BOSTON UNIVERSITY

Deep Learning for Data Science DS 542

https://dl4ds.github.io/sp2026/

Data Preparation and Augmentation

Plan for Today

- Standardizing data
- Augmenting data
- Randomizing data
- Rethinking generalization
- Random pre-training

What is Standardization?

- Standardization is a set of preprocessing techniques to make data easier to model.

- Standardization used to be an obligatory detail in papers about neural network since it often made a big difference in whether the network could successfully train.

- Basic standardization techniques are available in scikit-learn.
  - https://scikit-learn.org/stable/modules/preprocessing.html

Standardizing Mean and Variance

1. Subtract out the mean of the training distribution.
2. Divide by the standard deviation of the training distribution.

Details:

- Usually doing this column/element-wise.
- For images, sometimes channel-wise.
- Save these training means and standard deviations to apply to other data.
  - Validation/test/production usage uses values from training!

https://scikit-learn.org/stable/modules/generated/sklearn.preprocessing.StandardScaler.html

What Does This Standardization Do?

- Standardizing mean makes the transformed input have mean zero.
- Standardizing the standard deviation makes the transformed input have standard deviation one.
- Assuming later inputs are from a similar distribution.

Why Does Standardization Help?

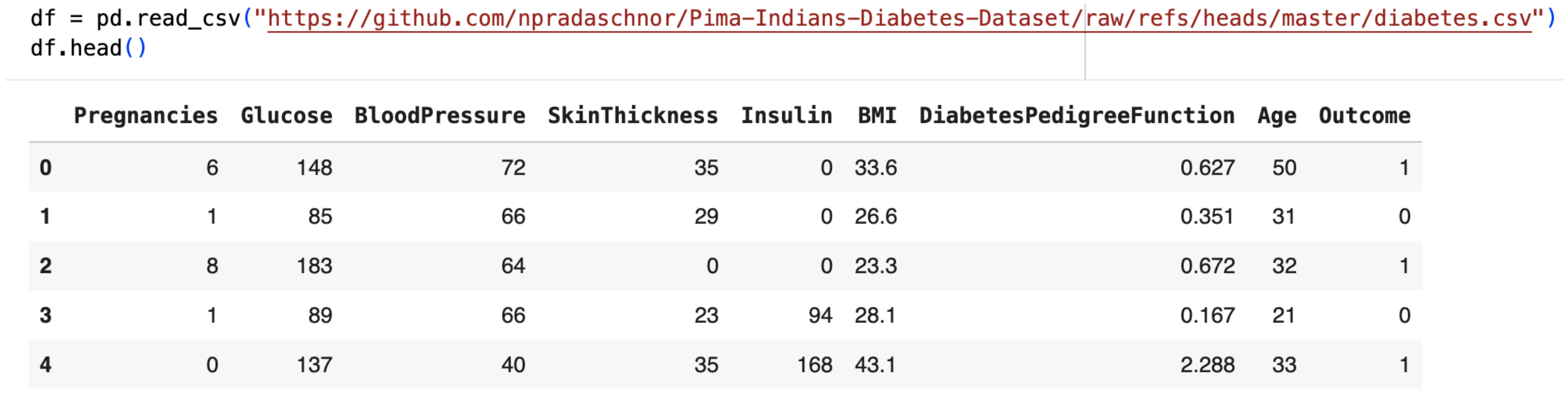
Think back to backpropagation…

At beginning of training,

- Forward pass values are proportional to the input values.

- Parameter gradients computed in backpropagation are multiplied by those forward values.

Homework 3 – Logistic Regression

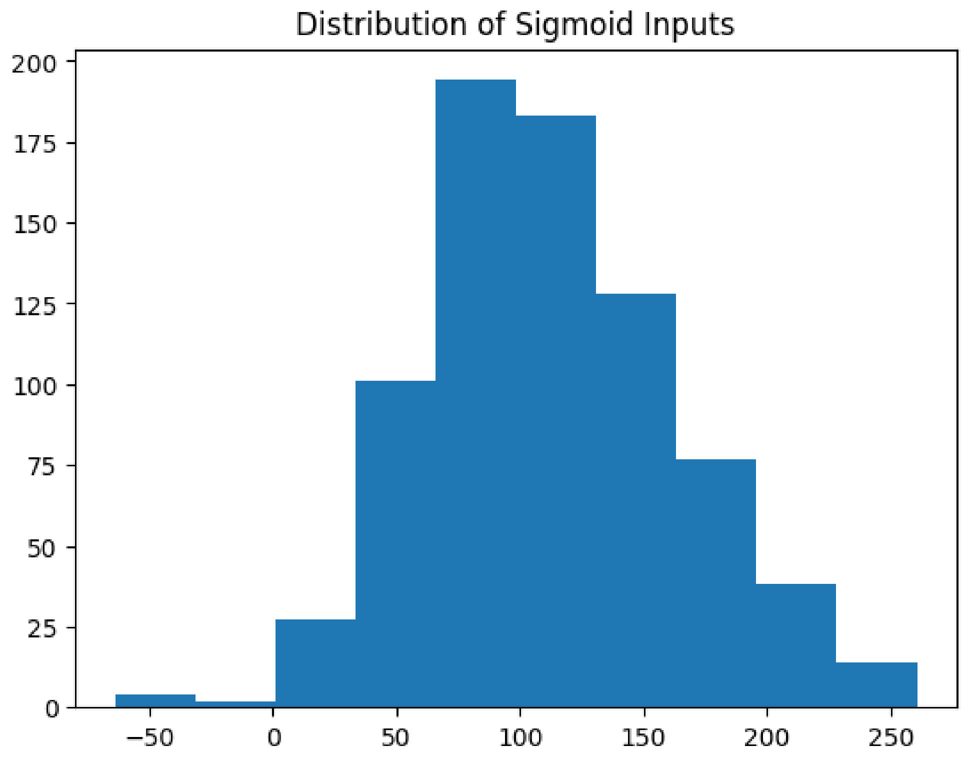


```
df = pd.read_csv("https://github.com/npradaschnor/Pima-Indians-Diabetes-Dataset/raw/refs/heads/master/diabetes.csv")
df.head()
```

