Contextual Candidate Matching:
An Intelligent Approach to Resume Retrieval for a given Job Description

Presented by Group 32

CSCI 544 NATURAL LANGUAGE PROCESSING

Agenda

1. Introduction
2. Dataset Description & Preparation
3. Implementation
4. Results & Discussion
5. Future Scope
6. Q&A

Let's get Started!

Meet Our Group

Akhilaa
(Introduction)

Aanandhi
(Dataset Description)

Mohan
(Implementation)

Mona
(Results & Discussion)

Emma
(Future Scope)

Introduction

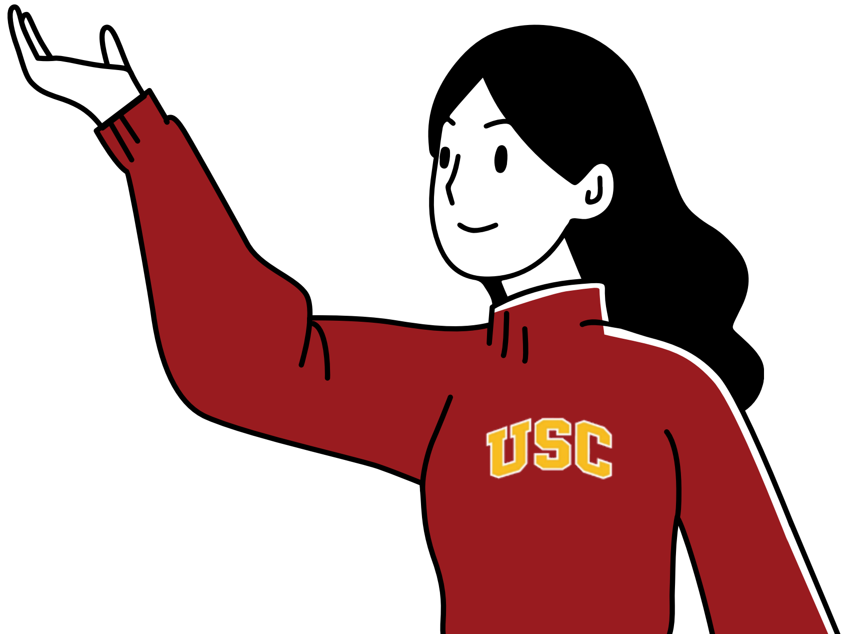
Traditional job-matching methods focus on simple key word matching, often failing to capture the true depth of an applicant's skills and experiences.

This project reimagines the job-matching process, introducing word and sentence embeddings to uncover the hidden context within each application. By transforming how matches are made, it brings a new level of precision and accuracy to connecting candidates with opportunities.

