Capstone Project: Predicting Career Domain and Seniority from LinkedIn Profiles

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1 Introduction and Motivation

Job titles, employment histories, and organizational affiliations provide valuable signals about a person's current role, yet these signals are expressed in free text and can vary strongly across industries, languages and career stages. For companies that rely on structured CRM or sales intelligence systems, this heterogeneity poses a major challenge.

SnapAddy aims to automatically enrich and structure contact data in order to support sales, recruiting and business intelligence processes. A key aspect of this enrichment is the ability to reliably infer a person's professional department and seniority level from their LinkedIn CV. Accurate predictions of these attributes enable better lead qualification, segmentation and prioritization, while reducing the need for manual data cleaning and annotation.

However, predicting department and seniority from LinkedIn profiles can be a challenging task. Job titles are often short, ambiguous and context dependent. The same title may correspond to different departments across organizations and seniority is not always explicitly stated. In addition, real-world LinkedIn data can be noisy and multilingual. These characteristics make simple heuristics unreliable and motivate the use of more robust NLP-based approaches.

The goal of this project is to develop and compare different methods for predicting the department and seniority of the current job. Starting from a transparent rule-based baseline, we progressively explore more expressive machine learning approaches that can capture contextual information and implicit patterns in job titles. Throughout the project, we emphasize fair evaluation and comparison of each approach in order to understand both the strengths and limitations of each approach.

By systematically comparing rule-based matching, classical machine learning models, and more advanced NLP techniques, this project aims to provide practical insights into how LinkedIn CV data can be transformed into structured, actionable information for a real world business application at SnapAddy.

2 Data Overview and Preprocessing

The implementation is available in the GitHub repository under *data_prep_eda*.

2.1 Label Datasets (department labels & seniority labels)

The department and seniority files were loaded into dataframes. The department labels file has 10.145 rows and the seniority labels file has 9.428 rows. Both files have 2 columns, one column corresponds to the job title, the other one to the label (department/seniority). There are 11 distinct department labels. Among them, Marketing is the most common, followed by Sales and Information Technology. Very rare are the labels Other, Purchasing, Customer Support, with Human Resources being the most rare. And there are 5 distinct seniority level labels. Among them, Senior is the most common, followed by Lead. Director, Management are less common and Junior the least. Furthermore, we found no missing values in the datasets.

2.2 CV Datasets (annotated & not annotated)

The original CV data is stored in a nested, three level hierarchical format where each CV contains a list of job entries. The datasets are a list of CVs, each CV is a list of job entries, and each job entry is a dictionary whith values. Since no job field contains nested lists or dictionaries, the hierarchy ends at the job level. Furthermore, we have 609 CVs with labels and 390 CVs without labels and there are 2.638 jobs in the annotated data and 1.886 jobs in the not annotated data.

For modeling purposes, the hierarchical CV data is transformed into a job-level table, where each row represents one job entry. For that we create the following dataframe schema where each column corresponds to a field (key) from the job dictionary:

- organization : name of the employer for a given job
- position : job title text
- startDate : start date of the job
- endDate : end date of the job
- status : indicates the status of a job
- department (annotated dataset only, not annotated dataset is filled with None here) : department label for a job
- seniority (annotated dataset only, not annotated dataset is filled with None here) : seniority level for a job

We removed the linkedin field, because it only contains a URL to a linkedin page.

Because we want to perserve the hierarchy information (CV identity and job order), we explicitly add these columns to our dataframe schema:

- cv_id : this links each job back to a CV (unique identifier for each CV)
- job_index : this preserves the job order within a CV (position of a job within a CVs job list)

This is necessary because job entries are not independent observations, they belong to the same individual and form a temporal sequence. The variables cv_id and job_index are derived from the positional indices of CVs and jobs within the nested list structure using enumerate. All remaining columns are obtained by directly reading the corresponding fields from each job dictionary using key access.

We also inspected missing values in the datasets. Here it is important to note that some missing values are expected in our data, such as in the endDate for active jobs (status=active). Also missingness is expected for department and seniority in the not annotated data. We found 118 missing values in startDate and 741 in endDate in the annotated data and 58 in startDate and 477 in endDate in the not annotated data. We found that all missing end dates occur for jobs with status active or unkown, while all inactive jobs have an end date. Furthermore, we also found that all jobs marked with status unkown lack both a start date and an end date. This inspections showed us that incomplete temporal metadata is consistently captured via the unknown status rather than occurring randomly. This indicates that incomplete temporal metadata is consistently reflected in the job status and does not represent random missingness. Overall, any missingness in the data was expected, missing end dates correspond to ongoing (active) positions and therefore represent meaningful missingness rather than data quality issues. Jobs with unknown status lack temporal information (both start and end dates).

3 EDA

The EDA aims to understand the structure, quality, and challenges of the data. The implementation is available in the GitHub repository under *data_prep_eda*.

3.1 Department Distribution

We take a look at the distribution of the department label in the datasets and understand how balanced or imbalanced the department labels are distributed. This is especially important since department is one of our target variables and its distribution helps us understand the difficulty of the prediction task.

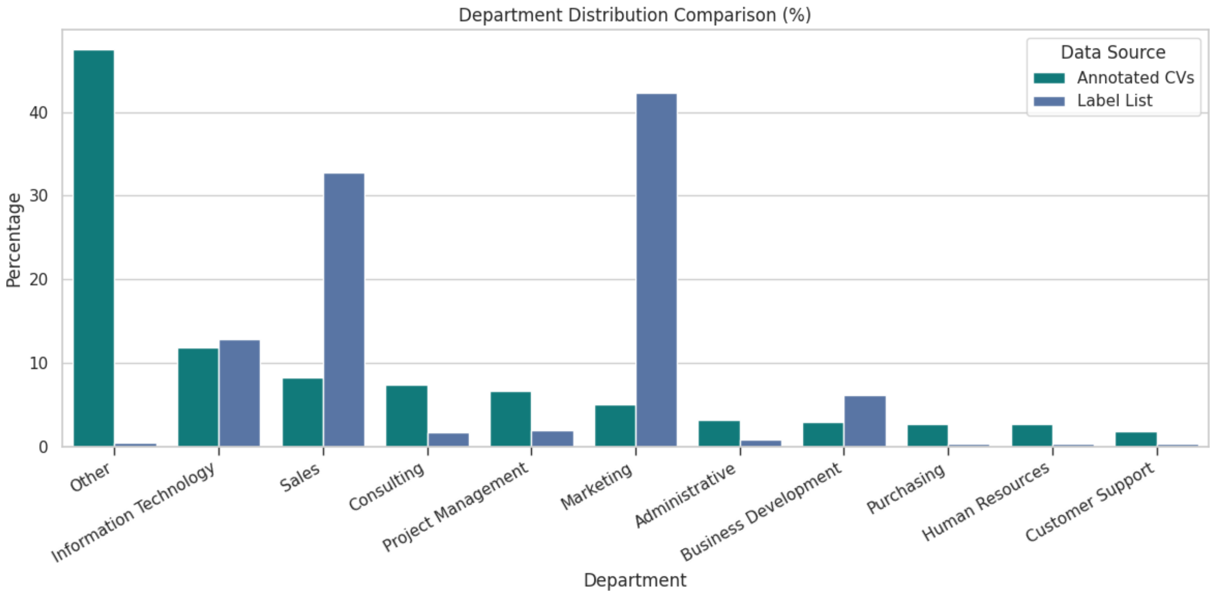


Figure 1: Department Distribution

The annotated CV data and the Label List have the same 11 departments. Departments are very imbalanced for both data. There are few departments that have a much higher percentage. However they are different for the CV data and the Label List: for the CV data the label Other dominates, while for the Label List it is Marketing. Sales and Information Technology is strong for both. The undefined label Other is much less common in the Label List than it is in the CV data.

3.1.1 How often people change Departments

We want to analyse if we can assume that it is rather unlikely that people change the department over time. We compare each job to the previous one in a CV by counting how often the department changes.

Department Change Count	CV count
0	288
1	94
2	78
3	57
4	31
5	25
6	21
7	4
8	7
9	2
10	1
24	1

Table 1: Department Change Counts and their CV Count

We can see that there is a strong department stability for many people. 288 CVs (47%) never change department and 382 CVs (63%) change at most once. But department change is not completely rare, about 37% changed department multiple times. While department changes do occur, particularly for a subset of highly mobile careers, the overall pattern indicates substantial departmental stability.

3.2 Seniority Distribution

We also take a look at the distribution of the seniority label in the datasets and understand how balanced or imbalanced the department labels are distributed. This is especially important since seniority is the other one of our target variables and its distribution helps us understand the difficulty of the prediction task.

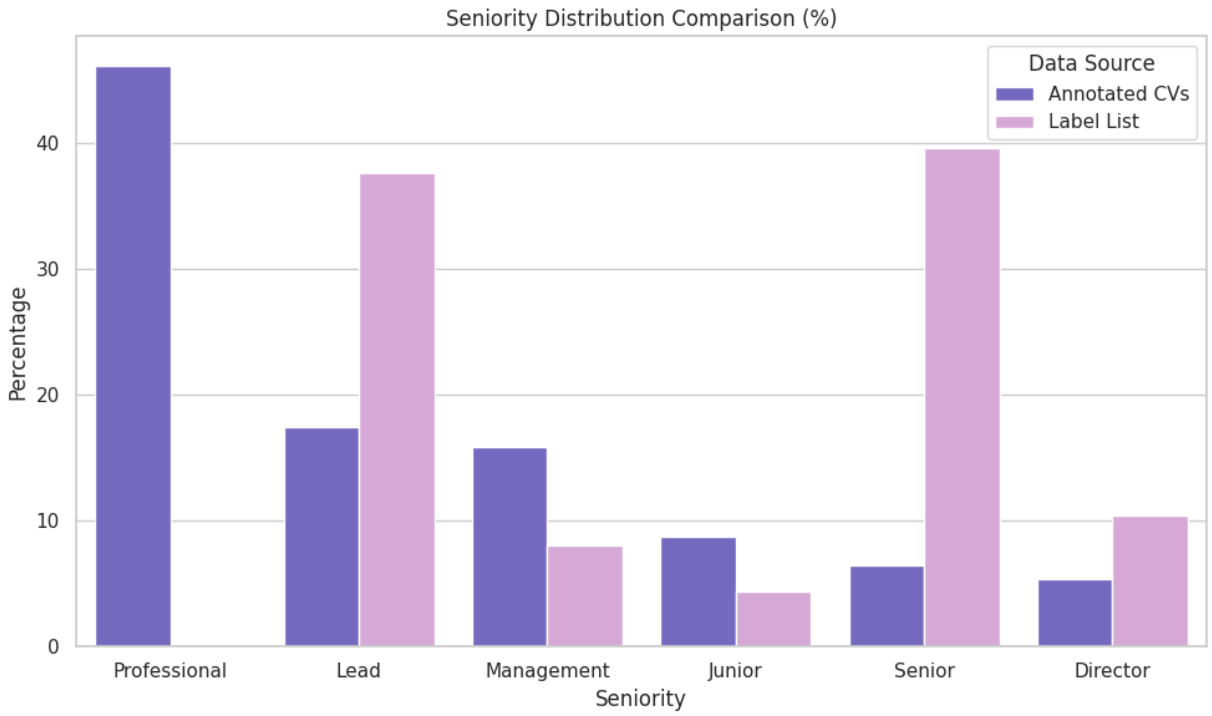


Figure 2: Seniority Distribution

The plots show a big discrepancy: we have a seniority label missing in the Seniority Label List. We have 6 seniorities in the annotated CV, but only 5 in the Label List. The label Professional is completely absend from the Label List. This is especially problematic since Professional is the most common Label in the CV data. Overall the distribution of seniority labels is more balanced compared to the distribution of department labels. Professional is the most common seniority in the annotated CVs, followed by Lead and Management. Senior is the most common seniority in the Label List, followed by Lead.

3.2.1 Comparison of current Seniority to previous Seniority

This analysis compares the seniority level of the current position to earlier roles within the same CV, highlighting whether individuals are currently in higher, similar, or lower seniority positions relative to their past experience. For that we map seniority manually to an ordinal scale (Junior = 0, Professional = 1, Senior = 2, Lead = 3, Management = 4, Director = 5) and check seniority changes between consecutive jobs in a CV.