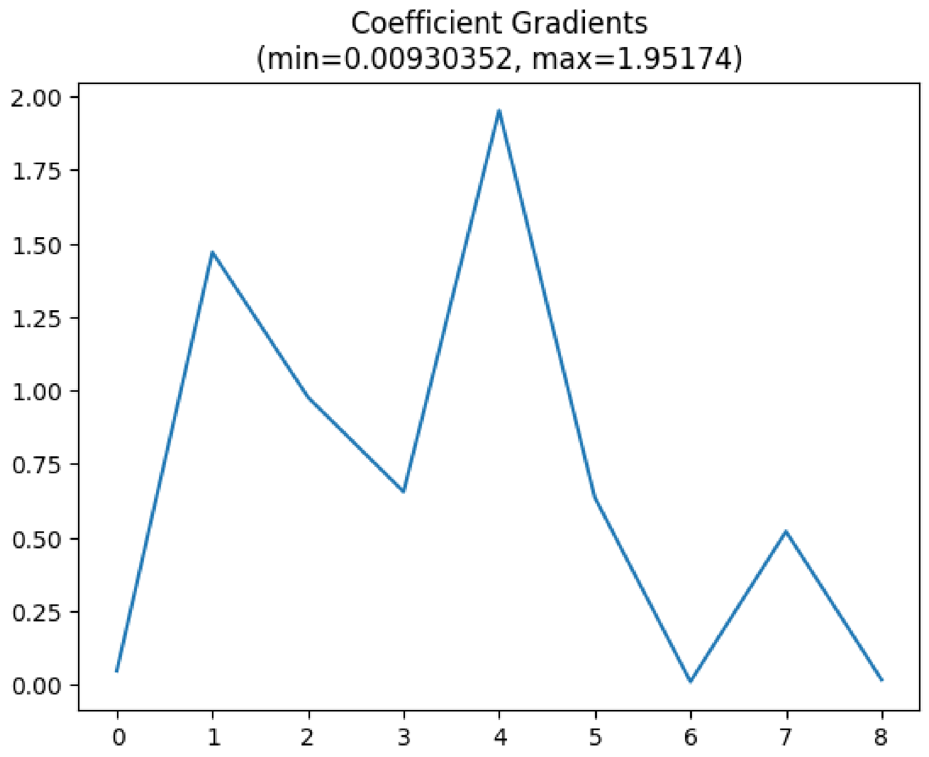
	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

Normally Distributed Initializations

Sigmoid Inputs

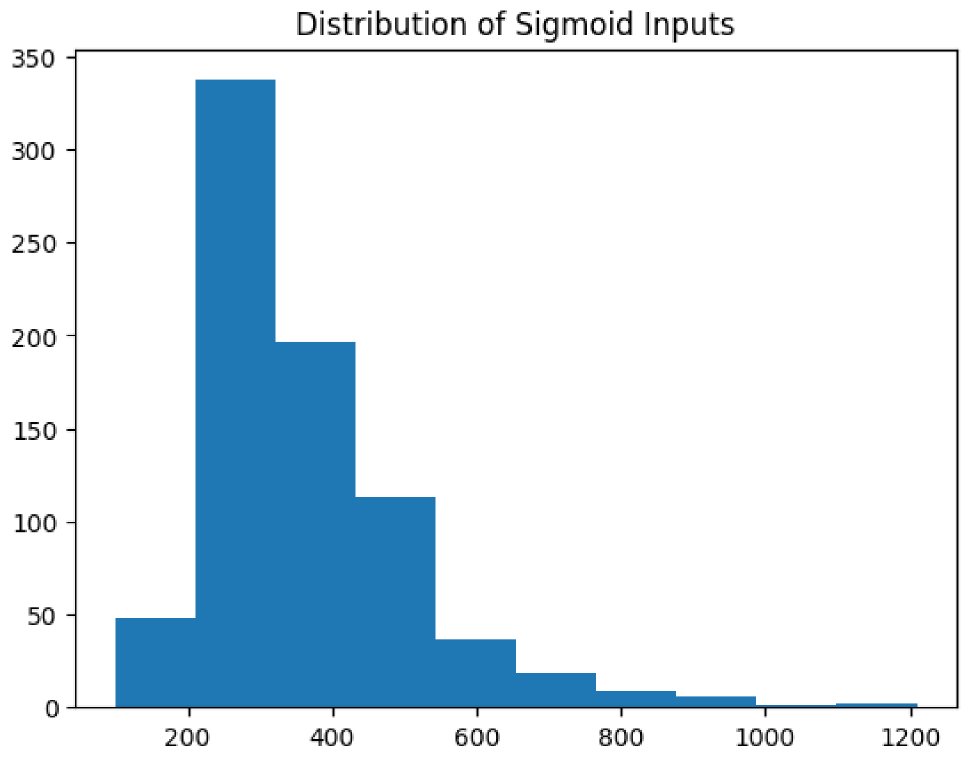


Coefficient Gradients

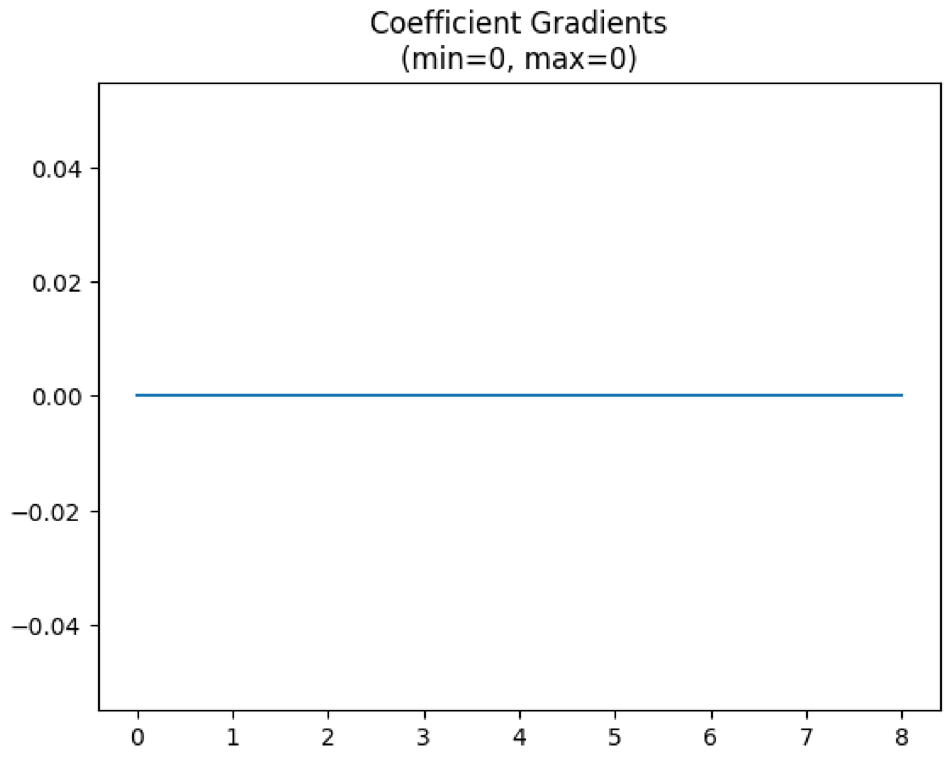


Constant Initialization (all 1)

