Robust fine-tuning of zero-shot models

Обзор-рецензия

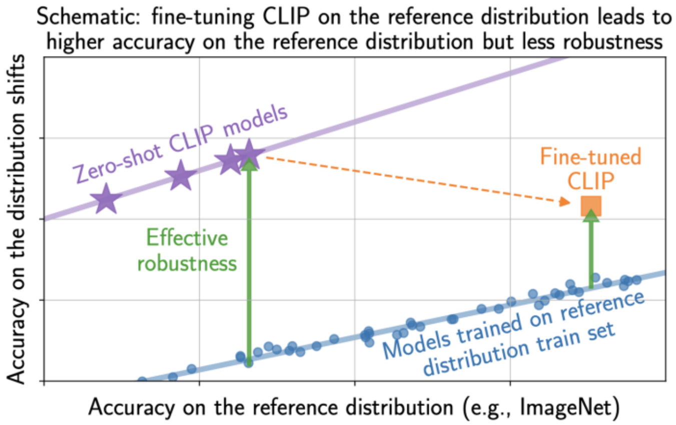
Алексей Шишков, БПМИ192

Основная идея

Can zero-shot models be fine-tuned without reducing accuracy under distribution shift?

- Раньше при дообучении zero-shot нейросетей их “устойчивость” (качество на других наборах данных) снижалась
- При дообучении новым способом она повышается

Было:



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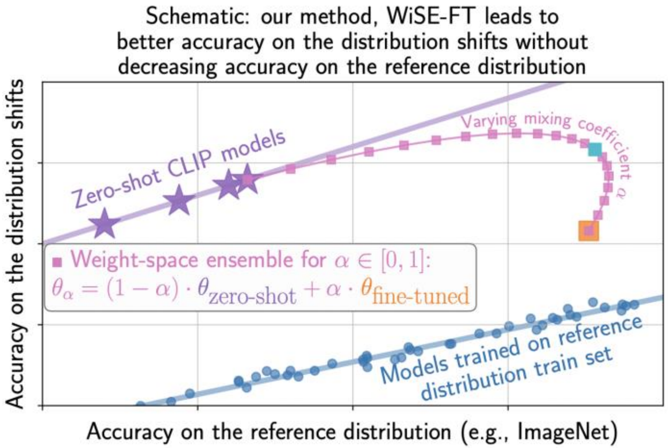

Про статью

- Первая версия – сентябрь 2021
- Финальная – июнь 2022, для конференции CVPR 2022
- Статья-финалист конкурса на лучшую работу

Robust fine-tuning of zero-shot models

Mitchell Wortsman[*†] Gabriel Ilharco[*†] Jong Wook Kim[§] Mike Li[‡]
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Abstract

Large pre-trained models such as CLIP or ALIGN offer consistent accuracy across a range of data distributions when performing zero-shot inference (i.e., without fine-tuning on a specific dataset). Although existing fine-tuning methods substantially improve accuracy on a given target distribution, they often reduce robustness to distribution shifts. We address this tension by introducing a simple and effective method for improving robustness while fine-tuning: ensembling the weights of the zero-shot and fine-tuned models (WiSE-FT). Compared to standard fine-tuning, WiSE-FT provides large accuracy improvements under distribution shift, while preserving high accuracy on the target distribution. On ImageNet and five derived distribution shifts, WiSE-FT improves accuracy under distribution shift by 4 to 6 percentage points (pp) over prior work while increasing ImageNet accuracy by 1.6 pp. WiSE-FT achieves similarly large robustness gains (2 to 23 pp) on a diverse set of six further distribution shifts, and accuracy gains of 0.8 to 3.3 pp compared to standard fine-tuning on seven commonly used transfer learning datasets. These improvements come at no additional computational cost during fine-tuning or inference.

