Skill Extraction from Job Postings using Weak Supervision

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Abstract
Aggregated data obtained from job postings provide powerful insights into labor market demands, and emerging skills, and aid job matching. However, most extraction approaches are supervised and thus need costly and time-consuming annotation. To overcome this, we propose Skill Extraction with Weak Supervision. We leverage the European Skills, Competences, Qualifications and Occupations taxonomy to find similar skills in job ads via latent representations. The method shows a strong positive signal, outperforming baselines based on token-level and syntactic patterns.

Keywords
Skill Extraction, Weak Supervision, Information Extraction, Job Postings, Skill Taxonomy, ESCO

1. Introduction
The labor market is under constant development—often due to changes in technology, migration, and digitization—and so are the skill sets required [1, 2]. Consequently, large quantities of job vacancy data is emerging on a variety of platforms. Insights from this data on labor market skill set demands could aid, for instance, job matching [3]. The task of automatic skill extraction (SE) is to extract the competences necessary for any occupation from unstructured text.

Previous work on supervised SE frame it as a sequence labeling task (e.g., [4, 5, 6, 7, 8, 9, 10]) or multi-label classification [11]. Annotation is a costly and time-consuming process with little annotation guidelines to work with. This could be alleviated by using predefined skill inventories.

In this work, we approach span-level SE with weak supervision: We leverage the European Skills, Competences, Qualifications and Occupations (ESCO; [12]) taxonomy and find similar spans that relate to ESCO skills in embedding space (Figure 1). The advantages are twofold: First, labeling skills becomes obsolete, which mitigates the cumbersome process of annotation. Second, by extracting skill phrases, this could possibly enrich skill inventories (e.g., ESCO) by finding paraphrases of existing skills. We seek to answer: How viable is Weak Supervision in the context of SE? We contribute:

1. A novel weakly supervised method for SE; 2. A linguistic analysis of ESCO skills and their presence in job postings; 3. An empirical analysis of different embedding pooling methods for SE for two skill-based datasets.

2. Methodology
Formally, we consider a set of job postings \( \mathcal{D} \), where \( d \in \mathcal{D} \) is a set of sequences (e.g., job posting sentences) with the \( i \)-th input sequence \( \mathcal{T}_d^i = [t_1, t_2, ..., t_n] \) and a target sequence of BIO-labels \( \mathcal{Y}_d^i = [y_1, y_2, ..., y_n] \) (e.g., "B-SKILL", "I- SKILL", "O"). The goal is to use an algorithm, which predicts skill spans by assigning an output label sequence \( \mathcal{Y}_d^i \) for each token sequence \( \mathcal{T}_d^i \) from a job posting based on representational similarity of a span to any skill in ESCO.

Reference
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Table 1
Statistics of Datasets. Indicated is each dataset and their respective number of sentences, tokens, skill spans, and the average length of skills in tokens.

| Statistics | Sayfullina | SkillSpan |
|------------|------------|------------|
| Train      |            |            |
| # Sentences| 3,703      | 5,866      |
| # Tokens   | 53,095     | 122,608    |
| # Skill Spans | 3,703   | 3,325      |
| Dev.       |            |            |
| # Sentences| 1,856      | 3,992      |
| # Tokens   | 26,519     | 52,084     |
| # Skill Spans | 1,856   | 2,697      |
| Test       |            |            |
| # Sentences| 1,848      | 4,680      |
| # Tokens   | 26,569     | 57,528     |
| # Skill Spans | 1,848   | 3,093      |
| Avg. Len. Skills | 1.77 | 2.92 |

2.1. Data

We use the datasets from [8] (SkillSpan) and a modification of [4] (Sayfullina). In Table 1, we show the statistics of both. SkillSpan contain nested labels for skill and knowledge components [12]. To make it fit for our weak supervision approach, we simplify their dataset by considering both skills and knowledge labels as one label (i.e., B-KNOWLEDGE becomes B-SKILL).

