Introduction to Deep Learning (I2DL)

Exercise 10: Semantic Segmentation

Today's Outline

- Exercise 09: Example Solutions
- Exercise 10: Semantic Segmentation
  - Task & Loss Function
  - Architecture and Upsampling

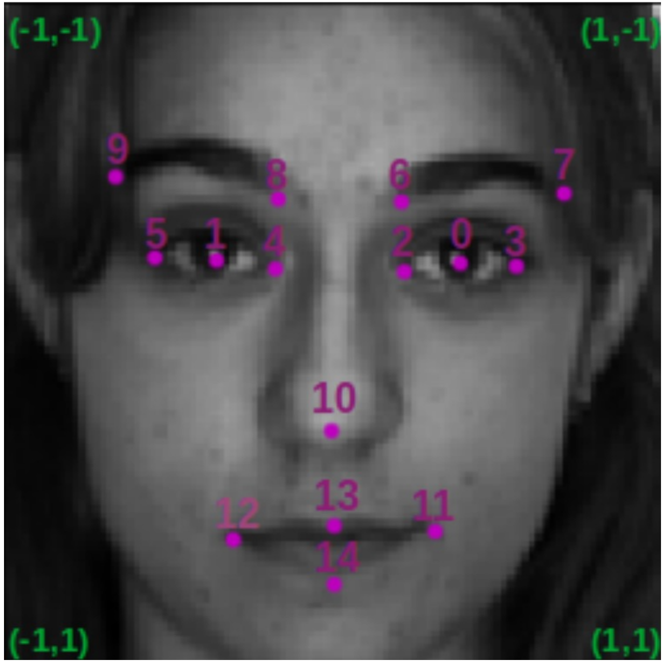
Exercise 9: Solutions

Facial Keypoints

(1, 96, 96) grayscale image

Score: 1/(2*MSE)

Threshold: Score of 100
(⇔ MSE < 0.005)



Leaderboard

#	User	Score
1	u1180	1584.89
2	u1345	1361.77
3	u1605	1246.78
4	u0497	1180.40
5	u0225	1157.30
6	u0318	1153.99
7	u0798	1132.49
8	u0088	1093.72
9	u1479	1093.33
10	u0832	1002.68
11	u0462	972.42
12	u0472	924.34

MSE 0.00032

Leaderboard (earlier semester)

Leaderboard: Submission 9

Rank	User	Score	Pass
#1	s0672	942.66	✔
#2	s0463	940.88	✔
#3	s0770	792.80	✔
#4	s0303	722.08	✔
#5	s0587	689.02	✔
#6	s0747	656.89	✔
#7	s0555	654.95	✔
#8	s0400	615.63	✔
#9	s0322	607.35	✔
#10	s0288	602.19	✔

MSE 0.00053

Case Study: Model

```python
self.model = nn.Sequential(
    nn.Conv2d(1, 32, (3, 3), stride=1, padding=2),
    # nn.BatchNorm2d(32),
    # nn.Dropout2d(0.2),
    nn.PReLU(),

    nn.MaxPool2d(3),

    nn.Conv2d(32, 64, (3, 3), stride=1, padding=2),
    # nn.BatchNorm2d(64),
    # nn.Dropout2d(),
    nn.PReLU(),

    nn.MaxPool2d(3, stride=2),

    nn.Conv2d(64, 64, (3, 3), stride=1, padding=1),
    # nn.BatchNorm2d(64),
    # nn.Dropout2d(0.3),
    nn.PReLU(),

    nn.MaxPool2d(2, stride=2),

    nn.Conv2d(64, 128, (2, 2), stride=1, padding=1),
    # nn.BatchNorm2d(128),
    # nn.Dropout2d(0.3),
    nn.PReLU(),

    Flatten(),
    nn.Linear(10368, 256),
    # nn.BatchNorm1d(256),
    nn.Dropout(0.1),
    nn.PReLU(),

    nn.Linear(256, 30),
)
```

Classic ConvNet architecture:

