Truth or DeGPTion: Evaluating Lie Detection Capabilities of GPT-3.5 through Fine-Tuning on Personal Opinions, Autobiographical Memories, and Intentions

Tanner Graves
tanneraaron.graves@studenti.unipd.it

Marco Uderzo
marco.uderzo@studenti.unipd.it

Francesco Vo
francesco.vo@studenti.unipd.it

Mehran Faraji
mehran.faraji@studenti.unipd.it

Claudio Palmeri
claudio.palmeri@studenti.unipd.it

Abstract

This paper aims at evaluating the capabilities of GPT3.5 in the task of Lie Detection. This is done through the fine-tuning of GPT-3.5 on three English-language datasets encompassing personal opinions, autobiographical memories, and future intentions. Fine-tuning of LLMs consists in adapting a pre-trained language model to a specific task by further training the model on task-specific data, thereby enhancing its ability to generate contextually relevant and coherent text in line with the desired task objectives. In our investigation, the objective is to discern and classify instances of truth or deception.

1. Introduction

Numerous academic publications consistently assert that the human capacity to discriminate between veracity and deception rests at chance-level proficiency. Consequently, an escalating interest has emerged in the application of machine learning (ML) methodologies, particularly those rooted in the Transformer Model, to enhance the accuracy of truthfulness prediction for statements. The intrinsic aptitude of ML models for pattern recognition empowers them to discern subtle cues that elude human perception. This research endeavors to employ OpenAI's GPT-3.5 Large Language Model (LLM) as the focal point, commencing with a comprehensive assessment of the base model's performance. Subsequently, an in-depth examination will be conducted on a fine-tuned GPT-3.5 model, specifically calibrated using the Personal Opinion Dataset (Deceptive Opinions), the Autobiographical Memories Dataset (Hippocorpus), and the Future Intentions Dataset.

1.1. Personal Opinion Dataset

The participants of this study were divided in 4 groups (HIT's) and asked to provide either a truthful or a deceptive opinion on the following topics: Abortion, Cannabis Legalization, Euthanasia, Gay Marriage, Policy on Migrants. An extract from the table is shown below.

Domain	HIT1	HIT2	HIT3	HIT4
Abo	D	T	D	T
CL	T	T	D	D
Eut	T	D	T	D
GM	T	D	T	D
PoM	D	T	D	T

1.2. Autobiographical Memories Dataset

This dataset contains 6854 diary-like short stories about salient life events gathered in 3 steps from 2 groups of people (A,B). The study was conducted as following:

- Stage 1: Group A writes 15-25 sentence truthful stories with a 2-3 sentence summary and a timeframe
- Stage 2: Group B is tasked to write an imaginative story with the summary of group A as a prompt
- Stage 3: After 2 months group A is asked to retell the story starting with their summary as a prompt

At the end a questionnaire was posed.

	# stories	# sents	# words
recalled	2,779	17.8	308.9
imagined	2,756	17.5**	274.2**
retold	1,319	17.3*	296.8**
total	6,854		

1.3. Future Intentions Dataset

The study from which this dataset was collected was conducted as following.

All participants are divided into either the truthful or deceptful group. The former were asked to describe a non-work-related activity that would be doing in the next seven days answering the following questions:

- Q1: "Please describe your activity as specific as possible"
- Q2: "Which information can you give us to reassure us that you are telling the truth"

The latter were given 3 activities from the former group, asked which ones didn't apply to them and get randomly assigned one of those. After they were required to answer Q1, Q2 like the former group. At the end a questionnaire was posed.

Veracity	Activity	Statement given by participant
Truthful	Going swimming with my daughter	We go to a Waterbabies class every week, where my 16-month-old is learning to swim. We do lots of activities in the water, such as learning to blow bubbles, using floats to aid swimming, splashing and learning how to save themselves should they ever fall in. I find this activity important as I enjoy spending time with my daughter and swimming is an important life skill.
Deceptive	Going swimming with my daughter (assigned)	I will be taking my 8-year-old daughter swimming this Saturday. We'll be going early in the morning, as it's generally a lot quieter at that time, and my daughter is always up early watching cartoons anyway (5 am!). I'm trying to teach her how to swim in the deep end before she starts her new school in September as they have swimming lessons there twice a week.

In total, the Future Intentions Dataset is comprised of 1640 examples.

