ASSIGNMENT 1C

CAB420, Machine Learning

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Problem 1: Clustering and Recommendations

Description and Justification of Clustering Method

Data Chosen to Cluster

The data sets chosen for the approach were the movies and ratings csv files. These data sets were manipulated by averaging the movies ratings, extracting each genre from the movies, and applying this extraction to the user's ratings for the movies they've seen. Then, as can be seen in *Table 1* below, the data was grouped by the user ID's and their rating for each genre. All NaN values (genres the users have not seen) were replaced with zeros to indicate that no rating was given. This data was chosen and formatted in this way to allow the clustering process to detect similar viewing preferences of the users based on their genre ratings.

userId	(no genres listed)	Mystery	Action	Horror	Comedy
1	0	4.166667	4.322222	3.470588	4.277108
2	0	4.000000	3.954545	3.000000	4.000000
3	0	5.000000	3.571429	4.687500	1.000000
4	0	3.478261	3.320000	4.250000	3.509615
5	0	4.000000	3.111111	3.000000	3.466667

Table 1: An example of the data used; snippet of users and genres from the data.

Selected Clustering Method

Clustering users based on their movie genre preferences allows the recommendation process to be more accurate and personalised to specific likes and dislikes. To select a method for this, both KMeans and GMM methods were investigated. As seen in *Figure 1* below, the distributions formed circular-like groupings that the KMeans method was able to categorise in uniform clusters around the centroids (centre points). For GMM the clusters were more spread out, therefore creating fewer uniform shapes. Due to this, the KMeans method was chosen as the final method implemented as it provided the best clusters for providing accurate recommendations to the target users. The KMeans method will also easily adapt to new examples, so users added to the system should be effectively factored into a cluster.

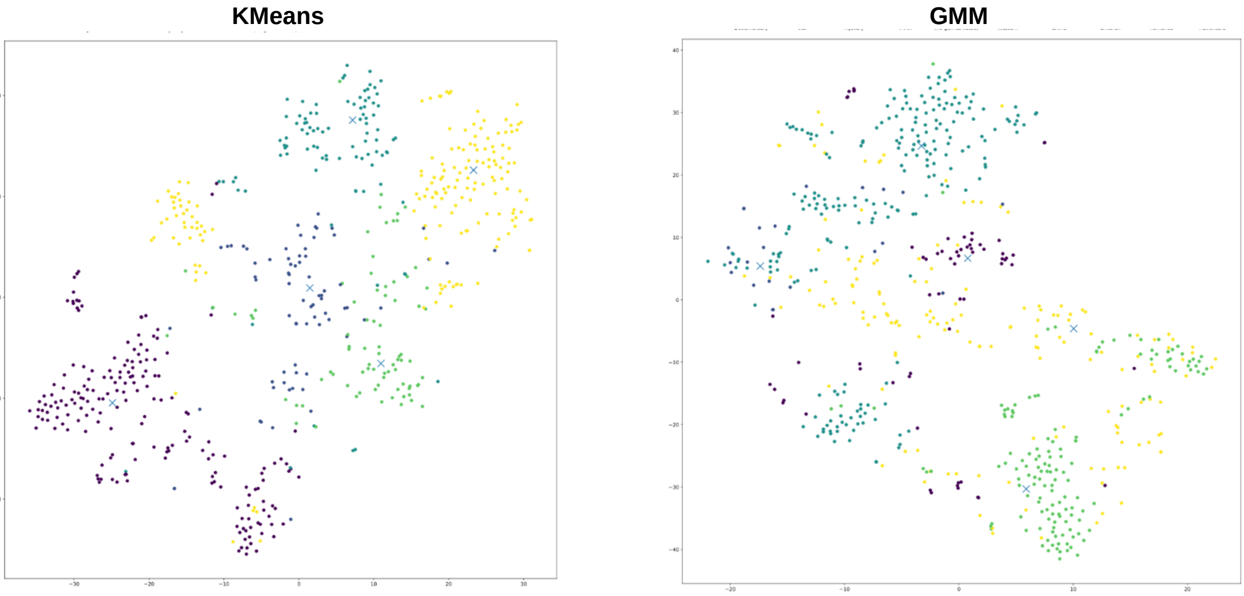


Figure 1: The clustering distributions, shown via TSNE models, of both the KMeans and GMM methods.

Selected Clustering Hyper-Parameters

The KMeans hyperparameters are *random_state*, which sets a random seed useful for reproducing exact clusters, and the number of clusters (*n_clusters*, or *k*). The random_state parameter was set to 4 through testing and fine tuning. The value for *k* was set to 5 through modelling the Bayesian Information Criterion (BIC) against *k*; the best *k* minimises the BIC. As seen in *Figure 2* below, the lowest approximate BIC occurs when the *k* value is also low, showing a smaller *k* is ideal; the approximated best *k* was 1, but as clusters were required this was increased. Having few clusters with large user groups would provide the most accurate recommendations to the target users as the average rating calculations would have higher variance to account for, which is why *k* was set to 5.

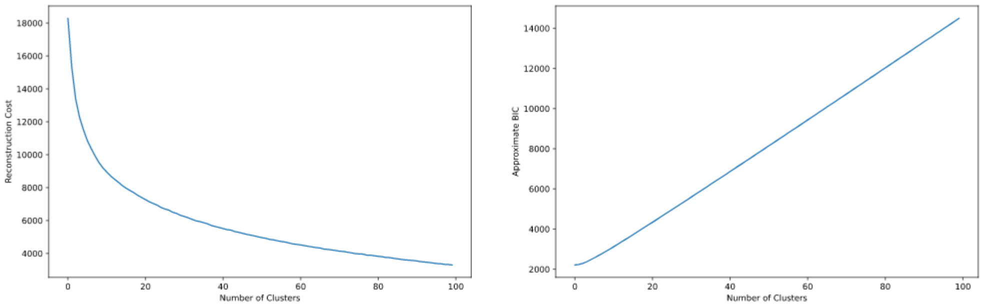


Figure 2: BIC curve for KMeans to approximate the number of clusters (k).

Discussion and Analysis of Clustering Results

As stated, the KMeans clustering outlined circular-like, uniform distributions in the data. As can be seen in *Figure 3* below, there are five distinct clusters, though one cluster (yellow) holds a small group of outliers. A few other outliers are also present in the model, possibly skewing the average movie ratings in those clusters.

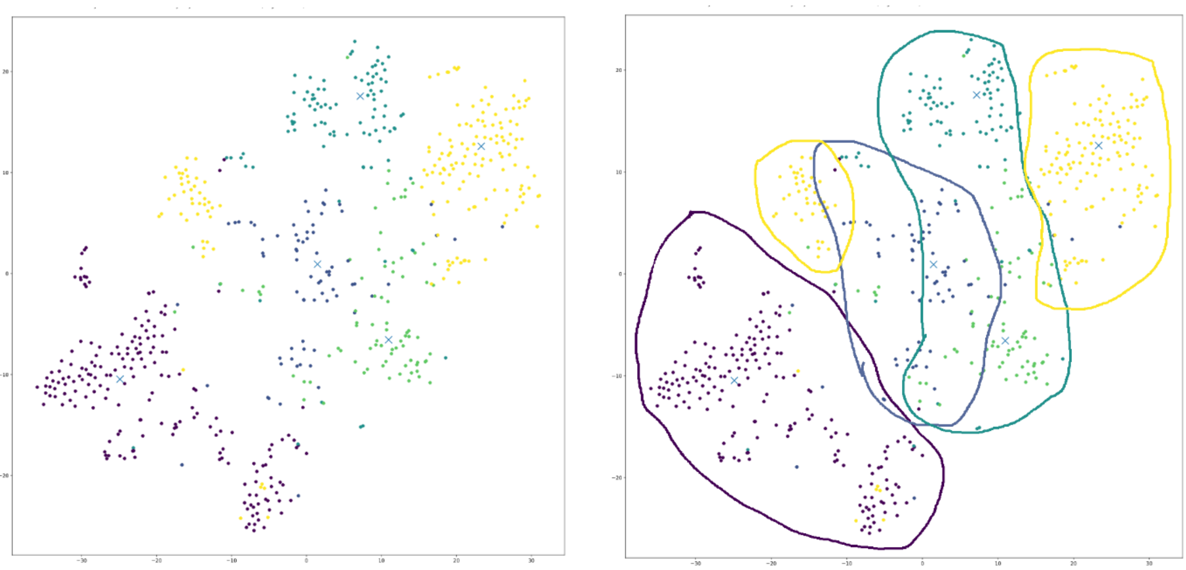


Figure 3: The TSNE model for the clusters created and outlined cluster distributions.

In *Figure 4* below, the average movie ratings for each cluster can be seen. For most genres, the ratings are similar in each cluster; most users enjoy similar genres. Though, there is some variation in each cluster's ratings. For example, in cluster 3, Western is ~0.02, and for cluster 4, Film-Noir is ~0.1. As this variance exists and is different for each cluster, the clusters obtained accurately capture the different viewer habits present in the data.

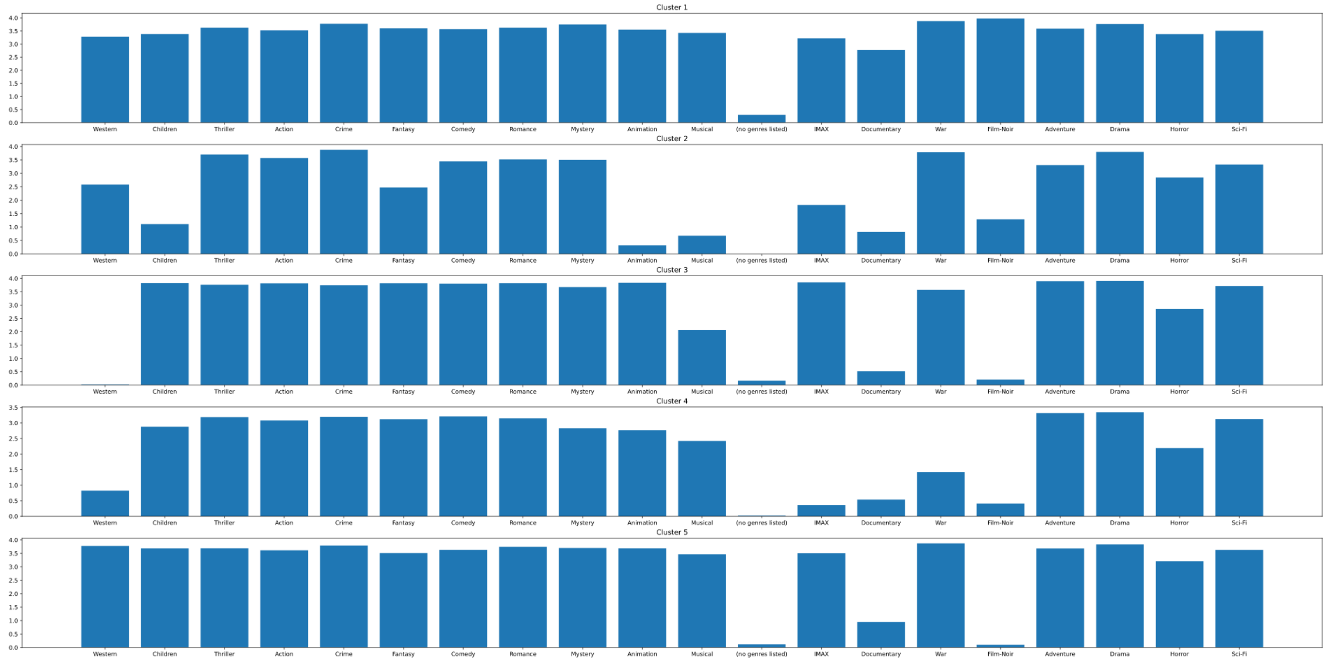


Figure 4: The clusters created for the dataset, showcasing each movies average ratings.

The clusters that each target user belonged to were cluster 1 for users 4 and 42, and cluster 5 for user 314. In *Figure 5* below, each user's average movie ratings can be seen. The ratings for users 4 and 42 are quite uniform; each genre is rated above ~2.9 (excluding no genres) which matches the ratings seen in cluster 1. For user 314, they have not seen the Documentary and Film-Noir genres, meaning the ratings are 0 and therefore match the ratings seen in cluster 5. As these rating results match these users have been clustered accurately.

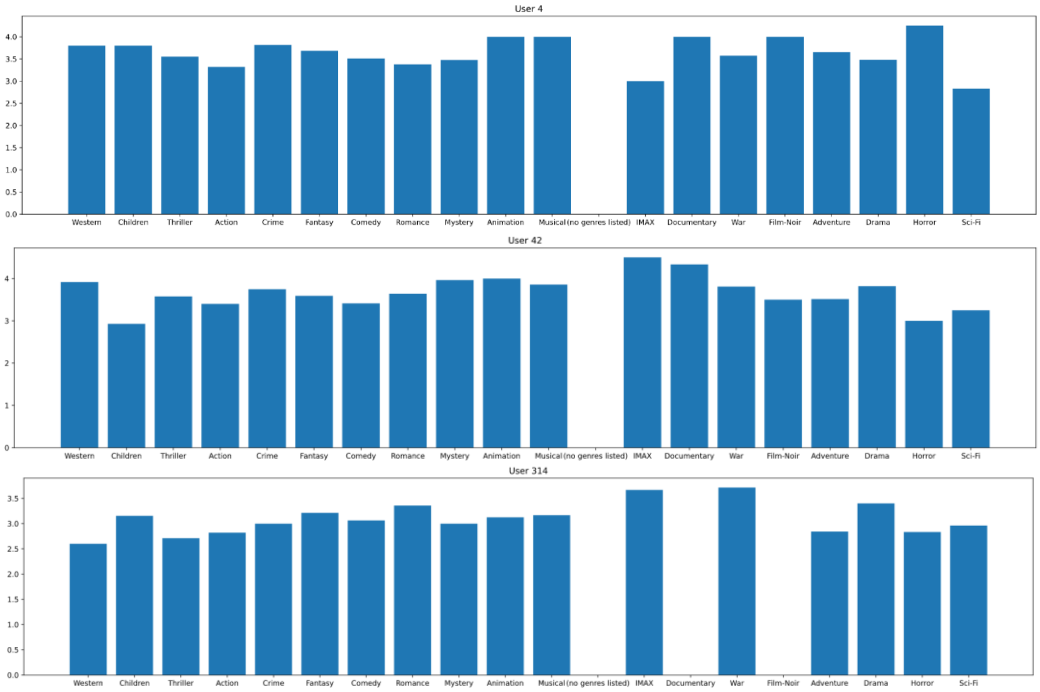


Figure 5: The average movie ratings for each target user 4, 42, and 314.

Recommendations for Users 4, 42, and 314

Description and Justification of Recommendation Method

The method used to provide recommendations was structured as follows:

1. Obtain a list for each target user containing the IDs of movies they have not seen. This was done by taking the movies they have rated and comparing that to the full movies dataset; any movie ID present in both sets were removed, leaving only the movies the user has not seen (rating of 0).
2. Obtain a list for each target cluster (1 and 5) containing the IDs of all the users present in that cluster.
3. Create a DataFrame for each target user containing the full set of movie ratings given by the users in the corresponding target cluster, excluding any ratings for movies the target user has seen. An example can be seen in *Figure 5* below.
4. Create a final DataFrame for each target user containing the averaged ratings for the movies from the previous DataFrame (final recommendations); done using the average ratings method provided. An example can also be seen in *Figure 5* below.

DataFrame of ALL user's movie ratings			
userId	**movieId**	**rating**	**timestamp**
1	1	4.0	964982703
1	3	4.0	964981247
1	6	4.0	964982224
...	...	...	...
610	8961	5.0	1493844829
610	8983	3.5	1493845284
610	8985	2.5	1493845630

→

DataFrame of AVERAGED movie ratings	
movieId	**rating**
4142	5.00
1631	5.00
495	5.0
...	...
1328	0.5
4580	0.5
5356	0.5

Figure 5: DataFrame's for User 4 Cluster 1, containing only the movies User 4 has NOT seen. Displaying tables for both the user ratings and the averaged ratings (final recommendations).

This method was used to find recommendations for each target user as it provided an accurate way to obtain movies the user may enjoy. Due to the clustering of similar preferences, by taking the user ratings given for movies not seen by the target users, and averaging them to obtain the clusters top-rated movies, the preferences of the target users have been considered and allowed for accurate recommendations to be made.

Validity of Recommendations

Recommendations for User 4 (67 total)				
Rec No.	**Movie ID**	**Movie Title**	**Rating**	**Genre(s)**
1	4142	Left Behind: The Movie (2000)	5.0	Action|Adventure|Drama|Thriller
2	1631	Assignment, The (1997)	5.0	Action|Thriller
3	495	In the Realm of the Senses (Ai no corrida) (1976)	5.0	Drama
4	5416	Cherish (2002)	5.0	Comedy|Drama|Thriller
5	3678	Man with the Golden Arm, The (1955)	5.0	Drama

Table 2: Top 5 movie recommendations for User 4.

For user 4, the top five movie recommendations are displayed in *Table 2* above. The genres recommended were action, adventure, drama, thriller, and comedy. As can be seen in *Table 3* below, the genres of these movies lie around the middle of user 4 and their cluster's ratings. It was expected that the movies recommended would be from genres rated highest by the cluster and fit with the user's preferences, so the highest rated movies not being a part of these genres is interesting. An explanation for the discrepancy may be that more people have seen the top-rated movies, therefore given them their high rankings. While the genres recommended were not a part of the top three for the cluster's rankings, due to the ranking ranges and genre positions it is not invalid that these movies would be highly ranked and therefore recommended to the user. Also, as these movies have not been seen by the user, they are valid.

User 4 Average Genre Ratings									
(no genres listed)	Sci-Fi	IMAX	Action	Romance	Mystery	Drama	Comedy	Thriller	War
0.0000	2.8333	3.0000	3.3200	3.3793	3.4783	3.4833	3.5096	3.5526	3.5714
Adventure	Fantasy	Western	Children	Crime	Animation	Musical	Documentary	Film-Noir	Horror
3.6552	3.6842	3.8000	3.8000	3.8148	4.0000	4.0000	4.0000	4.0000	4.2500
Cluster 1 Average Genre Ratings									
(no genres listed)	Documentary	IMAX	Western	Horror	Children	Musical	Sci-Fi	Action	Animation
0.2974	2.7762	3.2202	3.2828	3.3804	3.3826	3.4268	3.5087	3.5301	3.5537
Comedy	Adventure	Fantasy	Romance	Thriller	Mystery	Drama	Crime	War	Film-Noir
3.5706	3.5893	3.6018	3.6274	3.6275	3.7503	3.7693	3.7803	3.8806	3.9762

Table 3: The average genre ratings for User 4 and Cluster 1 rounded to 4 decimal places. The recommended genres are highlighted.

Recommendations for User 42 (68 total)				
Rec No.	**Movie ID**	**Movie Title**	**Rating**	**Genre(s)**
1	3851	I'm the One That I Want (2000)	5.0	Comedy
2	5244	Shogun Assassin (1980)	5.0	Action|Adventure
3	4116	Hollywood Shuffle (1987)	5.0	Comedy
4	4135	Monster Squad, The (1987)	5.0	Adventure|Comedy|Horror
5	389	Colonel Chabert, Le (1994)	5.0	Drama|Romance|War

Table 4: Top 5 movie recommendations for User 42.

The top five recommendations for user 42 are displayed in *Table 4* above. The genres recommended were comedy, action, adventure, horror, drama, romance, and war. Like the recommendations for user 4, these genres fit around the middle of the clusters and user's preferences, though the recommended war genre is ranked 2nd for the cluster, as can be seen in *Table 5* below. As both these users are from the same cluster, the recommendations were expected to follow the same trend, while considering the individual's preferences, which they did. Due to this, and the fact the user has not seen the movies, these rankings are valid for the user.

User 42 Average Genre Ratings									
(no genres listed)	Children	Horror	Sci-Fi	Action	Comedy	Film-Noir	Adventure	Thriller	Fantasy
0.0	2.928571	3.0	3.25	3.4	3.412322	3.5	3.513889	3.577586	3.590909
Romance	Crime	War	Drama	Musical	Western	Mystery	Animation	Documentary	IMAX
3.640449	3.746479	3.809524	3.818713	3.857143	3.916667	3.962963	4.0	4.333333	4.5
Cluster 1 Average Genre Ratings									
(no genres listed)	Documentary	IMAX	Western	Horror	Children	Musical	Sci-Fi	Action	Animation
0.2974	2.7762	3.2202	3.2828	3.3804	3.3826	3.4268	3.5087	3.5301	3.5537
Comedy	Adventure	Fantasy	Romance	Thriller	Mystery	Drama	Crime	War	Film-Noir
3.5706	3.5893	3.6018	3.6274	3.6275	3.7503	3.7693	3.7803	3.8806	3.9762

Table 5: The average genre ratings for User 42 and Cluster 1 rounded to 4 decimal places. The recommended genres are highlighted.

