How to use Learning Curves to Diagnose Machine Learning Model Performance

by **Jason Brownlee** on February 27, 2019 in **Deep Learning Performance**

Last Updated on August 6, 2019

A learning curve is a plot of model learning performance over experience or time.

Learning curves are a widely used diagnostic tool in machine learning for algorithms that learn from a training dataset incrementally. The model can be evaluated on the training dataset and on a hold out validation dataset after each update during training and plots of the measured performance can created to show learning curves.

Reviewing learning curves of models during training can be used to diagnose problems with learning, such as an underfit or overfit model, as well as whether the training and validation datasets are suitably representative.

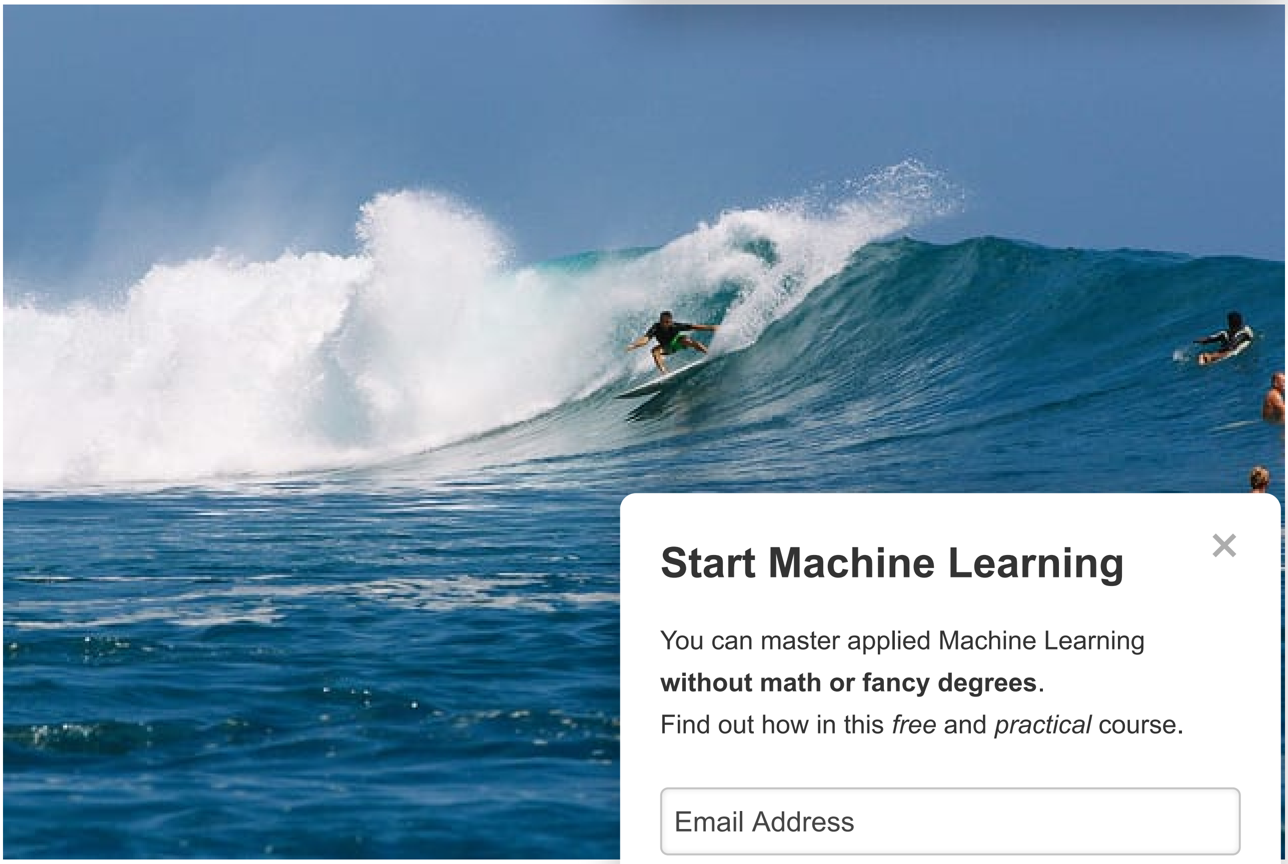
In this post, you will discover learning curves and how they can be used to diagnose the learning and generalization behavior of machine learning models, with example plots showing common learning problems.

After reading this post, you will know:

- Learning curves are plots that show changes in learning performance over time in terms of experience.
- Learning curves of model performance on the train and validation datasets can be used to diagnose an underfit, overfit, or well-fit model.
- Learning curves of model performance can be used to diagnose whether the train or validation datasets are not relatively representative of the problem domain.

Kick-start your project with my new book Better Deep Learning, including *step-by-step tutorials* and the *Python source code* files for all examples.

Let's get started.



A Gentle Introduction to Learning Curves for
Photo by Mike Sutherl

Overview

This tutorial is divided into three parts; they are:

1. Learning Curves
2. Diagnosing Model Behavior
3. Diagnosing Unrepresentative Datasets

Learning Curves in Machine Learning

Generally, a learning curve is a plot that shows time or experience on the x-axis and learning or improvement on the y-axis.

> *Learning curves (LCs) are deemed effective tools for monitoring the performance of workers exposed to a new task. LCs provide a mathematical representation of the learning process that takes place as task repetition occurs.*

— Learning curve models and applications: Literature review and research directions, 2011.

For example, if you were learning a musical instrument, your skill on the instrument could be evaluated and assigned a numerical score each week for one year. A plot of the scores over the 52 weeks is a learning curve and would show how your learning of the instrument has changed over time.

- **Learning Curve**: Line plot of learning (y-axis)

Learning curves are widely used in machine learning for algorithms that learn (optimize their internal parameters) incrementally over time, such as deep learning neural networks.

The metric used to evaluate learning could be maximizing, meaning that better scores (larger numbers) indicate more learning. An example would be classification accuracy.

It is more common to use a score that is minimizing, such as loss or error whereby better scores (smaller numbers) indicate more learning and a value of 0.0 indicates that the training dataset was learned perfectly and no mistakes were made.

During the training of a machine learning model, the current state of the model at each step of the training algorithm can be evaluated. It can be evaluated on the training dataset to give an idea of how well the model is "*learning*." It can also be evaluate of the training dataset. Evaluation on the validation d "*generalizing*."

- **Train Learning Curve**: Learning curve calcul how well the model is learning.
- **Validation Learning Curve**: Learning curve c ives an idea of how well the model is generalizing.

It is common to create dual learning curves for a m training and validation datasets.

In some cases, it is also common to create learning curves for multiple metrics, such as in the case of classification predictive modeling problems, where the model may be optimized according to cross-entropy loss and model performance is evaluated using classification accuracy. In this case, two plots are created, one for the learning curves of each metric, and each plot can show two learning curves, one for each of the train and validation datasets.

- **Optimization Learning Curves**: Learning curves calculated on the metric by which the parameters of the model are being optimized, e.g. loss.
- **Performance Learning Curves**: Learning curves calculated on the metric by which the model will be evaluated and selected, e.g. accuracy.

Now that we are familiar with the use of learning curves in machine learning, let's look at some common shapes observed in learning curve plots.

Diagnosing Model Behavior

The shape and dynamics of a learning curve can be used to diagnose the behavior of a machine learning model and in turn perhaps suggest at the type of configuration changes that may be made to improve learning and/or performance.

There are three common dynamics that you are likely to observe in learning curves; they are:

- Underfit.
- Overfit.
- Good Fit.

We will take a closer look at each with examples. T
minimizing metric, meaning that smaller relative sc .

Underfit Learning Curves

Underfitting refers to a model that cannot learn the

> *Underfitting occurs when the model is not a*
> *training set.*

— Page 111, Deep Learning, 2016.

An underfit model can be identified from the learning curve of the training loss only.

It may show a flat line or noisy values of relatively high loss, indicating that the model was unable to learn the training dataset at all.

An example of this is provided below and is common when the model does not have a suitable capacity for the complexity of the dataset.

Example of Training Learning Curve Showing An Underfit Model That Does Not Have Sufficient Capacity

An underfit model may also be identified by a training loss that is decreasing and continues to decrease at the end of the plot.

This indicates that the model is capable of further learning and possible further improvements and that the training process was halted prematurely.

Example of Training Learning Curve Showing an Underfit Model That Requires Further Training

A plot of learning curves shows underfitting if:

- The training loss remains flat regardless of training.
- The training loss continues to decrease until the end of training.

Overfit Learning Curves

Overfitting refers to a model that has learned the training dataset too well, including the statistical noise or random fluctuations in the training dataset.

> *… fitting a more flexible model requires estimating a greater number of parameters. These more complex models can lead to a phenomenon known as overfitting the data, which essentially means they follow the errors, or noise, too closely.*

— Page 22, An Introduction to Statistical Learning: with Applications in R, 2013.

