

Project DeiT presentation

DeiT: Data-efficient Image Transformers

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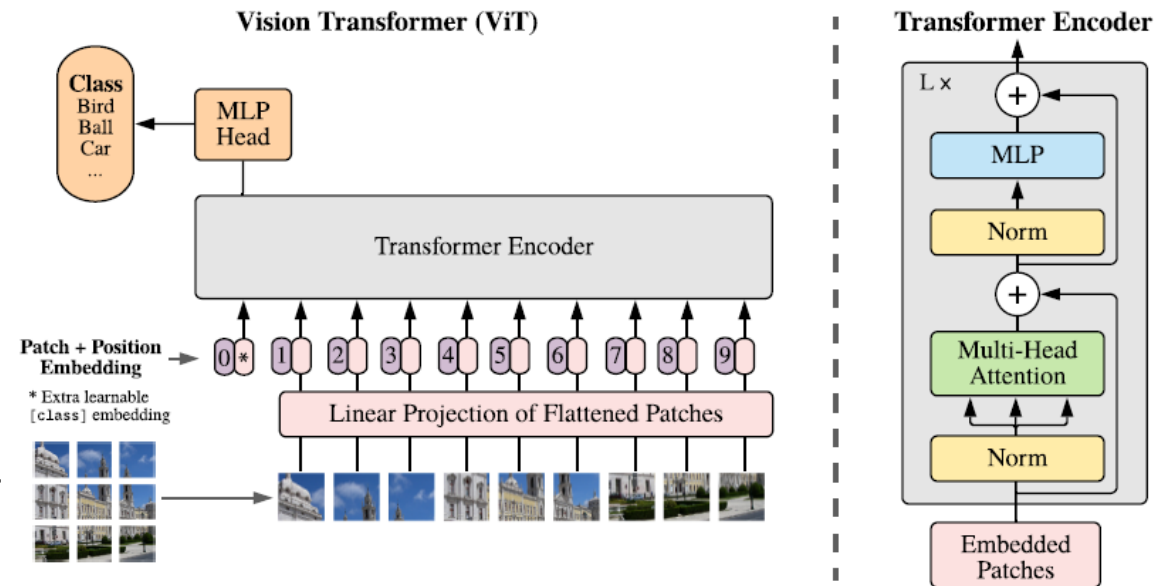
- 1. Available packages**
- 2. My modifications**
- 3. Some results**

1. Available packages

Introducing Vision Transformers

- **Attention mechanisms for NLP**
 - Greatly improved in 2017 by Vaswani et al.
 - Focused on NLP tasks (language translation, parsing)
- **Attention mechanisms for Computer Vision**
 - Dosovitskiy et al. (2021) have adapted Transformers for vision tasks
 - Models have to be trained on large datasets to achieve good results

Fig. 1: Vision Transformer architecture



1. Available packages

- **Data-efficient Vision Transformers (2021)**

- Small changes to ViT (lots of data aug) to allow training on smaller datasets
- Introduced teacher-student distillation (concatenated token & loss)

Model	ImageNet	CIFAR-10	CIFAR-100	Flowers	Cars	iNat-18	iNat-19	im/sec
Grafit ResNet-50 [49]	79.6	-	-	98.2	92.5	69.8	75.9	1226.1
Grafit RegNetY-8GF [49]	-	-	-	99.0	94.0	76.8	80.0	591.6
ResNet-152 [10]	-	-	-	-	-	69.1	-	526.3
EfficientNet-B7 [48]	84.3	98.9	91.7	98.8	94.7	-	-	55.1
ViT-B/32 [15]	73.4	97.8	86.3	85.4	-	-	-	394.5
ViT-B/16 [15]	77.9	98.1	87.1	89.5	-	-	-	85.9
ViT-L/32 [15]	71.2	97.9	87.1	86.4	-	-	-	124.1
ViT-L/16 [15]	76.5	97.9	86.4	89.7	-	-	-	27.3
DeiT-B	81.8	99.1	90.8	98.4	92.1	73.2	77.7	292.3
DeiT-B \uparrow 384	83.1	99.1	90.8	98.5	93.3	79.5	81.4	85.9
DeiT-B \uparrow	83.4	99.1	91.3	98.8	92.9	73.7	78.4	290.9
DeiT-B \uparrow 384	84.4	99.2	91.4	98.9	93.9	80.1	83.0	85.9