Recommendations for User 314 (139 total)				
Rec No.	**Movie ID**	**Movie Title**	**Rating**	**Genre(s)**
1	9010	Love Me If You Dare (Jeux d'enfants) (2003)	5.0	Drama|Romance
2	2924	Drunken Master (Jui kuen) (1978)	5.0	Action|Comedy
3	1011	Herbie Rides Again (1974)	5.0	Children|Comedy|Fantasy|Romance
4	6549	How to Deal (2003)	5.0	Comedy|Drama|Romance
5	3020	Falling Down (1993)	5.0	Action|Drama

Table 6: Top 5 movie recommendations for User 314.

For user 314, the top five movie recommendations are displayed in *Table 6* above. The genres recommended were drama, romance, action, comedy, children, and fantasy. Again, these genre rankings follow the same trend as the others, with some higher rated genres being recommended this time, seen in *Table 7* below. As most of these genre rankings fit to the user's preferences, for example drama, romance, and fantasy are ranked 3rd, 4th, and 5th respectively, whilst considering the cluster's rankings, these movie recommendations were also valid.

User 314 Average Genre Ratings									
(no genres listed)	Documentary	Film-Noir	Western	Thriller	Action	Horror	Adventure	Sci-Fi	Crime
0.0000	0.0000	0.0000	2.6000	2.7105	2.8200	2.8333	2.8421	2.9615	3.0000
Mystery	Comedy	Animation	Children	Musical	Fantasy	Romance	Drama	IMAX	War
3.0000	3.0625	3.1250	3.1538	3.1667	3.2143	3.3571	3.4000	3.6667	3.7143
Cluster 5 Average Genre Ratings									
Film-Noir	(no genres listed)	Documentary	Horror	Musical	IMAX	Fantasy	Action	Sci-Fi	Comedy
0.1017	0.1177	0.9490	3.2103	3.4684	3.5053	3.5123	3.6166	3.6287	3.6300
Adventure	Children	Animation	Thriller	Mystery	Romance	Western	Crime	Drama	War
3.6814	3.6839	3.6873	3.6929	3.6997	3.7455	3.7745	3.7970	3.8334	3.8717

Table 7: The average genre ratings for User 314 and Cluster 5 rounded to 4 decimal places. The recommended genres are highlighted.

Problem 2: Multi-Task Learning

Data Pre-processing and Augmentation

Augmentation

An autoencoder was used to generate augmented data for the problem. This augmentation included rotations between -45 and +45 degrees, translations of horizontal and vertical shifts by +/- 50% of the image's width/height, a shearing transform with a range of 0.5, image scaling changes with a range of 50%, and reflections on the x axis (horizontal flips). These augmentation values were chosen as they were realistic for the data set whilst preserving the image information that could be gained. By increasing the number of images available to classify through augmentation the solution could be generalised. Due to this generalisation, the solution could then be used for different data inputs if required in future iterations of the problem.

Handling Missing Data

The missing values present in the data were handled by creating new classes for them. For example, for the gender image trait, the classes were increased from 2 (0 = male, 1 = female) to 3 (0 = male, 1 = female, 3 = unknown). This allowed the training process to run smoothly without error as no negative values were present. One caveat to this approach was that it can reduce the accuracy in trait predictions as the unknown class is included in the training set. This affected around 13 of the 520 values for the 'train_y' set and 17 of the values for the 'test_y' set. If there had been more unknown data present, another approach could have been taken (i.e., filter out these values when modelling), but it was decided these numbers were acceptable.

Description and Justification of Approach

Network Design

The designed DCNN evaluated on the training set, architecture shown in *Figure 6* below, included several filters and dense layers to ensure classification accuracy. Three convolution layers, each followed by a max pooling layer, were used to filter the data. These layers used 8, 16, and 32 filters respectively to learn how to distinguish traits in the data, increasing the classification accuracy. The max pooling layers are present to down sample the data, allowing only the relevant and information data to remain, aiding the filtering process. These layers were flattened into a single vector and dense layers were created, one for each desired output (the six traits), each using their respective class sizes (e.g., gender has 2 classes, etc.). By creating an output layer for each trait, it allowed the multi-task classification of the traits for the training process.

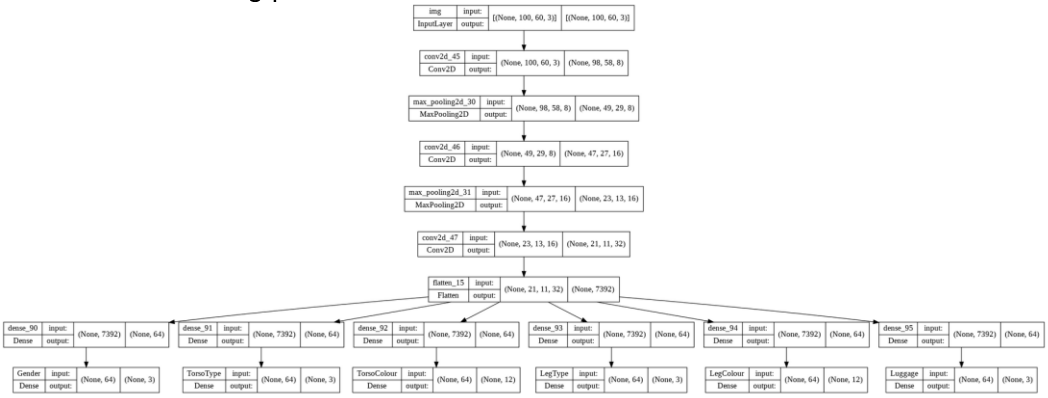


Figure 6: Multi-task classification model architecture.

Model Training Hyper-Parameters

The model was trained from scratch using a Sparse Categorical Cross Entropy loss type and an RMSprop optimiser. The batch size, number of epochs, and the steps for epochs were set to 64, 10, and 32 respectively. These numbers were selected due to the loss graphs and confusion matrices produced during fine-tuning; the fine-tuning process included changing these values so the best number could be chosen for each.

Performance Evaluation

Model Performance

A confusion matrix was modelled on the test data using the trained model for each trait in that data, as can be seen in *Figure 8* below. Some matrices are unbalanced even though they have the same number of classes (e.g., ‘gender’ versus ‘torso_type’) as not all are present in the test set. This is due to a severe class imbalance present in the data and can be seen throughout each matrix in *Figure 8*. Only two matrices, ‘luggage’ and ‘leg_colour’, and the anomaly ‘torso_type’, will be discussed further due the trend present in each.

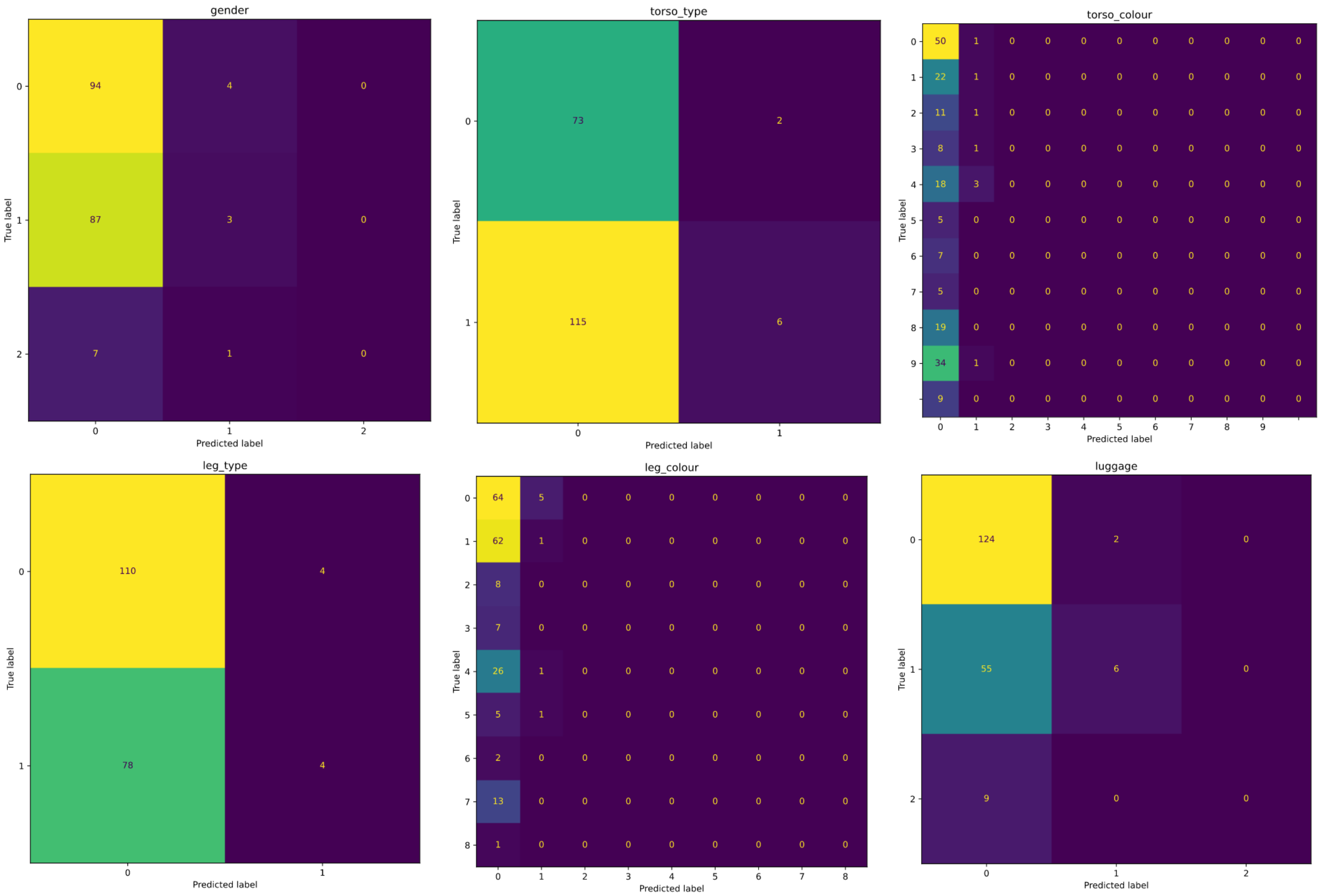


Figure 8: The confusion matrices for each trait: gender, torso clothing type, torso clothing colour, leg clothing type, leg clothing colour, and the presence of luggage.

Looking at the 'luggage' matrix the class imbalance and the issues it causes can be clearly seen. Here, there are 126 values of 0 (luggage present), 61 values of 1 (no luggage present), and 9 values of 2 (unknown). Due to this imbalance, the model has been unevenly trained for the example within the data; it received much more training to predict values for the majority class than the minority. This can be seen in the matrix as when the true label is 0 (majority class) it correctly predicts the trait 124 times, and only predicts it incorrectly, as 1, twice. When the true label is 1 it is wildly inaccurate as it is predicted to be zero 55 times, and only correctly predicted 6 times. For the true label 2 two (minority class) these predictions are the worst, only predicting it to be 0.

Moving on to the 'leg_colour' matrix, this trait had 12 different classes available to it: black (0), brown (1), blue (2), green (3), grey (4), orange (5), pink (6), purple (7), red (8), white (9), yellow (10) and unknown (11). Only 9 classes were present in the data, though once again there was severe imbalance of each, the majority class as 0 and minority (ignoring those not present) as 8. Due to this, once again the prediction heavily favoured the majority class, for most classes only predicting the value to be 0.

The trait matrices all follow this trend of the majority class being predicted correctly but creating incorrect predictions for each other class. The only exception being the matrix for 'torso_type', as the majority class is 1 (short) and the minority 0 (long), yet the matrix still predicts the 0 value more than 1. This could be due to the ongoing trend for each trait, so the algorithm has learnt that the prediction value should be 0 most of the time.

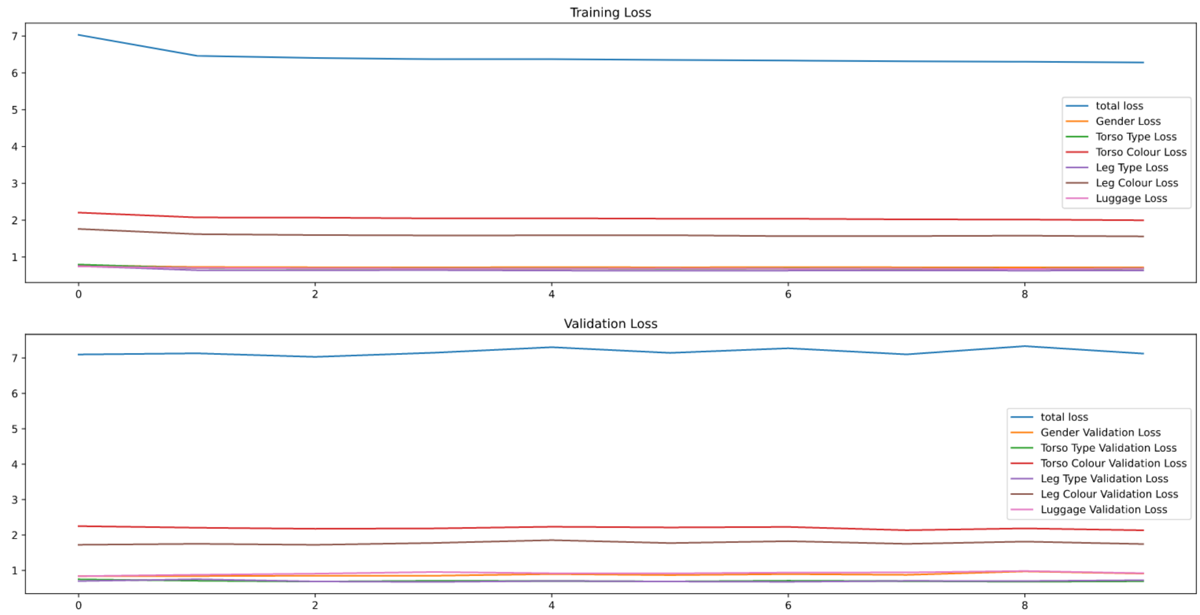


Figure 8: The training and validation loss for the data.

As seen in *Figure 8* above, the overall loss for both the training and validation sets is quite high, meaning the incorrect trait predictions make sense. The traits with the highest loss for both sets are the torso and leg colours, due to there being a high number of classes in these traits that have been incorrectly predicted. Interestingly, while these losses show the issues within the data, the losses do stabilise, meaning some outputs were easier to optimise within the data than others.

Semantic Search

Semantic search solves the problem of context for the images. For example, where the machine may recognise that a person’s leg clothing colour is red by understanding it is on the bottom half of their body, a human could recognise if that colour is the leg clothing or if it is just a jacket tied around their waist, showing that context for the image matters when classifying.

As the performance of the models were low, it is likely that when a semantic search query is placed the search would fail as images that do not fit the query would likely be returned. For better performance for the semantic search more evenly balanced classes should be used to train the model so the best possible results could be achieved. The semantic segmentation masks could also be used for the training and testing sets to further aid the classification of trait values.

Appendix

All code used was built upon using code from Lecture examples and Tutorial solutions.

n10477659 Final Assignment_1C

June 5, 2022

1 Assignment 1B

2 Import Functions

[1]:
```python
from google.colab import drive
drive.mount('/content/drive', force_remount=True)

# numpy handles pretty much anything that is a number/vector/matrix/array
import numpy as np
# pandas handles dataframes
import pandas as pd
# matplotlib emulates Matlabs plotting functionality
import matplotlib.pyplot as plt
# seaborn is another good plotting library. In particular, I like it for␣
↪heatmaps (https://seaborn.pydata.org/generated/seaborn.heatmap.html)
import seaborn as sns;
# stats models is a package that is going to perform the regression analysis
from statsmodels import api as sm
from scipy import stats
from sklearn.metrics import mean_squared_error, r2_score
# os allows us to manipulate variables on out local machine, such as paths and␣
↪environment variables
import os
# self explainatory, dates and times
from datetime import datetime, date
# a helper package to help us iterate over objects
import itertools

import time


## Q1
from sklearn.cluster import KMeans
from sklearn.mixture import GaussianMixture
from scipy.spatial import distance
from sklearn.manifold import TSNE
```

```python
from scipy.cluster.hierarchy import dendrogram
from matplotlib import cm

## Q2
import tensorflow as tf
from tensorflow import keras
from tensorflow.keras import layers
from tensorflow.keras import activations
from tensorflow.keras.preprocessing.image import ImageDataGenerator

from tensorflow.keras.layers import Input, Dense
from tensorflow.keras.models import Model
from tensorflow.keras.datasets import fashion_mnist

from tensorflow.keras import regularizers

from tensorflow.keras.layers import Input, Dense, Conv2D, MaxPooling2D,␣
 ↪UpSampling2D
from tensorflow.keras.models import Model
from tensorflow.keras import backend as K
from tensorflow.keras.utils import model_to_dot, plot_model

import sklearn
from sklearn.metrics import confusion_matrix, ConfusionMatrixDisplay
from sklearn.metrics import precision_score, recall_score, f1_score,␣
 ↪classification_report
from sklearn.svm import SVC, NuSVC
from tensorflow.keras.callbacks import ModelCheckpoint


# To export as pdf with better quality plots
from IPython.display import set_matplotlib_formats
set_matplotlib_formats('pdf', 'svg')
```

```
Mounted at /content/drive
```

```
/usr/local/lib/python3.7/dist-packages/statsmodels/tools/_testing.py:19:
FutureWarning: pandas.util.testing is deprecated. Use the functions in the
public API at pandas.testing instead.
  import pandas.util.testing as tm
```

3 Problem 1. Clustering and Recommendations.

Using the provided data, and (optionally) the above described code you are to develop a method to cluster users based on their movie viewing preferences. Having developed this, provide recommendations for the users with the IDs 4, 42, and 314.

A suggested approach to solving this problem is to: * Cluster the combined table that contains the average rating each user has reported for movies belonging to each genre. You will have to decide how you treat genres that have an average rating of NaN, which indicates that the user has not watched any movies from this genre; and select an appropriate clustering method and clustering hyper-parameters.

- Identify the clusters that contain the target users, 4, 42, and 314.
- Find the most popular movies within clusters that contain the target users, that the target users have not already seen.

Note that the above is simply a suggested approach, and you are welcome to select an alter- nate method.

