WEIGHT MAP LAYER FOR NOISE AND ADVERSARIAL ATTACK ROBUSTNESS

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ABSTRACT

Convolutional neural networks (CNNs) are known for their good performance and generalization in vision-related tasks and have become state-of-the-art in both application and research-based domains. However, just like other neural network models, they suffer from a susceptibility to noise and adversarial attacks. An adversarial defence aims at reducing a neural network’s susceptibility to adversarial attacks through learning or architectural modifications. We propose a weight map layer (WM) as a generic architectural addition to CNNs and show that it can increase their robustness to noise and adversarial attacks. We further explain the enhanced robustness of the two WM variants introduced via an adaptive noise-variance amplification (ANVA) hypothesis and provide evidence and insights in support of it. We show that the WM layer can be integrated into scaled up models to increase their noise and adversarial attack robustness, while achieving the same or similar accuracy levels.

1 Introduction

Despite their wide adoption in vision tasks and practical applications, convolutional neural networks (CNNs) [Fukushima and Miyake 1980, LeCun et al. 1989, Krizhevsky et al. 2012] suffer from the same noise susceptibility problems manifested in the majority of neural network models. Noise is an integral component of any input signal that can arise from different sources, from sensors and data acquisition to data preparation and pre-processing. Szegedy et al. [2013] opened the door to an extreme set of procedures that can manipulate this susceptibility by applying an engineered noise to confuse a neural network to misclassify its inputs.

The core principle in this set of techniques, called adversarial attacks, is to apply the least possible noise perturbation to the neural network input, such that the noisy input is not visually distinguishable from the original and yet it still disrupts the neural network output. Generally, adversarial attacks are composed of two main steps:

- **Direction sensitivity estimation:** In this step, the attacker estimates which directions in the input are the most sensitive to perturbation. In other words, the attacker finds which input features will cause the most degradation of the network performance when perturbed. The gradient of the loss with respect to the input can be used as a proxy of this estimate.

- **Perturbation selection:** Based on the sensitivity estimate, some perturbation is selected to balance the two competing objectives of being minimal and yet making the most disruption to the network output.

The above general technique implies having access to the attacked model and thus is termed a whitebox attack. Blackbox attacks on the other hand assume no access to the target model and usually entail training a substitute model

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to approximate the target model and then applying the usual whitebox attack [Chakraborty et al., 2018]. The effectiveness of this approach mainly depends on the assumption of the transferability between machine learning models [Papernot et al., 2016a].

Since their introduction, a lot of research have been done to guard against these attacks. An adversarial defence is any technique that is aimed at reducing the effect of adversarial attacks on neural networks. This can be through detection, modification to the learning process, architectural modifications or a combination of these techniques. Our approach consists of an architectural modification that aims to be easily integrated into any existing convolutional neural network architecture.

The core hypothesis we base our approach on starts from the premise that the noise in an input is unavoidable and in practise is very difficult to separate from the signal effectively. Instead, if the network can adaptively amplify the noise early in its representations based on the relative importance of different features, then subsequent layers can absorb this noise and map the representations to the correct output. This means that if a feature is very important to the output calculation, then its noise should be adequately amplified at training time to allow the classification layers to be robust to this feature’s noisiness at inference time, since it is crucial to performance. In the context of CNNs, this kind of feature-wise amplification can be achieved by an adaptive elementwise scaling of feature maps.

We introduce a weight map layer (WM), which is an easy to implement layer composed of two main operations: elementwise scaling of feature maps by a learned weight grid of the same size, followed by a non-adaptive convolution reduction operation. We use two related operations in the two WM variants we introduce. The first variant, smoothing WM, uses a non-adaptive smoothing convolution filter of ones. The other variant, unsharp WM, adds an extra step to exploit the smoothed intermediate output of the first variant to implement an operation similar to unsharp mask filtering [Gonzalez et al., 2002]. The motivation for the second variant was to decrease the over-smoothing effect produced by stacking multiple WM layers. Smoothing is known to reduce adversarial susceptibility [Xu et al., 2017], however, if done excessively this can negatively impact accuracy, which motivates the unsharp operation as a counter-measure to help control the trade-off between noise robustness and overall accuracy. We show and argue that the weight map component, can increase robustness to noise through an effect we call adaptive noise-variance amplification (ANVA). Basically, we argue that amplifying the noise during the training phase in an adaptive way, based on feature importance, can help networks absorb noise more effectively. In a way, this can be thought of as implicit adversarial training [Goodfellow et al., 2014, Lyu et al., 2015, Shaham et al., 2015]. We show that the two components, weight map and reduction operations, can give rise to robust CNNs that are resistant to uniform and adversarial noise.

