TEMPLATE

search & replace the following keywords, e.g.: `:%s/\[name of model\]/brand_new_bert/g`

-[lowercase name of model] # e.g. brand_new_bert

-[camelcase name of model] # e.g. BrandNewBert

-[name of mentor] # e.g. Peter

-[link to original repo]

-[start date]

-[end date]

How to add [camelcase name of model] to 🤗 Transformers?

Mentor: [name of mentor]

Begin: [start date]

Estimated End: [end date]

Adding a new model is often difficult and requires an in-depth knowledge of the 🤗 Transformers library and ideally also of the model's original repository. At Hugging Face, we are trying to empower the community more and more to add models independently.

The following sections explain in detail how to add [camelcase name of model] to Transformers. You will work closely with [name of mentor] to integrate [camelcase name of model] into Transformers. By doing so, you will both gain a theoretical and deep practical understanding of [camelcase name of model]. But more importantly, you will have made a major open-source contribution to Transformers. Along the way, you will:

- get insights into open-source best practices
- understand the design principles of one of the most popular NLP libraries
- learn how to do efficiently test large NLP models
- learn how to integrate Python utilities like `black`, `isort`, `make fix-copies` into a library to always ensure clean and readable code

To start, let's try to get a general overview of the Transformers library.

General overview of 🤗 Transformers

First, you should get a general overview of 🤗 Transformers. Transformers is a very opinionated library, so there is a chance that you don't agree with some of the library's philosophies or design choices. From our experience, however, we found that the fundamental design choices and philosophies of the library are crucial to efficiently scale Transformers while keeping maintenance costs at a reasonable level.

A good first starting point to better understand the library is to read the documentation of our philosophy. As a result of our way of working, there are some choices that we try to apply to all models:

- Composition is generally favored over abstraction

- Duplicating code is not always bad if it strongly improves the readability or accessibility of a model
- Model files are as self-contained as possible so that when you read the code of a specific model, you ideally only have to look into the respective `modeling_....py` file.

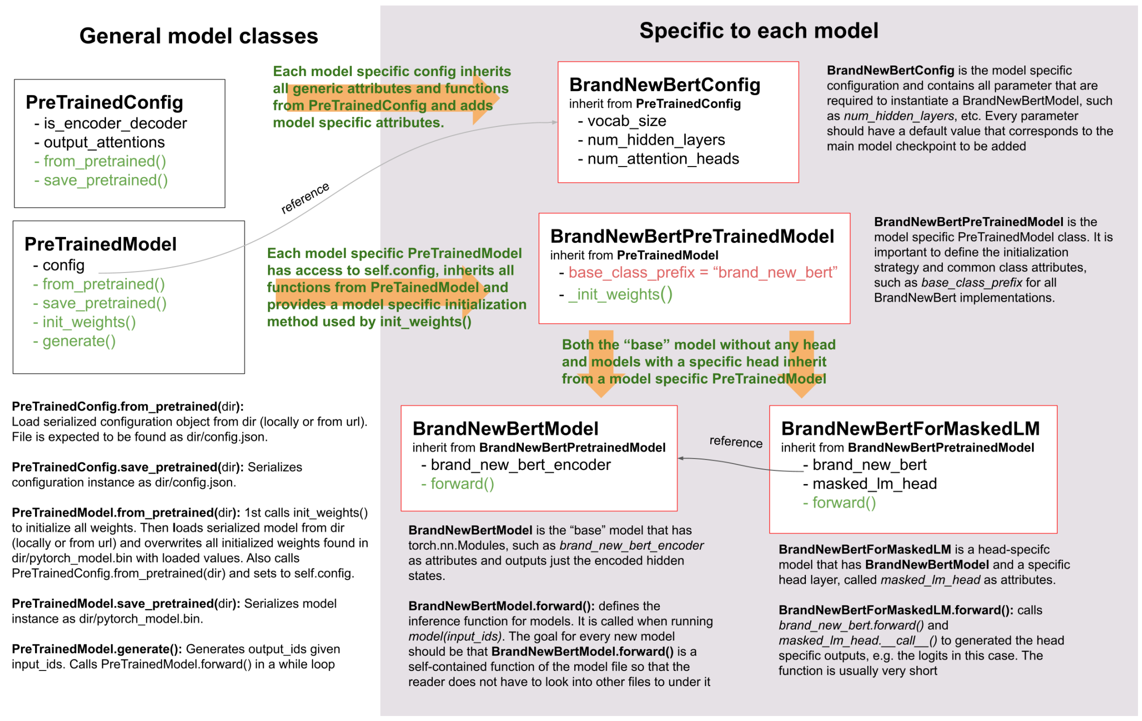
In our opinion, the library's code is not just a means to provide a product, *e.g.*, the ability to use BERT for inference, but also as the very product that we want to improve. Hence, when adding a model, the user is not only the person that will use your model, but also everybody that will read, try to understand, and possibly tweak your code.

With this in mind, let's go a bit deeper into the general library design.

Overview of models

To successfully add a model, it is important to understand the interaction between your model and its config, `PreTrainedModel`, and `PretrainedConfig`. For exemplary purposes, we will call the PyTorch model to be added to 🤗 Transformers `BrandNewBert`.

