IDENTIFY FASHION PRODUCT TYPE BASED ON ITS IMAGE

CNN Classifier for Fashion Product Images

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Classify the fashion products. Why? Who would care?

- Fashion e-commerce accounted for roughly 29.5 percent of the total fashion retail sales in the United States (2020).
- One of main challenges for e-commerce - **categorizing/labeling the products from the images**.
- Many businesses have developed and advanced their algorithms to classify/label products further into **multi-categories/features** (ex: the product's color, texture or pattern, style, or look).
- Build the **product recommendation system** based on the product features.
- Well-known e-commences specializing in customizing or matching fashion products to customers: Stitch Fix, DAILYLOOK, and Nordstrom's Trunk Club for fashion appeals; Birchbox for personal care products, to name a few.

Problem Formulation

- Image classification poses an exciting computer vision puzzle.
- Building a classification model for fashion product images would be an excellent start to dive into deep neural networks.

- Project goals:
  - To deal with the **imbalanced fashion image dataset**.
  - Build **Convolutional Neural Networks (CNN)** for image classification with **Keras API**.
  - Evaluate the model performances.

Data Information

- Image labels: **styles.csv**
  - **Number of fields**: **10**
    (id, masterCategory, subCategory, articleType, etc.)
  - **Number of rows**: **44440** hourly records.
- Image files: **44440 images** (80-by-60)

(image_id*.jpg).

Data Wrangling & Feature Engineering

- Deal with the Imbalanced Labels
  - Defined a new categorical feature - **Class**
    It combines the three hierarchical labels (masterCategory, subCategory, articleType).
  - **Class** has **30** product labels.

Data Wrangling & Feature Engineering

- Reassign Class to Images Under the Ambiguous Category (Free Items)
  - For each mislabeled item, compute **Text Similarity** (cosine similarly) between its productDisplayName and the **30 labels**.
  - Among the 30 labels, the maximal one should be assigned to the product.

Fashion Product Category

Fashion Product Category (reassigned)

Proportion of Categorical Labels

General Balance Measurement for Categorical Variable

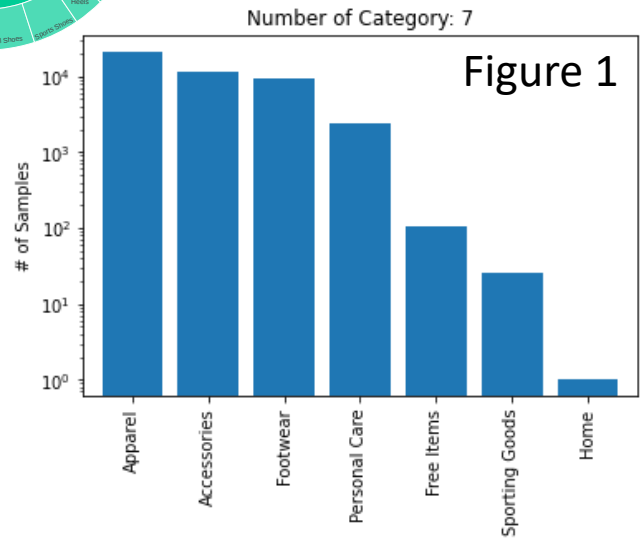
$$p_i = \frac{n_i}{N}, \qquad N = \sum_{i=1}^{C} n_i\,, \qquad H = -\sum_{i=1}^{C} p_i \log p_i\,, \qquad H_{max} = \log C$$

