Deep Learning

BCSE-332L

Module 6:

Advanced Neural Networks

Dr . Saurabh Agrawal

Faculty Id: 20165

School of Computer Science and Engineering

VIT, Vellore-632014

Tamil Nadu, India

Outline

- ❑Transfer Learning
- ❑Transfer Learning Models
- ❑Generative Adversarial Network and their variants
- ❑Region based CNN
- ❑Fast RCNN
- ❑You Only Look Once
- ❑Single Shot Detector

Transfer Learning

- Transfer learning is a smart method in machine learning where a model uses knowledge from one task to help with a different, but related, task.
- Instead of learning from zero, the model uses what it already knows to solve new problems faster and better.
- This is especially helpful when there isn't much data available.
- Transfer learning is making a big impact in areas like understanding language and recognizing images.

Transfer Learning

❑What is Transfer Learning?

❑Transfer learning is a technique in machine learning where a model trained on one task is used as the starting point for a model on a second task.

❑This can be useful when the second task is similar to the first task, or when there is limited data available for the second task.

❑By using the learned features from the first task as a starting point, the model can learn more quickly and effectively on the second task.

❑This can also help to prevent overfitting, as the model will have already learned general features that are likely to be useful in the second task.

Transfer Learning

❑Why do we need Transfer Learning?

❑**Limited Data**: In many real-world scenarios, obtaining a large amount of labeled data for training a model from scratch can be difficult and expensive. Transfer learning allows us to leverage pre-trained models and their knowledge, reducing the need for vast amounts of data.

❑**Improved Performance**: By starting with a pre-trained model, which has already learned from a large dataset, we can achieve better performance on new tasks more quickly. This is especially useful in applications where accuracy and efficiency are crucial.

❑**Time and Cost Efficiency**: Transfer learning saves time and resources because it speeds up the training process. Instead of training a new model from scratch, we can build on existing models and fine-tune them for specific tasks.

❑**Adaptability**: Models trained on one task can be adapted to perform well on related tasks. This adaptability makes transfer learning suitable for a wide range of applications, from image recognition to natural language processing.

Transfer Learning

❑**How does Transfer Learning work?:** This is a general summary of how transfer learning works:

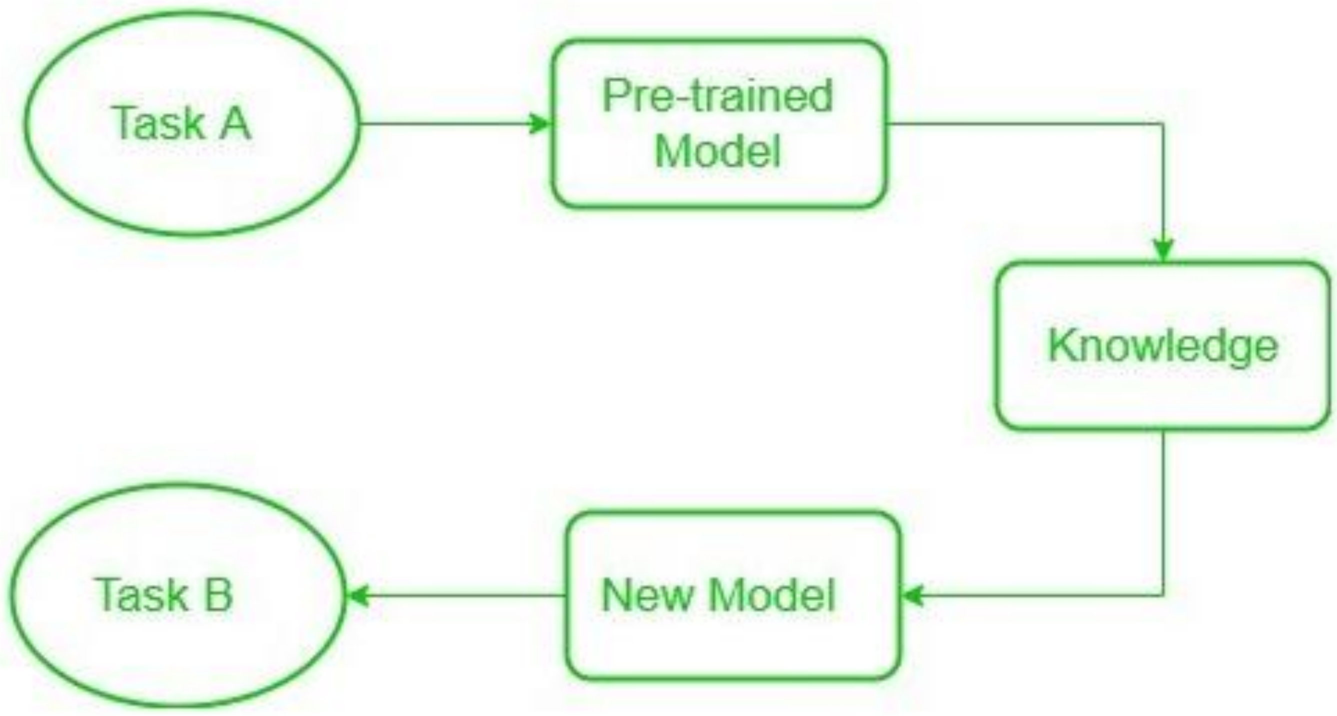
❑**Pre-trained Model:** Start with a model that has previously been trained for a certain task using a large set of data. Frequently trained on extensive datasets, this model has identified general features and patterns relevant to numerous related jobs.

❑**Base Model:** The model that has been pre-trained is known as the base model. It is made up of layers that have utilized the incoming data to learn hierarchical feature representations.

❑**Transfer Layers:** In the pre-trained model, find a set of layers that capture generic information relevant to the new task as well as the previous one. Because they are prone to learning low-level information, these layers are frequently found near the top of the network.