Sigmoid Inputs

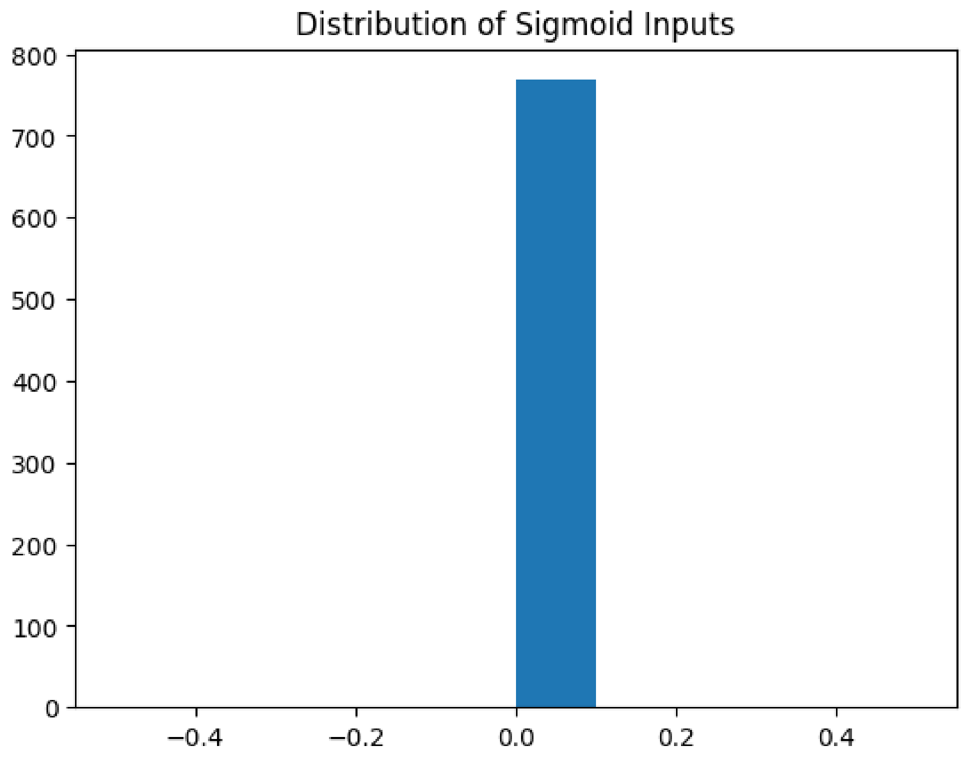


Coefficient Gradients

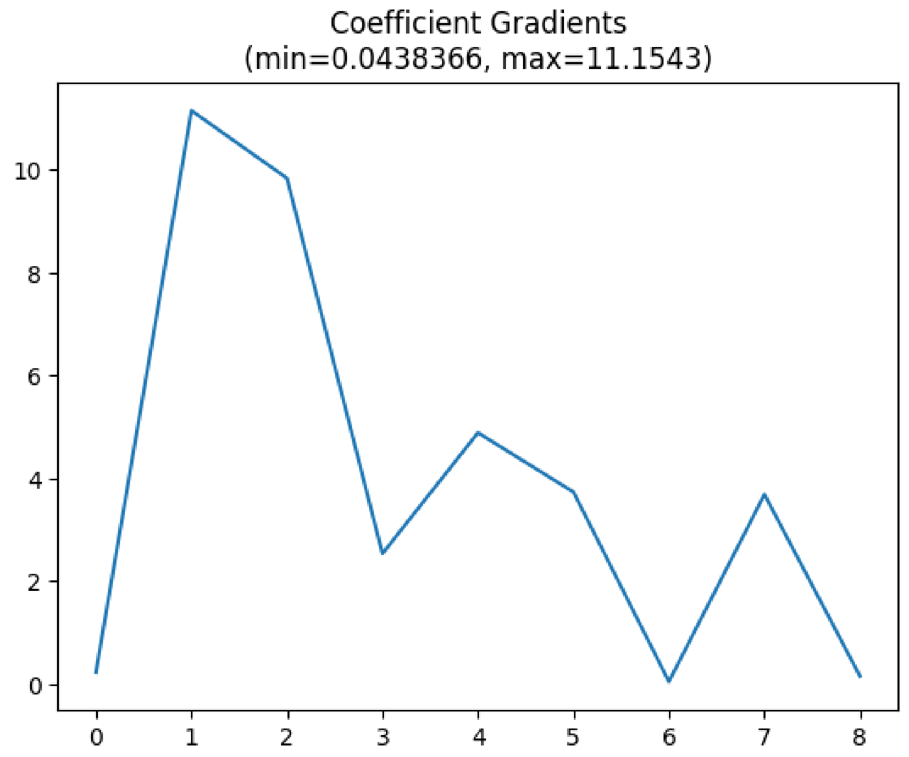


Zero Initialization

Sigmoid Inputs

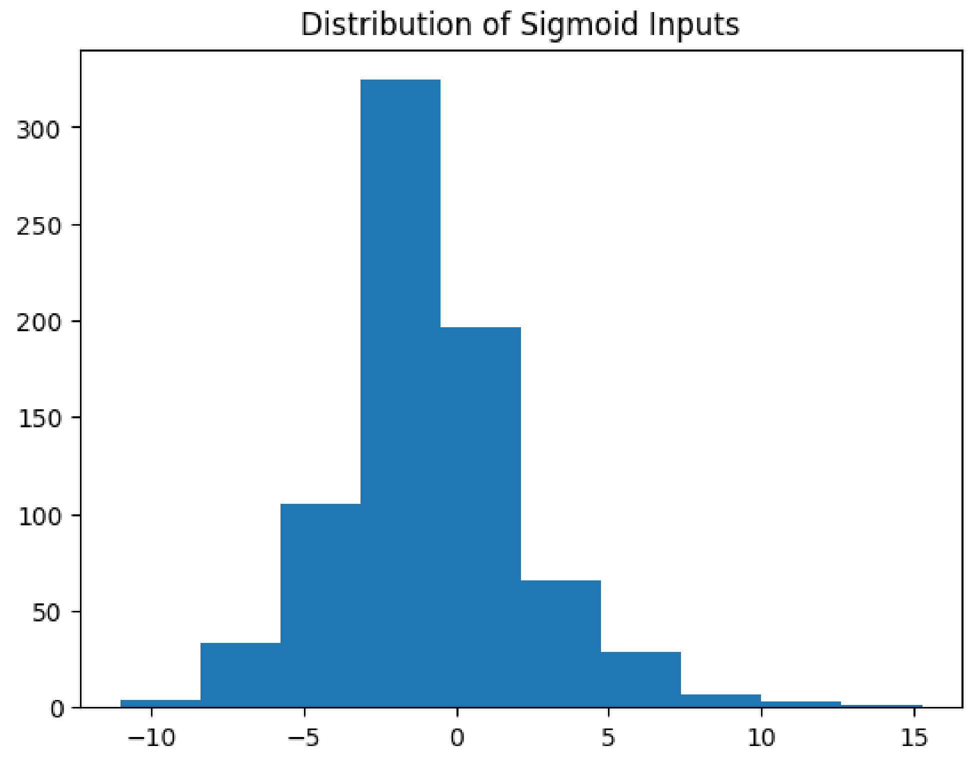


Coefficient Gradients

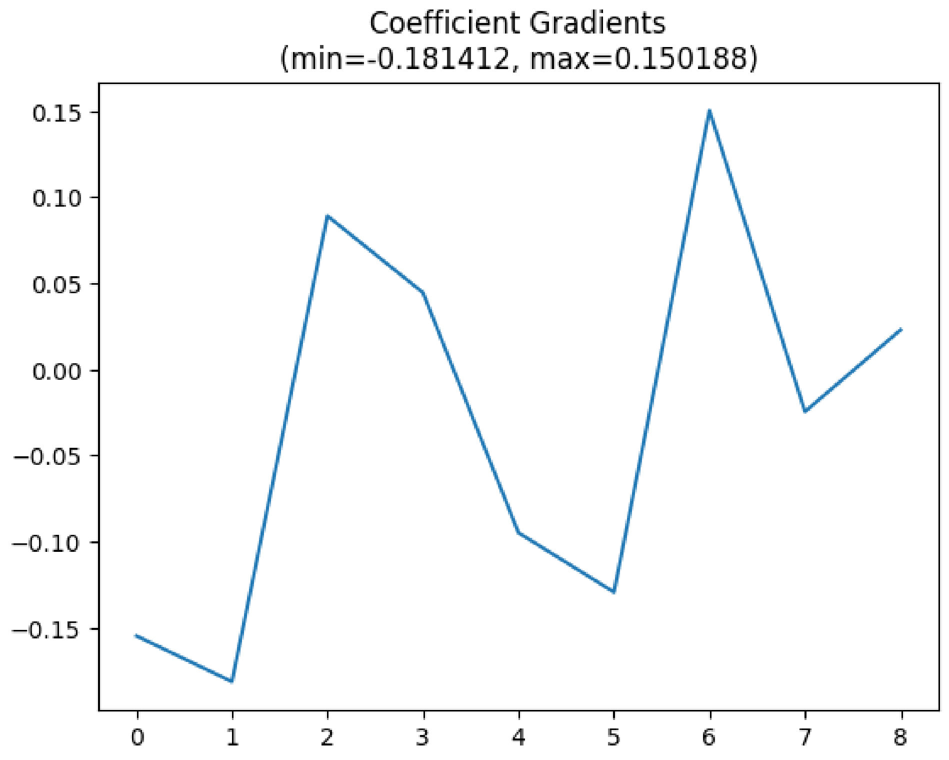


