**Open-Domain Question Answering**

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**Introduction:**

* Open-ended Open Questionnaire (OpenQA) is an important function in Natural Language Processing (NLP), which aims to answer a question in a natural language based on large informal texts.
* Natural language processing (NLP) refers back to the branch of laptop science—and more specifically, the branch of synthetic intelligence or AI—concerned with giving computers the capability to understand textual content and spoken phrases in lots the equal way human beings can.
* Sub – domain 🡪Open-domain Question Answering

**Problem Statement:**

* Question answering (QA) is a computer science discipline within the fields of information retrieval and natural language processing (NLP), which is concerned with building systems that automatically answer questions posed by humans in a natural language. To accomplish this, we will use a Python library and TensorFlow wrapper that makes deep learning and AI.

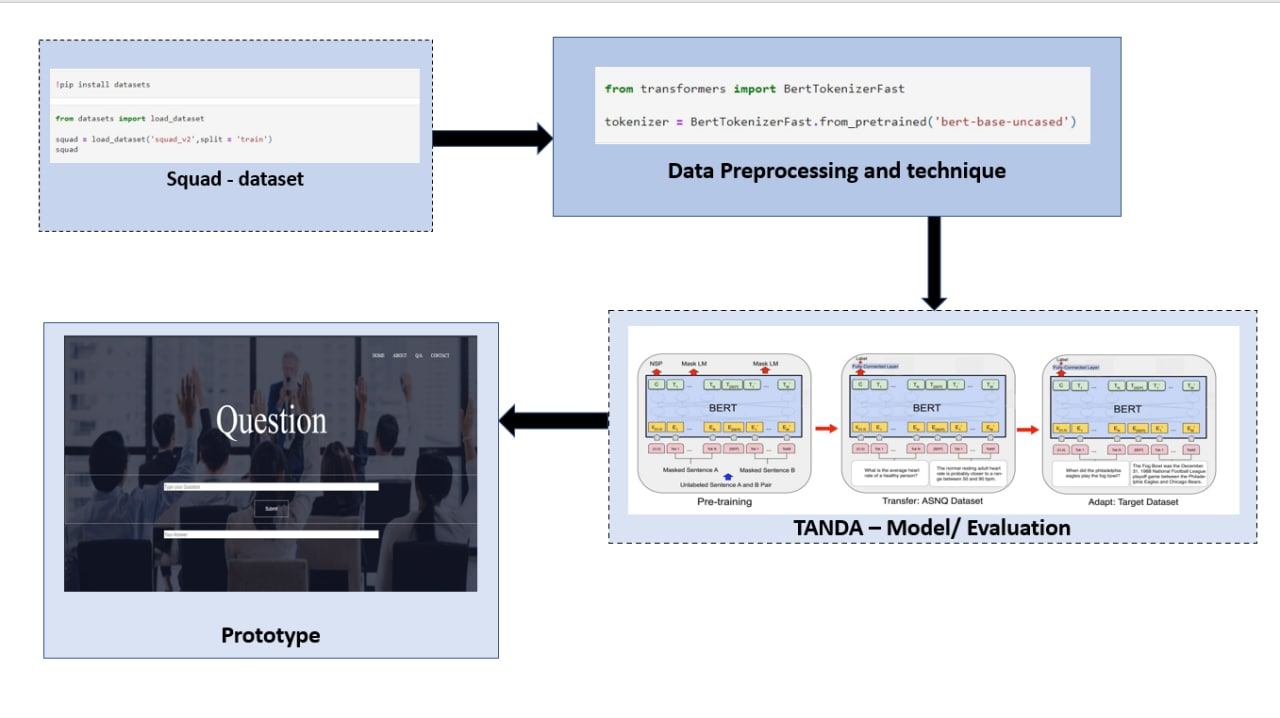
**Motivation:**

* Aims to answer the question in the form of a natural language based on large informal texts.

