知识蒸馏

https://blog.csdn.net/qq_29462849/article/details/122445107

1. KD: Knowledge Distillation

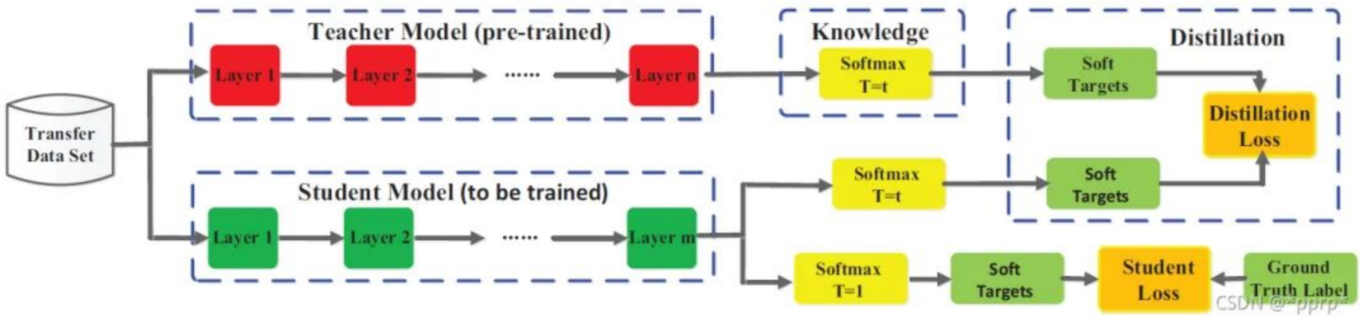
全称：Distilling the Knowledge in a Neural Network

链接：https://arxiv.org/pdf/1503.02531.pd3f

发表：NIPS14

最经典的，也是明确提出知识蒸馏概念的工作，通过使用带温度的softmax函数来软化教师网络的逻辑层输出作为学生网络的监督信息，

使用KL divergence来衡量学生网络与教师网络的差异，具体流程如下图所示（来自Knowledge Distillation A Survey）



对学生网络来说，一部分监督信息来自hard label标签，另一部分来自教师网络提供的soft label。代码实现：

基础KD损失 Plain Text 复制代码

```
class DistillKL(nn.Module):
"""Distilling the Knowledge in a Neural Network"""
  def __init__(self, T):
    super(DistillKL, self).__init__()
    self.T = T
  def forward(self, y_s, y_t):
    p_s = F.log_softmax(y_s/self.T, dim=1)
    p_t = F.softmax(y_t/self.T, dim=1)
    loss = F.kl_div(p_s, p_t, size_average=False) * (self.T**2) / y_s.shape[0]
    return loss
```

核心就是一个kl_div函数，用于计算学生网络和教师网络的分布差异。

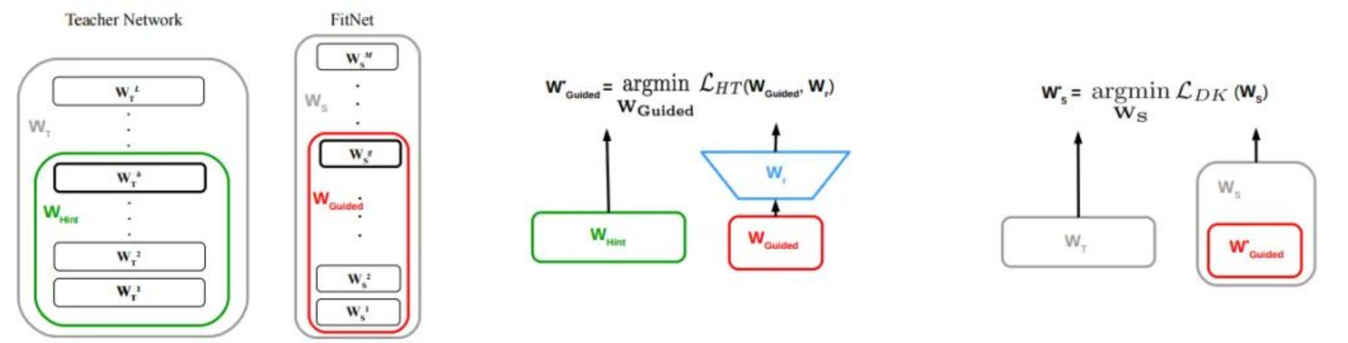
2. FitNet: Hints for thin deep nets

全称：Fitnets: hints for thin deep nets

链接：https://arxiv.org/pdf/1412.6550.pdf

发表：ICLR 15 Poster

对中间层进行蒸馏的开山之作，通过将学生网络的feature map扩展到与教师网络的feature map相同尺寸以后，使用均方误差MSE Loss来衡量两者差异。



(a) Teacher and Student Networks (b) Hints Training (c) Knowledge Distillation

实现如下：

中间特征KD损失

```
class HintLoss(nn.Module):
"""Fitnets: hints for thin deep nets, ICLR 2015"""
  def __init__(self):
    super(HintLoss, self).__init__()
    self.crit = nn.MSELoss()
  def forward(self, f_s, f_t):
    loss = self.crit(f_s, f_t)
 return loss
```

实现核心就是MSELoss。

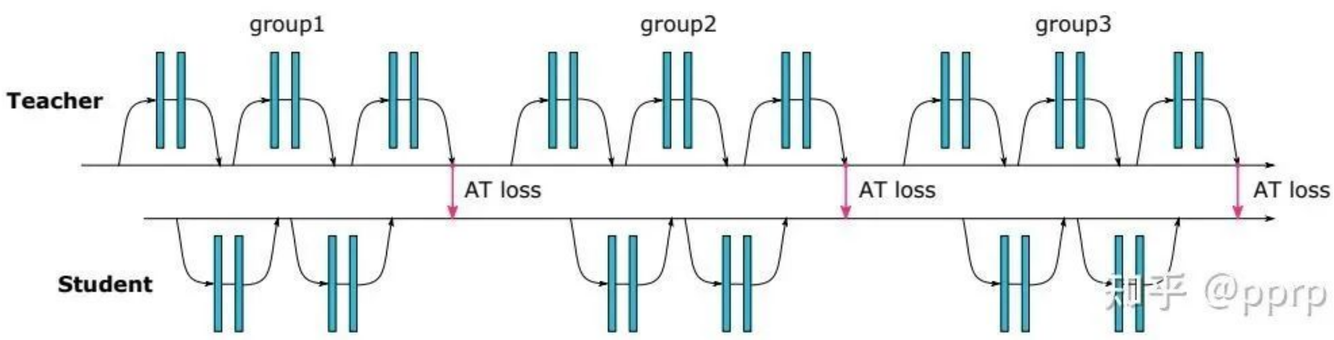
3. AT: Attention Transfer

全称：Paying More Attention to Attention: Improving the Performance of Convolutional Neural Networks via Attention Transfer

链接：https://arxiv.org/pdf/1612.03928.pdf

发表：ICLR16

为了提升学生模型性能提出使用注意力作为知识载体进行迁移，文中提到了两种注意力，一种是activation-based attention transfer，另一种是gradient-based attention transfer。实验发现第一种方法既简单效果又好。



