



THE UNIVERSITY
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Search is not only the Web IR Applications

Youssef Al Hariri

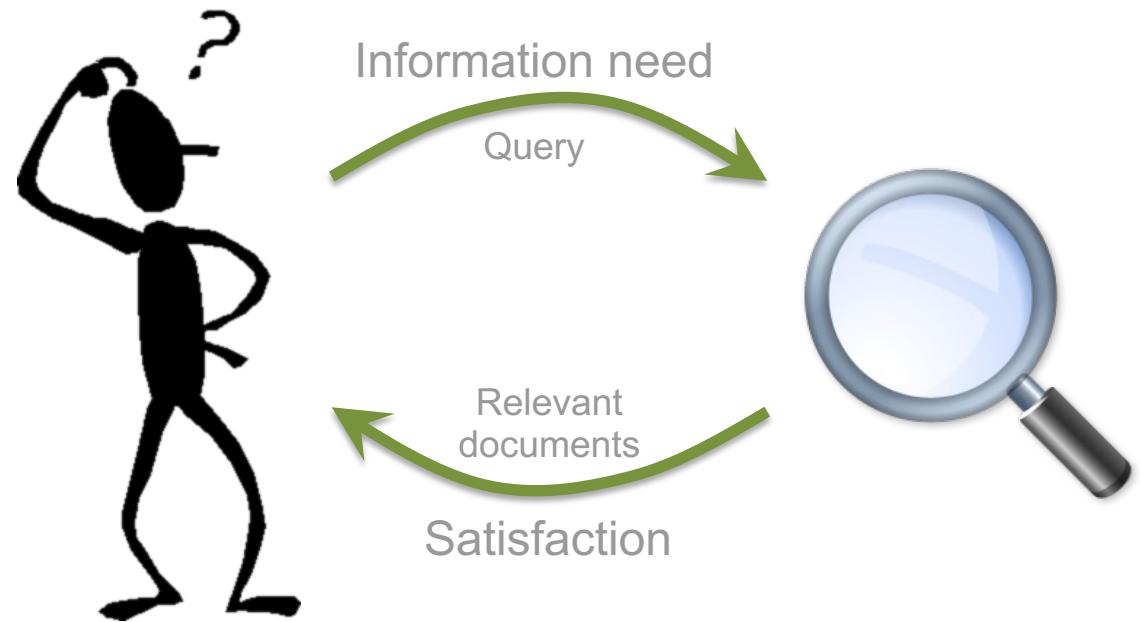
School of Informatics
University o Edinburgh

Objectives

- Main objective of IR
- Two search tasks
 - Printed documents search
 - Patent search
- Possible ideas for Group Project ☺

Information Retrieval Objective

- IR is finding material of an unstructured nature that satisfies an information need from within large collections.
- **Information need**
 - Expected search scenario?
 - Modeling the task?
- **Data nature**
 - Approach?
 - Scalable? Fast?
- **User Satisfaction**
 - More relevant documents?
 - Effective evaluation?

