

Βουκούτης Λέων – A.M.: 7115182200003 – leonvouk@gmail.com

Ρουσοπούλου Αλεξάνδρα - A.M.: 7115182200020 – alexiarouso@gmail.com

Σαϊβανίδου Αλεξάνδρα - A.M.: 7115182200021 – alexansaivan1999@gmail.com

Τυροκομάκη Αργυρή - A.M.: 7115182200025 – irotyrokomaki@gmail.com

M908 Υπολογιστική Γλωσσολογία και Επεξεργασία Φυσικής Γλώσσας και Επεξεργασία και Διαχείριση Γλωσσικών Πόρων

Mini Project: GNTLM (Guidance couNseling Tuned Language Model)

Table of Contents

1. Task overview.....	2
2. Related work.....	2
3. Data acquisition and preprocessing.....	3
4. Methodology.....	6
4.1. Falcon-7B.....	6
4.2. Instruction tuning.....	7
4.3. QLoRa.....	7
4.4. Our implementation.....	7
4.5. Inference.....	11
5. Experimental results.....	12
6. Evaluation.....	15
7. Challenges and limitations.....	17
7.1. Dataset biases.....	17
7.2. Base model biases.....	18
7.3. Implementation biases.....	18
8. Recommended steps – Further work.....	18
9. Conclusions.....	19
Bibliography.....	20

1. Task overview

Our goal was the creation of a task specific, guidance counseling conversational agent, based on a methodology that would allow us to fine-tune an open-source LLM and conduct inference, on a single commercial GPU making it accessible to a much broader spectrum of people, in comparison to other implementations. We deemed the task feasible, based on literature pointing towards skills and early life experiences affecting a person's vocational future.

2. Related work

Career and occupation choice is a multifaceted process influenced by various factors, including individual characteristics, socio-cultural contexts and factors, and personal experiences. Among these influences, early life experiences have been recognized as crucial in shaping individuals' career development trajectories. This review aims to make an overview to provide insights into how early life experiences impact future career and occupation choices.

To begin with, the importance of early life experiences is crucial in shaping career development. Porfeli and Lee, 2012 suggest that early childhood experiences, such as exposure to diverse activities and supportive environments, can play a significant role in developing career-related interests and skills. The need for parents, educators, and policymakers is highlighted to provide opportunities for exploration and skill development to foster career development during childhood and adolescence.

Career exploration involves the process of self-reflection and examining the world of work to gain a better understanding of one's own characteristics and to discover potential career options that align with these traits. The core objective revolves around answering a fundamental question - "Which vocations would be most befitting for my skill set?". This answer, often influenced by both intentional and unintentional exposure to work experiences via parental influence or media consumption, illuminates one's unwavering commitment towards realizing their professional aspirations through thoughtful decision-making and discerning choices. Several personal attributes exert their influence upon shaping responses towards this seminal inquiry, with gender, social class, and age emerging as significant determinants. During childhood years, children tend to gravitate towards professions predominantly held by individuals sharing the same gender or societal standing. Elevated attraction toward high-profile roles infused with glamour – such as athletes, models or movie stars – is often witnessed during this developmental stage before ultimately steering their trajectory in entirely different career directions as they mature. Young children learn about various careers through sources such as textbooks, adults in their lives, and multimedia platforms, without having a specific focus on particular occupations. Adolescents typically undergo an incremental journey towards attaining confidence in making judicious career choices over time; albeit punctuated by diverse patterns unique to each individual's narrative.

Societal gender roles mediate the relationship between childhood experiences and occupational choice capability (Koçak et al., 2022). The study suggests that traditional gender expectations and stereotypes can limit career choices for individuals, particularly for women. The paper calls for interventions aimed at challenging and dismantling gender stereotypes to enable individuals to make career choices based on their abilities and interests rather than societal expectations.

Hirschi, 2011 focuses on the developmental trajectories of career-choice readiness during adolescence. The research highlights that career development is a dynamic process that evolves over time, influenced by individual differences and contextual factors, such as self-efficacy, career exploration, and decision-making skills, which contribute to career-choice readiness in adolescence.

Lastly, an overview of career development theories and interventions for children and adolescents is provided at Skorikov and Patton, 2007. It emphasizes the importance of early career exploration and the influence of parental support and career-related experiences in shaping future career choices. The paper highlights the need for comprehensive career development programs that integrate academic, personal, and vocational domains to facilitate informed career decision-making.

In conclusion, it is observed that early life experiences have a significant impact on future career and occupational choices. Childhood and adolescence provide critical periods for developing career-related interests, skills, and decision-making abilities. Individual differences, societal gender roles, and contextual factors also play a role in shaping career choices. Therefore, it is essential to provide supportive environments, challenge gender stereotypes, and promote comprehensive career development programs to empower individuals in making informed and fulfilling career decisions.

3. Data acquisition and preprocessing

For the purposes of this project, with the goal of creating a conversational agent that could provide guidance counseling, we decided to use Wikipedia as a data source. To tackle the task at hand, regarding the aforementioned related work, we chose to acquire Wikipedia pages referring to people and take advantage of their structure for our needs.

The purpose of the data collection procedure was to acquire data on living people from Wikipedia and extract their occupations based on the content of their summary sections. The data acquisition process involved gathering the necessary pages, extracting the required information, and creating a mapping between a list of predetermined occupations and the extracted ones.