In contrast to SkillSpan, Sayfullina has a skill in every sentence, where they focus on categorizing sentences for soft skills.

ESCO Statistics

We use ESCO as a weak supervision signal for discovering skills in job postings. There are 13,890 ESCO skills. In Figure 2, we show statistics of the taxonomy: (A) On average most skills are 3 tokens long. In (C-D), we show n-grams frequencies with range [1; 4]. We can see that the most frequent uni- and bigrams are verbs, while the most frequent trigrams consist of nouns. Additionally, we show an analysis of ESCO skills from a linguistic perspective. We tag the training data using the publicly available MaChAmp v0.2 model [14] trained on all Universal Dependencies 2.7 treebanks [15]. Then, we count the most frequent Part-of-Speech (POS) tags in all sources of data (E-G). ESCO’s most frequent tag sequences are VERB-NOUN, these are not as frequent in Sayfullina nor SkillSpan. Sayfullina mostly consists of adjectives, which is attributed to the categorization of soft skills. SkillSpan mostly consists of NOUN sequences. Overall, we observe most skills consist of verb and noun phrases.

2.2. Baselines

As our approach is to find similar n-grams based on ESCO skills, we choose an n-gram range of [1; 4] (where 4 is the median) derived from Figure 2 (A). For higher matching probability, we apply an additional pre-processing step to the ESCO skills by removing non-tokens (e.g., brackets)

Per 25-03-2022, taking ESCO v1.0.9.

A Udeny-based [16] multi-task model for POS, lemmatization, dependency parsing, built on top of the transformers library [17], and specifically using mBERT [18].
We investigate several encoding strategies to match n-gram representations with embedded ESCO skills, the approaches are inspired by Litschko et al. [19], where they applied them to Information Retrieval. The language models (LMs) used to encode the data are RoBERTa [13] and the domain-specific JobBERT [8]. All obtained vector representations of skill phrases with the three previous encoding methods are compared pairwise with each n-gram created from Scyfullina and SkillSpan. An explanation of the methods (see Figure 3):

Span in Isolation (ISO): We encode skill phrases $t_i$ from ESCO in isolation using the aforementioned LMs, without surrounding contexts.

Average over Contexts (AOC): We leverage the surrounding context of a skill phrase $t_i$ by collecting all the sentences containing $t_i$. We use all available sentences in the job postings dataset (excluding Test). For a given job posting sentence, we encode $t_i$ by using one of the previous mentioned LMs. We average the embeddings of its constituent subwords to obtain the final embedding $t_i$.

Weighted Span Embedding (WSE): We obtain all inverse document frequency (idf) values of each token $t_i$ via

$$\text{idf} = -\log \frac{n_i}{N},$$

where $n_i$ is the number of occurrences of $t_i$ and $N$ the total number of tokens in our dataset. We encode the

## Algorithm 1 Weakly Supervised Skill Extraction

**Require:** $M \in \{\text{RoBERTa, JobBERT}\}$

**Require:** $E \in \{\text{ISO, AOC, WSE}\}$

**Require:** $\tau \in [0, 1]$

1. $P \leftarrow D$ \quad \triangleright \text{A set of sentences from job postings}
2. $S \leftarrow S_E$ \quad \triangleright \text{ESCO Skill embeddings of type $E$}
3. $L \leftarrow \emptyset$
4. for $p \in P$ do
   5. \quad $\theta \leftarrow 0$
   6. \quad for $n \in p$ do \quad \triangleright Each ngram $n$ of size $1 - 4$
   7. \quad \quad $E \leftarrow M(n)$
   8. \quad \quad $\Theta \leftarrow \text{CosSim}(S, E)$
   9. \quad \quad if $\max(\Theta) > \tau \land \max(\Theta) > \theta$ then
   10. \quad \quad \quad $\theta \leftarrow \max(\Theta)$
   11. \quad end if
12. \quad end for
13. \quad $L \leftarrow [L, \theta]$
14. end for
15. return $L$
Table 2

