Boosting Convolutional Features for Robust Object Proposals

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Abstract

Deep Convolutional Neural Networks (CNNs) have demonstrated excellent performance in image classification, but still show room for improvement in object-detection tasks with many categories, in particular for cluttered scenes and occlusion. Modern detection algorithms like Regions with CNNs (Girshick et al., 2014) rely on Selective Search (Uijlings et al., 2013) to propose regions which with high probability represent objects, where in turn CNNs are deployed for classification. Selective Search represents a family of sophisticated algorithms that are engineered with multiple segmentation, appearance and saliency cues, typically coming with a significant runtime overhead. Furthermore, (Hosang et al., 2014) have shown that most methods suffer from low reproducibility due to unstable superpixels, even for slight image perturbations. Although CNNs are subsequently used for classification in top-performing object-detection pipelines, current proposal methods are agnostic to how these models parse objects and their rich learned representations. As a result they may propose regions which may not resemble high-level objects or totally miss some of them. To overcome these drawbacks we propose a boosting approach which directly takes advantage of hierarchical CNN features for detecting regions of interest fast. We demonstrate its performance on ImageNet 2013 detection benchmark and compare it with state-of-the-art methods.

1. Introduction

Visual object detection is at the heart of many applications in science and engineering, ranging from microscopic scales in medicine to macroscopic scale in space exploration. Historically these problems are mostly formulated as classification problems in a sliding-window framework. To this end a classifier is trained to differentiate one or more object classes from a background class by sliding a window over the whole image with a given stride and on multiple scales and aspect ratios predicting the class label for every single window. In practice, this demands the classification of more than a million windows for common images, resulting in a trade-off between run-time performance and classification accuracy for real-time applications.

Recent years have seen a paradigm shift in object-detection systems replacing the sliding window step with objectproposal algorithms prior to classification (Girshick et al., 2014; Szegedy et al., 2014b; Cinbis et al., 2013; Wang et al., 2013; He et al., 2014). These algorithms propose regions in an image which are predicted to contain the objects of interest with high likelihood. Such an approach not only reduces the number of regions which have to be classified from a million to a few thousands but also allows for spanning across a larger range of scales and aspect ratios for regions of interest. Depending on the execution time of the proposal method and the classifier, the reduction of regions for classification can lead to a significantly faster run time and allow the use of more sophisticated classifiers.

Frameworks with region proposal methods and subsequent classification which are based on Convolutional Neural Networks (Girshick et al., 2014) achieve state-of-the-art performance on the ImageNet (Deng et al., 2009) detection. A popular pipeline consists of three main steps: (i) several regions that are likely to be objects are generated by a proposal algorithm; (ii) deep CNNs with multi-way Softmax or Support Vector Machines (SVMs) on the top

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classify these regions in order to detect all possible classes and instances per image; (iii) finally, an optional regression step further refines the location of the detected objects.

A large body of work of region proposal algorithms exists (Hosang et al., 2014). The majority of them are engineered to merge different segmentation, saliency and appearance cues, and some hierarchical scheme, with parameters tuned to specific datasets. Here we propose a data-driven regionproposal method which is based on features extracted directly from lower convolutional layers of a CNN. We use a fast binary boosting framework (Appel et al., 2013) to predict the objectness of regions, and finally deploy a regressor which uses features from the upper convolutional layer after pooling to refine the localization. The proposed framework achieves the top recall rate on ImageNet 2013 detection for Intersection over Union (IoU) localization between 50 - 65%. Finally, we apply our proposal algorithm instead of Selective Search in the baseline Regions-with-CNN pipeline (Girshick et al., 2014) resulting in 8% improvement over the state-of-the-art with a single prediction model while achieving considerably faster test time.

In the two following subsections we briefly review region proposal algorithms and present the motivation behind our work. In Section 2 we present the details of our algorithm and in Section 3 we show the experimental study and results. In Section 4, we place our algorithm in line with the Regions-with-CNN framework and benchmark its performance on the ImageNet 2013 detection challenge. Finally, in Section 5 we state our conclusions and point out directions for future research.

