# Low-Cost Construction of a Multilingual Lexicon from Bilingual Lists


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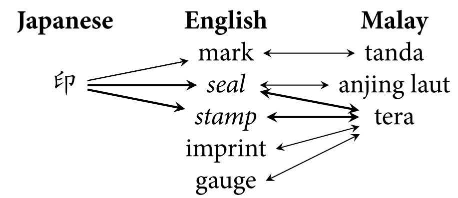
## Introduction

- Bilingual MRDs are good resources for building multilingual lexicons
- But MRDs have heterogeneous contents and structures
  - Not all contain rich information (gloss, domain) (Especially so for under-resourced languages)
  - Different structures (sense granularity, distinctions)
- Lowest common denominator: list of *source language item* → *target language item(s)*
- Construct multilingual lexicon using only bilingual lists

## One-time Inverse Consultation [1]

- Generates a bilingual lexicon for a new language pair from existing bilingual lists
- Given bilingual lexicons $L_1$–$L_2$, $L_2$–$L_3$, $L_3$–$L_2$, generate bilingual lexicon $L_1$–$L_3$
- Example: JP–EN, EN–MS, MS–EN lexicons ⇒ JP–MS




$$\text{score}(\text{`tera'}) = 2 \times \frac{|\mathbb{E}_1 \cap \mathbb{E}_2|}{|\mathbb{E}_1| + |\mathbb{E}_2|} = 2 \times \frac{2}{3+4} = 0.57$$

∴ '印' ↔ 'tera' is more likely to be valid

## Discussion

- Low thresholds ($\alpha, \beta$): more coverage; low precision
- High thresholds: good precision; low coverage
- $\alpha \approx 0.6, \beta \approx 0.2$ gives good trade-off between coverage, precision and recall
- Results are encouraging for such simple input data! Especially suitable for under-resourced language pairs
- **Future plan:** Integrate multilingual lexicon into an MT system with WSD and user interaction features

## Related Work

- Many multilingual lexicon projects [2, 3]) aligned with Princeton WordNet [4]
  - Overly fine sense distinctions in Princeton WordNet
- Pan Lexicon [5]: compute context vectors of words from monolingual corpora of different languages, then grouping into translation sets by matching context vectors via bilingual lexicons
  - Sense distinctions derived from corpus evidence
  - Produces many translation sets that contain semantically related but not synonymous words, e.g. 'shoot' and 'bullet' (lower precision)
  - 44 % precision based on evaluators' opinions (75 % if inter-evaluator agreement is not required)
  - Does not handle multi-word expressions
- Markó, Schulz and Hahn [6] use cognate mappings to derive new translation pairs, validate by processing parallel corpora (medical domain)
  - Complex terms indexed on the level of sub-words e.g. 'pseudo⊕hypo⊕para⊕thyroid⊕ism'
  - 46 % accuracy for each language pair
  - Requires large aligned thesaurus corpora (easier to acquire for specialised domains?)
  - Cognate-based approach not applicable for language pairs that are not closely related
- Lafourcade [7]: compute contextual vectors for translation pairs based on gloss text and associated class labels from semantic hierarchy; compare vectors from different bilingual lexicons to detect synonymy
  - Resource requirements not available for all language pairs, costly task of assigning class labels

## References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[3] D. Tufiş, D. Cristeau, and S. Stamou. "BalkaNet: Aims, Methods, Results and Perspectives – A General Overview". In: *Romanian Journal of Information Science and Technology Special Issue* 7.1 (2004), pp. 9–43.

[4] C. Fellbaum, ed. *WordNet: An Electronic Lexical Database*. Language, Speech, and Communication. Cambridge, Massachusetts: MIT Press, 1998.

[5] M. Sammer and S. Soderland. "Building a sense-distinguished multilingual lexicon from monolingual corpora and bilingual lexicons". In: *Proceedings of Machine Translation Summit XI*. Copenhagen, Denmark, 2007, pp. 399–406.

[6] K. Markó, S. Schulz, and U. Hahn. "Multilingual Lexical Acquisition by Bootstrapping Cognate Seed Lexicons". In: *Proceedings of the International Conference on Recent Advances in Natural Language Processing (RANLP) 2005*. Borovets, Bulgaria, 2005.

[7] M. Lafourcade. "Automatically Populating Acception Lexical Database through Bilingual Dictionaries and Conceptual Vectors". In: *Proceedings of PAPILLON-2002*. Tokyo, Japan, Aug. 2002.

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## Contact


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## Merging Translation Triples into Sets

- Retain OTIC 'middle' language links
- For each 'head' language LI, filter only triples whose score exceed thresholds (See Algorithm 1)
- Merge all triples with common bilingual pairs
- Malay–English–Chinese example:

**MS–EN** Kamus Inggeris–Melayu untuk Penterjemah
**EN–ZH** XDict **ZH–EN** CC-CEDICT

**(garang, 凶猛) 0.143**
(garang, ferocious, 凶猛)
(garang, fierce, 凶猛)

~~**(garang, 黑体) 0.048**~~
~~(garang, bold, 黑体)~~

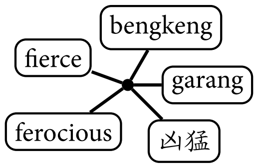
**(garang, 激烈) 0.125**
(garang, jazzy, 激烈)