Standardization and Normally Distributed Initializations

Sigmoid Inputs

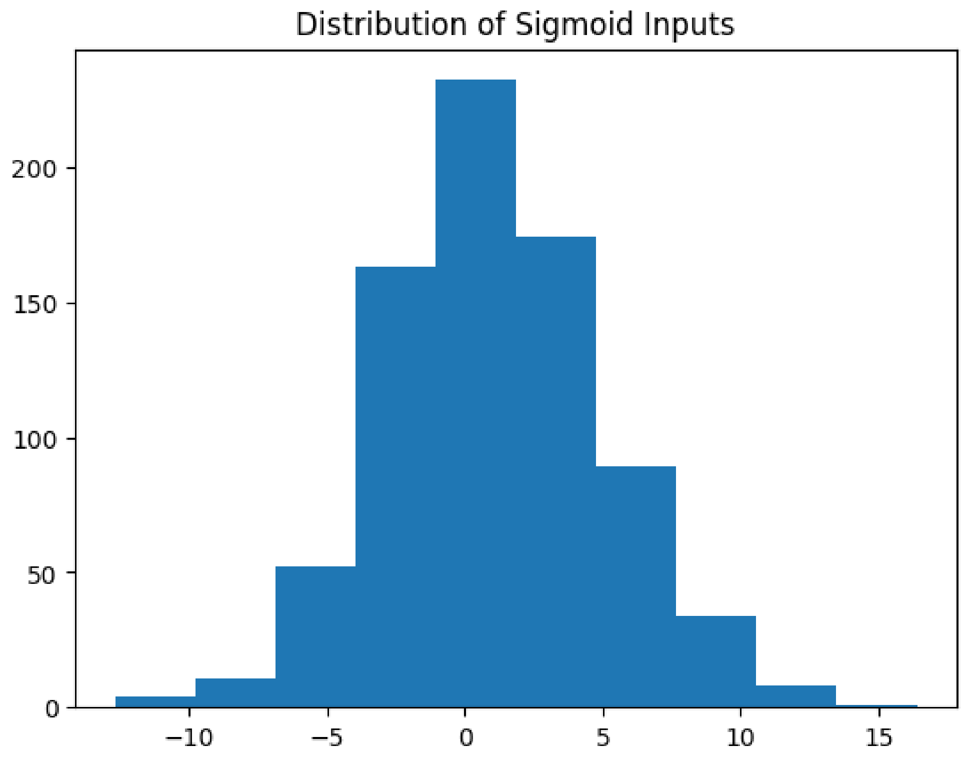


Coefficient Gradients

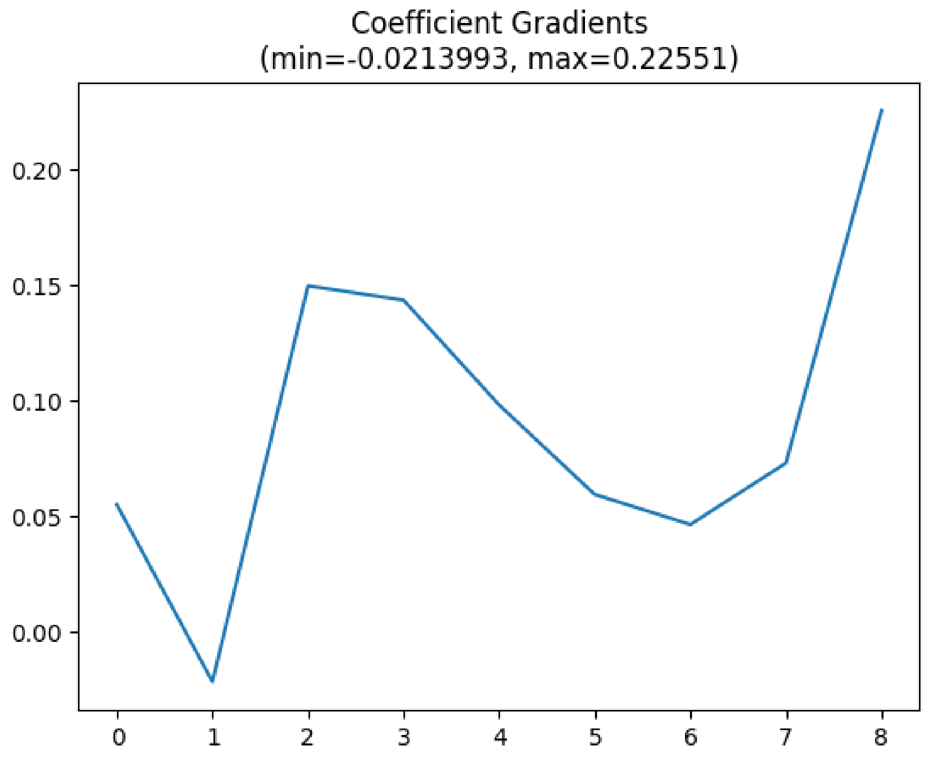


Standardization and Constant Initializations (all 1)