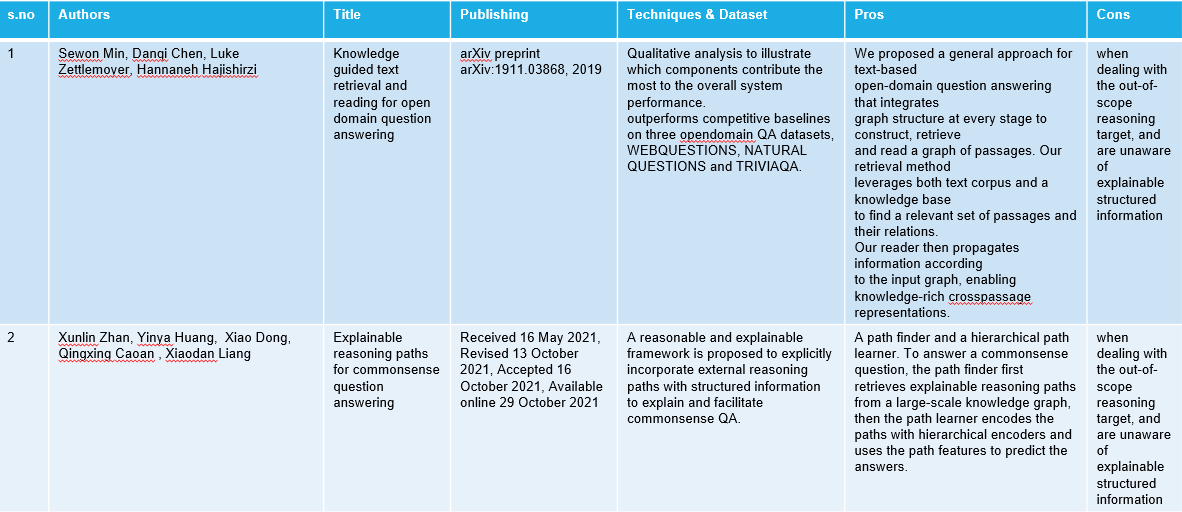
**Objectives:**

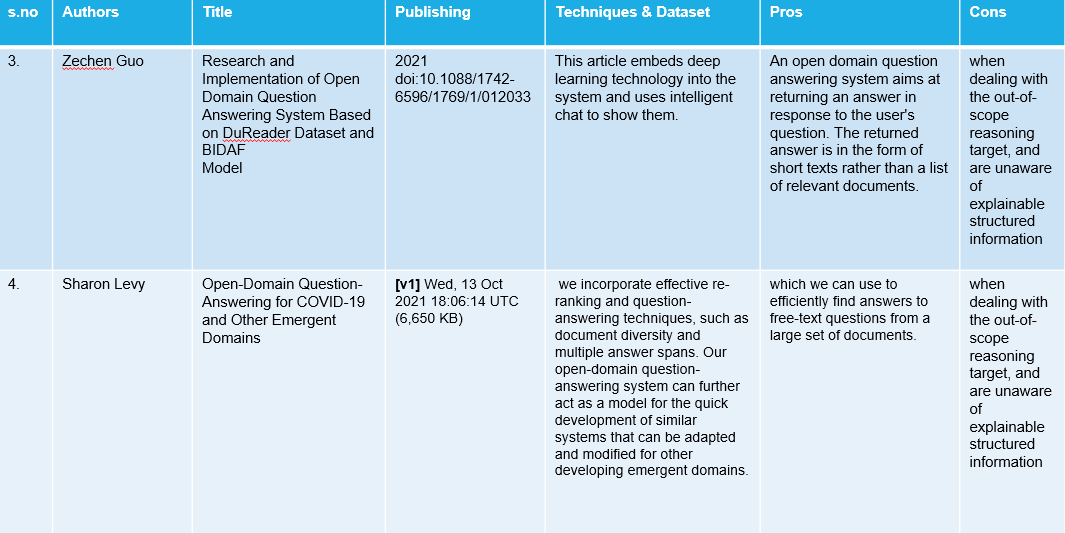
* Objective of the question answering system (QA) is to generate brief answers to the summary questions asked in natural language.
* This kind of information retrieval is required with the growth of digital information.
* Previously QAS were developed for a specific domain and had limited efficiency.
* Present QAS Target on types of questions commonly asked by users, characteristics of data source, and correct answer generated. We aim to build a web-scale QA system
* Most QA systems before answer extraction do question classification for predicting entity type of answer of the question.

