

CoNLL 2019



Multilingual model using cross-task embedding projection

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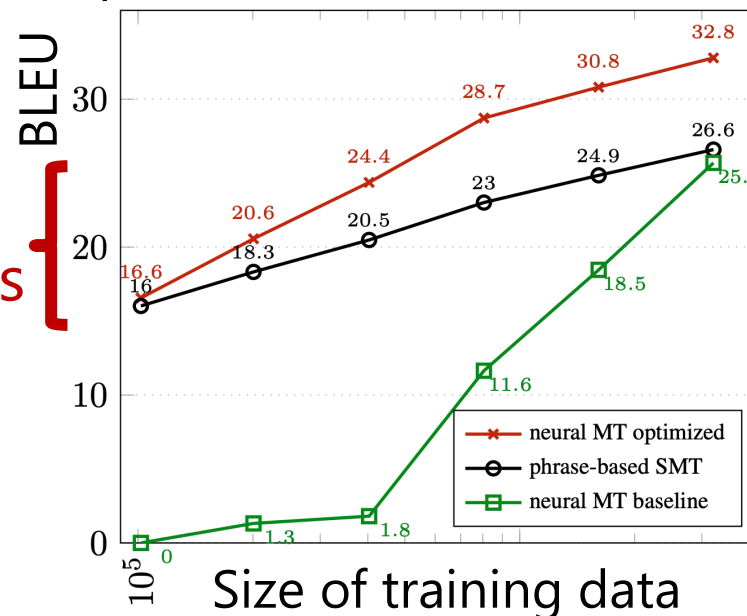
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Needs for resources in deep learning

Improvements in various tasks by deep learning

- Task-specific representation learning needs more data

Translation performance (DE->EN) [Sennrich+ 2019]



Small gain
with poor resources

Large gain
with rich resources

Need massive data for every pair of task and lang

Gaps in available resources across langs

Among 7097 languages in the world [Simons+ 2018], massive resources are obtainable only in few

- Universal dependencies project covers only 76 [Nivre+ 201X]

Large gap in model performances among languages

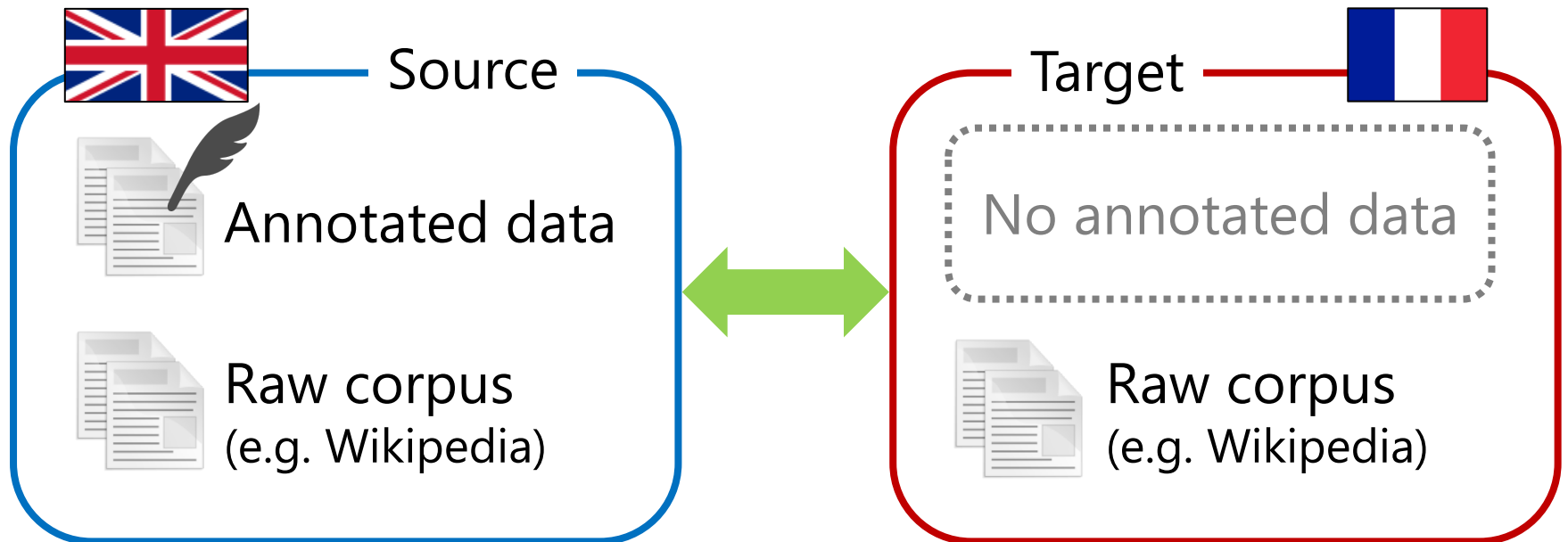


Can we exploit resources of resource-rich languages for training in resource-poor languages?