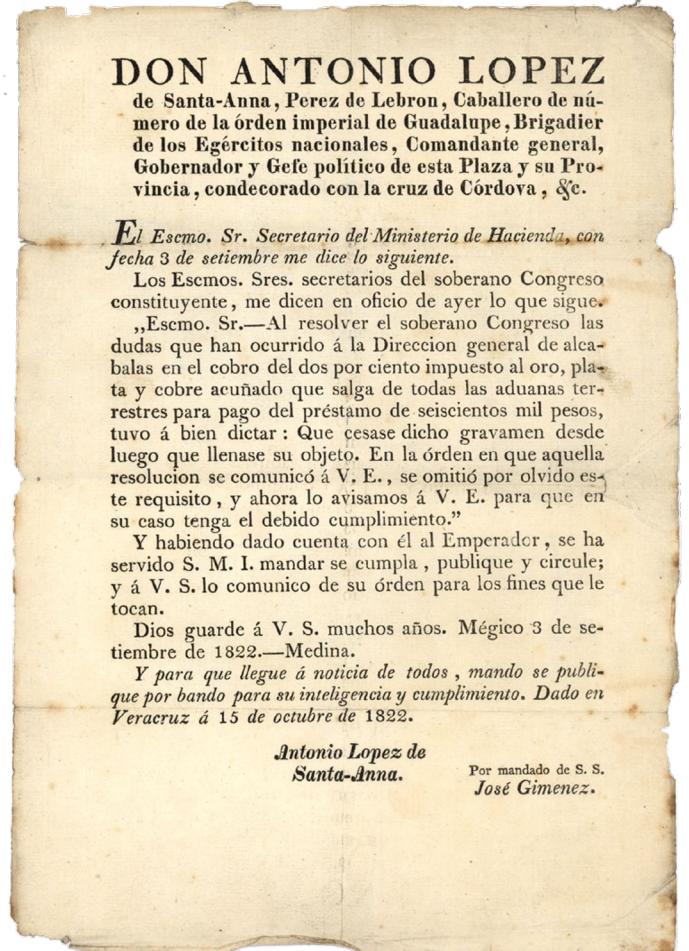


Printed Documents Retrieval



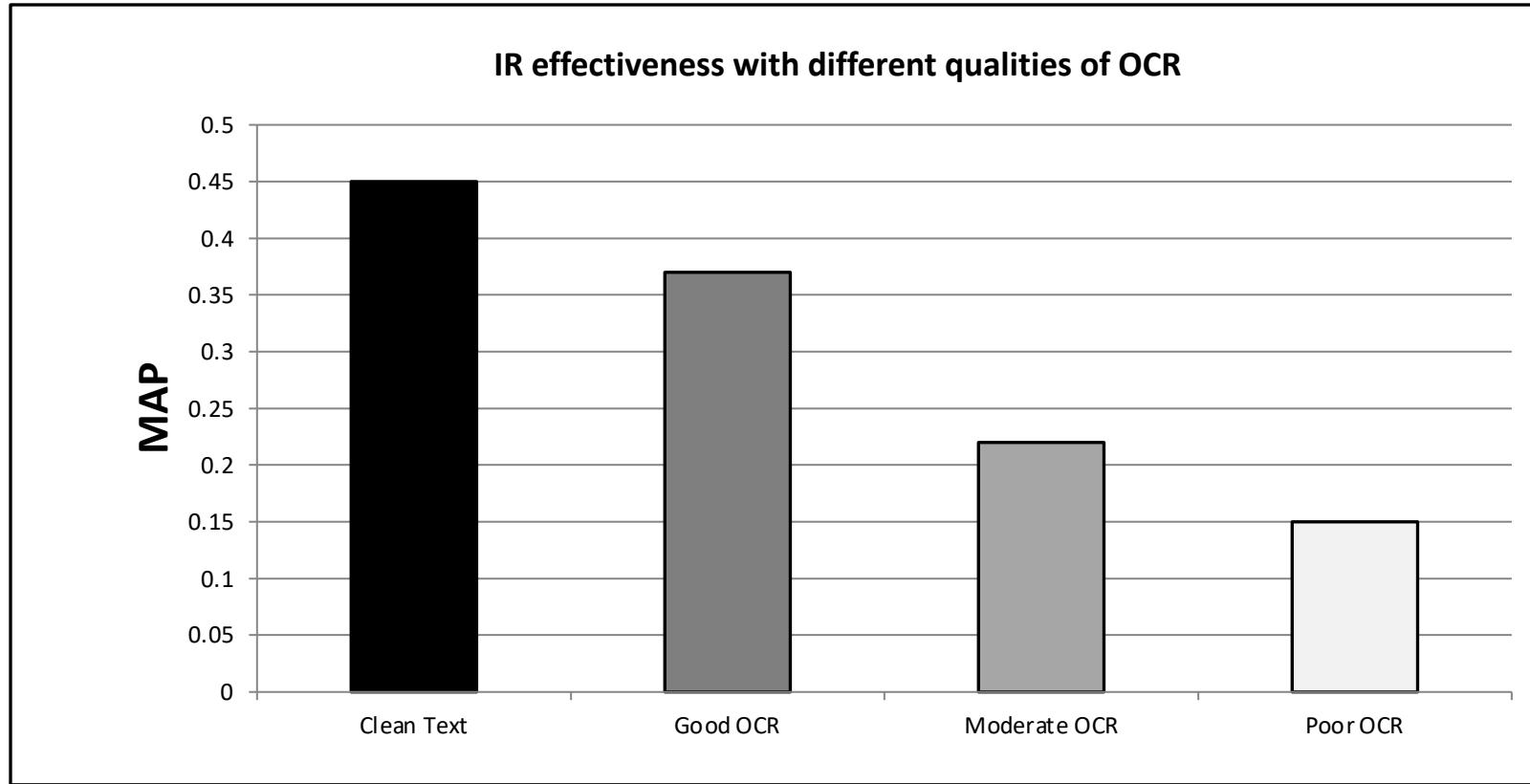
Printed Documents Retrieval

- **Documents:**
text on printed papers (books)
- **Information need:**
Information within these books
- **Challenge:**
It is an image of text
- **Common Approach:**
OCR → Recognized text ← Search
- **Challenges in Common Approach:**
OCR → Text with mistakes ($WER_{Ar} \approx 40\%$)
OCR → Not available for all languages



Problem

- Text with errors (sometime many errors)



n-gram Char Representation of OCR

- **Original:**

example sentence

- - Significantly improves retrieval when compared to word search
 - Still significantly worse than clean text
 - Unsupervised!