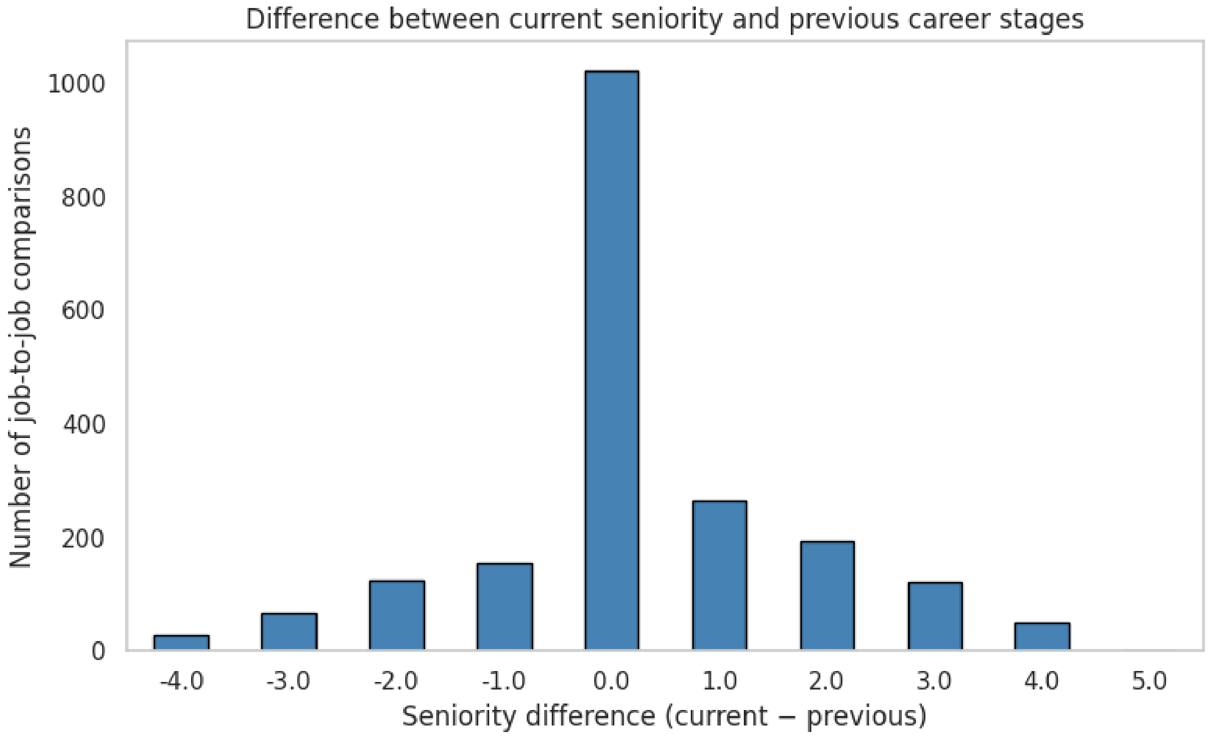


Figure 3: Seniority Changes

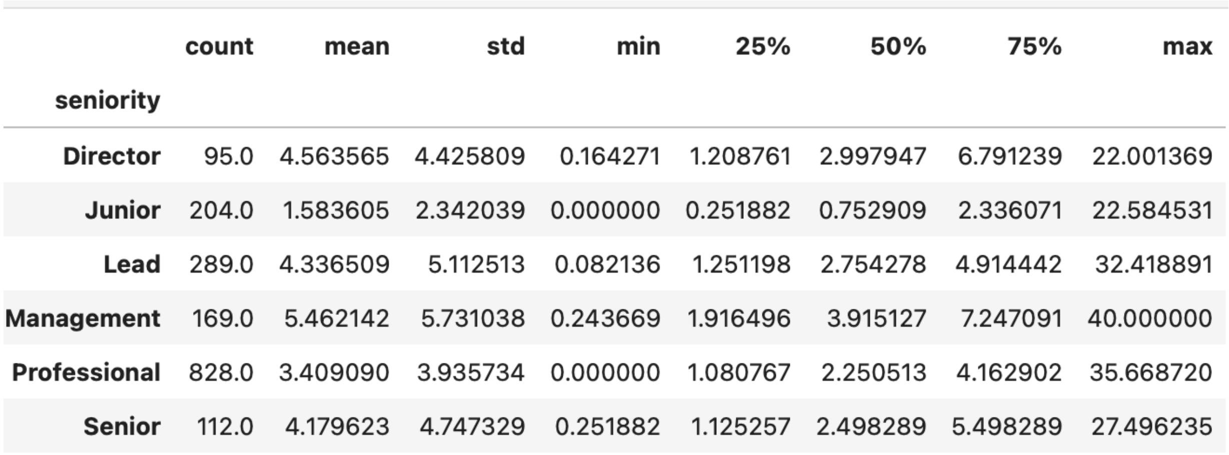
Job-to-Job seniority comparison	Percentage
current_higher_than_previous	31.1%
current_same_as_previous	50.37%
current_lower_than_previous	18.53%

Table 2: Job-to-Job Seniority Comparison

The majority of job-to-job comparisons show no change in seniority between the current position and earlier roles. Upward deviations are more frequent than downward deviations. This shows that seniority does not consistently increase relative to earlier roles. A large proportion of current positions remain at the same seniority level (50%).

3.2.2 How many years do people spend on each Seniority Level

We want to analyze how long (years) individuals typically remain in each seniority level. Therefore we compute the duration of job positions using their start and end dates. We restrict the analysis to inactive jobs, because we do not have a time period for active jobs. We also only use those inactive jobs with both a start and end date. Job durations are calculated in years and then aggregated by seniority level.



seniority	count	mean	std	min	25%	50%	75%	max
Director	95.0	4.563565	4.425809	0.164271	1.208761	2.997947	6.791239	22.001369
Junior	204.0	1.583605	2.342039	0.000000	0.251882	0.752909	2.336071	22.584531
Lead	289.0	4.336509	5.112513	0.082136	1.251198	2.754278	4.914442	32.418891
Management	169.0	5.462142	5.731038	0.243669	1.916496	3.915127	7.247091	40.000000
Professional	828.0	3.409090	3.935734	0.000000	1.080767	2.250513	4.162902	35.668720
Senior	112.0	4.179623	4.747329	0.251882	1.125257	2.498289	5.498289	27.496235

Figure 4: Seniority Duration

Junior positions tend to be relatively short-lived, lasting on average for one year (mean=1.58 and median=0.75 years). Professional roles represent a stable mid-career stage, with longer typical durations than junior roles but shorter durations than management or director positions. On average they last for 2-3 years (mean=3.41 and median=2.25 years). Senior and Lead roles show comparable job durations. They last on average for 2-4 years (Senior: mean=4.18 and median=2.5 years and Lead: mean=4.34 and median=2.75 years). Management positions tend to be more stable, with individuals remaining in these roles the longest. On average they last for 3-5 years (mean=5.46 and median=3.91 years). Director roles also show relatively long durations, although slightly shorter median tenure than management positions. On average they last for 3-4 years (mean=4.56 and median=2.98 years).

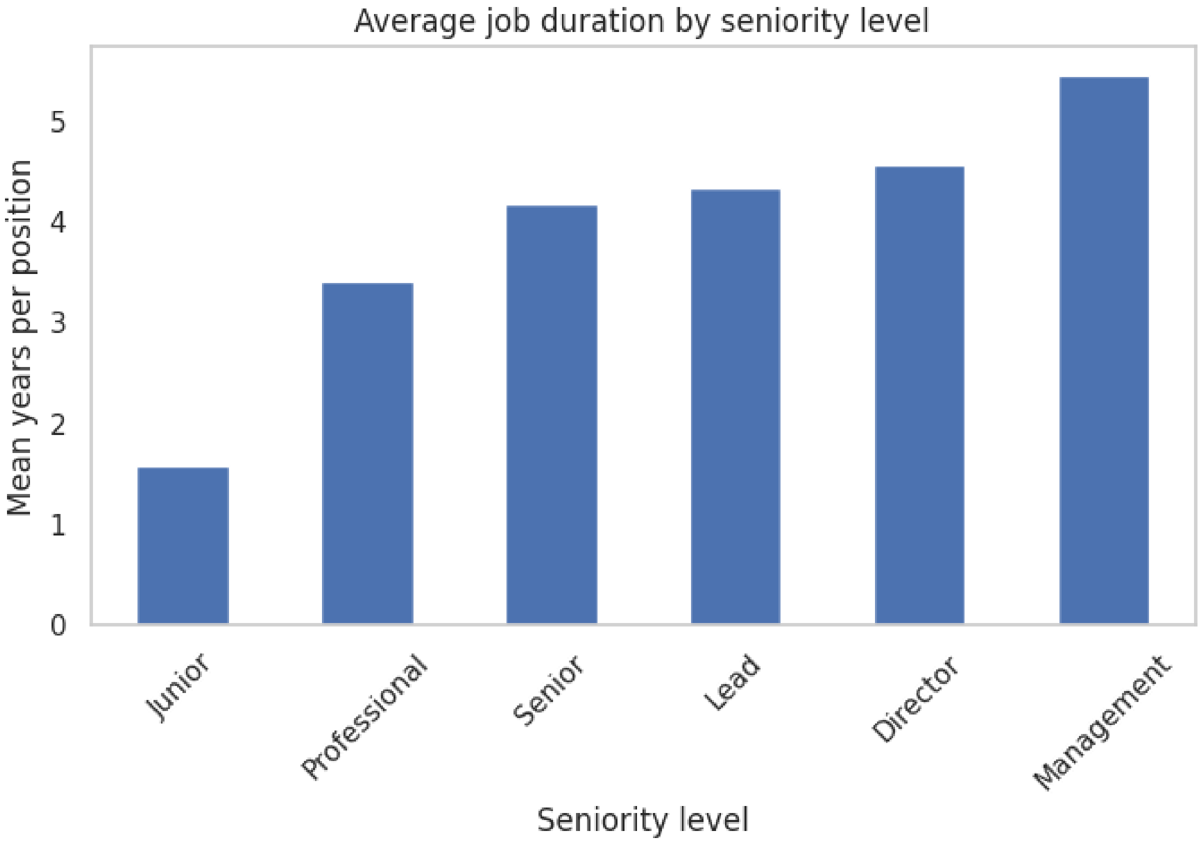


Figure 5: Average Seniority Duration

We can see that the average (mean) job duration increases with seniority level, with junior roles exhibiting the shortest average tenure and management-level roles showing the longest.

3.3 Job Status Distribution

We now take a look at the status distribution of jobs in the annotated CVs. This is important as our prediciton will be based on the characteristics of the current job, meaning where the status is active. We want to understand how many active jobs there are in the data and whether CVs can have multiple active jobs.

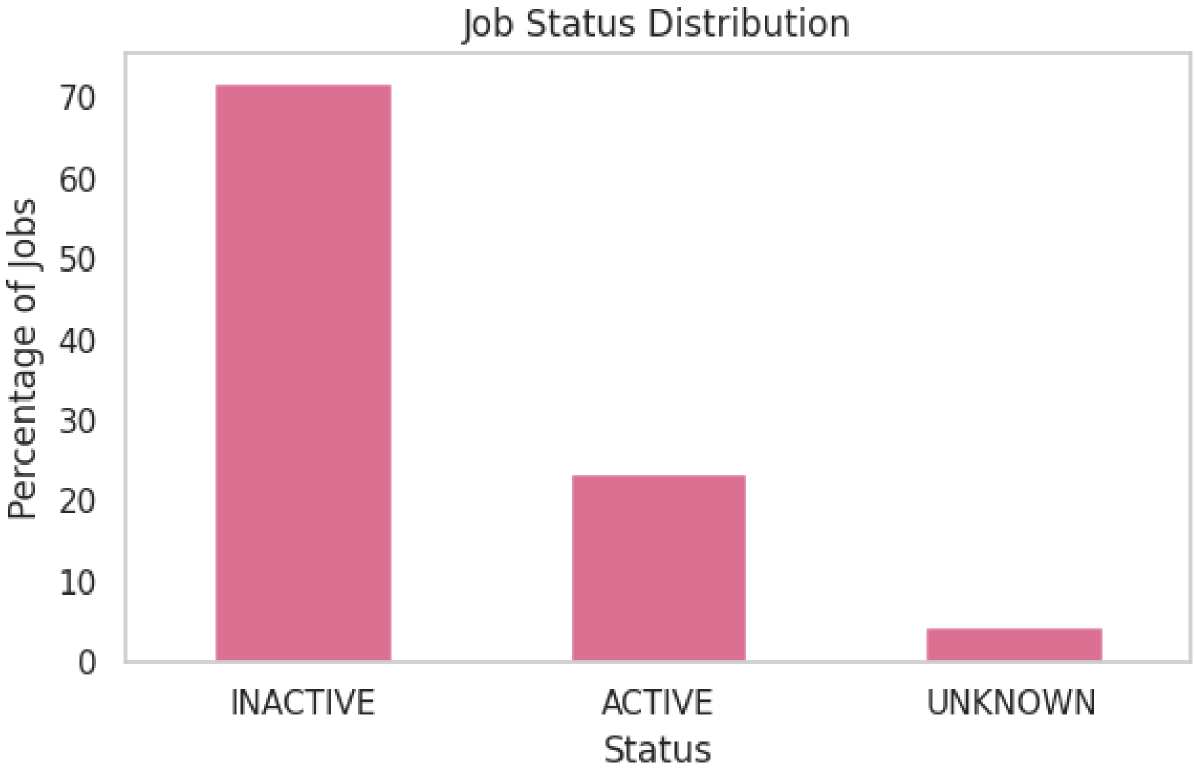


Figure 6: Job Status Distribution

We can clearly see that most jobs are inactive and historical, given by the fact that 72% of all job entries are of status inactive. This however is a logical consequence of CV data and confirms to us that the CVs contain rich career history. Approximately 24% of jobs are labeled as active, while a small fraction has a status unknown likely due to incomplete temporal metadata.

Our first intuition based on common sense and also based on the data (24% of jobs are labeled as active) is that there is 1 active job per CV. To support this intuition we take a look at the distribution of active jobs per CV.

