

# Image and AI

**ConvNets and humans are not biased towards the same information in images**

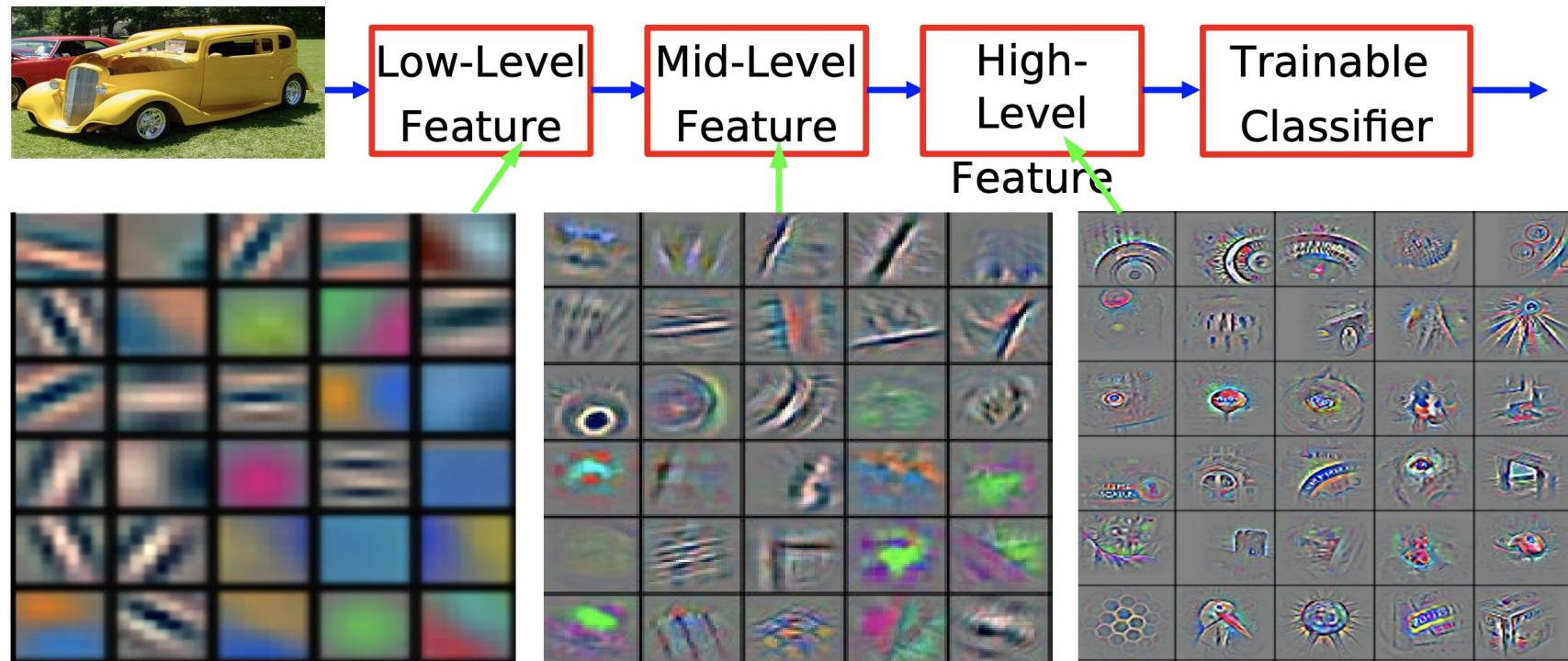
March 4, 2021

MARIE Alban

# What is learned by ConvNets to perform so well on images?

# What is learned by ConvNets to perform so well on images?

A common thought...



...from low to high level features, use of global objects shape

# Are humans looking at the same kind of features in images?

Not obvious at all...

# Are humans looking at the same kind of features in images?

Let's play a game! **Cat or elephant?**



# Are humans looking at the same kind of features in images?

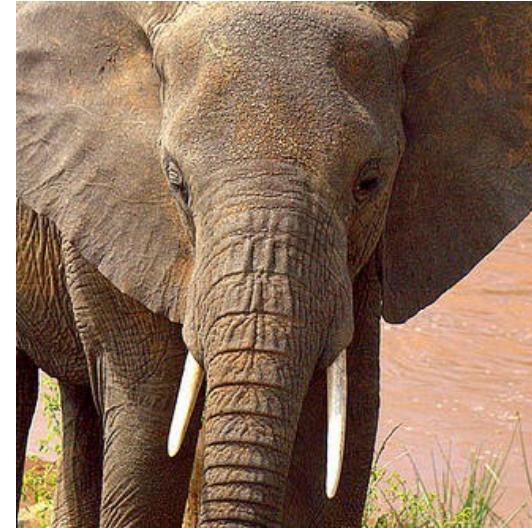
Let's play a game! **Cat or elephant?**



Huh... that's too easy  
what's the point of asking this?

