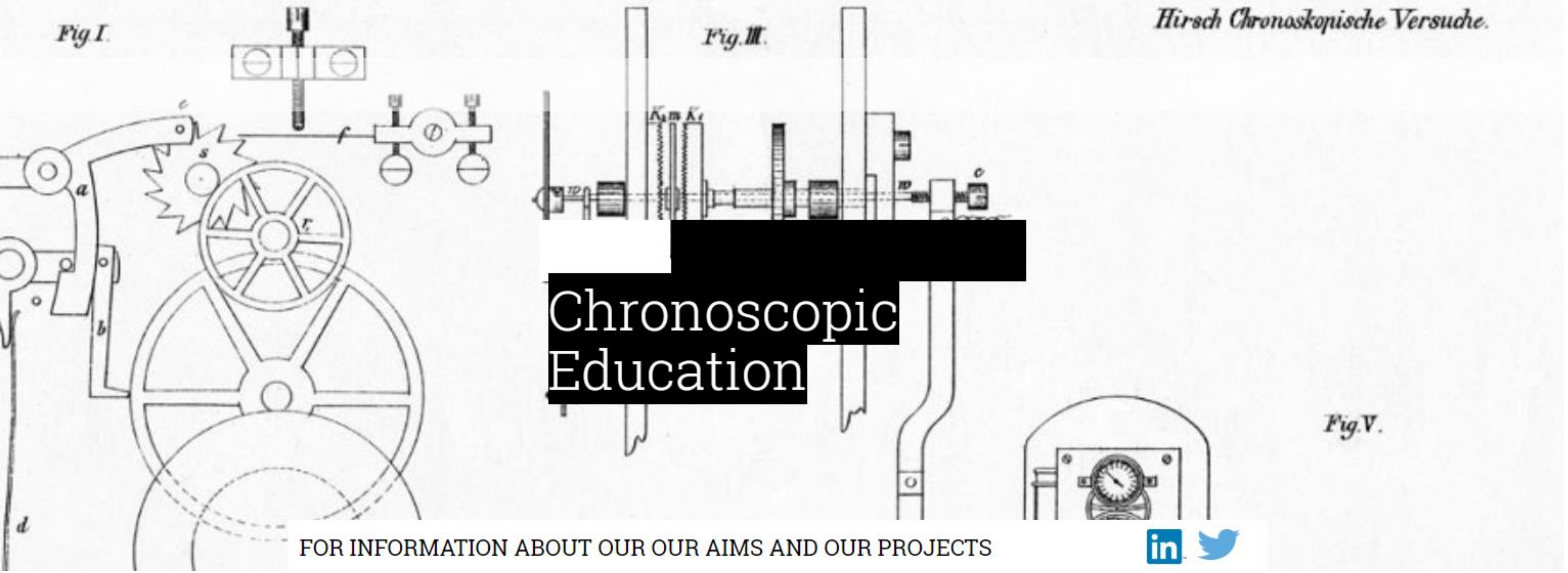
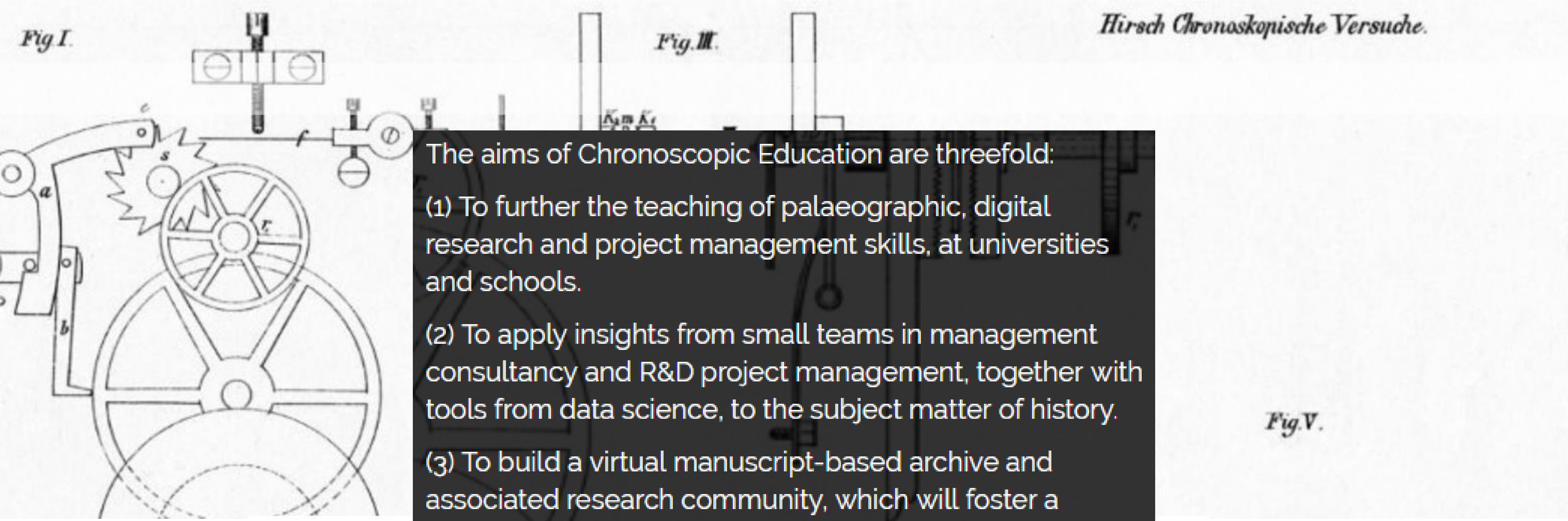


Signs of Literacy
Kaggle Research Competition
Background Pack, Ver. 1.4

Colin Greenstreet

Saturday, June 30th, 2018

Our social aims



The aims of Chronoscopic Education are threefold:

(1) To further the teaching of palaeographic, digital research and project management skills, at universities and schools.

(2) To apply insights from small teams in management consultancy and R&D project management, together with tools from data science, to the subject matter of history.

(3) To build a virtual manuscript-based archive and associated research community, which will foster a culture of collaborative scholarship.

http://www.chronoscopic.org

Project portfolio

MarineLives

Signs of Literacy

Maphackathon

EM Textiles, Garments & Dyestuffs Glossary

EM Maritime & Mercantile Gazetteer

http://www.chronoscopic.org

Signs of Literacy Kaggle Research Competition, Nov 2018 – Jan 2019

Google owned Kaggle has selected us as one of a small number of pro bono competitions they support each year on the merits of our proposal, and the potential impact on the research field and community of the competition.

Kaggle will cover the running costs of the competition. We will provide the prize pool, and are now seeking to raise US $30,000 from potential sponsors and partners.

The Proof of Concept will contain two parts:

(1) Algorithmic identification of markes, initials and signatures.

(2) Algorithmic discrimination between degrees of "sophistication" within the three categories of "marke"; "initial(s)", and "signature".

Having proven the concept, we will seek out an image or vision oriented computational laboratory with which to develop a grant funded collaboration to take the work further in 2019 and beyond.

https://www.linkedin.com/pulse/proposed-signs-literacy-kaggle-research-competition-2018-greenstreet/

Technical vision & role of the Kaggle competition

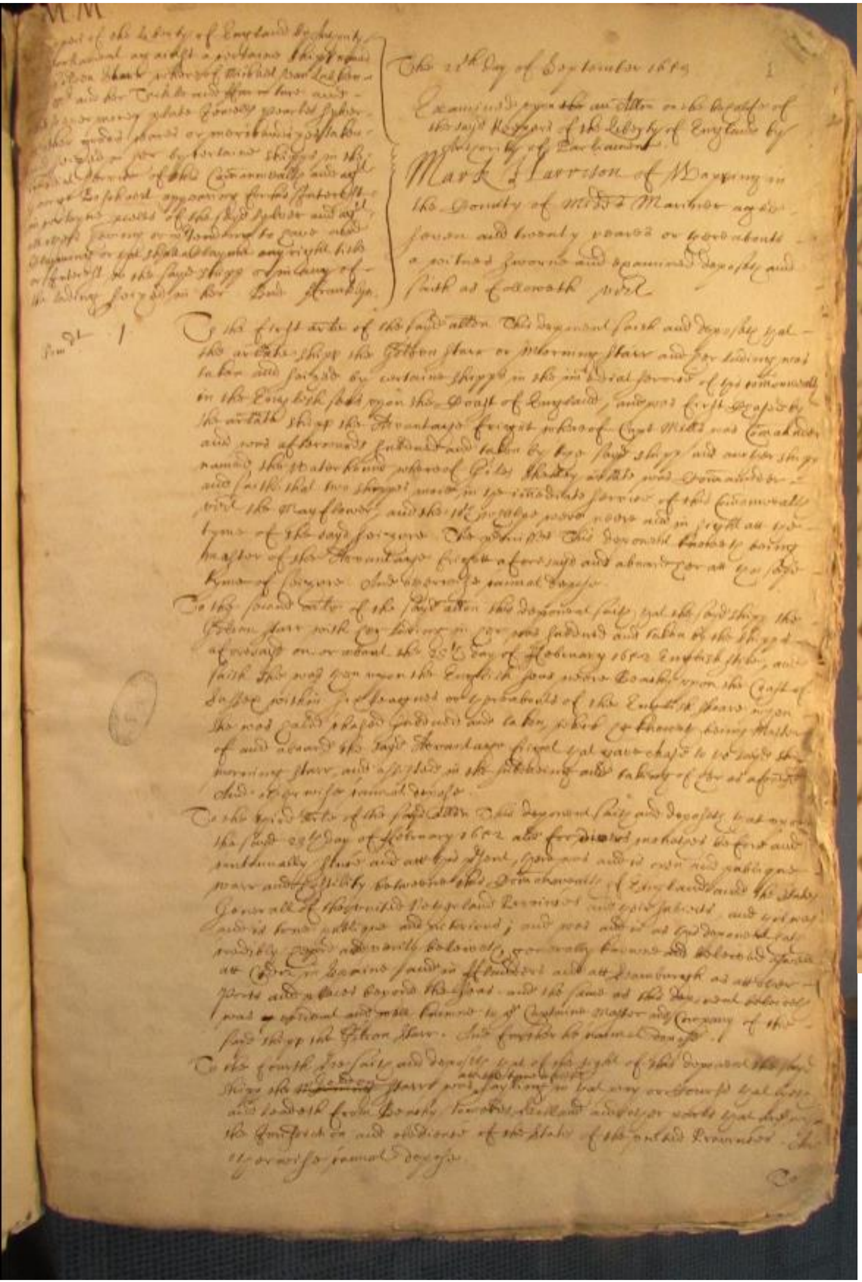
- Automatic identification of manuscript pages containing signoffs
- Markup of manuscript pages to isolate signoffs (markes, initials, signatures)
  - Hand markup of manuscript pages, but ideally automated markup
  - Signoffs can be single or multiple, for single or multiple depositions
  - Deponent signoffs; interpreter signoffs
- Automatic differentiation between classes of markes, initials and signatures
- Automatic differentiation within each class as to sophistication of execution & other parameters as a surrogate for literacy
- Automatic identification of manuscript pages containing deponent metadata (name; age; occupation; place of residence; date of deposition)
- Markup of manuscript pages to isolate deponent metadata
- Hand writing text recognition of deponent metadata and associate metadata with correct signoff

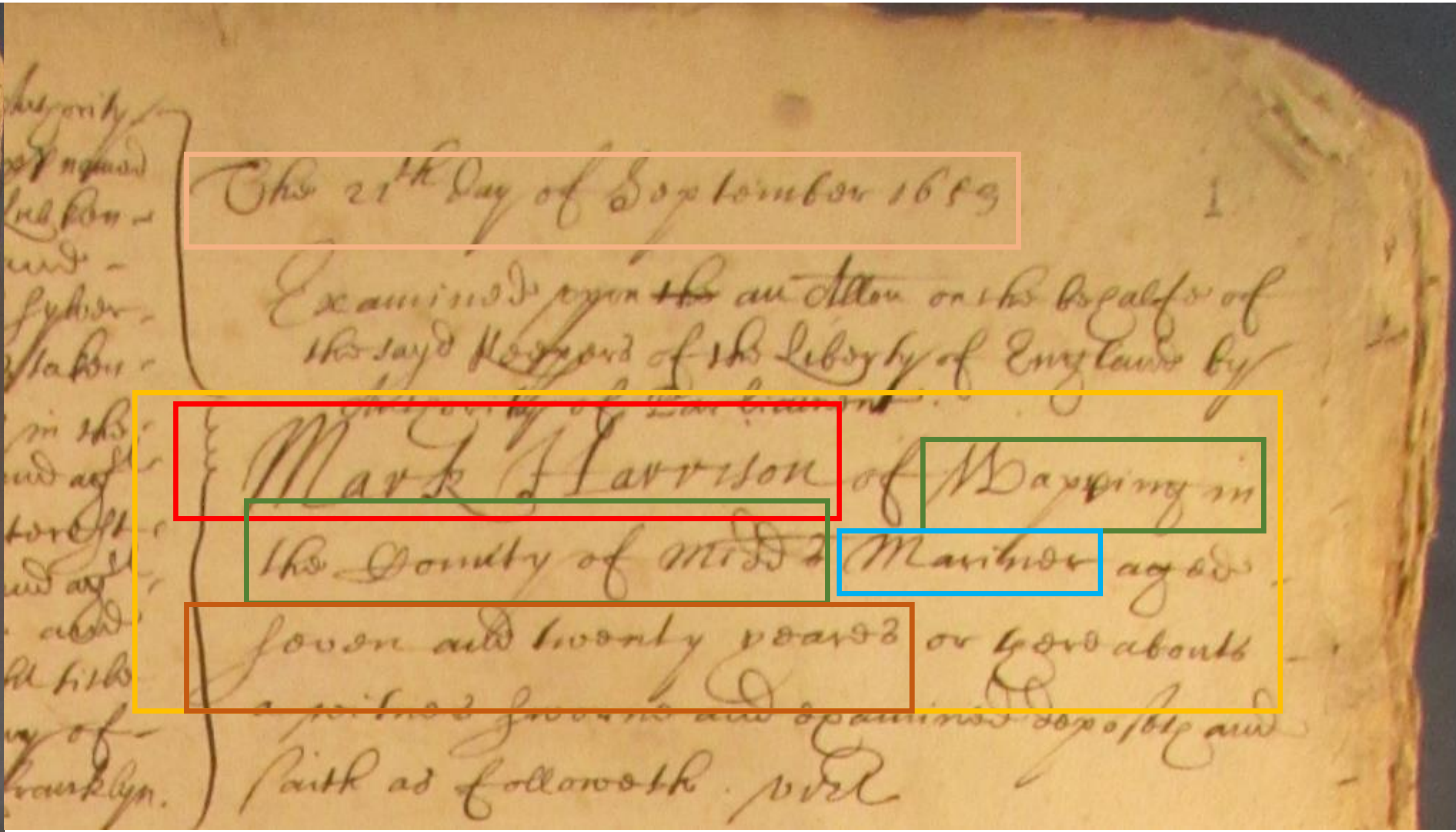
Legal deposition

Deposition of Mark Harrison; mariner and master; resident in Wapping, Middlesex; age 27;
Dated September 21st 1659 (TNA, HCA 13/68, ff. 1r-3r)

http://www.marinelives.org/wiki/HCA_13/68_f.1r_Annotate; http://www.marinelives.org/wiki/HCA_13/68_f.1v_Annotate; http://www.marinelives.org/wiki/HCA_13/68_f.2r_Annotate ; http://www.marinelives.org/wiki/HCA_13/68_f.2v_Annotate; http://www.marinelives.org/wiki/HCA_13/68_f.3r_Annotate