Sigmoid Inputs

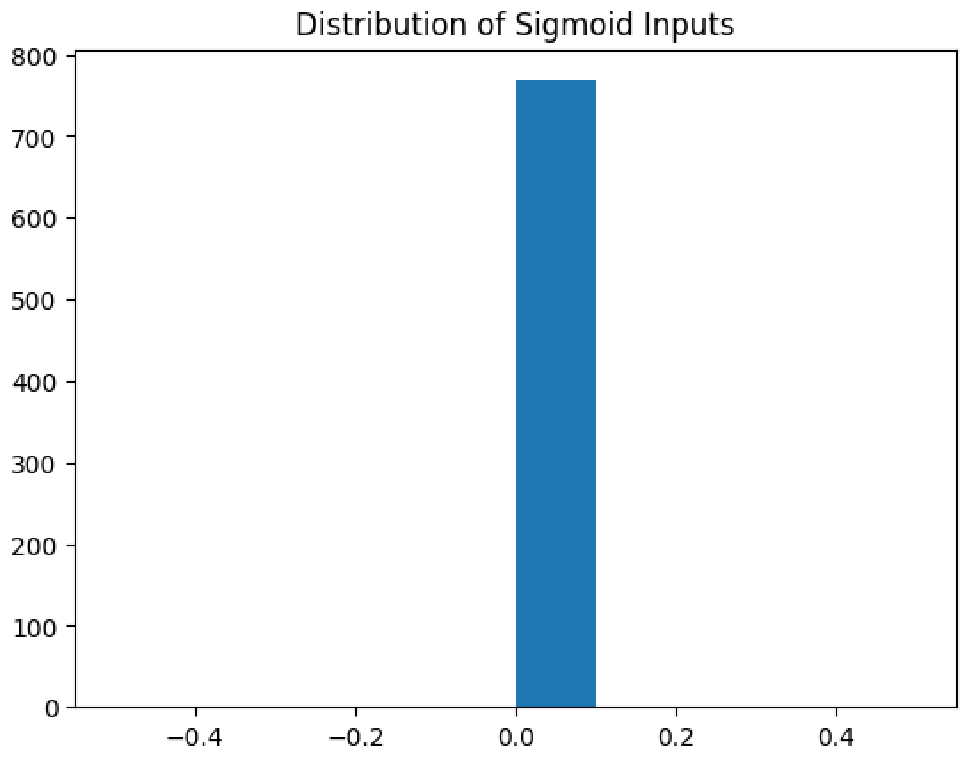


Coefficient Gradients

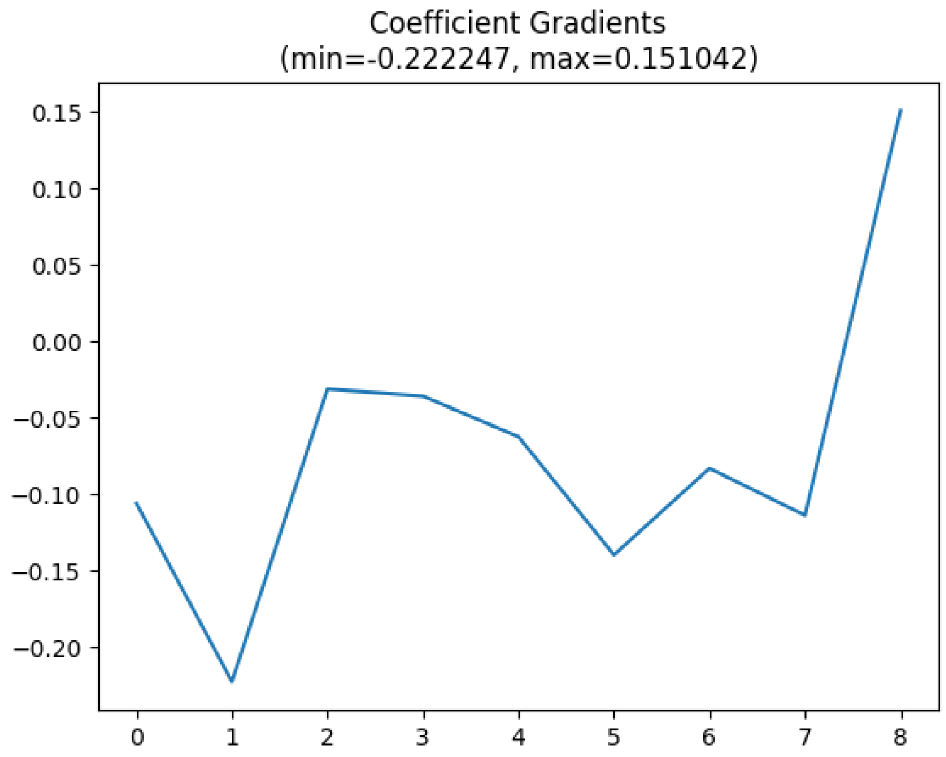


Standardization and Zero Initializations

Sigmoid Inputs



Coefficient Gradients



Whitening

- Standardizing means and variance still allows correlations between variables.
  - Covariance matrix Σ
  - Standardizing variance gives ones along the diagonal.
  - Off-diagonal non-zero covariances are still allowed.

- Whitening is a linear transformation of the variables that removes those covariances too.
  - Removing correlations makes some modeling easier.
  - But new variables are linear combination of old variables, so slightly opaque.

Usually implemented via sklearn.decomposition.PCA w/whiten=True

So why less talk about standardization?

- Still is relevant to many real-world problems.
  - Usually, data comes in most convenient / easily checkable form.
  - Distinct from easiest to model form.

- Less important if your inputs start in a known small range.
  - Images with pixel values mapped from [0,255] to [0.0,1.0].

  - Language models with input tokens one-hot encoded and run through feature embeddings.
    - Language models would be a lot harder if they took in integer token ids as inputs.

Any Questions?

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Moving on

- Standardizing data
- Augmenting data
- Randomizing data
- Rethinking generalization
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Data Augmentation