01 Understanding Current Challenges in Candidate Matching

02 Building a model that dishes out most relevant resumes

03 Discussing Limitations and Probable Solutions

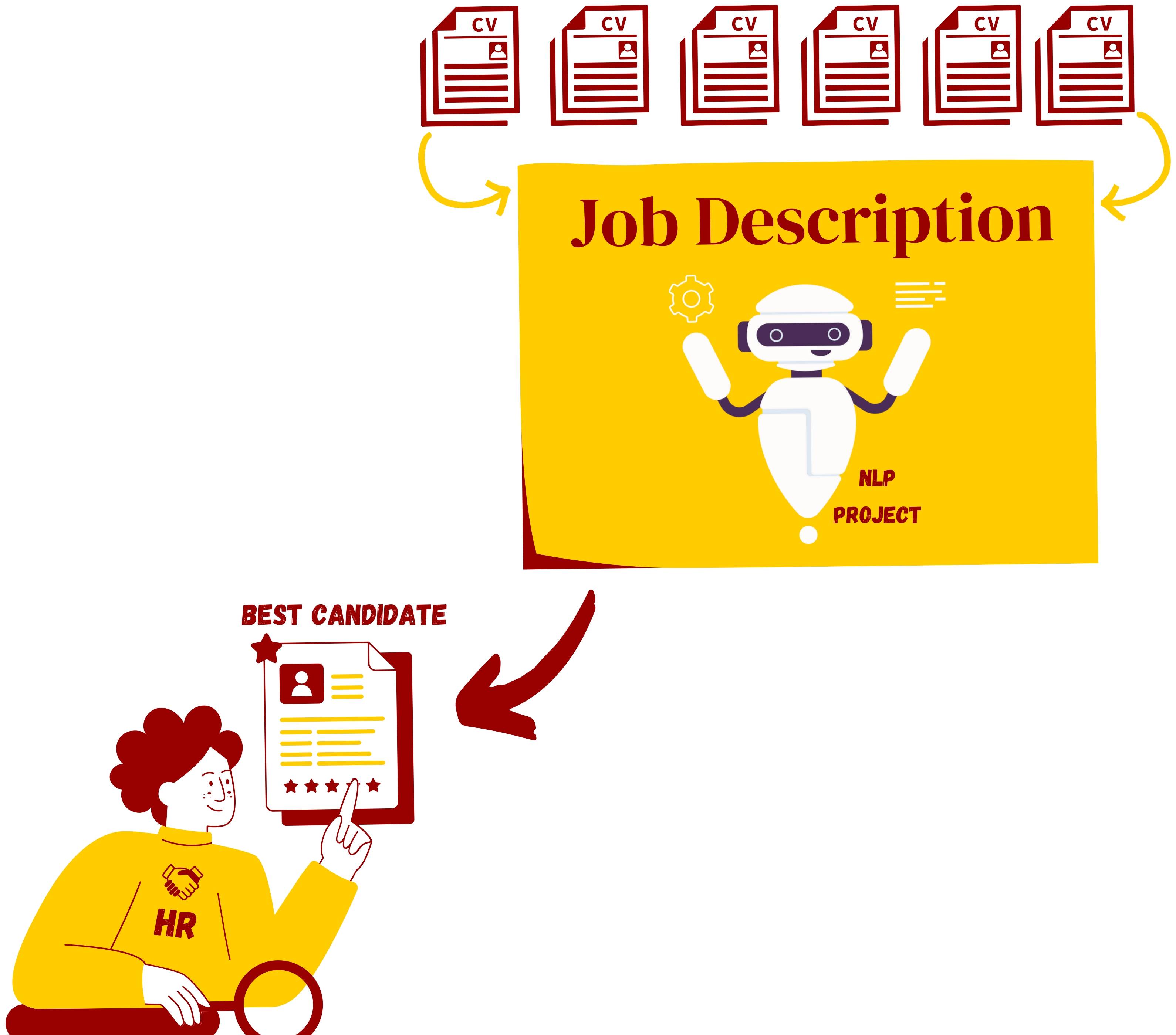


TRADITIONAL PROCESS

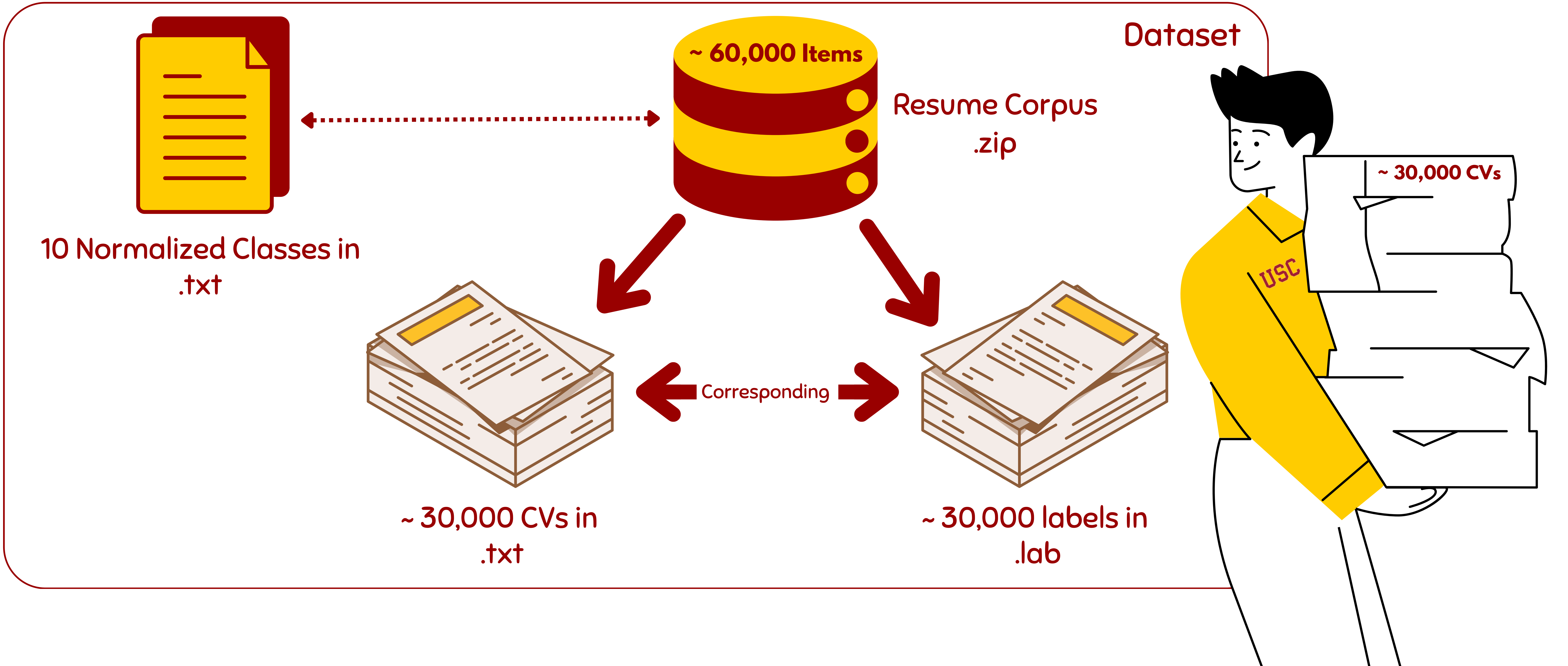
Keyword Based – Best Matching 25 (BM-25)

