6번째 미팅발표

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성능 향상을 위한 아이디어 새로운 시도, 방법 고안···

아쉬운 성능 향상

활용하지 못했던 Feature Distillation Loss

```
\mathcal{L}_F(T, F; \theta_c, \theta_t) = \sum_{i=1}^n ||\phi(T_i) - \phi(F_i)||_2
           class Attention(nn.Module):
               def init (self, args):
                    super(Attention, self). init ()
                    self.p = 2
                    self.kd = DistillKL(args)
                    self.alpha = args.alpha
                    self.beta = args.beta
                def forward(self, o_s, o_t, g_s, g_t):
                    loss = self.alpha * self.kd(o s, o t)
                    loss += self.beta * sum([self.at_loss(f_s, f_t.detach()) for f_s, f_t in zip(g_s, g_t)])
                    return loss
               def at loss(self, f s, f t):
                    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))
```

Reminder: Various distillation methods

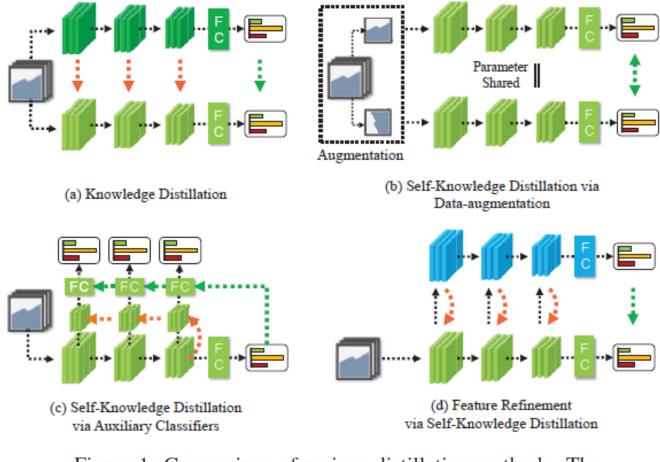


Figure 1: Comparison of various distillation methods. The black line is the forward path; the green line is the soft label distillation; and the orange line is the feature distillation.

개선 아이디어

- 1. Pretrained (teacher) model 없이 self-knowledge distillation하는 코드로 구성
 - Utilize an auxiliary network
- 2. Attention을 제대로 활용 → 1D data에서는 how?