# Are humans looking at the same kind of features in images?

Let's play a game! **Cat or elephant?**



# Are humans looking at the same kind of features in images?

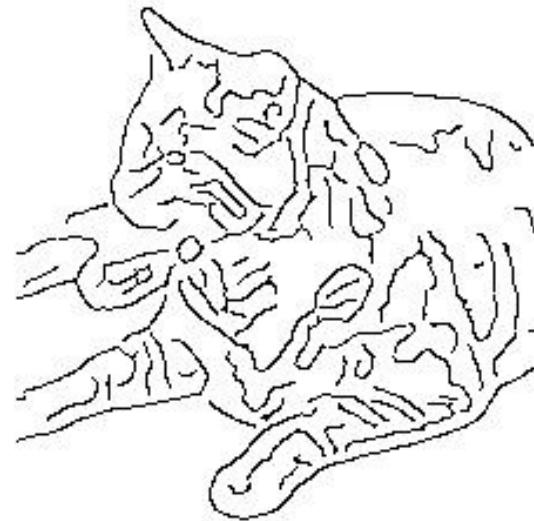
Let's play a game! **Cat or elephant?**



Will it ever become hard?

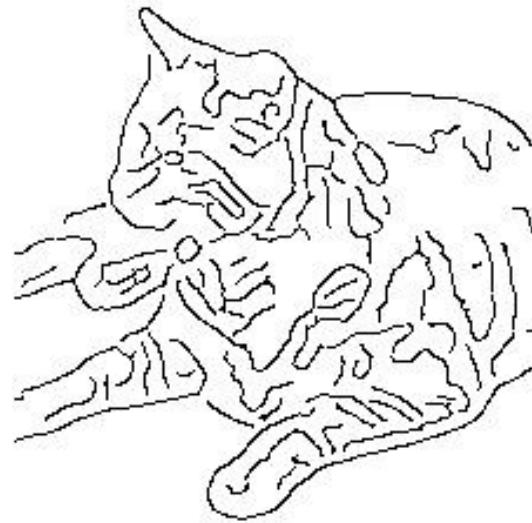
# Are humans looking at the same kind of features in images?

Let's play a game! **Cat or elephant?**



# Are humans looking at the same kind of features in images?

Let's play a game! **Cat or elephant?**



A cat I guess ?

# Are humans looking at the same kind of features in images?

Let's play a game! **Cat or elephant?**



# Are humans looking at the same kind of features in images?

Let's play a game! **Cat or elephant?**



Elephant skin!

# Are humans looking at the same kind of features in images?

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# Are humans looking at the same kind of features in images?

Let's play a game! **Cat or elephant?**



Well.  
It depends...

Ok cool. And what opinion ConvNets have on this?



(a) Texture image  
81.4% **Indian elephant**  
10.3% indri  
8.2% black swan



(b) Content image  
71.1% **tabby cat**  
17.3% grey fox  
3.3% Siamese cat



(c) Texture-shape cue conflict  
63.9% **Indian elephant**  
26.4% indri  
9.6% black swan

It looks like **ConvNets care about texture to answer.**

Accuracies given by a ResNet-50 classifier trained on ImageNet.

And what about humans?

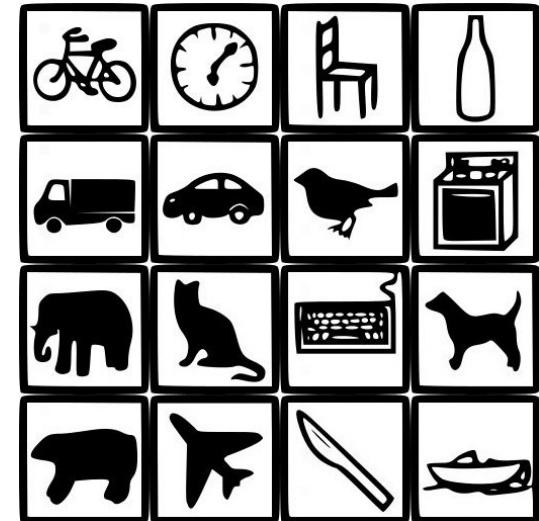
Does we mostly look at texture too?