| Gold | Predicted |
|------|-----------|
| Sayfullina | ...a dynamic customer focused person to join... |
|        | ...strong leadership and team management skills... |
|        | ...team environment and working independently skills... |
|        | ...tangible business benefit extremely articulate and... |
|        | ...standards and procedures accessing and updating records... |
|        | ...with a passion for education to... |
|        | ...understands Agile as a mindset... |
|        | ...experience with AWS, GCP, Microsoft Azure... |

input sentence and compute the weighted sum of the embeddings \( \hat{s}_j \) of the specific skill phrase in the sentence, where each \( t_i \)'s IDF scores are used as weights. Again, we only use the first subword token for each tokenized word. Formally, this is

\[
\hat{s}_j = \sum_i (-\log \frac{n_t}{N}) \cdot \hat{t}_i.
\]

Matching  We rank pairs of ESCO embeddings \( \hat{t} \) and encoded candidate n-grams \( \hat{g} \) in decreasing order of cosine similarity (CosSim), calculated as

\[
\text{CosSim}(\hat{t}, \hat{g}) = \frac{\hat{t}^T \hat{g}}{||\hat{t}|| \cdot ||\hat{g}||}.
\]

We show our pseudocode of the matching algorithm in Algorithm 1. Note that in SkillSpan we have to set a threshold for CosSim, as there are sentences with no skills. A threshold allows us to have a "no skill" option. As seen in Figure 5, Appendix A the threshold sensitivity

3. Analysis of Results

Results  Our main results (Figure 4) show the baselines against ISO, AOC, and WSE of both datasets. We evaluate with two types of F1, following van der Goot et al. [20]: strict and loose-F1. For full model fine-tuning, RoBERTa achieves 91.31 and 98.55 strict and loose F1 on Sayfullina respectively. For SkillSpan, this is 23.21 and 44.72 strict and loose F1 (on the available subsets of SkillSpan). JobBERT achieves 90.18 and 98.19 strict and loose F1 on Sayfullina, 49.44 and 74.41 strict and loose F1 on SkillSpan. The large difference between results is most likely due to lack of negatives in Sayfullina, i.e., all sentences contain a skill, which makes the task easier. These results highlight the difficulty of SE on SkillSpan, where

Figure 4: Results of Methods. Results on Sayfullina and SkillSpan are indicated by “Baseline” showing performance of Exact, Lemmatized (Lemma), and Part-of-Speech (POS). The performance of ISO, AOC, and WSE are separated by model, indicated by “RoBERTa” and “JobBERT”. The performance of RoBERTa and JobBERT on SkillSpan is determined by the best performing CosSim threshold (0.8).
there are negatives as well (sentences with no skills).

The exact match baseline on SkillSpan is higher than Sayfullina. We attribute this to SkillSpan also containing "hard skills" (e.g., "Python"), which is easier to match substrings with than "soft skills". For the performance of the skill representations on Sayfullina, RoBERTa and JobBERT outperform the Exact and Lemmatized baseline on strict-F1. For the POS baseline, only the ISO method of both models is slightly better. JobBERT performs better than RoBERTa in strict-F1 on both datasets.

There is a substantial difference between strict and loose-F1 on both datasets. This indicates that there is partial overlap among the predicted and gold spans. RoBERTa performs best for Sayfullina, achieving 59.61 loose-F1 with WSE. In addition, the best performing method for JobBERT is also WSE (52.69 loose-F1). For SkillSpan we see a drop, JobBERT outperforms RoBERTa with AOC (32.30 vs. 26.10 loose-F1) given a threshold of CosSim = 0.8. We hypothesize this drop in performance compared to Sayfullina could be attributed again to SkillSpan containing negative examples as well (i.e., sentences with no skill).

Qualitative Analysis A qualitative analysis (Table 2) reveals there is strong partial overlap with gold vs. predicted spans on both datasets, e.g., "...strong leadership and team management skills..." vs. "...strong leadership and team management skills...", indicating the viability of this method.

