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AI & Security Project

Using adversarial attacks to cause misclassification

Group 1

Harman Singh
Sadiksha Sapkota

Project overview

- **Project 2.2**
  - **Part 1**: Adversarial Attacks on Image Classification Models
    - Investigate the vulnerability of image classification models to adversarial attacks
    - Use pre-trained image classifiers
    - Explore adversarial attack methods
  - **Part 2**: Defense Mechanisms against Adversarial Attacks
    - Explore and investigate defense techniques that enhance robustness

Implementation

- **Part 1: Attack**
  - **Dataset**: TinyImageNet, Pretrained patches
  - **Attacks**:
    - Method 1: Adversarial attacks (FGSM, PGD, C&W)
    - Method 2: Adversarial patches (SGD)
  - **Pre-trained models**:
    - Method 1: ResNet18, ResNet50, ResNet152, VGG16, VGG19
    - Method 2: ResNet34, DensNet12
- **Part 2: Defense**
  - **Mechanism**: Adversarial training

Workflow of method 1 – Adversarial attacks

- **Evaluation order**
  1) baseline performance (without attack)
  2) attack performance (with all attacks)
  3) defense performance (with defense against all attacks)
- **Metrics**
  - **Top-1 error**: the number of times the correct class was not the predicted class
  - **Top-5 error**: the number of times the correct class was not in the top 5 predicted classes by certainty

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Workflow of method 2 – Adversarial patches

Terminology: Adversarial patches are small, specially made images or patterns designed to trick AI models into making incorrect predictions.

- Here we have 5 pretrained patches so that we can fool the network into the desired label.
- The pretrained patches include toaster, goldfish, school bus, lipstick, pineapple
- We have for each patches 32 pixels, 48 pixels, 64 pixels.

Workflow of method 2 – Adversarial patches

Accuracy: Top-1, Top-5

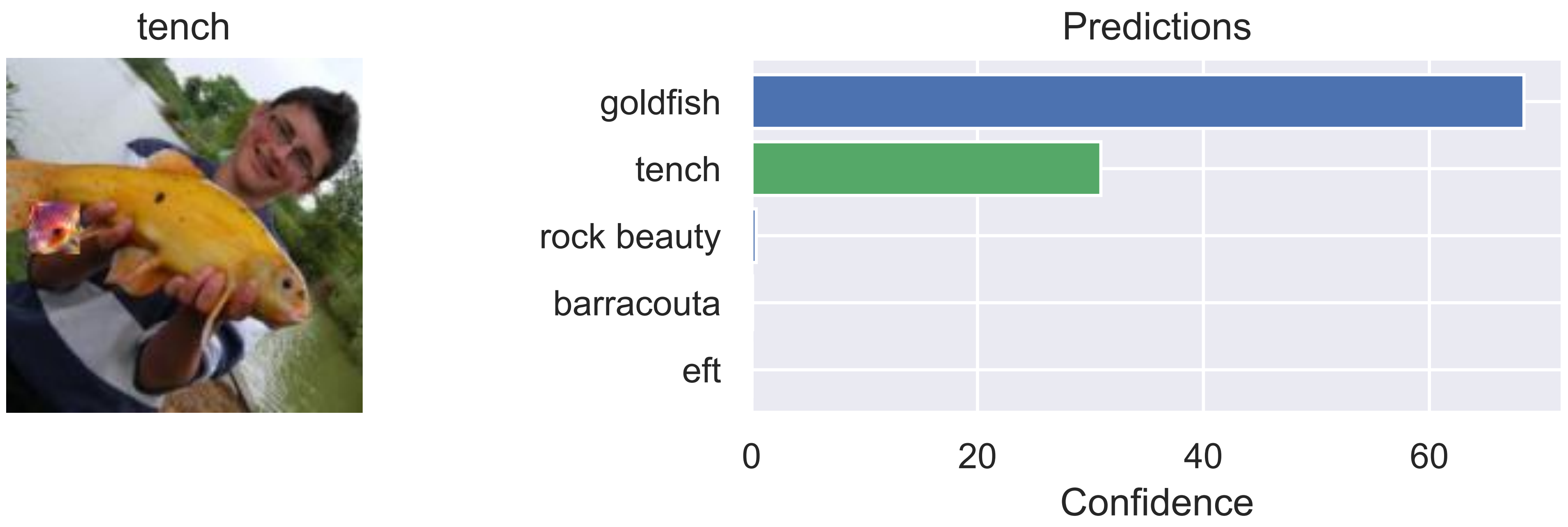
```
show_table(top_1=True)
```

Class name	Patch size 32x32	Patch size 48x48	Patch size 64x64
toaster	48.89%	90.48%	98.58%
goldfish	69.53%	93.53%	98.34%
school bus	78.79%	93.95%	98.22%
lipstick	43.36%	86.05%	96.41%
pineapple	79.74%	94.48%	98.72%