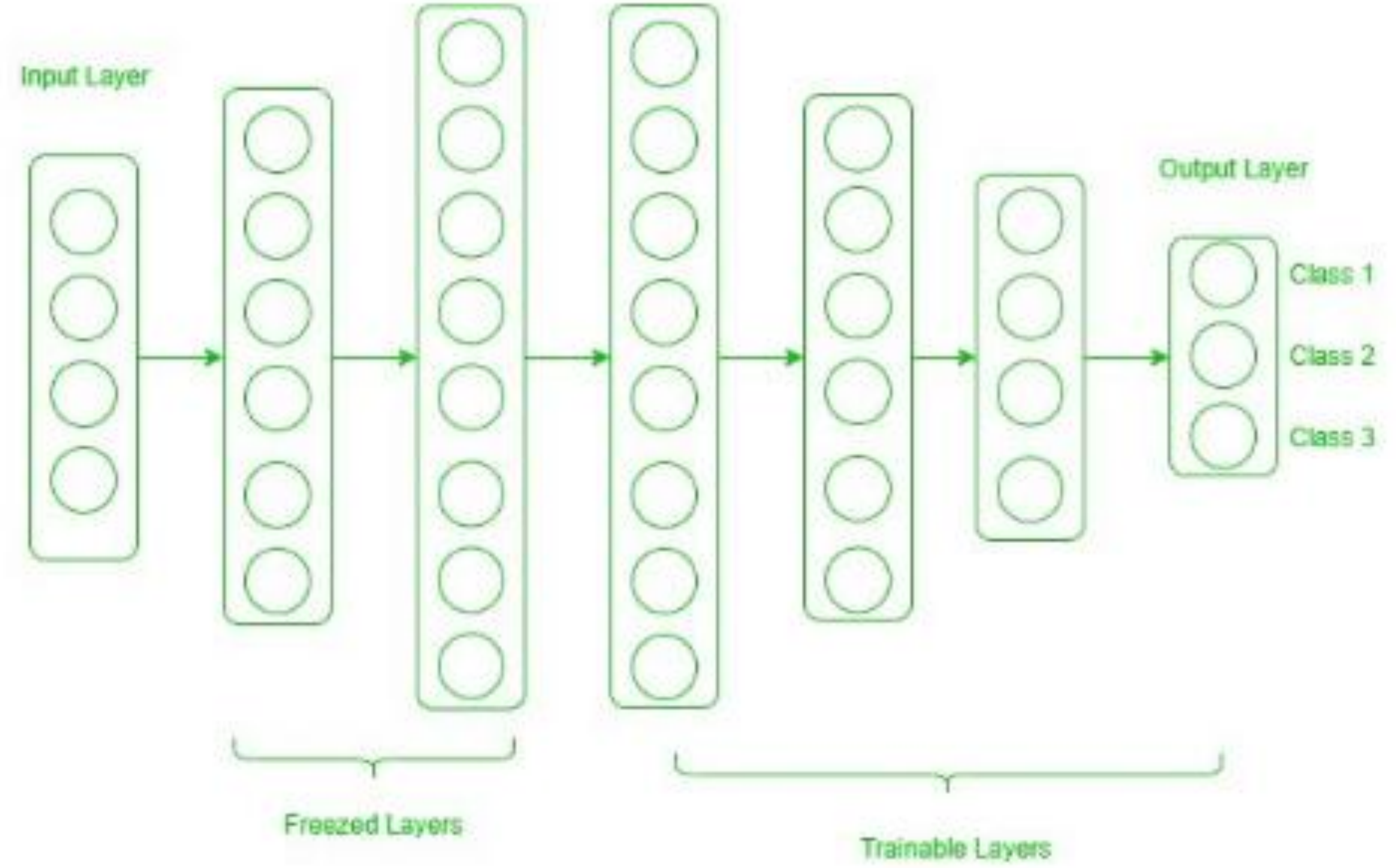
❑**Fine-tuning:** Using the dataset from the new challenge to retrain the chosen layers. We define this procedure as fine-tuning. The goal is to preserve the knowledge from the pre-training while enabling the model to modify its parameters to better suit the demands of the current assignment.

❑How does Transfer Learning work?



❑Low-level features learned for task A should be beneficial for learning of model for task B.

❑**How does Transfer Learning work?: Freezed and Trainable Layers:**



Transfer Learning

❑**How does Transfer Learning work?: Freezed and Trainable Layers:**

❑In transfer learning, there are two main components: frozen layers and modifiable layers.

1. **Frozen Layers**: These are the layers of a pre-trained model that are kept unchanged during the fine-tuning process. Frozen layers retain the knowledge learned from the original task and are used to extract general features from the input data.
2. **Modifiable Layers**: These are the layers of the model that are adjusted or re-trained during fine-tuning. Modifiable layers learn task-specific features from the new dataset. By focusing on these layers, the model can adapt to the specific requirements of the new task.

Transfer Learning

❑How does Transfer Learning work?

❑Now, one may ask how to determine which layers we need to freeze, and which layers need to train.

❑The answer is simple, the more you want to inherit features from a pre-trained model, the more you have to freeze layers.

Transfer Learning

- Let's consider all situations where the size and dataset of the target task vary from the base network.
- **The target dataset is small and similar to the base network dataset:** Since the target dataset is small, that means we can fine-tune the pre-trained network with the target dataset. But this may lead to a problem of overfitting. Also, there may be some changes in the number of classes in the target task. So, in such a case we remove the fully connected layers from the end, maybe one or two, and add a new fully connected layer satisfying the number of new classes. Now, we freeze the rest of the model and only train newly added layers.
- **The target dataset is large and similar to the base training dataset:** In such cases when the dataset is large, and it can hold a pre-trained model there will be no chance of overfitting. Here, also the last full-connected layer is removed, and a new fully-connected layer is added with the proper number of classes. Now, the entire model is trained on a new dataset. This makes sure to tune the model on a new large dataset keeping the model architecture the same.

Transfer Learning

- Let's consider all situations where the size and dataset of the target task vary from the base network.
- **The target dataset is small and different from the base network dataset:** Since the target dataset is different, using high-level features of the pre-trained model will not be useful. In such a case, remove most of the layers from the end in a pre-trained model, and add new layers a satisfying number of classes in a new dataset. This way we can use low-level features from the pre-trained model and train the rest of the layers to fit a new dataset. Sometimes, it is beneficial to train the entire network after adding a new layer at the end.
- **The target dataset is large and different from the base network dataset:** Since the target network is large and different, the best way is to remove the last layers from the pre-trained network and add layers with a satisfying number of classes, then train the entire network without freezing any layer.

Transfer Learning V1

- In transfer learning, the knowledge of an already trained machine learning model is applied to a different but related problem.
- For example, if you trained a simple classifier to predict whether an image contains a backpack, you could use the knowledge that the model gained during its training to recognize other objects like sunglasses.
- With transfer learning, we basically try to exploit what has been learned in one task to improve generalization in another.
- We transfer the weights that a network has learned at “task A” to a new “task B.”

Transfer Learning V1

- The general idea is to use the knowledge a model has learned from a task with a lot of available labeled training data in a new task that doesn’t have much data.
- Instead of starting the learning process from scratch, we start with patterns learned from solving a related task.
- Transfer learning is mostly used in computer vision and natural language processing tasks like sentiment analysis due to the huge amount of computational power required.
- Transfer learning isn’t really a machine learning technique, but can be seen as a “design methodology” within the field.
- It is also not exclusive to machine learning. Nevertheless, it has become quite popular in combination with neural networks that require huge amounts of data and computational power.

Transfer Learning V1

❑How Transfer Learning Works

❑In computer vision, for example, neural networks usually try to detect edges in the earlier layers, shapes in the middle layer and some task-specific features in the later layers.

❑In transfer learning, the early and middle layers are used and we only retrain the latter layers.

❑It helps leverage the labeled data of the task it was initially trained on.

❑This process of retraining models is known as fine-tuning.

❑In the case of transfer learning, though, we need to isolate specific layers for retraining.

❑There are then two types of layers to keep in mind when applying transfer learning:

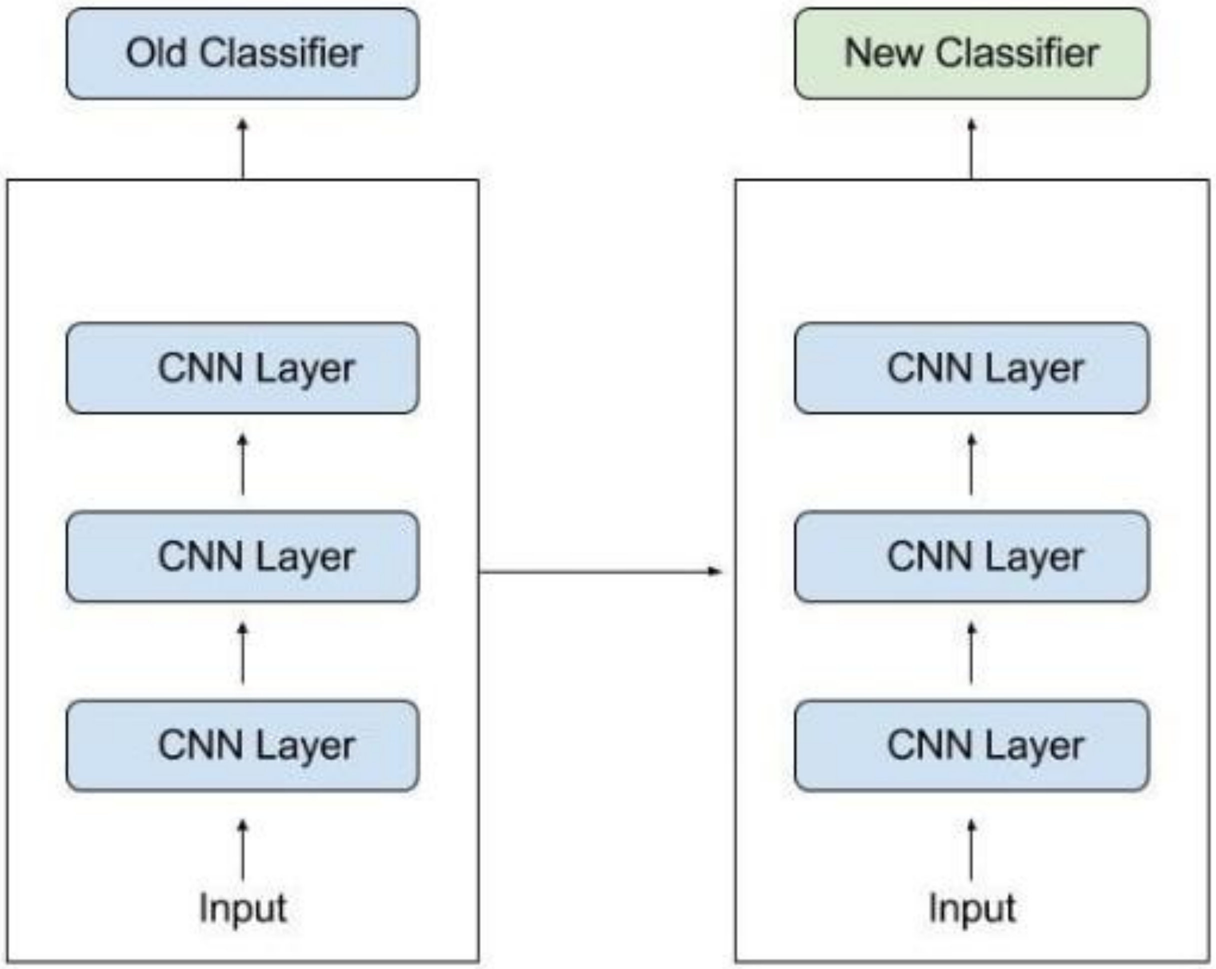
1. **Frozen layers:** Layers that are left alone during retraining and keep their knowledge from a previous task for the model to build on.
2. **Modifiable layers:** Layers that are retrained during fine-tuning, so a model can adjust its knowledge to a new, related task.

Transfer Learning V1

❑How Transfer Learning Works

❑Let’s go back to the example of a model trained for recognizing a backpack in an image, which will be used to identify sunglasses.

❑In the earlier layers, the model has learned to recognize objects, so we will only retrain the latter layers to help it learn what separates sunglasses from other objects.



Transfer Learning V1

❑How Transfer Learning Works

❑In transfer learning, we try to transfer as much knowledge as possible from the previous task the model was trained on to the new task at hand.

❑This knowledge can be in various forms depending on the problem and the data.

❑For example, it could be how models are composed, which allows us to more easily identify novel objects.

Transfer Learning V1

❑Why Use Transfer Learning

❑The main advantages of transfer learning are saving training time, improving the performance of neural networks (in most cases) and not needing a lot of data.

❑Usually, a lot of data is needed to train a neural network from scratch, but access to that data isn't always available.

❑With transfer learning, a solid machine learning model can be built with comparatively little training data because the model is already pre-trained.

❑This is especially valuable in natural language processing because mostly expert knowledge is required to create large labeled data sets.

❑Additionally, training time is reduced because it can sometimes take days or even weeks to train a deep neural network from scratch on a complex task.

Transfer Learning V1

❑When to Use Transfer Learning

❑As is always the case in machine learning, it is hard to form rules that are generally applicable, but here are some guidelines on when transfer learning might be used:

1. **Lack of training data:** There isn't enough labeled training data to train your network from scratch.
2. **Existing network:** There already exists a network that is pre-trained on a similar task, which is usually trained on massive amounts of data.
3. **Same input:** When task 1 and task 2 have the same input.

Transfer Learning V1

❑Approaches to Transfer Learning

1. Training a Model to Reuse it: Imagine you want to solve task A but don’t have enough data to train a deep neural network. One way around this is to find a related task B with an abundance of data. Train the deep neural network on task B and use the model as a starting point for solving task A. Whether you’ll need to use the whole model or only a few layers depends heavily on the problem you’re trying to solve. If you have the same input in both tasks, possibly reusing the model and making predictions for your new input is an option. Alternatively, changing and retraining different task-specific layers and the output layer is a method to explore.

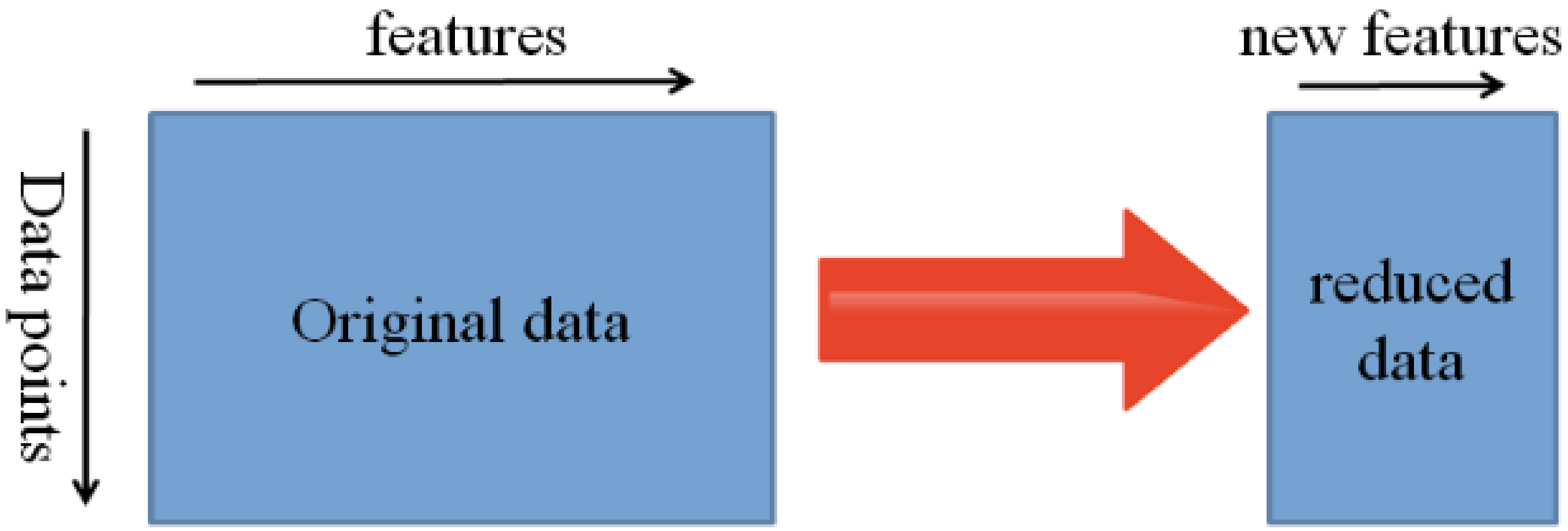
Transfer Learning V1

❑Approaches to Transfer Learning

2. Using a Pre-Trained Model: The second approach is to use an already pre-trained model. There are a lot of these models out there, so make sure to do a little research. How many layers to reuse and how many to retrain depends on the problem. Keras, for example, provides numerous pre-trained models that can be used for transfer learning, prediction, feature extraction and fine-tuning. You can find these models, and also some brief tutorials on how to use them, here. There are also many research institutions that release trained models.This type of transfer learning is most commonly used throughout deep learning.