Problem settings of this study

Available resources:

- Labeled data for training in the source language
- Raw corpora in both languages

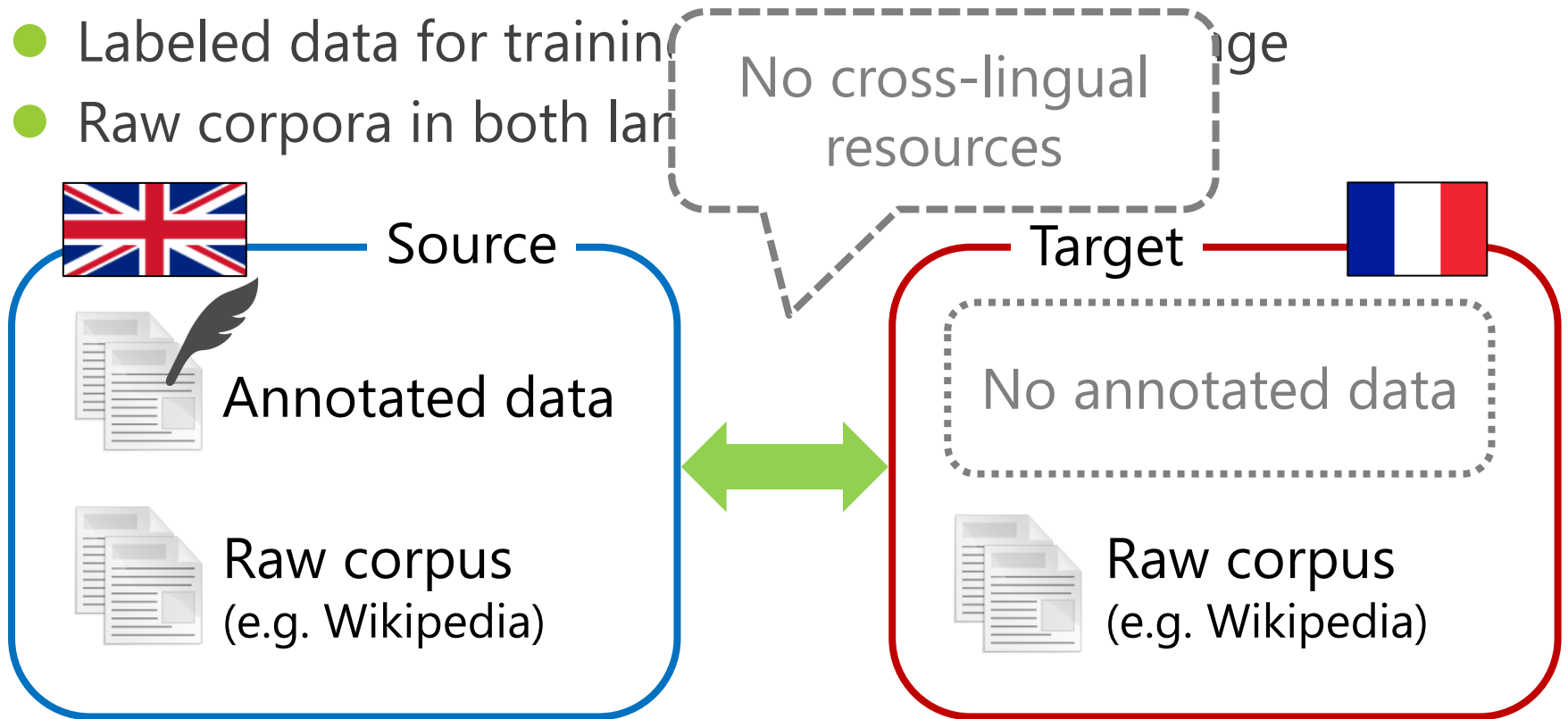


Applicable to various target languages and tasks

Problem settings of this study

Available resources:

- Labeled data for training
- Raw corpora in both languages

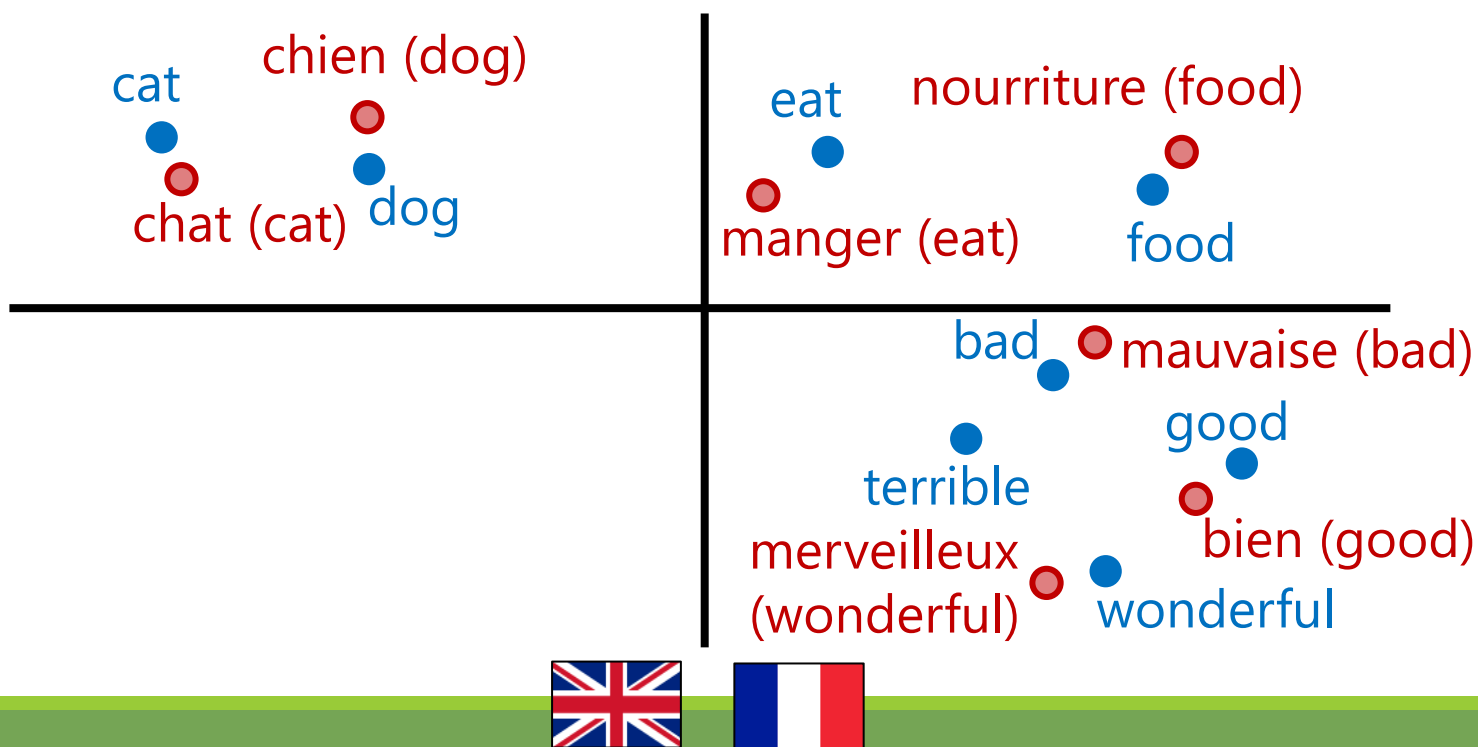


Applicable to various target languages

Preliminary: Cross-lingual word embeddings (CLWE)

Language-independent representation of words
[Mikolov+ 13]

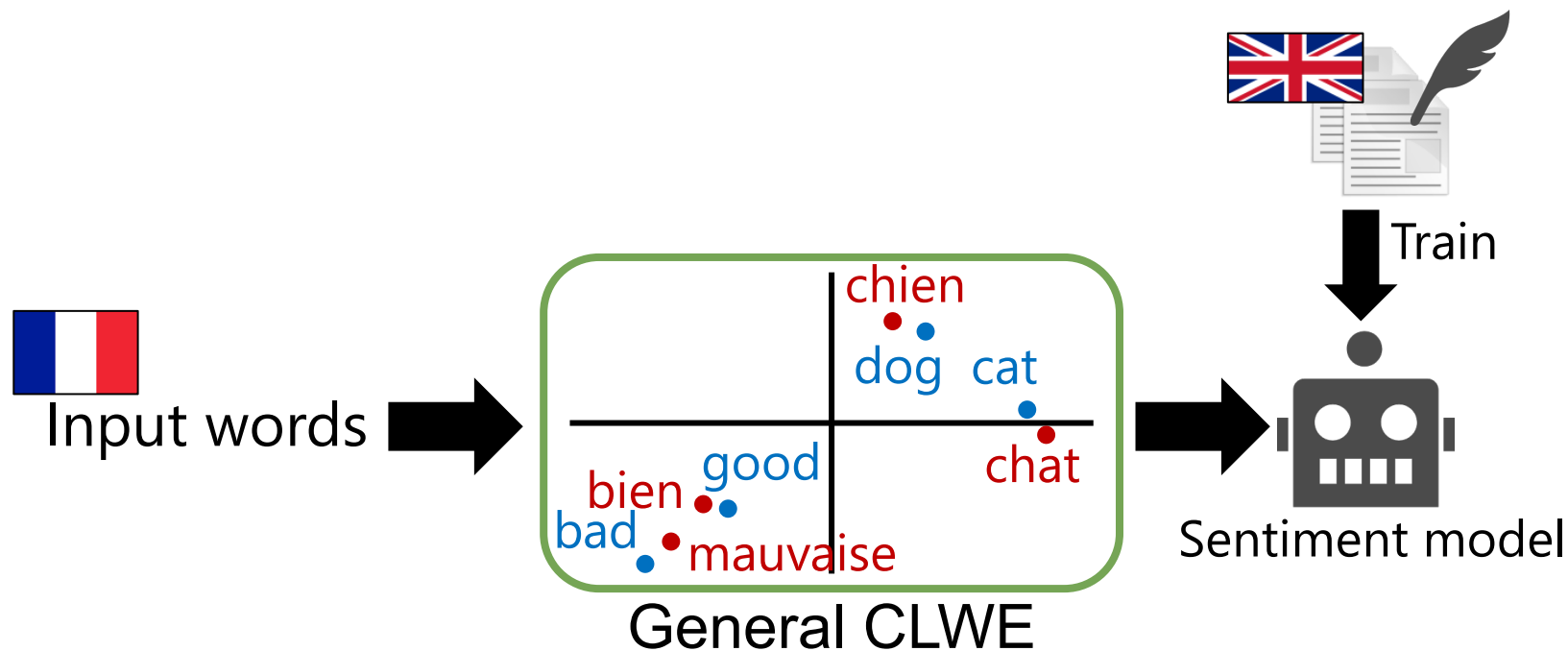
- Words from two lang. are represented in a shared space
- Similar words from different languages are close



Existing multilingual models

Fix the emb. layer to general CLWE during training

[Duong+ 17, Chen+ 18]