实现如下：

注意力损失

```
class Attention(nn.Module):
"""Paying More Attention to Attention: Improving the Performance of Convolutional Neural Networks    via Attention Transfer    code: https://github.com/szagoruyko/attention-transfer"""
  def __init__(self, p=2):
    super(Attention, self).__init__()
    self.p = p
  def forward(self, g_s, g_t):
    return [self.at_loss(f_s, f_t) for f_s, f_t in zip(g_s, g_t)]
  def at_loss(self, f_s, f_t):
    s_H, t_H = f_s.shape[2], f_t.shape[2]
    if s_H > t_H:
      f_s = F.adaptive_avg_pool2d(f_s, (t_H, t_H))
    elif s_H < t_H:
      f_t = F.adaptive_avg_pool2d(f_t, (s_H, s_H))
    else:
      pass
    return (self.at(f_s) - self.at(f_t)).pow(2).mean()
  def at(self, f):
    return F.normalize(f.pow(self.p).mean(1).view(f.size(0), -1))
```

首先使用avgpool将尺寸调整一致，然后使用MSE Loss来衡量两者差距。

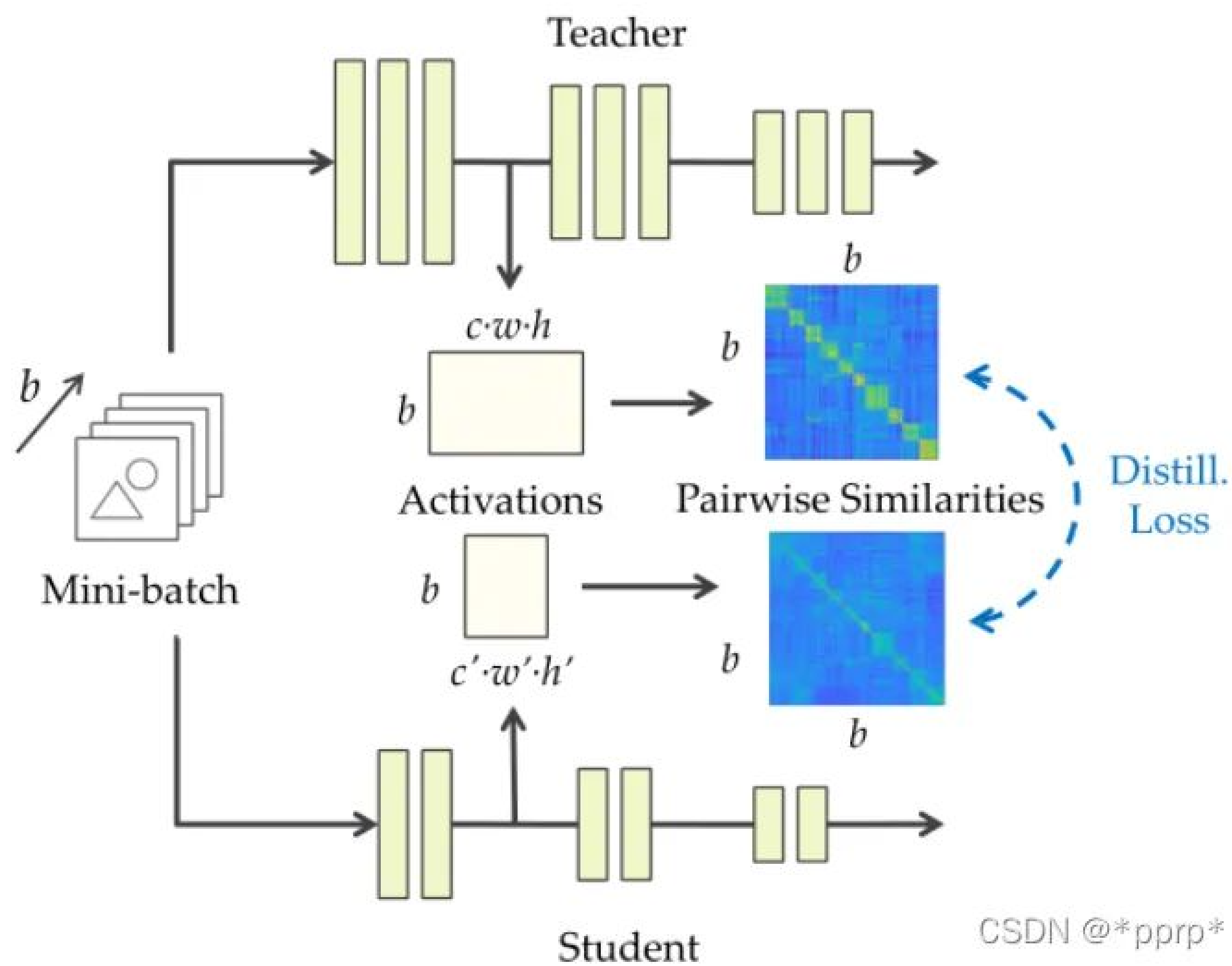
4. SP: Similarity-Preserving

全称：Similarity-Preserving Knowledge Distillation

链接：https://arxiv.org/pdf/1907.09682.pdf

发表：ICCV19SP

归属于基于关系的知识蒸馏方法。文章思想是提出相似性保留的知识，使得教师网络和学生网络会对相同的样本产生相似的激活。可以从下图看出处理流程，教师网络和学生网络对应feature map通过计算内积，得到bsxbs的相似度矩阵，然后使用均方误差来衡量两个相似度矩阵。



最终Loss为：

G代表的就是bsxbs的矩阵。实现如下：

相似损失　Plain Text　复制代码

```
class Similarity(nn.Module):
"""Similarity-Preserving Knowledge Distillation, ICCV2019, verified by original author"""
  def __init__(self):
  super(Similarity, self).__init__()
  def forward(self, g_s, g_t):
    return [self.similarity_loss(f_s, f_t) for f_s, f_t in zip(g_s, g_t)]

  def similarity_loss(self, f_s, f_t):
    bsz = f_s.shape[0]
    f_s = f_s.view(bsz, -1)
    f_t = f_t.view(bsz, -1)
    G_s = torch.mm(f_s, torch.t(f_s))
    # G_s = G_s / G_s.norm(2)
    G_s = torch.nn.functional.normalize(G_s)
    G_t = torch.mm(f_t, torch.t(f_t))
    # G_t = G_t / G_t.norm(2)
    G_t = torch.nn.functional.normalize(G_t)
    G_diff = G_t - G_s
    loss = (G_diff * G_diff).view(-1, 1).sum(0) / (bsz * bsz)
    return loss
```

5. CC: Correlation Congruence

全称：Correlation Congruence for Knowledge Distillation

链接：https://arxiv.org/pdf/1904.01802.pdf

发表：ICCV19

CC也归属于基于关系的知识蒸馏方法。不应该仅仅引导教师网络和学生网络单个样本向量之间的差异，还应该学习两个样本之间的相关性，而这个相关性使用的是Correlation Congruence 教师网络雨学生网络相关性之间的欧氏距离。

