Prompting Language Models

In ths notebook, we'll be evaluating different model prompting strategies on a publicly available language model. We will then perform soft-prompt tuning on GPT-2 and compare it against hard prompting.

Install required packages

In [1]:
```
!pip install transformers
!pip install inflect
!pip install cohere
```

```
Collecting transformers
  Downloading transformers-4.35.1-py3-none-any.whl (7.9 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 7.9/7.9 MB 46.1 MB/s eta 0:00:00
Requirement already satisfied: filelock in /usr/local/lib/python3.10/dist-packages (from transformers) (3.13.1)
Collecting huggingface-hub<1.0,>=0.16.4 (from transformers)
  Downloading huggingface_hub-0.19.1-py3-none-any.whl (311 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 311.1/311.1 kB 39.6 MB/s eta 0:00:00
Requirement already satisfied: numpy>=1.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (1.23.5)
Requirement already satisfied: packaging>=20.0 in /usr/local/lib/python3.10/dist-packages (from transformers) (23.2)
Requirement already satisfied: pyyaml>=5.1 in /usr/local/lib/python3.10/dist-packages (from transformers) (6.0.1)
Requirement already satisfied: regex!=2019.12.17 in /usr/local/lib/python3.10/dist-packages (from transformers) (2023.6.3)
Requirement already satisfied: requests in /usr/local/lib/python3.10/dist-packages (from transformers) (2.31.0)
Collecting tokenizers<0.15,>=0.14 (from transformers)
  Downloading tokenizers-0.14.1-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (3.8 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 3.8/3.8 MB 61.2 MB/s eta 0:00:00
Collecting safetensors>=0.3.1 (from transformers)
  Downloading safetensors-0.4.0-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (1.3 MB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 1.3/1.3 MB 64.1 MB/s eta 0:00:00
Requirement already satisfied: tqdm>=4.27 in /usr/local/lib/python3.10/dist-packages (from transformers) (4.66.1)
Requirement already satisfied: fsspec>=2023.5.0 in /usr/local/lib/python3.10/dist-packages (from huggingface-hub<1.0,>=0.16.4->transformers) (2023.6.0)
Requirement already satisfied: typing-extensions>=3.7.4.3 in /usr/local/lib/python3.10/dist-packages (from huggingface-hub<1.0,>=0.16.4->transformers) (4.5.0)
Collecting huggingface-hub<1.0,>=0.16.4 (from transformers)
  Downloading huggingface_hub-0.17.3-py3-none-any.whl (295 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━ 295.0/295.0 kB 32.0 MB/s eta 0:00:00
Requirement already satisfied: charset-normalizer<4,>=2 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (3.3.2)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (3.4)
Requirement already satisfied: urllib3<3,>=1.21.1 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (2.0.7)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests->transformers) (2023.7.22)
Installing collected packages: safetensors, huggingface-hub, tokenizers, transformers
Successfully installed huggingface-hub-0.17.3 safetensors-0.4.0 tokenizers-0.14.1 transformers-4.35.1
Requirement already satisfied: inflect in /usr/local/lib/python3.10/dist-packages (7.0.0)
Requirement already satisfied: pydantic>=1.9.1 in /usr/local/lib/python3.10/dist-packages (from inflect) (1.10.13)
Requirement already satisfied: typing-extensions in /usr/local/lib/python3.10/dist-packages (from inflect) (4.5.0)
Collecting cohere
  Downloading cohere-4.34-py3-none-any.whl (48 kB)
     ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━
```

```
━━━ 48.2/48.2 kB 5.7 MB/s eta 0:00:00
Requirement already satisfied: aiohttp<4.0,>=3.0 in /usr/local/lib/python3.10/dist-packages (from cohere) (3.8.6)
Collecting backoff<3.0,>=2.0 (from cohere)
  Downloading backoff-2.2.1-py3-none-any.whl (15 kB)
Collecting fastavro==1.8.2 (from cohere)
  Downloading fastavro-1.8.2-cp310-cp310-manylinux_2_17_x86_64.manylinux2014_x86_64.whl (2.7 MB)
    ━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━━
━━━ 2.7/2.7 MB 37.3 MB/s eta 0:00:00
Requirement already satisfied: importlib_metadata<7.0,>=6.0 in /usr/local/lib/python3.10/dist-packages (from cohere) (6.8.0)
Requirement already satisfied: requests<3.0.0,>=2.25.0 in /usr/local/lib/python3.10/dist-packages (from cohere) (2.31.0)
Requirement already satisfied: urllib3<3,>=1.26 in /usr/local/lib/python3.10/dist-packages (from cohere) (2.0.7)
Requirement already satisfied: attrs>=17.3.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.0->cohere) (23.1.0)
Requirement already satisfied: charset-normalizer<4.0,>=2.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.0->cohere) (3.3.2)
Requirement already satisfied: multidict<7.0,>=4.5 in /usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.0->cohere) (6.0.4)
Requirement already satisfied: async-timeout<5.0,>=4.0.0a3 in /usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.0->cohere) (4.0.3)
Requirement already satisfied: yarl<2.0,>=1.0 in /usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.0->cohere) (1.9.2)
Requirement already satisfied: frozenlist>=1.1.1 in /usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.0->cohere) (1.4.0)
Requirement already satisfied: aiosignal>=1.1.2 in /usr/local/lib/python3.10/dist-packages (from aiohttp<4.0,>=3.0->cohere) (1.3.1)
Requirement already satisfied: zipp>=0.5 in /usr/local/lib/python3.10/dist-packages (from importlib_metadata<7.0,>=6.0->cohere) (3.17.0)
Requirement already satisfied: idna<4,>=2.5 in /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.25.0->cohere) (3.4)
Requirement already satisfied: certifi>=2017.4.17 in /usr/local/lib/python3.10/dist-packages (from requests<3.0.0,>=2.25.0->cohere) (2023.7.22)
Installing collected packages: fastavro, backoff, cohere
ERROR: pip's dependency resolver does not currently take into account all the packages that are installed. This behaviour is the source of the following dependency conflicts.
llmx 0.0.15a0 requires openai, which is not installed.
llmx 0.0.15a0 requires tiktoken, which is not installed.
Successfully installed backoff-2.2.1 cohere-4.34 fastavro-1.8.2
```

In [36]:
```
import pickle as pkl
import os
import json
import cohere
import random
import inflect
import numpy as np
import matplotlib.pyplot as plt
import pickle as pkl
import torch
from torch import nn
import time
from collections import deque

random.seed(0)
np.random.seed(0)
```

Load the dataset

We will be using the Common Sense QA dataset, which is a collection of questions about everyday life. The cells below download the data from [https://www.tau-nlp.sites.tau.ac.il/commonsenseqa (https://www.tau-nlp.sites.tau.ac.il/commonsenseqa)](https://www.tau-nlp.sites.tau.ac.il/commonsenseqa) .

