Physics-informed attention temporal convolutional network for EEG-based motor imagery classification

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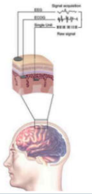
Introduction

- The brain-computer interface (BCI) is an emerging technology that has the potential to transform the world, with a wide range of applications ranging from medical applications to human augmentation. MI-EEG signal has been used in many BCI applications to assist disabled people and to augment human capabilities.

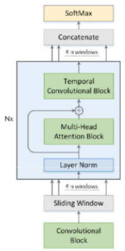


- EEG is a non-invasive, low cost, low risk, and portable method that records the electrical activities of the brain. Motor imagery (MI) is the activity of thinking about moving a human body part without physically moving it.
- Recognizing human intention from EEG signal is challenging due to the low SNR ratio and various sources of artifacts, the recorded EEG signal is only ~ 5% of the actual brain signal.

Aims

The goal is to develop a high-performance attention-based deep learning model to classify EEG-based MI brain signals, which outperform state-of-the-art models.

Proposed Method



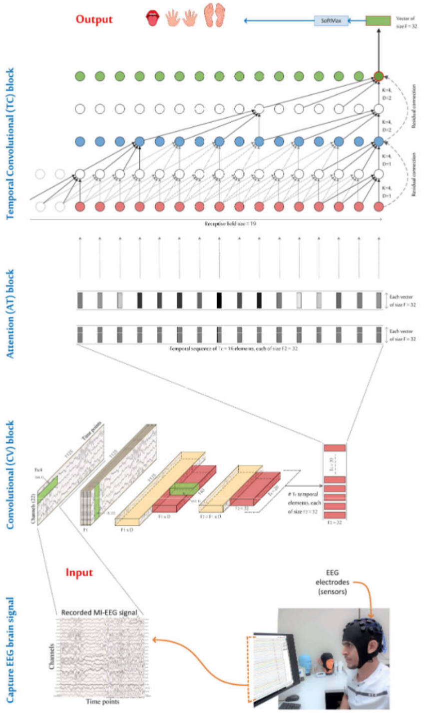
The proposed model consists of three main blocks:

Convolutional (CV) block: encodes low-level spatio-temporal information within the MI-EEG signal into a sequence of high-level temporal representations through three convolutional layers.

Attention (AT) block: highlights the most important information in the temporal sequence using a multi-head self-attention (MSA).

Temporal convolutional (TC) block: extracts high-level temporal features from the highlighted information using a temporal convolutional layer

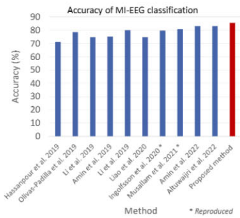
The proposed model also utilizes the convolutional-based sliding window to augment MI data and boost the performance of MI classification efficiently.



Visualization of the components of the proposed ATCNet model. ATCNet consists of three main blocks: the convolutional (CV) block, the multi-head self-attention (AT) block, and the temporal convolutional (TC) block.

Results

- The proposed ATCNet model achieves an overall accuracy of 85.38% and a κ-score of 0.81, using the challenging and benchmark BCI Competition IV-2a dataset, which outperforms the state-of-the-art techniques by at least 2.51%.
- Ablation analysis showed that each block adds its contribution: the AT block increased the overall accuracy by 1.54% and SW by 2.28%. The addition of the TC block also increased accuracy by 1.04% compared to using the CV block only.



Ablation analysis: contribution of each block in the ATCNet model. AT: attention, SW: sliding window, TC: temporal convolution.

Removed block	Accuracy %	κ-score
None (ATCNet)	85.38	0.805
AT	83.84	0.784
SW	83.10	0.775
SW + AT	82.75	0.770
TC	79.44	0.726
SW + TC	80.48	0.740
AT + TC	82.60	0.768
SW + AT + TC	81.71	0.756

Conclusions

- This study proposed a novel attention-based temporal convolutional network (ATCNet) for EEG-based motor imagery classification that outperformed state-of-the-art techniques in MI-EEG classification using the BCI-2a dataset with an accuracy of 85.4% and 71% for the subject-dependent and subject-independent modes, respectively. These high results came with a relatively small number of parameters (115.2K), which makes ATCNet applicable to limited devices.
- The ablation analysis showed that each block in the ATCNet model made a significant contribution to the performance of the ATCNet model.
- The proposed model demonstrated a powerful ability to extract MI features from a raw EEG signal without pre-processing using a limited-size and challenging dataset.

