Exploring the impact of machine learning algorithms with unlabelled data

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1 Introduction

In the current digital age, many recruiters seek to find suitable candidates through multiple channels — e.g., online job portals, professional networks — as well as traditional avenues, such as word of mouth and mass media (Shenoy and Aithal, 2018).

The dataset is derived from the large dataset called *mycareersfuture* (Bhola et al., 2020). The dataset has a total of 17377 data, consisting of 13902 train data, 1738 validation data, and 1737 test data. The dataset is shown in the table 1:

Table 1: Dataset Information

Data Type	Labeled	Unlabeled	Total
Train	8000	5902	13902
Validation	1738	-	1738
Test	-	1737	1737
Total	9738	7639	17377

To answer the question "Does Unlabelled data improve Job salary prediction?", We will analyse and compare the performance of different machine learning algorithms for this dataset (labelled and unlabelled data) and finally explore whether unlabelled data can be effectively combined to increase the performance of the model.

2 Literature review

3 Methods

In this study, our objective is to predict the salary bin through the given job description. We use both TFIDF (Manning et al., 2008) and word embedding which computed with a pretrained language model, called the Sentence Transformer (Reimers and Gurevych, 2019) to represent the job description, and use these information for model and error analysis. We designed our experiment in three parts, focus in supervised learning, unsupervised learning, and semi-supervised learning. And we will compare

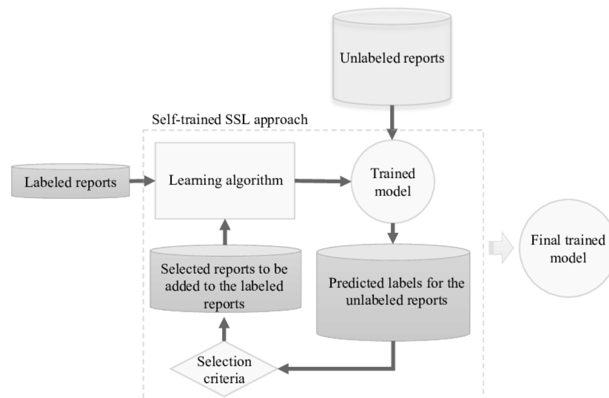

Figure 1. Self-trained semi-supervised learning architecture (Hassanzadeh et al., 2018)

3.1 Supervised learning

In the supervised learning part, we adapt 9 different machine learning algorithms to predict the salary bin.

3.2 Unsupervised learning

3.3 Semi-supervised learning

we will use the architecture shown in figure 1 to train the model.

4 Results

5 Discussion / Critical Analysis

6 Conclusions

References

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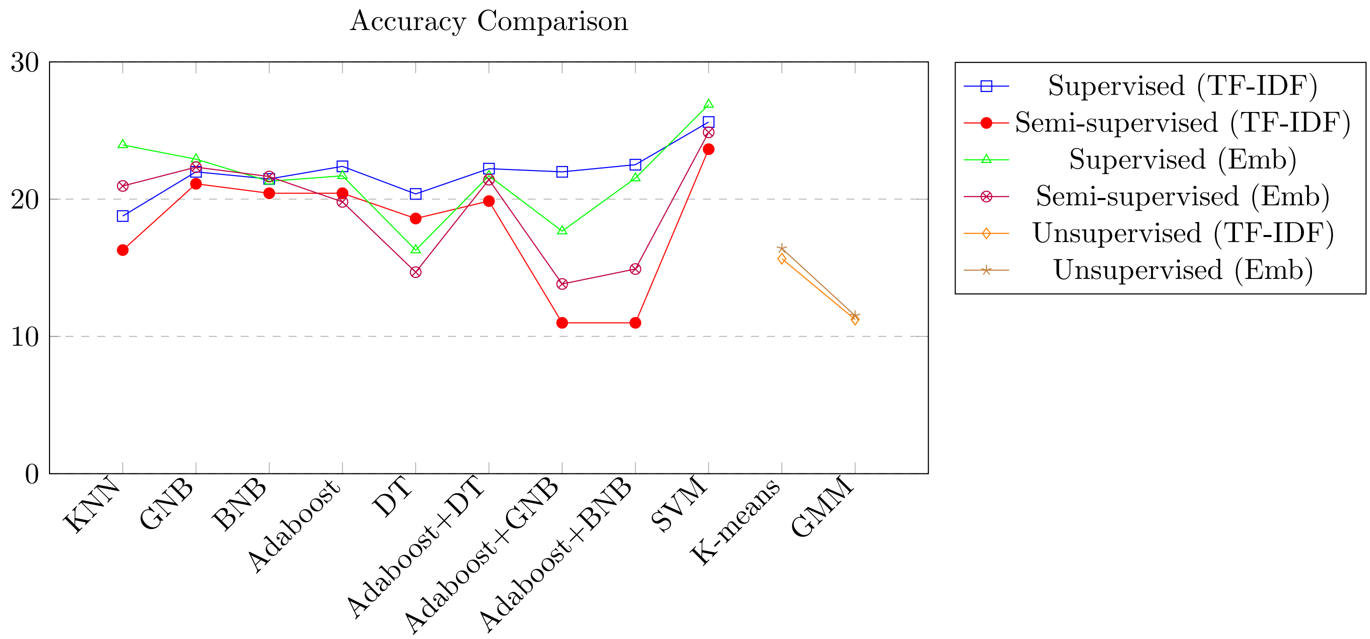

Table 2: Accuracy Comparison

Model	TFIDF		Embedding	
	Labaled data	Unlabeled data	Labaled data	Unlabaled data
KNN	18.77	16.29	23.95	20.96
GNB	21.99	21.12	22.91	22.33
BNB	21.47	20.43	21.3	21.65
Adaboost	22.39	20.43	21.7	19.8
Decision Tree (DT)	20.38	18.59	16.29	14.68
Adaboost + DT	22.22	19.86	21.7	21.42
Adaboost + GNB	21.99	10.99	17.67	13.82
Adaboost + BNB	22.51	10.99	21.53	14.91
SVM	**25.62***	**24.64***	**26.89***	**24.87***
K-means	-	**15.66***	-	**16.41***
GMM	-	11.23	-	11.51

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