In [38]:
```
# Load dataset from jsonl file
def make_dataset(path):
    dataset = []
    with open(path) as f:
        for line in f:
            dataset.append(json.loads(line))
    return dataset
```

In [39]:
```
#@title download the dataset
!curl https://s3.amazonaws.com/commensenseqa/train_rand_split.jsonl -o train_rand_s
!curl https://s3.amazonaws.com/commensenseqa/dev_rand_split.jsonl -o dev_rand_split
!curl https://s3.amazonaws.com/commensenseqa/test_rand_split_no_answers.jsonl -o te
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100 3697k  100 3697k    0     0  6441k      0 --:--:-- --:--:-- --:--:-- 6441k
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100  460k  100  460k    0     0  1192k      0 --:--:-- --:--:-- --:--:-- 1196k
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100  413k  100  413k    0     0   935k      0 --:--:-- --:--:-- --:--:--  934k
```

In [40]:
```
train_set = make_dataset('train_rand_split.jsonl')
val_set = make_dataset('dev_rand_split.jsonl')

# Print the lengths of the train and validation sets
print(len(train_set), len(val_set))
```

```
9741 1221
```

Here are a few examples of the dataset format:

In [41]:
```
val_set[:3]
```

Out[41]:
```
[{'answerKey': 'A',
  'id': '1afa02df02c908a558b4036e80242fac',
  'question': {'question_concept': 'revolving door',
   'choices': [{'label': 'A', 'text': 'bank'},
    {'label': 'B', 'text': 'library'},
    {'label': 'C', 'text': 'department store'},
    {'label': 'D', 'text': 'mall'},
    {'label': 'E', 'text': 'new york'}],
   'stem': 'A revolving door is convenient for two direction travel, but it also
serves as a security measure at a what?'}},
 {'answerKey': 'A',
  'id': 'a7ab086045575bb497933726e4e6ad28',
  'question': {'question_concept': 'people',
   'choices': [{'label': 'A', 'text': 'complete job'},
    {'label': 'B', 'text': 'learn from each other'},
    {'label': 'C', 'text': 'kill animals'},
    {'label': 'D', 'text': 'wear hats'},
    {'label': 'E', 'text': 'talk to each other'}],
   'stem': 'What do people aim to do at work?'}},
 {'answerKey': 'B',
  'id': 'b8c0a4703079cf661d7261a60a1bcbff',
  'question': {'question_concept': 'magazines',
   'choices': [{'label': 'A', 'text': 'doctor'},
    {'label': 'B', 'text': 'bookstore'},
    {'label': 'C', 'text': 'market'},
    {'label': 'D', 'text': 'train station'},
    {'label': 'E', 'text': 'mortuary'}],
   'stem': 'Where would you find magazines along side many other printed work
s?'}}]
```

Make an Cohere account, generate a **trial** API key at [https://dashboard.cohere.ai/api-keys (https://dashboard.cohere.ai/api-keys)](https://dashboard.cohere.ai/api-keys), and paste it below.

In [42]:
```
# Set the api key from https://dashboard.cohere.ai/api-keys
# my trial API
# MingZwhy

co = cohere.Client('DVlh1qOXWwaTCNthG68iZQUR8g4B2YOWW9pxxmS6')
```

In this notebook, we'll explore different hard-prompting strategies. Run the cells below to see a few example strategies.

In [43]:

```
def make_simple_prompt(data_point):
    prompt = f"""{data_point['question']['stem']}
 {data_point['question']['choices'][0]['label']} {data_point['question']['choices'][
 {data_point['question']['choices'][1]['label']} {data_point['question']['choices'][
 {data_point['question']['choices'][2]['label']} {data_point['question']['choices'][
 {data_point['question']['choices'][3]['label']} {data_point['question']['choices'][
 {data_point['question']['choices'][4]['label']} {data_point['question']['choices'][
"""
    return prompt

def make_simple_qa_prompt(data_point):
    prompt = f"""Question: {data_point['question']['stem']}
Choice {data_point['question']['choices'][0]['label']}: {data_point['question']['cho
Choice {data_point['question']['choices'][1]['label']}: {data_point['question']['cho
Choice {data_point['question']['choices'][2]['label']}: {data_point['question']['cho
Choice {data_point['question']['choices'][3]['label']}: {data_point['question']['cho
Choice {data_point['question']['choices'][4]['label']}: {data_point['question']['cho
Answer:"""
    return prompt

def get_instruction():
    return "Answer the following question with A, B, C, D, or E.\n"

def make_qa_instruction_prompt(data_point):
    prompt = get_instruction()
    prompt += make_simple_qa_prompt(data_point)
    return prompt

def make_few_shot_prompt(data_point, num_shots):
    prompt = get_instruction()
    for i in range(num_shots):
        prompt += make_simple_qa_prompt(train_set[i])
        prompt += f" {train_set[i]['answerKey']}\n"
    prompt += make_simple_qa_prompt(data_point)
    return prompt

# This is like the prompt above, but the answers in the examples given are random, n
def make_incorrect_few_shot_prompt(data_point, num_shots):
    prompt = get_instruction()
    for i in range(num_shots):
        prompt += make_simple_prompt(train_set[i])
        valid_answers = ['A', 'B', 'C', 'D', 'E']
        valid_answers.remove(train_set[i]['answerKey'])
        # Randomly choose an incorrect answer
        random_answer = random.choice(valid_answers)
        prompt += f"{random_answer}\n"
    prompt += make_simple_qa_prompt(data_point)
    return prompt
```

In [44]:

```
# Print one example of each prompt type
print('='*40, 'Simple Prompt', '='*40)
print(make_simple_prompt(train_set[0]))
print('='*40, 'Simple QA Prompt', '='*40)
print(make_simple_qa_prompt(train_set[0]))
print('='*40, 'QA Instruction Prompt', '='*40)
print(make_qa_instruction_prompt(train_set[0]))
print('='*40, 'Few Shot Prompt', '='*40)
print(make_few_shot_prompt(train_set[8], 4))
print('='*40, 'Incorrect Few Shot Prompt', '='*40)
print(make_incorrect_few_shot_prompt(train_set[8], 4))
```

```
======================================== Simple Prompt ==========================
==============
The sanctions against the school were a punishing blow, and they seemed to what t
he efforts the school had made to change?
 A ignore
 B enforce
 C authoritarian
 D yell at
 E avoid

======================================== Simple QA Prompt =======================
=================
Question: The sanctions against the school were a punishing blow, and they seemed
to what the efforts the school had made to change?
Choice A: ignore
Choice B: enforce
Choice C: authoritarian
Choice D: yell at
Choice E: avoid
Answer:
======================================== QA Instruction Prompt ==================
======================
Answer the following question with A, B, C, D, or E.
Question: The sanctions against the school were a punishing blow, and they seemed
to what the efforts the school had made to change?
Choice A: ignore
Choice B: enforce
Choice C: authoritarian
Choice D: yell at
Choice E: avoid
Answer:
======================================== Few Shot Prompt ========================
================
Answer the following question with A, B, C, D, or E.
Question: The sanctions against the school were a punishing blow, and they seemed
to what the efforts the school had made to change?
Choice A: ignore
Choice B: enforce
Choice C: authoritarian
Choice D: yell at
Choice E: avoid
Answer: A
Question: Sammy wanted to go to where the people were.  Where might he go?
Choice A: race track
Choice B: populated areas
Choice C: the desert
Choice D: apartment
Choice E: roadblock
Answer: B
Question: To locate a choker not located in a jewelry box or boutique where would
you go?
Choice A: jewelry store
Choice B: neck
Choice C: jewlery box
Choice D: jewelry box
Choice E: boutique
Answer: A
Question: Google Maps and other highway and street GPS services have replaced wha
t?
Choice A: united states
Choice B: mexico
```

```
Choice C: countryside
Choice D: atlas
Choice E: oceans
Answer: D
Question: What do people use to absorb extra ink from a fountain pen?
Choice A: shirt pocket
Choice B: calligrapher's hand
Choice C: inkwell
Choice D: desk drawer
Choice E: blotter
Answer:
======================================== Incorrect Few Shot Prompt ==============
==========================
Answer the following question with A, B, C, D, or E.
The sanctions against the school were a punishing blow, and they seemed to what t
he efforts the school had made to change?
 A ignore
 B enforce
 C authoritarian
 D yell at
 E avoid
E
Sammy wanted to go to where the people were.  Where might he go?
 A race track
 B populated areas
 C the desert
 D apartment
 E roadblock
E
To locate a choker not located in a jewelry box or boutique where would you go?
 A jewelry store
 B neck
 C jewlery box
 D jewelry box
 E boutique
B
Google Maps and other highway and street GPS services have replaced what?
 A united states
 B mexico
 C countryside
 D atlas
 E oceans
C
Question: What do people use to absorb extra ink from a fountain pen?
Choice A: shirt pocket
Choice B: calligrapher's hand
Choice C: inkwell
Choice D: desk drawer
Choice E: blotter
Answer:
```

Running the model

The cells below contain code to query Cohere's command-xlarge-nightly model. You can read more about it here: [https://docs.cohere.ai/reference/generate (https://docs.cohere.ai/reference/generate)](https://docs.cohere.ai/reference/generate).