PROPOSED PROCESS

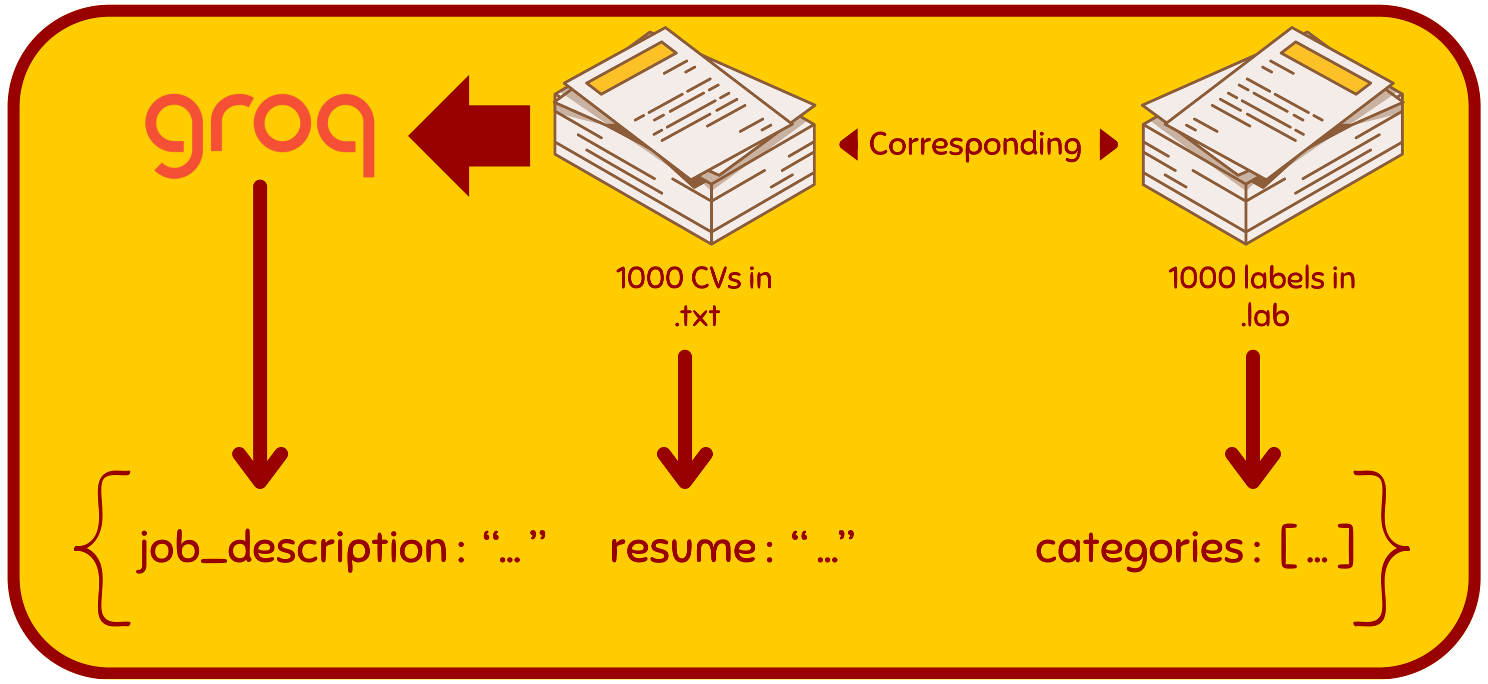
Semantic Based – Proposed Architecture



DATASET DESCRIPTION

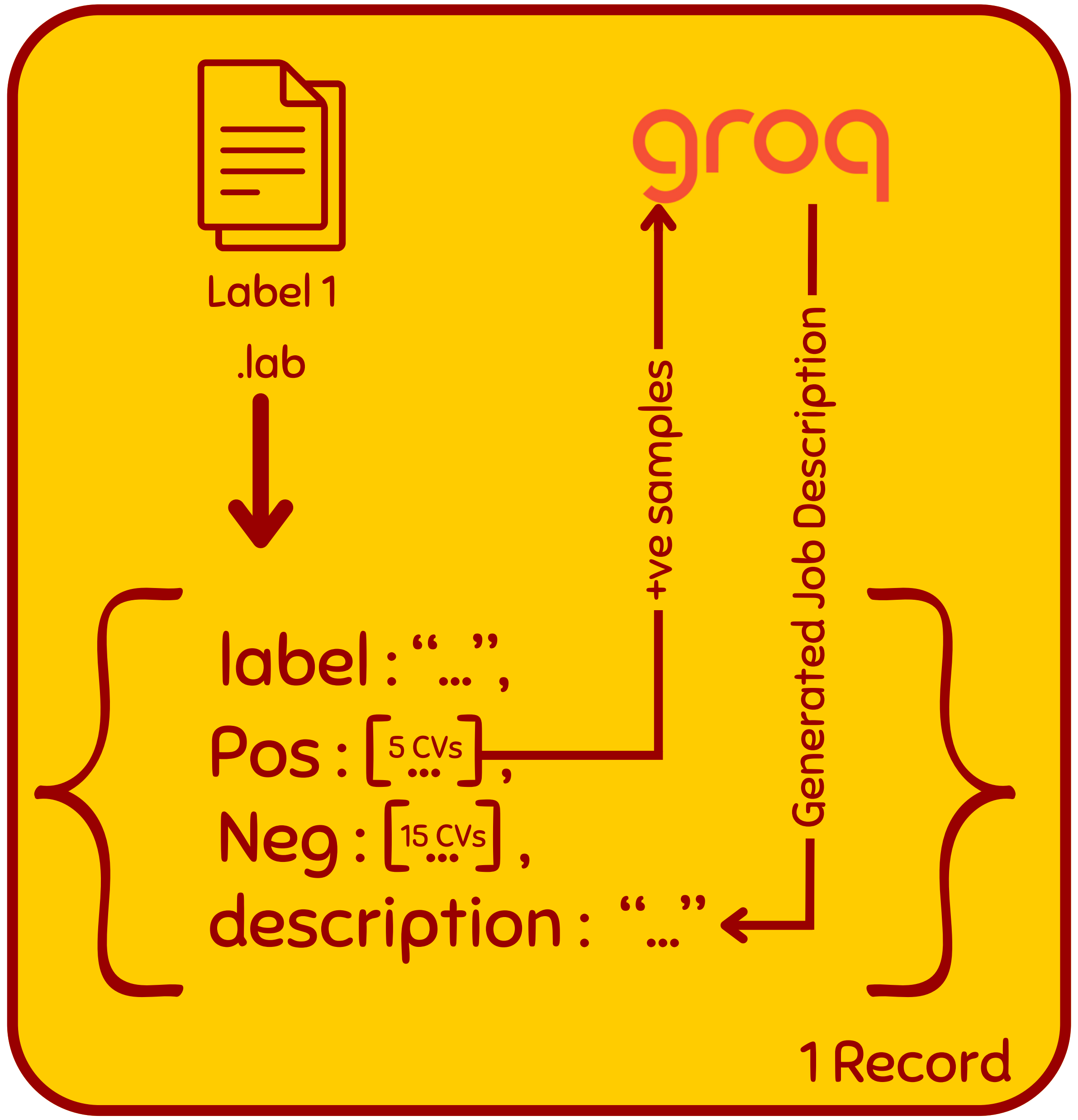


DATASET PREPARATION



Train Data

(data.json) – 1000 records



Valid Data & Test Data

100 records (10 for each category)

(20 samples per record – 5 +ve, 15 –ve)

Similarity

Query (Job Description) — Passage (Resume)