1.1. Prior work

Most currently leading frameworks use various segmentation methods and engineered cues in hierarchical algorithms to merge smaller areas (e.g., superpixels) to larger ones. During this hierarchical process boxes which likely are objects are proposed. In turn CNNs are applied as region descriptors, whose receptive fields are rectangular. This relaxes the need to perform accurate segmentation. Instead a rectangle around regions that are most probably objects is sufficient.

We briefly review some representative methods which are evaluated in detail in (Hosang et al., 2014).

Selective Search (Uijlings et al., 2013), which is currently the most popular algorithm, involves no learning. Its features and score functions are carefully engineered on Pascal VOC and ILSVRC so that low-level superpixels (Felzenszwalb & Huttenlocher, 2004) are gradually merged to represent high-level objects in a greedy fashion. It achieves very high localization accuracy due to the initial oversegmentation at a time overhead. *RandomizedPrim's* (Manen et al., 2013) is similar to Selective Search in terms of features and the process of merging superpixels. However, the weights of the merging function are learned and the whole merging process is randomized.

Then there is a family of algorithms which invest significant time in a good high-level segmentation. *Constrained Parametric Min-Cuts (CPMC)* (Carreira & Sminchisescu, 2012) generates a set of overlapping segments. Each proposal segment is the solution of a binary segmentation problem. Up to 10,000 segments are generated per image, which are subsequently ranked by objectness using a trained regressor. (Rantalankila et al., 2014), similar in principle to (Uijlings et al., 2013) and (Carreira & Sminchisescu, 2012), merges a large pool of features in a hierarchical way starting from superpixels. It generates several segments via seeds like CPMC does.

(Endres & Hoiem, 2010; 2014) combine a large set of cues and deploy a hierarchical segmentation scheme. Additionally, they learn a regressor to estimate boundaries between surfaces with different orientations. They use graph cuts with different seeds and parameters to generate diverse segments similar to CPMC. *Multiscale Combinatorial Grouping (MCG)* (Arbeláez et al., 2014) combines efficient normalized cuts and CPMC (Carreira & Sminchisescu, 2012) and achieves competitive results within a reasonable time budget.

In the literature several methods which engineer objectness have been proposed in the past. *Objectness* (Alexe et al., 2012) was one of the first to be published, although its performance is inferior to most modern algorithms (Hosang et al., 2014). Objectness estimates a score based on a combination of multiple cues such as saliency, colour contrast, edge density, location and size statistics, and the overlap of proposed regions with superpixels. (Rahtu et al., 2011) improves Objectness by proposing new cues and combine them more effectively.

Moreover, fast algorithms with approximate detection have been recently introduced. *Binarized Normed Gradients for Objectness (BING)* (Cheng et al., 2014) is a simple linear classifier over edge features and is used in a sliding window manner. In stark contrast to most other methods, BING takes on average only 0.2s per image on CPU. *EdgeBoxes* (Zitnick & Dollár, 2014) is similar in spirit to BING. A scoring function is evaluated in a sliding window manner, with object boundary estimates and features which are obtained via structured decision forests.

Given that engineering an algorithm for specific data is not always a desired strategy, there are recent region-proposal algorithms which are data-driven. Data-driven Objectness (Kang et al., 2014) is a practical method, where the likelihood of an image corresponding to a scene object is estimated through comparisons with large collections of example object patches. This method can prove very effective when the notion of object is not well defined through topology and appearance, such as daily activities.

A contemporary work which follows the data-driven path is Scalable, High-quality object detection (Szegedy et al., 2014b). After they revisited their Multibox algorithm (Erhan et al., 2014), they are able to integrate region proposals and classification in one step end-to-end. By deploying an ensemble of models with robust loss function and their newly introduced *contextual features*, they achieve stateof-the-art performance on the detection task.

1.2. Motivation

Recent top-performing approaches on ILSVRC detection are based on hand-crafted methods for region proposals, such as Selective Search (Uijlings et al., 2013). However, although these methods are tuned on this benchmark, they miss several objects. For example, Selective Search proposes on average 2, 403 regions per image in (Girshick et al., 2014) with 91.6% recall of ground truth objects (for 0.5 IoU threshold). In that case, even with *oracle* classification and subsequent localization, more than 8% of object instances will not be detected. This leaves significant room for improvement in future algorithms.

Furthermore, algorithms which build on superpixels can be unstable even for slight image perturbations resulting in low generalizations (Hosang et al., 2014) on different data.