- **Query:**

example sentence →

\$ex exa xam amp mpl ple le\$ \$se sen ent nte ten enc nce ce\$

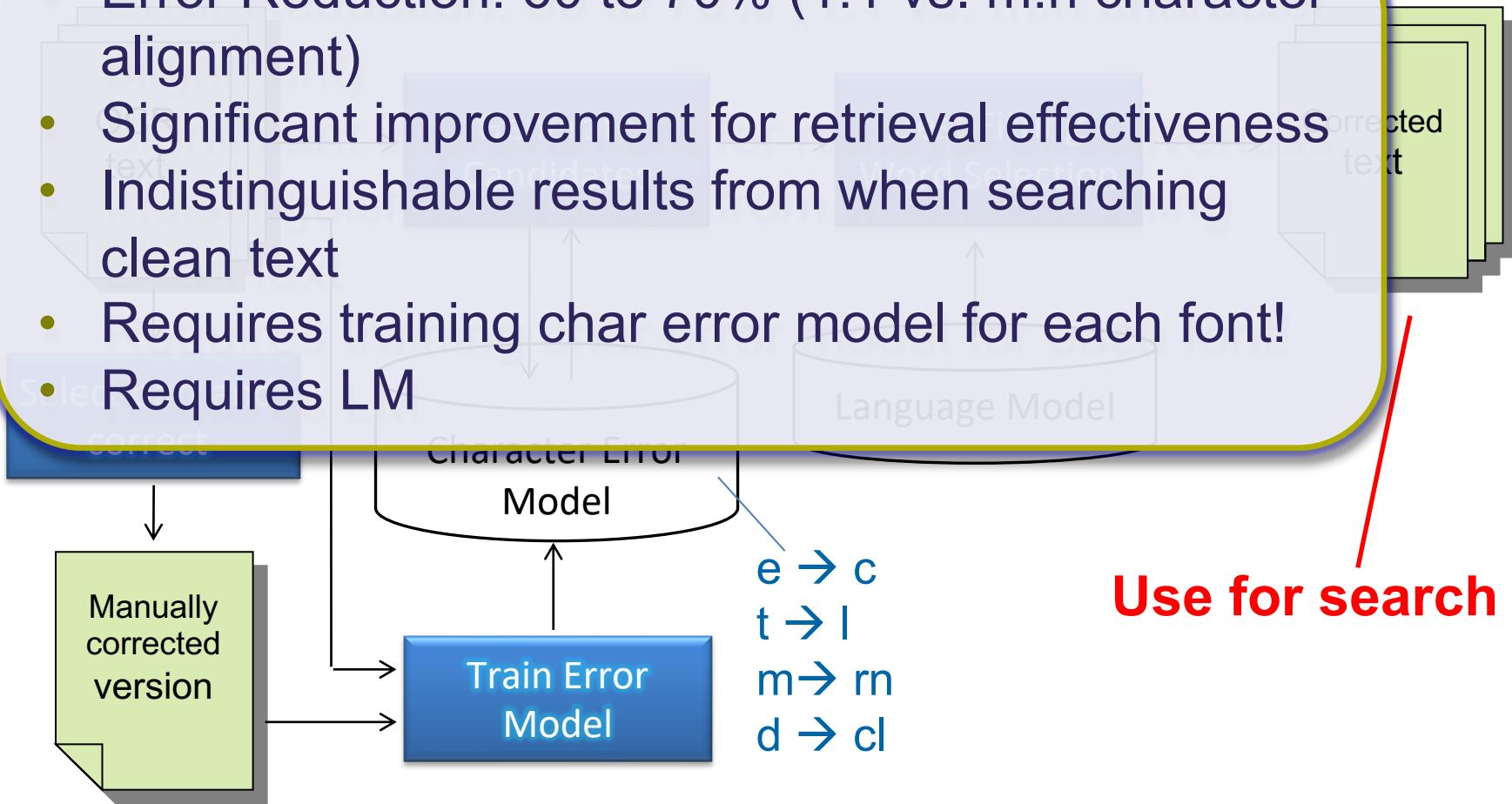
- **Matching:**

\$ex exa xar arn rnp npl ple le\$ \$se sen enl nlc lcn cnc nce ce\$

\$ex exa xam amp mpl ple le\$ \$se sen ent nte ten enc nce ce\$

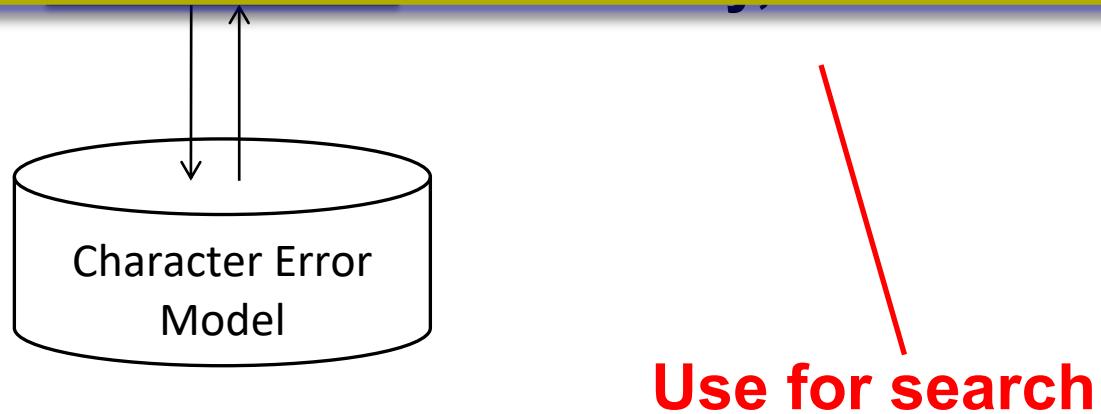
OCR Correction using Error Model

- Error Reduction: 60 to 70% (1:1 vs. m:n character alignment)
- Significant improvement for retrieval effectiveness
- Indistinguishable results from when searching clean text
- Requires training char error model for each font!
- Requires LM



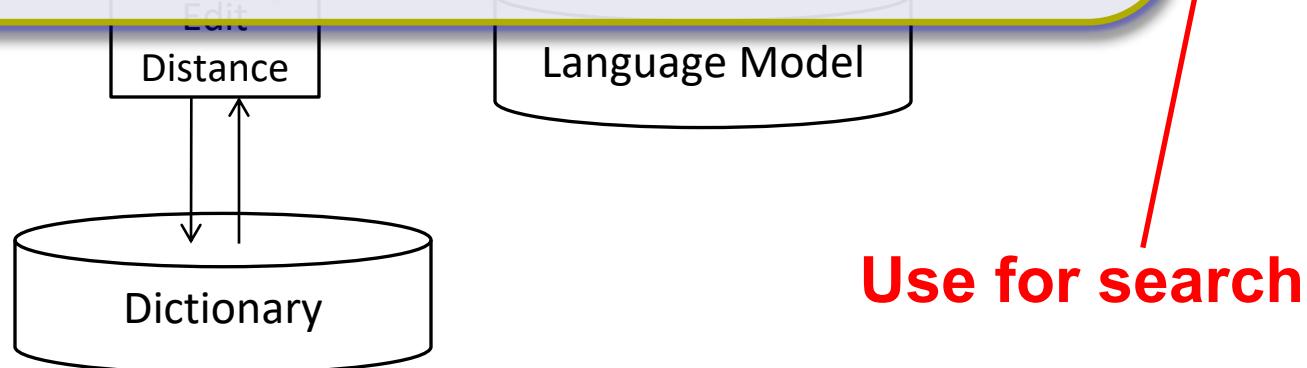
Query Garbling using Error Model

- Significant improvement for retrieval effectiveness
- Still worse than when searching clean text
- No LM required, but requires char error model!



OCR Correction using Edit Distance

- Error Reduction: 56% (vs. 70% when using error model)
- Significant improvement for retrieval effectiveness
- Indistinguishable results from when searching clean text
- No char error model, but requires LM



Multi-OCR Text Fusion

- $WER_{fused} << \min\{WER_{OCR}\}$
- Fusion of OCR documents using the same OCR system but at different scan resolutions reduces the WER

	Word Alignment	Best Fitting Selection	Page Model
OCR1	200 dpi 56.2%	3.98%	9.4%
	300 dpi 11.90%	2.10%	2.50%
OCR2	16.5%	3.37%	9.1%

