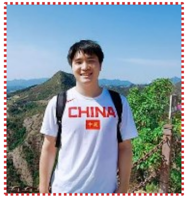
TAble Pre-training via Learning a Neural SQL Executor





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ICLR

10th International Conference on
Learning Representations (ICLR 2022)

Background: Table-based Question Answering

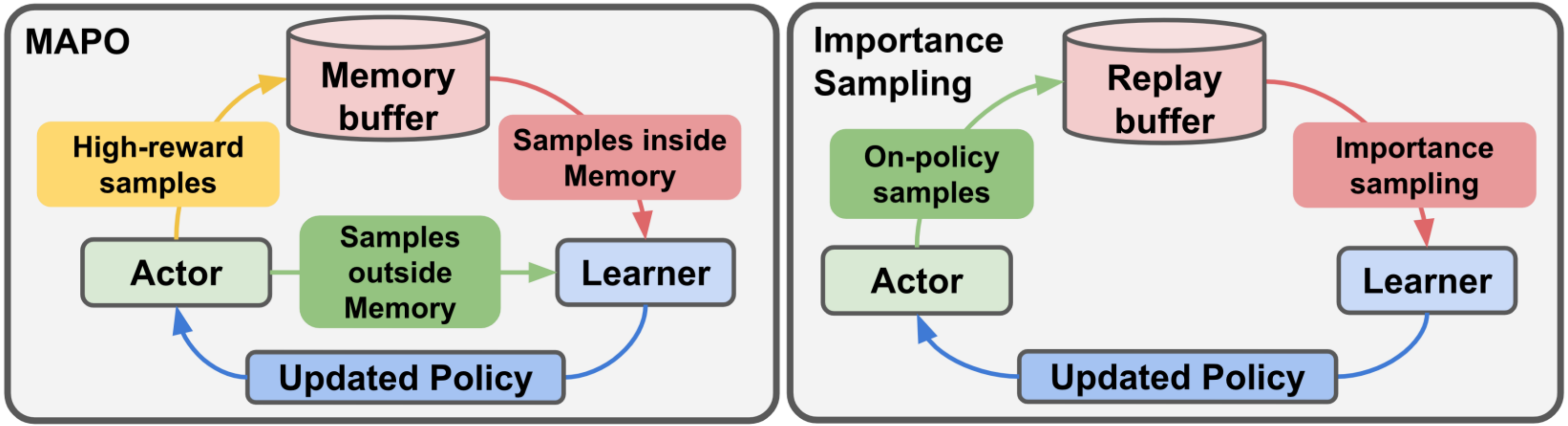
Year	City	Country	Nations
1896	Athens	Greece	14
1900	Paris	France	24
1904	St. Louis	USA	12
…	…	…	…
2004	Athens	Greece	201
2008	Beijing	China	204

Greece held its last Summer Olympics in which year?

2004

Previous Work: Reinforcement Learning

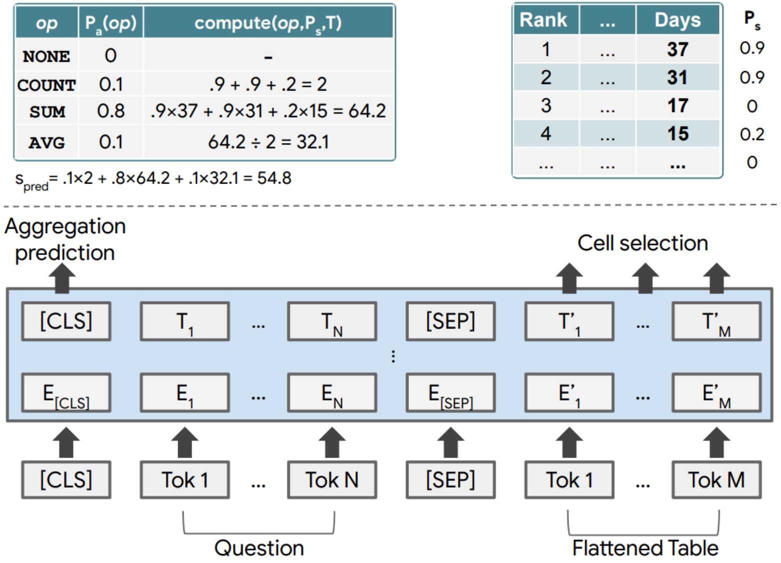
Obtain rewards by comparing execution results of sampled SQL queries with golden answers to train a text-to-SQL semantic parser. Hard to scale to complex scenarios.



