# Edinburgh at SemEval-2022 Task 1: Jointly Fishing for Word Embeddings and Definitions


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## SemEval 2022 Task 1

Mickus et al. (2022) organised two reciprocal sub-tasks :

1. **reverse dictionary:** generate a word embedding from a textual definition;
2. **definition modelling:** generate a textual definition from a word embedding.

The task covers **5 languages**: English, Spanish, French, Italian, and Russian, and provides words in **3 embedding architectures**: *sgns* (skip-gram with negative sampling), *char* (character-level autoencoding), and *electra*.

In reverse dictionary, embedding similarity is measured by MSE, cosine and ranking scores. For definition modelling, sense-BLEU, lemma-BLEU and MoverScore are used. Organisers provided a baseline which is a single Transformer block.

## Our *Unified* Approach

A definition and the corresponding word embedding has the **same meaning, presented in different forms** (human words and vectors). We utilize a model we proposed earlier as illustrated in Figure 1. It learns to encode definitions and words **into a shared space**, then generates both forms in a **multi-task** fashion (Chen and Zhao, 2022).

As the workflow indicates, only half of the model is utilized during inference for either sub-task. The system is fairly comparable with the baseline.

Besides the architecture selection, we also create ensembles for reverse dictionary and construct naive n-grams for definition modelling.

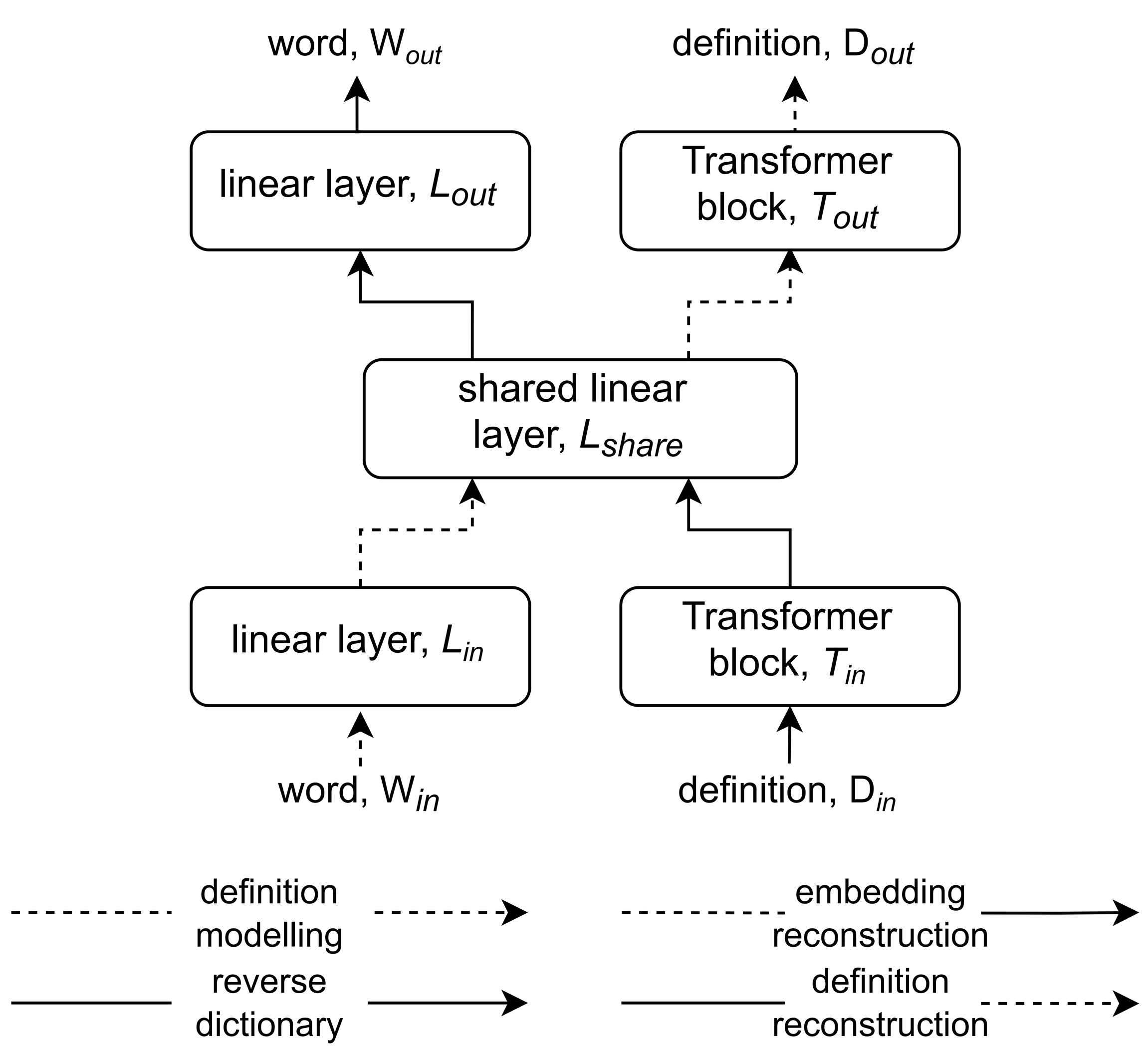



Figure 1. The unified model.