整体Loss如下：

实现如下：

归属损失 Plain Text 复制代码

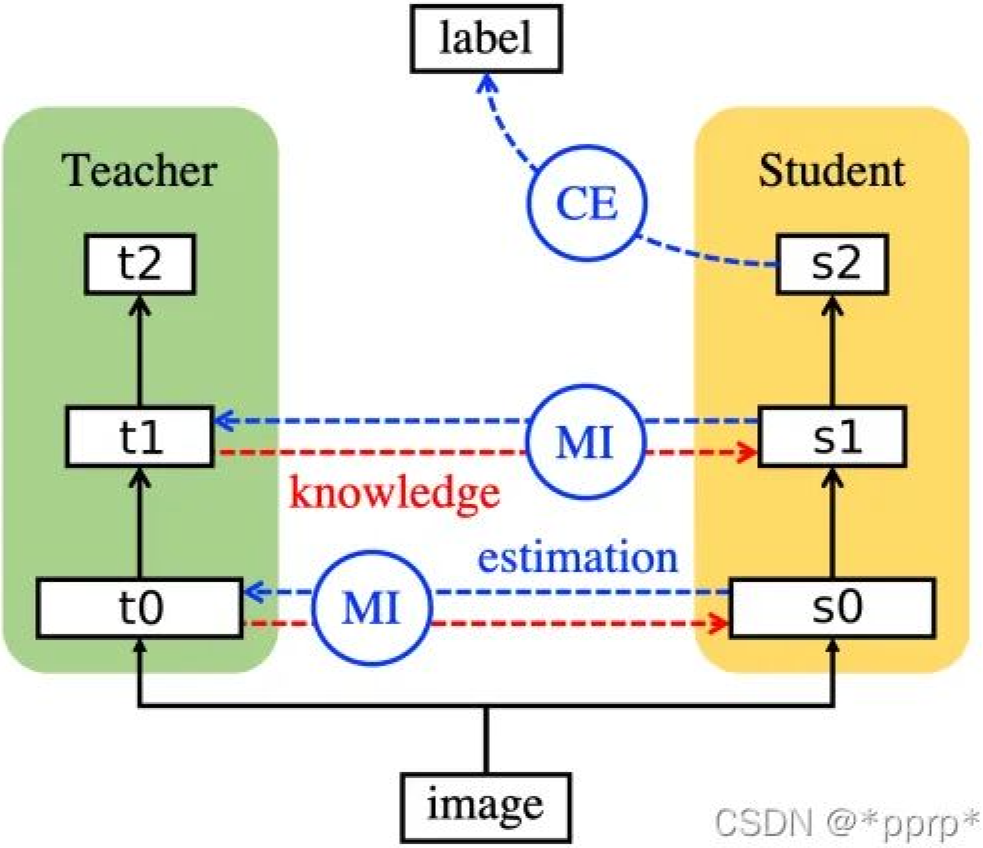
```
class Correlation(nn.Module):
"""Similarity-preserving loss. My origianl own reimplementation    based on the paper before emailing the original authors."""
  def __init__(self):
  super(Correlation, self).__init__()
  def forward(self, f_s, f_t):
    return self.similarity_loss(f_s, f_t)
  def similarity_loss(self, f_s, f_t):
    bsz = f_s.shape[0]
    f_s = f_s.view(bsz, -1)
    f_t = f_t.view(bsz, -1)
    G_s = torch.mm(f_s, torch.t(f_s))
    G_s = G_s / G_s.norm(2)
    G_t = torch.mm(f_t, torch.t(f_t))
    G_t = G_t / G_t.norm(2)
    G_diff = G_t - G_s
    loss = (G_diff * G_diff).view(-1, 1).sum(0) / (bsz * bsz)
    return loss
```

6. VID: Variational Information Distillation

全称：Variational Information Distillation for Knowledge Transfer

链接：https://arxiv.org/pdf/1904.05835.pdf

发表：CVPR19



利用互信息（Mutual Information）来衡量学生网络和教师网络差异。互信息可以表示出两个变量的互相依赖程度，其值越大，表示变量之间的依赖程度越高。互信息计算如下：

互信息是教师模型的熵减去在已知学生模型条件下教师模型的熵。目标是最大化互信息，因为互信息越大说明H(t|s)越小，即学生网络确定的情况下，教师网络的熵会变小，证明学生网络已经学习的比较充分。整体loss如下：

由于p(t|s)很难计算，可以使用变分分布q(t|s)去接近真实分布。

其中q(t|s)是使用方差可学习的高斯分布模拟（公式中的log_scale）：

实现如下：

互关系损失 Plain Text 复制代码

```
class VIDLoss(nn.Module):
"""Variational Information Distillation for Knowledge Transfer (CVPR 2019),    code from author: https://github.com/ssahn0215/variational-information-distillation"""
  def __init__(self,
      num_input_channels,
      num_mid_channel,
      num_target_channels,
      init_pred_var=5.0,
      eps=1e-5):
    super(VIDLoss, self).__init__()
    def conv1x1(in_channels, out_channels, stride=1):
      return nn.Conv2d(in_channels, out_channels,
                kernel_size=1, padding=0,
                bias=False, stride=stride)
    self.regressor = nn.Sequential(conv1x1(num_input_channels, num_mid_channel),            nn.ReLU(),            conv1x1(num_mid_channel, num_mid_channel),
                nn.ReLU(),
                conv1x1(num_mid_channel, num_target_channels),)
    self.log_scale = torch.nn.Parameter(np.log(np.exp(init_pred_var-eps)-1.0) * torch.ones(num_target_channels))
    self.eps = eps
  def forward(self, input, target):
    # pool for dimentsion match
    s_H, t_H = input.shape[2], target.shape[2]
    if s_H > t_H:
      input = F.adaptive_avg_pool2d(input, (t_H, t_H))
    elif s_H < t_H:
      target = F.adaptive_avg_pool2d(target, (s_H, s_H))
    else:
      pass
    pred_mean = self.regressor(input)
    pred_var = torch.log(1.0+torch.exp(self.log_scale))+self.eps
    pred_var = pred_var.view(1, -1, 1, 1)
    neg_log_prob = 0.5*((pred_mean-target)**2/pred_var+torch.log(pred_var))
    loss = torch.mean(neg_log_prob)
    return loss
```

