Fine-Tuning Large Language Model with Custom Dataset for Ansible Code Generation

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Increase efficiency and quality of IaC coding for DevOps

- Manual Ansible playbooks are complex and time-consuming
- Research lacks of domain-specific LLMs for the Academic Chair
- Sensitive information in the code sequences that are used as prompts can create issues with commercial LLM’s

Ansible Playbooks are like recipe books for servers

Key concepts of Ansible

- Written in YAML code
- Defines tasks (e.g. install package xy)
- each playbook contains one or more “plays” (sets of tasks)
- each play targets specific machines and performs actions in a defined order.
- Target the servers where tasks should run

Simple Code snippet

```
- name: Say hello
  hosts: localhost
  tasks:
    - name: Print a message
      debug:
        msg: "May the Force be with you”
```

What methodology can be used to gather and prepare a custom dataset for fine-tuning large language models?

Methodology

- Created a custom Input-Output paired dataset
- Used specialized tools to gather Ansible code samples
- Cleaned and preprocessed data to remove noise
- Split into train, validation, and test sets for robust evaluation

Expected Result

- A clean, structured dataset ready for fine-tuning a large language model

What steps are involved in implementing the fine-tuning process for the large language model?

Methodology

- Selected a pre-trained LLM (Phi-4)
- Integrated LoRA for efficient fine-tuning
- Used Unsloth and PyTorch frameworks
- Executed training with the custom Ansible dataset

Expected Result

- A fine-tuned LLM optimized for Ansible code generation in SAP environments

To what extend does the fine-tuned LLM meet the requirements?

Methodology

- Evaluated with ROUGE, METEOR, CHRF, and Ansible-lint
- Measured accuracy, syntax correctness, and code quality

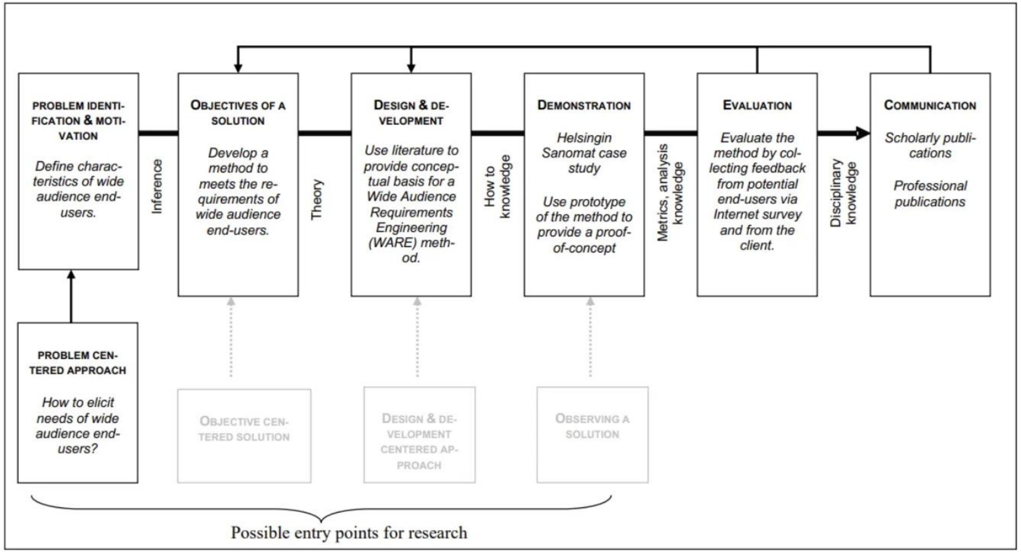
Expected Result

- Clear insights on how well the model performs in Ansible code generation tasks

Leaning on the DSR methodology of Hevner et al.