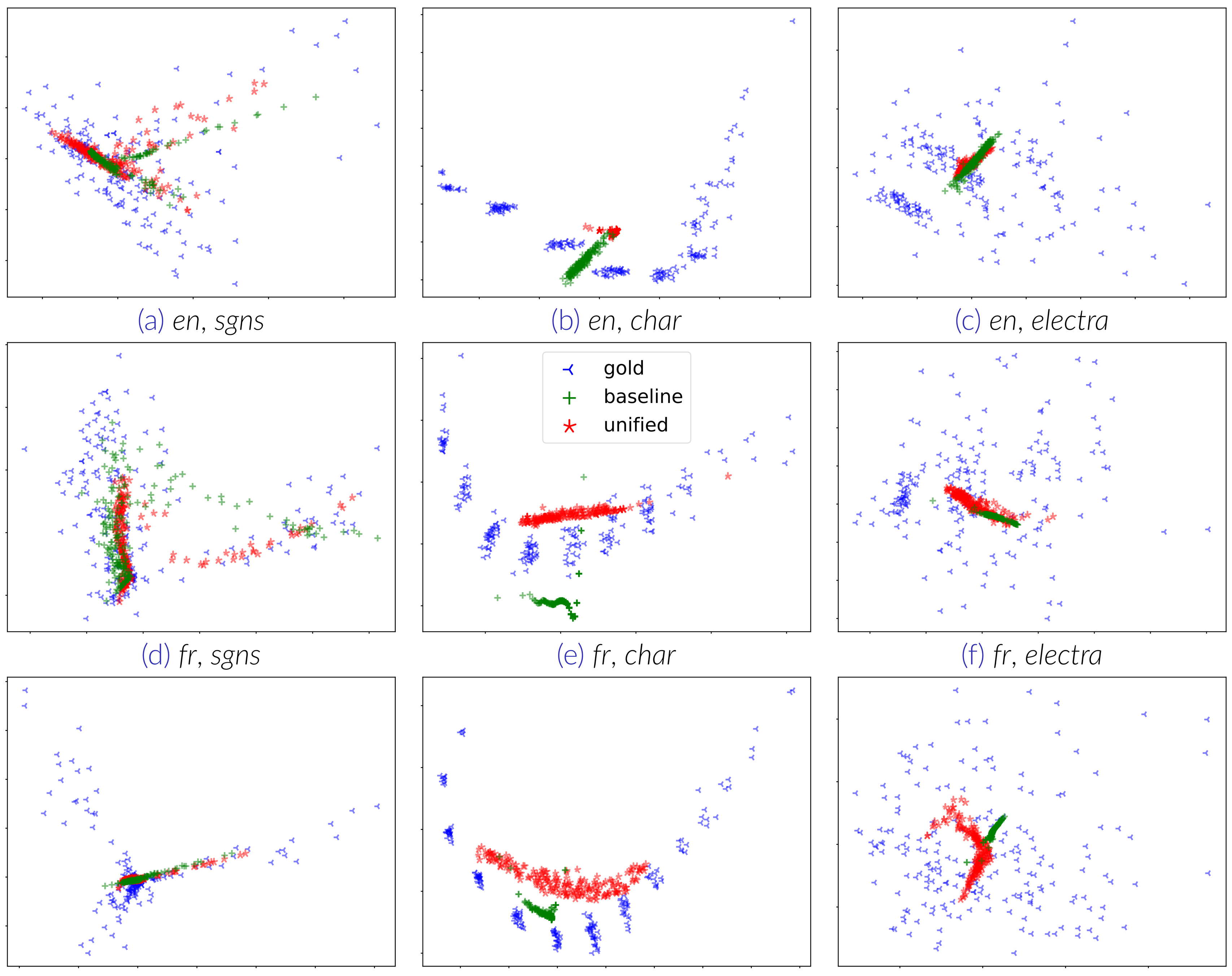
## Results: 8× 🥇, 4× 🥈, 4× 🥉

We submitted to all 18 sub-tracks, and attained first place in 8, second place in 4, and third place in 4. In terms of team ranking, our systems did **better in reverse dictionary** than in definition modelling. Especially, our submissions dominated reverse dictionary with char and electra embeddings.

However, when comparing reverse dictionary's retrieval ranking scores across different embeddings **internally, *sgns* works the best with our models**.

The overall definition modelling performance in this task is poor; our nonsensical n-grams top the French sense-BLEU leaderboard. **BLEU scores are inflated** by stop words and smoothing.

