[CL-AFF Shared Task] Modeling Happiness Using One-Class Autoencoders

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Abstract. In this paper, we present a semi-supervised approach to modeling social and agentic characteristics of happiness. For this, we build four one-class autoencoder models, respectivley trained with 1) only social, 2) non-social, 3) agentic, and 4) non-agentic happiness. Then, we extract data from unlabeled data that are likely to belong to a prescribed type, as determined by the models. This paper presents the performance of predicting agency and social class with and without the extracted data. Our evaluation shows that the results are promising.

Keywords: Happiness modeling · Deep Learning · Autoencoders.

1 Introduction

Emotion is a crucial factor for the understanding of humans and human activities. As we are not purely logical, emotions do affect our actions, responses, and thoughts. A great deal of human artifacts (e.g., fine arts, novels, architectures) might not be created without emotions, whether they are positive (e.g., happiness, love) or negative (e.g., sadness, anger, fear). Emotion researchers often employ two different types of emotion models to describe various aspects of emotions - either categorical or dimensional. In the categorical emotion model, several discrete emotions are labeled distinctively as six basic emotions (joy, sadness, anger, fear, disgust, and surprise) [17, 9] or eight fundamental emotion types with trust and anticipation added to the six basic emotions [18]. Some emotions (such as joy, trust, and anticipation) have positive valence and others (such as sadness, anger, fear, disgust) have negative valence.

In the dimensional model, different types of emotions can be mapped into either a two-dimensional (valence-arousal) [19] or a three-dimensional (valence-arousal-dominance) space [15]. Using the dimensional model, different emotion types in the categorical model can be compared with one another. For example, joy or happiness can be mapped into a region where valence (i.e., pleasantness) is positive and arousal is positive. Sadness/anger, in contrast, can be mapped into a region where valence is negative and arousal is positive/negative, respectively.

Happiness is an abstract term that locates in an emotional state with positive valence. Its definition includes various metaphors and metonomies [12]. The concept of happiness shares that of 'joy', 'satisfaction', or 'being glad' as metonomies. The causes of happiness (e.g., goal achievements) and responses to happiness (e.g., expressive, physiological, and behavioral) are various as well. As the definition of happiness is broad and varies from person to person, the analysis of happiness require a hierarchical or multi-level framework. In psychology, happiness is often measured as the notion of subjective well-being, an umbrella term referring to "people's evaluations of their lives - evaluations that are both affective and cognitive"[7]. While happiness or subjective well-being is highly subjective and hard to given an objective definition, it certainly includes several categories such as "life satisfaction overall", "satisfaction with important domain (e.g., work satisfaction)", "positive affect", "low levels of negative affect", etc. As an effort to explore the possible causes of subjective well-being, a multilevel framework of happiness (either from personal level to nationwide level with seven categories [8] or including four levels - individual, household, district, and region [2]) has been suggested. It makes sense as individual happiness is often dependent upon the happiness of others who are related to ourselves at different levels - family members, contemporary people living in the same town, same city, or same country.

As Internet and smartphones are widely used, it is getting easier to gather a variety of (unlabelled) data. Labelling or annotation of the data, however, is still time-consuming and expensive. Thus interests and demand in semi-supervised learning is increasing, as it can classify or cluster a large amount of unlabelled data using a small set of labelled data. [21, 3, 11, 16, 20]. In semi-supervised learning, two distinct settings can be considered - transductive and inductive. The goal of transductive learning is to predict the labels of unlabelled data using the predetermined labels. The inductive learning, in contrast, concerns to learn the prediction rule for the unseen data by employing both labeled and unlabelled data as training data [21, 3, 20]. In this paper we limit our focus on transductive learning for the prediction of labels of unlabeled data. The recent advances in hardware (in particular graphics processing units - GPUs) and wide availability of big data in various fields have been drawing a great deal of attention to deep learning approaches and their applications [13]. Among those, Autoencoder (AE) is often used to learn generative models in an unsupervised learning environment [6, 13]. The autoencoder model is a deep learning architecture that consists of two neural networks - the encoding network compressing the input and the decoding network that reconstructs the compressed vector to its own input vector.