2. Methods

2.1. Dataset Preprocessing

The dataset was processed according to 'Scenario 3' of Loconte et al.[?]. In Scenario 3, aggregation was performed on the three train and test sets from Scenario 1 (opinions, memories, intentions), followed by fine-tuning the model on the aggregated sets. This scenario evaluates the model's overall ability to simultaneously classify truthful and deceptive statements across various contexts, without fine tuning the model specifically to one single type of statement. That is to say, the goal is to evaluate the one model on opinions, memories and future intentions indistinctly, treating them just as a randomly shuffled set of statements to be classified as truthful or deceptive.

Regarding the implementation of this process, the single datasets were merged into a single one after being cleaned and shuffled. Then we divided it into training, validation and test set. It is worth noting that we did not use all the data on the initial dataset, this is because the training of a LLM was made simpler by using a smaller training dataset. Finally, the datasets were formatted into JSON to align with the expected input format of the OpenAI API. You can find the Python code in the Appendix section of this paper.

In particular, the model was trained on two versions of the dataset:

- a subset of the original dataset (Train: 210 examples; Validation: 45 examples; Test: 45 examples).
- the full dataset (Train: 6765 examples; Validation: 1450 examples; Test: 1450 examples).

2.2. GPT-3.5 Fine-Tuning

The model was trained utilizing the OpenAI API, and its performance was assessed through testing and comparison with GPT-3.5. Further experimentation was conducted to assess the impact of engineering the system prompt on overall performance.

Specifically, we noticed that the baseline GPT-3.5 prefers giving verbose or indecisive answers. Verbose answers, that actually classify a statement as genuine or deceptive can be classified easily. Nonetheless, the model decides not to give a definitive answer when it thinks it does not have enough information to classify the statement. The following example shows this behaviour.

```
User: "Each and every abortion
is essentially a tragedy. The
potential mother will suffer
unforeseen consequences. Society
as a whole will be deprived of
the potential it could have
received from the new life."


Baseline GPT-3.5: "There is no
objective truth to the statement
as it expresses subjective opinions
and beliefs about abortion. It cannot
be definitively classified as
'True' or 'False'."
```

To address this issue it was necessary to engineer a system prompt that discourages this behaviour and adequately explains the task. This prompt is provided to the model at every example query, so instructions should be concise to minimize any token overhead that leads to increased cost of training and queries.

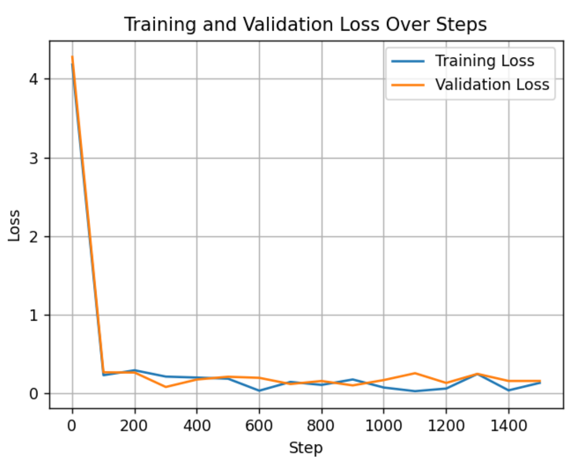
```
System Prompt to Fine-Tuned GPT-3.5:

"You are an expert capable of
discerning truthful from deceptive
opinions based on speech patterns.
Definitively classify the following
statement as 'True' or 'False',
based on the likelihood the statement
represents a genuinely held belief
or a deception."
```

This issue is avoided in the fine-tuned models as the training process rewards our expected behaviour and output format.

The hyperparameters used for fine-tuning the model are declared in the table below, together with the fine-tuning training loss over the steps.

Model	Hyperparameter	Value
Model 1	Learning Rate	0.001
	Epochs	50
	Batch Size	32
Model 2	Learning Rate	0.01
	Epochs	30
	Batch Size	64



10-fold cross validation is a practice to be talked about carefully when it comes to experiments with cost constraints. Indeed, such validation becomes very expensive, since OpenAI API calls are charged with a fee. (To be decided if we want to do this or not). To keep costs low, we decided to perform 10-fold cross validation only on the smaller model. Of course tough, we would expect a slightly better performance using the full model. (Also explain)

2.3. Stylometric Analysis

3. Results

3.1. Lie Detection Task Performance

Firstly, we evaluated the non-fine-tuned GPT-3.5 model, achieving 71.1% accuracy. After fine-tuning the 300 and 1500 model, we evaluated them in the same way. Both the '300 Model' and '1500 Model' achieved 82.2% accuracy, showing a considerable improvement in performance. Moreover, the size difference in training example did not affect the accuracy whatsoever, showing that fine-tuning on a smaller dataset is a good option when training costs have to be minimized.

