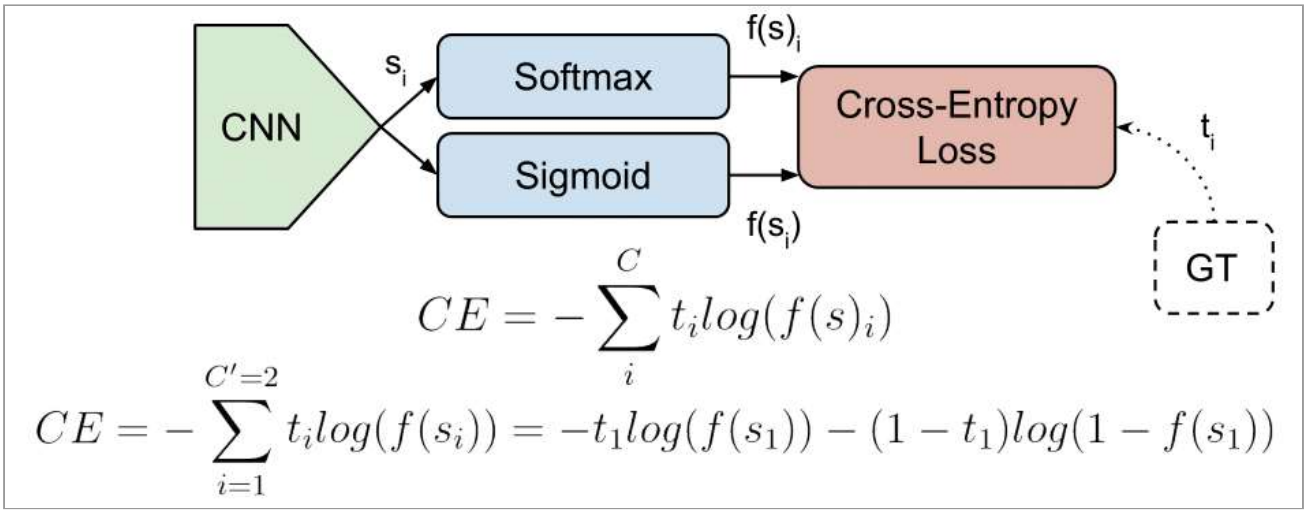
Understanding Categorical Cross-Entropy Loss, Binary Cross-Entropy Loss, Softmax Loss, Logistic Loss, Focal Loss and all those confusing names

May 23, 2018

People like to use cool names which are often confusing. When I started playing with CNN beyond single label classification, I got confused with the different names and formulations people write in their papers, and even with the loss layer names of the deep learning frameworks such as Caffe, Pytorch or TensorFlow. In this post I group up the different names and variations people use for **Cross-Entropy Loss**. I explain their main points, use cases and the implementations in different deep learning frameworks.



First, let's introduce some concepts:

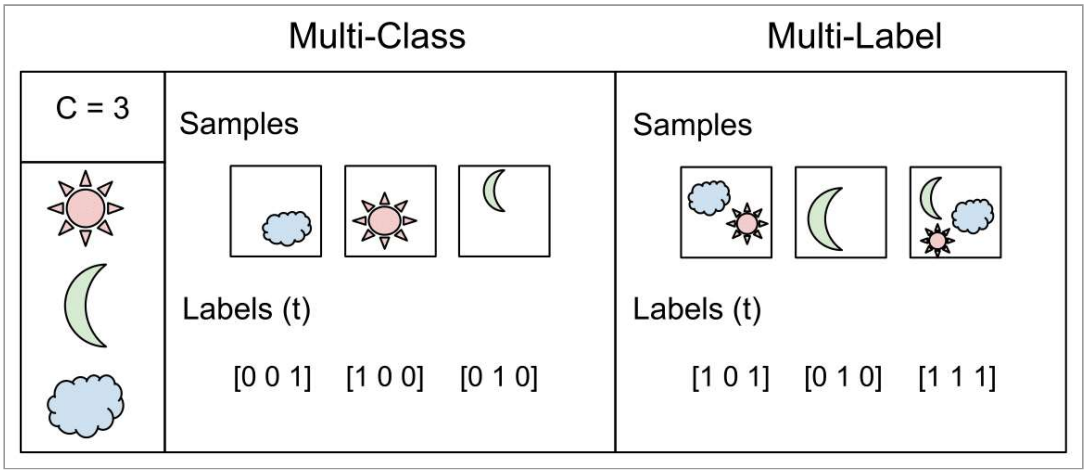
Tasks

Multi-Class Classification

One-of-many classification. Each sample can belong to ONE of C classes. The CNN will have C output neurons that can be gathered in a vector s (Scores). The target (ground truth) vector t will be a one-hot vector with a positive class and $C-1$ negative classes.
This task is treated as a single classification problem of samples in one of C classes.