2 Related Work

Since the intriguing discovery by [Szegedy et al., 2013] that neural networks can be easily forced to misclassify their input by applying an imperceptible perturbation, many attempts have been made to fortify them against such attacks. These techniques are generally applied to either learning or architectural aspects of networks. Learning techniques modify the learning process to make the learned model resistant to adversarial attacks, and are usually architecture agnostic. Architectural techniques, on the other hand, make modifications to the architecture or use a specific form of architecture engineered to exhibit robustness to such attacks.

[Goodfellow et al., 2014] suggested adversarial training, where the neural network model is exposed to crafted adversarial examples during the training phase to allow the network to map adversarial examples to the right class. [Tramèr et al., 2017] showed that this can be bypassed by a two step-attack, where a random step is applied before perturbation. [Jin et al., 2015] used a similar approach of training using noisy inputs, with some modifications to network operators to increase robustness to adversarial attacks. [Seltzer et al., 2013] also applied a similar technique in the audio domain, namely, multi-condition speech, where the network is trained on samples with different noise levels. They also benchmarked against training on pre-processed noise-suppressed features and noise-aware training, a technique where the input is augmented with noise estimates.

Distillation [Hinton et al., 2015] was proposed initially as a way of transferring knowledge from a larger teacher network to a smaller student network. One of the tricks used to make distillation feasible was the usage of softmax with a temperature hyperparameter. Training the teacher network with a higher temperature has the effect of producing softer targets that can be utilized for training the student network. [Papernot et al., 2016b, Papernot and McDaniel, 2017] showed that distillation with a high temperature hyperparameter can render the network resistant to adversarial attacks. Feature squeezing [Xu et al., 2017] corresponds to another set of techniques that rely on desensitizing the model to input, e.g. through smoothing images, so that it is more robust to adversarial attacks. This, however, decreases the model’s accuracy. [Hosseini et al., 2017] proposed NULL labeling, where the neural network is trained to reject inputs that are suspected to be adversarials.
We introduce the WM layer, an adversarial defence which requires a minimal architectural modification since it can be inserted between normal convolutional layers. They act as regularizers for different hidden layers, effectively correcting representations that deviate from the expected distribution. A related approach was proposed by Ghosh et al. [2018], where a Variational Autoencoder (VAE) was used with a mixture of Gaussians prior. The adversarial examples could be detected at inference time based on their high reconstruction errors and could then be correctly reclassified by optimizing for the latent vector that minimized the reconstruction error with respect to the input. DeepCloak [Gao et al., 2017] is another approach that accumulates the difference in activations between the adversarials and the seeds used to generate them at inference time and, based on this, a binary mask is inserted between hidden layers to zero out the features with the highest contribution to the adversarial problem. The nearest to our approach, is the method proposed by Sun et al. [2017]. This work made use of a HyperNetwork [Ha et al., 2016] that receives the mean and standard deviation of the convolution layer and outputs a map that is multiplied elementwise with the convolution weights to produce the final weights used to filter the input. The dependency of the weights on the statistics of the data renders the network robust to adversarial attacks.

From the architectural family, Lamb et al. [2018] proposed inserting Denoising Autoencoders (DAEs) between hidden layers. They act as regularizers for different hidden layers, effectively correcting representations that deviate from the expected distribution. A related approach was proposed by Ghosh et al. [2018], where a Variational Autoencoder (VAE) was used with a mixture of Gaussians prior. The adversarial examples could be detected at inference time based on their high reconstruction errors and could then be correctly reclassified by optimizing for the latent vector that minimized the reconstruction error with respect to the input. DeepCloak [Gao et al., 2017] is another approach that accumulates the difference in activations between the adversarials and the seeds used to generate them at inference time and, based on this, a binary mask is inserted between hidden layers to zero out the features with the highest contribution to the adversarial problem. The nearest to our approach, is the method proposed by Sun et al. [2017]. This work made use of a HyperNetwork [Ha et al., 2016] that receives the mean and standard deviation of the convolution layer and outputs a map that is multiplied elementwise with the convolution weights to produce the final weights used to filter the input. The dependency of the weights on the statistics of the data renders the network robust to adversarial attacks.