The problem with overfitting, is that the more specialized the model becomes to training data, the less well it is able to generalize to new data, resulting in an increase in generalization error. This increase in generalization error can be measured by the performance of the model on the validation dataset.

> *This is an example of overfitting the data, […]. It is an undesirable situation because the fit obtained will not yield accurate estimates of the response on new observations that were not part of the original training data set.*

— Page 24, An Introduction to Statistical Learning: with Applications in R, 2013.

This often occurs if the model has more capacity than is required for the problem, and, in turn, too much flexibility. It can also occur if the model is trained for too long.

A plot of learning curves shows overfitting if:

- The plot of training loss continues to decrease
- The plot of validation loss decreases to a poin

The inflection point in validation loss may be the p e
after that point shows the dynamics of overfitting.

The example plot below demonstrates a case of o

Example of Train and Validation Learning Curves Showing an Overfit Model

Good Fit Learning Curves

A good fit is the goal of the learning algorithm and

A good fit is identified by a training and validation loss that decreases to a point of stability with a minimal gap between the two final loss values.

The loss of the model will almost always be lower on the training dataset than the validation dataset. This means that we should expect some gap between the train and validation loss learning curves. This gap is referred to as the "generalization gap."

A plot of learning curves shows a good fit if:

- The plot of training loss decreases to a point of stability.
- The plot of validation loss decreases to a point of stability and has a small gap with the training loss.

Continued training of a good fit will likely lead to ar

The example plot below demonstrates a case of a

Example of Train and Validation Learning Curves Showing a Good Fit

Diagnosing Unrepresentative Datasets

Learning curves can also be used to diagnose properties of a dataset and whether it is relatively representative.

An unrepresentative dataset means a dataset that may not capture the statistical characteristics relative to another dataset drawn from the same domain, such as between a train and a validation dataset. This can commonly occur if the number of samples in a dataset is too small, relative to another dataset.

There are two common cases that could be observed; they are:

- Training dataset is relatively unrepresentative.
- Validation dataset is relatively unrepresentative.

Unrepresentative Train Dataset

An unrepresentative training dataset means that the training dataset does not provide sufficient information to learn the problem, relative to the val

This may occur if the training dataset has too few e

This situation can be identified by a learning curve similarly a learning curve for validation loss that sh en both curves.

Example of Train and Validation Learning Curves Showing a Training Dataset That May Be too Small Relative to the Validation Dataset

Unrepresentative Validation Datase

An unrepresentative validation dataset means that the validation dataset does not provide sufficient information to evaluate the ability of the model to generalize.

This may occur if the validation dataset has too few examples as compared to the training dataset.

This case can be identified by a learning curve for training loss that looks like a good fit (or other fits) and a learning curve for validation loss that shows noisy movements around the training loss.

Example of Train and Validation Learning Curves Showing a Validation Dataset That May Be too Small Relative to the Training Dataset

It may also be identified by a validation loss that is lower than the training loss. In this case, it indicates that the validation dataset may be easier for the model to predict than the training dataset.

Example of Train and Validation Learning Curves Showing a Validation Dataset That Is Easier to Predict Than the Training Dataset

Further Reading

This section provides more resources on the topic if you are looking to go deeper.

Books

- Deep Learning, 2016.
- An Introduction to Statistical Learning: with Applications in R, 2013.

Papers

- Learning curve models and applications: Literature review and research directions, 2011.

Posts

- How to Diagnose Overfitting and Underfitting of LSTM Models
- Overfitting and Underfitting With Machine Learning Algorithms

Articles

- Learning curve, Wikipedia.
- Overfitting, Wikipedia.

Summary

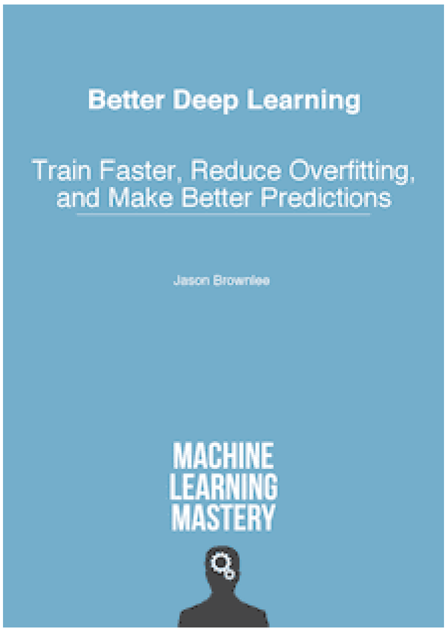
In this post, you discovered learning curves and how they can be used to diagnose the learning and generalization behavior of machine learning models.

Specifically, you learned:

- Learning curves are plots that show changes in learning performance over time in terms of experience.
- Learning curves of model performance on the train and validation datasets can be used to diagnose an underfit, overfit, or well-fit model.
- Learning curves of model performance can be
  datasets are not relatively representative of th

Do you have any questions?
Ask your questions in the comments below and I w

Develop Better Deep I



Train Fa

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It provides **self-study tutorials** on topics like:
weight decay, *batch normalization*, *dropout*, *model stacking* and much more...

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About Jason Brownlee

Jason Brownlee, PhD is a machine learning specialist who teaches developers how to get results with modern machine learning methods via hands-on tutorials.

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Roland Fernandez February 28, 2019 at 4:09

Thanks for article on this core ML techniqu... of underfutting since loss on y axis is already so lov... called "under trained" to avoid confusion with "havi... Also the summary paragraph for underfitting has ty...

Jason Brownlee February 28, 2019 at 6:45 am # REPLY

Thanks Roland.

Roland Fernandez February 28, 2019 at 4:11 am # REPLY

My own typo :). 2nd to last word above should be "says"

Angelos Angelidakis February 28, 2019 at 5:26 am # REPLY

Very informative!

Jason Brownlee February 28, 2019 at 6:46 am # REPLY

Thanks.

phz April 3, 2019 at 7:18 pm # REPLY

Theres still a typo here:
A plot of learning curves shows overfitting if:

The training loss remains flat regardless of training.
The training loss continues to decrease until the end of training.

=> this is underfitting.

Jason Brownlee April 4, 2019 at 7:47 am # REPLY

Correct, fixed. Thank you!

Ashish March 6, 2019 at 1:10 am #

The methods like genaralization are used

Jason Brownlee March 6, 2019 at 7:56 a

Sorry, I don't understand, can you plea

Adrien Kinart March 21, 2019 at 8:06 pm # REPLY

I would have said that the error from the training set should increase to converge to the error from the validation set to indicate good fit. What do you think about that? (https://www.dataquest.io/blog/learning-curves-machine-learning)

Jason Brownlee March 22, 2019 at 8:24 am # REPLY

Does not happen in practice in my experience because often the test/val are smaller and less representative than the train and have different error profile.

George April 3, 2019 at 6:22 pm # REPLY

Hi Jason and thanks for the post.

I have one question not related with this post though and I wanted your opinion.

Lets's say I have I am training some data and during the preprocessing I am cleaning that data. I remove some weird/wrong values from it.

Now, when I am going to use the predict to the uns
to that data before making the prediction?

Are there any caveats for doing or not doing this?

I guess I should the same cleaning but it confuses me that we have unseen data and it can be anything..

(I am not talking about scaling or that kind of preprocessing which I already apply to the train and unseen data)

Thank you very much!

George

Jason Brownlee April 4, 2019 at 7:41 am #

REPLY

Great question.

Yes, if you can use generic but domain-specific idea to use this process consistently when fittir predictions in the future.

The risk is data leakage, e.g. using knowledge
This might help (and be a bit too strict):
https://machinelearningmastery.com/data-leaka

JG April 3, 2019 at 9:35 pm #

Great post Jason. Tahnks.

– My summary, that I appreciate if you can evaluate if am I right about all this stuff is:

overfitting appears when we learn so much details that are irrelevant to the main stream ideas to be learned (general concepts). This can be the situation when you have, on one side a very big complex model (with many layers and many weight to be adjusted.i.e. with a very "hight entropic information capacity") and on the other side a few amount of data to be trained …so the solution could be the simplify the model or increase de train dataset.
On the other side underfitting appears when we need more experience (more epochs) to train the model, so learning curves trend are continually down..until you get the right stabilization with the appropriate set of epochs …

– My second question it is , how do you interpret the case when validation data get better performance (high level) than training data…is it a good indication of good generalization ?.

thank you Jason to allow us to share your knowledge !!

Jason Brownlee April 4, 2019 at 7:56 am #

REPLY

Yes, but you can underfit if the model does not have sufficient capacity to learn from the data. This can be from epochs or from model complexity/size.

It is a sign that the validation dataset is too small and not representative of the problem – very common.