- Significant improvement in retrieval results
- Requires LM

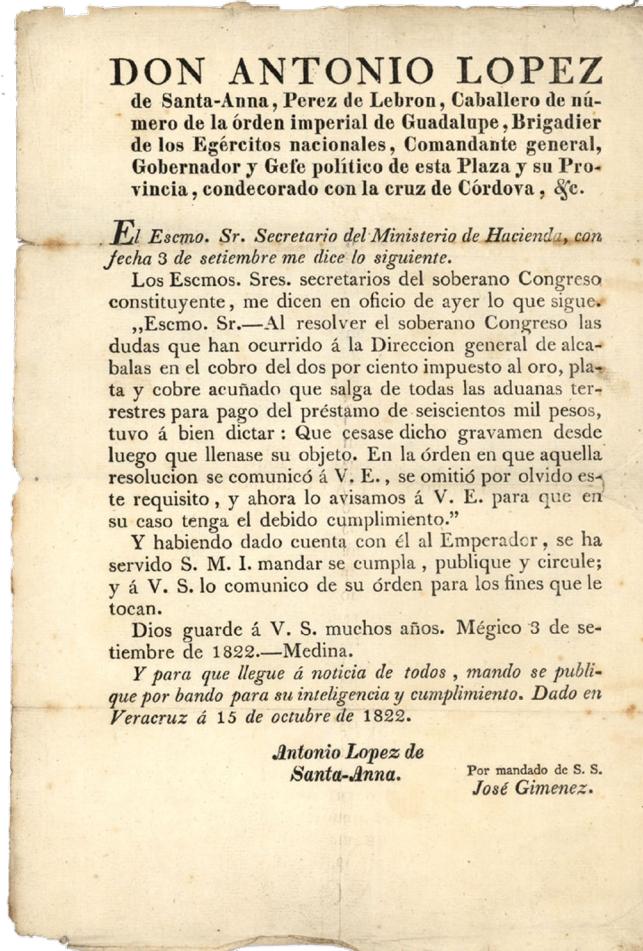
Use for search

OCR Search

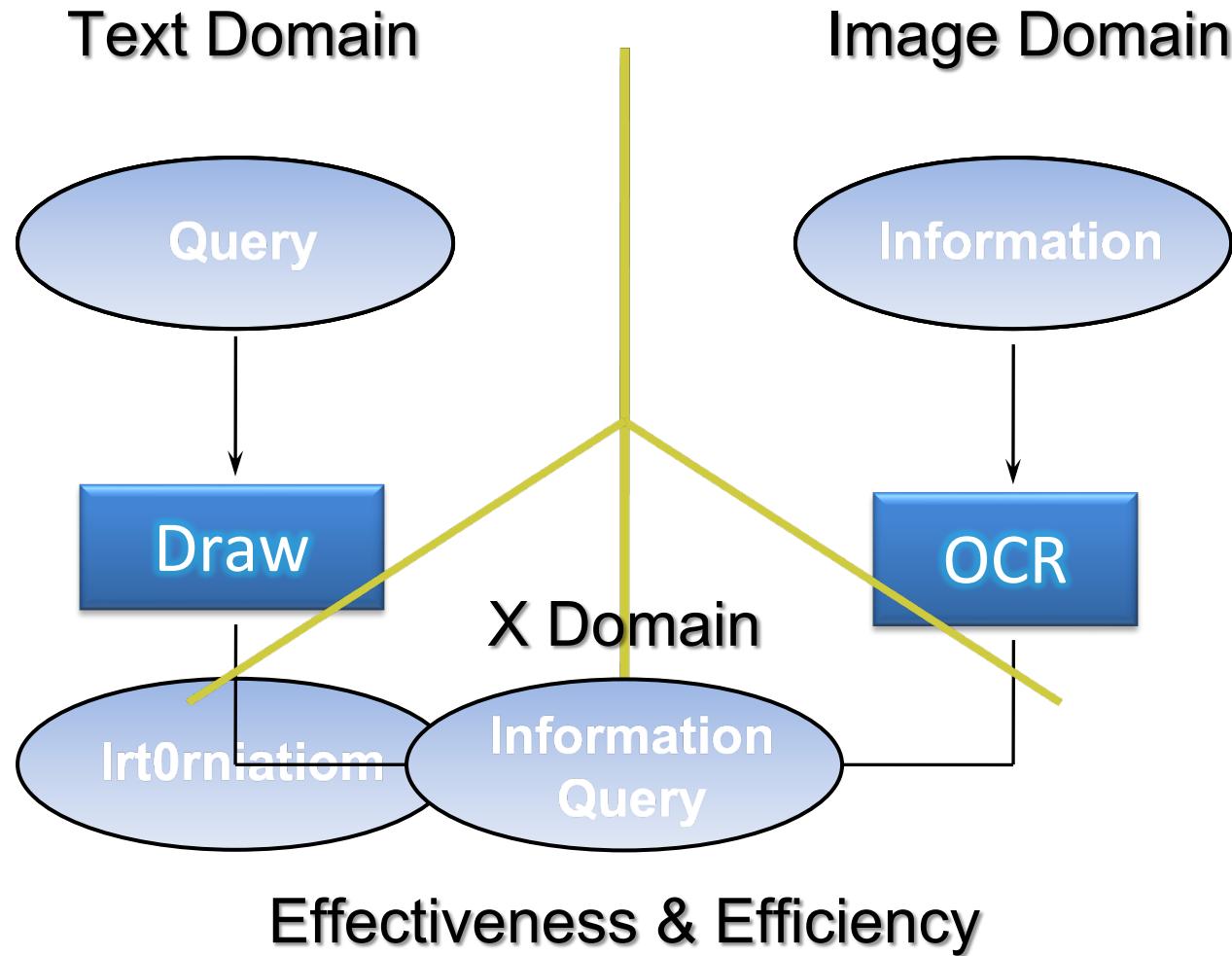
- Recognition errors in OCR text degrades retrieval
- Different methods of text processing can overcome the negative effect on retrieval and improves search
- n-gram character representation improves retrieval, but not that much
- Some training and resources are needed which can be manual correction, trained language model, or both
- Previous methods fail when errors are large ($WER>50\%$)

Solution – back to Information Need

- **Information need:**
the printed papers
- **Question:**
Why convert image to text?
- **Related work:**
Word Spotting



Modeling the Problem

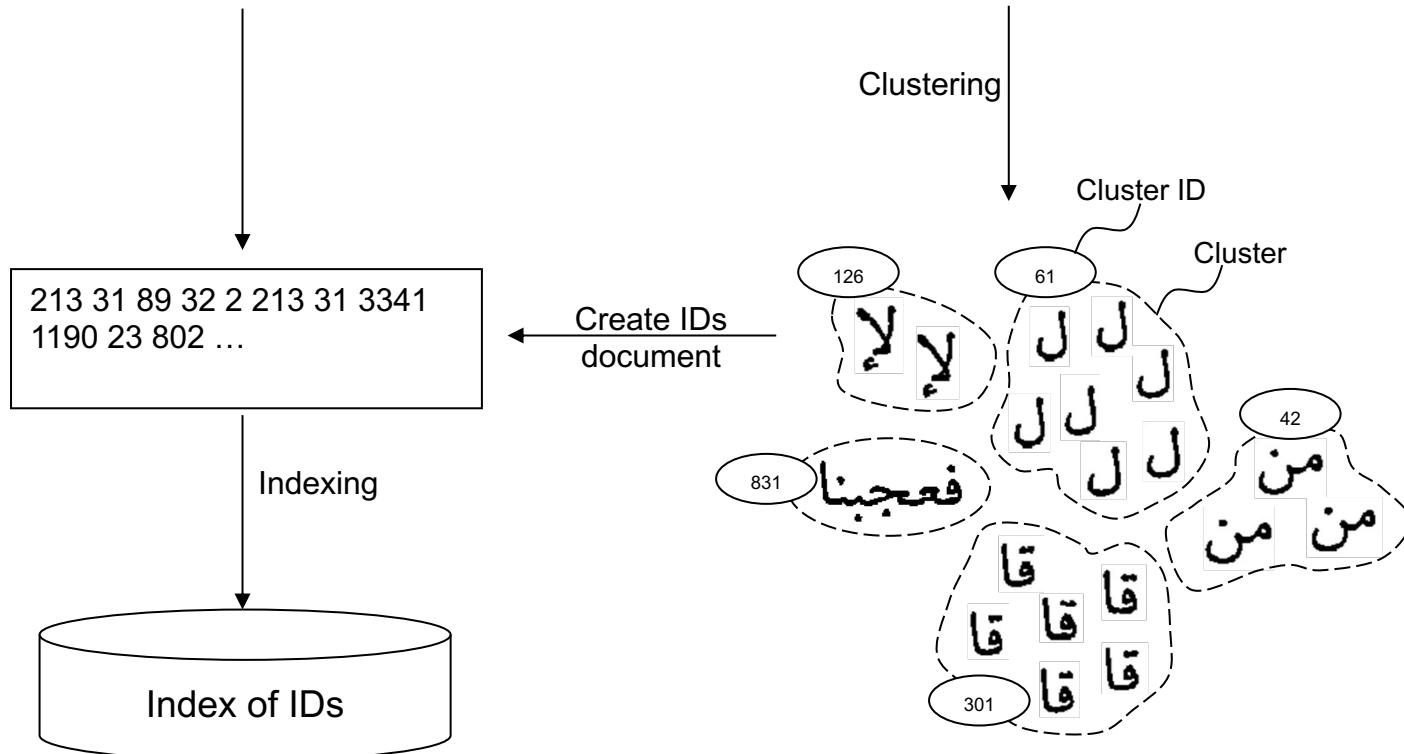


OCRless Search

قال : صدقت ، قال : فعجينا له يسأله ويصدقه ، قال : فأخبرنى عن الإيمان ؟ قال : « أن تؤمن بالله ، وملائكته ، وكتبه ، ورسله ، واليوم الآخر ، وتؤمن بالقدر خيره وشره » ، قال : صدقت ، قال : فأخبرنى عن الإحسان ؟ قال : « أن تعبد الله كأنك تراه ، فإن لم تكن تراه ، فإنه يراك » ، قال : صدقت ، قال : فأخبرنى عن الساعة ؟ قال : « ما المسؤول عنها بأعلم من السائل » ، قال : فأخبرنى عن أماراتها ؟ قال : « أن تلد الأمة ربها ، وأن ترى الحفاة العراة العالة رعاء الشاء يتظاولون في البنيان » .

