

Facial landmarking made (possible and) easy with R!

—
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- 2 Selected challenges of the application
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Quick introduction and motivation

- human facial attractiveness perception is data-based and irrespective of a perceiver

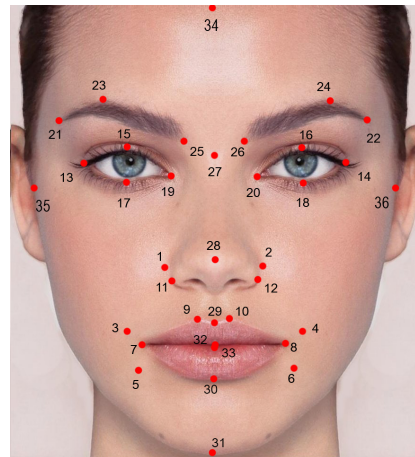
Quick introduction and motivation

- there is a large community of R speaking people
 - many of them would probably like to work with image data
- however, image processing is not so much natural for R
 - there are some R-available API's to C++ or Python libraries, though
- a shiny application may be a way to connect all of that

Manual landmarking

- based on uploading an image into application
- landmarking a displayed image using `imageOutput()` and an argument `click = clickOpts(id = "plot_click")` to get coordinates of a click

```
1 imageOutput(  
2   ...,  
3   click = clickOpts(  
4     id = "plot_click"  
5   )  
6 )
```



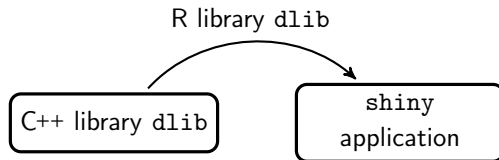
dlib packages and automated landmarking

- (i) a C++ toolkit containing machine learning algorithms and automated procedures (not only) for computer vision¹
- (ii) an R language based API package² bridging the C++ library above

¹Davis E. King. "Dlib-ml: A Machine Learning Toolkit". In: *Journal of Machine Learning Research* 10 (2009), pp. 1755–1758

²Jan Wijnfjels et al. *dlib: Allow Access to the 'Dlib' C++ Library*. R package version 1.0.3. 2018

Integrating of dlib package into shiny application



- desktop/server installation of C++ library dlib is required

Usage of automated landmarking

- still experimental (...)
- based on registration of functions
 - `face_landmark_detection.py`
or rather
 - `face_landmark_detection_ex.cpp`

via Rccp package to the application/R environment

```
1 | f <- system.file(  
2 |   ...,  
3 |   "face_landmark_detection_ex.cpp",  
4 |   package = "dlib"  
5 | )  
6 | cat(readLines(f), sep = "\n")  
7 | sourceCpp(f)  
8 | # ...  
9 | dlib_face_landmark_detection_ex(my_image.bmp)
```


Quick introduction

- rhinoplasty
 - a correction of a nose size or shape
 - one of the most common facial aesthetic surgeries
- which geometric facial features and their changes after rhinoplasty increase facial attractiveness the most?

Aims of this case study

- to identify geometric features of a face associated with an increase of facial attractiveness after undergoing rhinoplasty and therefore should be treated by plastic surgery preferentially³

³Lubomir Stepanek, Pavel Kasal, and Jan Mestak. "Evaluation of facial attractiveness for purposes of plastic surgery using machine-learning methods and image analysis". In: *20th IEEE International Conference on e-Health Networking, Applications and Services, Healthcom 2018, Ostrava, Czech Republic, September 17-20, 2018*. 2018, pp. 1–6. DOI: 10.1109/HealthCom.2018.8531195. URL: <https://doi.org/10.1109/HealthCom.2018.8531195>

Data of interest

- about 40 patients undergoing rhinoplasty (two images per patient – one before, one after the surgery)
- facial attractiveness of patients' data was measured using Likert scale by a board of independent observers

Brief methodology of facial attractiveness evaluation

- profile facial image data were collected for each patient before and after rhinoplasty (about 80 images)
- images were
 - processed
 - landmarked
 - analyzed
- linear regression was performed to select predictors increasing facial attractiveness after undergoing rhinoplasty

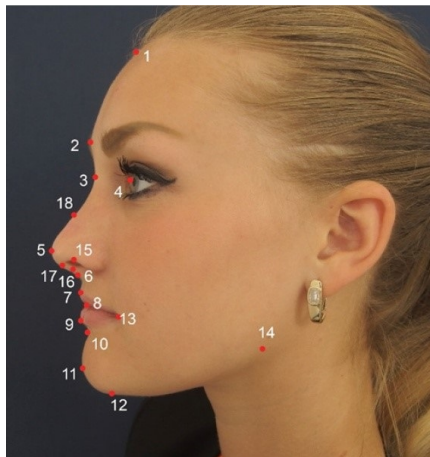
Landmarking

- new coordinates $[x'_i, y'_i]$
computed using

$$x'_i = \frac{x_i - \min\{\mathbf{x}\}}{\max\{\mathbf{x}\} - \min\{\mathbf{x}\}}$$