Jakub May 21, 2019 at 8:27 pm # REPLY

Great post!
Thank you very much.

Jason Brownlee May 22, 2019 at 8:04 am # REPLY

You're welcome, I'm happy it helped.

Tanuja Shrestha January 27, 2020 at 4:5

Hi Jason,

Sorry I asked this question over LinkedIn too. F
for thought.

I ran a VGG16 model with a very less amount
However, when I predicted for the test dataset
divided into train, valid, and test..

What could go wrong here? Any explanation would be so helpful. And, thank you for the learning curves blog. Was indeed helpful …

Also, can you make predictions using validation data? What could go wrong/right here?

Jason Brownlee January 27, 2020 at 7:09 am # REPLY

Perhaps the test dataset is too small or not reprensetative of the broader dataset.

Perhaps try a 50/50 split? or get more data?

Tanuja Shrestha January 27, 2020 at 3:37 pm # REPLY

Thanks!

Pritam June 29, 2019 at 10:15 pm # REPLY

Sir, though is something of the track question, still felt like asking. How can I "mathematically" explain the benefit of centered and scaled data for machine learning models instead of raw data. Accuracy and convergence no doubt improves for the normalized data. but can I show it mathematically?

Jason Brownlee June 30, 2019 at 9:41 am # REPLY

Sorry, don't have a good answer.

Frank July 4, 2019 at 3:32 am # REPLY

It is correct to create a learning curve graph using three sets of data (training, validation, and testing). Using the "training" set to train the model and use the "validation" and "test" sets to generate the learning curves?

Jason Brownlee July 4, 2019 at 7:52 am

Typically just train and validation sets.

Chen July 5, 2019 at 12:25 pm #

Thank you for your post!! It helps a lot!! Co got (http://zhuchen.org.cn/wp-content/uploads/201 problem using random forest.

Jason Brownlee July 6, 2019 at 8:19 am # REPLY

Looks underfit.

zeinab July 22, 2019 at 9:11 am # REPLY

A very great and useful tutorial, thank you

Jason Brownlee July 22, 2019 at 2:02 pm # REPLY

Thanks.

zeinab July 22, 2019 at 10:54 am # REPLY

Can I ask about the meaning of "flat line" in case of under-fitting?

Jason Brownlee July 22, 2019 at 2:05 pm # REPLY

It suggests the model does not have sufficient capacity for the problem.

zeinab July 23, 2019 at 12:58 am # REPLY

If the loss increases then decreases then increases then decreases and so on..
What does this means?
Does it means that the data is unrepresentative in that model? or
Does it means that an overfitting happens?

Jason Brownlee July 23, 2019 at 8:04 ar

Great question!

It could mean that the data is noisy/unrepreser
size or scaling of input data).

Tanuja Shrestha January 27, 2020 at 5:11 am #

Hey Jason, I had this problem exactly. What do you mean by the model being unstable – the batch size and scaling? Can you elaborate more? Also, does this explanation apply to both – training and validation dataset? Or just one? Which dataset are you referring to by saying the fluctuation in loss – training or validation?

Thanks, and great post

Jason Brownlee January 27, 2020 at 7:10 am # REPLY

More on batch size:
https://machinelearningmastery.com/how-to-control-the-speed-and-stability-of-training-neural-networks-with-gradient-descent-batch-size/

More on scaling:
https://machinelearningmastery.com/how-to-improve-neural-network-stability-and-modeling-performance-with-data-scaling/

Tanuja Shrestha January 27, 2020 at 3:45 pm #

Thanks Jason!

Also –

I am trying to train, and develop a model which classifies images from camera traps.

From your experience – what would be the best model to solve a camera trap image classification to classify wild animals. The animals as seen in the images are boar, deer, fox, and monkey.

Also, if our main objective is to detect boar and not boar – can I make dataset like – 1000 images with boar, and rest 1000 with all the other animals combined with monkey, deer, and fox – rather than getting 1000 images for each animal

Any suggestion would be so nice, and thanks always

Jason Brownlee January

I would recommend trans
https://machinelearningmastery.co
convolutional-neural-network-mode

Yes exactly. A "boar 'class and an

zeinab July 23, 2019 at 1:43 pm #

I use Pearson correlation coefficient as the accuracy metric for a regression problem.

Can I use the correlation coefficient as the Optimization learning curve?

Jason Brownlee July 23, 2019 at 2:41 pm # REPLY

Consider using r^2 as your metric instead?

zeinab July 30, 2019 at 4:07 am # REPLY

sorry, but what do mean by r^2?

Jason Brownlee July 30, 2019 at 6:23 am # REPLY

r-squared or R^2:
https://en.wikipedia.org/wiki/Coefficient_of_determination

jake July 27, 2019 at 3:28 am # REPLY

Hi Jason.

I post two pictures of my training model here

https://stackoverflow.com/questions/57224353/is-my-training-data-set-too-complex-for-my-neural-network

would you be able to tell me if my model is over fitting or under fitting. I believe it is under fitting.

how can i fix this problems?

Thanks once again Jaso, You dont know how much you have helped me

Jason Brownlee July 27, 2019 at 6:12 am # REPLY

The post above will help you determin

I teach how to diagnose performance and then
https://machinelearningmastery.com/start-here

zeinab August 4, 2019 at 11:40 pm #

can I ask you about the need for the perfo
I understand from this tutorial that the optimization
fitness?
But what is the importance of the performance learning curves?

Jason Brownlee August 5, 2019 at 6:53 am # REPLY

What do you mean by performance learning curve?

zeinab August 5, 2019 at 12:23 pm # REPLY

performance learning curve that represent the accuracy over epochs

Jason Brownlee August 5, 2019 at 2:04 pm # REPLY

I see, good question.

The performance curve can give you an idea of whether changes in loss connect with real tangible gains in skill on the problem.

zeinab August 4, 2019 at 11:41 pm # REPLY should I stop training the model when the it reaches the minimum loss?

Jason Brownlee August 5, 2019 at 6:53 am # REPLY

Yes, on the validation set.

Zeinab August 5, 2019 at 8:22 pm # REPLY

If I reaches the minimum validation loss value
However, the validation accuracy value is r
In this case, Have I stop learning?

Jason Brownlee August 6, 201

Minimum loss is 0, if you hit z
needed) or the model has overfit.

zeinab August 6, 2019 at 11:16 pm #

Sorry, I want to say, if I reach a minimum validation loss value (not 0) but at this epoch the validation accuracy is not the highest value(after this epoch, the validation accuracy is higher).

At this situation, should I stop training?

Jason Brownlee August 7, 2019 at 7:57 am #

Perhaps try it and see.

zeinab August 5, 2019 at 12:26 pm # REPLY

Can I measure the model fitness from the accuracy learning curves instead of the loss learning curves?

Jason Brownlee August 5, 2019 at 2:04 pm # REPLY

Sure. It just may not be as helpful in di

zeinab August 5, 2019 at 10:50 pm # REPLY

what do you mean by learning dynamics ?

Jason Brownlee August 6, 2019 at 6:38 am # REPLY

How the model learns over time, reflected in the learning curve.

zeinab August 5, 2019 at 12:37 pm #

Is there is a problem , if the loss curve is a

Jason Brownlee August 5, 2019 at 2:04

Loss should decrease.

zeinab August 5, 2019 at 12:38 pm # REPLY

If you please, Can you suggest for me a good reference to read more about learning curves?

Jason Brownlee August 5, 2019 at 2:04 pm # REPLY

Yes, see the references at the end of the post.

Zeinab August 5, 2019 at 8:01 pm # REPLY

Does the validation loss value must be lower than the training loss value?

Jason Brownlee August 6, 2019 at 6:34 am # REPLY

For a well fit model, validation and training loss should be very similar.

zeinab August 6, 2019 at 4:22 am # REPLY

which is preferred using:
– the early stopping or
– analyzing the output to find the minimum validation loss

Jason Brownlee August 6, 2019 at 6:41 am #

REPLY

It depends on the model and on the dataset.

Perhaps experiment and see what is reliable for your specific scenario.

Zeinab August 6, 2019 at 11:19 am #

Which is preferred using early stop with lo

Jason Brownlee August 6, 2019 at 2:05

It depends on your choice of model ar

Zeinab August 6, 2019 at 11:22 am #

REPLY

If I reaches the minimum validation loss value, while at this epoch there is a gap between the training accuracy and the validation accuracy.
Should i stop learning or not?

Jason Brownlee August 6, 2019 at 2:05 pm #

REPLY

Maybe. Perhaps test this strategy.

zeinab August 6, 2019 at 11:19 pm #

REPLY

Why should I stop when I reaches a minimum validation loss and not when I reaches the minimum gap between the validation and training loss?