In this paper we present a deep-learning based semi-supervised approach to the prediction of possible labels relating to happiness using the Happy DB data set [1, 10]. The primary contributions of this paper are twofold: 1) to employ a one-class deep learning method to model a certain type of happiness; 2) to devise a mechanism to extract additional data using the proposed learning model with confidence.

2 Our Approach

We test if two factors (socialness and agency) of happiness can be indicated by the textual description of the happy moment with a one-class autoencoder deep learning model. For this, we first convert the data into one-hot encoding representation for the deep learning model, and carry out an initial evaluation of predicting social and agency classes. Next, we build four autoencoders, each modeled using only a certain social and agency label. Those models are employed to label subsets from the unlabeled data for further training. Lastly, the expanded train data are used to build the final classification models for comparison.

2.1 Preprocessing

The preprocessing step encodes a moment in the HappyDB [1] using one-hot encoding scheme. First, the moments were word-tokenized and their stop words were removed using the NLTK 3 package [14]. Then, each sentence was encoded in the bag of words (BoW) manner using different vocabulary sizes, e.g., 128, 256, 512, 1024, and 2048. Other features (concepts, agency, social, age, country, gender, married, parenthood, reflection, duration) were not used.

2.2 Data extraction from the unlabeled data set

While autoencoders are often used for dimensionality reduction and generation tasks [4], we employ an autoencoder for classification purposes. Figure 1 illustrates a conceptual model, which consists of 7 layers. The 512 dimensional input vector is fully connected to the 256 nodes of the next hidden layer, which are fully connected to 128 nodes and the 64 nodes in the middle layer. At this point, the 512 dimensional input is compressed as 64 dimensional vector. This process is called encoding. The short code can describe latent attributes of the input moment. Then, these compressed vector nodes are fully connected to a greater number of nodes in the hidden layer, until the number of nodes reaches the dimension of the input representation. This process is called decoding.

The basic idea of our approach is to build an autoencoder that reconstructs the given input as close as possible to the learned pattern. We hypothesize that the model trained with social happiness only will try to recover any input moment as close as possible to the description of a socially happy moment. Therefore, if a given input belongs to a non-social happiness, for example, it is likely that the recovered output is significantly different from the input. We can then determine whether the data that result in small differences (e.g., Mean Square Error, Cross Entropy Error, L1) between the input and the output belongs to the class which the model is trained with. The next section describes our experiments to test this hypothesis.

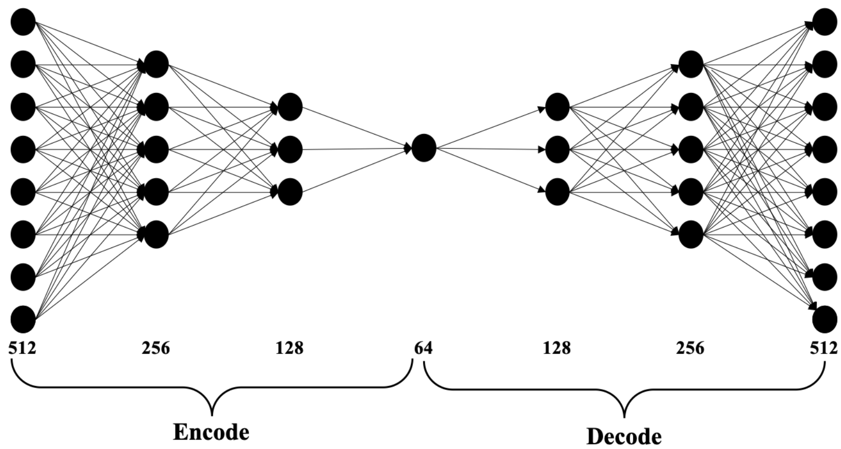

Fig. 1. The autoencoder structure

3 Evaluation of Social Class Prediction

3.1 Model Configuration and Data sets

We built our autoencoder model using the Keras framework [5]. We experimented with varying the number of hidden layers and the number of input neurons to find the best model for the given task. For social class prediction, the best model consists of one 1024 dimensional input layer, 7 hidden fully connected layers with 512, 256, 128, 64, 128, 256, and 512 nodes respectively, and one 1024 dimensional output layer to match the input size.