[ ]:
```
## Utils

#
# Utility functions for CAB420, Assignment 1C, Q1
# Author: Simon Denman (s.denman@qut.edu.au)
#

import pandas   # to load csvs and manipulate the resulting data frames
import math     # for isnan
import os       # for path stuff

# load the data, in particular the movies and ratings files
#   base_path: directory that contains the quetions CSV files
#
#   returns:   dataframes for movies.csv and ratings.csv
#
def load_data(base_path):
    # simply using pandas.read_csv here
    movies = pandas.read_csv(os.path.join(base_path, 'movies.csv'))
    ratings = pandas.read_csv(os.path.join(base_path, 'ratings.csv'))
    return movies, ratings

# get a modified version of the ratings table, that has the average rating fo␣
 ↪each film
#   ratings_table: data frame for the movies ratings
#
#   returns:       dataframe that contains movie IDs and the average ratings␣
 ↪for each movie
#
def get_average_rating_per_film(ratings_table):
    # drop userId and timestamp as the average of these is meaningless
    # group the data by the movieId, and average the remaining columns (rating)
    return ratings_table.drop(columns=['userId', 'timestamp']).
 ↪groupby('movieId').mean()
```

```python
# replace the 'genre' column with a series of columns, one per genre, where a␣
↪value of 1
# indicates that the genre is presnet in the movie. Any genre not present will␣
↪be set
# to NaN
#   movies_table: dataframe for the movies
#
#   returns:      modified dataframe, where the genre column has been expanded␣
↪to have one column for each genre, and the
#                 set of genres
#
def expand_genres(movies_table):

    # copy the table to create a working copy
    movies = movies_table.copy()
    # build a set of all the different genres, start with an empty set
    genres = set()
    # loop through all the movies
    for i, row in movies.iterrows():
        # build a set of genres for each movie, and get the union of this and␣
↪the overall genre set
        genres = genres.union(set(row['genres'].split('|')))

    # create a column for each of our new genres
    for g in genres:
        movies[g] = float("Nan")

    # loop through the movies
    for i, row in movies.iterrows():
        # and the genres present in each movie
        for g in set(row['genres'].split('|')):
            # and where a genre is present in a movie, set it to 1
            movies.loc[i,g] = 1

    # drop the original genres column
    movies = movies.drop(columns=['genres'])

    # return expanded table
    return movies, genres

# build a table that has the details of all movies a user has seen. This will␣
↪essentially replace the movieID with
# the genre flags for a film, and change the 1.0's that indicate what genre a␣
↪movie is to the user rating for the film.
# This representation is primarily intended as an intermediate step to getting␣
↪an average rating per user across
```

```
# genres, but you may use this (or vary it to get other aggregrated data) if␣
↪you so choose.
#   ratings_table: dataframe of ratings
#   movies_table:  dataframe of movies, expanded to have individual columns for␣
↪each genres
#   genres:        set of genres
#
#   returns:       merged dataframe, consisting of user IDs and the genres of␣
↪all movies they've watched and the rating
#
def movies_per_user(ratings_table, movies_table, genres):
    # merge of movieId
    merged = pandas.merge(ratings_table, movies_table, how='left', on="movieId")
    # loop across the merged table
    for i, row in merged.iterrows():
        # and the set of genres
        for g in genres:
            # and for any genre that is set for a movie
            if not math.isnan(row[g]):
                # set it's value to the rating the user gave the movie
                merged.loc[i, g] = row["rating"]

    # drop the movieId, rating, timestamp, and title columns
    merged_all_movies = merged.drop(columns=['movieId', 'rating', 'timestamp',␣
↪'title'])

    # return merged table
    return merged_all_movies

# get the average rating per genre for each user
#   movies_per_user_table: dataframe, that's the output of movies_per_user()
#
#   returns:               dataframe with one row per user, which contains the␣
↪average rating given to movies of each
#                          genre. Genres that the user has never seen will have␣
↪a value of NaN
#
def average_per_user(movies_per_user_table):
    return movies_per_user_table.groupby(['userId']).mean()
```

[ ]:

```
# Load the data
movies, ratings = load_data('/content/drive/My Drive/Assignment 1C/
↪CAB420_Assessment_1C_Data/Q1/')
print(movies.shape)
print(ratings.shape)
print(movies.head())
```

```
print(ratings.head())
```

```
(9742, 3)
(100836, 4)
   movieId                               title  \
0        1                    Toy Story (1995)
1        2                      Jumanji (1995)
2        3             Grumpier Old Men (1995)
3        4            Waiting to Exhale (1995)
4        5  Father of the Bride Part II (1995)

                                        genres
0  Adventure|Animation|Children|Comedy|Fantasy
1                   Adventure|Children|Fantasy
2                               Comedy|Romance
3                         Comedy|Drama|Romance
4                                       Comedy
   userId  movieId  rating  timestamp
0       1        1     4.0  964982703
1       1        3     4.0  964981247
2       1        6     4.0  964982224
3       1       47     5.0  964983815
4       1       50     5.0  964982931
```

3.1 From Utils Demo

3.1.1 Average Rating Per Film

Note that the output is now 9,724 rows, which suggests that 18 movies in the database have not been watched by anyone.

[ ]:
```
average_rating_per_film = get_average_rating_per_film(ratings)
print(average_rating_per_film.shape)
average_rating_per_film.head()
```

```
(9724, 1)
```

[ ]:
```
           rating
movieId
1        3.920930
2        3.431818
3        3.259615
4        2.357143
5        3.071429
```

3.1.2 Pulling Our Genres

```
[ ]: movies_with_genres, genres = expand_genres(movies)
     print(movies_with_genres.shape)
     movies_with_genres.head()
```

```
(9742, 22)
```

```
[ ]:    movieId                               title  Western  Children  Thriller  \
     0        1                    Toy Story (1995)      NaN       1.0       NaN
     1        2                      Jumanji (1995)      NaN       1.0       NaN
     2        3             Grumpier Old Men (1995)      NaN       NaN       NaN
     3        4            Waiting to Exhale (1995)      NaN       NaN       NaN
     4        5  Father of the Bride Part II (1995)      NaN       NaN       NaN

        Action  Crime  Fantasy  Comedy  Romance  …  Musical  (no genres listed)  \
     0     NaN    NaN      1.0     1.0      NaN  …      NaN                 NaN
     1     NaN    NaN      1.0     NaN      NaN  …      NaN                 NaN
     2     NaN    NaN      NaN     1.0      1.0  …      NaN                 NaN
     3     NaN    NaN      NaN     1.0      1.0  …      NaN                 NaN
     4     NaN    NaN      NaN     1.0      NaN  …      NaN                 NaN

        IMAX  Documentary  War  Film-Noir  Adventure  Drama  Horror  Sci-Fi
     0   NaN          NaN  NaN        NaN        1.0    NaN     NaN     NaN
     1   NaN          NaN  NaN        NaN        1.0    NaN     NaN     NaN
     2   NaN          NaN  NaN        NaN        NaN    NaN     NaN     NaN
     3   NaN          NaN  NaN        NaN        NaN    1.0     NaN     NaN
     4   NaN          NaN  NaN        NaN        NaN    NaN     NaN     NaN

     [5 rows x 22 columns]
```

3.1.3 Detailed Data For Users

Users movie ratings for what they've seen

```
[ ]: user_movies = movies_per_user(ratings, movies_with_genres, genres)
     print(user_movies.shape)
     user_movies.head()
```

```
(100836, 21)
```

```
[ ]:    userId  Western  Children  Thriller  Action  Crime  Fantasy  Comedy  \
     0       1      NaN       4.0       NaN     NaN    NaN      4.0     4.0
     1       1      NaN       NaN       NaN     NaN    NaN      NaN     4.0
     2       1      NaN       NaN       4.0     4.0    4.0      NaN     NaN
     3       1      NaN       NaN       5.0     NaN    NaN      NaN     NaN
     4       1      NaN       NaN       5.0     NaN    5.0      NaN     NaN
```

```
   Romance  Mystery  …  Musical  (no genres listed)  IMAX  Documentary  War  \
0      NaN      NaN  …      NaN                 NaN   NaN          NaN  NaN
1      4.0      NaN  …      NaN                 NaN   NaN          NaN  NaN
2      NaN      NaN  …      NaN                 NaN   NaN          NaN  NaN
3      NaN      5.0  …      NaN                 NaN   NaN          NaN  NaN
4      NaN      5.0  …      NaN                 NaN   NaN          NaN  NaN

   Film-Noir  Adventure  Drama  Horror  Sci-Fi
0        NaN        4.0    NaN     NaN     NaN
1        NaN        NaN    NaN     NaN     NaN
2        NaN        NaN    NaN     NaN     NaN
3        NaN        NaN    NaN     NaN     NaN
4        NaN        NaN    NaN     NaN     NaN

[5 rows x 21 columns]
```

Group user movie ratings by user ID

```
[ ]: user_genre_ratings = average_per_user(user_movies)
     print(user_genre_ratings.shape)
     user_genre_ratings.head()
```

```
(610, 20)
```

```
[ ]:         Western  Children  Thriller    Action     Crime   Fantasy    Comedy  \
     userId
     1       4.285714  4.547619  4.145455  4.322222  4.355556  4.297872  4.277108
     2       3.500000       NaN  3.700000  3.954545  3.800000       NaN  4.000000
     3            NaN  0.500000  4.142857  3.571429  0.500000  3.375000  1.000000
     4       3.800000  3.800000  3.552632  3.320000  3.814815  3.684211  3.509615
     5       3.000000  4.111111  3.555556  3.111111  3.833333  4.142857  3.466667

             Romance   Mystery  Animation   Musical  (no genres listed)      IMAX  \
     userId
     1       4.307692  4.166667   4.689655  4.681818                 NaN       NaN
     2       4.500000  4.000000        NaN       NaN                 NaN  3.750000
     3       0.500000  5.000000   0.500000  0.500000                 NaN       NaN
     4       3.379310  3.478261   4.000000  4.000000                 NaN  3.000000
     5       3.090909  4.000000   4.333333  4.400000                 NaN  3.666667

            Documentary       War  Film-Noir  Adventure     Drama    Horror  \
     userId
     1              NaN  4.500000        5.0   4.388235  4.529412  3.470588
     2         4.333333  4.500000        NaN   4.166667  3.882353  3.000000
     3              NaN  0.500000        NaN   2.727273  0.750000  4.687500
     4         4.000000  3.571429        4.0   3.655172  3.483333  4.250000
```

```
5                NaN  3.333333        NaN   3.250000  3.800000  3.000000

          Sci-Fi
userId
1       4.225000
2       3.875000
3       4.200000
4       2.833333
5       2.500000
```

This is one suggested dataset to cluster, which would allow you to characterise a users taste in films, much like the practical question looked at the trip advisor data.

Q. With Q1, if we use genres as suggested above, what do we do if a user has never seen a film from a particular genre?

A. You could replace this value with the average, set it to the minimum (assume that having never seen a genre is an indication that they are not a fan), or come up with a distance metric that allows you to compare in spite of the missing data. Note that the last option is a bit tricky (but cool and interesting), and if you're not confident don't go there.

[ ]:
```
## Replace all NaN values with the minimum
#Now, we can replace them
user_genre_ratings_use = user_genre_ratings.fillna(0)
user_genre_ratings_use
```

[ ]:
```
         Western  Children  Thriller    Action     Crime   Fantasy    Comedy  \
userId
1       4.285714  4.547619  4.145455  4.322222  4.355556  4.297872  4.277108
2       3.500000  0.000000  3.700000  3.954545  3.800000  0.000000  4.000000
3       0.000000  0.500000  4.142857  3.571429  0.500000  3.375000  1.000000
4       3.800000  3.800000  3.552632  3.320000  3.814815  3.684211  3.509615
5       3.000000  4.111111  3.555556  3.111111  3.833333  4.142857  3.466667
…            …         …        …         …         …         …         …
606     3.411765  3.448980  3.525126  3.178808  3.654135  3.597938  3.565321
607     4.000000  3.421053  4.114754  3.722222  3.814815  3.571429  3.327273
608     2.636364  2.460227  3.536680  3.330325  3.613014  3.000000  2.736620
609     4.000000  3.000000  3.285714  3.090909  3.500000  3.000000  3.285714
610     3.742424  3.651786  3.573529  3.600580  3.800366  3.592715  3.731144

         Romance   Mystery  Animation   Musical  (no genres listed)      IMAX  \
userId
1       4.307692  4.166667   4.689655  4.681818                 0.0  0.000000
2       4.500000  4.000000   0.000000  0.000000                 0.0  3.750000
3       0.500000  5.000000   0.500000  0.500000                 0.0  0.000000
4       3.379310  3.478261   4.000000  4.000000                 0.0  3.000000
5       3.090909  4.000000   4.333333  4.400000                 0.0  3.666667
…            …         …          …         …                   …         …
```

```
606     3.740845  3.791209   3.714286  3.727273                 0.0  3.062500
607     3.517241  4.647059   3.333333  3.600000                 0.0  5.000000
608     2.886792  3.550725   3.118182  2.757576                 0.0  4.000000
609     3.200000  0.000000   3.000000  0.000000                 0.0  3.000000
610     3.731092  3.766667   3.901515  3.928571                 0.0  3.628049

        Documentary       War  Film-Noir  Adventure     Drama    Horror  \
userId
1          0.000000  4.500000     5.0000   4.388235  4.529412  3.470588
2          4.333333  4.500000     0.0000   4.166667  3.882353  3.000000
3          0.000000  0.500000     0.0000   2.727273  0.750000  4.687500
4          4.000000  3.571429     4.0000   3.655172  3.483333  4.250000
5          0.000000  3.333333     0.0000   3.250000  3.800000  3.000000
…               …         …        …         …         …         …
606        3.800000  3.792308     3.8125   3.503401  3.787966  3.346154
607        0.000000  4.166667     0.0000   3.466667  4.012195  4.114286
608        3.000000  3.578947     3.7500   3.220994  3.437500  3.319588
609        3.000000  3.500000     0.0000   3.200000  3.368421  3.500000
610        4.200000  3.776596     4.3500   3.705993  3.874739  3.506601

          Sci-Fi
userId
1       4.225000
2       3.875000
3       4.200000
4       2.833333
5       2.500000
…            …
606     3.556962
607     3.250000
608     3.296407
609     3.000000
610     3.659363

[610 rows x 20 columns]
```

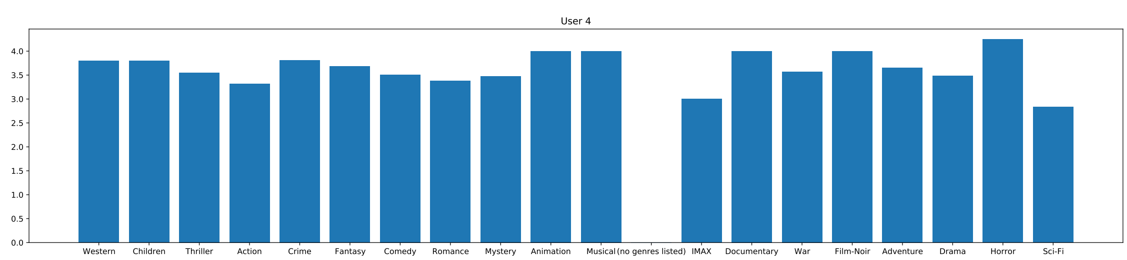
3.2 Plot the Target User's Ratings

[ ]:
```
## User 4
user4_data = user_genre_ratings_use.iloc[3]
print(user_genre_ratings_use.iloc[3:4])
x = ['Western',         'Children',          'Thriller',          'Action',␣
↪         'Crime',         'Fantasy',          'Comedy',          'Romance',␣
↪         'Mystery',         'Animation',          'Musical', '(no genres␣
↪listed)',
```

```
                  'IMAX',           'Documentary',          'War',␣
↪         'Film-Noir',          'Adventure',          'Drama',          'Horror',␣
↪         'Sci-Fi']


fig = plt.figure(figsize=[25, 5])
ax = fig.add_subplot(1, 1, 1)
ax.bar(x, user4_data)
ax.set_title('User 4')
```

```
        Western  Children  Thriller  Action     Crime   Fantasy    Comedy  \
userId
4           3.8       3.8  3.552632    3.32  3.814815  3.684211  3.509615

        Romance   Mystery  Animation  Musical  (no genres listed)  IMAX  \
userId
4       3.37931  3.478261        4.0      4.0                 0.0   3.0

        Documentary       War  Film-Noir  Adventure     Drama  Horror  \
userId
4               4.0  3.571429        4.0   3.655172  3.483333    4.25

          Sci-Fi
userId
4       2.833333
```

[ ]: Text(0.5, 1.0, 'User 4')

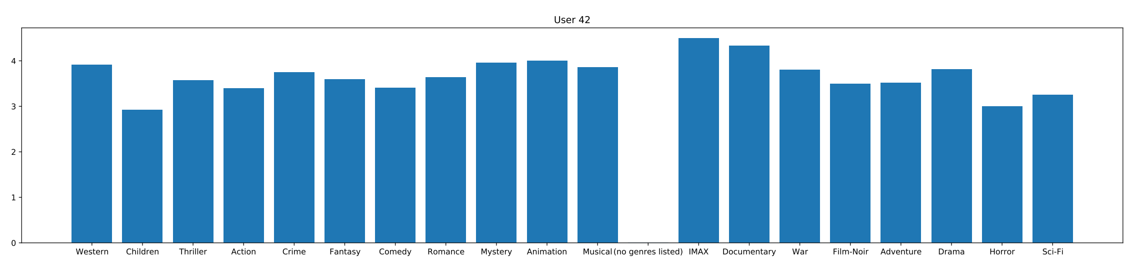


[ ]:
```
## User 42
user42_data = user_genre_ratings_use.iloc[41]
print(user_genre_ratings_use.iloc[41:42])
x = ['Western',         'Children',         'Thriller',         'Action',␣
↪         'Crime',         'Fantasy',         'Comedy',         'Romance',␣
↪         'Mystery',         'Animation',         'Musical', '(no genres␣
↪listed)',
```

```
                     'IMAX',          'Documentary',          'War',␣
↪         'Film-Noir',          'Adventure',          'Drama',          'Horror',␣
↪         'Sci-Fi']
fig = plt.figure(figsize=[25, 5])
ax = fig.add_subplot(1, 1, 1)
ax.bar(x, user42_data)
ax.set_title('User 42')
```

```
         Western  Children  Thriller  Action     Crime   Fantasy    Comedy  \
userId
42      3.916667  2.928571  3.577586     3.4  3.746479  3.590909  3.412322

         Romance   Mystery  Animation   Musical  (no genres listed)  IMAX  \
userId
42      3.640449  3.962963        4.0  3.857143                 0.0   4.5

        Documentary       War  Film-Noir  Adventure     Drama  Horror  Sci-Fi
userId
42         4.333333  3.809524        3.5   3.513889  3.818713     3.0    3.25
```

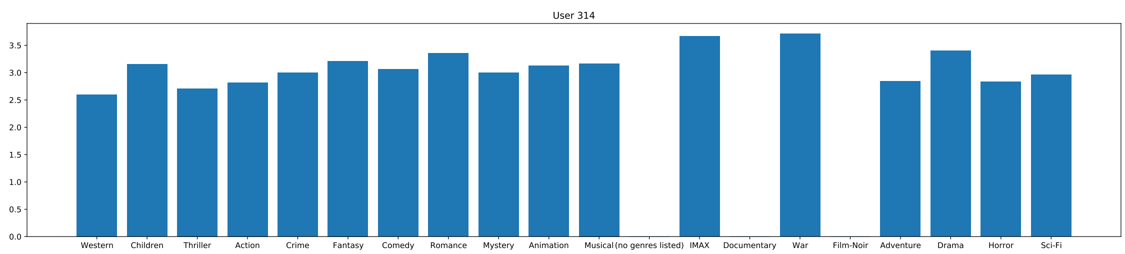
[ ]: Text(0.5, 1.0, 'User 42')



[ ]:
```
## User 314
user4_data = user_genre_ratings_use.iloc[313]
print(user_genre_ratings_use.iloc[313:314])
x = ['Western',          'Children',          'Thriller',          'Action',␣
↪         'Crime',          'Fantasy',          'Comedy',          'Romance',␣
↪         'Mystery',          'Animation',          'Musical', '(no genres␣
↪listed)',
                     'IMAX',          'Documentary',          'War',␣
↪         'Film-Noir',          'Adventure',          'Drama',          'Horror',␣
↪         'Sci-Fi']
fig = plt.figure(figsize=[25, 5])
ax = fig.add_subplot(1, 1, 1)
ax.bar(x, user4_data)
ax.set_title('User 314')
```

```
        Western  Children  Thriller  Action  Crime   Fantasy  Comedy  \
userId
314         2.6  3.153846  2.710526    2.82    3.0  3.214286  3.0625

         Romance  Mystery  Animation   Musical  (no genres listed)      IMAX  \
userId
314     3.357143      3.0      3.125  3.166667                 0.0  3.666667

        Documentary       War  Film-Noir  Adventure  Drama    Horror    Sci-Fi
userId
314             0.0  3.714286        0.0   2.842105    3.4  2.833333  2.961538
```

[ ]: Text(0.5, 1.0, 'User 314')



[ ]:
```
user_genre_ratings_use.iloc[3]
```

[ ]:
```
Western               3.800000
Children              3.800000
Thriller              3.552632
Action                3.320000
Crime                 3.814815
Fantasy               3.684211
Comedy                3.509615
Romance               3.379310
Mystery               3.478261
Animation             4.000000
Musical               4.000000
(no genres listed)    0.000000
IMAX                  3.000000
Documentary           4.000000
War                   3.571429
Film-Noir             4.000000
Adventure             3.655172
Drama                 3.483333
Horror                4.250000
Sci-Fi                2.833333
Name: 4, dtype: float64
```

3.3 Cluster the data based on users AND Identify Clusters of Users 4, 42, 314

Q. For Q1, what should I cluster?

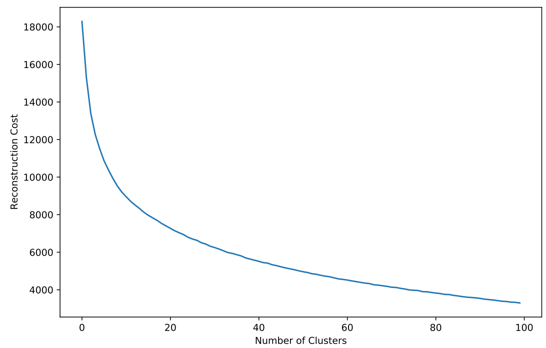
A. Consider that our main aim is to **recommend a movie to a user**, thus one approach would be to **cluster users**, and then **for a new user**, **work out which cluster they belong** to and **recommend movies based on what other people** in that cluster enjoyed. For this, you could **use the genres rather than movies** and use a **person's average scores across genres** to characterise them.