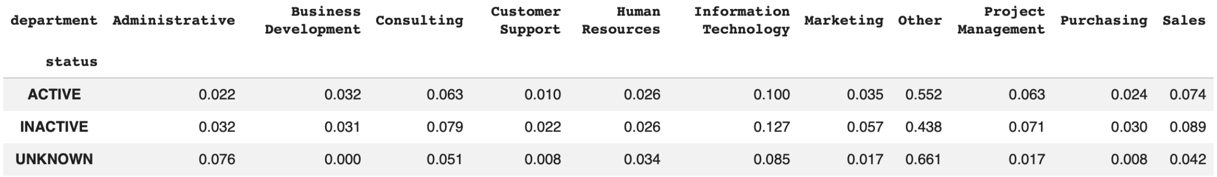
Count of active jobs	CV count
0	131
1	380
2	78
3	10
4	3
5	4
7	1
8	1
10	1

Table 3: CV counts and their amount of active jobs

Most CVs (380) have exactly 1 active job and represents the largest group. However, we also have a high amount of CVs (131) without a current job. Some have 2 (78) or 3 (10), and there are some minor edge cases with a maximum 10 current jobs in one CV. This tells us CVs can have multiple active jobs, this however are minority cases.

3.4 Department vs Job Status

We want to understand how the departments are distributed among the different job status.



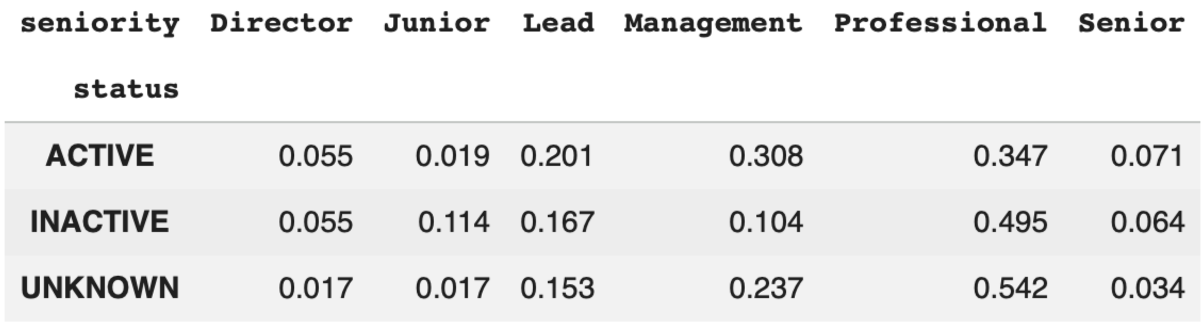
department	Administrative	Business Development	Consulting	Customer Support	Human Resources	Information Technology	Marketing	Other	Project Management	Purchasing	Sales
status											
ACTIVE	0.022	0.032	0.063	0.010	0.026	0.100	0.035	0.552	0.063	0.024	0.074
INACTIVE	0.032	0.031	0.079	0.022	0.026	0.127	0.057	0.438	0.071	0.030	0.089
UNKNOWN	0.076	0.000	0.051	0.008	0.034	0.085	0.017	0.661	0.017	0.008	0.042

Figure 7: Department Distribution across Job Status

Status active clearly shows a dominance of department Other. After that, IT and Sales are the strongest specific departments. This suggests that current job titles often lack strong department specific signal. Status inactive also has Other dominating but less extreme percentage wise and shows more diversity across departments. Historical jobs show broader departmental diversity than current roles. Status unknown is extremely dominated by Other and has a sparse representation elsewhere. These unknown status jobs lack sufficient structure for reliable department inference. Overall, the distribution of department labels differs by job status. Active jobs are strongly dominated by the Other category, whereas inactive jobs exhibit greater departmental diversity.

3.5 Seniority vs Job Status

We take the same look at seniority and their distribution among the different job status.



seniority	Director	Junior	Lead	Management	Professional	Senior
status						
ACTIVE	0.055	0.019	0.201	0.308	0.347	0.071
INACTIVE	0.055	0.114	0.167	0.104	0.495	0.064
UNKNOWN	0.017	0.017	0.153	0.237	0.542	0.034

Figure 8: Seniority Distribution across Job Status

Active jobs are strongly skewed toward mid to high seniority levels. Junior roles are rare among current jobs. Management amd Lead together alone represent 51%. Current positions tend to represent later career stages. Junior roles are much more common in inactive jobs. Earlier career stages are more prevalent in past positions.

3.6 Job Titles

Since all our approaches use the job titles as predictor, we must understand their overall structure: how long they are and how diverse / noisy they are linguistically.

3.6.1 Job Title Length Distribution

Th job title length tells us how much information is available per sample and whether titles are mostly short or descriptive. For that we measure the number of words per title.

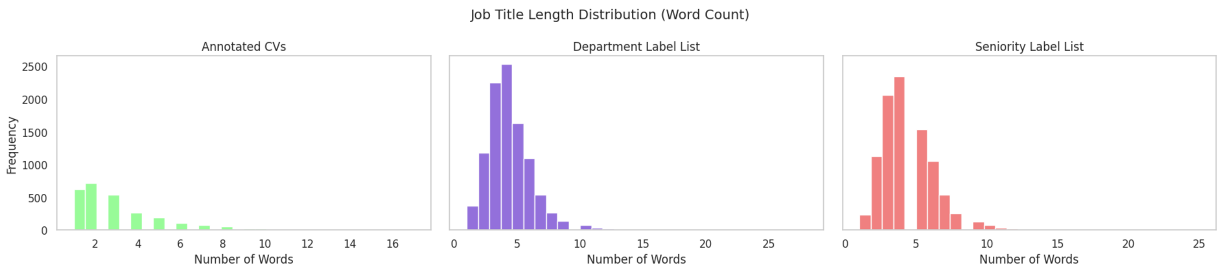


Figure 9: Job Title Length Distribution

Overall most job titles are short for all 3 datasets, ranging between 1-6 words on average per title. We can see the annotated CV data has overall shorter titles, with most of them being between 1-2 words.

3.6.2 Language and Character Diversity of Job Titles

To not overkill the analysis, we look at random samples of about 100 jobs for each dataset to get an overall view on the diversity of languages and characters in the titles. Looking at the samples, we primarily inspect the following: we analyse if non-English titles exist and we look for any special characters and whitespacing. For space reasons the full samples are only printed out in our notebook. The main insights we gained are that we have non-English titles and we have special characters (such as /, (), -, &) and whitespacing in the data for all datasets.

We also checked for the proportion of non-ASCII characters. Non-ASCII characters typically indicate: non-English titles (e.g. German, French, Spanish), localized spellings (ä, ö, ü, ß, é, ñ, etc.) or mixed-language titles.

Data	Titles with non-ASCII characters
Annotated CVs	11.1%
Department Label-List	7.1%
Seniority Label-List	9.7%

Table 4: Amount of non-ASCII characters in the job titles

For each datafile the job titles contain a small proportion of non-ASCII characters, indicating the presence of non-English or language-specific titles. This linguistic diversity introduces additional variability and noise, however the non-ascii amount is very small. Note that these are a lower bound, not an upper bound: English titles can still exist in other languages and ASCII-only does not mean "English".

4 Preparation

The implementation is available in the GitHub repository under the folder *src/utils*. For evaluation, we use the following metrics to evaluate and compare all approaches:

- Accuracy: shows the overall fraction of correctly classified samples
- macro-averaged F1-Score: is the harmonic mean of precision and recall, computed independently for each class and averaged across classes. This metric is particularly important due to the strong class imbalance in both department and seniority labels, as it ensures that performance on minority classes is weighted equally.
- MAE: measures the average absolute difference between predicted and true labels. It is only meaningful for ordinal or numerical labels, where it captures how far predictions deviate from the correct class on average; for nominal class labels, the metric is not applicable.

Together, these metrics allow us to assess how often each model is correct overall and how well it performs across all classes, including rare ones.

The function *evaluate_predictions* is created in *eval_utils.py* for each model to use and computes the evaluation metrics. Some approaches have different metrics (numbers or strings). The function assigns None to the metric that cannot be computed for a model. This ensures a consistent output structure across different models and label types.

5 Experiments

5.1 Rule Based Matching

The rule based matching is performed with the annotated CV dataset transformed to a job-level and the Seniority and Department Label Lists. The implementation is available in the GitHub repository under the folder *src/model-1-baseline*.

For the rule-based matching, job titles and label-list entries are normalized using lowercasing and whitespace stripping before applying the substring matching. This is done to avoid any accidental mismatching due to lower/uppercasing or spacing (spaces, tabs, line breaks). No additional text preprocessing is performed in order to preserve the original lexical content and keep the rule-based baseline fully interpretable. The same normalization procedure is applied consistently to both CV job titles and label-list entries.

Furthermore, we only include CVs that contain exactly one active job (= current job) in order to ensure an unambiguous definition of the current position. CVs with zero active jobs do not provide a target position for prediction, while CVs with multiple active jobs introduce ambiguity regarding which role should be considered the primary current position. Restricting the dataset to CVs with exactly one active job therefore ensures a consistent and well-defined evaluation setup.

Rule-based Matching Logic Our rule-based matching functions implement a rule-based classifier using the provided department and seniority label lists, where job titles from the LinkedIn CV data are matched against predefined keywords via substring rules. Unmatched titles to departments are assigned to the label 'Other'. For seniority we explicitly use "Professional" as default for unmatched titles, because no label such as "Other" exists in seniority. There are two reasons as to why we use "Professional" as the fallback: first, this is the most frequent seniority class and using it as the fallback label avoids artificially inflating rare classes. Second, it is present in the CV annotations but not in the predefined seniority keyword list. Whenever no seniority-specific keyword is matched, the model can default to "Professional".

Rule Based Matching Results. Results show that for department prediction, the baseline achieves an accuracy of 60.26% and a macro-averaged F1 score of 0.449. For seniority prediction, the accuracy is in comparison lower at 53.68% with a lower macro F1 score of 0.426.

The relatively higher accuracy compared to the macro F1 score in both tasks reflects the strong class imbalance present in the data. Dominant classes such as Other (department) and Professional (seniority) are frequently predicted due to the fallback behavior of the rule-based system, which inflates overall accuracy while reducing performance on minority classes.

Baseline	Accuracy	Macro F1
Department prediction	60.26%	0.449
Seniority prediction	53.68%	0.426

Table 5: Rule-based matching evaluation results

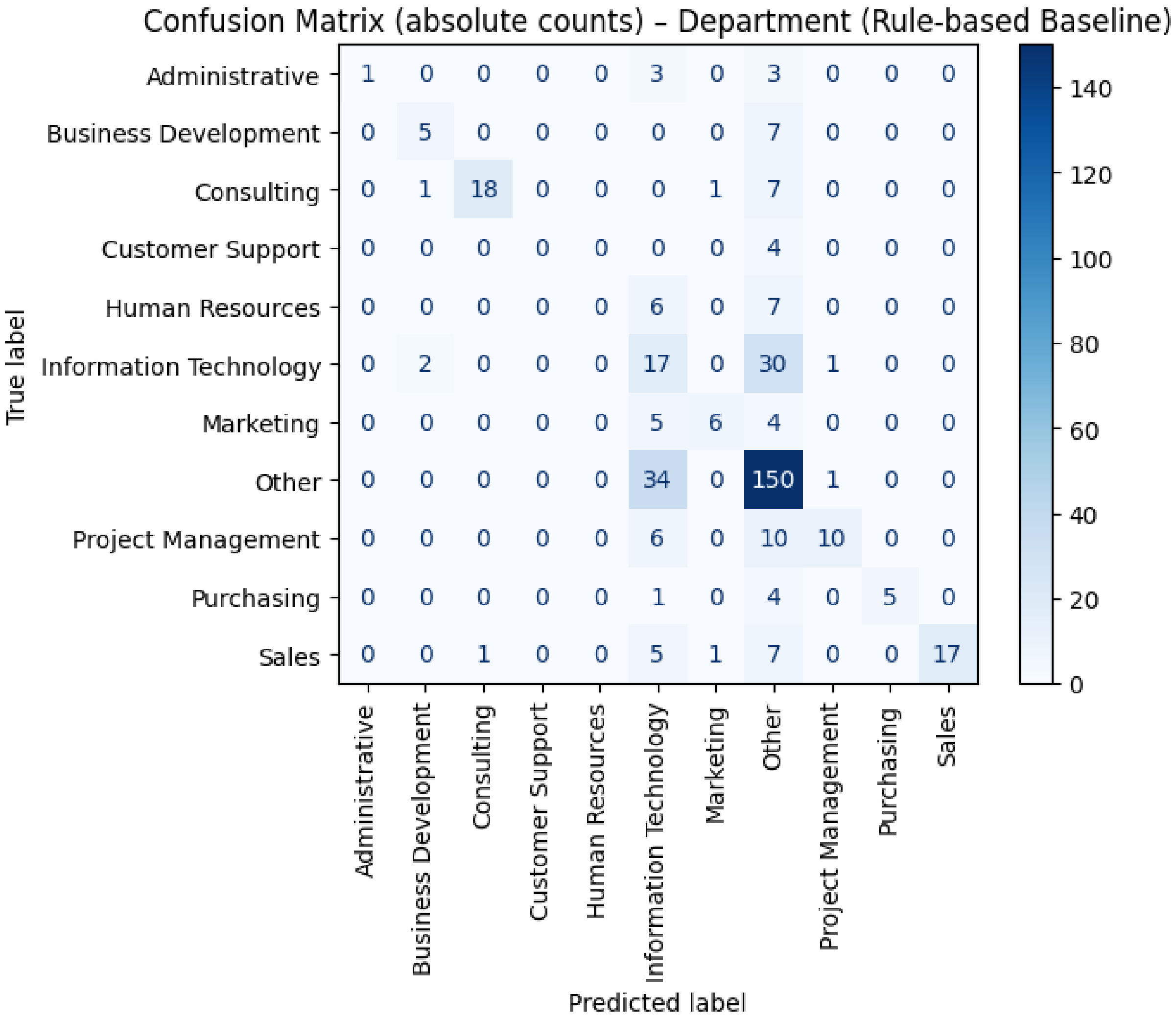


Figure 10: Confusion Matrix Department

The department confusion matrix reveals that the rule-based baseline strongly relies on explicit keywords and defaults to the “Other” category when no clear match is found. While domains such as Sales and Consulting are identified reasonably well, many roles from related or ambiguous departments are misclassified as “Other”, indicating limited contextual understanding.

