# Tailoring Chatbots for Higher Education: Some Insights and Experiences

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The general availability of powerful Large Language Models had a powerful impact on higher education, yet general models may not always be useful for the associated specialized tasks. When using these models, oftentimes the need for particular domain knowledge becomes quickly apparent, and the desire for customized bots arises. Customization holds the promise of leading to more accurate and contextually relevant responses, enhancing the educational experience. The purpose of this short technical experience report is to describe what "customizing" Large Language Models means in practical terms for higher education institutions. This report thus relates insights and experiences from one particular technical university in Switzerland, ETH Zurich.

# I. LARGE LANGUAGE MODELS

Large Language Models (LLMs) are only one particular class of artificial intelligence systems, yet they have garnered enormous attention due to their ease-of-use, public availability, reasoning capabilities, and general, broad knowledge base. This impact was also felt in higher education [1–3]. Due to the in-depth and specialized nature of higher education, LLMs could frequently benefit from more in-depth knowledge of particular domains. The most frequently used way of accessing these models is through chatbot interfaces, and thus the term "custom chatbot" gained traction for specialized LLMs.

LLMs are sophisticated AI systems driven by numerous parameters, particularly weights, which play a crucial role in their operation. At the heart of LLMs is an auto-complete-like mechanism based on a neural network, which, based on a sequence of existing text and those weights predicts what should come next in the sequence. This is somewhat similar to the next-word suggestions on a smartphone when sending a text message, only that the algorithm operates on smaller units called tokens. These tokens, which can represent whole words, parts of words, individual characters or punctuation, are the building blocks the model uses to generate text. The network learns probable sequences of tokens from existing documents, its training corpus.

Generating novel text by an LLM is called inference. Typically, chatbots generate these token sequences in response to user input, so-called prompts. Due to the probabilistic nature of LLMs, these responses were initially derided by some skeptics (including the author) as nothing more than "plausible fiction," but in the meantime, the systems have proven to be useful across a wide spectrum of applications. Inference involves large-scale matrix operations that are usually performed on processing units that were originally designed for graphics operations, GPUs. In addition to well-known chatbot interfaces, and of possibly equal importance to higher education institutions, are application programming interfaces (APIs), so other systems can make use of the LLM capabilities.

# II. CUSTOMIZED LARGE LANGUAGE MODELS

To customize Large Language Models, there are basically three routes with very different complexities.

#### A. Training from Scratch

By far the most complex and resource-intensive way to get a customized LLM is to build a model from scratch. Besides having to decide on crucial architectural features, today's models have billions of weight parameters, which require an enormous amount of training materials to properly adjust and optimize; the training corpuses of today's general-purpose models encompass trillions of tokens.

## 1. Commercial Systems

Common lore is that powerful commercial systems like GPT-4 have essentially ingested the "whole internet;" while that may be a hyperbole, curating the training corpus is extremely work-intensive, followed by computationally intensive training over months, followed by supervised and unsupervised tuning and detoxing. The origin of the training materials is sometimes questionable and the legal situation murky [4], the computing requires enormous resources and power (associated with large CO<sub>2</sub> production [5]), and the manual tuning at times employs questionable work practices [6].

Due to the high associated cost (said to be in the billions of dollars for powerful foundation models like OpenAI/Microsoft's GPT-4 [7], Google's Gemini [8], Meta's (maker of Facebook) Llama [9], or Apple Intelligence [10]), this remains largely the domain of large corporations, even though models made by smaller companies such as Mistral [11] and Anthropic's Claude [12] have also shown remarkably high promise.

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Models like GPT-40 [13] and Gemini are also multimodal, so they accept auditory and visual input, and they can produce corresponding output. In the area of higher education, multimodality is particularly interesting for lecture transcriptions (voice and blackboard), as well as handwriting recognition for grading tasks [14, 15]. This generalized multimodality currently is the domain of the largest commercial models; university-generated systems usually implement multimodality only in research settings.

