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

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Abstract

This paper aims at evaluating the capabilities of GPT-3.5 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. Our fine-tuned model achieved an overall 82.2% accuracy on the test set.

1. Introduction

Numerous academic publications consistently prove 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 leveraging the Transformer architecture, 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 paper employs OpenAI's GPT-3.5 Large Language Model (LLM) as the focal point, starting with an 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, following *'Scenario 3'* from Loconte et al.[3]. As stated in Capuozzo et al. [1], previous findings showed a general decrease in classifiers' performance when training and test data belonging to different domains. Interestingly, by employing *Scenario 3*, this study will also take into account both different domains and different types of deception, shedding a broader light on the actual capabilities of Large Language Models in generalizing detection of deceptive linguistic behaviours.

1.1. Personal Opinion Dataset

The participants of this study [1] were divided in 4 groups (Human Intelligent Tasks, HITs) and asked to provide either a truthful or a deceptive opinion on the following topics: Abortion, Cannabis Legalization, Euthanasia, Gay Marriage, Policy on Migrants. The description of the HITs' structure is presented 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

Example of the Personal Opinions Dataset.

	EN	IT
writers	500	500
opinions	2500	2500
sentence count	11219	6302
word count	181016	137709
unique words	7177	10193

Descriptive Statistics of the Personal Opinions Dataset.

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 [4] 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

	# 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		

Descriptive Statistics of the Autobiographical Memories Dataset.

1.3. Future Intentions Dataset

The Future Intentions Dataset is comprised of 1640 examples with two answers each, as each test subject had to answer 2 questions (Q1,Q2). The study [2] 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 they 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 participants of the Deceitful Group 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. Through a questionnare, they excluded those who failed the manipulation check, provided no or too short input, and whose answers to the second question resembled their answer on the first question too much.

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.

Example of the Future Intentions Dataset.

	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		
	M (SD)	Median	Range	M (SD)	Median	Range
Number of words	53.39 (32.20)	46	15; 274	40.21 (26.45)	34	10; 308
Number of sentences	2.59 (1.61)	2	1; 13	2.08 (1.31)	2	1; 12
Characters per word	4.73 (0.35)	4.70	3.43; 6.75	4.74 (0.42)	4.71	3.07; 6.64

Descriptive Statistics of the Future Intentions Dataset.

2. Methods

2.1. Dataset Preprocessing

In our methodology, we adopted *Scenario 3* as outlined by Loconte et al. [3]. This scenario involved the aggregation of three distinct train and test sets from *Scenario 1*, which encompassed statements related to opinions, memories, and future intentions. Subsequently, the model underwent a fine-tuning process using the aggregated sets. The objective of *Scenario 3* was to assess the model's overall capability to classify both truthful and deceptive statements across diverse contexts. Notably, in this scenario, the model was not fine-tuned to a specific type of statement; instead, it was evaluated on opinions, memories, and future intentions collectively, treating them as a randomly shuffled set of statements to be classified without bias towards any particular category.

The implementation of this process involved the merging of individual datasets into a unified one after cleaning and shuffling them. In particular, in the Autobiographical Memories Dataset, the retord category was discarded. This reduced the total number of stories in that dataset to 5,535. It is essential to highlight that we intentionally did not utilize the entire initial dataset. Since we assumed that linguistic styles in deceptive statements change with the actual chosen language, we discarded the Italian sentences in the Deceptive Opinions Dataset. This decision stems from the fact that only the Opinions Dataset presents Italian-language sentences, whereas the majority of the

entire dataset is in English. Keeping the Italian part of the dataset could have represented a challenge for the model to learn deceptive patterns in a single-language context, possibly hindering the overall performances, not to mention it being an additional uncontrolled variable in our study. Moreover, sentences written in Italian would have constituted a minority class, resulting in a massively unbalanced dataset, which is a phenomenon extensively documented in the machine learning field and regarded as problematic. The resulting dataset was then partitioned into training, validation, and test sets. We also created two different training datasets, one smaller and one utilizing the entire data. The former was aimed to computationally simplify the training process of the LLM, while still ensuring effective learning and generalization.

As a final step, the datasets were formatted into `JSON` format to align with the expected input format of the OpenAI API, ensuring seamless integration with the API itself. For a detailed understanding of the implementation code, please refer to the Appendix section of this paper, where the Python code is provided for reference.