Multi-Label Classification

Each sample can belong to more than one class. The CNN will have as well C output neurons. The target vector t can have more than a positive class, so it will be a vector of 0s and 1s with C dimensionality.
This task is treated as C different binary $(C'=2, t'=0 \text{ or } t'=1)$ and independent classification problems, where each output neuron decides if a sample belongs to a class or not.

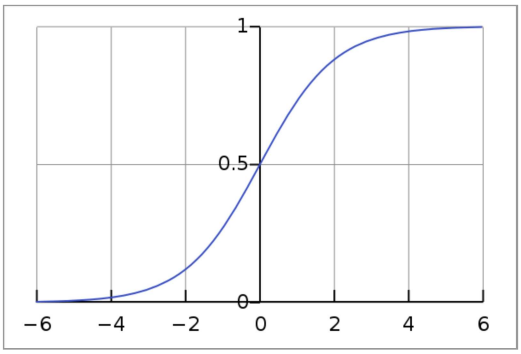


Output Activation Functions

These functions are transformations we apply to vectors coming out from CNNs (s) before the loss computation.

Sigmoid

It squashes a vector in the range (0, 1). It is applied independently to each element of s s_i. It's also called **logistic function**.



$$f(s_i) = \frac{1}{1 + e^{-s_i}}$$

Softmax

Softmax it's a function, not a loss. It squashes a vector in the range (0, 1) and all the resulting elements add up to 1. It is applied to the output scores s. As elements represent a class, they can be interpreted as class probabilities.
The Softmax function cannot be applied independently to each s_i, since it depends on all elements of s. For a given class s_i, the Softmax function can be computed as:

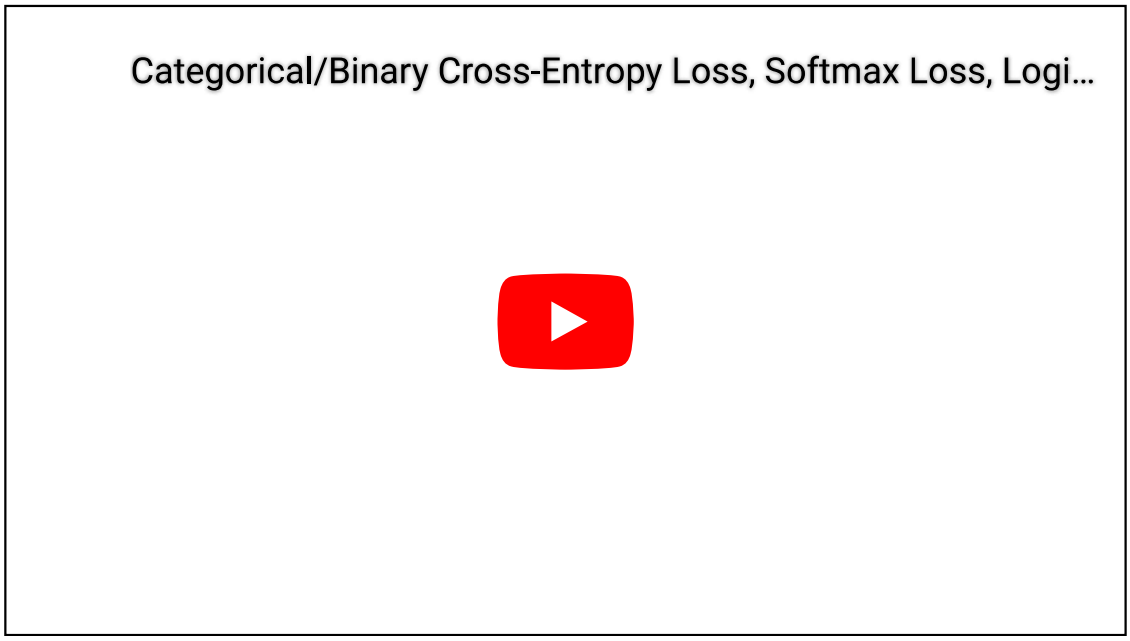
$$f(s)_i = \frac{e^{s_i}}{\sum_j^C e^{s_j}}$$

Where s_j are the scores inferred by the net for each class in C. Note that the Softmax activation for a class s_i depends on all the scores in s.

> *An extense comparison of this two functions can be found here*

> *Activation functions are used to transform vectors before computing the loss in the training phase. In testing, when the loss is no longer applied, activation functions are also used to get the CNN outputs.*

If you prefer video format, I made a video out of this post. Also available in Spanish:



Losses

Cross-Entropy loss

The **Cross-Entropy Loss** is actually the only loss we are discussing here. The other losses names written in the title are other names or variations of it. The CE Loss is defined as:

$$CE = -\sum_{i}^{C} t_i log(s_i)$$

Where t_i and s_i are the groundtruth and the CNN score for each class $_i$ in C. As **usually an activation function (Sigmoid / Softmax) is applied to the scores before the CE Loss computation**, we write $f(s_i)$ to refer to the activations.