We introduce the WM layer, an adversarial defence which requires a minimal architectural modification since it can be inserted between normal convolutional layers. We propose adaptive noise-variance amplification as the working principle behind it, which can be considered as a form of dynamic implicit adversarial training. Finally, we show that the WM layer can be integrated into scaled up models to achieve noise robustness with the same or similar accuracy.

### 3 Methods

The main operation involved in a weight map layer Fig. 1 is an elementwise multiplication of the layer input with a map of weights. For a layer $l$ with an input $x_l \in R^{C_l \times D_l \times D_l}$ with $C_l$ input channels and spatial dimension $D_l$ and an output $o_l \in R^{C_o \times D_o \times D_o}$ with $C_o$ output channels and $D_o$ spatial dimension, the channel map of the $c_o$th output channel contributing to the $c_i$th input channel used to is calculated as

$$m^{(c_i,c_o)}_l = W^{(c_i,c_o)}_l \odot x^{(c_i)}_l$$

where $W^{(c_i,c_o)}_l \in R^{D_l \times D_l}$ is the weight mapping between $c_i$ and $c_o$, $x^{(c_i)}_l$ is the $c_i$th input channel and $\odot$ is the elementwise multiplication operator. We used two techniques for producing the pre-linearity output of the weight map layer. The first variant, smoothing weight map layer, produces the $c_o$th output channel $o^{(c_o)}_l$ by convolving the maps with a kernel $k \in R^{C_i \times D_o \times D_o}$ of ones with $D_o$ spatial dimension as follow,

$$o^{(c_o)}_l = m^{(c_o)}_l \ast k + b^{(c_o)}_l$$

where $m^{(c_o)}_l$ is the set of intermediate maps contributing to output channel $c_o$, $b^{(c_o)}_l \in R^{D_o \times D_o}$ is a bias term and $\ast$ is the convolution operator. The other variant, unsharp weight map layer, produces the output by an operation similar to unsharp filtering as follow,

$$s^{(c_o,c_o)}_l = 2m^{(c_i,c_o)}_l - m^{(c_i,c_o)}_l \ast k$$

$$o^{(c_o)}_l = \sum_{c_i} s^{(c_i,c_o)}_l + b^{(c_o)}_l$$

where $k \in R^{D_o \times D_o}$ is a kernel of ones applied with a suitable padding element to ensure similar spatial dimensions between the convolution input and output.

### 4 Results

We use MNIST as the main dataset in our experiments. In all the trials we partition the 60K training set into 90% for training and 10% for validation. The test set is the standard 10K images. During training, the inputs are zero padded
and randomly cropped to the size 28x28. This is the only data augmentation used. Adam is used for the optimization with its default parameters. All the test errors are reported as a mean and standard deviation over three trials.

### 4.1 Preliminary Experiments

For examining the performance of the proposed weight map layer, we used a three layered CNN as our baseline. We benchmarked the performance of the same network skeleton but with the normal convolutional layers replaced by a weight map layer variant. The skeleton body is a stack of three layers, where the first two have either 32 channels, if it is a weight map network variant, or 33 channels if it is a normal CNN table [1]. This difference was adopted to maintain approximately the same number of floating point operations per second (FLOPS) between the two architectures. In just one of the CNN variants, we increased the channels of the first two layers to 200 and 500, respectively, to compare with the weight map network having the same number of parameters. We will refer to this scaled up variant as "wide" in the results. The final layer in the skeleton body has 8 channels. Classification output is made by a 2 layer fully connected multilayer perceptron (MLP), where the first layer has 64 nodes followed by an output layer. Kernel size is the same for all convolutional layers. We compare two kernel sizes, 3 and 9, and we include batchnorm [1] layers in some of the variants to test the interaction with the proposed layer. When batchnorm is included, it is inserted in all the convolutional layers just before the nonlinearity. In one of the variants, we elementwise multiply the input with a learnable weight map to probe the effect of the input weight map on noise robustness.
The results are summarized in table 2. The basic weight map network has better performance than the corresponding basic CNN with the same number of FLOPS. The unsharp version is better by a larger margin but with slightly higher FLOPS. Increasing the CNN parameters to the level of the corresponding weight map network results in lowering its performance. Including batchnorm in either the CNN or the weight map network boosted the performance of both variants to nearly the same level. On the other hand, increasing the kernel size to 9 boosted the CNN performance, whilst degrading the weight map network performance.

