Introduce famous models and techniques in deep learning

TRAN TRUNG TRUC

Table of contents

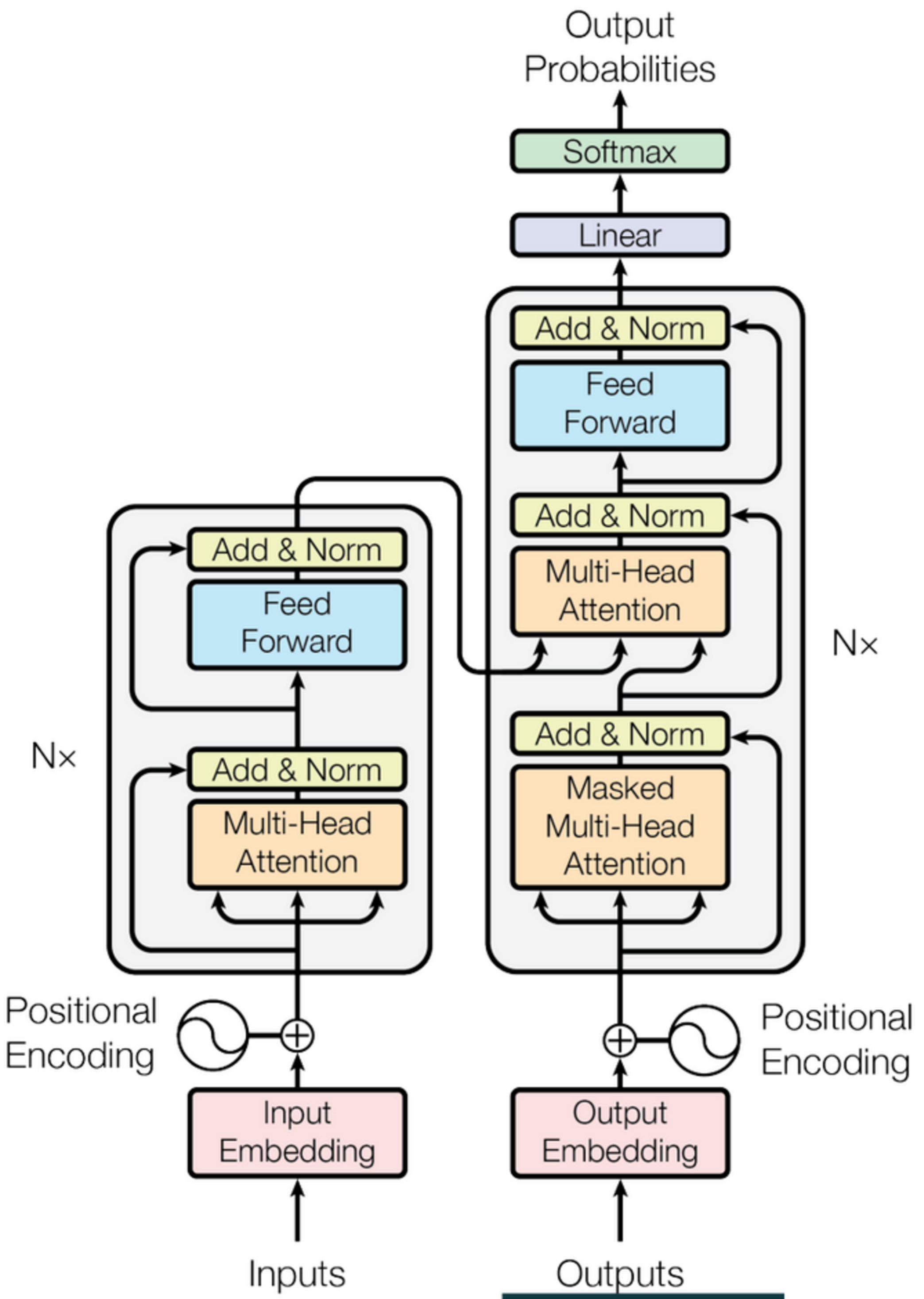
Bert

is a pre-trained deep learning model developed by Google for natural language processing (NLP) tasks. It is designed to understand the context of words in a sentence, which makes it highly effective for tasks like question answering, language inference, and sentiment analysis.

Tranformer

BERT

Encoder



GPT

Decoder

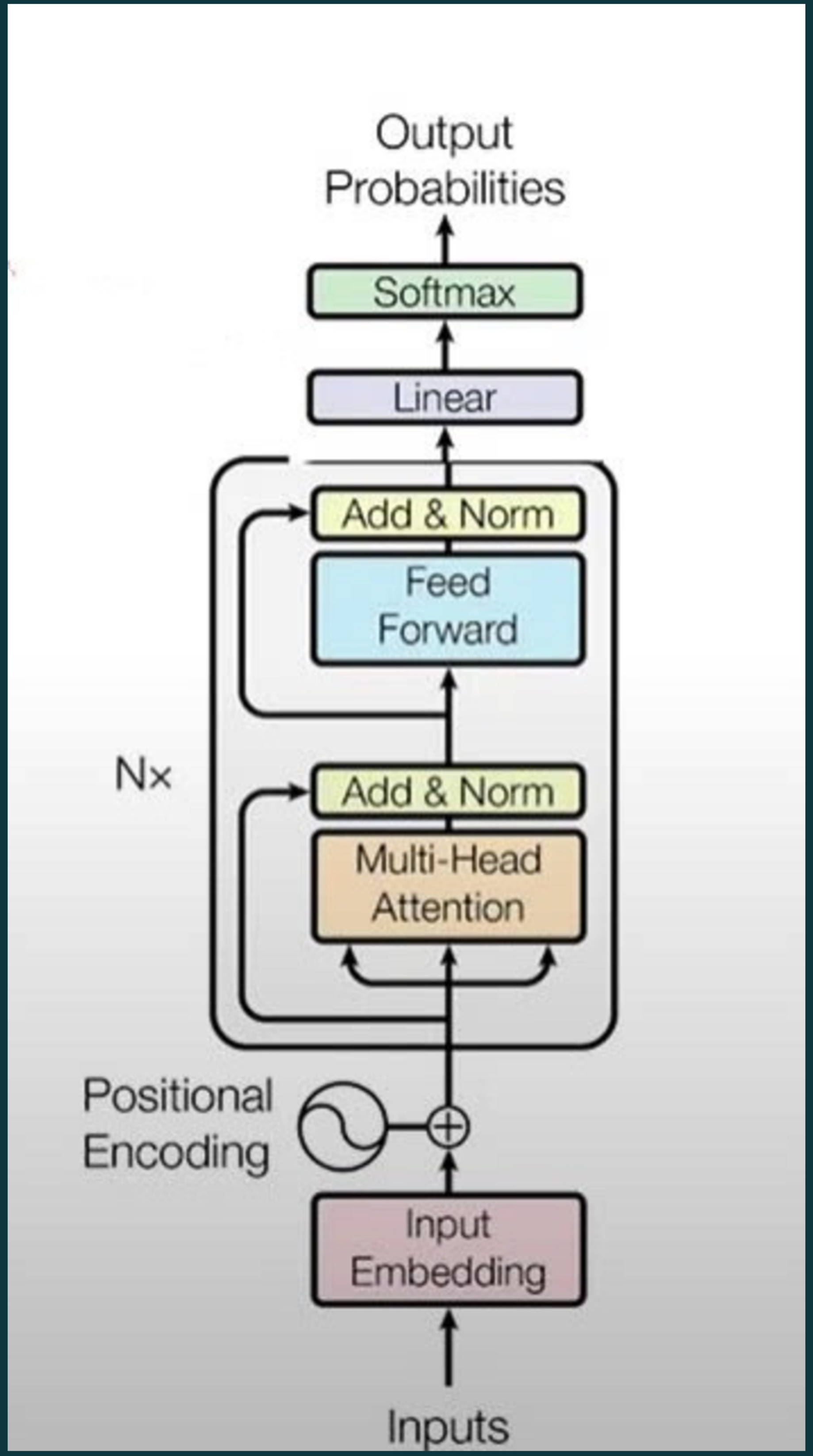
Bert Model

Bert Base

- 12 Encoder Layers
- HiddenSize is 786
- 12 self-attention heads

Bert Large

- 24 Encoder Layers
- HiddenSize is 1024
- 16 self-attention heads



4 main tasks

Pre-Trained

- Masked LM
- Next Sentence Prediction (NSP)

