Improving the robustness of ImageNet classifiers using elements of human visual cognition

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Abstract

We investigate the robustness properties of image recognition models equipped with two features inspired by human vision, an explicit episodic memory and a shape bias, at the ImageNet scale. As reported in previous work, we show that an explicit episodic memory improves the robustness of image recognition models against small-norm adversarial perturbations under some threat models. It does not, however, improve the robustness against more natural, and typically larger, perturbations. Learning more robust features during training appears to be necessary for robustness in this second sense. We show that features derived from a model that was encouraged to learn global, shape-based representations (Geirhos et al., 2019) do not only improve the robustness against natural perturbations, but when used in conjunction with an episodic memory, they also provide additional robustness against adversarial perturbations. Finally, we address three important design choices for the episodic memory: memory size, dimensionality of the memories and the retrieval method. We show that to make the episodic memory more compact, it is preferable to reduce the number of memories by clustering them, instead of reducing their dimensionality.

1   Introduction

ImageNet-trained deep neural networks (DNNs) are state of the art models for a range of computer vision tasks and are currently also the best models of the human visual system and primate visual systems more generally [20]. Yet, they have serious deficiencies as models of human and primate visual systems: 1) they are extremely sensitive to small adversarial perturbations imperceptible to the human eye [22], 2) they are much more sensitive than humans to larger, more natural perturbations [6], 3) they rely heavily on local texture information in making their predictions, whereas humans rely much more on global shape information [7, 3], 4) a fine-grained, image-by-image analysis suggests that images that ImageNet-trained DNNs find hard to recognize do not match well with the images that humans find hard to recognize [16].

Here, we add a fifth under-appreciated deficiency: 5) human visual recognition has a strong episodic component lacking in DNNs. When we recognize a coffee mug, for instance, we do not just recognize it as *a* mug, but as *this particular* mug that we have seen before or as a novel mug that we have not seen before. This sense of familiarity/novelty comes automatically, involuntarily, even when we are not explicitly trying to judge the familiarity/novelty of an object we are seeing. More controlled psychological experiments also confirm this observation: humans have a phenomenally good long-term recognition memory with a massive capacity even in difficult one-shot settings [21, 2]. Standard deep vision models, on the other hand, cannot perform this kind of familiarity/novelty computation naturally or automatically, since this information is available to a trained model only indirectly and implicitly in its parameters.

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What does it take to address these deficiencies and what are the potential benefits, if any, of doing so other than making the models more human-like in their behavior? In this paper, we address these questions. We show that a minimal model incorporating an explicit key-value based episodic memory does not only make it psychologically more realistic, but also reduces the sensitivity to small adversarial perturbations. It does not, however, reduce the sensitivity to larger, more natural perturbations and it does not address the heavy local texture reliance issue. In the episodic memory, using features from DNNs that were trained to learn more global shape-based representations [7] addresses these remaining issues and moreover provides additional robustness against adversarial perturbations. Together, these results suggest that two basic ideas motivated and inspired by human vision, a strong episodic memory and a shape bias, can make image recognition models more robust to both natural and adversarial perturbations at the ImageNet scale.

2   Related work

In this section, we review previous work most closely related to ours and summarize our own contributions.

To our knowledge, the idea of using an episodic cache memory to improve the adversarial robustness of image classifiers was first proposed in [24] and [15]. [24] considered a differentiable memory that was trained end-to-end with the rest of the model. This makes their model computationally much more expensive than the cache models considered here, where the cache uses pre-trained features instead. The deep k-nearest neighbor model in [15] and the "CacheOnly" model described in [14] are closer to our cache models in this respect, however these works did not consider models at the ImageNet scale. More recently, [4] did consider cache models at the ImageNet scale (and beyond) and demonstrated substantial improvements in adversarial robustness under certain threat models.

None of these earlier papers addressed the important problem of robustness to natural perturbations and they did not investigate the effects of various cache design choices, such as the retrieval method (i.e. a continuous cache vs. nearest neighbor retrieval), cache size, dimensionality of the keys or the feature type used (e.g. texture-based vs. shape-based features), on the robustness properties of the cache model.