- TLDR make data set bigger by synthesizing new inputs from old inputs…

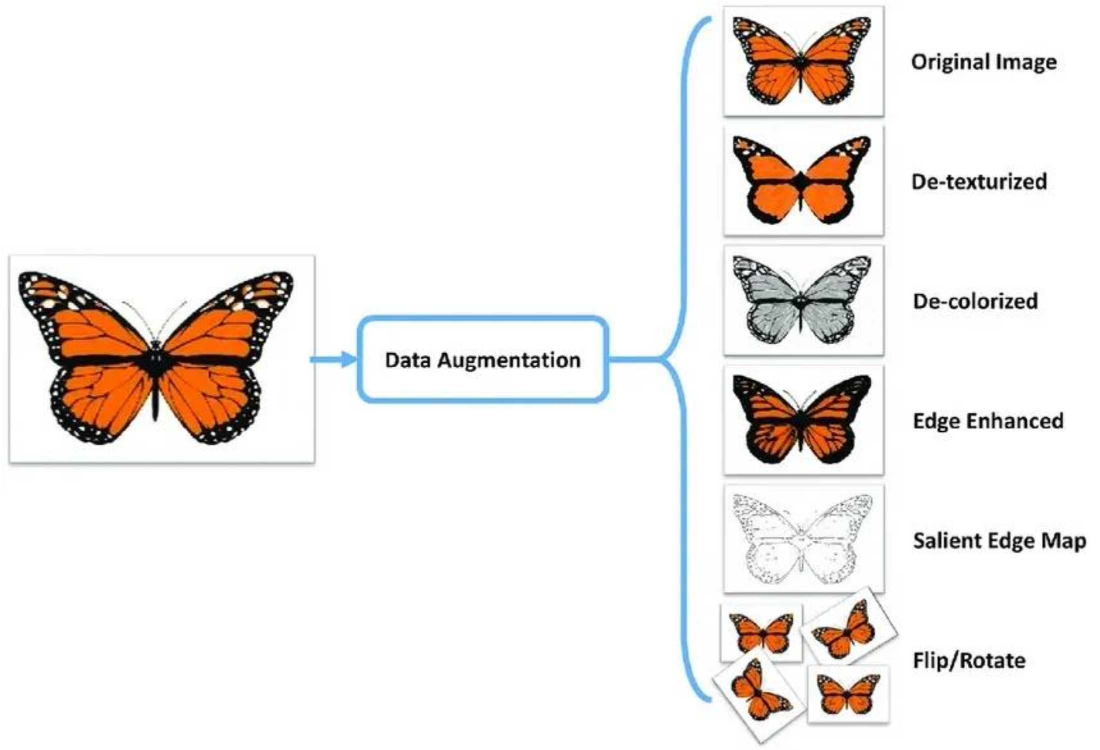
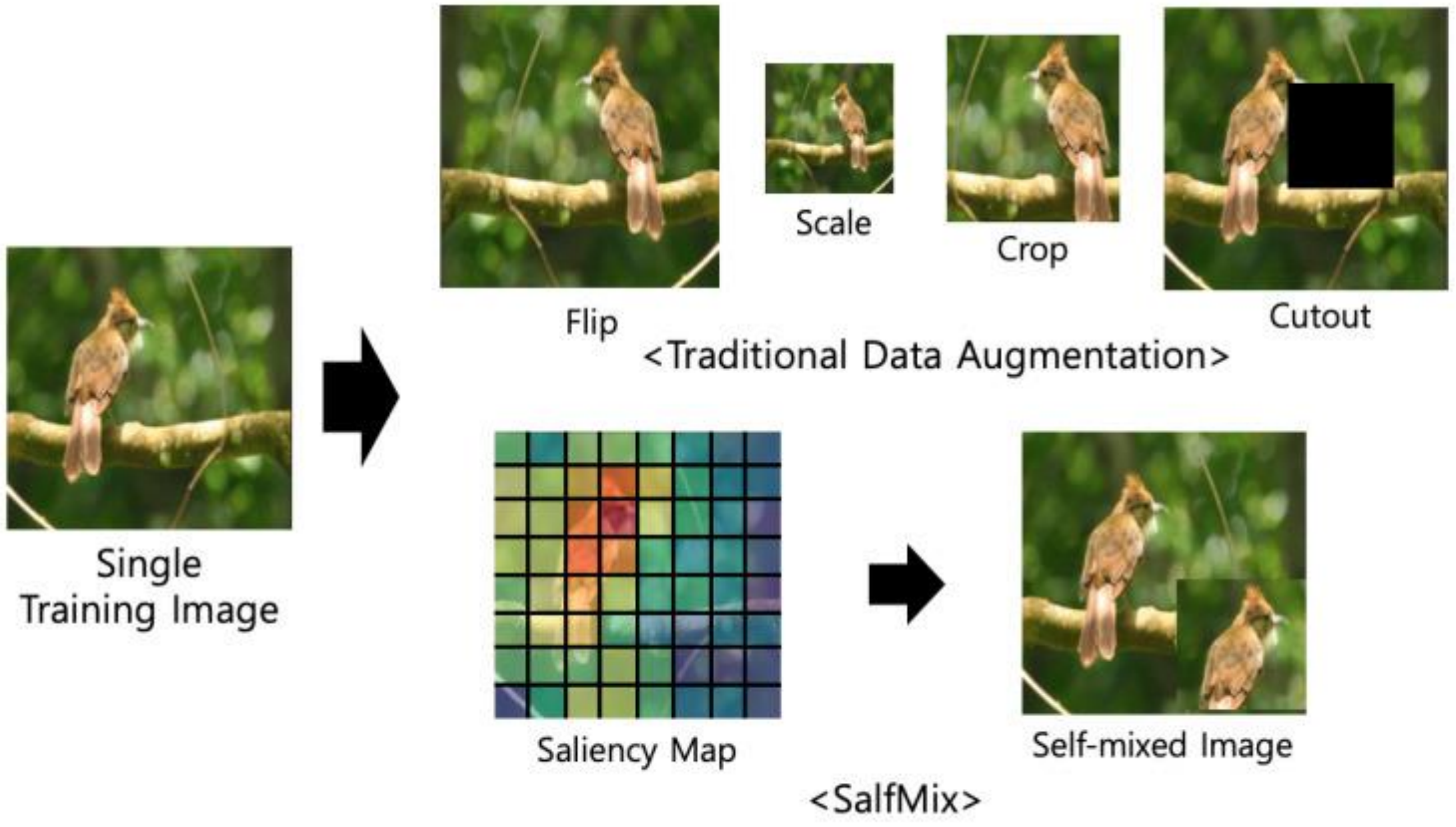


Image source: https://www.labellerr.com/blog/what-is-data-augmentation-techniques-examples-benefits/

New Examples of Data Augmentation



https://pubmed.ncbi.nlm.nih.gov/34960539/

Key Properties for Data Augmentation

1. The transformations for data augmentation should not change the correct answer!
2. The new data ideally fits within existing distribution and does not add new competing features to learn.

- For Project 1 (tree or not),
  - Horizontal flips 👍
  - Vertical flips 👎
  - Color changes 🤔

What if Data Augmentation Changes the Label?

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Any Questions?

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Randomization in Data Augmentation

- Most data augmentation code introduces more randomization…
- You pick a set of possible transformations.
  - A random subset of transforms are applied.
  - Some transformations have built-in random choices too.
    - E.g. How many pixels to shift an image.
- Effectively infinite set of augmented images?
  - But shared structure among them, so not quite as good.

Randomization in Training Labels?

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Classification Probabilities after Randomizing Training Labels

If you deliberately change 1% of training labels,

- What is the highest probability that should be predicted?

- What is the lowest probability that should be predicted?

Cross Entropy Loss after Randomizing Training Labels

- What did overfitting look like before randomization?

- Can that still happen after randomization?

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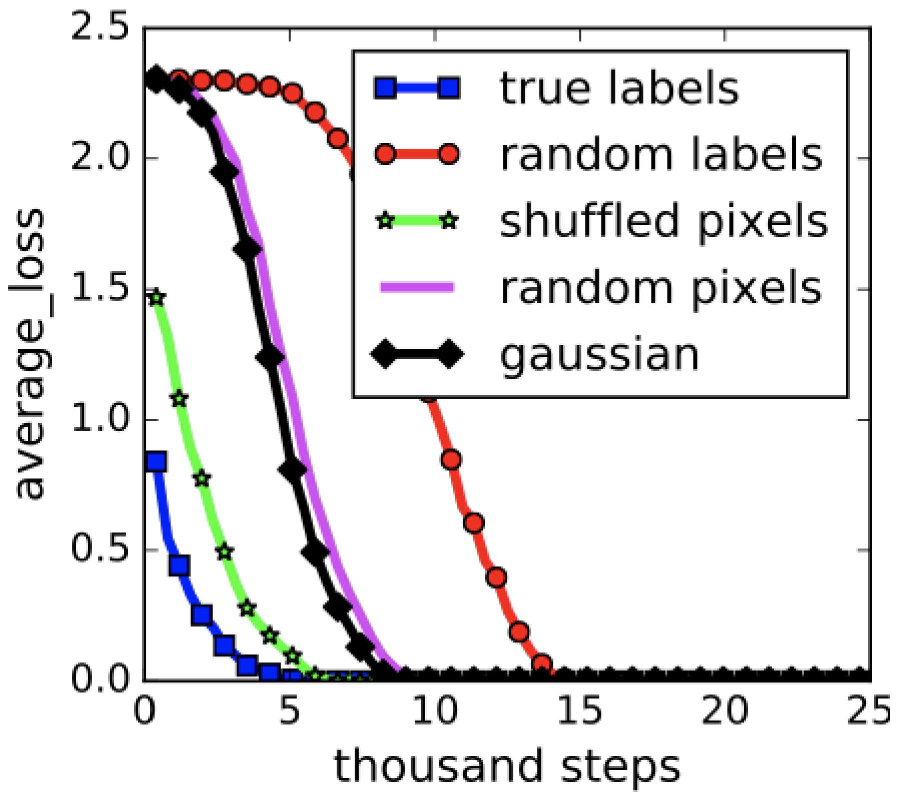
Understanding deep learning requires rethinking generalization (Zhang et al, 2016)