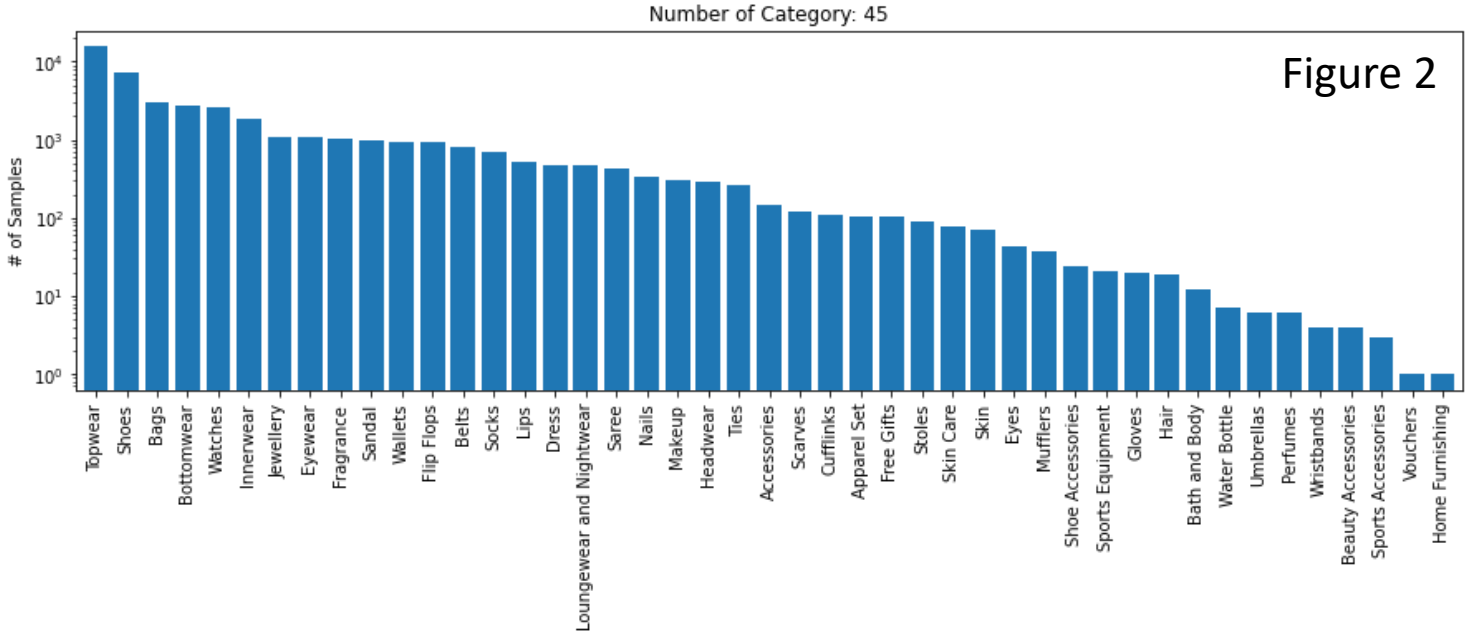
$$Balence = \frac{H}{H_{max}} = -\frac{1}{\log C}\sum_{i=1}^{C}\frac{n_i}{N}\log\frac{n_i}{N}\,,$$

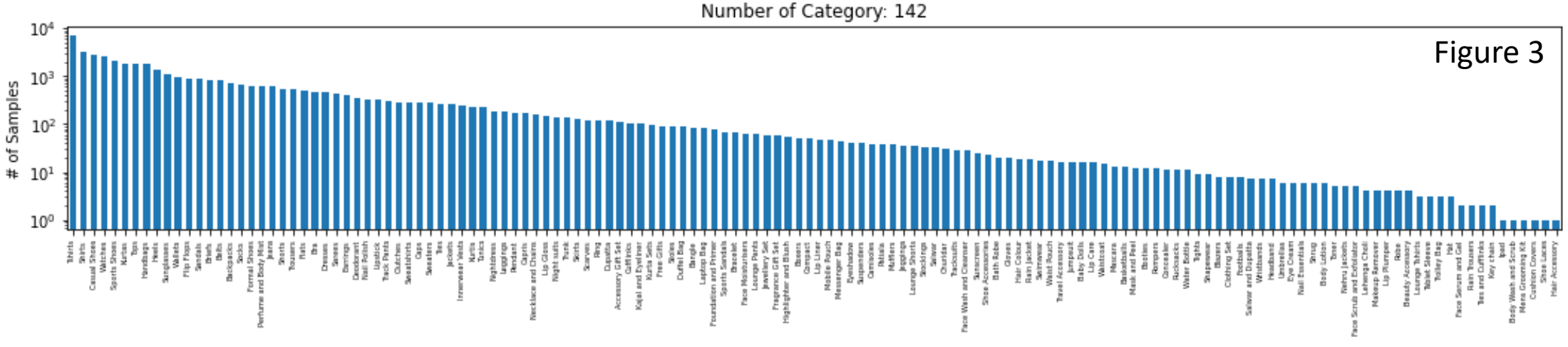
N: the total number of samples across all classes.
n_i: sample count of class i.

