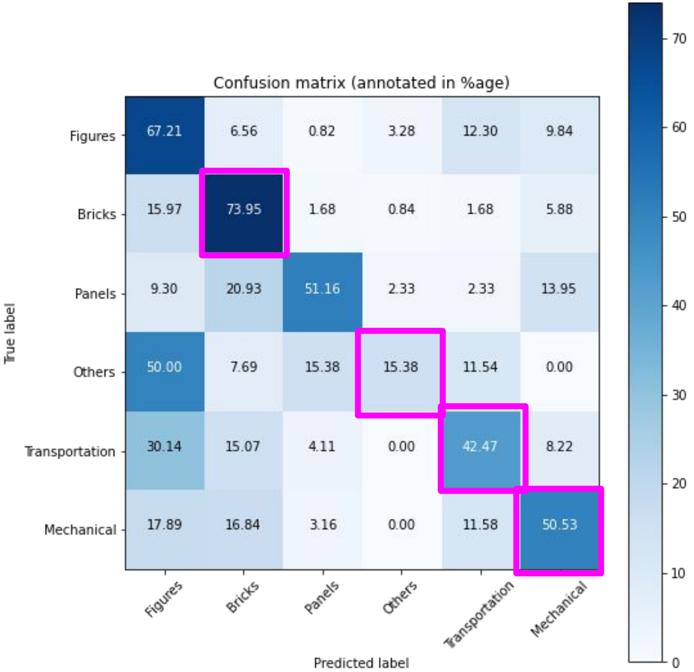
True: Bricks
Predicted: Mechanical

Learning Algorithm (Light GBM) -Feature Importance



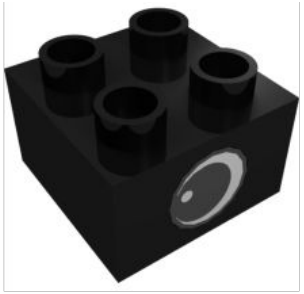
- The HOG feature descriptors are **most** important features for the conventional model
- Means of image are the **least** significant

Learning Algorithm (Light GBM with topological features)



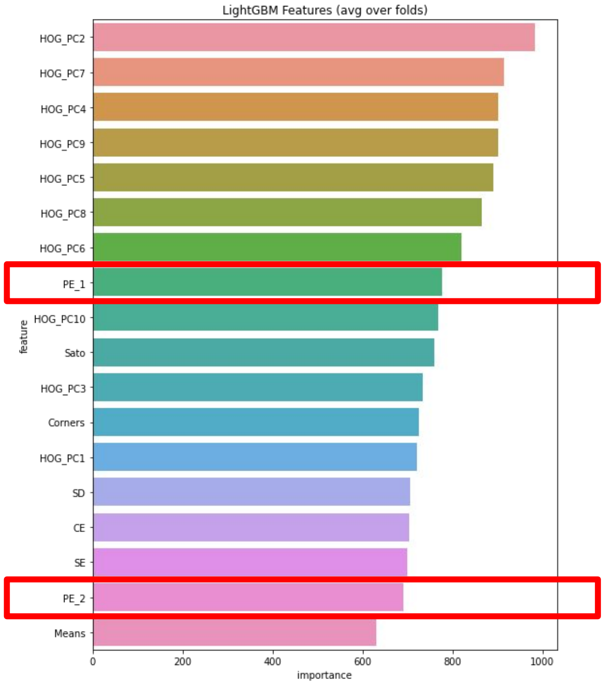
- Using conventional geometrical features with topological homology features (2 dimensional persistence image features)
- Used 10-fold cross-validation for hyper-parameter tuning
- **Validation-set accuracy of 66%** (error rate: 0.34)
- **Test-set accuracy of 57%** (on completely unobserved data)

True: Bricks
Predicted: Bricks



True: Bricks
Predicted: Bricks

Learning Algorithm (Light GBM with topological features)-Feature Importance



- The HOG feature descriptors are still the **most** important features.
- However, the persistence homology feature (1st component) appears in the top 8 features by significance.
- The second component is one of the least significant features.

Next Steps

- Build a model with persistence landscapes and amplitude of persistence images
  - Observe and compare performance
  - Evaluate variable significance
- Tune and evaluate model for only select categories: Figures, Bricks, Panels
  - Try combining categories ‘Mechanical and Technic’ and ‘Transportation’ into 1 bigger category to evaluate model performance
- Explore ensemble models :
  - Neural network model only on persistence images
  - Existing model with both conventional features and Topological features
  - Neural network model on point cloud of base images itself

Challenges

- **Current learning models are overfitting** and need to be tuned for a better prediction.
- **Category 'Others'** has a lot of diverse parts that are not geometrically or functionally homogeneous. We need to avoid these parts for current analysis and tune the category for further analysis.
- A lot of categories have parts that are **functionally similar but not geometrically.** Topological features alone will not be able to capture these details.

Appendix: Features List

- Features in conventional model:
  - CE: Canny Edge (averaged by # of image pixels)
  - SE: Shannon Entropy
  - Sato: Sato tubeness (averaged by # of image pixels)
  - SD: Standard Deviations of image
  - Mean: Means of image
  - Corners: Number of corners detected in the image
  - HOG: 10 Principal Components
- Additional features in TDA model:
  - PE: Persistence Entropy for 2D components derived from the persistence diagram