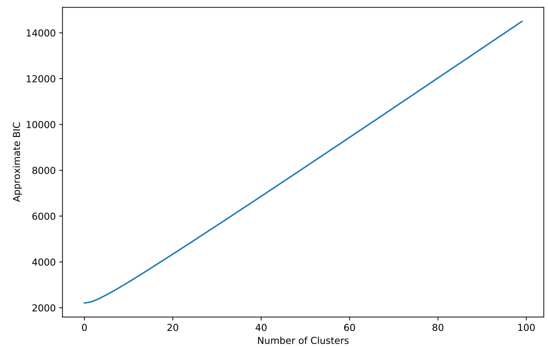
The provided code will set the data up for this approach, but are you are free to do something else.

3.3.1 Using K-Means Method (prac wk8 Q1 solution)

3.3.2 1. Find the best K

[ ]:
```
num_itts = 10

costs = [];
approx_bic = []
for i in range(100):
    c = 0
    a_b = 0
    for r in range(num_itts):
        kmeans = KMeans(n_clusters=i+1, random_state=r).
 ↪fit(user_genre_ratings_use)

        c += kmeans.inertia_

        k = np.shape(kmeans.cluster_centers_)[0]*(np.shape(kmeans.
 ↪cluster_centers_)[1] + 1)
        m = len(user_genre_ratings_use)
        a_b += m*np.log(kmeans.inertia_ / m) + k*np.log(m)

    costs.append(c / num_itts)
    approx_bic.append(a_b / num_itts)

fig = plt.figure(figsize=[20, 6])
ax = fig.add_subplot(1, 2, 1)
ax.plot(costs)
ax.set_xlabel('Number of Clusters')
ax.set_ylabel('Reconstruction Cost');

ax = fig.add_subplot(1, 2, 2)
ax.plot(approx_bic)
ax.set_xlabel('Number of Clusters')
ax.set_ylabel('Approximate BIC');
```



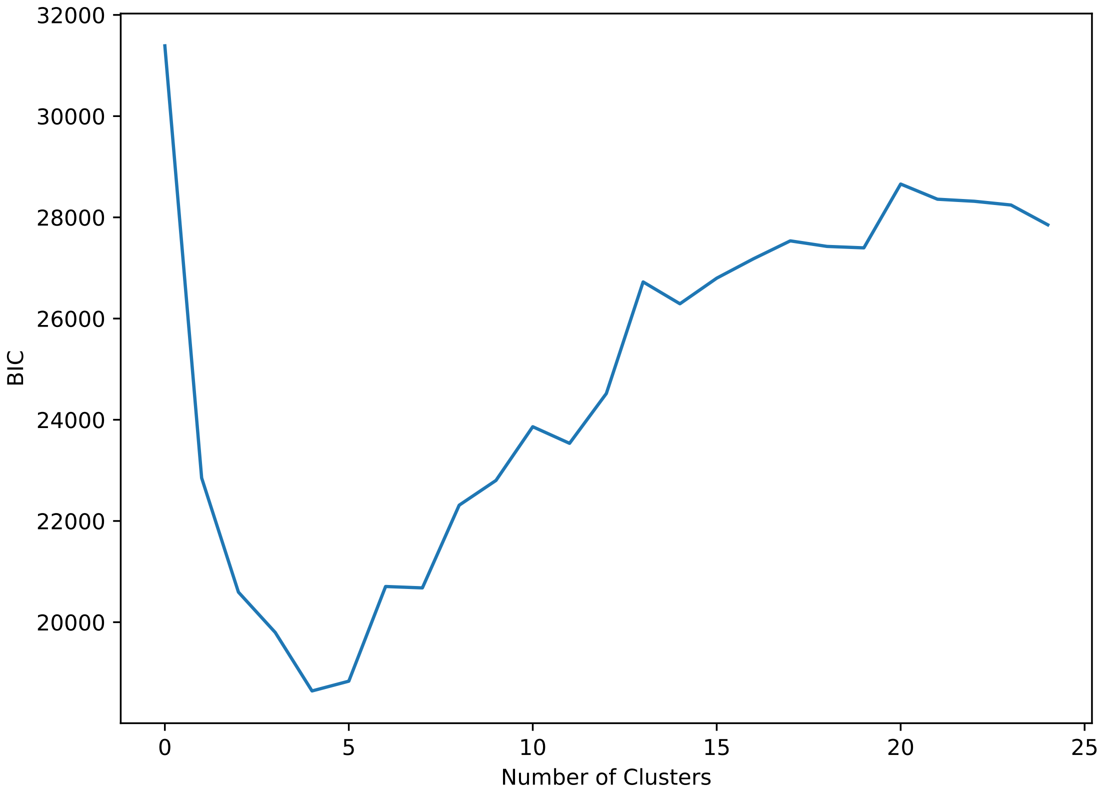


[ ]:
```
np.argmin(approx_bic) + 1
```

[ ]: 1

3.3.3 GMM

[ ]:
```
bics = []
for i in range (25):
    b = 0
    for r in range(num_itts):
        gmm = GaussianMixture(i+1, random_state=r)
        gmm.fit(user_genre_ratings_use)
        b += gmm.bic(user_genre_ratings_use)
    bics.append(b / num_itts)

fig = plt.figure(figsize=[8, 6])
ax = fig.add_subplot(1, 1, 1)
ax.plot(bics)
ax.set_xlabel('Number of Clusters')
ax.set_ylabel('BIC');
```




```
[ ]: np.argmin(bics) + 1
```

```
[ ]: 5
```

3.3.4 2 & 3. Visualisation and …

```
[ ]: def do_kmeans_analysis(n_clusters, random_state, data, abnormal_threshold = 2):

         # train the k-means model
         kmeans = KMeans(n_clusters=n_clusters, random_state=random_state).fit(data)

         # plot the cluster centres
         x = ['Western',          'Children',          'Thriller',          'Action',␣
      ↪         'Crime',          'Fantasy',          'Comedy',          'Romance',␣
      ↪         'Mystery',          'Animation',          'Musical', '(no genres␣
      ↪listed)',
                        'IMAX',          'Documentary',          'War',␣
      ↪         'Film-Noir',          'Adventure',          'Drama',          'Horror',␣
      ↪         'Sci-Fi']
         fig = plt.figure(figsize=[40, 20])
```

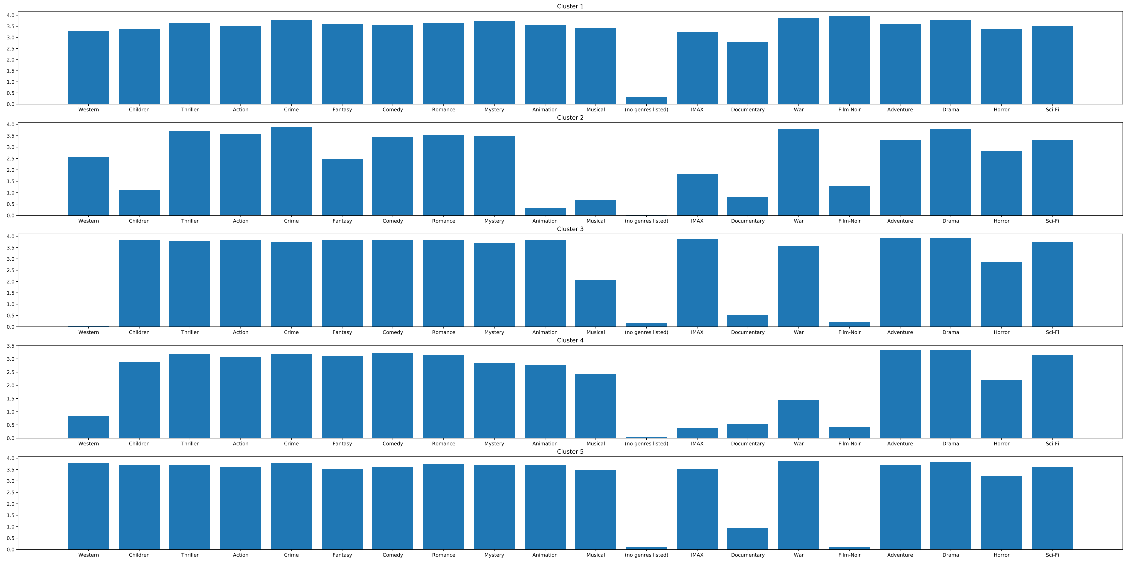
```
    for i in range(n_clusters):
        ax = fig.add_subplot(n_clusters, 1, i + 1)
        ax.bar(x, kmeans.cluster_centers_[i,:])
        ax.set_title('Cluster %d' % (i+1))
        print(kmeans.cluster_centers_[i,:])

    # plot the data, we can't plot 10-d data, so we'll run TSNE and show that
    fig = plt.figure(figsize=[20,20])
    ax = fig.add_subplot(1, 1, 1)
    tsne_embeddings = TSNE(random_state=4).fit_transform(np.vstack([data,␣
↪kmeans.cluster_centers_]))
    ax.scatter(tsne_embeddings[:-n_clusters,0], tsne_embeddings[:
↪-n_clusters,1], c = kmeans.labels_);
    # add cluster centres to the plot
    ax.scatter(tsne_embeddings[-n_clusters:,0], tsne_embeddings[-n_clusters:
↪,1], s=200, marker='x')

    # Identify the clusters that contain the target users, 4, 42, and 314
    # print(kmeans.labels_)

    user_4_cluster = kmeans.labels_[3]
    user_42_cluster = kmeans.labels_[41]
    user_314_cluster = kmeans.labels_[313]

    print(user_4_cluster) # 0
    print(user_42_cluster) # 0
    print(user_314_cluster) # 4

    return kmeans

    # ## Recommend movies
    # user_4_rec =

    # for i in range(n_clusters):
    #     #For cluster 0
    #     if (i == 0):
    #       user_4_notSeen =
    #       user_42_notSeen =
    #     #For cluster 4
    #     elif (i == 4):



    #     ax = fig.add_subplot(n_clusters, 1, i + 1)
    #     ax.bar(x, kmeans.cluster_centers_[i,:])
    #     ax.set_title('Cluster %d' % (i+1))
```

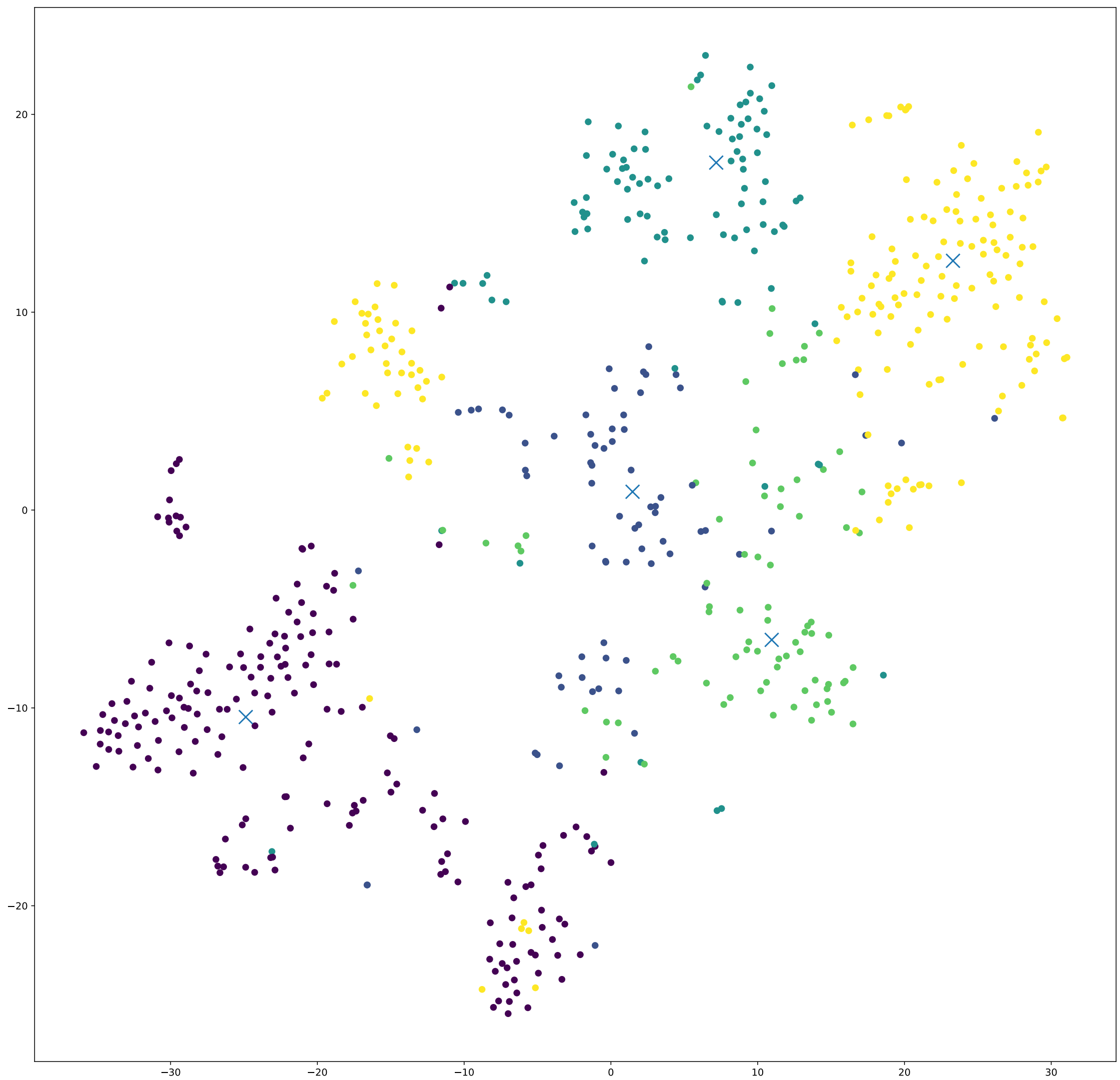
[ ]:
```
kmeans = do_kmeans_analysis(5, 4, user_genre_ratings_use)
```

```
[3.28281877 3.38257496 3.62745047 3.53010377 3.78031566 3.60178313
 3.57055161 3.62737193 3.75033281 3.55372696 3.4268246  0.29736842
 3.22015288 2.77624584 3.88060486 3.9761641  3.5892752  3.76930725
 3.3804055  3.50873666]
[2.58125220e+00 1.10893923e+00 3.70048851e+00 3.57156526e+00
 3.87928205e+00 2.47303980e+00 3.44605712e+00 3.51899063e+00
 3.50202027e+00 3.16971081e-01 6.75962166e-01 8.32667268e-17
 1.82452707e+00 8.23548598e-01 3.78736996e+00 1.28767123e+00
 3.30800489e+00 3.79819845e+00 2.84420473e+00 3.32830975e+00]
[0.02631579 3.82291808 3.76250525 3.81577737 3.7429276  3.81866381
 3.80627443 3.82052649 3.67709939 3.83450204 2.06680718 0.16315789
 3.85523573 0.51776316 3.57127193 0.21052632 3.89696556 3.90583967
 2.85530065 3.71620338]
[0.8246131  2.8796615  3.18962409 3.07957617 3.19901889 3.12308317
 3.21174735 3.14801366 2.83206795 2.76756847 2.42325124 0.021875
 0.36299388 0.53645833 1.42104902 0.41354167 3.31708167 3.34780528
 2.19099169 3.12825399]
[3.77449254 3.68385814 3.69289002 3.61658107 3.79703437 3.5123172
 3.62995036 3.74545461 3.69972815 3.68730232 3.46840184 0.11773256
 3.50526779 0.94896216 3.87168464 0.10174419 3.68135428 3.83337996
 3.21028606 3.6287088 ]
```

```
/usr/local/lib/python3.7/dist-packages/sklearn/manifold/_t_sne.py:783:
FutureWarning: The default initialization in TSNE will change from 'random' to
'pca' in 1.2.
  FutureWarning,
/usr/local/lib/python3.7/dist-packages/sklearn/manifold/_t_sne.py:793:
FutureWarning: The default learning rate in TSNE will change from 200.0 to
'auto' in 1.2.
  FutureWarning,
```

```
0
0
4
```


Cluster 1
Cluster 2
Cluster 3
Cluster 4
Cluster 5
Western
Children
Thriller
Action
Crime
Fantasy
Comedy
Romance
Mystery
Animation
Musical
(no genres listed)
IMAX
Documentary
War
Film-Noir
Adventure
Drama
Horror
Sci-Fi




```
[ ]: user_4_cluster = kmeans.labels_[3]
     user_42_cluster = kmeans.labels_[41]
     user_314_cluster = kmeans.labels_[313]

     print(user_4_cluster)
     print(user_42_cluster)
     print(user_314_cluster)
```

```
0
0
4
```

```
[ ]: ## Clusters:
     # 4 - in 0
```

```
# 42 - in 0
# 314 - in 4
#labels = gmm.predict(embeddings)
```

3.4 Find the most popular movies within clusters that contain the target users, that the target users have not already seen.

Q. For Q1 again, do we have any train/test splits? If not, how can we confirm that our approach works?

A. There are no train/test splits. One possible way to test your model is to pick a few users and remove (at random) some of the movies that they've watched. Then try to recommend movies to them. If the system is recommending movies that you removed but they've actually enjoyed, it's doing something right. Note that if you do this, I'd suggest that for your test subjects make sure you pick users who've watched lots of moves, and only remove a small number of films. This will help ensure that your changes to their viewing history don't change the cluster to which they are assigned.

Q. For Q1, how can tell if my recommendations make sense?

A. One way would be to create some test subjects. Pick a few subjects at random, remove a bunch of the movies that they've seen, and then see if you're approach can recommend movies that they've enjoyed. Note that if you do this, I'd suggest that for your test subjects make sure you pick users who've watched lots of moves, and only remove a small number of films. This will help ensure that your changes to their viewing history don't change the cluster to which they are assigned.

