

Embedding Learning Through Multilingual Concept Induction

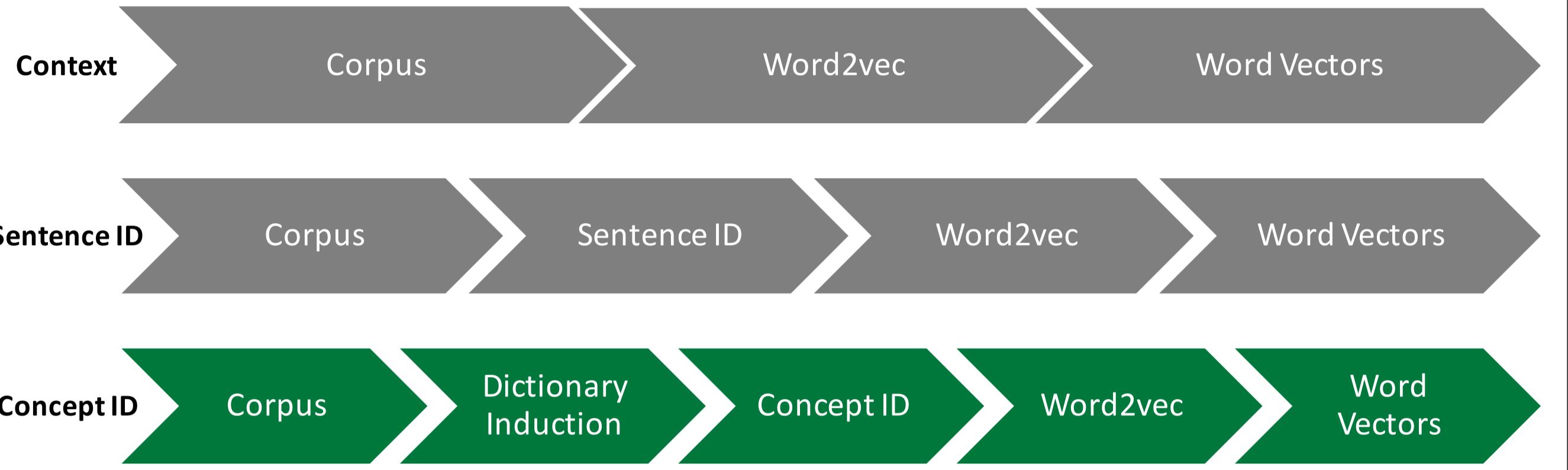
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Motivation



Objective: **Multilingual wordspace with 1000s (low-resource) languages.**

New feature: **concept-IDs.**

Data

- Parallel Bible Corpus [Mayer and Cysouw, 2014]: 7958 verses, 1259 languages, 1664 editions.

English King James Version	German Elberfelder 1905	Spanish Americas
And he said , Do it the second time . And they did it the second time ... And he said , Do it the third time ...third time .	Und er sprach : Füllt vier Eimer mit Wasser , und gießet es auf das Brandopfer und auf das Holz . Und er sprach : Tut es zum zweiten Male ! Und sie taten es zum zweiten Male ... Und er sprach : Tut es zum dritten Male ! Und sie taten es zum dritten Male .	Y dijio : Llenad cuatro cantaros de agua y derramala sobre el holocausto y sobre la leña . Después dijo : Hacedlo por segunda vez ; y lo hicieron por segunda vez ... Y añadió : Hacedlo por tercera vez ; y lo hicieron por tercera vez .

Dictionary Induction

- Creating $\mathcal{O}(n^2)$ dictionaries for n languages not scalable
⇒ selection of $p = 10$ pivot languages
- Computing $p(p - 1)/2 + pn$ dictionaries (intra-pivot and pivot-target) by aggregating fast-align alignments.