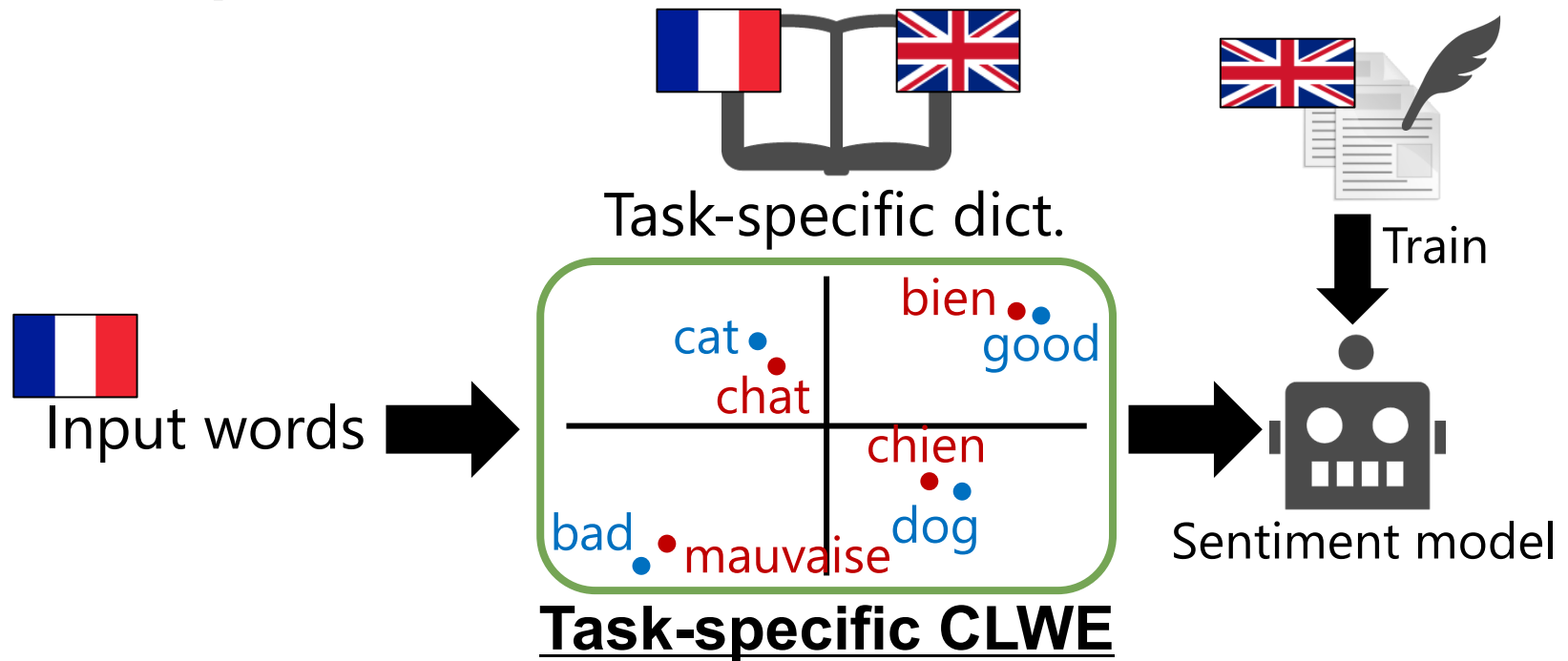


- 😊 Enables cross-lingual transfer
- 😞 The embedding layer is not optimized for the task

Related work:

Task-specific CLWE with specialized dict.

Utilize task-specific bilingual dict. to obtain CLWE
[Gouws+ 15]



😊 The embedding layer is optimized for the task

😞 Additional cross-lingual resources are required

Related work:

Task-specific CLWE with specialized dict.

Utilize task-specific bilingual dict. to obtain CLWE
[Gouws+ 15]



Task-specific dict.



Train

In this study:

Obtain task-specific CLWE without relying on
any cross-lingual resources

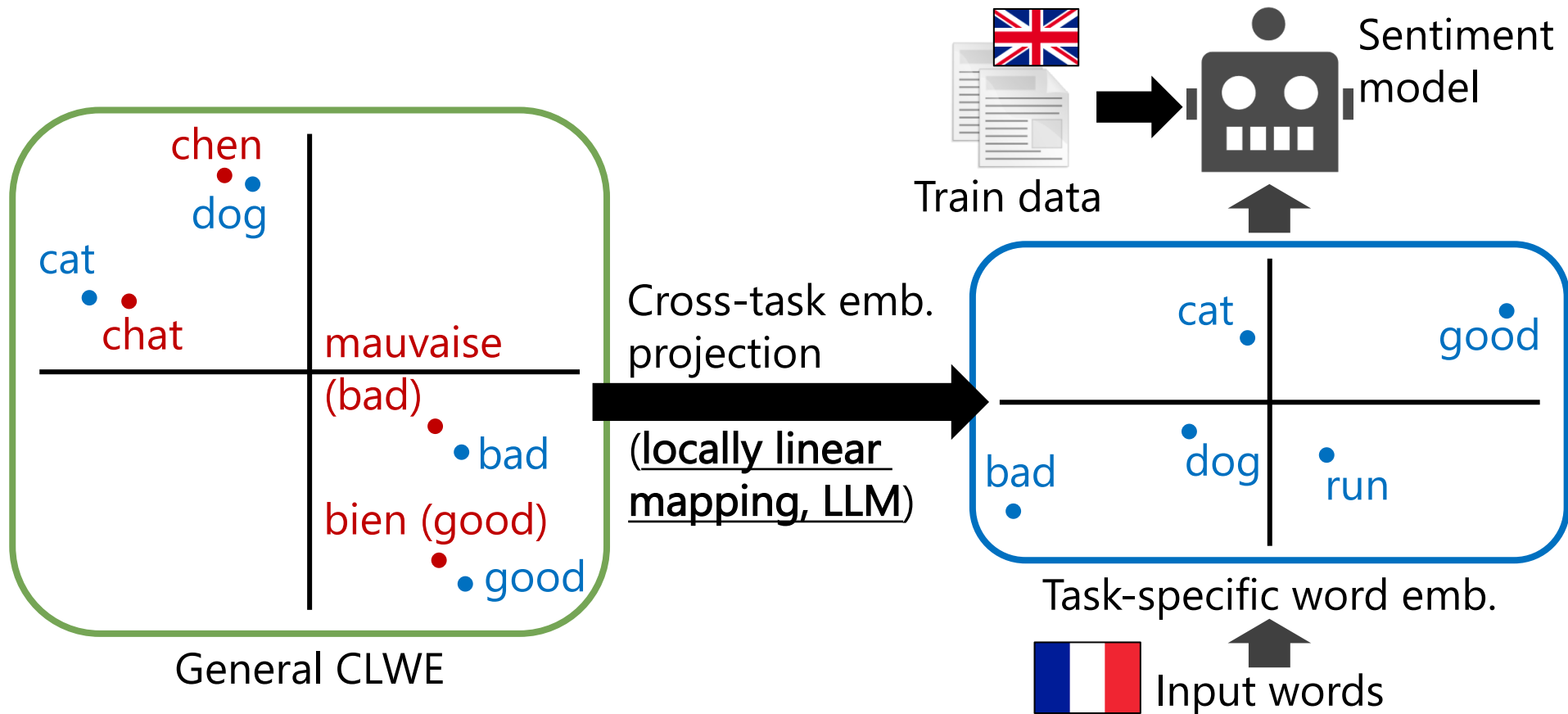
Task-specific CLWE

- The embedding layer is optimized for the task
- Requires additional cross-lingual resources

Proposal:

Multilingual model with task-spec emb.

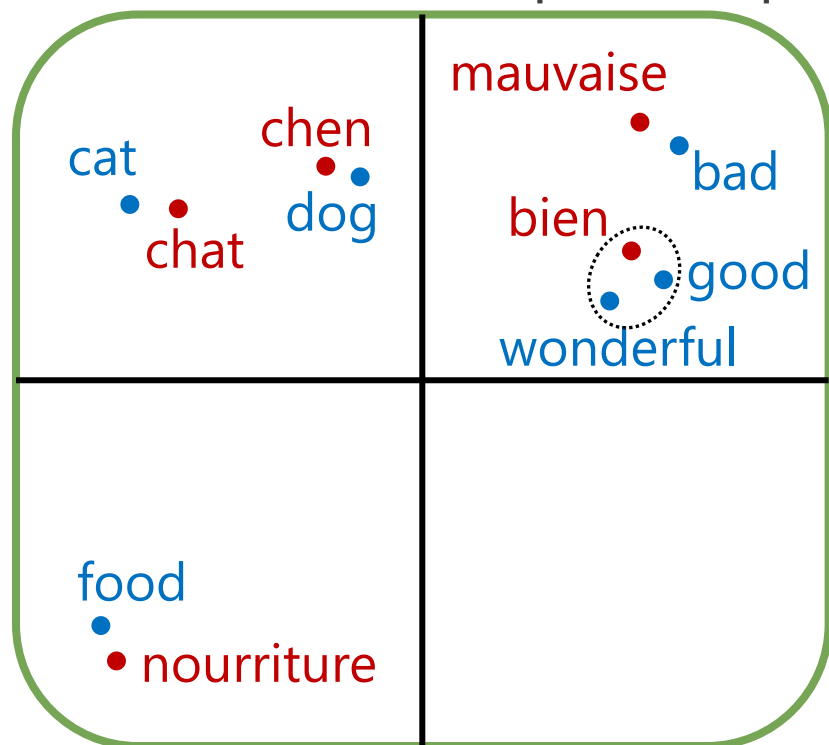
Project general CLWE to the emb. layer optimized for the task by cross-task embedding projection



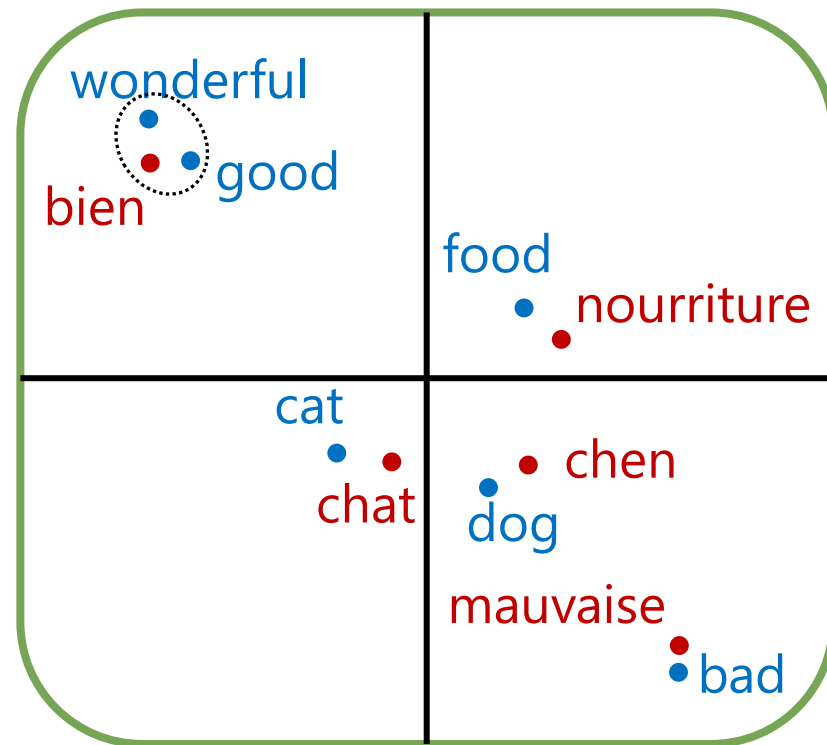
Locally linear mapping: Idea: local topology of embeddings

Assumption:

- Words adequately close in the general CLWE are also close in task-specific space