- Can deep neural networks fit random labels?
  - Of course!
- How big do they need to be?
  - Previously: nd parameters for n inputs and d dimensions.
  - New: $2n + d$ parameters using 2 layers and RELU.

Fitting Pure Random Labels

- Learning random labels takes longer than learning true labels.
- In between
  - Adding noise to pixels
  - Permuting pixels

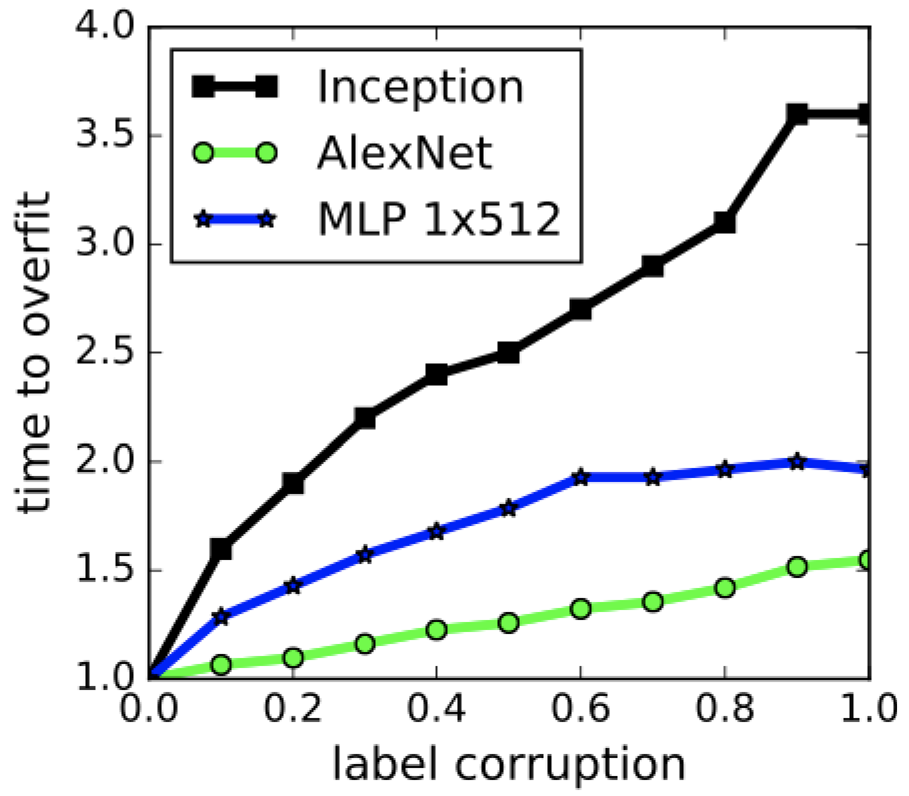
Tested on CIFAR10 and Inception architecture.



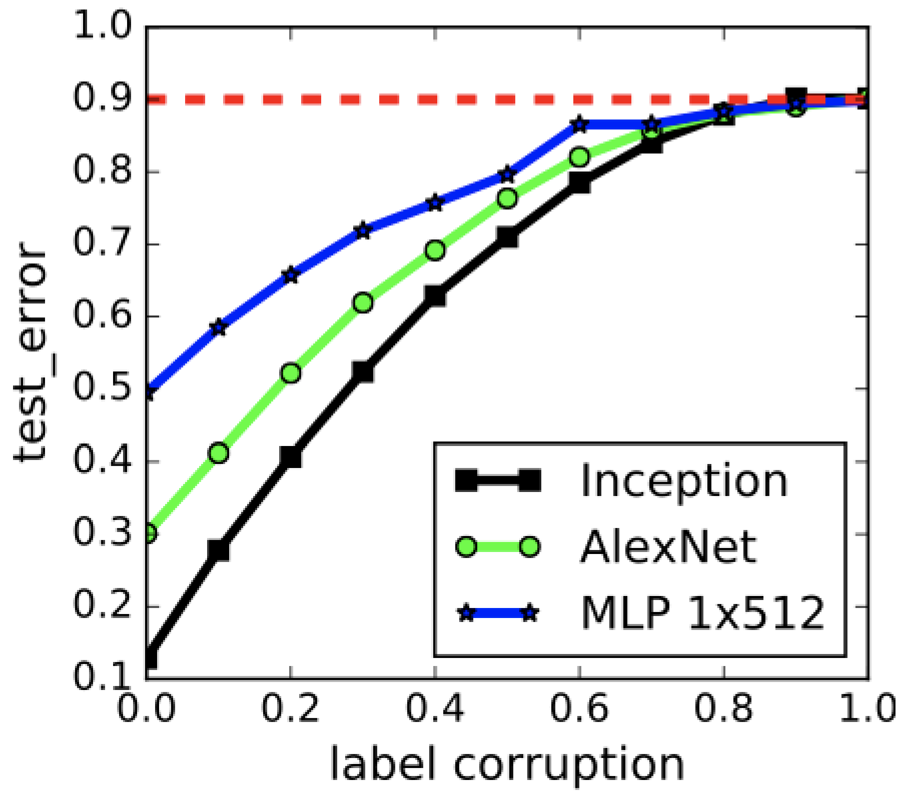
(a) learning curves

Image source: Understanding deep learning requires rethinking generalization (Zhang et al, 2016)

Fitting Partially Corrupted Labels



(b) convergence slowdown



(c) generalization error growth

Image source: Understanding deep learning requires rethinking generalization (Zhang et al, 2016)

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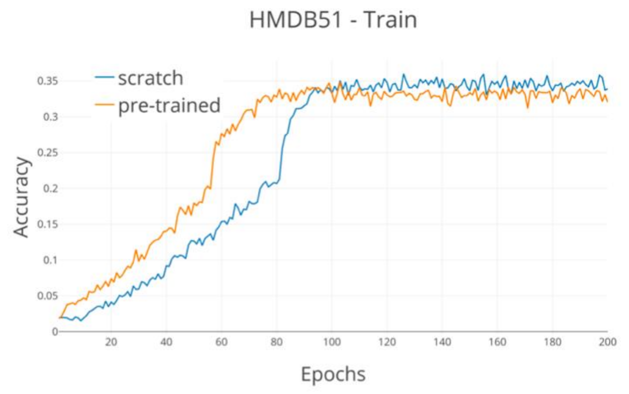
Leveraging Random Label Memorization for Unsupervised Pre-Training (Pondenkandath et al, 2018)