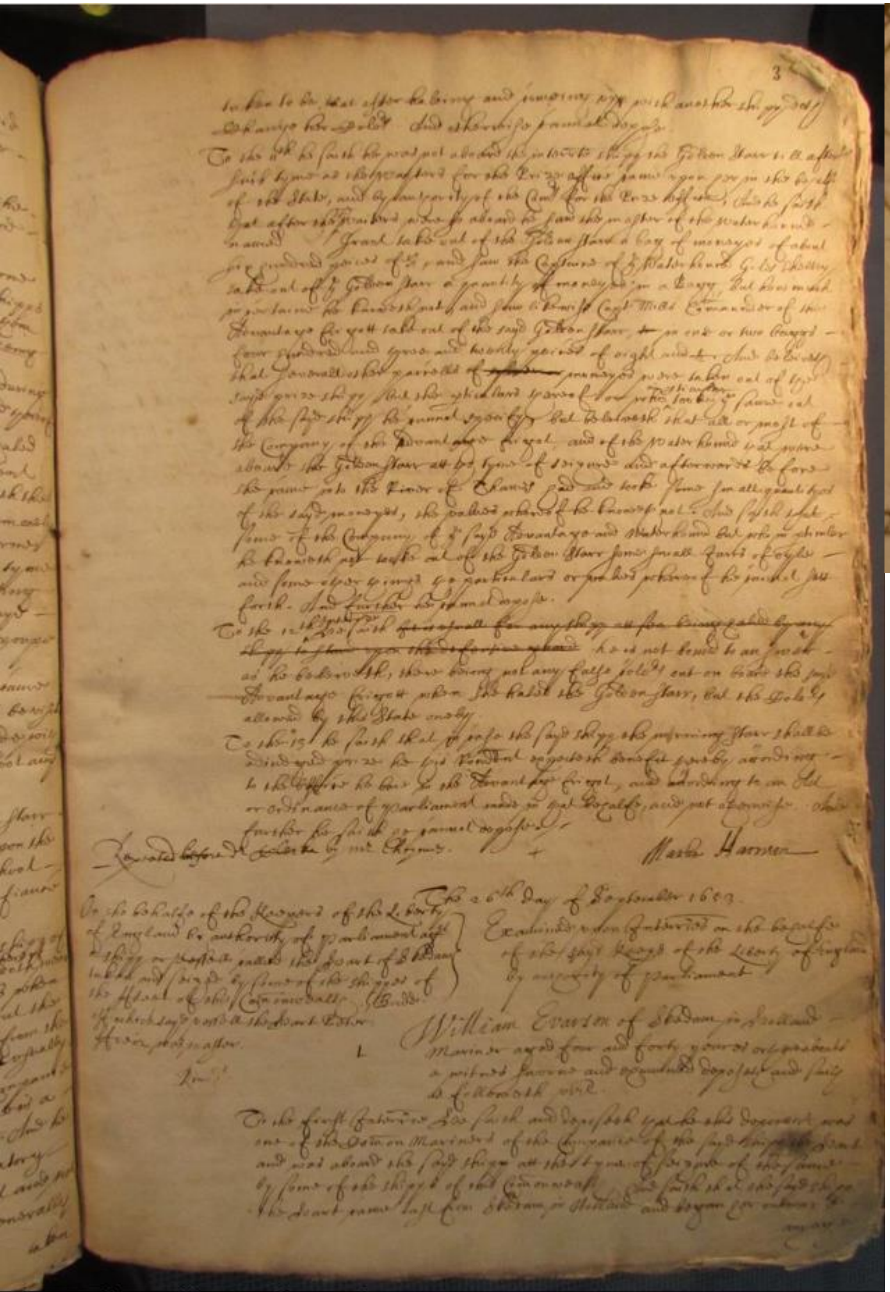
Metadata

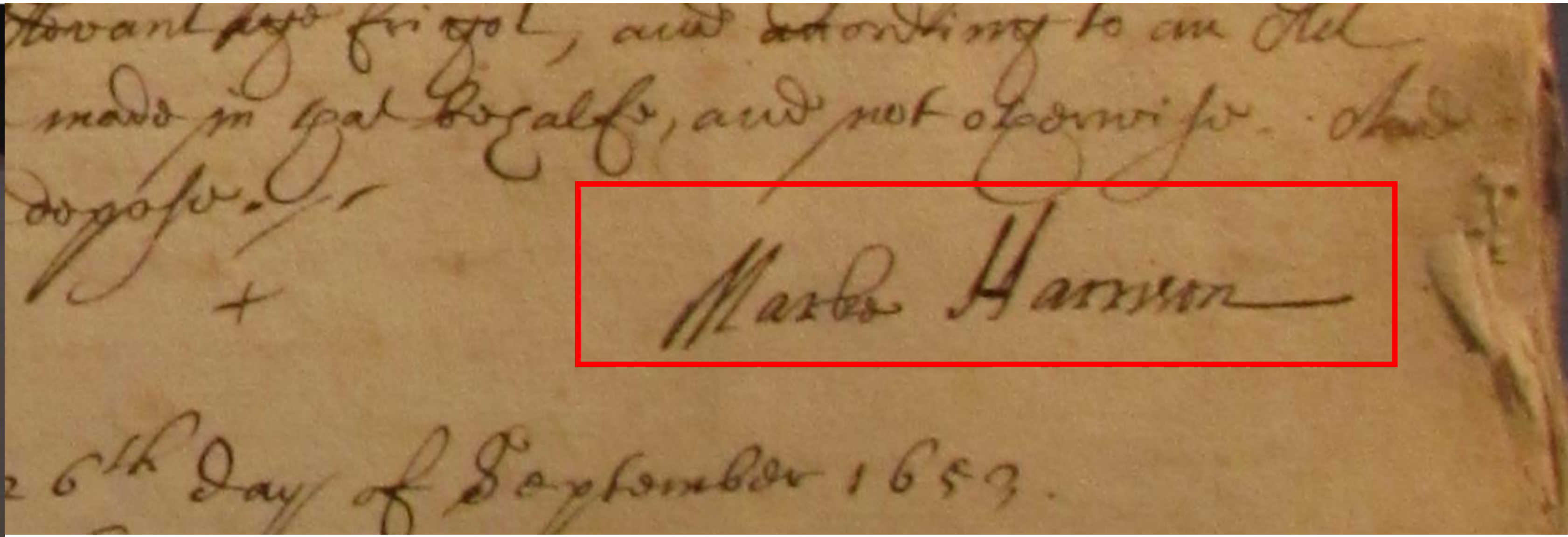




http://www.marinelives.org/wiki/HCA_13/68_f.1r_Annotate;
http://www.marinelives.org/wiki/Mark_Harrison

Signoff

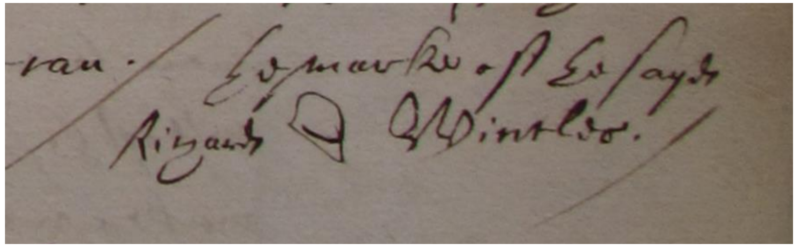




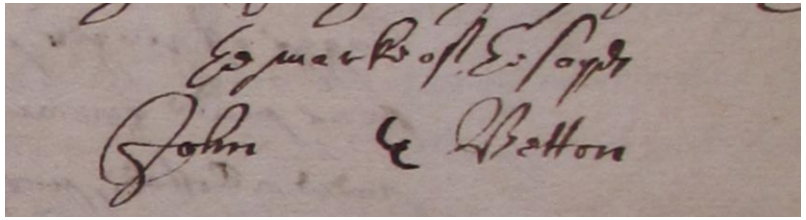
http://www.marinelives.org/wiki/HCA_13/68_f.3r_Annotate

Porters handling coals, whale oil, ginger & corn

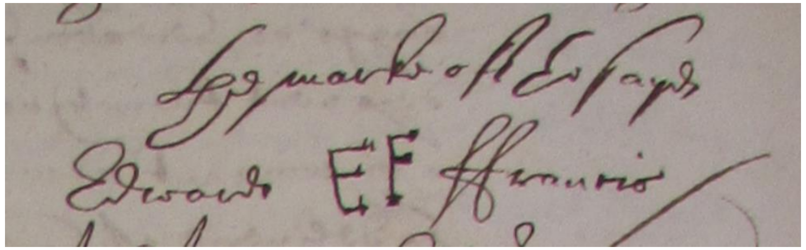
Richard Wincles, thirty-three year old porter, of the parish of Stepney, Middlesex, Dec. 15, 1656; employed as a labourer with fifteen other men to unload coals from the *Implyment* moored near Execution Dock, Wapping, into lighters for fixed rate of 12 *s* per man (HCA 13/70 f.554r)



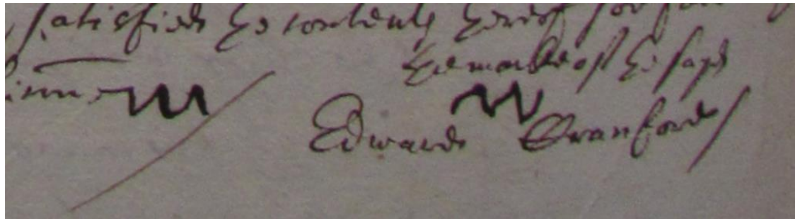
John Betton, fifty-four year old citizen and white baker of London, of the parish of Saint Buttolph Algate, London, Jul. 31, 1655; self-described as a porter employed by the Commissioners for Prize Goods to deliver ginger from a warehouse at Ralphes Key (HCA 13/70 f.449r)



Edward ffrancis, citizen and merchant taylor of London, of the parish of Saint Olave in Southwarke, Jul. 31, 1655; self-described as a porter employed by the Commissioners for Prize Goods to deliver ginger from a warehouse at Ralphes Key (HCA 13/70 f.450v)

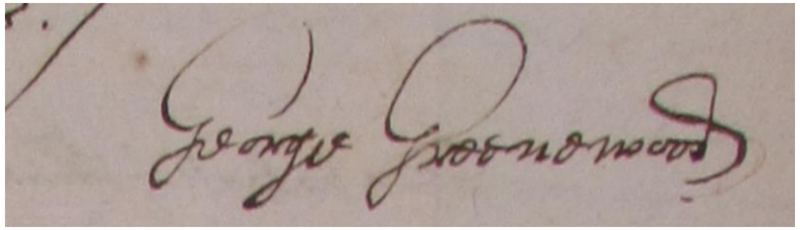


Edward Cranford, forty-four year old coale heaver or porter, of the parish of Stepney, Middlesex, Dec. 15, 1656; employed as a labourer with fifteen other men to unload coals from the *Implyment* moored near Execution Dock, Wapping, into lighters for fixed rate of 12 *s* per man (HCA 13/70 f.555v)

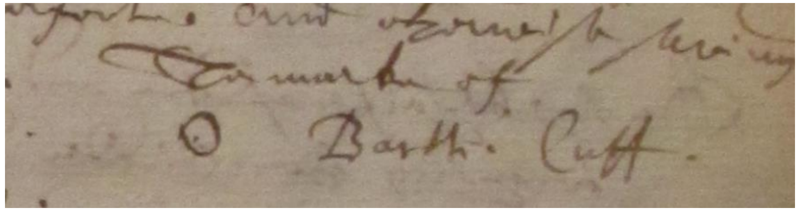


Edward Sherwin, fifty-six year old cittizen and leatherseller, of the parish of Little Allhallowes, London, Jul. 31, 1655; self-described as a porter employed by the Commissioners for Prize Goods to deliver ginger from a warehouse at Ralphes Key (HCA 13/70 f.449v)

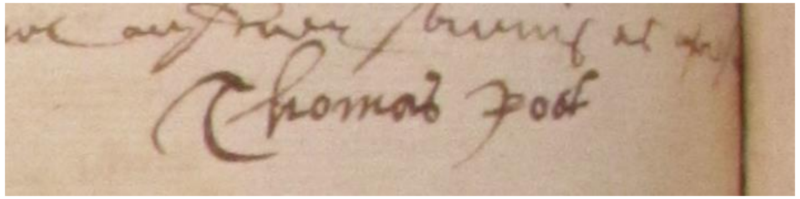
George Greenwood, thirty year old citizen and vintner of London, of the parish of Saint Buttolph Bishopsgate, London, Jul. 31, 1655; self-described as a porter employed by the Commissioners for Prize Goods to deliver ginger from a warehouse at Ralphes Key (HCA 13/70 f.454r)



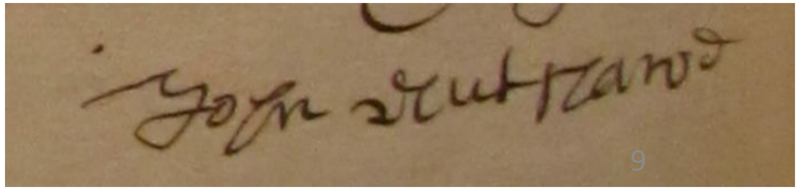
Bartholomew Cuff, sixty year old porter of the Stillyard, of the parish of Allhallowes the Greate, London, May 15, 1658; assisted in the landing of whale oil from lighters at the Stillyard Key and loading them away into a warehouse (HCA 13/70 f.555v)



Thomas Roots, twenty-nine year old porter, of the parish of Greate Allhallowes, London, May 15, 1658; assisted in the landing of whale oil from lighters at the Stillyard Key, as one of the Stillyard porters, and loading them away into a warehouse (HCA 13/72 f.330v)

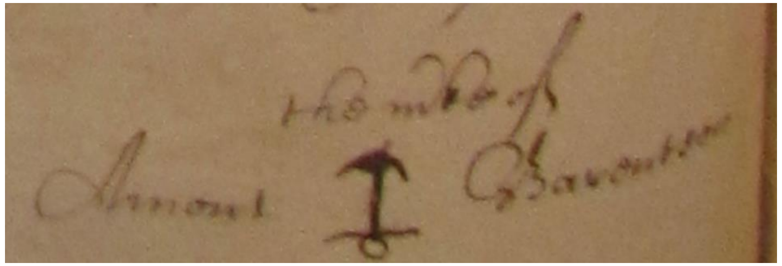


John Nutshall, fifty-five year old corne porter, of the parish of Saint Saviours Southwarke, Nov. 19, 1653; employed with a barber chyrurgeon/corne meter, an additional corne-meter, and other labourers to unlade a cargo of what in the *ffortune* of Stettin, moored against Limehouse; eight years of experience as a corne porter (HCA 13/70 f.352v)

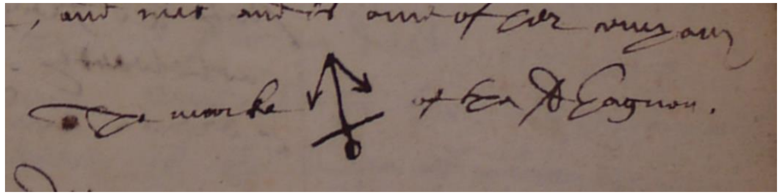


Anchors

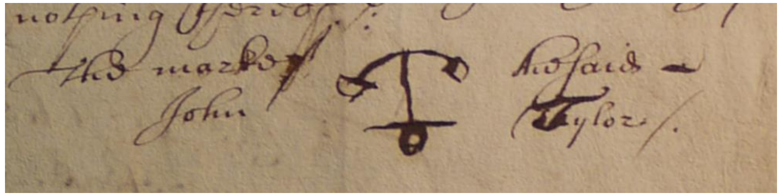
Amons Barentsen, thirty-five year old mariner, of Copenhagen, Denmark, October 13th, 1653; self-described as an “ordinary mariner”, hired to sail from the Sound to Hamburg on the *Golden Hawke* of Stockholm (HCA 13/68 f.81v)



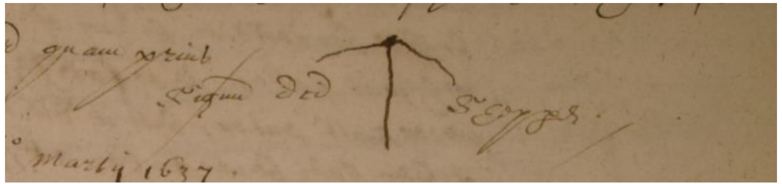
Claude de Gagnon, twenty-five year old mariner, of Melon, near Brest in Britanny, May 22nd, 1656 (HCA 13/71 f.225r)



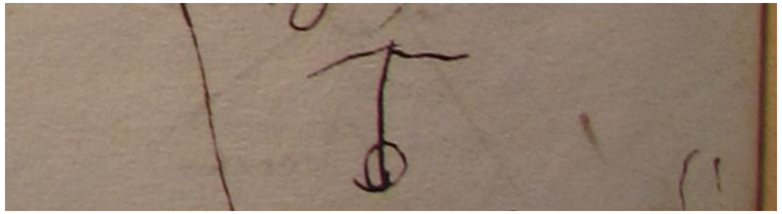
John Tylor, forty-two year old shipwright, of Lower Shadwell, in the parish of Stepney, Middlesex, February 14th, 1659 (HCA 13/73 f.36r)



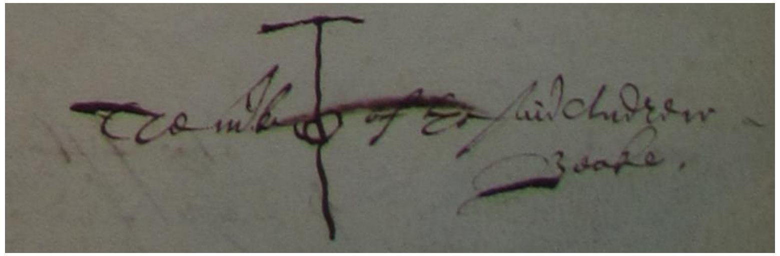
Richard Shepperd, fifty-eight year old cooke, of Brixton, Devon, March 29th, 1637; self-described cooke of the *Hope* of Ipswich (HCA 13/53 f.87r)



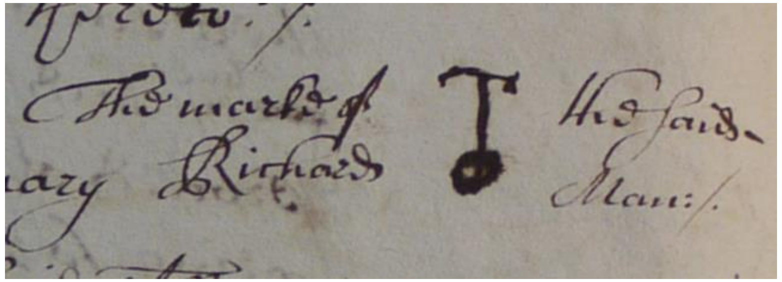
Andrew Beake, thirty-six year old lookeinglassemaker and formerly seaman, of Rose alley without Bishopsgate, London, January 21st, 1655 (HCA 13/70 f.252v)



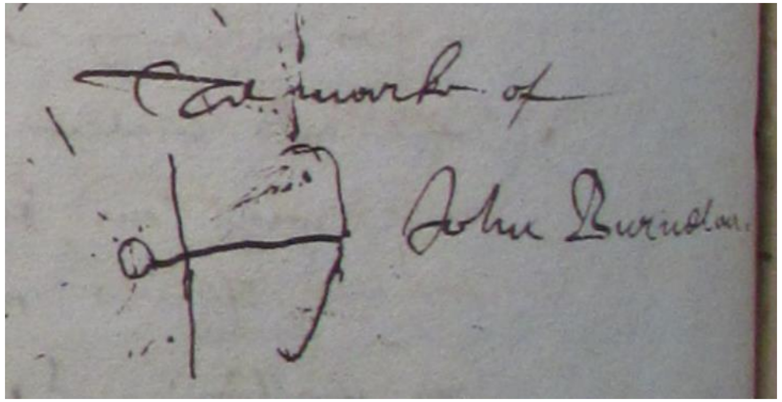
Andrew Beake, thirty-six year old looking-glasse maker, of Rose-Alley in Bishopsgate streete, London, February 13th, 1655 (HCA 13/70 f.252v)



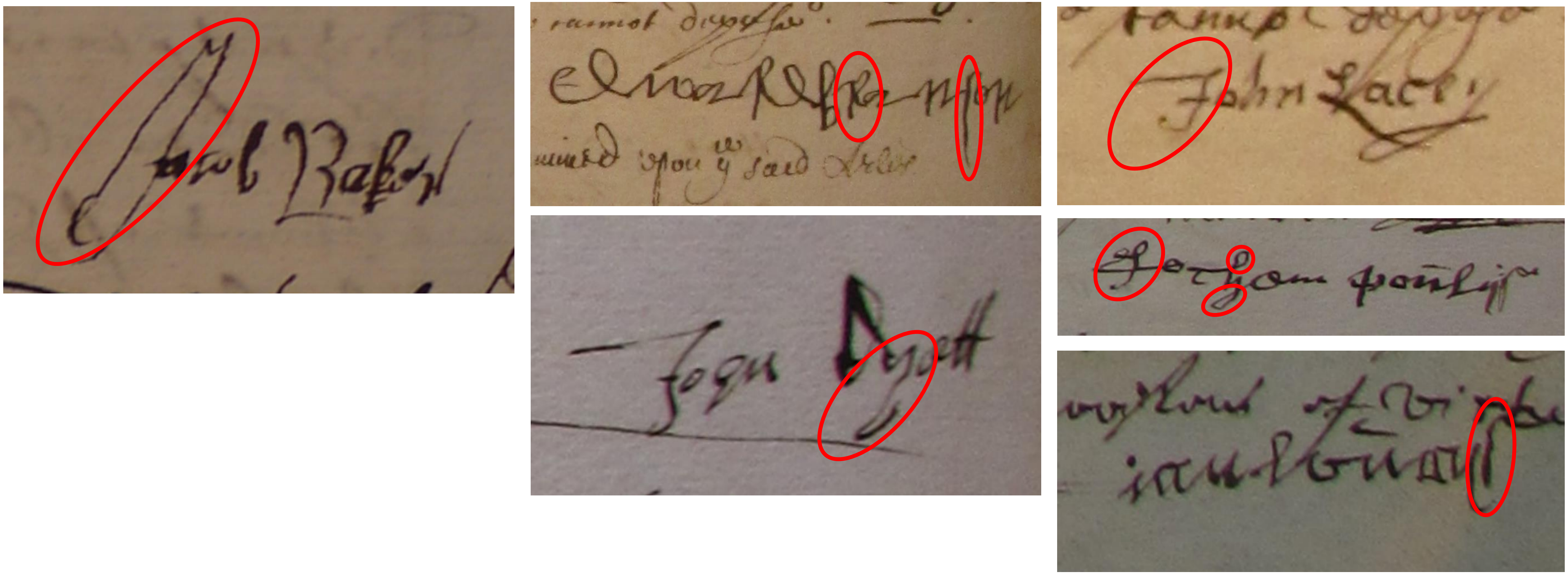
Richard Man, thirty-one year old mariner, of Southampton, January 8th, 1659; self-described common man of the *Lisbone ffrigott* on voyage to Oratava (HCA 13/73 f.26v)