Object proposal algorithms which are based on low-level cues are agnostic on how a learned network perceives the class of objects in the space of natural images. A CNN which is trained in a supervised manner to recognize 1000 object categories on ILSVRC, has learned a rich set of representations to identify local parts and hierarchically merge them toward certain class instances at the top layers. As opposed to Segmentation-based methods which merge segments based on simple binary criteria like existence of boundaries and color or not, CNN features ideally span the manifold of natural images which is a very small subspace inside a high dimensional feature space.

In practice, Selective Search is not scale-invariant. Nevertheless, it is engineered to work well on ILSVRC and Pascal VOC data with careful parameter tuning. To this end, Regions with CNN (Girshick et al., 2014) resizes all images to a width of 500 pixels to serve its purpose. However, a data-driven algorithm which is not constrained to build on superpixels bypasses this step.

Regions with CNN uses a linear regressor after classifying the proposed regions to better localize the bounding boxes around the object. For this purpose they deploy *pool-5* CNN features. This techinque can be applied to proposals in the first place. Of course, class-specific regressors are applicable only after classification, but neverthess generic object regressors can also enhance region localization.

All in all, the motivation of this work is to address the conceptual discontinuity between the object proposal method and the subsequent classification. Using hand-crafted scores in the proposal stage and applying a convolutional neural network for classification results not only typically in slow run-time but also in the aforementioned instabilities. The key idea is to utilize the convolutional responses of a network whose weights are learned to recognize different object classes also for proposals. Finally, we formulate the problem with a boosting framework to guarantee fast execution time.

2. Algorithm

Detector: We are deploying a binary boosting framework to learn a classifier with desired output $y_i \in \{-1, 1\}$ for an image patch $i, i \in \{1, ..., N\}$, where 1 stands for *object* and -1 for *background*. The input samples x_i are feature vectors which describe an image patch i. The features x_i are a selected subset of convolutional responses $conv_j^{k_j}$ from a Proposal CNN (cf. Fig. 1), where j pertains to convolutional layer $j \in \{1, ..., L\}$ and k_j spans the number of feature maps for this layer (e.g., *alexNet* (Krizhevsky et al., 2012) uses L = 5 and $k_1 \in \{1, ..., 96\}$). Our Proposal CNN is the *VGGs* model from (Chatfield et al., 2014), whose first-layer convolutional responses are 110×110 pixels, and therefore provides double resolution compared to alexNet.

Aggregate-channel features from (Dollár et al., 2009) are used, where deep convolutional responses serve the role of channels, while we deploy a modified version of the fast setting provided by (Appel et al., 2013). Thus, efficient AdaBoost is used to train and combine 2,048 depth-two trees over the $d \times d \times F$ candidate features (channel pixel lookups), where d is the baseline classifier's size and Fis the number of convolutional responses, i.e., the patch descriptors (e.g., VGGs architecture has F = 96 kernels in the first layer). The convolutional responses from all positive and negative patches which are extracted from the training set are rescaled to a fixed $d \times d$ size (e.g. d = 25) before they serve as input to the classifier. In practice, classifiers with various d can be trained to capture different resolutions of these representations. On testing all classifiers are applied to the raw image and their detections are aggregated and non-maximally suppressed jointly.

Hierarchical features: In order to evaluate *objectness* in different patches, we train the classifier with several positive and negative samples, which are extracted from Pascal 2007 VOC (Everingham et al., 2010). Positive samples



Figure 1. Proposed object detection framework based on boosting hierarchical features. Regions which correspond to objects and background patches are extracted from training images. Then the convolutional responses from first layers of a Proposal CNN are used to describe these patches. These are the input to a boosting model which differentiates object proposals from background. Finally a Category CNN is employed to classify the proposals from the Boosting classifier into object categories.

are the ones that correspond to the ground truth annotated objects, while negatives are defined as rectangular samples randomly extracted from the training set at different scales and aspect ratios, which have less than 0.3 Intersection over Union overlap with the positives. For our experiments we considered patches sampled from the validation sets of VOC 2007 and ImageNet 2013 detection datasets, since both of them are exhaustively annotated¹. Naturally there is a margin for improvement with more sophisticated sampling, given that the VOC and ILSVRC categories do not include all possible object classes that can appear in an image.