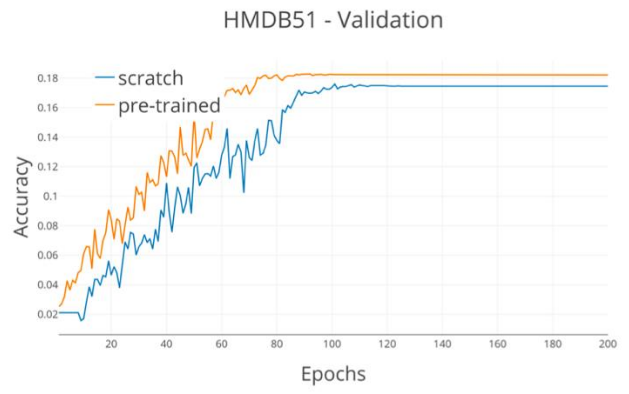
- What if we pre-train on random labels first, then real labels?

- Why would we do that?

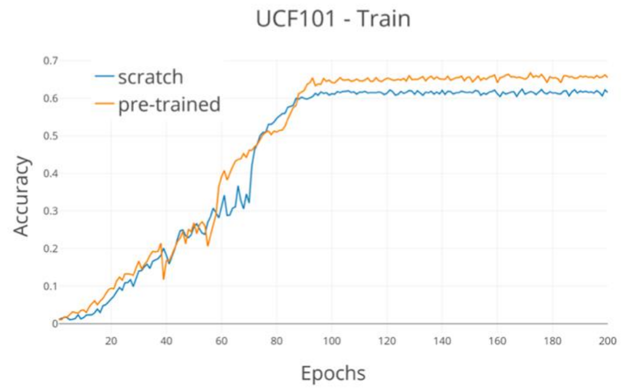
Faster Training and Higher Test accuracy?



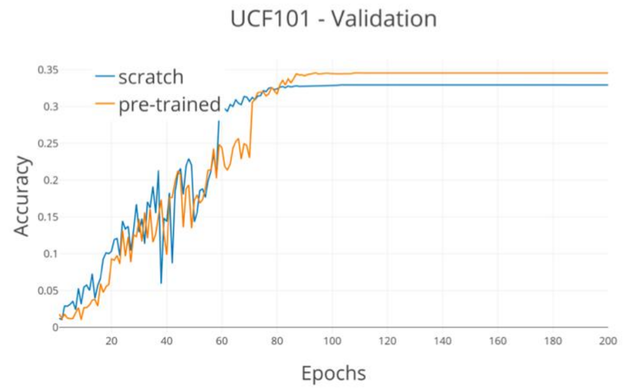
(a)



(b)



(c)



(d)

Leveraging Random Label Memorization for Unsupervised Pre-Training (Pondenkandath et al, 2018)

Transfer Learning

- General term for leveraging training effort on one task for another task…
- Original usage
  - Train model for one task.
  - Copy weights to new model.
  - Change output size if necessary.
  - Fine-tune for new task.
- Previously saw this reusing pre-trained models (e.g. BERT).

Why Transfer Learning?

- Decrease training time for tasks with similar inputs?

- Generalize better by combining learnings across tasks?

Why Does Transfer Learning Work with Random Labels?

- It doesn’t always work. ⍰

- But recognizing image structure seems to help distinguishing images.
  - So, pre-training on random labels may learn useful features for distinguishing images…

What Do Neural Networks Learn When Trained With Random Labels? (Maennel et al, 2020)

"In this paper, we show analytically for convolutional and fully connected networks that an alignment between the principal components of network parameters and data takes place when training with random labels. We study this alignment effect by investigating neural networks pre-trained on randomly labelled image data and subsequently fine-tuned on disjoint datasets with random or real labels. We show how this alignment produces a positive transfer: networks pre-trained with random labels train faster downstream compared to training from scratch even after accounting for simple effects, such as weight scaling. We analyze how competing effects, such as specialization at later layers, may hide the positive transfer."

So, It Depends

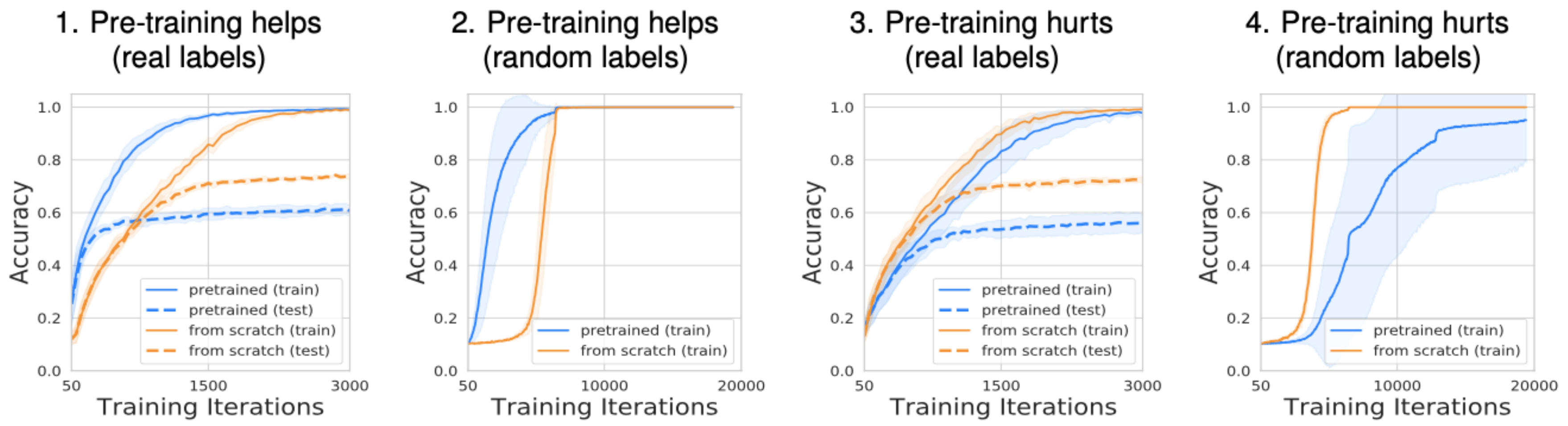


Figure 1: Pre-training on random labels may exhibit both positive (1 & 2) and negative (3 & 4) effects on the downstream fine-tuning depending on the setup. VGG16 models are pre-trained on CIFAR10 examples with random labels and subsequently fine-tuned on the fresh CIFAR10 examples with either real labels (1 & 3) or 10 random labels (2 & 4) using different hyperparameters.

What Do Neural Networks Learn When Trained With Random Labels? (Maennel et al, 2020)

Interesting Tidbits

- They were able to reproduce the performance the random initialization performance by approximating the principal components with sampling…
  - This worked over multiple layers too.

- One mechanism that they noted hurting transfers was inactive (dead) ReLUs.

Any Questions?

???

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