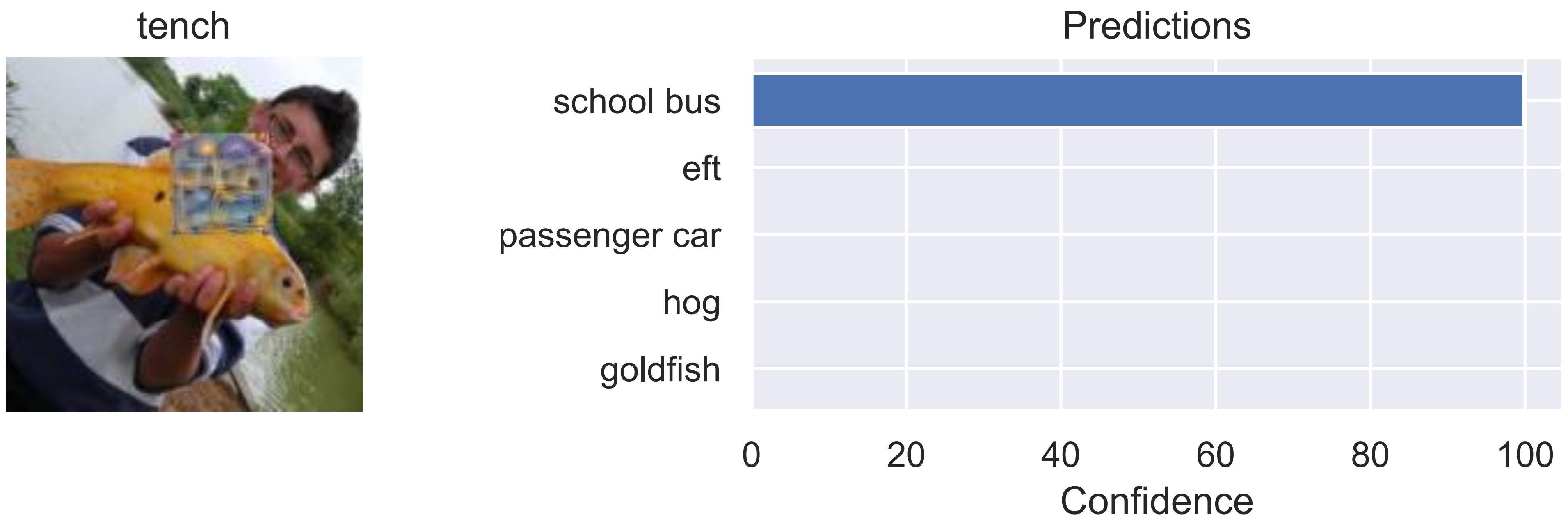
```
show_table(top_1=False)
```

Class name	Patch size 32x32	Patch size 48x48	Patch size 64x64
toaster	72.02%	98.12%	99.93%
goldfish	86.31%	99.07%	99.95%
school bus	91.64%	99.15%	99.89%
lipstick	70.10%	96.86%	99.73%
pineapple	92.23%	99.26%	99.96%

Workflow of method 2 – Adversarial patches




```
perform_patch_attack(patch_dict['goldfish'][32]['patch'])
```




```
perform_patch_attack(patch_dict['school bus'][64]['patch'])
```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Workflow of method 2 – Adversarial patches

Transferability

```python
transfer_model = torchvision.models.densenet121(weights='IMAGENET1K_V1')
transfer_model = transfer_model.to(device)

# No gradients needed for the network
transfer_model.eval()
for p in transfer_model.parameters():
    p.requires_grad = False
```

```python
class_name = 'pineapple'
patch_size = 64
print(f"Testing patch \"{class_name}\" of size {patch_size}x{patch_size}")

results = eval_patch(transfer_model,
                     patch_dict[class_name][patch_size]["patch"],
                     data_loader,
                     target_class=label_names.index(class_name))

print(f"Top-1 fool accuracy: {(results[0] * 100.0):4.2f}%")
print(f"Top-5 fool accuracy: {(results[1] * 100.0):4.2f}%")
```