In short, training a competitive LLM from scratch seems inadvisable to individual higher education institutions; it appears virtually impossible for academic projects to reach the same level of general knowledge, reasoning, and multimodality that commercial models achieve.

## 2. Public Systems

Smaller, domain-specific LLMs can be generated on the scale of countries or university consortia, such as the efforts currently undertaken by our Swiss AI project [16]. Such a project requires a large repository of carefully curated training materials, which can be challenging to obtain while respecting author rights; the custom material alone would be insufficient to establish language and reasoning skills in the models.

For the education model in particular, there are publicly available datasets for "basic training," that is, content for typical high school and introductory college curricula, but it turned out to be an uphill battle to obtain specialized and institution-specific course materials from faculty. There is a notable availability gap between basic content and research content, which is again readily available, for example from preprint servers or open-access publications.

On the flip side, a significant advantage of this approach is the control over training materials, which enhances the trustworthiness, transparency, and compliance of the resulting AI systems. The Swiss AI Initiative aims to develop advanced, large-scale AI models aligned with Swiss values, leveraging the country's supercomputing capabilities to foster innovation and accessibility in AI technology. Throughout all its efforts, the initiative adheres to guiding principles of using region-specific datasets, respecting copyright, and honoring website restrictions regarding content processing. This approach not only ensures legal and ethical compliance but also contributes to the creation of AI systems tailored to Switzerland's needs and values. Also here, training a model from scratch requires considerable super-computing resources; for example, Swiss AI will use a machine with 10,000 high-end NVIDIA GPUs, which recently came online and has vet to be used for this purpose. Once again, an ambitious effort, which should not be lightly undertaken.

This approach seems appropriate for specialized do-

mains when large-scale resources are available. Since the resulting model will be non-mainstream, it needs to be clarified early on where the model should eventually run (inference).

#### B. Fine-Tuning

Fine-tuning takes an already pre-trained model and modifies the weights of the neural net (in some approaches, this is only done with a subset of tokens in the later layers of the network). This is similar to editing a pre-written paper: the core content is already in place, and now it is being refined and enhanced. A big advantage is that the model already "knows" how to talk and reason, and one only needs to provide the custom data, alas usually after extensive preparation in specialized formats. This requires much less, but still considerable computational effort. After downloading the weights for the pre-trained model, fine-tuning usually requires several rounds of fine-tuning; there are common libraries for such efforts, and typical projects make use of the Hugging Face ecosystem [17].

With the notable exception of Llama 3, large, full-featured commercial models are not available as "openweight" pre-trained models to start from for these independent projects. For Gemini and Mistral, however, smaller versions are available open-weight, and for Claude, older versions are open-weight. None of these smaller models have multimodal capabilities, and smaller models are usually worse for non-English languages [18] (this is an issue in Switzerland, which has four official non-English languages, one of them lesser spoken). Llama 3.1, on the other hand, is a full-featured openweight model, available up to 405 billion parameters; it also has the capability of producing multimodal output.

While GPT allows for limited fine-tuning, this has to be done on OpenAI's platform at considerable cost per token [19], and the resulting model needs to be run there; it also *can* be run there, which might be advantageous if no other inference platform is available.

Within the Swiss AI initiative, an educational model is currently in development, with a first version based on Llama 3.1. A key focus is on domain-specific finetuning, allowing for targeted performance improvements in particular areas of importance to Swiss society and industry.

While the effort is reasonable, there are caveats. The open-weight models are already carefully pre-trained and tuned, and fine-tuning them can lead to overall worse results: the system may gain factual knowledge, but lose language and reasoning capabilities, and it will likely "forget" other things [20]. Finding the right level of finetuning is a balancing act [21]. It also should be kept in mind that fine-tuned models still "hallucinate," which is the term commonly used for producing incorrect responses not founded in training materials. Also, to take advantage of newer versions of the open-weight model, for example going from Llama 3.0 to Llama 3.1, the finetuning would have to be repeated, as all of the weight adjustments would need to be recalculated.