- Feature extraction
- Classification

Case Study: Model Summary

```
#!pip install torchsummary
import torchsummary

torchsummary.summary(model, (1, 96, 96))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 32, 98, 98]             320
             PReLU-2           [-1, 32, 98, 98]               1
         MaxPool2d-3           [-1, 32, 32, 32]               0
            Conv2d-4           [-1, 64, 34, 34]          18,496
             PReLU-5           [-1, 64, 34, 34]               1
         MaxPool2d-6           [-1, 64, 16, 16]               0
            Conv2d-7           [-1, 64, 16, 16]          36,928
             PReLU-8           [-1, 64, 16, 16]               1
         MaxPool2d-9             [-1, 64, 8, 8]               0
           Conv2d-10            [-1, 128, 9, 9]          32,896
            PReLU-11            [-1, 128, 9, 9]               1
          Flatten-12               [-1, 10368]               0
           Linear-13                 [-1, 256]       2,654,464
          Dropout-14                 [-1, 256]               0
            PReLU-15                 [-1, 256]               1
           Linear-16                  [-1, 30]           7,710
================================================================
```

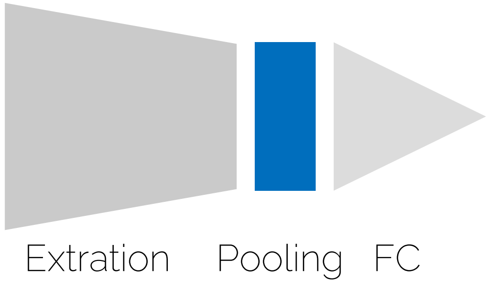
```
Total params: 2,750,819
Trainable params: 2,750,819
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.04
Forward/backward pass size (MB): 6.72
Params size (MB): 10.49
Estimated Total Size (MB): 17.25
----------------------------------------------------------------
```

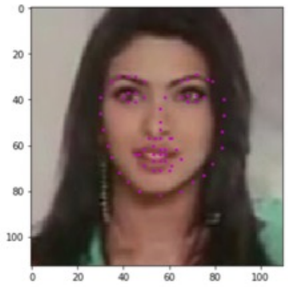
(9x9x128 = 10368)

```
    Flatten(),
    nn.Linear(10368, 256),
    # nn.BatchNorm1d(256),
    nn.Dropout(0.1),
    nn.PReLU(),

    nn.Linear(256, 30),
)
```

Case Study: Smaller Linear Layer?

1. Convolutional layer to reduce size to 1x1
   - Here: 9x9 kernel, 128 filters, no padding => 1X1X128 = 128
2. Global Average Pooling (GAP)
   - Here: 9x9 kernel => 128
   - Disadvantage: lose spatial relations
3. Flatten
   - Solutions: first use 1x1 convolutions





Case Study: With 1x1 Conv

```
# After adding 1x1 layers
# nn.Conv2d(128, 16, (1, 1), stride=1, padding=0),
# Flatten(),
# nn.Linear(9*9*16, 256),

torchsummary.summary(model, (1, 96, 96))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1           [-1, 32, 98, 98]             320
             PReLU-2           [-1, 32, 98, 98]               1
         MaxPool2d-3           [-1, 32, 32, 32]               0
            Conv2d-4           [-1, 64, 34, 34]          18,496
             PReLU-5           [-1, 64, 34, 34]               1
         MaxPool2d-6           [-1, 64, 16, 16]               0
            Conv2d-7           [-1, 64, 16, 16]          36,928
             PReLU-8           [-1, 64, 16, 16]               1
         MaxPool2d-9             [-1, 64, 8, 8]               0
           Conv2d-10            [-1, 128, 9, 9]          32,896
            PReLU-11            [-1, 128, 9, 9]               1
           Conv2d-12             [-1, 16, 9, 9]           2,064
          Flatten-13                 [-1, 1296]               0
           Linear-14                  [-1, 256]         332,032
          Dropout-15                  [-1, 256]               0
            PReLU-16                  [-1, 256]               1
           Linear-17                   [-1, 30]           7,710
================================================================
```

```
Total params: 430,451
Trainable params: 430,451
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.04
Forward/backward pass size (MB): 6.66
Params size (MB): 1.64
Estimated Total Size (MB): 8.34
----------------------------------------------------------------
```