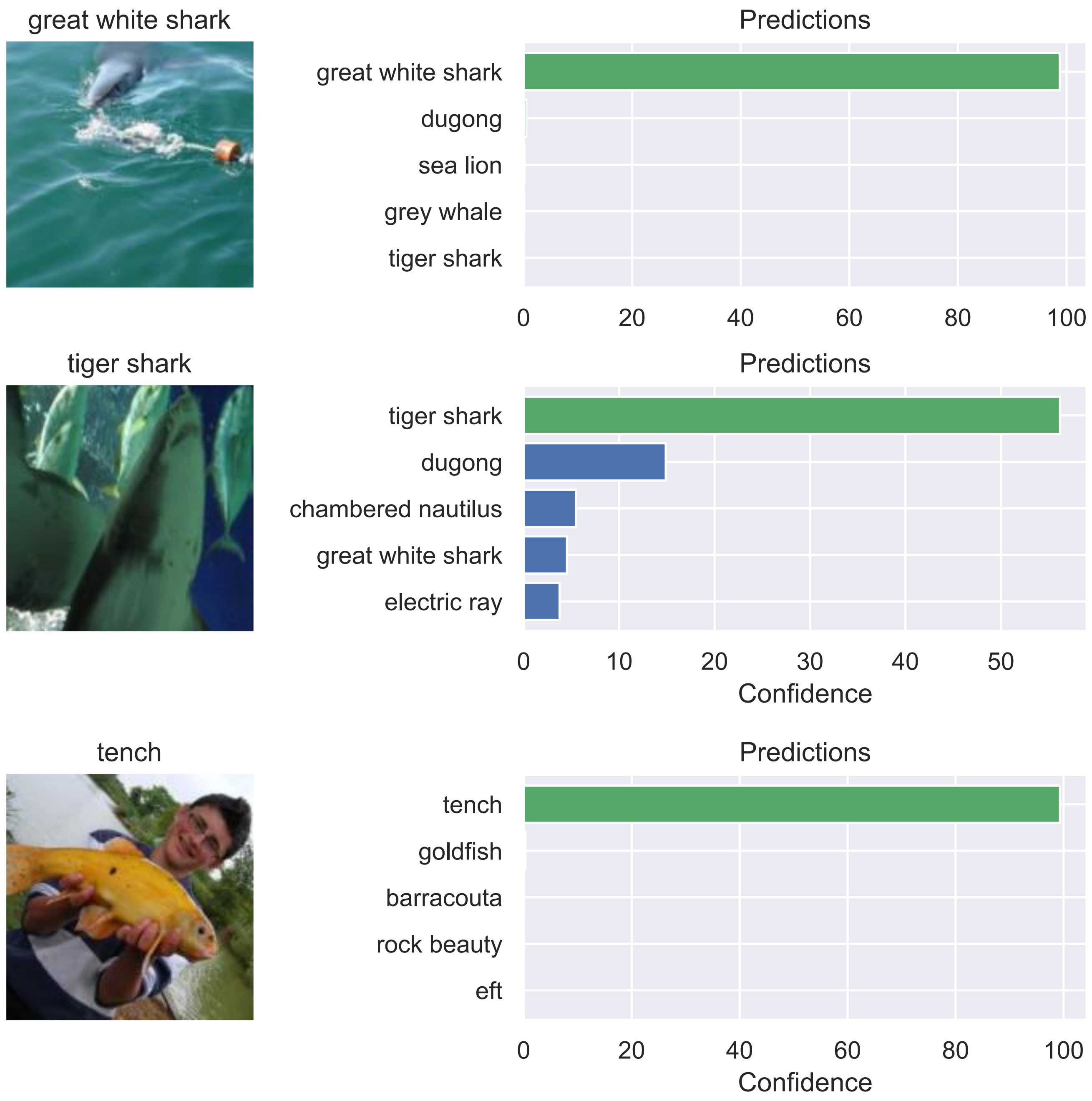
```
Testing patch "pineapple" of size 64x64

Validating...:   0%|          | 0/157 [00:00<?, ?it/s]

Top-1 fool accuracy: 64.89%
Top-5 fool accuracy: 82.21%
```

