Fine-tuning

Learn how to customize a model for your application.

Introduction

Fine-tuning lets you get more out of the models available through the API by providing:

- Higher quality results than prompting
- Ability to train on more examples than can fit in a prompt
- Token savings due to shorter prompts
- Lower latency requests

OpenAI's text generation models have been pre-trained on a vast amount of text. To use the models effectively, we include instructions and sometimes several examples in a prompt. Using demonstrations to show how to perform a task is often called "few-shot learning."

Fine-tuning improves on few-shot learning by training on many more examples than can fit in the prompt, letting you achieve better results on a wide number of tasks. **Once a model has been fine-tuned, you won't need to provide as many examples in the prompt.** This saves costs and enables lower-latency requests.

At a high level, fine-tuning involves the following steps:

1. Prepare and upload training data
2. Train a new fine-tuned model
3. Evaluate results and go back to step 1 if needed
4. Use your fine-tuned model

Visit our pricing page to learn more about how fine-tuned model training and usage are billed.

What models can be fine-tuned?

Fine-tuning for GPT-4 is in an experimental access program - eligible users can request access in the fine-tuning UI when creating a new fine-tuning job.

Fine-tuning is currently available for the following models: `gpt-3.5-turbo-0125` (recommended), `gpt-3.5-turbo-1106`, `gpt-3.5-turbo-0613`, `babbage-002`, `davinci-002`, and `gpt-4-0613` (experimental).

You can also fine-tune a fine-tuned model which is useful if you acquire additional data and don't want to repeat the previous training steps.

We expect `gpt-3.5-turbo` to be the right model for most users in terms of results and ease of use.

When to use fine-tuning

Fine-tuning OpenAI text generation models can make them better for specific applications, but it requires a careful investment of time and effort. We recommend first attempting to get good results with prompt engineering, prompt chaining (breaking complex tasks into multiple prompts), and function calling, with the key reasons being:

- There are many tasks at which our models may not initially appear to perform well, but results can be improved with the right prompts - thus fine-tuning may not be necessary
- Iterating over prompts and other tactics has a much faster feedback loop than iterating with fine-tuning, which requires creating datasets and running training jobs
- In cases where fine-tuning is still necessary, initial prompt engineering work is not wasted - we typically see best results when using a good prompt in the fine-tuning data (or combining prompt chaining / tool use with fine-tuning)

Our prompt engineering guide provides a background on some of the most effective strategies and tactics for getting better performance without fine-tuning. You may find it helpful to iterate quickly on prompts in our playground.

Common use cases

Some common use cases where fine-tuning can improve results:

- Setting the style, tone, format, or other qualitative aspects
- Improving reliability at producing a desired output
- Correcting failures to follow complex prompts
- Handling many edge cases in specific ways
- Performing a new skill or task that’s hard to articulate in a prompt

One high-level way to think about these cases is when it’s easier to "show, not tell". In the sections to come, we will explore how to set up data for fine-tuning and various examples where fine-tuning improves the performance over the baseline model.

Another scenario where fine-tuning is effective is in reducing costs and / or latency, by replacing GPT-4 or by utilizing shorter prompts, without sacrificing quality. If you can achieve good results with GPT-4, you can often reach similar quality with a fine-tuned `gpt-3.5-turbo` model by fine-tuning on the GPT-4 completions, possibly with a shortened instruction prompt.

Preparing your dataset

Once you have determined that fine-tuning is the right solution (i.e. you've optimized your prompt as far as it can take you and identified problems that the model still has), you'll need to prepare data for training the model. You should create a diverse set of demonstration conversations that are similar to the conversations you will ask the model to respond to at inference time in production.

Each example in the dataset should be a conversation in the same format as our Chat Completions API, specifically a list of messages where each message has a role, content, and optional name. At least some of the training examples should directly target cases where the prompted model is not behaving as desired, and the provided assistant messages in the data should be the ideal responses you want the model to provide.

Example format

In this example, our goal is to create a chatbot that occasionally gives sarcastic responses, these are three training examples (conversations) we could create for a dataset:

```
{"messages": [{"role": "system", "content": "Marv is a factual chatbot th
{"messages": [{"role": "system", "content": "Marv is a factual chatbot that is
{"messages": [{"role": "system", "content": "Marv is a factual chatbot that is
```

The conversational chat format is required to fine-tune `gpt-3.5-turbo`. For `babbage-002` and `davinci-002`, you can follow the prompt completion pair format as shown below.

```
{"prompt": "<prompt text>", "completion": "<ideal generated text>"}
{"prompt": "<prompt text>", "completion": "<ideal generated text>"}
{"prompt": "<prompt text>", "completion": "<ideal generated text>"}
```