→ Comparison between:

- **ConvNets**: AlexNet / GoogLeNet / VGG-16 / ResNet-50
- **Humans**

→ 16 classes classification [1] (using WordNet hierarchy)

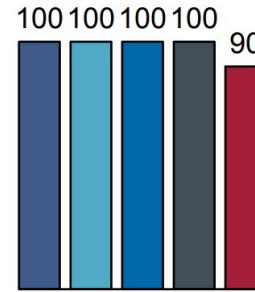
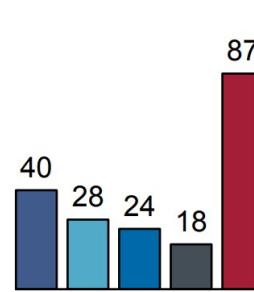
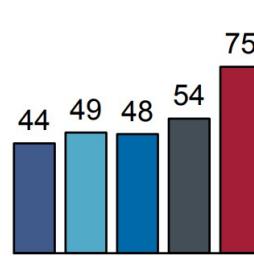
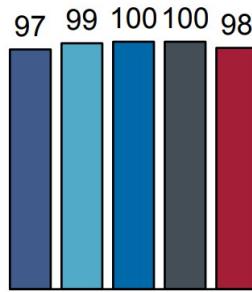
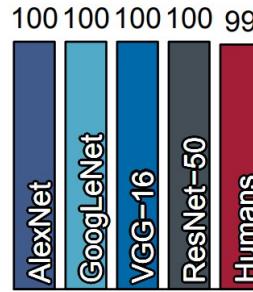
→ **Five experiments**: original, greyscale, silhouette, edges and texture images



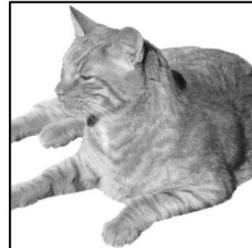
All 16 classes used for this experiment (\*)

(\*) ConvNets are regular models trained on ImageNet (1000 classes). Each class is mapped to one of the 16 above. See [1] for more details

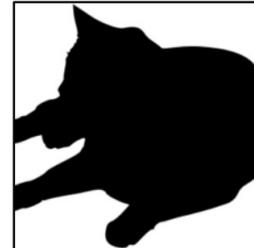
[1] : Geirhos, R., Temme, C. R. M., Rauber, J., Schütt, H. H., Bethge, M., & Wichmann, F. A. (2018). Generalisation in humans and deep neural networks. arXiv preprint arXiv:1808.08750.



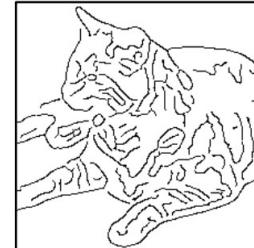
original



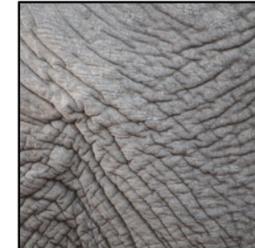
greyscale



silhouette



edges



texture

Accuracies obtained for humans and ConvNets under 5 different experiments

It looks like humans can answer right without texture.