7. RKD: Relation Knowledge Distillation

全称：Relational Knowledge Disitllation

链接：http://arxiv.org/pdf/1904.05068

发表：CVPR19

RKD也是基于关系的知识蒸馏方法，RKD提出了两种损失函数，二阶的距离损失和三阶的角度损失。

- Distance-wise Loss
- Angle-wise Loss

实现如下：

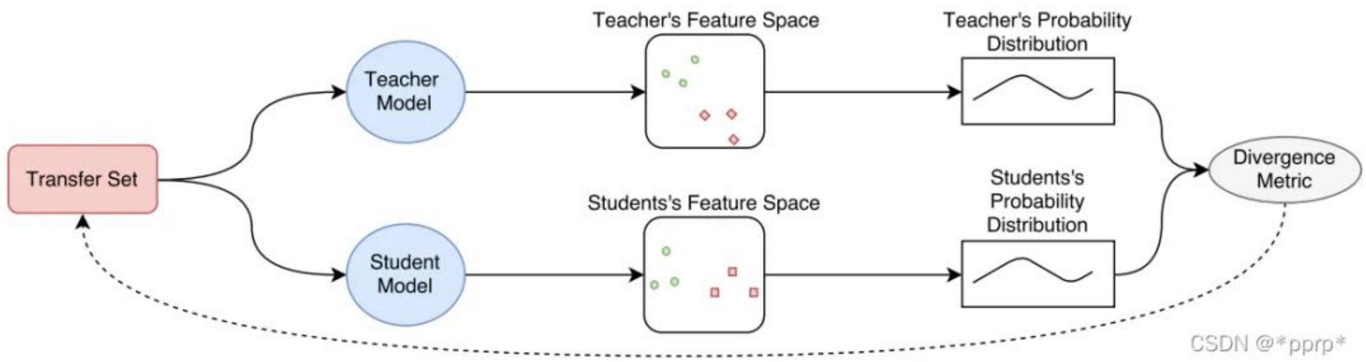
RKD损失 Plain Text 复制代码

```
class RKDLoss(nn.Module):
"""Relational Knowledge Disitllation, CVPR2019"""
  def __init__(self, w_d=25, w_a=50):
    super(RKDLoss, self).__init__()
    self.w_d = w_d
    self.w_a = w_a
  def forward(self, f_s, f_t):
    student = f_s.view(f_s.shape[0], -1)
    teacher = f_t.view(f_t.shape[0], -1)
    # RKD distance loss
    with torch.no_grad():
      t_d = self.pdist(teacher, squared=False)
      mean_td = t_d[t_d > 0].mean()
      t_d = t_d / mean_td
      d = self.pdist(student, squared=False)
      mean_d = d[d > 0].mean()
      d = d / mean_d
    loss_d = F.smooth_l1_loss(d, t_d)
    # RKD Angle loss
    with torch.no_grad():
      td = (teacher.unsqueeze(0) - teacher.unsqueeze(1))
      norm_td = F.normalize(td, p=2, dim=2)
      t_angle = torch.bmm(norm_td, norm_td.transpose(1, 2)).view(-1)
      sd = (student.unsqueeze(0) - student.unsqueeze(1))
      norm_sd = F.normalize(sd, p=2, dim=2)
      s_angle = torch.bmm(norm_sd, norm_sd.transpose(1, 2)).view(-1)
    loss_a = F.smooth_l1_loss(s_angle, t_angle)
    loss = self.w_d * loss_d + self.w_a * loss_a
    return loss
  @staticmethod
  def pdist(e, squared=False, eps=1e-12):
    e_square = e.pow(2).sum(dim=1)
    prod = e @ e.t()
    res = (e_square.unsqueeze(1) + e_square.unsqueeze(0) - 2 * prod).clamp(min=eps)
    if not squared:
      res = res.sqrt()
      res = res.clone()
      res[range(len(e)), range(len(e))] = 0
    return res
```

8. PKT:Probabilistic Knowledge Transfer

全称：Probabilistic Knowledge Transfer for deep representation learning链接：https://arxiv.org/abs/1803.10837发表：CoRR18

提出一种概率知识转移方法，引入了互信息来进行建模。该方法具有可跨模态知识转移、无需考虑任务类型、可将手工特征融入网络等有点。



实现如下:

概率转移损失 Plain Text 复制代码

```
class PKT(nn.Module):
"""Probabilistic Knowledge Transfer for deep representation learning    Code from author: https://github.com/passalis/probabilistic_kt"""
  def __init__(self):
    super(PKT, self).__init__()
  def forward(self, f_s, f_t):
    return self.cosine_similarity_loss(f_s, f_t)
  @staticmethod
  def cosine_similarity_loss(output_net, target_net, eps=0.0000001):
    # Normalize each vector by its norm
    output_net_norm = torch.sqrt(torch.sum(output_net ** 2, dim=1, keepdim=True))
    output_net = output_net / (output_net_norm + eps)
    output_net[output_net != output_net] = 0
    target_net_norm = torch.sqrt(torch.sum(target_net ** 2, dim=1, keepdim=True))
    target_net = target_net / (target_net_norm + eps)
    target_net[target_net != target_net] = 0
    # Calculate the cosine similarity
    model_similarity = torch.mm(output_net, output_net.transpose(0, 1))

    target_similarity = torch.mm(target_net, target_net.transpose(0, 1))
    # Scale cosine similarity to 0..1
    model_similarity = (model_similarity + 1.0) / 2.0
    target_similarity = (target_similarity + 1.0) / 2.0
    # Transform them into probabilities
    model_similarity = model_similarity / torch.sum(model_similarity, dim=1, keepdim=True)        target_similarity = target_similarity / torch.sum(target_similarity, dim=1, keepdim=True)        # Calculate the KL-divergence        loss = torch.mean(target_similarity * torch.log((target_similarity + eps) / (model_similarity + eps)))
    return loss
```

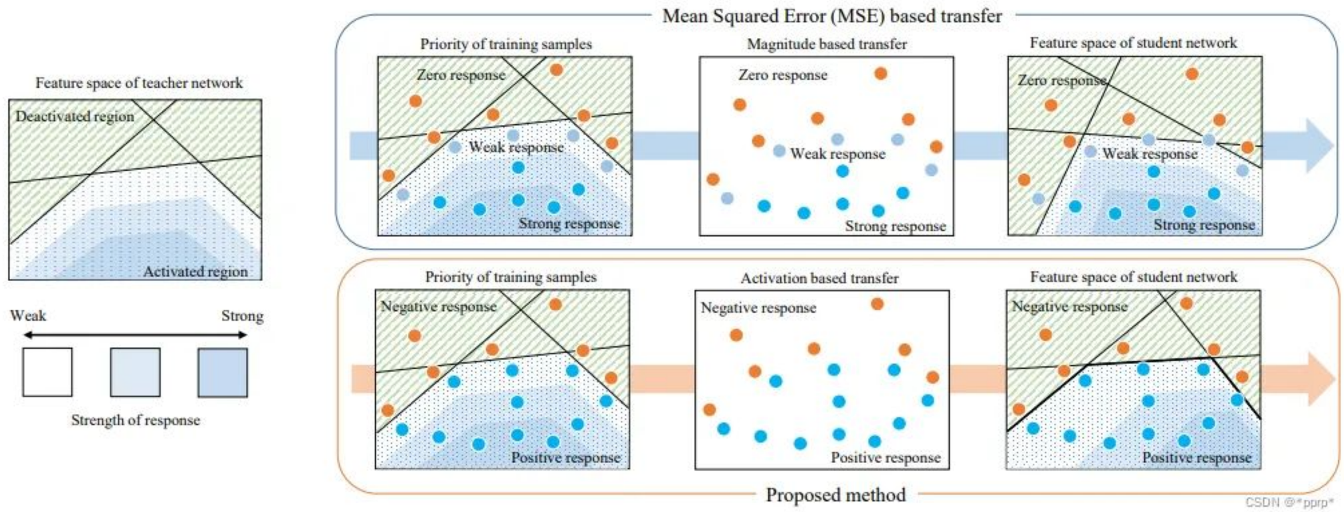
9. AB: Activation Boundaries

全称：Knowledge Transfer via Distillation of Activation Boundaries Formed by Hidden Neurons

链接：https://arxiv.org/pdf/1811.03233.pdf

发表：AAAI18

目标：让教师网络层的神经元的激活边界尽量和学生网络的一样。所谓的激活边界指的是分离超平面（针对的是RELU这种激活函数），其决定了神经元的激活与失活。AB提出的激活转移损失，让教师网络与学生网络之间的分离边界尽可能一致。



实现如下：

激活损失

```
class ABLoss(nn.Module):
"""Knowledge Transfer via Distillation of Activation Boundaries Formed by Hidden Neurons    code: https://github.com/bhheo/AB_distillation    """
  def __init__(self, feat_num, margin=1.0):
    super(ABLoss, self).__init__()
    self.w = [2**(i-feat_num+1) for i in range(feat_num)]
    self.margin = margin
  def forward(self, g_s, g_t):
    bsz = g_s[0].shape[0]
    losses = [self.criterion_alternative_l2(s, t) for s, t in zip(g_s, g_t)]
    losses = [w * l for w, l in zip(self.w, losses)]
    # loss = sum(losses) / bsz
    # loss = loss / 1000 * 3
    losses = [l / bsz for l in losses]
    losses = [l / 1000 * 3 for l in losses]
    return losses
  def criterion_alternative_l2(self, source, target):
    loss = ((source + self.margin) ** 2 * ((source > -self.margin) & (target <= 0)).float() +  (source - self.margin) ** 2 * ((source <= self.margin) & (target > 0)).float())
    return torch.abs(loss).sum()
```

