job image

Introduction

Students and junior developers often face an important uncertainty during their studies:

Are they learning skills that are actually required by the job market, or are they spending time on technologies that are outdated or rarely used in practice?

Instead of relying on assumptions, personal opinions, or general advice, this project approaches the problem using real job vacancy data.

Job descriptions contain direct information about which skills employers currently require. However, this information is hidden inside unstructured text and cannot be easily analyzed.

This project transforms raw vacancy text into structured skill data in order to objectively understand:

- which skills are truly demanded on the job market,
- how combinations of skills define different job roles,
- and how this knowledge can help students understand what they should focus on learning.

Target of the Project

The target of this project is to build a system that extracts, normalizes, and analyzes skills from real job vacancies and uses this information to:

1. Reveal which skills are most demanded by the market,
2. Discover how job roles are formed through combinations of skills,
3. Predict required skills for a given job description.

Ultimately, the goal is to provide an evidence-based view of the job market that can help students and junior developers understand which skills are relevant and modern.

Technical workflow of the solution

To answer the question of which skills are truly required by the job market, the project follows a structured analytical pipeline:

1. Cleaning and combining vacancy text into a consistent format
2. Extracting skills from unstructured descriptions using a transparent dictionary-based method
3. Normalizing and filtering skills to remove noise and duplicates
4. Exploring how extracted skills are distributed across vacancies (EDA)
5. Analyzing how skills co-occur and form natural job role groups through clustering
6. Training a model that can predict required skills directly from vacancy text

This workflow transforms raw job descriptions into structured skill representations that can be analyzed to understand how professions are defined by market-required competencies.

```
# Imports
import re
from collections import Counter
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt

plt.rcParams.update({
    "figure.facecolor": "white",
    "axes.facecolor": "white",
    "savefig.facecolor": "white",
    "axes.edgecolor": "black",
    "text.color": "black",
    "axes.labelcolor": "black",
    "xtick.color": "black",
    "ytick.color": "black",
    "grid.color": "0.85",
})

from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.decomposition import PCA
```

Dataset imports

Vacancy dataset imported from Kaggle: https://www.kaggle.com/code/mpwolke/yandex-jobs and translated to english by myself

```
# Load data
CSV_PATH = "data/yandex_vacancies_eng.csv"
df = pd.read_csv(CSV_PATH)

df.head()
```

```
                                              Header Emoji  \
0                      Senior Java Developer at Music     □
1                    Python developer at Yandex.Lavka     □
2                     Front-end developer at Vertical     □
3                iOS Developer at Vertical (Bootcamp)     □
4  Senior Developer in the Serverless Computing D...     □

                                         Description  \
0  You'll be working with high-load, large-data p...
1  Yandex.Lavka is a 15-minute grocery delivery s...
2  The verticals are classifieds services: Avto.r...
3  The verticals are classifieds services: Avto.r...
```

```
4  Yandex Functions is a serverless computing sys...

                                         Requirements  \
0  • Strong knowledge of Java, DBMS, and Linux\n•...
1  • Three years of experience in Python\n• Exper...
2  • Experience developing with JS and Node.js\n•...
3  • At least two years of commercial iOS develop...
4  • experience developing in C++\n• understand t...

                                                Tasks  \
0  • design new features, support and develop exi...
1  • create new features\n• work on product archi...
2  • Develop desktop and mobile interfaces for va...
3  • design new application features, support and...
4  • address issues of isolation of both data and...

                                               Pluses
Hashtags  \
0  • experience developing distributed systems wi...  Senior Java
Frontend
1  • experience in designing and developing high-...
python
2  • experience with TypeScript, Docker and CI/CD...        React
frontend
3  • experience in multithreaded programming and ...            mobile
iOS
4  • experience with virtualization and container...
CPP

                            Link  \
0  https://ya.cc/t/26NhxwD4CH6Ur
1  https://ya.cc/t/XcMZJL3TCH7gZ
2  https://ya.cc/t/P-Ndw5BUCGcUm
3  https://ya.cc/t/9eoluR6OCGcqY
4  https://ya.cc/t/zFsx4utJCP6MH

                                             Raw text
0  Senior Java Developer at Music\n\nYou'll be w...
1  Python Developer at Yandex.Lavka \n\nYandex.L...
2  Frontend Developer at Vertical \n\nVerticals ...
3  iOS Developer in Verticals (Bootcamp)\n\nVert...
4  Senior Developer in the Serverless Computing D...
```

Skills dataset in order to expand skill dictionary with more skills. Imported from Kaggle: https://www.kaggle.com/datasets/zamamahmed211/skills and converted into csv

```
# Dataset full of different skills (May be useful)
import pandas as pd
import re
```

```python
SKILLS_PATH = "data/skills_dataset.csv"
skills_df = pd.read_csv(SKILLS_PATH)

skills_df.head()
```

```
       Skills
0      Python
1        Java
2  JavaScript
3         C++
4          C#
```

Text preparation

Before extracting skills, all relevant text fields are cleaned and combined into a single text block per vacancy.

This step ensures that:

- missing values do not break later processing,
- all relevant information is available in one place,
- duplicated text segments are removed.

Combining the text fields allows the skill extraction step to work on a consistent and complete representation of each job vacancy.

```python
# Basic cleaning

for col in ["Requirements", "Description", "Pluses", "Hashtags"]:
    if col in df.columns:
        df[col] = df[col].fillna("").astype(str)
    else:
        df[col] = ""

# Combine text fields for skill extraction
# Use set to remove duplicated text blocks

def combine_unique_text(row):
    parts = {
        row["Requirements"].strip().lower(),
        row["Description"].strip().lower(),
        row["Pluses"].strip().lower(),
        row["Hashtags"].strip().lower(),
    }
    parts.discard("")  # remove empty strings
    return "\n".join(parts)
```

```
df["text"] = df.apply(combine_unique_text, axis=1)
```

Skill extraction

To transform vacancies into structured data, the first step is to extract skills from raw text.