Jason Brownlee August 7, 2019 at 7:58 am #

REPLY

Try a range of approaches and see what results in a robust and skillful model for your dataset.

In general, you want to stop training when the train and validation loss is lowest and before validation loss starts to rise.

Jim Peyton August 17, 2019 at 12:12 am #

REPLY

Great tutorial!

On the second graph showing an undertrained model, it seems like the validation data loss should track higher than the training data loss, which is different then what the graph shows. Perhaps an editing error?

Again, great work here. Thanks for sharing.

Jason Brownlee August 17, 2019 at 5:48

No error, the val set in that case was p
was the shape of the train/val curves showing t

Chetan Patil September 6, 2019 at 5:23 pm #

Hi Jason, this is a very informative post. However, one question regarding the section Unrepresentative Validation Dataset:-

An unrepresentative validation dataset means that the validation dataset does not provide sufficient information to evaluate the ability of the model to generalize.
This may occur if the validation dataset has too few examples as compared to the training dataset.

My question is, if you have more validation examples, say 30% of the entire dataset, then will the curve smooth-out ?

Or, the fault is in the distribution of the validation set itself ? (the val_data might not contain the same distribution as the train_data contained).

If the above sentence is not a case of Unrepresented validation dataset, then how would the curves look like when the validation data distribution is completey different from the training_dataset. And what are the remedies to counter-act this issue ?

Jason Brownlee September 7, 2019 at 5:21 am #

REPLY

It depends on the specifics of the data and the size of the dataset you're sampling.

A good solution is to get more data and use a 50/50 split.

Hamed September 7, 2019 at 8:44 am #

Very Nice! Would appreciate if you let me know which of these models is better when applied to the same training/validation sets: the one that produces lower validation loss and also lower training loss but its generalization gap is higher than the one with higher validation and training set. I give you an example:
Model1: tr_loss =0.5 val_loss =1.5 gap =1
Model2: tr_loss = 0.8 val_loss = 1.6 gap =0.8

Thank you!

Jason Brownlee September 8, 2019 at 5:09 am # REPLY

Generally, model selection is specific

It is a good idea to choose a model that meets s is good skill on a hold out dataset and low com

Hamed September 8, 2019 at 7:12 am

I hear you!
Thanks!

Felipe September 21, 2019 at 1:41 pm # REPLY

How bad is this noise ?

https://imgur.com/sSL3DRJ

Jason Brownlee September 22, 2019 at 9:24 am # REPLY

Not so bad!

Radhouane Baba September 30, 2019 at 12:59 am # REPLY

Hi Jason,

Can the training curve be used to assess a model that predicts Time Series?
As i know, we cannot use Cross-Validation for time series, (Walk-forward validation)

so how meaningful is it to use the learning curve?
Is experience, training size? or epochs?

Jason Brownlee September 30, 2019 at 6:12 am # REPLY

Yes, each time the model is fit, the learning curve can be a invaluable diagnostic into learning behavior.

Radhouane Baba September 30, 2019 at 7:15 am # REPLY

So the experience is training size?
How can i have a more training size in time series? (By going backward (for example add 1 day each time and appending the last train and test loss??

Jason Brownlee September 3

Not sure I follow, sorry.

You can have more data to train a time
variables measured at each time step.

Not sure how that is related to learning

Radhouane Baba October 1, 2019 at 12:43 am #

as i understood, the x-axis in the learning curve is not the epoch numbers, it is the size of our training set, right?

Jason Brownlee October 1, 2019 at 6:54 am #

No.

The x-axis of a learning curve plot is epochs.

Alex Tagbo October 10, 2019 at 8:02 pm # REPLY

Hi Jason,

I have been following your tutorials for awhile and has been very helpful! Thank you very much!

My question is directed to the unrepresentative validation dataset (the second graph), what remedial measure would you recommend in this case, apart from getting more data etc?

Can one also apply the dropout technique or it is restricted only for overfitting?

Thanks!

Alex..

Jason Brownlee October 11, 2019 at 6:17 am # REPLY

You can use a larger validation dataset, such as half the training dataset.

More on how to reduce overfitting here:
https://machinelearningmastery.com/introduction-to-regularization-to-reduce-overfitting-and-improve-generalization-error/

Alex Tagbo October 11, 2019 at 6:12

Thanks for your reply!

One more question please but not related t
random seed generator as low as maybe 7
change the seed again from a value let say
shape.

Is this normal? Or do I have to always stick

Thanks again!

Alex

Jason Brownlee October 12, 2019 at 6:50 am # REPLY

Yes, see this:
https://machinelearningmastery.com/faq/single-faq/why-do-i-get-different-results-each-time-i-run-the-code

Gerhard Lemmer October 11, 2019 at 10:36 pm # REPLY

This is normal. Deep learners (and some classical ML algorithms) are highly stochastic. This is why you should always do multiple experiments and get statistics of your results. For example average training-/validation loss and std on the losses over multiple experiments with the same hyperparameters (experiments differing only by RNG seed). Here're some other articles on this blog about randomness in results: https://machinelearningmastery.com/reproducible-results-neural-networks-keras/, https://machinelearningmastery.com/evaluate-skill-deep-learning-models/ and https://machinelearningmastery.com/randomness-in-machine-learning/.

Also: Some pseudo random number generators don't work well with small seeds. So if you get certain results with multiple different small seeds and different results with significantly larger seeds, that may be an indication that the RNG used by your libraries doesn't work well with small seeds. Use larger seeds in stead.

Jason Brownlee October 12, 2019 at 6:59 am # REPLY

Spot on!

Except the stuff on seeds. I think all libs use good random number generators these days, the results with different seeds are very likely "lucky" and not representative.

Alex Tagbo October 14, 2019 at 4:13 pm # REPLY

Ok, that has answered my question!

Thank you very much!

Alex

Jason Brownlee October 15, 2019 at 6:0

Happy to hear that.

Mohammad October 19, 2019 at 1:09 am # REPLY

There is something very strange going on with these plots. The training loss seems to be always much higher than the validation's. But how is that possible? Except for the case of unrepresentative data, when you train a model you expect to see a much lower loss on the training set (where the model parameter are optimized for the set) versus the validation set where the training model needs to generalize (the parameters are not optimized for this set).
Check out Andrew Ng's notes here:
http://www.holehouse.org/mlclass/10_Advice_for_applying_machine_learning.html
The training loss is always (except corner cases) lower than the validation set.

Jason Brownlee October 19, 2019 at 6:46 am # REPLY

Typically people will use 30% or smaller of the training set as a val set, which makes the loss on that set noisy/unreliable.

It's super common, sadly.

A 50% split might be more appropriate if there is sufficient data.

Mohammad October 21, 2019 at 1:37 pm # REPLY

I think the loss function needs to be normalized by the size of the dataset. That is, have 1/m_{training size} when calculating the training loss function and 1/m_{cv size} for the other set.

Jason Brownlee October 21, 2019 at 1:43 pm # REPLY

Not sure I agree.

OXPHOS October 21, 2019 at 8:26 pm # REPLY

Hi Jason,

Thanks for the detailed explanation. It helped a lot. and repost it on my blog, with the address to your p

Thanks!

Jason Brownlee October 22, 2019 at 5:4

Please do not translate the posts: https://machinelearningmastery.com/faq/single language

Shabnam October 22, 2019 at 5:29 am # REPLY

I was wondering if you can clarify on loss values and boundaries. In other words, what does loss value of greater than 1 mean?
(with accuracy over epoch, all of the values are between 0 and 1 – or 0% and 100%)

Shabnam October 22, 2019 at 5:32 am # REPLY

I have one another question. Based on this post loss-over-epoch is informative in terms of fit. How about accuracy-over-epoch (accuracy of train and validation sets)?

Jason Brownlee October 22, 2019 at 6:00 am # REPLY

Typically not as useful. Too coarse grained.

Jason Brownlee October 22, 2019 at 6:0

Loss is relative to a model/dataset.

I recommend interpreting broad dynamics only, not specific values.

Shabnam October 22, 2019 at 9:28 am # REPLY

Thanks a lot for your explanation and clarification.

Jason Brownlee October 22, 2019 at 1:45 pm # REPLY

You're welcome.

Shabnam October 23, 2019 at 4:15 pm #

I have some cases that the loss plot has i
example in your post. I was wondering which categ

Jason Brownlee October 24, 2019 at 5:35 am # REPLY

If training loss is increasing, it is probably a sign of overfitting.

There are examples of this in the above tutorial.

Adam November 28, 2019 at 2:51 pm # REPLY

Hello Jason, I have impemented a RNN and my validation loss starts increasing after 2 epochs indicating that the model probably is overfitting. However, I compared the evaluation results of Precision and Recall and a run on 2 epochs and on 10 epochs just gives me almost similar results.

