Handwriting Recognition

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Problem Statement

The George Washington dataset contains 20 pages of letters written by George Washington and his associates in 1755 and thereby categorized into historical collection. The images are annotated at word level and contain approximately 5,000 words.

270 Letters Orders and Instructions. October 135.

only for the publick use unlift by partieular Orders from me. You are to send down a Barrel of Hinds with the arms, to Winchester, and about two thousand wight of Flour, for the two bompanies of Rangers; twelve hundred of which to be delivered hoplain. Ishly and bompany, at the Plantation of Charles Sellars—the rest tolying todai bompany, at Nicholas Reasmers. October 26.

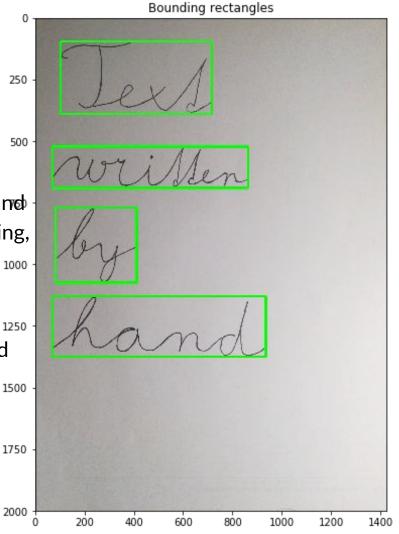
Winchester October 25.1755.

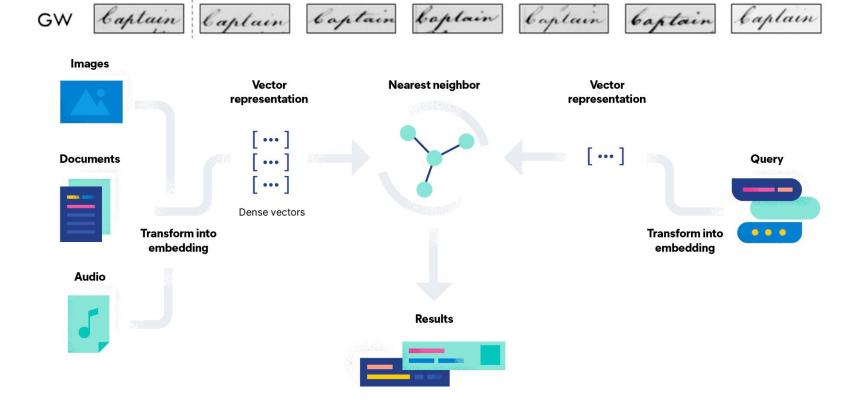
The officers who came down from Fort bumberland with bolonel Hashington are immediately to go kearing ling; and they are allowed until the I of De comber; at which time if they do not punctually appear at the place of Rendez vous assigned them they will be ties by a bout Markal, for disobedience of aders. They are to wait upon the air de camp at one of the block to receive their Receive. ling Instructions back Officer present to give in a Reburn immediately of the number of men he has oblisted . One Jubaltur, one Sugeant, one Corporal, one Dummer and twenty-five private men, are to mount Guard to-day, and to be relieved to monow are to be made to the air de camp.

Motivation

Handwriting recognition is essential for digitizing handwritten content, enabling efficient data entry, improving accessibility for people with disabilities, and enhancing applications in education, language learning, and search engines.

It has broad practical applications in document
management, signature verification, AI, robotics, and
more, making it a valuable technology with
widespread implications for various industries and
everyday life.