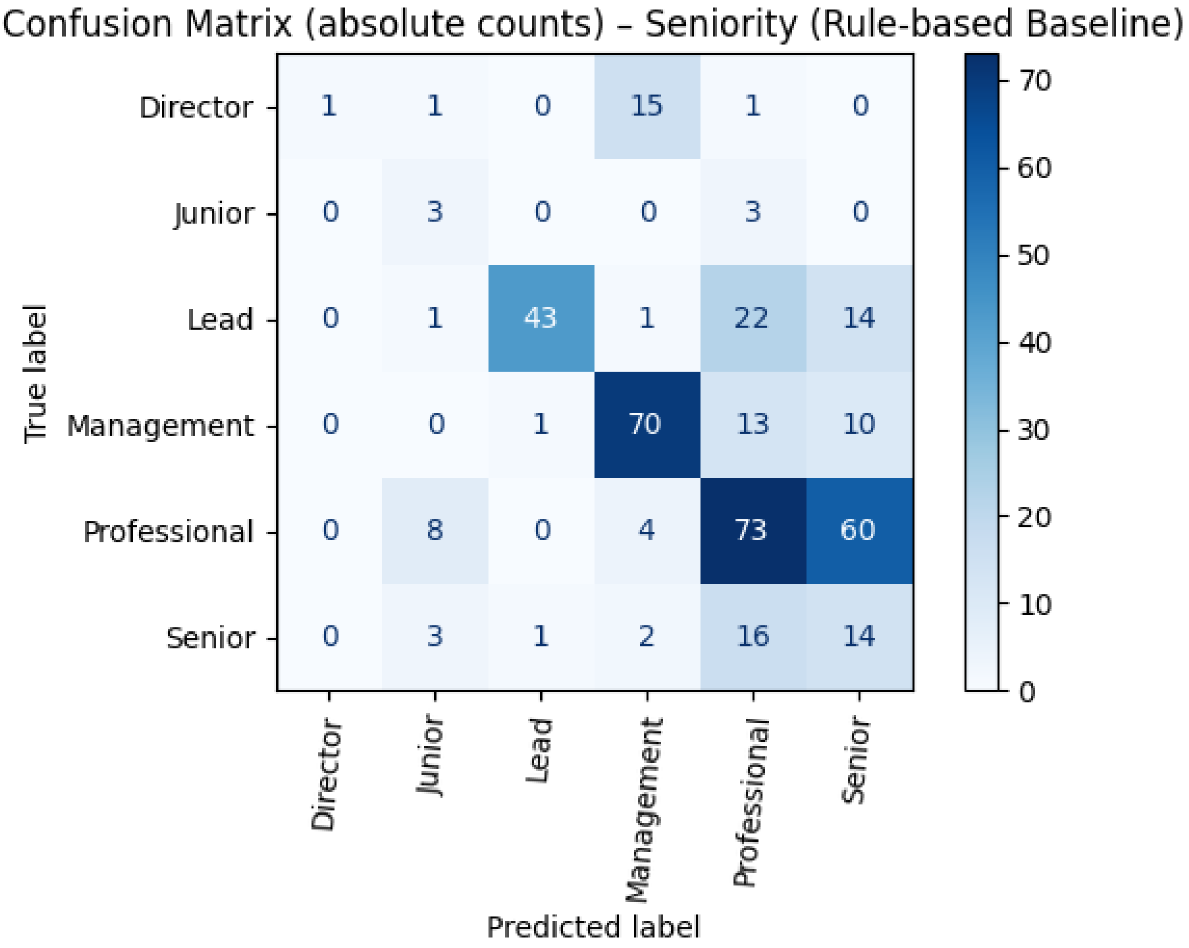


Figure 11: Confusion Matrix Seniority

The seniority confusion matrix is strongly influenced by the role of “Professional” as a fallback class in the rule-based baseline. The frequent assignment of the “Professional” class is likely driven by the absence of explicit seniority markers in many job titles. This effect is further reinforced by the fact that “Professional” is not explicitly represented in the seniority keyword list and is therefore only reachable via the default assignment. While seniority levels with clear keywords (e.g. Lead or Management) are recognized reasonably well, substantial confusion arises for mid-level roles. A lot of Professionals are assigned to Senior. This behavior highlights the limitations of keyword-based matching and motivates the use of context-aware machine learning models.

Confusion matrix analysis shows that the baseline performs reasonably well for labels associated with explicit keywords in job titles, such as Sales, Consulting, Lead, and Management. However, substantial confusion occurs between semantically related classes and for ambiguous job titles that lack clear indicators. In these cases, predictions are often assigned to the fallback categories.

Overall, the rule-based baseline provides a transparent and interpretable reference point. While its predictive performance is limited, particularly in terms of balanced classwise performance, it establishes a lower bound and highlights the need for more expressive and context aware machine learning models.

5.2 Prompt Engineering

We use prompt engineering to benchmark how far a large language model can go on our labeling tasks without training a dedicated classifier. In addition, we use the same setup to generate synthetic labels for unlabeled job titles as extra training data for downstream experiments. The implementation is available in the GitHub repository under the folder *src/prompt_engineering/*.

5.2.1 Evaluation with Test Set

We evaluate a prompt-based approach using `gemini-2.0-flash` to predict two labels from job titles: (1) an ordinal seniority level mapped to {1.0,...,6.0} and (2) a department label from an 11-class closed set. The system prompt specifies the task and the allowed labels, includes a small set of in-prompt examples, and enforces JSON-only output. To make predictions machine-readable and consistent, each response is validated against a strict schema (both fields are restricted to predefined enums). For ambiguous titles, we apply a fixed fallback (`Other` and `2.0`). Predictions are generated row-by-row; the pipeline uses retries and persists results after each row to remain robust to intermittent API errors.

Table 6 summarizes the evaluation results. On the annotated test set, seniority prediction reaches 58.43% accuracy (macro F1 = 0.54, weighted F1 = 0.60). The per-class report shows strong asymmetries: *Junior* has very low precision (0.14) and high recall (0.83), indicating substantial overprediction of this class. *Professional* and *Lead* show the inverse pattern (precision 0.82 / 0.88; recall 0.47 / 0.41), meaning these labels are correct when predicted but are assigned too rarely. *Senior* and *Management* are comparatively stable (F1 $\approx$ 0.66 each). For *Director*, recall is 1.00 but precision is 0.36, i.e., all true Director cases are retrieved, but many non-Director titles are also mapped to this top level.

Department prediction performs better in prompt engineering, achieving 79.61% accuracy (macro F1 = 0.73, weighted F1 = 0.80). The strongest categories in the class-wise report are Sales (F1 0.87), Purchasing (0.83), Information Technology (0.82), Human Resources (0.80), and Customer Support (0.91). The weakest categories are Business Development (F1 0.36) and Administrative (F1 0.55).

Task	Accuracy	Macro F1	Weighted F1
Seniority prediction	58.43%	0.540	0.601
Department prediction	79.61%	0.734	0.804

Table 6: Prompt-engineering evaluation results on the annotated test set.

5.2.2 Prompt Engineering for Synthetic Data

We additionally apply the same prompting setup to unlabeled job titles to generate synthetic labels as extra training data. We use prompt-based labeling instead of a purely rule-based approach because it achieved higher department accuracy on the annotated dataset and because it can produce labels that are missing (or strongly underrepresented) in the supervised training data (e.g., *Professional* for seniority). The resulting file `gemini_synthetic.csv` is concatenated with the supervised training split and used for fine-tuning transformer classifier/regressor models.

Figures 12 and 13 illustrate why this augmentation is relevant: the label distributions differ substantially between the training data and the CV (out-of-production) dataset.

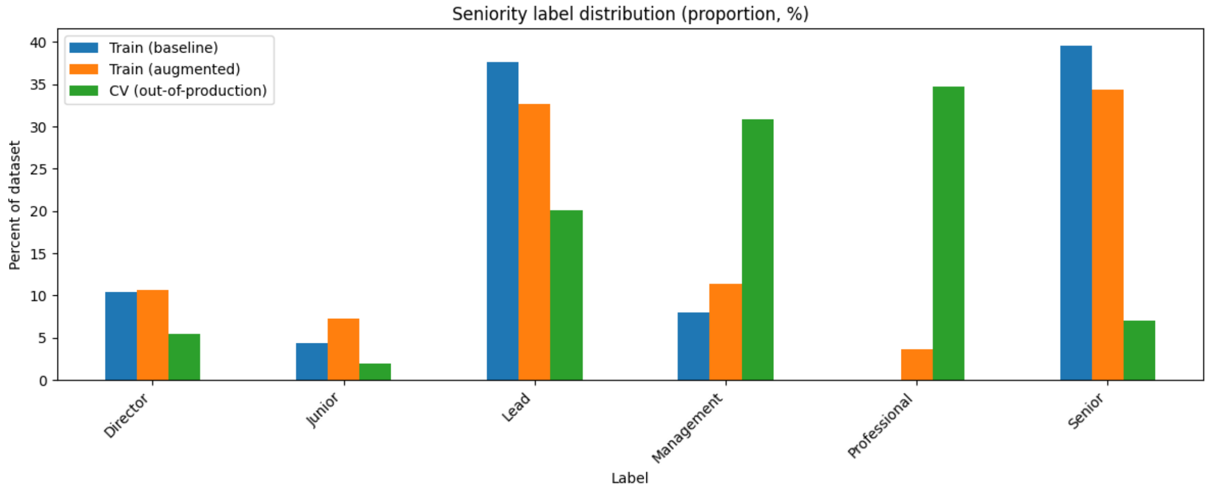


Figure 12: Distribution of seniority labels in different datasets

In Figure 12, the CV dataset is dominated by *Professional*, while the original training data contains almost no *Professional* examples. By adding prompt-labeled synthetic data, we introduce at least a small amount of *Professional* supervision and move the training distribution slightly closer to the CV distribution.

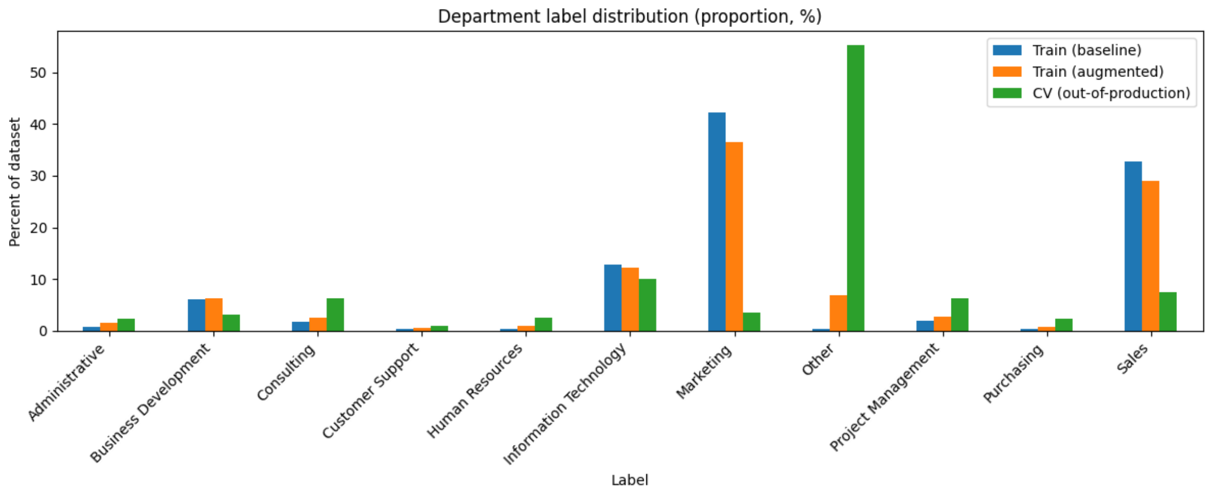


Figure 13: Distribution of department labels in different datasets

In Figure 13, *Other* is the most frequent class in the CV dataset, but is underrepresented in the original training data; synthetic augmentation increases the number of *Other* samples available during fine-tuning, which is expected to help the model learn this class better.

At the same time, we need to account for potential label noise in the synthetic data: in the prompt evaluation, *Business Development* was the weakest department category (lowest F1), so synthetic labels for this class may be less reliable. We therefore treat synthetic augmentation as an empirical experiment and evaluate downstream performance to determine whether the additional data improves robustness on the CV (out-of-production) distribution.