Segment to elements

قا و صد
فعجينا ل و
يصل ، ل



Solution – OCRless Search

- Effective and fast
- Robust to OCR errors (video)
- No training resources required
- Language independent

الإيمان

Draw
query

عن

العربية

English

熊 猫

Rep
candidate IDs and
formulate query



syn(1284, 21, 673, 1208)
syn(430, 4, 6412, 3094)
syn(231, 9011, 32, 721)
syn(40, 110, 2213, 2214)

- Microsoft TechFest Demo
- List of ranked documents Search Index of IDs
- The same engine for searching printed documents in:
- Arabic, English, Chinese, Hebrew, and Hieroglyphic

Printed Documents Retrieval

- **Text-based solutions:** correction
- **Image-based:** clustering

- **Current State-of-the-art:** CAPTCHA

- **Information need → Approach**

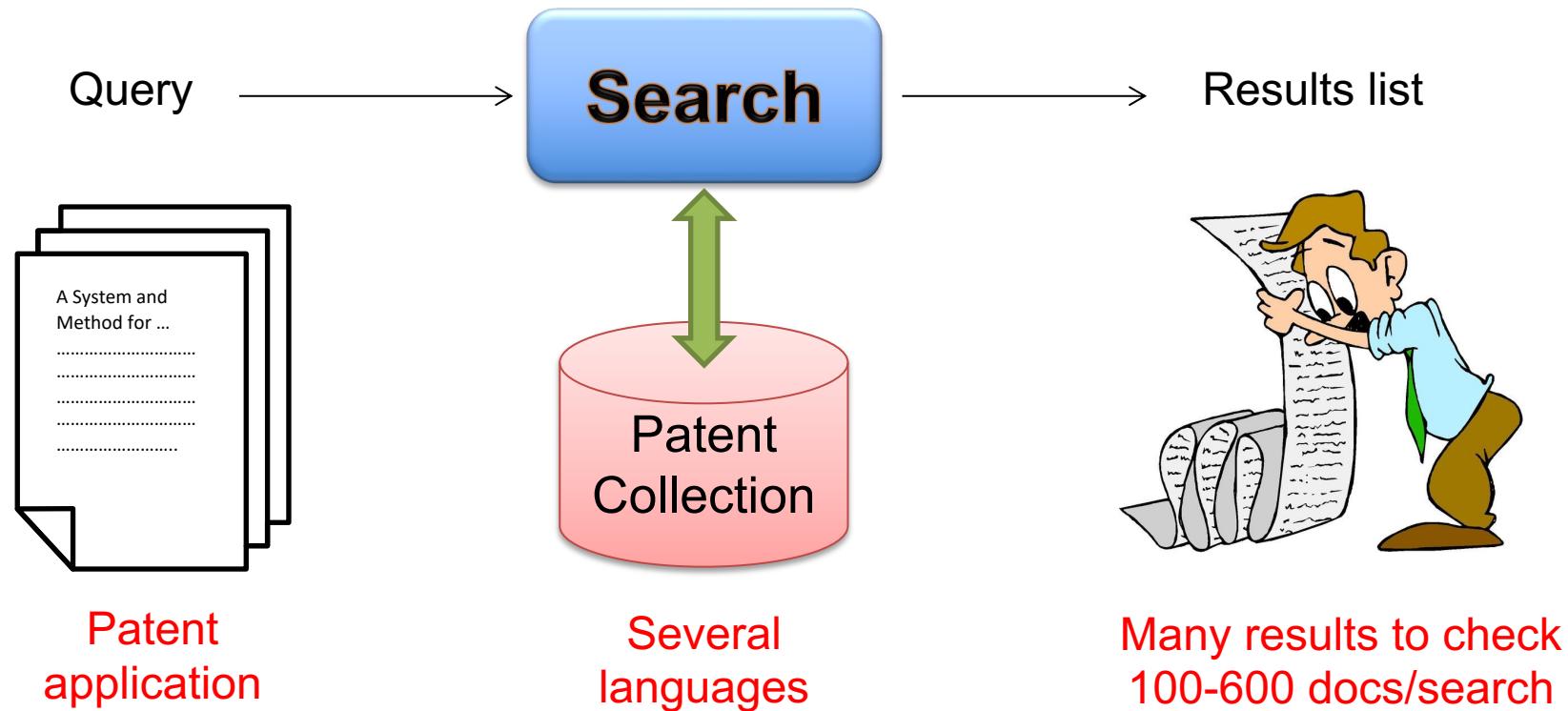


Patent Search



Patent Search

- Given a patent application, check if the invention described is novel



Patent Search – User Satisfaction

- NTCIR, CLEF, TREC
- Recall-oriented → Try not to miss a relevant document
 - Recall is the objective
- Precision is also important
- Huge # documents checked (100-600 documents)
- Evaluation: average precision (AP)!!
 - Focuses on finding relevant docs early in ranked list
 - Less focus on recall

Example

For a topic with 4 relevant docs and 1st 100 docs to be examined:

System1: relevant ranks = {1}

System2: relevant ranks = {50, 51, 53, 54}

System3: relevant ranks = {1, 2, 3, 4}

$$AP_{\text{system1}} = 0.25$$

$$AP_{\text{system2}} = 0.0481$$

$$AP_{\text{system3}} = 1$$

$$R_{\text{system1}} = 0.25$$

$$R_{\text{system2}} = 1$$

$$R_{\text{system3}} = 1$$

- We need a metric that reflects recall and ranking quality in one measure

PRES: Patent Retrieval Evaluation Score

$$PRES \square 1 = \frac{\sum r_i - \frac{n \square 1}{2}}{N_{\max}}$$

n: number of relevant docs

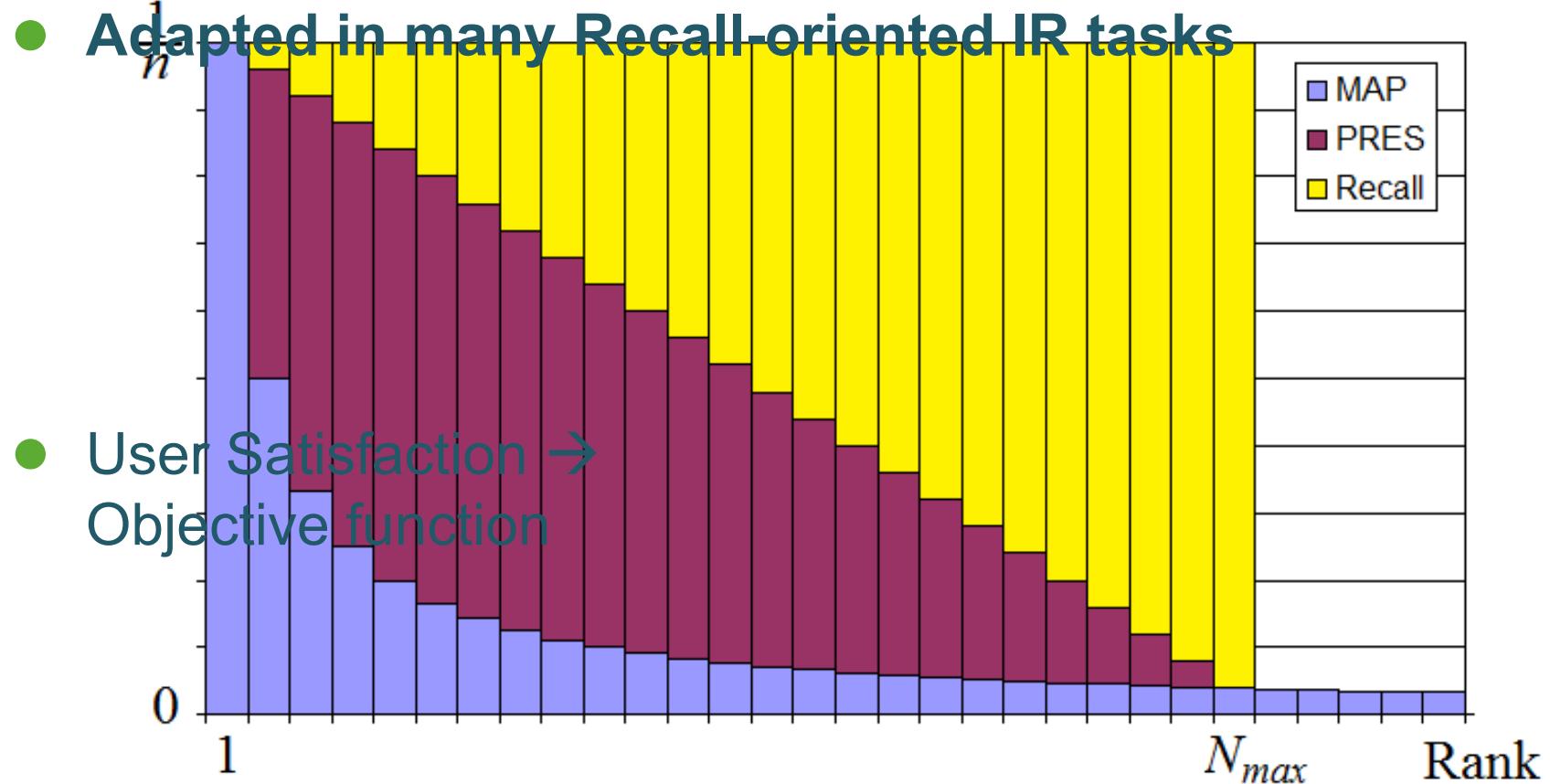
r_i : rank of the i^{th} relevant document

N_{\max} : max number of checked docs

- Derived from R_{norm} (Rocchio, 1964)
- Gives higher score for systems achieving higher recall and better average relative ranking
- Dependent on user's potential/effort (N_{\max})
- Robust to incomplete relevance judgements

PRES: as a cumulative gain

- Official score in CLEF-IP since 2010
Value added to score when finding relevant document
- Adapted in many Recall-oriented IR tasks



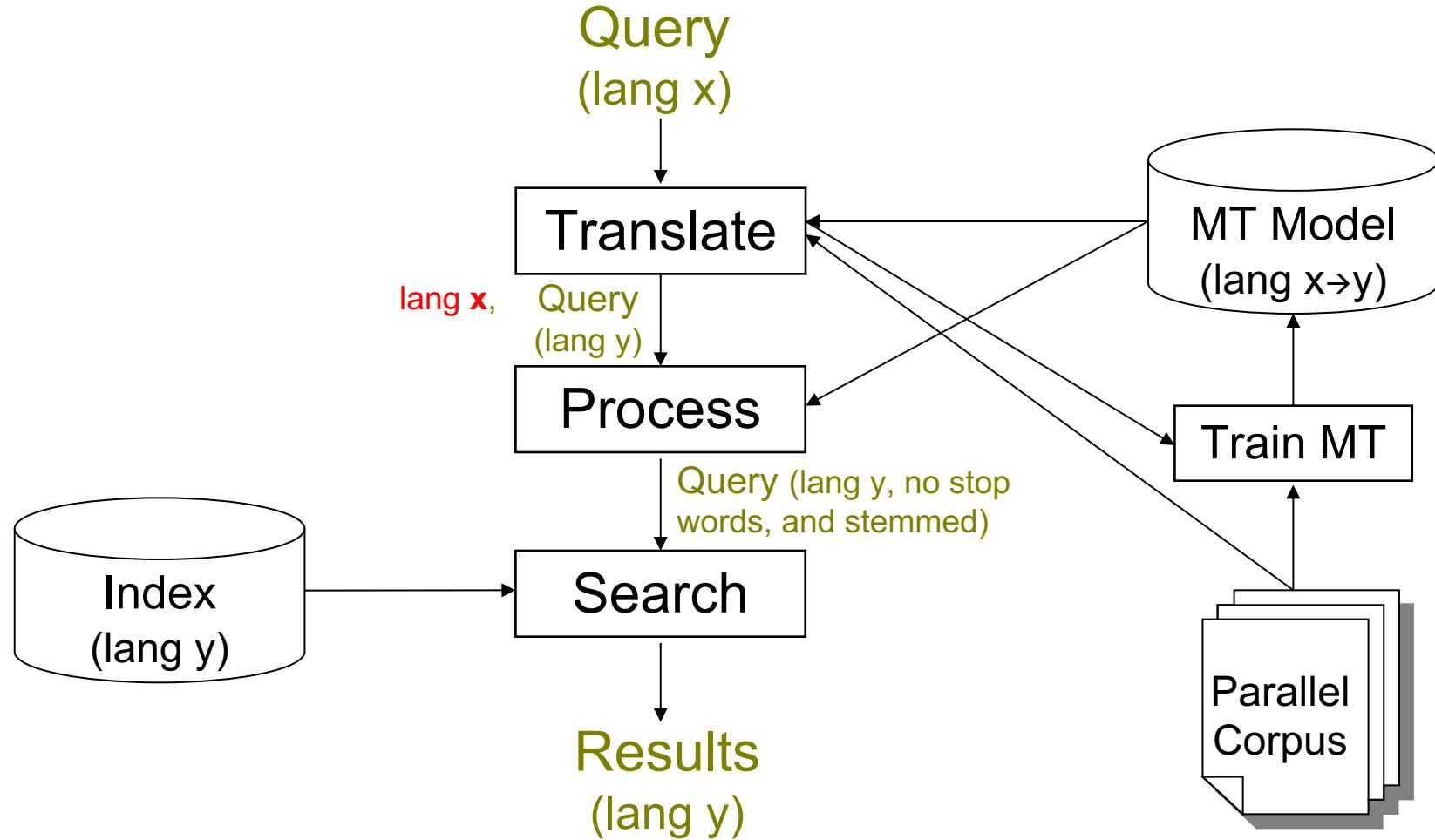
Patent Search – CLIR

- **Query: Full patent application**
- **Common approach: MT (the best)**
- **Challenge: training recourses + speed!**
- **Ideal: Query + Document translation**

Patent Search – CLIR – Objective?

