Handwriting Personality Prediction

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Introduction

Overview

Applications

Psychological analysis

Graphology is used clinically by counsellors and psychotherapists.

Employment profiling

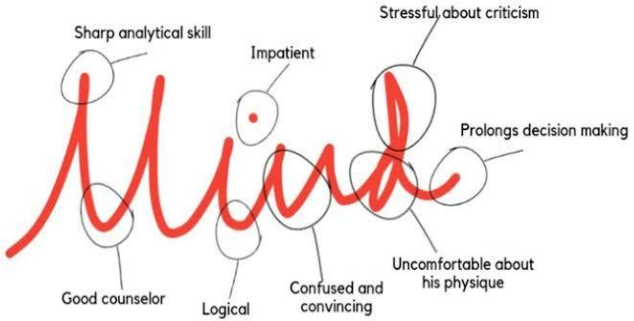
A graphological report is meant to be used in conjunction with other tools, such as comprehensive background checks, practical demonstration or record of work skills.

Problem Statement

A system is proposed to **automate** the basic handwriting analysis tasks of graphology to determine a few important **personality traits**.

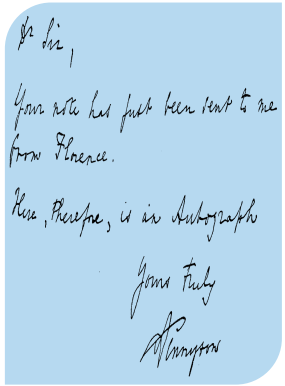
Analysis example

Analysis example

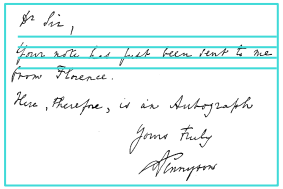


Sample walkthrough

Sample text

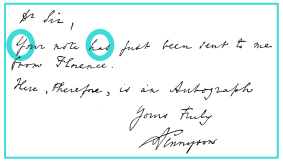


1



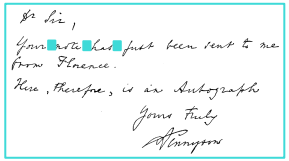
Alignment and size of letter

2



Match the template

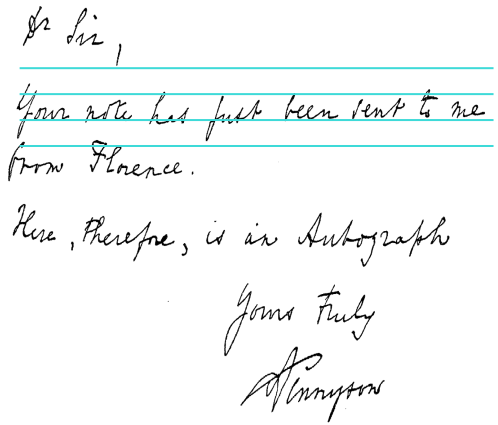
3



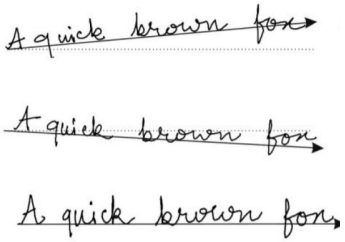
Spacing

Feature examples

Alignment and size



Alignment

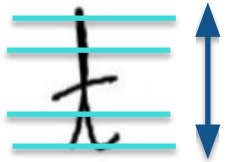


Ascending baseline

Descending baseline

Level baseline

Size



Data sourcing and cleaning

Data sourcing

Data from the **IAM Handwriting Database of Research Group** on Computer Vision and Artificial Intelligence INF, University of Bern, Switzerland is obtained.

IAM Handwriting Database of Research Group

672 pages of scanned text

Data cleaning

Data input

Preprocessing

Feature extraction

Training the classifier

Predict personality traits

Methods

Image Resolution and Cropping

The original images contain **unwanted printed texts, lines** and **free space** which are not suitable for further processing. We will be writing a script to **crop out** the left and right margins, **resize** all the images with 850 pixels width and perspective height, and save the images in PNG format.

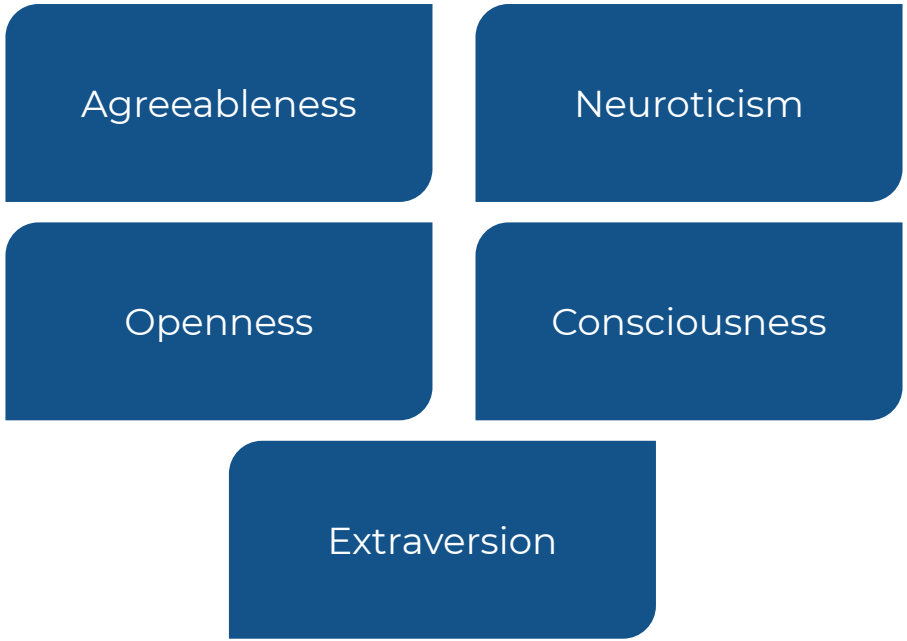
Noise Removal

Image noise is defined as **random variation of brightness** or **colour** information in images. Noise can be removed by **filtering** the images.