5.3 Simple interpretable baseline: Bag of words/ TF-IDF + Logistic Regression

This section presents a classic bag-of-words approach to the automatic classification of job titles. A combination of TF−IDF vectorization and logistic regression is used as the baseline model, as this approach is easy to interpret and allows for a structured comparison with finely tuned transformer models. The implementation of the bag-of-words/TF−IDF + logistic regression model is available in the GitHub repository at
src/model6_Bag_of_Words_TF−IDF_+_Logistic_Regression/. The models use the curated, labeled datasets (`seniority_df` and `department_df`), which are first divided into training and test sets. A pipeline consisting of TF−IDF vectorizer and logistic regression is used for classification. The model is then trained on the training data, followed by an in-distribution evaluation on the test sets and an out-of-distribution evaluation on real, annotated CV data. Several model variants are available for analysis: a baseline model without synthetic data or oversampling, and a final, optimized model with synthetic data, oversampling, and an adapted pipeline. The out-of-distribution results of the intermediate

stages (model with synthetic data and model with synthetic data and oversampling) are only briefly compared, while the focus is on the comparison between the baseline model and the best pipeline. Model performance is evaluated using accuracy, macro-F1, and a classification report, supplemented by an analysis of the most important features (top features) to ensure the traceability of classification decisions.

5.3.1 Seniority: bag of words approaches and results

We tried out different model configurations which are highlighted in 15. We will only discuss further our (1) baseline model for our bag of words approach and (2) our best performing model configuration. For the first model without synthetic data and oversampling, a pipeline consisting of a TF−IDF vectorizer and logistic regression is used. The vectorizer takes unigrams and bigrams into account and filters out very rare (min_df=3) and extremely frequent terms (max_df=0.9). A multinomial logistic regression with an increased number of iterations (max_iter=1000) and balanced class weights (class_weight="balanced") serves as the classifier.

(1) Seniority Baseline Model The in-distribution evaluation in Table 7 shows very high model performance. With an accuracy of 0.97 and a macro F1 score of 0.956, most seniority levels are classified reliably. As can be seen in Table 7, the Lead, Senior, and Director classes in particular have very high precision and recall values. Although the Junior and Management classes achieve a slightly lower precision, they are recognized completely.

Class	Precision	Recall	F1-score	Support
Director	0.99	0.98	0.98	197
Junior	0.85	1.00	0.92	82
Lead	0.97	0.98	0.98	709
Management	0.92	0.93	0.92	151
Senior	0.99	0.97	0.98	747
Accuracy		0.97		1886
Macro F1		0.956		

Table 7: In-distribution evaluation of baseline seniority classification

Class	Precision	Recall	F1-score	Support
Director	0.58	0.88	0.70	34
Junior	0.18	0.33	0.24	12
Lead	0.33	0.71	0.45	125
Management	0.90	0.59	0.72	192
Professional	0.00	0.00	0.00	216
Senior	0.23	0.80	0.36	44
Accuracy		0.437		623
Macro F1		0.409		

Table 8: Out-of-distribution evaluation of baseline seniority classification

The out-of-distribution evaluation of Table 8 reveals a significant drop in performance. With an accuracy of 0.437 and a macro F1 score of 0.409, it is clear that the model generalizes only to a limited extent outside the training distribution. The Professional class in particular is never predicted correctly, as it is not included in the training dataset.

Class	Top Terms
Director	marketing director, managing directors, director sales, abteilungsdirektor, director
Junior	junior, assistant, analyst, referent, employee
Lead	department head, project lead, team lead, leadership, head of
Management	ceo, vice president, cio, founder, executive management
Senior	senior, manager, marketing manager, engineer, consultant

Table 9: Top terms per seniority class

As Table 9 shows, the model predominantly uses specific keywords to distinguish between seniority levels. For example, we can see that the top terms for the Director class all include the word “director,” while the Junior class is characterized by terms such as “junior” and “assistant.” This indicates that the model relies heavily on explicit lexical cues present in job titles to make classification decisions. While this approach works well for titles containing clear seniority indicators, it may struggle with more ambiguous or nuanced titles that lack such keywords.

(2) Best performing seniority model configuration: seniority model with synthetic data The procedure for our best performing seniority model corresponds to the baseline model. The only difference is that the training data set is expanded with synthetic seniority data before being divided into training and test sets in order to better cover underrepresented classes such as “Professional.”

Class	Precision	Recall	F1-score	Support
Director	0.50	0.85	0.63	34
Junior	0.17	0.58	0.26	12
Lead	0.86	0.50	0.63	125
Management	0.85	0.72	0.78	192
Professional	0.69	0.61	0.64	216
Senior	0.35	0.77	0.48	44
Accuracy		0.645		623
Macro F1		0.571		

Table 10: Out-of-distribution evaluation of seniority classification with synthetic data

The out-of-distribution evaluation on real CV data shows improved generalization compared to the baseline model without synthetic data. Accuracy increases to 0.645 and macro F1 to 0.571. In particular, the Professional class is now recognized correctly much more frequently, reducing confusion between neighboring seniority levels. However, uncertainties remain for some classes, particularly Junior and Senior. We also tried different model variants to boost accuracy and macro F1 further (like e.g. oversampling), but the results did not improve.

5.3.2 Department: bag of words approaches and results

Similar to the seniority models, synthetic data and oversampling are also integrated in the same way for the department classification.

(1) Baseline Department Model. The in-distribution evaluation on the test set shows very good model performance. With an accuracy of 0.934 and a macro F1 score of 0.860, most departments are classified reliably. As can be seen in Table 11, purchasing, marketing, sales, and information technology in particular have very high precision and recall values. Smaller classes such as Administrative, Other, or Project Management achieve slightly lower precision, but are mostly recognized correctly.

Class	Precision	Recall	F1-score	Support
Administrative	0.62	0.94	0.74	17
Business Development	0.83	0.99	0.90	124
Consulting	0.82	0.97	0.89	33
Customer Support	0.88	1.00	0.93	7
Human Resources	0.75	1.00	0.86	6
Information Technology	0.92	0.95	0.94	261
Marketing	0.99	0.92	0.96	859
Other	0.50	1.00	0.67	8
Project Management	0.57	0.88	0.69	40
Purchasing	0.89	1.00	0.94	8
Sales	0.96	0.93	0.94	666
Accuracy		0.934		2029
Macro F1		0.860		

Table 11: In-distribution evaluation of baseline department classification

Class	Precision	Recall	F1-score	Support
Administrative	0.17	0.07	0.10	14
Business Development	0.38	0.30	0.33	20
Consulting	0.86	0.46	0.60	39
Customer Support	1.00	0.17	0.29	6
Human Resources	0.73	0.50	0.59	16
Information Technology	0.31	0.44	0.36	62
Marketing	0.17	0.41	0.24	22
Other	0.00	0.00	0.00	344
Project Management	0.27	0.56	0.37	39
Purchasing	0.80	0.53	0.64	15
Sales	0.12	0.85	0.21	46
Accuracy		0.223		623
Macro F1		0.338		

Table 12: Out-of-distribution evaluation of baseline department classification (ACTIVE jobs)

As with the seniority classification, performance drops significantly on real CV data (accuracy 0.223, macro-F1 0.338), showing that the model is strongly tied to the training distribution and that generalization to new positions is limited. Particularly striking is the *Other* category, which comprises almost half of the CV data but is practically not recognized, while smaller classes such as Purchasing or Consulting are classified much more reliably.

Department	Top Terms
Administrative	assistentin des, geschäftsführung, gf, assistent der, geschäftsleitung, der, sekretärin, assistent, assistenz, assistentin
Business Development	business intelligence, crm, digital business, of business, business process, ebusiness, it business, development, business development, business
Consulting	senior berater, sap, coach, senior consultant, von, senior, recruitment, beraterin, berater, consultant
Customer Support	service and, it systems, customer, technical, it support, it, customer support, technical support, supporter, support
Human Resources	qualitätsmanagement, director digital, project director, gl, manager hr, of human, resources, human resources, human, hr
Information Technology	digitalization, administrator, entwickler, digitale, administration, digitalisierung, sap, digital, it, crm
Marketing	marketing und, marketing sales, marketing manager, messen, sales marketing, kommunikation, messe, communications, communication, marketing
Other	transformation and, customer management, of commercial, senior director, operations officer, chief operations, of, operations manager, of operations, operations
Project Management	projektingenieur, projects, projekt, projektmanagerin, projekte, projektleitung, projektmanager, projektmanagement, projektleiter, project
Purchasing	strategische, einkauf und, and global, und it, operative, leiter einkauf, einkäuferin, einkäufer, purchasing, einkauf
Sales	account, sales manager, of sales, vertriebsinnendienst, vertriebsleitung, account manager, vertriebsleiter, salesforce, vertrieb, sales

Table 13: Top terms per department – baseline department model

The top words show that the model predominantly uses specific keywords to distinguish between departments. For example, we can see that the top terms for the Sales department all include the word “sales” or “vertrieb,” while the Information Technology department is characterized by terms such as “it” and “digital.” This indicates that the model relies heavily on explicit lexical cues present in job titles to make classification decisions. While this approach works well for titles containing clear department indicators, it may struggle with more ambiguous or nuanced titles that lack such keywords.

(2) Best performing department model: synthetic data and oversampling. In our experiments, we observed that while adding the synthetic data alone already improved performace (accuracy 0.676, macro-F1 0.563), combining synthetic data with oversampling of minority classes led to further enhancements in out-of-distribution generalization. The oversampling technique helps to balance the class distribution during training, allowing the model to better learn the characteristics of underrepresented departments. This combination proved effective in boosting the model's ability to generalize to real CV data.

Department	**Precision**	**Recall**	**F1-Score**	**Support**
Administrative	0.28	0.36	0.31	14
Business Development	0.24	0.60	0.35	20
Consulting	0.71	0.62	0.66	39
Customer Support	1.00	0.83	0.91	6
Human Resources	0.62	0.62	0.62	16
Information Technology	0.60	0.52	0.56	62
Marketing	0.59	0.45	0.51	22
Other	0.77	0.77	0.77	344
Project Management	0.68	0.64	0.66	39
Purchasing	0.67	0.67	0.67	15
Sales	0.79	0.65	0.71	46
Accuracy		0.685		623
Macro F1		0.612		

Table 14: Out-of-distribution evaluation of department classification with synthetic data and oversampling (ACTIVE jobs)

As with previous models, performance remains limited to real CV data. Oversampling and synthetic data improve the detection of underrepresented classes, especially *Other*, which is now reliably classified with a recall of 0.77. Overall performance is 0.685 accuracy and 0.612 macro-F1.

5.3.3 Comparison of all bag of words models

Table 15 summarizes the most important evaluation results of all seniority and department models. The overview highlights that the biggest improvement of the models came with adding synthetic data.

Model / Target	Accuracy	Macro F1
Seniority – Label Data		
Baseline (TF–IDF + LR)	0.970	0.956
+ Synthetic data	0.871	0.811
+ Oversampling	0.888	0.824
+ Optimized pipeline	0.877	0.818
Seniority – ACTIVE Jobs		
Baseline	0.437	0.409
+ Synthetic data	**0.645**	**0.571**
+ Oversampling	0.544	0.506
+ Optimized pipeline	0.555	0.522
Department – Label Data		
Baseline (TF–IDF + LR)	0.934	0.860
+ Synthetic data	0.888	0.779
+ Oversampling	0.921	0.839
+ Optimized pipeline	0.908	0.819
Department – ACTIVE Jobs		
Baseline	0.223	0.338
+ Synthetic data	0.676	0.563
+ Oversampling	**0.685**	**0.612**
+ Optimized pipeline	**0.682**	**0.618**

Table 15: Comparison of all bag-of-words-based models for seniority and department classification on label data and real CV data (ACTIVE jobs).

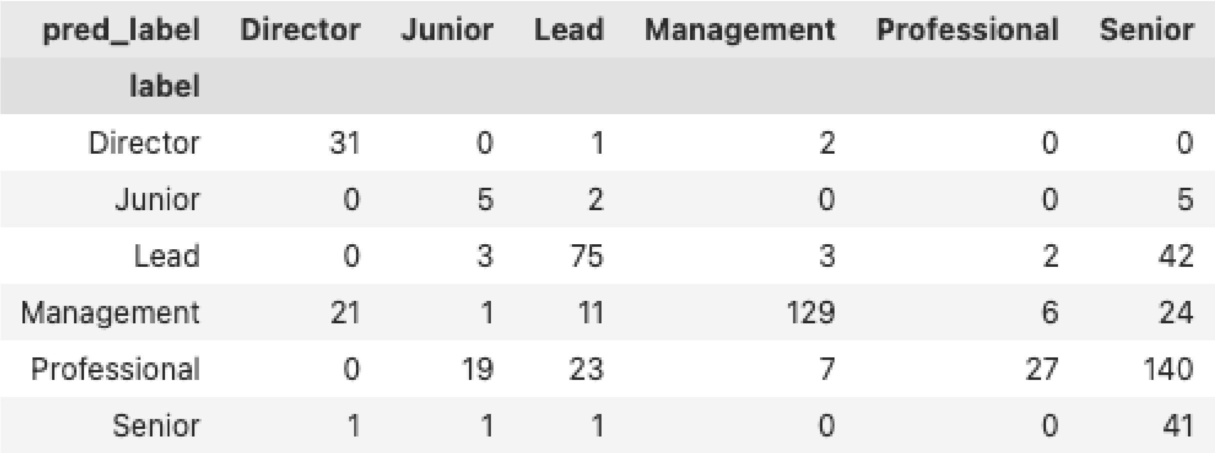
5.4 Fine-tuned classification model

The implementation of our fine-tuning experiments is provided in the GitHub repository under the folder *src/fine_tuning_pretrained/*. We train transformer-based models to predict seniority level and department directly from job titles, and we evaluate both in-distribution performance (on the curated fine-tuning datasets) and out-of-distribution performance on real CV data. Across all experiments we use `xlm-roberta-base`, since job titles in our data are multilingual and, in our preliminary runs, it generalized better to CV data than smaller alternatives (e.g., `distilbert`). For in-distribution evaluation, we split the curated datasets (`df_seniority` and `df_department`) into train/validation/test. Training updates are performed on the train split, early stopping and model selection use the validation split, and we report final in-distribution performance on the held-out test split. For out-of-distribution evaluation, we use `jobs_annotated_df` (real CV job titles) exclusively as a post-training benchmark; it is never used for training or early stopping.