Let's take a look:


General model classes
Specific to each model
PreTrainedConfig
- is_encoder_decoder
- output_attentions
- from_pretrained()
- save_pretrained()
PreTrainedModel
- config
- from_pretrained()
- save_pretrained()
- init_weights()
- generate()
reference
Each model specific config inherits all generic attributes and functions from PreTrainedConfig and adds model specific attributes.
Each model specific PreTrainedModel has access to self.config, inherits all functions from PreTainedModel and provides a model specific initialization method used by init_weights()
BrandNewBertConfig
inherit from PreTrainedConfig
- vocab_size
- num_hidden_layers
- num_attention_heads
BrandNewBertPreTrainedModel
inherit from PreTrainedModel
- base_class_prefix = "brand_new_bert"
- _init_weights()
Both the "base" model without any head and models with a specific head inherit from a model specific PreTrainedModel
BrandNewBertModel
inherit from BrandNewBertPretrainedModel
- brand_new_bert_encoder
- forward()
reference
BrandNewBertForMaskedLM
inherit from BrandNewBertPretrainedModel
- brand_new_bert
- masked_lm_head
- forward()

BrandNewBertConfig is the model specific configuration and contains all parameter that are required to instantiate a BrandNewBertModel, such as *num_hidden_layers*, etc. Every parameter should have a default value that corresponds to the main model checkpoint to be added

BrandNewBertPreTrainedModel is the model specific PreTrainedModel class. It is important to define the initialization strategy and common class attributes, such as *base_class_prefix* for all BrandNewBert implementations.

PreTrainedConfig.from_pretrained(dir**):** Load serialized configuration object from dir (locally or from url). File is expected to be found as dir/config.json.

PreTrainedConfig.save_pretrained(dir**):** Serializes configuration instance as dir/config.json.

PreTrainedModel.from_pretrained(dir**):** 1st calls init_weights() to initialize all weights. Then loads serialized model from dir (locally or from url) and overwrites all initialized weights found in dir/pytorch_model.bin with loaded values. Also calls PreTrainedConfig.from_pretrained(dir) and sets to self.config.

PreTrainedModel.save_pretrained(dir**):** Serializes model instance as dir/pytorch_model.bin.

PreTrainedModel.generate(): Generates output_ids given input_ids. Calls PreTrainedModel.forward() in a while loop

BrandNewBertModel is the "base" model that has torch.nn.Modules, such as *brand_new_bert_encoder* as attributes and outputs just the encoded hidden states.

BrandNewBertModel.forward(): defines the inference function for models. It is called when running *model(input_ids)*. The goal for every new model should be that **BrandNewBertModel.forward()** is a self-contained function of the model file so that the reader does not have to look into other files to under it

BrandNewBertForMaskedLM is a head-specifc model that has **BrandNewBertModel** and a specific head layer, called *masked_lm_head* as attributes.

BrandNewBertForMaskedLM.forward(): calls *brand_new_bert.forward()* and *masked_lm_head.__call__()* to generated the head specific outputs, e.g. the logits in this case. The function is usually very short

As you can see, we do make use of inheritance in 🤗 Transformers, but we keep the level of abstraction to an absolute minimum. There are never more than two levels of abstraction for any model in the library. `BrandNewBertModel` inherits from `BrandNewBertPreTrainedModel` which in turn inherits from `PreTrainedModel` and that's it. As a general rule, we want to make sure that a new model only depends on `PreTrainedModel`. The important functionalities that are automatically provided to every new model are `PreTrainedModel.from_pretrained` and `PreTrainedModel.save_pretrained`, which are used for serialization and deserialization. All of the other important functionalities, such as `BrandNewBertModel.forward` should be completely defined in the new `modeling_brand_new_bert.py` module. Next, we want to make sure that a model with a specific head layer, such as `BrandNewBertForMaskedLM` does not inherit from `BrandNewBertModel`, but rather uses `BrandNewBertModel` as a component that can be called in its forward pass to keep the level of abstraction low. Every new model requires a configuration class, called

`BrandNewBertConfig`. This configuration is always stored as an attribute in `PreTrainedModel`, and thus can be accessed via the `config` attribute for all classes inheriting from `BrandNewBertPreTrainedModel`

```
# assuming that `brand_new_bert` belongs to the organization `brandy`
model = BrandNewBertModel.from_pretrained("brandy/brand_new_bert")
model.config  # model has access to its config
```

Similar to the model, the configuration inherits basic serialization and deserialization functionalities from `PretrainedConfig`. Note that the configuration and the model are always serialized into two different formats - the model to a `pytorch_model.bin` file and the configuration to a `config.json` file. Calling `PreTrainedModel.save_pretrained` will automatically call `PretrainedConfig.save_pretrained`, so that both model and configuration are saved.

Overview of tokenizers

Not quite ready yet :-(This section will be added soon!

Step-by-step recipe to add a model to 🤗 Transformers

Everyone has different preferences of how to port a model so it can be very helpful for you to take a look at summaries of how other contributors ported models to Hugging Face. Here is a list of community blog posts on how to port a model:

1. Porting GPT2 Model by Thomas
2. Porting WMT19 MT Model by Stas

From experience, we can tell you that the most important things to keep in mind when adding a model are:

- Don't reinvent the wheel! Most parts of the code you will add for the new 🤗 Transformers model already exist somewhere in 🤗 Transformers. Take some time to find similar, already existing models and tokenizers you can copy from. grep and rg are your friends. Note that it might very well happen that your model's tokenizer is based on one model implementation, and your model's modeling code on another one. *E.g.*, FSMT's modeling code is based on BART, while FSMT's tokenizer code is based on XLM.
- It's more of an engineering challenge than a scientific challenge. You should spend more time on creating an efficient debugging environment than trying to understand all theoretical aspects of the model in the paper.
- Ask for help when you're stuck! Models are the core component of 🤗 Transformers so we, at Hugging Face, are more than happy to help you at every step to add your model. Don't hesitate to ask if you notice you are not making progress.

In the following, we try to give you a general recipe that we found most useful when porting a model to 🤗 Transformers.

