ML-AAS

Machine Learning

As a Service

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ML-AAS

Al Platform providing Services in the Cloud

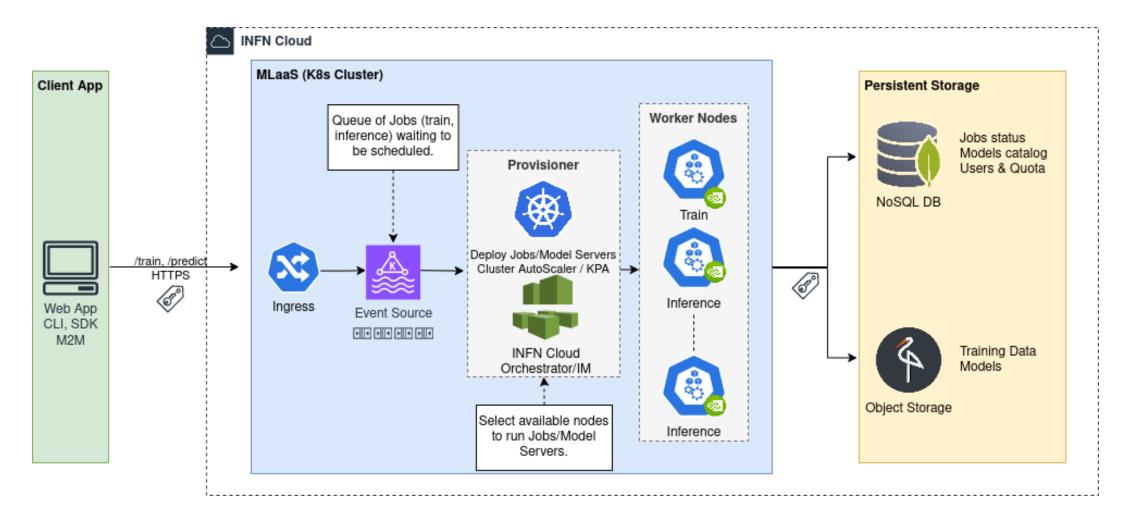
- Train/fine-tune machine learning models at scale
- Host/share datasets and trained models in the cloud
- Serve models to make **predictions** about new data
- Manage models and versions through a public INFN catalog

Al Platform Building Blocks - Technologies

- **Computing resources:** CPUs, RAM, GPUs + Networking INFN Cloud
- Container Orchestrator: automate deployment, scaling, and management of workloads on physical/virtual nodes – Kubernetes
- Event Source: decouple jobs submissions from their execution Kafka
- Provisioner:
 - **Train**: run distributed training jobs, hyperparameters tuning **Kubeflow Training Operator, Kueue, Katlib**
 - Inference: models serving KServe, Knative + KPA, Batching, Deployment Strategies, Inference Pipelines
 - Cluster Scaling K8s AutoScaler, INFN Cloud Orchestrator/IM
- NoSQLDB: keep jobs status; maintain public catalogs Mongo DB
- Object Storage: host data and models S3, MinIO, Longhorn
- **Client Apps/Tools**: Web App, CLI, SDKs, etc. to accelerate integration with the platform