A different line of recent work addressed the question of robustness to natural perturbations in ImageNet-trained DNNs. In well-controlled psychophysical experiments with human subjects, Geirhos and colleagues [6] compared the sensitivity of humans and ImageNet-trained DNNs to several different types of natural distortions and perturbations, such as changes in contrast, color or spatial frequency content of images, image rotations etc. They found that ImageNet-trained DNNs are much more sensitive to such perturbations than human subjects. More recently, Hendrycks and Dietterich [11] introduced the ImageNet-C and ImageNet-P benchmarks to measure the robustness of neural networks against some common perturbations and corruptions that are likely to occur in the real world. [7]. We use the ImageNet-C benchmark below to measure the robustness of different models against natural perturbations.

This second line of work, however, did not address the question of adversarial robustness. An adequate model of the human visual system should be robust to both natural and adversarial perturbations.[1] Moreover, both properties are clearly desirable properties in practical image recognition systems, independent of their value in building more adequate models of the human visual system.

Our main contributions in this paper are as follows: 1) as reported in previous work [24, 15, 14, 4], we show that an explicit cache memory improves the adversarial robustness of image recognition models at the ImageNet scale; 2) we investigate the effects of various design choices for the cache memory, such as the retrieval method, cache size, dimensionality of the keys and the feature type; 3) we show that caching, by itself, does not improve the robustness of classifiers against natural perturbations; 4) using more global, shape-based features [7] in the cache does not only improve robustness against natural perturbations, but also provides extra robustness against adversarial perturbations as well.[2]

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[1] Two recent papers [5, 25] suggested that humans might be vulnerable, or at least sensitive, to adversarial perturbations too. However, these results apply only in very limited experimental settings (e.g. very short viewing times in [5]) and require relatively large and transferable perturbations, which often tend to yield meaningful features resembling the target class.

[2] Code for reproducing the results is available at: `https://github.com/eminorhan/robust-vision`

3 Methods

3.1 Models

Throughout the paper, we use pre-trained ResNet-50 models either on their own or as feature extractors (or "backbones") to build cache models that incorporate an explicit episodic memory storing low-dimensional embeddings (or keys) for all images seen during training [14]. The cache models in this paper are essentially identical to the "CacheOnly" models described in [14]. A schematic diagram of a cache model is shown in Figure 1.

We used one of the higher layers of a pre-trained ResNet-50 model as an embedding layer. Let $\phi(\mathbf{x})$ denote the d-dimensional embedding of an image $\mathbf{x}$ into this layer. The cache was a key-value dictionary consisting of the keys $\mu_k \equiv \phi(\mathbf{x}_k)$ for each training image $\mathbf{x}_k$ and the values are the corresponding class labels represented as one-hot vectors v_k. We normalized all keys to have unit l_2-norm.

When a new test image $\mathbf{x}$ is presented, the similarity between its key and all other keys in the cache was computed through:

$$\sigma_k(\mathbf{x}) \propto \exp(\theta\phi(\mathbf{x})^\top \mu_k) \qquad (1)$$

A distribution over labels was obtained by taking a weighted average of the values stored in the cache:

$$p_{\text{cache}}(\mathbf{y}|\mathbf{x}) = \frac{\sum_{k=1}^{K} v_k \sigma_k(\mathbf{x})}{\sum_{k=1}^{K} \sigma_k(\mathbf{x})} \qquad (2)$$

where K denotes the number of items stored in the cache. The hyper-parameter θ in Equation 1 controls the sharpness of this distribution, with larger θ values producing sharper distributions. We optimized θ only in one of the experimental conditions below (the gray-box adversarial setting) by searching over 9 uniformly spaced values between 10 and 90 and fixed its value for all other conditions.

