



A SIMPLE AND FAST WORD SPOTTING METHOD

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Joint work with Alon Kovalchuk and Nachum Dershowitz

Images → Text

OCR is very hard for handwritten material

Instead:

- Approximate match
- **Word spotting**
- Transcript alignment

אדזבעיכישעידודארוליעחנוניס
ידסראזנויוביסיארראאונחבל
שתומצרישאולצאוניצדוגוןאמ
צאובשםידוארראאנאידודלטס
שינויידודוצדידואדינוסרחסשן
ערתאיסזוזדליייליידושיעשן
בינשילסנוחכיכידודגמלעיכ
כיחלצתנשימועאעעניסדסעד
אערגליאעדלךלניידודבארדחי
פדאסנעיכיאדבראניגליאעדל

אהבתי כי ישמע יהוה את
קולי תחנוני כי הטה אזננו לי
ובימי אקרא אפפוני חבלי מות
ומצרי שאול מצאוני צרה
ויגון אמצא ובשם יהוה
אקרא אנה יהוה מלטה
נפשי חנון יהוה וצדיק ואלוהינו
מרחם שומר פתאים יהוה
דלותי ולי יהושיע שובי נפשי
למנוחיכי כי יהוה גמל עליכי
כי חלצת נפשי ממות את עיני
מדמעה את רגלי מדחי
אתהלך לפני יהוה בארצות
החיים האמנותי כי אדבר אני



OCR

Transcription

Word spotting

Given an image of a query word, identify all other occurrences of the same word in a set of input images

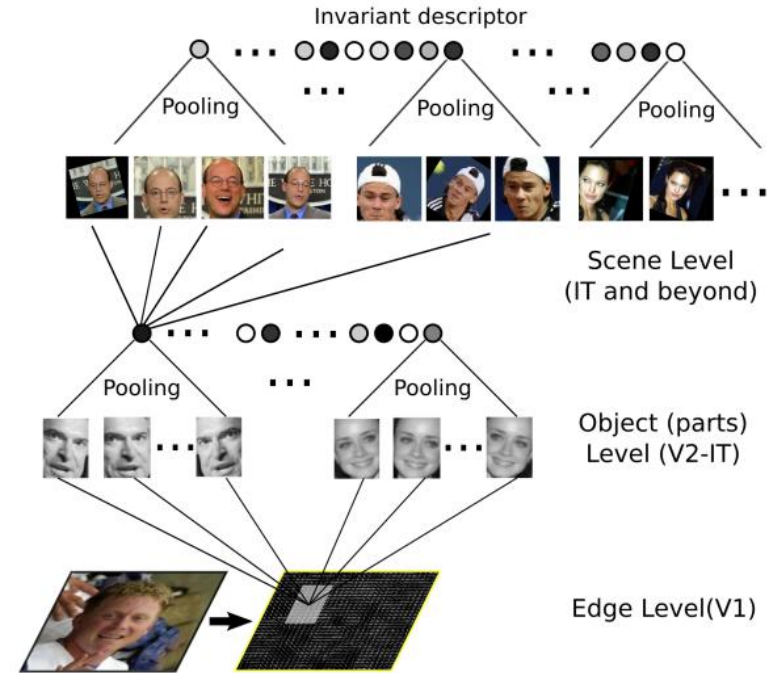
Query: Socrates

Socrates was a Classical Greek philosopher. Credited as one of the founders of Western philosophy, he is an enigmatic figure known only through the classical accounts of his students. Plato's dialogues are the most comprehensive accounts of Socrates to survive from antiquity. Forming an accurate picture of the historical Socrates and his philosophical viewpoints is problematic at best. This issue is known as the Socratic problem. The knowledge of the man, his life, and his philosophy is based on writings by his students and contemporaries; foremost among them is Plato; however, works by Xenophon, Aristotle, and Aristophanes also provide important insights. The difficulty of finding the real Socrates arises because these works are often philosophical or dramatic texts rather than straightforward histories. Aside from Thucydides who makes no mention of Socrates or philosophers in general, there is in fact no such thing as a straightforward history contemporary with Socrates that dealt with his own time and place.

