Generative-AI Powered Inference with gpi-pack

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gpi-pack: https://gpi-pack.github.io/

GPI: GenAI-Powered Inference

GPI

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- Customizing Your Analysis
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/ GPI: Generative-AI Powered Inference

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pypi v0.1.0 python 3.8 | 3.9 | 3.10 | 3.11

GPI

gpi_pack is a Python library for the statistical inference powered by Generative Artificial Intelligence (AI). It provides a set of tools and utilities for performing statistical inference using the internal representation of the Generative AI models. The library is designed to be easy to use and flexible, allowing users to perform a wide range of statistical analyses.

Note

We released **gpi_pack** version 0.1.0 on February 27th, 2025. This is the first version of the package, and we currently only support the setting of Text-as-Treatment based on our paper. We have been working hard to make this package as useful and user-friendly as possible. If you have any feedback or suggestions, please feel free to reach out to the maintainer.

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- Check if GPU is available:

```
import torch
print(torch.cuda.is_available())
```

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- Colab Pro/Pro+ offers more compute and access to premium GPUs

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     - Website: https://nnsight.net/
     - Plan to release the functionality for `nnsight` soon

Example: Deploying models locally (1)

- Find your favorite model from https://huggingface.co/

```
from transformers import AutoTokenizer, AutoModelForCausalLM
import torch

checkpoint = 'meta-llama/Meta-Llama-3.1-8B-Instruct'

tokenizer = AutoTokenizer.from_pretrained(checkpoint)
model = AutoModelForCausalLM.from_pretrained(
    checkpoint,
    device_map="auto",
    torch_dtype=torch.float16
)
```

Example: Deploying models locally (1)

- Find your favorite model from `https://huggingface.co/`
  - Typically, the documentation shows how to deploy the model

```python
from transformers import AutoTokenizer, AutoModelForCausalLM
import torch

checkpoint = 'meta-llama/Meta-Llama-3.1-8B-Instruct'

tokenizer = AutoTokenizer.from_pretrained(checkpoint)
model = AutoModelForCausalLM.from_pretrained(
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)
```

Example: Deploying models locally (2)

- Use `extract_and_save_hidden_states` function in `gpi_pack`

```
from gpi_pack.llm import extract_and_save_hidden_states

prompts = [
    'Create a biography of a politician named John Doe',
    'Create a biography of a politician named Jane Smith',
]

extract_and_save_hidden_states(
    prompts = prompts,
    output_hidden_dir = <YOUR HIDDEN DIR>,
    save_name = <YOUR SAVE NAME>,
    tokenizer = tokenizer,
    model = model,
    task_type = "create"
)
```

Example: Deploying models locally (3)

- To repeat the input texts, set `task_type == "repeat"`

```python
from gpi_pack.llm import extract_and_save_hidden_states

prompts = [
    'The Airports Commission, an independent body established...',
    'History show us that most large infrastructure projects...',
]

extract_and_save_hidden_states(
    prompts = prompts,
    output_hidden_dir = <YOUR HIDDEN DIR>,
    save_name = <YOUR SAVE NAME>,
    tokenizer = tokenizer,
    model = model,
    task_type = "repeat"
)
```

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  - `gpi_pack` offers the class `TarNetHyperparameterTuner`

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- `Optuna` offers efficient hyperparameter optimization
  - `gpi_pack` offers the class `TarNetHyperparameterTuner`
  - Only need to specify data and the choice of hyperparameters

Example: Hyperparameter Tuning with Optuna

```python
from gpi_pack.TarNet import TarNetHyperparameterTuner
import optuna

obj = TarNetHyperparameterTuner(
    # Data
    T = df['TreatmentVar'].values,
    Y = df['OutcomeVar'].values,
    R = hidden_states,
    # Hyperparameters
    learning_rate = [1e-4, 1e-5],
    dropout = [0.1, 0.2],
    architecture_y = ["[200, 1]", "[100,1]"],
    architecture_z = ["[1024]", "[2048]"]
)

# Hyperparameter tuning with Optuna
study = optuna.create_study(direction='minimize')
study.optimize(obj.objective, n_trials=100)
```

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    - Propensity score function needs to be Lipschitz continuous
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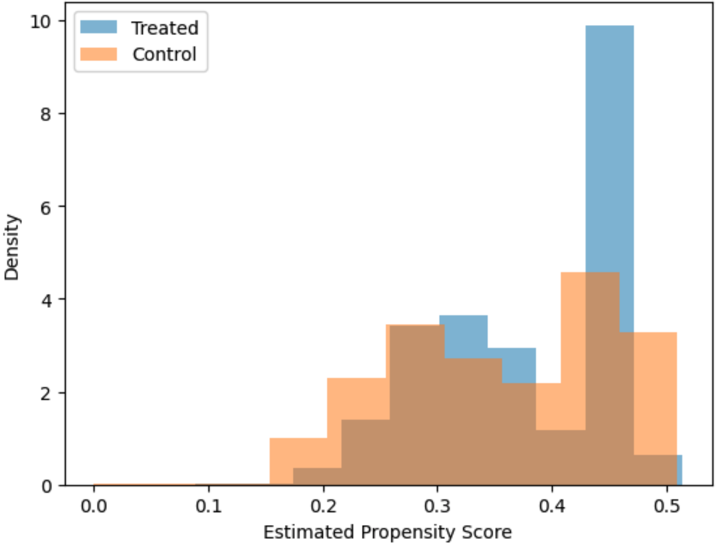
- You should always plot the estimated propensity score distributions
    - For text/image-as-treatment, it works as a diagnosis of separability assumption

Example: Estimate Treatment Effect

```python
# estimate treatment effects
ate, se = estimate_k_ate(
    R= hidden_states,
    Y= df['OutcomeVar'].values,
    T= df['TreatmentVar'].values,
    K=2, #K-fold cross-fitting
    lr = 2e-5, #learning rate
    architecture_y = [200, 1], #outcome model architecture
    architecture_z = [2048], #deconfounder architecture
    plot_propensity = True, #visualize propensity scores
)
```

Example: Propensity Score Distributions



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  2. Email me at knakamura [at] g.harvard.edu