

Grammatical Facial Expression Recognition with Supervised Classifiers

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Outline

- 1 Introduction
- 2 Recognize a GFE
- 3 Recognize two People using Same GFE
- 4 Recognize different GFE
- 5 The Mysterious Animation

What is a GFE

Grammatical facial expression (GFE) is a kind of sign language widely used by deaf people to communicate.

These languages consist of facial expressions, head movements, and hence are intrinsically multimodal languages

GFE

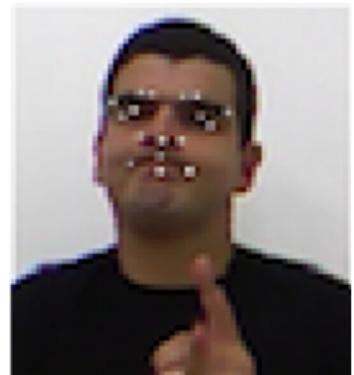
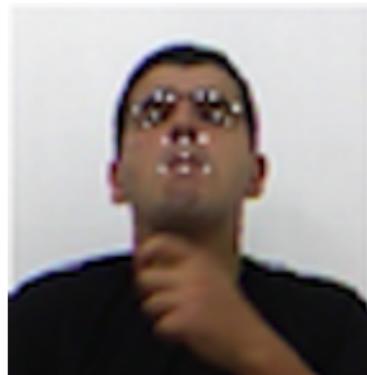


⁰Fernando de Almeida Freitas, et al. (2014)

Data Set

- Data set comes from UCI machine learning repository
- The data set is composed by eighteen videos recorded using Microsoft Kinect sensor
- In each video, a user performs (five times), in front of the sensor, five sentences in Libras (Brazilian Sign Language) that require the use of a grammatical facial expression