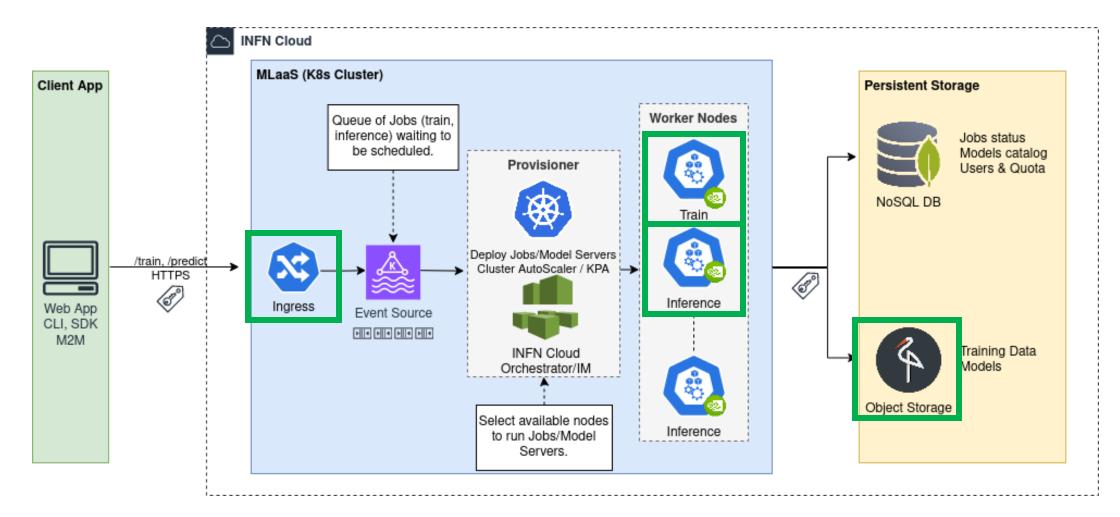
on top of **INFN Cloud**

Al Platform High Level Architecture – TO BE

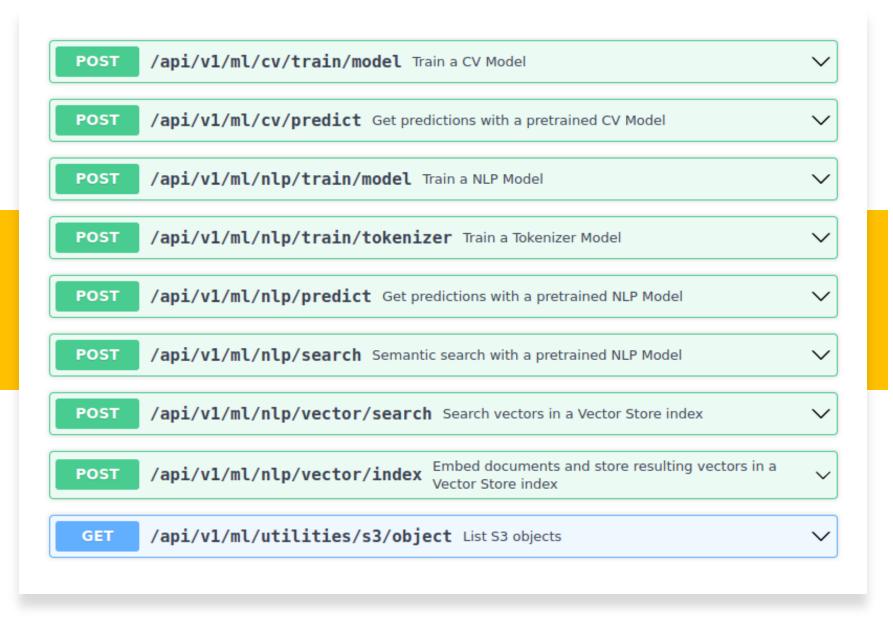


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Al Platform High Level Architecture – AS IS



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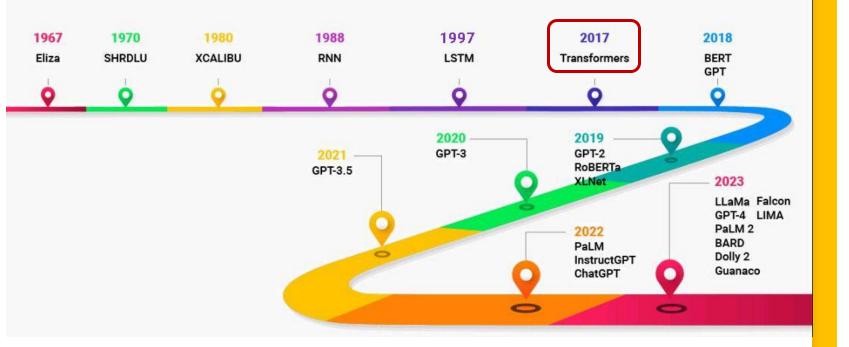
ML-AAS RESTful API

NLP

- NLP is a field of <u>linguistics</u> and <u>machine learning</u> focused on understanding the <u>human</u> <u>language</u>.
- A key event in the history of Language Models is the introduction of the <u>Transformers</u> architecture in June 2017 (Google Brain team).
- Transformer models have proven to be very powerful in solving NLP tasks.