Meta

Dense Passage Retrieval

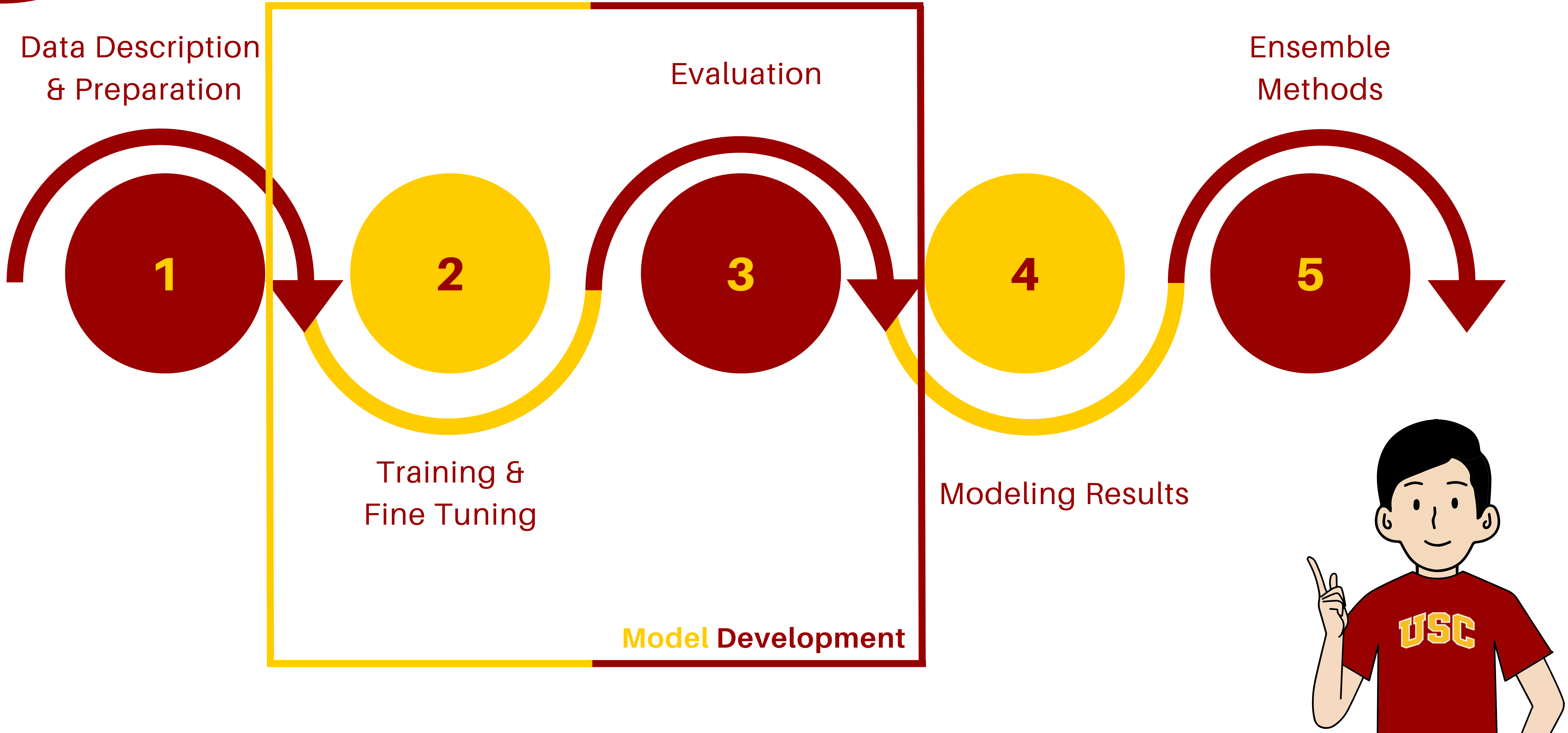
Modeling Choices

01 Two Encoders

02 Bi-Directional Attention (BERT)

03 Contrastive Learning (in-batch negative)

PROCESS OVERVIEW



Training & Fine Tuning

Query Encoder

Passage Encoder

$$Q = \begin{bmatrix} \leftarrow q_1 \rightarrow \\ \leftarrow q_2 \rightarrow \\ \vdots \\ \leftarrow q_N \rightarrow \end{bmatrix}_{N \times d} \qquad P = \begin{bmatrix} \leftarrow p_1 \rightarrow \\ \leftarrow p_2 \rightarrow \\ \vdots \\ \leftarrow p_N \rightarrow \end{bmatrix}_{N \times d}$$

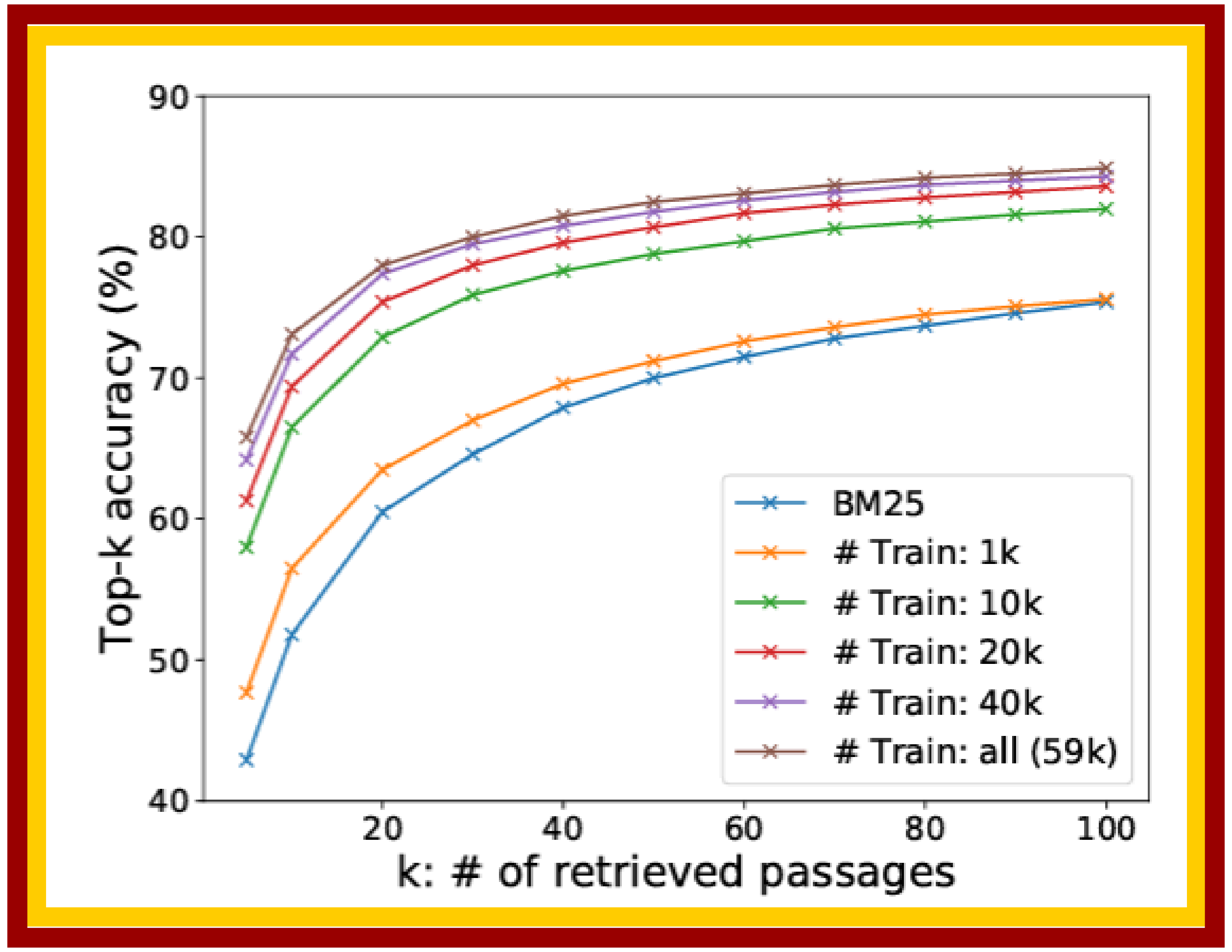
$$S = \begin{bmatrix} s(q_1, p_1) & s(q_1, p_2) & \dots & s(q_1, p_N) \\ s(q_2, p_1) & s(q_2, p_2) & \dots & s(q_2, p_N) \\ \vdots & \vdots & \ddots & \vdots \\ s(q_N, p_1) & s(q_N, p_2) & \dots & s(q_N, p_N) \end{bmatrix}_{N \times N}$$