Skills are extracted using a dictionary-based regex approach. Each skill is mapped to a regular expression that captures common variations and spelling differences.

This method was chosen because:

- the dataset does not contain labeled entities for training NER models,
- the list of skills should be interpretable and controllable,
- false positives can be manually handled and corrected.

Compared to black-box NLP models, this approach offers full transparency and is suitable for an applied, exploratory project.

```
# Key = canonical name, value = regex that matches common variants
skills_regex = {
    # Languages
    "python": r"\bpython\b",
    "java": r"\bjava\b",
    "kotlin": r"\bkotlin\b",
    "swift": r"\bswift\b",
    "go": r"\bgolang\b|\bgo\s+(language|lang|developer|dev)\b",
    "ruby": r"\bruby\b",
    "php": r"\bphp\b",
    "scala": r"\bscala\b",
    "c": r"\bc\b(?!\+|\#)",              # tries to avoid catching c++ / c#
    "c++": r"\bc\+\+\b|\bcpp\b",
    "c#": r"\bc\#\b|c\s*sharp",
    ".net": r"\.net\b|dotnet",
    "javascript": r"\bjavascript\b|\bjs\b",
    "typescript": r"\btypescript\b|\bts\b",

    # Web / frontend
    "html": r"\bhtml\b",
    "css": r"\bcss\b",
    "sass": r"\bsass\b|\bscss\b",
    "react": r"\breact\b",
    "next.js": r"\bnext\.?js\b",
    "vue": r"\bvue\b|\bvue\.?js\b",
    "angular": r"\bangular\b",
    "redux": r"\bredux\b",

    # Backend / frameworks
    "node.js": r"\bnode\.?js\b|\bnodejs\b",
```

```python
    "express": r"\bexpress\b",
    "nestjs": r"\bnest\.?js\b|\bnestjs\b",
    "spring": r"\bspring\b",
    "spring boot": r"\bspring\s*boot\b",
    "django": r"\bdjango\b",
    "flask": r"\bflask\b",
    "fastapi": r"\bfastapi\b",
    "laravel": r"\blaravel\b",
    "rails": r"\brails\b|ruby on rails",

    # Databases
    "sql": r"\bsql\b",
    "postgresql": r"\bpostgres(?:ql)?\b",
    "mysql": r"\bmysql\b",
    "mongodb": r"\bmongo(?:db)?\b",
    "redis": r"\bredis\b",
    "elasticsearch": r"\belasticsearch\b|\belk\b",

    # DevOps / cloud
    "linux": r"\blinux\b",
    "git": r"\bgit\b",
    "docker": r"\bdocker\b",
    "kubernetes": r"\bkubernetes\b|\bk8s\b",
    "terraform": r"\bterraform\b",
    "ansible": r"\bansible\b",
    "ci/cd": r"\bci\/cd\b|\bcicd\b|\bcontinuous integration\b",
    "aws": r"\baws\b|amazon web services",
    "gcp": r"\bgcp\b|google cloud",
    "azure": r"\bazure\b|microsoft azure",

    # APIs / messaging
    "rest": r"\brest\b|\brestful\b",
    "graphql": r"\bgraphql\b",
    "grpc": r"\bgrpc\b",
    "kafka": r"\bkafka\b",
    "rabbitmq": r"\brabbitmq\b",

    # Data / ML
    "pandas": r"\bpandas\b",
    "numpy": r"\bnumpy\b",
    "scikit-learn": r"scikit[-\s]?learn|\bsklearn\b",
    "pytorch": r"\bpytorch\b",
    "tensorflow": r"\btensorflow\b",
    "spark": r"\bspark\b|\bpyspark\b",
    "airflow": r"\bairflow\b",
}

# IMPORTANT: keep a clean copy of manual dict
skills_regex_manual = dict(skills_regex)
```

```python
print("Manual skills_regex size:", len(skills_regex_manual))
```

```
Manual skills_regex size: 60
```

Skill normalization

After raw skill extraction, different variants of the same skill are normalized into a single canonical form.

For example:

- "node.js", "nodejs", and "node_js" → "nodejs"
- "ci/cd", "ci cd", and "cicd" → "ci_cd"

Normalization reduces noise in the data and ensures that the same skill is not counted multiple times under different names. This step is crucial for reliable statistics, clustering, and model training.

```python
# --- Skill normalization: config & helpers ---

SKILL_CANONICAL_MAP = {
    # JS ecosystem
    "node.js": "nodejs",
    "nodejs": "nodejs",
    "node_js": "nodejs",
    "express": "express",
    "expressjs": "express",

    # CI/CD variants
    "ci/cd": "ci_cd",
    "cicd": "ci_cd",
    "ci-cd": "ci_cd",
    "ci cd": "ci_cd",

    # Spark variants
    "pyspark": "spark",
    "apache spark": "spark",
    "spark": "spark",

    # DB variants
    "postgres": "postgresql",
    "postgresql": "postgresql",
    "postgre": "postgresql",

    # ML libs
    "scikit-learn": "sklearn",
    "scikit learn": "sklearn",
    "sklearn": "sklearn",
```

```
    # C-family
    "c": "c",
    "c++": "cpp",
    "cpp": "cpp",
    "c#": "csharp",
    "csharp": "csharp",

    # Go
    "golang": "go",
    "go": "go",
    "go lang": "go",

    # Common skills
    "python": "python",
    "java": "java",
    "kotlin": "kotlin",
    "javascript": "javascript",
    "js": "javascript",
    "typescript": "typescript",
    "ts": "typescript",
    "react": "react",
    "reactjs": "react",
    "redux": "redux",
    "html": "html",
    "css": "css",
    "git": "git",
    "linux": "linux",
    "docker": "docker",
    "sql": "sql",
    "mysql": "mysql",
    "tensorflow": "tensorflow",
    "tf": "tensorflow",
    "pytorch": "pytorch",
    "torch": "pytorch",
}
```

Handling ambiguous skills

Some skill names, such as "C" or "Go", are ambiguous and may appear in text without referring to a programming language.