**Flowchart**

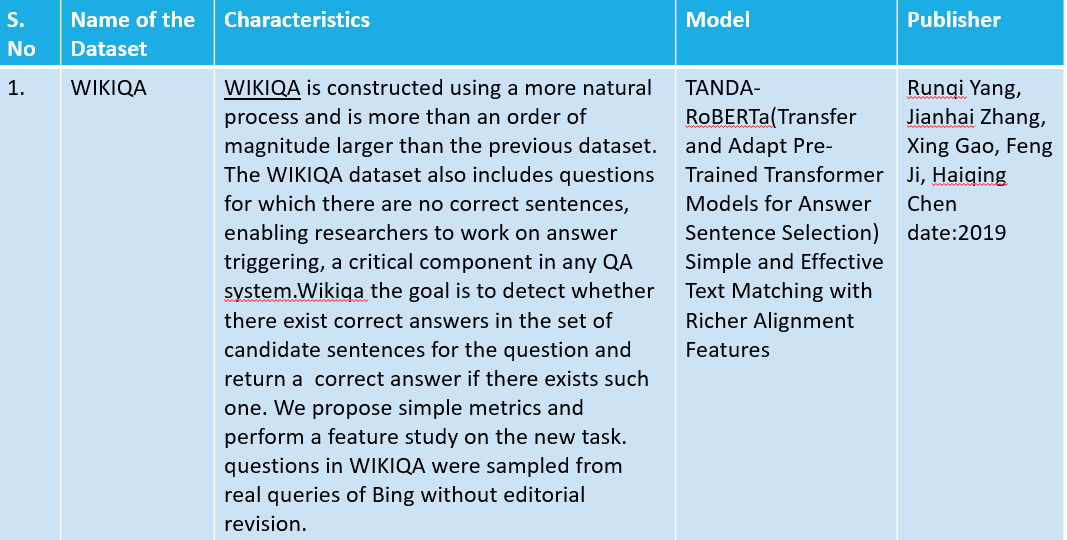
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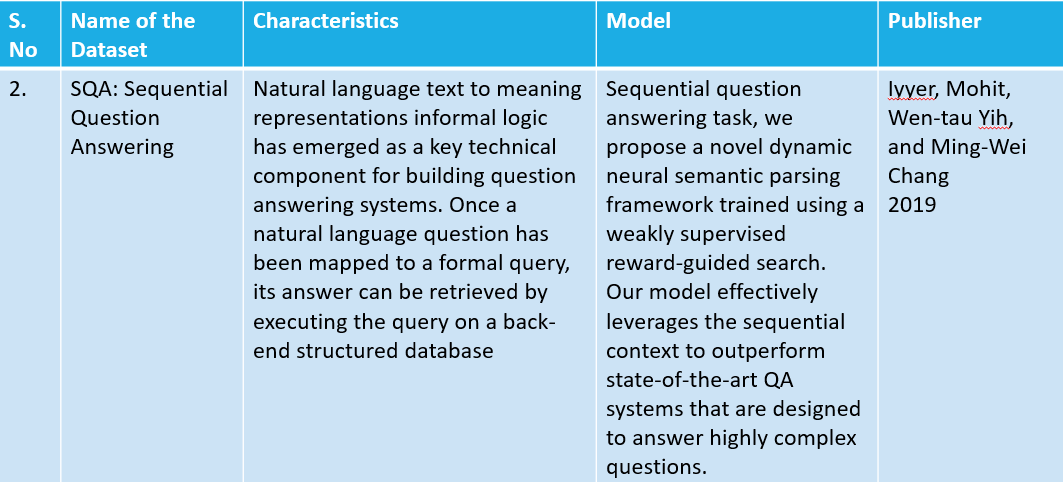
**Literature Survey**

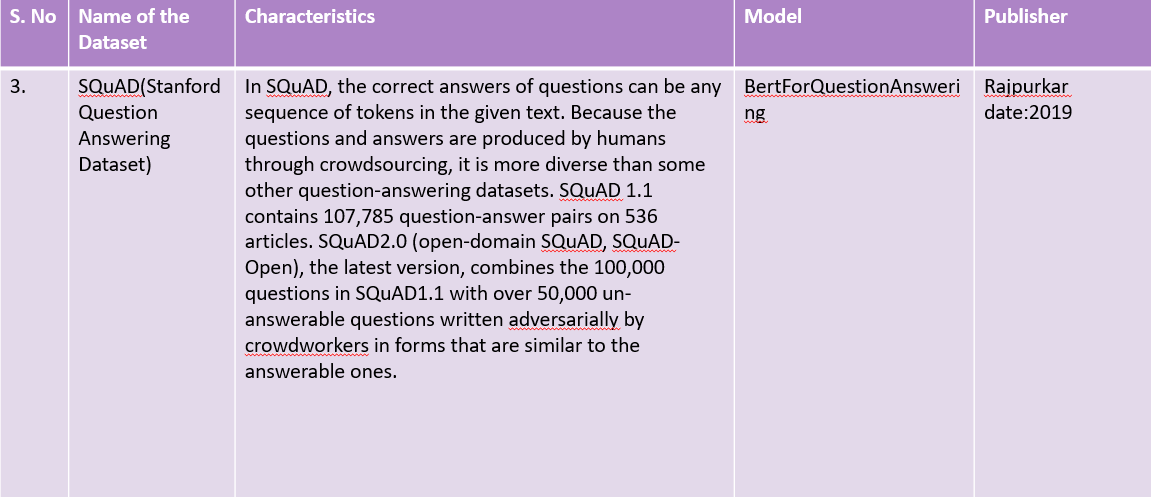
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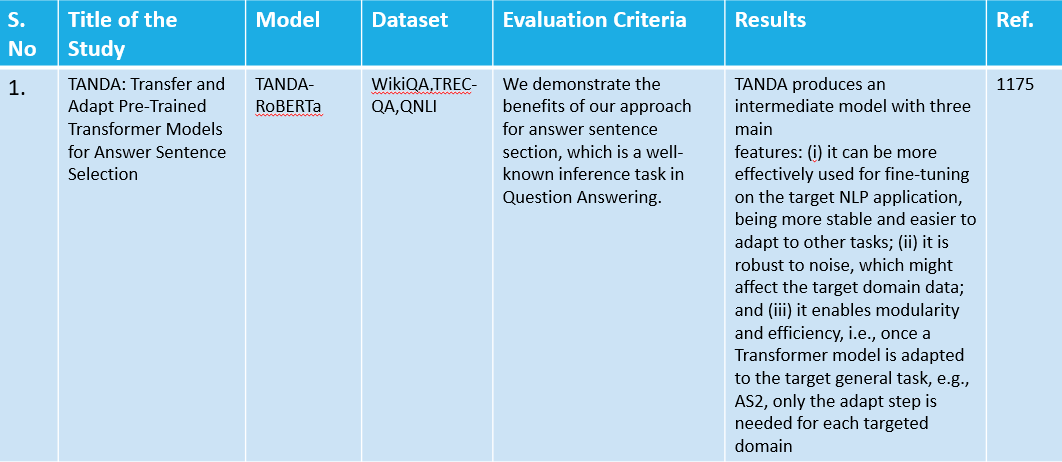
**Dataset:**