Handwriting features

Attribute	Writing categories	Psychological personality behavior
Letter size	Large letters	Likes being noticed, stands out in a crowd
	Small letters	Introspective, not seeking attention, modest
	Average letters	Adaptable, fits into a crowd, practical, balanced
Letter slant	Right slant	Sociable, responsive, interested in others, friendly
	Left slant	Reserved, observant, self-reliant, non-intrusive
	Vertical slant	Practical, independent, controlled, self-sufficient
Pen pressure	Light pen pressure	Can endure traumatic experiences w/o seriously affected.
	Heavy pen pressure	Have very deep and enduring feelings
Baseline	Raising baseline	Optimistic, upbeat, positive attitude, ambitious and hopeful
	Falling baseline	Tired, overwhelmed, pessimistic, not hopeful
	Straight baseline	Determined, stays on track, self-motivated, reliable, steady
	Erratic baseline	Wavering, lacks definite direction, unpredictable
Word spacing	Far spaced words	Desires more space, enjoys privacy
	Close spaced words	Closeness of sentiment and intelligence

Labels


Agreeableness
Neuroticism
Openness
Consciousness
Extraversion

Modeling

Model overview

CNN	The input image is fed into the CNN layers. These layers are trained to extract relevant features from the image.
ANN	Computational models inspired by an animal's central nervous systems. It is capable of machine learning as well as pattern recognition
Random forest	An ensemble learning method for classification, regression and other tasks that operates by constructing a multitude of decision trees at training time.

CNN Methodology

Data Preprocessing

- Separated the data into training set, validation set, and test set samples
- **Data Augmentation** was used to increase the number of samples

Model Building

- **Transfer learning** was used to learn the lower level features
- The base model was **InceptionResnetv2** with pre-trained weights flowing in from **ImageNet** dataset
- The base model was followed by **Max Pooling**, **Dropout**, **Batch Normalization** and a fully connected layer of **50 units**

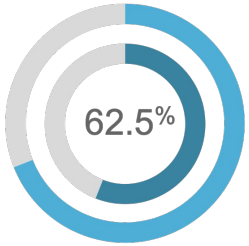
Model Features

- **Relu** activation function for the hidden layers
- **SoftMax** activation is used for the output layer
- **Adam Optimization** is used for Gradient Descent
- Incorporated **model checkpoints** to store the best weights

Hyperparameter Tuning

- **Epochs**: set the number of epochs to 30
- **Batch size**: tried batch sizes of 16, 32, and 64
- **Learning rate**: 0.001

CNN Results and Next Steps



Results

Accuracy on the training set - 78.9%
Accuracy on the validation set - 65.3%
Accuracy on the test set - 62.5%

Next steps

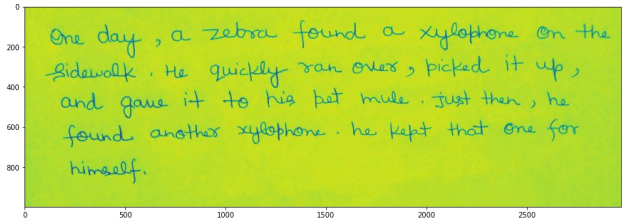
Unfreeze certain layers and try re training the model with our dataset for those layers

Try other architectures which could potentially outperform Inception Resnet V2 for the given dataset

Augment the data further for the imbalanced classes.
Also tune parameters like the optimizer, number of layers etc

ANN

Sample text



Arrays of Pixels

```
array([[174, 174, 174, ..., 173, 172, 173],
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       [174, 173, 173, ..., 173, 171, 172],
       ...,
       [162, 162, 163, ..., 166, 166, 165],
       [162, 162, 162, ..., 166, 165, 165],
       [162, 162, 162, ..., 165, 165, 164]], dtype=uint8)
```
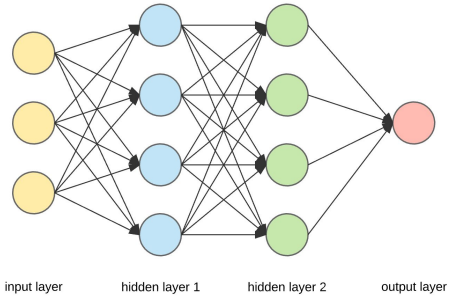

ANN



ANN

Data Preprocessing

- Encoded the data
- Splitted the data into train, validation, and test data sets

Model Building

- Rescaled and flattened the data
- **ReLU activation function** for the hidden layers
- **Softmax** for the output layer
- Regularized each hidden layers to prevent overfitting.