In order to properly crop the objects from the convolutional responses along the hierarchy, the image level annotations have to be mapped to the corresponding regions from the intermediate representations effectively. Therefore, the supports of pooling and convolutional kernels determine a band within the rectangular box which has to be cropped out, so that information outside the object's area can be safely ignored. In practice after two pooling stages the area that should be cropped without including too much background information becomes very narrow. In our experiments we consider filter responses from the first two layers. We have found that using only kernels from the first convolutional layer, before any spatial pooling is applied, gives the best performance.

Most first-layer kernels resemble anisotropic Gaussians and color blobs (cf. Fig. 1). As a matter of fact our method relates to BING and EdgeBoxes, which use edge features, and methods that use scores which account for color similarity (e.g., Selective Search). By inspecting the convolutional responses of the first layer, we observe that some kernels are able to capture the texture of certain objects and thus *disentangle* them from the background and the other objects (such as the first and third kernels at Fig. 2). This family of features provides quick detection, as the timeconsuming high-level segmentation is avoided. However, it has the drawback that local information from lower layers cannot naturally compose non-rigid high-level objects. Nevertheless, a subsequent regression step which leverages features from the upper convolutional layers can help with these cases. This is described at a following paragraph.

¹This means that all object instances belonging to C classes are fully annotated (C = 20 for Pascal, and C = 200 for ImageNet data), which prevents us from extracting supposedly negative samples which actually correspond to objects.



Figure 2. An image from Pascal VOC (Everingham et al., 2010) and its convolutional responses with representative first-layer filters. In order to classify object candidates a binary boosting framework is trained with positive (green) and negative (red) samples which are extracted from CNN's lower layers.

Testing: In order to detect objects in previously unseen images we apply the learned classifier in a sliding window manner densely in S different scales and R aspect ratios. We typically sample S = 12 scales and R = 3 aspect ratios. Non-maximum suppression (NMS) is used to reject detections with more than U Intersection over Union overlap for every (scale, aspect ratio) combination. Finally, after detections from all scales and aspect ratios are aggregated, another joint NMS with V IoU is applied. We experimented with different parameters and we use U = 63%and V = 90% in our reported results in Fig. 3.

Bounding-Box Regression: After extracting the proposals per image, a subsequent regression step can be deployed to refine their localization. As proposed by (Girshick et al., 2014), a linear regressor is used with regularization constant $\lambda = 1,000$. For training we use all ground truth annotations G^i and our best detection P^i per ground truth for all training images $i, i \in \{1, ..., N\}$ from Pascal VOC 2007. The best detection is defined as the one with the highest overlap with the ground truth. We throw away pairs with less than 70% IoU overlap. The goal of the regressor is to learn how to shift the locations of P towards G given the description of detected bounding box ϕ . The transformations are modeled as linear functions of $pool_5$ features, which are obtained by forward propagating the P regions through the Proposal CNN.

3. Experiments

In order to test the efficacy and performance of our algorithm we performed experiments on data from the ImageNet 2013 detection challenge² (Deng et al., 2009). We follow the approach proposed in the review paper of (Hosang et al., 2014) and we report the obtained performance vs. localization accuracy (Fig. 3) and number of candidates per image (Fig. 4). Specifically, we calculate the recall of ground truth objects for various localization thresholds using the Intersection-over-Union (IoU) criterion, which is the standard metric on Pascal VOC. In Fig. 3 we demonstate our performance compared to stateof-the-art methods and three baselines, as they have been evaluated by (Hosang et al., 2014). Each algorithm is allowed to propose up to 10,000 regions per image on average. The methods are sorted based on the Area-Under-the-Curve (AUC) metric, while in parentheses is the average number of proposed regions per image.

Recall vs. localization: Our method belongs to the family of algorithms with fast and approximate object detection, such as BING and EdgeBoxes. These algorithms provide higher recall rate but poorer localization as opposed to methods that use high-level segmentation cues like Selective Search. The latter ones are considerably slower but more accurate in localizing the objects due to boundary information. In Table 1 we provide the recall rate for varying localization accuracy via IoU criterion. Our method provides the highest recall until around 65% IoU overlap. We also provide in Fig. 3 and Table 1 the gain in performance when we jointly use Selective Search and our method while still constraining the number of proposals to be less than 10,000. In that case the benefit is mutual, as Selective Search provides better localization, while our algorithm higher recall, i.e, higher retrieval rate of ground truth objects for localization accuracy less than 65% IoU. A small subset of images have been blacklisted in the evaluation process per ILSVRC policy.