Fine Tune

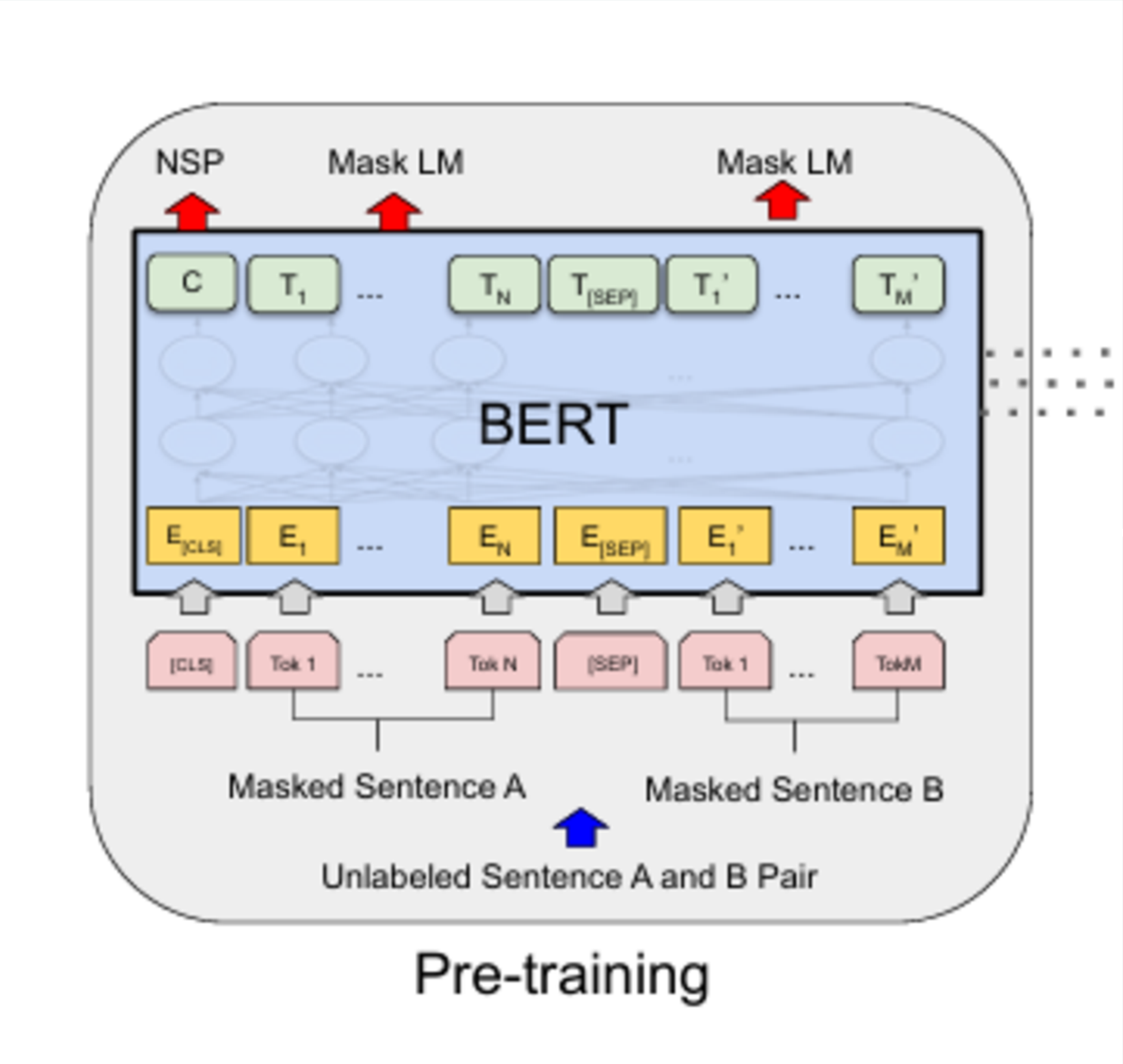
- Text Classification
- Question Answering

Pre-Training

Masked LM

Input Sentences

Mask token



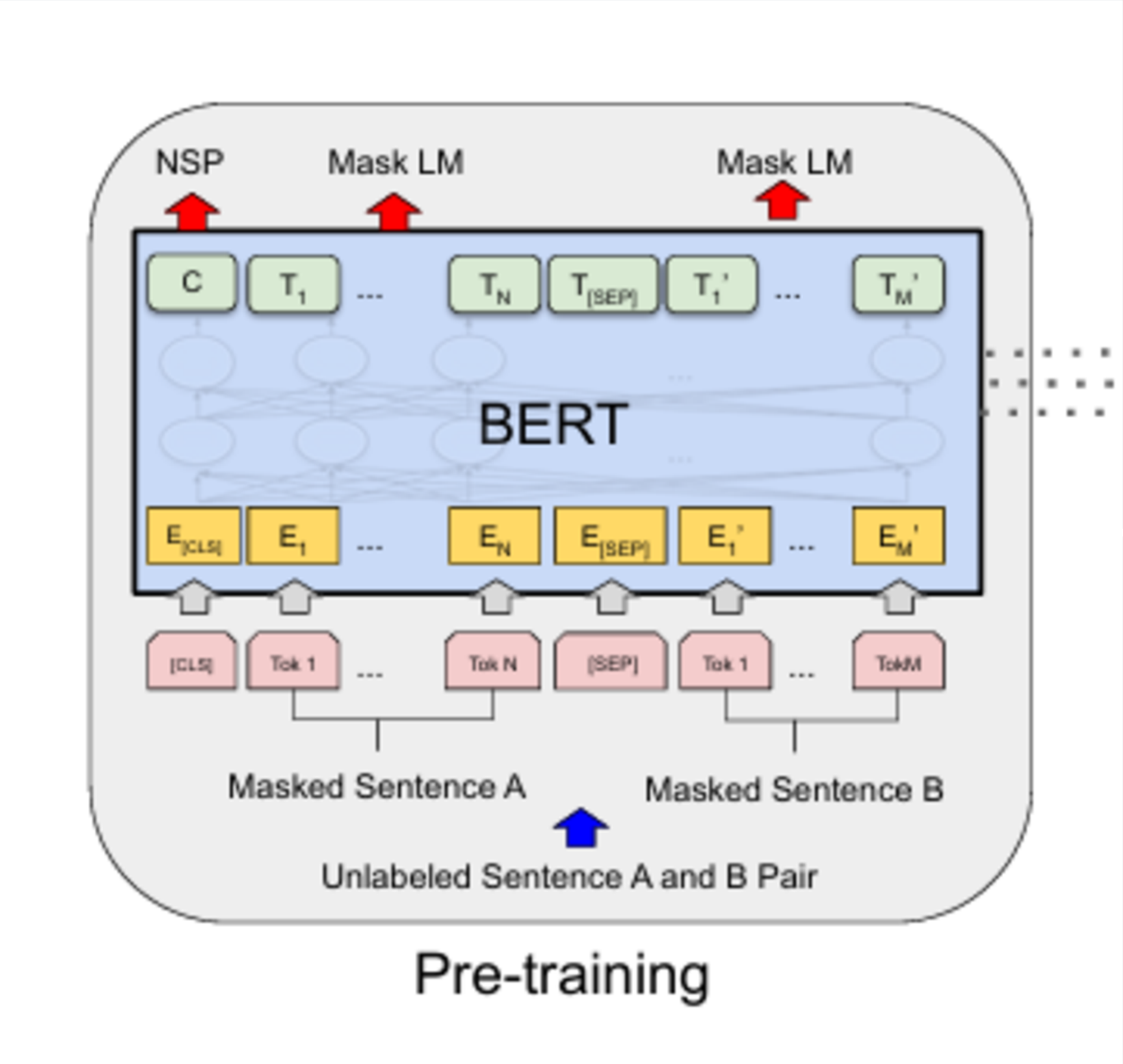
Predict mask token

(1) the [MASK] token 80% of the time.
(2) a random token 10% of the time.
(3) the unchanged token 10% of the time.

Next Sentence Prediction

Input Sentences

Next/Not Next Sentence

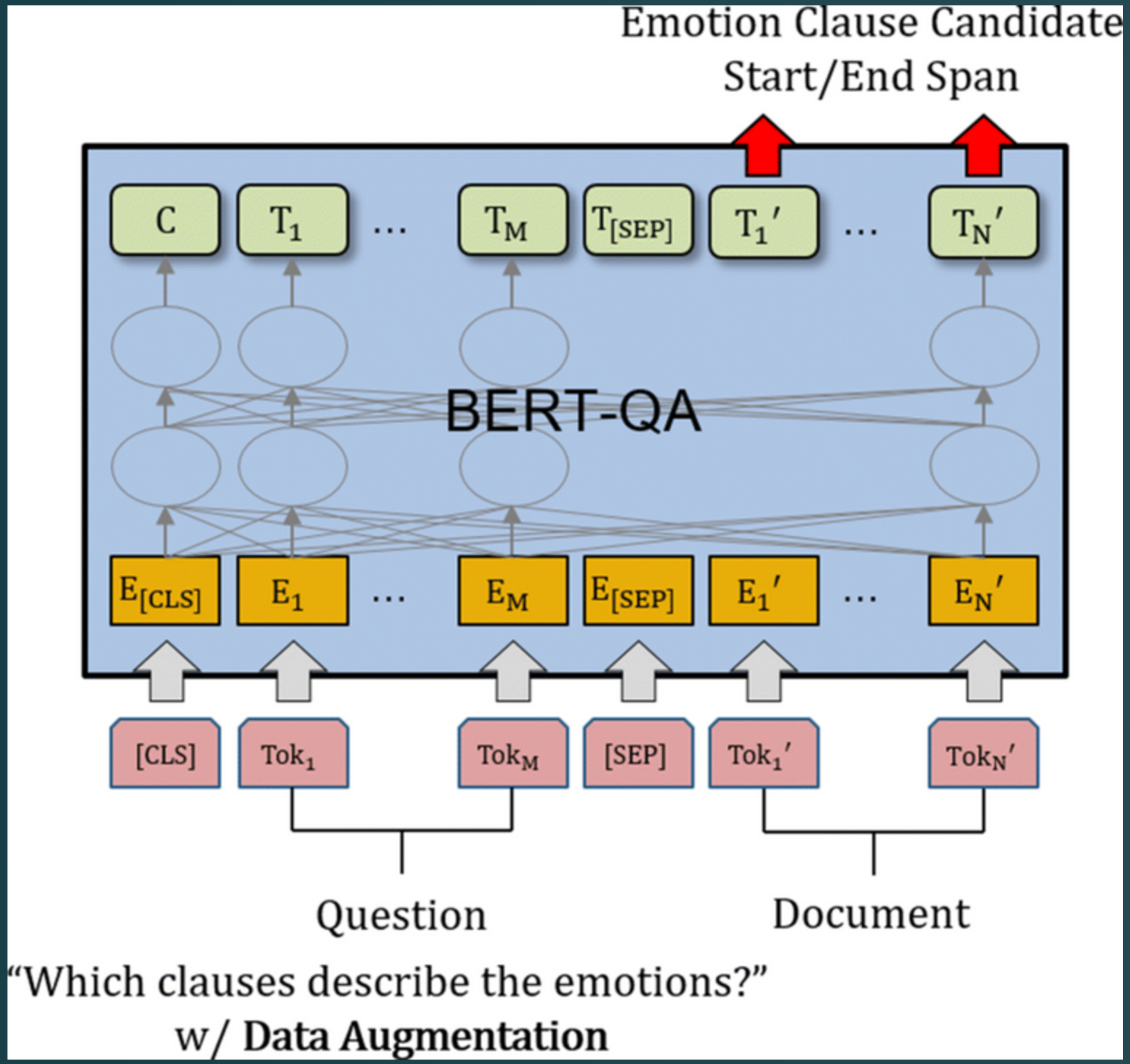


Predict next sentence

50% of the time B is the actual next sentence that follows A (labeled as IsNext), and 50% of the time it is a random sentence from the corpus (labeled as NotNext).