4.2 Scaling Up

To assess the scalability of the proposed weight map layer, we integrated it into two popular CNN skeletons by replacing some or all of the convolutional layers by one of the weight map layer variants. For our experiments, we used two main skeletons, which were variants of ResNet [He et al., 2015] and DenseNet [Huang et al., 2016]. Table 3 shows the skeleton of the ResNet variant. ResBlock was composed of two layers of 3x3 convolutions with ReLU activations. At layer transitions characterized by doubling of the number of channels, downsampling to half of the spatial dimension was done by the first layer of the first block. Residual connections were established from the input to each ResBlock to its output, following the pattern used in the original paper [He et al., 2015], where projections using 1x1 convolutions were applied when there was a mismatch of the number of channels or spatial dimensions. Table 4 shows the skeleton of DenseNet. Each Dense layer is assumed to be followed by a ReLU nonlinearity. For integrating WM layers into the architectures, we either replace all the layers by one of the WM layer variants or replace half of the layers by skipping one layer and replacing the next.

The results are summarized in table 5. For ResNet, the all-convolutional variant exhibited the best performance. Among the weight map variants, the alternating smoothing variant had a relatively good performance. DenseNet results showed a similar pattern, however, with less discrepancy between the vanilla network and the WM variants. Moreover, the alternating unsharp variant had a performance on par with the vanilla model.

4.3 Noise Robustness and Adversarial Attacks

When testing models for noise robustness, we added random uniform noise to the input, which always had a lower boundary of zero. We varied the upper boundary to assess the degree of robustness. After the addition of noise, the input was renormalized to be within the range [0, 1]. The robustness measure is reported as the average test error achieved by the model on the noisy test dataset averaged over three trials. For testing the models against adversarial attacks, we followed the fast gradient sign method (FSGM) [Goodfellow et al., 2014] approach, where we varied the $\epsilon$ parameter to control the severity of the attack. For both the uniform noise and adversarial attacks, besides test error, we calculated the mean square error (MSE) between the activations produced at the last convolutional layer in response to the original input (prior to the addition of noise) and the noisy/perturbed input.
| Layer          | Hyperparams | Repeat |
|---------------|-------------|--------|
| Conv          | channels: 16 | 1      |
| ReLU          | channels: 16 | 1      |
| Dense         | Growth rate: 8 | 2      |
| Max pool      | size: 2, stride: 2 | 1      |
| Dense         | Growth rate: 8 | 4      |
| Max pool      | size: 2, stride: 2 | 1      |
| Dense         | Growth rate: 8 | 8      |
| Max pool      | size: 2, stride: 2 | 1      |
| Dense         | Growth rate: 8 | 16     |
| Global average pool | out: 256 | 1      |
| Fully connected | out: 10     | 1      |

Table 4: DenseNet skeleton

| Variant                  | Test error (%) |
|--------------------------|----------------|
| ResNet                   |                |
| Conv                     | 0.50 ± 0.05    |
| Smoothing WM             | 0.80 ± 0.09    |
| Unsharp WM               | 0.91 ± 0.14    |
| Alternating Conv/Smoothing WM | 0.65 ± 0.08 |
| DenseNet                 |                |
| Conv                     | 0.52 ± 0.09    |
| Smoothing WM             | 0.67 ± 0.05    |
| Unsharp WM               | 0.60 ± 0.04    |
| Alternating Conv/Unsharp WM | 0.54 ± 0.04 |

Table 5: ResNet and DenseNet results

The relative noise test error results fig. 2a between different models show that the weight map layers introduce strong resistance to additive uniform noise, regardless of the architecture used. For CNN variants, this is followed by the CNN with scaled input and then the smoothing weight map variant. The baseline condition (the all convolutional CNN) approaches the random limit, i.e 90% error, very early on in the noise scale. Batchnorm introduces some noise robustness relative to the vanilla CNN, however, it is not as powerful as the weight map variants. The robustness margin between the weight map layer and the baseline architecture is more pronounced in the DenseNet model, where even with the highest noise level, the alternating unsharp variant still has a test error around 60%, while the baseline is around 85%. For ResNet variants, the vanilla ResNet shows a decent noise robustness on its own, but the alternating smoothing variant has an even better robustness.