In a **binary classification problem**, where $C' = 2$, the Cross Entropy Loss can be defined also as [discussion]:

$$CE = -\sum_{i=1}^{C'=2} t_i log(s_i) = -t_1 log(s_1) - (1 - t_1) log(1 - s_1)$$

Where it's assumed that there are two classes: C_1 and C_2. t_1 [0,1] and s_1 are the groundtruth and the score for C_1, and $t_2 = 1 - t_1$ and $s_2 = 1 - s_1$ are the groundtruth and the score for C_2. That is the case when we split a Multi-Label classification problem in C binary classification problems. See next Binary Cross-Entropy Loss section for more details.

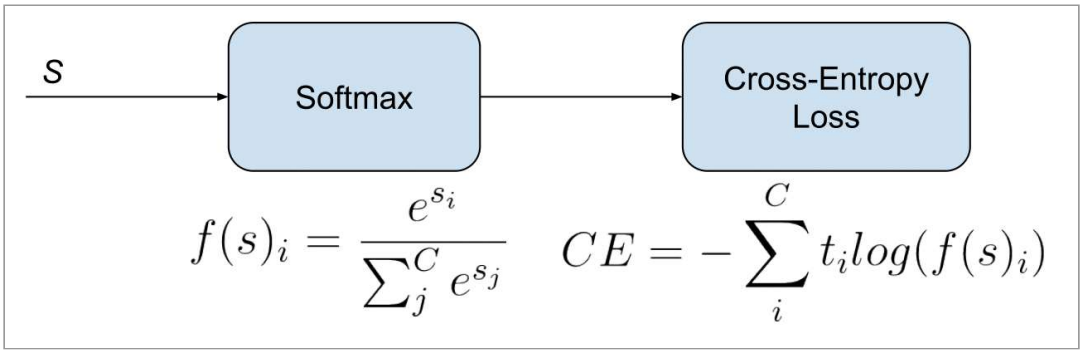
Logistic Loss and **Multinomial Logistic Loss** are other names for **Cross-Entropy loss**. [Discussion]

The layers of Caffe, Pytorch and Tensorflow than use a Cross-Entropy loss without an embedded activation function are:

- Caffe: Multinomial Logistic Loss Layer. Is limited to multi-class classification (does not support multiple labels).
- Pytorch: BCELoss. Is limited to binary classification (between two classes).
- TensorFlow: log_loss.

Categorical Cross-Entropy loss

Also called **Softmax Loss**. It is a **Softmax activation** plus a **Cross-Entropy loss**. If we use this loss, we will train a CNN to output a probability over the C classes for each image. It is used for multi-class classification.



In the specific (and usual) case of Multi-Class classification the labels are one-hot, so only the positive class C_p keeps its term in the loss. There is only one element of the Target vector t which is not zero $t_i = t_p$. So discarding the elements of the summation which are zero due to target labels, we can write:

$$CE = -log\left(\frac{e^{s_p}}{\sum_j^C e^{s_j}}\right)$$

Where **Sp** is the CNN score for the positive class.

Defined the loss, now we'll have to compute its **gradient respect to the output neurons** of the CNN in order to backpropagate it through the net and optimize the defined loss function tuning the net parameters. So we need to compute the gradient of CE Loss respect each CNN class score in s. The loss terms coming from the negative classes are zero. However, the loss gradient respect those negative classes is not cancelled, since the Softmax of the positive class also depends on the negative classes scores.

The gradient expression will be the same for all C except for the ground truth class C_p, because the score of C_p (s_p) is in the nominator.

After some calculus, the derivative respect to the positive class is:

$$\frac{\partial}{\partial s_p}\left(-log\left(\frac{e^{s_p}}{\sum_j^C e^{s_j}}\right)\right) = \left(\frac{e^{s_p}}{\sum_j^C e^{s_j}} - 1\right)$$

And the derivative respect to the other (negative) classes is:

$$\frac{\partial}{\partial s_n}\left(-log\left(\frac{e^{s_p}}{\sum_j^C e^{s_j}}\right)\right) = \left(\frac{e^{s_n}}{\sum_j^C e^{s_j}}\right)$$

Where s_n is the score of any negative class in C different from C_p.

- Caffe: SoftmaxWithLoss Layer. Is limited to multi-class classification.
- Pytorch: CrossEntropyLoss. Is limited to multi-class classification.
- TensorFlow: softmax_cross_entropy. Is limited to multi-class classification.