Fine-Tuning

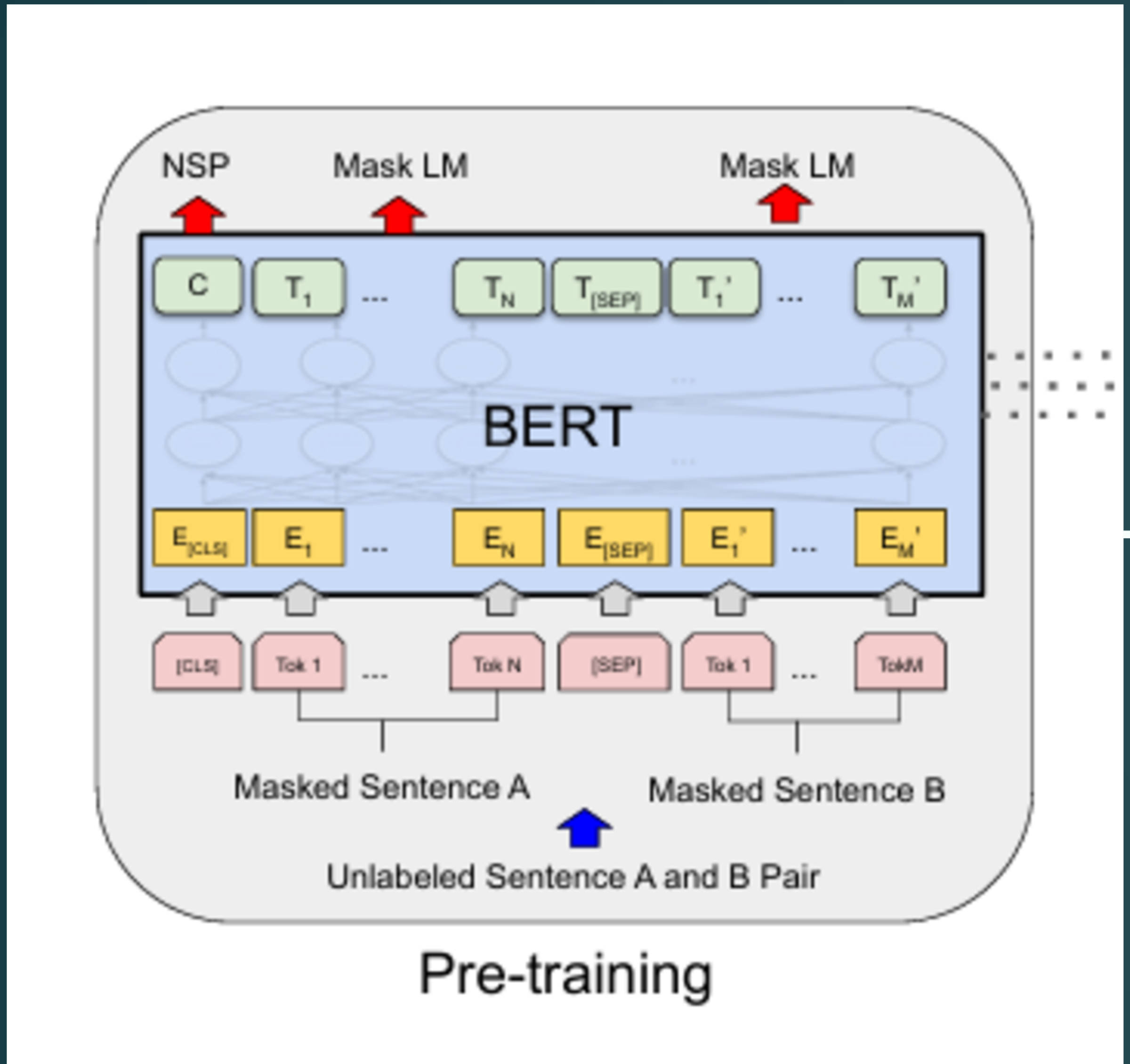
Question Answering

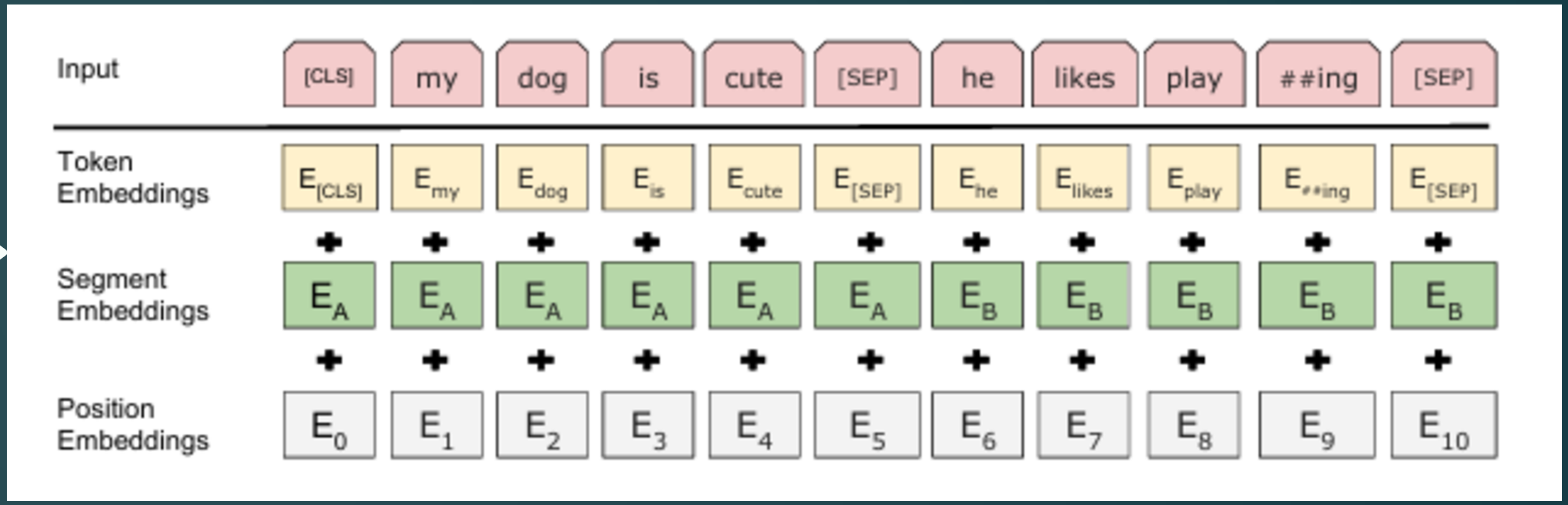


- Input The question and the Document (the Answer).
- Return the start and end token of the answer.