Model Features

- **Sparse Categorical Cross entropy** loss function
- **RMSprop** optimizer

Hyperparameter Tuning

- **Epochs**: 60
- **Batch size**: tried batch sizes of 16, 32, and 64

ANN

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Hyperparameter Tuning

- **Epochs**: 60
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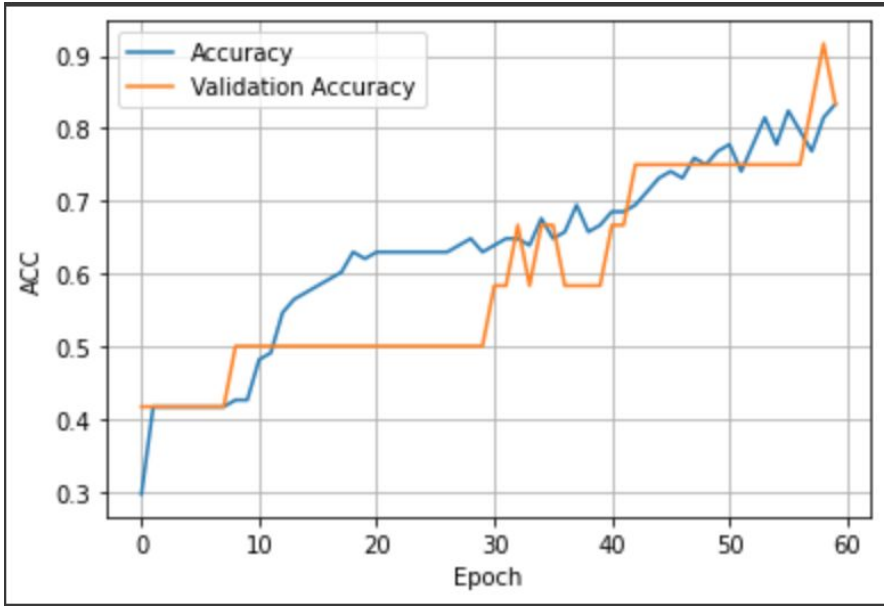
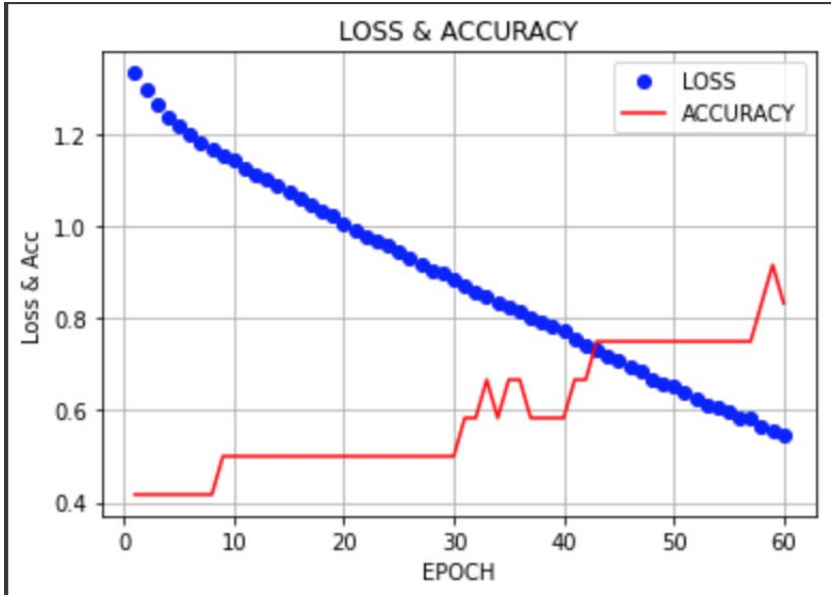
ANN

Model accuracy

Accuracy on the training set - 83%
Accuracy on the validation set - 83.3%
Accuracy on the test set - 79%





ANN Challenges and Next Steps

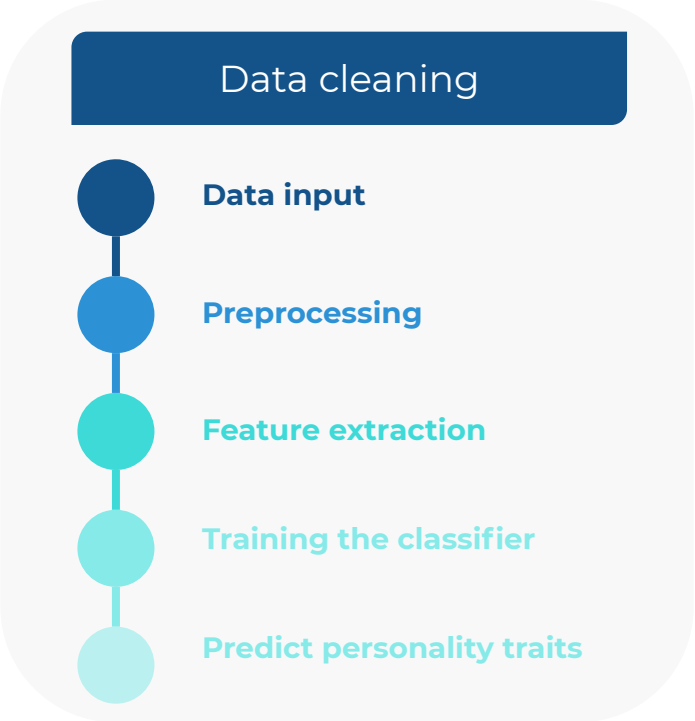
Challenges

- Tabular Data Input
- Hard to Interpret

Next Steps

- Try Different Hyperparameters
- ADAM optimizer

Pre-processing and data cleaning



Pre-processing and data cleaning

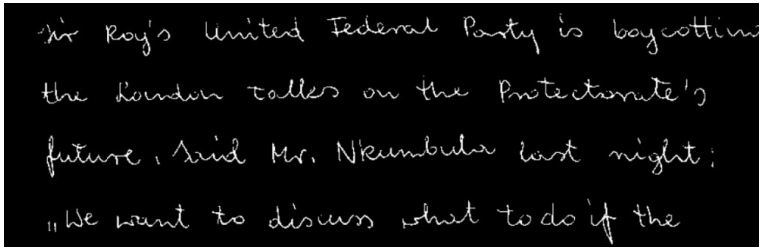
The handwriting images we obtained contains unwanted noise, printed texts and lines

The aim of pre-processing is to make the image data suitable for feature extraction

No.	Pre-processing stages	Pre-processing steps
1	**Image resolution and cropping**	• Crop left and right margins • Resize the images with 850 pixels width
2	**Noise removal**	• Bilateral filter
3	**Grayscale and binarization**	• Converted to grayscale • Binarized using inverted global thresholding
4	**Contour and transformation**	• Straightening using dilation • Find the contours • Affine transformation
5	**Horizontal and vertical projections**	• **Horizontal projection:** list of sum of all the pixel values of each row of the image • **Vertical projection:** list of sum of all the pixel values in each column of the image

Pre-Processing

Inverted Binarization



Dilation

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Word spacing	Far spaced words	Desires more space, enjoys privacy
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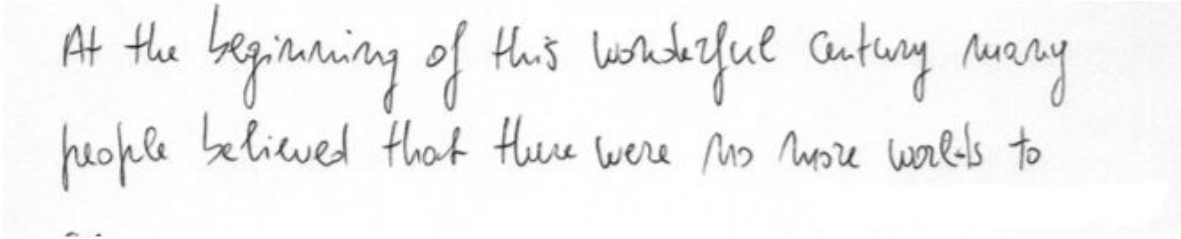
Feature Extraction