3.2. Explainability Analysis (?)

4. Discussion

Even though the baseline GPT-3.5 model is still capable of outperforming human capabilities, which are at chance level, by a solid margin, the fine tuning process improves performance by 11.1% in terms of accuracy.

After examining the performance by class we found that the '1500 Model' performs poorly on the Future Intentions Dataset, with a 69.7% accuracy, which drags the overall performace down.

5. TO DO

To do list (+ things we might do that the Loconte paper mentions)

- fine tuning explaination
- cross-validation on smaller model (so we are in the same setting as Loconte, even if it might cost a bit more)
- rerunning performance 3 times for statistical significance (mean +/- 0.x)
- training hyperparams (see table)
- stylometric analysis if possible (see supplemental file at end of loconte paper)
- better discussion, seems to lack a bit (if there are interesting considerations to be made)
- any idea why the Future Intentions Dataset has lower accuracy?

6. Code Availability

The datasets used and all the code used for this project is available at the following GitHub Repository.

References

[1] Loconte et al. Verbal lie detection using large language models. 2023.

7. Appendix

7.1. Python Code: Scenario 3 Dataset Preprocessing

The following code preprocesses the dataset according to Scenario 3. The original Python Notebook is located at the following link in our GitHub Repository

```
import numpy as np
import pandas as pd
from sklearn.model_selection import train_test_split

dc = pd.read_csv('DecOp_data_EN_500.csv', sep=',', encoding='UTF-8')

d1 = []
for i in range(dc.shape[0]):
  row = dc.iloc[i]
  d1.append({'ID': row['ID'],
      'age' :row['age'], 'gender': row['gender'],
  'sent' : row['A'].replace('\n', " ") ,
  'labels'  : row['GT.A']})

  d1.append({'ID': row['ID'],
      'age' :row['age'], 'gender': row['gender'],
  'sent' : row['E'].replace('\n', " ")  ,
  'labels'  : row['GT.E']})
  d1.append({'ID': row['ID'],
      'age' :row['age'], 'gender': row['gender'],
  'sent' : row['GM'].replace('\n', " ")  ,
  'labels'  : row['GT.GM']})

  d1.append({'ID': row['ID'],
      'age' :row['age'], 'gender': row['gender'],
  'sent' : row['Pom'].replace('\n', " ")  ,
  'labels'  : row['GT.Pom']})

  d1.append({'ID': row['ID'],
      'age' :row['age'], 'gender': row['gender'],
  'sent' : row['CL'].replace('\n', " ")  ,
  'labels'  : row['GT.CL']})

decop = pd.DataFrame.from_records(d1)

decop = decop[['ID', 'sent', 'labels']]
decop['type'] = 'A'

decop

hc = pd.read_csv('hcV3-stories.csv', sep=',', encoding='UTF-8')

mem = hc[hc['memType']!='retold']
mem = mem.dropna(subset=['story', 'memType'])
mem = mem[['story', 'memType']]
mem['memType'][mem['memType']=='recalled'] = 'T'
mem['memType'][mem['memType']=='imagined'] = 'F'
mem = mem.rename(columns={'story': 'sent', 'memType': 'labels'})
```

```
mem['type'] = 'B'

mem

intent = pd.read_csv('sign_events_data_statements.csv', encoding="UTF-8")

intent.loc[intent['outcome_class']=='t', 'outcome_class'] = 'T'
intent.loc[intent['outcome_class']=='d', 'outcome_class'] = 'F'
intent['q1'] = intent['q1'].apply(lambda x: x.replace('\n', ''))
intent = intent.rename(columns={'q1': 'sent', 'outcome_class': 'labels'})
intent = intent[['sent', 'labels']]
intent['type'] = 'C'

intent

k = 300
seed = 42

'''
shuffled_df = decop.sample(frac=0.1, random_state=seed).copy()
sample_decop = shuffled_df.iloc[:k,].copy()
sample_decop.drop('ID', axis=1, inplace=True)
sample_decop

data = pd.concat([sample_decop, mem.iloc[:k,].copy(), intent.iloc[:k,].copy()],
                 ignore_index=True)
'''

decop.drop('ID', axis=1, inplace=True)

data = pd.concat([decop, mem, intent], ignore_index=True)
data_shuffle = data.sample(frac=1, random_state=seed+27).reset_index(drop=True)
data_shuffle['labels'] = data_shuffle['labels'].map({'T': 1, 'F': 0})
data_shuffle.rename(columns={'sent': 'text', 'labels': 'label', 'type': 'set'},
                                                                    inplace=True)

data_shuffle = data_shuffle.iloc[:k,]

train_data, temp_data = train_test_split(data_shuffle, test_size=0.3, random_state=42)

val_data, test_data = train_test_split(temp_data, test_size=0.5, random_state=42)

train_data.to_json(f'train_data_{k}.json', orient='records', lines=True)

val_data.to_json(f'val_data_{k}.json', orient='records', lines=True)

test_data.to_json(f'test_data_{k}_class.json', orient='records', lines=True)

data_shuffle.shape

train_data.shape
```