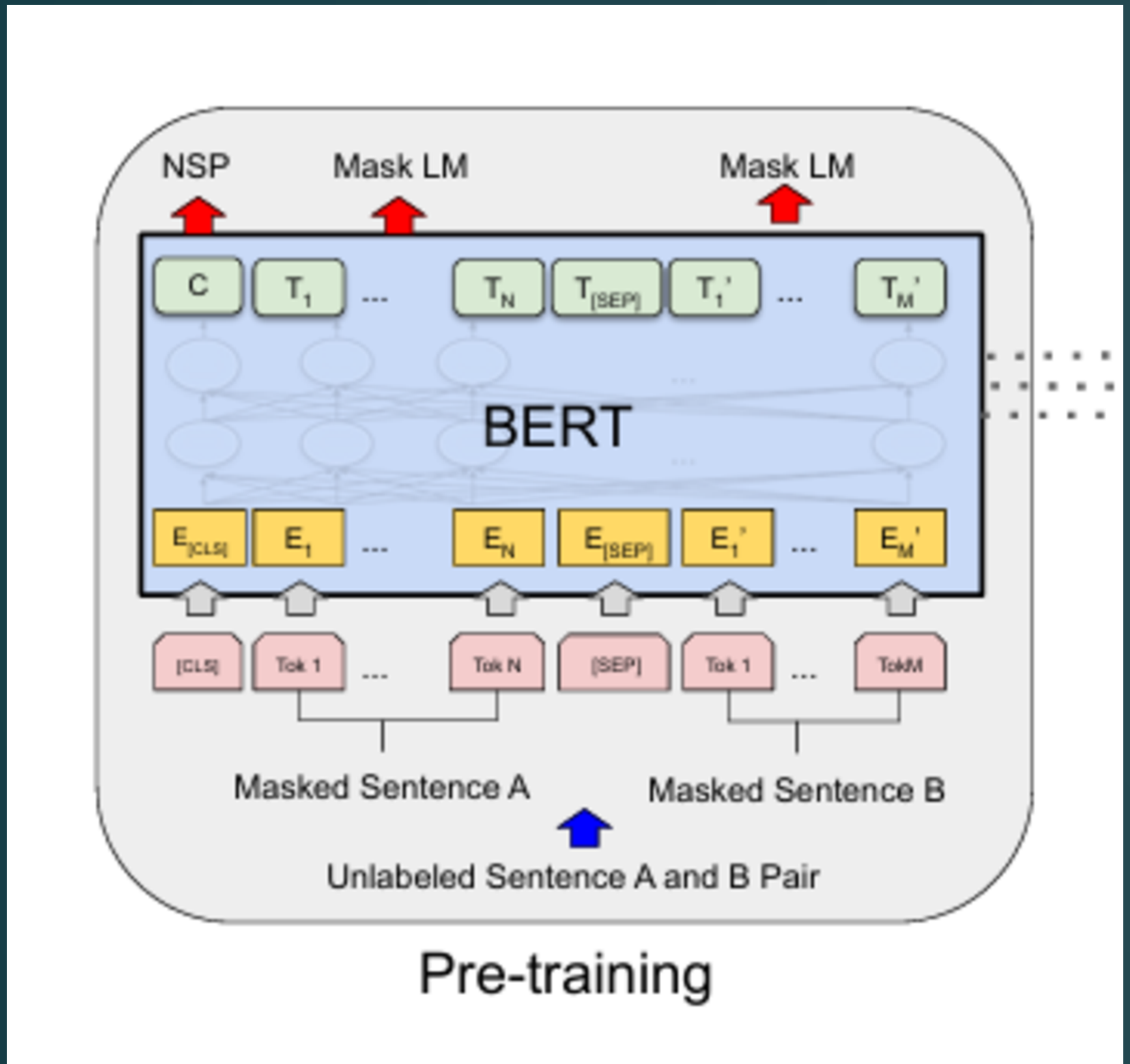
Sumary

Sumary


NSP
Mask LM
Mask LM
C
BERT
Masked Sentence A
Masked Sentence B
Unlabeled Sentence A and B Pair
Pre-training


Input
[CLS]
my
dog
is
cute
[SEP]
he
likes
play
##ing
[SEP]
Token Embeddings
Segment Embeddings
Position Embeddings

Sumary

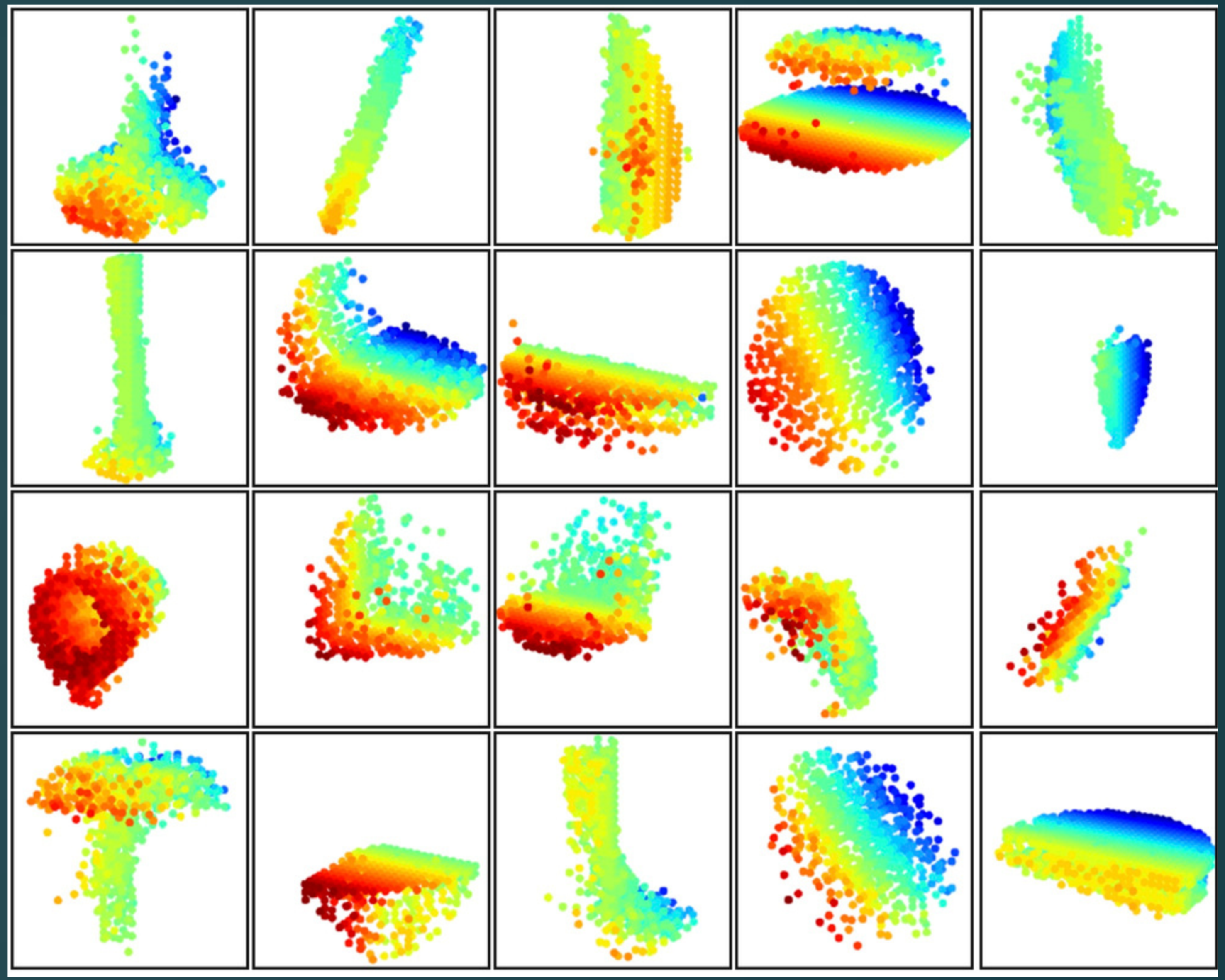


Soft-Max Layer with 30k neurons

Actual Word

PointNet ++

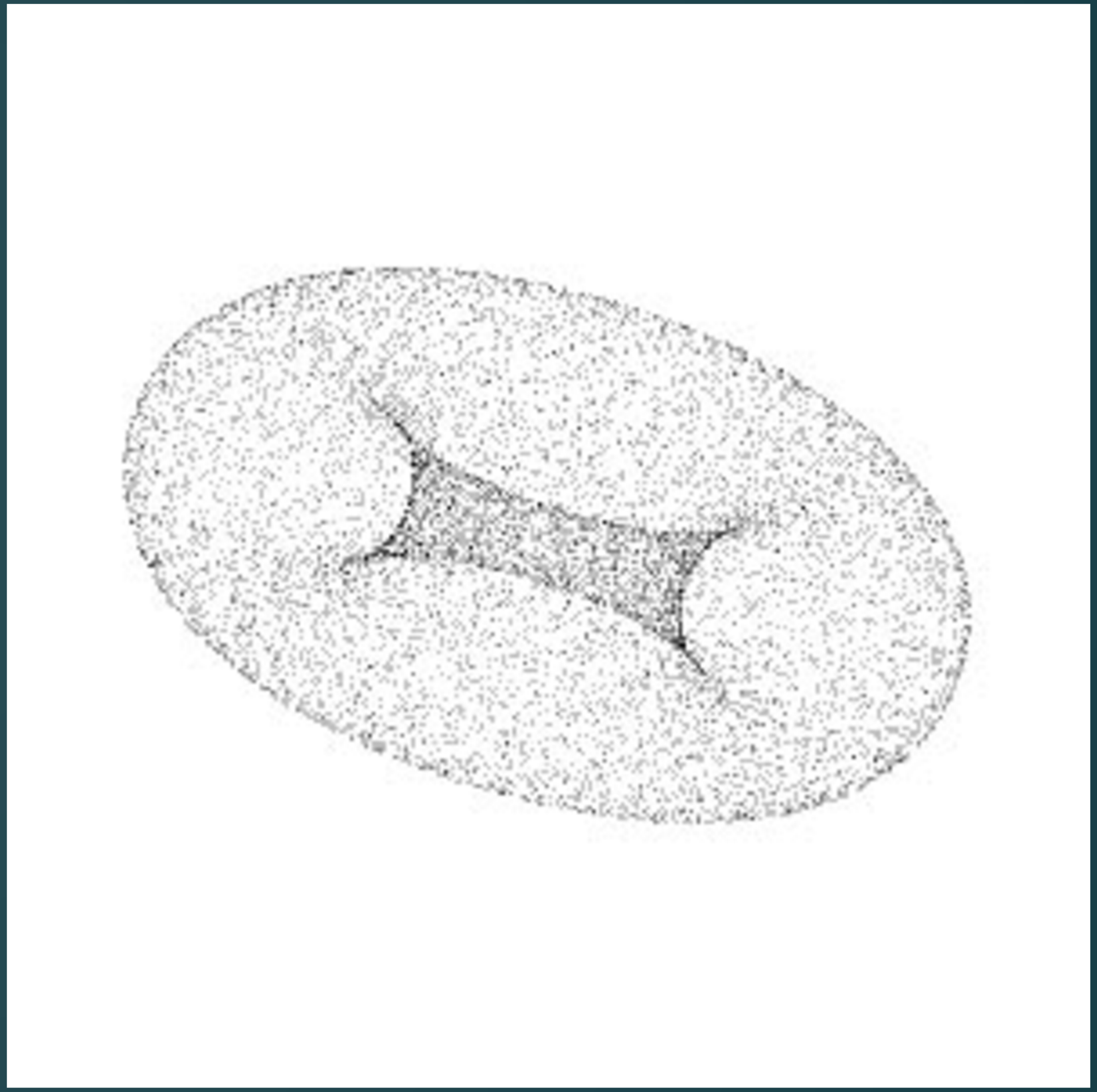
PointNet++ is an advanced neural network architecture designed for 3D point cloud data, building upon the foundation of the original PointNet. While PointNet introduced a groundbreaking method to directly process raw point cloud data without requiring conversion to a regular grid, it had limitations in capturing local geometric features due to its independent point processing approach.