> *In this Facebook work they claim that, despite being counter-intuitive,* ***Categorical Cross-Entropy loss****, or* ***Softmax loss*** *worked better than* ***Binary Cross-Entropy loss*** *in their multi-label classification problem.*

→ Skip this part if you are not interested in Facebook or me using Softmax Loss for multi-label classification, which is not standard.

When Softmax loss is used is a multi-label scenario, the gradients get a bit more complex, since the loss contains an element for each positive class. Consider M are the positive classes of a sample. The CE Loss with Softmax activations would be:

$$CE = \frac{1}{M}\sum_p^M -log\left(\frac{e^{s_p}}{\sum_j^C e^{s_j}}\right)$$

Where each s_p in M is the CNN score for each positive class. As in Facebook paper, I introduce a scaling factor $1/M$ to make the loss invariant to the number of positive classes, which may be different per sample.

The gradient has different expressions for positive and negative classes. For positive classes:

$$\frac{\partial}{\partial s_{pi}}\left(\frac{1}{M}\sum_{p}^{M}-log\left(\frac{e^{s_p}}{\sum_{j}^{C}e^{s_j}}\right)\right)=\frac{1}{M}\left(\left(\frac{e^{s_{pi}}}{\sum_{j}^{C}e^{s_j}}-1\right)+(M-1)\frac{e^{s_{pi}}}{\sum_{j}^{C}e^{s_j}}\right)$$

Where s_pi is the score of any positive class.

For negative classes:

$$\frac{\partial}{\partial s_{n}}\left(\frac{1}{M}\sum_{p}^{M}-log\left(\frac{e^{s_p}}{\sum_{j}^{C}e^{s_j}}\right)\right)=\frac{e^{s_n}}{\sum_{j}^{C}e^{s_j}}$$

This expressions are easily inferable from the single-label gradient expressions.

As Caffe Softmax with Loss layer nor Multinomial Logistic Loss Layer accept multi-label targets, I implemented my own PyCaffe Softmax loss layer, following the specifications of the Facebook paper. Caffe python layers let's us easily customize the operations done in the forward and backward passes of the layer:

Forward pass: Loss computation

```
def forward(self, bottom, top):
    labels = bottom[1].data
    scores = bottom[0].data
    # Normalizing to avoid instability
    scores -= np.max(scores, axis=1, keepdims=True)
    # Compute Softmax activations
    exp_scores = np.exp(scores)
    probs = exp_scores / np.sum(exp_scores, axis=1, keepdims=True)
    logprobs = np.zeros([bottom[0].num,1])
    # Compute cross-entropy loss
    for r in range(bottom[0].num): # For each element in the batch
        scale_factor = 1 / float(np.count_nonzero(labels[r, :]))
        for c in range(len(labels[r,:])): # For each class
            if labels[r,c] != 0:  # Positive classes
                logprobs[r] += -np.log(probs[r,c]) * labels[r,c] * scale_factor #
```

```
    data_loss = np.sum(logprobs) / bottom[0].num

    self.diff[...] = probs  # Store softmax activations
    top[0].data[...] = data_loss # Store loss
```

We first compute Softmax activations for each class and store them in *probs*. Then we compute the loss for each image in the batch considering there might be more than one positive label. We use an *scale_factor* (M) and we also multiply losses by the labels, which can be binary or real numbers, so they can be used for instance to introduce class balancing. The batch loss will be the mean loss of the elements in the batch. We then save the *data_loss* to display it and the *probs* to use them in the backward pass.

Backward pass: Gradients computation

```
def backward(self, top, propagate_down, bottom):
    delta = self.diff   # If the class label is 0, the gradient is equal to probs
    labels = bottom[1].data
    for r in range(bottom[0].num):  # For each element in the batch
        scale_factor = 1 / float(np.count_nonzero(labels[r, :]))
        for c in range(len(labels[r,:])):  # For each class
            if labels[r, c] != 0:  # If positive class
                delta[r, c] = scale_factor * (delta[r, c] - 1) + (1 - scale_factor
    bottom[0].diff[...] = delta / bottom[0].num
```