Because we take all items in the cache into account in Equation 2, weighted by their similarity to the test item, we call this type of cache a *continuous cache* [10].
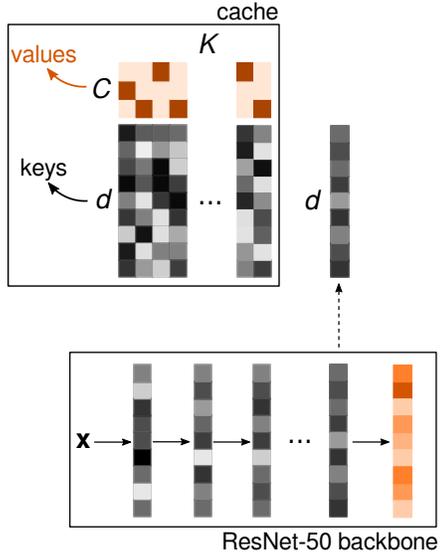

Figure 1: Schematic illustration of the cache model. The key for a new image $\mathbf{x}$ is compared with the keys in the cache. A prediction is made by a linear combination of the values weighted by the similarity to the corresponding keys.

An alternative (and more scalable) approach would be to perform a nearest neighbor search in the cache and consider only the most similar items in making predictions [9, 4]. We compare the relative performance of these two approaches below.

For the embedding layer, we considered four choices in descending order (using the layer names from the `keras.applications` implementation of ResNet-50): `fc1000`, `avg_pool`, `activation_46`, `activation_43`. `fc1000` corresponds to the final softmax layer (post-nonlinearity), `avg_pool` corresponds to the global average pooling layer right before the final layer and `activation_46`, `activation_43` are the final layers of the preceding two bottleneck layers respectively. The latter two are $7 \times 7 \times 2048$-dimensional spatial layers (unlike [4], we used post-relu activations) and we applied a global spatial average pooling operation to these layers to reduce their dimensionality. This gave rise to $d = 1000$ dimensional keys for `fc1000` and $d = 2048$ dimensional keys for the other three layers.

To investigate the effect of different feature types on the robustness of the models, we also considered a ResNet-50 model jointly trained on ImageNet and Stylized-ImageNet datasets and then fine-tuned on ImageNet [7] (we used the pre-trained model provided by the authors). Following [7], we call this model Shape-ResNet-50. Geirhos et al. [7] argue that Shape-ResNet-50 learns more global, shape-based representations than a standard ImageNet-trained ResNet-50 (which instead relies more heavily on local texture) and produces predictions more in line with human judgments in texture vs. shape cue conflict experiments.

All experiments were conducted on the ImageNet dataset containing approximately 1.28M training images from 1000 classes and 50K validation images [18]. We note that using the full cache (i.e. a continuous cache) was computationally feasible in our experiments at the ImageNet scale. The largest cache we used (of size 1.28M × 2048) takes up ∼ 10.5GB of disk space when stored as a single-precision floating-point array.

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3.2 Perturbations

Ideally, we want our image recognition models to be robust against both adversarial perturbations and more natural perturbations. This subsection describes the details of the natural and adversarial perturbations considered in this paper.

3.2.1 Adversarial perturbations

Our experiments on adversarial perturbations closely followed the experimental settings described in [4]. In particular, we considered three different threat models: white-box attacks, gray-box attacks, and black-box attacks.

White-box attacks In this scenario, the attacker has full knowledge of the model and the training data the model was trained on.

Gray-box attacks The attacker only has access to the backbone model, but does not know the training data the model was trained on. In practice, for the cache models, the gray-box scenario corresponds to running white-box attacks against the backbone model and testing the resulting adversarial examples on the cache model.

Black-box attacks This is the least restrictive attack scenario where the attacker is not assumed to have access to the model or the training data. For the cache models, the black-box scenario corresponds to running white-box attacks against a model different from the model used as the backbone and testing the resulting adversarial examples on the cache model as well as on the backbone itself. In practice, we used an ImageNet-trained ResNet-18 model to generate adversarial examples in this setting (note that we always use a ResNet-50 backbone in our models).

