
Project-II by Group Rome

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Abstract

This report presents experimental results and performance comparison of common machine learning methods on two different tasks. The first task is a computer vision problem, a people detection task. We implemented classifiers that are able to predict to a certain degree if an image contains a standing person or not. The performance was measured using ROC curves. The second task is a music recommendation problem. For this task, we need to predict how many times an user will listen to an artist based on the listening counts history of the users and their friendship information. The performance of the various methods was measured using the mean average error of the transformed data.

1 Music Recommendation

1.1 Music recommendation

Collaborative filtering is the part of recommender systems that predicts users' preferences for particular items. The major challenge in predicting users' listening counts, as in our task, is that the available user-artist entries are usually too few and sometimes a method's performance relies on a good initial estimation of the unknown entries. We therefore decided to implement besides the common KNN, Kmeans also ALS [1], which uses only the known listening counts and avoids dependency on initial estimations.

1.2 Data description

The training data consists in a matrix Y_{train} of 1774 users and 15802 artists. Entry $Y_{train}(i, j)$ expresses how many times user i has listened to artist j . An entry of 0 means we do not have information for that $(user, artist, count)$ triple. We are also given the friendship graph of the 1774 users stored as an adjacency matrix.

1.3 Exploratory Data Analysis

The matrix Y_{train} is very sparse with a density of only 0.26%, corresponding to 69617 $(user, artist, count)$ triples. The variance of the entries' values is very high, the maximum being 352698 and average listening count per user and per artist of 5.52 and 5.46 respectively. There were also 1262 artists for which no information was provided.

A histogram of all the listening counts tell us that the known entries follow a heavy tail distribution. The large counts represent a small number of popular items, the well-known artists, and the rest are located in the long tail. One method to transform skewed data such that it becomes more gaussian distributed is to use the Box-Cox transform which is equivalent with taking the log of the data (for high and positive values). This transformation will make the distances between listening counts much smaller and will reduce the influence on error of the $(user, artist, count)$ triples with very large counts.

The results after the data transformation can be seen in Fig. 1. The distribution of the user counts and of the artist counts are closer to a normal distribution. We notice there are a few larger entries with values greater than 10. These will have a higher impact on the untransformed data evaluation.

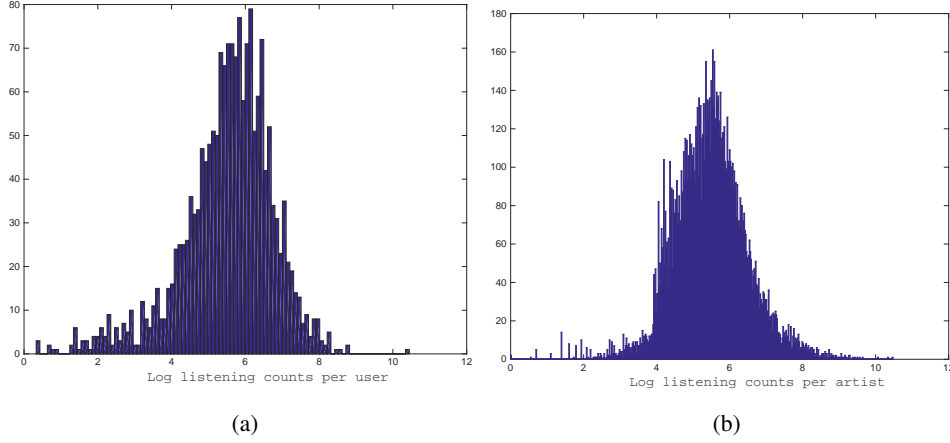


Figure 1: Distribution of listening counts

1.4 Task 1 - Weak Prediction

In all our experiments we used 10-fold cross validation and repeated the experiments twice. For the first task, we randomly omit 10 entries for every artist. Splitting the data was more difficult since we needed to make sure we do not remove all the entries for an artist. In the training data, if an artist has m entries with $m < 10$, then we keep $m - 1$ entries for testing, such that we still have at least one element for training.

1.5 Baseline

There are three simple basic predictions one can try: the global average count, the average count per user and the average count per artist prediction. All of these methods give similar MAE results: $1.11(\pm 0.0079)$, $0.64(\pm 0.0042)$ and $1.21(\pm 0.0092)$. User mean average performed twice as good as the others. As it can be seen in the user mean plot (Fig. 6), the variation of the counts per user are pretty small, less than 1 for most of the users with a few exceptions. The mean of the listening counts of an user is a good estimate for a weak prediction entry of that user.