General CLWE

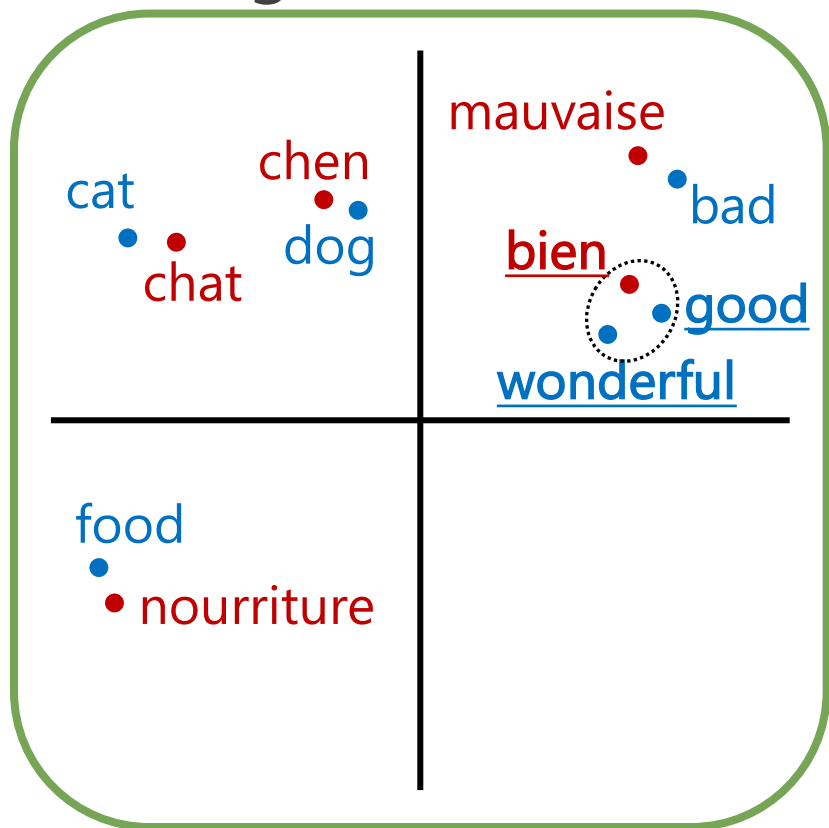


(Ideal) task-specific CLWE

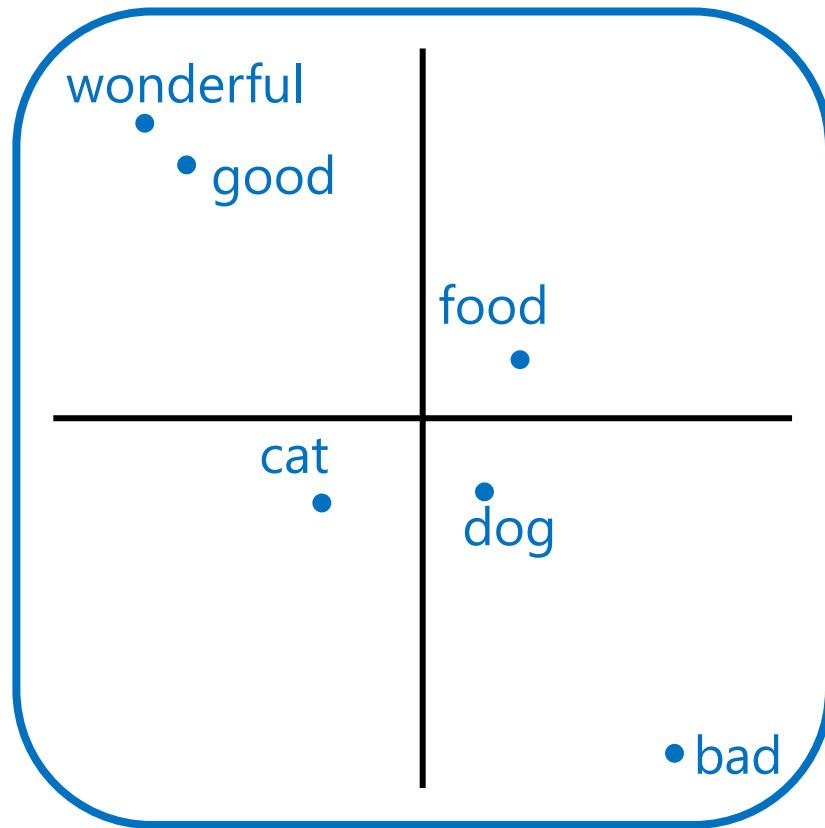
Locally linear mapping:

Step 1: selecting nearest neighbors

For each **target word** (bien), select **k-nearest neighbors** in the general CLWE