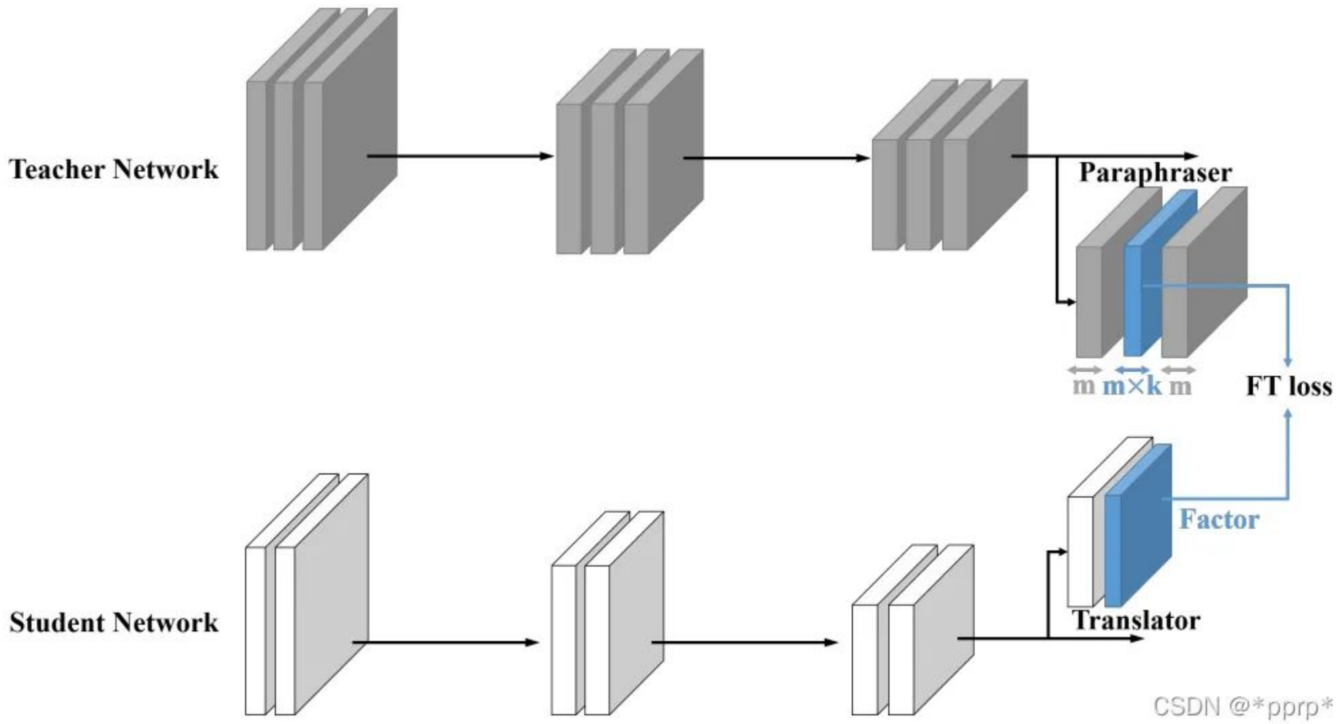
10. FT: Factor Transfer

全称：Paraphrasing Complex Network: Network Compression via Factor Transfer

链接：https://arxiv.org/pdf/1802.04977.pdf

发表：NIPS18

提出的是factor transfer的方法。所谓的factor，其实是对模型最后的数据结果进行一个编解码的过程，提取出的一个factor矩阵，用教师网络的factor来指导学生网络的factor。



FT计算公式为：

实现如下：

FT损失 Plain Text 复制代码

```
class FactorTransfer(nn.Module):
"""Paraphrasing Complex Network: Network Compression via Factor Transfer, NeurIPS 2018"""
  def __init__(self, p1=2, p2=1):
    super(FactorTransfer, self).__init__()
    self.p1 = p1
    self.p2 = p2
  def forward(self, f_s, f_t):
    return self.factor_loss(f_s, f_t)
  def factor_loss(self, f_s, f_t):
    s_H, t_H = f_s.shape[2], f_t.shape[2]
    if s_H > t_H:
      f_s = F.adaptive_avg_pool2d(f_s, (t_H, t_H))
    elif s_H < t_H:
      f_t = F.adaptive_avg_pool2d(f_t, (s_H, s_H))
    else:
      pass
    if self.p2 == 1:
      return (self.factor(f_s) - self.factor(f_t)).abs().mean()
    else:
      return (self.factor(f_s) - self.factor(f_t)).pow(self.p2).mean()
  def factor(self, f):
    return F.normalize(f.pow(self.p1).mean(1).view(f.size(0), -1))
```

