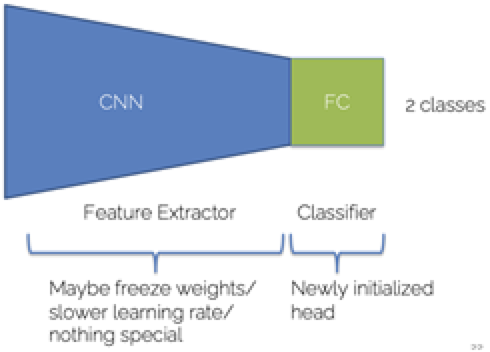
Introduction to Deep Learning (I2DL)

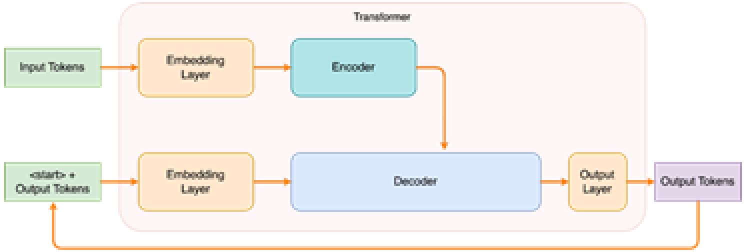
Exercise 11: NLP

Today's Outline

- Exercise 10 Review

- Natural Language Processing
  - Exercise 11





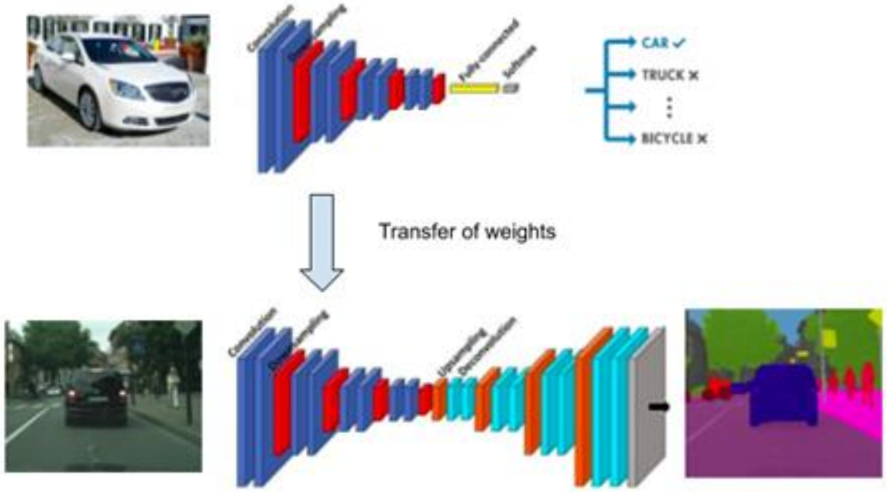
Exercise 10

Exercise 10: Semantic Segmentation

- **Goal:** Assign a label to each pixel of the image
- **Output of the network:** Segmentation mask with same shape as input image
- **Dataset:** MSRC v2 dataset, 23 object classes, contains 591 images with "accurate" pixel-wise labeled images

Suggested Approach

- **Idea:** Encoder-Decoder Architecture
- **Transfer Learning:** CNNs trained for image classification contain meaningful information that can be used for segmentation -> Encoder
- **Check out:** pre-trained networks like MobileNets