Point Cloud

A point cloud is a discrete set of data points in space. The points may represent a 3D shape or object. Each point position has its set of Cartesian coordinates (X, Y, Z).

- Widely used in 3D scanning, autonomous vehicles, and robotics.
- Not like images, point cloud is unordered.



Challenges in Point Cloud Analysis

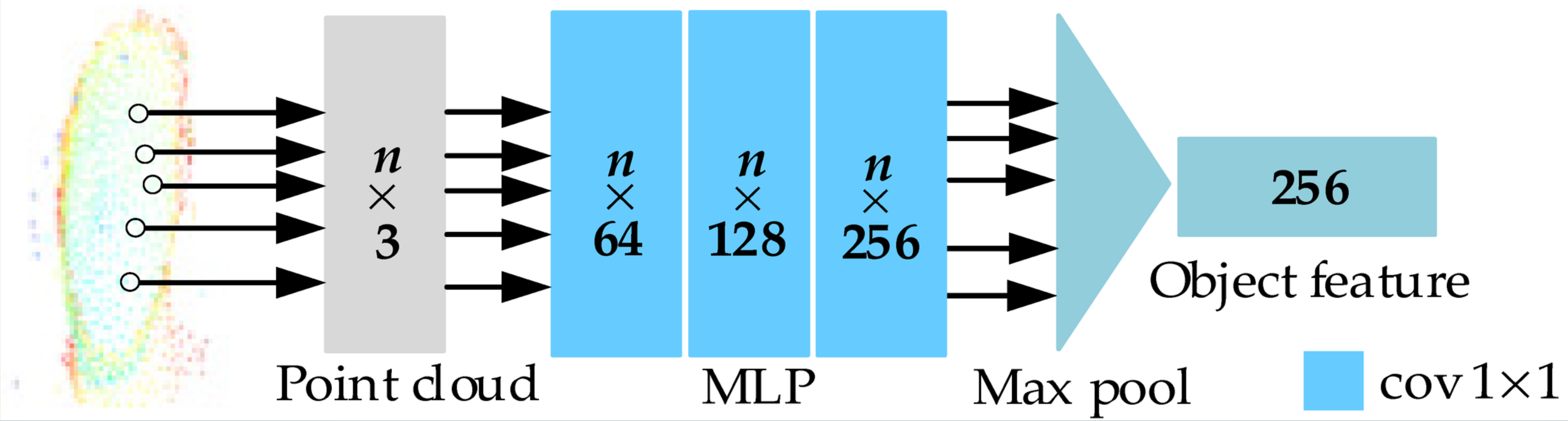
- Irregular & Unordered Data: Points have no inherent order.
- Varying Density: Different regions have different point densities.
- Local Structure Capture: Difficulty in detecting fine local patterns.

Solution?

PointNet

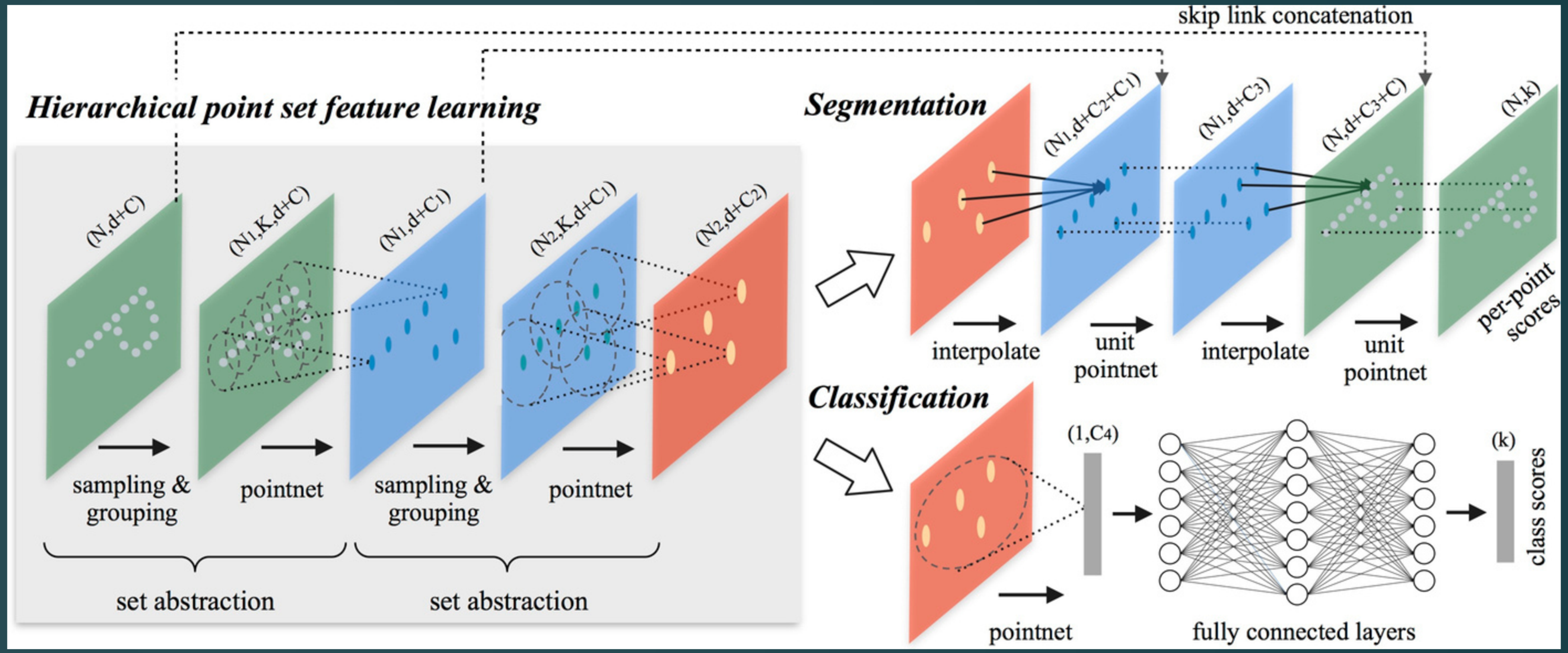
PointNet is designed to process unordered point clouds directly, making it groundbreaking for 3D data processing.

- Input Invariance: The model is invariant to the order of input points, meaning it treats the same set of points identically, regardless of the order.
- Global Feature Aggregation: Uses a symmetric function (max-pooling) to aggregate point features into a global signature.
- Architecture: Processes each point independently through shared MLPs (Multi-Layer Perceptrons) and aggregates features to capture the overall shape of the object.



PointNet++

PointNet++ extends PointNet by capturing local structures in point clouds using hierarchical learning.



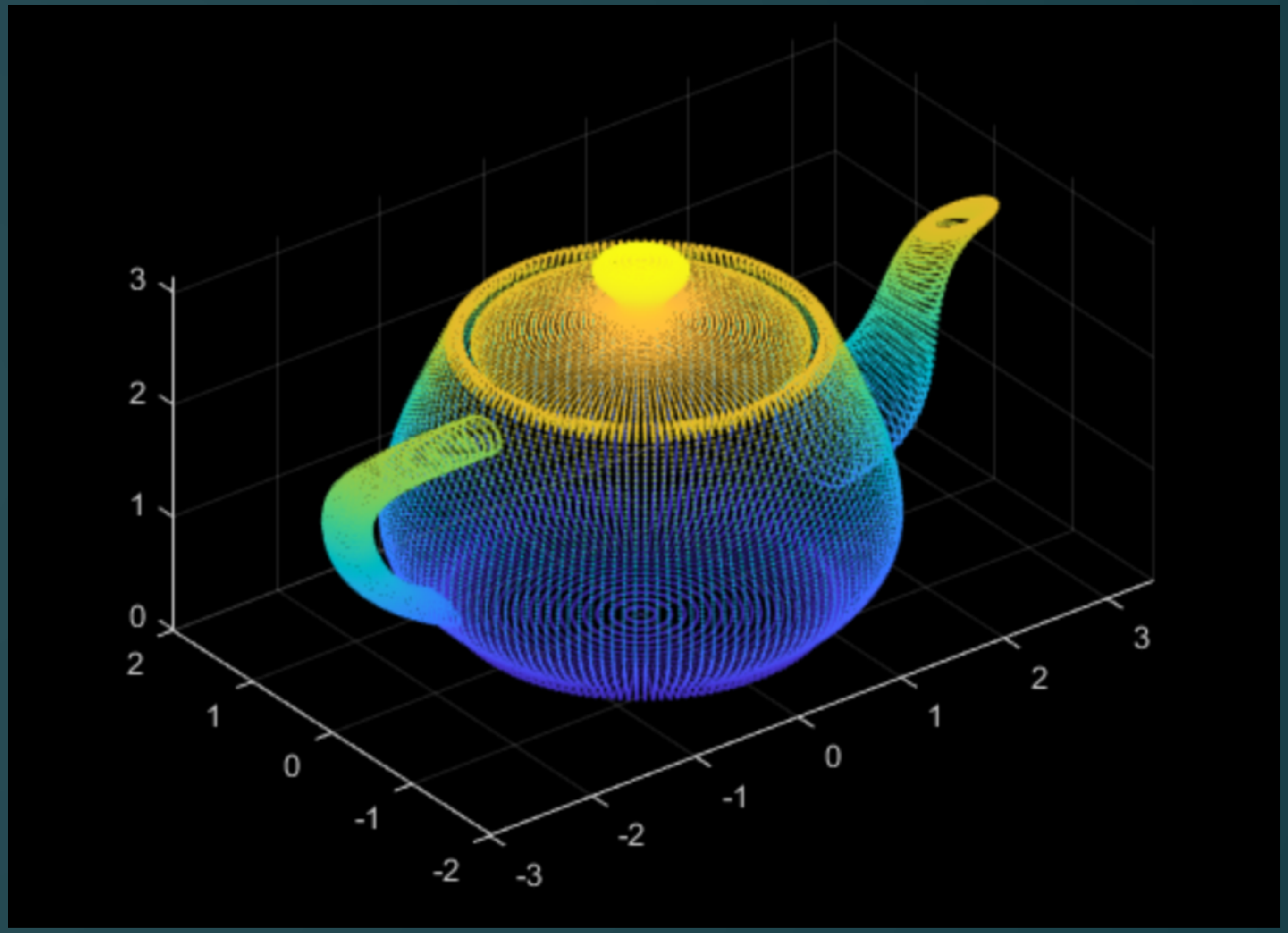
Key Features:

- Hierarchical Learning: Captures features at different scales.
- Local & Global Context: Combines local details with global structures.
- Handling Varying Densities: Adapts to different point densities.