The algorithm is as follows:

1. Format the multiple-choice question as a prompt such that the expected continuation is the answer to the question.
2. Query the model with the prompt.
3. Parse the model's response to extract the answer.

Since we are using the trial keys, we are rate limited to 5 queries per minute. We have implemented the code to wait for a minute if you get close to the rate limit. If you run into rate limits, just wait a bit and retry. (Previous queries will stay in the cache, so you won't have to re-query them.)

In [10]:
```
# Parameters for the query.
# Run with the defaults first, then if you want try changing them to see how it affe
model = "command-xlarge-nightly"  # This is the biggest (and most expensive) model.
temperature = 0 # Control randomness. For more randomness, set to a higher value. Fo
max_tokens = 1 # Only generate 1 token (the answer). The Cohere API
num_generations = 5 # How many outputs to generate
return_likelihoods = 'GENERATION'  # Return the likelihoods for the generations

# To avoid errors due to hitting API rate limits, we'll maintain a running tracker o
MAX_QUERIES = 5   # 5 queries per 60s in the cohere free tier
QUERY_TIMEWINDOW = 60 # seconds
timestamps = deque()

def query_cohere(prompt):
    response = co.generate(
      model=model,
      prompt=prompt,
      temperature=temperature,
      max_tokens=max_tokens,
      num_generations=num_generations,
      return_likelihoods=return_likelihoods,
    )
    return response


# We will store the results in a cache so we don't have to query Cohere every time
# This will avoid hitting the API rate limit
cache = {}
if os.path.exists('cache.pkl'):
    with open('cache.pkl', 'rb') as f:
        cache = pkl.load(f)

def post_process_response_text(response):
    """Removes trailing and preceding whitespace and newlines. Returns the first cha
    r = response.strip()
    if r:
        return r[0]
    return r

# Return the log probability of the correct answer and the most probable answer
def query_model(prompt, correct_answer):
    global query_count, timestamps
    # Check if the query is in the cache
    inputs = (prompt, correct_answer, model, temperature, max_tokens, return_likelih
    if inputs in cache:
        response = cache[inputs]
    else:
        # If more than 5 queries have been run in the last 60s, wait for cooldown
        if len(timestamps) >= MAX_QUERIES and time.time() - timestamps[0] <= QUERY_
            print("Sleeping for a minute to cooldown API limits.")
            time.sleep(60)
            timestamps.clear()

        # Run query
        response = query_cohere(prompt)

        # Update timestamps
        timestamps.append(time.time())
        if len(timestamps) > MAX_QUERIES:
            timestamps.popleft()
```

```python
        # Cache inputs
        cache[inputs] = response
        # Save cache to file
        with open('cache.pkl', 'wb') as f:
            pkl.dump(cache, f)
    log_prob = response.data[0].likelihood
    most_probable = post_process_response_text(response.data[0].text)
    return log_prob, most_probable
```

In [11]:

```
# For simplicity (and to save time), we'll only use the first 10 data points
# You can get more reliable results by using more data points, but it will
# take longer to run because of API rate limits.
num_points = 10
mini_train = val_set[:num_points]
num_shots = 4

# Consider adding additional prompts of your own here.
prompt_strategies = {
    'simple': make_simple_prompt,
    'simple_qa': make_simple_qa_prompt,
    'qa_instruction': make_qa_instruction_prompt,
    'few_shot': lambda x: make_few_shot_prompt(x, num_shots),
    'incorrect_few_shot': lambda x: make_incorrect_few_shot_prompt(x, num_shots)
}

def compute_acc(data_points, prompt_strategy):
    accuracies = []
    valid_responses = []
    for data_point in data_points:
        print(f'Question: {data_point["question"]["stem"]}, Answer: {data_point["ans
        prompt = prompt_strategy(data_point)
        correct_answer = f'{data_point["answerKey"]}'

        log_prob, most_probable = query_model(prompt, correct_answer)
        accuracies += [int(most_probable == correct_answer)]
        valid_responses += [most_probable in ['A', 'B', 'C', 'D', 'E']]
        print(f'    LM predicted |{most_probable}|, accuracy: {accuracies[-1]}')
    return np.mean(accuracies), np.mean(valid_responses)

def plot_all_accs(data_points, prompt_strategies):
    accuracies = []
    valid_responses = []
    for prompt_name, prompt_strategy in prompt_strategies.items():
        accuracy, valid_rate = compute_acc(data_points, prompt_strategy)
        accuracies += [accuracy]
        valid_responses += [valid_rate]
    # Plot a bar chart of the accuracies
    plt.figure(figsize=(10, 5))
    plt.bar(prompt_strategies.keys(), accuracies)
    plt.title('Accuracies')
    plt.show()
    # Plot a bar chart of the valid responses
    plt.figure(figsize=(10, 5))
    plt.bar(prompt_strategies.keys(), valid_responses)
    plt.title('Valid Responses')
    plt.show()
```

In [14]:
```
plot_all_accs(mini_train, prompt_strategies)
```

```
Question: A revolving door is convenient for two direction travel, but it also serves as a security measure at a what?, Answer: A, Choices: ['bank', 'library', 'department store', 'mall', 'new york']
   LM predicted |E|, accuracy: 0
Question: What do people aim to do at work?, Answer: A, Choices: ['complete job', 'learn from each other', 'kill animals', 'wear hats', 'talk to each other']
   LM predicted |A|, accuracy: 1
Question: Where would you find magazines along side many other printed works?, Answer: B, Choices: ['doctor', 'bookstore', 'market', 'train station', 'mortuary']
   LM predicted |B|, accuracy: 1
Question: Where are  you likely to find a hamburger?, Answer: A, Choices: ['fast food restaurant', 'pizza', 'ground up dead cows', 'mouth', 'cow carcus']
   LM predicted |A|, accuracy: 1
Question: James was looking for a good place to buy farmland.  Where might he look?, Answer: A, Choices: ['midwest', 'countryside', 'estate', 'farming areas', 'illinois']
   LM predicted |E|, accuracy: 0
```

Analysis

TODO: in the cells below, implement code to analyze the model's performance.

- What kinds of failures do you see with different prompting strategies?
- Does providing correct labels in few-shot prompting have a significant impact on accuracy?
- Observe the model’s log probabilities. Does it seem more confident when it is correct than when it is incorrect?

A function to plot the model's confidence has been implemented for you, but you should feel free to write code to do additional analysis.