Fig. 2: Comparison of accuracy between ViT and DeiT models

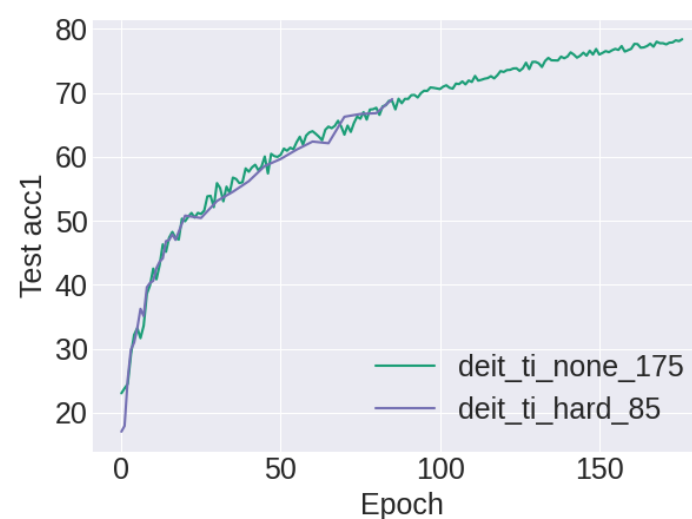
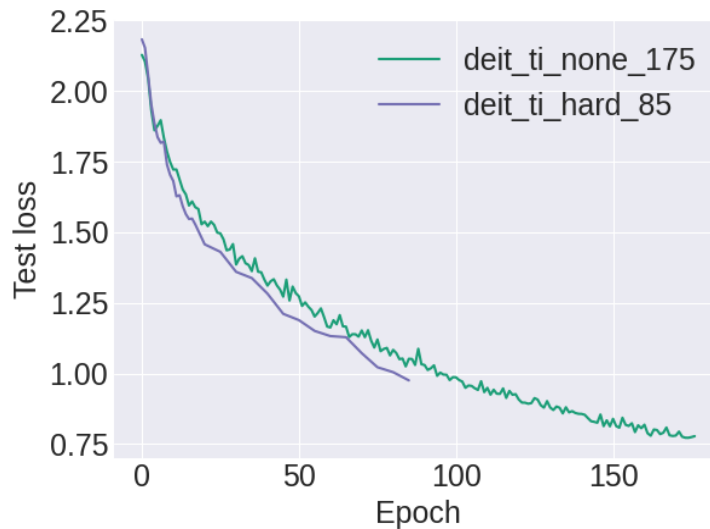
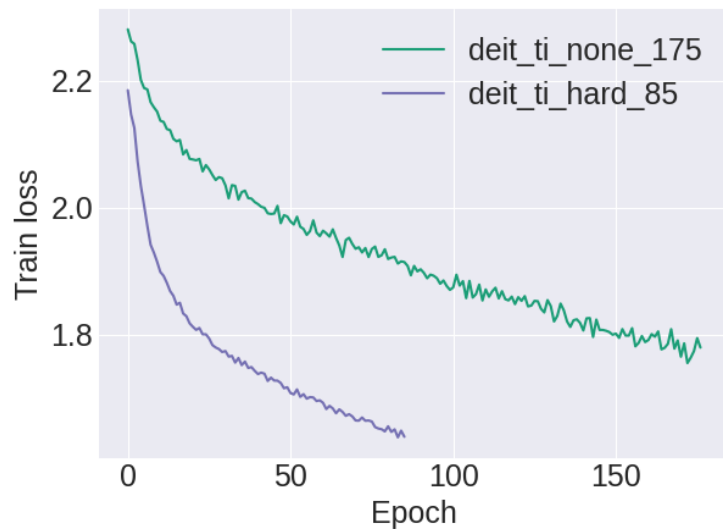
- **Expediting Vision Transformers via Token Reorganization (2022)**