To reduce false positives, additional contextual checks are applied. A skill is only kept if the surrounding text clearly indicates that it refers to the programming language and not a general word or abbreviation.

This filtering step improves precision without removing valid skill mentions.

```
DANGEROUS_CANONICAL = {"c", "go"}
```

```python
def _valid_dangerous(canonical: str, text: str) -> bool:
    t = (text or "").lower()

    if canonical == "go":
        return ("golang" in t) or ("go lang" in t)

    if canonical == "c":
        return (
            "ansi c" in t
            or "c language" in t
            or "embedded c" in t
            or "iso c" in t
        )

    return True

def normalize_skills(raw_skills: list[str], text: str) -> list[str]:
    norm = []
    for s in raw_skills:
        s0 = str(s).strip().lower()
        canonical = SKILL_CANONICAL_MAP.get(s0, s0)

        if canonical in DANGEROUS_CANONICAL and not
_valid_dangerous(canonical, text):
            continue

        norm.append(canonical)

    out = set(norm)

    if ("cpp" in out) or ("csharp" in out):
        out.discard("c")

    return sorted(out)

print("Normalization ready.")
```

```
Normalization ready.
```

Using an external skills dataset

To extend the initial skill dictionary, an additional skills dataset from Kaggle is used. This dataset contains many technical skills that may not be present in the manually defined list.

The dataset is used to improve coverage of skill extraction. All skills are cleaned and normalized using the same rules as before and are only kept if they appear in the vacancy dataset.

This prevents adding irrelevant or very rare skills and keeps the final skill dictionary focused and usable for further analysis.

```python
# --- Process Kaggle skills dataset ---

raw = (
    skills_df["Skills"]
    .astype(str)
    .str.replace('"', '', regex=False)
    .str.strip()
    .str.lower()
)

raw = raw[raw.notna()]
raw = raw[~raw.isin(["", "nan", "none", "null"])]
raw = raw[raw.str.len() >= 2]

# Noise filtering (non-capturing group to avoid pandas warning)
BAD_PATTERNS = [
    r"[^\x00-\x7F]",  # non-latin
    r"\d",            # digits
    r"\b(?:pay|salary|equity|insurance|travel|student|retention|
payback|bullet)\b",
]
bad_re = re.compile("|".join(BAD_PATTERNS))

raw = raw[~raw.str.contains(bad_re, regex=True)]

raw_unique = sorted(set(raw.tolist()))

# Normalize Kaggle skills using normalization
norm_skills = []
for s in raw_unique:
    out = normalize_skills([s], text=s)  # context = itself
    if out:
        norm_skills.extend(out)

norm_unique = sorted(set(norm_skills))

def _safe_regex(skill: str) -> str:
    return rf"(?<!\w){re.escape(skill)}(?!\w)"

# --- FILTER by vacancy dataset frequency (document frequency) ---
MIN_DOC_FREQ = 5  # tune: 3, 5, 10

# compile patterns once for speed
cand_compiled = {s: re.compile(_safe_regex(s), flags=re.IGNORECASE)
for s in norm_unique}

doc_freq = {s: 0 for s in norm_unique}
texts = df["text"].astype(str).tolist()

for text in texts:
```

```
    for s, pat in cand_compiled.items():
        if pat.search(text):
            doc_freq[s] += 1

kaggle_kept = sorted([s for s, c in doc_freq.items() if c >=
MIN_DOC_FREQ])

# RESET to manual dict, then add only kept Kaggle skills
skills_regex = dict(skills_regex_manual)

added = 0
for s in kaggle_kept:
    if s not in skills_regex:
        skills_regex[s] = _safe_regex(s)
        added += 1

print(f"[skills_dataset] Raw unique: {len(raw_unique)}")
print(f"[skills_dataset] Normalized unique: {len(norm_unique)}")
print(f"[skills_dataset] Kept by df >= {MIN_DOC_FREQ}:
{len(kaggle_kept)}")
print(f"[skills_dataset] Added to skills_regex: {added}")
print(f"[skills_dataset] Final skills_regex size:
{len(skills_regex)}")
```

```
[skills_dataset] Raw unique: 2412
[skills_dataset] Normalized unique: 2410
[skills_dataset] Kept by df >= 5: 67
[skills_dataset] Added to skills_regex: 40
[skills_dataset] Final skills_regex size: 100
```

```
# Skill extraction (regex)
def extract_skills(text: str) -> list[str]:
    found = []
    for skill, pattern in skills_regex.items():
        if re.search(pattern, text, flags=re.IGNORECASE):
            found.append(skill)
    return found

# 1) raw extraction
df["skills_raw"] = df["text"].apply(extract_skills)

# 2) canonical normalization + dedup per vacancy
df["skills"] = df.apply(lambda r: normalize_skills(r["skills_raw"],
r["text"]), axis=1)

df["skills_count"] = df["skills"].apply(len)

df[["skills", "skills_count"]].head()
```

	skills	skills_count
0	[java, linux, mongodb, processing]	4

```
1                                          [git, python]              2
2  [ci_cd, docker, javascript, nodejs, react, red...              7
3                                  [objective-c, swift]              2
4                    [cpp, processing, virtualization]              3
```

Why Skill Analysis is Important

Before clustering jobs or training prediction models, it is necessary to understand whether the extracted skills realistically represent how vacancies describe requirements.

