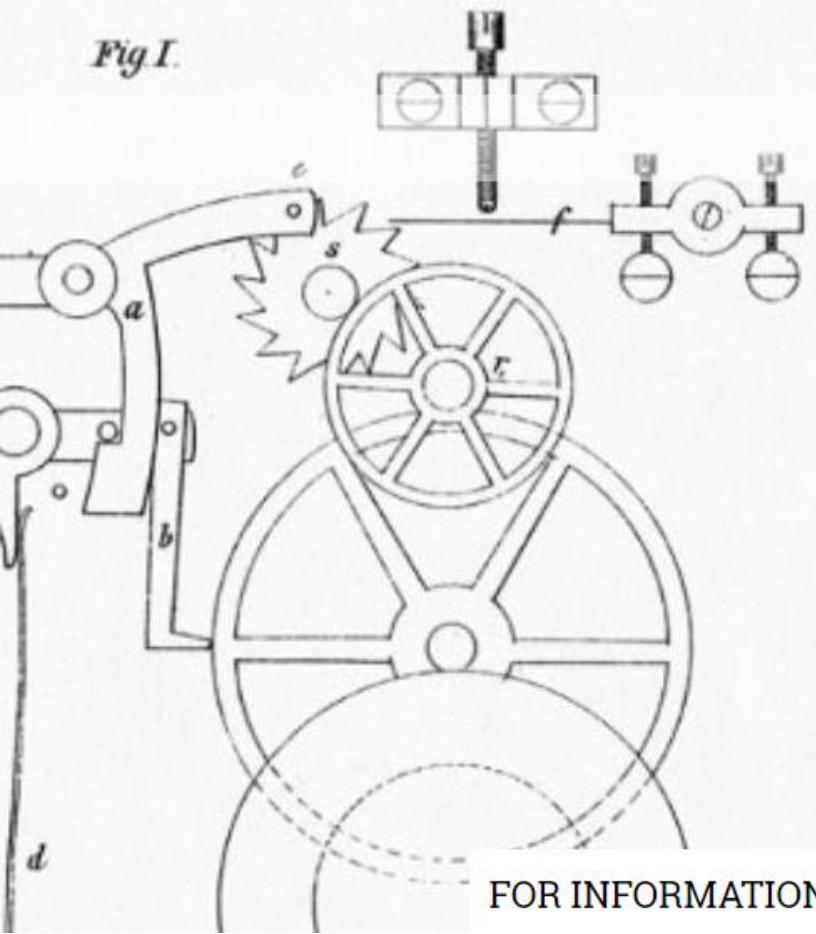
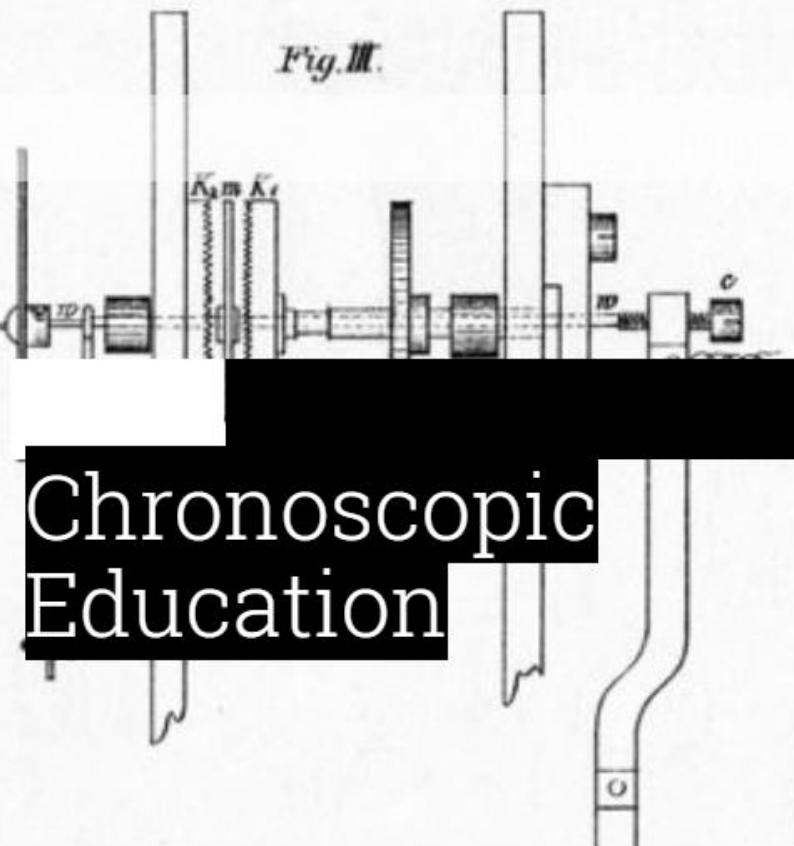


*Fig.I.*



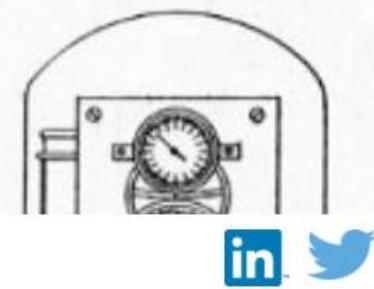
FOR INFORMATION ABOUT OUR OUR AIMS AND OUR PROJECTS

*Fig.III.*



*Hirsch Chronoskopische Versuche.*

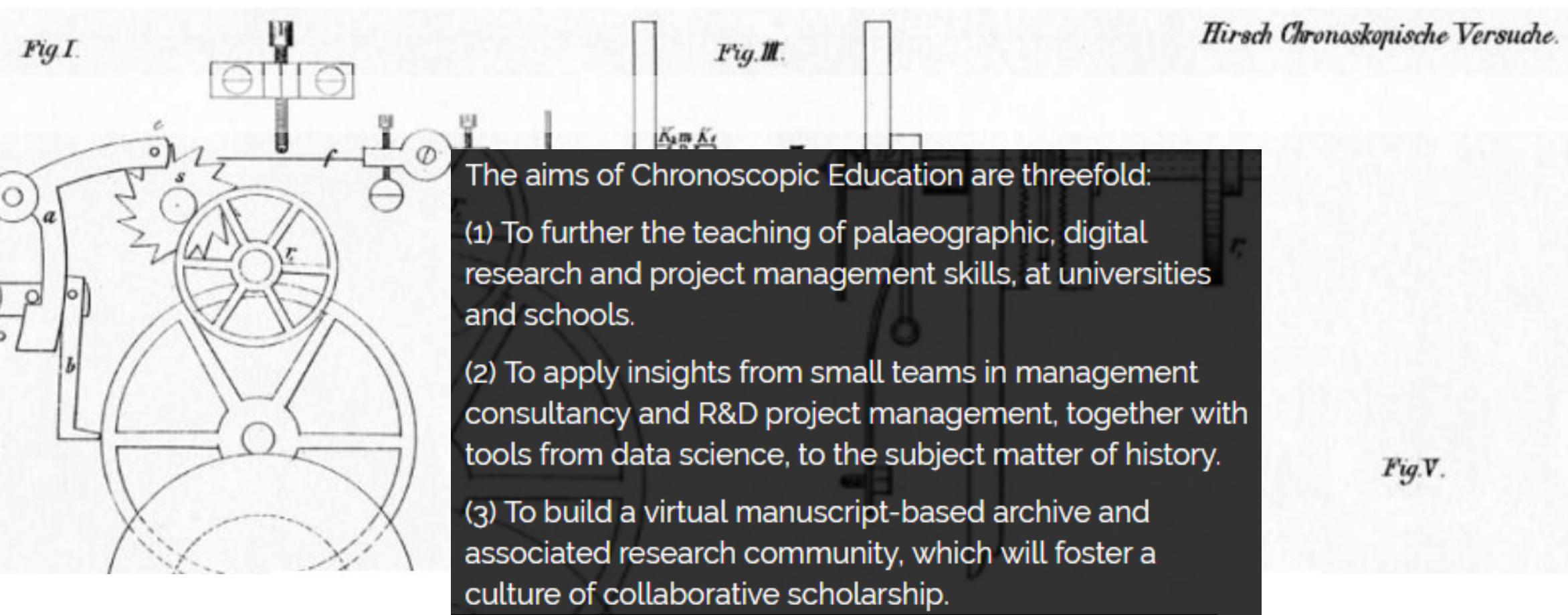
*Fig.V.*



Signs of Literacy  
Kaggle Research Competition  
Background Pack, Ver. 1.12

Colin Greenstreet  
Thursday, July 19<sup>th</sup> 2018

# Our social aims



# Project portfolio

<http://www.chronoscopic.org>

## MarineLives



## Signs of Literacy



## Maphackathon



## EM Textiles, Garments & Dyestuffs Glossary



## EM Maritime & Mercantile Gazetteer



# 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 marks, initials and signatures.
- (2) Algorithmic discrimination between degrees of "sophistication" within the three categories of "mark"; "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.

# Technical vision & role of the Kaggle competition

- Automatic identification of manuscript pages containing signoffs
- Markup of manuscript pages to isolate signoffs (marks, 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 marks, 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 21<sup>st</sup> 1659 (TNA, HCA 13/68, ff. 1r-3r)



# Metadata

part of the liberty of England by force  
and violence against a quietus ~~quietus~~ <sup>quietus</sup>  
free man without his will or knowledge  
and for the goods and labour of men  
and for every place of ground called  
the land and meadow pasture  
and for all other things which  
are to be taken up in the  
service of the Commonwealth and  
of the Parliament government friends, soldiers,  
or other persons of the like place and  
things given over to their use  
against the King and his  
subjects in the said country any right title  
or interest in the said things of any kind  
in the King's forces or for the King's service.

The 25<sup>th</sup> Day of September 1642

Examin'd & sworn to an Oath to be kept of  
the said Register of the liberty of England by  
the County of Lancashire.

Mark Lavers of Warrington  
in the County of Middle Mortimer aged  
fourty and twenty years or thereabouts  
a painted glass and glazier by trade  
and such as Coleridge now

¶ The first article of the first act of the Parliament passed and done by you -  
the authorising his soldiers or followers to have and to hold and  
take and receive by custome shippes in the river Mersey or in the  
in the Lancashire firth upon the Coast of Lancashire, and in the firth opposite  
the castle ship the Starcough, first alias of Great Mills and Coleridge  
and now of Birkenhead built and taken by Capt. John Shippe and another shipp  
named the Starcough whiche was commanded  
and for the shipp was shipp'd into the firth of Lancashire from the  
time the warre began, and the shipp was never out of the firth all  
time of the said warre. The shipp had this name by reason  
whereof the Lancashire people a fore said and about two or three  
years before. And divers of several shippes

¶ The second article of the first act of the Parliament passed and done by you -  
the same year with the first act the shipp above named being the  
Fame farr with Capt. Lavers in 1642 was paddled and taken by the shipp  
abovementioned on or about the 25<sup>th</sup> Day of February 1642 last by them  
with the warre begun upon the English people, whereon Boarding upon the Coast of  
Lancashire within the firth of Lancashire and commandement of the Earl of Derby wherein  
he was called shipp'd paddled and taken, and so forth having thence  
of and about the said Starcough farr of late was cheft to be sold to the  
merchants there and alld to the soldiers of the army of the Parliament  
and it is given for a true record.

¶ The third article of the first act of the Parliament passed and done by you -  
the said 25<sup>th</sup> Day of February 1642 also for divers shippes to be first and  
subsequently paddled and sent by Land, River and sea or otherwise  
where and by divers shippes of Lancashire and the cities  
of Liverpool, Preston and Runcorn and other places, and to be  
paid and bound with you and in Lancashire and were and is at present  
and by divers shippes delivered, generally knowne as Coleridge shipp  
at Birkenhead farr in Lancashire and at Liverpool as well  
as alld about Birkenhead farr and the same at the Mersey side  
and upon land and water knowne to all Englishmen and Company of the  
said shipp of Birkenhead shipp. And further to make good the  
same shipp of Birkenhead shipp and for the same to be  
alld paddled from Birkenhead to the Mersey side and to be sold by  
the first shipp and all divers of the shipp of the said shipp of Birkenhead shipp  
and divers of several shippes.

The 21<sup>st</sup> Day of September 1689 1  
Examined upon the affidavit on the behalfs of  
the sayd Head of the Liberty of England by  
Mark Harrison of Wapping in  
the County of Middlesex aged  
severall twenty years or thereabout  
a witness from him and examined upon oaths and  
swore as followeth vizt

# Signoff

to be to be set off to Birne and comyns 1700 worth another shillings day  
Chamys Readelet did acknowledge fownd downys

To the 10th he saith he was yet aborded the intent to shew the Golden Starre to the admiral  
first hym as helpe aftord for the purr of his greate paine upon hym in his wch  
of the State, and by divers mifit of the Court for the 2000 before him, hee fath  
that after shewnesse where he aborded to have hym in other of the waters hee  
named. Found to be wch of the Golden Starre a Coyt of menysse of about  
a hundred yeres of age and from the Comyns of Waterhead Gylle Chally  
in the land of Lyllyon bare & greately of menysse in a barge, but hee was  
an ymbur of the Barke shalpe and from the Court of Englemeete Commander of the  
Tremoult for fayre tale out of the said Golden Starre to seeke or tyme brought  
four stundres and yarde and hward yarde of eighte yarde. And hee sayd  
that hee had yarde of ~~the~~ journaynes purer to have out of hym  
suffisoun shipp, And the ychard yarde hee had vnto take uppon him self  
of the purer shipp hee yarde hee had vnto take uppon him self  
the Company of the Remoult and fayre tale and of the Master hee had vnto have  
about the Golden Starre at the tyme of 1700 and afterwarrds to the fayre  
the purer to the Faire of Chamys. And hee took purer for all yarde yarde  
of the said purer, hee calld vnto the Comyns and the purer shipp  
pur of the Company of purer Chamys and Master hee had vnto have  
hee had vnto have with the Golden Starre purer fayre yarde of eighte  
and fayre yarde vnto a purer land or purer place of hee had vnto have  
forth. And further hee had vnto have.

To the 11th hee had yarde for any shipp hee had vnto have  
~~shipp to have~~ the fayre hee had vnto have hee had vnto have  
as hee calld hee, there being no any fayre held out on boord the purer  
fayre hee had vnto have the fayre the Golden Starre, But the Gold Starre  
allured by the State eadly.

To the 12th hee fath that of vnto the said shipp the remayning heare shall be  
wch and pur 2000 hee had vnto have the fayre purer, according  
to the fayre hee had vnto have to the fayre fryst, and according to an old  
or ordynance of ymperiale made in ynt Regale, and purer signifys. And  
further hee had vnto have

Sworn before M. Gellatly of me Chayre. + *Masta Harrion*

In the behalfe of the Kinge of the Landes the 20th Day of September 1653.  
of Englande by authority of the Parliament  
of those or people entituled the Count of Chamys  
lived and dwelt by reason of the place of  
the fayre of Chamys in the shire of  
Yorke sayd count the Count of Chamys  
Heres yor signifys. I. William Euston of Edom in Scotland  
Mariner aged four and forty yeres and present  
a portent fayre and purer doggys and pur  
as follows  
I. William Euston of Edom in Scotland  
Mariner aged four and forty yeres and present  
a portent fayre and purer doggys and pur  
as follows

To the fourth fayre in the year and purer yre hee had  
one of the Comyns Mervyn of the Company of the purer  
and was aborded the said shipp at the tyme of 1700 of the purer  
of fayre shipp of the Comyns. And hee had vnto have  
the said shipp in the purer of the purer and purer

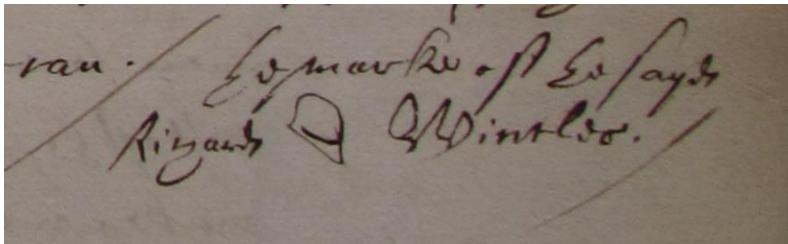
to want fayre fryst, and according to an old  
made in ynt Regale, and purer signifys. And  
doggys.

+ *Masta Harrion*

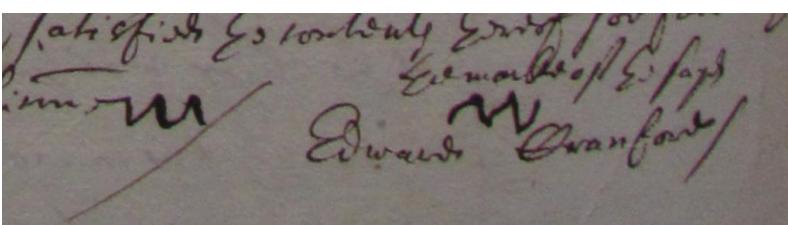
26th Day of September 1653.

# Porters handling coals, whale oil, ginger & corn

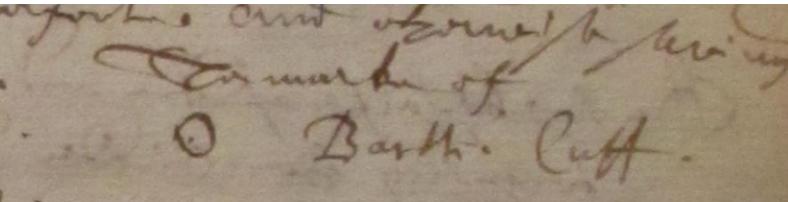
Richard Wincles, thirty-three year old porter, of the parish of Stepney, Middlesex, Dec. 15, 1656; employed as a labourer with fifteen other men to unload coals from the *Imployment* moored near Execution Dock, Wapping, into lighters for fixed rate of 12 s per man ([HCA 13/70 f.554r](#))



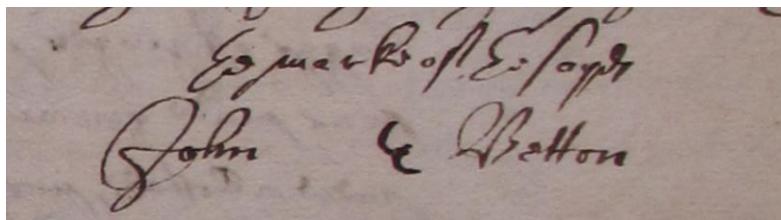
Edward Cranford, forty-four year old coale heaver or porter, of the parish of Stepney, Middlesex, Dec. 15, 1656; employed as a labourer with fifteen other men to unload coals from the *Imployment* moored near Execution Dock, Wapping, into lighters for fixed rate of 12 s per man ([HCA 13/70 f.555v](#))



Bartholomew Cuff, sixty year old porter of the Stillyard, of the parish of Allhallows 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](#))



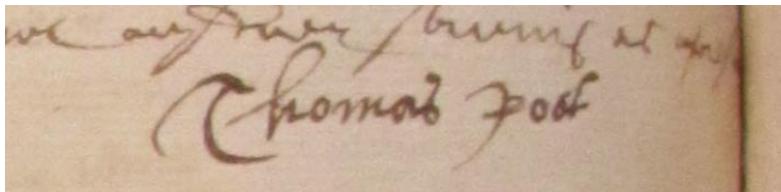
John Betton, fifty-four year old citizen and white baker of London, of the parish of Saint Buttolph Algate, London, Jul. 31, 1655; self-described as a porter employed by the Commissioners for Prize Goods to deliver ginger from a warehouse at Ralphes Key ([HCA 13/70 f.449r](#))



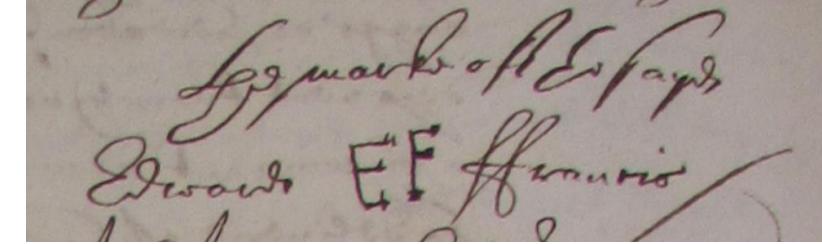
Edward Sherwin, fifty-six year old cittien and leatherseller, of the parish of Little Allhallowes, London, Jul. 31, 1655; self-described as a porter employed by the Commissioners for Prize Goods to deliver ginger from a warehouse at Ralphes Key ([HCA 13/70 f.449v](#))



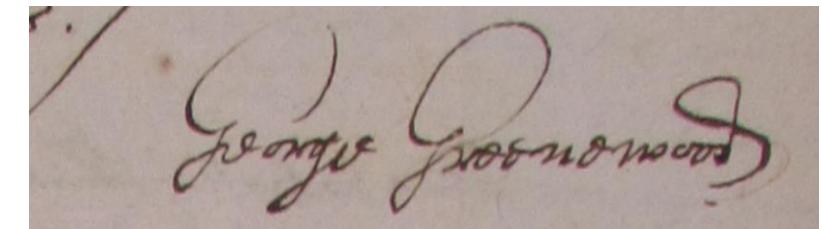
Thomas Roots, twenty-nine year old porter, of the parish of Greate Allhallowes, London, May 15, 1658; assisted in the landing of whale oil from lighters at the Stillyard Key, as one of the Stillyard porters, and loading them away into a warehouse ([HCA 13/72 f.330v](#))



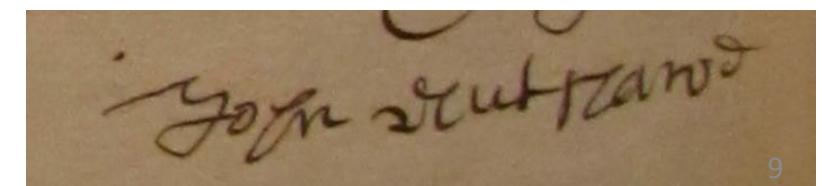
Edward ffrancis, citizen and merchant taylor of London, of the parish of Saint Olave in Southwarke, Jul. 31, 1655; self-described as a porter employed by the Commissioners for Prize Goods to deliver ginger from a warehouse at Ralphes Key ([HCA 13/70 f.450v](#))



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](#))

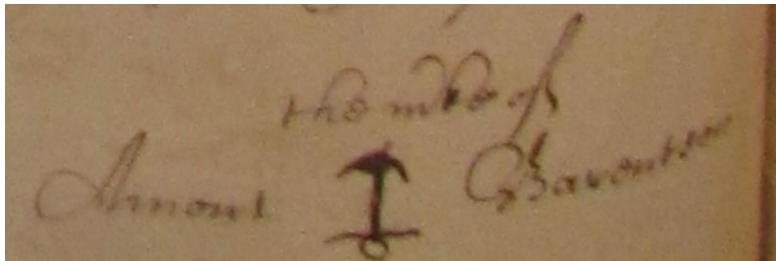


John Nutshall, fifty-five year old corne porter, of the parish of Saint Saviours Southwarke, Nov. 19, 1653; employed with a barber chyrurgeon/corne meter, an additional corne-meter, and other labourers to unlade a cargo of what in the *ffortune* of Stettin, moored against Limehouse; eight years of experience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

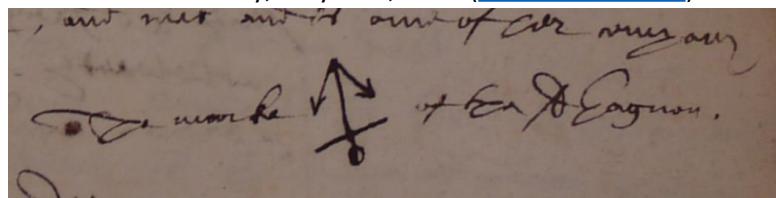


# Anchors

Amons Barentsen, thirty-five year old mariner, of Copenhagen, Denmark, October 13<sup>th</sup>, 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](#))



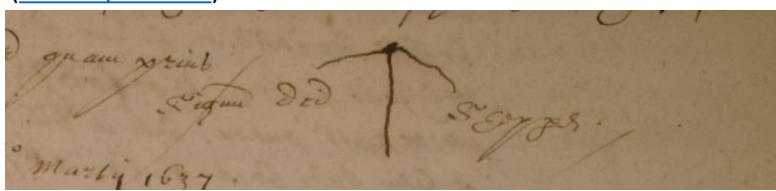
Claude de Gagnon, twenty-five year old mariner, of Melon, near Brest in Britanny, May 22<sup>nd</sup>, 1656 ([HCA 13/71 f.225r](#))



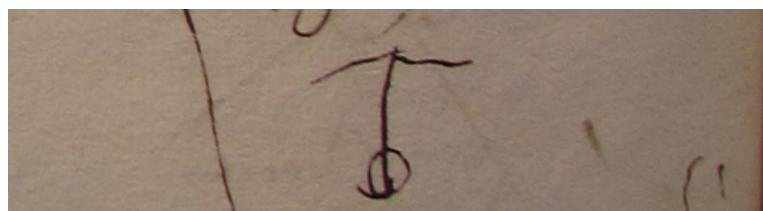
John Tylor, forty-two year old shipwright, of Lower Shadwell, in the parish of Stepney, Middlesex, February 14<sup>th</sup>, 1659 ([HCA 13/73 f.36r](#))



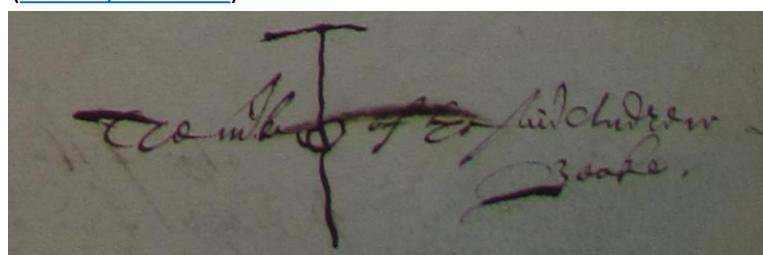
Richard Shepperd, fifty-eight year old cooke, of Brixton, Devon, March 29<sup>th</sup>, 1637; self-described cooke of the *Hope of Ipswich* ([HCA 13/53 f.87r](#))



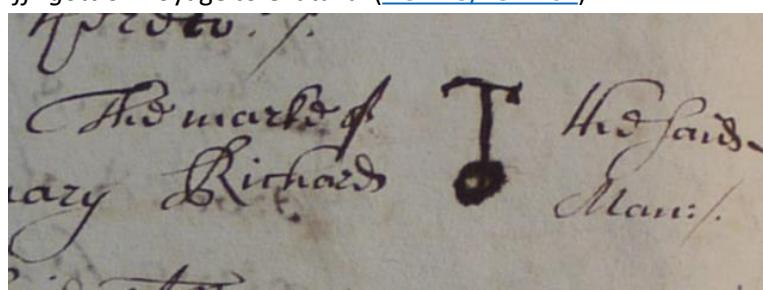
Andrew Beake, thirty-six year old lookeinglassemaker and formerly seaman, of Rose alley without Bishopsgate, London, January 21<sup>st</sup>, 1655 ([HCA 13/70 f.252v](#))



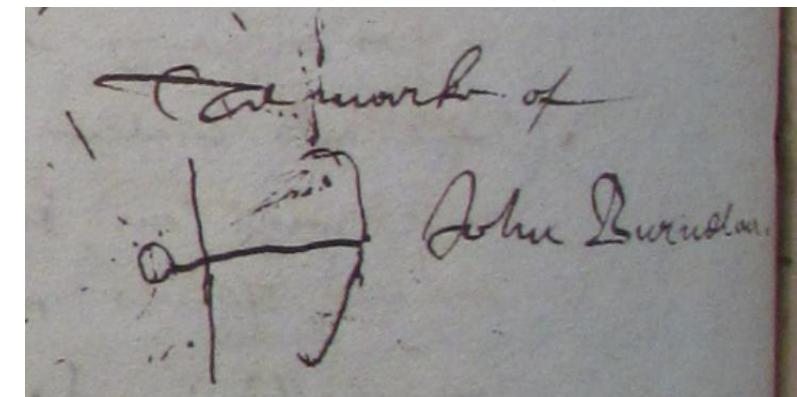
Andrew Beake, thirty-six year old looking-glasse maker, of Rose-Alley in Bishopsgate streete, London, February 13th, 1655 ([HCA 13/70 f.252v](#))



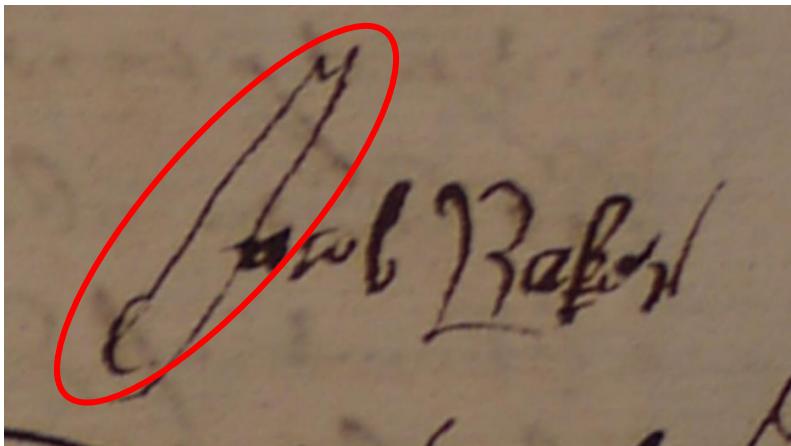
Richard Man, thirty-one year old mariner, of Southampton, January 8<sup>th</sup>, 1659; self-described common man of the *Lisbone ffrigott* on voyage to Oratava ([HCA 13/73 f.26v](#))