7.2. Python Code: GPT-3 Fine-Tuning

The following code fine-tunes GPT-3 using the official OpenAI APIs. The original Python Notebook is located at the following link in our GitHub Repository

```
import os
from openai import OpenAI
import pandas as pd
import json

key = os.environ.get("OPENAI_API_KEY")
client=OpenAI(api_key=key)

import json

def sanitize_to_utf8(input_str):
    """
    Sanitizes a string field to UTF-8.
    """
    return input_str.encode('utf-8', 'replace').decode('utf-8')

def process_jsonl_file(input_jsonl_path, output_jsonl_path):
    """
    Processes a JSONL file line by line, sanitizes each line to UTF-8,
    and saves it to a new JSONL file.
    """
    with open(input_jsonl_path, 'r', encoding='utf-8') as input_file, \
         open(output_jsonl_path, 'w', encoding='utf-8') as output_file:

        for line in input_file:
            # Parse JSON line
            json_obj = json.loads(line)

            # Sanitize data
            sanitized_json_obj = {key: sanitize_to_utf8(value) if isinstance(value, str)
                                  else value for key, value in json_obj.items()}

            # Write sanitized JSON object to new JSONL file
            output_file.write(json.dumps(sanitized_json_obj) + '\n')

"""Generating intermediate 1500 example sets.

TODO: Preserve what dataset examples come from so we can breakdown performance by dataset.
"""

# Paths to your files
input_jsonl_path = 'train_data_full.json'
output_jsonl_path = 'output.jsonl'

# Process the JSONL file
process_jsonl_file(input_jsonl_path, output_jsonl_path)

sys_prompt = "You are an expert capable of discerning truthful from deceptive opinions
                                                                based on speech patterns."
```

```
def gen_finetune(input, output, test=False):
    with open(input, 'r', encoding='utf-8') as data_in, \
        open(output, 'w') as gpt_out:
        for i, line in enumerate(data_in):
            user_prompt = json.loads(line)['text']
            sys_reply = "True" if json.loads(line)["label"] == 1 else "False"
            if not test:
                payload = {"messages": [{"role": "system", "content": sys_prompt},
                {"role": "user", "content": user_prompt}, {"role": "assistant",
                                                          "content": sys_reply}]}
            else:# exclude response from test set
                payload = {"messages": [{"role": "system", "content": sys_prompt},
                {"role": "user", "content": user_prompt}]}
            gpt_out.write(json.dumps(payload) + '\n')

gen_finetune('train_data_300.json', 'train300_gpt.jsonl')
gen_finetune('val_data_300.json', 'val300_gpt.jsonl')

gen_finetune('train_data_1500.json', 'train1500_gpt.jsonl')
gen_finetune('val_data_1500.json', 'val1500_gpt.jsonl')

gen_finetune('train_data_full.json', 'train_full_gpt.jsonl')
gen_finetune('val_data_full.json', 'val_full_gpt.jsonl')

"""Example of querying model for classification.
Example on model trained on 300 example set.
"""

test_lie = "One morning three months ago I was in a hurry and tripped on the steps
while running to take a shower before work. I ended up fracturing 4 metatarsal bones
that required two surgeries to fix. I was really having a hard time not being able
to walk whenever I wanted to. I really had such a bad attitude at the beginning
because I was so used to being independent. Now that I have recovered I have a
new appreciation for my ability to walk. I feel like the whole time I couldn't
walk I was thinking about how much I took that ability for granted. But now I
choose to walk more than I ever had before. When I walk the dogs I go further
out of my way just to enjoy the ability to do it. I am completely recovered
and I am going to take this as a lesson learned. Nothing is more important
that my personal health. I need to make sure that even if I am running late,
I need to take my time and be careful. Instead f making it to work on time,