How can I interpret that? Does it mean that the model converges in 2 epochs and does not need more training? And can I argue that it would be the best point to stop after 2 epochs even though the validation loss increases after 2 epochs and indicates overfitting?

Thanks!

Jason Brownlee November 29, 2019 at 6:42 am # REPLY

Yes, your reasoning seems good. Perhaps try smaller learning rates to slow down the learning?

Abeer December 20, 2019 at 10:29 am # REPLY

How much of a gap between validation and training loss is acceptable?

Jason Brownlee December 20, 2019 at 1:07 pm # REPLY

Good question.

As small as possible. At some point it becomes a judgement call.

Abeer December 21, 2019 at 7:06 am #

Thanx Jason.

Itaru Kishikawa January 24, 2020 at 12:23 pm

How do you generate these graphs? Also

Jason Brownlee January 24, 2020 at 1:33 pm # REPLY

You can generate line graphs in python using matplotlib and calling the plot() function.

See this on reducing overfitting:
https://machinelearningmastery.com/introduction-to-regularization-to-reduce-overfitting-and-improve-generalization-error/

Gabriele Valvo January 25, 2020 at 7:09 pm # REPLY

Good morning, I build a neural network in order to predict a physical quantity (regression task), I plotted the chart “training loss/validation loss vs epochs”, I can see that, at first, both are decresing and than they become constant but the validation loss is always just below the training loss (this difference is very small). Is it overfitting? If both (train and val loss) became constant (after decresing) is it importan if one stay over the other or vice versa?
I would like to send you some plot but I don’t now how can I do.

Jason Brownlee January 26, 2020 at 5:16 am # REPLY

A small difference between the loss values might mean a good fit.

Gabriele Valvo January 27, 2020 at 2:25 am #

REPLY

Thanks for the answer, I upload in a google drive folder 5 loss function chart where the val loss is under the train loss. Can you check if it is a case of overfitting? Because I'm a bit confused. Thank you!!

This is the link: https://drive.google.com/open?id=1sv1Qn9RhLRL7UXBgLOzFNWga5JHzJHCF

Jason Brownlee January 27, 2020 at 7:06 am #

REPLY

Sorry, I cannot.

Joglas February 25, 2020 at 10:11 am #

Hi Jason,

Thank you for the post. In case of an unbalanced c resampled, we are very likely to have a chart like tl Dataset" as the validation dataset is still unbalance have to analyze the performance of the model in a

Thanks.

Jason Brownlee February 25, 2020 at 11:19 am #

REPLY

Perhaps. You could try plotting a metric you're using for evaluation rather than the loss.

Xuebo March 3, 2020 at 4:47 pm #

REPLY

Thanks, the article is very helpful.

But I still have question about how you define a good fit. You say there could be a small generalization gap. But how I should define the "small"?

I got a curve and the validation loss decreases to a point of stability around 0.06, while the training loss is stable around 0.03. How should I evaluate it?

Jason Brownlee March 4, 2020 at 5:50 am #

REPLY

Good question. It is relative, e.g. is the gap relatively small, shrinking, stable.

David March 10, 2020 at 3:34 pm # REPLY

Hey Jason, great job as always.
Regarding Roland Fernandez reply, the first reply to this article. I have built some models and compiled them with 'mse' loss and I'm getting at the first epoch a value of 0.0090,and at second a value of 0.0077,and it keeps learning but just a little bit per epoch, drawing at the end an almost flat line like the one on the First Learning Curve "Example of Training Learning Curve Showing An Underfit Model That Does Not Have Sufficient Capacity". So I want your opinion on this.
Does these model as Roland say aren't representative of underfitting due to the low values, or are in fact underfitting as you established in the article?
I most add that the obtained predictions with these models are in the expected range.

Jason Brownlee March 11, 2020 at 5:19

If loss stays flat during learning, that is
trivial or unlearnable – perhaps the former in th
good predictions. Just a guess, perhaps more

David March 11, 2020 at 7:51 am #

What do you suggest that I should do then to determine the reliability of this models, or if they are an applicable solution to the problem.

Jason Brownlee March 11, 2020 at 8:07 am # REPLY

Start by selecting a metric that best captures the objectives of the project for you and stakeholders.

Then design a test harness that evaluates models using available data. E.g. for modest amounts of data for regression/classification, use repeated stratified k-fold cross-validation.

Compare results using the mean of each sample of scores. Support decisions using statistical hypothesis testing that differences are real.

Use variance to comment on stability of the model. Use ensembles to reduce the variance in final predictions.

Each of these topics is covered on the blog, use the search feature or contact me.

Learning curves can provide a useful diagnostic for a single run of a single model to aid in tuning model hyperparameters.

David March 11, 2020 at 8:45 am # REPLY

Thanks very much

Jason Brownlee March 11, 2020 at 8:47 am #

REPLY

You're welcome.

David March 11, 2020 at 12:40 pm #

REPLY

Hey again, the results of the loss I explain before are at fit all the samples in each epoch for almost 100 epoch.
The data dimensions are as follows:
inputs 5395,23,1.
outputs 5395,23.
And each sample as I explained in other o
Inputs:________Outputs:
1,2,3___________4, 5,6
2,3,4___________5, 6,7
3,4,5___________6, 7,8
Could this be causing that the learning cur

Jason Brownlee March 11, 2020 at 1:58 pm #

REPLY

Perhaps, it is hard to know.

Maybe explore other model architectures? other learning rates? other optimizers? etc.

Fatih March 25, 2020 at 12:46 am #

REPLY

Hi Jason,

I tried to finetune CNNs for 14 class image classification. Dataset has 2000 image. Each models produced similiar loss values range 0.1 to 0.4. For example:

Best epoch:20/50
train_acc: 0.9268600344657898 train_loss: 0.27140530943870544
val_acc: 0.9145728349685669 val_loss: 0.358508825302124

Do you think models are good for publication, or a good model has to loss value under 0.1?

Jason Brownlee March 25, 2020 at 6:34 am #

REPLY

I cannot know if the results are good objectively

Good results are relative to a naive model and to other models on the same dataset.

Fatih March 26, 2020 at 12:23 am #

REPLY

1-) Can it be said that my models are not sufficient just by looking at the loss values and should I decrease my loss values below 0.1 and increase the accuracies above 0.95?

2-) Or are val_acc (0.89 ~ 0.94) and val_loss (0.1 ~ 0.4) values sufficient for 14 classes with high similarity?

Jason Brownlee March 26, 20

Not really, you can interpret th
https://machinelearningmastery.com/cr

It is much better to select a metric and
https://machinelearningmastery.com/fa
performance

Bel April 5, 2020 at 5:35 pm #

Hello Jason,
Is there any range which is considerd good for the Loss values (y-axis), say, the highest loss value must be above some specific value?
Or that each problem has it's own range of values, where only the shape of the curves matter?
Thank you

Jason Brownlee April 6, 2020 at 6:03 am #

REPLY

Yes, you can interpet cross-entropy:
https://machinelearningmastery.com/cross-entropy-for-machine-learning/

Generally, it is better to compare the results to a naive model.

ENGİN SEVEN April 14, 2020 at 10:33 am #

REPLY

Hello, Jason. I met Your Website two weeks ago. You inspired me. I'd want to meet you and shake your hand and thank you. Please don't stop writing.

İstanbul..

Jason Brownlee April 14, 2020 at 10:39 am # REPLY

Thanks!

shivan AB April 14, 2020 at 10:48 pm # REPLY

Hello Sir
what if i obtain a high validation accuracy, but the curve is not smooth?
what is the reasons of that?
thanks

Jason Brownlee April 15, 2020 at 7:59 a

Perhaps the dataset is small or the mo

Shivan AB April 15, 2020 at 9:36 am #

So is it bad or not? If yes, how ca
For my case : i use alexnet model with 1 GB of .dicom file (1000 .dicom) dataset , divided into 2 classes.

Thanks sir.

Jason Brownlee April 15, 2020 at 1:21 pm # REPLY

It is only good or bad relative to other results that you can achieve on your dataset, e.g. relative to a naive model.

Arkesha June 16, 2020 at 2:59 am # REPLY

what is generalization error? is it a gap between training and validation loss?

Jason Brownlee June 16, 2020 at 5:43 am # REPLY

Generalization error is the error the model makes on data not used to train the model. Error on new data.

Sarthika June 22, 2020 at 3:12 am # REPLY

Hi, I m not clear about whether learning curve can be used as accuracy metric for LSTM ? Can we use learning curve on any predictive model irrespective of the prediction algorithm used? What accuracy metric is best for deep learning algorithms?

Jason Brownlee June 22, 2020 at 6:17 am # REPLY

Yes, see this:
https://machinelearningmastery.com/diagnose-overfitting-underfitting-lstm-models/

This can help with choosing a metric for classif
https://machinelearningmastery.com/tour-of-ev

Jay June 24, 2020 at 5:53 am #

This article is very helpful along with chart understanding so that code & chart can go side-by-

Is it possible you provide example with code ???