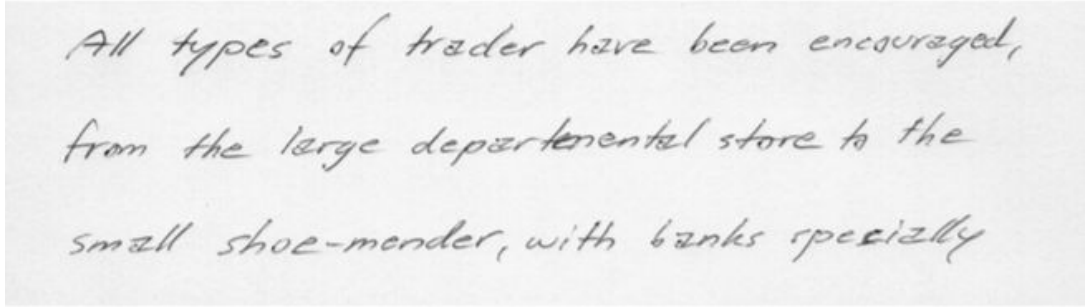
- Baseline
- Letter Size
- Line Spacing
- Word Spacing
- Top Margin
- Pen Pressure
- Slant of Letters

Baseline

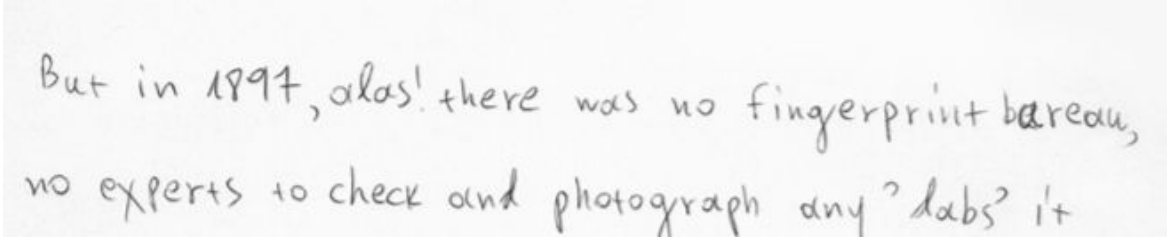
Normal



Rising

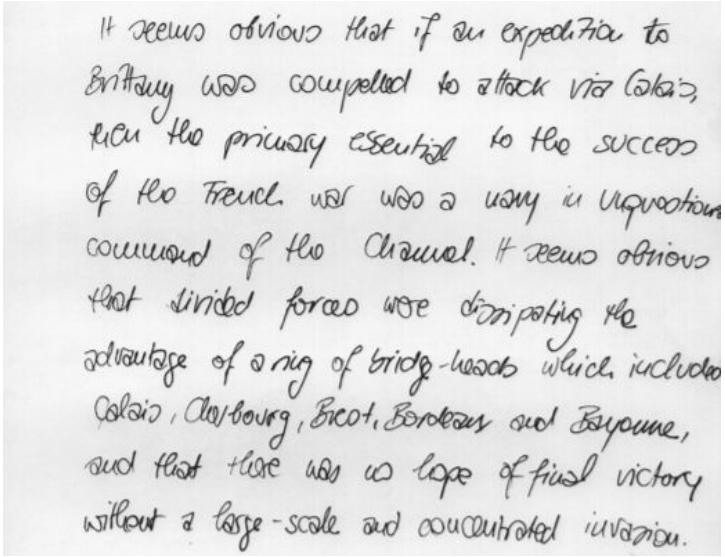


Falling

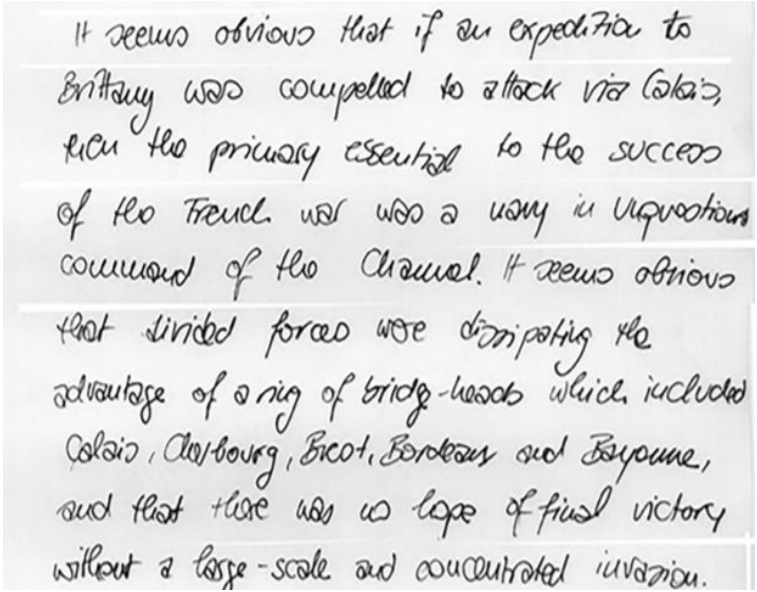


Affine & Warp Transformation

Before

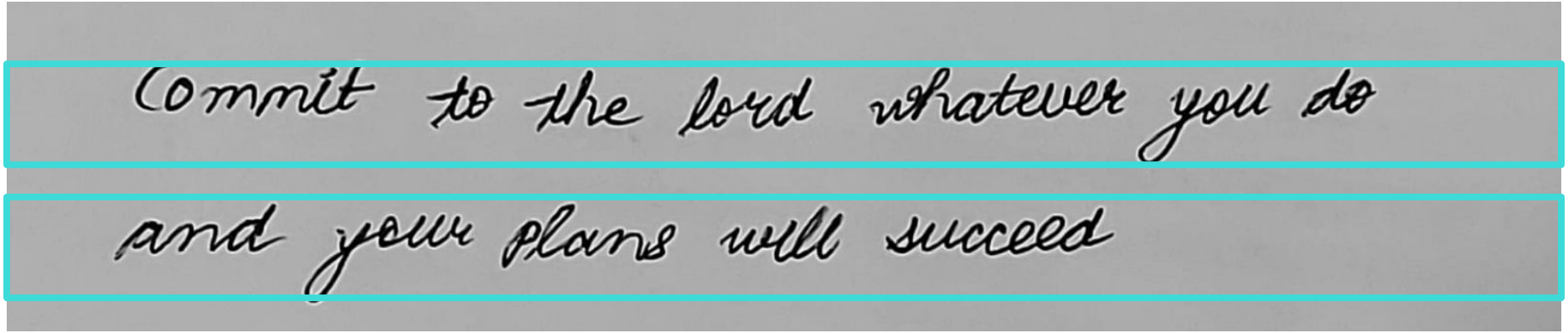


After



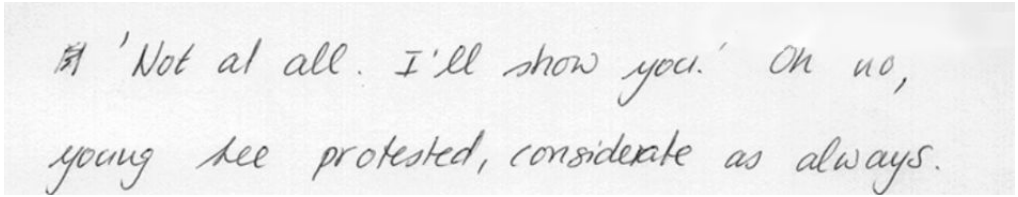
Extracting Lines

Horizontal Projection

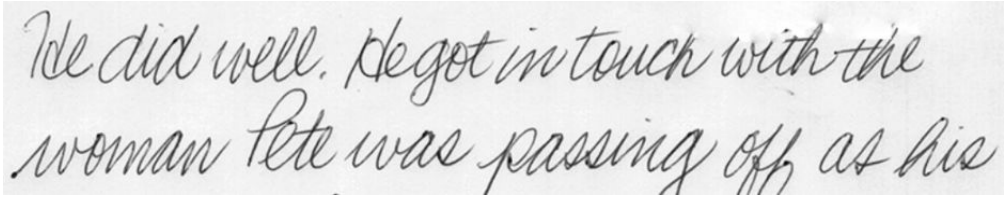


