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LLM Deployment And Service Integration

Google Cloud Vertex AI Deployment.

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Contents:

- Google Cloud Vertex AI's and its role in deployment.
- Endpoints and Models.
- Costs of Using Models and Endpoints.
- Service integration with Python SDK Google Cloud Vertex AI.
- Decoder Strategies (Generation Parameters) for LLMs.
- Use Case.

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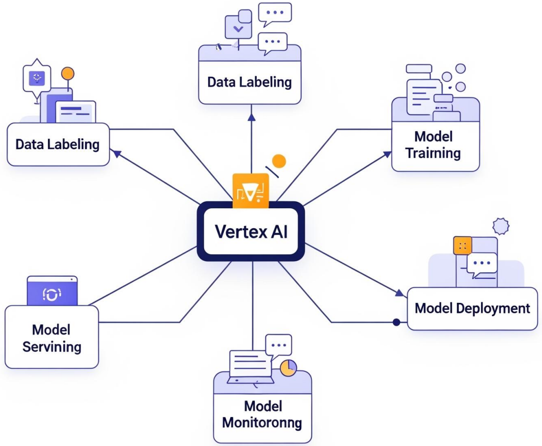


What is Vertex AI?

- Managed Machine Learning Platform
- Supports Custom and AutoML Models.
- Vertex AI accelerates MLOps workflows efficiently.
- It integrates seamlessly with other Google Cloud services.
- Jupyter notebooks and Training Infrastructure.
- Scalable and Cost-Effective(Autopilot).

Vertex AI Deployment

- Managed service for deploying LLMs.
- Scalable, robust, and secure infrastructure.
- Simplifies model hosting and serving.
- Integrates with Google Cloud services and Hugging Face for model upload.
- Model Registry.
- Endpoint Creation.
- Model Deployment to Endpoint.
- Prediction Options (REST API calls and batch prediction).
- Monitoring and Logging (Google Cloud Monitoring and Logging).

Endpoint, Model Deployment

- First step is to define and create an Endpoint for model serving.
- Deploy the trained model to the created Endpoint.
- Endpoint handles predictions and serves the model.
- Endpoints can be created using **Google Cloud Console**, **Vertex AI Python SDK** or **gcloud CLI**.
- Creating an endpoint **does not automatically deploy a model**.

Model & Endpoint Costs

- No cost for empty endpoint.
- Billing starts after deployment.
- Charged for allocated VM resources (e.g., CPUs, RAM, GPUs) whether or not predictions are being made:
    - **Per-hour pricing** for each replica.
    - Based on the **machine type** (e.g., `g2-standard-16, NVIDIA_L4,` etc.)
- Online prediction charges

https://cloud.google.com/compute/all-pricing?hl=en
https://cloud.google.com/vertex-ai/pricing?utm_source=chatgpt.com#text-data

Python SDK Google Cloud Vertex AI

- The SDK is part of the `google-cloud-aiplatform` package.
- Simplifies working with models, datasets, endpoints, pipelines, and jobs.
- Initialization:

```python
from google.cloud import aiplatform

aiplatform.init(
    project = "your-project-id",
    location = "us-central1"
)
```

- Create endpoint reference:

```python
ENDPOINT = aiplatform.Endpoint(
    endpoint_name=(
        f"projects/your-project-id"
        f"/locations/us-central1"
        f"/endpoints/your-endpoint-id"
    )
)
```

- Make prediction:

```python
prediction = ENDPOINT.predict(
    instances=["".join(prompt)],
    parameters={
        "temperature": 1.0,
        "max_new_tokens": 512,
        "top_k": 50,
        "top_p": 1.0,
        "repetition_penalty": 1.0
    }
)
```

Generation Parameters
Temperature (randomness of predictions)

Let:

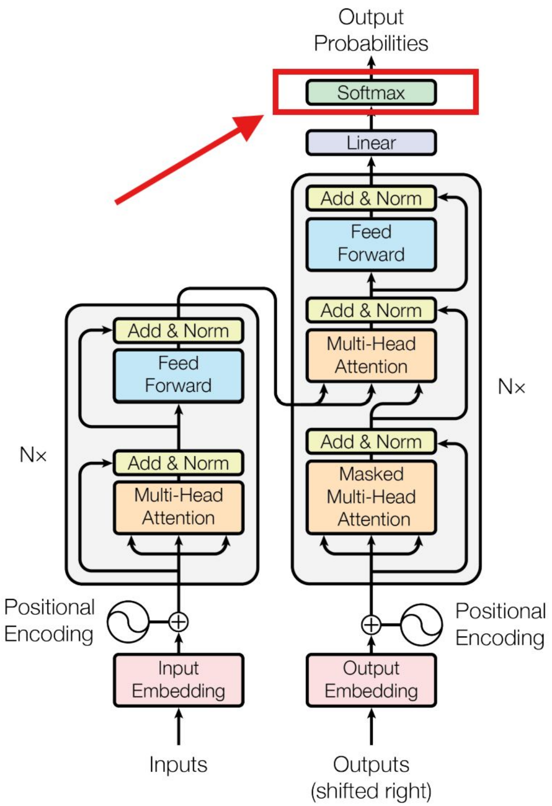
- z_i be the logit (unnormalized score) for token i
- V be the vocabulary size

The **standard softmax** computes the probability p_i of token i as:

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^{V} e^{z_j}}$$

To apply temperature $T > 0$, the logits are **divided by** T:

$$p_i^{(T)} = \frac{e^{z_i/T}}{\sum_{j=1}^{V} e^{z_j/T}}$$



- $T = 1$: Regular softmax (default).
- $T < 1$: Makes the distribution **sharper** (more confident).
- $T > 1$: Makes the distribution **flatter** (more random).

Generation Parameters
Top K (pick top-k most likely tokens)

Let:

- z_i: logit for token i
- V: vocabulary of size N
- p_i: softmax probability for token i

Compute probabilities:

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

- Identify the **set** $S_k \subseteq V$ of the **k tokens with the highest probabilities.**

$$S_k = \{i \in V \mid p_i \text{ is among the top } k \text{ values in } \{p_j\}_{j=1}^{N}\}$$

Example (k = 3)

Token	p_i
A	0.50
B	0.25
C	0.15
D	0.07
E	0.03

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Generation Parameters
Top P (pick group of tokens with total probability ≥ p)

Let:

- z_i: logit for token $i \in V$, the vocabulary
- p_i: softmax probability

$$p_i = \frac{e^{z_i}}{\sum_{j=1}^{N} e^{z_j}}$$

Create a sorted list of tokens $T = \{t_1, t_2, \ldots, t_N\}$, such that:

$$p_{t_1} \geq p_{t_2} \geq \cdots \geq p_{t_N}$$

Define S_p as the smallest set of tokens such that:

cumulative probability $$\sum_{t_i \in S_p} p_{t_i} \geq p$$

Example (top-p = 0.9)

Token	p_i
A	0.40
B	0.30
C	0.15
D	0.10
E	0.05

Cumulative sum:

- A: 0.40
- A + B: 0.70
- A + B + C: 0.85
- A + B + C + D: **0.95** → first time ≥ 0.9

Generation Parameters
Repetition Penalty (penalizes frequent tokens to avoid repetition)

Let:

- $\mathcal{V}$: vocabulary
- $L \in \mathbb{R}^{|\mathcal{V}|}$: the vector of logits output by the model at time step t
- $R > 1$: the **repetition penalty** factor (e.g., 1.1, 1.2, ...)

Let $G = \{g_1, g_2, \ldots, g_{t-1}\}$ be the set of **previously generated tokens**.

For each token $i \in \mathcal{V}$:

$$L'_i = \begin{cases} \frac{L_i}{R} & \text{if } i \in G \text{ and } L_i > 0 \\ L_i \cdot R & \text{if } i \in G \text{ and } L_i < 0 \\ L_i & \text{otherwise} \end{cases}$$

$$p_i = \frac{e^{L'_i}}{\sum_{j \in \mathcal{V}} e^{L'_j}}$$

Example ($R = 1.2$)

- Vocabulary: `["cat", "dog", "mouse"]`
- Original logits: `L = [3.0, 1.0, 0.5]`
- Generated so far: `["cat"]`

Apply the penalty:

- `"cat"`: $3.0/1.2 = 2.5$
- `"dog"` and `"mouse"` stay the same

New logits: `[2.5, 1.0, 0.5]` → lower chance of picking "cat" again

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Use Case

01 Upload Hugging Face model to Google Vertex AI Model Registry

02 Create endpoint and deploy model into Vertex AI

03 Test model using https request

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Bibliography

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Next Talk

- Retrieval-augmented Generation (RAG).
- Grounding and Context.
- Vectorized Database - Distance Measurements.
- Real-world use case:
    - RAG implementation to enhance community well-being.

Questions

Thanks for your attention!!!