Transkribus User Conference 2018 - Vienna (Austria)

Indexing and Searching of Manuscript Collections

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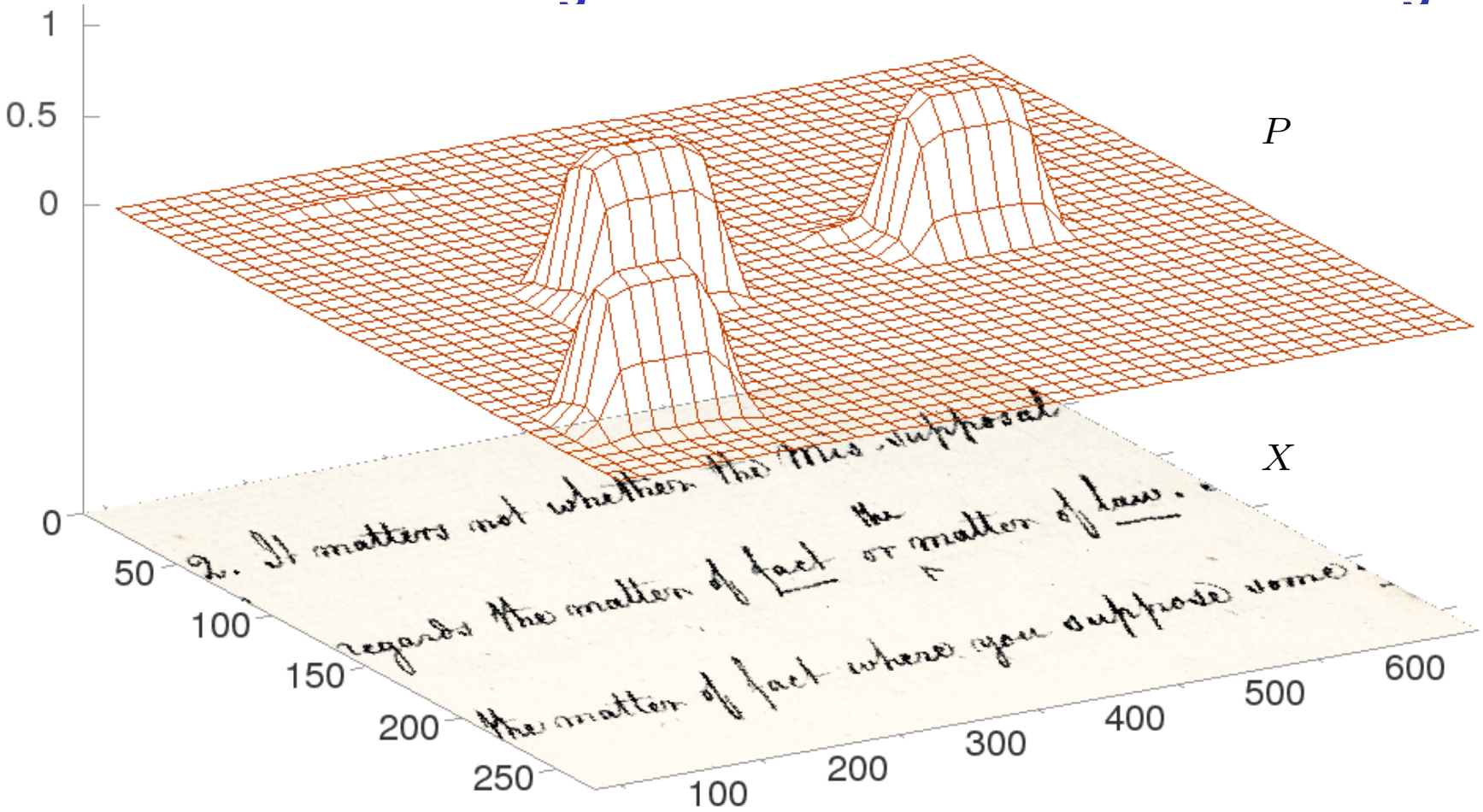
Outline

Textual access to Untranscribed Manuscripts

- Massive text image collections have been compiled by libraries and archives all over the world, but their textual content remains practically inaccessible
- If perfect or sufficiently accurate text image transcripts were available, image textual context could be straightforwardly indexed for plaintext textual access.
- But manual or even interactive-predictive, assisted transcription is entierely prohibitive to deal with massive image collections
- And fully automatic transcription results lack the level of accuracy needed for useful text indexing and search purposes

Good news: *indexing and textual search* can be directly carried out on *untrascribed images*, as we will see now.

Handwritten Text Indexing and Search: Pixel-level Posteriorgram



Pixel-level posterior probabilities (P) for a text image X and word $v =$"**matter**".