Regarding the fine-tuning process, the two different models were trained using the smaller and full dataset as follows:

- 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

This problem is a natural application for large language models, as the embeddings they learn in tandem with their ability for self attention would seem a good model for lie detection, and have shown promise with similar problems. GPT-3.5 has been trained on an incredibly diverse dataset, but does not outperforms humans at lie detection without any fine-tuning, as it is not specifically aware of cues of deception. We aim to improve the capability of GPT-3.5 on the task through the process of fine-tuning. OpenAI has maintained a high degree of secrecy about their fine tuning process, not releasing the specifics of which parameters in the model are tuned, or even how. The loss function employed is able to assess both differences between style and content between text, but in the case of a binary classifier loss is seen to loosely parody accuracy. In similarly large models, however, task specific fine-tuning will typically adjust the parameters in the last couple layers before output.

In our study, we trained the model using the OpenAI API and evaluated its performance through testing and comparison with the baseline GPT-3.5. We also conducted additional experiments to understand how engineering the system prompt affects overall performance. One specific observation we made was regarding the baseline GPT-3.5's tendency to provide verbose or indecisive answers. When faced with statements that could be easily classified as genuine or deceptive, the model tended to provide detailed responses. Moreover, in cases where it lacked sufficient information to confidently categorize a statement, the model often chose not to give a definitive answer.

To exemplify this behavior, let's consider the situation where the model encounters uncertainty regarding a statement, and it chooses not to offer a definitive classification. This characteristic underscores the model's cautious approach when confronted with a potential lack of information, prioritizing the avoidance of incorrect responses over providing answers that may be inaccurate. The actual prompt and response are the following:

```
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 mitigate this issue, we engineered a system prompt designed to discourage the verbose or indecisive behavior exhibited by the model. This tailored prompt also served the crucial purpose of clearly conveying the task requirements to the model. Each time the model encountered an example query, it was presented with this prompt to guide its understanding and response.

Recognizing the importance of efficiency in both training and query costs, we took care to ensure that the instructions in the prompt were concise. The goal was to minimize any unnecessary token overhead that could contribute to an increased cost associated with 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."
```

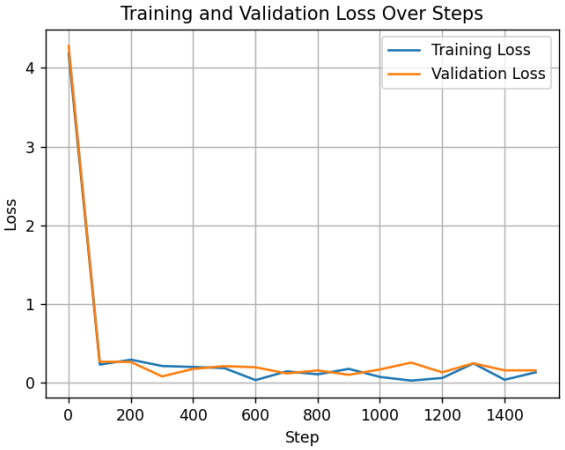
During the fine-tuning process, the model was incentivized to adopt the expected behavior and adhere to the specified output format. This reinforcement mechanism ensured that the model learned and internalized the desired characteristics, minimizing the likelihood of verbose or indecisive responses.

The hyperparameters used for fine-tuning the models are declared in the tables below, together with the fine-tuning training and validation losses over the steps. It is important to clarify that the batch size - the number of training examples used to train a single forward and backward pass - is not something under our control when fine-tuning. By default, the batch size will be dynamically configured to be roughly 0.2% of the number of examples in the training set.

300-Model Fine-Tuning

Hyperparameter	Value
Learning Rate	2.0
Epochs	3
Batch Size	1

Fine-Tuning Hyperparameters of the Cross-Validated model.

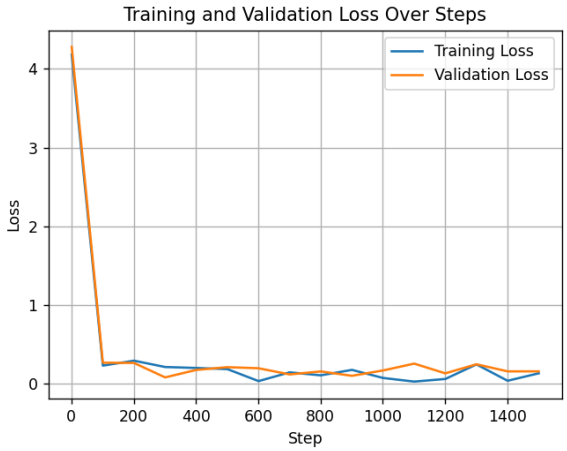


Training Loss of the 300-Model.