Categorical Feature	Measure of Balance	Sample Distribution
masterCategory	0.671	Figure 1
subCategory	0.644	Figure 2
articleType	0.731	Figure 3
Class	0.815	Figure 5

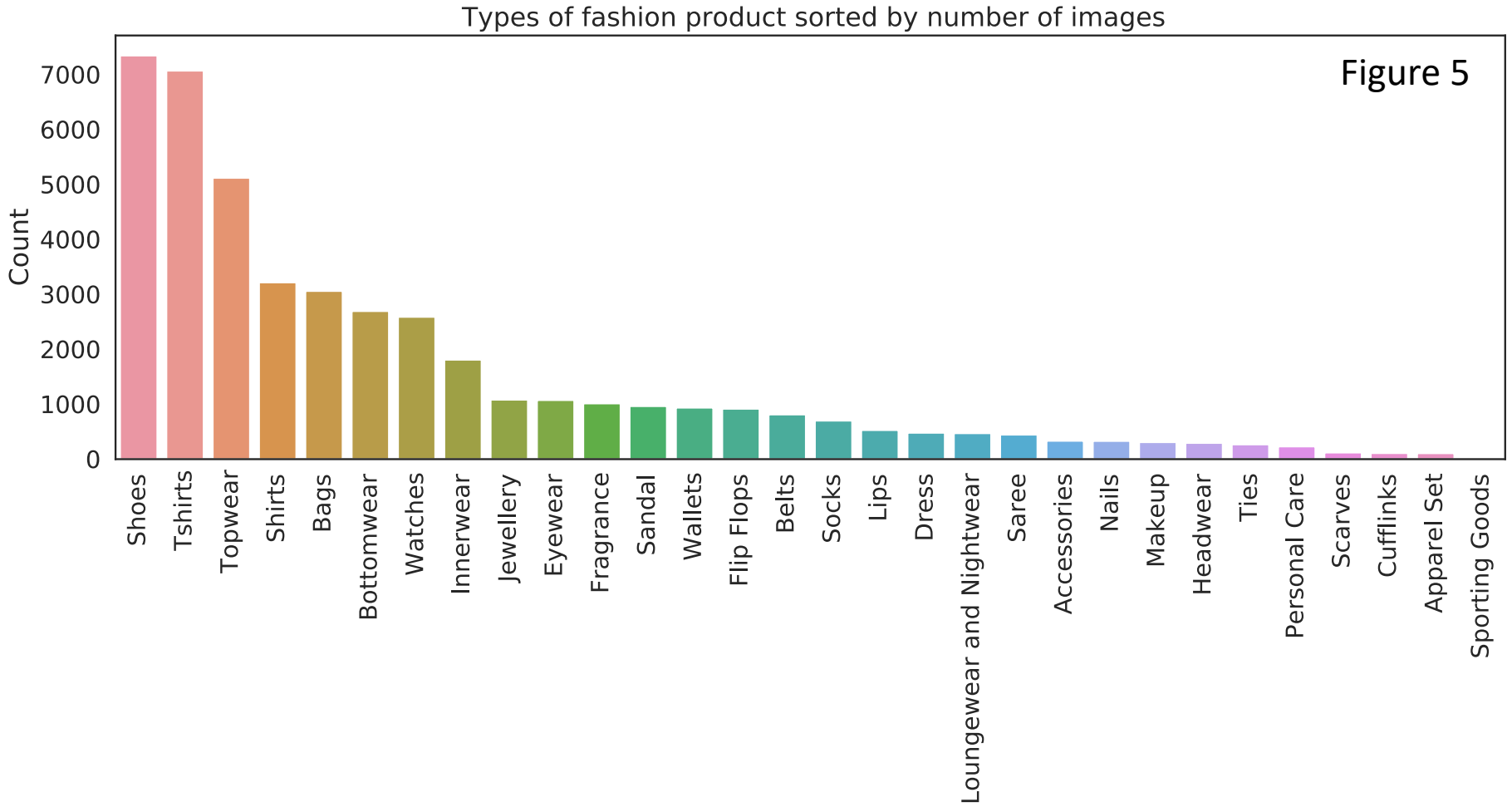
Product Counts (Original Categorical Labels)