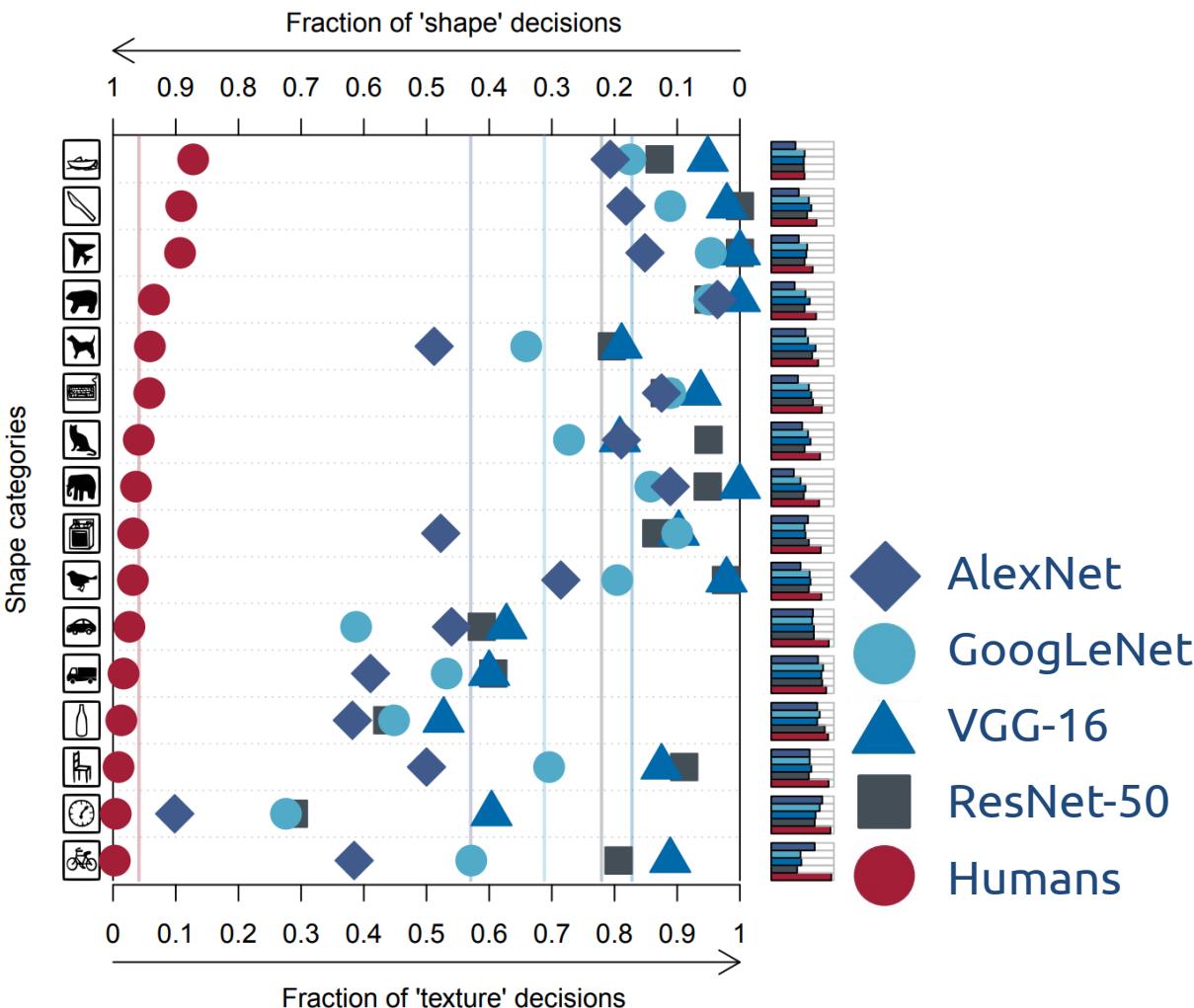
For an image obtained with style transfer,  
there is **no right answer** for classification



However, we can use these images to know  
**which information** (texture or shape)  
**is used** by ConvNets and humans

# ImageNet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness

2018, Robert Geirhos, Patricia Rubisch, Claudio Michaelis, Matthias Bethge, Felix A. Wichmann and Wieland Brendel



Shape decision : cat  
Texture decision : elephant

- ◆ AlexNet
- GoogLeNet
- ▲ VGG-16
- ResNet-50
- Humans

**Shape vs texture decisions**  
for humans and ConvNets

Humans and ConvNets do **NOT** pay attention  
to the same information

Do we really care? As long at it works...

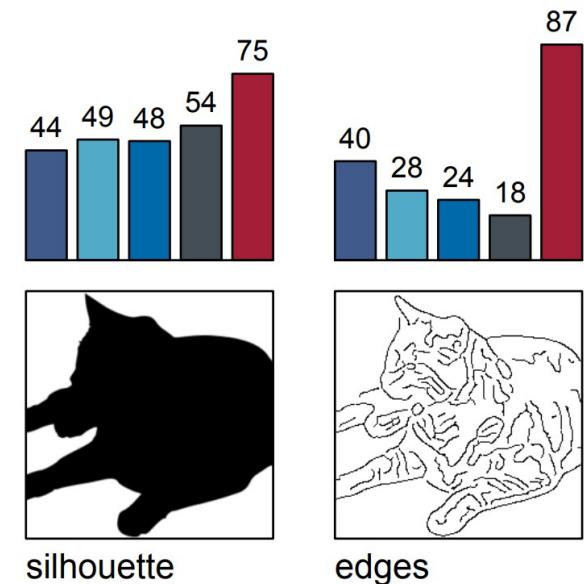
# Do we really care? As long at it works...