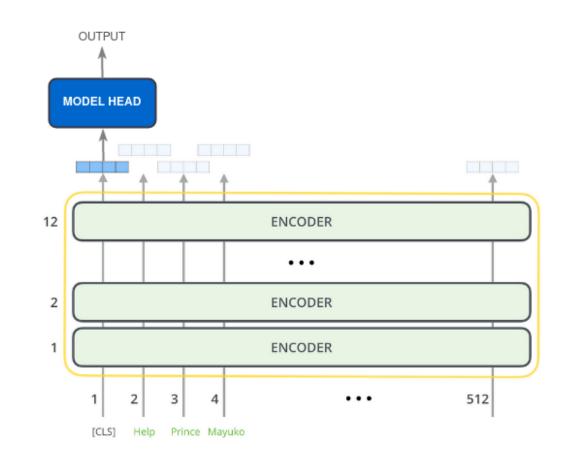
Evolution of Large Language Models

Analytics Vidhya



Transformer Architecture

- Stack of **encoding layers** (now we are not interested in the decoding stack)
- Each layer captures a different level of **linguistic information**, from surface features to deep semantic features in the higher layers
- Each layer outputs an **embedding vector** for each input sentence token – a dense vector that represents the contextual understanding of the token/sentence by the Transformer model
- Last layer's output is given to a custom **Model Head** designed for a specific task, e.g. Text Classification



Text Classification

Use case:

• predict <u>INFN structure name</u> from author's affiliation string

Training:

- model: distilbert
- **dataset**: labeled author's affiliation strings:
 - ~6k positive samples
 - ~6k negative samples
 - dataset augmented to ~400k samples by adding "smart" typos
- training:
 - 6 hours (Nvidia Tesla T4)
 - 95% accuracy

Author's affiliation	INFN Structure
Catania Univ, Ist Nazl Fis Nucl, Lab Naz Sud, Catania, Italy	ст
Bari INFN, Via E Orabona 4, I-70125 Bari, Italy	BA
Dell INFN Frascati, Lab Nazl, Frascati, Italy	LNF
INAF IASF Milano, I-20133 Milan, Italy	[NoSite]
Training Dataset	

Text Classification Let's try on ML-AAS

```
tokenizer: {
  path: path/to/tokenizer,
  storage_type: s3 | hugging_face_hub | local
},
model: {
  path: path/to/model,
  storage_type: s3 | hugging_face_hub | local,
  objective: text-classification
},
predict_input: {
  input_text: [
    "Frascati Natl Lab INFN LNF, Natl Inst Nucl Phys, Italy"
```

Masked Language Modeling

Use case:

• fine-tune the Language Model to understand the semantics of sentences about physics

Training:

- model: bert, longformer
- dataset:
 - ~60k publication abstracts
 - 10% masked tokens

Sentence	Masked Sentence
The determination of the spin-	The determination of the spin-
parity properties of the discovered Higgs	parity [Masked] of the discovered Higgs
Boson is one of the main goals of the	Boson is one of the main [Masked] of the
ongoing analyses at LHC. This note	ongoing [Masked] at LHC. This note
describes the experimental technique used	describes the experimental technique used
by the ATLAS collaboration to test different	by the ATLAS collaboration to
spin-parity hypotheses []	test [Masked] spin-parity hypotheses []

Training Dataset

MLM Models

Model	Nr. Hidden Layers	Nr. Parameters	Training Time (10 epochs – 16M tokens)	Accuracy	Max Input Length
BERT	12	109M	8:24:03	71%	512
BERT Large	24	335M	1 day, 2:20:31	75%	512
LONGFormer	12	148M	1 day, 1:43:29	74%	4096
LONGFormer Large	24	434M	3 days, 7:26:04	78%	4096