||| Magic faces

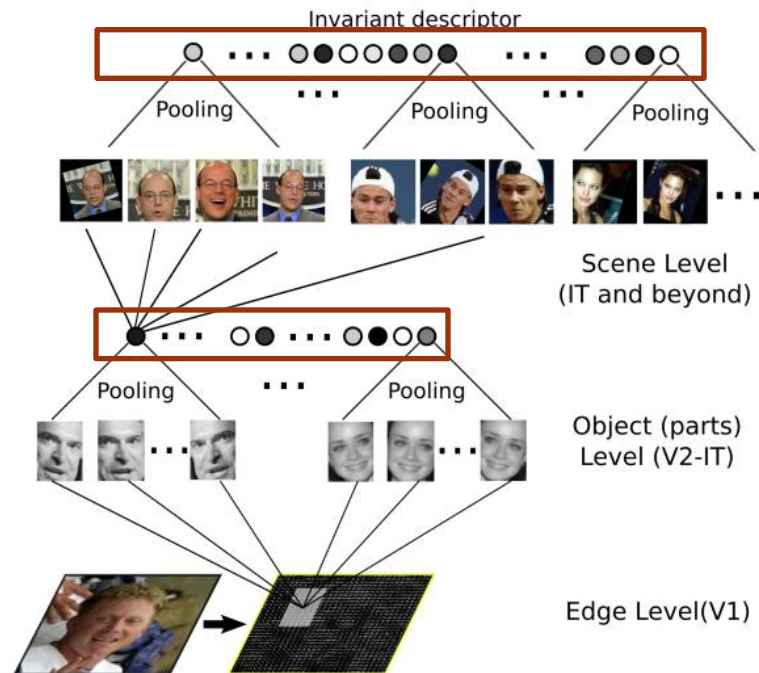
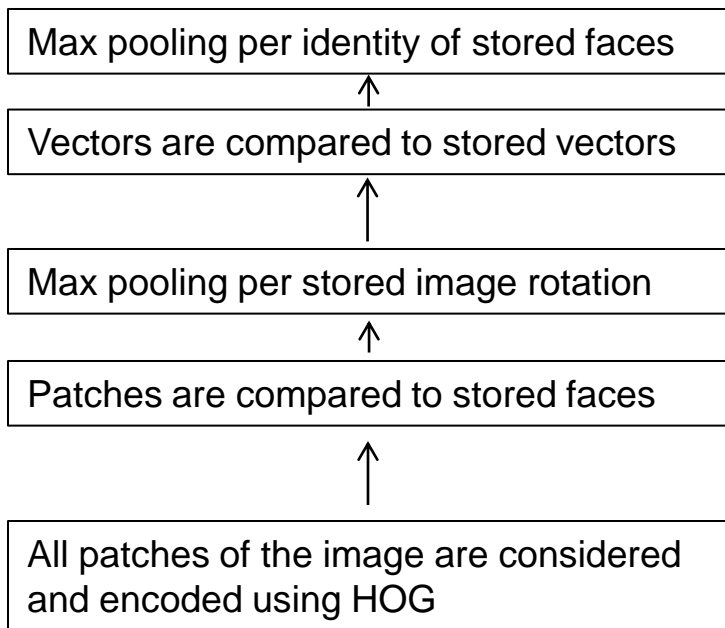
Our system resembles the biologically plausible face-recognition architecture by Poggio

That system has a very simple architecture; however, it achieves excellent performance



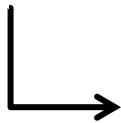
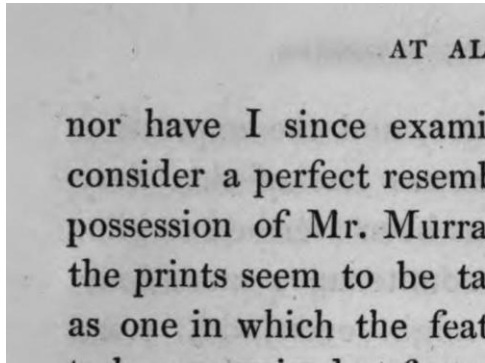
Q. Liao Q, J.Z. Leibo, Y. Mroueh, T. Poggio. **Can a biologically-plausible hierarchy effectively replace face detection, alignment, and recognition pipelines?** arXiv 2014.

Magic faces

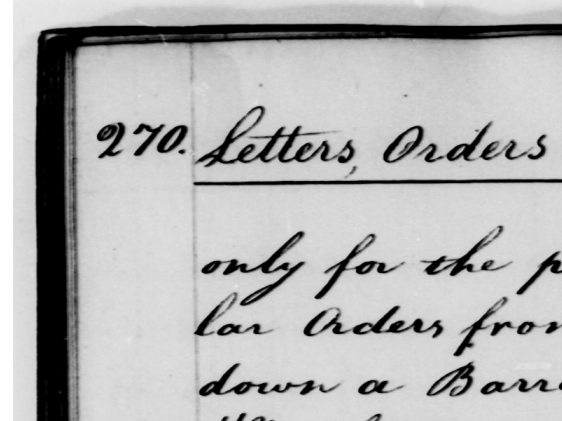


Binarization

Simple threshold at 85% of mean pixel intensity



AT AL
nor have I since exami
consider a perfect resem
possession of Mr. Murra
the prints seem to be ta
as one in which the feat



270. Letters, Orders
only for the p
lar Orders from
down a Barre

Candidate patch extraction

An elaborate heuristic based on the connected components extracted from the binary image.