The following list is a summary of everything that has to be done to add a model and can be used by you as a To-Do List:

1. ☐ (Optional) Understood theoretical aspects
2. ☐ Prepared transformers dev environment
3. ☐ Set up debugging environment of the original repository
4. ☐ Created script that successfully runs forward pass using original repository and checkpoint

5. [ ] Successfully opened a PR and added the model skeleton to Transformers
6. [ ] Successfully converted original checkpoint to Transformers checkpoint
7. [ ] Successfully ran forward pass in Transformers that gives identical output to original checkpoint
8. [ ] Finished model tests in Transformers
9. [ ] Successfully added Tokenizer in Transformers
10. [ ] Run end-to-end integration tests
11. [ ] Finished docs
12. [ ] Uploaded model weights to the hub
13. [ ] Submitted the pull request for review
14. [ ] (Optional) Added a demo notebook

To begin with, we usually recommend to start by getting a good theoretical understanding of `[camelcase name of model]`. However, if you prefer to understand the theoretical aspects of the model *on-the-job*, then it is totally fine to directly dive into the `[camelcase name of model]`'s code-base. This option might suit you better, if your engineering skills are better than your theoretical skill, if you have trouble understanding `[camelcase name of model]`'s paper, or if you just enjoy programming much more than reading scientific papers.

1. (Optional) Theoretical aspects of [camelcase name of model]

You should take some time to read *[camelcase name of model]'s* paper, if such descriptive work exists. There might be large sections of the paper that are difficult to understand. If this is the case, this is fine - don't worry! The goal is not to get a deep theoretical understanding of the paper, but to extract the necessary information required to effectively re-implement the model in 🤗 Transformers. That being said, you don't have to spend too much time on the theoretical aspects, but rather focus on the practical ones, namely:

- What type of model is *[camelcase name of model]*? BERT-like encoder-only model? GPT2-like decoder-only model? BART-like encoder-decoder model? Look at the `model_summary` if you're not familiar with the differences between those.
- What are the applications of *[camelcase name of model]*? Text classification? Text generation? Seq2Seq tasks, *e.g.,* summarization?
- What is the novel feature of the model making it different from BERT/GPT-2/BART?
- Which of the already existing 🤗 Transformers models is most similar to *[camelcase name of model]*?
- What type of tokenizer is used? A sentencepiece tokenizer? Word piece tokenizer? Is it the same tokenizer as used for BERT or BART?

After you feel like you have gotten a good overview of the architecture of the model, you might want to write to [name of mentor] with any questions you might have. This might include questions regarding the model's architecture, its attention layer, etc. We will be more than happy to help you.

Additional resources

Before diving into the code, here are some additional resources that might be worth taking a look at:

- [link 1]
- [link 2]

- [link 3]
- ...

Make sure you've understood the fundamental aspects of [camelcase name of model]

Alright, now you should be ready to take a closer look into the actual code of [camelcase name of model]. You should have understood the following aspects of [camelcase name of model] by now:

- [characteristic 1 of [camelcase name of model]]
- [characteristic 2 of [camelcase name of model]]
- ...

If any of the mentioned aspects above are **not** clear to you, now is a great time to talk to [name of mentor].

2. Next prepare your environment

1. Fork the repository by clicking on the 'Fork' button on the repository's page. This creates a copy of the code under your GitHub user account.

2. Clone your `transformers` fork to your local disk, and add the base repository as a remote:

    ```
    git clone https://github.com/[your Github handle]/transformers.git
    cd transformers
    git remote add upstream https://github.com/huggingface/transformers.git
    ```

3. Set up a development environment, for instance by running the following command:

    ```
    python -m venv .env
    source .env/bin/activate
    pip install -e ".[dev]"
    ```

and return to the parent directory

```
cd ..
```

4. We recommend adding the PyTorch version of *[camelcase name of model]* to Transformers. To install PyTorch, please follow the instructions here.

Note: You don't need to have CUDA installed. Making the new model work on CPU is sufficient.

5. To port *[camelcase name of model]*, you will also need access to its original repository:

```
git clone [link to original repo].git
cd [lowercase name of model]
pip install -e .
```

Now you have set up a development environment to port *[camelcase name of model]* to 🤗 Transformers.

Run a pretrained checkpoint using the original repository

3. Set up debugging environment

At first, you will work on the original *[camelcase name of model]* repository. Often, the original implementation is very "researchy". Meaning that documentation might be lacking and the code can be difficult to understand. But this should be exactly your motivation to reimplement *[camelcase name of model]*. At Hugging Face, one of our main goals is to *make people stand on the shoulders of giants* which translates here very well into taking a working model and rewriting it to make it as **accessible, user-friendly, and beautiful** as possible. This is the number-one motivation to re-implement models into 🤗 Transformers - trying to make complex new NLP technology accessible to **everybody**.

You should start thereby by diving into the [original repository]([link to original repo]).

Successfully running the official pretrained model in the original repository is often **the most difficult** step. From our experience, it is very important to spend some time getting familiar with the original code-base. You need to figure out the following:

- Where to find the pretrained weights?
- How to load the pretrained weights into the corresponding model?
- How to run the tokenizer independently from the model?
- Trace one forward pass so that you know which classes and functions are required for a simple forward pass. Usually, you only have to reimplement those functions.
- Be able to locate the important components of the model: Where is the model's class? Are there model sub-classes, *e.g.*, EncoderModel, DecoderModel? Where is the self-attention layer? Are there multiple different attention layers, *e.g.*, *self-attention*, *cross-attention*...?
- How can you debug the model in the original environment of the repo? Do you have to add `print` statements, can you work with an interactive debugger like ipdb, or should you use an efficient IDE to debug the model, like PyCharm?