Fine-tuning, however, can help a model better "speak the language" of particular disciplines. The most viable route here seems to be using Llama and perform a limited amount of fine-tuning with carefully curated and prepared custom data on university research-computing infrastructure. The Swiss AI initiative will also follow this approach for some models. As discussed later, just like for models trained from scratch, this effort should not be undertaken without having arrangements for eventually running the model (inference).

### C. Augmentation

Some commercial models allow for straightforward but limited customizations, such as GPTs [22], where a limited number of documents, roles, and prompt-wrappers can be supplied. On the downside, this service requires users to have a subscription, and the amount of data is limited. Also, the documents would reside at OpenAI, which at least at our university limits them to those classified as public.

Very similar to this, Retrieval Augmented Generation (RAG) [23] is a method of customizing a chatbot without changing the LLM. The basic concept is to send relevant reference material alongside the user input: the user submits a prompt to the bot, the bot finds relevant text segments in its database of custom documents, and it then prompts the LLM along the lines of "Reply to [user prompt] using the following background materials: [relevant text segments]." Additional items injected into the prompt or the role may contain instructions of how to deal with situations where no relevant information could be found.

For any sufficiently useful custom chatbot, the amount of data in the provided documents is larger than what can be submitted to LLMs due to token limits. Thus, the art is to locate relevant text segments and only send those. A common approach is to convert the provided documents to plain text and then separate those text files into chunks which may correspond to paragraphs or semantically related segments of texts, depending on the algorithm used; this would be like cutting apart a paper into smaller pieces (though, most algorithms include some overlap between the pieces, which would not be possible with paper and scissors).

The standard method for determining relevance is converting these text chunks into token vectors, using so-called embeddings, for example OpenAI's adaembeddings [24]. Embedding is also charged by token, but it turned out that the cost is negligible, even for large document sets. Once the bot is running, the user prompts are also embedded, and the most relevant reference material is identified using cosine-similarity between the text-chunk embedding and the user-promptembedding, usually between four and ten chunks. This method often succeeds in finding semantically related text chunks, but it is not a search engine. An alternative approach uses standard indexing search engines to identify chunks, but these struggle with synonyms and when the user prompt is in a different language than the documents (like in Fig. 1). A combination of semantic and indexed search is possible.

This approach entails creating a local infrastructure for RAG either through a few hundred lines of code [25, 26] on a local low-power server using standard tools like LangChain [27] (the local machine does not do any heavy computing) or buying this service from a cloud provider ("RAG as a service"). For local installations, the service also requires access to a standard LLM via its API as the conversation and reasoning agent [28]. Figure 1 gives an example of a dialogue with such a system.

Local systems can be set up in a day or two, using a dedicated server or VM. Integration into the local IT landscape, for example, setting up access control, can take a little longer. Code examples are openly available [26].

At higher education institutions, it makes sense to set up one bot instance per course, each one using its own database file or database collection within the shared RAG infrastructure. The one-bot-per-course approach ensures that answers are specific to that course and follow the established notations. Most of all, though, learner questions about Calculus 1 should not be answered using concepts from Calculus 3. Documents for each course (scripts, exercise sheets, syllabi, etc.) can be collected in a folder (instructors frequently deliver them in a ZIP file); at ETH Zurich, these are usually a few hundred pages across ten to twenty documents.

For the semantic search, these documents need to be embedded, which can take a few seconds for single documents to minutes for course scripts and hours for extensive databases (this includes artificial wait times, since API-access to the embeddings is usually subject to tokenrate restrictions; we found it practical to submit ten chunks at a time with a two-second wait in-between). Once the embedding and/or indexing is finished, the bot instance can be started.

RAG has many advantages, as it is fast to implement and using standard LLMs, so inference is readily available. The system can be "rewired" (even on-the-fly) to take advantage of different LLMs or switch to a newer version of the LLM; at ETH, we are considering building a "model garden." It can also be used in combination with customized LLMs. If prompted to say "I don't know" in case the documents provide no relevant information, it is low on hallucinations (but also potentially less useful).