1.5.1 KNN

K-nearest neighbors (KNN) algorithm is the first approach we tried for task 1. In KNN, we tried to find the most similar k users as nearest neighbors of a given user, and predict the listening count(s) of a user for a given artist. The algorithm has two important steps- calculating the similarity between users and analyzing the nearest neighbors to predict the listening count(s) of a given user.

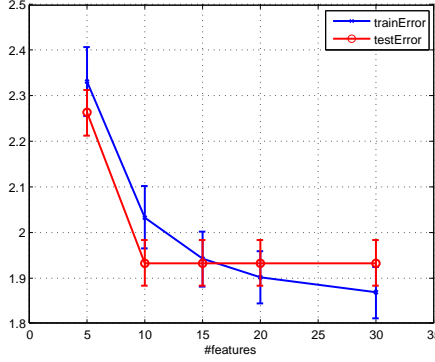
For measuring similarity between two users, we used the Pearson metric. We note $C(u, v)$ holds the set of artists that is common for users u and v , and $\bar{Y}train_u, \bar{Y}train_v$ are average listening count for user u and v respectively:

$$similarity(u, v) = \frac{\sum_{i \in C(u, v)} (Ytrain_{u,i} - \bar{Y}train_u)(Ytrain_{v,i} - \bar{Y}train_v)}{\sqrt{\sum_{i \in C(u, v)} (Ytrain_{u,i} - \bar{Y}train_u)^2} \sqrt{\sum_{i \in C(u, v)} (Ytrain_{v,i} - \bar{Y}train_v)^2}} \quad (1)$$

In recommendation phase, the following formula gives the predicted listening count of user u for artist i :

$$p(u, i) = \frac{\sum_{k \in Neighbor(u)} similarity(u, k)(Ytrain_{k,i} - \bar{Y}train_k)}{\sum_{k \in Neighbor(u)} |similarity(u, k)|} + \bar{Y}train_u \quad (2)$$

The best value for the number of nearest neighbors, k depends on the data. Therefore, among $[5, 10, 15, 20, 30]$, we selected the best k value using cross-validation technique. As can be seen from the Fig. 2, increasing the k value up to 10 reduces both test and train error. After 10, further increasing the value of k doesn't change the test error much but continues to reduce the train error for our data. From the cross validation result, we found the optimal number of nearest neighbors to be 15.



k	MAE train	MAE test
5	2.33 (± 0.05)	2.26 (± 0.076)
10	2.03 (± 0.049)	1.93 (± 0.068)
15	1.94 (± 0.049)	1.93 (± 0.060)
20	1.90 (± 0.049)	1.93 (± 0.057)
30	1.86 (± 0.049)	1.93(± 0.056)

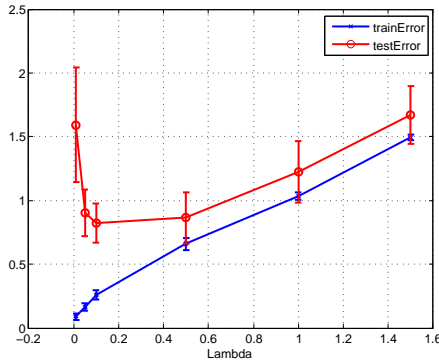
Figure 2: Estimated Train and Test MAE for K-Nearest Neighbors

With the best MAE of 1.5, the performance of the user-based KNN algorithm is not as good as alternative algorithms.

1.5.2 ALS

We do not review here the details of ALS algorithm, the reader can consult the paper [1] beforehand, since this was not the goal of this report.

Using 20 features and λ varying in $[0.01, 0.05, 0.1, 0.5, 1]$ we obtain the results in Fig. 3. The experiments were repeated twice with different seed. We note that we stopped the update steps in the algorithm only after 5 iterations because the update step was very computational intensive.



lambda	MAE train	MAE test
0.01	0.088 (± 0.0008)	1.591 (± 0.015)
0.05	0.163 (± 895)	0.901 (± 0.0061)
0.1	0.259 (± 851)	0.822 (± 0.0012)
0.5	0.660 (± 851)	0.864 (± 0.0016)
1	1.035 (± 842)	1.222(± 0.0010)
1.5	1.493 (± 837)	1.670(± 0.0007)

Figure 3: Estimated Train and Test MAE for different lambdas

We can see that a value of 0.05 for λ is a reasonable choice, so we selected lambda $\lambda = 0.05$ for the next experiments.