Next steps:
Make deeper and use residual connection to make it train

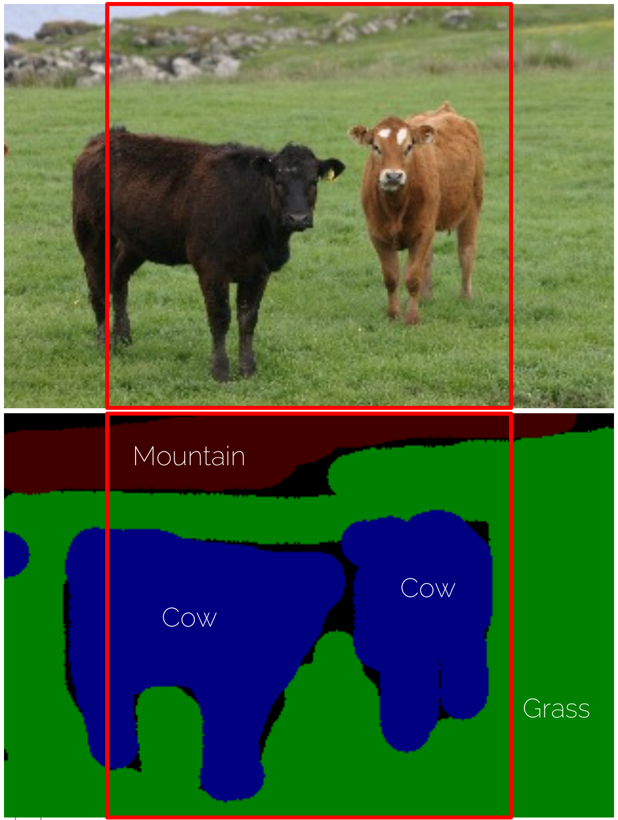
Case Study: Hyperparameters

```
hparams = {
    "lr": 0.0001,
    "batch_size": 512,
    # TODO: if you have any model arguments/hparams, define them here
}
```

- Default learning rate
- Experiment with batch normalization / Dropout
- Forms of ReLU activations (PReLu, ELU)
- Appropriate weight initialization

Exercise 10
Semantic Segmentation

Semantic Segmentation



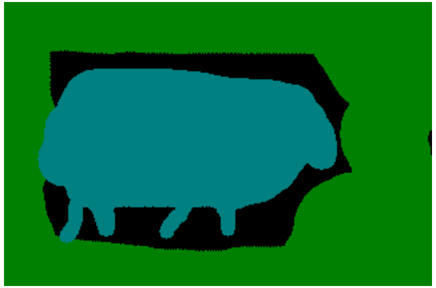
Input:
(3xWxH) RGB image

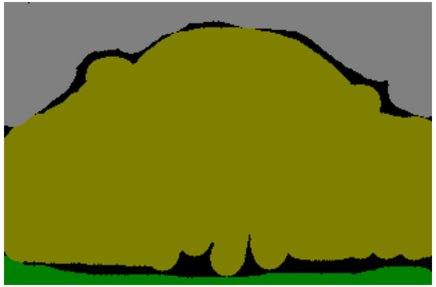
Output:
(23xWxH) segmentation map with scores for every class in every pixel

Semantic Segmentation Labels

object class	R	G	B	Colour
void	0	0	0	
building	128	0	0	
grass	0	128	0	
tree	128	128	0	
cow	0	0	128	
horse	128	0	128	
sheep	0	128	128	
sky	128	128	128	
mountain	64	0	0	

"void" for unlabelled pixels





Metrics: Loss Function

- Averaged per pixel cross-entropy loss

```
for (inputs, targets) in train_data[0:4]:
    inputs, targets = inputs, targets
    outputs = dummy_model(inputs.unsqueeze(0))
    loss = torch.nn.CrossEntropyLoss(ignore_index=-1, reduction='mean')
    losses = loss(outputs,targets.unsqueeze(0))
    print(losses)
```

- **ignore_index** (*int*, *optional*) – Specifies a target value that is ignored and does not contribute to the input gradient. When `size_average` is `True`, the loss is averaged over non-ignored targets.