In [15]:

```python
# Printing the log probs for the generated tokens
prompt_strategies = {
    # 'simple': make_simple_prompt, # removed since it's always incorrect
    'simple_qa': make_simple_qa_prompt,
    'qa_instruction': make_qa_instruction_prompt,
    'few_shot': lambda x: make_few_shot_prompt(x, num_shots),
    'incorrect_few_shot': lambda x: make_incorrect_few_shot_prompt(x, num_shots)
}

argmax_lp_correct = []
argmax_lp_incorrect = []
for prompt_name, prompt_strategy in prompt_strategies.items():
    argmax_lp_correct_prompt = []
    argmax_lp_incorrect_prompt = []
    for data_point in val_set[:num_points]:
        prompt = prompt_strategy(data_point)
        correct_answer = f'{data_point["answerKey"]}'
        print(f"Prompt: {prompt}")
        log_probs, most_probable = query_model(prompt, correct_answer)
        log_prob_argmax = log_probs
        if most_probable == correct_answer:
            argmax_lp_correct_prompt += [log_prob_argmax]
        else:
            argmax_lp_incorrect_prompt += [log_prob_argmax]
        print(f'LM predicted |{most_probable}|, correct answer: {correct_answer}')

    argmax_lp_correct += [np.mean(argmax_lp_correct_prompt)]
    argmax_lp_incorrect += [np.mean(argmax_lp_incorrect_prompt)]

# Plot a bar chart of the accuracies. The bar chart has two bars for each prompt str
# These bars are placed side by side, so you can compare the accuracies of the two s
plt.figure(figsize=(10, 5))
plt.bar(np.arange(len(prompt_strategies)) - 0.2, np.exp(argmax_lp_correct), width=0.
plt.bar(np.arange(len(prompt_strategies)) + 0.2, np.exp(argmax_lp_incorrect), width=
plt.title('Confidence (Probability of most likely token)')
plt.xticks(np.arange(len(prompt_strategies)), prompt_strategies.keys())
plt.legend()
plt.show()
```

```
Prompt: Question: A revolving door is convenient for two direction travel, but
it also serves as a security measure at a what?
Choice A: bank
Choice B: library
Choice C: department store
Choice D: mall
Choice E: new york
Answer:
LM predicted |A|, correct answer: A
Prompt: Question: What do people aim to do at work?
Choice A: complete job
Choice B: learn from each other
Choice C: kill animals
Choice D: wear hats
Choice E: talk to each other
Answer:
LM predicted |C|, correct answer: A
Prompt: Question: Where would you find magazines along side many other printed
works?
```

Training GPT-2 for soft prompt tuning

GPT-2 is the smaller predecessor model to GPT-3. We will use GPT-2 for soft prompt tuning as it is publicly available(unlike GPT-3) and small enough to train on the free version of the colab GPU (unlike GPT-J).

Soft prompt tuning is described in this [paper (https://arxiv.org/abs/2104.08691v1)](https://arxiv.org/abs/2104.08691v1), which we encourage you to learn more about. In essence, instead of generating answers by putting in token prompts, we use fine tuning to train the embeddings of new learned tokens. This allows us to generate answers by putting in the new learned tokens instead of tokens which correspond to real words.

Most of the code has been implemented for you, but you should still read through the code to understand what it's doing. There is one TODO which asks you to set up the optimizer. Think about which parameters should get passed into the optimizer.

In [45]:

```python
#@title Define soft embedding for GPT-2
#@markdown code adapted from [this github repo](https://github.com/kipgparker/soft-p
class SoftEmbedding(nn.Module):
    def __init__(self,
                wte: nn.Embedding,
                n_tokens: int = 10,
                random_range: float = 0.5,
                initialize_from_vocab: bool = True):
        """
        Here, we concatentate a new task-specific learned embedding to the existing
        Args:
            wte (nn.Embedding): original transformer word embedding
            n_tokens (int, optional): number of tokens for task. Defaults to 10.
            random_range (float, optional): range to init embedding (if not initiali
            initialize_from_vocab (bool, optional): initalizes from default vocab. D
        """
        super(SoftEmbedding, self).__init__()
        self.wte = wte
        self.n_tokens = n_tokens
        self.learned_embedding = nn.parameter.Parameter(self.initialize_embedding(wt
                                                                                   n_tok
                                                                                   rando
                                                                                   initi

    def initialize_embedding(self,
                             wte: nn.Embedding,
                             n_tokens: int = 10,
                             random_range: float = 0.5,
                             initialize_from_vocab: bool = True):
        """initializes learned embedding
        Args:
            same as __init__
        Returns:
            torch.float: initialized using original schemes
        """
        if initialize_from_vocab:
            return self.wte.weight[:n_tokens].clone().detach()
        return torch.FloatTensor(n_tokens, wte.weight.size(1)).uniform_(-random_ran

    def forward(self, tokens):
        """run forward pass
        Args:
            tokens (torch.long): input tokens before encoding
        Returns:
            torch.float: encoding of text concatenated with learned task specifc emb
        """
        # The first n_tokens embeddings are reserved for the learned embeddings
        # The rest of the embeddings are the original GPT-2 embeddings
        input_embedding = self.wte(tokens[:, self.n_tokens:])
        learned_embedding = self.learned_embedding.repeat(input_embedding.size(0), 1
        return torch.cat([learned_embedding, input_embedding], 1)
```

In [58]:

```
#@markdown Set up a soft embedding version of GPT-2
from transformers import GPT2LMHeadModel, GPT2TokenizerFast
tokenizer = GPT2TokenizerFast.from_pretrained("gpt2", padding_side='left')
tokenizer.pad_token=tokenizer.eos_token
device = torch.device("cuda" if torch.cuda.is_available() else "cpu")
n_tokens = 100

def initialize_soft_model():
    model = GPT2LMHeadModel.from_pretrained('gpt2')

    initialize_from_vocab = True

    # Set the input embeddings to the GPT2 model
    s_wte = SoftEmbedding(model.get_input_embeddings(),
                          n_tokens=n_tokens,
                          initialize_from_vocab=initialize_from_vocab)
    model.set_input_embeddings(s_wte)
    model.to(device)
    return model

# While we didn't need to do this for GPT-3 earlier, training the model means we nee
# into tokens that the model can understand via the embedding layer.
def process_dataset(dataset, mapper_fn, pad_length=119):
    mapped_dataset = [mapper_fn(item) for item in dataset]
    if pad_length is None:
        out = tokenizer(mapped_dataset, return_tensors='pt', padding=True)
    else:
        out = tokenizer(mapped_dataset, return_tensors='pt', padding="max_length", m
    # Need to add a space as GPT differentiates between " A" and "A" and it will be
    answerkey = [' ' + item['answerKey'] for item in dataset]
    out['answerkey'] = tokenizer(answerkey, return_tensors='pt', max_length=1)['inpu
    return out

def pad_soft_inputs(inputs):
    """
    We need to pad the attention_mask and input_ids with an extra n_learned_tokens
    It does not matter what you pad input_ids with since these will be overwritten b
    """
    batch = len(inputs['input_ids'])
    inputs['input_ids'] = torch.cat([torch.full((batch, n_tokens), 50256).to(device)
    inputs['attention_mask'] = torch.cat([torch.full((batch, n_tokens), 1).to(device
    return inputs

# Train the model
def train_model(model, train_set, val_set, dataset_processor, batch_size=8, epochs=
    train_dataset = process_dataset(train_set, dataset_processor)
    val_dataset = process_dataset(val_set, dataset_processor)

    # Get the parameters of the new embedding layer
    #new_embedding_params = list(model.get_input_embeddings().parameters())
    new_embedding_params = [model.get_input_embeddings().learned_embedding]
    parameters_to_train = new_embedding_params

    optimizer = torch.optim.Adam(parameters_to_train, lr=1e-4)
    criterion = nn.CrossEntropyLoss()
    model.to(device)
    model.train()
    epoch_train_losses = []
    for i in range(epochs):
        epoch_loss = 0
        for j in range(0, len(train_dataset['input_ids']), batch_size):
```

```
            # Calculate cross entropy loss between predicted last token and actual l
            optimizer.zero_grad()
            inputs = {k: v[j:j+batch_size].to(device) for k, v in train_dataset.ite
            inputs = pad_soft_inputs(inputs)
            labels = inputs.pop('answerkey')
            outputs = model(**inputs).logits[:, -1, :] # (batch_size, vocab_size)
            loss = criterion(outputs, labels.squeeze())
            loss.backward()
            optimizer.step()
            # loss calculated by criterion is averaged over batch, so multiply by ba
            epoch_loss += loss.item() * labels.shape[0]
            if j % print_every == 0:
                print(f'Epoch {i}, Item {j}, loss: {loss.item()}')
        epoch_loss /= train_dataset['input_ids'].shape[0]
        epoch_train_losses.append(epoch_loss)

        # Evaluate on validation set
        model.eval()
        val_loss = 0
        for j in range(0, len(val_dataset['input_ids']), batch_size):
            inputs = {k: v[j:j+batch_size].to(device) for k, v in val_dataset.items
            inputs = pad_soft_inputs(inputs)
            labels = inputs.pop('answerkey')
            outputs = model(**inputs).logits[:, -1, :]
            if j == 0: print(f'decoding {tokenizer.decode(outputs.argmax(dim=-1))}'
            loss = criterion(outputs, labels.squeeze())
            val_loss += loss.item() * labels.shape[0]
        val_loss /= val_dataset['input_ids'].shape[0]
        print('-'*20)
        print(f'Epoch {i}, Validation loss: {val_loss}')


# This function lets us sample the next token (or, in our case, the next answer) fro
def generate_output(model, inputs, pad_soft=True):
    """
    Given a string text or a tokenized input (or list of these, if batched), returns
    next token in the sequence.
    """
    model.eval()
    if type(inputs) is str or type(inputs) is list and type(inputs[0]) is str:
        inputs = tokenizer(inputs, return_tensors="pt").to(device)

    if pad_soft:
        inputs = pad_soft_inputs(inputs)
    outputs = model(**inputs).logits[0, -1, :]
    outputs = outputs.argmax(dim=-1)
    return tokenizer.decode(outputs)
```