$$L = \frac{1}{N} \sum_{i=1}^{N} -\log\left(\mathrm{diag}\left(\mathrm{softmax}_{\mathrm{row}}(S)\right)\right)$$

N – Batch Size
d – Embedding Dimensions
Q – Query Matrix (Job Desc Embeddings) (q1, q2, ... qn)
P – Passage Matrix (Resume Embeddings) (p1, p2, ... pn)
S – Similarity Matrix
L – Loss Function

Evaluation

Here are few evaluation metrics we computed to measure the model's performance



Reference from Main DPR Paper

01 Accuracy

$$\text{Accuracy} = \frac{\text{Number of Correct Predictions}}{\text{Total Number of Predictions}} \times 100$$

02 Mean Average Precision (MAP)

$$\text{mAP} = \frac{1}{Q} \sum_{q=1}^{Q} \text{AP}(q)$$

- **AP(q)**: Average Precision for query q, calculated as:

$$\text{AP}(q) = \frac{\sum_{k=1}^{n} P(k) \cdot \text{Rel}(k)}{\text{Total Relevant Items}}$$

where:

- n: Number of retrieved items.
- $P(k)$: Precision at rank k.
- $\text{Rel}(k)$: Relevance indicator at rank k (1 if relevant, 0 otherwise).

- **Q**: Total number of queries.

Modeling Results

We fine tuned different parameters for these models and the best results for each model (checkpoint) is shown in the below table

BM-25	DPR-BASE	DPR-FT	DPR-FT2
Best Matching 25	Deep Passage Retrieval (Base Model)	Deep Passage Retrieval Fine Tuned (Batch Size: 8)	Deep Passage Retrieval Fine Tuned v2 (Batch Size: 16)

MAP – Mean Average Precision

METRIC	BM-25	DPR-BASE	DPR-FT	DPR-FT2	BM-25 + DPR-FT2
ACCURACY	63%	48.6%	63%	65%	68.2%
MAP	0.9368	0.7101	0.8549	0.8966	0.9510