It is very important that before you start the porting process, that you can **efficiently** debug code in the original repository! Also, remember that you are working with an open-source library, so do not hesitate to open an issue, or even a pull request in the original repository. The maintainers of this repository are most likely very happy about someone looking into their code!

At this point, it is really up to you which debugging environment and strategy you prefer to use to debug the original model. We strongly advise against setting up a costly GPU environment, but simply work on a CPU both when starting to dive into the original repository and also when starting to write the 🤗 Transformers implementation of the model. Only at the very end, when the model has already been successfully ported to 🤗 Transformers, one should verify that the model also works as expected on GPU.

In general, there are two possible debugging environments for running the original model

- Jupyter notebooks / google colab
- Local python scripts.

Jupyter notebooks have the advantage that they allow for cell-by-cell execution which can be helpful to better split logical components from one another and to have faster debugging cycles as intermediate results can be stored. Also, notebooks are often easier to share with other contributors, which might be very helpful if you want to ask the Hugging Face team for help. If you are familiar with Jupiter notebooks, we strongly recommend you to work with them.

The obvious disadvantage of Jupyther notebooks is that if you are not used to working with them you will have to spend some time adjusting to the new programming environment and that you might not be able to use your known debugging tools anymore, like `ipdb`.

4. Successfully run forward pass

For each code-base, a good first step is always to load a **small** pretrained checkpoint and to be able to reproduce a single forward pass using a dummy integer vector of input IDs as an input. Such a script could look like this (in pseudocode):

```
model = [camelcase name of
model]Model.load_pretrained_checkpoint("/path/to/checkpoint/")
input_ids = [0, 4, 5, 2, 3, 7, 9]  # vector of input ids
original_output = model.predict(input_ids)
```

Next, regarding the debugging strategy, there are generally a few from which to choose from:

- Decompose the original model into many small testable components and run a forward pass on each of those for verification
- Decompose the original model only into the original *tokenizer* and the original *model*, run a forward pass on those, and use intermediate print statements or breakpoints for verification

Again, it is up to you which strategy to choose. Often, one or the other is advantageous depending on the original code base.

If the original code-base allows you to decompose the model into smaller sub-components, *e.g.*, if the original code-base can easily be run in eager mode, it is usually worth the effort to do so. There are some important advantages to taking the more difficult road in the beginning:

- at a later stage when comparing the original model to the Hugging Face implementation, you can verify automatically for each component individually that the corresponding component of the 🤗 Transformers implementation matches instead of relying on visual comparison via print statements
- it can give you some rope to decompose the big problem of porting a model into smaller problems of just porting individual components and thus structure your work better
- separating the model into logical meaningful components will help you to get a better overview of the model's design and thus to better understand the model
- at a later stage those component-by-component tests help you to ensure that no regression occurs as you continue changing your code

Lysandre's integration checks for ELECTRA gives a nice example of how this can be done.

However, if the original code-base is very complex or only allows intermediate components to be run in a compiled mode, it might be too time-consuming or even impossible to separate the model into smaller testable sub-components. A good example is T5's MeshTensorFlow library which is very complex and does not offer a simple way to decompose the model into its sub-components. For such libraries, one often relies on verifying print statements.

No matter which strategy you choose, the recommended procedure is often the same in that you should start to debug the starting layers first and the ending layers last.

It is recommended that you retrieve the output, either by print statements or sub-component functions, of the following layers in the following order:

1. Retrieve the input IDs passed to the model
2. Retrieve the word embeddings
3. Retrieve the input of the first Transformer layer
4. Retrieve the output of the first Transformer layer
5. Retrieve the output of the following n - 1 Transformer layers
6. Retrieve the output of the whole [camelcase name of model] Model

Input IDs should thereby consists of an array of integers, *e.g.*, `input_ids = [0, 4, 4, 3, 2, 4, 1, 7, 19]`

The outputs of the following layers often consist of multi-dimensional float arrays and can look like this:

```
[[
 [-0.1465, -0.6501,  0.1993,  ...,  0.1451,  0.3430,  0.6024],
 [-0.4417, -0.5920,  0.3450,  ..., -0.3062,  0.6182,  0.7132],
 [-0.5009, -0.7122,  0.4548,  ..., -0.3662,  0.6091,  0.7648],
 ...,
 [-0.5613, -0.6332,  0.4324,  ..., -0.3792,  0.7372,  0.9288],
 [-0.5416, -0.6345,  0.4180,  ..., -0.3564,  0.6992,  0.9191],
 [-0.5334, -0.6403,  0.4271,  ..., -0.3339,  0.6533,  0.8694]]],
```

We expect that every model added to 🤗 Transformers passes a couple of integration tests, meaning that the original model and the reimplemented version in 🤗 Transformers have to give the exact same output up to a precision of 0.001! Since it is normal that the exact same model written in different libraries can give a slightly different output depending on the library framework, we accept an error tolerance of 1e-3 (0.001). It is not enough if the model gives nearly the same output, they have to be the almost identical. Therefore, you will certainly compare the intermediate outputs of the 🤗 Transformers version multiple times against the intermediate outputs of the original implementation of *[camelcase name of model]* in which case an **efficient** debugging environment of the original repository is absolutely important. Here is some advice to make your debugging environment as efficient as possible.