Letter Size

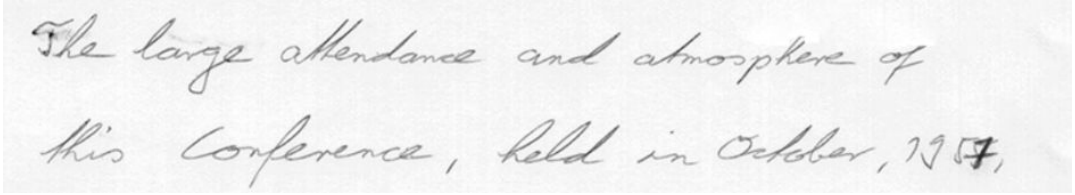
Normal size



Large size

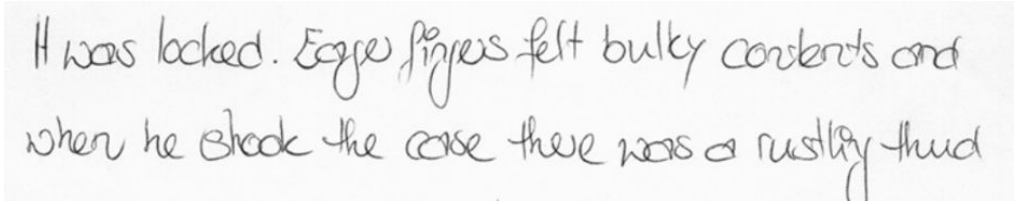


Small size

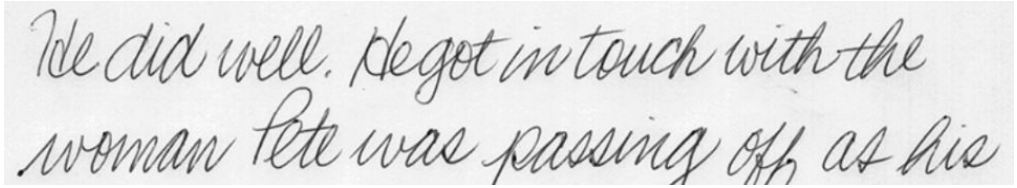


Line Spacing

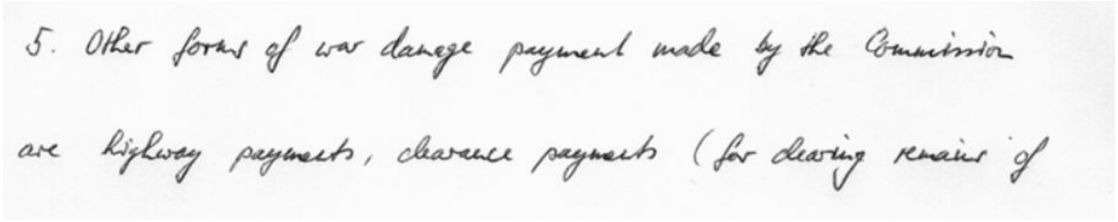
Normal Spacing



Crowded Spacing

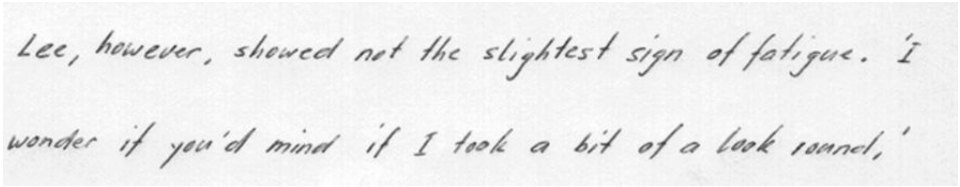


Large Spacing

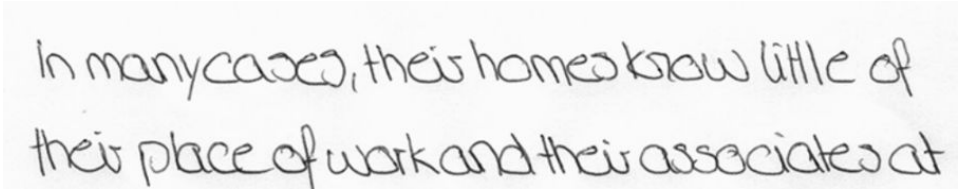


Word Spacing

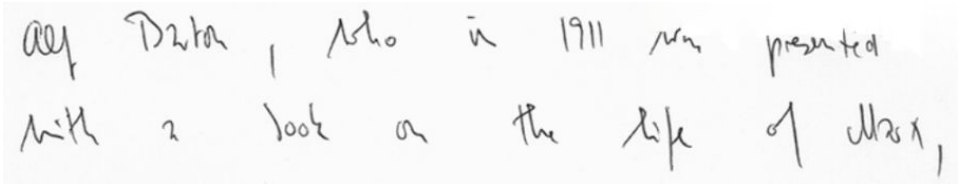
Normal Spacing



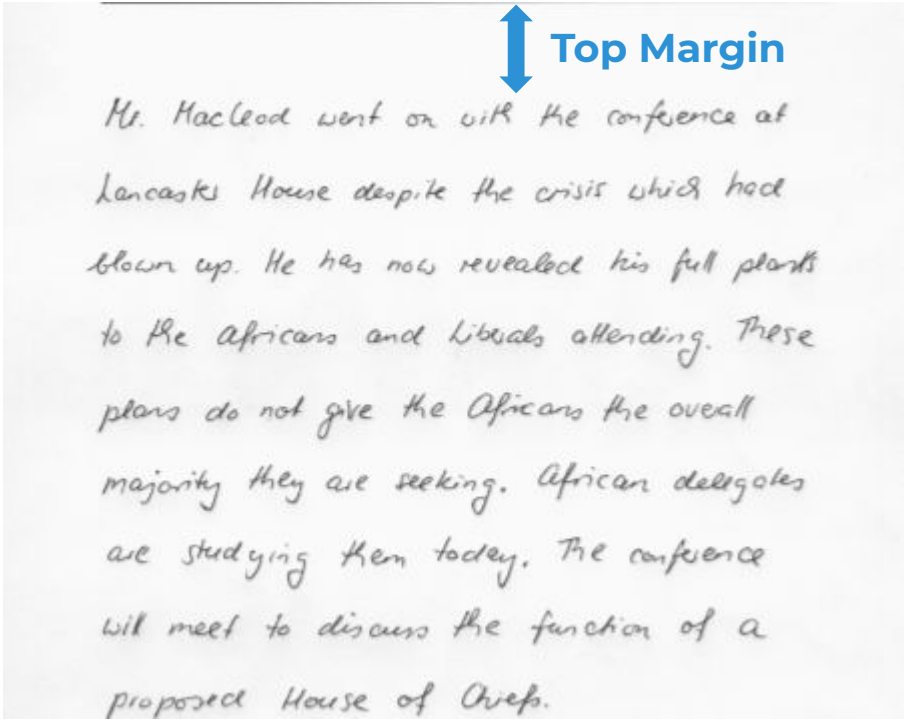