We chose a strong, state-of-the-art, gradient-based attack method called projected gradient descent (PGD) with random starts [13] to generate adversarial examples in all three settings. We used the Foolbox implementation of this attack [17], `RandomStartProjectedGradientDescentAttack`, with the following attack parameters: `binary_search=False`, `stepsize=2/225`, `iterations=10`, `random_start=True`. We also controlled the total size of the adversarial perturbation as measured by the l_2-norm of the perturbation normalized by the l_2-norm of the clean image $\mathbf{x}$: $\epsilon \equiv ||\mathbf{x}_{\mathrm{adv}} - \mathbf{x}||/||\mathbf{x}||$. We considered six different ϵ values: 0.01, 0.02, 0.04, 0.06, 0.08, 0.1. In general, the attacks are expected to be more successful for larger ϵ values.

As recommended by [1], we used targeted attacks, where for each validation image we first chose a target class label different from the correct class label for the image and then ran the attack to return an image that was misclassified as belonging to the target class. In cases where the attack was not successful, the original clean image was returned, therefore the model had the same baseline accuracy on such failure cases as on clean images.

Due to its high computational cost, we ran only 150 trials in the white-box setting with the ResNet-50 based cache models and 1000 trials in the white-box setting with the Shape-ResNet-50 based cache models, starting from a randomly sampled validation image in each trial. In all other settings, we ran attacks starting from all validation images.

3.2.2 Natural perturbations

To measure the robustness of image recognition models against natural perturbations, we used the recently introduced ImageNet-C benchmark [11]. ImageNet-C contains 15 different natural perturbations applied to each image in the ImageNet validation set at 5 different severity levels, for a total of $15 \times 5 \times 50\mathrm{K} = 3.75\mathrm{M}$ images. The perturbations in ImageNet-C come in four different categories: 1) *noise* perturbations (Gaussian, shot, and impulse noise), 2) *blur* perturbations (defocus, glass, motion, and zoom blur), 3) *weather* perturbations (snow, frost, fog, and brightness), and 4) *digital* perturbations (contrast, elasticity, pixelation, and JPEG compression). We refer the reader to [11] for further details about the dataset.

To measure the robustness of a model against the perturbations in ImageNet-C, we use the *mCE* (mean corruption error) measure [11]. A model's *mCE* is calculated as follows. For each perturbation c, we first average the model's classification error over the 5 different severity levels s and divide the result by the average error of a reference classifier (which is taken to be the AlexNet): $CE_c \equiv \langle E_{s,c} \rangle_s / \langle E_{s,c}^{\mathrm{AlexNet}} \rangle_s$. The overall performance on ImageNet-C is then measured by the mean CE_c averaged over the 15 different perturbation types c: $mCE \equiv \langle CE_c \rangle_c$. Dividing by the performance of a reference model in calculating CE_c ensures that different perturbations have roughly similar sized contributions to the overall measure mCE. Note that smaller mCE values indicate more robust classifiers.
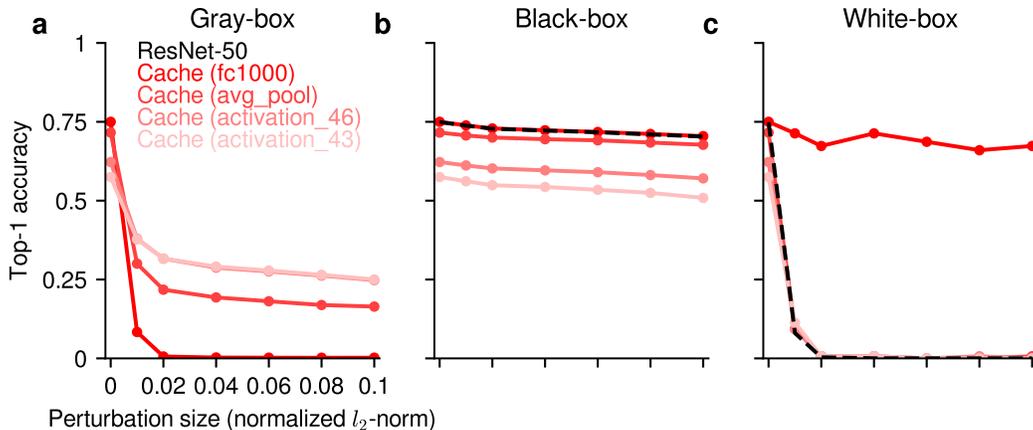
Figure 2: Top-1 accuracy of the ResNet-50 backbone and cache models in the (**a**) gray-box, (**b**) black-box and (**c**) white-box adversarial settings. The 0 perturbation size corresponds to the clean images. Note that the gray-box setting is not well-defined for the ResNet-50 model, since it is used as the backbone.