❑Approaches to Transfer Learning

3. Feature Extraction: Another approach is to use deep learning to discover the best representation of your problem, which means finding the most important features. This approach is also known as representation learning, and can often result in a much better performance than can be obtained with hand-designed representation.



Transfer Learning V2

❑What is Transfer Learning?

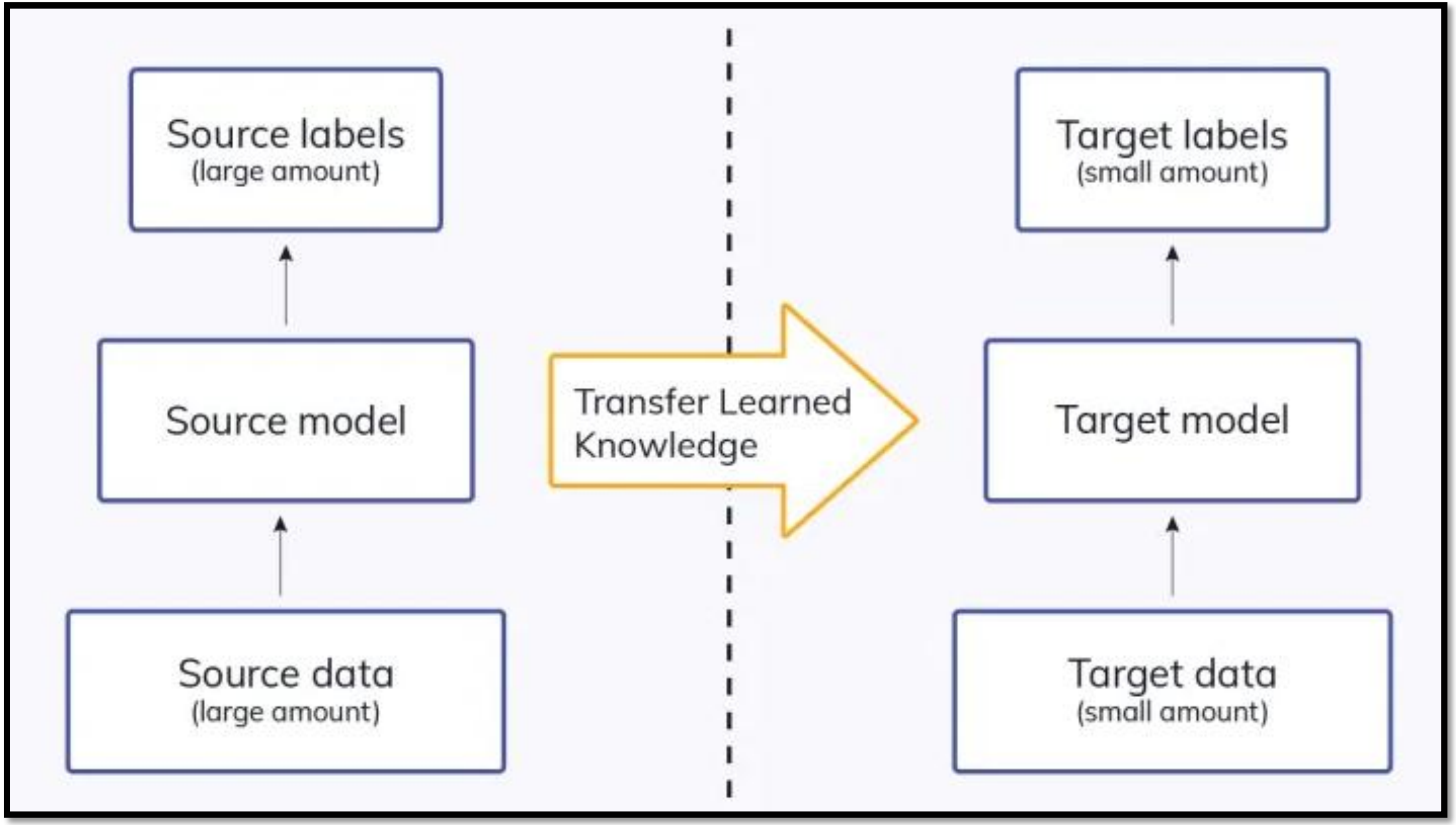
❑Transfer learning is a method for feature representation from a pre-trained model facilitating us that we don’t need to train a new model from scratch.

❑A pre-trained model is usually trained on a huge dataset such as ImageNet and the weights obtained from the trained model can be used for any other related application with your custom neural network.

❑These newly built models can directly be used for predictions on relatively new tasks or can be used in training processes for related applications.

❑This approach not only reduces the training time but also lowers the generalization error.

❑What is Transfer Learning?



Transfer Learning Models

❑Transfer Learning Strategies (Types)

❑The strategy you use to facilitate TL will depend on the domain of the model you are building, the task it needs to complete, and the availability of training data.

Transfer Learning Models

❑Transfer Learning Strategies (Types)

1. Transductive transfer learning:

❑Transductive transfer learning involves transferring knowledge from a specific source domain to a different but related target domain, with the primary focus being on the target domain. It is especially useful when there is little or no labeled data from the target domain.

❑Transductive transfer learning asks the model to make predictions on target data by using previously-gained knowledge. As the target data is mathematically similar to the source data, the model finds patterns and performs faster.

❑For example, consider adapting a sentiment analysis model trained on product reviews to analyze movie reviews. The source domain (product reviews) and the target domain (movie reviews) differ in context and specifics but share similarities in structure and language use. The model quickly learns to apply its understanding of sentiment from the product domain to the movie domain.

❑Transfer Learning Strategies (Types)

2. Inductive transfer learning:

❑Inductive transfer learning is where the source and target domains are the same, but the tasks the model must complete differ. The pre-trained model is already familiar with the source data and trains faster for new functions.

❑An example of inductive transfer learning is in natural language processing (NLP). Models are pre-trained on a large set of texts and then fine-tuned using inductive transfer learning to specific functions like sentiment analysis. Similarly, computer vision models like VGG are pre-trained on large image datasets and then fine-tuned to develop object detection.

❑Transfer Learning Strategies (Types)

3. Unsupervised transfer learning

❑Unsupervised transfer learning uses a strategy similar to inductive transfer learning to develop new abilities. However, you use this form of transfer learning when you only have unlabeled data in both the source and target domains.

❑The model learns the common features of unlabeled data to generalize more accurately when asked to perform a target task. This method is helpful if it is challenging or expensive to obtain labeled source data.

❑For example, consider the task of identifying different types of motorcycles in traffic images. Initially, the model is trained on a large set of unlabeled vehicle images. In this instance, the model independently determines the similarities and distinguishing features among different types of vehicles like cars, buses, and motorcycles. Next, the model is introduced to a small, specific set of motorcycle images. The model performance improves significantly compared to before.

Transfer Learning Models

❑Transfer Learning Strategies (Types)

3. Unsupervised transfer learning

❑Unsupervised transfer learning uses a strategy similar to inductive transfer learning to develop new abilities. However, you use this form of transfer learning when you only have unlabeled data in both the source and target domains.