- Find the best way of debugging intermediate results. Is the original repository written in PyTorch? Then you should probably take the time to write a longer script that decomposes the original model into smaller sub-components to retrieve intermediate values. Is the original repository written in Tensorflow 1? Then you might have to rely on TensorFlow print operations like tf.print to output intermediate values. Is the original repository written in Jax? Then make sure that the model is **not jitted** when running the forward pass, *e.g.*, check-out this link.
- Use the smallest pretrained checkpoint you can find. The smaller the checkpoint, the faster your debug cycle becomes. It is not efficient if your pretrained model is so big that your forward pass takes more than 10 seconds. In case only very large checkpoints are available, it might make more sense to create a dummy model in the new environment with randomly initialized weights and save those weights for comparison with the 🤗 Transformers version of your model
- Make sure you are using the easiest way of calling a forward pass in the original repository. Ideally, you want to find the function in the original repository that **only** calls a single forward pass, *i.e.* that is often called `predict`, `evaluate`, `forward` or `__call__`. You don't want to debug a function that calls `forward` multiple times, *e.g.*, to generate text, like `autoregressive_sample`, `generate`.
- Try to separate the tokenization from the model's forward pass. If the original repository shows examples where you have to input a string, then try to find out where in the forward call the string input is changed to input ids and start from this point. This might mean that you have to possibly write a small script yourself or change the original code so that you can directly input the ids instead of an input string.
- Make sure that the model in your debugging setup is **not** in training mode, which often causes the model to yield random outputs due to multiple dropout layers in the model. Make sure that the forward pass in your debugging environment is **deterministic** so that the dropout layers are not used. Or use `transformers.utils.set_seed` if the old and new implementations are in the same framework.

More details on how to create a debugging environment for [camelcase name of model]

[TODO FILL: Here the mentor should add very specific information on what the student should do] [to set up an efficient environment for the special requirements of this model]

Port [camelcase name of model] to 🤗 Transformers

Next, you can finally start adding new code to 🤗 Transformers. Go into the clone of your 🤗 Transformers' fork:

```
cd transformers
```

In the special case that you are adding a model whose architecture exactly matches the model architecture of an existing model you only have to add a conversion script as described in this section. In this case, you can just re-use the whole model architecture of the already existing model.

Otherwise, let's start generating a new model with the amazing Cookiecutter!

Use the Cookiecutter to automatically generate the model's code

To begin with head over to the 🤗 Transformers templates to make use of our `cookiecutter` implementation to automatically generate all the relevant files for your model. Again, we recommend only adding the PyTorch version of the model at first. Make sure you follow the instructions of the `README.md` on the 🤗 Transformers templates carefully.

Open a Pull Request on the main huggingface/transformers repo

Before starting to adapt the automatically generated code, now is the time to open a "Work in progress (WIP)" pull request, *e.g.*, "[WIP] Add *[camelcase name of model]*", in 🤗 Transformers so that you and the Hugging Face team can work side-by-side on integrating the model into 🤗 Transformers.

You should do the following:

1. Create a branch with a descriptive name from your main branch

```
git checkout -b add_[lowercase name of model]
```

2. Commit the automatically generated code:

```
git add .
git commit
```

3. Fetch and rebase to current main

```
git fetch upstream
git rebase upstream/main
```

4. Push the changes to your account using:

```
git push -u origin a-descriptive-name-for-my-changes
```

5. Once you are satisfied, go to the webpage of your fork on GitHub. Click on "Pull request". Make sure to add the GitHub handle of [name of mentor] as a reviewer, so that the Hugging Face team gets notified for future changes.

6. Change the PR into a draft by clicking on "Convert to draft" on the right of the GitHub pull request web page.

In the following, whenever you have done some progress, don't forget to commit your work and push it to your account so that it shows in the pull request. Additionally, you should make sure to update your work with the current main from time to time by doing:

```
git fetch upstream
git merge upstream/main
```

In general, all questions you might have regarding the model or your implementation should be asked in your PR and discussed/solved in the PR. This way, [name of mentor] will always be notified when you are committing new code or if you have a question. It is often very helpful to point [name of mentor] to your added code so that the Hugging Face team can efficiently understand your problem or question.

To do so, you can go to the "Files changed" tab where you see all of your changes, go to a line regarding which you want to ask a question, and click on the "+" symbol to add a comment. Whenever a question or problem has been solved, you can click on the "Resolve" button of the created comment.

In the same way, [name of mentor] will open comments when reviewing your code. We recommend asking most questions on GitHub on your PR. For some very general questions that are not very useful for the public, feel free to ping [name of mentor] by Slack or email.

5. Adapt the generated models code for [camelcase name of model]

At first, we will focus only on the model itself and not care about the tokenizer. All the relevant code should be found in the generated files `src/transformers/models/[lowercase name of model]/modeling_[lowercase name of model].py` and `src/transformers/models/[lowercase name of model]/configuration_[lowercase name of model].py`.

Now you can finally start coding :). The generated code in `src/transformers/models/[lowercase name of model]/modeling_[lowercase name of model].py` will either have the same architecture as BERT if it's an encoder-only model or BART if it's an encoder-decoder model. At this point, you should remind yourself what you've learned in the beginning about the theoretical aspects of the model: *How is the model different from BERT or BART? *". Implement those changes which often means to change the *self-attention* layer, the order of the normalization layer, etc… Again, it is often useful to look at the similar architecture of already existing models in Transformers to get a better feeling of how your model should be implemented.

Note that at this point, you don't have to be very sure that your code is fully correct or clean. Rather, it is advised to add a first *unclean*, copy-pasted version of the original code to `src/transformers/models/[lowercase name of model]/modeling_[lowercase name of model].py` until you feel like all the necessary code is added. From our experience, it is much more efficient to quickly add a first version of the required code and improve/correct the code iteratively with the conversion script as described in the next section. The only thing that has to work at this point is that you can instantiate the 🤗 Transformers implementation of *[camelcase name of model]*, *i.e.* the following command should work:

```
from transformers import [camelcase name of model]Model, [camelcase name of
model]Config
model = [camelcase name of model]Model([camelcase name of model]Config())
```

The above command will create a model according to the default parameters as defined in `[camelcase name of model]Config()` with random weights, thus making sure that the `init()` methods of all components works.