[Chen et al. 2018]

Previous Work: Table Parsing

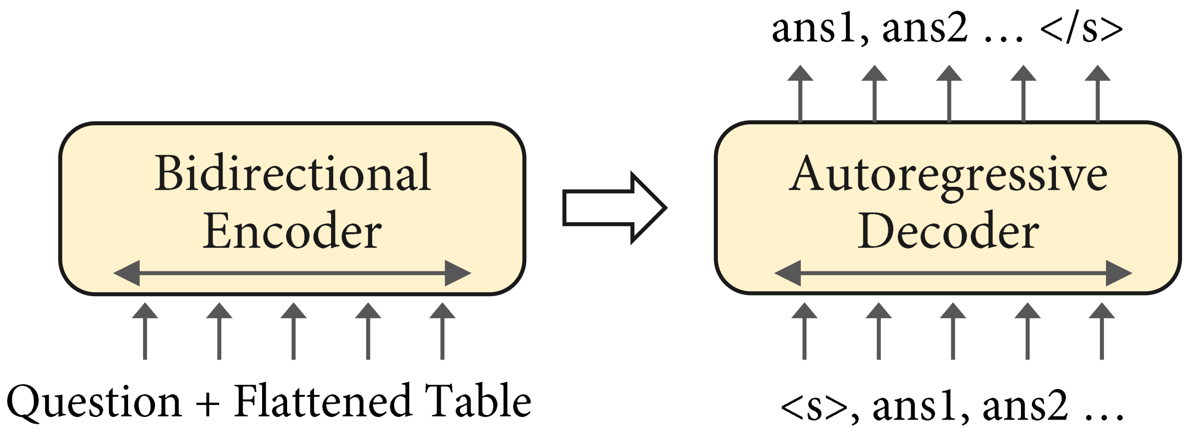
Predict answer by selecting table cell values and optionally applying an aggregation operator to the selected region. Flexibility is limited.



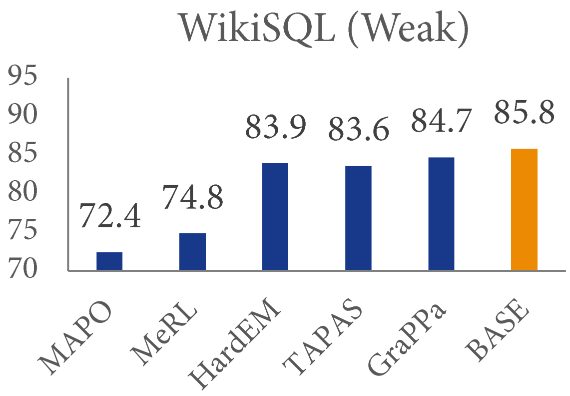
[Herzig et al. 2020]

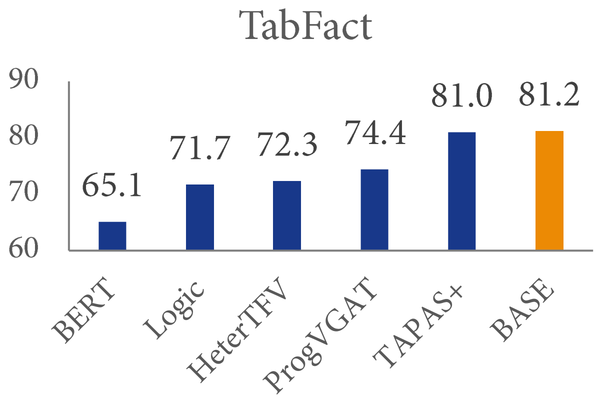
Our Proposal: Generative Language Model

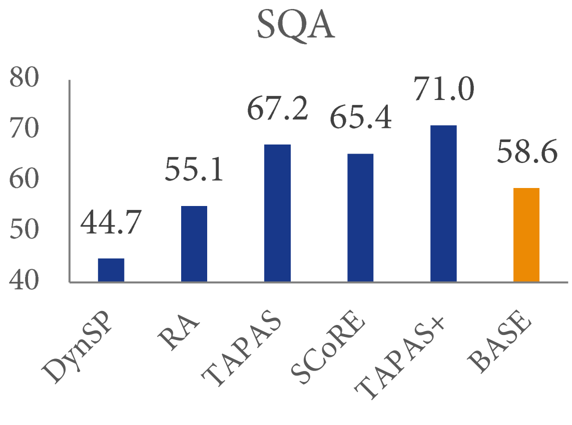
We formulate the task of table-based question answering as answer generation, and leverages generative language models (e.g., BART) to output autoregressively.