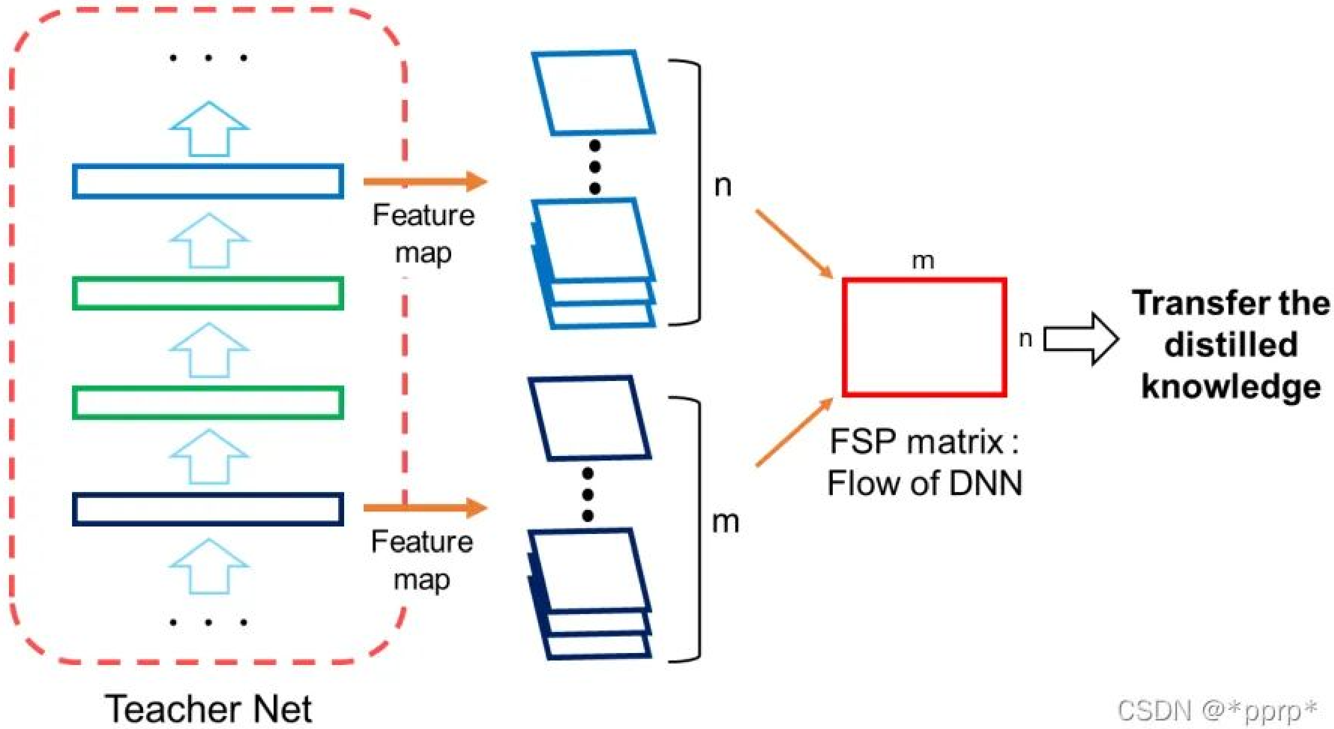
11. FSP: Flow of Solution Procedure

全称：A Gift from Knowledge Distillation: Fast Optimization, Network Minimization and Transfer Learning

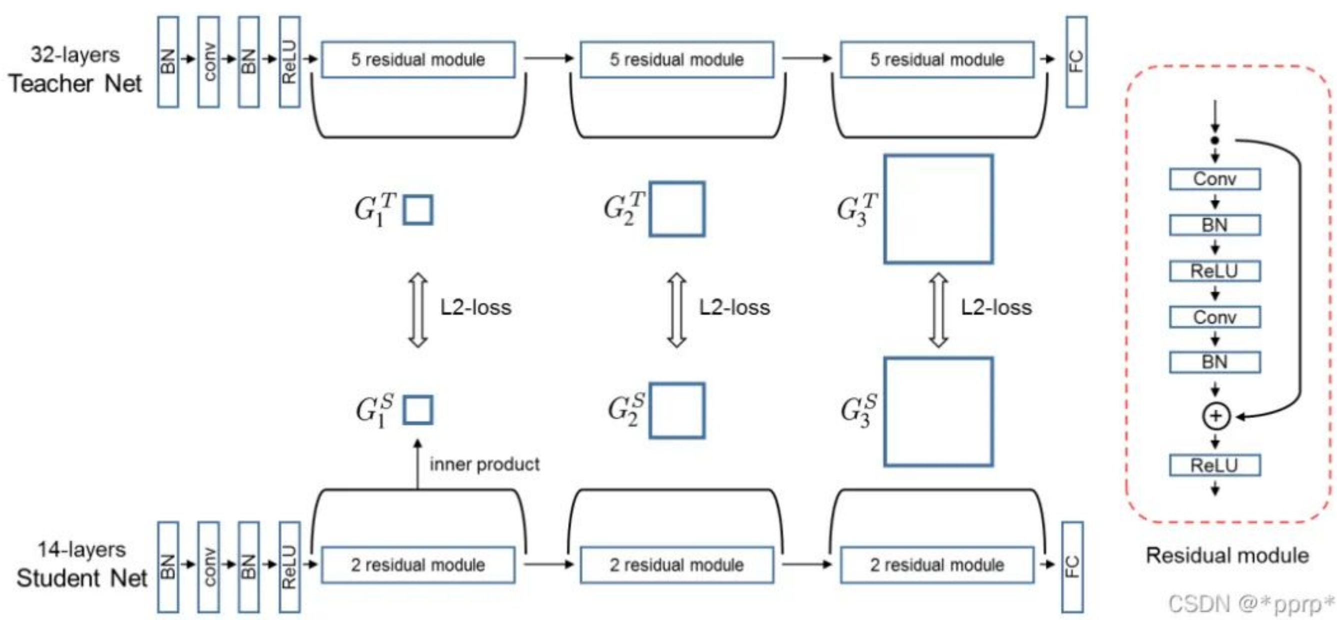
链接：https://openaccess.thecvf.com/content_cvpr_2017/papers/Yim_A_Gift_From_CVPR_2017_paper.pdf

发表：CVPR17

FSP认为教学生网络不同层输出的feature之间的关系比教学生网络结果好



定义了FSP矩阵来定义网络内部特征层之间的关系，是一个Gram矩阵反映老师教学生的过程。



使用的是L2 Loss进行约束FSP矩阵。实现如下：

FSP损失 Plain Text 复制代码

```
class FSP(nn.Module):
"""A Gift from Knowledge Distillation:    Fast Optimization, Network Minimization and Transfer Learning"""
  def __init__(self, s_shapes, t_shapes):
    super(FSP, self).__init__()
    assert len(s_shapes) == len(t_shapes), 'unequal length of feat list'

    s_c = [s[1] for s in s_shapes]
    t_c = [t[1] for t in t_shapes]
    if np.any(np.asarray(s_c) != np.asarray(t_c)):
      raise ValueError('num of channels not equal (error in FSP)')
  def forward(self, g_s, g_t):
    s_fsp = self.compute_fsp(g_s)
    t_fsp = self.compute_fsp(g_t)
    loss_group = [self.compute_loss(s, t) for s, t in zip(s_fsp, t_fsp)]

    return loss_group
  @staticmethod
  def compute_loss(s, t):
    return (s - t).pow(2).mean()
  @staticmethod
  def compute_fsp(g):
    fsp_list = []
    for i in range(len(g) - 1):
    bot, top = g[i], g[i + 1]
    b_H, t_H = bot.shape[2], top.shape[2]
    if b_H > t_H:
      bot = F.adaptive_avg_pool2d(bot, (t_H, t_H))
    elif b_H < t_H:
      top = F.adaptive_avg_pool2d(top, (b_H, b_H))
    else:
      pass
    bot = bot.unsqueeze(1)
    top = top.unsqueeze(2)
    bot = bot.view(bot.shape[0], bot.shape[1], bot.shape[2], -1)
    top = top.view(top.shape[0], top.shape[1], top.shape[2], -1)
    fsp = (bot * top).mean(-1)
    fsp_list.append(fsp)
    return fsp_list
```