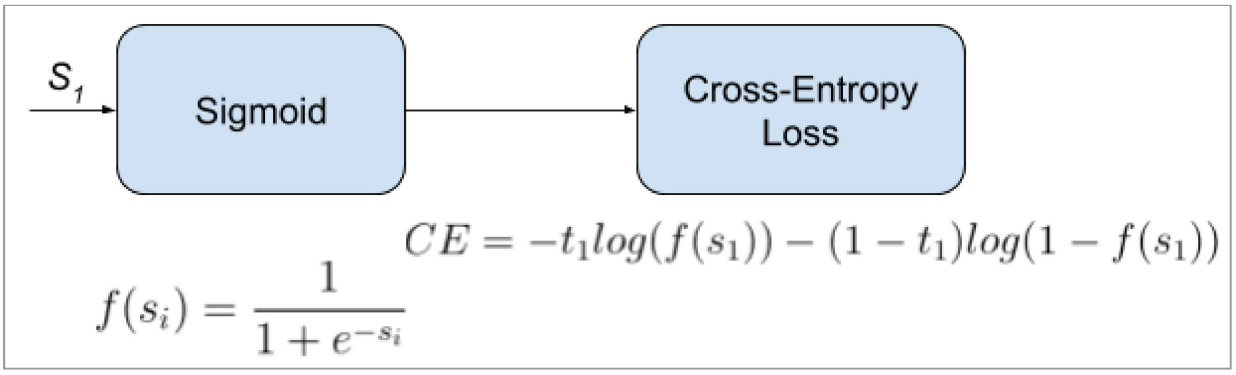
In the backward pass we need to compute the gradients of each element of the batch respect to each one of the classes scores s. As the gradient for all the classes C except positive classes M is equal to *probs*, we assign *probs* values to *delta*. For the positive classes in M we subtract 1 to the corresponding *probs* value and use *scale_factor* to match the gradient expression. We compute the mean gradients of all the batch to run the backpropagation.

> *The Caffe Python layer of this Softmax loss supporting a multi-label setup with real numbers labels is available here*

Binary Cross-Entropy Loss

Also called **Sigmoid Cross-Entropy loss**. It is a **Sigmoid activation** plus a **Cross-Entropy loss**. Unlike **Softmax loss** it is independent for each vector component (class), meaning that the loss computed for every CNN output vector component is not affected by other component values. That's why it is used for **multi-label classification**, were the insight of an element belonging to a certain class should not influence the decision for another class. It's called **Binary Cross-Entropy Loss** because it sets up a binary classification problem between $C' = 2$ classes for every class in C, as explained above. So when using this Loss, the formulation of **Cross Entroypy Loss** for binary problems is often used:

$$CE = -\sum_{i=1}^{C'=2} t_i log(f(s_i)) = -t_1 log(f(s_1)) - (1 - t_1) log(1 - f(s_1))$$



This would be the pipeline for each one of the C clases. We set C independent binary classification problems $(C' = 2)$. Then we sum up the loss over the different binary problems: We sum up the gradients of every binary problem to backpropagate, and the losses to monitor the global loss. s_1 and t_1 are the score and the gorundtruth label for the class C_1, which is also the class C_i in C. $s_2 = 1 - s_1$ and $t_2 = 1 - t_1$ are the score and the groundtruth label of the class C_2, which is not a "class" in our original problem with C classes, but a class we create to set up the binary problem with $C_1 = C_i$. We can understand it as a background class.

The loss can be expressed as:

$$CE = \begin{cases} -log(f(s_1)) & if \quad t_1 = 1 \\ -log(1 - f(s_1)) & if \quad t_1 = 0 \end{cases}$$

Where $t_1 = 1$ means that the class $C_1 = C_i$ is positive for this sample.

In this case, the activation function does not depend in scores of other classes in C more than $C_1 = C_i$. So the gradient respect to the each score s_i in s will only depend on the loss given by its binary problem.

The gradient respect to the score $s_i = s_1$ can be written as:

$$\frac{\partial}{\partial s_i}(CE(f(s_i)) = t_1(f(s_1) - 1) + (1 - t_1)f(s_1)$$

Where $f()$ is the **sigmoid** function. It can also be written as:

$$\frac{\partial}{\partial s_i}(CE(f(s_i)) = \begin{Bmatrix} f(s_i) - 1 & if & t_i = 1 \\ f(s_i) & if & t_i = 0 \end{Bmatrix}$$

> *Refer here for a detailed loss derivation.*

- Caffe: Sigmoid Cross-Entropy Loss Layer
- Pytorch: BCEWithLogitsLoss
- TensorFlow: sigmoid_cross_entropy.

Focal Loss

Focal Loss was introduced by Lin et al., from Facebook, in this paper. They claim to improve one-stage object detectors using **Focal Loss** to train a detector they name RetinaNet. **Focal loss** is a **Cross-Entropy Loss** that weighs the contribution of each sample to the loss based in the classification error. The idea is that, if a sample is already classified correctly by the CNN, its contribution to the loss decreases. With this strategy, they claim to solve the problem of class imbalance by making the loss implicitly focus in those problematic classes.
Moreover, they also weight the contribution of each class to the lose in a more explicit class balancing. They use Sigmoid activations, so **Focal loss** could also be considered a **Binary Cross-Entropy Loss**. We define it for each binary problem as:

$$FL = -\sum_{i=1}^{C=2}(1 - s_i)^{\gamma} t_i log(s_i)$$

Where $(1 - s_i)\gamma$, with the focusing parameter $\gamma >= 0$, is a modulating factor to reduce the influence of correctly classified samples in the loss. With $\gamma = 0$, **Focal Loss** is equivalent to **Binary Cross Entropy Loss**.