- Merged inattentive image patches between each Transformer to speed up both training & testing

2. My modifications

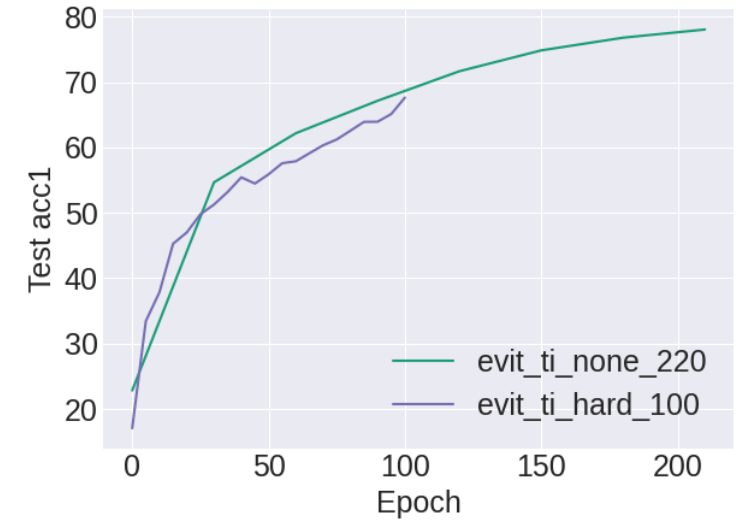
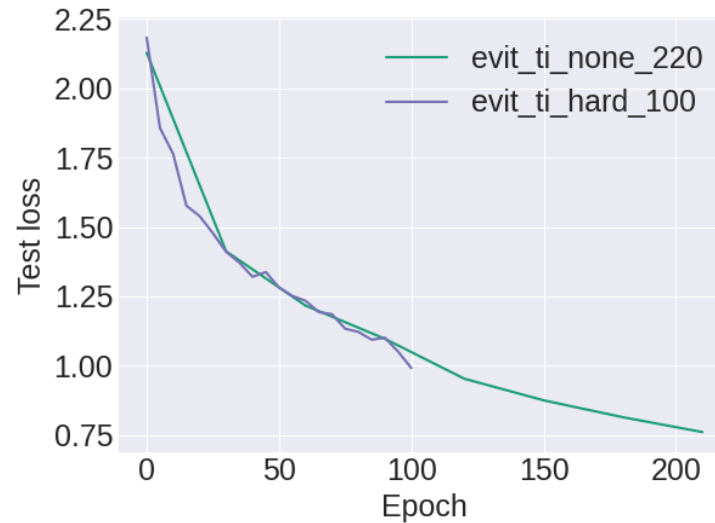
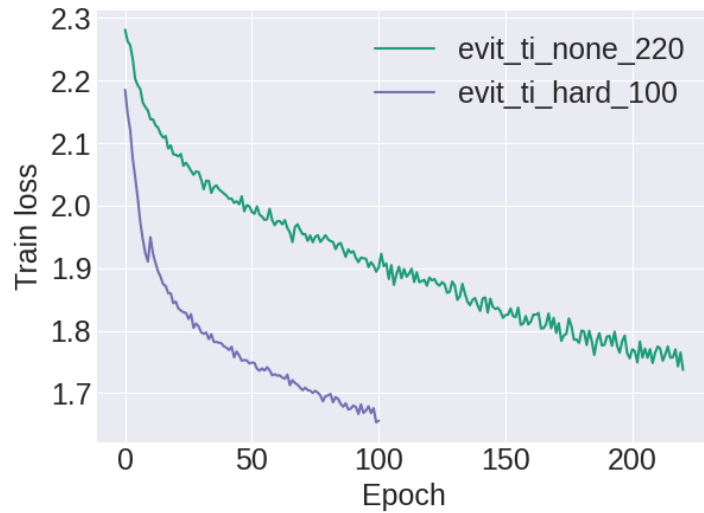
- **Forked repo**
 - See code: <https://github.com/sebastienmeyer2/Project-deit>
- **Support for CIFAR10**
 - Added CIFAR10 to the datasets preparation
 - Transfer learning of a teacher RegNetY for distillation
- **Integration of EviT for comparison**
 - Largely taken from <https://github.com/youweiliang/evit>
 - Combine both distillation and token pooling?