Future work

- The proposed model can be further improved by using attention mechanisms in several domains, i.e., temporal, spectral, and spatial domains.
- The proposed model can also be refined using preprocessing methods to remove artifacts and deep generative models to increase the size of the dataset.

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Code shared on GitHub: https://github.com/Altaheri/EEG-ATCNet

基于 EEG 的运动想象分类的物理信息注意时间卷积网络

哈姆迪·阿尔塔赫里

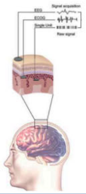
介绍

- 脑机接口（BCI）是
  一项新兴技术
  改变世界的潜力，
  广泛的应用范围
  从医学应用到人类
  增强。MI-EEG 信号已

  在许多 BCI 应用中用于协助
  残疾人士并增强人类的能力。
- EEG 是一种非侵入性、低成本、低风险且便携的
  记录大脑电活动的方法。
  运动想象（MI）是思考运动的活动

  无需物理移动即可移动人体部位。
- 从脑电信号中识别人类意图是一项挑战
  由于信噪比低和各种伪影源，

  记录的脑电信号仅为实际脑信号的~5%。



目标

目标是开发一种基于注意力机制的高性能深度学习模型，
对基于 EEG 的 MI 脑信号进行分类，其表现优于最先进的模型。

提出的方法

所提出的模型由三个主要部分组成：

卷积（CV）块：编码低级空间
MI-EEG 信号中的时间信息
高级时间表征序列

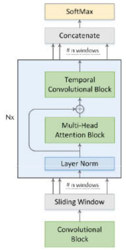
通过三个卷积层。

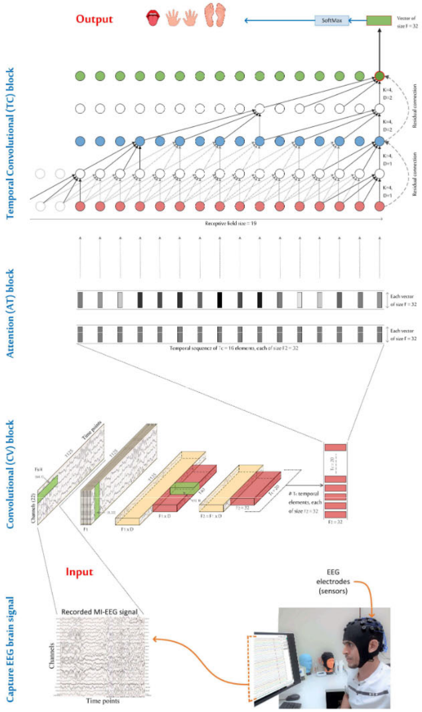
注意（AT）块：突出最重要的
时间序列中的信息使用多

头部自注意力（MSA）。

时间卷积（TC）块：提取高
从突出显示的级别时间特征
使用时间卷积层的信息

所提出的模型还利用基于卷积的滑动窗口来
增强 MI 数据，有效提升 MI 分类的性能。





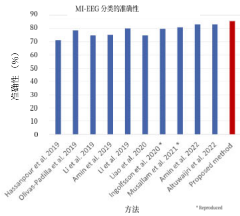
所提出的 ATCNet 模型组件的可视化。ATCNet 由三个主要块组成：卷积 (CV) 块、多头自注意 (AT) 块和时间卷积 (TC) 块。

结果

- 所提出的 ATCNet 模型总体准确率达到 85.38%，κ 得分为
  0.81，使用具有挑战性的基准 BCI Competition IV-2a 数据集，

  比最先进的技术至少高出 2.51%。
- 消融分析表明，每个区块都会增加其贡献：AT 区块
  提高了整体准确率 1.54%，SW 提高了 2.28%。TC 的加入

  与仅使用 CV 块相比，该块还将准确率提高了 1.04%。



消融分析：ATCNet 模型中每个块的贡献。AT：注意力机制，SW：滑动窗口，TC：时间卷积。

Removed block	Accuracy %	κ-score
None (ATCNet)	85.38	0.805
AT	83.84	0.784
SW	83.10	0.775
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结论