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



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



cannot do worse.  
Elmer Reffel Mop  
wined you & said Arles

John Duggett

John Lacy

George Franklin

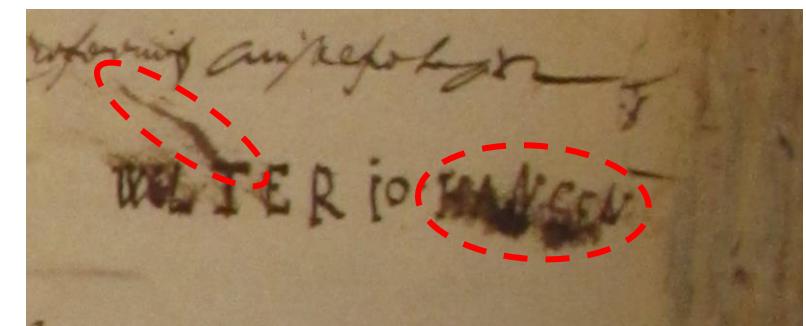
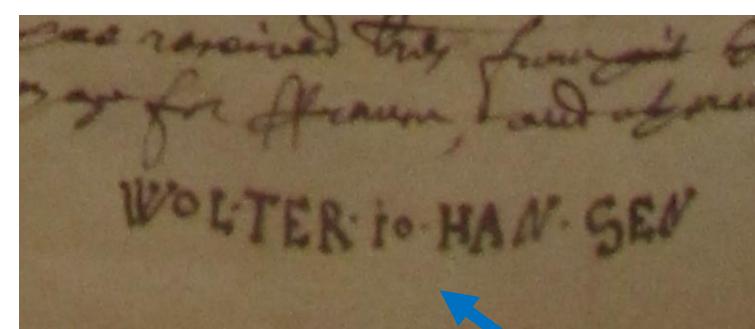
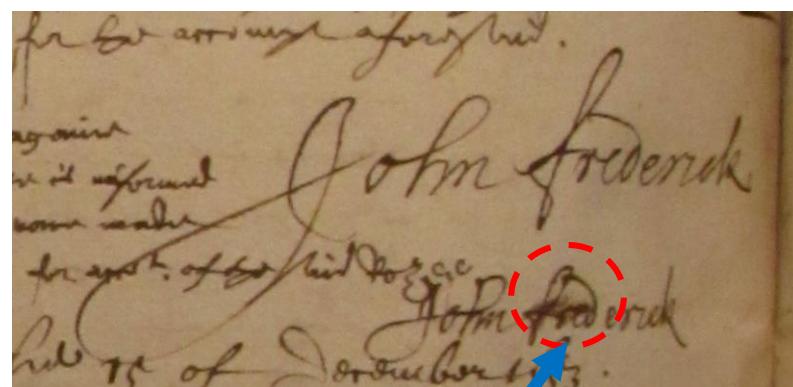
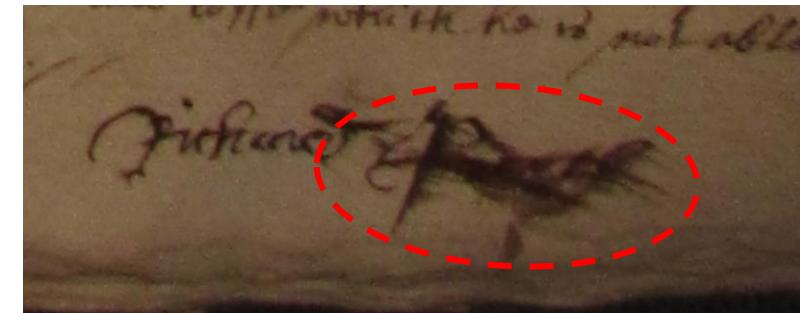
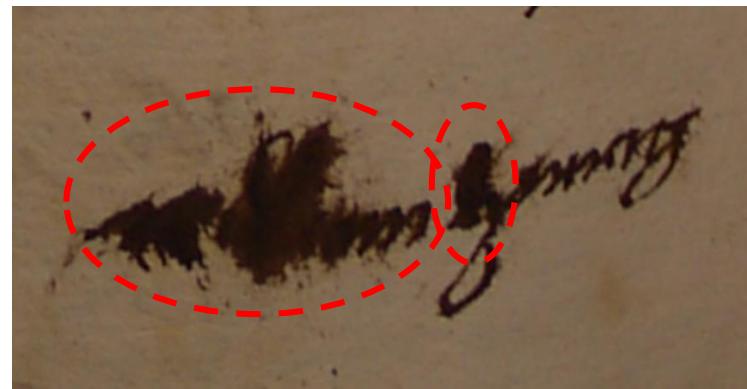
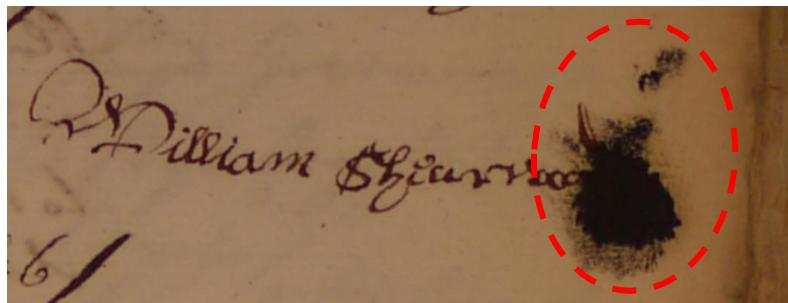
out of order  
is all over



Shaky straight lines and/or loops

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

# 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

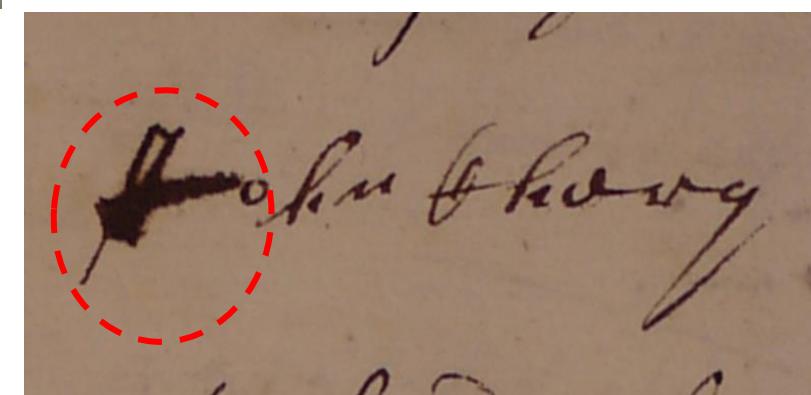
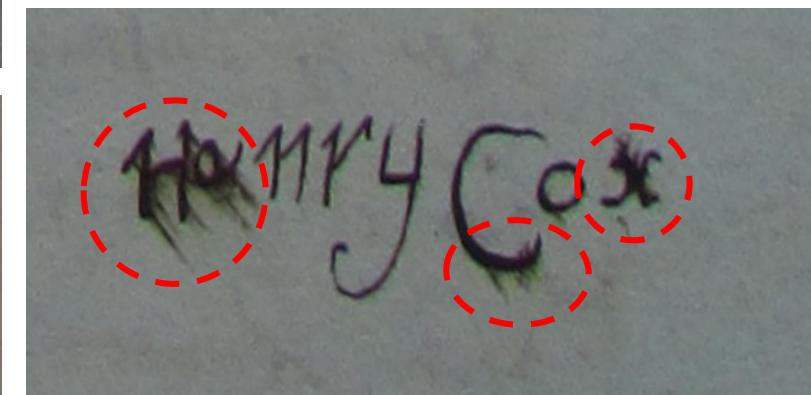
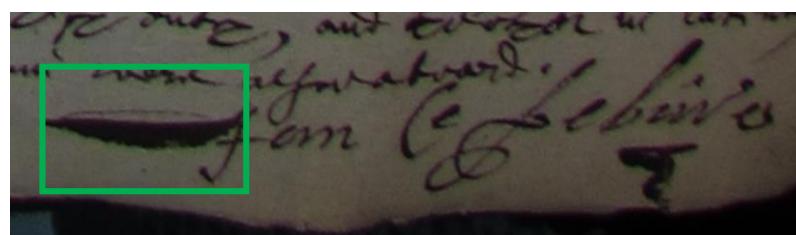
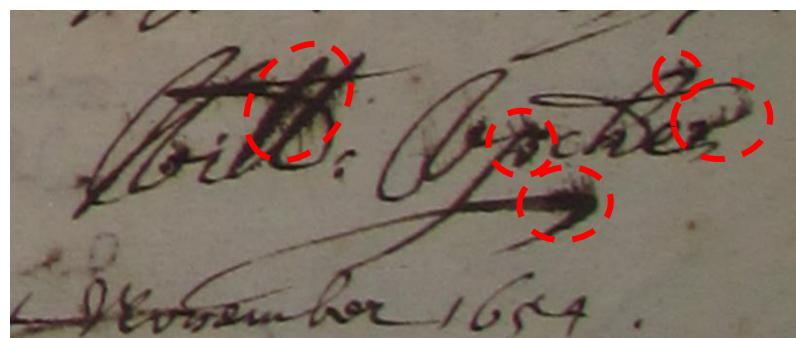
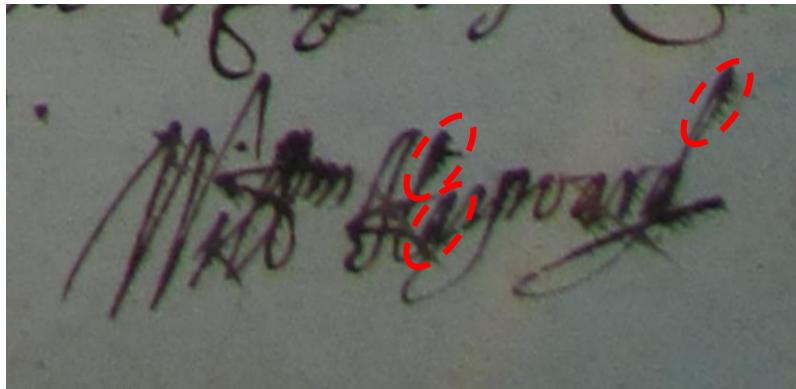
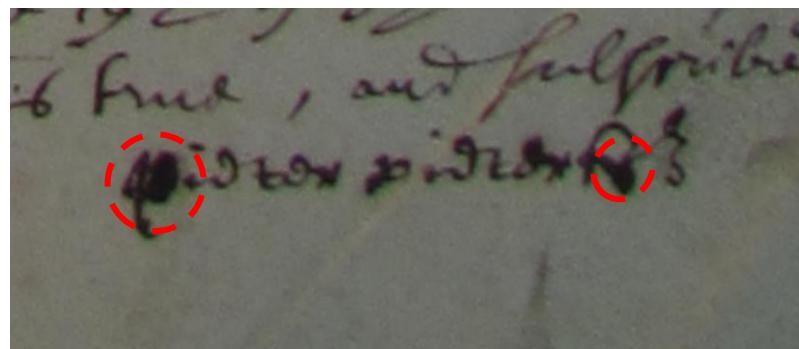
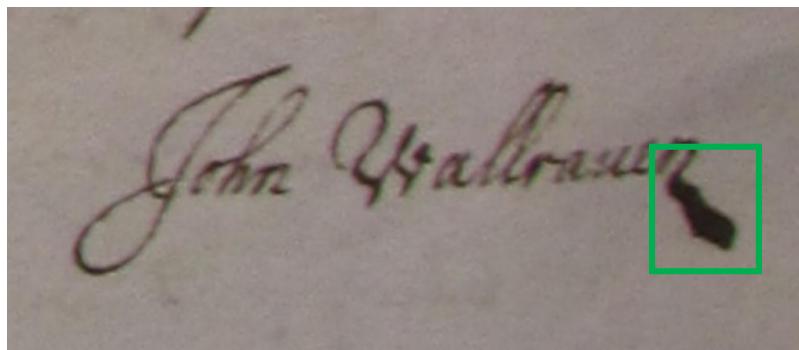
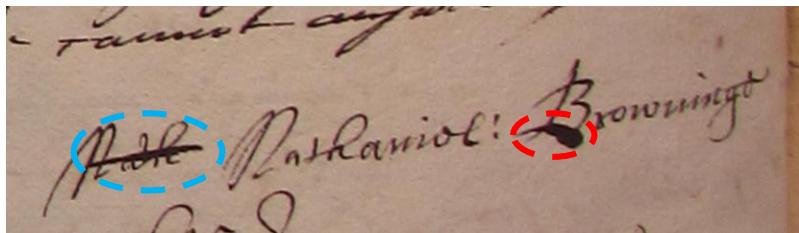


Ink blots or smudges

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

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

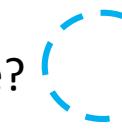
# Can machine detection distinguish blots, smudges, stylistic features, & deletions? (1)



Ink blots or smudges



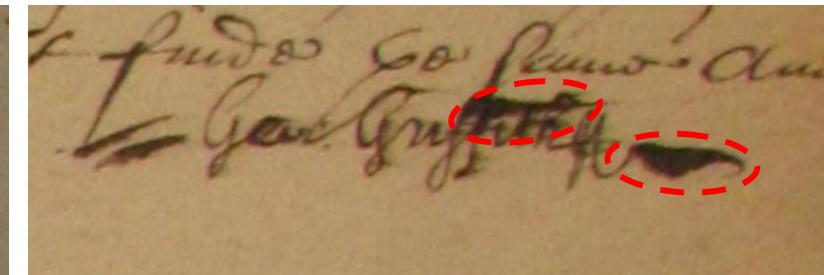
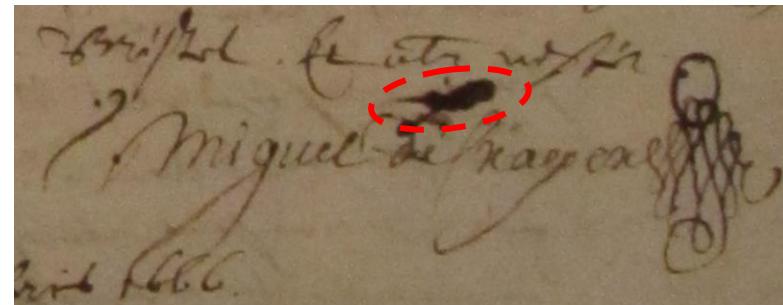
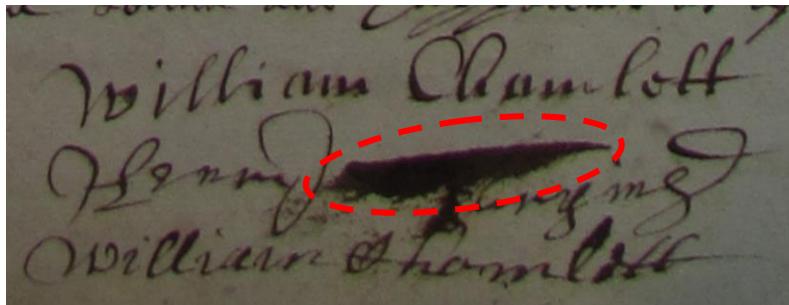
Stylistic feature or smudge?



Deletion

Source: Clockwise from top LH side:  
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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,

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



Ink blots or smudges



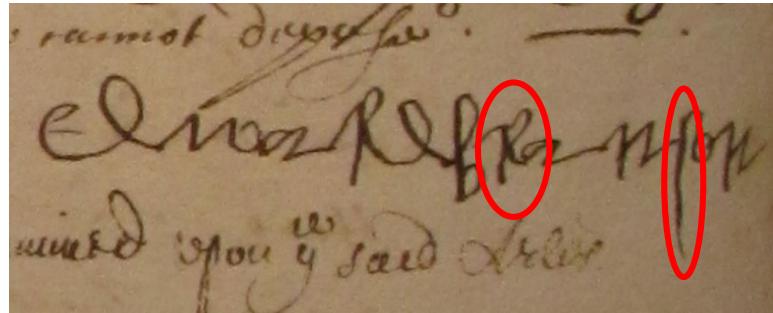
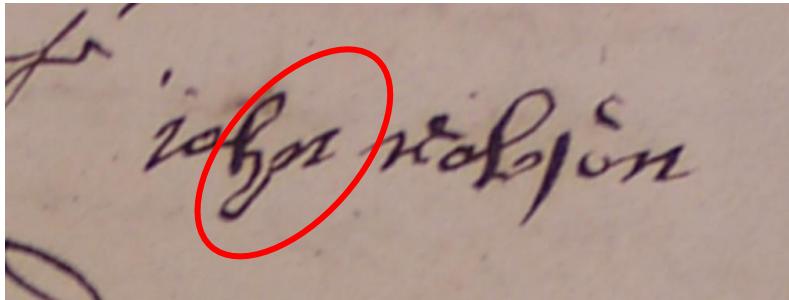
Stylistic feature or smudge?



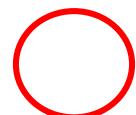
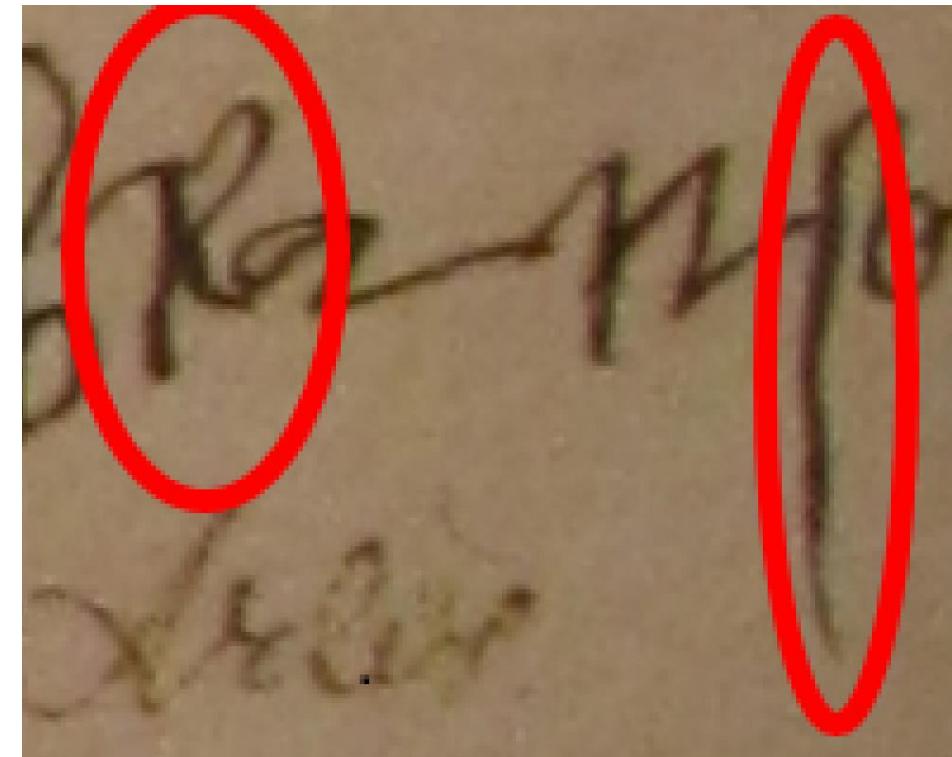
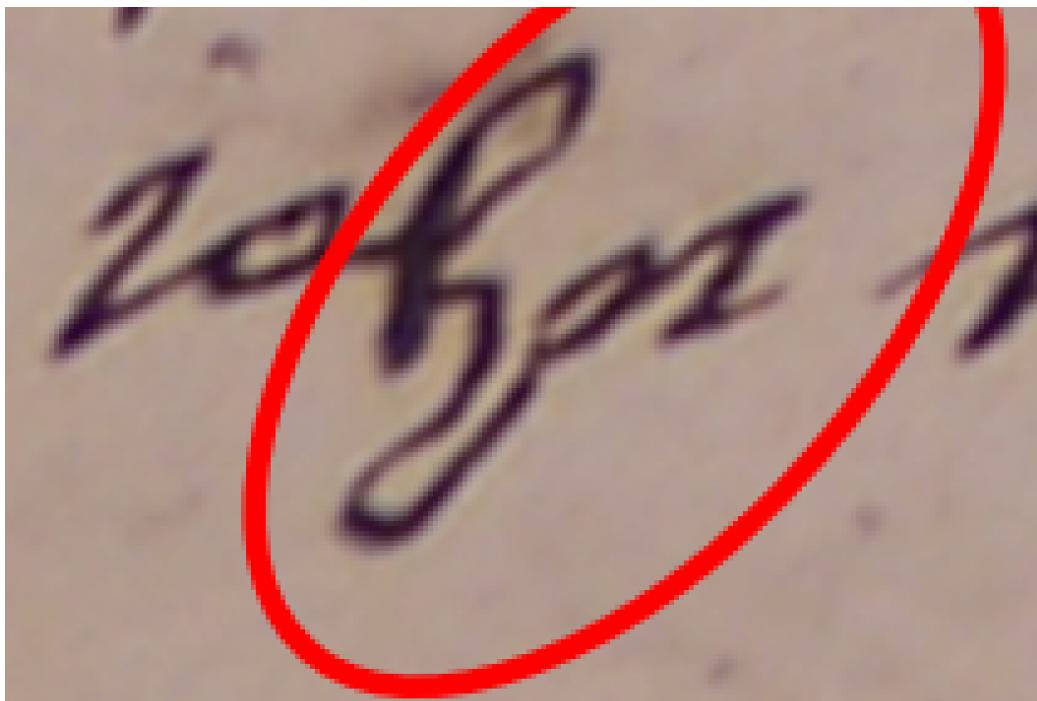
Deletion

Source: Clockwise from top LH side:  
KaggleTestSnippet\_HCA\_1370\_f.51r.PNG,  
KaggletestSnippet\_HCA\_1376\_f.14r.PNG,  
KaggleTestSnippet\_HCA\_1354\_f.22r.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



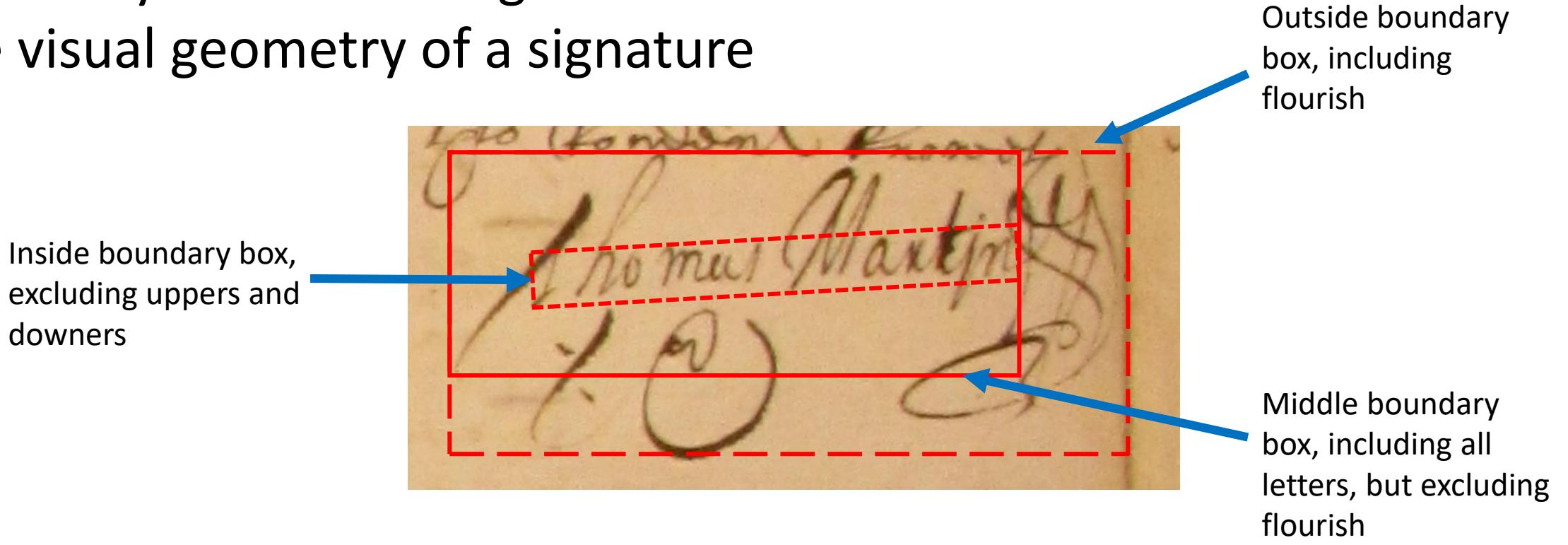
Shaky straight lines and/or loops

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\_PIXELS.PNG

# Putting boundary boxes on C17th signatures

Putting boundary boxes on C17th signatures

# Boundary boxes marking the visual geometry of a signature



## Statistics

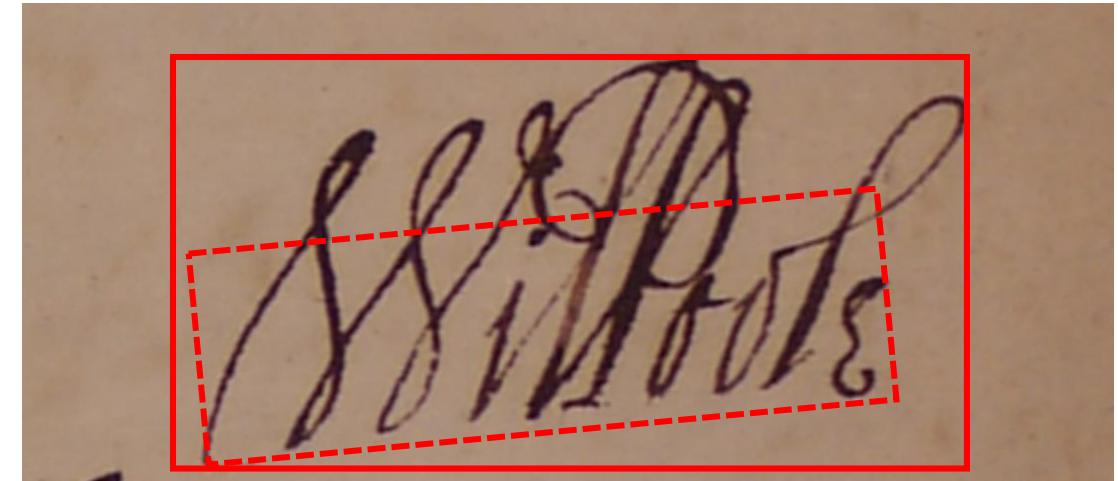
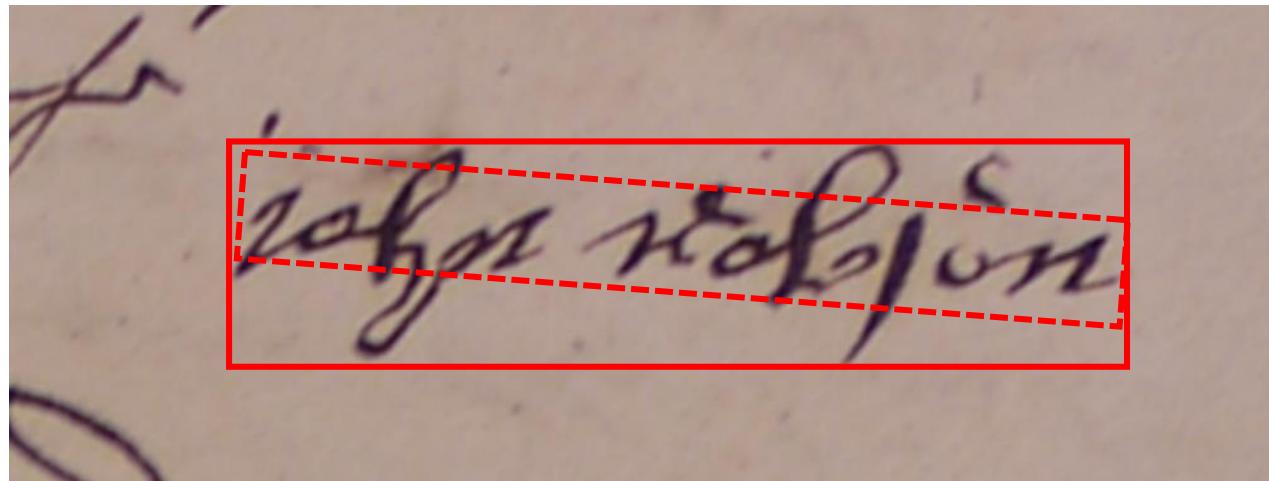
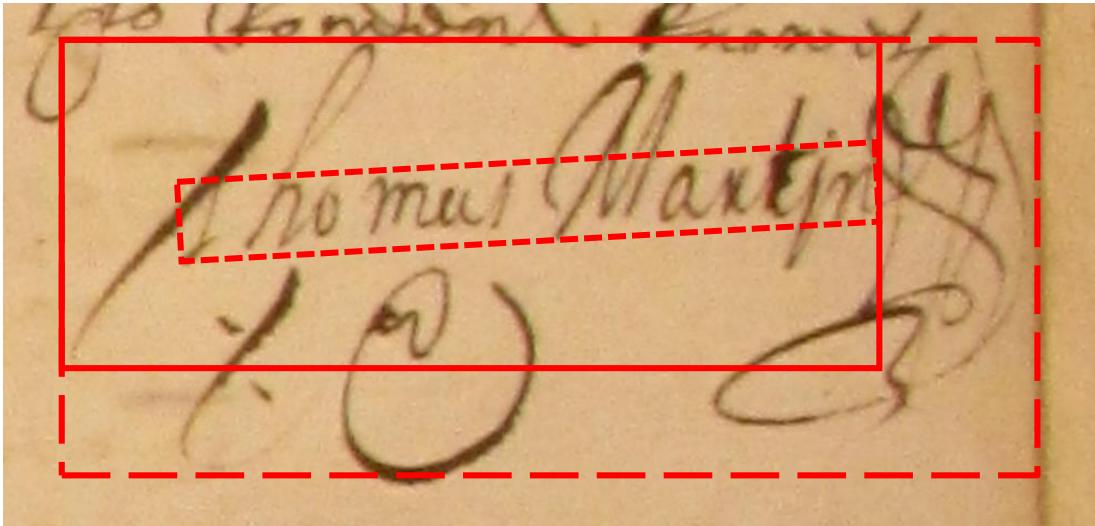
Inside boundary box: 9.0 x 1.1