Well... yes!

- An **image** is a signal representation **specifically made for humans**
- Image are almost always adapted to the HVS (\*) (i.e. though compression)

→ **Humans** still have **more generalisation** ability compared to ConvNets

→ Let's first have similar performances with AI before considering a different approach compared to the HVS



(\*) HVS: Human Visual System

# How to change ConvNets texture bais into a shape bais like humans?

→ Style transfer!

- Texture is now irrelevant, you are forced to use something else to answer right
- We hope to develop a shape bias

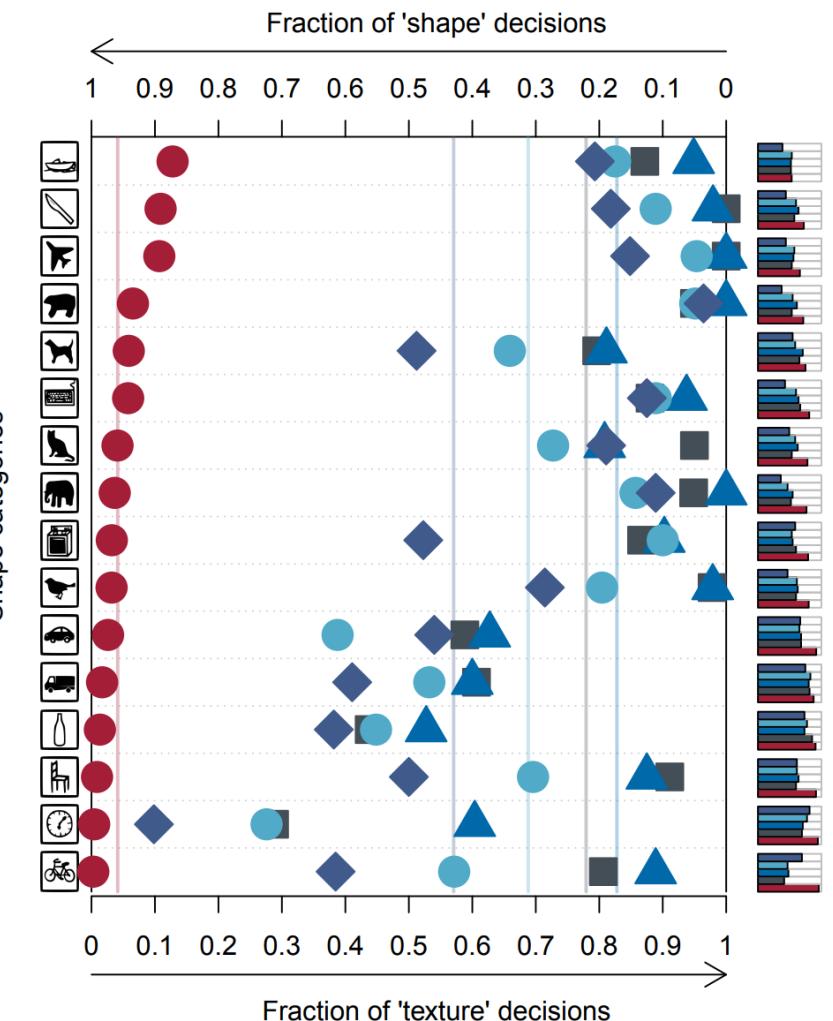


Visualisation of Stylized-ImageNet (SIN), created by applying AdaIN [2] style transfer to ImageNet images

[2] : Huang, X., & Belongie, S. (2017). Arbitrary style transfer in real-time with adaptive instance normalization. In Proceedings of the IEEE International Conference on Computer Vision (pp. 1501-1510).