We converted the moment texts into 1024 dimensional vectors as described previously in the Preprocessing section. The training data were prepared by selecting randomly 80% from the labeled data in the train set. The rest 20% were used as the test set. We further split the training data into 2 groups (SY, SN) based on the social feature value (see Table 1), where SY refers to the data whose social values are 'yes', and SN denotes the data whose social values are 'no'; $SY+$ and $SN+$ are extended data sets that include the extracted accounts from the unlabeled data in the train set classified as social and non-social respectively using our approach.

3.2 Prediction with labeled data

We applied three representative machine learning algorithms as the classifiers: SVM, Xgboost, and KNN. The results show that the SVM algorithm (with Linear/RBF Kernel) performs best in predicting the social and non-social classes from the textual description of happy moments. We obtained the best performance 0.91 of F1-score when SVM with linear kernel is used as the classifier (see Table 2).

Table 1. The number of accounts in each dataset for social class prediction. Note that the unlabeled means the partially extracted unlabeled data.

Task	Dataset	Data Source	value	count
Train	**SY**	labeled	yes	4,515
	SY+	labeled + unlabeled	yes	6,684
	SN	labeled	no	3,935
	SN+	labeled + unlabeled	no	6,104
Test	**SYT**	labeled	yes	1,110
	SNT	labeled	no	1,002

Table 2. F1-score for social class prediction when SVM, Xgboost, and KNN algorithms are applied where k denotes the K hyperparameter. The best performance is written in bold. For SVM classifier, Linear and RBF kernels are used. (Note: SY: original data whose social values are 'yes', SN: original data whose social values are 'no'; $SY+$ and $SN+$: extended data sets that include the extracted accounts from the unlabeled data in the train set classified as social and non-social respectively.)

Test Set	Train Set	SVM		Xgboost	KNN				
		Linear Kernel	RBF Kernel		k=3	k=5	k=10	k=20	k=40
SYT	**SY**	**0.905**	0.889	0.818	**0.668**	**0.668**	0.602	0.555	0.476
	SY+	**0.899**	0.889	0.797	**0.713**	0.697	0.650	0.624	0.616
SNT	**SN**	**0.905**	0.894	0.847	0.743	**0.753**	0.744	0.732	0.711
	SN+	**0.900**	0.893	0.835	**0.752**	0.749	0.746	0.735	0.737

3.3 Data extraction from the unlabeled set

This section describes the process of extracting additional data from the unlabeled set. As mentioned above, we hypothesize that the model trained with social happiness only would recover any input moment as close as possible to the description of socially happy moment. Likewise, the model trained with non-social happiness will try to recover the input close to the non-socially happy pattern. We compute the error as the difference between the input and output. If the error is small, we can determine that the input account belongs to the class which the model is trained with.

We applied the autoencoder model to the unlabeled data in the train set. The model employs SGD as the optimizer and Categorical Cross Entropy as the loss function. The hidden layers use LeakyRelu as the activation function and the output layer uses sigmoid as the activation function. Each node is initalized using Xavier normal initializer. The batch size is 32, and the epoch is 32 as determined via numerous experimentations. We did not use dropout nor batch normalization, because the application of these normalization techniques degrades the performance, especially when predicting the non-social happiness. The difference between the input and the output was computed with the L1 function. Our evaluation shows that the precision is very high with the top 3%

of the output that displayed the smallest error or the difference compared to the input. For example, when the model extracts accounts which generate errors that are smaller than the top 3% threshold of the output, the precision of the social happiness reached 0.9 and that of the non-social was 1. The precision of the social happiness went up to 0.95 when the top 1% was set.