Table 1: Clean and adversarial accuracies of texture- and shape-based ResNet-50 backbones and cache models. The adversarial accuracies report the results for a standard normalized perturbation size of $\epsilon = 0.06$.

Model	Clean	Gray-box	Black-box	White-box
ResNet-50	0.749	–	0.717	0.003
Cache (`activation_46`, texture)	0.622	0.276	0.590	0.000
Shape-ResNet-50	0.741	–	0.702	0.004
Cache (`activation_46`, shape)	0.687	0.362	0.638	0.001

4 Results

4.1 Caching improves robustness against adversarial perturbations

Figure 2 shows the adversarial accuracy in the gray-box, black-box and white-box settings for cache models using different layers as embeddings. In the gray-box setting, the earlier layers (`activation_46` and `activation_43`) showed more robustness at the expense of a reduction in clean accuracy. In the black-box setting, we found that even large perturbation adversarial examples for the ResNet-18 model were not effective adversarial examples for the backbone ResNet-50 model (dashed line) or for the cache models, hence the models largely maintained their performance on clean images with a slight general decrease in accuracy for larger perturbation sizes.

In the white-box setting, we observed a divergence in behavior between `fc1000` and the other layers. The PGD attack was generally unsuccessful against the `fc1000` cache model, whereas for the other layers it was highly successful even for small perturbation sizes. The softmax non-linearity in `fc1000` was crucial for this effect, as it was substantially easier to run successful white-box attacks when logits were used as keys instead. We thus attribute this effect to gradient obfuscation in the `fc1000` cache model [1], rather than consider it as a real sign of adversarial robustness. Indeed, the gray-box adversarial examples (generated from the backbone ResNet-50 model) were very effective against the layer `fc1000` cache model (Figure 2a).

Qualitatively similar results were observed when Shape-ResNet-50 was used as the backbone instead of ResNet-50 (Figure 3). Table 1 reports the clean and adversarial accuracies for a subset of the conditions.
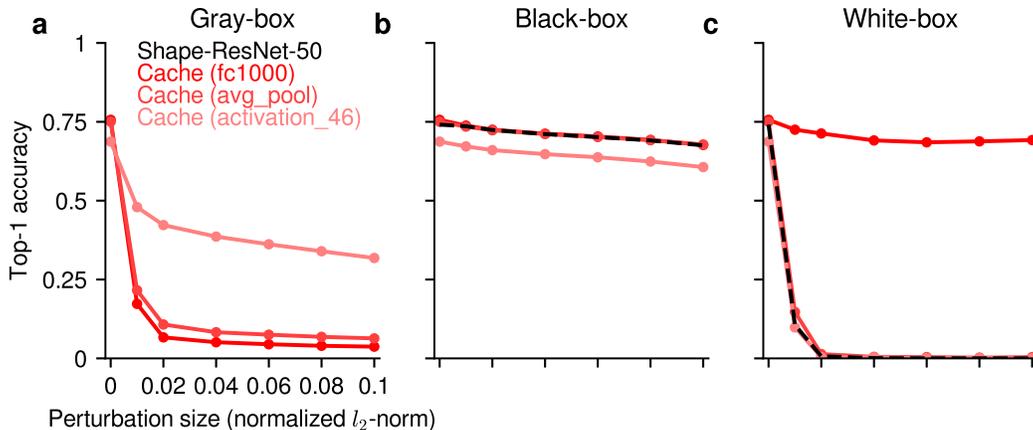
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Figure 3: Similar to Figure 2, but with Shape-ResNet-50 as the backbone.