[TODO FILL: Here the mentor should add very specific information on what exactly has to be changed for this model] […] […]

6. Write a conversion script

Next, you should write a conversion script that lets you convert the checkpoint you used to debug *[camelcase name of model]* in the original repository to a checkpoint compatible with your just created 🤗 Transformers implementation of *[camelcase name of model]*. It is not advised to write the conversion script from scratch, but rather to look through already existing conversion scripts in 🤗 Transformers for one that has been used to convert a similar model that was written in the same framework as *[camelcase name of model]*. Usually, it is enough to copy an already existing conversion script and slightly adapt it for your use case. Don't hesitate to ask [name of mentor] to point you to a similar already existing conversion script for your model.

- If you are porting a model from TensorFlow to PyTorch, a good starting point might be BERT's conversion script here
- If you are porting a model from PyTorch to PyTorch, a good starting point might be BART's conversion script here

In the following, we'll quickly explain how PyTorch models store layer weights and define layer names. In PyTorch, the name of a layer is defined by the name of the class attribute you give the layer. Let's define a dummy model in PyTorch, called `SimpleModel` as follows:

```python
from torch import nn

class SimpleModel(nn.Module):
    def __init__(self):
            super().__init__()
            self.dense = nn.Linear(10, 10)
            self.intermediate = nn.Linear(10, 10)
            self.layer_norm = nn.LayerNorm(10)
```

Now we can create an instance of this model definition which will fill all weights: `dense`, `intermediate`, `layer_norm` with random weights. We can print the model to see its architecture

```python
model = SimpleModel()

print(model)
```

This will print out the following:

```
SimpleModel(
  (dense): Linear(in_features=10, out_features=10, bias=True)
  (intermediate): Linear(in_features=10, out_features=10, bias=True)
  (layer_norm): LayerNorm((10,), eps=1e-05, elementwise_affine=True)
)
```

We can see that the layer names are defined by the name of the class attribute in PyTorch. You can print out the weight values of a specific layer:

```python
print(model.dense.weight.data)
```

to see that the weights were randomly initialized

```
tensor([[-0.0818,  0.2207, -0.0749, -0.0030,  0.0045, -0.1569, -0.1598,  0.0212,
         -0.2077,  0.2157],
        [ 0.1044,  0.0201,  0.0990,  0.2482,  0.3116,  0.2509,  0.2866, -0.2190,
          0.2166, -0.0212],
        [-0.2000,  0.1107, -0.1999, -0.3119,  0.1559,  0.0993,  0.1776, -0.1950,
         -0.1023, -0.0447],
        [-0.0888, -0.1092,  0.2281,  0.0336,  0.1817, -0.0115,  0.2096,  0.1415,
         -0.1876, -0.2467],
        [ 0.2208, -0.2352, -0.1426, -0.2636, -0.2889, -0.2061, -0.2849, -0.0465,
          0.2577,  0.0402],
        [ 0.1502,  0.2465,  0.2566,  0.0693,  0.2352, -0.0530,  0.1859, -0.0604,
          0.2132,  0.1680],
        [ 0.1733, -0.2407, -0.1721,  0.1484,  0.0358, -0.0633, -0.0721, -0.0090,
          0.2707, -0.2509],
        [-0.1173,  0.1561,  0.2945,  0.0595, -0.1996,  0.2988, -0.0802,  0.0407,
          0.1829, -0.1568],
        [-0.1164, -0.2228, -0.0403,  0.0428,  0.1339,  0.0047,  0.1967,  0.2923,
          0.0333, -0.0536],
        [-0.1492, -0.1616,  0.1057,  0.1950, -0.2807, -0.2710, -0.1586,  0.0739,
          0.2220,  0.2358]]).
```

In the conversion script, you should fill those randomly initialized weights with the exact weights of the corresponding layer in the checkpoint. *E.g.*,

```
# retrieve matching layer weights, e.g. by
# recursive algorithm
layer_name = "dense"
pretrained_weight = array_of_dense_layer

model_pointer = getattr(model, "dense")

model_pointer.weight.data = torch.from_numpy(pretrained_weight)
```

While doing so, you must verify that each randomly initialized weight of your PyTorch model and its corresponding pretrained checkpoint weight exactly match in both **shape and name**. To do so, it is **necessary** to add assert statements for the shape and print out the names of the checkpoints weights. *E.g.*, you should add statements like:

```
assert (
     model_pointer.weight.shape == pretrained_weight.shape
), f"Pointer shape of random weight {model_pointer.shape} and array shape of
checkpoint weight {pretrained_weight.shape} mismatched"
```

Besides, you should also print out the names of both weights to make sure they match, *e.g.*,

```
logger.info(f"Initialize PyTorch weight {layer_name} from {pretrained_weight.name}")
```

If either the shape or the name doesn't match, you probably assigned the wrong checkpoint weight to a randomly initialized layer of the 🤗 Transformers implementation.

An incorrect shape is most likely due to an incorrect setting of the config parameters in `[camelcase name of model]Config()` that do not exactly match those that were used for the checkpoint you want to convert. However, it could also be that PyTorch's implementation of a layer requires the weight to be transposed beforehand.

Finally, you should also check that **all** required weights are initialized and print out all checkpoint weights that were not used for initialization to make sure the model is correctly converted. It is completely normal, that the conversion trials fail with either a wrong shape statement or wrong name assignment. This is most likely because either you used incorrect parameters in `[camelcase name of model]Config()`, have a wrong architecture in the 🤗 Transformers implementation, you have a bug in the `init()` functions of one of the components of the 🤗 Transformers implementation or you need to transpose one of the checkpoint weights.