General CLWE

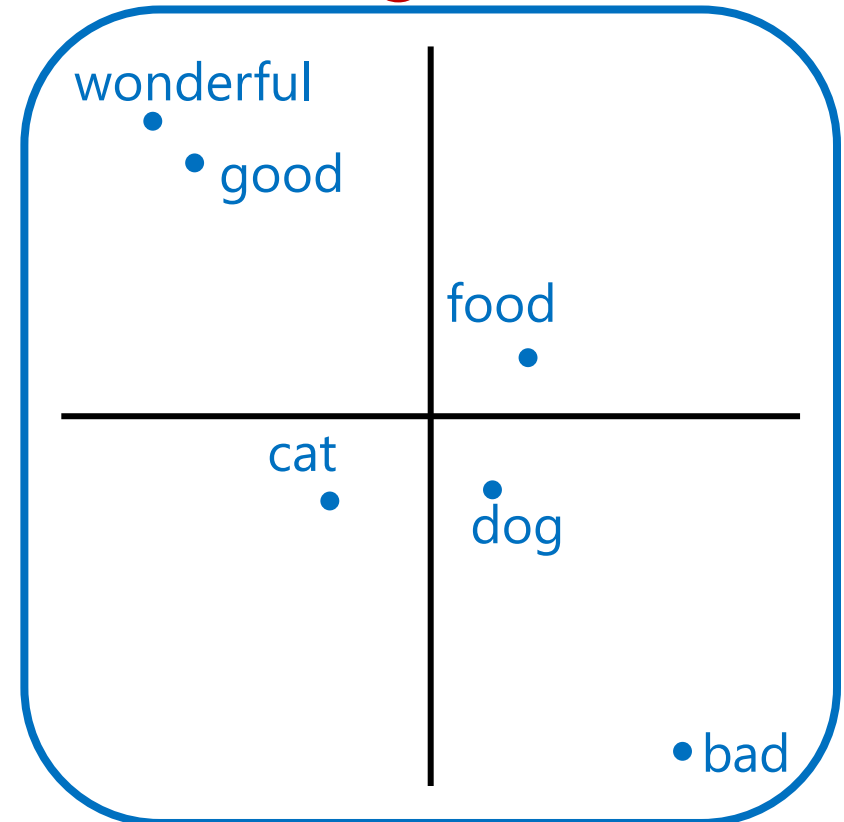
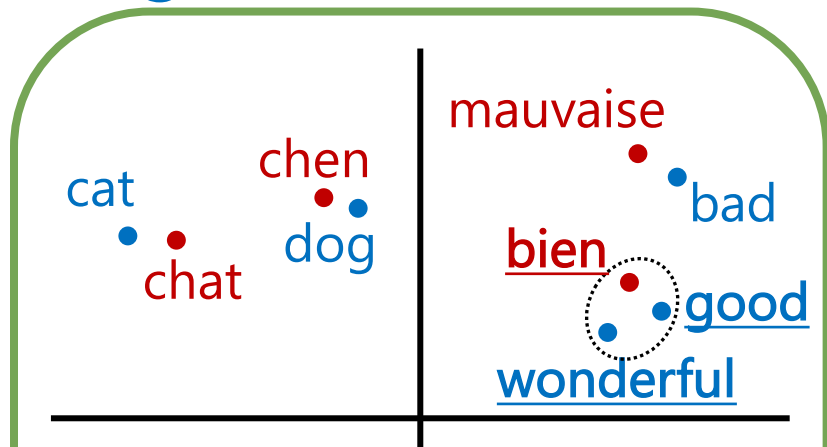


Task-specific word emb.

Locally linear mapping:

Step 2: local topology in general space

In general CLWE, learn linear combination of nearest neighbors that reconstructs the the target word



$$\hat{\alpha}_{w*} = \arg \min_{\alpha_{w*}} \left| Y_w^{\text{gen}} - \sum_{i \in N_w} \alpha_{wi} X_i^{\text{gen}} \right|^2$$

Diagram illustrating the reconstruction of the target word 'bien' (red) using a linear combination of its nearest neighbors 'good' and 'wonderful' (blue) in the general CLWE embedding space. The equation shows the reconstruction of the target word Y_w^{gen} as a linear combination of the nearest neighbors X_i^{gen} with weights α_{wi} .

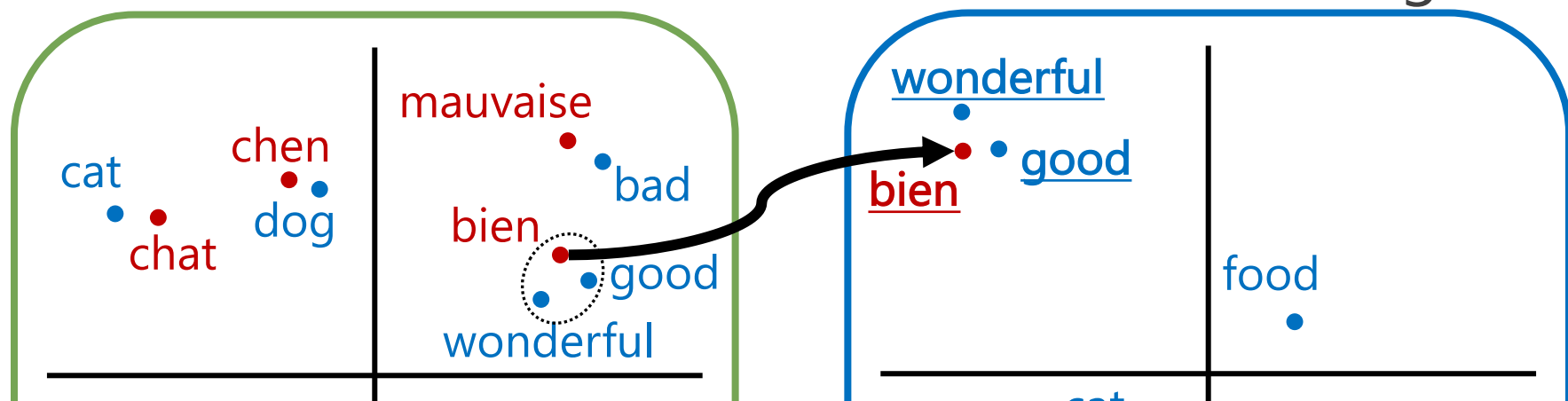
General CLWE

Task-specific word emb.

Locally linear mapping:

Step 3: task-specific word embeddings

Compute task-specific word emb. of the target word as the linear combination with the induced weights



$$\hat{\alpha}_{w*} = \arg \min_{\alpha_{w*}} \left| Y_w^{\text{gen}} - \sum_{i \in N_w} \alpha_{wi} X_i^{\text{gen}} \right|^2$$

Diagram illustrating the General CLWE equation. A red speech bubble contains the word "bien". A blue speech bubble contains the words "good, wonderful".