❑The model learns the common features of unlabeled data to generalize more accurately when asked to perform a target task. This method is helpful if it is challenging or expensive to obtain labeled source data.

❑For example, consider the task of identifying different types of motorcycles in traffic images. Initially, the model is trained on a large set of unlabeled vehicle images. In this instance, the model independently determines the similarities and distinguishing features among different types of vehicles like cars, buses, and motorcycles. Next, the model is introduced to a small, specific set of motorcycle images. The model performance improves significantly compared to before.

Transfer Learning Models

❑Transfer Learning Algorithms (Types)

❑Transfer learning involves specialized algorithms to facilitate knowledge transfer. Notable algorithms include:

1. **Feature-based Transfer Learning:** Transfers shared features between domains to enhance target task performance.
2. **Instance-based Transfer Learning:** Adapts source instances to the target domain, useful for dissimilar domains.
3. **Model-based Transfer Learning:** Transfers pre-trained models to adapt to target tasks.
4. **Self-taught Learning:** Trains on a large source domain without target labels to extract useful features.
5. **Domain-adversarial Training:** Learns domain-invariant features by minimizing domain differences.

Transfer Learning Models

❑Transfer Learning Algorithms (Types)

❑Transfer learning involves specialized algorithms to facilitate knowledge transfer. Notable algorithms include:

6. **Zero-shot Learning:** Predicts objects or categories not seen during training using semantic descriptions.
7. **Multi-task Learning:** Trains on multiple tasks simultaneously to leverage shared knowledge.
8. **Inductive Transfer Learning via Matrix Completion:** Adapts knowledge between domains with common objects and different relationships.
9. **Transfer Component Analysis:** Separates shared and domain-specific structures to align domains effectively.

Transfer Learning Models

❑Transfer Learning Algorithms (Types)

❑Transfer learning involves specialized algorithms to facilitate knowledge transfer. Notable algorithms include:

6. **Zero-shot Learning:** Predicts objects or categories not seen during training using semantic descriptions.
7. **Multi-task Learning:** Trains on multiple tasks simultaneously to leverage shared knowledge.
8. **Inductive Transfer Learning via Matrix Completion:** Adapts knowledge between domains with common objects and different relationships.
9. **Transfer Component Analysis:** Separates shared and domain-specific structures to align domains effectively.

Transfer Learning Models

❑Transfer Learning Models

❑In the transfer learning, pre-trained models play a central role.

❑These models come with pre-acquired knowledge from various domains and tasks, serving as a starting point for efficient knowledge transfer.

❑Some popular transfer learning models include:

1. **ImageNet Models:** Perfect for computer vision tasks, models like VGG, ResNet, and Inception Excel in image-related applications.
2. **BERT (Bidirectional Encoder Representations from Transformers):** A game-changer in NLP, BERT handles tasks like sentiment analysis and text summarization.
3. **GPT (Generative Pre-trained Transformer):** GPT models are NLP powerhouses, known for natural language generation and understanding.

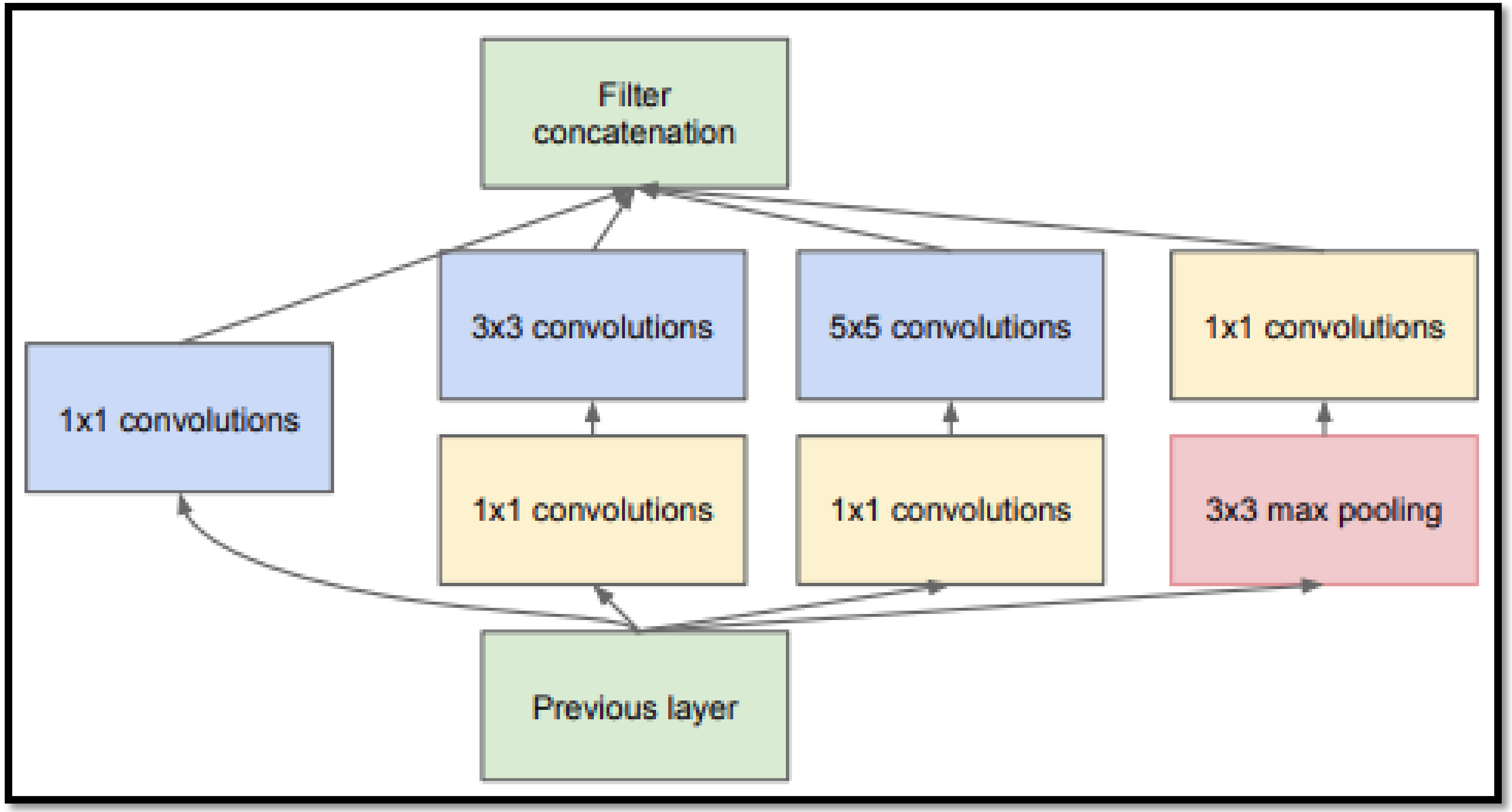
Transfer Learning Models

❑Transfer Learning Models

5. **MobileNet:** Designed for mobile and embedded vision, MobileNet efficiently handles object detection and image classification.
6. **YOLO (You Only Look Once):** Real-time object detection is YOLO's strength, making it valuable for custom solutions.
7. **VGG (Visual Geometry Group Network):** A simple yet effective choice for image classification.
8. **ResNet (Residual Network):** ResNet's deep architecture excels in image classification and object detection.
9. **Inception (GoogLeNet):** Known for resource-efficient computations in computer vision.
10. **Xception:** A model with exceptional performance in image classification.