In [47]:
```
model = initialize_soft_model()
hard_embedding_model = GPT2LMHeadModel.from_pretrained('gpt2').to(device)
print(generate_output(hard_embedding_model, 'Deep learning is an', pad_soft=False))

# Print out the embeddings so you can see their shpaes
print('Embedding object', model.get_input_embeddings())
print('Learned embeddings', model.get_input_embeddings().learned_embedding.shape)
print('Original vocab embeddings', model.get_input_embeddings().wte.weight.shape)
```

```
 important
Embedding object SoftEmbedding(
  (wte): Embedding(50257, 768)
)
Learned embeddings torch.Size([100, 768])
Original vocab embeddings torch.Size([50257, 768])
```

In [55]:
```
model.get_input_embeddings().learned_embedding
```

Out[55]:
```
Parameter containing:
tensor([[-0.1101, -0.0393,  0.0331,  ..., -0.1364,  0.0151,  0.0453],
        [ 0.0403, -0.0486,  0.0462,  ...,  0.0861,  0.0025,  0.0432],
        [-0.1275,  0.0479,  0.1841,  ...,  0.0899, -0.1297, -0.0879],
        ...,
        [-0.0452, -0.1365,  0.2744,  ..., -0.0197,  0.0351,  0.0310],
        [-0.1119, -0.3235,  0.2215,  ..., -0.1014, -0.1176, -0.3013],
        [-0.0216, -0.0870,  0.1747,  ...,  0.0212, -0.0963,  0.0858]],
       device='cuda:0', requires_grad=True)
```

In [59]:
```
prompt_strategy = 'qa_instruction'
if prompt_strategy not in prompt_strategies:
    print('prompt strategy must be one of', [i for i in prompt_strategies])
else:
    prompt_strategy = prompt_strategies[prompt_strategy]
    train_model(model, train_set, val_set, prompt_strategy, batch_size=8, epochs=2)
```

```
Truncation was not explicitly activated but `max_length` is provided a specifi
c value, please use `truncation=True` to explicitly truncate examples to max l
ength. Defaulting to 'longest_first' truncation strategy. If you encode pairs
of sequences (GLUE-style) with the tokenizer you can select this strategy more
precisely by providing a specific strategy to `truncation`.

Epoch 0, Item 0, loss: 5.448526859283447
Epoch 0, Item 200, loss: 5.202822685241699
Epoch 0, Item 400, loss: 5.431475639343262
Epoch 0, Item 600, loss: 5.3505425453186035
Epoch 0, Item 800, loss: 5.271484375
Epoch 0, Item 1000, loss: 4.894003868103027
Epoch 0, Item 1200, loss: 5.4230265617370605
Epoch 0, Item 1400, loss: 5.299588680267334
Epoch 0, Item 1600, loss: 4.069270610809326
Epoch 0, Item 1800, loss: 4.201892852783203
Epoch 0, Item 2000, loss: 4.038343906402588
Epoch 0, Item 2200, loss: 4.373899459838867
Epoch 0, Item 2400, loss: 5.140368461608887
Epoch 0, Item 2600, loss: 3.764720916748047
```

In [60]:
```
# Save the model to a pickle file (If your runtime crashes, you can load the model f
with open('soft_embeddings_model_qa.pkl', 'wb') as f:
    pkl.dump(model, f)
```

Compare the performance of the model with hard prompting and with soft prompt tuning. If your implementation is correct, you should get around 21% correct and 0% invalid with the soft prompt. Answer the analysis questions in the written portion of the assignment.

In [61]:

```
#@title Let's compare a few examples from our prompts
def compare_models(model1, model1_pad_soft, model2, model2_pad_soft, dataset, datase
    processed_set = process_dataset(dataset, dataset_processor)
    for i in range(n_entries):
        data_point_idx = np.random.choice(len(dataset))
        point = dataset[data_point_idx]
        processed_point = processed_set[data_point_idx]
        prompt = dataset_processor(point)
        print(prompt)
        output1 = generate_output(model1, dataset_processor(point), pad_soft=model1_
        output2 = generate_output(model2, dataset_processor(point), pad_soft=model2_
        print(f'gt: {point["answerKey"]}. model1: {repr(output1)}. model2: {repr(out
        print('-' * 20)


compare_models(model, True, hard_embedding_model, False, val_set, prompt_strategy)
```

Answer the following question with A, B, C, D, or E.
Question: The surgeon's clients had begun to reduce, it seemed girls no longer wa nt to what?
Choice A: reduction
Choice B: make larger
Choice C: augment
Choice D: gain weight
Choice E: expand
Answer:
gt: C. model1: ' B'. model2: ' The'

Answer the following question with A, B, C, D, or E.
Question: The teacher knew her students understood division, what was she hoping they would learn next?
Choice A: multiplication
Choice B: multiply
Choice C: putting together
Choice D: unity
Choice E: pay debts
Answer:
gt: A. model1: ' A'. model2: ' The'

Answer the following question with A, B, C, D, or E.
Question: What would you do to a rock when climb up a cliff?
Choice A: grab
Choice B: look down
Choice C: throw
Choice D: falling
Choice E: may fall
Answer:
gt: A. model1: ' A'. model2: ' A'