[ ]:
```
print(kmeans.labels_)
```

```
[0 1 3 0 4 4 0 4 0 2 1 3 1 4 4 0 0 0 0 0 0 0 0 2 2 1 0 0 0 2 2 4 0 4 4 1 4
 4 0 4 0 0 4 3 4 4 1 2 2 0 0 4 1 4 3 2 0 4 0 2 1 0 0 0 1 0 4 0 1 4 3 1 4 0
 4 1 2 2 0 2 3 4 2 0 3 4 3 1 4 3 0 2 4 4 0 0 2 2 4 4 2 4 0 0 0 2 4 4 0 1 4
 4 0 3 0 4 4 1 0 3 4 0 4 2 0 4 1 1 0 4 0 0 4 4 0 4 0 2 3 0 4 4 2 4 4 2 3 2
 1 3 3 0 3 2 4 0 3 3 2 0 3 4 3 1 4 0 0 0 4 4 4 4 2 4 3 4 0 4 4 3 4 0 1 2 2
 0 0 0 2 0 0 1 2 1 0 2 1 0 0 0 4 0 4 0 4 3 1 1 2 2 2 0 2 3 0 0 3 1 0 4 0 0
 0 2 3 4 0 3 4 3 1 0 0 4 4 3 2 1 0 4 4 4 2 1 3 0 0 2 0 4 2 2 0 0 3 4 3 2 3
 0 1 3 0 2 1 0 4 1 3 3 3 4 4 0 0 2 3 4 0 2 2 4 2 4 1 0 0 0 4 0 2 4 3 3 1 4
 1 0 1 1 4 1 2 4 0 4 0 3 0 4 3 0 0 4 3 3 0 0 2 2 2 0 4 3 0 0 4 0 3 4 0 0 1
 4 1 0 4 1 0 4 4 3 0 4 3 0 4 4 4 3 0 0 4 0 4 0 0 2 4 1 2 0 3 3 3 2 0 1 4 2
 0 0 4 4 2 0 0 4 4 0 4 4 1 3 0 3 0 2 3 4 0 3 0 1 4 3 1 4 2 2 4 2 4 4 0 3 2
 4 4 0 4 0 1 0 0 1 2 0 0 0 1 0 1 0 0 2 1 0 4 2 1 0 1 4 4 4 1 0 2 0 2 3 2 4
 4 4 4 0 1 4 3 0 0 1 4 3 3 4 4 2 1 0 2 0 0 2 3 4 0 4 2 1 3 0 4 4 0 4 4 0 1
 4 0 0 4 4 2 0 0 2 2 2 1 1 0 2 2 4 3 2 3 4 2 4 3 4 4 3 0 0 4 4 4 0 2 3 3 2
 1 0 3 0 2 4 0 2 0 0 3 1 3 1 4 0 3 1 1 4 2 0 4 4 4 3 1 3 1 1 1 2 0 0 1 4 0
 2 2 2 4 0 0 0 2 4 4 4 0 4 4 4 3 4 0 2 1 3 4 3 2 0 2 4 2 4 0 4 0 4 1 0 4 4
 0 4 3 0 0 2 0 0 4 0 0 4 4 0 4 0 4 0]
```

3.4.1 Get the List of Movie IDs for Movies the Users Have Not Seen

[ ]:
```
## Set variables
movie_IDs = list(range(len(movies)))

user_4_seen = []
user_4_not = movie_IDs

user_42_seen = []
user_42_not = movie_IDs

user_314_seen = []
user_314_not = movie_IDs

i = 0
j = len(ratings)
```

[ ]:
```
## Get movies seen by user 4
while i < j:
  user_ID = int(ratings.iloc[i]['userId'])
  if user_ID == 4:
    # user_4_not = ratings_cluster_4.append(ratings.iloc[[i]],␣
 ↪ignore_index=True)
    user_4_seen.append(int(ratings.iloc[i]['movieId']))
  i = i + 1

## Get movies seen by user 42
i = 0
while i < j:
  user_ID = int(ratings.iloc[i]['userId'])
  if user_ID == 42:
    # user_4_not = ratings_cluster_4.append(ratings.iloc[[i]],␣
 ↪ignore_index=True)
    user_42_seen.append(int(ratings.iloc[i]['movieId']))
  i = i + 1

## Get movies seen by user 314
i = 0
while i < j:
  user_ID = int(ratings.iloc[i]['userId'])
  if user_ID == 314:
    # user_4_not = ratings_cluster_4.append(ratings.iloc[[i]],␣
 ↪ignore_index=True)
    user_314_seen.append(int(ratings.iloc[i]['movieId']))
  i = i + 1
```

```
[ ]: ## Get movies NOT seen by user 4
user_4_not = [x for x in movie_IDs if x not in user_4_seen]
user_4_not.remove(0)

## Get movies NOT seen by user 42
user_42_not = [x for x in movie_IDs if x not in user_42_seen]
user_42_not.remove(0)

## Get movies NOT seen by user 314
user_314_not = [x for x in movie_IDs if x not in user_314_seen]
user_314_not.remove(0)
```

3.4.2 Get Movies Seen by Users in Cluster 0 and 4

```
[ ]: ## Get list of User IDs in clusters 0 and 4
users_0 = []
users_4 = []
i = 0
while i < len(kmeans.labels_):
  if kmeans.labels_[i] == 0:
      users_0.append(i + 1)
  elif kmeans.labels_[i] == 4:
      users_4.append(i + 1)
  i = i + 1

print(len(users_0))
print(users_0)

print(len(users_4))
print(users_4)
```

```
190
[1, 4, 7, 9, 16, 17, 18, 19, 20, 21, 22, 23, 27, 28, 29, 33, 39, 41, 42, 50, 51,
57, 59, 62, 63, 64, 66, 68, 74, 79, 84, 91, 95, 96, 103, 104, 105, 109, 113,
115, 119, 122, 125, 129, 131, 132, 135, 137, 140, 152, 156, 160, 166, 167, 168,
177, 182, 186, 187, 188, 190, 191, 195, 198, 199, 200, 202, 204, 212, 215, 216,
219, 221, 222, 223, 227, 232, 233, 239, 246, 247, 249, 253, 254, 260, 263, 266,
274, 275, 279, 286, 287, 288, 290, 298, 305, 307, 309, 312, 313, 317, 318, 322,
325, 326, 328, 331, 332, 336, 339, 343, 346, 351, 352, 354, 356, 357, 362, 367,
371, 372, 376, 377, 380, 385, 387, 391, 393, 405, 410, 412, 414, 415, 418, 419,
420, 422, 424, 425, 428, 432, 438, 440, 448, 452, 453, 462, 464, 465, 469, 474,
477, 480, 483, 484, 488, 489, 495, 509, 510, 514, 520, 522, 525, 527, 528, 534,
540, 551, 552, 555, 560, 561, 562, 567, 573, 580, 585, 587, 590, 593, 596, 597,
599, 600, 602, 603, 606, 608, 610]
172
[5, 6, 8, 14, 15, 32, 34, 35, 37, 38, 40, 43, 45, 46, 52, 54, 58, 67, 70, 73,
```

```
75, 82, 86, 89, 93, 94, 99, 100, 102, 107, 108, 111, 112, 116, 117, 121, 123,
126, 130, 133, 134, 136, 141, 142, 144, 145, 155, 162, 165, 169, 170, 171, 172,
174, 176, 178, 179, 181, 201, 203, 205, 220, 226, 229, 234, 235, 240, 241, 242,
250, 256, 267, 272, 273, 278, 282, 284, 289, 292, 296, 301, 304, 306, 310, 314,
323, 327, 330, 334, 337, 340, 341, 344, 347, 348, 349, 353, 355, 359, 369, 373,
374, 378, 379, 381, 382, 390, 395, 398, 401, 403, 404, 408, 409, 411, 429, 434,
435, 436, 444, 445, 446, 447, 450, 455, 458, 459, 468, 470, 475, 476, 478, 479,
482, 485, 486, 498, 502, 504, 506, 507, 511, 512, 513, 524, 533, 538, 541, 542,
543, 554, 559, 564, 565, 566, 568, 569, 570, 572, 577, 582, 584, 586, 588, 591,
592, 594, 601, 604, 605, 607, 609]
```

3.4.3 Get Ratings for Movies for Clusters 0 and 4

[ ]:
```
## Set variables
ratings_cluster_0_user4 = pd.DataFrame(columns=['userId', 'movieId', 'rating',␣
 ↪'timestamp'])

i = 0
j = len(ratings)

## Get movie ratings for cluster 0, user 4
while i < j:
  user_ID = int(ratings.iloc[i]['userId'])
  movie_ID = int(ratings.iloc[i]['movieId'])
  for id in users_0:
    if user_ID == id and movie_ID in user_4_not:
      ratings_cluster_0_user4 = ratings_cluster_0_user4.append(ratings.
 ↪iloc[[i]], ignore_index=True)
  i = i + 1

ratings_cluster_0_user4
```

[ ]:
```
      userId movieId  rating   timestamp
0          1       1     4.0   964982703
1          1       3     4.0   964981247
2          1       6     4.0   964982224
3          1      50     5.0   964982931
4          1      70     3.0   964982400
…        …       …       …           …
45142    610    8950     4.5  1493849533
45143    610    8957     3.0  1493847395
45144    610    8961     5.0  1493844829
45145    610    8983     3.5  1493845284
45146    610    8985     2.5  1493845630

[45147 rows x 4 columns]
```

[ ]:
```
## Set variables
ratings_cluster_0_user42 = pd.DataFrame(columns=['userId', 'movieId', 'rating',␣
 ↪'timestamp'])

i = 0
j = len(ratings)

## Get movie ratings for cluster 0, user 42
while i < j:
  user_ID = int(ratings.iloc[i]['userId'])
  movie_ID = int(ratings.iloc[i]['movieId'])
  for id in users_0:
    if user_ID == id and movie_ID in user_42_not:
      ratings_cluster_0_user42 = ratings_cluster_0_user42.append(ratings.
 ↪iloc[[i]], ignore_index=True)
  i = i + 1

ratings_cluster_0_user42
```

[ ]:
```
      userId movieId  rating   timestamp
0          1       1     4.0   964982703
1          1       6     4.0   964982224
2          1      70     3.0   964982400
3          1     101     5.0   964980868
4          1     151     5.0   964984041
…        …     …     …          …
39148    610    8950     4.5  1493849533
39149    610    8957     3.0  1493847395
39150    610    8961     5.0  1493844829
39151    610    8983     3.5  1493845284
39152    610    8985     2.5  1493845630

[39153 rows x 4 columns]
```

[ ]:
```
## Set variables
ratings_cluster_4_user314 = pd.DataFrame(columns=['userId', 'movieId',␣
 ↪'rating', 'timestamp'])

i = 0
j = len(ratings)

## Get movie ratings for cluster 4, user 314
while i < j:
  user_ID = int(ratings.iloc[i]['userId'])
  movie_ID = int(ratings.iloc[i]['movieId'])
  for id in users_4:
     if user_ID == id and movie_ID in user_314_not:
```

```
    ratings_cluster_4_user314 = ratings_cluster_4_user314.append(ratings.
↪iloc[[i]], ignore_index=True)
  i = i + 1

ratings_cluster_4_user314
```

```
[ ]:      userId  movieId  rating  timestamp
0          5       34     4.0  847434881
1          5       36     4.0  847435292
2          5       58     5.0  847435238
3          5      232     4.0  847435292
4          5      247     5.0  847435337
…        …      …      …        …
9869     609      892     3.0  847221080
9870     609     1056     3.0  847221080
9871     609     1059     3.0  847221054
9872     609     1150     4.0  847221054
9873     609     1161     4.0  847221080

[9874 rows x 4 columns]
```

3.4.4 Final Recommendations for Users

```
[ ]: ## User 4
average_rating_4 = get_average_rating_per_film(ratings_cluster_0_user4)
print(average_rating_4.shape)
average_rating_4.sort_values(by='rating', ascending=False)
```

```
(4963, 1)
```

```
[ ]:         rating
movieId
4142         5.0
1631         5.0
495          5.0
5416         5.0
3678         5.0
…          …
6371         0.5
1325         0.5
1328         0.5
4580         0.5
5356         0.5

[4963 rows x 1 columns]
```

[ ]:
```python
## User 42
average_rating_42 = get_average_rating_per_film(ratings_cluster_0_user42)
print(average_rating_42.shape)
average_rating_42.sort_values(by='rating', ascending=False).iloc[:69,:]
```

```
(4739, 1)
```

[ ]:
```
         rating
movieId
3851       5.00
5244       5.00
4116       5.00
4135       5.00
389        5.00
…          …
8580       5.00
8804       5.00
6201       5.00
6192       5.00
3302       4.75

[69 rows x 1 columns]
```

[ ]:
```python
## User 314
average_rating_314 = get_average_rating_per_film(ratings_cluster_4_user314)
print(average_rating_314.shape)
average_rating_314.sort_values(by='rating', ascending=False).iloc[:139,:]
```

```
(2138, 1)
```

[ ]:
```
         rating
movieId
9010        5.0
2924        5.0
1011        5.0
6549        5.0
3020        5.0
…          …
1252        5.0
176         5.0
1300        5.0
2318        5.0
7025        5.0

[139 rows x 1 columns]
```

4 Problem 2. Multi-Task Learning.

Using this data you are to implement a multi-task deep learning approach that, given an input image, classifies the traits:

- Gender
- Torso Clothing Type
- Primary Torso Clothing Colour
- Leg Clothing Type
- Primary Leg Clothing Colour, and
- Presence of Luggage.

Pose and the semantic segmentation data may optionally be used when developing your ap- proach (though remember that semantic segmentation data is only available for the training set, so cannot be used as a model input). Additional traits (clothing texture, secondary and tertiary torso and leg colours) should be ignored.

[ ]:
```
## Utils

#
# Utility functions for CAB420, Assignment 1C, Q2
# Author: Simon Denman (s.denman@qut.edu.au)
#

import pandas
import cv2
import os
import tensorflow as tf
import numpy
import matplotlib.pyplot as plt     # for plotting

# load a set of masks that represent the semantic regions of a person. This␣
↪will load the image into a
# (width, height, 8) array if merge_skin is false; or a (width, height, 6)␣
↪array is merge_skin is true
#   base_path:  path to the images
#   base_name:  common name for the images
#   merge_skin: bool to indicate if we are going to merge the skin regions into␣
↪a single channel, or
#               leave them as arms, face, legs
#
#   returns:    a (width, height, 9) or (width, height, 7) image. Really it's␣
↪just all the binary masks
#               stacked up
#
```

```python
def load_mask(base_path, base_name, merge_skin = False):

    # hard-coding warning, but really dataset structure can be considered a bit␣
↪of a constant
    components = ['_hair', '_legs', '_luggage', '_shoes', '_torso',␣
↪'_skin_arms', '_skin_face', '_skin_legs']
    # loop through and load all the components
    images = []
    for c in components:
        images.append(cv2.imread(os.path.join(base_path, base_name + c + '.
↪png'), cv2.IMREAD_GRAYSCALE) / 255.0)

    # this is a bit ugly, but we know that we have skin in the last three␣
↪channels, so we can just add
    # those together and then cut the last two channels out
    if (merge_skin):
        images[-3] = images[-3] + images[-2] + images[-1]
        images = images[:-2]

    # convert our list to a numpy array, and then transpose it to get the␣
↪channels in the correct spot
    return numpy.transpose(numpy.array(images), (1, 2, 0))

# adds a background channel to the mask. This channel is 1.0 (i.e on) when all␣
↪other channels are 0.0 (off), and
# indicates that there's nothing there. This may seem odd, but is needed if we␣
↪want to use this mask for a
# semantic segmentation output, in which case we'd need a channel to indicate␣
↪the absence of anything interesting,
# i.e. the backgorund.
#  mask:    mask to add a background channel to
#
#  returns: mask image with a new channel
#
def add_background_channel_to_mask(mask):
    # create the background
    background = 1.0 - mask[:,:,0]
    for i in range(1, mask.shape[2]):
        background = background - mask[:,:,i]

    # stack the background with the original mask. You can put the background␣
↪first or last
    # (or in the middle - but first or last makes more sense I think), it␣
↪doesn't really matter
    return numpy.dstack((mask, background))
```

```
# load a dataset. This will optionally load masks, and resize images (and␣
↪masks) and convert images to a new
# colour space
#   csv_path:      path to the csv file that contains all the meta-data, ground␣
↪truth, etc
#   image_path:    path to the image of the people for whom we need to␣
↪recognise traits
#   mask_path:     where are the mask images? If there are none, set this to␣
↪None
#   target_size:   what size images do you want? This will resize and pad, so␣
↪will preserve the aspect ratio.
#   target_colour: what colour space do you want to convert to? Default is cv2.
↪COLOR_BGR2RGB to go from
#                  opencv's default backwards world to RGB, but you may also␣
↪want cv2.COLOR_BGR2GRAY
#                  (though, don't you need to recognise colour?), or something␣
↪more exotic like HSV or LAB.1
#   merge_skin:    bool to indicate if we are going to merge the skin regions␣
↪into a single channel, or
#                  leave them as arms, face, legs. Only does anything if␣
↪mark_path is not None
#
#   returns        two dictionaries: x, which contains the images; and y, which␣
↪contains all the target things
#                  (gender, colours, etc) and potentially the masks
#
def load_set(csv_path, image_path, mask_path = None, target_size = (60, 100),␣
↪target_colour = cv2.COLOR_BGR2RGB, merge_skin = False):

    # create storage
    # first for likley model inputs
    x = {}
    x['images'] = []

    # now for likely model outputs
    y = {}
    y['gender'] = []
    y['torso_type'] = []
    y['torso_colour'] = []
    y['leg_type'] = []
    y['leg_colour'] = []
    y['luggage'] = []
    if (mask_path is not None):
        y['mask'] = []
```

```
    # load the csv file, which contains paths to images and all the ground␣
↪truth data
    csv = pandas.read_csv(csv_path)
    for i, row in csv.iterrows():
        # there's a bit going on here, working from the inside out:
        #  - load the file
        #  - convert the colour space
        #  - resize with padding (using tensorflow)
        #  - convert back to numpy (because we used tensorflow)
        x['images'].append(tf.image.resize_with_pad(cv2.cvtColor(cv2.imread(os.
↪path.join(image_path, row['filename'])), target_colour) / 255.0,␣
↪target_size[1], target_size[0]).numpy())

        # pull out the various bits of ground truth we need
        y['gender'].append(row['gender'])
        y['torso_type'].append(row['tortyp'])
        y['torso_colour'].append(row['torcol'])
        y['leg_type'].append(row['legtyp'])
        y['leg_colour'].append(row['legcol'])
        y['luggage'].append(row['luggage'])
        # is there some other piece of data you want to use? maybe the pose? or␣
↪some other label? if so then just pull it out too!

        # pull out the mask, if we are doing that
        if (mask_path is not None):
            # a bit like the above, we'll
            #  - load the image
            #  - resize and pad the image
            #  - convert back to numpy
            #  - add a background channel
            # The background channel is done last to ensure that the newly␣
↪added padded regions are included as
            # background (i.e. contain nothing of interest)
            y['mask'].append(add_background_channel_to_mask(tf.image.
↪resize_with_pad(load_mask(mask_path, os.path.splitext(row['filename'])[0],␣
↪merge_skin), target_size[1], target_size[0]).numpy()))

    x['images'] = numpy.array(x['images'])
    for key in y:
        y[key] = numpy.array(y[key])

    return x, y

# load the data
#   base_path:     the path to the data, within the directory that this points␣
↪to there should be the Train_Data
```

```
#                   and Test_Data directories
#   target_size:   what size images do you want? This will resize and pad, so␣
↪will preserve the aspect ratio.
#   target_colour: what colour space do you want to convert to? Default is cv2.
↪COLOR_BGR2RGB to go from
#                   opencv's default backwards world to RGB, but you may also␣
↪want cv2.COLOR_BGR2GRAY
#                   (though, don't you need to recognise colour?), or something␣
↪more exotic like HSV or LAB.1
#   merge_skin:    bool to indicate if we are going to merge the skin regions␣
↪into a single channel, or
#                   leave them as arms, face, legs. Only does anything if␣
↪mark_path is not None
#
#   returns:       loaded training and testing data
#
def load_data(base_path, target_size = (60, 100), target_colour = cv2.
↪COLOR_BGR2RGB, merge_skin = False):

    train_x, train_y = load_set(os.path.join(base_path, 'Train_Data', 'Train.
↪csv'), os.path.join(base_path, 'Train_Data', 'Originals'), os.path.
↪join(base_path, 'Train_Data', 'Binary_Maps'), target_size = target_size,␣
↪target_colour = target_colour, merge_skin = merge_skin)
    test_x, test_y = load_set(os.path.join(base_path, 'Test_Data', 'Test.csv'),␣
↪os.path.join(base_path, 'Test_Data', 'Originals'), target_size =␣
↪target_size, target_colour = target_colour, merge_skin = merge_skin)

    return train_x, train_y, test_x, test_y

# does what it says on the box, makes a mask a bit prettier and a lot more␣
↪practical for display
#   mask_image: input, N channel mask image
#
#   returns:    mask collapsed to a single channel, channels have been weighted␣
↪and summed such that each
#               channel should occupy it's own space in the colour map of your␣
↪choice
#
def make_a_mask_image_ready_for_display(mask_image):
    num_channels = mask_image.shape[2]
    im = mask_image[:,:,0]*(1.0/mask_image.shape[2])
    for i in range(1, num_channels):
        im = im + mask_image[:,:,i]*(i/mask_image.shape[2])
    return im

# Plot some images. Will plot the first 50 samples in a 10x5 grid
```

```
#  x: array of images, of shape (samples, width, height, channels)
#
def plot_images(images):
    fig = plt.figure(figsize=[15, 18])
    for i in range(50):
        ax = fig.add_subplot(5, 10, i + 1)
        ax.imshow(images[i,:], cmap=plt.get_cmap('Greys'))
        ax.axis('off')

# Plot some images and their masks. Will plot the first 25 samples in a 10x5␣
↪grid,
# alternating between images and masks
#  x: array of images, of shape (samples, width, height, channels)
#  masks: array of masks, of shape (samples, width, height, channels)
#
def plot_images_and_masks(images, masks):
    fig = plt.figure(figsize=[15, 18])
    for i in range(25):
        ax = fig.add_subplot(5, 10, i*2 + 1)
        ax.imshow(images[i,:], cmap=plt.get_cmap('Greys'))
        ax.axis('off')
        ax = fig.add_subplot(5, 10, i*2 + 2)
        ax.imshow(make_a_mask_image_ready_for_display(masks[i,:]), cmap=plt.
↪get_cmap('RdYlBu'))
        ax.axis('off')
```