The initial step of the data acquisition process involved web scraping to retrieve all the pages from the “Category:Living people” on Wikipedia. After obtaining the pages from this

Wikipedia category, we utilized the Wikipedia-API package to automatically collect the necessary data (Majlis, 2021). We focused on extracting the summaries and early life sections, only when both were available, from the collected Wikipedia pages. The main objective of the process was to establish a mapping between the content of the occupation list, created manually, and the content of the summary sections for each living person. This mapping would allow the determination of the profession of each individual by isolating the first sentence of their summary section, since we observed that the main occupations were mentioned in the first sentence. Another factor that lead us to this decision, was that in some cases some of the professions mentioned in the rest of the summary section were also in the list of occupations but did not identify the professional status of the person in question, but a contribution or activity of the person or a reference to another person’s professional status, e.g.

```
"Jorrit_Faassen": {
  "occupation": [
    "businessman"
  ],
  "summary": "Jorrit Joost Faassen (born 24 February 1980) is a Dutch businessman. He was allegedly the husband of Maria Vorontsova and the son-in-law of Russian president Vladimir Putin.",
```

In order to correctly map the person’s occupations to our predetermined list, we considered only discrete words as occupations and not character sequences that might contain the letters of a profession from the list of occupations, as in the following example where the character sequence “dj” in the person’s name in the summary section was taken into account and this individual was incorrectly categorized as a “DJ” and not a “footballer”, as shown below:

```
"Mehdi_Baaloudj": {
  "occupation": [
    "footballer"
  ],
  "summary": "Mehdi Baaloudj (Arabic: \u0645\u0647\u062f\u064a \u0628\u0639\u0644\u0648\u062c; born 2 February 2001) is a professional footballer who plays as a forward for Championnat National club Martigues on loan from Guingamp. Born in France, he is a youth international for Algeria.",
```

We also made sure to incorporate the printing of multiword occupations, so that they would correctly assign to the occupations that were provided by Wikipedia, e.g.

```
"4th_Disciple": {
  "occupation": [
    "audio engineer",
    "record producer"
  ],
```

The decision was made to maintain all occupations as included as each data points output. Including more of an individual’s career paths could lead to better training of the model, in which the causality of a particular career choice and the evidence for the future choice of a particular occupation based on stimuli from early life would be better shown. In the next stage, we redefined the list of occupations, as we manually added some that we considered important, while removing others that did not correspond to those we had extracted from Wikipedia. Lastly, the acquired data on living people, along with their corresponding occupations, was stored in a JSON file.

The final dataset includes 9172 living people and the 5 most frequent occupations together with their frequency of occurrence are presented in the table below:

Occupations and their frequency (in descending order)
footballer: 2417 times
politician: 1565 times
singer: 1032 times
producer: 903 times
artist: 829 times

The average number of tokens in the early life section was 252 tokens, while the maximum number of tokens was 3176. Due to the specifications in the context length of the pre-trained model used, which we'll cover in 4.1, any data points with more than 500 tokens were not injected into the model.

Having formed our final dataset, we proceeded to the annotation process to be utilized in experiment 3, in which we set some guidelines. We annotated only segments in the early life section that we could perceive as “evidence” and influence on future career choice of each individual, e.g.

```
"Lisa_Ho": {
  "occupation": [
    "fashion designer"
  ],
  "early_life": "Ho <<<began sewing at age 4 inspired by her grandmother>>> of African descent, a tailor, whom Ho says she 'probably drove mad'. Ho <<<made patterns out of newspaper and by age 10 had a sewing machine>>>at the end of the kitchen table 'that nobody was allowed to move,' which she used every day to make things for herself and four sisters.\nHo attended Pennant Hills High School. She <<<later trained in fashion design>>> at East Sydney Technical College, graduating in 1981 and spent a year working for three other companies, which she 'hated', before going out on her own.\nLike many of Australia's fashion designers, fresh out of college in 1982, Ho started her career at the Paddington markets for only 6 weeks with her designs that quickly brought her retail and media attention and began the Lisa Ho brand.\nThe Lisa Ho brand was one of the most recognized brands in Australia and had a strong celebrity following with the signature pieces being worn by Delta Goodrem, Bec Cartwright, Sarah Wynter, Elle Macpherson, Sarah Michelle Gellar, Olivia Newton-John and Jennifer Lopez.Her international reputation was first recognized during the Sydney 2000 opening ceremony, which featured a special segment she designed celebrating her role in Australian fashion. She was also asked to design the gown worn by Newton-John for her performance to welcome the Olympic athletes.\nHo's businesses employed 80 staff (excluding out-workers) across 12 signature stores and head office. Her label was also stocked in David Jones stores and available worldwide via her online store.\nHo is engaged to Nick Jacenko.\nHo was one of the victims of serial conman Hamish McLaren (ultimately losing her companies and $350,000 personally) who she met in 2011. She was interviewed during the award-winning 2019 podcast based on his crimes, Who the Hell Is Hamish?.\n"
```

In many cases the annotated pieces of evidence were not “snapshots” and experiences from the family and social environment during childhood and adolescence, but only the person’s academic career.

