WeightWatcher:
A Diagnostic Tool for Deep Neural Networks

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(in joint with Michael Mahoney, UC Berkeley)

pip install weightwatcher

Open source tool: weightwatcher

https://github.com/CalculatedContent/WeightWatcher

WeightWatcher (WW): is an open-source, diagnostic tool for analyzing Deep Neural Networks (DNN), without needing access to training or even test data. It can be used to:

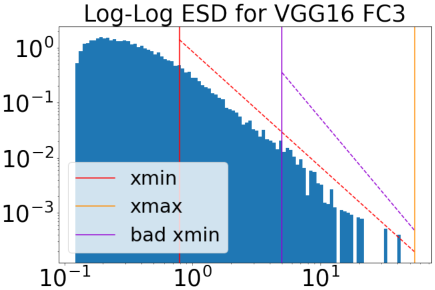
- analyze pre/trained pyTorch and keras models
- inspect models that are difficult to train
- gauge improvements in model performance
- predict test accuracies across different models
- detect potential problems when compressing or fine-tuning pretrained models

It is based on theoretical research (done injoint with UC Berkeley) into *Why Deep Learning Works*, using ideas from Random Matrix Theory (RMT), Statistical Mechanics, and Strongly Correlated Systems.

pip install weightwatcher

Shape and Scale Metrics

WeightWatcher (WW): analyzes the shape and scale of the correlations in the layer weight matrices:



WW: extracts, plots, and fits the Empirical Spectral Density (ESD, or eigenvalues) for each layer weight matrix (or tensor slice).

The *tail of the ESD* contains the most informative components.

The shape of the tail carries useful information!

WeightWatcher: Usage

Usage

import weightwatcher as ww
watcher = ww.WeightWatcher(model=model)
details = watcher.analyze(plot=True)
summary = watcher.get_summary(details)

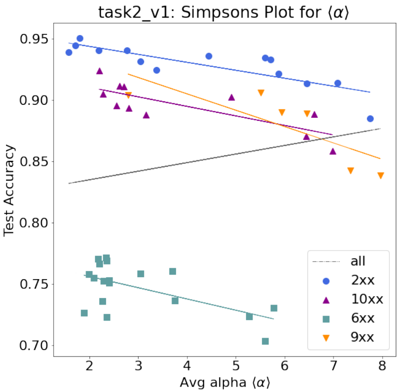
	layer_id	name	D	M	N	alpha	alpha_weighted	has_esd	lambda_max	layer_type	...	rand_num_spikes	rand_sigma_mp	ra
0	2	None	0.240111	3.0	64.0	2.400712	2.627967	1.0	12.435451	LAYER_TYPE.CONV2D	...	135.0	1.000000	
1	5	None	0.112669	64.0	128.0	7.116304	4.721276	1.0	4.607285	LAYER_TYPE.CONV2D	...	25.0	0.551250	
2	8	None	0.076209	128.0	256.0	2.981087	1.739893	1.0	3.833927	LAYER_TYPE.CONV2D	...	17.0	0.451562	
3	10	None	0.068890	256.0	256.0	5.667264	2.600458	1.0	2.876445	LAYER_TYPE.CONV2D	...	0.0	0.935068	
4	13	None	0.084938	256.0	512.0	2.593428	1.432684	1.0	3.568032	LAYER_TYPE.CONV2D	...	8.0	0.431523	
5	15	None	0.038416	512.0	512.0	3.309962	2.216486	1.0	4.673487	LAYER_TYPE.CONV2D	...	0.0	0.939111	
6	18	None	0.052924	512.0	512.0	3.446656	1.859810	1.0	3.464163	LAYER_TYPE.CONV2D	...	0.0	0.888574	
7	20	None	0.034290	512.0	512.0	3.261262	2.524426	1.0	5.943799	LAYER_TYPE.CONV2D	...	0.0	0.942012	
8	25	None	0.032563	4096.0	25088.0	2.325065	3.583809	1.0	34.784030	LAYER_TYPE.DENSE	...	1.0	0.898506	
9	28	None	0.030891	4096.0	4096.0	2.167513	3.858526	1.0	60.278519	LAYER_TYPE.DENSE	...	1.0	0.959863	
10	31	None	0.039773	1000.0	4096.0	2.825653	4.999373	1.0	58.786867	LAYER_TYPE.DENSE	...	206.0	1.000000	

summary = watcher.get_summary(details)

```
{'log_norm': 2.11,
 'alpha': 3.06,
 'alpha_weighted': 2.78,
 'log_alpha_norm': 3.21,
 'log_spectral_norm': 0.89,
 'stable_rank': 20.90,
 'mp_softrank': 0.52}]
```

α: a Regularization / Shape metric

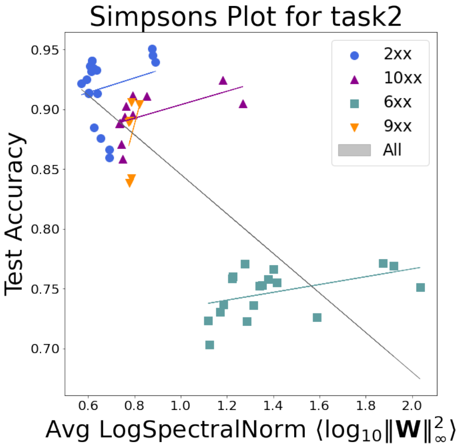
The WW $\langle\alpha\rangle$ metric: predicts test accuracy for a model when varying the regularization hyper-parameters (such as batch size, weight decay, momentum, etc.)—*without access to the test or training data.*