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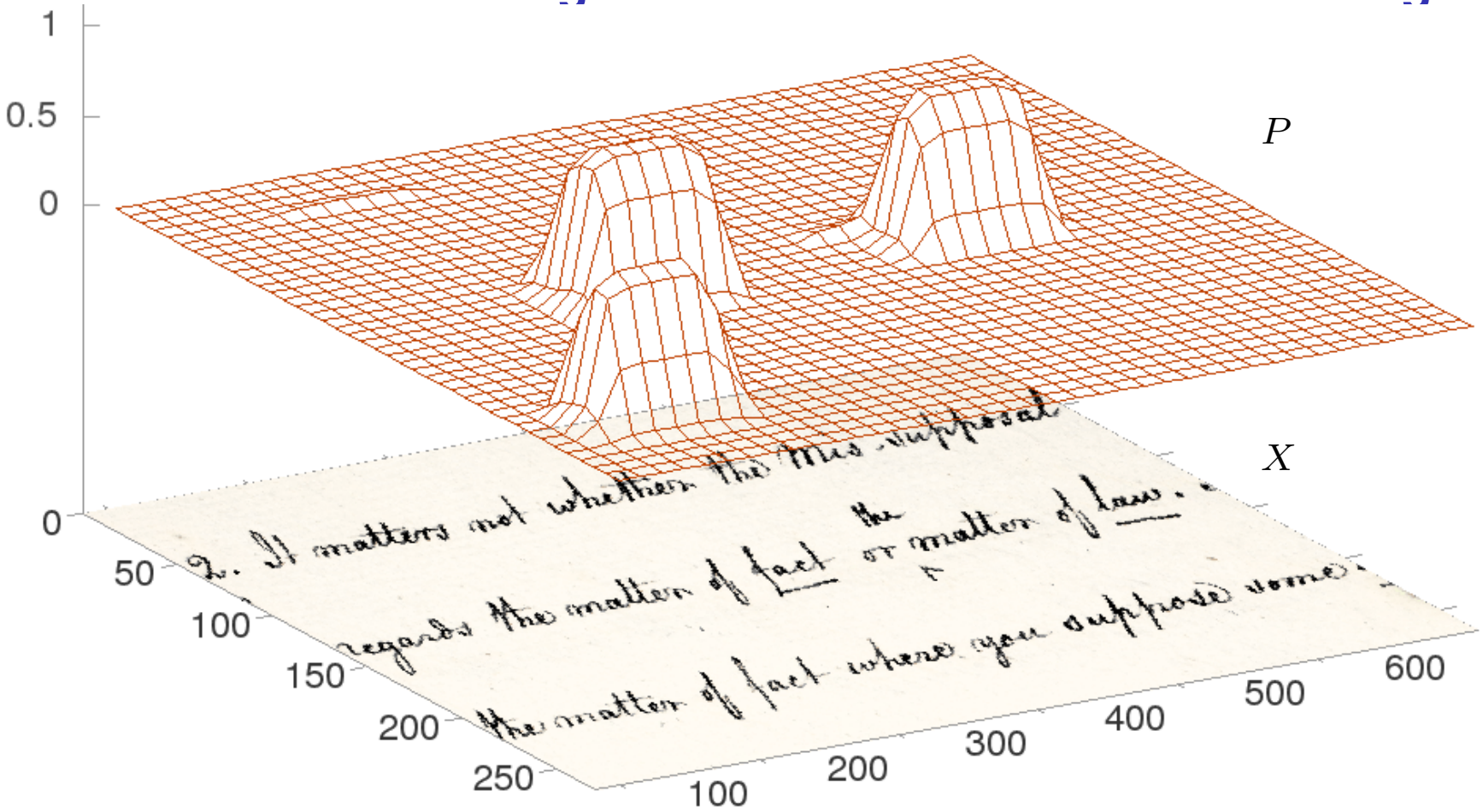
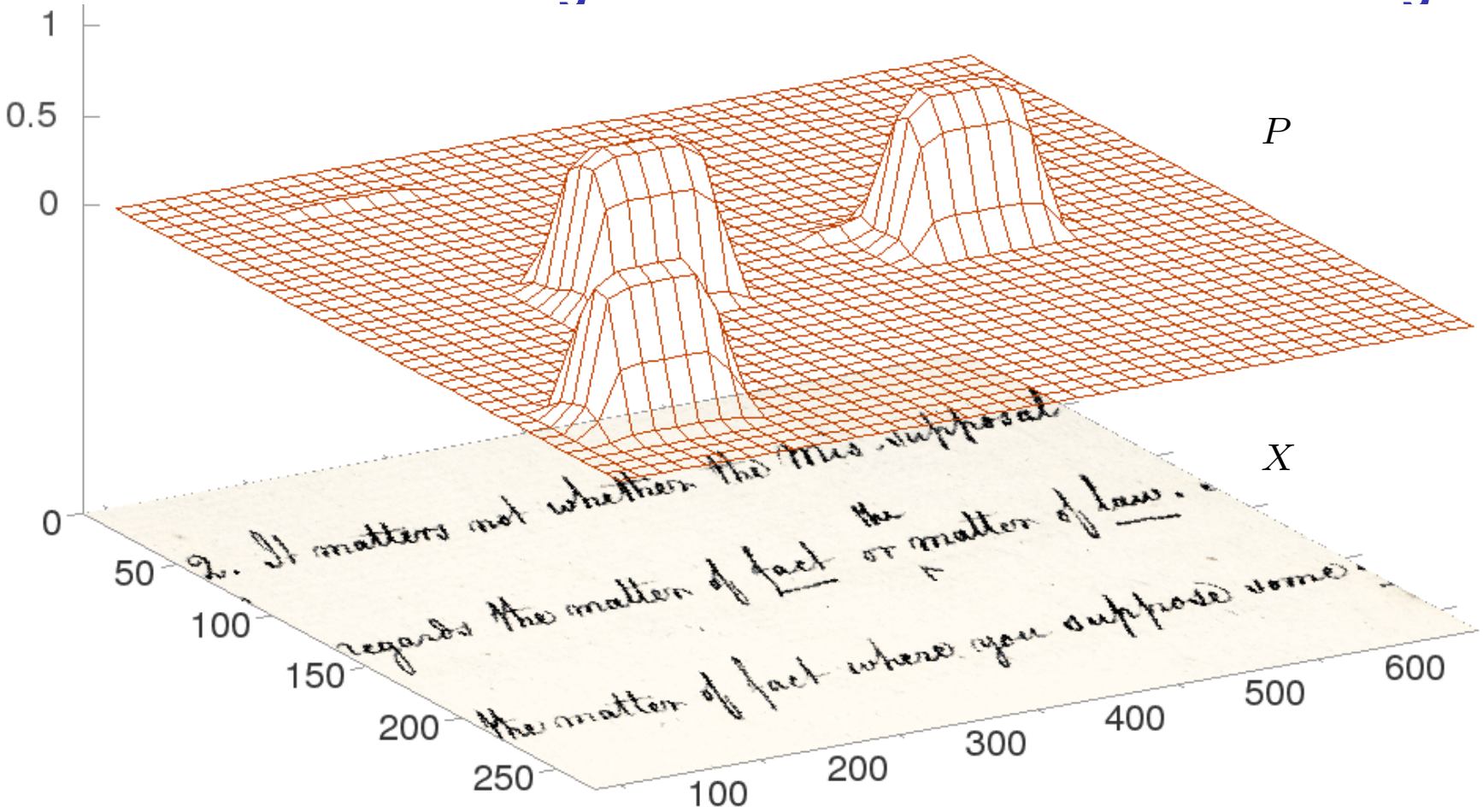


Pixel-level posterior probabilities (P) for a text image X and word $v =$"**matter**".

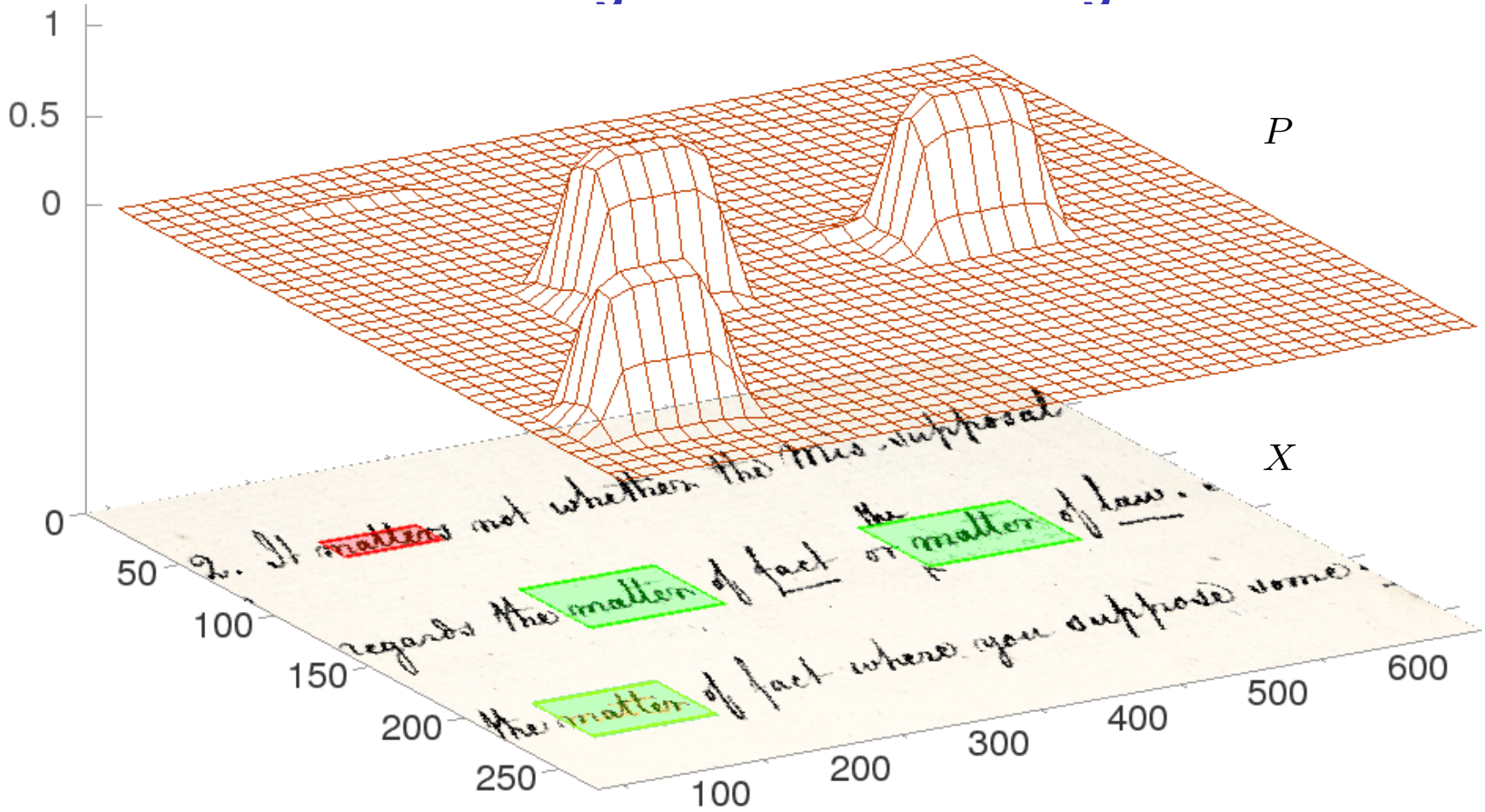
To compute P an accurate, contextual (n-gram based) *word classifier* can be used. In this example, this helped to achieve very low posteriors in a region of X around $(i = 100, j = 60)$, where a very similar (but *different*) word, "**matters**", is written.