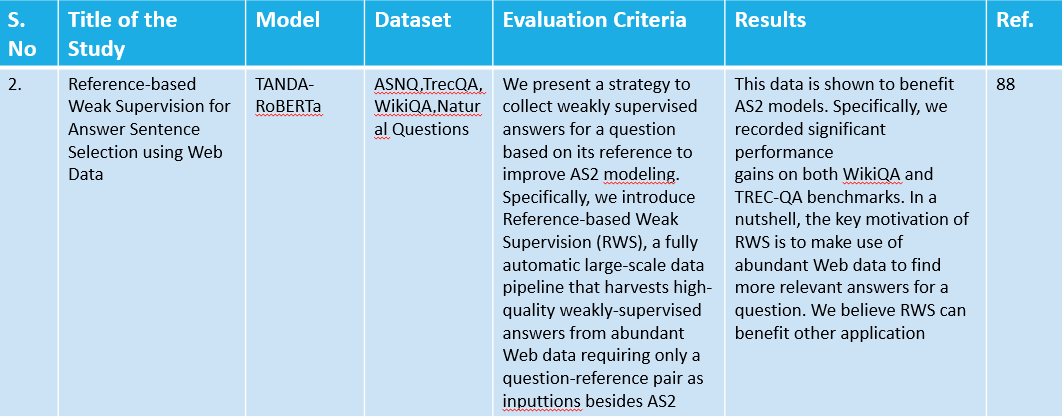
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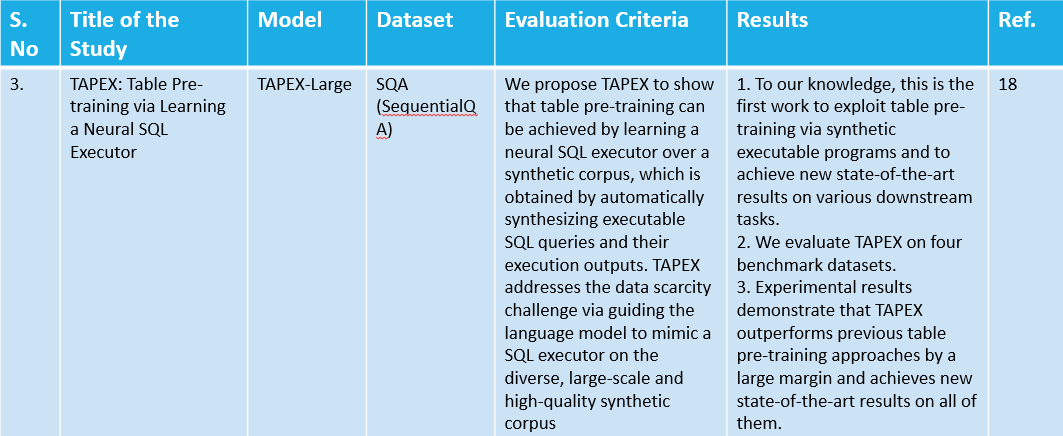
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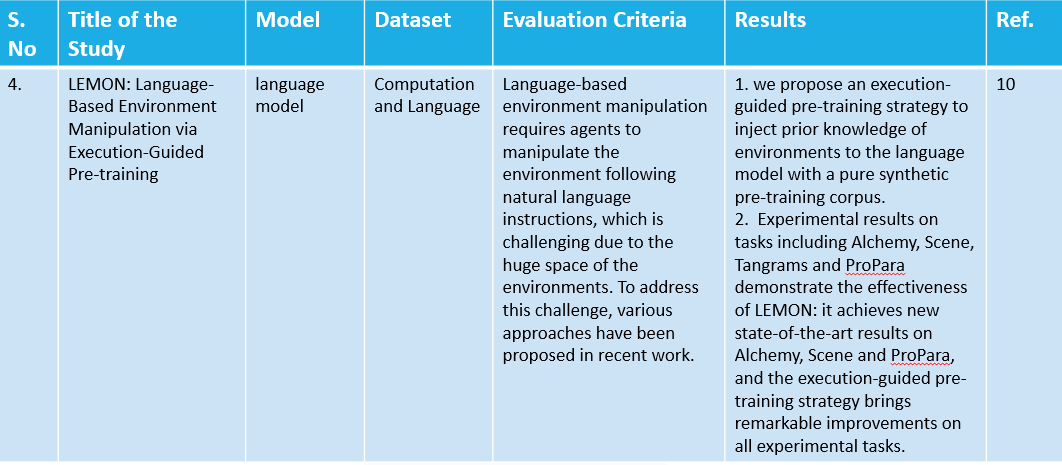
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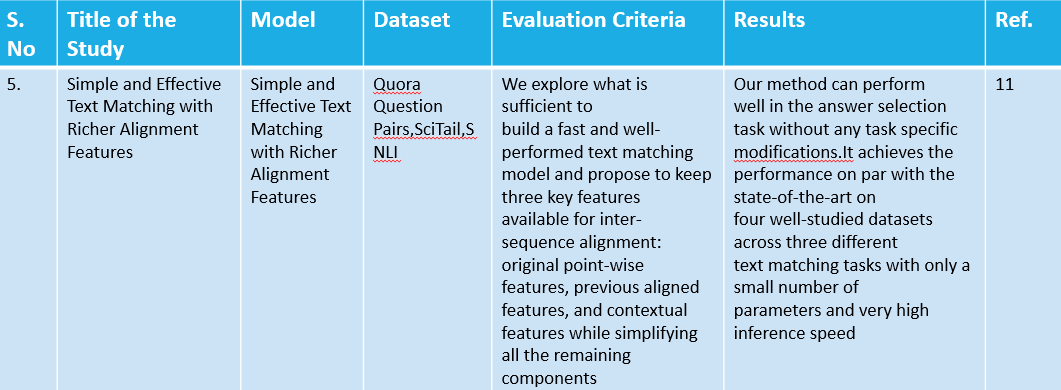
**Technique:**