We set the threshold of top 3% of the output data to obtain a larger size data. In other words, if an account in the unlabeled data displays an error smaller than the top 3% threshold set above, it can be interpreted that the unlabeled data is labeled as social happiness with the model trained with the SY set. Non-social happiness can be classified in the same fashion. A total of 2,169 moments each are added to make the SY+ set and SN+ set respectively (Table 1).

Table 2 shows that SVM and Xgboost perform worse, though with a trivial margin, when the unlabeled data were added to the train set. When KNN was used, on the other hand, adding the unlabeled data to the train set improves the performance marginally. The best F1-sore was 0.71 (k=3) for social happiness prediction when trained with extended data set and 0.75 (k=5) for non-social happiness prediction with original data.

4 Evaluation of Agency Class Prediction

4.1 Model Configuration and Data sets

We initially prepared the data sets for agency class prediction using the same training data that were prepared for the social class prediction. However, it turns out that the agency class was imbalanced: 6,209 accounts of yes and 2,239 accounts of no in the train set, and 1,587 accounts of yes and 525 accounts of no. When these data sets were used, the best performance of F1-score was about 0.87 for the agency class prediction regardless of the algorithms used. Adding extra data from the unlabeled data set lowered the best performance down to 0.58. On the other hand, the highest F1-scores for non-agency class prediction was about 0.49. The use of extra unlabeled data also degraded the performance down to 0.35. We attribute this bad performance to class imbalance, hence we prepared another data set to balance the yes and no classes.

We randomly under-sampled the agency data from the train and the test data, to balance the two classes (see Table 3). Since the number of moments in the train set are less than that in the social train data, we only chose 1.5% from the unlabeled data and obtained additional 1,084 moments. For agency prediction, the best model consists of one 512 dimensional input layer, 5 hidden fully connected layers each with (256,128,64,128,256) nodes and one 512 dimensional output layer to match the input size.

4.2 Results and Discussions

As Table 4 shows, the best performances were obtained when SVM with RBF kernel was used. The highest prediction of the happiness with agency was obtained when the model trained with the original labeled data (F1-score = 0.75).

Table 3. The number of accounts in each data set for agency class prediction. Note that the unlabeled means the partially extracted unlabeled data prediction.

Task	Dataset	Data Source	value	count
Train	**AY**	labeled	yes	2,436
	AY+	labeled + unlabeled	yes	3,520
	AN	labeled	no	2,207
	AN+	labeled + unlabeled	no	3,291
Test	**AYT**	labeled	yes	604
	ANT	labeled	no	557

Table 4. F1-score for agency class prediction when SVM, Xgboost, and KNN algorithms are applied where k denotes the K hyperparameter. The best performance is written in bold. For SVM classifier, Linear and RBF kernels are used. (Note: AY: original data whose agency values are 'yes', AN: original data whose agency values are 'no'; *AY+* and *AN+*: extended data sets that include the extracted accounts from the unlabeled data in the train set classified as agency and non-agency respectively.)

Test Set	Train Set	SVM		Xgboost	KNN				
		Linear Kernel	RBF Kernel		k=3	k=5	k=10	k=20	k=40
AYT	**AY**	0.739	**0.751**	0.732	0.689	0.698	0.690	**0.712**	0.707
	AY+	0.725	**0.747**	0.697	0.685	0.685	0.682	**0.709**	0.691
ANT	**AN**	0.696	**0.702**	0.590	**0.628**	0.599	0.561	0.532	0.570
	AN+	0.711	**0.725**	0.628	**0.603**	0.566	0.573	0.567	0.605

Yet, it is noted that the prediction of the happiness without agency was greatest when the extracted unlabeled data were added to the train set (F1-score=0.73). Figure 2 illustrates the performances of SVM algorithms in terms of F1-score when different train sets were used.