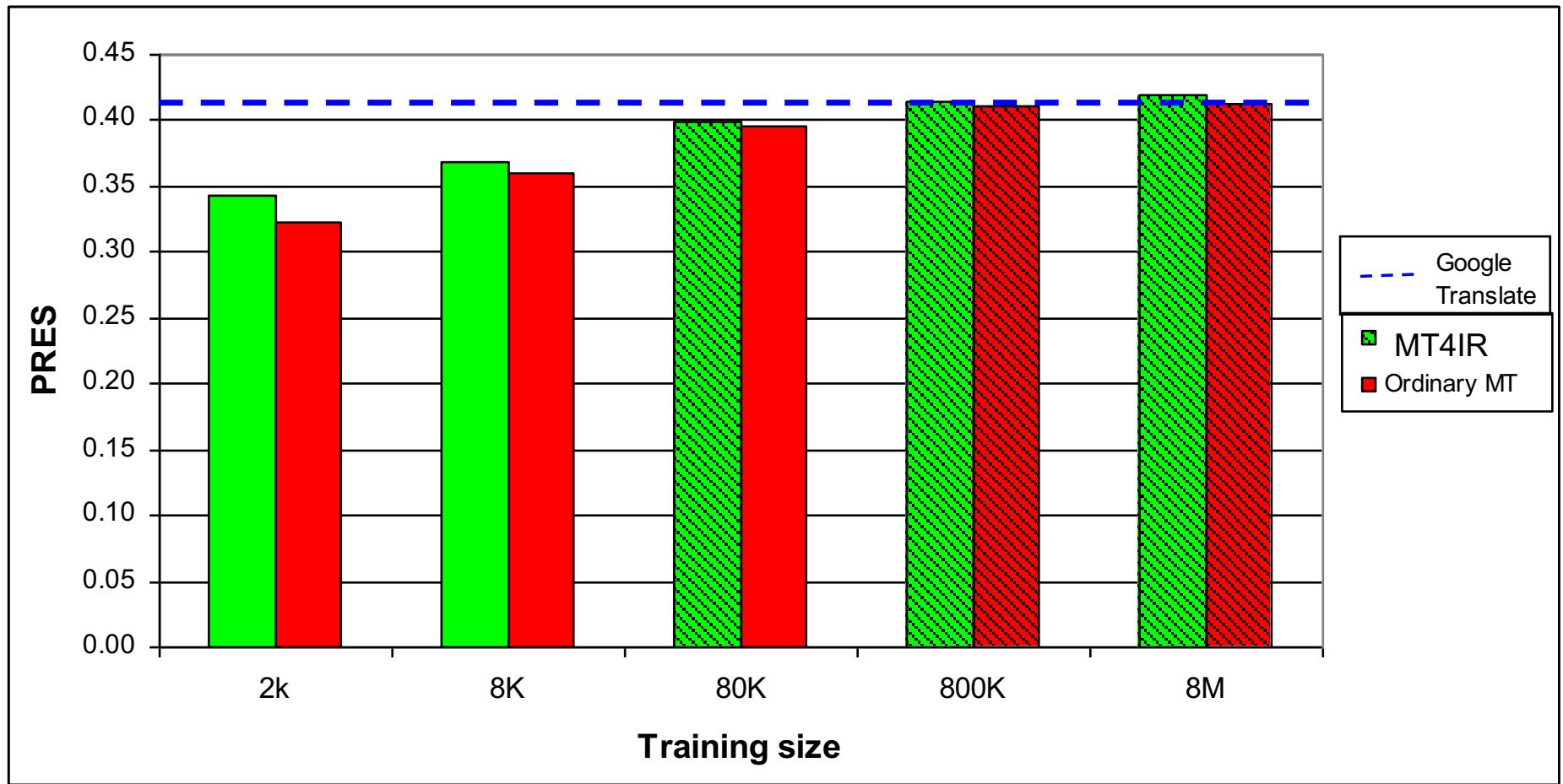
- **MT evaluation:** MT sucks
- **IR evaluation:** MT rocks ☺
- **MT4IR:** An efficient MT that neglects morphological and syntactic features of output