MLM Let's try on ML-AAS

```
tokenizer: {
  path: path/to/tokenizer,
  storage_type: s3 | hugging_face_hub | local
},
model: {
  path: path/to/model,
  storage_type: s3 | hugging_face_hub | local,
  objective: masked-lm
},
predict_input: {
  input text: [
    "Particles have corresponding antiparticles with the same mass
but with [MASK] electric charges. Thus, the positron, which is a
positively [MASK] [MASK], is the antiparticle of the negatively
charged electron."
```

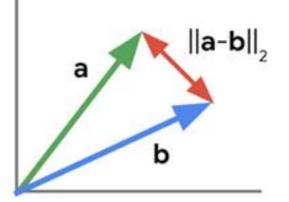
Semantic Search

Use Case:

find the <u>INFN project</u> that "best" matches a publication abstract

Vector Store Search:

- **embeddings**: MLM-tuned Language Model dense vectors that capture the semantics of a sentence;
- **dataset**: ~20k publication abstracts;
- vectore store: FAISS Facebook AI Similarity Search efficient storage and searching for embeddings;
- similarity search with score (L2 distance lower is better).



L2 distance

Vector Search Let's try on ML-AAS

```
tokenizer: ...,
model: {
  path: path/to/model,
  storage_type: s3 | hugging_face_hub | local,
  objective: no-objective
},
dataset: {
  path: path/to/vector/store/to/load,
  format: vector_store,
  storage_type: s3 | local
},
search_input: {
  input_text: [
    "Angular correlations between charged trigger and ..."
```

Training Input

```
tokenizer: ...,
model: {
  path: path/to/model/to/load,
  storage_type: s3 | hugging_face_hub | local,
  objective: causal-Im | masked-Im | next-sentence-prediction | text-classification | ...
},
model_train: {
  epochs: 10,
  batch_size: 32,
  optimizer: {
    name: "AdamW",
    init_lr: 2e-5,
    num_warm_steps: 1000,
    weight_decay_rate: 0.01
dataset: {
  path: path/to/dataset/to/load,
  storage_type: s3 | local,
  train_test_split: 0.1
},
model_save: {
  path: path/to/model/to/save,
  storage type: s3 | local
```

Training Output

```
task_id: "0751bf4c-95f7-4463-bc47-dd901561e1df",
task_status: succeeded,
stats: {
  submitted: "2023-09-13T06:30:48",
  elapsed: "1 day, 2:20:31",
  •••
},
history: {
  loss: [1.67, 1.46, ..., 1.17],
  accuracy: [0.67, 0.70, ..., 0.75]
  •••
},
evaluation: {
  loss: 1.16,
  accuracy: 0.76,
  •••
},
dataset: {
  samples_train: 51227,
  samples_test: 6325,
  tokens: 13756616,
  •••
```

7 Results	s (61 Variations)	Hotness	• 🗉	₩		
∞	Ilama-2 Llama 2 is a collection of pretrained and fine-tuned generative text models ranging in scale from 7 billion to 70 Meta · 12 Variations · 16 Notebooks	0 billion pa	^ 231			
∞	CodeLlama Code Llama is a family of large language models for code based on Llama 2 providing state-of-the-art perform Meta · 18 Variations · 1 Notebook	mance am	^ 29			
	Alpaca The Alpaca model is fine-tuned from a 7B LLaMA model on 52K instruction-following data generated by the te tatsu-lab · 1 Variation · 0 Notebooks	echniques	1 8		Web Ap Models Ca	p
G	flan-t5 Scaling Instruction-Finetuned Language Models Google · 5 Variations · 37 Notebooks		^ 284		Models Ca	talog
LMSYS Large Model Systems Organization	vicuna Vicuna is a chat assistant trained by fine-tuning LLaMA on user-shared conversations collected from ShareGF LMSYS ORG · 7 Variations · 2 Notebooks	РТ	• 72			
1	smartreply Smart Reply model. TensorFlow · 1 Variation · 0 Notebooks		1 8			