Keeping λ fixed, we varied the number of features from 10, 20, 30, 40, 50, 100 with $\lambda = 0.05$ (see figure 4), and the train error increased from 0.122 to 0.253 while the test MAE is 0.989 for maximum and 0.88 for minimum. Even though value 50 for features is best for train error, we choosed 40 because it give slightly better results on the test set. The best setup gave a MAE less than 0.8 for the test error when $\lambda = 0.05$, and feature count is 40.

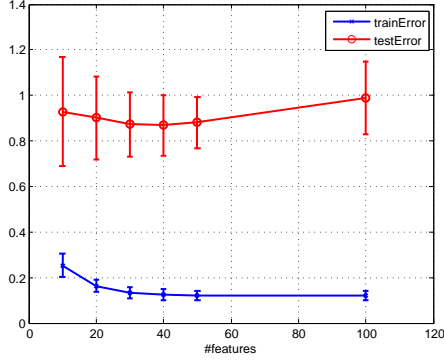


Figure 4: Estimated Train and Test MAE for different features

1.5.3 K-means

For this model, we chose to implement K-means with clustering of users instead of artists so that we can use the clusters obtained here also in Task 2.

The missing entries in the matrix were initialized with the user average. We then sorted the users according to their average score and initialized the clusters with equally spaced samples from the sorted users array. The goal of this cluster initialization was to have a more equilibrated assignment of users to clusters and to make sure we have clusters from both highly active and also from less active users.

Inspired by the friendship graph information, we tried K-means with varying number of clusters from [3,10,20,30,40,50,100]. We plot the mean train and test error using 10 fold cross validation in Fig 5. Using only 3 clusters both the train and the test error was high, while for 100 clusters the difference between train and test error became larger, giving signs of overfitting.

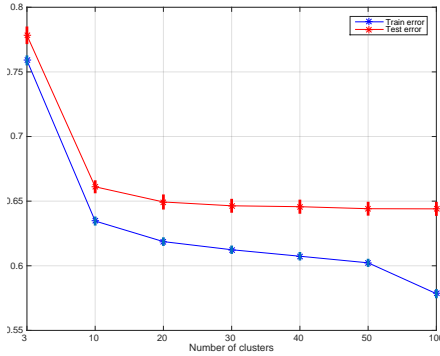


Figure 5: Estimated Train and Test MAE for different cluster counts

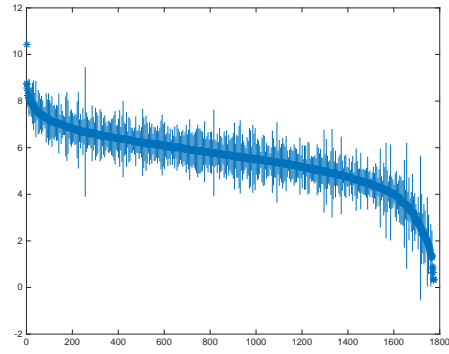


Figure 6: Average count per user

In all the experiments with more than 20 clusters we obtained a test MAE close to 0.64. This was our best test MAE so far. For computational reasons, we picked 20 clusters for the next task.

We also tried K-Means in the update step, only the entries for artists that were known were updated. We expected this to perform better, but the algorithm had problems with overfitting, always giving a train error less than 0.4 (much less than the normal Kmeans) but a test error a bit over 0.7 (higher than the normal KMeans). This happened for all the cluster sizes we experimented with.

1.6 Comparison

KNN algorithm is unsuccessful compared to other methods, even worst than baseline global average. The possible reasons are the high sparsity of our data and the choice of the similarity measure. It is known that KNN has limitations in performing well on sparse data matrices. Even though ALS method gave better results, it still didn't perform better than user mean baseline method and k-means. The K-means algorithm is similar to the expectation-maximization algorithm for mixtures of Gaussians meaning that they both attempt to find the centers of natural clusters in the data. Our results show that K-means appears to be a suitable approach for our problem, but we believe that its good performance comes from the sparsity-reduction step where we initialize the missing values. Both KMeans and user mean average baseline perform well because they incorporate good estimates on the missing entries.

1.7 Task 2

In this task we make predictions for a set of new users using their friendship information with a set of old users for which partial listening history is available. In other words, we try to see if there is a correlation between users' friendship and users' preference in music.