This analysis helps answer key questions relevant to the original problem:

- Do vacancies mention many skills or only a few focused ones?
- Are some skills dominating the market?
- Is the distribution of skills realistic for actual job roles?

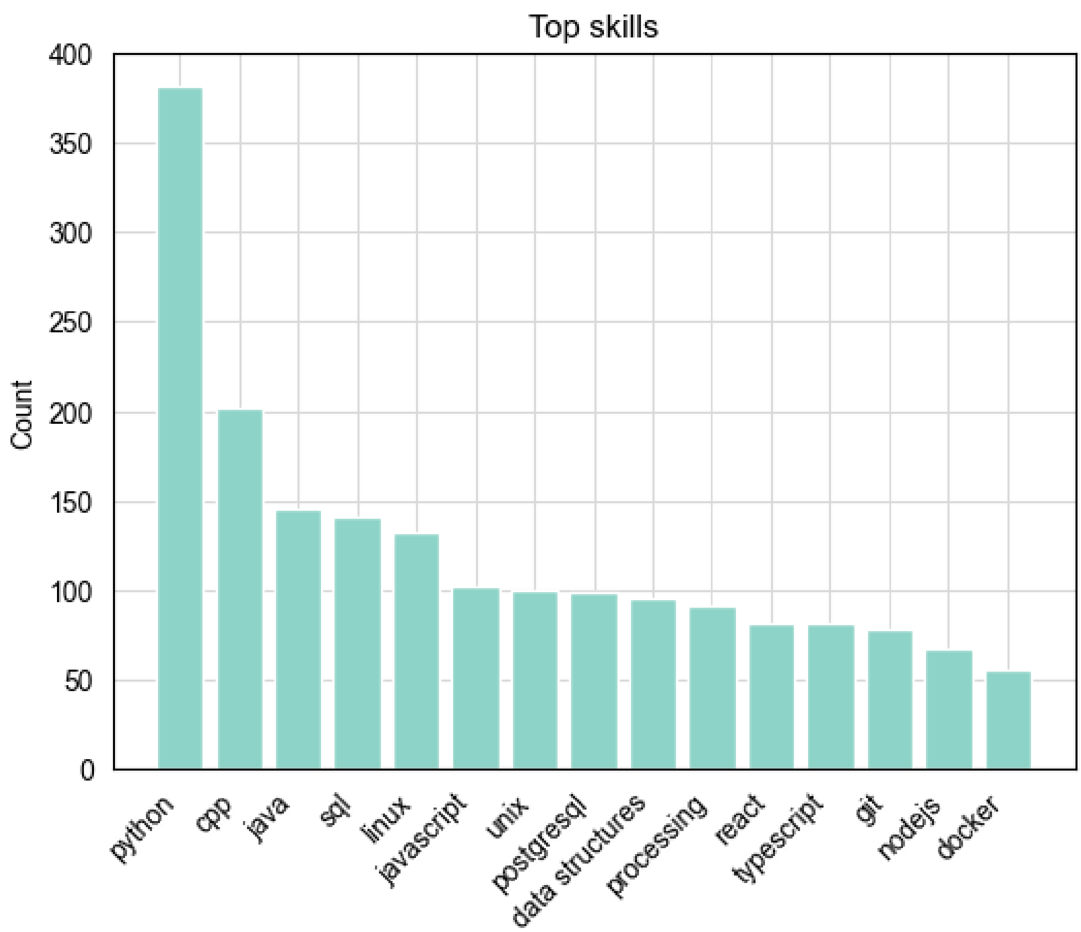
Understanding this is essential before using skills to represent professions.

Plots and analysis of extracted skills

The goal of this exploratory analysis is to understand how extracted skills are distributed across job vacancies. This helps to evaluate whether the extraction approach is reasonable and to decide if additional filtering or normalization steps are needed.

```python
# Plot helpers
def plot_hist(series, title, xlabel, ylabel, bins=30):
    plt.figure()
    plt.hist(series.dropna(), bins=bins)
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.show()


def plot_bar(series, title, xlabel, ylabel="Count"):
    counts = series.value_counts().sort_index()

    plt.figure()
    plt.bar(counts.index, counts.values)
    plt.title(title)
    plt.xlabel(xlabel)
    plt.ylabel(ylabel)
    plt.show()

# Skill frequency
all_skills = [s for row in df["skills"] for s in row]
skill_freq = Counter(all_skills)
```

```python
top = skill_freq.most_common(15)
labels = [k for k, _ in top]
values = [v for _, v in top]

plt.figure()
plt.bar(labels, values)
plt.xticks(rotation=45, ha="right")
plt.title("Top skills")
plt.ylabel("Count")
plt.show()
```