Our findings

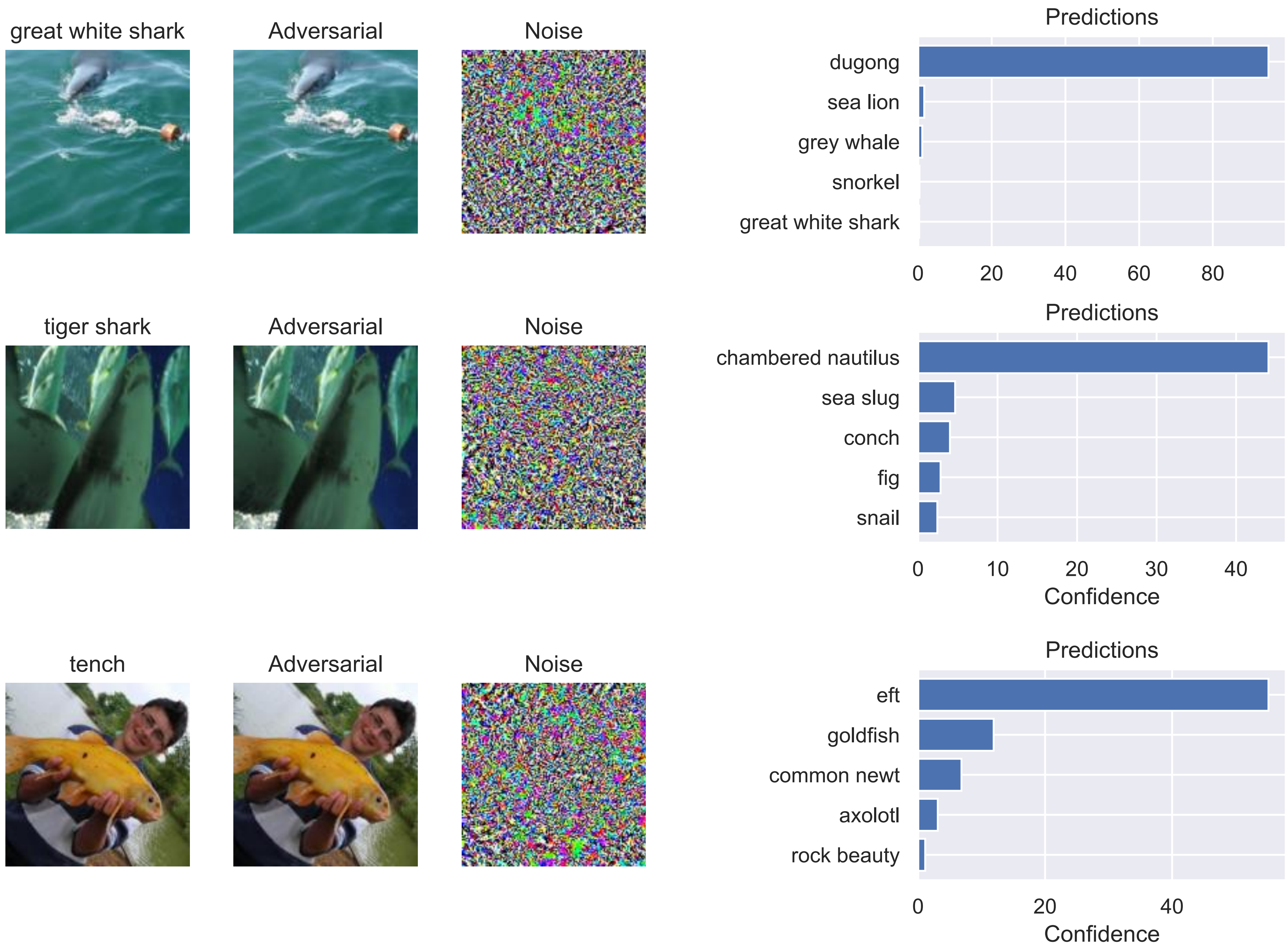
- **Attacking the models decreases model confidence, and increases likelihood of spreading predictions across multiple classes instead of just picking 1 class**
- The bigger the epsilon, the bigger the error
- PGD was the most effective attack method (up to 500% increase in Top-1 error rate)
  - Adversarial training against PGD did not seem to improve the model's performance as much
- For ResNet18 and ResNet50, adversarial training made the model perform better after it had been attack, than the baseline performance
- Adversarial training did not seem to have an impact on VGG16 nor VGG19