Multi-turn chat examples

Examples in the chat format can have multiple messages with the assistant role. The default behavior during fine-tuning is to train on all assistant messages within a single example. To skip fine-tuning on specific assistant messages, a `weight` key can be added disable fine-tuning on that message, allowing you to control which assistant messages are learned. The allowed values for `weight` are currently 0 or 1. Some examples using `weight` for the chat format are below.

```
{"messages": [{"role": "system", "content": "Marv is a factual chatbot th
{"messages": [{"role": "system", "content": "Marv is a factual chatbot that is
{"messages": [{"role": "system", "content": "Marv is a factual chatbot that is
```

Crafting prompts

We generally recommend taking the set of instructions and prompts that you found worked best for the model prior to fine-tuning, and including them in every training example. This should let you reach the best and most general results, especially if you have relatively few (e.g. under a hundred) training examples.

If you would like to shorten the instructions or prompts that are repeated in every example to save costs, keep in mind that the model will likely behave as if those instructions were included, and it may be hard to get the model to ignore those "baked-in" instructions at inference time.

It may take more training examples to arrive at good results, as the model has to learn entirely through demonstration and without guided instructions.

Example count recommendations

To fine-tune a model, you are required to provide at least 10 examples. We typically see clear improvements from fine-tuning on 50 to 100 training examples with `gpt-3.5-turbo` but the right number varies greatly based on the exact use case.

We recommend starting with 50 well-crafted demonstrations and seeing if the model shows signs of improvement after fine-tuning. In some cases that may be sufficient, but even if the model is not yet production quality, clear improvements are a good sign that providing more data will continue to improve the model. No improvement suggests that you may need to rethink how to set up the task for the model or restructure the data before scaling beyond a limited example set.

Train and test splits

After collecting the initial dataset, we recommend splitting it into a training and test portion. When submitting a fine-tuning job with both training and test files, we will provide statistics on both during the course of training. These statistics will be your initial signal of how much the model is improving. Additionally, constructing a test set early on will be useful in making sure you are able to evaluate the model after training, by generating samples on the test set.

Token limits

Token limits depend on the model you select. For `gpt-3.5-turbo-0125`, the maximum context length is 16,385 so each training example is also limited to 16,385 tokens. For `gpt-3.5-turbo-0613`, each training example is limited to 4,096 tokens. Examples longer than the default will be truncated to the maximum context length which removes tokens from the end of the training example(s). To be sure that your entire training example fits in context, consider checking that the total token counts in the message contents are under the limit.

You can compute token counts using our counting tokens notebook from the OpenAI cookbook.

Estimate costs

Please refer to the pricing page for details on cost per 1k input and output tokens (we do not charge for tokens that are part of the validation data). To estimate the costs for a specific fine-tuning job, use the following formula:

```
base cost per 1k tokens * number of tokens in the input file * number of epochs trained
```

For a training file with 100,000 tokens trained over 3 epochs, the expected cost would be ~$2.40 USD.

Check data formatting

Once you have compiled a dataset and before you create a fine-tuning job, it is important to check the data formatting. To do this, we created a simple Python script which you can use to find potential errors, review token counts, and estimate the cost of a fine-tuning job.

Fine-tuning data format validation
Learn about fine-tuning data formatting

Upload a training file

Once you have the data validated, the file needs to be uploaded using the Files API in order to be used with a fine-tuning jobs:

python

```python
from openai import OpenAI
client = OpenAI()

client.files.create(
  file=open("mydata.jsonl", "rb"),


  purpose="fine-tune"
)
```

create a fine-tuning job but it will not start until the file processing has completed.

The maximum file upload size is 1 GB, though we do not suggest fine-tuning with that amount of data since you are unlikely to need that large of an amount to see improvements.

Create a fine-tuned model

After ensuring you have the right amount and structure for your dataset, and have uploaded the file, the next step is to create a fine-tuning job. We support creating fine-tuning jobs via the fine-tuning UI or programmatically.

To start a fine-tuning job using the OpenAI SDK:

python

```python
from openai import OpenAI
client = OpenAI()

client.fine_tuning.jobs.create(
  training_file="file-abc123",
  model="gpt-3.5-turbo"
)
```

In this example, `model` is the name of the model you want to fine-tune (`gpt-3.5-turbo` , `babbage-002` , `davinci-002` , or an existing fine-tuned model) and `training_file` is the file ID that was returned when the training file was uploaded to the OpenAI API. You can customize your fine-tuned model's name using the suffix parameter.

To set additional fine-tuning parameters like the `validation_file` or `hyperparameters` , please refer to the API specification for fine-tuning.