John Burnelau, twenty-eight year old sailor, of Mornar, France,March 30th, 1661 (HCA 13/73 f.486v)



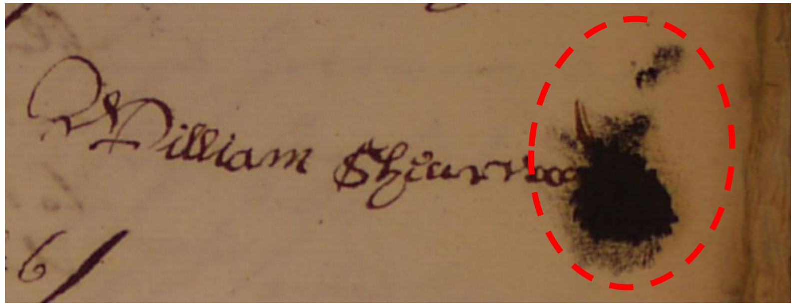
Physical characteristics of poorly executed signatures for machine detection – Part 1

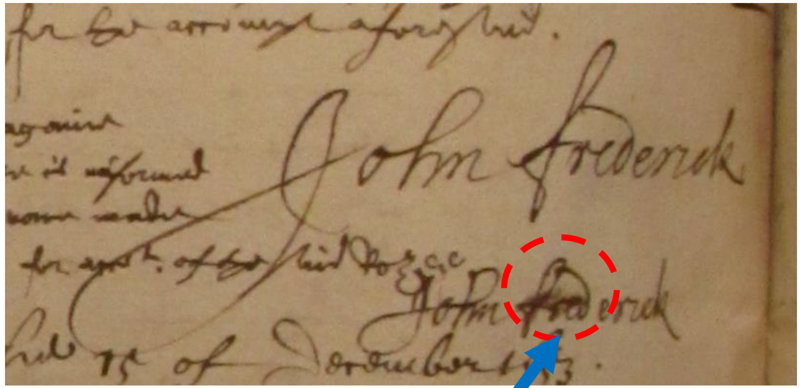


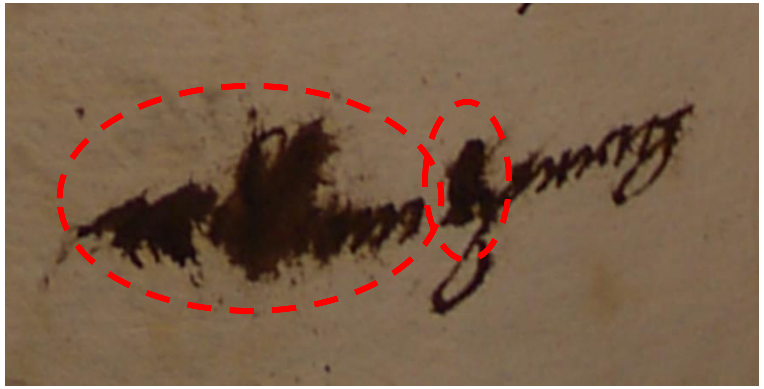
Source: Clockwise from top LH side:
KaggleTestSnippet_HCA_1371_f.263v.PNG,
KaggleTestSnippet_HCA_1368_f.483v.PNG,
KaggleTestSnippet_HCA_1368_f.51v.PNG,
KaggleTestSnippet_HCA_1370_f.20v.PNG,
KaggleTestSnippet_HCA_1370_f.22r_Two,
KaggleTestSnippet_HCA_1370_f.168v.PNG

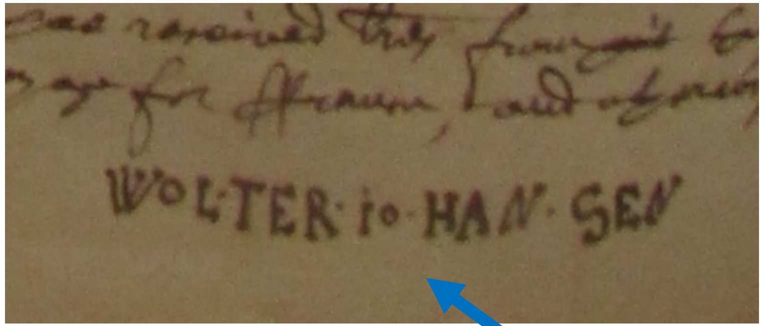
Shaky straight lines and/or loops

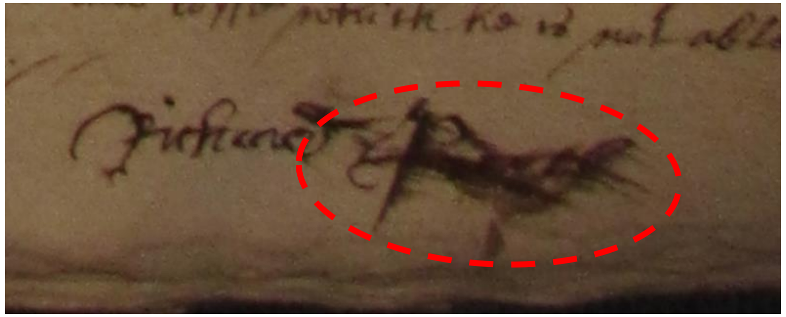
Physical characteristics of poorly executed signatures for machine detection – Part 2

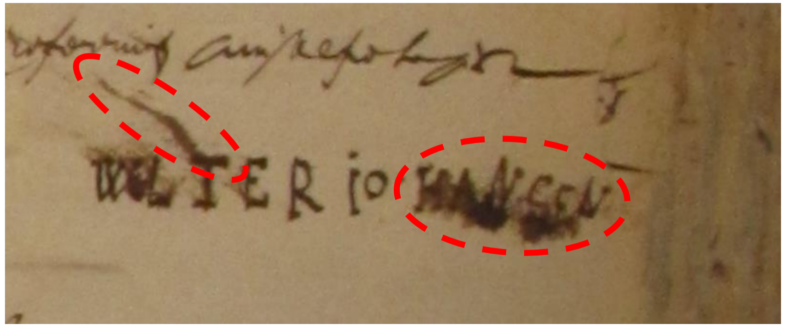












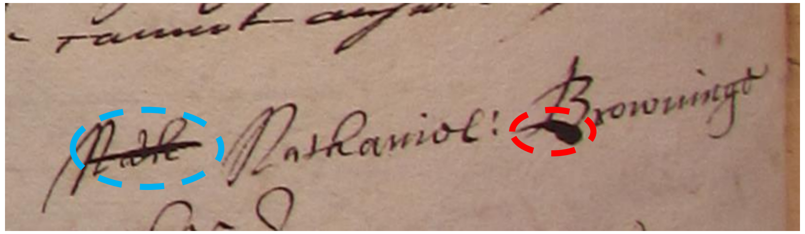
Even London alderman & merchant, John Frederick, could smudge his signature, when signing an addendum to his deposition three weeks after the first deposition

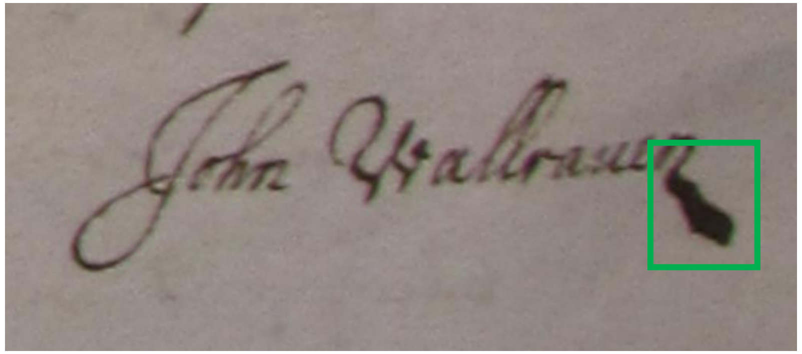
Wolter Johansen signed a second deposition smudge free, whilst signing both times with capitals

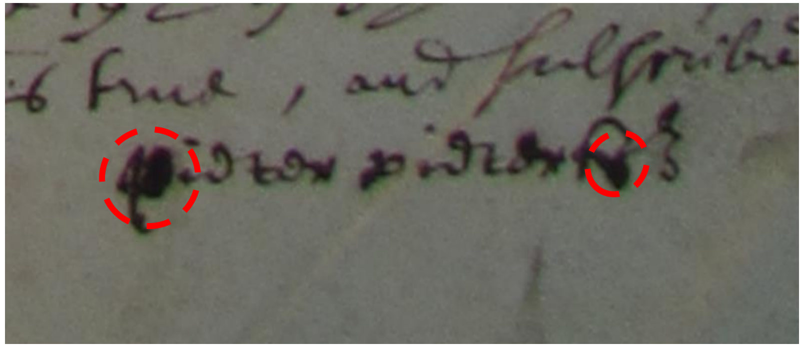
Ink blots or smudges

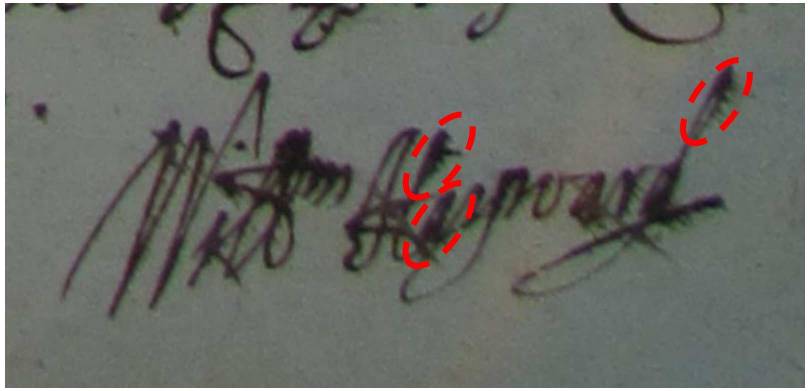
Source: Clockwise from top LH side: KaggleTestSnippet_HCA_1371_f.503r.PNG, KaggleTestSnippet_HCA_1373_f.498v.PNG, KaggleTestSnippet_HCA_1368_f.59r.PNG, KaggleTestSnippet_HCA_1368_f.231r.PNG, KaggleTestSnippet_HCA_1368_f.239v.PNG, KaggleTestSnippet_HCA_1368_f.241v.PNG

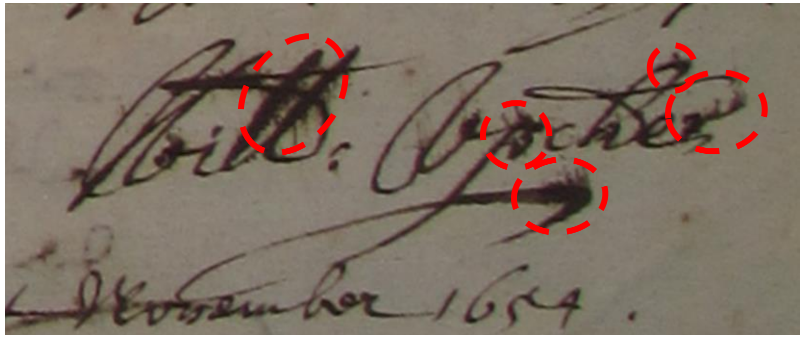
Can machine detection distinguish blots, smudges, stylistic features, & deletions? (1)

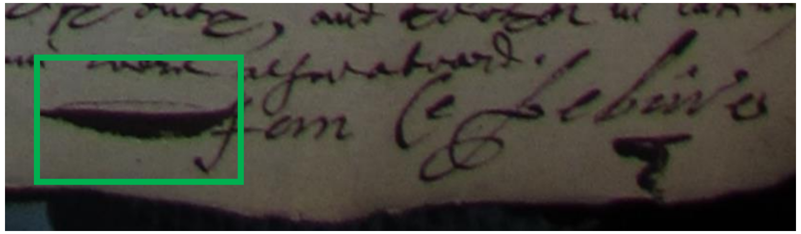




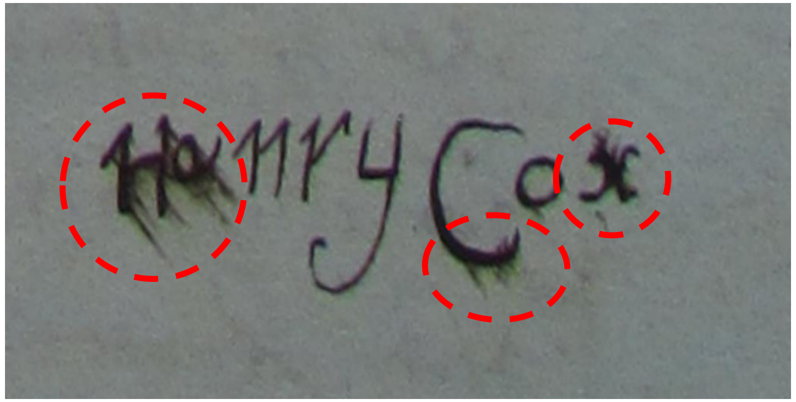


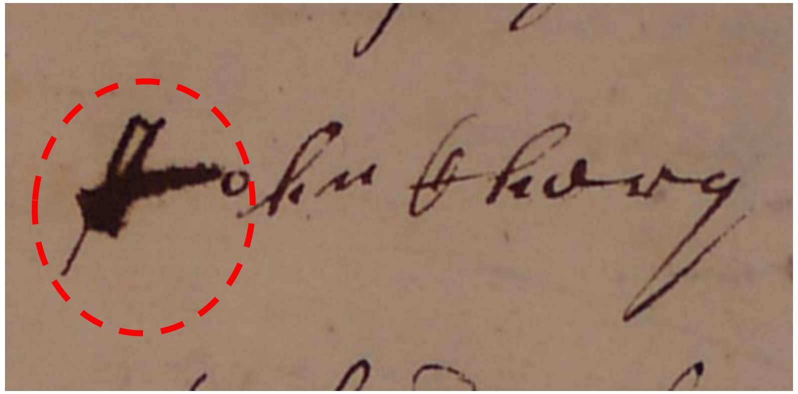






Source: Clockwise from top LH side:
KaggleTestSnippet_HCA_1370_f.387v.PNG,
KaggleTestSnippet_HCA_1370_f.13r.PNG,
KaggleTestSnippet_HCA_1370_f.167r.PNG,
KaggleTestSnippet_HCA_1371_f.456r.PNG,
KaggleTestSnippet_HCA_1370_f.15r.PNG,
KaggleTestSnippet_HCA_1370_f.19r.PNG,
KaggleTestSnippet_HCA_1370_f.41v.PNG,
KaggleTestSnippet_HCA_1370_f.17v.PNG,



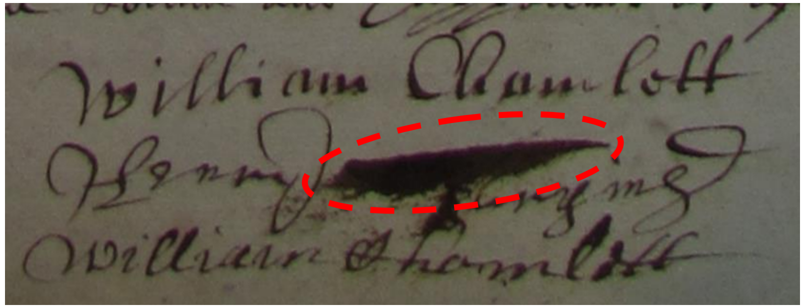


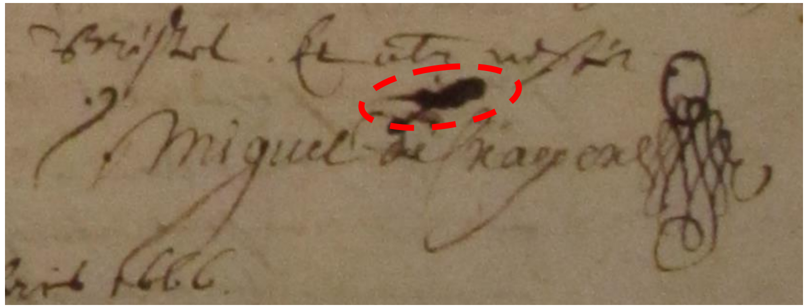
Ink blots or smudges

Stylistic feature or smudge?

Deletion

Can machine detection distinguish blots, smudges, stylistic features, & deletions? (2)





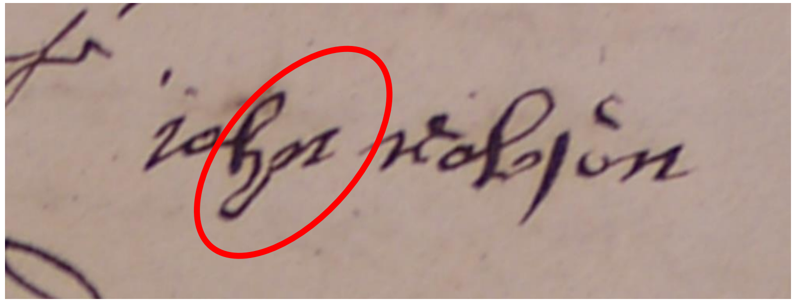
Ink blots or smudges

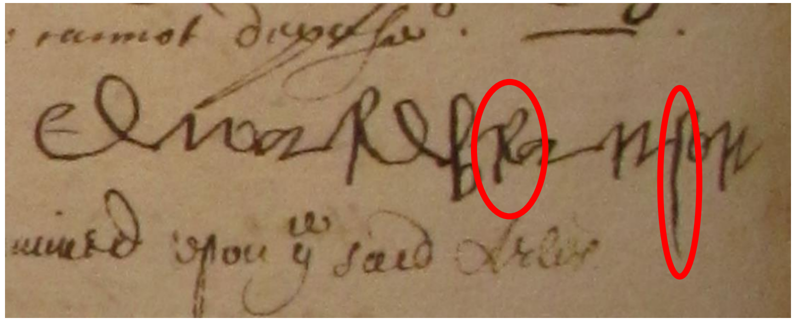
Stylistic feature or smudge?