Connected components are grouped to form clusters that are:

- “not too big”
- continuous in the x-axis
- components are aligned in y-axis
- contains all components in its bounding box

AT AL
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1:2

270. Letters, Orders

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1:30

Patch normalization

A margin of 8 pixels is placed around the bounding box of each patch

The enlarged patches are then resized to a fixed size of 160 x 56 pixels

Grid of 20 x 7 cells, each 8 x 8 pixels



HOG + LBP encoding

Each cell is represented by:

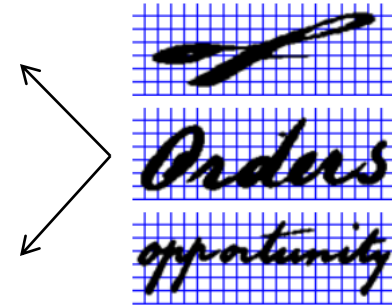
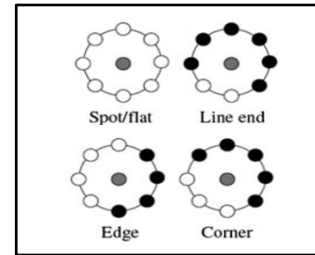
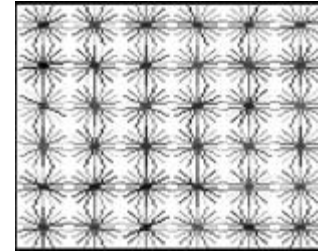
A HOG vector in R^{31}

An LBP vector in R^{58}

All HOG vectors are concatenated to one vector of size $20 \times 7 \times 31 = 4,340$

Same for LBP $20 \times 7 \times 58 = 8,120$

Both vectors are normalized and concatenated to a vector $v \in R^{12460}$



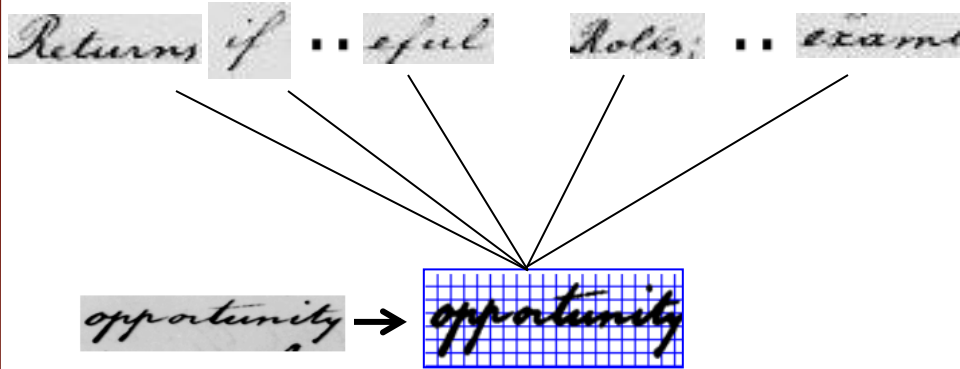
[HOG] N. Dalal and B. Triggs. **Histograms of Oriented Gradients for Human Detection**. CVPR, 2005
[LBP] T. Ojala, M. Pietikäinen, and D. Harwood. **Performance evaluation of texture measures with classification based on Kullback discrimination of distributions**. ICPR 1994.

Similarity to prototypes

3,750 random patches are sampled and split into 250 groups of 15 patches $C \downarrow i, i=1..250$

$M \in \mathbb{R}^{12460 \times 3750}$ holds their hog+lbp vectors

A patch is first represented by its cosine similarity to the 3,750 prototypes $u = Mv$



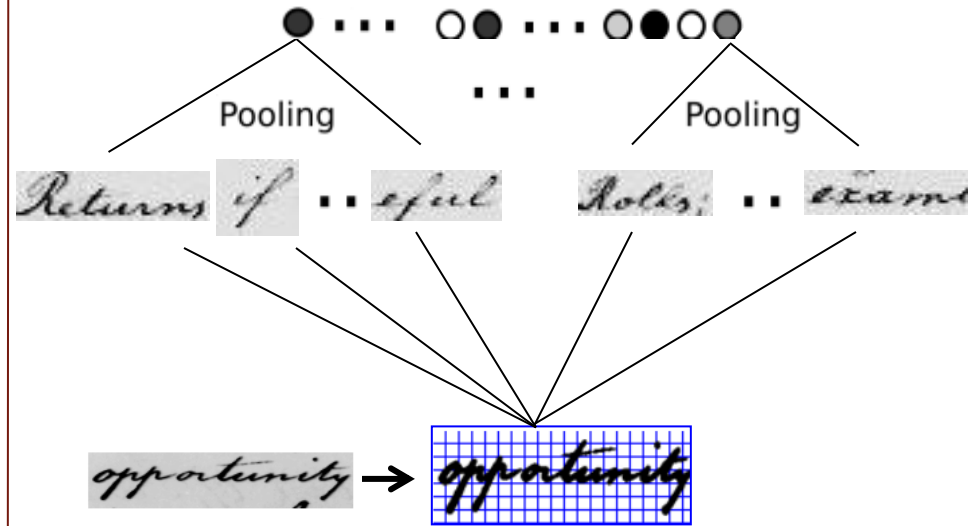
Max pooling

3,750 random patches are sampled and split into 250 groups of 15 patches $C_i, i = 1..250$

