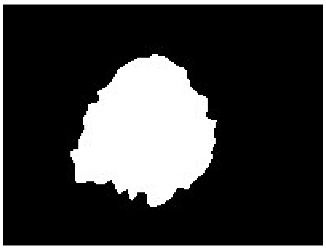
Semantic Segmentation

1.Для начала мы скачаем датасет: [ADDI project (https://www.fc.up.pt/addi/ph2%20database.html)](https://www.fc.up.pt/addi/ph2%20database.html).

1. Разархивируем .rar файл.
2. Обратите внимание, что папка `PH2 Dataset images` должна лежать там же где и ipynb notebook.

Это фотографии двух типов **поражений кожи:** меланома и родинки. В данном задании мы не будем заниматься их классификацией, а будем сегментировать их.

In [0]:

```
import numpy as np
import torch

def seed_init(SEED = 1500):
    np.random.seed(SEED)
    torch.manual_seed(SEED)
    torch.cuda.manual_seed(SEED)
    torch.backends.cudnn.deterministic = True

seed_init()
```

Стуктура датасета у нас следующая:

```
IMD_002/
    IMD002_Dermoscopic_Image/
        IMD002.bmp
    IMD002_lesion/
        IMD002_lesion.bmp
    IMD002_roi/
        ...
IMD_003/
    ...
    ...
```

Для загрузки датасета я предлагаю использовать skimage: [`skimage.io.imread()` (https://scikit-image.org/docs/dev/api/skimage.io.html)](https://scikit-image.org/docs/dev/api/skimage.io.html)

In [0]:

```
images = []
lesions = []
from skimage.io import imread
import os
root = '/content/drive/My Drive/Colab Notebooks/Segmentation/data/PH2Dataset/'

for root, dirs, files in os.walk(os.path.join(root, 'PH2 Dataset images')):
    if root.endswith('_Dermoscopic_Image'):
        images.append(imread(os.path.join(root, files[0])))
    if root.endswith('_lesion'):
        lesions.append(imread(os.path.join(root, files[0])))
```

Изображения имеют разные размеры. Давайте изменим их размер на $256\times256 $ пикселей. [`skimage.transform.resize()` (https://scikit-image.org/docs/dev/api/skimage.transform.html#skimage.transform.resize)](https://scikit-image.org/docs/dev/api/skimage.transform.html#skimage.transform.resize) можно использовать для изменения размера изображений. Эта функция также автоматически нормализует изображения в диапазоне $[0,1]$.

In [0]:

```
from skimage.transform import resize
size = (256, 256)
X = [resize(x, size, mode='constant', anti_aliasing=True,) for x in images]
Y = [resize(y, size, mode='constant', anti_aliasing=False) > 0.5 for y in lesions]
Y_ = [resize(y, size, mode='constant', anti_aliasing=False) for y in lesions]
```

In [4]:

```
import numpy as np
X = np.array(X, np.float32)
Y = np.array(Y, np.float32)
Y_ = np.array(Y_, np.float32)
print(f'Loaded {len(X)} images')
```

```
Loaded 199 images
```

In [5]:

```
len(lesions)
```

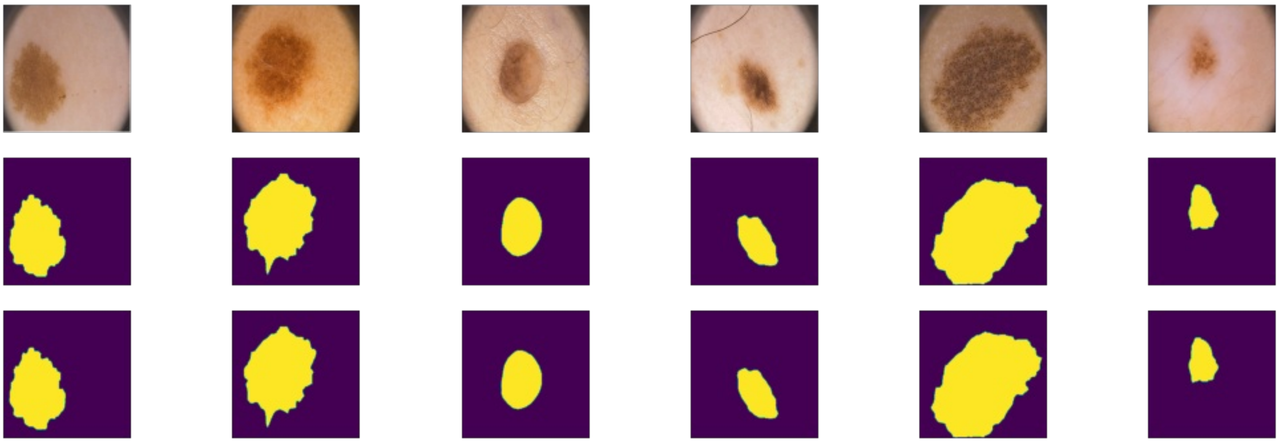
Out[5]:

```
199
```

Чтобы убедиться, что все корректно, мы нарисуем несколько изображений

In [6]:

```
import matplotlib.pyplot as plt
from IPython.display import clear_output

plt.figure(figsize=(18, 6))
for i in range(6):
    plt.subplot(3, 6, i+1)
    plt.axis("off")
    plt.imshow(X[i])

    plt.subplot(3, 6, i+7)
    plt.axis("off")
    plt.imshow(Y[i])

    plt.subplot(3, 6, i+13)
    plt.axis("off")
    plt.imshow(Y_[i])

plt.show();
```



Разделим наши 200 картинок на 100/50/50 для валидации и теста

In [0]:

```
ix = np.random.choice(len(X), len(X), False)
tr, val, ts = np.split(ix, [100, 150])
```

In [8]:

```
print(len(tr), len(val), len(ts))
```

```
100 50 49
```

PyTorch DataLoader

In [0]:

```
from torch.utils.data import DataLoader
batch_size = 25
data_tr = DataLoader(list(zip(np.rollaxis(X[tr], 3, 1), Y[tr, np.newaxis])),
                     batch_size=batch_size, shuffle=True)
data_val = DataLoader(list(zip(np.rollaxis(X[val], 3, 1), Y[val, np.newaxis])),
                      batch_size=batch_size, shuffle=True)
data_ts = DataLoader(list(zip(np.rollaxis(X[ts], 3, 1), Y[ts, np.newaxis])),
                     batch_size=batch_size, shuffle=True)
```

In [11]:

```
import torch
device = torch.device('cuda' if torch.cuda.is_available() else 'cpu')
device
```

Out[11]:

```
device(type='cuda')
```

In [0]:

```
import copy
def save_weights(net, name):
    net_weights = copy.deepcopy(net.state_dict())
    torch.save(net_weights, name)
    !mv '/content/{name}' '/content/drive/My Drive/Colab Notebooks/Segmentation/weights'
```

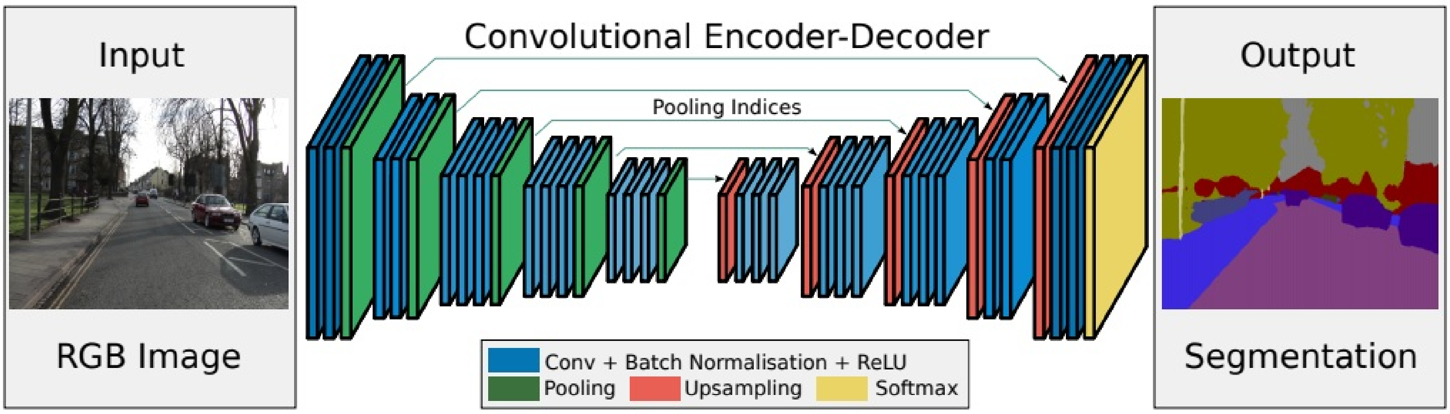
In [0]:

```
def load_weights(*nets, paths):
    for net, path in zip(nets, paths):
        net.load_state_dict(torch.load(path))
```

Реализация различных архитектур:

Ваше задание будет состоять в том, чтобы написать несколько нейросетевых архитектур для решения задачи семантической сегментации. Сравнить их по качеству на тесте и испробовать различные лосс функции для них.

SegNet [2 балла]



- Badrinarayanan, V., Kendall, A., & Cipolla, R. (2015). [SegNet: A deep convolutional encoder-decoder architecture for image segmentation (https://arxiv.org/pdf/1511.00561.pdf)](https://arxiv.org/pdf/1511.00561.pdf)

In [0]:

```
import gc
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim
from time import time
from torchsummary import summary

from matplotlib import rcParams
rcParams['figure.figsize'] = (15,8)
```

In [0]:

```
def clear_memory():
    gc.collect()
    torch.cuda.empty_cache()
```

In [0]:

```
class SegNet(nn.Module):
    def __init__(self):
        super().__init__()

        self.enc_conv0 = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
        )

        self.pool0 = nn.MaxPool2d(kernel_size=2, stride=2)  # 256 -> 128
        self.enc_conv1 = nn.Sequential(
            nn.Conv2d(32, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
        )
        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2) # 128 -> 64
        self.enc_conv2 = nn.Sequential(
            nn.Conv2d(64, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(128, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),

        )
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2) # 64 -> 32
        self.enc_conv3 = nn.Sequential(
            nn.Conv2d(128, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.35),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),

        )
        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2) # 32 -> 16

        # bottleneck
        self.bottleneck_conv = nn.Sequential(
            nn.Conv2d(256, 512, kernel_size=3, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.45),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.BatchNorm2d(512),
```

```
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True),
        )

        # decoder (upsampling)
        self.upsample0 =  nn.Upsample(scale_factor=2, mode="bilinear") # 16 -> 32
        self.dec_conv0 =  nn.Sequential(
            nn.Conv2d(512, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.35),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
        )
        self.upsample1 =  nn.Upsample(scale_factor=2, mode="bilinear")# 32 -> 64
        self.dec_conv1 =  nn.Sequential(
            nn.Conv2d(256, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(128, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
        )
        self.upsample2 =  nn.Upsample(scale_factor=2, mode="bilinear") # 64 -> 128
        self.dec_conv2 =  nn.Sequential(
            nn.Conv2d(128, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
        )
        self.upsample3 =  nn.Upsample(scale_factor=2, mode="bilinear") # 128 -> 256
        self.dec_conv3 =  nn.Sequential(
            nn.Conv2d(64, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 1, kernel_size=3, padding=1),
            nn.BatchNorm2d(1)
        )
    def forward(self, x):
        # encoder
        e0 = self.pool0(self.enc_conv0(x))
        e1 = self.pool1(self.enc_conv1(e0))
        e2 = self.pool2(self.enc_conv2(e1))
        e3 = self.pool3(self.enc_conv3(e2))

        # bottleneck
        b = self.bottleneck_conv(e3)

        # decoder
        d0 = self.dec_conv0(self.upsample0(b))
        d1 = self.dec_conv1(self.upsample1(d0))
        d2 = self.dec_conv2(self.upsample2(d1))
        d3 = self.dec_conv3(self.upsample3(d2))  # no activation
        return d3
```

In [17]:

```
summary(SegNet().to(device), input_size=(3, 256, 256))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 32, 256, 256]             896
       BatchNorm2d-2         [-1, 32, 256, 256]              64
              ReLU-3         [-1, 32, 256, 256]               0
            Conv2d-4         [-1, 32, 256, 256]           9,248
       BatchNorm2d-5         [-1, 32, 256, 256]              64
              ReLU-6         [-1, 32, 256, 256]               0
         MaxPool2d-7         [-1, 32, 128, 128]               0
            Conv2d-8         [-1, 64, 128, 128]          18,496
```

```
       BatchNorm2d-9        [-1, 64, 128, 128]             128
              ReLU-10        [-1, 64, 128, 128]               0
            Conv2d-11        [-1, 64, 128, 128]          36,928
       BatchNorm2d-12        [-1, 64, 128, 128]             128
              ReLU-13        [-1, 64, 128, 128]               0
         MaxPool2d-14          [-1, 64, 64, 64]               0
            Conv2d-15         [-1, 128, 64, 64]          73,856
       BatchNorm2d-16         [-1, 128, 64, 64]             256
              ReLU-17         [-1, 128, 64, 64]               0
         Dropout2d-18         [-1, 128, 64, 64]               0
            Conv2d-19         [-1, 128, 64, 64]         147,584
       BatchNorm2d-20         [-1, 128, 64, 64]             256
              ReLU-21         [-1, 128, 64, 64]               0
         MaxPool2d-22         [-1, 128, 32, 32]               0
            Conv2d-23         [-1, 256, 32, 32]         295,168
       BatchNorm2d-24         [-1, 256, 32, 32]             512
              ReLU-25         [-1, 256, 32, 32]               0
         Dropout2d-26         [-1, 256, 32, 32]               0
            Conv2d-27         [-1, 256, 32, 32]         590,080
       BatchNorm2d-28         [-1, 256, 32, 32]             512
              ReLU-29         [-1, 256, 32, 32]               0
            Conv2d-30         [-1, 256, 32, 32]         590,080
       BatchNorm2d-31         [-1, 256, 32, 32]             512
              ReLU-32         [-1, 256, 32, 32]               0
         MaxPool2d-33         [-1, 256, 16, 16]               0
            Conv2d-34         [-1, 512, 16, 16]       1,180,160
       BatchNorm2d-35         [-1, 512, 16, 16]           1,024
              ReLU-36         [-1, 512, 16, 16]               0
         Dropout2d-37         [-1, 512, 16, 16]               0
            Conv2d-38         [-1, 512, 16, 16]       2,359,808
       BatchNorm2d-39         [-1, 512, 16, 16]           1,024
              ReLU-40         [-1, 512, 16, 16]               0
            Conv2d-41         [-1, 512, 16, 16]       2,359,808
       BatchNorm2d-42         [-1, 512, 16, 16]           1,024
              ReLU-43         [-1, 512, 16, 16]               0
          Upsample-44         [-1, 512, 32, 32]               0
            Conv2d-45         [-1, 256, 32, 32]       1,179,904
       BatchNorm2d-46         [-1, 256, 32, 32]             512
              ReLU-47         [-1, 256, 32, 32]               0
         Dropout2d-48         [-1, 256, 32, 32]               0
            Conv2d-49         [-1, 256, 32, 32]         590,080
       BatchNorm2d-50         [-1, 256, 32, 32]             512
              ReLU-51         [-1, 256, 32, 32]               0
            Conv2d-52         [-1, 256, 32, 32]         590,080
       BatchNorm2d-53         [-1, 256, 32, 32]             512
              ReLU-54         [-1, 256, 32, 32]               0
          Upsample-55         [-1, 256, 64, 64]               0
            Conv2d-56         [-1, 128, 64, 64]         295,040
       BatchNorm2d-57         [-1, 128, 64, 64]             256
              ReLU-58         [-1, 128, 64, 64]               0
         Dropout2d-59         [-1, 128, 64, 64]               0
            Conv2d-60         [-1, 128, 64, 64]         147,584
       BatchNorm2d-61         [-1, 128, 64, 64]             256
              ReLU-62         [-1, 128, 64, 64]               0
          Upsample-63       [-1, 128, 128, 128]               0
            Conv2d-64        [-1, 64, 128, 128]          73,792
       BatchNorm2d-65        [-1, 64, 128, 128]             128
              ReLU-66        [-1, 64, 128, 128]               0
            Conv2d-67        [-1, 64, 128, 128]          36,928
       BatchNorm2d-68        [-1, 64, 128, 128]             128
              ReLU-69        [-1, 64, 128, 128]               0
          Upsample-70        [-1, 64, 256, 256]               0
            Conv2d-71        [-1, 32, 256, 256]          18,464
       BatchNorm2d-72        [-1, 32, 256, 256]              64
              ReLU-73        [-1, 32, 256, 256]               0
            Conv2d-74        [-1, 32, 256, 256]           9,248
       BatchNorm2d-75        [-1, 32, 256, 256]              64
              ReLU-76        [-1, 32, 256, 256]               0
            Conv2d-77         [-1, 1, 256, 256]             289
       BatchNorm2d-78         [-1, 1, 256, 256]               2
================================================================
Total params: 10,611,459
Trainable params: 10,611,459
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 462.50
Params size (MB): 40.48
Estimated Total Size (MB): 503.73
----------------------------------------------------------------
```

```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2973: UserWarning: Default upsamp
ling behavior when mode=bilinear is changed to align_corners=False since 0.4.0. Please specify
align_corners=True if the old behavior is desired. See the documentation of nn.Upsample for det
ails.
  "See the documentation of nn.Upsample for details.".format(mode))
```

Метрика

В данном разделе предлагается использовать следующую метрику для оценки качества:

$I o U=\frac{\text {target } \cap \text { prediction }}{\text {target } \cup{prediction }}$

Пересечение (A ∩ B) состоит из пикселей, найденных как в маске предсказания, так и в основной маске истины, тогда как объединение (A ∪ B) просто состоит из всех пикселей, найденных либо в маске предсказания, либо в целевой маске.

To clarify this we can see on the segmentation:

And the intersection will be the following:

In [0]:

```python
def iou_pytorch(outputs: torch.Tensor, labels: torch.Tensor):
    # You can comment out this line if you are passing tensors of equal shape
    # But if you are passing output from UNet or something it will most probably
    # be with the BATCH x 1 x H x W shape
    outputs = outputs.squeeze(1).byte()  # BATCH x 1 x H x W => BATCH x H x W
    labels = labels.squeeze(1).byte()
    SMOOTH = 1e-8
    intersection = (outputs & labels).float().sum((1, 2))  # Will be zero if Truth=0 or Prediction=0
    union = (outputs | labels).float().sum((1, 2))         # Will be zzero if both are 0

    iou = (intersection + SMOOTH) / (union + SMOOTH)  # We smooth our devision to avoid 0/0

    thresholded = torch.clamp(20 * (iou - 0.5), 0, 10).ceil() / 10  # This is equal to comparing with thresolds

    return thresholded
```

функция лосса [1 балл]

Теперь не менее важным, чем построение архитектуры, является определение **оптимизатора** и **функции потерь.**

Функция потерь - это то, что мы пытаемся минимизировать. Многие из них могут быть использованы для задачи бинарной семантической сегментации.

Популярным методом для бинарной сегментации является *бинарная кросс-энтропия*, которая задается следующим образом:
$$\mathcal L_{BCE}(y, \hat y) = -\sum_i \left[y_i\log\sigma(\hat y_i) + (1-y_i)\log(1-\sigma(\hat y_i))\right].$$

где y это таргет желаемого результата и $\hat y$ является выходом модели. σ - это [*логистическая* функция (https://en.wikipedia.org/wiki/Sigmoid_function)](https://en.wikipedia.org/wiki/Sigmoid_function), который преобразует действительное число $\mathbb R$ в вероятность $[0,1]$.