5.4.1 Seniority: fine-tuning approaches and results

We study two seniority fine-tuning modeling strategies, motivated by a strong distribution shift between curated fine-tuning data and real CV job titles (see also the label distribution plots in Figure 12).

1) Regression fine-tuning (no synthetic data, no oversampling). We first map seniority labels to a numeric ordinal scale and fine-tune a regression head. To keep results comparable to classification setups, we additionally report thresholded accuracy/F1 by mapping predicted scores back into label bins. In-distribution performance is very strong: on the test split we obtain MAE = 0.1578 with thresholded accuracy = 0.9929. However, on the annotated CV dataset performance drops substantially to MAE $\approx$ 0.78, indicating that the model does not transfer well to production-like job titles under distribution shift, especially because the CV data contains the label *Professional* while the original fine-tuning dataset does not.



pred_label	Director	Junior	Lead	Management	Professional	Senior
label						
Director	31	0	1	2	0	0
Junior	0	5	2	0	0	5
Lead	0	3	75	3	2	42
Management	21	1	11	129	6	24
Professional	0	19	23	7	27	140
Senior	1	1	1	0	0	41

Figure 14: Confusion Matrix (All Predictions) – Counts (True label = rows, Predicted = columns)

The confusion matrix (Figure 14) reveals the following insights about our predictions on the CV data:

- **Clear distribution shift:** *Professional* is the most frequent label in CV data but does not exist in the fine-tuning dataset, which explains many downstream confusions.
- ***Professional* $\rightarrow$ *Senior/Lead*:** The model often predicts *Senior* or *Lead* for *Professional* CV titles, consistent with these being the most frequent (and closest) classes seen during training. Misclassifications into *Junior* occur less often, likely because *Junior* is underrepresented in the fine-tuning data.
- **Class imbalance effect:** *Senior* and *Lead* dominate the fine-tuning data, which biases the model toward these labels in ambiguous cases. This motivates using oversam-

pling in the next approach.
- **Rare CV labels:** *Junior* and *Director* are underrepresented in the CV data, making their predictions less stable. We also address this via oversampling in the next step.
- **Consistent error pattern:** Most mistakes occur between adjacent seniority levels, which is expected given the ordinal structure of the labels and the shifted label distribution.

2) Multi-class classification with synthetic data and oversampling To align the label space with the CV setting, we switch to a multi-class classification setup and augment the *training split* with synthetic samples generated via prompt engineering. This adds the previously missing label *Professional* to the training data without using any CV annotations (i.e., without leakage). Since the augmented training data is still imbalanced, we apply oversampling on the training split only, while keeping validation and test unchanged for fair early stopping and model selection.

In-distribution performance on the original test split remains high (accuracy = 0.9611, macro F1 = 0.7926). More importantly, performance on the CV dataset improves substantially compared to the regression baseline, reaching CV accuracy $\approx$ 0.6517 and CV macro F1 $\approx$ 0.5840. Note that *Professional* has zero support in the in-distribution validation/test classification reports by construction: synthetic samples are added only to training, while validation and test remain clean samples from the original dataset.

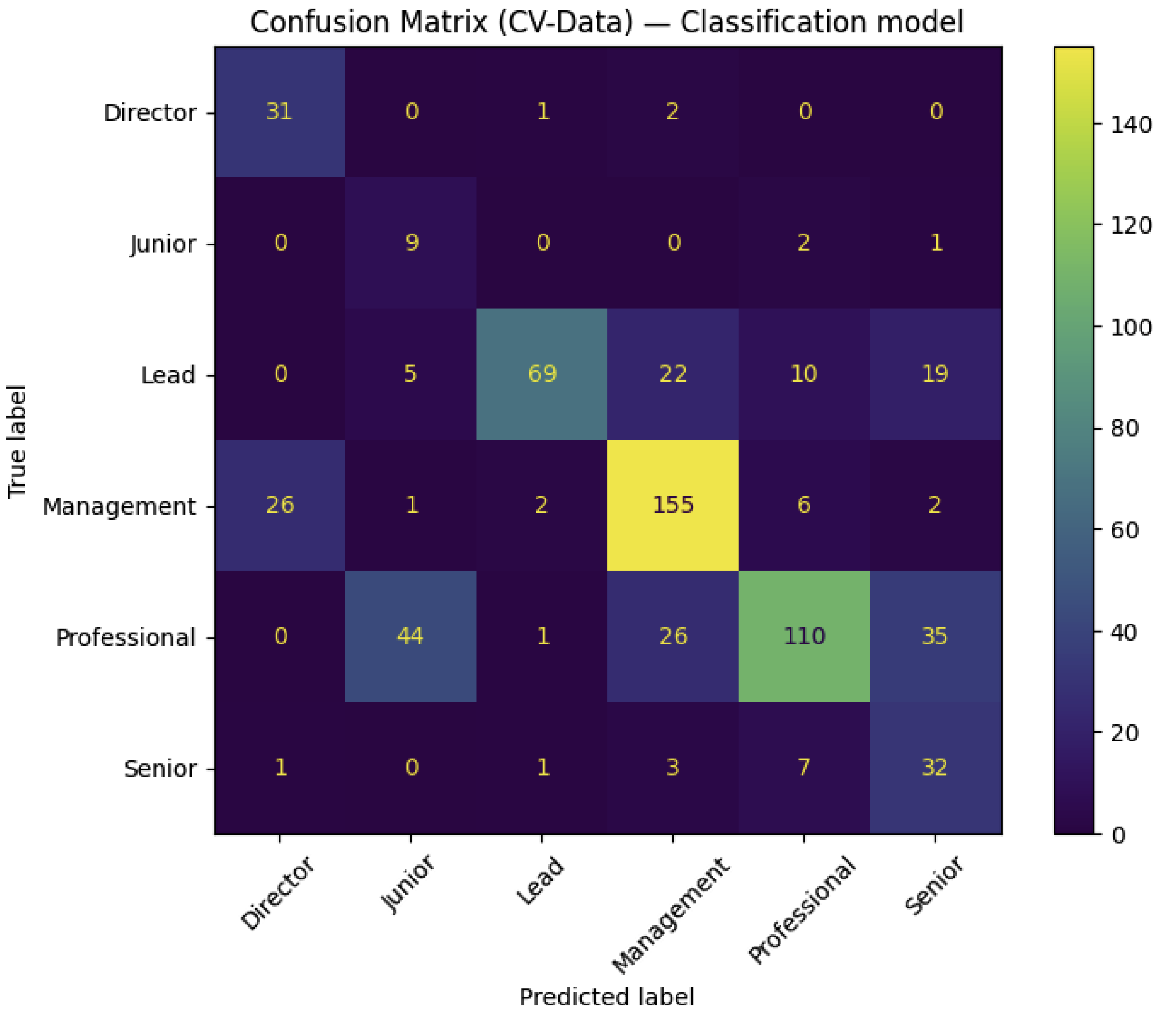


Figure 15: Confusion matrix on the CV dataset after adding synthetic training data and applying oversampling.

Figure 15 shows that the model learns several seniority classes reliably on CV data. *Management* is classified strongly, and *Director* also exhibits comparatively few confusions, which indicates that these categories contain clearer job-title cues. *Junior* is mostly predicted correctly when present, suggesting that explicit junior-level markers are learned effectively.

The remaining errors are concentrated in semantically overlapping or adjacent levels. *Professional* is frequently confused with *Junior*, *Senior*, and *Management*, reflecting that *Professional* is a broad category and often not explicitly expressed in job titles. *Lead* is commonly misclassified as *Senior* or *Management*, which is consistent with ambiguous titles that can describe either technical leadership or people management. Confusions between *Senior* and *Professional* remain common, indicating that the boundary between these classes is still difficult to learn from job titles alone.

These error patterns likely persist for three reasons: (1) even with synthetic augmentation, *Professional* remains relatively heterogeneous and is still underrepresented compared to its frequency in CV data, (2) many CV job titles do not explicitly encode seniority and would require additional context beyond the title, and (3) synthetic and curated training titles differ in style and noise level from real CV titles, which limits generalization.

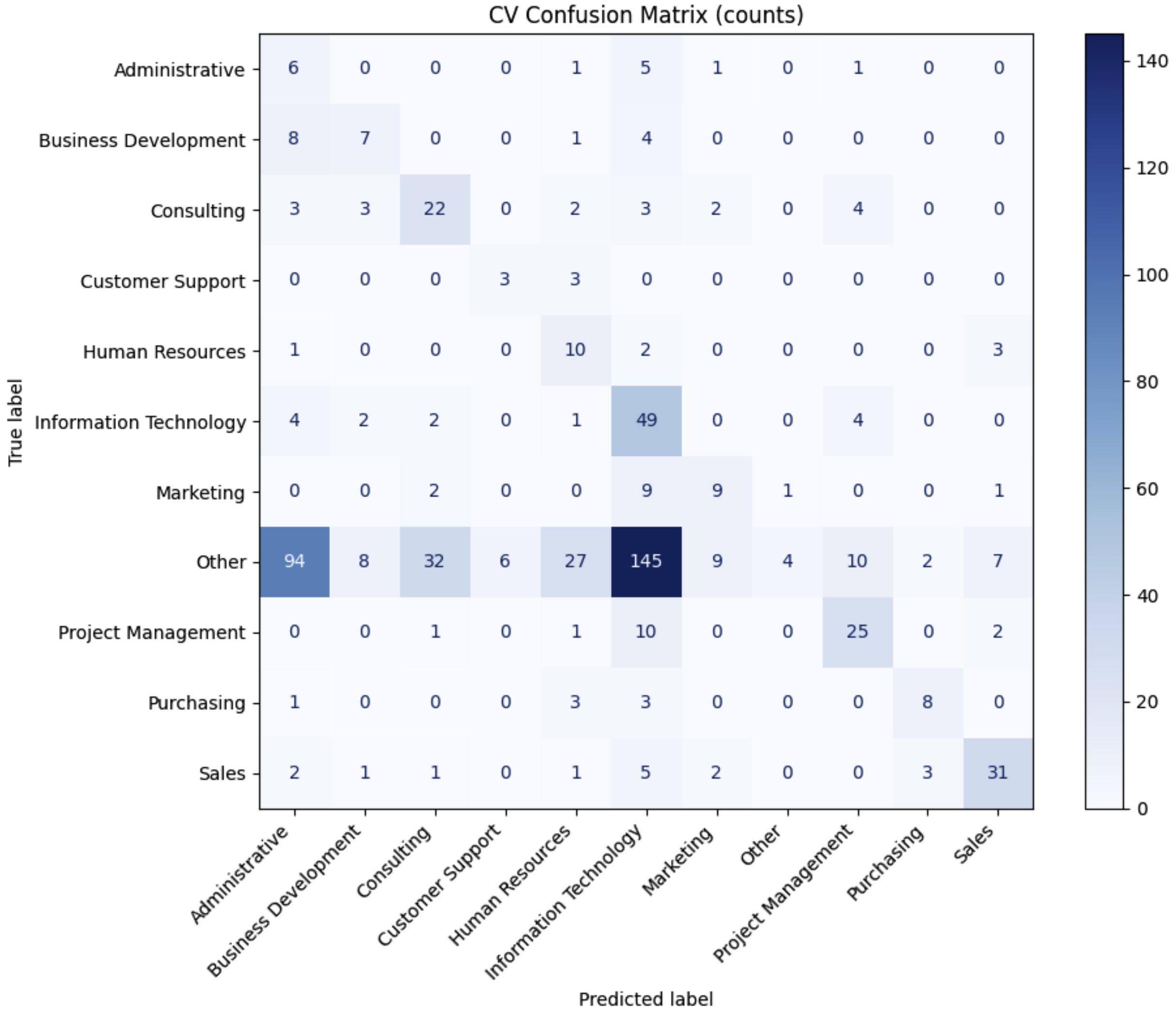
Overall, synthetic augmentation plus oversampling improves robustness on real CV job titles (CV accuracy $\approx$ 0.65, macro F1 $\approx$ 0.58). However, the dominant remaining failure mode is still ambiguity between neighboring seniority levels, especially around the broad *Professional* category.