Hierarchical Learning

PointNet++ uses its hierarchical structure to capture fine-grained local features and combine them into global features, ensuring both local and global context are utilized effectively.

- Nested Regions: PointNet++ organizes points into nested regions, processing small local neighborhoods first and then combining them into larger ones.
- Feature Aggregation: It aggregates features from these local regions progressively to build a global understanding of the point cloud.



Handling Varying Point Densities

Both Multi-Scale Grouping (MSG) and Multi-Resolution Grouping (MRG) play crucial roles in effectively managing non-uniform point cloud data. Together, they enhance the model's ability to process and analyze complex, unevenly distributed data with greater accuracy and flexibility.

Multi-Scale Grouping (MSG)

- Utilizes multiple radii to group points at different scales.
- Captures features from both fine-grained small regions and broader large regions.
- Enhances the model’s ability to understand detailed and structural information simultaneously.

Multi-Resolution Grouping (MRG)

- Combines features from various layers of the neural network.
- Balances detailed information from lower layers with broader context from higher layers.
- Improves the model's flexibility in dealing with regions of varying point densities, enhancing overall robustness.

Result

MNIST Digit Classification:

- Error Rate: 0.51% (compared to 1.30% for vanilla PointNet and 0.80% for LeNet5).

ModelNet40 Shape Classification:

- Accuracy: 90.7% with only point cloud coordinates.
- Accuracy: 91.9% with normals as additional features (compared to 89.2% for PointNet).

ScanNet Semantic Scene Labeling:

- Accuracy: 84.5% with MSG+DP (Multi-Scale Grouping with Dropout).

SHREC15 Non-Rigid Shape Classification:

- Accuracy: 96.09% using non-Euclidean metric space with intrinsic features.

Conclusion

PointNet++ marks a major advancement in point cloud processing by introducing hierarchical feature learning, which allows the model to capture both local and global features effectively. Its robustness to varying sampling densities ensures that the model can handle complex, non-uniform data with high accuracy. These strengths make PointNet++ a powerful tool, delivering promising results in a wide range of challenging 3D tasks, including classification, segmentation, and more.

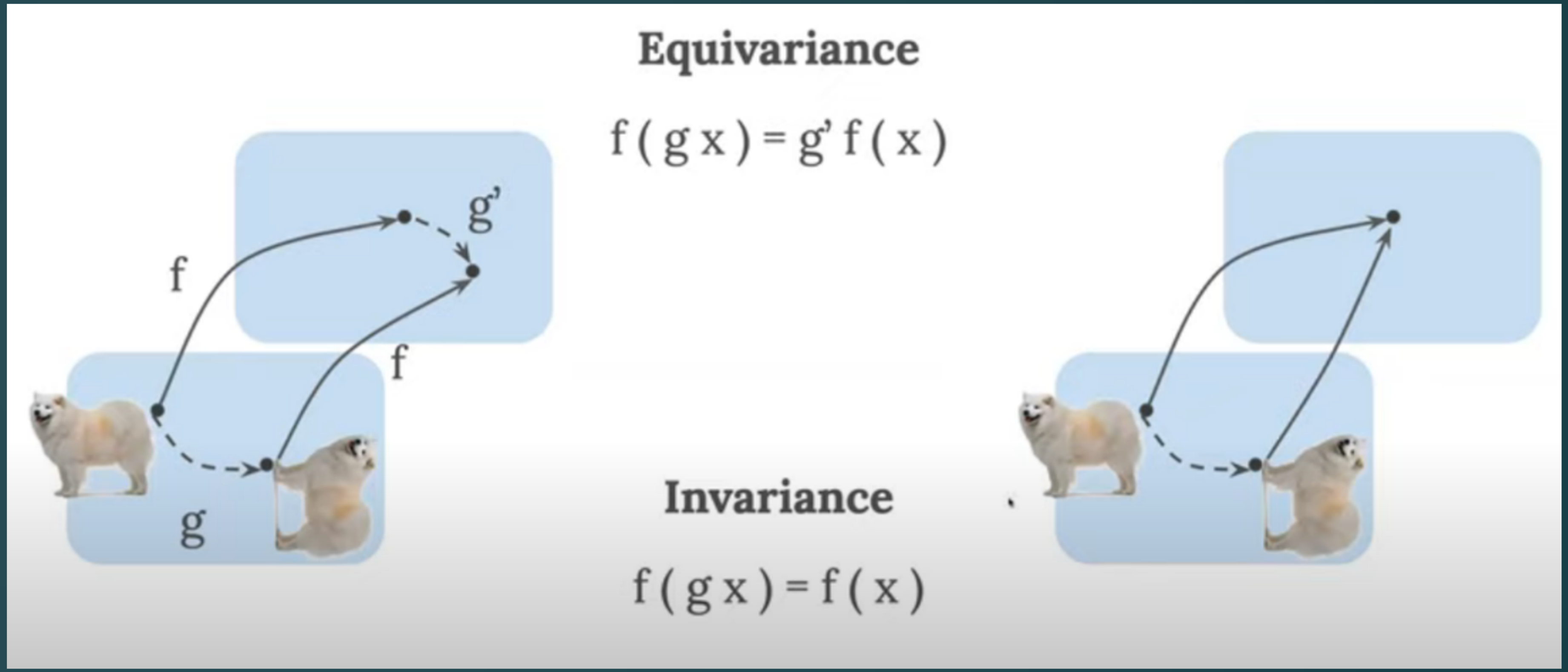
E(n)-Equivariant Graph Neural Networks

Exploring Symmetry in Graph Neural Networks

What is Equivariance?

Equivariance is when a transformation applied to the input corresponds to a predictable transformation in the output.

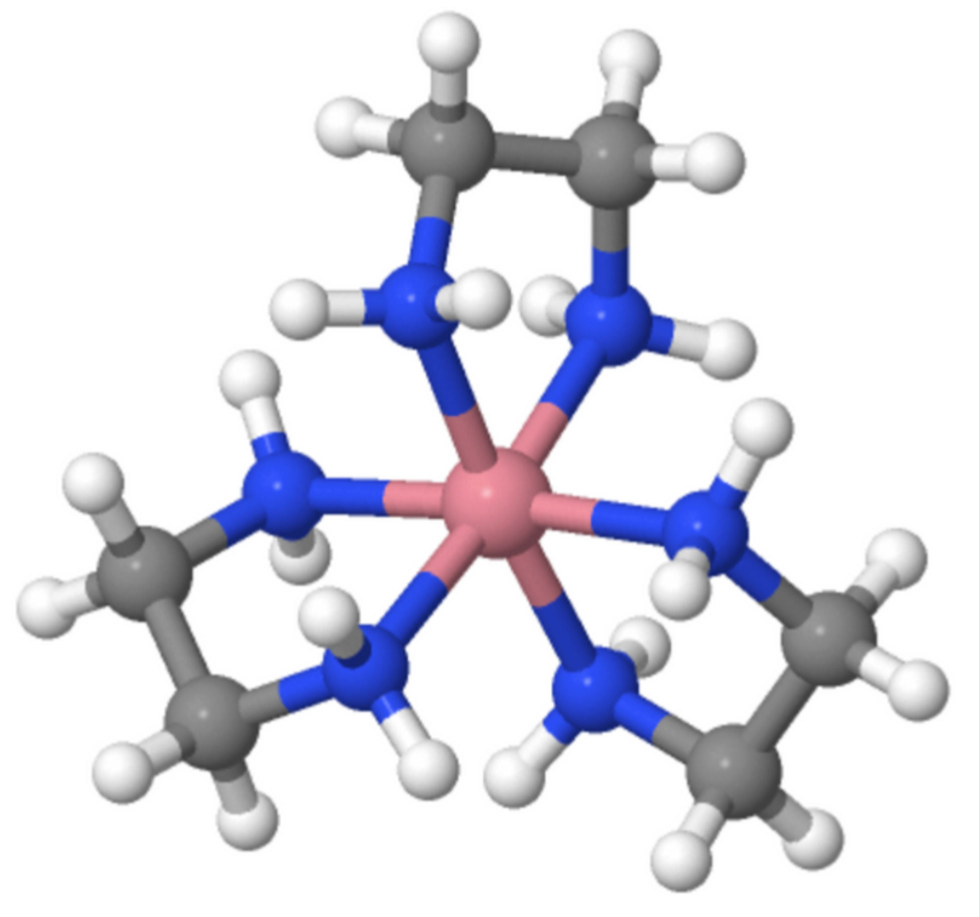
- Importance in ensuring model stability and consistency.
- Examples in image processing