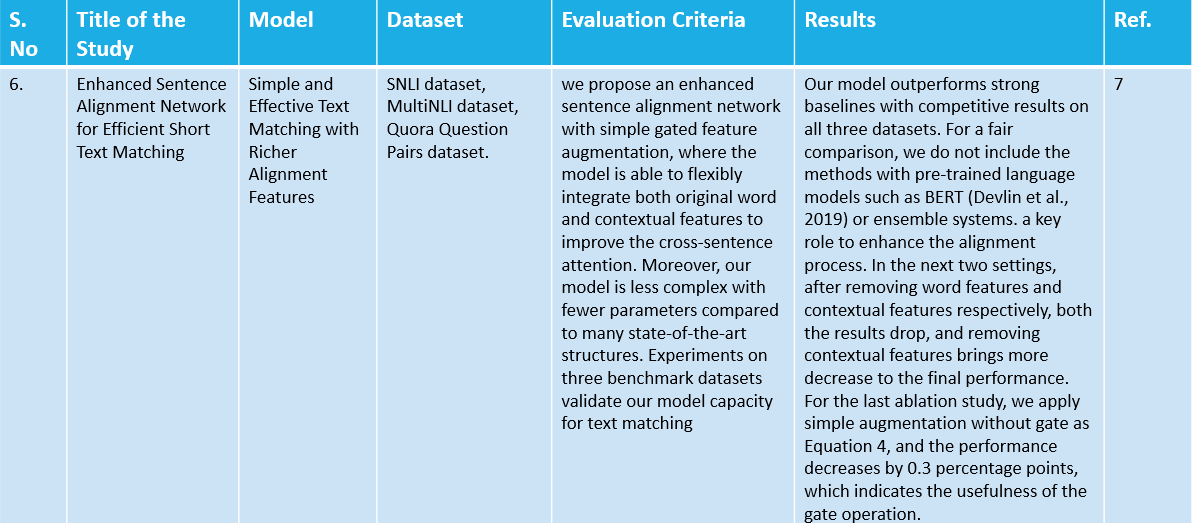
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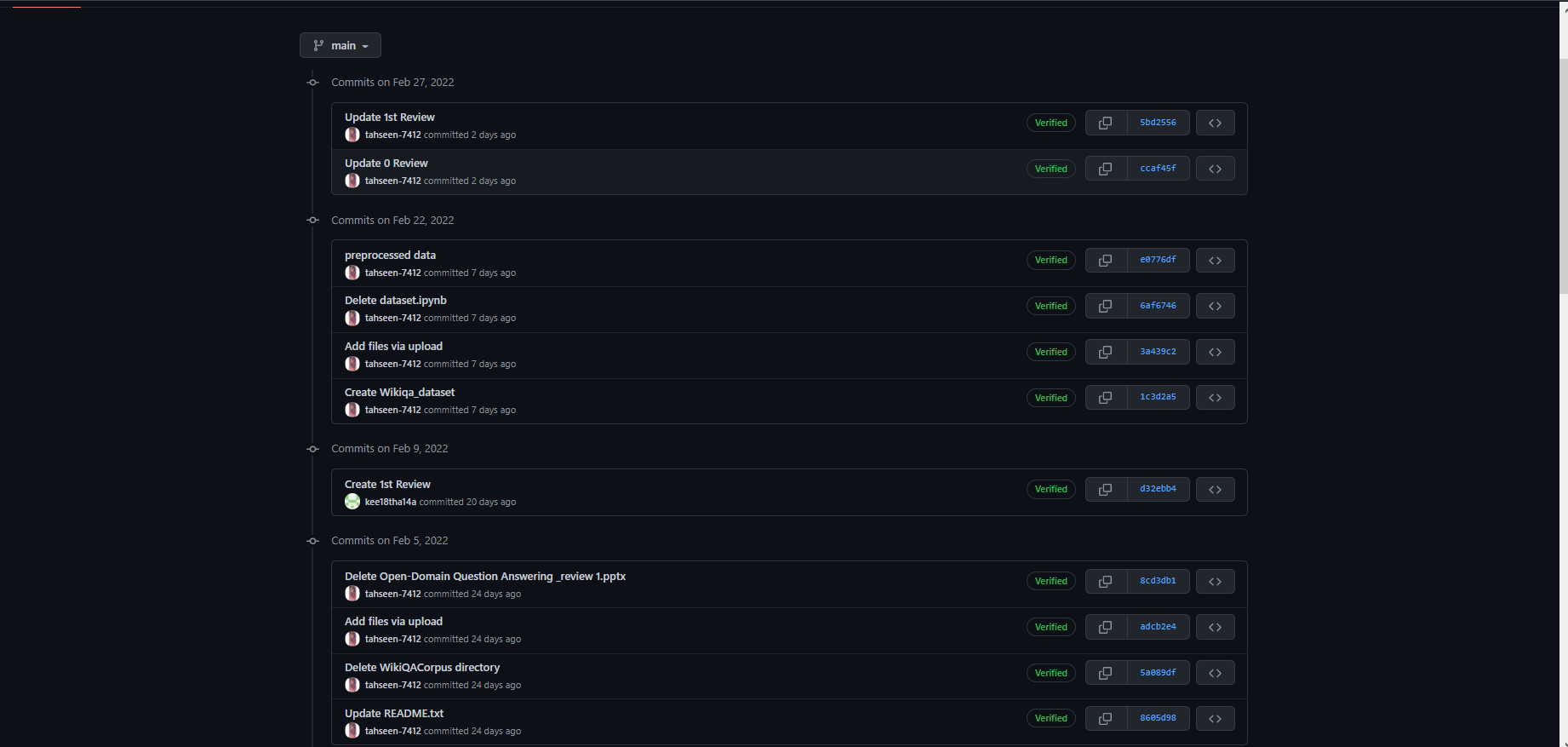
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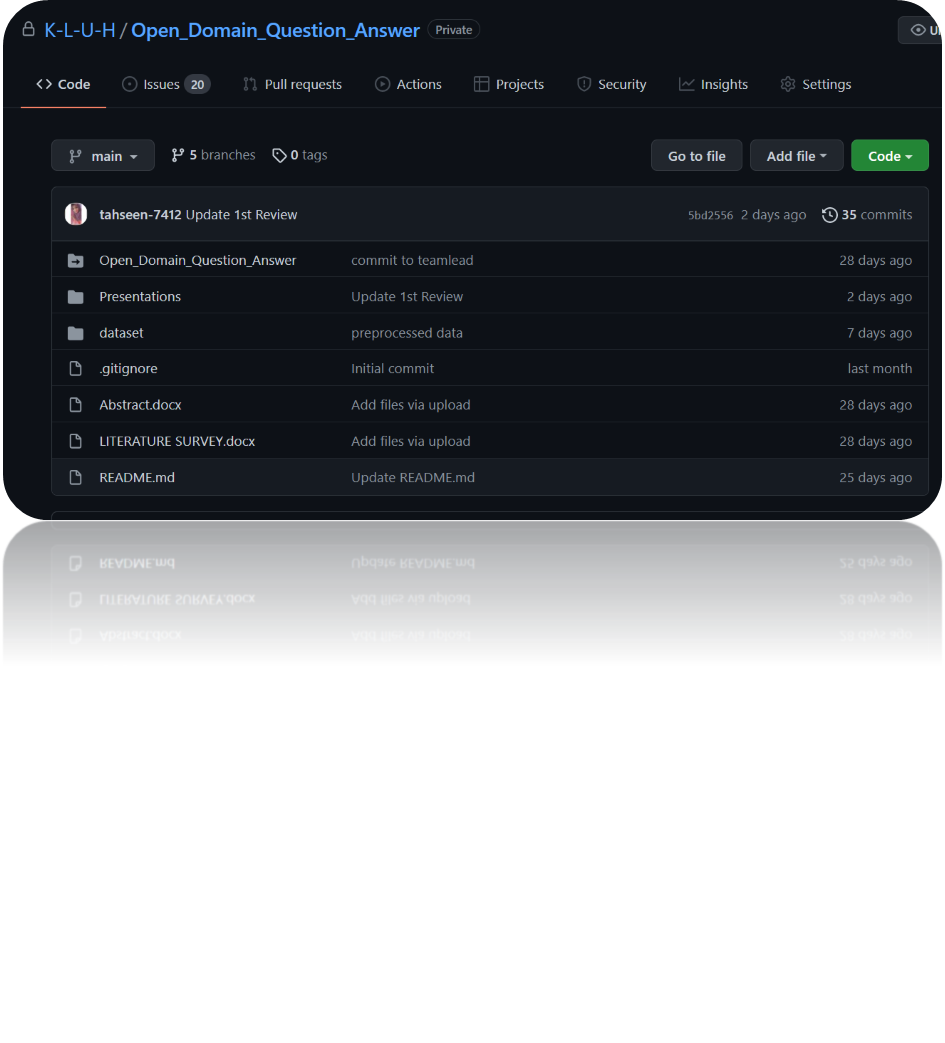