Middle boundary box: 9.75 x 4.25

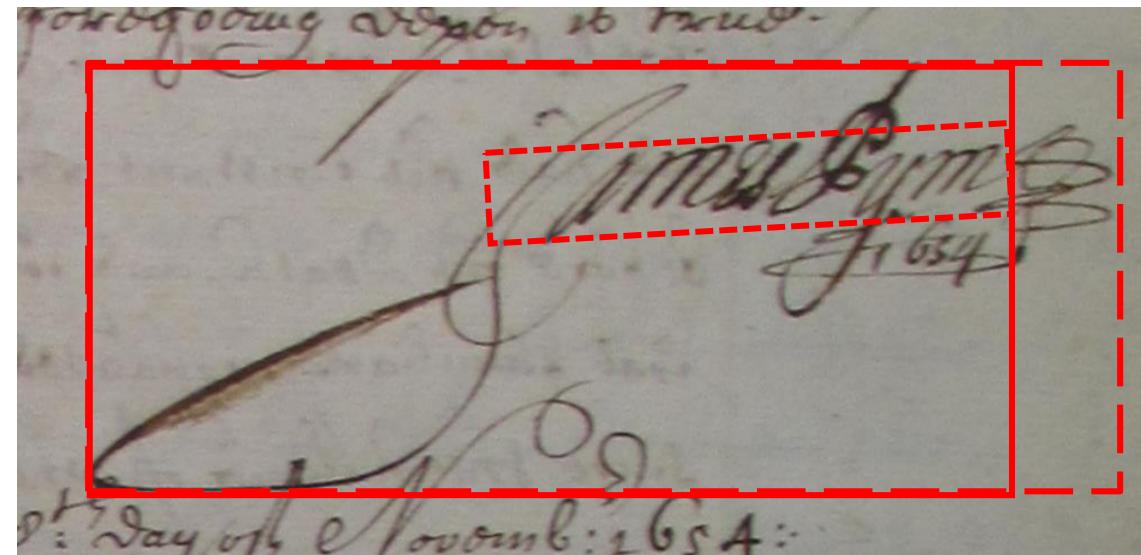
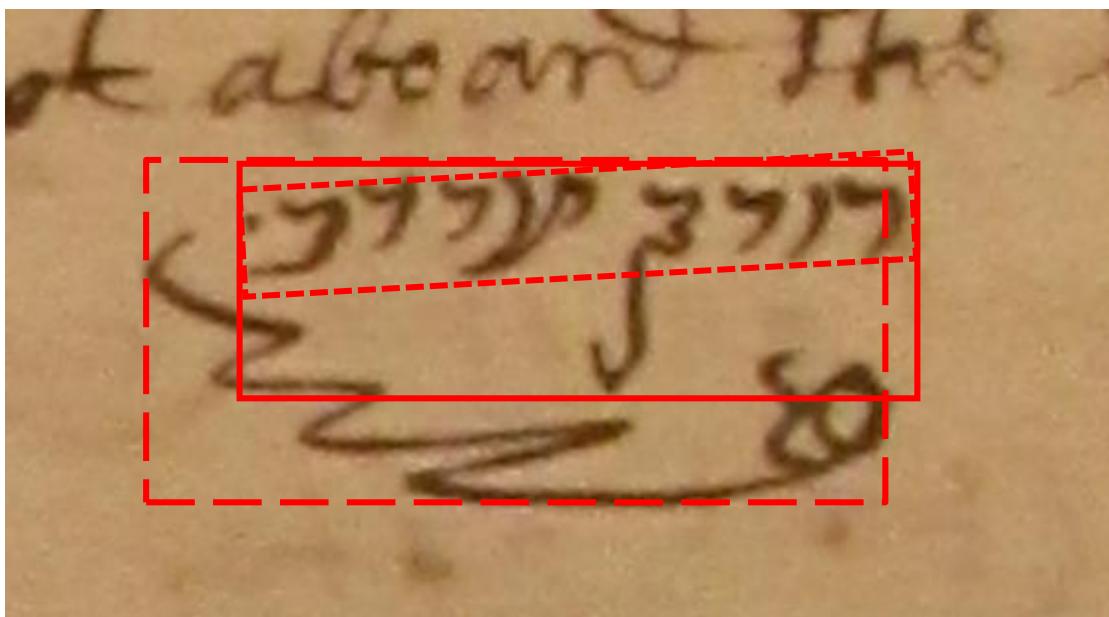
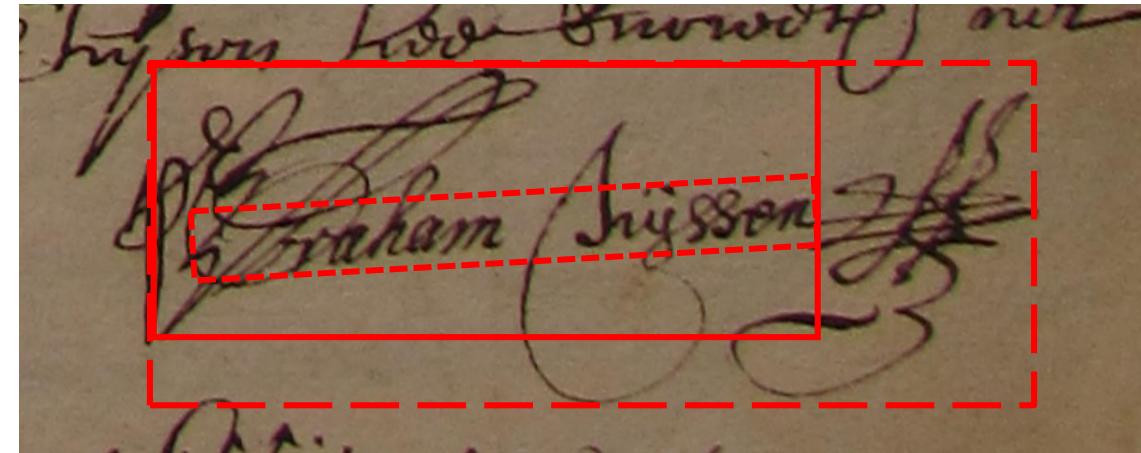
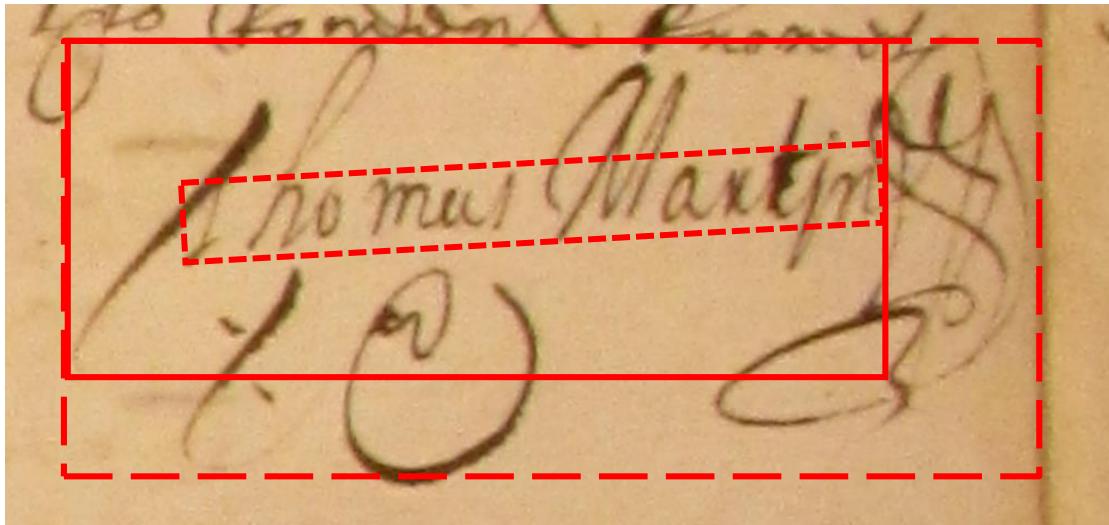
Outside boundary box: 12.75 x 5.75

Rotation from horizontal: ca. 340 degrees

# Different visual geometries of signatures

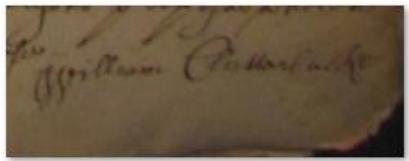


# Visual geometries of flourishes – C17th Irish, Dutch, English & Moroccan merchants

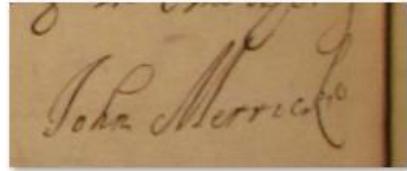


Source: Clockwise from top LH side: KaggleTestSnippet\_HCA\_1368\_f.34v.PNG, KaggleTestSnippet\_HCA\_1370\_f.366r.PNG, KaggleTestSnippet\_HCA\_1370\_f.134r.PNG, KaggleTestSnippet\_HCA\_1368\_f.58r.PNG

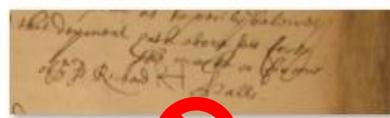
Challenge One: Identify the 11 image snippets on this page which contain signatures and highlight the 2 image snippets which contain signatures belonging to the same person



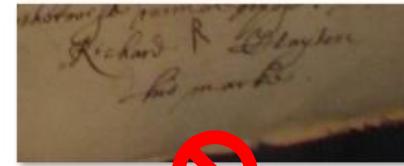
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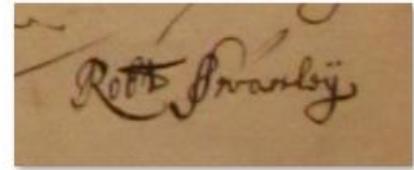
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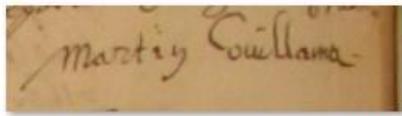
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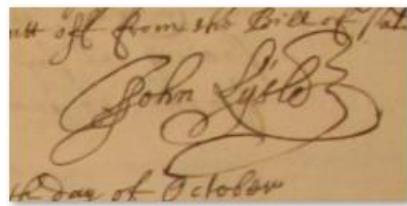
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KaggleTestSnippet\_HCA\_1368\_f.148r.PNG



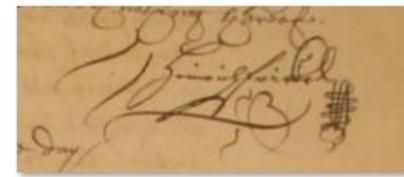
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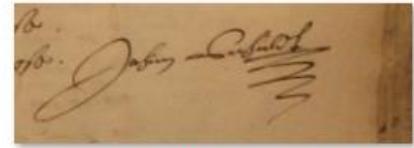
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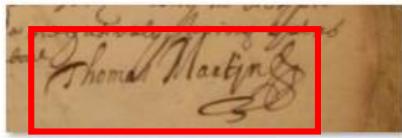
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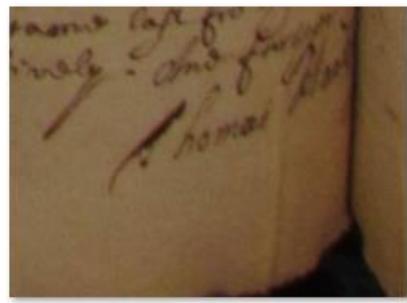
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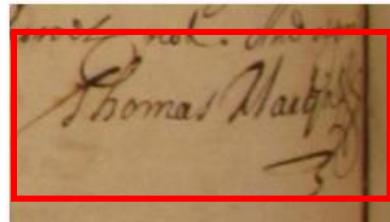
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KaggleTestSnippet\_HCA\_1368\_f.158r.PNG



KaggleTestSnippet\_HCA\_1368\_f.159v.PNG

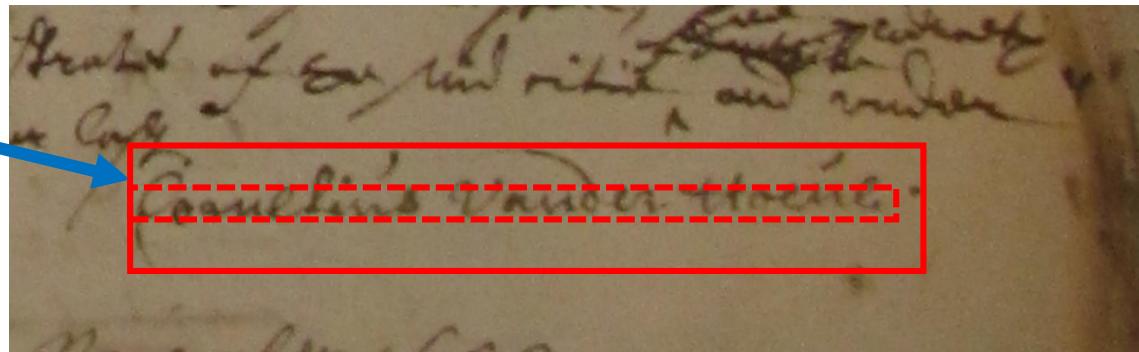


KaggleTestSnippet\_HCA\_1368\_f.161v.PNG

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

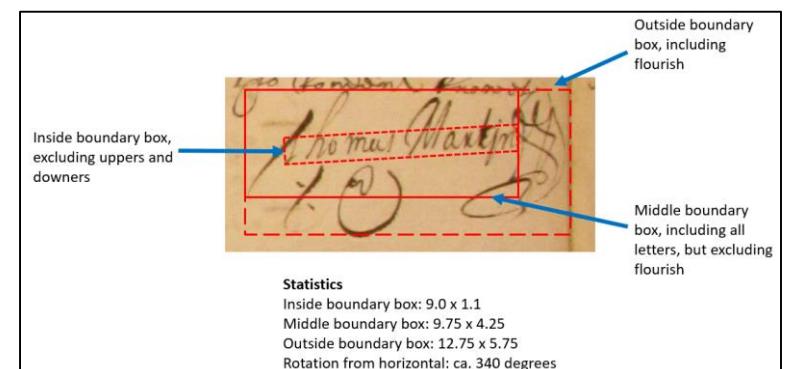
### Semantic giveaways

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

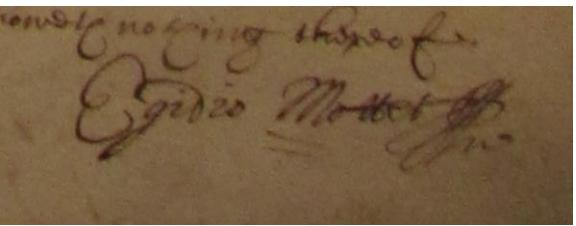
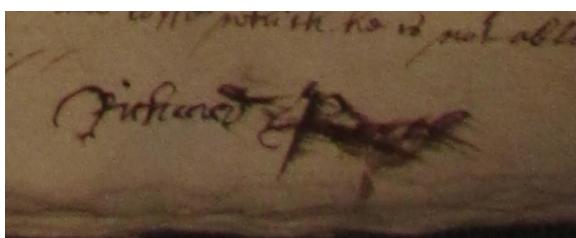
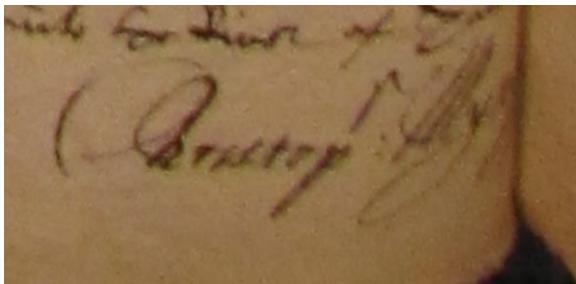
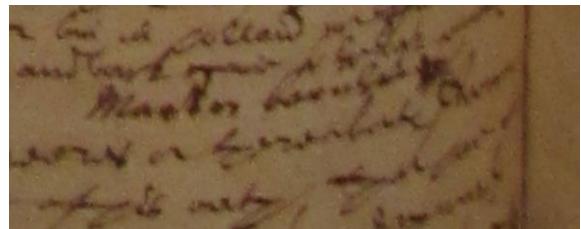
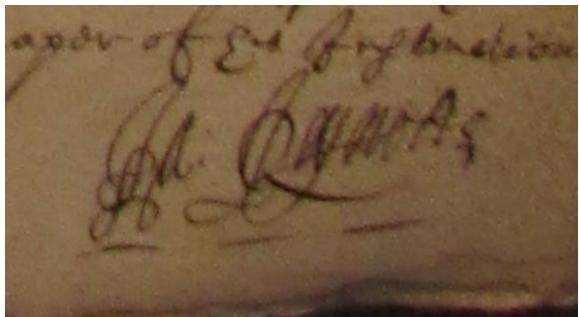


### Physical giveaways

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



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



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## 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)

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DBLP - CS Bibliography

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Samuel F. Dodge

Lina J. Karam

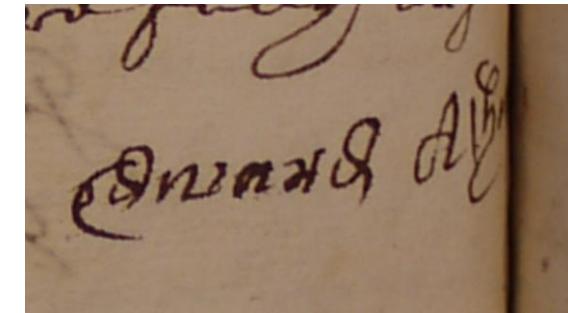
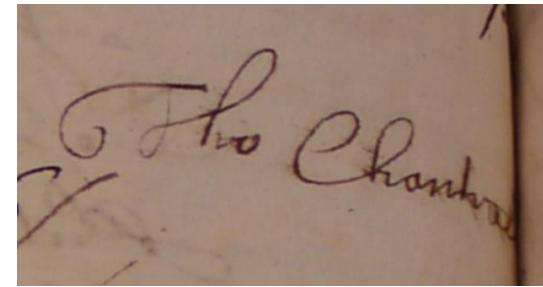
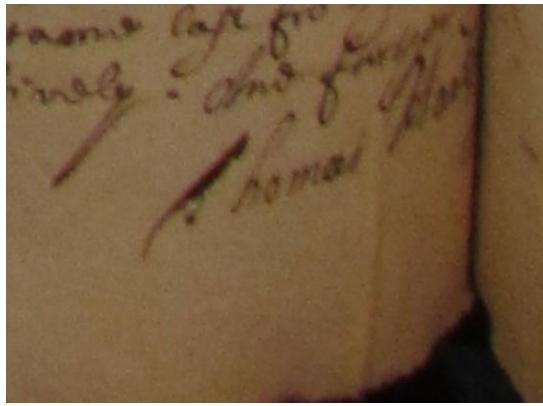
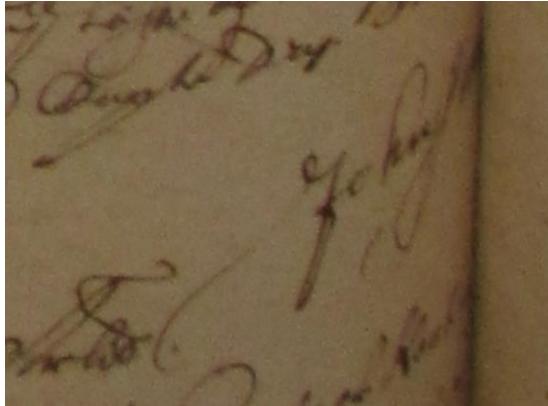
Bookmark [what is this?](#)



Source: Clockwise from top LH side:

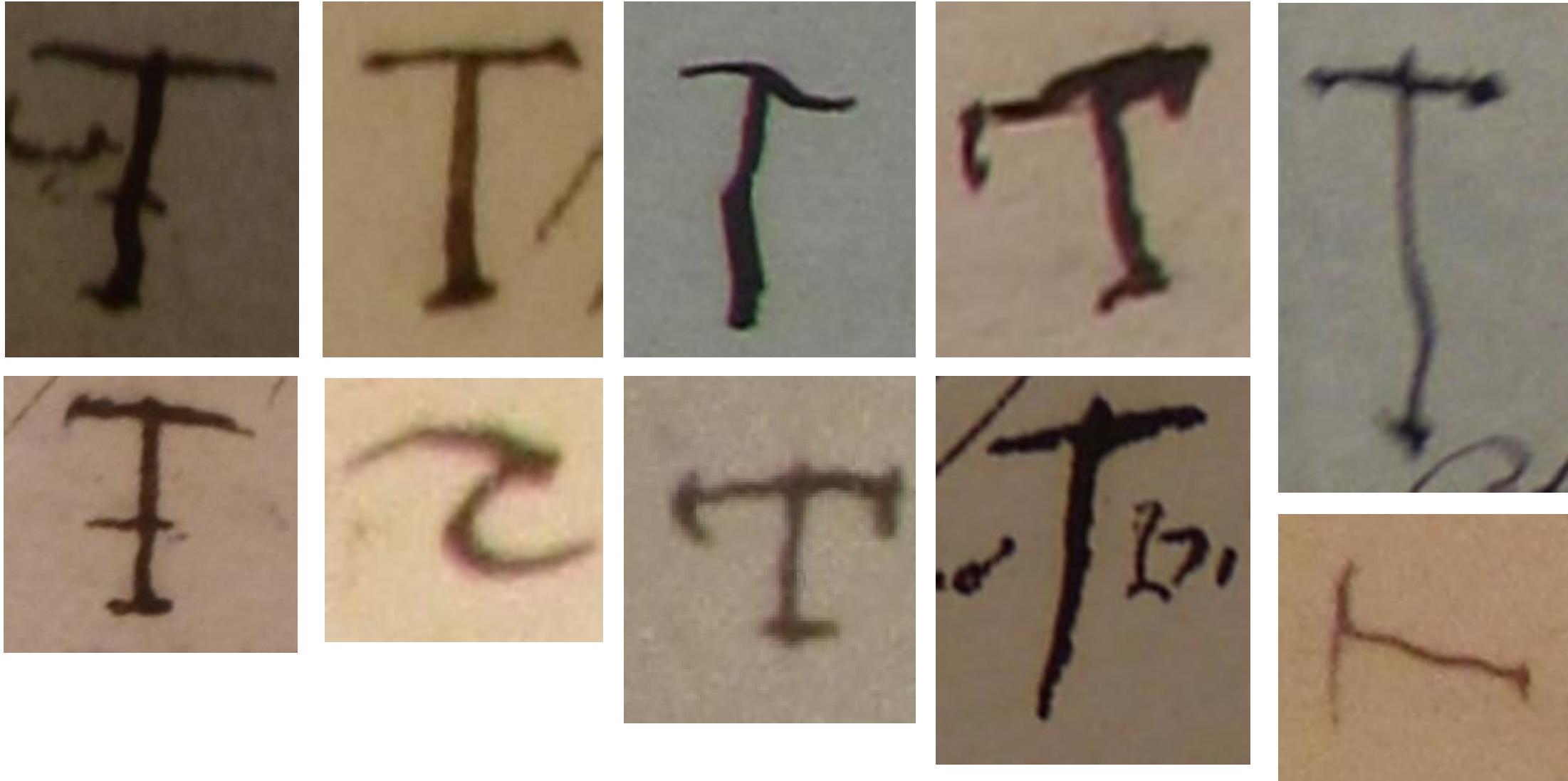
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- KaggleTestSnippet\_HCA\_1368\_f.55r\_Two.PNG,
- KaggleTestSnippet\_HCA\_1370\_f.11v.PNG,
- KaggleTestSnippet\_HCA\_1368\_f.62r.PNG,
- KaggleTestSnippet\_HCA\_1368\_f.121v\_Two.PNG ,
- KaggleTestSnippet\_HCA\_1368\_f.59r.PNG,

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?