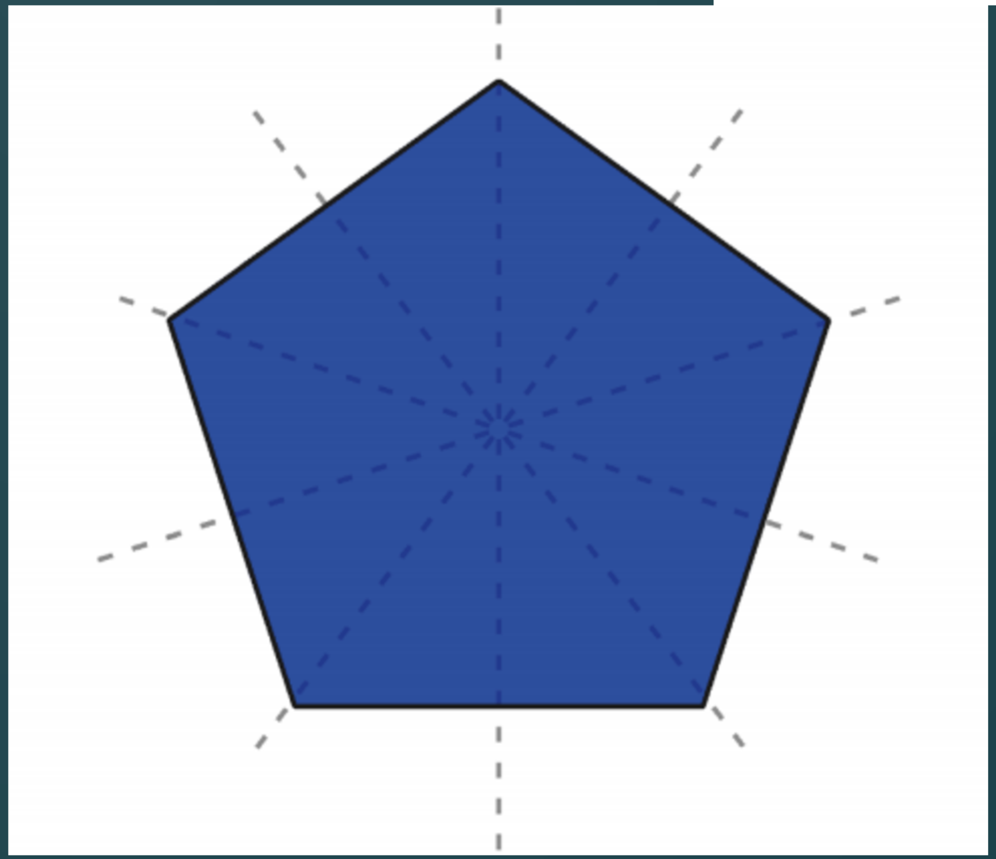


What is the E(n) Group?

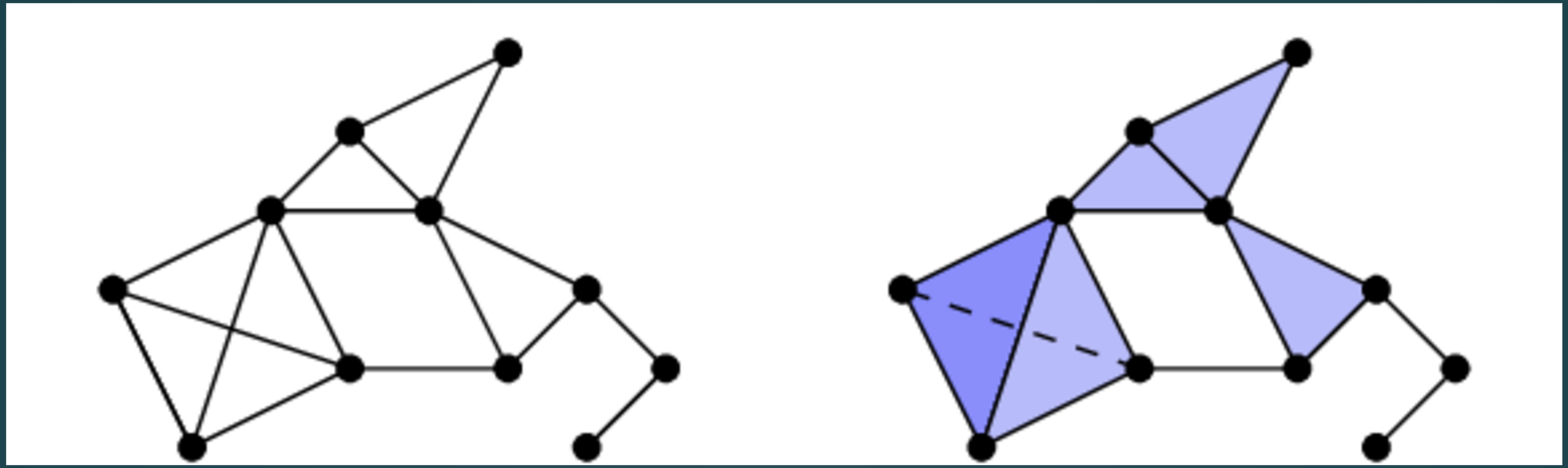
The Euclidean group in n dimensions, denoted as E(n), includes all possible translations, rotations, and reflections in n-dimensional space.

- Translations: Shifting objects in space.
- Rotations: Rotating objects around an axis.
- Reflections: Mirroring objects.