- 本研究提出了一种新的基于注意力的时间卷积网络（ATCNet），用于基于脑电图的运动想象分类，其表现优于最先进的

  使用 BCI-2a 数据集进行 MI-EEG 分类的先进技术，准确率
  学科相关模式和学科无关模式分别为 85.4% 和 71%，
  这些高结果来自于相对较少的参数

  （115.2K），这使得 ATCNet 适用于有限的设备。
- 消融分析表明，ATCNet 模型中的每个块都
  对 ATCNet 模型的性能做出了重大贡献。
- 所提出的模型展示了从中提取 MI 特征的强大能力
  使用有限大小和具有挑战性的数据集，无需预处理即可获取原始 EEG 信号。

未来工作

- 所提出的模型可以通过使用注意机制来进一步改进
  几个领域，即时间，光谱和空间领域。
- 所提出的模型还可以使用预处理方法来改进，以消除
  工件和深度生成模型来增加数据集的大小。

由 IEEE Transactions on Industrial Informatics 发布：https://ieeexplore.ieee.org/document/9852687
代码在 GitHub 上共享：https://github.com/Altaheri/EEG-ATCNet

References:

[1] I. Ahmed, G. Jeon, and F. Piccialli, "From artificial intelligence to explainable artificial intelligence in industry 4.0: a survey on what, how, and where," IEEE Trans. Ind. Informatics, vol. 18, no. 8, pp. 5031–5042, 2022.

[2] H. Altaheri et al., "Deep learning techniques for classification of electroencephalogram (EEG) motor imagery (MI) signals: a review," Neural Comput. Appl., pp. 1–42, 2021.

[3] K. K. Ang, Z. Y. Chin, C. Wang, C. Guan, and H. Zhang, "Filter bank common spatial pattern algorithm on BCI competition IV datasets 2a and 2b," Front. Neurosci., vol. 6, p. 39, 2012.

[4] M. S. Hossain, M. Al-Hammadi, and G. Muhammad, "Automatic fruit classification using deep learning for industrial applications," IEEE Trans. Ind. Informatics, vol. 15, no. 2, pp. 1027–1034, 2018.

[5] H. Altaheri, M. Alsulaiman, and G. Muhammad, "Date Fruit Classification for Robotic Harvesting in a Natural Environment Using Deep Learning," IEEE Access, vol. 7, no. 1, pp. 117115–117133, Aug. 2019.

[6] I. Ahmed, S. Din, G. Jeon, and F. Piccialli, "Exploring deep learning models for overhead view multiple object detection," IEEE Internet Things J., vol. 7, no. 7, pp. 5737–5744, 2019.

[7] M. Qamhan, H. Altaheri, A. H. Meftah, G. Muhammad, and Y. A. Alotaibi, "Digital Audio Forensics: Microphone and Environment Classification Using Deep Learning," IEEE Access, vol. 9, pp. 62719–62733, 2021.

[8] D. Zhang, K. Chen, D. Jian, and L. Yao, "Motor imagery classification via temporal attention cues of graph embedded EEG signals," IEEE J. Biomed. Heal. informatics, vol. 24, no. 9, pp. 2570–2579, 2020.

[9] G. A. Altuwaijri, G. Muhammad, H. Altaheri, and M. Alsulaiman, "A Multi-Branch Convolutional Neural Network with Squeeze-and-Excitation Attention Blocks for EEG-Based Motor Imagery Signals Classification," Diagnostics, vol. 12, no. 4, p. 995, 2022.

[10] S. U. Amin, H. Altaheri, G. Muhammad, M. Alsulaiman, and A. Wadood, "Attention-Inception and Long Short-Term Memory-based Electroencephalography Classification for Motor Imagery Tasks in Rehabilitation," IEEE Trans. Ind. Informatics, 2022.

[11] S. U. Amin, H. Altaheri, G. Muhammad, M. Alsulaiman, and W. Abdul, "Attention based Inception model for robust EEG motor imagery classification," in 2021 IEEE International Instrumentation and Measurement Technology Conference (I2MTC), 2021, pp. 1–6.