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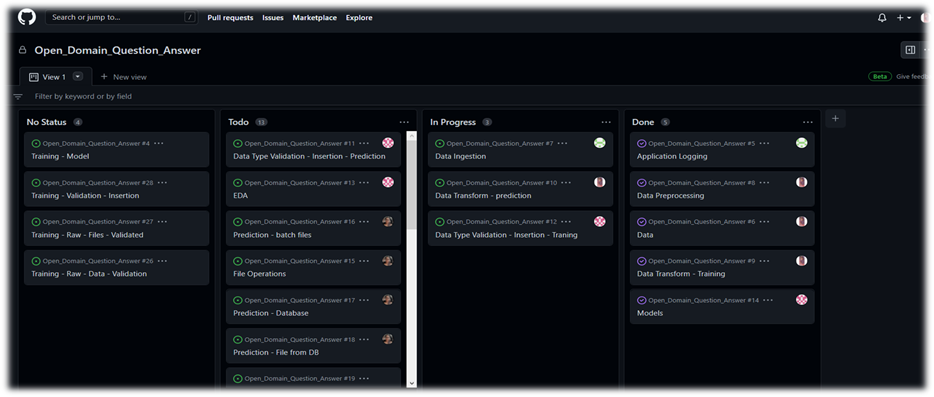
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**Git commits (Interval 31 commits after 1st review)**