❑Transfer Learning Models

❑**Inception:** The Inception microarchitecture was introduced by Szegedy in 2014 in their paper Going deeper with convolution the complete architecture with dimension reduction looks like as given below:



❑Transfer Learning Models

❑**Inception:** The goal of this module is to act as a multi-level *feature extractor* by computing 1×1, 3×3, and 5×5 convolution within the same module of the network.

❑The output of these filters is then stacked along the channel dimension and before being fed into the next layer in the network.

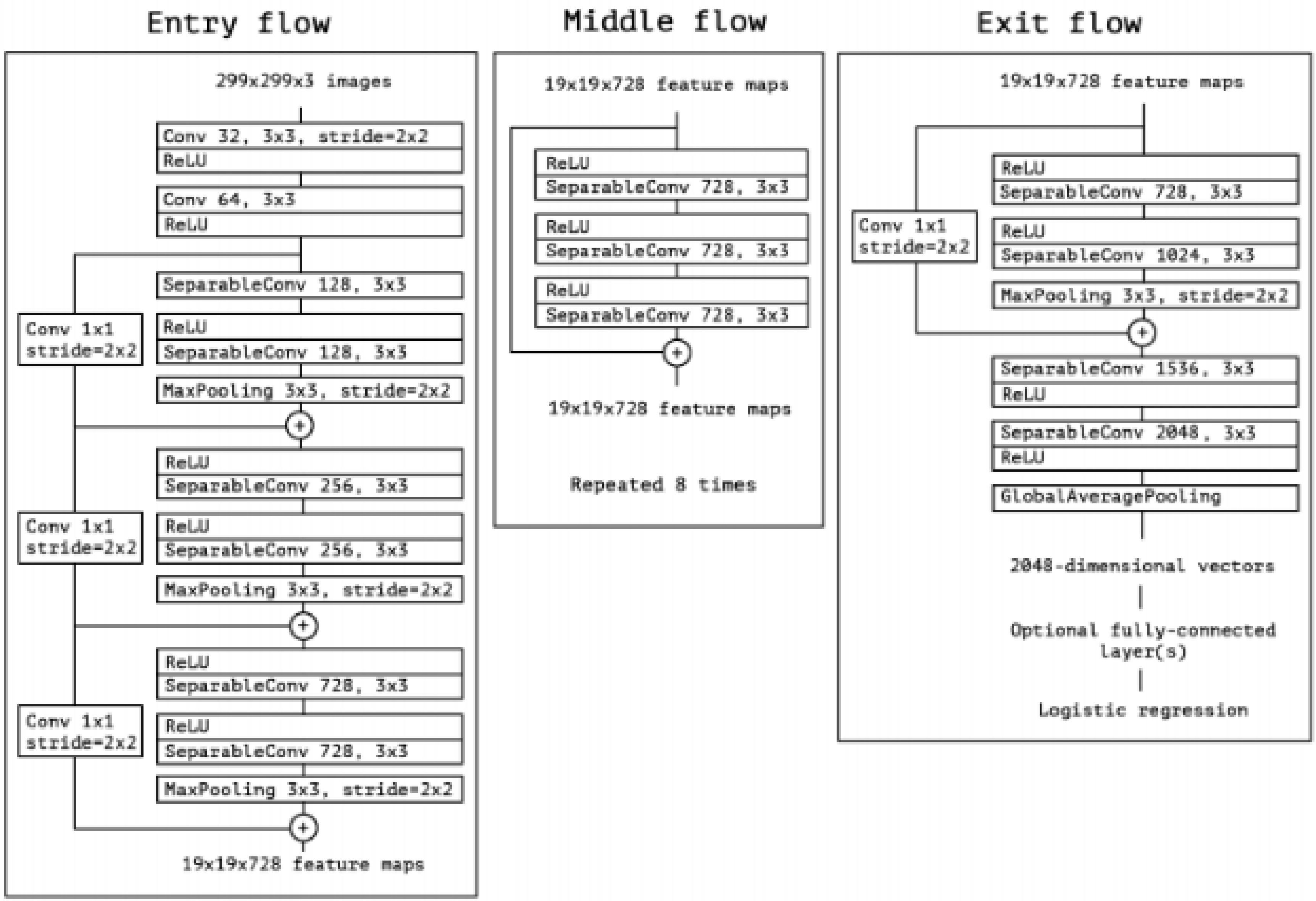
❑The architecture of this model includes:

1. 1×1 convolution with 128 filters for dimensions and reductions and rectified linear activations
2. Fully connected layer with 1024 units and a rectified linear activation
3. Dropout layer with 70% ratio
4. Linear layer with softmax loss as the classifier
5. Originally this architecture was called GoogleNet subsequently it has simply been called InceptionN where N refers to the version of the model.

- **Transfer Learning Models**
- **Xception**
- This model was proposed by Francois *Chollet* the creator and maintainer of the Keras library.
- The Xception is an extension of inception architecture that replaces the standard inception model with depth wise separable convolutions.
- From the below architecture, it is clear that Xception is a linear stack of depthwise separable convolution layers with residual connections.
- This makes architecture very easy to define and modify; it takes only 40 lines of code by using high-level APIs such as Keras or Tensorflow.
- As you can see below, the data first goes through the Entry flow, then through the middle flow which is repeated eight times and finally through the exit flow.
- All convolutional layers follow batch normalization.

❑Transfer Learning Models

❑Xception



Transfer Learning Models

- **Transfer Learning Models**
- **VGG Family**
- This model was first proposed by Zisserman and Simonyan from the Visual Geometry Group (VGG) of the University of Oxford in their paper *Very deep convolutional networks for large scale image recognition.*
- The network is recognized by its simplicity using only a stack of 3×3 convolutional layers on top of each increasing depth and volume size handled by the max-pooling layers.
- Two fully connected layers each with 4096 nodes are then followed by a softmax layer.
- During training the input to the model is fixed-sized RGB images and only preprocessing is done at the training is subtracting the mean RGB values computed on the training set for each pixel.
- The image is then passed through the stack of convolutional layers where it uses filter very small receptive files of 3×3 which is fair enough to capture the smallest notation.
- Spatial pooling is carried out by five max-pooling layers which follow some convolutional layer over a 2×2 pixel with strides of 2 and the last is usually the same for all architectures, i.e., softmax.

❑Transfer Learning Models

❑VGG Family

❑As the depth of the network increases, it becomes slow at training and network architectures themselves also become quite large.

❑The architectures of all the VGG variants are shown below with their parameters:

ConvNet Configuration					
A	A-LRN	B	C	D	E
11 weight layers	11 weight layers	13 weight layers	16 weight layers	16 weight layers	19 weight layers
input (224 × 224 RGB image)					
conv3-64	conv3-64 **LRN**	conv3-64 **conv3-64**	conv3-64 conv3-64	conv3-64 conv3-64	conv3-64 conv3-64
maxpool					
conv3-128	conv3-128	conv3-128 **conv3-128**	conv3-128 conv3-128	conv3-128 conv3-128	conv3-128 conv3-128
maxpool					
conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256	conv3-256 conv3-256 **conv1-256**	conv3-256 conv3-256 **conv3-256**	conv3-256 conv3-256 conv3-256 **conv3-256**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512	conv3-512 conv3-512 **conv1-512**	conv3-512 conv3-512 **conv3-512**	conv3-512 conv3-512 conv3-512 **conv3-512**
maxpool					
FC-4096					
FC-4096					
FC-1000					
soft-max					

Table 2: **Number of parameters** (in millions).

Network	A,A-LRN	B	C	D	E
Number of parameters	133	133	134	138	144

❑**What are transfer learning strategies in generative AI?**

❑Transfer learning strategies are critical for generative AI adoption in various industries.