Mitchell Wortsman

Gabriel Ilharco

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CVPR, 2022 **(oral, best paper finalist)**
arxiv / code

OpenCLIP: An open source implementation of CLIP
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GitHub, 2021

Learning Neural Network Subspaces
Mitchell Wortsman, Maxwell Horton, Carlos Guestrin, Ali Farhadi, Mohammad Rastegari
ICML, 2021
arxiv / code

Supermasks in Superposition
Mitchell Wortsman*, Vivek Ramanujan*, Rosanne Liu, Aniruddha Kembhavi, Mohammad Rastegari, Jason Yosinski, Ali Farhadi
NeurIPS, 2020
arxiv / code

Soft Threshold Weight Reparameterization for Learnable Sparsity
Aditya Kusupati, Raghav Somani*, Vivek Ramanujan*, **Mitchell Wortsman***, Prateek Jain, Sham Kakade, Ali Farhadi
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arxiv / code

What's Hidden in a Randomly Weighted Neural Network?
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Discovering Neural Wirings
Mitchell Wortsman, Ali Farhadi, Mohammad Rastegari
NeurIPS, 2019

Mitchell Wortsman

- 2022.06: I'll be presenting Robust fine-tuning of zero-shot models at CVPR 2022, come say hi!
- 2022.05: I'm very thankful for the recognition of outstanding reviewer at CVPR 2022
- 2022.04: Our open-source repository for training CLIP models has reached 1000 stars!
- 2022.03: Model soups set a new state-of-the-art on ImageNet
- 2022.03: What makes zero-shot CLIP models robust? Find out here
- 2022.03: Check out our work using CLIP for zero-shot object navigation.
- 2021.10: I'm excited to be starting an internship with Jacob Eisenstein at Google Research
- 2021.09: Check our our new work Robust fine-tuning of zero-shot models!
- 2021.08: I'm very thankful for the recognition of outstanding reviewer at ACL 2021
- 2021.06: Our paper exploring the relation between visual and text representations has been accepted to NAACL
- 2021.04: Our MultiModalQA paper on complex QA over text, tables and images is out
- 2021.03: Our paper on contrastive representation learning is out
- 2020.11: We'll be presenting a tutorial on High Performance NLP at EMNLP 2020
- 2020.06: I'm very excited to be starting an internship with Peter Anderson and Ashish Vaswani at Google Research
- 2020.05: Check out our new preprint exploring similarities between vision and language representations
- 2020.04: Our work Evaluating NLP models via contrast sets is out
- 2020.02: Check out our new paper exploring the dynamics of fine-tuning in NLP
- 2020.01: Our paper Toward ML-Centric Cloud Platforms made the cover of the Communications of the ACM
- 2019.12: Don't miss our spotlight presentation on SDTW at ViGIL, NeuRIPS 2019.
- 2019.11: Our CoNLL 2019 paper was awarded Honorable Mention for Best Paper in Research Inspired by Human Language Learning!