Narrow Spacing



Wide Spacing

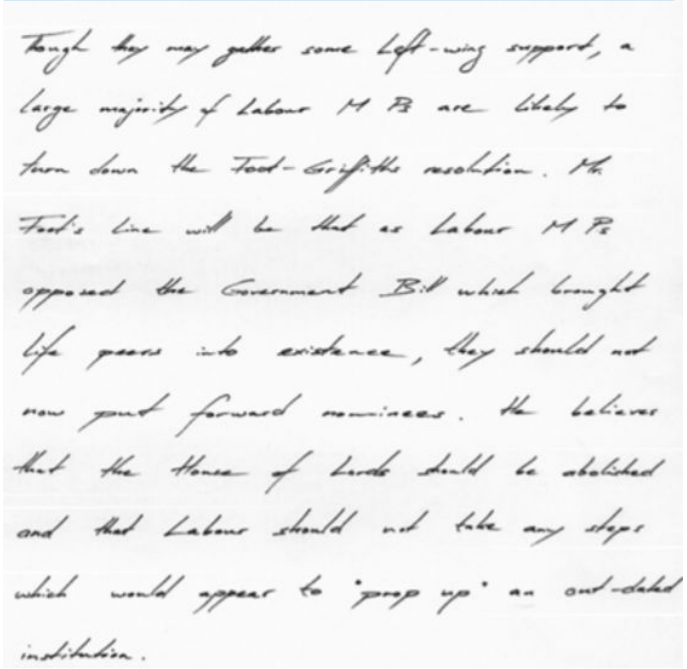


Top Margin

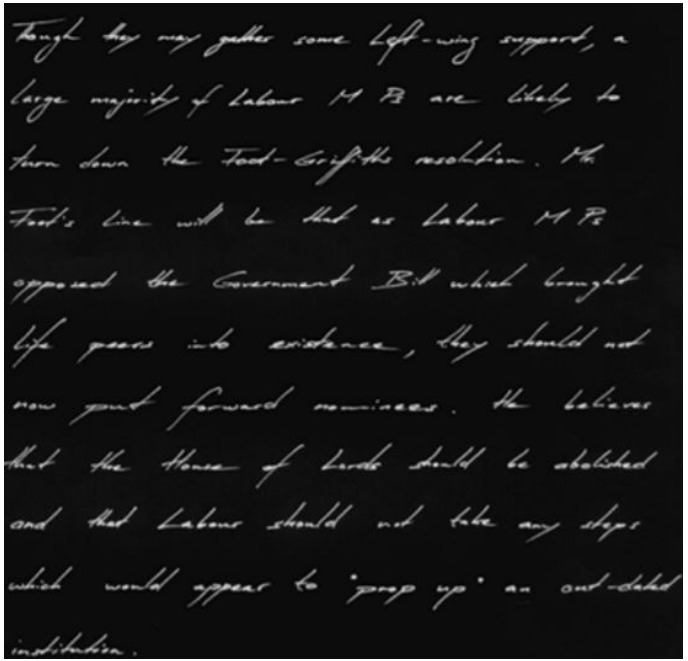

Top Margin
Mr. Macleod went on with the conference at
Lancaster House despite the crisis which had
blown up. He has now revealed his full plans
to the Africans and Liberals attending. These
plans do not give the Africans the overall
majority they are seeking. African delegates
are studying them today. The conference
will meet to discuss the function of a
proposed House of Chiefs.