This step should be iterated with the previous step until all weights of the checkpoint are correctly loaded in the Transformers model. Having correctly loaded the checkpoint into the 🤗 Transformers implementation, you can then save the model under a folder of your choice `/path/to/converted/checkpoint/folder` that should then contain both a `pytorch_model.bin` file and a `config.json` file:

```
model.save_pretrained("/path/to/converted/checkpoint/folder")
```

[TODO FILL: Here the mentor should add very specific information on what exactly has to be done for the conversion of this model] [...] [...]

7. Implement the forward pass

Having managed to correctly load the pretrained weights into the 🤗 Transformers implementation, you should now make sure that the forward pass is correctly implemented. In Get familiar with the original repository, you have already created a script that runs a forward pass of the model using the original repository. Now you should write an analogous script using the 🤗 Transformers implementation instead of the original one. It should look as follows:

[TODO FILL: Here the model name might have to be adapted, *e.g.*, maybe [camelcase name of model]ForConditionalGeneration instead of [camelcase name of model]Model]

```
model = [camelcase name of
model]Model.from_pretrained("/path/to/converted/checkpoint/folder")
input_ids = [0, 4, 4, 3, 2, 4, 1, 7, 19]
output = model(input_ids).last_hidden_states
```

It is very likely that the 🤗 Transformers implementation and the original model implementation don't give the exact same output the very first time or that the forward pass throws an error. Don't be disappointed - it's expected! First, you should make sure that the forward pass doesn't throw any errors. It often happens that the wrong dimensions are used leading to a `"Dimensionality mismatch"` error or that the wrong data type object is used, *e.g.*, `torch.long` instead of `torch.float32`. Don't hesitate to ask [name of mentor] for help, if you don't manage to solve certain errors.

The final part to make sure the 🤗 Transformers implementation works correctly is to ensure that the outputs are equivalent to a precision of `1e-3`. First, you should ensure that the output shapes are identical, *i.e.* `outputs.shape` should yield the same value for the script of the 🤗 Transformers implementation and the original implementation. Next, you should make sure that the output values are identical as well. This one of the most difficult parts of adding a new model. Common mistakes why the outputs are not identical are:

- Some layers were not added, *i.e.* an activation layer was not added, or the residual connection was forgotten

- The word embedding matrix was not tied
- The wrong positional embeddings are used because the original implementation uses on offset
- Dropout is applied during the forward pass. To fix this make sure `model.training is False` and that no dropout layer is falsely activated during the forward pass, *i.e.* pass `self.training` to PyTorch's functional dropout

The best way to fix the problem is usually to look at the forward pass of the original implementation and the 🤗 Transformers implementation side-by-side and check if there are any differences. Ideally, you should debug/print out intermediate outputs of both implementations of the forward pass to find the exact position in the network where the 🤗 Transformers implementation shows a different output than the original implementation. First, make sure that the hard-coded `input_ids` in both scripts are identical. Next, verify that the outputs of the first transformation of the `input_ids` (usually the word embeddings) are identical. And then work your way up to the very last layer of the network. At some point, you will notice a difference between the two implementations, which should point you to the bug in the 🤗 Transformers implementation. From our experience, a simple and efficient way is to add many print statements in both the original implementation and 🤗 Transformers implementation, at the same positions in the network respectively, and to successively remove print statements showing the same values for intermediate presentions.

When you're confident that both implementations yield the same output, verifying the outputs with `torch.allclose(original_output, output, atol=1e-3)`, you're done with the most difficult part! Congratulations - the work left to be done should be a cakewalk 😊.

8. Adding all necessary model tests

At this point, you have successfully added a new model. However, it is very much possible that the model does not yet fully comply with the required design. To make sure, the implementation is fully compatible with 🤗 Transformers, all common tests should pass. The Cookiecutter should have automatically added a test file for your model, probably under the same `tests/test_modeling_[lowercase name of model].py`. Run this test file to verify that all common tests pass:

```
pytest tests/test_modeling_[lowercase name of model].py
```

[TODO FILL: Here the mentor should add very specific information on what tests are likely to fail after having implemented the model , e.g. given the model, it might be very likely that `test_attention_output` fails] [...] [...]

Having fixed all common tests, it is now crucial to ensure that all the nice work you have done is well tested, so that

- a) The community can easily understand your work by looking at specific tests of *[camelcase name of model]*
- b) Future changes to your model will not break any important feature of the model.

At first, integration tests should be added. Those integration tests essentially do the same as the debugging scripts you used earlier to implement the model to 🤗 Transformers. A template of those model tests is already added by the Cookiecutter, called `[camelcase name of model]ModelIntegrationTests` and only has to be filled out by you. To ensure that those tests are passing, run

```
RUN_SLOW=1 pytest -sv tests/test_modeling_[lowercase name of model].py::[camelcase
name of model]ModelIntegrationTests
```

Note: In case you are using Windows, you should replace `RUN_SLOW=1` with `SET RUN_SLOW=1`

Second, all features that are special to *[camelcase name of model]* should be tested additionally in a separate test under `[camelcase name of model]ModelTester` / `[camelcase name of model]ModelTest`. This part is often forgotten but is extremely useful in two ways:

- It helps to transfer the knowledge you have acquired during the model addition to the community by showing how the special features of *[camelcase name of model]* should work.
- Future contributors can quickly test changes to the model by running those special tests.

[TODO FILL: Here the mentor should add very specific information on what special features of the model should be tested additionally] [...] [...]

9. Implement the tokenizer

Next, we should add the tokenizer of *[camelcase name of model]*. Usually, the tokenizer is equivalent or very similar to an already existing tokenizer of 🤗 Transformers.