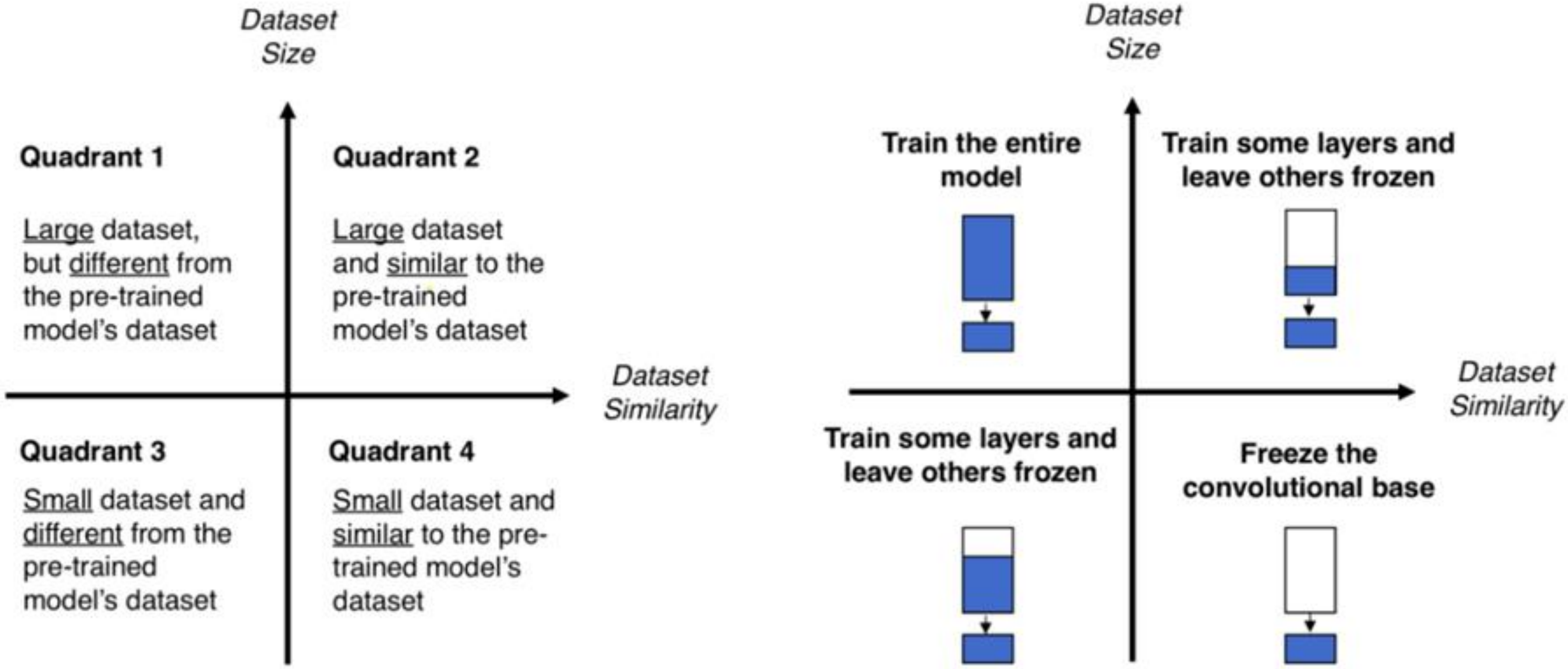


“Default” Approach (93.15)

- Take an already pretrained segmentation network
- Change the output layer to our number of classes
- Success!

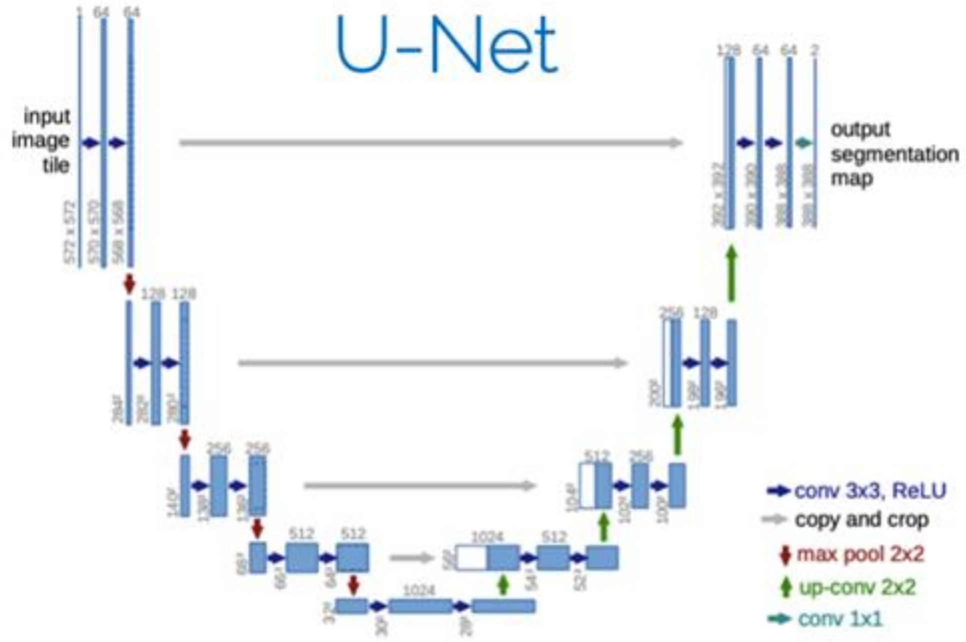
```
from torchvision.models.segmentation import lraspp_mobilenet_v3_large
from torchvision.models.segmentation.lraspp import LRASPPHead

self.mobilenet = lraspp_mobilenet_v3_large(pretrained=True)
self.mobilenet.classifier = LRASPPHead(40, 960, hparams['n_classes'],
128)
```

When/what to finetune?