Full-Model Fine-Tuning

Hyperparameter	Value
Learning Rate	2.0
Epochs	3
Batch Size	13

Fine-Tuning Hyperparameters of the Full-Model.



Training Loss of the Full-Model.

2.3. Cross-Validation

Wanting to mitigate potential performance variation caused by the small test set of the `300-Model`, we implemented k-fold cross-validation for another set of models. However, k-fold cross validation is a very resource-intensive process, and since we were using the official OpenAI API, we were constrained by costs. Indeed, such validation becomes very expensive: GPT-3.5's pricing is $0.0010 per 1,000 tokens for input and $0.0020 per 1,000 tokens for output, where 1000 tokens equal about 750 words. Because of the cost prohibitive nature of fine tuning large language models we would be training on 3 folds. Each of these folds will have 100 examples from each dataset sampled without replacement. This results in 3 models that were trained on 600 total examples and validated on a set of 300 examples. The OpenAI API uses the validation sets for hyperparameter selection, so a final test set is used to evaluate all models of 600 examples (200 from each set). The decision to give the classes equal representation in each fold was made as a consequence of previous models which underperformed on the Future Intentions Dataset and was a minority class (16.6% of training data for other models).

Below, the diagram explaining the cross-validation process is presented:

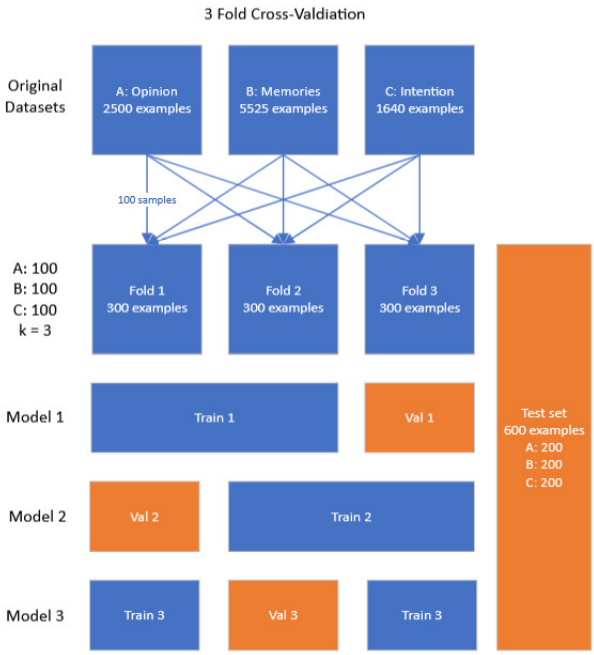
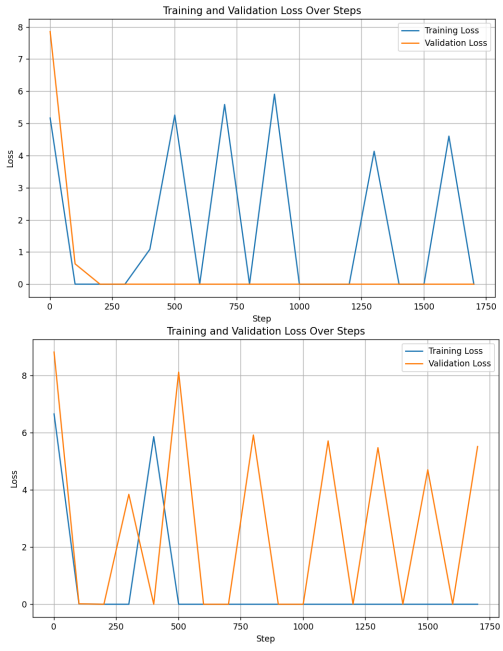
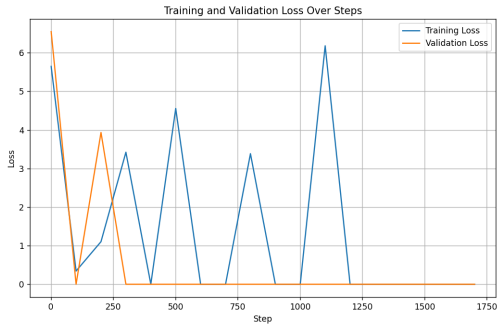


Diagram of the Cross-Validation Process.