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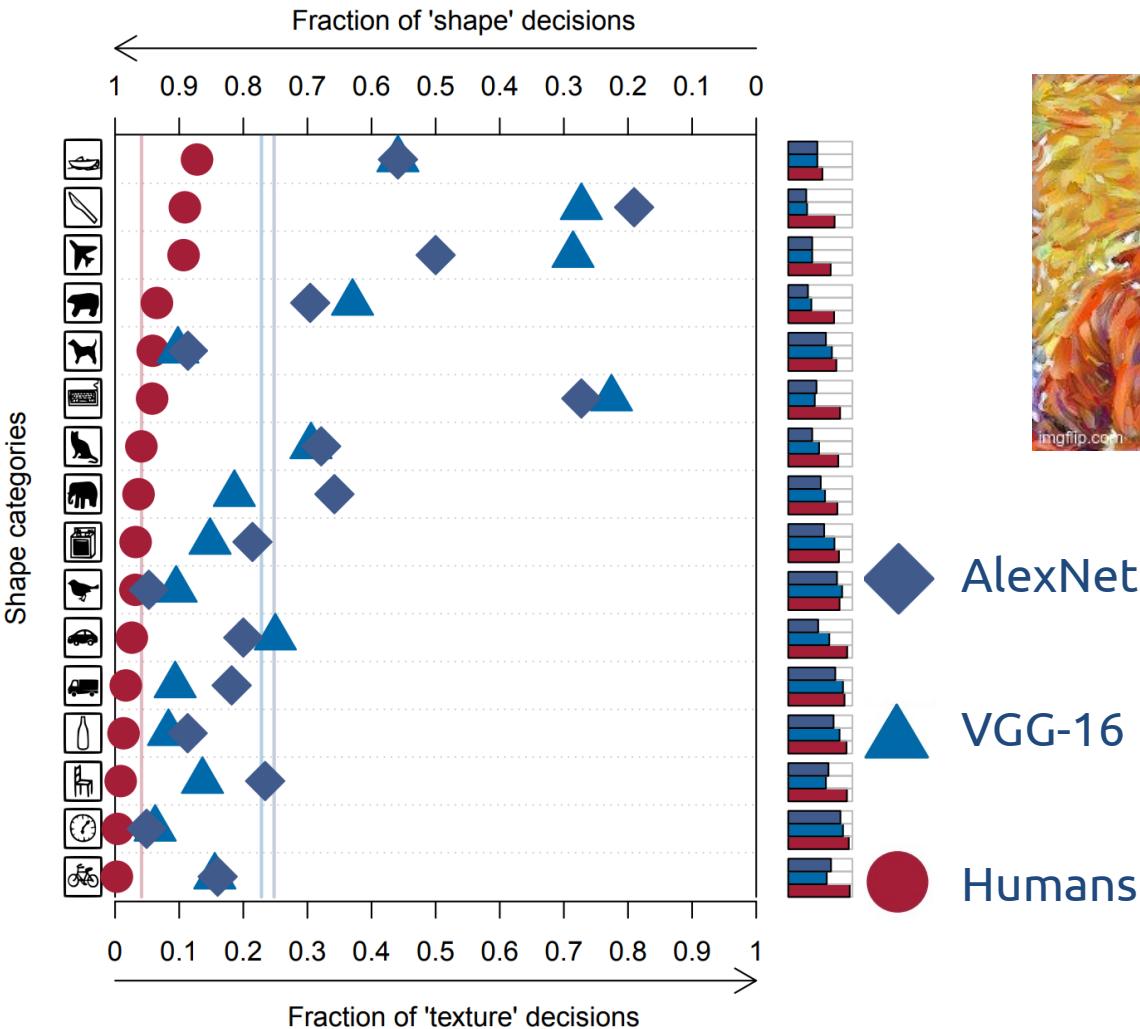
Train a  
model using  
ImageNet

-  AlexNet
-  GoogLeNet
-  VGG-16
-  ResNet-50
-  Humans

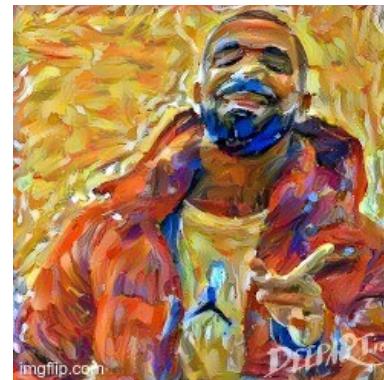
Shape vs texture decisions  
for humans and ConvNets