Table 2: Clean and gray-box adversarial accuracies of different cache models. As in Figure 4, only the results for the `activation_46` layer are shown. Colors highlight the retrieval method (continuous or 50-nn), cache dimensionality (full, 4- or 8-times reduced), and cache size (full, 4- or 8-times reduced).

Model	Clean	Gray-box ($\epsilon = 0.06$)
Cache (continuous, full-dims., full-cache)	0.622	0.276
Cache (50-nn, full-dims., full-cache)	0.605	0.267
Cache (50-nn, full-dims., 1/4-cache)	0.570	0.223
Cache (50-nn, full-dims., 1/8-cache)	0.553	0.213
Cache (50-nn, 1/4-dims., full-cache)	0.524	0.170
Cache (50-nn, 1/8-dims., full-cache)	0.497	0.154

4.2 Cache design choices

In this subsection, we consider the effect of three cache design choices on the clean and adversarial accuracy of cache models: the size and dimensionality of the cache and the retrieval method.

Dubey et al. [4] recently investigated the adversarial robustness of cache models with very large databases (databases of up to $K = 50B$ items). Scaling up the cache model to very large databases requires making the cache memory as compact as possible and using a fast approximate nearest neighbor algorithm for retrieval from the cache (instead of using a continuous cache). There are at least two different ways of making the cache more compact: one can either reduce the number of items in the cache by clustering them, or alternatively one can reduce the dimensionality of the keys.

Dubey et al. [4] made the keys more compact by reducing the original 2048-dimensional embeddings to 256 dimensions (an 8-fold compression) with online PCA and used a fast 50-nearest neighbor (50-nn) method for retrieval.

In our experiments, replacing the continuous cache with a 50-nn retrieval method resulted in a small decrease in adversarial and clean accuracies (Figure 4 and Table 2). This suggests that the continuous cache can be safely replaced with an efficient nearest neighbor algorithm to scale up the cache size without much effect on the model accuracy.

On the other hand, reducing the dimensionality of the keys from 2048 to 256 using online PCA over the training set resulted in a substantial drop in both clean and adversarial accuracies (Figure 4 and Table 2). Even a 4-fold reduction to 512 dimensions resulted in a large drop in accuracy. This implies that the higher layers of the backbone used for caching are not very compressible and drastic dimensionality reduction measures should be avoided to prevent a substantial decrease in accuracy.

Reducing the cache size by the same amount (4-fold or 8-fold compression) by clustering the items in the cache with a mini-batch k-means algorithm resulted in a significantly smaller
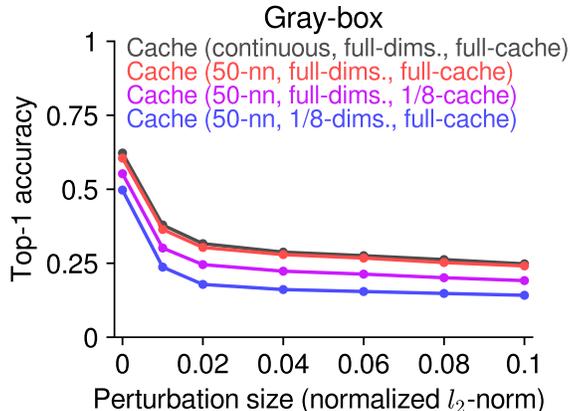
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Figure 4: The effects of three cache design choices on the clean and adversarial accuracy in the gray-box setting. The results shown here are for the `activation_46` layer. Similar results were observed for other layers.

Table 3: ImageNet-C results. The numbers indicate corruption errors (CE) for specific corruption types and the mean CE scores as percentages. More robust models correspond to smaller numbers. For the cache models, we only show the results for the best models (the `fc1000` cache model in both cases). Colors represent noise, blur, weather and digital perturbations.