Hyperparameter	Value
Learning Rate	2.0
Epochs	3
Batch Size	1

Fine-Tuning Hyperparameters of the Cross-Validated model(s).





Training Loss of the Cross-Validated model(s).

It is evident from the above graphs that the losses of the cross-validated models do not look as smooth as expected. This behaviour can be attributed to the low training set size used for cross-validation, causing the gradient to be inexact. Nonetheless, they are still generalizing well as seen in the Validation curves.

3. Results

3.1. Lie Detection Task Performance

Initially, our evaluation began with the assessment of the non-fine-tuned baseline GPT-3.5 model, resulting in an accuracy of 49%, which is at chance level. Subsequently, we fine-tuned two distinct models: the `300-Model` and the `Full-Model`, meaning that the models were trained with 300 examples and the full training set respectively. Upon completion of the fine-tuning process, we subjected both models to the same evaluation methodology.

As expected, the `300-Model` performed worse than the `Full-Model`. The latter exhibited a remarkable improvement in performance, achieving an overall accuracy of 82.2%, whereas the former achieved an overall accuracy of 65.5%. This observation suggests that when fine-tuning, performance positively scales with the size of the training set. Considering that the base GPT-3.5 model was performing at chance level, the fine-tuning process yielded consistent and substantial enhancements in accuracy when it came to differenciating between truthful and deceptive statements, even across multiple contexts. However, the aforementioned finding raises the problem of the trade-off between overall performance of the model and training costs for fine-tuning when cross-validating. In fact, each OpenAI's API call is subject to a small fee, which, considering the total amount of calls needed and its positive relationship with the dimension of the training set, can result in great training costs.

In adherence to established Machine Learning best practices, the cross-validation approach allows for a comprehensive assessment of the model's generalization

capabilities and robustness across diverse data samples, giving more accurate and reliable results. The choice of `k` is crucial for this process, and also determines the amount of resources that will be used. Ideally, 10-fold cross-validation is to be chosen. Though, to keep the cost low, we decided to perform 3-fold cross validation on the `300-Model`. Considering this, it was expected that the cross-validated smaller model would perform worse than the Full-Model, and we could safely assume that, without training costs as a factor, cross-validating the `Full-Model` would have performed way better, closely to the non-cross-validated `Full-Model`. The cross-validated `CV-Model` achieved 75.2% accuracy, showing cross-validation to improve the performace over the `300-Model`, although, as expected, not being as accurate as the `Full-Model`.

The following table provides a detailed breakdown of the models' performances, specifically focusing on accuracy:

Model	Overrall Accuracy
Baseline GPT-3.5	49.5%
300-Model	65.5%
Full-Model	82.2%
CV-Model	75.2%

Overall Accuracy of the models compared.

Model	Dataset	Accuracy
Base GPT-3.5	Personal Opinions	49.5%
	Autobio. Memories	47.5%
	Future Intentions	51.5%
300-Model	Personal Opinions	79.1%
	Autobio. Memories	67.3%
	Future Intentions	50.2%
Full-Model	Personal Opinions	86.3%
	Autobio. Memories	82.3%
	Future Intentions	69.7%

Class-wise accuracy of the models compared.

	Model 1	Model 2	Model 3
Personal Op.	83.5%	83.5%	80.0%
Autobio. Memories	68.0%	69.5%	70.5%
Future Intentions	72.5%	72.5%	70.0%
Macro avg. Acc.	74.7%	75.2%	73.5%

Class-wise accuracy of Cross-Validated model.

4. Discussion

In the present study, we delved into the effectiveness of Large Language Models, specifically GPT-3.5, in the task of lie detection. We considered both the baseline non-fine-tuned GPT-3.5 and two instances fine-tuned accordingly with *'Scenario 3'* from Loconte et al.[3]. Our primary objective was to investigate the model's capacity to learn and generalize intrinsic linguistic representations of deception across a spectrum of contexts. This investigation was conducted using three distinct datasets, each comprising statements related to personal opinions, autobiographical experiences, and future intentions, thereby ensuring a comprehensive exploration of the model's capabilities.