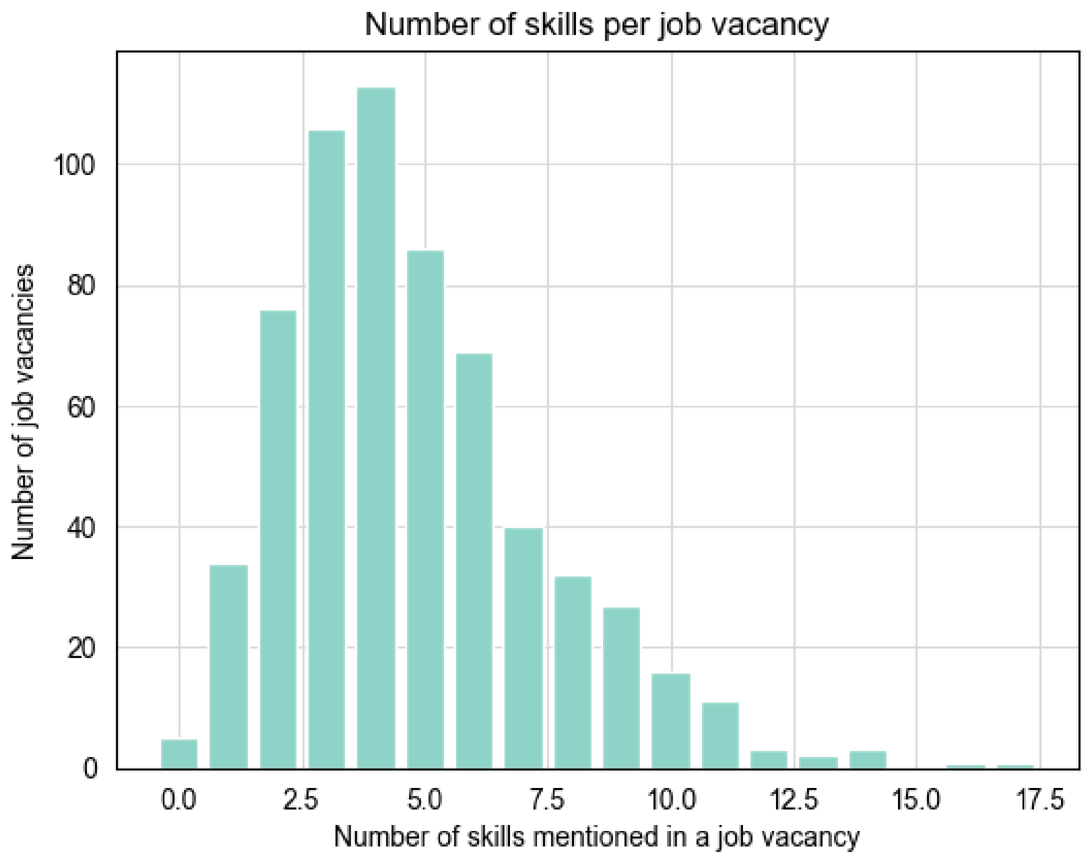


Some skills, such as Python and SQL, appear much more often than others. This shows that the dataset is dominated by a small number of very common skills.

This behavior is expected, as these skills are required across many different job roles.

```python
# Skills per job
plot_bar(
    df["skills_count"],
    title="Number of skills per job vacancy",
    xlabel="Number of skills mentioned in a job vacancy",
```

```
    ylabel="Number of job vacancies"
)


# for example 150 vacancies require 2 skills, 60 vacancies require 4
skills, etc.
```

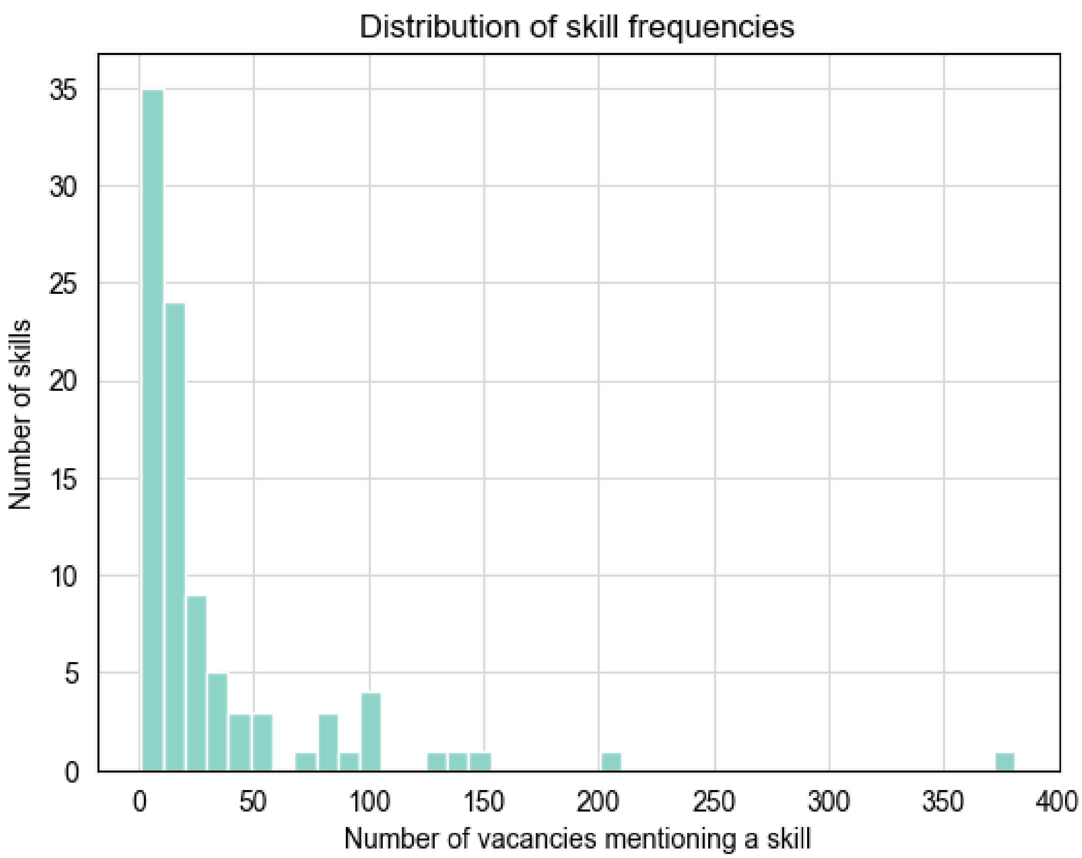


This plot shows how many skills are mentioned in each job vacancy. Most vacancies list only a small number of skills, while only a few vacancies mention many skills.