Metrics: Accuracy

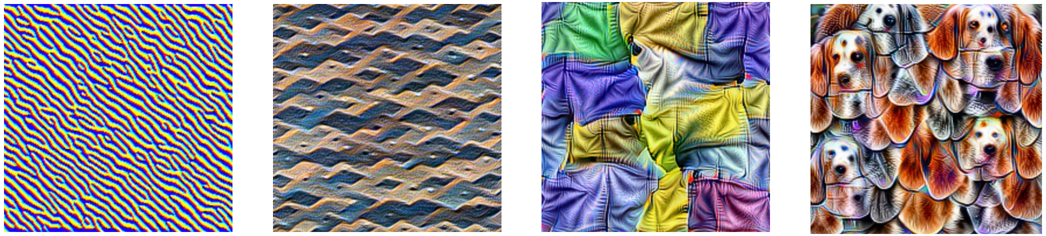
- Only consider pixels which are not „void"

```
def evaluate_model(model):
    test_scores = []
    model.eval()
    for inputs, targets in test_loader:
        inputs, targets = inputs.to(device), targets.to(device)

        outputs = model.forward(inputs)
        _, preds = torch.max(outputs, 1)
        targets_mask = targets >= 0
        test_scores.append(np.mean((preds == targets)[targets_mask].data.cpu().numpy()))


    return np.mean(test_scores)
print("Test accuracy: {:.3f}".format(evaluate_model(dummy_model)))
```

Model Architecture

Semantic Segmentation Task

- Input shape: (N, num_channels, H, W)
  Output shape: (N, num_classed, H, W)
- We want to:
  - Maintain dimensionality (H, W)
  - Get features at different spatial resolutions

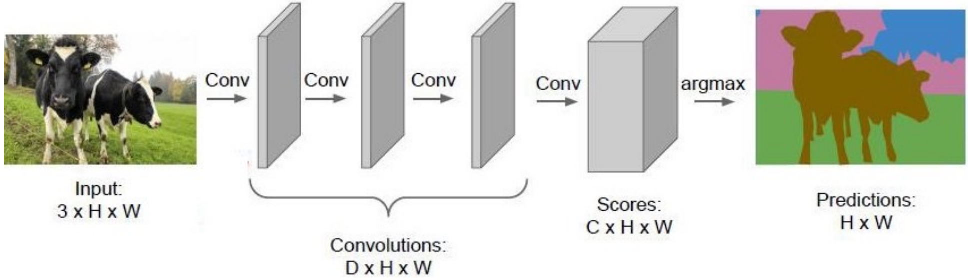


Edges Textures Parts Objects

Image source: https://distill.pub/2017/feature-visualization/

Naive Solution

- Keep dimensionality constant throughout the network
- Use increasing filter sizes

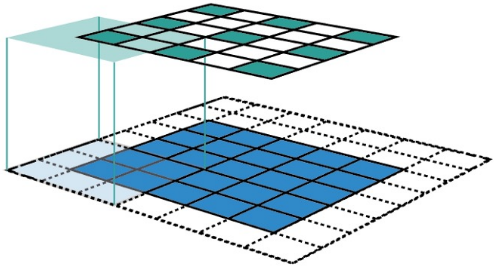


- Problem:
  – Increased memory consumption
    - Filter size would be the same
      e.g., 128 filters a (64x3x3) -> 73k params
    - But we have to save inputs and outputs for every layer
      e.g., 128 filters a (64xWxH) -> millions of params!

Image source: towardsdatascience.com – Divyanshu Mishra

Excursion: Receptive Field (RF)

- Region in input space a feature in a CNN is looking at



- E.g., after 2 (5x5) convolutions with stride 1 we have a receptive field of 9x9
  (RF after first conv: 5
  RF after second conv: 5+4)