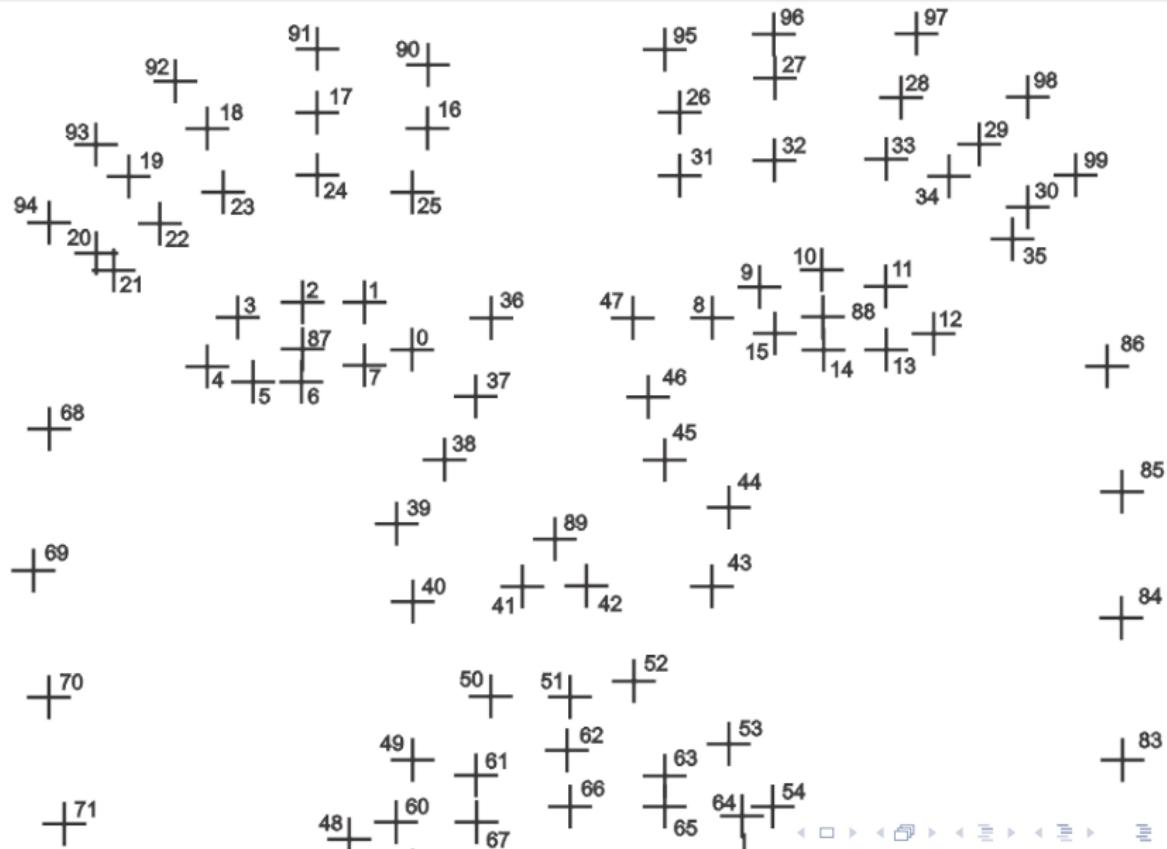
Data Set



Data Set - Kinect Sensor Record

- There are 27 frames captured by the kinect each second
- Each frame contains a picture that includes 100 coordinates(x,y,z) of points from eye, nose, eyebrows, face contour and iris
- Each frame contains one facial expression that might or might not be a valid GFE, and are labelled manually by specialists