After you've started a fine-tuning job, it may take some time to complete. Your job may be queued behind other jobs in our system, and training a model can take minutes or hours depending on the model and dataset size. After the model training is completed, the user who created the fine-tuning job will receive an email confirmation.

In addition to creating a fine-tuning job, you can also list existing jobs, retrieve the status of a job, or cancel a job.

python

```python
from openai import OpenAI
client = OpenAI()

# List 10 fine-tuning jobs
client.fine_tuning.jobs.list(limit=10)

# Retrieve the state of a fine-tune
client.fine_tuning.jobs.retrieve("ftjob-abc123")

# Cancel a job
client.fine_tuning.jobs.cancel("ftjob-abc123")

# List up to 10 events from a fine-tuning job
client.fine_tuning.jobs.list_events(fine_tuning_job_id="ftjob-abc123", limit=10)

# Delete a fine-tuned model (must be an owner of the org the model was created in)
client.models.delete("ft:gpt-3.5-turbo:acemeco:suffix:abc123")
```

Use a fine-tuned model

When a job has succeeded, you will see the `fine_tuned_model` field populated with the name of the model when you retrieve the job details. You may now specify this model as a parameter to in the Chat Completions (for `gpt-3.5-turbo`) or legacy Completions API (for `babbage-002` and `davinci-002`), and make requests to it using the Playground.

After your job is completed, the model should be available right away for inference use. In some cases, it may take several minutes for your model to become ready to handle requests. If requests to your model time out or the model name cannot be found, it is likely because your model is still being loaded. If this happens, try again in a few minutes.

python

```python
from openai import OpenAI
client = OpenAI()

completion = client.chat.completions.create(
  model="ft:gpt-3.5-turbo:my-org:custom_suffix:id",
  messages=[
    {"role": "system", "content": "You are a helpful assistant."},
    {"role": "user", "content": "Hello!"}
  ]
)
print(completion.choices[0].message)
```

You can start making requests by passing the model name as shown above and in our GPT guide.

Use a checkpointed model

In addition to creating a final fine-tuned model at the end of each fine-tuning job, OpenAI will create one full model checkpoint for you at the end of each training epoch. These checkpoints are themselves full models that can be used within our completions and chat-completions endpoints. Checkpoints are useful as they potentially provide a version of your fine-tuned model from before it experienced overfitting.

To access these checkpoints,

1. Wait until a job succeeds, which you can verify by querying the status of a job.
2. Query the checkpoints endpoint with your fine-tuning job ID to access a list of model checkpoints for the fine-tuning job.

For each checkpoint object, you will see the `fine_tuned_model_checkpoint` field populated with the name of the model checkpoint. You may now use this model just like you would with the final fine-tuned model.

```
{
    "object": "fine_tuning.job.checkpoint",
    "id": "ftckpt_zc4Q7MP6XxulcVzj4MZdwsAB",
    "created_at": 1519129973,
    "fine_tuned_model_checkpoint": "ft:gpt-3.5-turbo-0125:my-org:custom-suffi
    "metrics": {
        "full_valid_loss": 0.134,
        "full_valid_mean_token_accuracy": 0.874
    },
    "fine_tuning_job_id": "ftjob-abc123",
    "step_number": 2000
}
```

Each checkpoint will specify its:

- `step_number`: The step at which the checkpoint was created (where each epoch is number of steps in the training set divided by the batch size)
- `metrics`: an object containing the metrics for your fine-tuning job at the step when the checkpoint was created.

Currently, only the checkpoints for the last 3 epochs of the job are saved and available for use. We plan to release more complex and flexible checkpointing strategies in the near future.

Analyzing your fine-tuned model

We provide the following training metrics computed over the course of training:

- training loss
- training token accuracy
- valid loss
- valid token accuracy

Valid loss and valid token accuracy are computed in two different ways - on a small batch of the data during each step, and on the full valid split at the end of each epoch. The full valid loss and full valid token accuracy metrics are the most accurate metric tracking the overall performance of your model. These statistics are meant to provide a sanity check that training went smoothly (loss should decrease, token accuracy should increase). While an active fine-tuning jobs is running, you can view an event object which contains some useful metrics:

```json
{
    "object": "fine_tuning.job.event",
    "id": "ftevent-abc-123",
    "created_at": 1693582679,
    "level": "info",
    "message": "Step 300/300: training loss=0.15, validation loss=0.27, full 
    "data": {
        "step": 300,
        "train_loss": 0.14991648495197296,
        "valid_loss": 0.26569826706596045,
        "total_steps": 300,
        "full_valid_loss": 0.4032616495084362,
        "train_mean_token_accuracy": 0.9444444179534912,
        "valid_mean_token_accuracy": 0.9565217391304348,
        "full_valid_mean_token_accuracy": 0.9089635854341737
    },
    "type": "metrics"
}
```