General CLWE

$$Y_w^{\text{spec}} = \sum_{i \in N_w} \hat{\alpha}_{wi} X_w^{\text{spec}}$$

Diagram illustrating the Task-specific word embedding equation. A red speech bubble contains the word "bien". A blue speech bubble contains the words "good, wonderful".

Task-specific word emb.

Proposal:

Hyperparameter search

Dev. set in the target language is required to tune the hyperparameter k (size of nearest neighbors)

Tuning to the task (no additional resources)

Assume the best k is independent of language

Apply LLM to the embeddings of **the source language** and evaluate on the dev. set of **the source language**

(Tuning to the task/language)

Utilize small development set (100 examples) of **the target language**

Experimental setup (1/2)

Goal:

- Does out task-specific word embeddings improve the multilingual model?

Task:

- Topic classification task (and sent. analysis)

Languages:

- Source language: English (en)
- Target languages:
 - Danish (da), Italian (it), French (fr), Swedish (sv)

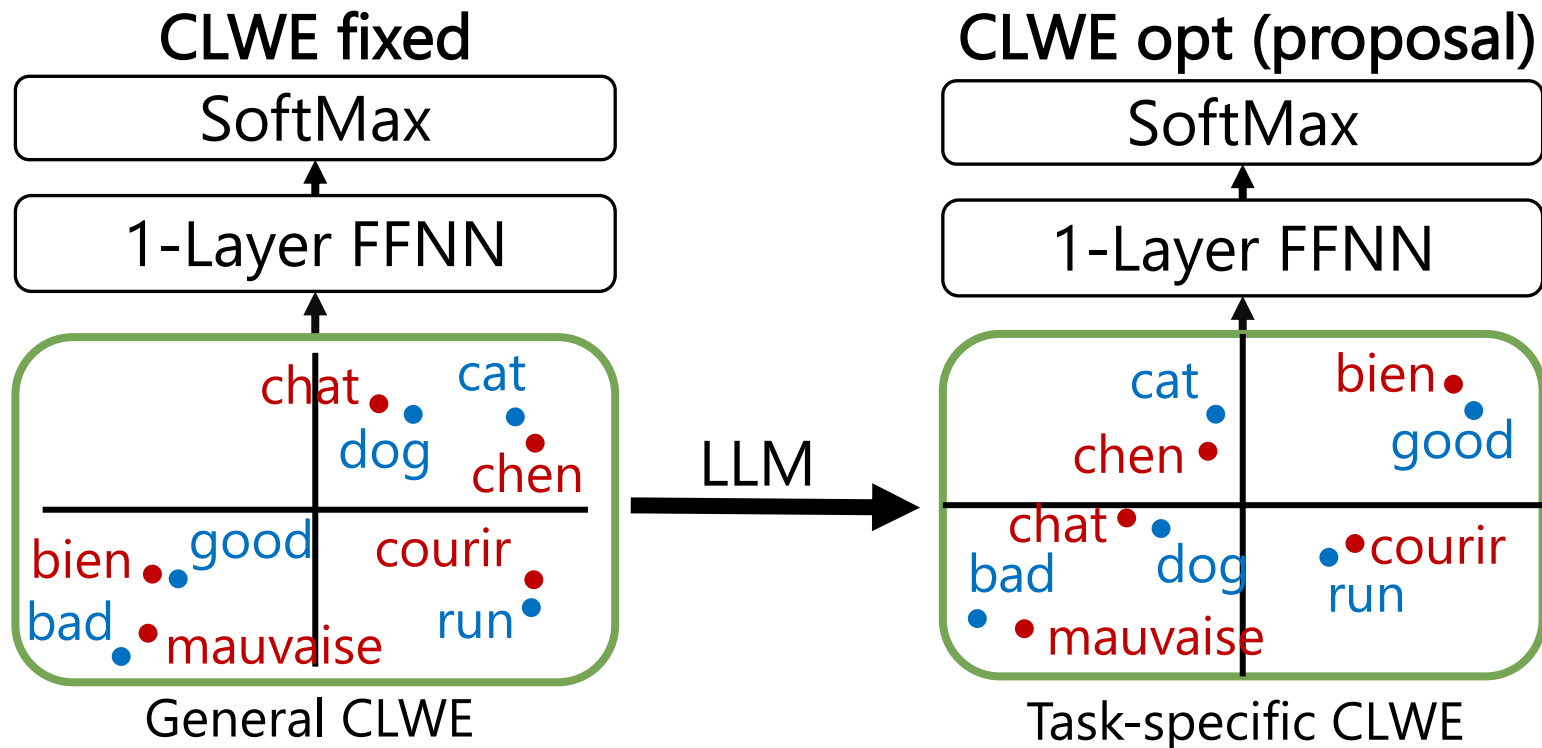
Datasets:

- RCV1/2 dataset (four topics)

Experimental setup (2/2): Models to compare

Compare the following two models to evaluate the effect of task-specific CLWE

- Experiments on more models on the paper



Results:

Topic classification task

Classification accuracies in four languages

Method	k -tuning	en-da	en-it	en-fr	en-sv
CLWE fixed	-	0.621	0.535	0.772	0.816
CLWE opt (Proposed)	task	0.672	<u>0.623</u>	<u>0.885</u>	<u>0.831</u>
CLWE opt (Proposed)	task/lang	<u>0.687</u>	0.615	0.879	0.830

- CLWE opt outperforms the baseline
- Tuning k for task and language is not necessary

Conclusion and future work

Conclusion

- Proposed a method to build a multilingual model with task-specific word embeddings
- Evaluated our method on real tasks and confirmed its effectiveness

Future work

- Evaluate this method on wider range of tasks, languages, and models
- Further improve the quality of locally linear mapping