Jason Brownlee June 24, 2020 at 6:40 am # REPLY

How would the code help in interpreting the plots?

Abs June 28, 2020 at 9:16 am # REPLY

Hi Jason,

I have a question for you. This is not related to this post.

Im doing a small research project based on Deep Learning. i'm trying to predict the ratings that a user will give to an unseen movie, based on the ratings he gave to other movies. I'm using the movielens dataset.The Main folder, which is ml-100k contains informations about 100 000 movies.To create the recommendation systems, the model 'Stacked Autoencoder' is being used. I'm using Pytorch for coding implementation.

I split the dataset into training(80%) set and testing set(20%). My loss function is MSE. When I plot Training Loss curve and Validation curve, the loss curves, look fine. Its shows minimal gap between them.
But when I changed my loss function to RMSE and plotted the loss curves. There is a huge gap between training loss curve and validation loss curve.(epoch: 200 training loss: 0.0757. Test loss: 0.1079)

In my code, I only changed the loss function part(MSE to RMSE). I applied the Regularization techniques such as Batch Normalization and Dropout but still t

I'm new to deep learning, but do you know whats the reason why there is huge gap between the curves when applying RMSE?
Is it something to do with the Evalaution metric or something wrong in the coding part?
Thanks.

Jason Brownlee June 29, 2020 at 6:26 am # REPLY

I recommend using mse loss, but perhaps calculate metrics for rmse, e.g. don't use rmse to train the model but only to evaluate the predictions.

Abs June 29, 2020 at 9:28 am #

Hi Jason.
Thanks for your feedback.
So I only use 'RMSE' (Loss Function) for te
And for training the model, I leave out the l
training the model?

Abs June 29, 2020 at 10:27 am #

https://towardsdatascience.com/stacked-auto-encoder-as-a-recommendation-system-for-movie-rating-prediction-33842386338

My project is based on this.(Click the link).

Jason Brownlee June 29, 2020 at 1:24 pm #

Sorry, I get sent 100s of links/code/data each week.

I don't have the capacity to review third party stuff for you:
https://machinelearningmastery.com/faq/single-faq/can-you-explain-this-research-paper-to-me

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Jason Brownlee June 29, 2020 at 1:20 pm # REPLY

Use RMSE as a metric. Do not use RMSE as a loss function (e.g. do not minimize rmse when fitting the model), use MSE.

Abs July 1, 2020 at 9:51 am #

Thanks Jason.
I will try that.
By the way,I have a list of questions for you.
I'm still new to Deep Learning and I'm confused with the terminologies of Validation Loss and Test Loss. Are they the same or completely different?

And also you can't train the model on the test data?
Is it only reserved for testing(evaluate the predictions)?

I know you can't review my data, but when I added the validation loss to my code, I reused the training loop and removed the backward and optimizer.step() calls. My metric for that is MSE. I assumed that validation loss is the same as Test loss. But I may be wrong.

I like to hear your feedback on this

Jason Brownlee July 1, 2

Yes, we can calculate loss
set and validation set, see them de
https://machinelearningmastery.co

After we choose a model and confi
cannot fit the model on test data in
on data not used to train it to give a fair estimate of performance.

Abs July 4, 2020 at 10:48 am # REPLY

Thanks Jason.
Now I understand the concept of Validation and Training sets.

In my mini project, i'm predicting the ratings that a user will give to an unseen movie, based on the ratings he gave to other movies. The model, i'm using is Stacked Autoencoder.
For my another task, I want to compare with other Deep Learning models. For instance I want to use MLP (Multilayer perceptron) or Logistic Regression(Machine Learning Model). Is it possible to employ those models for movie rating prediction from 0 to 5?
Thanks.

Jason Brownlee July 5, 2020 at 6:52 am # REPLY

Yes.

Aaron July 14, 2020 at 12:04 am # REPLY

I'm building a LSTM model for prediction. The validation error curve is flat, validation mse is less than training mse in the end. val_loss=0.00002, training_loss = 0.013533.

I read your article carefully but I'm not sure whether my validation set is unrepresentative. Should I expand my validation set?

Here is the chart and problem:
https://stackoverflow.com/questions/62877425/validation-loss-curve-is-flat-and-training-loss-curve-is-higher-than-validation

Thanks.

Jason Brownlee July 14, 2020 at 6:28 ar

It may be the case that your validatior

QUANG HUY CHU July 21, 2020 at 9:46 pm

Hi Jason.

Thank to your post I know what is Under, Over and

I am also currently a small ANN model (95 input, 3
30 nodes respectively).

My dataset is small dataset (105 samples with 95 features as each samples) with shape (105, 95). I split my data into Train data (80 samples), Validation data (10 samples) and Test data (15 samples).

My question is I tried to train, validate and predict my model for 10 times. for about 7 or 8 times I observed a Good fit (Train-Validation Accuracy and Loss Graph) and other 3 or 2 times I got Overfitting. Is this phenomenon is alright? and although its Overfilling the prediction on Test data quite good (over 85%).

Thank you very much for your help.

Jason Brownlee July 22, 2020 at 5:31 am # REPLY

Perhaps you can change the configuration so the model is more stable on average.

QUANG HUY CHU July 22, 2020 at 10:13 am # REPLY

Hi Jason. Thank you for your reply.

The configuration here you mean is the hyperparameters (like number os layer, nodes or train test split, etc,..) right ?

Jason Brownlee July 22, 2020 at 1:40 pm # REPLY

Correct.

Jay July 23, 2020 at 5:01 am # REPLY

DO we have real world example on learning curves ????

That will be much better to understand & how to plot it.

Jason Brownlee July 23, 2020 at 6:26 ar

Yes many – search the blog, perhaps
https://machinelearningmastery.com/how-to-de
classification/

nkm July 23, 2020 at 4:47 pm #

Hi Jason,

thanks for your great support.

I would like to ask possible reasons for the zigzag/crowdy validation curve over training epochs and also, how can I minimise/mitigate it. Generally, training curve changes smoothly but validation curve not. Guidance please.

Jason Brownlee July 24, 2020 at 6:23 am # REPLY

It might be the case that the validation set is too small and/or not representative.

Julia August 5, 2020 at 3:57 am # REPLY

Hi Jason,
Is there any way to attribute these behaviors to model architecture/hyperparameter settings rather than the training/validation data distributions? The reason I ask is that I have run a hyperparameter search with the exact same training/validation data and achieved models that have training/validation curves that look like 3 of the above examples that you give (if I could embed images here I would).

Model 1: Curves appear like the example you give for “Unrepresentative Train Dataset”, Model 2: appears like the example you give for “Unrepresentative Valid Dataset” ,and Model 3: appears like the “validation dataset may be easier for the model to predict than the training dataset” example that you give.

Have you got any intuition about this? It would be appreciated.

Thanks for your blog, I've referenced it numerous times!

Jason Brownlee August 5, 2020 at 6:19 am #

REPLY

The learning curves are impacted by the structure of the model and configuration of the learning algorithm, the data has much less effect – if prepared correctly.

Here "unrepresentative" means your sample is too small.

chouchou August 11, 2020 at 8:27 pm #

Hello !

This post is very interesting, thank you for that. Ho
I'm new in deep-learning, and I used a code that w
curve for validation (I think you mean what I would
validation, but not the one for test. I trained my neu
-the intermediate accuracy values for validation (nc
-the value of accuracy after training + validation at
-the accuracy for the test set.

I have an accuracy of 94 % after training+validation and 89,5 % after test. Concerning loss function for training+validation, it stagnes at a value below 0.1 after 35 training epochs. There is a total of 50 training epochs.

Is the only little difference between accuracy of training+validation and test sufficient to say that my network does'nt overfitt ?

chouchou August 11, 2020 at 8:30 pm #

REPLY

I wanted to say "it stagnates at a value …"

Jason Brownlee August 12, 2020 at 6:10 am #

REPLY

Thanks!

No problem, use val instead of test.

If the hold out dataset is too small the results will be unstable.

chouchou August 12, 2020 at 6:30 am #

REPLY

Thank you for your answer. I don't understand why you say "Use val instead of test." In fact, the only think I can do with my code is :
-draw accuracy curve for validation (the accuracy is known every 5 epochs)
-knowing the value of accuracy after 50 epochs for validation
-knowing the value of accuracy for test

Michelle August 15, 2020 at 12:13 am #

REPLY

Hi Jason,
thanks again for the article.
During the whole deep network training, both of val
with the increase of the epochs. But the reduction c
reduction of training data loss, is it normal and repr

when epoch is small from 0, the curve of training d
the validation data loss curve starts already small a
Thank you.