Points Recorded

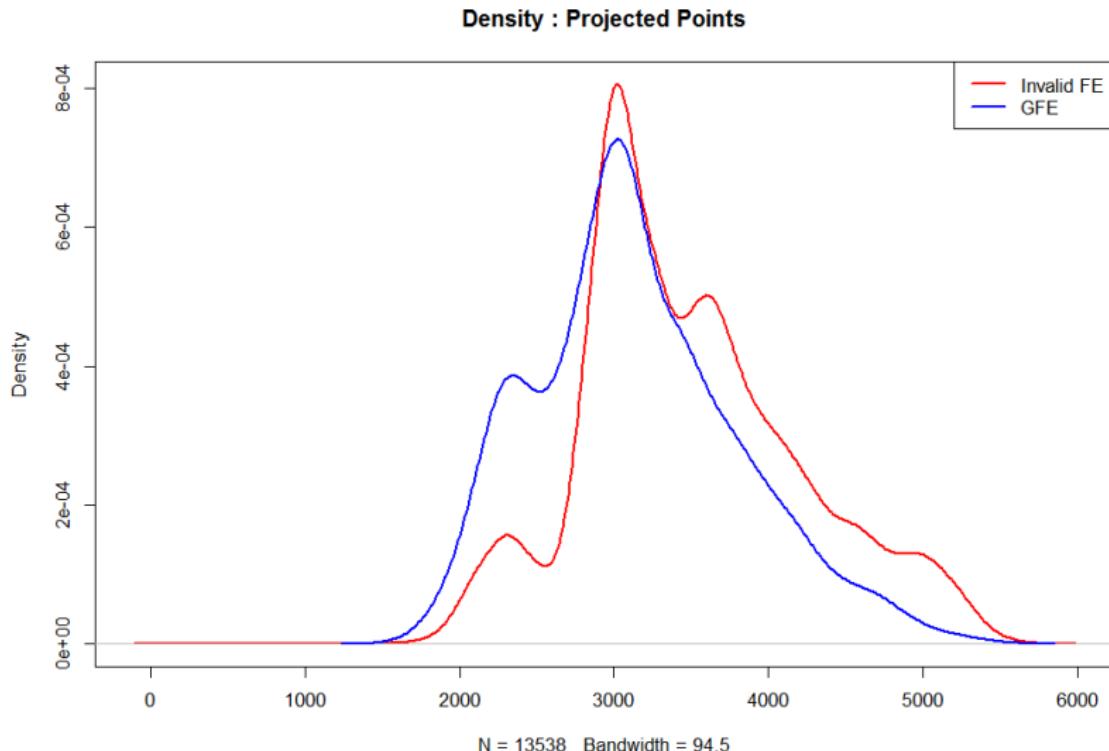


Final Data Set

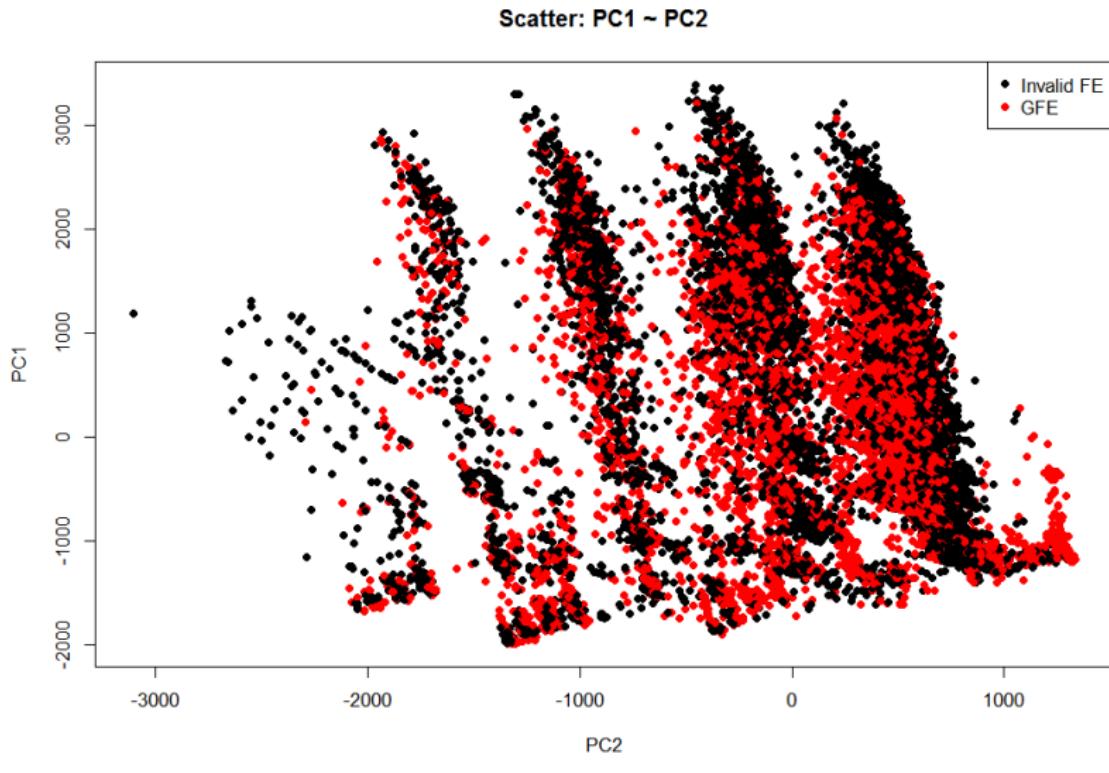
Collapse each frame to a one line vector and attach the label to it. We finally have a 27936×301 matrix.

20951 (75%) of them are used for model training, the rest 6985 are used for testing.