Handwritten Text Indexing and Search: Pixel-level Posteriorgram



Directly computing and using a full pixel-level posteriorgram would entail a formidable computational load and would require prohibitive amounts of indexing storage.

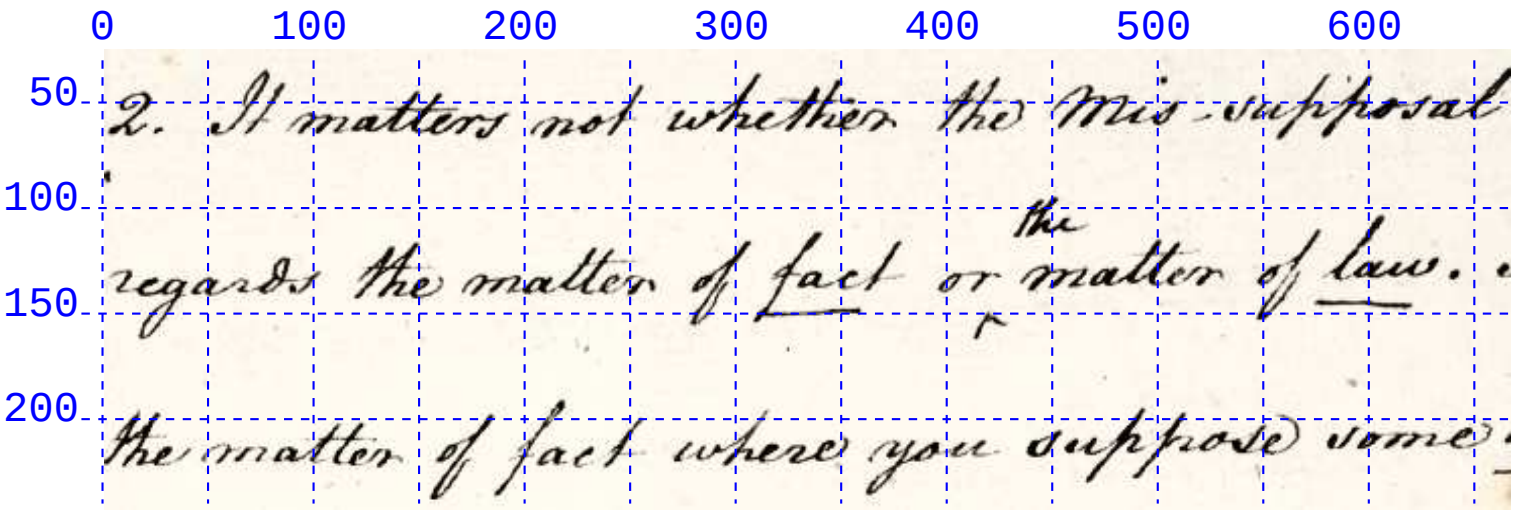
Probabilistic Word Indexing from the Posteriorgram



Directly computing and using a full pixel-level posteriorgram would entail a formidable computational load and would require prohibitive amounts of indexing storage.

But, for each word, image region *relevance probabilities* and *locations* are easily derived from the Posteriorgram – and used to probabilistically index the word in an efficient way.

Lexicon-free Probabilistic Index: Example




```
# pageID="Bentham-071-021-002-part"
#    keyword relPrb    bounding box
#
          2  0.929    1  36  20 31
         21  0.064    1  36  24 31
         IT  0.982   33  36  27 31
         IF  0.012   33  36  26 31
    MATTERS  0.989   77  36  99 31
     MATTER  0.011   77  36  93 31
        NOT  0.999  216  36   7 31
    WHETHER  1.000  256  36  99 31
        THE  0.997  389  36  33 31
MIS-SUPPOSAL 1.000  455  36 193 31

        THE  0.927  430  88  30 31
        LHE  0.056  434  88  25 31
        ...  ...      ...     ...
```

```
REGARDS  0.857    5 115  84 31
UGARDS   0.138    5 115  80 31
   THE   0.993  110 115  43 31
MATTER   0.998  160 115  93 31
    OF   0.996  271 115  23 31
  FACT   0.999  306 115  49 31
    OR   0.973  377 115  37 31
    ON   0.021  377 115  42 31
MATTER   0.990  425 116 100 31
    OF   0.995  542 115  25 31
   LAM   0.407  575 115  30 31
  BIMR   0.175  575 115  55 31
   ...   ...      ...     ...
   LAW   0.032  575 115  36 31
  TAUE   0.031  575 115  55 31
   ...   ...      ...     ...
  LANE   0.012  575 115  59 31
```