Answer the following question with A, B, C, D, or E.
Question: To see new films you must?
Choice A: open eyes
Choice B: go to movies
Choice C: kick ball
Choice D: make art
Choice E: look for
Answer:
gt: B. model1: ' A'. model2: ' To'

Answer the following question with A, B, C, D, or E.
Question: On a hot day what can you do to enjoy something cool and sweet?
Choice A: dive
Choice B: cool off
Choice C: fresh cake
Choice D: go for swim
Choice E: eat ice cream
Answer:
gt: E. model1: ' A'. model2: ' On'

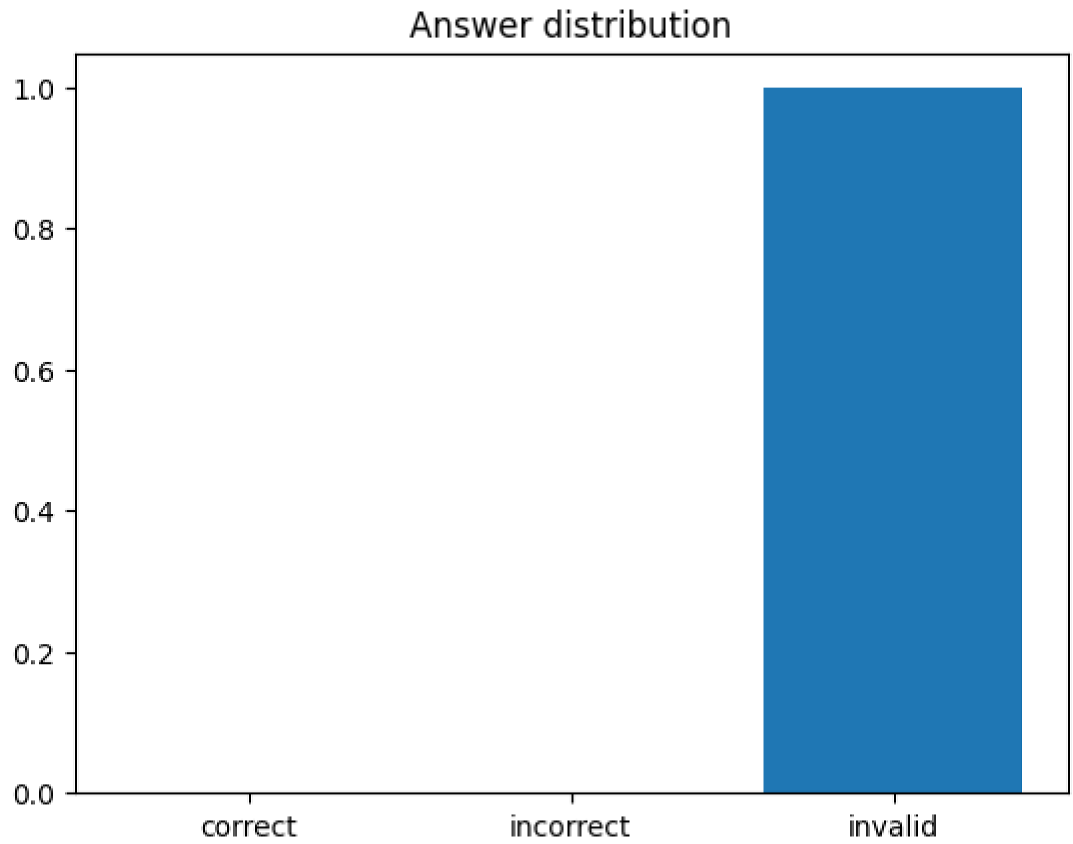
In [62]:
```
#@title Bar plot the distribution of incorrect answers, invalid answers, and correct
def get_answer_stats(model, dataset, dataset_processor, verbose, pad_soft):
    processed_set = process_dataset(dataset, dataset_processor)
    correct = 0
    incorrect = 0
    invalid = 0
    for i in range(len(dataset)):
        inputs = {k: v[i:i+1].to(device) for k, v in processed_set.items()}
        point = dataset[i]
        prompt = dataset_processor(point)
        label = inputs.pop('answerkey')
        output = generate_output(model, inputs, pad_soft).strip()
        if verbose: print(f'Prompt: {prompt}, output: |{output}|, answerkey |{point[
        if output == point["answerKey"]:
            correct += 1
        elif output in ['A', 'B', 'C', 'D', 'E'] or not point['answerKey'] in ['A'
            incorrect += 1
        else:
            invalid += 1
    correct, incorrect, invalid = correct/len(dataset), incorrect/len(dataset), inva
    return correct, incorrect, invalid

def plot_answer_stats(model, dataset, dataset_processor, verbose=False, pad_soft=Tr
    correct, incorrect, invalid = get_answer_stats(model, dataset, dataset_processor
    plt.bar(['correct', 'incorrect', 'invalid'], [correct, incorrect, invalid])
    plt.title('Answer distribution')
    plt.show()
```

In [63]:
```
plot_answer_stats(model, val_set, prompt_strategy, verbose=True, pad_soft=True)
```

```
Streaming output truncated to the last 5000 lines.
Prompt: Answer the following question with A, B, C, D, or E.
Question: Where would you expect to find a dictionary along side other writing
s you can borrow?
Choice A: classroom
Choice B: shelf
Choice C: explain meaning of words
Choice D: table
Choice E: library
Answer:, output: |B|, answerkey |E|
Prompt: Answer the following question with A, B, C, D, or E.
Question: What would be necessary for getting in shape?
Choice A: good health
Choice B: exercise
Choice C: muscle tone
Choice D: sweat
Choice E: feel better
Answer:, output: |B|, answerkey |B|
Prompt: Answer the following question with A, B, C, D, or E.
```

In [64]:
```
plot_answer_stats(hard_embedding_model, val_set, prompt_strategies['qa_instruction']
```



In [65]:
```
model_soft_qa = model
```

Pluralize task

As you can see above, the soft embedding model does not perform very well on this task. We'll show how soft prompting does better on a second, very simple task - pluralizing a word.

The dataset we use was found here, and consists of a list of English nouns: [https://www.kaggle.com/datasets/leite0407/list-of-nouns?select=nounlist.csv (https://www.kaggle.com/datasets/leite0407/list-of-nouns?select=nounlist.csv)](https://www.kaggle.com/datasets/leite0407/list-of-nouns?select=nounlist.csv). For simplicity, we will only consider words where the output is a single token (to avoid needing to deal with sequential generation for evaluation), but you could adapt the code to generate arbitrarily long outputs.

If you get memory errors when running this part, re-run the notebook while skipping loading the previous dataset and soft model.

!! If you run into an error during training complaining about batch size dimensions, this is an edge-case issue where we get errors when the last batch in an epoch length 1. You can fix this by removing the item in the train set. !!

In [66]:
```
!curl https://inst.eecs.berkeley.edu/~cs182/fa22/assets/assignments/nounlist.csv -c
```

```
  % Total    % Received % Xferd  Average Speed   Time    Time     Time  Current
                                 Dload  Upload   Total   Spent    Left  Speed
100 54860  100 54860    0     0   138k      0 --:--:-- --:--:-- --:--:--  138k
```

We'll create targets for this dataset using the inflect library, which is a Python library for inflecting English words. You can read more about it here: [https://pypi.org/project/inflect/ (https://pypi.org/project/inflect/)](https://pypi.org/project/inflect/). This library can convert word to plural forms (though it is not 100% reliable).