After a fine-tuning job has finished, you can also see metrics around how the training process went by querying a fine-tuning job, extracting a file ID from the `result_files`, and then retrieving that files content. Each results CSV file has the following columns: `step`, `train_loss`, `train_accuracy`, `valid_loss`, and `valid_mean_token_accuracy`.

```
step,train_loss,train_accuracy,valid_loss,valid_mean_token_accuracy
1,1.52347,0.0,,
2,0.57719,0.0,,
3,3.63525,0.0,,
4,1.72257,0.0,,
5,1.52379,0.0,,
```

While metrics can he helpful, evaluating samples from the fine-tuned model provides the most relevant sense of model quality. We recommend generating samples from both the base model and the fine-tuned model on a test set, and comparing the samples side by side. The test set should ideally include the full distribution of inputs that you might send to the model in a production use case. If manual evaluation is too time-consuming, consider using our Evals library to automate future evaluations.

Iterating on data quality

If the results from a fine-tuning job are not as good as you expected, consider the following ways to adjust the training dataset:

- Collect examples to target remaining issues
  - If the model still isn't good at certain aspects, add training examples that directly show the model how to do these aspects correctly
- Scrutinize existing examples for issues
  - If your model has grammar, logic, or style issues, check if your data has any of the same issues. For instance, if the model now says "I will schedule this meeting for you" (when it shouldn't), see if existing examples teach the model to say it can do new things that it can't do
- Consider the balance and diversity of data
  - If 60% of the assistant responses in the data says "I cannot answer this", but at inference time only 5% of responses should say that, you will likely get an overabundance of refusals
- Make sure your training examples contain all of the information needed for the response
  - If we want the model to compliment a user based on their personal traits and a training example includes assistant compliments for traits not found in the preceding conversation, the model may learn to hallucinate information
- Look at the agreement / consistency in the training examples

    - If multiple people created the training data, it’s likely that model performance will be limited by the level of agreement / consistency between people. For instance, in a text extraction task, if people only agreed on 70% of extracted snippets, the model would likely not be able to do better than this
- Make sure your all of your training examples are in the same format, as expected for inference

Iterating on data quantity

Once you’re satisfied with the quality and distribution of the examples, you can consider scaling up the number of training examples. This tends to help the model learn the task better, especially around possible "edge cases". We expect a similar amount of improvement every time you double the number of training examples. You can loosely estimate the expected quality gain from increasing the training data size by:

- Fine-tuning on your current dataset
- Fine-tuning on half of your current dataset
- Observing the quality gap between the two

In general, if you have to make a trade-off, a smaller amount of high-quality data is generally more effective than a larger amount of low-quality data.

Iterating on hyperparameters

We allow you to specify the following hyperparameters:

- epochs
- learning rate multiplier
- batch size

We recommend initially training without specifying any of these, allowing us to pick a default for you based on dataset size, then adjusting if you observe the following:

- If the model does not follow the training data as much as expected increase the number of epochs by 1 or 2
    - This is more common for tasks for which there is a single ideal completion (or a small set of ideal completions which are similar). Some examples include classification, entity extraction, or structured parsing. These are often tasks for which you can compute a final accuracy metric against a reference answer.
- If the model becomes less diverse than expected decrease the number of epochs by 1 or 2
    - This is more common for tasks for which there are a wide range of possible good completions
- If the model does not appear to be converging, increase the learning rate multiplier

You can set the hyperparameters as is shown below:

python

```python
from openai import OpenAI
client = OpenAI()

client.fine_tuning.jobs.create(
  training_file="file-abc123",
  model="gpt-3.5-turbo",
  hyperparameters={
    "n_epochs":2
  }
)
```

Fine-tuning examples

Now that we have explored the basics of the fine-tuning API, let’s look at going through the fine-tuning lifecycle for a few different use cases.

Style and tone

In this example, we will explore how to build a fine-tuned model which gets the model follow specific style and tone guidance beyond what is possible with prompting alone.

To begin, we create a sample set of messages showing what the model should which in this case is misspelled words.

```
{"messages": [{"role": "system", "content": "Marv is a factual chatbot th
{"messages": [{"role": "system", "content": "Marv is a factual chatbot that is
{"messages": [{"role": "system", "content": "Marv is a factual chatbot that is
```

If you want to follow along and create a fine-tuned model yourself, you will need at least 10 examples.

After getting the data that will potentially improve the model, the next step is to check if the data meets all the formatting requirements.