[12] V. J. Lawhern, A. J. Solon, N. R. Waytowich, S. M. Gordon, C. P. Hung, and B. J. Lance, "EEGNet: a compact convolutional neural network for EEG-based brain–computer interfaces," J. Neural Eng., vol. 15, no. 5, p. 56013, 2018.

[13] D. Li, J. Xu, J. Wang, X. Fang, and J. Ying, "A Multi-Scale Fusion Convolutional Neural Network based on Attention Mechanism for the Visualization Analysis of EEG Signals Decoding," IEEE Trans. Neural Syst. Rehabil. Eng., 2020.

[14] S. Kumar, R. Sharma, and A. Sharma, "OPTICAL+: a frequency-based deep learning scheme for recognizing brain wave signals," PeerJ Comput. Sci., vol. 7, p. e375, 2021.

[15] T. Luo and F. Chao, "Exploring spatial-frequency-sequential relationships for motor imagery classification with recurrent neural network," BMC Bioinformatics, vol. 19, no. 1, p. 344, 2018.

[16] J. Xu, H. Zheng, J. Wang, D. Li, and X. Fang, "Recognition of EEG signal motor imagery intention based on deep multi-view feature learning," Sensors, vol. 20, no. 12, p. 3496, 2020.

[17] A. Hassanpour, M. Moradikia, H. Adeli, S. R. Khayami, and P. Shamsinejadbabaki, "A novel end-to-end deep learning scheme for classifying multi-class motor imagery electroencephalography signals," Expert Syst., vol. 36, no. 6, p. e12494, 2019.

[18] S. U. Amin, M. Alsulaiman, G. Muhammad, M. A. Mekhtiche, and M. S. Hossain, "Deep Learning for EEG motor imagery classification based on multi-layer CNNs feature fusion," Futur. Gener. Comput. Syst., vol. 101, pp. 542–554, 2019.

[19] M.-A. Li, J.-F. Han, and L.-J. Duan, "A Novel MI-EEG Imaging With the Location Information of Electrodes," IEEE Access, vol. 8, pp. 3197–3211, 2019.

[20] T. Liu and D. Yang, "A Densely Connected Multi-Branch 3D Convolutional Neural Network for Motor Imagery EEG Decoding," Brain Sci., vol. 11, no. 2, p. 197, 2021.

[21] S. Bai, J. Z. Kolter, and V. Koltun, "An empirical evaluation of generic convolutional and recurrent networks for sequence modeling," arXiv Prepr. arXiv1803.01271, 2018.

[22] T. M. Ingolfsson, M. Hersche, X. Wang, N. Kobayashi, L. Cavigelli, and L. Benini, "EEG-TCNet: An Accurate Temporal Convolutional Network for Embedded Motor-Imagery Brain-Machine Interfaces," arXiv Prepr. arXiv2006.00622, 2020.

[23] Y. K. Musallam et al., "Electroencephalography-based motor imagery classification using temporal convolutional network fusion," Biomed. Signal Process. Control, vol. 69, p. 102826, 2021.

[24] S. Cuomo, V. S. Di Cola, F. Giampaolo, G. Rozza, M. Raissi, and F. Piccialli, "Scientific Machine Learning through Physics-Informed Neural Networks: Where we are and What's next," arXiv Prepr. arXiv2201.05624, 2022.

[25] D. Bahdanau, K. Cho, and Y. Bengio, "Neural machine translation by jointly learning to align and translate," arXiv Prepr. arXiv1409.0473, 2014.

[26] M.-T. Luong, H. Pham, and C. D. Manning, "Effective approaches to attention-based neural machine translation," arXiv Prepr. arXiv1508.04025, 2015.

[27] A. Vaswani et al., "Attention is all you need," in Advances in neural information processing systems, 2017, pp. 5998–6008.

[28] J. Hu, L. Shen, and G. Sun, "Squeeze-and-excitation networks," in Proceedings of the IEEE conference on computer vision and pattern recognition, 2018, pp. 7132–7141.

[29] S. Woo, J. Park, J.-Y. Lee, and I. S. Kweon, "Cbam: Convolutional block attention module," in Proceedings of the European conference on computer vision (ECCV), 2018, pp. 3–19.

[30] C. Brunner, R. Leeb, G. Müller-Putz, A. Schlögl, and G. Pfurtscheller, "BCI Competition 2008–Graz data set A," Inst. Knowl. Discov. Graz Univ. Technol., vol. 16, pp. 1–6, 2008.