I ended up missing weeks of work. Now all I do at work is try and catch up
with everything I missed. It was really nice that people at work came and
visited me at the hospital. I really appreciated all the flowers and candy
and food that was delivered. I think that this showed me how loved I truly am."

test_truth = "Each and every abortion is essentially a tragedy.
The potential mother will suffer unforeseen consequences. Society as a whole will
be deprived of the potential it could have received from the new life."

response = client.chat.completions.create(
  model="ft:gpt-3.5-turbo-0613:personal::8S542QSs",
  messages=[
```

```
    {"role": "system", "content": sys_prompt},
    {"role": "user", "content": test_lie},
    {"role": "user", "content": test_truth},
  ]
)
response.choices[0].message.content

mdls = {
    '300':"ft:gpt-3.5-turbo-0613:personal::8S542QSs",
    '3.5':"gpt-3.5-turbo",
    '1500':"ft:gpt-3.5-turbo-0613:personal::8TAkdwiX"
    }

def predict(text, model, sys_prompt):
    response = client.chat.completions.create(
    model=model,
    messages=[
        {"role": "system", "content": sys_prompt},
        {"role": "user", "content": text}
    ]
    )
    return response.choices[0].message.content

test_truth

test_lie

def eval(test_file, mdl, return_df = False, sys_prompt=sys_prompt, by_class=False):
    msgs = []
    preds = []
    trues = []
    replies = []
    set = []
    with open(test_file, 'r') as f:
        for ex in f:
            ex = json.loads(ex)
            msg = ex['text']
            #pred = predict(msg, mdl) == 'True' #'True' if predict(msg) else 'False'
            reply = predict(msg, mdl, sys_prompt) #for debug
            pred = reply == 'True'
            true = ex['label'] == 1
            msgs.append(msg)
            preds.append(pred)
            trues.append(true)
            replies.append(reply) # debug
            if by_class:
                set.append(ex['set'])
    if by_class:
         test_df = pd.DataFrame.from_dict({'msg': msgs, 'reply':replies,
                             'preds': preds, 'target': trues, 'set':set})
    else:
        test_df = pd.DataFrame.from_dict({'msg': msgs, 'reply':replies,
                             'preds': preds, 'target': trues})
```

```
    acc = (test_df['preds'] == test_df['target']).mean()
    if return_df:
        return (test_df, acc)
    else:
        return acc


test_truth

sys_prompt_base = sys_prompt + ' Definitively classify the following statement
                as \'True\' or \'False\', based on the likelihood  the statement
                represents a genuinely held beleif or a deception.'
#base_df, base_acc = predict('test_data_300.json', mdls['3.5'])
predict(test_truth, mdls['300'], sys_prompt=sys_prompt)

test300_df, test300_acc = eval('test_data_300.json', mdls['300'], True,
                                                             sys_prompt=sys_prompt)
print(test300_acc)
test300_df

test300_acc

test35_df, test35_acc = eval('test_data_300.json', mdls['3.5'], True,
                                                         sys_prompt=sys_prompt_base)
print(test35_acc)
test35_df

len(test1500_df)

# Takes a lot of time, cost = $1
#test1500_df, test1500_acc = eval('test_data_1500.json',mdls['1500'],True,
                                                             sys_prompt=sys_prompt)
print(test1500_acc)
test1500_df

test1500_df.to_csv('results1500.csv')

"""Model / Dataset Bias analysis:"""

print('Model truth classification rate: ')
print(test300_df['preds'].mean())
print('Dataset truthful statement rate: ')
print(test300_df['true'].mean())

"""Model performance by dataset"""

sys_prompt

class_df, class_acc = eval('test_data_1500.json', mdl=mdls['1500'],
                            sys_prompt=sys_prompt, return_df=True, by_class=True)

class_df['correct'] = class_df['preds'] == class_df['target']
class_df.groupby('set')['correct'].mean()
```

```
class_df.to_csv('results_class.csv')
```