Next, max pooling is performed over the groups C_i , resulting in $w \in R^{250}$

$$w_i = \max_{j \in C_i} u_j$$

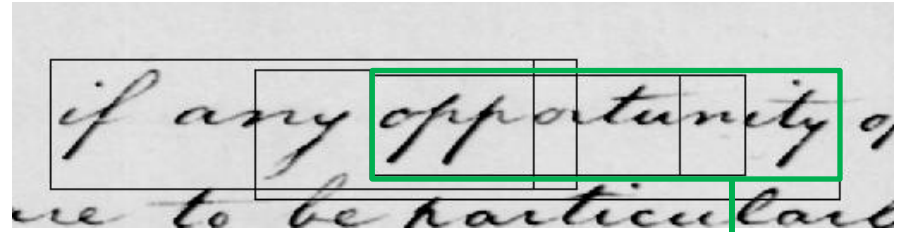
Unlike other deep network architectures pooling here is random



Overlap Suppression

Out of all patches that share a large connected component, only the one most similar to the query is retrieved

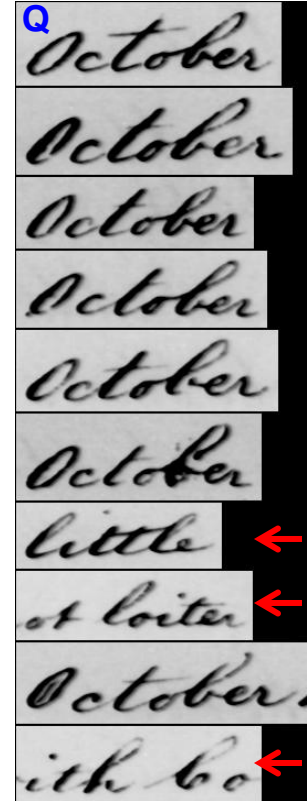
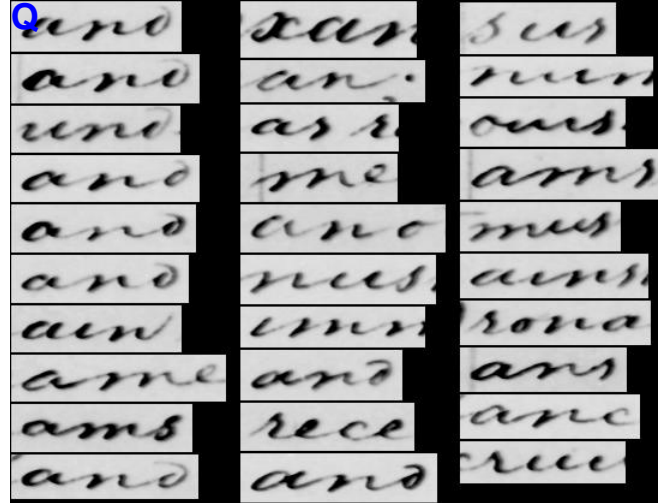
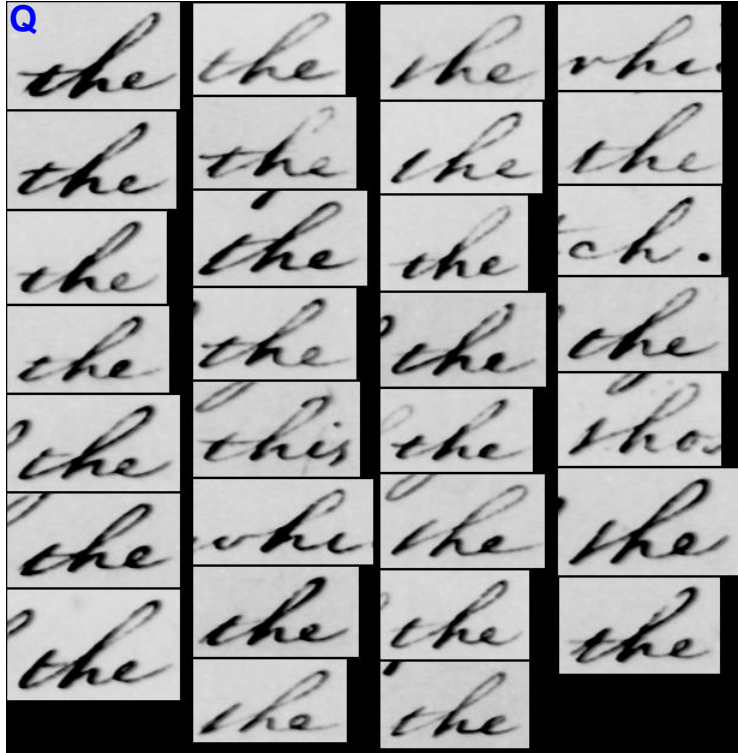
Query: *opportunity*