Our findings

Baseline



Attacked with FGSM



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Our findings

The bigger the epsilon, the bigger the error finding precise number is not always easy

```
Evaluating ResNet18 (FGSM) with epsilon 0.01:

        Top-1 error: 79.18%
        Top-5 error: 58.74%

Evaluating ResNet18 (FGSM) with epsilon 0.02:

        Top-1 error: 82.66%
        Top-5 error: 62.82%

Evaluating ResNet18 (FGSM) with epsilon 0.03:

        Top-1 error: 84.86%
        Top-5 error: 66.16%

Evaluating ResNet18 (FGSM) with epsilon 0.05:

        Top-1 error: 88.04%
        Top-5 error: 71.52%

Evaluating ResNet18 (FGSM) with epsilon 0.1:

        Top-1 error: 91.22%
        Top-5 error: 78.86%
```

Our findings

- Attacking the models decreases model confidence, and increases likelihood of spreading predictions across multiple classes instead of just picking 1 class
- The bigger the epsilon, the bigger the error
- **PGD was the most effective attack method**
  - **Adversarial training against PGD did not seem to improve the model's performance as much**
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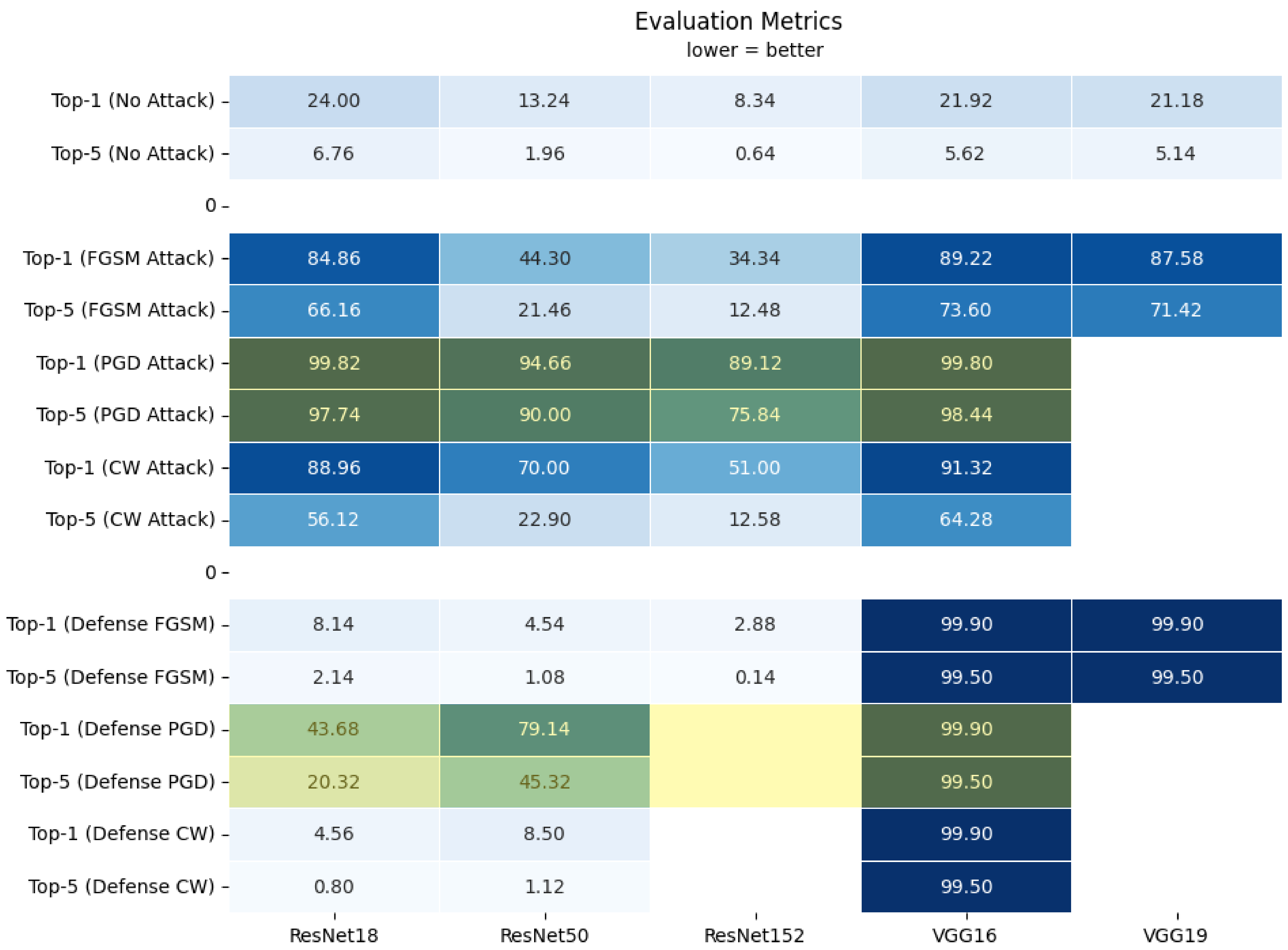
Evaluation Metrics
lower = better
Top-1 (No Attack)
24.00
13.24
8.34
21.92
21.18
Top-5 (No Attack)
6.76
1.96
0.64
5.62
5.14
0
Top-1 (FGSM Attack)
84.86
44.30
34.34
89.22
87.58
Top-5 (FGSM Attack)
66.16
21.46
12.48
73.60
71.42
Top-1 (PGD Attack)
99.82
94.66
89.12
99.80
Top-5 (PGD Attack)
97.74
90.00
75.84
98.44
Top-1 (CW Attack)
88.96
70.00
51.00
91.32
Top-5 (CW Attack)
56.12
22.90
12.58
64.28
0
Top-1 (Defense FGSM)
8.14
4.54
2.88
99.90
99.90
Top-5 (Defense FGSM)
2.14
1.08
0.14
99.50
99.50
Top-1 (Defense PGD)
43.68
79.14
99.90
Top-5 (Defense PGD)
20.32
45.32
99.50
Top-1 (Defense CW)
4.56
8.50
99.90
Top-5 (Defense CW)
0.80
1.12
99.50
ResNet18
ResNet50
ResNet152
VGG16
VGG19