In [67]:
```
# Set of words with unusual plurals
noun_test = ['foot', 'man', 'person', 'self', 'wife', 'wolf', 'woman']

engine = inflect.engine()

# Load new noun_list dataset from csv file
with open('nounlist.csv', 'r') as f:
    noun_list = f.read().splitlines()
    noun_list = [i.strip() for i in noun_list]
random.seed(0)
# shuffle the noun list
random.shuffle(noun_list)
# Remove all list items which are in the nouns list (our test set)
noun_list = [i for i in noun_list if i not in noun_test]
# Remove the last 10% for validation
noun_train = noun_list[:-int(len(noun_list)*0.1)]
noun_val = noun_list[-int(len(noun_list)*0.1):]

# Plural task
def format_dataset(noun_list):
    dataset = []
    for noun in noun_list:
        plural = engine.plural(noun)
        dataset.append({'answerKey': plural, 'input': noun})
    return dataset


noun_train = format_dataset(noun_train)
noun_val = format_dataset(noun_val)
noun_test = format_dataset(noun_test)


# Only include nouns where the plural is a single token
noun_train = [i for i in noun_train if len(tokenizer(i['answerKey'])['input_ids'])
noun_val = [i for i in noun_val if len(tokenizer(i['answerKey'])['input_ids']) == 1
noun_test = [i for i in noun_test if len(tokenizer(i['answerKey'])['input_ids']) ==

# Print the first 10 items in the dataset
print([point['input'] for point in noun_train[:10]])
print([point['answerKey'] for point in noun_train[:10]])

print(f'Lengths: train: {len(noun_train)}, val: {len(noun_val)}, test: {len(noun_tes
```

```
['laugh', 'con', 'script', 'hop', 'jury', 'fourths', 'door', 'ray', 'fall', 'do
c']
['laughs', 'cons', 'scripts', 'hops', 'juries', 'fourth', 'doors', 'rays', 'fall
s', 'docs']
Lengths: train: 315, val: 29, test: 7
```

Compare hard prompting with soft prompting on this task, then answer the analysis questions in the written part of this homework. You should get over 60% correct on the val set with soft prompting.

In [68]:
```
def basic_format(point):
    if isinstance(point, dict):
        point = point['input']
    return f"The plural of {point} is"

examples = ['pasta', 'sweater', 'wave', 'mouse', 'attorney', 'bottle', 'phone', 'gra
            'keyhole', 'economy', 'grace', 'finance', 'midnight', 'cushion', 'platea
            ]

def make_few_shot(i):
    def few_shot(point):
        prompt = ''
        for j in range(i):
            prompt += basic_format(examples[j]) + ' ' + engine.plural(examples[j]) -
        prompt += basic_format(point)
        return prompt
    return few_shot
```

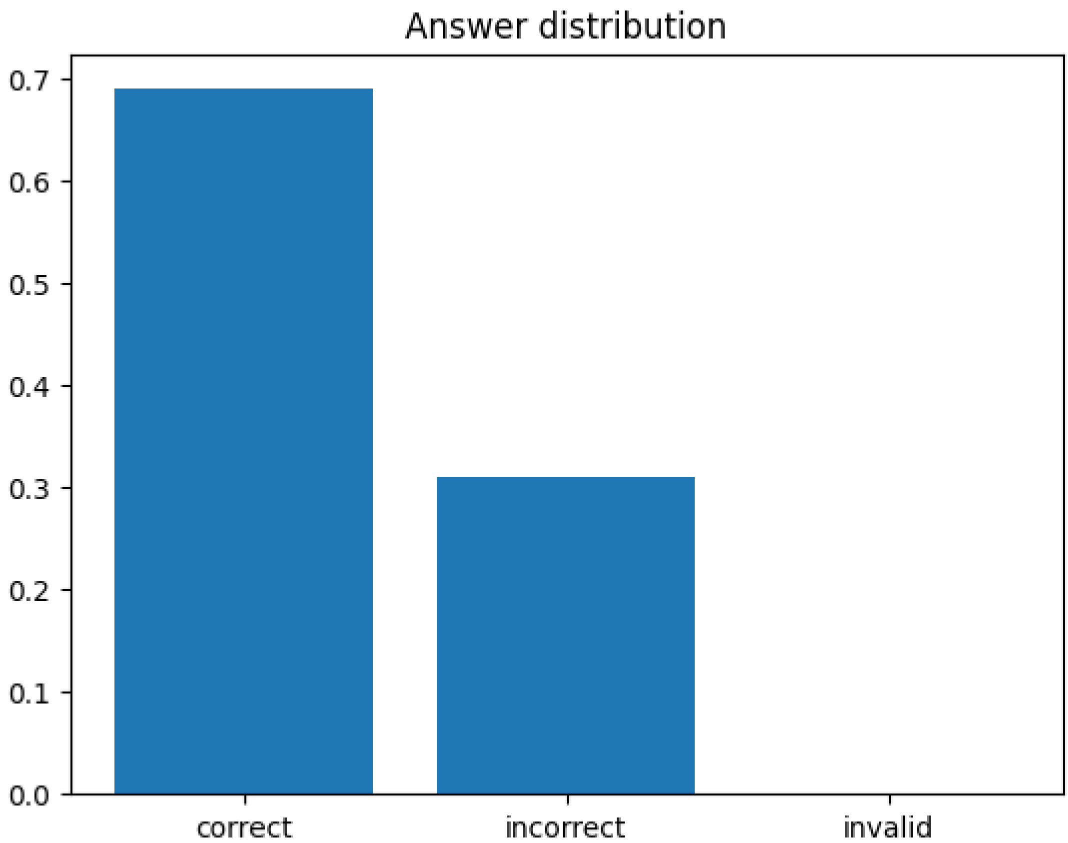
In [69]:
```
model_pluralize = initialize_soft_model()
train_model(model_pluralize, noun_train, noun_val, basic_format, batch_size=8, epoch
```

```
Epoch 0, Item 0, loss: 8.19461727142334
Epoch 0, Item 200, loss: 7.940502643585205
decoding  a a a a a a a is
--------------------
Epoch 0, Validation loss: 7.001628316681961
Epoch 1, Item 0, loss: 7.225864410400391
Epoch 1, Item 200, loss: 6.434726238250732
decoding  a is is a work a a is
--------------------
Epoch 1, Validation loss: 6.226219966493804
Epoch 2, Item 0, loss: 6.232832431793213
Epoch 2, Item 200, loss: 6.016568660736084
decoding  a is is service work is a is
--------------------
Epoch 2, Validation loss: 5.7039381882240034
Epoch 3, Item 0, loss: 5.566977500915527
Epoch 3, Item 200, loss: 5.785000801086426
decoding  a is is service work is a inch
--------------------
```