Pen Pressure

Normal

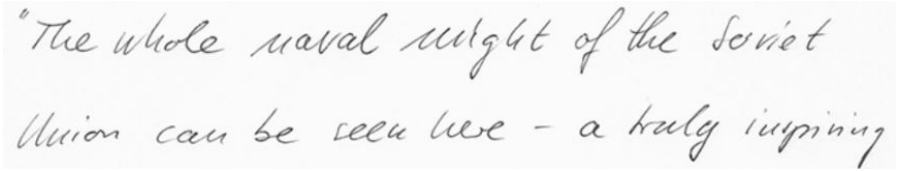


Inverted

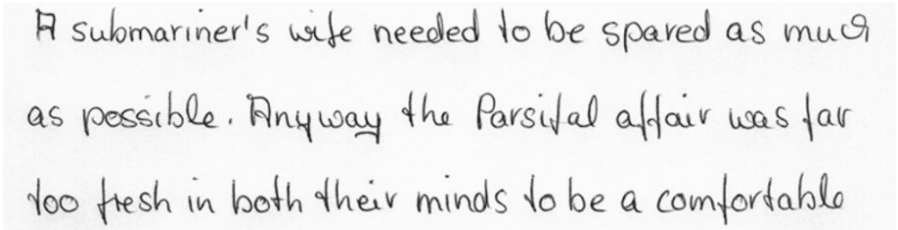


Slant of Letters

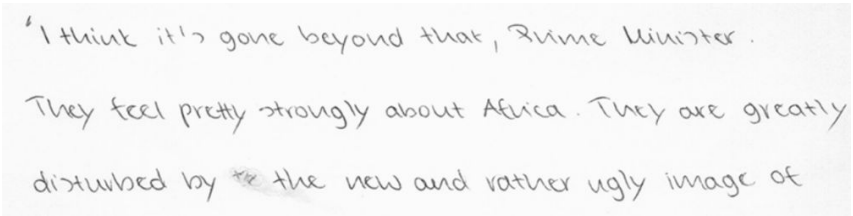
Inclined



Normal



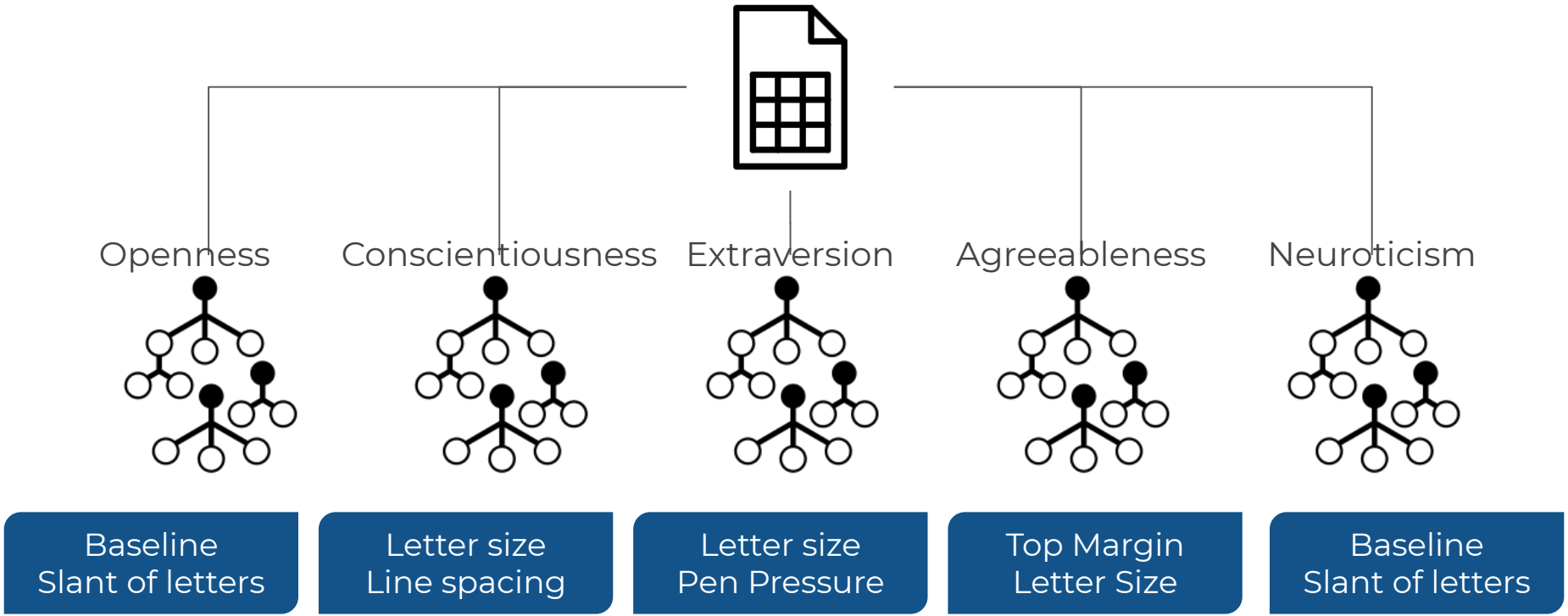
Reclined



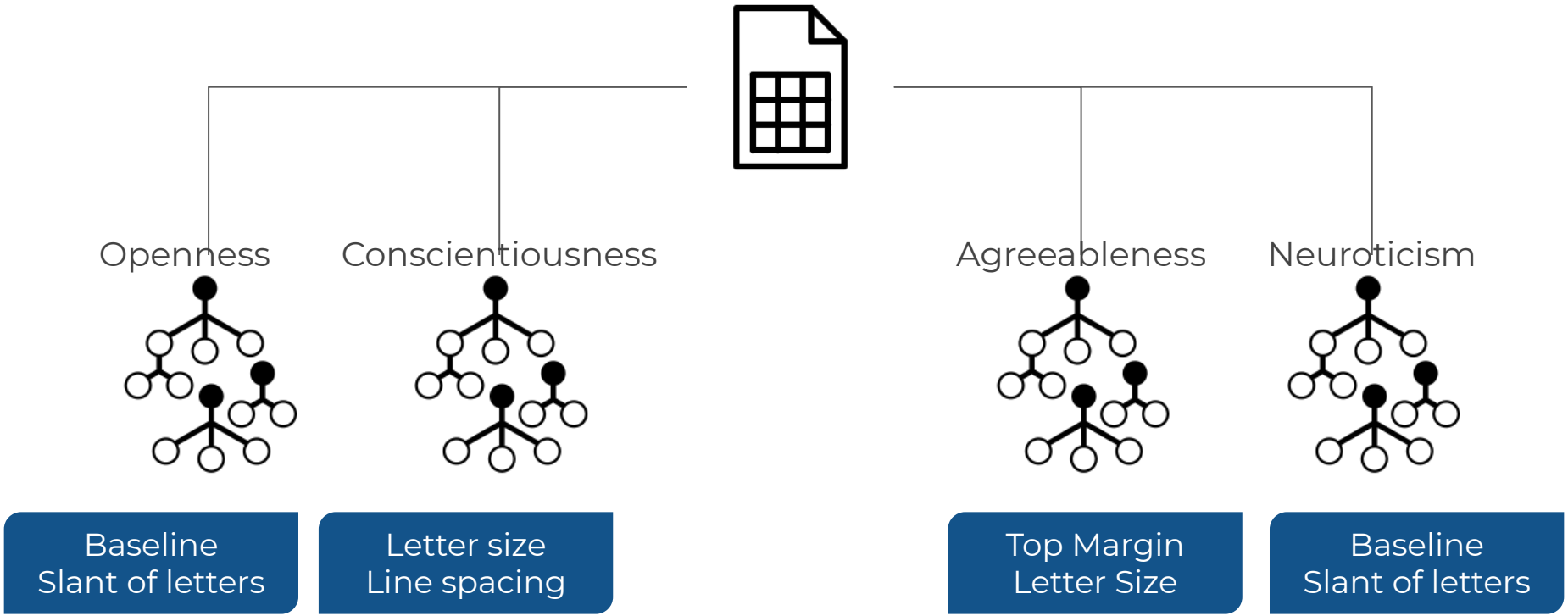
Processed Data

Baseline	Letter Size	Line Spacing	Word Spacing	Top Margin	Pen Pressure	Slant of Letters
-0.39	5.7	12.29	4.37	2.46	171.38	-15
0.05	3.07	17.29	2.89	1.74	194.71	-15
-1.1	2.02	16.36	3.14	1.65	170.29	-15
-0.01	1.91	15.73	3.32	1.6	165.56	45
0	2.1	15.7	3.25	1.69	171.55	-15
-0.27	2.14	16.33	3.16	1.54	174.16	-15
0.29	2.62	14.1	3.82	1.93	170.93	-15
-0.06	2.8	14.3	3.58	1.92	171.9	-15
0.11	2.43	14	3.78	1.78	171.28	45
-0.19	2.74	13.88	3.79	1.95	169.14	-15
0.13	2.8	14.63	3.94	1.93	167.94	-15
-0.39	3.08	14.6	3.66	1.92	169.14	-15
-0.16	1.96	17.36	2.94	1.38	182.99	-15
-0.26	2.22	15.33	3.41	1.76	169.25	30
-0.47	2.7	14.8	3.56	1.69	170.08	-15
-1.04	2.68	14.56	3.58	1.66	171.68	-15
-0.76	3.54	13	4.04	1.77	162.82	30
-0.33	3.04	14.82	3.62	1.91	158.97	-15
-0.23	2.63	14.82	3.58	1.74	168.45	-15
-0.02	3.29	14	3.81	1.72	167.25	-15
-0.7	2.73	15	3.59	1.76	160.74	45

Random Forest



Random Forest



Conclusion

Key takeaways

Pre-processing is a key step for accuracy

Hyper parameter tuning importance

Insights from our data

Key limitations

Extreme cases

Sample limitation