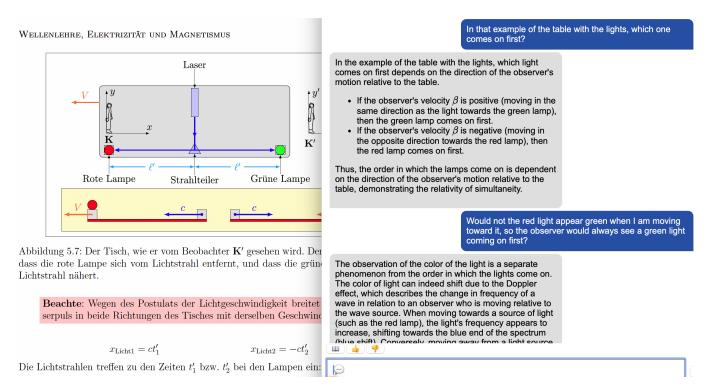


FIG. 1. Example of the chatbot component of Ethel. Shown on the left is a short excerpt of the lecture script, on the right a dialogue with the system.

#### III. INFERENCE

A frequently overlooked issue when discussing customized bots is: the associated LLM needs to run somewhere. For mainstream commercial models, inference services are readily available in the cloud. While several services are available as freebies after registration (user access to everyday model versions, developer access to APIs), the more advanced systems usually come with a cost: individual subscriptions or site-licenses [29] for advanced chatbot interfaces, usage-based or contingentbased payments-per-token for production APIs. In practice, for our RAG-based bot, it turned out that inference costs \$7.50 per student per course per semester for Azure AI Services.

As a cloud service, privacy and data security concerns are an issue. These can be addressed by constructing a proxy that anonymizes the requests of chatbots (e.g. ProxyGPT [30] or HAWKI [31]) or using existing Azure contracts [32]. The latter also guarantees that interactions are not used for training, which is crucial, as intentionally or unintentionally confidential information is submitted to the bot by users.

Running inference for open-weight models also comes at a price. At our university, it is still an open question where to run inference for new models that have been trained from scratch or fine-tuned. While inference takes less compute-power than training, it still requires several GPUs in 24/7-operation. Most universities have access to supercomputing resources, but these systems are usually designed for batch operation, and it is a challenge to permanently take nodes out of research commission. Obtaining cloud-computing resources is an option, for example using AWS SageMaker [33], but this can be costly and has the same privacy concerns mentioned earlier.

# IV. DISCLAIMER

This report was put together in the hopes that it may be useful. It can be no more than a snapshot in time, written from the perspective of a technical university on September 12, 2024. The LLM landscape, and in particular the landscape of associated services, is rapidly evolving: systems come and go at a pace that can make this report obsolete within months.

## V. CONCLUSION

There is no one-size-fits-all for customization of chatbots. Figure 2 summarizes the different options. For most purposes, RAG may be sufficient. Careful finetuning can help the system "learn the language" of its target users and infuse some basic knowledge about the discipline into general pre-trained models, but it requires an order of magnitude more effort to set up and requires a custom inference service. Training a model from scratch is prohibitively complex and expensive in all but a few special situations.

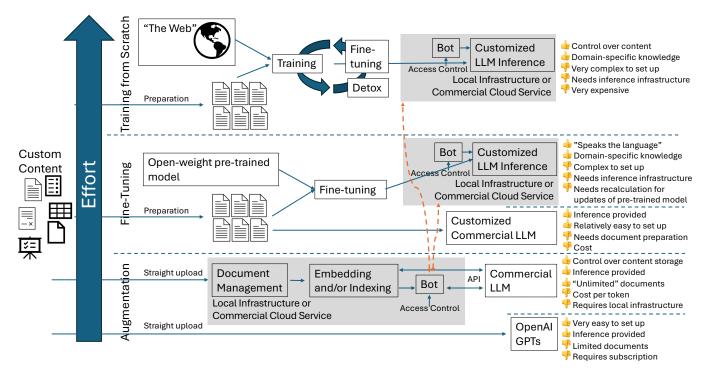


FIG. 2. Overview of the customization methods. The "Effort"-axis can be considered logarithmic.

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