Overall, our approach shows higher performance for predicting the social class than for predicting the agency class. It also shows that training the SVM model with the labeled data in the train set generally results in a slightly better performance than training the model with a combined data set. However, training with the combined data enhanced the model non-trivially for the prediction of the non-agency happiness. We also noted that the social class prediction performs best when the linear kernel was used, while the agency class prediction performs best when the RBF kernel was used. This may indicate that the problem of agency class prediction is non-linear.

5 Conclusions

This paper presented a deep learning based semi-supervised approach to characterize the description of happy moments in terms of socialness and agency. We suggested a novel method of using an autoencoder model to extract relevant

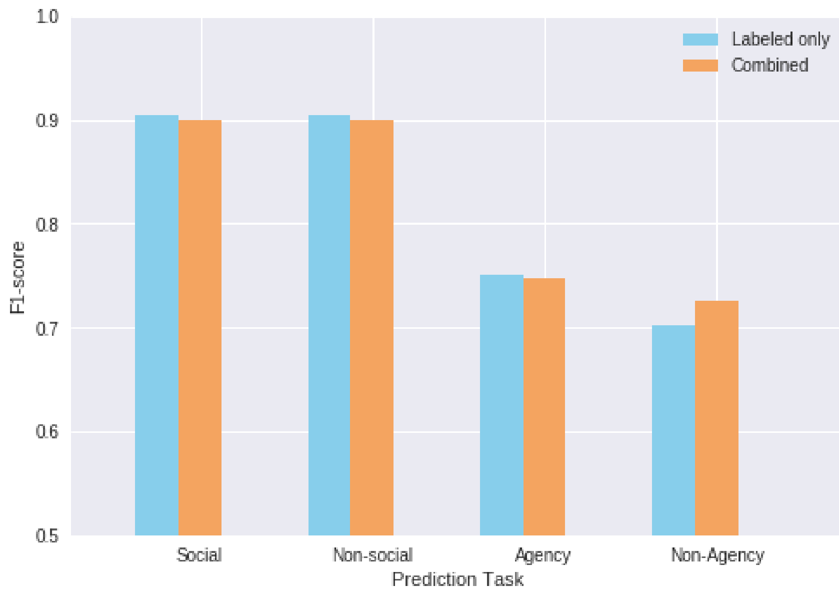

Fig. 2. Comparison of prediction performances when SVM was used. Note that linear kernel was used for social class prediction while RBF kernel was used for agency class prediction.

data for training from unlabeled data. We experimented with SVM, Xgboost, and KNN trained with using the textual description of the original train set with and without the data extracted from the unlabeled set. We obtained the best performance 0.91 of F1-score when SVM was trained with the original train set for the social class prediction. For the agency class prediction, F1-score of 0.75 was obtained for the prediction of the happiness with agency when SVM was trained with the under-sampled labeled data. Yet, the highest prediction of the happiness without agency was (F1-score=0.73) obtained when the model was trained with the combined data. We found that the adding extra data enhances the prediction performance for the non-agentic happiness without harming the prediction performance for the other classes.

Our evaluation is not conclusive due to the following problems. First, since our input vector is large and the autoencoder model is complex, a larger data set is necessary to train the model. Second, we ran the tests with only several model structures and a limited number of hyper-parameter settings.

Our autoencoder-based approach for predicting labels from the unlabeled data offers two main advantages. First, our model can extract data with confidence. Therefore, when the available data is large, we can choose the accounts with a very high confidence as extra training data. Second, our approach is very useful especially when the dataset is extremely imbalanced. When most data belong to a certain class, the autoencoder trained with such data without labeling successfully models the class. Therefore, a moment that induces high difference between the input and the output is likely to not belong to the class in question.

As future work we will enhance the model varying the autoencoder model structure and hyper-parameters. We also plan to test various word embeddings. Finally, we plan to investigate deeper into a general model of happiness considering previous studies on subjective well-being (e.g., features such as levels of negative affect, satisfaction in particular domains, etc.) in addition to a proposed autoencoder learning model.

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