# 汇总

**题目**：Scaling Deep Learning-based Decoding of Polar Codes via Partitioning

**来源**：Sebastian Cammerer, Tobias Gruber, Jakob Hoydis, Stephan ten Brink," Scaling Deep Learning-based Decoding of Polar Codes via Partitioning ", http://cn.arxiv.org/abs/1702.06901

**Abstract**：The training complexity of deep learning-based channel decoders scales exponentially with the codebook size and therefore with the number of information bits. Thus, neural network decoding (NND) is currently only feasible for very short block lengths. In this work, we show that the conventional iterative decoding algorithm for polar codes can be enhanced when sub-blocks of the decoder are replaced by neural network (NN) based components. Thus, we partition the encoding graph into smaller sub-blocks and train them individually, closely approaching maximum a posteriori (MAP) performance per sub-block. These blocks are then connected via the remaining conventional belief propagation decoding stage(s). The resulting decoding algorithm is non-iterative and inherently enables a highlevel of parallelization, while showing a competitive bit error rate (BER) performance. We examine the degradation through partitioning and compare the resulting decoder to state-of-theart polar decoders such as successive cancellation list and belief propagation decoding

**摘要**：基于深度学习的信道解码器的训练复杂度与码本大小呈指数关系，因此与信息比特的数量成比例。因此，神经网络解码（NND）是目前唯一可行的非常短的块长度。在这项工作中，我们表明，传统的迭代解码算法的极性代码可以增强时，解码器的子块被替换为基于神经网络（NN）的组件。因此，我们将编码图分割成更小的子块，并独立地训练它们，密切地逼近每个子块的最大后验（MAP）性能。然后通过剩余的常规置信传播解码阶段来连接这些块。所得到的解码算法是非迭代的，并且固有地能够实现高层次的并行化，同时表现出竞争的误码率（BER）性能。我们通过分区来检查退化，并将得到的解码器与连续极性解码器和置信传播解码等状态极性解码器的状态进行比较。

**题目**：Online Label Recovery for Deep Learning-based Communication through Error Correcting Codes

**来源**：Stefan Schibisch, Sebastian Cammerer, Sebastian Dörner, Jakob Hoydis, Stephan ten Brink," Online Label Recovery for Deep Learning-based Communication through Error Correcting Codes ", http://cn.arxiv.org/abs/1807.00747

**Abstract**：We demonstrate that error correcting codes (ECCs) can be used to construct a labeled data set for finetuning of “trainable” communication systems without sacrificing resources for the transmission of known symbols. This enables adaptive systems, which can be trained on-the-fly to compensate for slow fluctuations in channel conditions or varying hardware impairments. We examine the influence of corrupted training data and show that it is crucial to train based on correct labels. The proposed method can be applied to fully end-to-end trained communication systems (autoencoders) as well as systems with only some trainable components. This is exemplified by extending a conventional OFDM system with a trainable pre-equalizer neural network (NN) that can be optimized at run time.

**摘要**：我们证明，纠错码（ECC）可以用来构造用于“可训练”通信系统的精细化的标记数据集，而不牺牲用于已知符号的传输的资源。这使得自适应系统能够在飞行中被训练，以补偿信道条件的缓慢波动或不同的硬件损伤。我们研究的影响，损坏的培训数据，并显示，它是至关重要的培训基于正确的标签。所提出的方法可以应用于完全端到端训练的通信系统（自动编码器）以及仅具有一些可训练部件的系统。这是通过将传统OFDM系统扩展到可在运行时优化的可训练预均衡器神经网络（NN）来例证的。