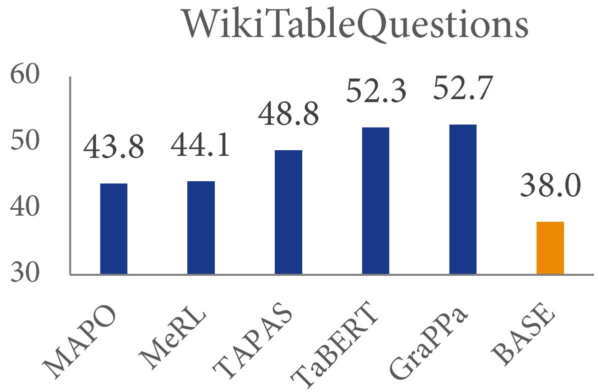


Preliminary Result: Models Are Data-Hungry









Motivation: Program as Proxy

Programming Context : Database

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Program:

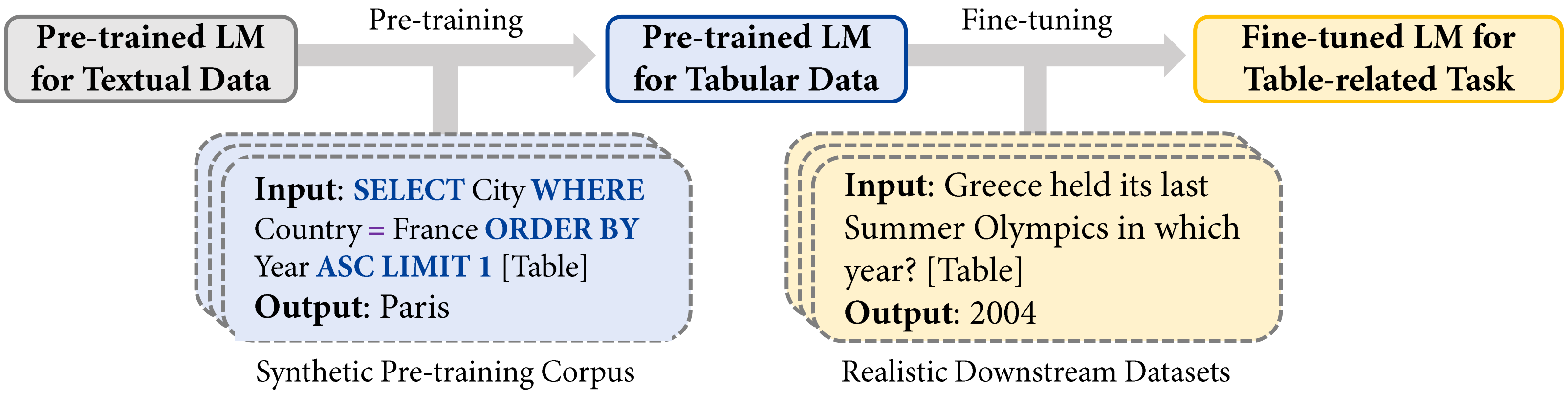
SELECT City **WHERE** Country = France **ORDER BY** Year **ASC LIMIT** 1

Executor

Paris

Our Proposal: SQL Execution Pre-training

Pre-training a model to mimic the behavior of a symbolic execution engine.



Our Proposal: SQL Execution Pre-training

If we train a model to mimic the SQL query execution procedure over databases, we believe it learns latent programmatic operations from the execution engine.