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**Work In Progress**

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**Pre-processing code and techniques**

step1:

!pip install datasets

step2:

from datasets import load\_dataset

squad = load\_dataset('squad\_v2',split = 'train')

Squad

step3:

print(squad[0]['context'][:60])

print(squad[0]['answers']['answer\_start'])

step4:

squad[0]['answers']['answer\_start'][0] + len(squad[0]['answers']['text'][0])

step5:

squad[0]['context'][269:286]

step6:

context = squad[0]['context']

gold\_text = squad[0]['answers']['text'][0]

start\_idx = squad[0]['answers']['answer\_start'][0]

end\_idx = start\_idx +len(gold\_text)

print(gold\_text)

print(start\_idx,end\_idx)

print(context[start\_idx:end\_idx])

step7:

squad[2075]

step8:

def get\_char\_positions(sample):

if len(sample['answers']['text']) == 0:

text = ''

answer\_start = 0

answer\_end = 0

else:

text = sample['answers']['text'][0]

answer\_start = sample['answers']['answer\_start'][0]

answer\_end = answer\_start + len(text)

return {

'text': text,

'answer\_start': answer\_start,

'answer\_end': answer\_end

}

squad = squad.map(lambda x: {

'answers': get\_char\_positions(x)

})

step9:

squad[0]

step10:

!pip install transformers

step11:

from transformers import BertTokenizerFast

tokenizer = BertTokenizerFast.from\_pretrained('bert-base-uncased')

step12:

squad = squad.map(lambda x: tokenizer(

x['question'], x['context'], max\_length = 384,

padding = 'max\_length', truncation = True,

return\_offsets\_mapping = True

))

step13:

squad[0]

step14:

tokenizer.decode(squad[0]['input\_ids'])

step15:

squad[0]['token\_type\_ids’]

step16:

question\_len = 0

for x in squad[0]['token\_type\_ids']:

if x != 1:

question\_len += 1

else:

break

context\_len = sum(squad[0]['token\_type\_ids'])

question\_len, context\_len

step17:

tokenizer.decode(squad[0]['input\_ids'][:question\_len])

step18:

tokenizer.decode(squad[0]['input\_ids'][question\_len:context\_len+question\_len])

step19:

context\_mappings = squad[0]['offset\_mapping'][question\_len:][:context\_len-1]

char\_start = squad[0]['answers']['answer\_start']

char\_end = squad[0]['answers']['answer\_end']

for i, mapping in enumerate(context\_mappings):

if char\_start >= mapping[0] and char\_start <= mapping [0]:

token\_start = question\_len + i

if char\_end >= mapping[0] and char\_end <= mapping[1]:

token\_end = question\_len + i + 1

break

if i == len(context\_mappings) - 1:

token\_start, token\_end = 0, 0

break

squad[0]['answers']['text']

step20:

squad

step21:

squad = squad.remove\_columns(['id','title','context','question','answers','offset\_mapping'])

squad

step22:

!pip install transformers

step23:

from transformers import BertForQuestionAnswering

model = BertForQuestionAnswering.from\_pretrained('bert-base-uncased')

step24:

from transformers import TrainingArguments

batch\_size = 24

epochs = 3

args = TrainingArguments(

'bert-base-uncased-squad2',

learning\_rate=2e-5,

per\_device\_eval\_batch\_size=batch\_size,

num\_train\_epochs=epochs,

weight\_decay=0.1,

warmup\_steps=int(len(squad) \* epochs \* 0.1)

)

from transformers import default\_data\_collator

data\_collator = default\_data\_collator

import torch

print(torch.cuda.is\_available)

from transformers import Trainer

import torch

device = 'cuda : 0' if torch.cuda.is\_available() else 'cpu'

trainer = Trainer(

model.to(device),

args,

train\_dataset = squad,

data\_collator = data\_collator,

tokenizer = tokenizer

)

trainer.train()

**Alpha Testing**

<!DOCTYPE html>

<html>

<head>

<meta name="viewport" content="with=device-width, initial-scale=1.0">

<title>Open Domain Question And Answer</title>

<link rel ="stylesheet" href="style.css">

<link rel="preconnect" href="https://fonts.googleapis.com">

<link rel="preconnect" href="https://fonts.gstatic.com" crossorigin>

<link rel="stylesheet" href="https://stackpath.bootstrapcdn.com/font-awesome/4.7.0/css/font-awesome.min.css">

</head>

<body>

<section class="header">

<nav>

<div class="nav-links" id="navLinks">

<i class="fa fa-times-circle" onclick="hideMenu()"></i>

<ul>

<li><a href="index.html">HOME</a></li>

<li><a href="about.html">ABOUT</a></li>

<li><a href="QA.html">Q/A</a></li>

<li><a href="contact.html">CONTACT</a></li>

</ul>

</div>

<i class="fa fa-bars" onclick="showMenu()"></i>

</nav>

<div class="text-box">

<p>Open Domain Question And Answer</p>

<a href="" class="hero-btn">Click here to ask Question</a>

</div>

</section>

<!---------- call to action-------->

<center>

<section class="cta">

<h1>Team Contact</h1>

<a href="" class="hero-btn">CONTACT US</a>

</section>

<!----- footer ---------->

<section class="footer">

<h4>About Us</h4>

<p>Students from koneru lakshmaiah education foundation hyderabad</p>

<div class="icons">

<i class="fa fa-facebook"></i>

<i class="fa fa-twitter"></i>

<i class="fa fa-instagram"></i>

<i class="fa fa-linkedin"></i>

<i class="fa fa-github"></i>

</section>

</center>

<!-----JavaScript for Toggle Menu----->

<script>

var navLinks = document.getElementById("navLinks");

function showMenu(){

navLinks.style.right = "0";

}

function hideMenu(){

navLinks.style.right = "-200px";

}</script>

</body>

</html>



**Division of work among the group members**

Preprocessing code and Techniques – Tahseen Begum

Alpha Testing – E. Pravallika and N. Sowgna

Documentation, PowerPoint, Flowchart– N. Sowgna, Keerthana

**Conclusion**

We have completed the front-end for this project.

Next we will work on the back-end.

The question answering system to produce relevant, correct, and complete answers to the point.

Hence many evaluation metrics were developed to measure such ambiguous terminologies.

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