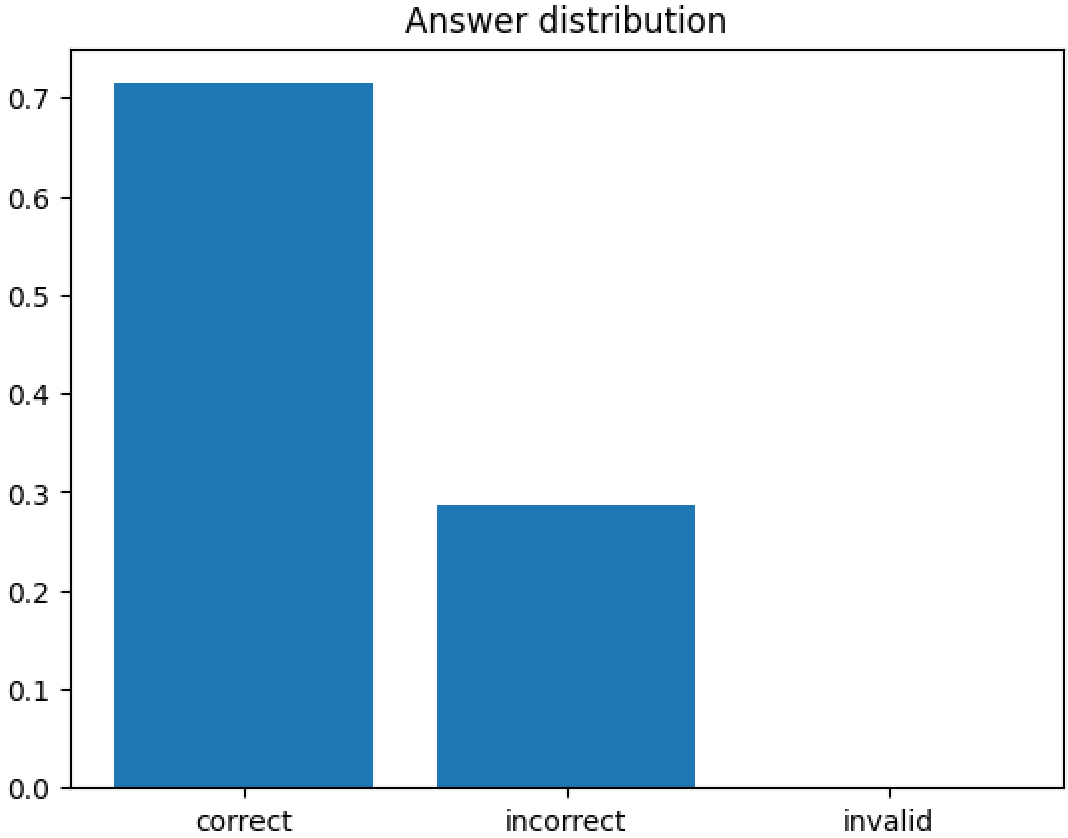
In [70]:
```
# Save the model to a pickle file (If your runtime crashes, you can load the model f
with open('soft_embeddings_model_pluralize.pkl', 'wb') as f:
    pkl.dump(model, f)
```

In [71]:
```
plot_answer_stats(model_pluralize, noun_val, basic_format, verbose=True, pad_soft=T
plot_answer_stats(model_pluralize, noun_test, basic_format, verbose=True, pad_soft=
```

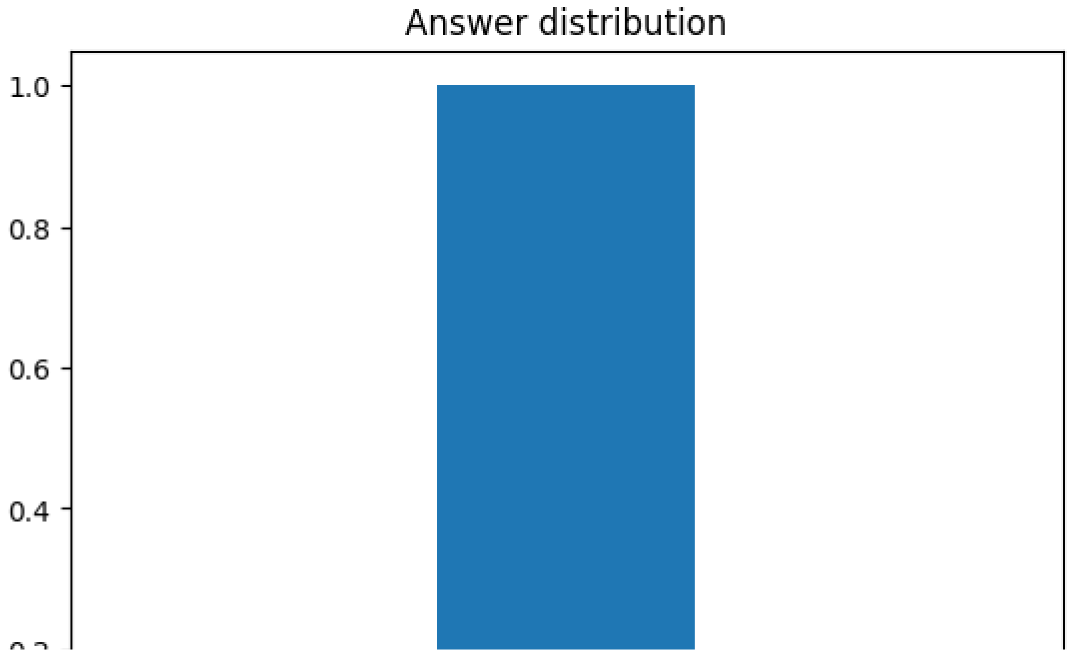
```
Prompt: The plural of skirt is, output: |skirts|, answerkey |skirts|
Prompt: The plural of ink is, output: |ink|, answerkey |inks|
Prompt: The plural of fish is, output: |fishes|, answerkey |fish|
Prompt: The plural of service is, output: |services|, answerkey |services|
Prompt: The plural of work is, output: |works|, answerkey |works|
Prompt: The plural of step is, output: |steps|, answerkey |steps|
Prompt: The plural of thanks is, output: |thanks|, answerkey |thank|
Prompt: The plural of inch is, output: |inches|, answerkey |inches|
Prompt: The plural of rice is, output: |rice|, answerkey |rices|
Prompt: The plural of tic is, output: |t|, answerkey |tics|
Prompt: The plural of hops is, output: |hops|, answerkey |hop|
Prompt: The plural of gun is, output: |guns|, answerkey |guns|
Prompt: The plural of series is, output: |series|, answerkey |series|
Prompt: The plural of stair is, output: |stair|, answerkey |stairs|
Prompt: The plural of thing is, output: |things|, answerkey |things|
Prompt: The plural of version is, output: |versions|, answerkey |versions|
Prompt: The plural of view is, output: |views|, answerkey |views|
Prompt: The plural of face is, output: |faces|, answerkey |faces|
Prompt: The plural of leader is, output: |leaders|, answerkey |leaders|
Prompt: The plural of group is, output: |groups|, answerkey |groups|
Prompt: The plural of cell is, output: |cells|, answerkey |cells|
Prompt: The plural of code is, output: |codes|, answerkey |codes|
Prompt: The plural of light is, output: |lights|, answerkey |lights|
Prompt: The plural of marines is, output: |marines|, answerkey |marine|
Prompt: The plural of flag is, output: |flags|, answerkey |flags|
Prompt: The plural of ability is, output: |abilities|, answerkey |abilities|
Prompt: The plural of savings is, output: |savings|, answerkey |saving|
Prompt: The plural of blog is, output: |blogs|, answerkey |blogs|
Prompt: The plural of hole is, output: |holes|, answerkey |holes|
```



```
Prompt: The plural of foot is, output: |feet|, answerkey |feet|
Prompt: The plural of man is, output: |men|, answerkey |men|
Prompt: The plural of person is, output: |persons|, answerkey |people|
Prompt: The plural of self is, output: |subs|, answerkey |selves|
Prompt: The plural of wife is, output: |wives|, answerkey |wives|
Prompt: The plural of wolf is, output: |wolves|, answerkey |wolves|
Prompt: The plural of woman is, output: |women|, answerkey |women|
```



In [72]:
```
# Plot results with hard prompts of various lengths
for num_shots in range(10):
    plot_answer_stats(hard_embedding_model, noun_val, make_few_shot(num_shots), verb
```



Deliverables

Please submit this completed notebook and complete all the written questions.