The relative adversarial test errors results fig. 3a show a similar ranking between models in the CNN variants, except for the variant with batchnorm, which seems not to help much with adversarial attacks. ResNet shows the same pattern, where the vanilla ResNet occupies a middle robustness between the WM variants. For the DenseNet variants and for high values of epsilon, the baseline (the all convolutional DenseNet) gets slightly better than the alternating unsharp variant approximately when epsilon is larger than 0.4. However, contrary to the uniform noise experiments, we notice that high epsilon values drive all the models near to the boundary of random guessing.

The activation map MSEs for the uniform noise conditions fig. 2b show that for the CNN models, the WM variants exhibit the largest activation variations under uniform noise input. All the CNN variants, including the one with scaled inputs, exhibited limited variability in their MSEs. DenseNet variants showed the opposite pattern, where WM variants scored lower than the vanilla DenseNet by a large margin. ResNet variants show a somewhat in-between pattern, where the vanilla ResNet shows greater variation than WM variants, but not by the large margin seen in DenseNet. In the case of adversarial attack MSEs fig. 3b we see the same patterns emerge again for CNN, ResNet and DenseNet variants.

5 Discussion

For the preliminary experiments based on small models, the WM variant (no batchnorm and kernel size of 3) has a better performance than the corresponding vanilla CNN having the same number of FLOPS. We attribute this to two main factors. First, the higher capacity of the WM variant, due to its larger number of parameters, makes it more
expressive. WM representation doesn’t, however, need to be in the same space as the CNN variant. The Grad-CAM [Selvaraju et al., 2016] visualization of both vanilla CNN and the two WM variants fig. 4 shows a substantial difference. While the CNN CAM is a blurry, diffused distortion of the input and sometimes activating for a large proportion of the background, the WM CAM is sharper, sparser and more localized with almost no diffused background activation, specially for the unsharp WM variant. We attribute this background activation sparsity to the feature selection ability of WM. Much like the way attentional techniques [Bahdanau et al., 2014, Vinyals et al., 2014, Xu et al., 2015, Hermann et al., 2015] can draw the network to focus on a subset of features, WM includes an elementwise multiplication by a weight map, that can in principle achieve feature selection on a pixel by pixel basis. On the other hand, normal convolution can’t achieve a similar effect because of weight sharing. The second possible reason for better performance consists of the scaling properties of the WM layer. This can in principle act like the normalization done by batchnorm layers. However, applying batchnorm can boost the performance of both CNN and WM variants, which indicates that the two approaches have an orthogonal component between them. Moreover, as we discuss below, batchnorm alone doesn’t protect against uniform noise and adversarial attacks. If we fix the number of parameters, instead of FLOPS, along with depth, we observe a clear advantage for WM variants. The WM variant with the same number of parameters and depth is better in performance by a large margin, and cheaper in FLOPS by around 100x. We attribute this to the large width compared to depth of the CNN variant, which makes it harder to optimize. On the other hand, WM can pack larger degrees of freedom without growing in width.

Increasing the kernel size enhances the performance of the CNN variant, while it lowers the performance of the WM variant. The enhanced CNN performance is due to increased capacity and a larger context made available by the larger receptive field. In the case of WM, the increased kernel size results in over smoothing and larger overlapping between adjacent receptive fields, effectively sharing more parameters and limiting the model’s effective capacity.

The scaled up ResNet and DenseNet WM variants show a degradation in performance with respect to the corresponding convolutional baseline. This is more prominent in the ResNet than the DenseNet variants. We attribute this to the
accumulated distortion made by stacking many layers depth-wise and feature map additions made by residual connections. This hypothesis is consistent with ResNet having the greatest distortion since the early feature maps are not available to the deeper layers. In DenseNet, the skip connections alleviate this problem by allowing access to earlier less distorted feature maps. This asymmetry between ResNet and DenseNet allowed the latter to maintain accuracy levels by alternating between unsharp WM and convolutional layers, while harvesting the noise and adversarial robustness of the WM layers. The same approach in ResNet could achieve the same noise robustness, but with some loss in accuracy.

