## **Experiment reproduction**

PyTorch BIVL<sup>2</sup>ab







#### Agenda

- Why should I even care?
- Good practices for experiment reproducibility
- Demo

## Why should I even care?

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Finding an academic paper on the algorithm you want to implement



#### Dirac-Chebyshev Degulsion with Tripolsive Tail Canceling and other shit that's over your head

In this model, when the probability density of two series as a triplewise function which is sum on the positive integer.

$$y = \beta 0 + \beta 1.x + \beta 2x^2 + a \sum_{n=-}^{\infty} f^*(m) g(m + n) (f * g)(n)$$

For each unit increased from x to x + 1 units, the expected yield changes by

$$\prod^{N} \partial^{T} e_{i} e^{i\phi}_{+} j \omega t (A \times M^{\phi}_{\phi}) E_{\phi}) \rightarrow (\widetilde{M} \{x : x : E_{\phi}\}) \times \inf (x_{0})$$

Where of its given by:

$$\mathbf{N} \pm t_1^{\mu} \sigma^{3/2} \otimes b_2^{\mu} \mathcal{J}'(\lambda x.\lambda t_j) \mathbf{j} \stackrel{\text{def}}{=} \int_{-\pi}^{\pi} s_1 - \mathbf{g}'(\nabla s_j) ds$$

It can then be solved using:

$$\begin{vmatrix} \Gamma_1^1 & \Gamma_1^1 & \Gamma_1^1 & \dots & \Gamma_1^1 \\ \Gamma_2^1 & \Gamma_1^1 & \Gamma_2^1 & \dots & \Gamma_2^1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ \Gamma_{dr} & \Gamma_{dt} & \Gamma_{dt} & \dots & \Gamma_{dn} \end{vmatrix} = \begin{vmatrix} s_1^l - \lambda & s_1^l & s_1^l & \dots & s_n^l \\ s_1^l & s_2^l - \lambda & s_2^l & \dots & s_n^l \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ s_{dt} & s_{dt} & s_{dt} & \dots & s_{dt} - \lambda \end{vmatrix}$$

Which yields the depations curve of:

$$\sum \beta \mu l x l t \tau$$





The most used tools are easy to use and easy to access.



- AlexNet
- ConvNeXt
- DenseNet
- EfficientNet
- EfficientNetV2
- GoogLeNet
- Inception V3
- MaxVit
- MNASNet
- MobileNet V2

- MobileNet V3
- RegNet
- ResNet
- ResNeXt
- ShuffleNet V2
- SqueezeNet
- SwinTransformer
- VGG
- VisionTransformer
- Wide ResNet



There are lots of researchers using older architectures instead of newer ones just because there are plenty of implementations on the internet.

Even though you may find a paper excellent, you may not choose to use it just because the barriers preventing you from using it. Some of these barriers could be:

- No codebase
- "We use 80% to train and 20% for test" —— Dataset splits are not specified

Even though you may find a paper excellent, you may not choose to use it just because the barriers preventing you from using it. Some of these barriers could be:

- No codebase
- Codebase, executes on your machine, dependencies failed ——— Environment not specified
- "We use 80% to train and 20% for test" —— Dataset splits are not specified

And it's fine to not put everything on the paper, at the end, a scientific paper purpose is to present novel ideas. Nevertheless, nowadays exist many tools to record all the little details that go into creating your work.



Also, having things organized and being able to reproduce your results is cool

- Someone asks for your code? Share your github repo with clear instructions.
- Want to test your method on other datasets? Fine, create a dataloader and run the experiment.
- Your model weights were magically deleted? No problem, run the experiment again with the same configuration.

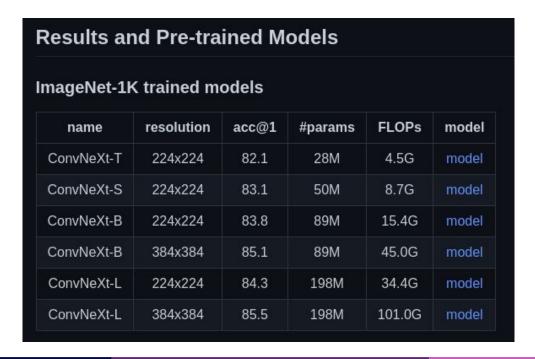
# Good practices for experiment reproducibility

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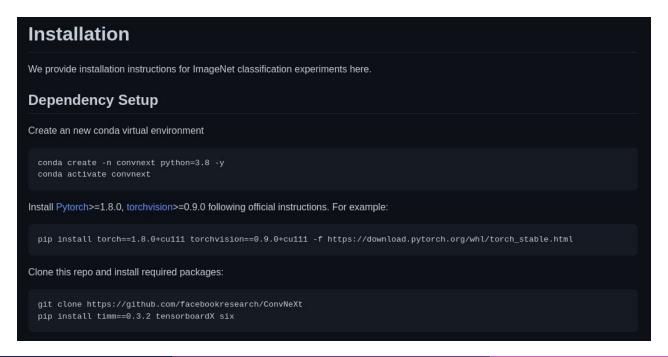




ConvNeXt



ConvNeXt



- ConvNeXt
- <u>Vision Transformer</u>

# Installation Make sure you have Python>=3.6 installed on your machine. Install JAX and python dependencies by running: # If using GPU: pip install -r vit\_jax/requirements.txt # If using TPU: pip install -r vit\_jax/requirements-tpu.txt

- ConvNeXt
- Vision Transformer

#### Fine-tuning a model

You can run fine-tuning of the downloaded model on your dataset of interest. All models share the same command line interface.

For example for fine-tuning a ViT-B/16 (pre-trained on imagenet21k) on CIFAR10 (note how we specify b16, cifar10 as arguments to the config, and how we instruct the code to access the models directly from a GCS bucket instead of first downloading them into the local directory):

```
python -m vit_jax.main --workdir=/tmp/vit-$(date +%s) \
    --config=$(pwd)/vit_jax/configs/vit.py:b16,cifar10 \
    --config.pretrained_dir='gs://vit_models/imagenet21k'
```

### Demo

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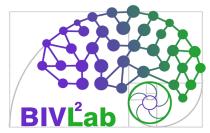


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# Thank You!

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