Product Counts (Refined Categorical Labels)



Pre-processing and Training Data Development

- **Scale the Pixel Values**
  - 3 color channels, in the range of 0 to 255
    → rescale by 1/255 to transform the pixel values to range of 0-1, as preferred by the neural network models.
  - Also, Keras API provides option to train with color (default setting) or grayscale images.
- **Image Augmentation**
  - Horizontally flipping randomly on images.
  - Most of the pictures are well centered and correctly orientated. Applying shifts or rotations would not improve the model performances.
- **Split Train-validation and Hold-on Sets**
  - Training (72%); validation (18%); hold-on (10%).
  - Set a **batch size of 32**.
    Each of the train and validation datasets are divided into groups of 32 images.

```
## Build the model using the Keras API
chanDim = -1  # RGB Channel is last
model = tf.keras.models.Sequential()

# 1st CONV & RELU => BatchNorm => POOL layer set
model.add(Conv2D(32, (3, 3), activation='relu', padding='same'
                 input_shape=inputShape))
model.add(BatchNormalization(axis=chanDim))
model.add(Conv2D(32, (3, 3), activation='relu', padding='same'
model.add(BatchNormalization(axis=chanDim))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.2))

# 2nd CONV & RELU => BatchNorm => POOL layer set
model.add(Conv2D(64, (3, 3), activation='relu', padding='same'
model.add(BatchNormalization(axis=chanDim))
model.add(Conv2D(64, (3, 3), activation='relu', padding='same'
model.add(BatchNormalization(axis=chanDim))
model.add(MaxPooling2D(pool_size=(2, 2)))
model.add(Dropout(0.2))

# first (and only) set of FC(fully connected) => RELU layers
model.add(Flatten())
model.add(Dense(512, activation='relu'))
model.add(BatchNormalization())
model.add(Dropout(0.25))

# softmax classifier
model.add(Dense(classes, activation='softmax'))
```

CNN Model Architectures

Input → Convo (ReLU) → BatchNorm
→ Convo (ReLU) → BatchNorm
→ Max Pooling 1 → Dropout (0.2)

→ Convo (ReLU) → BatchNorm
→ Convo (ReLU) → BatchNorm
→ Max Pooling 2 → Dropout (0.2)

→ FC layer (ReLU) → BatchNorm
→ Dropout (0.25)
→ Output (Softmax)

```
Model: "sequential"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv2d (Conv2D)              (None, 80, 60, 32)        896
_________________________________________________________________
batch_normalization (BatchNo (None, 80, 60, 32)        128
_________________________________________________________________
conv2d_1 (Conv2D)            (None, 80, 60, 32)        9248
_________________________________________________________________
batch_normalization_1 (Batch (None, 80, 60, 32)        128
_________________________________________________________________
max_pooling2d (MaxPooling2D) (None, 40, 30, 32)        0
_________________________________________________________________
dropout (Dropout)            (None, 40, 30, 32)        0
_________________________________________________________________
conv2d_2 (Conv2D)            (None, 40, 30, 64)        18496
_________________________________________________________________
batch_normalization_2 (Batch (None, 40, 30, 64)        256
_________________________________________________________________
conv2d_3 (Conv2D)            (None, 40, 30, 64)        36928
_________________________________________________________________
batch_normalization_3 (Batch (None, 40, 30, 64)        256
_________________________________________________________________
max_pooling2d_1 (MaxPooling2 (None, 20, 15, 64)        0
_________________________________________________________________
dropout_1 (Dropout)          (None, 20, 15, 64)        0
_________________________________________________________________
flatten (Flatten)            (None, 19200)             0
_________________________________________________________________
dense (Dense)                (None, 512)               9830912
_________________________________________________________________
batch_normalization_4 (Batch (None, 512)               2048
_________________________________________________________________
dropout_2 (Dropout)          (None, 512)               0
_________________________________________________________________
dense_1 (Dense)              (None, 30)                15390
=================================================================
Total params: 9,914,686
Trainable params: 9,913,278
Non-trainable params: 1,408
```