Time analysis: The complexity on testing is linear to each of the number of deployed classifiers, scales, aspect ratios, and image size, when the other parameters are held constant. In Table 1 an estimation of average time on testing is shown at the last column for our framework and others, as the latter ones have been evaluated by (Hosang et al., 2014). Our algorithm is quite efficient in both training and testing. More specifically, extracting convolutional responses for the validation image set of ImageNet 2013 detection benchmark takes only a few minutes with Caffe (Jia et al., 2014) on a modern machine (e.g., testing one image with a single K40 GPU takes 2ms) mainly because of time needed to save the features. However, this can be done of

²As opposed to the training set for both the boosting framework and the regressor, which is Pascal 2007 VOC.



Figure 3. Proposals quality on ImageNet 2013 validation set when at most 10,000 regions are proposed per image. On recall versus IoU threshold curves, the number indicates area under the curve (AUC), and the number in parenthesis is the obtained average number of proposals per image. Statistics of comparison methods come from (Hosang et al., 2014). Our curves are drawn dashed.

Recall (%) for various IoU thresholds	$IoU \ge 0.5$	$IoU \geq 0.65$	$IoU \ge 0.8$	Testing time (s)
Selective Search (Uijlings et al., 2013)	94.6	89.0	72.2	10
Randomized Prim (Manen et al., 2013)	92.3	82.0	61.2	1
MCG (Arbeláez et al., 2014)	91.8	81.0	60.6	30
Edge Boxes (Zitnick & Dollár, 2014)	93.1	86.6	49.7	0.3
Boosting Convolutional Features	98.1	89.4	38.7	2
Endres 2010 (Endres & Hoiem, 2010)	81.1	67.7	46.4	100
BING (Cheng et al., 2014)	95.5	43.0	7.2	0.2
Boosting Conv Features and Selective Search	97.7	91.9	75.3	12
Gaussian	85.3	72.5	51.3	0
Sliding window	90.8	56.9	14.1	0
Superpixels	51.3	26.7	10.0	1

Table 1. A comparison of our method with various category-independent object detectors on the Validation set of ImageNet2013 detection data. We compare in terms of recall of ground truth object annotations for various overlap thresholds. In order to be consistent with the literature, the strict Intersection-over-Union (IoU) Pascal VOC criterion is used. The methods are sorted according to the AUC, similarly to Fig. 3. In bold font the top-2 methods per IoU threshold. Representative testing times are shown at the last column.

fline for popular datasets. Training a modified version of boosting framework (Appel et al., 2013) which is now part of Dollar's Matlab toolbox (Dollár, 2013) on Pascal VOC 2007 data (train-val and test, i.e., 9,963 images with 24, 640 annotated objects) with a high-end multi-core CPU takes about three hours. This consists of training on all positives and 20k negatives, and additionally three rounds of bootstrapping, when at each round 20k more negatives are extracted among classifier's false positives. The training time increases for larger values of baseline detector's size, such as d = 40. But this still does not affect the testing time.

When testing the learned classifier is applied densely in sliding window fashion on 20, 121 validation images from ImageNet detection. All possible windows in S = 12 different scales and R = 3 different aspect ratios are evaluated by the classifier, which outputs for each window its confidence to be an object. Greedy non-maximal suppression is performed, where bounding boxes are processed in order of decreasing confidence, and once a box is suppressed it can no longer suppress other boxes. Separate and joint NMS are deployed with U = 63% and V = 90% IoU thresholds, correspondingly. Testing on a multi-core CPU takes about 2s per image.

In Fig. 4 we show performance comparisons in terms of at least 50% IoU recall for different number of proposed regions. Our scheme is the most effective when at least 1,000 regions are proposed. For a smaller number of proposals the performance degrades fast. This is mainly because of significant non-maximal suppression that is applied to reduce the number of proposals, while starting from a large number of scales and aspect ratios. In practice a more sophisticated design for less proposals can improve the recall rate further especially in [100 - 1,000] region. For small number of candidates an alternative strategy could be to deploy regression to cluster neighboring regions in unique detection, instead of using non-maximum suppression.