Gabriel Ilharco

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Связанные статьи

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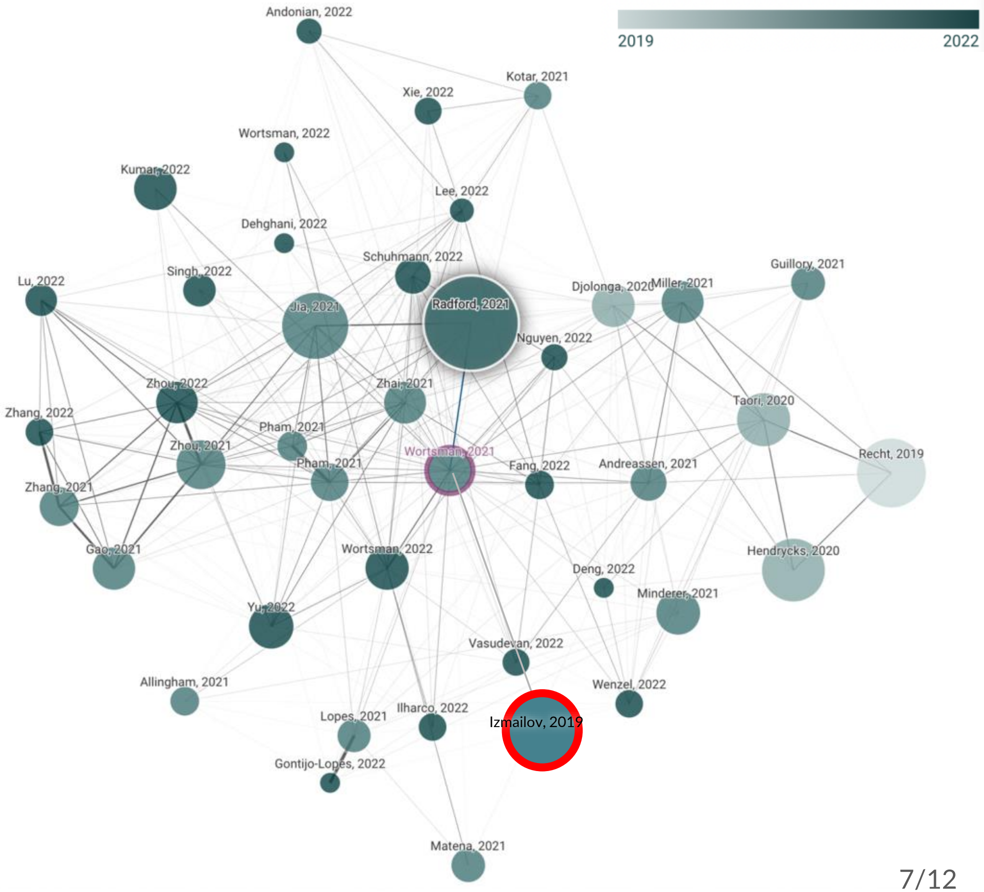
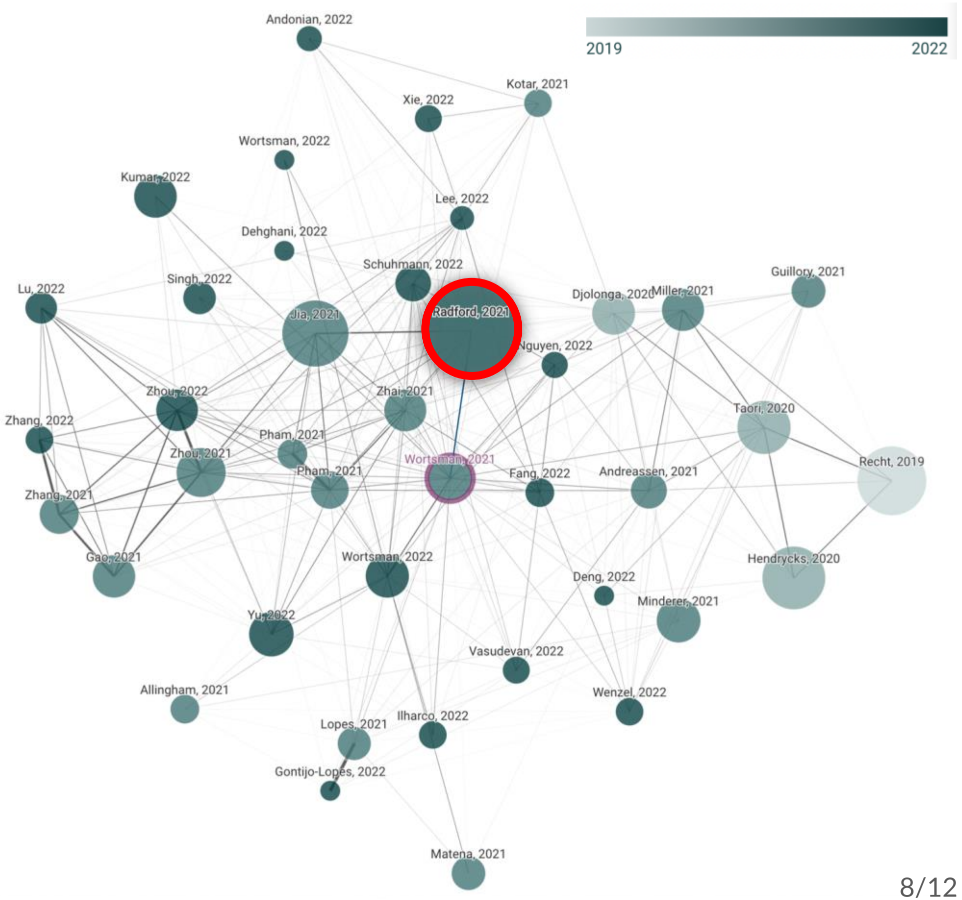