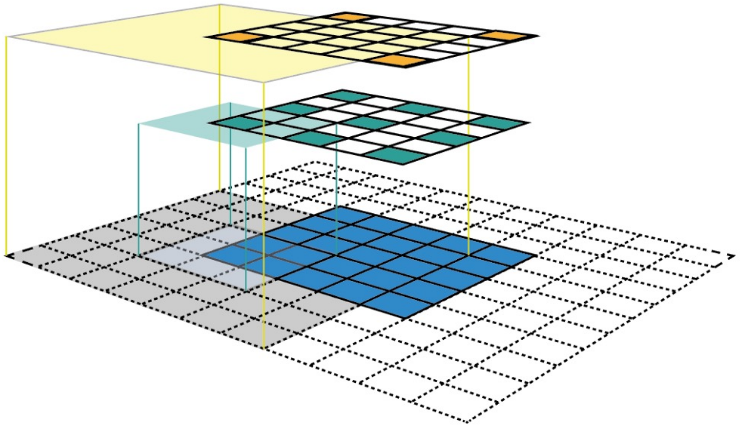
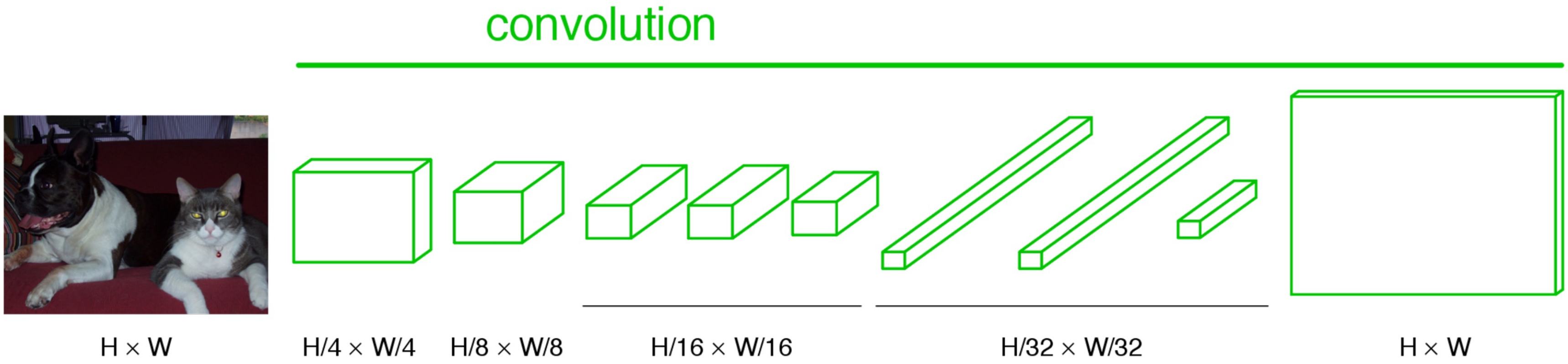


Image source: medium.com – Dang Ha The Hien

Coming from Classification

- Use strided convolutions and pooling to increase the receptive field
- Upsample result to input resolution



Better Solution

- Slowly reduce size -> slowly increase size
  - Pooling -> Upsampling
  - Strided convolution -> Transposed convolution
- Combine with normal convolutions, bn, dropout, etc.

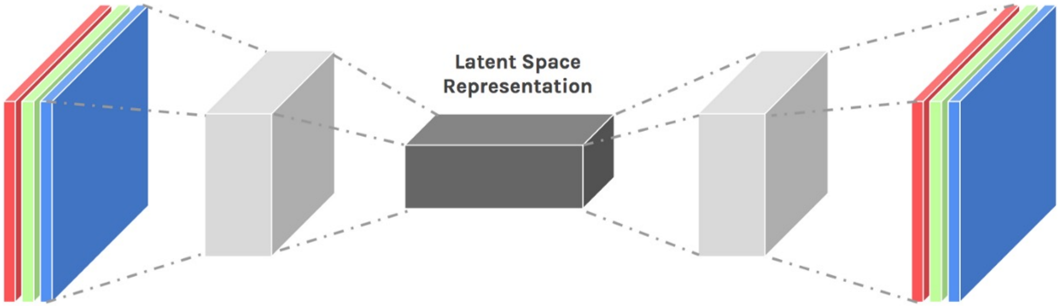
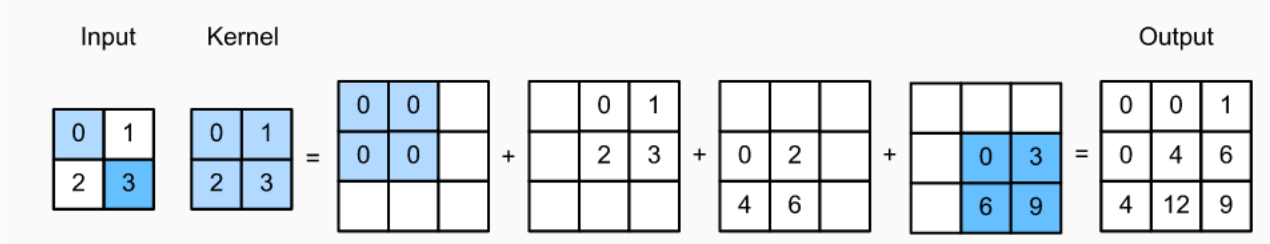