Однако эта потеря страдает от проблем численной нестабильности. Самое главное, что $\lim_{x\rightarrow0}\log(x)=\infty$ приводит к неустойчивости в процессе оптимизации. Рекомендуется посмотреть следующее [упрощение (https://www.tensorflow.org/api_docs/python/tf/nn/sigmoid_cross_entropy_with_logits)](https://www.tensorflow.org/api_docs/python/tf/nn/sigmoid_cross_entropy_with_logits) в Тарая функция эквивалентна и не так подвержена численной неустойчивости.
$$\mathcal L_{BCE} = \hat y - y\hat y + \log\left(1+\exp(-\hat y)\right).$$

In [0]:

```python
def bce_loss(y_pred, y_real, reduce=True):
    # TODO
    # please don't use nn.BCELoss. write it from scratch
    y_pred = torch.sigmoid(y_pred)
    preout = y_pred.sub(y_real.mul(y_pred))
    out = preout.add((1 + (-y_pred).exp()).log())
    return out.mean() if reduce else out
```

Тренировка [1 балл]

Мы определим цикл обучения в функции, чтобы мы могли повторно использовать его.

In [0]:

```
def eval_epoch(model, val_loader, criterion, metric, threshold):
    running_loss = .0
    running_score = .0
    processed_size = len(val_loader)

    model = model.to(device)
    model.eval()
    for inputs, real_masks in val_loader:
        inputs = inputs.to(device)
        real_masks = real_masks.to(device)

        with torch.no_grad():
            outputs = model(inputs)
            loss = criterion(outputs, real_masks)
            pred_masks = torch.sigmoid(outputs) > threshold

        running_score += metric(pred_masks, real_masks).mean().item()
        running_loss += loss.item()


    val_loss = running_loss / processed_size
    val_score = running_score / processed_size
    return val_loss, val_score
```

In [0]:

```
def fit_epoch(model, train_loader, criterion, metric, op, threshold):
    running_loss = .0
    running_score = .0
    processed_data = len(train_loader)

    model = model.to(device)
    model.train()
    for inputs, real_masks in train_loader:
        inputs = inputs.to(device)
        real_masks = real_masks.to(device)
        op.zero_grad()

        outputs = model(inputs)
        loss = criterion(outputs, real_masks)
        loss.backward()
        op.step()

        pred_masks = torch.sigmoid(outputs) > threshold
        running_score += metric(pred_masks, real_masks).mean().item()
        running_loss += loss.item()


    train_loss = running_loss / processed_data
    train_score = running_score / processed_data
    return train_loss, train_score
```

In [0]:

```
def get_lr(optimizer):
    for param_group in optimizer.param_groups:
        return param_group['lr']
```

In [0]:

```
def train(name_model, model, opt, loss_fn, metric, epochs, data_tr, data_val, threshold=.7):
    X_val, Y_val = next(iter(data_val))
    history = list()
    best_score = 0.
    scheduler = torch.optim.lr_scheduler.StepLR(opt, step_size=35, gamma=0.1)

    for epoch in range(epochs):
        tic = time()
        print('* Epoch %d/%d' % (epoch+1, epochs))

        train_loss, train_score = fit_epoch(model,
                                            data_tr,
                                            loss_fn,
                                            metric,
                                            opt,
                                            threshold
                                            )

        toc = time()
        print(f'* train_loss: {np.round(train_loss, 4)}, train_score: {np.round(train_score, 4)}')

        val_loss, val_score = eval_epoch(model,
                                         data_val,
                                         loss_fn,
                                         metric,
                                         threshold
                                         )

        print(f'* val_loss: {np.round(val_loss, 4)}, val_score: {np.round(val_score, 4)}')

        scheduler.step()
        print("* lr:", get_lr(opt))
        history.append((train_loss, train_score, val_loss, val_score))

        if best_score < val_score:
            save_weights(model, f"model_{name_model}.pth")
            best_score = val_score

        # show intermediate results
        model.eval()  # testing mode
        Y_hat = model(X_val.to(device)).detach().cpu() # detach and put into cpu


        # Visualize tools
        clear_output(wait=True)
        for k in range(6):
            plt.subplot(4, 6, k+1)
            plt.imshow(np.rollaxis(X_val[k].numpy(), 0, 3), cmap='gray')
            plt.title('Real')
            plt.axis('off')

            plt.subplot(4, 6, k+7)
            plt.imshow(Y_val[k].numpy().squeeze(), cmap='gray')
            plt.title('Real_mask')
            plt.axis('off')

            plt.subplot(4, 6, k+13)
            plt.imshow(Y_hat[k, 0], cmap='gray')
            plt.title('Output')
            plt.axis('off')

            plt.subplot(4, 6, k+19)
            plt.imshow(torch.sigmoid(Y_hat[k, 0]) > threshold, cmap='gray')
            plt.title('Output_mask')
            plt.axis('off')

        info = f'{epoch+1} / {epochs} - train_loss: {np.round(train_loss, 4)}, train_score: {np.round(train_
score, 4)}, val_loss: {np.round(val_loss, 4)}, val_score: {np.round(val_score, 4)}, max_val_score: {np.round
(best_score, 4)}'
        if (epoch+1) % 10 == 0 and not (epoch+1) == epochs:
            plot_stat(history)
        plt.suptitle(info)
        plt.show()

    load_weights(model, paths=[f"/content/drive/My Drive/Colab Notebooks/Segmentation/weights/model_{name_mo
del}.pth"])
    return history
```

In [0]:

```
def plot_stat(history, figsize=(15, 9)):
    train_loss, train_score, val_loss, val_score = zip(*history)
    max_score_train = np.max(train_score)
    max_score_loss_train = train_loss[np.argmax(train_score)]
    max_score_val = np.max(val_score)
    max_score_loss_val = val_loss[np.argmax(val_score)]
    print(f'max score on train: {max_score_train} with loss: {max_score_loss_train} \nmax score on val: {max
_score_val} with loss: {max_score_loss_val} ')
    plt.figure(figsize=figsize)
    plt.subplot(2, 1, 1)
    plt.plot(train_score, label="train_score")
    plt.plot(val_score, label="val_score")
    plt.legend(loc='best')
    plt.xlabel("epochs")
    plt.ylabel("score")
    plt.grid()
    plt.subplot(2, 1, 2)
    plt.plot(train_loss, label="train_loss")
    plt.plot(val_loss, label="val_loss")
    plt.legend(loc='best')
    plt.xlabel("epochs")
    plt.ylabel("loss")
    plt.grid()
    plt.show()
```

Инференс [1 балл]

После обучения модели эту функцию можно использовать для прогнозирования сегментации на новых данных:

In [0]:

```
def eval(model, loader, criterion, metric, threshold=.7):
    running_loss = .0
    running_score = .0
    processed_size = len(loader)

    model = model.to(device)
    model.eval()
    for inputs, real_masks in loader:
        inputs = inputs.to(device)
        real_masks = real_masks.to(device)

        with torch.no_grad():
            outputs = model(inputs)
            loss = criterion(outputs, real_masks)
            pred_masks = torch.sigmoid(outputs) > threshold

        running_score += metric(pred_masks, real_masks).mean().item()
        running_loss += loss.item()


    data_loss = running_loss / processed_size
    data_score = running_score / processed_size
    return data_loss, data_score
```

In [0]:

```
def score_model(model, metric, data, threshold=.7):
    model.eval()  # testing mode
    scores = 0
    for X_batch, Y_label in data:
        Y_pred = torch.sigmoid(model(X_batch.to(device)))
        scores += metric(Y_pred > threshold, Y_label.to(device)).mean().item()
    return scores/len(data)
```

Основной момент: обучение

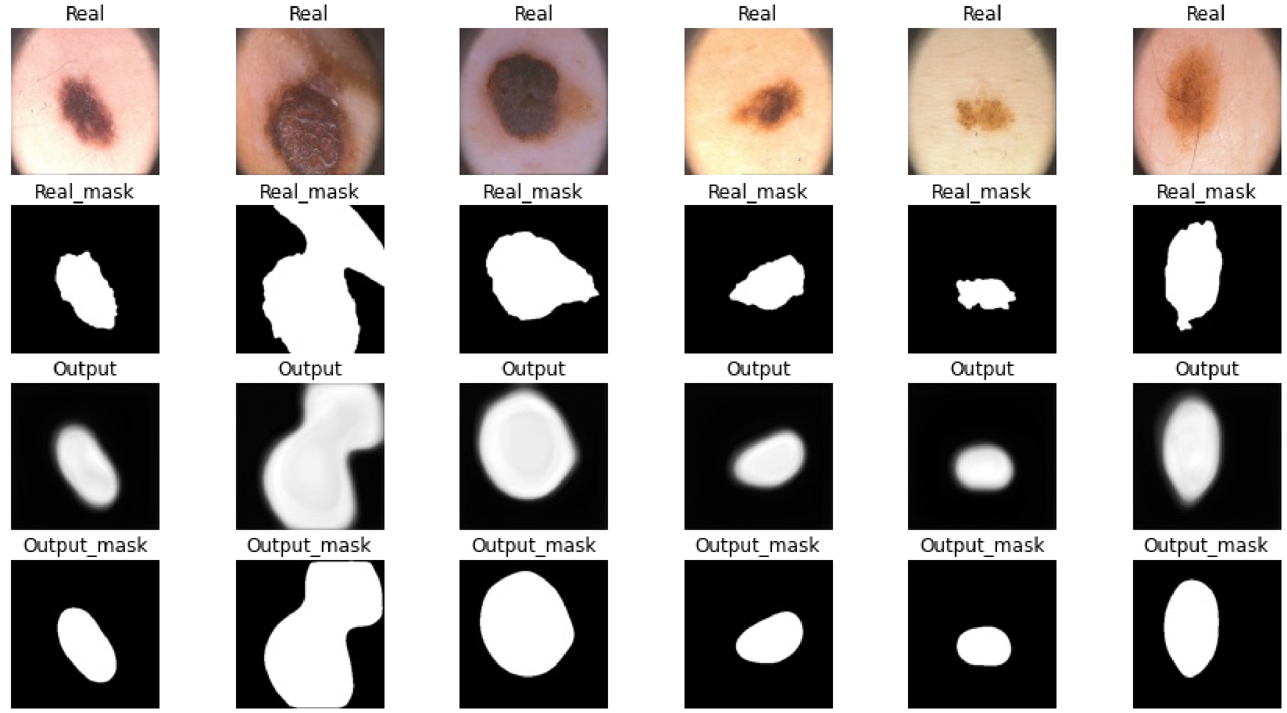
In [0]:

```
lr = 1e-4
max_epochs = 40
```

In [28]:

```
seed_init()
clear_memory()
model_bce = SegNet().to(device)


opt = optim.Adam(model_bce.parameters(), lr=lr)
history_bce = train('bce', model_bce, opt, bce_loss, iou_pytorch, max_epochs, data_tr, data_val)
```

40 / 40 - train_loss: 0.7153, train_score: 0.667, val_loss: 0.718, val_score: 0.654, max_val_score: 0.668



In [29]:

```
score_model(model_bce, iou_pytorch, data_val)
```

```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2973: UserWarning: Default upsamp
ling behavior when mode=bilinear is changed to align_corners=False since 0.4.0. Please specify
align_corners=True if the old behavior is desired. See the documentation of nn.Upsample for det
ails.
  "See the documentation of nn.Upsample for details.".format(mode))
```

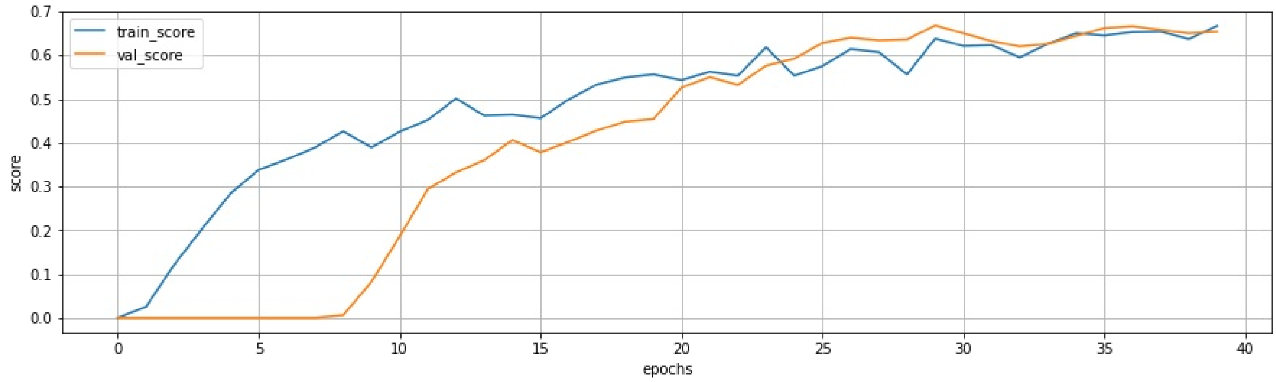
Out[29]:

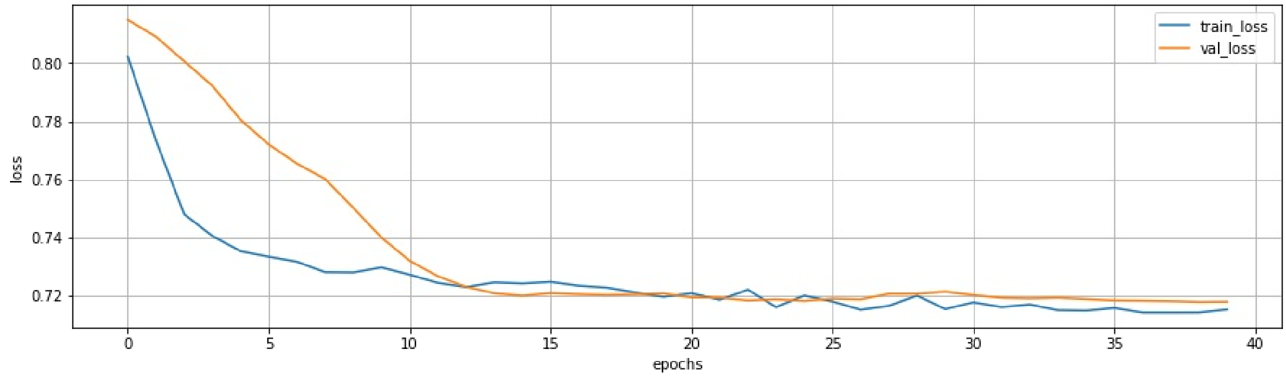
```
0.6679999828338623
```

In [30]:

```
plot_stat(history_bce)
```

```
max score on train: 0.6670000404119492 with loss: 0.7152881622314453
max score on val: 0.6680000126361847 with loss: 0.7214172184467316
```





Дополнительные функции лосса [2 балла]

В данном разделе вам потребуется имплементировать две функции потерь: DICE и Focal loss.

1. Dice coefficient: Учитывая две маски X и Y, общая метрика для измерения расстояния между этими двумя масками задается следующим образом:
$$D(X,Y)=\frac{2|X\cap Y|}{|X|+|Y|}$$

Эта функция не является дифференцируемой, но это необходимое свойство для градиентного спуска. В данном случае мы можем приблизить его с помощью:
$$\mathcal L_D(X,Y) = 1-\frac{1}{256 \times 256} \times \sum_i\frac{2X_iY_i}{X_i+Y_i}.$$

// Не забудьте подумать о численной нестабильности.

In [0]:

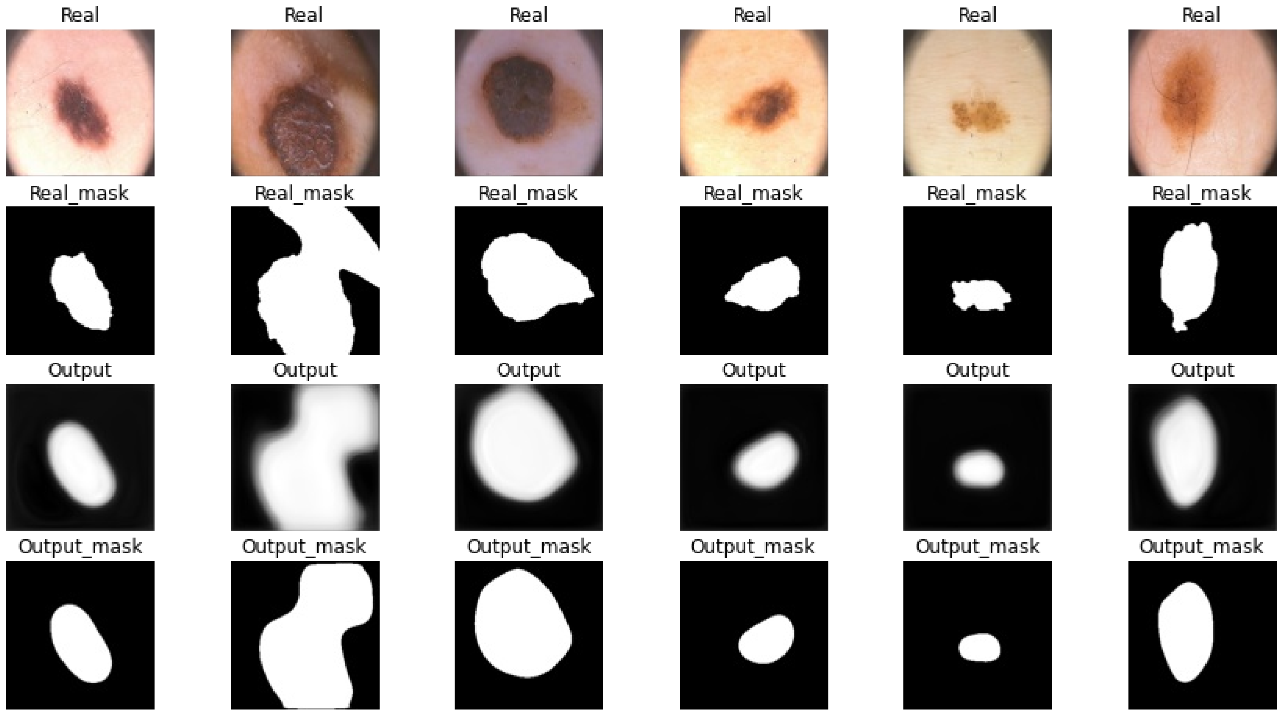
```
def dice_loss(y_pred, y_real, eps=1e-8):
    y_pred, y_real = torch.sigmoid(y_pred.view(-1)), y_real.view(-1)
    num = 2. * y_pred * y_real
    den =  y_pred + y_real + eps
    res = torch.mean(num / den)
    return 1. - res
```

Проводим тестирование:

In [32]:

```
seed_init()
clear_memory()
model_dice = SegNet().to(device)

optimaiz = optim.Adam(model_dice.parameters(), lr=lr)
history_dice = train('dice', model_dice, optimaiz, dice_loss, iou_pytorch, max_epochs, data_tr, data_val)
```

40 / 40 - train_loss: 0.7104, train_score: 0.61, val_loss: 0.7351, val_score: 0.612, max_val_score: 0.642



In [33]:

```
score_model(model_dice, iou_pytorch, data_val)
```

```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2973: UserWarning: Default upsamp
ling behavior when mode=bilinear is changed to align_corners=False since 0.4.0. Please specify
align_corners=True if the old behavior is desired. See the documentation of nn.Upsample for det
ails.
  "See the documentation of nn.Upsample for details.".format(mode))
```

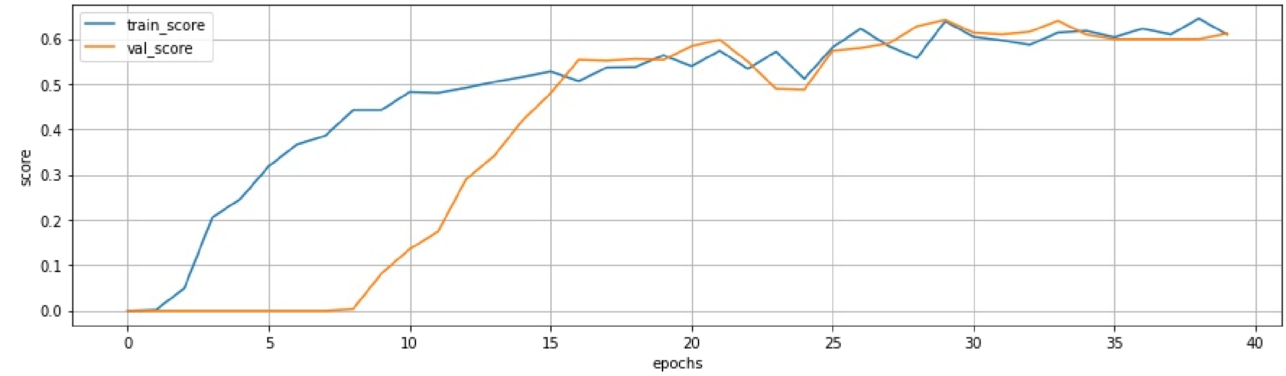
Out[33]:

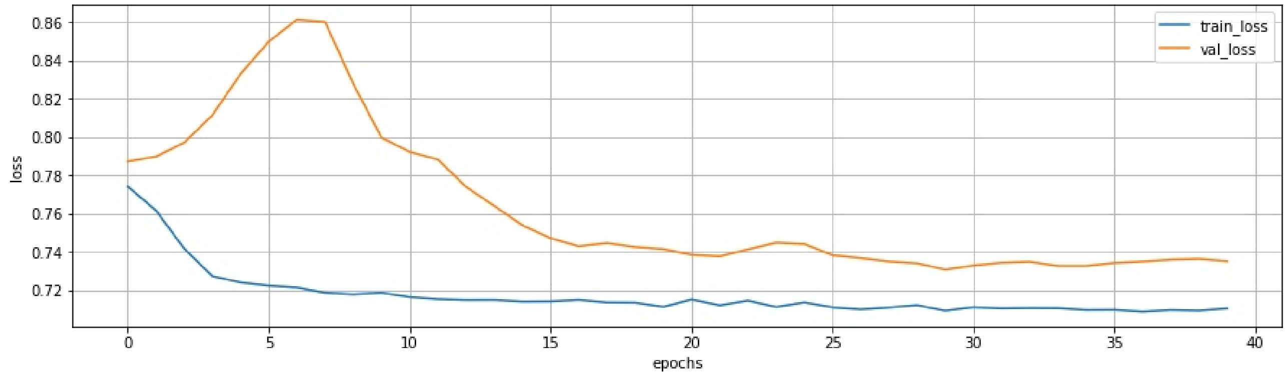
```
0.6420000195503235
```

In [34]:

```
plot_stat(history_dice)
```

```
max score on train: 0.6449999958276749 with loss: 0.7093066871166229
max score on val: 0.6420000195503235 with loss: 0.7307058572769165
```





[**2. Focal loss:** (https://arxiv.org/pdf/1708.02002.pdf)](https://arxiv.org/pdf/1708.02002.pdf)

Окей, мы уже с вами умеем делать BCE loss:
$$\mathcal L_{BCE}(y, \hat y) = -\sum_i \left[y_i\log\sigma(\hat y_i) + (1-y_i)\log(1-\sigma(\hat y_i))\right].$$

Проблема с этой потерей заключается в том, что она имеет тенденцию приносить пользу классу **большинства** (фоновому) по отношению к классу **меньшинства** (переднему). Поэтому обычно применяются весовые коэффициенты к каждому классу:
$$\mathcal L_{wBCE}(y, \hat y) = -\sum_i \alpha_i\left[y_i\log\sigma(\hat y_i) + (1-y_i)\log(1-\sigma(\hat y_i))\right].$$

Традиционно вес α_i определяется как обратная частота класса этого пикселя i, так что наблюдения миноритарного класса весят больше по отношению к классу большинства.

Еще одним недавним дополнением является взвешенный пиксельный вариант, которая взвешивает каждый пиксель по степени уверенности, которую мы имеем в предсказании этого пикселя.
$$\mathcal L_{focal}(y, \hat y) = -\sum_i \left[\left(1-\sigma(\hat y_i)\right)^\gamma y_i\log\sigma(\hat y_i) + (1-y_i)\log(1-\sigma(\hat y_i))\right].$$

Зафиксируем значение $\gamma=2$.

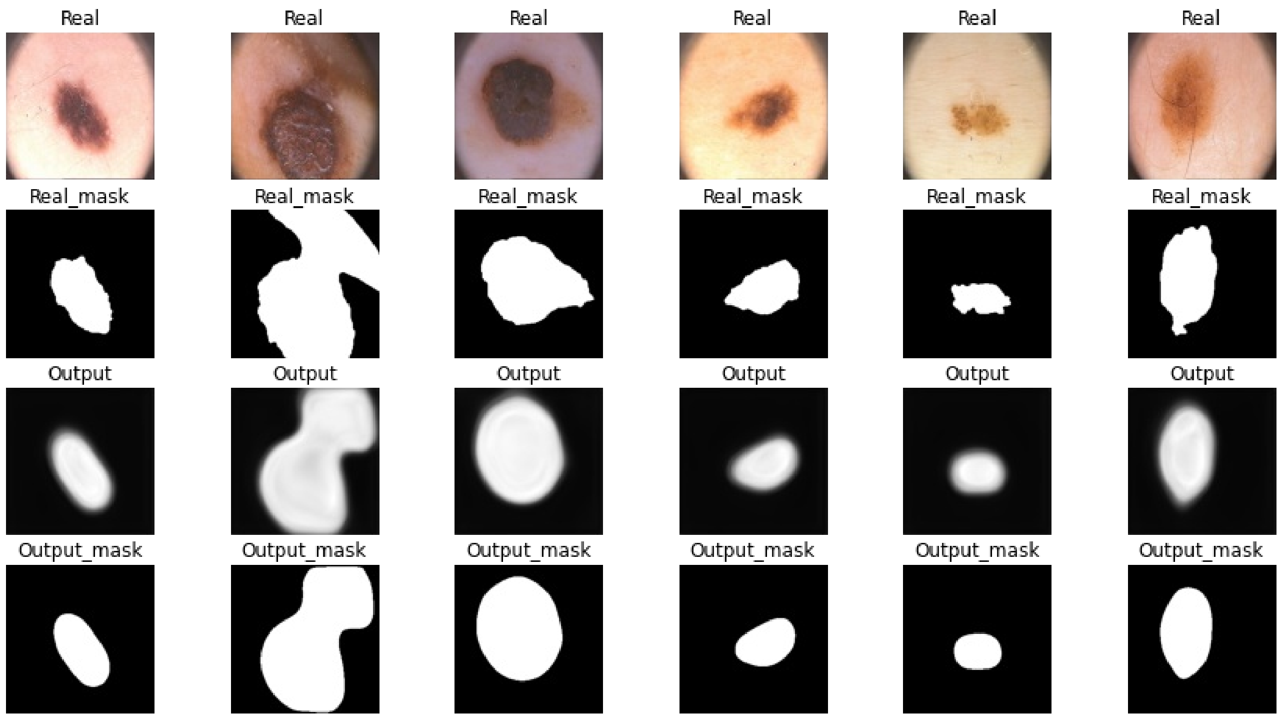
In [0]:

```python
def focal_loss(y_pred, y_real, alpha=1, gamma=2, eps=1e-8, bce_loss=bce_loss):
    y_pred, y_real = y_pred.view(y_pred.shape[0], -1), y_real.view(y_pred.shape[0], -1)
    bce = bce_loss(y_pred, y_real, reduce=False) # F.binary_cross_entropy_with_logits(y_pred, y_real, reduce
=False)
    pt = torch.exp( - bce)
    loss = alpha * ((1 - pt) ** gamma) * bce
    # y_pred = hint: torch.clamp
    return loss.mean()
```

In [36]:

```
seed_init()
clear_memory()
model_focal = SegNet().to(device)

optimaiz = optim.Adam(model_focal.parameters(), lr=lr)
history_focal = train('focal', model_focal, optimaiz, focal_loss, iou_pytorch, max_epochs, data_tr, data_val
)
```

40 / 40 - train_loss: 0.2157, train_score: 0.643, val_loss: 0.2164, val_score: 0.602, max_val_score: 0.63



In [37]:

```
score_model(model_focal, iou_pytorch, data_val)
```

```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2973: UserWarning: Default upsamp
ling behavior when mode=bilinear is changed to align_corners=False since 0.4.0. Please specify
align_corners=True if the old behavior is desired. See the documentation of nn.Upsample for det
ails.
  "See the documentation of nn.Upsample for details.".format(mode))
```

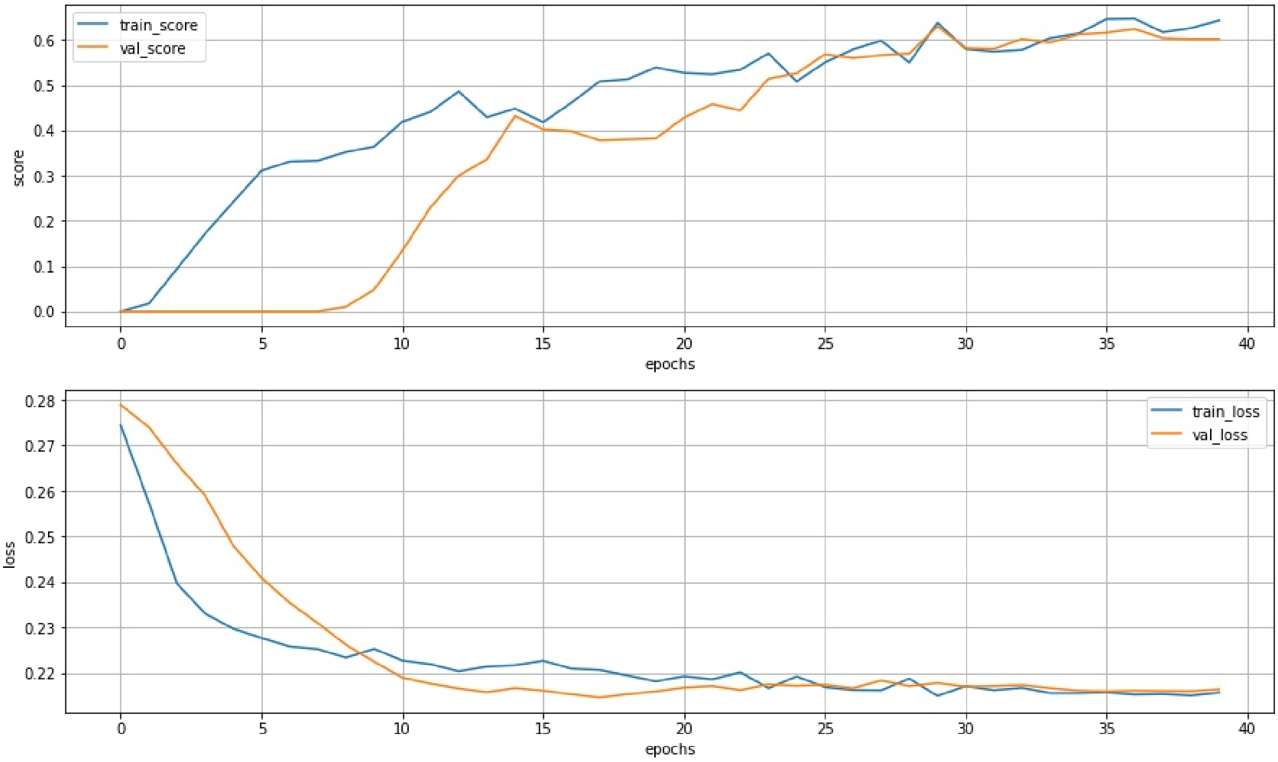
Out[37]:

```
0.6299999952316284
```

In [38]:

```
plot_stat(history_focal)
```

```
max score on train: 0.6470000147819519 with loss: 0.21528907120227814
max score on val: 0.6300000250339508 with loss: 0.21781566739082336
```



[BONUS] Мир сегментационных лоссов [5 баллов]

В данном блоке предлагаю написать вам 1 функцию потерь самостоятельно. Для этого необходимо прочитать статью и имплементировать ее. Кроме тако провести численное сравнение с предыдущими функциями. Какие варианты?

1) Можно учесть Total Variation 2) Lova 3) BCE но с Soft Targets (что-то типа label-smoothing для многослассовой классификации) 4) Tversky loss 5) Любой другой

- Physiological Inspired Deep Neural Networks for Emotion Recognition (https://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=8472816&tag=1)". IEEE Access, 6, 53930-53943.
- Boundary loss for highly unbalanced segmentation (https://arxiv.org/abs/1812.07032)
- Tversky loss function for image segmentation using 3D fully convolutional deep networks (https://arxiv.org/abs/1706.05721)
- Correlation Maximized Structural Similarity Loss for Semantic Segmentation (https://arxiv.org/abs/1910.08711)
- Topology-Preserving Deep Image Segmentation (https://papers.nips.cc/paper/8803-topology-preserving-deep-image-segmentation)

> ***Exercise:*** Add the total variation term to the loss.

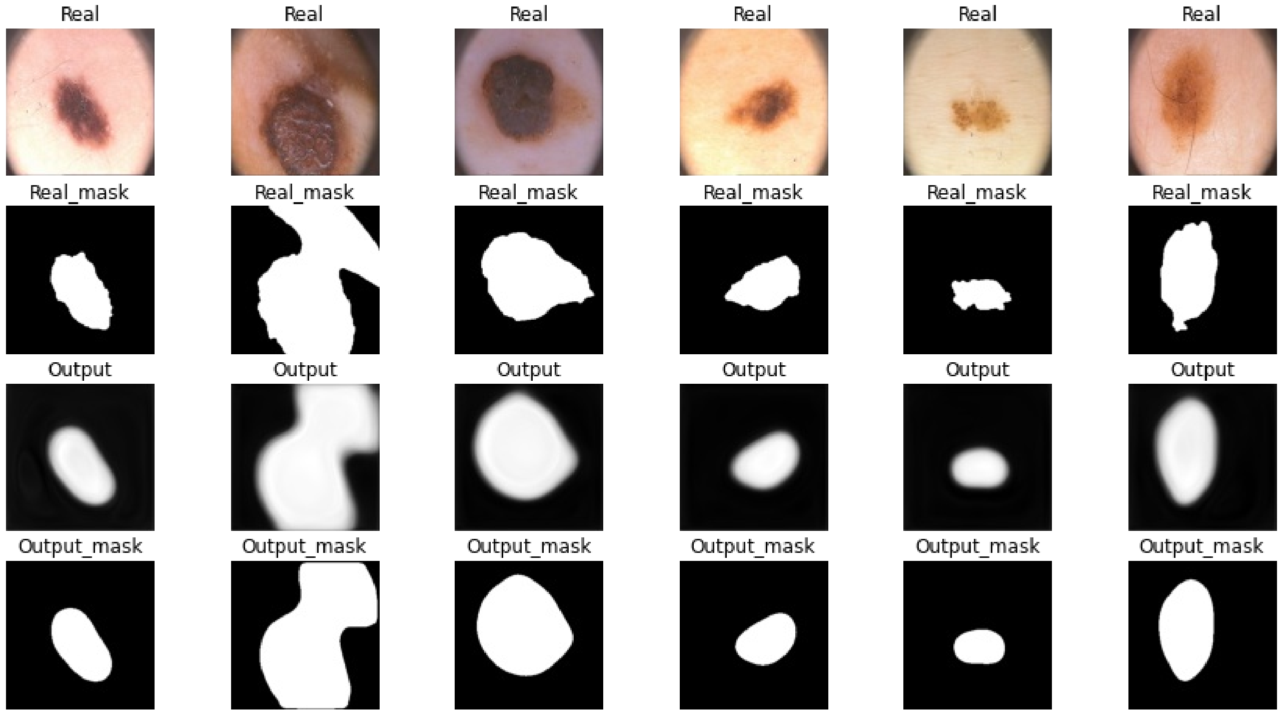
In [0]:

```
#<TODO>
def tversky_loss(beta, eps = 1e-8):
    def loss(y_pred, y_real):
        y_pred, y_real = torch.sigmoid(y_pred.view(-1)), y_real.view(-1)
        numerator = torch.sum(y_real * y_pred)
        denominator = y_real * y_pred + beta * (1. - y_real) * y_pred + (1. - beta) * y_real * (1. - y_pred)
        return 1. - numerator / (torch.sum(denominator) + eps)
    return loss
```

In [40]:

```
seed_init()
clear_memory()
model_tversky = SegNet().to(device)
tversky_loss_07 = tversky_loss(beta=.3)

optima = optim.Adam(model_tversky.parameters(), lr=lr)
history_tversky = train('tversky', model_tversky, optima, tversky_loss_07, iou_pytorch, max_epochs, data_tr,
data_val)
```

40 / 40 - train_loss: 0.3305, train_score: 0.637, val_loss: 0.3476, val_score: 0.652, max_val_score: 0.658



In [41]:

```
score_model(model_tversky, iou_pytorch, data_val)
```

```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2973: UserWarning: Default upsamp
ling behavior when mode=bilinear is changed to align_corners=False since 0.4.0. Please specify
align_corners=True if the old behavior is desired. See the documentation of nn.Upsample for det
ails.
  "See the documentation of nn.Upsample for details.".format(mode))
```

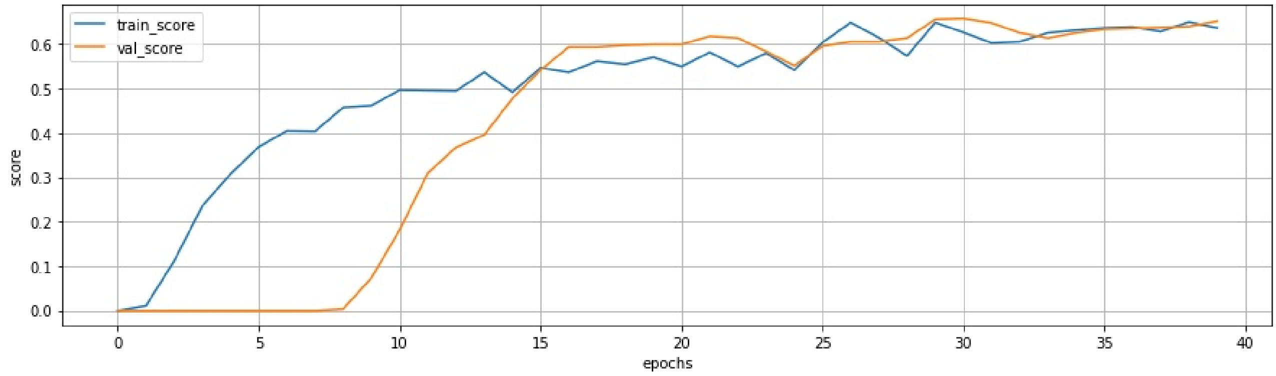
Out[41]:

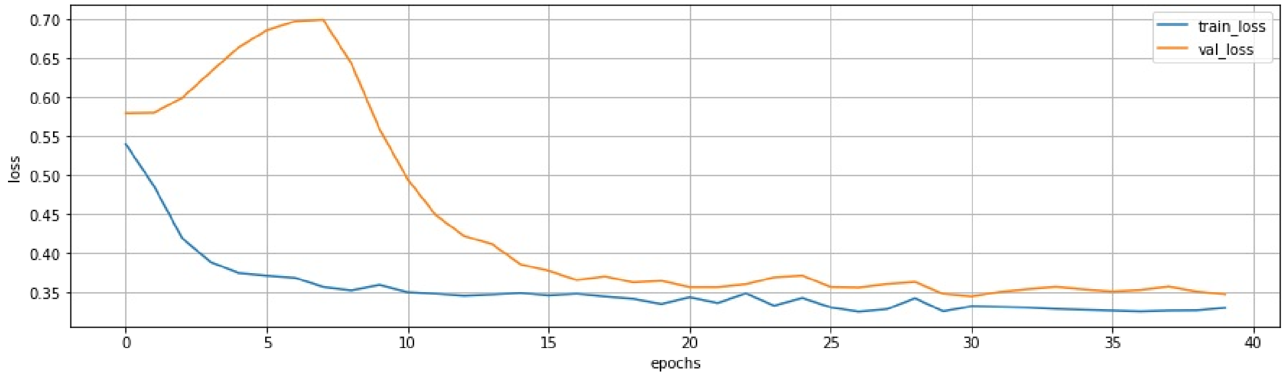
```
0.6579999923706055
```

In [42]:

```
plot_stat(history_tversky)
```

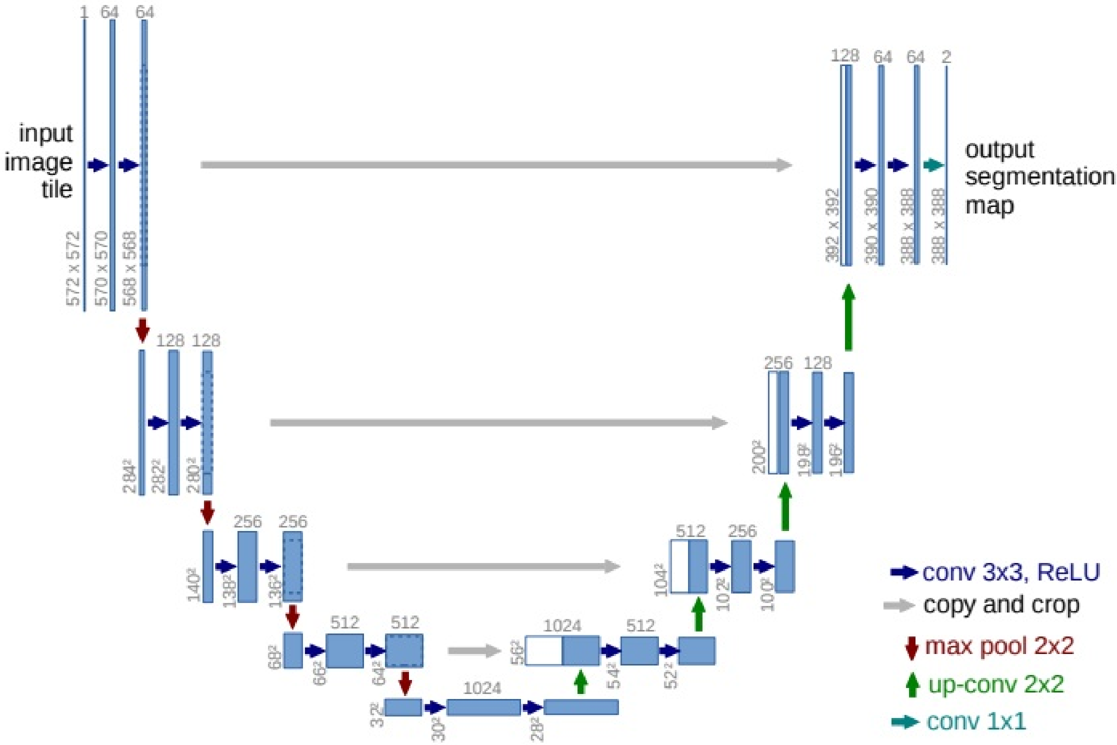
```
max score on train: 0.6500000059604645 with loss: 0.3270793706178665
max score on val: 0.6579999923706055 with loss: 0.3447708189487457
```





U-Net [2 балла]

U-Net [(https://arxiv.org/abs/1505.04597)](https://arxiv.org/abs/1505.04597) это архитектура нейронной сети, которая получает изображение и выводит его. Первоначально он был задуман для семантической сегментации (как мы ее будем использовать), но он настолько успешен, что с тех пор используется в других контекстах. Учитывая медицинское изображение, он выводит изображение в оттенках серого, представляющее вероятность того, что каждый пиксель является интересующей областью.



У нас в архитектуре все так же существует енкодер и декодер, как в **SegNet**, но отличительной особеностью данной модели являются skip-conenctions. Элементы соединяющие части декодера и енкодера. То есть для того чтобы передать на вход декодера тензор, мы конкатенируем симметричный выход с энкодера и выход предыдущего слоя декодера.

- Ronneberger, Olaf, Philipp Fischer, and Thomas Brox. "[U-Net: Convolutional networks for biomedical image segmentation. (https://arxiv.org/pdf/1505.04597.pdf)](https://arxiv.org/pdf/1505.04597.pdf)" International Conference on Medical image computing and computer-assisted intervention. Springer, Cham, 2015.

In [0]:

```
class UNet(nn.Module):
    def __init__(self):
        super().__init__()

        # encoder (downsampling)
        self.enc_conv0 = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),

        )

        self.pool0 = nn.MaxPool2d(kernel_size=2, stride=2)  # 256 -> 128
        self.enc_conv1 = nn.Sequential(
            nn.Conv2d(32, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),

        )

        self.pool1 = nn.MaxPool2d(kernel_size=2, stride=2) # 128 -> 64
        self.enc_conv2 = nn.Sequential(
            nn.Conv2d(64, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(128, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),


        )
        self.pool2 = nn.MaxPool2d(kernel_size=2, stride=2) # 64 -> 32
        self.enc_conv3 = nn.Sequential(
            nn.Conv2d(128, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),


        )


        self.pool3 = nn.MaxPool2d(kernel_size=2, stride=2) # 32 -> 16

        # bottleneck
        self.bottleneck_conv = nn.Sequential(
            nn.Conv2d(256, 512, kernel_size=3, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True),
        )

        # decoder (upsampling)
        self.upsample0 =  nn.Upsample(scale_factor=2, mode="bilinear") # 16 -> 32
        self.dec_conv0 =  nn.Sequential(
            nn.Conv2d(512, 256, kernel_size=3, padding=1),
```

```
            nn.Conv2d(512, 256, kernel_size=3, padding=1),

            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),

        )
        # *2 - because concatenation
        self.upsample1 =  nn.Upsample(scale_factor=2, mode="bilinear") # 32 -> 64
        self.dec_conv1 =  nn.Sequential(
            nn.Conv2d(256*2, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(128, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),

        )
        # *2 - because concatenation
        self.upsample2 =  nn.Upsample(scale_factor=2, mode="bilinear") # 64 -> 128
        self.dec_conv2 =  nn.Sequential(
            nn.Conv2d(128*2, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),

        )
        # *2 - because concatenation
        self.upsample3 =  nn.Upsample(scale_factor=2, mode="bilinear") # 128 -> 256
        self.dec_conv3 =  nn.Sequential(
            nn.Conv2d(64*2, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),

        )
        # *2 - because concatenation
        self.dec_final = nn.Sequential(nn.Conv2d(32*2, 1, kernel_size=3, padding=1),
                                       nn.BatchNorm2d(1)
                                       )

    def forward(self, x):
        # encoder
        e0 = self.pool0(self.enc_conv0(x))
        e1 = self.pool1(self.enc_conv1(e0))
        e2 = self.pool2(self.enc_conv2(e1))
        e3 = self.pool3(self.enc_conv3(e2))

        # bottleneck
        b = self.bottleneck_conv(e3)

        # decoder
        # print('enc_part: ', self.enc_conv3(e2).shape,'+', 'dec_part: ', self.dec_conv0(self.upsample0(b)).
shape)
        d0 = torch.cat((self.enc_conv3(e2), self.dec_conv0(self.upsample0(b))), 1)
        # print('enc_part: ', self.enc_conv2(e1).shape,'+', 'dec_part: ', self.dec_conv1(self.upsample1(d0))
.shape)
        d1 = torch.cat((self.enc_conv2(e1), self.dec_conv1(self.upsample1(d0))), 1)
        # print('enc_part: ', self.enc_conv1(e0).shape,'+', 'dec_part: ', self.dec_conv2(self.upsample2(d1))
.shape)
        d2 = torch.cat((self.enc_conv1(e0), self.dec_conv2(self.upsample2(d1))), 1)
        # print('enc_part: ', self.enc_conv0(x).shape,'+', 'dec_part: ', self.dec_conv3(self.upsample3(d2)).
shape)
        d3 = torch.cat((self.enc_conv0(x), self.dec_conv3(self.upsample3(d2))), 1)
        # print(d3.shape)
        dfin = self.dec_final(d3)    # no activation
        # print(dfin.shape)
        return dfin
```

In [44]:

```
summary(UNet().to(device), input_size=(3, 256, 256))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1        [-1, 32, 256, 256]             896
       BatchNorm2d-2        [-1, 32, 256, 256]              64
              ReLU-3        [-1, 32, 256, 256]               0
            Conv2d-4        [-1, 32, 256, 256]           9,248
       BatchNorm2d-5        [-1, 32, 256, 256]              64
              ReLU-6        [-1, 32, 256, 256]               0
         MaxPool2d-7        [-1, 32, 128, 128]               0
            Conv2d-8        [-1, 64, 128, 128]          18,496
       BatchNorm2d-9        [-1, 64, 128, 128]             128
             ReLU-10        [-1, 64, 128, 128]               0
           Conv2d-11        [-1, 64, 128, 128]          36,928
      BatchNorm2d-12        [-1, 64, 128, 128]             128
             ReLU-13        [-1, 64, 128, 128]               0
        MaxPool2d-14          [-1, 64, 64, 64]               0
           Conv2d-15         [-1, 128, 64, 64]          73,856
      BatchNorm2d-16         [-1, 128, 64, 64]             256
             ReLU-17         [-1, 128, 64, 64]               0
        Dropout2d-18         [-1, 128, 64, 64]               0
           Conv2d-19         [-1, 128, 64, 64]         147,584
      BatchNorm2d-20         [-1, 128, 64, 64]             256
             ReLU-21         [-1, 128, 64, 64]               0
        MaxPool2d-22         [-1, 128, 32, 32]               0
           Conv2d-23         [-1, 256, 32, 32]         295,168
      BatchNorm2d-24         [-1, 256, 32, 32]             512
             ReLU-25         [-1, 256, 32, 32]               0
        Dropout2d-26         [-1, 256, 32, 32]               0
           Conv2d-27         [-1, 256, 32, 32]         590,080
      BatchNorm2d-28         [-1, 256, 32, 32]             512
             ReLU-29         [-1, 256, 32, 32]               0
        MaxPool2d-30         [-1, 256, 16, 16]               0
           Conv2d-31         [-1, 512, 16, 16]       1,180,160
      BatchNorm2d-32         [-1, 512, 16, 16]           1,024
             ReLU-33         [-1, 512, 16, 16]               0
        Dropout2d-34         [-1, 512, 16, 16]               0
           Conv2d-35         [-1, 512, 16, 16]       2,359,808
      BatchNorm2d-36         [-1, 512, 16, 16]           1,024
             ReLU-37         [-1, 512, 16, 16]               0
           Conv2d-38         [-1, 256, 32, 32]         295,168
      BatchNorm2d-39         [-1, 256, 32, 32]             512
             ReLU-40         [-1, 256, 32, 32]               0
        Dropout2d-41         [-1, 256, 32, 32]               0
           Conv2d-42         [-1, 256, 32, 32]         590,080
      BatchNorm2d-43         [-1, 256, 32, 32]             512
             ReLU-44         [-1, 256, 32, 32]               0
         Upsample-45         [-1, 512, 32, 32]               0
           Conv2d-46         [-1, 256, 32, 32]       1,179,904
      BatchNorm2d-47         [-1, 256, 32, 32]             512
             ReLU-48         [-1, 256, 32, 32]               0
        Dropout2d-49         [-1, 256, 32, 32]               0
           Conv2d-50         [-1, 256, 32, 32]         590,080
      BatchNorm2d-51         [-1, 256, 32, 32]             512
             ReLU-52         [-1, 256, 32, 32]               0
           Conv2d-53         [-1, 128, 64, 64]          73,856
      BatchNorm2d-54         [-1, 128, 64, 64]             256
             ReLU-55         [-1, 128, 64, 64]               0
        Dropout2d-56         [-1, 128, 64, 64]               0
           Conv2d-57         [-1, 128, 64, 64]         147,584
      BatchNorm2d-58         [-1, 128, 64, 64]             256
             ReLU-59         [-1, 128, 64, 64]               0
         Upsample-60         [-1, 512, 64, 64]               0
           Conv2d-61         [-1, 128, 64, 64]         589,952
      BatchNorm2d-62         [-1, 128, 64, 64]             256
             ReLU-63         [-1, 128, 64, 64]               0
        Dropout2d-64         [-1, 128, 64, 64]               0
           Conv2d-65         [-1, 128, 64, 64]         147,584
      BatchNorm2d-66         [-1, 128, 64, 64]             256
             ReLU-67         [-1, 128, 64, 64]               0
           Conv2d-68        [-1, 64, 128, 128]          18,496
      BatchNorm2d-69        [-1, 64, 128, 128]             128
             ReLU-70        [-1, 64, 128, 128]               0
           Conv2d-71        [-1, 64, 128, 128]          36,928
      BatchNorm2d-72        [-1, 64, 128, 128]             128
             ReLU-73        [-1, 64, 128, 128]               0
         Upsample-74       [-1, 256, 128, 128]               0
           Conv2d-75        [-1, 64, 128, 128]         147,520
      BatchNorm2d-76        [-1, 64, 128, 128]             128
             ReLU-77        [-1, 64, 128, 128]               0
```

```
           Conv2d-78        [-1, 64, 128, 128]          36,928
      BatchNorm2d-79        [-1, 64, 128, 128]             128
             ReLU-80        [-1, 64, 128, 128]               0
           Conv2d-81        [-1, 32, 256, 256]             896
      BatchNorm2d-82        [-1, 32, 256, 256]              64
             ReLU-83        [-1, 32, 256, 256]               0
           Conv2d-84        [-1, 32, 256, 256]           9,248
      BatchNorm2d-85        [-1, 32, 256, 256]              64
             ReLU-86        [-1, 32, 256, 256]               0
         Upsample-87       [-1, 128, 256, 256]               0
           Conv2d-88        [-1, 32, 256, 256]          36,896
      BatchNorm2d-89        [-1, 32, 256, 256]              64
             ReLU-90        [-1, 32, 256, 256]               0
           Conv2d-91        [-1, 32, 256, 256]           9,248
      BatchNorm2d-92        [-1, 32, 256, 256]              64
             ReLU-93        [-1, 32, 256, 256]               0
           Conv2d-94         [-1, 1, 256, 256]             577
      BatchNorm2d-95         [-1, 1, 256, 256]               2
================================================================
Total params: 8,630,979
Trainable params: 8,630,979
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 689.50
Params size (MB): 32.92
Estimated Total Size (MB): 723.17
----------------------------------------------------------------

/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2973: UserWarning: Default upsamp
ling behavior when mode=bilinear is changed to align_corners=False since 0.4.0. Please specify
align_corners=True if the old behavior is desired. See the documentation of nn.Upsample for det
ails.
  "See the documentation of nn.Upsample for details.".format(mode))
```

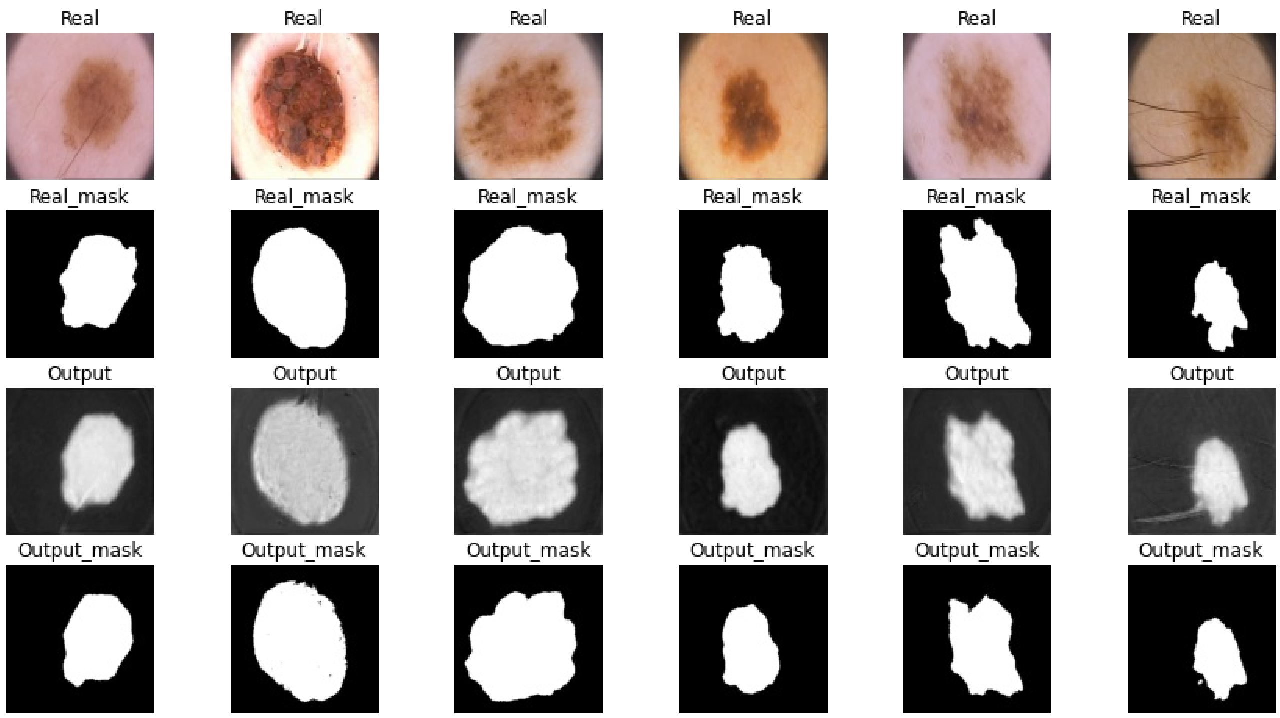
In [0]:

```
seed_init()
clear_memory()

unet_model = UNet().to(device)
op = optim.Adam(unet_model.parameters(), lr=lr)
```

In [46]:

```
history_unet = train("unet", unet_model, op,  bce_loss, iou_pytorch, max_epochs, data_tr, data_val)
```

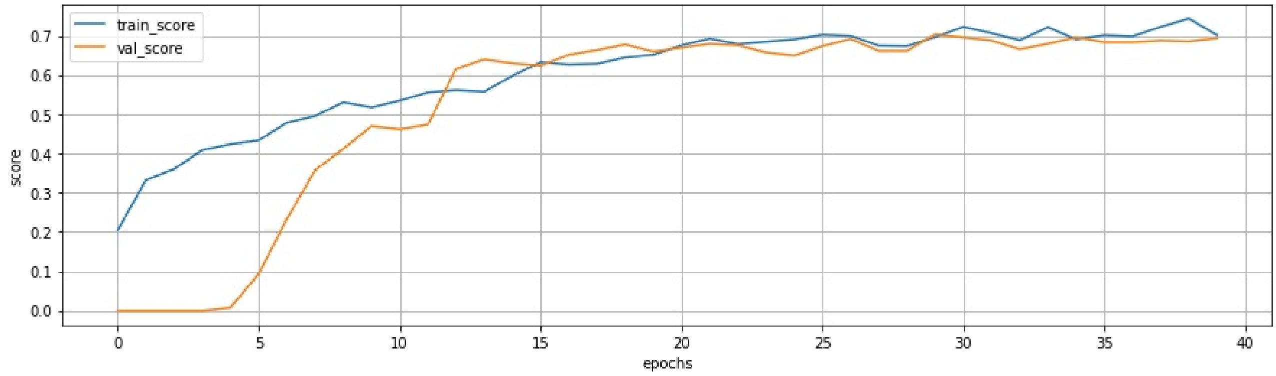
40 / 40 - train_loss: 0.7128, train_score: 0.702, val_loss: 0.7179, val_score: 0.694, max_val_score: 0.704

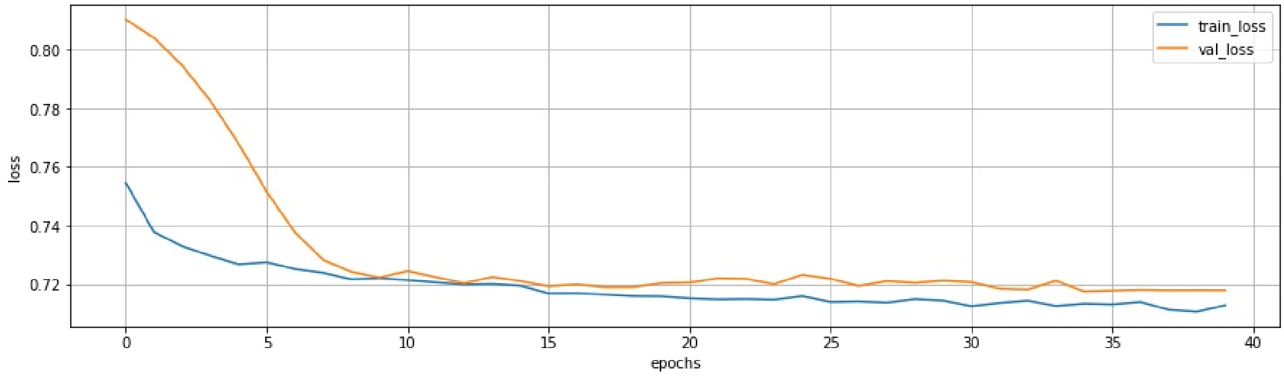


In [47]:

```
plot_stat(history_unet)
```

```
max score on train: 0.7439999878406525 with loss: 0.7105973958969116
max score on val: 0.7039999961853027 with loss: 0.7212292850017548
```





In [48]:

```
score_model(unet_model, iou_pytorch, data_val)
```

```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2973: UserWarning: Default upsamp
ling behavior when mode=bilinear is changed to align_corners=False since 0.4.0. Please specify
align_corners=True if the old behavior is desired. See the documentation of nn.Upsample for det
ails.
  "See the documentation of nn.Upsample for details.".format(mode))
```

Out[48]:

```
0.7039999663829803
```

Новая модель путем изменения типа пулинга:

Max-Pooling for the downsampling and **nearest-neighbor Upsampling** for the upsampling.