Связанные статьи

Alec Radford et al., Learning transferable visual models from natural language supervision

Способ повышения устойчивого дообучения предобученной модели



Связанные статьи

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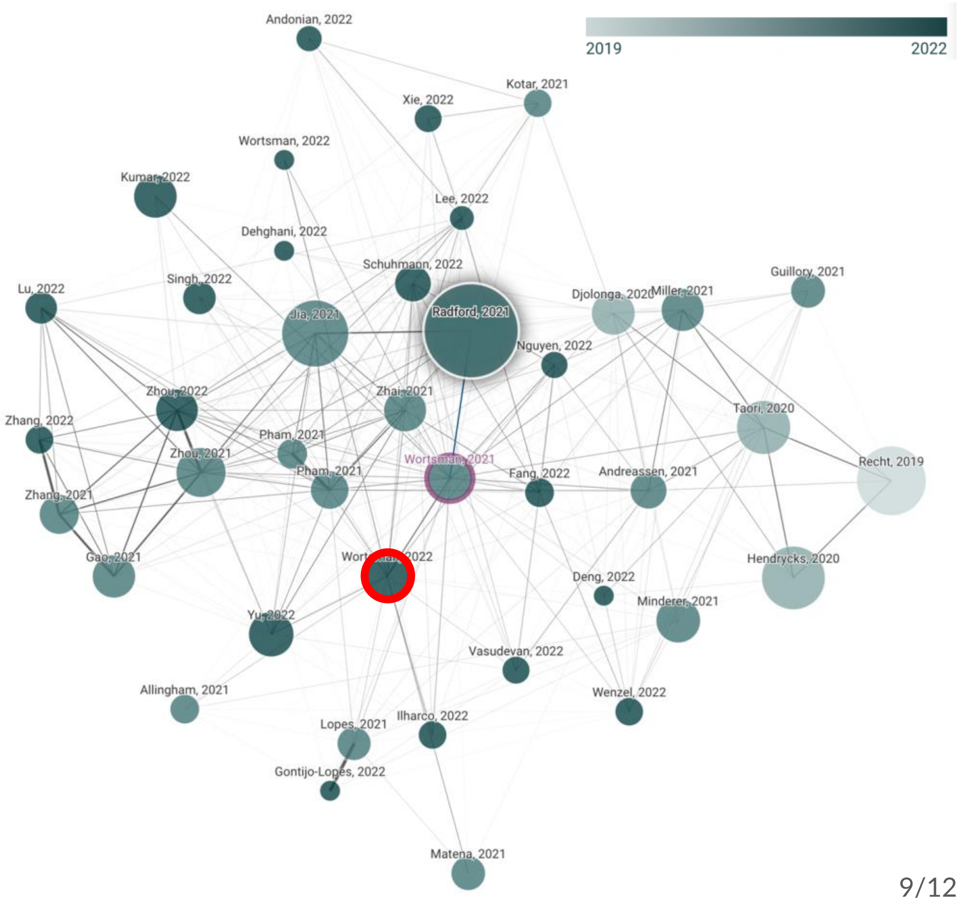
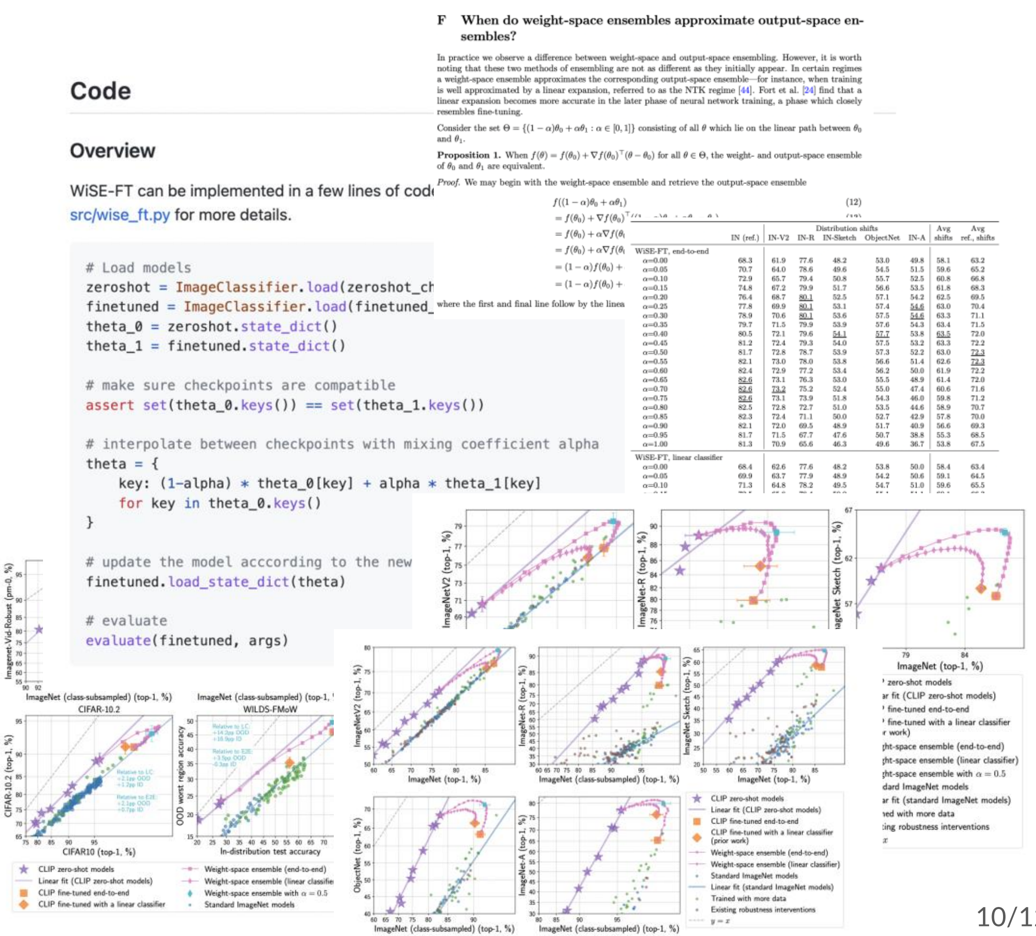