Image source: https://hackernoon.com/autoencoders-deep-learning-bits-1-11731e200694

Transposed Convolutions

- Upsampling with learnable parameters



- Output size computation:
  - Regular conv layer:

$$out = \frac{(in - kernel + 2 * pad)}{stride} + 1$$

  - Transpose convolution for multiples of 2

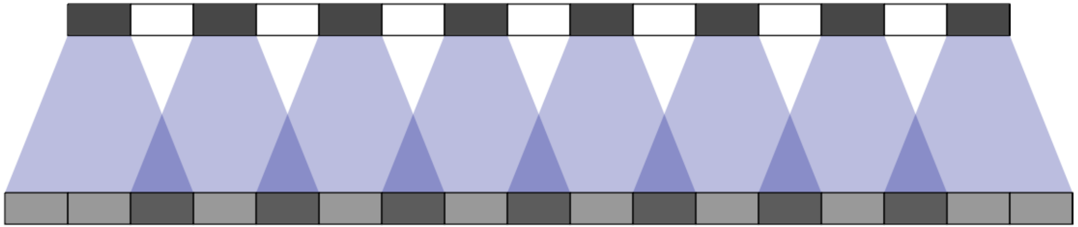
$$out = (in - 1) * stride - 2 * pad + kernel$$

(Transpose computation not relevant for the exam,
more info here: https://github.com/vdumoulin/conv_arithmetic)

Image source: towardsdatascience.com – Divyanshu Mishra

Are transpose convolutions superior?

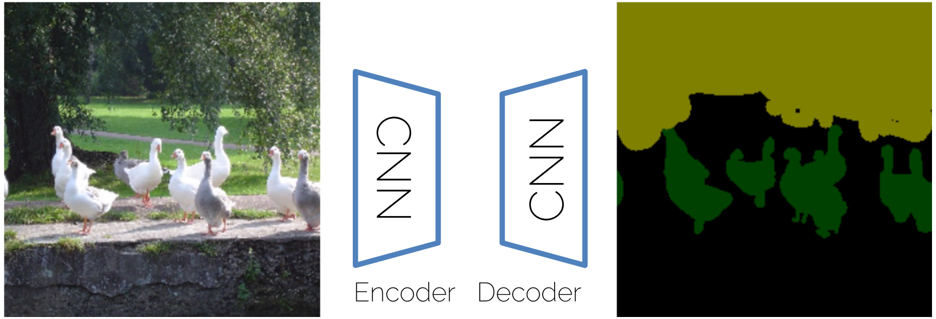
- Short answer: no, not always
- Long answer: possible checkerboard artifacts for general image generation, see https://distill.pub/2016/deconv-checkerboard/



- My personal go-to:
  - Regular upsampling, followed by a convolution layer

How to compete/get results quickly?

- Transfer Learning!



- Possible solutions
  - "The Oldschool"
    - Take pretrained Encoder, set up decoder and only train decoder
    - Encoder candidates: AlexNet, MobileNets
  - "The Lazy"
    - Take a fully pretrained network and adjust outputs

Summary

- Monday 18.07.22: Watch Lecture 11
  - Recurrent Neural Networks
- Monday 18.07.22: Exercise 10 Submission
  - Semantic Segmentation: 18.07.2022 23.59
- Tuesday 19.07.22: Tutorial Session 11

Good luck & see you next week ☺