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   THE  0.990    1 198  28 31
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    OF  0.988  141 198  28 31
  FAST  0.367  182 198  62 31
   FAR  0.186  182 198  36 31
   ...  ...      ...     ...
  FACT  0.017  182 198  46 31
    AS  0.142  200 198  29 31
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  GOUS  0.064  372 198  47 31
SUPPOSE 0.975  429 198 120 31
SUPFROSE 0.024 429 198 125 31
  SOME  0.834  570 198  78 31
 SONER  0.016  576 198  83 31
   OME  0.109  580 198  65 31
    ME  0.022  620 198  22 31
```

All character strings or “pseudo-words” which are likely enough to be real words are indexed.

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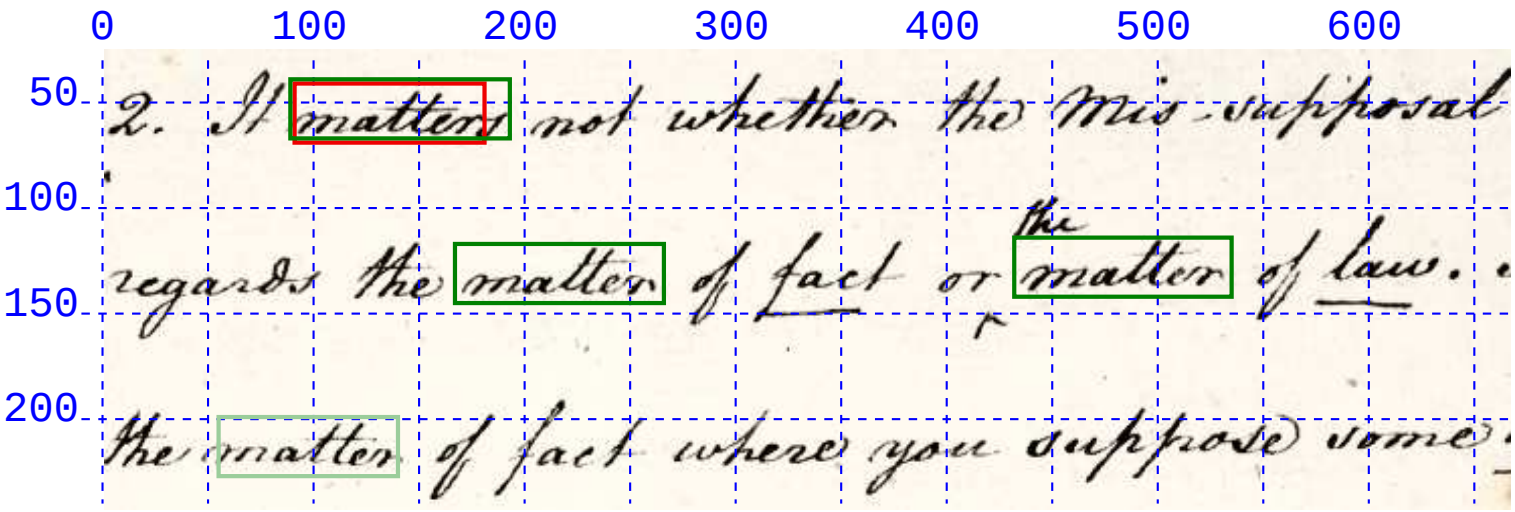


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```
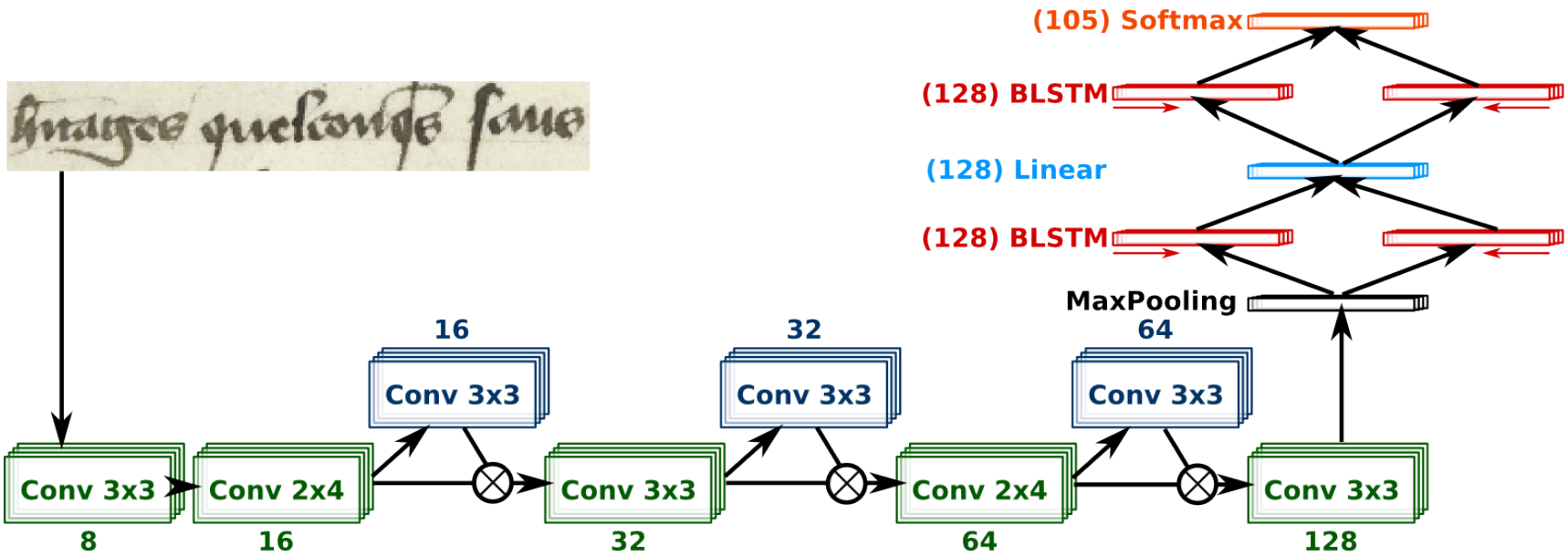
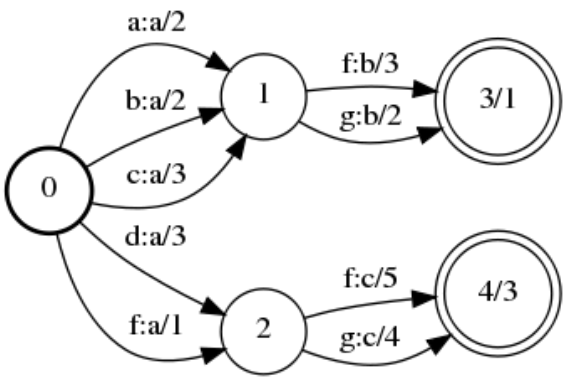

Spots for **MATTER** and **MATTERS** marked in colors according to their Relevance Probabilities.

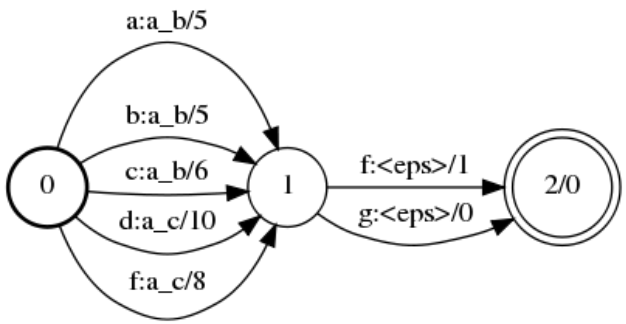
Technologies Involved

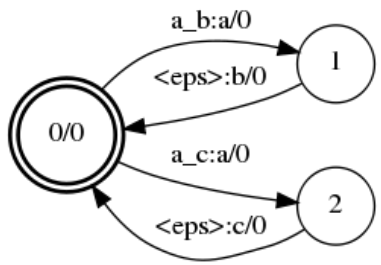
- Optical modelling: Deep CNN-RNN network:



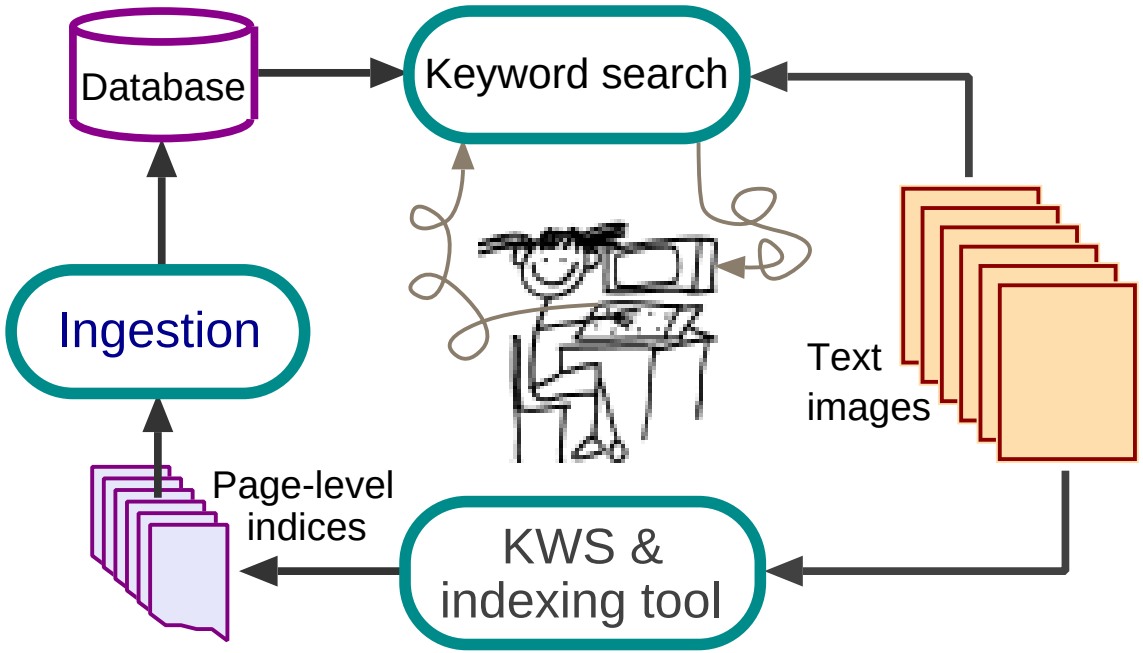