In terms of noise and adversarial robustness, WM variants have a clear advantage relative to the convolutional variants across almost all tested conditions. We think this effect can be explained based on two factors, namely smoothing and our postulated hypothesis of Adaptive Noise-Variance Amplification (ANVA). Smoothing is known to introduce noise robustness, specially for adversarial attacks, a process called feature squeezing [Xu et al., 2017]. However, the scaled input CNN condition shows that a mere elementwise adaptive scaling of input can introduce noise robustness. This is the underlying principle behind WM layers. Basically, since the WM layer is adaptively scaling feature maps elementwise, it can be thought of as a feature selection operation. This means that the weight magnitude at a given input pixel will be proportional to the importance of this pixel in explaining the output. This means that the variance of different pixels will be amplified adaptively based on their importance. During the training process, upper and classification layers, will learn to tolerate large pixel variances proportional to their intrinsic variance amplified by their importance. This will make the network resistant to uniform noise relative to the baseline. For adversarial attacks, and since gradient-based whitebox techniques depend on the sensitivity of the network’s loss relative to the input, which is correlated with the latter’s importance in explaining the output, the network which adapted to amplified variance of the important input elements will be more resistant than the baseline. This operating principle is related to adversarial training and can be thought of as doing it dynamically and implicitly.
The activation MSE results fig. 2b and fig. 3b provide further evidence for this hypothesis. For both uniform noise and adversarial attacks, WM variants exhibit considerable changes in final layer activations in response to noise. This is expected since they have WM layers just before the measured activations, and WM layers according to our hypothesis exhibit adaptive noise amplification. On the other hand, the CNN with scaled input condition doesn’t show this pattern despite operating partly using the same principle. For the scaled input CNN the adaptive amplification happens early in the network, just at the input. This means that all the network layers, including convolutional layers, will adapt to this specific noise variation, thus dampening the effect at the final layer, despite the condition being noise robust.

For vanilla CNN and DenseNet we see two apparently contradictory patterns: CNN has a very low variation in response to noise, while DenseNet has the opposite, a very high variation. Both networks degrade in response to noisy input in comparison to the WM variants. In the case of CNN, the network changes poorly in response to noise, which was also the case during training. This means that its classification layer wasn’t trained to accommodate large variations in the input. This is why at inference time, slight changes to its activations could have deleterious effects on its outputs. In the case of DenseNet, the feature maps are easily distorted by noise. Obviously, it is very hard for the classification layers to absorb such a high deviation in representation. The WM variants seem to strike a good balance between excessively weak noise amplification, which doesn’t help the upper layers absorb noise during training, and too much amplification, which makes the model susceptible to noise. This is furthermore confirmed by the inherent noise robustness we observe in vanilla ResNet. While the origin of this inherent robustness compared to other vanilla models is currently unclear, its activation MSEs show a similar modest smooth increase with noise level, which supports the hypothesis that a regulated noise amplification can increase noise robustness.

6 Conclusion

We introduced a weight map layer with its two variants as a generic architectural modification that can increase the robustness of convolutional neural networks to noise and adversarial attacks. We showed that it can be used to boost performance and increase noise robustness in small convolutional networks. Moreover, we showed that WM layers can be integrated into a scaled up network, DenseNet, to increase its noise and adversarial attacks robustness, while maintaining its accuracy. Despite not being fully compatible, as measured by accuracy, with ResNet due its architectural nature, we showed that WM layers can be integrated with it to increase its noise and adversarial attacks robustness without too much loss of accuracy. We introduced the adaptive noise-variance amplification (ANVA) hypothesis to explain the noise and adversarial attack robustness and the associated experimental observations regarding the dynamics of the weight map layer. Future work has multiple promising directions with regards to finding more effective ways to integrate with architectures like ResNet to achieve noise robustness without losing accuracy, investigating the inherent noise robustness in ResNet and if it links to WM mechanisms, integrating with more architectures, providing more insights and experimental results into the validity of the ANVA hypothesis and exploiting it further to enhance the accuracy and noise robustness of neural networks in general.
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