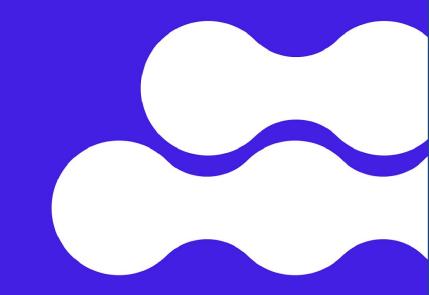


# Intel® GenAl Hackathon

Team Name: TEAM VELOCE

Problem Statement: AI FOR SOCIAL IMPACT



intel.



#### AI FOR SOCIAL IMPACT

Challenge participants to use Stable Diffusion and Transformers to develop AI models that can address social issues. This could involve predicting areas at risk of natural disasters, generating educational content for underprivileged students, etc. The focus here is on open innovation for social good.





# intel.

### UNIQUE IDEA

The Indo-LLaMA tool interprets the text while keeping the essence of what is to be conveyed.

To achieve this the tool scans through  $\{paragraphs \rightarrow lines\}$  rather than  $\{word \rightarrow word\}$  interpretation.

This keeps the meaning intact. The tool also provides a summary of the content provides to get a jist of what is to be conveyed.

ARTIFICIAL RESPONSIBLE INTELLIGENCE?

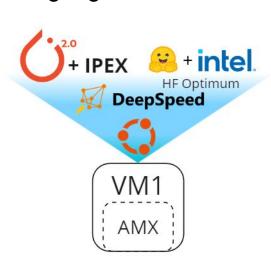
LETS TALK LLAMA



# intel

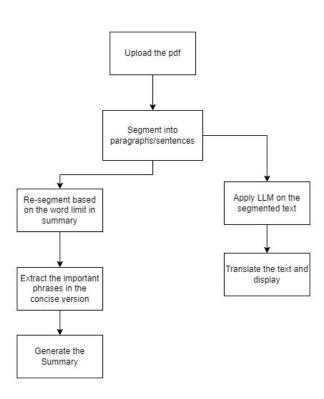
#### FEATURES OFFERED

- Translating from and to multiple national/ international languages.
- Inclusion of new languages due to presence of independent tokenizer code
- Provision of a concise summary to understand the gist of the content
- Due to uses of INTEL's Xeon VM, computation time is reduced.
- Large volume of data can be stored on INTEL cloud.



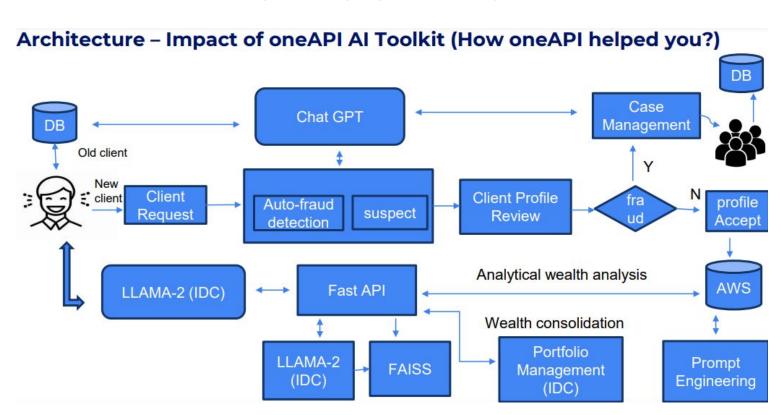


# PROCESS FLOW





#### ARCHITECTURE DIAGRAM





#### **TECHNOLOGIES USED**

intel-extension-for-pytorch : ipex

Tensorflow

Transformers

deep\_translator

Both pytorch and ipex are used due to dependency issues.

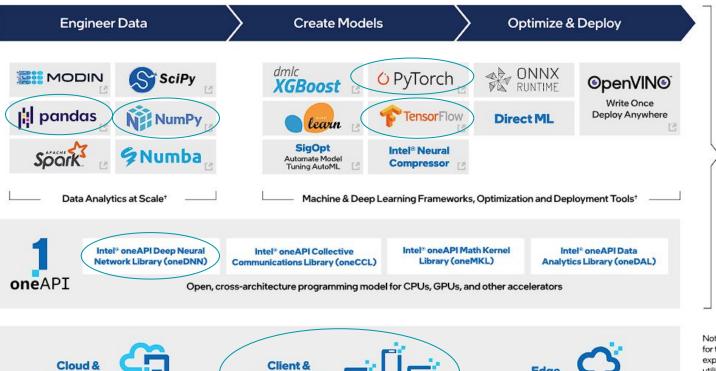




Transformers is a library exclusively for interacting with models on hugging face

At this stage we use these libraries primarily but on development of our own LLM's with large amount of data, the other tools will come to be useful