1.7.1 Friendship information

The initial friendship graph G_{train} of 1776 nodes and 22904 edges contained 22 connected components, but the majority of the components contained just a few nodes. Using the Gephi¹ tool we were able to find some properties of the graph such as the number of communities, 32 (out of these, only 8 had more than 150 members). These statistics were run so that we get an idea of the number of friendship clusters present. The number of connected components and of communities are similar with our choice of 20-30 clusters in KMeans.

We have tried two approaches using the friendship information, one based on the mean average per user and one based on Kmeans clustering of users.

1.7.2 Baseline Methods

As a reference method, we predict for a missing value the global average of all the available counts, which gave us a MAE of 1.078($\pm 0,044$). Taking the average per artist gave us a MAE of 1.767(± 0.09), significantly worse than the above.

1.8 Mean of Friends Method

"You are the average of your friends". In this approach, a prediction for a new user $Y_{strong}(u, a)$ is computed as the average count of its friends' listening counts $Y_{train}(f, a)$ for that artist or global average count for an user without friends (sad).

$$Y_{strong}(u, a) = \frac{\sum_{f \in Friends(u), Y_{train}(f, a) \neq 0} Y_{train}(f, a)}{n_{fa}}, n_{fa} \neq 0 \\ = global_average, n_{fa} = 0$$

where n_{fa} is the cardinality of the set $\{Y_{train}(f, a) \neq 0, f \in Friends(u)\}$

For this setup we obtained a test MAE=1.52 (± 0.29) which is smaller than our global average baseline prediction. If we also take into account the friends of the friends of user u we obtain a MAE of 1.08(± 0.041). This result is comparable with our best baseline solution.

1.8.1 KMeans

We clustered the users into 20 groups using the KMeans setup from Task 1 and repeated the experiments. For a new user, we predict the count as the mean of its friends and its friends' friends clusters. This gave us a MAE of 1.08(± 0.04). This is similar with the best prediction from the previous approach and with the global average baseline. Although KMeans with 20 clusters does not seem to

¹<http://gephi.github.io/>

outperform the other methods, we decided to use this on our newly predicted data. Increasing the number of clusters did not seem to help, as we obtained the same performance with 30 clusters and worse results with 100 clusters (test MAE = 1.55).

We mention that we had other unsuccessful experiments where the prediction was done using the mean of the unique friends' clusters or using only the most frequent cluster among friends (test MAE = 1.49).

1.9 Conclusions

Our proposed methods did not outperform the global average prediction, giving comparable performance. These results are not conclusive enough to say if friendship information is indeed correlated with users' music listening counts (we believe it is). As further steps, we could analyze the correlation of the friendship information of the old users with their listening history. Basically, we could try to predict weak entries using only friendship information, information which we actually did not use in Task 1. Another helpful analysis is to see a histogram of the individual errors and the characteristics of the users for which friendship information is not useful.

2 People Detection

2.1 Data description

The training data *imgs* contains 8545 color images of size 105x43. From every image a HOG descriptor 26x10x36 was extracted and converted into a vector of total length 9360. All of these descriptors make up the training data on which we will work on. We noticed that there are more images without people (7308 negative samples) than with people (1237 positive samples).

Our task is to train various classifiers, so that we will be able to detect the presence of people in new images. For this purpose we evaluate five classifiers, measuring the accuracy of their estimations using Receiver Operating Characteristics (ROC) curves.

2.2 Data preprocessing

We assume that there are no outliers, since the images are manually annotated. We work on the extracted features so we normalize the 9360 dim vectors to have 0 mean and standard deviation 1. For all the methods presented below we used 5 fold cross validation.

The methods that we compare are: Naive Bayes classifier, Logistic and Penalized Logistic Regression, Support Vector Machine (SVM), K-NN, and Neural Network classifier. We note that before the experiments we tried using PCA for reducing the dimensionality of the feature descriptors. The reduction in dimensionality was minimal but at a huge computational cost so we decided to drop it.

2.3 Naive Bayes classifier

In this part we tried to fit a Naive Bayes classifier to our data. For this, we made the assumption that the data is normally distributed and the estimates of the prior probabilities can be estimated empirically from the relative frequencies of the classes in training samples.

The results from the K-fold validation were not very satisfying, since the average TPR was very low (0.031). This may be caused by the strong assumptions that we made in order to fit this model. Naive Bayes model assumes that the processed data follows a specific distribution (in our case Gaussian), but also that the features are independent. In our data, this is possibly not the case, so the classifier cannot fit an appropriate model.