Despite the baseline GPT-3.5 model's initial incapability to surpass human performance - where human capabilities typically hover around chance level - the fine-tuning process on the non-cross-validated `Full-Model` further enhanced its performance by 32.7% in terms of accuracy. This substantial improvement underscores the efficacy of the model to capture the nuances of deceptive language use.

Upon closer examination of performance by class, a noteworthy finding emerged for the `Full-Model`: the models exhibited suboptimal performance on the Future Intentions Dataset, achieving a modest 69.7% accuracy. This specific performance dip in one dataset had a discernible impact on the overall accuracy of the model.

When taking the `300-Model` into consideration, the overall accuracy gain compared to the baseline GPT-3.5 was 16%. Interestingly, this model did not see any improvements in the Future Intentions Dataset, performing slightly worse than baseline, although this can be considered coincidental.

Of particular interest was the observation that training GPT-3.5 on a smaller subset of data compromised results when compared to training on a larger set. This observation has significant implications, making the fine-tuning process problematic in terms of training costs, expecially when following best practices like performing k-fold cross-validation.

The cross-validated `CV-Model`, instead, represents the most accurate representation of the capability of the model trained on a smaller dataset, improving its accuracy by an additional 9.7% from the `300-Model` and by 25.7% from the base GPT-3.5. Interestingly, this model had a way better accuracy in the Future Intentions Dataset compared to both the `300-Model` and `Full-Model`, showing cross-validation to be particularly effective in this case. This variability in accuracy across different dataset sizes shows that the Future Intentions Dataset is affected the most compared to the other datasets used.

Overall, we can confidently state that fine-tuning massively improved the performance of GPT-3.5 in the task of lie deception, confirming the assumption that Transformer-based Large Language Models are effective in deceptive pattern recognition. Findings from our study also demonstrate that size of datasets is positively correlated to better performance, and that cross-validation is effective in further consolidating it.

Future improvements on the project could be performing 10-fold cross-validation on the `Full-Model` to have a better understanding of the full capabilities of GPT-3.5 in detecting deception leveraging the full dataset. Moreover, the use of stylometric analysis could shed light on the linguistic styles of liars and how they differ from truth tellers.

5. Code Availability

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

References

[1] Capuozzo et al. Decop: A multilingual and multi-domain corpus for detecting deception in typed text. 2020.

[2] Kleinberg et al. How humans impair automated deception detection performance. 2021.

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

[4] Sap et al. Quantifying the narrative flow of imagined versus autobiographical stories. 2022.

6. Appendix

We encourage to browse the Python Code directly from the GitHub repository at the following link.