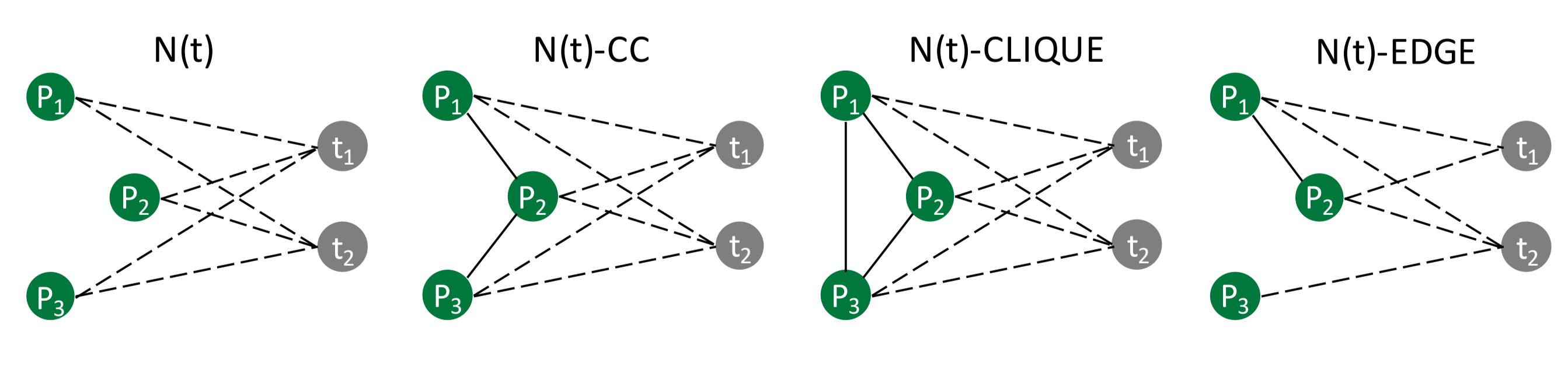
Concept Induction

1) CLIQUE Projection

- In ideal world: concepts correspond to cliques in the multilingual dictionary graph.
- In real-world: identify quasi-cliques to accommodate noise.
- Identify concepts in pivot dictionary graph and project them onto target languages.

2) Target Neighborhoods $N(t)$

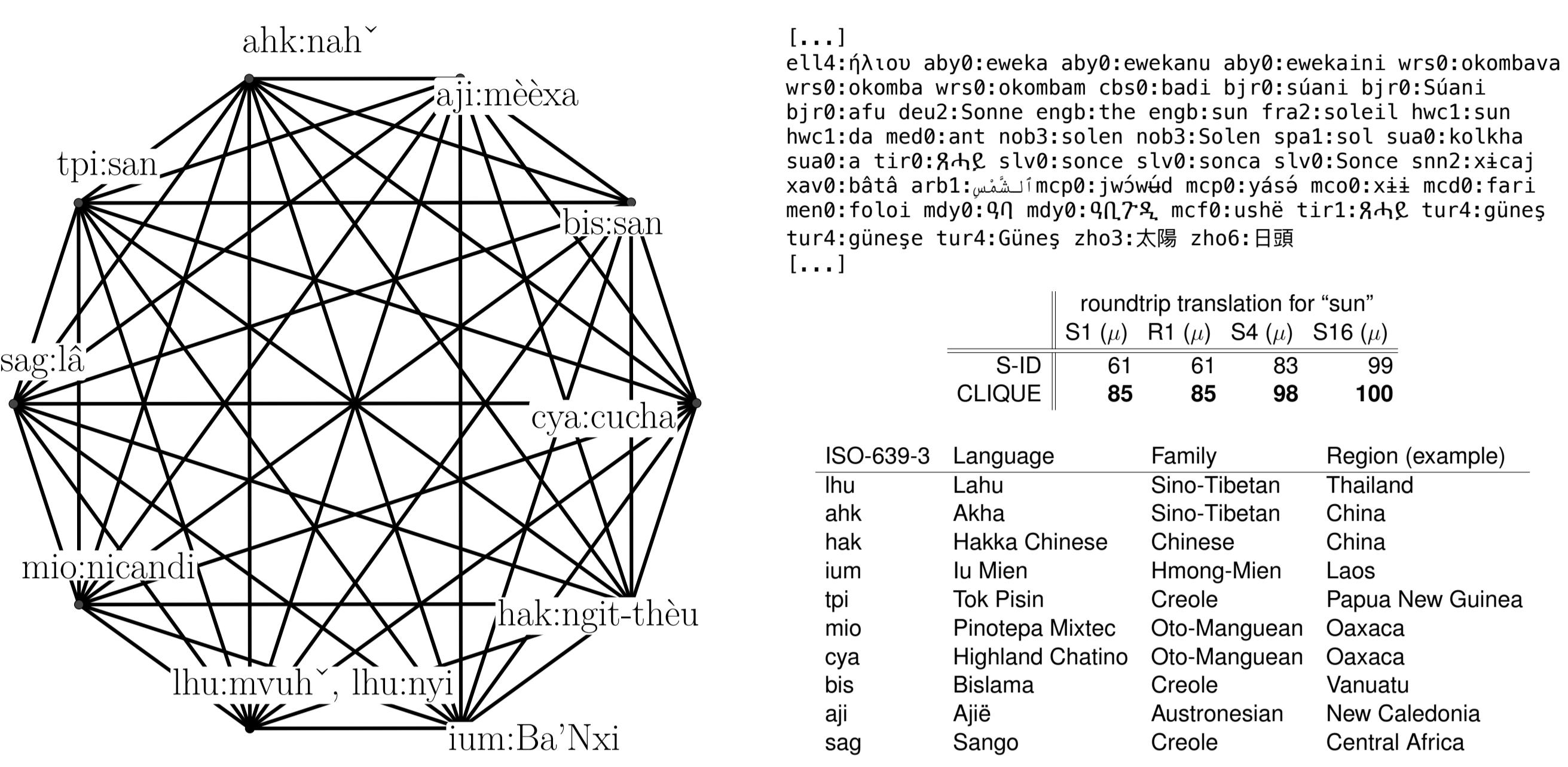
- Define target neighborhood for a word t by $N(t) := \{w \in V_p \mid (w, t) \in E_D\}$.
- Two words t_1 and t_2 are in the same concept if $N(t_1) = N(t_2)$.