Model	mCE	Gauss	Shot	Impul.	Defoc.	Glass	Motion	Zoom	Snow	Frost	Fog	Bright	Contr.	Elastic	Pixel	JPEG
ResNet-50	79.4	79	81	82	79	92	84	82	84	80	73	62	76	87	74	77
Cache (texture)	79.4	79	81	82	79	92	84	82	84	80	73	62	76	87	74	77
Shape-ResNet-50	75.4	73	75	75	75	89	78	80	77	76	68	59	70	83	76	75
Cache (shape)	75.5	73	75	75	75	89	78	80	77	76	68	59	70	84	77	76

decrease in accuracy (Figure 4 and Table 2): for example, an 8-fold reduction in dimensionality led to a clean accuracy of 49.7%, whereas an 8-fold reduction in the cache size instead resulted in a clean accuracy of 55.3%. This suggests that the cluster structure in the keys is more prominent than the linear correlation between the dimensions. Therefore, to make the cache more compact, given a choice between reducing the dimensionality vs. reducing the number of items by the same amount, it is preferable to choose the second option for better accuracy.

4.3 Caching does not improve robustness against natural perturbations

We have seen that caching can improve robustness against gray-box adversarial perturbations. Does it also improve robustness against more natural perturbations? Table 3 shows that the answer is no. On ImageNet-C, the backbone ResNet-50 model yields an mCE of 0.794. The best cache model obtained approximately the same mCE score. We suggest that this is because caching improves robustness only against small-norm perturbations, whereas natural perturbations in ImageNet-C are typically much larger (even the smallest size perturbations in ImageNet-C are clearly visible to the eye [11]). We conjecture that robustness against such large perturbations cannot be achieved with test-time only interventions such as caching and requires learning more robust backbone features in the first place.

4.4 Using shape-based features in the cache improves both adversarial and natural robustness

To investigate the effect of different kinds of features in the cache, we repeated our experiments using cache models with the Shape-ResNet-50 model as the backbone (see *Methods* for further details about Shape-ResNet-50). It has been argued that Shape-ResNet-50 learns more global, shape-based representations than a standard ImageNet-trained ResNet-50 and it has already been shown to improve robustness on the ImageNet-C benchmark [7]. We confirm
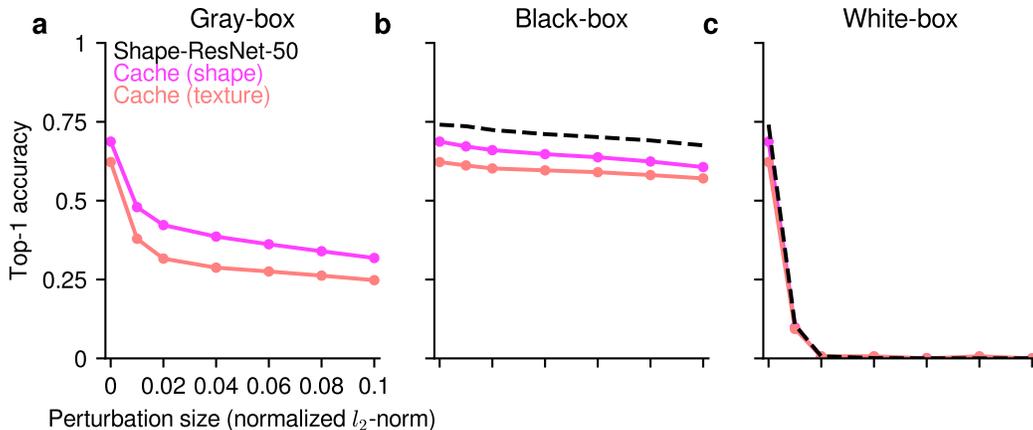
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Figure 5: The effect of using Shape-ResNet-50 (shape) vs. ResNet-50 (texture) derived features in the cache on clean and adversarial accuracies in the (**a**) gray-box, (**b**) black-box and (**c**) white-box settings. The results shown here are for the `activation_46` layer.

Table 4: Summary of our main results. This table is a distilled version of Tables 1 and 3. In each cell, the first number represents the adversarial accuracy (gray-box accuracy for cache models and white-box accuracy for cacheless models, both with $\epsilon = 0.06$); the second number represents the *mCE* score. Note that better models have higher accuracy and lower *mCE* score. Starting from a baseline model with no cache and no shape bias (bottom right), adding a cache memory (bottom left) only improves adversarial accuracy; adding a shape bias (top right) only improves natural robustness; adding both (top left) improves both natural and adversarial robustness with a synergistic improvement in the latter.