4. Methodology

We set out to create a model, which anyone could query and match their tendencies, abilities and preferences to potential fitting occupations. Our goal wasn't just to solve a classification problem, but instead to create a model which could perform in zero-shot scenarios and could function as a conversational guidance counseling agent, providing reasoning, direction and alternatives to the user.

In the current landscape of ever emerging LLMs (Large Language Models), such a task could be undertaken by any of the 'titanic' implementations with an exorbitant number of parameters (40B ++). So why did we even bother? Not only the training, but even just the utilization of such LLMs is costly both in financial and environmental terms. Given that, our goal was to create a model whose training and, in extent inference, could be conducted on a single midrange commercial GPU.

To achieve this, we decided to fine-tune an existing open-source LLM for our specific task. Such a process in and of itself would normally require the usage of multiple GPUs, so we conducted it following the Quantum Low-Rank Adaptation approach (QLoRA), which makes the fine-tuning and inference of such LLMs possible on just one GPU.

Since the leak of the source code of Meta's LLaMa model in early 2023 (Touvron et al., 2023), the open-source community has raced to create ever better open LLMs. Such a model is Falcon-7B (tiiuae, 2023), which we chose to fine-tune to our task's needs, based on the instruction tuning methodology.

4.1. Falcon-7B

The Falcon-7B model is a decoder-only causal LM trained on – mostly English and to a lesser extent French – 1.5T tokens. The dataset used comprises both crawled and curated corpora, such as a highly curated version of CommonCrawl, conversations from online forums, technical data from publication portals, code and books.

When choosing between using the base Falcon-7B model and the Falcon-7B-instruct, we went with the base model, since it is recommended for fine tuning on more specific tasks, whereas the instruct model, having already undergone instruction fine tuning, would be harder to focus. One of the main advantages of using the Falcon model family for a task, specifically to be ran on a single commercial GPU is the decoder architecture optimized for inference through the use of multi-query and FlashAttention. The multi-query attention architecture stipulates that the keys and values tensors are shared across attention heads, which subsequently reduces their size and memory requirements during inference. Since each token is incrementally inferred and these tensors require constant loading. FlashAttention on the other hand distributes the attention operations, in a manner that speeds up computation without sacrificing model quality.

It is important to note that the context window for the Falcon-7B is 2048 tokens, which in our case is enough to encapsulate all the information we would like the model to take as an input and provide as an output.

4.2. Instruction tuning

The instruction tuning methodology is a training method used to ‘teach’ LMs how to face certain tasks and generalize their ability to follow instructions and increase their effectiveness in unseen tasks. The method can be focused, as a supervised fine-tuning technique to help the LLM focus on specific task at hand (Wei et al., 2021).

4.3. QLoRA

The LoRA technique proposes a fine-tuning method, where the initial pre-trained model parameters are frozen and rank decomposition matrices of each chosen layer are trained and concatenated to the initial frozen weights, thus greatly reducing the numbers of trainable parameters without sacrificing quality or inference time (Hu et al., 2021).

The QLoRA methodology is an evolution of the LoRA technique and makes the training and inference of LLMs possible on a single commercial GPU (Dettmers et al., 2023). QLoRA proposes a method of quantizing the initial 16-bit model parameters and LoRA adapters into 4-bit tensors (specifically their proposed NF4 type) for storage in two quantization steps to save memory, while de-quantizing them back to 16-bit (specifically BFloat16) during computation, while also parallelizing them through a paged optimizer for gradient updates.

4.4. Our implementation

Our fine-tuning implementation was conducted on a 12GB VRAM GPU, while inference can easily run on a GPU with 8GB of VRAM making the model accessible to single commercial mid-range GPUs.

To fine-tune our model for the task at hand, it was given one specific instruction regardless of the experiment conducted. Which looks as follows:

```
def generate_prompt(doc):
    """
    Generate training prompt
    """
    prompt = f"""
    Below is an instruction that describes a task,
    paired with an input that provides further context. Write a response that appropriately completes the request.
    ### Instruction:
    Based on the information given in the input, predict this person's future occupation.
    ### Input:
    {doc["input"]}
    ### Response:
    {doc["response"]}
    """
    return prompt
```

Using this instruction the model was guided to predict the person's future occupation, basing its decisions on the input.

In all our experiments we used the same QLoRA configuration, as follows:

The Falcon-7B model was loaded in 4-bit, meaning that all parameters were NF4 tensors with double quantization enabled. Ergo, on computation time, the LoRA adapters are dequantized twice into BFloat16 tensors.

Said LoRA adapters were created for the query, key, value tensors of the attention layers with a 5% dropout factor, $r = 16$ and $\alpha = 32$ with r being the rank of the decomposition matrices BA and α/r being the constant amount these matrices are scaled per gradient update step (in our case $\alpha/r = 2$). Our LoRA adapters reduce the amount of required trainable parameters to ~4.7M, making it a much more manageable task for a single GPU.

Shared training parameters:

- For all our experiments a QLoRA specific optimizer was used, namely the `paged_adamw_8bit` optimizer, which deals with the distribution of the gradient updates required to all the devices participating in the calculation.
- During training each mini-batch fed to the model consisted of one training input, since any larger mini-batch size would result in Out of Memory (OOM) errors due to the limited VRAM of the training device.
- During training, all models had a 5% step warmup ratio.