2.4 Logistic and Penalized Logistic Regression

Our goal in this part was to train a simple Logistic Regression model and its Penalized version as baseline methods. We chose a learning parameter $\alpha = 10^{-2}$, since all the values close to this performed well enough for our experiments. Regarding the value λ for penalized logistic regression,

all of the values that were used performed the same. Both of the methods gave the same results, with average TPR equal to 0.754.

By adding a penalization term, we tried to prevent overfitting by imposing penalty on large fluctuations of the model parameters and reduce the influence of the outliers to our model. The data, as we mentioned before, does not have outliers and the fluctuations at the model parameters are avoided by the nature of our data. This is possibly the reason that both models performed similarly.

2.5 Support Vector Machines

For this part of the experiments we used the LIBSVM 3.20² toolbox that supports SVM with various kernels. We performed analysis and K-fold validation on linear-kernel SVM, polynomial-kernel SVM with degrees 2 and 3, radial-basis-function SVM and sigmoid-kernel SVM. In all the models we used the prediction scores to compute the TPR and the FPR. A comparison of the various model is given in Fig 7a.

We observe that the RBF SVM performs significantly better. This fact can be seen not only by looking at the average TPR, equal to 0.893, but also observing the whole range of the FPR, where the classifier gives better results than all of the other SVM models. The second best in performance is polynomial SVM with degree 2, which has very similar results with the RBF case for FPR greater than $10e-3$. The rest of the classifiers perform well for FPR greater than $10e-2$, with the exception of the linear case, which has quite good results for lower rates, too. Cubic SVM performed worse than Quadratic SVM probably due to overfitting on the training data.

Moreover, in Table 1 we present the average percentage of the successful classifications that were made during the K-fold validation:

SVM kernel	Linear	Quadratic	Cubic	RBF	Sigmoid
Average success rate (%)	94.81	97.22	91.45	98.43	84.68

Table 1: Average percentage for the success rate of SVM classifiers.

2.6 K-NN classifier

For this experiments we used a KNN library, which we modified in order to compute and return as output not only the class labels, but also the scores of the prediction. We used Euclidean Distance as distance measure between samples and varied the number of neighbours between 5, 9, 15, 19 and 25.

Fig 7b presents the resulting ROC curves that were created using the scores obtained from the K-fold validation runs. All the classifiers show good performance, especially for FPR greater than 10^{-3} . Only the 9-NN classifier seems to perform a bit worse for FPR between 10^{-4} and 10^{-3} . For FPR greater than 10^{-3} the algorithms perform similarly, resulting in almost overlapping curves.

2.7 Neural Network

Neural Networks are powerfull tools able to learn complex decisions boundaries. Besides the computational cost, their major drawback is the high amount of parameters needed to be tuned for a specific problem, making them harder to train.

The parameters we considered for our problem were the number of epochs, the learning rate α (parameter in gradient descent update), the number of hidden layers and their size. We fixed the batch size to 50 and the number of epochs to 10, since we experimentally saw that the error starts to converge after 10 passes through the data. The activation functions were also kept fixed to tanh (hyperbolic tangent) for intermediate layers and sigmoid at the last layer.

Using cross validation for a network with just one hidden layer of 50 neurons we determined the learning parameter α , which we later used for bigger network setups. Fig.8a shows the ROC curves for α in $[0.01, 0.1, 1, 10]$.