So… something else? (92.38)

- Idea: Let's build a UNet



Let's start with pretrained backbone

- Get pretrained network and identify skip connection candidates

```
# get pretrained net
self.feature_extractor = mobilenet_v2(True).features
for params in self.feature_extractor.parameters():
    params.detach()
#output size should be: [-1, 1280, 8, 8]

# define forward hooks
# interesting layers:1:(16,120) 3:(24,60): 6:(32,30); 10:(64,15); 13:
(96,15); 16:(160,8); 17:(320,8); 18(1280,8)
self.horizontalLayerIndices = [6, 13, 18]
```

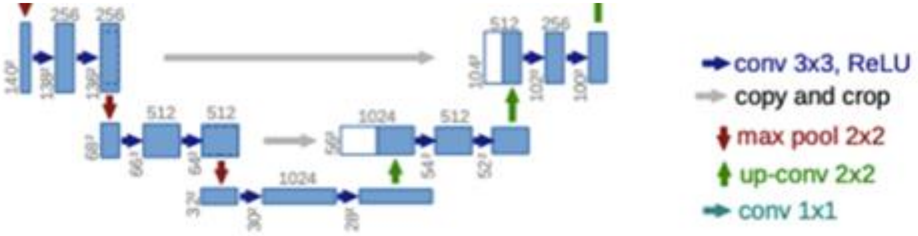
Let's check forward

- Forward backbone but keep track of skips
- "Bottleneck"
- Upsampling and filling in skips

```
layeroutputs = []
for i in range(len(self.feature_extractor)):
    x = self.feature_extractor[i](x)
    if i in self.horizontalLayerIndices:
        layeroutputs.append(x)

x = layeroutputs[-1]
x = self.initialConv(x)

k = 3 if self.use30features else 4

for i in range(len(self.upsampler)):
    x = self.upsampler[i](x)
    if i < len(self.upsampler)-k:
        x = torch.concat((x, layeroutputs[-2-i]), dim=1)
    x = self.convs[i](x)
```

Some comments

- Bottleneck seems to be too tight
  - Make room for multiple non-linearities before upsampling and merging



- Bottleneck is using 8x8 with 1280 features
  - Use 1x1 convolutions to shrink down size first (we are not imagenet with 1000 classes where would need it)

0	feature_extractor	Sequential	2.2 M
1	input_normalization	Normalize	0
2	upsampler	ModuleList	0
3	convs	ModuleList	1.6 M
4	initialConv	Sequential	$\boxed{\text{410 K}}$
5	lossFcn	CrossEntropyLoss	0

Some comments

- Good: usage of variables for filter/network size
  - Just don't hardcore numbers in your init unless you really want to keep them

```
featureSize = np.linspace(featureSize, num_classes, 5)
featureSize = featureSize.astype('int')
```

- Don't forget to use data augmentation even when transfering weights
  - Could have been done outside of notebook, just a reminder ☺

Natural Language Processing

Natural Language Processing

- So far, it has always been clear how to feed data into our model
- Tabular Data -> Load each row as vector and normalize data
- Images -> Convert Image into Matrix for convolution or flatten into vector for linear layers
- Text -> „What should I do with this?" -> ?

Tokenization

- Split text into individual tokens
- Tokens can be
  - Individual words like „Hi", „these", „are", „tokens"
  - Subwords like "sub" and „words"
  - Letters like „h", „i"
  - Punctuations and white spaces like „!", „," or „ "
  - Combination of all

- Assign each token an ID: „Hi" -> 53, „Bye" -> 647

Tokenization - Training

- For simple Tokenizer:
  - Loop through dataset and split strings by whitespace
  - Add every new „word" into dictionary and assign ID
  - That's it!

- Problems:
  - What happens with words that were not in the dataset?

- Possible Solutions:
  - Add unknown token placeholder
  - Use a more sophisticated tokenizer like Byte-Pair Encoder

Exercise 11
Notebook 1

Map Style Datasets

- So far we have always used a map style Dataset:
    - Given an index, return the item at this index

- This approach works great for
    - Small Tables -> simply return the row where row_id = index
    - Images -> load image from disk by indexing a list of paths

Map Style Datasets

- Advantages:
  - Data can be prefetched
  - Data shuffling is easy to implement
  - Parallelization is easy to implement

- Problems:
  - What happens if your data is stored in very large text files of tables? We cannot load everything in memory to properly index it
  - What happens if our data is coming in as a stream? (Think of live audio or video feed!)

Iterable Datasets

- Do we really need to index the data? All we want is to get the next sample!
- Iterable Datasets: Instead of a __getitem__(index) method we implement a __iter__() method
- Read through the file/table line by line and yield the current sample
    - We do not have to load the entire file into memory!