The training process, training resources required and dataset of our approach is different for each of the following experiments:

4.4.1. Whole Dataset using one instruction with a simple output

- Dataset: All 8000 collected data points were used as a corpus, 7700 as a training set and 300 as an evaluation set.

- Prompt: Below we illustrate an example of a simple input training prompt. We can see the whole early life of the person given as an input to the instruction and only the found occupations as the output.

```
{
  "instruction": "Based on the information given in the input, predict this person's future occupation.",
  "input": ""Ikeduba although being a native of Delta State was born in Ebute-Meta in Lagos State a south-western geopolitical zone of Nigeria predominantly occupied by the Yoruba-speaking people of Nigeria and is from a family of six - four children, two male, two female, a mother, and a father of which he is the first born child. Ikeduba was raised from a tender age into adulthood in Lagos state, precisely in Okokondosa Street in Ebute-Meta. Ikeduba received both primary and secondary school education in Lagos State but in bid to obtain a university degree he relocated to the Benin city, a south-south geopolitical zone of Nigeria where he applied to the University of Benin to study Economics. Ikeduba was accepted and eventually graduated from there with a B.Sc. degree in Economics.\n\nIn an interview with Vanguard, a Nigerian print media press, Ikeduba stated that he debuted in the Nigerian movie industry in the year 2000. He described his venture into the Nigerian movie industry as a coincidence as he initially only wanted to accompany a friend to an audition for actors but on reaching their destination he decided to audition also and was successful in it as he was called back and given a movie role. Ikeduba's ability to understand and communicate in all three major languages in Nigeria has been pivotal to his career, he acknowledges this fact and speaks publicly about it. Ikeduba debuted his acting career into the English language only conventional and mainstream Nigerian movie industry known commonly as Hollywood but eventually crossed over to the Yoruba movie industry in Nigeria with the help of Femi Ogundegbe who introduced him to Saheed Balogun who gave him a movie role in a Yoruba movie he was producing titled Omo Alaba. Ikeduba has been stereotyped in the Nigerian movie industry as a "Bad Boy" which he attributed to his appearance, hence in almost all the movies he has featured in, he was always the antagonist or as the Nigerian media puts it "The Bad Boy".\n\nIkeduba is multilingual as he can speak the Yoruba language, the Hausa language the Igbo language as well as the English language, which is the official language of communication in Nigeria.\n""",
  "output": "actor"
}
```

- Process: We passed the training dataset only once through the training process with a low learning rate. This configuration helps with avoiding overfitting to our given instruction and our model doesn't 'forget' previous knowledge, keeping its capability to generalize to unseen data, improving its zero-shot potential.
- Training: Gradient accumulation and weight update batches would happen every four mini-batches, more gradient accumulation steps would result in an OOM error. As mentioned earlier, the model was trained for one epoch only with a starting learning of 0.0003 changing based on a cosine function.
- Resources: The training and evaluation process utilized 10.5 GB of VRAM and 4.4 GB of RAM over 5 hours.

4.4.2. Dataset subset using one instruction with a simple output

- Dataset: A subset of 1500 data points were used as a corpus, 1200 as a training set and 300 as an evaluation set.
- Prompt: Below we illustrate an example of a simple input training prompt. We can see the whole early life of the person given as an input to the instruction and only the found occupations as the output.

```
{
  "instruction": "Based on the information given in the input, predict their future occupation.",
  "input": ""Ojo was acting professionally as a child. At the age of 8, he worked with Akin Lewis, who played a barber on the NTA Ibadan 1980s television series Why Worry. At age 12, he moved with his family to England, where he also attended university. Ojo credits his career on influences from his mother, who was an actress and supportive of his career, Chief Male Ogunyemi, Tunji Oyelana, playwright Wole Soyinka, and Zulu Sofola.\n""",
  "output": "actor"
},
```

- Process: We passed the training dataset four times through the training process. In this experiment we tried to evaluate the effectiveness of our model on unseen data, after training it with a higher focus on a smaller number of examples.
- Training: Gradient accumulation and weight update batches would happen every 4 mini-batches, more gradient accumulation steps would result in an OOM error. The model was trained for four epochs with a starting learning of 0.0003 changing based on a cosine function.

- Resources: The training and evaluation process utilized 10.5 GB VRAM 4.4 GB of RAM over 4.5 hours.