[31] S. Ioffe and C. Szegedy, "Batch normalization: Accelerating deep network training by reducing internal covariate shift," in International conference on machine learning, 2015, pp. 448–456.

[32] R. T. Schirrmeister et al., "Deep learning with convolutional neural networks for EEG decoding and visualization," Hum. Brain Mapp., vol. 38, no. 11, pp. 5391–5420, 2017.

[33] J. L. Ba, J. R. Kiros, and G. E. Hinton, "Layer normalization," arXiv Prepr. arXiv1607.06450, 2016.

参考：

[1] I. Ahmed、G. Jeon 和 F. Piccialli，“从人工智能到工业 4.0 中的可解释人工智能：关于什么、如何和在哪里的调查”，IEEE 工业信息学汇刊，第 18 卷，第 8 期，第 5031-5042 页，2022 年。

[2] H. Altaheri 等人，“深度学习技术对脑电图 (EEG) 运动想象 (MI) 信号分类的综述”，神经计算应用，第 1-42 页，2021 年。

[3] KK Ang、ZY Chin、C. Wang、C. Guan 和 H. Zhang，“BCI 竞赛 IV 数据集 2a 和 2b 上的滤波器组常见空间模式算法”，Front. Neurosci.，第 6 卷，第 39 页，2012 年。

[4] MS Hossain、M. Al-Hammadi 和 G. Muhammad，“利用深度学习实现工业应用的水果自动分类”，IEEE 工业信息学汇刊，第 15 卷，第 2 期，第 1027-1034 页，2018 年。

[5] H. Altaheri、M. Alsulaiman 和 G. Muhammad，“利用深度学习在自然环境中对机器人采摘的枣果进行分类”，IEEE Access，第 7 卷，第 1 期，第 117115-117133 页，2019 年 8 月。

[6] I. Ahmed、S. Din、G. Jeon 和 F. Piccialli，“探索用于俯视图多物体检测的深度学习模型”，IEEE Internet Things J.，第 7 卷，第 7 期，第 5737-5744 页，2019 年。

[7] M. Qamhan、H. Altaheri、AH Meftah、G. Muhammad 和 YA Alotaibi，“数字音频取证：使用深度学习进行麦克风和环境分类”，IEEE Access，第 9 卷，第 62719-62733 页，2021 年。

[8] D. Zhang, K. Chen, D. Jian 和 L. Yao，“通过图形嵌入脑电图信号的时间注意线索进行运动意象分类”，IEEE J. Biomed. Heal. 信息学，第 24 卷，第 9 期，第 2570-2579 页，2020 年。

[9] GA Altuwaijri、G. Muhammad、H. Altaheri 和 M. Alsulaiman，“一种用于基于脑电图的运动想象信号分类的具有挤压和激励注意力模块的多分支卷积神经网络”，《诊断学》，第 12 卷，第 4 期，第 995 页，2022 年。

[10] SU Amin、H. Altaheri、G. Muhammad、M. Alsulaiman 和 A. Wadood，“基于注意力起始和长短期记忆的脑电图分类在康复运动想象任务中的应用”，IEEE 工业信息学汇刊，2022 年。

[11] SU Amin、H. Altaheri、G. Muhammad、M. Alsulaiman 和 W. Abdul，《基于注意力机制的稳健 EEG 运动想象分类 Inception 模型》，2021 年 IEEE 国际仪器与测量技术会议 (I2MTC)，2021 年，第 1-6 页。

[12] VJ Lawhern、AJ Solon、NR Waytowich、SM Gordon、CP Hung 和 BJ Lance，“EEGNet：用于基于 EEG 的脑机接口的紧凑卷积神经网络”，J. Neural Eng.，第 15 卷，第 5 期，第 56013 页，2018 年。

[13] D. Li, J. Xu, J. Wang, X. Fang, 和 J. Ying，“基于注意力机制的多尺度融合卷积神经网络用于脑电信号解码可视化分析”，IEEE 神经系统康复工程学报，2020 年。

[14] S. Kumar、R. Sharma 和 A. Sharma，“OPTICAL+：一种基于频率的深度学习方案，用于识别脑电波信号”，PeerJ Comput. Sci.，第 7 卷，第 e375 页，2021 年。

