Interactive Refinement of Cross-Lingual Word Embeddings

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NLP for Low-resource Languages

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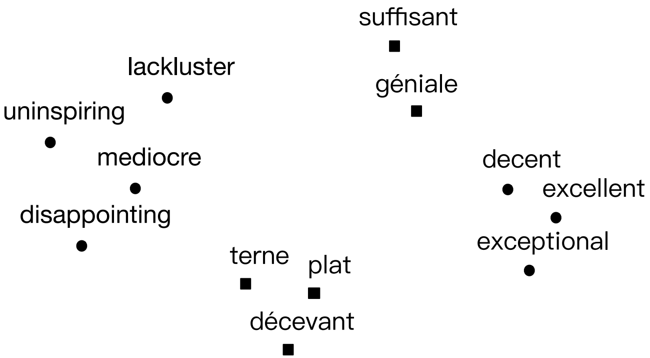
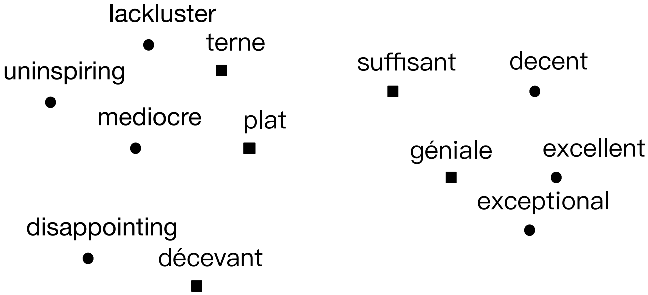
How can we quickly refine CLWE for low-resource NLP?

Refining CLWE



Refining CLWE



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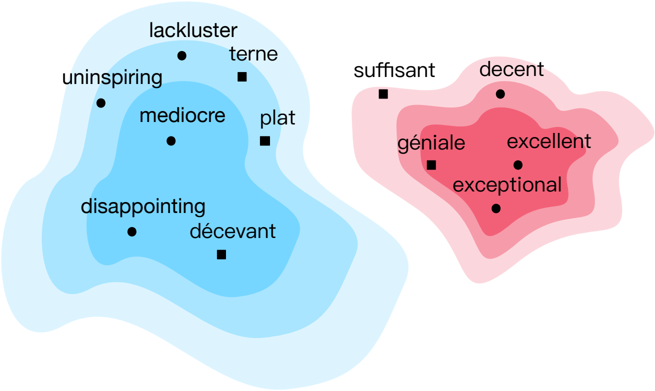

Classification clime: Areas in embedding space where words induce similar labels for a task

CLIME

CLassifying **I**nteractively with **M**ultilingual **E**mbeddings

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Input: pre-trained CLWE

1. Select keywords with *gradient-based salience* (Li et al., 2016)
2. Collect user feedback
3. Refine embeddings on user feedback through *retrofitting* (Mrkšić et al., 2017)

Keyword Selection

1. **Local salience** of word x_i in x:

$$S_{\mathbf{x}}(x_i) = \left\| \nabla_{\mathbf{E}_{x_i}} L(\mathbf{x}, y) \right\|_2 .$$

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3. Select keywords that have highest global salience

Keyword Selection

Example sentences

`A disappointing dinner...meatballs were undercooked.` (negative)

`I was frustrated with the customer service.  Very disappointing.` (negative)

`An exceptional film.` (positive)

`I disliked waiting in line, but the ride was exceptional.` (positive)

Keyword Selection

Compute local salience

`A disappointing dinner...meatballs were undercooked.` (negative)

`I was frustrated with the customer service. Very disappointing.` (negative)

`An exceptional film.` (positive)

`I disliked waiting in line, but the ride was exceptional.` (positive)

Keyword Selection

Find words with highest global salience

`disappointing`

`exceptional`

Video Demo for User Interface

Retrofitting CLWE

1. **Feedback cost:** Pull positive neighbors p closer and negative neighbors n away

$$C_f(\mathbf{E}) = \sum_{k \in \mathcal{K}} \left(\sum_{n \in \mathcal{N}_k} \mathbf{E}_k^\top \mathbf{E}_n - \sum_{p \in \mathcal{P}_k} \mathbf{E}_k^\top \mathbf{E}_p \right).$$

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2. **Regularization:** Updated embeddings should not be too far away from original embeddings