Baselines

- Non-wordspace based: **RTSIMPLE**. Roundtrip translation directly on the dictionary graph.
- Context-based wordspaces: bag-of-words (**BOW**) [Vulić et al., 2015], sentence-ID (**S-ID**) [Levy et al., 2017].
- Alternative concept-identification method: **SAMPLE** [Lardilleux et al., 2009]. Sampling based approach for identifying concepts in a sentence-aligned corpus. Projection step same as for CLIQUE.

The concept “sun”



S-ID vs. C-ID

“...and gather his wheat into the garner ; but he will burn up the chaff with unquenchable fire .”	
S-ID	$q \Rightarrow I_e(q) \Rightarrow T_e(q)$
	burn ⇒ gogoro ⇒ harvest labourers fowls wheat sow gather tares gnashing
	⇒ gbi ⇒ fire burned brimstone hell burn burning smoke Sodom flame goats gnashing offerings vial devour wheat perdition
CLIQUE	$burn \Rightarrow agbi \Rightarrow$
	burn burned burning burning furnace fire flame warming unquenchable
	⇒ gbi ⇒ burning burn fire furnace burned unquenchable flame warming smoke lampstands candle lamps extinguished lamp pool Hell
roundtrip translation for “burn”	
S-ID	S1 (μ) 0.06 R1 (μ) 0.18 S4 (μ) 0.14 S16 (μ) 0.72
CLIQUE	0.72 0.92 0.95 1.00

• Roundtrip translation fails for query **burn** in language **sag**.
 • Reason: **sag:gogoro** occurs only in the context of **burning**
 • Nearest neighbours of **sag:gbi** within eng reflect the context of **burn** instead of semantically related words

WORD vs. CHAR

[ksw]	Many hard-to-tokenize and morphologically rich languages
[cso]	⇒ create 2 versions per edition: WORD and CHAR
[eng]	WORD (whitespace tok.): Neither, can, they, prove, the, things, ...
	CHAR (overlapping byte ngrams): [Neit, eith, ithe, ther, her@, er@ca, r@can, ...

Adjustments:

- χ^2 based dictionary: iteratively select word pair with highest χ^2 . Then remove cooccurrence of this pair.
- Query selection RTT: find ngrams for each query word which correspond uniquely to this word.
- Groundtruth in RTT: select words based on degree of correspondance between ngram and query word.
- Sentiment analysis: consider only ngrams which have been aligned.

Embedding Learning

- Word2vec skipgram model with mostly default hyperparameters.

	roundtrip translation						sentiment analysis			
	WORD			CHAR			WORD		CHAR	
	S1	R1	S4	S16	S1	R1	S4	S16	μ Md	μ Md
1	RTSIMPLE	33	24	37	67	21	13	32	70	70
2	BOW	7	5	8	713	1226	2869	3	2	3
3	S-ID	46	46	52	5563	7679	9165	9	5	9
4	SAMPLE	33	23	43	4254	5982	9665	53	59	59
5	CLIQUE	43	36	59	6367	7793	9969	42	46	48
6	N(t)	54	59	61	69	80	8794	100	69	88
7	N(t)-CC	52	56	59	67	8693	9969	40	45	42
8	N(t)-CLIQUE	11	0	11	0	16	0	18	39	45
9	N(t)-EDGE	35	30	43	36	56	5587	94	69	84

Contributions

- Novel embedding learning method: **concept-based embedding learning**.
- New word-/character-level **dictionary and concept induction** methods.
- Word translation and sentiment analysis **across 1259 languages**.

Conclusions

- Concept-based methods outperform** previous approaches.
- New roundtrip evaluation is an **excellent wordspace quality indicator**.
- Character-level is better than word-level** for sentiment classification.

Evaluation

Roundtrip translation

q	$\Rightarrow I_e(q) \Rightarrow T_e(q)$	\Rightarrow	$T_e(q)$	$S1$	$R1$	$S4$	$S16$
woman	⇒ mujer	⇒ wife	woman women widows daughters				
		daughter marry married					+0 +0 +1 +1
	⇒ esposa	⇒ marry wife woman married marriage	virgin daughters bridegroom				

• 70 English queries taken from a list of universal words by Swadesh (1946).

• Strict and relaxed groundtruth: $G_s(q) = \{q\}$, $G_r(q)$ contains words with the same lemma as q .

• Accuracy computed by $1/|E| \sum_{e \in E} \min\{1, |T_e(q) \cap G_i(q)|\}$, aggregated over queries.

Sentiment Analysis

Now is come salvation ... the power of his Christ: for the accuser ... cast down, which accused them before our God ...”
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- Creation of English silver standard using the Vader-Classifier in combination with manual annotations
- Unclear sentiment: ⇒ 2 tasks: “contains positive sentiment” and “contains negative sentiment”
- Assumption: each verse has unchanged sentiment across languages.
- Linear SVMs for classification and report of average F_1 scores (across languages)

Results

	roundtrip translation						sentiment analysis			
	WORD			CHAR			WORD		CHAR	
	S1	R1	S4	S16	S1	R1	S4	S16	μ Md	μ Md

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