Jason Brownlee August 15, 2020 at 6:30

Maybe your validation dataset is too s

Michelle August 17, 2020 at 2:35 am #

REPLY

Thank you, Jason, I have tried to get more samples from training data to validation data to increase the validation data sample size, still the learning curve shows that although both validation data loss and training data loss reduces along with epochs, but the reduction of validation data loss is much smaller than training data, finally, the loss (mse, standardised data with mean 0 and std 1) of training data is 0.25 while the loss of validation data is 0.41, is it still overfitting?
Different literature always says good fit is that the validation loss is slighter higher than training loss, but how high is slightly higher, could you please give some hint?

Thank you as always.

Jason Brownlee August 17, 2020 at 5:49 am #

REPLY

Nice work.

Perhaps try slowing down the learning with an alternate learning rate or adding regularization.

If the behavior remains stubbornly the same, perhaps you are reaching the limits of your chosen model on your dataset.

Chouchou August 26, 2020 at 6:54 pm #

REPLY

Thank you for your answer of the 12th of August. But I'm still not sure to understand. In this article (of this page), what is for you "training" and "validation" ? Has it the same meaning like in this article ? : https://machinelearningmastery.com/difference-test-validation-datasets/

I have results (F1 score, precision, recall, …) after the last validation for my neural network. I have also results after using test set to evaluate performances of neural networks on new images. The results on the validation set and the test set are slightly different (4,5% difference on accuracy), the accuracy on the test set are a little worser (of 4,5%). Is this what we call "generalization gap " ? Why the results on test set are little worser (of 4,5%) ?

Thank you for your help

Jason Brownlee August 27, 2020 at 6:13

Yes, you can expect small differences

perhaps this will help:
https://machinelearningmastery.com/different-r

Chouchou August 28, 2020 at 1:35 am #

REPLY

Thank you very much for your answer. This other article is very interesting. In my case, I use a neural network for semantic segmentation (SegNet). After the last validation (=results on the validation dataset for final model), I got 91,1 % accuracy. Using this final model on the test dataset, I got 85,9 %. From your article "Different results each time…", I suppose I can explain this difference by a high variance of my model (the validation dataset and the test dataset have different images, 3 images of 5000*5000 pixels for each). Is it right ? In your article you seem to speak about variance only for training data, so I'm not sure of my assumption.

Thank you for your help

Jason Brownlee August 28, 2020 at 6:50 am #

REPLY

Nice work!

Yes, variance in the final model is common, which can be overcome by using an ensemble of final models:
https://machinelearningmastery.com/ensemble-methods-for-deep-learning-neural-networks/

sezar September 1, 2020 at 11:32 pm #

REPLY

Hi, Jason, thanks for this post and your blog! I've recently started my ML/DL journey and I found your blog extremely helpful.

I have a question about train/val loss. What if a model learns only during first n iterations and then the loss and accuracy reach a plateau during the very first epoch, and the val loss after that first epoch is huge? I'm using Adam with default parameters.

Jason Brownlee September 2, 2020 at 6:29 am # REPLY

Stop training when the model stops learning. Perhaps try alternate configurations of the model or learning algorithm.

Tethys September 15, 2020 at 9:16 am #

For the 3rd figure, it is clearly an overfitting
Cause the continuing training didn't increase the va
asked is I have seen one specific behavior that the
Accuracy and IoU for validation set still increase if

Jason Brownlee September 15, 2020 at 2:50 pm # REPLY

The third figure titled "Example of Train and Validation Learning Curves Showing an Overfit Model" shows overfitting.

Continued training in this case will result in better performance on the training set and worse generalization error on the hold out set and any other new data.

The behaviour of loss typically corresponds to other metrics. But good point, perhaps plot the metric you intend to use to choose your model.

ayesh November 3, 2020 at 4:47 pm # REPLY

What could be possibly done as improvements in the case of an unrepresentative train dataset? (if I do not have the option to increase the dataset)

Jason Brownlee November 4, 2020 at 6:35 am # REPLY

Your model will only be as effective as your training dataset.

Perhaps try oversampling, such as smote.
Perhaps try data cleaning to make the decision boundary more clear.
Perhaps try transforms to find a more appropriate representation

Kodjovi November 13, 2020 at 12:19 am #

REPLY

Hi, Nice article. I have a question though.
What is the difference between:
– a ML Learning curve (as described here) and
– a learning curve theory as a graphical representation of the relationship between how proficient someone is at a task and the amount of experience they have)
https://en.wikipedia.org/wiki/Learning_curve

Thanks for your time

Jason Brownlee November 13, 2020 at 6

Thanks!

No relationship.

Tanuja Shrestha November 19, 2020 at 9:07 p

Hi Jason,

What is your suggestion on the model learning curves having – loss 0 and accuracy 1 on the first epoch itself?

Also, what are the probable reasons for this?

Any link where this question is addressed?

Thanks always.

Jason Brownlee November 20, 2020 at 6:45 am #

REPLY

It suggests a trivial problem that probably does not need machine learning:
https://machinelearningmastery.com/faq/single-faq/why-cant-i-get-100-accuracy-or-zero-error-with-my-model

Marlon Lohrbach December 22, 2020 at 3:58 am #

REPLY

Hello Jason,

I have a question regarding my learning curves. I wanted to post my question on stat.stackexchange, but I have a feeling that I can trust you more….

1.) I have a dataset with 23.000 entries and i have a binary classification task. The target variable is distributed like 87% vs 13%. XGB Classifer perform with 97.88%.

My curve looks like this:
https://ibb.co/NsnY1qH

As you can see I am using Logloss for evaluation. My interpretation is that it doesn't over- or underfit the data and that I am good to go.

2.) I have a regression task for the last 13% of the data (positive samples) and I have to predict the different contract values.

My learning curve looks like this:
https://ibb.co/MnZbB15

My interpretation here is that I need more data to make a good prediction. The contract values range from 0 to 200.000 $ and distribution is super skewe

Thanks as always for all your support!

Marlon

Jason Brownlee December 22, 2020 at 6

I try to avoid interpreting results for re

Perhaps explore additional models, configs, da
otherwise perhaps yu have hit the limit for your dataset.

Marlon December 22, 2020 at 5:11 pm # REPLY

Sorry I didn't know that and thank you

Felipe Araya January 27, 2021 at 11:04 am # REPLY

Excellent post, very informative. Just have a couple of questions if you don't mind please:

1. When you refer to validation set, you actually mean validation set from a 3 split dataset (Train/validation/test)? it is just to make sure since in some places they call the test set, the validation test.

2. Is there any code available that we can use to replicate the charts that you showed? (it would be much appreciated)

3. Please correct if me I am wrong, if I was to do a nested cross validation, I think that I wouldn't need to do learning curves since I am already arriving to the best possible model performance and generalization, theoretically (given a sufficient amount of data, the right number of iterations and features, and the right hyperparameter values). So, in my mind by using nested cross validation, there isn't anything else that I could have done to reduce overfitting, hence making learning curves unnecessary, right?

Jason Brownlee January 27, 2021 at 1:22 pm # REPLY

Thanks!

Correct, validation set as a subset of the training set:
https://machinelearningmastery.com/difference-test-validation-datasets/

Yes, I have tons of examples on the blog, use the search box. Perhaps start here:
https://machinelearningmastery.com/display-deep-learning-model-training-history-in-keras/

Correct, learning curve is a diagnostic for poor model performance, not helpful for model selection / general test harness like nested cv.

Vaishnavi February 12, 2021 at 12:07 am #

Hi Jason,

If the data set has 3 or more features X1, X2,… an
features X1,X2,…, how should I do that? What wou

Thank you

Jason Brownlee February 12, 2021 at 5:46 am # REPLY

Perhaps pair-wise scatter plots, one for each pair of variables.

Vaishnavi February 12, 2021 at 7:26 am # REPLY

Thank you so much for help.
I looked through this article https://machinelearningmastery.com/visualize-machine-learning-data-python-pandas/

Tanuja Shrestha February 12, 2021 at 9:17 pm # REPLY

Hi, Jason
I have model learning curves with loss curves – both, train and test – okay, however, both training and the testing accuracy is at 100% from the first epoch.

What should I do?

Any suggestions?

Always thank you!

Jason Brownlee February 13, 2021 at 6:06 am # REPLY

This is a common question that I answer here:
https://machinelearningmastery.com/faq/single-faq/what-does-it-mean-if-i-have-0-error-or-100-accuracy

Beny March 31, 2021 at 11:36 pm # REPLY

Hello,
I would be grateful if you can diagnose my learning
The accuracy that I got is 97%, but I don't know wh
the learning curves that I got.
Thank you.