4.4.3. Annotated dataset attempting to provide chain-of-thought

- Dataset: As described in section 3 we annotated a subset of 945 data points from the dataset in an attempt to create prompts that can provide a chain-of-thought to the model, improving its inferential power and providing further context for its answers. We kept 845 as a training set and 100 as an evaluation set (Wei et al., 2022).
- Prompt: Below we illustrate an example of an input training prompt. We can see the whole early life of the person given as an input to the instruction and then the annotated “evidence” given as context in the output along with the occupation found.

```
{
  "instruction": "Based on the information given in the input, predict this person's future occupation.",
  "input": "Tatiana was born in Moscow into the family of an engineer. Her great grandfather on her mother's side was Sergey Vasilievich Baskakov, the Russian composer, a nobleman. Her great grandmother was a Polish gypsy. When Tatiana was 16 years old, her parents divorced. Tatiana left home and became a street musician. She travelled from city to city with her boyfriend, who was also a musician. They stayed at the houses of friends and played guitar. At 18 Tatiana got married, and soon gave birth to her eldest daughter Margarita. Because of her husband's lifestyle, the marriage was unsuccessful and ended in divorce. Tatiana tried many different jobs. She sang on the streets, worked as an insurance agent, and was a bar-tender in one of Moscow's theaters. She also worked as a university secretary and laboratory assistant. Eventually she became a real estate agent and continued working in this area for ten years, until she decided to write her first book. Tatiana is currently in her second marriage. She has three children, Margarita, Anastasia and Anthony.\n",
  "output": "Based on the following pieces of evidence:\n0) Tatiana was born in Moscow into the family of an engineer. Her great grandfather on her mother's side was Sergey Vasilievich Baskakov, the Russian composer, a nobleman. Her great grandmother was a Polish gypsy. When Tatiana was 16 years old, her parents divorced. Tatiana left home and became a street musician.\n1) She travelled from city to city\n2) Because of her husband's lifestyle, the marriage was unsuccessful and ended in divorce. Tatiana tried many different jobs\n3) She also worked as a university secretary and laboratory assistant\nThis person should become: writer\n",
}
```

- Process: We passed the training dataset five times through the training process. In this experiment we tried to evaluate the effectiveness of our model on unseen data, after training it with a higher focus on a smaller number of examples, while providing the model with a structured chain-of-thought for each output, originating from our annotation.
- Training: Gradient accumulation and weight update batches would happen every 2 mini-batches, more gradient accumulation steps would result in an OOM error. The model was trained for five epochs with a starting learning of 0.0003 changing based on a cosine function.
- Resources: The training and evaluation process utilized 11.5 GB of VRAM and 5 GB of RAM over 4 hours.

4.4.4. GPT-3.5 enhanced dataset attempting to provide chain-of-thought

- Dataset: As described in section 3 a subset of 868 data points from the dataset was passed into the GPT-3.5 OpenAI API with a prompt, as follows:

```
{
  "role": "user",
  "content": "Based on the input in quotation marks, tell me in three sentences what affected this person's decision to become a artist, record producer.\n\n\"input\": \"Kardolus grew up in Almere, Netherlands. He graduated with honors from the saxophone at the Utrecht Conservatory with Piet Hoordijk. He is a classically trained jazz musician who holds a master's degree in music. In the 1980s, he performed with Ebbe and he played in Sound of Impact and worked in the 1990s as DJ Mac Attack and made two EPs under that name. He played in The Hindeminders. He then played with the band include at Lowlands, Pinkpop, Dynamo Open Air and the Drum Rhythme Festival. Published in 2000 album Breathe of Life by Ellen Helmus was produced by Kardolus and then he played saxophone and keyboards. With Helmus and The Hindeminders he played in 2001 at the North Sea Jazz Festival. He moved to Brooklyn in 2001 to get a start in music. He spread his music for free on weblogs. Chew Fu got his start in the industry working for Diddy and Quincy Jones's record label Quest, as well as utilizing a worldwide network of dance music bloggers. In 2005, he began producing his hip hop with house music back in 2005, because he wanted to play it in the clubs but no-one was making it.\" He switched to house music until it caught on in 2010 when he began to produce remixes for Lady Gaga, Tinbaland, and Rihanna. As a producer, Chew Fu has created original productions with Wiley, Seanie Man, Donna Summer, Kerli and Doug E Fresh, to be included on his debut album slated for release in July 2011. In 2012 produced original songs for Breedlove, Perry Mystique, Steve Clisby, A-Clay, J-cast.\\n\\n\"\"\"
}
```

- Prompt: Each GPT-3.5 completion was added to the output of each data point as context, in an attempt to create prompts that can provide a more natural chain-of-thought to the model in comparison to the previous experiment. We kept 768 as a training set and 100 as an evaluation set.

```
{
  "instruction": "Based on the information given in the input, predict this person's future occupation.",
  "input": "John Fitzgerald Coates was born in January 1970, the son of Peter Coates, chairman of Stoke City F.C. and director of Bet365. He attended Bristol University where he studied Law. Coates started his career as a lawyer. In 2001, after selling some of their father's betting shops to large bookmaker Coral, his sister convinced him to join her in launching bet365. He is married, with two children, and lives in Stoke-on-Trent.",
  "output": "This person's decision to become a businessman may have been influenced by their family background, as their father was the chairman of Stoke City F.C. and director of Bet365. Additionally, their sister played a role in convincing them to join her in launching bet365, suggesting that family connections and entrepreneurial opportunities were factors in their decision. Their education in Law at Bristol University may have also provided them with skills and knowledge relevant to the business world.\\n\\nThis person should become: businessman"
},
```

- Process: We passed the training dataset four times through the training process. In this experiment we tried to evaluate the effectiveness of our model on unseen data, after training it with a higher focus on a smaller number of examples, while providing the model with free-form chain-of-thought for each output, originating from the generated GPT-3.5 completions.
- Training: Gradient accumulation and weight update batches would happen every 4 mini-batches, more gradient accumulation steps would result in an OOM error. The model was trained for four epochs with a starting learning of 0.0003 changing based on a cosine function.
- Resources: The training and evaluation process utilized 11.5 GB of VRAM and 4.7 GB of RAM over 3.5 hours.