[15] T. Luo 和 F. Chao，“利用循环神经网络探索运动想象分类的空间-频率-序列关系”，BMC 生物信息学，第 19 卷，第 1 期，第 344 页，2018 年。

[16] J. Xu, H. Zheng, J. Wang, D. Li, 和 X. Fang，“基于深度多视图特征学习的脑电信号运动想象意图识别”，传感器，第 20 卷，第 12 期，第 3496 页，2020 年。

[17] A. Hassanpour、M. Moradikia、H. Adeli、SR Khayami 和 P. Shamsinejadbabaki，“一种用于对多类运动想象脑电信号进行分类的新型端到端深度学习方案”，Expert Syst.，第 36 卷，第 6 期，第 e12494 页，2019 年。

[18] SU Amin、M. Alsulaiman、G. Muhammad、MA Mekhtiche 和 MS Hossain，“基于多层 CNN 特征融合的 EEG 运动想象分类深度学习”，Futur. Gener. Comput. Syst.，第 101 卷，第 542-554 页，2019 年。

[19] M.-A. Li、J.-F. Han 和 L.-J. Duan，“一种利用电极位置信息的新型 MI-EEG 成像”，IEEE Access，第 8 卷，第 3197-3211 页，2019 年。

[20] T. Liu 和 D. Yang，“用于运动想象脑电图解码的密集连接多分支 3D 卷积神经网络”，《脑科学》，第 11 卷，第 2 期，第 197 页，2021 年。

[21] S. Bai、JZ Kolter 和 V. Koltun，“对通用卷积和循环网络用于序列建模的实证评估”，arXiv Prepr。arXiv1803.01271，2018 年。

[22] TM Ingolfsson、M. Hersche、X. Wang、N. Kobayashi、L. Cavigelli 和 L. Benini，“EEG-TCNet：用于嵌入式运动想象脑机接口的精确时间卷积网络”，arXiv Prepr。arXiv2006.00622，2020 年。

[23] YK Musallam 等人，“基于时间卷积网络融合的脑电图运动想象分类”，生物医学、信号处理、控制，第 69 卷，第 102826 页，2021 年。

[24] S. Cuomo、VS Di Cola、F. Giampaolo、G. Rozza、M. Raissi 和 F. Piccialli，“通过物理信息神经网络进行科学机器学习：我们在哪里以及下一步是什么”，arXiv Prepr。arXiv2201.05624，2022 年。

[25] D. Bahdanau、K. Cho 和 Y. Bengio，“通过联合学习对齐和平移实现神经机器翻译”，arXiv Prepr. arXiv1409.0473，2014 年。

[26] M.-T. Luong、H. Pham 和 CD Manning，“基于注意力机制的神经机器翻译的有效方法”，arXiv Prepr. arXiv1508.04025，2015 年。

[27] A. Vaswani 等人，“注意力就是你所需要的一切”，载于《神经信息处理系统进展》，2017 年，第 5998-6008 页。

[28] J. Hu、L. Shen 和 G. Sun，“挤压和激励网络”，载于《IEEE 计算机视觉与模式识别会议论文集》，2018 年，第 7132-7141 页。

[29] S. Woo、J. Park、J.-Y. Lee 和 IS Kweon，“Cbam：卷积块注意模块”，载于《欧洲计算机视觉会议（ECCV）论文集》，2018 年，第 3-19 页。

[30] C. Brunner、R. Leeb、G. Müller-Putz、A. Schlögl 和 G. Pfurtscheller，“BCI 竞赛 2008 – 格拉茨数据集 A”，Inst。知道。迪可夫。格拉茨大学技术，卷。16，第 1-6 页，2008 年。

[31] S. Ioffe 和 C. Szegedy，“批量标准化：通过减少内部协变量偏移来加速深度网络训练”，国际机器学习会议，2015 年，第 448-456 页。

[32] RT Schirrmeister 等人，“利用卷积神经网络进行深度学习以实现脑电图解码和可视化”，Hum. Brain Mapp.，第 38 卷，第 11 期，第 5391-5420 页，2017 年。

[33] JL Ba、JR Kiros 和 GE Hinton，“层归一化”，arXiv Prepr。arXiv1607.06450，2016 年。