Сильные стороны статьи

- Проведено большое число обучений и экспериментов, много моделей
- Приложен код
- Идея несложная, но описано, как к ней пришли авторы, сама идея описана хорошо



Слабые стороны статьи

- Новизна подхода
- Похоже на обучение на двух датасетах
- Выбор θ

Сравнить качество с обучением на двух датасетах?

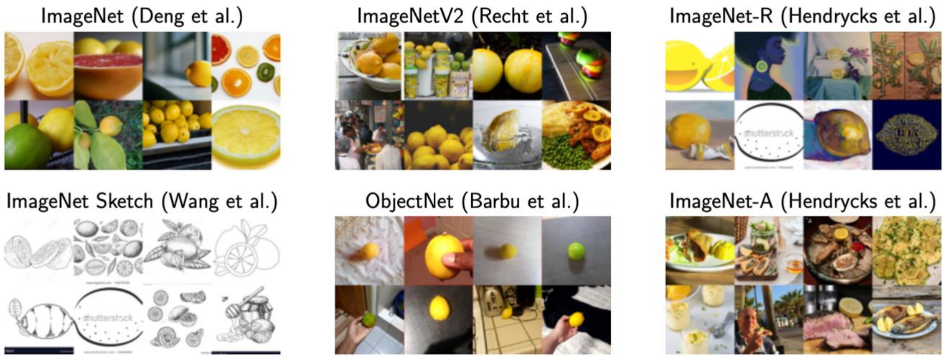


Figure 2: Samples of the class *lemon*, from the reference distribution ImageNet [17] and the derived distribution shifts considered in our main experiments: ImageNet-V2 [83], ImageNet-R [37], ImageNet Sketch [100], ObjectNet [4], and ImageNet-A [38].

Выводы

- Умеем хорошо дообучать сетки, получаем лучшее качеств
- Простые идеи неплохо работают
- Ещё одно применение усреднений весов моделей
- В статье важна не только идея, но и оформление результатов