It fits tail of the ESD to a Truncated Power Law (PL): $\rho(\lambda) := \lambda^{-\alpha}$

$\log \lambda^{max}$: log Spectral Norm / Scale metric

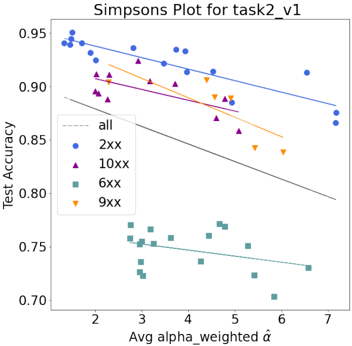
The WW $\langle \log \lambda^{max} \rangle$ **metric**: also predicts test accuracies, but has the oppostie behavior than expected–larger norms give better results!



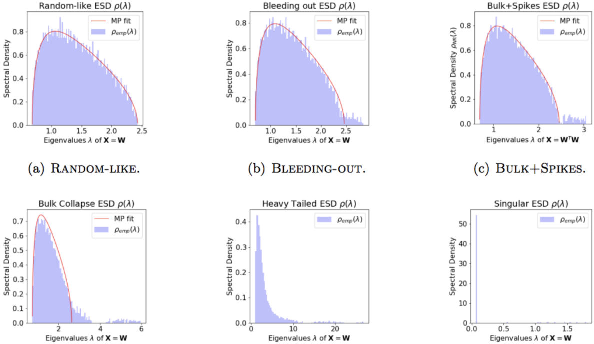
This is a classic *Simpson's Paradox*

$\hat{\alpha}$: a multi-purpose metric

The WW $\hat{\alpha}$ metric: predicts test accuracy for models in the same architecture series across varying *both* depth and regularization hyper-parameters—-*without access to the test or training data.*



The $\hat{\alpha} = \sum \alpha_l \log \lambda_l^{max}$ metric is a weighted average of **shape** (α) and **scale** (λ_{max}) metrics. ... from Statistical Mechanics (see blog, in press) https://CalculatedContent.com



(a) RANDOM-LIKE. (b) BLEEDING-OUT. (c) BULK+SPIKES.

(d) BULK-DECAY. (e) HEAVY-TAILED. (f) RANK-COLLAPSE.

TOWARDS A NEW THEORY OF LEARNING: STATISTICAL MECHANICS OF DEEP NEURAL NETWORKS

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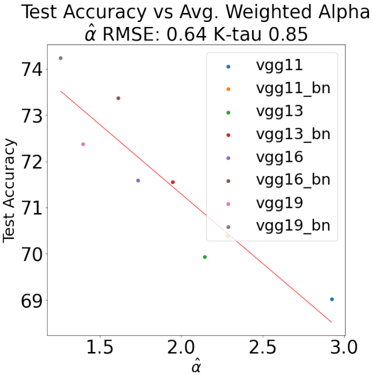

We have studied 100s of pre-trained CV (and NLP) models; featured in our latest paper in **Nature Communications**

Article | Open Access | Published: 05 July 2021

Predicting trends in the quality of state-of-the-art neural networks without access to training or testing data

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Nature Communications **12**, Article number: 4122 (2021) | Cite this article

Abstract

In many applications, one works with neural network models trained by someone else. For such pretrained models, one may not have access to training data or test data. Moreover, one may not know details about the model, e.g., the specifics of the training data, the loss function, the hyperparameter values, etc. Given one or many pretrained models, it is a challenge to say anything about the expected performance or quality of

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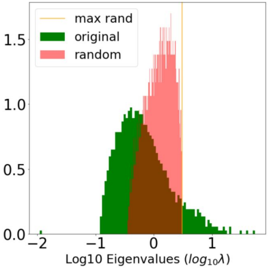
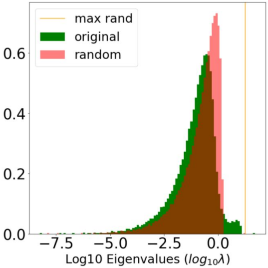
ge by providing a detailed meta-

Research Update: Heavy Tails in **W** and **X**

Correlation Traps We *conjecture* that when the unusually large elements $W_{i,j}$ arise in the weight matrices, these act like traps (in the ESD of **X** that prevent good generalization.



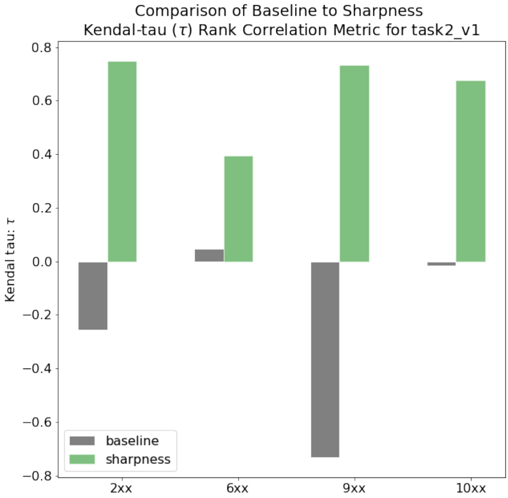
(a) ESD of **W** and randomized **W**.



(b) ESD of **W** and randomized **W**.

These can be seen using the [randomize] option in **weightwatcher**.
We beleive we can use this to detect overfitting and are investigating this.

Research Update: Sharpness Transform



Research Update: SVD Smoothing