Deletion

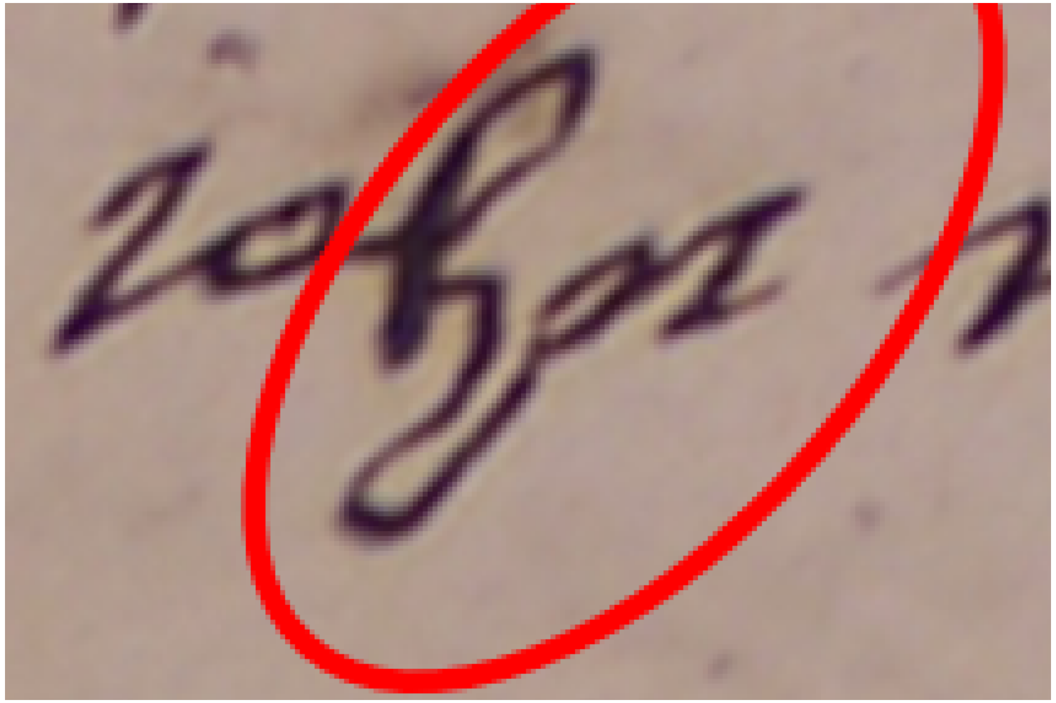
Source: Clockwise from top LH side:
KaggleTestSnippet_HCA_1370_f.51r.PNG,
KaggletestSnippet_HCA_1376_f.14r.PNG

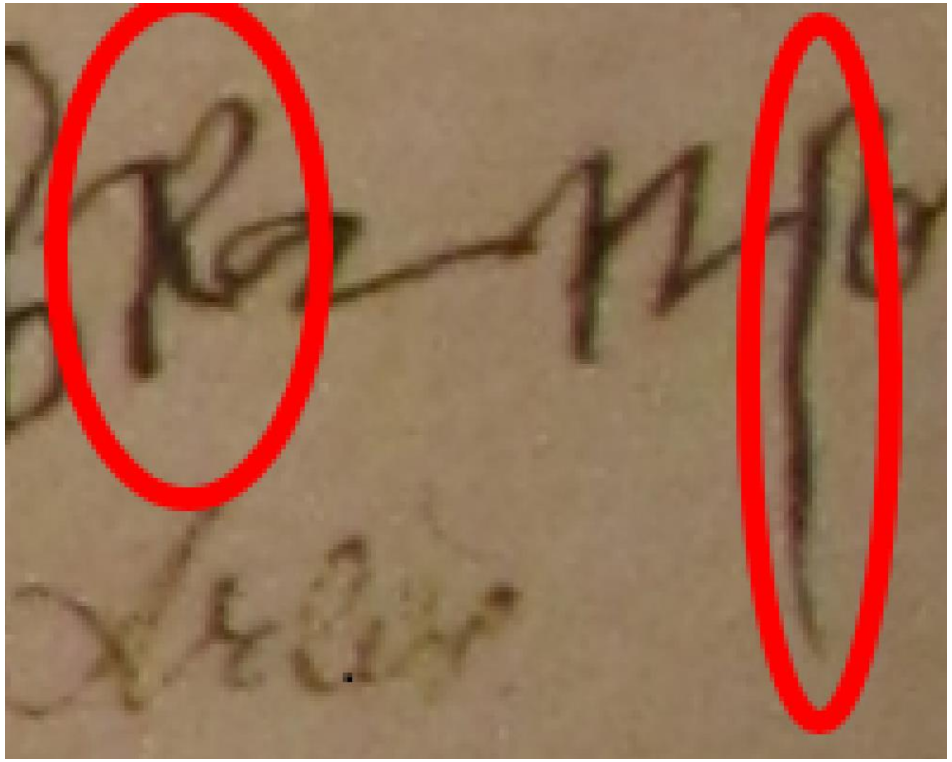
We are looking for algorithms to detect “shake” in straight and curved lines





HYPOTHESIS: Shaky lines are a sign of poor signature execution (and by inference, poor handwriting execution) suggesting lower level of literacy than smooth executed lines





Shaky straight lines and/or loops

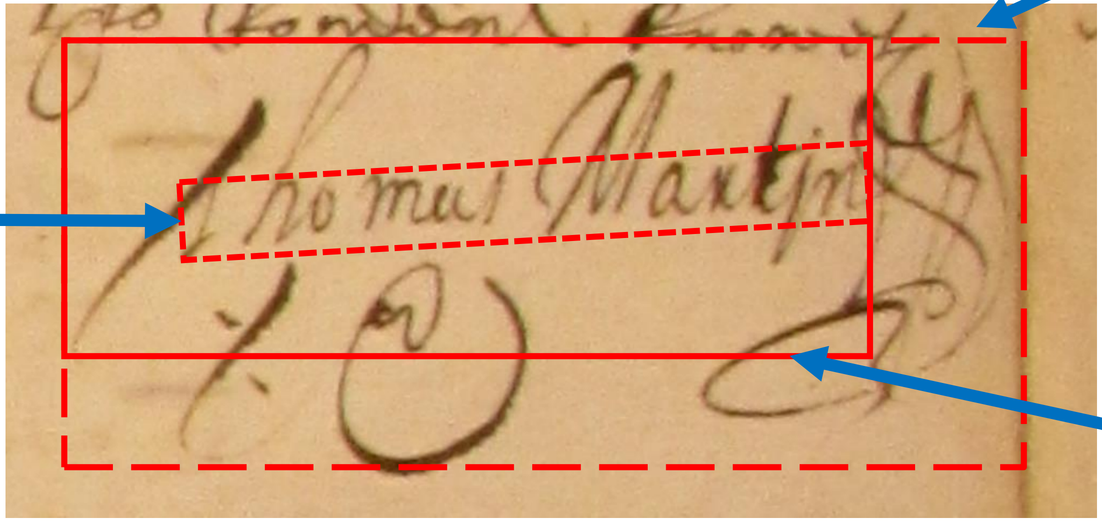
Clockwise, from top LH: KaggleTestSnippet_HCA_1371_f.435v.PNG, KaggleTestSnippet_HCA_1368_f.483v.PNG, KaggleTestSnippet_HCA_1368_f.483v_PIXELS.PNG, KaggleTestSnippet_HCA_1371_f.435v.PNG_PIXELS.PNG

Putting boundary boxes on C17th signatures

Boundary boxes marking
the visual geometry of a signature

Outside boundary box, including flourish

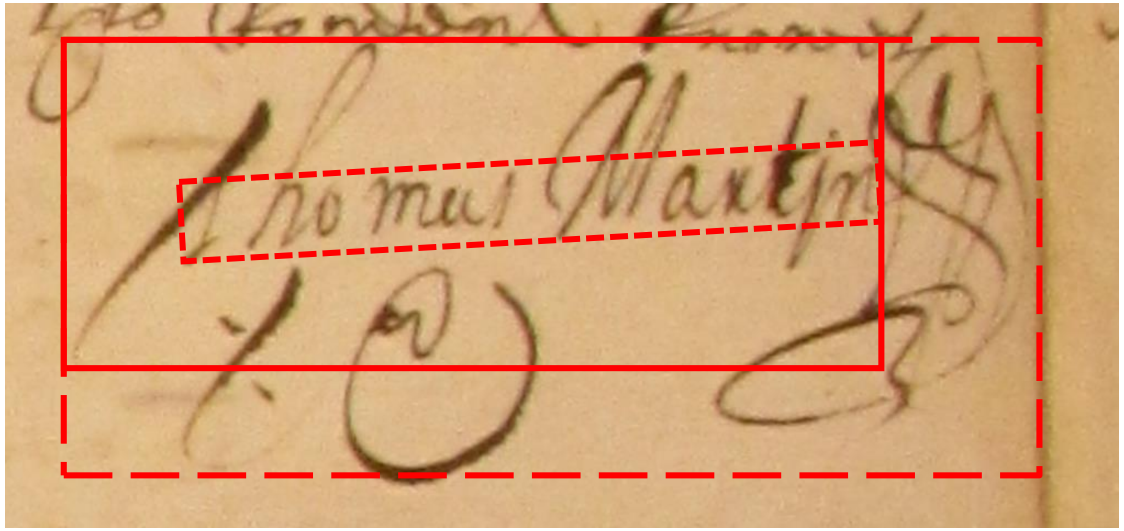
Inside boundary box, excluding uppers and downers

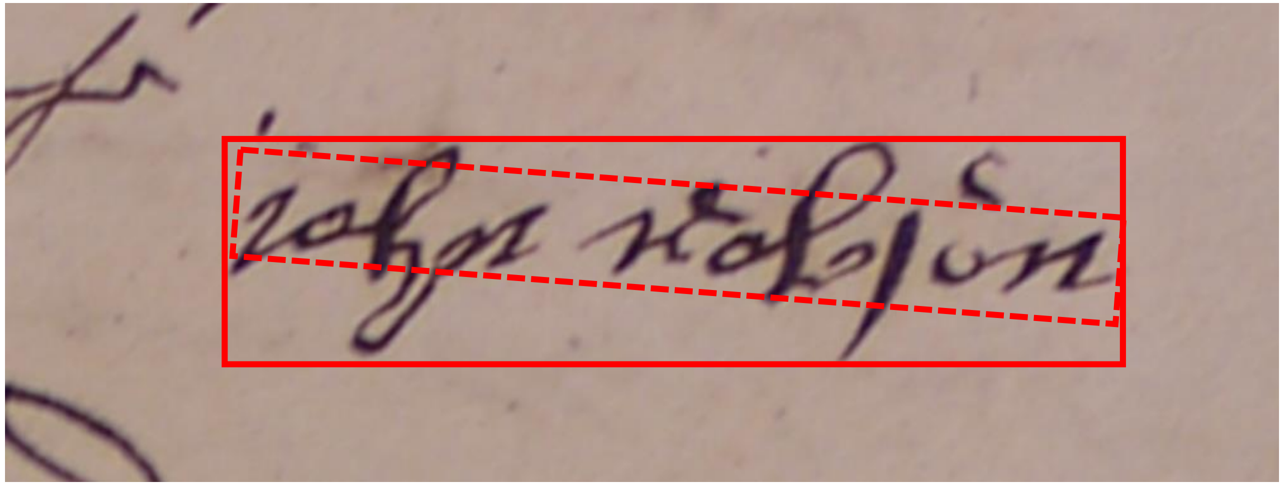


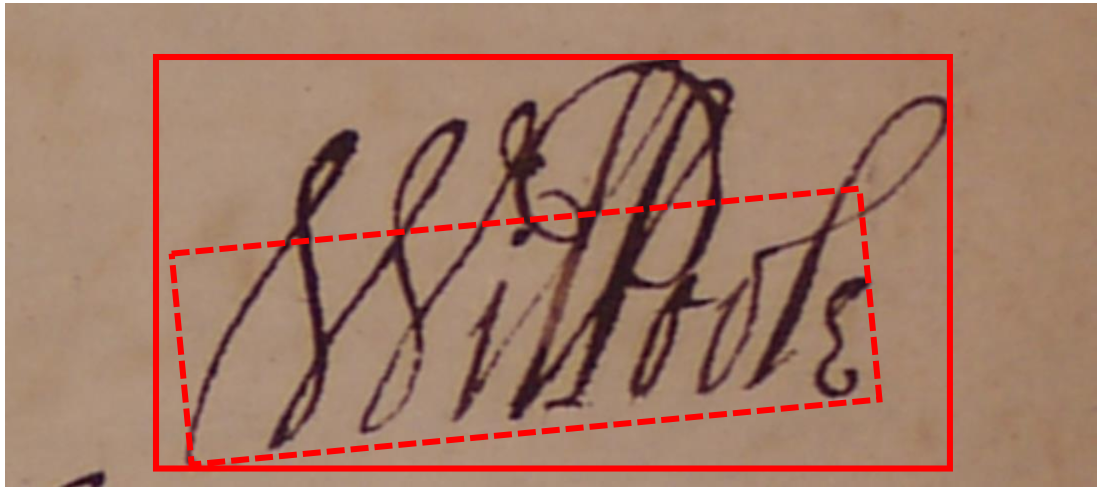
Middle boundary box, including all letters, but excluding flourish

Statistics
Inside boundary box: 9.0 x 1.1
Middle boundary box: 9.75 x 4.25
Outside boundary box: 12.75 x 5.75
Rotation from horizontal: ca. 340 degrees

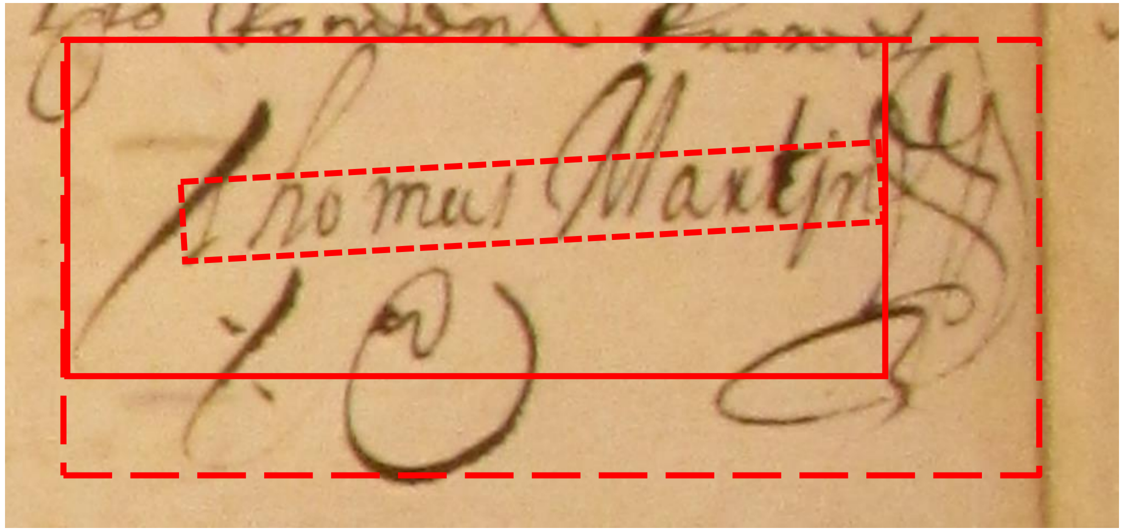
Different visual geometries of signatures

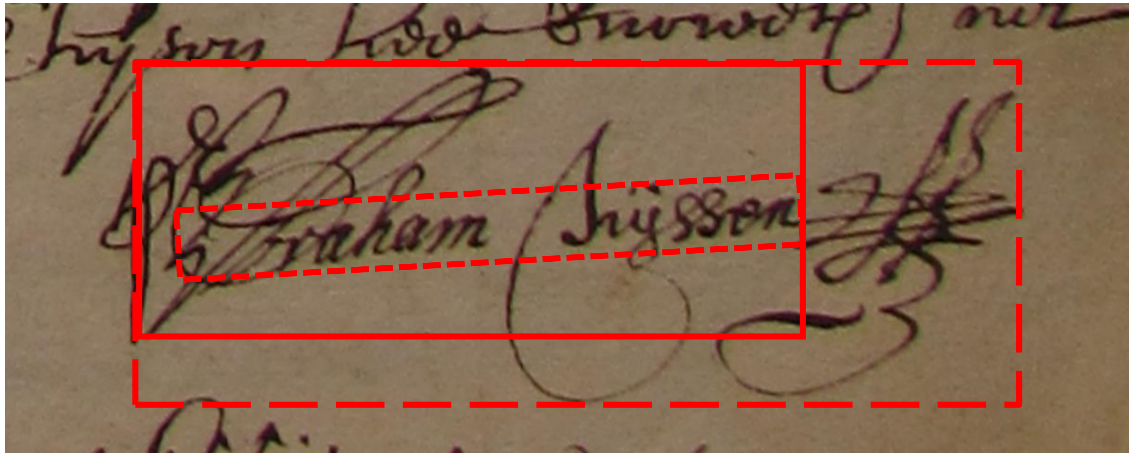


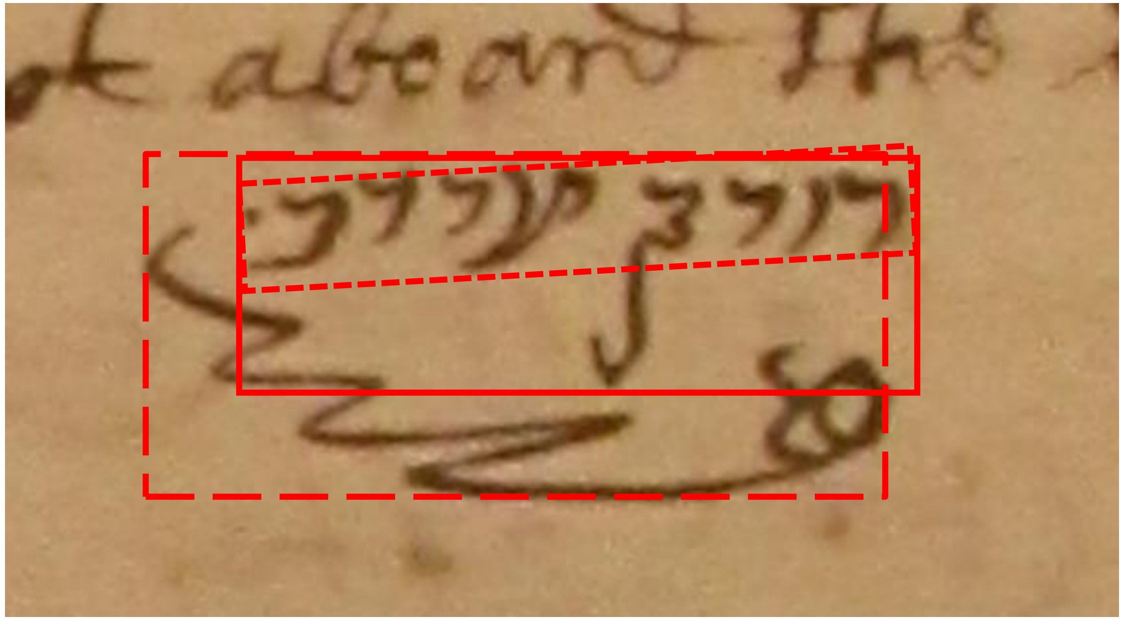


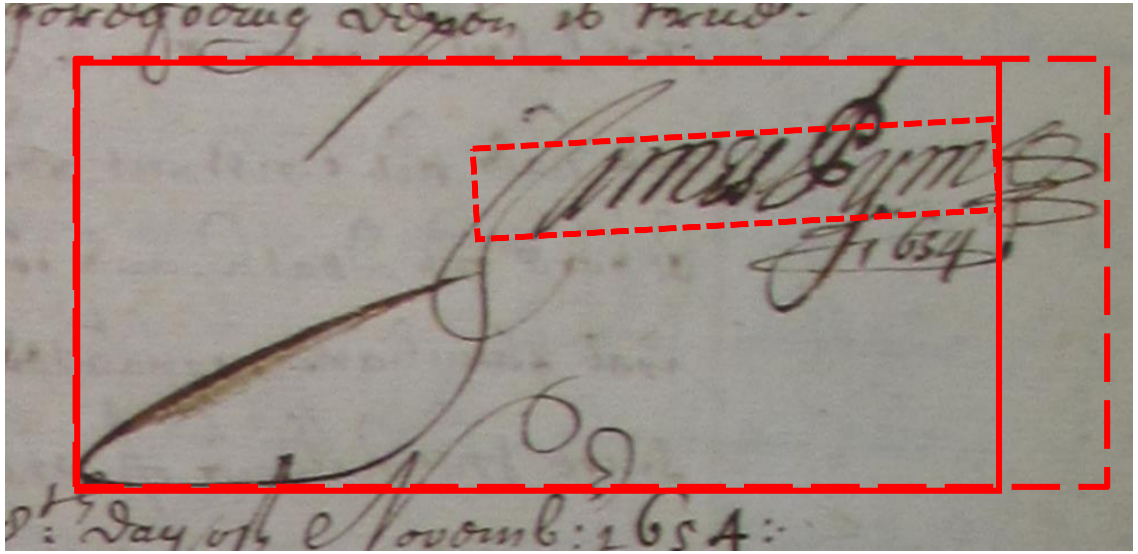


Visual geometries of flourishes – C17th Irish, Dutch, English & Moroccan merchants



