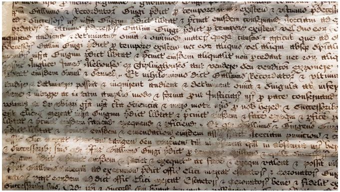
AI: fact and fiction

Ron Wehrens

September 27, 2023

Biometris
Wageningen University & Research

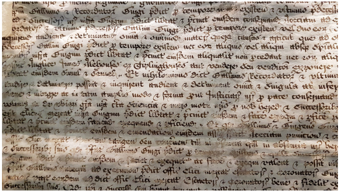
Decyphering example



Goal:

- Find the decoding table!

Decyphering example



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Approaches:

- Letter frequencies (Al-Kindi, 850AD, Iraq)

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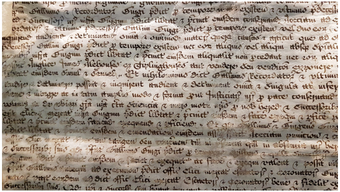


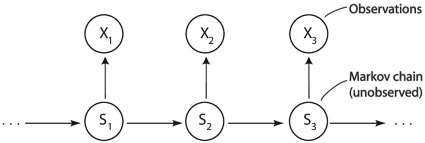
Goal:

- Find the decoding table!

Approaches:

- Letter frequencies (Al-Kindi, 850AD, Iraq)
- Frequencies of letter combinations

Demo 1



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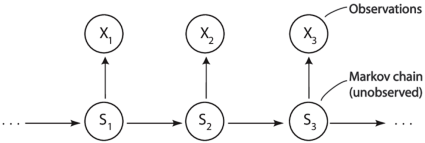

- Transition table based on 86743 characters
- Test string:
  528 characters
  (first two paragraphs)
- EM algorithm,
  100 iterations

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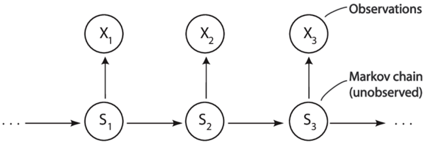

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  528 characters
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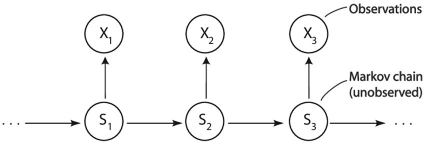
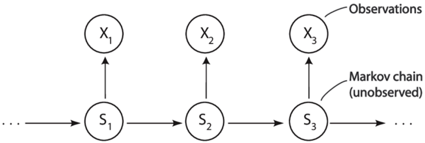
```
jevel and a core us cror
the ckeld collofang the s
ath an sanghe cale anthou
gh a ar casthen cket thea
d of har andone fatchang
us cror the coutongoupe c
an see jevels crayed and
broven sthat hat a full h
ead above ry oun the sath
 qund sthanght as a squll
```

Demo 2



- Same as Demo 1, but...
- Test string:
  7144 characters
  (first two chapters)

Demo 2



- Same as Demo 1, but...
- Test string: 7144 characters (first two chapters)

```
jewel and i come up from
the field following the p
ath in single file althou
gh i am fifteen feet thea
d of him anyone watching
us from the cottongouse c
an see jewels frayed and
broken straw hat a full h
ead above my own the path
 juns straight as a plumb
```

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- AI models:
  - flexible structure - fits all
  - completely determined by the data
  - example: neural networks

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  - flexible structure - fits all
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  - example: neural networks
- Causal models:
  - maths describing causality
  - very few data needed (if any)
  - example: physical laws
- Statistical models:
  - maths describing correlation
  - data essential
  - example: regression line

AI successes

- Chess, go, poker, ...

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- Object recognition

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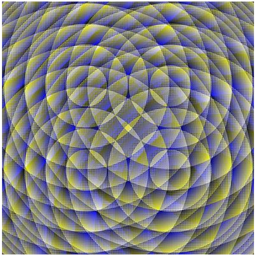

Applications in agriculture and horticulture

frontiers in Plant Science

ORIGINAL RESEARCH
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doi: 10.3389/fpls.2020.571299

Check for updates

Tomato Fruit Detection and Counting in Greenhouses Using Deep Learning

Manya Afonso[1], Hubert Fonteijn[1], Felipe Schadeck Fiorentin[1], Dick Lensink[2], Marcel Mooij[2], Nanne Faber[2], Gerrit Polder[1] and Ron Wehrens[1]*

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agronomy

MDPI

Article

Automatic Phenotyping of Tomatoes in Production Greenhouses Using Robotics and Computer Vision: From Theory to Practice

Hubert Fonteijn [1,*,†], Manya Afonso [1,†], Dick Lensink [2], Marcel Mooij [2], Nanne Faber [2], Arjan Vroegop [3], Gerrit Polder [3] and Ron Wehrens [1]

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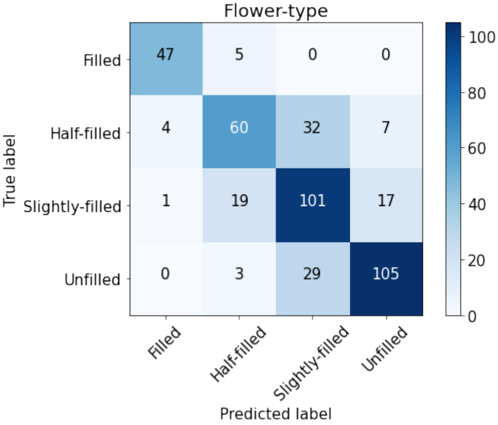
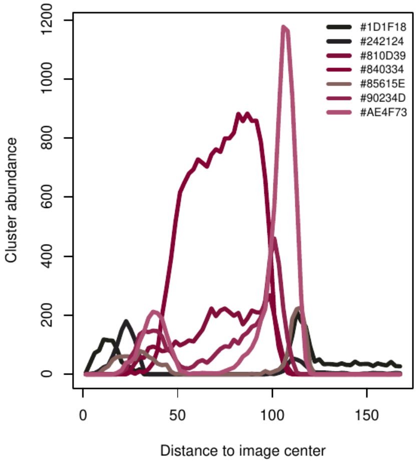
Automatic Trait Estimation in Floriculture using Computer Vision and Deep Learning

Manya Afonso[a], Maria-João Paulo[a], Hubert Fonteijn[a], Mary van den Helder[b], Henk Zwinkels[b], Marcel Rijsbergen[c], Gerard van Hameren[c], Raoul Haegens[c], Ron Wehrens[a]

Flower traits: gerbera flower type



Color traits



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- Problem difficulty hard to predict
- Gross errors are possible
- Data biases
- If bespoke solutions are available...

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- What do we need, exactly?
- AI advantages: performance, speed, flexibility, ...
- Data availability: bottleneck