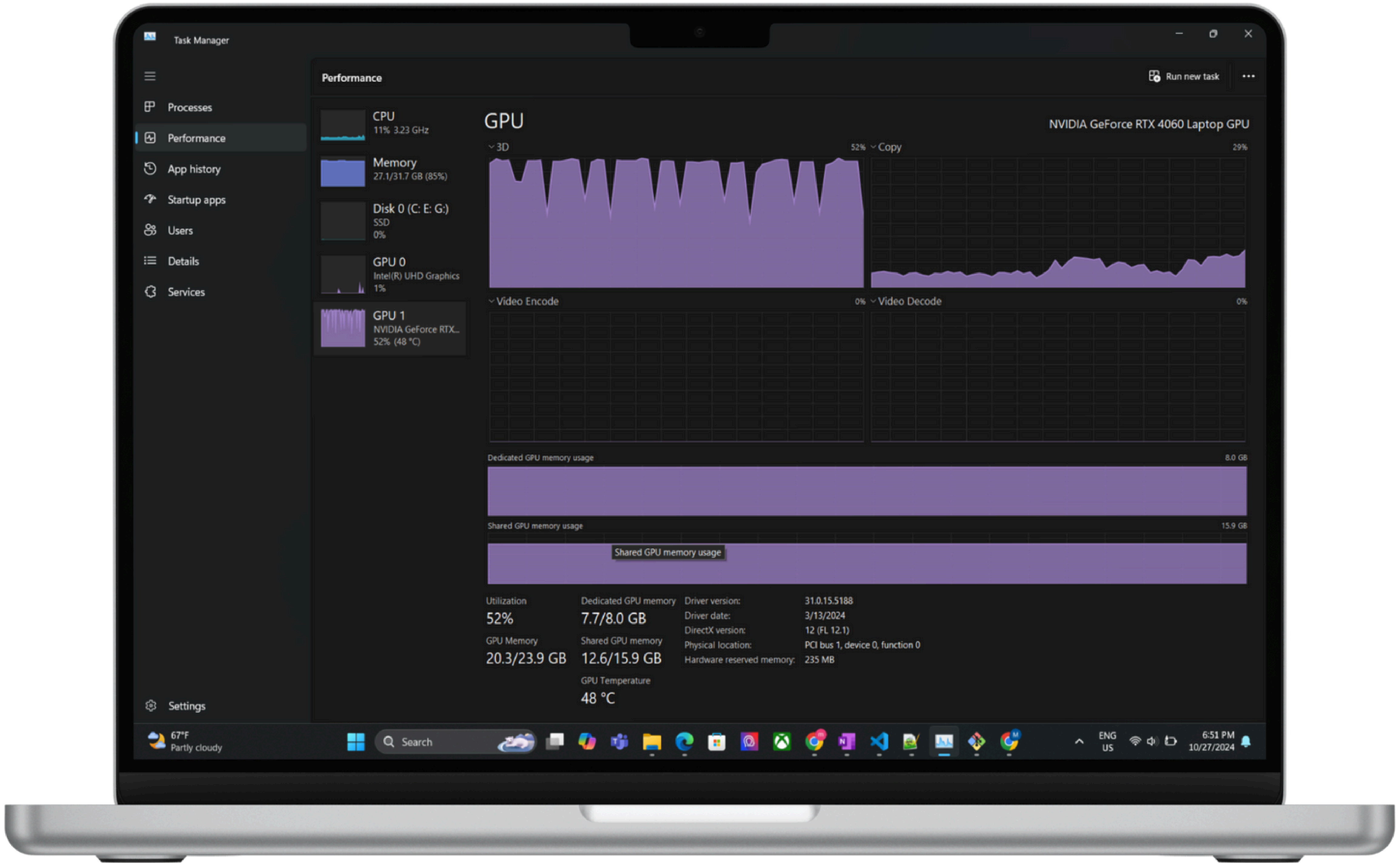
Limitations

We are currently facing limitations with the Groq API and Computational constraints. Details are as follows :

01 groq API Limitations

Each Record (Job Description)	2500 Tokens
Daily Limit	5,00,000 Tokens
1000 records	25,00,000 Tokens
5000 records	1,25,00,000 Tokens

02 Computation



Future Scope

Try to leverage Data Augmentation to generate Job Descriptions

Explore the possibility to increase Train Samples to 3K, 5K, 10K, 20K etc. using API Rotation Techniques

Try more Ensemble Methods & Evaluation Metrics

BM-42?

Q & A

Special Thanks to...

Ting-Yun (Charlotte) Chang

Thank You!