- Primary artifact is fine-tuned large language model
- Iterative cycles of evaluation and improvement in development

→ Artifact aims to enhance quality, efficiency and accuracy of code generation



Utilizing RedHat‘s Ansible-Content-Parser to create our custom dataset

- Extracted code data from existing GitHub repositories
- Split the dataset into a ratio of 70/15/15 (train/val/test)


```
{"data_source_description": "",
"input": "---\n# Ansible Playbook for SAP NetWeaver (JAVA) with IBM Db2 Sandbox
installation\n\n# Use include_role / include_tasks inside Ansible Task block, instead of using
roles declaration or Task block with import_roles.\n# This ensures Ansible Roles, and the tasks
within, will be parsed in sequence instead of parsing at Playbook initialisation.\n\n\n####
Begin Infrastructure-as-Code provisioning ####\n\n- name: Ansible Play to gather input for
gathering vars and VM provisioning\n  hosts: localhost\n  gather_facts: false\n\n  # pre_tasks
used only for Interactive Prompts only and can be removed without impact\n  pre_tasks:\n\n    -
name: Playbook Interactive - Check if standard execution with an Ansible Extravars file is
requested by end user",
"license": "",
"module": "ansible.builtin.set_fact",
"output": "      ansible.builtin.set_fact:\n        playbook_enable_interactive_prompts: \"{{
true if (sap_vm_provision_iac_type is undefined and sap_vm_provision_iac_platform is undefined)
else false }}\"\n",
"path": "deploy_scenarios/sap_nwas_java_ibmdb2_sandbox/ansible_playbook.yml",
"repo_name": "ansible",
"repo_url": "https://github.com/sap-linuxlab/ansible.playbooks_for_sap"}
```

Microsoft‘s Phi-4 LLM is outperforming larger LLM‘s

- Phi-4 is a 14 billion parameter **transformer-based** LLM
- architecture of Phi-4 follows a **decoder-only** transformer

→ It reads the input prompt as part of the sequence, then it **predicts** one token at a time (also called **causal** or **auto-regressive**)

Benchmarks	Models						
	Phi-4 14B	Phi-3 14B	Qwen 2.5 14B instruct	GPT 4o-mini	LLaMA-3.3 70B instruct	Qwen 2.5 72B instruct	GPT 4o
MMLU	84.8	77.9	79.9	81.8	86.3	85.3	**88.1**
GPQA	**56.1**	31.2	42.9	40.9	49.0	50.6	50.6
MATH	**80.4**	44.6	75.6	73.0	66.3	74.6	74.6
HumanEval	82.6	67.8	72.1	86.2	78.9	87.1	**90.6**
MGSM	80.6	63.9	77.9	86.5	89.1	82.8	**90.4**
SimpleQA	3.0	7.6	7.6	39.4	9.3	8.6	9.3
DROP	75.5	58.3	59.7	79.9	82.4	80.9	**85.6**
MMLUPro	70.4	51.3	63.2	63.4	69.6	69.6	**73.0**
HumanEval+	82.8	69.2	79.1	82.4	77.8	84.0	**88.0**
ArenaHard	75.4	67.0	68.3	73.1	76.4	79.2	**85.6**
LiveBench	47.6	28.1	49.8	58.7	57.1	64.6	**72.4**
IFEval	63.0	57.9	78.7	78.7	**89.3**	85.6	84.8
PhiBench (internal)	56.2	43.9	49.8	58.7	57.1	64.6	**72.4**

Second Iteration metrics showcase significant increase in model performance

First Iteration Evaluation Scores	Second Iteration Evaluation Scores
'rouge1': np.float64(0.9030472630117133), 'rouge2': np.float64(0.8750916994262085), 'rougeL': np.float64(0.8937407874924173), 'rougeLsum': np.float64(0.8968060509310674)	'rouge1': np.float64(0.9089512020276276), 'rouge2': np.float64(0.8815313156096819), 'rougeL': np.float64(0.8997117333753821), 'rougeLsum': np.float64(0.9046659338280736)
'meteor': np.float64(0.8737622872894732)	'meteor': np.float64(0.8850545846138909)
'score': 97.2683986738109, 'char_order': 6, 'word_order': 0, 'beta’: 2	'score': 97.84404601871951, 'char_order': 6, 'word_order': 0, 'beta': 2
Overall Ansible Lint Score: 0.56	Overall Ansible Lint Score: 0.76

Limitations

- Dataset inherits **code quality & security issues** from public GitHub sources
- No **semantic evaluation** by professional IaC developers

  →Evaluation lacks **real-world deployment testing**

Potential implementation and deployment of the fine tuned LLM on SAP BTP

- Embed the model in a **Fiori-based web application** on **SAP BTP**
- Deploy via **SAP AI Core** (side-by-side extensibility) or deploy via **FastAPI** or **Flask**, containerized with **Docker**
- Call the **REST API service** from the frontend using a **POST/GET request**

Thank you for your attention!

Questions?