Interactive Refinement of Cross-Lingual Word Embeddings

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NLP for Low-resource Languages

- Scarcity of both labeled and unlabeled data holds back applications in low-resource languages
- Cross-lingual word embeddings (CLWE) can bridge the gap by mapping words from different languages to a shared vector space

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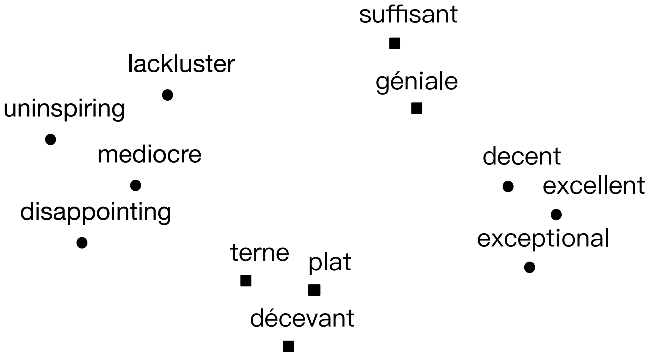
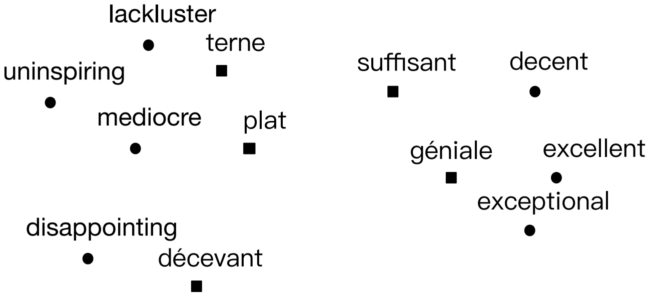
How can we quickly refine CLWE for low-resource NLP?

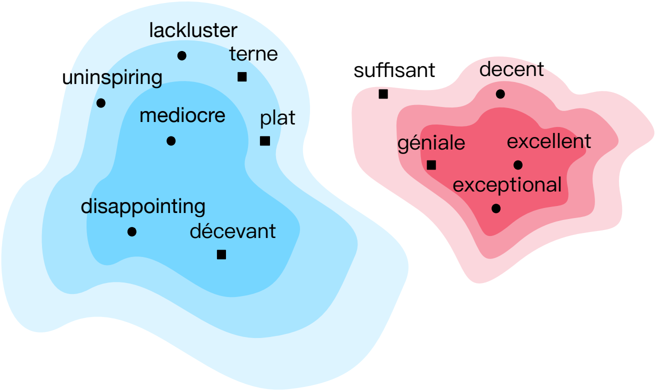
Refining CLWE



Refining CLWE



Refining CLWE



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

CLIME

CLassifying Interactively with Multilingual Embeddings

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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

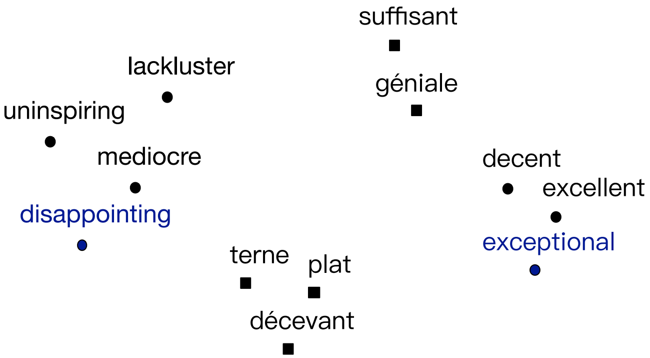
Find words with highest global salience

`disappointing`

`exceptional`

Keyword Selection

Areas to focus on in embedding space



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

$$R(\mathbf{E}) = \sum_{w \in \mathcal{V}} \left\| \hat{\mathbf{E}}_w - \mathbf{E}_w \right\|_2^2.$$