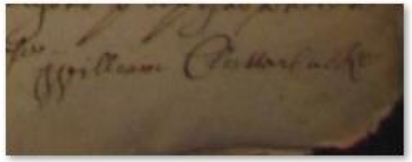




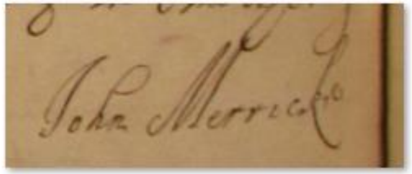


Source: Clockwise from top LH side: KaggleTestSnippet_HCA_1368_f.34v.PNG, KaggleTestSnippet_HCA_1370_f.366r.PNG, KaggleTestSnippet_HCA_1370_f.134r.PNG, KaggleTestSnippet_HCA_1368_f.58r.PNG

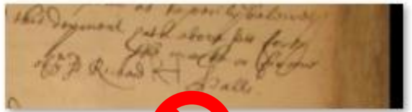
Challenge One: Identify the 11 image snippets on this page which contain signatures and highlight the 2 image snippets which contain signatures belonging to the same person



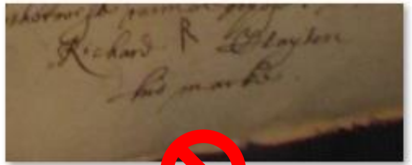
KaggleTestSnippet_HCA_1368_f.140r.PNG



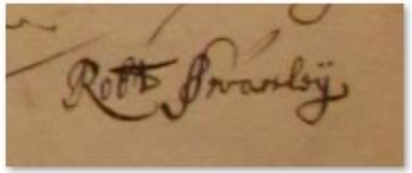
KaggleTestSnippet_HCA_1368_f.142r.PNG



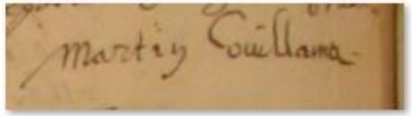
KaggleTestSnippet_HCA_1368_f.143r.PNG



KaggleTestSnippet_HCA_1368_f.145r.PNG



KaggleTestSnippet_HCA_1368_f.148r.PNG

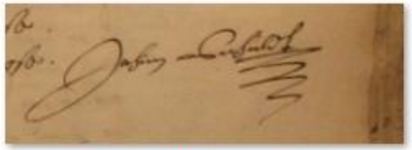


KaggleTestSnippet_HCA_1368_f.150v.PNG

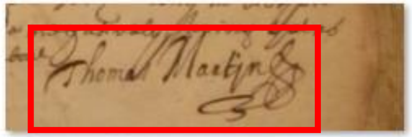
KaggleTestSnippet_HCA_1368_f.151v.PNG

KaggleTestSnippet_HCA_1368_f.153v.PNG

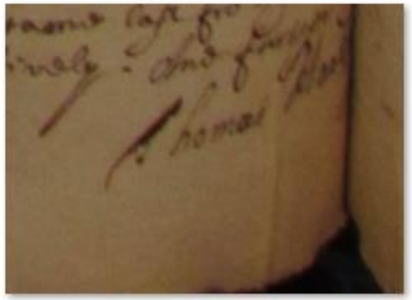
KaggleTestSnippet_HCA_1368_f.155r.PNG



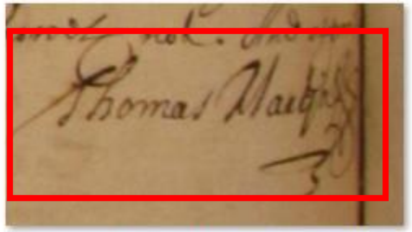
KaggleTestSnippet_HCA_1368_f.156r.PNG



KaggleTestSnippet_HCA_1368_f.158r.PNG



KaggleTestSnippet_HCA_1368_f.159v.PNG



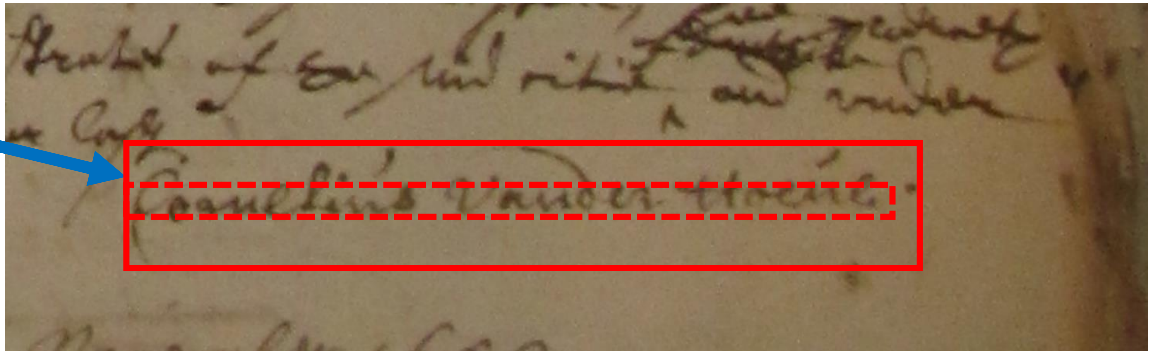
KaggleTestSnippet_HCA_1368_f.161v.PNG

Source: KaggleTestSnippets data set

Challenge Two: Detect a London based merchant, who has Dutch origin, from physical characteristics of signature, rather than spelling of name

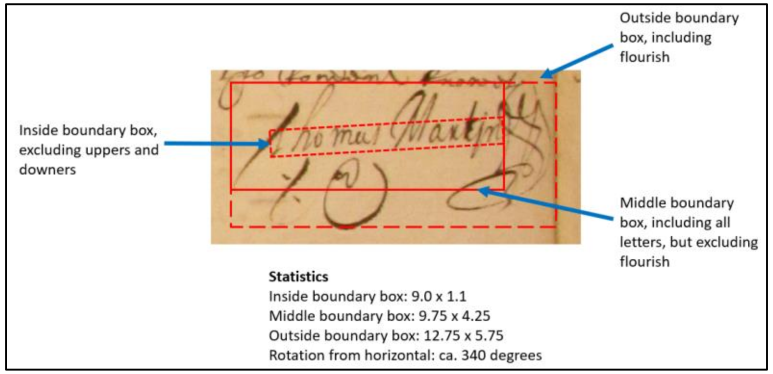
Semantic giveaways

- 3 names, not 2
- Specific names ["Cornelius"; "Vander"; "Hoene"]



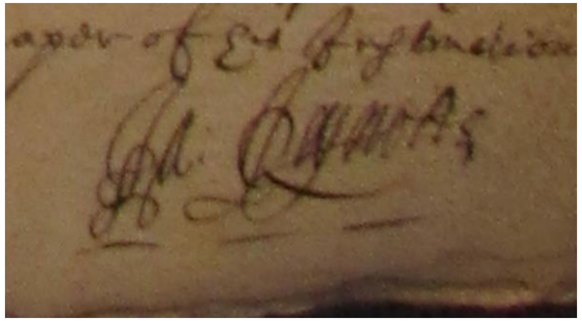
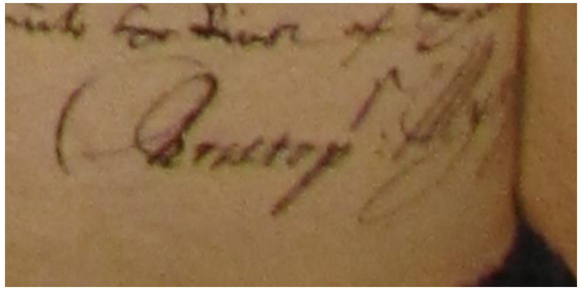
Physical giveaways

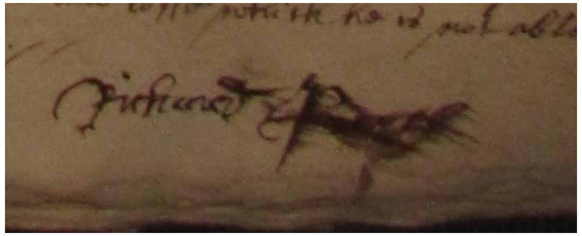
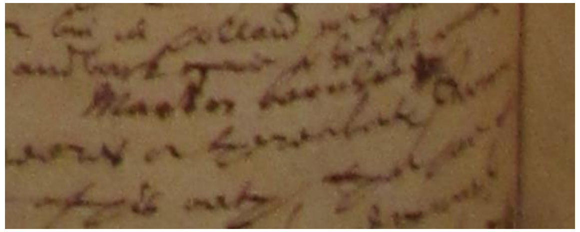
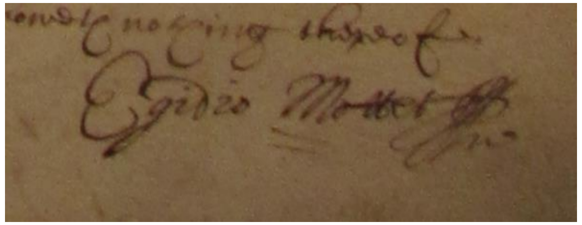
- Long, narrow signature
- No flourish
- Limited capitalisation
- Middle bounding box close to inner bounding box, with no outside bounding box

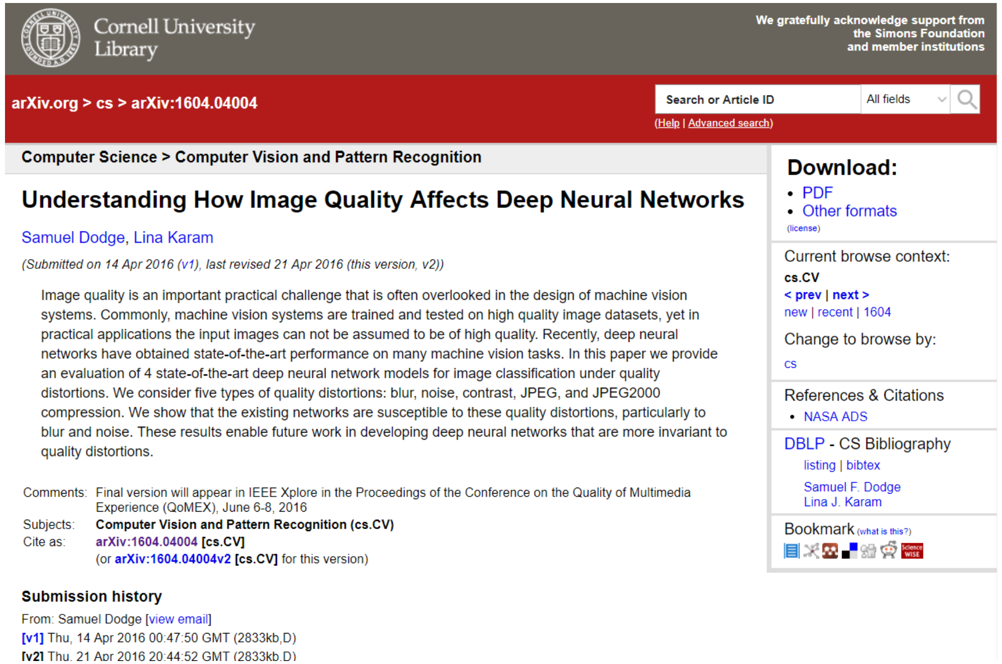


Source: KaggleTestSnippet_HCA_1368_f.233r_Two.PNG

Research question - methodology: How will poor resolution imagery affect the ability of a machine to learn from an image?



Cornell University Library

We gratefully acknowledge support from the Simons Foundation and member institutions

arXiv.org > cs > arXiv:1604.04004

Search or Article ID | All fields

(Help | Advanced search)

Computer Science > Computer Vision and Pattern Recognition

Understanding How Image Quality Affects Deep Neural Networks

Samuel Dodge, Lina Karam

(Submitted on 14 Apr 2016 (v1), last revised 21 Apr 2016 (this version, v2))

Image quality is an important practical challenge that is often overlooked in the design of machine vision systems. Commonly, machine vision systems are trained and tested on high quality image datasets, yet in practical applications the input images can not be assumed to be of high quality. Recently, deep neural networks have obtained state-of-the-art performance on many machine vision tasks. In this paper we provide an evaluation of 4 state-of-the-art deep neural network models for image classification under quality distortions. We consider five types of quality distortions: blur, noise, contrast, JPEG, and JPEG2000 compression. We show that the existing networks are susceptible to these quality distortions, particularly to blur and noise. These results enable future work in developing deep neural networks that are more invariant to quality distortions.

Comments: Final version will appear in IEEE Xplore in the Proceedings of the Conference on the Quality of Multimedia Experience (QoMEX), June 6-8, 2016

Subjects: **Computer Vision and Pattern Recognition (cs.CV)**

Cite as: **arXiv:1604.04004 [cs.CV]**

(or **arXiv:1604.04004v2 [cs.CV]** for this version)

Submission history

From: Samuel Dodge [view email]

[v1] Thu, 14 Apr 2016 00:47:50 GMT (2833kb,D)

[v2] Thu, 21 Apr 2016 20:44:52 GMT (2833kb,D)

Download:
- PDF
- Other formats

(license)

Current browse context:

cs.CV

< prev | next >

new | recent | 1604

Change to browse by:

cs

References & Citations
- NASA ADS

DBLP - CS Bibliography

listing | bibtex

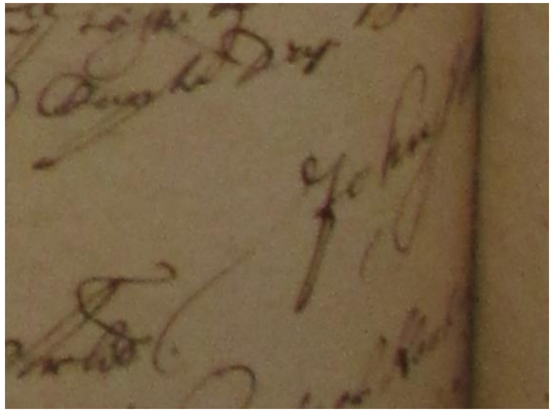
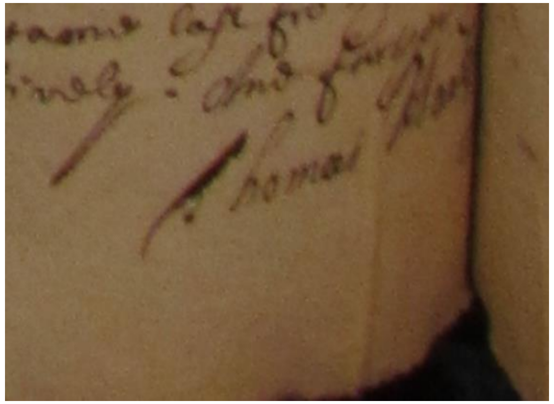
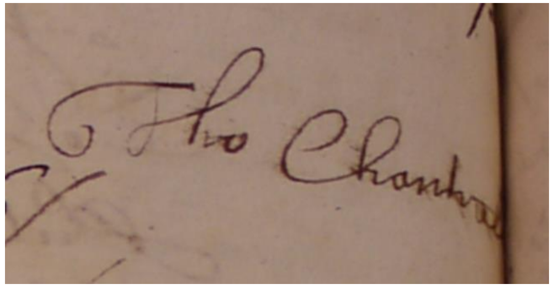
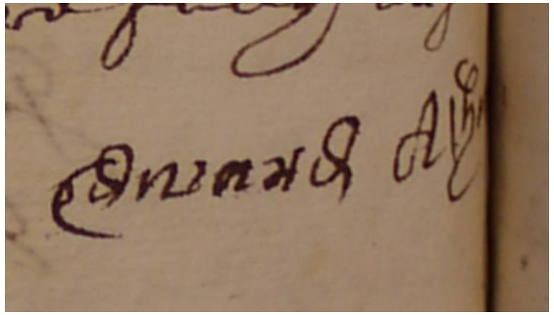
Samuel F. Dodge

Lina J. Karam

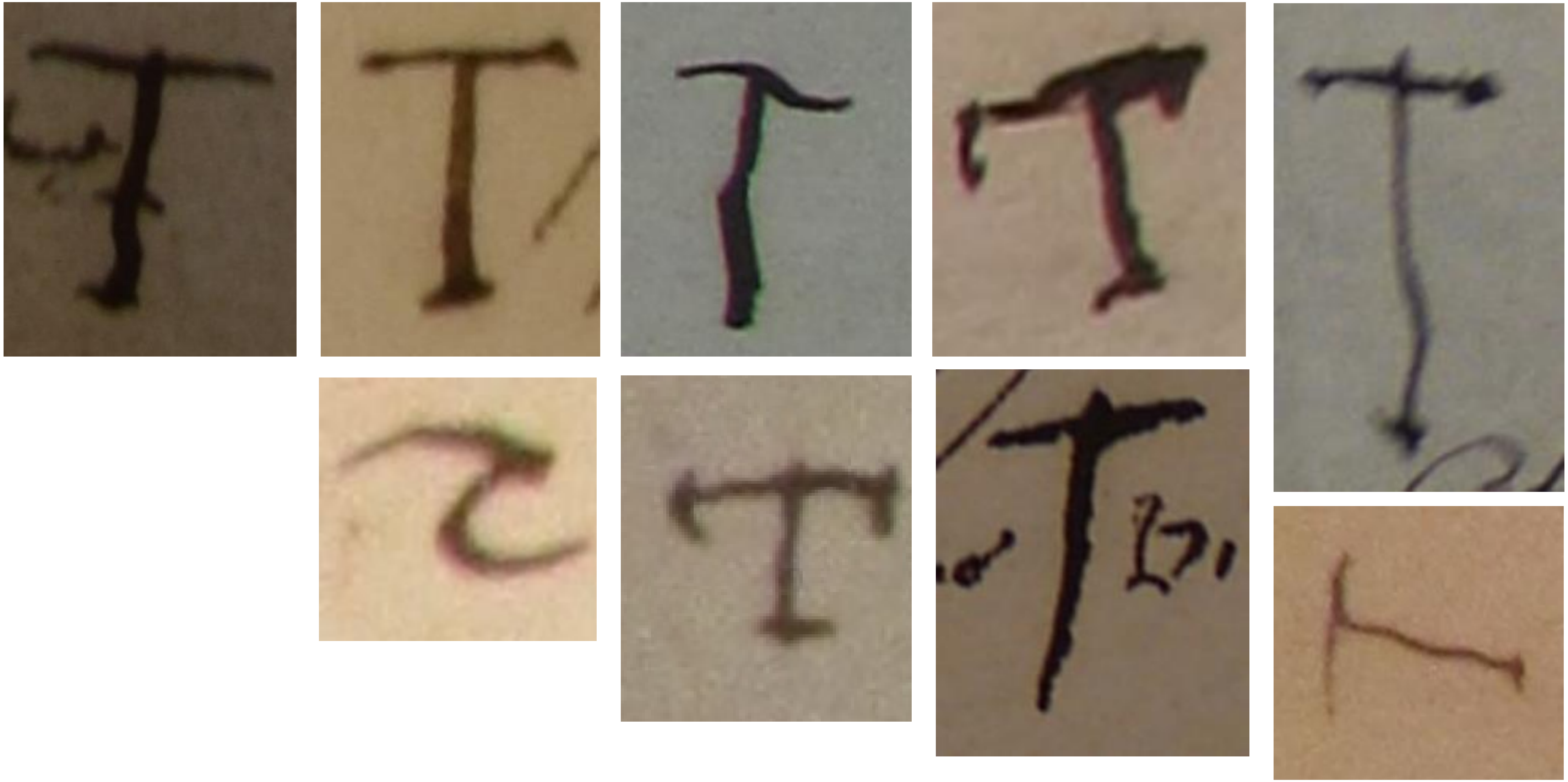
Bookmark (what is this?)