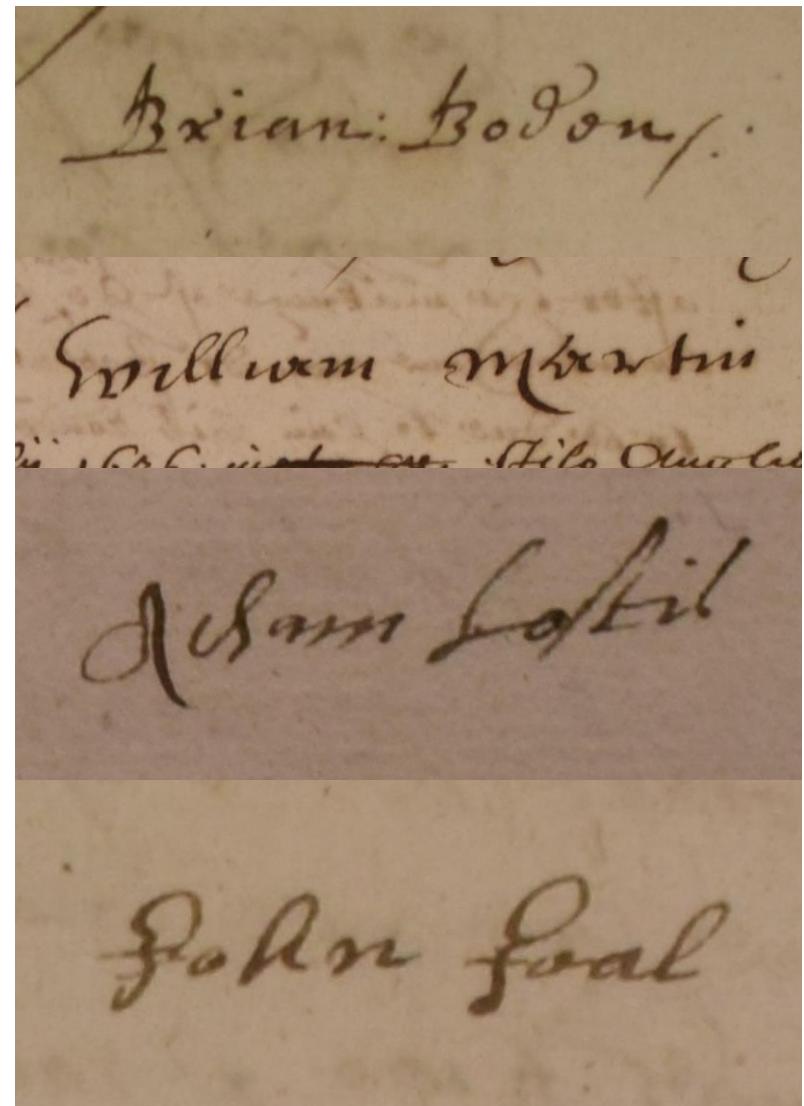
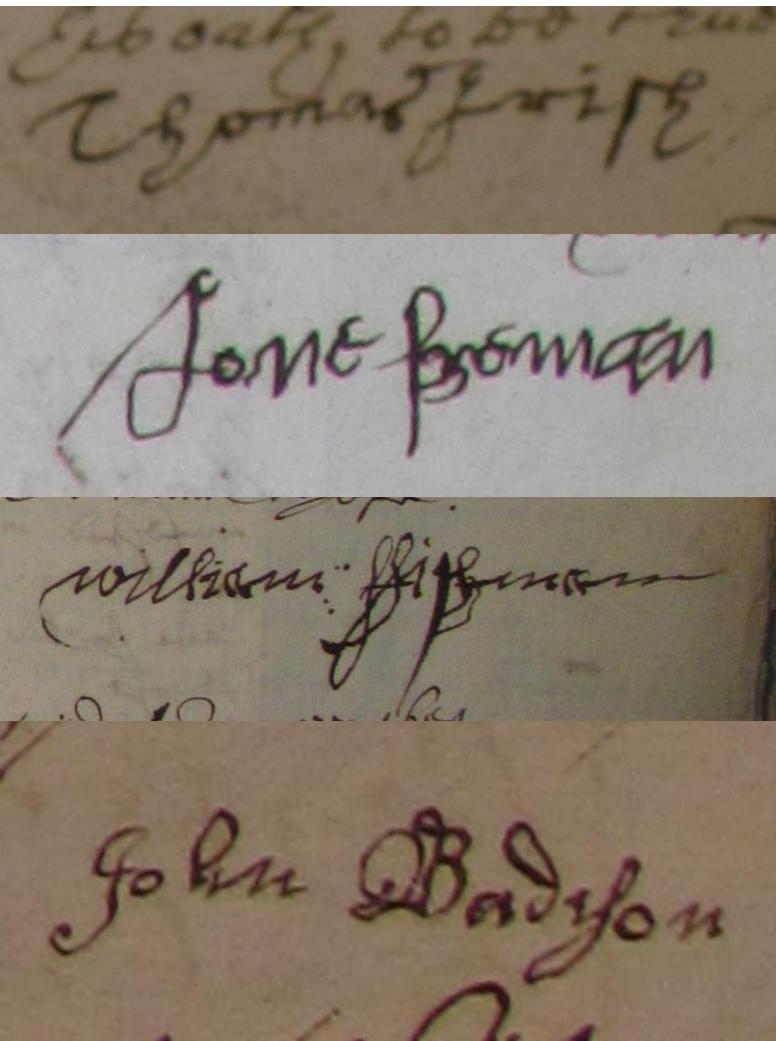
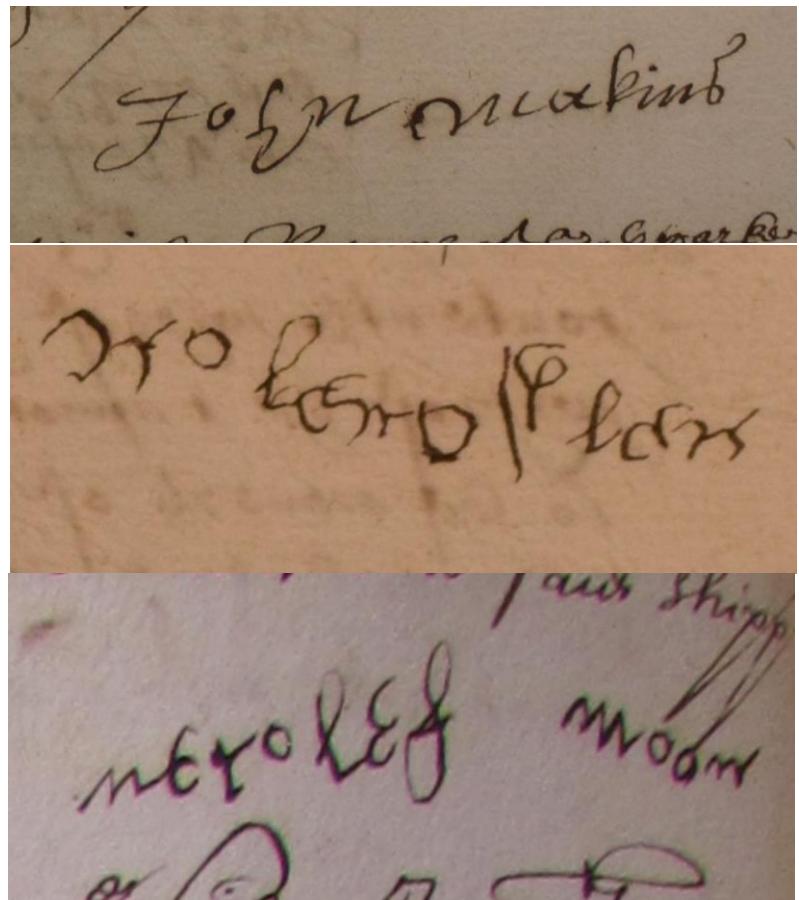


Source: Clockwise from top LH side: KaggleTestSnippet\_HCA\_1368\_f.274v.PNG, KaggleTestSnippet\_HCA\_1368\_f.159v.PNG, KaggleTestSnippet\_HCA\_1373\_f.490v.PNG, KaggleTestSnippet\_HCA\_1373\_f.493v.PNG,

Research question - methodology: Can a machine distinguish between the authors of a specific initial?

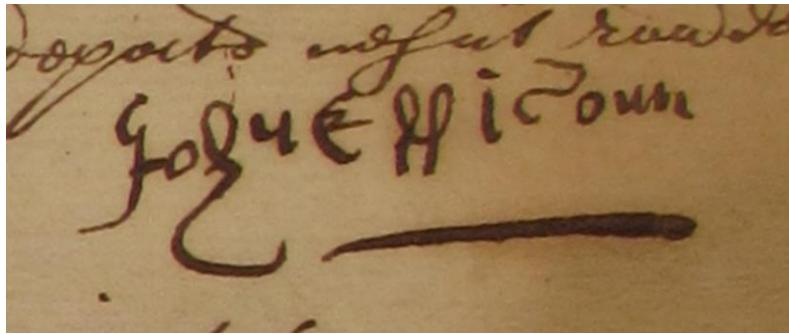


Research question – methodology/content: Why do these some of these unadorned signatures by C17th Englishmen/women appear less well executed than others to a C21st eye? (1)

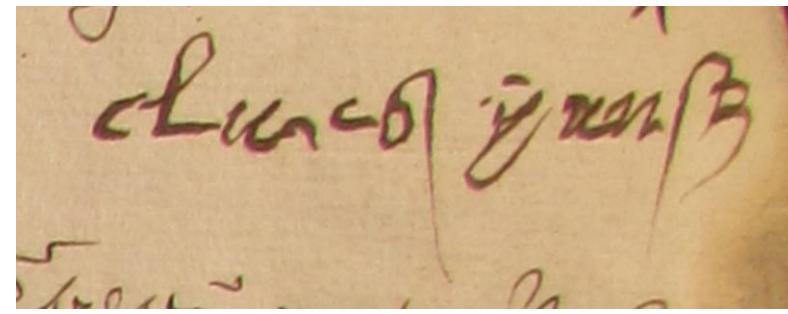
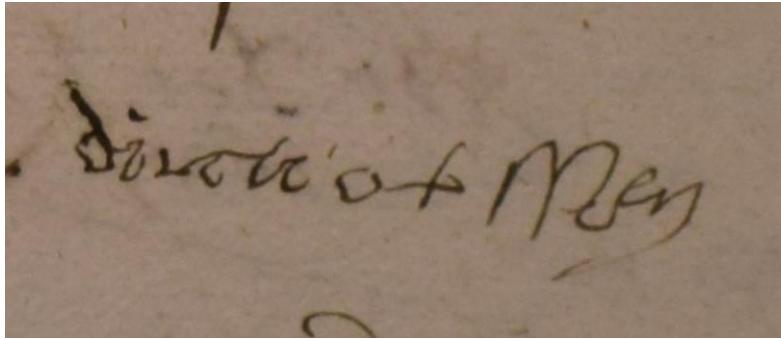


Source: Down from top LH side: KaggleTestSnippet\_HCA\_1353\_f.24v.PNG, KaggleTestSnippet\_HCA\_1353\_f.188r.PNG;  
Down from top Middle: KaggleTestSnippet\_HCA\_1353\_f.66r.PNG; KaggleTestSnippet\_HCA\_1370\_f.193r\_One.PNG,  
KaggleTestSnippet\_HCA\_1370\_f.203r.PNG, KaggleTestSnippet\_HCA\_1370\_f.218r.PNG  
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/content: Why do these some of these unadorned signatures by C17th Englishmen/women appear less well executed than others to a C21st eye? (2)



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

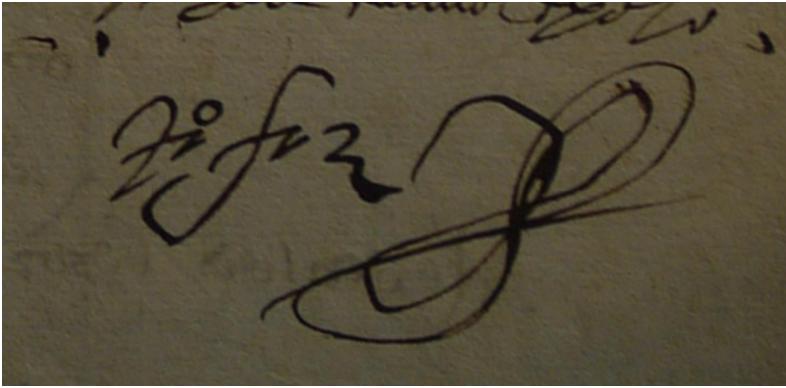


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Down from top Middle: KaggleTestSnippet\_HCA\_1363\_f.5r.PNG

Down from top RH SIDE: XXXXX

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

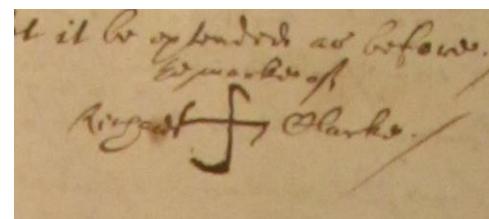
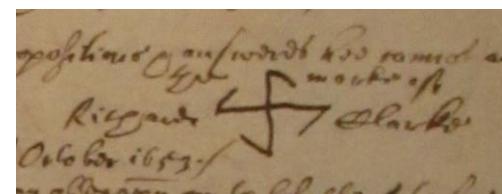
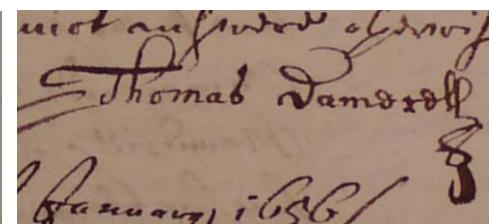
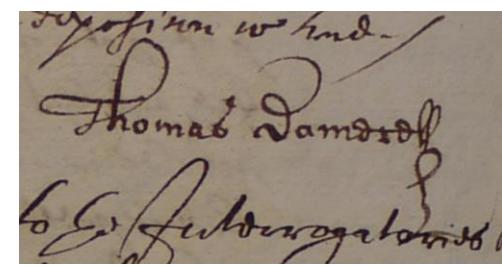
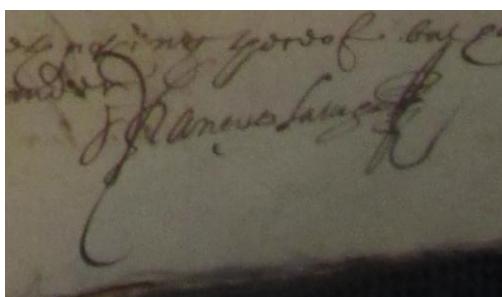
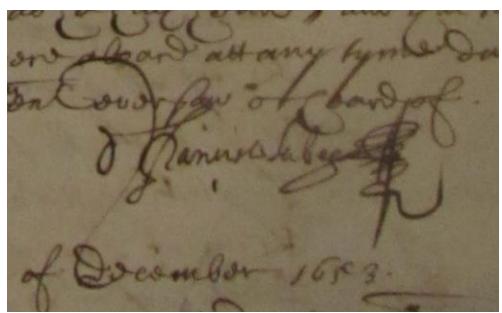
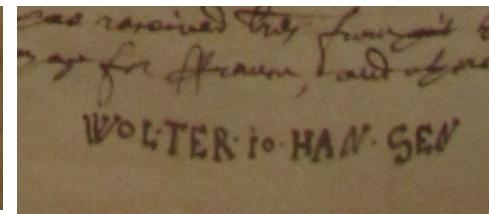
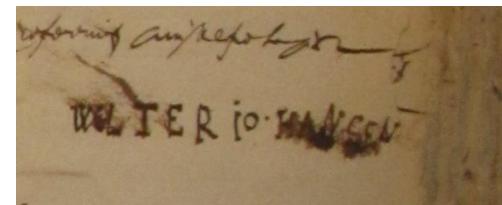
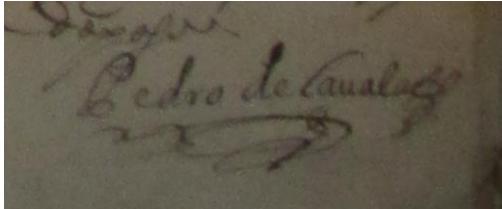
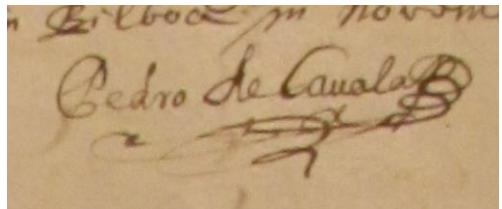
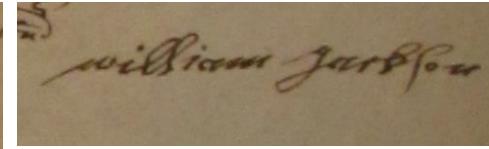
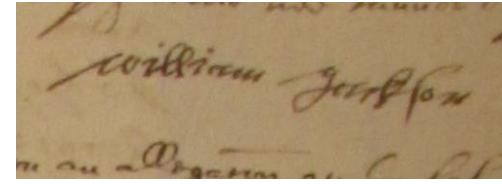
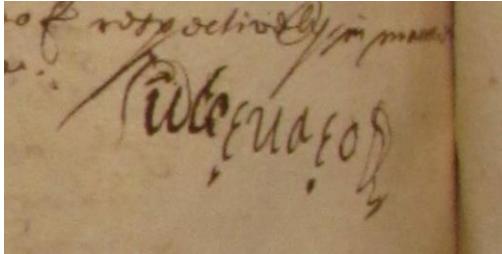
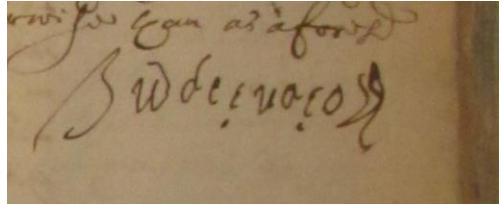


Source: Down from top LH side: KaggletestSnippet\_HCA\_1353\_f.68r.PNG  
Down from top Middle: XXXX  
Down from top RH SIDE: XXXXX

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

Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

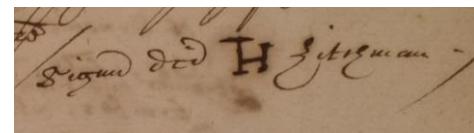
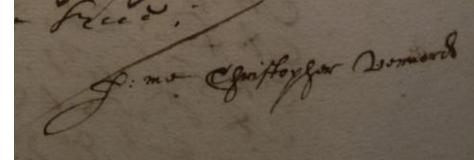
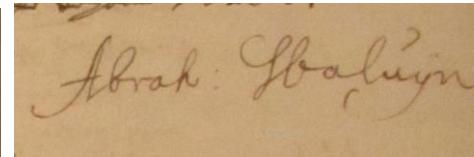
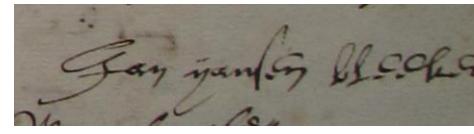
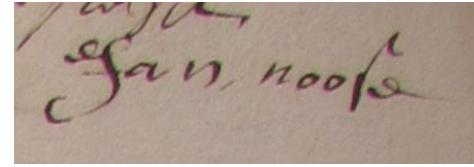
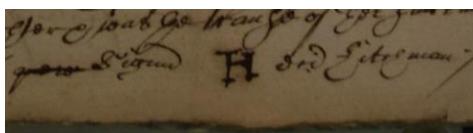
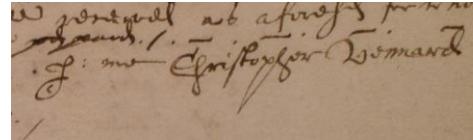
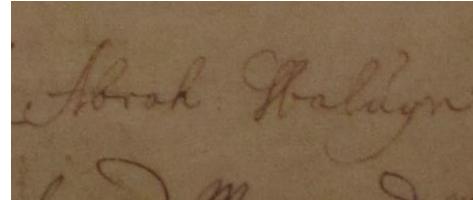
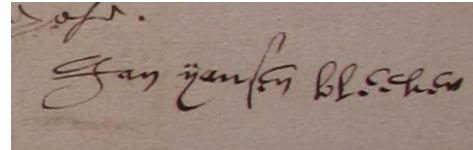
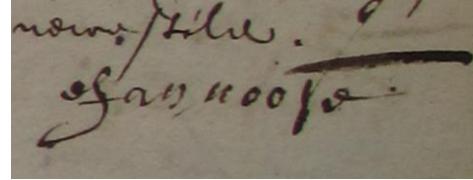
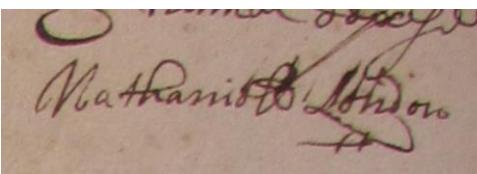
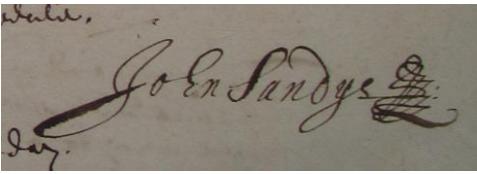
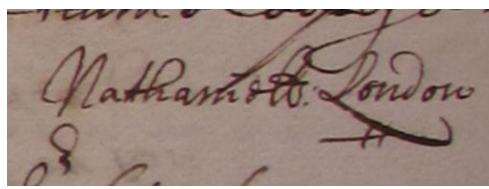
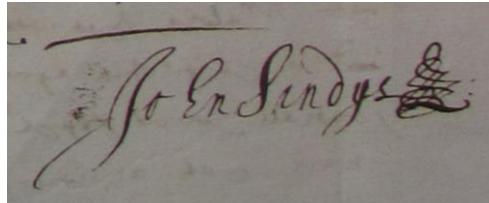
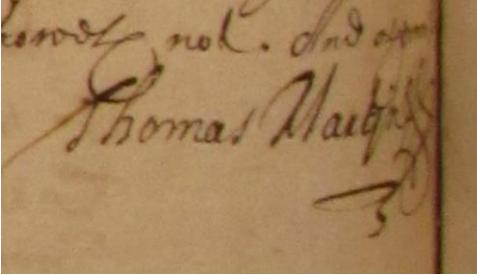
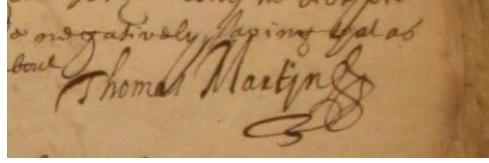
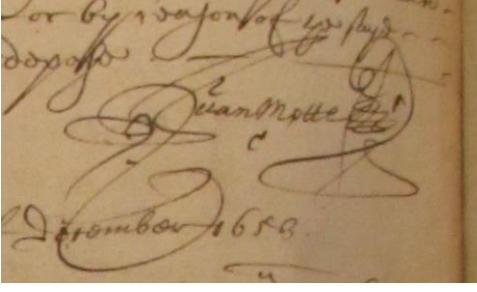
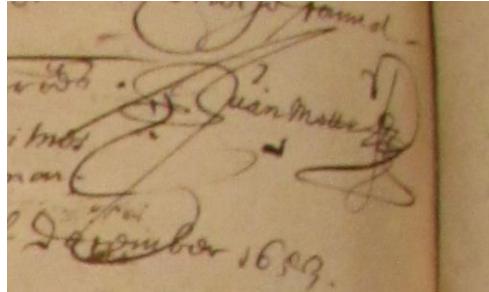


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet\_HCA\_1368\_f.253r.PNG, KaggleTestSnippet\_HCA\_1368\_f.254v.PNG; (2) KaggleTestSnippet\_HCA\_1368\_f.255v.PNG, KaggleTestSnippet\_HCA\_1368\_f.256r.PNG; (3) KaggleTestSnippet\_HCA\_1368\_f.257r.PNG, 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 & mark snippets? (2)

Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

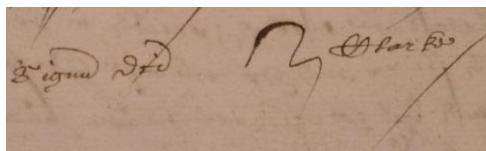
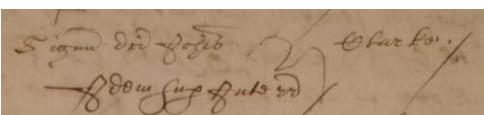
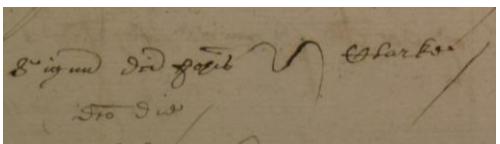
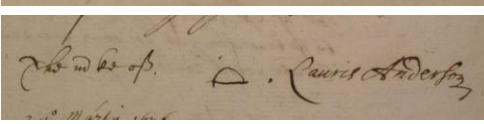
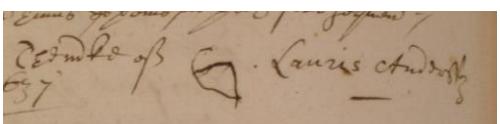
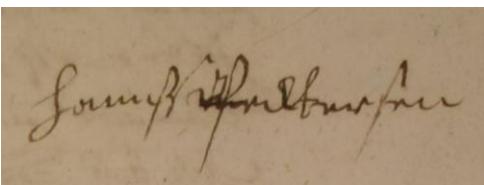
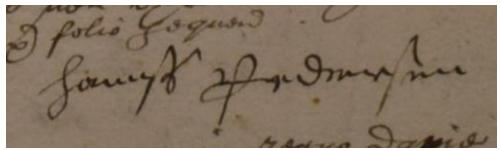
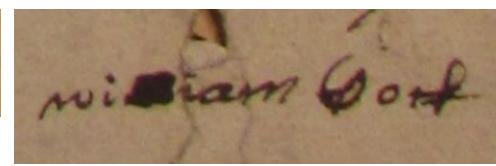
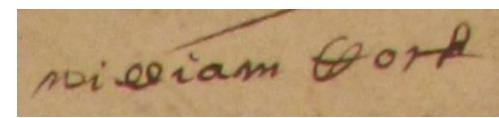
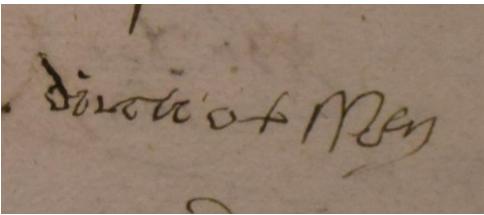
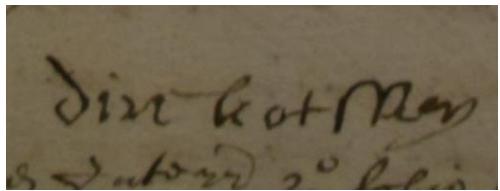
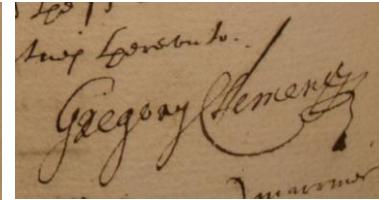
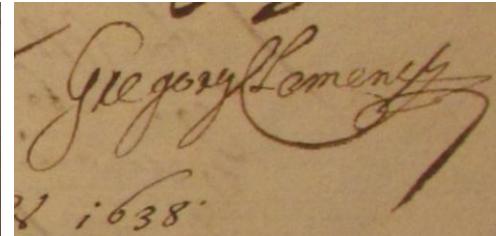
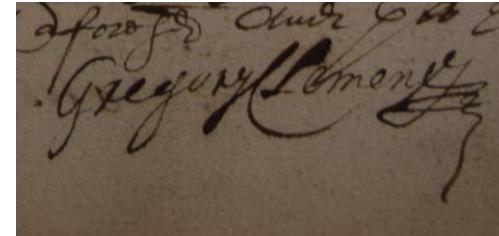
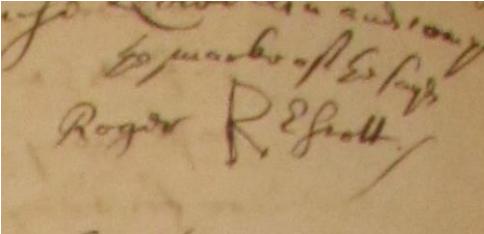
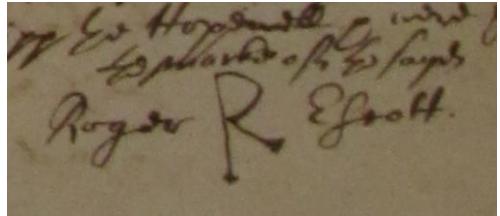


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet\_HCA\_1368\_f.296v.PNG, KaggleTestSnippet\_HCA\_1368\_f.299v.PNG (2) KaggleTestSnippet\_HCA\_1368\_f.158r.PNG, KaggleTestSnippet\_HCA\_1368\_f.161v.PNG (3) KaggleTestSnippet\_HCA\_1370\_f.6v.PNG, KaggleTestSnippet\_HCA\_1370\_f.9r.PNG (4) KaggleTestSnippet\_HCA\_1370\_f.13v\_One.PNG, KaggleTestSnippet\_HCA\_1370\_f.14v.PNG (5) KaggleTestSnippet\_HCA\_1370\_f.23r.PNG, KaggleTestSnippet\_HCA\_1370\_f.25v.PNG (6) KaggleTestSnippet\_HCA\_1370\_f.23v.PNG, KaggleTestSnippet\_HCA\_1370\_f.26r.PNG (7) KaggleTestSnippet\_HCA\_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\_HCA\_1353\_f.26v\_Two.PNG, KaggleTestSnippet\_HCA\_1353\_f.28r.PNG

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

Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

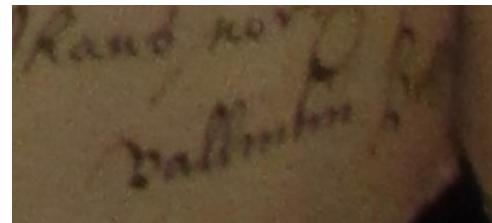
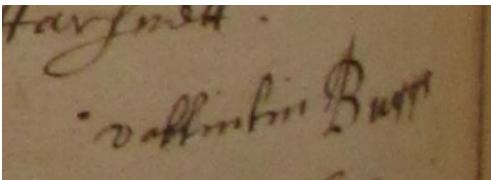
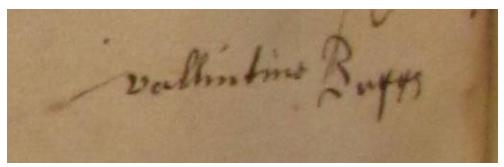
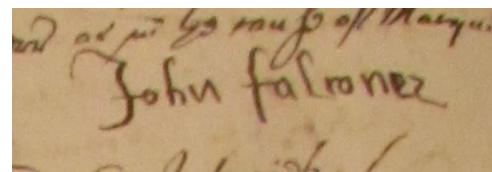
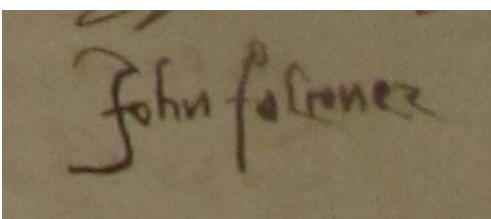
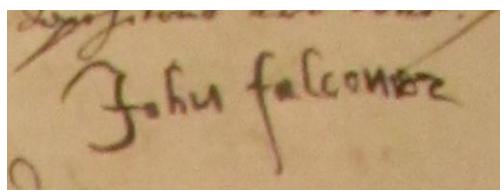
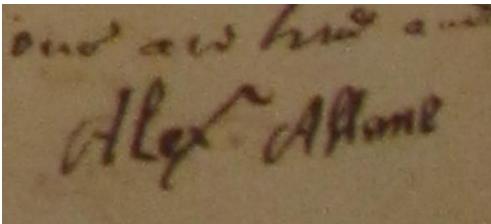
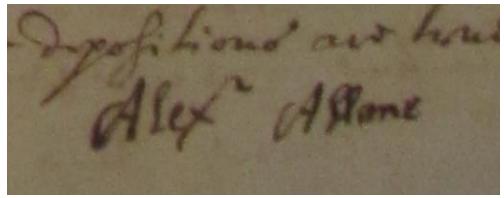
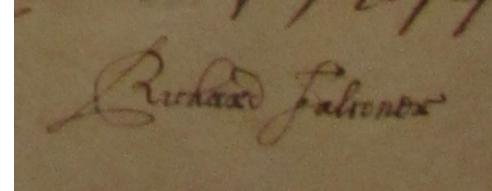
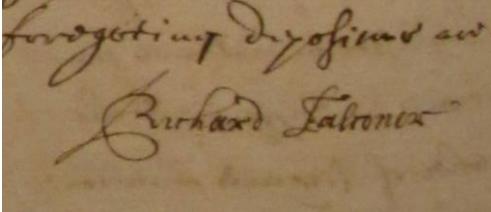
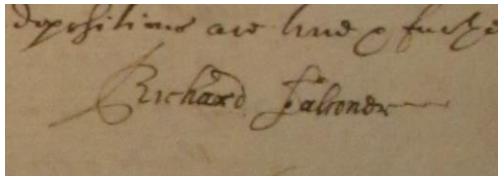
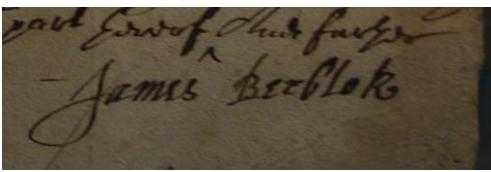
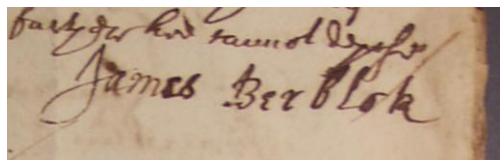