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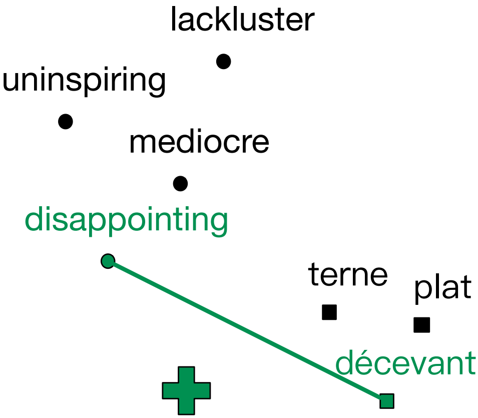
3. **Total loss function:**

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

Retrofitting CLWE



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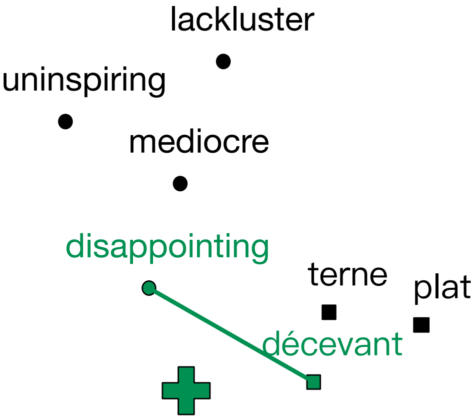

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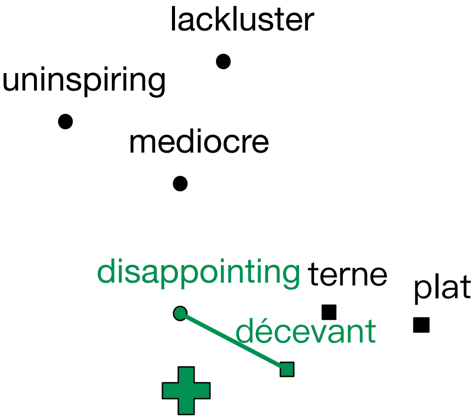

Experiments: Task

Document classification for detecting medical emergencies in low-resource languages

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Document classification for detecting medical emergencies in low-resource languages

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: Setting

- **Source language:** English
- **Target language:** Ilocano
- **Embeddings:** fastText aligned with RCSLS
- **Classifier:** CNN (max-pooling)

Experiments: 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

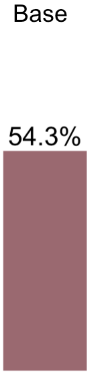
ambulance

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

Experiments: Methods

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

Experiments: Results



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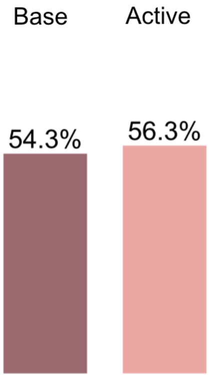

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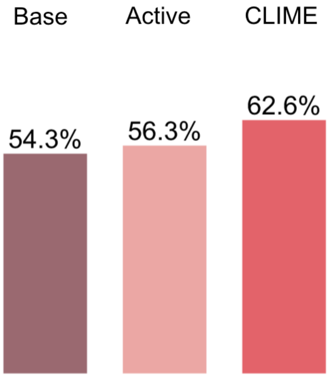

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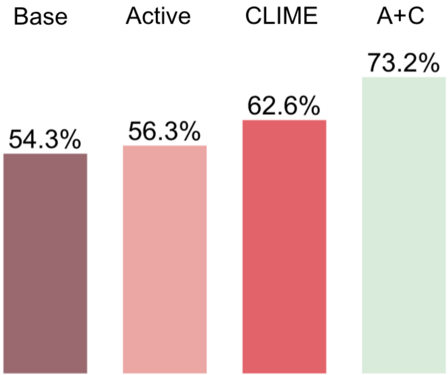

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Nikola Mrkšić, Ivan Vulić, Diarmuid Ó Séaghdha, Ira Leviant, Roi Reichart, Milica Gašić, Anna Korhonen, and Steve Young. 2017. Semantic specialisation of distributional word vector spaces using monolingual and cross-lingual constraints. *TACL*, 5:309–324.