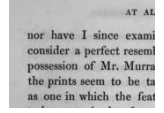
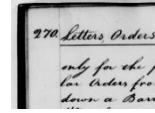
Results: ^Q *opportunity*
opportunity
opportunity
opportunity
Virginia. Re
xpeditiously



Results – examples

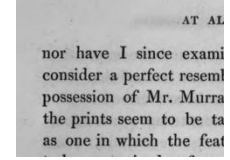
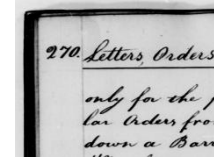


Results – accuracy



	Method	GW	LB
literature	“Browsing heterogeneous document collections by a segmentation-free word spotting method” M. Rusiñol, D. Aldavert, R. Toledo, J. Lladós, ICDAR, 2011	30.5%	42.8%
	“Efficient exemplar word spotting” J. Almazán, A. Gordo, A. Fornés, E. Valveny, BMVC, 2012	54.5%	85.5%
our system	Complete pipeline	50.1%	90.7%
	Same applied to segmented words	66.3%	92.9%
	Without max-pooling ()	48.8%	90.8%
	Without max-pooling, random subset ()	47.6%	90.7%

Results – run time



	Method	GW	LB
	Number of queries	4,860	4,988
"Efficient exemplar word spotting", Almazán et al. BMVC'12	All queries	5,058sec	4,159sec
	Average per query	1.04sec	0.83sec
Our system	All queries	158sec	46sec
	Average per query	0.03sec	0.01sec
	Single query	0.08sec	0.03sec
	Preprocessing per page	46sec	3sec
	Average memory per page	1,875KB	136KB

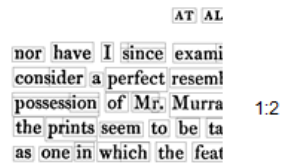
Summary

Candidate patch extraction

An elaborate heuristic based on the connected components extracted from the binary image.

Connected components are grouped to form clusters that are:

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HOG + LBP encoding

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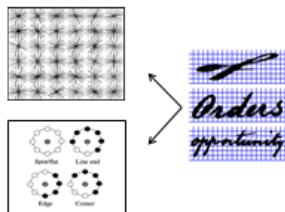
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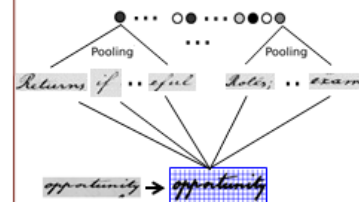
Network based representation

3,750 random patches are sampled and split into 250 groups of 15 patches $C_i, i = 1..250$

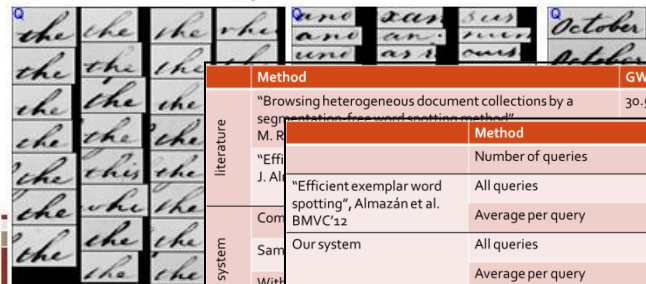
Then, the patch is represented by a vector $w \in R^{250}$ by pooling

$$w_i = \max_{j \in C_i} u_j$$

Unlike other deep network architectures pooling is random!