- Textual context modelled by finite state character n-grams.







Probabilistic Text Image Indexing and Search: System Diagram



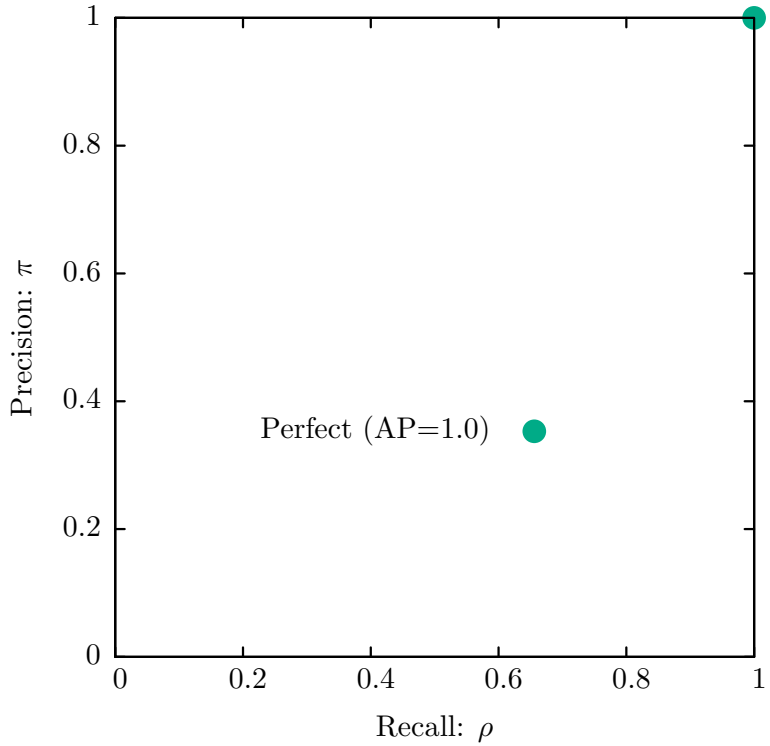
- *"KWS & indexing tool"*: Off-line pre-computation of probabilistic indices
- *"Ingestion"*: Off-line creation of the actual database. Typically a simple and computationally cheap process
- *"Keyword search"*: On-line user query analysis, find the requested information and present the retrived images. Short response times needed.

Probabilistic Indexing & Search: Precision-Recall Tradeoff Model

Indexing and search quality can be assessed by means of *precision* (π) & *recall* (ρ) performance.

Precision is high if most of the retrieved results are correct while recall is high if most of the existing correct results are retrieved.

If perfectly correct text were indexed, you'd get a single, "ideal" point with $\rho = \pi = 1$.



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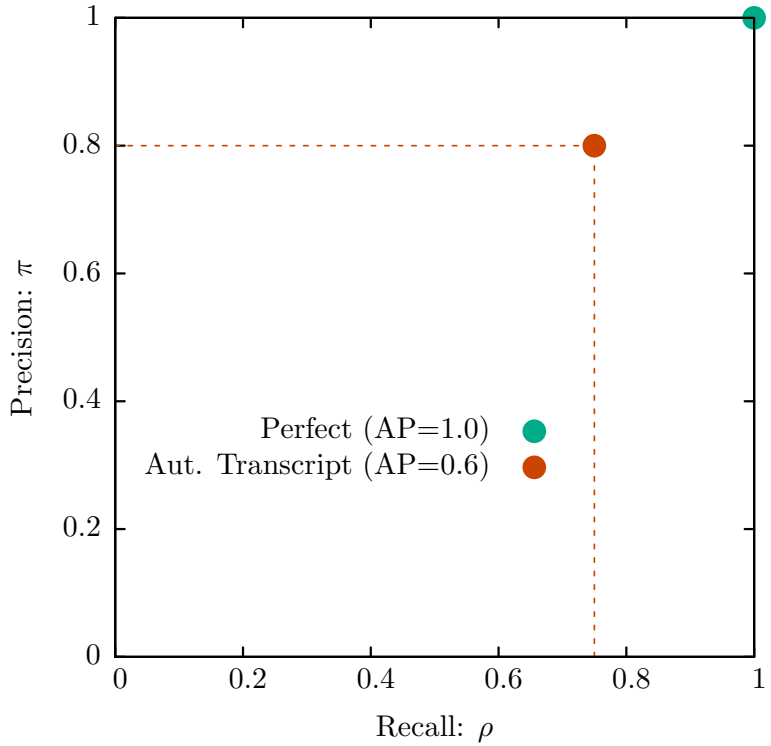

If automatic (typically noisy) handwritten text transcripts are naively indexed just as plaintext, precision and recall are also fixed values, albeit not "ideal" (pehaps something like, with Average Precision AP 0.6).