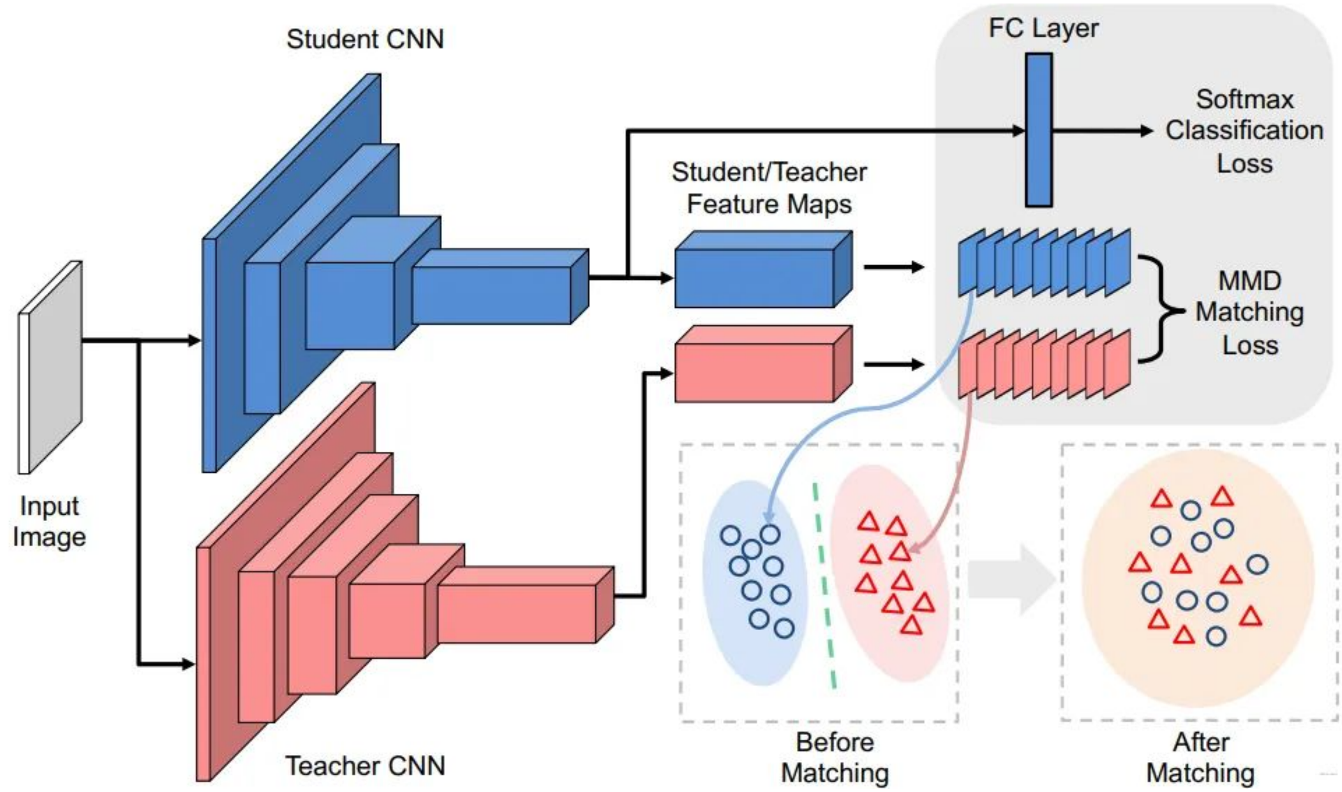
12. NST: Neuron Selectivity Transfer

全称：Like what you like: knowledge distill via neuron selectivity transfer

链接：https://arxiv.org/pdf/1707.01219.pdf

发表：CoRR17

使用新的损失函数最小化教师网络与学生网络之间的Maximum Mean Discrepancy（MMD), 文中选择的是对其教师网络与学生网络之间神经元选择样式的分布。



使用核技巧(对应下面poly kernel)并进一步展开以后可得：

实际上提供了Linear Kernel、Poly Kernel、Gaussian Kernel三种，这里实现只给了Poly这种，这是因为Poly这种方法可以与KD进行互补，这样整体效果会非常好。实现如下：

NST损失

```
class NSTLoss(nn.Module):
"""like what you like: knowledge distill via neuron selectivity transfer"""
  def __init__(self):
    super(NSTLoss, self).__init__()
    pass
  def forward(self, g_s, g_t):
    return [self.nst_loss(f_s, f_t) for f_s, f_t in zip(g_s, g_t)]
  def nst_loss(self, f_s, f_t):
    s_H, t_H = f_s.shape[2], f_t.shape[2]
    if s_H > t_H:
      f_s = F.adaptive_avg_pool2d(f_s, (t_H, t_H))
    elif s_H < t_H:
      f_t = F.adaptive_avg_pool2d(f_t, (s_H, s_H))
    else:
      pass
    f_s = f_s.view(f_s.shape[0], f_s.shape[1], -1)
    f_s = F.normalize(f_s, dim=2)
    f_t = f_t.view(f_t.shape[0], f_t.shape[1], -1)
    f_t = F.normalize(f_t, dim=2)
    # set full_loss as False to avoid unnecessary computation
    full_loss = True
    if full_loss:
      return (self.poly_kernel(f_t, f_t).mean().detach() + self.poly_kernel(f_s, f_s).mean() - 2 * self.poly_kernel(f_s, f_t).mean())
    else:
      return self.poly_kernel(f_s, f_s).mean() - 2 * self.poly_kernel(f_s, f_t).mean()
  def poly_kernel(self, a, b):
    a = a.unsqueeze(1)
    b = b.unsqueeze(2)
    res = (a * b).sum(-1).pow(2)
    return res
```

13. CRD: Contrastive Representation Distillation

全称：Contrastive Representation Distillation

链接：https://arxiv.org/abs/1910.10699v2

发表：ICLR20

将对比学习引入知识蒸馏中，其目标修正为：学习一个表征，让正样本对的教师网络与学生网络尽可能接近，负样本对教师网络与学生网络尽可能远离。构建的对比学习问题表示如下：

整体的蒸馏Loss表示如下：

实现如下：https://github.com/HobbitLong/RepDistiller

CRD损失 Plain Text 复制代码

```
class ContrastLoss(nn.Module):
"""    contrastive loss, corresponding to Eq (18)    """
  def __init__(self, n_data):
    super(ContrastLoss, self).__init__()
    self.n_data = n_data
  def forward(self, x):
    bsz = x.shape[0]
    m = x.size(1) - 1
    # noise distribution
    Pn = 1 / float(self.n_data)
    # loss for positive pair
    P_pos = x.select(1, 0)
    log_D1 = torch.div(P_pos, P_pos.add(m * Pn + eps)).log_()
    # loss for K negative pair
    P_neg = x.narrow(1, 1, m)
    log_D0 = torch.div(P_neg.clone().fill_(m * Pn), P_neg.add(m * Pn + eps)).log_()
    loss = - (log_D1.sum(0) + log_D0.view(-1, 1).sum(0)) / bsz
    return loss
class CRDLoss(nn.Module):
    """CRD Loss function    includes two symmetric parts:
    (a) using teacher as anchor, choose positive and negatives over the student side
    (b) using student as anchor, choose positive and negatives over the teacher side
    Args:
    opt.s_dim: the dimension of student's feature
    opt.t_dim: the dimension of teacher's feature
    opt.feat_dim: the dimension of the projection space
    opt.nce_k: number of negatives paired with each positive
    opt.nce_t: the temperature
    opt.nce_m: the momentum for updating the memory buffer
    opt.n_data: the number of samples in the training set, therefor the memory buffer is: opt.n_data x opt.feat_dim """
  def __init__(self, opt):
    super(CRDLoss, self).__init__()
    self.embed_s = Embed(opt.s_dim, opt.feat_dim)
    self.embed_t = Embed(opt.t_dim, opt.feat_dim)
    self.contrast = ContrastMemory(opt.feat_dim, opt.n_data, opt.nce_k, opt.nce_t, opt.nce_m)
    self.criterion_t = ContrastLoss(opt.n_data)
    self.criterion_s = ContrastLoss(opt.n_data)
  def forward(self, f_s, f_t, idx, contrast_idx=None):
    """
    Args:
```

```
        f_s: the feature of student network, size [batch_size, s_dim]
        f_t: the feature of teacher network, size [batch_size, t_dim]
        idx: the indices of these positive samples in the dataset, size [batch_size]
        contrast_idx: the indices of negative samples, size [batch_size, nce_k]
        Returns:
        The contrastive loss
        """
        f_s = self.embed_s(f_s)
        f_t = self.embed_t(f_t)
        out_s, out_t = self.contrast(f_s, f_t, idx, contrast_idx)
        s_loss = self.criterion_s(out_s)
        t_loss = self.criterion_t(out_t)
        loss = s_loss + t_loss
        return loss
```

