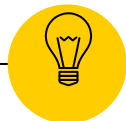


Hardware-effective Approaches for **Skill Extraction** in Job Offers and Resumes



Laura Vásquez-Rodríguez, Bertrand Audrin, Samuel Michel, Samuele Galli,
Julneth Rogenhofer, Jacopo Negro Cusa, Lonneke van der Plas



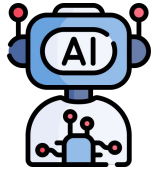
1

Introduction

Skill Extraction Task **Overview**



Skill Extraction Task



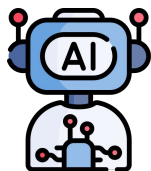
Data analysis using Python and Pandas

SKILL

SKILL



Skill Extraction Task



Data analysis using Python and Pandas

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SKILL



Data analysis using Python and Pandas

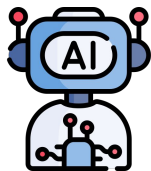
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Skill Extraction Task



Data analysis using Python and Pandas

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Data analysis using Python and Pandas

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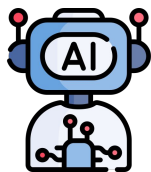
SKILL



Data analysis using Python and Pandas



Skill Extraction Task



Data analysis using Python and Pandas
SKILL SKILL



Data analysis using Python and Pandas
SKILL SKILL SKILL



Data analysis using Python and Pandas



Scope: Skill Extraction

- Focus on hard skills and occupations
 - Soft skills for future work
- Task based on Named Entity Recognition (NER)
 - Span-based skill extraction
 - Straight-forward with existing datasets
- Evaluation exact and partial schema

2

Motivation

Hardware-effective Skill Extraction Task (Job offers and Resumes)



Our Motivation

- Understand current situation
 - Skill extraction in job offers and resumes
- Make the difference
 - Soft skills, bias, optimal hardware resources
 - Hardware requirements not a priority



Our Contributions

- A comparative evaluation of rule-based, semantic and neural models in skill extraction
 - Both job offers (public) and resumes (private)
- Hardware requirements analysis
 - Trade off performance and resources
- Qualitative evaluation of systems' outputs

3

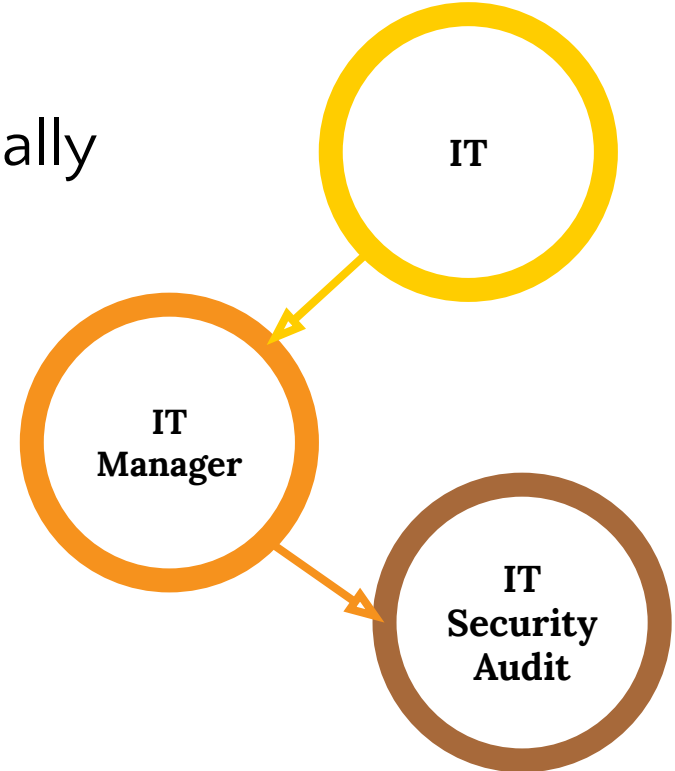
Comparative Evaluation

Rule-based, Semantic and Neural Models



Skills Taxonomy

- Collection of skills hierarchically connected to occupations
- Taxonomy:
 - ESCO
 - 131,623 entities, public
 - Arca24 company
 - 10,379 entities, private



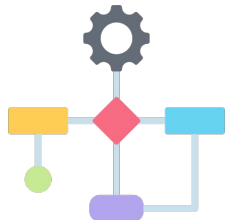


Methods in a Nutshell

Rule-based

Keyword-based
search, words
standardization.

Python development
-> Python develop



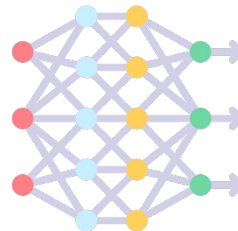
Semantic

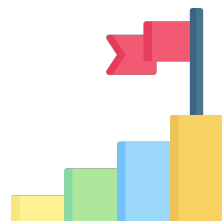
Similarity (spacy)
computation
between taxonomy
and texts spans in job
offer, resumes.