This indicates that job descriptions are usually focused on a specific role and do not contain long or exhaustive skill lists.

```
from collections import Counter

all_skills = [s for skills in df["skills"] for s in skills]
skill_freq = Counter(all_skills)

skill_freq_series = pd.Series(skill_freq.values())

plot_hist(
    series=skill_freq_series,
    title="Distribution of skill frequencies",
```

```
    xlabel="Number of vacancies mentioning a skill",
    ylabel="Number of skills",
    bins=40
)

# for example 25 skills are mentioned in ~7 vacancies, 1 skill is mentioned in ~280 vacancies, etc
# for example sql or python are mentioned in ~280 vacancies, while some rare skills (around 28 of them) are mentioned in only several vacancies
```



The distribution shows that most skills are mentioned in only a small number of vacancies, while a few skills occur very frequently.

This long-tail pattern is typical for job market data, where common technologies appear everywhere and specialized skills are required only in specific roles.

Conclusion of skill analysis

Overall, the exploratory analysis shows a clear imbalance in skill frequencies. A small number of skills (such as Python or SQL) appear in many vacancies, while most skills are relatively rare.

Most job vacancies mention only a few skills, which suggests that job descriptions are concise and role-specific. This confirms that a dictionary-based skill extraction approach is suitable for this dataset.

The observed imbalance also motivates later steps such as skill normalization and frequency-based filtering, in order to reduce noise and improve the quality of clustering and classification.

Skill frequency filtering

To reduce noise and improve model stability, skills are filtered based on how often they appear across vacancies.

Very rare skills are removed because they:

- provide little statistical value,
- increase sparsity,
- make clustering and classification harder.

Very common skills are also limited to avoid dominance. The remaining skills form a balanced feature set for later analysis.

A minimum document frequency threshold is applied to remove very rare skills. In this project, a value of 5 was chosen to keep useful but less frequent skills, while still reducing sparsity and noise in the data.

```
# Filter skills by document frequency
N = len(df)
skill_doc_freq = Counter()

for row in df["skills"]:
    for s in set(row):
        skill_doc_freq[s] += 1

min_df = 5 # previously was max(2, int(0.01 * N)); set to 5 because
skipped a lot of useful skills
max_df = int(0.7 * N)

kept_skills = [
    s for s, c in skill_doc_freq.items()
    if min_df <= c <= max_df
]

kept_skills
```

```
['linux',
 'java',
 'mongodb',
 'processing',
 'git',
 'python',
 'redux',
```

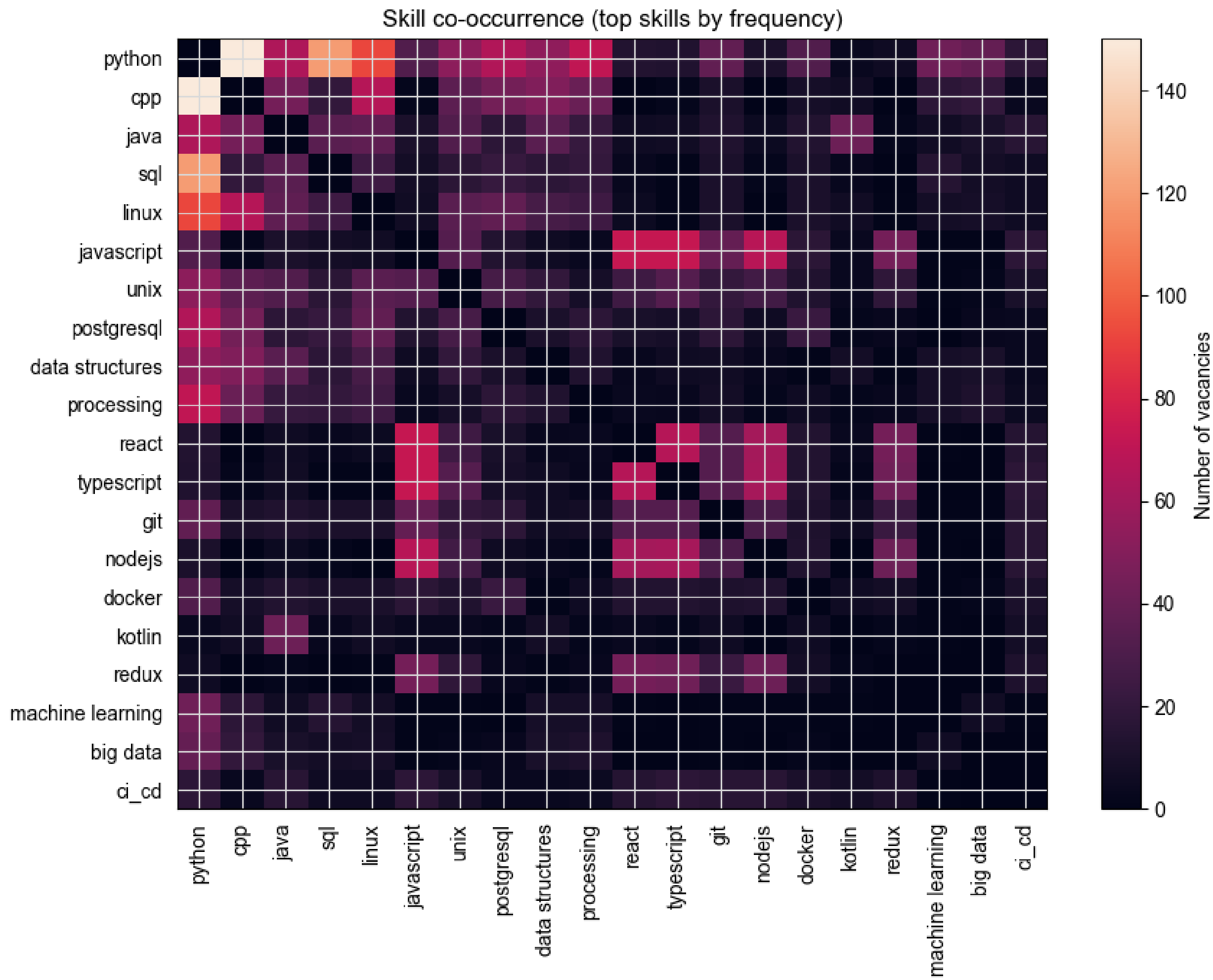
```
'react',
'docker',
'nodejs',
'ci_cd',
'javascript',
'typescript',
'objective-c',
'swift',
'virtualization',
'cpp',
'mysql',
'tcp/ip',
'ansible',
'devops',
'postgresql',
'rest',
'flask',
'django',
'microservices',
'data structures',
'spring',
'graphql',
'kotlin',
'unix',
'css',
'html',
'sql',
'recommender systems',
'design patterns',
'data analysis',
'hadoop',
'tableau',
'spark',
'teamcity',
'neural networks',
'machine learning',
'backend development',
'redis',
'big data',
'networking',
'oracle',
'tensorflow',
'nosql databases',
'bash',
'collaboration',
'computer vision',
'kafka',
'a/b testing',
'deep learning',
```

```
 'pytorch',
 'express',
 'code review',
 'decision-making',
 'airflow',
 'rabbitmq',
 'nlp',
 'control systems',
 'macos',
 'pandas',
 'spring boot',
 'blogging',
 'communication',
 'kubernetes',
 'terraform',
 'azure',
 'aws',
 'vue',
 'angular',
 'csharp',
 'data visualization',
 'server-side rendering',
 'php',
 'customer support',
 'flutter',
 'numpy',
 'go']

kept_skills = sorted(kept_skills)

def filter_skills(skills):
    return [s for s in skills if s in kept_skills]

df["skills_filtered"] = df["skills"].apply(filter_skills)

mlb = MultiLabelBinarizer(classes=kept_skills)
X = mlb.fit_transform(df["skills_filtered"])

print("X shape:", X.shape)

X shape: (625, 83)
```