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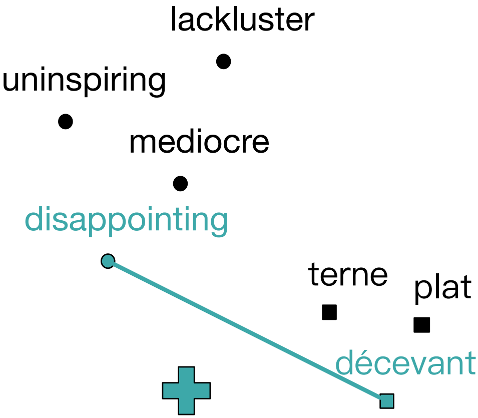
3. **Total cost function:**

$$C(\mathbf{E}) = C_f(\mathbf{E}) + \lambda R(\mathbf{E}).$$

Retrofitting CLWE



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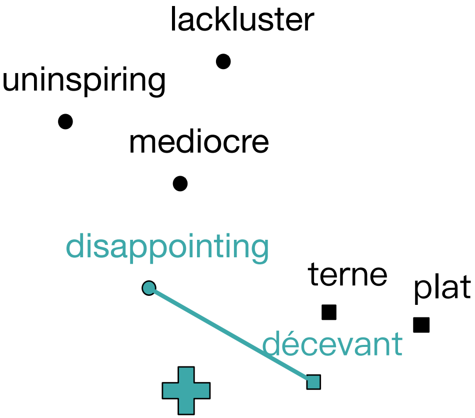

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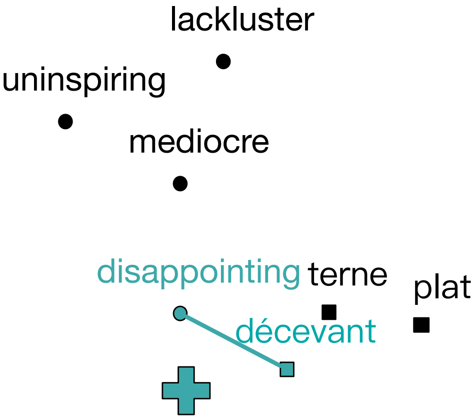

Task

Document classification for detecting medical emergencies in low-resource languages

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Ilocano	... Nagtalinaed dagiti pito a balod ti Bureau of Jail Management and Penology (BJMP) ditoy ciudad ti Laoag iti isolation room gapo iti tuko ...

Experiments

- **Embeddings:** fastText (Bojanowski et al., 2017) aligned with RCSLS (Joulin et al., 2017)
- **Classifier:** CNN (Kim, 2014)
- **Source language:** English
- **Target language:** Ilocano

User Study

We want to classify documents into two categories:

1. Documents describing a medical emergency.
2. Documents **not** describing a medical emergency.

Which words are likely to appear in the same category as

ambulance

ENGLISH	ILOCANO
ambulances	ospital
medics	nars
hospital	tulong
emergency	pagbakuitan
nurses	pammaregta
Add word	Add word

Comparison

- **Base:** original CLWE and original training dataset

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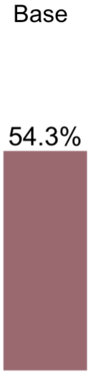
- **CLIME:** refined CLWE and original training dataset
- **A+C:** refined CLWE and training dataset augmented by active learning

Results



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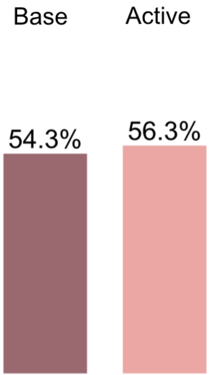

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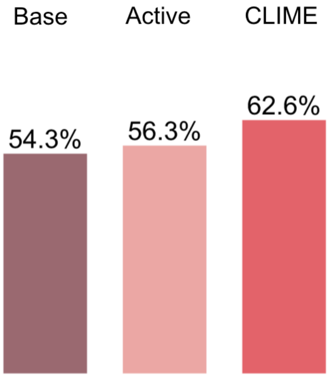

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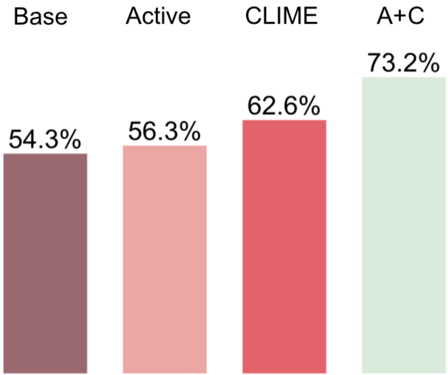

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