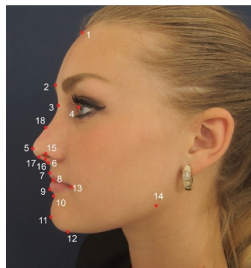
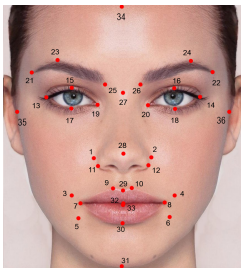
$$y'_i = \frac{y_i - \min\{\mathbf{y}\}}{\max\{\mathbf{y}\} - \min\{\mathbf{y}\}},$$

where $[x_i, y_i]$ are original coordinates of i -th landmark and \mathbf{x} , \mathbf{y} are vectors of all x - and y -coordinates



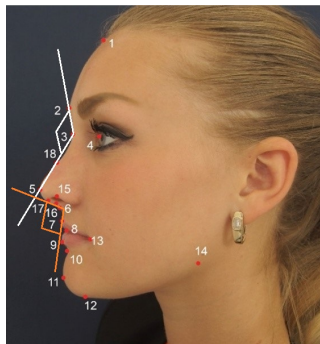
Some derived metrics and angles

metrics/angles	definition
nasofrontal angle	angle between landmarks 2, 3, 18 (profile)
nasolabial angle	angle between landmarks 7, 6, 17 (profile)
nasal tip	horizontal Euclidean distance between landmarks 6, 5 (profile)
nostril prominence	Euclidean distance between landmarks 15, 16 (profile)
cornea-nasion distance	horizontal Euclidean distance between landmarks 3, 4 (profile)
outer eyebrow	Euclidean distance between landmarks 21, 22 (portrait)
inner eyebrow	Euclidean distance between landmarks 25, 26 (portrait)
lower lip	Euclidean distance between landmarks 30, 33 (portrait)
mouth height	Euclidean distance between landmarks 6, 8 (profile)
angular height	Euclidean distance between landmarks 7 (or 8) and 33 (portrait)



Evaluation of rhinoplasty effect on facial attractiveness

predictor	estimate	<i>t</i> -value	<i>p</i> -value
intercept _{after-before}	3.832	1.696	0.043
nasofrontal angle _{after-before}	0.353	1.969	0.049
nasolabial angle _{after-before}	0.439	1.986	0.047
nasal tip _{after-before}	-3.178	0.234	0.068
nostril prominence _{after-before}	-0.145	0.128	0.266
cornea-nasion distance _{after-before}	-0.014	0.035	0.694



Quick introduction

- current plastic surgery deals with aesthetic indications such as an improvement of the attractiveness of a smile or other facial emotions
- total face impression is also dependent on presently expressed facial emotion
- there is no face without facial emotion at all

Aims of this case study

- to explore how accurate classification of faces into sets of facial emotions and their facial manifestations is⁴

⁴Lubomir Stepanek, Pavel Kasal, and Jan Mestak. “Evaluation of facial attractiveness for purposes of plastic surgery using machine-learning methods and image analysis”. In: *20th IEEE International Conference on e-Health Networking, Applications and Services, Healthcom 2018, Ostrava, Czech Republic, September 17-20, 2018*. 2018, pp. 1–6. DOI: 10.1109/HealthCom.2018.8531195. URL: <https://doi.org/10.1109/HealthCom.2018.8531195>

Data of interest

- the sets of used facial emotions and other facial manifestation originate from Ekman-Friesen FACS scale, but was improved a bit

cluster of emotions	quality
contact	positive
helpfulness	positive
evocation	positive
defence	negative
aggression	negative
reaction	neutral
decision	neutral
well-being	positive
fun	positive
rejection	negative
depression	negative
fear	negative
deliberation	positive
expectation	positive

Brief methodology of facial emotions classification

- portrait facial image data were collected for each person just in the moment they show a facial expression according to the given incentive (about 170 images)
- images were
 - processed
 - landmarked
 - analyzed
- Bayesian naive classifiers (e1071), decision trees (CART) (rpart) and neural networks (neuralnet) were learned to allow assigning a new face image data into one of facial emotions