[ ]:
```
## Load the data
train_x, train_y, test_x, test_y = load_data('/content/drive/My Drive/
↪Assignment 1C/CAB420_Assessment_1C_Data/Q2/Q2')
for key in train_y:
    print(key)
```

```
gender
torso_type
torso_colour
leg_type
leg_colour
luggage
mask
```

[ ]:
```
## Set -1 values as a new class
# ML = ['gender', 'torso_type', 'torso_colour', 'leg_type', 'leg_colour',␣
↪'luggage']
class_3 = ['gender', 'torso_type', 'leg_type', 'luggage']
class_12 = ['torso_colour', 'leg_colour']

## Test
```

```python
for x in class_3:
  for i in range(len(test_y[x])):
    if (test_y[x][i] == -1):
      test_y[x][i] = 2

for x in class_12:
  for i in range(len(test_y[x])):
    if (test_y[x][i] == -1):
      test_y[x][i] = 11

## Train
for x in class_3:
  for i in range(len(train_y[x])):
    if (train_y[x][i] == -1):
      train_y[x][i] = 2

for x in class_12:
  for i in range(len(train_y[x])):
    if (train_y[x][i] == -1):
      train_y[x][i] = 11
  # print(x)
  # print(len(a))
  # print(a)
  # print(len(no_negative))
  # print(no_negative)
```

[ ]:
```python
train_y
```

[ ]:
```
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```

```
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```

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```

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```

```
  …,
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…,


[[[0., 0., 0., …, 0., 0., 1.],
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  …,
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 …,

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  …,
```

```
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  …,
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  …,
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 …,

 [[0., 0., 0., …, 0., 0., 1.],
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  …,
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```

```
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  …,
```

```
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         0,  9,  9,  9,  9,  0,  9,  4,  7,  7,  8,  8,  9,  1,  0,  0,  0,
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```

```
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        2,  9,  4,  4,  9,  3,  6, 10,  0,  9,  2,  0,  9,  8,  0,  0,  0,
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        1, 0, 0, 1, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0])}
```

4.1 From Datagen Example

4.1.1 Data Generator

[ ]:
```python
# Class for the data generator
class DataGenerator(keras.utils.Sequence):
    'Generates data for Keras'

    # Input arguments are as follows:
    #   x:              our X data array that we'll augment
    #   y_one:          y labels for the first output
    #   y_two:          y labels for the second ouput
    #   y_three:        y labels for the first output
    #   y_four:         y labels for the second ouput
```

```
    #  y_five:       y labels for the first output
    #  y_six:        y labels for the second ouput
    #  data_aug:     our data augmentor
    #  batch_size:   the batch size to return from the generator
    #  dim:          size of images
    #  n_channels:   number of image channels
    #  shuffle:      flag to indicate if we should shuffle the data at the end␣
↪of the epoch
    def __init__(self, x, y_one, y_two, y_three, y_four, y_five, y_six,␣
↪data_aug,
                 batch_size=32, dim=(100,60), n_channels=3,
                 shuffle=True):
        'Initialization'
        self.dim = dim
        self.batch_size = batch_size
        self.x = x
        self.y_one = y_one
        self.y_two = y_two
        self.y_three = y_three
        self.y_four = y_four
        self.y_five = y_five
        self.y_six = y_six
        self.data_aug = data_aug
        self.list_IDs = np.arange(0, self.x.shape[0])
        self.n_channels = n_channels
        self.shuffle = shuffle
        self.on_epoch_end()

    def __len__(self):
        'Denotes the number of batches per epoch'
        return int(np.floor(len(self.list_IDs) / self.batch_size))

    def __getitem__(self, index):
        'Generate one batch of data'
        # Generate indexes of the batch
        indexes = self.indexes[index*self.batch_size:(index+1)*self.batch_size]

        # Find list of IDs
        list_IDs_temp = [self.list_IDs[k] for k in indexes]

        # Generate data
        X, y = self.__data_generation(list_IDs_temp)

        return X, y

    def on_epoch_end(self):
        'Updates indexes after each epoch'
```

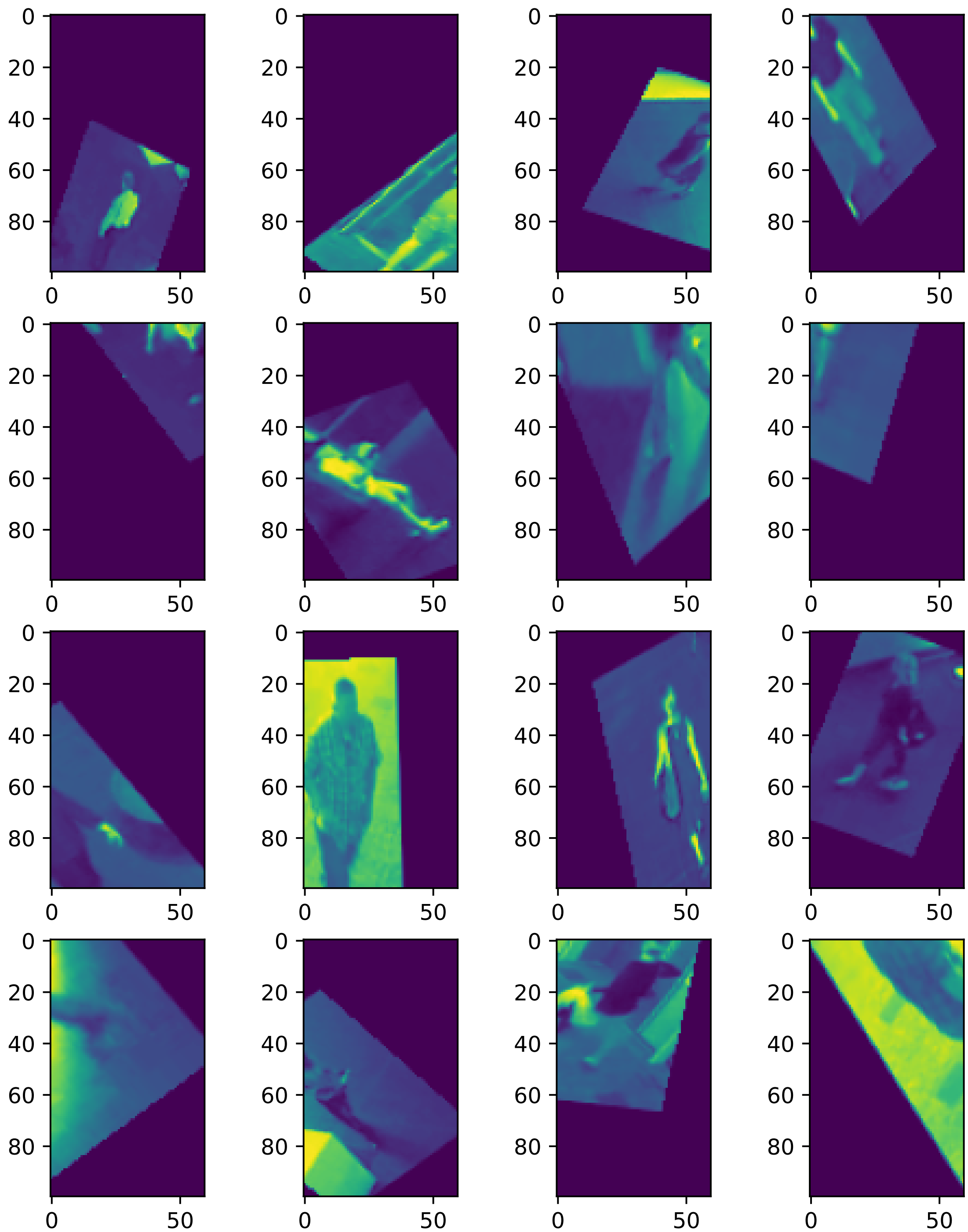
```
        self.indexes = np.arange(len(self.list_IDs))
        if self.shuffle == True:
            np.random.shuffle(self.indexes)


    # Function to generate data. This will take in a list of sample indicies,␣
↪and then for each
    # these apply augmentation, and return the augmented data and labels
    #
    # If you wish to check the mechanics out in more detail, you can uncomment␣
↪the two print lines
    # which will show you the IDs that are being manipulated and help show␣
↪what's going on - however
    # this will also generate a lot of output text during model training.
    #
    def __data_generation(self, list_IDs_temp):
        'Generates data containing batch_size samples' # X : (n_samples, *dim,␣
↪n_channels)
        # Initialization - creating space for X and y data
#         print(list_IDs_temp)
        X = np.empty((self.batch_size, *self.dim, self.n_channels))
        # creating a list of empty arrays to hold our data labels.
        # would initialise this for the number of output labels we have
        y = [np.empty((self.batch_size), dtype=int),
             np.empty((self.batch_size), dtype=int),
             np.empty((self.batch_size), dtype=int),
             np.empty((self.batch_size), dtype=int),
             np.empty((self.batch_size), dtype=int),
             np.empty((self.batch_size), dtype=int)]

        # Generate data, loop through the list of IDs we have and generate data␣
↪for each in turn
        for i, ID in enumerate(list_IDs_temp):
#             print(ID)
            # apply random transformation based of our datagen instance
            X[i,] = self.data_aug.random_transform(self.x[ID,])
            # copy our y labels across
            y[0][i,] = self.y_one[ID]
            y[1][i,] = self.y_two[ID]
            y[2][i,] = self.y_three[ID]
            y[3][i,] = self.y_four[ID]
            y[4][i,] = self.y_five[ID]
            y[5][i,] = self.y_six[ID]

        return X, y
```

4.1.2 Augmentation

[ ]:
```
# creating image aug with some really wild and extreme augmentation params
# Ad noted above: these params are not suitable, just used to demo it in␣
↪practice
data_aug = ImageDataGenerator(
                            # rotate between -45, +45 degrees
                            rotation_range=45,
                            # horiziontal shift by +/- 50% of the image width
                            width_shift_range=0.5,
                            # vertical shift by +/- 50% of the image width
                            height_shift_range=0.5,
                            # range for randomly applying a shearing transform
                            shear_range=0.5,
                            # range for zooming
                            zoom_range=0.5,
                            # allow horizontal flips of data
                            horizontal_flip=True,
                            # what value to place in new pixels, given the␣
↪nature of our data (clothes on a black backround)
                            # we'll set this to a constant value of 0
                            fill_mode='constant', cval=0)
```

[ ]:
```
# create generator for our dataset

datagen = DataGenerator(train_x['images'], train_y['gender'],␣
↪train_y['torso_type'], train_y['torso_colour'], train_y['leg_type'],␣
↪train_y['leg_colour'], train_y['luggage'], data_aug, batch_size=16)
```

[ ]:
```
# lets just test how it works
# will just get a random batch from here (just pick the first one)
x_, y_ = datagen[1]
fig = plt.figure(figsize=[8, 10])
for i in range(0, 16):
    ax = fig.add_subplot(4, 4, i + 1)
    ax.imshow(x_[i, :,:,0])
```



```
[ ]: ## We'll now confirm that we have two y outptus, i.e. two set of layers. In our
     ↪case this should return the same set of labels twice.
     print(y_)
```

```
[array([1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0, 0, 1, 1]), array([1, 1, 0, 1, 0,
```

```
0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1]), array([ 9,  9,  4,  4, 10,  9,  7,  0,  4,
0,  9,  4,  5,  8,  9,  4]), array([1, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 1,
1]), array([ 0,  1,  0,  1,  0, -1,  0,  0,  1,  1,  0,  1,  1,  0,  1,  4]),
array([0, 0, 0, 1, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 0, 0])]
```

4.2 Q2 Working:

Using this data you are to implement a multi-task deep learning approach that, given an input image, classifies the traits:

- Gender
- Torso Clothing Type
- Primary Torso Clothing Colour
- Leg Clothing Type
- Primary Leg Clothing Colour, and
- Presence of Luggage

4.3 Design DCNN architecture

[ ]:
```
## Build model

# function to build a model, takes the number of classes. Can optionally change␣
↪the output activation.
# See the discussion at bottom of this script for more details about that.
def build_model():
    # our model, input in an image shape
    inputs = keras.Input(shape=(100, 60, 3, ), name='img')

    # run pairs of conv layers, all 3s3 kernels
    x = layers.Conv2D(filters=8, kernel_size=(3,3), activation='relu')(inputs)
    x = layers.MaxPool2D(pool_size=(2, 2))(x)
    x = layers.Conv2D(filters=16, kernel_size=(3,3), activation='relu')(x)
    x = layers.MaxPool2D(pool_size=(2, 2))(x)
    x = layers.Conv2D(filters=32, kernel_size=(3,3), activation='relu')(x)

    # flatten layer
    x = layers.Flatten()(x)

    # we'll use a couple of dense layers here, mainly so that we can show what␣
↪another dropout layer looks like
    # in the middle
    # x = layers.Dense(64, activation='relu')(x)
    # x = layers.Dropout(0.5)(x)
    # x = layers.Dense(64, activation='relu')(x)
    # x = layers.Dropout(0.5)(x)
```

```python
    # x = layers.Dense(64, activation='relu')(x)
    # # the output
    # outputs = layers.Dense(num_classes, activation=output_activation)(x)

    x1 = layers.Dense(64, activation='relu')(x)
    output_1 = layers.Dense(3, name='Gender')(x1)
    x2 = layers.Dense(64, activation='relu')(x)
    output_2 = layers.Dense(3, name='TorsoType')(x2)
    x3 = layers.Dense(64, activation='relu')(x)
    output_3 = layers.Dense(12, name='TorsoColour')(x3)
    x4 = layers.Dense(64, activation='relu')(x)
    output_4 = layers.Dense(3, name='LegType')(x4)
    x5 = layers.Dense(64, activation='relu')(x)
    output_5 = layers.Dense(12, name='LegColour')(x5)
    x6 = layers.Dense(64, activation='relu')(x)
    output_6 = layers.Dense(3, name='Luggage')(x6)

    # build the model, and print a summary
    # multitask_cnn = keras.Model(inputs=inputs, outputs=outputs,␣
 ↪name='kmnist_cnn_model')
    multitask_cnn = keras.Model(inputs=inputs, outputs=[output_1, output_2,␣
 ↪output_3, output_4, output_5, output_6], name='fmnist_dummy_model')

    return multitask_cnn

multitask_cnn = build_model()
multitask_cnn.summary()
```

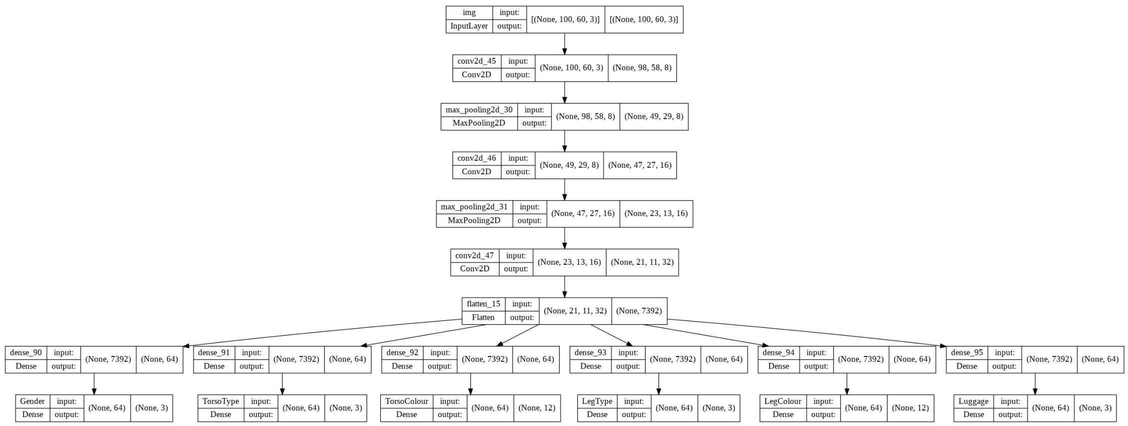
```
Model: "fmnist_dummy_model"

________________________________________________________________________________
__________________
 Layer (type)                   Output Shape          Param #     Connected to
================================================================================
==================
 img (InputLayer)               [(None, 100, 60, 3)   0           []
                                ]

 conv2d_45 (Conv2D)             (None, 98, 58, 8)     224         ['img[0][0]']

 max_pooling2d_30 (MaxPooling2D  (None, 49, 29, 8)    0
['conv2d_45[0][0]']
 )

 conv2d_46 (Conv2D)             (None, 47, 27, 16)    1168
['max_pooling2d_30[0][0]']

 max_pooling2d_31 (MaxPooling2D  (None, 23, 13, 16)   0
```

```
['conv2d_46[0][0]']
 )

 conv2d_47 (Conv2D)           (None, 21, 11, 32)   4640
['max_pooling2d_31[0][0]']

 flatten_15 (Flatten)         (None, 7392)         0
['conv2d_47[0][0]']

 dense_90 (Dense)             (None, 64)           473152
['flatten_15[0][0]']

 dense_91 (Dense)             (None, 64)           473152
['flatten_15[0][0]']

 dense_92 (Dense)             (None, 64)           473152
['flatten_15[0][0]']

 dense_93 (Dense)             (None, 64)           473152
['flatten_15[0][0]']

 dense_94 (Dense)             (None, 64)           473152
['flatten_15[0][0]']

 dense_95 (Dense)             (None, 64)           473152
['flatten_15[0][0]']

 Gender (Dense)               (None, 3)            195
['dense_90[0][0]']

 TorsoType (Dense)            (None, 3)            195
['dense_91[0][0]']

 TorsoColour (Dense)          (None, 12)           780
['dense_92[0][0]']

 LegType (Dense)              (None, 3)            195
['dense_93[0][0]']

 LegColour (Dense)            (None, 12)           780
['dense_94[0][0]']

 Luggage (Dense)              (None, 3)            195
['dense_95[0][0]']

================================================================================
==================
Total params: 2,847,284
```

```
Trainable params: 2,847,284
Non-trainable params: 0
--------------------------------------------------------------------------------
------------------
```

[ ]:
```
keras.utils.plot_model(multitask_cnn, show_shapes=True)
```

[ ]:



4.4 Train the data

[ ]:
```
## Data loss
def masked_cce(y_true, y_pred):
    y_true_masked = tf.boolean_mask(y_true, tf.reduce_any(tf.not_equal(y_true,␣
 ↪-1), 1))
    y_pred_masked = tf.boolean_mask(y_pred, tf.reduce_any(tf.not_equal(y_true,␣
 ↪-1), 1))
    return K.mean(K.sparse_categorical_crossentropy(y_true_masked,␣
 ↪y_pred_masked))
```