Iterable Datasets

Exercise 11
Notebook 2

- Advantages
  - Less Memory Usage
  - Easy to seamlessly cycle through multiple files

- Disadvantages
  - Shuffling data in data loader not possible
  - Parallel Processing and using multiple workers for data loading not as easy to implement

Data Collator

- So far data usually always had the same dimensions
  - We can easily create batches by adding a tensor dimension!
- Problem with natural language: Not every sentence is the same length!

Data Collator

- Solution: Add padding tokens to the shorter sentences in a batch to match the lengths

    - ["Hi" "how" "are" "you" "?"] -> 5 Tokens
    - ["Good" "and" "you" "?" "<pad>"] -> 4 Tokens -> Add pad to match lengths!

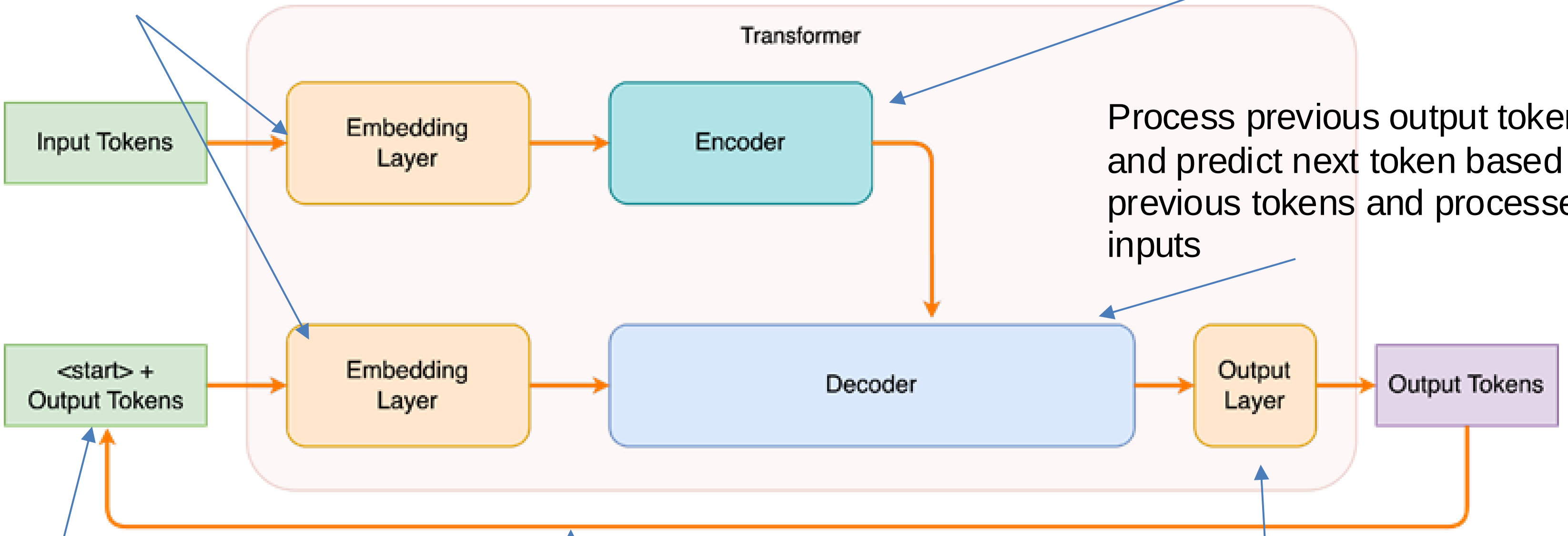
- This is implemented in the Data Collator, which is part of the Data Loader!

Exercise 11
Notebook 2

Transformers –High Level

Convert Token IDs
into Dense Vectors

Process input sequence



Process previous output tokens and predict next token based on previous tokens and processed inputs

Initialized sequence with ”empty” start token

Append new output to sequence

Transform decoder output Into probability distribution over Word IDs

Exercise 11

Exercise 11: Content and Goal

- Notebook 1
  - Introduction to Byte Pair Tokenization
  - Training Algorithm and Examples
  - Goal: Train own tokenizer on a dataset

- Notebook 2
  - Iterable Datasets
  - Data Collators
  - Goal: Implement your own iterable dataset

Exercise 11: Content and Goal

- Notebook 3
  - Intuition behind Word Embeddings
  - Intuition behind Attention Mechanism
  - Transformer Models
  - Goal: Implement a transformer model from scratch and train it to translate english to german!

Good Luck with the exercise and exam!

☺