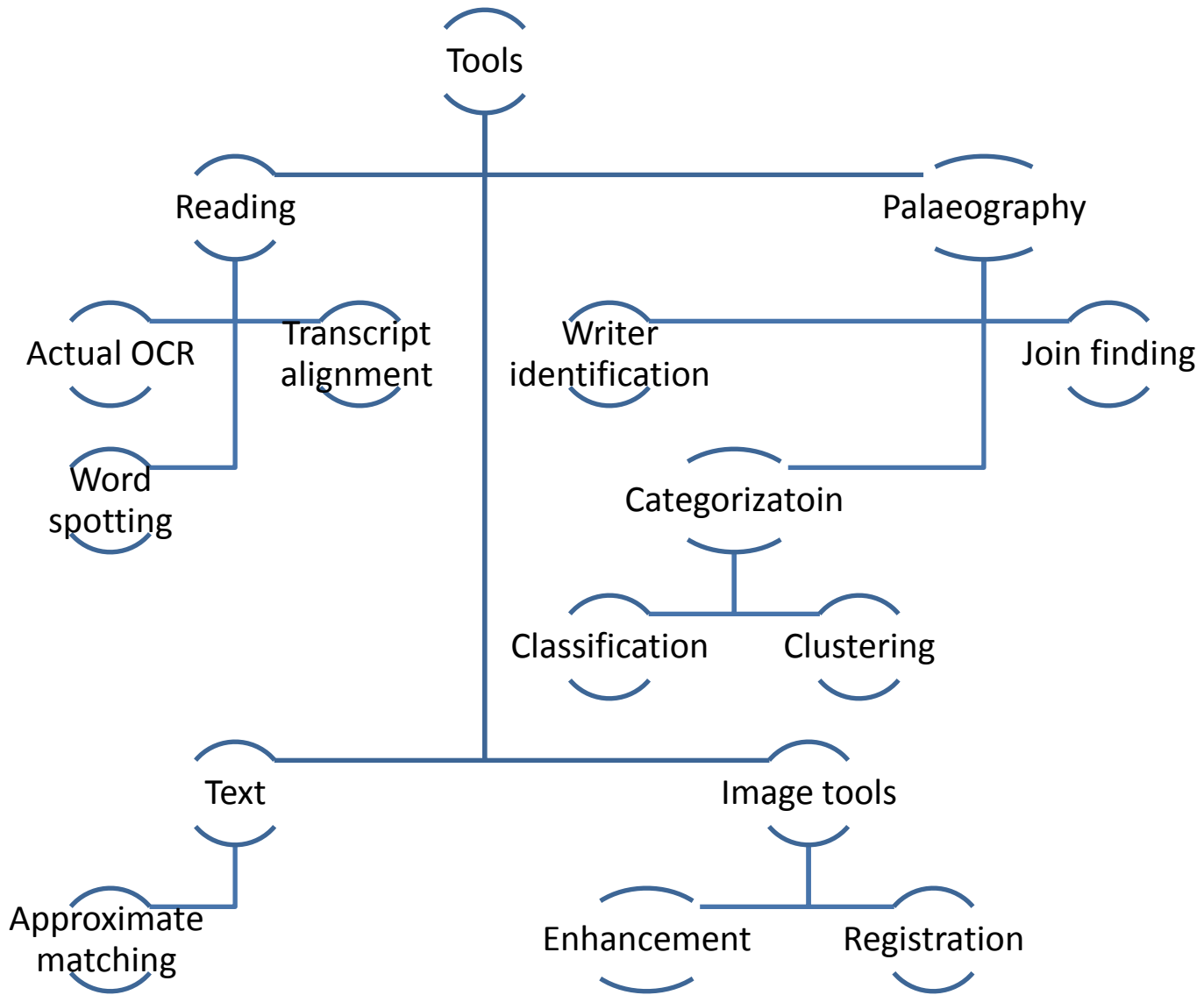


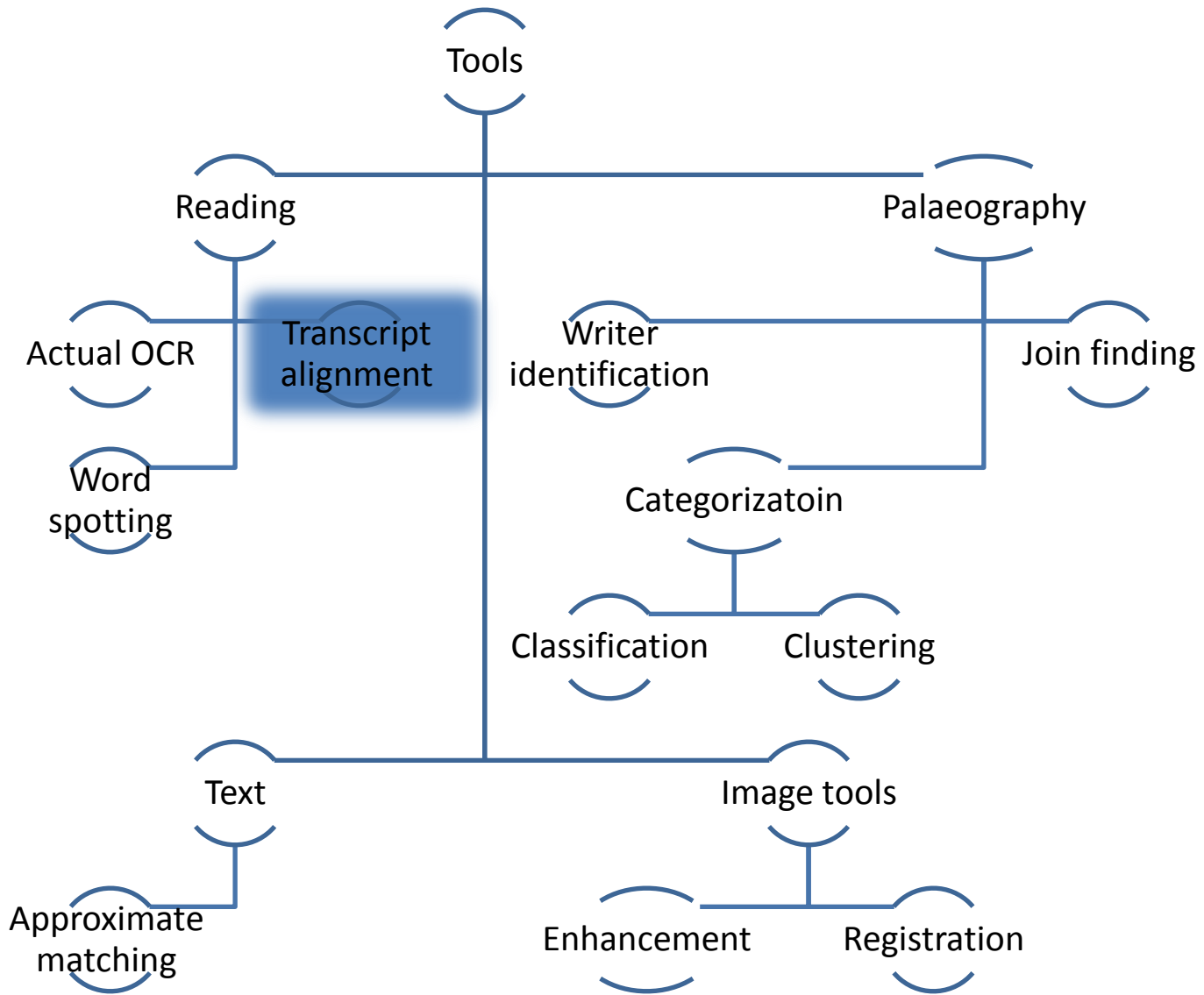
Results



Method	GW	LB
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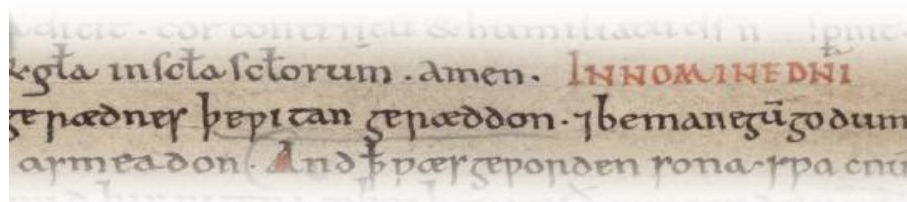
thank
{you}





OCR Free Transcript Alignment

Image:

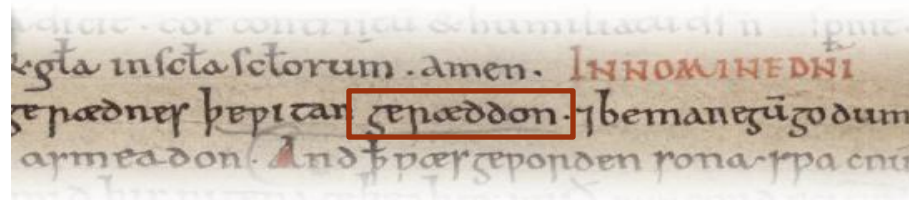


Transcription:

þe witan geræddon . 7 be manegum g
And þæt wæs geworden sona swa cnūt

OCR Free Transcript Alignment

Image:

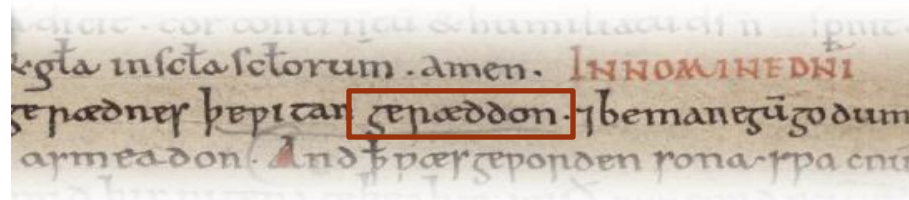


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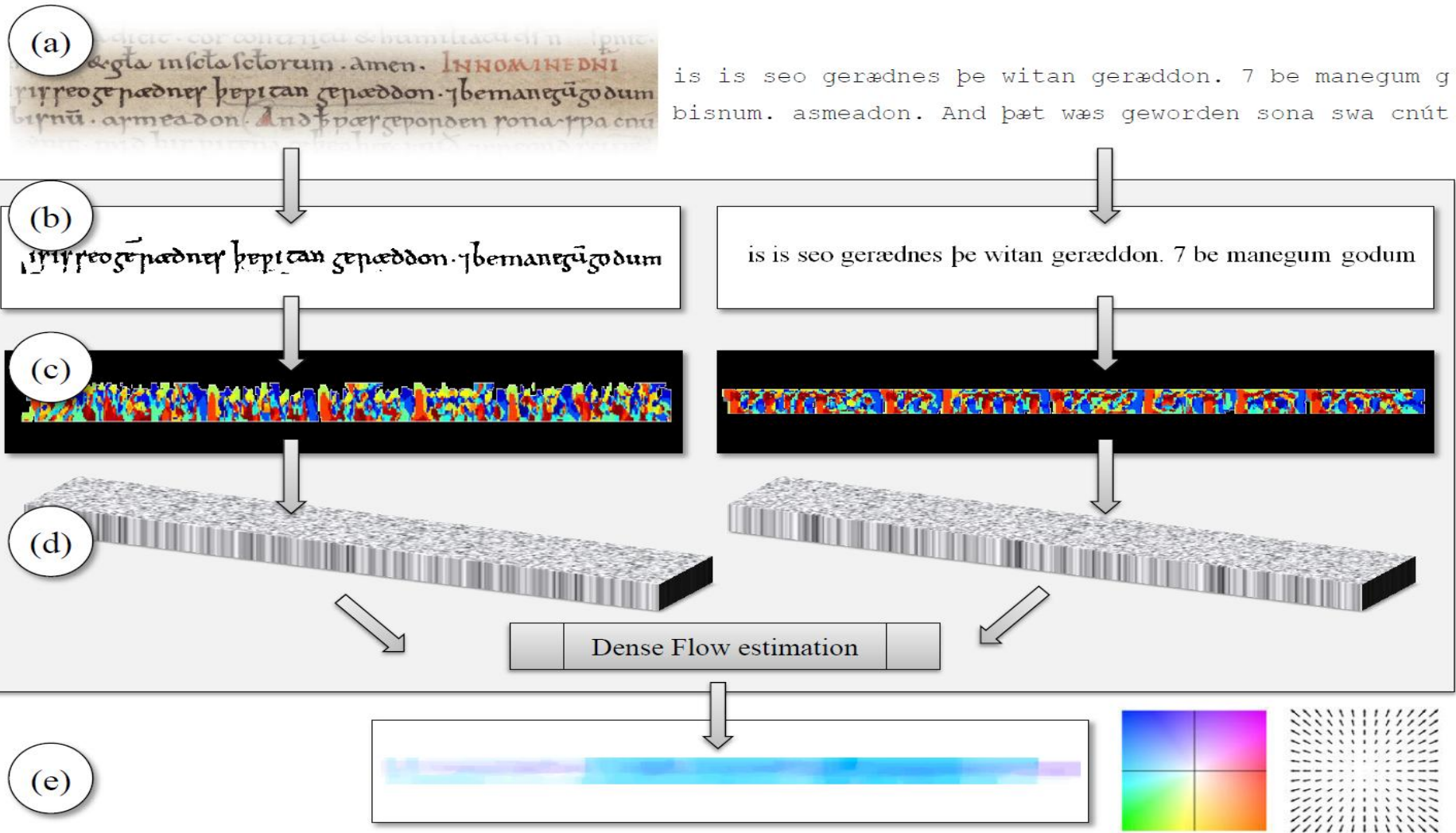
Image:



Transcription:

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Motivation for alignment: the human user (UI); the computer user (word spotting)



Dead Sea Scrolls

ויתרוממו למעלה לכול. אתה הוא יהוה בחרתה באבותינו למקדם.
יירוממו למעלה לכול. אתה הוא יהוה בחרתה באבותינו למקדם.
ויתרמו ע' למעלה לכול אתה הוא יהוה בחרתה באבותינו למקדם

Genizah

אלהינו הוא ירחם עלינו וירויח לנו מצרותינו
אלהינו הוא ירחם עלינו וירויח לנו מצרותינו
אֱלֹהֵינוּ הוּא יִרְחַם עָלֵינוּ וַיִּרְוֶיחַ לָנוּ מִצְרוֹתֵינוּ

אסתגאת אלעזר הדא אלי וקתנא הדא לם יקדמה אחד אלי בית דין ולא שהד אחד בחצרה בית
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מִסְתַּגֵּאת אֶלְעֶזֶר הַדָּא אֵלַי וְקִתְנָא הַדָּא לְמִי יִקְדָּמָה אֶחָד אֵלַי בֵּית דִּין וְלֹא שְׁהַד אֶחָד בְּחִצְרָה בֵּית

Tibetan bKa gdams gsung bum

ཏྲུག་རྣམ་དཔྱད་ཀྱི།	ལམ་ཏུ་ཡོན་ཏན་བཟང་ལྷན་ལྷན་ལ།	འོད་རློང་དུ།	ཐིག་པ་ཚེན་པོ་ལ་འཇུག་པ་ཞེས་བྲ།	ཁོཅམ་ལྷན་འདས་
ཏྲུག་རྣམ་དཔྱད་ཀྱི།	ལམ་ཏུ་ཡོན་ཏན་བཟང་ལྷན་ལྷན་ལ།	དཔྱད་ཀྱི།	ཐིག་པ་ཚེན་པོ་ལ་འཇུག་པ་ཞེས་བྲ།	ཁོཅམ་ལྷན་
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Cnut's Oxford code

is is seo gerædnes þe witan geræddon. 7 be manegum godum
 is is seo gerædnes þe witan geræddon. 7 be manegum godum
 is is seo gerædnes þe witan geræddon. 7 be manegum godum

Codex Sinaiticus

TOY KAI O TIAN ΠΡΟΣ
 TOY KAI O TIAN ΠΡΟΣ