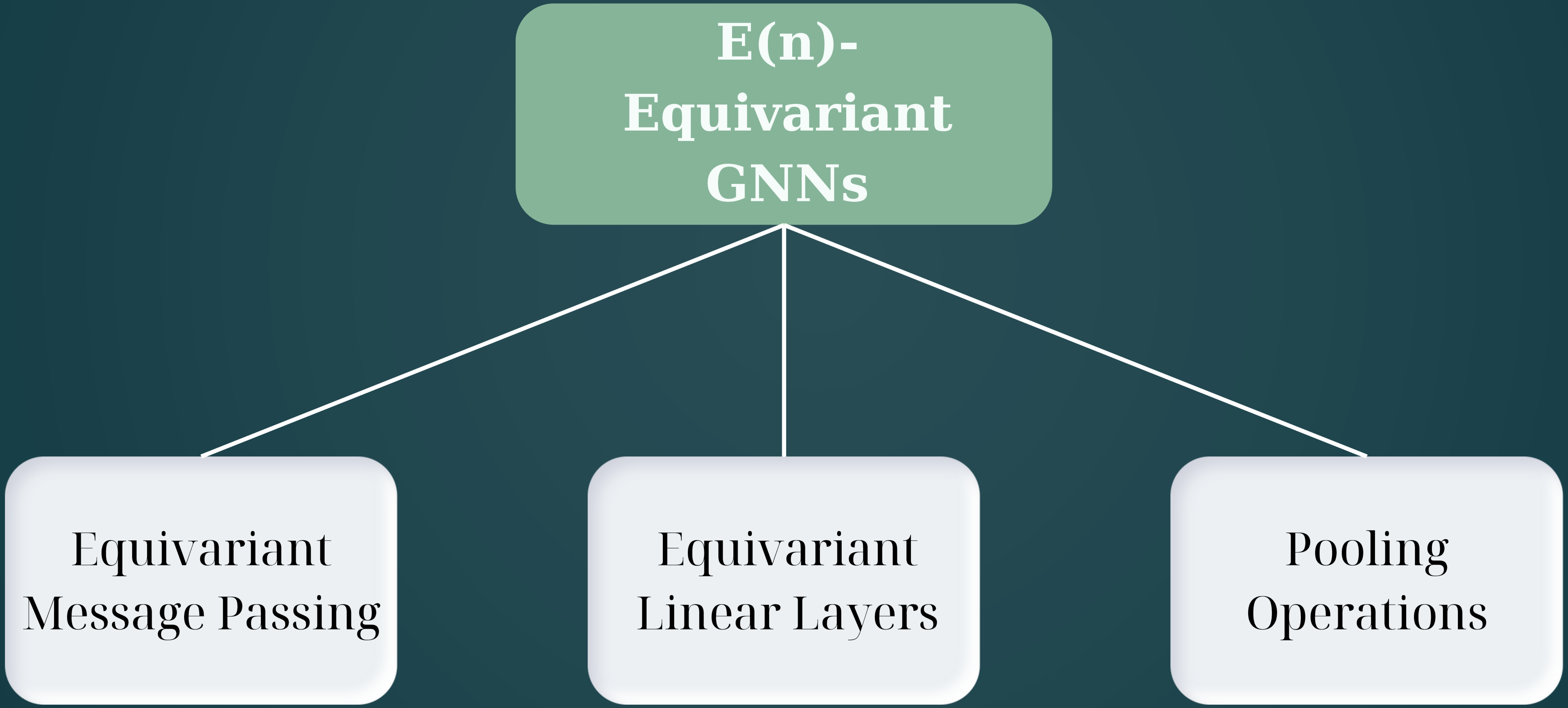


E(n)-Equivariant Graph Neural Networks



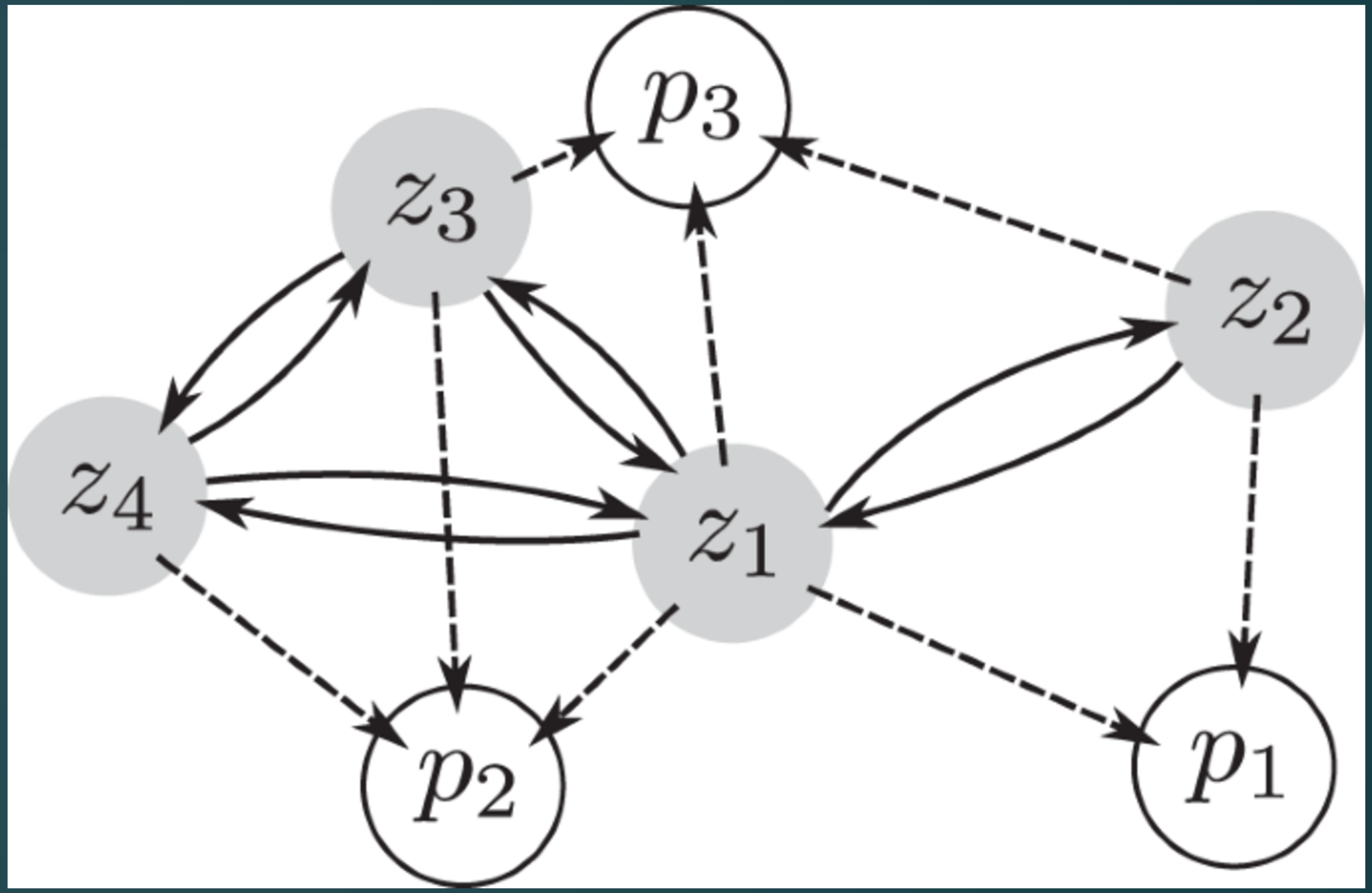
E(n)-Equivariant Graph Neural Networks are GNNs that are specifically designed to respect the symmetries of the E(n) group. This means they are capable of processing and making predictions on graph-structured data in a way that is consistent with the physical transformations that might be applied to the data.

Mechanisms in E(n)-Equivariant GNNs



Equivariant Message Passing

Equivariant Message Passing is a key concept in E(n)-Equivariant Graph Neural Networks (GNNs) that ensures the message passing mechanism—the process by which nodes in a graph exchange information—preserves the symmetries of the E(n) group.



Equivariant Linear Layers

Linear transformations designed to be equivariant, meaning they apply the same rules across the entire space.

Instead of a standard matrix multiplication, equivariant linear layers often use operations that are inherently equivariant. These might include:

- Dot Product.
- Cross Product.
- Norms.

Standard activation functions like ReLU, Sigmoid, or Tanh operate element-wise and do not inherently disrupt symmetry. However, to maintain equivariance, the functions must ensure that the relationship between features remains consistent under transformations.

Pooling Operations

Graph-Level Pooling: For graph classification tasks, pooling might be done across all nodes in the graph. In E(n)-Equivariant GNNs, the pooling function must combine the node features in a way that is independent of the graph's orientation in space.

Subgraph Pooling: Sometimes, pooling might be applied to specific subgraphs or neighborhoods within the larger graph. The pooling must ensure that the relative positions of nodes within the subgraph are preserved after transformation.

Summary

E(n) Equivariant Graph Neural Networks (GNNs) are designed to respect the symmetries in Euclidean space, ensuring that the model's outputs change predictably under transformations like rotations, translations, or reflections. This allows the model to generalize better to tasks involving geometric data, such as molecular structures or 3D objects, where spatial relationships are crucial.

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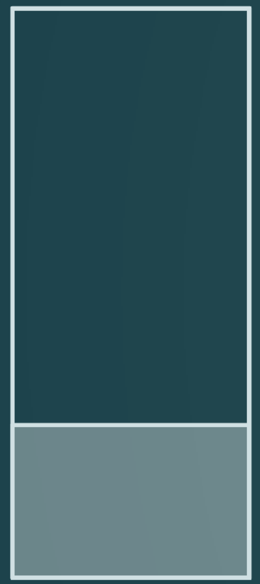
Our success

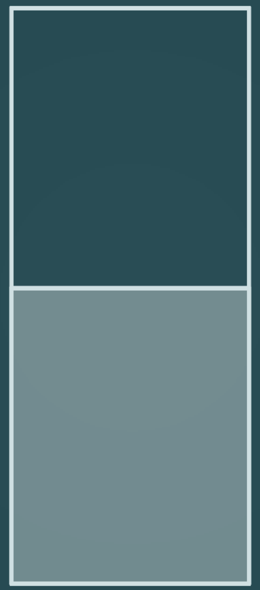
25%



Academic

Mercury is the closest planet to the Sun and the smallest of them all

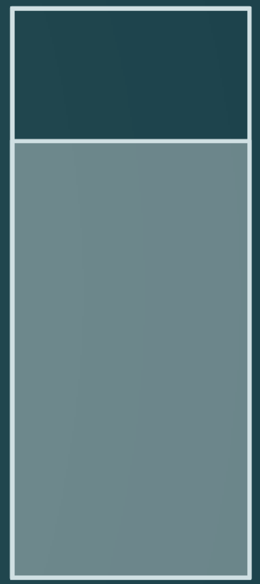
50%



Innovation

Venus has a beautiful name and is the second planet from the Sun

75%

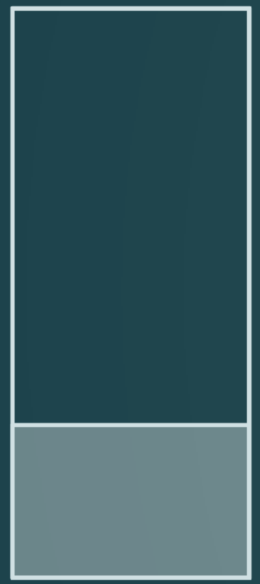


Attendance

Despite being red, Mars is actually a cold place. It’s full of iron oxide dust

Our success

25%



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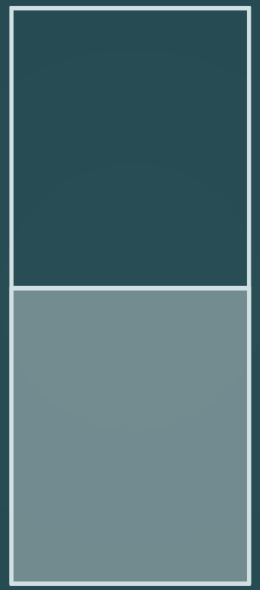

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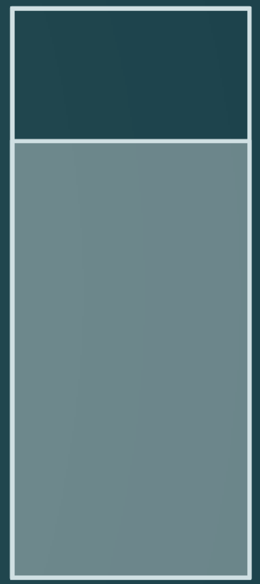

Attendance

Despite being red, Mars is actually a cold place. It’s full of iron oxide dust

Class progress

Mercury

Mercury is the closest planet to the Sun and the smallest one in the Solar System—it's only a bit larger than the Moon

Follow the link in the graph to modify its data and then paste the new one here. **For more info, click here**

Where are we located?

Mercury

Mercury is the closest planet to the Sun and the smallest one in the Solar System—it's only a bit larger than the satellite Moon

Our teachers

Sofia Hill

You can speak a bit about this person here

Kaliyah Harris

You can speak a bit about this person here

Our goals

	Mercury is the closest planet to the Sun
	Mars is actually a very cold place
	Venus is the second planet from the Sun
	Jupiter is the biggest planet of them all
	Saturn is composed of hydrogen and helium
	Neptune is the farthest planet from the Sun

Student progress

1st term

Assistance

Saturn is a gas giant and has several rings

Summary

Mercury is the closest planet to the Sun

2nd term

3rd term

Study

Despite being red, Mars is a cold planet

Test

Venus is the second planet from the Sun

4th term

Enrollment process

01

Venus is the second planet from the Sun

02

Despite being red, Mars is actually a cold place

03

Jupiter is the biggest planet of them all

04

Saturn is composed of hydrogen and helium

05

Neptune is the farthest planet from the Sun

Thanks!

Do you have any questions?

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