5.4.2 Department fine tuning approaches and results

As already mentioned in figure 13, the department fine-tuning dataset is highly imbalanced: most job titles fall into *Marketing* and *Sales*, while classes such as *Human Resources*, *Customer Support*, *Purchasing*, *Administrative*, and especially *Other* are sparsely represented. In contrast, the out-of-production CV dataset follows a markedly different distribution where *Other* dominates and *Marketing* and *Sales* are much less frequent. This mismatch represents a strong distribution shift between training and deployment data. Additionally, department labels are non-ordinal and can overlap semantically (e.g., *Sales* vs. *Business Development* vs. *Consulting*), while *Other* acts as a catch-all category in CV data, increasing ambiguity.

We evaluate three training variants on the same splits: **(1) baseline fine-tuning with department csv data**, **(2) fine-tuning with oversampling on the training split**, and **(3) fine-tuning with synthetic data augmentation**. Since the oversampling did not improve our performance, we will not further discuss it here.

1) Baseline fine-tuning. In-distribution results are near-perfect (test accuracy $\approx$ 0.9980, macro F1 $\approx$ 0.9913), indicating that the model fits the fine-tuning distribution extremely well. However, performance drops sharply on CV data (accuracy $\approx$ 0.2793, macro F1 $\approx$ 0.3813), demonstrating that the learned decision boundaries do not transfer to production-like titles under distribution shift. Figure 16 highlights a systematic failure mode: many CV examples with the true label *Other* are predicted as more specific departments such as *Information Technology* or *Administrative*. This is consistent with *Other* being rare in the training data but dominant in CV data, and with the model relying on training-specific lexical patterns.

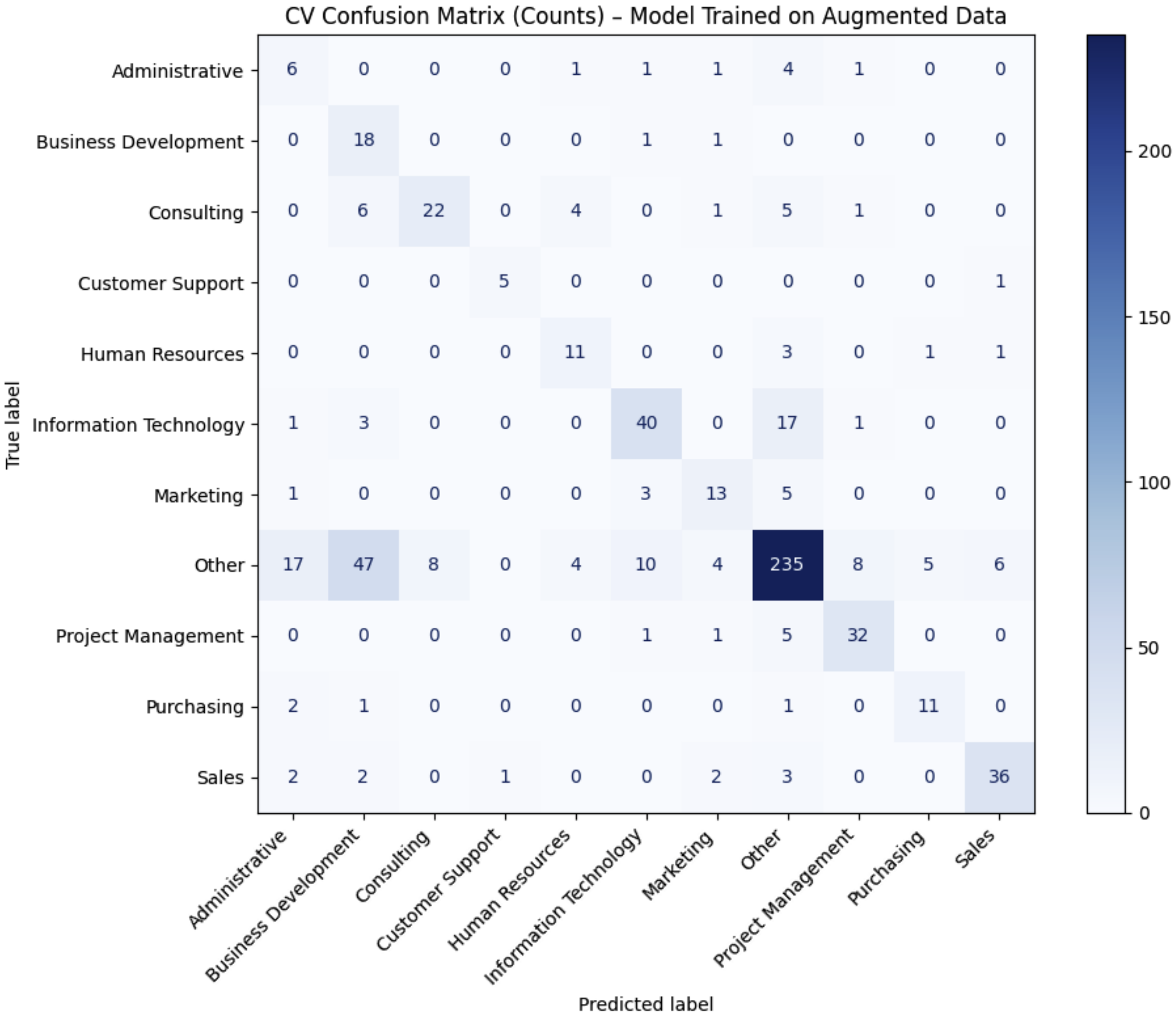


True label \ Predicted label	Administrative	Business Development	Consulting	Customer Support	Human Resources	Information Technology	Marketing	Other	Project Management	Purchasing	Sales
Administrative	6	0	0	0	1	5	1	0	1	0	0
Business Development	8	7	0	0	1	4	0	0	0	0	0
Consulting	3	3	22	0	2	3	2	0	4	0	0
Customer Support	0	0	0	3	3	0	0	0	0	0	0
Human Resources	1	0	0	0	10	2	0	0	0	0	3
Information Technology	4	2	2	0	1	49	0	0	4	0	0
Marketing	0	0	2	0	0	9	9	1	0	0	1
Other	94	8	32	6	27	145	9	4	10	2	7
Project Management	0	0	1	0	1	10	0	0	25	0	2
Purchasing	1	0	0	0	3	3	0	0	0	8	0
Sales	2	1	1	0	1	5	2	0	0	3	31

Figure 16: Confusion matrix on the CV dataset for the baseline department classifier.

2) Fine-tuning with synthetic data augmentation. While we also tried oversampling, it did not improve the overall model performance. Therefore we now augment the training split with synthetic department labels generated via prompt engineering. The primary goal is to increase both coverage and diversity of job-title formulations, especially for *Other* and other underrepresented departments, thereby reducing the training–CV distribution gap. With synthetic augmentation, in-distribution performance remains strong but decreases compared to the baseline (test accuracy $\approx$ 0.9947, macro F1 $\approx$ 0.9770), which is expected because the task becomes harder and the synthetic labels introduce additional variability.

Crucially, out-of-distribution performance on CV data improves substantially (accuracy $\approx$ 0.6886, macro F1 $\approx$ 0.6374). Figure 17 illustrates why: the model predicts *Other* much more reliably (235 correct *Other* predictions), directly addressing the dominant failure mode of the baseline and oversampling variants. At the same time, the diagonal mass for core departments (e.g., *Sales*, *Information Technology*, *Project Management*) remains visible, indicating that improved *Other* handling does not simply collapse predictions into a single class. Remaining confusions are primarily between *Other* and *Business Development*.



	Administrative	Business Development	Consulting	Customer Support	Human Resources	Information Technology	Marketing	Other	Project Management	Purchasing	Sales
Administrative	6	0	0	0	1	1	1	4	1	0	0
Business Development	0	18	0	0	0	1	1	0	0	0	0
Consulting	0	6	22	0	4	0	1	5	1	0	0
Customer Support	0	0	0	5	0	0	0	0	0	0	1
Human Resources	0	0	0	0	11	0	0	3	0	1	1
Information Technology	1	3	0	0	0	40	0	17	1	0	0
Marketing	1	0	0	0	0	3	13	5	0	0	0
Other	17	47	8	0	4	10	4	235	8	5	6
Project Management	0	0	0	0	0	1	1	5	32	0	0
Purchasing	2	1	0	0	0	0	0	1	0	11	0
Sales	2	2	0	1	0	0	2	3	0	0	36

Figure 17: Confusion matrix on the CV dataset after training with synthetic department data.

Across variants, we observe a consistent pattern: the model can achieve extremely high in-distribution scores on the curated dataset, but this does not translate to real CV data due to a pronounced distribution shift, dominated by the *Other* class. Oversampling improves in-distribution balance but does not improve CV robustness. In contrast, synthetic augmentation reduces the distribution mismatch and yields a large gain in out-of-distribution performance, making it the most effective approach for department prediction in the CV setting.

Model variant	**Target**	**Accuracy**	**Macro F1**	**MAE**
Fine-tuned pretrained	Seniority	0.4943	0.4756	0.7751
Fine-tuned pretrained + synthetic	Seniority	**0.6516**	**0.5840**	–
Fine-tuned pretrained	Department	0.2792	0.3813	–
Fine-tuned pretrained + synthetic	Department	**0.6886**	**0.6374**	–

Table 16: Summary of out-of-distribution results on the annotated CV dataset for the fine-tuned pretrained models. Synthetic augmentation consistently improves robustness under distribution shift for both seniority and department prediction.

5.5 Hybrid Approach (Rule-Based + Fine Tuning

Given the relatively strong performance of the rule-based baseline, we explored a hybrid strategy: we first apply rule-based matching, and only if no rule fires we classify the remaining titles with the fine-tuned model (instead of using a baseline fallback label). The implementation is provided in *src/baseline_hybrid_finetuned_approach.ipynb*.

Seniority. A key limitation of the rule-based system is that it does not cover the label *Professional*. Since *Professional* is present in the CV dataset but missing from the supervised fine-tuning data, we first measure baseline performance in a setting where *Professional* is excluded and no fallback is applied. In this restricted evaluation, the rule-based baseline achieves an accuracy of 73% (300 predictions). This suggests that, when the label space matches the rules, the baseline can be competitive.

Motivated by this, we tested whether adding synthetic data (which includes *Professional*) could make the hybrid approach viable without relying on a fallback. However, when we apply the rule-based baseline with the synthetic augmentation, performance drops to an accuracy of 58% . This is below the performance of the fine-tuned model and indicates that the additional synthetic labels introduce too much noise for this hybrid setup to be beneficial. Therefore, we do not pursue the hybrid approach further for seniority.

Department. We also tested the hybrid idea for department prediction, where the label space is consistent across datasets (i.e., there is no missing label analogous to *Professional*). Nevertheless, the rule-based baseline without fallback achieves only 49% accuracy (204 predictions), which is not competitive. As a result, we also discard the hybrid approach for department prediction.

5.6 Embedding-based labeling

Several embedding backbones were evaluated for the prototype-based labeling approach. We start with a lightweight baseline, and then test stronger multilingual alternatives, namely:

1. `all-MiniLM-L6-v2` (baseline)
2. `sentence-transformers/paraphrase-multilingual-mpnet-base-v2`
3. `sentence-transformers/distiluse-base-multilingual-cased-v2`
4. `intfloat/multilingual-e5-base`
5. `BAAI/bge-m3`

These models are combined with incremental data strategies (synthetic label generation and oversampling of label descriptions) to assess their impact on out-of-distribution performance. While all variants are reported in the final comparison Table 21, the following discussion focuses on the baseline setup and the best-performing configuration, which together illustrate the performance gap between a minimal embedding baseline and the strongest embedding-based approach. The implementation of the embedding based labeling model is available in the GitHub repository at src/model2-embedding-based/.

This approach uses the curated, labeled datasets (`seniority_df` and `department_df`) to construct prototypical representations for each class. To do this, the text descriptions are embedded for each label and a centroid (mean value of the embeddings) is calculated for each class, which serves as a class prototype. For prediction, the embeddings of the real, annotated CV data (`jobs_annotated_active_df`) are compared with these prototypes. The assignment is made using the highest cosine similarity (nearest prototype classification).

5.6.1 Seniority: embedding-based approaches and results

(1) Baseline Seniority Model. For the first embedding model, a pre-trained Sentence Transformer model
(`all-MiniLM-L6-v2`) is used to project job titles and label descriptions into a common semantic vector space. As shown in Table 17, the embedding-based baseline model achieves an accuracy of 0.409 and a macro F1 score of 0.350 on the real CV data. The Management class in particular is recognized relatively consistently, while the Professional class is not predicted correctly. This is consistent with the training setup, as the label Professional is not included in the original label data but only occurs in the annotated CV data. Overall, the results show that pure prototype assignment in the embedding space is limited in its generalizability for seniority classification.

Class	Precision	Recall	F1-Score	Support
Director	0.41	0.82	0.55	34
Junior	0.07	0.33	0.12	12
Lead	0.39	0.43	0.41	125
Management	0.73	0.70	0.71	192
Professional	0.00	0.00	0.00	216
Senior	0.19	0.77	0.31	44
Accuracy		0.409		623
Macro F1		0.350		

Table 17: Embedding-based seniority classification – out-of-distribution evaluation (ACTIVE jobs), baseline model

(2) Best Seniority Model with synthetic data and optimized embedding model. To improve the baseline model, we experimented with different strategies, summarized in Table 21. When we added synthetic data to our baseline embedding model, performance improved significantly to an accuracy of 0.478 and a macro F1 score of 0.409 as shown in Table 21. Building on this, we then experimented with different pre-trained embedding models. The best results were achieved with the combination of synthetic data and embedding model "BAAI/bge-m3", which we are now going to explain further.