❑Organizations can customize existing foundation models without having to train new ones on billions of data parameters at scale.

❑The following are some transfer learning strategies used in generative AI.

1. **Domain adversarial training**

❑Domain adversarial training involves training a foundation model to produce data that is indistinguishable from real data in the target domain. This technique typically employs a discriminator network, as seen in generative adversarial networks, that attempts to distinguish between true data and generated data. The generator learns to create increasingly realistic data.

❑For example, in image generation, a model trained on photographs might be adapted to generate artwork. The discriminator helps ensure the generated artwork is stylistically consistent with the target domain.

❑**What are transfer learning strategies in generative AI?**

2. Teacher-student learning

❑Teacher-student learning involves a larger and more complex “teacher” model teaching a smaller and simpler “student” model. The student model learns to mimic the teacher model's behavior, effectively transferring knowledge. This is useful for deploying large generative models in resource-constrained environments.

❑For example, a large language model (LLM) could serve as a teacher to a smaller model, transferring its language generation capabilities. This would allow the smaller model to generate high-quality text with less computational overhead.

3. Feature disentanglement

❑Feature disentanglement in generative models involves separating different aspects of data, such as content and style, into distinct representations. This enables the model to manipulate these aspects independently in the transfer learning process.

❑For example, in a face generation task, a model might learn to disentangle facial features from artistic style. This would allow it to generate portraits in various artistic styles while maintaining the subject's likeness.

❑What are transfer learning strategies in generative AI?

4. Cross-modal transfer learning

❑Cross-modal transfer learning involves transferring knowledge between different modalities, like text and images. Generative models can learn representations applicable across these modalities. A model trained on textual descriptions and corresponding images might learn to generate relevant images from new text descriptions, effectively transferring its understanding from text to image.

5. Zero-shot and few-shot learning

❑In zero-shot and few-shot learning, generative models are trained to perform tasks or generate data for which they have seen few or no examples of during training. This is achieved by learning rich representations that generalize well. For example, a generative model might be trained to create images of animals. Using few-shot learning, it could generate images of a rarely seen animal by understanding and combining features from other animals.

❑**What are transfer learning strategies in generative AI?**

4. **Cross-modal transfer learning**

❑Cross-modal transfer learning involves transferring knowledge between different modalities, like text and images. Generative models can learn representations applicable across these modalities. A model trained on textual descriptions and corresponding images might learn to generate relevant images from new text descriptions, effectively transferring its understanding from text to image.

5. **Zero-shot and few-shot learning**

❑In zero-shot and few-shot learning, generative models are trained to perform tasks or generate data for which they have seen few or no examples of during training. This is achieved by learning rich representations that generalize well. For example, a generative model might be trained to create images of animals. Using few-shot learning, it could generate images of a rarely seen animal by understanding and combining features from other animals.

Generative Adversarial Network and Their Variants

❑What is a GAN?

❑A generative adversarial network (GAN) is a deep learning architecture.

❑It trains two neural networks to compete against each other to generate more authentic new data from a given training dataset.

❑For instance, you can generate new images from an existing image database or original music from a database of songs.

❑A GAN is called adversarial because it trains two different networks and pits them against each other.

❑One network generates new data by taking an input data sample and modifying it as much as possible.

❑The other network tries to predict whether the generated data output belongs in the original dataset.

❑In other words, the predicting network determines whether the generated data is fake or real.

❑The system generates newer, improved versions of fake data values until the predicting network can no longer distinguish fake from original.

❑What are some use cases of generative adversarial networks?

❑The GAN architecture has several applications across different industries.

❑Next, we give some examples.

1. Generate images

▪Generative adversarial networks create realistic images through text-based prompts or by modifying existing images.

▪They can help create realistic and immersive visual experiences in video games and digital entertainment.

▪GAN can also edit images—like converting a low-resolution image to a high resolution or turning a black-and-white image to color.

▪It can also create realistic faces, characters, and animals for animation and video.

❑**What are some use cases of generative adversarial networks?**

2. Generate training data for other models

- In machine learning (ML), data augmentation artificially increases the training set by creating modified copies of a dataset using existing data.
- You can use generative models for data augmentation to create synthetic data with all the attributes of real-world data.
- For instance, it can generate fraudulent transaction data that you then use to train another fraud-detection ML system.
- This data can teach the system to accurately distinguish between suspicious and genuine transactions.

Generative Adversarial Network and Their Variants

❑**What are some use cases of generative adversarial networks?**

3. Complete missing information

❑Sometimes, you may want the generative model to accurately guess and complete some missing information in a dataset.

❑For instance, you can train GAN to generate images of the surface below ground (sub-surface) by understanding the correlation between surface data and underground structures.

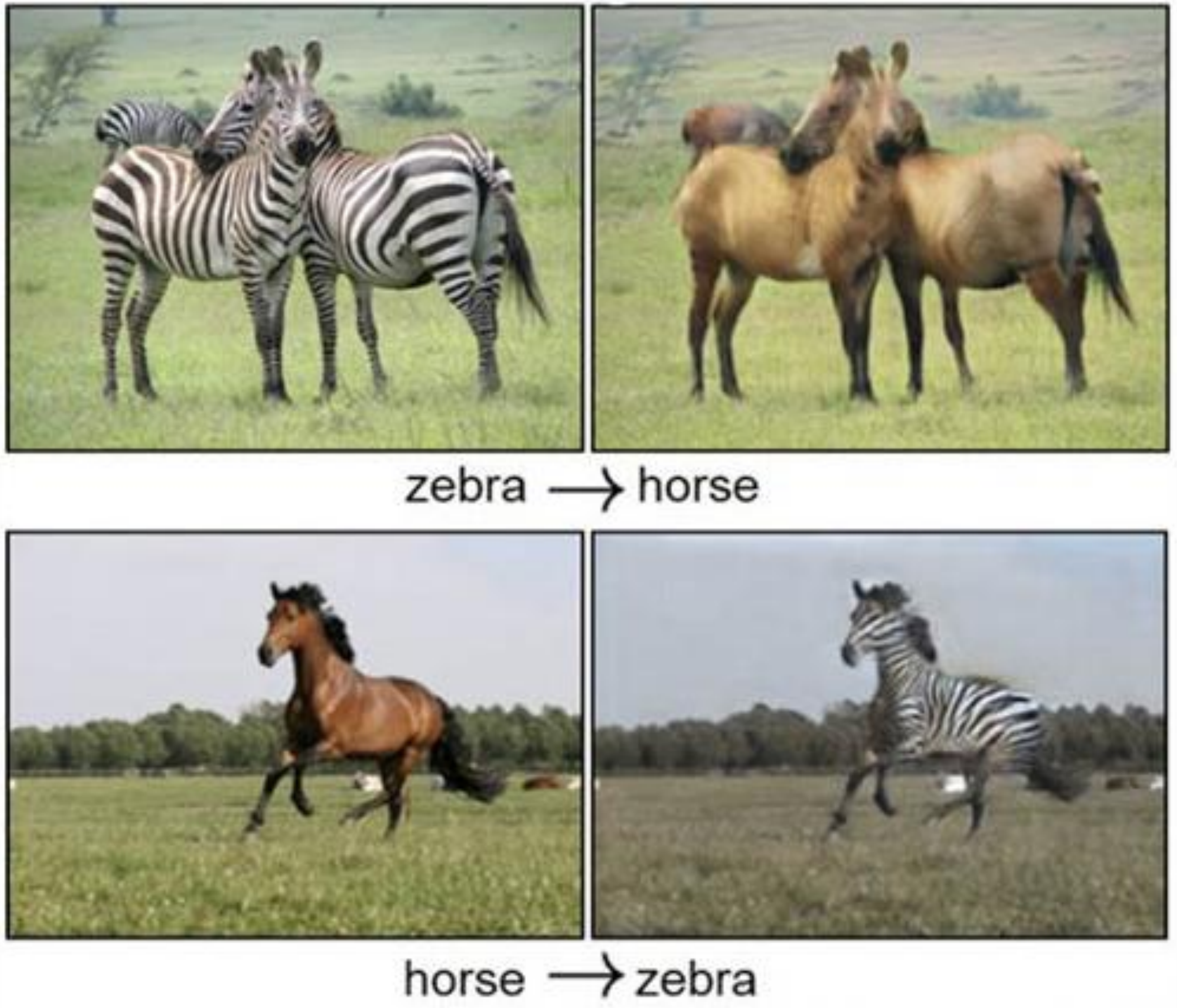
❑By studying known sub-surface images, it can create new ones using terrain maps for energy applications like geothermal mapping or carbon capture and storage.