Down-sampling:

```
conv = nn.Conv2d(3, 64, 3, padding=1)
pool = nn.MaxPool2d(3, 2, padding=1)
```

Up-Sampling

```
upsample = nn.Upsample(32)
conv = nn.Conv2d(64, 64, 3, padding=1)
```

Замените max-pooling на convolutions с stride=2 и upsampling на transpose-convolutions с stride=2.

In [0]:

```
class UNet2(nn.Module):
    def __init__(self, near_neigh=True):
        super().__init__()

        # encoder (downsampling)
        self.enc_conv0 = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=3, padding=1)
```

```
            nn.Conv2d(32, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),


        )

        self.pool0 = nn.MaxPool2d(kernel_size=3, stride=2, padding=1) if near_neigh else nn.Conv2d(32, 32, k
ernel_size=2, stride=2)  # 256 -> 128
        self.enc_conv1 = nn.Sequential(
            nn.Conv2d(32, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),


        )
        self.pool1 = nn.MaxPool2d(kernel_size=3, stride=2, padding=1) if near_neigh else nn.Conv2d(64, 64, k
ernel_size=2, stride=2) # 128 -> 64
        self.enc_conv2 = nn.Sequential(
            nn.Conv2d(64, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(128, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),


        )
        self.pool2 = nn.MaxPool2d(kernel_size=3, stride=2, padding=1) if near_neigh else nn.Conv2d(128, 128,
kernel_size=2, stride=2) # 64 -> 32
        self.enc_conv3 = nn.Sequential(
            nn.Conv2d(128, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),


        )
        self.pool3 = nn.MaxPool2d(kernel_size=3, stride=2, padding=1) if near_neigh else nn.Conv2d(256, 256,
kernel_size=2, stride=2) # 32 -> 16

        # bottleneck
        self.bottleneck_conv = nn.Sequential(
            nn.Conv2d(256, 512, kernel_size=3, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True),

        )

        # decoder (upsampling)
        self.upsample0 =  nn.Upsample(scale_factor=2, mode='nearest') if near_neigh else nn.ConvTranspose2d(
512, 512, kernel_size=2, stride=2) # 16 -> 32 # torch.nn.ConvTranspose2d(in_channels=512, out_channels=256,
kernel_size=3, stride=2, padding=1, output_padding=1)
        self.dec_conv0 =  nn.Sequential(
            nn.Conv2d(512, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),

        )
        # *2 - because concatenation
        self.upsample1 =  nn.Upsample(scale_factor=2, mode='nearest') if near_neigh else nn.ConvTranspose2d(
256*2, 256*2, kernel_size=2, stride=2) # 32 -> 64
        self.dec_conv1 =  nn.Sequential(
            nn.Conv2d(256*2, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
```

```
            nn.Dropout2d(p=0.3),

            nn.Conv2d(128, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),

        )
        # *2 - because concatenation
        self.upsample2 =  nn.Upsample(scale_factor=2, mode='nearest') if near_neigh else nn.ConvTranspose2d(
128*2, 128*2, kernel_size=2, stride=2) # 64 -> 128
        self.dec_conv2 =  nn.Sequential(
            nn.Conv2d(128*2, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),


        )
        # *2 - because concatenation
        self.upsample3 =  nn.Upsample(scale_factor=2, mode='nearest') if near_neigh else nn.ConvTranspose2d(
64*2, 64*2, kernel_size=2, stride=2) # 128 -> 256
        self.dec_conv3 =  nn.Sequential(
            nn.Conv2d(64*2, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),


        )
        # *2 - because concatenation
        self.dec_final = nn.Sequential(nn.Conv2d(32*2, 1, kernel_size=3, padding=1),
                                       nn.BatchNorm2d(1)
                                       )

    def forward(self, x):
        # encoder
        e0 = self.pool0(self.enc_conv0(x))
        e1 = self.pool1(self.enc_conv1(e0))
        e2 = self.pool2(self.enc_conv2(e1))
        e3 = self.pool3(self.enc_conv3(e2))

        # bottleneck
        b = self.bottleneck_conv(e3)

        # decoder
        # print('enc_part: ', self.enc_conv3(e2).shape,'+', 'dec_part: ', self.dec_conv0(self.upsample0(b)).
shape)
        d0 = torch.cat((self.enc_conv3(e2), self.dec_conv0(self.upsample0(b))), 1)
        # print('enc_part: ', self.enc_conv2(e1).shape,'+', 'dec_part: ', self.dec_conv1(self.upsample1(d0))
.shape)
        d1 = torch.cat((self.enc_conv2(e1), self.dec_conv1(self.upsample1(d0))), 1)
        # print('enc_part: ', self.enc_conv1(e0).shape,'+', 'dec_part: ', self.dec_conv2(self.upsample2(d1))
.shape)
        d2 = torch.cat((self.enc_conv1(e0), self.dec_conv2(self.upsample2(d1))), 1)
        # print('enc_part: ', self.enc_conv0(x).shape,'+', 'dec_part: ', self.dec_conv3(self.upsample3(d2)).
shape)
        d3 = torch.cat((self.enc_conv0(x), self.dec_conv3(self.upsample3(d2))), 1)
        # print(d3.shape)
        dfin = self.dec_final(d3)    # no activation
        # print(dfin.shape)
        return dfin
```

In [50]:

```
summary(UNet2().to(device), input_size=(3, 256, 256))
```

```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 32, 256, 256]             896
       BatchNorm2d-2         [-1, 32, 256, 256]              64
              ReLU-3         [-1, 32, 256, 256]               0
            Conv2d-4         [-1, 32, 256, 256]           9,248
       BatchNorm2d-5         [-1, 32, 256, 256]              64
              ReLU-6         [-1, 32, 256, 256]               0
         MaxPool2d-7         [-1, 32, 128, 128]               0
```

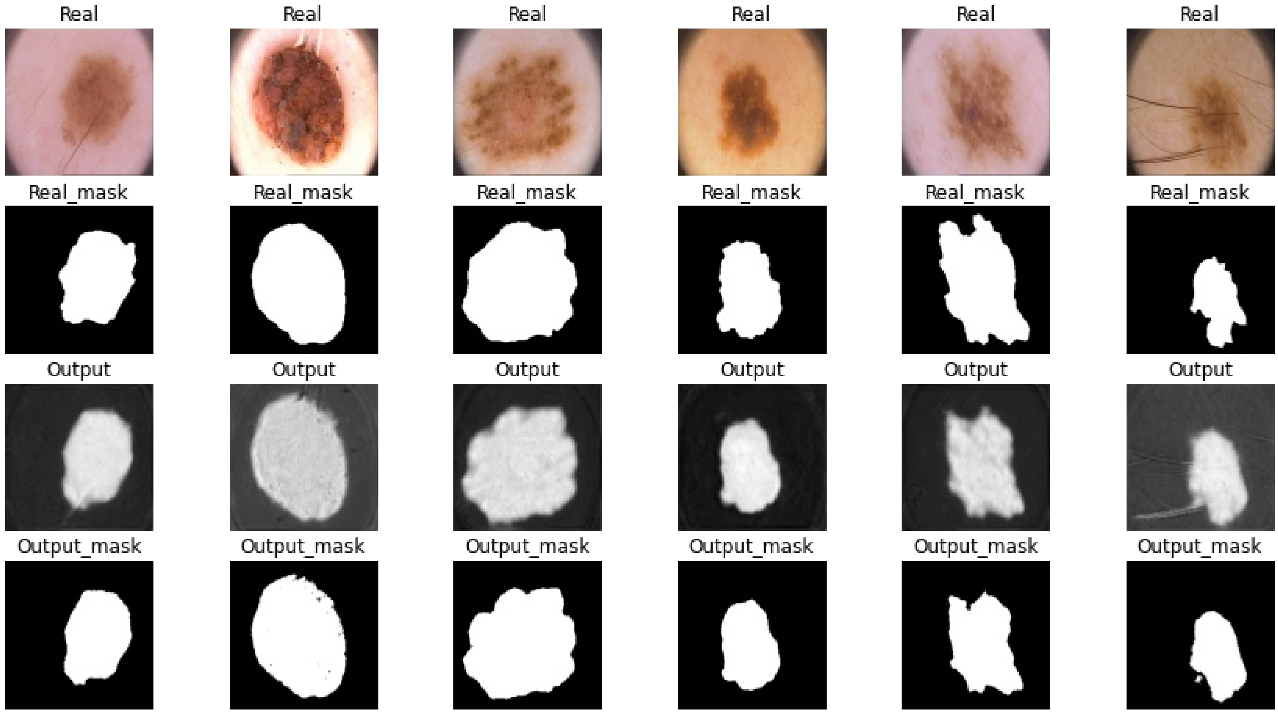
Conv2d-8	[-1, 64, 128, 128]	18,496
BatchNorm2d-9	[-1, 64, 128, 128]	128
ReLU-10	[-1, 64, 128, 128]	0
Conv2d-11	[-1, 64, 128, 128]	36,928
BatchNorm2d-12	[-1, 64, 128, 128]	128
ReLU-13	[-1, 64, 128, 128]	0
MaxPool2d-14	[-1, 64, 64, 64]	0
Conv2d-15	[-1, 128, 64, 64]	73,856
BatchNorm2d-16	[-1, 128, 64, 64]	256
ReLU-17	[-1, 128, 64, 64]	0
Dropout2d-18	[-1, 128, 64, 64]	0
Conv2d-19	[-1, 128, 64, 64]	147,584
BatchNorm2d-20	[-1, 128, 64, 64]	256
ReLU-21	[-1, 128, 64, 64]	0
MaxPool2d-22	[-1, 128, 32, 32]	0
Conv2d-23	[-1, 256, 32, 32]	295,168
BatchNorm2d-24	[-1, 256, 32, 32]	512
ReLU-25	[-1, 256, 32, 32]	0
Dropout2d-26	[-1, 256, 32, 32]	0
Conv2d-27	[-1, 256, 32, 32]	590,080
BatchNorm2d-28	[-1, 256, 32, 32]	512
ReLU-29	[-1, 256, 32, 32]	0
MaxPool2d-30	[-1, 256, 16, 16]	0
Conv2d-31	[-1, 512, 16, 16]	1,180,160
BatchNorm2d-32	[-1, 512, 16, 16]	1,024
ReLU-33	[-1, 512, 16, 16]	0
Dropout2d-34	[-1, 512, 16, 16]	0
Conv2d-35	[-1, 512, 16, 16]	2,359,808
BatchNorm2d-36	[-1, 512, 16, 16]	1,024
ReLU-37	[-1, 512, 16, 16]	0
Conv2d-38	[-1, 256, 32, 32]	295,168
BatchNorm2d-39	[-1, 256, 32, 32]	512
ReLU-40	[-1, 256, 32, 32]	0
Dropout2d-41	[-1, 256, 32, 32]	0
Conv2d-42	[-1, 256, 32, 32]	590,080
BatchNorm2d-43	[-1, 256, 32, 32]	512
ReLU-44	[-1, 256, 32, 32]	0
Upsample-45	[-1, 512, 32, 32]	0
Conv2d-46	[-1, 256, 32, 32]	1,179,904
BatchNorm2d-47	[-1, 256, 32, 32]	512
ReLU-48	[-1, 256, 32, 32]	0
Dropout2d-49	[-1, 256, 32, 32]	0
Conv2d-50	[-1, 256, 32, 32]	590,080
BatchNorm2d-51	[-1, 256, 32, 32]	512
ReLU-52	[-1, 256, 32, 32]	0
Conv2d-53	[-1, 128, 64, 64]	73,856
BatchNorm2d-54	[-1, 128, 64, 64]	256
ReLU-55	[-1, 128, 64, 64]	0
Dropout2d-56	[-1, 128, 64, 64]	0
Conv2d-57	[-1, 128, 64, 64]	147,584
BatchNorm2d-58	[-1, 128, 64, 64]	256
ReLU-59	[-1, 128, 64, 64]	0
Upsample-60	[-1, 512, 64, 64]	0
Conv2d-61	[-1, 128, 64, 64]	589,952
BatchNorm2d-62	[-1, 128, 64, 64]	256
ReLU-63	[-1, 128, 64, 64]	0
Dropout2d-64	[-1, 128, 64, 64]	0
Conv2d-65	[-1, 128, 64, 64]	147,584
BatchNorm2d-66	[-1, 128, 64, 64]	256
ReLU-67	[-1, 128, 64, 64]	0
Conv2d-68	[-1, 64, 128, 128]	18,496
BatchNorm2d-69	[-1, 64, 128, 128]	128
ReLU-70	[-1, 64, 128, 128]	0
Conv2d-71	[-1, 64, 128, 128]	36,928
BatchNorm2d-72	[-1, 64, 128, 128]	128
ReLU-73	[-1, 64, 128, 128]	0
Upsample-74	[-1, 256, 128, 128]	0
Conv2d-75	[-1, 64, 128, 128]	147,520
BatchNorm2d-76	[-1, 64, 128, 128]	128
ReLU-77	[-1, 64, 128, 128]	0
Conv2d-78	[-1, 64, 128, 128]	36,928
BatchNorm2d-79	[-1, 64, 128, 128]	128
ReLU-80	[-1, 64, 128, 128]	0
Conv2d-81	[-1, 32, 256, 256]	896
BatchNorm2d-82	[-1, 32, 256, 256]	64
ReLU-83	[-1, 32, 256, 256]	0
Conv2d-84	[-1, 32, 256, 256]	9,248
BatchNorm2d-85	[-1, 32, 256, 256]	64
ReLU-86	[-1, 32, 256, 256]	0
Upsample-87	[-1, 128, 256, 256]	0

```
         Conv2d-88          [-1, 32, 256, 256]          36,896
    BatchNorm2d-89          [-1, 32, 256, 256]              64
           ReLU-90          [-1, 32, 256, 256]               0
         Conv2d-91          [-1, 32, 256, 256]           9,248
    BatchNorm2d-92          [-1, 32, 256, 256]              64
           ReLU-93          [-1, 32, 256, 256]               0
         Conv2d-94           [-1, 1, 256, 256]             577
    BatchNorm2d-95           [-1, 1, 256, 256]               2
================================================================
Total params: 8,630,979
Trainable params: 8,630,979
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 689.50
Params size (MB): 32.92
Estimated Total Size (MB): 723.17
----------------------------------------------------------------
```

In [51]:

```
seed_init()
clear_memory()

unet2_1_model = UNet2().to(device)
op = optim.Adam(unet2_1_model.parameters(), lr=lr)
history_unet_2_1 = train('unet2_1', unet2_1_model, op, bce_loss, iou_pytorch, max_epochs, data_tr, data_val)
```

40 / 40 - train_loss: 0.7117, train_score: 0.714, val_loss: 0.7176, val_score: 0.694, max_val_score: 0.718



In [52]:

```
score_model(unet2_1_model, iou_pytorch, data_val)
```

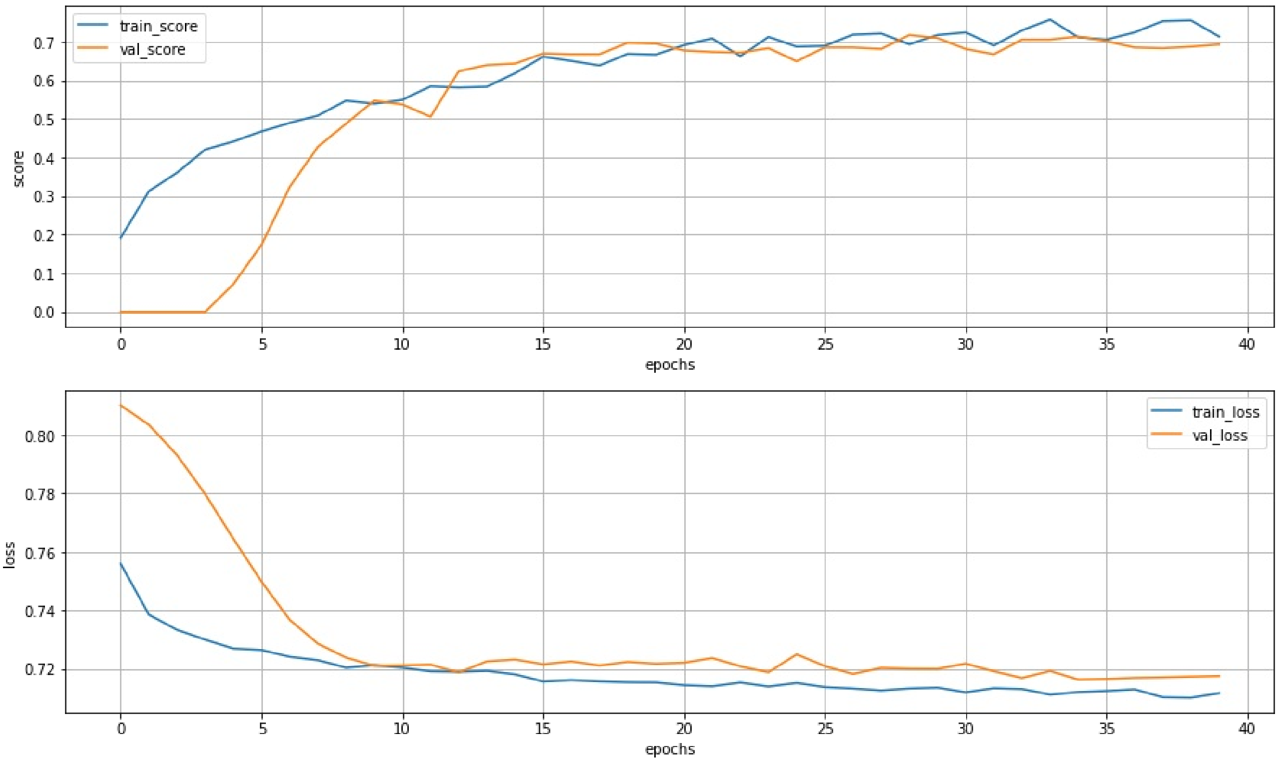
Out[52]:

0.7179999649524689

In [53]:

```
plot_stat(history_unet_2_1)
```

```
max score on train: 0.757999986410141 with loss: 0.7112099975347519
max score on val: 0.7179999947547913 with loss: 0.720087319612503
```