CNN Model Architectures

Input → Convo (ReLU) → BatchNorm
→ Convo (ReLU) → BatchNorm
→ Max Pooling 1 → Dropout (0.2)

→ Convo (ReLU) → BatchNorm
→ Convo (ReLU) → BatchNorm
→ Max Pooling 2 → Dropout (0.2)

→ FC layer (ReLU) → BatchNorm
→ Dropout (0.25)
→ Output (Softmax)

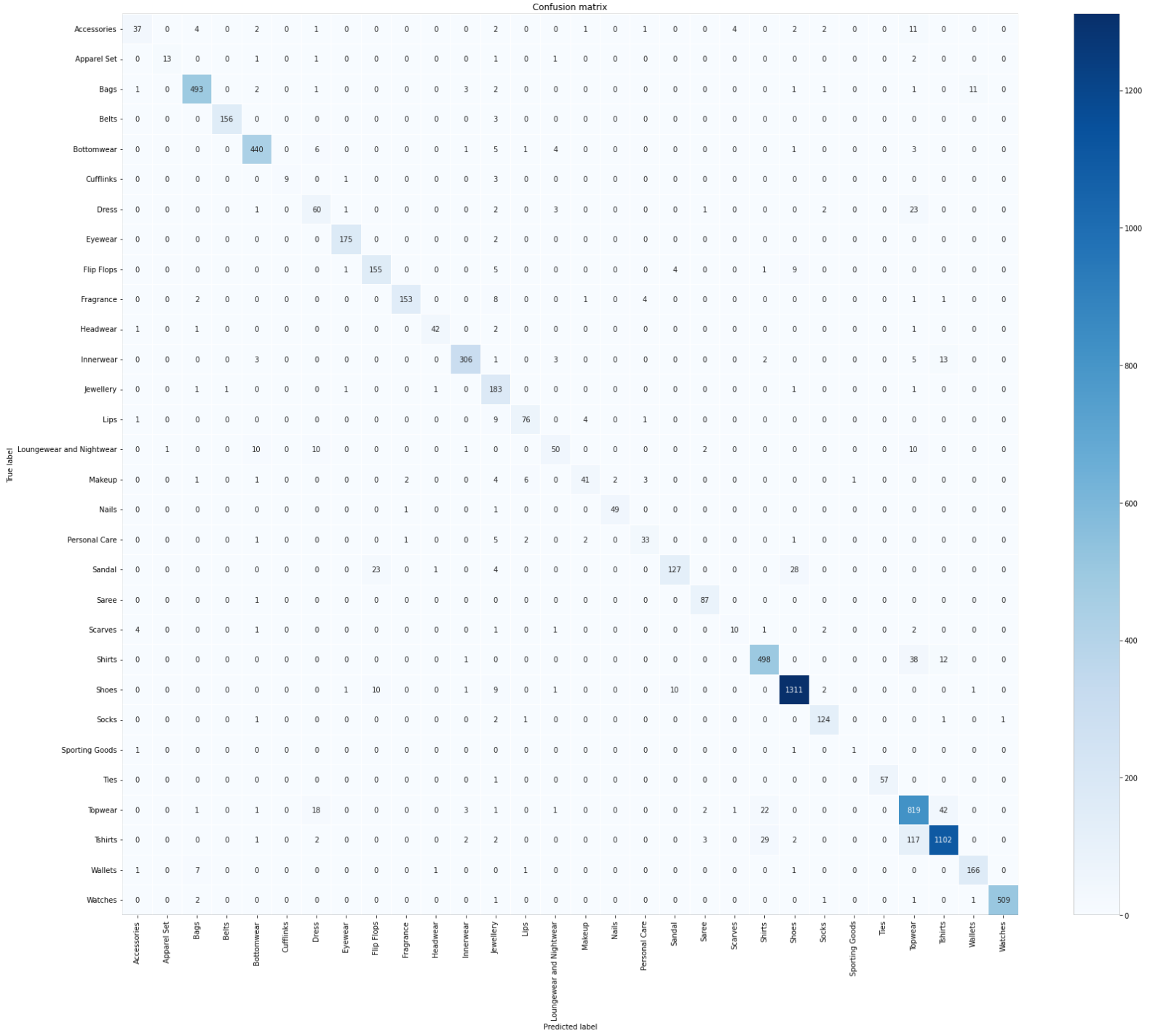
Loss & Accuracy

Dataset		*Loss*	*Accuracy*
Color images (80 x 60 x 3)	Training	0.196	0.935
	Validation	0.285	0.913
	Hold-on (test)	0.189	0.940
Gray images (80 x 60 x 1)	Training	0.162	0.946
	Validation	0.273	0.917
	Hold-on (test)	0.191	0.938

CNN model with the same architecture but trained with either color or grayscale images. The two model have similar performances.

Confusion Matrix

CNN classifier trained with the color images. The model is commonly confused with “Sandal” and “Shoes”; “Topwear” and “Shirts”.



MISCLASSIFIED ITEMS

PREDICT THE NEW ITEMS (LABEL UNKNOWN)

Predicted as: Fragrance

Predicted as: Tshirts

Predicted as: Eyewear

Predicted as: Bags

Predicted as: Scarves

Predicted as: Bags

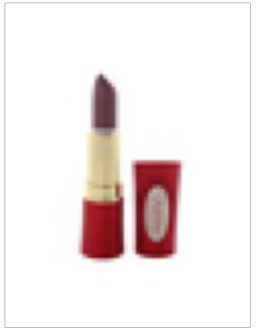
Predicted as: Bags

Predicted as: Bags

Predicted as: Bags

Predicted as: Eyewear

Predicted as: Lips



Predicted as: Bags

Predicted as: Eyewear

Predicted as: Watches

Predicted as: Eyewear

Predicted as: Eyewear

Predicted as: Bags

Predicted as: Eyewear

Predicted as: Bags

Predicted as: Eyewear

Predicted as: Wallets

Predicted as: Eyewear

Predicted as: Fragrance

Predicted as: Shoes

Conclusion

- The provided product labels are imbalanced and have high cardinality (too many unique values).
  → we defined a new set of **30 classes** based on the 3 categorical features in the original data.
- Trained CNN models on classifying fashion product images (color and grayscale) into **30 classes.**
  → Both reached the **accuracy of 0.91 - 0.92** on the validation set.
  → The model has the least performance in the class with fewest samples ("Sporting Goods," 25 images).
- The classifier is commonly confused when
  - Images belong to the same master category
    (ex: "Topwear", "T-shirt" and "Shirts" are in the same mastercategory "Topwear").
  - High similarity in product shape (Sandal" and "Shoes").

  → Improved by using images with higher resolution, data augmentation, or refining the image labels.

Future Work

- To improve the model classifying the fined details in products:
  - Use higher resolution images for training.
    Yet, this would cost more training time as trainable parameters will be scaled up with the input dimensions.
  - Try fine tune the current CNN architectures.
    Ex: adding a pooling layer after each convolutional layer; for the fully connect layers, using two small dense layers (at size of 256 and 128) instead of a single large dense layer.

- There are countless CNN architectures or pre-trained models.
  → Use transfer learning to take advantage of those pre-trained models (ResNet, VGG).

- Computer vision is the thrived research field, and new ideas/models are coming out time by time. The recent one capturing my eye is Vision Transformer (ViT) in 2021.