14. Overhaul

全称：A Comprehensive Overhaul of Feature Distillation链接：http://openaccess.thecvf.com/content_ICCV_2019/papers/发表：CVPR19

- teacher transform中提出使用margin RELU激活函数。

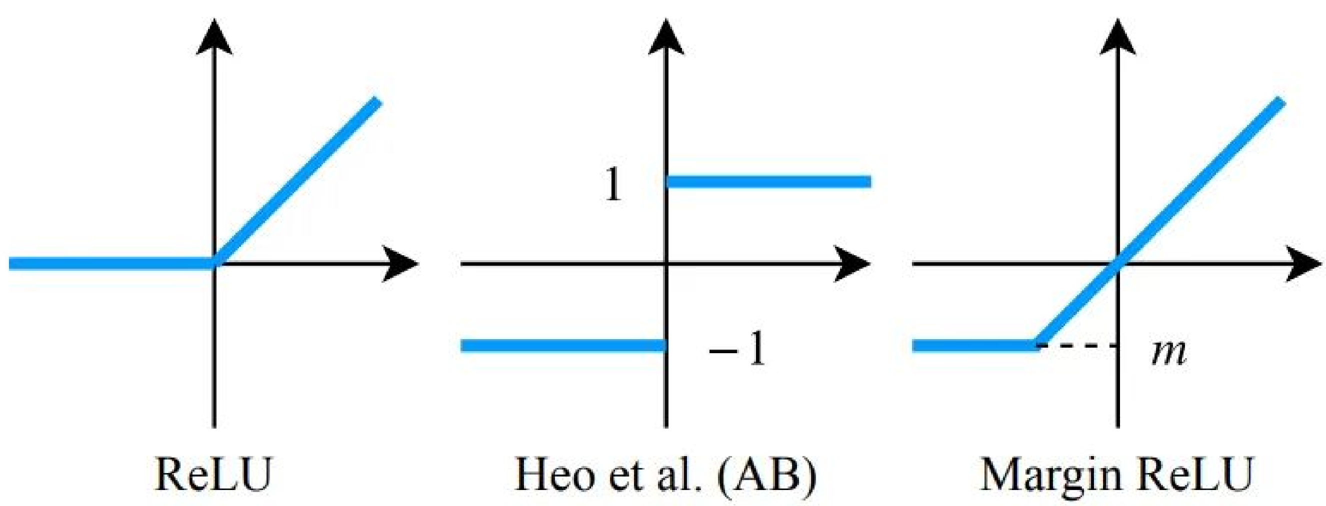


Figure 4. A comparison of the conventional ReLU, teacher transforms in Heo *et al.* [7] and our proposed method.

- student transform中提出使用1x1卷积。
- distillation feature postion选择Pre-ReLU。

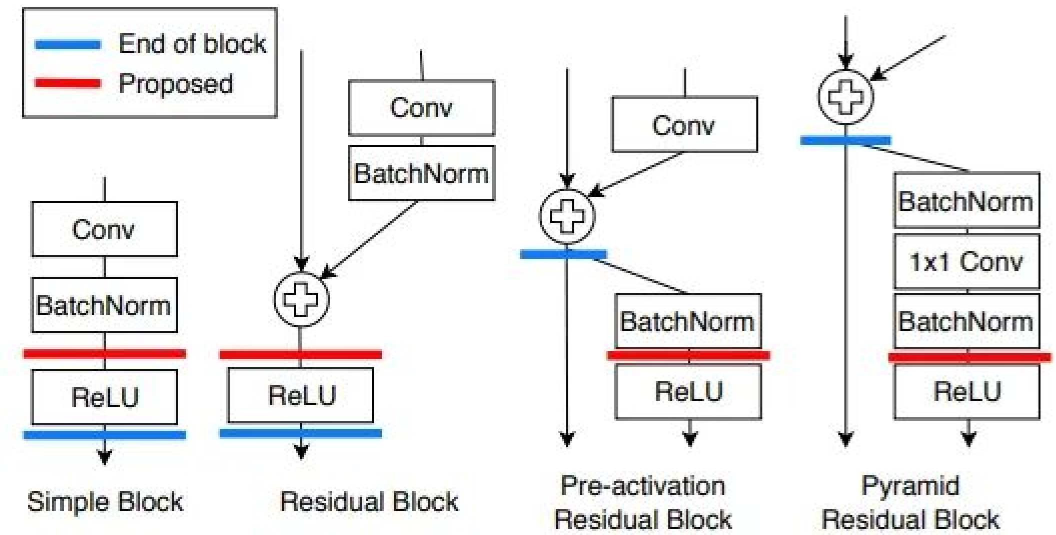


Figure 3. Position of distillation target layer. We place the distillation layer between the last block and the first ReLU. The exact location differs according to the network architecture.

- distance function部分提出了Partial L2 损失函数。

Method	Teacher transform	Student transform	Distillation feature position	Distance	Missing information
FitNets [22]	None	1×1 conv	Mid layer	L_2	None
AT [30]	Attention	Attention	End of group	L_2	Channel dims
FSP [28]	Correlation	Correlation	End of group	L_2	Spatial dims
Jacobian [26]	Gradient	Gradient	End of group	L_2	Channel dims
FT [13]	Auto-encoder	Auto-encoder	End of group	L_1	Auto-encoded
AB [7]	Binarization	1×1 conv	Pre-ReLU	Marginal L_2	Feature values
Proposed	Margin ReLU	1×1 conv	Pre-ReLU	Partial L_2	Negative features

Table 1. Difference in various kinds of feature distillation. Most distillation use teacher transform with information loss.

部分实现如下：

OFD损失　Plain Text　复制代码

```
class OFD(nn.Module):
  '''
  A Comprehensive Overhaul of Feature Distillation
  http://openaccess.thecvf.com/content_ICCV_2019/papers/Heo_A_Comprehensive_Overhaul_of_Feature_Distillation_ICCV_2019_paper.pdf
  '''
  def __init__(self, in_channels, out_channels):
    super(OFD, self).__init__()
    self.connector = nn.Sequential(*[
    nn.Conv2d(in_channels, out_channels, kernel_size=1, stride=1, padding=0, bias=False),
    nn.BatchNorm2d(out_channels)
    ])
    for m in self.modules():
      if isinstance(m, nn.Conv2d):
        nn.init.kaiming_normal_(m.weight, mode='fan_out', nonlinearity='relu')
      if m.bias is not None:
        nn.init.constant_(m.bias, 0)
      elif isinstance(m, nn.BatchNorm2d):
        nn.init.constant_(m.weight, 1)
        nn.init.constant_(m.bias, 0)
  def forward(self, fm_s, fm_t):
    margin = self.get_margin(fm_t)
    fm_t = torch.max(fm_t, margin)
    fm_s = self.connector(fm_s)
    mask = 1.0 - ((fm_s <= fm_t) & (fm_t <= 0.0)).float()
    loss = torch.mean((fm_s - fm_t)**2 * mask)
    return loss
  def get_margin(self, fm, eps=1e-6):
    mask = (fm < 0.0).float()
    masked_fm = fm * mask
    margin = masked_fm.sum(dim=(0,2,3), keepdim=True) / (mask.sum(dim=(0,2,3), keepdim=True)+eps)
    return margin
```

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