~~**(garang, 粗体) 0.048**~~
~~(garang, bold, 粗体)~~

~~**(garang, 大胆) 0.111**~~
~~(garang, bold, 大胆)~~

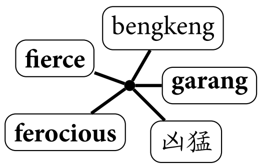
⋮

(garang, ferocious, 凶猛)
(garang, fierce, 凶猛)
(bengkeng, fierce, 凶猛)
⟶



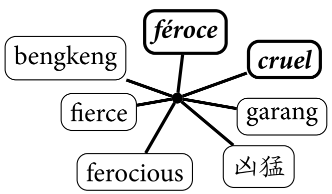

## Adding More Languages

- Construct $L_1$–$L_2$–$L_4$ triples
- Add $L_4$ members to existing $L_1$–$L_2$–$L_3$ clusters with common $L_1$ & $L_2$ members
- Example: Malay–English–Chinese + French, using 'ready-made' triples from FeM




+ (***cruel***, **ferocious**, **garang**)
(***féroce***, **fierce**, **garang**)

↓

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**Algorithm 1:** Generating trilingual translation chains

**forall the** *lexical items* $w_h \in L_1$ **do**
  $\mathbb{W}_m \leftarrow$ translations of $w_h$ in $L_2$
  **forall the** $w_m \in \mathbb{W}_m$ **do**
    $\mathbb{W}_t \leftarrow$ translations of $w_m$ in $L_3$
    **forall the** $w_t \in \mathbb{W}_t$ **do**
      Output a translation triple $(w_h, w_m, w_t)$
      $\mathbb{W}_{m_r} \leftarrow$ translations of $w_t$ in $L_2$
      score$(w_h, w_m, w_t) \leftarrow$
      $$\sum_{w \in \mathbb{W}_m} \frac{|\text{common words in } w_{m_r} \in \mathbb{W}_{m_r} \text{ and } w|}{|\text{words in } w_{m_r} \in \mathbb{W}_{m_r}|}$$
    **end**
    $$\text{score}(w_h, w_t) \leftarrow 2 \times \frac{\sum_{w \in \mathbb{W}_m} \text{score}(w_h, w, w_t)}{|\mathbb{W}_m| + |\mathbb{W}_{m_r}|}$$
  **end**
  $X \leftarrow \max_{w_t \in \mathbb{W}_t} \text{score}(w_h, w_t)$
  **forall the** *distinct translation pairs* $(w_h, w_t)$ **do**
    **if** *score*$(w_h, w_t) \geq \alpha X$ *or* $(\textit{score}(w_h, w_t))^2 \geq \beta X$ **then**
      Place $w_h \in L_1, w_m \in L_2, w_t \in L_3$ from all triples $(w_h, w_{\ldots}, w_t)$ into same translation set
      Record score$(w_h, w_t)$ and score$(w_h, w_m, w_t)$
    **else**
      Discard all triples $(w_h, w_{\ldots}, w_t)$
      `// The sets are now grouped by` $(w_h, w_t)$
    **end**
  **end**
**end**
Merge all sets containing triples with same $(w_h, w_m)$
Merge all sets containing triples with same $(w_m, w_t)$

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**Algorithm 2:** Adding $L_{k+1}$ to multilingual lexicon $\mathbb{L}$ of $\{L_1, L_2, \ldots, L_k\}$

$T \leftarrow$ translation triples of $L_{k+1}, L_m, L_n$ generated by Algorithm 1 where $L_m, L_n \in \{L_1, L_2, \ldots, L_k\}$
**forall the** $(w_{L_m}, w_{L_n}, w_{L_{k+1}}) \in T$ **do**
  Add $w_{L_{k+1}}$ to all entries in $\mathbb{L}$ that contains both $w_{L_m}$ and $w_{L_n}$
**end**

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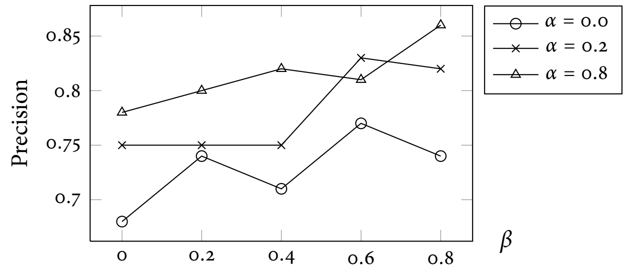
## Precision of 100 Random Translation Sets




- Precision increases with threshold parameters $\alpha$ and $\beta$
- Precision generally around 0.70–0.82; max 0.86
- Most false positives are not ranked at top of the list
- Many errors caused by incorrect POS assignments

## $F_1$ and Rand Index of Selected Translation Sets

- False positives will frequently arise when 'middle' language members are polysemous, e.g. 'plant', 'target'
- Evaluate accuracy of selected sets with polysemous 'middle' language members

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$
$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$
$$F_1 = \frac{2 \times \text{Precision} \times \text{Recall}}{\text{Precision} + \text{Recall}}$$
$$\text{RI} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FP} + \text{FN} + \text{TN}}$$

| Test | Rand Index | | $F_1$ | | Best accuracy when | |
|---|---|---|---|---|---|---|
| word | min | max | min | max | $\alpha$ | $\beta$ |
| 'bank' | 0.417 | 0.611 | 0.588 | 0.632 | 0.6 | 0.4 |
| 'plant' | 0.818 | 0.927 | 0.809 | 0.913 | 0.6 | 0.2 |
| 'target' | 0.821 | 1.000 | 0.902 | 1.000 | 0.4 | 0.2 |
| 'letter' | 0.709 | 0.818 | 0.724 | 0.792 | 0.8 | 0.2 |

- $F_1$ and RI increases with $\alpha$ and $\beta$
- But may decrease when they are too high and reject valid members (false negatives)