4.5. Inference

The same QLoRA configuration is used during the inference step, to be feasible on a single commercial GPU, bringing the resources required for inference to 5.8 GB. Each inference query takes around one minute to yield a result. The slow inference is due to the 4-bit quantization and double de-quantization required during computation. An 8-bit model would have faster inference, requiring one less quantization and de-quantization step but would also require more memory.

The implementation of the conversational agent during inference, was done through the use of LangChain, providing us with the functionality to give the model an initial instruction and add chat memory. We gave the agent a memory of 5 conversational turns and wanted the initial instruction to set the tone of its responses, as follows:

```

"""The following is a conversation between a human and an guidance counseling AI.
The AI is talkative and provides lots of specific details from its context and focuses on answering the question posed by the human.
If the AI does not know the answer to a question, it truthfully says it does not know.
Current conversation:
{history}
Human: {input}
AI:"""

```

We set up the inference pipeline as a text generation task, with 0.7 temperature and selecting from the tokens that account for 70% of the scenarios. Moreover, we can provide the pipeline a stopping criterion, since ‘talkative’ LLMs tend to ramble, predicting the continuation of the conversation as well. So, we added a stopping criterion, that stops inference when the LLM starts predicting new user inputs. After observing a tendency of phrase repetition, we penalize repetition quite strongly, to make way for other sequences. Finally, we set the maximum token generation limit to 128, attempting to keep the whole conversation within the initial context window of 2048, since the entire chat memory is passed through the model on each timestep.

5. Experimental results

During the runtime of this project, our goals evolved based on each experiment conducted. In the best-case scenario, we wanted our agent to be able to handle a conversation of two to three sets of questions and answers. Said answers would have to be detailed and accurate based on the question asked, while also being able to follow further instructions e.g provide alternatives. To zero in to a model that would satisfy these specifications to the higher possible extent, we conducted the following four experiments:

- *Initial experiment*

Our initial goal was to create a model that would provide short-form answers for the person’s future occupation based on the input given. The resulting model described in 4.4.1, provided such results, containing only the predicted occupations whenever it worked correctly. Having said that, the model would frequently also just duplicate the question asked, give a random answer or give only obvious answers. The agent couldn’t hold a conversation further than the first answer. The following example showcases the limitation of our initial experiment. The model first outputs a huge amount of single occurrence occupations and then continues predicting the next question, again only providing a profession as an output.

```

"question": I have a strong sense of justice and can persuade people with my speech prowess. What should my future occupation be?
"answer": politician, lawyer, diplomat, judge, professor, writer, journalist, artist, musician, athlete, scientist, engineer, doctor, teacher, etc.
"question": I am a person who is able to adapt to any situation. What should my future occupation be?
"answer": politician,

```

- 2nd experiment

After observing the results of the initial experiment, we tried to create a more accurate and focused model, resulting in the model described in 4.4.2. The outputs were similar in structure to those of the initial experiment, performing better on questions that would result in answers containing seen occupations, but worse when having to predict unseen target occupations. The following example showcases the limitation of our 2nd experiment. The model gives a more natural answer, providing only one occupation as a choice, but then rambles on nonsensically.

```
"question": I have a strong sense of justice and can persuade people with my speech prowess. What should my future occupation be?  
"answer": I should be a lawyer.  
  
I'm not sure if I'm right, but I think that's what it means. I think it's a bit more complicated than that.  
  
I think it's more about the ability to persuade people with your speech.
```

- 3rd experiment

Based on the limitations observed in the outputs of the previous implementations, we were hoping that the process described in 4.4.3., using the annotated dataset to provide further context to the model, would give the agent's output further reasoning, while also increasing the effectiveness of its answers and its ability to continue a conversation. These expectations were met, with the caveat of 'overfitting' on seen data. As much as overfitting can be measured for such tasks, where there is no actual correct answer, the agent would perform much better on professions that were part of our training set, in comparison to those that were unseen. The following example, showcases the improvements of our 3rd experiment. The output of the model contains three different choices, is structured in a similar way to the fine-tuning prompts and is trying to provide a reasoning, even though the reasoning is basically a copy of the question. Again, we can see that it is trying to predict the continuation of the conversation, by copying the input.

```
"question": I have a strong sense of justice and can persuade people with my speech prowess. What should my future occupation be?  
"answer": I should be a lawyer, politician, or journalist.  
"reason": I have a strong sense of justice and can persuade people with my speech prowess.  
"next": "question": I have a strong sense of justice and can persuade people with my speech prowess. What should my future occupation
```

- Final experiment

To counteract the issues observed in the previous experiment, we proceeded with utilizing the GPT-3.5 completions as can be seen in 4.4.4. This setup allowed the agent to supply more accurate and detailed information for both seen and zero-shot examples, while simultaneously providing the desired chatbot functionalities. The following example showcases the

improvements of our final experiment. Where we can see a more conversation approach, with context provided. There are some repetitions and weird inclusions e.g which we believe can be tuned, based on the initiating prompt.