[ ]:
```
multitask_cnn = build_model() # so that it runs from scratch each time

# model_cnn.compile(loss=[keras.losses.
 ↪SparseCategoricalCrossentropy(from_logits=True),
#                          keras.losses.
 ↪SparseCategoricalCrossentropy(from_logits=True)],
#                optimizer=keras.optimizers.RMSprop())
loss_type = keras.losses.SparseCategoricalCrossentropy(from_logits=True)
opt_type = keras.optimizers.RMSprop()
# multitask_cnn.compile(optimizer='adam', loss=[masked_cce, masked_cce,␣
 ↪masked_cce, masked_cce, masked_cce, masked_cce]) #, metrics=['accuracy'])
multitask_cnn.compile(optimizer=opt_type, loss=[loss_type, loss_type,␣
 ↪loss_type, loss_type, loss_type, loss_type]) #, metrics=['accuracy'])
```

```python
# model_cnn.fit(datagen,
#            epochs=10,
#            validation_data=(x_test, [y_test, y_test]))

# history = multitask_cnn.fit(test_x['images'], [test_y['gender'],␣
 ↪test_y['torso_type'], test_y['torso_colour'], test_y['leg_type'],␣
 ↪test_y['leg_colour'], test_y['luggage']],
history = multitask_cnn.fit(datagen,
                            batch_size=64,
                            epochs=10,
                            validation_data=(test_x['images'], [test_y['gender'],␣
 ↪test_y['torso_type'], test_y['torso_colour'], test_y['leg_type'],␣
 ↪test_y['leg_colour'], test_y['luggage']]))
```

```
Epoch 1/10
32/32 [==============================] - 6s 119ms/step - loss: 7.0311 -
Gender_loss: 0.7702 - TorsoType_loss: 0.7958 - TorsoColour_loss: 2.2057 -
LegType_loss: 0.7556 - LegColour_loss: 1.7619 - Luggage_loss: 0.7419 - val_loss:
7.0987 - val_Gender_loss: 0.8380 - val_TorsoType_loss: 0.7474 -
val_TorsoColour_loss: 2.2509 - val_LegType_loss: 0.6992 - val_LegColour_loss:
1.7244 - val_Luggage_loss: 0.8389
Epoch 2/10
32/32 [==============================] - 3s 104ms/step - loss: 6.4645 -
Gender_loss: 0.7290 - TorsoType_loss: 0.6959 - TorsoColour_loss: 2.0750 -
LegType_loss: 0.6412 - LegColour_loss: 1.6207 - Luggage_loss: 0.7027 - val_loss:
7.1311 - val_Gender_loss: 0.8404 - val_TorsoType_loss: 0.7082 -
val_TorsoColour_loss: 2.2057 - val_LegType_loss: 0.7495 - val_LegColour_loss:
1.7504 - val_Luggage_loss: 0.8769
Epoch 3/10
32/32 [==============================] - 3s 106ms/step - loss: 6.4073 -
Gender_loss: 0.7213 - TorsoType_loss: 0.6877 - TorsoColour_loss: 2.0695 -
LegType_loss: 0.6400 - LegColour_loss: 1.5957 - Luggage_loss: 0.6931 - val_loss:
7.0314 - val_Gender_loss: 0.8504 - val_TorsoType_loss: 0.6859 -
val_TorsoColour_loss: 2.1754 - val_LegType_loss: 0.6884 - val_LegColour_loss:
1.7231 - val_Luggage_loss: 0.9082
Epoch 4/10
32/32 [==============================] - 3s 105ms/step - loss: 6.3714 -
Gender_loss: 0.7174 - TorsoType_loss: 0.6883 - TorsoColour_loss: 2.0487 -
LegType_loss: 0.6430 - LegColour_loss: 1.5859 - Luggage_loss: 0.6879 - val_loss:
7.1478 - val_Gender_loss: 0.8495 - val_TorsoType_loss: 0.7054 -
val_TorsoColour_loss: 2.1864 - val_LegType_loss: 0.6756 - val_LegColour_loss:
1.7753 - val_Luggage_loss: 0.9555
Epoch 5/10
32/32 [==============================] - 3s 104ms/step - loss: 6.3719 -
Gender_loss: 0.7266 - TorsoType_loss: 0.6881 - TorsoColour_loss: 2.0515 -
LegType_loss: 0.6315 - LegColour_loss: 1.5883 - Luggage_loss: 0.6858 - val_loss:
```

```
7.3038 - val_Gender_loss: 0.8961 - val_TorsoType_loss: 0.7001 -
val_TorsoColour_loss: 2.2328 - val_LegType_loss: 0.7015 - val_LegColour_loss:
1.8548 - val_Luggage_loss: 0.9185
Epoch 6/10
32/32 [==============================] - 3s 105ms/step - loss: 6.3506 -
Gender_loss: 0.7195 - TorsoType_loss: 0.6803 - TorsoColour_loss: 2.0406 -
LegType_loss: 0.6285 - LegColour_loss: 1.5914 - Luggage_loss: 0.6903 - val_loss:
7.1440 - val_Gender_loss: 0.8678 - val_TorsoType_loss: 0.6888 -
val_TorsoColour_loss: 2.2133 - val_LegType_loss: 0.6871 - val_LegColour_loss:
1.7725 - val_Luggage_loss: 0.9144
Epoch 7/10
32/32 [==============================] - 3s 105ms/step - loss: 6.3345 -
Gender_loss: 0.7264 - TorsoType_loss: 0.6866 - TorsoColour_loss: 2.0395 -
LegType_loss: 0.6310 - LegColour_loss: 1.5669 - Luggage_loss: 0.6841 - val_loss:
7.2740 - val_Gender_loss: 0.8954 - val_TorsoType_loss: 0.7083 -
val_TorsoColour_loss: 2.2276 - val_LegType_loss: 0.6790 - val_LegColour_loss:
1.8253 - val_Luggage_loss: 0.9383
Epoch 8/10
32/32 [==============================] - 3s 105ms/step - loss: 6.3173 -
Gender_loss: 0.7212 - TorsoType_loss: 0.6830 - TorsoColour_loss: 2.0226 -
LegType_loss: 0.6356 - LegColour_loss: 1.5693 - Luggage_loss: 0.6856 - val_loss:
7.1017 - val_Gender_loss: 0.8743 - val_TorsoType_loss: 0.6959 -
val_TorsoColour_loss: 2.1354 - val_LegType_loss: 0.7032 - val_LegColour_loss:
1.7500 - val_Luggage_loss: 0.9429
Epoch 9/10
32/32 [==============================] - 3s 105ms/step - loss: 6.3019 -
Gender_loss: 0.7193 - TorsoType_loss: 0.6780 - TorsoColour_loss: 2.0178 -
LegType_loss: 0.6301 - LegColour_loss: 1.5799 - Luggage_loss: 0.6767 - val_loss:
7.3345 - val_Gender_loss: 0.9710 - val_TorsoType_loss: 0.6811 -
val_TorsoColour_loss: 2.1864 - val_LegType_loss: 0.6996 - val_LegColour_loss:
1.8139 - val_Luggage_loss: 0.9825
Epoch 10/10
32/32 [==============================] - 3s 105ms/step - loss: 6.2838 -
Gender_loss: 0.7166 - TorsoType_loss: 0.6858 - TorsoColour_loss: 1.9975 -
LegType_loss: 0.6340 - LegColour_loss: 1.5600 - Luggage_loss: 0.6899 - val_loss:
7.1240 - val_Gender_loss: 0.9099 - val_TorsoType_loss: 0.6930 -
val_TorsoColour_loss: 2.1333 - val_LegType_loss: 0.7229 - val_LegColour_loss:
1.7446 - val_Luggage_loss: 0.9203
```

4.5 Final Output Visualisation

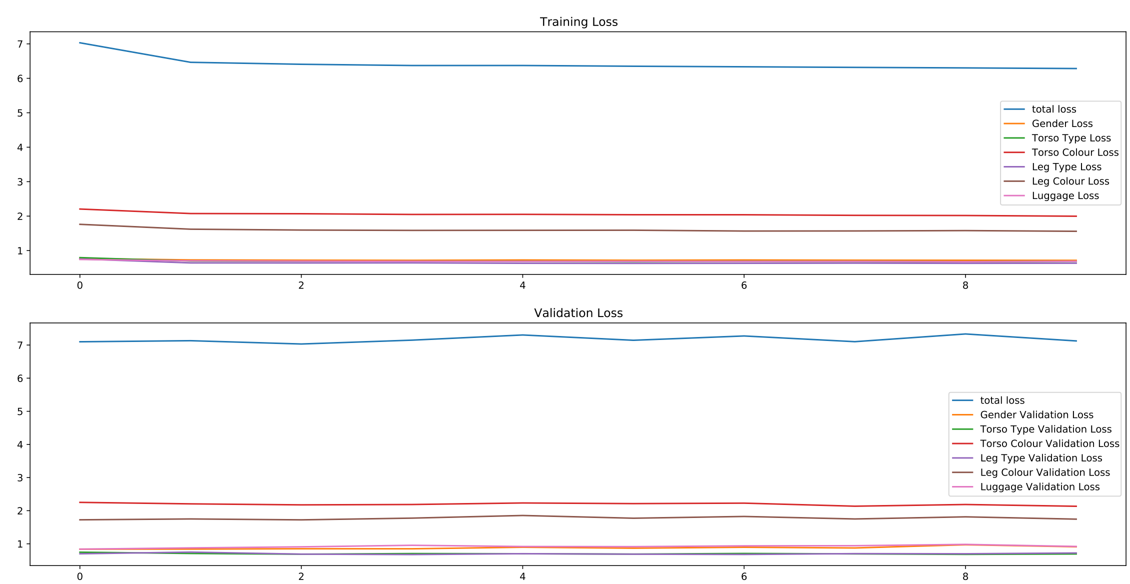
4.5.1 Plot loss

```
[ ]: print(history.history)
```

{'loss': [6.858940124511719, 6.465349197387695, 6.408232688903809, 6.36802864074707, 6.367767810821533, 6.33784818649292, 6.301400184631348, 6.292325496673584, 6.30463981628418, 6.2925238609313965], 'Gender_loss': [0.7674791812896729, 0.7347944974899292, 0.727027416229248, 0.7234300374984741, 0.7250304222106934, 0.7212717533111572, 0.7051653265953064, 0.7193406820297241, 0.7188973426818848, 0.7196298837661743], 'TorsoType_loss': [0.7464948296546936, 0.6954213976860046, 0.7025436162948608, 0.6905550360679626, 0.6862001419067383, 0.6832119226455688, 0.68450528383255, 0.679217100143432 6, 0.6756273508071899, 0.6843464374542236], 'TorsoColour_loss': [2.1708061695098877, 2.0812158584594727, 2.061927318572998, 2.056994915008545, 2.0570034980773926, 2.056914329528808 6, 2.029306411743164, 2.02854323387146, 2.025566101074218 8, 2.0425024032592773], 'LegType_loss': [0.679161548614502, 0.6472030878067017, 0.6293489933013916, 0.6367167234420776, 0.6304967999458313, 0.6228106617927551, 0.6267357468605042, 0.6230990886688232, 0.6309705376625061, 0.6244314908981323], 'LegColour_loss': [1.7312713861465454, 1.6071587800979614, 1.593424916267395, 1.57188081741333, 1.5786116123199463, 1.5693918466567993, 1.5726993083953857, 1.5653924942016602, 1.569687008857727, 1.5436302423477173], 'Luggage_loss': [0.7637266516685486, 0.6995555758476257, 0.6939615607261658, 0.6884508728981018, 0.6904250979423523, 0.6842483282089233, 0.6829886436462402, 0.6767328977584839, 0.6838914155960083, 0.6779822111129761], 'val_loss': [7.070468902587891, 7.125211238861084, 6.996547698974609, 7.054129600524902, 7.065083980560303, 7.212453842163086, 7.250545501708984, 7.335566997528076, 7.400391101837158, 7.498331069946289], 'val_Gender_loss': [0.8741154670715332, 0.8676681518554688, 0.8428791761398315, 0.8416348099708557, 0.8517574667930603, 0.885100781917572, 0.8760655522346497, 0.9228101372718811, 0.8944522142410278, 0.9264271855354309], 'val_TorsoType_loss': [0.696270763874054, 0.6935350298881531, 0.7092276811599731, 0.7111238837242126, 0.7022356390953064, 0.7118133306503296, 0.7494308352470398, 0.7011706829071045, 0.7219914793968201, 0.7297655940055847], 'val_TorsoColour_loss': [2.2275378704071045, 2.205714702606201, 2.210235834121704, 2.1904354095458984, 2.2289793491363525, 2.2046780586242676, 2.25449800491333, 2.268311023712158, 2.2018725872039795, 2.207395553588867], 'val_LegType_loss': [0.6826310157775879, 0.6879153251647949, 0.6738821268081665, 0.6984872817993164, 0.6701391339302063, 0.682951033115387, 0.6954875588417053, 0.6780556440353394, 0.7525702714920044, 0.749017059803009], 'val_LegColour_loss': [1.7286864519119263, 1.716179370880127, 1.6920853853225708, 1.7207350730895996, 1.750560998916626, 1.739353895187378, 1.7303977012634277, 1.7772618532180786, 1.7908692359924316, 1.8146884441375732], 'val_Luggage_loss': [0.8612279295921326, 0.9541992545127869, 0.8682377934455872, 0.8917131423950195, 0.8614115715026855, 0.9885566234588623, 0.9446654915809631, 0.9879575967788696, 1.0386351346969604, 1.0710370540618896]}

[ ]:
```
fig = plt.figure(figsize=[20, 10])
ax = fig.add_subplot(2, 1, 1)
ax.plot(history.history['loss'], label='total loss')
ax.plot(history.history['Gender_loss'], label='Gender Loss')
ax.plot(history.history['TorsoType_loss'], label='Torso Type Loss')
ax.plot(history.history['TorsoColour_loss'], label='Torso Colour Loss')
ax.plot(history.history['LegType_loss'], label='Leg Type Loss')
ax.plot(history.history['LegColour_loss'], label='Leg Colour Loss')
ax.plot(history.history['Luggage_loss'], label='Luggage Loss')
ax.set_title('Training Loss')
ax.legend()
ax = fig.add_subplot(2, 1, 2)
ax.plot(history.history['val_loss'], label='total loss')
ax.plot(history.history['val_Gender_loss'], label='Gender Validation Loss')
ax.plot(history.history['val_TorsoType_loss'], label='Torso Type Validation␣
↪Loss')
ax.plot(history.history['val_TorsoColour_loss'], label='Torso Colour Validation␣
↪Loss')
ax.plot(history.history['val_LegType_loss'], label='Leg Type Validation Loss')
ax.plot(history.history['val_LegColour_loss'], label='Leg Colour Validation␣
↪Loss')
ax.plot(history.history['val_Luggage_loss'], label='Luggage Validation Loss')
ax.set_title('Validation Loss')
ax.legend()
```

[ ]: <matplotlib.legend.Legend at 0x7fb76f666790>



4.5.2 Plot confusion matrix

Gender: -1 (unknown), 0 (male), 1 (female)

- Pose: -1 (unknown), 0 (front), 1 (back), 2 (45 degrees), 3 (90 degrees)

Torso Clothing Type: -1 (unknown), 0 (long), 1 (short)

Torso Clothing Colour: -1 (unknown), 0 (black), 1 (blue), 2 (brown), 3 (green), 4 (grey), 5 (orange), 6 (pink), 7 (purple), 8 (red), 9 (white), 10 (yellow)

- Torso Clothing Texture: -1 (unknown) , 0 (irregular), 1 (plaid), 2 (diagonal plaid), 3 (plain), 4 (spots), 5 (diagonal stripes), 6 (horizontal stripes), 7 (vertical stripes)

Leg Clothing Type: -1 (unknown), 0 (long), 1 (short)

Leg Clothing Colour: -1 (unknown), 0 (black), 1 (brown), 2 (blue), 3 (green), 4 (grey), 5 (orange), 6 (pink), 7 (purple), 8 (red), 9 (white), 10 (yellow)

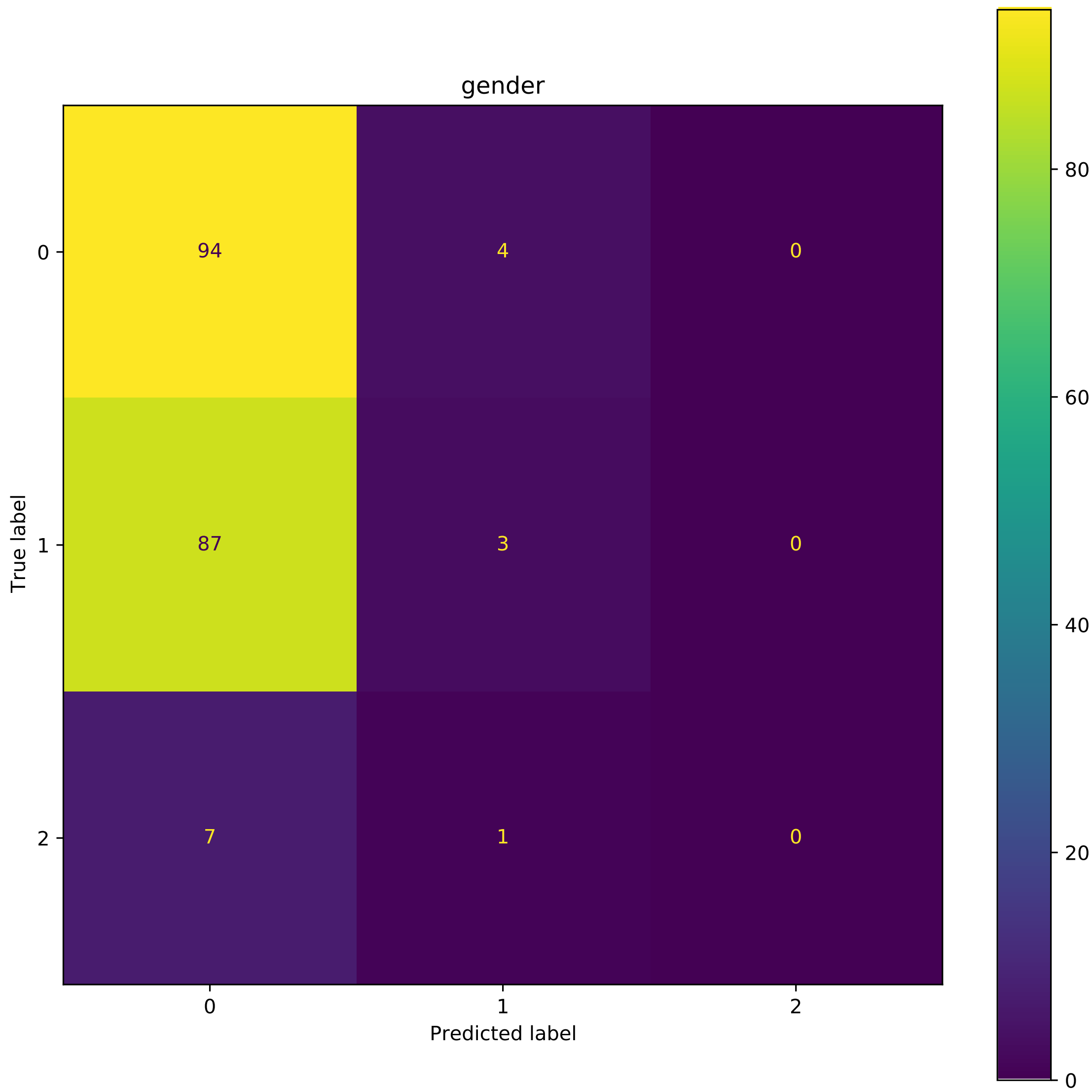
- Leg Clothing Texture: -1 (unknown) , 0 (irregular), 1 (plaid), 2 (diagonal plaid), 3 (plain), 4 (spots), 5 (diagonal stripes), 6 (horizontal stripes), 7 (vertical stripes)

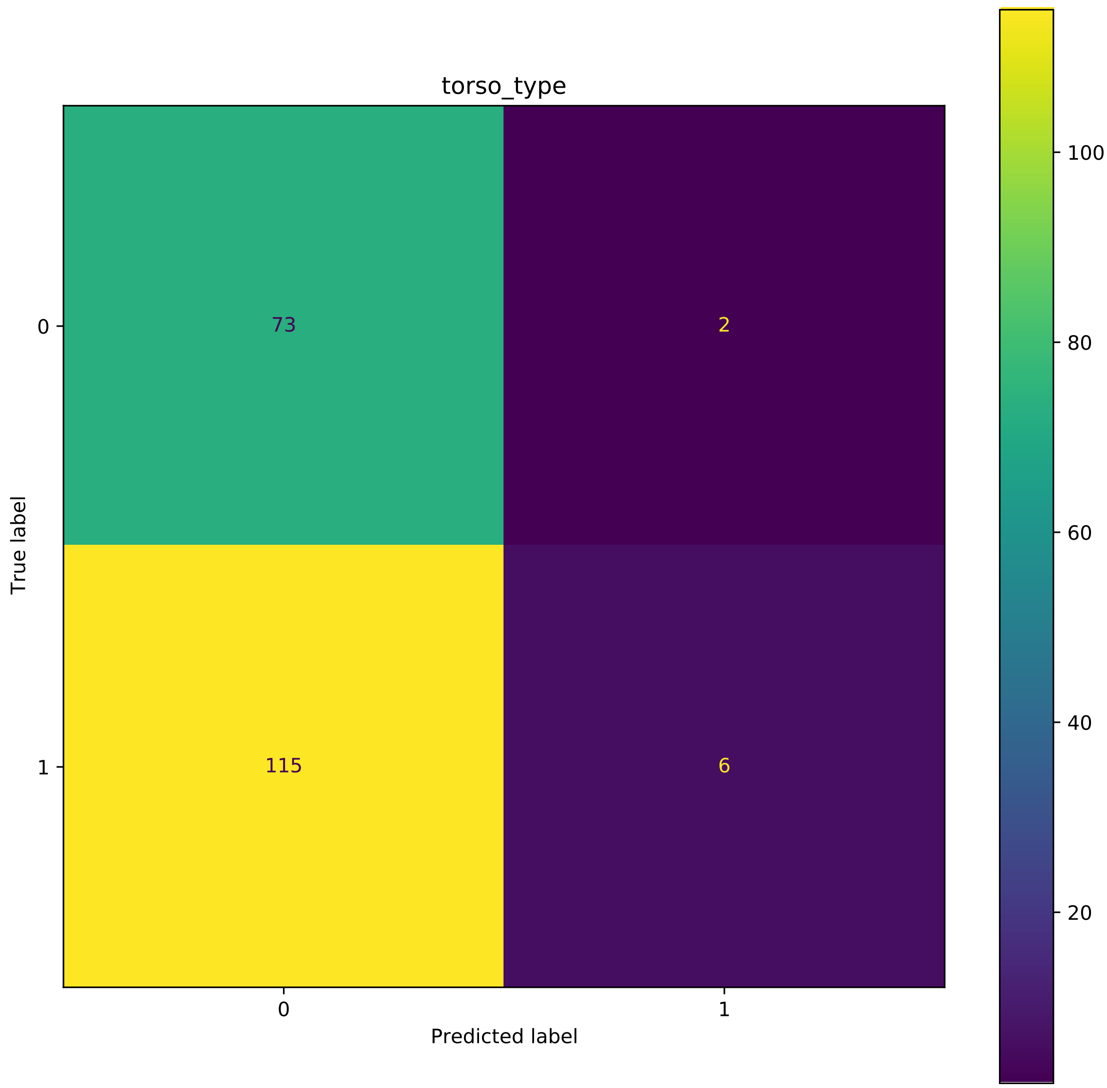
Luggage: -1 (unknown), 0 (yes), 1 (no)