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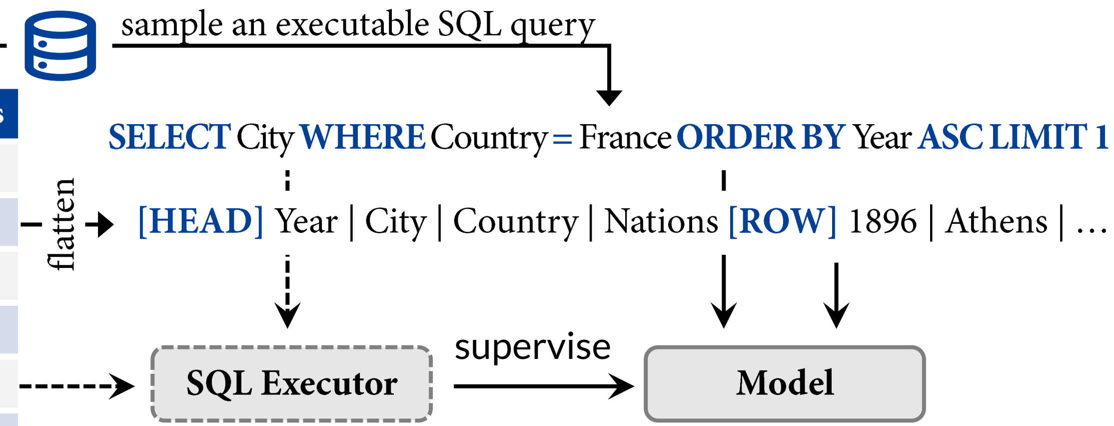
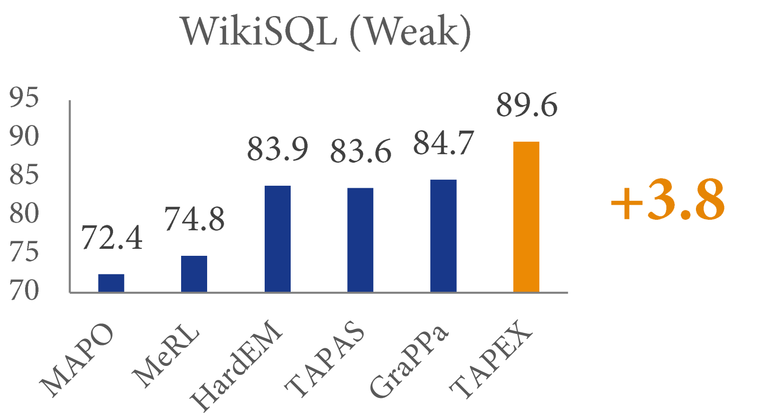
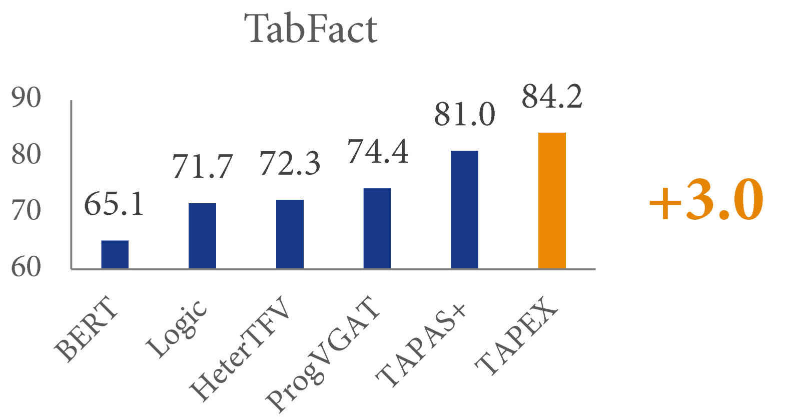
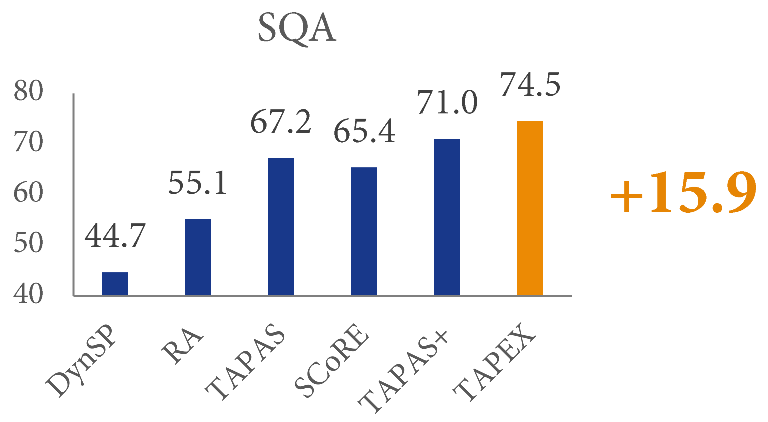
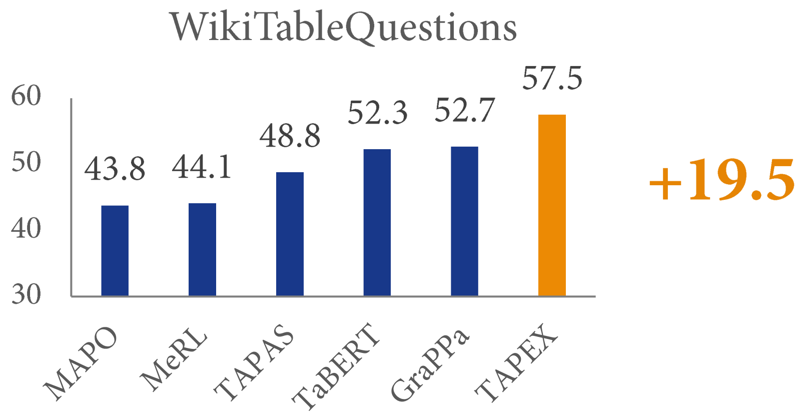