In [54]:

```
summary(UNet2(near_neigh=False).to(device), input_size=(3, 256, 256))
```

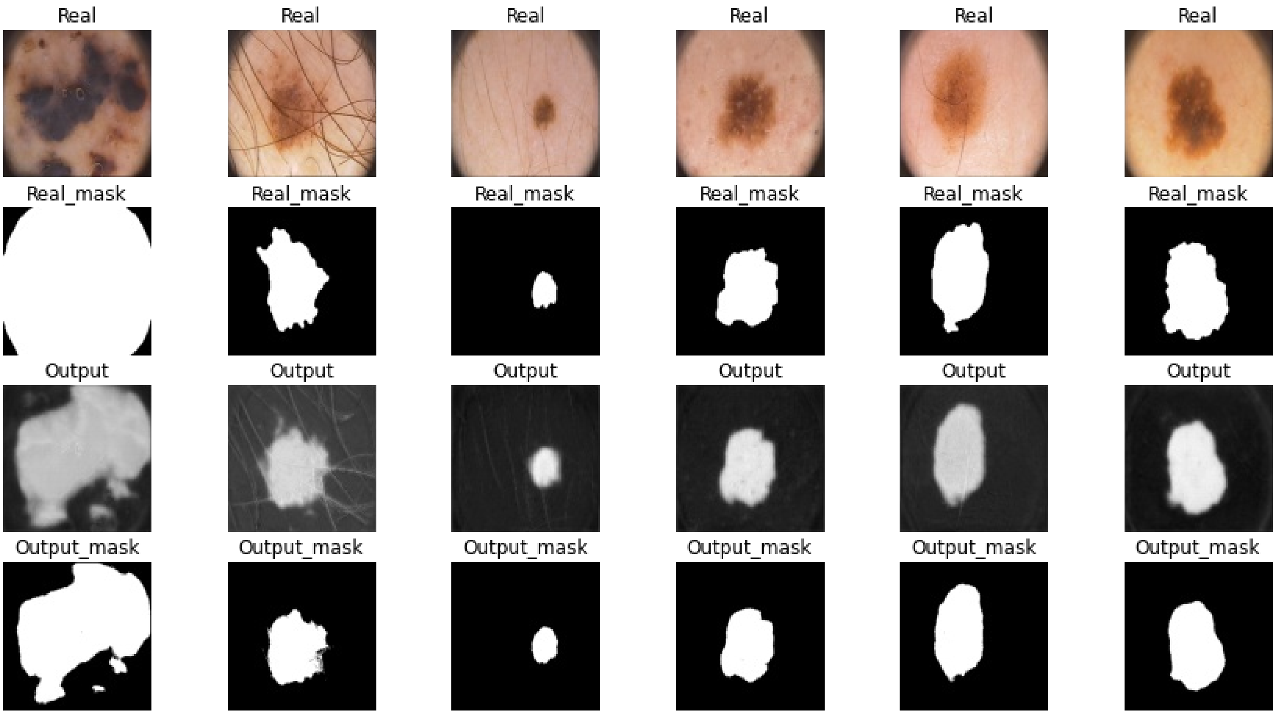
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 32, 256, 256]             896
       BatchNorm2d-2         [-1, 32, 256, 256]              64
              ReLU-3         [-1, 32, 256, 256]               0
            Conv2d-4         [-1, 32, 256, 256]           9,248
       BatchNorm2d-5         [-1, 32, 256, 256]              64
              ReLU-6         [-1, 32, 256, 256]               0
            Conv2d-7         [-1, 32, 128, 128]           4,128
            Conv2d-8         [-1, 64, 128, 128]          18,496
       BatchNorm2d-9         [-1, 64, 128, 128]             128
             ReLU-10         [-1, 64, 128, 128]               0
           Conv2d-11         [-1, 64, 128, 128]          36,928
      BatchNorm2d-12         [-1, 64, 128, 128]             128
             ReLU-13         [-1, 64, 128, 128]               0
           Conv2d-14           [-1, 64, 64, 64]          16,448
           Conv2d-15          [-1, 128, 64, 64]          73,856
      BatchNorm2d-16          [-1, 128, 64, 64]             256
             ReLU-17          [-1, 128, 64, 64]               0
        Dropout2d-18          [-1, 128, 64, 64]               0
           Conv2d-19          [-1, 128, 64, 64]         147,584
      BatchNorm2d-20          [-1, 128, 64, 64]             256
             ReLU-21          [-1, 128, 64, 64]               0
           Conv2d-22          [-1, 128, 32, 32]          65,664
           Conv2d-23          [-1, 256, 32, 32]         295,168
      BatchNorm2d-24          [-1, 256, 32, 32]             512
             ReLU-25          [-1, 256, 32, 32]               0
        Dropout2d-26          [-1, 256, 32, 32]               0
           Conv2d-27          [-1, 256, 32, 32]         590,080
      BatchNorm2d-28          [-1, 256, 32, 32]             512
             ReLU-29          [-1, 256, 32, 32]               0
           Conv2d-30          [-1, 256, 16, 16]         262,400
           Conv2d-31          [-1, 512, 16, 16]       1,180,160
      BatchNorm2d-32          [-1, 512, 16, 16]           1,024
             ReLU-33          [-1, 512, 16, 16]               0
        Dropout2d-34          [-1, 512, 16, 16]               0
           Conv2d-35          [-1, 512, 16, 16]       2,359,808
      BatchNorm2d-36          [-1, 512, 16, 16]           1,024
             ReLU-37          [-1, 512, 16, 16]               0
```

```
          Conv2d-38         [-1, 256, 32, 32]         295,168
     BatchNorm2d-39         [-1, 256, 32, 32]             512
            ReLU-40         [-1, 256, 32, 32]               0
       Dropout2d-41         [-1, 256, 32, 32]               0
          Conv2d-42         [-1, 256, 32, 32]         590,080
     BatchNorm2d-43         [-1, 256, 32, 32]             512
            ReLU-44         [-1, 256, 32, 32]               0
 ConvTranspose2d-45         [-1, 512, 32, 32]       1,049,088
          Conv2d-46         [-1, 256, 32, 32]       1,179,904
     BatchNorm2d-47         [-1, 256, 32, 32]             512
            ReLU-48         [-1, 256, 32, 32]               0
       Dropout2d-49         [-1, 256, 32, 32]               0
          Conv2d-50         [-1, 256, 32, 32]         590,080
     BatchNorm2d-51         [-1, 256, 32, 32]             512
            ReLU-52         [-1, 256, 32, 32]               0
          Conv2d-53         [-1, 128, 64, 64]          73,856
     BatchNorm2d-54         [-1, 128, 64, 64]             256
            ReLU-55         [-1, 128, 64, 64]               0
       Dropout2d-56         [-1, 128, 64, 64]               0
          Conv2d-57         [-1, 128, 64, 64]         147,584
     BatchNorm2d-58         [-1, 128, 64, 64]             256
            ReLU-59         [-1, 128, 64, 64]               0
 ConvTranspose2d-60         [-1, 512, 64, 64]       1,049,088
          Conv2d-61         [-1, 128, 64, 64]         589,952
     BatchNorm2d-62         [-1, 128, 64, 64]             256
            ReLU-63         [-1, 128, 64, 64]               0
       Dropout2d-64         [-1, 128, 64, 64]               0
          Conv2d-65         [-1, 128, 64, 64]         147,584
     BatchNorm2d-66         [-1, 128, 64, 64]             256
            ReLU-67         [-1, 128, 64, 64]               0
          Conv2d-68        [-1, 64, 128, 128]          18,496
     BatchNorm2d-69        [-1, 64, 128, 128]             128
            ReLU-70        [-1, 64, 128, 128]               0
          Conv2d-71        [-1, 64, 128, 128]          36,928
     BatchNorm2d-72        [-1, 64, 128, 128]             128
            ReLU-73        [-1, 64, 128, 128]               0
 ConvTranspose2d-74       [-1, 256, 128, 128]         262,400
          Conv2d-75        [-1, 64, 128, 128]         147,520
     BatchNorm2d-76        [-1, 64, 128, 128]             128
            ReLU-77        [-1, 64, 128, 128]               0
          Conv2d-78        [-1, 64, 128, 128]          36,928
     BatchNorm2d-79        [-1, 64, 128, 128]             128
            ReLU-80        [-1, 64, 128, 128]               0
          Conv2d-81        [-1, 32, 256, 256]             896
     BatchNorm2d-82        [-1, 32, 256, 256]              64
            ReLU-83        [-1, 32, 256, 256]               0
          Conv2d-84        [-1, 32, 256, 256]           9,248
     BatchNorm2d-85        [-1, 32, 256, 256]              64
            ReLU-86        [-1, 32, 256, 256]               0
 ConvTranspose2d-87       [-1, 128, 256, 256]          65,664
          Conv2d-88        [-1, 32, 256, 256]          36,896
     BatchNorm2d-89        [-1, 32, 256, 256]              64
            ReLU-90        [-1, 32, 256, 256]               0
          Conv2d-91        [-1, 32, 256, 256]           9,248
     BatchNorm2d-92        [-1, 32, 256, 256]              64
            ReLU-93        [-1, 32, 256, 256]               0
          Conv2d-94         [-1, 1, 256, 256]             577
     BatchNorm2d-95         [-1, 1, 256, 256]               2
================================================================
Total params: 11,405,859
Trainable params: 11,405,859
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 689.50
Params size (MB): 43.51
Estimated Total Size (MB): 733.76
----------------------------------------------------------------
```

In [55]:

```
seed_init()
clear_memory()

unet2_2_model = UNet2(near_neigh=False).to(device)
opt = optim.Adam(unet2_2_model.parameters(), lr=lr)
history_unet_2_2 = train('unet2_2', unet2_2_model, opt, bce_loss, iou_pytorch, max_epochs, data_tr, data_val
)
```

40 / 40 - train_loss: 0.7111, train_score: 0.735, val_loss: 0.7205, val_score: 0.632, max_val_score: 0.684



In [56]:

```
score_model(unet2_2_model, iou_pytorch, data_val)
```

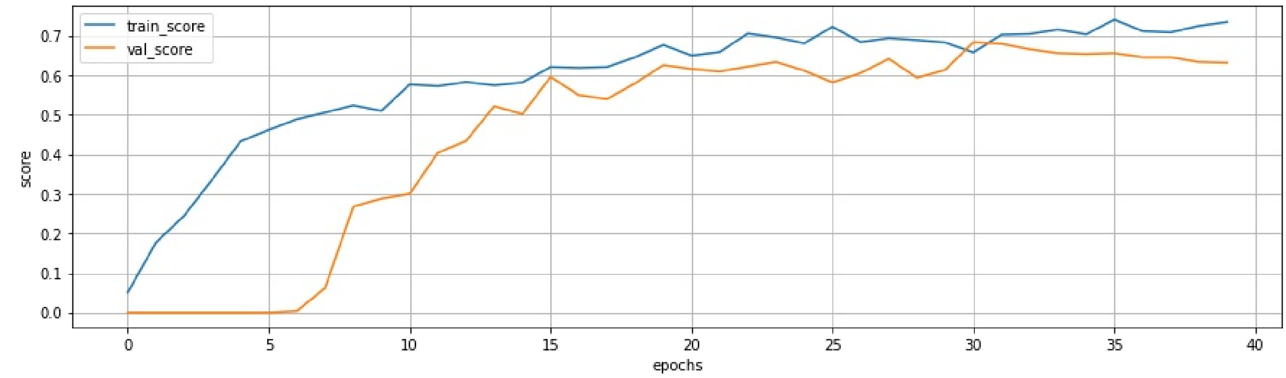
Out[56]:

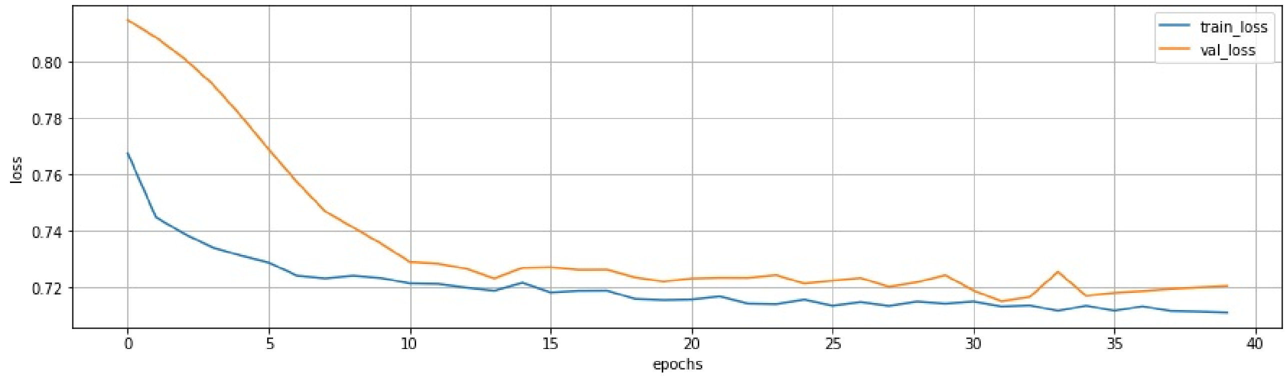
0.6840000152587891

In [57]:

```
plot_stat(history_unet_2_2)
```

```
max score on train: 0.7409999668598175 with loss: 0.7117146849632263
max score on val: 0.6840000152587891 with loss: 0.7189147472381592
```





Сделайте вывод какая из моделей лучше

Dilated convolutions [1 балл]

Еще один из вариантов делать upsampling и downsampling - использовать для этого *dilated convolutions*:

- Yu, Fisher, and Vladlen Koltun. "[Multi-scale context aggregation by dilated convolutions. (https://arxiv.org/pdf/1511.07122.pdf)](https://arxiv.org/pdf/1511.07122.pdf)" arXiv preprint arXiv:1511.07122 (2015).

попробуйте написать сеть DilatedUNet, которая использует в одной из предыдущих моделей dilated свертки.

In [0]:

```
class DilatedUNet(nn.Module):
    def __init__(self):
        super().__init__()

        # encoder (downsampling)
        self.enc_conv0 = nn.Sequential(
            nn.Conv2d(3, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),
            nn.Conv2d(32, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),


        )

        self.pool0 =  nn.Conv2d(32, 32, kernel_size=2, stride=2, padding=1, dilation=2)  # 256 -> 128
        self.enc_conv1 = nn.Sequential(
            nn.Conv2d(32, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),


        )
        self.pool1 = nn.Conv2d(64, 64, kernel_size=2, stride=2, padding=1, dilation=2) # 128 -> 64
```

```
        self.pool1 = nn.Conv2d(64, 64, kernel_size=2, stride=2, padding=1, dilation=2) # 128 -> 64
        self.enc_conv2 = nn.Sequential(
            nn.Conv2d(64, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(128, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),


        )
        self.pool2 = nn.Conv2d(128, 128, kernel_size=2, stride=2, padding=1, dilation=2) # 64 -> 32
        self.enc_conv3 = nn.Sequential(
            nn.Conv2d(128, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
        )
        self.pool3 = nn.Conv2d(256, 256, kernel_size=2, stride=2, padding=1, dilation=2) # 32 -> 16

        # bottleneck
        self.bottleneck_conv = nn.Sequential(
            nn.Conv2d(256, 512, kernel_size=3, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(512, 512, kernel_size=3, padding=1),
            nn.BatchNorm2d(512),
            nn.ReLU(inplace=True),
        )

        # decoder (upsampling)
        self.upsample0 =  nn.ConvTranspose2d(512, 512, kernel_size=2, stride=2, padding=1, output_padding=1,
dilation=2) # 16 -> 32 # torch.nn.ConvTranspose2d(in_channels=512, out_channels=256, kernel_size=3, stride=2
, padding=1, output_padding=1)
        self.dec_conv0 =  nn.Sequential(
            nn.Conv2d(512, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(256, 256, kernel_size=3, padding=1),
            nn.BatchNorm2d(256),
            nn.ReLU(inplace=True),

        )
        # *2 - because concatenation
        self.upsample1 = nn.ConvTranspose2d(256*2, 256*2, kernel_size=2, stride=2, padding=1, output_padding
=1, dilation=2)  # 32 -> 64
        self.dec_conv1 =  nn.Sequential(
            nn.Conv2d(256*2, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),
            nn.Dropout2d(p=0.3),
            nn.Conv2d(128, 128, kernel_size=3, padding=1),
            nn.BatchNorm2d(128),
            nn.ReLU(inplace=True),

        )
        # *2 - because concatenation
        self.upsample2 =  nn.ConvTranspose2d(128*2, 128*2, kernel_size=2, stride=2, padding=1, output_paddin
g=1, dilation=2) # 64 -> 128
        self.dec_conv2 =  nn.Sequential(
            nn.Conv2d(128*2, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),
            nn.Conv2d(64, 64, kernel_size=3, padding=1),
            nn.BatchNorm2d(64),
            nn.ReLU(inplace=True),



        )
        # *2 - because concatenation
        self.upsample3 = nn.ConvTranspose2d(64*2, 64*2, kernel_size=2, stride=2, padding=1, output_padding=1
, dilation=2)  # 128 -> 256
        self.dec_conv3 =  nn.Sequential(
            nn.Conv2d(64*2, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
```

```
            nn.ReLU(inplace=True),

            nn.Conv2d(32, 32, kernel_size=3, padding=1),
            nn.BatchNorm2d(32),
            nn.ReLU(inplace=True),

        )
        # *2 - because concatenation
        self.dec_final = nn.Sequential(nn.Conv2d(32*2, 1, kernel_size=3, padding=1),
                                       nn.BatchNorm2d(1)
                                       )

    def forward(self, x):
        # encoder
        e0 = self.pool0(self.enc_conv0(x))
        e1 = self.pool1(self.enc_conv1(e0))
        e2 = self.pool2(self.enc_conv2(e1))
        e3 = self.pool3(self.enc_conv3(e2))

        # bottleneck
        b = self.bottleneck_conv(e3)

        # decoder
        # print('enc_part: ', self.enc_conv3(e2).shape,'+', 'dec_part: ', self.dec_conv0(self.upsample0(b)).
shape)
        d0 = torch.cat((self.enc_conv3(e2), self.dec_conv0(self.upsample0(b))), 1)
        # print('enc_part: ', self.enc_conv2(e1).shape,'+', 'dec_part: ', self.dec_conv1(self.upsample1(d0))
.shape)
        d1 = torch.cat((self.enc_conv2(e1), self.dec_conv1(self.upsample1(d0))), 1)
        # print('enc_part: ', self.enc_conv1(e0).shape,'+', 'dec_part: ', self.dec_conv2(self.upsample2(d1))
.shape)
        d2 = torch.cat((self.enc_conv1(e0), self.dec_conv2(self.upsample2(d1))), 1)
        # print('enc_part: ', self.enc_conv0(x).shape,'+', 'dec_part: ', self.dec_conv3(self.upsample3(d2)).
shape)
        d3 = torch.cat((self.enc_conv0(x), self.dec_conv3(self.upsample3(d2))), 1)
        # print(d3.shape)
        dfin = self.dec_final(d3)    # no activation
        # print(dfin.shape)
        return dfin
```

In [59]:

```
summary(DilatedUNet().to(device), input_size=(3, 256, 256))
```

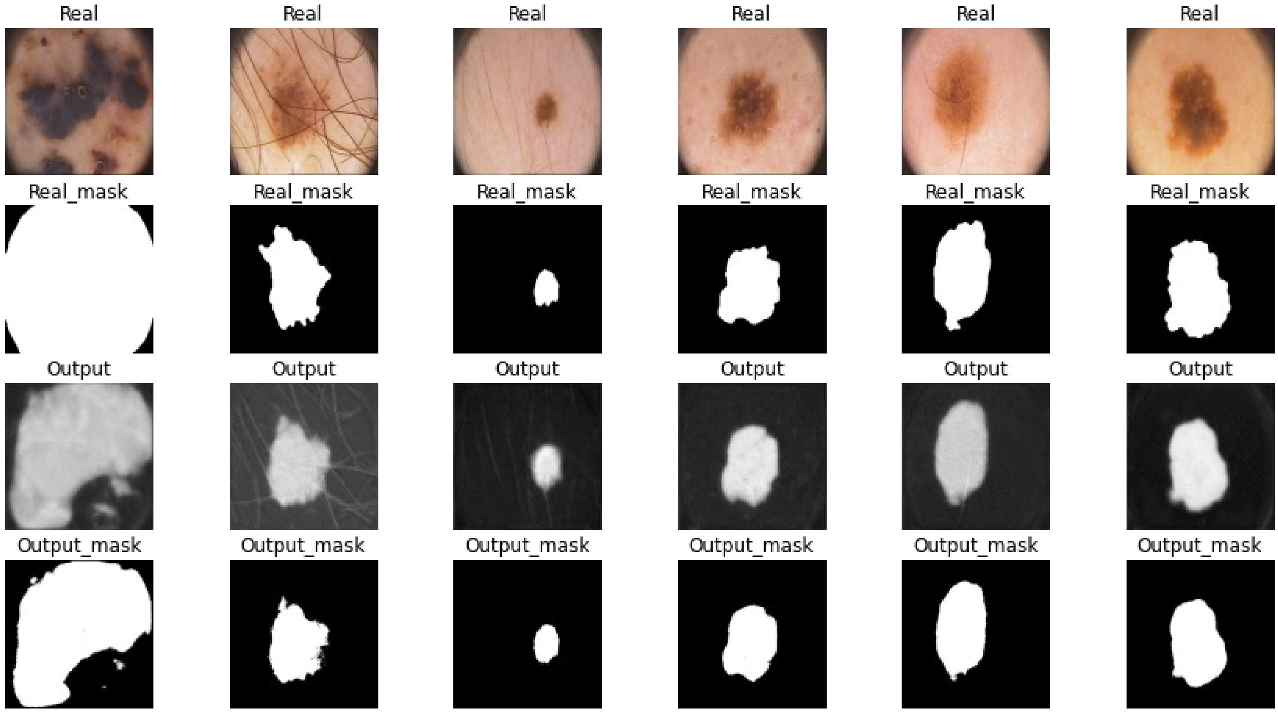
```
----------------------------------------------------------------
        Layer (type)               Output Shape         Param #
================================================================
            Conv2d-1         [-1, 32, 256, 256]             896
       BatchNorm2d-2         [-1, 32, 256, 256]              64
              ReLU-3         [-1, 32, 256, 256]               0
            Conv2d-4         [-1, 32, 256, 256]           9,248
       BatchNorm2d-5         [-1, 32, 256, 256]              64
              ReLU-6         [-1, 32, 256, 256]               0
            Conv2d-7         [-1, 32, 128, 128]           4,128
            Conv2d-8         [-1, 64, 128, 128]          18,496
       BatchNorm2d-9         [-1, 64, 128, 128]             128
             ReLU-10         [-1, 64, 128, 128]               0
           Conv2d-11         [-1, 64, 128, 128]          36,928
      BatchNorm2d-12         [-1, 64, 128, 128]             128
             ReLU-13         [-1, 64, 128, 128]               0
           Conv2d-14           [-1, 64, 64, 64]          16,448
           Conv2d-15          [-1, 128, 64, 64]          73,856
      BatchNorm2d-16          [-1, 128, 64, 64]             256
             ReLU-17          [-1, 128, 64, 64]               0
        Dropout2d-18          [-1, 128, 64, 64]               0
           Conv2d-19          [-1, 128, 64, 64]         147,584
      BatchNorm2d-20          [-1, 128, 64, 64]             256
             ReLU-21          [-1, 128, 64, 64]               0
           Conv2d-22          [-1, 128, 32, 32]          65,664
           Conv2d-23          [-1, 256, 32, 32]         295,168
      BatchNorm2d-24          [-1, 256, 32, 32]             512
             ReLU-25          [-1, 256, 32, 32]               0
        Dropout2d-26          [-1, 256, 32, 32]               0
           Conv2d-27          [-1, 256, 32, 32]         590,080
      BatchNorm2d-28          [-1, 256, 32, 32]             512
             ReLU-29          [-1, 256, 32, 32]               0
           Conv2d-30          [-1, 256, 16, 16]         262,400
           Conv2d-31          [-1, 512, 16, 16]       1,180,160
      BatchNorm2d-32          [-1, 512, 16, 16]           1,024
             ReLU-33          [-1, 512, 16, 16]               0
```

```
       Dropout2d-34         [-1, 512, 16, 16]               0
          Conv2d-35         [-1, 512, 16, 16]       2,359,808
     BatchNorm2d-36         [-1, 512, 16, 16]           1,024
            ReLU-37         [-1, 512, 16, 16]               0
          Conv2d-38         [-1, 256, 32, 32]         295,168
     BatchNorm2d-39         [-1, 256, 32, 32]             512
            ReLU-40         [-1, 256, 32, 32]               0
       Dropout2d-41         [-1, 256, 32, 32]               0
          Conv2d-42         [-1, 256, 32, 32]         590,080
     BatchNorm2d-43         [-1, 256, 32, 32]             512
            ReLU-44         [-1, 256, 32, 32]               0
 ConvTranspose2d-45         [-1, 512, 32, 32]       1,049,088
          Conv2d-46         [-1, 256, 32, 32]       1,179,904
     BatchNorm2d-47         [-1, 256, 32, 32]             512
            ReLU-48         [-1, 256, 32, 32]               0
       Dropout2d-49         [-1, 256, 32, 32]               0
          Conv2d-50         [-1, 256, 32, 32]         590,080
     BatchNorm2d-51         [-1, 256, 32, 32]             512
            ReLU-52         [-1, 256, 32, 32]               0
          Conv2d-53         [-1, 128, 64, 64]          73,856
     BatchNorm2d-54         [-1, 128, 64, 64]             256
            ReLU-55         [-1, 128, 64, 64]               0
       Dropout2d-56         [-1, 128, 64, 64]               0
          Conv2d-57         [-1, 128, 64, 64]         147,584
     BatchNorm2d-58         [-1, 128, 64, 64]             256
            ReLU-59         [-1, 128, 64, 64]               0
 ConvTranspose2d-60         [-1, 512, 64, 64]       1,049,088
          Conv2d-61         [-1, 128, 64, 64]         589,952
     BatchNorm2d-62         [-1, 128, 64, 64]             256
            ReLU-63         [-1, 128, 64, 64]               0
       Dropout2d-64         [-1, 128, 64, 64]               0
          Conv2d-65         [-1, 128, 64, 64]         147,584
     BatchNorm2d-66         [-1, 128, 64, 64]             256
            ReLU-67         [-1, 128, 64, 64]               0
          Conv2d-68        [-1, 64, 128, 128]          18,496
     BatchNorm2d-69        [-1, 64, 128, 128]             128
            ReLU-70        [-1, 64, 128, 128]               0
          Conv2d-71        [-1, 64, 128, 128]          36,928
     BatchNorm2d-72        [-1, 64, 128, 128]             128
            ReLU-73        [-1, 64, 128, 128]               0
 ConvTranspose2d-74       [-1, 256, 128, 128]         262,400
          Conv2d-75        [-1, 64, 128, 128]         147,520
     BatchNorm2d-76        [-1, 64, 128, 128]             128
            ReLU-77        [-1, 64, 128, 128]               0
          Conv2d-78        [-1, 64, 128, 128]          36,928
     BatchNorm2d-79        [-1, 64, 128, 128]             128
            ReLU-80        [-1, 64, 128, 128]               0
          Conv2d-81        [-1, 32, 256, 256]             896
     BatchNorm2d-82        [-1, 32, 256, 256]              64
            ReLU-83        [-1, 32, 256, 256]               0
          Conv2d-84        [-1, 32, 256, 256]           9,248
     BatchNorm2d-85        [-1, 32, 256, 256]              64
            ReLU-86        [-1, 32, 256, 256]               0
 ConvTranspose2d-87       [-1, 128, 256, 256]          65,664
          Conv2d-88        [-1, 32, 256, 256]          36,896
     BatchNorm2d-89        [-1, 32, 256, 256]              64
            ReLU-90        [-1, 32, 256, 256]               0
          Conv2d-91        [-1, 32, 256, 256]           9,248
     BatchNorm2d-92        [-1, 32, 256, 256]              64
            ReLU-93        [-1, 32, 256, 256]               0
          Conv2d-94         [-1, 1, 256, 256]             577
     BatchNorm2d-95         [-1, 1, 256, 256]               2
================================================================
Total params: 11,405,859
Trainable params: 11,405,859
Non-trainable params: 0
----------------------------------------------------------------
Input size (MB): 0.75
Forward/backward pass size (MB): 689.50
Params size (MB): 43.51
Estimated Total Size (MB): 733.76
----------------------------------------------------------------
```

In [60]:

```
seed_init()
clear_memory()

unetdil_model = DilatedUNet().to(device)
opt = optim.Adam(unetdil_model.parameters(), lr=lr)
history_unetdil = train('unet_dil', unetdil_model, opt, bce_loss, iou_pytorch, max_epochs, data_tr, data_val
)
```

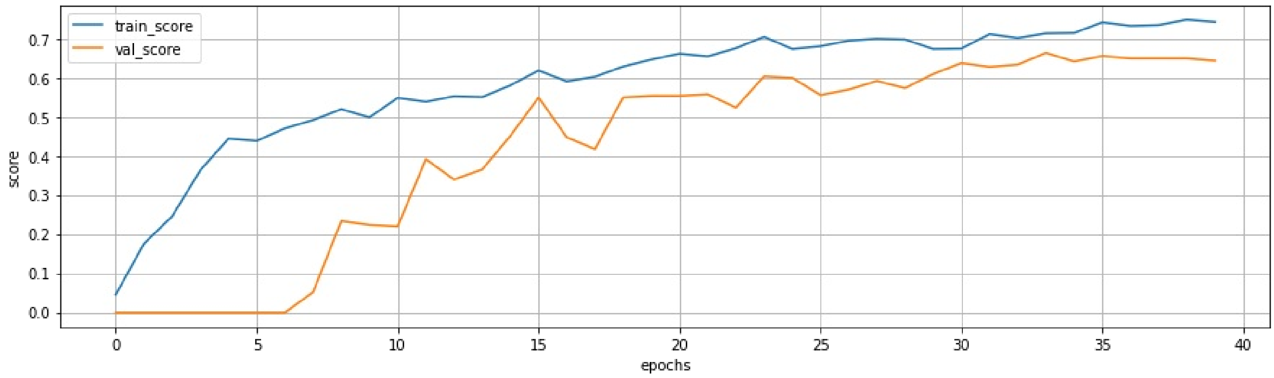
40 / 40 - train_loss: 0.7109, train_score: 0.743, val_loss: 0.7206, val_score: 0.644, max_val_score: 0.664

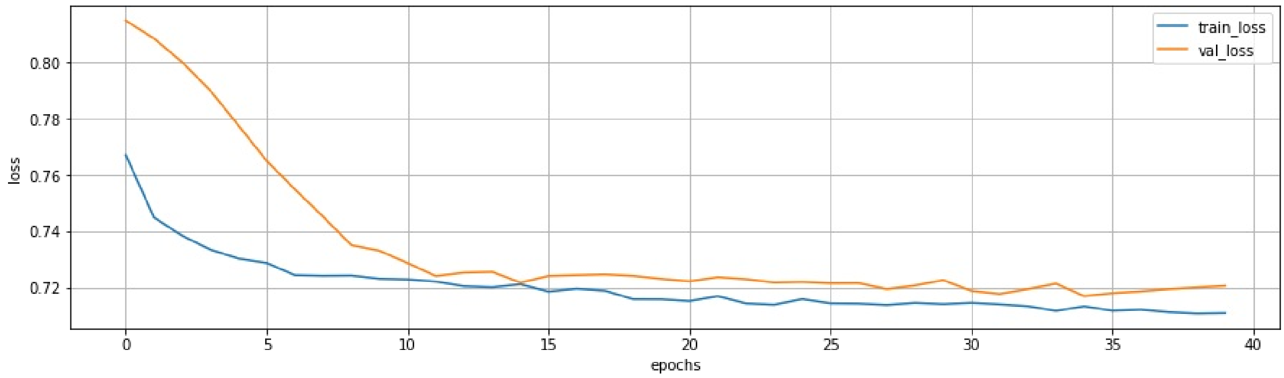


In [61]:

```
plot_stat(history_unetdil)
```

```
max score on train: 0.7490000277757645 with loss: 0.7107290476560593
max score on val: 0.6639999747276306 with loss: 0.7213621139526367
```





In [62]:

```
score_model(unetdil_model, iou_pytorch, data_val)
```

Out[62]:

```
0.664000004529953
```

Отчет (5 баллов):

Ниже предлагается написать отчет о проделанно работе и построить графики для лоссов, метрик на валидации и тесте.

Аккуратно сравните модели между собой и соберите наилучшую архитектуру. Проверьте каждую модель с различными лоссами. Мы не ограничиваем вас в формате отчета, но проверябщий должен отчетливо понять для чего построен каждый график, какие выводы вы из него сделали и какой общий вывод можно сделать на основании данных моделей. Если вы захотите добавить что-то еще, чтобы увеличить шансы получения максимального балла, то добавляйте отдельное сравнение.

In [63]:

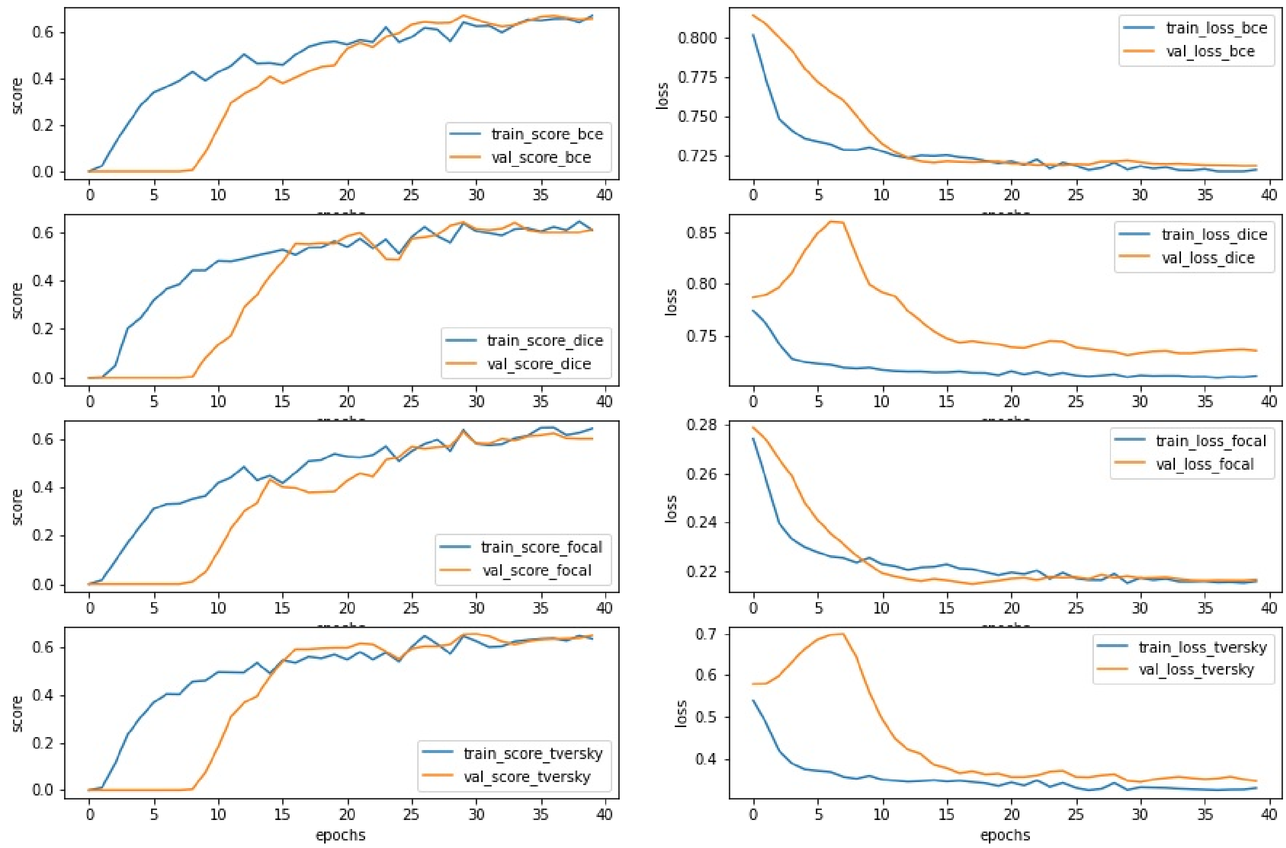
```
# Loss and Score on test

stat_on_test = dict()
losses_fn = [bce_loss, dice_loss, focal_loss, tversky_loss(beta=0.3), bce_loss, bce_loss, bce_loss, bce_loss
]
names = ['bce', 'dice', 'focal', 'tversky', 'maxpool(2,2) & upsamp(bilin)', 'maxpool(3,2,1) & upsamp(nearest
)', 'conv(2,2) & conv trans(2, 2)', 'dilation']
models = [model_bce, model_dice, model_focal, model_tversky, unet_model, unet2_1_model, unet2_2_model, unetd
il_model]

for name, model, loss_fn in zip(names, models, losses_fn):
    stat_on_test[name] = dict(zip(['loss', 'score'], eval(model, data_ts, loss_fn, iou_pytorch, threshold=.7
)))
```

```
/usr/local/lib/python3.6/dist-packages/torch/nn/functional.py:2973: UserWarning: Default upsamp
ling behavior when mode=bilinear is changed to align_corners=False since 0.4.0. Please specify
align_corners=True if the old behavior is desired. See the documentation of nn.Upsample for det
ails.
  "See the documentation of nn.Upsample for details.".format(mode))
```

In [64]:

```
plt.figure(figsize=(15, 10))
i = 1
for name, history in zip(['bce', 'dice', 'focal', 'tversky'], [history_bce, history_dice, history_focal, his
tory_tversky]):
    train_loss, train_score, val_loss, val_score = zip(*history)
    max_score_train = np.max(train_score)
    max_score_loss_train = train_loss[np.argmax(train_score)]
    max_score_val = np.max(val_score)
    max_score_loss_val = val_loss[np.argmax(val_score)]
    ts_score, ts_loss = stat_on_test[name]['score'], stat_on_test[name]['loss']

    print(f'\nloss_fn {name}: \nmax score on train, eph = {np.argmax(train_score)}: {np.round(max_score_trai
n, 4)} with loss: {np.round(max_score_loss_train, 4)}')
    print(f'mean 5 last ephs score on train: {np.round(np.mean(train_score[max_epochs-5:]), 4)} with loss: {
np.round(np.mean(train_loss[max_epochs-5:]), 4)}')
    print(f'\nmax score on val, eph = {np.argmax(val_score)}: {np.round(max_score_val, 4)} with loss: {np.ro
und(max_score_loss_val, 4)}')
    print(f'mean 5 last ephs score on val: {np.round(np.mean(val_score[max_epochs-5:]), 4)} with loss: {np.r
ound(np.mean(val_loss[max_epochs-5:]), 4)}')
    print(f'\nscore on test: {np.round(ts_score, 4)} with loss: {np.round(ts_loss, 4)}')
    print('='*100)


    plt.subplot(4, 2, i)
    plt.plot(train_score, label=f"train_score_{name}")
    plt.plot(val_score, label=f"val_score_{name}")
    plt.legend(loc='best')
    plt.xlabel("epochs")
    plt.ylabel("score")

    plt.subplot(4, 2, i+1)
    plt.plot(train_loss, label=f"train_loss_{name}")
    plt.plot(val_loss, label=f"val_loss_{name}")
    plt.legend(loc='best')
    plt.xlabel("epochs")
    plt.ylabel("loss")
    i += 2

plt.show()
```

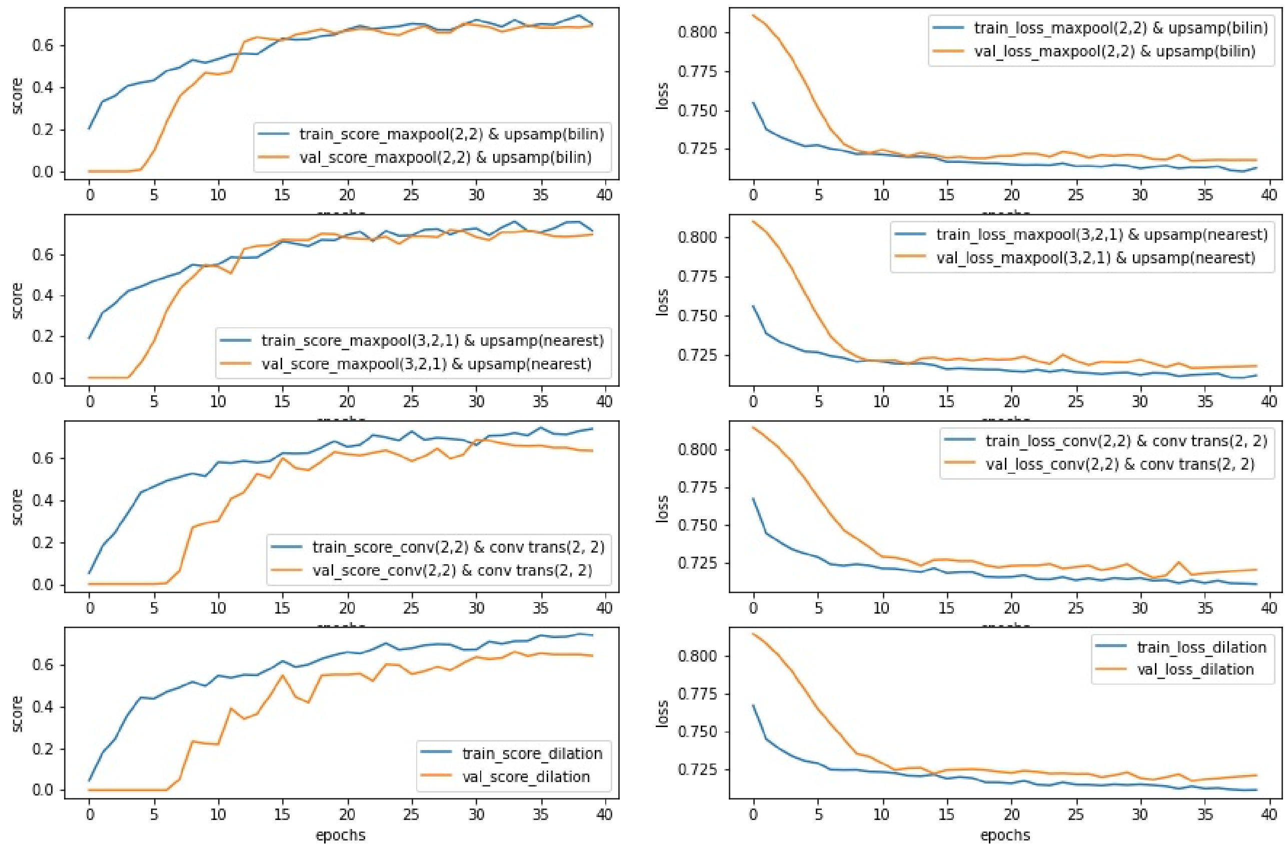
```
loss_fn bce:
max score on train, eph = 39: 0.667 with loss: 0.7153
mean 5 last ephs score on train: 0.6512 with loss: 0.7148

max score on val, eph = 29: 0.668 with loss: 0.7214
mean 5 last ephs score on val: 0.658 with loss: 0.7181

score on test: 0.6618 with loss: 0.7338
===============================================================================================
=====

loss_fn dice:
max score on train, eph = 38: 0.645 with loss: 0.7093
mean 5 last ephs score on train: 0.6184 with loss: 0.7096

max score on val, eph = 29: 0.642 with loss: 0.7307
mean 5 last ephs score on val: 0.6024 with loss: 0.7353

score on test: 0.6061 with loss: 0.7365
===============================================================================================
=====

loss_fn focal:
max score on train, eph = 36: 0.647 with loss: 0.2153
mean 5 last ephs score on train: 0.6358 with loss: 0.2155

max score on val, eph = 29: 0.63 with loss: 0.2178
mean 5 last ephs score on val: 0.6096 with loss: 0.2161

score on test: 0.6655 with loss: 0.2242
===============================================================================================
=====

loss_fn tversky:
max score on train, eph = 38: 0.65 with loss: 0.3271
mean 5 last ephs score on train: 0.6384 with loss: 0.3274

max score on val, eph = 30: 0.658 with loss: 0.3448
mean 5 last ephs score on val: 0.64 with loss: 0.3522

score on test: 0.653 with loss: 0.3332
===============================================================================================
=====
```



In [65]:

```
plt.figure(figsize=(15, 10))
i = 1
for name, history in zip(['maxpool(2,2) & upsamp(bilin)', 'maxpool(3,2,1) & upsamp(nearest)', 'conv(2,2) & c
onv trans(2, 2)', 'dilation'], [history_unet, history_unet_2_1, history_unet_2_2, history_unetdil]):
    train_loss, train_score, val_loss, val_score = zip(*history)
    max_score_train = np.max(train_score)
    max_score_loss_train = train_loss[np.argmax(train_score)]
    max_score_val = np.max(val_score)
    max_score_loss_val = val_loss[np.argmax(val_score)]
    ts_score, ts_loss = stat_on_test[name]['score'], stat_on_test[name]['loss']

    print(f'\nunet with {name}: \nmax score on train, eph = {np.argmax(train_score)}: {np.round(max_score_tr
ain, 4)} with loss: {np.round(max_score_loss_train, 4)}')
    print(f'mean 5 last ephs score on train: {np.round(np.mean(train_score[max_epochs-5:]), 4)} with loss: {
np.round(np.mean(train_loss[max_epochs-5:]), 4)}')
    print(f'\nmax score on val, eph = {np.argmax(val_score)}: {np.round(max_score_val, 4)} with loss: {np.ro
und(max_score_loss_val, 4)}')
    print(f'mean 5 last ephs score on val: {np.round(np.mean(val_score[max_epochs-5:]), 4)} with loss: {np.r
ound(np.mean(val_loss[max_epochs-5:]), 4)}')
    print(f'\nscore on test: {np.round(ts_score, 4)} with loss: {np.round(ts_loss, 4)}')
    print('='*100)

    plt.subplot(4, 2, i)
    plt.plot(train_score, label=f"train_score_{name}")
    plt.plot(val_score, label=f"val_score_{name}")
    plt.legend(loc='best')
    plt.xlabel("epochs")
    plt.ylabel("score")

    plt.subplot(4, 2, i+1)
    plt.plot(train_loss, label=f"train_loss_{name}")
    plt.plot(val_loss, label=f"val_loss_{name}")
    plt.legend(loc='best')
    plt.xlabel("epochs")
    plt.ylabel("loss")
    i+=2

plt.show()
```

```
unet with maxpool(2,2) & upsamp(bilin):
max score on train, eph = 38: 0.744 with loss: 0.7106
mean 5 last ephs score on train: 0.714 with loss: 0.7123

max score on val, eph = 29: 0.704 with loss: 0.7212
mean 5 last ephs score on val: 0.6872 with loss: 0.7179

score on test: 0.6872 with loss: 0.7301
===============================================================================================
=====

unet with maxpool(3,2,1) & upsamp(nearest):
max score on train, eph = 33: 0.758 with loss: 0.7112
mean 5 last ephs score on train: 0.731 with loss: 0.7115

max score on val, eph = 28: 0.718 with loss: 0.7201
mean 5 last ephs score on val: 0.6908 with loss: 0.7171

score on test: 0.6963 with loss: 0.7318
===============================================================================================
=====

unet with conv(2,2) & conv trans(2, 2):
max score on train, eph = 35: 0.741 with loss: 0.7117
mean 5 last ephs score on train: 0.7244 with loss: 0.7118

max score on val, eph = 30: 0.684 with loss: 0.7189
mean 5 last ephs score on val: 0.6428 with loss: 0.7193

score on test: 0.6963 with loss: 0.725
===============================================================================================
=====

unet with dilation:
max score on train, eph = 38: 0.749 with loss: 0.7107
mean 5 last ephs score on train: 0.7404 with loss: 0.7113

max score on val, eph = 33: 0.664 with loss: 0.7214
mean 5 last ephs score on val: 0.65 with loss: 0.7193

score on test: 0.6968 with loss: 0.7248
===============================================================================================
=====
```



Выводы

Segnet with different Losses

	BCE loss	dice loss	focal loss	tversky loss (beta=0.7)
max val score	0.668	0.642	0.63	0.658
mean 5 last ephs val score	0.658	0.6024	0.6908	0.64
test score	0.6618	0.6061	0.6655	0.653

В таблице приведена метрика IoU на валидации при обучении, а также на тесте после обучения:
model = *SegNet*
optimaizer = *Adam*
lr = *1e-4*
scheduler = *gamma = 0.1*, *step_size = 35*
epochs = *40*

Заключения по таблице:
Лучший результат наблюдается при использовании целевой функции **focal loss**:

	focal loss
max val score	0.63
mean 5 last ephs val score	0.6908
test score	0.6655

Unet with Downsampling & Upsampling

	downsample & upsampling	downsample & upsampling	downsample & upsampling	Dilated convolutions downsample & upsampling
Unet with	MaxPool2d(kernel_size = 2, stride = 2) Upsample(scale_factor = 2, mode = "bilinear")	MaxPool2d(kernel_size = 3, stride = 2, padding = 1) Upsample(scale_factor = 2, mode = 'nearest')	Conv2d(input, output, kernel_size = 2, stride = 2) ConvTranspose2d(input, output, kernel_size = 2, stride = 2)	Conv2d(input, output, kernel_size = 2, stride = 2, padding = 1, dilation = 2) ConvTranspose2d(input, output, kernel_size = 2, stride = 2, padding = 1, output_padding = 1, dilation = 2)
max val score	0.704	0.718	0.684	0.664
mean 5 last ephs val score	0.6872	0.6908	0.6428	0.65
test score	0.6872	0.6963	0.6963	0.6968

В таблице приведена метрика IoU на валидации при обучении, а также на тесте после обучения:
model = *Unet*
optimaizer = *Adam*
scheduler = *gamma = 0.1*, *step_size = 35*
lr = *1e-4*
epochs = *40*

Заключения по таблице:
Лучший результат наблюдается при использовании в качестве
Downsampling - *Conv2d(input, output, kernel_size = 2, stride = 2, padding = 1, dilation = 2)*,
Upsampling - *ConvTranspose2d(input, output, kernel_size = 2, stride = 2, padding = 1, output_padding = 1, dilation = 2)*:

	Dilated convolutions downsample & upsampling
Unet with	Conv2d(input, output, kernel_size = 2, stride = 2, padding = 1, dilation = 2) ConvTranspose2d(input, output, kernel_size = 2, stride = 2, padding = 1, output_padding = 1, dilation = 2)
max val score	0.664
mean 5 last ephs val score	0.65
test score	0.6968

Результаты на тесте имеет наивысший приоритет:
test score = 0.6968

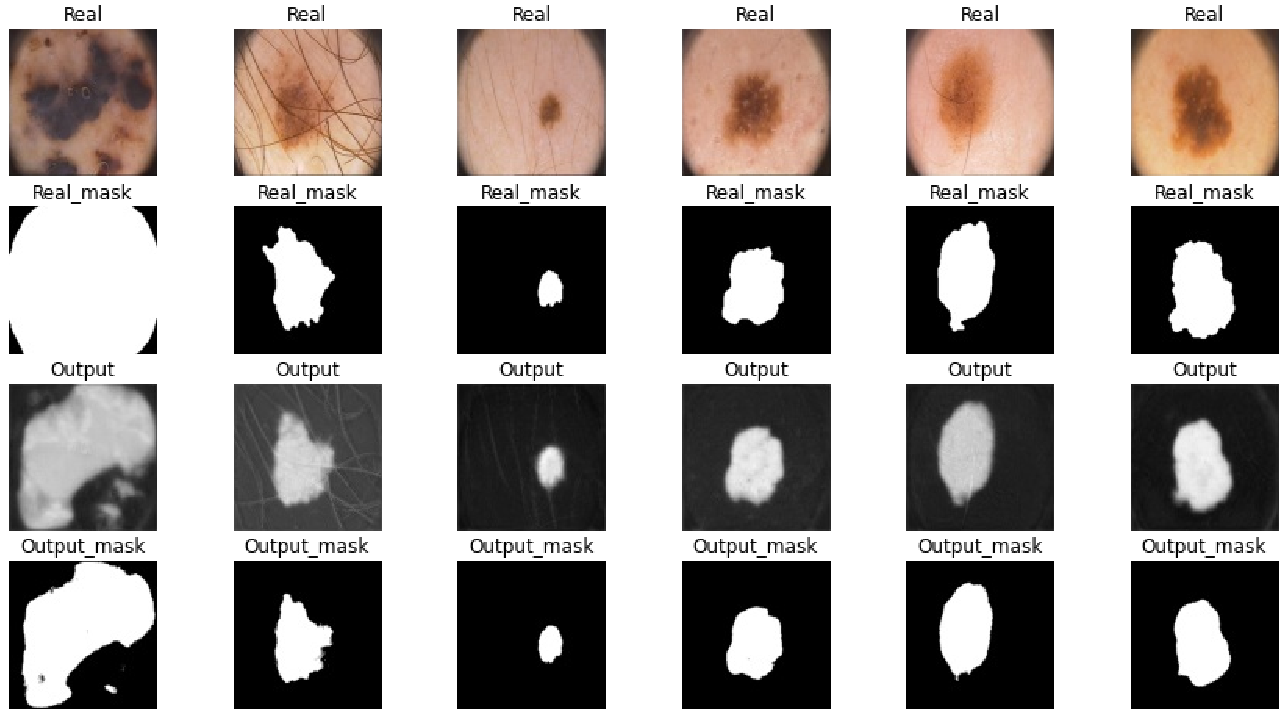
Наилучшая архитектура

Unet with Dilated convolutions
Downsampling - *Conv2d(input, output, kernel_size = 2, stride = 2, padding = 1, dilation = 2),*
Upsampling - *ConvTranspose2d(input, output, kernel_size = 2, stride = 2, padding = 1, output_padding = 1, dilation = 2)*
Loss - *focal loss*

In [66]:

```
seed_init()
clear_memory()

model_final = DilatedUNet().to(device)
op = optim.Adam(model_final.parameters(), lr=lr)
history_final = train('final', model_final, op, focal_loss, iou_pytorch, max_epochs, data_tr, data_val)
```

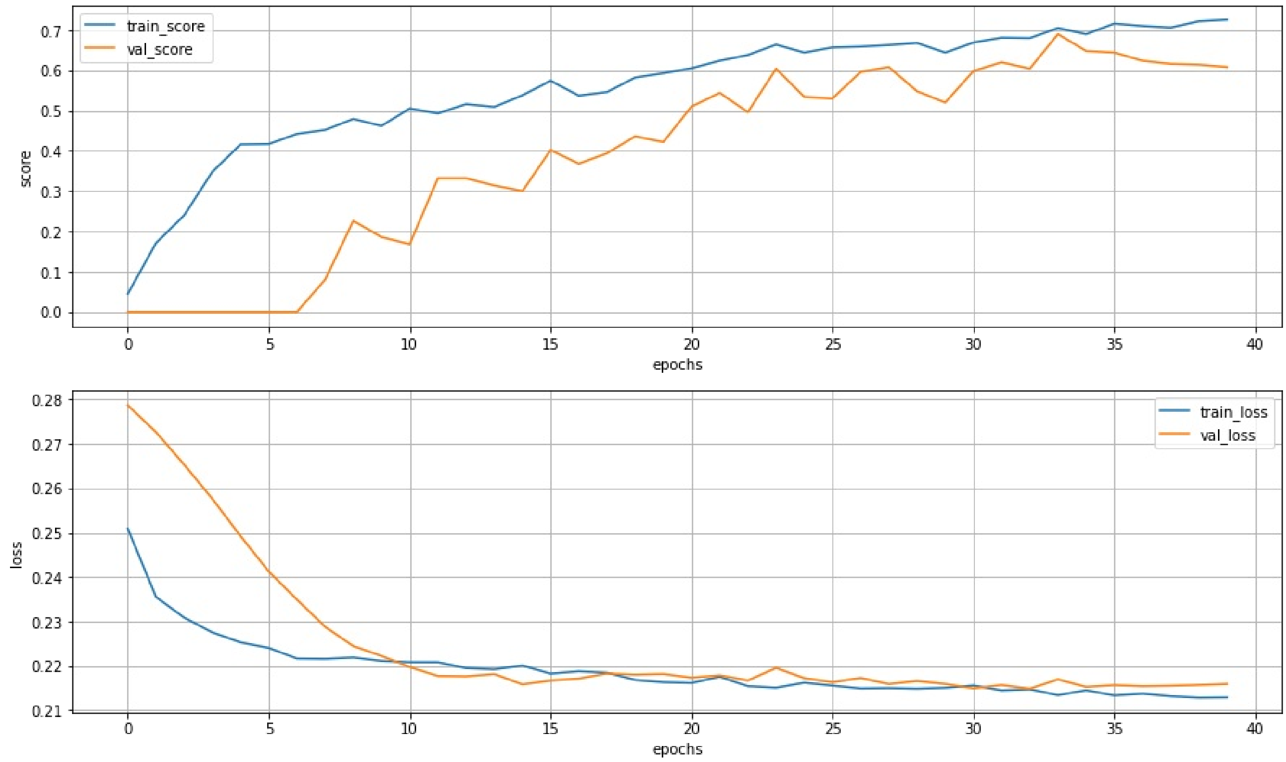
```
40 / 40 - train_loss: 0.2129, train_score: 0.726, val_loss: 0.2159, val_score: 0.608, max_val_score: 0.69
```



In [67]:

```
plot_stat(history_final)
```

```
max score on train: 0.7260000109672546 with loss: 0.21290815249085426
max score on val: 0.6899999976158142 with loss: 0.2169673666357994
```



In [70]:

```
print('the best score on val: ')
score_model(model_final, iou_pytorch, data_val)
```

```
the best score on val:
```

Out[70]:

```
0.6899999678134918
```

In [69]:

```
train_loss_final, train_score_final, val_loss_final, val_score_final = zip(*history_final)
model_final_ts_score, model_final_ts_loss = eval(model_final, data_ts, bce_loss, iou_pytorch, threshold=.8)

print(f'\nfinalmodel: \nmax score on train, eph = {np.argmax(train_score)}: {np.round(np.max(train_score_fin
al), 4)} with loss: {np.round(train_loss_final[np.argmax(train_score_final)], 4)}')
print(f'mean 5 last ephs score on train: {np.round(np.mean(train_score_final[max_epochs-5:]), 4)} with loss:
{np.round(np.mean(train_loss_final[max_epochs-5:]), 4)}')
print(f'\nmax score on val, eph = {np.argmax(val_score)}: {np.round(np.max(val_score_final), 4)} with loss:
{np.round(val_loss_final[np.argmax(val_score_final)], 4)}')
print(f'mean 5 last ephs score on val: {np.round(np.mean(val_score_final[max_epochs-5:]), 4)} with loss: {np
.round(np.mean(val_loss_final[max_epochs-5:]), 4)}')
print(f'\ntest score: {model_final_ts_score}, test loss: {model_final_ts_loss}')
```

```
finalmodel:
max score on train, eph = 38: 0.726 with loss: 0.2129
mean 5 last ephs score on train: 0.716 with loss: 0.2132

max score on val, eph = 33: 0.69 with loss: 0.217
mean 5 last ephs score on val: 0.6212 with loss: 0.2157

test score: 0.7242080569267273, test loss: 0.5523333251476288
```

Такая архитектура даёт test score = 0.7242