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet\_HCA\_1368\_f.286r.PNG, KaggleTestSnippet\_HCA\_1368\_f.287v.PNG (2) KaggleTestSnippet\_HCA\_1353\_f.84v\_Two.PNG, KaggleTestSnippet\_HCA\_1353\_f.86r\_Two.PNG (3) KaggleTestSnippet\_HCA\_1353\_f.85r.PNG, KaggleTestSnippet\_HCA\_1353\_f.86v\_One.PNG (4) KaggleTestSnippet\_HCA\_1353\_f.85v.PNG, KaggleTestSnippet\_HCA\_1353\_f.86v\_Two.PNG (5) KaggleTestSnippet\_HCA\_1353\_f.101v.PNG, KaggleTestSnippet\_HCA\_1353\_f.102r\_One.PNG, KaggleTestSnippet\_HCA\_1353\_f.102r\_Two.PNG (6) KaggleTestSnippet\_HCA\_1354\_f.14r.PNG, KaggleTestSnippet\_HCA\_1353\_f.32v.PNG, KaggleTestSnippet\_HCA\_1353\_f.173v.PNG (7) KaggleTestSnippet\_HCA\_1354\_f.16v\_One.PNG, KaggleTestSnippet\_HCA\_1354\_f.16v\_Two.PNG

# Research question - methodology: How well will machine learning cope with recognising and matching signature, initial & mark snippets? (4)

Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

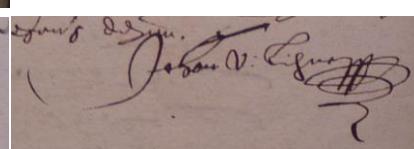
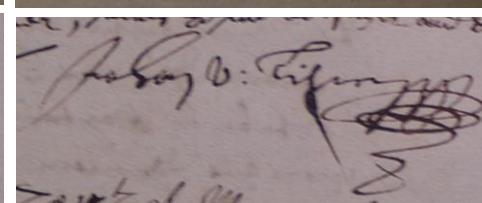
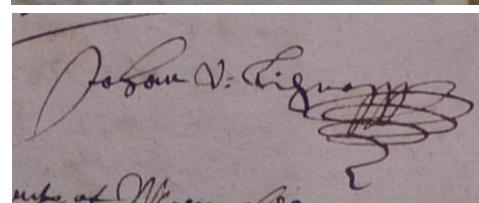
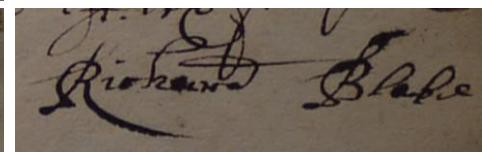
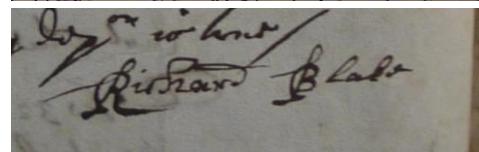
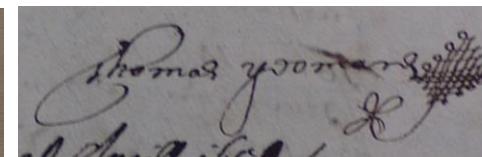
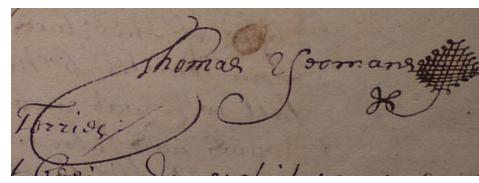
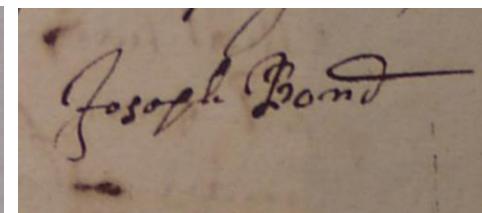
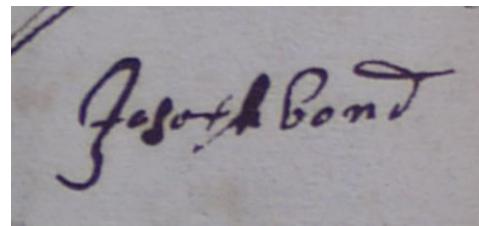
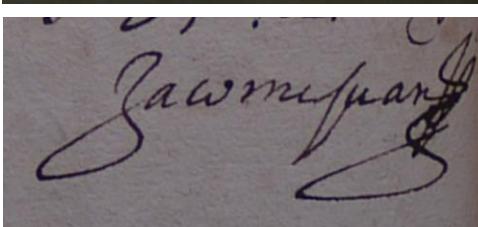
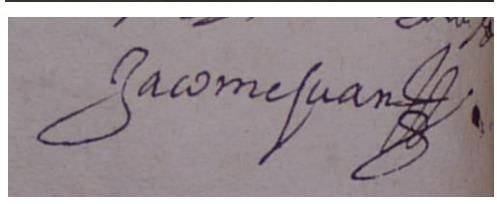
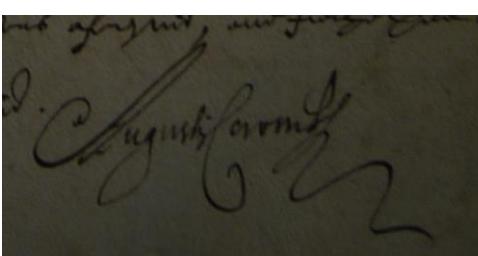
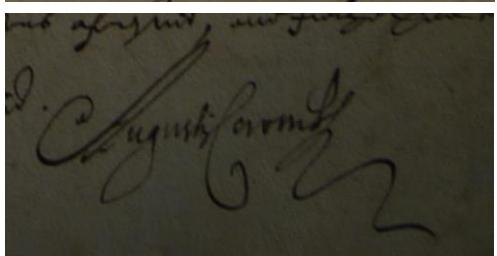
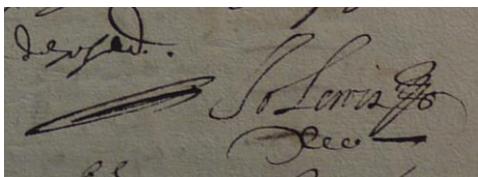
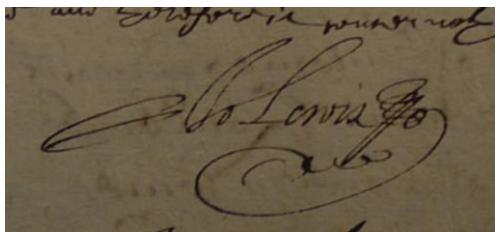
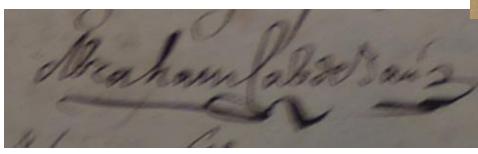
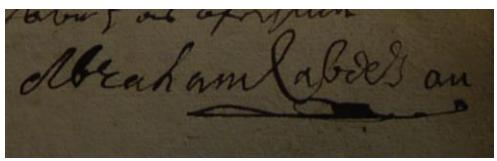
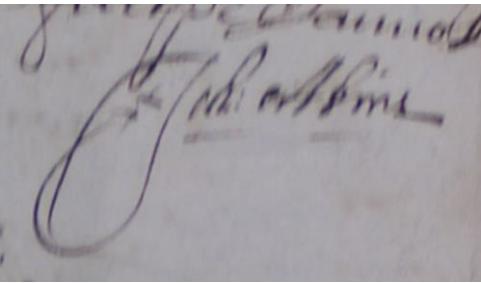
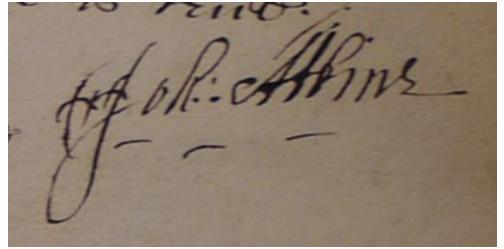
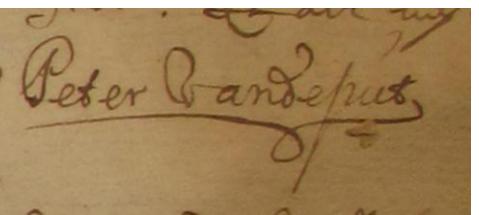
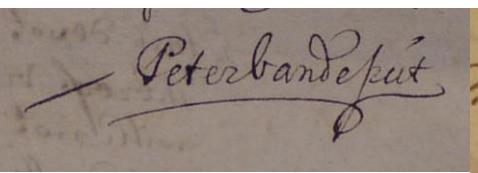
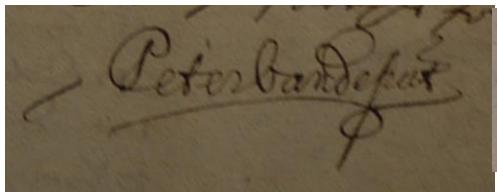


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet\_HCA\_1373\_f.16r\_One.PNG, KaggleTestSnippet\_HCA\_1373\_f.16r\_Two.PNG (2) KaggleTestSnippet\_HCA\_1368\_f.288r.PNG, KaggleTestSnippet\_HCA\_1368\_f.288v.PNG, KaggleTestSnippet\_HCA\_1368\_f.291v\_Two.PNG (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 & mark snippets? (5)

Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

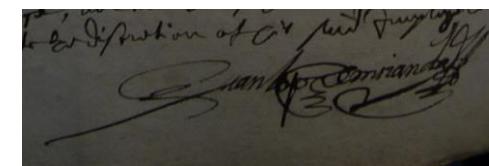
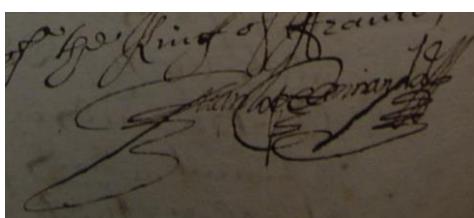
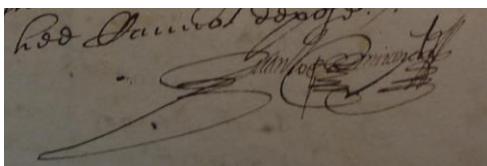
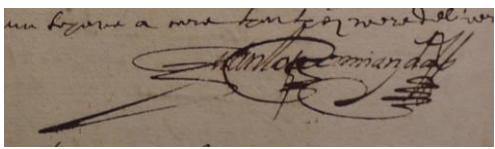
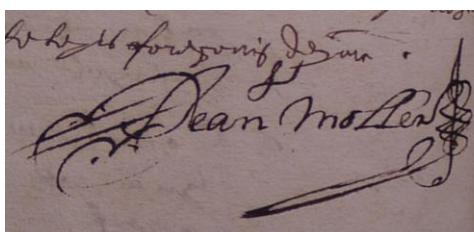
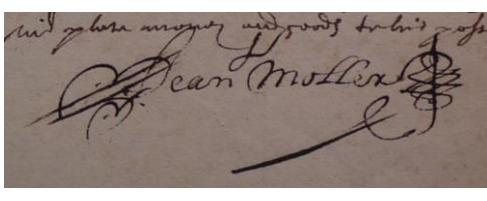
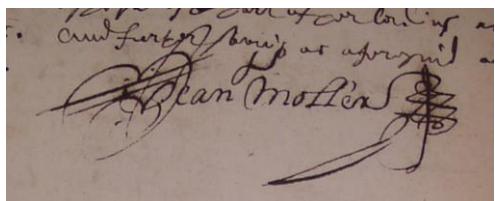
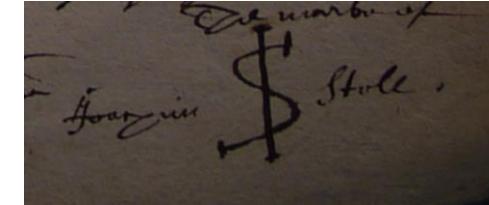
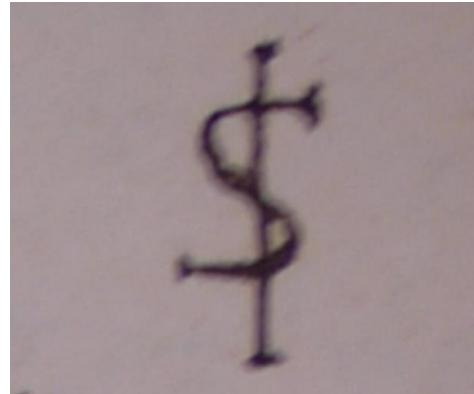
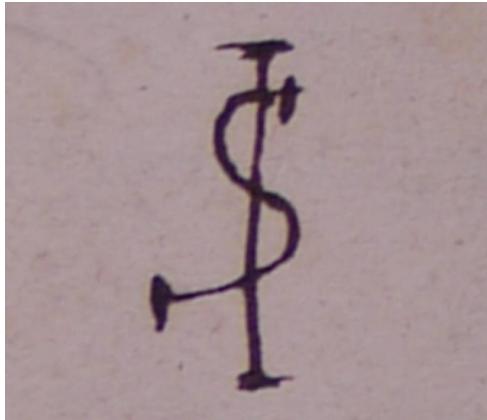


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet\_HCA\_1373\_f.54r.PNG, KaggleTestSnippet\_HCA\_1373\_f.56v.PNG, KaggleTestSnippet\_HCA\_1363\_f.391r\_One.PNG (2) KaggleTestSnippet\_HCA\_1373\_f.55r.PNG, KaggleTestSnippet\_HCA\_1373\_f.57v.PNG (3) KaggleTestSnippet\_HCA\_1373\_f.58r.PNG, KaggleTestSnippet\_HCA\_1373\_f.58v.PNG (4) KaggleTestSnippet\_HCA\_1373\_f.74r.PNG, KaggleTestSnippet\_HCA\_1373\_f.74v.PNG (5) KaggleTestSnippet\_HCA\_1373\_f.131v\_One.PNG, KaggleTestSnippet\_HCA\_1373\_f.131v\_Two.PNG (6) KaggleTestSnippet\_HCA\_1373\_f.86r.PNG, KaggleTestSnippet\_HCA\_1373\_f.90v.PNG (7) KaggleTestSnippet\_HCA\_1373\_f.86v.PNG, KaggleTestSnippet\_HCA\_1373\_f.87v.PNG (8) KaggleTestSnippet\_HCA\_1373\_f.102r.PNG, KaggleTestSnippet\_HCA\_1373\_f.104v.PNG (9) KaggleTestSnippet\_HCA\_1373\_f.10v.PNG, KaggleTestSnippet\_HCA\_1373\_f.107r.PNG (10) KaggleTestSnippet\_HCA\_1373\_f.151v.PNG, KaggleTestSnippet\_HCA\_1373\_f.152v.PNG, KaggleTestSnippet\_HCA\_1373\_f.153v.PNG

# Research question - methodology: How well will machine learning cope with recognising and matching signature, initial & mark snippets? (6)

Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

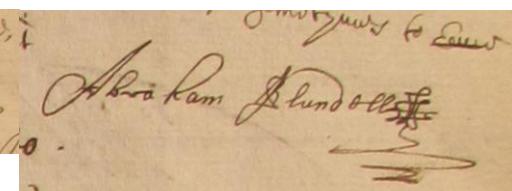
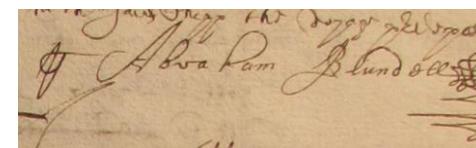
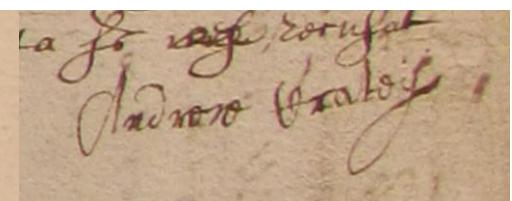
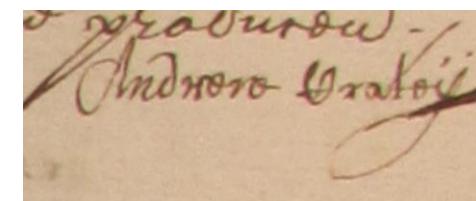
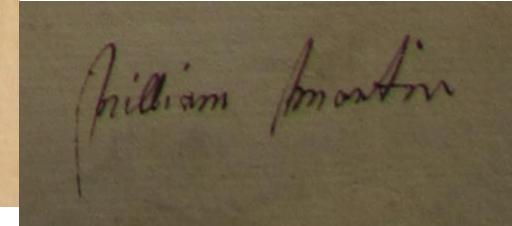
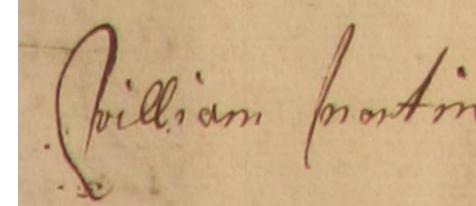
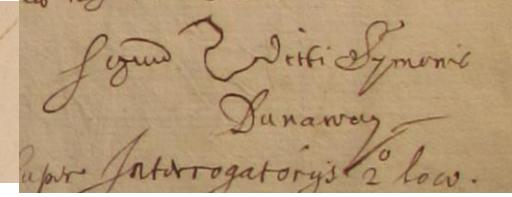
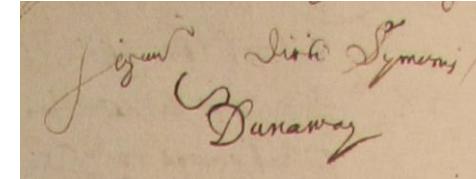
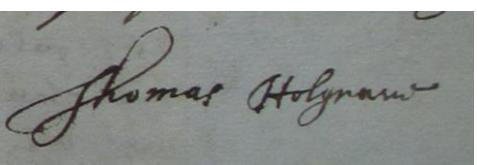
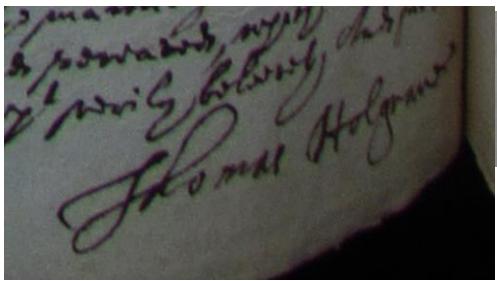
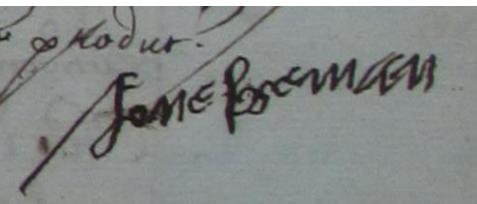
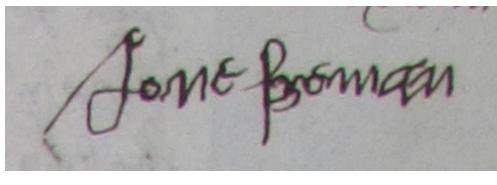
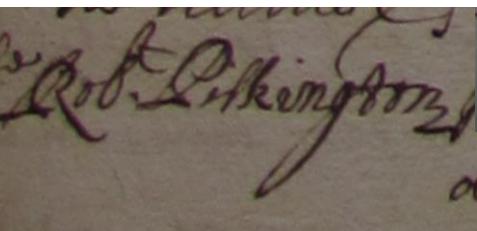
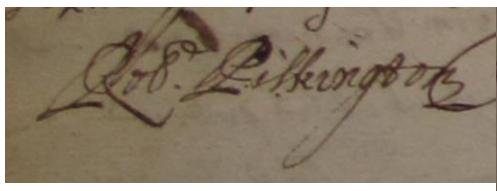
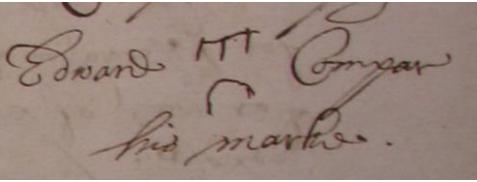
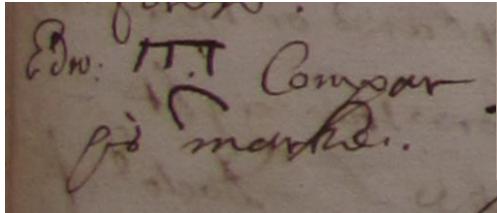


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet\_HCA\_1373\_f.155v.PNG, KaggleTestSnippet\_HCA\_1373\_f.156v.PNG, KaggleTestSnippet\_HCA\_1373\_f.157v.PNG, KaggleTestSnippet\_HCA\_1373\_f.158r.PNG (2) KaggleTestSnippet\_HCA\_1373\_f.164r.PNG, KaggleTestSnippet\_HCA\_1373\_f.165r.PNG, KaggleTestSnippet\_HCA\_1373\_f.165v.PNG (3) KaggleTestSnippet\_HCA\_1373\_f.180v.PNG, KaggleTestSnippet\_HCA\_1373\_f.181v.PNG, KaggleTestSnippet\_HCA\_1373\_f.182v.PNG, KaggleTestSnippet\_HCA\_1373\_f.183v.PNG

# Research question - methodology: How well will machine learning cope with recognising and matching signature, initial & mark snippets? (7)

Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

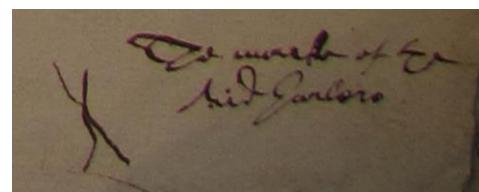
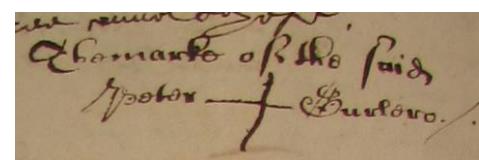
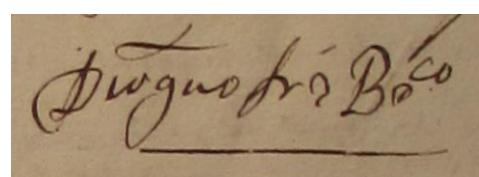
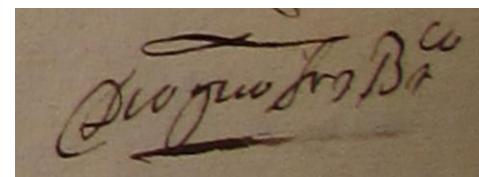
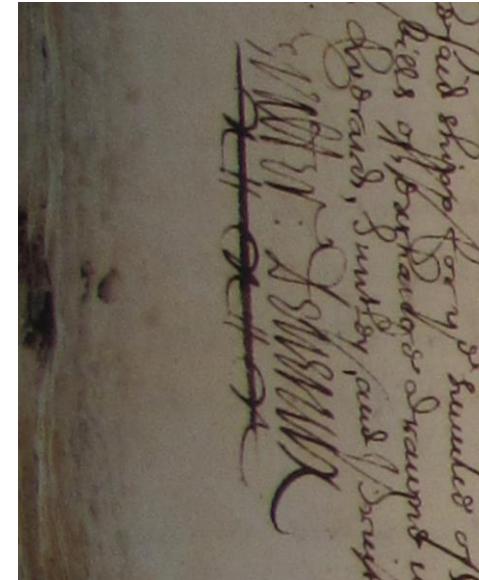
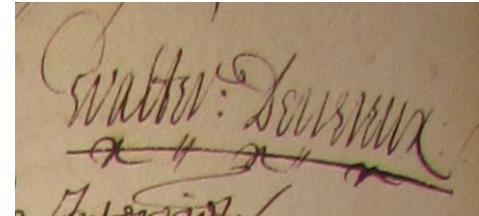
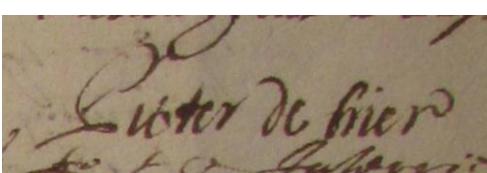
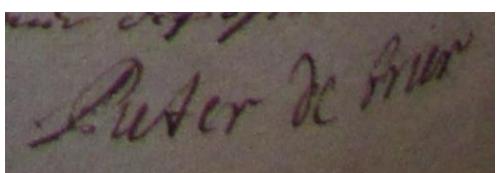
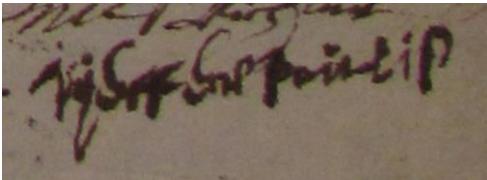
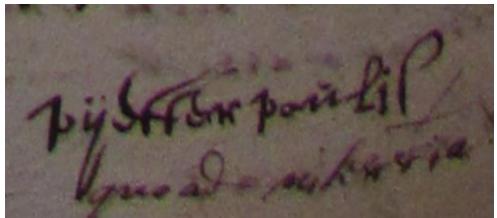
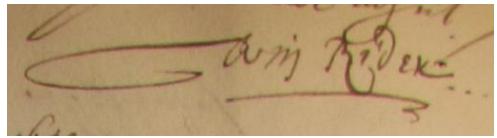
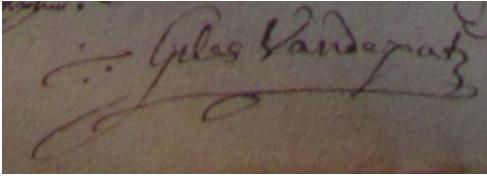
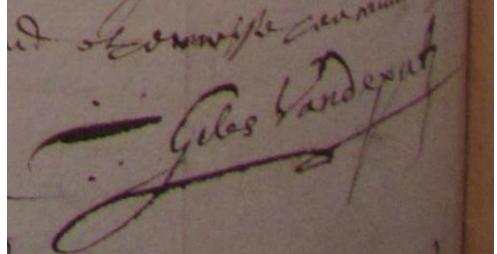
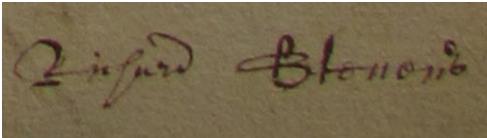
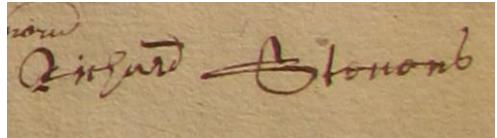


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggletestSnippet\_HCA\_1370\_f.109r.PNG, KaggletestSnippet\_HCA\_1370\_f.109v.PNG (2) KaggleTestSnippet\_HCA\_1370\_f.129v.PNG, KaggleTestSnippet\_HCA\_1370\_f.130r\_One.PNG, KaggleTestSnippet\_HCA\_1370\_f.130r\_Two.PNG (3) KaggleTestSnippet\_HCA\_1370\_f.193r\_One.PNG, KaggleTestSnippet\_HCA\_1370\_f.193r\_Two.PNG (4) KaggleTestSnippet\_HCA\_1370\_f.196v.PNG, KaggleTestSnippet\_HCA\_1370\_f.197r.PNG (5) KaggleTestSnippet\_HCA\_1363\_f.2v.PNG, KaggleTestSnippet\_HCA\_1363\_f.196v.PNG, KaggleTestSnippet\_HCA\_1363\_f.197r.PNG (6) KaggleTestSnippet\_HCA\_1363\_f.3r\_One.PNG, KaggleTestSnippet\_HCA\_1363\_f.3r\_Three.PNG (7) KaggleTestSnippet\_HCA\_1363\_f.7v.PNG, KaggleTestSnippet\_HCA\_1363\_f.8v\_Two.PNG (8) KaggleTestSnippet\_HCA\_1363\_f.9r.PNG, KaggleTestSnippet\_HCA\_1363\_f.10r\_One.PNG

# Research question - methodology: How well will machine learning cope with recognising and matching signature, initial & mark snippets? (8)

Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

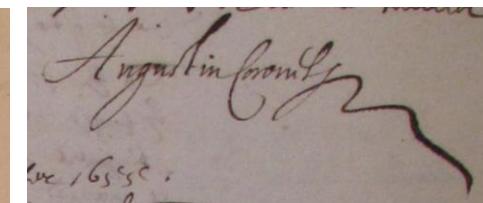
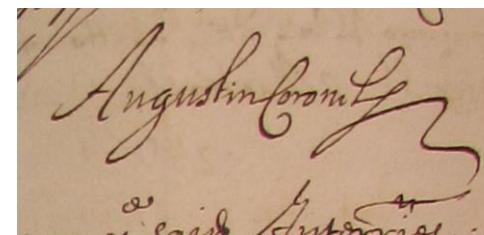
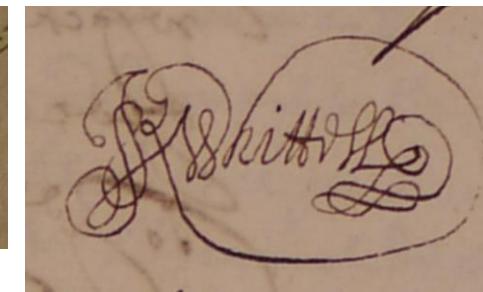
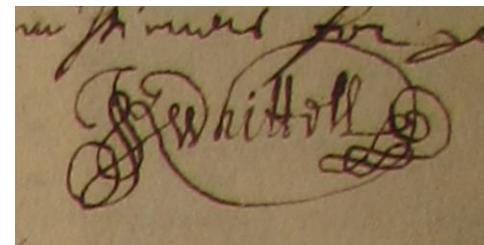
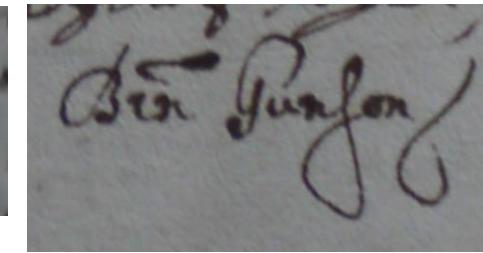
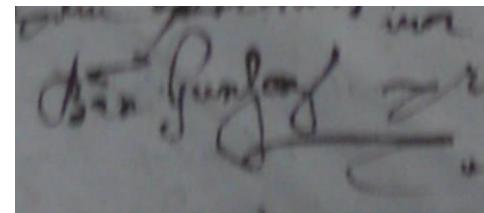
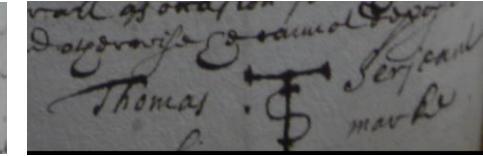
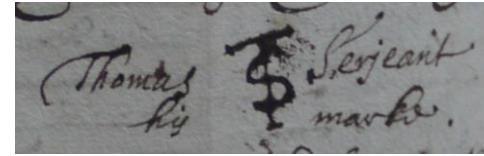
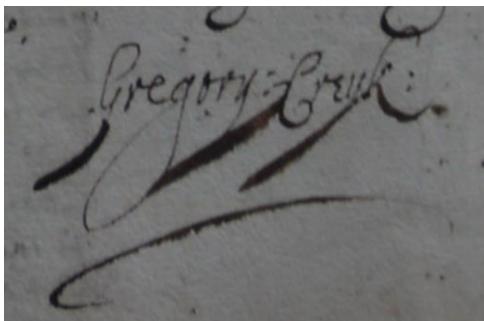
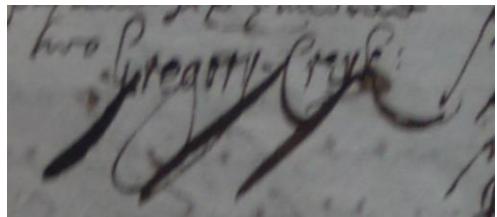
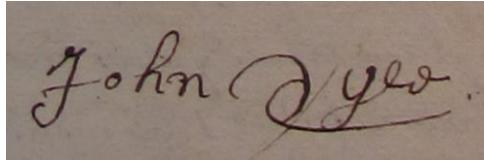
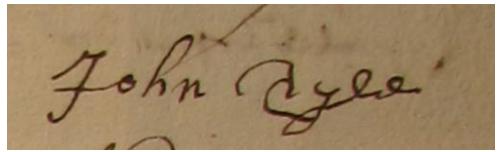
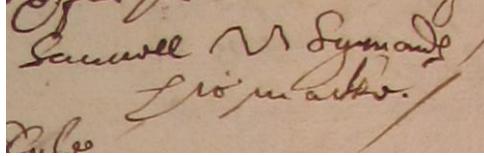
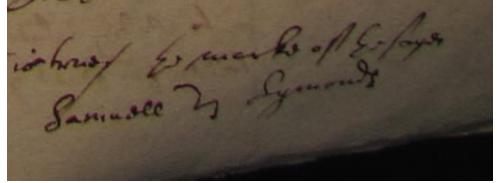
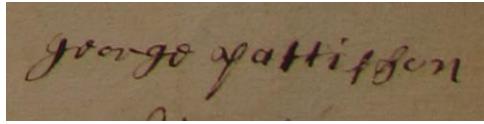
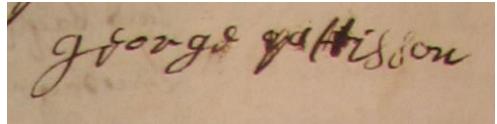


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet\_HCA\_1363\_f.20r\_One.PNG, KaggleTestSnippet\_HCA\_1363\_f.20r\_Two.PNG (2) KaggleTestSnippet\_HCA\_1370\_f.225v\_One.PNG, KaggleTestSnippet\_HCA\_1370\_f.225v\_Two.PNG (3) KaggleTestSnippet\_HCA\_1363\_f.13r.PNG, KaggleTestSnippet\_HCA\_1370\_f.240r.PNG (4) KaggleTestSnippet\_HCA\_1370\_f.254v.PNG, KaggleTestSnippet\_HCA\_1370\_f.256r\_Two.PNG (5) KaggleTestSnippet\_HCA\_1370\_f.255v, KaggleTestSnippet\_HCA\_1370\_f.256r\_One.PNG (6) KaggleTestSnippet\_HCA\_1370\_f.247v\_One.PNG, KaggleTestSnippet\_HCA\_1370\_f.247v\_Two.PNG (7) KaggleTestSnippet\_HCA\_1370\_f.272r.PNG, KaggleTestSnippet\_HCA\_1370\_f.273r.PNG (8) KaggleTestSnippet\_HCA\_1370\_f.304v.PNG, KaggleTestSnippet\_HCA\_1370\_f.305r.PNG

# Research question - methodology: How well will machine learning cope with recognising and matching signature, initial & mark snippets? (9)

Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

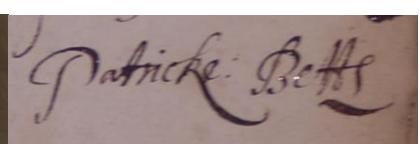
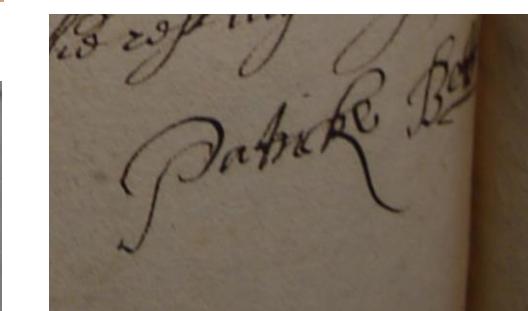
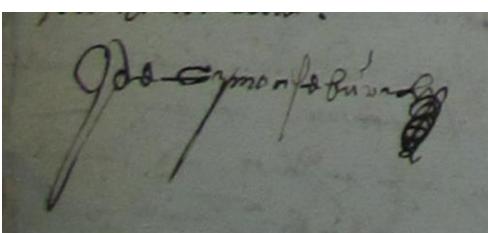
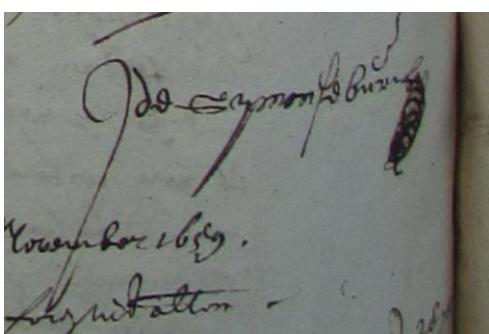
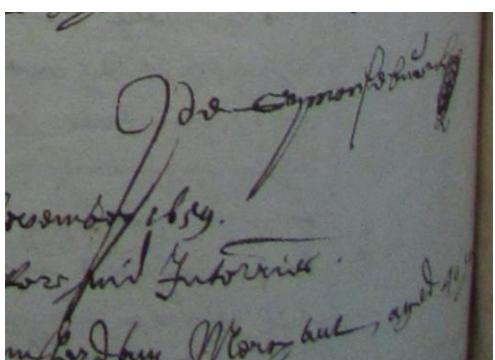
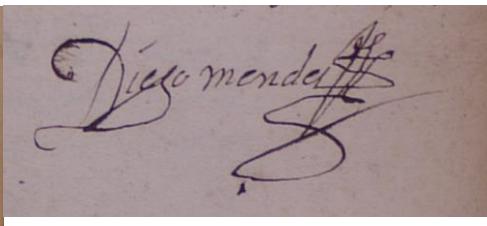
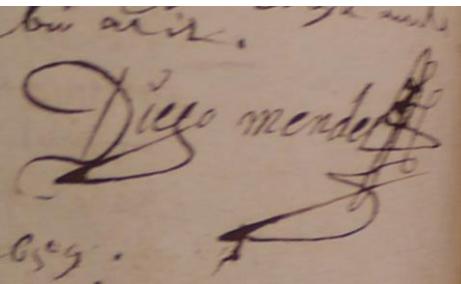
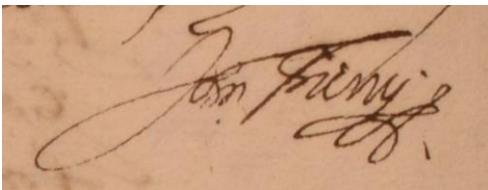
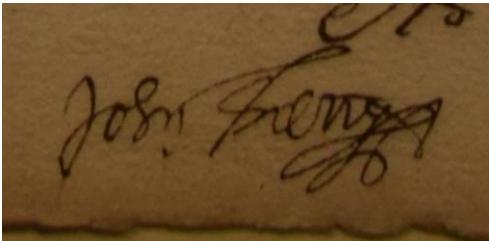
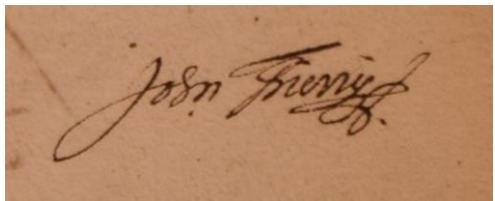
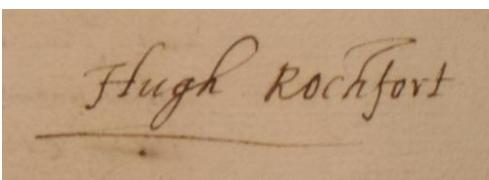
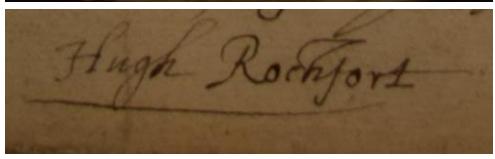
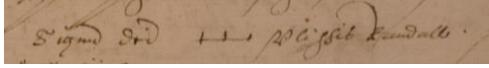
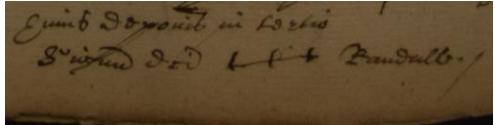


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet\_HCA\_1370\_f.320v.PNG, KaggleTestSnippet\_HCA\_1370\_f.322r\_Two.PNG (2) KaggleTestSnippet\_HCA\_1370\_f.321r.PNG, KaggleTestSnippet\_HCA\_1370\_f.322v\_One.PNG (3) KaggleTestSnippet\_HCA\_1370\_f.322r\_One.PNG, KaggleTestSnippet\_HCA\_1370\_f.322v\_Two.PNG (4) KaggleTestSnippet\_HCA\_1371\_f.25v\_Two.PNG, KaggleTestSnippet\_HCA\_1371\_f.26v.PNG (5) KaggleTestSnippet\_HCA\_1371\_f.27v\_One.PNG, KaggleTestSnippet\_HCA\_1371\_f.27v\_Two.PNG (6) KaggleTestSnippet\_HCA\_1371\_f.31v.PNG, KaggleTestSnippet\_HCA\_1371\_f.32v.PNG (7) KaggleTestSnippet\_HCA\_1370\_f.332r.PNG, KaggleTestSnippet\_HCA\_1371\_f.118v.PNG (8) KaggleTestSnippet\_HCA\_1370\_f.414v.PNG, KaggleTestSnippet\_HCA\_1370\_f.619r.PNG

# Research question - methodology: How well will machine learning cope with recognising and matching signature, initial & mark snippets? (10)

Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

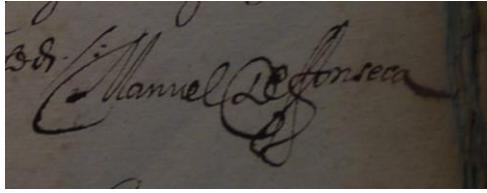
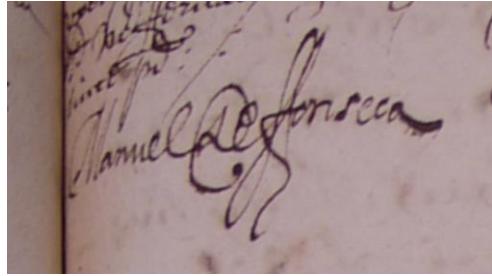


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet\_HCA\_1353\_f.114v.PNG, KaggleTestSnippet\_HCA\_1353\_f.116r\_One.PNG (2) KaggleTestSnippet\_HCA\_1353\_f.160v.PNG, KaggleTestSnippet\_HCA\_1353\_f.161v.PNG (3) KaggleTestSnippet\_HCA\_1353\_f.213r.PNG, KaggleTestSnippet\_HCA\_1353\_f.214v.PNG, KaggleTestSnippet\_HCA\_1353\_f.216v.PNG (4) KaggleTestSnippet\_HCA\_1373\_f.458v, KaggleTestSnippet\_HCA\_1373\_f.466v\_One.PNG, KaggleTestSnippet\_HCA\_1373\_f.466v\_Two.PNG (5) KaggleTestSnippet\_HCA\_1373\_f.186v.PNG, KaggleTestSnippet\_HCA\_1373\_f.187r.PNG (6) KaggleTestSnippet\_HCA\_1373\_f.189r.PNG, KaggleTestSnippet\_HCA\_1373\_f.190v.PNG (7) KaggleTestSnippet\_HCA\_1373\_f.194v.PNG, KaggleTestSnippet\_HCA\_1373\_f.195v.PNG

# Research question - methodology: How well will machine learning cope with recognising and matching signature, initial & mark snippets? (11)

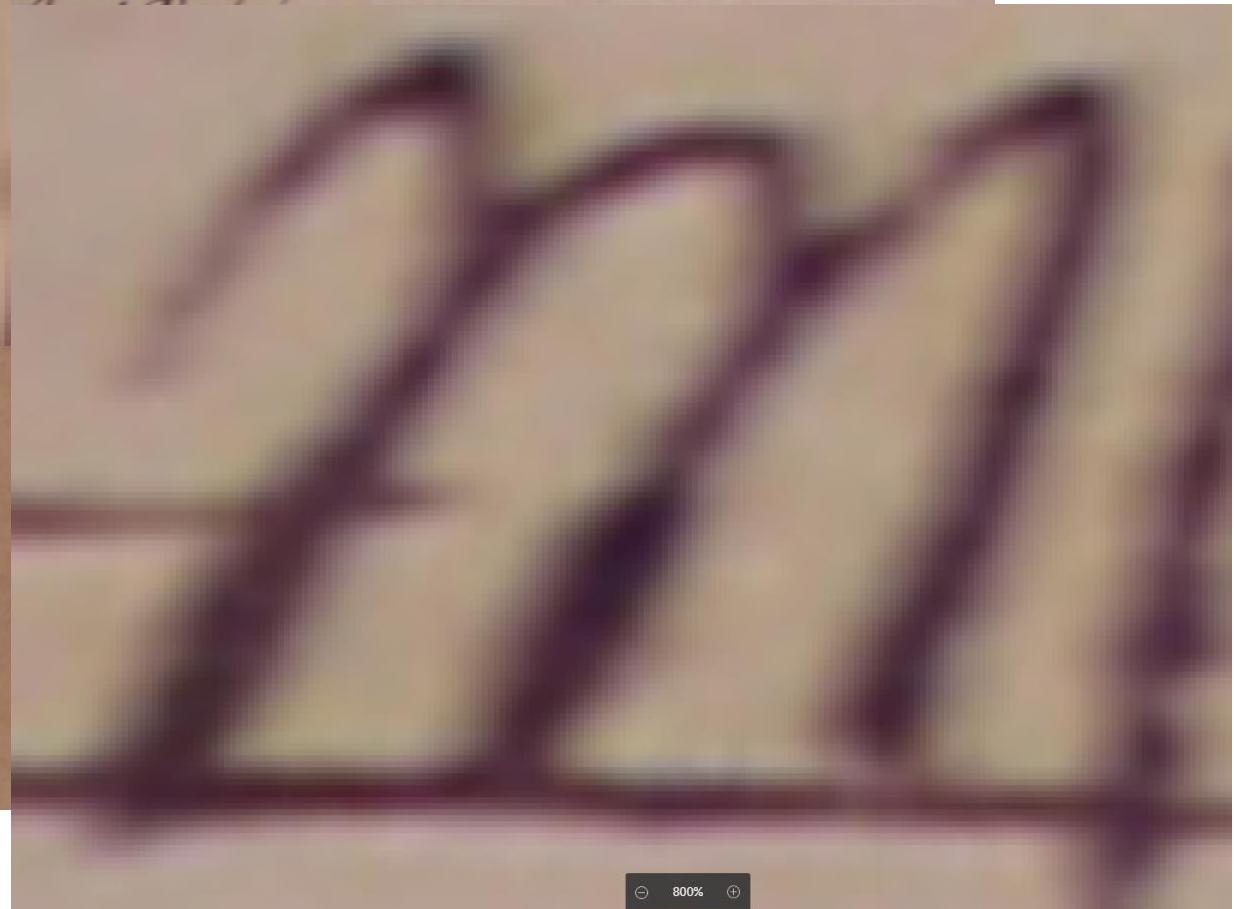
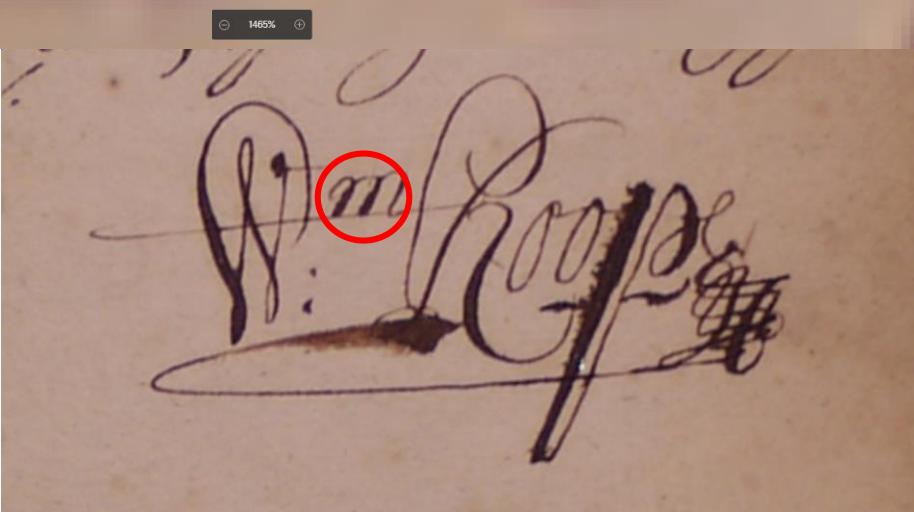
Are certain parts of a signature more stable than others?

Are less confident signers less able to replicate their signatures, marks & initials?

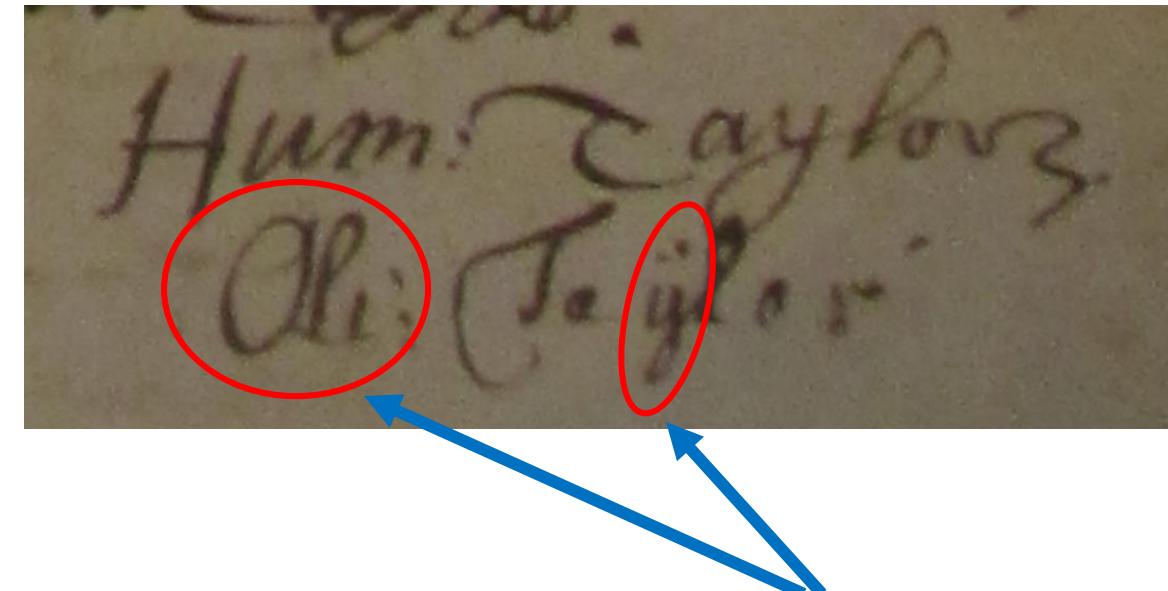
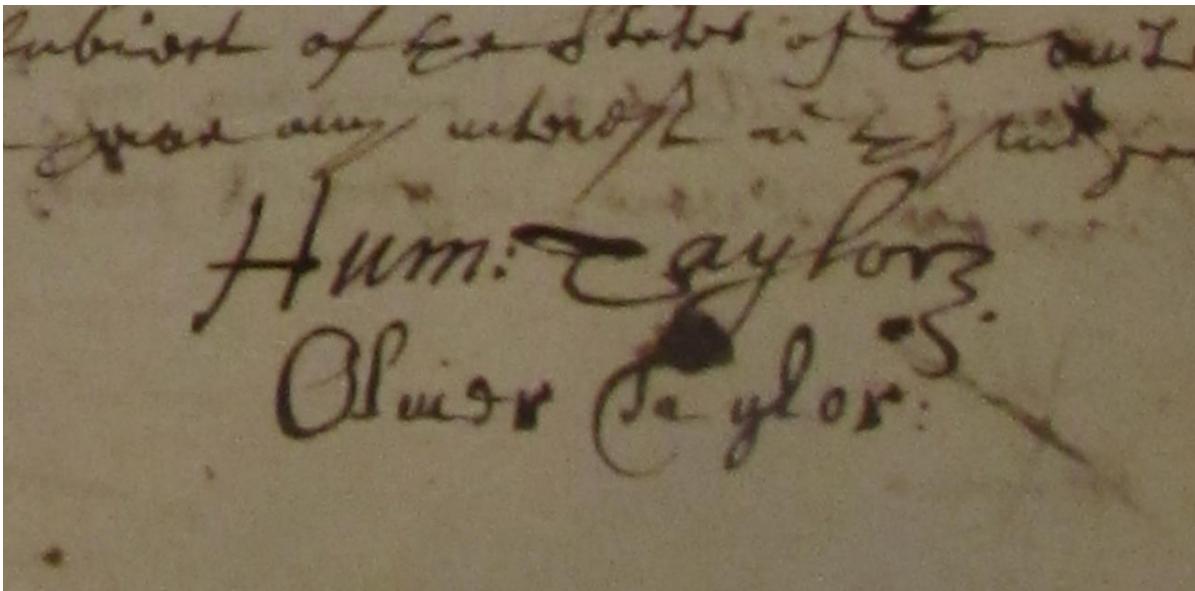


Source: In pairs, from top LH side downwards, then from top RH side downwards: (1) KaggleTestSnippet\_HCA\_1373\_f.201r\_One.PNG, KaggleTestSnippet\_HCA\_1373\_f.201r\_Two.PNG

## Research question - methodology: Measuring pixel dimensions



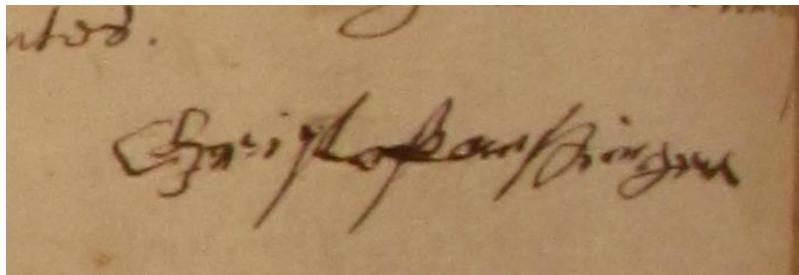
Research question - content: Can a family resemblance be detected in signatures from the same biological family from the same date and place?



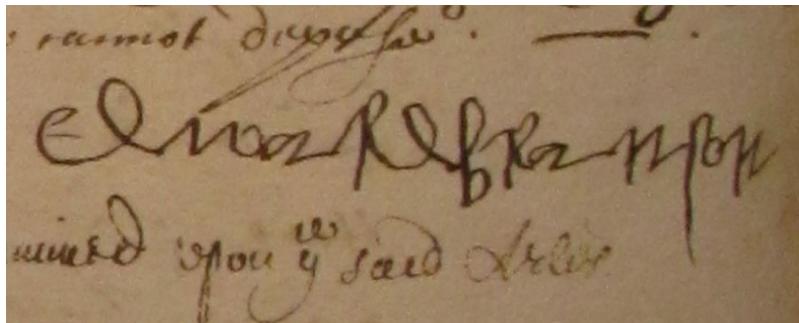
Depositions in the English High Court of Admiralty of **Humphrey Taylor** of London merchant aged 29 yeares or thereabouts and **Oliver Taylor** of the same citie merchant aged 27 yeares, dated December 8<sup>th</sup>, 1653 and again on December 9th, 1653

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

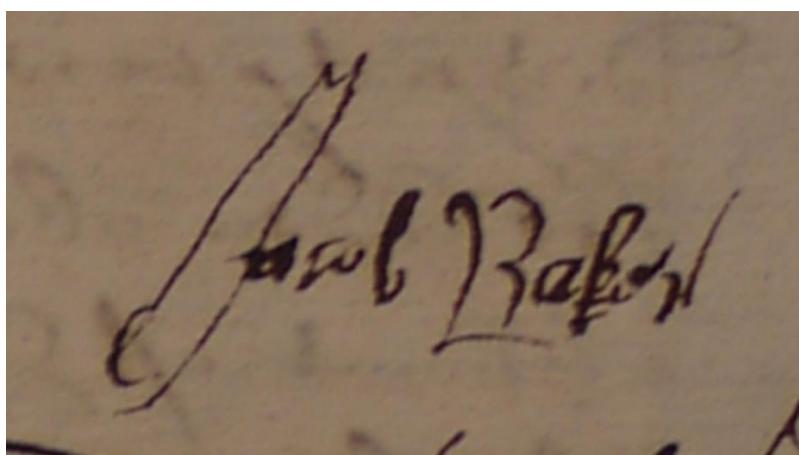
Research question - content: Is there an age effect in terms of physical control of pen, independent of any age-independent physical infirmity, and independent of a tendency for lower literacy (and possibly lower control of pen) amongst earlier age cohorts in our samples of signatures from the mid-C17th?



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

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

Steven pieterse

Bonifacius van der Deyppen.  
Lars & Albertus  
of October 1653.