Neural

Supervised
BERT-based models
trained on public and
private annotated
data (sentences)



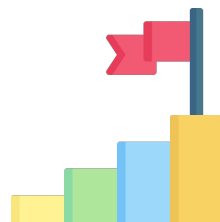


Performance (exact, highest, F1)

	ArcaDB	ESCO	ArcaDB	ESCO
System	Job Offers		Resumes	
Rule-based	18.3%	20%	18,2%	14%
Semantic	12.9%	11.4%	8.6%	8.8%
BERT Supervised (no taxonomy)	45.9%		51%	



Green_JOB (8,669, 964, 335)
Arca24_CV (1,564, 195, 195)

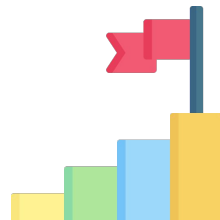


Performance (**exact**, highest, F1)

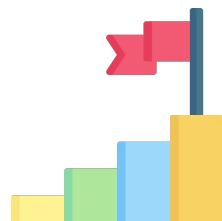
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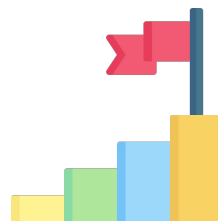


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Performance (**partial**, highest, F1)

	ArcaDB	ESCO	ArcaDB	ESCO
System	Job Offers		Resumes	
Rule-based	31.2%	39.8%	30.5%	26.9%
Semantic	24.8%	32.4%	24.5%	24.2%
BERT Supervised (no taxonomy)	66%		59.8%	



Performance (**partial**, highest, F1)

	ArcaDB	ESCO	ArcaDB	ESCO
System	Job Offers		Resumes	
Rule-based	31.2%	39.8%	30.5%	26.9%
Semantic	24.8%	32.4%	24.5%	24.2%
BERT Supervised (no taxonomy)	66%		59.8%	

4

Hardware Analysis

Trade-off between Resources and Performance



Hardware (HW) Analysis: **Report**

- Total time (m/h):
 - Preprocessing / training and test time per model
- CPU memory used (8GB)
 - AMD EPYC 7742 64-Core Processor
- GPU memory used (24GB)
 - NVIDIA GeForce RTX 3090



HW Analysis: Rule-based / Semantic

- Rule-based and semantic use less than 5GB RAM
 - They are solely run in CPU
 - Explainability, why a concept was chosen?
- Taxonomies comparisons can take long, but methods can still be improved



HW Analysis: **Neural**

- BERT and JobBERT models (~100M) use less than 8GB RAM (CPU)
- Although we do use GPUs..
 - Total time is less than 7 min
 - Using less than 9GB GPU RAM



HW Analysis: Neural

What about ESCOXLM-R?¹ (559M)

- Model is 5X bigger
- It uses about 3-4X more resources
- It showed less than 1% improvement (F1)

- More data? Limits of the skill annotation task?

¹Mike Zhang, Rob van der Goot, and Barbara Plank. 2023. ESCOXLM-R: Multilingual Taxonomy-driven Pre-training for the Job Market Domain. In Proceedings of the 61st Annual Meeting of the Association for Computational Linguistics.

5

Qualitative Analysis

Systems outputs & error analysis



Evaluation: System Outputs

Rule-based, ESCO_DB

The Test Consultant Automation Test Analyst will ideally be confident with Selenium and good experience of web-based testing HTML and Javascript

Semantic, Arca_DB

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Supervised, Green

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Evaluation: Error Analysis

- 120 random sentences in total
 - *bert-based-cased* (best)
 - *escoxmlr_skill_extraction* (larger)
- Classify sentences according to categories proposed by Nguyen et al., 2024¹

¹Khanh Nguyen, Mike Zhang, Syrielle Montariol, and Antoine Bosselut. 2024. Rethinking Skill Extraction in the Job Market Domain using Large Language Models. In Proceedings of the First Workshop on Natural Language Processing for Human Resources (NLP4HR 2024).



Evaluation: Error Analysis

1. Skill definition misalignment
2. Wrong extraction
3. Conjoined skills
4. Extended span
5. Incorrect annotations
6. Others, e.g., partial detection





Evaluation: Error Analysis

- Category #1, skill definition misalignment (~50%)
- Category #2, wrong extraction (16.76%)
- The remaining sentences are distributed along the other categories

Do not underestimate the **power** of **simple** solutions. They can be essential to shorten the gap between **research** and the **application**

“



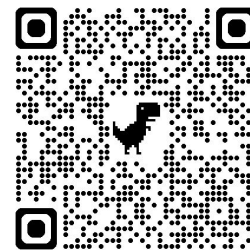


Thanks!

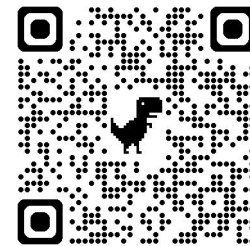
Any **questions** ?

You can find me at

- Laura Vásquez-Rodríguez
- laura.vasquez@idiap.ch



Paper



LinkedIn