3. Some results



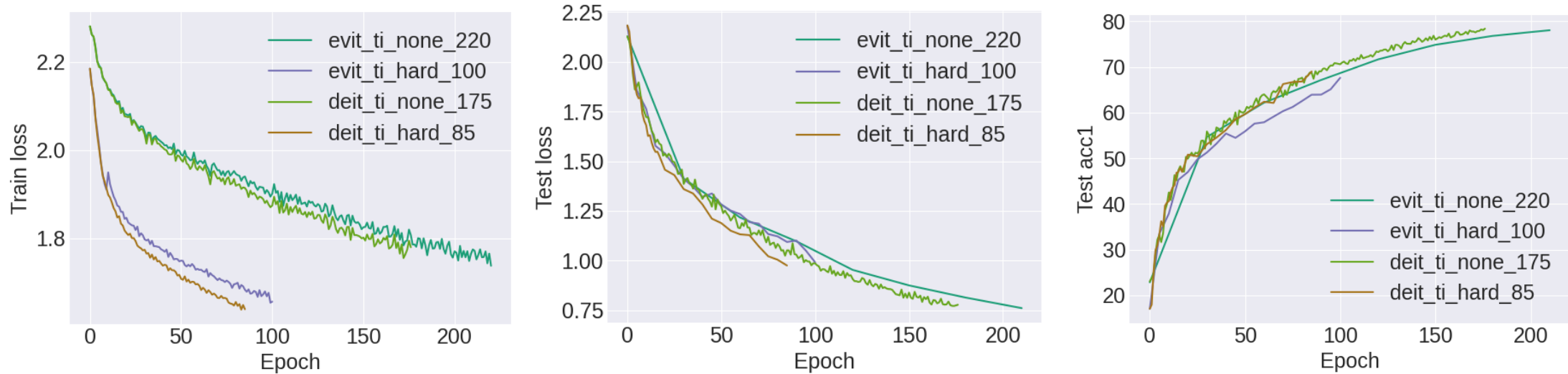
- **Comparison of training with and without distillation of DeiT (tiny, patch 16, size 224)**
 - Only the last classification layer of the teacher was modified
 - Approx. accuracy on CIFAR10 is 78% for the teacher after 100 epochs (can do much better!)

3. Some results



- **Comparison of training with and without distillation of EViT (tiny, patch 16, size 224)**
 - Same teacher as for DeiT - does not seem to help as much

3. Some results



- **Comparison of DeiT with EViT**

- As specified by the authors, EViT is slightly less accurate than DeiT
- No speed difference for CIFAR10: EViT 785 img/s & DeiT 785 img/s

Concluding remarks

- **Easy-to-use models but very long to train -> use timm!**
- **Speed up training by precomputing teacher's predictions?**

References

- Ashish Vaswani et al. *Attention Is All You Need*. December 2017. (Available at: <https://arxiv.org/abs/1706.03762>)
- Alexey Dosovitskiy et al. *An Image is Worth 16x16 Words: Transformers for Image Recognition at Scale*. ICLR 2021. (Available at: <https://arxiv.org/abs/2010.11929>)
- Touvron et al. *Training data-efficient image transformers & distillation through attention*. January 2021. (Available at: <https://arxiv.org/abs/2012.12877>)
- Liang et al. *Not all Patches are What You Need: Expediting Vision Transformers via Token Reorganizations*. ICLR 2022. (Available at: <https://arxiv.org/abs/2202.07800>)