Projecting the Data onto the Mean Difference



First Two PC



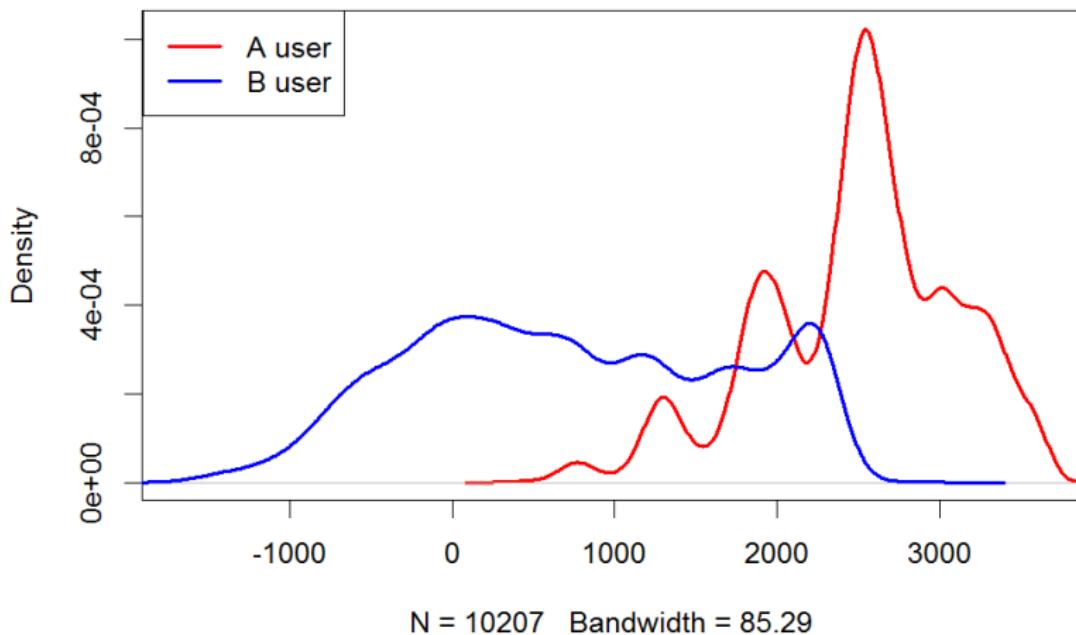
Model and Results Comparison

Table: Classifier Comparison

Classifier	Accuracy	Parameter	Training Time
LDA	0.82	Moment Way	14.34s
QDA	0.76	Moment Way	4.33s
Logistic	0.83	—	26.98s
Logistic LASSO	0.80	$\lambda = 0.00026$	2889.742s
NaiveBayes	0.58	$laplace = 0$	64.73
SVM	0.86	radical	580.03s
ada	0.86	exponential	1518.81s

Projecting onto User a and b

Density: Projected Points



Model and Results Comparison

Table: Classifier Comparison

Classifier	Accuracy	Parameter	Training Time
LDA	0.9996	Moment Way	14.58s
QDA	0.9757	Moment Way	4.36s
Logistic	0.9997	—	82.38s
Logistic LASSO	1	$\lambda = 0.000226$	
NaiveBayes	0.9933	$laplace = 0$	63.51s
SVM	0.9996	radical kernel	42.14s
ada	0.86	exponential/100 iter	1548.80s

Model and Results Comparison

Table: Classifier Comparison

Classifier	Accuracy	Parameter	Training Time
SVM	0.8802	default setting	469.017s
CART	0.6062	$xval = 5, cp = 0.01$	27.870s
Random Forest	0.9756	50 trees	7.382s
Gradient Boosting	0.9682	$depth = 2, \eta = 1$	19.82s
Multinomial Logistic	—	—	∞

tsne

The scatter at the very beginning is a visualization of these high dimensional data set in the 2-D plane through t-stochastic neighbour embedding.

Idea behind tsne

We try to properly reflect the euclidean distance structure of the high dimensional data set, by finding it's 2-D representation through minimize the KL divergence of them two.

t-sne Assumption

Given a point i in the data matrix, the probability that the data point j is in the same cluster as i does is given by:

$$p_{j|i} = \frac{\exp(-||x_i - x_j||^2 / \sigma_i^2)}{\sum_{k \neq i} \exp(-||x_i - x_k||^2 / \sigma_i^2)}$$

We assume a similar structure in the lower dimension:

$$q_{j|i} = \frac{\exp(-||y_i - y_j||^2 / \sigma_i^2)}{\sum_{k \neq i} \exp(-||y_i - y_k||^2 / \sigma_i^2)}$$

y is the lower-dimension representation of the higher dimensional data-points.

t-sne

We want to find y_i s, that minimize the KL divergence of these two density:

$$C = \sum_i KL(P_i || Q_i) = \sum_i \sum_j p_{j|i} \log \left\{ \frac{p_{j|i}}{q_{j|i}} \right\}$$

More Demonstration

Reference

- [1] FREITAS, F. A. ; Peres, S. M. ; Lima, C. A. M. ; BARBOSA, F. V. . Grammatical Facial Expressions Recognition with Machine Learning. In: 27th Florida Artificial Intelligence Research Society Conference (FLAIRS), 2014, Pensacola Beach. Proceedings of the 27th Florida Artificial Intelligence Research Society Conference (FLAIRS). Palo Alto: The AAAI Press, 2014. p. 180-185.
- [2] Lichman, M. (2013). UCI Machine Learning Repository [<http://archive.ics.uci.edu/ml>]. Irvine, CA: University of California, School of Information and Computer Science.