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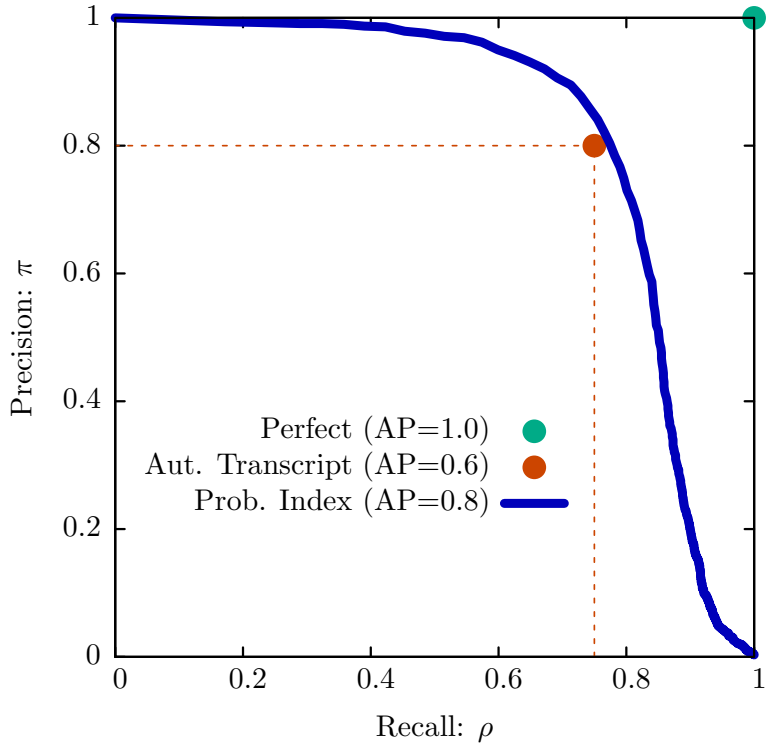

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This flexible *"precision-recall tradeoff model"* obviously allows for better search and retrieval performance than naive plaintext searching on automatic noisy transcripts.

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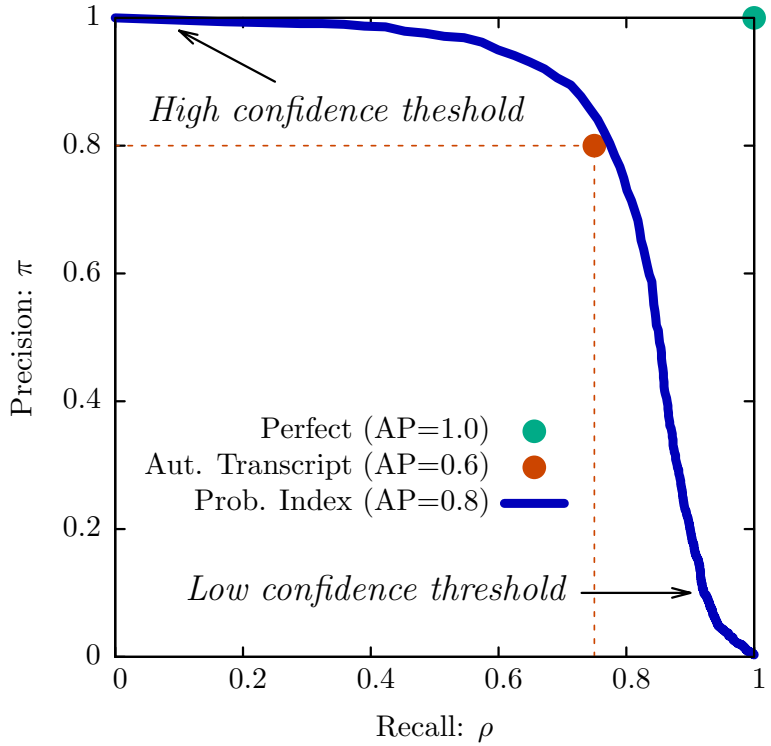

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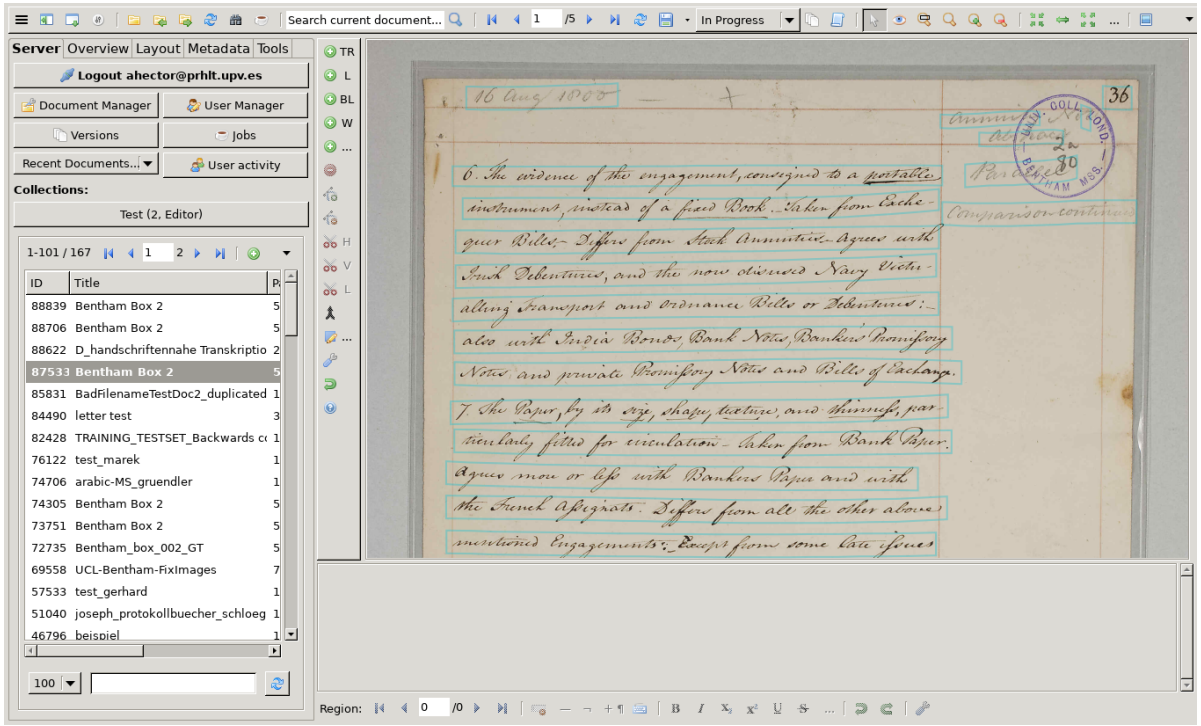
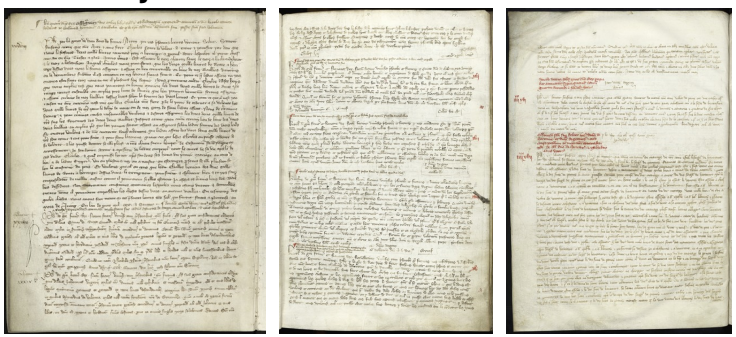
Preparatory Steps: Use of TransKribus Tools



- Line detection
- Transcribing (or page-image text aligning) a small number of training pages.
- Resizing images as required to approximately achieve uniform resolution.

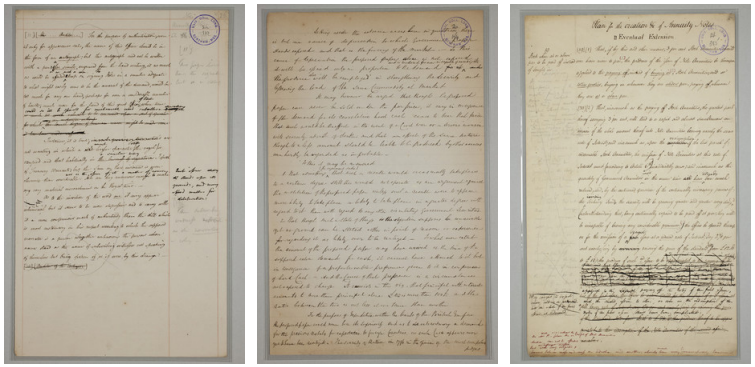
Large Scale Collections: Laboratory Results

Chancery



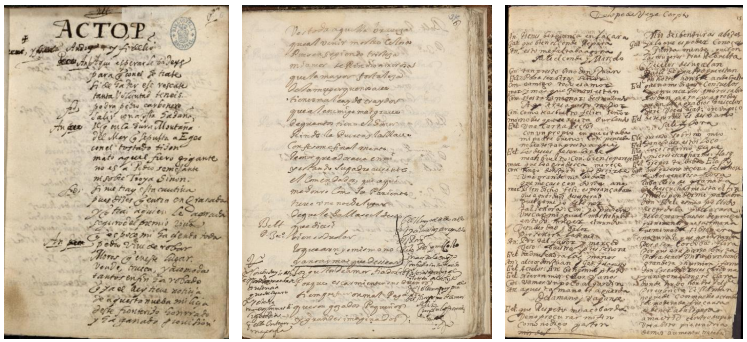
XIV-XV century medieval registers written in old French by many hands.

Bentham

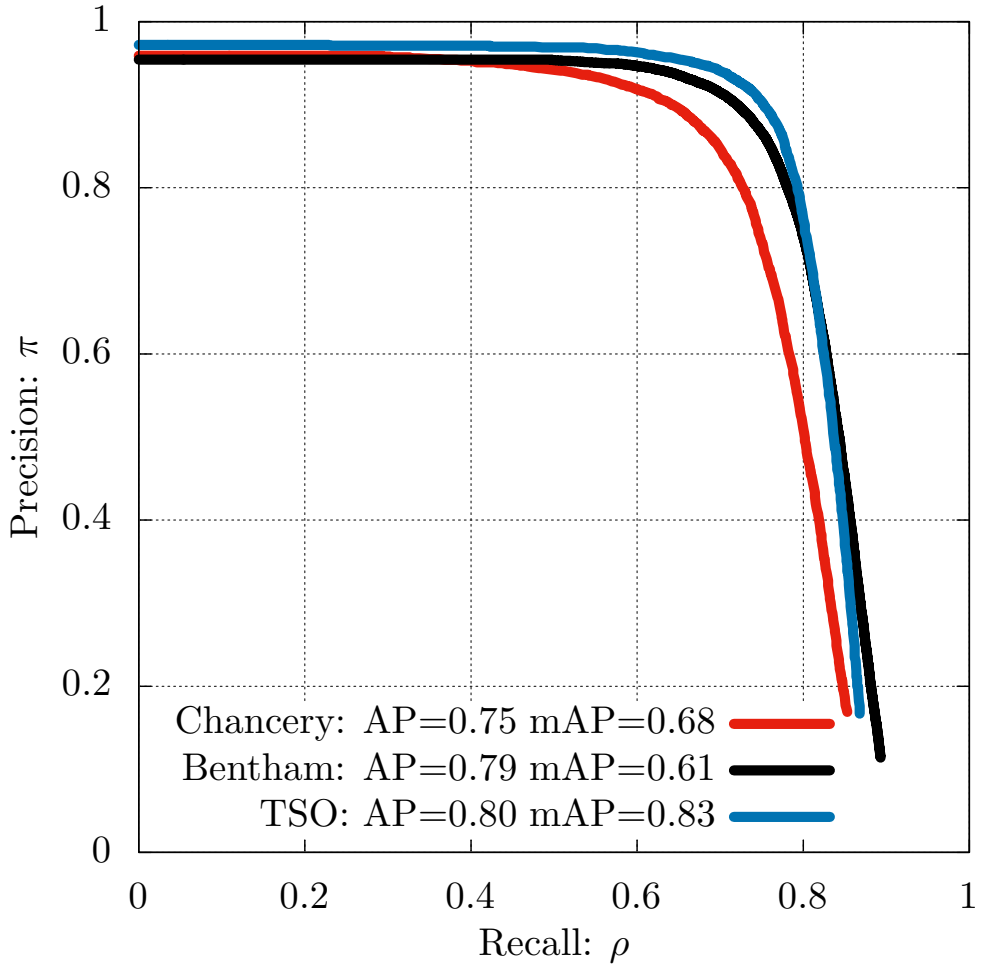


18th-19th century manuscripts written in English by many hands.

TSO



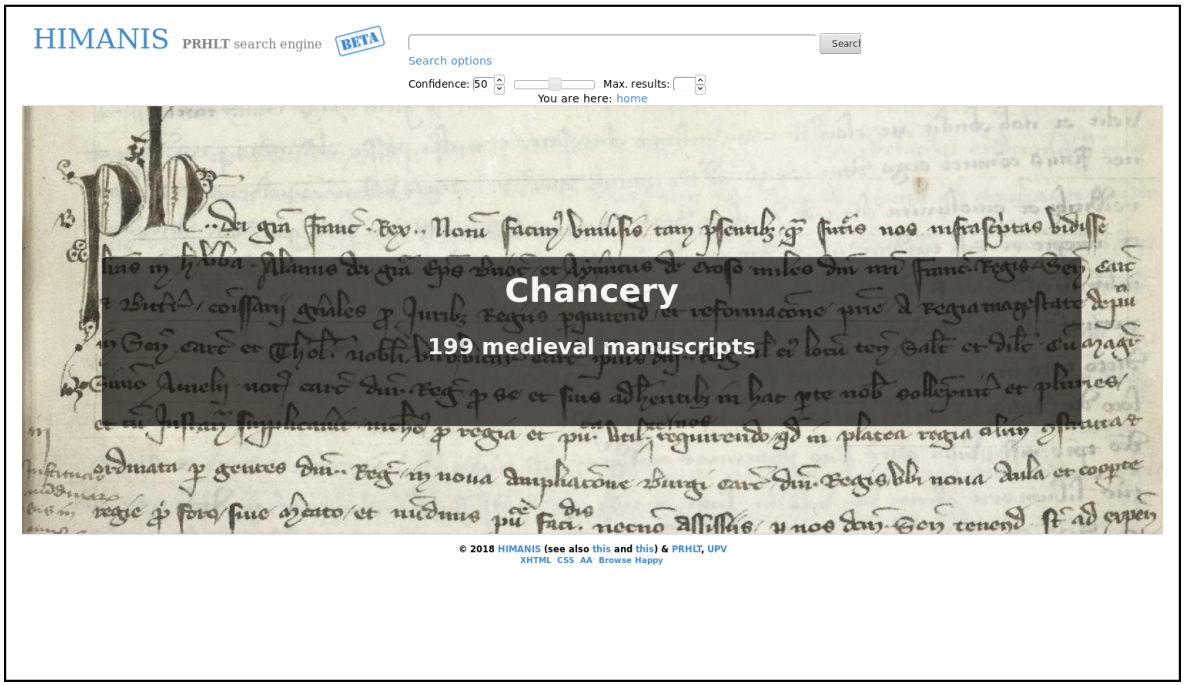