Experimental Result: SOTA Across Benchmarks



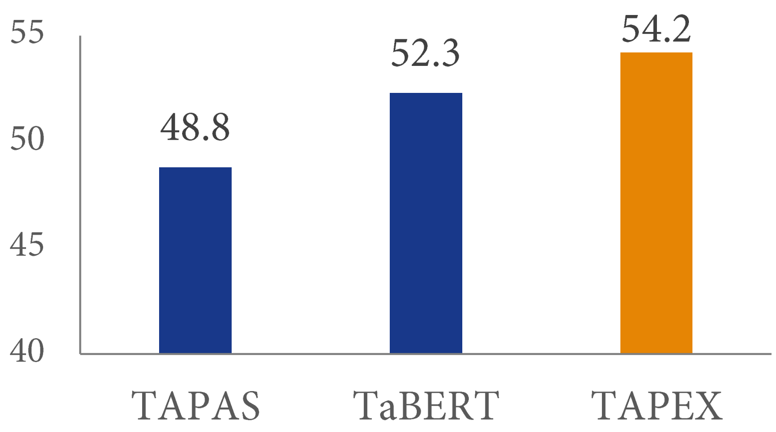




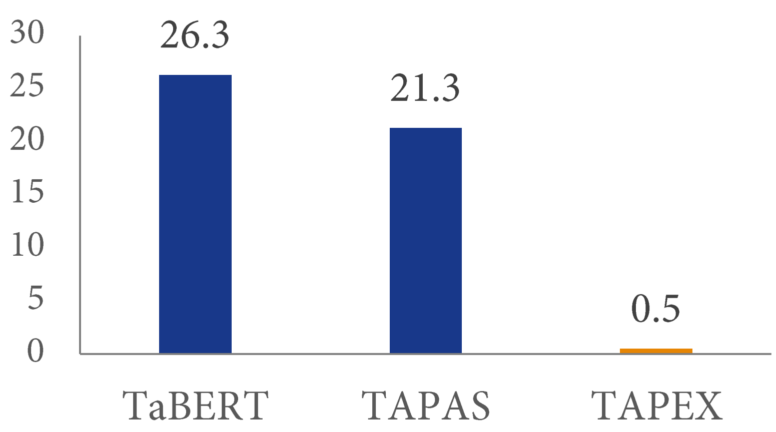


Experimental Result: Cost-Effective Pre-training

Fine-tuning Performance



Pre-training Corpus (Million)



Compared with TaBERT, **2%** of corpus yields **2%** improvement!

Take Away: Pre-training without Real Data

When performing continual pre-training, instead of mining a large noisy web corpus, we can also try to synthesize an accurate and small corpus.

Take Away: Pre-training without Language Modeling

When performing continual pre-training, instead of performing the general-purpose language modeling, we can also try to simulate the specialized skill.

Take Away: Pre-training without Natural Language

When performing continual pre-training for natural language tasks, instead of natural language, we can also try to leverage programs.

We introduce a new language representation model called **BERT**, which stands for **B**idirectional **E**ncoder **R**epresentations from **T**ransformers. Unlike recent language representation models (Peters et al., 2018a; Radford et al., 2018), BERT is designed to pre-train deep bidirectional representations from unlabeled text by jointly conditioning on both left and right context in all layers. As a result, the pre-trained BERT model can be fine-tuned with just one additional output layer to create state-of-the-art models for a wide range of tasks, such as question answering and language inference, without substantial task-specific architecture modifications.

```
def start_link(name, opts \\ []) do
  GenServer.start_link(__MODULE__, {name}, opts)
end

def init({name}) do
  require Logger
  Logger.log :debug, "Started channel #{name}!"
  :pg2.join(:channels, self)
  :ets.insert(:channels, {name, self})
  users = :ets.new(:users, [:set, :protected])
  {:ok, {name, users, []}}
end

def handle_call({:send, message}, _from, {name, _users, _buffer} = state
  Kaguya.Util.sendPM(name, message)
  {:reply, :ok, state}
end

def handle_call({:rename_user, {old_nick, new_nick}}, _from, {_name, use
  case :ets.lookup(users, old_nick) do
    [{^old_nick, user}] ->
      new_user = %{user | nick: new_nick}
      :ets.delete(users, old_nick)
      :ets.insert(users, {new_nick, new_user})
    [] -> :ok
  end
  {:reply, :ok, state}
end
```