4. ImageNet detection challenge

In order to investigate in practice how the recalllocalization trade-off affects the effectiveness of the object candidates on a detection task, we put the challenge to the test and evaluate the overall performance on ImageNet 2013 benchmark. We introduce our algorithm into Regions-with-CNN detection framework (Girshick et al., 2014) by replacing Selective Search (Uijlings et al., 2013) and proposing our regions instead at the first step.

In Table 2 we show the mean and median average precision on a subset of validation set. We use the $\{val1, val2\}$ split as was performed by (Girshick et al., 2014). We use their pretrained CNN and SVM models as category CNN, which are trained on $\{val_1, train_{1k}\}$, i.e., 9,887 validation



Figure 4. Proposals quality on ImageNet 2013 validation set in terms of detected objects with at least 50% IoU for various average number of candidates per image. Compared to all other methods from (Hosang et al., 2014), our method is the most effective in terms of ground truth object retrieval when at least 1,000 regions are proposed and accurate localization is not a major concern.

images and 1,000 ground truth positives per class from c lassification set. The deployed Proposal CNN is the *VGGs* model from (Chatfield et al., 2014), which is pretrained on ILSVRC2012 classification dataset. Given that Selective Search is not scale-invariant, all images are rescaled to have 900 pixels width while preserving the aspect ratio. Thus, Selective Search proposes on average 5, 826 regions per image. In (Girshick et al., 2014) all images are rescaled to have 500 pixels width, which yields 29.7 and 29.2 mean and median AP for 2, 403 regions on average. For our method we used the model that we demonstrate in Figs. 3 and 4, which generates 9, 927 proposals on average.

Our improvement is a product of two factors; first, higher recall of ground truth objects within roughly 50 - 70%

Average Precision (AP)	Mean AP	Median AP
Selective Search	31.5	30.2
Boosting Deep Feats	34.0	32.5

Table 2. Mean and median average precision on ImageNet 2013 detection task. We deploy the state-of-the-art Regions with Convolutional Neural Networks (R-CNN). Comparison when regions are proposed by Selective Search and our method, correspondingly. There is no post-processing regression step.

IoU threshold and, second, a larger number of proposals. Coarse localization is corrected to some extent from subsequent steps of R-CNN due to the robustness of convolutional neural network in terms of object location and partial occlusion. Further improvement is expected if class-specific regression is introduced at the top of prediction, so that the detected bounding boxes are better located around the objects, which could prove to be especially helpful in our algorithm given that we leverage no boundary/segmentation cues. Finally, an ensemble of models along with more sophisticated architectures (e.g., GoogLeNet (Szegedy et al., 2014a), MSRA PReLU-nets (He et al., 2015), very-deep nets (Simonyan & Zisserman, 2014), etc.) could further improve our results.

5. Discussion

Features learned in convolutional neural networks have been proven to be very discriminative in recognizing objects in natural images by mapping them on small manifolds of a very higher-dimensional feature space. The boosting classifier learns to map image data points to the union of all these low-dimensional manifolds. We hypothesize that it is still a relatively small subspace, which preserves the notion of object and includes most instances that can be found in popular visual datasets such as Pascal VOC and ILSVRC.

In this paper we propose a framework which is able to benefit from the hierarchical and data-adaptive features extracted from a convolutional neural network, as well as from the quick training and test time of state-of-the-art boosting algorithms. There are many directions to explore this idea further: in this paper the feature responses extracted from different layers have equal weight during training, but exploiting the hierarchy in a top-down fashion might result in faster and more accurate predictions. Additionally, a data-driven regression mechanism which captures gradient information could improve the localization of regions proposed by our framework.

Our framework can also be applied to other areas, such as medical imaging, text detection and planetary science. Hand-engineering proposal detectors is quite challenging, as we need to come up with new similarity metrics, saliency and segmentation cues. However, instead of designing score functions and features from scratch for each new domain, learned deep convolutional features can be used, after a network has been trained on a sufficiently large and representative sample of related data. Finally, non-linear tree-based classifiers like boosting or random forests can provide a framework for fast inference, while avoiding the overhead of complete propagation in deep neural networks and at the same time being flexible to opt for a subset of actionable features for the task.

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