#### **SCALABILITY**



Workstation

**Enterprise** 



Intel® Developer Intel® De Cloud Cat

Intel® Developer Catalog

Try Latest Intel Tools and Hardware, and access optimized AI Models

#### cnvrg.io

Full stack ML Operating System



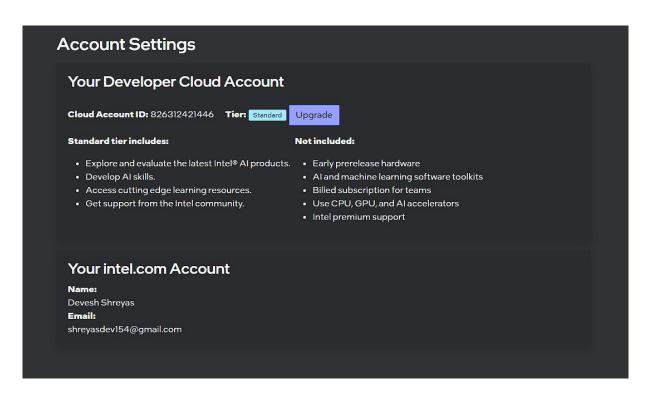
Intel optimizations and fine-tuning recipes, optimized inference models, and model serving

Note: components at each layer of the stack are optimized for targeted components at other layers based on expected AI usage models, and not every component is utilized by the solutions in the rightmost column

<sup>†</sup> This list includes popular open source frameworks that are optimized for Intel hardware



# Intel® Developer Cloud Account (Screenshot)





## Use case of Intel® Developer Cloud (IDC)

#### Evaluating and optimizing performance:

 IDC provides access to a variety of powerful Intel Xeon processors and GPUs, allowing you to benchmark INDO LLAMA on different hardware configurations and optimize its performance for specific use cases. This can lead to faster processing times and improved efficiency.

#### Scaling development and testing:

 IDC's cloud-based nature allows you to easily scale your development and testing environment up or down as needed. This is crucial for handling large datasets or complex text analysis tasks without worrying about hardware limitations.

#### Experimenting with advanced AI frameworks:

 IDC offers pre-installed deep learning frameworks like TensorFlow and PyTorch, which INDO LLAMA can leverage for advanced text analysis tasks like sentiment analysis or topic modeling.
 You can experiment with different frameworks and configurations to find the best fit for your specific needs.

#### EFFICIENCY AND EFFECTIVENESS BENCHMARK

```
model = MBartForConditionalGeneration.from pretrained("facebook/mbart-large-50-one-to-many-mmt")
         pytorch model.bin: 100%
                                                                        2.44G/2.44G [00:38<00:00, 32.6MB/s]
        /usr/local/lib/python3.10/dist-packages/torch/ utils.py:831: UserWarning: TypedStorage is deprecate
           return self.fget. get (instance, owner)()
         generation config.json: 100%
                                                                            261/261 [00:00<00:00, 14.8kB/s]
        tokenizer = MBart50TokenizerFast.from pretrained("facebook/mbart-large-50-one-to-many-mmt", src
        tokenizer config.json: 100%
                                                                            528/528 [00:00<00:00, 28.0kB/s]
        sentencepiece.bpe.model: 100%
                                                                                5.07M/5.07M [00:00<00:00, 19.8MB/s]
        special tokens map.json: 100%
                                                                               717/717 [00:00<00:00, 42.0kB/s]
1m [10]
         # translate from English to Hindi
         generated tokens = model.generate(
             **model inputs,
             forced bos token id=tokenizer.lang code to id["hi IN"]
```

$$T_{total} = 111s$$

Run on Google Colab Runtime

```
In [14]: %%timeit
           from transformers import MBartForConditionalGeneration, MBart50TokenizerFast
           import torch
           from intel extension for pytorch.transformers.optimize import optimize
           1.01 \mus \pm 118 ns per loop (mean \pm std. dev. of 7 runs, 1,000,000 loops each)
 In [15]: %%timeit
          model = MBartForConditionalGeneration.from_pretrained("facebook/mbart-large-50-one-to-many-mmt")
          tokenizer = MBart50TokenizerFast.from pretrained("facebook/mbart-large-50-one-to-many-mmt", src lang="en XX")
           2.18 s ± 638 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
  In [16]: %%timeit
          article en = "Morality or moral behaviour is not necessarily the result of philosophical reflections. Thesephilosophical reflecti
          model_inputs = tokenizer(article_en, return_tensors="pt")
           266 µs ± 1.93 µs per loop (mean ± std. dev. of 7 runs, 1,000 loops each)
In [17]: %%timeit
         # translate from English to Hindi
         generated_tokens = model.generate(
             **model inputs.
             forced_bos_token_id=tokenizer.lang_code_to_id["hi_IN"]
         12.9 s ± 737 ms per loop (mean ± std. dev. of 7 runs, 1 loop each)
In [18]: %%timeit
         translation = tokenizer.batch_decode(generated_tokens, skip_special_tokens=True)
         71.3 µs ± 13.2 µs per loop (mean ± std. dev. of 7 runs, 10,000 loops each)
In [20]: %%timeit
         translation
         8.18 ns ± 2.14 ns per loop (mean ± std. dev. of 7 runs, 100,000,000 loops each)
```

Run on Intel Xeon VM and optimised libraries.

$$T_{total} = 15s$$

$$\eta = 86\%$$



# Thank you so much!