Jason Brownlee April 1, 2021 at 8:19 am

Sorry, I avoid trying to interpet results

Instead, I provide general advice so you can in

Gaken April 28, 2021 at 1:36 pm # REPLY

HI, thanks for the informative post! What if after each run of my python app the learning curves generated by it looks too different from each other. sometimes the validation curve is too noisy and sometimes it converges with the training curve. Does it say something about the dataset, or it's just that my code for generating the curves is wrong? Thank you!

Jason Brownlee April 29, 2021 at 6:23 am # REPLY

You're welcome.

Good question, this may help:
https://machinelearningmastery.com/faq/single-faq/why-do-i-get-different-results-each-time-i-run-the-code

David Espinosa June 2, 2021 at 2:38 pm # REPLY

Hello Jason,

Thanks for the tutorial, nothing like refreshing the basics.

You know, I have had many times behaviours similar to the graph labeled as "Example of Train and Validation Learning Curves Showing a Validation Dataset That Is Easier to Predict Than the Training Dataset". We should increase the size of the validation set and reduce the one of training, right?

Putting some figures on that example: if I obtained that figure with a split of 80% train and 20% validation, a good approach for a better fit would be trying 70%-30% then? I'd love some "based-on-experience" reply here, because you know, "trial and error" sometimes might take hours…

I have always tackled that issue by using callbacks, but maybe I'm limiting the learning capability of my model, so this could be the right momnt to realize something I (probably) have been doing wrong the whole time…

Thank you and best regards.

Jason Brownlee June 3, 2021 at 5:29 an

Thanks.

I go for 50-50 quite often… then repeat the exp

Ibtissam June 10, 2021 at 11:16 pm #

Hello sir ,

mu problem is regression , i have 2 models
when i plot with firt model : give a good fit but the value of RMSE it is not good
but when i plot second model i have test loss plot below of train loss plot with difference between them nearly similair of "Unrepresentative Validation Dataset" (train loss decrease and stable) but with the RMSE value better then of first model
i have 191981 sample for train / 47996 sample for test
please the second model is correct ?

Jason Brownlee June 11, 2021 at 5:15 am #

REPLY

Perhaps test a suite of different models and use the one that gives the best performance for your specific chosen metric.

Sylvia June 16, 2021 at 5:35 pm #

REPLY

Thanks for the informative article Jason.

May i please know any possible solutions to Unrepresentative Validation Dataset problem?

I am applying it to ECG problem where different patients have different cardiac cycle patterns. So even though there are about 4000 normal training patterns to learn from but they all look different because of the inherent nature of the problem itself (i.e. some

Thanks.

Jason Brownlee June 17, 2021 at 6:14 am #

REPLY

You could try using a large dataset for validation, e.g. a 50/50 split of training.

Not sure how validation sets work for time series, might not be a valid concept.

Sylvia June 24, 2021 at 3:52 am #

REPLY

okay, Thank you.

Sylvia June 25, 2021 at 10:58 am #

Hello Jason

I always get loss: 0.0000e+00 – val_loss: (
training and hence a straight line at 0 learn

Do you advice any possible reasons regar
Thanks.

Jason Brownlee June 26, 2021 at 4:51 am #

REPLY

It may suggest that your problem is easily solved / trivial, e.g.:
https://machinelearningmastery.com/faq/single-faq/what-does-it-mean-if-i-have-0-error-or-100-accuracy

Bill June 23, 2021 at 11:26 pm #

REPLY

Hello,
Is this overfit?
https://ibb.co/Z6nrXM4

Thank you very much

Jason Brownlee June 24, 2021 at 6:02 am #

REPLY

Sorry, I try to avoid interpreting results for readers.

Sylvia June 30, 2021 at 2:00 am # REPLY

Okay, thank you very much for the reference.

Jason Brownlee June 30, 2021 at 5:21 am # REPLY

You're welcome.

puneet sai August 12, 2021 at 3:55 am # REPLY

https://docs.google.com/document/d/1Va_
usp=sharing&ouid=107190645093315861813&rtpo

i wanted to ask jason what are best practices to fin

in above learning curve, we can see loss continues

val_loss@ 0,01 (epoch 0 – 20) point A inflection p

Does people use % decrease in loss and % increa

I earlier used inflextion point B b/w epoch 40-60 wh
prediction error.

Then I observed that b/w epoch 15-50 (these are approx), there was 8% decrease in loss vs 100% increase in val_loss.

will that be sufficient crieria to stop training and choose point A as inflextion point?

thx

Adrian Tam August 12, 2021 at 6:09 am # REPLY

It is normal to see the loss keep decreasing when you train but validation loss may go up after a while. That's overfitting starts. You can see the post on early stopping to learn more: https://machinelearningmastery.com/how-to-stop-training-deep-neural-networks-at-the-right-time-using-early-stopping/

puneet August 13, 2021 at 4:27 am # REPLY

Unless i didnt understand earlystopping and bestmodel correctly, i think below algorithm will give the best epoch and i dont think it is given by neither.

for an epoch to best epoch, loss shud be minimum across all epochs AND for that epoch val_loss shud be also minimum. for example if the best epoch has loss of .01 and val_loss of .001, there is no other epoch where loss<=.01 and val_loss<.001.

bestmodel only takes into account val_loss

so we need to implement above algorithm to get best epoch because not all learning curves are smooth and have bumps.
not sure earlystopping also helps here to get to exactly that best epoch.

thoughts?

Adrian Tam August 13, 2021 at 5:03 am # REPLY

From Keras documentation on the earlystopping module, "Stop training when a monitored metric has stopped improving." And you can decide what metric you want to monitor. The default is val_loss, however. Hope this helps.

Onur August 13, 2021 at 9:19 pm #

Hello,

I am trying to built 3D CNN Regression Network. M
values between 0-5. I tried some models in literatu
normalization and standardization for my output da
nodes in fully connected part, I couldn't obtained a
decreasing.

The validation loss slightly increase such as from 0.016 to 0.018. But the validation loss starts with very small number even in first epoch. What should I do ?

Thanks for reply

Adrian Tam August 14, 2021 at 3:22 am # REPLY

Validation loss value depends on the scale of the data. The value 0.016 may be OK (e.g., predicting one day's stock market return) or may be too small (e.g. predict the total trading volume of the stock market). To check, you can see how is your validation loss defined and how is the scale of your input and think if that makes sense.

HackerCop September 5, 2021 at 8:41 pm # REPLY

Sir these are the results from my model. https://snipboard.io/7kWsuz.jpg Presumably this is because I have an unrepresentative dataset, maybe if you could clarify that would be great. Thanks

Jason Brownlee September 6, 2021 at 5:18 am # REPLY

Looks like the validation set is small/n

sam October 11, 2021 at 3:13 am # REPLY

hello dr. Jason ;

my dataset training is 30.000 images and for testing 5000. I got the plot like
https://ibb.co/Wpmzmh3
how can I solve this problem, please ? epochs stopped at epoch 26

Adrian Tam October 13, 2021 at 7:14 am # REPLY

The loss difference between training a
your model converged quickly.

Bruce December 24, 2021 at 2:18 pm #

Hi, Dr Jason, your posts are very useful. I
curves shown within the link. How do you say for th
https://docs.google.com/document/d/1_OjzPLk9QE
usp=sharing

James Carmichael January 10, 2022 at 11:33 am # REPLY

Hi Bruce…While I cannot speak directly to your project, I would recommend establishing a baseline of performance by utilizing a naive model and then comparing the performance of each against this baseline in terms of root mean square error.

AGGELOS PAPOUTSIS January 13, 2022 at 6:35 pm # REPLY

hi all

I a trying to understand this learning curve of a classification problem. But I am not sure what to infer. I believe that I have overfitting but I cannot sure.

1.Very low training loss that's very slightly increasing upon adding training examples.
2."Gradually decreasing validation loss (without flattening) upon adding training examples".
However, I do not see any gap at the end of the lines something that is usually can be found in an overfitting model

On the other hand, I might have underfitting as:

1. The learning curve of an underfit model has a low training loss at the beginning which gradually increases upon adding training examples and stay flat, indicating the addition of more training examples can't improve the model performance on unseen da
2.Training loss and validation loss are close to eac

However, the train error is not to big something that usually is found on underfitting models

I am confused Can you please provide me with some advice?

https://i.stack.imgur.com/xGKAj.png
https://i.stack.imgur.com/gkRMn.png

James Carmichael January 14, 2022 at 8:57 am # REPLY

Hello Aggelos…The following may be of interest to you:

https://machinelearningmastery.com/improve-deep-learning-performance/

Leave a Reply

Name (required)

Email (will not be published) (required)

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SUBMIT COMMENT

Welcome!
I'm *Jason Brownlee* PhD
and I **help developers** get results with **machine learning**.
Read more

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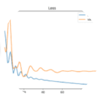
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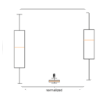
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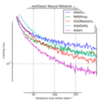
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