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Description. De	ploy a single master Kubernetes 1.24.12 cluster	
Deployment desc	iption	
K8s-GPU		
Configuration	Advanced	
number_of_nodes	i de la constante de la constan	
1		~
Number of K8s no	de VMs	
number_of_nodes	_with_gpu	
2		\$
master_flavor		
Select		•
Number of vCPUs	and memory size of the K8s master VM	
node_flavor		
Select		•
Number of vCPUs	and Memory Size of each K8s node VM	
node_flavor_with_	gpu	
	RAM, 1 TB disk, 1 T4 GPU	•
8 VCPUs, 64 GB		

INFN Cloud K8s GPU Support

Kubernetes with Kafka cluster

Description: Deploy a single master Kubernetes 1.24.12 cluster with a Kafka instance

Deployment description	
K8s-Kafka	
General Kafka Advanced	
kafka_enabled	
true	*
Install a Kafka cluster	
Warn: Ensure to select a K8s worker nodes flavor suitable for your Kafka cluster configuration. Notice that a broker instance requests 750 milliCPU and 10 GB disk size, a controller instance 500 milliCPU and 2 GB disk size, the we milliCPU.	b UI 750
kafka_replicas	
2	$\hat{\cdot}$
Number of Kafka broker instances	
Info: The number of Kafka brokers should be less than or equal to the number of K8s nodes.	
kafka_enable_public_connections	
false	•
Enable public connections	
kafka_public_port	
30092	\$
Port to listen for public connections	
Info: The port to listen for public connections (if enabled) to broker instances, must be in the range 30000-32767. Public connections are currently supported via master node (single point of failure).	

INFN Cloud K8s Kafka Support



INFN Cloud Managed PaaS Service

INFN Cloud ML-AAS



Deploy a private K8s cluster with ML-AAS

TODO

Architecture

- Finalize platform architecture and technologies
- Develop INFN Cloud connectors, e.g. K8s Auto-Scaler

NLP

- Implement other NLP objectives, e.g. NER, Question-Answering, etc.
- Integrate non Transformer-based models

NLP – Use Cases for INFN Research Products catalog

- Consider smaller/larger language models
- Collect more data for training

ML

. . .

 Add ML use cases to support INFN core research, e.g. ML for HEP (High Energy Physics)

Thank You

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Democratizing AI

- Share data, algorithms, computing resources, and knowledge
- Provide tools to automate and accelerate the lifecycle of an AI project
- Reduce time and cost of AI development, increase productivity
- Promote collaboration and openness, foster creativity
- Promote widespread adoption of AI

Use Cases

Training on data extracted from INFN publications.

• Text Classification

Predict <u>INFN structure name</u> from author's affiliation string:

- "CNAF, Ist Nazl Fis Nucl, Bologna, Italy" -> CNAF
- "CSDC, Sez INFN Firenze, Florence, Italy" -> FI
- MLM (Masked Language Modeling)

Predict missing tokens in sentences about physics:

- "The determination of the spin-[Masked] properties of the discovered Higgs Boson..." -> parity
- Semantic Search

Find the <u>INFN project</u> that "best" matches a publication abstract:

- "The black hole images obtained with the Event Horizon..." -> CSN4/Teongrav
- "We investigate the density distributions acquired by a..." -> CSN2/Fish

Vector Index

```
tokenizer: ...,
model: {
  path: path/to/model,
  storage_type: s3 | hugging_face_hub | local,
  objective: no-objective
},
dataset: {
  path: path/to/dataset/to/load,
  storage_type: s3 | local,
  loader_kwargs: {
    page_content_column: column-name
},
vector_store_save: {
  path: path/to/vector/store/to/save,
  format: vector_store,
  storage_type: s3 | local
```

Python Dependencies

Web Server:

• FastAPI, Uvicorn, KServe

ML:

• Tensorflow, Keras, Transformers, Datasets, Evaluate, Scikit-learn

Vector Index/Search:

• LangChain, FAISS, Doctran

Other:

• Pydantic, Numpy, Pandas, Boto3, typo, clean-text, graphviz, ...