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Shape vs texture decisions  
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Train a  
model using  
Stylized-ImageNet

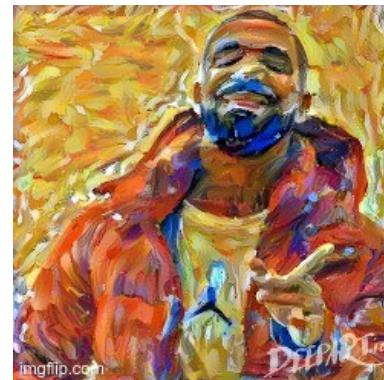
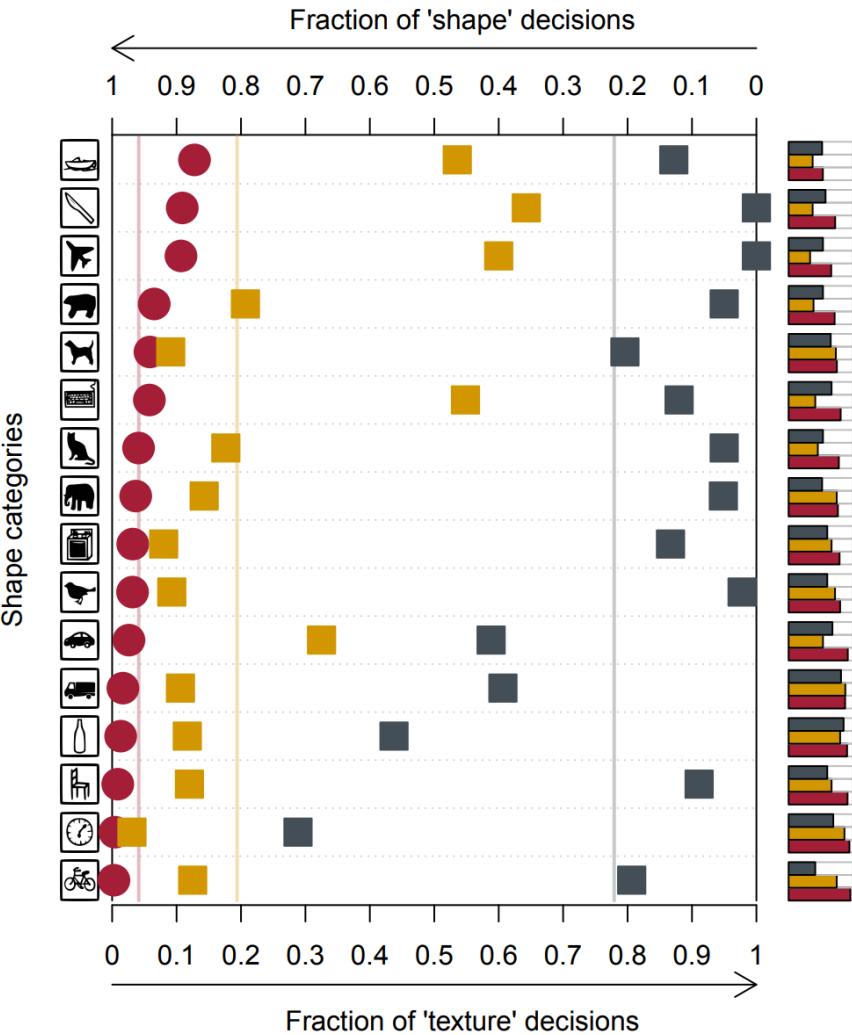
AlexNet

VGG-16

Humans

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Train a model using Stylized-ImageNet

ResNet (IN)

ResNet (SIN)

Humans

Another proof that ConvNets mostly relies on texture

architecture	IN→IN	IN→SIN	SIN→SIN	SIN→IN (*)
ResNet-50	92.9	16.4	79.0	82.6
(**) BagNet-33 (mod. ResNet-50)	86.4	4.2	48.9	53.0
BagNet-17 (mod. ResNet-50)	80.3	2.5	29.3	32.6
BagNet-9 (mod. ResNet-50)	70.0	1.4	10.0	10.9

Comparison between models trained/evaluated  
on ImageNet (IN) and Stylized ImageNet (SIN)

scores are top-5 accuracy on the validation set

(\*) train data → test data

(\*\*) BagNet-33 stands for a model with a maximum receptive field of 33 by 33 pixels