	Cache +		Cache -	
Shape bias +	**36.2%**	**75.5**	0.4%	**75.4**
Shape bias -	27.6%	79.4	0.3%	79.4

this improvement (Table 3; ResNet-50 vs. Shape-ResNet-50) and show that caching with Shape-ResNet-50 leads to roughly the same *mCE* as the backbone Shape-ResNet-50 itself.

Remarkably, however, when used in conjunction with caching, these Shape-ResNet-50 features also substantially improved the adversarial robustness of the cache models in the gray-box and black-box settings, compared to the ImageNet-trained ResNet-50 features. Figure 5 illustrates this for the `activation_46` cache model. This effect was more prominent for earlier layers.

5   Discussion

In this paper, we have shown that a combination of two basic ideas motivated by the cognitive psychology of human vision, an explicit cache-based episodic memory and a shape bias, improves the robustness of image recognition models against both natural and adversarial perturbations at the ImageNet scale. Caching alone improves (gray-box) adversarial robustness only, whereas a shape bias improves natural robustness only. In combination, they improve both, with a synergistic effect in adversarial robustness (Table 4).

Why does caching improve adversarial robustness? [14] suggested that caching acts as a regularizer. More specifically it was shown in [14] that caching significantly reduces the Jacobian norm at test points, which could explain its improved robustness against small-norm perturbations such as adversarial attacks. However, since Jacobian norm only measures local sensitivity, this does not guarantee improved robustness against larger perturbations, such as the natural perturbations in the ImageNet-C benchmark and indeed we have shown that caching, by itself, does not provide any improvement against such perturbations.

It should also be emphasized that caching improves adversarial robustness only under certain threat models. We have provided evidence for improved robustness in the gray-box setting only, [24] and [4] also provide evidence for improved robustness in the black-box setting. The results in [4] are particularly encouraging, since they suggest that the caching approach can scale up in the gray-box and black-box attack scenarios in the sense that larger cache sizes lead to more robust models. On the other hand, neither of these two earlier works, nor our own results point to any substantial improvement in adversarial robustness in the white-box setting at the ImageNet scale. The white-box setting is the most challenging setting for an adversarial defense. Theoretical results suggest that in terms of sample complexity, robustness in the white-box setting may be fundamentally more difficult than achieving high generalization accuracy in the standard sense [19, 8] and it seems unlikely that it can be feasibly achieved via test-time only interventions such as caching.

Why does a shape bias improve natural robustness? Natural perturbations modeled in ImageNet-C typically corrupt local information, but preserve global information such as shape. Therefore a model that can integrate information more effectively over long distances, for example by computing a global shape representation is expected to be more robust to such natural perturbations. In Shape-ResNet-50 [7], this was achieved by removing the local cues to class label in the training data. In principle, a similar effect can be achieved through architectural inductive biases as well. For example, [11] showed that the so-called feature aggregating architectures such as the ResNeXt architecture [23] are substantially more robust to natural perturbations than the ResNet architecture, suggesting that they are more effective at integrating local information into global representations. However, it remains to be seen whether such feature aggregating architectures accomplish this by computing a *shape* representation.

In this work, we have also provided important insights into several cache design choices. Scaling up the cache models to datasets substantially larger than ImageNet would require making the cache as compact as possible. Our results suggest that other things being equal, this should be done by clustering the keys rather than by reducing their dimensionality. For very large datasets, the continuous cache retrieval method that uses the entire cache in making predictions (Equations 1 and 2) can be safely replaced with an efficient k-nearest neighbor retrieval algorithm (e.g. Faiss [12]) without incurring a large cost in accuracy. Our results also highlight the importance of the backbone choice (for example, Shape-ResNet-50 vs. ResNet-50): in general, starting from a more robust backbone should make the cache more effective against both natural and adversarial perturbations.

In future work, we are interested in applications of naturally and adversarially robust features in few-shot recognition tasks and in modeling neural and behavioral data from humans and monkeys [20].

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