Source: Clockwise from top LH side:
KaggleTestSnippet_HCA_1368_f.42r.PNG,
KaggleTestSnippet_HCA_1368_f.46v.PNG,
KaggleTestSnippet_HCA_1368_f.55r_Two.PNG,
KaggleTestSnippet_HCA_1370_f.11v.PNG,
KaggleTestSnippet_HCA_1368_f.62r.PNG,
KaggleTestSnippet_HCA_1368_f.121v_Two.PNG ,
KaggleTestSnippet_HCA_1368_f.59r.PNG,

Research question - methodology: How much of a signature does a machine need to predict the physical character of the whole signature & to assess it stylistically?

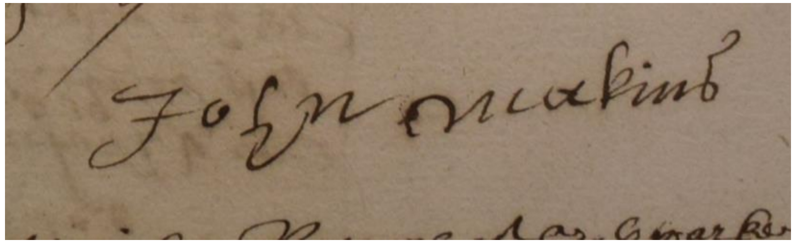





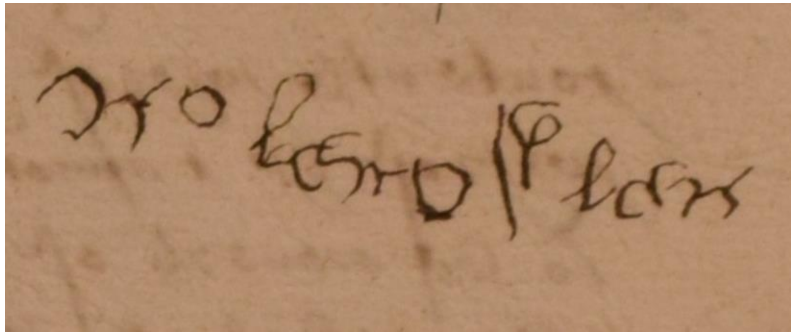
Source: Clockwise from top LH side: KaggleTestSnippet_HCA_1368_f.274v.PNG, KaggleTestSnippet_HCA_1368_f.159v.PNG, KaggleTestSnippet_HCA_1373_f.490v.PNG, KaggleTestSnippet_HCA_1373_f.493v.PNG, Research question - methodology: Can a machine distinguish between the authors of a specific initial?

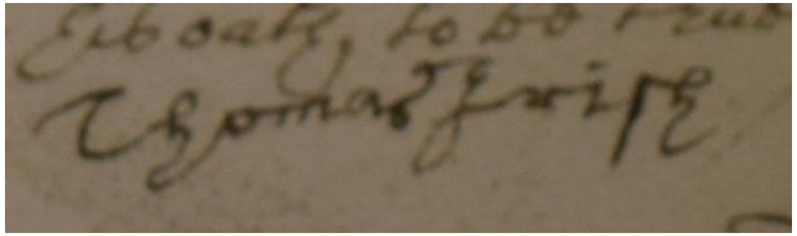


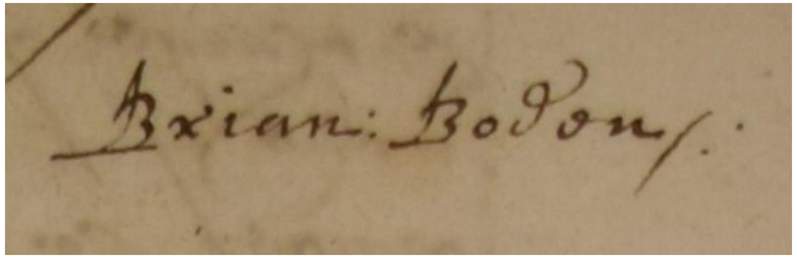
Source: KaggleTestSnippets

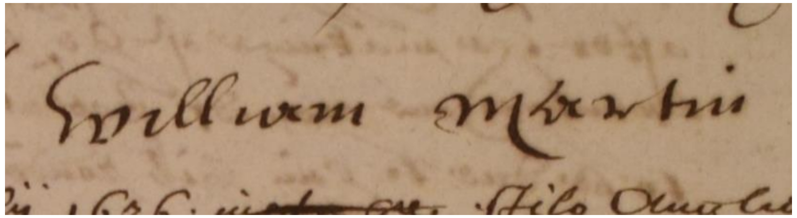
Research question – methodology/content: Why do these some of these unadorned signatures by C17th Englishmen appear less well executed than others to a C21st eye?

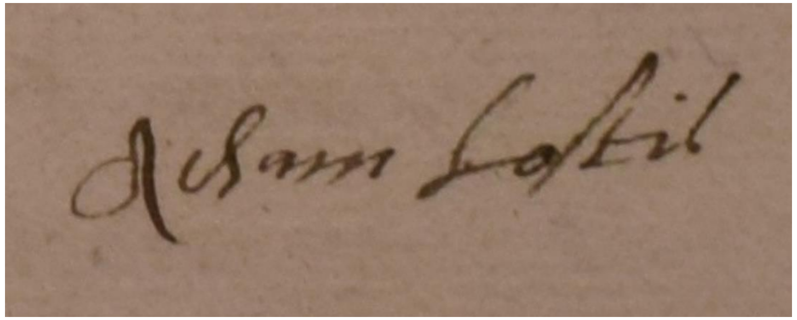


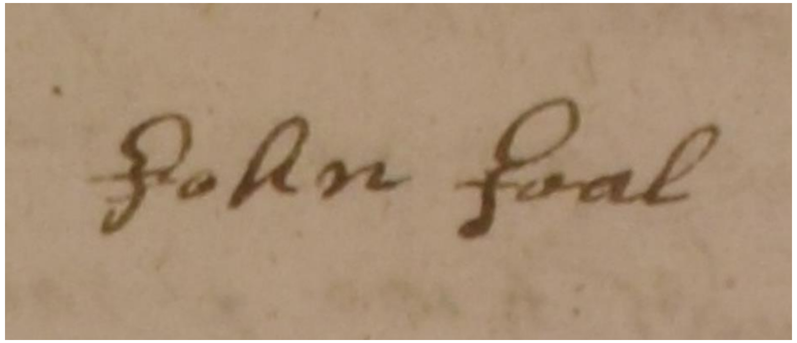












Source: Down from top LH side: KaggleTestSnippet_HCA_1353_f.24v.PNG,
KaggleTestSnippet_HCA_1353_f.188r.PNG;
Down from top Middle: KaggletestSnippet_HCA_1353_f.66r.PNG;
Down from top RH SIDE: KaggleTestSnippet_HCA_1353_f.28v.PNG,
KaggleTestSnippet_HCA_1353_f.29v_One.PNG, KaggleTestSnippet_HCA_1353_f.35r.PNG,
KaggleTestSnippet_HCA_1353_f.36v.PNG

Research question - methodology: How well will machine learning cope with recognising and matching signature, initial & marke snippets? (1)

Are certain parts of a signature more stable than others?

Source: In pirss, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet_HCA_1368_f.253r.PNG, KaggleTestSnippet_HCA_1368_f.254v.PNG; (2) KaggleTestSnippet_HCA_1368_f.255v.PNG, KaggleTestSnippet_HCA_1368_f.256r.PNG; (3) KaggleTestSnippet_HCA_1368_f.257r.PNG, KaggleTestSnippet_HCA_1368_f.258r.PNG; (4) KaggleTestSnippet_HCA_1368_f.283r.PNG, KaggleTestSnippet_HCA_1368_f.284r.PNG; (5) KaggleTestSnippet_HCA_1368_f.231r.PNG, KaggleTestSnippet_HCA_1368_f.239v.PNG (6) KaggleTestSnippet_HCA_1371_f.481v.PNG, KaggleTestSnippet_HCA_1371_f.484r.PNG (7) KaggleTestSnippet_HCA_1368_f.278r.PNG, KaggleTestSnippet_HCA_1368_f.279r.PNG

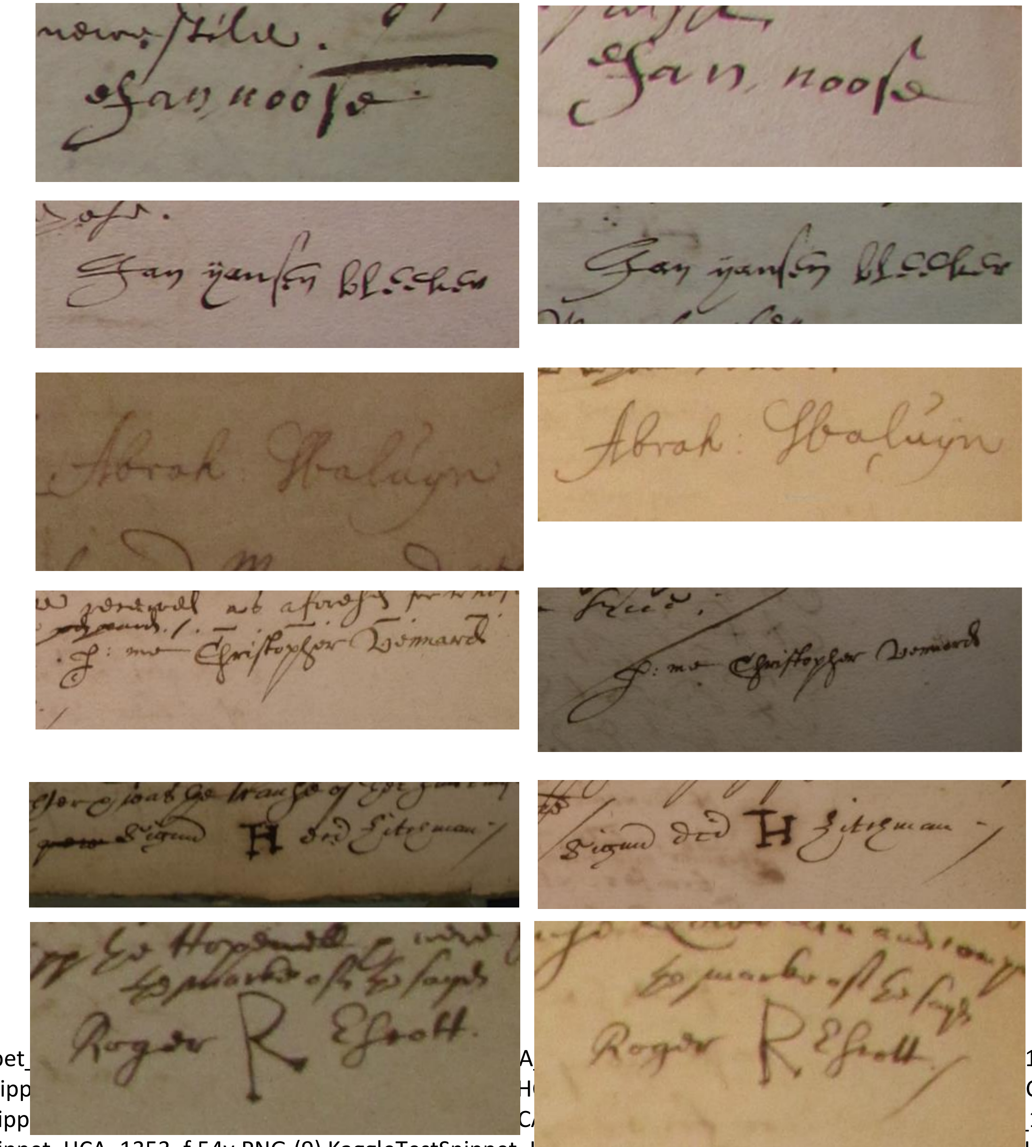
Research question - methodology: How well will machine learning cope with recognising and matching signature, initial & marke snippets? (2)

Are certain parts of a signature more stable than others?

Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet_HCA_1373_f.16r_One.PNG, KaggleTestSnippet_HCA_1373_f.16r_Two.PNG (2) KaggleTestSnippet_HCA_1368_f.288r.PNG, KaggleTestSnippet_HCA_1368_f.288v.PNG, KaggleTestSnippet_HCA_1368_f.291v_Two.PNG (3) KaggleTestSnippet_HCA_1368_f.289r.PNG, KaggleTestSnippet_HCA_1368_f.289v.PNG (4) KaggleTestSnippet_HCA_1368_f.290v.PNG, KaggleTestSnippet_HCA_1368_f.291r.PNG, KaggleTestSnippet_HCA_1368_f.291v_One.PNG (5) KaggleTestSnippet_HCA_1368_f.293v_One.PNG, KaggleTestSnippet_HCA_1368_f.293v_Two, KaggleTestSnippet_HCA_1368_f.293v_Three

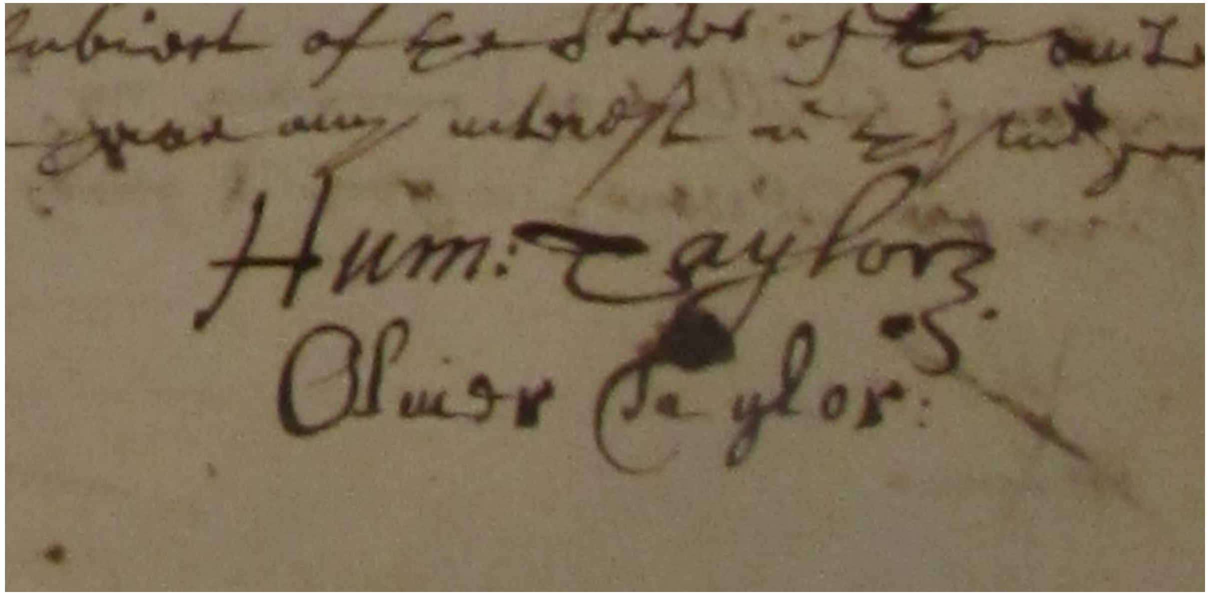
Research question - methodology: How well will machine learning cope with recognising and matching signature, initial & marke snippets? (3)

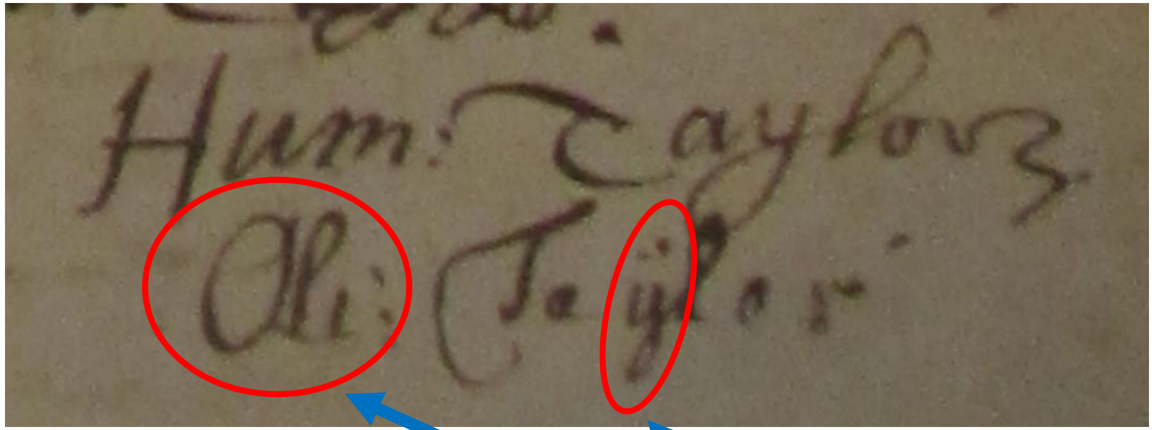
Are certain parts of a signature more stable than others?



Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet_[illegible] 1368_f.158r.PNG, KaggleTestSnippet_HCA_1368_f.161v.PNG (3) KaggleTestSnippet_HCA_1370_f.6v.PNG, KaggleTestSnipp[illegible] CA_1370_f.14v.PNG (5) KaggleTestSnippet_HCA_1370_f.23r.PNG, KaggleTestSnippet_HCA_1370_f.25v.PNG (6) KaggleTestSnipp[illegible] 1376_f.17v.PNG, KaggleTestSnippet_HCA_1376_f.18v.PNG (8) KaggleTestSnippet_HCA_1353_f.13r.PNG, KaggleTestSnippet_HCA_1353_f.54v.PNG (9) KaggleTestSnippet_[illegible] HCA_1353_f.28r.PNG (10) KaggleTestSnippet_HCA_1368_f.286r.PNG, KaggleTestSnippet_HCA_1368_f.287v.PNG

Research question - content: Can a family resemblance be detected in signatures from the same biological family from the same date and place?



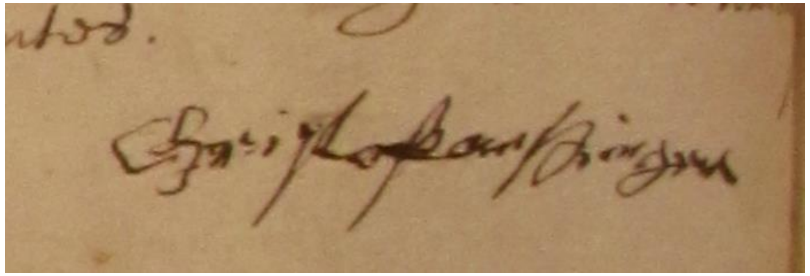


Depositions in the English High Court of Admiralty of **Humphrey Taylor** of London merchant aged 29 yeares or thereabouts and **Oliver Taylor** of the same citie merchant aged 27 yeares, dated December 8th, 1653 and again on December 9th, 1653

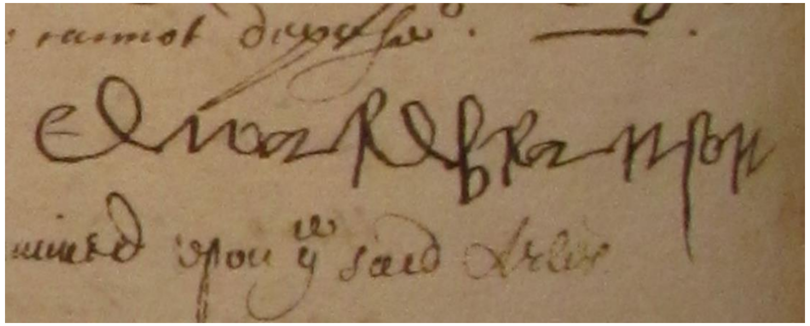
One day after his first signature, **Oliver Taylor** abbreviates his first name and writes the "y" in "Taylor" with a diaeresis ("Ÿ")

Source: KaggleTestSnippet_HCA_1368_f.240r.PNG, KaggleTestSnippet_HCA_1368_f.246r_Two.PNG

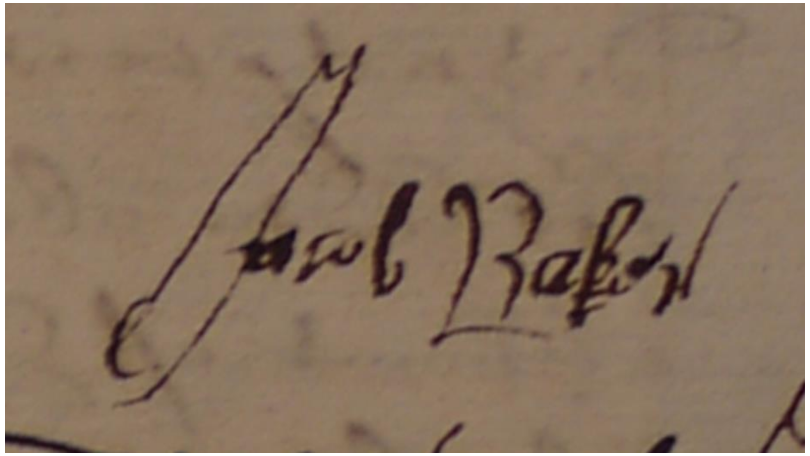
Research question - content: Is there an age effect in terms of physical control of pen, independent of any age-independent physical infirmity, and independent of a tendency for lower literacy (and possibly lower control of pen) amongst earlier age cohorts in our samples of signatures from the mid-C17th?



Christopher Drake, 86 year old sugar refiner, of Saint Mary Street, London, born 1567, signature dated Nov 2, 1653



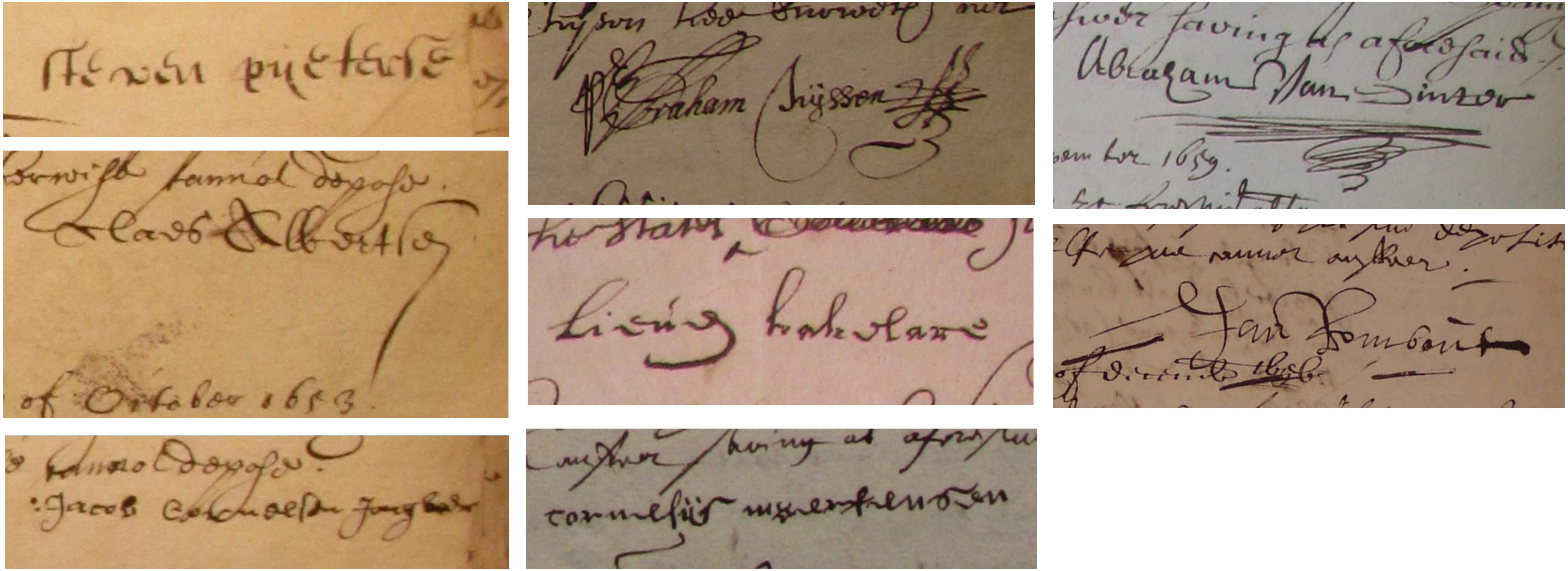
Edward Branston, 47 year old rope maker, of Saint Mary Matsellon alias Whitechapel, born 1607, signature dated Jan 25, 1654



James Baker, 21 year old mariner, of Wapping, one of the company of the ship the *Plaine Dealeing*, born 1635, signature dated Jun 21, 1656

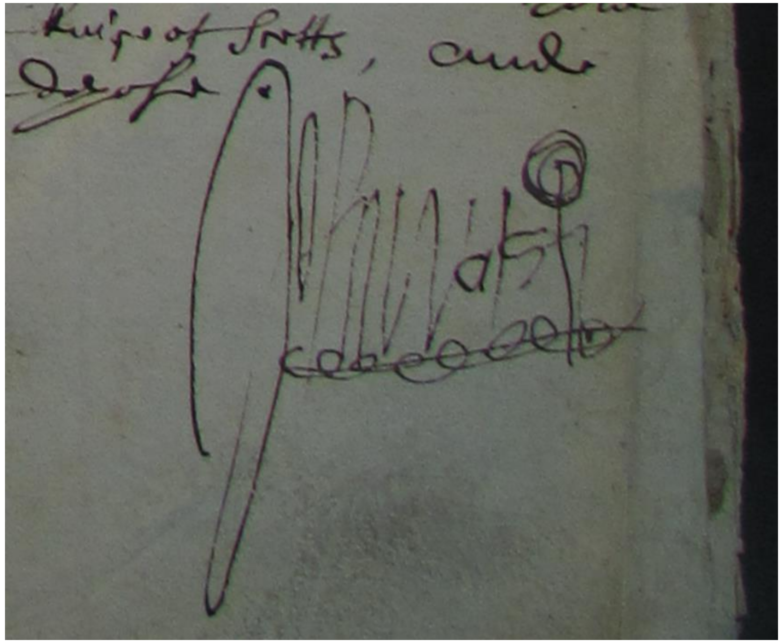
Source: Top to bottom, KaggleTestSnippet_HCA_1368_f.60v.PNG, KaggleTestSnippet_HCA_1368_f.483v.PNG, KaggleTestSnippet_HCA_1371_f.263v.PNG

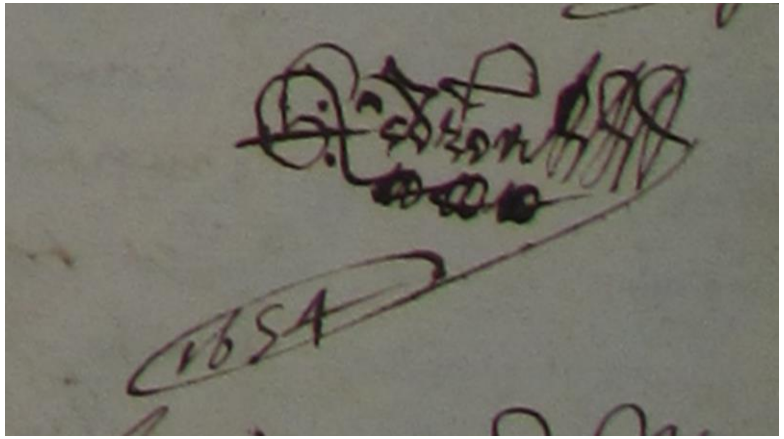
Research question - content: Was it less common to use capital letters in Dutch rather than English language signatures in the C17th?

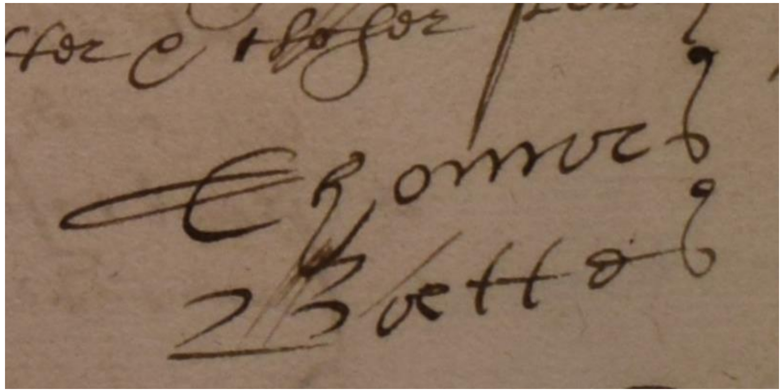


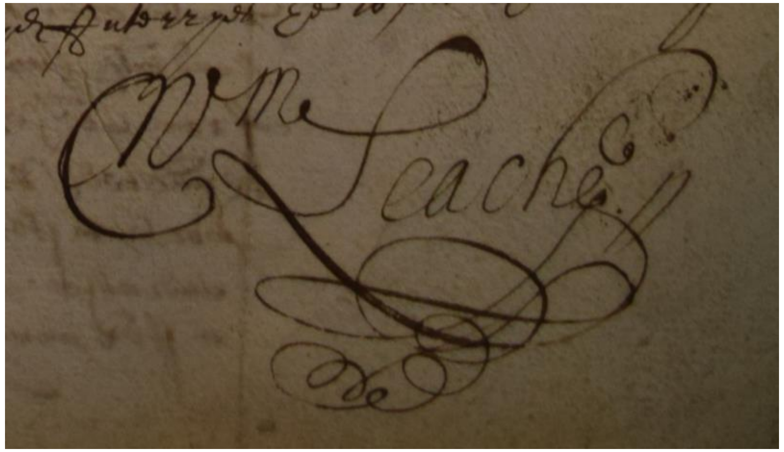
Source: Clockwise from top LH side: XXXXX

Data: Unusual signatures









Source: Clockwise from top LH side: KaggleTestSnippet_HCA_1370_f.7r.PNG, KaggleTestSnippet_HCA_1370_f.37r.PNG, KaggleTestSnippet_HCA_1353_f.10r.PNG, KaggleTestSnippet_HCA_1353_f.29v_Two.PNG, KaggleTestSnippet_HCA_1353_f.42v.PNG

SUPPLEMENTARY MATERIAL

Issues

Pre-processing

- Scaling images
- Converting to grayscale
    - Some image processing & computer vision algorithms use grayscale images not colour images
    - Grayscale processing 3x faster than colour processing
- Normalising an image
    - Avoid larger feature values dominating smaller feature values [THINK ABOUT THIS]

Image processing packages

- OpenCV: reads & plots an image in BGR format. Reads PNG & JPG on 0 to 255 range
- Matplotlib: reads & plots an image in RGB format. Reads JPEG in 0 to 255 and PNG on 0 to 1 range

Do images need to be square for typical neural network models? Or at least have identical aspect ratios? Do we need to scale all images to a standard number of pixels for height & width? Do snippets need to be cropped to isolate the signoff? What does the mean image of a marke, an initial and a signature look like? [mean value of each pixel across all training examples]. Can also look at the standard deviation of the pixels for a group of images.

Reading

Colin Greenstreet, Pattern recognition of signatures and markes in historical manuscripts as the basis for sub-population recognition, March 2018 [available Signsofliteracy Github repository: Signsoliteracy/Signoff]

Colin Greenstreet, C17th alphabet of initials, 4th edn., April 4th, 2018 [available Signsofliteracy Github repository: Signsoliteracy/Signoff]

[Mark Hailwood, 'The Rabble that Cannot Read', Ordinary Peoples Literacy in Seventeenth-Century England, October 13th, 2014]

[David Cressy, Literacy and the Social Order: Reading & Writing in Tudor and Stuart England, 1980]

Reading

My Text in Your Handwriting

Tom S. F. Haines, Oisin Mac Aodha, Gabriel J. Brostow

Journal
ACM Transactions on Graphics (TOG) TOG Homepage archive
Volume 35 Issue 3, June 2016
Article No. 26
ACM New York, NY, USA
table of contents doi>10.1145/2886099

Abstract: There are many scenarios where we wish to imitate a specific author's pen-on-paper handwriting style. Rendering new text in someone's handwriting is difficult because natural handwriting is highly variable, yet follows both intentional and involuntary structure that makes a person's style self-consistent. The variability means that naive example-based texture synthesis can be conspicuously repetitive.

We propose an algorithm that renders a desired input string in an author's handwriting. An annotated sample of the author's handwriting is required; the system is flexible enough that historical documents can usually be used with only a little extra effort. Experiments show that our glyph-centric approach, with learned parameters for spacing, line thickness, and pressure, produces novel images of handwriting that look hand-made to casual observers, even when printed on paper.


My Text in Your Handwriting

Tom S. F. Haines, Oisin Mac Aodha and Gabriel J. Brostow
University College London

1. INTRODUCTION

http://visual.cs.ucl.ac.uk/pubs/handwriting/handwriting_visual_main.pdf

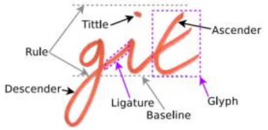


Fig. 2. Glossary of the key parts of handwritten text.

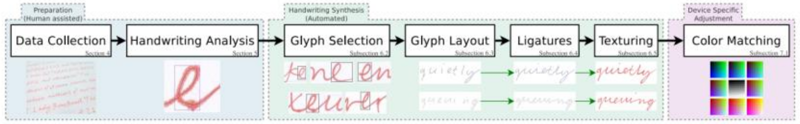


Fig. 4. System diagram showing our processing pipeline, with representative images for each stage. After samples are collected and analyzed, the rendering system selects a glyph to represent each character, *e.g.* "e" as shown here. If there are many choices, it must choose one that fits the surrounding text. The glyphs are then positioned on the page, and ligatures added if the author uses joined up writing. Two example words are given for these three stages, "quietly" and "queuing." Finally, the texture is transfered from the original input to the vector output and, if being printed, color correction is applied.

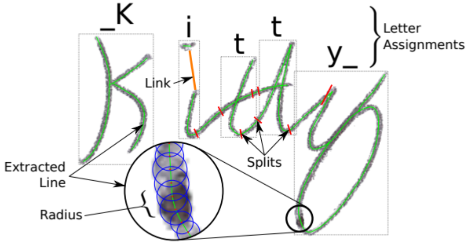


Fig. 5. Visualization of the output of the tagging process. The *line* is vectorized, and has *radius* calculated at every pixel along it. Not shown is the ink *density*, which is also calculated for every pixel as the average within the circle defined by the radius. The line forms a graph, to which *splits* are added to delineate each letter and ligature. If a letter has multiple parts then a *link* combines them. Finally, the parts are *tagged* with the relevant letter/digit/punctuation and *underscores* used to indicate the starts and ends of words. *Ligatures* are left implicit, as any path that connects two tagged glyphs.

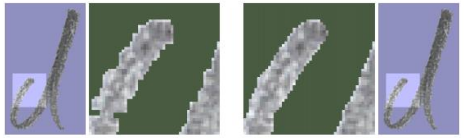


Fig. 6. Segmentation on the left shows the graph cuts result without line aware smoothing. The right side shows the improvement of smoothing. Writing implement is a pencil.

Fig. 7. Comparison of automatic only (left column) with human assisted tagging (right column). Ground truth, a sample of the authors actual writing, is in the central column.

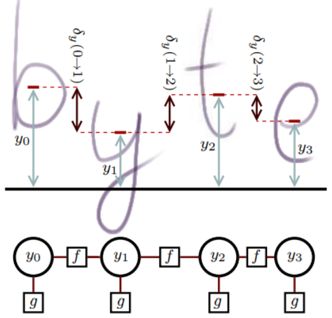


Fig. 12. Factor graph of Kalman smoothing, used to ensure the synthesized text flows. The y_i random variables (circles) indicate how far off the baseline to position each glyph. Factors (squares) indicate probabilities over the random variables to which they are connected. Kalman smoothing finds the most probable assignment of y_i values. There are two types of factor. g factors indicate that the glyphs are probably on the baseline, as a Gaussian distribution where the mean is the displacement of the glyph in the training data, h_i. This factor is $y_i \sim \mathcal{N}(h_i, 1)$. f factors indicate the displacement between adjacent glyphs, δ_y, as given in (7). When ligatures exist they provide this term, but when omitted (e.g. print handwriting) it is provided by a regression forest.