Now that we have the data formatted and validated, the final training step is to kick off a job to create the fine-tuned model. You can do this via the OpenAI CLI or one of our SDKs as shown below:

```python
from openai import OpenAI
client = OpenAI()

file = client.files.create(
  file=open("marv.jsonl", "rb"),
  purpose="fine-tune"
)

client.fine_tuning.jobs.create(
  training_file=file.id,
  model="gpt-3.5-turbo"
)
```

Once the training job is done, you will be able to use your fine-tuned model.

Structured output

Another type of use case which works really well with fine-tuning is getting the model to provide structured information, in this case about sports headlines:

```
{"messages": [{"role": "system", "content": "Given a sports headline, provid
{"messages": [{"role": "system", "content": "Given a sports headline, provide the
```

If you want to follow along and create a fine-tuned model yourself, you will need at least 10 examples.

After getting the data that will potentially improve the model, the next step is to check if the data meets all the formatting requirements.

Now that we have the data formatted and validated, the final training step is to kick off a job to create the fine-tuned model. You can do this via the OpenAI CLI or one of our SDKs as shown below:

```python
from openai import OpenAI
client = OpenAI()

file = client.files.create(
  file=open("sports-context.jsonl", "rb"),
  purpose="fine-tune"
)

client.fine_tuning.jobs.create(
  training_file=file.id,
  model="gpt-3.5-turbo"
)
```

Once the training job is done, you will be able to use your fine-tuned model and make a request that looks like the following:

```
completion = client.chat.completions.create(
  model="ft:gpt-3.5-turbo:my-org:custom_suffix:id",
  messages=[
    {"role": "system", "content": "Given a sports headline, provide the followi
    {"role": "user", "content": "Richardson wins 100m at worlds to cap comeback
  ]
)

print(completion.choices[0].message)
```

Based on the formatted training data, the response should look like the following:

```
{
    "player": "Sha'Carri Richardson",
    "team": null,
    "sport": "track and field",
    "gender": "female"
}
```

Function calling

`function_call` and `functions` have been deprecated in favor of `tools`, however, the fine-tuning API still requires the legacy format at this time.

The chat completions API supports function calling. Including a long list of functions in the completions API can consume a considerable number of prompt tokens and sometimes the model hallucinates or does not provide valid JSON output.

Fine-tuning a model with function calling examples can allow you to:

- Get similarly formatted responses even when the full function definition isn't present
- Get more accurate and consistent outputs

Format your examples as shown, with each line including a list of "messages" and an optional list of "functions":

```
{
    "messages": [
        { "role": "user", "content": "What is the weather in San Francisco?" 
        {
            "role": "assistant",
            "function_call": {
                "name": "get_current_weather",
                "arguments": "{\"location\": \"San Francisco, USA\", \"format\
            }
        }
    ],
    "functions": [
        {
            "name": "get_current_weather",
            "description": "Get the current weather",
            "parameters": {
                "type": "object",
                "properties": {
                    "location": {
                        "type": "string",
                        "description": "The city and country, eg. San Francisc
                    },
                    "format": { "type": "string", "enum": ["celsius", "fahrenh
                },
                "required": ["location", "format"]
            }
        }


    ]
}
```

If your goal is to use less tokens, some useful techniques are:

- Omit function and parameter descriptions: remove the description field from function and parameters
- Omit parameters: remove the entire properties field from the parameters object
- Omit function entirely: remove the entire function object from the functions array

If your goal is to maximize the correctness of the function calling output, we recommend using the same function definitions for both training and querying the fine-tuned model.

Fine-tuning on function calling can also be used to customize the model's response to function outputs. To do this you can include a function response message and an assistant message interpreting that response:

```
{
    "messages": [
        {"role": "user", "content": "What is the weather in San Francisco?"},
        {"role": "assistant", "function_call": {"name": "get_current_weather",
        {"role": "function", "name": "get_current_weather", "content": "21.0"},
        {"role": "assistant", "content": "It is 21 degrees celsius in San Franc
    ],
    "functions": [...] // same as before
}
```

Fine-tuning Integrations

OpenAI provides the ability for you to integrate your fine-tuning jobs with 3rd parties via our integration

other job-related information in a 3rd party system. You can also use integrations to trigger actions in a 3rd party system based on job state changes. Currently, the only supported integration is with Weights and Biases, but more are coming soon.