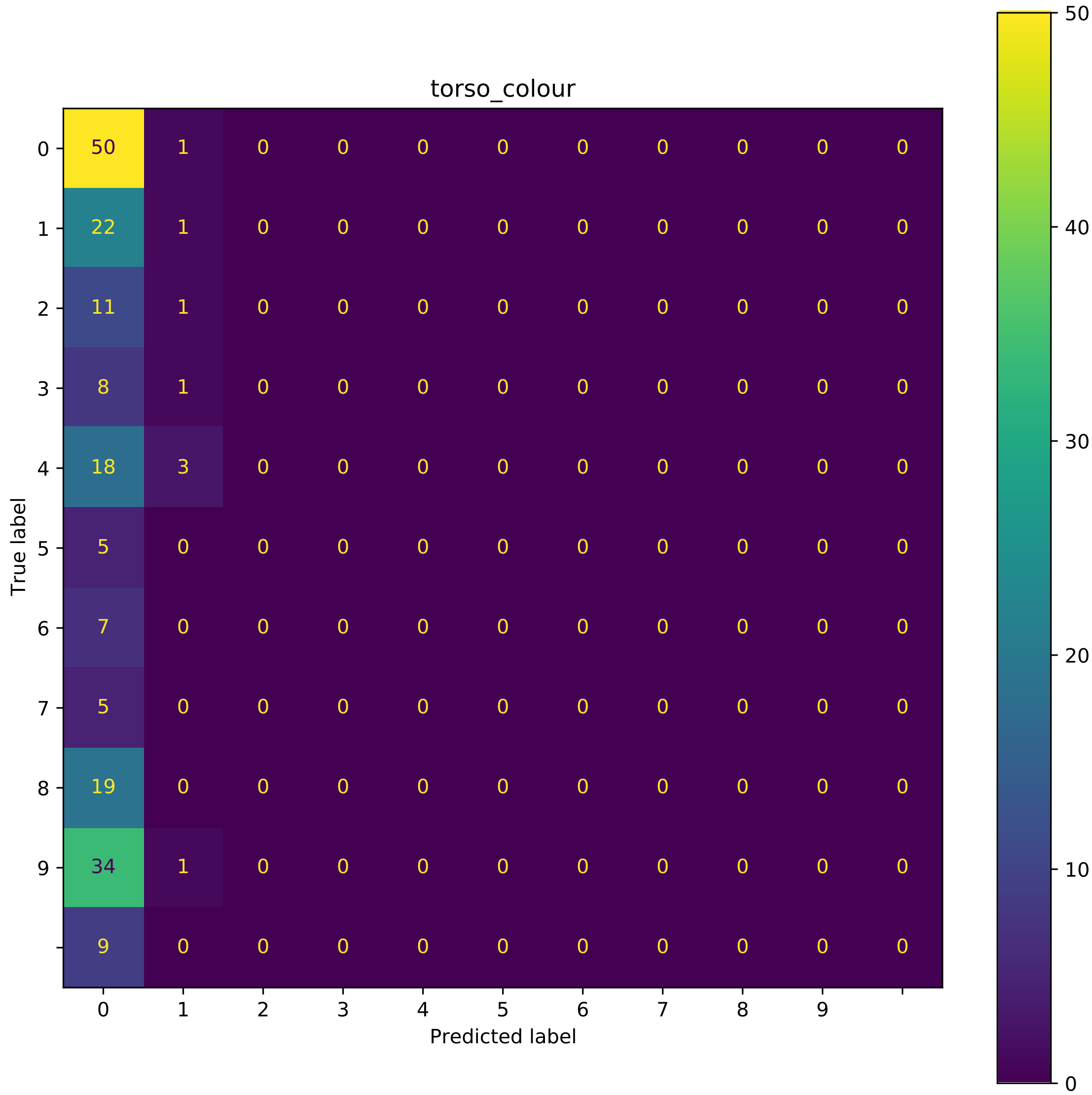
[ ]:
```
print(multitask_cnn.output_shape)
```

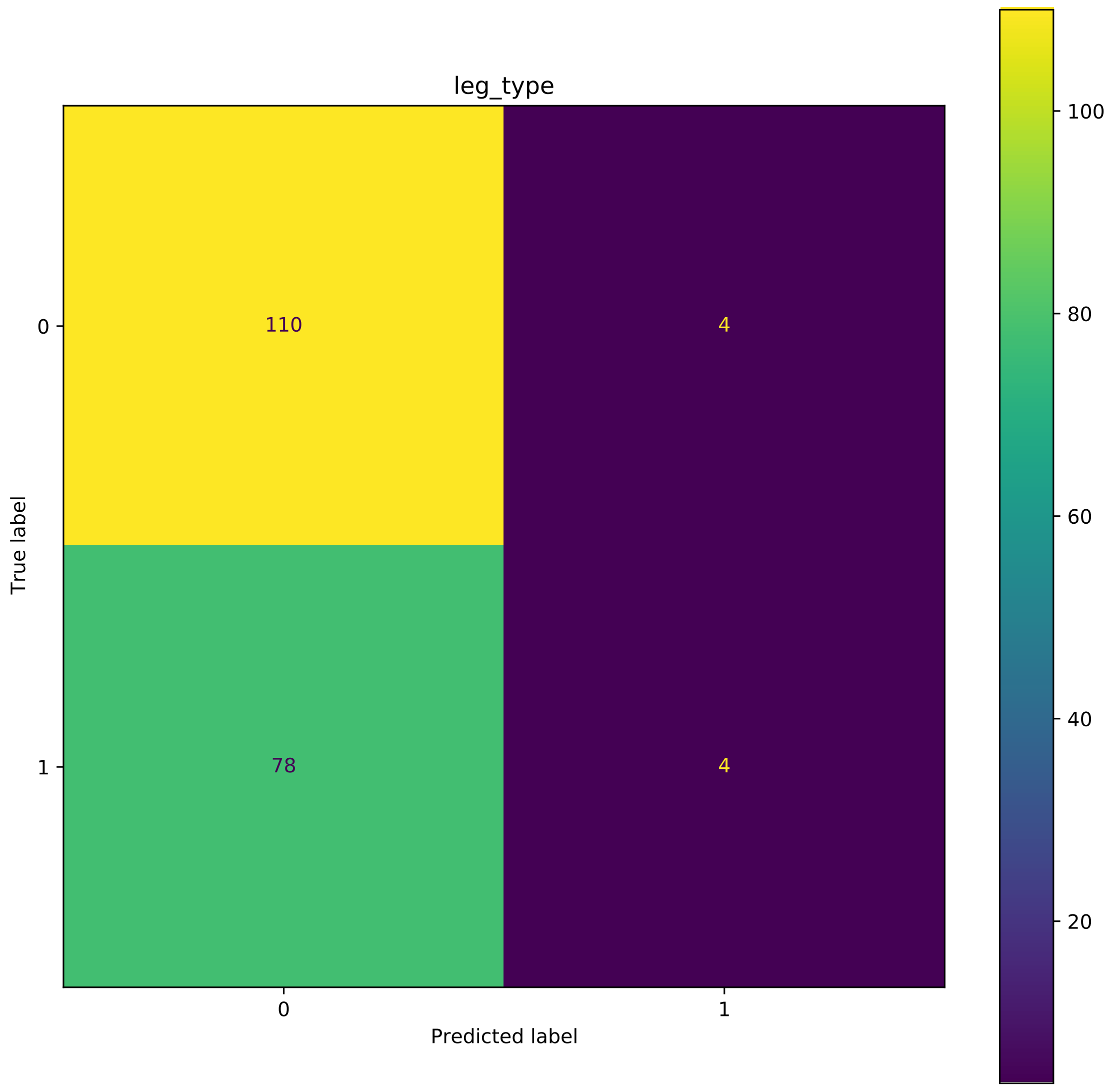
```
[(None, 3), (None, 3), (None, 12), (None, 3), (None, 12), (None, 3)]
```

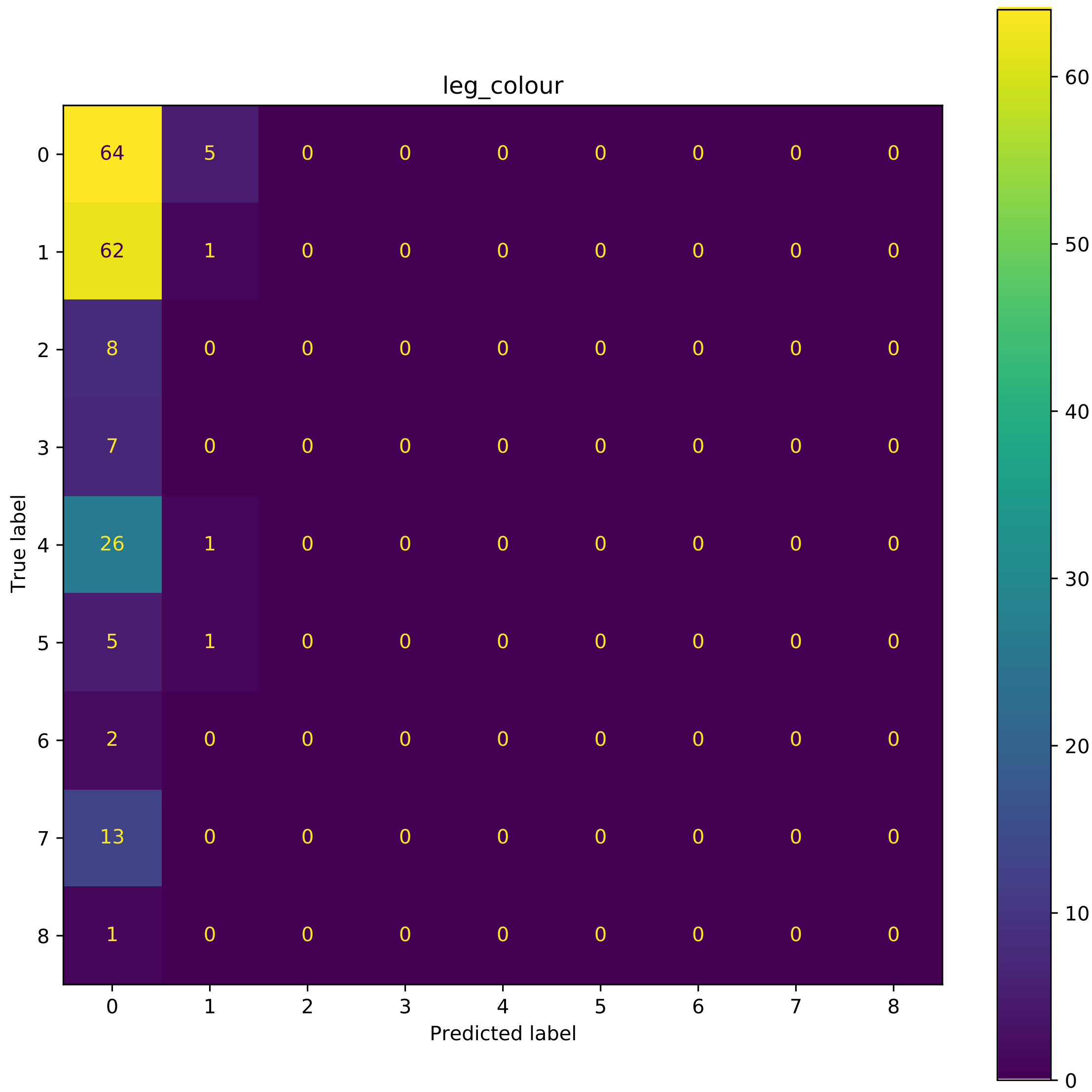
[ ]:
```
def eval_models(model, x_test, y_test, title):

    # y_test = tf.argmax(y_test['gender'],axis=1)
    predictions_label = model.predict(x_test)
    # print(predictions_label)
    # indexes = tf.argmax(predictions_label, axis=1)
    indexes = tf.argmax(predictions_label[0],axis=1)
    fig = plt.figure(figsize=[10, 10])
    ax = fig.add_subplot(1, 1, 1)
    cm = confusion_matrix(y_test, indexes)
    c = ConfusionMatrixDisplay(cm, display_labels=range(10))
    c.plot(ax = ax)
    c.ax_.set_title(title);

# eval_models(model_cnn, x_test, y_test_rot, y_test, history)
# [test_y['gender'], test_y['torso_type'], test_y['torso_colour'],␣
 ↪test_y['leg_type'], test_y['leg_colour'], test_y['luggage']]
ML = ['gender', 'torso_type', 'torso_colour', 'leg_type', 'leg_colour',␣
 ↪'luggage']
for T in ML:
  eval_models(multitask_cnn, test_x['images'], test_y[T], T)
```

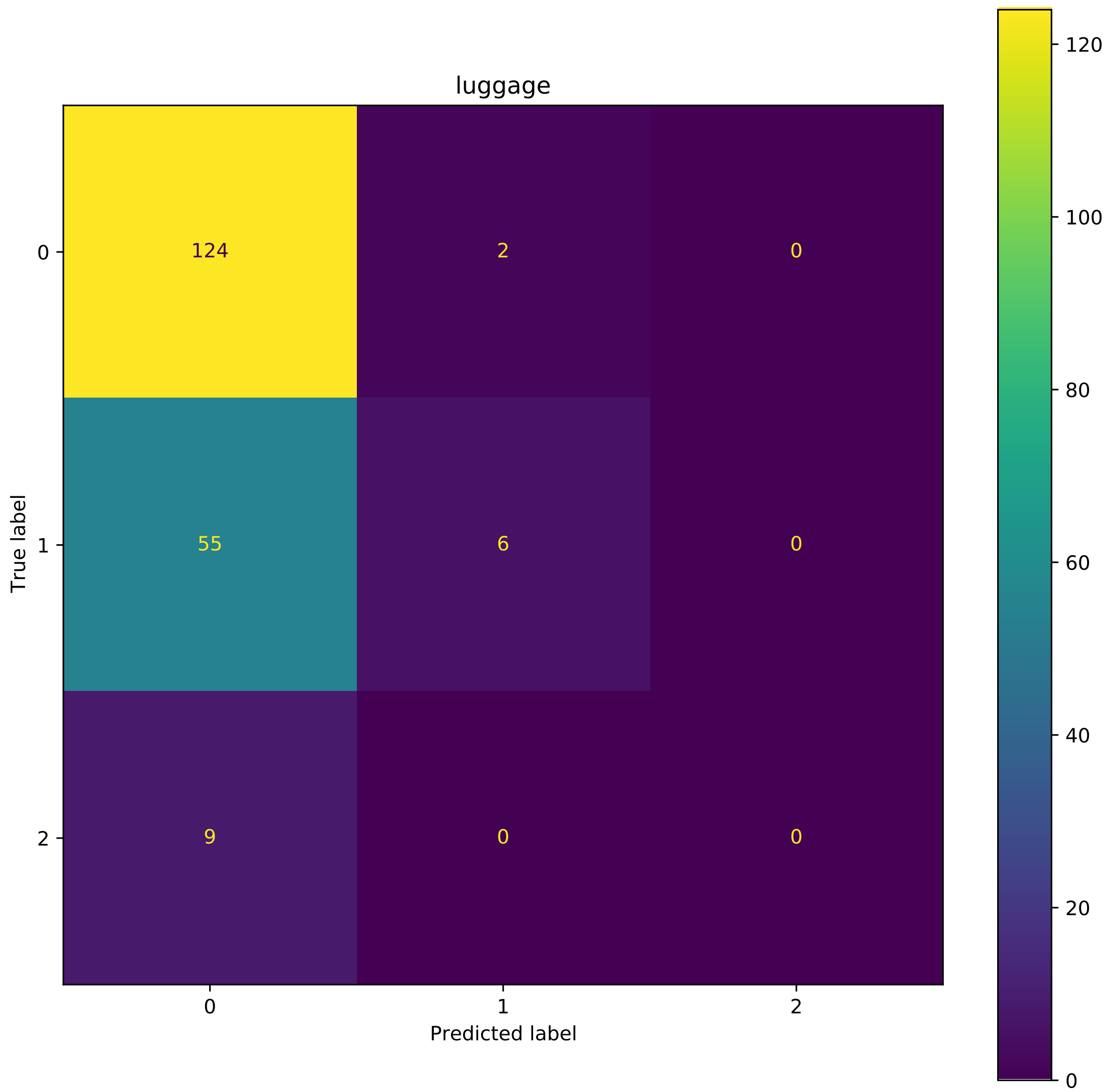

gender
True label
Predicted label
0
1
2
0
1
2
94
4
0
87
3
0
7
1
0
80
60
40
20
0


torso_type
True label
0
1
73
2
115
6
0
1
Predicted label
100
80
60
40
20


torso_colour
True label
Predicted label
0
1
2
3
4
5
6
7
8
9
50
40
30
20
10
0
50 1 0 0 0 0 0 0 0 0 0
22 1 0 0 0 0 0 0 0 0 0
11 1 0 0 0 0 0 0 0 0 0
8 1 0 0 0 0 0 0 0 0 0
18 3 0 0 0 0 0 0 0 0 0
5 0 0 0 0 0 0 0 0 0 0
7 0 0 0 0 0 0 0 0 0 0
5 0 0 0 0 0 0 0 0 0 0
19 0 0 0 0 0 0 0 0 0 0
34 1 0 0 0 0 0 0 0 0 0
9 0 0 0 0 0 0 0 0 0 0


leg_type
0
1
110
4
78
4
True label
0
1
Predicted label
100
80
60
40
20


leg_colour
True label
Predicted label
0
1
2
3
4
5
6
7
8
64
5
62
1
8
7
26
13
60
50
40
30
20
10



5 Export as PDF

[ ]:
```
!wget -nc https://raw.githubusercontent.com/brpy/colab-pdf/master/colab_pdf.py
from colab_pdf import colab_pdf
colab_pdf('n10477659 Final Assignment_1C.ipynb')
```

```
--2022-06-05 11:21:58--  https://raw.githubusercontent.com/brpy/colab-
pdf/master/colab_pdf.py
```

```
Resolving raw.githubusercontent.com (raw.githubusercontent.com)…
185.199.108.133, 185.199.109.133, 185.199.110.133, …
Connecting to raw.githubusercontent.com
(raw.githubusercontent.com)|185.199.108.133|:443… connected.
HTTP request sent, awaiting response… 200 OK
Length: 1864 (1.8K) [text/plain]
Saving to: ‘colab_pdf.py’

colab_pdf.py        100%[===================>]   1.82K  --.-KB/s    in 0s

2022-06-05 11:21:58 (32.2 MB/s) - ‘colab_pdf.py’ saved [1864/1864]


WARNING: apt does not have a stable CLI interface. Use with caution in scripts.


WARNING: apt does not have a stable CLI interface. Use with caution in scripts.

Extracting templates from packages: 100%
```