After filtering the skill set, the remaining skills form a cleaner and more stable representation of job vacancies. This representation is used to analyze how skills co-occur within the same vacancies.

```
import numpy as np
import matplotlib.pyplot as plt
from collections import Counter
```

```python
# compute co-occurrence matrix
co = (X.T @ X).astype(int)
np.fill_diagonal(co, 0)

# choose top skills by frequency
skill_freq = Counter()

for row in df["skills_filtered"]:
    for s in row:
        skill_freq[s] += 1

TOP_N = 20
top_skills = [s for s, _ in skill_freq.most_common(TOP_N)]

# indices of these skills in kept_skills / X
idx = [kept_skills.index(s) for s in top_skills]

co_top = co[np.ix_(idx, idx)]

# plot
plt.figure(figsize=(9, 7))
plt.imshow(co_top, aspect="auto")
plt.xticks(range(len(top_skills)), top_skills, rotation=90)
plt.yticks(range(len(top_skills)), top_skills)
plt.title("Skill co-occurrence (top skills by frequency)")
plt.colorbar(label="Number of vacancies")
plt.tight_layout()
plt.show()
```



Interpretation of skill co-occurrence

The co-occurrence heatmap shows which skills frequently appear together in job vacancies. Strong co-occurrence patterns reflect typical technology stacks, such as backend, frontend, or data-oriented roles.

These relationships justify clustering vacancies based on skill vectors, as jobs with similar skill combinations naturally form groups.

From Skills to Professions

If certain skills frequently appear together in vacancies, this indicates that they represent real job roles.

By clustering vacancies based on skill combinations, we can observe how professions naturally emerge from required skill sets.

This directly supports the project goal of understanding how professions are defined by skills.

Clustering job vacancies

Job vacancies are clustered based on their extracted skill sets using HDBSCAN. Each vacancy is represented as a binary skill vector.

HDBSCAN was chosen because:

- the number of clusters is unknown in advance,
- job roles naturally form dense groups with varying sizes,
- noisy or unclear vacancies can be assigned to a noise cluster.

This allows meaningful job role groups to emerge from the data without forcing every vacancy into a cluster.

```
import hdbscan

clusterer = hdbscan.HDBSCAN(
    min_cluster_size=10,      # role minimal size
    min_samples=5,
    metric="euclidean",
    cluster_selection_method="eom"
)

labels = clusterer.fit_predict(X)

df["cluster"] = labels

df["cluster"].value_counts().sort_index()
```

```
cluster
-1    439
 0     39
 1     38
 2     43
 3     52
 4     14
Name: count, dtype: int64
```

```
from collections import Counter

cluster_skills = []

for cl in sorted(df["cluster"].unique()):
    if cl == -1:
        continue

    subset = df[df["cluster"] == cl]
    freq = Counter([s for row in subset["skills_filtered"] for s in
row])

    cluster_skills.append({
```

```
        "cluster": cl,
        "size": len(subset),
        "top_skills": ", ".join([s for s, _ in freq.most_common(10)])
    })

pd.DataFrame(cluster_skills).sort_values("size", ascending=False)
```

```
   cluster  size                                         top_skills
3        3    52  cpp, python, data structures, linux, processin...
2        2    43  python, linux, java, unix, big data, processin...
0        0    39  sql, python, processing, tableau, big data, li...
1        1    38  java, kotlin, swift, ci_cd, objective-c, git, ...
4        4    14       cpp, linux, data structures, computer vision
```

The presence of a noise cluster is expected, as not all vacancies clearly match a single dominant skill pattern.