John Deyppen.  
Jacob Colmaes den jonghe

My son John Snowdon our  
Graham Sijssen

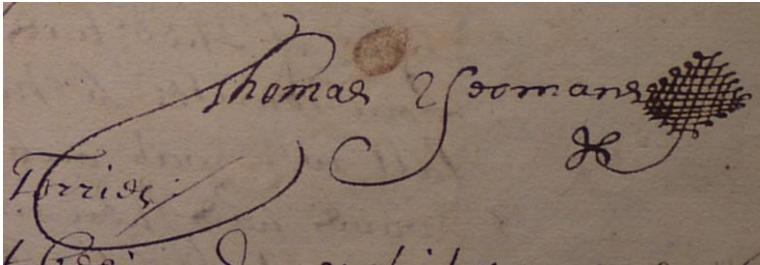
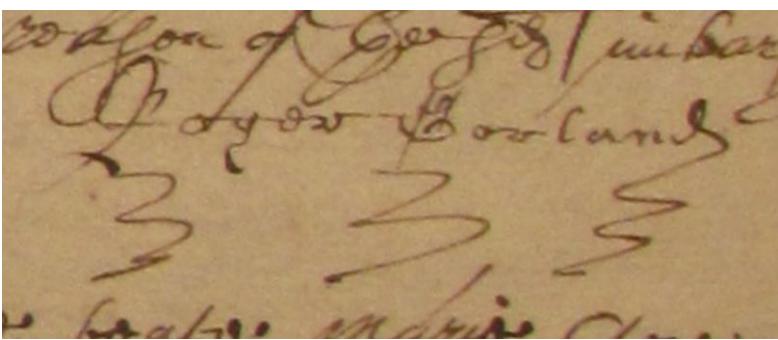
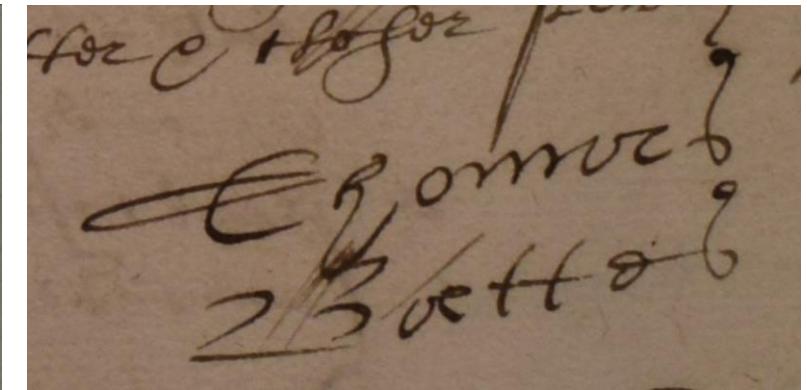
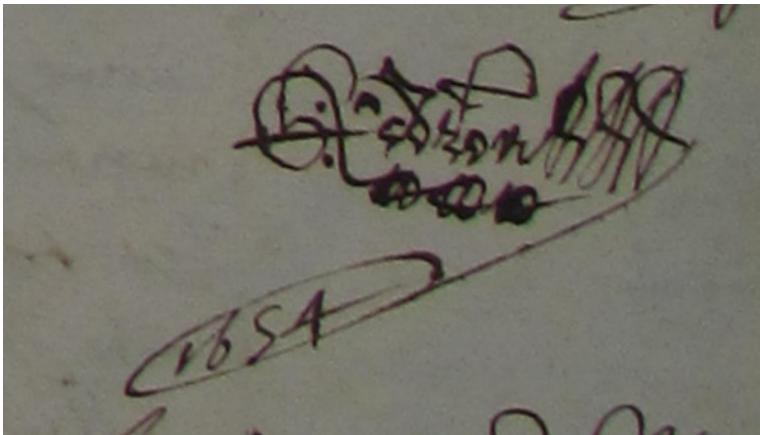
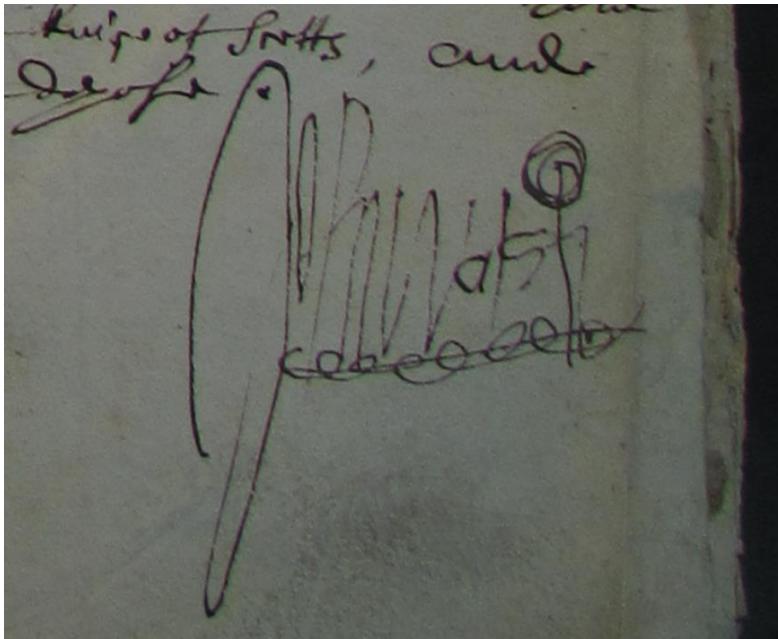
No name, ~~Colman~~  
living bakstane

Another being as aforesaid  
commissary mercer to

for having as aforesaid  
Abraham Van Dinter  
November 1659.

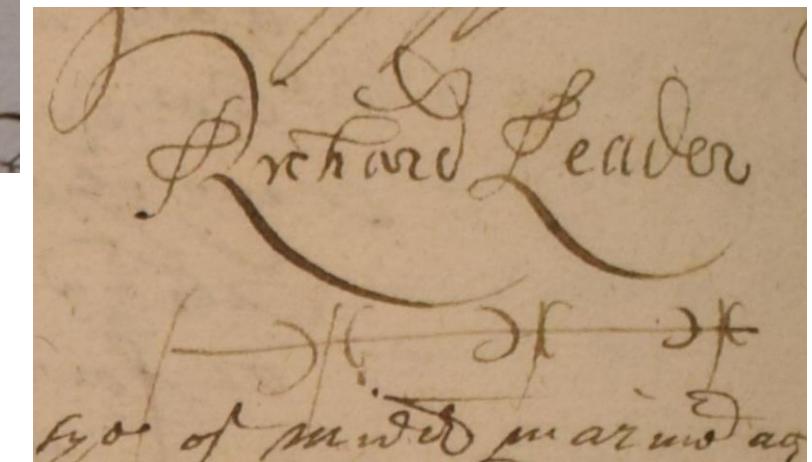
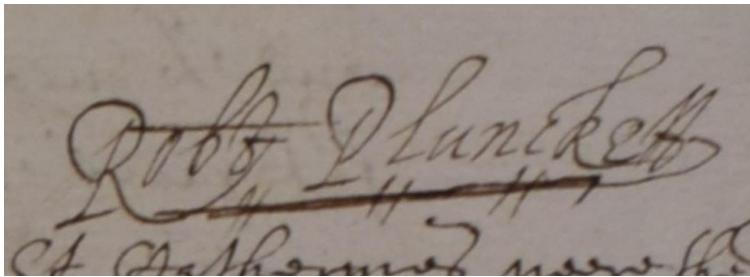
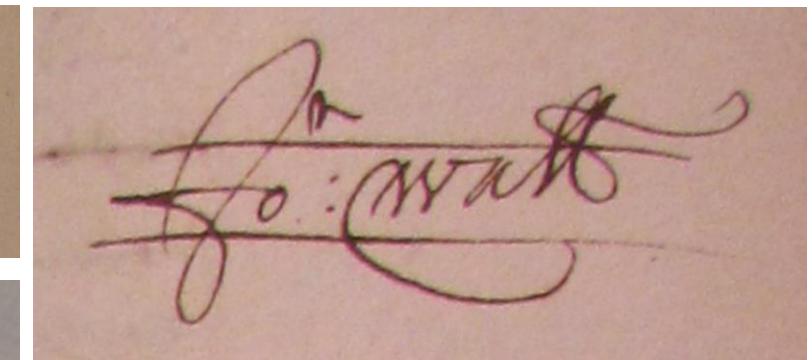
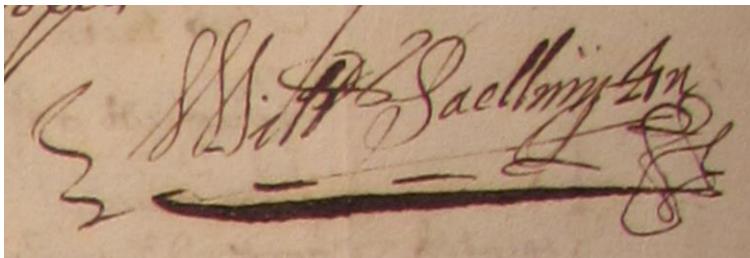
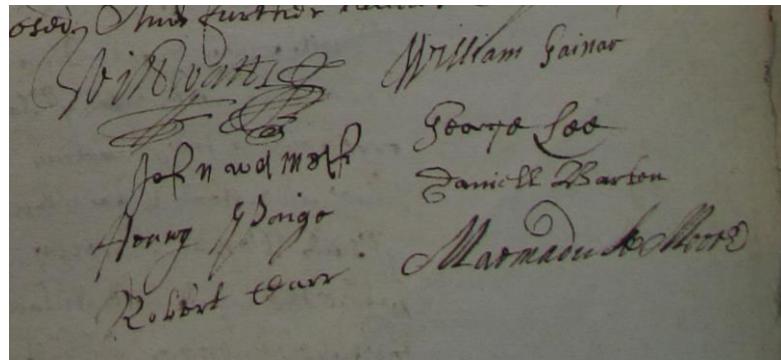
Another being as aforesaid  
Jan Lombant  
December 1659.

## Data: Unusual signatures (1)



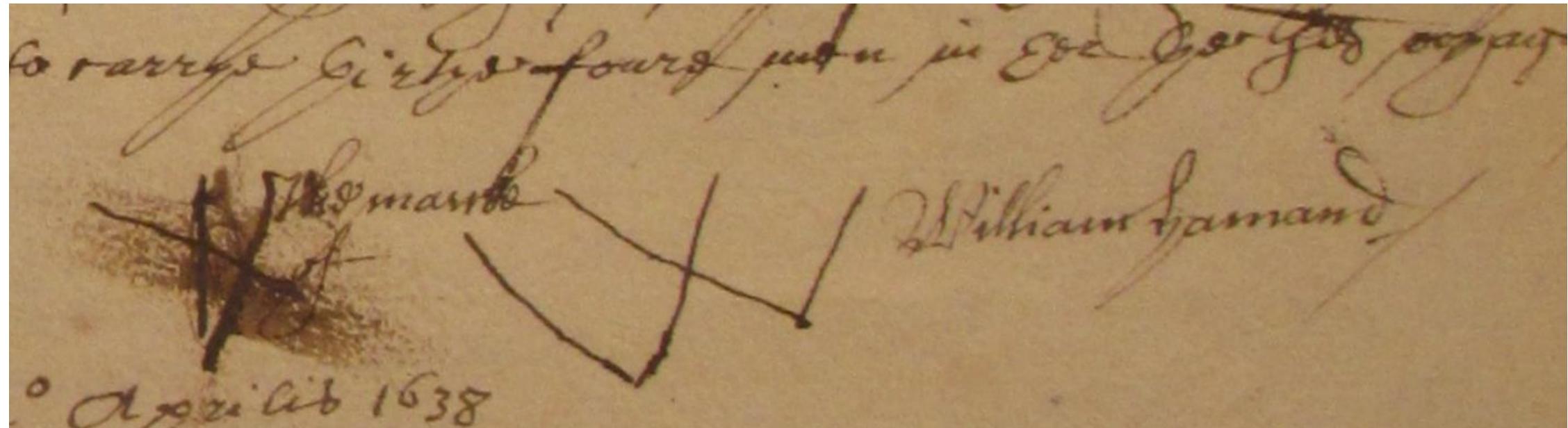
Source: Clockwise from top LH side: KaggleTestSnippet\_HCA\_1370\_f.7r.PNG, KaggleTestSnippet\_HCA\_1370\_f.37r.PNG, KaggleTestSnippet\_HCA\_1353\_f.10r.PNG, KaggleTestSnippet\_HCA\_1353\_f.29v\_Two.PNG, KaggleTestSnippet\_HCA\_1373\_f.102r.PNG, KaggleTestSnippet\_HCA\_1354\_f.3r.PNG, KaggleTestSnippet\_HCA\_1353\_f.42v.PNG

## Data: Unusual signatures (2)

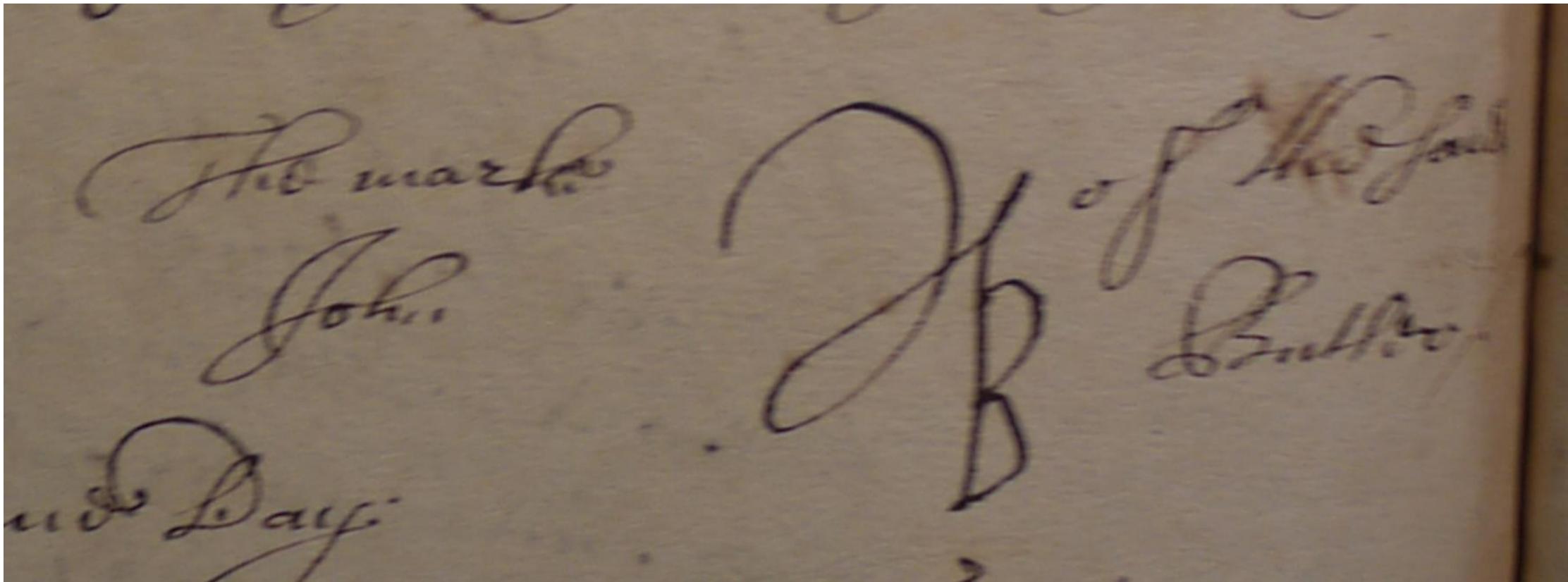


Source: Clockwise from top LH side: KaggleTestSnippet\_HCA\_1370\_f.98r.PNG.PNG, KaggleTestSnippet\_HCA\_1370\_f.221v.PNG, KaggleTestSnippet\_HCA\_1370\_f.345v\_One.PNG, KaggleTestSnippet\_HCA\_1353\_f.118v\_One.PNG, KaggleTestSnippet\_HCA\_1362\_f.3v\_One.PNG

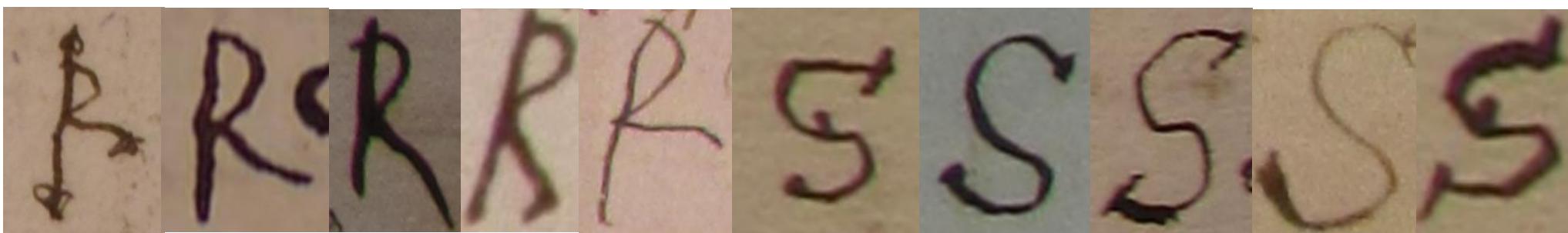
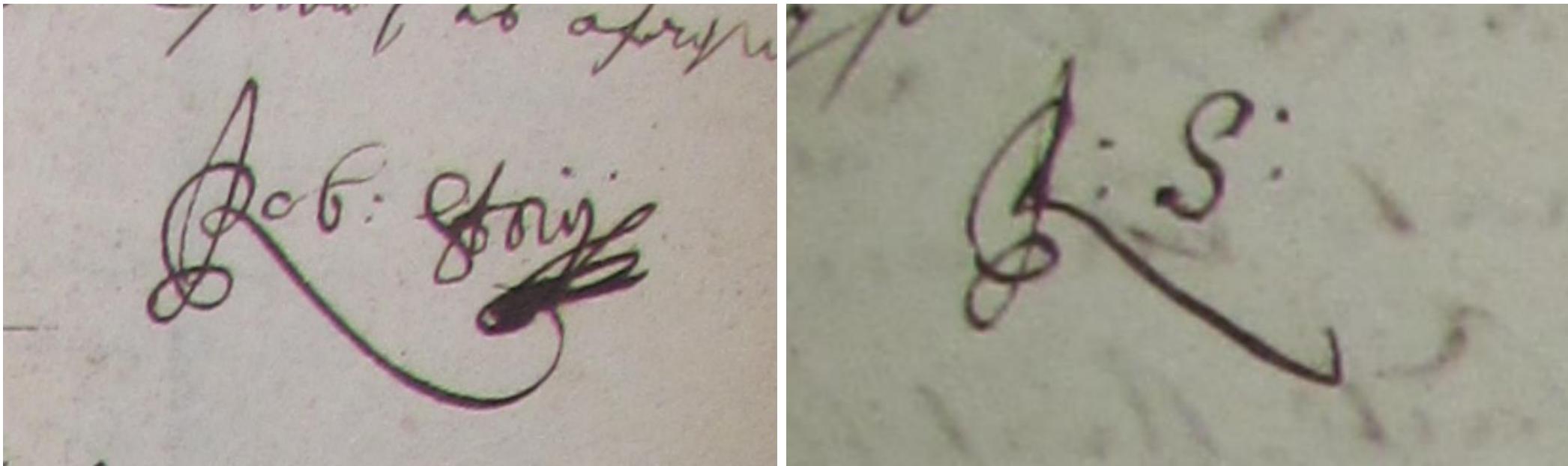
Data: Notarial comments “the marke” (or more commonly “the marke of”) – in this case clearly the markes of William Hamand were added after the notary’s comments



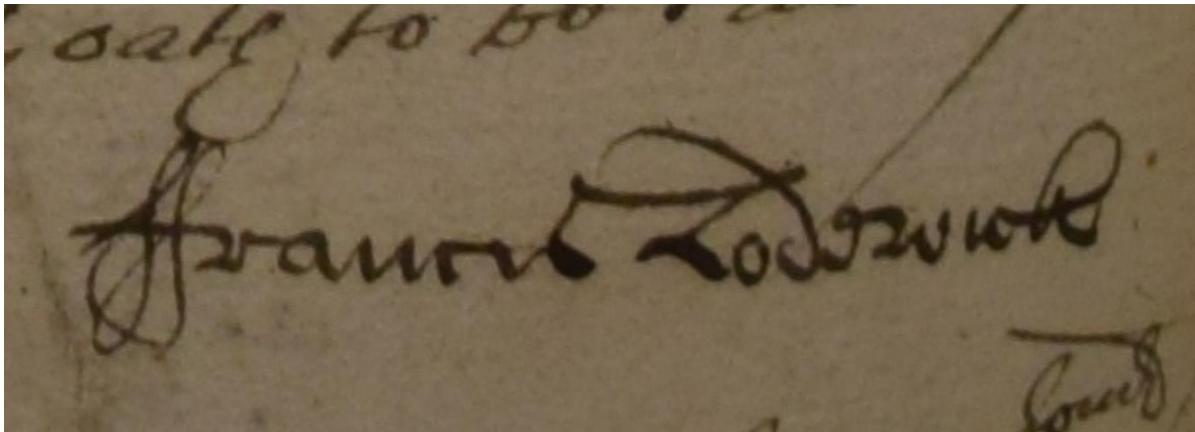
Data: Rare case of combined lower case and upper case initials



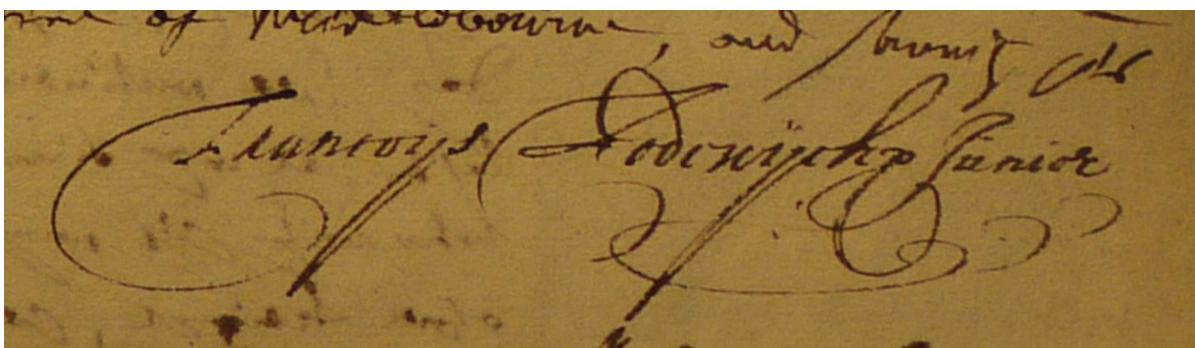
Data: Rare case of individual capable of a sophisticated signature and flourish using initials to acknowledge a marginal insertion in his deposition; contrast with pure initials



## Data: Two ffrancis Lodwick's (1637 & 1656) - father & son?

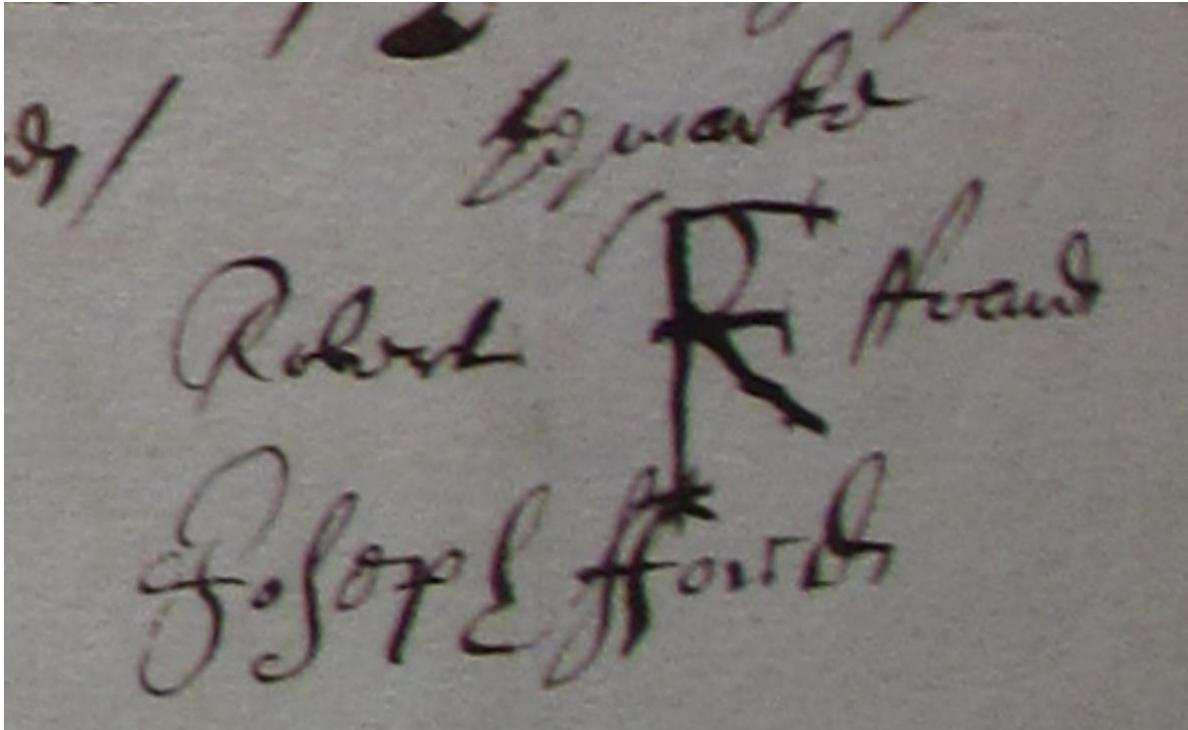


**ffrancis Lodwicke** of the parishe of Saint George Bottulph Lane  
London merchant aged about 38 yeares [April 5<sup>th</sup>, 1637]



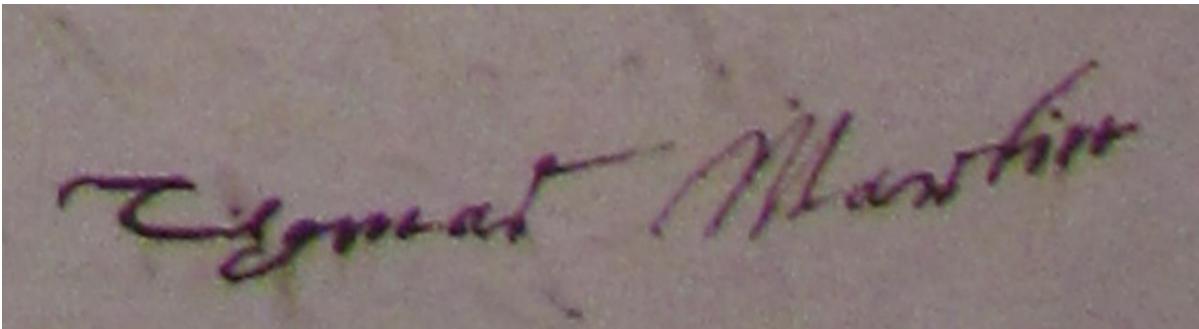
The claime of the afore said Vander Goos in the *Hare in the ffeild*...**Francis Lodwick junior** of London merchant aged 24 years...hee well knoweth the producent Marcello Vander Goos and hath so donne for theise nine yeeres last or thereabouts, this deponent for all that time (and even from his birth till about two years since that hee came to dwell in London) living in Middleborowe [Deposed on Feb 22<sup>nd</sup> 1656]

Data: Two presumably related mariners from Ipswich, one signing with initials & one with a signature

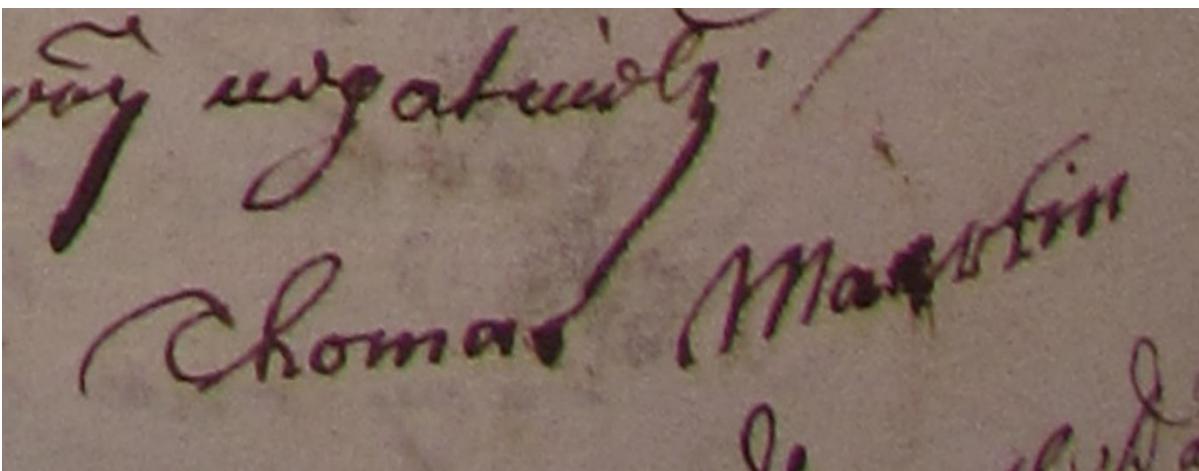


An affidavit made by **Robert ffoard** of Ipswich in the county of Suffolke mariner and **Joseph ffoard** of the same mariner touching certaine anchors and tackle belonging to a certaine hoye called the *Richard* of Ipswich cast awaye neere a place called the Shoe [December 38<sup>th</sup> 1654]

Data: Two presumably related mariners from Redriff in Middlesex, signing with distinct signatures