Cosine Distance

1. Data Preprocessing:

Input: Handwritten text images
Output: Preprocessed images

2. Binary Vector Conversion:

Input: Preprocessed images

Output: Binary representation of images

3. Cosine Distance Calculation:

Input: Binary vectors

Output: Cosine distances bw all pairs of vectors

5. Evaluation Metrics:

Input: Cosine distances, Ground truth labels Output: Precision-Recall metrics, AP values

6. Mean Average Precision (MAP) Calculation:

Input: Individual AP values

Output: Overall recognition performance

Results: Stage 1

Mean Average Precision (MAP) for the dataset: 0.3114319259338441

```
→ Ouery Data Point:
    Label: d-o
    Cosine Distances: [0.38228272 0.27470845 0.32385437 ... 0.15140344 0.4391105 0.40655764]
    Top 10 Closest Data Points:
    Label: d-o
    Cosine Distance: 1.1657341758564144e-13
    Label: o-r-s mi
    Cosine Distance: 0.045102731461981294
    Label: a-n-y
    Cosine Distance: 0.05328777315483302
    Label: H-o-q-q-s
    Cosine Distance: 0.05509417581635956
    Label: l-e-a-v-e
    Cosine Distance: 0.05590934198609143
    Label: m-a-r-c-h
    Cosine Distance: 0.05628044174575364
    Label: C-l-o-t-h-e-s
    Cosine Distance: 0.056608082863565445
    Label: q-l-a-d
    Cosine Distance: 0.0567882471914698
    Label: u-n-d-e-r
    Cosine Distance: 0.05694799905125025
    Label: D-r-u-m-s_cm
    Cosine Distance: 0.05702428174819274
```

Euclidian Distance

Improved Handling of Dissimilarity: L2 (Euclidean) distances are more effective in measuring dissimilarity. They perform well when recognizing characters with significant variations, artistic elements, or diverse writing styles, making the method more robust.

More Comprehensive Feature Representation: L2 distances allow for a more comprehensive representation of handwriting, as they capture various features like stroke thickness, pen pressure, and subtle differences in character structure, which Method 1 might miss.

Results: Stage 2

→ Mean Average Precision (MAP) for the subset of the dataset: 0.5246844500066226 Mean Recall (MRecall) for the subset of the dataset: 0.7506343826342283

```
Query Data Point:
    Label: o-r
    L2 Distances: 0.0
    Top 10 Closest Data Points:
    Label: o-r
    L2 Distance: 0.0
    Label: o-f
    L2 Distance: 0.37578922561439365
    Label: t-o
    L2 Distance: 0.3813298767930956
    Label: t-h-a-t
    L2 Distance: 0.39100947664003005
    Label: y-o-u
    L2 Distance: 0.3913327432348945
    Label: n-e-l-s
    L2 Distance: 0.39652320027810467
    Label: a-r-r-i-v-e
    L2 Distance: 0.4031411928542059
    Label: s-u-p-p-l-i-e-d
    L2 Distance: 0.40869229405449203
    Label: n-o-n-e
    L2 Distance: 0.4099049895081434
    Label: r-e-c-e-i-v-e
    L2 Distance: 0.41087349376335086
```

Query Data Point: Label: t-o L2 Distances: 0.0 Top 10 Closest Data Points: Label: t-o L2 Distance: 0.0 Label: T-o L2 Distance: 0.4018648490959157 Label: t-h-o-s-e L2 Distance: 0.41272989802840987 Label: n-e-c-e-s_s-s-a-r-i-e-s L2 Distance: 0.42213313061367674 Label: a-t L2 Distance: 0.4238384694908548 Label: b-e L2 Distance: 0.4283414292480474 Label: c-a-n L2 Distance: 0.4323604430595629 Label: A-r-m-s L2 Distance: 0.4456172648703772 Label: p-a-r-t-i-c-u-l-a-r L2 Distance: 0.4500375366987378

L2 Distance: 0.4516357262168649

Label: I

Future Directions

- Improving these models
- Improving the features
 - Variable Length Features: Projection Profile
 - Variable Length Features: Upper and lower-word profile
 - Dynamic Time Wrapping
 - HOG, SIFT, SURF and Others
- Using better models
 - Voting classifiers
 - Bag of Visual Words

Conclusion

- The most significant personal learning from this project was the importance of iterative experimentation and the value of understanding the intricacies of data preprocessing, feature extraction, and distance calculation in the context of handwriting recognition.
- Top 3 Technical Learnings
 - -Feature Extraction Techniques
 - -Distance calculation methods
 - -Evaluation metrics and performance analysis