Discussion

- Low thresholds (α, β): 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

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Low-Cost Construction of a Multilingual Lexicon from Bilingual Lists

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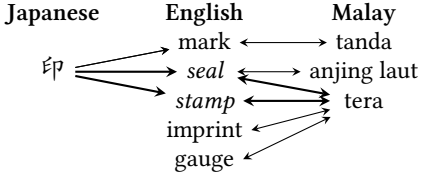
Introduction

- 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

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, 激烈) 0.125
(garang, jazzy, 激烈)

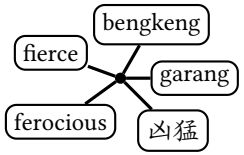
(garang, 大胆) 0.111
(garang, bold, 大胆)

(garang, 黑体) 0.048
(garang, bold, 黑体)

(garang, 粗体) 0.048
(garang, bold, 粗体)

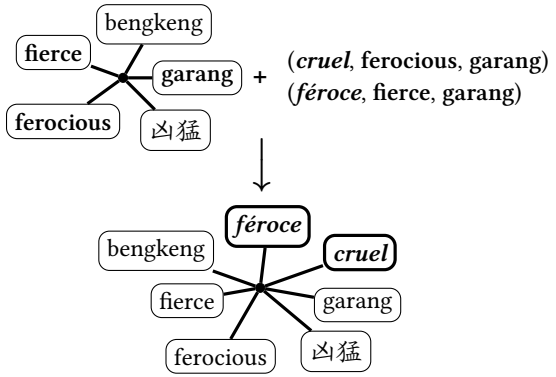
⋮

(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



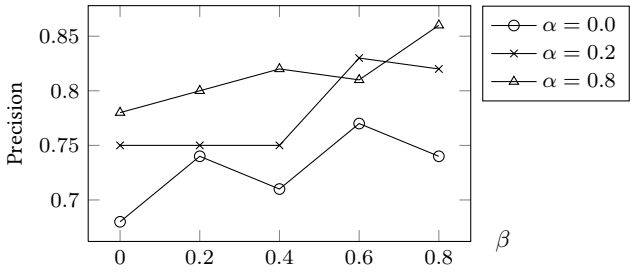
Algorithm 1: Generating trilingual translation chains

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
      $\text{score}(w_h, w_m, w_t) \leftarrow \sum_{w \in \mathbb{W}_m} \frac{|\text{common words in } w_{m_r} \in \mathbb{W}_{m_r} \text{ and } w|}{|\text{words in } w_{m_r} \in \mathbb{W}_{m_r}|}$
    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 $\text{score}(w_h, w_t)$ and $\text{score}(w_h, w_m, w_t)$
    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)

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

Precision of 100 Random Translation Sets



- Precision increases with threshold parameters α and β
- 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 word	Rand Index min	Rand Index max	F_1 min	F_1 max	Best accuracy when α	Best accuracy when β
'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 α and β
- But may decrease when they are too high and reject valid members (false negatives)