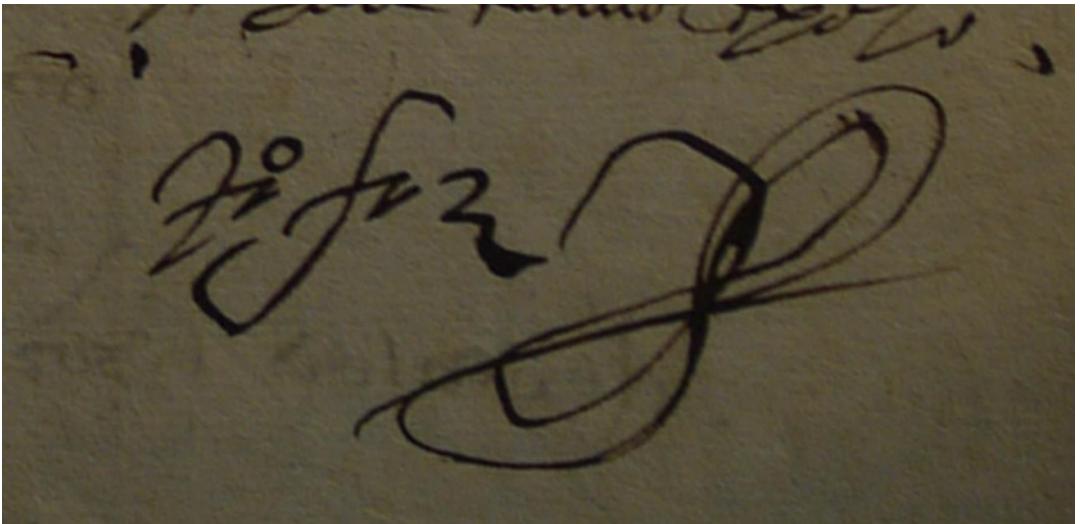


**Thomas Martyn** of Redriffe in the county of Middlesex maryner aged 48 yeares or thereabouts... hee was one of the Company of the shipp *Dove* whereof Walter Cable was and is master the voyage in question which was about the beginning of August last past [January 5<sup>th</sup> 1655]

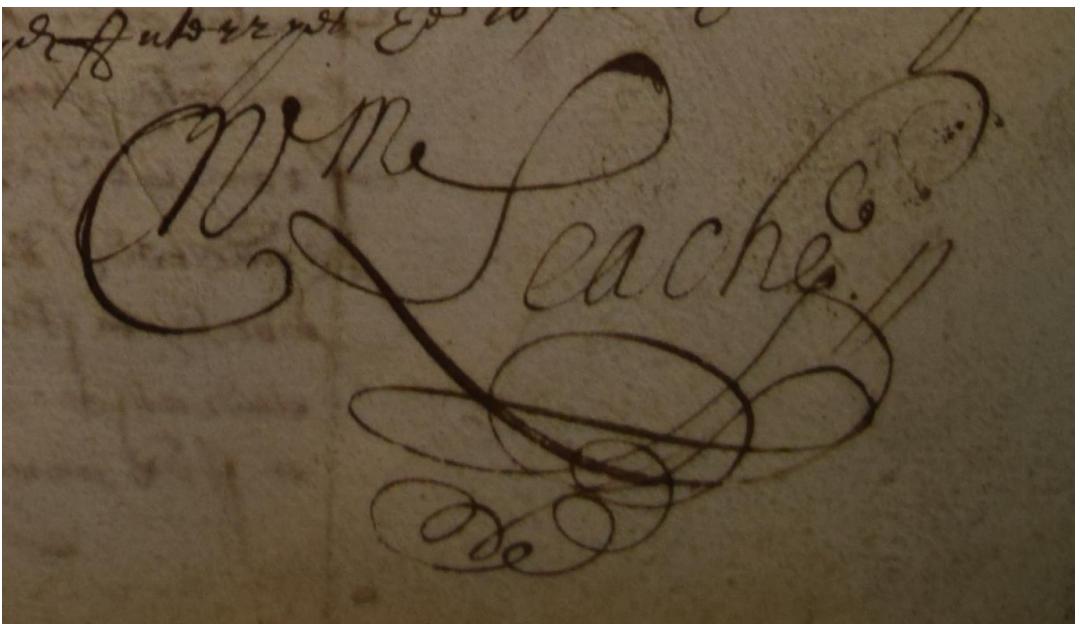


**Thomas Martyn the younger** of Redriffe in the county of Middlesex maryner: aged 16 yeares or thereabouts...which this deponent knoweth being one of the company of the said shipp *Dove* and being on board her all the said voyage [January 5<sup>th</sup> 1655]

## Data: Flourishes of differing technical proficiency

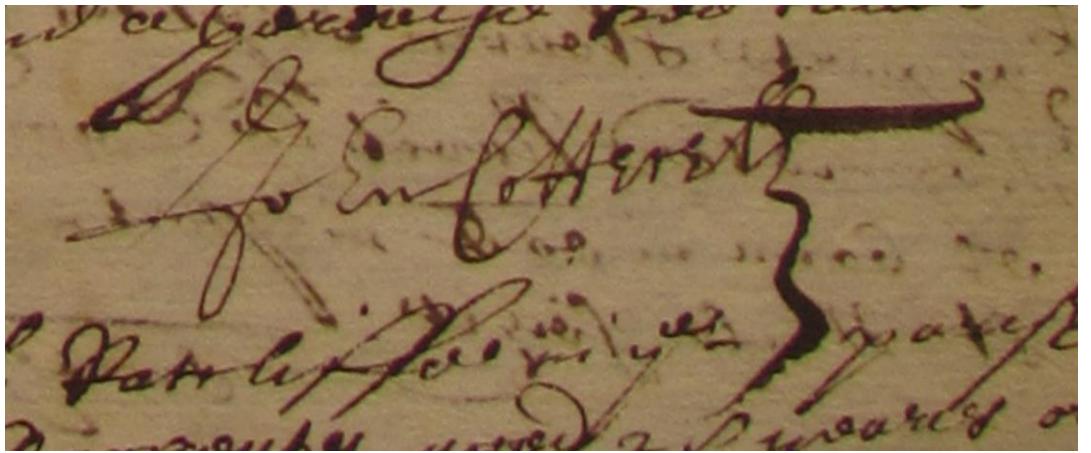


xxxx

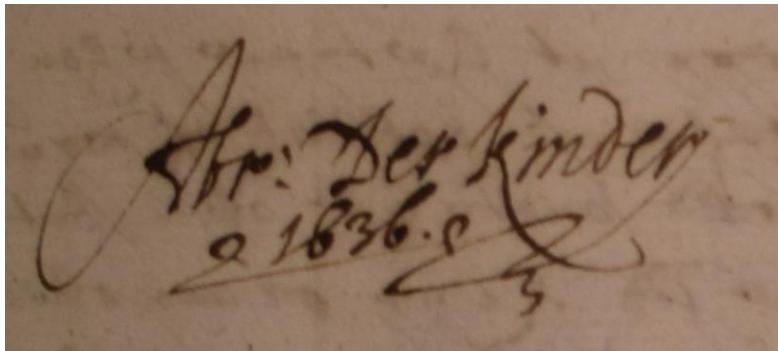


**William Leache** of the parishe of Saint Ethelborowe London gouldsmyth  
aged about 36 years  
[Deposed on February 6<sup>th</sup> 1637]

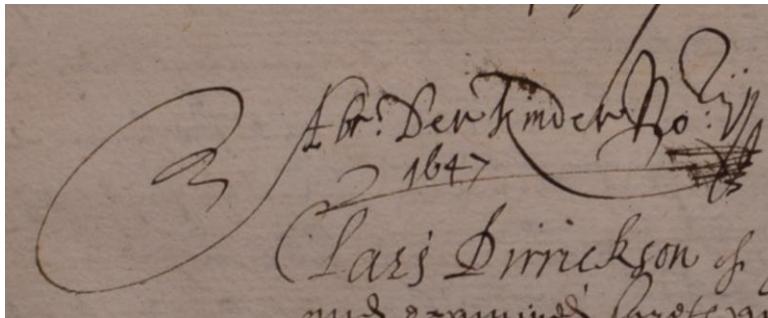
## Data: Hard to isolate signatures



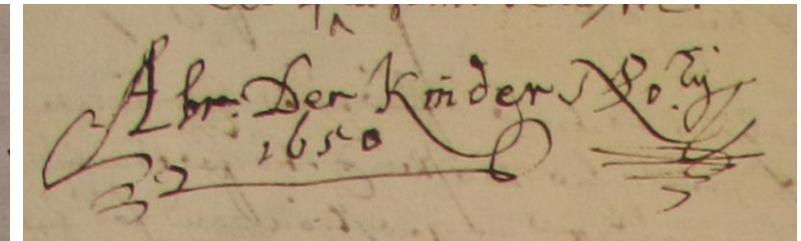
# Data: Deterioration in signature of a notary with age, 1636, 1637, 1647 & 1650?



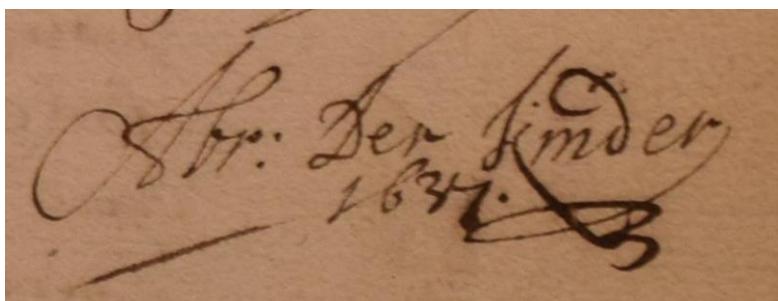
Abt. Der Kinder  
1636.



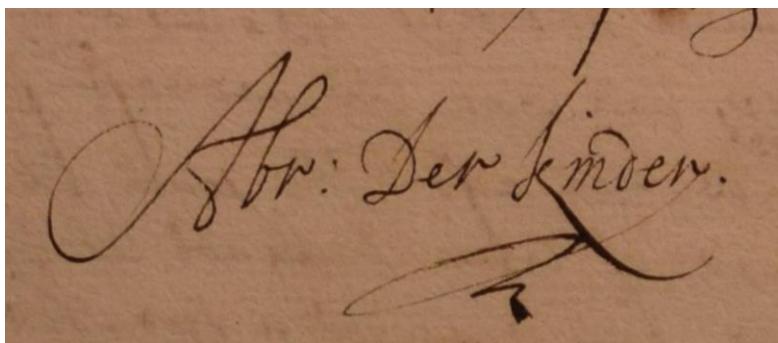
Abt. Der Kinder Ro:ij  
1647  
Lars Dirickson of  
and Annaes Andersen



Abt. Der Kinder Ro:ij  
1650



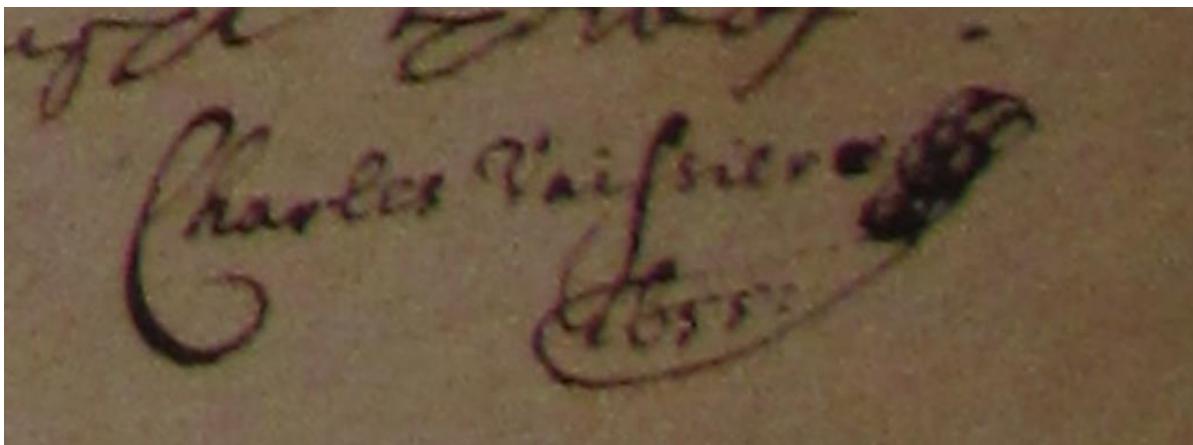
Abt. Der Kinder  
1637.



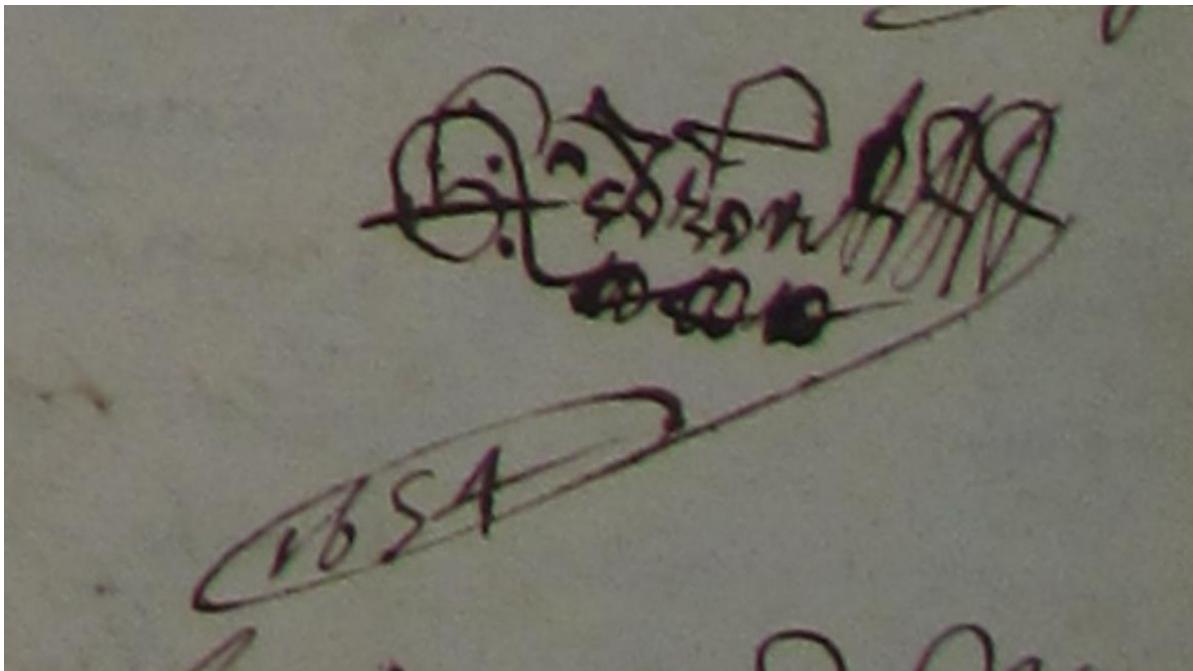
Abt. Der Kinder.

Source: KaggletestSnippet\_HCA\_1353\_f.68r\_Two.PNG, KaggleTestSnippet\_HCA\_1353\_f.219r\_One.PNG, KaggleTestSnippet\_HCA\_1353\_f.228r\_Two.PNG,  
KaggleTestSnippet\_HCA\_1362\_f.4r\_Two.PNG, KaggleTestSnippet\_HCA\_1363\_f.311v\_Two.PNG

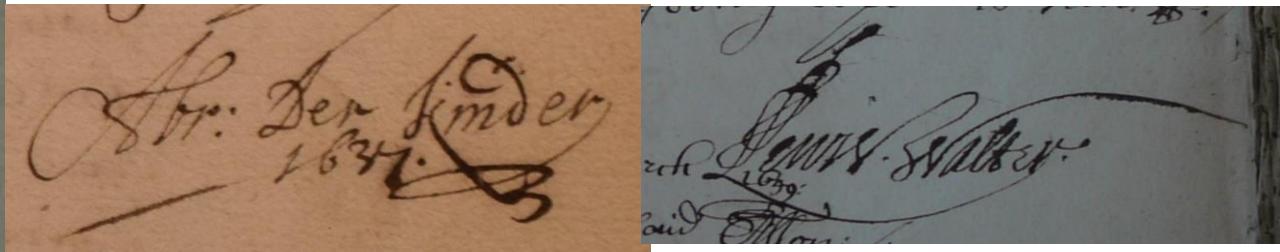
## Data: Dates incorporated into signature



**Charles Vaissiere** of London Merchant aged 25 yeares or thereabouts  
[July 18<sup>th</sup> 1655]



**Hervey Pedron** of Penarf in Bretany in the Realme of ffrance mariner,  
aged 50 years  
[December 14<sup>th</sup> 1654]



# **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 marks in historical manuscripts as the basis for sub-population recognition, March 2018 [available Signsoliteracy Github repository: Signsoliteracy/Signoff]

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

[Mark Hailwood, 'The Rabble that Cannot Read', Ordinary Peoples Literacy in Seventeenth-Century England, October 13<sup>th</sup>, 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](https://doi.org/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

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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.

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http://doi.acm.org/10.1145/2886099

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Additional Key Words and Phrases: Texture Synthesis, Handwriting, Generative Models

ACM Reference Format:

Haines, T. S. F., Mac Aodha, O., and Brostow, G. J. 2016. My Text in Your Handwriting. ACM Trans. Graph. 35, N, Article XXXX (XXXX), 15 pages.

1. INTRODUCTION

The worldwide adoption of digital messaging has given handwritten communication a new lease of life. It is a personal, intimate, and personally expressive message, but what can an author do if it is not their own handwriting? Can they still express their intent by impacting their style and letting the legibility of their messages? Handwriting is a complex skill, and there are two main ways to learn it [Brostow et al. 2011] represent two families of solutions that may help, but look obviously synthetic. One problem algorithm is a new alternative solution that uses a computer to print the text in a specific original pen-on-paper handwriting style.

An alternative solution is for an end-user to annotate an author's historical handwriting sample and follow a simple principle called imitation. The user can then ask us to synthesize any

new text that they like into handwriting that looks like it.

Figure 1 shows a message synthesized after our original author learned the handwriting style of another Arthur Conan Doyle.

Real-world scenarios are similar and those shown include personal messages, but they are rendered in an impressive font.

Computer games are another application of this technology.

Sensitive materials, such as credit cards, can be interpreted when they are handwritten, so it is important to be able to synthesize handwriting, which can be improved. Graeme [2003] demonstrates how to synthesize handwriting from a photograph to increase the response rate from 33% to 70% – more than double.

Our work is the first contribution to the design of a system that can generate text in a specific handwriting style, and it is the first to demonstrate its adoption in a specific scenario.

We perform a pose-based user study and demonstrate an approach that is able to synthesize handwriting in a specific style and font.

This approach is also flexible. Handwriting is simply scanned from a page and the system performs a series of steps to analyze and synthesize the scanned samples. Samples may be joined up (cursive), print (blocky), or have ligatures (joined letters). The system can either than fill out a grid with isolated letter sequences of letters, or scan a page with a grid of letters and then synthesize the overall writing of historic figures, as demonstrated by Figure 1. The realism of the synthesized writing is measured through a study of a specific person's style, and the apparent authenticity of the written document is measured through a study of the visual quality of the output. We provide extensive experimental results, most of which are in the video and supporting material.

Our generative model is built around glyphs. From training samples, the system extracts features such as stroke order, character classes, inter-character ligatures, pen-line texture, and vertical/horizontal spacing. It bears some resemblance to non-synthetic handwriting, but it is not a copy of the original handwriting. To enable synthesis, our system also includes a semi-supervised, near-linear method for tagging handwriting in a training image.

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Haines, T. S. F., Mac Aodha, O., and Brostow, G. J. 2016. My Text in Your Handwriting. ACM Trans. Graph. 35, N, Article XXXX (XXXX), 15 pages.

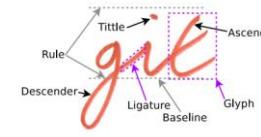


Fig. 2. Glossary of the key parts of handwritten text.

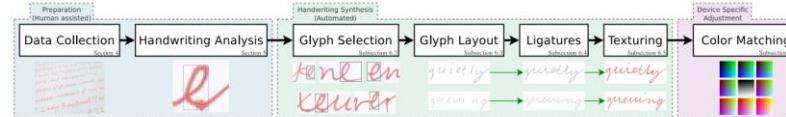


Fig. 4. System diagram showing our processing pipeline, with representative images for each stage. After samples are collected and analyzed, the rendering system selects a glyph to represent each character, e.g. "e" as shown here. If there are many choices, it must choose one that fits the surrounding 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 transferred from the original input to the vector output and, if being printed, color correction is applied.

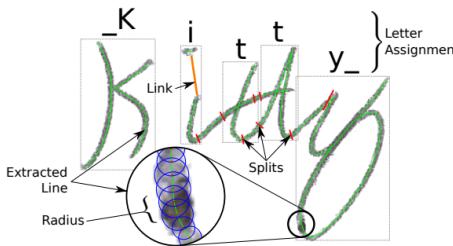


Fig. 5. Visualization of the output of the tagging process. The line is vectorized, and has radius calculated at every pixel along it. Not shown is the ink density, which is also calculated for every pixel as the average within the circle defined by the radius. The line forms a graph, to which splits 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.

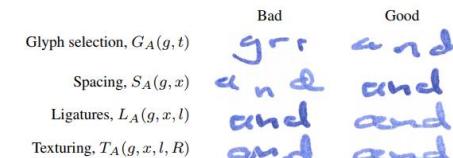


Fig. 8. Synthesis of the word "and", demonstrating what each component of the cost function does. All steps are dependent on the author's specific style, e.g. here we show that having ligatures is preferred, but if the author has print handwriting then the inclusion of ligatures would be wrong. Note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

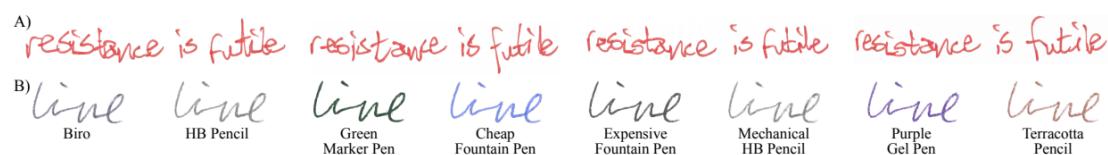


Fig. 10. A) Same sentence generated multiple times, to demonstrate output variability. The first instance is the maximum likelihood output, which would otherwise be returned every time. B) Line replacement, where one writing implement is replaced with another. First on the left is the source with the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

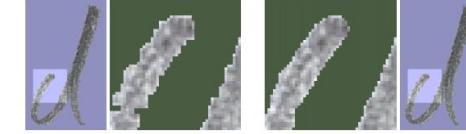


Fig. 6. Segmentation on the left shows the graph cuts result without line aware smoothing. The right side shows the improvement of smoothing. Writing implement is a pencil.

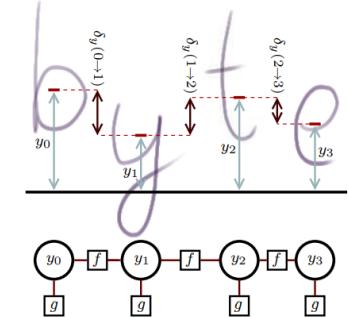


Fig. 12. Factor graph of Kalman smoothing, used to ensure the synthesized text flows. The  $y_i$  random variables (circles) indicate how far off the baseline to position each glyph. Factors (squares) indicate probabilities over the random variables to which they are connected. Kalman smoothing finds 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,  $\delta_y$ , 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.

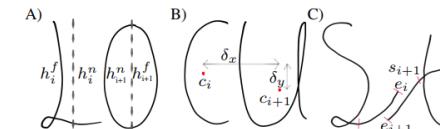


Fig. 11. A) The near-far labeling scheme for halves of a glyph, as used for the distance learning feature. B) Two glyphs, "c" and "u", with their centers ( $c_i$  and  $c_{i+1}$ ) and the horizontal ( $\delta_x$ ) and vertical ( $\delta_y$ ) offsets between them marked. C) Two glyphs, "s" and "t", with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

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!



## Reading

*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

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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)

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

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# Reading

## Labeled Faces in the Wild



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### 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.

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# Reading

## Siamese Convolutional Neural Networks for Authorship Verification

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### 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.

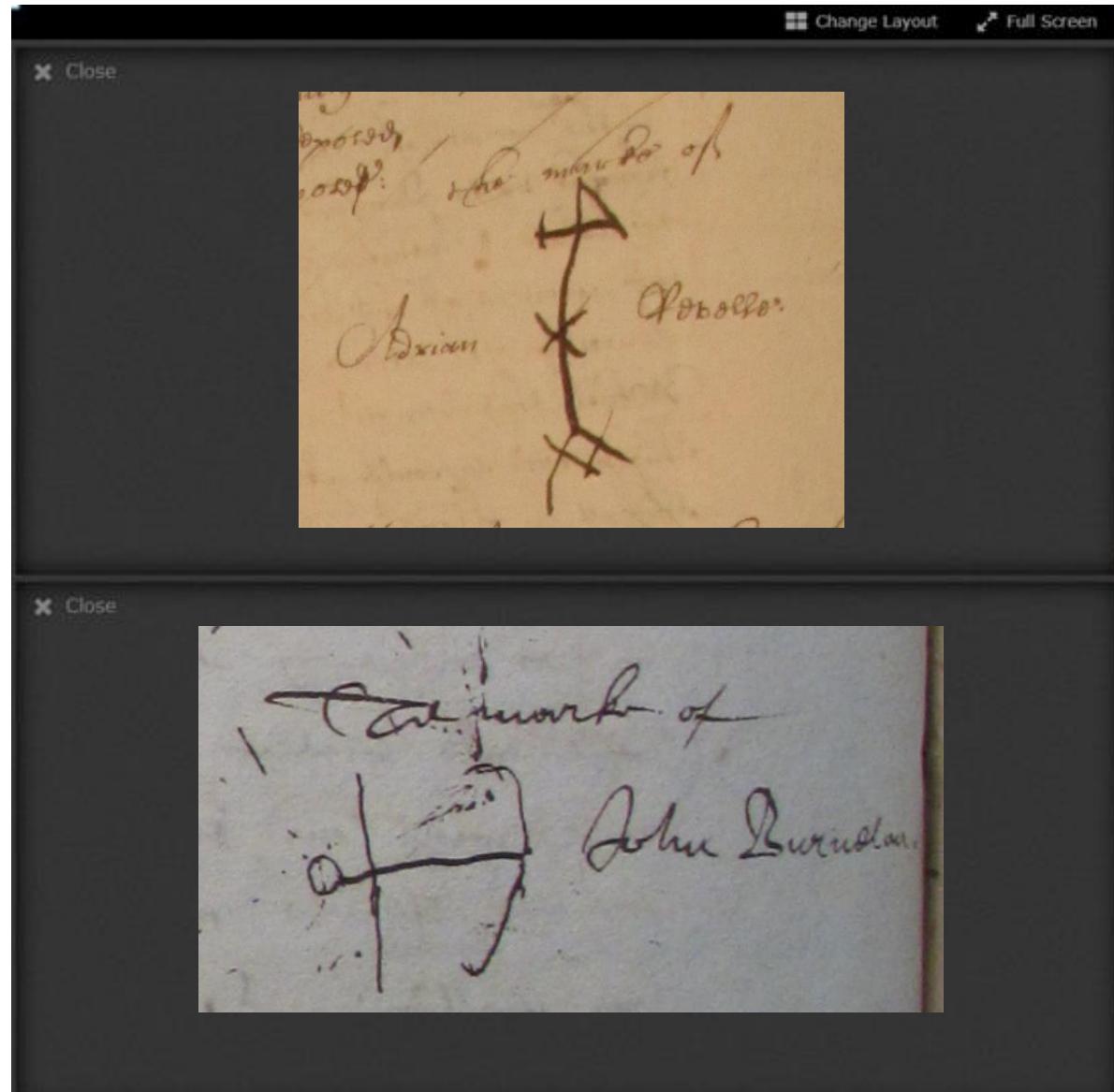
### 2. Background and Related Work

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

The screenshot shows a browser extension for the David Rumsey Map Collection. At the top, it says "David Rumsey Map Collection - MapTab" with a "ADD TO CHROME" button. Below that is a map of the United States with a red arrow pointing from the West Coast to the East Coast, labeled "7:44 AM". The date is "Tuesday, September 29, 2015". To the right of the map is a sidebar with "Runs Offline" and "Compatible with your device" checkboxes, a description of the extension, and links to "Report Abuse", "Additional Information", "Developer", and "Privacy Policy". Below the map are sections for "OVERVIEW", "REVIEWS", "SUPPORT", and "RELATED". The "RELATED" section shows thumbnails for "National Gallery of Art Collection Highlights" (featuring Vincent van Gogh's self-portrait) and "Self-Portrait Dedicated to Paul Gauguin" (featuring another self-portrait by van Gogh).



Adrian Revele,  
twenty-three year  
old mariner, of  
Dunquirke in  
fflanders, November  
12<sup>th</sup>, 1653; "hee  
only speaketh the  
flemish speech"  
(HCA 13/68 f.183v)

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