Class	Precision	Recall	F1-Score	Support
Director	0.62	0.94	0.74	34
Junior	0.13	0.75	0.23	12
Lead	0.93	0.43	0.59	125
Management	0.83	0.81	0.82	192
Professional	0.61	0.50	0.55	216
Senior	0.17	0.32	0.23	44
Accuracy		0.60		623
Macro F1		0.527		

Table 18: Embedding-based seniority classification – out-of-distribution evaluation (ACTIVE jobs), final embedding model (`BAAI/bge-m3`)

Compared to the initial embedding baseline model, the final model shows a significant improvement in performance. Accuracy increases from 0.409 to 0.600, while Macro-F1 increases from 0.35 to 0.527. In particular, the previously unrecognized class *Professional* now shows improved predictions, and *Director* and *Management* are also classified much more reliably. Despite this progress, the classes *Junior* and *Senior* remain difficult to distinguish.

5.6.2 Department: embedding-based approaches and results

The department models follow the same methodology as the previously presented seniority models. In particular, identical strategies are used to expand the label data with synthetic examples, for oversampling, and the same pre-trained embedding models are used. To avoid redundancy, only the results achieved are reported below, while a detailed description of the procedure is omitted.

(1) Baseline Department model. The baseline model shows low overall performance on the real CV data (accuracy 0.315, macro-F1 0.315). While individual departments such as project management or marketing are moderately recognized, several classes—especially administrative and purchasing—remain difficult to classify. The results illustrate the limited generalizability of pure embedding-based prototype assignment for department classification.

Class	**Precision**	**Recall**	**F1-Score**	**Support**
Administrative	0.03	0.21	0.05	14
Business Development	0.17	0.35	0.23	20
Consulting	0.28	0.67	0.40	39
Customer Support	0.29	0.33	0.31	6
Human Resources	0.31	0.62	0.42	16
Information Technology	0.35	0.31	0.32	62
Marketing	0.39	0.50	0.44	22
Other	0.74	0.22	0.33	344
Project Management	0.57	0.59	0.58	39
Purchasing	0.02	0.07	0.03	15
Sales	0.29	0.43	0.35	46
Accuracy		0.315		623
Macro F1		0.315		

Table 19: Embedding-based department classification – out-of-distribution evaluation (ACTIVE jobs), baseline model

(2) Best Department model with synthetic data, oversampling To improve the baseline model, we tried different strategies, summarized in Table 21. The highest improvements were achieved by combining synthetic data, but then we also improved our model further by incorporating oversampling and using a more powerful pre-trained embedding model. The final results are presented in Table 20. Our best model uses the synthetic data, oversampling and the embedding model "intfloat/multilingual-e5-base" which we will now describe in more detail.

The model achieves an accuracy of 0.698 and a macro F1 score of 0.601. Table 20 shows that improvements are particularly evident for Other, Project Management, and Sales, which are recognized more reliably with higher recall and F1 scores.

Class	Precision	Recall	F1-Score	Support
Administrative	0.13	0.43	0.20	14
Business Development	0.25	0.45	0.32	20
Consulting	0.69	0.62	0.65	39
Customer Support	0.86	1.00	0.92	6
Human Resources	0.62	0.62	0.62	16
Information Technology	0.64	0.52	0.57	62
Marketing	0.64	0.41	0.50	22
Other	0.84	0.79	0.82	344
Project Management	0.73	0.77	0.75	39
Purchasing	0.44	0.80	0.57	15
Sales	0.93	0.54	0.68	46
Accuracy		0.698		623
Macro F1		0.601		

Table 20: Embedding-based department classification – out-of-distribution evaluation (ACTIVE jobs) using `intfloat/multilingual-e5-base`

5.6.3 Comparison of all embedding-based models

Table 21 summarizes the evaluation results of all embedding-based models for the *Seniority* and *Department* tasks. The starting point in each case is a baseline model with the pre-trained Sentence Transformer `all-MiniLM-L6-v2`. Building on this, synthetic data, oversampling of label descriptions, and more powerful pre-trained embedding models are successively integrated.

Compared to the respective baseline models, both tasks show significant performance gains through the gradual expansion of the approach. The integration of synthetic data alone already improves the results noticeably, especially for previously underrepresented classes, while oversampling alone achieves only minor additional effects.

Model / Target (ACTIVE Jobs)	Accuracy	Macro F1
Seniority – Baseline (MiniLM)	0.409	0.350
Seniority – with Synthetic Data	0.478	0.409
Seniority – + Oversampling	0.474	0.405
Seniority – + MPNet	0.528	0.453
Seniority – + DistilUSE	0.502	0.398
Seniority – + E5	0.576	0.483
Seniority – + BGE-M3	**0.600**	**0.527**
Department – Baseline (MiniLM)	0.315	0.315
Department – with Synthetic Data	0.496	0.440
Department – + Oversampling	0.502	0.446
Department – + MPNet	0.623	0.512
Department – + DistilUSE	0.661	0.546
Department – + E5	**0.698**	**0.601**
Department – + BGE-M3	0.695	0.545

Table 21: Comparison of all embedding-based models for seniority and department classification on real CV data (ACTIVE jobs).

6 Conclusion

Table 22 summarizes the out-of-distribution results of all approaches on annotated CV data (ACTIVE jobs). Overall, the strongest seniority model is the fine-tuned transformer with synthetic augmentation, while department prediction performs best with the prompt-engineering approach (followed closely by the strongest embedding-based configuration). A central takeaway from the comparison is that in-distribution performance on curated label datasets can be near-perfect, yet transfer to real CV titles is substantially weaker. This highlights a pronounced distribution shift between training-style job titles and production-like LinkedIn data.

The most effective strategy to improve robustness under this shift is synthetic data. For seniority, synthetic augmentation is particularly important because it introduces the otherwise missing but dominant CV label *Professional* into the training signal, directly addressing the largest systematic error source. For department, augmentation primarily improves the handling of the catch-all label *Other*, which dominates CV data but is strongly underrepresented in the original label datasets. In line with this, the models that generalize best are those that combine a strong backbone (fine-tuned transformer or high-quality multilingual embeddings) with synthetic augmentation, whereas models optimized purely on the curated distribution tend to transfer poorly.

Beyond augmentation, oversampling shows mixed benefits: it can help when it increases exposure to minority patterns, but it is not a reliable substitute for fixing label coverage and distribution mismatches. The remaining errors are also structurally plausible given the tasks. Seniority confusions occur mainly between neighboring levels, reflecting the ordinal structure and the fact that many titles do not explicitly encode rank. For department, confusions concentrate around the boundary between *Other* and semantically adjacent categories, most notably *Business Development*.

Model	Target	Accuracy	Macro F1	MAE
Rule-based	Department	0.6026	0.4492	–
Rule-based	Seniority	0.5368	0.4262	–
Prompt-engineered	**Department**	**0.7961**	**0.7340**	–
Prompt-engineered	Seniority	0.5843	0.5402	–
Transformer-Fine-Tuned	Seniority	0.4943	0.4756	0.7751
Transformer-Fine-Tuned-augmented	**Seniority**	**0.6516**	**0.5840**	–
Transformer-Fine-Tuned	Department	0.2792	0.3813	–
Transformer-Fine-Tuned-augmented	Department	0.6886	0.6374	–
Bag-of-words	Seniority	0.4366	0.4093	–
Bag-of-words-augmented	Seniority	0.6453	0.5714	–
Bag-of-words	Department	0.2231	0.3382	–
Bag-of-words-augmented + oversampling	Department	0.6854	0.6119	–
Embedding-based	Seniority	0.4093	0.3504	–
Embedding-based-augmented + oversampling	Seniority	0.6003	0.5271	–
Embedding-based	Department	0.3146	0.3150	–
Embedding-based-augmented + oversampling	Department	0.6982	0.6008	–

Table 22: Overall comparison of all models on annotated CV data (ACTIVE jobs). MAE is reported only for the regression-based seniority setup. Best-performing models per target are highlighted.

7 Limitations and Future Work

The central limitation is distribution shift. Curated label datasets differ from CV job titles in wording, multilingual noise, and—most importantly—label frequencies. This makes in-distribution test performance an overly optimistic indicator of production robustness.

A second limitation is class ambiguity. Seniority is ordinal and many titles do not explicitly encode rank, which makes boundaries between adjacent levels inherently fuzzy; *Professional* remains especially hard because it is broad and inconsistently expressed. For department, labels can overlap semantically (e.g., *Sales* vs. *Business Development*), and the catch-all label *Other* is intrinsically heterogeneous, leading to systematic confusions.

Third, synthetic augmentation trades coverage for noise: it improves label coverage and better matches CV distributions, but prompt-labeled samples can be imperfect, particularly for the most ambiguous classes. Class imbalance also persists for small categories even with oversampling, limiting stable learning on rare labels.

Future work should prioritize adding richer context beyond job titles (e.g., job descriptions, skills, employer information, and career history signals), and improving synthetic labeling quality via targeted prompt iterations and selective human validation in the most confusing class boundaries.

8 Dashboard Implementation

To complement the experimental results, we implemented an interactive dashboard using `Streamlit`. The dashboard is intended as a lightweight presentation and exploration tool rather than a full reproduction of all experiments, as some approaches require GPU resources or offline training and are therefore not suitable for interactive execution.

The dashboard allows users to enter a single job title, representing the current position in a CV, and returns predictions for seniority level, department, and an associated confidence score. Three inference modes are supported: a rule-based baseline using substring matching, a Bag-of-Words model based on TF−IDF features and logistic regression, and a prompt-engineering approach using a large language model (Gemini). The Streamlit entry point is located in `homepage.py`, while all dashboard-specific logic is organized in the `dashboard/` folder. This structure follows Streamlit deployment conventions and cleanly separates the user interface from the modeling components.

The prompt-engineering mode relies on the Google Gemini API and therefore requires a valid API key. For security reasons, the key is not hard-coded but must be provided via a Streamlit secrets variable during deployment, with the entry

```
GEMINI_API_KEY = "YOUR_API_KEY"
```

During the correction of this report, the API key may be expired, as it was created under a free trial. In this case, clicking the *Predict* button in prompt-engineering mode will not produce a response. Importantly, this behavior does not indicate a coding error: when the *Debug* option in the sidebar is enabled, the dashboard explicitly shows that the request fails due to an invalid or missing API key, allowing the issue to be clearly attributed to authentication rather than implementation.

All dashboard predictions include a confidence value in the range $[0, 1]$, where low values indicate high uncertainty and higher values suggest more reliable predictions. For the rule-based and Bag-of-Words approaches, this score is computed heuristically based on match specificity or model output probabilities, while for prompt engineering it is generated directly by the language model and reflects its own uncertainty assessment. The confidence score is intended as an interpretability aid for demonstration purposes and should not be interpreted as a calibrated probability.

The dashboard can be found here: `https://prediction-prototype.streamlit.app/`

9 Appendix

9.1 Code Repository

The complete implementation of our project is available in the following GitHub repository: `https://github.com/luisadosch/Final-Project-snapAddy`.

9.2 Group Member Contributions

In this section we summarize the role of each group member:

1. **Sonia Bronner:** Data overview, data preprocessing and preparation, exploratory data analysis (EDA), and implementation of the rule-based matching baseline.
2. **Laura Hüsam:** Implementation of the bag-of-words approach and the embedding-based labeling approach (implementation of models with and without synthetic data).
3. **Luisa Dosch:** Implementation of the prompt-engineering pipeline (test-set evaluation and synthetic data generation), fine-tuned classification model experiments (with and without synthetic data), and the hybrid approach (rule-based + fine-tuning), and the streamlit dashboard.

9.3 Use of Gen-AI

We used GitHub Copilot as a coding assistant during implementation. Since Copilot suggestions are generated interactively inside the IDE and are not stored as a persistent prompt log, we cannot provide a complete, reproducible record of the exact Copilot prompts and outputs used throughout development.

However, we also used ChatGPT. These are the specific prompts we used:

- **Prompt 1:** When my train accuracy is 99% and my test accuracy is 32%, what can I do? I predict departments from job titles (different languages) and use `MODEL_CKPT = "xlm-roberta-base"`.
- **Prompt 2:** "CV Confusion Matrix (counts) – trained on augmented data" Improve this title.
- **Prompt 3:** "Which Hugging Face model would you recommend for classifying multilingual job titles into departments and seniority levels?"
- **Prompt 4:** "Explain the difference between macro F1 and weighted F1."
- **Prompt 5:** At the end I will have a second notebook for department prediction. For both notebooks, I will write a README to make it easier to understand what I did. Can you improve this README and convert it to Markdown: …
- **Prompt 6:** Based on my comments, improve this README (also include the main results at the end as a Markdown table): `# Fine-Tuning Models for Seniority and Department Prediction`
- **Prompt 7:** Improve this text for our report so it is written in correct English: …

- **Prompt 8:** Here is a list of instructions I want to use for text improvement. Can you help me write them in a more formal way for an academic report?
- **Prompt 9:**“Rephrase this paragraph to improve clarity and academic tone.”
- **Prompt 10:**“Format this classification report as a LaTeX table.”
- **Prompt 11:**“Explain the difference between precision, recall, and F1-score.”
- **Prompt 12:**“Reformulate this sentence to avoid repetition and improve flow.”
- **Prompt 13:**“Check this paragraph for grammatical or stylistic issues.”

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