²<http://www.csie.ntu.edu.tw/~cjlin/libsvm/>

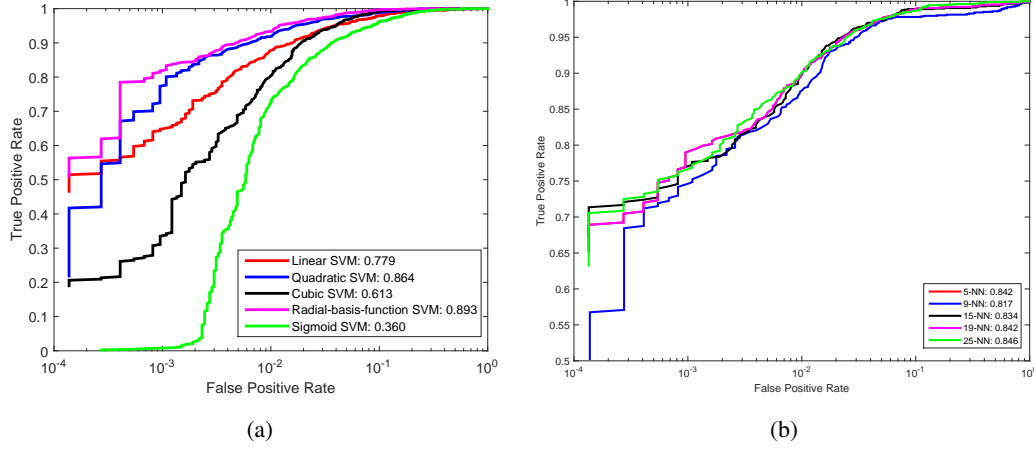


Figure 7: ROC curves created using: (a) SVM with various kernel types (linear, quadratic, cubic, real-basis-function, sigmoid), (b) K-NN classifier for various number of neighbours (5, 9, 15, 19, 25).

The results for bigger setups can be seen in Fig 8b. Choosing $\alpha = 1$, we experimented with 2 hidden layers of sizes $[50, 20]$, $[100, 50]$, $[200, 50]$, $[200, 100]$ and $[300, 50]$. The smallest NN performed just slightly worse than the others for FPR less than 10^{-3} , meaning we can increase a bit the model complexity by adding more neurons per layer or more hidden layers. We could have easily increased and test larger networks if it were not for the time and computational constraints. Not suprisingly, our best setup consists in the biggest network. We see that increasing the size of the network leads to smaller FPR and better performance in general, meaning we have not yet reached an overfitting point.

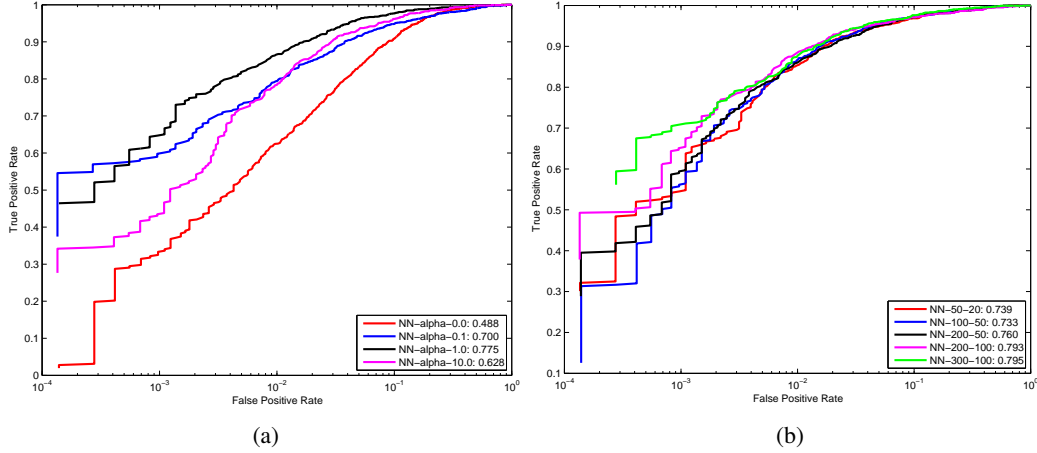


Figure 8: ROC curves created using: (a) NN with one hidden layer of 50 neurons, α in $[0.01, 0.1, 1, 10]$ (b) NN with two layers of various sizes. In the legend, NN-50-20 corresponds to a network of 50 and respectively 20 neurons for the 1st and 2nd hidden layer.

2.8 Comparison

To sum up, the models that performed best on the people detection data were SVM (with RBF or Quadratic kernels) followed closely by KNN with 25 neighbours and Euclidean Distance as metric. Although our NN setups performed just a little better than Penalized Logistic Regression, we believe different setups (e.g. 3 intermediate layers) would have fitted better. We note that our models depend

on the discriminative power of the HOG features. Using the same models but with different feature descriptors would have changed the rankings of our best models.

Acknowledgments

We would like to thank the course teaching assistants that helped us a lot during this project preparation, not only during the exercise session, but also at their office hours. Furthermore, the help that our teacher Mohammad Emtiyaz Khan offered us was very important, and we would want to thank him, too. All of the code used and submitted along with this report was written by equally by all of our group members.

References

- [1] Yunhong Zhou, Dennis Wilkinson, Robert Schreiber, and Rong Pan. Large-scale parallel collaborative filtering for the netflix prize. In *Proceedings of the 4th International Conference on Algorithmic Aspects in Information and Management*, AAIM '08, pages 337–348, 2008.