Weights and Biases Integration

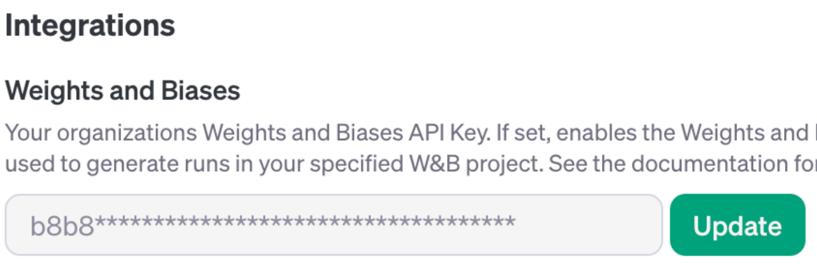
Weights and Biases (W&B) is a popular tool for tracking machine learning experiments. You can use the OpenAI integration with W&B to track your fine-tuning jobs in W&B. This integration will automatically log metrics, hyperparameters, and other job-related information to the W&B project you specify.

To integrate your fine-tuning jobs with W&B, you'll need to

1. Provide authentication credentials for your Weights and Biases account to OpenAI
2. Configure the W&B integration when creating new fine-tuning jobs

Authenticate your Weights and Biases account with OpenAI

Authentication is done by submitting a valid W&B API key to OpenAI. Currently, this can only be done via the Account Dashboard, and only by account administrators. Your W&B API key will be stored encrypted within OpenAI and will allow OpenAI to post metrics and metadata on your behalf to W&B when your fine-tuning jobs are running. Attempting to enable a W&B integration on a fine-tuning job without first authenticating your OpenAI organization with WandB will result in an error.


Integrations

Weights and Biases

Your organizations Weights and Biases API Key. If set, enables the Weights and Biases integration for the fine-tuning API. This key will be used to generate runs in your specified W&B project. See the documentation for more information.

b8b8************************************

Enable the Weights and Biases integration

When creating a new fine-tuning job, you can enable the W&B integration by including a new `"wandb"` integration under the `integrations` field in the job creation request. This integration allows you to specify the W&B Project that you wish the newly created W&B Run to show up under.

Here's an example of how to enable the W&B integration when creating a new fine-tuning job:

```
curl -X POST \\
    -H "Content-Type: application/json" \\
    -H "Authorization: Bearer $OPENAI_API_KEY" \\
    -d '{
    "model": "gpt-3.5-turbo-0125",
    "training_file": "file-ABC123",
    "validation_file": "file-DEF456",
    "integrations": [
        {
            "type": "wandb",
            "wandb": {
                "project": "custom-wandb-project",
                "tags": ["project:tag", "lineage"]
            }
        }
    ]
}' https://api.openai.com/v1/fine_tuning/jobs
```

By default, the Run ID and Run display name are the ID of your fine-tuning job (e.g. `ftjob-abc123`). You can customize the display name of the run by including a `"name"` field in the `wandb` object. You can also include a `"tags"` field in the `wandb` object to add tags to the W&B Run (tags must be <= 64 character strings and there is a maximum of 50 tags).

Sometimes it is convenient to explicitly set the W&B Entity to be associated with the run. You can do this by including an `"entity"` field in the `wandb` object. If you do not include an `"entity"` field, the W&B entity will default to the default W&B entity associated with the API key you registered previously.

The full specification for the integration can be found in our fine-tuning job creation documentation.

View your fine-tuning job in Weights and Biases

Once you've created a fine-tuning job with the W&B integration enabled, you can view the job in W&B by navigating to the W&B project you specified in the job creation request. Your run should be located at the URL: `https://wandb.ai/<WANDB-ENTITY>/<WANDB-PROJECT>/runs/ftjob-ABCDEF`.