Cluster interpretation

Each cluster is characterized by a set of frequently co-occurring skills. These skill combinations correspond to typical job roles such as backend, data, or systems-oriented positions.

Vacancies labeled as noise do not strongly match any dominant skill pattern and likely represent hybrid or uncommon roles. Overall, the clustering results show that job roles can be identified using skill-based representations.

```
df[df["cluster"] == 0][["Header", "skills"]].head(5)
```

```
                                    Header                      skills
60                Product Analyst at Search              [python, sql]
75   Warehouse Logistics Analyst at Market  [processing, python, sql]
76               Regional Analyst at Market              [python, sql]
80                       Analyst at Rover    [big data, python, sql]
119                     Analyst at Search              [python, sql]
```

Using HDBSCAN, similar job vacancies were grouped into clusters based on shared skills. The clusters represent common job roles such as frontend, backend, data, and DevOps, while less clear vacancies were labeled as noise. Overall, the results show that job roles can be identified using skill-based representations.

While clustering groups similar job roles, a classification model is used to predict required skills directly from vacancy text for new or unseen cases.

From Understanding the Market to Predicting Skills

After showing that professions can be represented through skill patterns, the next step is to check whether required skills can be predicted directly from vacancy text.

This allows us to simulate a practical scenario:

Given a job description, what skills does the market expect for this role?

Skill prediction model

In addition to clustering, a multi-label classification model is trained to predict required skills directly from vacancy text.

The model uses:

- TF-IDF features extracted from job descriptions,
- a One-vs-Rest logistic regression classifier,
- multi-label output to allow prediction of multiple skills per vacancy.

This model enables skill prediction for new or unseen job descriptions.

```
import numpy as np
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import MultiLabelBinarizer
from sklearn.feature_extraction.text import TfidfVectorizer
from sklearn.multiclass import OneVsRestClassifier
from sklearn.linear_model import LogisticRegression
from sklearn.pipeline import Pipeline
from sklearn.metrics import f1_score, hamming_loss
from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS

df_train = df[df["skills_filtered"].apply(len) > 0].copy()

X_text = df_train["text"].fillna("").astype(str)
y_lists = df_train["skills_filtered"]

mlb = MultiLabelBinarizer()
Y = mlb.fit_transform(y_lists)

X_train, X_val, Y_train, Y_val = train_test_split(
    X_text, Y, test_size=0.2, random_state=42
)

custom_stop = set(ENGLISH_STOP_WORDS)
custom_stop.discard("go")   # keep "go" token
custom_stop = list(custom_stop)
```

```
clf = Pipeline([
    ("tfidf", TfidfVectorizer(
        lowercase=True,
        ngram_range=(1, 3),     # was (1, 2)
        min_df=2,
        max_df=0.9,
        sublinear_tf=True,
        max_features=250_000,
        stop_words=custom_stop   # reduce noise in vacancy text
    )),
    ("ovr", OneVsRestClassifier(
        LogisticRegression(
            solver="liblinear",
            max_iter=3000,
            class_weight="balanced"
        )
    ))
])

clf.fit(X_train, Y_train)

Y_val_proba = clf.predict_proba(X_val)
Y_val_pred = (Y_val_proba >= 0.5).astype(int)

micro_f1 = f1_score(Y_val, Y_val_pred, average="micro",
zero_division=0)
macro_f1 = f1_score(Y_val, Y_val_pred, average="macro",
zero_division=0)
weighted_f1 = f1_score(Y_val, Y_val_pred, average="weighted",
zero_division=0)
hamming = hamming_loss(Y_val, Y_val_pred)

def predict_skills(text: str, top_k: int = 10, return_proba: bool =
False):
    p = clf.predict_proba([str(text)])[0]
    idx = np.argsort(p)[::-1][:top_k]

    if return_proba:
        return [(mlb.classes_[i], float(p[i])) for i in idx]
    return [mlb.classes_[i] for i in idx]

print(f"Micro F1:          {micro_f1:.4f}")
print(f"Macro F1:          {macro_f1:.4f}")
print(f"Weighted F1:       {weighted_f1:.4f}")
print(f"Hamming loss:      {hamming:.4f}")
```

```
Micro F1:          0.8164
Macro F1:          0.5547
Weighted F1:       0.7850
Hamming loss:      0.0200
```

Model evaluation

The Micro F1 score is relatively high, indicating good performance on common skills. The lower Macro F1 score shows that rare skills are harder to predict, which is expected given the imbalanced skill distribution.

The low Hamming loss indicates that the model makes few label-level mistakes. Overall, the model performs well for predicting typical skill requirements from job descriptions.

Lets check the model in action

```
predict_skills("backend developer", top_k=10)
```

The trained model can predict relevant skills for new job descriptions by analyzing the text and outputting the most probable skills based on learned patterns from the training data.

```
vocab = clf.named_steps["tfidf"].vocabulary_
print("go" in vocab)
```

```
True
```

```
go_count = sum(s == "go" for row in y_lists for s in row)
print("go label frequency:", go_count)
```

```
go label frequency: 12
```

Conclusion

This project started from a practical student problem: uncertainty about which skills are truly important to learn for a career in software engineering.

By analyzing real job vacancy data, extracting and normalizing skills, and applying clustering and classification techniques, vacancies were transformed into structured representations of market-required competencies.

The results show that:

- Job roles can be clearly identified through combinations of skills,
- Market-demanded skills can be objectively observed,
- Required skills for a role can be predicted from vacancy text.

This provides an evidence-based understanding of the job market that can help students and junior developers focus on relevant and modern technologies. It allows students to rely on real market data instead of assumptions when deciding what to learn.