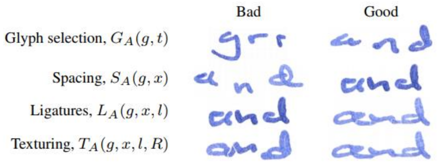


Fig. 8. Synthesis of the word "and", demonstrating what each component of the cost function does. All steps are dependent on the author's specific style, e.g. here we show that having ligatures is preferred, but if the author has print handwriting then the inclusion of ligatures would be wrong. Note that the last two *good* exemplars are different, as visible between the "a" and "n."

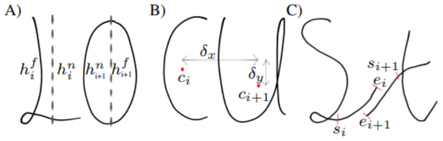


Fig. 11. A) The near-far labeling scheme for halves of a glyph, as used for the distance learning feature. B) Two glyphs, "c" and "u", with their centers (c_i and c_{i+1}) and the horizontal (δ_x) and vertical (δ_y) offsets between them marked. C) Two glyphs, "s" and "t", with attached ligatures delineated by the regions within the red marks. The ligature end points are labeled with the variables used for their coordinates.

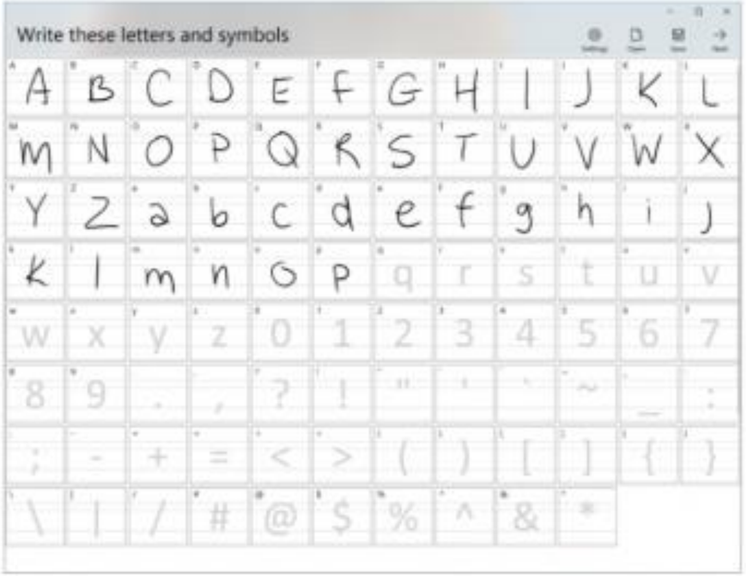
Fig. 10. A) Same sentence generated multiple times, to demonstrate output variability. The first instance is the maximum likelihood output, which would otherwise be returned every time. B) Line replacement, where one writing implement is replaced with another. First on the left is the source with the original texture. While the replacement is visually coherent, the geometric path and density variability of the previous pen is kept, which is sometimes unrealistic.

WindowsInk @WindowsInk · Jun 27

if you are a #WindowsInsider you can create your own #font out of your **#handwriting** Please try it out, and send us a screenshot of what you create, and what you think of it! #WindowsInk

Microsoft Font Maker app

Have you tried it out yet? With the Microsoft Font Maker app you can use your pen to create a custom font based on the nuances of your own handwriting – currently available via the Microsoft Store and we'd love to hear your feedback! Install the fonts you create to add a personal touch to everything you do!



Note: Currently you can use the app to create a basic English font – interested in support for more characters and languages? Let us know!

Reading

Reading

Cornell University Library

We gratefully acknowledge support from the Simons Foundation and member institutions

arXiv.org > cs > arXiv:1604.04004

Search or Article ID | All fields

(Help | Advanced search)

Computer Science > Computer Vision and Pattern Recognition

Understanding How Image Quality Affects Deep Neural Networks

Samuel Dodge, Lina Karam

(Submitted on 14 Apr 2016 (v1), last revised 21 Apr 2016 (this version, v2))

Image quality is an important practical challenge that is often overlooked in the design of machine vision systems. Commonly, machine vision systems are trained and tested on high quality image datasets, yet in practical applications the input images can not be assumed to be of high quality. Recently, deep neural networks have obtained state-of-the-art performance on many machine vision tasks. In this paper we provide an evaluation of 4 state-of-the-art deep neural network models for image classification under quality distortions. We consider five types of quality distortions: blur, noise, contrast, JPEG, and JPEG2000 compression. We show that the existing networks are susceptible to these quality distortions, particularly to blur and noise. These results enable future work in developing deep neural networks that are more invariant to quality distortions.

Comments: Final version will appear in IEEE Xplore in the Proceedings of the Conference on the Quality of Multimedia Experience (QoMEX), June 6-8, 2016

Subjects: **Computer Vision and Pattern Recognition (cs.CV)**

Cite as: **arXiv:1604.04004 [cs.CV]**

(or **arXiv:1604.04004v2 [cs.CV]** for this version)

Submission history

From: Samuel Dodge [view email]

[v1] Thu, 14 Apr 2016 00:47:50 GMT (2833kb,D)

[v2] Thu, 21 Apr 2016 20:44:52 GMT (2833kb,D)

Download:

- PDF
- Other formats

(license)

Current browse context:

cs.CV

< prev | next >

new | recent | 1604

Change to browse by:

cs

References & Citations

- NASA ADS

DBLP - CS Bibliography

listing | bibtex

Samuel F. Dodge
Lina J. Karam

Bookmark (what is this?)

Reading

Labeled Faces in the Wild

Menu
- LFW Home
  - Mailing
  - Explore
  - Download
  - Train/Test
  - Results
  - Information
  - Errata
  - Reference
  - Resources
  - Contact
  - Support
  - Changes
- Part Labels
- UMass Vision

Labeled Faces in the Wild Home

NEW SURVEY PAPER:

Erik Learned-Miller, Gary B. Huang, Aruni RoyChowdhury, Haoxiang Li, and Gang Hua.
Labeled Faces in the Wild: A Survey.
In *Advances in Face Detection and Facial Image Analysis*, edited by Michal Kawulok, M. Emre Celebi, and Bogdan Smolka, Springer, pages 189-248, 2016.
[Springer Page] [Draft pdf]

NEW RESULTS PAGE:

WE HAVE RECENTLY UPDATED AND CHANGED THE FORMAT AND CONTENT OF OUR RESULTS PAGE. PLEASE REFER TO THE NEW TECHNICAL REPORT FOR DETAILS OF THE CHANGES.

Welcome to Labeled Faces in the Wild, a database of face photographs designed for studying the problem of unconstrained face recognition. The data set contains more than 13,000 images of faces collected from the web. Each face has been labeled with the name of the person pictured. 1680 of the people pictured have two or more distinct photos in the data set. The only constraint on these faces is that they were detected by the Viola-Jones face detector. More details can be found in the technical report below.

There are now four different sets of LFW images including the original and three different types of "aligned" images. The aligned images include "funneled images" (ICCV 2007), LFW-a, which uses an unpublished method of alignment, and "deep funneled" images (NIPS 2012). Among these, LFW-a and the deep funneled images produce superior results for most face verification algorithms over the original images and over the funneled images (ICCV 2007).

Related:

[new] Collected resources related to LFW - updated 2017/05/09.

LFW Deep Funneled Images.

LFW attributes file (see Attribute and Simile Classifiers for Face Verification, Kumar et al.).

Face Detection Data set and Benchmark (FDDB), our new database for face detection research.

Faces in Real-Life Images workshop at the European Conference on Computer Vision 2008, run by Erik Learned-Miller, Andras Ferencz, and Frederic Jurie.

Reading

Labeled Faces in the Wild: A Survey

Erik Learned-Miller, Gary Huang, Aruni RoyChowdhury, Haoxiang Li, Gang Hua

Abstract In 2007, Labeled Faces in the Wild was released in an effort to spur research in face recognition, specifically for the problem of face verification with unconstrained images. Since that time, more than 50 papers have been published that improve upon this benchmark in some respect. A remarkably wide variety of innovative methods have been developed to overcome the challenges presented in this database. As performance on some aspects of the benchmark approaches 100% accuracy, it seems appropriate to review this progress, derive what general principles we can from these works, and identify key future challenges in face recognition. In this survey, we review the contributions to LFW for which the authors have provided results to the curators (results found on the LFW results web page). We also review the cross cutting topic of alignment and how it is used in various methods. We end with a brief discussion of recent databases designed to challenge the next generation of face recognition algorithms.

Erik Learned-Miller
University of Massachusetts, Amherst, Massachusetts, e-mail: elm@cs.umass.edu

Gary B. Huang
Howard Hughes Medical Institute, Janelia Research Campus, e-mail: gbhuang@cs.umass.edu

Aruni RoyChowdhury
University of Massachusetts, Amherst, Massachusetts, e-mail: aruni@cs.umass.edu

Haoxiang Li
Stevens Institute of Technology, Hoboken, New Jersey, e-mail: hli18@stevens.edu

Gang Hua
Stevens Institute of Technology, Hoboken, New Jersey, e-mail: ganghua@gmail.com

Reading

Siamese Convolutional Neural Networks for Authorship Verification

William Du
Stanford University
450 Serra Mall, Stanford, CA 94305
willadu@stanford.edu

Michael Fang
Stanford University
450 Serra Mall, Stanford, CA 94305
mjfang@stanford.edu

Margaret Shen
Stanford University
450 Serra Mall, Stanford, CA 94305
marshen@stanford.edu

Abstract

Determining handwriting authorship of a written text has practical significance in the realm of forensics, signature verification, and literary history. While there have been studies in signature verification and handwriting classification, a vast literature review reveals that very little work has been done in handwriting verification. Recent advances in convolutional architectures, particularly those involving facial verification, suggest that the task can be tackled effectively. In this study, we build a Siamese convolutional neural network to determine whether two pieces of handwriting are written by the same author. We examine questions such as whether long pieces of handwriting must be present to achieve good results, how many samples are needed, what features are important, and how different architectures perform on this task. We explore different convolutional architectures like VGG, GoogLeNet and ResNet, to determine which architecture produces the best encoding of each sample. We note that our best performing single model, TinyResNet, achieves a 92.08% accuracy on the held out test set.

1. Introduction

Determining the authorship of a written text has practical significance in the realm of forensics, signature verification, and literary history [3]. In manuscript analysis, for instance, historians frequently ask questions regarding the number of authors for a text, whether an anonymous work can be confidently attributed to a historical figure, and what time period a text might be from. These kinds of analyses are all based upon comparisons between different writing samples [1]. Techniques in the field have remained largely subjective, however, making the transition to automatic tools difficult.

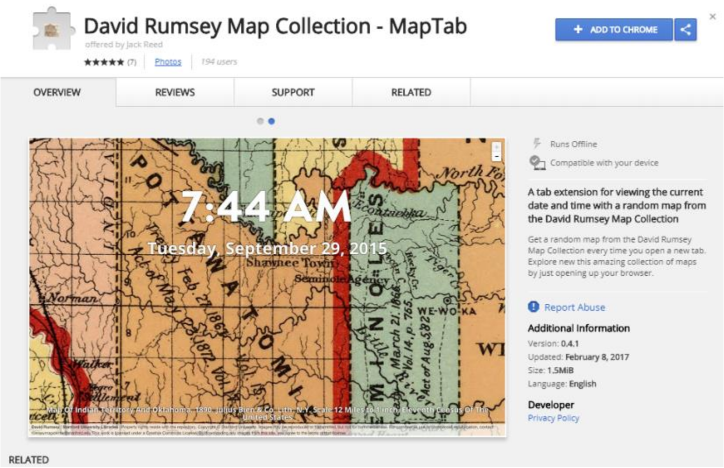
In addition, handwriting analysis is an established area of study in forensics, but there has not yet been any formal experiments measuring the accuracy of such analysis. As a result, the field is surrounded by much skepticism because of how subjective the process is (compared to, say, DNA testing) [5]. In addition, forensic handwriting analysis is time-intensive and requires two years of training for a person to obtain proper qualifications. The primary objective of this project is to develop an automatic, high-accuracy system which can determine if any two writing samples are written by the same person. In addition, our system should be able to handle authors it has never encountered before.

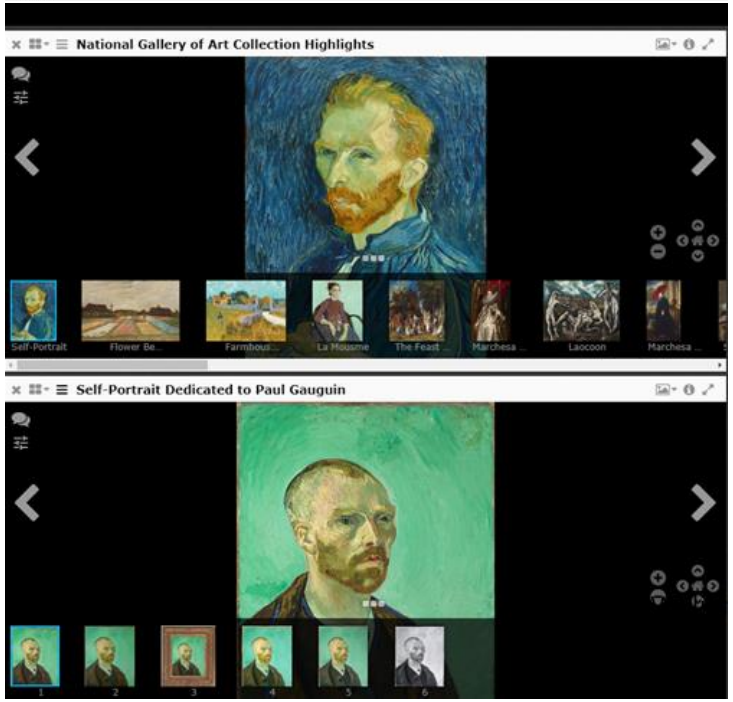
2. Background and Related Work

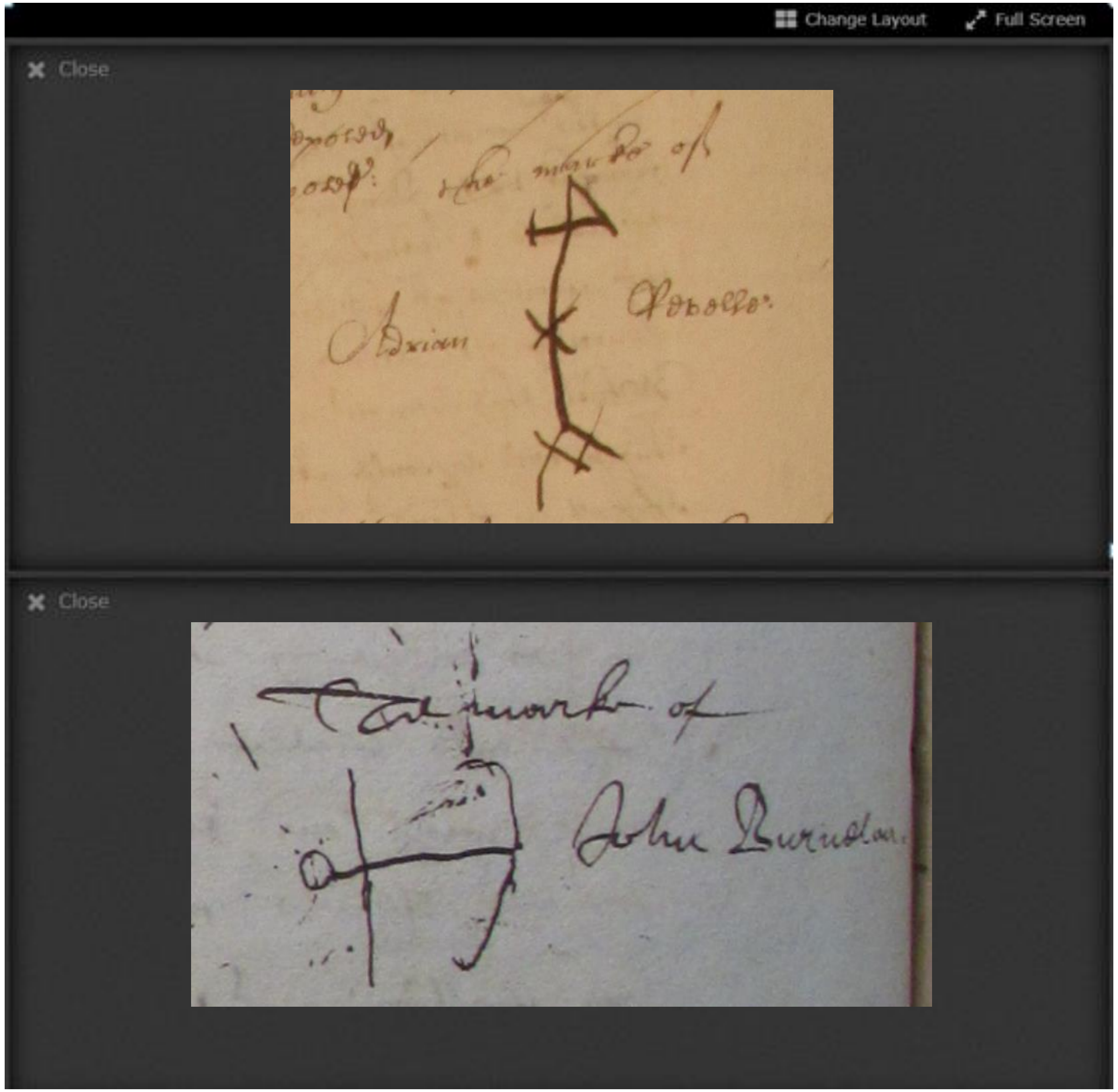
Our objective fits well with the Siamese CNN neural network architecture, which was first developed in 1993 to tackle the signature verification problem. [3] This type of architecture takes in two inputs and outputs a distance metric for the inputs. Bromley et al. was able to detect 95% of genuine signatures using this architecture. However, note that the signature verification problem expects a pair of inputs to be very similar to each other to be considered a match. This setup would not be effective for the problem we are trying to tackle, because our system should be agnostic to the actual text in a writing sample.

Other researchers have focused more closely on the authorship identification problem. A study in 2015 by Xing et al. reported an accuracy of 97% in classifying English writing samples for 657 authors. [11] They used the same dataset we will be using in this paper, the IAM Handwriting Database, and a 4-layer CNN. This study gave us confidence that we can achieve high accuracies on authorship problems using the IAM dataset. In a very recent research study from 2016, Yang et al. was able to achieve a 95% accuracy in classifying the authors for Chinese text samples,

Potential tool: conjoint analysis IIIF viewer plugin







Adrian Revelle, twenty-three year old mariner, of Dunquirke in fflanders, November 12th, 1653; “hee onely speaketh the flemmish speech” ([HCA 13/68 f.183v](#))

John Burnelau, twenty-eight year old sailor, of Mornar, France,March 30th, 1661 ([HCA 13/73 f.486v](#))

Jack Reed, David Rumsey MapTab Chrome extension; http://projectmirador.org/demo/; Conjoint analysis IIIF viewer plugin vapourware