

# Weekly Progress Report

[25/06/2023]

## Introduction:

This Weekly Progress Report highlights the advancements made in the field of computer vision and deep learning during the past week. The report provides an overview of the progress made in three key areas: Convolutional Neural Networks for Computer Vision, Deep Generative Modeling, and Robust and Trustworthy Deep Learning. Each area focuses on different aspects of computer vision and presents the latest developments and techniques. The report also includes an exploration of various applications within each area and their implications for real-world scenarios.

## 1. Convolutional Neural Networks for Computer Vision:

The first part of the week was dedicated to understanding and implementing Convolutional Neural Networks (CNNs) for computer vision tasks. CNNs have revolutionized the field of computer vision by enabling the extraction of visual features directly from raw images. This section delves into the importance of learning visual features and introduces the concept of feature extraction and convolution.

The report provides a detailed explanation of the convolution operation, which lies at the heart of CNNs. Convolution allows for the extraction of local features from images by applying filters or kernels across the image. This process enables the network to learn and identify patterns and shapes.

Convolutional Neural Networks (CNNs) are widely used for various computer vision tasks, such as image classification, object detection, and segmentation. This section explores the architecture and components of CNNs, including convolutional layers, non-linear activation functions, and pooling operations. The report discusses the benefits of these components in capturing hierarchical features and reducing the spatial dimensions of the input.

To provide a practical understanding, the report includes an end-to-end code example that showcases the steps involved in training a CNN for a specific task. The example demonstrates data loading, model creation, training, and evaluation. By following this

example, one can gain hands-on experience in implementing CNNs for computer vision tasks.

Furthermore, the report highlights various applications of CNNs, emphasizing their significance in real-world scenarios. Object detection, a key application of computer vision, is explored in detail. Object detection algorithms combine the power of CNNs with additional techniques such as bounding box regression and non-maximum suppression to accurately locate and classify objects within an image.

Another important application discussed is end-to-end self-driving cars. CNNs play a vital role in autonomous vehicles by analyzing sensor data, identifying objects, and making critical decisions. This section outlines the challenges and advancements in applying CNNs for self-driving cars, paving the way for safer and more efficient transportation systems.

## **2. Deep Generative Modeling:**

The second part of the week focused on deep generative modeling, which plays a crucial role in creating realistic and diverse synthetic data. Generative models aim to capture the underlying distribution of a given dataset, allowing the generation of new samples with similar characteristics. This section explores the motivation behind generative models and their significance in the field of deep learning.

The report introduces latent variable models, including autoencoders and variational autoencoders (VAEs). Autoencoders are neural networks designed to learn an efficient representation of input data by encoding it into a lower-dimensional latent space and decoding it back to the original data format. VAEs take this concept further by incorporating probabilistic modeling and enabling the generation of new samples by sampling from the latent space.

The concept of priors on the latent distribution is discussed, emphasizing the importance of encoding prior knowledge into generative models. The report introduces the reparameterization trick, a technique that enables efficient training of VAEs by decoupling the sampling process from the model's parameters.

This trick allows for backpropagation and gradient-based optimization, making VAEs tractable to train.

The section further explores latent perturbation and disentanglement. Generative models offer the ability to manipulate latent variables to generate novel samples or control specific attributes of the generated data. This capability has applications in debiasing and disentangling underlying factors in datasets, promoting fairness and interpretability in AI systems.

The report delves into Generative Adversarial Networks (GANs), an alternative approach to generative modeling. GANs consist of a generator network and a discriminator network that compete against each other in a two-player minimax game. The generator aims to generate realistic samples, while the discriminator aims to distinguish between real and generated samples. The report provides insights into the intuition behind GANs and their training process.

Additionally, recent advances in GANs, including conditional GANs and CycleGAN for unpaired translation, are discussed. Conditional GANs allow for conditional generation based on specific labels or attributes, enabling fine-grained control over the generated output. CycleGAN, on the other hand, allows for unpaired image-to-image translation, demonstrating the potential of GANs in various domains, such as style transfer and domain adaptation.

In conclusion, the report presents a summary of VAEs and GANs, highlighting their strengths and limitations. Both VAEs and GANs contribute to the field of generative modeling and have different applications based on their characteristics. VAEs excel in capturing data distributions and enabling latent space manipulation, while GANs excel in generating realistic samples and capturing high-frequency details.

### **3. Robust and Trustworthy Deep Learning:**

The final part of the week's progress focused on robust and trustworthy deep learning. Deep learning models often face challenges related to algorithmic bias, class imbalance, and uncertainty estimation. This section aims to address these challenges and provide insights into ensuring the robustness and trustworthiness of AI systems.

The report explores the concept of algorithmic bias and its implications in AI systems. Algorithmic bias refers to the systematic and unfair treatment of certain groups or individuals due to biases present in the data or model. The report discusses class imbalance, a common issue in classification tasks, and presents techniques to handle it, such as oversampling, undersampling, and cost-sensitive learning.

Furthermore, the report addresses the importance of estimating and quantifying uncertainty in deep learning models. Uncertainty estimation helps AI systems make more informed and reliable decisions. The distinction between aleatoric and epistemic uncertainty is explained, along with methods for estimating both types of uncertainty. Aleatoric uncertainty captures the inherent variability in the data, while epistemic uncertainty represents uncertainty arising from model ambiguity.

Evidential deep learning, a framework that leverages probability theory to estimate uncertainty, is introduced as a promising approach to robust deep learning. The report presents a recap of the challenges associated with achieving robustness in deep learning models and emphasizes the need for trustworthy AI systems that are aware of their own limitations.

The report concludes by showcasing Themis AI, a transformative platform that aims to enhance the risk-awareness of AI models. Themis AI provides tools and techniques to assess and mitigate risks associated with AI systems. The Capsa open-source risk-aware AI wrapper is introduced as a means to unlock the future of trustworthy AI by incorporating risk analysis and decision-making processes.

## **Conclusion:**

In conclusion, the progress made during the week has been significant in advancing the understanding and implementation of computer vision and deep learning techniques. The exploration of Convolutional Neural Networks, Deep Generative Modeling, and Robust and Trustworthy Deep Learning has provided insights into the latest developments and their practical applications. The acquired knowledge and hands-on experience gained throughout the week will serve as a solid foundation for future work in the field. Moving forward, the focus will be on further exploring and refining these techniques, as well as investigating new approaches and applications.

## **References:**

[https://www.youtube.com/watch?v=FHeCmnNe0P8&list=PLtBw6njQRU-rwp5\\_\\_7C0oIVt26ZgjG9NI&index=7](https://www.youtube.com/watch?v=FHeCmnNe0P8&list=PLtBw6njQRU-rwp5__7C0oIVt26ZgjG9NI&index=7)

Thank you.

yours sincerely

Shadab. A. Sheikh