Explore

AI Studio - Published Service

1.0.0 OAS 3.0

Servers

https://localhost:51120

invocations

MLflow model invocation

POST /invocations Do a Model Invocation

description

Parameters

Cancel

Reset

No parameters

Request body required

application/json

Input from model signature

```json
{
  "inputs": {
    "query": ["graph neural networks"],
    "max_results": [1],
    "chunk_size": [1200],
    "chunk_overlap": [400],
    "do_extract": [true],
    "do_analyze": [true],
    "do_generate": [true],
    "analysis_prompt": ["Summarize the content in English (≈150 words)."],
    "generation_prompt": [
      "Create a concise 5-point presentation script based on the summary."
    ]
  },
  "params": {}
}
```


Execute | Clear

Responses

Curl

```
curl -X 'POST' \
  'https://localhost:51120/invocations' \
  -H 'accept: application/json' \
  -H 'Content-Type: application/json' \
  -d '{
  "inputs": {
    "query": ["graph neural networks"],
    "max_results": [1],
    "chunk_size": [1200],
    "chunk_overlap": [400],
    "do_extract": [true],
    "do_analyze": [true],
    "do_generate": [true],
    "analysis_prompt": ["Summarize the content in English (≈150 words)."],
    "generation_prompt": [
      "Create a concise 5-point presentation script based on the summary."
```

```
      ]
    },
    "params": {}
  }'
```


Request URL

```
https://localhost:51120/invocations
```

Server response

Code	Details
200	**Response body**


```
{
  "predictions": [
    {
      "extracted_papers": "[{\"title\": \"A Survey on Graph Classification and Link Prediction based on GNN\", \"text
\": \"1\\nA Survey on Graph Classification and\\nLink Prediction based on GNN\\nXingyu Liu\\nJuan Chen\\nQuan Wen\\nSch
ool of Computer Science and Engineering\\nUniversity of Electronic Science and Technology of China\\nChengdu, Sichuan,
611730, P.R. China\\nAbstract: Traditional convolutional neural networks are limited to handling Euclidean space\\ndat
a, overlooking the vast realm of real-life scenarios represented as graph data, including\\ntransportation networks, so
cial networks, and reference networks. The pivotal step in transferring\\nconvolutional neural networks to graph data a
nalysis and processing lies in the construction of\\ngraph convolutional operators and graph pooling operators. This co
mprehensive review article\\ndelves into the world of graph convolutional neural networks. Firstly, it elaborates on th
e\\nfundamentals of graph convolutional neural networks. Subsequently, it elucidates the graph neural\\nnetwork models
based on attention mechanisms and autoencoders, summarizing their application\\nin node classification, graph classific
ation, and link prediction along with the associated datasets.\\nKeywords: Graph convolutional neural network, Node cla
ssification, Link prediction.\\nI. Introduction\\nThe characteristic of deep learning is the accumulation of multiple l
ayers of neural networks,\\nresulting in better learning representation ability. The rapid development of convolutional
neural\\nnetworks (CNN) has taken deep learning to a new level[1, 2]. The translation invariance, locality,\\nand combi
natorial properties of CNN make it naturally suitable for tasks such as processing\\nEuclidean structured data such as
images[3, 4], At the same time, it can also be applied to\\nvarious other fields of machine learning[5-7]. The success
of deep learning partly stems from\\nthe ability to extract effective data representations from Euclidean data for effi
cient processing.\\nAnother reason is that thanks to the rapid development of GPUs, computers have powerful\\ncomputing
and storage capabilities, It can train and learn deep learning models in large-scale\\ndata sets, which makes deep lear
ning perform well in natural language processing[8], machine\\nvision[9], recommendation systems[10] and other fields
\\nHowever, existing neural networks can only process conventional Euclidean structured data.\\nAs shown in Figure. 1
(a), Euclidean data structures are characterized by fixed arrangement rules\\nand orders of nodes, such as 2D grids and
1D sequences. Currently, more and more practical\\narXiv:2307.00865v1  [cs.LG]  3 Jul 2023\\n\\n2\\napp
s must consider non Euclidean data, such as Figure. 1(b), where nodes in\\nnon Euclidean data structure
xed arrangement rules and orders, This makes it\\ndifficult to directly transfer traditional deep learning models to ta
```


Download

Response headers

```
access-control-allow-origin: https://localhost:51120
content-length: 46671
content-type: application/json
date: Fri,11 Jul 2025 23:38:38 GMT
```

Code	Details
	server: envoy vary: Origin x-envoy-upstream-service-time: 85726

Responses

Code	Description	Links
200	Successful operation	*No links*

Media type

application/json

Controls `Accept` header.

Example Value Schema


```
{
  "extracted_papers": "string",
  "script": "string"
}
```


Schemas

ModelInput

ModelOutput