## Visualization of Output Embeddings




(a) *en, sgns* (b) *en, char* (c) *en, electra* (d) *fr, sgns* (e) *fr, char* (f) *fr, electra* (g) *ru, sgns* (h) *ru, char* (i) *ru, electra*

Figure 2. Visualization of gold and output embeddings after 2D PCA, across different languages and embedding architectures.

## Results by Data Features

We inspect our unified model's results categorised by linguistic features: polysemy, part-of-speech, word length, definition length, frequency. Our observation is that **the highest scores from the two sub-tasks emerge in differing categories**, regardless of the feature. We present three features below; more can be found in our paper.

| Polysemy | sgns | | char | | electra | |
|---|---|---|---|---|---|---|
| | cosine | lemma-BLEU | cosine | lemma-BLEU | cosine | lemma-BLEU |
| Yes | 0.232 | **4.34** | 0.804 | **3.20** | 0.836 | **3.61** |
| No | **0.360** | 2.82 | **0.813** | 2.53 | **0.845** | 3.09 |

Table 1. Performance across polysemy annotations for *en*.

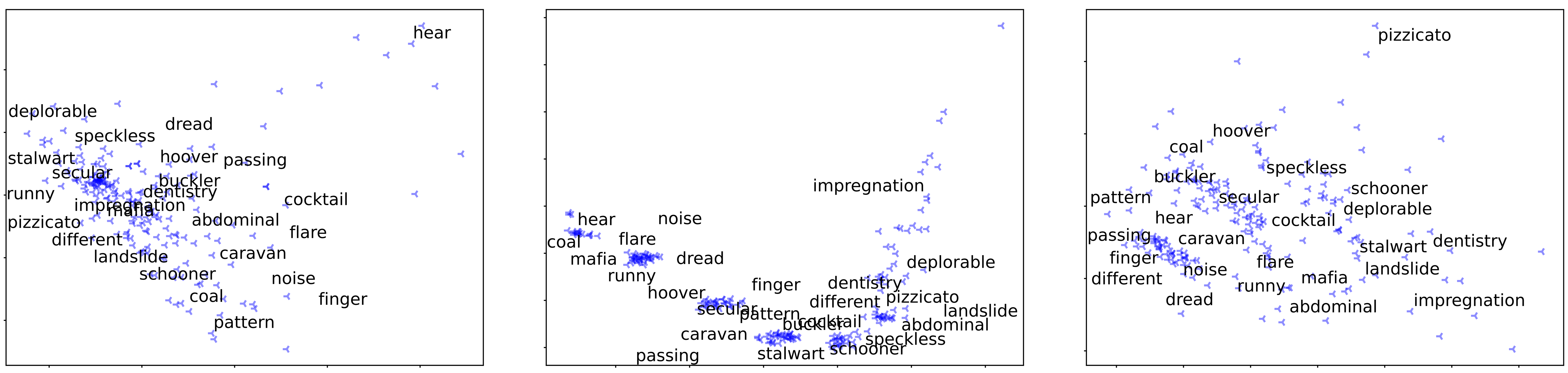
| POS | sgns | | char | | electra | |
|---|---|---|---|---|---|---|
| | cosine | lemma-BLEU | cosine | lemma-BLEU | cosine | lemma-BLEU |
| Adj | 0.319 | 3.36 | 0.801 | 2.76 | 0.811 | 2.81 |
| Adv | 0.134 | **6.56** | 0.798 | **5.45** | 0.815 | **5.93** |
| Verb | **0.383** | 3.20 | **0.839** | 2.50 | 0.853 | 3.83 |
| Noun | 0.314 | 2.97 | 0.806 | 2.53 | **0.860** | 2.99 |

Table 2. Performance across POS tags for *en*.

| Word length | sgns | | char | | electra | |
|---|---|---|---|---|---|---|
| | cosine | lemma-BLEU | cosine | lemma-BLEU | cosine | lemma-BLEU |
| short | **0.332** | 3.19 | **0.845** | 2.58 | 0.817 | 3.10 |
| medium | 0.314 | 3.19 | 0.842 | 2.74 | **0.867** | **3.41** |
| long | 0.327 | **3.66** | 0.694 | **3.00** | 0.854 | 3.33 |

Table 3. Performances across word lengths for *en*.

## Embeddings and Words




(a) *sgns* no obvious pattern (b) *char* clustered by word length (c) *electra* clustered by word frequency

Figure 3. Visualization of gold embeddings with word labels for English.

### References


Mickus, T., Paperno, D., Constant, M., and van Deemter, K. (2022). SemEval-2022 Task 1: CODWOE – comparing dictionaries and word embeddings. SemEval.
Chen, P. and Zhao, Z. (2022). A unified model for reverse dictionary and definition modelling. arXiv.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