[TODO FILL: Here the mentor should add a comment whether a new tokenizer is required or if this is not the case which existing tokenizer closest resembles [camelcase name of model]'s tokenizer and how the tokenizer should be implemented] [...] [...]

It is very important to find/extract the original tokenizer file and to manage to load this file into the 🤗 Transformers' implementation of the tokenizer.

For [camelcase name of model], the tokenizer files can be found here:

- [To be filled out by mentor]

and having implemented the 🤗Transformers' version of the tokenizer can be loaded as follows:

[To be filled out by mentor]

To ensure that the tokenizer works correctly, it is recommended to first create a script in the original repository that inputs a string and returns the `input_ids`. It could look similar to this (in pseudo-code):

```
input_str = "This is a long example input string containing special characters .$?-,
numbers 2872 234 12 and words."
model = [camelcase name of
model]Model.load_pretrained_checkpoint("/path/to/checkpoint/")
input_ids = model.tokenize(input_str)
```

You might have to take a deeper look again into the original repository to find the correct tokenizer function or you might even have to do changes to your clone of the original repository to only output the `input_ids`. Having written a functional tokenization script that uses the original repository, an analogous script for 🤗 Transformers should be created. It should look similar to this:

```
from transformers import [camelcase name of model]Tokenizer
input_str = "This is a long example input string containing special characters .$?-,
numbers 2872 234 12 and words."

tokenizer = [camelcase name of
model]Tokenizer.from_pretrained("/path/to/tokenizer/folder/")

input_ids = tokenizer(input_str).input_ids
```

When both `input_ids` yield the same values, as a final step a tokenizer test file should also be added.

[TODO FILL: Here mentor should point the student to test files of similar tokenizers]

Analogous to the modeling test files of *[camelcase name of model]*, the tokenization test files of *[camelcase name of model]* should contain a couple of hard-coded integration tests.

[TODO FILL: Here mentor should again point to an existing similar test of another model that the student can copy & adapt]

10. Run End-to-end integration tests

Having added the tokenizer, you should also add a couple of end-to-end integration tests using both the model and the tokenizer to `tests/test_modeling_[lowercase name of model].py` in 🤗 Transformers. Such a test should show on a meaningful text-to-text sample that the 🤗 Transformers implementation works as expected. A meaningful text-to-text sample can include *e.g.* a source-to-target-translation pair, an article-to-summary pair, a question-to-answer pair, etc... If none of the ported checkpoints has been fine-tuned on a downstream task it is enough to simply rely on the model tests. In a final step to ensure that the model is fully functional, it is advised that you also run all tests on GPU. It can happen that you forgot to add some `.to(self.device)` statements to internal tensors of the model, which in such a test would show in an error. In case you have no access to a GPU, the Hugging Face team can take care of running those tests for you.

11. Add Docstring

Now, all the necessary functionality for *[camelcase name of model]* is added - you're almost done! The only thing left to add is a nice docstring and a doc page. The Cookiecutter should have added a template file called `docs/source/model_doc/[lowercase name of model].rst` that you should fill out. Users of your model will usually first look at this page before using your model. Hence, the documentation must be understandable and concise. It is very useful for the community to add some *Tips* to show how the model should be used. Don't hesitate to ping [name of mentor] regarding the docstrings.

Next, make sure that the docstring added to `src/transformers/models/[lowercase name of model]/modeling_[lowercase name of model].py` is correct and included all necessary inputs and outputs. It is always to good to remind oneself that documentation should be treated at least as carefully as the code in 🤗 Transformers since the documentation is usually the first contact point of the community with the model.

Code refactor

Great, now you have added all the necessary code for *[camelcase name of model]*. At this point, you should correct some potential incorrect code style by running:

```
make style
```

and verify that your coding style passes the quality check:

```
make quality
```

There are a couple of other very strict design tests in 🤗 Transformers that might still be failing, which shows up in the tests of your pull request. This is often because of some missing information in the docstring or some incorrect naming. [name of mentor] will surely help you if you're stuck here.

Lastly, it is always a good idea to refactor one's code after having ensured that the code works correctly. With all tests passing, now it's a good time to go over the added code again and do some refactoring.

You have now finished the coding part, congratulation! 🎉 You are Awesome! 😎

12. Upload the models to the model hub

In this final part, you should convert and upload all checkpoints to the model hub and add a model card for each uploaded model checkpoint. You should work alongside [name of mentor] here to decide on a fitting name for each checkpoint and to get the required access rights to be able to upload the model under the author's organization of *[camelcase name of model]*.

It is worth spending some time to create fitting model cards for each checkpoint. The model cards should highlight the specific characteristics of this particular checkpoint, *e.g.*, On which dataset was the checkpoint pretrained/fine-tuned on? On what down-stream task should the model be used? And also include some code on how to correctly use the model.

13. (Optional) Add notebook

It is very helpful to add a notebook that showcases in-detail how *[camelcase name of model]* can be used for inference and/or fine-tuned on a downstream task. This is not mandatory to merge your PR, but very useful for the community.

14. Submit your finished PR

You're done programming now and can move to the last step, which is getting your PR merged into main. Usually, [name of mentor] should have helped you already at this point, but it is worth taking some time to give your finished PR a nice description and eventually add comments to your code, if you want to point out certain design choices to your reviewer.

Share your work!!

Now, it's time to get some credit from the community for your work! Having completed a model addition is a major contribution to Transformers and the whole NLP community. Your code and the ported pre-trained models will certainly be used by hundreds and possibly even thousands of developers and researchers. You should be proud of your work and share your achievement with the community.

You have made another model that is super easy to access for everyone in the community! 🤯