6.1. 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
```

6.2. Python Code: GPT-3.5 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):
    return input_str.encode('utf-8', 'replace').decode('utf-8')

def process_jsonl_file(input_jsonl_path, output_jsonl_path):

    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:
            json_obj = json.loads(line)
            sanitized_json_obj = {key: sanitize_to_utf8(value) if isinstance(value, str)
                                  else value for key, value in json_obj.items()}
            output_file.write(json.dumps(sanitized_json_obj) + '\n')


input_jsonl_path = 'train_data_full.json'
output_jsonl_path = 'output.jsonl'

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')

# 3 fold CV
```

```
gen_finetune('train_data_CV1.json', 'trainCV1_gpt.jsonl')
gen_finetune('val_data_CV1.json', 'valCV1_gpt.jsonl')
gen_finetune('train_data_CV2.json', 'trainCV2_gpt.jsonl')
gen_finetune('val_data_CV2.json', 'valCV2_gpt.jsonl')
gen_finetune('train_data_CV3.json', 'trainCV3_gpt.jsonl')
gen_finetune('val_data_CV3.json', 'valCV3_gpt.jsonl')

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

gen_finetune('train_data_full.json', 'trainfull_gpt.jsonl')
gen_finetune('val_data_full.json', 'valfull_gpt.jsonl')

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

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 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",
    'full':"ft:gpt-3.5-turbo-0613:personal::8TAkdwiX",
    'CV1':"ft:gpt-3.5-turbo-0613:personal::8ioZ39pz",
    'CV2':"ft:gpt-3.5-turbo-0613:personal::8ipwpWND",
    'CV3':"ft:gpt-3.5-turbo-0613:personal::8ipyhT2n"
    }

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


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

"""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"""

class_df, class_acc = eval('test_data_full.json', mdl=mdls['300'],
                    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')

CV1_df, CV1_acc = eval('CV_test_final.json', mdls['CV1'], return_df=True,
                                                          by_class=True)

CV1_df['correct'] = CV1_df['preds'] == CV1_df['target']
CV1_df.groupby('set')['correct'].mean()

CV1_acc

CV2_df, CV2_acc = eval('CV_test_final.json', mdls['CV2'], return_df=True,
                                                          by_class=True)
CV2_acc

CV2_df['correct'] = CV2_df['preds'] == CV2_df['target']
CV2_df.groupby('set')['correct'].mean()
```

```
CV3_df, CV3_acc = eval('CV_test_final.json', mdls['CV3'], return_df=True,
                                                          by_class=True)
CV3_acc

CV3_df['correct'] = CV3_df['preds'] == CV3_df['target']
CV3_df.groupby('set')['correct'].mean()

base_df, base_acc = eval('CV_test_final.json', mdls['3.5'], return_df=True,
                                                          by_class=True)
base_acc

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

base300_df, base300_acc = eval('test_data_300_class.json', mdls['3.5'],
                                          return_df=True, by_class=True)
base300_acc

base300_df['correct'] = base300_df['preds'] == base300_df['target']
base300_df.groupby('set')['correct'].mean()

def count_jsonl_elements(file_path):
    count = 0
    with open(file_path, 'r', encoding='utf-8') as file:
        for line in file:
            count += 1
    return count

files = [
    'train300_gpt.jsonl', 'val300_gpt.jsonl', 'test_data_300.json',
    'job_trainfull_gpt.jsonl', 'job_valfull_gpt.jsonl', 'test_data_full.json'
        ]
for f in files:
    print(f, count_jsonl_elements(f))

"""Compiling Datafile"""

print("CV1")
CV1_df_ds, CV1_acc_ds = eval('CV_test_final.json', mdls['CV1'], return_df=True,
                                                          by_class=True)
print(CV1_acc_ds)
print("CV2")
CV2_df_ds, CV2_acc_ds = eval('CV_test_final.json', mdls['CV2'], return_df=True,
                                                          by_class=True)
print(CV2_acc_ds)
print("CV3")
CV3_df_ds, CV3_acc_ds = eval('CV_test_final.json', mdls['CV3'], return_df=True,
                                                          by_class=True)
print(CV3_acc_ds)

DATAFILE = pd.concat([
    CV1_df_ds.rename(columns={'msg':'prompt','reply':'mdl1.reply',
```

```
                                                    'preds':'mdl1.pred'}),
    CV2_df_ds.loc[:,['reply','preds']].rename(columns={'reply':'mdl2.reply',
                                                    'preds':'mdl2.pred'}),
    CV3_df_ds.loc[:,['reply','preds']].rename(columns={'reply':'mdl3.reply',
                                                    'preds':'mdl3.pred'})
    ], axis=1)
DATAFILE['mdl1.correct'] = DATAFILE['mdl1.pred'] == DATAFILE['target']
DATAFILE['mdl2.correct'] = DATAFILE['mdl2.pred'] == DATAFILE['target']
DATAFILE['mdl3.correct'] = DATAFILE['mdl3.pred'] == DATAFILE['target']
classes = {'A':'opinion', 'B':'memories', 'C':'intention'}
DATAFILE['set'].replace(classes, inplace=True)
DATAFILE['fold'] = 'test'
col_order = ['prompt','set','fold','target','mdl1.reply','mdl1.pred',
            'mdl1.correct','mdl2.reply','mdl2.pred','mdl2.correct',
            'mdl3.reply','mdl3.pred','mdl3.correct']
DATAFILE = DATAFILE[col_order]
folds = pd.read_csv('FOLDS.csv')[['prompt','target','set','fold']]
folds['set'].replace(classes, inplace=True)
DATAFILE = pd.concat([DATAFILE, folds])
DATAFILE.to_csv('DATAFILE.csv')
#DATAFILE.to_excel('DATAFILE.xlsx')
DATAFILE

CV1_df.to_csv('dat_mdl1.csv')
CV2_df.to_csv('dat_mdl2.csv')
CV3_df.to_csv('dat_mdl3.csv')
```