15th-16th century manuscripts written in old Spanish by many hands.



Collection	train/test	Char LM	Query words
Chancery	341/95 acts	5-gram	6,506
Bentham	155/846 pgs	8-gram	3,597
TSO	cross-val 286 pgs	8-gram	5,409

Chancery: Indexing and Search Live Demonstration

PRHLT Search Interface: http://prhlt-kws.prhlt/himanis



Probabilistic Index basic statistics (as of Sep-2017)

Computed:

#Volumes	167
#Page Indexed	67,413
#Spots	266,301,333
Average #Spots / Page	1,594,619

Estimated from index probabilities:

Running words	44,216,365
Running words / Page	264,769
Average #Spots / Running word	6.0

Bentham papers: Indexing and Search Large Scale Demonstrator

PRHLT Search Interface: http://prhlt-carabela.prhlt.upv.es/bentham

Probabilistic Index basic statistics (as of Nov-2018)

Computed:

#Boxes	173
#Page images / *Indexed*	95,247 / *89,911*
#Spots	197,651,336
Average #Spots / Page	2,198

Estimated from index probabilities:

Running words	25,487,932
Running words / Page	283
Average #Spots / Running word	7.8

TSO: Indexing and Search Large-Scale Demonstrator

PRHLT Search Interface: http://prhlt-carabela.prhlt.upv.es/tso

Probabilistic Index basic statistics (as of Nov-2018)

Computed:

#Manuscripts	328
#Page images/*Indexed*	41,122 / *36,010*
#Spots	42,477,144
Average #Spots / Page	1,180

Estimated from index probabilities:

Running words	5,396,497
Running words / Page	150
Average #Spots / Running word	7.9

TSO Large Scale Demonstrator: Query Examples

PRHLT TSO search interface: http://prhlt-carabela.prhlt.upv.es/tso

A small sample of query possibilities:

Austria
otomano

teniente || alferez || sargento
sol && español

(valor || dolor) && (amor || honor)
Isabel (belleza || hermosura || nobleza)

[Don Juan Austria]
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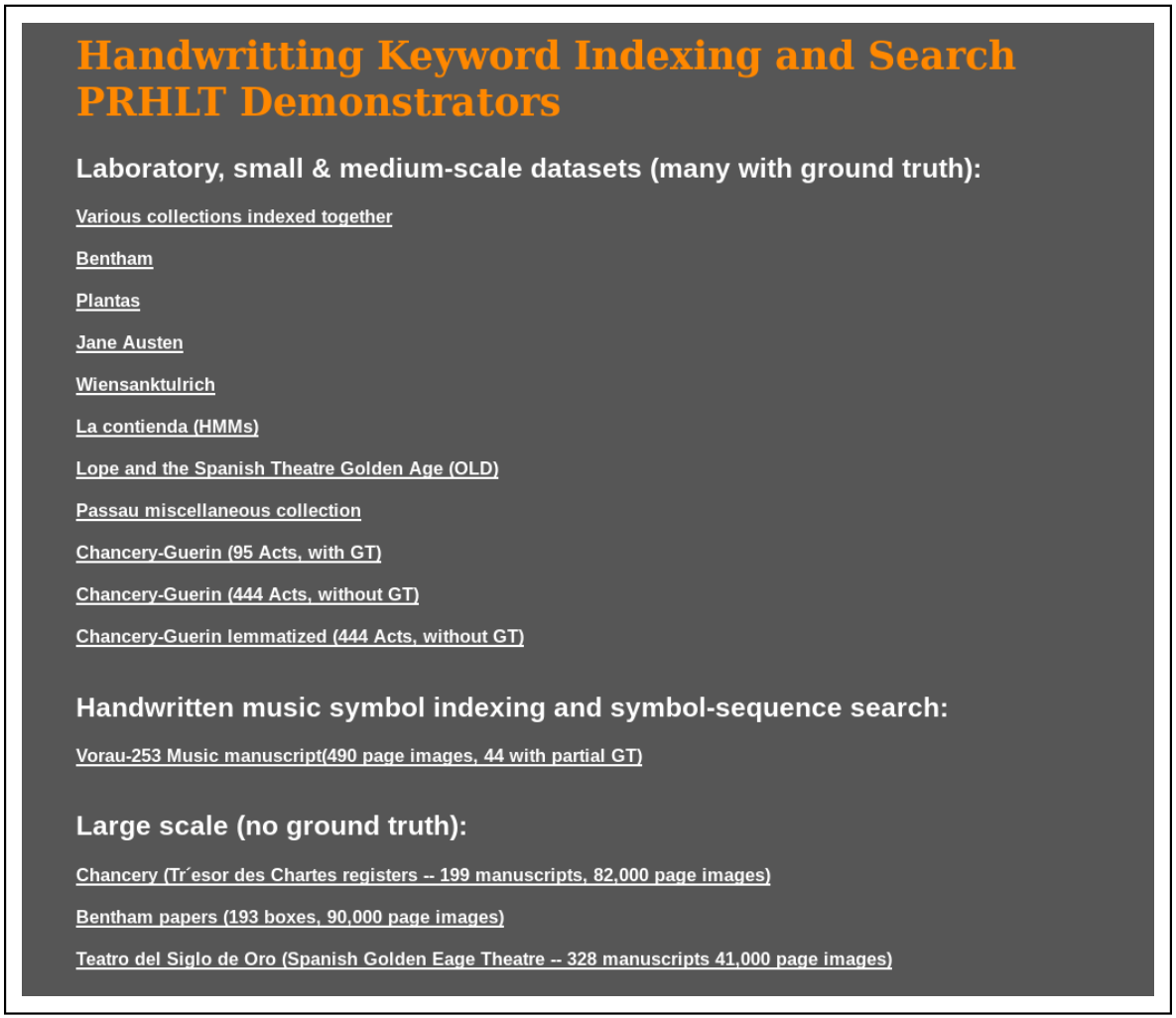
Other KWS Demonstrators

Several others *Handwritting Text Keyword Indexing and Search* PRHLT demonstrators can be tried at:

http://transcriptorium.eu/demots/KWSdemos



Thanks for Your Attention !

Average Precision (AP) versus Mean Average Precision (mAP)

	AP	**mAP**
Type of Ranking	Global spot list	One spot list for each query
Averaging type	Micro: over all query events	Macro: over the APs of isolated queries
Is it invariant to monotonic score transformations?	no	yes
Does score consistency have an impact?	yes	no
Need all queries be relevant?	no	yes