The loss can be also defined as :

$$FL = \begin{Bmatrix} -(1 - s_1)^{\gamma} log(s_1) & if & t_1 = 1 \\ -(1 - (1 - s_1))^{\gamma} log(1 - s_1) & if & t_1 = 0 \end{Bmatrix}$$

Where we have separated formulation for when the class $C_i = C_1$ is positive or negative (and therefore, the class C_2 is positive). As before, we have $s_2 = 1 - s_1$ and $t2 = 1 - t_1$.

The gradient gets a bit more complex due to the inclusion of the modulating factor $(1 - s_i)\gamma$ in the loss formulation, but it can be deduced using the **Binary Cross-Entropy** gradient expression.

In case C_i is positive ($t_i = 1$), the gradient expression is:

$$\frac{\partial}{\partial s_i}(FL(f(s_i))) = (1 - f(s_i))^{\gamma}(\gamma f(s_i) log(f(s_i)) + f(s_i) - 1) \quad if \quad t_1 = 1$$

Where $f()$ is the **sigmoid** function. To get the gradient expression for a negative $C_i (t_i = 0)$, we just need to replace $f(s_i)$ with $(1 - f(s_i))$ in the expression above.

> *Notice that, if the modulating factor $\gamma = 0$, the loss is equivalent to the **CE Loss**, and we end up with the same gradient expression.*

I implemented **Focal Loss** in a PyCaffe layer:

Forward pass: Loss computation

```
def forward(self, bottom, top):
    labels = bottom[1].data
    scores = bottom[0].data
    scores =  1 / (1 + np.exp(-scores)) # Compute sigmoid activations
    logprobs = np.zeros([bottom[0].num, 1])

    # Compute cross-entropy loss
    for r in range(bottom[0].num):  # For each element in the batch
        for c in range(len(labels[r, :])):
            # For each class we compute the binary cross-entropy loss
            # We sum the loss per class for each element of the batch
            if labels[r, c] == 0: # Loss form for negative classes
                logprobs[r] += self.class_balances[str(c+1)] * -np.log(1-scores[r,
            else: # Loss form for positive classes
                logprobs[r] += self.class_balances[str(c+1)] * -np.log(scores[r, c
                # The class balancing factor can be included in labels by using sc

    data_loss = np.sum(logprobs) / bottom[0].num
```

```
    top[0].data[...] = data_loss
```

Where *logprobs[r]* stores, per each element of the batch, the sum of the binary cross entropy per each class. The *focusing_parameter* is γ, which by default is 2 and should be defined as a layer parameter in the net prototxt. The *class_balances* can be used to introduce different loss contributions per class, as they do in the Facebook paper.

Backward pass: Gradients computation

```
def backward(self, top, propagate_down, bottom):
    delta = np.zeros_like(bottom[0].data, dtype=np.float32)
    labels = bottom[1].data
    scores = bottom[0].data
    # Compute sigmoid activations
    scores =  1 / (1 + np.exp(-scores))



    for r in range(bottom[0].num):  # For each element in the batch
        for c in range(len(labels[r, :])):  # For each class
            p = scores[r, c]
            if labels[r, c] == 0:
                delta[r, c] = self.class_balances[str(c+1)] * -(p ** self.focusing
            else:  # If the class label != 0
                delta[r, c] = self.class_balances[str(c+1)] * (((1 - p) ** self.fo
                self.focusing_parameter * p * np.log(
                    p) + p - 1))  # Gradient for classes with positive labels

    bottom[0].diff[...] = delta / bottom[0].num
```

> *The Focal Loss Caffe python layer is available here.*

Additional Resources

Keras Loss Functions Guide: Keras Loss Functions: Everything You Need To Know

Raúl Gombru Moderador

4 years ago

I made a video explaining the same I explain in this post:

So if you prefer video format, check it! It is also available in Spanish

0 1 Responder

TIN Nguyen Cong

5 years ago

thank you

6 1 Responder

adin-pro

4 years ago

Thank you! It is clear and really helpful for beginners like me :)

2 0 Responder

Raúl Gombru Moderador → adin-pro

4 years ago

Thank you, I'm glad it helped you!

0 0 Responder

sid

4 years ago

thank you

1 0 Responder

B

BaVo

4 years ago

In this section of Categorical Cross-Entropy loss, just above the "Facebook work"
"And the derivative respect to the other (negative) classes is:"
In the function, the Sp inside the log should be Sn
Anyway, a great topic. Really helpful.

1 0 Responder

Raúl Gombru Moderador → BaVo

4 years ago

Thank you. In that equation, we are computing the gradient of the Softmax of the positive class score respect to each negative class in C, which includes the class producing Sn. But the Sp in the log is correct, because we are deriving the softmax of the positive class. Am I right?