4. Generate 3D models from 2D data

❑GAN can generate 3D models from 2D photos or scanned images.

❑For instance, in healthcare, GAN combines X-rays and other body scans to create realistic images of organs for surgical planning and simulation.

❑What are some use cases of generative adversarial networks?



Generative Adversarial Network and Their Variants

- **How does a generative adversarial network work?**
- A generative adversarial network system comprises two deep neural networks—the generator network and the discriminator network.
- Both networks train in an adversarial game, where one tries to generate new data and the other attempts to predict if the output is fake or real data.

❑How does a generative adversarial network work?

❑GAN works as follows.

1. The generator neural network analyzes the training set and identifies data attributes
2. The discriminator neural network also analyzes the initial training data and distinguishes between the attributes independently
3. The generator modifies some data attributes by adding noise (or random changes) to certain attributes
4. The generator passes the modified data to the discriminator
5. The discriminator calculates the probability that the generated output belongs to the original dataset
6. The discriminator gives some guidance to the generator to reduce the noise vector randomization in the next cycle

Generative Adversarial Network and Their Variants

❑How does a generative adversarial network work?

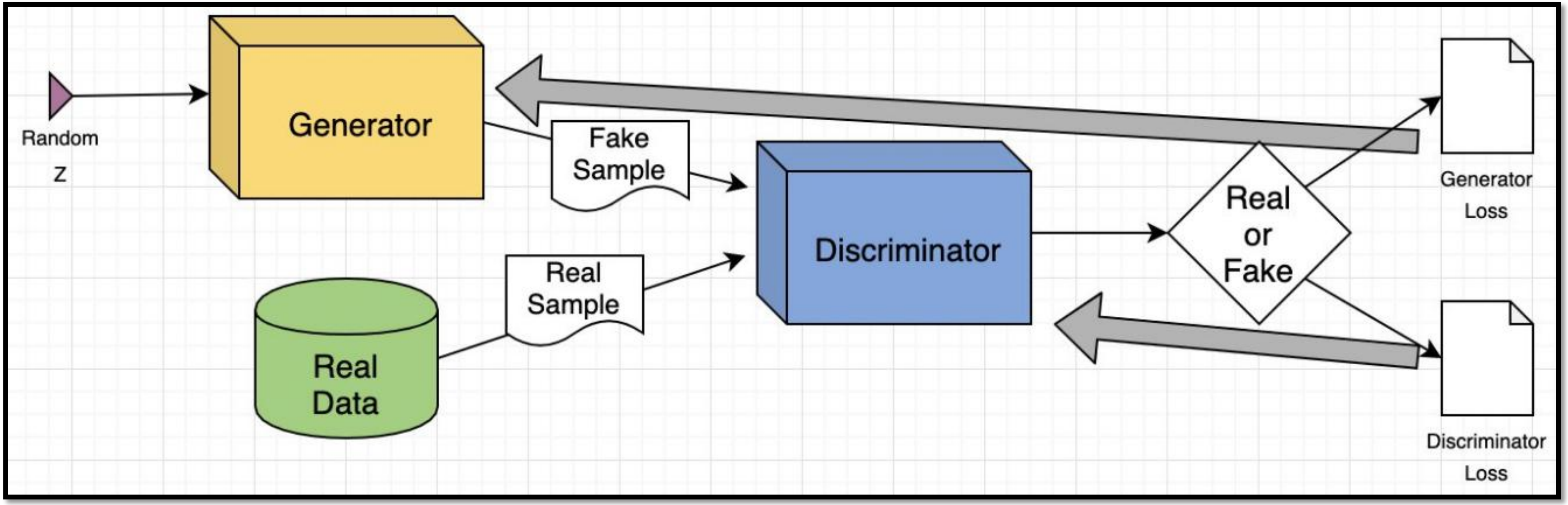
❑The generator attempts to maximize the probability of mistake by the discriminator, but the discriminator attempts to minimize the probability of error.

❑In training iterations, both the generator and discriminator evolve and confront each other continuously until they reach an equilibrium state.

❑In the equilibrium state, the discriminator can no longer recognize synthesized data. At this point, the training process is over.

Generative Adversarial Network and Their Variants

❑How does a generative adversarial network work?



❑GAN training example

❑Let's contextualize the above with an example of the GAN model in image-to-image translation.

❑Consider that the input image is a human face that the GAN attempts to modify.

❑For example, the attributes can be the shapes of eyes or ears.

❑Let's say the generator changes the real images by adding sunglasses to them. The discriminator receives a set of images, some of real people with sunglasses and some generated images that were modified to include sunglasses.

❑If the discriminator can differentiate between fake and real, the generator updates its parameters to generate even better fake images.

❑If the generator produces images that fool the discriminator, the discriminator updates its parameters.

❑Competition improves both networks until equilibrium is reached.

❑What are the types of generative adversarial networks?

❑There are different types of GAN models depending on the mathematical formulas used and the different ways the generator and discriminator interact with each other.

❑We give some commonly used models next, but the list is not comprehensive.

❑There are numerous other GAN types—like StyleGAN, CycleGAN, and DiscoGAN—that solve different types of problems.

1. **Vanilla GAN:** This is the basic GAN model that generates data variation with little or no feedback from the discriminator network. A vanilla GAN typically requires enhancements for most real-world use cases.
2. **Conditional GAN:** A conditional GAN (cGAN) introduces the concept of conditionality, allowing for targeted data generation. The generator and discriminator receive additional information, typically as class labels or some other form of conditioning data.

❑What are the types of generative adversarial networks?

3. **Deep xonvolutional GAN:** Recognizing the power of convolutional neural networks (CNNs) in image processing, Deep convolutional GAN (DCGAN) integrates CNN architectures into GANs. With DCGAN, the generator uses transposed convolutions to upscale data distribution, and the discriminator also uses convolutional layers to classify data. The DCGAN also introduces architectural guidelines to make training more stable.
4. **Super-resolution GANS (SRGANs):** focus on upscaling low-resolution images to high resolution. The goal is to enhance images to a higher resolution while maintaining image quality and details.
5. **Laplacian Pyramid GANs (LAPGANs):** address the challenge of generating high-resolution images by breaking down the problem into stages. They use a hierarchical approach, with multiple generators and discriminators working at different scales or resolutions of the image. The process begins with generating a low-resolution image that improves in quality over progressive GAN stages.

Note for Students

- **This power point presentation is for lecture, therefore it is suggested that also utilize the text books and lecture notes.**