Ordinary MT vs. MT4IR

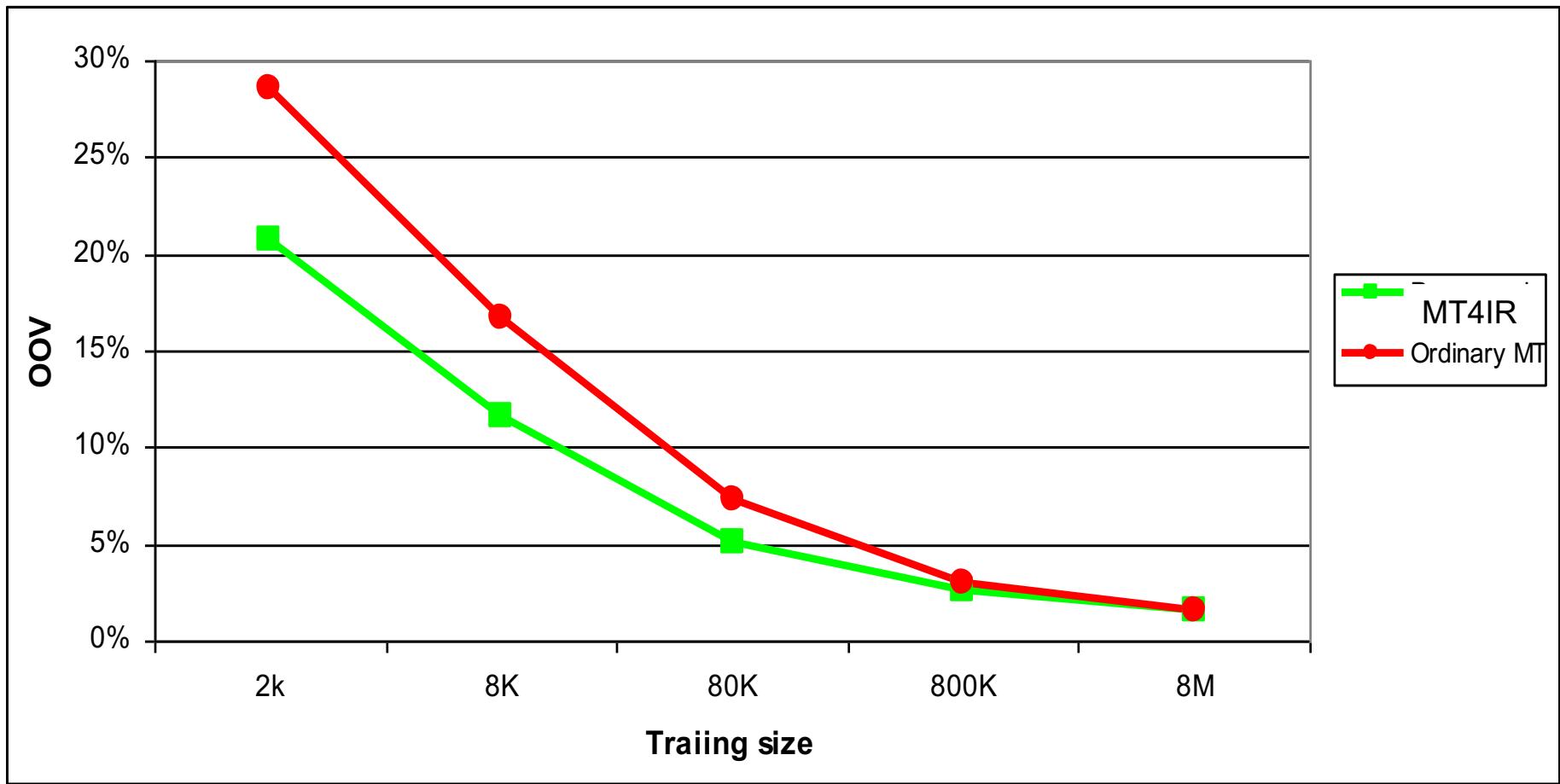


Patent Search – MT4IR

Retrieval effectiveness for a Patent CLIR En-Fr task



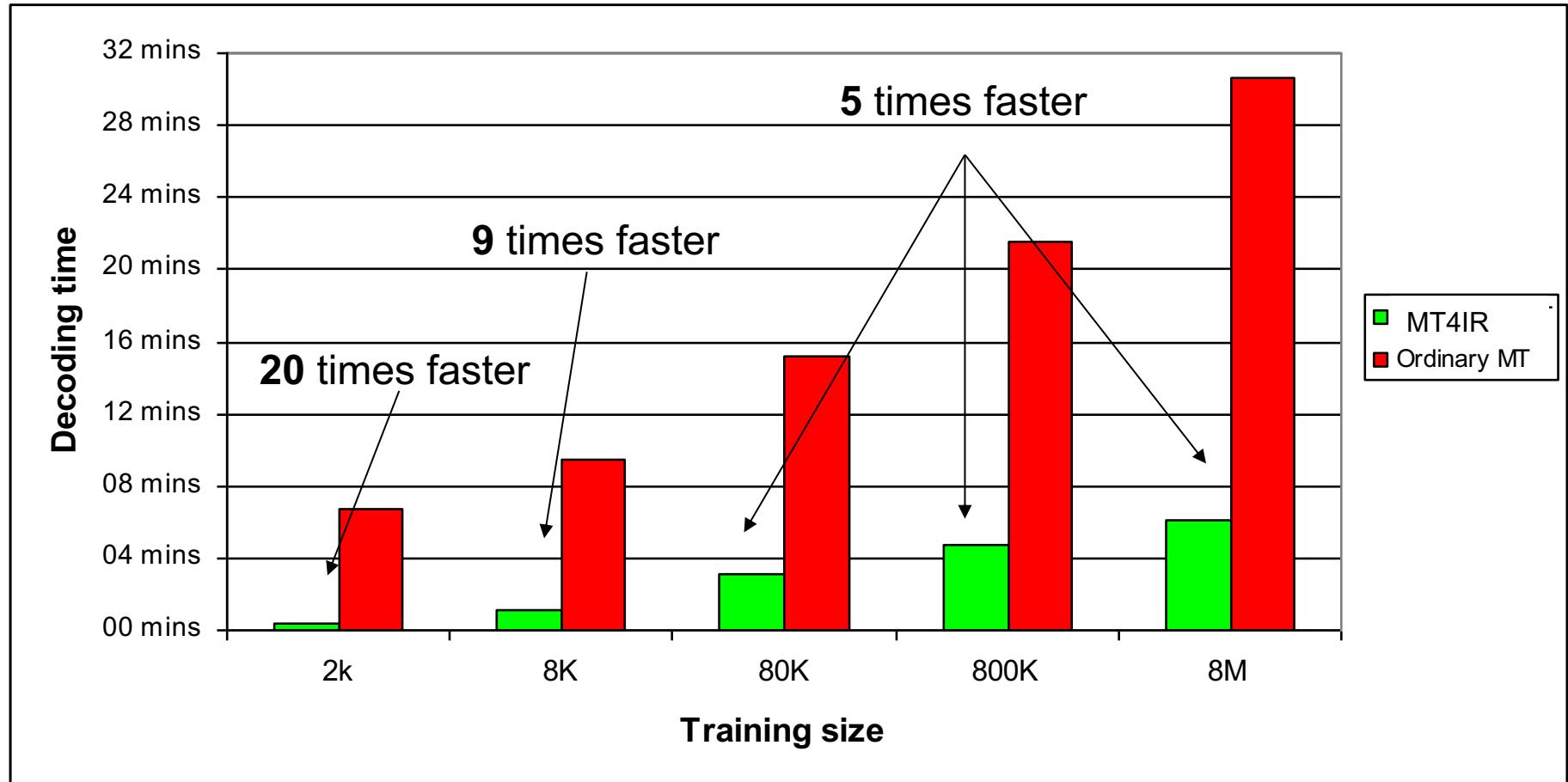
Patent Search – MT4IR



E.g. play, plays, played, playing

Patent Search – MT4IR

- Task → Approach
Decoding speed for a Patent CLIR En-Fr task



Summary

- The objective is IR is “User Satisfaction”
- Understand the user needs well
- Design the IR task carefully
- You do not have to stick to the path in the literature
- Are you sure performance is measured correctly?

Readings

- Magdy W. and G. J. F. Jones. Studying Machine Translation Technologies for Large-Data CLIR Tasks: A Patent Prior-Art Search Case Study. *Springer, Information Retrieval, 2013*
- Magdy W. and G. J. F. Jones. PRES: A Score Metric for Evaluating Recall-Oriented Information Retrieval Applications. *SIGIR 2010*
- Magdy W. , K. Darwish, and M. El-Saban. Efficient Language-Independent Retrieval of Printed Documents without OCR. *SPIRE 2009*
- Magdy W. and K. Darwish. Effect of OCR Error Correction on Arabic Retrieval. *Springer, Information Retrieval, 2008*