0 0 Responder

Taehun Kim

4 years ago

You makes me fully understand the loss and correct the confusing names :)
Thank you.

1 0 Responder

Raúl Gombru Moderador → Taehun Kim

4 years ago

Thank you, I'm glad it helped you!

0 0 Responder

Hichame Yessou
5 years ago

Great explanation.
One detail, in the Focal Loss would be better to define it as function of the resulting sigmoid, like for the Binary Cross Entropy.

1 0 Responder

Heidi Peterson
5 years ago

Thank you

1 0 Responder

oren A
5 years ago

Thanks for the detailed explanation :)

1 0 Responder

Yang Gu
5 years ago

Good article. You might miss a "-" in the `sigmoid` function though. It should be `f(s_{i}) = \frac{1}{1 + e^{-s_{i}}}`.

1 0 Responder

Raúl Gombru Moderador → Yang Gu
5 years ago

Thanks! You are right, fixed!

0 0 Responder

Yunsoo Jung
5 years ago

Thanks!

1 0 Responder

Nguyen Minh Tuong
4 years ago

Thank you so much,
I have a multi label classification problem where I have 6 binary output. In that case should

I have a multi label classification problem where I have 6 binary output. In that case should the output of the last hidden layer be sigmoid and the loss be Binary Cross-Entropy Loss ?

1 1 Responder

Raúl Gombru Moderador → Nguyen Minh Tuong

4 years ago

Yes, that setup seems adequate for your problem.

0 0 Responder

Nguyen Minh Tuong → Raúl Gombru

4 years ago

Oh thank you Can I use the focal loss for multilabel classification also ?

0 0 Responder

Raúl Gombru Moderador → Nguyen Minh Tuong

4 years ago

Yes you can. But I'd start with the simplest baseline.

0 0 Responder

mladefer

2 years ago

Hi! First of all, thanks for the nicely written blog!

I have a few concerns about Facebook's multi-label loss. As a start, is it really invariant of M as it seems at first glance, just because there is division by M?

In the paper they say this:

"The target is a vector with k non-zero entries each set to 1/k corresponding to the k ≥ 1 hashtags for the image"

Let's say there are just 4 classes and 2 of them are active (M=2). The labels are then e.g. [0.5, 0.5, 0, 0]. In your loss implementation, this is reflected by labels[r,c]. Multiplication by this term is missing in the Latex formula.

Furthermore, let's say we have a perfect prediction: [0.5, 0.5, 0, 0]. What's the loss? We might expect it to be zero, but it isn't:

loss = (-log(0.5) * 0.5) - log(0.5) * 0.5)) / 2 = -log(0.5) * 0.5

In general, it is equal to -log(1/M) * 1/M. We have M terms and we divide by M, but the resulting loss term still depends on M for the case of perfect prediction.

If there is an example that has 100 active tags, and we make a perfect prediction of 1/100 where each is active, the loss is log(100)/100. Whereas, if we have 2 active tags with a perfect prediction, it is log(2)/2.

The loss will penalize examples with less tags more, and even in the cases where the prediction is equal to the ground truth.

Do we have the public implementation to see what they did?
"Our model computes probabilities over all hashtags in the vocabulary using a softmax activation and is trained to minimize the cross-entropy between the predicted softmax distribution and the target distribution of each image."

Kullback–Leibler loss would be more intuitive here, as we would not have this issue that the loss is not zero for perfect predictions.

For example:
ground_array = [0.5, 0.5, 0, 0]
predicted_array = [0.5, 0.5, 0, 0]

KL_loss = np.sum(ground_array * np.log(ground_array / predicted_array)) = 0 (after adding small epsilon to prevent division by zero)

This would give zero loss for any number of active tags.

Of course, CE still works since the entropy part -np.sum(ground_array * np.log(ground_array)) is fixed for each example and can't be optimized. Still, it's less straightforward, and it is divided by the number of non-zero labels.

Another question is for inference time. Which threshold do we use? E.g, if there were 10 active tags, ideally we'll have 0.1 10 times as prediction. For 2 active tags, the perfect prediction will have 0.5 two times. How do we binarize a given probability vector in test time in a principled way, not knowing the number of tags to predict?

There is a same question on Stackoverflow and I've just answered how I'd go about it:
https://stackoverflow.com/a...

The same tag position could have completely different ground truth values: 1.0 when alone, 0.5 when together with another one, 0.1 with 10 of them, and so on. A fixed threshold couldn't tell which was the correct case.

Instead, we can check the descending sort of predicted values and the corresponding cumulative sum. As soon as that sum is above a certain number (let's say 0.95), that's the number of tags that we predict. Tweaking the exact threshold number for the cumulative sum would serve as a way to influence precision and recall.