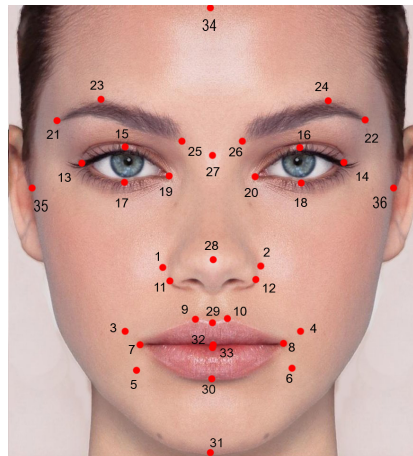
Landmarking (once more)

- new coordinates $[x'_i, y'_i]$
computed using

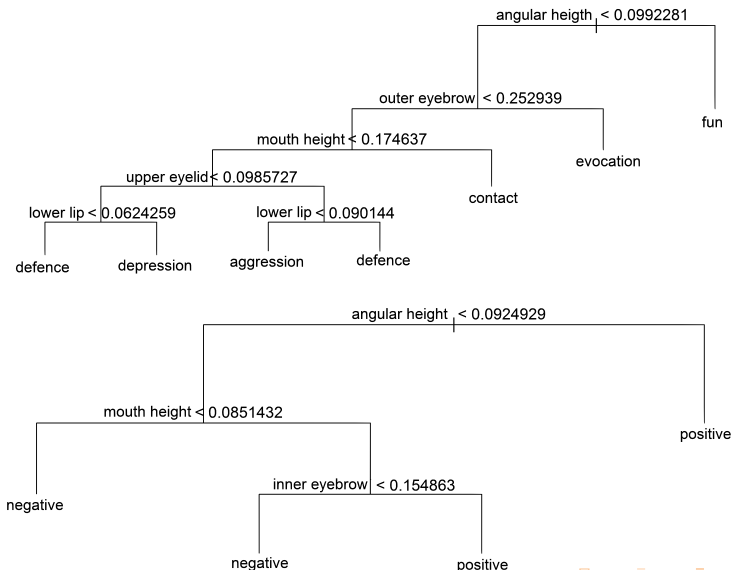
$$x'_i = \frac{x_i - \min\{\mathbf{x}\}}{\max\{\mathbf{x}\} - \min\{\mathbf{x}\}}$$

$$y'_i = \frac{y_i - \min\{\mathbf{y}\}}{\max\{\mathbf{y}\} - \min\{\mathbf{y}\}},$$

where $[x_i, y_i]$ are original coordinates of i -th landmark and \mathbf{x} , \mathbf{y} are vectors of all x - and y -coordinates



Trees for prediction of the cluster & quality of emotions



Predictions of the emotional quality based on the naive Bayes classifiers, CART's and neural networks, respectively

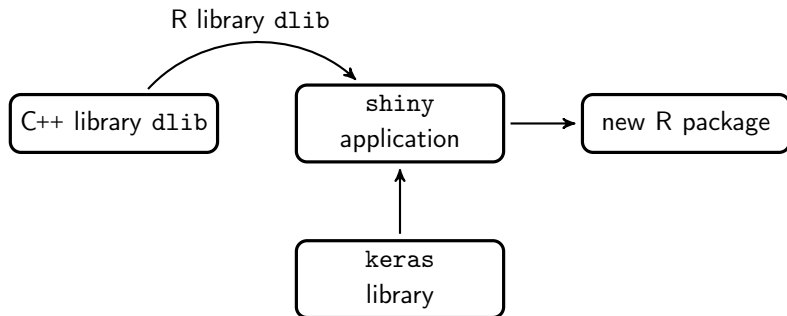
		predicted class		
		negative	neutral	positive
true class	negative	34	11	16
	neutral	16	39	8
	positive	4	10	30

		predicted class		
		negative	neutral	positive
true class	negative	35	7	15
	neutral	12	40	9
	positive	4	12	31

		predicted class		
		negative	neutral	positive
true class	negative	36	6	6
	neutral	12	54	18
	positive	3	4	32

Going further

- improvement of automated facial landmarking using C++ library dlib
- connection to Python library keras



Conclusion

- a shiny application providing manual and automated landmarking and some machine-learning analysis is possible to work out in R
- enlargements of both a nasolabial and nasofrontal angle within rhinoplasty were determined as statistically significant predictors increasing facial attractiveness
- neural networks manifested the highest predictive accuracy of a new face classification into facial emotions
- geometrical shape of mouth, then eyebrows and finally eyes affect in descending order the classification of facial images into emotions and emotional qualities

Thank you for your attention!

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http://shiny.statest.cz:3838/facial_attractiveness/

► GitHub

https://github.com/LStepanek/whyR_2019