Our findings

- Attacking the models decreases model confidence, and increases likelihood of spreading predictions across multiple classes instead of just picking 1 class
- The bigger the epsilon, the bigger the error but finding percise.
- PGD was the most effective attack method (up to 500% increase in Top-1 error rate)
  - Adversarial training against PGD did not seem to improve the model's performance as much
- **For ResNet18 and ResNet50, adversarial training made the model perform better after it had been attack, than the baseline performance**
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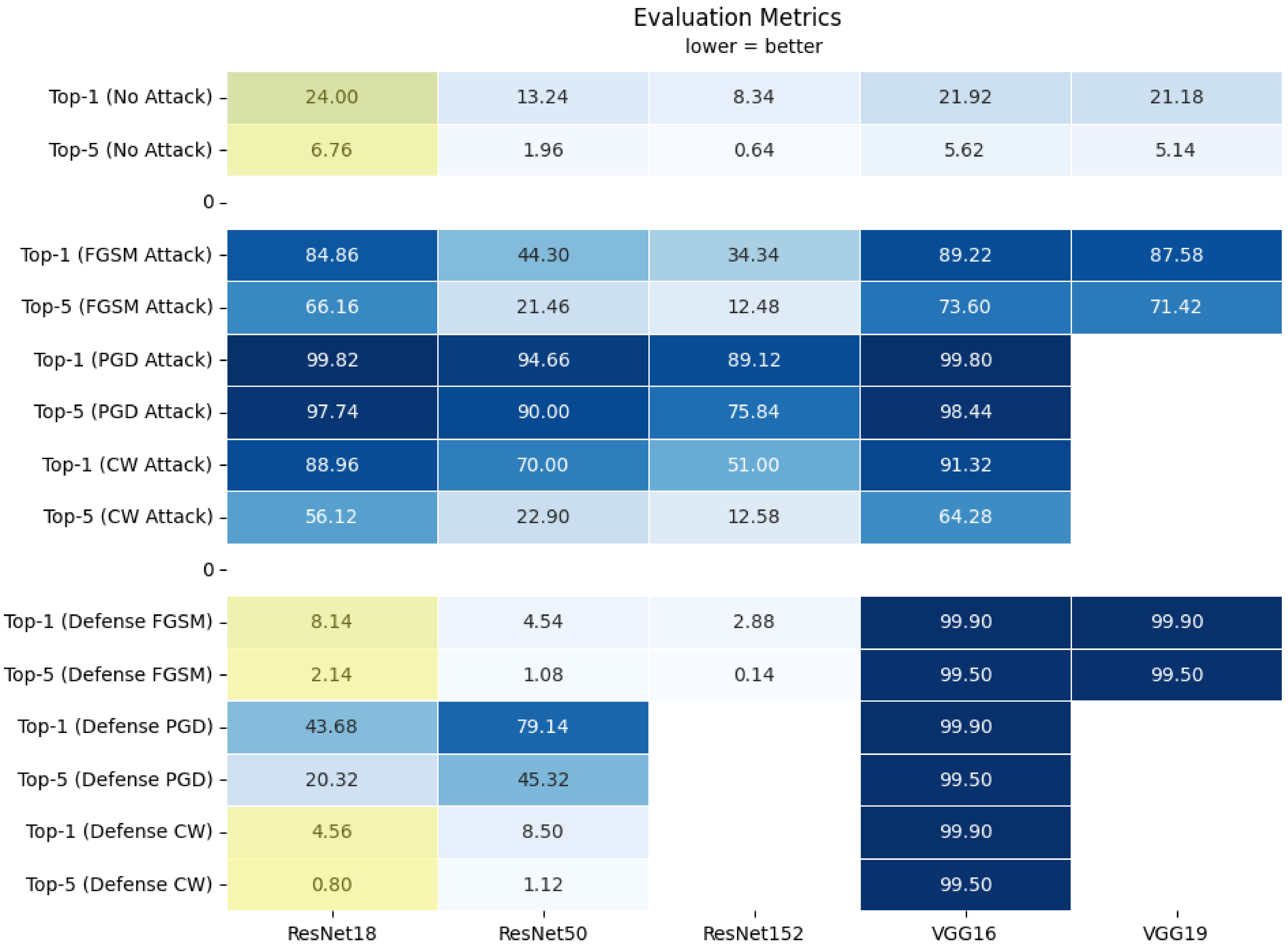
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Top-1 (FGSM Attack) 84.86 44.30 34.34 89.22 87.58
Top-5 (FGSM Attack) 66.16 21.46 12.48 73.60 71.42
Top-1 (PGD Attack) 99.82 94.66 89.12 99.80
Top-5 (PGD Attack) 97.74 90.00 75.84 98.44
Top-1 (CW Attack) 88.96 70.00 51.00 91.32
Top-5 (CW Attack) 56.12 22.90 12.58 64.28
0
Top-1 (Defense FGSM) 8.14 4.54 2.88 99.90 99.90
Top-5 (Defense FGSM) 2.14 1.08 0.14 99.50 99.50
Top-1 (Defense PGD) 43.68 79.14 99.90
Top-5 (Defense PGD) 20.32 45.32 99.50
Top-1 (Defense CW) 4.56 8.50 99.90
Top-5 (Defense CW) 0.80 1.12 99.50
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Evaluation Metrics

lower = better

	ResNet18	ResNet50	ResNet152	VGG16	VGG19
Top-1 (No Attack)	24.00	13.24	8.34	21.92	21.18
Top-5 (No Attack)	6.76	1.96	0.64	5.62	5.14
0					
Top-1 (FGSM Attack)	84.86	44.30	34.34	89.22	87.58
Top-5 (FGSM Attack)	66.16	21.46	12.48	73.60	71.42
Top-1 (PGD Attack)	99.82	94.66	89.12	99.80	
Top-5 (PGD Attack)	97.74	90.00	75.84	98.44	
Top-1 (CW Attack)	88.96	70.00	51.00	91.32	
Top-5 (CW Attack)	56.12	22.90	12.58	64.28	
0					
Top-1 (Defense FGSM)	8.14	4.54	2.88	99.90	99.90
Top-5 (Defense FGSM)	2.14	1.08	0.14	99.50	99.50
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