0 0 Responder

Raúl Gombru Moderador → mladefer

2 years ago editado

Interesting discussion. I haven't seen Facebook's implementation, but I'd say:
- Regarding training, even if loss is not 0 for a perfect prediction, is still minimum, so the optimization works.
- Regarding inference, I don't think is a big deal finding a threshold. I'd find the optimum threshold for each class leveraging a validation set

optimum threshold for each class leveraging a validation set.

0 0 Responder

mladefer Raúl Gombru

2 years ago

Right, the CE optimization works. This is always the case when considering KL vs CE for such classification problems: the difference is in the constant entropy part that only depends on the dataset and varies from one example to another. Changing model parameters doesn't influence that part. It's just that CE is less intuitive here. There is also the question to what extent dividing by M really makes a difference. In the KL formulation, we wouldn't have such division.

Regarding inference, this was my initial thought as well. But if there is a high variation in the number of tags, this could become problematic. Imagine that you want to optimize the threshold for a particular tag. If that tag is sometimes alone, and sometimes with a 100 other tags in the validation set, its ground truth label varies between 1.0 and 0.01. It then becomes difficult to pick a single binarization threshold that works well for all those ground truth cases. That's why I suggested the approach that takes into account cumulative probability for the number of predicted tags. Class specific threshold could then be optimized more easily after that, conditionally after we already determined the approximate total number of tags to predict. It would be interesting to know what they actually did. I saw it in different places that people are asking about this.

0 0 Responder

Raúl Gombru Moderador mladefer

2 years ago editado

Yes, that makes a lot of sense.

However, note that in this large sacale scenarios, the most optimization objective that seems to fir best the task is not always the one chosen or performing better. Other things, such as the efficiency, the optimization speed, or the sensitivity to hyperparameters play a key role.
Actually if that was the case, why not go with a simple MLC in that Facebook paper?

Note for instance the loss used in the succesfull CLIP paper by OpenAI https://openai.com/blog/clip/
- Sometimes positive images (aligned to the anchor text) will be used as negatives in a batch.
- Similarly as you mentioned in this case, an image featuring a dog, might not have the word dog in its caption (or might have it diluted in a long caption)
And still in the one learning superior image representations right

now.

0 0 Responder

Felix Hong-Soog Kim

3 years ago editado

Thanks for your efforts on best explanation on confused losses and related things.
In Focal Loss function latex should be corrected, I cannot see it. Maybe you want to display

$$
FL =
\begin{cases}
- (1 - s_{1})^{\gamma }log(s_{1}) &\text{if } t_{1} = 1 \\

- (1 - (1 - s_{1}))^{\gamma } log(1 - s_{1}) &\text{if } t_{1} = 0
\end{cases}
$$

If so, please reflect above latex into the Focal Loss function.

Thanks again

0 0 Responder

Anusorn

4 years ago

Thanks

0 0 Responder

F

Faiyaz Lalani

4 years ago

Nicely done Raul

0 0 Responder

Raúl Gombru Moderador Faiyaz Lalani

4 years ago

Thank you!

0 0 Responder

Bruh Momento

4 years ago

thank you so much for this post and the video. but can you please fix some of the latex image in your post please.

0 0 Responder

Raúl Gombru Moderador → Bruh Momento

4 years ago

Thank you, I'm glad it was useful.
About the images, do you mean that they are not displayed correctly? Right now they are working fine for me, but these days I noticed that www.codecogs.com, the site that renders them, is not working properly, so sometimes the images are not displayed. In that case, refreshing the page might solve it.

1 0 Responder

Nguyen Dung

5 years ago editado

Thanks for the post.

In case of Facebook's multi-label loss, how does one do inference? For eg, the scores returned would be [0.7, 0.1, 0.2], and the actual label is [1 0 1] (not known beforehand). How could we determine that this sample would have 2 positive labels?

0 0 Responder

Raúl Gombru Moderador → Nguyen Dung

5 years ago

The per-class weighted Focal Loss is just a training strategy. When doing inference, one can use directly the sigmoid output to get the score for each class.

0 0 Responder

Nguyen Dung → Raúl Gombru

5 years ago

Thanks for the info. I meant Categorical Cross-Entropy loss (from the paper "Exploring-the-limits-of-weakly-supervised-pretraining"), not Focal Loss. Do we compare the sofmax scores with 1/n?

0 0 Responder

Raúl Gombru Moderador → Nguyen Dung

5 years ago

Okey. Anyway, the answer would be the same. Using Softmax in the Categorical Cross-Entropy loss is a training strategy. The 1/M term to weight the loss is used to make each sample have the same contribution to the loss, no matter how many positive labels has.
In inference, I would directly use class scores (before softmax), or use a sigmoid over class scores and threshold there.

0 0 Responder

Daniel Salvadori

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Computer vision, deep learning and image processing stuff by Raúl Gómez Bruballa, PhD in computer vision.