4. Conclusion

We investigate whether the ESCO skill taxonomy suits as weak supervision signal for Skill Extraction. We apply several skill representation methods based on previous work. We show that using representations of ESCO skills can aid us in this task. We achieve high loose-F1, indicating there is partial overlap between the predicted and gold spans, but need refined off-set methods to get the correct span out (e.g., human post-editing or automatic methods such as candidate filtering). Nevertheless, we see this approach as a strong alternative for supervised Skill Extraction from job postings.

Future work could include going towards multilingual Skill Extraction, as ESCO consists of 27 languages, exact matching should be trivial. For the other methods several considerations need to be taken into account, e.g., a POS-tagger and/or lemmatizer for another language and a language-specific model.

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| Dataset → | Sayfullina | SkillSpan |
|-----------|-----------|-----------|
| ↓ Method, Metric → | Strick (P | R | F1) | Loose (P | R | F1) | Strick (P | R | F1) | Loose (P | R | F1) |
| Baseline | Exact | 9.27 | 1.30 | 2.28 | 25.48 | 3.95 | 6.84 | 23.82 | 3.21 | 5.62 | 43.68 | 8.27 | 13.79 |
| Lemmatized | 8.49 | 1.19 | 2.09 | 25.87 | 4.00 | 6.93 | 23.90 | 2.97 | 5.21 | 41.09 | 7.49 | 12.52 |
| POS | 5.99 | 5.95 | 5.97 | 36.55 | 34.51 | 35.50 | 5.97 | 7.88 | 6.79 | 19.34 | 34.71 | 24.80 |
| RobBERTa | ISO | 6.26 | 6.25 | 6.26 | 26.90 | 28.98 | 27.90 | 2.90 | 4.24 | 3.43 | 12.69 | 28.61 | 17.56 |
| | AOC | 3.24 | 3.24 | 3.24 | 64.04 | 55.53 | 59.48 | 2.23 | 2.93 | 2.53 | 20.08 | 37.56 | 26.10 |
| | WSE | 3.67 | 3.67 | 3.67 | 64.64 | 55.32 | 59.61 | 2.29 | 2.93 | 2.57 | 20.90 | 37.79 | 26.85 |
| JobBERT | ISO | 7.71 | 7.72 | 7.71 | 27.76 | 29.95 | 28.82 | 4.17 | 4.65 | 4.39 | 17.07 | 29.48 | 21.61 |
| | AOC | 4.04 | 4.05 | 4.05 | 56.50 | 48.41 | 52.14 | 4.44 | 2.96 | 3.54 | 33.64 | 31.28 | 32.30 |
| | WSE | 4.15 | 4.16 | 4.15 | 56.98 | 49.00 | 52.69 | 4.78 | 3.08 | 3.74 | 34.01 | 30.33 | 31.95 |

**Table 3**

We show the exact numbers of the performance of the methods.

**Figure 5: Results of Methods.** Results of the baselines are in (X), the performance of ISO, AOC, and WSE on *Sayfullina* in (A–C), and the same performance on *SkillSpan* in (D–I) based on the model (RoBERTa or JobBERT). In D–F, we show the precision (P), recall (R), and F1 differences when taking an increasing CosSim.

**A. Exact Results**

**Definition F1** As mentioned, we evaluate with two types of F1-scores, following van der Goot et al. [20]. The first type is the commonly used span-F1, where only the correct span and label are counted towards true positives. This is called *strict-F1*. In the second variant, we seek for partial matches, i.e., overlap between the predicted and gold span including the correct label, which counts towards true positives for precision and recall. This is called *loose-F1*. We consider the loose variant as well, because we want to analyze whether the span is "almost
correct”.

**Exact Numbers Results**  We show the exact numbers of Figure 4 in Table 3 and more detailed results in Figure 5. Results show that there is high precision among the baseline approaches compared to recall. This is balanced using the representation methods for *Sayfullina*. However, we observe that there is much higher recall for *SkillSpan* than precision.