"question": I have a strong sense of justice and can persuade people with my speech prowess. What should my future occupation be?
 "answer": Justice-oriented: You are drawn to careers that directly impact the legal systes and its processes.
 You are passionate about falness and justice, and you want to make a difference in the world.
 Your strong communication skills and persuasive nature make you well suited for positions in law, public relations

Experiment overview



In the training and dev loss curves above we can observe the differences between each experiment. Even though we display each curve for the whole training/evaluation duration, the final models used, where the best models derived from the procedure based on the minimum training/evaluation loss delta.

It is noteworthy to mention the similar trends between the first two experiments and the projected ‘overfit’ observed in the third experiment.

As mentioned above, our proposed model is the model derived from the final conducted experiment, providing us with the most suitable, to our goals, implementation. In the evaluation section we will further explore the advantages, drawbacks, and quirks of the proposed agent.

6. Evaluation

Evaluating the results of a language model is not as straightforward as the evaluation of traditional supervised tasks since there is no single ‘correct’ answer in the sentence level. As it is hard to give an actual rating to individual answers, to provide examples, we decided to use a simple scale of, bad – mediocre – good, based on internal guidelines. We also decided to provide qualitative evaluations based on human preferences and pit our model’s answers against outputs on the same prompts from ChatGPT. Of course, this evaluation methodology contains inherent biases and is reported only for the purposes of this project.

More specifically, an example of evaluating an answer as bad is the following, as it does not take into account the general context of the first prompt and throws up a multitude of unrelated professions that one can associate with not requiring a steady hand, even though it shouldn’t have given that much weight to that part of the question when picking a profession to choose, rather than using it as a regulator. Subsequent chatting in the second question states in the prompt that the user does not wish to become a doctor and the model offers a variety of medical professions.

"question": I like to study the human body and I am not disgusted by blood, but I do not have a very steady hand.
What should my future occupation be?

"answer": Well, there are many occupations that involve studying or working with the human body. You could become a doctor, nurse, scientist, researcher, teacher, artist, writer, etc. These jobs often require good manual dexterity, so you may want to consider adjusting your career path if this is something important to you. Alternatively, perhaps you would prefer a job where your hands aren't as involved in the work. Jobs such as programmer, designer, architect, engineer, technician, machinist, etc. might suit you better. Lastly, maybe you just don't feel passionate about any particular field. In that case

"question": Could you please give me a couple more choices? I do not really want to become a doctor.

"answer": Of course! There are still many different avenues open to you based on your interest in medicine. Besides becoming a physician, surgeon, dentist, pharmacist, psychologist, psychiatrist, veterinarian, optometrist, podiatrist, chiropractor, midwife, acupuncturist, naturopath, nutritionist, oncologist, ophthalmologist, orthopedist, otolaryngologist, pediatrics, pathology, psychiatry, radiology, urology, surgery, toxicology, endocrinology, emergency medical services, forensic science, gerontology, immunology, nephrology, neurology, obstetrics/gynecology, oncology,

The following model response could be marked as mediocre, as the model’s response reiterates the user’s interests mentioned in the first prompt, while even though the second part of the chain looks like an interaction with a human guidance counselor, it ends up mentioning too many general occupations, without focusing on a more specific suggestion for the user.

"question": From a young age I loved reading and writing. At home we listened to classical music. I prefer theater over cinema. What should my future occupation be?

"answer": You have many interests! It seems like you enjoy listening to different types of music and going to see plays or performances. These activities definitely influence your preferences in entertainment and art. They also show that you are curious about various topics and interested in learning more about them. Perhaps these hobbies sparked your interest in becoming a writer or journalist. Maybe they inspired you to create stories or articles based on what you learned through experiencing those things firsthand. Whatever led you down this path, there's no doubt that your love for literature has played a significant role in shaping who you are today.

"question": Could you please give me a couple more choices? I do not really want to become a writer or journalist.

"answer": Okay, let's explore some other options then. Do you enjoy being around people and interacting with others? Are you good at communicating ideas clearly and effectively? Being able to express yourself creatively could mean pursuing roles as a designer, artist, actor, performer, etc. Or maybe you would rather work behind the scenes as part of a production team such as directing, producing, editing, marketing, public relations, costume design, set design, lighting design, sound design, stage management, wardrobe supervisor, etc. There are so many possibilities when considering careers related to communication and creativity!

Finally, we could evaluate the following model response as good, as it suggests several related professions to the context of the prompt, although the answer to the second prompt does infer that the user is interested in writing and communication, which is not necessarily inferred from what is referred to in the previous question of the user.

"question": I have a strong sense of justice and can persuade people with my speech prowess. What should my future occupation be?

"answer": You are very persuasive and passionate about your beliefs. Your ability to communicate effectively makes you well suited for public speaking or debate competitions. Perhaps becoming a lawyer or politician would also suit you as these careers often require persuasion skills. However, if you prefer working independently rather than in teams, consider being a writer or consultant. These occupations typically involve communicating ideas and persuading others through written text or spoken words respectively.

"question": Could you please give me a couple more choices? I do not really want to become a politician.

"answer": Based on your interest in writing and communication, perhaps you could explore other options such as authoring books, screenwriter, journalist, editor, commentator, or blogger. All of these professions allow individuals to express their thoughts and opinions while earning money doing so. Additionally, many writers work independently and only collaborate when necessary. Being able to choose your own projects may appeal to you. Becoming a politician requires extensive training and experience which might take up too much time and energy for you at this point in your life.