ANN trainable parameters

Looking forward

Next steps:

- Neural Net to Extract Features
- ROC
- CNN next steps
- Add more features
- Plan to test professor’s handwriting

Looking forward

To-do list

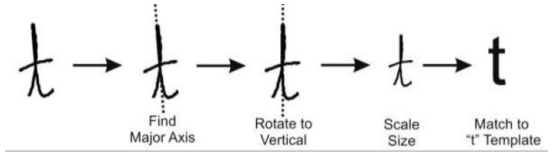
- ROC
- Computation and manual effort
- Neural Net to Extract Features
- Plan to test professor’s handwriting

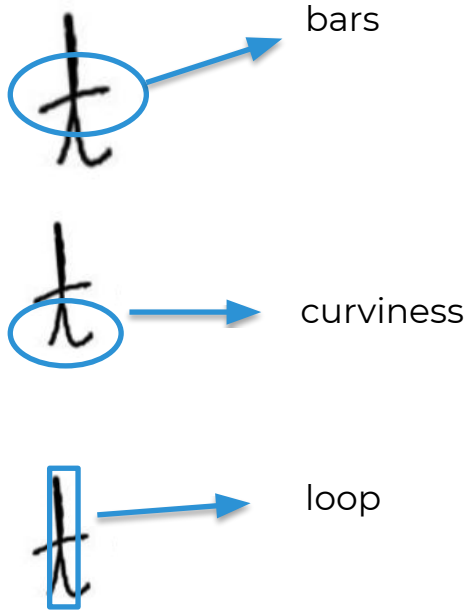
Thank you, Questions?

Appendix

Feature examples

Template matching





Overview

Applications

Psychological analysis

Graphology is used clinically by counsellors and psychotherapists.

Employment profiling

A graphological report is meant to be used in conjunction with other tools, such as comprehensive background checks, practical demonstration or record of work skills.

Problem Statement

A system is proposed to **automate** the basic handwriting analysis tasks of graphology to determine a few important **personality traits**.

Seven features/characteristics of a handwriting are considered to be extracted from a sample handwriting image.

Each of the seven resulting **raw values** will be put into **corresponding categories** of respective feature variations. A **combination** of these discrete values will be used to train each **support vector machine** for a **personality trait**. The classifier will then be able to predict the personality traits of the writer