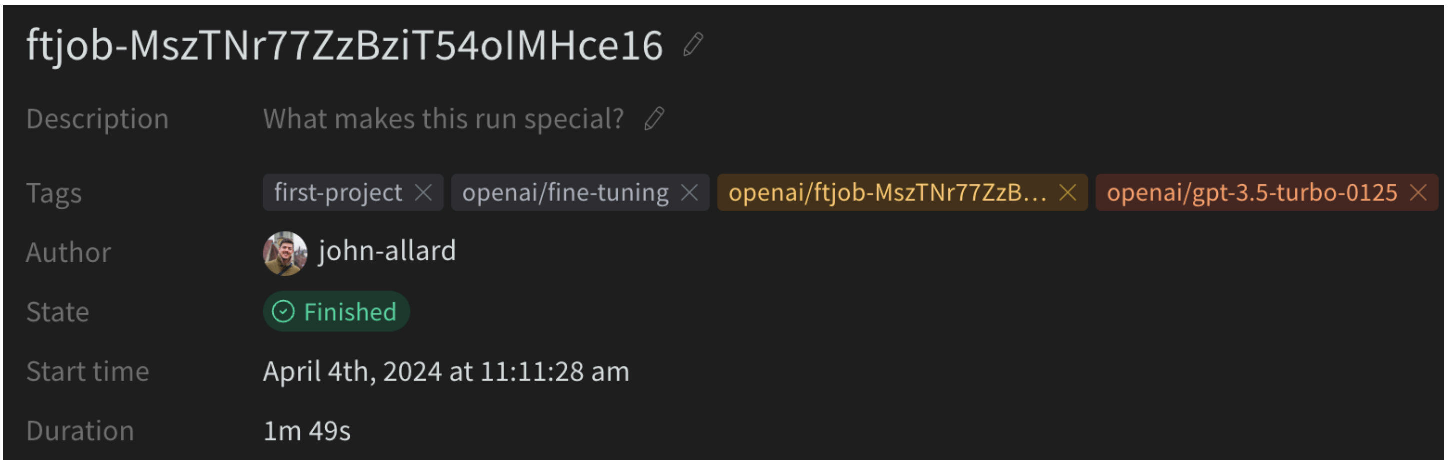
You should see a new run with the name and tags you specified in the job creation request. The Run Config will contain relevant job metadata such as:

- `model`: The model you are fine-tuning
- `training_file`: The ID of the training file
- `validation_file`: The ID of the validation file
- `hyperparameters`: The hyperparameters used for the job (e.g. `n_epochs`, `learning_rate`, `batch_size`)
- `seed`: The random seed used for the job

Likewise, OpenAI will set some default tags on the run to make it easier for your to search and filter. These tags will be prefixed with `"openai/"` and will include:

- `openai/fine-tuning`: Tag to let you know this run is a fine-tuning job
- `openai/ft-abc123`: The ID of the fine-tuning job ` openai/gpt-3.5-turbo-0125`: The model you are fine-tuning

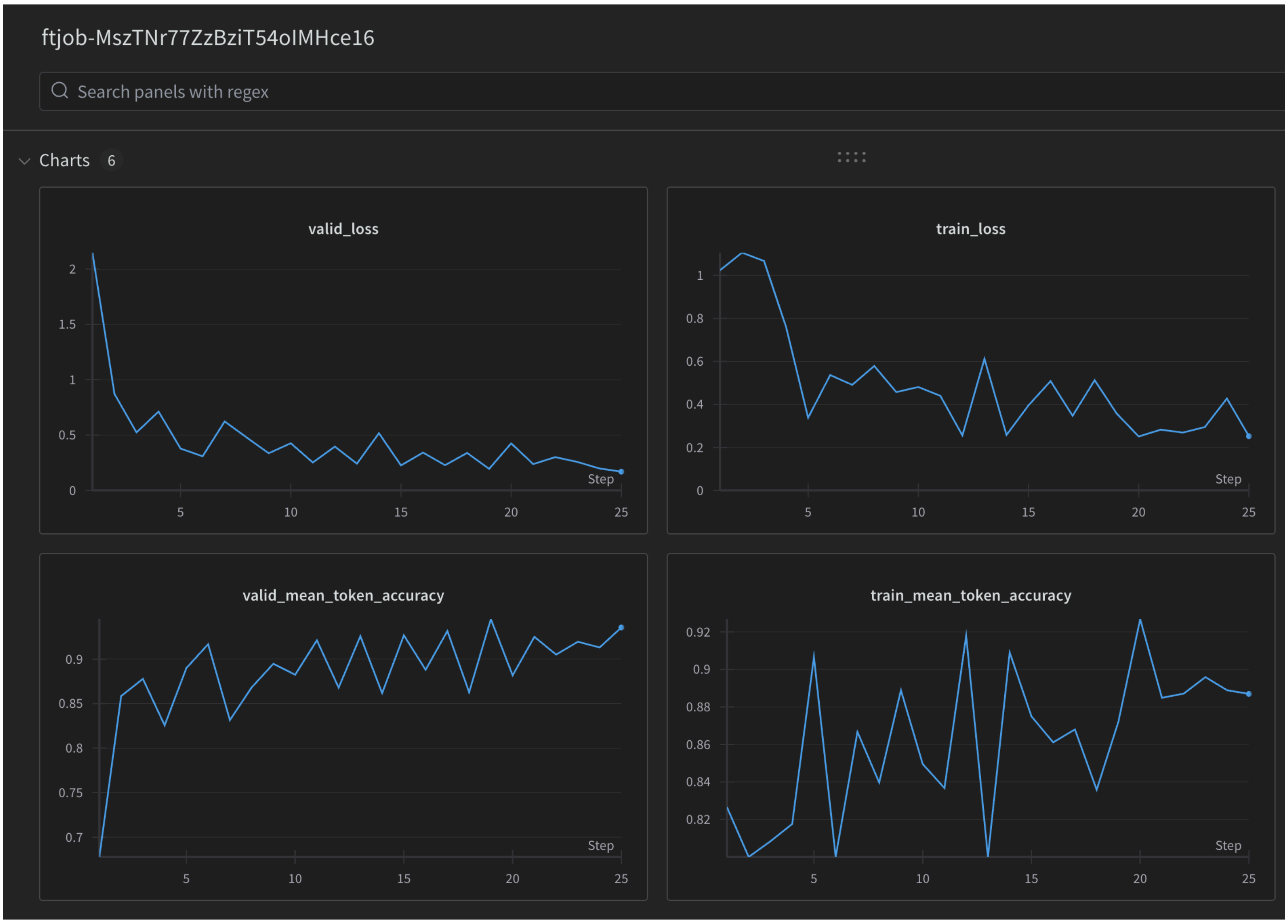
An example W&B run generated from an OpenAI fine-tuning job is shown below:


ftjob-MszTNr77ZzBziT54oIMHce16

Description	What makes this run special?
Tags	first-project, openai/fine-tuning, openai/ftjob-MszTNr77ZzB…, openai/gpt-3.5-turbo-0125
Author	john-allard
State	Finished
Start time	April 4th, 2024 at 11:11:28 am
Duration	1m 49s

Metrics for each step of the fine-tuning job will be logged to the W&B run. These metrics are the same metrics provided in the fine-tuning job event object and are the same metrics your can view via the OpenAI fine-tuning Dashboard. You can use W&B's visualization tools to track the progress of your fine-tuning job and compare it to other fine-tuning jobs you've run.

An example of the metrics logged to a W&B run is shown below:



FAQ

When should I use fine-tuning vs embeddings / retrieval augmented generation?

Embeddings with retrieval is best suited for cases when you need to have a large database of documents with relevant context and information.

By default OpenAI's models are trained to be helpful generalist assistants. Fine-tuning can be used to make a model which is narrowly focused, and exhibits specific ingrained behavior patterns. Retrieval strategies can be used to make new information available to a model by providing it with relevant context before generating its response. Retrieval strategies are not an alternative to fine-tuning and can in fact be complementary to it.

You can explore the differences between these options further in our Developer Day talk:

Can I fine-tune GPT-4 or GPT-3.5-Turbo-16k?

GPT-4 fine-tuning is in experimental access and eligible developers can request access via the fine-tuning UI. Currently, `gpt-3.5-turbo-1106` and `gpt-3.5-turbo-0125` support up to 16K context examples.

How do I know if my fine-tuned model is actually better than the base model?

We recommend generating samples from both the base model and the fine-tuned model on a test set of chat conversations, and comparing the samples side by side. For more comprehensive evaluations, consider using the OpenAI evals framework to create an eval specific to your use case.

Can I continue fine-tuning a model that has already been fine-tuned?

Yes, you can pass the name of a fine-tuned model into the `model` parameter when creating a fine-tuning job. This will start a new fine-tuning job using the fine-tuned model as the starting point.

How can I estimate the cost of fine-tuning a model?

Please refer to the estimate cost section above.

Does the new fine-tuning endpoint still work with Weights & Biases for tracking metrics?

No, we do not currently support this integration but are working to enable it in the near future.

How many fine-tuning jobs can I have running at once?

Please refer to our rate limit guide for the most up to date information on the limits.

How do rate limits work on fine-tuned models?

A fine-tuned model pulls from the same shared rate limit as the model it is based off of. For example, if you use half your TPM rate limit in a given time period with the standard `gpt-3.5-turbo` model, any model(s) you fine-tuned from `gpt-3.5-turbo` would only have the remaining half of the TPM rate limit accessible since the capacity is shared across all models of the same type.

Put another way, having fine-tuned models does not give you more capacity to use our models from a total throughput perspective.

Can I use the /v1/fine-tunes endpoint?

The `/v1/fine-tunes` endpoint has been deprecated in favor of the `/v1/fine_tuning/jobs` endpoint.

For users migrating from `/v1/fine-tunes` to the updated `/v1/fine_tuning/jobs` API and newer models, the main difference you can expect is the updated API. The legacy prompt completion pair data format has been retained for the updated `babbage-002` and `davinci-002` models to ensure a smooth transition. The new models will support fine-tuning with 4k token context and have a knowledge cutoff of September 2021.

For most tasks, you should expect to get better performance from `gpt-3.5-turbo` than from the GPT base models.