Comparing our model's answers above, against outputs on the same prompts from ChatGPT, we can observe that ChatGPT gives more targeted, to-the-point and short answers, while providing explanatory information about the choice of occupation without being vague and chattering, as is mostly the case with our model's answers.



I like to study the human body. I am not disgusted by blood. I don't have a very steady hand. What should my future occupation be?



Based on your interest in studying the human body and your tolerance for blood, a potential occupation for you could be a Pathologist or a Medical Researcher specializing in human anatomy. These roles involve in-depth study and analysis of the human body, including examination of tissues, organs, and bodily fluids for diagnostic and research purposes.





From a young age I loved reading literature and writing. At home we listened to classical music. I prefer theatre over cinema. What should my future occupation be?



Based on the information you provided, a suitable occupation for you could be a Writer or Author.



Naturally, when having to choose between the outputs of our model and those of ChatGPT all members of the team picked the titanic LLM's answers, although we would prefer a more conversational style, which of course could be extracted with a different starting prompt.

7. Challenges and limitations

Our data acquisition procedure faced challenges in establishing a causal relationship between the selected individuals' childhood experiences and their chosen occupations. Firstly, we had to ground our approach and consider the differences in occupational standards and decisions between different generations. To combat this, we decided to only take into account the living people found in Wikipedia. This approach aimed to gather data on a diverse range of individuals and their respective fields of expertise.

However, as we delved deeper into the project, we encountered several challenges that affected the smooth progress of our work. It became evident that finding a direct causal relationship was not always possible. Some early life sections primarily provided information about the educational background, studies, and notable achievements of the individuals or their close associates. While these details were valuable in understanding their journey to their chosen professions, they often lacked explicit references to specific childhood experiences that could be directly linked to their occupational choices. This absence of explicit causal connections posed a significant challenge to our project, as it limited our ability to establish a comprehensive understanding of the relationship between early life experiences and professional outcomes.

7.1. Dataset biases

Given that our dataset originates from Wikipedia, it is important to note that the distribution of occupations linked to the people referred, is tightly dependent on the fact that people of a specific profession have a higher chance to be included in a Wikipedia article over others, based solely on the type of occupation. As a result, the variety of occupations found were not only limited by our predetermined list, but also the inherent Wikipedia biases, e.g no plumbers were seen.

7.2. Base model biases

As the base Falcon-7B model has been trained, among others, on crawled corpora from the web, it will carry any biases found in its pre-training data, making it susceptible to providing harmful outputs, e.g it could reiterate racial or sexual biases that can be found online.

7.3. Implementation biases

Our fine-tuning dataset originates from Wikipedia and the Falcon base model has been trained on general web-crawled corpora, but not specifically on the Wikipedia corpus. As a result, we expect that a lot of inputs would already be seen during pre-training in the same or a different form, leading our model to potentially match information instead of learning. Especially considering the lack of anonymization during fine-tuning, a fact we're going to address in 8.

In the proposed implementation, the context added to the outputs of the training examples were created themselves, from GPT-3.5. In our ballpark of training examples that is not a problem, but when scaling to larger models, this methodology could lead to the model imitating GPT-3.5 instead of learning on the provider data (Gudibande et al., 2023).

8. Recommended steps – Further work

We recognize that the current approach and implementation can benefit from several improvements.

Having arrived at a proposed model, one of the main changes we would propose would be to gather data from various sources more targeted towards our initial hypothesis. On such a dataset, we would attempt to perform a larger number of annotations with stricter guidelines.

As mentioned in section 3 from the initial steps of data acquisition, we had to tackle the problem of obtaining target occupations. Due to the structure of the personal Wikipedia pages, we made the concession to limit our search of predetermined occupations in the first sentence of the summary section. Of course, this decision introduces problems of discoverability and correctness. Many occupations that we hadn't accounted for were ignored and we couldn't be 100% positive that the occupation found was actually the occupation of the person in question. In the future we would like to train and utilize a dedicated Named Entity Recognition (NER) and relation extraction model to automatically extract all found occupations that refer to the person representing the training data point.

Another problem derived from the structure of our data is the existence of personal names and references in each training example. In the future we would like to add a different NER and relation extraction model to the pipeline, performing Anonymization on our training data. This would cover ethical issues that arise with the use of personal information for LLM training,

even though the extracted information is readily available on the web, while also helping with the previously described potential pitfall of matching names to occupations and situations instead of learning about the person as a generic entity.

Due to the timely-constrained nature of our project, we decided to run multiple experiments with limited amounts of training data, experiment-discrete instruction strategies and low training time. In the future we would like to iterate upon our implementation, as follows:

1. Provide multiple task related instructions and prompt strategies to our model for better generalization.
2. With more data, and maybe more resources to create a more complex model, we would be able to augment our chain-of-thought implementations with input examples, without risking overfitting our model on the training examples.
3. Opt into longer training sessions, utilizing more data and hyperparameter tuning to approach the best model possible.

9. Conclusion

After conducting a series of experiments, we propose and describe GNTLM as a conversational agent based on a fine-tuned Falcon-7B LLM that can provide vocational guidance and hold basic conversation on this specific task, while only requiring one commercial-grade GPU for use. Of course, the model has its own inherent biases and limitations, that can be ironed out with further work both in the technical implementation and dataset specification stages.

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