Another proof that ConvNets mostly relies on texture

SIN can't be solved with texture features only

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Comparison between models trained/evaluated on ImageNet (IN) and Stylized ImageNet (SIN)

Smaller receptive field → cannot extract global shapes → lower accuracies

scores are top-5 accuracy on the validation set

(\*) train data → test data

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Stylized-ImageNet can be perceived as data augmentation to neglect texture bias

name	training	fine-tuning	top-1 IN accuracy (%)	top-5 IN accuracy (%)	Pascal VOC mAP50 (%)
vanilla ResNet	IN	-	76.13	92.86	70.7
	SIN	-	60.18	82.62	70.6
	SIN+IN	-	74.59	92.14	74.0
Shape-ResNet	SIN+IN	IN	<b>76.72</b>	<b>93.28</b>	<b>75.1</b>

Benefits of Stylized-ImageNet (SIN) for classification and object detection

(\*) Classifiers (e.g. Shape-ResNet) are used as backbone features for Faster R-CNN [3]

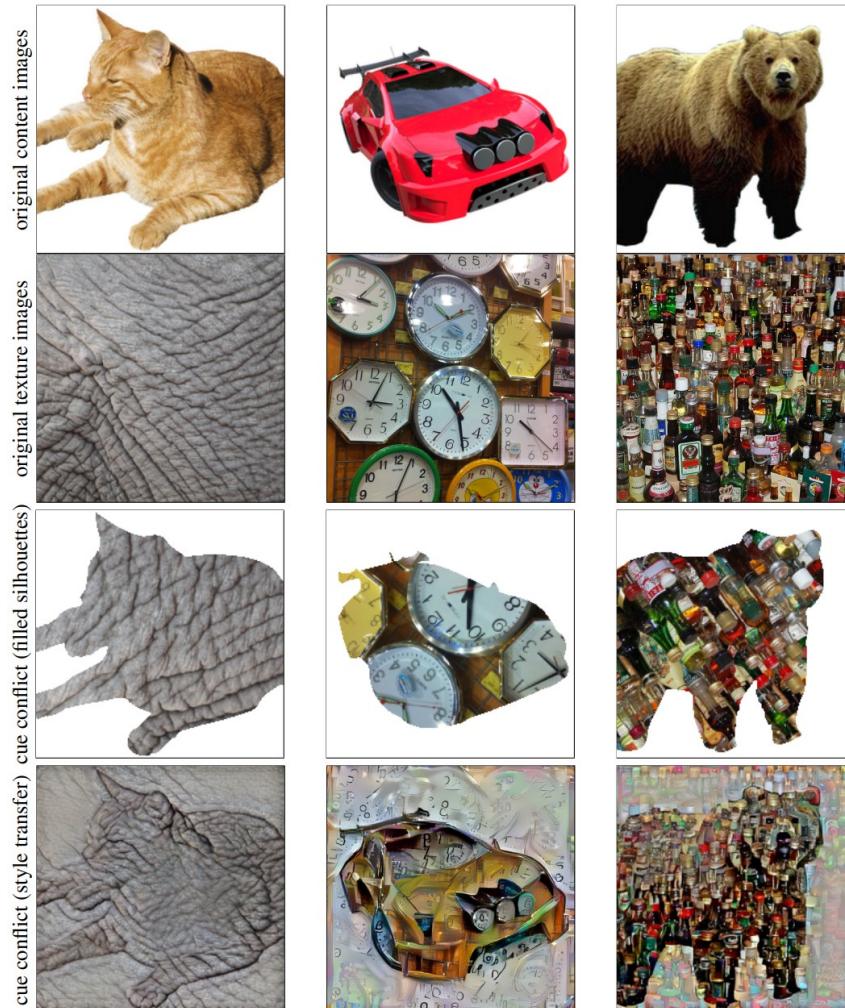
[3] : Ren, S., He, K., Girshick, R., & Sun, J. (2015). Faster r-cnn: Towards real-time object detection with region proposal networks. arXiv preprint arXiv:1506.01497.

That's basically it.

Thank you for your attention!

# ImageNet-trained CNNs are biased towards texture; increasing shape bias improves accuracy and robustness

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Hack used to obtain texture of an object without texture (e.g. glass bottle)